

Sentiment Analysis for Social Media Comments

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Abstract

Analyzing customer experience offers valuable data for Business Intelligence. Especially in e-commerce, where users write reviews about products and services, the analysis of the customers' sentiment towards these entities yields significant insights into potential strengths and weaknesses of the product or service.

Our work focuses on evaluating customer experience through the application of aspect-based sentiment analysis on social media posts. The data set contains a year's worth of Facebook comments on the pages of the two supermarket chains Tesco and Sainsbury. The goal is to extract as many triplets (e, a, s) as possible, where e is an entity (product or service), a is an aspect of this entity (performance, battery, politeness, etc.), and s is the sentiment polarity label (negative, neutral, positive).

To accomplish this task, many different subtasks need to be solved. After a rudimentary preprocessing routine, the posts need to be identify the part of speech (POS) category for every word. Then Named Entity Recognition (NER) must be applied and words containing sentiment need to be detected and evaluated. As a significant number of social media texts do not follow the grammatical rules or contain a lot of misspellings the complexity of those tasks is increased significantly. With the completed analysis we identify potential products and services, their corresponding aspects and sentiment words, which are scored and aggregated into opinions.

The results obtained from this analysis are visualized to get a better understanding of the customers' feelings towards these products, services, and their aspects. The visualization supports businesses in a wide range of decisions, such as product positioning and pricing. This can lead to better customer satisfaction, faster reactions to trends and overall revenue growth.

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1 Introduction

Sentiment analysis or opinion mining uses techniques from natural language processing (NLP), text analysis, and computational linguistics to extract subjective information from texts. In applications that involve analyzing customer experience, this subjective information typically represents the position of a person towards a certain entity. Quantifying feelings and opinions that customers possess towards products and services offers valuable information for the company.

Such information can be used to monitor their reputation or improve the understanding of the market's needs. In contrast to generic sentiment analysis, this information can only be acquired by precisely identifying the entities and aspects towards which a sentiment is expressed. This specific task is referred to as Aspect Based Sentiment Analysis (ABSA).

The project presented in this document focuses on ABSA, finding and analyzing customers' opinions on products and their aspects from social media posts of a supermarket chain.

In today's world, social media is a big part of the social life. On social networks like Facebook, many companies represent themselves through a corporate account. This opens up the possibility for many people to interact with those companies. Everyone can leave a comment on the page of a company, celebrity or a sports teams. People can review or comment with a lot of context. General posts can be created, as well as reactions to news or a posting that concerns a specific product. These comments or reviews are often filled with positive or negative sentiments.

It should therefore be possible to collect the information in these posts and extract sentiments about products or aspects of the company that offer valuable insight. Our approach on a solution will be presented in this report, starting with a description of the related work that already exists. Afterwards, our approach and the single steps that are performed will be introduced. Then, the results that have been obtained will be discussed, as well as the visualization that has been implemented. To finish up the report, a conclusion will be drawn.

2 Related work

The related work presented in this section should give a quick overview over two of the main techniques that we used to identify entities and their aspects.

2.1 POS-Tagging

POS-Tagging (part-of-speech tagging), also called grammatical tagging or word-category disambiguation, refers to the process of identifying particular parts of speech like nouns or verbs. Identifying the role of a certain word within a sentence is important for the task of sentiment analysis, as identifying entities

and their corresponding aspects can be handled much easier relying on certain assumptions about the part of speech of words.

While being important POS-Tagging is also a complex problem. Word-forms in natural language are often ambiguous. For example the word 'dogs' is usually thought of as a plural noun, but can be used as a verb as well:

The sailor dogs the hatch.

Due to the complexity, machine learning techniques are often applied in POS-Taggers. Popular approaches such as the Viterbi algorithm, the Brill tagger or the Baum-Welch algorithm work with techniques such as dynamic programming, supervised learning or hidden Markov models.

2.2 NER-Tagging

Named-Entity recognition (NER) is a task that seeks to locate and classify specific information in text. This information is called a named entity and can refer to categories such as the names of persons, locations, times or many others.

An annotated sentence could look like this :

[Tim Cook]_[Person] has a Net worth of [785 million USD]_[MonetaryValue]
as of [March 16. 2017]_[Time].

While state-of-the-art NER-Taggers perform very well and produce near-human performance they are also brittle and do not perform well in domains they were not designed for.

2.3 Lexicon-based sentiment analysis

An approach to determine sentiment polarities is the lexicon-based sentiment analysis.

The method created by (Liu, 2003) can be broken down to the following four steps:

In the first step, all sentiment words and phrases in the text are marked with the help of a sentiment lexicon. This is done by assigning positive or negative values to those sentiments, e.g. [+1] for a positive or [-1] for a negative sentiment.

In the second step, sentiment shifters will be applied. A sentiment shifter can be described as a word that negates the value that has been applied in the first step, changing its value from positive to negative or the other way around. Typically, these words are negation words like *not*.

In the third step, but-clauses and further contrary words are handled. With these contrary words, sentences can be split up into two parts. Depending on the value of the sentiments mentioned in the first part, the sentiments in the second part receive the opposite value.

In the fourth and last step, the opinions are aggregated according to the following function:

$$score(a_i, s) = \sum_{sw_j \in s} \frac{sw_j.so}{dist(sw_j, a_i)}$$

where sw_j is a sentiment word in s , $dist(sw_j, a_i)$ is the distance between aspect a_i and sentiment word sw_j in s . $sw_j.so$ is the sentiment score of sw_j . Depending on the score, it can be determined whether the opinion on the aspect a_i in s is positive or negative. If the final score neither positive or negative, it is a neutral aspect.

3 Approach

3.1 Preprocessing

We pre-processed the data by extracting the actual text of the posts into separate files. We decided to exclude posts that are less than 20 characters long or include images. This is due to the fact that posts which are too short do not yield much information most of the time. Furthermore, posts that include images often refer to objects in the image, which makes it hard to understand the author’s sentiment without analyzing the image content.

3.2 Extracting entities and aspects

For each post, the POS tags as well as different entities are obtained, with the entities being created through different Named Entity Recognition models. Both POS-tagging and Named Entity Extraction are accomplished with OpenNLP. They use maximum entropy, which takes the data and classifies it, while not assuming anything about the probability distribution, besides the things that have been observed.

The Named Entity Recognition in the English language is available for different entities, each with their own model. We utilized the following models: *person*, *location*, *organization*, *date* and *money*.

Because no pre-trained model exists for the Named Entity Recognition of products or services, we decided to use the OpenNLP model for organization to appropriately tag these. Most nouns in the English language are written in lower case, but organizations as well as products contain capital letters. The OpenNLP model for organizations is a fitting alternative to bypass the non-existent models for products and services because of this. Therefore, we consider everything that is tagged as *Organization* as a product or service.

Searching for aspects is done by iterating over the complete set of posts for each entity. If a post contains the product, we identify the sentences it appears in. We then look for other nouns in these sentences and count their frequency. From those potential aspects, we consider the ones to be real aspects that occur at least in 10% of the posts that mentioned the product.

After identifying a set of aspects for each entity, we merge similar entities and their aspect lists by tokenizing the entities' names and lemmatizing them. This results in a reduction of entities, e.g. *Customer Service* and *Customer Services* are considered as the same entity. The entities' aspect lists are merged accordingly. All aspects that are also part of the entity's name are removed from the aspect list. Amongst other things, this removes the aspects *tesco* and *express* from the list of aspects for the entity *Tesco Express*.

If no aspects can be found for a specific entity, it is removed from the final list of entities. For every entity that is part of the final list, the aspect *general* is added as well.

3.3 Determining sentiment polarities

nlTK's Vader module Specifically developed for social media

4 Results

We were given a data set containing a year's worth of Facebook comments on the pages of two supermarket chains Tesco and Sainsbury. However, we decided to perform our approach only on the Tesco data set.

Through performing our pre-processing tasks of removing posts with less than 20 characters or an image, we were able to reduce the amount of posts by 40.6%, from 37701 original posts down to 22395 afterwards.

By executing the POS- and NER-tagger, we came up with 1598 products that were mentioned in the posts. Because there were a lot of products that did not make sense, we removed some of them by hand, resulting in 1379 products. Furthermore, products that did not possess an aspect were removed as well. Therefore, 1256 products that at least contain one aspect were identified, decreasing the product list by 21.5%.

The original goal was to extract as many quintuples $(e_i, a_{ij}, s_{ijkl}, h_k, t_l)$ as possible, where e_i is the i 'th entity and a_{ij} is the j 'th aspect of entity i the opinion is expressed on. s_{ijkl} is the sentiment polarity, which can take on the values *positive* or *negative*. h_k describes the opinion holder and t_l the time at which the opinion was expressed.

However, from the data set that was given to us, it was not possible to determine the person that wrote a post. Moreover, we did not focus on extracting the time a certain sentiment was expressed, as we did not aim to provide a temporal overview over the shifting of opinions towards the products and services.

We labeled a small subset of posts concerning the entity *Customer Service* by hand. This includes 200 posts with 254 extracted sentiment triples with unknown sentiment.

After labeling these triples with the Vader module, 139 of the 254 triples (i.e. 54.72%) result in the same sentiment.

4.1 Visualization

We will use the sentiment lexicon by (Liu, 2008), which includes misspellings, morphological variants, slang and social-media mark-up of 2006 positive and 4783 negative words.

On the server side, we use Python with the library Flask. On the client side, we use the JavaScript libraries d3.js, vue.js and jQuery.

For the visualization, we use the *JSON* file containing the aggregated opinions that are the result of executing the pipeline as well as a *JSON* containing the positive and negative sentiment words that are provided by the lexicon-based sentiment analysis.

The data is visualized with each product having its own page that is loaded from a dropdown menu and each aspect of the product being visualized with a bar chart as well as the specific posts being shown below the bar chart. The bar chart can be seen in Figure 1. It shows the amount of negative, neutral and positive sentiments regarding the combination of product and aspect.

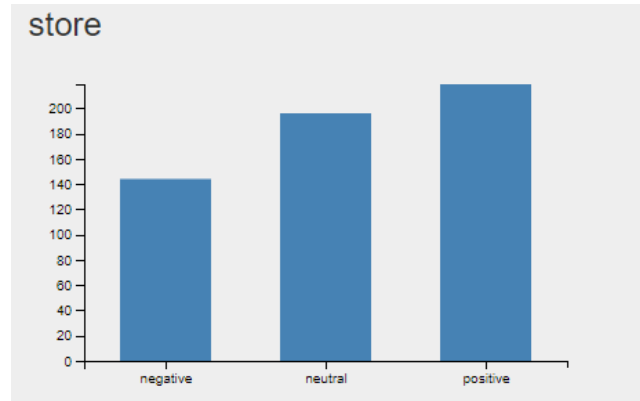


Figure 1: Bar chart displaying the sentiments regarding the customer service with aspect 'store'

An excerpt of posts regarding the combination of product and aspect is shown below each bar chart, with a maximum of 10 posts per aspect. In Figure 2, the highlighted posts can be seen. Positive and negative sentiments are highlighted in colors green and red, respectively. Mentions of the product are highlighted in orange and the aspect is shown with a cyan highlighting.

Posts

I am not **happy** I would **like** you to contact me back as I m not having any job both with your **store** nor **customer services**

I would just **like** to take some time to comment on the **excellent customer service** I recieve by your **customer** delivery drivers in the craigavon extra **store** they are all very **well** mannered.

Hi I am very **happy** with your **customer service** I just would **like** to see more organic cosmetics in your **stores**

I would just **like** to say what **great customer service** the hexham **store** has as this isnt the first time they have gone out the way to help me.

I was originally told via your **customer service** that they would check in **store** re baking to make sure all was being cooked **correctly** as its a express **store** I know the staff and we have had many a conversation regarding the cooking process I have even purchased **bread** and cooked myself to check it and it s the bread not the **store**

Been to your cartlon superstore today and as I was paying at self **serve** I heard a woman getting quite **frustrated** and emotional at the **customer service** desk.

just wanted to say that you should be very **proud** of your **customer service** staff at the gaywood kings lynn **store** they **helped** me with a **problem** that they could have walked away from regarding one of the coffee machines **thank** you Kelly Delves and lorraine wellard ... they were angels when i was very stressed xx

Tesco **customer service** says to take it back to **store** for a **refund**

Just wanted to alert you to the **fantastic customer service** I ve received this morning at the tesco superstore in penistone.

On the rare occasions I have to pee there you wouldn t believe how many men don t wash their hands then they are picking up baskets/handling produce etc I've asked the **friendly customer service** about this 4 times it may make some men think twice...it s a food **store** !

Figure 2: Highlighted posts regarding the customer service with aspect 'store'

5 Discussion and Conclusion

The accuracy of 54.72% as mentioned in Section 4 leaves a lot of potential for improvement. Several factors contribute to this rather bad accuracy score. First of all, the 200 posts that were labeled by hand are by no means indicative of the actual data set. Furthermore, we did not test different target functions for the polarity determination. Due to the lack of time, each of the four contributors tagged 50 posts. There is no guarantee that two people agree with what the other person labeled (would need Kappa measure).

We do not account for multi token aspects, since we only identify common nouns, which are single words.

Like mentioned in Section 3.2, we consider every organization found as product or service. This has many caveats. For one, it is required that services like *Customer Service* actually appear capitalized in our data set at least once to be found. Moreover, a lot of things that are not actually organizations are tagged as such. This could be improved by incorporating more knowledge regarding common nouns and noun phrases. Moreover, the results could be improved by finding a model that has been trained on products, which would result in more accurate entities and aspects.

6 Appendix

6.1 Using the code

To reproduce our work, the provided code has to be executed in a certain sequence. The following will talk about the needed steps.