Using Sentiment Analysis to Assess Customer Satisfaction in an Online Job Search Company

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Abstract. The Internet is a reality in people's lives, enabling the growth of many online services companies. However, to maintain their activities and stay in the market, it's important for these companies to worry about the quality of the provided services. In this context, it becomes important to be able to assess the client satisfaction regarding those services. The objective of this work is to propose a tool for aiding the evaluation of customer satisfaction in a Brazilian Online Job Search Company through the use of Sentiment Analysis. Sentiment Analysis, or Opinion Mining, refers to the techniques used to extract and evaluate sentiment expressed in textual data. We analyzed a database of an online job search company containing client comments collected from a service cancellation form. This database, among other parameters, has a score assigned by the client and a comment about the services. We performed the classification of the sentiment expressed in the user comments with the aid of a software written in Python, and then calculated the correlation of the sentiment score with the score assigned by the clients. The results lead to the conclusion that the use of Sentiment Analysis serves as a support tool to enrich the customer satisfaction assessment.

Keywords: Quality · Services · Customer satisfaction · Opinion mining · Sentiment analysis

1 Introduction

The Internet allowed several changes in economic, social, political, cultural and philosophical relations. These changes are still open, and continue to happen as the Internet itself redefines its scope and reach [1].

In this scenario, many companies that offer online services have emerged. Among them, there are online job search companies. Such companies have as one main characteristic, the maintenance of large databases of candidates and jobs, and try, using a multitude of methods, to make the connection between candidates and job positions.

To keep up in a competitive market, it's important for the companies to worry about the quality of the provided services. According to [2], the quality in services is a comparison between the client's expectations and the service's performance.

However, in the case of online services, it's difficult to know in advance the expectations of customers because, according to [3], customers of online services,

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in many cases, do not have well-defined expectations about the service. Therefore, knowing the sentiment of the customers after the service delivery can be of great help for evaluating their satisfaction regarding the services.

Therefore, in order to evaluate the quality of services in an online job search company, it's important to measure the customer satisfaction, that is, the gap between their expectations and the actually delivered service performance. Hence, there is the need to know the sentiment of the customers of the company regarding the services. However, because of the high volume of data to be analyzed, it is almost impractical to assess all of it manually.

In this context emerge the Sentiment Analysis, which is the set of computational techniques used to extract, classify, understand and evaluate the sentiments and opinions expressed by users in textual sources. It can be used, for example, to understand the opinions of voters about political events or the opinions of consumers about a company's products [4].

The goal of this work is to propose a tool to assist the evaluation of customer satisfaction in an online job search company, through the use of Sentiment Analysis. In addition, we intend to sustain the viability of this tool through a bibliographic research on the covered topics and exploratory research with real data from a company.

The Sect. 2 presents a brief overview of the company that yielded the data for this study, followed by the theoretical framework on service quality and customer satisfaction. Section 3 presents the theoretical framework on Sentiment Analysis. Section 4 presents the methods and materials and Sect. 5 discusses the results. Section 6 concludes this paper.

2 Service Quality in an Online Job Search Company

Online job search companies are companies that provide services of online job listings. They also provide the registration of candidates' resumes for those seeking placement in the labor market, sometimes also putting these resumes online.

The business model of these companies may vary. A company may charge the hiring companies that advertise job positions and allow access to such information by the professionals looking for a job, or they may charge the job seekers to have access to the job positions information.

The company used as the basis of this study uses the later business model, i.e., charges the service from job seekers who can put their resumes online and have access and apply to job positions advertised by hiring companies.

Through the company's website, the customers can apply for the advertised job positions. Only the company's customers have access to this information and must apply to the positions through company's website.

This company also offers some additional services, for example, tools for the hiring companies to manage the incoming resumes and arrange interviews.

For the service companies in this segment, the customer satisfaction is a critical factor for success. It's related to meeting implied and stated needs of the consumer by means of service attributes [5].

However, services have certain characteristics that differ from other sectors of the economy regarding the perception of quality. These characteristics are intangibility, heterogeneity and inseparability [2].

Services are intangible because they are performances, not objects. Many services cannot be measured, counted, inventoried, tested and checked before the act of providing it, in order to ensure its quality [6].

Services are heterogeneous, because their performance is variable. It depends on the supplier and the customer. And the experience that the company intends to provide may be different from the expectations of the customer [7].

Services are inseparable, for its production and consumption cannot be separated. For this reason, one cannot guarantee the quality during the production in the factory plant and then deliver it intact to the customer [8].

The quality of e-services, i.e., those services provided through sites in the Internet has some peculiarities. According to [2], the perception of the quality of such services depends on the customer's familiarity with technology.

According to [3], the perceived quality in a website is based on five criteria:

- Information availability and content;
- Easy of use or usability;
- Privacy or security;
- Graphic style;
- Fulfillment.

Customer expectations when using online services are different from expectations of customers from traditional (offline) services. In most cases, customers do not have well-defined expectations, and often their previous consumption patterns are nonexistent or inaccurate [3].

3 Sentiment Analysis

The emergence of Web 2.0 and social media has created many opportunities to understand the opinion of the general public and consumers about social events, political movements, corporate strategy, marketing campaigns and product preferences. Many questions concerning consumers' opinions on certain subject could be answered by analyzing the thousands of comments on blogs, media and social networks like Twitter, Facebook and YouTube or news sites.

It's important to note that the term Sentiment Analysis is also used to refer to Opinion Mining, and vice versa. The term Opinion Mining is more common in academia, while the term Sentiment Analysis is more common in organizations. However, the two terms refer to the same concept [9].

Sentiment Analysis, a sub discipline within Data Mining and computational linguistics, and refers to the computational techniques to extract, classify, understand and evaluate the opinions expressed in various online news sources, social media comments and other content created by users [4].

In this work, the content created by each user is called document. For example, a post on a forum, a comment or post on a blog, or a review of a product, are called document, with the goal to standardizing the terminology.

Sentiment Analysis is not concerned in identifying the subject of a document, but to identify and classify the opinions expressed therein [4]. The document's textual data can be divided into two broad categories; they can be facts or opinions. Facts are objective statements, while opinions are subjective statements [10].

In order to identify the opinions expressed in a document, one may use, for example, Sentiment Analysis at the aspect level, for example, identifying the opinions on aspects or characteristics of a product, and thus discovering the sentiment associated with different aspects of the subject [11].

The work in [12] describes a technique for summarizing the opinions expressed in a number of reviews written by users of a product. This process consists of two main steps. The first step if the feature extraction and the second step is the identification of the opinion associated with those features, where the opinion may be positive or negative. The Fig. 1 shows the architecture used by [12].

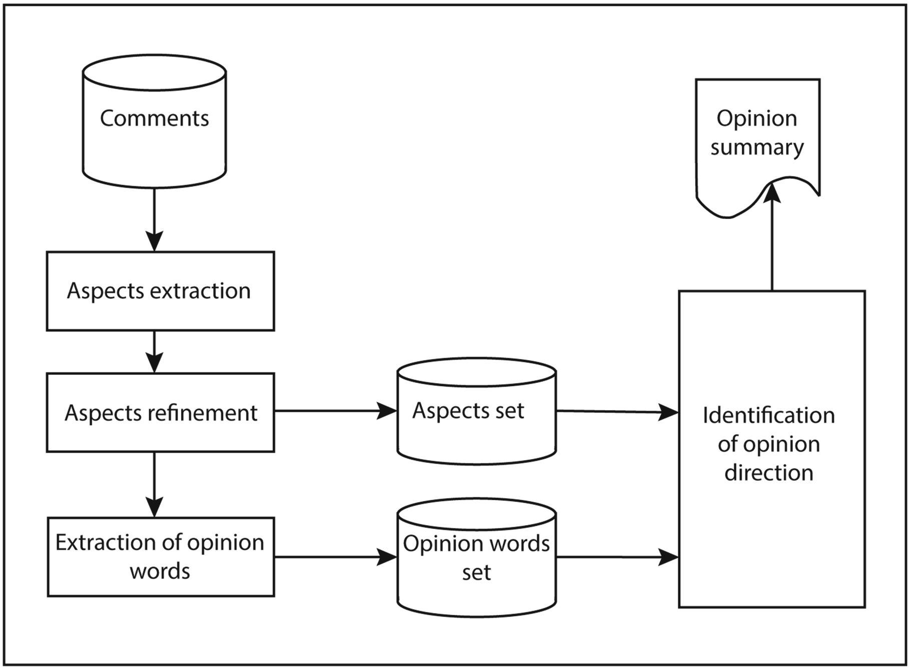

Fig. 1. Opinion mining architecture. Source: Adapted from [12].

As seen in Fig. 1, the system inputs are the name of a product and an input page containing links to all the product reviews available. The system output is a summary of the characteristics and opinions as in the example in Table 1 wherein the product is a digital camera.

Table 1. Example of a summary of opinions on a product

Picture quality		
	Positive:	253
	Negative:	6
Camera size		
	Positive:	134
	Negative:	10

Source: [12].

According to [13], Sentiment Analysis can be performed in three levels. The first is the document level, which is concerned with extracting the general opinion expressed in a document. In this level, it's important that the document addresses only one entity. The second level is the sentence level, where each individual sentence in a document is classified separately. The third level is the aspect level, which is concerned to identify exactly which aspects of the entity the author liked or disliked. The work in [12] used the aspect level.

In general, opinions are expressed in unstructured texts, and this complicates their study. To solve this problem, it is necessary to have a formal definition, presenting an opinion in a structured manner, so that is can be processed computationally. In order to solve this problem, [13] defines an opinion as a quintuple (1):

$$O = \left(e_i,\ a_{ij},\ s_{ijkl},\ h_k,\ t_l\right) \tag{1}$$

Where:

- e_i is the name of an entity;
- a_{ij} is an aspect of entity e_i. If the opinion is about the entity itself, the special value GENERAL is used;
- s_{ijlk} is the sentiment associated with the aspect a_{ij} of the entity e_i. Can be positive, negative or neutral, or be expressed in different levels of intensity;
- h_k is the opinion holder;
- t_l is the time when the opinion was emitted by the holder h_k;

In this definition, it's important to note, and this is reinforced by the subscripts, that there must be a direct correspondence between the items of the quintuple. It's also noteworthy that all components are essential. For example, the lack of the time (t_l) prevents the analysis regarding the time. This can be problematic, since and outdated opinion regarding a product characteristic may not be relevant in the present day.

4 Methodology

Initially, a bibliographic research was carried out on the topics covered, in order to ground the study and see how far the research about Sentiment Analysis and customer satisfaction has advanced.

Real data were collected from a Brazilian online job search company. Data from this database were captured on an online form filled out by customers to cancel the service. It's worth to note that the fact that the customer cancelled the service does not necessarily mean that his or her opinion tends to be negative, because as it comes to an online job search service, it's common for the client to cancel the service right after getting a new job, which would imply a positive feeling about the service, even if the client is cancelling.

The parameters of this database are:

- Comment identification code;
- User identification code;
- Date when the comment was written;
- Comment.

These parameters can be related to the quintuple defined by Liu in [13]. In this study the comments were processed in order to extract the general sentiment of the customer about the services, not trying to extract the feelings about specific aspects of the service. In this way, the values of the parameters e_i and a_{ij} are equal. In addition to these parameters, the database also holds a score of 1 to 10, assigned by the customers to the services provided by the company. Table 2 lists these parameters and this relation with the quintuple.

Table 2. Parameters related to customer opinions.

	Parameter	Description
e_i	Services	The entity is the service provided by the company
a_{ij}	Services	GENERAL – Refers to the entity, because no aspect is being analyzed
s_{ijlk}	Sentiment	Refers to the sentiment associated to the service. Parameter to be computed
h_k	User	Customer who emitted the opinion. Identified by an id code
t_l	Date	Date when the opinion was emitted

Source: The author.

The classification of texts in the Portuguese language suffers from a lack of tools for Sentiment Analysis and Opinion Mining. The lack of such tools and annotated corpus and databases to support the natural language processing in this language, as for example a Portuguese version of WordNet [14], is an obstacle to perform natural language processing and Sentiment Analysis in Portuguese.

A possible solution for this obstacle is to use machine translation to automatically translate the comments from Portuguese to English and then use resources available in English to classify the sentiment. But machine translation software is not perfect, and sometimes can lead to semantic information loss. However, some authors have used this machine translation approach for cross-language sentiment analysis in the past, with reasonable results. Examples of works using machine translation can be found in [15–18]. For this reason, we chose to perform the translation of the comments to the English language, using the approach described in [18] and after that, to use well-established Sentiment Analysis tools and data.

The process used to classify the user comments consisted of three main steps. The first being the pre-processing, involving the selection of the user comments.

The second step was the translation of the comments to the English language. Finally, the last step is the generation of the sentiment score for each comment. Figure 2 below illustrates this process.

Following, each step from Fig. 2 is detailed.

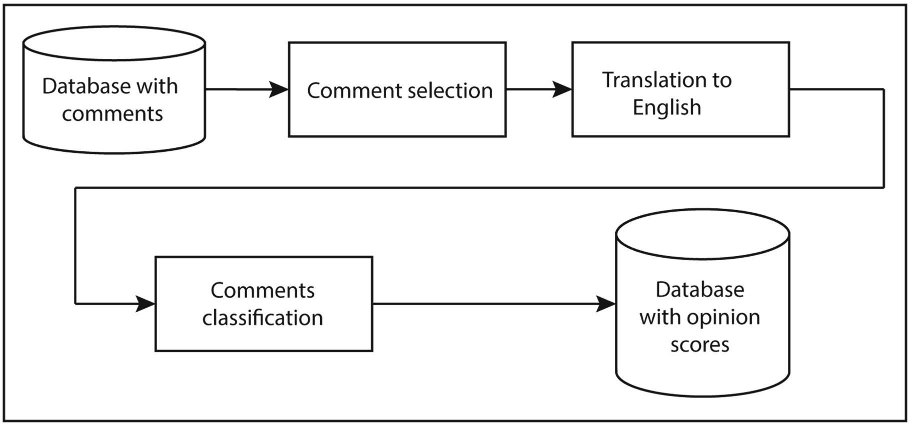

Fig. 2. Comment classification process. Source: Author.

Comment Selection. Data is stored in a relational database management system, and has more than 6 million comments. I this study, however, only the most recent reviews were considered, covering the period from January to July 2013 and a total of 680,478 comments.

In order to eliminate spurious comments, while at the same time selecting those that have at least one complete sentence, only comments containing 50 or more characters were selected. The number of comments dropped then to 193,077. However, as will become evident in the next two sections, due to limitations in the use of the translation software to the English language and the API for sentiment classification, from the previous set a random sample of 2,055 comments was selected.

Translation to the English Language. For the translation of comments to English language, Google Translate [19] was used. As the API (Application Programmer Interface) for translation by Google is a paid service [20], we used the translation service through the form freely available on [19].

The form provided has limitations regarding the number of characters it can process in each request. Thus, it was only possible to perform the translation of about 100 comments at a time. This was one of the reasons that led to the selections of a reduced random sample of 2,055 comments.

The selected comments were formatted in JSON [21] in a list of objects that contains the identifier code of the comment and a comment in Portuguese. Then they were submitted manually, 100 at a time, to the form available on [19]. The translated comments were then collected and stored in a new file in JSON format. Thus, at the end of this process, there were 2,055 comments translated into English, with references to the original comments in Portuguese.

Classification of the Comments. The classification of the comments was performed with the help of an API called Repustate [22]. The free license was used, which allows up to 1,000 monthly API calls.

An application for classification of the comments was developed using the Python language [23]. This language was chosen for its easy in creating prototypes (Python Software Foundation). The software reads a file in JSON format containing a list of comments already translated into English and their identifying codes. With these codes, the software assembles the API calls to Repustate.

We used the bulk-score call from the API, which receives a list of text chunks (comments, in our case), and returns a list of sentiment scores related to the comments. The score is a decimal number between -1.0 and 1.0 and indicates the sentiment expressed in the text block. Negative scores represent negative sentiment, or unfavorable opinion. Positive scores represent positive sentiment or favorable opinion, and scores close to 0.0 represent neutrality in relation of feelings [24]. Table 3 indicates which intervals were used for considering the sentiment expressed in a comment as negative, positive or neutral. It's important to note that the interval for neutral comments was chose based on the API's documentation [24].

Table 3. Considered intervals for sentiment classification.

Interval	Sentiment
$-1.00 <= score < -0.10$	Negative
$-0.10 <= score <= 0.10$	Neutral
$0.10 < score <= 1.00$	Positive

Source: Author.

After making the API call, the resulting score, as well as the corresponding identifier code are recorded in a relational database under the MySQL Database Management System (DBMS) [25]. The table where the scores are recorded relates to the table containing the comments through the identifier code.

5 Results

From the scores obtained through the software developed and the Repustate API, we could classify the comments as positive, negative or neutral. In addition, through Pearson's correlation coefficient [26], there was a relationship between the computed sentiment scores and the scores assigned by customers to the company's services.

The comments have been classified according to the ranges defined in Table 3 and the results obtained are shown in Table 4.

There's a greater amount of positive comments, but there's also a lot of sentiment neutral feedback. It's noteworthy that a sentiment neutral review does not mean it cannot be positive or negative, it only means that feeling was not identified, or there is no sentiment expressed in the comment. That means in this case that the comments were not passionate. The graph in Fig. 3 shows the distribution of scores by ranges, giving a better view of the strength of sentiment detected in the comments.

Table 4. Comments classification

Sentiment	Quantity	Percentage
Negative	479	23,31
Neutral	699	34,01
Positive	877	42,68
Total	2055	100,00

Source: Author

In the graph of Fig. 3, at the abscissa axis there are the range intervals of the sentiment score, while in the axis of ordinates there is the number of comments classified in that range.

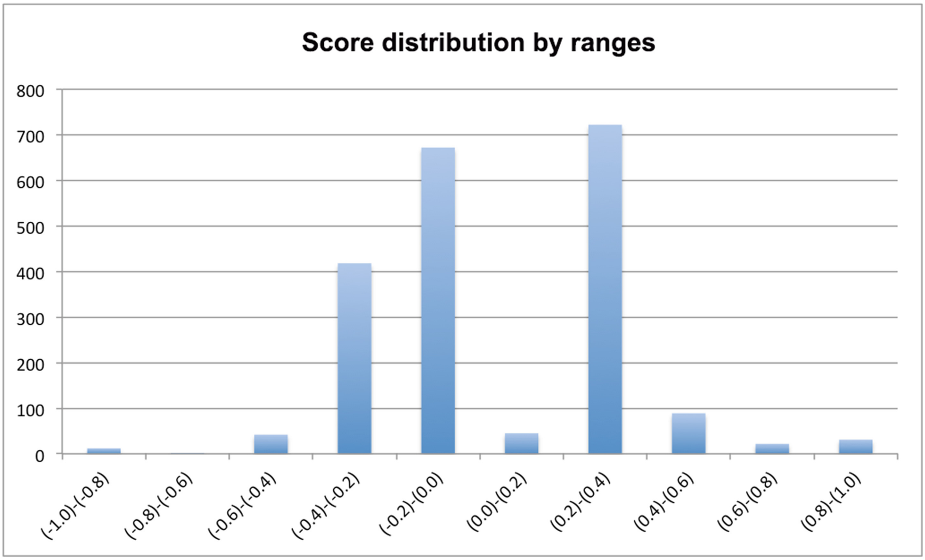

Fig. 3. Sentiment scores distribution. Source: The author.

The results of the sentiment classification were interesting, as they show that although over 42 % of the company's customers have positive feelings about the provided services, a very significant proportion (34 %) did not express feelings in their comments.

The distribution graph also show that the majority of the comments received scores in the region between −0.4 and 0.4. This indicates that the services of this company do not tend to arise very strong feelings in its customers.

Correlation with the scores given by customers. In order to verify that the sentiment score of a comment is correlated with the score directly assigned by the customer, we calculated the Pearson's correlation coefficient for the two scores. The value obtained was r = 0.3270, which indicates that there is a moderate, almost weak, correlation between the two variables [26].

The fact that the correlation between the two variables is moderate, almost weak, can be explained by interpreting the meaning of the two variables. The assignment of the score by the customer takes into account his or her entire experience with the service, and try to be more rational and takes into account all his good and bad experiences during the service delivery. However, while writing the comments about the service, he hardly considers all his experience, but tends to concentrate on few aspects, especially those that caused stronger feelings.

6 Conclusion

In this study, Sentiment Analysis was used for evaluating the customer satisfaction in a Brazilian online job search company. Data collection was facilitated because the company already has the practice of collecting, through an online form, the opinion of its customers about its services at the time of the service cancellation. Due to the nature of the service, the cancellation does not necessarily mean that the client is not satisfied, because it's common for clients of this kind of service to cancel his or her subscription after getting a new job.

We stumbled with the problem of finding tools for Sentiment Analysis for processing texts in Portuguese. However, by introducing the translation step in the process, as seen in Fig. 2, we could circumvent this difficulty. This extra step consisted in translating the comments into English and then using Sentiment Analysis tools available for the English language. The literature validated this approach.

As the database already had, as one of its parameters, a score assigned by the customers, it was necessary to compare this variable with the sentiment score computed from the comment. Using Pearson's correlation coefficient, we arrived to a moderate to weak correlation ($r = 0.3270$).

The fact that the correlation between the score assigned by the customer and the sentiment score is almost weak shows that the study of the customer sentiment regarding the provided services is important. Interestingly, one customer satisfaction assessment method does not exclude the other, but the two are complimentary.

The assigned score gives a measure of the general satisfaction, while the comments can be more specific, giving information about aspects of the service, which would be inaccessible otherwise. For this reason, it is interesting to study Sentiment Analysis as a support tool for customer satisfaction assessment.

As a sequel of this study, we intend to seek alternatives to WordNet for implementing Sentiment Analysis tools capable of processing texts in Portuguese. Furthermore, we intend to conduct further research to mine this company's database at the level of aspects, thereby increasing the utility and value of Sentiment Analysis within the company.

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