ASPECT BASED OPINION MINING ON TURKISH TWEETS

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MASTER OF SCIENCE

By

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July, 2012

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

ASPECT BASED OPINION MINING ON TURKISH TWEETS

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Understanding opinions about entities or brands is instrumental in reputation management and decision making. With the advent of social media, more people are willing to publicly share their recommendations and opinions. As the type and amount of such venues increase, automated analysis of sentiment on textual resources has become an essential data mining task. Sentiment classification aims to identify the polarity of sentiment in text. The polarity is predicted on either a binary (positive, negative) or a multi-variant scale as the strength of sentiment expressed. Text often contains a mix of positive and negative sentiments, hence it is often necessary to detect both simultaneously. While classifying text based on sentiment polarity is a major task, analyzing sentiments separately for each aspect can be more useful in many applications.

In this thesis, we investigate the problem of mining opinions by extracting aspects of entities/topics on collection of short texts. We focus on Turkish tweets that contain informal short messages. Most of the available resources such as lexicons and labeled corpus in the literature of opinion mining are for the English language. Our approach would help enhance the sentiment analyses to other languages where such rich sources do not exist. After a set of preprocessing steps, we extract the aspects of the product(s) from the data and group the tweets based on the extracted aspects. In addition to our manually constructed Turkish opinion word list, an automated generation of the words with their sentiment strengths is proposed using a word selection algorithm. Then, we propose a new representation of the text according to sentiment strength of the words, which we refer to as sentiment based text representation. The feature vectors of the text are constructed according to this new representation. We adapt machine learning methods to generate classifiers based on the multi-variant scale feature vectors to

detect mixture of positive and negative sentiments and to test their performance on Turkish tweets.

Keywords: Opinion mining, Sentiment analysis, Twitter, Text mining, Summarization.

ÖZET

TÜRKCE TWEETLERDE KONU BAZLI DÜŞÜNCE ANALİZİ

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Kişiler ve markalar hakkındaki görüşleri anlamak, itibar yönetimi ve karar verme konularında yardımcı olur. Sosyal medyanın gelişiyle, daha çok insan tavsiye ve görüşlerini aleni şekilde paylaşmaya istekli hale gelmiştir. Sosyal alanların tip ve miktarı arttığı için, metinsel kaynaklardaki duygu analizini otomatize etmek, zaruri bir veri madenciliği görevi haline gelmiştir. Duygu sınıflandırma, metindeki duygu kutupluluğunu belirlemeyi amaçlar. Kutupluluk, duygunun güçlülüğü belirtildiği kadar, ya ikili (pozitif, negatif) ya da çok değişkenli skalada tahmin edilir. Metinler çoğu kez pozitif ve negatif duyguların karışımını ihtiva ederler; dolayısıyla, bu iki tip duyguyu sıkça aynı anda saptamak gereklidir. Metni duygu kutupluluğuna göre sınıflandırmak ana bir görev iken, duyguları her alt konular için ayrı ayrı analiz etmek, çoğu uygulama için daha faydalı olabilir.

Biz bu çalışmada, bir kısa metin koleksiyonu üzerinde kişi ve başlıklar hakkındaki alt konuları çıkararak, düşünce analizi problemi üzerinde inceleme yapmaktayız. Resmi olmayan kısa mesajlar içeren Türkçe tweetler üzerinde yoğunlaşmaktayız. Düşünce analizi üzerinde literatürde yer alan kelime sözlüğü ve etiketli derlemler gibi kaynakların çoğu İngilizce içindir. Bizim yaklaşımımızın, böyle zengin kaynakların olmadığı diğer diller için duygu analizini geliştirmeye yardımcı olması mümkündür. Birtakım önişleme adımlarından sonra, veriden ürün(ler) hakkındaki alt konular çıkarıp, bu konulara dayanarak tweetleri gruplamaktayız. Elle işletilerek oluşturduğumuz Türkçe duygusal kelime listesine ek olarak, bir kelime seçme algoritması kullanıp, kelimelerin duygu güçlülüğü ile birlikte bir otomatize oluşum yöntemi geliştirildi. Daha sonra, duygu tabanlı metin gösterim şekli olarak ifade edilen, kelimelerin duygu güçlülüğüne göre metnin yeni bir gösterim şekli oluşturuldu. Metinlerin öznitelik vektörü, bu yeni gösterim şekline göre oluşturulmaktadır. Pozitif ve negatif duygu karışımını belirlemek için çok değişkenli skalada öznitelik vektörlerine dayanan sınıflandırıcıları

oluşturmak ve bunların performansını Twitter API vasıtasıyla zamanla toplanan Türkçe tweet verisinde test etmek için makine öğrenmesi yöntemlerini uyarlamaktayız.

Anahtar sözcükler: Düşünce Analizi, Twitter, Yazı madenciliği, Ozetleme.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

While making decisions, people usually rely on opinions of other people and ask recommendations. Thanks to public social media, people share their recommendations online. According to a survey [8], users generally do an online search about a product before buying it, and online reviews about the product affect their opinion significantly. Learning peoples opinions and preferences are more valuable for companies to get feedback on their products both through the public web and private channels of information. They can monitor their brand reputation, analyze how peoples opinion changes over time and decide whether a marketing campaign is effective. Figure 1.1 shows a simple example that we produced which illustrates the sentiment of tweets over time for the three major Wireless Carriers in Turkey, which we refer to as Carrier-X, Carrier-Y, and Carrier-Z in this thesis.

As the type and amount of venues for sharing opinions increase, getting useful information of sentiments on textual resources has become an essential data mining goal. The task of sentiment classification aims to identify the polarity of sentiment in text. In other words, text is classified according to sentiment type. The text unit can be a word, phrase, sentence or a document. The polarity is predicted on either a binary (positive, negative) or multi-variant scale as the strength of sentiment expressed in the text. However, a text often contains a mix of positive and negative sentiment, hence it is often necessary to detect both of

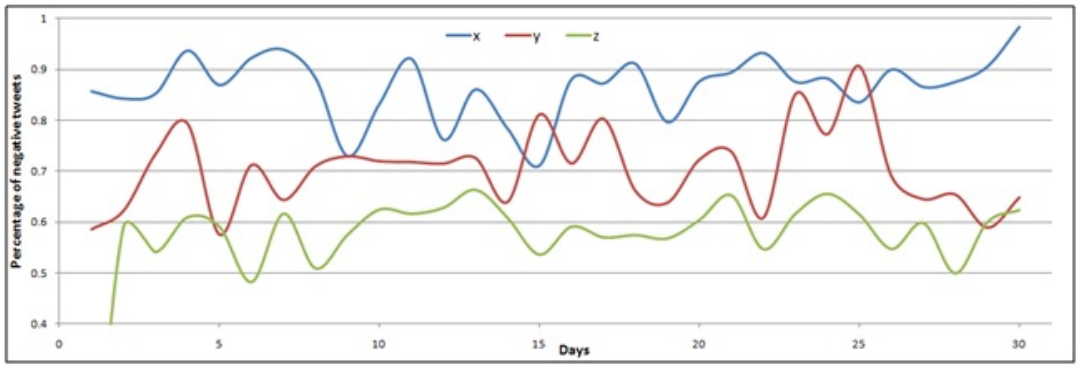


Figure 1.1: The sentiment of tweets over time for the three major Wireless Carriers

them simultaneously [27]. An example of mixture text that shows this mixture is:

"Z kalitelisin ama çok pahalısın"

It is stated in the example that Z has quality but its cost is also too high. These are negative and positive aspects of the product in the same text.

Extracting polarity from textual resources involves many challenges. Distinguishing positive text from negative text is relatively easy for human, especially in comparison to other traditional text mining problems such as topic categorization. However, automated identification of keywords that convey sentiment polarity is more difficult as the topics are often identifiable by keywords alone. Moreover, sentiment can be expressed in a more hidden attitude, as a result of this, it is difficult to be identified by any of a sentence or documents terms [8]. Note that a sentence that includes opinion word does not necessarily indicate sentiment; and a sentence that does not include any opinion words may contain sentiment. Additionally, sentiment is context sensitive and domain dependent because same or similar words can indicate different sentiment in different domains.

A major challenge in our work has been handling a non-English and informal short-text in Twitter. Current studies typically focus on sentiment classification on English reviews, e.g., on movies and restaurants, blogs, and news. These data

sets often consist of relatively well-formed, coherent and at least paragraph-length pieces of text. Furthermore, resources such as polarity lexicons, and parsers are usually available for these domains and for English. Sentiment analysis on Twitter, however, is different from the sentiment analysis models on reviews or blogs based on machine learning. In a tweet message, a sentiment is conveyed in one or two sentence passages, which are rather informal, including abbreviations and typos. These messages are less consistent in terms of language usage, and usually cover a much wider array of topics. Also, sentiment is not always as obvious when discussing human-generated status updates; many tweets are ambiguous even to a human reader as to their sentiment. Finally, a considerably large fraction of tweets convey no sentiment whatsoever, such as advertisements and links to news articles, which provide some difficulties in data gathering, training and testing [5]. There are many studies to detect sentiment of a text written in English. Most of them use supervised machine learning methods with the raw word representation as features to construct a model. Some follows a lexical approach which uses a dictionary of sentiment words with associated strength measures.

While classifying text based on sentiment polarity is a major task, a more useful variant is usually to mine the opinions based on the particular aspects (features) of entities or topics. Instead of extracting the overall sentiment of a topic, analyzing sentiments separately for each aspect can be more useful in many applications. For instance, while users may like the quality of a product, they may not be satisfied with its cost. So, exploring more detailed information about a product is better for sentiment analysis done by users of a product or a company. This summarization task includes three steps [26]:

- Extracting features/aspects of entity/topic
- Mining opinions in each text and their polarity
- Producing a useful aspect based summary from the results such as number of positive and negative reviews about an aspect, average of sentiment, life cycle of sentiment of an aspect over time

Several methods are proposed to identify the aspect of the products. There

are different features of a product that opinions are expressed on, and same or similar aspects of a product can be expressed with different words. So, after extracting the aspects, they need to be grouped to obtain an effective summary.

A contribution of this thesis is the methods to generate aspect based sentiments on short Turkish texts. Most of the available resources such as lexicons and labeled corpus in the literature are in English. We focus on Turkish texts in Twitter that contain informal short messages and show a methodology to construct resources, lexicon and corpus for non-English languages. Our approach would help enhance the sentiment analyses to other languages where such rich sources do not exist. After constructing the Turkish data set and applying a set of preprocessing steps, we propose an algorithm to extract the words for specified aspects of the topic and group text according to words of aspects. Then, we combine machine learning and lexical methods to measure the sentiment strength of the text. In addition to the manually constructed Turkish opinion word list, an automated generation of the words with their sentiment strengths is developed using a proposed word selection algorithm. Then, we propose a new representation of the text according to sentiment strength of the words, called sentiment based text representation. Feature vectors of the text are constructed according to the new representation. We adapt machine learning methods to generate classifiers based on these new type of feature vectors to detect mixture of positive and negative sentiments and to test their performance on a Turkish tweet data collected over time via Twitter API.

The rest of the thesis is organized as follows: Section 2 gives background information about topic extraction and sentiment analysis and presents the related work. Section 3 describes the details of our model. In Section 4, our experimental results are discussed and some applications results of our model are given. Finally, we conclude and include future work in Section 5.

Chapter 2

Background

2.1 Sentiment Analysis

Opinion mining is one of the tasks of sentiment analysis, which is to track attitudes and feelings in an opinionated document with classifying it as either positive or negative according to the sentiment expressed in it. As an important discipline in the areas of NLP, text mining and information retrieval, it dates back to the late 1990s but it has gained a lot of interest in the recent years [8].

A large collection of research on mining opinions from text is done. Most of these works detect sentiment as positive-negative, or add a natural class to them. There are also some studies [27, 31] that detect positive-negative sentiment strength with predicting the human ratings on a scale (e.g. Sentiment in the text is classified as 2 in the scale between 0-10 (extremely negative - extremely positive). Also some recent approaches try to extract multiple emotions and their strengths from an informal text [27, 30]. These methods are commonly performed on large texts, e.g., newspaper articles and movie reviews. Recently, many researches are done on short texts such as Twitter corpora to mine public opinion and interesting trends using different approaches. Most existing sentiment extraction approaches assumes that the document includes only subjective

expression as opinion of the author. However, text materials usually contain mixture information as opinion and facts, objective information about events and entities. Therefore, some of applications try to separate factual and opinion texts as document level subjectivity classification (e.g. The document is subjective or objective) before extracting sentiment of the text.

Although most of sentiment extraction approaches are based on supervised learning, some approaches use unsupervised methods as well.

2.1.1 The lexical (Unsupervised) Approaches

The lexical approach utilizes a dictionary or a lexicon of pre-tagged (positive-negative or strength of sentiment) opinion words known as polar words and sentiment words. Positive opinion words are used to state positive sentiment (e.g. iyi, güzel). On the other hand, negative opinion words are used to state negative sentiment (e.g. kötü, çirkin) [25, 12]. Each word that presents in a text is compared against the dictionary and sentiment of the text, according to the results of some functions based on occurring positive and negative opinion words in the dictionary is determined [27, 21, 20]. Especially, polarity of the text is computed with counting how often words in the dictionary occur in the text. Moreover, there are some other works that use negation terms and words that enhance sentiment of the upcoming words to improve the results of extracting sentiment of text[36]. It is enough to look at the number of positive and negative terms in a text to determine sentiment of the text. If number of the positive words is higher than number of the negative terms, the text is classified as positive and as negative if it contains more negative terms. If the numbers of them are equal, it is classified as neutral [21]. GI [35], which contains information about English word senses, as positive, negative, negation, overstatement, or understatement, is used as a dictionary of opinion words.

In some works [27, 31], strength of positive-negative sentiment is detected on a scale. The lexicon used in these works not only contains negative and positive words but also contains sentiment strength of them in a scale. The polarity

weighted strength of each word is accumulated to compute the sentiment strength x_t of a text t. It is defined formally as:

$$x_t = \sum_{i=1}^{n}(p_i * s_i)$$

where n is the number of words in the text, $p_i \in \{$ -1,+1 $\}$ is the word polarity and $s_i \in \{$ 1,2,3,4 $\}$ is the word strength.

Opinion Lexicon Generation

There are different types of this dictionary. Some of them include only adjectives and adverbs such as iyi, kötü and çirkin. The reason of it is that adjectives and adverbs are more important than the other words such as noun and verbs for sentiment classification. Although, some of them has also noun and verbs that indicate sentiment such as sevmek, eğlenmek, aldatmak. Different approaches can be used to construct this word list. The first one is manual approach. Each term is labeled as positive-negative or in scale as sentiment strength by humans. However, constructing it manually is a time consuming task and finishing the construction in a short time is more difficult. The second one is dictionary based approach. It starts with collecting a small set of opinion words manually with known orientations and then to grow this set by searching in an online dictionary, e.g. Wordnet [33] for their synonyms and antonyms. Another one is corpus based approach based on co-occurrence patterns of words in a large corpus [25].

- **Dictionary Based Approach**

Kampus et al [20], construct the opinion word list using wordnet. The geodesic distance s used to measure the similarity of meaning of word. GI to words, "good" and "bad" is computed for each adjective in a dictionary, According to a function EVA, a value between -1 (for words on the bad side of the lexicon) to 1 (for words on the good side of the lexicon) is assigned to each word.

$$EVA(w) = (d(w, bad) - d(w, good))/d(good, bad)$$

765 positive and 873 negative words are obtained by this way. The percentage of agreement between their word list and the General Inquirer list is 68.19 %.

- **Corpus Based Approach**

Hatzivassiloglou and mckeown [18] propose a novel approach to extract semantic orientation of a set of adjectives based on linguistic features. They try to find semantic orientation of other adjectives in large corpus with using a set of linguistic constraints and a small list of opinion adjective words. They look whether an adjective is linked to another one known as positive or negative by a conjunction or disjunction or not. They assume that adjectives, which co-occur more frequently in conjunction such as "and" , have same sentiment orientation where as adjectives, co-occur more frequently in disjunction such as but, usually share opposite sentiment orientation. According to this assumption, they extract some adjectives with their semantic orientation from the corpus. The algorithm is tested with 1.336 manually labeled adjectives and approximately 78% accuracy is obtained. They use four steps in this method:

1. All conjunctions of adjectives are extracted from the corpus.
2. Using a log-linear regression model constructed with training set, it is determined that whether each two conjoined adjectives are same or opposite orientation. According to the result of the model on the different test sets, a graph is obtained. Nodes of it are adjectives and links of it show orientation between adjectives.
3. According to a clustering algorithm, the graphs is partitioned into two sets.
4. Items are labeled as positive and negative based on frequency of positive adjectives in the sets.

In [32] similar to [18], the pointwise mutual information is used to label phrases with their semantic orientations according to two set of positive and negative seed words ;

$$S_p = \{ \text{ good,nice,excellent,positive,fortunate,correct,superior } \}$$

$$S_p = \{ \text{ bad,nasty,poor,negative,unfortunate,wrong,inferior } \}$$

Phrases that includes adjective and adverbs are extracted from the text using a part of speech tagger. The point wise mutual information (PMI) between words is calculates by using word co-occurrence statistics that is defined as follows:

$$PMI(word_1, word_2) = \log_2(p(word_1 \& word_2)/p(word_1)p(word_2))$$

$p(word_1 \& word_2)$ shows the co-occurrence statistics of $word_1$ and $word_2$. After computing PMI between seed words and extracted words, labels ($semanticorientation = SO$) of these extracted words is given according to a formula as follows;

$$SO(t) = \sum_{t_i \in S_p} PMI(t, t_i) - \sum_{t_j \in S_n} PMI(t, t_j)$$

Then, the sentiment of the text is predicted as the average of SO scores of the extracted phrases in it. This approach finds domain specific opinion words. Since it is difficult to construct a list that cover all opinion words in the language using a small corpus [25]. This fact differs this approach from dictionary based approach. This may be both an advantage and disadvantage for sentiment classification. As an advantage, some words can be used in different meanings in different corpora. Therefore, we can extract this information with this approach. On the other hand, this constructed list may not be used for a different domain.

2.1.2 Supervised Approaches

Similar to other topic based text classification in the machine learning approach, a classifier is trained with a collection of tagged corpus using a chosen feature

vector and a supervised machine learning method, such as Support vector machines (SVM), decision tree, Naive Bayes and maximum entropy. For using in classification, there are different kinds of feature vector that text is converted into. When all terms in the corpus are used as feature, dimensionality of feature vector becomes very high. Moreover, entire document does not contain sentiment information. This redundant information can reduce the effectiveness of data mining. Hence, different feature extraction and feature selection algorithms are applied in the literature of text classification and sentiment analysis for faster learning and better classification results.

Feature Types

A basic feature is terms and their frequency that are individual words or word n-grams. Each document d is represented by a vector of frequencies of the terms in it:

$$d = (tf_1, tf_2, ..., tf_m)$$

As an alternative to term frequency tf, inverse document frequency (idf) is also used as a feature. Furthermore, presence of terms is used as binary-valued feature vector that a feature shows whether a term occurs 1 n the document or not (0). Pang et al. [7] show that using presence of the terms rather than frequency gives better results. Moreover, n-grams, i.e. a contiguous sequence of n terms from a given sequence of text are used in the feature vector. In [7], it is reported that unigrams yield better results than bigrams. Another approach is using part of speech tags such as adjectives, nouns, verbs and adverbs for sentiment analysis. However, other tags also contribute to expression of sentiment [24]. In addition to these, emoticons, punctuation $e.g., ?, !, ..$, opinion and negation word and the number of them are also exploited as a feature type [25, 16]. Emoticons are textual expressions that represent facial expressions. Table 2.1 lists frequently used emoticons.

In [10], sentence length in words, number of "!" and "?" characters in the sentence, number of quotes in the sentence and number of capitalized/all capitals

Glyph	Meaning
$:-), :)$	Smile
$;-),;)$	Wink
$:-(, :($	Frown
$:-D, :D$	Wide grin
$:-P, :P$	Tongue sticking out
$:-O, :O$	Surprise
$:'($	Crying
$:-\|$	Disappointed
$:-S, :S$	Confused
$:-@$	Angry
$:-\$$	Embarrassed

Table 2.1: Frequently used emoticons

words in the sentence are used as features.

Most commonly, the raw word representation (n-grams) is chosen as the feature vector for text classification. However, there are lots of words that have no effect on the classification. Also, computing complexity increases as a result of high dimensionality. For long texts, effective results can be obtained using bag of words approach, since each document includes many words and they may have same words. However, the frequency of the words in short text is relatively low in comparison with their frequency in long documents while both cardinalities of their corpus is high. Therefore, short text has spare feature vector that has hundreds or thousands of dimensions but there is a few feature of this vector that has a value different from 0. As a solution for these problems, different feature selection and extraction algorithms are applied for text classification. In addition to these, many research are done such as expanding and enriching the sparse texts for overcoming sparsity of short text. Furthermore, domain specific solutions are also developed [6]. One of them is to classify using a small set of domain-specific features, such as the author information and features extracted from the tweets

Feature Selection Algorithms

An important difficulty of text mining is the high dimensionality of the feature space. All terms, whose number may be more than thousands in the corpus of documents, do not contain essential information. Feature selection algorithms try to extract these essential knowledge with removing non-informative terms according to corpus statistics [38]. Basically, one can select words that have sufficient frequency using a threshold, since too specific terms may not have any effect on the sentiment of the text. In addition to this, a score is given to each of the features after evaluating all of them independently using some evaluation function on a single feature. According to the assigning score, best features are selected as a subset. The number of features can be predefined or a threshold can be used for score of features [29, 11].

There are different evaluation function used for scoring. Some of them are as follows [11]:

- Docfrequency$(f, C_i) = P(f|C_i)$
- Odds Ratio$(f, C_i) = ((P(f|C_i) * (1 - P(f|\bar{C}_i)))/((P(f|\bar{C}_i) * (1 - P(f|C_i)))$
- Entropy$(f) = P(f) \sum_i P(C_i|f) \log(P(C_i|f)/P(C_i))(Entropy)$
- Infgain$(f) = P(f) \sum_i P(C_i|f) \log(P(C_i|f)/P(C_i)) + P(\bar{f}) \sum_i P(C_i|\bar{f}) \log(P(C_i|\bar{f})/P(C_i))$ (Information Gain)
- MI$(f; C) = P(f, C) * \log((P(f, C))/(P(f) * P(C)))$ (Mutual Information)

Information Gain, Infgain (f), is commonly used in decision tree for selection of best discriminative feature. Mutual Information, MI (f; C), is used to measure dependency between 2 variables. It is one of the most commonly used feature selection method in text mining. It selects features according to mutual dependency between a term f and a class C (positive or negative) [29]. P(f; C) is the conditional probability of the feature f occurring in class C.

In the best term (BT) approach [11], for each class C, all documents in C are examined and a set of positive words, as given in the definition 1 below, that

are more frequent are selected as good predictors of that class. A top scoring positive feature is selected for each document. Documents that do not contain at least one of the positive words eliminated with the thought of not including useful information after extracting positive words for all class. Later, a set of negative features, as given in definition 2, are selected as a good representer of that documents with looking documents that are not in C. For each documents out of class C the top scoring negative feature is selected.

Definition 1: A feature w is called positive for a class c if and only if the following relation holds:

$$P(c|w) > 0.5 * p + 0.5 * P(c)$$

where p is a parameter that is used in order to counteract the cases where the simpler relation $P(c|w) > P(c)$ leads to a trivial acceptor/rejecter, for too small/large values of P(c).

Definition 2: A feature w is called negative for a class c if and only if the following relation holds:

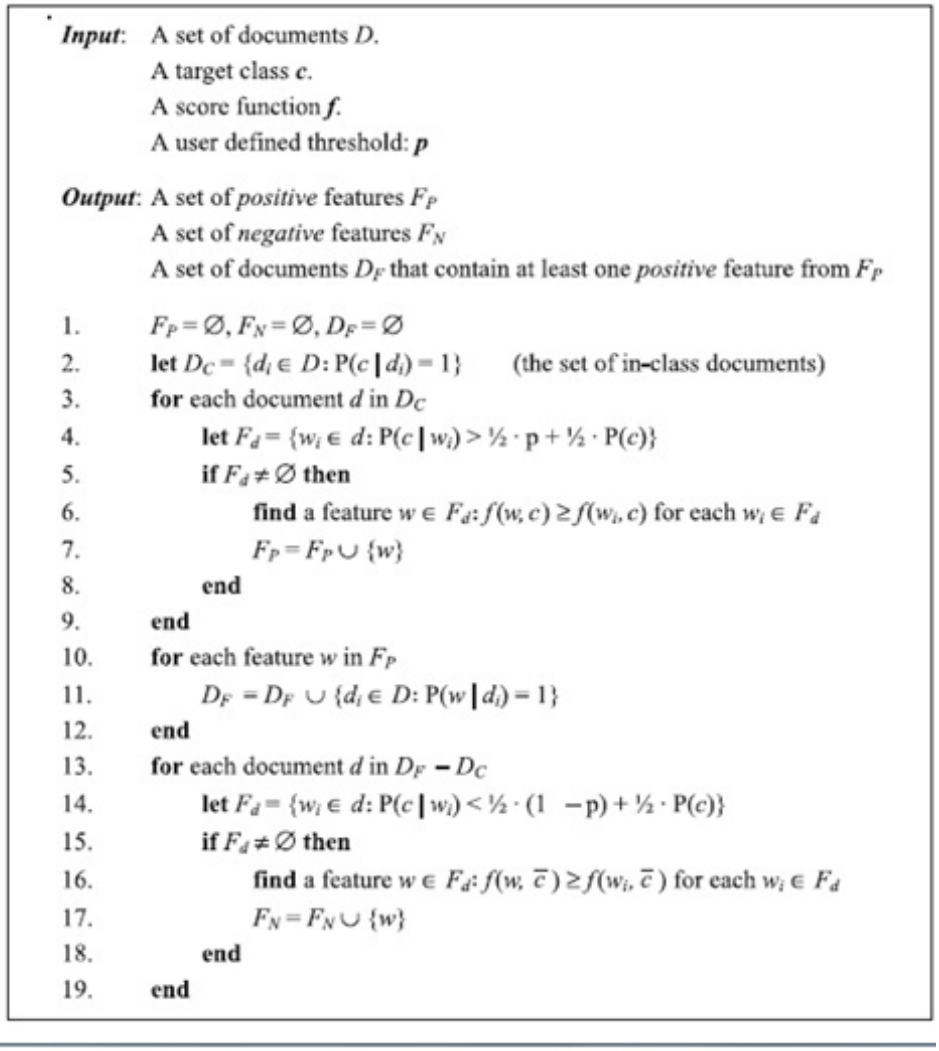
$$P(\bar{c}|w) > 0.5p + 0.5P(\bar{c})$$

$$P(c|w) < 0.5(1-p) + 0.5P(c)$$

The algorithm has a linear time complexity with respect to the number of training documents. Complexity does not depend on the number of vocabularies but depends on the number of documents as different from the other feature selection algorithms. In the Figure 2.1, a more detailed presentation of the BT algorithm is given.

Short Text Enrichment Methodologies

In [19], three enrichment approaches are explored. First one is the lexical-based enrichment where word and character n-grams and orthogonal sparse word



Input: A set of documents D.
A target class c.
A score function f.
A user defined threshold: p

Output: A set of *positive* features F_P
A set of *negative* features F_N
A set of documents D_F that contain at least one *positive* feature from F_P

1. $F_P = \emptyset, F_N = \emptyset, D_F = \emptyset$
2. **let** $D_C = \{d_i \in D: \mathrm{P}(c \mid d_i) = 1\}$ (the set of in-class documents)
3. **for** each document d in D_C
4. **let** $F_d = \{w_i \in d: \mathrm{P}(c \mid w_i) > \frac{1}{2} \cdot \mathrm{p} + \frac{1}{2} \cdot \mathrm{P}(c)\}$
5. **if** $F_d \neq \emptyset$ **then**
6. **find** a feature $w \in F_d: f(w, c) \geq f(w_i, c)$ for each $w_i \in F_d$
7. $F_P = F_P \cup \{w\}$
8. **end**
9. **end**
10. **for** each feature w in F_P
11. $D_F = D_F \cup \{d_i \in D: \mathrm{P}(w \mid d_i) = 1\}$
12. **end**
13. **for** each document d in $D_F - D_C$
14. **let** $F_d = \{w_i \in d: \mathrm{P}(c \mid w_i) < \frac{1}{2} \cdot (1 - \mathrm{p}) + \frac{1}{2} \cdot \mathrm{P}(c)\}$
15. **if** $F_d \neq \emptyset$ **then**
16. **find** a feature $w \in F_d: f(w, \bar{c}) \geq f(w_i, \bar{c})$ for each $w_i \in F_d$
17. $F_N = F_N \cup \{w\}$
18. **end**
19. **end**

Figure 2.1: BT algorithm: selecting the positive and negative words, the best representer of the documents

bigrams are applied to enrich the sparse text. Second one is the external based enrichment in which each text is enlarged with features extracted from an external resource, such as Wikipedia. Moreover, web pages linked by URLs in the text give useful information to expand the short text. One can also use WorldNet to extract relationships among words. In another approach, associated words are identified with examining collections. The closeness between words is measured using an association measure between words based on the count of occurrence of words and co-occurrences between pair of words.

Pinto et al.[9] present a novel methodology called self-term expansion to improve the representation of short text. It is based on replacing terms of a document with a set of co-related terms using only the corpus instead of any external resource. In order to do this, a co-occurrence term list is constructed using the point-wise mutual information (PMI) measure. After expanding the short text, three different term selection techniques which are document frequency, term strength and transition point, are used to filter unnecessary words and to decrease the number of them cite25.

2.2 Machine learning Methods

2.2.1 Naive Bayes

Naive Bayes is a classification algorithm based on Bayes' Theorem that uses conditional probabilities by counting the frequency of values and combinations of them in a data set. It is commonly used in text categorization and works well on it. The algorithm calculates the probability of B given A with counting the number of cases where A and B occur together and dividing it by the number of cases where A occurs.

For sentiment classification, when a document d, that contains m terms $f_1, ..., f_m$ is given, Naive Bayes classifier aims to find the class (positive or negative) with the highest probability with using the following formula;

$$P(c|d) = (P(c) * (\prod_{i=1}^{m}(P(f_i|c))^{n_i(d)}))/(P(d))$$

Where $n_i(d)$ represents the count of term f in document d. $P(c)$ and $P(f|c)$ can be computed by maximum likelihood estimates according to frequency.

2.2.2 Support Vector Machine

SVM constructs a decision surface or a set of optimal hyperplanes as the decision rule given by

$$f_{w,b}(x) = sgn(w^T x + b)$$

that makes a good separation between members of different classes. If the training data is linearly separable, a pair (w, b) exists such that

$$w^T x_i + b \geq 1, \text{ for all } x_i \in P$$

$$w^T x_i + b \leq -1, \text{ for all } x_i \in N$$

If the data is linearly separable, the optimum separating hyperplane is found with minimizing $|w|$ to maximize the margin which is the distance between hyperplanes. Data points on the planes are known as support vector points and the decision rule as a classifier is a representation of a linear combination of these points (see Figure 2.2) [22].

2.2.3 Decision Tree

Decision trees classify the data by hierarchically sorting them based on feature values. Each node in the tree represents a feature of the data, and each branch of it represents a value for that feature. At the beginning, The best feature that divides the training data better than other features is found to construct the root

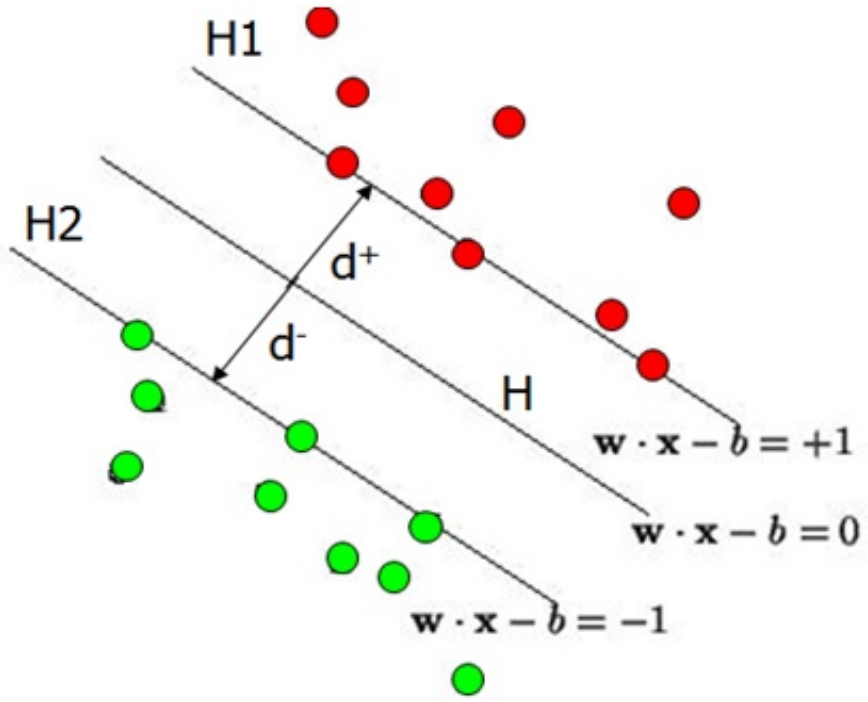


Figure 2.2: An example of SVM, Linear separating hyperplanes for the separable case. The support vectors are circled

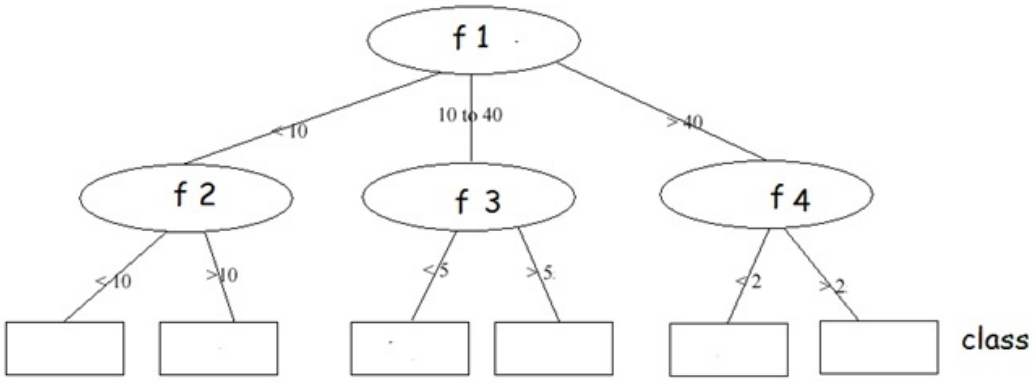


Figure 2.3: An example of Decision Tree

node of the tree. Different methods are used to select the best feature. Most commonly used ones are entropy and information gain measure. At each step, the best feature is selected according to information gain which is obtained by separating the data using the feature. Feature selection is continued until a stop condition is obtained. New data is classified with starting from the root node of the tree. At each node, value of the selected feature in the node of the data is compared with the value of the branch of that node. Figure 2.3 is an example of a decision tree [22].

Previous researches in the literature

As a baseline in this area, Pang et al. [7] classify documents according to their sentiment as positive or negative. They use different machine learning algorithms (Naive Bayes, maximum entropy classification and support vector machines) and analyze their effectiveness on sentiment classification. For this work, they use standard bag of words feature vector as $f_1, f_2, ..., f_m$ and compare the different types of feature which are unigrams, bigrams, frequency-presence, part of speech and position. According to their experiment, although accuracy results are not as good as standard topic classification, SVM gives best results (82.9%) for sentiment classification with unigrams and presence as feature type on the movie review corpus.

Similar to [7], Alec et al. [17] propose an approach to classify Twitter messages as either positive or negative automatically. Instead of labeling the tweets manually to construct training data set, they use distant supervision where each tweet is labeled with emoticons that it includes. For instance, while tweets with :) is labeled as positive, tweets with :(is labeled as negative. Then, they omit emoticons from text and use other non-emotion terms as features. Additionally, some feature reduction processes are applied to reduce the number of features. Each term starting with @ indicates user name in Twitter that is replaced with token "USERNAME". Then the links in the tweets are converted to the token "URL". Finally repeated letters are removed from terms. Similar to Pang et al. [7], results of different feature types are analyzed and best accuracy results are obtained with SVM with Unigrams and presence as feature type on the Twitter

corpus.

In [34], Kim and Hovy construct a system called Crystal to analyze the predictive opinions about an election on the Web. After extracting lexical patterns that people frequently use from opinions about a coming election posted on the Web, SVM-based supervised learning is applied to predict the result of the election using an n- gram feature pattern. Firstly, valence of sentence s computes and then with combining them final valence of parties are computed and one that has maximum valence is selected as winner.

There are also some studies that have sentiment categories different from positive-negative. In [4], a psychological text analysis is given called Text Investigator for Psychological Disorders (TIPD). Four categories of sentiment phrases; depressed, non-depressed, anxious and non-anxious are detected for Turkish language. With different types of features are used to construct feature vector. These are;

- Words mostly used by each group of documents
- Frequency of tenses used in the documents(simple present, past, perfect ...)
- Frequency values of pronouns (ben, sen, o, biz ...)
- Bag of words

A system is constructed and tested Using Naive Bayes and Support Vector Machines as machine learning algorithm .

2.3 Clustering text based on aspects of the topics

An important task of opinion mining is to extract opinions on features of a product from online text. This is different from traditional text summarization task that

a subset of sentence from review is selected or rewrite to extract main points in the text [26].

As a simple method, reviews about a product can be clustered/categorized based on the features of the product and then each cluster/category is assigned to an aspect of the it. However, as a result of the high dimensionality of the data, traditional clustering algorithms cannot perform well on text documents. Also sparseness of the short text is a particularly challenging task, as the similarity between two short texts usually is small or equal to zero.

To overcome this problem, different clustering algorithms are proposed. One of them is frequent term-based text clustering [15]. Instead of using all words in the collection as features in the feature vector, it uses low dimensional frequent term sets, whose co-occurrences in the text is higher than a threshold. A cluster is constructed with documents containing all terms of a frequent term set after extracting frequent item sets using an association rule mining algorithm, Aprori . Selection of the frequent item set for constructing cluster is done according to the overlap and selects the one that has minimum overlap. Overlapping is calculated based on distribution of the documents in the cluster candidates.

Extracting and Grouping Aspects of Products

There are also methods to summarize customer reviews in which different features/aspects of a product is detected and reviews are grouped according to these features. For extracting features of a product, different studies were done [26, 14, 23]. Also, same features of a product can be expressed with different words, these can be synonyms or not. For instance, picture and photo have same meaning for cameras although appearance and design do not have the same meaning, they can be used for same aspects of the product. So for effective summary, extracted aspect words should be grouped. However grouping manually is time consuming and difficult since there is so many feature expression in a text corpus [39].

In [26], for identifying product features, association rules are used. It is thought that in a sentence noun or noun phrase are the candidate of aspects

of products. There are lots of words(noun/noun phrase) but not all of them are directly an aspect of a product, frequent words are usually used to express an aspect. So, after identifying part of speech tags of the word, they extract frequent itemset of noun/ noun phrases as possible feature with running the association miner CBA based on Apriori Algorithm. Then some of them are eliminated using two different pruning methods. In the first one, compactness of candidate phrase is checked with looking position of the words in the phrase and sentences and if not it is deleted. As a second one, redundant phrase are eliminated according to p-support value.

In [14], Popescu and Etzioni use the pointwise mutual information between the candidate feature and product class is computed to evaluate the noun phrases and extract the explicit features. The comparison with [26] show a precision 22% better than Hu's precision and a recall 3% lower than the others.

For grouping similar aspects of products, Zhai at al. [39] apply a semi-supervised learning algorithm with using sharing words and lexical similarity. Expectation maximization algorithm is run to assign a label to an aspect of a feature. Besides, topic modeling approaches as a clustering algorithm can be used for this purpose. One of the most popular topic modeling method is LDA.

According to some study [13, 40], standard Latent Dirichlet Allocation (LDA) is not sufficient for detecting aspect in product reviews since global topics are extracted with it instead of domain aspects. To overcome this problem, different types of LDA are proposed with applying some changes on it. In[13], an unsupervised aspect extraction system is introduced as local topic modeling based on LDA. With evaluating the output of the LDA, optimal number of the aspects is determined. After scoring nouns based on probabilities obtained from LDA, top k words are selected as the representatives of the aspects.

Z. Zhai et al [40] use prior knowledge as constraint in the LDA models to improve grouping of features by LDA. They extract must link and cannot-link constraint from the corpus. Must link indicates that two features must be in the same group while cannot-link restricts that two features cannot be in the same group. These constraints are extracted automatically. If at least one of the terms

of two product features are same, they are considered to be in the same group as must link. On the other hand, if two features are expressed in the same sentence without conjunction "and", they are considered as different feature and should be in different groups as cannot-link.

Chapter 3

Mixture Model for Aspect Based Sentiment Analysis

In this section, we present the steps and details of our proposed methodology, as summarized in Figure 3.1. First, we gathered data and applied preprocessing on them. We also applied manual labeling only for the methods that use them, as not all do. Then, in addition to lexicon constructed manually, we construct the opinion lexicon automatically using labeled data. After obtaining lexicon, word selection is done according to that. Later, text data are transformed into a set of feature vectors. For this transformation, a novel sentiment based text representation is proposed as a new feature vector type, as discussed later. Finally, a system is then trained and tested using a variety of machine learning algorithms.

3.1 Data

Twitter is a popular microblogging service that has several millions of users. Each user submits periodic status updates, known as tweets, that consist of short messages of maximum size 140 characters as informal text. Most of them include opinions of users about several topics relevant to users daily lives. The number of the tweets posted per day has an exponential increase as shown in [2].

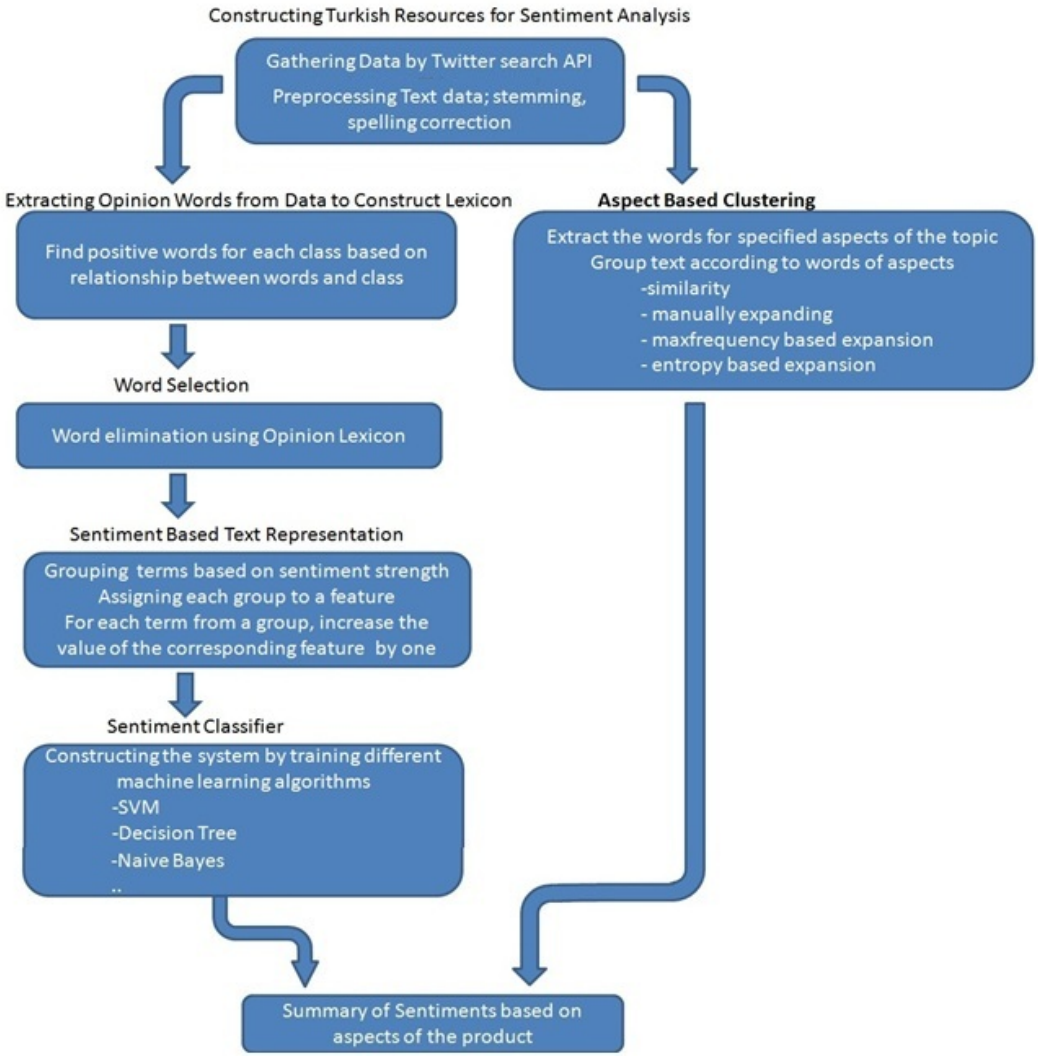


Figure 3.1: Structure of our system

A collection of tweets is used as the corpus for our experiments and telecommunication is chosen as a good example involving competition. There are three major Turkish companies on Wireless Communication, namely Carrier-X, Carrier-Y, and Carrier-Z. These are defined as keywords for querying tweets. Tweets posted hourly are gathered over 3 months by querying the Twitter search API. Each record in the corpus contains the time at which the tweet was written, user nickname and the actual tweet body. Firstly, over ten thousands tweets collected in approximately a month are selected from the gathered tweets to be judged on a 5 point scale as follows for both positive and negative sentiment as in [27]. We eliminate junk tweets that include no information about a subject because we try to measure sentiment of users about aspects of that topic. Moreover, we remove same tweets posted by several times from the training data. At the end, training data set included 1420 tweets. Other tweets in the next 2 months are used in the application part. There is no manual elimination on this part.

The following shows the 5-point scales for positive and negative sentiment strengths respectively.

[no positive emotion or energy] 1 - 2 - 3 - 4 - 5 [very strong positive emotion]

[no negative emotion] 1 - 2 - 3 - 4 - 5 [very strong negative emotion]

Emotions are perceived differently by individuals, because of their life experiences, personality issues and genders. Two coders were selected for labeling manually and the mean of the their results was assigned to the tweet as the labels of it. These labels are used as the gold standard for our experiments. Final manually labeled corpus includes tweets with two labels as positive and negative sentiment strength from 1; 5 (-1; -5). According to this labeling process, we have 10 different class labels in the corpus. An example of labeled tweet:

"X tarifelerin ok gzel ama kaliten sfr bizim evi getim darda bile ful ekmiyorsun" p:+3 n:-4 (for this particular tweet, the positive and negative sentiment scores are 3 and -4, respectively. It roughly states that Carrier-X has very good deals but the quality is zero.)

Then, we generate Turkish lexicon using dictionary based approaches as our opinion word list. After constructing a small list of opinion words manually, it is expanded by searching in online same and significantly closer meaning dictionary of TDK. The constructed lexicon includes 220 positive and negative words, each with a value from 1 to 5 and -1 to-5, following the format in SentiStrength [27] such as harika: 5, berbat: -5.

There is also a booster word list that contains words that boost or reduce the emotion of subsequent words such as "fazla", " çok".

3.2 Preprocessing

Different processes are applied before converting text into feature vectors. As the first one, punctuation marks are removed. Username are used as a different feature in the tweets to see the effect of it on the sentiment. Thus, it is removed from the text part of the tweets. Then, @user tags which are used to state another user are replaced with only @ symbol since users are special words and may not have any effect on the sentiment of the tweet.

There are different types of emoticons in the text. While some of them are used to express positive sentiment, some of them are used for negative emotion. So, they are grouped according to their corresponding sentiment value as positive, negative and others. After searching emoticons in , the list, they are replaced with their sentiment symbols. the list of emoticons and their symbols are given in Table 3.1 .

Emoticon	Meaning	Symbol
$:-),:),;-),;),:)),:-)),:-D,:D,:=D,:=),=),=D,$	Positive	Post
$:-(,:(,:'(,:-\|,:\|,:-@,:\|\|,:(($	Negative	Negv
$:-p,:p,:-S,:S,:-,:,:-o,:o$	Others	Oth

Table 3.1: Emoticon list, their corresponding sentiments and symbols used to replace

In addition to these, there are many words that have been misspelled, because tweets are written informally. Hence spelling correction was also applied to identify the correct spellings of the misspelled words. Firstly, the words are checked to see whether they are misspelled or not. If a word is not correctly written, repeated letters are searched in the words. Since people may write some letters of the words more than ones to emphasize. If there are some repeated letters, these are deleted. Then, a spell checker tries to find the correct words with comparing misspelled one against a correctly spelled word list. During this process, if more than one option is obtained for both stemming and spelling correction, first one is used.

There are a lot of words using the same root with different suffixes in Turkish, and these suffixes do not usually change the sentiment of the words that is added. To avoid using two different features for two words with the same root but different suffixes, we apply a stemming process and discard the suffixes except the negation suffix. In Turkish, negation is expressed with addition (-me-ma) to the end of the word. If a word has a negator, the word is changed to root of the word with extra word değil to express the negation of it. Otherwise, only the root of it is kept.

A morphological analyzer can be used to achieve this process. We utilize Turkish parser Zemberek [1] for capturing negation, stemming and spell checking of the data. Zemberek is most commonly used and publicly available NLP tool for Turkish. It is an open source program and has java libraries which can be embedded in an application code. However it is not perfect. There are some words that Zemberek cannot find its root or correct spelling. Thus, words like this are left without any changes.

Furthermore, we remove stop words from the tweets. Since these words includes redundant information and do not have effect on the sentiment of the text positively, but may have negative effect with increasing number of features. For these processes, the stop word list from Fatih University NLP Group is used [3]. Besides, numbers in the tweet are removed from text with the idea that they have no influence on the sentiment.

As an example of a tweet after preprocessing;

A raw tweet ;

"aaa Carrier-Z niye byle yapyorsun? Ne gerei vard imdi 5 mb internetin? Nasl sevindim? Nasl mutluyum? Anlatamam.."

After preprocessing;

"a Carrier-Z niye boyle yap ne gerek var simdi mb internetin? Nasil sevin nasil mutlu degil anlat"

3.3 Extracting Subtopics

To understand and summarize people's opinions about a product, tweets are clustered based on the aspects of the product. After extracting the aspects from the data, text are grouped based on these aspects. General structure of our proposed algorithm used to extract aspects and to cluster tweets based on extracted aspects is given in Algorithm 1.

An LDA based approach is used to extract the aspects. As mentioned before, standard Latent Dirichlet Allocation (LDA) is not sufficient for detecting aspect in product reviews since global topics are extracted with it instead of domain aspects. Therefore, after finding topics and their words, they are matched with the manual aspects of the product given by the user.

The words of topics obtained by LDA that has higher frequency are used for this process. From these words, one term is selected for each manual aspect as a representative of it. However, these particular terms are not sufficient to group the tweets and more representative terms of the aspects are needed. Since all tweets about an aspect may not include that particular term of the aspect and one aspect of the product can be expressed with different words. In other words, these aspect words should be expanded to obtain better clusters. As a result of constructing clusters using only one term for each aspect, small portion of the data can be clustered. To cluster remaining data, we should find more words for

Algorithm 1: General structure of proposed algorithm to construct groups of tweet based on aspects of the product

Data: A set of tweets D, A user defined threshold : p
Result: WL: representative words of the aspects, groups of tweets $\{D_1, D_2, ..., D_k\}$

1 $WL = \emptyset$
2 FWL: Extract Frequent Word List using LDA
3 WL=select one word from FWL as the representative of each aspect k aspects
4 $\{D_1, D_2, ..., D_k, D_r\}$ = find tweets of each k Aspect based on selected terms of the aspect $\{D_r$ = *remaning tweets that can not be clustered*$\}$
5 Assign remaining tweets D_r To $\{D_1, D_2, D_k\}$ based on one of the proposed algorithms using p
6 Return $\{D_1, D_2, ..., D_k, D_r\}$, WL

each aspect or apply different algorithm for the remaining ones.

In our first solution, we utilize similarity measures to assign remaining tweets to the clusters. For each cluster, similarity between a tweet and tweets of the cluster is computed and accumulated. Then it is divided by the number of the tweets in the cluster to obtain the average similarity as the similarity between that tweet and the cluster. After computing this for all clusters, the cluster that has the highest similarity is found for each tweet. If the similarity of that cluster is higher than a threshold, the tweet is assigned to that cluster. Otherwise, it is said that the tweet is out-of-clusters. However, since tweets contain a small number of terms as short text, any two of them do not usually include the same terms. Thus, similarity between tweets may not always provide meaningful results.

As a second solution, we expand the representative terms of the aspects. Besides expanding them manually, the dataset can be used for automatic expansion. For expansion, two different approaches are proposed.

In the first approach, clusters are obtained with initial one representative terms of the aspects. Then, a word list is constructed with their frequency in the clusters. For each term in the list, "max frequency" is computed. It is defined as

$$Maxfreq(W_T, C_I) = \alpha * \sum_{C_j \in C, j \neq i} P(W_T|C_J) + \beta * p(W_T|C_I)$$

$P(W_T|C_J)$ =(Number of documents in cluster j that contains word W_T (freq. Of the W_T in C_J))/(Number of the documents in cluster C_j)

It is expected that if the probability of a word being in the documents of the Cluster Ci is high and also the total probability of the word being in the documents of the other clusters is low, it is an important word for that cluster and can be a representative word for it. After computing 'max frequency' for each term, a number of the term that has high 'max frequency' is selected until the number of the remaining tweets is smaller than a defined threshold p .

In our second approach, an entropy measure is used to expand representative terms of the aspect. At the beginning, a word list is obtained with LDA. After running LDA in some iterations, words that has higher frequency is extracted. Each word in the list is considered as a representative term of a cluster and the tweets that contain these words are found and then they are clustered based on these terms. The entropy of each cluster is computed according to aspects. For this process, representative words of aspects are used. If most of tweets in a cluster include representative words of same aspect, the entropy of the cluster becomes low and the term of that cluster can be considered as associative with that representative word of the aspect that has high frequency in the cluster. If they include representative words of different aspects, its entropy becomes high and term of that cluster cannot be considered as representative word of any aspect. So, after computing entropy of each cluster, cluster that has minimum entropy is selected and word of that cluster is associated with the representative words of the aspect that has highest frequency in the cluster. This process is repeated until the stopping condition is obtained. A user defined Iteration number, p, is used as the stopping condition in this work.

After selecting one term for each aspect, tweets are grouped based on them. Firstly, tweets that include the term are found as a separate group for each term. Then, the group that has the highest number of tweets is selected and selection is continued until there is no aspect that has not been selected. At the end of this process, tweets that contain one of the representative terms of the aspect are group to obtain a cluster for each aspect. To cluster the remaining tweets,

after expanding representative words of the aspects, tweets are assigned to groups based on expanded word list.

3.4 Extracting Sentiment Orientation

3.4.1 Constructing sentiment word list

Constructing sentiment word list manually is time consuming. Therefore, we need some automated methods for this process. As mentioned before, there are some works on constructing word lists automatically using dictionary based and corpus based approaches. They are based on co-occurrence of the words in the corpus with the words in the seed list. Most of the time, they use unlabeled data. As an alternative to the existing approaches, we propose to extract opinion words and their sentiment strength from labeled corpus using relationships between words and classes. We use different measure to calculate the relationships.

In [11], positive and negative words are selected for each document. Similar to [11], we select only positive words for each class using equation given in definition 1 in the part 2.1.2 with different p, threshold, values. We have both 10 class values and 10 sentiment strength values for words from 1 to 5 and -1 to -5. So, we give class values to the selected words of that class as sentiment strength of them. The intuition is that if a word is seen more frequently in the documents that have high sentiment strength, sentiment strength of that words should be also high and vice versa. Structure of the algorithm is given as Algorithm 2.

3.4.2 Twitter Sentiment strength detection

We construct two systems to measure the sentiment strength of tweets. In the first one, lexical and machine learning approaches are combined. In the second one, a new feature type is used to represent the tweets. In addition to these two systems, Sentistrength [27] is configured for Turkish as the third system.

Algorithm 2: Our Proposed Sentiment Lexicon Construction Algorithm

Data: A set of tweets D, A user defined threshold : p
Result: $F_p(w_i, c)$: A set of opinion words, w_i, with their sentiment strengths, c

```
WL = ∅
for each class c do
    for each word w_i ∈ D do
        if P(c|w_i) > 0.5 * p + 0.5 * P(c) then
            F_p = F_p ∪ {w_i, c}
        end
    end
end
```

3.4.2.1 Feature Selection Using Sentiment Lexicon

In the machine learning approach, text is converted into feature vectors using the bag-of-words approach that construct a feature set, where each element represents the frequency or presence of a word in the document. While this approach is applicable to general cases, all words in the text do not contribute to the sentiment of the text. Therefore, different feature selection methods are applied to select a subset of the features that is sufficient for learning. We use our lexicon to eliminate the words that do not affect the sentiment of the text. Instead of looking only presence of these words in the tweets as in the lexical approaches, we train a system using the words in the lexicon as the features. For this goal, two lexicons are used. One of them is constructed manually and the other one is constructed automatically as mentioned in the Section 3.4.1.

3.4.2.2 Opinion Based Text Representation

Different approaches are used to represent the text as feature vectors. Most commonly used one is bag of words and it constructs high dimensional feature vectors. Each word in the documents represents a feature in the feature vector. However two words that have the same sentiment strength would have the same effect on the overall strength of the text. So, we do not need to consider them separately. For example, two synonymous words have same influence on the

sentiment strength of the text, so, it does not matter which one is in the text. A feature can represent the presence of both of them.

Therefore, words are grouped according to their sentiment strength. Since there are 5 groups for positive and 5 groups for negative sentiment strength of the words, ten groups are obtained. Also one group for negation words such as değil, hayır and one group for booster word such as "çok", "fazla" are added to them. In this new representation, each dimension of the feature vector corresponds to each group of the words.

The emotion words from a group in the word list are searched in the text. If found, value of the corresponding dimension of the feature vector of that text based on sentiment strength of the emotion words is raised to 1. For instance, the word "güzel" has strength of 3 as the positive sentiment. If a text includes this word, third dimension of its feature vector is increased by one. As another example, the word "işkence" has strength of -4 value as negative sentiment. One is added to the value of the ninth (5+(-(-4)) dimension of the feature vector of the text that contains this word. The last dimension of the feature vector is used to represent the sentiment strength (positive-negative) of the tweet as the class value. Here is an example of the process of the converting a text to a feature vector.

A tweet;

"Carrier-Z tarifelerin çok güzel ama kaliten sıfır bizim evi geçtim dışarda bile full çekmiyorsun" p:3 n:−4

Feature vector of the tweet; $< 0, 0, 2, 1, 0, 0, 1, 0, 1, 0, 1, 2, (2, 4) >$

This shows that there are two words from group three and one word from group 4 and so on. After constructing feature vectors of tweets according to the proposed representation, a classifier with one of machine learning algorithms is trained and used to find the sentiment of test data.

3.4.2.3 An Alternative Approach: Turkish Configuration of SentiStrength

In [27], a dual 5-point system for positive and negative sentiment is introduced. It utilizes several novel methods to simultaneously measure positive and negative sentiment strength from short informal text in English. It uses a dictionary of sentiment words with associated strength measures from 1 to 5 as positive or negative and exploits a range of recognized nonstandard spellings and other common textual methods of expressing sentiment. Also a machine learning approach is used to optimize sentiment term weightings, methods for extracting sentiment from repeated-letter nonstandard spelling informal text and a related spelling correction method.

It is designed for English since its source are in English. To use it for Turkish text, we changed its source. We use our lexicon that includes words with their sentiment strength and booster and negation words, as explained before. Then the sentiment of tweets are found with it.

Chapter 4

Experimental Testbed, Application and Results

Tools. We utilize a list of tools for developing our system and for experimental evaluation purposes. These are listed as follows.

- **Weka.** Weka [37] is an open source java library that can be used in different java project code. It includes several well known machine learning algorithm as classifier used to train and test on different data set. It also prove algorithm to convert text into feature vector.
- **Zemberek.** It[1] a Turkish morphological analyzer used for capturing negation, stemming and spell checking of the data. It is most commonly used and publicly available NLP tool for Turkish. It is an open source program and has java libraries which can be embedded in the code.
- **Mallet.** MALLET [28] is a Java-based package for statistical natural language processing, document classification, clustering, topic modeling, information extraction, and other machine learning applications to text. In this thesis, it is used for topic modeling. The MALLET topic modeling toolkit contains efficient, sampling-based implementations of Latent Dirichlet Allocation, Pachinko Allocation, and Hierarchical LDA.

Evaluation Measures. Precision, Recall and accuracy measure are used to evaluate the proposed clustering and to measure the performance of classifiers trained by proposed sentiment algorithms. Precision is obtained by dividing the number of the relevant items by the number of relevant items in the dataset, and Recall is obtained by dividing the number of the relevant items by the number of retrieved(clustered). R precision is the precision obtained with retrieving R items that is the number of the relevant items in the data set. Accuracy is defined as the percentage of correct classification. Here are the formulas to calculate precision and recall.

precision = number of relevant items / total number of items retrieved

recall = number of relevant items retrieved / number of relevant items in collection

In our data set, relevant items are the tweets that are labeled as about an aspect of the topic. We try to measure how many of them are accurately clustered by our systems.

4.1 Experiment

4.1.1 Aspect based Clustering

To test and compare the proposed algorithms that are used to extract aspects of the products, a pre-classified data set is needed. A manual aspect list is specified for the product. It includes 5 aspects of the product. For evaluation, 370 tweets are selected randomly from the sentiment data set, and classified manually based on specified aspects of the products. One more class is used for tweets out of these aspects. If a tweet is not about one of the specified aspects of the product, it is classified as the remaining. 35% of the 370 tweets is out of specified aspects. Table 4.1 shows the specified aspect of the product and their distribution in the

Aspect Name	Distribution%
Çekim	%28
Fatura	%14
Reklam	%0.02
Internet	%14
Mesaj	%13
Out of	%35

Table 4.1: Distribution of the aspects of the products

	Precision	Recall	Accuracy
One term (without extension)	0.87	0.61	0.73
Extend manually	0.88	0.70	0.78
Similarity based	0.45	0.71	0.45
Extentionwithmaxfreq	0.51	0.70	0.60
Extensionwithentropy	0.68	0.66	0.66

Table 4.2: Results of clustering with different algorithm

data set. After clustering tweets based on specified aspects, results are compared with tags given manually.

To evaluate the proposed method, precision, recall and accuracy measures are used and given in Table 4.2. Precision and recall are computed by assuming that tweets of 5 clusters are relevant and remaining tweets are out of cluster.

As we see from the table 4.2, when we construct clusters of the tweets with only one term of them, precision is high but recall is low since small number of all tweets can be clustered. After applying other algorithms to assign remaining tweets to clusters, recall increase but the number of the tweets assigned wrong cluster increase and besides tweets out of clusters start to be included in the clusters. As mentioned above, in the "extensionwithentropy" method, the list is obtained with LDA. After running LDA in some iteration, words that have higher

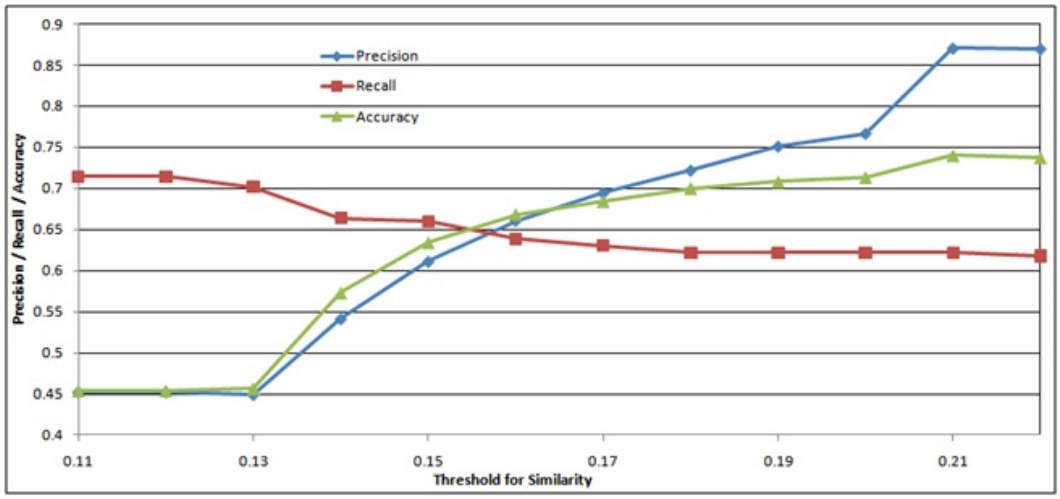


Figure 4.1: Precision, recall and accuracy results for clustering based on similarity versus value of threshold

frequency are extracted. For LDA, Mallet topic modeling toolkit is used.

There are thresholds of proposed algorithms and results are change according to value of the thresholds. So, precision, recall and accuracy results versus threshold are given in Figure 4.1 and 4.2 below.

As we see from the Figure 4.1 and 4.2, with increasing precision and accuracy recall start to decrease. Since with assigning reaming tweets to clusters, there are some tweets that are assigned to cluster but not be.

4.1.2 Opinion Mining

We test the new feature vectors constructed according to proposed sentiment based text representation, called Grouped in the following and proposed algorithms on the 1420 Turkish tweet data set with using cross-validation approach. Algorithm with new representation is called as Grouped automatic when word list is "constructed automatically" and "Grouped manual" when word list is constructed manually. Also, the algorithms that we make feature selection with lexicons are called combination manual" and "combination automatic". In the

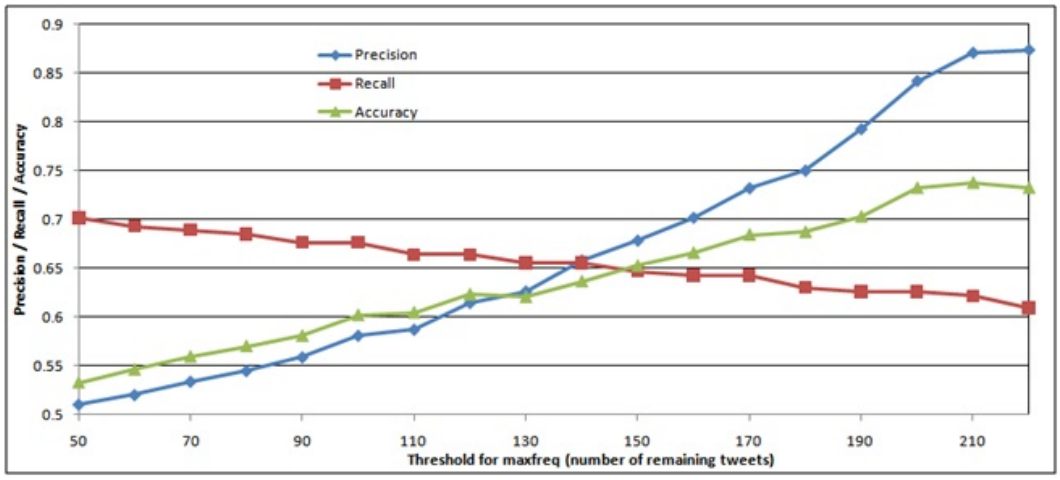


Figure 4.2: Precision, recall and accuracy results for clustering based on maxfreq versus value of threshold

		1	2	3	4	5
Distribution	Positive	74.54 %	5.06%	7.24%	10.47%	2.67%
	Negative	19.33%	3.51%	15.82%	43.10%	18.21%

Table 4.3: Distribution of class in the dataset

dataset, positive sentiment strength of 74.54% of the tweets is 1. The distribution of the sentiment polarity of the tweets in the training data set is given in table 4.3.

To train classifiers and to test our new feature type and algorithm, we perform 10-fold cross validation using different machine leaning algorithms. These are Support Vector Machine(SMO), SMO Logistic, Naive Bayes, Decision tree, Decision Table, Jrip. These classification algorithms are used from Weka Data mining tool [37]. The results were compared to the baseline majority class classification, results of classification obtained using bag of words feature vectors type and results of SentiStrength configured for Turkish. Also effects of adding different features such as author and time and applying preprocessing are examined and results are given in tables below.

When we change p threshold values in the sentiment word list construction

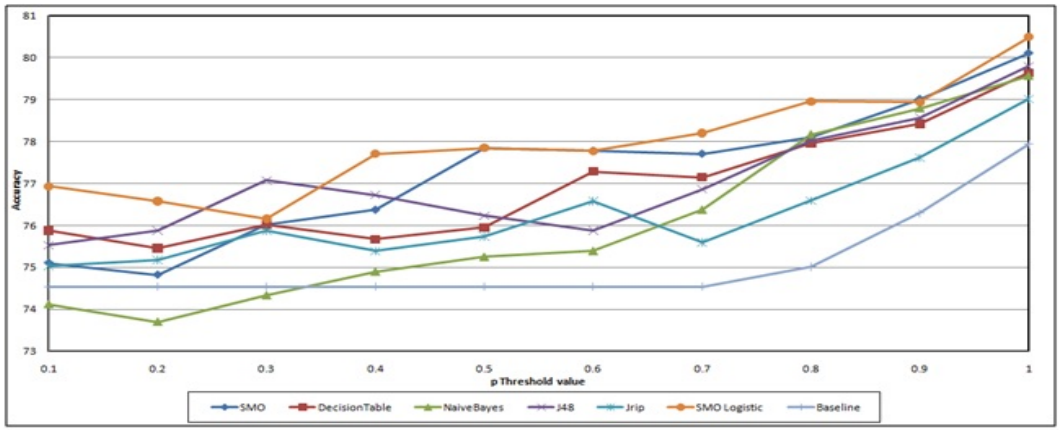


Figure 4.3: Accuracy results of "grouped automatic" algorithm according to threshold value for positive sentiment strength

algorithm, different words are selected. According to selected words, the results of classifications change. Firstly, to find the best threshold value in the sentiment word list construction and to select one of machine learning algorithms that give best result, a test is done with different value of threshold and using different machine learning algorithms. Accuracy results according to threshold value are given in Figures 4.3 and 4.4. Based on this result, one of threshold value and machine learning methods that give the best result based on baseline is selected for other test. After selecting words, instances that do not contain any of selected words are removed from the data set with the thought of not including useful information. Feature vectors of them only consist of zero regardless of their class values. So, we cannot do any learning from them. As a result of these elimination, baseline of data set is changed according to selected words.

Then, the accuracy results of selected threshold value and machine learning algorithm are given in Table 4.4 and 4.5 for positive and negative sentiment strength with the results of other methods used for comparison. We select the threshold value that gives the best result based on baseline. As we see from Figure 4.3 and 4.4, the best threshold value is 0.4 for negative sentiment strength and 0.8 for positive. From Figure 4.3, the accuracy results of 1 for threshold value is the highest one but baseline is also highest at that point. So, it is not the

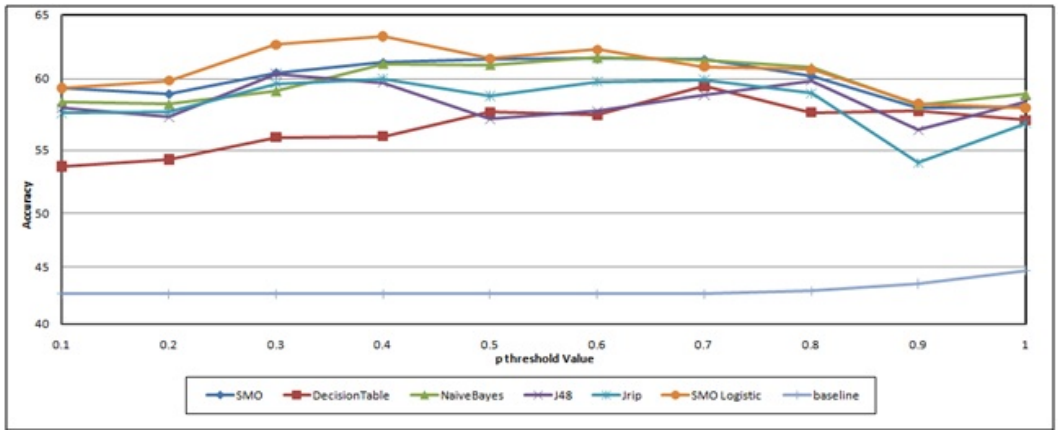


Figure 4.4: Accuracy results of "grouped automatic" algorithm according to threshold value for negative sentiment strength

best one. So, with looking difference between results of classifier and baseline, the best threshold value is selected among machine learning algorithms, SMO logistic gives best result for positive and negative sentiment strength detection with the selected threshold values. Accuracy to within one class is also given in the tables. There is no big difference between 2 sentiment strength such as 3 and 4 or 4 and 5. So, this measure also important for our experiment.

As we see from the Table 4.4 and 4.5, using bag of word feature types is not sufficient for both positive and negative sentiment learning. Since all words does not affect the sentiment of the text and much feature cause harder the learning and get worse the results. After selecting features with using lexicon results get better but not best. After grouping them based on their sentiment strength, we obtain best results. Also, constructing lexicon automatically instead of manually give better results. Since it is constructed based on data set, sentiment and strength of words may be different in different datasets. So, sentiment of words in the lexicon constructed manually may be different from the data set, so, result may not be good. Only constructing word list automatically get worse the results of positive sentiment strength with combination feature type.

Algorithms		Accuracy	Accuracy ±1
Baseline		74.54%	79.60%
BofW		57.45%	79.25%
SentiStrength		56.90%	73.17%
Combination	Manual Lexicon	74.51%	82.78%
	Automatic Lexicon	55.70%	74.54%
Grouped	Manual Lexicon	75.50%	82.21%
	Automatic Lexicon	**78.95**%	**86.99**%

Table 4.4: Performance of algorithms on positive sentiment strength detection

Algorithms		Accuracy	Accuracy ±1
Baseline		43.10%	77.14%
BofW		40.08%	73.14%
SentiStrength		30.77%	47.11%
Combination	Manual Lexicon	48.42%	79.71%
	Automatic Lexicon	56.27%	81.59%
Grouped	Manual Lexicon	49.96%	81.17%
	Automatic Lexicon	**62.94**%	**84.32**%

Table 4.5: Performance of algorithms on negative sentiment strength detection

Pos ML Algorithm	Accuracy				
	BofW	Combination		Grouped	
		Manual	Automatic	Manual	Autamatic
Baseline	74.54%	75.87%	74.54%	75.41%	75.02%
SVM (SVO)	71.02%	76.47%	74.05%	75.68%	78.10%
Decision Table	75.17%	76.13%	75.04%	75.85%	77.95%
Naive Bayes	68.14%	71.36%	72.01%	72.80%	78.17%
J48	74.82%	76.39%	74.89%	76.20%	78.02%
Jrip	74.26%	75.70%	74.26%	75.50%	76.59%
SMO logistic	57.45%	74.51%	55.70%	75.50%	78.95%

Table 4.6: Performance of various algorithms on positive sentiment strength detection (Accuracy)

Result of different machine learning algorithms

In addition to these, accuracy results of other different machine learning algorithms used to train classifier and to compare results of our new feature type with other methods and algorithms are also given in Table 4.6, 4.7, 4.8 and 4.9 for positive and negative sentiment strength.

As seen from the tables 4.6-4.9, for all machine learning algorithms, the best result is obtained with grouped feature types that word list is constructed automatically. Constructing word list automatically improve the results of grouped feature type for all machine learning algorithms. However, for some learning algorithms, results of combination feature type are decreased. When we compare the results with baseline and results of BofW, for most of learning algorithm, results of our four different proposed feature types is higher than baseline and results of BofW feature type. Although there is no big improvement on the result of positive sentiment, the increase of accuracy of positive sentiment is significantly important, especially with "grouped automatic" feature type.

Pos ML Algorithm	Accuracy ±1 class				
	BofW	Combination		Grouped	
		Manual	Automatic	Manual	Autamatic
Baseline	79.60%	81.32%	79.60%	80.99%	79.60%
SVM (SVO)	82.21%	83.29%	81.93%	82.65%	86.01%
Decision Table	81.43%	82.95%	81.29%	82.48%	85.30%
Naive Bayes	82.14%	82.95%	80.59%	80.56%	86.50%
J48	82.63%	83.46%	81.22%	82.65%	85.86%
Jrip	79.47%	81.50%	79.75%	81.08%	81.43%
SMO logistic	79.25%	82.78%	74.54%	82.21%	86.99%

Table 4.7: Performance of various algorithms on positive sentiment strength detection (Accuracy ±1 class)

Pos ML Algorithm	Accuracy				
	BofW	Combination		Grouped	
		Manual	Automatic	Manual	Autamatic
Baseline	43.10%	43.47%	44.52%	43.41%	43.10%
SVM (SVO)	43.95%	49.28%	56.59%	48.47%	61.11%
Decision Table	47.96%	48.42%	40.07%	47.34%	55.98%
Naive Bayes	40.50%	47.06%	51.41%	47.17%	61.04%
J48	41.49%	48.76%	50.77%	49.26%	59.70%
Jrip	45.21%	48.68%	47.53%	46.38%	59.99%
SMO logistic	40.08%	48.42%	56.27%	49.96%	62.94%

Table 4.8: Performance of various algorithms on negative sentiment strength detection (Accuracy)

Pos ML Algorithm	Accuracy ±1 class				
	BofW	Combination		Grouped	
		Manual	Automatic	Manual	Autamatic
Baseline	77.14%	79.19%	77.61%	78.72%	77.14%
SVM (SVO)	74.54%	80.05%	81.59%	80.12%	84.25%
Decision Table	79.18%	82.01%	79.37%	80.99%	82.49%
Naive Bayes	75.53%	79.62%	79.92%	78.73%	84.25%
J48	72.22%	81.33%	80.56%	80.47%	82.91%
Jrip	77.85%	81.50%	78.97%	79.25%	84.67%
SMO logistic	73.14%	79.71%	81.59%	81.17%	84.32%

Table 4.9: Performance of various algorithms on negative sentiment strength detection (Accuracy ±1 class)

Comparison of effect of preprocessing and different feature types

As we see from the table 4.10 and 4.11, especially for negative sentiment strength, preprocessing step has an important effect on the result. It increases the accuracy of all classifiers for negative sentiment strength. For positive sentiment, it improves the result of classifier that use grouped feature type with automatic word list construction.

To understand the effect of author and time information on the sentiment of the text, we add an extra feature to feature vector to represent the author ad time information of the text. The intuition of author feature is that, most of the time, authors have an opinion about a topic that they like or dislike. So, it is expected that adding author feature increase the accuracy. However, there is no significant changes on the result and while some of classifier get worse a little, some of them get better with adding author or time feature.

	Accuracy				
	BofW	Combination		Grouped	
		Manual	Automatic	Manual	Autamatic
Standard	57.45%	76.47(75.87)%	75.04(74.54)%	75.50(75.41)%	78.95(75.02)%
Without Preprocessing	55.32%	76.63(76.73)%	75.14(74.64)%	74.40(74.39)%	76.85(74.87)%
Author	56.82%	75.10(74.54)%	75.03(74.54)%	75.67(75.41)%	79.09(75.01)%
Time	56.82%	75.10(74.54)%	75.03(74.54)%	75.67(75.41)%	79.09(75.01)%

Table 4.10: Performance of various algorithms on positive sentiment strength detection (Baseline)

	Accuracy				
	BofW	Combination		Grouped	
		Manual	Automatic	Manual	Autamatic
Standard	40.08%	49.28(43.47)%	56.27(44.52)%	49.95(43.41)%	62.94(43.10)%
Without Preprocessing	38.20%	44.15(43.86)%	51.66(44.20)%	45.96(42.33)%	61.60(43.46)%
Author	39.78%	47.46(43.10)%	53.86(43.10)%	50.13(43.41)%	61.88(43.10)%
Time	40.68%	47.25(43.10)%	54.14(43.10)%	49.78(43.41)%	62.23(43.10)%

Table 4.11: Performance of various algorithms on negative sentiment strength detection (Baseline)

4.2 Application

As we see from Figure 4.5, number of tweets changes over the time. There are different reasons of this changing. These reason may also have effect on the opinion of the people. So, sentiment of products are changed over the time.

Aspect based review summary

Using the proposed tools, one can summarize the sentiments of the tweets by clustering them according to their topics and then finding sentiment strength of each of them. Table 12 shows an example of summarized results for our 3 different carriers. We show average of positive and negative sentiment strength of tweets in two sub topics of our data set that contains tweets written about 3 different telecommunication brands in Turkey. With these results, we can compare sub topics of a brand, we can understand that which part of a brand is liked or disliked and also we can compare different brands based on one aspect.

In our dataset, each tweet has 2 labels as positive and negative sentiment strength. As an aggregate measure, we define a z value for a day as the proportion of average of positive sentiment strength of tweets written in a day 'd' about an aspect 'a' of the topic. If it is higher than 1, people are more positive but it is lower than 1 people are more negative about that aspect in that day. Also higher z value states higher positive sentiment while comparing two aspects or topics.

$$Z_{d,a} = avgp_{d,a}/avgn_d$$

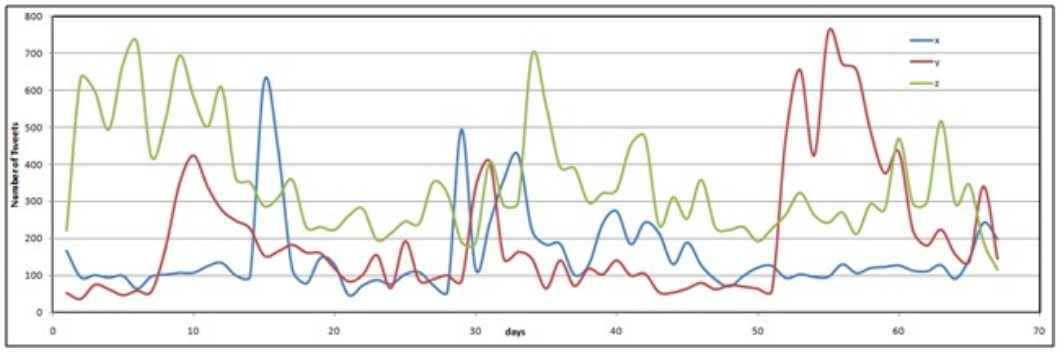


Figure 4.5: Number of tweets over 2 months

Average of positive sentiment strength of tweets written in day d about aspect a

$$avgp_{d,a} = (\sum_{i \in d,a} p_i)/t$$

Average of negative sentiment strength of tweets written in day d about aspect a

$$avgn_{d,a} = (\sum_{i \in d,a} n_i)/t$$

p_i: positive sentiment strength of tweet in written in day d about aspect a
n_i: negative sentiment strength of tweet in written in day d about aspect a

For instance, according to the results given in Table 4.12, the strength of positive sentiment expressed about the quality aspect of Carrier-Z is higher than its cost aspect, and the strength of negative sentiment expressed about quality of Carrier-Z is lower than about its cost.

	Quality			Cost			General		
	P	N	Z	P	N	Z	P	N	Z
X(a)	0.75	2.25	0.33	0.43	2.62	0.16	0.54	2.46	0.22
Y(v)	1.43	1.60	0.89	0.74	2.18	0.34	1.12	1.75	0.64
Z(t)	1.15	1.62	0.71	0.98	1.85	0.53	1.20	1.75	0.69

Table 4.12: Average of positive, negative sentiment strength and z value of two aspects, quality and cost, and general of three brands

Aspect Sentiment Life Cycle

After extracting aspects of the products and clustering tweets based on these aspects, each tweet is associated with positive and negative sentiment strength. From the sentiment strength dynamics of a topic, the user can get deeper understanding of how the opinions about a topic or one specific aspect of the topic

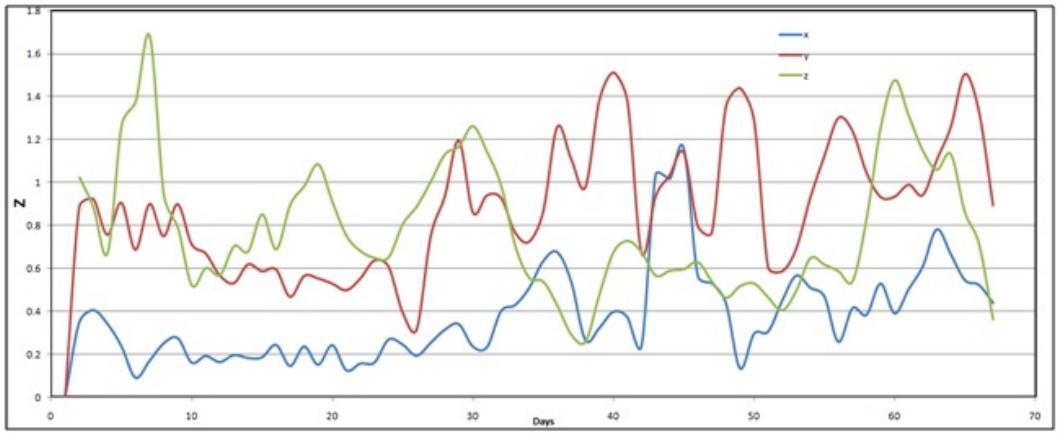


Figure 4.6: Z value of Quality aspect of tree brands over time

change over time, which aspect of the topic is best or worst. In figure 14,15 and 16, examples of results of application are given. We apply a simple moving average to smooth out short-term fluctuations and highlight longer-term trends or cycle.

$$Z_{sma,i} = Z_{i-1} + Z_i + Z_{i+1}$$

In Figure 4.6 and 4.7 z value of quality and cost aspects of 3 different brands during about 2 months are given. With these figures, we can see that people do not like both aspect of brand x. Moreover, at the beginning, people find better quality of brand z than quality of brand y but after a while it gets worse than the other. In Figure 4.8 z value of quality and cost aspects of Carrier-y during about 2 months are given. as we understand from the figure, while people like quality of it, they do not satisfied with the cost of it.

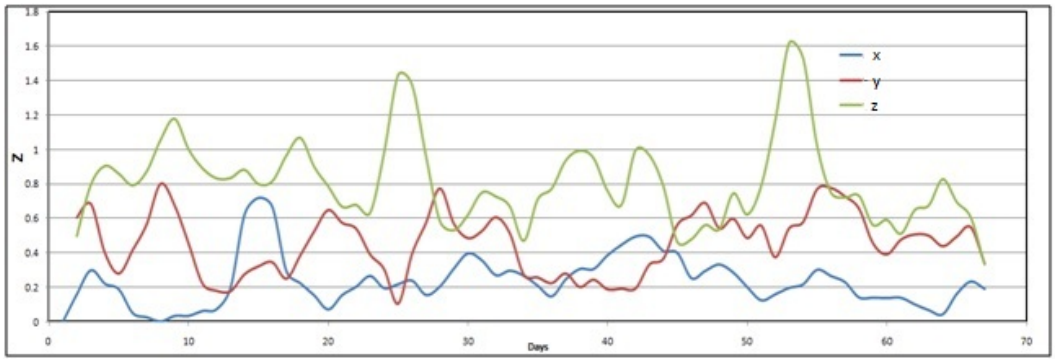


Figure 4.7: Z value of Cost aspect of tree brands over time

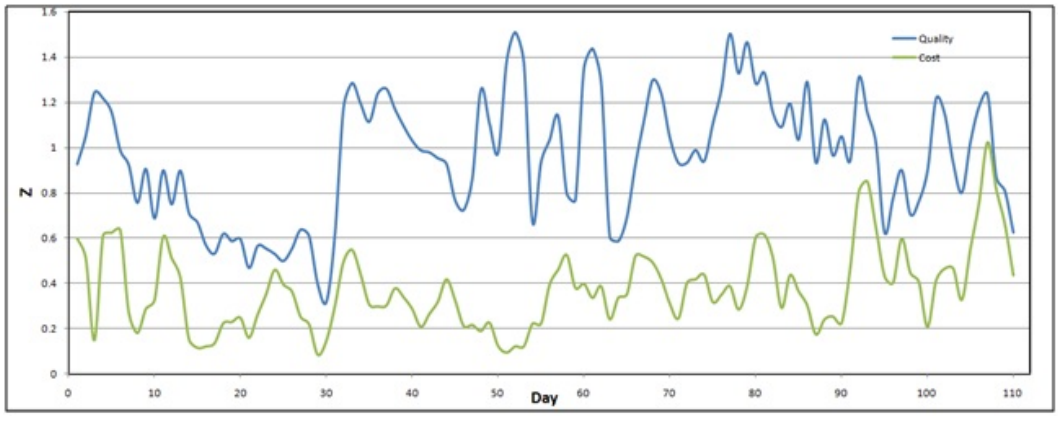


Figure 4.8: Z value of two aspect of brand y over time

Chapter 5

Conclusion

In this thesis, we constructed a system for extracting aspect based sentiment summaries on Turkish tweets. Our work represents the first study of this type on informal short text. For extracting aspects of topics and finding sentiments, a methodology is presented which can be applied to other languages. Our algorithms are tested on Turkish tweet data collected over time via Twitter API.

To construct sentiment summaries, the aspects are extracted and the tweets are grouped according to these aspects. Manually extracted aspect list are expanded with algorithms to assign tweets to groups. After clustering the tweets, their opinion polarity are determined as their sentiment strength. Novel feature types are proposed for sentiment extraction, and feature selection is applied using sentiment lexicons, where novel methods are proposed to construct the lexicon. The performance evaluation illustrates significant improvements over the methods adapted from the literature.

We built an overall system that puts all the pieces together to enable analyses and generate useful aspect based sentiment summaries.

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