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Lekker, yummy, délicieux

Towards aspect-based sentiment analysis in Dutch, English and French

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Abstract


Aspect-based sentiment analysis is the task where a computer tries to identify which aspects or features of a particular product are expressed in reviews of consumer products. It also automatically determines whether the reviewer’s attitude towards each of the aspects is positive, negative or neutral. Originally ABSA systems were developed based on reviews written in English (Hu & Liu, 2004, Thet et al., 2010, Pontiki et al., 2014). Currently systems are being trained and developed for other languages as well. Because of the continuing globalization, the challenge is to create a multilingual system.

To this purpose, we first analysed a corpus of French, English and Dutch restaurant reviews to discover how aspects and sentiments are expressed in the different target languages. Our results revealed that there is a difference if we consider the amount of aspect terms per sentence. The French reviews contain 1.48 aspect terms per sentence whereas the English and Dutch reviews contain 1.25 and 1.06 respectively. This is because the French reviewers immediately got to the point, in all sentences they discussed at least one aspect of the restaurant in question. Another notable difference between the languages concerns the use of common nouns and proper nouns. In French aspect terms are almost never (0.1%) expressed by a proper noun. In English, however, 9.7% of the aspect terms are proper nouns and in Dutch 5%. The top three most frequently mentioned aspects in all three languages are service, food and restaurant. When it comes to polarity, the statistics revealed that the French reviews were the most critical with only 46.1% positive reviews. The English reviews were the most positive (66.1%) and the Dutch reviews could be found somewhere in between, with 57.6% positive annotations.

Next, for all three languages polarity lexicons were composed, after which their added value was tested using a lexicon-based approach. For each language, three different types of lexicons were developed. The first setup only looked for a match with a sentiment word in our single-word subjectivity lexicon. In the second setup, we also added a multiword lexicon. In the final setup, we investigated whether the efficiency of our system could be improved by adding a third lexicon consisting of negation markers to flip the sentiment.

Our results revealed that for French and English the system performed best when all three lexicons were applied, resulting in both higher accuracy and F-1 scores. For Dutch, most progress was achieved during the second setup. Even though flipping the polarity improved F-1 score for the positive class, this was outweighed by a lower overall accuracy and lower F-1 for the negative and neutral classes.

Finally, we performed a qualitative error analysis with a focus on the positive and negative classes to detect why, in some instances, our system was not able to predict the correct sentiment.
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Part 1
Chapter 1
Introduction

Today the Internet has more than ever become an outlet to ventilate and share our ideas, feelings, experiences and opinions. Blogs, Facebook, Twitter and fora are only a few platforms which we can use to do so. They allow us to reach far more people than just our friends and family. Consumers worldwide have recognised the potential of the World Wide Web. Before people would trust on traditional word-of-mouth (WOM) recommendations from acquaintances, friends, family, colleagues at work when buying a car, fridge, television, etc. (Bone, 1995). Nowadays consumers worldwide type in the product of their choice in their web browser and get direct access to numerous reviews. This ‘digital’ advice is called electronic word-of-mouth and can be defined as any statement consumers share via the Internet (e.g. web sites, social networks, instant messages, news feeds) about a product, service, brand, or company (Kietzmann & Canhoto, 2013).

The information added by site visitors is called user-generated content (Moens et al., 2014). User-generated content comes from regular people who voluntarily contribute data, information, or media that then appears before others in a useful or entertaining way, usually on the Web - for example, restaurant ratings, wikis, and videos (Krumm et al., 2008). User-generated content contains a lot of subjective material in the sense that people express their positive, negative or neutral opinion about all sorts of things, including specific products in the case of consumer reviews. These reviews also offer valuable information for companies and can actually influence buying behaviour (Bickart & Schindler, 2001). Companies can use the information provided by their customers to their advantage to improve products or services.

The objective of sentiment analysis is the automatic extraction of subjective information from text, rather than factual information (Liu, 2012). Applied to consumer reviews, the task of sentiment analysis is to automatically determine whether the reviewer’s attitude towards a product and its various aspects is positive, negative or neutral. This is known as aspect-based sentiment analysis (De Clercq, 2015). The challenge of aspect-based sentiment analysis is that it tries to identify which individual aspects or features of a particular product are expressed in the review. A review on a television, for example, is likely to contain the writer’s opinion on the quality of the screen, sound, width, design, power consumption, etc. whereas a review on a hotel is more likely to talk about the quality of the breakfast, bed, room service, hotel staff, etc.

Originally ABSA systems were developed based on reviews written in English (e.g., Hu & Liu, 2004, Thet et al., 2010, Pontiki et al., 2014). Currently systems are being trained and developed
for other languages as well (Pontiki et al., 2016). Because of the continuing globalization, the challenge is to create a multilingual system. To this purpose, we will first analyze a corpus of French, English and Dutch restaurant reviews to discover how aspects and sentiments are expressed in the different target languages. Next, we will investigate whether a multilingual lexicon-based system can be designed to automatically detect and predict the sentiment in the French, English and Dutch reviews. The main focus will be on exploring the added value of applying three different subjectivity lexicons to our approach. The first lexicon exclusively consists of single words. Next, we create and add a lexicon of multiword expressions. Finally, we investigate whether the efficiency of our system can be improved by adding a third and final lexicon consisting of negation markers that can flip the sentiment of the single-word sentiment expressions.

This Master’s thesis consists of six chapters and is structured as follows. Chapter 2 discusses the research and progress that has been made in the field of aspect-based sentiment analysis including definitions of relevant terminology. Chapter 3 describes how we composed and analyzed a multilingual corpus of French, English and Dutch consumer reviews. In chapter 4, we build a lexicon-based system to automatically perform the task of polarity classification. Furthermore, we explore the added value of creating and applying three different subjectivity lexicons to our system. Chapter 5 presents and discusses all experimental results. We perform both a quantitative and qualitative analysis. In chapter 6, we finish this thesis with a conclusion and prospects for future work.
Chapter 2
Literature overview

2.1 Sentiment analysis

Sentiment Analysis is the task of automatically deriving the opinion of the writer (Liu, 2012). The original focus of this research domain was on automatically deriving the sentiment from an entire document. The writer’s sentiment or opinion could be described as negative, positive or neutral. In relation to consumer reviews this means that sentiment analysis would try to find out whether the reviewer expressed a predominantly positive, negative or neutral attitude towards a specific product.

When consumers browse the Internet in search for reviews on the product they are looking to buy, they could be interested in this overall sentiment. It is more likely, however, that a potential buyer will be interested in the reviewer’s opinion on specific aspects of a product. When looking to buy a television: Do reviewers think the quality of the screen was poor, mediocre, good, excellent,...? How did they like the sound quality? The build quality? The connectivity options? When looking to book a hotel: What was the quality of the breakfast? Where the beds comfortable? Where the rooms clean? And the bathroom? Was the staff friendly?, etc.

These reviews also offer valuable information for companies. Bickart & Schindler (2001) showed that product reviews actually influence buying behaviour. Companies can use the information provided by their customers to their advantage to improve products or services. Given the large amount of information on the World Wide Web, it would take a considerable amount of time to analyze reviews manually. Therefore the availability of an automatic aspect-based analysis system is a valuable asset.

Such a fine-grained approach to sentiment analysis allows to identify opinions expressed towards specific entities and their attributes and is known as aspect-based sentiment analysis or ABSA (Pontiki et al., 2016). Liu (2012) defines an opinion as a quintuple, \((e_i; a_{ij}; s_{ijkl}; h_k; t_l)\), where \(e_i\) is the name of an entity, \(a_{ij}\) is an aspect of \(e_i\), \(s_{ijkl}\) is the sentiment on aspect \(a_{ij}\) of entity \(e_i\), \(h_k\) is the opinion holder, and \(t_l\) is the time when the opinion is expressed by \(h_k\). The sentiment \(s_{ijkl}\) is positive, negative, or neutral, or can be expressed with different strength or intensity levels.

ABSA comprises five subtasks (Liu 2012, De Clercq 2015), which will now be explained in closer detail based on an example review, as presented in Figure 2.1. This review was included in a
corpus of 100 game reviews manually annotated for an unpublished Bachelor’s thesis (Neve, 2016).

EN: Skate 3 is a fun skateboarding game. You can also play online which is a fun part of the game as well.

1. **Entity extraction and categorization**: Extract all entity expressions in a document collection, and categorize or group synonymous entity expressions into entity clusters (or categories). Each entity expression cluster should indicate a unique entity \( e_i \). The collection in our example consists of game reviews and the entity presented here is ‘Skate 3’, belonging to the category **PS3 games**.

2. **Aspect extraction and categorization**: Extract all aspect expressions of the entities, and categorize these aspect expressions into clusters. Each aspect expression cluster of entity \( e_i \) represents a unique aspect \( a_{ij} \). These aspects can be both explicit and implicit. The explicit
aspects in our example are 'spel' (game) and 'online' (online gaming). Other categories could be: Graphics, Gameplay, Multiplayer,..

3. **Opinion holder extraction and categorization**: Extract opinion holders - $h_i$ - for opinions from text or structured data and categorize them. In this review the writer's (nick)name could be derived from the metadata. For privacy reasons we chose to change the name into 'Reviewer X'.

4. **Time extraction and standardization**: Extract the times when opinions are given and standardize different time formats, $t_i$. This information can also be easily derived from the time stamp attached to the review: the review was written on September 8, 2015.

5. **Aspect sentiment classification**: Determine whether an opinion on an aspect $a_{ij}$ is positive, negative or neutral, or assign a numeric sentiment rating to the aspect, $s_{ijk}$. From our example we can deduce that the reviewer expressed a positive sentiment on the game as a whole. Furthermore the reviewer shared a positive sentiment on playing this game online.

The generated quintuples from our example are:

- (Skate 3, Online Gaming, positive, Reviewer X, September-8-2015)
- (Skate 3, Game, positive, Reviewer X, September-8-2015)

Aspect-based sentiment analysis can provide customers with a clear overview of what people who have bought and played Skate 3 thought about the game, graphics, gameplay, etc. These sentiments can then be summarized and visualized in an aspect-sentiment table like the one presented in Figure 2.2 (Pontiki et al., 2015).

![Figure 2.2: Table summarizing the average sentiment for each aspect of an entity](image)

The website [www.bol.com](http://www.bol.com) offers its visitors a similar overview (see Figure 2.3). The difference with the table presented in Figure 2.2 is that the customer has had to manually indicate whether positive or negative sentiment was expressed on a specific aspect. The objective of ABSA systems is to automatically extract this information from reviews (Pontiki et al. 2014, 2015, 2016). Since we assume that no mistakes were made in our manual annotation of the review in Figure 2.1, this is called a gold standard annotation. For a system to become efficient, it will need a considerable number of gold standard annotations to use as a train dataset. We will look more closely at how such a system works in the next section.
For the task of sentiment analysis in general, two existing approaches can be distinguished: a lexicon-based versus machine learning-based approach. Lexicon-based methods (e.g. Taboada et al., 2011) use subjectivity lexicons to determine the overall sentiment of a text. These lexicons consist of opinion words combined with their polarity. Words like magnificent, awesome, great will be tagged as positive, whereas awful, dreadful will be recognized as words with a negative connotation. Subjectivity lexicons have been created for different languages: Duoman (Jijkoun & Hofmann, 2009) and the pattern (De Smedt & Daelemans, 2012) for Dutch, SentiWordNet (Baccianella et al., 2010) and the MPQA lexicon (Wilson et al., 2005) for English.

The machine learning approach, on the other hand, requires a train dataset before being able to automatically perform sentiment analysis. Machine learning systems basically consist of classification algorithms (e.g. Naïve Bayes or Support Vector Machines (Mullen & Collier, 2004)) and a set of effective features to capture context and the relations between words (Liu, 2012). The classification algorithms are trained on a labeled dataset (Pang & Lee, 2008), which can be divided into three parts (Kotsiantis et al., 2007). The largest set comprises about two-thirds of your total dataset. This data is used to train a classifier and will most likely consist of gold standard annotations. The other third is split into two equal parts, i.e. a validation and test set. During the validation phase the system can still be fine-tuned for optimal performance. In a final step the system ready for production will be tested for performance on the test set.

For aspect-based sentiment analysis no generally accepted evaluation methodology exists yet (Schouten & Frasincar, 2016). Recently the International Workshop on Semantic Evaluation or SemEval (Pontiki et al., 2014, 2015, 2016) aimed to establish a controlled evaluation methodology to directly compare different approaches to the problem. SemEval can be described as a competition in which teams compete to build the best system to tackle the task of aspect-based sentiment analysis. First, each team receives the same gold standard train data annotated by the task organizers on the basis of which a system can be built. Next, unseen data, also annotated by the task organizers, is released during one to three days for each team to test their system. Each team’s system output is then evaluated by the organization using the same controlled evaluation methodology to facilitate the comparison of the different approaches.
2.2 Current state of the art in ABSA

ABSA is a fine-grained approach that aims to identify the aspects of the entities being reviewed and to determine the sentiment the reviewers express for each aspect (Pontiki et al. 2016). In this rapid growing field of research, ABSA systems have been developed for different domains: movie reviews (Thet et al. 2010), customer reviews of electronic products like digital cameras (Hu & Liu, 2004a), laptops (Brody & Elhadad, 2010, Pontiki et al. 2014, 2015), services (Long et al. 2010), restaurants (Ganu et al. 2009, Brody & Elhadad, 2010, Pontiki et al. 2014, 2015, De Clercq 2015) and hotels (Pontiki et al. 2015).

In general, creating an ABSA system goes as follows. First a corpus is collected from websites allowing users to review a product (Thet et al., 2015, De Clercq 2015). Next, the reviews are manually annotated creating a gold standard. A tool frequently used (Pontiki et al. 2014, 2015, De Clercq 2015) for annotation is BRAT1, the rapid annotation tool (Stenetorp et al., 2012). BRAT is a web-based tool supported by Natural Language Processing (NLP) and is available under an open-source license. The gold standard annotations can then be used as a training dataset for an ABSA system (Pontiki et al., 2014, 2015) to learn to automatically perform the annotation by indicating the various aspects and sentiments expressed towards these aspects. A good system also depends on a set of effective features to capture context and the relations between words (Liu, 2012).

ABSA systems consist of three tasks: aspect term extraction, aspect term aggregation or classification and aspect term polarity estimation (Liu, 2012, Pavlopoulos & Androutsopoulos, 2014; Pontiki et al., 2016; Schouten & Frasincar, 2016). Below we will discuss these three steps and present some of the most successful methods to deal with these subtasks.

The first task is called Aspect term extraction and aims to extract terms corresponding to aspects (e.g., 'Fifa 16', 'the visuals',...). We will discuss three approaches to tackle this task: frequency-based, syntax-based and supervised. Extraction based on frequency is one of the most common approaches. It aims to identify all nouns and noun phrases by using a part-of-speech (POS) tagger. In a next phase only the frequent ones are kept (Hu & Liu, 2004b). This method is effective because people tend to use the same vocabulary when they review the different aspects of a product. A disadvantage is that not all frequent nouns are aspects and not all aspects are frequently mentioned. Very specific aspects will therefore be missed. Hu & Liu (2004b) only extract single nouns and compound nouns and only those compound nouns appearing in more than one percent of all sentences are labeled as aspects. Frequency-based methods often produce many false positives. Scaffidi et al. (2007) designed a system, Red Opal, to deal with this problem. It incorporates baseline statistics from a corpus of 100 million English words. The frequency of a potential aspect in a review has to be higher than its baseline frequency to be labeled as an aspect.

Aspect term extraction can also be performed by using a syntax-based method. Not the frequency of a word is important, but the syntactical relations between individual words. Contrary to the frequency-based approach, not only nouns or noun phrases can be aspects. Experiments have shown that nearly 15% of the aspects are missed when only taking into

1 http://brat.nlplab.org/
consideration nouns and noun phrases as potential aspects (Zhao et al., 2010). The task of aspect term extraction can also be tackled by using supervised learning. Basically a classifier is trained by offering a set of gold standard annotations. Next Aspect term aggregation or classification aims to assign aspect categories (e.g., ‘gameplay’, ‘graphics’, ...). The approach for the SemEval task was different since several predefined and domain-specific categories had to be predicted, which transformed the aggregation task into a multiclass classification task (De Clercq, 2015). For this task a classifier (e.g. Naïve Bayes or Support Vector Machines (Mullen & Collier, 2004)) is trained by offering a set of gold annotations. The features that are derived from the data are often lexical in nature, but in more recent work semantic information is also incorporated. De Clercq (2015) used semantic information provided by the Wikipedia-based knowledge base (Hovy et al., 2013) DBpedia (Lehmann et al., 2013) and by Cornetto (Vossen et al., 2013) which combines the Dutch wordnet (Vossen, 1998) and the Referentie Bestand Nederlands (Maks et al., 1999, Martin 2005).

The final task of Aspect term polarity estimation aims to evaluate the sentiment expressed towards each aspect of a specific entity. A positive, negative or neutral label can be assigned. Polarity estimation is similar to the standard sentiment classification which was discussed in the previous section.

2.3 Cross-language sentiment classification

Originally ABSA systems were developed based on reviews written in English (e.g., Hu & Liu, 2004, Thet et al. 2010, Pontiki et al. 2014). Currently systems are being trained and developed in other languages as well. De Clercq (2015) was the first to compile and annotate a corpus of Dutch (restaurant) reviews and built an ABSA system to handle these reviews. In 2016 the SemEval task became multilingual with datasets available to test ABSA systems in the following languages: English (consumer electronics and restaurants), Arabic (hotels), Chinese (consumer electronics), Dutch (restaurant and consumer electronics), French (restaurants), Russian (restaurants), Spanish (restaurants) and Turkish (restaurants and telecom) (Pontiki et al., 2016). All data was annotated using the same annotation guidelines to increase the comparability of the multilingual datasets and the applicability of the systems. The task has three subtasks: Sentence-level (SB1), Text-level (SB2) and Out-of-domain ABSA (SB3). These subtasks are further divided into three slots: The first is Aspect Category Detection and consists of an Entity#Attribute (E#A) pair. The second is Opinion Target Expression (OTE) and the last slot is Sentiment Polarity which is a ternary classification task (positive, negative or neutral). Each team could submit two runs per slot and domain in each phase: constrained (C) and unconstrained (U). The former only allows the provided train data to be used, whereas for the latter the system could be trained using other resources (e.g. publically available lexica) and additional data of any kind (Pontiki et al., 2016).

http://alt.qcri.org/semeval2016/task5/
For this master’s thesis we focus on two other languages as well, i.e. French and Dutch. This section discusses the progress made for both languages with a focus on polarity classification since this will be the subject of our experimental setup.

**French**

Sentiment lexicons play a major role in sentiment analysis. For French few sentiment lexicons exist. The French WordNet (FREWN) was created as part of the EuroWordNet project (Vossen, 1999). Sagot and Fiser (2008) developed a freely available wordnet for French called WOLF\(^3\) (Wordnet Libre du Français). Mathieu (2000, 2006) created a sentiment lexicon of French verbs of emotion. Furthermore Chen and Skiena (2014) developed sentiment lexicons for 136 major languages, including French.

In recent years more and more systems have been built for French sentiment analysis. Zhang et al. (2012) present a compositional model for French sentiment analysis and focus on the importance of valence shifters when interpreting polarity. Examples are negation (*pas beau* - *not pretty*), intensifiers (*très vite* - *very fast*) and diminishers (*un peu cher* - *a bit expensive*). Vincent & Winterstein (2013) compiled a corpus of French hotel, movie and book reviews. Before training a SVM all of the reviews were tokenized, lemmatized and POS-tagged using MElt\(^4\), a freely available state-of-the-art sequence labeller for French, English, Spanish and Italian. Other tools for annotating French text with part-of-speech and lemma information are the language independent Treetagger (Schmid, 1995), available for numerous languages including French, English and Dutch and the LeTs Preprocess Toolkit (Van de Kauter, 2013) supporting French, English, Dutch and German. For French, the lemmatizer of the LeTs Preprocess toolkit was trained on the French Morphalou lexicon (Romary et al., 2004), which contains 580,000 tokens. The POS-Tagger was trained on the Dutch Parallel Corpus (Macken et al., 2011) containing more than ten million words. In 2015 DEFT\(^5\), the annual text-mining challenge for French, focused on the automatic sentiment analysis of French tweets. One of the participating teams (Abdaoui et al., 2015) built a supervised machine learning system and created two new French sentiment lexicons. The first lexicon FEEL (Abdaoui et al., 2014) is a translation of the NRC lexicon (Mohammad & Turney, 2010). The second lexicon was automatically extracted from the corpus of tweets compiled for the 2015 DEFT task.

Apidianaki et al. (2016) participated in the multilingual SemEval–2016 ABSA task (Pontiki et al., 2016) and were the first to annotate French datasets for ABSA. The first dataset comprised 457 restaurant reviews which were manually annotated and used to tackle the first subtask of in-domain sentence-level ABSA. The second set consisted of 162 museum reviews for out-of-domain ABSA (subtask 3). No particular problems were reported for the annotation of the French datasets following the guidelines for English ABSA–2015 (Pontiki et al., 2015), mainly because these languages are closely related and the entities and attributes in the reviews were very similar (Apidianaki, 2016). However, additional guidelines had to be described for the recurrent use of some expressions frequently used in French reviews, e.g. “*rapport qualité/prix*” (*value for money*). This expression evaluates two aspects, price and quality. Therefore sentences containing the expression were generally assigned two labels (e.g. Restaurant#Prices, Food#Quality). A second difficulty was the identification of entities. This task

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\(^3\) [http://alpage.inria.fr/~sagot/wolf.html](http://alpage.inria.fr/~sagot/wolf.html)


turned out to be easier in English because the dish names are often compound nouns (e.g. Shepherd’s pie, Pease pudding) whereas in French, dish names often consist of multiword expressions containing prepositional phrases. These prepositions are often ambiguous which complicates the correct identification of the entity. Apidianaki et al. (2016) presents the following examples:

“Nous avons pris les pâtes au foie gras et cèpes, celles-ci baignaient dans de la crème et de la crème balsamique!”

English: “We took the foie gras and porcini mushrooms pasta, which was floating in cream and balsamic cream!”

Here, the entity comprises the noun pâtes (pasta) and the prepositional phrase au foie gras et cèpes (with foie gras and porcini mushrooms). A negative sentiment is expressed towards the entire entity and the label FOOD#QUALITY is assigned. In the second example, the multiword expression is split:

“Les frites maison sont à volonté.”

English: “Homemade French fries at will.”

The entity only comprises the noun frites (French fries), because maison (homemade) and à volonté (at will) respectively expresses positive sentiment on the preparation and serving mode. Therefore the label FOOD#STYLE&OPTIONS was assigned.

In total 5 systems participated in subtask 1 for French. The system obtaining the best results for the task of polarity classification was XRCE/C (C = Constrained) with an accuracy of 78.826%. XRCE also ranked first for English, reaching an accuracy of 88.126%.

Dutch

In comparison to English, relatively few studies have focused on Dutch sentiment analysis and ABSA. Two sentiment lexicons for Dutch are publically available, Duoman (Jijkoun & Hofmann, 2009) and pattern (De Smedt & Daelemans, 2012). Maks and Vossen (2011) developed a lexicon model for subjectivity description of Dutch verbs. The model aims to serve as a framework for sentiment analysis systems. Chen and Skiena (2014) developed sentiment lexicons for 136 major languages, including Dutch.

Several tools to preprocess Dutch text have been developed. The LeTs Preprocessing toolkit (Van de Kauter, 2013) is a lemmatizer and POS-Tagger available for Dutch, English, French and German. For Dutch the lemmatizer was trained on the Celex lexicon (Baayen, 1993) comprising 200,000 tokens, whereas the POS-Tagger was trained on the Dutch Parallel Corpus (Macken et al., 2011) and Lassy Small (Van Noord et al., 2013). The latter is part of a large scale syntactic annotation project of written Dutch, i.e. SoNaR (Oostdijk et al., 2013) and actually consists of a second corpus, i.e. Lassy Large. The difference between the corpora is both quantitative and qualitative. Lassy Large is a 500-million-word corpus automatically annotated for POS, lemma and syntactic dependency. Lassy Small on the other hand comprises only one million words and the annotations were all manually verified. Other tools are the language independent TreeTagger (Schmid, 1995), available for Dutch, French and English and the Dutch Alpino Parser (Bouma et al., 2001).
De Clercq (2015) was the first to create an ABSA system for Dutch. The system incorporated semantic information provided by the Wikipedia-based knowledge base (Hovy et al., 2013) DBpedia (Lehmann et al., 2013) and by Cornetto (Vossen et al., 2013) which combines the Dutch wordnet (Vossen, 1998) and the Referentie Bestand Nederlands (Maks et al., 1999, Martin 2005). For the task of polarity classification, a polarity classifier used by Van Hee et al. (2014) was modified to analyze Dutch text.

For Dutch, four teams participated in the multilingual SemEval-2016 ABSA task (Pontiki et al., 2016). The Dutch dataset included 300 restaurant reviews or 1,722 sentences. The TGB system by Çetin et al. (2016) obtained the best results for slot 3, i.e. sentiment polarity detection with an accuracy of 77.814.
Chapter 3

Data

In this chapter the annotated French, English and Dutch reviews will be discussed in close detail. We will first elaborate on the origins of the datasets and how they have been annotated (Section 3.1). Next, the data is closely analyzed with respect to the annotated aspect terms, categories and polarities (Section 3.2).

3.1 Data collection and annotation

The French reviews were collected from TripAdvisor\(^1\) and discuss restaurants in France (Apidianaki et al., 2016). The annotation was executed by a linguist, native speaker of French and then checked and corrected by the task organizers.

The English reviews only discussed American restaurants and were retrieved from the online Yellow Pages\(^2\) and Citysearch\(^3\). The data was first annotated by an experienced linguist, also annotator for SE-ABSA14 and 15. Next, one of the task organizers checked the annotations and corrected if necessary.

The Dutch reviews evaluate Belgian restaurants and were retrieved from TripAdvisor\(^4\) (De Clercq & Hoste, 2016). The reviews were first annotated by a trained linguist before being verified by another linguist. Finally, the annotated data was checked, and if necessary corrected, by the task organizers.

All reviews have been annotated following the annotation guidelines that had been developed for the SemEval 2016 task. We will now describe these guidelines in more detail.

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4. [http://www.tripadvisor.be](http://www.tripadvisor.be)
First a review is split into sentences and each sentence is annotated with aspect terms, aspect categories and the sentiment expressed towards these aspects. Below is an example for all three languages.

**FR:** Et l'équipe est adorable!  
*target*="équipe" *category*="SERVICE#GENERAL" *polarity*="positive"

**EN:** Great food.  
*target*="food" *category*="FOOD#QUALITY" *polarity*="positive"

**DU:** Het buffet was zielig.  
*target*="buffet" *category*="FOOD_style" *polarity*="negative"

A distinction is made between explicit and implicit mentions. In the examples above, the reviewers explicitly mentioned the aspect terms *équipe, food* and *buffet*. In the examples below the reviewers implicitly review the restaurant. These implicit mentions are indicated with the term ‘NULL’.

**FR:** Nous reviendrons!  
*target*="NULL" *category*="RESTAURANT#GENERAL" *polarity*="positive"

**EN:** You can't go wrong here!  
*target*="NULL" *category*="RESTAURANT#GENERAL" *polarity*="positive"

**DU:** Goed maar niet schitterend!  
*target*="NULL" *category*="RESTAURANT#GENERAL" *polarity*="neutral"

In the examples above we saw some possible categories: *service, food, restaurant*. The SemEval annotation guidelines distinguish between Entities and Attributes. This can also be referred to as main and subcategories of aspects. This distinction allows for a more fine-grained analysis (Pontiki et al., 2014, 2015). In the SemEval ABSA task (Task 12) for annotating restaurant reviews Pontiki et al. (2015) defines several entities: *food, service, drinks,...* as well as some subcategories or attributes: *general, quality, price,...* This allows to make pairs combining entities and attributes {E#A}. An overview of the entities and attributes and their possible combinations can be found in Table 3.1.

<table>
<thead>
<tr>
<th>ASPECTS</th>
<th>General</th>
<th>Price</th>
<th>Quality</th>
<th>Style_options</th>
<th>Miscellaneous</th>
</tr>
</thead>
<tbody>
<tr>
<td>RESTAURANT</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>SERVICE</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOOD</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>AMBIENCE</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DRINKS</td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOCATION</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Table 3.1: Possible aspect-attribute combinations*
In Table 3.1 the combination RESTAURANT#STYLE_OPTIONS was not checked, even though it was used in one French review. This combination was, however, not included in the SemEval 2016 annotation guidelines.

FR: On en ressort avec la faim et la mauvaise impression de s’être fait plumé, avec la manière (Le saumon est disposé de telle sorte qu'il cache la forêt de salade verte qui donne l'impression d'un plat consistant.

Since other similar reviews for all three languages were all annotated with the RESTAURANT#GENERAL pair, we assumed the example above was not representative and therefore added the annotation to RESTAURANT#GENERAL in our statistics.

Finally, the sentiment expressed towards each aspect is evaluated. A positive, negative or neutral label can be assigned to the E#A pair. The neutral label does not imply the sentence was objective, rather it indicates a mildly positive or negative sentiment. Examples can be found above.

## 3.2 Corpus analysis

Based on the annotation corpus analysis was performed. Our corpus consisted of a train and test set, but it is important to note that the corpus analysis includes both sets. We envisaged to find out which aspect terms are used and whether we can pinpoint differences between the three studied languages. Next, we consider the aspect categories to find out which categories are referred to most often. Finally, the sentiment expressed towards the aspect terms is scrutinized.

### 3.2.1 Aspect terms

In total, our corpus of French, English and Dutch reviews included 6,656 sentences. 8,428 aspect terms or targets have been annotated including 6,035 explicit targets (=71.6%) and 2,393 (=28.4%) implicit targets, as visualized in Table 3.2.

<table>
<thead>
<tr>
<th>LANGUAGE</th>
<th>SENTENCES</th>
<th>EXPLICIT ASPECT TERMS</th>
<th>IMPLICIT ASPECT TERMS</th>
<th>ASPECT TERMS/SENTENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>2359</td>
<td>2488</td>
<td>996</td>
<td>1.48</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>2000</td>
<td>1875</td>
<td>624</td>
<td>1.25</td>
</tr>
<tr>
<td>DUTCH</td>
<td>2297</td>
<td>1672</td>
<td>773</td>
<td>1.06</td>
</tr>
</tbody>
</table>

Table 3.2: Number of aspect terms in the French, English and Dutch reviews.
No notable differences were observed between the three languages regarding the number of explicit/implicit aspect terms. However, there is a difference if we consider the amount of aspect terms per sentence, which is clearly higher in our French dataset. The French reviews contain 1.48 aspect terms per sentence whereas the English and Dutch reviews contain 1.25 and 1.06 respectively.

Two reasons could explain the higher aspect terms to sentence ratio for the French reviews. First, in the annotated French reviews only a few number of sentences did not discuss an aspect. Almost all sentences discuss at least one aspect of the restaurant in question. In the English and Dutch reviews the reviewers often give more context, more trivia, as exemplified below.

**NL:** Op aanraden van Carolien van **B&B Côte Canal** in Brugge kwamen we hier terecht .
(We came here on the recommendation of Carolien from **B&B Côte Canal** in Bruges)

**EN:** The two star chefs left quite some time ago to open their own place.

Second, the French reviews often discuss more than three aspect terms per sentence, whereas the Dutch and French sentences mostly only deal with one or two. Below is an example of a French review in which nine targets were annotated.

Menu complet de très bon rapport qualité/prix (produits proposés, cuisson et présentation des assiettes) et service rapide mais il faut améliorer quelques points pour être un bon restaurant : entretien des appareils sanitaires dans la "salle d'eau", chaleur de l'accueil et choix des vins proposés (je viens juste de voir sur tripadvisor qu'il s'agissait d'un bar à vins, je n'ai pas compris le concept alors.)

1. <Opinion target="Menu" category="FOOD#PRICES" polarity="positive">
2. <Opinion target="Menu" category="FOOD#QUALITY" polarity="positive">
3. <Opinion target="produits" category="FOOD#QUALITY" polarity="positive">
4. <Opinion target="assiettes" category="FOOD#STYLE_OPTIONS" polarity="positive">
5. <Opinion target="service" category="SERVICE#GENERAL" polarity="positive">
6. <Opinion target="restaurant" category="RESTAURANT#GENERAL" polarity="negative">
7. <Opinion target="NULL" category="RESTAURANT#MISCELLANEOUS" polarity="negative">
8. <Opinion target="accueil" category="SERVICE#GENERAL" polarity="negative">
9. <Opinion target="vins" category="DRINKS#STYLE_OPTIONS" polarity="negative">

In our literature overview (Section 2.2) it was mentioned that nearly 15% of the aspect terms are missed when only taking into consideration nouns and noun phrases as potential aspects (Zhao et al., 2010). We therefore looked at the parts of speech of our aspect terms in closer detail. To this purpose, the LeTs Preprocessing toolkit (Van de Kauter, 2013) was used. The result was a list of annotated aspect terms for each language combined with their lemmas and parts of speech. The list contained 1,363 French targets, 1,193 English targets and 1,654 Dutch targets from our corpus. Afterwards, these extensive, automatically generated lists were manually verified to detect and correct possible errors. In the examples below, the actual aspect term is followed by the lemma and the tags generated by the LeTs toolkit. A list of all errors and their corrections can be found in appendix A.
Each language has its own tagset to indicate to which part of speech a word belongs. To make the comparison between the languages more transparent, we used the same tags and parts of speech for French, English and Dutch. We therefore made a selection out of the three tagsets to keep what was relevant for our three languages. The different verb tags in English, for example, were not retained because these tags were not included in the French and Dutch tagsets. In addition, the minor number of verbs in our corpus did not justify a further division. In the Dutch tagset foreign words and the names of the restaurants and waiters were classified under the SPEC-tag, whereas in English there is a specific tag for foreign words (FW) and another for proper nouns (NNP). We chose the English tags and manually changed the Dutch SPEC-tags into FW or NNP. Furthermore, the French tagset not only distinguishes between prepositions (PRP) and articles (DET:ART), but includes a third tag, i.e. PRP:det which is a combination of both. This is because in French a preposition and an article are contracted in some cases, as exemplified by the example below.

FR: mousse au chocolat = mousse (à + le) chocolat

The tag PRP:det occurred 55 times (=3.1%) in the French corpus, the tag PRP 75 times (=4.3%) and the tag DET:ART 7 times (=0.4%). We did not retain the tag PRP:det, but chose to add the 55 tags to both the tag PRP (75 +55) and the tag DET:ART (7+55). The final list of word classes and the respective statistics of all aspect terms in French, English and Dutch are presented in Table 3.3.

<table>
<thead>
<tr>
<th>WORD CLASS</th>
<th>FRENCH</th>
<th>ENGLISH</th>
<th>DUTCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOUN</td>
<td>87.1%</td>
<td>75.4%</td>
<td>83.4%</td>
</tr>
<tr>
<td>PROPER NOUN</td>
<td>0.1%</td>
<td>9.7%</td>
<td>5%</td>
</tr>
<tr>
<td>PREPOSITION</td>
<td>7.2%</td>
<td>1.7%</td>
<td>3%</td>
</tr>
<tr>
<td>DETERMINER</td>
<td>3.4%</td>
<td>0.8%</td>
<td>0.8%</td>
</tr>
<tr>
<td>ADJECTIVE</td>
<td>3.3%</td>
<td>6.6%</td>
<td>3.5%</td>
</tr>
<tr>
<td>PRONOUN</td>
<td>0.1%</td>
<td>0.2%</td>
<td>0.1%</td>
</tr>
<tr>
<td>FOREIGN WORD</td>
<td>0.1%</td>
<td>2%</td>
<td>1%</td>
</tr>
<tr>
<td>SYMBOL</td>
<td>0.3%</td>
<td>0.8%</td>
<td>1%</td>
</tr>
<tr>
<td>ADVERB</td>
<td>0.2%</td>
<td>0%</td>
<td>0.04%</td>
</tr>
<tr>
<td>VERB</td>
<td>0.3%</td>
<td>0.5%</td>
<td>0%</td>
</tr>
<tr>
<td>NUMERAL</td>
<td>0.2%</td>
<td>0.4%</td>
<td>0.4%</td>
</tr>
<tr>
<td>CONJUNCTION</td>
<td>0.3%</td>
<td>1.2%</td>
<td>1%</td>
</tr>
</tbody>
</table>

Table 3.3: Percentage of targets belonging to a specific word class.

In all three languages aspect terms are expressed most often by a noun. Our results confirm that nearly 15% of the aspect terms are missed when only taking into consideration nouns
and noun phrases as potential aspects (Zhao et al., 2010). For English, 14.9% of the aspect terms would be missed, for French 12.8% and for Dutch 11.6%. However, there is a notable difference between the languages when we distinguish between common nouns and proper nouns. In French aspect terms are almost never (0.1%) expressed by a proper noun. In the English reviews, on the other hand, 9.7% of the aspect terms is a proper noun and in the Dutch 5%. This is because the English and Dutch reviewers often explicitly mention the name of the restaurant and sometimes the name of a waiter or waitress. No such mentions were found in the French reviews.

A second outspoken difference between the French aspect terms and the English and Dutch aspect terms is the number of determiners and prepositions. Multiword expressions in French often take a preposition and a determiner. In Dutch the words are mostly contracted to form one longer word and in English the words are contracted or simply separated by a whitespace. Below are three examples per language.

FR: mousse au chocolat, fruits de mer, pommes de terre
EN: chocolate mousse, seafood, potatoes
DU: chocolademousse, zeevruchten, aardappelen

The results in Table 3.3 indicate that the French, English and Dutch reviewers use very few or no verbs to express an aspect term. This is only partially true. Initially the LeTs POS-tagger generated a higher number of verbs. However, when manually verifying the tags, we saw that most verb-tags were actually verbs used as an adjective. We therefore changed the label to adjective. Below is an example for each language.

FR: salade composée
EN: grilled potato
DU: gefrituurde pijlinktvis

In a next phase, we manually verified our aspect term list to discover how many words each target consists of and in which language the most multiword aspect terms were used. For each language the percentage of single- and multiword targets was calculated in relation to the total number of targets for the respective languages, as illustrated in Figure 3.1.

![Figure 3.1: Percentage of single- and multiword aspect terms in our corpus.](image)
The French corpus, for example, consists of 1,363 targets, 1,179 (86.5%) of which are single-word targets against 184 (13.5%) multiword targets. Figure 3.1 clearly shows that the (American) English reviews contain the most multiword targets and the least single-word targets.

Finally, we investigated which targets were discussed most frequently in each language. We therefore generated frequency lists using Python 2.7, a programming tool which can be legally downloaded for free from the official website. The top 10 French, English and Dutch targets are presented in Table 3.4. The complete lists can be found in appendix B.

<table>
<thead>
<tr>
<th>FRENCH</th>
<th>ENGLISH</th>
<th>DUTCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Service</td>
<td>Food</td>
<td>Bediening (service)</td>
</tr>
<tr>
<td>2 Plats (dishes/meals)</td>
<td>Service</td>
<td>Eten (food)</td>
</tr>
<tr>
<td>3 Restaurant</td>
<td>Place</td>
<td>Restaurant</td>
</tr>
<tr>
<td>4 Cuisine (kitchen)</td>
<td>Restaurant</td>
<td>Personeel (staff)</td>
</tr>
<tr>
<td>5 Accueil (reception)</td>
<td>Staff</td>
<td>Gerechten (dishes/meals)</td>
</tr>
<tr>
<td>6 Cadre (setting)</td>
<td>Pizza</td>
<td>Sfeer (atmosphere)</td>
</tr>
<tr>
<td>7 Carte (menu)</td>
<td>Atmosphere</td>
<td>Zaak (a business)</td>
</tr>
<tr>
<td>8 Produits (products)</td>
<td>Sushi</td>
<td>Ober (waiter)</td>
</tr>
<tr>
<td>9 Repas (dishes/meals)</td>
<td>Decor</td>
<td>Keuken (kitchen)</td>
</tr>
<tr>
<td>10 Personnel (staff)</td>
<td>Menu</td>
<td>Wijn (wine)</td>
</tr>
</tbody>
</table>

Table 3.4: Original top 10 French, English and Dutch targets in our corpus.

Important to note is that we manually verified the lists generated by Python to optimize the top ten. The target wine, for example, initially was not included in the French and English lists. This was because the reviewers frequently mentioned this aspect in combination with a bottle of or a glass of. We therefore chose to only consider the head noun when dealing with multiword targets. The same goes for plurals. For French, for example, the target plats (meals/dishes) was also frequently mentioned in the singular form plat. For Dutch we added the target service to the target bediening (service) because they dealt with the exact same topic. Except for the target wine, this manual check only implied some minor changes to the original top ten lists, as shown in Table 3.5.

<table>
<thead>
<tr>
<th>FRENCH</th>
<th>ENGLISH</th>
<th>DUTCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Service</td>
<td>Food</td>
<td>Bediening (service)</td>
</tr>
<tr>
<td>2 Plats (dishes/meals)</td>
<td>Service</td>
<td>Eten (food)</td>
</tr>
<tr>
<td>3 Restaurant</td>
<td>Place</td>
<td>Restaurant</td>
</tr>
<tr>
<td>4 Cuisine (kitchen)</td>
<td>Staff</td>
<td>Wijn (wine)</td>
</tr>
<tr>
<td>5 Accueil (reception)</td>
<td>Pizza</td>
<td>Personeel (staff)</td>
</tr>
<tr>
<td>6 Carte (menu)</td>
<td>Restaurant</td>
<td>Gerechten (dishes/meals)</td>
</tr>
<tr>
<td>7 Vin (wine)</td>
<td>Atmosphere</td>
<td>Sfeer (atmosphere)</td>
</tr>
<tr>
<td>8 Repas (dishes/meals)</td>
<td>Wine</td>
<td>Ober (waiter)</td>
</tr>
<tr>
<td>9 Cadre (setting)</td>
<td>Sushi</td>
<td>Zaak (a business)</td>
</tr>
<tr>
<td>10 Produits (products)</td>
<td>Menu</td>
<td>Keuken (kitchen)</td>
</tr>
</tbody>
</table>

Table 3.5: Updated top ten top 10 French, English and Dutch targets in our corpus.
Based on Table 3.5, we can state that the top three is rather similar for all three languages and deals with the same three topics: the food itself, where it is served and how it is served, i.e. the aspects FOOD, RESTAURANT, SERVICE.

Other targets appear to be more culture- or language-specific. The French aspect term *accueil* (*reception*), for example, is the number five most mentioned French aspect term, but does not even pop up in the English or Dutch top ten. This could lead us to the conclusion that the French consider a warm and welcoming reception more important than the American or Belgian reviewers.

The targets *Pizza* and *Sushi*, on the other hand, only appear in the English top ten. In contrast to our French and Dutch corpus, the English corpus included a large number of reviews discussing Asian and Italian restaurants. All other targets in the three top ten lists are more general and are more likely, we think, to appear in the top ten regardless of the type of restaurant.

### 3.2.2 Categories

Table 3.4 in the previous section showed that the top three targets for each language were all related to the same three categories, i.e. FOOD, RESTAURANT, SERVICE. By analyzing the main attribute categories in our corpus, we observe that those three aspects are in fact referred to most often with the aspect FOOD as a clear number one, as illustrated in Figure 3.2.

1. Food - 3,501 mentions (41.5%)
2. Restaurant - 1,899 mentions (22.5%)
3. Service - 1,750 mentions (20.8%)

![Figure 3.2: Pie chart representing the three most referred to categories](image)

These three aspects seem to be the most important criteria when reviewing a restaurant and can be considered as being the basics of a good restaurant. The other aspects DRINKS, LOCATION and AMBIENCE seem to be an added value, but not the most important part of a restaurant visit. Combined, the top three aspects are referred to 7,150 times (≈84.8% of all
aspects). The results show that in the Dutch reviews the aspect SERVICE is evaluated more frequently than the aspect RESTAURANT. Table 3.6 lists the top three annotated categories in each language.

<table>
<thead>
<tr>
<th>LANGUAGE</th>
<th>MOST POPULAR CATEGORIES</th>
<th>ANNOTATIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>1. FOOD</td>
<td>1477 - 42.4%</td>
</tr>
<tr>
<td></td>
<td>2. REST</td>
<td>794 - 22.8%</td>
</tr>
<tr>
<td></td>
<td>3. SERV</td>
<td>724 - 20.8%</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>1. FOOD</td>
<td>1071 - 42.9%</td>
</tr>
<tr>
<td></td>
<td>2. REST</td>
<td>599 - 24%</td>
</tr>
<tr>
<td></td>
<td>3. SERV</td>
<td>443 - 17.7%</td>
</tr>
<tr>
<td>DUTCH</td>
<td>1. FOOD</td>
<td>953 - 39%</td>
</tr>
<tr>
<td></td>
<td>2. SERV</td>
<td>583 - 23.8%</td>
</tr>
<tr>
<td></td>
<td>3. REST</td>
<td>506 - 20.7%</td>
</tr>
</tbody>
</table>

Table 3.6: Overview of the top three aspect categories for each language.

If we consider the aspect-attribute combinations, there are three combinations that were mentioned most often in all three languages. This is visualized in Table 3.7 and Figure 3.3.

<table>
<thead>
<tr>
<th>MOST POPULAR ASPECT-ATTRIBUTE COMBINATIONS</th>
<th>FRENCH</th>
<th>ENGLISH</th>
<th>DUTCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. FOOD-QUALITY</td>
<td>1002 - 28.8%</td>
<td>852 - 34.1%</td>
<td>675 - 27.6%</td>
</tr>
<tr>
<td>2. SERVICE-GENERAL</td>
<td>724 - 20.8%</td>
<td>443 - 17.7%</td>
<td>583 - 23.8%</td>
</tr>
<tr>
<td>3. RESTAURANT-GENERAL</td>
<td>529 - 15.2%</td>
<td>416 - 16.7%</td>
<td>437 - 17.8%</td>
</tr>
</tbody>
</table>

Table 3.7: Overview of the top three aspect-attribute combinations for each language.

Figure 3.3: Pie chart illustrating the distribution for the top three aspect-attribute combinations in our corpus.
We notice a considerable difference in mentions for all three languages between the most popular combination and the number two of the list. It seems that the absolute number one requirement for a good restaurant is good quality food. In comparison, the price of the food is one of the least mentioned aspect-attribute combinations. This could suggest that people are willing to pay a fair sum for their meal as long as the quality is up to par. The difference in popularity between the different aspect-attribute combinations for the aspect FOOD is shown in Figure 3.4.

The three least popular categories are AMBIENCE, DRINKS and LOCATION, as visualized in Figure 3.5. This could be because people do not consider these categories to be the most important aspects of a good restaurant visit. They expect a restaurant to get the basics right, i.e. food quality and good service.
3.2.3 Sentiment

If we consider the sentiment in the reviews, the statistics reveal that the French reviews were the most critical with only 46.1% positive reviews. The (American) English reviews were the most positive (66.1%) and the Dutch reviews can be found in between, with 57.6% positive annotations. This is visualized in Figure 3.6.

![Figure 3.6: Bar chart representing distribution of positive, negative and neutral sentiment in our corpus.](image)

A closer look at the sentiment expressed towards the top three aspects FOOD, RESTAURANT and SERVICE reveals that the French reviews are again the most negative, whereas the English reviews are the most positive. Furthermore, SERVICE is the only combination that gets more negative than positive comments in all three languages. This shows that our French, American and Belgian reviewers are very critical about the service they receive during a restaurant visit. Another explanation could be that they are more likely to mention the service when they had a negative experience. This is visualized in Table 3.8.

<table>
<thead>
<tr>
<th>LANGUAGE</th>
<th>MOST POPULAR CATEGORIES</th>
<th>+</th>
<th>-</th>
<th>NEUT</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>1. FOOD</td>
<td>45%</td>
<td>45%</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>2. REST</td>
<td>39%</td>
<td>54%</td>
<td>7%</td>
</tr>
<tr>
<td></td>
<td>3. SERV</td>
<td>40%</td>
<td>57%</td>
<td>3%</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>1. FOOD</td>
<td>69%</td>
<td>27%</td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td>2. REST</td>
<td>68%</td>
<td>28%</td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td>3. SERV</td>
<td>47%</td>
<td>50%</td>
<td>5%</td>
</tr>
<tr>
<td>DUTCH</td>
<td>1. FOOD</td>
<td>61%</td>
<td>30%</td>
<td>9%</td>
</tr>
<tr>
<td></td>
<td>2. SERV</td>
<td>45%</td>
<td>49%</td>
<td>6%</td>
</tr>
<tr>
<td></td>
<td>3. REST</td>
<td>59%</td>
<td>35%</td>
<td>6%</td>
</tr>
</tbody>
</table>

Table 3.8: Overview of the sentiment expressed towards the top three aspects in our corpus.
The difference in sentiment between the French and English reviews when discussing the aspects FOOD and RESTAURANT is remarkable. The English reviews are notably more positive than the French reviews, as illustrated in Figure 3.7.

In the previous section we observed that FOOD-QUALITY was by far the most popular aspect-attribute combination (Figure 3.4). The least popular combination with FOOD was FOOD-PRICES. When the price of the food is mentioned it is mostly combined with a negative sentiment. This is the case for the French, English and Dutch reviews. However, there is a difference between the languages in the proportion of positive-negative sentiment and in the number of times the price is mentioned. The combinations FOOD-PRICES and RESTAURANT-PRICES respective occur more than two and three times as often in the French reviews than in the Dutch reviews. We already mentioned that the French reviews were, in general, more critical and it appears that the French reviewers are especially more sensitive to a correct price setting. Figure 3.8 shows the number of times the price was mentioned in all three languages. Figure 3.9 presents the number of positive, negative and neutral mentions with regard to the price.

Figure 3.7: Bar chart visualizing the difference in sentiment towards the aspects FOOD and RESTAURANT in the French and English reviews.

Figure 3.8: Bar chart representing the mentions for the attribute PRICE in our corpus.
Based on Figure 3.9 we conclude that the customers in the French, English and Dutch reviews were rather negative when they discussed the price tag of the food, the drinks or the restaurant in general. There is, however, one exception to this observation as in the English reviews there were more positive than negative mentions of the DRINKS-PRICES combination. This is visualized in Figure 3.10. All other combinations with the attribute PRICES received a majority of negative comments.

If we have a closer look at the three least popular categories AMBIENCE, DRINKS and LOCATION we notice for all three languages that these categories get more positive than negative comments. As we already discussed earlier, this could be because people do not consider these categories to be the most important aspects of a good restaurant visit. They expect a restaurant to get the basics right, i.e. quality food and good service. The ambience, drinks and location are an added value and are more likely to be mentioned in a positive way. This is shown in Figure 3.11. More detailed statistics can be found in appendix C.
Figure 3.11: Bar chart representing the amount of positive and negative sentiment expressed with regard to the three least mentioned aspect-attribute combinations.
Chapter 4
Data

The objective of ABSA is threefold, i.e. to automatically: extract aspect terms related to the entities being reviewed, classify these terms into aspect categories and determine the sentiment the reviewers express for each aspect (Pontiki et al. 2014, 2015). For the experimental part of this thesis the focus is on the third step: polarity classification of the aspects. As mentioned in the literature overview two approaches can be followed to achieve these tasks: a lexicon-based approach and a machine learning-based approach. We will build a lexicon-based system based on our corpus of French, English and Dutch restaurant reviews. Section 4.1 discusses the data on which we will build our system. Next, section 4.2 describes our system in closer detail. Finally, section 4.3 explains how the results are evaluated.

4.1 Data

The corpus consists of the gold standard annotated French, English and Dutch restaurant reviews used for the SemEval 2016 task, which are divided into a larger train set and a smaller test set. Table 4.1 gives an overview of the number of sentences that are available for each subset.

<table>
<thead>
<tr>
<th></th>
<th>TRAIN SET</th>
<th>TEST SET</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>1733</td>
<td>694</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>1315</td>
<td>685</td>
</tr>
<tr>
<td>DUTCH</td>
<td>1722</td>
<td>575</td>
</tr>
</tbody>
</table>

Table 4.1: Number of sentences in the French, English and Dutch train and test sets of our corpus.
4.2 Lexicon-based approach

For this thesis, we manually set up French, English and Dutch subjectivity lexicons based on the restaurant reviews in the train set of our corpus to use in a lexicon-based approach to automatically determine the polarity of the test set. In a final step, the output will be compared to the gold standard annotations.

The lexicons consist of opinion words combined with their polarity, lemma and part of speech. We used the English tagset\(^5\) to specify the part of speech. Words like *wonderful, awesome, great* will be tagged as positive, whereas *awful, horrific* will be recognized as words with a negative connotation. For an overview of existing subjectivity lexicons for French, English and Dutch, we refer to section 2.3 in this thesis. The subjectivity lexicons we set up can be found in appendix C. Table 4.2 presents the number of positive and negative single words in the French, English and Dutch subjectivity lexicons.

<table>
<thead>
<tr>
<th></th>
<th>+</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>French</td>
<td>406</td>
<td>492</td>
</tr>
<tr>
<td>English</td>
<td>273</td>
<td>184</td>
</tr>
<tr>
<td>Dutch</td>
<td>376</td>
<td>362</td>
</tr>
</tbody>
</table>

Table 4.2: Number of positive and negative words in our single-words subjectivity lexicons.

We manually verified all sentences in the train set and extracted all words expressing positive or negative sentiment. Because both single and multiword sentiment expressions were found, we decided to draw up both single-word and multiword lexicons. Below are a few examples from both lexicons.

**FR:**
single-word: délicieux (delicious) - délicieux (lemma) - JJ (adjective)  
multiword: fond dans la bouche (melts in your mouth)

**EN:**
single-word: amazing - amazing - JJ  
multiword: hats off to the chef

**NL:**
single-word: braken (vomit) - braken - VB (verb)  
multiword: zijn geld waard (worth every penny)

When manually verifying the reviews and composing the subjectivity lexicons, we recognized a potential problem, i.e. sentences containing a sentiment word with a positive connotation, but preceded by (a) word(s) that flipped the sentiment. Let us consider the following examples from our corpus:

**FR:** Jamais déçu depuis trois ans. (Never been disappointed over the last three years.)

**EN:** The staff is not attentive.

\(^5\) [https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html](https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html)
DU: Dit is zeker geen aanrader. (I would definitely not recommend this place.)

All three sentences contain a negative or positive sentword (deçu, attentive, aanrader) preceded by a negation marker (jamais, not, geen) that can flip the sentiment. To explore the added value of these words with regard to the task of polarity classification, we created a third lexicon for each language, which can be found in appendix D.

In a next phase, a Python script was written to automatically perform the task of polarity classification based on the subjectivity lexicons. First, all reviews are preprocessed by the LeTs Preprocessing toolkit (Van de Kauter, 2013) to find the corresponding lemmas that can be matched to the lemmas in our single-word subjectivity lexicons. Next, the system aims to predict the polarity on sentence level. Three different experimental setups were designed. Setup 1 includes the single-word lexicons to find a lemma match. In the example below, the sentence is classified as positive, because our system detects a match between the lemmas of the words intimate (lemma: intimate) and superb (lemma: superb) in the sentence and in the subjectivity lexicons.

EN: Sentence 53: wish ny had more of these kind of places: intimate, superb
predicted: [u'RESTAURANT#PRICES', u'FOOD#QUALITY', u'SERVICE#GENERAL'] ['positive']
golden: [u'AMBIENCE#GENERAL', u'FOOD#QUALITY', u'RESTAURANT#GENERAL'] ['positive', 'positive', 'positive']

In setup 2, we add the multiword lexicons to look for a match on token level. Let us consider the same example:

EN: Sentence 53: wish ny had more of these kind of places: intimate, superb
predicted: [u'RESTAURANT#PRICES', u'FOOD#QUALITY', u'SERVICE#GENERAL'] ['positive']
golden: [u'AMBIENCE#GENERAL', u'FOOD#QUALITY', u'RESTAURANT#GENERAL'] ['positive', 'positive', 'positive']

The system not only found the two matches with the single-word lexicons, but was able to detect an expression, i.e. top notch from the multiword lexicon.

Setup 3 includes all three different lexicons, i.e. single-words, multiwords and negation markers to flip the sentiment. When a sentiment word from the single-word lexicons is detected amongst the first three words following the negation marker, then the polarity of the sentiment word in question will be flipped, as exemplified in the example below. First, the system adds positive sentiment to the sentence because it detects the word attentive from our positive subjectivity lexicon. Next, the system looks for negation markers and finds the word not, which correctly flips the sentiment from positive to negative.

EN: Sentence 614: the waitress was not attentive at all.
Negation present, flipping: positive
predicted: [u'SERVICE#GENERAL'] ['negative']
golden: [u'SERVICE#GENERAL'] ['negative']
4.3 System evaluation

To evaluate the efficiency of our system accuracy, precision, recall and the balanced F-1-measure will be calculated. Important to note is that our system predicted the sentiment on sentence level, whereas in the golden annotations sentiment is assigned on aspect level. When a sentence contains more positive than negative expressions, it is classified as positive, and vice versa. The neutral label is assigned in case an equal number of positive and negative expressions are detected. Undefined means the sentence did not contain any sentiment expression.

The starting point to grasp the meaning of the evaluation criteria, i.e. accuracy, precision, recall and F-1 is the 2-by-2 contingency table presented in Figure 4.1 (OpenCourseOnline, 2012).

<table>
<thead>
<tr>
<th></th>
<th>correct</th>
<th>not correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>selected</td>
<td>tp</td>
<td>fp</td>
</tr>
<tr>
<td>not selected</td>
<td>fn</td>
<td>tn</td>
</tr>
</tbody>
</table>

Figure 4.1: Screenshot of the 2-by-2 contingency table as presented by Professor Chris Manning, Stanford University.

When a system correctly (correct) assigns (selected) an aspect-label, then this is called a true positive (tp). If the system fails to identify (not selected) a real aspect (correct), this is called a false negative (fn). The term false positive (fp) is used when a system mistakenly assigns an aspect-label to a word that is not an aspect (aspect: not correct, selected). A true negative (tn) means that the system correctly did not select a word because it was, in fact, no aspect (aspect: not correct, not-selected).

Imagine a corpus of 100 manually annotated game reviews. Suppose the corpus contains 5000 words and we assigned the aspect-label to 200 words in our gold standard annotations. Let us say that our system found 150 out of the 200 aspects, but it also mistakenly assigned the aspect-label to 30 words. Our contingency table would look as follows:

<table>
<thead>
<tr>
<th></th>
<th>correct</th>
<th>not correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>SELECTED</td>
<td>150</td>
<td>30</td>
</tr>
<tr>
<td>NOT-SELECTED</td>
<td>50</td>
<td>4820</td>
</tr>
</tbody>
</table>

Table 4.3: 2-by-2 contingency table.

Given the fictive results presented in Table 4.3, accuracy, precision, recall and F-measure can now be calculated. For accuracy, the correct assignments are divided by the total number of assignments (Equation 4.1).
Accuracy = \frac{\text{true positives} + \text{true negatives}}{\text{true positives} + \text{true negatives} + \text{false positives} + \text{false negatives}} \tag{4.1}

\text{Accuracy} = 98.42\% 

Precision is the percentage of correct assignments by the system divided by the total number of assignments made by the system (Equation 4.2).

\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}} \tag{4.2}

\text{Precision} = 83.33\%

The precision of our fictive system is quite high, with 83.33\%. This means that when the system assigns the aspect-label to a word, it obtains a success rate of 83.33\%. This percentage also indicates whether a system produces a lot of noise, i.e. false positives. In our example the system produces few false positives and can therefore be labeled as not very noisy.

Recall is the second measure to evaluate the performance of a classifier. It represents the number of correct assignments found by the system divided by the total number of gold standard assignments (equation 4.3).

\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \tag{4.3}

\text{Recall} = 75\%

The recall percentage for our fictive system is relatively good with 75\%, which means that the system found 75\% of all aspects in the 100 reviews.

There is often a trade-off between precision and recall (OpenCourseOnline, 2012). The objective is to find a balance between good recall and good precision. A measure has been developed to combine precision and recall, i.e. F-measure (equation 4.4). \( P \) stands for precision and \( R \) stands for recall.

\[ F = \frac{1}{\frac{1}{p} + (1 - \frac{1}{R})} \tag{4.4} \]

This formula can be modified to change the importance of precision or recall for a specific system. In most cases a balanced F-1 measure is used (OpenCourseOnline, 2012) (equation 4.5).

\[ F1 = \frac{2PR}{P+R} \tag{4.5} \]

\[ F1 = 78.95 \]
Chapter 5
Evaluation

This chapter presents and discusses the results of our lexicon-based system that aimed to automatically perform the task of polarity classification. To this purpose, three different setups have been investigated. The first setup only looked for a match with a sentiment word in our single-word subjectivity lexicon. In the second setup, we added the multiword lexicon to increase our results. Finally, setup three not only looked for single and multiwords, but was also able to detect negation markers to flip the sentiment. Detailed results can be found in appendix E.

5.1 Setup 1: single words

Table 5.1 shows that our lexicon-based system based on single words alone performs average for accuracy on the French and Dutch test set. For English, the result is even less convincing with an accuracy rate of just over 50%.

<table>
<thead>
<tr>
<th></th>
<th>ACCURACY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setup 1</td>
<td></td>
</tr>
<tr>
<td>FRENCH</td>
<td>60.66</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>51.27</td>
</tr>
<tr>
<td>DUTCH</td>
<td>61.24</td>
</tr>
</tbody>
</table>

Table 5.1: Accuracy of our lexicon-based system in setup 1.

Accuracy only gives a general impression of how our system performed. As our focus is on polarity extraction, we also want to know how the system performed on extracting the individual sentiments. Therefore, precision, recall and F-1 measure were calculated. The results are presented in Tables 5.2, 5.3 and 5.4.
The results reveal that our system only performs reasonably well on both precision and recall when it comes to extracting positive sentiment. In section 3.3 we saw that the English and Dutch reviews contained considerably more positive sentiment expressions than the French. As a result, our French subjectivity lexicon comprised fewer positive single-word expressions than the English and Dutch lexicons (cfr. Table 4.2). We therefore expected to get the best results for the positive class on the English and Dutch dataset, which was corroborated by the results.

On the other hand, the more negatively oriented French corpus also resulted in a more extensive negative subjectivity lexicon with 492 negative single words against 362 for the Dutch lexicon and only 184 for the English. Surprisingly, the best results for precision on the negative class were, in fact, obtained on the English dataset. Recall, however, was a lot higher for French thanks to the larger negative lexicon. As shown in Table 5.3 the system by far missed the most negative expressions for English, which could be explained by the fact that the English train set, on which our subjectivity lexicon was based, contained a disproportionately low number of negative labels. The test set was more balanced with regards to positive-negative sentiment, as illustrated in Table 5.5.

Neutral sentences and sentences in which no sentiment can be found, i.e. the undefined class, are rarely correctly labeled by our system resulting in low precision. The relatively
good recall score in combination with low precision for the undefined class means that the system misses too many instances in which sentiment is, in fact, expressed.

5.2 Setup 2: single + multi

In a next phase, we added a multiword lexicon to our system resulting in a slightly better accuracy score for all three target languages, as shown in Table 5.6.

<table>
<thead>
<tr>
<th></th>
<th>Setup 1</th>
<th>Setup 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>60.66</td>
<td>61.32</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>51.27</td>
<td>53.69</td>
</tr>
<tr>
<td>DUTCH</td>
<td>61.24</td>
<td>63.03</td>
</tr>
</tbody>
</table>

Table 5.6: Accuracy of our lexicon-based system in setup 1 and 2.

The addition of the multiword lexicon was most beneficial to the extraction of positive sentiment in French and Dutch and to the extraction of negative sentiment in the Dutch test set. However, Table 5.7 below also shows that this step produced lower precision for English on both positive and negative sentiment. Precision for the neutral and undefined classes remained stable or improved slightly, except for the French undefined class falling from 29.68 to 29.61.

<table>
<thead>
<tr>
<th></th>
<th>+</th>
<th>-</th>
<th>NEUTRAL</th>
<th>UNDEFINED</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>72.73</td>
<td>77.57</td>
<td>15.56</td>
<td>29.61</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>72.03</td>
<td>77.97</td>
<td>8.16</td>
<td>19.37</td>
</tr>
<tr>
<td>DUTCH</td>
<td>74.14</td>
<td>75</td>
<td>6</td>
<td>43.59</td>
</tr>
</tbody>
</table>

Table 5.7: Precision of our lexicon-based system based on single words and multiwords.

This step was especially helpful to improve recall. Although recall on positive sentiment in Dutch went up from 75.90 to 77.84, it loses the number one spot to English scoring 78.85 coming from 74.45. This is visualized in Table 5.8.

<table>
<thead>
<tr>
<th></th>
<th>+</th>
<th>-</th>
<th>NEUTRAL</th>
<th>UNDEFINED</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>72.54</td>
<td>57.49</td>
<td>18.67</td>
<td>63.38</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>78.85</td>
<td>26.59</td>
<td>8.89</td>
<td>53.40</td>
</tr>
<tr>
<td>DUTCH</td>
<td>77.84</td>
<td>50.24</td>
<td>9.38</td>
<td>55.28</td>
</tr>
</tbody>
</table>

Table 5.8: Recall of our lexicon-based system based on single words and multiwords.
When calculating F-1, we observe that this step was beneficial to all three languages. Only the French undefined class did not improve, as shown in Table 5.9.

<table>
<thead>
<tr>
<th>F-1</th>
<th>+</th>
<th>-</th>
<th>NEUTRAL</th>
<th>UNDEFINED</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>72.63</td>
<td>66.04</td>
<td>16.97</td>
<td>40.36</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>75.29</td>
<td>39.66</td>
<td>8.51</td>
<td>28.43</td>
</tr>
<tr>
<td>DUTCH</td>
<td>75.94</td>
<td>60.17</td>
<td>7.32</td>
<td>48.74</td>
</tr>
</tbody>
</table>

Table 5.9: F-1 score of our lexicon-based system based on single words and multiwords.

5.3 Setup 3: single + multi + flip

In this final step, a third lexicon, which aimed to flip the sentiment when needed, was added. For obvious reasons, this step did not affect the undefined class. Table 5.10 shows the accuracy based on all three lexicons.

<table>
<thead>
<tr>
<th>ACCURACY</th>
<th>Setup 1</th>
<th>Setup 2</th>
<th>Setup 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>60.66</td>
<td>61.32</td>
<td>62.20</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>51.27</td>
<td>53.69</td>
<td>54.54</td>
</tr>
<tr>
<td>DUTCH</td>
<td>61.24</td>
<td>63.03</td>
<td>62.76</td>
</tr>
</tbody>
</table>

Table 5.10: Accuracy of our lexicon-based system in setup 1, 2 and 3

Again, accuracy improved for French and English. For Dutch, however, accuracy dropped slightly. Our results do not compare to the systems obtaining the highest accuracy for the task of polarity classification for the SemEval 2016 Task (See Section 2.3). For French and English, XRCE/C (C = Constrained) achieved an accuracy of respective 78.826% and 88.126% (Brun et al., 2016). The TGB system by Çetin et al. (2016) obtained the best results for Dutch with an accuracy of 77.814.

Although accuracy for Dutch did not improve, this does not implicate that the result was negative for all classes. Tables 11 and 12 show that precision on positive sentiment and recall on negative sentiment scored better. However, polarity flipping had the most impact on the extraction of neutral sentiment in Dutch with precision dropping from 6 to 3.70 and recall falling from 9.38 to 6.25.

<table>
<thead>
<tr>
<th>PRECISION</th>
<th>+</th>
<th>-</th>
<th>NEUTRAL</th>
<th>UNDEFINED</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>74.04</td>
<td>78.42</td>
<td>16.48</td>
<td>29.61</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>75.54</td>
<td>81.75</td>
<td>9.72</td>
<td>19.37</td>
</tr>
<tr>
<td>DUTCH</td>
<td>75.82</td>
<td>72.11</td>
<td>3.70</td>
<td>43.59</td>
</tr>
</tbody>
</table>

Table 5.11: Precision of our lexicon-based system based on single words, multiwords and polarity flipping.
A higher F-1 score was calculated for French and English when it comes to extracting positive, negative and neutral sentiment. For Dutch, the system only managed to improve the extraction of positive sentiment. Furthermore the addition of the third lexicon had a negative impact on the negative and neutral classes. This is presented in Table 5.13.

<table>
<thead>
<tr>
<th>RECALL</th>
<th>+</th>
<th>-</th>
<th>NEUTRAL</th>
<th>UNDEFINED</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>72.54</td>
<td>59.40</td>
<td>20</td>
<td>63.38</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>77.53</td>
<td>29.77</td>
<td>15.56</td>
<td>53.40</td>
</tr>
<tr>
<td>DUTCH</td>
<td>77.29</td>
<td>50.72</td>
<td>6.25</td>
<td>55.28</td>
</tr>
</tbody>
</table>

Table 5.12: Recall of our lexicon-based system based on single words, multiwords and polarity flipping.

<table>
<thead>
<tr>
<th>F-1</th>
<th>+</th>
<th>-</th>
<th>NEUTRAL</th>
<th>UNDEFINED</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRENCH</td>
<td>73.28</td>
<td>67.60</td>
<td>18.07</td>
<td>40.36</td>
</tr>
<tr>
<td>ENGLISH</td>
<td>76.52</td>
<td>43.65</td>
<td>11.97</td>
<td>28.43</td>
</tr>
<tr>
<td>DUTCH</td>
<td>76.55</td>
<td>59.55</td>
<td>4.65</td>
<td>48.74</td>
</tr>
</tbody>
</table>

Table 5.13: F-1 score for our lexicon-based system based on single words, multiwords and polarity flipping.

For French and English the system performed best when all three lexicons were applied resulting in higher accuracy and F-1 scores, whereas for Dutch, most progress was achieved during the second step. Even though flipping the polarity caused improved F-1 score for the positive class, this was outweighed by a lower overall accuracy and lower F-1 for the negative and neutral classes.
5.4 Error analysis

Figure 5.1: Evolution of French F-1 score for positive and negative sentiment.

Figure 5.2: Evolution of English F-1 score for positive and negative sentiment.
As shown in Figures 5.1, 5.2 and 5.3, our overall best performing system applied all three subjectivity lexicons. Still, it was far from perfect with accuracy values of 62.20 for French, 54.54 for English and 62.76 for Dutch. We therefore performed a manual error analysis with a focus on the positive and negative classes and observed several recurrent errors for which we will present a number of representative examples. In total, we checked 788 errors and for each error category we will add the relative frequency.

### 5.4.1 Single words – 17.51%

The first problem we will address is not an actual error, but is more due to our train set, on which the lexicons were built, being too small. As a result, our system missed a lot of positive or negative expressions because the subjectivity word was not included in the single-words lexicon, as shown in the examples below. The sentiment words in bold are missing from our subjectivity lexicons.

**FR:** Sentence 184 : vin âcre (acid).  
predicted: [u'DRINKS#PRICES'] ['undefined']  
golden: [u'DRINKS#QUALITY'] [u'negative']

**EN:** Sentence 141 : the hot dogs were juicy and tender inside and had plenty of crunch and snap on the outside.  
predicted: [] ['undefined']  
golden: [u'FOOD#QUALITY'] [u'positive']

**DU:** Sentence 34 : de chocolade mouse was verrukkelijk (delicious).  
predicted: [] ['undefined']  
golden: [u'FOOD_qual'] [u'very_positive']

![Figure 5.3: Evolution of Dutch F-1 score for positive and negative sentiment.](image)
5.4.2 Multiwords – 17.64%

In the English and Dutch output, we observed that a substantial number of sentences were not assigned the correct sentiment label because an idiom or multiword expression was missing from the multiword subjectivity lexicon. Again, the missing expressions are put in bold in the examples below.

EN: Sentence 1: not because you are "the four seasons"... - you are allowed to **charge an arm and a leg** for a romantic dinner.
predicted: [u'FOOD#QUALITY'] ['undefined']
golden: [u'RESTAURANT#PRICES'][u'negative']

DU: Sentence 36: het **water komt me terug in de mond** (makes my mouth water).
predicted: [] ['undefined']
golden: [u'FOOD_qual'] [u'positive']

5.4.3 Sentence level vs aspect level – 12.31%

Next, we consider a few examples in which the predicted sentiment did not match the golden annotation because our system predicted the sentiment on sentence level, whereas the golden annotation assigned the labels on aspect level. The system did, in fact, detect both the positive and negative sentiment in the sentence.

FR: Sentence 402: salle très **bruyante** (on n'arrivait plus à s'entendre), mais service **efficace**.
predicted: [u'AMBIENCE#GENERAL', u'SERVICE#GENERAL'] ['neutral']
golden: [u'SERVICE#GENERAL', u'AMBIENCE#GENERAL'] [u'positive', u'negative']

Sentence 455: de plus, l'accueil de la part du patron est **froid** contrairement aux serveurs très **gentils**.
predicted: [u'SERVICE#GENERAL'] ['neutral']
golden: [u'SERVICE#GENERAL', u'SERVICE#GENERAL'] [u'negative', u'positive']

EN: Sentence 180: for me dishes a little **oily**, but overall dining experience **good**.
predicted: [u'FOOD#QUALITY'] ['neutral']
golden: [u'FOOD#QUALITY', u'RESTAURANT#GENERAL'] [u'negative', u'positive']

Sentence 471: all in all the food was **good** - a little on the **expensive** side, but **fresh**.
predicted: [u'FOOD#QUALITY'] ['positive']
golden: [u'FOOD#QUALITY', u'FOOD#PRICES'][u'positive', u'negative']
DU: Sentence 397: het pizzadeeg was **goed**, maar de topping en zeker de prijs was een **tegenval**er.
predicted: [u'DRINKS_prices'][u'neutral']
golden: [u'FOOD_prices', u'FOOD_qual', u'FOOD_qual'][u'very_negative',
  u'negative', u'positive']

5.4.4 **Ambiguous words – 4.31%**

Another interesting error includes the problem of ambiguous words, which can have both a positive and negative connotation depending on the context. Our lexicon-based system, however, is not capable to take into account the specific context.

FR: Sentence 123: enfin la masterpiece : le riz au lait vanille sauce caramel beurre **salé** (divin).
predicted: [u'FOOD#QUALITY'][u'neutral']
golden: [u'FOOD#QUALITY'][u'positive']

In the example above, our system detects two sentiment words, i.e. **salé** (salty) and **divin** (divine). **Salé** can be found in the negative lexicon and **divin** in the positive lexicon, resulting in a neutral label. We included **salé** in the negative lexicon because in our train set it was mostly found in combination with addition, i.e. une addition salée (a huge bill). In sentence 123, however, **salé** just means salty and does not express any sentiment.

The word **gras** in the next example, is part of our negative lexicon because in the train set it was mostly used to indicate that something was too fat or greasy. In sentence 191, on the other hand, it does not express negative sentiment, because it is part of the combination **le foie** (sic) gras (the foie gras).

FR: Sentence 191: le foie **gras** est le meilleur de l'île . predicted: []['neutral']
golden: [u'FOOD#QUALITY'][u'positive']

Let us consider the following examples:

EN: Sentence 42: the stuff tilapia was horrid...tasted **like** cardboard.
predicted: []['positive']
golden: [u'FOOD#QUALITY'][u'negative']

DU: Sentence 86: kreeft op verschillende wijze **te** verkrijgen.
predicted: []['negative']
golden: [u'FOOD_style'][u'positive']

The word **like** in sentence 42 (EN) is used as a preposition and does not express sentiment. In the train set, however, it was often used as a verb to express positive sentiment and we therefore included it in our positive lexicon.

In sentence 86, the word **te** is used as a preposition in combination with the verb **verkrijgen** (to get). Used this way, **te** has no real English translation and no sentiment is expressed. The word **te** can also function as an adverb meaning too (or **trop** in French). **Te**, **too** and **trop** are all part of our negative subjectivity lexicon.
5.4.5 Flip sentiment – 3.68%

In the previous section, we already observed that adding a lexicon to flip the sentiment was beneficial to the overall efficiency of our system. When a sentence contains a word from this lexicon and one of the three following words is a sentword, the sentiment of the word in question would be flipped. It is interesting to see that in some cases it would have been helpful to flip the sentiment of the word preceding the sentiment modifier. Below are two examples:

FR: Sentence 319: n' hésitez pas.
(English: Don’t hesitate.)
predicted: [] ['negative']
golden: [u'RESTAURANT#GENERAL'] [u'positive']

Sentence 111: nous avons découvert ce restaurant avec groupon, je ne le conseille pas sans cette offre.
(English: We discovered this restaurant through groupon, I wouldn’t recommend it without this offer.)
predicted: [u'AMBIENCE#GENERAL'] ['positive']
golden: [u'RESTAURANT#GENERAL'] [u'negative']

For this step to be beneficial for English and Dutch as well, we would have to enlarge our scope to the two first words preceding the modifier:

EN: Sentence 108: had no flavor and the staff is rude and not attentive.
predicted: [u'SERVICE#GENERAL'] ['negative']
golden: [u'SERVICE#GENERAL', u'FOOD#QUALITY'] [u'negative', u'negative']

DU: Sentence 230: dat zoiets in onze mooie stad nog mag open zijn, dat begrijp ik niet.
(English: I don’t understand that this place is still allowed to be open in our beautiful city.)
predicted: [] ['positive']
golden: [u'RESTO_gen'] [u'negative']

There is however the risk that enlarging the scope will generate more false positives. It could be interesting for further research to explore the added value of these modifiers when building one lexicon-based system for multiple languages.

5.4.6 LeTs – 3.30%

In section 3.3.1 we observed that the LeTs POS-tagger is not flawless when lemmatizing or POS-tagging. That is why, in a few instances, no match could be found between the lemma in our subjectivity lexicon and the lemma generated by LeTs. In the first example, retournerons (lemma: retourner) is part of our subjectivity lexicon, but the lemma LeTs gives this verb is retournerer.
Sentence 126 : un formidable moment, nous y **retournerons (will return)** c’est sûr, et recommandons chaudement ce restaurant!

predicted: [u'AMBIENCE#GENERAL'] ['undefined']
golden: [u'RESTAURANT#GENERAL'] [u'positive']

In the second example, we notice that the word *verfijnd* was not recognized even though it is presented in our lexicon. LeTs, however, considers this to be a verb (lemma: *verfijnen*) whereas we consider *verfijnd* to be an adjective (lemma: *verfijnd*) in this specific case.

Sentence 457 : werkelijk zeer **verfijnd (sophisticated)** in alle opzichten.

predicted: [] ['undefined']
golden: [u'FOOD_gen'] [u'very_positive']

A third example shows that the word *superlekkere* (lemma: *superlekker*) was not labeled by the system because LeTs assigned the lemma *superlek*.

Sentence 559 : we kregen een **superlekkere (incredibly tasty)** schotel voorgeschoven in geen tijd.

predicted: [u'FOOD_qual'] ['undefined']
golden: [u'SERVICE_gen', u'FOOD_qual'] [u'positive', u'very_positive']

5.4.7 Context – 2.28%

The next problem deals with context. Our lexicon-based system can only take into account the words from our subjectivity lexicons, has no learning capacities and cannot understand the context of a specific word or sentence. In sentence 521 no sentiment words can be detected and it is therefore assigned the *neutral* label. The golden annotation, however, labeled the sentence as *positive* because it can take into account the context and the word *aussi (also)* refers to the positive opinion expressed in the previous sentence.

Sentence 520 : a la carte, plus cher, la sole meunière est un véritable délice (49 euros tout de même) et chacun sait à quel point c’est difficile de la réussir.

(English: A la carte, more expensive, the sole meunière is a real delicacy (yet it costs 49 euros) and everyone knows how difficult it is to get it right.)

predicted: [u'FOOD#PRICES'] ['undefined']
golden: [u'FOOD#QUALITY', u'FOOD#PRICES', u'FOOD#PRICES'] [u'positive', u'neutral', u'negative']

Sentence 521 : la côte de veau aussi.

predicted: [u'FOOD#QUALITY'] ['undefined']
golden: [u'FOOD#QUALITY'] [u'positive']

The following sentence was labeled as *negative* by the golden annotation, even though *bien* is the only sentiment word in the sentence, which is why our system indicated the sentence to be *positive*. Again, our system could not take into account the context, i.e. the word *pourtant*, which is not a sentiment word, and the following eight sentences in which the reviewer shared multiple negative experiences with this restaurant.
Sentence 27 : premiere fois dans ce restaurant dont on nous disait pourtant du bien .

(English: This was our first time visiting this restaurant, of which we've heard some good things though.)

predicted: [u'AMBIENCE#GENERAL'] ['positive']
golden: [u'RESTAURANT#GENERAL'] [u'negative']

We also found an example of the same problem in the English output. Sentence 588, 589 and 590 are all labeled as positive by the gold standard annotation, whereas our system only labeled sentence 588 because it detected a sentiment word (best).

EN: Sentence 588 : best .
predicted: [u'FOOD#QUALITY'] ['positive']
golden: [u'FOOD#QUALITY'] [u'positive']

Sentence 589 : sushi .
predicted: [u'FOOD#QUALITY'] ['undefined']
golden: [u'FOOD#QUALITY'] [u'positive']

Sentence 590 : ever .
predicted: [] ['undefined']
golden: [u'FOOD#QUALITY', u'FOOD#STYLE_OPTIONS'] [u'positive', u'positive']

5.4.8  Spelling – 0.89%

A number of errors were also due to bad spelling in the reviews. In the French example, our system was not able to find the transparent word exorbitant, which is in our negative lexicon, because it was misspelled exhorbitants. The example from the English output speaks for itself.

FR: Sentence 167 : ce service désagréable au possible est couronné d' une carte incompréhensible , aux prix exhorbitants .
predicted: [u'FOOD#PRICES', u'SERVICE#GENERAL'] ['neutral']
golden: [u'SERVICE#GENERAL', u'FOOD#STYLE_OPTIONS', u'FOOD#PRICES'] [u'negative', u'negative', u'negative']

EN: Sentence 162 : the bestt !
predicted: [] ['undefined']
golden: [u'RESTAURANT#GENERAL'] [u'positive']
5.4.9 Different language – 0.25%

Next, we present an error that was only detected in the Dutch output, i.e. a full sentence in a language different from the target language:

DU: Sentence 121: much ado about nothing!
   predicted: [] ['undefined']
   golden: [u'RESTO_gen'] [u'very_negative']

Sentence 452: this is the place to be!
   predicted: [] ['undefined']
   golden: [u'RESTO_gen'] [u'very_positive']

We verified our English lexicons and they would also have been unable to detect the sentiment expressed in the sentences above.

5.4.10 Irony – 0.13%

Another very interesting problem is how to deal with irony, sarcasm and cynicism. We detected one sentence containing sarcasm, which our lexicon-based system was not able to deal with:

FR: Sentence 341: on est rassuré "la patronne, interpellée, va faire des enquêtes" (sic), bref c'est parfait.
   (English: We were reassured by the fact that "the owner, to whom we've complained, is going to look into it" (sic), in short, it’s perfect.)
   predicted: [u'SERVICE#GENERAL'] ['positive']
   golden: [u'SERVICE#GENERAL'] [u'negative']

5.4.11 Gold standard – 1.14%

Finally, we focus on a number of sentences which we consider as correctly labeled by our system and not by the gold standard. This is of course rather subjective and can vary depending on the annotator(s).

FR: Sentence 3: correct.
   (English: correct.)
   predicted: [] ['positive']
   golden: [u'RESTAURANT#GENERAL'] [u'neutral']

Sentence 214: l'ambiance est bruyante mais relativement agréable.
   (English: Atmosphere was very loud, but relatively cozy.)
   predicted: [u'AMBIENCE#GENERAL'] ['neutral']
   golden: [u'AMBIENCE#GENERAL'] [u'positive']

EN: Sentence 123: the food and service were fine, however the maitre-d was incredibly unwelcoming and arrogant.
   predicted: [u'FOOD#QUALITY', u'SERVICE#GENERAL'] ['neutral']
 golden: [u'DRINKS#QUALITY'] [u'positive']

Sentence 592: creative, consistent, fresh.
predicted: [] ['positive']
golden: [u'FOOD#PRICES', u'FOOD#QUALITY'] [u'negative', u'positive']

DU: Sentence 349: het enige nadeel is dat er iets aan het afzuigsysteem mag gedaan worden (als ze er al een hebben), als je er 5 minuten binnen bent kan iedereen ruiken dat je van de marmiet komt.
(English: The only disadvantage is the poorly functioning ventilation system (if they have one), after only five minutes inside, everyone can smell you were at de marmiet.)
predicted: [u'AMBIENCE_gen'] ['negative']
golden: [u'RESTO_misc'] ['very_positive']

5.5 Machine learning

As a final experiment, we wanted to check whether a machine learning system would be able to detect the positive or negative sentiment in the Dutch sentences where our lexicon-based system failed.

We therefore used a demo on the website of the University of Ghent Language and Translation Technology Team. The demo enables visitors to enter Dutch sentences which will then be analyzed through a lexical based and a machine learning based way. After, the demo allows the visitor to add a gold standard annotation. This is visualized in Figure 5.4.

![Figure 5.4: Screenshot of the Sentiment Demo on the website of the UGent Language and Translation Technology Team.](image-url)
In Figure 5.2, we can see that the machine learning approach is able to detect the positive sentiment in the sentence, whereas our lexicon-based system failed:

```
DU: Sentence 127: hier kom ik zeker terug.
(English: I will definitely come back here.)
predicted: [] ['undefined']
golden: [u'RESTO_gen'] [u'positive']
```

Important to note is that we only performed this step on the Dutch sentences of which our system was not able to correctly predict the sentiment. We did not verify whether or not the machine learning approach would also accurately label the sentences of which our lexicon-based system correctly predicted the sentiment. This is why we only mention accuracy as an evaluation criteria for positive and negative sentiment.

In total, the machine learning approach was able to find the positive sentiment in 29 out of 80 sentences (accuracy of 36.25%) and the negative sentiment in 61 out of 103 sentences (accuracy of 58.65%).
Chapter 6
Conclusion

Aspect-based sentiment analysis is the task where a computer tries to identify which aspects or features of a particular product are expressed in reviews of consumer products. It also automatically determines whether the reviewer’s attitude towards each of the aspects is positive, negative or neutral. Originally ABSA systems were developed based on reviews written in English (Hu & Liu, 2004, Thet et al., 2010, Pontiki et al., 2014). Currently systems are being trained and developed for other languages as well. Because of the continuing globalization, the challenge is to create a multilingual system.

In this thesis, we first analyzed a corpus of French, English and Dutch restaurant reviews to discover how aspects and sentiments are expressed in the different target languages. Our results revealed that there is a difference if we consider the amount of aspect terms per sentence. The French reviews contain 1.48 aspect terms per sentence whereas the English and Dutch reviews contain 1.25 and 1.06 respectively. This is because the French reviewers immediately got to the point, in all sentences they discussed at least one aspect of the restaurant in question. The English and Dutch reviewers, on the other hand, share more context and trivia. Another notable difference between the languages concerns the use of common nouns and proper nouns. In French aspect terms are almost never (0.1%) expressed by a proper noun. In English, however, 9.7% of the aspect terms are proper nouns and in Dutch 5%. This is because the English and Dutch reviewers often explicitly mention the name of the restaurant and sometimes the name of a waiter or waitress. No such mentions were found in the French reviews. Furthermore, the French aspect term accueil (reception), is the number five most mentioned French aspect term, but does not even pop up in the English or Dutch top ten. This could lead us to the conclusion that the French consider a warm and welcoming reception more important than the American or Belgian reviewers. There is, however, a shared top three when it comes to the aspects that are mentioned most frequently in all three languages, i.e. service, food and restaurant. When it comes to polarity, the statistics revealed that the French reviews were the most critical with only 46.1% positive reviews. The English reviews were the most positive (66.1%) and the Dutch reviews could be found somewhere in between, with 57.6% positive annotations.

In the experimental part of this thesis, the focus was on the task of polarity classification. The reviews in all three languages were split in a train and test dataset. Based on the train set, polarity lexicons were created for each language, which could then be used in a lexicon-based approach to automatically detect and predict the sentiment on the held-out test set. We explored the added value of applying three different subjectivity lexicons to our approach.
The first setup only looked for a match with a sentiment word in our single-word subjectivity lexicon. In the second setup, we also added a multiword lexicon. In the final setup, we investigated whether the efficiency of our system could be improved by adding a third lexicon consisting of negation markers to flip the sentiment.

Our results revealed that applying three different types of subjectivity lexicons was beneficial for the task of automatic polarity classification. For French and English the system performed best when all three lexicons were applied, resulting in both higher accuracy and F-1 scores. For Dutch, most progress was achieved during the second setup. Even though flipping the polarity caused improved F-1 score for the positive class, this was outweighed by a lower overall accuracy and lower F-1 for the negative and neutral classes.

Finally, we performed a qualitative error analysis which revealed that our system missed a substantial amount (35.15%) of positive or negative expressions because the sentiment expressions were not included in our lexicons. This is due to our train set, on which the lexicons were built, being too small. Another interesting error included ambiguous words which can express both positive or negative sentiment, depending on the context. The limitation of a lexicon-based approach is that it is not able to take into account context. As a final experiment, we wanted to check whether a machine learning system would be able to detect the positive or negative sentiment in the Dutch sentences where our lexicon-based system failed. We used an existing machine-learning based approach for Dutch which was able to find the positive sentiment in an additional 29 out of 80 sentences (accuracy of 36.25%) and the negative sentiment in 61 out of 103 sentences (accuracy of 58.65%).

For this Master’s thesis we investigated how sentiment is expressed in French, English and Dutch. We think it would be interesting for further research to analyze the similarities and differences with more exotic languages such as Chinese, Russian or Arabic. We also built a lexicon-based system to automatically perform the task of polarity classification for our three target languages. Further research could focus on improving and expanding our subjectivity lexicons and comparing this approach with other approaches such as machine learning. The lexicons that have been created for this thesis can serve as a first basis for future research.
Bibliography


Apidianaki, M., Tannier, X., & Richart, C. Datasets for Aspect-Based Sentiment Analysis in French.


De Clercq, O. (2015). Tipping the scales: exploring the added value of deep semantic processing on readability prediction and sentiment analysis. Ghent University. Faculty of Arts and Philosophy, Ghent, Belgium.


Appendix A
LeTs: errors & corrections

French targets - lemma - part of speech

Tapas  tapas ADV(NOM)
menu enfant - menu  enfer(enfant) ver(NOM)
menus  menir(menu) ver:pper(NOM)
pavé de saumon - NAM(NOM)
emplacement  emplacemer(emplacement) VER:pres(NOM)
attente  attenter(attente) VER:pres(NOM)
restaurant  restau(restaurant) ADJ(NOM)
entrées  entrées(entrée) NUM(NOM)
tartare de saumon à la thaï  tartare de saumon à le thaï  NOM PRP NOM PRP DET:ART
NAM(ADJ)
cheesecake au toblerone  cheesecake au toblerone  NOM PRP:det NAM(NAM)
entrée/ plat / dessert  entrée/ plat / dessert  ABR(NOM PUN) NOM PUN NOM
déco  déco(décoration) NAM(NOM)
coquilles saint jacques  coquille saint jacques  NOM NAM(NOM) NAM(NOM)
serveuse  serveux(serveur/serveuse) ADJ(NOM)
cuisine  cuisiner(cuisine) VER:pres(NOM)
viande  viande(viande) VER:pres(NOM)
assortiment de charcuterie corse  assortiment de charcuterie corser(corse)  NOM PRP
NOM VER:pres(ADJ)
produit  produire(produit) VER:pres(NOM)
vie de boeuf  viande de boeuf  NOM PRP FW(NOM)
bouilli  bouilli(bouillie) ADJ(NOM) NOM
mimose  mimoser(mimosa) VER:simp(NOM)
Burger  burger FW(NOM)
nourriture  nourritur(nourriture) ADJ(NOM)
bière  bière bouteille(NOM) NOM ADJ(NOM)
carpaccio de st jacques sauvages  carpaccio de st jaques(jaques) sauvage  NOM PRP NOM
ADJ(NOM) NOM(ADJ)
purée a l'huile de truffe

assiette corse

millefeuille tomates mozzarella

sauces mayonnaises

sommerlier

rapport qualité-prix est excellent

loup de mer fraîchement pêché avec sa ratatouille sur purée accompagné d'une huile d'olive aux agrumes et herbes

serveuse

filet de boeuf sauce aux morilles

pizza

filet de vivaneau à la vietnamienne

spaguetti carbonara

st jacques

saumon fumé

formule tapas

salade fruit

décordécor

farandole de desserts

entrée plat dessert

ravioles

assiette découverte

apéroapéro

lièvre

bar restaurant

saumon

bavette échalotes

oeuf cocotte

patronne

cuisine
tarte tropézienne  tarte  tropézienn(tropézien)  NOM  VER:pres(ADJ)
endroit  endroire(endroit)  VER:pres(NOM)
salle  salle  ADJ(NOM)
espace  iounge  iounge(lounge)  NOM  NAM(NOM)
desserts  maisons  dessert  maiser(maison)  NOM  VER:pres(NOM)
terrasse  terrasser(terrasse)  VER:pres(NOM)
moelleux  speculos  /  chocolat  moelleux  speculo  /  chocolat  ADJ(NOM)  NOM  PUN  NOM
dattentes  dattent(d'attente)  ADJ(PRP  PUN  NOM)
échine  de  cochon  confite  échine  de  cochon  confiter(confire)  NOM  PRP  NOM
VER:pres(ADJ)

English targets + lemma + part of speech

pizza 33  pizza 33  NNP(NN)  CD
vitello  alla  marsala  vitello  alla  marsala  NN  NN  NN  (FW  FW  NNP)
somas  somosas  NN(FW)
patsy  's  pizza  patsy  's  pizza  NNP  POS  NNP(NN)
mens  bathroom  men(man)  bathroom  NNS  NN
restaraunt  restaraunt(restaurant)  NN
lobster  bisque  lobster  bisque  NNP  NNP(NN  NN)
new  england  chowder  new  england  chowder  NNP  NNP  NNP(NN)
prime  rib  prime  rib  NNP  NNP(NN  NN)
bottles  of  korbett  bottle  of  korbett(corbett)  NNS  IN  NNP
cocktail  with  citrus  vodka  and  lemon  and  lime  juice  and  mint  leaves  cocktail  with  citrus
vodka  and  lemon  and  lime  juice  and  mint  leaf  NN  IN  NNP(NN)  NNP(NN)  CC  NN  CC  NN  NN  CC
NN  NNS
belly  dancing  show  belly  dance  show  RB(NN)  VBG  NN
restaurant  restaurant  NNP(NN)
baba  ganoush  baba  ganoush  NN  NN(FW  FW)
baked  clams  octopus  baked  clam  octopus  JJ  NNS  IN(NN)
seasonal  beer  seasonal  beer  NNP(JJ)  NN
foie  gras  terrine  with  figs  foie  gra(gras)  terrine  with  fig  NN  VBZ(NN)  NN  IN  NNS
indian  indien  indien  NNP(JJ)
meat  dishes  meat  dish  NN  VBZ(NN)
grilled  chicken  special  with  edamame  puree  grilled  chicken  special  with  edamame  puree
JJ  NNP(NN)  JJ(NN)  IN  NNP(NN)  NNP(NN)
hot  dogs  hot  dogs  NNP  NNP  (JJ  NNS)
bark  bark  NNP(VBZ)
sushi  susushi(sushi)  NNS(NN)
martini  martinus(martini)  NNS(NN)
in-house  lady  dj  in-house  lady  dj  JJ  NN  NNP(NN)
roti  rolls  roti  roll  JJ(FW)  NNS
unda  (egg)  rolls  unda  (egg)  roll  NNP  NNP  )  NNS(FW  SYM  NN  SYM  NN)
guacamole+shrimp  appetizer  guacamole+shrimp  appetizer  NNP  NN(NN  SYM  NN
NN)
uni  hand  roll  uni  hand  roll  NNP(FW)  NNP(NN)  NN
lobster  teriyaki  lobster  teriyaki  NN  NNP(FW)
spicy  scallop  roll  spicy  scallop  roll  NNP(NN)  NNP(NN)  NN
ravioli

dining

waitstaff

yuka

egg noodles in the beef broth with shrimp dumplings and slices of bbq roast pork

bbq ribs

atmosphere

caesar salad

waitstaff

yuka

egg noodles in the beef broth with shrimp dumpling and slice of bbq roast pork

bbq ribs

dog

indo chinese food

indian food

thai food

1st ave spot

back room

sauce

cypriot restaurant

greek and cypriot dishes

suan

toostoon

spicy tuna roll

spicy tuna roll

indian restaurant

survice

sushimi cucumber roll

prix fixe menu

chicken teriyaki

lamb special

ravioli

pink pony

ambiance

martinis

tom kha soup

shabu-shabu restaurant

gulab jamun (dessert)
pastrami

indoor

portion sizes

back patio

dessert

stone bowl

thai style fried sea bass

NNP(NN)
interior decor      interior decor      NN(JJ)        NN
sashimi amuse bouche sashimus(sashimi) amuse bouche NNS VBP(NN NN) NN
back garden area back garden area NN(JJ) NN NN
gnocchi           gnocchi           NNP(NN)
pepperoni         pepperonus(pepperoni) NNS(NN)

Dutch targets + lemma + part of speech

mcdonalds restaurant mcdonalds restaurant ADJ(NP) N
eten eten        WW(N)
self-made ice tea self-made ice tea SPEC SPEC SPEC(N)
almaal         allemaal        BW(TW)
new havana new havana SPEC SPEC(NP NP)
service service      SPEC(N)
dessert dessert      WW(N)
sint jorispoort sint jorispoort SPEC SPEC(NP NP)
iets lekkers iets lekker VNW ADJ(N)
sangria sangria SPEC(N)
dame blanche dame blanche SPEC SPEC(N N)
cafe cafe      SPEC(N)
crème fraiche crème fraiche SPEC SPEC(N N)
gefrituurde pijlinktvissen frituren pijlinktvissen WW(ADJ) N
wildvang gamba wildvang gamba SPEC SPEC(N N)
tom.saus tom.saus(tomatensaus) WW(N)
klein constantia klein constantia SPEC SPEC(NP NP)
patrijs met rode biet & boschampignons patrijs met rood biet & boschampignon N VZ ADJ N SPEC(LET) N
aangepaste wijnen aanpassen wijn WW(ADJ) N
sushi sushi      ADJ(N)
astoria palace astoria palace SPEC SPEC (N N)
lam lam        ADJ(N)
eend eend        ADJ(N)
voorgerecht voorgerechten(voorgerecht) WW(N)
cafe belfort cafe belfort SPEC SPEC(NP NP)
the village the village SPEC SPEC(NP NP)
extra zachte gerookte zalm extra zacht roken zalm ADJ ADJ WW(ADJ) N
irish beef irish bijven(beef)N WW(SPEC SPEC)
gegrilde scampi in kruidenboter grillen scampi in kruidenboter WW(ADJ) N VZ N
the olive tree the olive tree SPEC SPEC(NP NP)
gegrilde inktvis grillen inktvis WWW(N)
park restaurant park restaurant SPEC SPEC (NP NP)
stoofvlees stoofvelegen(stoofvlees) WW(N)
amuse gueule amus(amuse) gueule ADJ(N) N
bijpassende wijnen bijpassen wijn WW(ADJ) N
the bistronomy the bistronomy SPEC SPEC (NP NP)
jus d’orange jus d’orange SPEC SPEC (N)
salade met zalm en een quiche salade met zalm en een quiche N VZ N VG LID ADJ(N)
filet pur met pepersaus filet pur met pepersau(pepersaus) N N VZ N
aangepaste wijnen aanpassen wijn WW(ADJ) N
de wilde vespers de wild vesper LID ADJ N (NP NP NP)
licht gebakken tonijn licht bakken tonijn ADJ WW(ADJ) N
ribbetje ribbe(rib) N
friet friet ADJ(N)
kreeft kreeven(kreeft) WW(N)
kaaskroketjes kaaskroke(kaaskroket) N
lhoofdgerecht stoofpotje lhoofdgerecht(hoofdgerecht) stoofpotje N (+N)
de zuidkant de zuidkant LID N(NP NP)
gerechten rechten(gerecht) WW(N)
steak bearnaise steak bearnaise N SPEC(N)
saus sa(saus) N
kabeljauw kabeljauw ADJ(N)
steaks steaks(steak) ADJ(N)
bar / lounge met rokers-annex bar / lounge met rokers-annex N LET SPEC(N) VZ N
garnaalkroketjes garnaalkroke(garnaalkroket) N
halve kreeftje half kreeftje(kreeft) ADJ N
pizza ' whisky ' pizza ' whisky ' N LET SPEC(N) LET
dame blanche daam blanch(dame blanche) VNW ADJ(N N)
sfeer sfeer(sfeer) WW(N)
lam , kip en scampi's lam , kip en scampi ADJ(N) LET N VG N
eigenares eigenare(eigenares) N
le kok le kok SPEC SPEC(N)
eigenaresse eigenaresse(eigenares) N
kabeljauw met jonge spinazie en mousseline kabeljauw met jong spinazie en mousseline ADJ(N) VZ ADJ N VG N
menu menu ADJ(N)
gempemolen gempemool(gempemolen) N(NP)
salade nicoise salade nicoise SPEC SPEC(S N NP)
terras terras BW(N)
chocoladesaus chocoladesau(chocoladesaus) N
chocolade mousse chocolade mousse(chocolademousse) ADJ N (N)
formule ' pizza party formule ' pizza party N LET SPEC SPEC (N N)
voorgerechten , hoofdgerechten en deserts voorgerecht, hoofdgerecht en desserts(dessert) N LET N VG BW(N)
apéritoef hugo aperitief hugo SPEC SPEC (N NP)
het laatste het laatste LID ADJ(N)
menu kaart menu kaart VNW(N) N
garnalen kroketten garnaal kroketten(kroket) N WW(N)
vegan chocolade mousse vegan chocolade mousse(chocolademousse) SPEC SPEC(N)
keuken van à l'infintise keuken van à l'infintise N VZ SPEC SPEC (NP NP)
witte sangria wit sangrium(sangria) ADJ N
gefrituurde peterselie frituren peterselie WW(ADJ) N
zaalbediende zaalbediende(zaalbediende) WW(N)
chi-chi's wemmel chi-chi wemmel N N (NP NP)
hertennootjes hertenno(hertennoot) N
personeel personeel ADJ(N)
salatje sala(salade) N
produkten produkt(product) N
buiten speeltuin  buiten speeltuin(buitenspeeltuin)  ADJ N (N)
keyserhof  keyserhof  N (NP)
pâté  pâté  SPEC(N)
Appendix B

Targets word count

**French**

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pain 5
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galette du jour 1
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cassoulet 1
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pieds de cochons 1
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Chantilly 1
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purée d’aubergine 1
maison à colombage 1
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chili 1
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restaurant indien 1
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Cadre 4
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Serveur 1
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complet 1
bouteille de vin du mois 1
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Guacamole+shrimp appetizer 1
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Usha 1
sushi chef 1
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Jekyll and Hyde Pub 1
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Rice Avenue 3
Lucky Strike 2
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brioche and lollies 1
penne a la vodka 1
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Haru on Park S 1
specials 3
half price sushi deal 1
beverage selections 1
back patio 1
Red Eye Grill 1
neighborhood 1
Cosette 1
dish 1
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drinks 8
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sangria 1
scallops 2
all you can eat sushi 1
Mizu 3
Faan 1
Prix Fixe menu 3
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kitchen food 1
wait 3
atomosphere 1
soup for the udon 1
Gigondas 1
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Staff 1
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Ravioli 1
Yellowtail 1
pistachio ice cream 1
Uni Hand roll 1
Chennai Garden 1
all-u-can-eat sushi 1
Chow fun 1
music 4
fried shrimp 2
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congee (rice porridge) 1
beers 2
Reuben sandwich 1
homemade pasta 1
rice to fish ration 1
foie gras terrine with figs 1
Heartland Brewery 1
room 2
salad 1
premium sake 1
Toons 1
dhosas 1
bruschettas 1
Rao's 1
Gnocchi 1
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foods 2
wine selection 2
lamb glazed with balsamic vinegar 1
Ambience 2
Moules 1
onions 1
parmesean porcini souffle 1
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Wine list selection 1
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Personal pans 1
spreads 1
frites 1
lobster teriyaki 1
pizza 20
lobster roll 1
lamb 1
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waitstaff 3
mozzarella en Carozza 1
Shabu-Shabu 1
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Downstairs lounge 1
drumsticks over rice 1
Casimir 1
Japanese comfort food 1
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Jazz Bar 1
Salads 2
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Vanilla Shanty 1
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La Rosa 1
pizza place 2
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Bombay beer 1
Pizza 33 1
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crabmeat lasagna 1
terrace 1
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salmon dish 1
pad penang 1
Dessert 1
bagels 9
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crew 1
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Grilled Chicken special with Edamame Puree
Prime Rib
sauce
penne w/ chicken
Chinese food
spicy Tuna roll
good
food
lunch
$10 10-piece dim sum combo
soupy dumplings
hall
Raga’s
Rao
pastas
Jeffll and Hydes
selection of wines
meal
hanger steak
semi-private booths
fish
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santa fe chopped salad
apppetizers
Suan
SEASONAL beer
tuna tartar appetizer
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Cheese plate
servings for main entree
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entertainment
green curry with vegetables
French food
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back room
pizzeria
arugula and goat cheese
shows
drink
Dal Bukhara
Lobster Bisque
wines
lobster sandwich
wasabe potatoes
Thai food
bottles of wine
pesto pizza
turkey burgers
sake list
People
sushi cucumber roll
Myagi
takeout
place
pepperoni
jukebox
waitress
cheese
feel
in-house lady DJ
scene
Wine list
Indian
owner
smoked salmon and roe appetizer
halibut special
tuna
management
Taiwanese food
service
sake menu
main dining room
ceiling
tramezzinis
cigar bar
Prune
atmosphere
interior decor
Pam's special fried fish
chef
Atmosphere
regular menu-fare
New England Chowder
french fries
cream cheeses
assorted sashimi
rice dishes
pork belly
dosas
spicy Italian cheese
dishes
MEAT dishes 1
pasta dish 1
rose special roll 1
candle-light 1
joint 1
clers 1
banana tempura 1
Beef noodle soup 1
BBQ Salmon 1
bar 3
Jekyll and hyde Pub 1
Winnie 1
grilled branzino 1
large whole shrimp 1
pastrami sandwich on a
roll 1
Shabu-Shabu Restaurant 1
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view 3
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Decor 2
marinara/arrabiatta sauce 1
seabass 1
Aero 1
Spreads 2
radichio 1
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Thin Crust Pizzas 1
noodles 1
Pad Thai 2
Waitstaff 1
house champagne 1
gentleman 1
Thai 2
selection of thin crust
pizza 2
Roth's 1
customer service 2
VT's 1
kitchen 1
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Fish 3
Ambiance 1
all you can eat deal 2
Cafe Spice 1
maître d' 1
Drinks 1
vent 1
tuna of gari 1
portion size 2
wait-staff 1
roti rolls 1
Baluchi's 1
Chef's tasting menu 1
mussels 1
bottles of Korbett 1
cart attendant 1
nigiri 1
mare 1
beef 1
French Onion soup 2
duck confit 1
Taxan 1
proprietor 1
baked clams octopus 1
Saul 1
ravioli 1
late night atmosphere 1
appetizer menu 1
Amma 1
backyard dining area 1
live jazz band 1
hostess 3
Sushi 1
restaurant 3
sea urchin 1
Traditional French
decour 1
hot sauce 1
wait staff 4
dumplings 2
Bagels 1
sushi 19
coffee 1
Planet Thailand 1
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ambient 1
anti-pasta 1
cuisine 1
decor 14
Crab salad 1
mushroom pizza 1
Thalia 1
appetizer selection 1
egg noodles in the beef broth with shrimp dumplings and slices of
BBQ roast pork 1
Patis 1
setting/atmosphere 1
Tom Kha soup 1
Ginger House 1
rock shrimp tempura 1
noodles with shrimp and chicken and coconut juice 1
characters 1
Gulab Jamun (dessert) 1
Wait staff 1
Change Mojito 1
spicy tuna roll 1
spices 1
Red Eye 1
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burgers 1
Manager 1
Japanese cuisine 1
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chicken vindaloo 1
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Service 21
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somas 1
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tables 2
specials menus 1
pumkin tortelini 1
dhal 1
Cafe Noir 2
location 4
YUKA 1
counter service 1
pasta mains 2
Corona 1
outdoor seating 2
Dutch

70 gastvrouw 9 concept 5 mensen 7 ribbetjes 3 eigenaresse 1 St Christophe 1 desserts 1 bazin 1 Keyserhof 2 pizza's 5 culinaire creaties 1 uitzicht 1 kabeljauw met pasta en zwarte truffel 1 groentjes 1 sausje 2 kabeljauw 1 dressing 2 couscous 1 gastheer 1 brownie met gember 1 3-gangen keuzemenu 1 Keuzemenu 1 dessert 10 welkom 1 aardappels 1 kreeft met de zes verschillende sausjes 1 keuzes 1 binnentuin 1 gins 1 topwijnen 1 keuzemenu 1 appeltaart 1 kaart 10 luxe ontbijt 2 tuin met vijver 1 amuse gueule 1 entourage 1 steaks 1 chef 11 Ontbijtbuffet 1 steppegraas 1 sorbets 1 Tanja 1 serranoham met stokbrood 1 machines 1 smaakssensaties 1 scampies doable 1 sangria 1 thee en chocolademelk 1 pladijs 2 gebakjes 1 recepten 1 eigenares 2 combinaties 1 tapasbar 1 adressen 1 fondue, kaasfondue of raclette 1 maaltijd-gerechten 1 tomaatjes 1 boter 2 pate 1 tapagerechtjes 1 kelner 1 kippenfilet 1 nieuwe eigenaar 1 opstelling 1 buiten speeltuin 1 roggel1 vrijdagsmarkt 1 atelier 1 hapjes 1 Abdel2 visbrochette 1 huisapertro 1 Friet met mayonaise 1 hoofdgerecht 4 tartaar van kingkrab 1 Vlees 1 vis 4 gerechten 23 wit 2 toiletbezoek 1 Tom 1 langoust 1 gastvrijheid 1 Dame Blanche 1 hertennootjes 1 tafel 1 spiezen 1 't Groot Cafe 1 babykreeft met waterzooi 1 Emanuelle met bananen, bananenlikeur en warme chocoladesaus 1 degustatiemenu 1 biefstuk 1 adresje 4 Astoria palace 1 voorgerecht 4 pasta carbonara 1 wijnkeuzes 1 producten 3 mevrouw 2 Shusi's 1 Inrichting 1 dagsoep 1 gelegenheid 1 Witte sangria 1 lam en kip 1 stoofvlees 1 ligging 4 village gras met bijhorende saus 1 buiten 1 gegrilde vlees 1 bieren 2 Zwitserseethuisje 1 Licht gebakken tonijn 1 patron 3 student(en) 1 afgebakken broodjes 1 LHofdgerecht stoofpotje 1 combinatorie met de wijn soorten 1 Pelt stoofvlees 1 wachtlijnen 1 Gamba's 1 liffaafje 1 frites 1 menus 1 steak tartaar 2 Varkenshaas 1 feta 1 Pouilly Fuisse 1 stokbrood met kruidenboter 2 pizza 3 lam 1 zaalbediende 2
vissuggestie van de dag  2
hesp en kaas  1
pizza frutti di mare  1
zondagsbrunch  1
extra zachte gerookte zalm  1
man  5
atmosfeer  1
tapas  2
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bejegening  1
akoestiek  1
menukaart  5
vissaus  1
herenhuis  2
Bedienend personeel  1
vissaus  1
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soepen  1
terras aan de Eiermarkt  1
Prosecco  1
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kelners  1
muziek  2
waterzooi  2
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tongrolletjes  1
Mensen  1
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Drankjes  1
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ballentent  2
soepje van asperge  2
Warme gerechten  1
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wijn  15
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plek  1
top-restaurant  1
Wijn , gin en whisky  1
zaakvoerder  1
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Ribbetjes  1
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Keteltje  1
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iberico  1
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Sla  1
KC  1
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amuse  1
tafels  2
serveerder  1
wicht  1
uitbaatster  2
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Hof van Heusden  1
servies en glazen  1
lam , kip en scampi's  1
serveerder  3
apero  1
allemaal  1
scampi's  1
kasteelrestaurant  1
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Kip  1
uitbaters  1
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Biertje  1
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Klein Constantia 1
gerechtje 2
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garnituren 1
Sfeer 1
eigenaars 1
quiches 1
groenten 1
halve kreeftje 1
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dranken 1
nagerecht 1
inrichting 2
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Terras 1
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korst 1
jongens van de bediening 1
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Boury 1
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Carpaccio van everzwijn 1
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steak 6
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brasserie 2
toetje 2
soep 4
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mosselen 6
smaken 6
hogeveelheid 1
mango tango - thee 1
restaurant 55
Indische eten 1
Parkrestaurant 1
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tentje 1
bar / lounge met rokers-annex 1
chorizo 1
gegrilde inktrvis 1
tong 1
harmonie 1
hoofdschotel 1
Thaise keuken 1
keuze 5
bordjes 1
ribbetjes a volonté 1
dame 5

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variaties 1
wachttijd 1
kabeljauw met jonge spinazie en mousseline 1
bordjes stokbrood 1
sauzen 2
lunchmenu's 2
brunch 2
Vicky1
voer 2
Tinne 1
sla 1
Cafe Belfort 1
menutje 1
sushi 1
kaas en de garnaal croketten 1
familiezaak 2
3 gang menu 1
cafe 1
pasta's 2
keuken 17
terras 11
Zuid-Afrikaanse wijnen 1
drankje 1
kokkin 1
maaltijden 4
The Village 1
plaats 1
stokbrood met knoflook 2
Bediening 10
tafeltjes 1
self-made ice tea 1
menu van de maand 1
tomatensop 1
Lasagne 1
huiswijn 1
Pannekoeken 1
menu's 1
Fawlty Towers taferel 1
interieur 12
deserties 1
bediening 95
steak saignant 1
menu 'PARELS VAN INDIA' 1
taarten 1
huisbereide garnaal kroketten 1
kaas 1
2010 châteauneuf du pape 1
wijnen 15
limonade 1
kaaskroketjes 1
tapasbarretje 1
vrouw 1
Bier 1
broodjes en koffiekoeken 1
Keuze 1
Eten 3
champignons 1
ham 1
eclairs 1
Limousin vlees 1
irish coffee 1
voorgerechten , hoofdgerechten en deserts 2
Wijnen 1
focaccia 3
ribbetje 1
couverts 1
huispecialiteiten 1
winkel met open keuken 1
salaatje 2
mayo 1
Mateo 1
Na-aper met vanille , chocomousse , banaan en advokaat 1
chateaubriand bouquetière 1
Pomperlut 1
Garcon 2
peterselie 1
suggesties 2
heer 1
bolletjes ijs 1
dienstverlening 1
fijnproeversbordje 1
risotto 1
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Home Cooking ' concept 1
pizza ' whisky ' 1
Sint Jorisoort 1
uitbater 2
ijs 2
Marc 1
formule ' pizza party 1
Tine 1
bord 1
tuin 8
rode vruchten 1
Personeel 3
fondue 3
kader11
cheesecake 1
keus 1
all-in-menu's 1
personeel 24
jus d'orange 1
iets lekkers1
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sanitair 1
pasta 1
McDonalds 1
maaltijd 2
taart 3
pannekoeken 1
garcon van dienst 1
Irish beef 1
chocolademelk 1
vlees in het stoofpotje 1
pannenkoeken 2
vrouwelijk personeelslid 1
Wijn 3
garnaalkroketten 1
omeletje 1
Moussaka 1
nagerechten 1
afrekening 1
eend 1
drank 1
vol au vent 1
Etna 1
John Cleese1
broodjes 3
gehaktballetjes in tomatensaus 1
ijsblokjes 1
Fonduehuis 1
steak tartare 1
Italiaans rest 1
salade met zalm en een quiche 1
dame blanche 1
steppengras fritten met biefstuk 1
friet 2
soepje 1
visgerechten 1
carpaccio 1
Parking 1
Gastvrijheid 1
fetuccine met curry 1
toilet 1
keuken van a L'infintise 1
prijzen 1
nagerechtje 1
rundvlees 1
NULL 563
broodje met vol-au-vent 1
aangepaste wijnen 3
Meneer 1
peter 1
handel 1
huisgemaakte Garnaalkroketten 1
setting 1
gefrituurdere peterselie 1
Park Restaurant 1
grand crus 1
mevrouw van de bediening 1
bediening van de zaakvoerster 1
Russisch ei 1
Italiaans restaurant 1
gerecht 5
eitje 1
eigenaar 4
carpaccio 1
patisserie 1
vertoning 1
Boury team 1
amuses 4
patroon 1
kip 2
# Appendix C

## Test and train data statistics

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Appendix D

Subjectivity lexicons

French

Single words

Positive

abordable abordable JJ
abordables abordable JJ
acceptable acceptable JJ
accessible accessible JJ
accueillant accueillant JJ
accro accro JJ
accueillant accueillant JJ
accueillante accueillant JJ
adapté adapté JJ
adaptée adapté JJ
adéquat adéquat JJ
adéquate adéquat JJ
adorable adorable JJ
adorer adorer VB
adoré adorer VB
affables affable JJ
agencé agencer VB
agréable agréable JJ
agreable agréable JJ
agrémentement agréablement RB
agréables agréable JJ
agreeables agréable JJ
aimable aimable JJ
aimables aimable JJ
aimablement aimablement RB
aime aimer VB
aimé aimer VB
alléchant alléchant JJ
alléchante alléchant JJ
alléchantes alléchant JJ
alléchans alléchant JJ
amabilité amabilité NN
amicale amical JJ
amicale amical JJ
amour amour NN
animer animer VB
appétissante appétissant JJ
appétissants appétissant JJ
appréciable appréciable JJ
appréciais apprécier VB
apprécie apprécier VB
apprécié apprécier VB
apprécier apprécier VB
appréciés apprécier VB
appréciions apprécier VB
attentionné attentionné JJ
attriré attirer VB
attirée attirer VB
attirés attirer VB
attractif attractif JJ
attractifs attractif JJ
attractive attractif JJ
authenticité authenticité NN
avantage avantage NN
avenant avenant JJ
beau beau JJ
beaux beau JJ
ensoleillée ensoleillé JJ
enthousiasme enthousiasme NN
entrez entrer VB
envie envie NN
épuré épuré JJ
equilibre équilibre NN
equilibré équilibré JJ
esthétique esthétique NN
étudié étudié JJ
excellemment excellemment RB
excellence excellence NN
excellent excellent JJ
excellente excellent JJ
excellentes excellent JJ
excellents excellent JJ
exceptionnel exceptionnel JJ
exceptionnelle exceptionnelle JJ
exploit exploit NN
exquis exquis JJ
extraordinaire extraordinaire JJ

fameux fameux JJ
fantastique fantastique JJ
favori favori JJ
fin fin JJ
fine fin JJ
fines fin JJ
finesse finesse NN
irréprochables irréprochable JJ
fraîche fraîche JJ
fraîchement fraîchement RB
fraîches fraîche JJ
fraîcheur fraîcheur NN
fraîcheur fraîcheur NN
frais frais JJ

gastronomique gastronomique JJ
généreuse généreux JJ
généreusement généreusement RB
généreuses généreuses JJ
généreux généreux JJ
géniales génial JJ
géniaux génial JJ
génie génie NN
gentil gentil JJ
gentil gentil JJ
gentilles gentil JJ
gentillesse gentil JJ
gourmands gourmand JJ
gouteux gouteux JJ
goûteuse goûteuse JJ
goûteux goûteux JJ
grâce grâce NN
guidé guidé JJ
habitués habitué NN
honnête honnête JJ
honneur honneur NN
honorables honorables JJ
humour humour NN

IDEAL idéal JJ
idéal idéal JJ
idéalement idéalement RB
imbatible imbatible JJ
impeccable impeccable JJ
impeccables impeccable JJ
impériosse impériosse JJ
imprenable imprenable JJ
impressionnant impressionnant JJ
incontournable incontournable JJ
incroyable incroyable JJ
indulgents indulgent JJ
intéressant intéressant JJ
intérêt intérêt NN
inventivité inventivité NN
irréprochable irréprochable JJ
irréprochables irréprochables JJ

joli joli JJ
jolie joli JJ
joliment joliment RB
jolis joli JJ
justifie justifier VB

large large JJ
légers léger JJ
légers léger JJ
lounge lounge JJ
lumineux lumineux JJ
luxe luxe JJ

magique magique JJ
magnifique magnifique JJ
maison  maison JJ
maisons  maison JJ
maîtrise  maîtriser VB
maîtrisé  maîtriser VB
maîtrisent  maîtriser VB
meilleur  meilleur JJ
meilleure  meilleur JJ
meilleures  meilleur JJ
ménagement  ménagement NN
mention  mention NN
merci  merci NN
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mesuré  mesuré JJ
moderne  moderne JJ
mythique  mythique JJ
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nickel  nickel JJ
oasis  oasis NN
original  original JJ
originale  original JJ
originales  original JJ
originalité  originalité NN
originaux  original JJ
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organisés  organisé JJ
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paradis  paradis NN
parfait  parfait JJ
parfaite  parfait JJ
parfaitement  parfaitement RB
parfumé  parfumé JJ
parfumée  parfumé JJ
passion  passion NN
patient  patient JJ
perle  perle NN
personnalisés  personnalisé JJ
phénoménale  phénoménale JJ
plaisant  plaisant JJ
plaisir  plaisir NN
plait  plaire VB
plâtre  plâtre VB
politesse  politesse NN
positif  positif JJ
positifs  positif JJ
positivement  positivement RB
possible  possible JJ
précautionneux  précautionneux JJ
précautionneux  précautionneux RB
précipitamment  précipitamment RB
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préférée  préféré JJ
prévenant  prévenant JJ
professionnel  professionnel JJ
professionnalisme  professionnalisme NN
propre  propre JJ
proximité  proximité NN
qg  Q.G. NN
qualité  qualité NN
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raffinée  raffiné JJ
raffinement  raffinement NN
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raisonnables  raisonnable JJ
rapide  rapide JJ
rapidement  rapidement RB
raides  rapide JJ
rattrape  rattraper VB
rattraper  rattraper VB
ravi  ravi JJ
ravie  ravi JJ
ravirons  ravi JJ
ravis  ravi JJ
recherchés  recherché JJ
recommande  recommander VB
recommandé  recommander VB
recommend  recommander VB
recommand  recommander VB
recommand  recommander VB
regal  régéal JJ
régal  régéal JJ
régale  régale JJ
régalés  régèal JJ
relaxant  relaxant JJ
remercier  remercier VB
remerciement  remerciement NN
renouée  renouvé JJ
repu  repu JJ
respecte  respecter VB
resservi  resservir VB
retournera  retourner VB
retournerai retourner VB
retournerais retourner VB
retournerons retourner VB
réto rétro JJ
réunir réunit VB
réussi réussi JJ
réussies réussi JJ
revenir revenir VB
reviendra revenir VB
reviendrons revenir VB
riche riche JJ

satisfait satisfait JJ
satisfaits satisfait JJ
satisfaissant satisfaisant JJ
satisfaissants satisfaisant JJ
savamment savamment RB
saveur saveur NN
couleur couleur NN
scrupuleuxux scrupuleux JJ
seduit séduire VB
serviable serviable JJ
simple simple JJ
sobre sobre JJ
soin soin NN
soigné soigné JJ
soignée soignée JJ
sophistiqué sophistiqué JJ
souriait sourire VB
souriab souriant JJ
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souriants souriant JJ
souri wyjaśni sourire VB
spacieux spacieux JJ
sublime sublime JJ
succès succès NN
succulentes succulent JJ
succulents succulent JJ
suffisante suffisant JJ
super super JJ
superbe superbe JJ
surprenant surprenant JJ
sympa sympathique JJ
sympas sympathique JJ
sympathies sympathie NN
sympathique sympathique JJ
sympathiques sympathique JJ
taxant talent NN
talentueux talentueux JJ
tamisée tamisé JJ
tendre tendre JJ
tip-top tip-top JJ
top top JJ
topissisme topissisme NN
traditionnelle traditionnel JJ
tranquille tranquille JJ
traînée travallé JJ
unique unique JJ
valorisée valorisé JJ
variée varié JJ
vaut valoir VB
verdoyante verdoyant JJ
volontiers volontiers RB

Negative

0 0 CD
abîmée abîmé JJ
abrupt abrupt JJ
absence absence NN
absentes absent JJ
acabit acabit NN
accuser accuser VB
acide acide JJ

addition addition NN
adieu adieu NN
affreuse affreux JJ
affreux affreux JJ
agaçant agacant JJ
agressif agressif JJ
agression agression NN
agressive agressif JJ
amas amas NN
améliorer améliorer VB
amer amer JJ
antipathique antipathique JJ
antipathiques antipathique JJ
approximatif approximatif JJ
arnaque arnaque NN
artifice artifice NN
astronomique astronomique JJ
attardes attarder VB
attend attendre VB
attendu attendre VB
attendre attendre VB
attente attente NN
attention attention NN
attrape attrape NN
austère austère JJ
avariée avarié JJ
avariées avarié JJ
aveugle aveugle JJ

baignaient baigner VB
baignanit baigner VB
baignant baigner VB
baigna baigner VB
baignée baigner VB
baissé baissier VB
banal banal JJ
banale banal JJ
banales banal JJ
bancales bancia JJ
bannir bannir VB
bémol bémol NN
beurk beurk UH
blague blague NN
blatte blatte NN
blattes blatte NN
blinde blinde NN
bondé bondé JJ
bouffé bouffer VB
bouilli bouillir VB
bouillis bouillir VB
bourratif bourratif JJ
bourru bourru JJ
broyé broyé JJ
bruillants bruyant JJ
bruit bruit NN
bûché bûché JJ
brulé brûlé JJ
brutale brutal JJ

bruyant bruyant JJ
bruyante bruyant JJ

choc ouf chocouf ouf JJ
caoutchouc caoutchouc NN
cartonnée cartonné JJ
catastrophe catastrophe NN
catastrophiques catastrophique JJ
cauhemar cauchemar NN
cauhemars cauchemar NN
charbonneuse charbonneux JJ
chewing gum chewing gum NN
chewing-gum chewing gum NN
chimique chimique JJ
cholesterol cholestérol NN
clinquante clinquant JJ
collantes collant JJ
comble comble NN
compliquéd compliqué JJ
concis concis JJ
congelé congelé JJ
gramé cramé JJ
crié crier VB
crie crier VB
croche-patte croquée-patte NN

danger danger NN
dattentes attente NN
débarrassé debarrasser VB
débarrasser débarrasser VB
débordé débordé JJ
débordée débordé JJ
débordés débordé JJ
déception déception NN
décevant décevant JJ
décevra décevoir VB
déclen déclin NN
| décongelée décongelé JJ | dur dur JJ |
| decongelé decongelé JJ | durci durcir VB |
| déconseiller déconseiller VB | dure durer VB |
| déconseiller déconseiller VB | écoeurantes écoeurant JJ |
| décu décu JJ | écoeurées écoeuré JJ |
| decu decu JJ | égarement égarement RB |
| déçue décu JJ | élevée élevée JJ |
| deçus déçu JJ | élevés élevés JJ |
| dédaigneux dédaigneux JJ | élevés élevés JJ |
| dégoût dégoûteur NN | embêter embêter VB |
| dégouté dégoûté JJ | empoiner empoiner VB |
| dégradé dégradé JJ | énervé énervé JJ |
| déguêulasse déguêulasse JJ | énervé énervé JJ |
| délabré délabré JJ | ennuyait ennuyer VB |
| délavées délavé JJ | entassé entassé JJ |
| délirants délirant JJ | envahissait envahir VB |
| dépassés dépassé JJ | épais épais JJ |
| deplacé déplacé JJ | éponges éponge NN |
| déplacé déplacé JJ | erreurs erreur NN |
| déplorable déplorable JJ | étonnant étonnant JJ |
| déprimant déprimant JJ | étrangement étrangement RB |
| dérangé dérangé JJ | éviter éviter VB |
| deranger deranger VB | EVITER éviter VB |
| dérangé deranger VB | éviterai éviter VB |
| dérangés deranger VB | Evitez éviter VB |
| dérangez deranger VB | exagéré exagéré JJ |
| désagréable désagréable JJ | exagérés exagéré JJ |
| désagréables désagréable JJ | excessif excessif JJ |
| désastre désastre NN | excessive excessive JJ |
| désastreux désastreux JJ | excréments excrément NN |
| désinvole désinvole JJ | exécrales exécrales JJ |
| désordonné désordonné JJ | exécrales exécrales JJ |
| désorganisation désorganisation NN | exorbitants exorbitant JJ |
| désorganisé désorganisé JJ | facture facture NN |
| desséché desséché JJ | facturés facturer VB |
| détériorer détériorer VB | fade fade JJ |
| dététable détetable JJ | fades fade JJ |
| difficile difficile JJ | faible faible JJ |
| difficilement difficilement RB | fatale fatale JJ |
| digestion digestion NN | fatale fatale JJ |
| discount discount NN | fatale fatale JJ |
| discuter discuter VB | fatales fatales JJ |
| disparu disparaître VB | fatigués fatigué JJ |
| dommage dommage NN | fausse faux JJ |
| douteuse douteux JJ | fausses faux JJ |
| douteux douteux JJ | fautes faute NN |
| draguer draguer NN | fautes faute NN |
| dubitative dubitatif JJ | faux faux JJ |
fermer fermé fermée fermées fermer fermé fermée fermées
fibreuse fibreux fibreuses fibreux
figé figé figé figées
flétries flétri flétries
flot flot
fondu fondu
force force
forcé forcé froids froid
frustrantes frustrant
fuir fuir fuire
fumer
fuyez
fuyezzzz

gâche gâcher gâché gâchées

gaché gâché

gâchée gâché

gâchis gâchis

gaspillage gaspillage

gelé gelé

gênante gênant

givrés givré

glacial glacial

gonflaient gonfler

graissee graisse

gras grâsses gras

grossier grossier

grossiers grossier

grossièrement grossièrement

grotesque grotesque

guindé guindé

halluciner halluciner

hautain hautain

hésiter hésiter

hic hic

honte honte

horrible horrible

huileuses huileux

ignorer ignorer
<table>
<thead>
<tr>
<th>French Word</th>
<th>Spanish Word</th>
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<tr>
<td>maigre</td>
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</table>

**Note:** The table above contains a list of French words along with their Spanish equivalents. The words are listed in categories based on their part of speech (JJ: adjective, NN: noun, VB: verb, RB: adverb, IN: adposition).
quelconques  quelconque JJ
quitter  quitter VB
racorni  racornir JJ
rassi  rassis JJ
raté  rater VB
rebute  rebuter VB
réchauffée  réchauffé JJ
réchauffer  réchauffer VB
réchauffés  réchauffé JJ
réchauffées  réchauffé JJ
réclamer  réclamer VB
réclamons  réclamer VB
recouvert  recouvert JJ
recouverte  recouvert JJ
rédibitoire  rédibitoire JJ
refroidissent  refroidir VB
refus  refus NN
refuse  refuser VB
refusé  refuser VB
regrettable  regrettable JJ
regrette  regretter VB
regrettions  regretter VB
renvoyés  renvoyer VB
reprocher  reprocher VB
ressaisir  ressaisir VB
restreint  restreint JJ
restreints  restreint JJ
retard  retard NN
ridicule  ridicule JJ
ridicules  ridicule JJ
rien  rien RB
ringard  ringard NN
ruiner  ruiner VB
sachet  sachet NN
sale  sale JJ
salé  salé JJ
salée  salé JJ
salées  salé JJ
sales  sale JJ
sans  sans RB
scandaleux  scandaleux JJ
sec  sec JJ
sèche  sec JJ
sèches  sec JJ
s'endorment  s'endormir VB
serrés  serré JJ
seul  seul JJ
seulement  seulement RB
seuls  seul JJ
sombre  sombre JJ
souci  souci NN
soucis  souci NN
souffrent  souffrir VB
speed  speed JJ
stress  stress NN
stricte  strict JJ
superflue  superflu JJ
surcuit  surcuire JJ
surcuits  surcuire JJ
surfaite  surfaire JJ
surgelée  surgelé JJ
surgelés  surgelé JJ
tâchant  tachant JJ
tendu  tendu JJ
terminé  terminé JJ
terrible  terrible JJ
tiède  tiède JJ
tièdes  tiède JJ
toiles  toile NN
trace  trace NN
traîne  traîner VB
triste  triste JJ
tristes  triste JJ
tristesse  tristesse NN
trop  trop RB
veines  veine NN
veilles  vieux JJ
vexe  vexer VB
vide  vide JJ
vieillot  vieillot JJ
vieillotte  vieillot JJ
vieux  vieux JJ
vol  vol NN
voleurs  voleur NN
zero  zéro NN
zéro  zéro NN
Flip

aucun
aucune
moins
pas

Multiwords

Positive

bon marché
bière chaude
donne envie
à volonté
a ne pas rater
coup de coeur
l’eau à la bouche
fond dans la bouche
grillé dans le fond
à l’écoute
un cas d’œcle
à tomber par terre
sont de saison
rien à dire
rien à redire
a donné envie
qui n’a pas son égal
geste commercial
à tester
point fort
rien à redire sur
cantine du soir
est à tomber par terre
se sent en famille
bonne volonté
est en accord avec
à se lécher les babines
ne sont pas en reste
prix bas
bon marché
avis ++++
cuisiné sur place
coucher de soleil
mettre à l’aise
un large choix
un buffet à volonté
une adresse à tester/noter
ça vaut le coup

est toujours au rendez-vous
une valeur sur
l’embarras du choix
à très vite
chargé d’histoire
que demander de plus
produits du terroir
mention spéciale
on y retournera
nous y retournerons
je retournerais
envie d’y retourner

Negative

ny connaît rien
à contre coeur
baissé en qualité
baisse la tête
laissent à désirer
toiles d’araignées
gauche dans
odeur de friture
un lance pierre
croche-patate
en boîte
n’y mettrais plus les pieds
n’y remettrais plus les pieds
n’y mettrons plus les pieds
ne plus y remettre les pieds
ne leur ferons pas de publicité
au détriment de
passez votre chemin
passer votre chemin
une espèce de
ne correspondent pas
ne correspond pas
ne correspond pas
ne veulent pas qu’
ne veulent pas que
remettez de l’ordre dans
ferait mieux de
se promener les mains dans les poches
une bière pression
une bière coupée à l’eau
sans intérêts
toujours pas
allez ailleurs
peut mieux faire
on y va les yeux fermés
on s’est fait pousser vers la sortie
ne laisse pas de souvenir
s’attendre à mieux
qu’est-ce que c’est que
s’attendre à beaucoup mieux
se casser le porte-monnaie
n’ayez pas peur
on reste sur sa faim
pas de rab
se font bien allégés le porte-feuille
devrait apprendre à
la barre était un peu haute
prenez vos jambes à votre cou
je ne parle pas des
bas de gamme
je donnerai même pas à mon chien
mieux vaut changer de
mieux vaut changer d’
pas cuit
pas cuite
pas cuits
pas cuites
je n’irai plus
porte de prison
claquements de doigts
micro onde
micro ondes
n’y retournerai pas
ne retournerai pas
n’y retournerons plus
n’y retournerons pas
n’retournerais plus
n’y retournerais pas
pas y retourner
nous n’y retournerons jamais
### English

#### Single words

**Positive**

<table>
<thead>
<tr>
<th>Positive Words</th>
<th>Cool Words</th>
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<tr>
<td>above-average above-average JJ</td>
<td>cool cool JJ</td>
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<tr>
<td>accommodating accommodating JJ</td>
<td>cordial cordial JJ</td>
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<tr>
<td>adequately adequately RB</td>
<td>correct correct JJ</td>
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<td>affordable affordable JJ</td>
<td>courteous courteous JJ</td>
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<td>amazing amazing JJ</td>
<td>cozy cozy JJ</td>
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<td>amazed amazed JJ</td>
<td>crave crave VB</td>
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<td>amazin amazing JJ</td>
<td>creamy creamy JJ</td>
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<td>art art NN</td>
<td>decent decent JJ</td>
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<td>awesome awesome JJ</td>
<td>delight delight NN</td>
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<td>balance balance NN</td>
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<td>bargain bargain NN</td>
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<td>beautifully beautifully RB</td>
<td>devoured devour VB</td>
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<td>best good JJ</td>
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difficult difficult JJ
disappointed disappointed JJ
disappointed disappointed JJ
disappointment disappointment NN
disapointed disappointing JJ
dissapointing disappointing JJ
dissapointment disappointment NN
dissapoints disappoint VB
disgusting disgusting JJ
downside downside NN
dramatic dramatic JJ
drawback drawback NN
drawbacks drawback NN
dry dry JJ
dumped dump VB

Negative

abrupt abruptly JJ
edible edible JJ
absurdly absurdly RB
empty empty JJ
annoying annoying JJ
evil evil JJ
arrogant arrogant JJ
expensive expensive JJ
average average JJ
finally finally RB
avoid avoid VB
fail fail VB
awful awful JJ
failed fail VB
bad bad JJ
fails fail VB
badly badly RB
fall apart fall apart JJ
bland bland JJ
fallback fallback NN
blasted blast VB
finally finally RB
blatantly blatantly RB
fishiest fishy JJ
bitter bitter JJ
flavorless flavorless JJ
average average JJ
fool fool VB
avoid avoid VB
fooled fool VB
bored bored JJ
forget forget VB
boring boring JJ
forgotten forget VB

cancel cancel VB
fail fail VB
canned canned JJ
finally finally RB
cheap cheap JJ
called called JJ
called called JJ
cold cold JJ
called called JJ
complain complain VB
called called JJ
complained complain VB
ghetto ghetto NN
complain complain VB
gimicks gimmick NN
complaint complaint NN
glorified glorified JJ
complaints complaint NN
grease grease NN
congestion congestion NN
greasy greasy JJ
cried cried JJ
crammed cram VB
gross gross JJ
cramped cramp VB
deficiencies deficiency NN
congestion congestion NN
despite despite RB

dearth death NN
heaviness heaviness NN
deficiencies deficiency NN
heaviness heaviness NN
deficiencies deficiency NN
hostile hostile JJ

dehalf death NN
heaviness heaviness NN
deficiencies deficiency NN
heaviness heaviness NN

ignored ignore VB
imposing impose VB
incompetent incompetent JJ
inconsistent inconsistent JJ
inedible inedible JJ
inexpertly inexpertly RB
infused infused JJ
intimidate intimidate VB
joke joke NN
lacking lack VB
limited limited JJ
long long JJ
loud loud JJ
lousy lousy JJ
mad mad JJ
mediocre mediocre JJ
mediocre mediocre JJ
mess mess NN
messy messy JJ
miserable miserable JJ
missing miss VB
moody moody JJ
muttering mutter VB
negative negative JJ
noise noise NN
noisy noisy JJ
no-so-fresh not-so-fresh JJ
offensive offensive JJ
oily oily JJ
old old JJ
old-fashioned old-fashioned JJ
over priced over-priced JJ
overrated overrated JJ
over-bearing over-bearing JJ
overcharged overcharged JJ
overcrowded overcrowded JJ
overdone overdone JJ
overhyped overhyped JJ
overlooked overlook VB
overpack overpack VB
overpriced overpriced JJ
overrated overrated JJ
packed packed JJ
panting pant VB
pass pass VB
pathetic pathetic JJ
poor poor JJ
poorly poorly RB
postal postal JJ
pretentious pretentious JJ
problem problem NN
quibbles quibble NN
refuse refuse VB
regret regret VB
rip-off rip-off NN
rubber rubber NN
rude rude JJ
rush rush VB
rushed rush VB
rushing rush VB
sadly sadly RB
salty salty JJ
scared scared JJ
scary scary JJ
shooed shoo VB
shredded shred VB
shut-down shut down VB
skimpy skimpy JJ
skip skip VB
slow slow JJ
snobby snobby JJ
soaked soaked JJ
soggy soggy JJ
sparse sparse JJ
spilled spill VB
spotty spotty JJ
stale stale JJ
stinks stink VB
stressed stressed JJ
subpar subpar JJ
tasteless tasteless JJ
thawed thaw VB
thinly-sliced thinly-sliced JJ
threw throw VB
tiny tiny JJ
tired tired JJ
trouble trouble NN
un-appetizing unappetizing JJ
unappealing unappealing JJ
unappreciative unappreciative JJ
unattractive  unattractive  JJ
uncomfortable  uncomfortable  JJ
uncourteous  uncourteous  JJ
unfriendly  unfriendly  JJ
unhelpful  unhelpful  JJ
unimposing  unimposing  JJ
unnecessary  unnecessary  JJ
unprofessional  unprofessional  JJ
vomit-inducing  vomit-inducing  JJ

wait  wait  VB
watery  watery  JJ
worried  worried  JJ
worst  bad  JJ
wrong  wrong  JJ

yawn  yawn  VB
yuck  yuck  UH
zero  zero  NN

Flip

never
No
not
nothing

Multiwords

Positive

#1
above average
a classic
a hit
a haven of
price is in line
prices are in line
are to die for
blew me away
blew us away
blows me away
blows us away
can't be beat
can't get enough
can't go wrong
can not go wrong
can't wait
caters to all your needs
check out
cooked to perfection
coming back here again
didn't find it here
do n't miss
down to earth
gave us lip
get more than enough
get the
go here
go for the
going back
half price sushi deal
has it all
hats off to the chef
haut cuisine
haute cuisine
have been going back again and again
have to try it
high quality
hits the spot
is not to be missed
it is to die for
keep up the
kicks ass
make it a point to visit
made upon request
must try
no nonsense
off-the-beaten path
is on point
are on point
was on point
were on point
open kitchen
out of this world
partial to the
repeat customers
short wait
small wait
thumbs up
top notch
try this place
try everything
we'd go back again
will be back
would go back
will return
will go back
will definitely go back

Negative

a little out of the way
doesn't quite match up
doubt I'll ever go back
had to ask
major attitude
just walked away
long wait
low quality
need to clean
never again
no flavor
no plans to return
not for the better
not up to par
small tip

stay away from
stepped on
take my business elsewhere
will never go back
wouldn't go back
would never go there again
would never go back
won't go back
doubt I'll ever go back
Dutch

Single words

Positive

aanbevelen aanbevelen VB
aanbevelen aanbevelen VB
aangenaam aangenaam JJ
aangenaam aangenaam JJ
aangepast aangepast JJ
aangepaste aangepast JJ
aangeprezen aanprijzen VB
aanraden aanraden VB
aanrader aanrader NN
aantrekkelijk aantrekkelijk JJ
aantrekkelijke aantrekkelijke JJ
aanvaardbaar aanvaardbaar JJ
aanvaardbare aanvaardbare JJ
accepteerbaar accepteerbaar JJ
afwisseling afwisseling NN
alaise à l’aise FW
appreciëren appreciëren VB
artisanaal artisanaal JJ
artisanale artisanale JJ
attent attent JJ
attente attent JJ
attentie attentie NN
attentvol attentvol JJ
authentiek authentiek JJ
authentieke authentieke JJ

bedankt bedankt UH
behulpzaam behulpzaam JJ
bekwame bekwaam JJ
beleefdheid beleefdheid NN
belevenis belevenis NN
bepreekbaar bespreekbaar JJ
beste goed JJ
betaalbaar betaalbaar JJ
bewonderen bewonderen VB
bijpassende bijpassend JJ
bijzonder bijzonder JJ
blij blij JJ
blindelings blindelings JJ
bravo bravo UH

casual casual JJ
charmant charmant JJ
fijnprovers fijnproever NN
flexibel flexibel JJ
formidabel formidabel JJ
fris fris JJ
gaar gaar JJ
gastvrij gastvrij JJ
gastvrijheid gastvrijheid NN
gefeliciteerd feliciteren VB
geinteresseerd geïnteresseerd JJ
gekoeld gekoeld JJ
gekuis kuisen JJ
geluk geluk NN
gelukkig gelukkig JJ
gemakkelijk gemakkelijk JJ
gemoedelijk gemoedelijk JJ
gemoedelijke gemoedelijk JJ
genieten genieten VB
genieters genieter NN
genog genog RB
genot genot NN
genoten genieten VB
gepassioneerd gepassioneerd JJ
geschikt geschikt JJ
geslaagd geslaagd JJ
geslaagde geslaagd JJ
gemaakt smaken VB
getoerd toveren VB
gevolgd gevolgd JJ
geweldig geweldig JJ
geweldige geweldig JJ
gelijk gelijk JJ
gelijk gelijk JJ
gelijkheid gelijkheid NN
glimlach glimlach NN
glimlachje glimlach NN
go goed JJ
goed goed JJ
goede goed JJ
goedkeuring goedkeuring NN
goei goed JJ
goee goed JJ
goedkoop goedkoop JJ
goedkope goedkoop JJ
graag graag RB
grappige grappig JJ
grote groot JJ
gul gul JJ
gunstig gunstig JJ
handig handig JJ
hartelijk hartelijk JJ
hartelijke hartelijk JJ
hartige hartig JJ
hartverwarmend hartverwarmend JJ
heerlijk heerlijk JJ
heerlijke heerlijk JJ
helpen helpen VB
herbruikbaar herbruikbaar JJ
hip hip JJ
hondvriendelijke hondvriendelijk JJ
hoogstandjes hoogstandje NN
hoogtepunt hoogtepunt NN
huisbereide huisbereide JJ
huisgemaakt huisgemaakt JJ
huisgemaakte huisgemaakte JJ
huiskamer huiskamer NN
hulpzaam hulpzaam JJ
ideaal ideaal JJ
ideale ideaal JJ
inbegrepen inbegrepen JJ
indrukwekkend indrukwekkend JJ
indrukwekkende indrukwekkende JJ
intense intens JJ
juiste juist JJ
juweeltjes juweel NN
kaarslicht kaarslicht NN
kersverse kersvers JJ
keurig keurig JJ
keurige keurig JJ
keuze keuze NN
klasse klasse NN
knetterende knetterend JJ
knus knus JJ
koning koning NN
krookant krookant JJ
kruidig kruidig JJ
kunstenaar kunstenaar NN
kwaliteitsvol kwaliteitsvol JJ
kwaliteitsvolle kwaliteitsvol JJ
lachje lach NN
legendair legendarisch JJ
legendarische legendarisch JJ
lekker lekker JJ
lekkere lekker JJ
lekkernijen lekkernij NN
lekkers lekkers NN
lekkerste lekker JJ
leuk leuk JJ
leuke leuk JJ
leukste leuk JJ
lichte licht JJ
lief lief JJ
livebandje liveband NN
lof lof NN
losse los JJ
luchtig luchtig JJ
luxe luxe JJ
mals mals JJ
meerwaarde meerwaarde NN
meester meester NN
meesterwerkje meesterwerkje NN
meevaller meevaller NN
microgolfvriendelijk microgolfvriendelijk JJ
modern modern JJ
mogelijkheid mogelijkheid NN
mooi mooi JJ
mooie mooi JJ
netjes netjes JJ
njam njam UH
no-nonsense no-nonsense FW
nonsense nonsens NN
onbeperkt onbeperkt JJ
ongedwongen ongedwongen JJ
ongeloofelijke ongelooftelijk JJ
ongelooflijk ongelooftelijk JJ
ontdekkingen ontdekkingen NN
ontdekt ontdekken VB
onthouden onthouden VB
ontspannen ontspannen JJ
onvergetelijk onvergetelijk JJ
oogstrelende oogstrelend JJ
opgeleide opgeleid JJ
origineel origineel JJ
originele origineel JJ
originelle origineel JJ
overheerlijk overheerlijk JJ
passie passie NN
perfect perfect JJ
perfecte perfect JJ
persoonlijke persoonlijk JJ
plaatjes plaat NN
plezier plezier NN
plezierig plezierig JJ
pluim pluim NN
plus plus NN
pluspunt pluspunt NN
pittig pittig JJ
positief positief JJ
positieve positief JJ
prachtig prachtig JJ
prachtige prachtig JJ
prettig prettig JJ
prettige prettige JJ
prima prima JJ
professionele professioneel JJ
proficiat proficiat UH
prompt prompt JJ
proper proper JJ
pure puur JJ
rap rap JJ
respect respect NN
romantiek romantiek NN
romantischromantisch JJ
romantische romantisch JJ
royaal royaal JJ
royale royaal JJ
ruggesteuntje ruggesteun JJ
ruim ruim JJ
ruime ruim JJ
rust rust NN
rustgevend rustgevend JJ
sappig sappig JJ
schappelijke schappelijk JJ
schilderijtjes schilderij JJ
schitterend schitterend JJ
schitterende schitterend JJ
schoon schoon JJ
seizoen gebonden seizoensgebonden JJ
sfeervol sfeervol JJ
sfeervolle sfeervol JJ
smaakbom smaakbom NN
smaakbommetjes smaakbom JJ
smaakfestival smaakfestival NN
smaakparadijzen smaakparadijs NN
smaaksensaties smaaksensatie NN
smaakvol smaakvol JJ
smakelijk smakelijk JJ
smakelijke smakelijk JJ
smile smile FW
smullen smullen VB
snelle snel JJ
speciaal speciaal JJ
speciale speciaal JJ
specialisatie specialisatie NN
spektakel spektakel NN
spontaan spontaan JJ
spontane spontaan JJ
sprookjesachtig sprookjesachtig JJ
ster ster NN
sterren sterren JJ
sterrenwaardig sterrenwaardig JJ
stijl stijl NN
stijlvol stijlvol JJ
stralend stralend JJ
subliem subliem JJ
sublieme sublieme JJ
subtiel subtiel JJ
super super JJ
su-per super JJ
superjammmie superjammmie UH
superlekker superlekker JJ
superlekkere superlekker JJ
supervriendelijke supervriendelijk JJ
sympathiek sympathiek JJ
sympathieke sympathiek JJ
sympatiekesympathiek JJ
talent talent NN
tevreden tevreden JJ
thuis thuis NN
toffe tof JJ
toffen tof JJ
tofste tof JJ
top top JJ
topkok topkok NN
topniveau topniveau NN
topper topper NN
toppers topper NN
topgastronomie topgastronomie NN
toprestaurant toprestaurant NN
topwijnen topwijin NN
toveren toveren VB
treffelijke treffelijk JJ
troef troef NN
trots trots NN
uitgebreid uitgebreid JJ
uitgebreide uitgebreide JJ
uitgelezen uitgelezen JJ
uitnodigend uitnodigend JJ
uitstekend uitstekend JJ
uitstekende uitstekend JJ
uniek uniek JJ
unieke uniek JJ
veel veel JJ
veelbelovend veelbelovend JJ
verademing verademing NN
verfijnd verfijnd JJ
verfijnde verfijnd JJ
verleidingen verleiding NN
verrasen verrassen VB
verrasend verrassend JJ
verrasende verrassend JJ
verrijking verrijking NN
verwend verwend JJ
verwennersj verwennersj JJ
vers vers JJ
verse vers JJ
versgemaakt versgemaakt JJ
versgemaakte versgemaakte JJ
vervelend vervelend JJ
verzorgd verzorgd JJ
verzorgde verzorgde JJ
visalternatief visalternatief NN
vlekkeloos vlekkeloos JJ
vlot vlot JJ
vlotte vloot JJ
voldaan voldaan JJ
voldoende voldoende JJ
voorkeur voorkeur NN
voorkomend voorkomend JJ
voortreffelijk voortreffelijk JJ
voortreffelijk voortreffelijk JJ
vriendelijk vriendelijk JJ
vriendelijke vriendelijk JJ
vriendelijkenheid vriendelijkheid NN
vriendelijke vriendelijk JJ
vriendschappelijke vriendschappelijk JJ
waard waardeer JJ
waardeerde waarderen VB
waarderen waarderen VB
waardig waardig JJ
warm warm JJ
warmere warm JJ
warmhartige warmhartig JJ
watten wat NN
welkom welkom UH
woonkamer woonkamer NN
wow-gevoel wow-gevoel NN
zachte zacht JJ
zalig zalig JJ
zelfgemaakt zelfgemaakt JJ
zelfgemaakte zelfgemaakt JJ
zin zin NN

Negative

aandachtspunt aandachtspunt NN
aandachtspunte aandachtspunt NN
afgeblaat afgeblaat JJ
afknapper afknapper NN
afraden afraden VB
afschuwelijk afschuwelijks JJ
agressieve agressief JJ
alder Aldi NNP
amateuristisch amateuristisch JJ
antwoord antwoord NN
antwoordde antwoorden VB
arme arm JJ
arrogant arrogant JJ
bah bah UH
ballentent ballentent NN
bedorven bedorven JJ
bedrieg bedriegen VB
bedrog bedrog NN
beklager beklag NN
beklagen beklagen VB
belediger beledigen VB
beperkt beperkt JJ
beperkte beperkt JJ
beschaaamd beschaaamdJJ
beschadigd beschadigdJJ
beschikbaar beschikbaar JJ
bespaart besparen JJ
binnenrijven binnenrijven VB
bitter bitter JJ
boertig boertig JJ
braken braken VB
brasseriekeuken brasseriekeuken NN
bruit bruit JJ
buitensporig buitensporig JJ
C4 C4 NN
chagrijnig chagrijnig JJ
chagrijniggechagrijnig JJ
chaotisch chaotisch JJ
doegen doegent Jabortant deugentant JJ
denigrerende denigrerend JJ
diaree diarree NN
dieptepunt dieptepunt NN
diepvries diepvries NN
diepvrieszevruchtenmix
diepvrieszevruchtmix NN
dieven dief NN
doodgewoonweg doodgewoongeweg RB
doodleuk doodleuk RB
doorbakken doorbakken JJ
doorsnee doorsnee JJ
doorweekte doorweekt JJ
droge droog JJ
droog droog JJ
druk druk JJ
drukdoend drukdoend JJ
drukke druk JJ
durven durven VB
duur duur JJ
duurder duurder JJ
duurt duuren VB
dwong dwingen VB
eikels eikel NN
eindelijk eindelijk RB
enkel enkel RB
erbarmelijke erbarmelijk JJ
ergerlijk ergerlijk JJ
ergernis ergernis NN
ergernissen ergernis NN
excuse excuses NN
flauw flauw JJ
flets flets JJ
flinters flinter NN
flop flop NN
fout fout NN
foute foute JJ
fouten fout NN
frank frank JJ
frietkot frietkot NN
frituur frituur NN
frutuurvet frituurvet NN
geantwoord antwoorden VB
gebrek gebrek NN
geforceerd geforceerd JJ
gehaast gehaast JJ
gehorig gehorig JJ
geklaagd klagen VB
geldverspilling geldverspilling NN
gemiste gemiste JJ
geroest geroest JJ
geruik rukken VB
geschrooken schrikken VB
gesloten gesloten JJ
gesmolten smelten VB
gevoelloos gevoelloos JJ
gewacht wachten VB
gewierd weigeren VB
gezwierd zwieren VB
gooide gooien VB
gore goor JJ
groothandel groothandel NN

industrieel industrieel JJ
inspiratieloos inspiratieloos JJ

hard hard JJ
harde hard JJ
haren haar NN
hel hel NN
helaas helaas UH
hopeloze hopeloos JJ
huilen huilen VB

inefficiënt inefficiënt JJ
insecten insect NN

jammer jammer UH
joeg jagen VB

kant-en-klaar kant-en-klaar JJ
kapot kapot JJ
karige karig JJ
kauwgom kauwgom NN
keihard keihard JJ
klakklachen klikklakken VB

knettergek nettergek JJ
knuppel knuppel NN
koud koud JJ
klagen klagen VB
klein klein JJ
kleven kleven VB
klungelen klungelen VB
kotsen kotsen VB
krakende krakend JJ
kritiek kritiek NN
kruipende kruipend JJ
kwader kwaad JJ
kwakken kwakker VB

lachertje lachertje NN
lachwekkende lachwekkend JJ
laf laf JJ
lang lang JJ
lange lange JJ
langzaam langzaam JJ
lauw lauw JJ
lauwe lauw JJ
lawaaierig lawaaierig JJ
liflafje liflafje NN

MacDonalds McDonalds NNP
magnetron magnetron NN
makro Makro NNP
matig matig JJ
meningsverschil meningsverschil NN
microgolf microgolf NN
mijden mijden VB
mijlen mijl NN
minderwaardig minderwaardig JJ
minimum minimum JJ
miniscule minuscuul JJ
minmuntje minpunt NN
minpunt minpunt NN
minpuntje minpunt NN
minuten minuut NN
minutenlang minutenlang RB
misdaad misdaad NN
mislukt mislukt JJ
mist mist NN
misten misten VB
moeilijk moeilijk JJ
moeite moeite NN

nadeel nadeel NN
nee nee UH
neen neen UH
negeren negeren VB
niemendalnetje niemendalnetje NN
nonchalant nonchalant NN
nors nors JJ
null null CD

omhooggevallen omhooggevallen JJ
onbegrijpelijk onbegrijpelijk JJ
onbeleefd onbeleefd JJ
onbeschonken onbeschonken JJ
onbelicht onbeschoten JJ
ondermaats ondermaats JJ
onduidelijk onduidelijk JJ
ongeduldig ongeduldig JJ
ongeënt ongeënter JJ
ongeluk ongeluk NN
ongemakkelijk ongemakkelijk JJ
ongenoegen ongenoegen NN
ongeënt ongeënter JJ
ongezellig ongezellig JJ
onhandig onhandig JJ
onhandigheid onhandigheid NN
onhygiënisch onhygiënisch JJ
onnoglijk onnoglijk JJ
onnodig onnodig JJ
onpersoonlijk onpersoonlijk JJ
onprofessionele onprofessioneel JJ
onsmakkelijk onsmakelijk JJ
ontbraken ontbreken VB
ontbreekt ontbreken VB
ontgoocheling ontgoocheling NN
ontnemen ontnemen VB
ontslagen ontslagen VB
onvoorstellbaar onvoorstellbaar JJ
onvriendelijk onvriendelijk JJ
onvriendelijke onvriendelijk JJ
onvriendelijkheid onvriendelijkheid JJ
opgave opgave NN
opgeslagen opslaan VB
opgewarmd opwarmen VB
opmerking opmerking NN
overbemand overbemand JJ
overgegeven overgeven VB
overgeven overgeven VB
overschaduwd overschaduwen VB
peperdure peperduur JJ
personenbezorgen personeelsbezorgen NN
pest pest NN
pezen pees NN
pijn pijn NN
plakkerig plakkerig JJ
plastic plastic JJ
platgebakken platgebakken JJ
platte plat JJ
politiebezoek politiebezoek NN
prijzig prijzig JJ
probleem probleem NN
problemen probleem NN
pseudo pseudo JJ
puin puin NN
puinhoop puinhoop NN

ramp ramp NN
ranzige ranzig JJ
rauw rauw JJ
rechtsonder rechtsommeer NN
reclameerde reclameren VB
rekening rekening NN
rioolruimte rioolruimte NN
roken roken VB
roomblok roomblok JJ
rotslecht rotslecht JJ
ruimen ruimen VB
rumoerig rumoerig JJ

schaandelig schandaalig JJ
schandaalige schandaalig JJ
schande schande NN
scheld schelden VB
schoenzool schoenzool NN
scheld schelden VB
simpele simpel JJ
slap slap JJ
slecht slecht JJ
slechte slecht JJ
slechter slechter JJ
slechts slechts RB
slechtste slechtste JJ
slechtte slechtte JJ
slenteren slenteren VB
sluiten sluiten VB
smaakstoffen smaakstof NN
smakeloos smakeloos JJ
smeren smeren VB
smerig smerig JJ
snaauw snaauw NN
sneer sneer NN
spijt spijt NN
spijtig spijtig JJ
spin spin NN
spuitbus spuitbus NN
standaardkwaliteit standaardkwaliteit
NN
stinken stinken VB
stoffige stoffig JJ
stoorde storen VB
stress stress NN
stuk stuk NN
stumpers stumper NN
stuurs stuurs JJ
taai taai JJ
te te RB
tegenvallen tegenvallen VB
tegenvallertegenvallerNN
tegenvieltegenvallen VB
teleurgesteld teleurstellen VB
teleurstelling teleurstelling NN
timide timide JJ
tja tja UH
toeschreeuwtoeschreeuwen VB
toeristich toeristisch JJ
toeristenval toeristenv val
NN
traag traag JJ
uteindelijkuiteindelijkRB
uitgedroogd uitdrogen VB
uitgedroogde uitgedroogd JJ
uitgelachen uitlachen VB
uitverkocht uitverkocht JJ

vacuüm vacuüm JJ
val val NN
varkensstalvarkensstalNN
verbrand verbrand JJ
verbrachte verbrand JJ
verdenken verdenken VB
verdwenen verdwenen VB
veredeld veredeld JJ
vergeet vergeten VB
vergeten vergeten VB
verheffen verheffen VB
verkeerde verkeerd JJ
verkreukt verkreukt JJ
verkwisting verkwisting NN
vermijden vermijden VB
verontwaardigd verontwaardigd JJ
verouderd verouderd JJ
verpesten verpesten VB
verplicht verplicht JJ
verschrikkelijk verschrikkelijk JJ
verschrikkelijke verschrikkelijk JJ
verspilling verspilling NN
verwaard verwaard JJ
vet vet NN
vies vies JJ
 vieze vies JJ
vliegen vlieg NN
vliegende vliegend JJ
vliegies vlieg NN
vreemd vreemd JJ
vrees vrees JJ
vreselijk vreselijk JJ
vreselijke vreselijk JJ
vuil vuil JJ
vulie vuli JJ
vuilnisbak vuilnisbak NN
vuilste vuil JJ
waardelooswaardeloosJJ
wachten wachten VB
wachtrijn wachtrijn NN
wachtijd wachtijd NN
wansmakelijk wansmakelijk JJ
wansmakelijke wansmakelijk JJ
waterachtig waterachtig JJ
waterig waterig JJ
web web NN
wegbliven wegbliven VB
wegdeemsteren wegedeemsteren VB
weggejaagged weggijagen VB
weggetrokken wegtrekken VB
weglopen weglopen VB
weigerde weigeren VB
weinig weinig CD
woester woest JJ
zeepsop zeepsop NN
zelfde zelfde JJ
zelfingenomen zelfingenomen JJ
zeveren zeveren VB
ziek ziek JJ
zielig zielig JJ
zielige zielig JJ
zogezegd zogezegd RB
zoutig zoutig JJ
zure zuur JJ
zwemden zwemmen VB

Flip

geen
minder
niet
zonder

Multiwords

Positive

aan te raden
à volonté
al meermaals geweest
allen daarheen
de moeite waard
deed haar best
die wel de tijd heeft
dikke sneden brood
doe zo verder
Doe zo voort
doen hun best
duidelijk uitgelegd
duimen en vingers
Een betere keuze had de jarige niet
conen maken
een van de betere
enorm grote bollen
gaan zeker nog eens terug
gaan zeker terug
gaan zeker en vast terug
gek is op
gek op
Heel redelijk van prijs
heel veel
het betere werk
het is hier allemaal
hier vaker moeten komen
hieraan kan tippen
hoog niveau
houden van
hun vak kennen
in de watten
in orde

jouw tevredenheid is echt hun
bezorgdheid
juiste adres
kan bijna niet beter
Keep up the good work
kom hier graag terug
komen graag nog eens terug
komen ooit nog terug
komen zeker terug
komen zeker en vast terug
komen zeker nog terug
komen we graag terug
komen we zeker terug
konden deze gerust bestellen
lactose- en glutenvrije recepten
luft het wel
maakt het verschil
meer dan waard
meest uitgelezen
met mate geprijsd
moet je bezoeken
must do
Na een tiental minuutjes
naar behoren
niets aan te merken
niets op aan te merken
nooit elders gezien
nooit geziene kwaliteit
om nog terug te keren
om terug te gaan
ontdekking van het jaar
op niveau
probeer ook eens
probeer zeker
ruim aanbod
schot in de roos
smelten in je mond
tip top in orde
Tot gauw weer
tot nog eens
tot tevredenheid
ruime keuze
veel keuze
verschillende keuze
brede keuze
vaste klanten geworden
vingers bij af te likken
voor elk wat wils
voor herhaling vatbaar
voor ieder wat wils
waar voor je geld
warmer sfeer
weinig op aan te merken
wel zeven of acht verschillende soorten
Zeer hoog culinair niveau
zeker dat ik naar hier terug kom
Zeker de kreeft met de zes verschillende
sausjes eens bestellen
zeker en vast nog terug
zeker in orde
zeker nog terug
zeker te proberen
zicht op zee
zijn geld waard
zonder stijf te zijn
zoveel als je wilt

Negative

2de rangs vlees
tweederangs vlees
stappen achteruit
uur gewacht
uur wachten
keer voorbijgekomen was zonder op te kijken
aan de hoge kant
af te raden
al betere heb gedronken voor veel minder dan 22 euro
alles was hen teveel
als de tafels proper waren
als het gras eens gemaaid werd
alsof ie al eens gegeten was

amper brood
beetje elementaire klasse ver te zoeken
beneden alle peil
begrijp niet dat dit een ster verdient
BETALEN ! !
bijna niet te vinden
bleek het restaurant dicht
blief hier gewoon weg
Blijkbaar moet je op zijn minst BV zijn
borden waren niet leeg
daar blijft het er ook bij
dan moet je het niet aanbieden
deed het meerdere malen niet
de mist in
Denk niet dat veel mensen voor een 2de
maal gaan
de volle mop betalen
die geen tijd had stond tussendoor frietjes
teen
don't go there
Echt geen restaurant waardig ! !
echt prijs kwaliteit
enkel besteld worden per glas
Enkel en alleen de ' kching ' van de kassa
telt
etensresten tussen haar tanden uit te
peuteren
ga ergens anders eten
gebrek aan opvoeding
Geef hier jullie geld niet aan ! !
geef je geld ergens anders uit
geen andere wijn te bestellen
geen crème brulée in het aanbod
geen drankkaart of wijnkaart aangeboden
geen excuses
geen fooi
geen lang leven beschoren
geen menukaart
geen non-alcoholische dranken
geen uitleg
geen volk
geen vrienden meer mee naar toe te
temen
geen woord
geen zin
god de vader
Goedkoop is het niet
groooote boog
grote mond
handen te kort
heikel punt
hele poos wachten
honger was dus over
iets dat gelijkt op
Ik kom zeker graag terug
indien de bediening vriendelijk was en de
wachttijden respectabel
kan beter
kan duidelijk beter
kan er niet af
kan mij echter niet voorstellen dat er
geen betere
kant en klaar maaltijden
kies maar iets anders
klopt niet altijd
kom, geef maar, en zet u
komen hier nooit meer
kon beter
kon niet dat hij dat niet gezien had
krijg je hier niet
kunnen de druk en bediening duidelijk
niet aan
lang wachten
laten staan
leek wel een kinderportie
leer uw personeel manieren
LET OP
liep weg
lukt gewoonweg niet
maande hem aan tot kalmte
maar half afgebakken
maar liefst 8 euro
maar soit
meer bot dan kip
meer klanten in het restaurant toegelaten
dan de bediening aankan
meer van verwacht
met zijn gsm te spelen
mij niet meer gezien
mij zien ze hier niet meer
minder ons ding
mocht alleen wel wat warmer zijn
mocht de presentatie toch een heel stuk
beter
mooier serveren en dan liefst niet in een
glas
nauwelijks nog iets voorradig
nauwelijks tafels afgeruimd
na anderhalf uur
naar de knoppen

namen gewoon niet op
namen ze wel erg hun tijd
net niet zwart
niemand die de leiding over de zaal neemt
niemand er aan gedacht ons hier van te
verwittigen
niemand om aan te vragen
niet al te best
niet boven water kan houden
niet de moeite getroost
niet erg groot
niet geneigd was van te betalen
niet genoteerd
niet gevraagd
niet het geval
niet kan voorstellen wat dit dan wel moet
zijn
niet meer aan te kijken
niet meer
niet met volle goesting
niet om aan te zien
niet op de kaart
niet op de lijst
niet te drinken
niet te verkrijgen
niet te vreten
niet wegesneden door de keuken
niets aan te merken
niets met mijn antwoord te doen
niets van dit
niet voor herhaling vatbaar
nog geen brasseriebeoordeling waard
nog veel werk
nooi meer
nooit meer
nooit nog terug
nooit willen dienen
NU ! ! !
of toch op zijn minst
om nog maar over te zwijgen
onderhoud nodig
ongelofelijke verbale manier aangepakt
Onze volgende reservatie ligt al vast
op twee paarden wedden
op voorhand op een bord aan je
voorgesteld
over datum
over ons heen gekeken
pas gemeld op het moment dat
pompen of verzuipen
poot kunnen uitdraaien
raden het aan iedereen af
rechtstreeks naar het toilet
regent binnen
sfeer was er niet meer
sla deze zaak dan over
slachtoffer van eigen succes
sloeg hier alles
stop gewoon
streling voor
swung is er blijkbaar uit
sympathiek zijn ze zeker niet
teggen haar zin
tveel betaald
tientallen andere adressen dan
Toen ik vroeg of men Nederlands sprak,
was het antwoord ' non '
uit de Adams familie
vaste waarde
veel geld
ver te zoeken
vergeet het maar
verre van hartelijk
viel behoorlijk tegen
viel echt tegen
volg een cursus elementaire beleefdheid
en klantvriendelijkheid ipv arrogantie en
onbeleefdheid
vooral veel heen en weer lopen met niets
of één iets in de hand
voor de prijs dat je daar betaalt
voor een fortuin
waar je de garnalen moest zoeken
Waar men in de regel
waren veel te ver
wat aan de kleine kant
wat gezelliger
wel wat verfijnder
zal nog maar zwijgen
hoge prijzen
zonder boe of ba
zonder uitleg
Appendix E
Results experimental setup

French

Setup 1

<table>
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<tr>
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</table>

Table 1: Results of the first setup on the French test set.

Accuracy

\[
\frac{290+202+14+46}{910} = 60.66
\]

Precision

Pos: \( \frac{290}{290+66+33+14} = 71.96 \)
Neg: \( \frac{202}{202+31+18+9} = 77.69 \)
Neutral: \( \frac{14}{14+29+47+2} = 15.22 \)
Undefined: \( \frac{46}{46+47+52+10} = 29.68 \)

Recall

Pos: \( \frac{290}{290+31+29+47} = 73.05 \)
Neg: \( \frac{202}{202+66+47+52} = 55.04 \)
Neutral: \( \frac{14}{14+10+33+18} = 18.67 \)
Undefined: \( \frac{46}{46+2+9+14} = 64.79 \)

F-1

Pos: \( 2 \times \frac{(71.96 \times 73.05)}{(71.96 + 73.05)} = 72.50 \)
Neg: \( 2 \times \frac{(77.69 \times 55.04)}{(77.69 + 55.04)} = 64.43 \)
Neutral: \( 2 \times \frac{(15.22 \times 18.67)}{(15.22 + 18.67)} = 16.77 \)
Undefined: \( 2 \times \frac{(29.68 \times 64.79)}{(29.68 + 64.79)} = 40.71 \)
Setup 2

<table>
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</table>

Table 2: Results of the second setup on the French test set.

Accuracy

\[
\frac{(288+211+14+45)}{910} = 61.32
\]

Precision

Pos: \(\frac{288}{288+61+33+14} = 72.73\)

Neg: \(\frac{211}{211+33+18+10} = 77.57\)

Neutral: \(\frac{14}{14+29+45+2} = 15.56\)

Undefined: \(\frac{45}{45+47+50+10} = 29.61\)

Recall

Pos: \(\frac{288}{288+33+29+47} = 72.54\)

Neg: \(\frac{211}{211+61+45+50} = 57.49\)

Neutral: \(\frac{14}{14+10+33+18} = 18.67\)

Undefined: \(\frac{45}{45+2+10+14} = 63.38\)

F-1

Pos: \(2 \times \frac{(72.73 \times 72.54)}{(72.73 + 72.54)} = 72.63\)

Neg: \(2 \times \frac{(77.57 \times 57.49)}{(77.57 + 57.49)} = 66.04\)

Neutral: \(2 \times \frac{(15.56 \times 18.67)}{(15.56 + 18.67)} = 16.97\)

Undefined: \(2 \times \frac{(29.61 \times 63.38)}{(29.61 + 63.38)} = 40.36\)
Setup 3

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<td>UNDEFINED</td>
<td>47</td>
<td>50</td>
<td>10</td>
<td>45</td>
</tr>
</tbody>
</table>

Table 3: Results of the third setup on the French test set.

Accuracy

\[(288+218+15+45) / 910 = 62.20\]

Precision

Pos: \[288 / (288+53+33+15) = 74.04\]
Neg: \[218 / (218+33+17+10) = 78.42\]
Neutral: \[15 / (15+29+46+1) = 16.48\]
Undefined: \[45 / (45+47+50+10) = 29.61\]

Recall

Pos: \[288 / (288+33+29+47) = 72.54\]
Neg: \[218 / (218+53+46+50) = 59.40\]
Neutral: \[15 / (15+10+33+17) = 20\]
Undefined: \[45 / (45+1+10+15) = 63.38\]

F-1

Pos: \[2x ((74.04x72.54) / (74.04+72.54)) = 73.28\]
Neg: \[2x ((78.42x59.40) / (78.42+59.40)) = 67.60\]
Neutral: \[2x ((16.48x20) / (16.48+20)) = 18.07\]
Undefined: \[2x ((29.61x63.38) / (29.61+63.38)) = 40.36\]
English

Setup 1

<table>
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<td>9</td>
<td>88</td>
<td>5</td>
<td>10</td>
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<td>24</td>
<td>4</td>
<td>6</td>
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<tr>
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<td>92</td>
<td>151</td>
<td>19</td>
<td>56</td>
</tr>
</tbody>
</table>

Table 4: Results of the first setup on the English test set.

Accuracy

\[
\frac{338+88+4+56}{948} = 51.27
\]

Precision

Pos : \( \frac{338}{338+83+17+31} = 72.07 \)
Neg : \( \frac{88}{88+9+5+10} = 78.57 \)
Neutral: \( \frac{4}{4+15+24+6} = 8.16 \)
Undefined: \( \frac{56}{56+92+151+19} = 17.61 \)

Recall

Pos: \( \frac{338}{338+9+15+92} = 74.45 \)
Neg: \( \frac{88}{88+83+24+151} = 25.43 \)
Neutral: \( \frac{4}{4+17+5+19} = 8.89 \)
Undefined: \( \frac{56}{56+6+10+31} = 54.37 \)

F-1

Pos: \( 2 \times \left( \frac{72.07 \times 74.45}{72.07 + 74.45} \right) = 73.24 \)
Neg: \( 2 \times \left( \frac{78.57 \times 25.43}{78.57 + 25.43} \right) = 38.42 \)
Neutral: \( 2 \times \left( \frac{8.16 \times 8.89}{8.16 + 8.89} \right) = 8.51 \)
Undefined: \( 2 \times \left( \frac{17.61 \times 54.37}{17.61 + 54.37} \right) = 26.60 \)
Setup 2

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<td>+</td>
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<tr>
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<td>70</td>
<td>142</td>
<td>17</td>
<td>55</td>
</tr>
</tbody>
</table>

Table 5: Results of the second setup on the English test set.

Accuracy

\[
\frac{(358+92+4+55)}{948} = 53.69
\]

Precision

\[
\text{Pos: } \frac{358}{358+88+19+32} = 72.03 \\
\text{Neg: } \frac{92}{92+11+5+10} = 77.97 \\
\text{Neutral: } \frac{4}{4+15+24+6} = 8.16 \\
\text{Undefined: } \frac{55}{55+70+142+17} = 19.37
\]

Recall

\[
\text{Pos: } \frac{358}{358+11+15+70} = 78.85 \\
\text{Neg: } \frac{92}{92+88+24+142} = 26.59 \\
\text{Neutral: } \frac{4}{4+17+5+19} = 8.89 \\
\text{Undefined: } \frac{55}{55+6+10+32} = 53.40
\]

F-1

\[
\text{Pos: } 2 \times \frac{(72.03 \times 78.85)}{(72.03 \times 78.85)} = 75.29 \\
\text{Neg: } 2 \times \frac{(77.97 \times 26.59)}{(77.97 \times 26.59)} = 39.66 \\
\text{Neutral: } 2 \times \frac{(8.16 \times 8.89)}{(8.16 \times 8.89)} = 8.51 \\
\text{Undefined: } 2 \times \frac{(19.37 \times 53.40)}{(19.37 \times 53.40)} = 28.43
\]
Setup 3

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<td>142</td>
<td>17</td>
<td>55</td>
</tr>
</tbody>
</table>

Table 6: Results of the third setup on the English test set.

Accuracy

\[
\frac{352+103+7+55}{948} = 54.54
\]

Precision

Pos: \( \frac{352}{352+66+16+32} = 75.54 \)
Neg: \( \frac{103}{103+6+5+12} = 81.75 \)
Neutral: \( \frac{7}{7+26+35+4} = 9.72 \)
Undefined: \( \frac{55}{55+70+142+17} = 19.37 \)

Recall

Pos: \( \frac{352}{352+6+26+70} = 77.53 \)
Neg: \( \frac{103}{103+66+35+142} = 29.77 \)
Neutral: \( \frac{7}{7+17+5+16} = 15.56 \)
Undefined: \( \frac{55}{55+4+12+32} = 53.40 \)

F-1

Pos: \( 2 \times \frac{(75.54 \times 77.53)}{(75.54 \times 77.53)} = 76.52 \)
Neg: \( 2 \times \frac{(81.75 \times 29.77)}{(81.75 \times 29.77)} = 43.65 \)
Neutral: \( 2 \times \frac{(9.72 \times 15.56)}{(9.72 + 15.56)} = 11.97 \)
Undefined: \( 2 \times \frac{(19.37 \times 53.40)}{(19.37 \times 53.40)} = 28.43 \)
Dutch

Setup 1

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</tbody>
</table>

Table 7: Results of the first setup on the Dutch test set.

Accuracy

\[
\frac{(274+99+3+68)}{725} = 61.24
\]

Precision

\[
\text{Pos: } \frac{274}{(274+53+19+33)} = 72.30 \\
\text{Neg: } \frac{99}{(99+16+4+16)} = 73.33 \\
\text{Neutral: } \frac{3}{(3+25+17+6)} = 5.88 \\
\text{Undefined: } \frac{68}{(68+46+40+6)} = 42.50
\]

Recall

\[
\text{Pos: } \frac{274}{(274+16+25+46)} = 75.90 \\
\text{Neg: } \frac{99}{(99+53+17+40)} = 47.37 \\
\text{Neutral: } \frac{3}{(3+4+6+19)} = 9.38 \\
\text{Undefined: } \frac{68}{(68+6+16+33)} = 55.28
\]

F-1

\[
\text{Pos: } 2 \times \left( \frac{(72.30 \times 75.90)}{(72.30 + 75.90)} \right) = 74.06 \\
\text{Neg: } 2 \times \left( \frac{(73.33 \times 47.37)}{(73.33 + 47.37)} \right) = 57.56 \\
\text{Neutral: } 2 \times \left( \frac{(5.88 \times 9.38)}{(5.88 + 9.38)} \right) = 7.23 \\
\text{Undefined: } 2 \times \left( \frac{(42.50 \times 55.28)}{(42.50 + 55.28)} \right) = 48.05
\]
Setup 2

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<td>6</td>
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</tbody>
</table>

Table 8: Results of the second setup on the Dutch test set.

Accuracy

\[
\frac{281+105+3+68}{725} = 63.03
\]

Precision

Pos: \( \frac{281}{281+47+20+31} = 74.14 \)
Neg: \( \frac{105}{105+14+3+18} = 75 \)
Neutral: \( \frac{3}{3+24+17+6} = 6 \)
Undefined: \( \frac{68}{68+42+40+6} = 43.59 \)

Recall

Pos: \( \frac{281}{281+14+24+42} = 77.84 \)
Neg: \( \frac{105}{105+47+17+40} = 50.24 \)
Neutral: \( \frac{3}{3+3+6+20} = 9.38 \)
Undefined: \( \frac{68}{68+6+18+31} = 55.28 \)

F-1

Pos: \( 2 \times \frac{(74.14 \times 77.84)}{(74.14+77.84)} = 75.94 \)
Neg: \( 2 \times \frac{(75 \times 50.24)}{(75+50.24)} = 60.17 \)
Neutral: \( 2 \times \frac{(6 \times 9.38)}{(6+9.38)} = 7.32 \)
Undefined: \( 2 \times \frac{(43.59 \times 55.28)}{(43.59+55.28)} = 48.74 \)
Table 9: Results of the third setup on the Dutch test set.

Accuracy

\[
\frac{(279+106+2+68)}{725} = 62.76
\]

Precision

\[
\text{Pos : } \frac{279}{279+39+19+31} = 75.82 \\
\text{Neg : } \frac{106}{106+18+5+18} = 72.11 \\
\text{Neutral: } \frac{2}{2+24+22+6} = 3.70 \\
\text{Undefined: } \frac{68}{68+42+40+6} = 43.59
\]

Recall

\[
\text{Pos: } \frac{279}{279+18+22+42} = 77.29 \\
\text{Neg: } \frac{106}{106+24+39+40} = 50.72 \\
\text{Neutral: } \frac{2}{2+5+6+19} = 6.25 \\
\text{Undefined: } \frac{68}{68+6+18+31} = 55.28
\]

F-1

\[
\text{Pos: } 2x \left(\frac{75.82 \times 77.29}{75.82 + 77.29}\right) = 76.55 \\
\text{Neg: } 2x \left(\frac{72.11 \times 50.72}{72.11 + 50.72}\right) = 59.55 \\
\text{Neutral: } 2x \left(\frac{3.70 \times 6.25}{3.70 + 6.25}\right) = 4.65 \\
\text{Undefined: } 2x \left(\frac{43.59 \times 55.28}{43.59 + 55.28}\right) = 48.74
\]