

An Opinion Mining Task in Turkish Language: A Model for Assigning Opinions in Turkish Blogs to the Polarities*

Çiğdem Aytekin

Marmara University, Istanbul, Turkey

Global changes took place at a neck-breaking speed in lots of fields along with the Web 2.0 era, which can be stated as the new Internet trend. Web pages which once were a static structure that can be said to become dynamic pages created by users, and in this regard they can be said to have been democratized by evolving. Social media, which were structured alongside with this era, by providing a large data flow for businesses, present new and improvable opportunities in the field of creating effective strategies. There are lots of blogs in today's Internet environment which includes customer ideas regarding the products/services that they possess. This environment, which in a way globalizes the customer ideas, is a new medium suitable for examination in terms of its increasing the business-customer interaction and due to its transporter nature; it provides the text data that may be analyzed in the field of Customer Relationship Management to businesses. Thus, businesses should follow blog environments to see how the product/service they provide is greeted in terms of the customer focus and it should be seen as an important job on which they can conduct effective analyses. For this purpose, a model proposal that will assign the ideas to the Turkish blogs was given in the study. Opinion mining methods were used in the model, and so to perceive a general look-on about products/services, a methodology was devised, which will assign the text based opinion data on the Turkish blogs to the poles. Success of the pole assignment of the model is evaluated with the precision measure.

Keywords: opinion mining, text classification, sentiment classification, semantic orientation, positive/negative polarity

Introduction

In our day, social networks are also called as the new generation media, which give the daily increasing users the change to gather at these environments and thus interactive environments get created with the messages noteworthy enough to share. Thereby, the cooperation of big masses and joint production are rendered possible and new tendencies are provided a change. Thanks to these environments, users improved their position from "content consumer" to "content creator". To wit, while the users share their views on the product/service with the ones they know and their close ones use the spreading by word of mouth method, they've already started to cover these environments as well. These environments, which in a way globalize the customer opinions, are analysis tools for businesses due to customer focused structuring of our day. By analyzing the data they acquire from such environments, businesses are required to develop suitable strategies

* **Acknowledgments:** The author would like to thank Sepandar Kamvar for allowing me to use the color codes regarding sentiment words in We Feel Fine web site. The author really appreciates that.
Çiğdem Aytekin, Ph.D., Faculty of Engineering, Marmara University.

as accordance with the customer choices and to update these strategies constantly.

On the other hand, these environments that include the customer opinions on the product/service possess text data and these data aren't structured the same way as the data saved into the database are structured. Significant information is procured by analyzing the structured data with the data mining techniques in our day. Yet, this form of the text data, that said the unstructured form, hardens the knowledge extraction from different topics. But beneficial the text data increase constantly and in lots of cases, the knowledge that can be extracted from these data is needed. Examination of these data manually is very hard, moreover, it is impossible in most cases. The need of analyzing of the text data and the desire to lessen the amount of time wasted manually created a structuring in this direction and thus, the concept text mining came to be. The text data become structured with the text mining method and thanks to refinement after being analyzed with data mining techniques, procurement process of the precious knowledge can be realized. Therefore, secret and unknown meanings among the text data can be derived. And when the mentioned text data are opinion-stating statements, tasks of opinion mining, which is an implementation field of the text mining, come into prominence.

Generally, opinion mining is the transition of automatically knowledge obtaining from the text data that state opinion. In this context, as stated in the *Wikipedia* (Sentiment Analysis, 2013) sources, opinion mining refers to a large field of Computational Linguistics, Text Mining, and Natural Language Processing. And when the opinion mining explanations in the literature are examined, it can be seen that different authors state opinions in the same parallel.

CHEN, ZHU, Kifer, and Lee (2010) based the opinion mining on the essence of the question "What do people think about ...?". According to them, this question becomes more important in the web platforms where people state their opinions. As people share their positive and negative opinions regarding products in these environments, they actually end up being a representative on the topic of general opinions regarding the product. These data belonging to the consumer experience can be analyzed with opinion mining methods, and consumption behaviors of new customers can be affected from these opinions.

Conrad and Schilder (2007) evaluated the customer opinions on the product/service within the scope of both the individual and businesses. According to them, individually-based consumer candidates may want to gain a general perspective regarding a product they want to purchase or the service itself. This need also applies to businesses. Similarly, they may also wish to gain a general view concerning how the service they provide or the product they present are greeted.

LIU (2013) also approached the topic from two angles just as Conrad and Schilder did (2007). For him, consumer experiences are vital in taking deliberative decisions on individual basis. With Opinion Mining implementations, a general perspective about the product or service can be obtained without reading lots of comments. Similarly, opinion mining is important for business as well. For example, a business must know how its product or service is perceived by the consumers. Not just that, it also should know the perspective regarding the rival products. Thus, it can conduct the necessary evaluations concerning the product or service and innovations on different topics can be developed on this direction.

While Falcon (2010) stated the opinion mining as "a technology whose validity was proved", he emphasized on it using statistical model and software and stated that it had been used widely as a listening, analysis, and relation tool in the defence, public administration, and marketing practices.

Works to be done with opinion mining can be evaluated within the tasks of opinion mining. As such, these tasks have been focused on below.

Opinion Mining Tasks

When the literature studies about the opinion mining tasks are examined, though different authors seem to conduct evaluations within the frame of different categories, there are some common points. The reason why these differences occur mostly bases on the purpose. Some certain opinion mining tasks were given below:

(1) Determining the positive-negative (PN) pole of the text. This is one of the most commonly-used tasks of opinion mining. In this task, which of the positive or negative poles do the user opinions partake in is tried to be determined. For example, answer to the question “Is the general take of the users on our products/services positive or negative?” could be tried to find. Esuli and Sebastiani (2006), LIU (2007a), and Abbasi, CHEN, and Salem (2008) are example authors who take up this task.

(2) Determining the intensity of the PN pole text. In this task, the text based opinion data that were assigned to the PN poles are ranked on certain levels. For example, answer to the question “How many of the opinions which approach positively/negatively to our products/services are poorly negative/positive, how many are moderately negative/positive and how many are strongly positive/negative?” could be tried to find. Esuli and Sebastiani (2006) is an example author who takes up this task.

(3) Feature-based mining. In this task, whether the findings regarding the features of the products/services which users possess are positive or negative is tried to be determined. For example, answer to the question “What do the users think about the Y feature of our X product/service?” could be tried to find. Leneve (2010), Verbeke and Eynde (2013), and QIU, LIU, BU, and CHEN (2010) are example authors who take up this task.

(4) Comparative sentence and relation deduction. In this task, comparative relation is tried to be deducted. By comparing an object with another, differences are determined. For example, evaluations regarding a brand being superior to another one can be deducted from the sentence “X brand car is cheaper than Y brand car”. Leneve (2010), LIU (2007b), and Verbeke and Eynde (2013) are example authors who take up this task.

(5) Mentioning an issue as classification problem. In this task, an issue gets mentioned and conducting a classification regarding this issue is tried. For example, a classification can be done concerning the person who deserts the brand in the sentence that “I will never an x brand product”. Verbeke and Eynde (2013) are example authors who take up this task.

On the other side, the opinion mining task regarding the subjectivity-objectivity of the text is one of the tasks partaking in the literature. Yet, it didn't receive as much attention as others. Due to the nature of opinion mining, text data being statements of opinion and these possessing a rightful subjectivity caused this to happen.

For the study is about determining the positive/negative pole of a Turkish opinion, this classification task is examined below in a more detailed way within the frame of literature studies.

Literature Review

Classification of the text data that state opinion has been the task on which, within the opinion mining tasks, most number of applications was developed. And most of these classifications base upon positive/negative pole differentiation. Yet, there are lots of hardships faced in the opinion mining. An important portion of these is within the scope of spell check as stated in the fourth part of the text—“A model for Assigning Opinions in Turkish Blogs to the Polarities”, and yet while the users write comments in which they state their opinions in web platforms, they generally use colloquial language. Because these environments are based upon an informal structure due to their nature. Stavrianou and Chauchat (2008) also emphasized on this

problem and defined it as the difference between “usage regarding the colloquial language” and “usage in an online newspaper”. Similarly, Pang and Lee (2008) stated that text behavior regarding the opinion would be different than classic text mining applications.

When the literature is checked in respect to classifying the opinion, it is seen that supervised, unsupervised, and semi-supervised learning techniques are the topics of subjects. For example, Turney (2002) used unsupervised learning techniques. In this study, he used some adjective and adverb based words as his focus and classified the user comments as “suggested ones” and “non-suggested ones”. Method has an accuracy value of 74% on average.

Another example is the study of Devitt and Ahmad (2007) in the field of financial news. But, here, in addition to determining the pole of a news text, establishing the pole intensity was also tried. As mentioned in the second part of the text—“Opinion Mining Tasks”, this is a different opinion mining task. In this direction, a scale was devised in the study to check how positive or negative the text is. Scale consists from seven levels from too positive to too negative. Suggested method has an accuracy value of 46% in determining the positive and negative differentiation.

Dave, Lawrence, and Pennock (2003) combined the scores from the education set to classify the positive/negative product comments with the method of choosing of the proper features and metrics and to this end, they put forth various techniques. The highest accuracy value of the method, in which text mining algorithms, such as Naive Bayes and Support Vector Machine are given comparatively, is 85.3%.

Esuli and Sebastiani (2005) suggested a method based on a semi-supervised learning basis so to determine the positive/negative orientation of the terms. According to them, definitions of similarly oriented terms tend to be similar. Method which makes use of the lexical relations such as synonymy, antonymy, and hypernymy is based on WordNet. Accuracy value of the method is given separately for three classifiers: 83%, 87%, and 88%.

Lastly, Kamps, Marx, Mokken, and De Rijke (2004), in their studies where they used WordNet to measure the semantic orientation of adjectives, made the suggestion of interpreting the topics on scales such as positive/negative, ugly/beautiful, powerful/weak, excellent/poor, and active/passive. Accuracy value of the method is 67.18%.

In this study, opinion classification task of opinion mining was given place and the suggestion of “a model which will assign the customer post/comments on Turkish Blogs to the poles positively or negatively” was presented. Here, the accuracy value is 72.71% and this will be discussed in the fourth part of the text—“A model for Assigning Opinions in Turkish Blogs to the Polarities”.

A Model for Assigning Opinions in Turkish Blogs to the Polarities

The new media used in this study is blogs. Blogs include user opinions that state sincere comments and sentiments regarding a specific subject. Besides, since the blogger and the user are voluntarily in this medium, clear and transparent user views, which are difficult to obtain through other ways, are reached easier. Blogs, which gather individuals who have similar interests, include millions of comments and their number is increasing day after day. Problems, expectations, approaches, complaints, all of them, can be found in this medium. Blogs are considered to be a “media that is developed by the consumers”. For this very reason, the text mass in the blogs include crucial data. Therefore, enterprises should follow the blogs in order to learn how the products and services they offer are received by the customers, and they should see the blogs as an important medium through which they can perform an effective analysis.

On the other hand, the comments in this medium are crucial sources of feedback since they are stated by the users themselves. However, feedback is limited in the traditional mass media. The information gathered from this medium will offer a solution for the limitation in feedback, and enterprises will be able to increase efficiency by developing the strategies regarding enterprise decision process. In addition, while the data on the enterprise's database are limited to the use of the enterprise, these blogs are open to anyone. Therefore, positive or negative opinions can be seen by anyone who reads that blog. For this reason, enterprises have to follow and analyze blogs in order to protect their reputations.

In this regard, this study proposes a model that will assign the text-based opinion data in Turkish blogs to positive and negative polarities in order to present a general view on products and services. The model is a semi-supervised learning model. Training set comprises of English words stating sentiments. In order to calculate the words' probability for being in positive or negative polarities, color codes that have been assigned to the words were used and through a repetitive test-investigation process, color-word meaning correlation was provided.

In order to perform polarity assignment process automatically, a program called "Opinion Polarity Detection" was developed. For this program, Visual Basic Language was used in Microsoft Net Framework environment and Microsoft SQL Server 2005 was used as database. The program classifies the text data according to the rules of Naive Bayes Algorithm, which is simple to use and produces efficient results. For spell-check, the error correction module of the Microsoft Word text editor was used. Besides, posts' and comments' length in terms of word number were analyzed and its effect on the success of polarity assignment was studied in the study.

Preparation of Data

The data in the model comprise of the customer opinions gathered from Turkish blogs. These text data can be blogger's posts regarding the comments of the readers as well they can be the readers' comments on the relevant post.

A test database was developed especially for the aim of the study. This database is a sample group comprising of 350 positive and 350 negative posts/comments. In the test database, posts/comments regarding the products and services under the headings of "white goods, built-in products, electronics, small home appliances, and heaters-air conditioners" were included. The most important factor for the selection of this heading is that the products give a chance for the posts and comments regarding services as well as the products themselves. On the other hand, using this heading will enable the posts and comments regarding both domestic and foreign products and services. While searching for posts/comments, Google Blog Search Engine was used in Turkish language and using brand names as keyword was found to be easiest way for finding text data regarding the enterprise in question. While searching for the post/comment; instead of searching for the posts regarding especially one single brand, the search was tried to be diversified through searching for as many brands as possible. In addition to these, following points were of importance in the posts/comments collected:

(1) Both long and short entries were included in the posts/comments. While the average word number of the negative post/comments was 86.66, and the average for the positive entries was 29.66;

(2) In data collecting, to the introductions that are evaluated semantically in positive or negative pole, a part was given;

(3) The posts/comments which included positive opinions for a property of the product and service and

negative opinions for other properties were not included. Yet, post/comment should take place in only one of the positive or negative poles semantically in terms of its every feature;

(4) Some of the collected posts/comments might be placed in the positive/negative polarity for only a single property while some might be placed in the related polarity for more than one property. In this regard, the posts/comments were not limited;

(5) The data in the posts/comments might be texts that are related to the properties of the products and services as well as they might be texts that are related to the enterprise's approach. The data were not differentiated in this sense;

(6) The negative posts/comments were text data including complaints in terms of discontent and dissatisfaction while the positive posts/comments were text data including recommendations in terms of content and satisfaction;

(7) The posts/comments were not differentiated based on time such as day, month, or year.

In order to ease collecting the posts/comments and transferring them to the program, a form in the Personal Home Page (PHP) language was developed and it was ensured that this form was uploaded on the Web after a domain name, "data collection form", was taken. The posts/comments found through the search engine on the basis of the points mentioned above were entered into this form. The text data which were manually determined to be in the positive/negative polarity were copied into this form with their Uniform Resource Locator (URL) addresses and a database was developed.

Setting up of the Model

XU and CHENG (2011), who have greatly contributed to the literature studies on opinion mining, correlated the words "opinion" and "sentiment" in this way. "An opinion contains often sentiment words which can be classified into polarities such as positive, negative, and neutral" (p. 11). From this point, it was assumed that the sentiment words could be used as the training set in polarity determination and as the result of the performed researches it was decided that the sentiment indicator words in the website called *We Feel Fine* would be used. In this way, a semi-supervised learning model was developed.

(1) English training set for semi-supervised learning.

Training set comprises of 2,178 sentiment indicator words that can be found in <http://www.wefeelfine.org/data/files/feelings.txt>. The methodology of the website can be summarized in this way (the explanations are limited to the information given in <http://www.wefeelfine.org/methodology.html>).

Data collection: *We Feel Fine* website includes a "collecting motor" which collects human feelings automatically from online sources such as LiveJournal, MSN Spaces, MySpace, Blogger, Flickr, and Technorati. The purpose is to find the statements "I feel" or "I am feeling" in the blog posts. These statements which are saved into the database get checked to see if they include valid feelings. Valid feelings consist from adjective/adverb based words, which are structured manually and determined beforehand, and there are 5000 of them. If a statement in the database includes even if a single one from these 5000 words, then it gets saved into the real database along with the name of the blogger. By sorting out the blogger's name from the URL address, that blogger's profile info can be accessed via blogging companies. Thus info about the blogger regarding his age, gender, city, country, and even the weather conditions at the time of his post becomes saved into this database. Repetition period of this process is 10 minutes.

Statistical measurements: *We Fell Fine* database can be questioned by the ones who will use its balls.

When the application begins, balls scatter around the screen and when one of these balls are clicked, statements including “I feel” or “I am feeling” appear. This screen is given in Figure 1. Also, screening conditions according to the gender, age, weather condition, location, date, and feelings can be created.

Colors of feeling: Color equivalents of feelings are based on this: Bright yellow colors represent happy positive feeling; dark blue colors represent sorrowful negative feeling, green color the feeling of calmness, and red represents angry feelings.

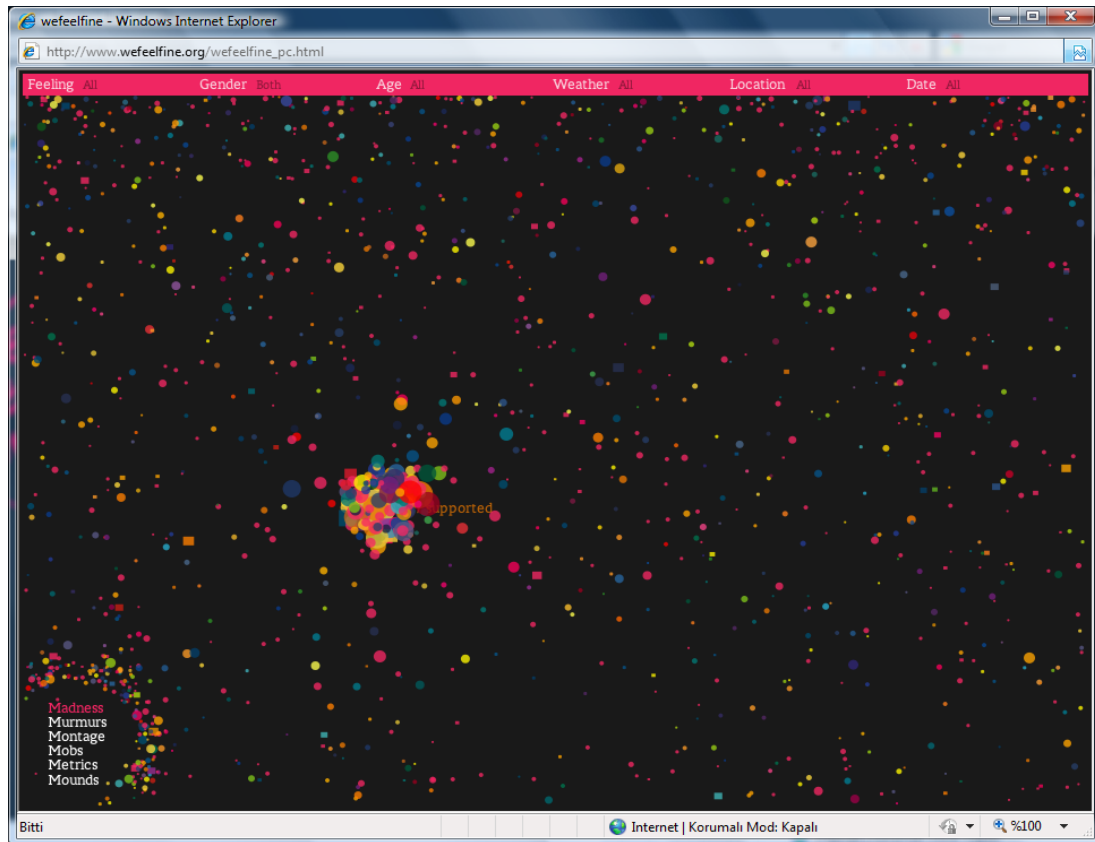


Figure 1. We Feel Fine balls in the opening screen. Resource: Retrieved February 28, 2013, from http://www.wefeelfine.org/wefeelfine_pc.html.

(2) Using Sentiment Dictionary in Turkish generated by English training set.

The full list of the 2,178 valid sentiments are given with their frequencies and assigned hexa color codes in the URL address of the *We Feel Fine* website below. A part of this list is presented in the Table 1.

It was stated above that the words which formed the sentiment list were basically adverbs and adjectives. Of all the 2,178 words in this list, 1,655 words that were used as adjective and/or adverb in Turkish were taken, and in total 4,744 Turkish word/word groups were obtained because a word can have more than one counterpart as adjective and/or adverb in Turkish. This dictionary comprising of 4,744 lines will be referred as “Sentiment Dictionary in Turkish” from now on. However, it should be noted that the meanings of some English words cannot be given with one Turkish word. For example, the word “best” is translated as “en iyi”, “en uygun”, ... with the superlative adjective “en”. For this reason, the Sentiment Dictionary in Turkish comprises of translated words or word groups.

Table 1

Some of the Sentiment Words in English.

Word	Frequency	Assigned hexa color code
better	128,155	FFA401
bad	93,390	07548A
good	76,610	FFF700
right	40,683	E97802
guilty	31,591	004E6F
sick	27,706	2E9127
same	25,389	017E94
sorry	23,779	00696F
well	22,428	E6C637
down	20,847	18213E
alone	17,988	595884
happy	17,849	FF7F00

Note. Retrieved February 28, 2013, from <http://www.wefeelfine.org/data/files/feelings.txt>.

Adjectives (“Adjectives”, 2007) come before nouns and qualify or determine them in different ways. Adjectives are divided into those groups in terms of task and meaning:

(1) Qualificative adjectives;

(2) Determinative adjectives;

(3) Demonstrative adjectives;

(4) Numeral adjectives: cardinal numeral adjectives, ordinal numeral adjectives, fractional numeral adjectives, distributive numeral adjective, and group number adjective;

(5) Indefinite adjectives;

(6) Interrogative adjectives.

The adjectives in the Sentiment Dictionary in Turkish can be classified in terms of their types as follows: Most of them were qualificative adjectives (“sakin”, “berrak”, “iyi”, “sözlü”, “rizikolu”, ...), a small part of them were indefinite adjectives (“bütün”, “başka”, ...), two of them were ordinal numeral adjectives (“birinci”, “ikinci”) and one of them was a group number adjective (“ikiz”). Due to the nature of text mining, cardinal numeral adjectives (“bir”, “iki”, ...) were not included and they were cleaned from the English dictionary having 2,178 words.

In terms of structure, adjectives (“Adjectives”, 2007) are divided into five groups: absolute adjectives, derived adjectives, compound adjectives, enhanced adjectives, and adjectives as word/word groups. “Kırmızı”, “iri”, “ufak”, ... can be given as examples of the absolute adjectives in the Sentiment Dictionary in Turkish; “ağlayan”, “oynayan”, “evsiz”, “çarpıklık”, and “yuvarlak” can be given as examples of derived adjectives; and “cana yakın”, “yurtsever”, “vatanperver”, “kısa boylu”, “ustalık”, and “evsiz barksız” can be given as examples of compound adjectives.

At this point, it is useful to explain derived adjective type further. If an addition is made to the verb stem, this type of derived adjective is called verbal adjective. Kurt (1998) defines verbal adjective in this way: The words that resemble verbs since they indicate action and that are considered to be adjectives since they form an adjective clause by qualifying a noun are called verbal adjectives. Verbal adjectives are derived with the affixes “-en, -esi, -mez, -(a)r, -dik, -ecek, and -miş” which are added to verb stems: giden çocuk, yıkılası şehir, pişmez

et, bakar kör, çalmadık kapı, gelecek yıl, sıkılmış limon, etc.. Some of the words given in the English training set have taken the affixes “ing” and “ed”. These word/word groups that correspond to the verbal adjective in Turkish were translated by adding the affixes “-en, -miş” to the ends of the verbs with which they were used. The examples of the English words that were translated in this way are given in the Table 2.

Table 2

Examples of Verbal Adjectives in English Training Set

English word	Turkish verbal adjective
crying	ağlayan
playing	oynayan
wasting	israf edilen
growing	artan
changing	değişen
turning	dönen
asking	soran
pushing	iten
acting	hareket eden
loved	sevilen
accomplished	başarılımış
used	alışılmış
overwhelmed	bunalmış
stressed	baskı yapılmış
trapped	set çekilmiş

However, in the training set, there are some English words which cannot be translated as verbal adjectives using the affixes “-en, -miş” although they have taken the affixes “ing/ed”: beginning-başlangıç, tired-yorgun, etc.

Adverbs, on the other hand, are words that affect the meanings of verbs, gerundials, adjectives, or adverbs in various ways (place, time, manner, amount, and interrogative), that determine and grade them. Most of the adverbs can be used as adjectives or nouns. However, while adjective comes before the noun and qualifies or determines it, adverb does not come before the noun (“Adverbs”, 2007). The examples of adverbs in the Sentiment Dictionary in Turkish are presented in Table 3 according to adverb kinds.

Table 3

Adverb Examples From the Sentiment Dictionary in Turkish According to Adverb Kinds

Adverbs of manner	Adverbs of time	Adverbs of place	Adverbs of amount
eğri	öğleden sonra	ileri	pek
çocukça	evvela	ileri doğru	çok
az yükle	sabah	geri	fazla
tıklım tıklım	geç	geride	azıcık
abartarak	sürekli	aşağı	çok az
övünerek	ilkin	aşağıya	sık
gül	hemen	yukarıya	Seyrek
hiç		üst kata	
elbette			
ne olursa olsun			
belki			

(3) Determining the polarity probability of the words using the assigned color codes.

The fact that the model established in order to determine polarities was a semi-supervised learning model was stated in the beginning of this section. In supervised learning, the texts that determine the class are used in order to train the system. In other words, the system is trained for finding the class of the new texts automatically, based on the given text. The vector of the text whose class is to be found is mixed with text mining algorithms and is assigned to the class to which it is related. However, in this study there are no polarity indicator texts to train the system. Nevertheless, there are sentiment word/word groups associated with the colors that will be used to determine the polarity. The model was considered to be a “semi-supervised learning model” for this reason. The probability of each word/word group in the Sentiment Dictionary in Turkish for being in positive/negative polarity was determined considering the color to which it was assigned and these probabilities were used in Naive Bayes Algorithm.

In regard to the determination of probability, firstly, word/word groups’ fill colors regarding the hexa color codes given in the English Training Set were formed. In order to do this, RGB color codes corresponding to the hexa code were used. Hexa codes were transformed into RGB color codes using transforming programs in order to be able to form fill colors.

RGB codes is a color space named after the first letters of the words “red-green-blue” (“kırmızı-yeşil-mavi”) in English and is used frequently. Based on the light, the codes of all colors in the nature are specified with reference to these three basic colors. When each color is mixed 100%, white is obtained, when mixed 0%, black is obtained (RGB Color Space, 2013), take FFFF4F hexa code as an example. Here, FF represents red, FF represents green, and 4F represents blue. When FFFF4F hexa code is transformed into RGB code, the value 255 is obtained for red, the value 255 is obtained for green, and the value 79 is obtained for blue. In RGB code, each of these three colors has a value between 0-255.

The fill colors regarding the all word/word groups in the Sentiment Dictionary in Turkish were obtained in Microsoft Excel Program using RGB codes. The sentiment words updated with fill colors will be referred as the “Sentiment Database in Turkish” from now on. In the database, there are 108 different hexa codes.

In the next step, HSL (hue-saturation-lightness) color codes of the word/word groups in the Sentiment Database in Turkish were obtained. While obtaining HSL codes using hexa or RGB codes, transforming programs were used again.












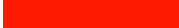





HSL is a coding system which has values separately for every single hue-saturation-lightness feature of the color. Hue is a feature which can take up a value between 0° - 360° and determines the place of the color on the wheel. It starts with red at 0° and ends with red at 360° . Saturation stated as “%” shows the dullness and brightness of the color. One hundred percent is the maximum value. It comes close to color grey with low color density and at 0% grey color scale takes effect. And in the lightness feature which defines the lightness and darkness of the color, while high L value means more white, low L value means more black, which means defining darkness (How to Calculate a Complementary Colour (Inc. RGB/HSL Conversion)). In Table 4, a part of the Sentiment Database in Turkish in which fill colors and HSL codes are included is presented. While calculating the probability of each of these word/word groups for being in positive/negative polarity, these HSL codes will be used.

The hypothesis regarding the calculation of the distance between colors: The color belonging to the word/word group which has the most positive value in terms of meaning is determined as the “starting point color”. The distance between the colors belonging to other word/word groups and the starting point color is

calculated. Therefore, while the word/word group belonging to the starting point color is in positive polarity with 100% probability, other colors and the word/word groups corresponding to these colors will gradually become distant from this point and their probability for being at positive polarity will decrease.

Table 4

A Part of the Sentiment Database in Turkish With Fill Colors and HSL Codes

Sentiment words	Frequencies	Hexa code	Fill color	H	S	L
en iyi	6,433	FFFF4F		60	100	65
hoş	76,610	FFF700		58	100	50
katkısız	3,098	FFD93C		48	100	62
büyük	17,058	FFD801		51	100	50
gururlu	3,604	FFB300		42	100	50
dayanıklı	4,128	FFB200		42	100	50
daha çok	128,155	FFA401		39	100	50
geçer	4,615	FF7F1C		26	100	55
bahtiyar	17,849	FF7F00		30	100	50
etkili	5,296	FF6600		24	100	50
cana yakın	3,884	FF4B02		17	100	50
acılı	3,283	FF1A00		6	100	50
kısmetli	5,716	FED73C		48	99	62
cümbüş	1,223	FEA740		33	99	62
başarılımış	5,312	FEA53F		32	99	62
bütün	8,151	FE992D		31	99	59
belirli	3,826	FE9901		36	99	50

The word/word group that may have the most positive value in terms of meaning in the Sentiment Database in Turkish was determined to be the Turkish correspondence of “best” and the 255-255-79 fill color determined by the RGB code was selected as the starting point color. This color was “bright yellow” and it coincided with the fact that the positive sentiments in We Feel Fine website were bright yellow. The HSL code of the starting point color was 60-100-65. The value of H (60) indicated that the color was yellow, the value of S (100) indicated that it was the brightest color, which means that it was in the most outer circle of the wheel and the value of L (65) indicated that the 50% pure color value converged to white. In Figure 2, the place of the starting point color in the color wheel is presented. In the HSL code, H indicates 60° and S indicates 100%. The L value will be used later.

Once the place of the starting point color in the color wheel is determined, the distance between the other colors, whose HSL values are known, and this point can be calculated. The calculation has two steps:

Calculating the length of the third edge of the triangle using H and S values;

Calculating the length of the hypotenuse of the right angled triangle using the length of the third edge and L value.

For example, calculating the distance between the color belonging to the word “ayrı (different)” and the starting point color.

Calculating the length of the third edge of the triangle using H and S values: For this word, H = 358, S = 81. In order to calculate the distance between two points, a triangle is formed through connecting the points with the central point of the wheel and with each other. Two edge lengths of triangle are known and equal to the S values of the HSL codes. In addition, the angle can be calculated using the H values of the HSL codes. Once

two edge lengths of the triangle and the angle between these two edges are known, the third edge length can be calculated using the Cosine Law.

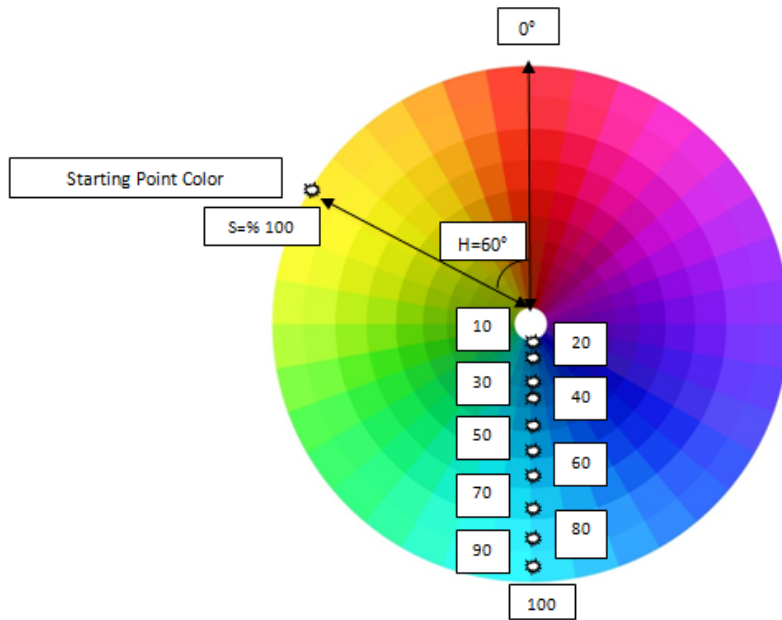


Figure 2. Place of the starting point color in the color wheel.

Calculating the length of the hypotenuse of the right angled triangle using the length of the third edge and L value: In the first step, calculation was made using the H and S values of the two points in HSL color code but L values were not included in the calculation. However, L values carry colors to a different point in vertical plane.

The middle point of the height of the cylinder corresponds to the L value of 50% and represents the pure color. While the ratio of 100% transforms the L value to white, the ratio of 0% transforms it to black. On the other hand, when H and S values are 0, only L values matter and at this point, grey color scale from white to black starts. In grey color scale, R, G, and B values are equal. For example, the HSL code of the color grey corresponding to the values R = 150, G = 150 and B = 150 is 0°, 0%, and 69%. Grey color scale can be seen in Figure 3 with its values of lightness and dullness.

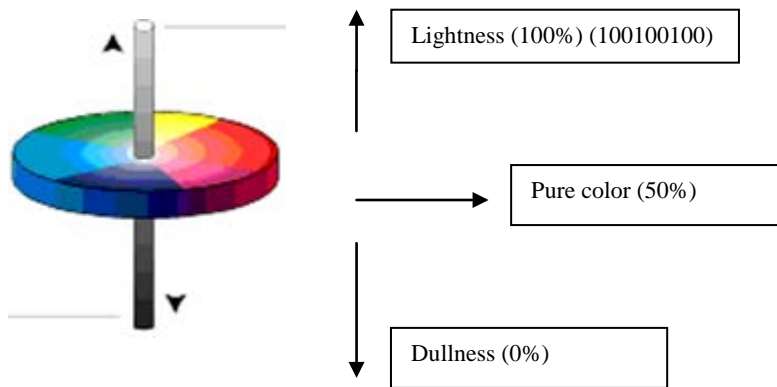


Figure 3. Grey color scale.

For example, the L value of the word “ayrı” is 55 while the L value of the starting point color is 65. The L value of the starting point color (65) is the maximum value in the Sentiment Database in Turkish. Therefore, the wheel belonging to the L = 65 value will always be on top of the other word/word groups. In this case, a perpendicular can be lowered to the all wheels that have different L values from the starting point color. On the other hand, the third edge length calculated using H and S values in the first step will form the other edge of the right-angled triangle. Therefore, the length of the hypotenuse can be calculated and the distance between the word “ayrı” and the starting point color can be found.

Now for 4,744 word/word groups, the probability of each for being in the positive polarity can be calculated using the above calculations. In the database, the probability for being in the positive polarity was taken as basis since when the probability for being in the positive polarity is subtracted from 100, the probability for being in the negative polarity can be obtained. Firstly, the Sentiment Database in Turkish was put in order from greater to lesser in terms of the distance to the starting point color. At this point, it was assumed that the word/word group regarding the starting point color would be in the positive polarity with the probability of 100% and the word/word group in the last line of the database would be in the positive polarity with the probability of 1% (since the result of the 0% probability value in the algorithm calculation would be 0 due to the absorbing element, the probability was taken to be 1%). In order to find the other probabilities, a coefficient had to be obtained according to these two values.

When looked to the color scale in the database put in order according to distance, it was found that it coincided greatly with the explanation stated in the beginning of this section: “Happy positive feelings are bright yellow. Sad negative feelings are dark blue. Angry feelings are red. Calm feelings are green”. In other words, the opposite polarities were put in order between the colors “bright yellow” and “dark blue”. Therefore, the probabilities might be put in order between 100% and 1%.

The most appropriate values regarding the probabilities of 4,744 word/word groups for being in the positive class for the interval between 100%-1% were obtained with the coefficient 0.5159. When the distance to the starting point color was multiplied with this coefficient and subtracted from 100, the values 99.9% and 1.01% were found, and these values were the values that were closest to the interval between 100%-1.106% unique probability values were calculated in this way. The probability values obtained were divided into 100 and values lesser than 1 were obtained and these values were used in the algorithm. As the result, it was found that 1,745 of 4,744 word/word groups had more than 50% probability for being in the positive polarity and 2,999 had less than 50% probability for being in the positive polarity. In Table 5, a part of the final version of the Sentiment Database in Turkish which includes the probability for being in the positive polarity can be seen.

(4) Assigning to polarities with Naive Bayes Algorithm.

Classification is a text mining task based on prediction. Text is incorporated, through prediction, into one class that has been determined in line with its properties. The procedure of assigning a text to one of the positive or negative polarities is also examined within the framework of text classification subject in text mining. Many algorithms have been developed for classification (Naive Bayes, support vector machine, rocchio, decision trees). In this study, Naive Bayes Algorithm which was simple to use and produced efficient results was used for the classification of the text data. This algorithm based on the calculation of each criterion’s effects to the result as probability is among the methods mostly preferred for the class determination in the cases including two probabilities (positive/negative). The algorithm works according to this principle:

$$P(\text{text-positive}) = P(\text{text-negative}) = 1/2;$$

Probability of the text for being in the positive polarity = $\frac{1}{2} \times$ Multiplication of the probability of each word/word group that is present both in the text and in the Sentiment Database in Turkish for being in the positive polarity;

Probability of the text for being in the negative polarity = $\frac{1}{2} \times$ Multiplication of the probability of each word/word group that is present both in the text and in the Sentiment Database in Turkish for being in the negative polarity.

Table 5

A Part of the Sentiment Database in Turkish including the Probability for Being in the Positive Polarity

Sentiment words	Frequencies	Hexa code	Fill color	Probability for being in the positive polarity
en iyi	6,433	FFFF4F		99.99
hoş	76,610	FFF700		92.05474706
kısmetli	5,716	FED73C		89.1455142
katkısız	3,098	FFD93C		89.10427035
büyük	17,058	FFD801		88.80089123
gururlu	3,604	FFB300		82.09990792
dayanıklı	4,128	FFB200		82.09990792
daha çok	128,155	FFA401		79.66678813
belirli	3,826	FE9901		77.28985031
cümbüş	1,223	FEA740		75.97838179
başarılımış	5,312	FEA53F		75.11009634
bütün	8,151	FE992D		74.10444177
bahtiyar	17,849	FF7F00		72.19642672

The greater of the statements will indicate the class of the text. The steps of the procedure of assigning to polarities with Naive Bayes Algorithm can be summarized in this way:

Since Text Mining Practices require working only on text, firstly, the post/comment data are cleaned from punctuations and numbers, all data are written in lower case letters;

The cleaned texts are spell checked. This spell check can be performed using various programs. For example, the error correction module in Microsoft Word text editor can be used;

Each word in the post/comment that will be analyzed is compared to the word/word group recorded in the Sentiment Database in Turkish and bit weighting is performed; for the words that are found value 1 and for the words that are not found value 0 is given. The repetitions in the text are not considered (The algorithms in which the repetition numbers are used work with different principles. For this reason, these algorithms were not used although they were in the English training set). At this point, it should be useful to refer to the task of finding stems: Some words in the post/comments may not be found in the Sentiment Database in Turkish because they have inflectional suffixes. However, this disadvantage could be resolved through an application directed at finding the stems of the words. But since the words in the Sentiment Database in Turkish are adjective and adverb based words, there is no need to find the stems of these words. Because when adjectives qualify or determine a noun, that is, when they are used as adjectives, cannot take the noun inflectional suffixes (case suffixes, possessive suffixes and plural suffixes) that they can take when they are used alone, that is, when they are considered as nouns ("Adjectives", 2007). Adverbs, on the other hand, are non-finite words. They do not take noun inflectional (case, possessive, plural suffixes etc.) suffixes. However, the adverbs that can be used as nouns can take these suffixes when they are used as nouns ("Adverbs", 2007). For this reason,

an application regarding finding stems were not developed;

In order to determine on which polarity is the weighted text vector, the probabilities of “1” cases are taken into consideration and two values are calculated. These values indicate the probability for being in positive/negative polarities. As the result of the comparison, post/comment is assigned to the polarity whose value is greater.

In addition, the length of the posts/comments in terms of word number was looked and the effect of the length to the success of polarity assignment was investigated in the study.

Using the Model

In order to use this model that will assign the post/comments to positive or negative polarities, a program that will automatically perform these procedures was developed. For this program called “Opinion Polarity Detection”, Visual Basic Language was used in Microsoft NET Framework environment and Microsoft SQL Server 2005 was used as database. Post/comment entry in the program interface is performed through these steps:

Posts/comments can be manually entered or copied;

The text, if required, can be spell checked. In this case, program gets into contact with the error correction module of the Microsoft Word text editor and offers alternatives regarding spell check;

Through this procedure, text can be assigned to positive or negative polarity with the help of the commands operating in the background or if none of the words is included in the Sentiment Database in Turkish, the words might not be classified.

Findings and Evaluation

(1) Findings Obtained with the Positive and Negative Precision Measures.

In order to test the success of the established model, a test database comprising of 350 positive and 350 negative samples was formed. A sample of the test database can be seen in Table 6.

Table 6

A Sample of the Test Database

Product/Service (Brand)	View	URL	Post/Comment
X	Positive	http://adimsoyadim.blogspot.com/	I am a positive comment
Y	Negative	http://adimsoyadim.blogcu.com/	I am a negative comment

The posts/comments obtained in this way were divided into two classes as the posts/comments in the positive polarity and in the negative polarity for test purposes and their contents were copied to the files named “pozitiforum.txt” and “negatiforum.txt”. For the automatic process of the posts/comments in two text files by the program, related combo options were developed. In this way, the posts/comments whose polarities are known can be read from the related text files and whole analyses can be performed. The program, depending on the hardware properties of the computer used, can perform the test of one word approximately in 0,002277 second. Both analyses are given in Table 7.

In this study, the model’s success of assigning to the related polarity was evaluated with Precision Measure. Precision Measure is among the frequently used methods in measuring text classification activities and can be stated as follows:

Precision = Number of the Posts/Comments classified as True/Total Number of Posts/Comments

Table 7

Results of the Assignment to the Related Polarity Obtained With the Test Database

Polarity	Total number of posts/comments	Number of the posts/comments classified as true	Number of the posts/comments classified as false	number of the posts/comments that cannot be classified
Positive	350	253	93	4
Negative	350	256	90	4

Positive precision measure = $0.7228 = 72.28\%$ /Negative precision measure = $0.7314 = 73.14\%$.

At this point, the method regarding the model assigning the positive/negative pole was compared with the Turney method that is a method about which it being close to this method within the frame of some certain criteria can be said and their similarities/differences were put forth (Turney, 2002).

Similarities:

- Both methods try to determine the positive/negative pole of the text and are examined within the context of the opinion mining task;
- Both methods are used in classifying the customer comments as “suggested ones/positive” or “non-suggested ones/negative”;
- Both methods were picked randomly from the domains where comments were;
- Both methods focus on the semantic orientation of the adjective/adverb based words.

Differences:

- Turney Method is based upon the English language, yet contrary to this, the model mentioned in the study is based on Turkish language;
- Turney Method functions according to the unsupervised learning basis, the model mentioned in the study functions accordingly with the semi-supervised learning basis;
- In the Turney Method, semantic orientation of a phrase is calculated as mutual information in between the phrase given with the words excellent/poor. And in the model mentioned in the study, words are arrayed according to the distance between the color codes and in this direction they possess the possibility of being at the positive/negative pole;
- Turney Method’s number of sample comments is 410; study model’s number of sample comments is 700;
- Database of the Turney Method comes from four different domains (automobiles, banks, movies and travel destinations) that are taken from the <http://www.epinions.com>. Comments that partake in this site present the objective views of real persons. And in the test database of the study model, comments come from a lot of different blogs. Comments that partake in the blogs present the objective views of real persons. Also here, the comment contents belong to the products/services titled as “white goods, built-in products, electronics, small home appliances and heaters-air conditioners”;
- For the comments in the Turney method come from four different domains, accuracy values were calculated separately. These values respectively are 84%, 80%, 65.83%, and 70.53%. Average accuracy value is 74.39%. And the average accuracy value of the study model is 72.71%.

(2) Descriptive Statistics Regarding the Word Number.

In this section, the descriptive statistics regarding the word number of the posts/comments were included and the effect of word number to the polarity assignment success was investigated. In order to perform this research, a module that counted the words of the posts/comments was added to the program. The data regarding

the column headings such as “post/comment”, “positive value”, “negative value”, “result”, and “word number” can be listed using the database button in the interface. In Table 8, a sample of the test database accessed with the database button can be seen. The columns regarding the results and word numbers for each polarity were copied to Microsoft Excel and the evaluations below were made.

Table 8

A Sample of the Test Database Accessed With the Database Button

Post/Comment	Positive value	Negative value	Result	Word number
Comment 1	3.41284223E-10	4.48293103037529E-07	Negative	185
Comment 2	0.008944502	3.07589510232533E-05	Positive	30
Comment 3	0.00147905317	6.00719609260089E-05	Positive	51
Comment 4	0.00393425	0.0212485840062161	Negative	22

While the average word number of the negative posts/comments in the test database is 86.55, the average word number for the positive entries is 29.66. From this, it can be inferred that contents are expressed with shorter entries while discontents and complaints are expressed with longer entries.

The average word number for the positive posts/comments in the test database is 29.66. In the obtained results, the average word number for the entries classified as true is 27.45 while the average word number for the entries classified as false is 36.15. From this, for the positive polarity it might be stated that the entries below the average word number are evaluated as true while the entries above the average word number are evaluated as false.

The average word number for the negative posts/comments in the test database is 86.55. In the obtained results, the average word number for the entries classified as true is 93.41 while the average word number for the entries classified as false is 70.41. From this, for the negative polarity it might be stated that the entries below the average word number are evaluated as false while the entries above the average word number are evaluated as true.

When looked to the standard deviations:

For the positive polarity, the standard deviation of the entries classified as true is 22.04 and the standard deviation of the entries classified as false is 36.30. The standard deviation of the 350 entries in this group is 26.82. From this, for the positive polarity, it might be argued that the entries in which the standard deviation is lesser, that is, the distribution is more balanced in terms of length, are evaluated as true.

For the negative polarity, the standard deviation of the entries classified as true is 143.46 and the standard deviation of the entries classified as false is 55.88. The standard deviation of the 350 entries in this group is 126.79. From this, for the negative polarity it might be stated that the entries in which the standard deviation is greater, that is, the distribution is more unbalanced (including extreme values), are evaluated as true. As a matter of fact, the values in this interval are between extreme points such as 2-1774.

(3) Some Factors Causing Incorrect Results.

The difficulties encountered in opinion mining field are mostly related to spell check. The program performs the spell check using Microsoft Word 2007 and offers alternatives for spell check if there is any. Spell check generally can be performed with the related alternative. However, Microsoft Word does not perform a semantic spell check, which is another text mining task. The cases in which the words are not underlined although they are misspelled can be given as an example. For example, the word “sakin” in the data collection

form might be copied as “sakin” by mistake (probably due to Turkish character problems). Since the word “sakin” is also a Turkish word, it will not be underlined and it will be accepted as a word which has been spelled right until the user realizes and corrects it manually. If these words which are assumed to be spelled right are included in the Sentiment Database in Turkish, the program will find this misspelled word and give it a probability value. This, in turn, will affect the classification and might cause a wrong evaluation of the polarities.

On the other hand, the deletion of the numbers and punctuations in the text due to the nature of text mining might cause other difficulties. For example, the statements “1.” or “2.” in the text are deleted in the first step. However, these two adjectives are included in the Sentiment Database in Turkish. If these statements written with numbers and spots were written with alphabetic characters, they would be in the Sentiment Database in Turkish.

The “ ’ ” character is a frequently used character for adding suffixes to the brand names in the posts/comments. However, since this character is also considered to be a punctuation mark, it can be deleted in the first step. For example, “x’tan çok memnunum” might be replaced by “x tan çok memnunum”. In this case, the suffix “tan (twilight)” will be considered to be a different word and will be searched in the Sentiment Database in Turkish. This word meaning “seher, alacakaranlık” is included in the database. Therefore, it will be analyzed and it might cause a wrong evaluation of the polarities. In order to prevent this error, the program was configured. The suffix is united with the word and becomes “xtan” when there is only an apostrophe. In this way, the evaluation of the suffix as a separate word is prevented.

The developers of the We Feel Fine website, Kamvar and Harris, state that “positive feelings tend to not co-occur often with negative feelings, with a few exceptions” (Kamvar & Harris, 2011). The following word/word groups, with their probabilities for being in the positive class, can be given as examples of these exceptional words: Obsessed (92.05%), damaged (75.11%), seedy (75.11%), failing (74.93%), wild (74.51%), cruel (74.1%), unhealthy (74.04%), rebel (72.20%), and unappreciated (69.49%). The Turkish correspondences of these words might cause that the texts in which they are included are assigned to wrong polarities.

Conclusions

In today’s world, there are many blogs on the internet that keep customer opinions on products and services and the number of these blogs increases day by day. These blogs, by their conveying nature, offer text data that will benefit the enterprises in terms of customer orientation in the area of Customer Relationship Management. Besides, while the data on the enterprise’s database are only accessible by the enterprise, these blogs are open to anyone. Therefore, positive or negative opinions can be seen by anyone who reads that blog. For this reason, enterprises have to follow and analyze these blogs in order to protect their reputations. In this way, enterprises can develop related strategies regarding the decision processes and ensure the increase in efficiency.

In this regard, this study uses the Opinion Mining methods and proposes a model that will assign the text-based opinion data in Turkish blogs to positive and negative polarities in order to present a general view on products and services. In order to use this model that will assign the posts/comments to the polarities, a program that will automatically perform these procedures was developed.

The model’s success of polarity assignment was evaluated with Precision Measure. The Positive Precision Measure was calculated to be 72.28% and the Negative Precision Measure was calculated to be 73.14%. These

obtained results support the validity of the methodology and give hope for the model's future. A test database that will be developed by taking more samples will provide for the possible predictions and controls and better results will be obtained. It is my wish that this study will contribute to the beginning of the "Opinion Mining Studies in Turkish Language".

When it comes to the difficulties encountered in the test level, it might be stated that most of these difficulties were in the area of spell check. As matter of fact, a semantic spell check is required, which is another text mining task. On the other hand, the deletion of the numbers and punctuations in the text due to the nature of text mining might cause other difficulties and might lead to wrong polarity evaluations. Besides, the developers of the We Feel Fine website, of which the sentiment words were used in the training set, state that positive feelings tend to not co-occur often with negative feelings, however, this might have a few exceptions. As a matter of fact, these exceptional words might cause that the texts in which they are included are assigned to wrong polarities.

This classification model, which might be considered as "Listening to the Social Media" in a sense, is also important in terms of showing the new dimension added to the enterprise-customer interaction. For this reason, enterprises have to pay attention to the voice of the masses in order to develop their strategies in the related area.

References

- Abbasi, A., CHEN, H., & Salem, A. (2008). Sentiment analysis in multiple languages: Feature selection for opinion classification in web forums (ACM Trans.). *Information Systems*, 26(3).
- Adjectives. (2007). Source website for Turkish language and literature. Retrieved February 28, 2013, from http://www.turkceciler.com/sozcuk_turleri/sifatlar.html
- Adverbs. (2007). Source Website for Turkish Language and Literature. Retrieved February 28, 2013, from http://www.turkceciler.com/sozcuk_turleri/zarflar.html
- CHEN, B., ZHU, L. L., Kifer, D., & Lee, D. (2010). What is an opinion about? Exploring political standpoints using opinion scoring model (In Proceedings of *The Twenty-Fourth AAAI Conference On Artificial Intelligence (AAAI)*, Atlanta, GA., July 11-15, 2010, p. 1).
- Conrad, J., & Schilder, F. (2007). Opinion mining in legal blogs. In Proceedings of *the International Conference on Artificial Intelligence and Law (ICAIL)*. New York, N. Y., USA: ACM, 2007, pp. 231-236.
- Dave, K., Lawrence, S., & Pennock, D. (2003). Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In *WWW '03: Proceedings of the 12th International Conference on World Wide Web*. New York, N. Y., USA, ACM, 2003, pp. 519-528.
- Devitt, A., & Ahmad, K. (2007). Sentiment polarity identification in financial news: A cohesion-based approach. In Proceedings of *the 45th Annual Meeting of the Association of Computational Linguistics, Association for Computational Linguistics*. Prague, Czech Republic, June 2007, pp. 984-991.
- LIU, B. (2013). Opinion mining. Retrieved February 28, 2013, from <http://www.cs.uic.edu/~liub/fbs/opinion-mining.pdf>
- Esuli, A., & Sebastiani, F. S. (2005). Determining the semantic orientation of terms through gloss analysis. In Proceedings of *CIKM-05, 14th ACM International Conference on Information and Knowledge Management*. Bremen, DE., 2005, pp. 617-624.
- Esuli, A., & Sebastiani, F. S. (2006). A publicly available lexical resource for opinion mining. In Proceedings of *Language Resources and Evaluation (LREC)*. Italy, Genoa, May 24-26, 2006, pp. 417-422.
- Falcon, J. (2010, August 19). Opinion mining in ediscovery. Retrieved February 28, 2013, from <http://jadefalconit.com/opinion-mining/opinion-mining-in-ediscovery>
- How to Calculate a Complementary Colour (Inc. RGB/HSL Conversion). Retrieved February 28, 2013, from <http://serennu.com/colour/rgbtohsl.php>
- Kamvar, S., & Harris, J. (2011). We feel fine and searching the emotional web, WSDM'11. In Proceedings of *the Fourth ACM International Conference on Web Search and Data Mining*. Hong Kong, February 9-12, 2011, pp. 117-126.

- Kamps, J., Marx, M., Mokken, R. J., & De Rijke, M. (2004). Using word net to measure semantic orientation of adjectives. In Proceedings of *LREC-04, 4th International Conference on Language Resources and Evaluation*. Volume IV, Lisbon PT, 2004, pp. 1115-1118.
- Kurt, H. (1998). *Grammar for elementary school 7th grade*. İstanbul, Morpa Kültür Yayınları.
- Levene, M. (2010). An introduction to search engines and web navigation (2 nd.). New Jersey, Wiley Publisher.
- LIU, B. (2007a). *Web data mining*. Chicago, Springer.
- LIU, B. (2007b). From web content mining to natural language processing. *ACL-2007 Tutorial, Prague*. Retrieved February 28, 2013, from <http://www.cs.uic.edu/~liub/acl-07-tutorial-wcm-to-nlp.pdf>
- Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis, foundation, and trends. *Information Retrieval*, 2(1-2).
- QIU, G., LIU, B., BU, J. J., & CHEN, C. (2010). Opinion word expansion and target extraction through double propagation. *Computational Linguistics*, 1(1), 1-18.
- RGB Color Space. (2013, February 13). *Wikipedia*. Retrieved February 28, 2013, from http://tr.wikipedia.org/wiki/RGB_renk_uzay%C4%B1
- Sentiment Analysis. (2013, February 28). *Wikipedia*. Retrieved from http://en.wikipedia.org/wiki/sentiment_analysis
- Stavrianou, A., & Chauchat, J. H. (2008). Opinion mining issues and agreement identification in forum texts (*FODOP 2008, Atelier Fouille Des Données D'opinions*, Fontainebleau, France, 27 May 2008, pp. 51-58).
- Turney, P. (2002). Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. In Proceedings of *the 40th Annual Meeting On Association For Computational Linguistics (ACL '02)*. Morristown, N. J., USA, July 2002, pp. 417-424).
- Verbeke, M., & Eynde, W. (2013). Opinion mining. Retrieved February 28, 2013, from <http://people.cs.kuleuven.be/~bettina.berendt/webmining10/13.pdf>
- XU, F. Y., & CHENG, X. W. (2011, January 19). Opinion mining. Retrieved June 7, 2011, from <http://ebookbrowse.com/opinion-mining-2011-lecture-pdf-d90656735>