Pattern-Based Automatic Induction of Domain Adapted Resources for Social Media Analysis

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Abstract

In this dissertation, we analyze different aspects of the language used in texts published along different social media, and we propose a set of methods for the automatic extraction of polar adjectives as well as for the automatic classification of these texts.

First of all, we propose a new classification of polar adjectives according to their lexical features, based on a case study.

Secondly, we implement a new domain adaptable system for the automatic extraction of polar adjectives (along with their polarity values), reducing the use of external language resources.

Finally, we propose two automatic classifiers (one rule-based and one based on Decision Trees) to identify documents belonging to different stages of the purchase process and texts that analyze different aspects of the product.

Resumen

En esta tesis, analizamos diferentes aspectos del lenguaje utilizado en los textos publicados en diferentes medios sociales y proponemos una serie de métodos para la extracción automática de adjetivos de opinión, así como para la clasificación automática de dichos textos.

En primer lugar, proponemos una nueva clasificación de los adjetivos de opinión de acuerdo con sus características léxicas, basada en un estudio de caso.

En segundo lugar, implementamos un nuevo sistema de extracción automática de adjetivos de opinión (junto con sus valores de polaridad), adaptable al dominio y que reduce el uso de recursos lingüisticos externos.

Finalmente, proponemos dos clasificadores automáticos (uno basado en reglas y otro basados en árboles de decisión) para identificar textos pertenecientes a distintas fases del proceso de compra y textos que analizan diferentes aspectos del producto.

Resum

En aquesta tesi, analitzem diferents aspectes del llenguatge utilitzat en els textos publicats en diferents mitjans socials i proposem una sèrie de mètodes per a l'extracció automàtica d'adjectius d'opinió així com per a la classificació automàtica d'aquests textos.

En primer lloc, proposem una nova classificació dels adjectius d'opinió, basada en un estudi de cas, més d'acord amb les seves característiques lèxiques.

En segon lloc, vam implementar un nou sistema d'extracció automàtica d'adjectius d'opinió (juntament amb els seus valors de polaritat), adaptable al domini i que reduce l'ús de recursos lingüístics externs.

Finalment, proposem dos classificadors automàtics (un basat en regles i un altre basats en arbres de decisió) per identificar textos que pertanyen a diferents fases del procés de compra i textos que analitzen diferents aspectes del producte.

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Chapter 1

INTRODUCTION

The terms “Sentiment Analysis” and “Opinion Mining” were officially coined in the same year, 2003, by Nasukawa and Yi (2003) [1] and Dave et al. (2003) [2], respectively. In Nasukawa and Yi, we can find the main objective of Sentiment Analysis shared by all the works in this field, included the present work.

> *The essential issues on Sentiment Analysis are to identify how sentiments are expressed in texts and whether the expressions indicate positive (favorable) or negative (unfavorable) opinions towards a subject.*

Nevertheless, research on the expression of subjectivity in natural language was not new, but it had started many years before.

From the 50’s to 80’s of the 20th century, several works on Psychology and Linguistics already studied the main features of the meaning and expression of subjectivity and evaluative language. Works such as Osgood et al. (1957) [3], Lehrer (1974) [4], Fillmore (1974) [5], Battistella (1990) [6], Lyons (1997) [7], or Boucher and Osgood (1969)[8], among many others, analyzed to a greater or lesser extent, this specific type of language used to express our private states. Actually, in 1957, Osgood et al. [3] posed a new definition of meaning that not only took into account the referential features of the sign, but it included the emotive response of humans to different signs. It is precisely this emotive response or evaluative factor of the meaning which some authors will call then “*semantic ori-*

entation" or "*polarity*", a basic term on Sentiment Analysis and one of the main topics of this dissertation.

Later, already in the 90's, a lot of works appeared studying the expression of different types of subjectivity. Within these early subjectivity studies, the works carried out by Wiebe (1900, 1994) [9, 10] and different authors [11, 12] are the most relevant and constitute the very first works on the field of Sentiment Analysis as such. These early works, following the methodologies used in similar fields, such as Information Extraction, started to annotate corpora with opinion indicators and to develop algorithms based on linguistic cues to automatically discriminate between objective and subjective sentences or documents. However, at this time, the quantity of documents to work with was still small and they had to focus their efforts mainly on the opinion sections of the newspapers or in the expression of subjectivity in narrative.

It is not until the year 2000, when industries and researchers start to glimpse the real possibilities of this area. Internet gets to the majority of our homes and everybody starts to express his/her opinions everywhere in the net. The proliferation of social media, such as social networks, blogs, microblogs, etc., where the users write all their likes and dislikes about everything in the world caused a huge increase in the number of available texts.

From that moment on, the goal of the field, more than carrying out theoretical studies about the differences between subjective and objective contents, began to be how to properly identify and summarize the opinions or sentiments of the users about the products, services or even people reviewed. The increasing availability of user-generated documents opened new research questions where the lack of materials to analyze was not a problem anymore but, at the same time, posed new challenges.

Millions of opinions about millions of products, people, or events are published every day. Currently, marketing departments of almost every company wants to efficiently manage all this information in order to develop their commercial strategies, personalize campaigns to their consumers, or improve their customer services. Therefore, they need new systems to extract relevant information from this large quantity of noisy user-generated documents as well as doing it in real time.

Although, at the beginning of the field, the tendency was to automatically classify entire documents depending on the predominant opinion conveyed in them, the investigation quickly started to go deeply on more fine-grained analysis of the texts. Document classification into positive or negative categories gave a brief summary of the user's opinion but customers and companies asked for more detailed information. Nowadays, marketers and, even customers that search for information about some products, want to have, not just a general vision of the customer's opinion about the product, but a very detailed description of which are the more and less appreciated features of it and the reasons for these specific judgments.

Current research on Sentiment Analysis is basically based on two main needs: accuracy and speed.

On the one hand, Sentiment Analysis needs accuracy because the use of this new "social networks' language" implies that the analysis of user's messages should be much more fine-grained than before. For example, we need to know the different orthographic variants of a word and/or the changes in its semantic orientation when it is used in one domain or another. Current Opinion Mining systems often suffer from low accuracy, since they usually put these specific aspects aside.

On the other hand, Sentiment Analysis needs speed because marketers want to know the opinion of users today and start running their commercial strategies based on them just tomorrow. Customers' reactions can become viral in few hours and companies want to be aware of them and design their action plans as soon as possible. For this reason, being capable to develop opinion mining systems quickly, without a great efforts of time and human resources, is a key point in the development of any system of this type.

The new types of documents analyzed, written by non-expert writers, differ a lot from those previously analyzed at the beginnings of the field, such as opinion sections of newspapers or magazines, or expressions of character's point of view in narrative. That were written by professional journalists or writers and followed specific types of textual structures. Currently, however, the research on Sentiment Analysis has to deal with linguistic issues at all levels (orthographic but also syntactic, semantic, or pragmatic), such as the use of slang words, emoticons, abbreviations or a dramatic reduction on the length of these kind of messages, among many other new issues. Changes in the language due to the appearance of certain social networks such as Twitter, where the user's messages are limited to 140 characters, or the massive use of electronical devices such as smartphones are one of the key issues in the analysis of these kinds of contents, revised by the main shared tasks on the field in the last years [13, 14].

The weight of the lexicon, even in these first attempts to classify entire documents by their main opinion, plays a crucial role in the development of systems capable of automatically summarizing the likes and dislikes of users. All the Sentiment Analysis or Opinion Mining algorithms used from then on are based, to a greater or lesser extent, on the information provided by lexical items. Counting positive and negative words to assess the general opinion of the texts, utilizing polarity lexicons to initialize the algorithms, or using specific lexical units as features in machine learning methods, all the current Sentiment Analysis research is based on lexical items.

Nowadays, the great majority of the systems on Sentiment Analysis are based on the use of *sentiment* or *polarity lexicons*, that is, extensive lists of words with information regarding the sentiment or opinion they convey (positive, negative or, in some cases, neutral). Some of them are publically available and were extensively used by a lot of works in this field until that moment. General Inquirer lexicon[1] [15], Sentiment lexicon[2] [16], MPQA subjectivity lexicon[3] [17], SentiWordNet[4] [18], or Emotion lexicon[5] [19] are the most used and well-known.

Although they size of these dictionaries is big (all of them have more than 5,000 entries), and some of them work for several languages apart from English, none of them takes into account variations across domains or contexts, nor includes slang or misspelled words (very common in the type of documents analyzed). This fact implies an important loss both in terms of accuracy, since the polarity or sentiment will be incorrectly assigned to some domain dependent words, and coverage, because all the slang or misspelled words will not be taken into

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[1] http://www.wjh.harvard.edu/ inquirer/spreadsheet_guide.htm
[2] http://www.cs.uic.edu/ liub/FBS/sentiment-analysis.html
[3] http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/
[4] http://sentiwordnet.isti.cnr.it/
[5] http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

account, even if they are polar.

We started our investigation measuring the importance of intra- and inter-domain polarity variations. This aspect, often overlooked in the works on the field, is closely related to the accuracy desired on Sentiment Analysis commented above. Revising the literature and the systems developed on the field, we realized that usually the used polarity lexicons were too general and omitted evident polarity changes suffered by polar words depending on the domains or contexts where they were being used. The omission of this lexical feature causes scalability and accuracy problems when the developed Sentiment Analysis systems want to be used in new domains, as well as a reduction in the coverage, since many words are not analyzed because they are not in the polarity lexicon. We carried out a case study to analyze to what extent these type of domain variations affected polar adjectives.

Secondly, taking into account the results achieved in the previous case study and the issues on the manual or general dictionary-based creation of sentiment dictionaries, we approached the automatic creation of polarity lexicons. We wanted to identify and extract polar words fast, avoiding the use of external language resources, and considering polarity variations across domains. Therefore, we developed a simple bootstrapping algorithm to automatically identify, extract and tag polar adjectives along with their polarity, as well as capable of identifying slang words and misspelled adjectives as polar elements.

Finally, we demonstrated the importance of the lexicon and specific linguistic structures in the development of real world information extraction algorithms through the complete implementation of two industrial systems primarily based on linguistic rules and Decision Trees. These rules include domain dependent, misspelled and slang polar words. Additionally, the real world systems created are capable to classify the customers' comments into different stages of the purchase process and to discover which of a set of topics the customer is talking about.

1.1 General Hypotheses

In this dissertation we explored the following hypotheses:

1. The polarity of a great majority of adjectives entirely depends on the domain where these lexical items are applied, that is, a great majority of adjectives are domain dependent. Additionally, there are a set of adjectives whose polarity can not be assigned *a priori* since it entirely depends on specific writer/speaker's point of view, varying even when they are used within the same domain.

2. It is possible to automatically induce domain polarity lexicons able to distinguish positive and negative from highly subjective adjectives (i.e. adjectives with intra-domain polarity variations) as well as including slang and misspelled words only based on a set of linguistic patterns.

3. Linguistic patterns and specific lexical units provide enough information to develop an industrial Social Media Analysis system with good results in terms of precision and recall.

1.2 Outline

The path we take in this dissertation is the following.

In Chapter 2, we present the study we conducted to assess to what extent polarity variations of polar adjectives were relevant or not. Along this chapter, we propose a new classification of adjectives according to their dependency or independency of the domain and to their intra-domain polarity variations.

Then, in Chapter 3, we describe the bootstrapping algorithm created in order to automatically induce polarity lexicons, we evaluate it and finally, present the results achieved by the algorithm.

Chapter 4 presents the industrial Social Media Analysis systems developed using linguistic patterns and relevant lexical items, their evaluation for Spanish and English and an analysis of the errors.

In Chapter 5, we describe the main contributions achieved with this work and other achievements reached during the PhD studies.

Finally, in Chapter 6 we pose the main conclusion of this dissertation and discuss different directions for future work.

Chapter 2

EXPLORING POLARITY VARIATIONS OF OPINION-BEARING ADJECTIVES

As we stated in the introduction of this dissertation, any Sentiment Analysis or Opinion Mining current application is based, to a greater or lesser extent, on the words and phrases that writers/speakers use to convey positive or negative sentiments towards a subject. These type of lexical elements, instrumental for tasks on Sentiment Analysis, appear in the literature under different names, such as *polar words*, *sentiment words*, *opinion words*, or *opinion-bearing words*.

All the polar words have a *polarity* or *semantic orientation* that can be positive or negative (to some approaches even neutral) depending on if they are used to express positive or negative opinions. Some examples of polar words with positive polarity are "nice", "good" or "excellent" whereas some negative ones can be "horrible", "bad" or "abysmal".

These sentiment words are collected in *sentiment* or *polarity lexicons* along with their corresponding polarity, in order to being used as basic information by different opinion mining algorithms. Polarity lexicons can include words pertaining to any morphological category, since the opinion can be expressed using different types of words, as we can see in the following examples[1] .

(1) *Apple is doing very* <u>*well*</u> *in this* <u>*lousy*</u> *economy*.

(2) *This camera* <u>*sucks*</u>*.*

(3) *Although the service is not that* <u>*great,*</u> *I still* <u>*love*</u> *this restaurant.*

In all the examples above, we underlined the words that play a role in the expression of the opinion. As we can observe, the opinion can be conveyed through adverbs ("well"), adjectives ("lousy") or even verbs ("love").

In any case, as previous works on subjectivity, such as Bruce and Wiebe (1999) [12], establishes, the probability that a sentence is subjective, simply given that there is at least one adjective in it, is 55.8%, even though there are more objective than subjective sentences in the sample. Therefore, in the case study presented in this chapter, we decided to specifically explore the features of adjectives found in opinion documents due to their relevance in the expression of sentiments or opinions.

Specifically, revising the literature and because of our hands-on experience in the field, we could observe that many adjectives presented a particular feature that was not reflected in any of the polarity lexicons examined. We found that some adjectives changed their polarity depending on the domain where they were being used. For instance, "big" could be positive when talking about cars, but negative when talking about mobile phones. Moreover, we found that some adjectives suffered polarity variations even when they were used within the same domain. For example, an "antique" car could be positive for some people, but negative for others.

A great amount of Sentiment Analysis systems count the occurrence of positive and negative adjectives in opinion texts, based on one or several polarity lexicons, to decide about the general opinion of each document. If the number of positive elements is higher than negative ones, the document will have higher probabilities to express a positive opinion, and the same with negative words.

Current polarity lexicons, however, do not take into account the possible polarity changes suffered by some adjectives depending on the domain where they

[1] All the examples are extracted from Liu(2012) [20]

occur, assigning just one semantic orientation value to each word. This fact can cause serious mistakes in the assessment of the general opinion conveyed by the Sentiment Analysis applications based on them.

Taking in mind the aforementioned gap in the current polarity dictionaries, we wanted to study to what extent this feature affected the adjectives of a sample of opinion texts, in order to assess the relevance of the problem.

Therefore, in this chapter we explore the first of the three general hypotheses proposed in Section 1.1

> *The polarity of a great majority of adjectives entirely depends on the domain where these lexical items are applied, that is, a great majority of adjectives are domain dependent. Additionally, there are a set of adjectives whose polarity can not be a priori assigned since it entirely depends on specific writer/speaker's point of view varying even when they are used within the same domain.*

This chapter is organized as follows. In Section 2.1, we describe the corpus where adjectives were extracted from. Section 2.2 presents the annotation instructions given to the annotators and the training process. Section 2.3 analyses the annotations of our dataset of adjectives and proposes two new classifications of polar adjectives depending on whether they depend or not on the domain and on their intra-domain polarity variations. In Section 2.4, we present the inter-annotator agreement results. Finally, in Section 2.5, we close the chapter with the conclusions reached through this experiment.

2.1 Corpus

For this experiment, we collected three different corpora of around 300.000 words each. Documents gathered belong to three different domains (automotive industry, movies, and cell phones), and are written in Spanish (from different Spanish-speaking countries).

The type of selected documents were reviews where the users of some products revise their pros and cons and express general opinion about the analyzed

Figure 2.1: Example of a car review collected in the corpus.

products. The reason to choose this type of documents against other social media user-generated texts was that reviews are extensively analyzed by the majority of currently available industrial Sentiment Analysis applications. We selected these specific domains for the intrinsic differences among the products.

All the documents were extracted from Ciao [2], a website dedicated to aggregate product reviews written by consumers. We chose this website because it provides Spanish reviews and demands its authors a minimum of order, length and quality in their texts. In any case, as the great majority of user generated contents, the texts have many lexical, orthographic or grammatical mistakes.

An example of the reviews collected in our corpus is in Figure 2.1.

Additionally, we had to carry out a cleaning pre-process step in which we removed elements such as asterisks, hashes and every non-informative sign used by authors of the texts primarily to mark the different parts of their documents.

Although the number of texts of each corpus depends on the domain [3], we used an average of 130 documents per domain.

Apart from the raw texts where the users analyze the products, we have also gathered the overall rating given to the product as well as the pros and cons of it

[2] www.ciao.es

[3] Because the length of the documents varies depending on the domain. For example, movies reviews tend to be longer than those about cell phones

proposed by the author. This part can be understood as a brief summary of the general opinion about the product reviewed.

All the documents were part-of-speech tagged using Freeling POS tagger [21].

2.2 Dataset Annotation

As our primarily intention with this experiment was to analyze the possible polarity changes suffered by adjectives depending on the domain where they were used, we annotated all the texts with part-of-speech information and we identified the lemmas of those words tagged as adjectives. Then, we compared the lists of adjectives' lemmas of the three domains, and extracted only those appearing in the three domains in order to compare their semantic orientation values. We obtained a list of 514 adjectives used along the three domains of interest.

In order to study the variability or invariability of polarity values of adjectives across the three selected domains, five human annotators tagged them according to this specific semantic feature.

As our objective was to demonstrate variations on semantic orientation across domains, and not context polarity shifts, annotators should understand each adjective as applied to the entire domain. For example, if they found "aggressive", they should directly apply it to the domain, that is, they should tag "aggressive car", "aggressive cell phone", and "aggressive movie".

The specific annotation guidelines provided to human annotators were the following:

- *Negative.* The adjective should be tagged with "-1" if it is felt as expressing a negative feature regarding target product/domain.

- *Neutral.* The adjective should be tagged with "0" if it is felt as expressing irrelevant or not clear positive or negative feature regarding target product/-domain.

- *Positive.* The adjective should be tagged with "1" if it is felt as expressing a positive feature regarding target product/domain.

	Cars	Cell Phones	Movies
Aggressive	0,1,0,1,-1	0,0,0,0,0	0,0,0,0,1
Big	1,1,-1,1,0	-1,-1,-1,-1,-1	1,0,0,0,1
Heavy	-1,0,-1,-1,0	-1,-1,-1,-1,-1	-1,0,0,-1,-1
Amazing	1,1,1,1,1	1,1,1,1,1	1,1,1,1,1

Table 2.1: Examples of the annotation task

All of the human annotators had a high education level and were frequent users of review websites.

As annotator training, we organized an informative meeting to explain the task and answer doubts and questions related to it. After that, they practiced with a small set of adjectives and discussed some difficult cases. Only when we judged that annotators had a clear idea of the task, they started the tagging work.

Each annotator tagged 1542 adjectives, that is the common 514 for each domain.

As a result of this annotation task, we obtained three lists of 514 adjectives (one for each domain) with five polarity evaluations per adjective. Some examples of the annotation task are provided in Figure 2.1.

2.3 Dataset Analysis

In a very first look to the tagged data, we already confirmed a great variability in the human annotations; humans did not seem to achieve an agreement but for a small subset of all the annotated adjectives.

In order to know if different tagging of the same adjective actually indicated intra- or inter-domain polarity variability, or if they were instead the result of small disagreements among annotators, not affecting the global polarity of the adjective, we proceeded to analyze the annotations more in detail.

Our first aim was to estimate an average semantic orientation of each adjective from the different tags given by the annotators. Therefore, for every adjective in each domain, we calculated the arithmetic mean of the five values assigned by the

Domain	Annotation	Average Polarity
Cars	1, 1, 1, 1, 1	1
Cell Phones	1, 1, 1, 1, 1	1
Movies	1, 1, 1, 1, 1	1

Table 2.2: Polarity annotation of **"alucinante" ("amazing")** by five humans along the three domains

Domain	Annotation	Average Polarity
Cars	-1, -1, -1, -1, -1	-1
Cell Phones	-1, -1, -1, -1, -1	-1
Movies	-1, -1, -1, -1, -1	-1

Table 2.3: Polarity annotation of **"pésimo" ("abysmal")** by five humans along the three domains

humans (-1, 0, or +1). If the average score calculated was higher than 0, the word was considered as having a general tendency to be positive, whereas if the score was lower than 0, it was considered as being prone to be negative. Finally, if the score obtained was 0, the adjective will be considered as a neutral word. Some examples of average polarity calculated can be examined in Tables 2.2, 2.3 and 2.4.

In Tables 2.2 and 2.3, we can observe that actually there are some adjectives, such as "alucinante" ("amazing") and "pésimo" ("abysmal") whose semantic ori-

Domain	Annotation	Average Polarity
Cars	-1, -1, 1, -1, 1	-0.2
Cell Phones	-1, -1, -1, 0, 0	-0.6
Movies	0, 1, 1, 1, 1	0.8

Table 2.4: Polarity annotation of **"antiguo" ("antique")** by five humans along the three domains

Adjective	Annotation	Average Polarity
Horrible	-1, -1, -1, -1, -1	-1
Soso	-1, -1, 0, 0, 0	-0.4

Table 2.5: Comparison of average polarity values of **"horrible" ("awful")** and **"soso" ("dull")** in cars domain.

entation is the same along the three analyzed domains. All the five human annotators tagged these words always as positive or negative and, therefore, the average polarity is also +1 or -1. In these cases, polarity truly seems to be a constant value, intrinsic and easily identifiable in polar words, independently of the domain or context where they appear. These type of words could be accurately collected in a polarity lexicon, since their polarity values do not change from one domain to another (at least, along the domains analyzed here).

However, in Table 2.4, we can see an example of an adjective whose semantic orientation is not so obvious to human annotators. The polarity of "antiguo" ("antique") has not a clear value that annotators can easily infer. Actually, humans not only vary their values between polar (positive or negative) vs. neutral, but even give opposite semantic orientation values (positive vs. negative) within the same domain, as we can observe in the car domain.

In a first stage, the arithmetic mean was assessed for assessing the degree of positivity, negativity or neutrality of the proposed adjectives, and for having a general vision about the variability or invariability of prior polarity across the revised domains. For example, comparing average polarity of some adjectives within the same domain, we saw that an "awful car" is more negative (average polarity (A.P.) = -1) than a "dull car" (A.P. = -0.4), and also that a "beautiful cell phone" (A.P. = +1) is more positive than a "popular cell phone" (A.P. = +0.6). Moreover, with this assessment, we could see that humans annotators found a "big cell phone" very negative (A.P. = -1) whereas they though that a "big movie"[4] and a "big car" are positive (A.M. = +0.4). Tables 2.5, 2.6 and 2.7 provide detailed tagging of these examples.

[4]With the meaning of a "great movie"

Adjective	Annotation	Average Polarity
Bonito	1, 1, 1, 1, 1	1
Popular	1, 1, 0, 1, 0	0.6

Table 2.6: Comparison of average polarity values of **"bonito" ("beautiful")** and **"popular" ("popular")** in cell phones domain.

Domain	Annotation	Average Polarity
Cars	1, 1, -1, 1, 0	0.4
Cell Phones	-1, -1, -1, -1, -1	-1
Movies	1, 0, 0, 0, 1	0.4

Table 2.7: Comparison of average polarity values of **"grande" ("big")** along the three domains analyzed.

Simply with this procedure, we could demonstrate that polarity is not an inherent semantic feature that polar adjectives have independently of the context or domain, easily inferred by humans. On the contrary, only a set of the analyzed adjectives presented invariability.

Therefore, this first assessment, although naive, was useful to make a first approach to our first hypothesis. In fact, there is a group of adjectives whose inter- but also intra-domain semantic orientation is variable.

Although the arithmetic mean of the scores given by the annotators showed a general tendency of adjectives of having or not a constant semantic orientation, we found some examples of adjectives in our dataset whose tendency to be positive, negative or neutral was wrongly assigned using the arithmetic mean due to their high variability even within the same domain (i.e., intra-domain variability). For example, "convencional" ("conventional") had an A.P. = 0 in car and cell phone domains because it was tagged as positive (+1) by two annotators, negative (-1) by other two, and neutral (0) by the last one. Therefore, we should consider this adjective more positive and negative than neutral, such as the A.P value seemed to show. We found that 4.5% of the adjectives in our sample presented mistakes of this type due to the variability in their tags.

Because of cases like those mentioned above, and in order to precisely demonstrate that prior polarity is not always an *a priori* value easily inferred by humans, we needed a measure to assess not only the tendency of an adjective to be positive, negative or neutral (as we did with average polarity), but the divergence among the different polarity tags given by the annotators to the same entity in the same domain. Therefore, we decided to calculate the standard deviation of all the scores given to adjectives over all the domains and annotators. With this new value, we could observe the dispersion or unification degree of opinions regarding the value of the arithmetic mean, besides the tendency of adjectives to be in positive or negative side of the polar scale. For example, if three annotators considered an adjective as positive but the other two tagged the same element as negative, there will be much more dispersion than if the first three consider this lexical element as neutral instead of positive.

These dispersion values were calculated using the Equation 2.1.

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}} \tag{2.1}$$

where $\overline{x}$ is the arithmetic mean previously calculated, *n* is the number of tags for each adjective, and x_i is each tag given to the adjective.

Some examples of calculated standard deviation values are in Table 2.8. As we can observe, deviation in “alucinante” (“amazing”) is 0 since, as showed in Table 2.2, all the human annotators agreed in their tagging. However, with deviation values, we could also see the little agreement among humans in the annotation of “grande” (“big”)[5] and, specially, in the annotation of “antiguo” (“antique”). This last adjective presents not just a huge deviation among the tags within the different domains, but it also has different polarity from one domain to another.

The combination of these two metrics (average polarity and deviation of tags) allowed us to assess both the inter-domain and intra-domain polarity changes suffered by a set of adjectives extracted from reviews of three different domains.

On the one hand, we found adjectives such as those in Table 2.2 and Table 2.3 that were unanimously tagged by all the annotators as negative, positive or neutral respectively in all the three domains proposed. In these cases, the stan-

[5]Except in cell phones domain, where they agreed in their tags

Adjective	Cars	Cell Phones	Movies
Alucinante	0	0	0
Antiguo	1.09	0.54	0.44
Grande	0.89	0	0.54

Table 2.8: Examples of calculated deviation values for “alucinante” (“amazing”), “antiguo” (“antique”) and “grande” (“big”).

dard deviation of the tags is equals 0 among domains and therefore, these lexical units were considered ***domain independent*** adjectives, i. e., they do not change their inter-domain nor intra-domain polarity; they always have the same polarity independently of the domain.

Additionally, we discovered that from all these domain independent adjectives, 25.49% of them were unanimously tagged as neutral, 5.84% as negative and 1.36% as positive. Therefore, from all the sample analyzed, only 7% of adjectives can be precisely collected in a polarity lexicon along with their polarity, that is invariable along different domains [6].

On the other hand, we found a set of adjectives whose polarity tags changed across domains, that is, human annotators generally agreed in their polarity labels within the same domain but these adjectives can have different semantic orientation from one domain to another. The biggest variability depending on the domain were found in “estrecho” (“narrow”) and “pequeño” (“small”): positive for mobile phones, negative for cars, and neutral for films. Words in this group were considered as ***domain dependent*** adjectives.

Figures 2.2 and 2.3 show the distribution of domain dependent and domain independent adjectives in the sample analyzed. In Figure 2.3, we can also observe the polarity distribution of the domain independent adjectives.

As we can see in Figure 2.2, the number of domain dependent elements is actually more than a half of the sample analyzed. This proportion confirms the hypothesis proposed at the beginning of this chapter. Not all the adjectives have *a priori*, domain independent semantic orientation, but only less than the 40%

[6] At least, among domains revised in the present study

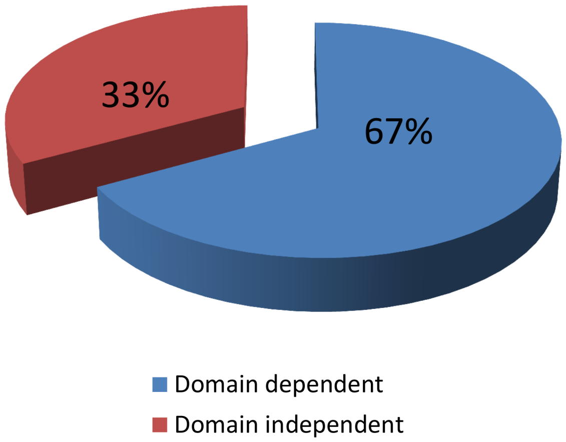


Figure 2.2: Proportion of domain dependent and independent adjectives

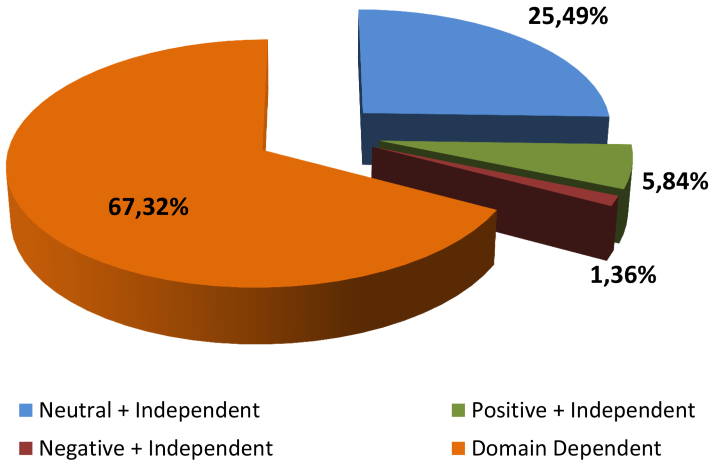


Figure 2.3: Proportion of domain dependent and independent adjectives with their corresponding polarity

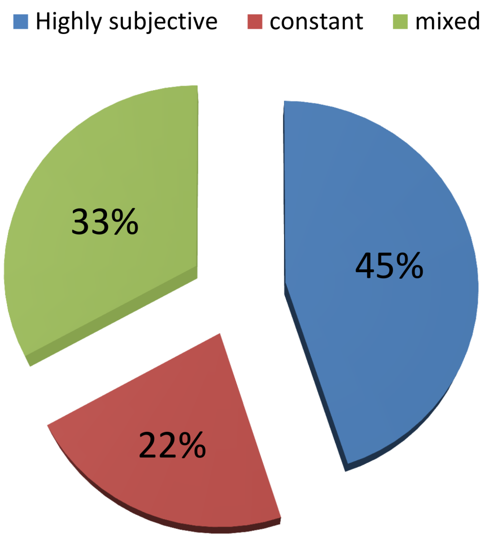


Figure 2.4: Proportion of constant, mixed and highly subjective adjectives

of adjectives analyzed actually showed this feature. In short, we can split polar adjectives in two types according to their dependence or independence of the context or domain where they appear: domain dependent and domain independent adjectives.

However, the assessment of standard deviation of the tags not only provided enough information to split our adjectives into domain dependent and domain independent adjectives, but also gave to us enough information to make a more fine-grained division of our adjectives. We found out that, according to the tagging provided by our annotators, we could split the set of adjectives in three categories instead of only two: highly subjective adjectives, mixed adjectives and constant adjectives. The proportion of each category can be examined in Figure 2.4.

Highly subjective adjectives are those adjectives that have a high or very high standard deviation value in all the domains. This fact highlights the wide range of opinions about some adjectives from one annotator to another. They are very subjective elements, there is no agreement about their annotation and their polarity entirely depend on the personal point of view of each annotator. For example, “antiguo” (“antique”).

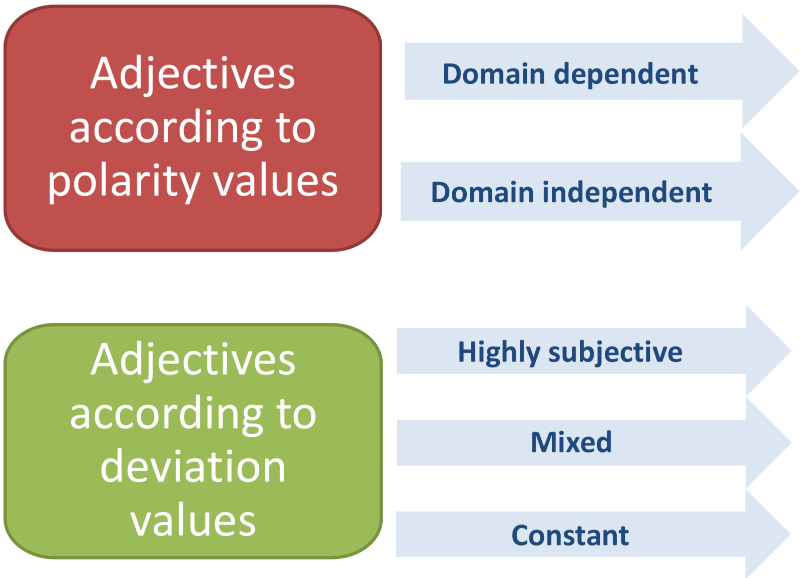


Figure 2.5: Proposed classification of adjectives

In the ***mixed adjectives*** group there are units with high standard deviation values, or very high standard deviation values for a domain but no deviation for other domain(s). These units are, obviously, domain dependent: in some cases, adjectives show a high subjective degree (that is, annotators do not reach an agreement about its polarity) and in other cases, the polarity of the adjective is clearly identified. An example is “agresivo” (“aggressive”) that has a deviation of 0.88 and 0.44 in the cars and movies domains, respectively, but it has total agreement in the cell phones domain.

The last group is made up of ***constant polarity adjectives***, that is, adjectives whose standard deviation value is always 0. In other words, annotators give the same tags in the same domains. Adjectives in this group can be precisely used in polarity lexicons of the domains analyzed but not in other domains, since it can have no deviation at all but a change in the polarity.

An overview of the proposed classification of adjectives is in Figure 2.5

Kappa	Description
< 0.00	Less than chance agreement
0.01-0.20	Slight agreement
0.21-0.40	Fair agreement
0.41-0.60	Moderate agreement
0.61-0.80	Substantial agreement
0.81-0.99	Almost perfect agreement

Table 2.9: Landis and Koch (1977) benchmark scale for Kappa.

2.4 Agreement Study

In order to measure the inter-annotator agreement, we used the Kappa statistics [22]. Kappa, *k*, is defined as follows

$$k = \frac{p_a - p_e}{1 - p_e} \tag{2.2}$$

where p_a denotes the relative observed agreement for the annotators, and p_e is the hypothetical probability of a chance agreement.

We chose the variant of Kappa statistic proposed by Fleiss (2004) [23] since it allows the metric to be calculated for a fixed number of annotators (Cohen's kappa [24] limits the number of raters to two). Several benchmark scales to interpret kappa were developed. One of the most well-know, followed in this work, was proposed by Landis and Koch (1977) [25]. The guidelines for interpreting kappa results are in Table 2.9.

The results of the Kappa's assessment for our annotators were 0.59 for the annotations of adjectives in the automotive industry and cell phones domains, and 0.51 for the annotation of adjectives from movie reviews. Following the table by Landis and Koch, we achieved a moderate agreement. However, if we follow the interpretation of kappa proposed by Krippendorff (2004)[26], which is an adopted standard in the NLP community, our results are far from the 0.67, required for drawing tentative conclusions.

Far from understanding these results as disappointing, we found that they were the direct consequence of the high degree of subjectivity of adjectives analyzed, demonstrated through the proportion of domain dependent adjectives presented in the last section. We also found that this high degree of subjectivity in the annotation of polar adjectives is even higher in domains such as movies reviews, where humans shortly surpass the .50 of agreement.

Theses results were a clear evidence of the difficulties in the assignment of a unique prior polarity to lexical elements that are inherently subjective and whose polarity depends, to a large extent, on the context or domain where they are applied.

Moreover, the agreement results obtained here are in line with those obtained in other works such as Andreevskaia and Bergler (2006)[27]. These authors see the disagreement between the annotators not necessarily as a quality problem in human annotation but rather as a structural property of this semantic category. They approach the category of sentiment words as a set of fuzzy classes: there are some words more prototypical or central such as "bad" and "good", but there are less prototypical polar words that may be understood differently by different people. This is exactly the fact that we empirically proved with the work carried out in this chapter.

2.5 Conclusions

In the development process of the great majority of current Sentiment Analysis systems, one or several polarity lexicons are used. These lexical resources provide huge lists of keywords as well as the opinion (i.e., polarity) they express. In short, all these polar words, along with their polarity values, are the key and basic element used to initialize complex Sentiment Analysis algorithms capable to extract fine-grained summaries from millions of user-generated, non-structured documents.

Polar words, instrumental for Sentiment Analysis, play a crucial role in the final identification of opinion conveyed in texts, therefore, high accuracy of polarity lexicons turns into higher accuracy of these specific types of information extraction systems.

Revision of the literature in the field and personal hands-on in several Sentiment Analysis projects showed us a big shortcoming in all the current and extensively used polarity lexicons developed so far. None of the current polarity lexicons, created by following different approaches (revised in more detailed in the next section), took into account any polarity modification due to different uses of polar adjectives across different domains.

As speakers, we are aware of the existence of some adjectives, such as "long" and "quiet" in the following examples, whose polarity changes depending on the domain where they are applied.

(4a) *The battery life is long.*

(4b) *This camera takes a long time to focus.*

(5a) *This car is very quiet.*

(5b) *The audio system in the car is very quiet.*

We know that "long" and "quite" in (a) are being used as positive features of the products, whereas in (b) they express negative opinions.

The hypothesis of our investigation was, then, to demonstrate that the number of adjectives with this feature (i.e., polarity variation depending on the domain) was bigger than those that do not present these changes.

Therefore, the main aim of the research presented here was to analyze what was the real proportion of adjectives whose polarity varies depending on the domain. This assessment could help us to decide to what extent this specific lexical feature was important and it should be reflected in the polarity lexicons or, on the contrary, if it was not relevant enough to be considered in the construction of these lexical resources.

In this work, we came to the conclusion that polarity variations depending on the domain have a high impact specifically for adjectives, after the comparison of polarity values assigned by five human annotators to 514 adjectives across three different domains (cars, cell phones, and movies). We proved that more than a half of these adjectives (67%) actually have a domain dependent polarity, that is, polarity changes from one domain to another. Moreover, after this experiment we concluded that, for some adjectives, humans showed very low agreement in what seems to be a phenomenon related to the high subjectivity of some of the adjectives analyzed. These particular adjectives suffered polarity changes not only from one domain to another, but also within the same domain.

By analyzing polarity variations from one domain to another, we could split adjectives into *domain dependent* and *domain independent*, finding out that only 33% of the revised adjectives actually have invariable polarity. Moreover, by analyzing deviation on the polarity values assigned by human annotators, we could classify target adjectives in three different categories: *constant*, *mixed*, and *highly subjective* adjectives. Elements collected within the last category (i.e. highly subjective adjectives) suffer from polarity variations even when they are used in the same domain; their polarity entirely depends on the point of view of the speaker/writer.

As demonstrated in this experiment, the high impact of domain polarity variation of particular adjectives is a crucial feature to take into account in the development of polarity lexicons. Nowadays, the number of domains to analyze is always increasing, therefore the inclusion of these feature in the polarity dictionaries could mean a great improvement in terms of precision and scalability, being possible to adapt the sentiment analysis tools to specific and new domains without suffering precision losses.

We are very aware that including these new features in polarity lexicons will increase the complexity of these type of lexical resources, that should be adapted to each domain, as well as their development process. Therefore, new methodologies for the automatic induction of sentiment dictionaries should be designed in order to create more precise and domain-dependent polarity lexicons. In the next chapter, we will propose a methodology that takes into account the new features investigated here.

Chapter 3

EXTRACTING POLAR ADJECTIVES FOR AUTOMATIC CREATION OF POLARITY LEXICONS

As commented in the past chapters, polar words are instrumental for Sentiment Analysis. Currently, the use of one or more polarity lexicons in the development of any Sentiment Analysis application is practically mandatory. For this reason, developing methodologies to quickly create precise polarity lexicons, adaptable to new domains, is a crucial aim in order to improve the final results of the entire Sentiment Analysis systems.

The results obtained in the case study presented in Chapter 2 demonstrated that a majority of adjectives suffer from polarity variations when used across different domains. This feature, however, is not reflected in any of the most well-known and broadly used polarity dictionaries so far.

Thanks to our case study, we also knew that there is a polar adjectives' feature even more important than polarity variability across domains; we discovered that the 55%[1] of the adjectives we analyzed present polarity variations even within the same domain. The polarity of these lexical elements entirely depends on writer/s-

[1]Constant plus highly subjective adjectives

peaker's point of view.

Taking into account this huge variability on the adjectives' polarity, we found that current polarity lexicons had serious failures both in terms of coverage and accuracy. Coverage because, if they only collect domain independent adjectives, the systems developed from them will ignore important information provided by the rest of polar adjectives used in the document. Accuracy because, even including variable polarity adjectives, they are not correctly tagged according to all their possible uses, introducing noise and incorrect polarity assignments.

Additionally, we found that even nowadays a great number of methodologies on polarity dictionaries creation continue to be based on manual tagging or other language resources which might not be available for many languages. Moreover, human annotation implies a huge effort in terms of time and human resources.

In a field such as Sentiment Analysis, that is continuously changing, evolving concurrently as the new uses of Internet, responding rapidly to changes is a crucial issue to take into account. Marketers and users want answers and summaries about an every day larger amount of topics, and this field should adapt its methods to these new needs.

Therefore, automation in the creation of polarity lexicons is crucial in order to reduce time and human resources in the development of the entire Sentiment Analysis applications. As we commented before, almost every current industrial or academic tool whose final goal is to summarize the opinion conveyed in a text does make use of these sets of polar words collected in polarity dictionaries. Automation in the creation of these language resources would drastically reduce development effort and time since human annotators and reviewers would be not needed (except for, maybe, some final checks).

Additionally, the incorporation of more fine-grained categories (beyond the classic positive vs. negative), taking into account the specific features of some adjectives (as polarity variations inter- and intra-domain), allows to induce more robust and reliable lexicons, with less mistakes getting to the next steps of the sentiment analysis.

In this chapter we present an algorithm based on linguistic cues that automatically discovers, extracts and labels polar adjectives (including slang and misspelled forms) as well as adjectives with intra-domain polarity variations (i.e.

highly subjective adjectives, as proposed in Chapter 2). The method proposed is corpus-based and only uses a part-of-speech tagger as external language resource.

The algorithm examined through this chapter allow us to demonstrate our second hypothesis, as proposed in Section 1.1.

> *It is possible to automatically induce domain polarity lexicons able to distinguish positive and negative from highly subjective adjectives (i.e. adjectives with intra-domain polarity variations) as well as including slang and misspelled words only based on a set of linguistic patterns.*

The remainder of this chapter is organized as follows. Section 3.1 revises the main approaches followed in the induction of polarity lexicons: manual, dictionary-based and corpus-based approaches. In Section 3.2, firstly we describe the bootstrapping algorithm proposed for the automatic creation of domain polarity dictionaries and then, we analyze the results of the obtained evaluation against a Gold Standard created for that. Finally, Section 3.3 closes the chapter and presents some conclusions about the method suggested in this work.

3.1 Related Work

Research on the automatic induction of polarity lexicons starts in the early 2000 as an evolution of the automatic creation of semantic lexicons traditionally used in Information Extraction works [28] [29] [30] [31] [32] [33]. These semantic lexicons were huge lists of words annotated along with their corresponding semantic class and they were used together with dictionaries of extraction patterns in almost every Information Extraction system. However, once the factual information extraction systems achieved great results a new challenge was posed: how to extract subjective information. In order to tackle this problem, the researchers started to develop similar resources adapted to this new task: polarity or sentiment lexicons.

In the next subsections, we will review the main approaches followed by researchers on the creation of this specific type of language resource. There are three main approaches to create polarity lexicons: manual, dictionary-based, and corpus-based.

3.1.1 Manually Created Sentiment Lexicons

There are a small set of works on Sentiment Analysis where authors totally or partially compiled lists of opinion words by hand, however this task is very time consuming and need great human efforts.

The precision of these dictionaries ought to be high since they were compiled and revised by human annotators but, in fact, they are usually error-prone and their coverage is limited due to the task inherent difficulties: time and human efforts for the compilation process. Generally, they have been used in combination with other automatic or semi-automatic approaches as the final check to compare the results obtained by automatic means. To our knowledge all of them are created as general dictionaries, without taking into consideration any inter- or intra-domain polarity variations.

The most early and well-known example of this approach is the General Inquirer [15]. This fully hand-crafted lexicon, although not specifically developed for Sentiment Analysis but for more general content analysis tasks, includes sets of words annotated with respect to Osgood's factors [3] of the affective or emotional meaning: evaluative factor (e.g., good-bad), potency factor (e.g., strong-weak) and activity factor (e.g., active-passive). There are 2,399 positive and 2,877 negative words for evaluative factor; 1,474 strong and 647 weak for the potency factor; and 1,568 active and 732 passive words for the activity factor. It does not contain neutral words. This lexicon has been used in a lot of works on Sentiment Analysis as a reliable resource to evaluate automatic methods as well as basic list of polarity words from which implementing complex sentiment analysis tools and classifiers.

Another broadly used list of subjective lexical items, specially in the early works on Sentiment Analysis, is the Levin's compilation of *desire* verbs [34]. Again, as General Inquirer, this lexical resource was not directly created for Opinion Mining purposes, but we want to cite it here because of its importance in the early works on the field.

Finally, a more recent example of fully manually created sentiment lexicon was carried out by Taboada et al. (2011) [35] where the authors manually labeled lists of adjectives (2252), nouns (1142), verbs (903) and adverbs (745) along with their prior polarity values using a -5/+5 scale. They used this polarity lexicon in a system called SO-CAL (Semantic Orientation CALculator) that classifies texts as positive or negative based on the contained polar words (and also valence shifters and negations). They evaluated the prior polarity tags assigned to a set of adjectives from their lexicon comparing them to those gave by six human annotators. They discovered low rates of pairwise agreement, specially between neutral vs positive and negative tags. This fact highlights the difficulty of the task without taking into account the domain or context where the words are applied, a general limitation of works that follow manual as well as, further commented below, dictionary-based approaches.

3.1.2 Dictionary-Based Polarity Lexicons

Dictionary-based approach utilizes external language resources such as lexicons and thesaurus which, although not always containing polarity information, help to increase the number of lexical elements from an initial set of opinion words by different methods. The most used lexical resource in works that follow this procedure is WordNet [36].

Hu and Liu (2004)[16] presented one of the first attempts of building an aspect-based summarization system to automatically summarize product reviews based on the features of the item analyzed by the customer. As the first step of this summarization process, they built a small set of seed adjectives whose semantic orientation is known and suggested a method to automatically add more items to this list by looking for the synonyms and antonyms of the seed elements in WordNet. Their hypothesis is that the synonyms of an adjective will have the same semantic orientation that it, whereas its antonyms will have the opposite one. Therefore, they run a bootstrapping algorithm that iteratively looks for synonyms and antonyms of each seed adjective and adds their corresponding semantic orientation following that hypothesis. The method is correct in cases where the word has only synonyms and antonyms with the same semantic orientations, however it does not take into account polarity variations within the same synset. Additionally, as all the dictionary-based works, it is not capable of finding adjectives that are not in this language resource, losing thus a lot of information that could be useful.

Another aspect-based summarization system is presented in Blair-Goldensohn et al. (2008) [37] where the authors follow the same hypothesis of Hu and Liu but enriching it with a confidence measure for each polar word. The lexicon construction process is, as in Hu and Liu, only a single step of the entire summarization system proposed.

Another example of this approach is the work by Kim and Hovy (2004) [38]. The authors also follow the same hypothesis than Hu and Liu (the synonyms of a positive seed word will be positive and their antonyms will have a negative polarity), and go beyond, also calculating the sentiment strength of each adjective using a probabilistic method. In this work, the authors also analyze some of the problems found in word's polarity classification task. One of them is that no all the synonyms and antonyms can be used since some of them have both strong positive and negative polarity, a feature that only can be resolve by taking into account the context where these lexical items appear. Some years later, the same authors presented another work [39] based on the same hypothesis but improved with a Bayesian formula to choose the most probable class and not simply all the synonyms and antonyms of the seed words. Unfortunately, although the results in the identification of neutral elements were encouraging, the performance achieved in the extraction of negative and, specially, positive words continued to be very low.

Works by Valitutti et al. (2004) [40] and Strapparava and Valitutti (2004) [41] manually enriched a set of WordNet synsets with affective labels in order to encode concept affective meaning. This subset of WordNet synsets representing affective concepts along with their corresponding affective labels conforms the WORDNET-AFFECT, a language resource for the lexical representation of affective knowledge. The approach of this work, even if it is based on Wordnet for creating a new emotion language resource, is completely developed by hand, therefore it is in a kind of borderline between manual and dictionary-based approaches.

The work carried out by Kamps et al. (2004) [42] to automatically find the semantic orientation of polar adjectives is also based on WordNet. In this case, the distance or similarity between words is used, instead of the different lexical relations established in this lexical resource. The authors used a function that measures the relative distance d of a term t to the two reference words "good" and "bad" within an interval from -1 to +1, in order to know the semantic orientation of the adjective as well as the strength of the sentiment (i.e., SO(t) = (d(t,bad) - d(t, good)) / d(good/bad). The idea of measuring the degree of positivity and negativity of a word based on the distance from the paradigmatic words "good" and "bad" is also developed in other dictionary-based works such as Turney and Littman (2003) [43], further commented in Section 3.1.3.

Rao and Ravichandran (2009) [44] proposed a semi-supervised label propagation method for the automatic induction of polarity lexicons. Their method uses WordNet (it can be used also with other lexical resources such as OpenOffice thesaurus, for example) as a graph, and some lexical relations are exploited, specifically synonymy and hypernymy. The proposed method is compared with those presented by Kim and Hovy (2004) and Kamps et al. (2004), showing that graph-based semi-supervised methods significantly improve results. The work actually obtained good results (they achieved a F-1 of about 85% on the extraction of adjectives), but it only considers words appeared in General Inquirer that also occur in WordNet, therefore the real recall of the method is biased. Additionally, it does not take into account the actual polarity variation among domains.

Mohammad et al. (2009) [45] presented a complete methodology to automatically create sentiment lexicons. In this case, the authors prefer to use a Roget-like thesaurus (specifically, the MacQuarie Thesaurus), instead of WordNet, along with a handful of antonym affix patterns (such as "honest-dishonest"). The idea is similar to previous works: words in the same subset of the thesaurus will have the same prior polarity. They evaluated their methodology intrinsically as well as extrinsically. As intrinsic evaluation, they compared the resulting lexicon against the high-coverage lexicon SentiWordNet [46] [18] [47], finding theirs has 14% more correct entries. As extrinsic assessment, they created a very simple sentiment analysis algorithm, and compared the results of using their lexicon with others sentiment lexicons such as Pittsburg Sentiment Lexicon [17], SentiWordNet and the lexicon developed by Turney and Littman (2003) [43]. The authors highlight the importance of errors due to the use of affix patterns, that not always instantiate antonym pairs (e.g., "immigrate-migrate") and also mistakes due to the fact that words in the same group may actually have different semantic orientation (e.g., "slender", "wiry").

The high-coverage sentiment lexicon that Mohammad and their colleagues compared with is SentiWordNet, described in Esuli and Sebastiani (2006) [46] [18] and Bacinella et al. (2010) [47]. As the rest of the commented works that follow dictionary-based approach, SentiWordNet starts from a set of seed elements (in this case, all the synsets containing 7 paradigmatic positive and negative terms) and then, expands it using certain lexical relations included in WordNet (for example, they use the "also-see" relation to gather words with the same polarity and the "direct antonymy" to collect words with opposite semantic orientation). In a second step, they train a semi-supervised classifier with the collected polarity words (plus a set of objective ones) in order to automatically classify glosses into Positive, Negative or Objective (i.e., neutral). As result of this process, all the synsets in WordNet are annotated according to their degree of positivity, negativity or neutrality.

Andreevskaia and Bergler (2006) [27] presented an interesting bootstrapping method based on a fuzzy logic approach to automatically annotate all the terms in WordNet. Apart from the automatic annotation of semantic orientation of adjectives, similar to the previously commented works, the authors analyzed the problems of low rates of inter-annotator agreement in tasks such as sentiment annotation, relating it with the structural properties inherent to certain semantic categories such as sentiment terms.

Halfway between dictionary-based and corpus-based approach is the work done by Takamura et al. (2005) [48]. The intuition behind this work is that words that appear in the gloss of a semantically oriented word tend to have the same polarity. The developed method is also based on lexical relations such as synonymy, antonymy and hypernymy and includes some conjunctive patterns found in Wall Street Journal and Brown corpora. The hypotheses of this work are similar to the investigations commented above, and the problems presented in the error analysis are similar to those as well: the ambiguity of word senses found in the thesaurus, the lack of structured information that causes misclassified words, and the semantic orientation of idiomatic expressions that the system is not capable to resolve only with the information provided in the thesaurus.

Also based on the lexical relations in WordNet, the work by Dragut et al. (2010) [49] also finds similar problems; numerous exceptions to the intuition that hypernyms of a synset have the same polarity as them or that the antonyms of a synset not always have the opposite polarity.

After an accurate revision of a great amount of works that follow this approach, we can state the main shortcomings all these studies suffer from. All of these investigations are based on external language resources, mainly WordNet but not limited to it, using also other available dictionaries and thesaurus. For this reason, although in many cases the proposed methods achieve good results, they will never be able to capture the semantic orientation of words that are not already collected in these specific lexical resources. Hence, slang or colloquial terms, misspelled words or neologisms will not be identified and therefore, not included in the polarity lexicons induced in this kind of works. Additionally, this approach strongly depends on the availability of these specific lexical resources. This implies that languages with scarce language resources will not be able to produce the polarity lexicons with the induction methods proposed by them.

The majority of the authors of the works previously commented provide precise error analyses in which they point out several limitations of their main hypotheses. The idea behind the great majority of the works that follow this approach indicates that the synonyms of an opinionated word have the same semantic orientation than it and its antonyms will have the opposite one. However, some of these works highlight the problems of following this idea, since not always is true and may introduce a great amount of semantic orientation errors, specially in bootstrapping methodologies that will increase the number of mistakes in each iteration.

Besides that, none of these works take into account the polarity variations across domains. As demonstrated in Chapter 2, and as we will further comment in the following sections, a great majority of the opinion adjectives are actually domain dependent: they could be positive in one domain but negative or even neutral in other. Hence, the use of dictionary-based approaches to create polarity lexicons suffer from a lack of portability since the adaptation to new domains of the lexical resources created in this way is a cumbersome task. Many domains contain jargon and specific terms of the field and thus, these dictionaries, which do not take into account these ambiguity problems across domains, will introduce errors in the polarity annotation of all those words that change their semantic orientation from one domain to another.

3.1.3 Corpus-Based Polarity Lexicons

In order to solve the limitations that dictionary-based approaches posed, some authors started to work on the automatic creation of polarity dictionaries by using corpora. This kind of language resources covers a lot more words than those collected in any dictionary or thesaurus and, simultaneously, increase the possibility to identify slang forms and neologisms. Additionally, basing the gathering of words on the corpus allows to adapt the dictionary to different domains only by changing the corpus used.

Hatzivassiloglou and McKeown (1997) [50] used the theory developed by Anscombre and Ducrot [51] and Elhadad and McKeown [52] on the conjunctions (i.e., “and”, “or”, “but”, etc.) behavior in order to implement a system to automatically identify the semantic orientation of adjectives. The main idea behind these works is that conjunctions between adjectives provide indirect information about their orientation. Note that we can say “The tax was simple and well-received by the public” while it could be odd saying “simplistic and well-received”. Generally, we do not use “and” to join adjectives with opposite semantic orientation, instead we prefer to use “but” in these cases. These kind of linguistic constraints are those used by the authors to build their algorithm.

The work of Hatzivassiloglou and Mckeown constitutes one of the first attempts to automatically induce adjective semantic orientation and it is the main work in which the investigation proposed in this chapter is based. Firstly, they extract all the conjunctions that join adjectives and, making use of a lineal regression model that combines the information given by the different conjunctions, decide if each pair of adjectives have the same or different semantic orientation. With this information, they design a graph where the edges between nodes (adjectives) mark if they have “same” or “different” semantic orientation. Then, a clustering algorithm splits the set into two groups of different polarity. Finally, following the Polyanna Hypothesis [8], the set with more elements is tagged as positive and the other as negative.

The work, although being revolutionary for the use of linguistic constraints as the unique clue to automatically uncover the semantic orientation of adjectives, has two main shortcomings.

On the one hand, they removed from the list of adjectives to annotate all those that have no orientation, for example “medical” or “domestic” (complementary, qualitative terms following the semantic theory of Lyons (1978) [53]). This would imply a great human effort in terms of time and the consequent delay if we want to develop an algorithm to work in a real world application. A complete polarity dictionary algorithm should be capable of automatically distinguishing between opinionated elements and neutral ones.

On the other hand, they also removed from their list of adjectives to annotate all these elements that do not have a unique label out of context. Again, in a real world application, the system must be able to choose the correct semantic orientation label for the different contexts where the words can appear. As we demonstrated in the last chapter, there is a majority of adjectives whose orientation change depending on the contexts where they appear, therefore a system that does not tag these types of terms will suffer from very low recall.

Turney and Littman (2003) [43] adopt a different approach to automatically inferring the direction (positive vs. negative) and intensity (mild vs. strong) of the semantic orientation of a word: they based their method on the statistical association of unknown words with a set of positive and negative paradigmatic words[2]. Statistical association among words is calculated using two different measures: Pointwise Mutual Information (PMI) [54] and Latent Semantic Analysis (LSA) [55]. They called their methodology SO-A (Semantic Orientation from Association). The results achieved were promising, but this work sufferred from the same limitations as the Hatzivassiloglou and McKeown’s one: they put the analysis of context dependent words aside. Two lexicons are used to evaluate the methodology proposed: General Inquirer [15] and the 1336 words manually annotated in the work of Hatzivassiloglou and McKeown commented above [50]. The former includes context dependent words, but the authors avoid all of these elements in

[2]Positive = good, nice, excellent, positive, fortunate, correct, and superior. Negative = bad, nasty, poor, negative, unfortunate, wrong, and inferior

the evaluation; the latter, as we remarked before, was built without this kind of ambiguous lexical units. Authors themselves state this issue as one of the limitations of their work.

Kaji and Kitsuregawa (2006, 2007)[56] [57] make use of lexico-syntactic cues appeared in a collection of Japanese HTML documents to build a lexicon for Sentiment Analysis tasks. As the first step, they manually create a list of cue words and phrases (such as "cons", "pros", etc.) frequently use to introduce polar sentences (positive and negative) in order to identify this kind of contents. Once they have built a corpus with this type of sentences, they work on the identification of polar phrases. One interesting point here is that they prefer to identify adjective phrases (noun + postpositional particle + adjective), instead of isolated adjectives, in order to avoid ambiguity problems. They also have a naive approach to negated phrases. Then, they compare how many times positive and negative phrases occur in positive and negative sentences. As the authors themselves state in their work, sentences like "Although the price is high, the shape is beautiful" can cause problems in the classification into positive and negative, therefore they opt to only take into account main clauses (in this case, "the shape is beautiful"). Counting the number of times that polar candidate phrases occur in positive ad negative sentences, they decide if the phrase should be considered polar (positive or negative) or should be removed because it is neutral. Only positive and negative phrases are collected then in their lexicon.

One of the shortcomings of this work is that it depends on an initial manually created list of cue words and phrases. As other works commented in this section, Kaji and Kitsuregawa also address the construction of domain independent lexicon, but they put domain dependency issues aside.

3.2 Automatic Creation of Domain Polarity Lexicons

In the following sections, we present a methodology to automatically create domain polarity lexicons. The method proposed is corpus-based, therefore is adaptable to every single domain for which we can obtain a corpus. It makes use of a set of linguistic patterns to iteratively find out polar adjectives (even slang or misspelled words) along with their corresponding polarity values. Additionally, it identifies *highly subjective adjectives*, that is, polar adjectives whose polarity exclusively depends on the writer's point of view and can vary even within the same domain, as described in Chapter 2.

3.2.1 Bootstrapping Approach

The principal aim of this experiment was to demonstrate that the use of simple linguistic patterns allows to automatically generate domain polarity lexicons. These lexicons include lexical elements often overlooked by sentiment dictionaries, such as adjectives whose polarity can change in the same domain, or slang and misspelled polar adjectives. The incorporation of these elements is crucial, as demonstrated in Chapter 2, to increase the accuracy of Sentiment Analysis applications based on this type of language resources.

We propose an innovative method to automatically create lists of polar adjectives relevant for a domain with a single bootstrapping algorithm. As demonstrated in several works on Information Extraction[31, 58, 59, 30], bootstrapping algorithms achieve great results in tasks such as automatic extraction of semantic lexicons. However, to our knowledge, the present work was the first attempt of using a bootstrapping algorithm for the automatic induction of polarity lexicons without using external language resources such as dictionaries or thesaurus.

The hypothesis behind the algorithm proposed is that there are some conjunctive patterns that provide linguistic evidence that a word has positive or negative orientation, thus this information can be iteratively used to find the polarity of new lexical elements. The linguistic patterns that we selected to initialize our bootstrapping algorithm were initially proposed by Anscombre and Ducrot (1983) [60] and Elhadad and McKeown (1983) [52], and used in Hatzivassiloglou and McKeown (1997) [50]. In these works, the authors hypothesized that two adjectives joined by "and" have the same semantic orientation, while two adjectives joined by "but" have the opposite one. This hypothesis is illustrated by the following examples:

(1) *The tax proposal was simple and well-received by the public.*

(2) *The tax proposal was simplistic but well-received by the public.*

(3) *The tax proposal was* <u>**simplistic and well-received*</u> *by the public.*

As we can see, sentences (1) and (2) are well constructed. In the example (1), both "simple" and "well-received" convey the same semantic orientation; they are positive. This correlation in terms of polarity requires the use of the conjunction "and". In the example (2), we find the opposite case; one of the adjectives used is positive ("well-received") but the other is negative ("simplistic"). In this case, the contrast on the semantic orientation of the adjectives requires the use of the conjunction "but". As we can observe in the third example, the use of "and" with two adjectives with opposite semantic orientation is not valid, creating contradictory sentences. In other words, conjunctions between adjectives provide indirect information about orientation.

In Hatzivassiloglou and McKeown (1997)[50], the authors used these linguistic constraints in a log-linear regression model that, combined with a clustering algorithm, separated adjectives into groups of different orientations and, finally, labeled adjectives as positive or negative. The method, although achieving great results in terms of accuracy (it has a precision of around 90%) is difficult to implement and puts aside adjectives whose semantic orientation suffer from inter- or intra-domain variation. We thought that the same hypothesis could be used in a much more simple way to achieve even better performance in less time.

We found that the same conjunctive patterns could be iteratively reused in a single bootstrapping algorithm that automatically tags adjectives appeared in these coordinated constructions with their corresponding semantic orientation. Just knowing the polarity of one of the two adjectives in the pattern, we know the polarity of the other one, then if the number of adjectives whose polarity is known increases, the probabilities of discovering the polarity of new adjectives increases as well.

The bootstrapping algorithm we propose here just needs a set of conjunctive patterns extracted from the corpus we want to analyze, and a small set of *seed words* to be initialized.

The initial set of seed words (28 positive and 7 negative adjectives) consists of all the domain independent adjectives that human annotators tagged as such in the case study described in Chapter 2. As they are domain independent elements,

Positive Seeds	Negative Seed
alucinante, bello, bueno, chulo, cojonudo, elegante, espectacular, estupendo, excelente, excepcional, extraordinario, fantástico, genial, hermoso, impecable, impresionante, increíble, inmejorable, insuperable, lindo, magnífico, maravilloso, novedoso, perfecto, precioso, recomendable, sensacional, único	terrible, pésimo, malo, horrible, feo, cutre, chungo.

Table 3.1: Positive[5] and negative[6] seeds used to initialize the bootstrapping process

they can be used as initial list of seeds in any domain that we want to work with. They can be examined in Table 3.1

The different number of positive and negative elements is a clear reflection of the Pollyanna Hypothesis proposed by Boucher and Osgood (1969) [8] that asserts there is a tendency to use positive words more frequently than negative ones in communication. We were just using the results of the human annotation task described in the last chapter.

These seed words form the initial polarity lexicon.

As commented before, the algorithm proposed followed a corpus-based approach. Therefore, from a wider corpus (aprox. 8 Million words) consisting of user-generated Spanish reviews of different products (cars, movies, cell phones, video games and sport teams), we extracted a car reviews corpus of around 300,000 words. This subcorpus is one of the three used in Chapter 2, therefore all of the documents were also collected from Ciao[7], the same review aggregation website described in last chapter.

The corpus was lemmatized and annotated with Part-Of-Speech information

[7]http://www.ciao.es/

Pattern	Example
Adjective + y + Adjective	bonito y resistente
Adjective + pero + Adjective	pequeño pero potente

Table 3.2: Examples of the linguistic patterns found in the corpus.

using Freeling POS tagger[21], and indexed using Corpus Query Processor (CQP) [61] in order to facilitate the search of coordinated adjectives.

To initialize the bootstrapping algorithm, we looked in the corpus for all the adjectives joined by the conjunctions listed before. Therefore, we looked in the corpus for the Spanish patterns in 3.1 and 3.2.

$$< adjective > y|e < adjective > \tag{3.1}$$

$$< adjective > pero|aunque < adjective > \tag{3.2}$$

We hypothesize that, as in English, two adjectives joined by "y" or "e" ("and") share the same semantic orientation, while two adjectives joined by "pero" or "aunque" ("but") have the opposite one.

In the corpus used for this experiment, 482 pairs of adjectives joined by the conjunctions "y" or "e" ("and") and "pero" or "aunque" ("but") were found. Some examples are in Table 3.2.

The first step in the bootstrapping process was looking for all the polar adjectives in the polarity lexicon [8] across the patterns extracted. The semantic orientation of the adjectives in the polarity lexicon (first the seed words and then the new adjectives added in the rest of the iterations) is always known.

Then, our algorithm operates on the following conditions:

- If an adjective in the polarity lexicon is joined by "y" ("and") with another adjective whose polarity is unknown (that is, an adjective that it is not in our

[8] In the first iteration, they are the seed words

polarity lexicon yet), and it does not appear in contradictory constructions[9], we will conclude that the adjective whose polarity was unknown has the same semantic orientation than the adjective in the polarity lexicon. Therefore, it can be added, along with its corresponding semantic orientation, to our polarity lexicon.

- If an adjective in the polarity lexicon is joined by "pero" ("but") with another adjective whose polarity is unknown, and it does not appear in contradictory constructions, we will conclude that the adjective whose polarity was unknown has the opposite semantic orientation of the adjective in the polarity lexicon. Therefore, it can be added, along with its corresponding semantic orientation, to our polarity lexicon.

- If an adjective in the polarity lexicon appears in a coordinated pattern which implies that its semantic orientation is positive, but also appears in a coordinated pattern which implies that its semantic orientation is negative, the polar adjective will be added to the highly subjective adjectives lexicon.

As in each step number of polar adjectives in the polarity lexicon is bigger, the probabilities of discovering the semantic orientation of new polar adjectives in the conjunctive patterns also increases in each iteration.

This procedure is iteratively repeated until no more polar adjectives are identified.

The bootstrapping process proposed can be examined in Figures 3.1 and 3.2.

3.2.2 Evaluation

As a result of running the bootstrapping algorithm proposed over the 482 instances of conjunctive patterns found in the car reviews corpus, we increased six times the number of polar adjectives that there were in the initial polarity dictionary (i.e., seed adjectives). We increased the number of positive adjectives from 28 (seeds) to 173, and the negative adjectives from 7 (seeds) to 37. Crucially, we identified 13 highly subjective adjectives that appeared with positive polarity in some contexts

[9] Positive adjective + and + negative adjective; negative adjectives + and + positive adjective; positive adjective + but + positive adjective; negative adjective + but + negative adjective.

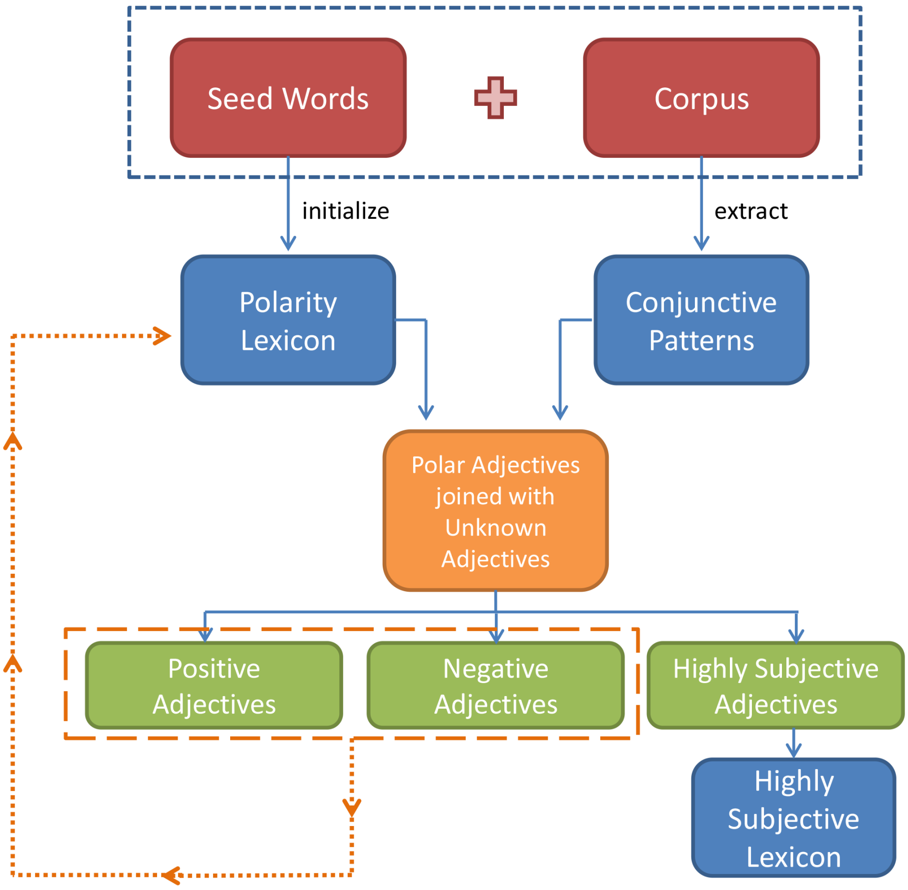


Figure 3.1: Bootstrapping algorithm proposed.

Extract all the conjunctive patterns from the corpus
$PolarityLexicon_{Pos}$ = {$\text{SeedWords}_{\text{Pos}}$}
$PolarityLexicon_{Neg}$ = {$\text{SeedWords}_{\text{Neg}}$}
HighlySubjectiveLexicon = {}
i := 0

BOOTSTRAPPING
1. Look for all the patterns that contain any element of $\text{PolarityLexicon}_{\text{Pos}}$ or $\text{PolarityLexicon}_{\text{Neg}}$
2. IF ([Adj_{Pos} + y + $\text{Adj}_{\text{Unknown}}$] OR [$\text{Adj}_{\text{Unknown}}$ + y + Adj_{Pos}]) THEN
   Add $\text{Adj}_{\text{Unknown}}$ to $PolarityLexicon_{Pos}$
3. IF ([Adj_{Neg} + y + $\text{Adj}_{\text{Unknown}}$] OR [$\text{Adj}_{\text{Unknown}}$ + y + Adj_{Neg}]) THEN
   Add $\text{Adj}_{\text{Unknown}}$ to $PolarityLexicon_{Neg}$
4. IF ([Adj_{Pos} + y + Adj_{Neg}] OR [Adj_{Neg} + y + Adj_{Pos}]) THEN
   Add Adj_{Pos} to *HighlySubjectiveLexicon*
   Add Adj_{Neg} to *HighlySubjectiveLexicon*
5. IF ([Adj_{Pos} + pero + $\text{Adj}_{\text{Unknown}}$] OR [$\text{Adj}_{\text{Unknown}}$ + pero + Adj_{Pos}]) THEN
   Add $\text{Adj}_{\text{Unknown}}$ to $PolarityLexicon_{Neg}$
6. IF ([Adj_{Neg} + pero + $\text{Adj}_{\text{Unknown}}$] OR [$\text{Adj}_{\text{Unknown}}$ + pero + Adj_{Neg}]) THEN
   Add $\text{Adj}_{\text{Unknown}}$ to $PolarityLexicon_{Pos}$
7. IF ([Adj_{Pos} + pero + Adj_{Pos1}] OR [Adj_{Neg} + pero + Adj_{Neg1}]) THEN
   Add Adj_{Pos} to *HighlySubjectiveLexicon*
   Add Adj_{Pos1} to *HighlySubjectiveLexicon*
   Add Adj_{Neg} to *HighlySubjectiveLexicon*
   Add Adj_{Neg1} to *HighlySubjectiveLexicon*
8. i := i + 1;
9. Go to Step 2

Figure 3.2: Bootstrapping process.

Polarity	Examples
Positive	versátil, preciso, recomendable, cojonudo, fardón
Negative	caro, feo, incómodo, lento, molesto
Highly Subjective	fuerte, juvenil, pequeño

Table 3.3: Examples of adjectives collected by the bootstrapping algorithm.

and with negative in others. Some examples of the adjectives[10] identified are in Table 3.3.

The growth in the number of adjectives in connection with the number of iterations is detailed in Figures 3.3, 3.4 and 3.5.

In order to evaluate the performance achieved by the algorithm proposed, however, we manually annotated a Gold Standard consisting in the 12% of the whole car review corpus used, that is, 200 documents of the entire corpus. In each document, all the polar adjectives that should be in the final polarity lexicon were identified and labeled with their corresponding semantic orientation (positive or negative) in the particular context where they appeared. For the annotation task, we used Brat[11] [62], a web-based annotation tool that allowed us to create our own labels, adapted to the experiment.

The instructions followed by the human annotator were the following: if an adjective is used to describe a positive or negative evaluation, opinion, emotion or speculation of any of the objects reviewed, then this word should be in our polarity lexicon and annotated with the label that better describe it according to its semantic orientation (positive or negative).

It is important to note here that some words that are typically used as subjective elements can also be found as objective ones.

For example, “pequeño” (“small”) works as a polar adjective in sentences like “este coche es pequeño y aburrido” (“this car is small and boring”). In these types of sentences, we can easily understand than the writer does not like the car

[10] Positive: versatile, precise, advisable, bitching, showy. Negative: expensive, ugly, uncomfortable, slow, annoying. Highly Subjective: strong, young, small.

[11] http://brat.nlplab.org/

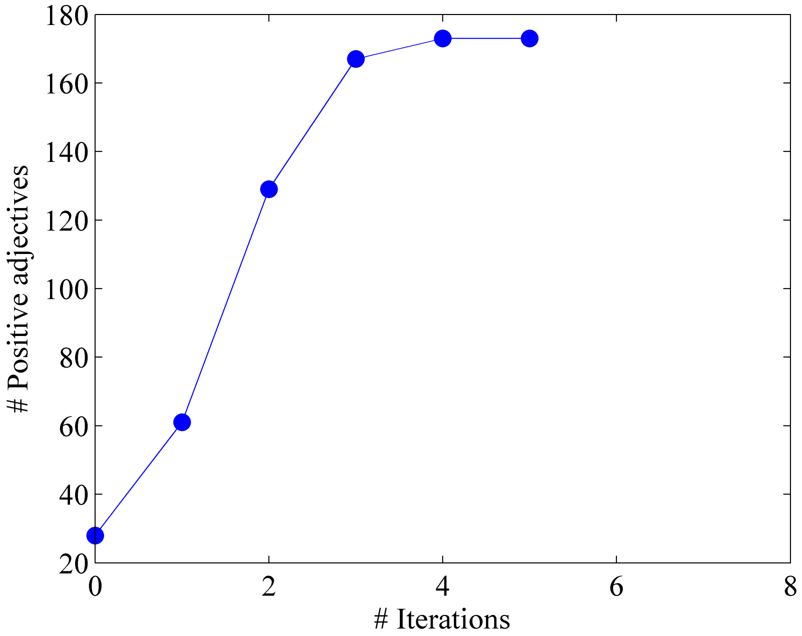


Figure 3.3: Positive adjectives collected and number of iterations.

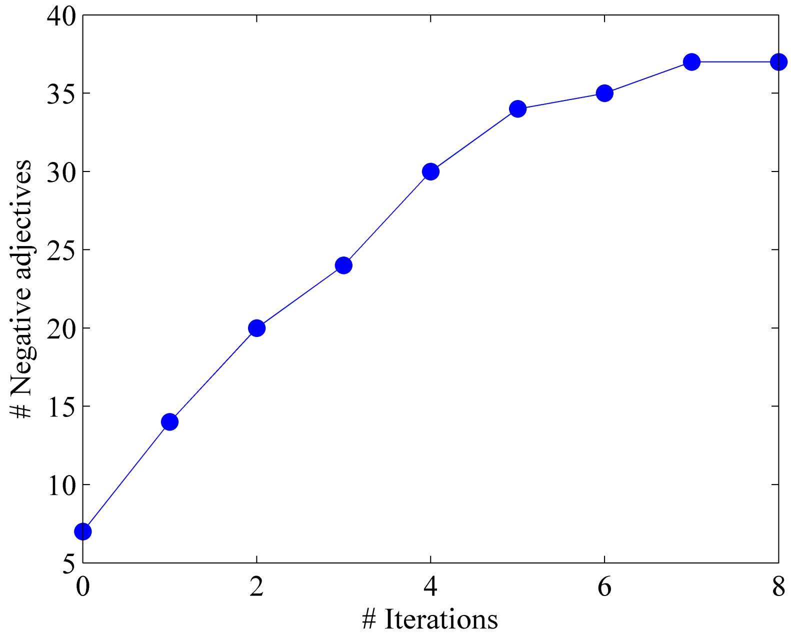


Figure 3.4: Negative adjectives collected and number of iterations.

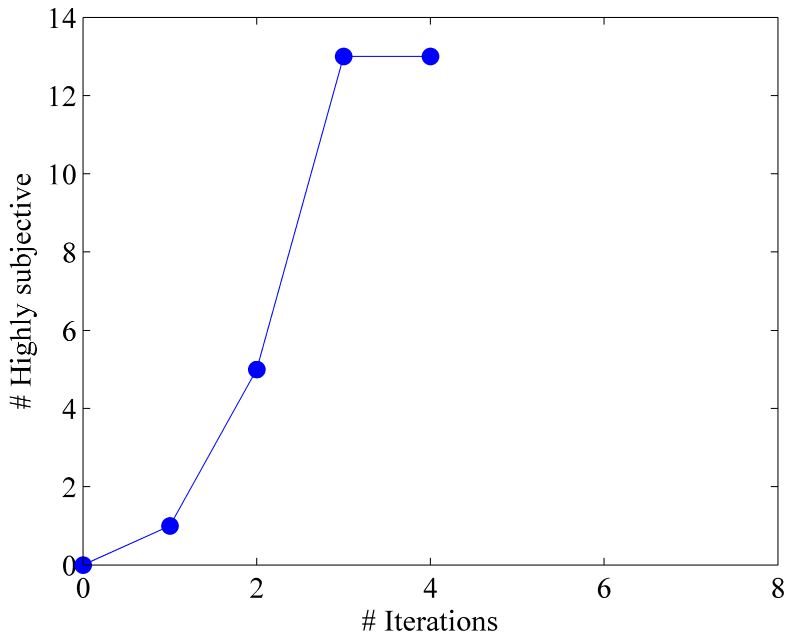


Figure 3.5: Highly Subjective adjectives collected and number of iterations.

since he joined the adjective "pequeño" with a negative adjective, (in this case, "aburrido"). However, if the writer was enumerating the general characteristics of the car (for example in "este coche es pequeño ya que solo tiene dos plazas, tiene 3 puertas y los vidrios tintados..." ("this car is small because it only has two seats, has three doors and smoked glasses..."), it does not imply that "pequeño" was positive nor negative. In this last example, the writer performed a merely informative function, the adjective acting as an objective unit. In these cases, if the adjective is actually polar, it was annotated with its corresponding polarity, while if it was objective it remained unannotated.

In the Gold Standard, 263 words were annotated as polar adjectives, being positive 199 of them and negative 52 of them. Additionally, 12 of the adjectives in our Gold Standard were actually highly subjective elements, since they were tagged sometimes as positive and other times as negative. Some examples of these highly subjective adjectives are "alto" ("high"), "grande" ("big") or "pequeño" ("small"). Again, the Pollyanna Hypothesis [8] was confirmed, supporting the different number of positive and negatives polar adjectives in our lists of seed

Label	Examples
Positive Adjective	afortunado, bestial, deportivo, poderoso
Negative Adjective	despreciable, renqueante, molesto, prohibitivo

Table 3.4: Examples of Gold Standard annotation.

words.

Some examples of the annotation task are in Table 3.4.

Therefore, in order to evaluate the bootstrapping algorithm proposed, we ran it again just over the documents that were used to extract the Gold Standard described.

We looked for all the conjunctive patterns and found 64 pairs of adjectives (103 adjectives in total) joined by "y" ("and") or "pero" ("but"). In other words, we collected 64 of the total of 482 instances of conjunctive patterns that appeared in the car corpus. Then, we repeated the bootstrapping process over this set of conjoined adjectives extracted from the Gold Standard.

Obviously, in this case, the growth in the number of adjectives collected is smaller, since we worked only with a 13% of the total pairs of adjectives joined by a conjunction. We augmented the positive adjectives from 28 (seeds) to 55, and the negative ones from 7 (seeds) to 14. In these run, due to the small size of the evaluation corpus, we did not identify any highly subjective adjective.

On the one hand, the recall of the bootstrapping algorithm proposed was calculated by comparing the total number of different adjectives that appeared in the conjunctive patterns with the number of polar adjectives that our method was capable to identify. We identified 67% of all the different 103 adjectives that appear in the 64 pairs of adjectives.

On the other hand, in order to know the precision of the algorithm, we compared the polarity tags identify by the bootstrapping process with the positive and negative adjectives in the Gold Standard. Thus, we found that from all the adjectives tagged as positive by the bootstrapping algorithm, 97.6% were correctly tagged. Additionally, from all the adjectives identified as negative by the algorithm, 71.5% were correctly tagged, according to the Gold Standard. The results in terms of performance are in Table3.5.

Recall	Precision for Positives	Precision for Negatives
67%	97.6%	71.5%

Table 3.5: Performance achieved by the bootstrapping algorithm proposed.

The results of the evaluation over the Gold Standard show that our bootstrapping algorithm is able to identify and label most of the polarity adjectives contained in conjunctive patterns. The results obtained show that our method achieves better rates of precision than other published works while maintaining recall.

3.3 Conclusions

Research on the creation of polarity lexicons is crucial in order to improve current Sentiment Analysis systems. Almost all of these complex systems of opinion extraction are based, to a greater or lesser extent, in a polarity lexicon for the first steps of the sentiment identification process. So far, however, polarity lexicons used to be general resources used across domains that overlooked lexical features such as polarity variation suffered by some adjectives when used in different domains. However, domain dependent polarity variation is very frequent, as we demonstrated in Chapter 2, and therefore, should be included in polarity lexicons. Additionally, the manual development of this type of resources often needs a great effort in terms of time, human resources and other external language resources.

We believe that polarity lexicons need to be constantly updated in order to cope with the new necessities of the Social Media analysis tools.

On the one hand, the number of domains to analyze is constantly growing (from cars to political campaigns, celebrities, etc.) thus, analysis systems should quickly adapt their tools to the new information to be mined. Therefore, sentiment dictionaries should include specific polarity uses of the words used by the writers/speakers, and also new polar words used in a specific domain (slang and neologisms) that normally are not collected in general language resources.

On the other hand, new domains can suddenly appear, getting viral after only some hours. Thus, the polarity lexicons on which the analysis systems rely on should be created on the fly, without great efforts in terms of time or human resources, and minimizing the use of existing resources that cannot be available.

In other words, the new polarity dictionaries should be produced fast and accurately to be used in Opinion Mining real world applications.

In this chapter, we presented a new methodology on domain polarity lexicon creation that takes into account the issues previously pointed out.

We can conclude that it is possible to automatically identify, extract and label polar adjectives, not only as positive or negative but also as highly subjective elements by the use of the bootstrapping algorithm proposed. Creating lists of highly subjective elements, polarity lexicons provide relevant information to the system about a set of polar elements the tool should be very aware of, because they can introduce important mistakes in the final results if not correctly analyzed.

Additionally, it is important to note that the proposed bootstrapping algorithm is meant to be ported to any domain from which we need to have a specific polarity lexicon, and also to other languages in which conjunctive patterns are used.

Moreover, the proposed method is capable of extracting slang polar adjectives (for instance, "cojonudo" ("bitchy") or "fardón" ("showy")) and misspelled words since it is not based on external language resources but on the real language usages.

The results of the proposed bootstrapping algorithm, although preliminary, showed an improvement over other methods based on the same hypothesis (i.e., conjunctive patterns) both in terms of precision and of implementation simplicity. The evaluation of the polar words extracted, however, is difficult since there are not other domain dependent lexicons available. In any case, we manually annotated a Gold Standard in order to evaluate our lists of polar words against it. The comparison against this manual annotations actually showed that our method achieved good results both in terms of recall (67%) and precision (97.6% for positive adjectives and 71.5% for negative ones).

Chapter 4

CLASSIFYING USER-GENERATED CONTENT FOR SOCIAL MEDIA ANALYSIS

The research carried out for the development of the experiments proposed in Chapters 2 and 3, as well as our hands-on on several social media projects, provided us with enough information to understand the weight of linguistic structures and lexical items in the expression of opinions in user-generated contents.

Due to the proliferation of new social media, such as social networks, personal blogs or microblogs, where speed is a basic feature which has changed text structure.

On the one hand, the new types of documents are shorter (or extremely short in sources such as microblogs, where users are only allowed to write messages up to 140 characters) than the news texts traditionally analyzed by Information Extraction.

Following the idea behind the bootstrapping algorithm proposed in the previous chapter, where we used a set of linguistic patterns to extract polar adjectives as well as information about their polarity, we wanted to investigate to what extent a Social Media Analysis system for other aspects than opinion based on polarity could be developed based only on this linguistic information.

The Social Media Analysis applications that we developed are industrial systems whose main aim is to automatically classify user-generated documents extracted from a variety of social media (social networks, blogs and microblogs) into a set of categories relevant to marketing analysis, such as the model of purchase process called Purchase Funnel [63] and the Marketing Mix elements [64].

On the one hand, the first developed system classifies documents into one of the four stages of the purchase process, that is, *awareness*, *evaluation*, *purchase* or *postpurchase experience*, which is known as Consumer Decision Journey. These categories exactly locate customers into the different steps of their purchasing process depending on the information that they are expressing on social channels. Hence, this information can be used by marketers to better know in which step a purchasing fails or why it is a success.

On the other hand, the second developed system is able to classify the same texts into a set of marketing categories, such as Price, Product, Promotion or Place, known as Marketin Mix, depending on the topic the customer is talking about. The classification on these categories provides information about which are the product features most commented by customers. For example, if a marketing company has issued an advertisement campaign for a specific product, knowing how many customers are talking about it can be a good indicator of its success or failure.

We found that specific lexical units and linguistic structures used to talk about each of these categories are actually very good indicators of the class to identify. Therefore, in this chapter, we demonstrate our last hypothesis, as proposed in Section 1.1:

> *Linguistic patterns and specific lexical units provide enough information to develop an industrial Social Media Analysis system with good results in terms of precision and recall.*

The chapter is organized as follow. In Section 4.1, we give an overview of the definition of Consumer Decision Journey and its importance in the marketing field. Section 4.2 briefly describes the concept of Marketing Mix and its elements. In Section 4.3, we revise other works related to ours. Section 4.4 explains the approach followed in this work. In Sections 4.5 and 4.6, we present the corpus used in the experiments, and the Gold Standard made up with human annotations. Section 4.7 explores the improvements achieved with the normalization of texts. In Section 4.8, we report on the experiment on automatic classification of the documents into the Consumer Decision Journey stages, and in Section 4.9 we tackle the automatic identification of different Marketing Mix elements. Section 4.10 presents the evaluation of all the classification experiments. Finally, in Sections 4.11 and 4.12 we provide an error analysis and the final conclusions, respectively.

4.1 The Consumer Decision Journey

The Purchase Funnel, proposed by Lewis (1903) [63], is a marketing model that illustrates the purchase process in several stages, from the moment when a customer is aware of the existence of the product (awareness) to the moment when he or she buys the product (purchase). The model evolved during the last years and, at present, there are many different purchase funnel models, some of them with many different intermediate stages. However, the basic conceptual framework and stages remain the same in all of them ([65],[66]).

Modern versions of the purchase funnel model additionally include the influence of Internet and social media in the decision making path of the customer, and also include a postpurchase stage. The version of the purchase funnel proposed by Forrester[1] is a good example of the introduction of the new technologies and social media to the classic Elmo Lewis' model. This work highlights the great influence of user-generated content on the final purchase decision of the customers. In the model proposed by McKinsey (2009) [67], the Consumer Decision Journey, the traditional funnel shape of the decision journey is transformed in a purchasing loop and the notion of trigger (as the cause because of which potential customers start to investigate the brand and therefore enter into the purchase funnel) is introduced.

Knowing the exact stage of the decision journey where the customer is located is essential in order to design specific promotional campaigns, interact with customers at the appropriate touch-points and improve customer relationships man-

[1] http://blogs.forrester.com/steven_noble/10-10-28-its_time_to_bury_the_marketing_funnel

agement (CRM) systems [68]. To discover this, the analysis of the different social media channels is crucial, since the online conversations between potential customers play a very important role in the purchase decision pathway [69]. Findings of Ng and Hill (2009) [70], Gupta and Harris (2010) [71] revealed that consumers do actively search the web for non-commercial bias opinions prior to making a purchase decision. Pookulangara and Koesler (2011) [72] state that, in addition to transforming the evaluation and purchase stages, online social networks enable consumers to become advocates of their preferred brands. Related work by other researchers found that online consumer conversations influence purchase decisions in a variety of ways, which include reinforcing of product involvement [73]. De Bruyn and Lilien (2008) [65] studied which factors affect consumers in the various phases of their online decision making processes, and found that while tie strength (i.e. closeness of relationship between two individuals) facilitates awareness, it has no apparent power over triggering interest or decision to buy. In summary, it is safe to say that social media have drastically changed the shopping experience, which calls for further research in this area.

In this work we adopt the following, widely agreed, purchase stage model: awareness, evaluation, purchase, and postpurchase experience. This straightforward model can be easily applied to a wide variety of products and purchase contexts.

Therefore, our aim is to use a consumer decision-making model whose basic stages can be reasonably traceable in a big data scenario consisting of online consumer texts, rather than using a sophisticated conceptual model that incorporates customer experience complexity to its fullest. Figure 4.1 illustrates the model adopted as conceptual framework in this work.

The first stage, *awareness*, refers to the very first contact of the customer with the product or brand, with or without the desire of purchase. Customers usually convey their interest through references or expressions about the advertising campaigns.

In the *evaluation* phase, the customer already knows the product or brand and evaluates it, frequently with respect to other similar products or brands. In this step, buyers actively investigate the brand in comparison with its competitors (asking for opinions, formulating questions, consulting product reviews, etc.) and/or

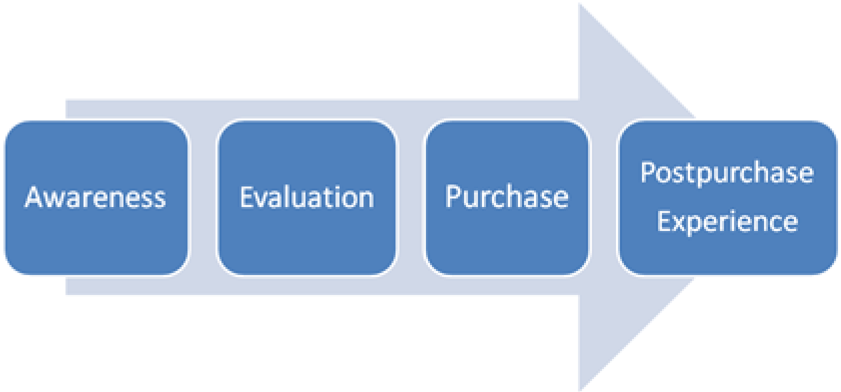


Figure 4.1: Consumer Decision Journey Stages adopted in this work

express their preference towards a specific brand or product.

In the *purchase* stage customers either explicitly convey their decision to buy the product or make comments referring to the transaction involved when buying the item.

Finally, the *postpurchase experience* phase refers to the moment when customers, having tried the product, criticize it, recommend it or simply talk about their personal experience with it.

4.2 The Marketing Mix

The concept of "marketing mix" was coined in 1964 by Borden [64] who identified twelve marketing elements to manage business operations in a more profitably way. Then, these twelve elements were reduced by McCarthy and Brogowicz (1981) [74] to just four: Product, Price, Promotion, and Place (the "4P's"). These four elements usually imply different subcategories that can vary depending on the interests of the marketing company. For example, in this work the element Product could be subdivided into Quality, Design and Warranty; within Place one could distinguish Point of Sale and Customer Service, and Promotion has also different subcategories such as Sponsorship, Loyalty Marketing, and Advertisement (that can also be divided into different subtypes of advertisement depending on the media used). The 4P's Marketing Mix framework was used by marketers

Product	Place	Price	Promotion
Quality	Point of Sale	Price	Promotion
Design	Customer Service		Sponsorship
Warranty			Loyalty Marketing
			Advertisement

Table 4.1: Subcategories of the Marketing Mix elements.

from all over the world, taking it as a basis to develop their operational marketing plans.

Table 4.1 identifies the subcategories in which we have divided each element of the Marketing Mix framework. We have developed classifiers for the following subcategories: Quality, Design, Point of sale, Customer Service, Price, Promotion, Sponsorship, and Advertisement.

4.3 Related Work

The work we present here offers a in-depth analysis of user-generated content that goes far beyond what has been referred as Sentiment Analysis. In this work, the aim is to identify critical information about consumer behavior: to provide information about how customers are distributed along the four stages of the Consumer Decision Journey and about the nature of their comments in terms of categories of the Marketing Mix. To the best of our knowledge, there is no previous work that addresses these tasks. Nevertheless, the identification of wishful sentences and the aspect-based Sentiment Analysis offer some similarities that allow for a basic comparison.

The first attempt to automatically classify sentences containing wishes was performed by Goldberg et al. (2009) [75]. The authors reported that, after a manual annotation of a corpus of wishful texts, a number of linguistic patterns related to wishes expression were identified. These patterns were used to automatically extract the sentences that contained wishes. The precision results stated by Goldberg et al. was 80%, but combining these linguistic patterns with the most frequent words and for user-generated texts related to the area of politics. When applying the same method to product reviews, precision falls to 56%.

More recent works in this area are those carried out by Ramanand et al. (2010) [76], and Wu and He (2011) [77]. In these studies, the authors investigate methods to automatically identify different types of wishes (specifically the wish to suggest and the wish to purchase) and find linguistic patterns to extract them.

Ramanand et al. (2010) also used linguistic patterns to discover two specific types of wishes, as mentioned before: sentences that make suggestions about existing products, and sentences that indicate purchasing interest. Note that Ramanand et al.'s wish types are similar to the evaluation and purchase stages of the Consumer Decision Journey we address in this paper. Ramanand et al. reported precision and recall are 62% and 48.5% respectively for suggestions and 86.7% and 57.8% for purchase.

Wu and He (2011), following the work of Ramanand et al., proposed that the occurrence of some modal verbs can be taken as indicators of wishful sentences. They developed a classifier for "wish sentence" and "non-wish sentence" using mined linguistic patterns based in this modal verbs set as a features. Precision reported is 47% while recall is 96%.

Besides the research done on the automatic identification of wishful sentences, the very recent work on aspect-based Sentiment Analysis has also some similarities with the Marketing Mix elements classifier proposed in this work.

Aspect-based Sentiment Analysis also goes beyond simple Sentiment Analysis, trying to detect not only the overall opinion conveyed in a document but also to identify the features of a set of target entities and the sentiment expressed towards each of these features. In this sense, our work on Marketing Mix classifiers would carry out the specific aspect detection task, since the main aim of this task is to identify a set of categories discussed in each sentence of a product review.

Shared tasks[2] proposed in SemEval 2014 already include this specific aspect-based Sentiment Analysis. Some of the works that achieved better results in this specific task were those carried out by Kiritchenko et al. (2014) [78] and Castel-

[2]http://alt.qcri.org/semeval2014/task4/

lucci et al. (2014) [79].

In their work, Kiritchenko and her colleagues, developed five binary Support Vector Machines (SVM) classifiers trained with several types of vectors containing different information (ngrams, stemmed ngrams, character ngrams, non-contiguous ngrams, word cluster ngrams and lexicon features) in order to identify five different aspects (food, service, price, ambiance and anecdotes/miscellaneous) commented along some sentences extracted from a corpus of restaurant reviews. They achieved a F-1 score of 88.5% for the overall task, but they did not provide information about the results on the classification of each category.

Castellucci et al. (2014) also built five binary SVM classifiers combined with a set of thresholds to classify each sentence in the corpus into one or more of the categories proposed. They achieved a F-1 of 85.3% but they neither gave more detailed information about the results attained along the different categories.

Our work on Marketing Mix elements classification, however, involves more difficulties since we tried to identify more categories (eight instead of five) and from a corpus made up of eight different domains instead of just one. In any case, our systems achieved similar results of F-1 in the identification of some categories such as Advertisement (88%).

4.4 Approach

In order to achieve the objectives of our research, i.e. to automatically classify user-generated texts into (i) a stage of the Consumer Decision Journey and (ii) an element of the Marketing Mix, we have carried out the following tasks:

1. First, a corpus of user-generated texts was gathered. The texts were extracted by Havas Media Group from different social media channels if they included a mention to a brand (from a set of commercial brand names). Details of this task are described in Section 4.5 .

2. After gathering the corpus, we created a Gold Standard for training and evaluation purposes. The process followed for creating the Gold Standard is described in Section 4.6.

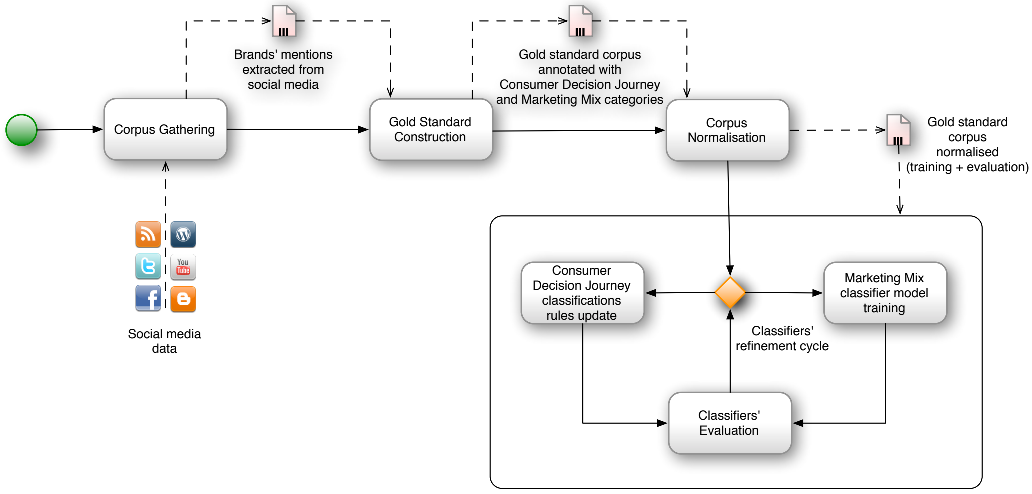


Figure 4.2: Approach followed

3. We developed a normalizer in order to correct misspellings and other social-network meta-language elements in the gathered texts, as described in Section 4.7 .

4. We developed a rule-based classifier for locating texts in a Consumer Decision Journey stages. Details about classifier development are in Section 4.8.

5. In order to classify texts into Marketing Mix elements, we trained a Decision Tree using the technique defined by Quinlan (1993)[80]. The details are provided in Section 4.9.

6. Finally, we have evaluated the classifiers developed, iterating over steps 4. and 5. until the results were satisfactory.

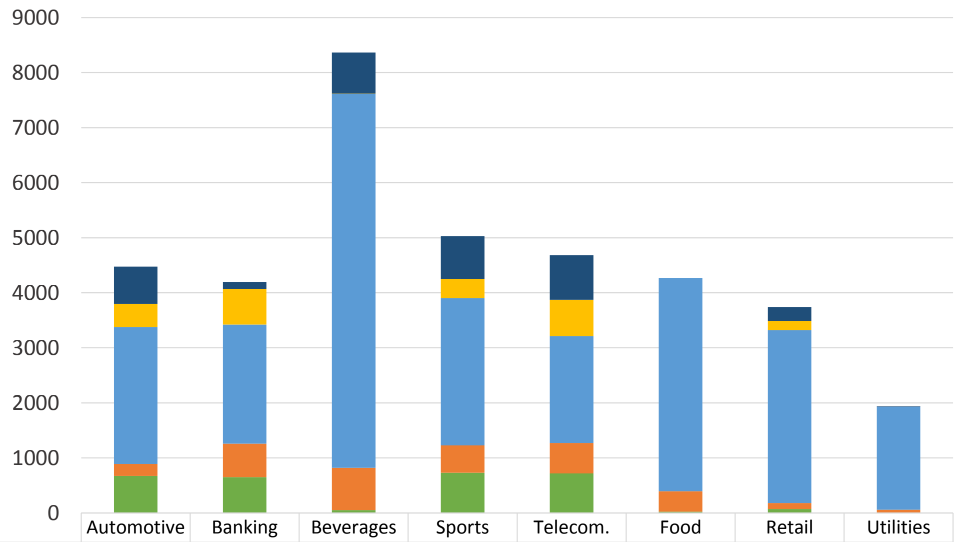
Figure 4.2 shows all the steps of the algorithm.

4.5 Corpus Gathering

Two corpora of user-generated texts, one for English and one for Spanish, were built. These corpora include different geographical language varieties (American Spanish, for example) in both cases. Documents were collected from five different social media sources (forums, blogs, reviews, social networks, and microblogs) and were selected to be on eight different domains or business sectors: automotive industry, banking, beverages, sports, telecommunications, food, retail, and utilities. Texts were extracted by looking for a set of 72 particular brands of the eight different business sectors.

For English, we have collected 13,980 mentions to brands, while for Spanish we have collected 22,721. The length of the documents ranges from 2 to 194 words. All the documents were part-of-speech tagged using Freeling POS tagger [21].

Figure 4.3 shows the distribution of the texts (in Spanish and English) along the sources and topics.



	Automotive	Banking	Beverages	Sports	Telecom.	Food	Retail	Utilities
Social Networks	678	122	746	778	809	0	248	9
Reviews	420	647	7	351	661	0	170	0
Microblogs	2488	2165	6792	2671	1940	3876	3140	1871
Blogs	219	608	768	498	553	371	110	55
Forums	673	652	54	731	720	23	72	5

Figure 4.3: Distribution of the texts along the sources and sectors
4.3

4.6 Gold Standard

In order to identify the linguistic patterns utilized to express the different stages of the Consumer Decision Journey, to learn the models for classifying texts according to the Marketing Mix elements, and also to carry out the final evaluations, we built a Gold Standard. Two experts on marketing annotated each text as belonging to one of the four Consumer Decision Journey stages (i.e. awareness, evaluation, purchase or postpurchase), and to one or more Marketing Mix elements (i.e. quality, design, point of sale, customer service, sponsorship, advertisement, promotion and price). All the annotations were then checked by one reviewer with social sciences background and by two reviewers with computational linguistics background.

4.6.1 Annotation of the Consumer Decision Journey Stages

Annotators were asked to tag each text with just one label following the description provided below.

- *Awareness*. All the texts that refer to advertisement campaigns or opinions about the advertisements, are generally expressed in first person. These texts should contain information about the user's experience with respect to the advertisement or the knowledge of the brand. For example: "I love Hyundai's ad".

- *Evaluation*. All the texts that state interest and/or show an active research towards the brand or product. For example: "My daughter and I are looking for a Peugeot-like van in good condition". The annotator should also tag as evaluation all the texts that express a preference (positive or negative) although we cannot infer user experience. For instance: "Well, I'd rather fly with Emirates than with Ryanair".

- *Purchase*. All the texts that explicitly express the decision to buy, are generally conveyed in first person and in future tenses. Texts that refer to the exact moment of the purchase also belong to this stage. For example: "The car is with the authorized dealer, I'm buying it tomorrow".

- *Postpurchase*. All the texts that explicitly refer to a past purchase and/or an actual user experience, are generally expressed in first person, in present as well as in past tenses. Texts that convey the possession or the use of some product are also annotated as "postpurchase", although there is no opinion about it. Some examples: "We went on the KIA"; "I bought a 2002 Citroen two days ago'"; "I've been using a pair of Nike for the past two years, and I'm delighted".

However, not all the texts in the corpus clearly pertained to one of the Consumer Decision Journey categories. It was obvious that a great amount of the texts did not imply user experience, or the stages appeared mixed. Therefore, we established two other categories under which the human annotator could tag the texts: ambiguous and no corresponding. The specific instructions to annotate these kinds of texts are the following:

- *Ambiguous*. All the texts where the author recommends or criticizes the product or brand but they do not imply active evaluation or user experience. Also all the texts in which one cannot distinguish if the author is expressing a postpurchase experience or an evaluation, or all those texts where the author explicitly recommends some product or brand. For instance: "I want the Peugeot"; "I love the clothes from Zara"; "I advise you not to buy this Bimbo bread".

- *No corresponding*. All the texts that contain news headlines or corporative or informative messages about the brand or product, without user's opinions or statements. Also: all the questions where one can not infer user experience, evaluation, or purchase intention; texts that express user experience, evaluation or purchase intention of a third person and texts that imply the sale of the product and do not contain user experience. Some examples: "Nike opens its first shop in Madrid"; "My father bought the gasoline 1.6 gls full"; "Hyundai car year '99 for sale".

The instructions provided to the annotators and reviewers regarding the Marketing Mix elements were as follows:

- *Quality*. All the texts that refer to the quality, performance, or positive or negative characteristics of a product that affect its user experience. For example: “Converse are extremely uncomfortable from the moment you put them on”.

- *Design*. All the texts that include a reference about specific traits or features of the product such as size, colour, packaging, presentation, and styling. For example: “Anybody notices the car GQ’s design collaboration with Citroen”.

- *Customer service*. All the texts that refer to the responsiveness and service given by companies to customers in every stage of the Consumer Decision Journey. Also, texts that refer to technical and post-purchase support to current and prospective customers. For example: “@MissTtheTeacher hiya, nope, I’m not through there. I’ve been on at that Scottish Power mob for weeks. Their customer service is laughable”.

- *Point of sale*. All the texts that include a mention to the physical place where the product can be found and purchased. Similarly, texts that convey difficulty with finding the product in the right distribution channels such as supermarkets, stores, outlets, dealerships, and stations. For example: “About to spend mad money at this Nike store!”.

- *Promotion*. All the texts that refer to marketing strategies oriented to increase demand such as contests, freebies, coupons, competitions, discounts, gifts, and offers. For example: “@Jennorocks lego promotion on at Shell garages :)”.

- *Price*. Texts that refer to the cost, value or price of the product. It may also comprise texts that refer to specific price promotion such as discounts and price cut, in which case the text should be annotated as “Price” and also as “Promotion”. This category also includes texts with numerical references to product prices. Some examples: “This Volkswagen I got my eye on is so sexy it’s an affordable price”, “@carllongs on lighter hearted note soreen on offer at tesco! 80p”, “1.47 and four slices have holes in them?! What on earth warburtons”.

- *Sponsorship*. Texts that refer to awards, competitions, teams, foundations, persons, charity fundraising, concerts and alike events which are organized, endorsed or financially supported by the company or brand. Some examples: “Breaking News Sainsbury’s becomes title sponsor of the first Sport Relief Games”, “School event this morning was sponsored by Scottish Power. Thinking of charging an extra 10% without telling them”.

- *Advertisement*. All the texts that include a reference to public, paid brand announcements or messages broadcasted in the media or placed in outdoor settings. Some examples: “These tv adverts are great aren’t they, Rory ’interestin’ McIlroy on Santander, and best of all Kerry Katona on pay day loans, priceless!”; “The lidl ad on Rte Two just now had deliscious written on the screen. Surely its delicious or is it subliminal advertising. lidl”.

4.7 Content Normalization

The analytic tools presented here rely on linguistic patterns. In order to apply these patterns to texts, these texts have to be processed and annotated with part-of-speech information. Linguistic processing is carried out by an automatic tagger which, however, cannot properly work with user-generated texts as the ones we analyzed since social media user-generated texts contain a large number of misspellings, abbreviations and jargon words. Badly written texts imply a great amount of errors in the part-of-speech annotation process, and consequently, without a normalization phase, the developed classifiers do not work correctly. For dealing with this issue, we have implemented the content normalization process shown in Figure 4.4.

A preliminary version of the content normalizer was described in Muñoz García, Vázquez, and Bel (2013) [81]. The specific tasks involved in the overall process are described in the following subsections.

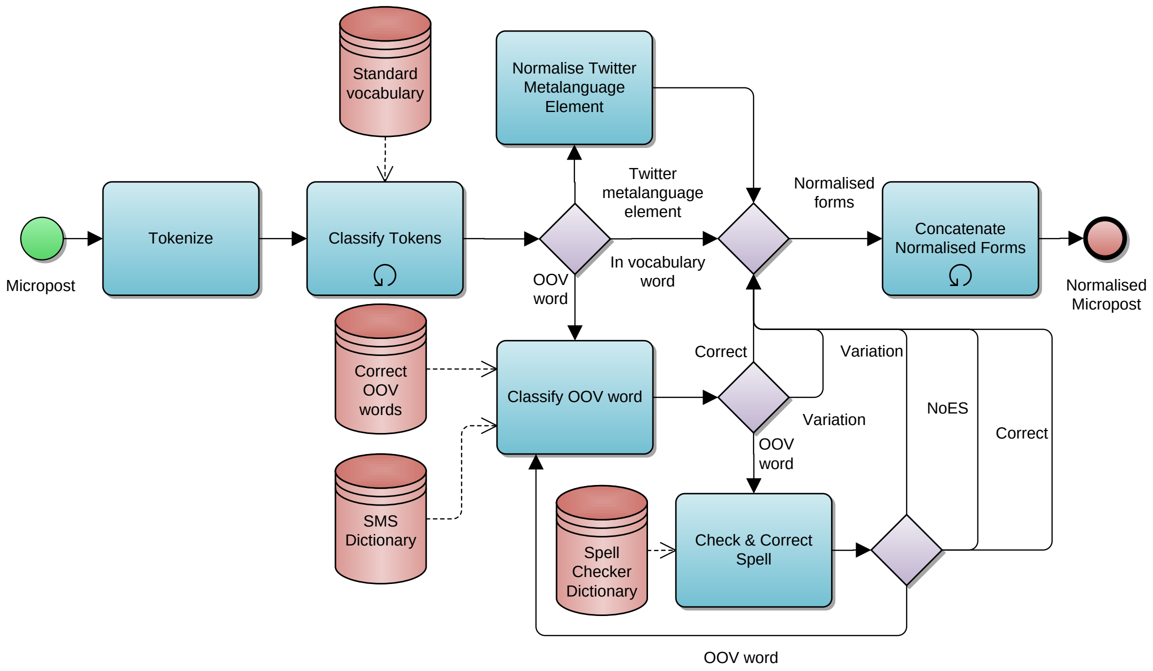


Figure 4.4: Content normalization process

4.7.1 Tokenization

This module receives the text to be normalized and segments it into words, Twitter metalanguage elements (e.g., hash-tags, user IDs), emoticons, URLs, etc. The output (i.e. the list of tokens) is sent to the *Classify Tokens* module.

We used Freeling [21] for social media content tokenization. Its specific tokenization rules and its user map module were adapted for dealing with smileys and particular elements typically used in Twitter, such as hash-tags, RTs, and user IDs.

4.7.2 Classifying Tokens

The input of this module is the list of tokens generated in the tokenization step. It classifies each of them into one of the following categories:

- Twitter metalanguage elements (i.e. hash-tags, user IDs, RTs and URLs). Such elements are detected by matching regular expressions against the token (e.g., if a token starts by the symbol "#", then it is a hash-tag). Each token classified in this category is sent to the *Normalize Twitter Metalanguage Element* module.

- Words contained in a standard language dictionary, excluding proper nouns. Each token classified in this category is sent to the *Concatenate Normalized Forms* module.

- Out-Of-Vocabulary (OOV) words. These are words not found in a standard dictionary that are not Twitter metalanguage elements. Each token classified in this category is sent to the *Classify OOV Word* module.

We used the POS-tagging module of Freeling in this task. As we deactivated Freeling's probability assignment and unknown word guesser module, all the words which were not contained in Freeling's POS-tagging dictionaries were not tagged, being considered as OOV words. Our standard vocabularies are, thus, the Freeling dictionaries themselves for English and Spanish. However, for Spanish, we extended the standard vocabulary with a list of correct forms generated from the lemmas found in the Real Academia Española Dictionary (DRAE) by Gamallo, García, and Pichel (2013)[82].

4.7.3 Classifying OOV Words

This module receives every token previously classified as OOV by the token classifier and detects if the token is correct, wrong, or unknown. Additionally, if the token is wrong, it returns the correct form of the token. These module executes the following steps:

1. Firstly, tokens are looked up in a secondary dictionary made up with words which are not in a standard dictionary but are correct forms (mostly proper nouns). We populated this secondary dictionary by making use of the list of articles' titles from Wikipedia[3]. In order to increase the coverage of this dictionary, we incorporated also two lists of first names obtained from United States Census Bureau[4] and from the Spanish National Institute of

[3]https://en.wikipedia.org/wiki Wikipedia:Database$_{download}$
[4]http://www.census.gov/

Statistics[5] to it. The list of first names for English contains 1218 male names and 4273 female names, while the list for Spanish contains 18,679 male names and 19,817 female names.

   (a) If an exact match of the token is found in the dictionary (e.g., both forms are capitalized), then the token is classified as *Correct* and sent to the *Concatenate Normalized Forms* module with any variation.

   (b) If the token is found with variations of case or accentuation, then it is classified as *Variation* and its correct form is sent to *Concatenate Normalized Forms* module.

   (c) If the token is not found in the dictionary, then the process continues in step 2.

2. The token is looked up in an SMS dictionary which contains tuples with the SMS term and its corresponding correct form. The search is case-insensitive, and does not consider accent marks. We have populated this dictionary with 898 common used SMS terms for English extracted from different Web sources. For Spanish, we have reused the SMS dictionary of the Spanish Association of Internet Users[6], which contains 53,281 entries.

   (a) If the token is found in the SMS dictionary, then it is classified as *Variation* and its correct form is retrieved and sent to *Concatenate Normalized Forms* module.

   (b) If the token is not found in the dictionary, then it is sent to the *Check and Correct Spell* module.

4.7.4 Checking and Correcting Spelling

This module checks the spelling of the token received and returns its correct form when possible. To do that, it executes the following process:

[5] http://www.ine.es/inebmenu/indice.htm
[6] http://aui.es/

1. First, the token is matched against regular expressions to find whether it contains characters (or sequences of characters) repeated more than twice (e.g., “looooooollll” and “hahaha”).

   (a) If the token contains repeated characters (or sequences of characters), then the repeated ones are removed (e.g., “lol”, and “ha”), and the resulting form is sent back to the *Classify OOV word* module, since the new form may be included into the correct words set.

   (b) If the token does not contain repeated characters (or sequences of characters), then the process continues to step 2.

2. The token is sent to an existing spell checking and correction implementation. We make use of Jazzy[7], an open-source Java library. For the creation of the spell checker dictionaries used by Jazzy, we made use of the different varieties of English and Spanish dictionaries[8]. The resulting dictionaries contain 237,667 terms for English and 683,462 terms for Spanish.

   (a) If the spelling is correct, then the token is classified as *Correct* and sent to the *Concatenate Normalized Forms* module without any variation.

   (b) If the spelling is not correct, then the token is classified as *Variation*, and the first correct form returned by the spell checker is sent to *Concatenate Normalized Forms* module.

   (c) If the spell checker is not able to propose a correct form, the token is classified as *Unknown* and sent to the *Concatenate Normalized Forms* module without any variation.

4.7.5 Normalizing Twitter Metalanguage Element

This module performs a normalization of Twitter metalanguage elements. Specifically, it executes a set of rules, previously proposed by Kaufmann and Jugal (2010) [83].

[7]http://jazzy.sourceforge.net/
[8]http://sourceforge.net/projects/jazzydicts/

1. Remove the sequence of characters “RT” followed by a mention to a Twitter user (marked by the symbol “@”) and, optionally, by a colon punctuation mark;

2. Remove user IDs that are not preceded by a conjunction, a preposition, or a verb;

3. Remove the word “via” followed by a user mentioned at the end of the tweet;

4. Remove all the hash-tags found at the end of the tweet;

5. Remove all the “#” symbols from the hash-tags that are maintained;

6. Remove all the hyper-links contained within the tweet;

7. Remove ellipsis points that are at the end of the tweet, followed by a hyper-link;

8. Replace underscores with blank spaces;

9. Divide camel-cased words in multiple words (e.g., “Barack-Obama” is converted to “Barack Obama”).

For example, after applying metalanguage normalization, the tweet “RT @AshantiOmkar: Fun moments with @ ShwetaMohan at the O2! She was wearing a DVY DarshanaVijayYesudas outfit! http://t.co/...” was converted into the following text: “Fun moments with Shweta Mohan at the O2! She was wearing a DVY Darshana Vijay Yesudas outfit!”. Obviously, this form is much easier for being processed by a part-of-speech tagger.

4.7.6 Concatenating Normalized Words

This module receives the normalized form of each token, and rebuilds the post.

4.8 Consumer Decision Journey Classification

As commented in the introduction, the main hypothesis behind this experiment is that customers utilize specific linguistic structures and lexical elements to talk about the different stages of the Consumer Decision Journey. Therefore, if it is possible to identify the particular linguistic expressions used in each of the stages of the purchase process, it should also be possible to classify the texts along the different phases and consequently, to locate the customer in the exact moment of this process.

A set of linguistic patterns was compiled in order to distinguish among the different stages of the Consumer Decision Journey and the developed classifier was based on the recognition of these particular linguistic structures.

4.8.1 Linguistic Rules to Identify Consumer Decision Journey Stages

The Consumer Decision Journey classifier is based on the recognition of linguistic patterns as sequences of particular words. These patterns are what we called "linguistic rules": descriptions of the linguistic patterns as particular conditions that have to be met in order to consider the text and example of a particular Consumer Decision Journey stage.

The general structure of the linguistic rules is the following:

$$< Linguistic\_Pattern > \rightarrow < Consumer\_Decision\_Journey\_Stage > \quad (4.1)$$

In order to generalize pattern matching, we used particular Natural Language Processing tools, specifically the tools provided by Freeling [21], to lemmatize (i.e. grouping together different inflected forms of a word to process them as one single element) and to add morphological information (i.e. part-of-speech, to distinguish between homographs such as "walk-verb" or "walk-noun", verb tense, and person). Thus, a text such as 4.2 gets the representation shown in Table 4.2, where DT means Determiner, NN means Noun, PRP means Pronoun, VBD means Verb in past tense, IN means Preposition, VBZ means Verb in present tense, RB

Word	Lemma	Part-Of-Speech
This	this	DT
Volkswagen	volkswagen	NN
I	i	PRP
got	get	VBD
my	my	PRP
eye	eye	NN
on	on	IN
is	be	VBZ
so	so	RB
sexy	sexy	JJ

Table 4.2: Example of lemmatization and part-of-speech tagging.

refers to Adverb, and JJ to Adjective. More information about the tags for English can be found in Santorini (1991) [84], and for Spanish in Leech and Wilson (1996) [85].

$$\textit{This Volkswagen I got my eye on is so sexy} \tag{4.2}$$

Linguistic rules are built to match the occurrence of a lemma and its synonyms and antonyms (to increase recall), and the particular context where they could occur is used as a restriction.

The description of the context includes morphosyntactic information as obtained with the tagger. The inclusion of morphosyntactic information allows to differentiate, for example, between "I bought" that is an expression related to postpurchase stage and "I'm buying" related to purchase stage.

Some examples of linguistic rules are given in Table 4.3. For example, the first pattern matches the gerund form of the verb "to laugh", followed by a preposition (any), the word "a" and the lemma "commercial" at a maximum distance of one word.

All the linguistic rules developed for Spanish and English are reported in Appendix A.

The following listing shows the BNF grammar of the linguistic rules:

Linguistic Rules	Consumer Decision Journey Stage
laugh#VBG [IN] “a” /1/ commercial	Awareness (English)
[PP1] [VA] gustar [DI] vídeo	Awareness (Spanish)
wonder if _ENTITY_ [MD] offer	Evaluation (English)
estar#V.IP1 buscar#V.G	Evaluation (Spanish)
i “will” buy	Purchase (English)
ir#V.I.1S “a” pillar [D]	Purchase (Spanish)
i call#VBD /1/ customer service	Postpurchase (English)
[PP1] quedar#V.I.1 con _ENTITY_	Postpurchase (Spanish)

Table 4.3: Examples of the linguistic rules.

```
<pattern> ::= (<word> | <lemma> | <part−of−speech> |
               <lemma−and−part−of−speech> | <entity> |
               <any−number−of−words−between> |
               <max−number−of−words−between>)+
<word> ::= ““’ <string> “”’
<lemma> ::= <string>
<part−of−speech> ::= <string>
<lemma−and−part−of−speech> ::= <word> # <lemma>
<entity> ::= _ENTITY_
<any−number−of−words−between> ::= “∗”
<max−number−of−words−between> ::= / <positive−number> /
```

Identifying Awareness

As commented in previous sections, in the texts belonging to the awareness stage authors tend to comment, criticize or talk about their experience with respect to specific advertising campaigns or promotions of the selected product or brand. Therefore, the rules that we created to identify sentences pertaining to this stage (96 for English and 65 for Spanish) mostly rely on particular lexical items belonging to the advertisement word family. Some examples are: “advertisement”, “campaign”, “promotion”, “video”, “sign”, etc. In the initial analysis of this kind of texts, we created more restrictive rules, matching longer portions of text, however further analysis of the classifier results showed that, when using more lexicalized and less restrictive rules (with a small set of part-of-speech tags and functional words), the final results of the classifier were equal or even better.

Identifying Evaluation

Rules designed to identify evaluative texts (440 for English and 167 for Spanish) showed more complexity than those created to distinguish awareness. For this Consumer Decision Journey stage, rules are longer and contain more morphosyntactic information, although the weight of the lexical elements continues to be high. Generally, the rules of this class are more restrictive than those for awareness.

Since in this step the user tends to compare products or brands, a great amount of the rules identify comparative constructions. For example: "all the best /1/" or "more [AQ] than".

There are also rules which incorporate specific vocabulary usually used to convey preference or comparisons such as "stand out", "prefer", "recommend" and "suggest".

Identifying Purchase

For this stage we have defined 1267 rules for English and 906 rules for Spanish. Generally, users tend to write a lot of comments before and after purchasing some product but the number of remarks about the specific moment of the transaction is low. Additionally, the number of different ways to express this specific stage is also shorter with respect to other stages. We identified a set of verbs, generally expressed in future tenses, whose meaning is related to "buy" or imply a purchase: "acquire", "hunt down", "reserve", "try", "grab", etc.

Identifying Postpurchase Experience

This is the stage with the most complex rules (710 for English and 769 for Spanish). The distinction between expressions belonging to this stage and those belonging to evaluation is vague and it is frequently based on extralinguistic knowledge more than on specific linguistic cues. For example, if we find a sentence such as “I like this beer” it can imply that the author has bought or tried the beer, and thus the text should be actually classified as postpurchase experience. However, a sentence such as “I like this car” does not entail that the author has effectively bought the car; he can just love it for its design, for example. Therefore, these kinds of sentences are not clearly associated with one of the stages, being ambiguous between evaluation and postpurchase experience.

We found that there is a strong relation between the type of product and the linguistic expression of the postpurchase experience, being ambiguous in many of the cases. In consequence, for this stage, we decided to build rules with a considerable amount of morphosyntactic information (to consider past tenses of the verbs, for example) and lexical elements related to postpurchase customer services (e.g., “complaint”, “unsubscribe”).

4.8.2 Rule-Based Classifier

In order to distinguish texts belonging to the different stages of the Consumer Decision Journey, we designed a rule-based classifier. The entire classification process consists of the following steps:

1. Firstly, the lemma and the part-of-speech tag of every token that form the text to analyze are identified, obtaining a sequence of tuples made up of the token, its lemma and its morphosyntactic category.

2. Secondly, the linguistic patterns that match the entire text or a part of the text are identified. If there are several expressions that overlap, then the system selects the most restrictive one (i.e. the one that matches the longest piece of text). As misspellings are frequent in user-generated content, the matching step is not case-sensitive, and the system strips accent marks from the text and patterns before performing the matching.

3. Finally, the system classifies the text according to one of the four categories of the Consumer Decision Journey, depending on the expressions that matched in the previous step. If the text is classified into more than one category, then the one that corresponds to the latest stage in the Consumer

Decision Journey workflow is selected, discarding the rest of the classifications.

4.9 Marketing Mix Classification

In order to automate the classification of texts based on the Marketing Mix elements conveyed in them, we trained a set of Decision Tree (DT) classifiers. We built a dataset with all the texts manually annotated as belonging to a given category (advertising, customer service, design, point of sale, price, promotion, quality, and sponsorship) as positive examples. For each category, we also utilized all the texts that do not belong to that given category as negative examples. The size of the datasets ranged between 85 and 1046 texts for the positive examples.

After building the dataset, we carried out the normalization explained in Section 8. Then, we annotated the texts with their corresponding part-of-speech tags using Freeling, and removed a list of stopwords that included not only functional words but also brands and proper nouns. We only worked with the lemmas of adjectives, verbs (with the exception of auxiliary verbs) and common nouns, considering the rest of categories irrelevant or less important for the identification of the attributes.

We adopted a bag-of-words approach where words occurring in texts are used as features of a vector. Then, each text is represented as the occurrence (or frequency) of words in it. This approach embodies the intuition that the more frequent the word is in the texts of the class (i.e. Marketing Mix element selected), the more it is representative of the content and therefore of the class.

A chi-square feature selection method was then applied in order to reduce vector dimensions by selecting the more relevant features. The idea behind this feature selection method is that the most relevant words to distinguish positive examples are those that are distributed most differently in the positive and negative class examples.

To classify the texts according to the Marketing Mix elements, we used the vectors previously created with a C4.5 [80] DT Classifier as implemented in Weka

[86]. [9] Additionally, DT shows relevant features for classification and therefore, is easily interpretable by humans. This fact made the results of these classifiers very useful for final visualization and human consumption purposes. In order to create real-life applications in the marketing field, this is a very important feature, being able to visually show customers of marketing agencies the criteria to be followed for text classification. Additionally, the DT model can also be manually revised in order to remove terms that can appear as relevant features due to biased samples. For example, "trainer" appeared as one of the discriminative features to decide if a text belongs to a design. With the direct visualization we could identify and eliminate it.

The classification for each category is made between the positive class (for example, Advertisement) and the negative class (for example, No Advertisement). The results for the negative class are generally much better than those obtained for the positive class due to the larger number of texts of the negative class used to train the classifiers. However, as the main objective of our work is being able to introduce this tool in a real marketing scenario, we find that it is preferable to classify a text in a negative class if the classifier does not find enough cues than to erroneously classify it in a positive class.

Finally, as a given text can belong to more than one category, we built multi-category classifier that combines all the binary classifiers in a parallel architecture that iteratively identifies the marketing mix elements expressed in each text.

4.10 Evaluation

This section presents the evaluation results. The section is structured as follows. Section 4.10.1 shows the evaluation results for the Consumer Decision Journey, while Section 4.10.2 presents an evaluation of the results for the Marketing Mix attributes. Section 4.10.3 discusses the improvement introduced by the content normalization technique. Finally, Section 4.10.4 discusses scalability issues related with the deployment of our tools in a Big Data environment.

[9] We also tried to use a Logistic Regression model classifier [87] as implemented in Weka [86] but the results were better with the DT classifier.

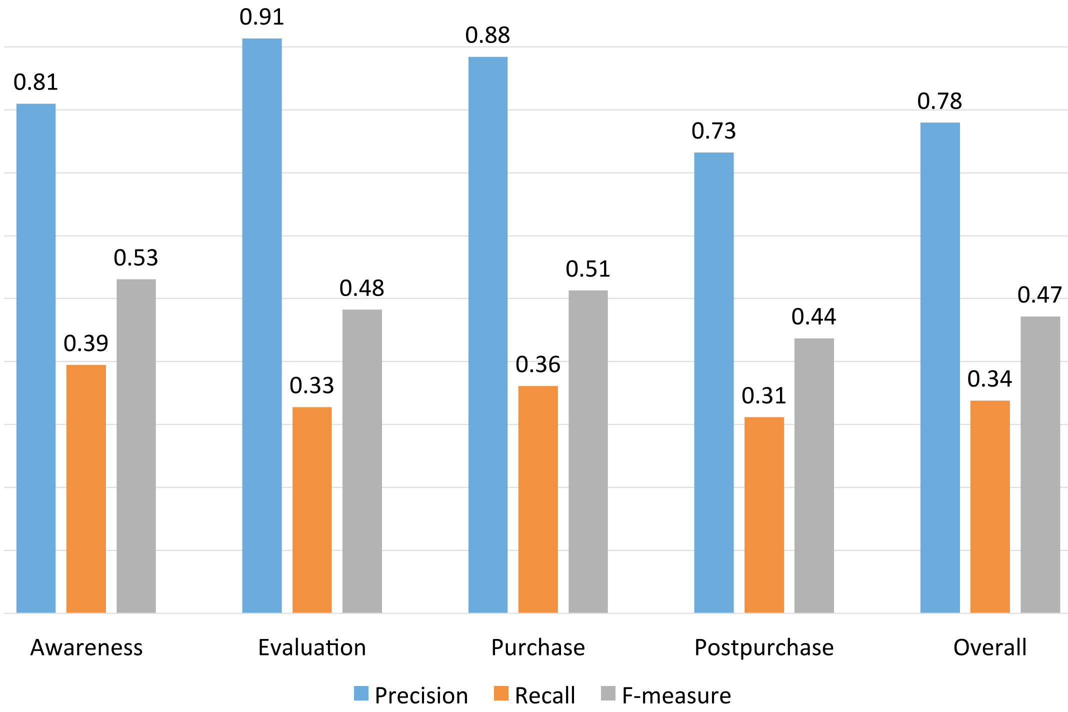


Figure 4.5: Accuracy of the Consumer Decision Journey classifier for English.

4.10.1 Evaluation of Consumer Decision Journey Classification

We evaluated our linguistic rules over the texts in our Gold Standard. The overall results of the textual classification in terms of precision[10] are 74%, while in terms of recall[11] are 35%, achieving an F-measure [12] of 48%. Figures 4.5 and 4.6 show the results by category and language.

In general, the rules achieved satisfactory results in terms of precision, especially in the awareness, evaluation, and purchase stages for English, and awareness for Spanish. Results in terms of recall were lower than those achieved in precision, as rules were designed very specifically in order to minimize the number of false positives. Generally, the stage where we obtained best results is awareness, specifically for Spanish.

[10] Precision = true positives / (true positives + false positives).

[11] Recall = true positives / (true positives + false negatives).

[12] F-measure = 2· Precision · Recall / (Precision + Recall).

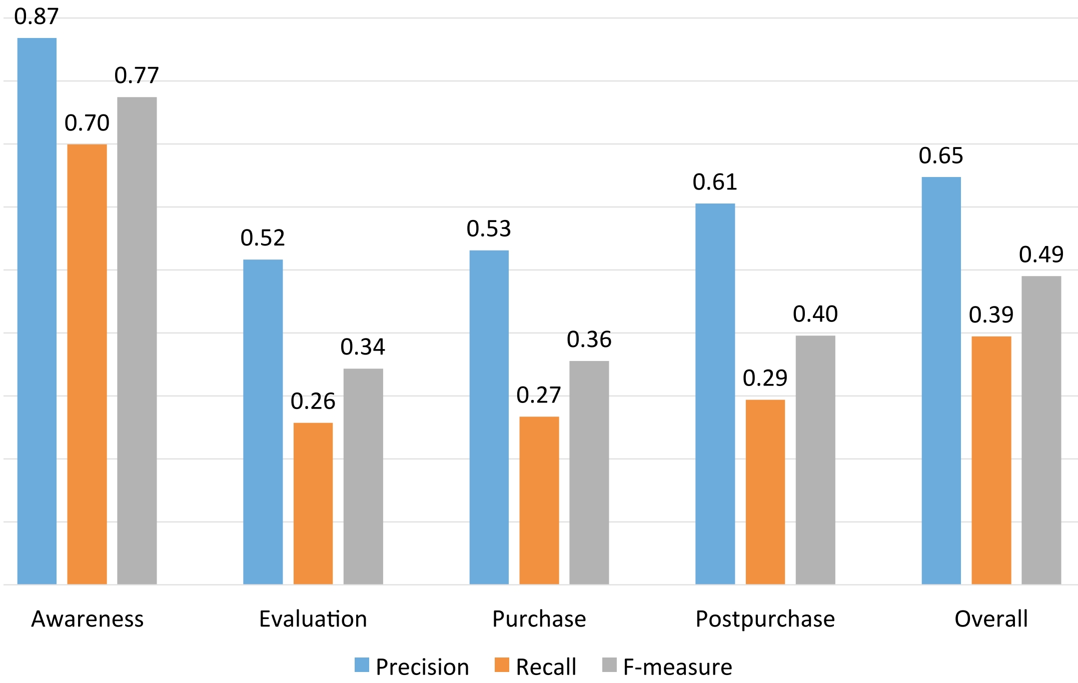


Figure 4.6: Accuracy of the Consumer Decision Journey classifier for Spanish.

We also offer the results for the classification along the different business sectors (Figure 4.7) in order to evaluate the difficulties of the classification depending on the domain. We found that banking and beverages were the business sectors where we obtained the best results, with the greatest values of F-measure.

4.10.2 Evaluation of Marketing Mix Classification

We have also evaluated how the DT classifiers perform in the classification of each user-generated text depending on the Marketing Mix element (or elements) expressed. We have used the 10-fold crossvalidation approach for evaluating the developed classifiers. We have obtained an overall precision of 75% and an overall recall of 37%, being the F-measure of 50%. The results obtained in this task for English and Spanish can be seen respectively in Figures 4.8 and 4.9.

As observed in the figures, the results are generally low (except for Advertisement) in terms of recall, which range from 4% to 80% for Spanish and from 9% to 83% for English. It seems that there is a relation between the number of

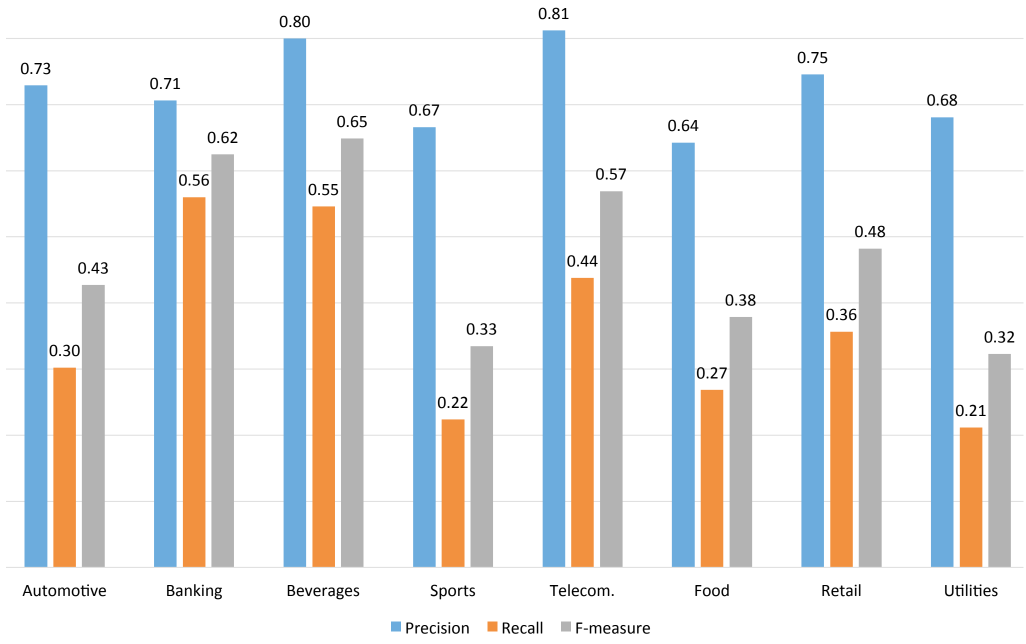


Figure 4.7: Accuracy of the Consumer Decision Journey classifier by sector.

texts of the positive class utilized to train the model and the corresponding results in terms of recall and precision. For example, in Spanish the classifier that was trained with the smallest number of texts, was the one for the positive class of Customer Service, where we only had 85 short texts. The results of the classification are 4% and 38% for recall and precision, respectively. In the same line are the results for English; one of the Marketing Mix elements trained with less texts of the positive class (238) is Point of Sale, therefore the results obtained are also the lowest ones: a recall of 9% and a precision of 48%. We can observe the same situation in the models trained with a larger number of texts; both in Spanish and English, the Advertisement classifier was trained with a lot of positive examples, and thus this class achieved very good results in terms of recall as well as precision (80% and 83% for recall and 88% and 93% for precision, for Spanish and English respectively).

It is also interesting to see how some Marketing Mix elements are much more difficult to identify than others.

For example, we can observe that the element Quality is very hard to classify, even increasing the number of texts used to train the model. In Spanish, the

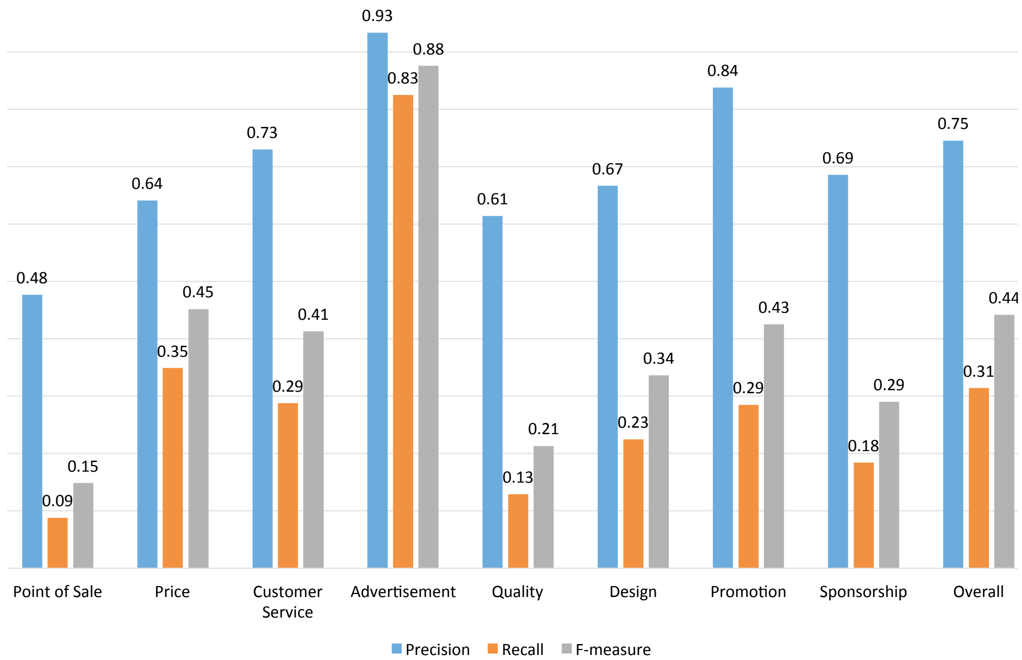


Figure 4.8: Accuracy of the Marketing Mix classifier for English.

number of texts used as positive examples is 371 and we obtained 18% and 56% of recall and precision respectively. However, in English, where the model was trained with a larger number of texts as positive examples (1046 texts), the results are in line with those obtained for Spanish: 13% of recall and 61% of precision.

These differences of difficulty among domains are due to the dispersion of the vocabulary used to talk about some Marketing Mix elements. For example, we observed that customers can talk about Quality making reference to the comfort (for Automotive industry, for example), to the security (in Banking, for instance) or to the taste (for Food or Beverages). Therefore, the reference to Quality can be made through a great variety of topics and thus, the reference to this element is much more varied than the reference to others Marketing Mix elements such as Price or Advertisement. The linguistic cues are more disperse and thus, the classifier finds more difficulties to relate a word with a specific class.

Finally, although the results specially in terms of recall should be improved, we consider that as a first attempt to automatically classify and filter user-generated content from social media in terms of Marketing Mix elements, the results ob-

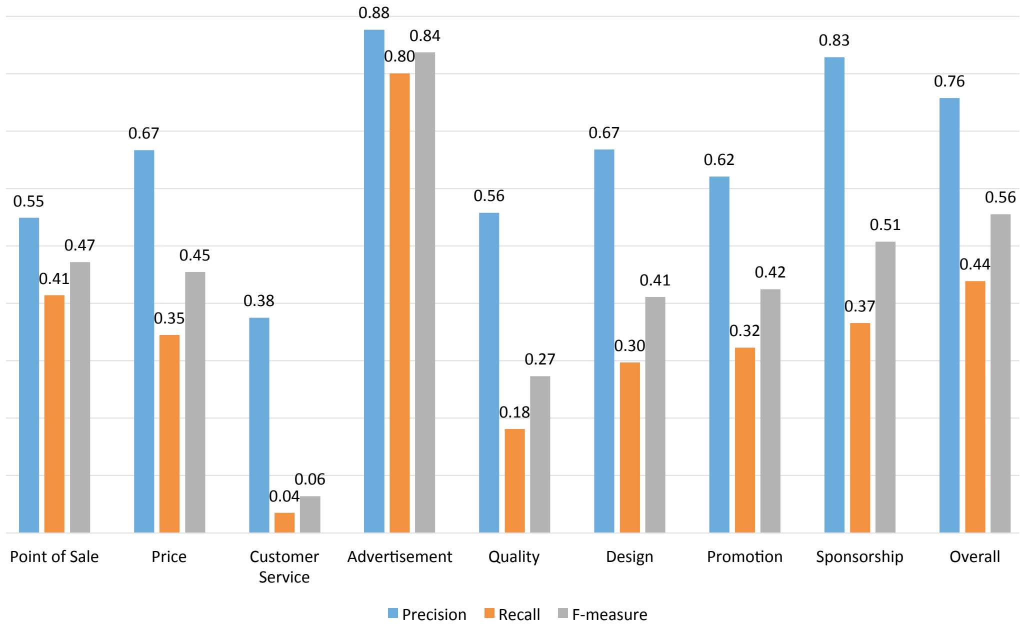


Figure 4.9: Accuracy of the Marketing Mix classifier for Spanish.

tained are very encouraging and very satisfactory for elements such as Advertisement.

4.10.3 Evaluation of Content Normalization

We have measured how the normalization process improves the Consumer Decision Journey classification (Table 4.4), finding that our content normalization technique slightly improves the overall performance for the Spanish language (the F-measure is increased by 2 points), and the precision for the English language, which is increased by 1 percentage point.

4.10.4 Evaluation of Scalability

Because of its scale, brands' earned media mentions extracted from social media channels and gathered by marketing and communications agencies can be considered "Big Data", as they are characterized by its huge volume of data, high velocity of production, and high heterogeneity [88].

Media agencies extract more that 1000 M posts a year from its social media

Language	Normalization	Precision	Recall	F-measure
English	Yes	0.78	0.34	0.47
	No	0.77	0.34	0.47
Spanish	Yes	0.66	0.39	0.49
	No	0.65	0.37	0.47

Table 4.4: Improvements of the consumer decision journey classification.

monitoring tools, including mentions to its monitored brands and their competitors. This represents a volume of more than 1.5 TB of raw data mainly consisting of text, associated content and authors' metadata. Such volume grows very significantly when is processed, augmented with different classifications, and integrated and indexed within databases.

The high velocity in which data is produced is a challenge, as data needs to be processed faster than content is produced, at a near real-time pace.

In addition, variety along several dimensions (e.g., content quality, multilinguality, multiplicity of formats, diversity of technologies and techniques to be integrated) has conditioned the infrastructure developed to evaluate the scalability of the work presented in this dissertation.

The classifier developed was integrated into a Big Data infrastructure deployed in Havas Media Group.

Measures of the time required for the multi-classification of each piece of text shows that it takes an average of 0.46 s per post (note that length of test varies across different sources). Therefore, we found it very useful in order to automatically tag the data stream continuously extracted and analyzed by marketing companies by Consumer Decision Journey stages and Marketing Mix elements.

4.11 Discussion and Error Analysis

In order to better understand the particular errors and problems we had to deal with, and to provide information for further improvements in the future, we distinguish the main types of difficulties that we found during the present experiment.

4.11.1 Ambiguity

The distinction among the different stages of the Consumer Decision Journey is not always clear. Frequently, belonging to one stage or another is strongly related to the type of product, and the differentiation among stages can only be performed applying extralinguistic knowledge. Sentences such as “I like this beer” and “I like this car” were frequently found in the corpus. In the first case, it is very likely that the user has already tried the product (postpurchase experience), since it would be strange for a customer to state that he likes a drink (or some food) without actually tasting it. In the second case, instead, the actual consumption of the product is less probable, and the customer can like the car just because of its television advertisement or its design, for example. These kinds of ambiguities are especially frequent between evaluation and postpurchase experience, and the linguistic patterns are not able to capture the differences between them since they are expressed through the same linguistic expression.

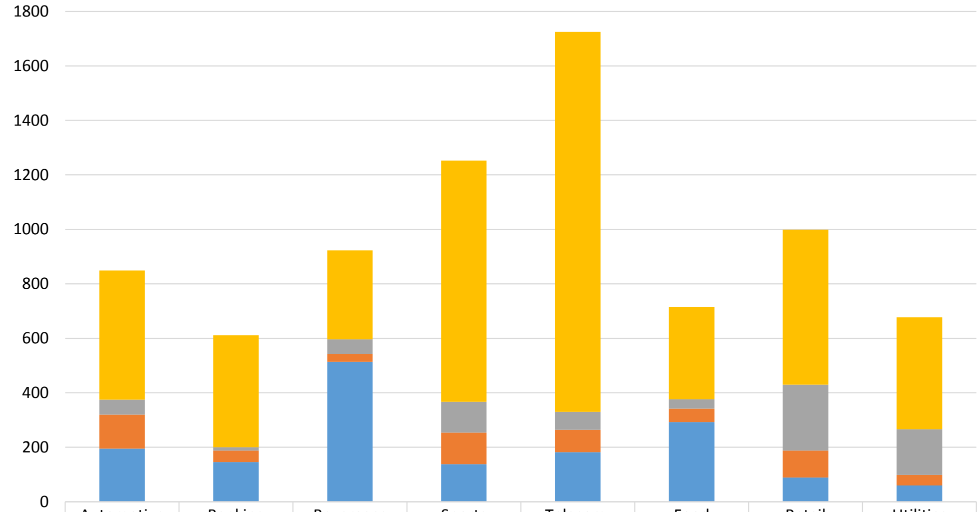
A further classification of products depending on domain dependent features, could be useful in order to discriminate between evaluation and postpurchase experience in these types of ambiguous cases.

4.11.2 Representation in the Corpus

As we can see in Figure 4.10, the number of texts per category is very unbalanced along the different stages of the Consumer Decision Journey.

We observed that there is a general tendency to comment or analyze the quality and other features of expensive or high involvement products, while cheaper ones received much less feedback. Particularly, in the case of cars, mobile providers or sportive clothes and shoes (sectors Automotive Industry, Telecommunication, and Sports respectively), we appreciated that customers tend to write more evaluative texts, investigating the pros and cons of different brands before buying them. Users are also inclined to comment their personal experiences with the product after using it. Accordingly, it is more difficult to find evaluative messages about consumer packaged goods such as beverages or food whose cost is typically much lower. In these cases, customers need less deliberation, show less involvement, and they usually do not compare these products with their competitors before purchasing them. However, in the case of cheaper products, consumers tend to pay much more attention to the advertising campaigns (awareness). Correspondingly, the number of comments about their postpurchase experience is also lower in this kind of products.

In the construction of the corpus we also could observe the difficulty of filtering texts by their belonging to one of the marketing mix categories; the great majority of the texts are irrelevant for our classification given that just a small group of them implies marketing mix elements (25% of the corpus).



	Automotive	Banking	Beverages	Sports	Telecom.	Food	Retail	Utilities
Postpurchase	474	411	327	886	1395	340	569	411
Purchase	55	12	53	113	66	34	242	167
Evaluation	125	42	29	116	82	49	99	39
Awareness	195	146	514	138	182	293	89	60

Figure 4.10: Distribution of the texts along the Consumer Decision Journey categories.

4.11.3 Language Varieties

There are multiple geographic varieties for English and Spanish that present lexical differences. This implies additional difficulties to pattern identification, since lexical units differ from a variety to another and are especially hard to detect.

Further work in this line (i.e. including specific lexical elements from different varieties of the languages analyzed) could help to improve the recall results.

4.12 Conclusions

In this chapter, we presented a novel analysis of user-generated texts in terms of their belonging to one of the four stages of the Consumer Decision Journey. Using a corpus made up of documents extracted from different social media sources and pertaining to several business sectors, we created specific linguistic patterns and used them in a rule-based classifier to unambiguously distinguish among texts belonging to the different stages. We achieved an overall precision of 78% and 65%, and an overall recall of 34% and 39%, for English and Spanish, respectively.

In addition, we have developed machine learning classifiers that enable us to identify Marketing Mix elements in user-generated texts. These allow a more accurate, fine-grained consumer buzz analysis (i.e. not only establishes purchase stages but identifies relevant, common topics of conversation among customers throughout their shopping experiences) and, in consequence, enables marketers to take better-informed business decisions. The system has been implemented training a set of Decision Tree classifiers achieving an overall precision of 76% and 75%, and an overall recall of 44% and 31%, for English and Spanish, respectively.

To our knowledge, at the time of this investigation, ours was the first attempt to automatically classify these business indicators such as Consumer Decision Journey and Marketing Mix elements using rule-based and machine learning classifiers. The automatic identification of these business indicators is very much needed in order to drastically reduce time and efforts in the manual annotation by marketing analysts. Due to the novelty of this research area, much work remains to be done, including its adaptation to other languages and the research on possible methods to improve the overall recall.

Additionally, the classifiers described in this work make use of a technique for user-generated content normalization that relies on existing web resources collectively developed, finding that such resources, useful for many NLP tasks, are also valid for the task of micropost normalization.

Finally, it was validated that the software components developed can be integrated within a Big Data processing platform.

Chapter 5

CONTRIBUTIONS

The research in this dissertation focuses on the analysis and resolution of several issues related to the task of the automatic extraction of information relevant for tasks such as Sentiment Analysis or, more generally, Social Media Analysis, from user-generated contents published on different social media. In this sense, the main contribution of this dissertation is *an empirical study about the impact of lexical information for Social Media Analysis tasks*.

The following are the contributions that resulted from the word presented in this thesis.

1. *A new classification of adjectives for the tasks of Sentiment Analysis and Social Media Analysis based on an empirical study that demonstrates the importance of subjectivity and domain.*

   In Chapter 2, we carried out a case study in order to empirically assess the proportion of adjectives whose polarity (positive, negative or neutral) suffered from variations depending on the domain where they are applied.

   In order to study the variability of the polarity values, we designed an annotation task to compare the different tags that a group of human annotators gave to a set of adjectives. We designed the guidelines to accomplish the annotation task and trained a group of five humans for the annotation of a set of 1542 adjectives (514 per domain) of the three domains selected. The guidelines were revised, before starting the annotation task, taking into account the comments and doubts of the annotators and other researchers, until they were clear and understandable for all the annotators. They are explained in Section 2.2.

With the information provided by the humans' annotations, we could assess the average polarity expressed by the adjectives as well as the dispersion of the tags given to them by the humans.

On the one hand, the average polarity provided information about the tendency of the adjectives to be positive or negative and let us to observe the first variations on the polarity values assigned depending on the domain. According to this measure, we discovered that we could split the adjectives into two different groups: *domain dependent* and *domain independent* elements. More importantly, we discovered that the number of domain dependent adjectives was much larger than the independent ones: the 67% of the adjectives were domain independent elements. That is, only the 33% of the adjectives have a prior polarity, independent of the domain and invariable.

On the other hand, we calculated the standard deviation of the tags given by the five humans to the different adjectives in our sample. The results on the assessment of the tags' deviation showed that adjectives could be also divided into three groups: constant, mixed and highly subjective adjectives. The classification of the adjectives in these categories was determined by the deviation of the humans' annotations. *Constant adjectives* did not present any deviation, that is, the annotators totally agreed in their tags in all the domains. *Mixed adjectives* presented disagreements on the tagging in some domains but total agreement in others. Finally, *highly subjective adjectives* showed total disagreement along all the domains analyzed.

This new classification of adjectives depending on the deviation of the tags assigned by the annotators confirmed that 45% of them (mixed plus highly subjective elements) actually present a variability on the polarity they express, changing even when the adjectives are used within the same domain.

The analysis carried out in this case study represents the first attempt in the field of Sentiment Analysis, not only in Spanish but in any language, to assessing the real proportion of adjectives that present domain dependency. Moreover, in this research, we did not only present a proportion of adjectives that change their polarity depending on the domain but also the proportion of adjectives that change this value even when being used within the same domain. This lexical feature, related to the gradability of adjectives ([6, 4, 89, 90, 7]), although briefly noted in some works in the field ([50, 91]), neither has been quantified before.

In our revision of the state-of-the-art literature, we did not find any work that gave this specific information so far. Moreover, the review of the most well-known and broadly used polarity dictionaries created until now showed that none of them takes into account these specific features, specially polarity changes within the same domain. Actually, general sentiment lexicons continue to be widely used in the development process of almost any current Sentiment Analysis tool. We strongly believed that taking into account the features discovered in these case study should be a must in the new polarity lexicons created from now in order to improve the precision of the Sentiment Analysis tools developed from them.

In this sense, our investigation contributes to the better understanding of the lexical features of polar words, specifically polar adjectives, giving empirical and exact information on the proportion of adjectives whose polarity actually change both inter- and intra-domains.

This experiment and its corresponding results are reported in Vázquez and Bel (2012) [92].

2. *A methodology for automatically inducing the relevant information of adjectives occurring in a corpus. This methodology was used in the development of a system for automatically producing lexical resources with the relevant information.*

   After achieving empirical insights of the importance of polarity variations in adjectives, we though that this feature should be reflected, because of its relevance, in the polarity lexicons currently used in Sentiment Analysis tools.

   An accurate revision of the works on the creation of sentiment dictionaries showed us that current lexicons had two main shortcomings.

On the one hand, none of the most well-known and broadly used polarity lexicons took into account inter- neither intra-domain semantic orientation variations. This feature went directly against the empirical results obtained in our case study thus, we found that current dictionaries presented a crucial gap in this sense that should be solved. Accurate polarity lexicons should include not only invariable positive and negative words but should also reflect the possible polarity variations that polar words can suffer from one domain to another or along the same domain.

On the other hand, approaches to induce polarity lexicons were very complex in terms of time and human resources needed and their dependency on external resources was very high. Many works on polarity lexicons induction were based on the use of general dictionaries or thesaurus (generally, WordNet), taking advantage of the synonymy and antonymy relations provided by them. However, this approach posed some issues. Firstly, general dictionaries used to induce polarity lexicons do not contain slang, misspelled words or neologisms therefore, the sentiment dictionaries generated from them neither contain these lexical elements. These types of words, however, are very common in user-generated contents thus, polarity lexicons should included them as important linguistic cues for opinion identification. Apart form that issue, these approaches can not be used for languages where these type of language resources are not available.

This dissertation contributes to overcome these issues proposing of a bootstrapping algorithm to automatically identify positive, negative but also highly subjective adjectives (i.e. polar adjectives whose semantic orientation can change even within the same domain) along with this corresponding polarity values. Additionally, the designed method is able to identify slang and misspelled words used as polar elements and is not based on any external language resources apart from a basic part-of-speech tagger.

The proposed algorithm can be easily adapted to any new domain where a set of user-generated documents is available, it can extract polar adjectives along with their polarity values in some minutes[1] and does not need any

[1]The run-time depends on the number of conjunctive patterns extracted form the corpus ana-

human annotator nor external language resources. Additionally, it achieves a precision of 97.6% and 71.5% for positive and negative adjectives respectively, and 67% in terms of recall.

This experiment and its corresponding results are reported in Vázquez et al. (2012) [93].

3. *A rule based system for the analysis of particular characteristics of user generated content related to the Purchase Funnel analysis model, popular in marketing studies.*

4. *A machine learning based system for the analysis of more characteristics of user generated content related to the Marketing Mix model which supports the fine grained analysis of relating opinion judgments to particular characteristics of a product, such as price, design, etc.*

   During the development process of the bootstrapping algorithm proposed, we also discovered that there were a lot of linguistic patterns that provided information about different aspects of the products, not expressing opinion but directly related to it. We found that customers were inclined to repeat or use similar linguistic structures to talk about different aspects of the product (such as price, advertisement, etc.). As a result of these discoveries, we started a project with a marketing company to develop a real social media analysis tool only based on linguistic knowledge.

   The social media analysis system designed is described in Chapter 4. For this task, we developed a set of linguistic rules capable to classify customers messages into the different stages of the purchase process (that is, awareness, evaluation, purchase or postpurchase experience) according to the step of the purchase process where the user is talking about.

   Additionally, we also designed a set of decision trees algorithms based only on lexical elements to automatically classify the same documents into Price, Promotion, Place, or Product according to the features of the product that the customer was talking about.

lyzed

The automation of the classification of these types of contents is a very important issue in fields such as marketing since it can drastically reduce time and human resources efforts, replacing the classic surveys and polls analysis for this automatic analysis, and going towards the real-time social media analysis.

In this sense, our work contributes to the automation of social media contents classification, being the first attempt to automatically classify user-generated content into one of the stages of the purchase funnel and classifying these types of documents into different categories of the marketing mix (such as Price, Product, Place or Promotion), exclusively basing on the language structures and lexical items used by the authors. The social media analysis tool created achieved very promising results in terms of precision (from 65% to 78% depending on the task and language) both in Spanish and English.

These two systems demonstrate that Sentiment Analysis can be further expanded, provided an appropriate linguistic analysis of user generated content.

Besides, both systems were deployed as actual industrial systems that considered also practical factors as the importance of benefiting precision vs. recall, or the speed required for processing large amounts of data.

The development process of these classifiers and the results obtained are reported in Vázquez et al. (2014) [ázquez201468].

5. *A number of datasets and resources that will be offered to the community for further research and comparison.*

   As a result of the annotation task, we obtained a dataset with all the tags that five annotators gave to a list of 514 adjectives appeared in three different domains as well as the average polarity and standard deviation of the tags of these annotated lexical items. We find that this dataset constitutes another of the big contributions of the research presented on this dissertation. This data, available now for new researchers on the field, provides information about how the humans feel a set of adjectives in terms of their semantic orientation with respect to a topic or domain. This dataset, the first of this type in Spanish, can be reused in other investigations not only on Sentiment Analysis or Social Media Analysis, but also on Psycholinguistics and related areas.

In order to obtain all the adjectives that were used in the case study described above, we also collected a set of corpora made up with reviews of different products written by their users. The corpus obtained with all subcorpora of the different domains or products is almost 8 Million words and is in Spanish. All the documents that form the corpus are product reviews about different products (cars, movies, cell phones, video games and sport teams) extracted from Ciao[2], a review aggregation website. From each evaluation published in this web, we extracted the text where the author explains their experience with the product and exposes his/her opinion about it, and a set of metadata that includes a small summary of the pros and cons of the product and a score (from 1 to 5) given by the user.

We believe that this corpus, as well as our annotated dataset, is a key contribution of this dissertation to the field of Sentiment Analysis and related areas, specifically for the language we analyzed, Spanish. Both language resources can help new researchers in the field to have available resources from which to continue the investigation started here or analyze the data from a new perspective. The availability of resources such these will reduce drastically the time dedicated to the construction of them, free to investigate other issues.

5.1 Publications and Merits during the PhD Studies

The main experiments presented in Chapters 2, 3 and 4 of this dissertation have been published in the following articles:

- Vázquez, S. and Bel, N. A Classification of Adjectives for Polarity Lexicons Enhancement. In *Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC'12).*

[2]http://www.ciao.es/

- Vázquez, S., Padró, M., Gonzalo, J., and Bel, N. Automatic Extraction of Polar Adjectives for the Creation of Polarity Lexicons. In *Proceedings of COLING 2012: Posters: 24th International Conference on Computational Linguistics (COLING 2012).*

- Vázquez, S., Muñoz-García, Ó., Campanella, I., Poch, M., Fisas, B., Bel, N., and Andreu, G. *A Classification of User-Generated Contents into Consumer Decision Journey Stages.* Neural Networks, 58, pp. 68-81. 2014.

Additionally, during the PhD studies, we have also published the following articles:

- Steinberger, J., Lenkova, P., Ebrahim, M., Ehrmann, M., Hurriyetoglu, A., Kabadjov, M., Steinberger, R., Tanev, H., Zavarella, V., and Vázquez, S. *Creating Sentiment Dictionaries via Triangulation.* Decision Support Systems, 53, Issue 4, 689-694. 2012.

- Marimon, M., Fisas, B., Bel, N., Arias, B., Vázquez, S., Vivaldi, J., Torner, S., Villegas, M., and Lorente, M. The IULA Treebank. In *Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC'12).*

- Muñoz-García, Ó., Vázquez, S., and Bel, N. Exploiting Web-Based Collective Knowledge for Micropost Normalisation. In *Proceedings of the Tweet Normalization Workshop at the Conference of the Spanish Society for Natural Language Processing (SEPLN 2013).*

- Arias, B., Bel, N., Fisas, B., Lorente, M., Marimon, M., Morell, C., Vázquez, S., and Vivaldi, J. The IULA Spanish LSP Treebank: building and browsing. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14).*

Apart from the scientific publications cited, the last experiment, presented in Chapter 4, was the result of a collaboration between the author of this dissertation and the international marketing company Havas Media Group through the project Cenit Social Media from 2012 to 2014. The goal of the project was to advance the state of the art in social media, particularly in the areas of communications, marketing and media, both in terms of research and industry impact. Research within the project had therefore a strong focus on large-scale empirical data analysis, with special considerations given to privacy, and to long-term prospects of social media for improving the effectiveness of businesses and improving customer experience.

Chapter 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This dissertation investigated specific lexical features of the language used in social media user-generated content; in particular, the importance of polarity changes that some polar adjectives exhibit in different domains and usages and the specific linguistic patterns in the expression of different user-generated contents. The language utilized in social media documents presents characteristics that make it different from the language used in other texts such as news or literature. Every day, millions of people express their opinions about a very large range of topics on their social networks, blogs or microblogs. In the great majority of these user-generated texts, writers, talking as users of something, convey their evaluations about some topics, either products, people or organizations.

The combination of fast and thematic variety that these new documents present was the main reason why marketers (but also other users) started to be interested in these types of information sources. Replacing the old markets surveys (or the words of mouth in the case of the customers), these new types of documents, directly written by the users of the products/services, provide a huge quantity of information about the pros and cons of million of topics.

Therefore, classic information extraction systems, originally developed to identify and extract objective information, found a new issue: how to identify the subjective contents written by the users and summarize them correctly. The first move in order to solve this problem was to adapt the traditional information extraction systems to these new types of documents, however, due to the specific features of these texts, they did not achieve the desired results. The investigation of suitable methods to identify this type of information lead to the origin of a new branch of Natural Language Processing: Sentiment Analysis (or Opinion Mining).

This is the field where this dissertation belongs to.

This variety of topics to analyze and how the change from one to another can affect the results of used tools is the specific issue that this dissertation analyzed. Specifically, in this dissertation, we presented three experiments that studied some of the features of this new type of language and how to incorporate these characteristics to the new Sentiment Analysis systems.

Firstly, in Chapter 2, we assessed the proportion of adjectives whose polarity (that is, if they express a positive, negative opinion) changes depending on the topic that the user is talking about. In the case study presented there, we concluded that the polarity of a great majority of adjectives entirely depends on the domain. We demonstrated that 67% of a total of 514 adjectives appeared in three different domain corpora of 300.000 words each, are indeed domain dependent. More interestingly, the study also found out that from the 33% of domain independent adjectives, almost 25.5% were neutral adjectives not affording polarity information. Therefore, only 5.8% of positive and 1.3% of negative adjectives could be included in general or domain independent lexicons. These data lead to the conclusion that lexicons must be tuned for actual systems to accurately capture sentiment expression in a particular domain.

Additionally, we concluded that there are adjectives whose polarity cannot be defined *a priori* because are used idiosyncratically. In the same experiment, by measuring standard deviation of annotations made by humans, it was found that 45% of the studied adjectives appear to be highly subjective, that is, they are used with a different polarity by different users even within the same domain.

Therefore, we proposed a new classification of adjectives: highly subjective, constant and mixed adjectives.

Highly subjective adjectives were those adjectives that have a high or very high standard deviation value in all the domains. This fact highlights the wide range of opinions about some adjectives from one annotator to another. They are very subjective elements, there is no agreement about the annotation and they entirely depend on the personal point of view of each annotator. For example, "antiguo" ("antique").

In the ***mixed adjectives*** group there are units with high standard deviation values, or very high standard deviation values for a domain but no deviation for other domain(s). These units are, obviously, domain dependent: in some cases, adjectives show a high subjective degree (that is, annotators do not reach an agreement about its polarity) and in other cases, the polarity of the adjective is clearly identified. An example is "agresivo" ("aggressive") that has a deviation of 0.88 and 0.44 in the cars and movies domains, respectively, but it has total agreement in the cell phones domain.

The last group is made up of ***constant polarity adjectives***, that is, adjectives whose standard deviation value is always 0. In other words, annotators give the same tags in the same domains. This group should not confuse with domain independent adjectives since here we are not talking about polarity but deviation or agreement among tags in different domains. Adjectives in this group can be precisely used in polarity lexicons of the domains analyzed but not in other domains, since it can have no deviation at all but a change in the polarity.

These results showed that, because of its relevance, polarity variation is actually a very important feature that should be taken into account in order to create accurate Sentiment Analysis tools. The conclusion reached with respect to the polarity of adjectives also introduces a practical problem. The case study suggests that a new lexicon has to be build in relation to a particular domain and a particular set of users. However, lexicon production is a very time consuming task, hence automation of lexicon production from a sample of texts has to be considered as the only solution to provide applications with accurate information.

We understood that adapting sentiment lexicons to different domains using the state of the art techniques to induce this type of language resources was cumbersome. Normally, they need great efforts in terms of time and human resources, external language resources that for some languages are not be available or huge corpora to train machine learning systems. Therefore, in Chapter 3 we presented the a methodology to automatically build domain dependent polarity lexicons on the fly only using a small corpus and a set of seed adjectives.

Our conclusion with this experiment was that it is possible to automatically build lists of polar adjectives (with their corresponding polarity) relevant to a specific domain in a few minutes and only based on the information provided by certain linguistic structures .

Despite the low dependency of the algorithm proposed on external resources or big corpora, it achieved great results in terms of precision (97.6% for positive and 71.5% for negative adjectives) and recall (67%), and it was capable to identify highly subjective adjectives[1] and slang and misspelled items. Additionally, it is easily portable to different and new domains for which a corpus can be collected and, more, importantly, to any language where the linguistic patterns proposed work in the same way.

The development of the two experiments and the hands-on on several social media analysis projects, provided us with enough knowledge on these new types of documents to conclude that the language structures used in them were informative enough to extract relevant information from them. This was the hypothesis of the last experiment presented in this dissertation.

Therefore, in Chapter 4, we approached the creation of a real world social media analysis application. In this experiment, we designed a set of automatic classifiers just based on linguistics patterns and lexical units that users often utilize to talk about different features of the products (such as price, place, etc.) and to express their evaluation about them.

The result in terms of precision obtained in this last experiment (from 65% to 78% depending on the task and language) led us to the conclusion that lexical information and linguistic structures often used by the users play a crucial role in the creation of social media analysis tools both in Spanish and English.

[1] Adjectives whose polarity can change even in the same domain. For example, “big”.

6.2 Future work

Sentiment Analysis is a very challenging branch of Natural Language Processing. The nature of the texts analyzed in this field, unstructured and written to be "consume" very fast, poses additional difficulties to the classic Information Extraction methodologies. Although the work proposed along this dissertation gave solutions to some of its issues, such as a new classification of polar adjectives and the development of linguistic-based methods to extract this type of subjective information, there are so many topics that still need to be investigated.

The task of lexicon induction and text classification has a clear limitation: generalization is limited because it is limited to the actual occurrence of words in the working corpus.

For lexicon induction, the method proposed is able to discover new polarity words when they are found in combination with known words. However, in case a polarity word happens to occur alone, it will not be discovered.

For text classification, the two proposed methods take lexical occurrence, and other grammatical patterns, as cues for assignment to a class. Again, words that can be clues are those that have been previously discovered as conveying information about the proposed classes.

In both cases, recall is critically limited. Only those words occurring in the working corpus will be found, but there is no way to generalize, that is, to discover that a word which does not occur in the working corpus is similar to one that do occur.

Recently, distributional semantic models (for a survey see: Turney and Pantel (2010)[94], Baroni and Lenci (2010)[95]) where words are represented in a semantic vector space have proven to be a word representation that can be used to generalize over particular words. Distributional semantic models propose representing words in terms of their contexts of occurrence, following the Distributional Hypothesis (Harris, 1954)[96]. The use of these word representations have proved to be very advantageous in the task of "semantic similarity evaluation" due to the fact that these representations, in a continuous dimensional space, permit the discovery of semantically similar words with Euclidean methods, such as the cosine distance, for instance[2]. The most relevant work in this area is Mikolov et al. (2013)[97], whose code and data experiments are available.

Distributed Word Representations or Word Embeddings (WE) are induced vector representations of words. WE are usually learned by Neural Networks. Intuitively, the network takes into account observed word-context pairs and induces latent parameters, in the form of vector components, on the basis that words that appear in the same contexts have similar parameters. The learned vectors capture syntactic and semantic similarities (Mikolov et al., 2013) and have proved to be very useful for different NLP tasks (Baroni et al., 2014)[98]. Therefore, our future work will be to exploit the use of WE for the tasks described in this thesis.

Apart from that we will analyze polarity changes in more domains. The case study presented here only analyzes three domains specially selected for their inherent differences but it would be interesting to know the human annotator agreements and disagreements if the domains to study are more similar between them. The results of this study will give important information about the possibility of creating polarity lexicons for similar domains, avoiding the need to build corpora for each domain to analyze.

Additionally, investigation on the automatic extraction of new morphological categories apart from adjectives is also needed.

We will also continue improving the bootstrapping algorithm proposed by comparing the results obtained using more seed words, and bigger corpora.

Finally, in order to improve the classifiers developed, we are planning to develop specific classifiers for each domain analyzed, in order to increase precision and reduce sparsity.

[2]When considering all this, we still have to consider different strategies to deal with frequent and rare words, but this seems to be due more to computational problems.

Appendix A

APPENDIX

A.1 Linguistic Rules for Consumer Decision Journey Classification

A.1.1 Linguistic Rules for Spanish

anuncio “de” _ENTITY_ = AWARENESS
campaña “de” _ENTITY_ = AWARENESS
canción “de” _ENTITY_ = AWARENESS
cancion “de” _ENTITY_ = AWARENESS
cartel “de” _ENTITY_ = AWARENESS
comercial “de” _ENTITY_ = AWARENESS
concurso “de” _ENTITY_ = AWARENESS
cuña “de” _ENTITY_ = AWARENESS
descuento “de” _ENTITY_ = AWARENESS
evento “de” _ENTITY_ = AWARENESS
marketing “de” _ENTITY_ = AWARENESS
noticia “de” _ENTITY_ = AWARENESS
oferta “de” _ENTITY_ = AWARENESS
patrocinio “de” _ENTITY_ = AWARENESS
presentación “de” _ENTITY_ = AWARENESS
presentacion “de” _ENTITY_ = AWARENESS

promoción “de” _ENTITY_ = AWARENESS
promoción “de” _ENTITY_ = AWARENESS
promocion “de” _ENTITY_ = AWARENESS
propaganda “de” _ENTITY_ = AWARENESS
publicidad “de” _ENTITY_ = AWARENESS
publi “de” _ENTITY_ = AWARENESS
spot “de” _ENTITY_ = AWARENESS
stand “de” _ENTITY_ = AWARENESS
valla “de” _ENTITY_ = AWARENESS
stand “de” _ENTITY_ = AWARENESS
vídeo “de” _ENTITY_ = AWARENESS
video “de” _ENTITY_ = AWARENESS
anuncio “de” [DA] _ENTITY_ = AWARENESS
campaña “de” [DA] _ENTITY_ = AWARENESS
canción “de”[DA] _ENTITY_ = AWARENESS
cancion “de” [DA] _ENTITY_ = AWARENESS
cartel “de” [DA] _ENTITY_ = AWARENESS
comercial “de” [DA] _ENTITY_ = AWARENESS
concurso “de” [DA] _ENTITY_ = AWARENESS
cuña “de” [DA] _ENTITY_ = AWARENESS
descuento “de” [DA] _ENTITY_ = AWARENESS
evento “de” [DA] _ENTITY_ = AWARENESS
marketing “de” [DA] _ENTITY_ = AWARENESS
noticia “de” [DA] _ENTITY_ = AWARENESS
oferta “de” [DA] _ENTITY_ = AWARENESS
patrocinio “de” [DA] _ENTITY_ = AWARENESS
presentación “de” [DA] _ENTITY_ = AWARENESS
presentacion “de” [DA] _ENTITY_ = AWARENESS
promoción “de” [DA] _ENTITY_ = AWARENESS
promoción “de” [DA] _ENTITY_ = AWARENESS
promocion “de” [DA] _ENTITY_ = AWARENESS
propaganda “de” [DA] _ENTITY_ = AWARENESS
publicidad “de” [DA] _ENTITY_ = AWARENESS

publi “de” [DA] _ENTITY_ = AWARENESS
spot “de” [DA] _ENTITY_ = AWARENESS
stand “de” [DA] _ENTITY_ = AWARENESS
valla “de” [DA] _ENTITY_ = AWARENESS
stand “de” [DA] _ENTITY_ = AWARENESS
vídeo “de” [DA] _ENTITY_ = AWARENESS
video “de” [DA] _ENTITY_ = AWARENESS
“1444” = AWARENESS
“1441” = AWARENESS
[PP1] [VA] gustar [DI] vídeo = AWARENESS
leer#V_I_1S “por” “ahí” = AWARENESS
leer#V_I_1S “por” “ahi” = AWARENESS
“anunciando” _ENTITY_ = AWARENESS
“publicitando” a _ENTITY_ = AWARENESS
alguien [DP1] poder = EVALUATION
ser#V_IP3 “el” “que” “más” /1/ convencer = EVALUATION
ser#V_IP3 “el” “que” “mas” /1/ convencer = EVALUATION
ser#V_IP3 “el” “que” “menos” /1/ convencer = EVALUATION
alguien [PP1] decir#V_IP = EVALUATION
alguien conocer#V_IP = EVALUATION
alguien saber#V_IP “si” = EVALUATION
alguien saber#V_IP [V_N] = EVALUATION
“¿” poder [V_N] = EVALUATION
[DI] ventaja = EVALUATION
[DI] desventaja = EVALUATION
[DA] ventaja = EVALUATION
[DA] desventaja = EVALUATION
[DA] [AO] que comprobar = EVALUATION
[DA] [AO] que asegurar = EVALUATION
[DA] [AO] que comparar = EVALUATION
[DA] [AO] que mirar = EVALUATION
[PP1] [V] ofrecer = EVALUATION
[PP1] [V] comentar = EVALUATION

[PP] ofrecia = EVALUATION
[PP] ofrecian = EVALUATION
[P] rechazar = EVALUATION
[P] comprobar = EVALUATION
“estoy” [V_P] en = EVALUATION
“estamos” [V_P] en = EVALUATION
“estamos” [V_G] para = EVALUATION
estar [V_G] entre = EVALUATION
estar#V_I_1 [V_G] para = EVALUATION
“no” [PP3] encontrar#V_IP1 = EVALUATION
“no” encontrar#V_IP1 /2/ _ENTITY_ = EVALUATION
problema “de” encontrar [PP3] = EVALUATION
problema “para” encontrar [PP3] = EVALUATION
fácil “de” encontrar = EVALUATION
facil “de” encontrar = EVALUATION
[V__C] comprobar = EVALUATION
[V__C] asegurar = EVALUATION
[V__C] comparar = EVALUATION
[V_II] comprobar = EVALUATION
[V_II] asegurar = EVALUATION
[V_II] comparar = EVALUATION
[V_II] “que” comparar = EVALUATION
“se” /1/ preguntar#V_IP1S = EVALUATION
preguntar cómo = EVALUATION
preguntar como = EVALUATION
como poder#V_IP1S = EVALUATION
cómo poder#V_IP1S = EVALUATION
preguntar qué = EVALUATION
preguntar que = EVALUATION
siempre [VA] estar muy [AQ] = EVALUATION
siempre estar muy [AQ] = EVALUATION
siempre [VA] estar [AQ] = EVALUATION
siempre estar [AQ] = EVALUATION

nunca [VA] estar muy [AQ] = EVALUATION
nunca estar muy [AQ] = EVALUATION
nunca [VA] estar [AQ] = EVALUATION
nunca estar [AQ] = EVALUATION
tener#V_I_3 /2/ pinta = EVALUATION
[PP1] [VA] pasar [DI__P] = EVALUATION
[PP1] [VA] recorrer [DI__P] = EVALUATION
[PP1] [VA] pasar por = EVALUATION
[PP1] [VA] recorrer por = EVALUATION
[PP1] pasar [DI__P] = EVALUATION
[PP1] recorrer [DI__P] = EVALUATION
[VA] pasar [DI__P] = EVALUATION
[VA] recorrer [DI__P] = EVALUATION
[VA_P1] pasar por = EVALUATION
recorrer [DI__P] = EVALUATION
igual “de” [AQ] = EVALUATION
“quería” ver “si” = EVALUATION
“queria” ver “si” = EVALUATION
“quería” saber “si” = EVALUATION
“queria” saber “si” = EVALUATION
querer#V_IP1 saber cuánto = EVALUATION
querer#V_IP1 saber cuanto = EVALUATION
“si” comparar = EVALUATION
menos [AQ] que = EVALUATION
salir#V_IP3 por = EVALUATION
mejor _ENTITY_ = EVALUATION
peor _ENTITY_ = EVALUATION
“con” _ENTITY_ “o” “con” _ENTITY_ = EVALUATION
ENTITY “o” _ENTITY_ = EVALUATION
entre _ENTITY_ /4/ “y” _ENTITY_ = EVALUATION
“lo” mismo “que” “en” = EVALUATION
[D] alternativa [AQ] = EVALUATION
precio /1/ ser#V_IP3 [AQ] = EVALUATION

“quien” vender = EVALUATION

“alguien” vender = EVALUATION

tener#V_IP1 /1/ duda = EVALUATION

pedir /1/ consejo = EVALUATION

sobresalir#V_IP3 = EVALUATION

mejor /1/ de todos = EVALUATION

peor /1/ de todos = EVALUATION

ENTITY “o” /1/ _ENTITY_ = EVALUATION

“de” /1/ “de” [D] segmento = EVALUATION

[V_G] /1/ [DA] posibilidad = EVALUATION

estar#V_IP1 buscar#V_G = EVALUATION

buscar#V_G “para” = EVALUATION

pintar#V_IP3 bien = EVALUATION

pintar#V_IP3 mal = EVALUATION

buscar /1/ info = EVALUATION

buscar /1/ información = EVALUATION

buscar /1/ informacion = EVALUATION

recopilar /1/ info = EVALUATION

recopilar /1/ información = EVALUATION

recopilar /1/ informacion = EVALUATION

necesitar#V_IP1 consejo = EVALUATION

pensar#V_G “en” comprar = EVALUATION

pensar#V_G /1/ “en” cambiar = EVALUATION

pensar#V_G “en” abrir = EVALUATION

pensar#V_G “en” pillar = EVALUATION

pensar#V_G /1/ abrir = EVALUATION

preferir#V_IP1 /4/ _ENTITY_ = EVALUATION

preferir#V_IC1 /4/ _ENTITY_ = EVALUATION

preferiria /4/ _ENTITY_ = EVALUATION

“que” [PP1] gustar#V_IP3 más = EVALUATION

“que” [PP1] gustar#V_IP3 mas = EVALUATION

“que” [PP1] gustar#V_IP3 menos = EVALUATION

“que” más [PP1] gustar#V_IP3 = EVALUATION

“que” mas [PP1] gustar#V_IP3 = EVALUATION
“que” menos [PP1] gustar#V_IP3 = EVALUATION
“quién” [PP1] aconsejar#V_IP3 = EVALUATION
“quien” [PP1] aconsejar#V_IP3 = EVALUATION
“qué” [PP1] aconsejar#V_IP3 = EVALUATION
“que” [PP1] aconsejar#V_IP3 = EVALUATION
[DP1] [VA_2] aconsejar#V_P = EVALUATION
[DP1] [VA_3] aconsejar#V_P = EVALUATION
[PP1] gustar#V_IP3 mas = EVALUATION
[PP1] gustar#V_IP3 más = EVALUATION
[PP1] gustar#V_IP3 menos = EVALUATION
[PP1] gustar#V__C1 = EVALUATION
[PP1] “gustaria” = EVALUATION
comparar#V_IS1 = EVALUATION
[PP1] parecer comparable = EVALUATION
[PP1] parecer interesante = EVALUATION
comparar#V_P /1/ “con” = EVALUATION
comparar#V_G /1/ “con” = EVALUATION
“en” búsqueda “de” = EVALUATION
“en” “busqueda” “de” = EVALUATION
“a” [DA] “busqueda” “de” = EVALUATION
“a” [DA] búsqueda “de” = EVALUATION
saber#V_IP2 “de” alguno = EVALUATION
saber#V_IP2 “donde” = EVALUATION
saber#V_IP2 “dónde” = EVALUATION
cuál ser /1/ mejor = EVALUATION
“cual” ser /1/ mejor = EVALUATION
“cuales” ser /1/ mejor = EVALUATION
“no” saber#V_IP1S “cuál” = EVALUATION
“no” saber#V_IP1S “cual” = EVALUATION
“no” “se” “cuál” = EVALUATION
“no” “se” “cual” = EVALUATION
dónde [PP] vender#V_IP3 = EVALUATION

donde [PP] vender#V_IP3 = EVALUATION
dar [D] consejo = EVALUATION
recomendar#V_IP2 = EVALUATION
“recomendais” = EVALUATION
recomendar#V_II2 = EVALUATION
“recomendarias” = EVALUATION
“recomendariais” = EVALUATION
“alguien” /1/ recomendar#V_IP3 = EVALUATION
“aconsejáis” = EVALUATION
ser#V_IP3 bueno opción = EVALUATION
ser#V_IP3 bueno “opcion” = EVALUATION
ser#V_IP3 malo opción = EVALUATION
ser#V_IP3 malo “opcion” = EVALUATION
“alguien” poder#V_IC3 [V_N] = EVALUATION
“alguien” podria [V_N] = EVALUATION
[PP1] apetecer = EVALUATION
“cual” preferir#V_IP = EVALUATION
“cuales” preferir#V_IP = EVALUATION
cuál preferir#V_IP = EVALUATION
estar#V_IP1 indeciso = EVALUATION
tiene#V_IP3 indeciso = EVALUATION
tener#V_IP1 gana “de” = EVALUATION
qué diferencia haber = EVALUATION
“que” diferencia haber = EVALUATION
barajar /1/ opción = EVALUATION
manejar /1/ opción = EVALUATION
opción “que” comtemplar#V_I_1 = EVALUATION
leer comentario = EVALUATION
[VA__1S] leer#V_P “que” = EVALUATION
sugerencia = EVALUATION
“me” tentar = EVALUATION
más [AQ] [D] _ENTITY_ = EVALUATION
[N] * más que * _ENTITY_ = EVALUATION

[N] * menos que * _ENTITY_ = EVALUATION
estar investigar = EVALUATION
nunca “hay” = EVALUATION
estar#V_IP1 plantear#V_G = EVALUATION
agradecer [D] ayuda = EVALUATION
“no” saber#V_IP1S “que” “hacer ”= EVALUATION
“no” saber#V_IP1S “qué” “hacer ” = EVALUATION
“en” /1/ _ENTITY_ estar#V_I_3 [AQ] = EVALUATION
“en” /1/ _ENTITY_ “estara” [AQ] = EVALUATION
elegir#V__C1 /3/ _ENTITY_ = EVALUATION
elegiria /3/ _ENTITY_ = EVALUATION
[DP1] quedar#V__C1 /3/ _ENTITY_ = EVALUATION
[DP1] quedaria /3/ _ENTITY_ = EVALUATION
“de” mejor calidad = EVALUATION
“de” peor calidad = EVALUATION
querer#V_IP1 cambiar “de” = EVALUATION
querer#V_IP1 /1/ _ENTITY_ = EVALUATION
querer#V_IP1 comprar = EVALUATION
“kiero” comprar = EVALUATION
“kiero” /2/ _ENTITY_ = EVALUATION
querer#V__C1 comprar = EVALUATION
comprar#V_IP1 /2/ _ENTITY_ = EVALUATION
ser#V_IP3S [DI] “de” /1/ opción = EVALUATION
estar#V_IP1 mirar#V_G “de” [V_N] = EVALUATION
estar#V_IP1 valorar#V_G = EVALUATION
indeciso = EVALUATION
necesitar#V_IP1 /1/ opinion = EVALUATION
necesitar#V_IP1 /1/ opinión = EVALUATION
tener “como” opción = EVALUATION
tener “como” opcion = EVALUATION
ser#V_IP3 /1/ [AQ] opción = EVALUATION
ser#V_IP3 /1/ [AQ] opcion = EVALUATION
[DP1] /1/ opcion = EVALUATION

[DP1] /1/ opción = EVALUATION
barajar#V_IP1 /1/ opcion = EVALUATION
barajar#V_IP1 /1/ opción = EVALUATION
opción “que” contemplar#V_IP1 = EVALUATION
opcion “que” contemplar#V_IP1 = EVALUATION
morir#V_IP1 “por” /1/ _ENTITY_ = EVALUATION
ir#V_I_1S [PP1] “por” [D] /1/ _ENTITY_ = PURCHASE
bajar [PP1] “por” [D] /1/ _ENTITY_ = PURCHASE
ir#V_I_1S “por” /3/ _ENTITY_ = PURCHASE
ir#V_I_1P “por” /3/ _ENTITY_ = PURCHASE
bajar “por” [D] /1/ _ENTITY_ = PURCHASE
bajare “por” [D] /1/ _ENTITY_ = PURCHASE
ir#V_I_1S “a” tomar /5/ _ENTITY_ = PURCHASE
ir#V_I_1S “a” beber /5/ _ENTITY_ = PURCHASE
ir#V_I_1S “a” comer /5/ _ENTITY_ = PURCHASE
ir#V_I_1S “a” comprar /5/ _ENTITY_ = PURCHASE
ir#V_I_1S “a” pillar /5/ _ENTITY_ = PURCHASE
bajar “a” tomar /5/ _ENTITY_ = PURCHASE
bajar “a” beber /5/ _ENTITY_ = PURCHASE
bajar “a” comprar /5/ _ENTITY_ = PURCHASE
bajar “a” pillar /5/ _ENTITY_ = PURCHASE
invitar “a” /2/ _ENTITY_ = PURCHASE
[P] ir “a” /3/ “por” [D] /2/ _ENTITY_ = PURCHASE
[P] bajar “a” /3/ “por” [D] /2/ _ENTITY_ = PURCHASE
ir#V_I_1S “a” /3/ “por” [D] /2/ _ENTITY_ = PURCHASE
bajar#V_I_1S “a” /3/ “por” [D] /2/ _ENTITY_ = PURCHASE
[PP1] [V_IP1] por = PURCHASE
“ya” estar enviar = PURCHASE
[PP1] [VA] subir = PURCHASE
[PP1] [VA] bajar = PURCHASE
[D] transferencia “a” = PURCHASE
[D] trasferencia “a” = PURCHASE
[D] transferencia = PURCHASE

[D] trasferencia = PURCHASE
ir#V_I_1S “a” comprar [PP] [D] = PURCHASE
ir#V_I_1S “a” adquirir [PP] [D] = PURCHASE
ir#V_I_1S “a” pillar [PP] [D] = PURCHASE
ir#V_I_1S “a” cazar [PP] [D] = PURCHASE
ir#V_I_1S “a” reservar [PP] [D] = PURCHASE
ir#V_I_1S “a” firmar [PP] [D] = PURCHASE
ir#V_I_1S “a” comprar [D] = PURCHASE
ire “a” comprar [D] = PURCHASE
ir#V_I_1S “a” adquirir [D] = PURCHASE
ir#V_I_1S “a” pillar [D] = PURCHASE
ire “a” pillar [D] = PURCHASE
ir#V_I_1S “a” cazar [D] = PURCHASE
ir#V_I_1S “a” reservar [D] = PURCHASE
ir#V_I_1S “a” firmar [D] = PURCHASE
ir#V_I_1S “a” probar = PURCHASE
ir#V_IP1 “a” llevar = PURCHASE
ser#V_I_3 [PX] = PURCHASE
“ya” tener#V_I_1S /1/ [D] = PURCHASE
“a” ver “si” /2/ comprar = PURCHASE
“a” ver “si” /2/ cazar = PURCHASE
“a” ver “si” /2/ pillar = PURCHASE
estar#V_IP1 comprar = PURCHASE
estar#V_IP1 adquirir = PURCHASE
estar#V_IP1 pillar = PURCHASE
estar#V_IP1 cazar = PURCHASE
estar#V_IP1 reservar = PURCHASE
estar#V_IP1 firmar = PURCHASE
[D] /1/ pedido = PURCHASE
[PP1] [P] pedir#V_IP1S = PURCHASE
[PP1] [P] comprar#V_IP1S = PURCHASE
[P] liberar#V_IF1 = PURCHASE
[PP1] pedir#V_IP1 = PURCHASE

[D] ir#V_I_1S “a” tener = PURCHASE
[D] ir#V_I_1S “a” comprar = PURCHASE
[PP1] ir#V_I_1S “a” comprar = PURCHASE
[D] ir#V_I_1S “a” pillar = PURCHASE
[PP1] ir#V_I_1S “a” pillar = PURCHASE
[D] ir#V_I_1S “a” cazar = PURCHASE
tener [D] ojo encima = PURCHASE
llevar /1/ tiempo “con” = PURCHASE
ya poder pasar [PP] “a” por = PURCHASE
ya poder pasar “a” por = PURCHASE
[PP1] cambiar#V_IP1 “de” _ENTITY_ “a” _ENTITY_ = PURCHASE
[PP1] pasar#V_IP1 “de” _ENTITY_ “a” _ENTITY_ = PURCHASE
[D] semana [PP1] comprar#V_IP1 = PURCHASE
[D] mes [PP1] comprar#V_IP1 = PURCHASE
comprar#V_IF1S = PURCHASE
“comprare” = PURCHASE
comer#V_IF1 [D] /4/ _ENTITY_= PURCHASE
comere [D] /4/ _ENTITY_= PURCHASE
poder#V_IF probar = PURCHASE
podre probar = PURCHASE
[PP1] beber#V_IF1 /3/ _ENTITY_ = PURCHASE
[PP1] bebi /3/ _ENTITY_ = PURCHASE
[PP1] tomar#V_IF1 /3/ _ENTITY_ = PURCHASE
[PP1] tome /3/ _ENTITY_ = PURCHASE
[PP1] probar#V_IF1 /3/ _ENTITY_ = PURCHASE
[PP1] probe /3/ _ENTITY_ = PURCHASE
[PP1] degustar#V_IF1 /3/ _ENTITY_ = PURCHASE
[PP1] deguste /3/ _ENTITY_ = PURCHASE
beber#V_IF1 /3/ _ENTITY_ = PURCHASE
bebi /3/ _ENTITY_ = PURCHASE
tomar#V_IF1 /3/ _ENTITY_ = PURCHASE
tome /3/ _ENTITY_ = PURCHASE
probar#V_IF1 /3/ _ENTITY_ = PURCHASE

probe /3/ _ENTITY_ = PURCHASE

degustar#V_IF1 /3/ _ENTITY_ = PURCHASE

deguste /3/ _ENTITY_ = PURCHASE

beber#V_IF1 [DA] = PURCHASE

bebi [DA] = PURCHASE

tomar#V_IF1 [DA] = PURCHASE

tome [DA] = PURCHASE

probar#V_IF1 [DA] = PURCHASE

probe [DA] = PURCHASE

degustar#V_IF1 [DA] = PURCHASE

deguste [DA] = PURCHASE

beber#V_IF1 [P] = PURCHASE

bebi [P] = PURCHASE

tomar#V_IF1 [P] = PURCHASE

tome [P] = PURCHASE

probar#V_IF1 [P] = PURCHASE

probe [P] = PURCHASE

degustar#V_IF1 [P] = PURCHASE

deguste [P] = PURCHASE

[PP] hacer#V_IP1 “con” = PURCHASE

tener#V_I_1 [D] [NC] con = POSTPURCHASE

[PP1] cambiar#V_I “de” _ENTITY_ “a” _ENTITY_ = PURCHASE

[PP1] pasar#V_I “de” _ENTITY_ “a” _ENTITY_ = PURCHASE

pasar#V_I_1S por = PURCHASE

[VA_P1] pasar#V_P por = PURCHASE

[PP1] pillar#V_IP1 = PURCHASE

pedir#V_IF1 [D] /1/ _ENTITY_ = PURCHASE

pedire [D] /1/ _ENTITY_ = PURCHASE

seguir esperar#V_G [DP] [NC] = PURCHASE

acabar#V_I_1S “de” contratar “con” _ENTITY_ = PURCHASE

acabar#V_I_1S “de” reservar = PURCHASE

acabar#V_I_1S “de” hacer [D] compra = PURCHASE

acabar#V_IF1 comprar#V_G = PURCHASE

tras comprar = PURCHASE
a comprar [PP1] = PURCHASE
para comprar [PP1] = PURCHASE
a llenar [D] [NC] = PURCHASE
llenar#V_G [D] carro = PURCHASE
pagar#v_G = PURCHASE
en [D] super = PURCHASE
[VA_P1] decidir /1/ adquirir = PURCHASE
acabar#V_I_1S “de” comprar = POSTPURCHASE
acabar#V_I_1S “de” activar = POSTPURCHASE
[PP1] quedar#V_I_1 con _ENTITY_ = POSTPURCHASE
quedar#V_I_1 con _ENTITY_ = POSTPURCHASE
[PP1] quedar#V_I_1 en _ENTITY_ = POSTPURCHASE
quedar#V_I_1 en _ENTITY_ = POSTPURCHASE
comer#V_IP _ENTITY_ = POSTPURCHASE
[V_I_1] beber [D] [AQ] [NC] = POSTPURCHASE
[V_I_1] tomar [D] [AQ] [NC] = POSTPURCHASE
[V_I_1] probar [D] [AQ] [NC] = POSTPURCHASE
[V_I_1] degustar [D] [AQ] [NC] = POSTPURCHASE
[V_I_1] destapar [D] [AQ] [NC] = POSTPURCHASE
[V_I_3] beber [D] [AQ] [NC] = POSTPURCHASE
[V_I_3] tomar [D] [AQ] [NC] = POSTPURCHASE
[V_I_3] probar [D] [AQ] [NC] = POSTPURCHASE
[V_I_3] degustar [D] [AQ] [NC] = POSTPURCHASE
[V_I_3] destapar [D] [AQ] [NC] = POSTPURCHASE
[V_I_1] beber [AQ] [NC] = POSTPURCHASE
[V_I_1] tomar [AQ] [NC] = POSTPURCHASE
[V_I_1] probar [AQ] [NC] = POSTPURCHASE
[V_I_1] degustar [AQ] [NC] = POSTPURCHASE
[V_I_1] destapar [AQ] [NC] = POSTPURCHASE
[V_I_3] beber [AQ] [NC] = POSTPURCHASE
[V_I_3] tomar [AQ] [NC] = POSTPURCHASE
[V_I_3] probar [AQ] [NC] = POSTPURCHASE

[V_I_3] degustar [AQ] [NC] = POSTPURCHASE
[V_I_3] destapar [AQ] [NC] = POSTPURCHASE
[V_I_1] beber [D] [NC] = POSTPURCHASE
[V_I_1] tomar [D] [NC] = POSTPURCHASE
[V_I_1] probar [D] [NC] = POSTPURCHASE
[V_I_1] degustar [D] [NC] = POSTPURCHASE
[V_I_1] destapar [D] [NC] = POSTPURCHASE
[V_I_3] beber [D] [NC] = POSTPURCHASE
[V_I_3] tomar [D] [NC] = POSTPURCHASE
[V_I_3] probar [D] [NC] = POSTPURCHASE
[V_I_3] degustar [D] [NC] = POSTPURCHASE
[V_I_3] destapar [D] [NC] = POSTPURCHASE
[V_I_1] beber [NC] = POSTPURCHASE
[V_I_1] tomar [NC] = POSTPURCHASE
[V_I_1] probar [NC] = POSTPURCHASE
[V_I_1] degustar [NC] = POSTPURCHASE
[V_I_1] destapar [NC] = POSTPURCHASE ç
[V_I_3] beber [NC] = POSTPURCHASE
[V_I_3] tomar [NC] = POSTPURCHASE
[V_I_3] probar [NC] = POSTPURCHASE
[V_I_3] degustar [NC] = POSTPURCHASE
[V_I_3] destapar [NC] = POSTPURCHASE
beber#V_G /2/ [NC] = POSTPURCHASE
tomar#V_G /2/ [NC] = POSTPURCHASE
probar#V_G /2/ [NC] = POSTPURCHASE
degustar#V_G /2/ [NC] = POSTPURCHASE
rodear "de" /2/ _ENTITY_ = POSTPURCHASE
acompañar "de" /2/ _ENTITY_ = POSTPURCHASE
"de" _ENTITY_ acabar#V_P = POSTPURCHASE
"de" _ENTITY_ terminar#V_P = POSTPURCHASE
disfrutar#V_G "de" [DP] /2/ [N] = POSTPURCHASE
disfrutar#V_G "de" [DI] /2/ [N] = POSTPURCHASE
disfrutar#V_G [DP] /2/ [N] = POSTPURCHASE

disfrutar#V_G [DI] /2/ [N] = POSTPURCHASE
botella “de” _ENTITY_ = POSTPURCHASE
botellín “de” _ENTITY_ = POSTPURCHASE
botellin “de” _ENTITY_ = POSTPURCHASE
lata “de” _ENTITY_ = POSTPURCHASE
lleno “de” _ENTITY_ = POSTPURCHASE
“que” [PP1] beber#V_I_1 = POSTPURCHASE
“que” [PP1] tomar#V_I_1 = POSTPURCHASE
“que” [PP1] probar#V_I_1 = POSTPURCHASE
“que” beber#V_I_1 = POSTPURCHASE
“que” tomar#V_I_1 = POSTPURCHASE
“que” probar#V_I_1 = POSTPURCHASE
“que” degustar#V_I_1 = POSTPURCHASE
[DP1_S] /2/ coche = POSTPURCHASE
[DP1_S] /2/ vehículo = POSTPURCHASE
[DP1_S] /2/ buga = POSTPURCHASE
[DP1_S] /2/ auto = POSTPURCHASE
[DP1_S] /2/ vehiculo = POSTPURCHASE
[DP1_S] /2/ carro = POSTPURCHASE
[DP1_S] /2/ banco = POSTPURCHASE
[DP1_S] /2/ oficina = POSTPURCHASE
[DP1_S] /2/ cuenta = POSTPURCHASE
[DP1_S] /2/ clave = POSTPURCHASE
[DP1_S] /2/ experiencia = POSTPURCHASE
[DP1_S] /2/ contrato = POSTPURCHASE
[DP1_S] /2/ tarjeta = POSTPURCHASE
[DP1_S] /2/ zapatilla = POSTPURCHASE
[DP1_S] /2/ zapato = POSTPURCHASE
[DP1_S] /2/ camiseta = POSTPURCHASE
[DP1_S] /2/ camisa = POSTPURCHASE
[DP1_S] /2/ calcetines = POSTPURCHASE
[DP1_S] /2/ calza = POSTPURCHASE
usar#V_I_1S /2/ _ENTITY_ = POSTPURCHASE

poseer#V_I_1S /2/ _ENTITY_ = POSTPURCHASE
manejar#V_I_1S /2/ _ENTITY_ = POSTPURCHASE
conducir#V_I_1S /2/ _ENTITY_ = POSTPURCHASE
llevar#V_I_1S /2/ _ENTITY_ = POSTPURCHASE
traer#V_I_1S /3/ _ENTITY_ = POSTPURCHASE
tener#V_I_1S /2/ coche = POSTPURCHASE
usar#V_I_1S /2/ coche = POSTPURCHASE
poseer#V_I_1S /2/ coche = POSTPURCHASE
manejar#V_I_1S /2/ coche = POSTPURCHASE
conducir#V_I_1S /2/ coche = POSTPURCHASE
llevar#V_I_1S /2/ coche = POSTPURCHASE
traer#V_IP1 /2/ coche = POSTPURCHASE
tener#V_I_1S /2/ vehículo = POSTPURCHASE
usar#V_I_1S /2/ vehículo = POSTPURCHASE
poseer#V_I_1S /2/ vehículo = POSTPURCHASE
manejar#V_I_1S /2/ vehículo = POSTPURCHASE
conducir#V_I_1S /2/ vehículo = POSTPURCHASE
llevar#V_I_1S /2/ vehículo = POSTPURCHASE
traer#V_IP1S /2/ vehículo = POSTPURCHASE
tener#V_I_1S /2/ buga = POSTPURCHASE
usar#V_I_1S /2/ buga = POSTPURCHASE
poseer#V_I_1S /2/ buga = POSTPURCHASE
manejar#V_I_1S /2/ buga = POSTPURCHASE
conducir#V_I_1S /2/ buga = POSTPURCHASE
llevar#V_I_1S /2/ buga = POSTPURCHASE
traer#V_IP1S /2/ buga = POSTPURCHASE
tener#V_I_1S /2/ auto = POSTPURCHASE
usar#V_I_1S /2/ auto = POSTPURCHASE
poseer#V_I_1S /2/ auto = POSTPURCHASE
manejar#V_I_1S /2/ auto = POSTPURCHASE
conducir#V_I_1S /2/ auto = POSTPURCHASE
llevar#V_I_1S /2/ auto = POSTPURCHASE
traer#V_IP1S /2/ auto = POSTPURCHASE

tener#V_I_1S /2/ vehiculo = POSTPURCHASE
usar#V_I_1S /2/ vehiculo = POSTPURCHASE
poseer#V_I_1S /2/ vehiculo = POSTPURCHASE
manejar#V_I_1S /2/ vehiculo = POSTPURCHASE
conducir#V_I_1S /2/ vehiculo = POSTPURCHASE
llevar /2/ vehiculo = POSTPURCHASE
traer#V_IP1 /2/ vehiculo = POSTPURCHASE
tener#V_I_1S /2/ carro = POSTPURCHASE
usar#V_I_1S /2/ carro = POSTPURCHASE
poseer#V_I_1S /2/ carro = POSTPURCHASE
manejar#V_I_1S /2/ carro = POSTPURCHASE
conducir#V_I_1S /2/ carro = POSTPURCHASE
llevar#V_I_1S /2/ carro = POSTPURCHASE
traer#V_IP1S /2/ carro = POSTPURCHASE
tener#V_I_1S /2/ banco = POSTPURCHASE
usar#V_I_1S /2/ banco = POSTPURCHASE
tener#V_I_1S /2/ oficina = POSTPURCHASE
usar#V_I_1S /2/ oficina = POSTPURCHASE
tener#V_I_1S /2/ cuenta = POSTPURCHASE
usar#V_I_1S /2/ cuenta = POSTPURCHASE
poseer#V_I_1S /2/ cuenta = POSTPURCHASE
tener#V_I_1S /2/ clave = POSTPURCHASE
usar#V_I_1S /2/ clave = POSTPURCHASE
poseer#V_I_1S /2/ clave = POSTPURCHASE
llevar#V_I_1S /2/ clave = POSTPURCHASE
traer#V_IP1 /2/ clave = POSTPURCHASE
tener#V_I_1S /2/ experiencia = POSTPURCHASE
poseer#V_I_1S /2/ experiencia = POSTPURCHASE
tener#V_I_1S /2/ contrato = POSTPURCHASE
usar#V_I_1S /2/ contrato = POSTPURCHASE
poseer#V_I_1S /2/ contrato = POSTPURCHASE
llevar#V_I_1S /2/ contrato = POSTPURCHASE
tener#V_I_1S /2/ tarjeta = POSTPURCHASE

usar#V_I_1S /2/ tarjeta = POSTPURCHASE
poseer#V_I_1S /2/ tarjeta = POSTPURCHASE
llevar#V_I_1S /2/ tarjeta = POSTPURCHASE
traer#V_I_1S /2/ tarjeta = POSTPURCHASE
tener#V_I_1S /2/ zapatilla = POSTPURCHASE
usar#V_I_1S /2/ zapatilla = POSTPURCHASE
poseer#V_I_1S /2/ zapatilla = POSTPURCHASE
llevar#V_I_1S /2/ zapatilla = POSTPURCHASE
traer#V_I_1S /2/ zapatilla = POSTPURCHASE
tener#V_I_1S /2/ zapato = POSTPURCHASE
usar#V_I_1S /2/ zapato = POSTPURCHASE
poseer#V_I_1S /2/ zapato = POSTPURCHASE
llevar#V_I_1S /2/ zapato = POSTPURCHASE
traer#V_I_1S /2/ zapato = POSTPURCHASE
tener#V_I_1S /2/ camiseta = POSTPURCHASE
usar#V_I_1S /2/ camiseta = POSTPURCHASE
poseer#V_I_1S /2/ camiseta = POSTPURCHASE
llevar#V_I_1S /2/ camiseta = POSTPURCHASE
traer#V_I_1S /2/ camiseta = POSTPURCHASE
tener#V_I_1S /2/ camisa = POSTPURCHASE
usar#V_I_1S /2/ camisa = POSTPURCHASE
poseer#V_I_1S /2/ camisa = POSTPURCHASE
llevar#V_I_1S /2/ camisa = POSTPURCHASE
traer#V_I_1S /2/ camisa = POSTPURCHASE
tener#V_I_1S /2/ calcetines = POSTPURCHASE
usar#V_I_1S /2/ calcetines = POSTPURCHASE
poseer#V_I_1S /2/ calcetines = POSTPURCHASE
llevar#V_I_1S /2/ calcetines = POSTPURCHASE
traer#V_I_1S /2/ calcetines = POSTPURCHASE
tener#V_I_1S /2/ calza = POSTPURCHASE
usar#V_I_1S /2/ calza = POSTPURCHASE
poseer#V_I_1S /2/ calza = POSTPURCHASE
llevar#V_I_1S /2/ calza = POSTPURCHASE

traer#V_I_1S /2/ calza = POSTPURCHASE
tener “a” “la” “venta” = POSTPURCHASE
tener “en” “venta” = POSTPURCHASE
“vendo” = POSTPURCHASE
“Vendo” = POSTPURCHASE
vender#V_IP1S = POSTPURCHASE
tener#V_I_1 [D] [NC] “desde” = POSTPURCHASE
poseer#V_I_1 [D] [NC] “desde” = POSTPURCHASE
manejar#V_I_1 [D] [NC] “desde” = POSTPURCHASE
conducir#V_I_1 [D] [NC] “desde” = POSTPURCHASE
llevar#V_I_1 [D] [NC] “desde” = POSTPURCHASE
tener#V_I_1 [D] /1/ problema = POSTPURCHASE
tener#V_I_1 [D] /1/ queja = POSTPURCHASE
“lo” usar#V_I_1 = POSTPURCHASE
“los” usar#V_I_1 = POSTPURCHASE
“la” usar#V_I_1 = POSTPURCHASE
“las” usar#V_I_1 = POSTPURCHASE
“lo” comprar#V_IS1 = POSTPURCHASE
“los” comprar#V_IS1 = POSTPURCHASE
“la” comprar#V_IS1 = POSTPURCHASE
“las” comprar#V_IS1 = POSTPURCHASE
[PP1] comprar#V_IS = POSTPURCHASE
“lo” adquirir#V_IS1 = POSTPURCHASE
“los” adquirir#V_IS1 = POSTPURCHASE
“la” adquirir#V_IS1 = POSTPURCHASE
“las” adquirir#V_IS1 = POSTPURCHASE
“lo” pillar#V_IS1 = POSTPURCHASE
“los” pillar#V_IS1 = POSTPURCHASE
“la” pillar#V_IS1 = POSTPURCHASE
“las” pillar#V_IS1 = POSTPURCHASE
“lo” coger#V_IS1 = POSTPURCHASE
“los” coger#V_IS1 = POSTPURCHASE
“la” coger#V_IS1 = POSTPURCHASE

“las” coger#V_IS1 = POSTPURCHASE
“lo” cazar#V_IS1 = POSTPURCHASE
“los” cazar#V_IS1 = POSTPURCHASE
“la” cazar#V_IS1 = POSTPURCHASE
“las” cazar#V_IS1 = POSTPURCHASE
“lo” reservar#V_IS1 = POSTPURCHASE
“los” reservar#V_IS1 = POSTPURCHASE
“la” reservar#V_IS1 = POSTPURCHASE
“las” reservar#V_IS1 = POSTPURCHASE
“lo” firmar#V_IS1 = POSTPURCHASE
“los” firmar#V_IS1 = POSTPURCHASE
“la” firmar#V_IS1 = POSTPURCHASE
“las” firmar#V_IS1 = POSTPURCHASE
“lo” alquilar#V_IS1 = POSTPURCHASE
“los” alquilar#V_IS1 = POSTPURCHASE
“la” alquilar#V_IS1 = POSTPURCHASE
“las” alquilar#V_IS1 = POSTPURCHASE
tener#V_I_1 domiciliar [D] = POSTPURCHASE
tener#V_I_1 contratar#V_P = POSTPURCHASE
contratar#V_IS “con” _ENTITY_ = POSTPURCHASE
tener#V_I_1 con [D] /1/ _ENTITY_ = POSTPURCHASE
tener#V_I_1 en [D] /1/ _ENTITY_ = POSTPURCHASE
abrir#V_I_1 [D] cuenta = POSTPURCHASE
tener#V_I_1 [D] cuenta = POSTPURCHASE
tener#V_I_1 [D] hipoteca = POSTPURCHASE
cerrar#V_I_1 [D] cuenta = POSTPURCHASE
abrir#V_I_1 cuenta = POSTPURCHASE
tener#V_I_1 cuenta = POSTPURCHASE
tener#V_I_1 hipoteca = POSTPURCHASE
cerrar#V_I_1 cuenta = POSTPURCHASE
de abrir [D] cuenta = POSTPURCHASE
de abrir cuenta = POSTPURCHASE
de tener [D] cuenta = POSTPURCHASE

de tener [D] hipoteca = POSTPURCHASE
de tener [D] ingreso = POSTPURCHASE
de tener [D] deposito = POSTPURCHASE
de tener [D] depósito = POSTPURCHASE
de tener cuenta = POSTPURCHASE
de tener hipoteca = POSTPURCHASE
de tener ingreso = POSTPURCHASE
de tener deposito = POSTPURCHASE
de tener depósito = POSTPURCHASE
de cerrar [D] cuenta = POSTPURCHASE
de cerrar [D] hipoteca = POSTPURCHASE
de cerrar [D] deposito = POSTPURCHASE
de cerrar [D] depósito = POSTPURCHASE
de cerrar cuenta = POSTPURCHASE
de cerrar hipoteca = POSTPURCHASE
de cerrar deposito = POSTPURCHASE
de cerrar depósito = POSTPURCHASE
de hacer [D] cuenta = POSTPURCHASE
de hacer [D] hipoteca = POSTPURCHASE
de hacer [D] ingreso = POSTPURCHASE
de hacer [D] deposito = POSTPURCHASE
de hacer [D] depósito = POSTPURCHASE
de hacer cuenta = POSTPURCHASE
de hacer hipoteca = POSTPURCHASE
de hacer ingreso = POSTPURCHASE
de hacer deposito = POSTPURCHASE
de hacer depósito = POSTPURCHASE
a abrir [D] cuenta = POSTPURCHASE
a abrir [D] hipoteca = POSTPURCHASE
a abrir [D] deposito = POSTPURCHASE
a abrir [D] depósito = POSTPURCHASE
a abrir cuenta = POSTPURCHASE
a abrir hipoteca = POSTPURCHASE

a abrir deposito = POSTPURCHASE
a abrir depósito = POSTPURCHASE
a tener [D] cuenta = POSTPURCHASE
a tener [D] hipoteca = POSTPURCHASE
a tener [D] ingreso = POSTPURCHASE
a tener [D] deposito = POSTPURCHASE
a tener [D] depósito = POSTPURCHASE
a tener cuenta = POSTPURCHASE
a tener hipoteca = POSTPURCHASE
a tener ingreso = POSTPURCHASE
a tener deposito = POSTPURCHASE
a tener depósito = POSTPURCHASE
a cerrar [D] cuenta = POSTPURCHASE
a cerrar [D] deposito = POSTPURCHASE
a cerrar [D] depósito = POSTPURCHASE
a cerrar cuenta = POSTPURCHASE
a cerrar hipoteca = POSTPURCHASE
a cerrar ingreso = POSTPURCHASE
a cerrar deposito = POSTPURCHASE
a cerrar depósito = POSTPURCHASE
a hacer [D] cuenta = POSTPURCHASE
a hacer [D] hipoteca = POSTPURCHASE
a hacer [D] ingreso = POSTPURCHASE
a hacer [D] deposito = POSTPURCHASE
a hacer [D] depósito = POSTPURCHASE
a hacer cuenta = POSTPURCHASE
a hacer hipoteca = POSTPURCHASE
a hacer ingreso = POSTPURCHASE
a hacer deposito = POSTPURCHASE
a hacer depósito = POSTPURCHASE
[V] abrir [D] cuenta = POSTPURCHASE
[V] tener [D] cuenta = POSTPURCHASE
[V] tener [D] hipoteca = POSTPURCHASE

[V] tener [D] ingreso = POSTPURCHASE
[V] tener [D] deposito = POSTPURCHASE
[V] tener [D] depósito = POSTPURCHASE
[V] cerrar [D] cuenta = POSTPURCHASE
[V] hacer [D] cuenta = POSTPURCHASE
[V] hacer [D] hipoteca = POSTPURCHASE
[V] hacer [D] ingreso = POSTPURCHASE
[V] hacer [D] deposito = POSTPURCHASE
[V] hacer [D] depósito = POSTPURCHASE
tener#V_P [D] dinero en /2/ _ENTITY_ = POSTPURCHASE
tener#V_P [D] pasta en /2/ _ENTITY_ = POSTPURCHASE
tener#V_P [D] ahorro en /2/ _ENTITY_ = POSTPURCHASE
tener#V_I_1 [D] dinero en /2/ _ENTITY_ = POSTPURCHASE
tener#V_I_1 [D] pasta en /2/ _ENTITY_ = POSTPURCHASE
tener#V_I_1 [D] ahorro en /2/ _ENTITY_ = POSTPURCHASE
abrir#V_I_1 [DI] cuenta [SP] = POSTPURCHASE
tener#V_I_1 [DI] cuenta [SP] = POSTPURCHASE
tener#V_I_1 [DI] hipoteca [SP] = POSTPURCHASE
cerrar#V_I_1 [DI] cuenta [SP] = POSTPURCHASE
abrir#V_I_1 [DI] [SP] = POSTPURCHASE
tener#V_I_1 [DI] [SP] = POSTPURCHASE
cerrar#V_I_1 [DI] [SP] = POSTPURCHASE
el [N] “que” mejor [PP1] ir = POSTPURCHASE
los [N] “que” mejor [PP1] ir = POSTPURCHASE
la [N] “que” mejor [PP1] ir = POSTPURCHASE
las [N] “que” mejor [PP1] ir = POSTPURCHASE
el “que” mejor [PP1] ir = POSTPURCHASE
los “que” mejor [PP1] ir = POSTPURCHASE
la “que” mejor [PP1] ir = POSTPURCHASE
las “que” mejor [PP1] ir = POSTPURCHASE
[AO] [NC] “de” _ENTITY_ = POSTPURCHASE
[Z] [NC] “de” _ENTITY_ = POSTPURCHASE
[AO] “de” _ENTITY_ = POSTPURCHASE

[Z] “de” _ENTITY_ = POSTPURCHASE
[AO] _ENTITY_ = POSTPURCHASE
[Z] _ENTITY_ = POSTPURCHASE
[AO] [NC] _ENTITY_ = POSTPURCHASE
[Z] [NC] _ENTITY_ = POSTPURCHASE
[VA_P1] beber = POSTPURCHASE
[VA_P1] tomar = POSTPURCHASE
[VA_P1] probar = POSTPURCHASE
probar#V_IS1 = POSTPURCHASE
[VA_P1] degustar = POSTPURCHASE
[PP1] beber#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
[PP1] tomar#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
[PP1] probar#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
[PP1] degustar#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
beber#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
tomar#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
probar#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
degustar#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
“con” /4/ “en” “la” “mano” = POSTPURCHASE
[NC] “de_la_mano_de” _ENTITY_ = POSTPURCHASE
beber#V_IS1 [DA] = POSTPURCHASE
tomar#V_IS1 [DA] = POSTPURCHASE
probar#V_IS1 [DA] = POSTPURCHASE
degustar#V_IS1 [DA] = POSTPURCHASE
beber#V_IS1 [P] = POSTPURCHASE
tomar#V_IS1 [P] = POSTPURCHASE
probar#V_IS1 [P] = POSTPURCHASE
degustar#V_IS1 [P] = POSTPURCHASE
sed “con” = POSTPURCHASE
regalar#V_IS1 /3/ _ENTITY_ = POSTPURCHASE
regresar /3/ _ENTITY_ = POSTPURCHASE
devolver /3/ _ENTITY_ = POSTPURCHASE
poner /2/ _ENTITY_ = POSTPURCHASE

usar#V_IP1 /3/ _ENTITY_ = POSTPURCHASE

[PP1] “lo” regalar#V_IS1 = POSTPURCHASE

[PP1] “los” regalar#V_IS1 = POSTPURCHASE

[PP1] “la” regalar#V_IS1 = POSTPURCHASE

[PP1] “las” regalar#V_IS1 = POSTPURCHASE

[PP1] regalar#V_IS1 = POSTPURCHASE

cambiar#V_I_1 /3/ “por” [D] _ENTITY_ = POSTPURCHASE

estrenar /3/ coche = POSTPURCHASE

estrenar /3/ vehículo = POSTPURCHASE

estrenar /3/ buga = POSTPURCHASE

estrenar /3/ auto = POSTPURCHASE

estrenar /3/ carro = POSTPURCHASE

estrenar /3/ zapatilla = POSTPURCHASE

estrenar /3/ zapato = POSTPURCHASE

estrenar /3/ camiseta = POSTPURCHASE

estrenar /3/ camisa = POSTPURCHASE

estrenar /3/ calcetines = POSTPURCHASE

estrenar /3/ calcetín = POSTPURCHASE

estrenar /3/ calza = POSTPURCHASE

[PP] comprar#V_IS “hace” = POSTPURCHASE

[PP] adquirir#V_IS “hace” = POSTPURCHASE

[PP] pillar#V_IS “hace” = POSTPURCHASE

[PP] coger#V_IS “hace” = POSTPURCHASE

[PP] cazar#V_IS “hace” = POSTPURCHASE

[PP] reservar#V_IS “hace” = POSTPURCHASE

[PP] firmar#V_IS “hace” = POSTPURCHASE

[PP] alquilar#V_IS “hace” = POSTPURCHASE

[PP] elegir#V_IS “hace” = POSTPURCHASE

[PP] usar#V_IS “hace” = POSTPURCHASE

[PP] usar#V_IS “desde” = POSTPURCHASE

[PP] comprar#V_P “hace” = POSTPURCHASE

[PP] adquirir#V_P “hace” = POSTPURCHASE

[PP] pillar#V_P “hace” = POSTPURCHASE

[PP] coger#V_P “hace” = POSTPURCHASE

[PP] cazar#V_P “hace” = POSTPURCHASE

[PP] reservar#V_P “hace” = POSTPURCHASE

[PP] firmar#V_P “hace” = POSTPURCHASE

[PP] alquilar#V_P “hace” = POSTPURCHASE

[PP] elegir#V_P “hace” = POSTPURCHASE

[PP] usar#V_P “hace” = POSTPURCHASE

[PP] usar#V_P “desde” = POSTPURCHASE

comprar#V_I_1 “hace” = POSTPURCHASE

adquirir#V_I_1 “hace” = POSTPURCHASE

pillar#V_I_1 “hace” = POSTPURCHASE

coger#V_I_1 “hace” = POSTPURCHASE

cazar#V_I_1 “hace” = POSTPURCHASE

reservar#V_I_1 “hace” = POSTPURCHASE

firmar#V_I_1 “hace” = POSTPURCHASE

alquilar#V_I_1 “hace” = POSTPURCHASE

elegir#V_I_1 “hace” = POSTPURCHASE

usar#V_I_1 “hace” = POSTPURCHASE

usar#V_I_1 “desde” = POSTPURCHASE

[PP] “compre” “hace” = POSTPURCHASE

“compre” “hace” = POSTPURCHASE

[PP] “compre” = POSTPURCHASE

[PP] hacer#V_IS1 “con” = POSTPURCHASE

[PP1] [VA_P1] costar#V_P = POSTPURCHASE

[VA_P1] costar#V_P = POSTPURCHASE

[PP1] costar#V_IS = POSTPURCHASE

costar#V_IS = POSTPURCHASE

ser [D] regalo = POSTPURCHASE

viajar#V_I_1 [P] [S] [D] _ENTITY_ = POSTPURCHASE

subir#V_I_1 [P] [S] [D] _ENTITY_ = POSTPURCHASE

viajar#V_I_1 [S] [D] _ENTITY_ = POSTPURCHASE

subir#V_I_1 [S] [D] _ENTITY_ = POSTPURCHASE

[PP1] [VA] pasar#V_P “con” [DI] = POSTPURCHASE

[PP1] pasar#V_IS “con” [DI] = POSTPURCHASE
[P] joder = POSTPURCHASE
[P] estropear = POSTPURCHASE
[P] dañar = POSTPURCHASE
[P] romper = POSTPURCHASE
“a” [DP] nombre = POSTPURCHASE
mecánico = POSTPURCHASE
mecanico = POSTPURCHASE
chapista = POSTPURCHASE
grúa = POSTPURCHASE
grua = POSTPURCHASE
desguace = POSTPURCHASE
precio /1/ [VA] ser [AQ] = POSTPURCHASE
precio /1/ ser#V_IS3 [AQ] = POSTPURCHASE
[VA_P1] [V_P] /1/ queja = POSTPURCHASE
[VA_P1] [V_P] /1/ problema = POSTPURCHASE
[V_IS1] /1/ problema = POSTPURCHASE
[V_IS1] /1/ queja = POSTPURCHASE
[VA] tratar /1/ bien = POSTPURCHASE
[VA] salir /1/ bien = POSTPURCHASE
[VA] tratar /1/ mal = POSTPURCHASE
[VA] salir /1/ mal = POSTPURCHASE
[VA] salir /1/ bueno = POSTPURCHASE
tratar /1/ bien = POSTPURCHASE
salir /1/ bien = POSTPURCHASE
tratar /1/ mal = POSTPURCHASE
salir /1/ mal = POSTPURCHASE
salir /1/ bueno = POSTPURCHASE
salir#V_IS /1/ [AQ] = POSTPURCHASE
con _ENTITY_ /1/ [PP1] [VA] pasar#V_P = POSTPURCHASE
con _ENTITY_ /1/ [PP1] [VA] ocurrir#V_P = POSTPURCHASE
con _ENTITY_ /1/ [PP1] [VA] suceder#V_P = POSTPURCHASE
con _ENTITY_ /1/ [PP1] pasar#V_IS1 = POSTPURCHASE

con _ENTITY_ /1/ [PP1] ocurrir#V_IS1 = POSTPURCHASE
con _ENTITY_ /1/ [PP1] suceder#V_IS1 = POSTPURCHASE
[PP1] solucionar [D] /1/ problema = POSTPURCHASE
[PP1] resolver [D] /1/ problema = POSTPURCHASE
solucionar#V_P /2/ problema con = POSTPURCHASE
resolver#V_P /2/ problema con = POSTPURCHASE
solucionar#V_IS1 /2/ problema con = POSTPURCHASE
resolver#V_IS1 /2/ problema con = POSTPURCHASE
problema que [PP1] [V_IS] = POSTPURCHASE
problema que [PP1] [V_II] = POSTPURCHASE
problema que [V_IS] = POSTPURCHASE
problema que [V_II] = POSTPURCHASE
ser#V_IP3 /2/ cómodo = POSTPURCHASE
ser#V_IP3 /2/ comodo = POSTPURCHASE
ser#V_IP3 /2/ comoda = POSTPURCHASE
ser#V_IP3 /2/ comodos = POSTPURCHASE
ser#V_IP3 /2/ comodas = POSTPURCHASE
ser#V_I_1 /1/ cliente = POSTPURCHASE
"ya" ser cliente = POSTPURCHASE
pirar "de" _ENTITY_ = POSTPURCHASE
estar#V_I_1 en [D] _ENTITY_ = POSTPURCHASE
estar#V_I_1 en _ENTITY_ = POSTPURCHASE
[PP1] [V_I_3] a comisión = POSTPURCHASE
[PP1] [V_I_3] a comision = POSTPURCHASE
todavía estar [V_G] = POSTPURCHASE
todavia estar [V_G] = POSTPURCHASE
[NC] de cancelación = POSTPURCHASE
[NC] de cancelacion = POSTPURCHASE
[PP1_S] estar cobrar#V_G = POSTPURCHASE
[PP1_S] "lo" cobrar#V_IS3 = POSTPURCHASE
[PP1_S] "los" cobrar#V_IS3 = POSTPURCHASE
[PP1_S] "la" cobrar#V_IS3 = POSTPURCHASE
[PP1_S] "las" cobrar#V_IS3 = POSTPURCHASE

[PP1_S] “lo” enviar#V_IS3 = POSTPURCHASE
[PP1_S] “los” enviar#V_IS3 = POSTPURCHASE
[PP1_S] “la” enviar#V_IS3 = POSTPURCHASE
[PP1_S] “las” enviar#V_IS3 = POSTPURCHASE
[PP1_S] enviar#V_IS3 = POSTPURCHASE
[PP1_S] [VA] timar = POSTPURCHASE
[PP1_S] [VA] estafar = POSTPURCHASE
[PP1_S] [VA] cobrar = POSTPURCHASE
[PP1_S] timar = POSTPURCHASE
[PP1_S] estafar = POSTPURCHASE
[PP1_S] cobrar = POSTPURCHASE
que [PP1] [VA] pillar = POSTPURCHASE
que [PP1] [VA] coger = POSTPURCHASE
que [PP1] [VA] comprar = POSTPURCHASE
que [PP1] [VA] adquirir = POSTPURCHASE
que [PP1] pillar#V_I_1 = POSTPURCHASE
que [PP1] coger#V_I_1 = POSTPURCHASE
que [PP1] comprar#V_I_1 = POSTPURCHASE
que [PP1] adquirir#V_I_1 = POSTPURCHASE
que pillar#V_I_1 = POSTPURCHASE
que coger#V_I_1 = POSTPURCHASE
que comprar#V_I_1 = POSTPURCHASE
que adquirir#V_I_1 = POSTPURCHASE
que [VA__1] pillar = POSTPURCHASE
que [VA__1] coger = POSTPURCHASE
que [VA__1] comprar = POSTPURCHASE
que [VA__1] adquirir = POSTPURCHASE
decidir#V_I_1 pillar = POSTPURCHASE
decidir#V_I_1 coger = POSTPURCHASE
decidir#V_I_1 comprar = POSTPURCHASE
decidir#V_I_1 adquirir = POSTPURCHASE
decidir#V_I_1 probar = POSTPURCHASE
decidir#V_IS1 por = POSTPURCHASE

[VA__1] decidir#V_P por = POSTPURCHASE
[VA__1] solicitar#V_P [SP] _ENTITY_ = POSTPURCHASE
[VA__1] pedir#V_P [SP] _ENTITY_ = POSTPURCHASE
solicitar#V_IS1 [SP] _ENTITY_ = POSTPURCHASE
hacer#V_I_1 [D] ingreso = POSTPURCHASE
hacer#V_I_1 [D] deposito = POSTPURCHASE
hacer#V_I_1 [D] depósito = POSTPURCHASE
hacer#V_I_1 [D] transferencia = POSTPURCHASE
hacer#V_I_1 ingreso = POSTPURCHASE
hacer#V_I_1 deposito = POSTPURCHASE
hacer#V_I_1 depósito = POSTPURCHASE
hacer#V_I_1 transferencia = POSTPURCHASE
hacer#V_N [D] ingreso = POSTPURCHASE
hacer#V_N [D] deposito = POSTPURCHASE
hacer#V_N [D] depósito = POSTPURCHASE
hacer#V_N [D] transferencia = POSTPURCHASE
hacer#V_N ingreso = POSTPURCHASE
hacer#V_N deposito = POSTPURCHASE
hacer#V_N depósito = POSTPURCHASE
hacer#V_N transferencia = POSTPURCHASE
llevar /2/ [V_G] con = POSTPURCHASE
a el [V_N] [D] [NC] en = POSTPURCHASE
presentar [RG] [D] /1/ reclamación = POSTPURCHASE
presentar [RG] [D] /1/ reclamacion = POSTPURCHASE
presentar [D] /1/ reclamación = POSTPURCHASE
presentar [D] /1/ reclamacion = POSTPURCHASE
estar#V_II1 [AQ] de = POSTPURCHASE
hartar#V_IS1 [SP] = POSTPURCHASE
cansar#V_IS1 [SP] = POSTPURCHASE
indignar#V_IS1 [SP] = POSTPURCHASE
cabrear#V_IS1 [SP] = POSTPURCHASE
enfadar#V_IS1 [SP] = POSTPURCHASE
[VA_P1] hartar [SP] = POSTPURCHASE

[VA_P1] cansar [SP] = POSTPURCHASE
[VA_P1] indignar [SP] = POSTPURCHASE
[VA_P1] cabrear [SP] = POSTPURCHASE
[VA_P1] enfadar [SP] = POSTPURCHASE
maraton “de” _ENTITY_ = AWARENESS
maratón “de” _ENTITY_ = AWARENESS
estar#V_I_1 tan [V_P] = POSTPURCHASE
estar#V_I_1 /1/ hasta [D] = POSTPURCHASE
[PP1] atender [RG] = POSTPURCHASE
[PP1] funcionar [RG] = POSTPURCHASE
aviso de descubierto = POSTPURCHASE
[PP1] [VA] pasar /2/ _ENTITY_ = POSTPURCHASE
[PP1] [VA] ocurrir /2/ _ENTITY_ = POSTPURCHASE
[PP1] [VA] suceder /2/ _ENTITY_ = POSTPURCHASE
[PP1] pasar /2/ _ENTITY_ = POSTPURCHASE
[PP1] ocurrir /2/ _ENTITY_ = POSTPURCHASE
[PP1] suceder /2/ _ENTITY_ = POSTPURCHASE
[V__S1] a /4/ abrir [PP1] [D] = POSTPURCHASE
[V__S1] a /4/ ingresar [PP1] [D] = POSTPURCHASE
[V__S1] a /4/ protestar [PP1] [D] = POSTPURCHASE
[VA] [V_P] a /4/ abrir [PP1] [D] = POSTPURCHASE
[VA] [V_P] a /4/ ingresar [PP1] [D] = POSTPURCHASE
[VA] [V_P] a /4/ protestar [PP1] [D] = POSTPURCHASE
[V__S1] a /4/ abrir [D] = POSTPURCHASE
[V__S1] a /4/ ingresar [D] = POSTPURCHASE
[V__S1] a /4/ protestar [D] = POSTPURCHASE
[VA] [V_P] a /4/ abrir [D] = POSTPURCHASE
[VA] [V_P] a /4/ ingresar [D] = POSTPURCHASE
[VA] [V_P] a /4/ protestar [D] = POSTPURCHASE
[V__S1] a /4/ abrir a [D] = POSTPURCHASE
[V__S1] a /4/ ingresar a [D] = POSTPURCHASE
[V__S1] a /4/ protestar a [D] = POSTPURCHASE
[VA] [V_P] a /4/ abrir a [D] = POSTPURCHASE

[VA] [V_P] a /4/ ingresar a [D] = POSTPURCHASE
[VA] [V_P] a /4/ protestar a [D] = POSTPURCHASE
[V__S1] a /4/ abrir [D] = POSTPURCHASE
[V__S1] a /4/ ingresar [D] = POSTPURCHASE
[V__S1] a /4/ protestar [D] = POSTPURCHASE
[VA] [V_P] a /4/ abrir [D] = POSTPURCHASE
[VA] [V_P] a /4/ ingresar [D] = POSTPURCHASE
[VA] [V_P] a /4/ protestar [D] = POSTPURCHASE
[PP1] decir en _ENTITY_ = POSTPURCHASE
[PP1] comentar en _ENTITY_ = POSTPURCHASE
exigir /4/ solución = POSTPURCHASE
exigir /4/ solucion = POSTPURCHASE
estar#V_I_1 /1/ [AQ] [SP] _ENTITY_ = POSTPURCHASE
[V_P] [D] nómina = POSTPURCHASE
[V_P] [D] nomina = POSTPURCHASE
[VA_P1] [V_P] [D] contrato = POSTPURCHASE
[VA] cambiar#V_P a /1/ _ENTITY_ = POSTPURCHASE
cambiar#V_IS1 a /1/ _ENTITY_ = POSTPURCHASE
[VA] cambiar#V_P de /1/ _ENTITY_ = POSTPURCHASE
cambiar#V_IS1 de /1/ _ENTITY_ = POSTPURCHASE
[V_IS1] [D] nómina = POSTPURCHASE
[V_IS1] [D] nomina = POSTPURCHASE
[V_IS1] [D] contrato = POSTPURCHASE
[VA] abrir#V_P [D] cuenta = POSTPURCHASE
[VA] abrir#V_P [D] hipoteca = POSTPURCHASE
[VA] cerrar#V_P [D] cuenta = POSTPURCHASE
[VA] cerrar#V_P [D] hipoteca = POSTPURCHASE
[VA] abrir#V_IS1 [D] cuenta = POSTPURCHASE
[VA] abrir#V_IS1 [D] hipoteca = POSTPURCHASE
[VA] cerrar#V_IS1 [D] cuenta = POSTPURCHASE
[VA] cerrar#V_IS1 [D] hipoteca = POSTPURCHASE
abrir#V_P [D] cuenta = POSTPURCHASE
abrir#V_P [D] hipoteca = POSTPURCHASE

cerrar#V_P [D] cuenta = POSTPURCHASE
cerrar#V_P [D] hipoteca = POSTPURCHASE
abrir#V_P cuenta = POSTPURCHASE
abrir#V_P hipoteca = POSTPURCHASE
cerrar#V_P cuenta = POSTPURCHASE
cerrar#V_P hipoteca = POSTPURCHASE
abrir#V_IS1 [D] cuenta = POSTPURCHASE
abrir#V_IS1 [D] hipoteca = POSTPURCHASE
cerrar#V_IS1 [D] cuenta = POSTPURCHASE
cerrar#V_IS1 [D] hipoteca = POSTPURCHASE
abrir#V_IS1 cuenta = POSTPURCHASE
abrir#V_IS1 hipoteca = POSTPURCHASE
cerrar#V_IS1 cuenta = POSTPURCHASE
cerrar#V_IS1 hipoteca = POSTPURCHASE
a sacar dinero de = POSTPURCHASE
a sacar pasta de = POSTPURCHASE
reclamar#V_I_1 = POSTPURCHASE
[D] cuenta con _ENTITY_ = POSTPURCHASE
[DP1] hipoteca con _ENTITY_ = POSTPURCHASE
[D] ingreso con _ENTITY_ = POSTPURCHASE
[D] dinero /1/ tener#V_P en /2/ _ENTITY_ = POSTPURCHASE
[D] pasta /1/ tener#V_P en /2/ _ENTITY_ = POSTPURCHASE
[D] ahorro /1/ tener#V_P en /2/ _ENTITY_ = POSTPURCHASE
[D] dinero /1/ tener#V_I_1 en /2/ _ENTITY_ = POSTPURCHASE
[D] pasta /1/ tener#V_I_1 en /2/ _ENTITY_ = POSTPURCHASE
[D] ahorro /1/ tener#V_I_1 en /2/ _ENTITY_ = POSTPURCHASE
[PP1] [P] dar#V_IS = POSTPURCHASE
[VA_P1] dar_de_alta [SP] = POSTPURCHASE
[VA_P1] dar_de_baja [SP] = POSTPURCHASE
[PP1] poner_en_contacto [SP] = POSTPURCHASE
[PP1] [VA_P1] dar_de_alta = POSTPURCHASE
[PP1] [VA_P1] dar_de_baja = POSTPURCHASE
[PP1] [VA] poner_en_contacto = POSTPURCHASE

[VA] dar_de_alta = POSTPURCHASE
[VA] dar_de_baja = POSTPURCHASE
dar_de_baja = POSTPURCHASE
[PP1] dar_de_alta = POSTPURCHASE
[PP1] dar_de_baja = POSTPURCHASE
[PP1] poner_en_contacto = POSTPURCHASE
[VA] dar de baja = POSTPURCHASE
dar de baja = POSTPURCHASE
escoger#V_IS1 [SP] _ENTITY_ = POSTPURCHASE
escogi [SP] _ENTITY_ = POSTPURCHASE
elegir#V_IS1 [SP] _ENTITY_ = POSTPURCHASE
elegi [SP] _ENTITY_ = POSTPURCHASE
decantar#V_IS1 [SP] _ENTITY_ = POSTPURCHASE
decante [SP] _ENTITY_ = POSTPURCHASE
decidir#V_IS1 [SP] _ENTITY_ = POSTPURCHASE
decidi [SP] _ENTITY_ = POSTPURCHASE
escoger#V_IS1 [D] _ENTITY_ = POSTPURCHASE
escogi [D] _ENTITY_ = POSTPURCHASE
elegir#V_IS1 [D] _ENTITY_ = POSTPURCHASE
elegi [D] _ENTITY_ = POSTPURCHASE
decantar#V_IS1 [SP] [D] _ENTITY_ = POSTPURCHASE
decante [SP] [D] _ENTITY_ = POSTPURCHASE
decidir#V_IS1 [SP] [D] _ENTITY_ = POSTPURCHASE
decidi [SP] [D] _ENTITY_ = POSTPURCHASE
escoger#V_IS1 _ENTITY_ = POSTPURCHASE
escogi _ENTITY_ = POSTPURCHASE
elegir#V_IS1 _ENTITY_ = POSTPURCHASE
elegi _ENTITY_ = POSTPURCHASE
domiciliar [SP] [D] _ENTITY_ = POSTPURCHASE
domiciliar [SP] _ENTITY_ = POSTPURCHASE
esperar#V__P1 que todo [V_S] bien = POSTPURCHASE
esperar#V__P1 que [V_S] bien = POSTPURCHASE
[PP1] /1/ [VA] conceder = POSTPURCHASE

[PP1] /1/ conceder = POSTPURCHASE
[VA_P1] comprar#V_P = POSTPURCHASE
[VA_P1] adquirir#V_P = POSTPURCHASE
[VA_P1] pillar#V_P = POSTPURCHASE
[VA_P1] cazar#V_P = POSTPURCHASE
[VA_P1] reservar#V_P = POSTPURCHASE
[VA_P1] firmar#V_P = POSTPURCHASE
[VA_P1] alquilar#V_P = POSTPURCHASE
adquirir#V_I_1 [D] = POSTPURCHASE
pillar#V_I_1 [D] = POSTPURCHASE
cazar#V_I_1 [D] = POSTPURCHASE
reservar#V_I_1 [D] = POSTPURCHASE
firmar#V_I_1S [D] = POSTPURCHASE
alquilar#V_I_1 [D] = POSTPURCHASE
tener#V_I_1S [D] _ENTITY_ = POSTPURCHASE
tener#V_I_1S a _ENTITY_ = POSTPURCHASE
tener#V_I_1S _ENTITY_ = POSTPURCHASE
pedir#V_IS1S [SP] _ENTITY_ = POSTPURCHASE
[D] /6/ ser#V_IS [NP] de abrir [D] cuenta [SP] = POSTPURCHASE
[DP1] _ENTITY_ = POSTPURCHASE
llevar#V_I_1 usar#V_G = POSTPURCHASE
[PP1] hacer#V_IS “mal” [D] _ENTITY_ = POSTPURCHASE
[PP1] hacer#V_IS “bien” [D] _ENTITY_ = POSTPURCHASE
[PP1] sentar#V_IS “mal” [D] _ENTITY_ = POSTPURCHASE
[PP1] sentar#V_IS “bien” [D] _ENTITY_ = POSTPURCHASE
tener [DI] “avería” = POSTPURCHASE
estar#V_I_1S harto = POSTPURCHASE
tener#V_I “hace” = POSTPURCHASE
[PP1] encantar#V_IS = POSTPURCHASE
“en” _ENTITY_ estar pagar#V_G = POSTPURCHASE
“a” terminar “con” _ENTITY_ = POSTPURCHASE
[PP] [VA] engañar = POSTPURCHASE
“permanencia” /1/ acabar = POSTPURCHASE

terminar [D] /1/ “permanencia” = POSTPURCHASE

acabar [D] /1/ “permanencia” = POSTPURCHASE

[PP] estar acabar#V_G [D] _ENTITY_ = POSTPURCHASE

ENTITY “en” /1/ “sangre” = POSTPURCHASE

cancelar#V_I_1 /1/ portabilidad = POSTPURCHASE

solicitar#V_I_1 /1/ portabilidad = POSTPURCHASE

portabilidad “a” _ENTITY_ = POSTPURCHASE

terminar /1/ permanencia con _ENTITY_ = POSTPURCHASE

[DP1] /1/ compañía = POSTPURCHASE

[DP1] /1/ compañia = POSTPURCHASE

tener#V_I_1 “con” /1/ [D] línea = POSTPURCHASE

tener#V_I_1 “con” /1/ [D] linea = POSTPURCHASE

tener#V_I_1 “con” _ENTITY_ [D] línea = POSTPURCHASE

tener#V_I_1 “con” _ENTITY_ [D] linea = POSTPURCHASE

[PP3] tener#V_IP1S “con” _ENTITY_ = POSTPURCHASE

tener#V_IP1S [D] /1/ “con” _ENTITY_ = POSTPURCHASE

tramitar [D] “baja” = POSTPURCHASE

servir#V_IS1 [DI] [NC] /4/ _ENTITY_ = POSTPURCHASE

ir#V_P “muy” [RG] = POSTPURCHASE

ir#V_IP3 “muy” [RG] = POSTPURCHASE

usar#V_IS1 = POSTPURCHASE

[PP3] comprar#V_IP1S “en” = POSPURCHASE

revisión /1/ _ENTITY_ = POSPURCHASE

estar /1/ bueno = POSPURCHASE

estar /1/ malo = POSPURCHASE

estar /1/ rico = POSPURCHASE

venir#V_IP1S “de” _ENTITY_ = POSPURCHASE

“en” [DP1] poder = POSPURCHASE

acabar#V_I_1S /1/ contrato “con” _ENTITY_ = POSPURCHASE

[PP1] hacer#V_I_3 /1/ descuento = POSPURCHASE

[VA__1S] usar#V_P “con” _ENTITY_ = POSPURCHASE

A.1.2 Linguistic Rules for English

"formula" "one" = AWARENESS

"formula" "1" = AWARENESS

f1 = AWARENESS

formula1 = AWARENESS

bike = AWARENESS

bankbike = AWARENESS

bank bike = AWARENESS

sponsorship = AWARENESS

movie = AWARENESS

championship = AWARENESS

grant = AWARENESS

cycle hire = AWARENESS

advert be so [J] = AWARENESS

advertisement be so [J] = AWARENESS

ad be so [J] = AWARENESS

jingle be so [J] = AWARENESS

commercial be so [J] = AWARENESS

advert be very [RB] [J] = AWARENESS

advertisement be very [RB] [J] = AWARENESS

ad be very [RB] [J] = AWARENESS

jingle be very [RB] [J] = AWARENESS

commercial be very [RB] [J] = AWARENESS

advert be very [J] = AWARENESS

advertisement be very [J] = AWARENESS

ad be very [J] = AWARENESS

jingle be very [J] = AWARENESS

commercial be very [J] = AWARENESS

advert be so [RB] [J] = AWARENESS

advertisement be so [RB] [J] = AWARENESS

ad be so [RB] [J] = AWARENESS

jingle be so [RB] [J] = AWARENESS

commercial be so [RB] [J] = AWARENESS

put on [DT] /1/ of

$_{E}NTITY$

$_{=}AWARENESS$

put on [DT] /1/ _ENTITY_ = AWARENESS

put on [DT] of _ENTITY_ = AWARENESS

put on [DT] _ENTITY_ = AWARENESS

put on /1/ _ENTITY_ = AWARENESS

put on _ENTITY_ = AWARENESS

put on [DT] /1/ _ENTITY_ = AWARENESS

put on /1/ _ENTITY_ = AWARENESS

put on [DT] _ENTITY_ = AWARENESS

put on _ENTITY_ = AWARENESS

[NP] be advertising _ENTITY_ = AWARENESS

[NP] be advertise _ENTITY_ = AWARENESS

[NP] advertising _ENTITY_ = AWARENESS

[NP] advertise _ENTITY_ = AWARENESS

ceremony [IN] _ENTITY_ = AWARENESS

i be go to [VB] _ENTITY_ for [J] advertising = AWARENESS

i be go to [VB] _ENTITY_ for advertising = AWARENESS

i have win [DT] _ENTITY_ = AWARENESS

i win [DT] _ENTITY_ = AWARENESS

have win [DT] _ENTITY_ = AWARENESS

backing from the _ENTITY_ = AWARENESS

backing from _ENTITY_ = AWARENESS

backing of the _ENTITY_ = AWARENESS

backing of _ENTITY_ = AWARENESS

support from the _ENTITY_ = AWARENESS

support from _ENTITY_ = AWARENESS

support of the _ENTITY_ = AWARENESS

support of _ENTITY_ = AWARENESS

logo = AWARENESS

icon = AWARENESS

abc = AWARENESS
i have be look /3/ but _ENTITY_ offer “a” [JJR] = EVALUATION
i have be look /3/ but _ENTITY_ offer “an” [JJR] = EVALUATION
i have be look /3/ but _ENTITY_ offer [JJR] = EVALUATION
i have be look /3/ but _ENTITY_ have “a” [JJR] = EVALUATION
i have be look /3/ but _ENTITY_ have “an” [JJR] = EVALUATION
i have be look /3/ but _ENTITY_ have [JJR] = EVALUATION
i have look /3/ but _ENTITY_ offer “a” [JJR] = EVALUATION
i have look /3/ but _ENTITY_ offer “an” [JJR] = EVALUATION
i have look /3/ but _ENTITY_ offer [JJR] = EVALUATION
i have look /3/ but _ENTITY_ have “a” [JJR] = EVALUATION
i have look /3/ but _ENTITY_ have “an” [JJR] = EVALUATION
i have look /3/ but _ENTITY_ have [JJR] = EVALUATION
i look /3/ but _ENTITY_ offer “a” [JJR] = EVALUATION
i look /3/ but _ENTITY_ offer “an” [JJR] = EVALUATION
i look /3/ but _ENTITY_ offer [JJR] = EVALUATION
i look /3/ but _ENTITY_ “a” [JJR] = EVALUATION
i look /3/ but _ENTITY_ “an” [JJR] = EVALUATION
i look /3/ but _ENTITY_ have [JJR] = EVALUATION
i have look /3/ and _ENTITY_ offer “the” [JJS] = EVALUATION
i have look /3/ and _ENTITY_ offer [JJS] = EVALUATION
i have look /3/ and _ENTITY_ have “the” [JJS] = EVALUATION
i have look /3/ and _ENTITY_ have [JJS] = EVALUATION
i look /3/ and _ENTITY_ offer “the” [JJS] = EVALUATION
i look /3/ and _ENTITY_ offer [JJS] = EVALUATION
i look /3/ and _ENTITY_ have “the” [JJS] = EVALUATION
i look /3/ and _ENTITY_ have [JJS] = EVALUATION
i have look /3/ and _ENTITY_ offer “the” most [J] = EVALUATION
i have look /3/ and _ENTITY_ offer “the” least [J] = EVALUATION
i have look /3/ and _ENTITY_ have “the” most [J] = EVALUATION
i have look /3/ and _ENTITY_ have “the” least [J] = EVALUATION
i look /3/ and _ENTITY_ offer “the” most [J] = EVALUATION
i look /3/ and _ENTITY_ offer “the” least [J] = EVALUATION

i look /3/ and _ENTITY_ have “the” most [J] = EVALUATION

i look /3/ and _ENTITY_ have “the” least [J] = EVALUATION

i be look at the = EVALUATION

tryna [TO] force me [TO] buy= EVALUATION

tryna force me [TO] buy = EVALUATION

tryna [TO] force me [TO] contract = EVALUATION

tryna force me [TO] contract = EVALUATION

try [TO] force me [TO] buy = EVALUATION

try force me [TO] buy = EVALUATION

try [TO] force me [TO] contract = EVALUATION

try force me [TO] contract = EVALUATION

maybe get “a” _ENTITY_ /3/ or = EVALUATION

maybe get [DT] _ENTITY_ /3/ or = EVALUATION

perhaps get “a” _ENTITY_ /3/ or = EVALUATION

perhaps get [DT] _ENTITY_ /3/ or = EVALUATION

possibly get “a” _ENTITY_ /3/ or = EVALUATION

possibly get [DT] _ENTITY_ /3/ or = EVALUATION

probably get “a” _ENTITY_ /3/ or = EVALUATION

probably get [DT] _ENTITY_ /3/ or = EVALUATION

might have [TO] jump on _ENTITY_ = EVALUATION

may have [TO] jump on _ENTITY_ = EVALUATION

might swap = EVALUATION

may swap = EVALUATION

might change = EVALUATION

may change = EVALUATION

ENTITY be [RB] price = EVALUATION

i be look at /3/ _ENTITY_ /3/ but = EVALUATION

i look at /3/ _ENTITY_ /3/ but = EVALUATION

finding /4/ _ENTITY_ be [JJR] /2/ than = EVALUATION

finding /4/ _ENTITY_ be [RBR] /2/ than = EVALUATION

finding /4/ _ENTITY_ have [JJR] /2/ than = EVALUATION

finding /4/ _ENTITY_ have [RBR] /2/ than = EVALUATION

look /4/ _ENTITY_ be [JJR] /2/ than = EVALUATION

look /4/ _ENTITY_ be [RBR] /2/ than = EVALUATION
look /4/ _ENTITY_ have [JJR] /2/ than = EVALUATION
look /4/ _ENTITY_ have [RBR] /2/ than = EVALUATION
finding /4/ [NP] be [JJR] than = EVALUATION
look /4/ [NP] be [JJR] than = EVALUATION
be _ENTITY_ any good = EVALUATION
be _ENTITY_ any worth = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” phone but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” iphone but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” tablet but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” mobile but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” landline but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” broadband but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” router but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” wifi but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” micro but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” sim but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” card but = EVALUATION
be#VBD go [TO] [VB] [IN] them for “a” simcard but = EVALUATION
be#VBD go [TO] [VB] [IN] _ENTITY_ /4/ but = EVALUATION
[WRB] do i switch /2/ _ENTITY_ = EVALUATION
i be consider switch to = EVALUATION
i be consider switching to = EVALUATION
i be consider go to = EVALUATION
i be consider change to = EVALUATION
i consider switch to = EVALUATION
i consider switching to = EVALUATION
i consider go to = EVALUATION
i consider change to = EVALUATION
im consider switch to = EVALUATION
im consider switching to = EVALUATION
im consider go to = EVALUATION
im consider change to = EVALUATION

be#VBP consider switch to = EVALUATION
be#VBP consider switching to = EVALUATION
be#VBP consider go to = EVALUATION
be#VBP consider change to = EVALUATION
be#VBD consider switch to = EVALUATION
be#VBD consider switching to = EVALUATION
be#VBD consider go to = EVALUATION
be#VBD consider change to = EVALUATION
i be consider contract = EVALUATION
im consider contract = EVALUATION
be#VBP consider contract = EVALUATION
be#VBD consider contract = EVALUATION
switch to _ENTITY_ /3/ [J] alternative = EVALUATION
switch to _ENTITY_ /3/ [J] option = EVALUATION
switching to _ENTITY_ /3/ [J] alternative = EVALUATION
switching to _ENTITY_ /3/ [J] option = EVALUATION
go to _ENTITY_ /3/ [J] alternative = EVALUATION
go to _ENTITY_ /3/ [J] option = EVALUATION
change to _ENTITY_ /3/ [J] alternative = EVALUATION
change to _ENTITY_ /3/ [J] option = EVALUATION
i be think about [VBG] = EVALUATION
i think about [VBG] = EVALUATION
im think about [VBG] = EVALUATION
be#VBP think about [VBG] = EVALUATION
be#VBD think about [VBG] = EVALUATION
i be consider “a” move to = EVALUATION
i consider “a” move to = EVALUATION
im consider “a” move to = EVALUATION
be#VBP consider “a” move to = EVALUATION
be#VBD consider “a” move to = EVALUATION
i be consider “a” switch to = EVALUATION
i consider “a” switch to = EVALUATION
im consider “a” switch to = EVALUATION

be#VBP consider “a” switch to = EVALUATION
be#VBD consider “a” switch to = EVALUATION
i be consider “a” change to = EVALUATION
i consider “a” change to = EVALUATION
im consider “a” change to = EVALUATION
be#VBP consider “a” change to = EVALUATION
be#VBD consider “a” change to = EVALUATION
about [TO] cancel /6/ go to = EVALUATION
be [RBR] price = EVALUATION
if anything /1/ i [MD] get = EVALUATION
i [MD] choose = EVALUATION
i [MD] select = EVALUATION
switch to _ENTITY_ /4/ think about it = EVALUATION
change to _ENTITY_ /4/ think about it = EVALUATION
[MD] prefer _ENTITY_ but = EVALUATION
[NP] /3/ have [JJR] [N] /3/ _ENTITY_ = EVALUATION
ENTITY /3/ have [JJR] [N] /3/ [NP] = EVALUATION
do _ENTITY_ work [RB] = EVALUATION
do _ENTITY_ work good = EVALUATION
“heard” someone say = EVALUATION
hear someone say = EVALUATION
i think i [MD] [RB] switch /3/ when = EVALUATION
i think we [MD] [RB] switch /3/ when = EVALUATION
i think i [MD] [RB] switch /3/ when = EVALUATION
i think we [MD] [RB] switch /3/ when = EVALUATION
i think i [MD] [RB] change /3/ when = EVALUATION
i think we [MD] [RB] change /3/ when = EVALUATION
i do not feel like = EVALUATION
i want to leave _ENTITY_ and go back to = EVALUATION
i want to leave _ENTITY_ and go to = EVALUATION
i want leave _ENTITY_ and go back to = EVALUATION
i want leave _ENTITY_ and go to = EVALUATION
i wanna leave _ENTITY_ and go back to = EVALUATION

i wanna leave _ENTITY_ and go to = EVALUATION
i want /3/ _ENTITY_ back = EVALUATION
i wish /3/ _ENTITY_ have /3/ like#IN = EVALUATION
i wish /3/ _ENTITY_ be as [J] as = EVALUATION
it be time [TO] switch to = EVALUATION
it be time [TO] change to = EVALUATION
it be time [TO] leave = EVALUATION
it be time for me [TO] switch to = EVALUATION
it be time for me [TO] change to = EVALUATION
it be time for me [TO] leave = EVALUATION
the [JJS] /3/ compare to = EVALUATION
[NP] seem [TO] be the [JJS] /3/ compare to = EVALUATION
seem [TO] be the [JJS] /3/ compare to = EVALUATION
look at /2/ price /3/ compare = EVALUATION
i /4/ review = EVALUATION
what be _ENTITY_ like#IN as = EVALUATION
how long do it take [TO] [VB]= EVALUATION
how long “does” it take [TO] [VB] = EVALUATION
i be#VBP consider join#VBG = EVALUATION
i consider join#VBG = EVALUATION
i be#VBP consider switch to = EVALUATION
i be#VBP consider switching to = EVALUATION
i be#VBP consider move to = EVALUATION
i consider switch to = EVALUATION
i consider switching to = EVALUATION
i consider move to = EVALUATION
i would “rather” go “to” = EVALUATION
i would “rather” switch “to” = EVALUATION
i would “rather” move “to” = EVALUATION
i would “preferably” go “to” = EVALUATION
i would “preferably” switch “to” = EVALUATION
i would “preferably” move “to” = EVALUATION
i would “certainly” go “to” = EVALUATION

i would “certainly” switch “to” = EVALUATION

i would “certainly” move “to” = EVALUATION

i would “rather” select = EVALUATION

i would “rather” choose = EVALUATION

i would “preferably” select = EVALUATION

i would “preferably” choose = EVALUATION

i would “certainly” select = EVALUATION

i would “certainly” choose = EVALUATION

what be “the” good place “for” = EVALUATION

i think i [MD] get “a” = EVALUATION

i think i [MD] get “the” = EVALUATION

[MD] be [V] at my /2/ insurance = EVALUATION

[MD] be [V] at my /2/ loan = EVALUATION

[MD] be [V] at my /2/ mortgage = EVALUATION

[MD] be [V] at the /2/ insurance = EVALUATION

[MD] be [V] at the /2/ loan = EVALUATION

[MD] be [V] at the /2/ mortgage = EVALUATION

[MD] be [V] at our /2/ insurance = EVALUATION

[MD] be [V] at our /2/ loan = EVALUATION

[MD] be [V] at our /2/ mortgage = EVALUATION

[MD] at [V] my /2/ insurance = EVALUATION

[MD] at [V] my /2/ loan = EVALUATION

[MD] at [V] my /2/ mortgage = EVALUATION

[MD] at [V] the /2/ insurance = EVALUATION

[MD] at [V] the /2/ loan = EVALUATION

[MD] at [V] the /2/ mortgage = EVALUATION

[MD] at [V] our /2/ insurance = EVALUATION

[MD] at [V] our /2/ loan = EVALUATION

[MD] at [V] our /2/ mortgage = EVALUATION

be go have “a” look = EVALUATION

be gonna have “a” look = EVALUATION

go#VBG to have “a” look at = EVALUATION

be go to compare _ENTITY_ with = EVALUATION gonna compare _ENTITY_ with = EVALUATION

compare _ENTITY_ with _ENTITY_ = EVALUATION

do you use = EVALUATION

do anybody use = EVALUATION

do anyone use = EVALUATION

do somebody use = EVALUATION

wonder if _ENTITY_ [MD] be = EVALUATION

wonder if _ENTITY_ [MD] have = EVALUATION

wonder if _ENTITY_ [MD] offer = EVALUATION

doubt whether _ENTITY_ be the most [J] choice = EVALUATION

doubt whether _ENTITY_ be the least [J] choice = EVALUATION

doubt whether _ENTITY_ be the [J] choice = EVALUATION

doubt if _ENTITY_ be the most [J] choice = EVALUATION

doubt if _ENTITY_ be the least [J] choice = EVALUATION

doubt if _ENTITY_ be the [J] choice = EVALUATION

i be go [TO] [VB] [IN] them /4/ but = EVALUATION

be go [TO] [VB] [IN] them /4/ but = EVALUATION

i be go [TO] [VB] [IN] /4/ but /8/ _ENTITY_ = EVALUATION

[WRB] do i switch to = EVALUATION

what be the difference = EVALUATION

ENTITY or _ENTITY_ = EVALUATION

be offer me = EVALUATION

mortgage offer be in the post = PURCHASE

get [PRP] _ENTITY_ contract through = PURCHASE

about to open “an” account = PURCHASE

about to take out “a” loan = PURCHASE

about to take on “a” loan = PURCHASE

about to take out “a” mortgage = PURCHASE

about to take on “a” mortgage = PURCHASE

about to apply “for” “a” loan = PURCHASE

about to apply “for” “a” loan = PURCHASE

open#VBG “a” /2/ account at = PURCHASE

open#VBG “an” /2/ account at = PURCHASE

open#VBG the /2/ account at = PURCHASE
open#VBG /2/ account at = PURCHASE
open#VBG /2/ account asap = PURCHASE
opening “a” /2/ account at = PURCHASE
opening “an” /2/ account at = PURCHASE
opening the /2/ account at = PURCHASE
opening /2/ account at = PURCHASE
opening /2/ account asap = PURCHASE
take#VBG out “a” /2/ loan “at” = PURCHASE
take#VBG out “a” /2/ loan = PURCHASE
take#VBG out “an” /2/ loan “at” = PURCHASE
take#VBG out “an” /2/ loan = PURCHASE
take#VBG out the /2/ loan “at” = PURCHASE
take#VBG out the /2/ loan = PURCHASE
take#VBG on “a” /2/ loan “at” = PURCHASE
take#VBG on “a” /2/ loan = PURCHASE
take#VBG on “an” /2/ loan “at” = PURCHASE
take#VBG on “an” /2/ loan = PURCHASE
take#VBG on the /2/ loan “at” = PURCHASE
take#VBG on the /2/ loan = PURCHASE
taking out “a” /2/ loan “at” = PURCHASE
taking out “a” /2/ loan = PURCHASE
taking out “an” /2/ loan “at” = PURCHASE
taking out “an” /2/ loan = PURCHASE
taking out the /2/ loan “at” = PURCHASE
taking out the /2/ loan = PURCHASE
taking on “a” /2/ loan “at” = PURCHASE
taking on “a” /2/ loan = PURCHASE
taking on “an” /2/ loan “at” = PURCHASE
taking on “an” /2/ loan = PURCHASE
taking on the /2/ loan “at” = PURCHASE
taking on the /2/ loan = PURCHASE
take#VBG out “a” /2/ mortgage on = PURCHASE

take#VBG out “an” /2/ mortgage on = PURCHASE
take#VBG out the /2/ mortgage on = PURCHASE
take#VBG on “a” /2/ mortgage on = PURCHASE
take#VBG on “an” /2/ mortgage on = PURCHASE
take#VBG on the /2/ mortgage on = PURCHASE
taking out “a” /2/ mortgage on = PURCHASE
taking out “an” /2/ mortgage on = PURCHASE
taking out the /2/ mortgage on = PURCHASE
taking on “a” /2/ mortgage on = PURCHASE
taking on “an” /2/ mortgage on = PURCHASE
taking on the /2/ mortgage on = PURCHASE
take#VBG out “a” /2/ mortgage = PURCHASE
take#VBG out “an” /2/ mortgage = PURCHASE
take#VBG out the /2/ mortgage = PURCHASE
take#VBG on “a” /2/ mortgage = PURCHASE
take#VBG on “an” /2/ mortgage = PURCHASE
take#VBG on the /2/ mortgage = PURCHASE
taking out “a” /2/ mortgage = PURCHASE
taking out “an” /2/ mortgage = PURCHASE
taking out the /2/ mortgage = PURCHASE
taking on “a” /2/ mortgage = PURCHASE
taking on “an” /2/ mortgage = PURCHASE
taking on the /2/ mortgage = PURCHASE
apply#VBG “for” “a” /2/ loan = PURCHASE
apply#VBG “for” “an” /2/ loan = PURCHASE
apply#VBG “for” the /2/ loan = PURCHASE
applying “for” “a” /2/ loan = PURCHASE
applying “for” “an” /2/ loan = PURCHASE
applying “for” the /2/ loan = PURCHASE
open#VBG “a” _ENTITY_ /2/ account = PURCHASE
open#VBG “an” _ENTITY_ /2/ account = PURCHASE
open#VBG the _ENTITY_ /2/ account = PURCHASE
opening “a” _ENTITY_ /2/ account = PURCHASE

opening “an” _ENTITY_ /2/ account = PURCHASE
opening the _ENTITY_ /2/ account = PURCHASE
open#VBD [DT] account = PURCHASE
open#VBD “an” account = PURCHASE
be#VBP get “a” _ENTITY_ = PURCHASE
be#VBP get “an” _ENTITY_ = PURCHASE
be#VBP get _ENTITY_ = PURCHASE
be#VBP gettin “a” _ENTITY_ = PURCHASE
be#VBP gettin “an” _ENTITY_ = PURCHASE
be#VBP gettin _ENTITY_ = PURCHASE
i can not wait [TO] have “a” = PURCHASE
i can not wait [TO] have “an” = PURCHASE
get me “a” [J] /2/ iphone = PURCHASE
get me “a” [J] /2/ phone = PURCHASE
get me “a” [J] /2/ tablet = PURCHASE
get me “a” [J] /2/ mobile = PURCHASE
get me “a” [J] /2/ landline = PURCHASE
get me “a” [J] /2/ broadband = PURCHASE
get me “a” [J] /2/ router = PURCHASE
get me “a” [J] /2/ wifi = PURCHASE
get me “a” [J] /2/ micro = PURCHASE
get me “a” [J] /2/ sim = PURCHASE
get me “a” [J] /2/ card = PURCHASE
get me “a” [J] /2/ simcard = PURCHASE
get me “an” [J] /2/ iphone = PURCHASE
get me “an” [J] /2/ phone = PURCHASE
get me “an” [J] /2/ tablet = PURCHASE
get me “an” [J] /2/ mobile = PURCHASE
get me “an” [J] /2/ landline = PURCHASE
get me “an” [J] /2/ broadband = PURCHASE
get me “an” [J] /2/ router = PURCHASE
get me “an” [J] /2/ wifi = PURCHASE
get me “an” [J] /2/ micro = PURCHASE

get me “an” [J] /2/ sim = PURCHASE
get me “an” [J] /2/ card = PURCHASE
get me “an” [J] /2/ simcard = PURCHASE
get me [J] /2/ iphone = PURCHASE
get me [J] /2/ phone = PURCHASE
get me [J] /2/ tablet = PURCHASE
get me [J] /2/ mobile = PURCHASE
get me [J] /2/ landline = PURCHASE
get me [J] /2/ broadband = PURCHASE
get me [J] /2/ router = PURCHASE
get me [J] /2/ wifi = PURCHASE
get me [J] /2/ micro= PURCHASE
get me [J] /2/ sim = PURCHASE
get me [J] /2/ card = PURCHASE
get me [J] /2/ simcard = PURCHASE
let us get = PURCHASE
let me get = PURCHASE
i [RB] sign [RP] with = PURCHASE
i sign [RP] with = PURCHASE
i [RB] contract = PURCHASE
i contract = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ phone = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ iphone = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ tablet = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ mobile = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ landline = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ broadband = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ router = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ wifi = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ micro = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ sim = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ card = PURCHASE
about [TO] go to _ENTITY_ /4/ get /1/ simcard = PURCHASE

about [TO] go to _ENTITY_ /4/ cop /1/ phone = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ iphone = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ tablet = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ mobile = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ landline = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ broadband = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ router = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ wifi = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ micro = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ sim = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ card = PURCHASE
about [TO] go to _ENTITY_ /4/ cop /1/ simcard = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ phone = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ iphone = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ tablet = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ mobile = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ landline = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ broadband = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ router = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ wifi = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ micro = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ sim = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ card = PURCHASE
about [TO] go to _ENTITY_ /4/ buy /1/ simcard = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ phone = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ iphone = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ tablet = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ mobile = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ landline = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ broadband = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ router = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ wifi = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ micro = PURCHASE

about [TO] go to _ENTITY_ /4/ contract /1/ sim = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ card = PURCHASE
about [TO] go to _ENTITY_ /4/ contract /1/ simcard = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ phone = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ iphone = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ tablet = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ mobile = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ landline = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ broadband = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ router = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ wifi = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ micro = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ sim = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ card = PURCHASE
bout [TO] go to _ENTITY_ /4/ get /1/ simcard = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ phone = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ iphone = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ tablet = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ mobile = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ landline = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ broadband = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ router = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ wifi = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ micro = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ sim = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ card = PURCHASE
bout [TO] go to _ENTITY_ /4/ cop /1/ simcard = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ phone = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ iphone = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ tablet = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ mobile = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ landline = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ broadband = PURCHASE

bout [TO] go to _ENTITY_ /4/ buy /1/ router = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ wifi = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ micro = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ sim = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ card = PURCHASE
bout [TO] go to _ENTITY_ /4/ buy /1/ simcard = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ phone = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ iphone = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ tablet = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ mobile = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ landline = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ broadband = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ router = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ wifi = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ micro = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ sim = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ card = PURCHASE
bout [TO] go to _ENTITY_ /4/ contract /1/ simcard = PURCHASE
about [TO] get /2/ phone = PURCHASE
about [TO] get /2/ iphone = PURCHASE
about [TO] get /2/ tablet = PURCHASE
about [TO] get /2/ mobile = PURCHASE
about [TO] get /2/ landline = PURCHASE
about [TO] get /2/ broadband = PURCHASE
about [TO] get /2/ router = PURCHASE
about [TO] get /2/ wifi = PURCHASE
about [TO] get /2/ micro = PURCHASE
about [TO] get /2/ sim = PURCHASE
about [TO] get /2/ card = PURCHASE
about [TO] get /2/ simcard = PURCHASE
about [TO] cop /2/ phone = PURCHASE
about [TO] cop /2/ iphone = PURCHASE
about [TO] cop /2/ tablet = PURCHASE

about [TO] cop /2/ mobile = PURCHASE
about [TO] cop /2/ landline = PURCHASE
about [TO] cop /2/ broadband = PURCHASE
about [TO] cop /2/ router = PURCHASE
about [TO] cop /2/ wifi = PURCHASE
about [TO] cop /2/ micro = PURCHASE
about [TO] cop /2/ sim = PURCHASE
about [TO] cop /2/ card = PURCHASE
about [TO] cop /2/ simcard = PURCHASE
about [TO] buy /2/ phone = PURCHASE
about [TO] buy /2/ iphone = PURCHASE
about [TO] buy /2/ tablet = PURCHASE
about [TO] buy /2/ mobile = PURCHASE
about [TO] buy /2/ landline = PURCHASE
about [TO] buy /2/ broadband = PURCHASE
about [TO] buy /2/ router = PURCHASE
about [TO] buy /2/ wifi = PURCHASE
about [TO] buy /2/ micro = PURCHASE
about [TO] buy /2/ sim = PURCHASE
about [TO] buy /2/ card = PURCHASE
about [TO] buy /2/ simcard = PURCHASE
about [TO] contract /2/ phone = PURCHASE
about [TO] contract /2/ iphone = PURCHASE
about [TO] contract /2/ tablet = PURCHASE
about [TO] contract /2/ mobile = PURCHASE
about [TO] contract /2/ landline = PURCHASE
about [TO] contract /2/ broadband = PURCHASE
about [TO] contract /2/ router = PURCHASE
about [TO] contract /2/ wifi = PURCHASE
about [TO] contract /2/ micro = PURCHASE
about [TO] contract /2/ sim = PURCHASE
about [TO] contract /2/ card = PURCHASE
about [TO] contract /2/ simcard = PURCHASE

bout [TO] get /2/ phone = PURCHASE
bout [TO] get /2/ iphone = PURCHASE
bout [TO] get /2/ tablet = PURCHASE
bout [TO] get /2/ mobile = PURCHASE
bout [TO] get /2/ landline = PURCHASE
bout [TO] get /2/ broadband = PURCHASE
bout [TO] get /2/ router = PURCHASE
bout [TO] get /2/ wifi = PURCHASE
bout [TO] get /2/ micro = PURCHASE
bout [TO] get /2/ sim = PURCHASE
bout [TO] get /2/ card = PURCHASE
bout [TO] get /2/ simcard = PURCHASE
bout [TO] cop /2/ phone = PURCHASE
bout [TO] cop /2/ iphone = PURCHASE
bout [TO] cop /2/ tablet = PURCHASE
bout [TO] cop /2/ mobile = PURCHASE
bout [TO] cop /2/ landline = PURCHASE
bout [TO] cop /2/ broadband = PURCHASE
bout [TO] cop /2/ router = PURCHASE
bout [TO] cop /2/ wifi = PURCHASE
bout [TO] cop /2/ micro = PURCHASE
bout [TO] cop /2/ sim = PURCHASE
bout [TO] cop /2/ card = PURCHASE
bout [TO] cop /2/ simcard = PURCHASE
bout [TO] buy /2/ phone = PURCHASE
bout [TO] buy /2/ iphone = PURCHASE
bout [TO] buy /2/ tablet = PURCHASE
bout [TO] buy /2/ mobile = PURCHASE
bout [TO] buy /2/ landline = PURCHASE
bout [TO] buy /2/ broadband = PURCHASE
bout [TO] buy /2/ router = PURCHASE
bout [TO] buy /2/ wifi = PURCHASE
bout [TO] buy /2/ micro = PURCHASE

bout [TO] buy /2/ sim = PURCHASE
bout [TO] buy /2/ card = PURCHASE
bout [TO] buy /2/ simcard = PURCHASE
bout [TO] contract /2/ phone = PURCHASE
bout [TO] contract /2/ iphone = PURCHASE
bout [TO] contract /2/ tablet = PURCHASE
bout [TO] contract /2/ mobile = PURCHASE
bout [TO] contract /2/ landline = PURCHASE
bout [TO] contract /2/ broadband = PURCHASE
bout [TO] contract /2/ router = PURCHASE
bout [TO] contract /2/ wifi = PURCHASE
bout [TO] contract /2/ micro = PURCHASE
bout [TO] contract /2/ sim = PURCHASE
bout [TO] contract /2/ card = PURCHASE
bout [TO] contract /2/ simcard = PURCHASE
hello _ENTITY_ = PURCHASE
i be go to _ENTITY_ = PURCHASE
i be go _ENTITY_ = PURCHASE
“ima” switch to = PURCHASE
“ima” switching to = PURCHASE
i be switch = PURCHASE
i be switching = PURCHASE
be switch = PURCHASE
be switching = PURCHASE
will switch = PURCHASE
we switching = PURCHASE
i switching = PURCHASE
i switch = PURCHASE
we switch = PURCHASE
need “a” _ENTITY_ = PURCHASE
need “an” _ENTITY_ = PURCHASE
port from [N] to _ENTITY_ = PURCHASE
port from _ENTITY_ to [N] = PURCHASE

port from _ENTITY_ to _ENTITY_ = PURCHASE
your phone be /1/ ready to collect from your _ENTITY_ = PURCHASE
my phone be /1/ ready to collect from my _ENTITY_ = PURCHASE
off to _ENTITY_ = PURCHASE
i do not want to be /1/ _ENTITY_ anymore = POSTPURCHASE
“ima” go buy = PURCHASE
i be go [TO] buy = PURCHASE
new _ENTITY_ customer = PURCHASE
get “a” [J] contract with = PURCHASE
get “a” contract with = PURCHASE
im [RB] gonna transfer = PURCHASE
i be [RB] gonna transfer = PURCHASE
im [RB] go to transfer = PURCHASE
i be [RB] go to transfer = PURCHASE
i be [VBG] to order = PURCHASE
need _ENTITY_ here = PURCHASE
i [RB] need [TO] go to = PURCHASE
didnt work = POSTPURCHASE
do not work = POSTPURCHASE
can not get it right = POSTPURCHASE
cant get it right = POSTPURCHASE
fix = POSTPURCHASE
simple /2/ process = POSTPURCHASE
slow = POSTPURCHASE
queue#VBG = POSTPURCHASE
queueing = POSTPURCHASE
appall#VBG [NN] = POSTPURCHASE
argue#V “with” _ENTITY_ = POSTPURCHASE
avoid _ENTITY_ = POSTPURCHASE
[PRP] [N] suck = POSTPURCHASE
should [RB] improve = POSTPURCHASE
should improve = POSTPURCHASE
must [RB] improve = POSTPURCHASE

must improve = POSTPURCHASE

should be [J] = POSTPURCHASE

should “not” be [VPN] = POSTPURCHASE

should be [VPN] = POSTPURCHASE

“bank” be “one” “of” “the” [J] = POSTPURCHASE

“bank” have “one” “of” “the” [J] = POSTPURCHASE

“bank” be “of” “the” [J] = POSTPURCHASE

“bank” have “of” “the” [J] = POSTPURCHASE

“bank” be “the” [J] = POSTPURCHASE

“bank” have “the” [J] = POSTPURCHASE

“bank” be [J] = POSTPURCHASE

“bank” have [J] = POSTPURCHASE

“bank” be “one” “of” [J] = POSTPURCHASE

“bank” have “one” “of” [J] = POSTPURCHASE

“bank” be “one” [J] = POSTPURCHASE

“bank” have “one” [J] = POSTPURCHASE

“bank” be “of” [J] = POSTPURCHASE

“bank” have “of” [J] = POSTPURCHASE

miss [V] [N] “to” “2me” = POSTPURCHASE

mis [V] [N] “to” “2me” = POSTPURCHASE

miss [V] [N] “2me” = POSTPURCHASE

mis [V] [N] “2me” = POSTPURCHASE

miss [V] [N] “to” “me” = POSTPURCHASE

mis [V] [N] “to” “me” = POSTPURCHASE

miss [V] [N] “me” = POSTPURCHASE

mis [V] [N] “me” = POSTPURCHASE

be “mis-sold” = POSTPURCHASE

ENTITY suck = POSTPURCHASE

ENTITY /3/ suck = POSTPURCHASE

“they” suck = POSTPURCHASE

“that” suck = POSTPURCHASE

be “not” [RB] /4/ “friendly” = POSTPURCHASE

be [RB] /4/ “friendly” = POSTPURCHASE

customer service be “so” [J] = POSTPURCHASE

customer service be [J] = POSTPURCHASE

customer support be [J] = POSTPURCHASE

do [RB] go “to” _ENTITY_ = POSTPURCHASE

do [RB] go “to” “them” = POSTPURCHASE

do go “to” _ENTITY_ = POSTPURCHASE

do go “to” “them” = POSTPURCHASE

faultless = POSTPURCHASE

until you need [TO] = POSTPURCHASE

hope “it” get sort#VBN [RB] = POSTPURCHASE

hope “it” be sort#VBN [RB] = POSTPURCHASE

hope “it” get solve#VBN [RB] = POSTPURCHASE

hope “it” be solve#VBN [RB] = POSTPURCHASE

hope “it” get sort#VBN = POSTPURCHASE

hope “it” be sort#VBN = POSTPURCHASE

hope “it” get solve#VBN = POSTPURCHASE

hope “it” be solve#VBN = POSTPURCHASE

i be go [TO] close “my” account = POSTPURCHASE

i be go [TO] fall “out” “with” = POSTPURCHASE

i be “not” happy “with” = POSTPURCHASE

i be happy “with” = POSTPURCHASE

i [MD] be close “my” account = POSTPURCHASE

i [MD] close “my” account = POSTPURCHASE

problem “with” “my” account = POSTPURCHASE

problem “w” “my” account = POSTPURCHASE

want [TO] close account = POSTPURCHASE

love “my” _ENTITY_ = POSTPURCHASE

nice staff = POSTPURCHASE

rude _ENTITY_ “bank” staff = POSTPURCHASE

rude _ENTITY_ staff = POSTPURCHASE

[J] banking service = POSTPURCHASE

[J] customer service [RB] “from” _ENTITY_ = POSTPURCHASE

[J] customer service [NN] “from” _ENTITY_ = POSTPURCHASE

[J] customer service “from” _ENTITY_ = POSTPURCHASE
[J] “for” customer service = POSTPURCHASE
[J] customer service = POSTPURCHASE
[J] service = POSTPURCHASE
[J] “for” customer support = POSTPURCHASE
[J] customer support = POSTPURCHASE
[J] support = POSTPURCHASE
service be [J] = POSTPURCHASE
bank service = POSTPURCHASE
the_best_of_the_best = POSTPURCHASE
the [JJS] i have [RB] [VBN] = POSTPURCHASE
[RB] helpful = POSTPURCHASE
[RB] reliable = POSTPURCHASE
helpful = POSTPURCHASE
unhelpful = POSTPURCHASE
reliable = POSTPURCHASE
useless = POSTPURCHASE
“waste” “of” time = POSTPURCHASE
“waste” “of” money = POSTPURCHASE
impress “with” _ENTITY_ = POSTPURCHASE
[JJS] [Fe] company [Fe] “ever” = POSTPURCHASE
[JJS] company [Fe] “ever” = POSTPURCHASE
[JJS] [Fe] company “ever” = POSTPURCHASE
[JJS] company “ever” = POSTPURCHASE
“disgusted” = POSTPURCHASE
“displeased” = POSTPURCHASE
“upset” = POSTPURCHASE
“dissatisfied” = POSTPURCHASE
“exasperated” = POSTPURCHASE
“annoyed” = POSTPURCHASE
complaint department = POSTPURCHASE
ENTITY be “brill” = POSTPURCHASE
prob = POSTPURCHASE

problem = POSTPURCHASE

“one” “of” “the” “most” [J] = POSTPURCHASE

“one” “of” “the” [J] = POSTPURCHASE

be [DT] [J] shit = POSTPURCHASE

be [J] [N] shit = POSTPURCHASE

be [N] shit = POSTPURCHASE

be [J] shit = POSTPURCHASE

be shit = POSTPURCHASE

be [J] [N] shits = POSTPURCHASE

be [N] shits = POSTPURCHASE

be [J] shits = POSTPURCHASE

be shits = POSTPURCHASE

hate “it” “when” = POSTPURCHASE

i hate it = POSTPURCHASE

hate “on” _ENTITY_ = POSTPURCHASE

hate _ENTITY_ = POSTPURCHASE

can not access the internet = POSTPURCHASE

have no internet = POSTPURCHASE

have no service = POSTPURCHASE

have no signal = POSTPURCHASE

have /2/ signal = POSTPURCHASE

have no [J] internet = POSTPURCHASE

have no [J] service = POSTPURCHASE

have no [J] signal = POSTPURCHASE

without internet = POSTPURCHASE

cut off my internet = POSTPURCHASE

problem with = POSTPURCHASE

restore my internet = POSTPURCHASE

still#RB no = POSTPURCHASE

sort /2/ out = POSTPURCHASE

stop /2/ internet = POSTPURCHASE

stop /2/ service = POSTPURCHASE

not work = POSTPURCHASE

not enough = POSTPURCHASE
work but = POSTPURCHASE
not load = POSTPURCHASE
not [RB] good = POSTPURCHASE
speed = POSTPURCHASE
still no reply = POSTPURCHASE
still no signal = POSTPURCHASE
still no broadband = POSTPURCHASE
still no joy = POSTPURCHASE
still not able [TO] = POSTPURCHASE
still nothing = POSTPURCHASE
still say = POSTPURCHASE
still wait = POSTPURCHASE
still await = POSTPURCHASE
still refuse [TO] /1/ work = POSTPURCHASE
still refuse [TO] work = POSTPURCHASE
still faulty = POSTPURCHASE
still “phone-less” = POSTPURCHASE
still do not understand = POSTPURCHASE
still do not have = POSTPURCHASE
under warranty = POSTPURCHASE
refuse [TO][V] me = POSTPURCHASE
refuse [TO][V] us = POSTPURCHASE
fail [TO] reply = POSTPURCHASE
what be go on with = POSTPURCHASE
please answer [PRP] = POSTPURCHASE
thank /2/ for reply = POSTPURCHASE
thank /2/ for look = POSTPURCHASE
thank /2/ for cashier at _ENTITY_ = POSTPURCHASE
cashier in _ENTITY_ = POSTPURCHASE
thank /2/ for fix = POSTPURCHASE
thank /2/ for answer = POSTPURCHASE
thank /2/ for follow = POSTPURCHASE

ENTITY thank for = POSTPURCHASE
thanks /2/ for reply = POSTPURCHASE
thanks /2/ for look = POSTPURCHASE
thanks /2/ for take = POSTPURCHASE
thanks /2/ for fix = POSTPURCHASE
thanks /2/ for answer = POSTPURCHASE
thanks /2/ for follow = POSTPURCHASE
thanks /2/ for give = POSTPURCHASE
ENTITY thanks for = POSTPURCHASE
i will await /1/ reply = POSTPURCHASE
await /1/ reply= POSTPURCHASE
i will wait /1/ rep= POSTPURCHASE
wait /1/ reply= POSTPURCHASE
i will await /1/ answer = POSTPURCHASE
await /1/ answer= POSTPURCHASE
i will wait /1/ answer = POSTPURCHASE
wait /1/ answer= POSTPURCHASE
take age = POSTPURCHASE
take forever = POSTPURCHASE
taking age = POSTPURCHASE
taking forever = POSTPURCHASE
no answer = POSTPURCHASE
never answer = POSTPURCHASE
[WRB] /2/ not answer = POSTPURCHASE
need /2/ answer = POSTPURCHASE
i have be wait over = POSTPURCHASE
hour wait = POSTPURCHASE
day wait = POSTPURCHASE
week wait = POSTPURCHASE
month wait = POSTPURCHASE
people wait = POSTPURCHASE
have /1/ be able = POSTPURCHASE
there be /2/ signal = POSTPURCHASE

terrible /2/ signal = POSTPURCHASE
decent /2/ signal = POSTPURCHASE
bloody /2/ signal = POSTPURCHASE
strong /2/ signal = POSTPURCHASE
proper /2/ signal = POSTPURCHASE
rubbish /2/ signal = POSTPURCHASE
shit /2/ signal = POSTPURCHASE
crappy /2/ signal = POSTPURCHASE
patchy /2/ signal = POSTPURCHASE
bar /1/ signal = POSTPURCHASE
no /2/ signal = POSTPURCHASE
the signal [VBZ] = POSTPURCHASE
i have [RB] have = POSTPURCHASE
my /1/ signal be = POSTPURCHASE
so /1/ slow = POSTPURCHASE
be not work#VBG = POSTPURCHASE
do not work = POSTPURCHASE
dont work = POSTPURCHASE
doesnt work = POSTPURCHASE
never work = POSTPURCHASE
nothing work = POSTPURCHASE
only /2/ work = POSTPURCHASE
my /2/ work = POSTPURCHASE
have stop work = POSTPURCHASE
work straight away = POSTPURCHASE
not enough [TO] work with = POSTPURCHASE
it work = POSTPURCHASE
work fine = POSTPURCHASE
work [RB] = POSTPURCHASE
can /1/ understand = POSTPURCHASE
i do not have /1/ service = POSTPURCHASE
i dont have /1/ service = POSTPURCHASE
i do not have /2/ coverage = POSTPURCHASE

i dont have /2/ coverage = POSTPURCHASE
i do not have /2/ speed = POSTPURCHASE
i dont have /2/ speed = POSTPURCHASE
[PRP] /2/ do not support = POSTPURCHASE
i /1/ can not see = POSTPURCHASE
i /1/ cant see = POSTPURCHASE
i /1/ couldnt see = POSTPURCHASE
i /1/ can not stop = POSTPURCHASE
i /1/ cant stop = POSTPURCHASE
i /1/ couldnt stop = POSTPURCHASE
i /1/ can not use = POSTPURCHASE
i /1/ cant use = POSTPURCHASE
i /1/ couldnt use = POSTPURCHASE
i /1/ can not receive = POSTPURCHASE
i /1/ cant receive = POSTPURCHASE
i /1/ couldnt receive = POSTPURCHASE
i /1/ can not access = POSTPURCHASE
i /1/ cant access = POSTPURCHASE
i /1/ couldnt access = POSTPURCHASE
i /1/ can not find = POSTPURCHASE
i /1/ cant find = POSTPURCHASE
i /1/ couldnt find = POSTPURCHASE
i /1/ can not deal = POSTPURCHASE
i /1/ cant deal = POSTPURCHASE
i /1/ couldnt deal = POSTPURCHASE
it would not send = POSTPURCHASE
please help = POSTPURCHASE
please explain = POSTPURCHASE
please sort = POSTPURCHASE
please fix = POSTPURCHASE
piss me = POSTPURCHASE
piece of shit = POSTPURCHASE
they be lame = POSTPURCHASE

stupid _ENTITY_ = POSTPURCHASE
be arsehole = POSTPURCHASE
be arseholes = POSTPURCHASE
be “a” twat = POSTPURCHASE
block me = POSTPURCHASE
drive me crazy = POSTPURCHASE
mug me = POSTPURCHASE
it have be [J] = POSTPURCHASE
“its” be [J] = POSTPURCHASE
“a” customer “first” company = POSTPURCHASE
they have strand me = POSTPURCHASE
never have any trouble = POSTPURCHASE
nothing but trouble with = POSTPURCHASE
give me /1/ signal = POSTPURCHASE
be not too bad = POSTPURCHASE
i [RB] “to” have /2/ bad experience “with” = POSTPURCHASE
my /2/ be stick = POSTPURCHASE
my phone be dead = POSTPURCHASE
my phone be /1/ dead = POSTPURCHASE
text me /2/ say = POSTPURCHASE
why /2/ do not [V] = POSTPURCHASE
why can not i [V] = POSTPURCHASE
why do i [V] = POSTPURCHASE
why do i [RB] [V] = POSTPURCHASE
why do my = POSTPURCHASE
the only one who = POSTPURCHASE
do other /2/ user = POSTPURCHASE
give me a solution = POSTPURCHASE
i can get /2/ with my _ENTITY_ = POSTPURCHASE
still not use [NP] = POSTPURCHASE
unable to connect = POSTPURCHASE
be the [J] bank = POSTPURCHASE
thank me for = POSTPURCHASE

be [RB] rude = POSTPURCHASE
"a" [J] letter from = POSTPURCHASE
the [JJS] [N] i have ever [V] = POSTPURCHASE
charge me for = POSTPURCHASE
i have to complain = POSTPURCHASE
can not tell me = POSTPURCHASE
never have any problem = POSTPURCHASE
never use to have "a" problem = POSTPURCHASE
sack them off = POSTPURCHASE
i use _ENTITY_ = POSTPURCHASE
loyal to _ENTITY_ = POSTPURCHASE
loyal to the brand = POSTPURCHASE
when i join = POSTPURCHASE
loyalty = POSTPURCHASE
fraud team = POSTPURCHASE
risk of fraud = POSTPURCHASE
fraud prevention = POSTPURCHASE
fraud detection = POSTPURCHASE
fraud dept = POSTPURCHASE
fraud departement = POSTPURCHASE
proud to be /2/ customer = POSTPURCHASE
my local _ENTITY_ = POSTPURCHASE
hold music = POSTPURCHASE
on hold = POSTPURCHASE
"on-hold" music = POSTPURCHASE
holding music = POSTPURCHASE
incompetent = POSTPURCHASE
tosser = POSTPURCHASE
tire#VBN of = POSTPURCHASE
thank to /3/ _ENTITY_ = POSTPURCHASE
fail to [V] mine = POSTPURCHASE
fail to [V] me = POSTPURCHASE
customer service at = POSTPURCHASE

customer support at = POSTPURCHASE
will not [V] me = POSTPURCHASE
service by _ENTITY_ be = POSTPURCHASE
happy i have = POSTPURCHASE
unhappy with = POSTPURCHASE
happy with = POSTPURCHASE
use of my = POSTPURCHASE
thank /4/ for alert = POSTPURCHASE
thanks /4/ for alert = POSTPURCHASE
i have /2/ use = POSTPURCHASE
ENTITY stupid = POSTPURCHASE
ENTITY /2/ bastard = POSTPURCHASE
ring me = POSTPURCHASE
send me = POSTPURCHASE
will not upgrade = POSTPURCHASE
withdraw /2/ my /2/ account = POSTPURCHASE
need to have word = POSTPURCHASE
get /2/ text from _ENTITY_ = POSTPURCHASE
get mine from _ENTITY_ = POSTPURCHASE
on the phone to _ENTITY_ = POSTPURCHASE
help from /3/ staff = POSTPURCHASE
taste “so” [J] = POSTPURCHASE
the [JJS] [N] ever = POSTPURCHASE
“according_to” _ENTITY_ i = POSTPURCHASE
cashier at _ENTITY_ = POSTPURCHASE
cashier [IN] _ENTITY_ /2/ give [PRP] /3/ point = PURCHASE
queue for /2/ be /3/ [J] = POSTPURCHASE
i be with _ENTITY_ = POSTPURCHASE
[Z] people wait = POSTPURCHASE
be bother about = POSTPURCHASE
argue#V “with” = POSTPURCHASE
get “a” letter from _ENTITY_ = POSTPURCHASE
look at the state = POSTPURCHASE

thank _ENTITY_ = POSTPURCHASE
change to _ENTITY_ or = EVALUATION
switch to _ENTITY_ or = EVALUATION
changing to _ENTITY_ or = EVALUATION
switching to _ENTITY_ or = EVALUATION
finally switch to _ENTITY_ = PURCHASE
ENTITY service be = POSTPURCHASE
service be ass = POSTPURCHASE
ENTITY tell me = POSTPURCHASE
when i switch#VBD = POSTPURCHASE
ENTITY do not /2/ want to [V] me = POSTPURCHASE
i be _ENTITY_ = POSTPURCHASE
close down /2/ service = POSTPURCHASE
closing down /2/ service = POSTPURCHASE
i have try = POSTPURCHASE
get no service = POSTPURCHASE
get no signal = POSTPURCHASE
have /2/ issue with = POSTPURCHASE
i be on /1/ _ENTITY_ = POSTPURCHASE
customer with /2/ for = POSTPURCHASE
customer w /3/ for = POSTPURCHASE
impress “with” /2/ service = POSTPURCHASE
i hate /2/ bastard = POSTPURCHASE
be on for = POSTPURCHASE
be it me = POSTPURCHASE
is it me = POSTPURCHASE
drink /3/ have _ENTITY_ = POSTPURCHASE
“drunk” on _ENTITY_ = POSTPURCHASE
bottle of /2/ finish = POSTPURCHASE
drink /1/ _ENTITY_ = POSTPURCHASE
drink /1/ _ENTITY_ /1/ tonight = PURCHASE
get chill = POSTPURCHASE
i have “a” _ENTITY_ = POSTPURCHASE

i have “a” bottle of = POSTPURCHASE
i will stick to /1/ _ENTITY_ = POSTPURCHASE
ill stick to /1/ _ENTITY_ = POSTPURCHASE
ENTITY save the day = POSTPURCHASE
in the freezer = POSTPURCHASE
sip#VBG = POSTPURCHASE
sippin = POSTPURCHASE
the first sip = POSTPURCHASE
i [RB] have a sip = POSTPURCHASE
be#VBP drink /2/ _ENTITY_ = POSTPURCHASE
drink /2/ _ENTITY_ with = POSTPURCHASE
drink /2/ _ENTITY_ at = POSTPURCHASE
do not taste = POSTPURCHASE
nothin good than = POSTPURCHASE
nothing good than = POSTPURCHASE
ENTITY taste like = POSTPURCHASE
i think _ENTITY_ be = POSTPURCHASE
nothing like “a” /2/ _ENTITY_ = POSTPURCHASE
nothin like “a” /2/ _ENTITY_ = POSTPURCHASE
go down good = POSTPURCHASE
enjoy _ENTITY_ = POSTPURCHASE
enjoying _ENTITY_ = POSTPURCHASE
shot of /1/ into my _ENTITY_ = POSTPURCHASE
much of a good time = POSTPURCHASE
be /1/ my favorite = POSTPURCHASE
be /1/ my favourite = POSTPURCHASE
all i drink is = POSTPURCHASE
it be straight _ENTITY_ = POSTPURCHASE
its straight _ENTITY_ = POSTPURCHASE
it be all about _ENTITY_ = POSTPURCHASE
“sitting” here with = POSTPURCHASE
ENTITY do me good = POSTPURCHASE
drink#VBD /3/ _ENTITY_ = POSTPURCHASE

drink#VBN = POSTPURCHASE

shame “on” /1/ _ENTITY_ = POSTPURCHASE

because _ENTITY_ be bullshit = POSTPURCHASE

ENTITY /2/ rant and rave = POSTPURCHASE

we be with _ENTITY_ = POSTPURCHASE

twist cap off = POSTPURCHASE

i get#VBD /2/ _ENTITY_ = POSTPURCHASE

taste /1/ much well = POSTPURCHASE

ENTITY taste [RB] like = POSTPURCHASE

ENTITY taste [J] = POSTPURCHASE

with [Z] bottle of _ENTITY_ = POSTPURCHASE

fridge stock with _ENTITY_ = POSTPURCHASE

drink /2/ beer = POSTPURCHASE

drink#VBG /2/ beer = POSTPURCHASE

get#VBD myself /3/ _ENTITY_ = POSTPURCHASE

got myself /3/ _ENTITY_ = POSTPURCHASE

i /1/ finish /1/ beer = POSTPURCHASE

have#VBG /2/ _ENTITY_ = POSTPURCHASE

have#VBG /2/ pint = POSTPURCHASE

have#VBD /3/ pint = POSTPURCHASE

cup of _ENTITY_ = POSTPURCHASE

end the day with _ENTITY_ = POSTPURCHASE

ending the day with _ENTITY_ = POSTPURCHASE

crack open = POSTPURCHASE

with [Z] can of _ENTITY_ = POSTPURCHASE

[Z] many _ENTITY_ = POSTPURCHASE

i /1/ now smell = POSTPURCHASE

with [Z] _ENTITY_ at = POSTPURCHASE

get [Z] [N] of _ENTITY_ [TO] drink = POSTPURCHASE

drink#VBD so much = POSTPURCHASE

drink#VBD too much = POSTPURCHASE

i /1/ finish my /1/ glass of = POSTPURCHASE

pop [Z] = POSTPURCHASE

service have /1/ become = POSTPURCHASE
ENTITY do not do it = POSTPURCHASE
ENTITY didnt do it = POSTPURCHASE
cut my [N] off = POSTPURCHASE
give me my [Z] back = POSTPURCHASE
sms not go = POSTPURCHASE
drop network coverage = POSTPURCHASE
improve your coverage = POSTPURCHASE
network be [J] since = POSTPURCHASE
your [N] be as /2/ as your = POSTPURCHASE
i be in /1/ _ENTITY_ contract = POSTPURCHASE
i never request#VBD = POSTPURCHASE
just get [JJR] = POSTPURCHASE
be get#VBG [JJR] = POSTPURCHASE
still surprise me = POSTPURCHASE
i have _ENTITY_ = POSTPURCHASE
get my [N] from _ENTITY_ = POSTPURCHASE
i have be with _ENTITY_ for = POSTPURCHASE
i be in “a” contract with _ENTITY_ = POSTPURCHASE
im in “a” contract with _ENTITY_ = POSTPURCHASE
ENTITY cut [PRP] off = POSTPURCHASE
i come to _ENTITY_ in = POSTPURCHASE
i be#VBD on _ENTITY_ until = POSTPURCHASE
i be#VBD on _ENTITY_ before = POSTPURCHASE
i always _ENTITY_ = POSTPURCHASE
currently on _ENTITY_ contract = POSTPURCHASE
ENTITY payment reminder = POSTPURCHASE
ENTITY do not even [V] = POSTPURCHASE
ENTITY can not even [RB] [V] = POSTPURCHASE
ENTITY do not even [RB] [V] = POSTPURCHASE
i do not even [V] = POSTPURCHASE
we do not even [V] = POSTPURCHASE
i can not even [RB] [V] = POSTPURCHASE

ENTITY be /1/ accept = POSTPURCHASE
ENTITY do /1/ accept = POSTPURCHASE
replace it [RB] = POSTPURCHASE
hear from me = POSTPURCHASE
glad to hear /1/ _ENTITY_ = POSTPURCHASE
i /1/ get#VBD _ENTITY_ = POSTPURCHASE
we can not even [RB] [V] = POSTPURCHASE
i do not even [RB] [V] = POSTPURCHASE
maybe _ENTITY_ be /2/ option = EVALUATION
maybe _ENTITY_ be /2/ alternative = EVALUATION
maybe _ENTITY_ be /2/ company = EVALUATION
perhaps _ENTITY_ be /2/ option = EVALUATION
perhaps _ENTITY_ be /2/ alternative = EVALUATION
perhaps _ENTITY_ be /2/ company = EVALUATION
we do not even [RB] [V] = POSTPURCHASE
i get call from _ENTITY_ = POSTPURCHASE
anyone one else /3/ have = POSTPURCHASE
have my [N] in _ENTITY_ = POSTPURCHASE
my _ENTITY_ be = POSTPURCHASE
i be /1/ satisfy = POSTPURCHASE
can /1/ [V] /2/ my _ENTITY_ = POSTPURCHASE
rage = POSTPURCHASE
ENTITY /2/ work#V = POSTPURCHASE
my tariff = POSTPURCHASE
upgrade me = POSTPURCHASE
my upgrade = POSTPURCHASE
get my /2/ back = POSTPURCHASE
on /1/ _ENTITY_ contract = POSTPURCHASE
have signal = POSTPURCHASE
ENTITY /2/ put my /1/ back = POSTPURCHASE
my /1/ bill#NN = POSTPURCHASE
phone bill = POSTPURCHASE
have to call _ENTITY_ = POSTPURCHASE

i [RB] have _ENTITY_ = POSTPURCHASE

ENTITY [V] /2/ but = POSTPURCHASE

i be use _ENTITY_ = POSTPURCHASE

personal experience = POSTPURCHASE

i be /1/ able to = POSTPURCHASE

“bye-bye” _ENTITY_ = POSTPURCHASE

need to get in touch = POSTPURCHASE

why can i not [V] = POSTPURCHASE

i be /2/ customer = POSTPURCHASE

mail from _ENTITY_ = POSTPURCHASE

everytime i try = POSTPURCHASE

every time i try = POSTPURCHASE

can not download = POSTPURCHASE

try to download = POSTPURCHASE

kind of service _ENTITY_ [V] = POSTPURCHASE

customer care = POSTPURCHASE

be _ENTITY_ [JJR] than = EVALUATION

i may be take my talent = EVALUATION

offer /1/ [JJR] = EVALUATION

consider#VBG /1/ move to _ENTITY_ = EVALUATION

maybe _ENTITY_ be /2/ option = EVALUATION

maybe _ENTITY_ be /2/ alternative = EVALUATION

maybe _ENTITY_ be /2/ company = EVALUATION

perhaps _ENTITY_ be /2/ option = EVALUATION

perhaps _ENTITY_ be /2/ alternative = EVALUATION

perhaps _ENTITY_ be /2/ company = EVALUATION

maybe _ENTITY_ or _ENTITY_ = EVALUATION

maybe _ENTITY_ or [NP] = EVALUATION

maybe [NP] or _ENTITY_ = EVALUATION

be it /1/ possible = EVALUATION

how about “a” [J] /1/ _ENTITY_ = EVALUATION

be [PRP] talk _ENTITY_ here = EVALUATION

[PRP] will have to try one = EVALUATION

ill have to try one = EVALUATION

“is” it too [J] to = EVALUATION

“Is” it too [J] to = EVALUATION

have anyone try = EVALUATION

debate on whether = EVALUATION

so why not [V] = EVALUATION

i may buy = EVALUATION

i “would” buy [N] = EVALUATION

i may contract = EVALUATION

i “would” contract = EVALUATION

i have be on _ENTITY_ for = POSTPURCHASE

[JJS] network “ever” = POSTPURCHASE

research /2/ look = EVALUATION

debate#VBG = EVALUATION

need to find /1/ alternative to = EVALUATION

[N] versus _ENTITY_ = EVALUATION

ENTITY versus [N] = EVALUATION

buy my /2/ from [N] rather than _ENTITY_ = EVALUATION

buy my /2/ from _ENTITY_ rather than [N] = EVALUATION

may /2/ pop into _ENTITY_ = EVALUATION

may /2/ go to _ENTITY_ to buy = EVALUATION

i be#VBD go to switch to = EVALUATION

i go#VBD to _ENTITY_ /1/ they do not [V] = EVALUATION

i will [RB] [V] at _ENTITY_ again = EVALUATION

i prefer _ENTITY_ to = EVALUATION

i only [V] /1/ _ENTITY_ = EVALUATION

[PP] thought on the new _ENTITY_ = EVALUATION

i need /5/ it be not in _ENTITY_ = EVALUATION

may have to /3/ start shop#VBG [IN] _ENTITY_ = EVALUATION

consider myself /1/ _ENTITY_ convert = EVALUATION

may do my next /1/ shop at _ENTITY_ = EVALUATION

[MD] prefer /2/ _ENTITY_ = EVALUATION

shall i /2/ to _ENTITY_ for = EVALUATION

ENTITY is not /1/ that [J]= EVALUATION
difference between /3/ _ENTITY_ = EVALUATION
may /2/ pop to _ENTITY_ = EVALUATION
may /2/ look for /2/ at _ENTITY_ = EVALUATION
may try /2/ _ENTITY_ /2/ and see if = EVALUATION
i can not afford to [V] at _ENTITY_ = EVALUATION
i am not [J] enough for _ENTITY_ = EVALUATION
tempt#VBN to buy = EVALUATION
the [JJS] i have notice = EVALUATION
[Z] at /6/ [Z] at = EVALUATION
i will be look#VBG at = EVALUATION
look#VBG up _ENTITY_ = EVALUATION
someone /2/ verify this = EVALUATION
i think they now [V] = EVALUATION
maybe /3/ _ENTITY_ later = EVALUATION
be it any good = EVALUATION
this _ENTITY_ /1/ advert = AWARENESS
that _ENTITY_ /1/ advert = AWARENESS
that _ENTITY_ /1/ ad = AWARENESS
[DT] _ENTITY_ /1/ jingle = AWARENESS
[DT] _ENTITY_ /1/ campaign be = AWARENESS
that _ENTITY_ /1/ commercial = AWARENESS
these _ENTITY_ /1/ ad = AWARENESS
i [V] “a” /2/ _ENTITY_ /1/ advert = AWARENESS
i [V] [DT] _ENTITY_ /1/ commercial = AWARENESS
in /1/ their advert = AWARENESS
on all /1/ advert = AWARENESS
on their advert = AWARENESS
on its /1/ ad = AWARENESS
on _ENTITY_ /1/ advert = AWARENESS
[IN] [DT] /2/ advert = AWARENESS
[IN] [DT] /2/ ad = AWARENESS
[IN] [DT] /2/ commercial = AWARENESS

[DT] /1/ _ENTITY_ /1/ ad = AWARENESS
[DT] /1/ _ENTITY_ /1/ advert = AWARENESS
“a” [J] _ENTITY_ advert = AWARENESS
[DT] _ENTITY_ /2/ advert [V] /1/ me = AWARENESS
[DT] _ENTITY_ /2/ ad [V] /1/ me = AWARENESS
the _ENTITY_ /1/ advert has = AWARENESS
the _ENTITY_ /1/ advert be [J] = AWARENESS
[DT] _ENTITY_ /1/ commercial be [J] = AWARENESS
the new _ENTITY_ /1/ advertisement = AWARENESS
the new _ENTITY_ /1/ ad = AWARENESS
these _ENTITY_ /2/ advert = AWARENESS
latest _ENTITY_ tv ad = AWARENESS
[DT] new _ENTITY_ /1/ advert = AWARENESS
[DT] new _ENTITY_ /1/ ad = AWARENESS
appear in their advert = AWARENESS
[VBG] in their ad = AWARENESS
[J] work _ENTITY_ for the /2/ ad = AWARENESS
i love [DT] /2/ ad = AWARENESS
i love [DT] /2/ commercial = AWARENESS
i hate [DT] /2/ commercial = AWARENESS
i [RB] love /2/ _ENTITY_ /1/ ad = AWARENESS
i [RB] understand /2/ _ENTITY_ commercial = AWARENESS
love /2/ _ENTITY_ /1/ ad = AWARENESS
love /2/ _ENTITY_ /1/ advert = AWARENESS
just see /1/ _ENTITY_ /1/ ad = AWARENESS
[DT] [VBG] _ENTITY_ /1/ ad = AWARENESS
i do /1/ [V] [DT] _ENTITY_ /1/ ad = AWARENESS
[J] _ENTITY_ /1/ commercial = AWARENESS
[JJS] /1/ commercial ever = AWARENESS
[DT] _ENTITY_ /1/ commercial be = AWARENESS
commercial be /1/ [JJR] = AWARENESS
fave _ENTITY_ /1/ commercial = AWARENESS
like em /1/ commercial = AWARENESS

like [DT] _ENTITY_ commercial = AWARENESS
every time [DT] _ENTITY_ /1/ commercial = AWARENESS
every time [DT] /1/ commercial from = AWARENESS
the /2/ _ENTITY_ /1/ commercial where = AWARENESS
time for _ENTITY_ /2/ event = AWARENESS
after this performance at the _ENTITY_ = AWARENESS
be [V] at the _ENTITY_ academy = AWARENESS
backstage /1/ at the _ENTITY_ = AWARENESS
want to [V] /3/ at the _ENTITY_ = AWARENESS
we play at the _ENTITY_ = AWARENESS
ENTITY /1/ advert be = AWARENESS
i pay [Z] to [V] /3/ _ENTITY_ = AWARENESS
can not wait for /2/ _ENTITY_ = AWARENESS
can not wait to = AWARENESS
on the way to /2/ _ENTITY_ = AWARENESS
be to the _ENTITY_ /3/ first time = AWARENESS
ENTITY gift card = AWARENESS
queue for the /1/ opening of= AWARENESS
the _ENTITY_ ad = AWARENESS
in the _ENTITY_ /1/ literature = AWARENESS
ENTITY pamphlet = AWARENESS
advertiser in today = AWARENESS
you have [V] /2/ page ad = AWARENESS
no ad /1/ in the mail from = AWARENESS
brand like [PRP] advertise = AWARENESS
your ad in the [NP] = AWARENESS
ENTITY /2/ commercial = AWARENESS
have /1/ advertising deal with = AWARENESS
on the _ENTITY_ /1/ advert = AWARENESS
have watch the _ENTITY_ /3/ ad = AWARENESS
advert song = AWARENESS
love the [N] on the _ENTITY_ /1/ advert = AWARENESS
advert put me /2/ good mood = AWARENESS

[DT] _ENTITY_ ad be [J] = AWARENESS

I [RB] enjoy [DT] _ENTITY_ /1/ ad = AWARENESS

the _ENTITY_ /1/ ad make me = AWARENESS

for their new ad = AWARENESS

the _ENTITY_ ad be quite = AWARENESS

on the _ENTITY_ /1/ advert = AWARENESS

I like the _ENTITY_ advert = AWARENESS

ENTITY /1/ session for = AWARENESS

ballad /1/ _ENTITY_ = AWARENESS

ENTITY opening soon in = AWARENESS

ENTITY /1/ opening /1/ next to my = AWARENESS

the opening of [PRP] /1/ _ENTITY_ = AWARENESS

ENTITY /1/ have open near my = AWARENESS

ENTITY /2/ birthday party = AWARENESS

the new _ENTITY_ near me = AWARENESS

ENTITY for your /1/ donation = AWARENESS

ENTITY be open /1/ shop in = AWARENESS

on a rented _ENTITY_ bankbike = AWARENESS

[J] _ENTITY_ ad = AWARENESS

[J] music in _ENTITY_ ad = AWARENESS

i love /2/ in the _ENTITY_ ad = AWARENESS

that _ENTITY_ ad = AWARENESS

i [RB] love [DT]_ENTITY_ advert = AWARENESS

i hate /2/ [DT] _ENTITY_ advert = AWARENESS

i love [DT] /1/ _ENTITY_ advert = AWARENESS

hear [DT] /1/ _ENTITY_ advert = AWARENESS

i will /1/ [V] [DT] /2/ _ENTITY_ advert = AWARENESS

i be /1/ [VBG] at /2/ _ENTITY_ advert = AWARENESS

[VBG] [DT] /2/ _ENTITY_ advert = AWARENESS

love the music in [DT] _ENTITY_ commercial = AWARENESS

[N] to _ENTITY_ for /1/ advertising = AWARENESS

ENTITY logo = AWARENESS

[DT] [J] _ENTITY_ i know be = AWARENESS

free /3/ for _ENTITY_ customer = AWARENESS

video /3/ by _ENTITY_ = AWARENESS

trailer of _ENTITY_ /1/ sponsorship = AWARENESS

the [J] _ENTITY_ center = AWARENESS

[DT] /1/ _ENTITY_ /1/ add = AWARENESS

the _ENTITY_ ad with = AWARENESS

that _ENTITY_ /2/ ad = AWARENESS

that _ENTITY_ add = AWARENESS

i love [DT] /2/ advert = AWARENESS

awesome /1/ _ENTITY_ ad = AWARENESS

amazing ad = AWARENESS

ENTITY /1/ advert be = AWARENESS

new _ENTITY_ /1/ advert = AWARENESS

new _ENTITY_ /1/ ad = AWARENESS

new _ENTITY_ /1/ add = AWARENESS

new ad /1/ _ENTITY_ = AWARENESS

[J] advert /1/ _ENTITY_ = AWARENESS

ENTITY /2/ add = AWARENESS

nice ad = AWARENESS

ENTITY spot = AWARENESS

i [V] /1/ _ENTITY_ ad = AWARENESS

awesome /1/ _ENTITY_ ad = AWARENESS

cool ad [IN] _ENTITY_ = AWARENESS

cool spot [IN] _ENTITY_ = AWARENESS

ENTITY have [V] /2/ ad = AWARENESS

their latest /2/ advert = AWARENESS

new /2/ advert = AWARENESS

great _ENTITY_ /1/ ad = AWARENESS

new ad [IN] _ENTITY_ = AWARENESS

[IN] [J] _ENTITY_ ad = AWARENESS

love [DT] /3/ _ENTITY_ ad = AWARENESS

love [DT] /2/ ad = AWARENESS

new spot [IN] _ENTITY_ = AWARENESS

in their new /1/ ad = AWARENESS
cool _ENTITY_ commercial = AWARENESS
this be /2/ advertisement = AWARENESS
have _ENTITY_ advertising = AWARENESS
just [VBN] /2/ _ENTITY_ /1/ commercial = AWARENESS
have /2/ commercial = AWARENESS
ENTITY /3/ commercial = AWARENESS
that _ENTITY_ commercial = AWARENESS
[DT] /1/ _ENTITY_ /2/ commercial be = AWARENESS
[DT] /1/ _ENTITY_ /2/ commercial [IN] = AWARENESS
ENTITY commercial = AWARENESS
every time _ENTITY_ show /3/ commercial = AWARENESS
i love commercial where = AWARENESS
[IN] /2/ _ENTITY_ commercial = AWARENESS
campaign _ENTITY_ make = AWARENESS
[DT] _ENTITY_/1/ campaign = AWARENESS
[JJS] /2/ advertising campaign at any time = AWARENESS
[JJS] /2/ advertising campaign ever = AWARENESS
most [J] /2/ advertising campaign ever = AWARENESS
most [J] /2/ advertising campaign at any time = AWARENESS
the _ENTITY_ /3/ festival = AWARENESS
product placement = AWARENESS
what be more /1/ than _ENTITY_ = AWARENESS
on every _ENTITY_ can = AWARENESS
the _ENTITY_ clydesdales = AWARENESS
go to see [DT] _ENTITY_ horse = AWARENESS
ENTITY clydesdales /1/ tribute = AWARENESS
as the _ENTITY_ horse = AWARENESS
ENTITY present = AWARENESS
ENTITY documentary = AWARENESS
documentary with _ENTITY_ = AWARENESS
check out _ENTITY_ /1/ documentary = AWARENESS
documentary /4/ from _ENTITY_ = AWARENESS

ENTITY present = AWARENESS
ENTITY partner for /5/ documentary = AWARENESS
in _ENTITY_ [POS] /5/ documentary = AWARENESS
from her _ENTITY_ documentary = AWARENESS
in /1/ _ENTITY_ documentary = AWARENESS
doc from _ENTITY_ = AWARENESS
ENTITY documentary about = AWARENESS
ENTITY documentary = AWARENESS
the _ENTITY_ documentary = AWARENESS
ENTITY doc = AWARENESS
watch _ENTITY_ sponsor /1/ documentary = AWARENESS
ENTITY present = AWARENESS
i like /1/ youtube video = AWARENESS
watch _ENTITY_ international cup = AWARENESS
these _ENTITY_ /2/ poster = AWARENESS
ENTITY /1/ festivity = AWARENESS
arthur [POS] day /1/ _ENTITY_ = AWARENESS
commercial /3/ _ENTITY_ = AWARENESS
[J] campaign = AWARENESS
ENTITY campaign = AWARENESS
ENTITY /1/ soccer fan = AWARENESS
twitter campaign = AWARENESS
casting = AWARENESS
in _ENTITY_ brewery = AWARENESS
[DT] launch of = AWARENESS
invite you to /2/ launch = AWARENESS
launch night in _ENTITY_ = AWARENESS
whether /3/ publicity /2/ worth = AWARENESS
ENTITY winner = AWARENESS
[PRP] favourite event = AWARENESS
ENTITY cup = AWARENESS
european cup = AWARENESS
ENTITY cup battle = AWARENESS

ENTITY cup debate = AWARENESS
ENTITY cup debate = AWARENESS
ENTITY cup discussion = AWARENESS
ENTITY cup final = AWARENESS
cup organiser = AWARENESS
have /3/ ticket = AWARENESS
your new _ENTITY_ cup shirt = AWARENESS
ENTITY experience = AWARENESS
[DT] _ENTITY_ /3/ experience = AWARENESS
at the _ENTITY_ experience = AWARENESS
the _ENTITY_ tour = AWARENESS
the old _ENTITY_ green energy = AWARENESS
world of _ENTITY_ = AWARENESS
ENTITY jazz fest = AWARENESS
ENTITY museum = AWARENESS
ENTITY music hall = AWARENESS
our _ENTITY_ fan zone = AWARENESS
i /6/ concert at /1/ _ENTITY_ = AWARENESS
we /6/ concert at /1/ _ENTITY_ = AWARENESS
go to /3/ concert at /1/ _ENTITY_ = AWARENESS
go to see /3/ at /1/ _ENTITY_ = AWARENESS
go to /4/ at = AWARENESS
i will be at = AWARENESS
we will be at = AWARENESS
at /3/ concert at = AWARENESS
concert at /1/ _ENTITY_ /4/ be = AWARENESS
concert at /1/ _ENTITY_ /4/ go = AWARENESS
i /6/ league = AWARENESS
we /6/ league = AWARENESS
me /6/ league = AWARENESS
us /6/ league = AWARENESS
my /6/ league = AWARENESS
our /6/ league = AWARENESS

we /5/ _ENTITY_ /1/ game = AWARENESS

[JJS] /2/ sponsorship = AWARENESS

“best” /2/ sponsorship = AWARENESS

i /8/ sponsorship = AWARENESS

we /8/ sponsorship = AWARENESS

me /8/ sponsorship = AWARENESS

us /8/ sponsorship = AWARENESS

my /8/ sponsorship = AWARENESS

our /8/ sponsorship = AWARENESS

sponsorship /4/ i = AWARENESS

sponsorship /4/ we = AWARENESS

sponsorship /4/ me = AWARENESS

sponsorship /4/ us = AWARENESS

sponsorship /4/ my = AWARENESS

sponsorship /4/ our = AWARENESS

i /6/ award = AWARENESS

we /6/ award = AWARENESS

me /6/ award = AWARENESS

us /6/ award = AWARENESS

my /6/ award = AWARENESS

our /6/ award = AWARENESS

award /4/ i = AWARENESS

award /4/ we = AWARENESS

award /4/ me = AWARENESS

award /4/ us = AWARENESS

award /4/ my = AWARENESS

award /4/ our = AWARENESS

team /2/ _ENTITY_ = AWARENESS

i /4/ ticket = AWARENESS

we /4/ ticket = AWARENESS

me /4/ ticket = AWARENESS

us /4/ ticket = AWARENESS

my /4/ ticket = AWARENESS

our /4/ ticket = AWARENESS
at the ticket counter = AWARENESS
just get /3/ ticket = AWARENESS
we /2/ get /3/ ticket = AWARENESS
i /2/ get /3/ ticket = AWARENESS
[MD] be /5/ wimbledon = AWARENESS
[PRP] sponsor = AWARENESS
be /3/ [J] sponsor = AWARENESS
be [PRP] [J] sponsor = AWARENESS
thankyou /6/ sponsor = AWARENESS
thank /6/ sponsor = AWARENESS
[PRP] /4/ sponsor = AWARENESS
we /6/ sponsor = AWARENESS
sponsor /3/ [PRP] = AWARENESS
i /6/ indigo = AWARENESS
we /6/ indigo = AWARENESS
ENTITY gig = AWARENESS
“a” [J] advert by _ENTITY_ = AWARENESS
“a” [J] ad by _ENTITY_ = AWARENESS
“a” [J] advertisement by _ENTITY_ = AWARENESS
“a” [J] campaign by _ENTITY_ = AWARENESS
i /6/ _ENTITY_ foundation = AWARENESS
we /6/ _ENTITY_ foundation = AWARENESS
my /6/ _ENTITY_ foundation = AWARENESS
our /6/ _ENTITY_ foundation = AWARENESS
me /6/ _ENTITY_ foundation = AWARENESS
us /6/ _ENTITY_ foundation = AWARENESS
ENTITY foundation /6/ i = AWARENESS
ENTITY foundation /6/ we= AWARENESS
ENTITY foundation /6/ my = AWARENESS
ENTITY foundation /6/ our = AWARENESS
ENTITY foundation /6/ me= AWARENESS
ENTITY foundation /6/ us= AWARENESS

i /4/ [IN] /2/ _ENTITY_ academy = AWARENESS
we /4/ [IN] /2/ _ENTITY_ academy = AWARENESS
me /4/ [IN] /2/ _ENTITY_ academy = AWARENESS
my /4/ [IN] /2/ _ENTITY_ academy = AWARENESS
our /4/ [IN] /2/ _ENTITY_ academy = AWARENESS
i /6/ _ENTITY_ arena = AWARENESS
we /6/ _ENTITY_ arena = AWARENESS
me /6/ _ENTITY_ arena = AWARENESS
us /6/ _ENTITY_ arena = AWARENESS
my /6/ _ENTITY_ arena = AWARENESS
our /6/ _ENTITY_ arena = AWARENESS
cant wait for /2/ _ENTITY_ = AWARENESS
cant wait to = AWARENESS
can not wait til = AWARENESS
cant wait til = AWARENESS
can not wait until = AWARENESS
cant wait until = AWARENESS
i /6/ concert [IN] _ENTITY_ center = AWARENESS
we /6/ concert [IN] _ENTITY_ center = AWARENESS
me /6/ concert [IN] _ENTITY_ center = AWARENESS
us /6/ concert [IN] _ENTITY_ center = AWARENESS
my /6/ concert [IN] _ENTITY_ center = AWARENESS
our /6/ concert [IN] _ENTITY_ center = AWARENESS
concert [IN] _ENTITY_ center /4/ i = AWARENESS
concert [IN] _ENTITY_ center /4/ we = AWARENESS
concert [IN] _ENTITY_ center /4/ me = AWARENESS
concert [IN] _ENTITY_ center /4/ us = AWARENESS
concert [IN] _ENTITY_ center /4/ my = AWARENESS
concert [IN] _ENTITY_ center /4/ our = AWARENESS
i /6/ concert [IN] _ENTITY_ centre = AWARENESS
we /6/ concert [IN] _ENTITY_ centre = AWARENESS
me /6/ concert [IN] _ENTITY_ centre = AWARENESS
us /6/ concert [IN] _ENTITY_ centre = AWARENESS

my /6/ concert [IN] _ENTITY_ centre = AWARENESS
our /6/ concert [IN] _ENTITY_ centre = AWARENESS
concert [IN] _ENTITY_ centre /4/ i = AWARENESS
concert [IN] _ENTITY_ centre /4/ we = AWARENESS
concert [IN] _ENTITY_ centre /4/ me = AWARENESS
concert [IN] _ENTITY_ centre /4/ us = AWARENESS
concert [IN] _ENTITY_ centre /4/ my = AWARENESS
concert [IN] _ENTITY_ centre /4/ our = AWARENESS
i /6/ music at _ENTITY_ center = AWARENESS
we /6/ music at _ENTITY_ center = AWARENESS
me /6/ music at _ENTITY_ center = AWARENESS
us /6/ music at _ENTITY_ center = AWARENESS
my /6/ music at _ENTITY_ center = AWARENESS
our /6/ music at _ENTITY_ center = AWARENESS
music at _ENTITY_ center /4/ i = AWARENESS
music at _ENTITY_ center /4/ we = AWARENESS
music at _ENTITY_ center /4/ me = AWARENESS
music at _ENTITY_ center /4/ us = AWARENESS
music at _ENTITY_ center /4/ my = AWARENESS
music at _ENTITY_ center /4/ our = AWARENESS
i /6/ music at _ENTITY_ centre = AWARENESS
we /6/ music at _ENTITY_ centre = AWARENESS
me /6/ music at _ENTITY_ centre = AWARENESS
us /6/ music at _ENTITY_ centre = AWARENESS
my /6/ music at _ENTITY_ centre = AWARENESS
our /6/ music at _ENTITY_ centre = AWARENESS
music at _ENTITY_ centre /4/ i = AWARENESS
music at _ENTITY_ centre /4/ we = AWARENESS
music at _ENTITY_ centre /4/ me = AWARENESS
music at _ENTITY_ centre /4/ us = AWARENESS
music at _ENTITY_ centre /4/ my = AWARENESS
music at _ENTITY_ centre /4/ our = AWARENESS
i /6/ _ENTITY_ garden = AWARENESS

we /6/ _ENTITY_ garden = AWARENESS
me /6/ _ENTITY_ garden = AWARENESS
us /6/ _ENTITY_ garden = AWARENESS
my /6/ _ENTITY_ garden = AWARENESS
our /6/ _ENTITY_ garden = AWARENESS
i /6/ arthur [POS] day = AWARENESS
we /6/ arthur [POS] day = AWARENESS
me /4/ arthur [POS] day = AWARENESS
us /4/ arthur [POS] day = AWARENESS
my /4/ arthur [POS] day = AWARENESS
our /4/ arthur [POS] day = AWARENESS
arthur [POS] day /4/ i = AWARENESS
arthur [POS] day /4/ we = AWARENESS
arthur [POS] day /4/ us = AWARENESS
arthur [POS] day /4/ me = AWARENESS
arthur [POS] day /4/ my = AWARENESS
arthur [POS] day /4/ our = AWARENESS
i /6/ competition = AWARENESS
we /6/ competition = AWARENESS
me /6/ competition = AWARENESS
us /6/ competition = AWARENESS
my /6/ competition = AWARENESS
our /6/ competition = AWARENESS
competition /6/ i = AWARENESS
competition /6/ we = AWARENESS
competition /6/ me = AWARENESS
competition /6/ us = AWARENESS
competition /6/ my = AWARENESS
competition /6/ our= AWARENESS
i be go to [V] /3/ at the _ENTITY_ = AWARENESS
we be go to [V] /3/ at the _ENTITY_ = AWARENESS
i play at the _ENTITY_ = AWARENESS
forget my bankcard = PURCHASE

[JJS] bank in the world = POSTPURCHASE
[JJS] beer in the world = POSTPURCHASE
i have /1/ have /1/ before = PURCHASE
i will buy /1/ many = PURCHASE
check the _ENTITY_ near = PURCHASE
ready for collection = PURCHASE
[VBG] /1/ _ENTITY_ shopping list = PURCHASE
ENTITY use#VBN to [V] = POSTPURCHASE
ENTITY use#VBD to [V] = POSTPURCHASE
i [VBD] /5/ i switch#VBD over = POSTPURCHASE
when i switch#VBD over = POSTPURCHASE
it be break = POSTPURCHASE
[N] be break = POSTPURCHASE
[PRP] end up [VBG] /2/ _ENTITY_ = POSTPURCHASE
i call#VBD /1/ customer service = POSTPURCHASE
i /1/ switch#VBD to = POSTPURCHASE
we /1/ switch#VBD to = POSTPURCHASE
i /1/ switch#VBD from = POSTPURCHASE
we /1/ switch#VBD from = POSTPURCHASE
i /1/ switch#VBD over = POSTPURCHASE
we /1/ switch#VBD over = POSTPURCHASE
i have /2/ contract with _ENTITY_ = POSTPURCHASE
i have#VBD to [V] back /1/ _ENTITY_ = POSTPURCHASE
i be sick of _ENTITY_= POSTPURCHASE
i be sick of [VBG] = POSTPURCHASE
i be sick of not [VBG] = POSTPURCHASE
i be sick with = POSTPURCHASE
im sick of _ENTITY_= POSTPURCHASE
im sick of [VBG] = POSTPURCHASE
im sick of not [VBG] = POSTPURCHASE
im sick with = POSTPURCHASE
staff be so [J] to = POSTPURCHASE
staff be so [J] [IN] = POSTPURCHASE

i be so [J] to = POSTPURCHASE
i be so [J] [IN] = POSTPURCHASE
we be so [J] to = POSTPURCHASE
we be so [J] [IN] = POSTPURCHASE
i have /2/ be so [J] to = POSTPURCHASE
i have /2/ be so [J] [IN] = POSTPURCHASE
we have /2/ be so [J] to = POSTPURCHASE
we have /2/ be so [J] [IN] = POSTPURCHASE
staff have /2/ be so [J] to = POSTPURCHASE
staff have /2/ be so [J] [IN] = POSTPURCHASE
i will buy = PURCHASE
in the queue /3/ today = PURCHASE
in the queue /3/ this morning = PURCHASE
in the queue /3/ this afternoon = PURCHASE
in the queue /3/ last night = PURCHASE
i be get it = PURCHASE
i /1/ go switch = PURCHASE
how can i /3/ so i can buy = PURCHASE
cancel /2/ and go to _ENTITY_ = PURCHASE
bout to go to _ENTITY_ soon = PURCHASE
i can not wait to have _ENTITY_ = PURCHASE
i be look for /1/ _ENTITY_ = PURCHASE
must get “a” _ENTITY_ = PURCHASE
must get “an” _ENTITY_ = PURCHASE
must get _ENTITY_ = PURCHASE
must gettin “a” _ENTITY_ = PURCHASE
must gettin “an” _ENTITY_ = PURCHASE
must gettin _ENTITY_ = PURCHASE
so i can get /1/ new = PURCHASE
it be#VBZ gonna be /1/ _ENTITY_ = PURCHASE
it be#VBZ go to be /1/ _ENTITY_ = PURCHASE
buy#VBG [Z] can /1/ _ENTITY_ = PURCHASE
buy#VBG [Z] bottle /1/ _ENTITY_ = PURCHASE

buy#VBD [Z] can /1/ _ENTITY_ = PURCHASE
buy#VBD [Z] bottle /1/ _ENTITY_ = PURCHASE
just buy /3/ of _ENTITY_ = PURCHASE
can of _ENTITY_ to [V] = PURCHASE
let us have it = PURCHASE
it be time to [V] [VBN] /1/ _ENTITY_ = PURCHASE
head#VBG /1/ for /1/ _ENTITY_ = PURCHASE
head#VBG down to _ENTITY_ to get = PURCHASE
gonna [V] /3/ down me stomach = PURCHASE
drink /1/ today = PURCHASE
gonna drink = PURCHASE
go#VBG to drink = PURCHASE
will drink = PURCHASE
will be /4/ drink = PURCHASE
drink#VBG _ENTITY_ /2/ tonight = PURCHASE
now for my = PURCHASE
be in order = PURCHASE
toast /3/ with /3/ of _ENTITY_ = PURCHASE
about to quench = PURCHASE
bout to quench = PURCHASE
bout to smack /1/ _ENTITY_ = PURCHASE
about to smack /1/ _ENTITY_ = PURCHASE
go _ENTITY_ and /3/ shop = PURCHASE
now out to get = PURCHASE
do#VBN /2/ shop = PURCHASE
“Looking” forward to [V] /2/ _ENTITY_ = PURCHASE
look forward to [V] /2/ _ENTITY_ = PURCHASE
[VBG] /4/ in _ENTITY_ /1/ as soon as = PURCHASE
it stink /3/ round /1/ _ENTITY_ = PURCHASE
it stink /3/ near /1/ _ENTITY_ = PURCHASE
it stink /3/ next /1/ _ENTITY_ = PURCHASE
it stink /3/ in /1/ _ENTITY_ = PURCHASE
it smell /3/ round /1/ _ENTITY_ = PURCHASE

it smell /3/ near /1/ _ENTITY_ = PURCHASE
it smell /3/ next /1/ _ENTITY_ = PURCHASE
it smell /3/ in /1/ _ENTITY_ = PURCHASE
do#VBG /3/ online shopping = PURCHASE
“doing” /3/ online shopping = PURCHASE
“Doing” /3/ online shopping = PURCHASE
stick#VBN /2/ in _ENTITY_ = PURCHASE
it be [VBG] in _ENTITY_ = PURCHASE
it be [J] in _ENTITY_ = PURCHASE
[J] _ENTITY_ shop = PURCHASE
ENTITY /1/ [J] [N] tonight = PURCHASE
start#VBZ [VBG] in _ENTITY_ = PURCHASE
strand#VBN in _ENTITY_ = PURCHASE
strand#VBD in _ENTITY_ = PURCHASE
will /2/ on /1/ way home = PURCHASE
excite /4/ will be in _ENTITY_ = PURCHASE
ENTITY [POS] delivery man = PURCHASE
ENTITY delivery man = PURCHASE
my /1/ replace = POSTPURCHASE
get replace = POSTPURCHASE
ENTITY will not replace = POSTPURCHASE
to replace my = POSTPURCHASE
ENTITY replace = POSTPURCHASE
ENTITY have replace = POSTPURCHASE
have to have /2/ replace = POSTPURCHASE
hurry up /2/ my shopping = PURCHASE
wait for my /2/ order /2/ deliver = PURCHASE
ENTITY /2/ bring my = PURCHASE
getting my /2/ _ENTITY_ delivery = PURCHASE
get#VBG my /2/ _ENTITY_ delivery = PURCHASE
[VBG] my /2/ in _ENTITY_ = PURCHASE
[J] in _ENTITY_ today = PURCHASE
feel /1/ [J] in _ENTITY_ = PURCHASE

feeling /1/ [J] in _ENTITY_ = PURCHASE
discover /3/ in _ENTITY_ = PURCHASE
discover /3/ at _ENTITY_ = PURCHASE
ENTITY /3/ go#VBG now = PURCHASE
going to _ENTITY_ /4/ to [V] if = PURCHASE
go#VBG to _ENTITY_ /4/ to [V] if = PURCHASE
go#VBG to _ENTITY_ /2/ to get = PURCHASE
go#VBG to _ENTITY_ /2/ to buy = PURCHASE
going to _ENTITY_ /2/ to get = PURCHASE
going to _ENTITY_ /2/ to buy = PURCHASE
buying /2/ from _ENTITY_ = PURCHASE
buy#VBG /2/ from _ENTITY_ = PURCHASE
about to go to _ENTITY_ /8/ get = PURCHASE
being at _ENTITY_ = PURCHASE
being in _ENTITY_ = PURCHASE
ill go /1/ buy = PURCHASE
i will go /1/ buy = PURCHASE
ENTITY here i come = PURCHASE
[VBG] _ENTITY_ /3/ shelf = PURCHASE
raid _ENTITY_ /3/ shelf = PURCHASE
[RB] shop#VBG /1/ _ENTITY_ = PURCHASE
just pop#VBG into _ENTITY_ = PURCHASE
buy#VBG /2/ for my = PURCHASE
buying /2/ for my = PURCHASE
ENTITY /1/ store /2/ to buy = PURCHASE
ENTITY /1/ superstore /2/ to buy = PURCHASE
to _ENTITY_ /2/ buy#VBG = PURCHASE
in _ENTITY_ /2/ buy#VBG = PURCHASE
i /3/ at _ENTITY_ /2/ buy#VBG = PURCHASE
be#VBP /1/ shopping at _ENTITY_ = PURCHASE
will go _ENTITY_ = PURCHASE
need to go to _ENTITY_ = PURCHASE
gonna go to _ENTITY_ /2/ get = PURCHASE

i will check in _ENTITY_ = PURCHASE
go to _ENTITY_ /2/ get one = PURCHASE
go over _ENTITY_ in my = PURCHASE
i be about to go to _ENTITY_ = PURCHASE
ENTITY have /4/ i want /3/ today = PURCHASE
just walk#VBD into _ENTITY_ = PURCHASE
gona have “a” look in _ENTITY_ = PURCHASE
gonna have “a” look in _ENTITY_ = PURCHASE
go /1/ have “a” look in _ENTITY_ = PURCHASE
walk to _ENTITY_ now = PURCHASE
put#VBG /4/ need /3/ trolley /2/ _ENTITY_ = PURCHASE
goin straight to _ENTITY_ for = PURCHASE
go straight to _ENTITY_ for = PURCHASE
will [V] to _ENTITY_ with me = PURCHASE
will [V] to _ENTITY_ with us = PURCHASE
i /2/ have /1/ blast /1/ _ENTITY_ = PURCHASE
me /2/ have /1/ blast /1/ _ENTITY_ = PURCHASE
i go to pay for = PURCHASE
must go to _ENTITY_ today = PURCHASE
must go to _ENTITY_ tonight = PURCHASE
ENTITY /1/ advert r = AWARENESS
ENTITY /1/ ad r = AWARENESS
ENTITY /1/ commercial r = AWARENESS
ENTITY /1/ advertisement r = AWARENESS
i like /3/ in the _ENTITY_ advert = AWARENESS
i like /3/ in the _ENTITY_ commercial = AWARENESS
i like /3/ in the _ENTITY_ ad = AWARENESS
i like /3/ in the _ENTITY_ advertisement = AWARENESS
be like /2/ _ENTITY_ ad = AWARENESS
be like /2/ _ENTITY_ advert = AWARENESS
be like /2/ _ENTITY_ advertisement = AWARENESS
be like /2/ _ENTITY_ commercial = AWARENESS
ENTITY /3/ ad get me = AWARENESS

ENTITY /3/ advert get me = AWARENESS
ENTITY /3/ advertisement get me = AWARENESS
ENTITY /3/ commercial get me = AWARENESS
ENTITY /3/ campaign get me = AWARENESS
ENTITY /3/ ad get us = AWARENESS
ENTITY /3/ advert get us = AWARENESS
ENTITY /3/ advertisement get us = AWARENESS
ENTITY /3/ commercial get us = AWARENESS
ENTITY /3/ campaign get us = AWARENESS
ENTITY can not even call = POSTPURCHASE
ENTITY can not even make = POSTPURCHASE
ENTITY can not even use = POSTPURCHASE
[N][VBG][IN] /5/ ad = AWARENESS
[N][VBG][IN] /5/ advert = AWARENESS
[N][VBG][IN] /5/ advertisement = AWARENESS
[N][VBG][IN] /5/ commercial = AWARENESS
[N][VBG][IN] /5/ spot = AWARENESS
[NP][IN] /3/ _ENTITY_ ad = AWARENESS
[NP][IN] /3/ _ENTITY_ advert = AWARENESS
[NP][IN] /3/ _ENTITY_ advertisement = AWARENESS
[NP][IN] /3/ _ENTITY_ commercial = AWARENESS
[NP][IN] /3/ _ENTITY_ tv = AWARENESS
[NP][IN] /3/ _ENTITY_ spot = AWARENESS
i [V] like [DT] [N] from /3/ _ENTITY_ ad = AWARENESS
i [V] like [DT] [N] from /3/ _ENTITY_ advert = AWARENESS
i [V] like [DT] [N] from /3/ _ENTITY_ advertisement = AWARENESS
i [V] like [DT] [N] from /3/ _ENTITY_ commercial = AWARENESS
i [V] like [DT] [N] from /3/ _ENTITY_ tv = AWARENESS
i [V] like [DT] [N] from /3/ _ENTITY_ spot = AWARENESS
i [V] like [DT] [N] in /3/ _ENTITY_ ad = AWARENESS
i [V] like [DT] [N] in /3/ _ENTITY_ advert = AWARENESS
i [V] like [DT] [N] in /3/ _ENTITY_ advertisement = AWARENESS
i [V] like [DT] [N] in /3/ _ENTITY_ commercial = AWARENESS

i [V] like [DT] [N] in /3/ _ENTITY_ tv = AWARENESS
i [V] like [DT] [N] in /3/ _ENTITY_ spot = AWARENESS
every time i [V] /3/ _ENTITY_ ad = AWARENESS
every time i [V] /3/ _ENTITY_ advert = AWARENESS
every time i [V] /3/ _ENTITY_ advertisement = AWARENESS
every time i [V] /3/ _ENTITY_ commercial = AWARENESS
every time i [V] /3/ _ENTITY_ tv = AWARENESS
every time i [V] /3/ _ENTITY_ spot = AWARENESS
if [PRP] do not [V] /6/ _ENTITY_ ad = AWARENESS
if [PRP] do not [V] /6/ _ENTITY_ advert = AWARENESS
if [PRP] do not [V] /6/ _ENTITY_ advertisement = AWARENESS
if [PRP] do not [V] /6/ _ENTITY_ commercial = AWARENESS
if [PRP] do not [V] /6/ _ENTITY_ tv = AWARENESS
if [PRP] do not [V] /6/ _ENTITY_ spot = AWARENESS
just saw /1/ _ENTITY_ /1/ ad = AWARENESS
ad i /1/ hear = AWARENESS
advert i /1/ hear = AWARENESS
advertisement i /1/ hear = AWARENESS
commercial i /1/ hear = AWARENESS
looking forward to /6/ at /2/ _ENTITY_ = AWARENESS
look forward to /6/ at /2/ _ENTITY_ = AWARENESS
outside /1/ _ENTITY_ /1/ [VBG] = AWARENESS
next /1/ _ENTITY_ /1/ [VBG] = AWARENESS
near /1/ _ENTITY_ /1/ [VBG] = AWARENESS
the /4/ at /2/ _ENTITY_ /2/ be = AWARENESS
this [VBG] _ENTITY_ ad = AWARENESS
this [J] _ENTITY_ ad = AWARENESS
that [VBG] _ENTITY_ ad = AWARENESS
that [J] _ENTITY_ ad = AWARENESS
this [VBG] _ENTITY_ advert = AWARENESS
this [J] _ENTITY_ advert = AWARENESS
that [VBG] _ENTITY_ advert = AWARENESS
that [J] _ENTITY_ advert = AWARENESS

this [VBG] _ENTITY_ advertisement = AWARENESS
this [J] _ENTITY_ advertisement = AWARENESS
that [VBG] _ENTITY_ advertisement = AWARENESS
that [J] _ENTITY_ advertisement = AWARENESS
this [VBG] _ENTITY_ commercial = AWARENESS
this [J] _ENTITY_ commercial = AWARENESS
that [VBG] _ENTITY_ commercial = AWARENESS
that [J] _ENTITY_ commercial = AWARENESS
this [VBG] _ENTITY_ tv = AWARENESS
this [J] _ENTITY_ tv = AWARENESS
that [VBG] _ENTITY_ tv = AWARENESS
that [J] _ENTITY_ tv = AWARENESS
this [VBG] _ENTITY_ spot = AWARENESS
this [J] _ENTITY_ spot = AWARENESS
that [VBG] _ENTITY_ spot = AWARENESS
that [J] _ENTITY_ spot = AWARENESS
this [VBG] _ENTITY_ campaign = AWARENESS
this [J] _ENTITY_ campaign = AWARENESS
that [VBG] _ENTITY_ campaign = AWARENESS
that [J] _ENTITY_ campaign = AWARENESS
this _ENTITY_ ad when = AWARENESS
that _ENTITY_ ad when = AWARENESS
this _ENTITY_ advert when = AWARENESS
that _ENTITY_ advert when = AWARENESS
this _ENTITY_ advertisement when = AWARENESS
that _ENTITY_ advertisement when = AWARENESS
this _ENTITY_ commercial when = AWARENESS
that _ENTITY_ commercial when = AWARENESS
this _ENTITY_ spot when = AWARENESS
that _ENTITY_ spot when = AWARENESS
this _ENTITY_ campaign when = AWARENESS
that _ENTITY_ campaign when = AWARENESS
ENTITY ad have = AWARENESS

ENTITY advert have = AWARENESS

ENTITY advertisement have = AWARENESS

ENTITY commercial have = AWARENESS

ENTITY campaign have = AWARENESS

ENTITY spot have = AWARENESS

i [RB] enjoy [DT] _ENTITY_ /1/ ad = AWARENESS

i like the _ENTITY_ advert = AWARENESS

ENTITY /3/ ad be /1/ [J] = AWARENESS

ENTITY /3/ advert be /1/ [J] = AWARENESS

ENTITY /3/ advertisement be /1/ [J] = AWARENESS

ENTITY /3/ commercial be /1/ [J] = AWARENESS

ENTITY /3/ spot be /1/ [J] = AWARENESS

ENTITY /3/ campaign be /1/ [J] = AWARENESS

ENTITY /3/ ad be [RB] = AWARENESS

ENTITY /3/ advert be [RB] = AWARENESS

ENTITY /3/ advertisement be [RB] = AWARENESS

ENTITY /3/ commercial be [RB] = AWARENESS

ENTITY /3/ spot be [RB] = AWARENESS

ENTITY /3/ campaign be [RB] = AWARENESS

ENTITY /3/ ad be /1/ [VBG] = AWARENESS

ENTITY /3/ advert be /1/ [VBG] = AWARENESS

ENTITY /3/ advertisement be /1/ [VBG] = AWARENESS

ENTITY /3/ commercial be /1/ [VBG] = AWARENESS

ENTITY /3/ spot be /1/ [VBG] = AWARENESS

ENTITY /3/ campaign be /1/ [VBG] = AWARENESS

we play at /1/ _ENTITY_ = AWARENESS

i play at /1/ _ENTITY_ = AWARENESS

saw /1/ _ENTITY_ ad = AWARENESS

saw /1/ _ENTITY_ advert = AWARENESS

saw /1/ _ENTITY_ advertisement = AWARENESS

saw /1/ _ENTITY_ campaign = AWARENESS

saw /1/ _ENTITY_ spot = AWARENESS

saw /1/ _ENTITY_ tv = AWARENESS

saw /1/ _ENTITY_ commercial = AWARENESS
see#VBD /1/ _ENTITY_ ad = AWARENESS
see#VBD /1/ _ENTITY_ advert = AWARENESS
see#VBD /1/ _ENTITY_ advertisement = AWARENESS
see#VBD /1/ _ENTITY_ campaign = AWARENESS
see#VBD /1/ _ENTITY_ spot = AWARENESS
see#VBD /1/ _ENTITY_ tv = AWARENESS
see#VBD /1/ _ENTITY_ commercial = AWARENESS
i [V] _ENTITY_ [V] /3/ photoshoots = AWARENESS
i /5/ _ENTITY_ /1/ photoshoot = AWARENESS
ENTITY /1/ photoshoot /3/ i = AWARENESS
in love with your _ENTITY_ /3/ shoot = AWARENESS
in love with your _ENTITY_ /3/ video = AWARENESS
do _ENTITY_ /1/ sponsor = AWARENESS
at /2/ _ENTITY_ /3/ expo = AWARENESS
at /2/ _ENTITY_ /3/ event = AWARENESS
with /2/ _ENTITY_ shirt = AWARENESS
ENTITY /2/ ad /1/ make me = AWARENESS
ENTITY /2/ advert /1/ make me = AWARENESS
ENTITY /2/ advertisement /1/ make me = AWARENESS
ENTITY /2/ commercial /1/ make me = AWARENESS
ENTITY /2/ campaign /1/ make me = AWARENESS
ENTITY /2/ video /1/ make me = AWARENESS
ENTITY /2/ spot /1/ make me = AWARENESS
ENTITY /2/ ad /1/ give me = AWARENESS
ENTITY /2/ advert /1/ give me = AWARENESS
ENTITY /2/ advertisement /1/ give me = AWARENESS
ENTITY /2/ commercial /1/ give me = AWARENESS
ENTITY /2/ campaign /1/ give me = AWARENESS
ENTITY /2/ video /1/ give me = AWARENESS
ENTITY /2/ spot /1/ give me = AWARENESS
ENTITY /2/ ad /1/ put me = AWARENESS
ENTITY /2/ advert /1/ put me = AWARENESS

ENTITY /2/ advertisement /1/ put me = AWARENESS
ENTITY /2/ commercial /1/ put me = AWARENESS
ENTITY /2/ campaign /1/ put me = AWARENESS
ENTITY /2/ video /1/ put me = AWARENESS
ENTITY /2/ spot /1/ put me = AWARENESS
[J] ad /1/ _ENTITY_ = AWARENESS
ENTITY /5/ snapchat = AWARENESS
snapchat /5/ _ENTITY_ = AWARENESS
i see /2/ in /2/ _ENTITY_ ad = AWARENESS
i see /2/ in /2/ _ENTITY_ advert = AWARENESS
i see /2/ in /2/ _ENTITY_ advertisement = AWARENESS
i see /2/ in /2/ _ENTITY_ commercial = AWARENESS
i see /2/ in /2/ _ENTITY_ campaign = AWARENESS
i see /2/ in /2/ _ENTITY_ spot = AWARENESS
sponsor by _ENTITY_ = AWARENESS
like _ENTITY_ [V] in /2/ ad = AWARENESS
like _ENTITY_ [V] in /2/ advert = AWARENESS
like _ENTITY_ [V] in /2/ advertisement = AWARENESS
like _ENTITY_ [V] in /2/ commercial = AWARENESS
like _ENTITY_ [V] in /2/ tv = AWARENESS
like _ENTITY_ [V] in /2/ spot = AWARENESS
like _ENTITY_ [V] in /2/ campaign = AWARENESS
like _ENTITY_ [V] in /2/ video = AWARENESS
loving /5/ ad from /1/ _ENTITY_ = AWARENESS
loving /5/ advert from /1/ _ENTITY_ = AWARENESS
loving /5/ advertisement from /1/ _ENTITY_ = AWARENESS
loving /5/ commercial from /1/ _ENTITY_ = AWARENESS
loving /5/ spot from /1/ _ENTITY_ = AWARENESS
loving /5/ campaign from /1/ _ENTITY_ = AWARENESS
loving /5/ video from /1/ _ENTITY_ = AWARENESS
loving /4/ _ENTITY_ ad = AWARENESS
loving /4/ _ENTITY_ advert = AWARENESS
loving /4/ _ENTITY_ advertisement = AWARENESS

loving /4/ _ENTITY_ commercial = AWARENESS
loving /4/ _ENTITY_ tv = AWARENESS
loving /4/ _ENTITY_ spot = AWARENESS
loving /4/ _ENTITY_ campaign = AWARENESS
loving /4/ _ENTITY_ video = AWARENESS
do not like /3/ logo = AWARENESS
who do you want /5/ sponsor = AWARENESS
who do u want /5/ sponsor = AWARENESS
preferably _ENTITY_ = EVALUATION
prefer /2/ over = EVALUATION
ENTITY over [NP] = EVALUATION
[NP] over _ENTITY_ = EVALUATION
[RB][J] to find = EVALUATION
will never [V] /1/ _ENTITY_ = EVALUATION
buying _ENTITY_ be so [J] = EVALUATION
buy#VBG _ENTITY_ be so [J] = EVALUATION
buying /3/ _ENTITY_ /3/ maybe = EVALUATION
buy /3/ _ENTITY_ /3/ maybe = EVALUATION
can [RB] decide [W] = EVALUATION
can [RB] decide between = EVALUATION
want to decide between = EVALUATION
consider buy /3/ _ENTITY_ = EVALUATION
considering buy /3/ _ENTITY_ = EVALUATION
do i get /3/ or = EVALUATION
do i buy /3/ or = EVALUATION
wether or not to buy = EVALUATION
whether or not to buy = EVALUATION
do not know [WP] /2/ to buy = EVALUATION
i be after /10/ though = EVALUATION
i be after /10/ but = EVALUATION
i [V] _ENTITY_ but /2/ be [JJR] = EVALUATION
i like _ENTITY_ [RB] many than = EVALUATION
any recommendation = EVALUATION

trying to decide /1/ i [V] /5/ or = EVALUATION
try to decide /1/ [V] /5/ or = EVALUATION
i [V] to choose /3/ or = EVALUATION
i want /5/ but /1/ can /1/ find = EVALUATION
i would rather spend /2/ on /3/ than = EVALUATION
will check _ENTITY_ = EVALUATION
may get /3/ _ENTITY_ = EVALUATION
might get /3/ _ENTITY_ = EVALUATION
might /3/ purchase /3/ _ENTITY_ = EVALUATION
may /3/ purchase /3/ _ENTITY_ = EVALUATION
i can do with [DT] = EVALUATION
should i get /3/ or = EVALUATION
should i get /3/ instead_of = EVALUATION
should i buy /3/ or = EVALUATION
should i buy /3/ instead_of = EVALUATION
ENTITY be many [J] = EVALUATION
may buy /2/ _ENTITY_ = EVALUATION
might buy /2/ _ENTITY_ = EVALUATION
be [J] /4/ loyal customer = POSTPURCHASE
from _ENTITY_ say = POSTPURCHASE
not work#VBG = POSTPURCHASE
would not work for my /3/ _ENTITY_ = POSTPURCHASE
work properly = POSTPURCHASE
i love _ENTITY_ = POSTPURCHASE
we love _ENTITY_ = POSTPURCHASE
i experience#V /2/ customer service = POSTPURCHASE
[VBN] /1/ my _ENTITY_ experience = POSTPURCHASE
my _ENTITY_ experience today = POSTPURCHASE
quite /1/ experience = POSTPURCHASE
i be in /3/ commercial = AWARENESS
i be in /3/ ad = AWARENESS
i be in /3/ advert = AWARENESS
i be in /3/ advertisement = AWARENESS

i be in /3/ campaign = AWARENESS
if [DT] /3/ ad /3/ make = AWARENESS
if [DT] /3/ advert /3/ make = AWARENESS
if [DT] /3/ advertisement /3/ make = AWARENESS
if [DT] /3/ commercial /3/ make = AWARENESS
if [DT] /3/ campaign /3/ make = AWARENESS
if [DT] /3/ video /3/ make = AWARENESS
if [DT] /3/ spot /3/ make = AWARENESS
[DT] _ENTITY_ /2/ ad /2/ with = AWARENESS
[DT] _ENTITY_ /2/ advert /2/ with = AWARENESS
[DT] _ENTITY_ /2/ advertisement /2/ with = AWARENESS
[DT] _ENTITY_ /2/ campaign /2/ with = AWARENESS
[DT] _ENTITY_ /2/ commercial /2/ with = AWARENESS
[DT] _ENTITY_ /2/ video /2/ with = AWARENESS
[DT] _ENTITY_ /2/ spot /2/ with = AWARENESS
ENTITY /1/ ad [VBZ][VBG] to = AWARENESS
ENTITY /1/ advert [VBZ][VBG] to = AWARENESS
ENTITY /1/ advertisement [VBZ][VBG] to = AWARENESS
ENTITY /1/ campaign [VBZ][VBG] to = AWARENESS
ENTITY /1/ commercial [VBZ][VBG] to = AWARENESS
ENTITY /1/ video [VBZ][VBG] to = AWARENESS
ENTITY /1/ spot [VBZ][VBG] to = AWARENESS
[JJS] thing [IN] _ENTITY_ ad = AWARENESS
[JJS] thing [IN] _ENTITY_ advert = AWARENESS
[JJS] thing [IN] _ENTITY_ advertisement = AWARENESS
[JJS] thing [IN] _ENTITY_ commercial = AWARENESS
[JJS] thing [IN] _ENTITY_ video = AWARENESS
[JJS] thing [IN] _ENTITY_ spot = AWARENESS
[JJS] thing [IN] _ENTITY_ campaign = AWARENESS
[JJS] thing [IN] _ENTITY_ tv = AWARENESS
be#VBZ /2/ [N][IN]/2/ _ENTITY_ ad = AWARENESS
be#VBZ /2/ [N][IN]/2/ _ENTITY_ advert = AWARENESS
be#VBZ /2/ [N][IN]/2/ _ENTITY_ advertisement = AWARENESS

be#VBZ /2/ [N][IN]/2/ _ENTITY_ commercial = AWARENESS
be#VBZ /2/ [N][IN]/2/ _ENTITY_ video = AWARENESS
be#VBZ /2/ [N][IN]/2/ _ENTITY_ spot = AWARENESS
be#VBZ /2/ [N][IN]/2/ _ENTITY_ campaign = AWARENESS
be#VBZ /2/ [N][IN]/2/ _ENTITY_ tv = AWARENESS
as /3/ _ENTITY_ ad = AWARENESS
as /3/ _ENTITY_ advert = AWARENESS
as /3/ _ENTITY_ advertisement = AWARENESS
as /3/ _ENTITY_ commercial = AWARENESS
as /3/ _ENTITY_ video = AWARENESS
as /3/ _ENTITY_ spot = AWARENESS
as /3/ _ENTITY_ campaign = AWARENESS
as /3/ _ENTITY_ tv = AWARENESS
enjoy#VBD /5/ ad = AWARENESS
enjoy#VBG /5/ ad = AWARENESS
enjoy#VBD /5/ advert = AWARENESS
enjoy#VBG /5/ advert = AWARENESS
enjoy#VBD /5/ advertisement = AWARENESS
enjoy#VBG /5/ advertisement = AWARENESS
enjoy#VBD /5/ commercial = AWARENESS
enjoy#VBG /5/ commercial = AWARENESS
enjoy#VBD /5/ video = AWARENESS
enjoy#VBG /5/ video = AWARENESS
enjoy#VBD /5/ spot = AWARENESS
enjoy#VBG /5/ spot = AWARENESS
enjoy#VBD /5/ tv = AWARENESS
enjoy#VBG /5/ tv = AWARENESS
enjoy#VBD /5/ radio = AWARENESS
enjoy#VBG /5/ radio = AWARENESS
why /2/ do /2/ keep /3/ announce = AWARENESS
why /2/ do /2/ continue /3/ announce = AWARENESS
why /2/ do /2/ keep /3/ advert = AWARENESS
why /2/ do /2/ continue /3/ advert = AWARENESS

why /2/ do /2/ keep /3/ advertise = AWARENESS
why /2/ do /2/ continue /3/ advertise = AWARENESS
ENTITY /2/ advert /1/ make me = AWARENESS
have [V][DT] /2/ ad = AWARENESS
have [V][DT] /2/ advert = AWARENESS
have [V][DT] /2/ advertisement = AWARENESS
have [V][DT] /2/ commercial = AWARENESS
have [V][DT] /2/ campaign = AWARENESS
have [V][DT] /2/ video = AWARENESS
have [V][DT] /2/ spot = AWARENESS
have [V][DT] /2/ tv = AWARENESS
have [V][DT] /2/ radio = AWARENESS
watch [DT] /3/ ad = AWARENESS
watching [DT] /3/ ad = AWARENESS
watch [DT] /3/ advert = AWARENESS
watching [DT] /3/ advert = AWARENESS
watch [DT] /3/ advertisement = AWARENESS
watching [DT] /3/ advertisement = AWARENESS
watch [DT] /3/ campaign = AWARENESS
watching [DT] /3/ campaign = AWARENESS
watch [DT] /3/ commercial = AWARENESS
watching [DT] /3/ commercial = AWARENESS
watch [DT] /3/ video = AWARENESS
watching [DT] /3/ video = AWARENESS
watch [DT] /3/ tv = AWARENESS
watching [DT] /3/ tv = AWARENESS
watch [DT] /3/ spot = AWARENESS
watching [DT] /3/ spot = AWARENESS
[N][IN][DT] _ENTITY_ ad [WP] = AWARENESS
[N][IN][DT] _ENTITY_ advert [WP] = AWARENESS
[N][IN][DT] _ENTITY_ advertisement [WP] = AWARENESS
[N][IN][DT] _ENTITY_ commercial [WP] = AWARENESS
[N][IN][DT] _ENTITY_ campaign [WP] = AWARENESS

[N][IN][DT] _ENTITY_ video [WP] = AWARENESS
[N][IN][DT] _ENTITY_ spot [WP] = AWARENESS
[N][IN][DT] _ENTITY_ tv [WP] = AWARENESS
i recognise [DT] /4/ _ENTITY_ ad = AWARENESS
i recognise [DT] /4/ _ENTITY_ advert = AWARENESS
i recognise [DT] /4/ _ENTITY_ advertisement = AWARENESS
i recognise [DT] /4/ _ENTITY_ commercial = AWARENESS
i recognise [DT] /4/ _ENTITY_ campaign = AWARENESS
i recognise [DT] /4/ _ENTITY_ video = AWARENESS
i recognise [DT] /4/ _ENTITY_ spot = AWARENESS
i recognise [DT] /4/ _ENTITY_ tv = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ ad = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ advert = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ advertisement = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ commercial = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ campaign = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ tv = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ spot = AWARENESS
why do /5/ [IN] /1/ _ENTITY_ radio = AWARENESS
go#VBG to try _ENTITY_ = PURCHASE
i /2/ have to try /2/ now = PURCHASE
i will /2/ get /2/ _ENTITY_ = PURCHASE
we will /2/ get /2/ _ENTITY_ = PURCHASE
go#VBG to collect _ENTITY_ = PURCHASE
gonna collect _ENTITY_ = PURCHASE
i will eat _ENTITY_ next time = PURCHASE
we will eat _ENTITY_ next time = PURCHASE
i will drink _ENTITY_ next time = PURCHASE
we will drink _ENTITY_ next time = PURCHASE
i will buy _ENTITY_ next time = PURCHASE
we will buy _ENTITY_ next time = PURCHASE
time to try /2/ _ENTITY_ = PURCHASE
ENTITY be too [J] = EVALUATION

it taste /3/ [JJR] than _ENTITY_ = EVALUATION
taste /2/ [J] to [NP] or _ENTITY_ = EVALUATION
taste /2/ [J] to _ENTITY_ = EVALUATION
[WP] /2/ be [JJR] = EVALUATION
ENTITY /4/ “preferably” = EVALUATION
i [RB] /2/ prefer /2/ _ENTITY_ to = EVALUATION
i [RB] /2/ prefer /3/ to _ENTITY_ = EVALUATION
[W] i like good = EVALUATION
no [N] [MD] [RB] equal _ENTITY_ = EVALUATION
ENTITY be /2/ much [J] than [NP] = EVALUATION
[NP] be /2/ much [J] than _ENTITY_ = EVALUATION
ENTITY be /2/ compare to = EVALUATION
[NP] be /2/ compare to _ENTITY_ = EVALUATION
eat#VBG /3/ while i be [VBG]= POSTPURCHASE
i change#VBD to /3/ _ENTITY_ = POSTPURCHASE
ENTITY should check [P] = POSTPURCHASE
write to _ENTITY_ /2/ complain = POSTPURCHASE
write /2/ complaint letter to _ENTITY_ = POSTPURCHASE
writing /2/ complaint letter to _ENTITY_ = POSTPURCHASE
open#VBD /3/ _ENTITY_ /3/ i can = POSTPURCHASE
last time i buy = POSTPURCHASE
treated myself to /4/ _ENTITY_ = POSTPURCHASE
treat#VBD myself to = POSTPURCHASE
will not be buy /3/ again = POSTPURCHASE
launch /1/ advert = AWARENESS
[VBP] /6/ event /6/ at = AWARENESS
i /6/ event /6/ at = AWARENESS
ENTITY /2/ ad /2/ work = AWARENESS
ENTITY /2/ advert /2/ work = AWARENESS
ENTITY /2/ advertisement /2/ work = AWARENESS
ENTITY /2/ campaign /2/ work = AWARENESS
ENTITY /2/ adv /2/ work = AWARENESS
ENTITY /2/ tv /2/ work = AWARENESS

ENTITY /2/ spot /2/ work = AWARENESS
ENTITY /2/ commercial /2/ work = AWARENESS
ENTITY /2/ advertising /2/ work = AWARENESS
ENTITY [POS] ad /2/ work = AWARENESS
ENTITY [POS] advert /2/ work = AWARENESS
ENTITY [POS] advertisement /2/ work = AWARENESS
ENTITY [POS] campaign /2/ work = AWARENESS
ENTITY [POS] adv /2/ work = AWARENESS
ENTITY [POS] tv /2/ work = AWARENESS
ENTITY [POS] spot /2/ work = AWARENESS
ENTITY [POS] commercial /2/ work = AWARENESS
ENTITY [POS] advertising /2/ work = AWARENESS
[J] _ENTITY_ ad [V] = AWARENESS
[J] _ENTITY_ advert [V] = AWARENESS
[J] _ENTITY_ advertisement [V] = AWARENESS
[J] _ENTITY_ adv [V] = AWARENESS
[J] _ENTITY_ campaign [V] = AWARENESS
[J] _ENTITY_ commercial [V] = AWARENESS
[J] _ENTITY_ spot [V] = AWARENESS
[J] _ENTITY_ advertising [V] = AWARENESS
hear /3/ _ENTITY_ ad = AWARENESS
hear /3/ _ENTITY_ advert = AWARENESS
hear /3/ _ENTITY_ advertisement = AWARENESS
hear /3/ _ENTITY_ campaign = AWARENESS
hear /3/ _ENTITY_ tv = AWARENESS
hear /3/ _ENTITY_ spot = AWARENESS
hear /3/ _ENTITY_ adv = AWARENESS
hear /3/ _ENTITY_ commercial = AWARENESS
formula /2/ race = AWARENESS
like the [N] [IN] the _ENTITY_ /1/ ad = AWARENESS
like the [N] [IN] the _ENTITY_ /1/ advertisement = AWARENESS
like the [N] [IN] the _ENTITY_ /1/ adv = AWARENESS
like the [N] [IN] the _ENTITY_ /1/ commercial = AWARENESS

like the [N] [IN] the _ENTITY_ /1/ campaign = AWARENESS
like the [N] [IN] the _ENTITY_ /1/ tv = AWARENESS
like the [N] [IN] the _ENTITY_ /1/ spot = AWARENESS
ENTITY /1/ ad [V] = AWARENESS
ENTITY /1/ ad [IN] = AWARENESS
ENTITY /1/ advert [V] = AWARENESS
ENTITY /1/ advert [IN] = AWARENESS
ENTITY /1/ advertisement [V] = AWARENESS
ENTITY /1/ advertisement [IN] = AWARENESS
ENTITY /1/ adv [V] = AWARENESS
ENTITY /1/ adv [IN] = AWARENESS
ENTITY /1/ campaign [V] = AWARENESS
ENTITY /1/ campaign [IN] = AWARENESS
ENTITY /1/ commercial [V] = AWARENESS
ENTITY /1/ commercial [IN] = AWARENESS
ENTITY /1/ spot [V] = AWARENESS
ENTITY /1/ spot [IN] = AWARENESS
car of the year = AWARENESS
film /2/ _ENTITY_ ad = AWARENESS
film /2/ _ENTITY_ advert = AWARENESS
film /2/ _ENTITY_ advertisement = AWARENESS
film /2/ _ENTITY_ adv = AWARENESS
film /2/ _ENTITY_ campaign = AWARENESS
film /2/ _ENTITY_ commercial = AWARENESS
film /2/ _ENTITY_ tv = AWARENESS
film /2/ _ENTITY_ spot = AWARENESS
film /2/ _ENTITY_ video = AWARENESS
[DT][J] _ENTITY_ ad [IN] /4/ be = AWARENESS
[DT][J] _ENTITY_ advert [IN] /4/ be = AWARENESS
[DT][J] _ENTITY_ advertisement [IN] /4/ be = AWARENESS
[DT][J] _ENTITY_ adv [IN] /4/ be = AWARENESS
[DT][J] _ENTITY_ campaign [IN] /4/ be = AWARENESS
[DT][J] _ENTITY_ commercial [IN] /4/ be = AWARENESS

[DT][J] _ENTITY_ tv [IN] /4/ be = AWARENESS
[DT][J] _ENTITY_ advertising [IN] /4/ be = AWARENESS
[DT][J] _ENTITY_ spot [IN] /4/ be = AWARENESS
ENTITY have /1/ [V] /3/ ad = AWARENESS
ENTITY have /1/ [V] /3/ advert = AWARENESS
ENTITY have /1/ [V] /3/ advertisement = AWARENESS
ENTITY have /1/ [V] /3/ adv = AWARENESS
ENTITY have /1/ [V] /3/ advertising = AWARENESS
ENTITY have /1/ [V] /3/ commercial = AWARENESS
ENTITY have /1/ [V] /3/ campaign = AWARENESS
ENTITY have /1/ [V] /3/ spot = AWARENESS
ENTITY have /1/ [V] /3/ tv = AWARENESS
[J] print#N = AWARENESS
[MD] drive [IN] _ENTITY_ = AWARENESS
watching video /2/ _ENTITY_ = AWARENESS
watch#VBG video /2/ _ENTITY_ = AWARENESS
it be /1/ [J] ad = AWARENESS
it be /1/ [J] advert = AWARENESS
it be /1/ [J] advertisement = AWARENESS
it be /1/ [J] advertising = AWARENESS
it be /1/ [J] adv = AWARENESS
it be /1/ [J] campaign = AWARENESS
it be /1/ [J] commercial = AWARENESS
it be /1/ [J] video = AWARENESS
it be /1/ [J] tv = AWARENESS
stare#VBG /1/ at /2/ _ENTITY_ = AWARENESS
i /1/ rather get /12/ than = EVALUATION
id rather get /12/ than = EVALUATION
i would rather get /12/ than = EVALUATION
think i be get = EVALUATION
think i be aim = EVALUATION
not /1/ buy /2/ unless = EVALUATION
would rather drive = EVALUATION

i would rather drive = EVALUATION
new car i buy will = EVALUATION
ENTITY be off the list = EVALUATION
browsing /2/ [N] = EVALUATION
browse#VBG /2/ [N] = EVALUATION
ENTITY /2/ or [NP] /4/ be my next = EVALUATION
[NP] /2/ or _ENTITY_ /4/ be my next = EVALUATION
can [RB] decide if = EVALUATION
buy#VBG /2/ will be the well = EVALUATION
buy#VBG /2/ would be the well = EVALUATION
my next [N] will either be = EVALUATION
close to get#VBG my = PURCHASE
my future [N] = PURCHASE
bout to get my _ENTITY_ = PURCHASE
buy#VBG /2/ _ENTITY_ /2/ if i = PURCHASE
buying /2/ _ENTITY_ /2/ if i = PURCHASE
decision /1/ make#VBN = PURCHASE
deffo get#VBG /3/ _ENTITY_ = PURCHASE
gonna have to buy = PURCHASE
found my next [N] = PURCHASE
i can not wait to get my _ENTITY_ = PURCHASE
i can not wait to get /2/ _ENTITY_ = PURCHASE
i will own /3/ _ENTITY_ = PURCHASE
be gonna buy /2/ _ENTITY_ = PURCHASE
be gonna trade my /3/ for /3/ _ENTITY_ = PURCHASE
i be save /2/ for /2/ _ENTITY_ = PURCHASE
ENTITY do /1/ seem to care = POSTPURCHASE
my /2/ _ENTITY_ not kick = POSTPURCHASE
power /3/ fail = POSTPURCHASE
my /2/ service = POSTPURCHASE
what be wrong with my = POSTPURCHASE
what be go on with my = POSTPURCHASE
what be going on with my = POSTPURCHASE

very disappoint = POSTPURCHASE
wait#VBG for /2/ resolution = POSTPURCHASE
wait#VBG for /2/ answer = POSTPURCHASE
wait#VBG for /2/ solution = POSTPURCHASE
in style /4/ _ENTITY_ = POSTPURCHASE
tell me my _ENTITY_ be [J] /6/ happy = POSTPURCHASE
i miss /3/ my _ENTITY_ = POSTPURCHASE
i [MD] never ever buy another = POSTPURCHASE
system /9/ be flaw = POSTPURCHASE
lose#VBD me as /2/ customer = POSTPURCHASE
wreck#VBD my _ENTITY_ = POSTPURCHASE
i usually get = POSTPURCHASE
not be#VBN in /3/ _ENTITY_ for = POSTPURCHASE
will never [V] /1/ _ENTITY_ /1/ again = POSTPURCHASE
guy /1/ work at _ENTITY_ = POSTPURCHASE
i will wear my = POSTPURCHASE
stick to /1/ _ENTITY_ = POSTPURCHASE
ENTITY or [NP] /2/ "?" = EVALUATION
[NP] or _ENTITY_ /2/ "?" = EVALUATION
should i [V] /1/ _ENTITY_ or = EVALUATION
should i [V] /1/ [NP] or _ENTITY_ = EVALUATION
ima go to _ENTITY_ or = EVALUATION
ima go to /2/ or _ENTITY_ = EVALUATION
if i want _ENTITY_ or = EVALUATION
if i want [NP] or _ENTITY_ = EVALUATION
i be [VBG] to _ENTITY_ or = EVALUATION
i be [VBG] to [NP] or _ENTITY_ = EVALUATION
may [V] to _ENTITY_ or = EVALUATION
may [V] to [NP] or _ENTITY_ = EVALUATION
new /1/ [N] _ENTITY_ or = EVALUATION
new /1/ [N] [NP] or _ENTITY_ = EVALUATION
choose /2/ [NP] or _ENTITY_ = EVALUATION
choose /2/ _ENTITY_ or = EVALUATION

if i /1/ [V] /1/ _ENTITY_ or = EVALUATION
if i /1/ [V] /1/ [NP] or _ENTITY_ = EVALUATION
[NP] or _ENTITY_ for [J] = EVALUATION
ENTITY or [NP] for [J] = EVALUATION
[VB] my /4/ _ENTITY_ or [NP] = EVALUATION
[VB] my /4/ [NP] or _ENTITY_ = EVALUATION
i /2/ either /2/ _ENTITY_ or = EVALUATION
i /2/ either /2/[NP] or _ENTITY_ = EVALUATION
write /2/ letter of complaint = POSTPURCHASE
think#VBG about [VBG] /3/ _ENTITY_ = EVALUATION
think#VBG about it = EVALUATION
hard choice = EVALUATION
difficult choice = EVALUATION
tough choice = EVALUATION
think i will /2/ look = EVALUATION
think we will /2/ look = EVALUATION
think i will /2/ buy = EVALUATION
think we will /2/ buy = EVALUATION
think i will /2/ shop = EVALUATION
think we will /2/ shop = EVALUATION
i /3/ research#N = EVALUATION
have to be substitute = POSTPURCHASE
i do not /2/ pay = POSTPURCHASE
trip to _ENTITY_ = POSTPURCHASE
just see#VBN /2/ in /1/ _ENTITY_ = POSTPURCHASE
just see#VBN /2/ in /1/ _ENTITY_ = POSTPURCHASE
just “saw” /2/ in /1/ _ENTITY_ = POSTPURCHASE
i be#VBP at _ENTITY_ = PURCHASE
i be#VBP in _ENTITY_ = PURCHASE
i be#VBD at _ENTITY_ = POSTPURCHASE
i be#VBD in _ENTITY_ = POSTPURCHASE
leave my /4/ at _ENTITY_ = POSTPURCHASE
leave my /4/ in _ENTITY_ = POSTPURCHASE

leave my /4/ on _ENTITY_ = POSTPURCHASE
ENTITY /2/ just see#VBN = POSTPURCHASE
i /1/ buy#VBD /3/ _ENTITY_ = POSTPURCHASE
buy#VBD my /2/ _ENTITY_ = POSTPURCHASE
buy#VBD myself /2/ _ENTITY_ = POSTPURCHASE
buy#VBN /3/ _ENTITY_ = POSTPURCHASE
never shop at _ENTITY_ = POSTPURCHASE
i have just switch#VBN /3/ _ENTITY_ = POSTPURCHASE
i have just be#VBN /3/ _ENTITY_ = POSTPURCHASE
i have just spend#VBN /3/ _ENTITY_ = POSTPURCHASE
i be#VBP buy /2/ _ENTITY_ = POSTPURCHASE
be#VBP buy /2/ _ENTITY_ = POSTPURCHASE
i be#VBP buy#VBG /1/ _ENTITY_ = PURCHASE
i be#VBP order#VBG /1/ _ENTITY_ = PURCHASE
i be#VBP purchase#VBG /1/ _ENTITY_ = PURCHASE
i be#VBP shop#VBG /1/ _ENTITY_ = PURCHASE
i be wear#VBG /1/ _ENTITY_ = POSTPURCHASE
i be drive#VBG /1/ _ENTITY_ = POSTPURCHASE
i be drink#VBG /1/ _ENTITY_ = POSTPURCHASE
i be use#VBG /1/ _ENTITY_ = POSTPURCHASE
wait for my new = POSTPURCHASE
just lace#V = POSTPURCHASE
lace#VBG = POSTPURCHASE
to go /1/ back to _ENTITY_ = PURCHASE
walk#VBG to _ENTITY_ = PURCHASE
walk#VBG around _ENTITY_ = PURCHASE
i be shop#VBG /3/ _ENTITY_ = PURCHASE
up the _ENTITY_ /5/ drink = PURCHASE
drink /5/ up the _ENTITY_ = PURCHASE
to run to _ENTITY_ /1/ to get = PURCHASE
to drive to _ENTITY_ /1/ to get = PURCHASE
to go to _ENTITY_ /1/ to get = PURCHASE
walk#VBG /1/ _ENTITY_ /4/ [V] = PURCHASE

be#VBP consider join = EVALUATION

never buy another = POSTPURCHASE

never buy /6/ again = POSTPURCHASE

i will get “a” _ENTITY_ = PURCHASE

i will get “an” _ENTITY_ = PURCHASE

i will get _ENTITY_ = PURCHASE

i /1/ gettin “a” _ENTITY_ = PURCHASE

i /1/ gettin “an” _ENTITY_ = PURCHASE

i /1/ gettin _ENTITY_ = PURCHASE

we will get “a” _ENTITY_ = PURCHASE

we will get “an” _ENTITY_ = PURCHASE

we will get _ENTITY_ = PURCHASE

we /1/ gettin “a” _ENTITY_ = PURCHASE

we /1/ gettin “an” _ENTITY_ = PURCHASE

we /1/ gettin _ENTITY_ = PURCHASE

let us see if = EVALUATION

let me see if = EVALUATION

win [Z] point = POSTPURCHASE

win [Z] points = POSTPURCHASE

earn [Z] point = POSTPURCHASE

earn [Z] points = POSTPURCHASE

win [DT] _ENTITY_ = AWARENESS

i dont /2/ understand /1/ _ENTITY_ commercial = AWARENESS

i dont /2/ understand /1/ _ENTITY_ ad = AWARENESS

i dont /2/ understand /1/ _ENTITY_ adv = AWARENESS

i dont /2/ understand /1/ _ENTITY_ advert = AWARENESS

i dont /2/ understand /1/ _ENTITY_ advertisement = AWARENESS

i dont /2/ understand /1/ _ENTITY_ campaign = AWARENESS

i do /2/ understand /1/ _ENTITY_ commercial = AWARENESS

i do /2/ understand /1/ _ENTITY_ ad = AWARENESS

i do /2/ understand /1/ _ENTITY_ adv = AWARENESS

i do/2/ understand /1/ _ENTITY_ advert = AWARENESS

i do /2/ understand /1/ _ENTITY_ advertisement = AWARENESS

i do /2/ understand /1/ _ENTITY_ campaign = AWARENESS
i dont /2/ understand [W] /3/ _ENTITY_ = POSTPURCHASE
i do /2/ understand [W] /3/ _ENTITY_ = POSTPURCHASE
love the _ENTITY_ app = POSTPURCHASE
love the _ENTITY_ /5/ ad = AWARENESS
love the _ENTITY_ /5/ adv = AWARENESS
love the _ENTITY_ /5/ advert = AWARENESS
love the _ENTITY_ /5/ advertisement = AWARENESS
love the _ENTITY_ /5/ commercial = AWARENESS
love the _ENTITY_ /5/ campaign = AWARENESS
wait [Z] minute = POSTPURCHASE
wait [Z] min= POSTPURCHASE
wait [Z] hour = POSTPURCHASE
wait [Z] week = POSTPURCHASE
wait [Z] month = POSTPURCHASE
my message go [IN] = POSTPURCHASE
i can not even use = POSTPURCHASE
i can not even call = POSTPURCHASE
i can not even receive = POSTPURCHASE
i can not even send = POSTPURCHASE
i can not even see = POSTPURCHASE
i can not even access = POSTPURCHASE
i can not even reply = POSTPURCHASE
we can not even use = POSTPURCHASE
we can not even call = POSTPURCHASE
we can not even receive = POSTPURCHASE
we can not even send = POSTPURCHASE
we can not even see = POSTPURCHASE
we can not even access = POSTPURCHASE
we can not even reply = POSTPURCHASE
laugh at /5/ ad = AWARENESS
laugh at /5/ adv = AWARENESS
laugh at /5/ advert = AWARENESS

laugh at /5/ advertisement = AWARENESS
laught at /5/ commercial = AWARENESS
laugh at /5/ campaign = AWARENESS
laugh at /5/ tv = AWARENESS
tire of /4/ ad = AWARENESS
tire of /4/ adv = AWARENESS
tire of /4/ advert = AWARENESS
tire of /4/ advertisement = AWARENESS
tire of /4/ commercial = AWARENESS
tire of /4/ campaign = AWARENESS
tire of /4/ tv = AWARENESS
sick of /4/ ad = AWARENESS
sick of /4/ adv = AWARENESS
sick of /4/ advert = AWARENESS
sick of /4/ advertisement = AWARENESS
sick of /4/ commercial = AWARENESS
sick of /4/ campaign = AWARENESS
sick of /4/ tv = AWARENESS
i /7/ at the _ENTITY_ arena = AWARENESS
i /7/ at the _ENTITY_ indigo = AWARENESS
i /7/ at the _ENTITY_ concert = AWARENESS
should /2/ [V] /6/ ad = AWARENESS
should /2/ [V] /6/ adv = AWARENESS
should /2/ [V] /6/ advert = AWARENESS
should /2/ [V] /6/ advertisement = AWARENESS
should /2/ [V] /6/ commercial = AWARENESS
should /2/ [V] /6/ campaign = AWARENESS
get invite to /4/ concert at _ENTITY_ = AWARENESS
put on /3/ of _ENTITY_ = AWARENESS
my new /4/ be so [J] /4/ _ENTITY_ = POSTPURCHASE
your /3/ be so [J] = POSTPURCHASE
staff /3/ be so [J] = POSTPURCHASE
be so /1/ rude = POSTPURCHASE

be so /1/ unhelpful = POSTPURCHASE
be so /1/ helpful = POSTPURCHASE
be so /1/ lazy = POSTPURCHASE
campaign be so [J] = AWARENESS
ENTITY /1/ bad = POSTPURCHASE

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