

## Assessment of Alternative International Organizations for Turkey Using Machine Learning Algorithms

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### Abstract

The distribution of power balances among countries has driven states to become part of an international system within the context of the principles of territorial integrity, sovereignty, and independence. Turkey's process of joining the European Union (EU), which dates back to 1959, has been supported by various reforms and harmonization packages. However, the prolonged negotiations have led Turkey to explore other organizations. In recent times, Turkey, while not completely abandoning its bid for EU membership, has been considering membership in alternative organizations, particularly the Shanghai Cooperation Organization (SCO). In this study, the proximity of Turkey to EU and SCO member countries is evaluated by creating a dataset that includes various indicators for 34 countries. Subsequently, the dataset was grouped based on various indicators. The Naive Bayes and K-Nearest Neighbors algorithms were applied to the five different datasets obtained. In these applications, Turkey was positioned in relation to two different classes based on the EU and SCO member countries, depending on various indicators. The results of the applications, along with the performance metrics obtained for the two different algorithms, are presented.

**Keywords:** European Union, Shanghai Cooperation Organization, machine learning, classification

## Türkiye için Alternatif Uluslararası Örgütlerin Makine Öğrenmesi Algoritmalarıyla Değerlendirilmesi

### Öz

Ülkelerin güç dengesindeki dağılımlar devletleri toprak bütünlüğü, egemenlik ve bağımsızlık ilkeleri bağlamında uluslararası bir sistemin parçası olmaya itmiştir. Türkiye'nin 1959 yılına kadar uzanan Avrupa Birliği (AB)'ne katılma süreci çeşitli reformlar ve uyum paketleriyle desteklenmektedir. Ancak uzun süren müzakerelerin neticelenmemesi Türkiye'yi farklı örgütlere yönelmeye itmiştir. Son dönemde Avrupa Birliği üyeliğinden tam olarak vazgeçmeyen Türkiye'nin başta Şangay İşbirliği Örgütü (ŞİÖ) olmak üzere alternatif örgütlere üyeliği değerlendirilmektedir. Bu çalışma kapsamında Türkiye'nin AB ve ŞİÖ üyesi ülkelere yakınlığının değerlendirilmesi amaçlanarak 34 ülkenin çeşitli göstergelerini içeren bir veri seti oluşturulmuştur. Sonrasında oluşturulan veri seti çeşitli göstergelere bağlı olarak gruplandırılmıştır. Elde edilen beş farklı veri setine Naive Bayes ve K En Yakın Komşu algoritması uygulanmıştır. Bu uygulamalarda çeşitli göstergelere bağlı olarak Türkiye, AB ve ŞİÖ üyesi ülkelerin yer aldığı iki farklı sınıfa göre konumlandırılmıştır. Yapılan uygulamalarda iki farklı algoritma için elde edilen performans metrikleriyle birlikte tahmin edilen değerlere yer verilmiştir.

**Anahtar Kelimeler:** Avrupa Birliği, Şangay İşbirliği Örgütü, makine öğrenmesi, sınıflandırma

## 1. Introduction

In today's world politics, the uncertainties that emerged in the aftermath of the Cold War have led to a search for a new order. The distribution in the balance of power has pushed states to become part of an international system in the context of the principles of territorial integrity, sovereignty and independence. At the beginning of a new order, the power of states over world politics is associated with their share in the world economy. Along with economic power, military power is also seen as an important element for states to maintain and strengthen their current situation [1]. Along with military and economic power, social indicators including consumption, education and health parameters are considered in determining the socioeconomic status of states [2]. Finally, environmental and infrastructural indicators are also considered important in assessing the welfare and holistic development of states [3]. In the light of all these indicators, various states come together to form international institutions and organizations. In this respect, Turkey's possible cooperation with international organizations and institutions is also evaluated. In particular, it is emphasized that the negotiations between Turkey and the European Union (EU), which started in 2005, are important for Turkey in terms of keeping up with the globalizing economy and politics [4]. With the start of the negotiations, Turkey has been inspired by the EU in its foreign policy and has developed a more active line [5]. However, there are ups and downs in the relationship between Turkey and the EU due to problems such as judicial independence, human rights, freedom of expression and the Cyprus problem [6]. In addition, elements such as the rule of law, democratic freedoms and respect for minorities are also taken as issues that have a negative impact on Turkey and the EU negotiations [7]. In addition to these negativities, the EU's migration policies have led to various partnerships and agreements with Turkey [8].

With the dissolution of the Union of Soviet Socialist Republics, the United States of America (USA) has become a unipolar power center by gaining power in world politics. On the other hand, Russia's desire to prevent the US from approaching the Eurasian region and the border problems between China and Central Asian countries brought Russia and China together. In addition to Russia and China, Kazakhstan, Tajikistan, and Kyrgyzstan also joined the talks. As a result of the negotiations of these 5 countries, the agreement, which is referred to as the foundation of Shanghai 5, was signed in 1996 and the Shanghai Cooperation Organization (SCO) was officially established in 2001 with the participation of Uzbekistan [9].

Turkey's full membership to the SCO started to be discussed due to the EU's attitude towards Turkey, uncertainties in the relations, and the negotiations that have not been concluded for a long time during the process in which financial markets were transferred to the east. Accordingly, Turkey applied for full membership to the SCO in 2011. Afterwards, it was accepted as a dialogue country [10]. In recent years, Turkey has been engaged in joint economic, social and cultural activities with the SCO member Turkic Republics [11]. Along with these activities, the trade relations developed with China increase the cooperation between Turkey and the SCO [12].

Turkey's process of joining the EU, which dates back to 1959, has been supported by various reforms and harmonization packages. However, the protracted negotiations have led Turkey to

turn to different organizations. Recently, Turkey, which has not completely given up on EU membership, has been considering membership in the SCO and the Eurasian Economic Union [13]. Especially the SCO is considered as an organization that Turkey can join commercially as an alternative to the EU [14].

The problems encountered in Turkey's accession process to the European Union bring along uncertainties. Along with these uncertainties, Turkey's SCO membership is being discussed. Turkey's membership to the European Union and other alternative international organizations is becoming complex. Various artificial intelligence techniques are used to solve such complex problems. With these techniques, data can be processed, interpreted, analyzed and classified. These techniques are frequently used in the field of International Relations to solve complex problems based on data analysis. For example, Katagiri and Min (2015) applied machine learning techniques to US diplomatic documents. These documents were obtained from the digitization of the US Foreign Relations 1945-1980 collection. The aim of the applications is to predict the perceived threat from the documents. As a result of the study, it was emphasized that the methods used will contribute to the testing of International Relations theories [15]. In another study, machine learning algorithms were used to detect patterns in North Korea's military provocations. For this purpose, news articles of the Korean Central News Agency between 1997 and 2013 were analyzed. As a result of the analysis, 82% success was achieved. As a result of the study, it was stated that the use of machine learning techniques in similar studies will be beneficial [16]. Another study using machine learning algorithms aims to predict country risk. For this purpose, four different algorithms were applied to a dataset consisting of macroeconomic indicators of 75 countries between 2015-2019. As a result of the study, it was stated that the highest success was obtained with the K Nearest Neighbor (KNN) algorithm and it was emphasized that high success was achieved in the applications [17]. In another study, the performance of two different algorithms was compared. In this direction, data from EU candidate and member countries were analyzed. In the light of these data, it was aimed to evaluate the effect of the factor of increasing the level of economic development on the EU membership of the countries. As a result of the study, the most effective variables in the EU membership process were revealed [18]. In another study, two different algorithms were used to detect terrorist attacks and their economic damage, which is one of the most difficult problems for governments to deal with. As a result of the study, performance metrics obtained from the algorithms were given and various suggestions were presented [19]. Within the scope of this study, a dataset was created to evaluate Turkey's relationship with the SCO and the EU. For the dataset consisting of 34 records, Naive Bayes and KNN algorithms were applied and performance metrics were compared.

The objective of this study is to illustrate the applicability of machine learning algorithms in addressing similar classification problems within the field through the applications conducted in the context of this research. Furthermore, the study offers a distinct perspective on the international organizations to which Turkey is aligned, based on various indicators and quantitative data.

The aim of this study is to demonstrate the applicability of machine learning algorithms in solving similar classification problems in the field with the applications made within the scope of this study. In addition, international organizations that Turkey is close to depending on different indicators are presented from a different perspective depending on quantitative values.

## **2. 2. Material and Methods**

### **2.1. Data Collection**

The dataset used in this study consists of general indicators, economic indicators, social indicators, environmental and infrastructural indicators of 35 countries, including 26 EU member states, 8 SCO member states and Turkey. The dataset, consisting of records from 2021, consists of eight different attributes. The records in the dataset were obtained from the data.un.org website developed by the United Nations (UN) Statistics Department. In the dataset, the class representing the SCO is assigned a value of 0 and the class containing EU member states is assigned a value of 1. Thirty percent of the records in the dataset were used for testing and 70 percent for training. Naive Bayes and KNN algorithms were applied to the obtained dataset. The applications were realized using Python sklearn library.

The dataset examined in this study consists of records related to various indicators of 35 different countries. It is anticipated that in future studies, more effective and efficient results can be achieved through applications conducted with more comprehensive datasets, which are supported by document-based research and expert opinions on these indicators and their related records.

### **2.2. Naive Bayes**

Naive Bayes, a probabilistic algorithm, is a popular algorithm based on Bayes' theorem. The algorithm is based on the assumption of independence between attributes, hence the name "naive". This independence assumption implies conditional independence between attributes. Although this is not suitable for concrete problems, it shows high performance in solving different problems in various fields [20].

In the Naive Bayes algorithm, where learning is performed on the training dataset, the learning process is performed on the training dataset. After the probabilistic calculation, the record with the highest value is assigned to the relevant class [21]. The formula used for this calculation is given below. In the formula below

- $P(A/B)$ , the probability of A in situation B,
- $P(B/A)$ , the probability of B in situation A,
- $P(A)$ , the probability of state A,
- $P(B)$  denotes the probability of state B.

$$P(A/B) = \frac{P(B/A) * P(A)}{P(B)}$$

### 2.3. K-Nearest Neighbor (KNN)

The KNN algorithm developed by Cover and Hart is frequently used to solve nonlinear classification problems. The K value in the calculations refers to the number of nearest neighbors. The distances of the value to be classified to K number of neighbors are calculated. This calculation process is based on Euclidean distance measurement [22]. For example, for K=7, the distances of the 7 points closest to the value to be classified are calculated. Then, the classes in which the 7 points are included are examined and assignment to the closest class is made.

### 2.4. Performance Metrics

In applications with machine learning algorithms, various metrics are used to evaluate the performance of the models. In this study, accuracy, precision, sensitivity and f1 score are among the most commonly used performance metrics. These performance metrics are calculated with the values in the confusion matrix. There are four basic variables in the confusion matrix: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP refers to the number of correctly predicted positive (1) values, while TN refers to the number of correctly predicted negative (0) values. Similarly, FN refers to the number of incorrectly predicted negative values and FP refers to the number of incorrectly predicted positive values.

The formulas used to calculate the accuracy, precision, sensitivity and f1 score based on these values are given in Table 1.

**Table 1.** Performance metrics

Accuracy	Precision	Recall	F1 Skoru
$\frac{(TP + TF)}{(TP + TF + FP + FN)}$	$\frac{TP}{(TP + FP)}$	$\frac{TP}{(TP + FN)}$	$2 * \frac{Precision * Recall}{Precision + Recall}$

### 3. Results and Discussion

Within the scope of the study, Naive Bayes and KNN algorithms were applied to the dataset consisting of indicators from Turkey, EU member countries and SCO member countries. The dataset used in the first application consists of 8 attributes. The dataset was then grouped into general indicators, social indicators, economic indicators, environmental and substructural indicators. The training dataset used in the study consists of records of EU and SCO countries. After the learning has taken place, Turkey's data is considered and it is aimed to predict the classes to which Turkey belongs depending on the indicators.

The attributes and the indicators used in the applications are given in Table 2.

**Table 2.** Attribute and groups

Attribute	Group
Population Density	General Indicators
Surface Area	
GDP	Economic Indicators
CPI	
Health Expenditures	Social Indicators
Education Expenditures	
Internet Usage	Environmental and Infrastructural Indicators
Energy Supply Per Capita	

The attributes considered in the study are given above. From these attributes, the classes in which Turkey is included are estimated. The class with EU member countries is labeled as 1 and the class with SCO member countries is labeled as 0.

The accuracy values obtained with Naive Bayes and KNN algorithms in the first application with the dataset including all indicators and the final results obtained from the algorithms are given in Table 3. In the table below, 1 represents the EU and 0 represents the SCO.

**Table 3.** Accuracy values and predicted values

	Naive Bayes	KNN
Accuracy	0.81	0.94
Predicted Class	1	1

As seen in Table 3, in the application with the dataset including all indicators, an accuracy value of 0.81 was obtained with the Naive Bayes algorithm and 0.94 with the KNN algorithm. In addition, a value of 1 was obtained for both algorithms in the predictions made for the class that Turkey will be in. This shows that Turkey is in the class of EU member states for all indicators in the predictions made with Naive Bayes and KNN algorithms.

In the applications, high accuracy values were obtained for both algorithms. However, the use of more than one performance metric in classification problems contributes to the reliability of the results. In this direction, the precision, sensitivity values and F1 scores obtained with the Naive Bayes algorithm applied to the dataset including all indicators are given in Table 4.

**Table 4.** Performance metrics (Naive Bayes)

	Precision	Recall	F1 Score
0	1,00	0,50	0,67
1	0,78	1,00	0.88

The performance metrics obtained with KNN in the application with the dataset including all indicators are also given in Table 5.

**Table 5.** Performance metrics (KNN)

	Precision	Recall	F1 Score
0	1,00	0,75	0,86
1	0,88	0,75	0,93

The performance metrics obtained in the applications with the dataset consisting of 8 different attributes are given above. In order to evaluate Turkey's proximity to EU and SCO member countries in terms of different parameters, four different datasets were created by grouping these attributes as general indicators, social indicators, economic indicators, environmental and infrastructural indicators. Each dataset consists of two attributes. The accuracy values and predicted values obtained with Naive Bayes and KNN algorithms in the applications with general indicators including population density and surface area records of the countries are given in Table 6.

**Table 6.** Accuracy values and predicted values (General Indicators)

	Naive Bayes	KNN
Accuracy	0.90	0.94
Predicted Class	0	1

As can be seen in Table 6, for general indicators, Turkey is in the class of SCO member countries in the application with the Naive Bayes algorithm, while it is in the class of EU member countries in the application with the KNN algorithm.

In the application with 34 different countries' economic indicators consisting of GDP and CPI records, the accuracy values and predicted values obtained with Naive Bayes and KNN algorithms are given in Table 7.

**Table 7.** Accuracy values and predicted values (Economic Indicators)

	Naive Bayes	KNN
Accuracy	0.90	0.97
Predicted Class	0	0

In the applications where high performance was obtained from both algorithms, it was observed that Turkey was in the class of SCO member countries in terms of economic indicators.

The accuracy values and predicted values obtained with Naive Bayes and KNN algorithms in the application with social indicators consisting of health and education expenditures, which are considered to evaluate the socioeconomic status of states, are given in Table 8.

**Table 8.** Accuracy values and predicted values (Social Indicators)

	Naive Bayes	KNN
Accuracy	0.62	0.79
Predicted Class	1	0

As can be seen in Table 8, lower accuracy values were obtained in the applications made with the dataset containing social indicators compared to the applications made with the datasets containing general indicators and economic indicators. In the application with the Naive Bayes algorithm, Turkey was positioned in the class of EU member countries, while in the application with the KNN algorithm, Turkey was positioned in the class of SCO member countries.

Finally, the accuracy and predicted values obtained in the applications with environmental and infrastructural indicators, including records on internet usage and per capita energy supply, are given in Table 9.

**Table 9.** Accuracy values and predicted values (Environmental and Infrastructural Indicators)

	Naive Bayes	KNN
Accuracy	0.54	0.85



Predicted Class	1	1
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With 5 different datasets, the performance metrics and predicted values obtained in the applications vary. In order to convey this situation as a whole, the accuracy values and predicted values obtained with Naive Bayes and KNN algorithms for 5 different datasets are given in Table 10.

**Table 10.** Accuracy values and predicted values

Group	Algorithm	Accuracy	Turkey's class
Indicators	Naive Bayes	0.81	EU
	KNN	0.94	EU
General Indicators	Naive Bayes	0.90	SCO
	KNN	0.94	EU
Economic Indicators	Naive Bayes	0.90	SCO
	KNN	0.97	SCO
Social Indicators	Naive Bayes	0.62	EU
	KNN	0.79	SCO
Environmental and Infrastructural Indicators	Naive Bayes	0.54	EU
	KNN	0.85	EU

#### 4. Conclusion

Despite long negotiations, reforms and harmonization packages, Turkey's EU accession process, which has not been finalized, has brought about various debates. Turkey's membership status in other international organizations is being evaluated since the membership process has not yielded a final result. In 2011, the SCO, which was applied for full membership and was accepted as a dialogue country, is one of these organizations.

In this study, a dataset consisting of various indicators of EU and SCO member countries was created with the aim of estimating Turkey's proximity to EU and SCO member countries. Naive

Bayes and KNN algorithms were applied to the dataset. In addition, four different groups were created for the evaluation of various indicators and different applications were made with a total of five different datasets.

In the applications made with the dataset consisting of records on surface area, population density, CPI, GDP, education expenditures, health expenditures, internet usage and energy supply per capita, Turkey is positioned in the class of EU member states. In line with the high performance metrics obtained from the applications with the dataset including all indicators, it can be said that Turkey is close to the EU in terms of general indicators.

In two different applications made with the dataset consisting of the population density and surface area records of the countries, it was observed that Turkey was positioned in different classes. While the population density of countries such as Finland, Latvia and Sweden in the class of EU member countries is low, the population density of Malta, the Netherlands and Belgium in the same class is high. Similarly, in the class of SCO member countries, India and Pakistan have high population densities while Kazakhstan and Kyrgyzstan have low population densities. It can be said that the difference in the result values obtained from the algorithms is due to this situation.

In the application with the dataset including education and health expenditures, the Naive Bayes algorithm achieved lower performance than the KNN algorithm. In the application with the KNN algorithm, it was observed that Turkey was positioned in the class of SCO member countries in terms of social indicators. While the average annual health expenditure of EU member countries is 8.21%, the average annual health expenditure of SCO member countries is 5.1%. Similarly, while the average education expenditure for EU member countries is 4.96%, the average for SCO member countries is 3.7%. The fact that Turkey's health expenditures are 4% and education expenditures are approximately 3% is similar to the result obtained in the application with the KNN algorithm. In addition, Iran and Kyrgyzstan allocate more to health expenditures than other SCO member countries.

High performance was obtained for both algorithms in the applications with the dataset including CPI and GDP records. In the applications with economic indicators, Turkey is positioned in the class of SCO member countries. In terms of economic indicators, Turkey is in the class of SCO member countries, while in terms of environmental and infrastructural indicators, Turkey is in the class of EU member countries. The same result was obtained for two different algorithms in the applications with environmental and infrastructural indicators.

It is important to process and transform raw data obtained from various sources in different disciplines into meaningful data. Processing and transforming data into information contributes to decision-making processes. In this study, machine learning algorithms were applied to the dataset created in line with the data obtained from the search engine provided by the United Nations System. In this direction, it is aimed to demonstrate the applicability of machine learning algorithms in forecasting applications involving different datasets. In addition, this study is expected to contribute to interdisciplinary studies using machine learning algorithms.

## Ethics in Publishing

There are no ethical issues regarding the publication of this study.

## References

- [1] Kut, G., (2019) Uluslararası sistem ve kurallara dayalı dünya düzeni: çok taraflı denge arayışları, Boğaziçi Üniversitesi-TÜSİAD Dış Politika Forumu Araştırma Raporu.
- [2] Danzer, A. M., Dietz, B., Gatskova, K., Schmillen, A., (2014) Showing off to the new neighbors? Income, socioeconomic status and consumption patterns of internal migrants, *Journal of Comparative Economics*, 42(1), 230-245.
- [3] Frischmann, B. M., (2012) *Infrastructure: The social value of shared resources*, Oxford University Press.
- [4] Zucconi, M., (2009) The impact of the EU connection on Turkey's domestic and foreign policy, *Turkish Studies*, 10(1), 25-36.
- [5] Müftüler-Baç, M., (2020) Turkish foreign policy, its domestic determinants and the role of the European Union, In *Turkey and the EU: Accession and Reform* (pp. 71-82), Routledge.
- [6] Özer, M. A., (2009) Avrupa Birliği'ne tam üyeliğin eşliğinde Türkiye, *Yönetim ve Ekonomi Dergisi*, 16(1), 89-105.
- [7] Uysal, C., (2001) Türkiye-Avrupa Birliği ilişkilerinin tarihsel süreci ve son gelişmeler, *Akdeniz İ.İ.B.F. Dergisi*, 1(1), 140-153.
- [8] Martin, N., (2019) From containment to realpolitik and back again: A realist constructivist analysis of Turkey–EU relations and the migration issue, *JCMS: Journal of Common Market Studies*, 57(6), 1349-1365.
- [9] Khaleqi, Z. A., Oghli, J. S., (2021) Şangay İşbirliği Örgütü ve Türkiye'nin olası ilişkileri, *Pearson Journal*, 6(12), 107-116.
- [10] Yener, M. C., (2013) Küresel düzende yeni arayışlar: Şangay İşbirliği Örgütü ve Türkiye, *Uluslararası Ekonomik Sorunlar*, 13 (46), 71-91.
- [11] Özalp, M., (2019) Türkiye'nin Şanghay İşbirliği Örgütü'ne olası üyeliğinin Avrasya politikasına etkileri, *Manas Sosyal Araştırmalar Dergisi*, 8(4), 3439-3469.
- [12] Günay, E., Çetiner, S., Sevinç, S., Kütükçü, E., (2019) Tarihi İpek Yolundan Modern İpek Yolu Projesine: Türkiye-Çin Ekonomik İşbirliği Çerçevesinde Orta Koridor ile Kuşak ve Yol Girişimi, *Kahramanmaraş Sütçü İmam Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 9(2), 157-175.

- [13] Saygın, D, Erdem, A. D., (2021) Avrupa Birliği'ne katılım sürecinin Türkiye siyasetine yansımaları: alternatif örgütler, *Uluslararası İlişkiler ve Diplomasi*, 4(1), 80-107.
- [14] Ongan, E., (2021) Avrupa Birliği ve Şangay İşbirliği Örgütü Türkiye ilişkilerinin değerlendirilmesi, *The Journal of Academic Social Science*, (112), 259-266.
- [15] Katagiri, A., Min, E., (2015) Identifying threats: Using machine learning in international relations, In annual meeting of the American Political Science Association.
- [16] Whang, T., Lammbrau, M., & Joo, H. M., (2018) Detecting patterns in North Korean military provocations: what machine-learning tells us, *International Relations of the Asia-Pacific*, 18(2), 193-220.
- [17] Doğan, S., Türe, H., (2022) Makine öğrenmesi teknikleri ile ülke riski tahmini, *Fiscaoeconomia*, 6(3), 1126-1151.
- [18] Altaş, D., Gülpınar, V., (2012) Karar ağaçları ve yapay sinir ağlarının sınıflandırma performanslarının karşılaştırılması: Avrupa Birliği örneği, *Trakya University Journal of Social Science*, 14(1).
- [19] Vaibhav, S., (2020) Predicting success of terrorist attack and extent of its economic impact using data mining, *International Journal for Research in Applied Science and Engineering Technology*, 8(5), 1965-1972.
- [20] Zhang, H., (2004) The optimality of Naive Bayes. *AA*, 1(2), 3.
- [21] Chandra, B., Gupta, M., (2011) An efficient statistical feature selection approach for classification of gene expression data. *Journal of biomedical informatics*, 44(4), 529-535.
- [22] Cover, T., Hart, P., (1967) Nearest neighbor pattern classification. *IEEE Transactions on Information Theory*, 13(1), 21-27.