REPUBLIC OF TURKEY
ADANA ALPARSLAN TURKES SCIENCE AND TECHNOLOGY UNIVERSITY
SOCIAL SCIENCES INSTITUTE
FACULTY OF BUSINESS ADMINISTRATION

ESTIMATION OF VOTER MOVEMENTS WITH MARKOV CHAINS

SEVİM GÜLİN KIRAL

MASTER'S THESIS

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ABSTRACT

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The concept of “future” is known to involve uncertainty and risk. It is highly probable that with the prediction of the future, the uncertainties would be eliminated to a great extent and the desired results would be achieved.The prediction of the future may lead the risks to be turned into opportunities thus, the opportunities to evolve into earnings. This fact is also valid for political parties. With the presumption of the future possibilities in advance, the management of the events will be easier, and thus, political parties will achieve greater success in the next elections by strengthening their management strategies. Studies to make predictions about the future with the help of Markov Chains and Hidden Markov Chains have remarkably became widespread in recent years. In this study, Markov Chains Model was used to estimate the votes of the political parties and Hidden Markov Model was used to determine hidden states underlying the reasons for voters' choice. In the study done using the Markov Chain application, it is aimed to estimate the probability of which party the voters will prefer in the future and how the voting rates of political parties will be in the long term by considering the party preferences of the voters in the previous election. As a result of the analysis of the data, it was observed that voting for the Adalet and Kalkınma Party for Adana province was the highest in the party loyalty (87.06%) and Cumhuriyet Halk Party’s and Milliyetçi Hareket Party’s voters would increase more in the long term than other parties. In addition, a road map on the changes that the parties should make on their current policies in order to achieve their goals is presented in the study considering equilibrium (fixed) vector. In the second part of the study, which the Hidden Markov Model was applied, the factors affecting the reasons for preference were examined. As a result it has been determined that socio-economic, religious and social characteristics have an effect on voter behavior as well as psychological tendencies and image-oriented factors such as party identity, ideology, demographic factors (age, income level, gender, occupation etc.), political candidate image, political party image, election campaigns and information sources. In this context, the aim of the research is to determine the factors underlying the party preferences of voters who vote in local elections by depending on these factors. The universe of work was limited to Adana city due to time and cost limitations. The sample group sizes were calculated considering the number of voters in Adana's districts, and face-to-face questionnaire was applied to randomly selected individuals.

Keywords: Markov Chain, Hidden Markov Model, Voter Preferences.

ÖZET

SEÇMEN HAREKETLERİNİN MARKOV ZİNCİRLERİ YARDIMI İLE TAHMİN EDİLMESİ

Sevim Gülin KIRAL

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Danışman: Dr. Öğr. Üyesi Selim GÜNDÜZ
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Gelecek kavramı, her zaman risk ve belirsizliği bünyesinde barındıran bir kavramdır. Geleceğin tahmin edilmesi ile birlikte belirsizlikler önemli ölçüde giderilerek istenilen sonuçlara yüksek olasılıkla ulaşılabilir. Gelecek tahmin edilebilirse risk fırsata, fırsat ise kazanca dönüşebilir. Bu olgu siyasi partiler için de geçerli olup, sonucu tahmin edilebilen olayların yönetilmesinin daha kolay olmasından dolayı, ileriye yönelik olarak yapılacak doğru tahminler ile parti ve seçim yönetim stratejileri güncellenip gelecek seçimlerde daha büyük başarılar yakalanabilir. Özellikle son yıllarda Markov zincirleri yardımı ile geleceğe yönelik tahminler yürütmek amacıyla yapılan çalışmalar oldukça yaygınlaşmıştır. Tezde hem Markov Zincirleri Modelini hem de Saklı Markov Modelini içeren iki farklı uygulama yapılmıştır Markov Zinciri uygulaması olan çalışmada; seçmenlerin bir önceki seçimdeki parti tercihleri göz önünde alınarak gelecekte hangi partiyi tercih edeceklerine dair olasılıkları ve uzun vadede siyasi partilerin oy oranlarının tahmin edilmesi amaçlanmıştır. Verilerin analizleri neticesinde, Adana ili için Adalet ve Kalkınma Partisi seçmenin parti sadakatinin en yüksek olduğu (%87,06) ve uzun vadede Milliyetçi Hareket Partisi ile Cumhuriyet Halk Partisinin gelecek seçimlerde diğer partilere oranla oyunu daha çok arttıracağı görülmüştür. Ayrıca, çalışmada durağan durum olasılıklarından yola çıkılarak uzun vadede partilerin güncel politikalarında değişiklik yapılmasına dair bir yol haritası da sunulmuştur. Saklı markov modelinin uygulandığı çalışmada ise seçmenlerin siyasi partiyi tercih etmelerinin altında yatan faktörlerin belirlenmesi amaçlanmıştır. Kişinin sosyo-ekonomik, dini, sosyal özellikleri, psikolojik eğilimler ve parti kimliği, ideolojisi, demografik faktörler (yaş, gelir düzeyi, cinsiyet, meslek vb), siyasal aday imajı, siyasal parti imajı gibi imaja yönelik faktörler, seçim kampanyaları ve bilgilendirme kaynakları gibi iletişim yönlü faktörlerin seçmen davranışları üzerinde etkiliği olduğu tespit edilmiştir. Bu bağlamda araştırmanın amacı, söz konusu faktörlerden yararlanarak yerel seçimlerde oy verebilecek seçmenlerin parti tercihlerinin altında yatan faktörlerin belirlenmesidir. Zaman ve maliyet açısından imkânların kısıtlı olması sebebiyle çalışma evreni Adana ili ile sınırlı tutulmuştur. Adana'nın ilçelerinin seçmen sayıları göz önünde bulundurularak örneklem büyüklükleri hesaplanmış ve bu doğrultuda rasgele seçilen kişilere yüz yüze anket yöntemi uygulanmıştır.

Anahtar Kelimeler: Markov Zincirleri, Saklı Markov Zincirleri, Seçmen Tercihleri.

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NOMENCLATURE

HMM : Hidden Markov Model
ANN : Artificial Neural Networks
AM : Additive Manufacturing
CM : Conventional Manufacturing
MAPE : Mean Absolute Percentage Error
MAE : Mean Absolute Error
RMSE : Root-Mean-Square Deviation
AK Party : Adalet and Kalkınma Party
CHP : Cumhuriyet Halk Party
MHP : Milliyetçi Hareket Party
TIP : Türkiye İşçi Party
BBP : Büyük Birlik Party
DP : Demokrat Party
GCD : Greatest Common Divisor

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CHAPTER I

INTRODUCTION

The state is an effective force that includes legislative, executive and judicial powers and regulates social life. The quality of the state is determined through the way that the people who hold and manage this power dominate these powers and how they use it. On the basis of the people's decision, provided that the legal arrangements are made, the state order, which manages the powers in the interests of the public is also called democracy (Aktan, 1994: 20). In the state systems, which are governed by the democracy order, where the people are governed by the people, the way to achieve the management of the powers is elections, because in this system, the public, provided that they provide the necessary qualifications, chooses its own rulers. As Atatürk stated, in governments based on democracy, domination belongs to the people, to the majority of the people. The principle of democracy favors that domination belongs to the nation and cannot be elsewhere (Aktan, 2000: 11). In modern democracies, the people who will govern the states are expected to be elected in elections. However, as of today, while some countries carry out this practice only for the people who will carry out the legislative and executive duties, others apply the election principle when designating the judiciary. In Turkey, determination of people to carry out tasks like The President, members of parliament, mayors, city council members, wards, etc. is done according to some important system changes and the election results.

The struggle for power has been an ongoing phenomenon since people clustered into states. People with common views and interests who want to continue these struggles effectively have formed political communities and have strived to achieve their goals. While the purpose of some of these communities is to have state administration, some of them aimed to obtain sanctions in line with their own interests by affecting political power. The most advanced organizations that aim to have political power and carry out actions in this direction are political parties (Sezen, 1994:32). These are the most important elements that ensure the correct and effective functioning of the democratic process and perform different functions in the society (Canöz, 2010; 96). However, in order for the political parties to realize their goals, they must first be positively distinguished from their competitors and gain power. The most effective power for politicians and political parties is that a high number of voters can be collected and party dependencies can be created on these voters. For achieving these, effective strategies should be determined and marketing science should be used (Divanoğlu, 2008: 106). Competent use of political marketing techniques by political parties and politicians in countries with democratic governance is considerably effective on voters' voting preferences and thus in obtaining power. Just as the marketing mix team members form the content of marketing activities (Grönroos, 1994: 5), political marketing mix team members form the content and basis of the activities in the electoral processes (Divanoğlu, 2008: 106). Provided that this basis and content are created correctly and effectively, the party and political candidates will be able to gain an advantage over their competitors.

Local elections differ from general elections at various points like participation rates, voter trends, outcomes and concerned parties. In addition to this, local elections are an act of electing local administrators and it is also considered as a way of voters delivering a message to the central power. From this point of view it is not always possible to evaluate local elections apart from general elections. Referring to Turkey's political tradition, if the local elections are held immediately after the general election, the results obtained are close to the general election results and can be considered as a crosscheck where Local elections before the general elections are considered as a kind of public opinion poll (Doğan and Göker, 2010). The first general elections in our country were held in 1877, while the local elections are a little older.

With the transition to multi-party life in the Turkish political system, divergence and dividedness started to emerge in certain segments of the society. To decision process on the political party to be chosen and to assimilate its ideals by the voters are functional and shapable. Therefore, before making their final decisions, the needs and demands of the voters should be considered by the political parties who want to increase their number of votes in the next election. The voters’ behaviors, demands and wishes must be taken into account by the politicians to influence the voters' preferences and the political programs of the party should be guided accordingly. Voters agree that the political system and the political regime are legitimate by the votes they cast (Kalaycıoğlu, 1984: 251). There are many factors that voters consider in voting for political parties. These are the image of the party leader, the ideology of the political party, the program of the political party, the use of mass media, the sociological, psychological, economic and ideological factors in public research such as the candidate of the political party (Avcı, 2015:145).

Theoretical studies on voter behavior are divided in to three main headings: sociological approach, socio-psychological approach (identification with the party) and economic approach (rational choice) (Akgün, 2007: 27; Harrop and Miller, 1987: 130; Kalender, 2005: 39). The idea that voter behavior is determined by social division in society is defended in sociological approach. Social division arises due to religious, professional and ethnic differences of voters. It is also defended that in the elections, the votes cast by the voters are actually claimed to reflect the voters' social identities on political preferences (Akgün, 2007:27). The socio-psychological approach, also called the party identification approach, focuses on the individual. It is also claimed that the political attitudes and ideological orientations they gained during the political socialization process, which took place under the influence of the voters' families and their surroundings from an early age, were extremely influential on their party preference at a later age (Akgün, 2007: 29) and that the people have psychological commitment to that political party (Kalender, 2005 : 46). The socio-psychological approach rejects the sociological approach (Özkan, 2004: 113). The economic preference approach, has features such as voters' focusing more on their political goals, disregarding their social environment, but desiring to have political knowledge (Harrop and Miller, 1987:145).

When the studies on the factors affecting the voters' preferences in the selection of political parties are examined, it is seen that many factors affect the election. Özsoy (2009) argues that the increase and decrease in unemployment rates, the amount of national income per capita and even the fluctuations in the inflation value are effective in the choice of the voters. Tokgöz (1978) emphasized that mass media play an active role in the process of political socialization, and this effect will even continue lifelong. According to Bal (2004), mass media is effective in creating an agenda and directing the public. Klapper (1957) believes that mass media can contribute to the formation of new ideas and help hesitant voters come to a conclusion on which political party to vote for. At the same time, it is known that visual media and other communication tools as well as mass media have a great influence on the formation of images of political parties. Mass media play a role in shaping the idea in favor of a political party by creating political images in the world of consciousness of the audience who is also the voter.When Duverger's (1984: 15) opinion that policy making is actually a war is observed, it can be seen that the most important weapon of the war is mass media. In some public opinion polls made by Devran (2003) it is argued that the political party leader is the most important factor when coosing a political party. Apart from these factors, the fact that the party leader stands behind his promises, is knowledgeable, and has the character needed to manage a nation, also has some characteristics that affect voters' decisions. Voters' trust, dignity and emotional commitment to the political party leader affect political party elections. Avcı (2015) in this context, stated that the most important features of a party leader loved and respected by the public are foresightedness, credibleness on the electorate, the soundness of his moral character and having high knowledge, political experience, good diction and high persuasion ability.

The situation that some voters want to vote for the party that will win, rather than vote for the party that will lose in the election of the political party is called “Bandwagon Effect” in the literature. It is the name given to voters' orientation towards beliefs and elections that are mostly accepted by other people. Şahin translated it into Turkish as "mızıkanın peşine takılma etkisi" (Şahin, 1999).

It is essential that political party administrators apply political marketing principles to ensure that voters use their choicein favour of them. In general, political marketing means besides using the techniques applied in any product or service marketing process, also determining the current needs of the state, society and voters' as well as the needs have not been met yet and creating a political party program that will respond to these requests / needs of their voters and persuading the voters to cast their votes for these parties (Çiftlikçi, 1996: 23).

It is desired by political parties to predict the consequences of future elections and the possible voting rates of their parties in the long term which are very important for them in order to react according to the current conditions and to determine the necessary election strategies accordingly. In the first application of the thesis, it is aimed to estimate the voting rates of political parties and the level of party loyalty of their voters in the next general elections by using Markov analysis. In another application, the voters studying in Adana province were chosen with the random sampling technique and the factors underlying the political party preferences were determined by using the Hidden Markov Model (HMM). The studies were carried out on the scale of Adana province due to various limitations. In the first part of the study, an extensive literature review was conducted to create a conceptual framework related to Markov Chains, HMM and factors affecting voter movements. In the second part of the study, Markov Chains and in the third part, HMM are explained in detail. The applications about Markov Chains and HMM are in the fourth section. In the last part of the study, the results are examined and suggestions are given.

1.1. Literature Review

No research involving Markov Chains or Hidden Markov Models has been found in the literature to predict future elections considering past voter preferences. Although there are a number of studies conducted on Markov Chains and Hidden Markov Models in various fields, the fact that no study on the prediction of political elections was conducted qualifies this first study as significant in the field. In the literature review, information about the studies on voter preferences and the factors affecting the election preferences are given, followed by some important studies in recent years using Markov Chains and Hidden Markov Model.

In the study conducted by Sitembölükbaşı (2001) on voter preferences, determining the social, cultural and economic effects on voters' voting tendencies and party loyalties were tried. In addition, a research was conducted by Sitembölükbaşı on the party preference reasons of voters living in Isparta Province in 2004 and the 1995, 1999 and 2002 general elections were compared in this study. When the results obtained from these studies are analyzed, it was determined that the ideology of the party was in the first rank of most important situations affecting the political party preferences of the voters, at the same time, it was stated that the party leader and the party’s actions affected the voters' choice in political elections. Another study on determining voter preferences was carried out by Canöz (2010) for the March 2009 local elections in the Konya sample. In this study, it was concluded that voters were most affected by the personal characteristics of the candidate's image and that they were least affected by the environmental characteristics of the candidate while determining their voting preferences in the political elections. A similar study was carried out by Damlapınar and Balcı (2013). In this study on the 2004 local elections, a survey was conducted among voters and influential variables for creating an image for the candidate were determined. As a result of the research, it was found that the characteristics of the candidate have the highest importance for the voters. Multi-layer Artificial Neural Networks (ANN) and Elman Artificial Neural Networks were used to conduct classification procedures by Avcılar and Yakut (2015) for investigating the extent that independent variables affect the probability of choosing party preferences. As a result of the survey applied to 500 people in Osmaniye province, it was concluded that the independent variable to influence the election preferences of AK Party (Adalet and Kalkınma Party) voters was the “image of the party” factor and of MHP (Milliyetçi Hareket Party) voters was the “nationalism” factor. Data mining technique which is quite popular was used by Bayır et al. (2016) to predict political election results. Voter preferences and movements in political party elections were determined with the help of Decision Tree Algorithm (C4.5.) The findings obtained in a public opinion survey conducted by a research company were used as a data set in order to estimate the outcome of the general (deputy) elections for 2011. The party preferences of the voters and the variables affecting these preferences were determined by analyzing this data set with data mining techniques. It is concluded that the decision tree algorithm is an important method in determining political trends due to the fact that the results of the analyzes overlap with the situation.

Many studies on factors affecting voters' preferences were found in political elections. Avcı (2015) conducted an empirical study on the elections of Ankara Metropolitan Municipality on March 30, 2014 in order to determine the most effective technics and communication tools used by political parties which influenced the voters' party preference in the election. The analysis of the data obtained from the survey results showed that the party leader is the most important factor affecting the electoral behavior of voters .

It is known that the expectations of the voters is needed to be analyzed well and policies should be applied towards their demands and needs by every political party that wants to reach the maximum number of votes at the elections. Aydın and Özbek (2004) emphasized that political parties that want to reach the highest vote should be voter-oriented. They specifically investigated whether the rate of being influenced from family members differed according to demographic characteristics of voters, which is one of the reasons that affects the voters. As a result of the research it was proved by the hypotheses that the voting behaviors of political party voters' family influence degree on the electoral choices differed depending on gender, age, education level, employment status, marital status, and whether they live with the family.

In the study carried out by Dağcı and Toksarı (2016), it was stated that all political parties in democratic countries make efforts to come to power alone and the brand value of the AK Party in terms of voters with its strong brand phenomenon was determined. Kurtbaş (2015) emphasized in his work that there were too many factors that would affect the preferences and decisions on voters' political party choices and applied a two-stage questionnaire to the voters. With the data obtained from these surveys, he observed the behavior of voters before and after voting for political parties.

In the study of Eroğlu and Bayraktar in 2009, the effects of political marketing practices on voters were examined according to their socio-economic characteristics. It was observed that political marketing activities did not cause any change in voters' voting decision. In other words, party ideology was found to be more effective than political marketing activities in voters' choice of party.

The influencing degree of religion perception, which is thought to be an effective factor, on voting behavior of voters was investigated by Turan and Temizel (2015). They examined the influence of religion on voters' political values and tried to identify its influence on their voting behavior. The relationship between the political identities that the voters use for defining themselves and their religious attitudes were examined. While conducting the research, a questionnaire technique was applied, a hypothesis was established by using the data obtained, and it was examined whether there was a significant relationship between the political identities of the voters that they defined themselves as and their religious attitudes. When the findings are examined, it is concluded that there is no statistical difference between the religious attitudes and political approaches of the voters, that is, the political identities of the voters with their perceptions of religion are largely the same. Therefore, when voters decide on the political party they will vote for, it is concluded that rather than religious sensitivity, the program of the political party, the influence of the leader and the staff of the political party is considered.

Cavusoglu and Pekkaya (2016) with the idea that young people have a significant impact on the results of the upcoming elections in Turkey, analyzed the causes that affect the political behavior of students studying at Bulent Ecevit University. The aim of the study is to determine which issues take into consideration in their political behavior in local elections and to determine how these topics vary according to demographic characteristics. When the answers given to the surveys are examined,it was found that while the reasons for the origin of the local party political leader candidate are not considered to be effective (ethnic origin, being from a ruling party, being in the same province as the candidate, etc.), the reasons for voter behavior (projects, feasibility, service experience, candidate's education level, etc.) are found to be quite effective.

Modeling of stock market data by using Markov chains was studied by McQueen and Thorley (1991) in the field of banking and finance. In other words, they investigated whether stock market data can be estimated using Markov chains. According to the information obtained as a result of the researches, they showed that the annual data of the New York Stock Exchange between 1947-1987 can be estimated by Markov chains.

Marsh (2000) modeled the problem as a two-state Markov chain to estimate the British, German and Japanese currency in his study. The exchange rate data used in the research was divided in three different periods as 1980-1985, 1980-1990 and 1980-1995. In line with the information obtained as a result of the research, it was observed that all series adapted to the Markov process and that the British Pound showed the lowest performance in modeling. It was observed that the performance of the models obtained from the researches has decreased slightly in the data of the 1990s.

In the study of Akyurt (2011) conducted in the field of banking and finance with the Markov analysis, the predictability of the country rating system with the Markov chains was observed. It was concluded that the changes in the grades of countries with high credit scores are less than that of countries with low credit ratings. Based on the transition matrix, for the country that has a high credit rating, the probability of the credit rating to increase is proved to be higher than the probability of its decrease. In the study conducted by Bairagi and Kakaty (2015), price behaviors in the stocks and bonds market were examined by using Markov chains. The changes in the stock prices of the Indian State Bank was taken as an example and the possibilities of increases and decreases in the price were tried to be foreseen. In the study of Cetin and Alp (2016) which is one of the studies carried out in the field of marketing, using the Markov chain method, the mobile phone brand preferences were analyzed with the Markov chain based on the data obtained by applying a questionnaire to 503 mobile phone users. Transition probabilities matrix and long-term equilibrium vector were calculated, the rates of transition between the brands and brand dependencies were found and users' brand preferences were evaluated in general. By making these analyzes separately by gender, it is concluded that male and female mobile phone users show different behaviors.

In the study conducted at the industrialfield by Cestana et al. (2019), the effect of Additive Manufacturing (AM) on the spare parts supply chain on slow-moving parts was examined and it was aimed to shorten the procurement time. Markov Chains are used to model production time and installation time. A numerical experiment was carried out to understand how optimal Additive Manufacturing (AM) is comparing to Conventional Manufacturing (CM). Looking at the results obtained, the setup time of the CM is longer (comparing to production time) so AM has proven to perform better than CM. Another recent study using Markov chains is the study by Hu et al. (2018), in which a short-term forecast of the precipitation of the Liusha River is projected, using rainfall data from the Menghai hydrological station from 1958 to 2016. The results show that the abundance foreseen in 2015 and 2016 is fully consistent with the real situation.

HMM was used by Rebagliati et al. (2015) to estimate euro and dollar prices. While making estimations, daily closing prices were used as data. Using the daily closing data from January 2, 2009 to December 31, 2010, Dollar and Euro values in the 6-month period from January 1, 2011 to June 30, 2011 were estimated.

Silva et al. (2010), used HMM to predict future crude oil price movements. As a result, they have issued future price trends. In their study, they aimed to predict medium-term price movements (20 to 30 days) instead of short-term movements. It is concluded that HMM is a good forecasting model for predicting oil price trends. It was proven that the proposed methodology can be a useful decision support tool for agencies participating in the crude oil market.

In the study by Khadr (2015), standard Rainfall Index in the short-medium term was used in developing HMM to predict drought. Model parameters were based on the values of precipitation series observed at 22 stations in the Nile River basin. The results show that the HMM provides a fairly good match between the values observed and estimated for the Standard Precipitation Index at various times. Therefore, it was concluded that the proposed model can be used as a suitable tool for drought management and early drought alert.

HMM and Artificial Neural Networks Model (ANN) was used by Hassan R. and Nath B. (2005) to estimate the stock prices of interrelated markets and the results obtained from the two were compared to find out which one is closer to the statistical realization. It was observed that the Mean Absolute Percentage Error (MAPE) values of the two methods were very close to each other. It was concluded that the method proposed by using HMM can be explained and has a solid statistical basis to estimate the stock price.

It has proved that with the use of HMM for the prediction of time series, accurate predictions can be achieved.

A new method based on HMM to predict earthquakes was developed and applied to basic shaking activity in Southern California and Western Nevada by Chambers et al. (2014). In the study, a method has been developed to predict possible earthquakes in the future by using data from February 1932 to July 1964. The estimates were then compared with the observed earthquake occurrence.

"Mass- flowering" is the name given to plants, mainly trees, to gather large quantities of seeds every few years. Tseng et al. (2020) proposed the HMM, which can be integrated to estimate annual birch pollen concentration using meteorological conditions affecting the stochastic process of “Mass- flowering” and flower formation. The Viterbi Algorithm gave the forecast results with an accuracy of 83.3% in the training period and 75.0% in the test period.

Can et al. (2013) estimated the frequency of earthquakes per year that may occur in Bilecik and its surroundings by using the HMM. Data obtained through the Earthquake Research Institute were used. By determining the hidden states by years, an analysis of the earthquake danger for the future was made.

Can and Öz (2009) conducted a study on mobile phone brand preference and the underlying reasons for the preference using the HMM. They created the model by benefiting the results of a questionnaire applied to 532 university students living in Istanbul. While making estimates, the first two of the three main problems in the HMM were used. The most preferred phone brand among the survey results was Nokia with 43.45%. It is concluded that Nokia and Sony-Ericsson brands are preferred because they have advanced features and Samsung brand is preferred because of price suitability.

A survey was by conducted Doğan and Göker (2010) on 1000 voters in Elazig in the March 29 Local Elections and the factors affecting the voters' preferences were analyzed. While family is found to be the most important factor in determining the political preferences, opinion leaders are concluded to be the second important factor. Devran (2003) argued that the political party leader was the most important factor in the choice of the political parties by voters depending on some public opinion polls he made. In the study by Çaha et al. (2002), it was found that the most important factors affecting the behavior of voters were the leader of the political party, the staff of the party and the political opinion. Çaha et al., also claim that voters who are not members of any political party make their party choices considering the policies produced by the political party. Mamipour and Jezeie (2015) used the Markov Switching Model to study the nonlinear properties of the three variables in the energy market for a decade. They examined the effect of gold and oil prices on the stock market. Gold, stock exchange and oil prices of Iran were used as data during the period of 2003 January - 2014 December. As a result of the research, consistent estimates of the effects of oil prices and gold prices on the stock market by using Markov models were reached. It was concluded that the effect of oil price on stock returns is positive and meaningful in the short term and negative in the long term. Yüksel and Akkoç (2016) in their study which was modeled with ANN determined the silver price, brent oil price, US dollar/EUR parity, EuroNext100 index, America Dow Jones index, 13-week maturity US bond interest rate and US CPI index as possible variables on the gold price. The actual values and the calculated values (Coefficient of determination (R^2), Root-mean-square deviation (RMSE), Mean Absolute Error (MAE), MAPE (%)) were compared in order to determine the performance of the model. As a result of the research, it was concluded that The Artificial Neural Networks Model can be used successfully in the estimation of gold prices and silver and oil prices were the main factors affecting gold price.

In the study of Rouhi, conducted with the Markov chains method (2019), which is one of the recent studies in the field of education, an estimation on the impact of the contraction in international initial registrations on the total number of students within the four year period after the study was made. The importance of the impact of different scenarios was measured by the t-test. An accuracy analysis is also provided based on real historical data compared to the estimated values provided by the model.

CHAPTER II

MARKOV CHAIN

The Markov analysis emerged in the early 20th century, when Russian mathematician Andrei Andreyevich Markov made the mathematical description of the Brownian movement which is the structure and behaviour of gas molecules in a closed box. The fundamentals of Markov chains are based on determining the future possibilities by using the possibilities of past and present activities. Markov analysis has been used in many different areas and has been used extensively to predict future events.

There are studies in many fields such as education (Alp, 2007; Gagne, 2015; Kıral et al., 2018, Rouhi, 2019), banking and finance (Fingleton, 1997; Betancourt, 1999; Öz and Erpolat, 2010; Büyüktatlı et al., 2013; İlarslan, 2014; Bairagi and Kakaty, 2015; Paksoy, 2017; Urrutia and Antonil, 2019), marketing (Arıtan and Akyüz, 2015; Şentürk and Alp, 2016; Çetin and Alp, 2016; Öztemiz and İplikçi, 2017; Kıral, 2018) with the Markov analysis method.

2.1. Stochastic Processes

The word Stochastic is of Greek origin and it means random. Stochastic processes are those processes whose behavior in general cannot be predicted completely. (Öztürk, 2004:117). The sequence of random variables bearing the time index (t) is called the stochastic process or time series. Stochastic process models include models based on the past values of an univariate stochastic process (Köse, 2014: 808).

The set containing all possible results of a random experiment is called **sample space** and it is indicated by Ω. Each subset of the sample space is called an event (Malliaris and Brock,1999). Stochastic process; $\Omega, \mathrm{F}, \mathrm{P}$ is the set of random variables with real values $\mathrm{X} = \{\mathrm{X_t}: \mathrm{t} \in \mathrm{T}\}$ on the probability space (Syski,1979). The stochastic process is the sum of random variables in state X during time t. If the state space has finite or countable infinite points, it is expressed as the discrete state-space; If not, it is expressed as a steady state-space (Cox and Miller, 2017:14).

The function $X\ (s, w)$ is called **d-dimensional** stochastic process if $\Omega, \mathrm{F}, \mathrm{P}$ is a probability space and $D \subset R^d$, where there is a random variable in Ω for each $s \in D$ space index constant. (Karapınar,2009:58).

If a stochastic process has the property of $E[|X(t)|] < \infty$for t ≥ 0 where $X = \{X(t), t \geq 0\}$, then the following equation will occur.

$$E[|X(t)|X(u), 0 \leq u \leq s] = X(s) \tag{1}$$

The meaning of this situation in the discrete time is that the following equation is realized. (Lyuu,2001:179)

$$E[|X_{n+1}|X_1, X_2, \dots, X_n] = X_n \tag{2}$$

X_n shows the current value as a result of n state. In the presence of Martingale property, $E[X_n] = E[X_1]$ equation occurs. Because the Martingale property is based on the assumption that the expected value of the next period is equal to the value in the current period (Wilmott,2013:120). In continuous time, $E[X_n] = E[X_0]$ equation occurs.

Stochastic processes can be classified according to different criteria as listed below:

i. According to the probability structure of the process
ii. Based on specific features of the process
iii. According to the problem and method used
iv. According to the applications of the process (Syski,1979:12)

While making classification procedures according to the probability structure of the process, the probability structure of the processes is taken into consideration. Stochastic processes are examined in four groups as Markov Processes, Martingales, Stationary Processes and Independent Incremental Processes (Protter,1990:20).

There are some points to be considered when classifying according to specific features of the process. Processes are characterized by specific features that Stochastic processes have. For example, Random Walks, Branching Processes, Regenerative Processes, Local Martingales, Gaussian Processes, Couchy Process, Bessel Process, Semi Markov Processes, Quasi Martingales are characteristics that can be classified according to each other.

While categorizing according to the problem and methods used, convergence problems, analysis of the behaviour of sampling functions, transition problems, properties related to distributions or transformations of processes can be used for categorization in terms of problem. In the stage of classification according to the methods used, different techniques such as Wiener-Hopf Technique, Stochastic Calculation, Functional Representation, Stochastic Approaches can be used. (Chung,1980; Williams,1979;Karatzas and Shreve,1987). During the classification procedures of stochastic processes according to application areas, even if the purpose of the research is the same, researches can be classified according to application areas such as operations research, basic sciences, economics, social sciences etc.

2.1.1. Brownian Motion and Wiener Process

The Brownian movement is defined as "movement that independently changes speed and direction". In 1828, Scottish scientist, Botanist Robert Brown observed that the dust of flowers in the water made irregular movements, and he called this movement the Brownian Movement (Karatzas and Shreve, 1987). He explained these irregular movements as random collisions of flower powders with the molecules of water. The state of the flower dust at the moment *t* is interpreted as w and the concept of stochastic process is interpreted as $B_t(w)$ (Oksendal, 1992:7). Brownian motion processes are processes that have a markovian feature and are independent incremental (Protter, 1990).

A real-valued stochastic process $W = \{W(t), t \geq 0\}$ is called Brownian motion if it satisfies the following conditions (Mishura and Shevchenko, 2017:24).

1. $W(0) = 0$,
2. The process $W(t)$ is continuous at point $t \geq 0$,
3. The process $W(t)$ is stationary and has an independent increase,
4. For any $0 \leq s < t$, the random variables $W(t) - W(s)$ have a zero distribution and a normal distribution with $\sigma^2{}_w = \sigma^2{}_{(t-s)}$ variance.

So, $W \sim N\ (0, \sigma^2{}_{(t-s)})$.

When the fourth feature was rebuilt together with the first feature; since W (0) = 0, the equation will be $W(t) = W(t) - W(0) \sim N\ (0,\ \sigma^2{}_{(t-0)}) = N\ (0,\ \sigma^2{}_t)$. When this equality is prsent, the Brownian movement is called the Wiener process (Ibe, 2013:260). The Standard Wiener process, which is a tool frequently used in financial applications, has been defined as a stochastic process consisting of single-layer and continuous normal random changes with a starting point W (0) = 0 (Brandimarte, 2006).

An exemplary standard Wiener process representation for one dimension is shown in Figure 1. In this example, it is seen that the Wiener process starts at the point W (0) = 0 and subsequently changes randomly as W (1) = 14, W (2) = 7, respectively (Yön, 2015).

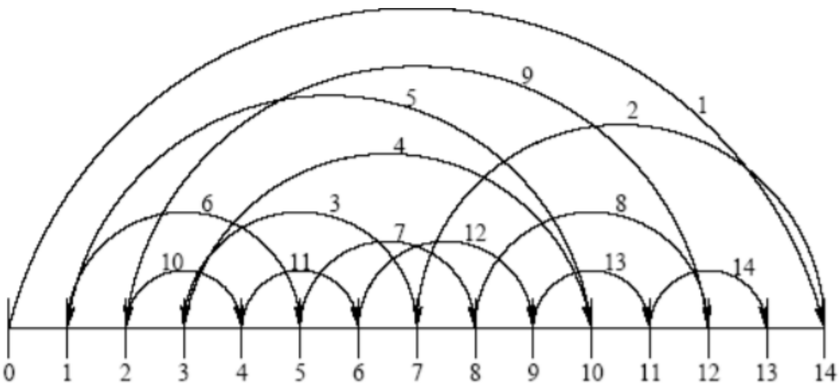

Figure 1. Standard Wiener process representation

Source: Yön, 2015:66

Symbolic representation of a multidimensional Wiener process is given in Figure 2.

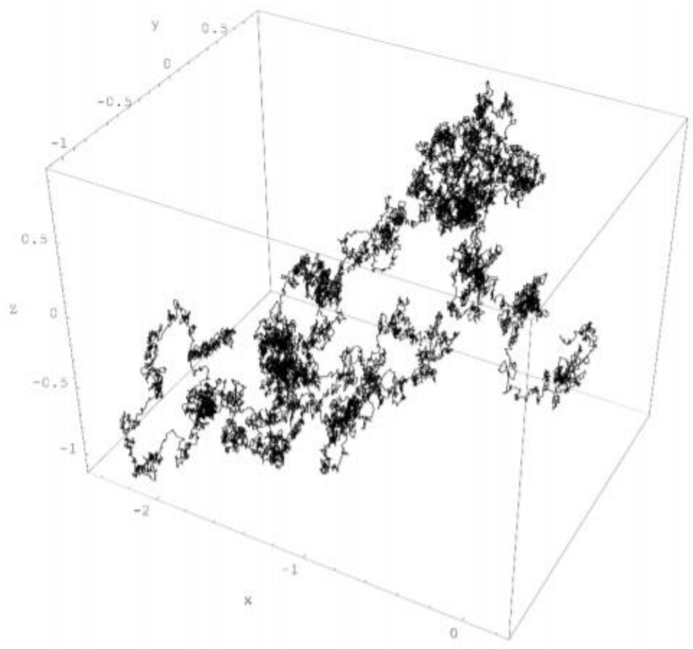

Figure 2. A multi-dimensional Wiener process representation

Source: Yön, 2015:66).

The standard normal random variable of z_i can be written as below within the scope of Brownian motion;

$$z_i = \frac{\big(B(t_i) - B(t_0)\big) - 0}{\sqrt{t_i - t_0}} = \frac{B(t_i)}{\sqrt{t_i}} \tag{3}$$

$$= B(t_i) = z_i\sqrt{t_i} \tag{3.a}$$

In this equation, $t_0 = 0$ and $B(0) = 0$. By making the necessary simplification, a vector can be created for $i = 0,1,2, \dots , N$.. Examplery Codes are given in Appendix 1 for the coding required to create Brownian motion through C ++ program.

i) $B(t)$ varies independently. The $B(t) - B(s)$ and B (u) - B (v) values are independent for the different $t > s \geq u > v \geq 0$ points.
ii) $B(t)$ shows homogeneous variation, B (t) - B (s) random variable does not depend on values t and s but only on values $t - s$.

Stochastic processes that fulfill the above two requirements for the Brownian movement are called the Lévy process (L (t)). Brown is the only Lévy process that has continuous movement. Although it is continuous, it is not a stochastic process that can be directly derived. Therefore, the representation of the differential expression of Brownian motion is used in the form of dB (t) or dW (t) instead of the derivative expression $\frac{dB(t)}{\mathrm{dt}}$ in the literature (Yön, 2015:67).

2.1.2. Stationary Markov Chains

Considering $X = \{X_n : n \geq O\}$ as a stochastic process;

i. If the distribution of $(X_1 > X_2, \dots X_n)$ and the distribution of $(X_{m+1} > X_{m+2}, \dots X_{m+n})$ for each value of n and m equals the same result, "absolutely stable"

ii. If $E\left[{X_n}^2\right] < \infty$, $E[X_n]$ is not dependent for each value of n and $E[X_n X_{n+m}]$ is dependent only on m, then the X process is called "second-order stationary" (Önalan, 1996;38-39)

The stationarity feature is independent of the probability rule of the stochastic process (Karr,1990;96). In this case, it can be said that one-dimensional distributions of a stationary process are all the same. So $P(X_n \leq x) = F(x)$ is not dependent on n.

If the average, variance and autocovariance of the variable in the time series containing stochastic process are constant, it is called stationary state. It refers to the convergence of the values in the time series to a number. If the stochastic process does not provide stability, it can be said that the behavior of the time series is valid only for the estimated period under study.

The set of data points $Y_1, Y_2 \dots, Y_t$ shows a special result of the combined probability distribution function P($Y_1, Y_2, \dots, Y_t$). If Y_t series are stationary;

The average of the series = $\mu_Y = E(Y_t)$
Variance of the series; = $\sigma^2 = Var(Y_t) = E[(Y_t - \mu_Y)^2]$
covariance for "k" delay = $\gamma_k = cov(Y_t, Y_{t+k}) = E[(Y_t - \mu_Y)(Y_{t+k} - \mu_Y)]$

$$P(Y_t, \dots, Y_{t+k}) = PY_{t+m}, \dots, Y_{t+k+m}) \quad (4)$$

$$P(Y_t) = P(Y_{t+m}) \quad (5)$$

2.1.3. Independently Increased Stochastic Process

Let $\{X(t), t \in T\}$ be a stochastic process. In order to provide the condition $t_1 < t_2 < \cdots < t_n$ in the set belonging to the parameter set T, where n is an arbitrary natural number, if the random variables $X(t_2) - X(t1), X(t_3) - X(t_2), \dots, X(t_n) - X(t_{n-1})$ are independent from each other, the case of $\{X(t), t \in T\}$ stochastic process is called **independent incremental stochastic process**. When the values are given in the formulation, it is given with the assumption that the smallest value has the t_1 element. Under the assumptions of $\{X(t), t \in T\}$ is an independent incremental stochastic process and the small element of T is t_0 and $X(t_0) = 0$, all finite dimensional distributions of this process, for each $s,t \in T$, $X(t) - X(s)$ is determined by the distribution random variable.

The probability function of the random vector $f_{X(t_1),\dots,X(t_n)}$ is obtained in;

$$\mathrm{X}(t_1) = x_1, X(t_2) = x_2, \dots, X(t_n) = x_n \Leftrightarrow X(t_1) \tag{6}$$

$$= x_1, X(t_2) - X(t_1) \tag{6.a}$$

$$= x_2 - x_1, \dots, X(t_n) - X(t_{n-1}) = x_n - x_{n-1} \tag{6.b}$$

$$fX(t_1, \dots, X(t_n)(x_1, \dots, x_n) \tag{7}$$

$$= fX(t_1), X(t_2) - X(t_1), \dots, X(t_n) - X(t_{n-1})(x_1, x_2 - x_1, \dots, x_n - x_{n-1}) \tag{7.a}$$

$$= fX(t_1)(x_1) fX(t_2) - X(t_1)(x_2 - x_1) \dots fX(t_n) - X(t_{n-1})(x_n - x_{n-1}) \tag{7.b}$$

Let $\{X(t), t \in T\}$ be a stochastic process. In order to provide the condition $t_1 < t_2 < \cdots < t_n$ in the set belonging to the parameter set T, where n is an arbitrary natural number, the random variables $X(t_2) - X(t1), X(t_3) - X(t_2), \dots, X(t_n) - X(t_{n-1})$ are independent from each other. In the case of $\{X(t), t \in T\}$ stochastic process is called **independent incremental stochastic process**. It is given with the assumption that the smallest value has the t_1 element while the values are given in the formulation. $\{X(t), t \in T\}$ is an independent incremental stochastic process, under the assumptions of the small element of T, t_0 and $X(t_0) = 0$, all finite dimensional distributions of this process, for each $s,t \in T$, $X(t) - X(s)$ random variable determined by the distribution.

The probability function of the random vector $f_{X(t_1),\dots,X(t_n)}$ is obtained in;

$$X(t_1) = x_1, X(t_2) = x_2, \dots, X(t_n) = x_n \Leftrightarrow X(t_1) \tag{8}$$

$$= x_1, X(t_2) - X(t_1) \tag{8.a}$$

$$= x_2 - x_1, \dots, X(t_n) - X(t_{n-1}) = x_n - x_{n-1} \tag{8.b}$$

$$fX(t_1, \dots, X(t_n)(x_1, \dots, x_n) \tag{9}$$

$$= fX(t_1), X(t_2) - X(t_1), \ldots, X(t_n) - X(t_{n-1})(x_1, x_2 - x_1, .., x_n - x_{n-1})$$

$$= fX(t_1)(x_1) fX(t_2) - X(t_1)(x_2 - x_1) \ldots fX(t_n) - X(t_{n-1})(x_n - x_{n-1}) \quad (9.a)$$

2.1.4. Stationary Incremental Stochastic Process

$\{X(t), t \in T\}$ is a stochastic process. If the distribution of the $X_{t+h} - X_t$ random variables for each $h > 0$ 0 and every $(t + h) \in T$ depends only on h (independent of t), this stochastic process is called a **stationary incremental process**. Stationary processes often occur in operational research models where a process that has changed over a long period of time is defined (Cinemre, 2003;485). The sets of data points $Y_1, Y_2 \ldots, Y_t$, show a special result of the compound probability distribution function $P(Y_1, Y_2, \ldots, Y_t)$. The Y_{t+1}'s conditional probability distribution function is shown as $P(Y_{t+1} | Y_1, \ldots, Y_t)$. Under the assumption that the Y_t series is stationary, the probability distribution function is shown as;

$$P(Y_t, \ldots, Y_{t+k}) = P(Y_{t+m}, \ldots, Y_{t+k+m}), \qquad P(Y_t) = P(Y_{t+m}) \quad (10)$$

2.1.5. Continuous-Time Stochastic Process

In continuous state stochastic processes, the state of the system can be observed at any time. For example, the number of customers existing in the market in any time period can be considered as a continuous time stochastic process. Under the assumption that t is a real number and constantly receives value, the total number of customers in the market is observed with X_t after the market is opened. Considering t as the time index, the variable X_{t_1} is considered as the state of the process at time t_1. Provided that $t_0 < t_1$, the state of the process at the moment t_1 depends only on the state of the process at the moment t_0, ie X_{t_0}. X_t is considered a discrete random variable. Thus, it is called continuous-time stochastic processes with discrete status. For each t value that satisfies the condition $t_0 < t_1 < \cdots < t_{n-1} < t_n$, where $S = \{x_0, x_{1,} x_2, \ldots, x_n\}$ is a state space, we can say that the process shows the markov feature if $P\left(X_{t_n} = x_n \middle| x_{n-1}, \ldots, X_{t_0} = x_0\right) = P(X_{t_n} = x_n | X_{t_{n-1}} = x_{n-1})$ equation is realized.

The only difference is that the t time index does not have to be an integer number. It takes the name of a continuous-time stochastic process since it does not have to be an integer number and any time period can be mentioned.

2.1.6. Markov Process

The fact that the future state of the stochastic process depends only on its current state regardless of the past is called the Markov feature (Borodin, 2017:43). That is, the $X_{(t_{n+1})}$ state depends only on the $X_{(t_n)}$state and it is completely independent of $X_{(t_{n-1})}$, $X_{(t_{n-2})}$, …, $X_{(t_0)}$ states. This state can be expressed as Markov dependency (Mathai and Haubold, 2008:258). The Markov process is a stochastic process that states that all the information about the future is available in today's conditions. It is expressed as follows when a stochastic process defined as $X = \{X(t), t \geq 0\}$is a Markov process (Lyuu, 2001:178).

$$P[X(t) \leq x | X(u), 0 \leq u \leq s] = P[X(t) \leq x | X(s)] \quad (11)$$

In the above definition, under the assumption of $s < t$, $X(t)$ shows the different random variables that occur for each time, and X represents the realized values.

Stochastic process;

$$P[X(t_{n+1}) = j \mid X(t_n) = i] = p_{ij} \quad (12)$$

If it satisfies its equation under the condition of n ≥ 0, the process is called the Markov process (Durrett, 2016:1). The probability of p_{ij} in the equation is called the probability of transition. While the system is in i at time t_n, the probability that the system will be in j at time $t_{(n+1)}$ indicates the probability of transition (Can, 2015:621).

If the conditional distribution of the k time points in the index set of the temporal $\{X(s), s \in R\}$ stochastic process by selecting $d = 1$ for any set of $s_1 < s_2 < \cdots < s_k$ depends only on the value of $X(s_{k-1})$, then {X (s), s∈R} stochastic process is called markov process.

For the numbers $x_1, x_2, \ldots, x_k$;

$$P(X(s_k) = x_k | X(s_{k-1}) = x_{k-1}) = P(X(s_k) = x_k | X(s_{k-1}) = x_{k-1}) \quad (13)$$

and this equation is called the Markov property. If the Markov process is handled intermittently by fixing the time values, it is specifically named as the Markov chain (Karapınar, 2009; 63).

2.2. Definition of Markov Chains

If the Markov process is defined at discrete time and if X (t) is countable or if it takes a finite number of integer values, the resulting stochastic process is called the Markov Chain (Wang, 2009:7). Markov Chains can be summarized as the calculation of determining the future state, finding long-term possibilities and revealing the equilibrium state with the help of knowing the current and past state related to the state (Markov Biography). The essence of the Markov analysis is based on Andrei Andreyevich Markov's mathematical description, in the early 20th century, of the Brownian movement which is defined as the structure and behavior of gas molecules in a closed box (Öztürk,2004;645-646). After this description, Markov analysis has been used in many different areas and has been used extensively to predict future events.

The Markov chains system is an analysis that includes the probability of future states using only existing possibilities, independent of past events (Alp and Öz, 2009: 39). The system is called to be dynamic if changes related to the system define the state of the system in at least two different moments. Most systems in daily life are dynamic systems, that is, they are systems that change over time (Cinemre, 2003: 48).

This study is based on the assumption that the election results of a country in the current period are independent from the previous election results. The political party, which is expected to be elected in the future, depends only on the election result that took place in the first previous period and thus it carries the Markov feature.

The stochastic process that satisfies the following conditions on the countable set S for $X = \{X_n : n \geq 0\}$, $\forall\, n \geq 0$ and $\forall\, i\ ve\ j \in S$ is called the Markov chain.

In the stochastic process, the value of each random variable is called the state (s), while the changes between the states of the system are expressed as transition (Winston, 2004; 931).

$$P\{X_{n+1} = j|X_0, X_1, \dots, X_n\} = P\{X_{n+1} = j|X_n\} \tag{14}$$

The above inequality is the markov feature. At any time n, while it is known to be in the X_n state, the next X_{n+1} state can be expressed as conditionally independent from $X_0, X_1, \dots, X_{n-1}$ past states. In other words, next the state depends on the current state (Farg and Khalil, 2014:184).

$$P\{X_{n+1} = j|X_n = i\} = p_{ij} \tag{15}$$

The second inequality given above shows that transition probabilities are independent of n (Serfozo, 2009: 2-3). p_{ij} is the probability of transition and indicates the probability of transition from state i to j on the matrix. Classical probability rules apply. $\forall\ i$ satisfies the condition $\sum p_{ij} = 1$ for $, j \in S$ and is the transition probability matrix of the $P = [p_{ij}]$ markov chain.

It is expressed as;

$$\begin{aligned} P\{S_{t+1} = j|S_t = i_t, S_{t-1} = i_{t-1}, S_1 = i_1, S_0 = i_0\} \\ = P\{S_{t+1} = j|S_t = i_t\} = p_{ij} \end{aligned} \tag{16}$$

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} & \cdots & P_{1n} \\ P_{21} & P_{22} & P_{23} & \cdots & P_{2n} \\ P_{31} & P_{32} & P_{33} & \cdots & P_{3n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ P_{n1} & P_{n2} & P_{n3} & \cdots & P_{nn} \end{bmatrix} \tag{17}$$

The transition probability matrix is as seen in the matrix above. It is a $n * n$ square matrix showing the transition from one state to another for n states. It is possible to calculate the transition probability matrix elements with the following equation.

$$p_{ij} = {}^{n_{ij}}/_{\sum n_i} \tag{18}$$

As $n = 0, 1, 2, 3, ...$,the probability distribution matrix of the next period is found with the formula;

$Q_{n+1} = Q_n P$ (where $n = 0, 1, 2, 3, ...$) (Grimshaw and Alexander, 2011: 268). As n increases, Q_{n+1} equilibrium (stationary) matrix approaches to Q and is found as;

$$lim Q_{n+1} = Q \tag{19}$$

2.2.1. Classification of States in Markov Chains

In case of a transition from state i to state j, state j is said to be accessible for state i, and n means $p_{ij}(n) > 0$ for $n > 0$ to indicate the number of steps (Ibe, 2013:62). If the transition from state i to j is also possible from state i to j, it is called communicative states (Ching, et al., 2013:7). Markov chains with communicative states are called irreducible Markov chains (Privault, 2013:118). f_i = 1 is shown to denote the probability that it will return from any i state to i state in a Markov chain. In case of f_i < 1, transitive state is in question (Ching, et al., 2013:8).

All Markov chains that have finite and irreducible properties can be called to be repetitive (Lefebvre, 2007:89). In a chain, if it is not possible for the process to leave the state that it came at, it is called the absorber case (Ibe, 2013:64).

If the chain starting from a state returns to the same state in multiples of time ($t, 2t, 3t, ...$) which can be expressed as t, the condition is called periodic, otherwise it is aperiodic (Öz, 2009:23). Within the definitions given above, if the states in a chain are repeated, aperiodic and communicative, then they are referred to as ergodic states (Winston, 1994:974).

2.2.2. Ergodic (Fully Connected) Markov Chains

Markov chains which are created under the possibility of transition from one state to all other states is called an ergodic chain.There is no obligation to switch from one state to another in one step within the ergodic chain, only the transition is concerned, even if the transition from one state to another is not direct (Öz, 2009:29).

If in the P transition matrix, transition from all states to another state can be achieved this chain is called the ergodic markov chain. Markov process should not contain absorbent condition in order to display ergodic chain feature. Markov chains have ergodic properties if they consist of repeated, non-periodic and periodic states in all their states

(Winston, 2004; 933). Markov chains, which have an ergonomic feature, are a process that cannot be minimized.

If the Markov chain is nonshrinkable, positive, repeated and aperiodic it is called the ergodic Markov chain (Çandır, 2015; 61). The states where the transition from any state to all other states is possible is called “the ergodic markov chain”. If the vector $v = (v_1, v_2, v_3, \dots, v_m)$ does not have a negative component and $\sum_{i=1}^{m} v_i = 1$, the vector v is called the probability vector (Cerit and Yüksel, 1993). As n grows, the P_{ij} value approaches to a fixed number, and each ${v_i}^n$ probability vector tends to be equal for all values of i.

$$[v_1 v_2 v_3 \dots v_m]P = [v_1 v_2 v_3 \dots v_m] \tag{20}$$

$$\lim_{n\to\infty} {P_{ij}}^n = v_j \; v_j > 0, \qquad 1 \le j \le r \tag{21}$$

The Ergodic markov chain has a single probability distribution for the transition probability matrix and is shown in the formula above (Koralov and Sinai, 2007).

2.2.3. Temporary Status

Let us assume that there are two states, i and j, on the stochastic process that we examined in the Markov chain. The first case represents i and the second case represents j. It can be said that if the transition from the first state i to the second state j is possible, while the transition from the second state j to the first state i is not possible, the first state i. can be called a temporary state. In other words, if the current state of the system is the first state, it is possible to reach the second state, whereas if the current state is the second state, the transition to the first state cannot be achieved.

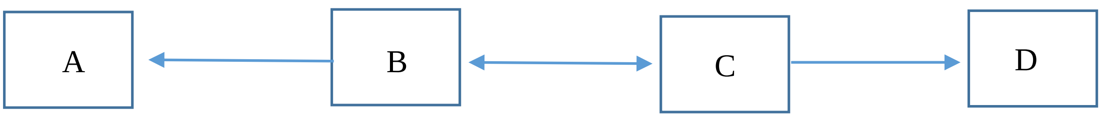

Figure 3. Four-State Markov Chain

Source: Kılıç and Çam, 2017; 5

The direction of the arrows in Figure 3 gives information about the transience states in order to be an example of temporary states. It is called a temporary state because bilateral switching between state B and state C is possible. While it is possible to switch from B and C to A and D, it is not possible to switch from A and D to C and B states (Kılıç and Çam, 2017; 5). Therefore, it can be said that while B and C are temporary states, A and D are not. Non-transient states are called recurring (repeating) states. Assuming that for each state i, p_i is likely to remain in state i then p_i=1 will be a recurring state. If the probability is less than 1, the state will be temporary. It can be said that the process will probably never return to the current state in temporary cases, whereas in repeated cases the process will constantly return to the current state.

$$\sum_{n=1}^{\infty} P^n{}_{ii} = \infty$$ i is expressed as a recurring state,

$$\sum_{n=1}^{\infty} P^n{}_{ii} < \infty$$ i is expressed as a temporary state.

Based on these statements, it can be said that all the states finite and nonshrinkable of the Markov Chains are recurring states.

2.2.4. Absorbing Markov Chains

In the Markov process, while transitioning from one state to another possible, in some cases it is not possible to switch to the other state (so $P_{ii} = 1, P_{ij} = 0$, j≠i). When entering the absorptive state, it can never be possible to exit from that state, and to skip to another state, only remaining constant in the same state is possible(Grinstead C. M., Snell J.L., 1997). Markov chains are called absorber Markov chains if a Markov chain has at least one absorber state and it is possible to switch from all non-absorber states to at least one absorber state (Shamblin and Stevens, 1974; 66). It can be said that Markov Chains containing absorbent processes will be absorbed at the end of a certain process. So the probability of being absorbed is equal to 1. When the Markov process reaches the state of being absorbed, it can not get out of it again. In other words, in the transition probability matrix;

$$P_{ij} = \begin{cases} 0 & \text{if j} \neq \text{i} \\ 1 & \text{if j} = \text{i} \end{cases} \tag{22}$$

If the chain containing these elements are Absorbing Markov chains (Can, 2015:672). In the absorbing markov chain analysis, the P transition matrix takes the form below.

$$\boldsymbol{P} = \begin{bmatrix} I & 0 \\ R & Q \end{bmatrix} \tag{23}$$

$\boldsymbol{I}$: The probability of transition from absorbing states to absorbing states is the unit matrix.

$\mathbf{0}$: Possibility of transition from absorbing to non-absorbing (Transition is impossible.)

$\boldsymbol{R}$**:** Probability of transition from non-absorbing to absorbing.

$\boldsymbol{Q}$: It is the possibility of transition from non-absorbing to non-absoring.

From the $E = (I - Q)^{-1}$ equation, the basic matrix (T) of the Markov chain is found. So, before the system goes into a absorbing state, an expression (T), indicating the average time that it will remain in any temporary state is found (Ravindran R. A. et al, 1987).

$$T = (I - Q)^{-1} \tag{24}$$

While the system is initially in i state, the average number of periods spent in each j state before absorbing is the (i, j) th element of the basic matrix (Alp S., 2007:7-8).

k = The number of non-absorbing steps of the absorber Markov chain,

T= (k × k) dimensional Basic matrix,

C = Assuming that there is a (k × 1) dimensional column vector with elements 1, the number of steps required until the process is absorbed. They are components of the EC vector.

If the probability of the process being absorbed in a certain absorbent condition is indicated by " B ", it is expressed as $B = (I - Q)^{-1}$ $*$R or $B = T * R$ (Çelik, 2013;31).

$$P\begin{bmatrix} 0,3 & 0,5 & 0,2 \\ 0,6 & 0,2 & 0,2 \\ 0 & 0 & 1 \end{bmatrix} \quad (25)$$

There is a transition from the first and second states to other states by looking at the P transition probability matrix. However, when the third state is achieved, it is only possible to stay in the third state.So the third state is said to be the absorbing state.

While the system containing the absorbing state is in the state of i, which is transient at the beginning of the process, the average number of periods spent in each j state before being absorbed is the (i, j)th element of the basic matrix, that is, the $(I - Q)^{-1}$ matrix. The average time spent in the case of i, which is temporary before the system is absorbed, is equal to the sum of the first line of the basic matrix. When the system is initially in the i state, the probability of going to j, which is the state that eventually absorbs, is $(I - Q)^{-1}$. It is the (i, j)th element of the matrix R (Alp, 2007;7-8).

2.2.5. Periodic Markov Chains

The period of the $x \in E$ state is defined as:

$$d(x) = GCD\,\{n \geq 1 | P(X_n = x | X_0 = x) > 0\} \quad (26)$$

$$for\ \forall n \geq 1,\ if\ P(X_n = x | X_0 = x) = 0,\ d(x) = \infty \quad (26.a)$$

If $d(x) = 1$, then x is aperiodic. When starting from a periodic state, the same state can be reached again with a finite number of steps (Çelik, 2013;48).

$if\ i \leftrightsquigarrow j,\ d(i) = d(j)$, in case j is periodic and period is d, j state can only be returned in steps $d, 2d, 3d,$ .... A process that was initially assumed to be in j status may return to j status at all other return times that may occur. If we indicate this return time as n, then $n \in \{0, d, 2d, \dots\}$, then $P^n(j, j) = P_j\{X_n = j\} > 0$ (Çelik, 2013;48).

2.2.6. Probability of Equilibrium in Markov Chains

In the long term, after a certain trial period, the expected values of the states can be reached by making use of the. Benefiting the equilibrium, comments can be made about the future status of the process. In some systems, it is seen that the state probability vector no longer changes after a certain moment (Turban and Meredith, 1998).

This state, which enables long-term analysis of the system, is called equilibrium state and mathematically the equation below is obtained:

$$\pi_1 = \pi_1 P_{11} + \pi_2 P_{21} + \cdots + \pi_n P_{n1} \tag{27}$$

$$\pi_2 = \pi_1 P_{12} + \pi_2 P_{22} + \cdots + \pi_n P_{n2} \tag{27.a}$$

$$\pi_n = \pi_1 P_{1n} + \pi_2 P_{2n} + \cdots + \pi_n P_{nn} \tag{27.b}$$

Given the transition matrix in one step and taking into account the total probability condition ($\pi_1 + \pi_2 + \cdots + \pi_n = 1$), the system of equation probability vector π for equilibrium state is obtained by solving the above equation system (Ross et al, 1996). Each π_i, $i = 1,2,\dots,n$ value in this vector gives the important information on the percentage of time the system is found in the long term in the ith state (Aytemiz and Şengönül, 2004;35).

CHATER III

HIDDEN MARKOV CHAINS

The Hidden Markov Models (HMM) are a stochastic processes and they are extension of the Markov Models. It was developed by a research conducted under the leadership of , L.E. Baum and Petrie in the 1960s and introduced as "probabilistic functions of finite-state Markov chains". HMM is a stochastic model whose process is modeled as a series of states that cannot be observed. Each observation belongs to a state, and the next state for the next observation is determined by the product of the multiplication of transition between the two states and the probability of the next observation of the next state. As in the discrete markov model in HMM, a state sequence is not observed. The state sequence must be derived from the observation sequence. Eventhough many different sets of states that have produced an array of observations may be present, the probability of each of these state sequences is different. The model consists of initial state probabilities, transition probabilities between states, and observation probabilities of a state. When the states of the system cannot be observed, it is possible that solutions can be found for stochastic modeling problems using HMM. In addition to many fields such as speech recognition (Rabiner, 1989; Bridle, 1990; Yang and Wang, 1990; Brugnara, et al., 1993; Chien and Wang, 1997; Nwe, et al., 2003; Najkar, et al., 2010; Vimala and Radha, 2012; Hoesen et al., 2016), studies on HMM are done on fields like, character recognition and machine translation(Agazzi and Kuo, 1993; Bose and Kuo, 1994; Elms and Illingworth, 1995; Kim, et al., 1998; Chan, 2002; Premaratne, et al., 2006; Al-Muhtaseb, et al., 2008; Fischer, et al., 2012; Ahmad, Mahmoud and Fink, 2016), biology / biochemistry(Baldi, et al., 1996; Burge and Karlin, 1998; Krogh, et al., 2001; Abecasis and Wigginton, 2005; Bidargaddi, et al., 2008; Krammer, et al., 2009; Larson, et al., 2013; Cheng and Mailun, 2015; Kamal, et al., 2017), , neurology (Rainer and Miller, 2000; Otterpohl, et al., 2000; Cassidy and Brown, 2002; Herbst, et al., 2008; Sukkar, et al., 2011; Seyhan, et al., 2013; Shankle, et al., 2016), geology (Thyer and Kuczera, 2003; Aspinall, et al., 2006; Beyreuther,et al., 2008; Zhang, et al., 2012; Charantonis, et al., 2015; Kwon, et al., 2017), economy (Chib, 1996; Chopin and Pelgrin, 2004; Wang and Alba, 2006; Korolkiewicz and Elliott, 2008; Erlwein, et al., 2010; Silva, et al., 2010; Hocaoglu and Karanfil, 2011; Date, et al., 2013; Yılmaz and Can, 2016; Hou, 2017), finance (Elliott, et al., 1998; Thomas, et al., 2002; Christensen, et al., 2004; Rossi and Gallo, 2006; Lin, et al., 2009; Zhao, 2011; Langrock, et al., 2012; Maheu and Yang, 2016) as well as studies in social sciences. Instead of the assumption of independence in HMM, it can be assumed that there is a relation of causality between the given examples. HMM is a discrete timed, finite-stated, stochastic model based on a homogeneous markov chain.

In the Markov model, the state can be observed by the observer, that is the reason why the probability of transition between states consists of a single parameter. In HMM, states cannot be directly observed, but outputs related to states can be observed. Each state has a probability distribution on possible output markers (Tuyen, 2013).

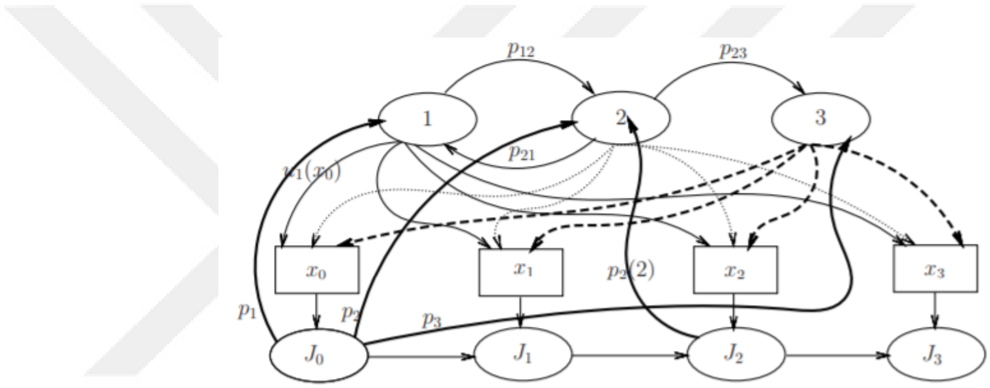

Figure 4. Representation of Hidden Markov Models
Source: Tuyen L.T., 2013

J_i: states,

p_{ij}: transition possibilities,

x_t: probable observations,

u_i (x_t): output probabilities.

With the assumption that the data is distributed independently and similarly, the data $D = \{x_1, x_2, \dots, x_N\}$ means that the random variable is sampled from x.

$$p(D \backslash M) = \prod_{n=1}^{N} p(X_n) \tag{28}$$

HMM; states are defined in terms of observations and probabilities. These are as follows:

N = Number of states in the model

M = Number of observations

T = Length of the observation sequence

V = $\{V_1, V_2, \ldots, V_M\}$ set of different possible observations

S = $\{S_i\}$, S_i = P (S_t = i), system's the initial probability will be in "i" state

A = $\{a_{ij}\}$, a_{ij} = P (S_{t+1} = j | S_t = i), probability that the system will be in j state at time t + 1 if the system is in i state at time t.

B = {bj (k)}, bj (k) = P (v_k, at t time | in S_t = j), if the system is in j state, the probability of observation will be v_k.

O_t, indicates the observation symbol at time t.

$\lambda = (A, B, \pi)$ it is a compact display used to show the hidden markov model (Gani et al, 2009).

Three main problems were offered by Rabiner (1989) for HMM to be useful in real-world applications. These are;

Problem 1: Given the observation sequence ($O = O_1, O_2, \ldots, O_t$) and model parameter λ=(P,B, π) in the hidden markov model, how can we effectively calculate the probability P (O | λ) of the observation sequence? Blunsom (2004) calls Problem1 the Evaluation Problem. It is about how to calculate the probability of producing the observation sequence by the model within the given information. $O = O_1, O_2, \ldots, O_t$ indicates the probability of the observation sequence. In other words, for the model and series of observations in question, it is about how to calculate the probability of the observed series that will be produced by the model. The solution of the problem, which can be called as finding the probability of occurrence of an observation sequence, is used with the Forward algorithm. The solution of the evaluation problem gives the value of the $\mathcal{L}(\theta; Y^{(T)})$ likelihood function of the hidden markov model, which has m states. The value obtained is interpreted and it determines how much the model and observations match. Regarding the motion of the likelihood value $\mathcal{L}$, it can be said that it is directly proportional to the consistency of the observations with the model. As the likelihood value increases, the consistency of the observations with the model increases. When deciding on the number of hidden states of the model, the solution of the problem will be provided by selecting the observation that best fits the model.

$$\mathcal{L}\left(\theta; Y^{(T)}\right) = P(Y^T \mid \theta) \tag{29}$$

$$= \sum_{All\ X^{(T)}} P\left(Y^{(T)}, X^{(T)} \middle| \theta\right) \tag{29.a}$$

$$= \sum_{All\ X^{(T)}} P(Y^{(T)} \left| X^{(T)}, \theta\right) P\left(X^{(T)} \middle| \theta\right) \tag{29.b}$$

The probability of the $X^{(T)}$ state sequence;

$$P\left(X^{(T)} \middle| \theta\right) = \pi_{x_1}\rho_{x_1x_2}\rho_{x_2x_3}\rho_{x_3x_4} \cdots \rho_{x_{T-2}x_{T-1}}\rho_{x_{T-1}x_T} \tag{30}$$

In the condition that the $X^{(T)}$ sequence is known and under the assumption of conditional independence of the observations, the probability of the observation sequence $Y^{(T)}$ is calculated as;

$$P\left(Y^{(T)} \middle| X^{(T)}, \theta\right) = \prod_{t=1}^{T} P(Y_t \mid X_t, \theta)$$
$$= b_{x_1}(Y_1)b_{x_2}(Y_2)b_{x_3}(Y_3) \ldots b_{x_{T-1}}(Y_{T-1})b_{x_T}(Y_T) \tag{31}$$

Equities are solved jointly and

$$\mathcal{L}\left(\theta; Y^{(T)}\right)$$
$$= \sum_{All\ X^{(T)}} \pi_{x_1}b_{x_1}(Y_1)\rho_{x_1x_2}b_{x_2}(Y_2)\rho_{x_2x_3}b_{x_3}(Y_3) \ldots b_{x_{T-1}}(Y_{T-1})\rho_{x_{T-1}x_T}b_{x_T}(Y_T) \tag{32}$$

equation is obtained. Assuming that the system is initially in probability π_{x_1} and X_1 state, Y_1 observation can be generated with probability $b_{x_1}(Y_1)$.

As it passes from the first time(t=1) to the second time (t=2), the system has the transition probability $\rho_{x_1x_2}$, and it changes from $X_1$to X_2. When it goes into X_2 state, probability $b_{x_2}(Y_2)$ and Y_2 observation are generated. When transition from t = 2 to t = 3, the system has the transition probability $\rho_{x_2x_3}$ and goes from X_2 to X_3. When it goes to the X_3 state, probability $b_{x_3}(Y_3)$ and Y_3 observation are generated. This cycle continues from the X_{T-1}state to the X_T state with the transition probability $a_{x_{T-1}x_T}$, until the Y_T observation is produced with the probability $b_{x_T}(Y_T)$. In order to calculate the likelihood value directly with the given formulation, it is necessary to perform $(2T-1)m^T$ multiplications and (m^T-1) addition operations (Ergün and Can, 2016;53-54).

Problem 2: Netzer et al. (2008) named the second problem as the coding problem. Considering λ = (P, B, π), it answers the question of how to select a series of states ($Q = q_1, q_2, \dots, q_t$) that can best explain observation. In other words, it is the problem that the hidden part of the model is tried to be revealed.When an observation sequence is given, the solution of the problem, which is summarized as finding the state sequence with the highest probability of obtaining this observation sequence, is used with the Viterbi algorithm.

Problem 3: The third problem is generally referred to as an education(learning) problem in the literature It searches an answer to the question of how to adjust the model parameters λ = (P, B, π) in order to to maximize the probability of P (O┤ | □). In other words, the problem is that the model parameters are tried to be optimized in order to best define how a particular set of observations occur (Semerci, 2006). The solution of the problem, which can be summarized as obtaining model parameters through a data set, is used with the Forward-Backward algorithm, Expectation Maximization or BaumWelch algorithm.

There are three basic algorithms in Hidden Markov Model: Forward Algorithm, Viterbi Algorithm and Baum-Welsch Algorithm.

3.1. Forward Algorithm

It is an algorithm to find the probability of producing the observation using the Hidden Markov Model. It is used to determine the order of the hidden states in the model. The Forward Algorithm is calculated by summing up the probabilities of all sequential states that may arise.

The forward direction variable is shown as $\alpha_t(i)$.

$$\alpha_t(i) = P(O_1, O_2, \dots, O_t, q_t = S_i|\lambda) \tag{33}$$

It refers to the λ model given in the formula. It shows the probability of the partial observation sequence of the system $O_1, O_2, \dots, O_t$ in the case of S_i at time t. An inductive method is used when solving the forward algorithm. First of all, it starts with giving the initial value,

$$\alpha_t(i) = P(O_1, q_1 = S_i|\ \lambda) = P(O_1|q_1 = S_i, \lambda)P(q_1 = S_i|\lambda) \tag{34}$$

$$\alpha_t(i) = \pi_i b_i(O_1), \qquad t = 1, \qquad 1 \le i \le N \tag{35}$$

Then repetition is done,

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j(O_{t+1}), \quad 1 \le t \le T-1, \qquad 1 \le j \le N \tag{36}$$

Finally, the desired P (O | λ) account,

$$P(O|\lambda) = \sum_{i=1}^{N} P(O, q_t = S_i|\lambda) = \sum_{i=1}^{N} \alpha_T(i) \tag{37}$$

$$\alpha_T(i) = P(O_1 O_2 \dots O_T, q_T = S_i|\lambda) \tag{37.a}$$

$\alpha_T(i)$ is reached by the sum of the last forward algorithm variables. (Can and Öz, 2009;5).

3.2. Viterbi Algorithm

It is an algorithm that aims to reveal the most probable hidden state that will cause the probability of observation sequence(O). Instead of collecting all possibilities in the Viterbi algorithm, the best match with the vector is chosen from each state sequence. It is an optimal solution that is achieved in a repetitive manner.

$$\delta_t(i) = \max_{q_1,q_2,\dots,q_{t-1}} P[q_1 q_2 \dots q_t = i, O_1 O_2 \dots O_t|\lambda] \tag{38}$$

Considering the given observation sequence (O=$\{O_1, O_2, \dots, O_t\}$), the expression "$\delta_t(i)$" is defined to find the single case sequence ($Q = \{q_1, q_2, \dots q_T\}$) that best matches. This statement shows the highest probability until t. At time t, the S_i state is reached.

$$\delta_{t+1}(j) = \max_i \delta_t(i)a_{ij}]b_j(O_{t+1}) \tag{39}$$

The above formulation must be repeated for each t and j so that we can reach the true value of the state sequence (Can and Öz, 2009;6).

Steps;

i) $\delta_1(i) = \pi_i b_i(O_1), \quad 1 \le i \le N$

$\Psi_1(i) = 0$

ii) $\delta_t(j) = \max_{1\le i\le N}\left[\delta_{t-1}(i)a_{ij}\right]b_j(O_t),\ 2 \le t \le T, \quad 1 \le j \le N$

$\Psi_t(j) = \arg\max_{1\le i\le N}\left[\delta_{t-1}(i)a_{ij}\right], \quad 2 \le t \le T, \quad 1 \le j \le N$

iii) $P^* = \max_{1\le i\le N}[\delta_T(i)]$

${q^*}_T = \arg\max_{1\le i\le N}[\delta_T(i)]$

iv) ${q^*}_t = \Psi_{t+1}\left({q^*}_{t+1}\right), \quad T = T-1, T-2, \dots, 1$

3.3. Baum-Welsch Algorithm

Baum-Welch Algorithm is used to solve the third problem. It is a maximization method that is used repeatedly using probabilities of forward-reverse direction variables. While reaching the solution in the algorithm, the initial values of P, π, π are used. Using the existing model, the process is repeated until the practice set generates all new possibilities. It is used to find the order of the states in the model. The possibilities of all the sequences that may arise are summed up.

Steps;

i) At t = 1, the first state estimate for the s_i state is $\bar{\pi} = \gamma_1(i)$.

ii) The initial values of $\overline{p_{ij}}$ and $\overline{\emptyset_j}(k)$ estimates are found.

iii) By collecting $\overline{p_{ij}}$ and $\overline{\emptyset_j}(k)$ values, the current model ($\lambda= P, \emptyset, \pi$) is reached. New iterations are used as $\bar{\lambda}= (\bar{P}, \bar{\emptyset}, \bar{\pi})$.

iv) Assuming that the predefined start value is δ, the process stops when $P[O|\bar{\lambda}] - P[O|\lambda] < \delta$, that is, when the model approaches the old model. All possibilities that may arise are obtained (Ayaz and Alp, 2018: 209).

Emission Matrix

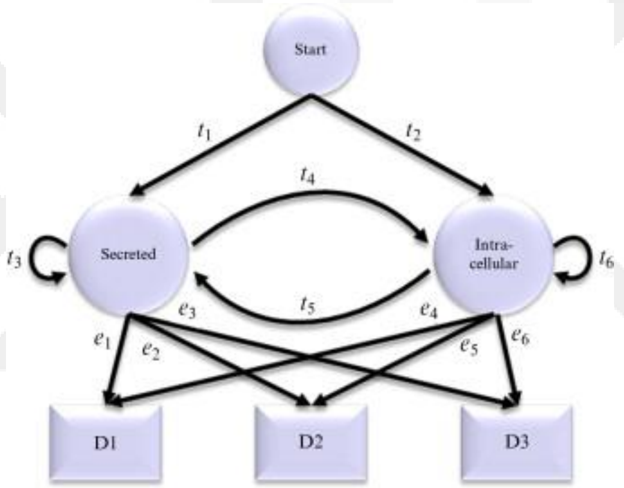

Figure 5. Hidden Markov Display

Transitions from states to other states are driven by a range of transitions and emission possibilities. Figure 5 shows a simple hidden markov model established to determine whether a state has occurred based on the D1-D3 domains sequence. Variables T1 - T6 show transition possibilities, while E1 - E6 show emission possibilities. The transition probability is the probability of moving from one state to another through linked paths, and the emission probability is the probability that a particular symbol will spread in a state. The probability of any sequence given in the model is calculated by multiplying the emission and transition possibilities of the transitions between states. An algorithm known as the Viterbi algorithm is known to provide the most suitable sequence of states for many purposes (Forney, 1973).

CHAPTER IV

APPLICATIONS

4.1. Prediction of Voter Preferences Using Markov Analysis

In this study, the participants were asked questions about the party they voted for in the general (parliamentary) elections of June 24, 2018, and which party they intend to vote in the next general election, and the transition probability matrix was determined by using this data.

From this point of view, the direction of the voters' party preferences for the next and future elections were tried to be predicted. This research was carried out exclusively in Adana province due to the limitations. The sample size representing the voter universe in Adana province where the study is conducted is calculated with the equation,

$$n = \frac{\mathcal{X}^2 Npq}{d^2(N-1) + \mathcal{X}^2 pq} \tag{40}$$

Here, n represents sample size, $\mathcal{X}^2$ represents table value (3,841 for 5% significance), N is for mass size, p is mass ratio (0.5 accepted), and d is accuracy or error margin (taken as 0.05). When these values are placed in the formula the results is as below:

$$n = \frac{3{,}841.1{,}524{,}922.0{,}5.0{,}5}{0{,}05^2(1{,}524{,}922-1)+3{,}841.0{,}5.0{,}5} \approx 384$$

As it can be seen, the minimum sample size required for the study with an error of 5% has been calculated as approximately 384 people. In order to make the research more reliable, the number of samples in the study was kept much higher than this value. Considering the number of voters in the districts of Adana, the rates of the samples to be selected according to the districts were determined and the questionnaires prepared for the randomly selected people were applied by face-to-face survey method. The study was carried out with the data obtained from the 2848 questionnaires that passed the pre-controls and conformed to the limitations of the study.

States in the Markov analysis method were determined as AK Party, CHP, HDP, Iyi Party, MHP, votes given to other parties and non-votings in the June 24, 2018 parliamentary elections. According to the data obtained, the procedures to be performed for estimation according to the Markov chains methodology are determining the voting preference of the voters in the previous election and the voting preference that they plan to use in the next elections, determining the transitions states, determining the number of transitions between states, creating the transition probabilities matrix between states, determining the initial probability and calculating equilibrium (fixed) vector.

First, the possible choices of the voters who voted in favor of the AK Party in the last election were examined. According to the results of the survey, there are 912 voters in the study sample who voted for the AK Party in the June 24, 2018 parliamentary elections. The distribution of the voters who voted for the AK Party in this election is presented in Table 1 according to the parties they intend to vote for in the next election. When this table is analyzed, 794 voters who voted for AK Party in the June 2018 elections will vote for AK Party in the next election, 19 voters for CHP, 2 voters for HDP, 9 voters for İYİ Party, 24 voters for MHP and 15 voters will vote for other parties and 49 voters will not vote.

Table 1. *Transition Numbers for AK Party Voters*

	AK Party	**CHP**	**MHP**	**HDP**	**Iyi Party**	**Other Parties**	**Will Not Vote**
AK Party	794	19	24	2	9	15	49

After the number of transition of political parties is determined, the transition probability matrix is created. The transition probability matrix obtained for AK Party is given in Table 2. The voter who voted for AK Party is 87.06% (794/912) likely to vote again for AK Party, the probability of voting for CHP is 2.08% (19/912), for MHP is 2%, 63 (24/912), for HDP is 0.22% (2/912), for IP is 0.99% (9/912), for other parties is 1.65% (15/912), and the probability of non-voting was calculated as 5.37% (49/912).

Table 2. *Transition Probability Matrix For The AK Party*

	AK Party	CHP	MHP	HDP	Iyi Party	Other Parties	Non-voting
AK Party	0,8706	0,0208	0,0263	0,0022	0,0099	0,0165	0,0537

The calculations made only for AK Party above were repeated in a similar way for all parties and the transition probability matrix for all political party states is presented in Table 3 and the transition probability matrix is presented in Table 4.

Table 3. *Number of Transitions Regarding Political Party States*

	AK Party	CHP	MHP	HDP	Iyi Party	Other Parties	Non-voting	Total
AK Party	794	19	24	2	9	15	49	912
CHP	10	579	23	10	24	13	20	679
MHP	26	15	227	3	12	8	19	310
HDP	5	54	2	285	0	5	4	355
Iyi Party	28	32	40	6	197	15	2	320
Other Parties	3	6	2	2	11	17	6	47
Non-voting	24	36	22	11	3	22	107	225

Table 4. *Transition Probabilities Matrix*

	AK Party	CHP	MHP	HDP	Iyi Party	Other Parties	Non-voting
AK Party	0,8706	0,0208	0,0263	0,0022	0,0099	0,0164	0,0537
CHP	0,0147	0,8527	0,0339	0,0147	0,0353	0,0191	0,0295
MHP	0,0839	0,0484	0,7323	0,0097	0,0387	0,0258	0,0613
HDP	0,0141	0,1521	0,0056	0,8028	0,0000	0,0141	0,0113
Iyi Party	0,0875	0,1000	0,1250	0,0188	0,6156	0,0469	0,0063
Other Parties	0,0638	0,1277	0,0426	0,0426	0,2340	0,3617	0,1277
Non-voting	0,1067	0,1600	0,0978	0,0489	0,0133	0,0978	0,4756

In addition, when Table 4 is examined, it was seen that the party loyalty among AK Party voters was 87.06%, followed by CHP voting with 85.27%. As of today, the parliamentary loyalty of MHP among the parties represented in the parliament was calculated as 73.23%, the loyalty of İYİ Party, which is a newly established party, was 61.56%, and the party loyalty of HDP voter was 80.28%.

In the process of finding the initial probability vector, the ratio of the number of party voters for each party to the number of general voters is taken. The elements of the initial probability vector (Q_0) are calculated using the data in the last column of Table 3.

Table 5. *Initial Probability Vector*

AK Party	CHP	MHP	HDP	Iyi Party	Other Parties	Non-Voting
0,320	0,238	0,109	0,125	0,112	0,017	0,079

Since 912 of the 2848 voters who participated in the survey voted for AK Party, the first element of the initial probability vector is 912/2848 = 0.32. Similarly, calculations were made for other states, and finally, since the last element of the initial probability vector is 225 people who did not vote, it was obtained as 225/2848 = 0.079.

In the Markov analysis, the values reach a fixed probability value in the long term and these probabilities are called equilibrium (fixed) vector. By using the initial probability vector given in Table 5, the other state vector is obtained and it is progressed step by step until it reaches the stability. The initial probability vector for the next election period has been calculated and its results are shown in Table 6 according to this information.

Table 6. *Initial Probability Vector For The Next Election Period*

AK Party	**CHP**	**MHP**	**HDP**	**Iyi Party**	**Other Parties**	**Non-Voting**
0,312	0,260	0,119	0,112	0,090	0,033	0,073

Initial probability vectors for subsequent periods are obtained separately for each election period by multiplying the initial probability vector and the transition probabilities matrix sequentially. The multiplication is continued until equilibrium point in the initial probability vector is achieved. In this study, it is determined that the initial probability vector is fixed after 25 election periods (in the long term). Table 7 shows the equilibrium (fixed) vector.

Table 7. *Equilibrium (Fixed) Vector*

AK Party	**CHP**	**MHP**	**HDP**	**Iyi Party**	**Other Parties**	**Non-Voting**
0,270	0,326	0,140	0,069	0,079	0,041	0,075

When the initial probability vector and the equilibrium (fixed) vector are compared, and with the assumption that current conjuncture will continue, it is concluded that the AK Party, which is the first party in Adana in the 24 June 2018 elections, will decrease from 32% to 27% in the long term. Similarly, CHP's vote will rise from 23% to 32.6% in the long term, HDP's vote will decrease from 12.4% to 6.9% in the long term, Iyi Party's vote will decrease from 11.2% to 7.9% in the long term, while the vote of the MHP is 10% at the beginning, it will increase to 14% in the long term and the votes of other parties are expected to increase from 1% to 4.1% in the long term. On the other hand, the proportion of voters who do not vote is expected to decrease from 7.9% to 6% in the long term.

4.2. Determination of Factors Affecting Voter Movements Using Hidden Markov Model

The aim of the research is to determine the factors that affect voter preferences, that is, to find hidden reasons underlying the election preferences of the voters. A questionnaire of ten questions, was applied to voters studying at universities in Adana using simple random sampling method. 1219 voters were used as a sample. The data obtained from the survey was first entered into Excel. Histograms and frequency tables were obtained by transferring the data to SPSS program. In order to apply the HMM, the Transition and Emision matrices obtained from the results were transferred to the MATLAB program and the reasons under the political party preference reasons were resolved with various algorithms.

Table 8. *Age*

		Percent
Age Range	**20-23**	76,6
	24-27	22,2
	28-31	0,7
	31+	0,3

Table 8 shows the ages of 1219 voters obtained from the survey results. When the data on the table is analysed, it can be said that the majority of the voters who participated in the survey with 76,6% were 20-23 years old. The second largest percentage belongs to 24-27 year old voters with 22,2%.

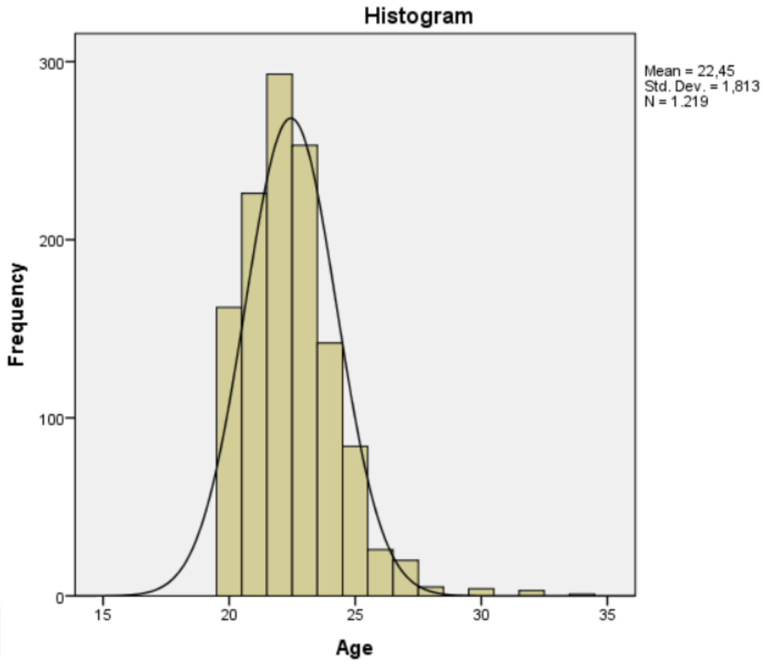

Figure 6. Age Histogram

Figure 6 shows the age of the voters on the histogram according to the answers obtained from the survey results. Figure 6 shows that the average is 22.45.

Table 9. *Gender*

		Frequency	Percent
Valid	**Female**	678	55,6
	Male	541	44,4
	Total	1219	100,0

When Table 9 is analysed, it is seen that while the total number of voters is 1219, 55.6%, that is, 678 of them are women and 44.4%, that is, 541 of them are men. It is seen that the number of female voters who answered the questionnaire was slightly higher than the number of male voters. The representation of the table with the pie chart is as follows.

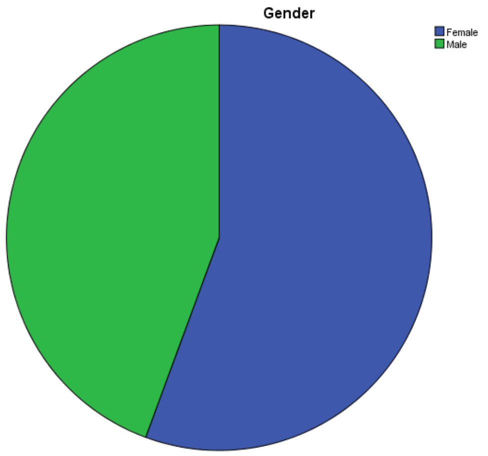

Figure 7. Gender Representation with Pie Chart

Table 10. *Education Level*

		Frequency	Percent
Valid	**Associate Degree**	91	7,5
	Undergraduate	1116	91,6
	Graduate / Doctorate	12	1,0
	Total	1219	100,0

When we look at Table 10, we see that 91 of 1219 voters are associate degree students, 1116 are undergraduate students and 12 are graduate / doctorate students. It is clear that the voters who responded to the questionnaire focused on the undergraduate student.

Table 11. *Political Though*

		Frequency	Percent
Valid	**Nationalist - Conservative**	370	30,4
	Leftist	354	29,0
	Rightist	61	5,0
	Radical Leftist	35	2,9
	Radical Rightist	7	,6
	Apolitical	7	,6
	Neo-nationalist	203	16,7
	Other	182	14,9
	Total	1219	100,0

When we look at Table 11, it is seen that 370 voters from 1219 voters have nationalist-conservative views, 354 voters are leftist, 61 voters are right-wingers, 35 voters are radical leftists, 7 voters are radical rightists, 7 voters are apolitical, 203 voters are Neo-nationalists, 182 voters are outside these groupings (like Kemalist, humanist, libertarian). It can be said that political thought is concentrated in two main branches and these are voters who have "**Nationalist - Conservative and Leftist**" mentality.

To create the transition and emision matrices, 4 answers obtained from the questionnaire questions were used.

These questions are listed below:

Q1) Which party did you vote in the June 24, 2018 general elections?

Q2) What is the most important factor that led you to choose the party you voted for in the 24 June 2018 general election?

Q3) Which party do you plan to vote for in the next general elections?

Q4) What will be the most important factor that will lead you to choose the party you intend to vote in the next general election?

In order to construct the transition probability matrix, the answers to the second question(What is the most important factor that led you to choose the party you voted for in the 24 June 2018 general election?) and the fourth question(What will be the most important factor that will lead you to choose the party you intend to vote in the next general election?) were taken into consideration. The factors that cause preference are numbered as follows.

D1- Image and charisma of the party leader,

D2- Projects and promises offered by the party,

D3- Political tendencies of my family and close friends,

D4- Parliamentary candidate living in the same province as voters,

D5- The ideology of the party is close to voter view,

D6- The staff of the party is reliable, respected, stable and strong,

D7- Religious sense of belonging and indispensable habits,

D8- Other,

D9- I did not vote / I have no idea.

As an example, if the answer given by the voter to the second question (What is the most important factor that led you to choose the party you voted for in the 24 June 2018 general election?) is D1(Image and charisma of the party leader), the answer to the fourth question (What will be the most important factor that will lead you to choose the party you intend to vote in the next general election?) is D2(Projects and promises offered by the party), it can be said that there is a transition from D1 to D2. In this way, the transition matrix is created by counting the transitions between the answers given by 1219 voters.

Table 12. *Transition Matrix*

Transition Number	D1	D2	D3	D4	D5	D6	D7	D8	D9	Total
D1	22	8	0	1	8	5	0	0	10	54
D2	1	102	4	4	20	22	0	0	22	175
D3	1	6	34	2	9	0	1	1	10	64
D4	0	1	1	7	12	8	0	0	4	33
D5	6	35	1	9	338	38	0	0	30	457
D6	2	10	1	2	16	89	1	0	5	126
D7	1	0	0	0	0	1	3	0	1	6
D8	0	1	0	0	1	0	0	0	1	3
D9	2	19	1	1	27	17	0	0	234	301

The number of transition matrix is divided by the total number of lines, and the transition probability matrix is created.

Table 13. *Transition Probability Matrix*

Transition Probability	D1	D2	D3	D4	D5	D6	D7	D8	D9
D1	0,41	0,15	0	0,01	0,15	0,09	0	0	0,19
D2	0,01	0,58	0,02	0,02	0,11	0,13	0	0	0,13
D3	0,02	0,09	0,52	0,03	0,14	0	0,02	0,02	0,16
D4	0	0,03	0,03	0,21	0,37	0,24	0	0	0,12
D5	0,01	0,08	0	0,02	0,74	0,08	0	0	0,07
D6	0,02	0,08	0	0,02	0,13	0,71	0	0	0,04
D7	0,17	0	0	0	0	0,17	0,49	0	0,17
D8	0	0,34	0	0	0,33	0	0	0	0,33
D9	0	0,06	0	0	0,10	0,06	0	0	0,78

When Table 13 is examined, it can be said that the elements on the diagonal indicate the degree of dependency on Di factor (the probability of the factor that influences the choice of the political party).

In other words, if the voter chooses the party because of the D1 factor (Image and charisma of the party leader) in the previous election, 41% probability that it will prefer the political party due to the D1 factor in the next political election, that is, the dependence of the voters on the D1 factor is 41%. Likewise, it is concluded that a voter who chooses the party due to the D2 factor (Projects and promises offered by the party) will vote for the D2 factor again with a probability of 58%, and a voter who chooses the party due to the D3 factor (Political tendencies of my family and close friends) will vote with the D3 factor again with a probability of 53%, who chooses the party due to the D4 factor (Parliamentary candidate living in the same province as voters) will vote with the D4 factor, again with a probability of 21%, who chooses the party due to the D5 factor (The ideology of the party is close to voter view) will vote with the D5 factor, again with a probability of 74% who chooses the party due to the D6 factor (The staff of the party is reliable, respected, stable and strong) will vote with the D6 factor again with a probability of 71%, who chooses the party due to the D7 factor (Religious belonging and indispensable habits) will vote with the D7 factor again with a probability of 50% and it was concluded that voters who did not vote in the previous election will not vote (D9) in the next election, with 78% probability. When the factors underlying the reason why voters prefer a political party are examined , it can be said that the most addictive factor is the D5 factor (The ideology of the party is close to voter view) and that the voters who do not want to vote or who are undecided will still remain undecided.

Given the states of hidden variables, there are a number of emission possibilities that regulate the distribution of the observed variable at a given time. Emission matrices consist of emission possibilities, which include the possibility of producing a particular element of the array. In the task of learning parameters in Hidden Markov Models, it is aimed to find the best case transition and set of emission possibilities, given an output sequence or a series of these sequences. Emission matrices have been created by considering the factors underlying the preference of political parties.

Table 14. *Emission Matrix*

Number of Transitions	V1	V2	V3	V4	V5	V6	V7
D1	18	3	6	1	6	1	0
D2	36	114	17	2	11	2	0
D3	11	17	12	2	0	0	0
D4	4	17	2	0	2	1	0
D5	38	288	61	5	24	15	0
D6	46	87	15	1	27	4	0
D7	0	2	2	0	1	0	0
D8	1	0	0	0	0	0	0
D9	0	0	0	0	0	0	317

In the table, the statements (Di) in the first column show the hidden states of the model, while the elements (Vi) in the first line show political parties. The emission matrix shows the number of voters who prefer the political party individually for each of the hidden states. Emission matrices are created based on the answers received from the questions asked to the voters in the survey. While creating the emission matrix, the political party preferred by the voter and the most important factor that would cause the preferring of this political party were taken into consideration. To create an emission matrix, first one of the factors underlying the reasons for choosing a political party is select. In order to explain it with an example, the factor D5 (The ideology of the party is close to voter view) as the factor that makes it preferable is chosen. While voting, the number of voters who prefer influenced by the D5 factor is 431. Any party can be chosen since distribution of factors according to the parties is aimed to be checked. For example, V3 (MHP) is considered, it can be seen that 61 voters made their choices while voting due to the D5 factor. In this way, it is possible to comment on the elements in the emission matrix.

The emission probability matrix can be found by proportioning each element in the line to the line totals. After the transition probability and emission matrices were calculated, the underlying factors affecting voter preferences were investigated by coding the MATLAB 9.6 program. The codes entered in the MATLAB program to find hidden states are shown in Appendix 2. When the outputs of the MATLAB program are examined, the Forward Algorithm result is reached in the pStates window.

Table 15. *Emission Probability Matrix*

Probability Matrix bj(k)	**V1**	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**
D1	0,514	0,086	0,171	0,029	0,171	0,029	0
D2	0,198	0,626	0,093	0,011	0,06	0,011	0
D3	0,262	0,405	0,286	0,048	0	0	0
D4	0,154	0,654	0,077	0	0,077	0,038	0
D5	0,088	0,668	0,141	0,012	0,056	0,035	0
D6	0,256	0,483	0,083	0,006	0,15	0,022	0
D7	0	0,4	0,4	0	0,2	0	0
D8	1	0	0	0	0	0	0
D9	0	0	0	0	0	0	1

It is the algorithm to find the probability of producing the observation by using the PStates of the Hidden Markov Model. It is used to determine the order of the hidden states in the model. The Forward-Backward Algorithm is calculated by summing up the possibilities of all sequential states that may arise. It is a 7 x 1 matrix. The EstimatedStates window obtained from the MATLAB program gives the result of the Viterbi algorithm. It is an algorithm that aims to reveal the most probable hidden state that will cause the observation sequence to occur. Instead of collecting all possibilities in the Viterbi algorithm, the best match with the vector is chosen from each case.

Table 16. *Probability Values and Hidden Conditions of Parties*

	Observation	**Possibility (%)**	**Hidden Status**
AK Party	V1	27.84	D1
CHP	V2	28.36	D5
MHP	V3	11.38	D5
HDP	V4	1.55	D5
IYI Party	V5	10.24	D5
Other Parties	V6	2.12	D1
Didn't vote	V7	18.51	D9

When the results of the calculations made using the Forward-Backward Algorithm in Table 16 are checked, it can be seen that AK Party and CHP preferences are very close to each other. According to the results of the survey, CHP has the highest probability of being preferred with 28.36%, and AK Party has a probability of being preferred with 27.84%. Considering the percentages of other parties, MHP is 11.38%, IYI Party 10.24%, Other parties 2.21% and HDP 1.55% respectively. Those who do not vote have 18.51% percentage.

The last column of Table 16 shows what is the hidden factor that affects voters' preferences when voting. These results are calculated with the Viterbi algorithm. The hidden state underlying the preference of CHP, which has the highest probability, is D5 (The ideology of the party is close to voter view). Similarly, the hidden factor under the choice of voters who support MHP, HDP and IYI Party is D5. It is seen in Table 16 that AK Party and Other Parties's voters were influenced by the D1 factor (Image and charisma of the party leader) when voting.

Using the "Second Basic Problem" of the Hidden Markov model, the matrix showing the hidden conditions underlying the preference of the parties in the next election period is shown in Table17.

Table 17. *Hidden States Underlying Transition Between Political Parties*

	V1	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**
V1	D1						
V2		D5					
V3			D5				
V4				D5			
V5					D5		
V6						D1	
V7							D9

The hidden states on the diagonal of the matrix show the hidden state underlying the preference of political parties for two consecutive terms. It is also possible to express it as an commitment for political parties. According to Table 17, the factor underlying the preference of V1 (AK Party) and V6 (Other Parties: TIP, BBP, DP, SAADET) is D1 (Image and charisma of the party leader) and it is determined that the hidden state underlying the preference of V2 (CHP), V3(MHP), V4 (HDP) and V5 (Iyi Party) is D5 (The ideology of the party is close to voter view).

CHAPTER V

CONCLUSION & RECOMMENDATIONS

In Turkey, most of the population consists of young people. For this reason, the young population has a great influence on the election results. The data of the two studies conducted in the thesis were obtained from the result of questionnaires by the voters who are university students' live in Adana province. In the election period, it is thought that it will be interesting for the political marketing theory to determine which political party will be elected and the determination of the hidden factor underlying the preference of the political party. With these implementations made throughout Adana province, considering the parties that the voters voted in the previous election, the probability of the party choices in the next elections and the voting rates of the political parties in the long term were estimated. Forecasting studies for the future with historical data are of great importance for many decision makers. The future is the most mysterious part of the time as it contains uncertainty and risk. This uncertainty occupies the human mind and urges it to use every means to obtain information about the future. In this case, the prediction of the future may lead the risks to be turned into opportunities thus, the opportunities to evolve into earnings. Predicting the future and eliminating uncertainty is vital particularly for political parties and leaders. It is known fact that uncertainty disappears with the predictions made using Markov Chain; In addition the Hidden Markov Model was used in the study, since it was aimed to find the hidden states underlying the reasons for political parties to be preferred. The results obtained from this study will guide party headquarters, especially local politicians and decision makers in Adana. It should not be forgotten that voters support political parties that meet their expectations and needs. Establishing the foresight before the elections, having the right predictions in hand and making the appropriate policy choices accordingly will enable the political party to achieve success in a short time. Thus, the number of voters can be increased and perhaps the democratic life of the party may be continued as the leading party. In order to achieve this goal, the behavior of the voters should be analysed well, the reasons of the voter to choose or not to choose their own party should be guessed well, and a powerful policy should be put in action in the light of these information.

According to the analysis results obtained from this study using Markov Model, it is predicted that in the long term, the votes of AK Party, IYI Party and HDP will decrease, and the votes of MHP, CHP and Other parties will increase. When the findings of the study conducted by applying the Hidden Markov Model are examined, it is seen that 28.36% of the students studying in Adana province prefer CHP, while the students who prefer AK Party have a very close percentage with 27.84%. When the factors underlying the preference of political parties were examined, it was reached to the conclusion that the voters of AK Party and other parties were influenced by the "Image and charisma of the party leader" (D1) when choosing the political party ; On the other hand, CHP, MHP, HDP and IYI Party voters prefer political parties by being influenced by the “ideology of the party is close to voters view” (D5). So, it can be interpreted that AK Party and other parties are "leader" parties where CHP, MHP, HDP and IYI Party are "ideology" parties. Based on the results of the research conducted, it was aimed for the political parties to make changes in their policies by considering the factors that the voters' attach importance to while voting, thus increase the number of votes they receive. The findings obtained from the study seem remarkable for both political parties and political marketing.

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APPENDICES

APPENDIX 1.: C ++ program codes to create the Brownian Movement

```
#include <stdio.h>
#include <math.h>
#include "lcgrand.h"
#include <string.h>
#include <conio.h>
#include <ctype.h>
#define REP 10000
float * q; // pointer
FILE *normalFuncFile; //dosyalar
FILE *output_st;
float normal_random_variete(float nu,float sigma); // normal random number
generator
int strm; // kök - seed, rassal sayı
int i,j; //sayaç
void main()
{
float Nor_d1, Nor_d2;
float norm1, norm2;
output_st = fopen("outfile_BM.xls", "w");
strm=1
fprintf(output_st,"\n");
for(j=1;j<=REP;)
{
if(strm>99) strm=1;
for(i=1;i<5;)
{
norm1=normal_random_variete(0,1); norm2=*q;
fprintf(output_st,"\t %f \t %f",norm1,norm2);
strm=strm+1;
i=i+1;
```

```
}
fprintf(output_st,"\n");
j=j+1;
}
fclose(output_st);
}
float normal_random_variete(float nu,float sigma)
{
int x;
float Ubir, Uiki, Vbir, Viki, W, Y, Xbir, Xiki;
float tempp;
for(;;)
{
Ubir=lcgrand(strm);
strm=strm+1;
Uiki=lcgrand(strm);
Vbir=2*Ubir-1;
Viki=2*Uiki-1;
W=Vbir*Vbir+Viki*Viki;
strm=strm-1;
if(W<1)
{
Y= sqrt(-2*log(W)/W);
Xbir=Vbir*Y;
Xiki=Viki*Y;
q=& Xiki;
return (nu + Xbir * sigma);
//return Xbir;
}
}
}
```

APPENDIX 2. Codes entered in MATLAB to identify hidden states in the HMM.

```
>> clear
emis  =  xlsread('Emission.xlsx');
trans =  xlsread('Transition.xlsx');
 [PSTATES,logpseq,FORWARD,BACKWARD,S] = hmmdecode(1,trans,emis);
[estTRbw ,estEbw] = hmmtrain([1,2,3,4],trans,emis);
[seq,states] = hmmgenerate(1,trans,emis);
estimatedStates = hmmviterbi(seq,trans,emis);
```