PREDICTING ECONOMIC GROWTH USING MACHINE LEARNING TECHNIQUES AND SENTIMENT ANALYSIS

A THESIS SUBMITTED TO
APPLIED DATA SCIENCE PROGRAM OF GRADUATE SCHOOL
OF
TED UNIVERSITY

BY

BERKAY AKIŞOĞLU

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
GRADUATE SCHOOL OF TED UNIVERSITY

AUGUST 2019

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I certify that I have examined this thesis and that in my opinion it is fully worthy of acceptance in terms of both quality and scope as a thesis for the degree of Master of Science.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

PREDICTING ECONOMIC GROWTH USING MACHINE LEARNING TECHNIQUES AND SENTIMENT ANALYSIS

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Supervisor: Dr. İnan Utku Türkmen

August 2019

The purpose of this paper is to construct sentiment index from financial and economic news and examine its potential relation with main economic and political events that affect economic activity in Turkey. Since there is no effective economic and financial lexicon (as in English) for sentiment analysis in Turkish language, we developed a sentiment index by using machine-learning algorithms for the period 2011-2019. Data set used in this study includes 131.601 news in Turkish, which were selected according to a carefully specified set of words, published in printed media. We classified the semantic orientation of news by a group of experts to construct annotated data set. It is observed that sentiment index covers the important events for Turkish economy. Considering time lag in official statistics, the sentiment index can be used as a leading economic indicator. It is planned to investigate whether the sentiment index increases the explanatory power of the econometrics models explaining economic activity in Turkey as a future work.

Keywords: Sentiment Analysis, Machine Learning, News Domain, Economic Indicator, Turkish

ÖZ

MAKİNE ÖĞRENMESİ TEKNİKLERİ VE DUYGU ANALİZİ İLE EKONOMİK BÜYÜMENİN TAHMİN EDİLMESİ

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Yüksek Lisans, Uygulamalı Veri Bilimi Bölümü
Tez Yöneticisi: Dr. İnan Utku Türkmen

Ağustos 2019

Bu çalışmanın amacı finansal ve ekonomik haberlerden duygu endeksi oluşturmak ve Türkiye'de ekonomik aktiviteyi etkileyen temel ekonomik ve politik olaylarla potansiyel ilişkisini incelemektir. Türkçe'de duygu analizi için etkin bir ekonomik ve finansal sözlük olmadığı için, 2011-2019 dönemi için makine-öğrenme algoritmalarını kullanarak bir duygu endeksi geliştirdik. Bu çalışmada kullanılan veri seti, 2011'den günümüze basında yayınlanan ve dikkatlice belirlenmiş bir kelime grubuna göre seçilen 131.601 haberi içermektedir. Duygu polaritesi belirlenmiş haber veri setini oluşturabilmek amacıyla uzman bir grup sayesinde haberler sınıflandırılmıştır. Duygu endeksinin Türkiye ekonomisi için önemli olayları kapsadığı görülmektedir. Resmi istatistiklerdeki gecikme dikkate alındığında, söz konusu endeks öncü ekonomik gösterge olarak kullanılabilir. Sonraki çalışma konusu olarak, duygu endeksinin ekonomik aktiviteyi açıklayan ekonometrik modellerin açıklayıcı gücünü arttırıp arttırmadığının araştırılması planlanmaktadır.

Anahtar Sözcükler: Duygu Analizi, Makine Öğrenmesi, Haber Alanı, Ekonomik Gösterge, Türkçe

To my son,

ACKNOWLEDGMENTS

I would like to express my sincere appreciations to my advisor Dr. İnan Utku Türkmen not only for his support throughout my thesis but also for the guidance and positive attitude for the last two years in the program at TED University.

I would also like to thank Associate Professor İbrahim Ünalmış for his valuable contribution to my study. He gave me great ideas for my future studies.

My colleagues from Central Bank of Turkey always supported me throughout my studies. Specifically, I want to thank to Canan Binal Yılmaz for her help at accessing the data set used in this study and Murat Topkaya and Mustafa Yıldırım for their help in the following works.

Last but not least, I want to thank Hande Yavuz. It would not have been possible to complete the thesis without her support and understanding.

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LIST OF ABBREVIATIONS

CBRT	The Central Bank of the Republic of Turkey
CV	Cross Validation
DTM	Document Term Matrix
GDP	Gross Domestic Product
ML	Machine Learning
NB	Naïve-Bayes
NLP	Natural Language Processing
RF	Random Forest
SVM	Support Vector Machine
TF	Term Frequency
XGB	XGBoost

CHAPTER 1

1. INTRODUCTION

1.1 Motivation

Economic policies are carried out by legal authorities to achieve targets such as economic growth, price stability, financial stability etc. by using different tools. Decisions taken to achieve those targets are mostly based on macro-economic statistics such as inflation rates, gross domestic product[1] (GDP) growth, unemployment etc. about the economy. Therefore, getting timely and accurate statistics has always become very important for any economic policy implementations. In other words, decision-taking process requires high quality and timely statistics covering all sectors of the economy.

On the other hand, collecting and disseminating macro-economic statistics take time. For example, time lag in GDP statistics, which is the key performance indicator for any economy, is more than 3 months. Similarly, monthly industrial production index, which are also used as leading indicator to GDP, are disseminated with nearly two months (t+47) later. In other words, changes in economic activity can be seen after a certain period of time. This phenomenon prevents authorities to react timely to the rapidly changing economic condition.

Public authorities around the world have started to take small steps to solve this problem by supplementing official statistics with un-official statistics. Although the purpose of these new statistics is not to replace existing ones, they provide timely insights about how the economy is going.

[1] Gross Domestic Product is the total value of goods and services produced in a country during one year

The aim of this thesis is applying sentiment classification methods to economic and financial news and to construct sentiment index. Main advantage of this index is that it is at daily frequency and cost nothing to compile compare to official statistics.

Preliminary results show that sentiment index captures the most important economic and political events that affect economic activity in Turkey. Therefore, this index can be used as a leading economic leading indicator.

Moreover, this index might be helpful to increase explanatory power of econometrics models explaining economic activity. This is another area of research that is planned to work on following this study.

1.2 Sentiment Analysis

In the last 20 years, the spread of the internet and social media changed the way how people communicate. This new way of communication has increased the volume of digital data at a tremendous speed. When the content of this data is examined, it is seen that majority of it is textual. Large amounts of this new data requires automatic analysis and classification methods.

Sentiment Analysis is a field of research aiming to determine subjective information such as emotion, opinion, attitude stated in textual document by using methods and techniques from fields such as natural language processing (NLP), statistics and computer science. Although the term was first used by Tetsuya and Jeonghee in 2003 [25], studies on this issue have begun previous years. It is not just a growing research area, but also a field of study currently used in almost every domain [10].

One of the main areas in sentiment analysis is the detection of polarity. What is to be done here is to classify texts in terms of the sentiment they have according to the content of the analysis. It can be either binary such as positive/negative or multiple level.

Sentiment analysis can be done at various levels. Mostly, these are document-level or sentence-level. In document-level analysis, the text is considered as a whole and it is classified according to the dominant sentiment [8]. In cases where the document level is insufficient for the analysis, same methodology is followed at sentence-level to classify texts.

There are basically two methods for determining the polarity of sentiment: machine-based methods and dictionary-based methods. As will be explained in detail in Chapter 3, each has advantages and disadvantages over each other [9].

1.3 News Domain

When people make economic decisions and build their expectations for the future economic activity, they apply to many sets of information. The financial and economic news published in the printed media constitute one of the important information sets that people frequently refer to in this sense. Therefore, the analysis of these news texts gives us information about how expectations change. Studies in this area have increased in recent years [30].

In this study, we choose to work with economic and financial news to construct sentiment index by using machine-learning algorithms. Our data set consist of all the economic and financial news from 2011 onwards. The news before this date is not included in the scope of the study since it is not available in text format in our data source (Interpress). This news were selected according to the carefully selected set of words they include. To the best of our knowledge, there is not any study using these techniques on Turkish language.

1.4 Outline of Thesis

In Chapter 2, literature survey of related work on Sentiment Analysis are given. This section examines the importance of sentiment for the economy by various authors from historical perspective and shows that why this study contributes to the current literature.

Chapter 3 covers background information about different methods and techniques used in this thesis.

In Chapter 4, data set and algorithms used in this study are explained shortly. This chapter also covers the sentiment indexes constructed in this study and shows how sentiment index captures the important economic and political events that affects economic activity in Turkey.

In Chapter 5, conclusions and future works are discussed.

CHAPTER 2

LITERATURE REVIEW

There are different studies in literature regarding the effects of economic sentiment on economic activity for a long time [7]. It is possible to classify these studies under two main groups. First one is called, broadly speaking, “animal spirits”. It refers to emotional and intuitive factors that taken into account by economic agents in decision-making processes. Though, the term was first coined by Keynes, J., M. (1936) [14], the idea were voiced earlier by others. For example, Pigou (1929) [22] stated that economic fluctuations were result of undue optimism or pessimism of entrepreneurs that change investment decisions, resulting in economic fluctuations. This idea was seen as one of the main reasons by scholars to explain recent economic fluctuations. For example, in an attempt to explain possible reasons behind 1990-1991 economic crises, Blanchard (1993) [5] stated that consumption shock was due to animal spirits. Aarle and Kappler (2012) [29] investigated the effects of sentiment shocks on Euro area economy. They concluded that change in economic sentiment amplify business cycle shocks. Similarly, Milani (2017) [18] showed that change in economic sentiment is one of the main drivers behind the economic fluctuations (more than forty percent) in US economy. On the other hand, Akerlof and Shiller (2009) [1] draw attention to the another aspect of this phenomenon. They stated that rational expectations theory does not hold all the time. Therefore, policymaker should not stick to it and pay attention to animal spirits.

Second, sentiment can include information about the future economic activity. This includes public opinion that not seen yet at official statistics [24]. For example, Barsky and Sims (2012) [4] showed that forward-looking questions from Michigan Survey of Consumer is one of the main determinants of the future economic activity. Wlezien et al. (2017) [30] studied more comprehensively the relations between public opinion and future economic development for different countries for more than 30 years. They found out that public opinion follows similar pattern with future change in economic activity.

While the consensus has not been reached on the mechanism how economic sentiment affects real economic variables, it has started to become an important indicator to evaluate todays' and future economic activity. Therefore, it is of great importance how economic sentiment is measured.

One way of learning expectations of decision-maker is to conduct a survey. It has been using by many institutions for a long time to collect information. On the other hand, conducting survey takes time and cost money. In addition to that, information content received from survey is limited to questionnaire design and become outdated quickly [17].

Another (innovative) method is to extract expectations of individuals from written documents. Written documents can give us important information about economy when examined by appropriate methods. In this manner, financial and economic news are a good source of market sentiment [19].

Studies try to extract sentiment from economic and financial news increased over the years. Some of these studies aim to estimate stock market indices and to increase returns. For example, Kelly and Ahmad (2018) [13] studied the impact of domain-specific news on price changes. They found that using news sentiment in trading strategy increases annual return. Calomiris and Mamaysky (2019) [6] investigate the effects of sentiment for different countries. Though they differ due to country type and time, news gives useful information for forecasting equity market risk and returns.

Some other studies try to quantify effects of sentiment on real economic variables. Shapiro et al. (2018) [24] investigate how correlate news sentiment with contemporaneous business cycle. They found that positive sentiment shock affects many real economic variables. Ardia et al. (2019) [2] propose optimized sentiment index for forecasting purposes. They found that sentiment index increases the forecasting power of US industrial production index, compare to other techniques based on economic and financial statistics. Baker et al. (2016) [3] constructed economic uncertainty index from newspaper coverage frequency and showed that it is associated with many real economic variables. Thorsrud (2018) [27] is constructed business cycle index from newspaper topics. It is shown that timeliness and accuracy of this index is better than other business cycle indicators. Tobback et al. (2018) [28], constructed policy uncertainty index from newspaper and showed that this index has predictive power for many macro and financial variables for Belgium.

There are basically two methods used in sentiment analysis: dictionary-based methods and machine-learning methods. In dictionary-based methods, sentiment is computed using the word lists that are pre-selected with a semantic sentiment assigned to them [15]. In other words, it requires pre-defined dictionary in which each word has sentiment score. On the other hand, in machine-learning methods, the system is trained with annotated data set and sentiment classification is made with the model that fitted over train data set. This method was first applied by Pang et al. (2002) [21] to classify movie interpretations as positive and negative.

Performance of each method differs according to the text given. In other words, no single algorithm or method outperforms others in all settings. For example, Hartman et al. (2018) [9] compares 10 algorithms (five dictionary-based, five machine-learning based) to evaluate which one performs better in text classification. They finds out that machine-learning based methods perform better than dictionary-based methods across 41 social media data sets.

To the best of our knowledge, there is no sentiment index constructed in Turkish using only economic and financial news and following economic developments. The contribution of this study to literature is to show that sentiment index constructed by using machine-learning methods on news can be used to follow economic activity.

CHAPTER 3

METHODOLOGY

In this chapter, the background information about text pre-processing, representing text documents in vector space and methods used in sentiment analysis are explained. Raw text data consists of a bunch of characters. Although, that is in a machine- readable format, it is not possible to analyze them before making some preprocessing steps. They may vary according to the area of interest. After pre-processing steps are done, text documents must be converted to numerical vectors representing them in order to make them ready for analysis. Finally, the sentiment analysis is carried out on textual document.

3.1 Text Preprocessing

Any data can be categorized as structured or non-structured. Structure data may be displayed in a tabular format or combination of tables as so in relational data model[2]. Definition is also valid for multi-dimensional data that can not be visualized in a tabular form. The key point here is that data has clearly defined attributes.

Unstructured data, on the other hand, is all the other data that does not have aforementioned attributes. Text documents are inherently non-structural data. Twitter messages, news, email etc. are all example of non-structural text data. Because non-structural data is in free format, there are many factors that will be useless or negatively affect analysis. In order to make them ready for analysis,

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[2] For more information: https://www.guru99.com/relational-data-model-dbms.html

some text pre-processing steps should be done on raw text data. The performance of analysis results is closely related to these pre-processing steps.

Text preprocessing methods vary according to the language and type of text document. For example, emoji usage is very common in social media messages while it is not the case for financial news article. Therefore, text pre-processing steps should be customized based on the document that will be analyzed.

In this section, data pre-processing steps used on economic and financial news in Turkish are explained. As shown in Figure 3.1, they consist of converting lower case, removing punctuations, number, white spaces, removing stop words, tokenization and stemming.

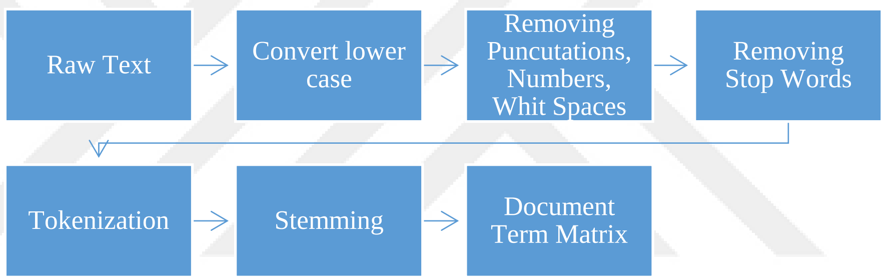

Figure 3. 1 Text pre-processing steps

The following news article will be used to show how each pre-processing step transform the raw text document. The news is about the price of a squaremeter of residentials in Turkey as of April 2018. It also make some comparasion between different dates.

"TÜRKİYE genelinde konut metrekare fiyatları nisan sonu itibarıyla son bir yılda yüzde 10 artışla 2 bin 182 liraya ulaştı. Türkiye Cumhuriyet Merkez Bankası (TCMB) verilerinden derlenen bilgilere göre, nisan itibarıyla konut metrekare fiyatı, son 5 yılda % 80,5, son bir yılda yüzde 10 ve bir önceki aya göre de yüzde 1,4 artış gösterdi. İstanbul'da konut metrekare fiyatı, 3 bin 928 liraya çıktı."

3.2.1 Convert Lower Case

It is a standard practice in text pre-processing. Although, writing with upper case may make difference in sentiment analysis, in case of we are concerned with frequency of terms, all the words in corpus are converted to lower case. For example, "Economy", "economy", "ecoNomy" need to be evaluated as “economy” in vector space. Otherwise, same words look like different features in analysis step and may result in different outputs.

When converting all the character to lower case, our example of news article will look like as follows;

"türkiye genelinde konut metrekare fiyatları nisan sonu itibarıyla son bir yılda yüzde 10 artışla 2 bin 182 liraya ulaştı. türkiye cumhuriyet merkez bankası (tcmb) verilerinden derlenen bilgilere göre, nisan itibarıyla konut metrekare fiyatı, son 5 yılda % 80,5, son bir yılda yüzde 10 ve bir önceki aya göre de yüzde 1,4 artış gösterdi. İstanbul'da konut metrekare fiyatı, 3 bin 928 liraya çıktı."

3.2.2 Removing Punctuations, Numbers and White Spaces

Punctuations, numbers and white spaces does not contain information in terms of text analysis. They are also not easy to process. Therefore, they are removed from the corpus in preprocessing step.

As shown earlier, our example of news article contain many punctuations and numbers. After removing them from the text document, our example of news article will look like as follows;

"türkiye genelinde konut metrekare fiyatları nisan sonu itibarıyla son bir yılda yüzde artışla bin liraya ulaştı türkiye cumhuriyet merkez bankası tcmb verilerinden derlenen bilgilere göre nisan itibarıyla konut metrekare fiyatı son yılda son bir yılda yüzde ve bir önceki aya göre de yüzde artış gösterdi İstanbulda konut metrekare fiyatı bin liraya çıktı"

3.2.3 Removing Stop Words

A stop word is a commonly used word in written documents like “ve”, “de”. Although, these words recur frequently, they generally includes redundant information and does not effect on the sentiment of a sentence. Therefore, it is better to remove them before text analysis. After removing stop words, our example of news article will look like as follows;

"türkiye genelinde konut metrekare fiyatları nisan sonu son yılda yüzde artışla liraya ulaştı türkiye cumhuriyet merkez bankası tcmb verilerinden derlenen bilgilere nisan konut

metrekare fiyatı son yılda son yılda yüzde önceki aya yüzde artış gösterdi İstanbulda konut metrekare fiyatı liraya çıktı"

As it may be seen from the example, our text document does not contain words like “ve” and “de” after transformation.

3.2.4 Tokenization

Tokenization is to identify the smallest meaningful units of a document. Tokens (single unit) can be single word (uni-gram) or words sequences (n-gram) depending on the content of the analysis to be made. It is a language-specific process. In Turkish, like many others, white space and punctuation are used to tokenize documents into smaller parts. It is a relatively straightforward procedure.

Tokenized form of our example news article is shown below. After this step, text document consist of words list.

"türkiye", "genelinde", "konut", "metrekare", "fiyatları", "nisan", "sonu", "son" , "yılda", "yüzde", "artışla", "liraya", "ulaştı", "türkiye", "cumhuriyet", "merkez", "bankası", "tcmb", "verilerinden", "derlenen", "bilgilere", "nisan", "konut", "metrekare", "fiyatı", "son", "yılda", "son", "yılda", "yüzde", "önceki", "aya", "yüzde", "artış", "gösterdi", "istanbulda" , "konut", "metrekare", "fiyatı", "liraya", "çıktı"

3.2.5 Stemming

One of the critical steps in text pre-processing is stemming. It aims to bring words into their root forms. It does not have to be the same with dictionary-based morphological root; it is just an equal or smaller part of a word. For example, “econ” may be stemmed version of “economy”. By this mean, words that looks different because of the suffixes they take, yet have the same meaning, are put together and evaluated.

The stemmed version of our example news article is shown below.

"türki", "genel", "konut", "metrekar", "fiyat", "nisa", "so", "son", "yıl", "yüz", "artış", "lira", "ulaş", "türki", "cumhuriyet", "merkez", "bankas", "tcmb", "veri", "derlene",

"bilgi", "nisa", "konut", "metrekar", "fiyat", "son", "yıl", "son", "yıl", "yüz", "öncek", "a", "yüz", "artış", "göster", "istanbul", "konut", "metrekar", "fiyat", "lira", "çık"

It is seen from the words list that words changed to their stemmed version consistently after stemming.

3.2 Document Term Matrix

It is not possible to make an analysis on raw text data. It should be represented in the vector-space. In order to that, text document must be converted to numerical vectors representing the text. In this thesis, document term matrix (DTM) was used to represent text documents in vector-space. DTM is a way of representing corpus (collection of text documents) as a table (or matrix) of numbers. Rows consist of documents, while columns are terms (words in our case). Mostly, it is a common starting point for further text analysis.

The elements of DTM may change according to the model. In this study, the term frequency (TF) of each term in document is considered. TF can be represented mathematically by the given formula;

$$fw_D = tf(w, D)$$

where fw_D represents TF of word w in document D. It is also possible to represent same document with another calculations. We will be using the raw frequency in our analysis.

If we use example text document that shown in the text-preprocessing steps and build DTM over it, some part of it would look like as shown in Table 3.1;

Table 3. 1 Document Term Matrix

Docs	artış	aya	Fiyat	konut	liraya	metrekare	nisan	son
1	2	1	2	3	2	3	2	3

DTM built over example news article has the following attributes shown in Table 3.2.

Table 3. 2 Attributes of DTM

<<DocumentTermMatrix (documents: 1, terms: 28)>>
Non-/sparse entries: 28/0
Sparsity : 0%
Maximal term length: 12
Weighting : term frequency (tf)

DTM consists of 28 unique words. Maximum term length in the DTM is 12. Because there is no empty cell in the matrix, sparsity is zero. On the other hand, if we add new documents to the corpus and build DTM, it results in sparce matrix. Because each term does not exists in each document.

3.3 Methods Used in Sentiment Analysis

There are two main methods used in sentiment analysis; machine-learning based (ML) and dictionary-based. Each has its own advantages and disadvantages. Language in which text analysis is carried out is also important issue in choosing the method. In this study, we prefer machine-learning based methods.

3.3.1 The Lexical Approaches

In this approach, sentiment is calculated by using the semantic orientation of word or phrases that occur in a text. To make that happen, it requires pre-defined dictionary. An advantage of using lexicon-based models compared to ML methods is that it is not necessary to have correctly labelled data set to train the model.

Classifying documents by using lexicon depends on very simple idea. A lexicon is a kind of dictionary in which each word has its degree of polarity. Classification of text are done by calculating word’s polarity scores.

Building lexicon is a time consuming and requires so many people with different background to come together. Therefore, automatic lexicon generating solutions were suggested. On the other hand, all methods are based on “prior polarity” of words. This polarity can change according to the context [31].

Choosing right lexicon affect the sentiment analysis considerably. Because sentiment scores of words may change according to the context. For example, ‘tax’ has negative meaning in general documents, while it has neutral in economy related documents. Loughran and McDonald (2011) [15] dictionary is widely used in sentiment analysis of financial text. However, the main problem is that these dictionaries are mainly developed for English. Even though several studied has been carrying out to develop dictionaries for other languages, including Turkish, they are not well developed compared to those ones.

3.3.2 Machine Learning Methods

The machine learning algorithms that deal with labeled data are called “supervised methods”. They apply some techniques on a set of training data to be able to predict the label of unseen test data. It is basically a classification problem. They need an annotated dataset of texts for training, which creates a model to discriminate between polarities.

There are numerous machine learning algorithm used in text classification problems. Some of them are Naïve Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), Xgboost (XGB), K-Nearest Neighbor (KNN). Each uses different techniques to classify documents. Each model is based on different assumptions. Naïve Bayes follows completely probabilistic approach while KNN is based on feature similarity calculated by distance. It should be kept in mind that each algorithm performs differently according to the type of data. Therefore, in practice, different algorithms are run on the same data set and results of each are compared with each other in terms of prediction performance and computational efficiency.

3.3.2.1 K-Nearest Neighbor

K-Nearest Neighbor (KNN) is a non-parametric and lazy algorithm that are widely used in text classification problems. It does not make any assumption about the data distribution such as Gaussian or linearly separable. This makes it easy to use it on any kind of dataset. It is also lazy algorithm. Lazy algorithm means that there is no learning or training step and all the dataset are used at the time of prediction. Lazy learners wait until the last minute before classifying any data point. When new data set is provided to the algorithm all the dataset are used. Therefore, training step does not take time. It is also called as an instance-based learners.

In this algorithm, K represents the number of nearest neighbors. It is the main parameter that needs to be choosen. When K = 1, the algorithm looks the nearest point and classification are done by label of nearest point. For example in Figure 3.2, K parameter is equal to 1. When new data point to which class it belongs to not known is provided, algorithm looks for the nearest point, which is Class A in this case.

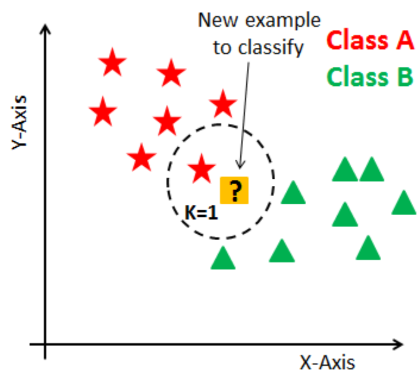

Figure 3. 2 Classifying data point when K = 1

K is generally chosen as odd number. Suppose K is bigger than 1. Then label of new point are decided by majority vote of k nearest points. Nearest points can be found by calculating distance. There are different distance measure such as Euclidean, Manhattan etc. Assuming K is chosen as 3 as shown in Figure 3.3. In this case, label of new data point are assigned according to the 3 nearest data points.

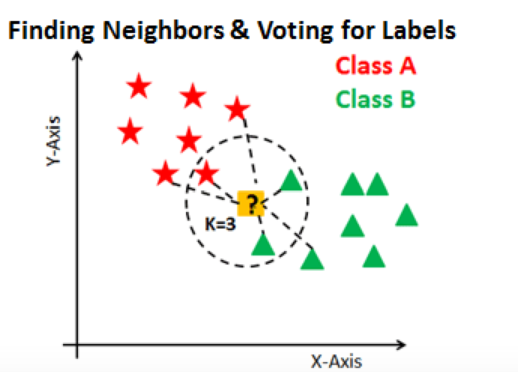

Figure 3. 3 Classifying data point when K = 3

Most important thing to consider when using this algorithm is to decide value of K. There is no optimal value of K. Each dataset has its optimal value of K. If the value of K is chosen small then the model will have low bias but high variance, vice versa.

3.3.2.2 Support Vector Machines

After developed in the 90s, support vector machines (SVM) has gained popularity as one of the best classifiers [12]. The concept behind the algorithm is quite simple; it uses hyperplanes in an N-dimensional space to classify observations and takes it as optimization problem. It tries to find best hyperplane in a higher dimensional space that separate documents to different classes.

In 2-dimensional space, hyperplane is a line and can be shown mathematically by the following formula. It can be extended three or infinite dimensional space. Any point of $X(X_1,X_2)^T$ that satisfy this condition lies on the hyperplane. If equation yields positive result then point falls into on side of the hyperplane, vice versa.

$$\beta 0 + \beta 1 X1 + \beta 2 X2 = 0$$

Now suppose that we have n observation in p-dimensional space. We also have a test observation with p-features. If we have a hyperplane separating training observations, it can be used a classifier. Label of a test observation is determined by looking at which part new point falls.

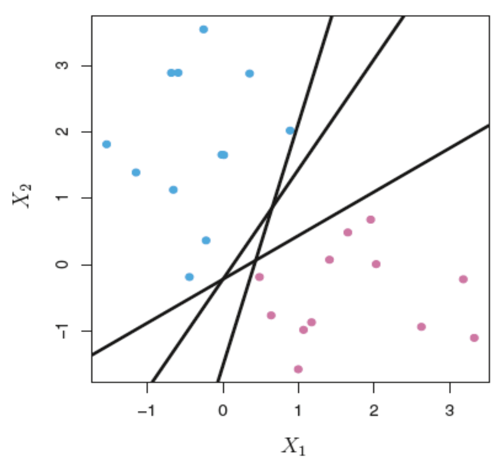

Figure 3. 4 Separating hyper-plane

If hyperplane separates data perfectly as shown in the Figure 3.4, then it is possible to draw infinite number of hyperplane by shifting or rotating it. To decide which one is optimal of these hyperplanes, distance of each training observation to the hyperplane is calculated; the smallest such distance is known as the *margin*. Where a test observation falls can be decided by using this optimal hyperplane.

According to the figure 3.5, optimal separating hyperplane is solid line. Distance from solid line to the dashed line is called margin. Points on the dashed line are called support vectors. Optimal separating hyperplane depends on small number of support vectors. The area between dashed line and solid line is the decision rule of classifier.

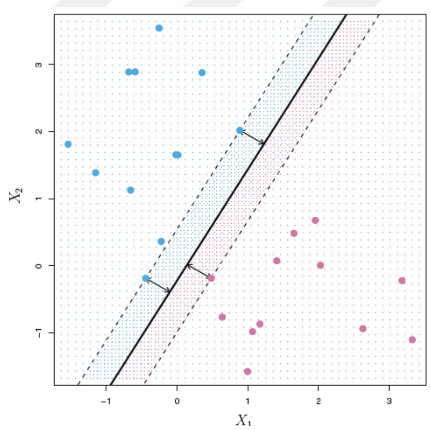

Figure 3. 5 Support Vectors

Up to now, we consider there is a hyperplane that completely separates data points. On the other hand, most of the time there is not a hyperplane separating data points such that. In such situation, algorithm tries to find best hyperplane that classify dataset [12].

3.3.2.3 Random Forest

Another classification algorithm used in text classification is Random Forest. It is basically based on decision tree algorithm. In decision tree, algorithm tries to find best splitting points and classify data set.

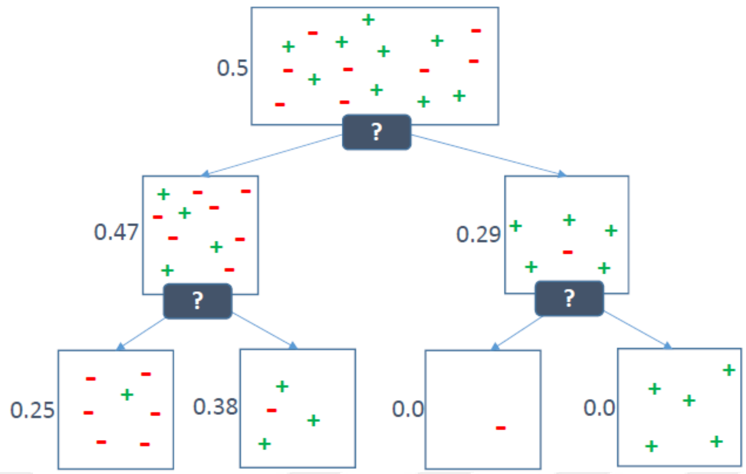

Figure 3. 6 Decision tree algorithm

According to the figure 3.6, each node corresponds to a question asked about the data. The algorithm searches through all available features and values of those features and then find a split point such that in each sub data set, the information gain is maximized. One way of calculation information gain is Gini Impurity coefficient. It can be calculated by the following formula;

$$1 - \sum pi^2$$

Where p_i corresponds to the ratio of total of each class to the proportion of all observation in each node. Numbers at the side of each node represents the Gini coefficients. Lower number is better in terms of information gain. This process continues until either impurity is zero or there is no splitting points available.

Decision trees have many advantages. It can handle huge datasets and missing values, easily ignore redundant variables, do not care about the scale of the data and small ones are easily interpreted.

Although it have many advantages, main problem of using single tree is that it is very noisy and subject to high variance. High variance can be solved by bagging (Bootstrap aggregating). This method resamples the training data set with replacement, say n times. Then, a tree is built on every resample data set and the algorithm averages the results of each tree. This method brings down variance compared to single tree.

Random Forest algorithm is improved version of bagging decision tree algorithm. The idea is to introduce additional randomness when growing a tree. In building each trees, algorithm uses only a subset of predictors. This is the main mechanism behind random forest that avoids overfitting, even with increasing number of trees [12].

3.3.2.4 XGBoost

It has recently become dominating machine-learning algorithm used in classification tasks. It is essentially another tree-based algorithm. It iterates over the data set many times. In each time, it evaluates how successful it is in classifying data points and reweights classifying procedure; it puts more weight to areas in which it is not successful. It grows other trees to fix those mistakes. It combines a set of weak learners and yields better accuracy.

The mechanism behind the algorithm are shown at Figure 3.7. Each iterations represents weak learners. Final classifier is the combination of these weak learners. This is called generalized boosting algorithm.

XGB is different from the generalized boosting algorithm. Tianqi Chen explains the difference by saying that *"name xgboost, though, actually refers to the engineering goal to push the limit of computations resources for boosted tree algorithms, which is the reason why many people use XGB*". Specifically, XGB uses a more regularized model formalization to control over-fitting, which gives it better performance.

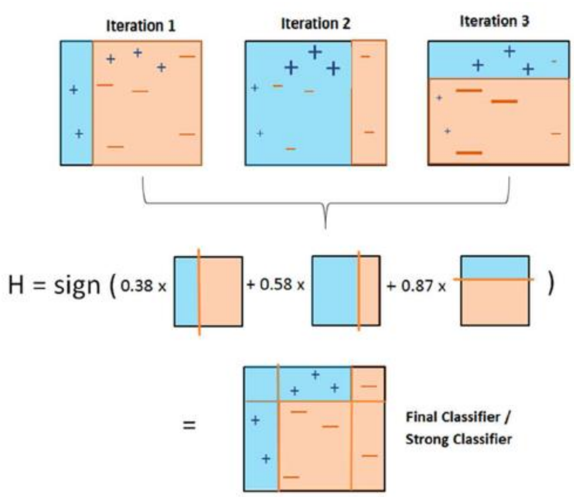

Figure 3. 7 Principals of generalized boosting algoritm

Assuming you have big datasets and you run a naive grid search on five different parameters and having for each of them 5 possible values, then you'll have 5^5 =3,125 iterations to go. If one iteration takes 10 minutes to run, you will have more than 21 days to wait before getting your parameters. XGB solves this problem by bringing efficiency to computation. That is one of the main advantages of XGB along with others.

3.3.2.5 Naïve- Bayes

This algorithm is based on Bayes' Theorem. It is a simple probabilistic algorithm. Its simplicity comes from the assumption that features of data are independent from each other and each feature is assumed to contribute to the result equally. In terms of text classification, this means that any word within the document is independent from each other and have equal weight in classification. The calculation is done by using the following formula;

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

where A is the class variable (semantic orientation in classification), while B represents the features (words in document). The algorithm calculates the conditional probabilities of words and decides which class they altogether belong to. Using these probabilities, documents are classified. Although, its assumption is fairly simple, it gives surprisingly good results in text classification problems [20].

CHAPTER 4

DATA SET

We constructed a time series index of sentiment from financial and economic news. The process involves 3 main steps; obtaining economic and financial news from Interpress Agency, labelling them according to the different algorithms and compares results, constructing monthly time series index.

4.1 Creating Corpus[3]

To create the corpus, the access has been taken to the archives of the Interpress. Founded in 1940, Interpress is first media monitoring company in Turkey. They monitor all kind of media branches, including the printed news[4]. We used all the economic and financial news in the printed media from 2011 onwards because news before 2011 were not available in text format.

News were selected according to carefully specified set of words, which includes all the news and columns about the economy published in printed media. These words are specified each year by the CBRT. They include words or phrases (Appendices A) such as “central bank”, “monetary policy”, “reserve option mechanism”, along with the names of top executives of the CBRT.

Financial and economic news gathered from Interpress are at a daily frequency from 2011 onwards. The media organs is not limited with the mainstream media, it includes local ones, as well. Total

[3] Corpus means collection of text documents.
[4] For more information about Interpress: https://www.interpress.com/

number of news and columns is 131.601, number of which per year is shown at Table 4.1 (as of April 2019);

Each news record consists of 4 components; headline (the author or column name), date, news source and news text along with number of circulation and other related information about the media organs.

Table 4. 1 Number of news article

Year	Number of News (as of April 2019)
2011	18.474
2012	21.042
2013	14.978
2014	15.400
2015	16.606
2016	15.227
2017	13.736
2018	13.397
2019	2.741
Total	**131.601**

4.2 Machine Learning Algorithms and Results

In this study, we used supervised machine learning algorithms because there is no well-developed financial lexicon in Turkish language. These models requires labelled data set whose sentiment orientation is known.

There was no ready-to-use financial news data set whose sentiment orientation is known. To construct data set used in fitting machine-learning models, news bundles were created to include approximately 40 news that selected randomly from the corpus having equal number of news from each year. Those news were evaluated by people with different levels of knowledge and experiences. CBRT employees, academicians, newly graduated and student of TED University took part in the survey. In addition to that, the same 15 news were added to each bundle to observe general evaluation behavior of readers.

The readers were asked to comment on the news from the economic point of view and to share what kind of expectation they form about the future economic activity. According to their evaluation, news were labelled as “-1”, “0”, “1”. While “-1” represents the expectation that economic activity will slow down, “1” does the opposite.

After the survey was over, the answers of the same questions were evaluated. Mean score of each news were considered as common sense. Reader whose answers differs consistently from common sense more than 2 standard deviations were considered outlier and excluded from the study (Only one reader).

As a result, dataset of 1357 news with labels were created. Distribution of the news based on sentiment distribution is as follow;

Table 4. 2 Labels breakdown by sentiment

Negative	**Neutral**	**Positive**	**Total**
524	438	395	1357

Having unbalanced data set may create biased results in machine learning algorithms. There are several methods to eliminate this risk. One of them is to adjust train data set to contain an equal number of documents from each class during model fitting step. In this study, a similar method was followed and positive and neutral classes are randomly reduced to the number of positive class.

There are different machine-learning algorithm that can be used in text classification. Each follows different procedure in model fitting step and their performance depend not only these procedure but also data set’s own structure. Therefore, in any study, different algorithms should be run on same data set, and make sure that which one is better in terms of given performance metric. In this study, KNN, SVM, RF, XGBoost and NB algorithms were used to classify data set. These algorithms are widely used in text classification problems.

We followed standard approaches in model fitting process. Data set was split as training and test data set. While 80 percent of data set was used in model fitting, 20 percent of data set was used in model evaluation. We also used 10-fold cross-validation (CV) approach. In this approach, dataset is split randomly into 10 folds. The first one is treated as a validation set, and model accuracy is computed this held-out fold. This process is repeated 10 times with different groups. The 10-fold

CV estimate is computed by taking into account all results from each fold. The main purpose of using this method is to observe how well a given model perform on independent data [12].

Following fitting different algorithms, confusion matrix was constructed to evaluate model performance of each algorithm. Confusion Matrix is a general performance indicator for any classification algorithm where output can be binary or multiple classes.

Table 4. 3 Confusion matrix

		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

One of the most common measure that derived from the confusion matrix is accuracy. The accuracy is the sum of the first diagonal of the confusion matrix divided by all the entries. Accuracy does not depend on which class is the positive class. It is the total number of correct predictions divided by all predictions. Different performance indicators can be calculated from this table. In this study, to evaluate model performance of each model, we used accuracy rate, which shows the correct prediction ratio; (TP + TN) / (TP + FP + FN + TN).

Other performance metrics that can be used in binary classification problems are precision and recall. Recall is the number of true positives divided by the number of true positives plus the number of false negatives. Recall can be seen as a model's ability to find all the data points of interest in a data set. On the other hand, precision is defined as the number of true positives divided by the number of true positives plus the number of false positives. While recall expresses the ability to find all relevant instances in a data set, precision expresses the proportion of the data points our model says was relevant actually were relevant. Which performance metrics will be chosen changes according to the study area.

In this study, readers labelled each news with three labels based on research question. Each of five algorithms were fitted on training data set and made prediction on test data set. As shown Table

4.4, RF algorithm gave the best performance with 51% accuracy on test data set, while KNN algorithm were least successful of all with 43%.

Table 4. 4 Accuracy values of different algorithms with 3 labels

Algorithm	Accuracy (%)
Random Forest	0.51
SVM	0.44
Naïve-Bayes	0.47
KNN	0.43
XGBoost	0.45

Later, how these algorithms work in case of binary label were investigated. For this purpose, the existing data set was reorganized. After the neutral news in the data set were removed, it was arranged to have same number of news from each class. Then, the models were fit by using 5 algorithms and the performance of each was compared. As it may be seen from the table 4.5, RF performed best with 65% accuracy, while KNN were least successful of all.

Table 4. 5 Accuracy values of different algorithms with 2 labels

Algorithm	Accuracy	Precision	Recall
Random Forest	0.65	0.65	0.67
SVM	0.61	0.62	0.58
Naïve-Bayes	0.61	0.59	0.66
KNN	0.57	0.55	0.66
XGBoost	0.61	0.60	0.66

4.3 Sentiment Indexes

To construct sentiment indexes, we labelled remaining 130.244 news in our dataset by using different models. We obtained time series for each model, taking averaging on a monthly basis. We followed similar approach for models with 2 labels.

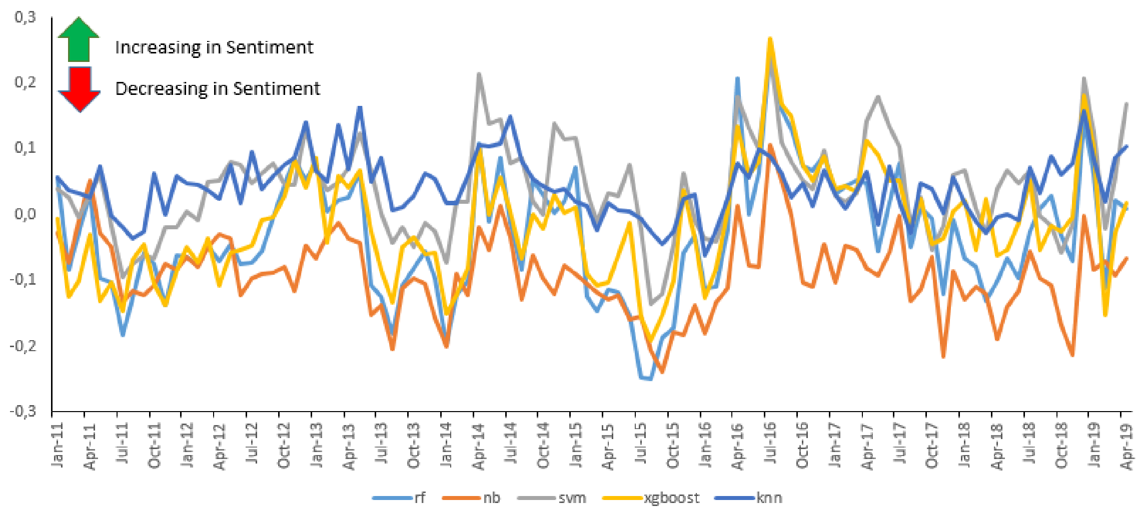

Figure 4. 1 Sentiment indexes with 3 labels

Sentiment indexes constructed by using different algorithms follow fairly similar patterns. The main upward or downward trends occur at the same dates. Similarities between different algorithms can also seen by correlation matrix. RF and XGB look like mostly correlated with 0.87, while NB and KNN are least correlated with 0.50.

Table 4. 6 Correlation between algorithms with 3 labels

	rf	**nb**	**svm**	**xgboost**	**knn**
rf	1.00	0.72	0.70	0.87	0.60
nb	0.72	1.00	0.60	0.55	0.50
svm	0.70	0.60	1.00	0.76	0.59
xgboost	0.87	0.55	0.76	1.00	0.51
knn	0.60	0.50	0.59	0.51	1.00

We used same methods to construct sentiment indexes with 2 labels. To do that, before fitting machine-learning models on training data set, we removed news with neutral sentiment. As shown in Figure 4.3., this time similarity between different models were more evident. They follows quite similar patter over time.

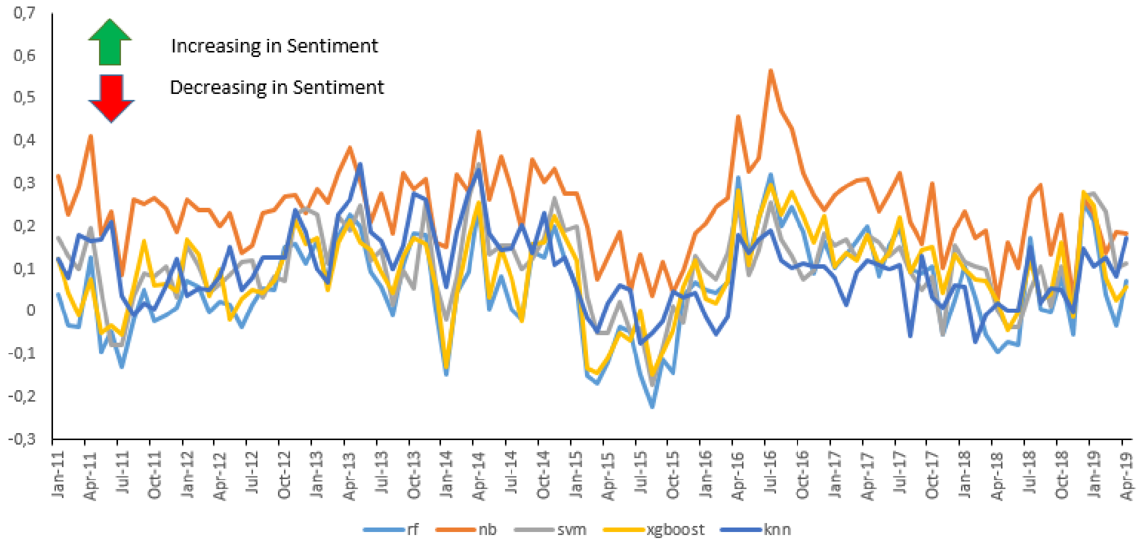

Figure 4. 2 Sentiment indexes with 2 labels

Increased similarity between different models can also be seen in correlation matrix. Again RF and XGB are mostly correlated series with 0.98 while NB and KNN are least correlated with 0.54.

Table 4. 7 Correlation between algorithms with 2 labels

	rf	**nb**	**svm**	**xgboost**	**knn**
rf	1.00	0.80	0.78	0.98	0.57
nb	0.80	1.00	0.69	0.73	0.54
svm	0.78	0.69	1.00	0.78	0.57
xgboost	0.93	0.73	0.78	1.00	0.49
knn	0.57	0.54	0.57	0.49	1.00

Correlations between different algorithms are not surprising. Each uses different assumption in model fitting. XGB and RF are somehow similar because both are based on tree based models. On the other hand, XGB and KNN use completely different approaches in model fitting as explained earlier.

4.4 Interpretation of Sentiment Index

This section examines how the sentiment index constructed within the scope of the thesis follows the important internal and external events affecting the economy activity. As explained in detail before, readers were asked what kind of expectations they formed about the future economic activity after reading each economic and financial news in order to fit machine-learning models used in the study. Since the expectations of individuals affect decision-making processes, following these expectations correctly constitutes an important information set for economic management.

As shown below, the sentiment index we have constructed can capture such events using financial and economic news only and exclusively. This sentiment index does not claim to replace traditional data sets about economic activity. On the other hand, those data sets are compiled after economic activity has reacted to the events and with a long time lag. If decision-taken process are data-driven, this may lead to a delay in policy reaction to the continuously changing economic environment. Therefore, it is possible to have an almost real-time insight into the course of economic activity by using sentiment index. This can help policy makers to take decisions much faster. Delays in policy reactions may be required more radical decisions to be taken for problems that can be solved by very small measures.

Although there are many internal and external events that have potential to affect the economy, as it may be seen from the Figure 4.3 below, there are many events on which everyone agrees. The sentiment index that we have constructed within the scope of the study can react to these events very quickly.

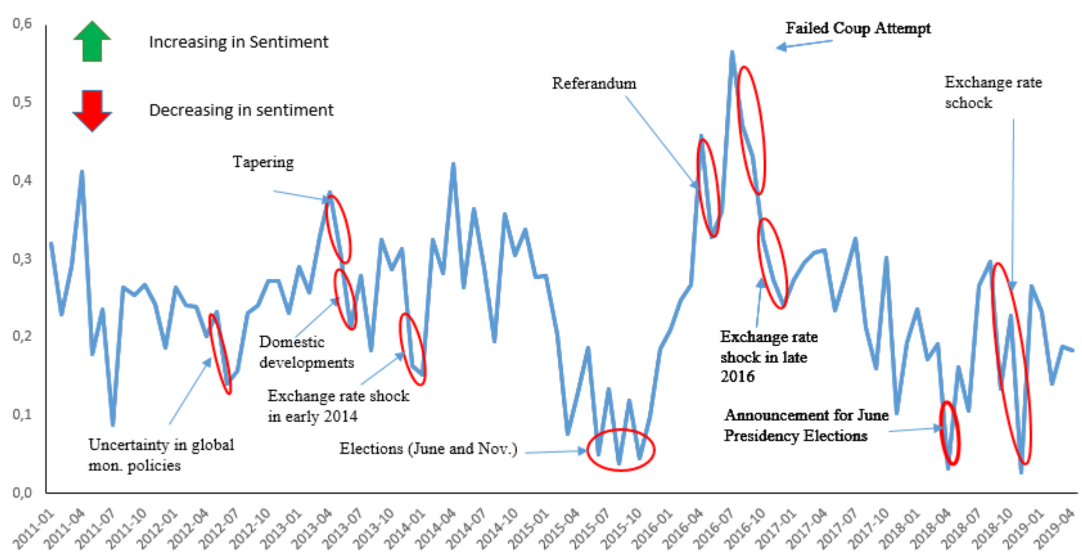

Figure 4. 3 Sentiment Index

For example, in early 2012 we observed deterioration in sentiment. This was mainly result of international developments, especially related to developed countries. Sovereign debt crises in

Europe was one of them. It started in 2009 with the Greece default on its debt and things got worse in 2012. So many countries within Eurozone affected badly, specifically, Portugal, Italy, Ireland and Spain. Another important international event was the concerns over growth of US economy. This kind of developments affects the expectations of economic units about future economic activity. Because, these event not only prevent international capital flows coming into the country, but also affect the economic sectors that export goods and services to foreign markets.

2013 was an important year for Turkish economy. An important event that raised concerns for economic outlook around the world was FED announcement about tapering[5]. They announced that they would reduce the purchases of Treasury bonds, which means that they reduce the amount of money they feed into the economy. This decision caused uncertainty in global markets. Because it had potential to affect international capital flows going into other countries, including Turkey. Therefore, expectations of economic units deteriorated badly in this period. On the domestic side, a wave of demonstration and civil unrest that started at the end of May resulted in deterioration in sentiment.

Another shock that Turkish economy experienced occurred at the beginning of 2014. Domestic currency depreciated significantly at this period. Because, exchange rates has always been an important indicator for the Turkish economy, drastic changes in prices directly affect expectations of individuals about economic activity. We can easily observe that sentiment index decreased at this period.

2015 was a problematic year for Turkish economy in terms of internal and external developments. On the internal side, elections that took place in June and November raised the concerns for future economic activity. On the external side, global growth concerns, geopolitical tensions and European immigration issue resulted in deterioration in sentiment. Domestic currency also depreciated 25% throughout the year.

The next period sentiment was decreased dramatically is 2016. There was a referendum in April about constitutional change, which raised concern for the Turkish economy. In addition to that,

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[5] Tapering is the gradual reversal of monetary policy that put into effect to stimulate economic growth.

failed coup attempt in June and subsequent development resulted in deterioration in sentiment. Moreover, domestic currency depreciated 20% at the second half of the year. Consequences of these events explain the sharp decrease in sentiment index.

Finally, we observed that sentiment deteriorated badly in 2018. Political developments was the main driving factor in the first half of the year. In the second half of the year, there was an exchange rate shock to the economy. Consequently, we observe that sentiment index reduced significantly.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

In this thesis, we have constructed a sentiment index for Turkey using machine-learning methods. To the best of our knowledge, this is the first study that is using aforementioned techniques on financial and economic news in Turkish.

Results of the study shows that the sentiment index captures the most important economic and political events in Turkey. We think that this index can be used in forecasting and nowcasting works trying to explain economic activity in Turkey.

5.2 Future Works

It is observed that the emotion index constructed on the data set used in the study captures important national and international events that are thought to affect the economic activity. Therefore, sentiment index can be evaluated as an important source of information and used as a separate independent variable in traditional econometric models. This may increase the explaining power of existing models.

Although the sentiment index we developed successfully captures important economic and political events that affect economic activity in Turkey, there is still room for improvement. First one is the stemming methods that followed in the text pre-processing step. In this study, one of the packages in R programming environment was used for stemming. This package ignores the morphological features of the words during the stemming process. It is possible to observe an increase in the accuracy rates of the machine-learning models in case of using other stemming tools, specific to

Turkish that take into account morphological features of the words. Because stemming is one of the important pre-processing steps in text analysis, it can directly affect model performance.

In the study, all economic and financial news in the printed media after 2011 were used to create the data set. These texts include news in the mainstream media as well as in the local ones. Since no distinction is made between the sources in which the news is published, it is assumed that each news has the same effect, implicitly. However, news in the mainstream media can reach more people and be more decisive in the formation of expectations. Therefore, certain distinctions should be made between news sources according to their level of influence. This contribution requires special expertise.

As a result of the survey conducted within the scope of the study, Central Bank employees, academicians, Ted University graduates and students evaluated 1357 financial and economic news. Time and resource constraints prevent the train data set used in the model fit phase to be much larger. The survey can be conducted with a broader participation of people with different levels of knowledge and experience. This method can increase the accuracy of machine-learning models.

Finally, five algorithms frequently used in the field of text analysis were used in this study to fit machine-learning models. Because each algorithm works on different assumptions,vother algorithms should be tested to make sure whether there is one that can work better on the financial and economic news.

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APPENDICES

APPENDIX A

Word lists

2011	2012
Durmuş Yılmaz	Durmuş Yılmaz
Erdem Başçı	Erdem Başçı
Burhan Göklemez	Mehmet Yörükoğlu
Mehmet Yörükoğlu	İbrahim Turhan
İbrahim Turhan	Vehbi Çıtak
Vehbi Çıtak	Lokman Gündüz
Lokman Gündüz	Turalay Kenç
Turalay Kenç	İlker Parasız
İlker Parasız	Necati Şahin
Necati Şahin	Necdet Şensoy
Necdet Şensoy	Hasan Türedi
Mehmet Tüfekçi	Mustafa Saim Uysal
Hasan Türedi	Abdullah Yalçın
Mustafa Saim Uysal	Abdullah Yavaş
Abdullah Yalçın	Yasin Aydın
Abdullah Yavaş	Sabri Orman
Tuğrul Gürgür	Ahmet Faruk Aysan
TCMB	TCMB

MB
Merkez Bankası
Banknot Matbaası
Para Politikası
PPK
Enflasyon Raporu
Finansal İstikrar Raporu
Banka Kredileri Eğilim Anketi
Ödemeler Dengesi Raporu
Tüketici Eğilim Anketi
Tüketici Güven Endeksi
Yüksek Faiz Düşük Kur
Düşük Kur Yüksek Faiz
Sahte Para
Sahte Banknot
Central Bank Review
Enflasyon Hedeflemesi

MB
Merkez Bankası
Merkez Bankamız
Banknot Matbaası
Para Politikası
PPK
Enflasyon Raporu
Finansal İstikrar Raporu
Banka Kredileri Eğilim Anketi
Ödemeler Dengesi Raporu
Tüketici Eğilim Anketi
Tüketici Güven Endeksi
Yüksek Faiz Düşük Kur
Düşük Kur Yüksek Faiz
Sahte Para
Sahte Banknot
Central Bank Review
Enflasyon Hedeflemesi
Politika bileşimi
Makro ihtiyati tedbirler
Faiz koridoru
Zorunlu karşılıklar
Politika faizi

2013

Abdullah Yalçın
Abdullah Yavaş
Ahmet Faruk Aysan
Ahmet Fethi Toptaş
Erdem Başçı
Hasan Türedi

2014

Abdullah Yalçın
Abdullah Yavaş
Ahmet Faruk Aysan
Ahmet Fethi Toptaş
Erdem Başçı
Hasan Türedi

İlker Parasız	İlker Parasız
Lokman Gündüz	Lokman Gündüz
Mehmet Yörükoğlu	Mehmet Yörükoğlu
Murat Çetinkaya	Murat Çetinkaya
Mustafa Saim Uysal	Mustafa Saim Uysal
Necati Şahin	Necati Şahin
Necdet Şensoy	Necdet Şensoy
Sabri Orman	Sabri Orman
Turalay Kenç	Turalay Kenç
Vehbi Çıtak	Vehbi Çıtak
Yasin Aydın	Yasin Aydın
TCMB	TCMB
MB	MB
Merkez Bankası	Merkez Bankası
Merkez Bankamız	Merkez Bankamız
Banknot Matbaası	Banknot Matbaası
Para Politikası	Para Politikası
PPK	Para Politikası Kurulu
Enflasyon Raporu	PPK
Finansal İstikrar Raporu	Enflasyon Raporu
Banka Kredileri Eğilim Anketi	Finansal İstikrar Raporu
Ödemeler Dengesi Raporu	Banka Kredileri Eğilim Anketi
Tüketici Eğilim Anketi	Ödemeler Dengesi Raporu
Tüketici Güven Endeksi	Tüketici Eğilim Anketi
Sahte Para	Tüketici Güven Endeksi
Sahte Banknot	Sahte Para
Central Bank Review	Sahte Banknot
Enflasyon Hedeflemesi	Central Bank Review
Politika bileşimi	Enflasyon Hedeflemesi
Makro ihtiyati tedbirler	Politika bileşimi
Faiz koridoru	Makro ihtiyati tedbirler

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2015

Abdullah Yalçın
Abdullah Yavaş
Ahmet Faruk Aysan
Ahmet Fethi Toptaş
Erdem Başçı
İlker Parasız
Lokman Gündüz
Mehmet Yörükoğlu
Mehmet Ziya Gökalp
Murat Çetinkaya
Mustafa Saim Uysal
Necati Şahin
Necdet Şensoy
Sabri Orman
Turalay Kenç
Vehbi Çıtak
Yasin Aydın
TCMB
MB

2016

Abdullah Yavaş
Ahmet Faruk Aysan
Ahmet Fethi Toptaş
Erdem Başçı
Ömer Duman
Lokman Gündüz
Mehmet Yörükoğlu
Mehmet Ziya Gökalp
Murat Çetinkaya
Mehmet Babacan
Necati Şahin
Necdet Şensoy
Sabri Orman
Turalay Kenç
Vehbi Çıtak
Nurullah Genç
TCMB
MB
Merkez Bankası

Merkez Bankası
Merkez Bankamız
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2017

Abdullah Yavaş
Ahmet Faruk Aysan
Emrah Şener

2018

Abdullah Yavaş
Emrah Şener
Erkan Kilimci

Erkan Kilimci
Lokman Gündüz
Mehmet Babacan
Mehmet Ziya Gökalp
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Mehmet Babacan
Mehmet Ziya Gökalp
Murat Çetinkaya
Murat Uysal
Necdet Şensoy
Nurullah Genç
Ömer Duman
Sabri Orman
Vehbi Çıtak
Fatih Güldamlasıoğlu
Mehmet Kaya
Zekeriya Kaya
Durmuş Yılmaz
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Rezerv Opsiyonu Mekanizması
Rezerv Opsiyonu Katsayısı
Kaldıraca Dayalı Zorunlu Karşılık
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