



T.C.
MANİSA CELAL BAYAR
ÜNİVERSİTESİ
MÜHENDİSLİK FAKÜLTESİ
BİLGİSAYAR MÜHENDİSLİĞİ
BÖLÜMÜ



Predict of Dollar Rate

Graduation Project I

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BİLGİSAYAR MÜHENDİSLİĞİ BÖLÜMÜ

Tasarım Projesi / Lisans Bitirme Tezi

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.....

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ABBREVIATION LIST

NLP	Natural Language Processing
ML	Machine Learning
SVM	Support Vector Machines
SVC	Support Vector Classification
KNN	K-Nearest Neighbors
DTC	Decision Tree Classification
OLS	Ordinary Least Squares
Adj.	Adjusted
RFC	Random Forest Classification
GNB	Gaussian Naive Bayes

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ABSTRACT

Machine learning is the case of optimizing and predicting by processing raw data. Its origin dates back to 1950. During these years, Alan Turing tried to distinguish between machine and human using the Turing Test.

In our project, we code a machine learning algorithm that can make dollar estimates using factors that affect the dollar rate. According to the information we have obtained from our researches on the internet, the factors affecting the dollar rate are:

- BIST 100 index
- Current account deficit
- The foreign trade deficit
- Interest rate
- Money supply
- Central bank foreign exchange reserves
- Inflation
- Import prices
- Export prices (ŞİT & KARADAĞ, 12-09-2019)
- Tweets

We did not know where to find these data, as a result of our research, we thought that these data could be in the database of Tüik and we contacted an authorized person in Tüik. Then, as a result of our communication, that some of the data in their databases, while some of the data reported to the Central Bank of the Republic of Turkey can be found in the database. In addition to these, following the advice of our advisor, we discovered that there is extra data that allows our estimation algorithm to give more accurate results. We will create this data from the social media statements made by the statesman and economist man. We used natural language processing algorithms and technologies while receiving data from social media.

Keywords: Economy, Data Science, dollar rate

1. INTRODUCTION

Finance; These are activities related to the provision of the needed funds under appropriate conditions and their effective use. It is the fact that people or institutions earn material income, make investments and evaluate these investments over time.

Manual processing and analysis of large amounts of data it is not possible for humans. It is much easier to process such data and predict future data with machine learning algorithms. Machine learning is actually a whole algorithm created by using statistics and mathematics together. Machine learning algorithms are examined in 3 categories: Supervised Learning, Unsupervised Learning, Reinforcement Learning.

In supervised learning, the machine is taught as an example. The operator provides the machine learning algorithm with a known data set containing the desired inputs and outputs, and the algorithm finds a method for determining how these inputs and outputs are reached.

Supervised learning algorithms are:

Linear Regression

Logistic Regression

Support Vector Machines

Decision Trees

Naive Bayes

K-Nearest Neighbor Algorithm

Linear Discriminant Analysis

Neural Networks

Semi-supervised machine learning is similar to supervised learning, but instead uses both tagged and untagged data. Tagged data is essentially information with meaningful tags so that untagged data lacks this information and the algorithm can understand the data. Using this combination, machine learning algorithms can learn to tag untagged data.

In an unsupervised learning process, the machine learning algorithm is left to interpret large data sets and handle these data accordingly. The algorithm tries to organize this data in some

way to describe its structure. This can mean grouping data into clusters or arranging them to look more organized.

Reinforcement learning focuses on regular learning processes that include a set of actions, parameters and end values to a machine learning algorithm. By setting the rules, the machine learning algorithm tries to explore different options and possibilities, monitoring and evaluating each result to determine which one is the most suitable.

We will use these machine learning algorithms in our project to make the program estimate its dollar situation.

2. MACHINE LEARNING ALGORITHMS WE USE IN OUR PROJECT

The machine learning algorithms we use in our project are:

- **Simple Linear Regression**
- **Multiple Linear Regression**
- **Polynomial Regression**
- **Support Vector Regression**
- **Decision Tree**
- **Random Forest**

We used the algorithms written above to make predictions.

- **Logistic Regression**
- **K-Nearest Neighbor**
- **Support Vector Classification**
- **Naive Bayes**
- **Decision Tree**
- **Random Forest**

We used the algorithms written above to make classifications.

2.1 Linear Regression

Linear Regression is a supervised machine learning algorithm where the predicted output is continuous and has a constant slope. It's used to predict values within a continuous range, (e.g. sales, price) rather than trying to classify them into categories (e.g. cat, dog). There are two main types: (ML-Cheatsheet, 2021)

2.1.1 Simple regression

Simple linear regression uses traditional slope-intercept form, where m and b are the variables our algorithm will try to “learn” to produce the most accurate predictions. x represents our input data and y represents our prediction. (ML-Cheatsheet, 2021)

$$y = mx + b$$

Figure 2.1.1: Simple Linear Regression

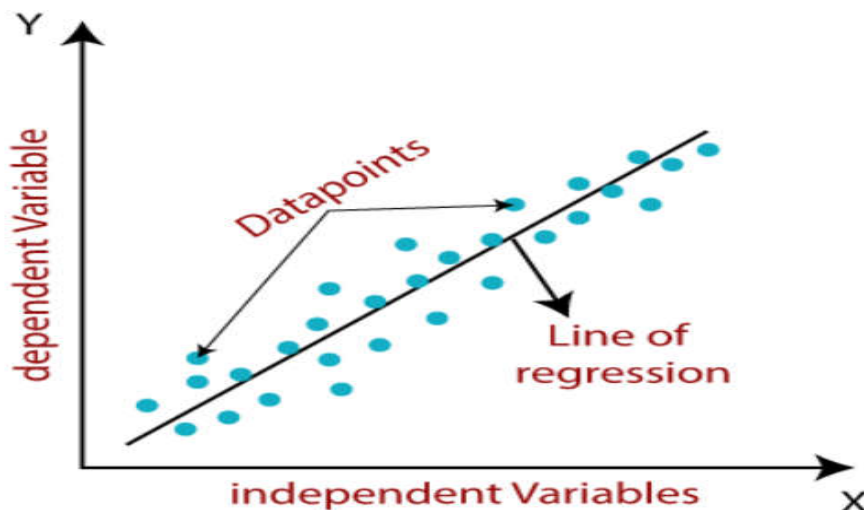


Figure 2.1.2: Graph of Simple Linear Regression (Javatpoint, 2021)

2.1.2 Multiple Linear Regression

In Multiple Linear Regression, the target variable(Y) is a linear combination of multiple predictor variables $x_1, x_2, x_3, \dots, x_n$. Since it is an enhancement of Simple Linear Regression, so the same is applied for the multiple linear regression equation, the equation becomes: (Medium, 2021)

**Multiple
Linear
Regression**

Dependent variable (DV) Independent variables (IVs)

$$y = b_0 + b_1 * x_1 + b_2 * x_2 + \dots + b_n * x_n$$

Figure 2.1.3: Multiple Linear Regression (Medium, 2021)

2.1.3 Polynomial Regression

If your data points clearly will not fit a linear regression (a straight line through all data points), it might be ideal for polynomial regression.

Polynomial regression, like linear regression, uses the relationship between the variables x and y to find the best way to draw a line through the data points. (W3Schools, 2021)

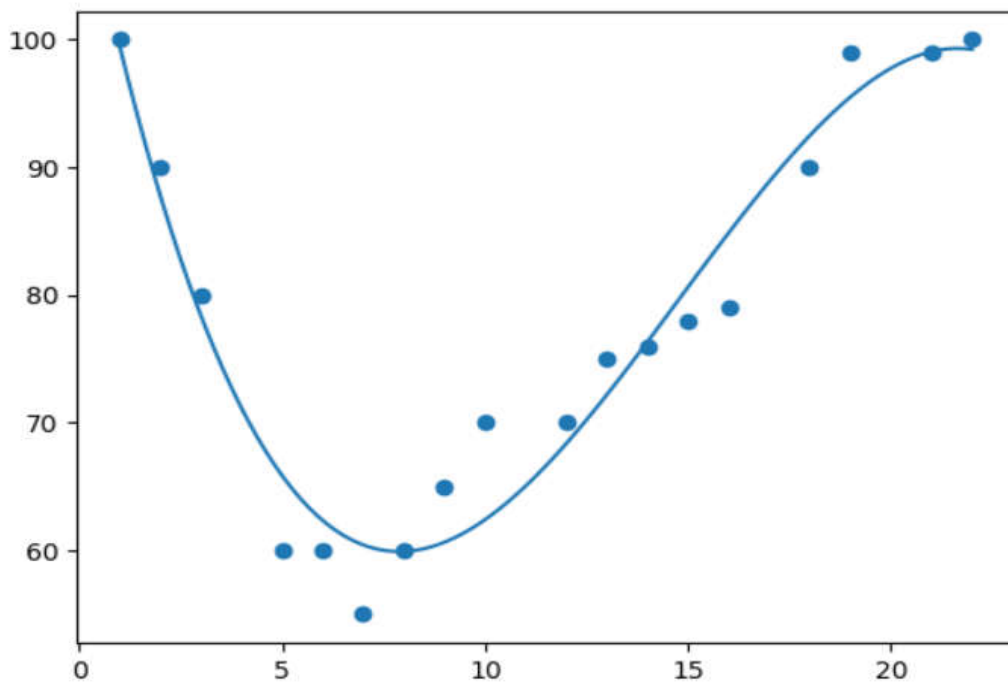


Figure 2.1.4: Polynomial Regression (W3Schools, 2021)

2.2 Logistic Regression

- Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables.
- Logistic regression predicts the output of a categorical dependent variable. Therefore the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, it gives the probabilistic values which lie between 0 and 1.
- Logistic Regression is much similar to the Linear Regression except that how they are used. Linear Regression is used for solving Regression problems, whereas Logistic regression is used for solving the classification problems.
- In Logistic regression, instead of fitting a regression line, we fit an "S" shaped logistic function, which predicts two maximum values (0 or 1).
- The curve from the logistic function indicates the likelihood of something such as whether the cells are cancerous or not, a mouse is obese or not based on its weight, etc.
- Logistic Regression is a significant machine learning algorithm because it has the ability to provide probabilities and classify new data using continuous and discrete datasets.
- Logistic Regression can be used to classify the observations using different types of data and can easily determine the most effective variables used for the classification. The below image is showing the logistic function: (Javatpoint, 2021)

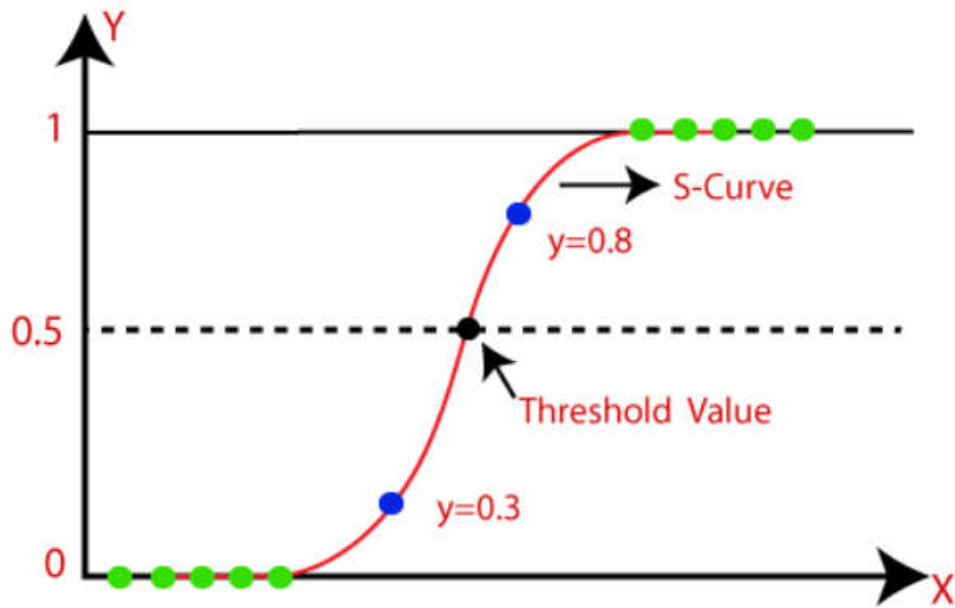


Figure 2.2.1: Graph of Logistic Regression (Javatpoint, 2021)

2.3 Support Vector Machines(SVM)

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane: (Javatpoint, 2021)

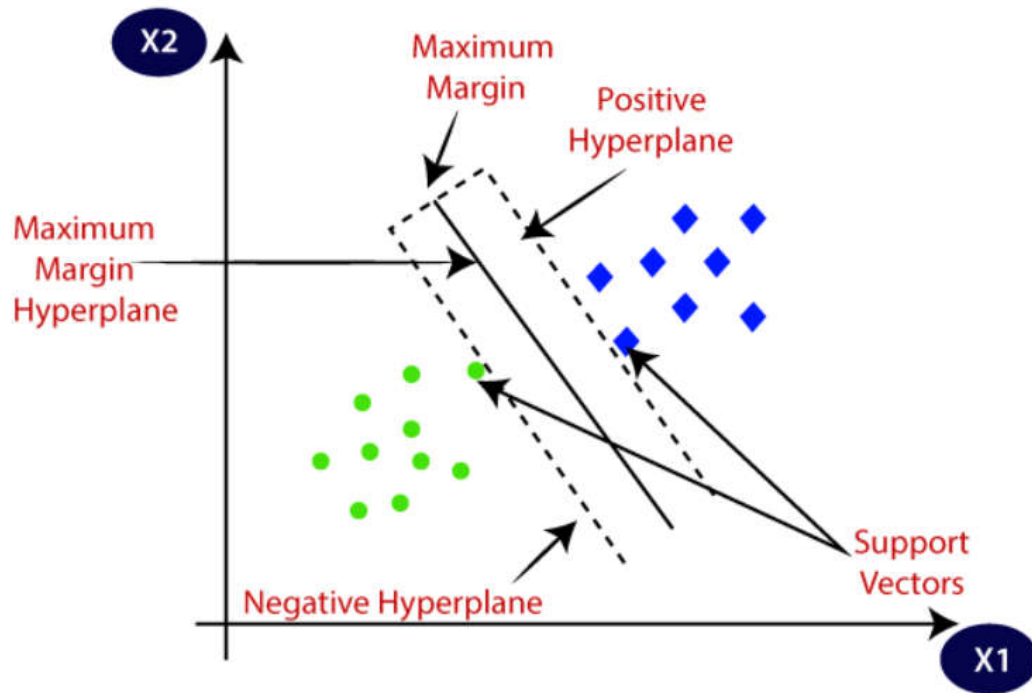


Figure 2.3.1: Graph of SVM (Javatpoint, 2021)

2.4 Decision Trees

- Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.
- In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.
- The decisions or the test are performed on the basis of features of the given dataset.
- It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions.

- It is called a decision tree because, similar to a tree, it starts with the root node, which expands on further branches and constructs a tree-like structure.
- In order to build a tree, we use the CART algorithm, which stands for Classification and Regression Tree algorithm.
- A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees.
- Below diagram explains the general structure of a decision tree:

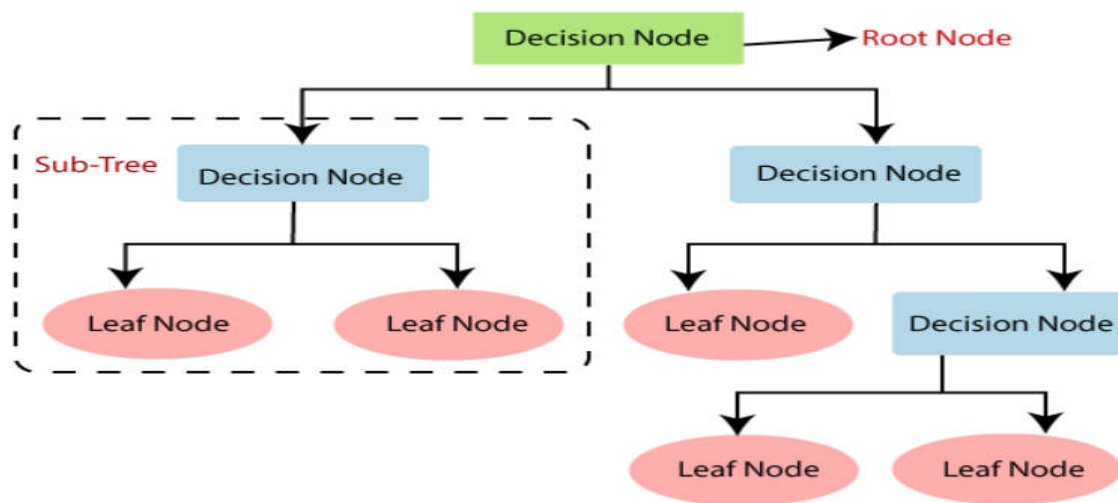


Figure 2.4.1: Decision Tree

Decision Tree Terminologies

- **Root Node:** Root node is from where the decision tree starts. It represents the entire dataset, which further gets divided into two or more homogeneous sets.
- **Leaf Node:** Leaf nodes are the final output node, and the tree cannot be segregated further after getting a leaf node.
- **Splitting:** Splitting is the process of dividing the decision node/root node into sub-nodes according to the given conditions.
- **Branch/Sub Tree:** A tree formed by splitting the tree.
- **Pruning:** Pruning is the process of removing the unwanted branches from the tree.
- **Parent/Child node:** The root node of the tree is called the parent node, and other nodes are called the child nodes.

2.4.1 Information Gain

- Information gain is the measurement of changes in entropy after the segmentation of a dataset based on an attribute.
- Information gain is the measurement of changes in entropy after the segmentation of a dataset based on an attribute.

$$\text{Information Gain} = \text{Entropy}(S) - [(\text{Weighted Avg}) * \text{Entropy}(\text{each feature})]$$

Figure 2.4.2: Calculation of Information Gain

Entropy: Entropy is a metric to measure the impurity in a given attribute. It specifies randomness in data. Entropy can be calculated as:

$$\text{Entropy}(s) = -P(\text{yes}) \log_2 P(\text{yes}) - P(\text{no}) \log_2 P(\text{no})$$

2.4.2 Gini Index

- Gini index is a measure of impurity or purity used while creating a decision tree in the CART(Classification and Regression Tree) algorithm.
- Gini index can be calculated using the below formula:

$$\text{Gini Index} = 1 - \sum_j P_j^2$$

Figure 2.4.3: Calculation of Gini Index (Javatpoint, 2021)

2.5 Random Forest

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees

on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

The below diagram explains the working of the Random Forest algorithm: (Javatpoint, 2021)

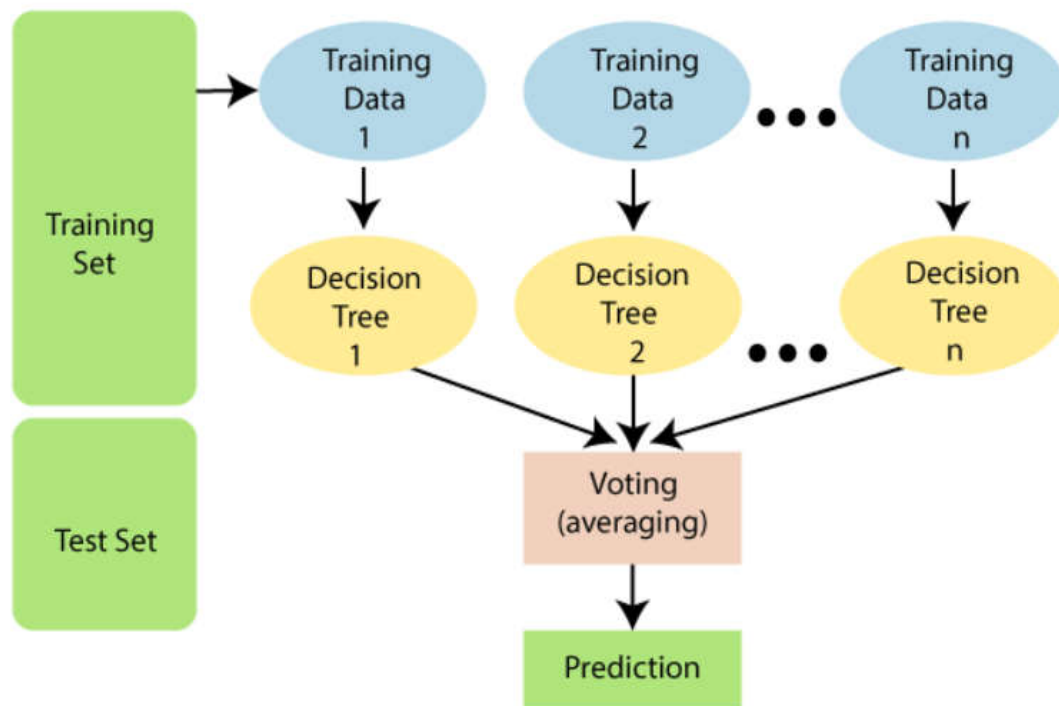


Figure 2.5.1: Random Forest (Javatpoint, 2021)

2.6 Naïve Bayes

- Naïve Bayes algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems.
- It is mainly used in text classification that includes a high-dimensional training dataset.
- Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.

- **It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.**
- Some popular examples of Naïve Bayes Algorithm are **spam filtration, Sentimental analysis, and classifying articles.**

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

Figure 2.6.1: Bayes' Theorem

2.7 K-Nearest Neighbor(KNN)

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN is a non-parametric algorithm, which means it does not make any assumption on underlying data.
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data. (Javatpoint, 2021)

2.7.1 Why do we need a K-NN Algorithm?

Suppose there are two categories, i.e., Category A and Category B, and we have a new data

point x_1 , so this data point will lie in which of these categories. To solve this type of problem, we need a K-NN algorithm. With the help of K-NN, we can easily identify the category or class of a particular dataset. Consider the below diagram: (Javatpoint, 2021)

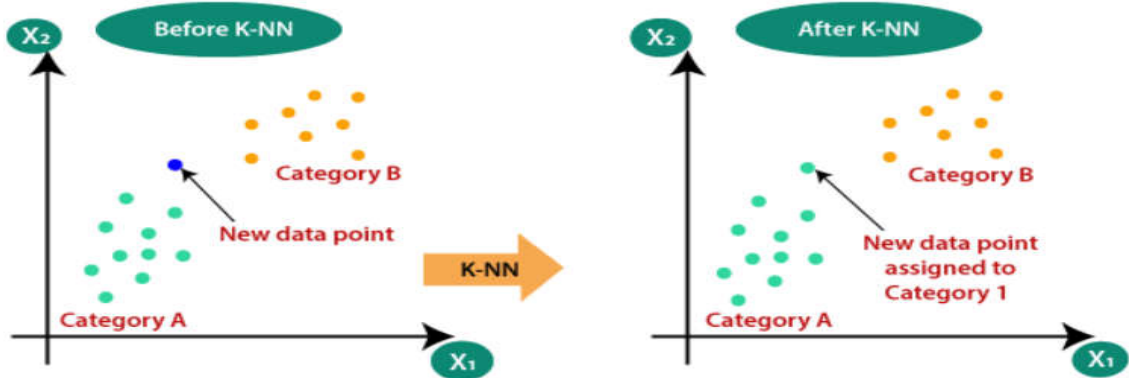


Figure 2.7.1: K-NN (Javatpoint, 2021)

Euclidean distance is used in the calculation of this algorithm.

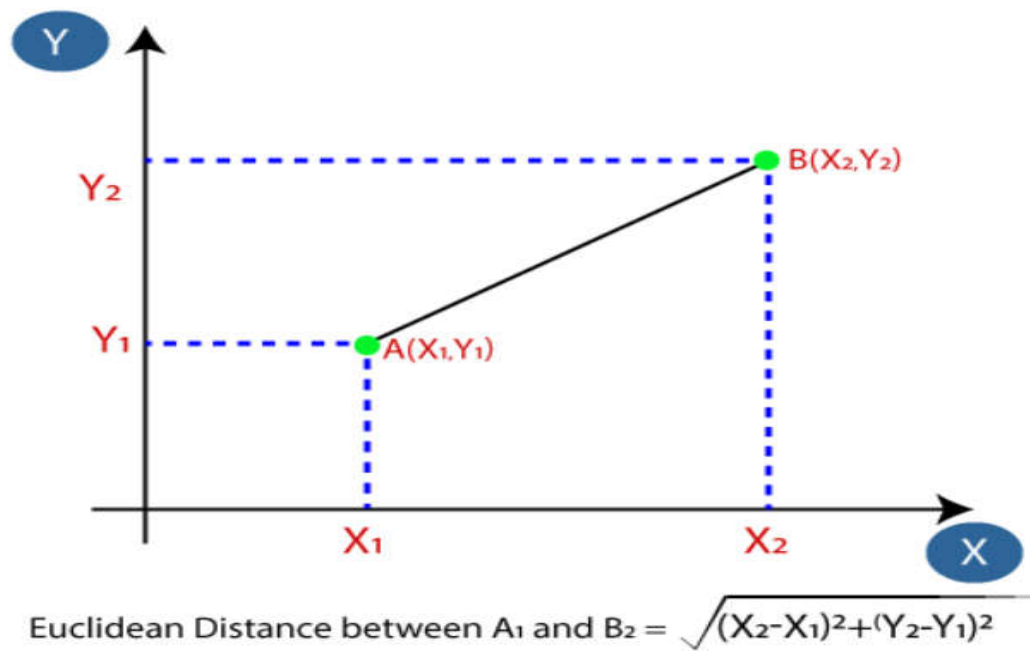


Figure 2.7.2: Euclidean Distance (Javatpoint, 2021)

3. PROJECT

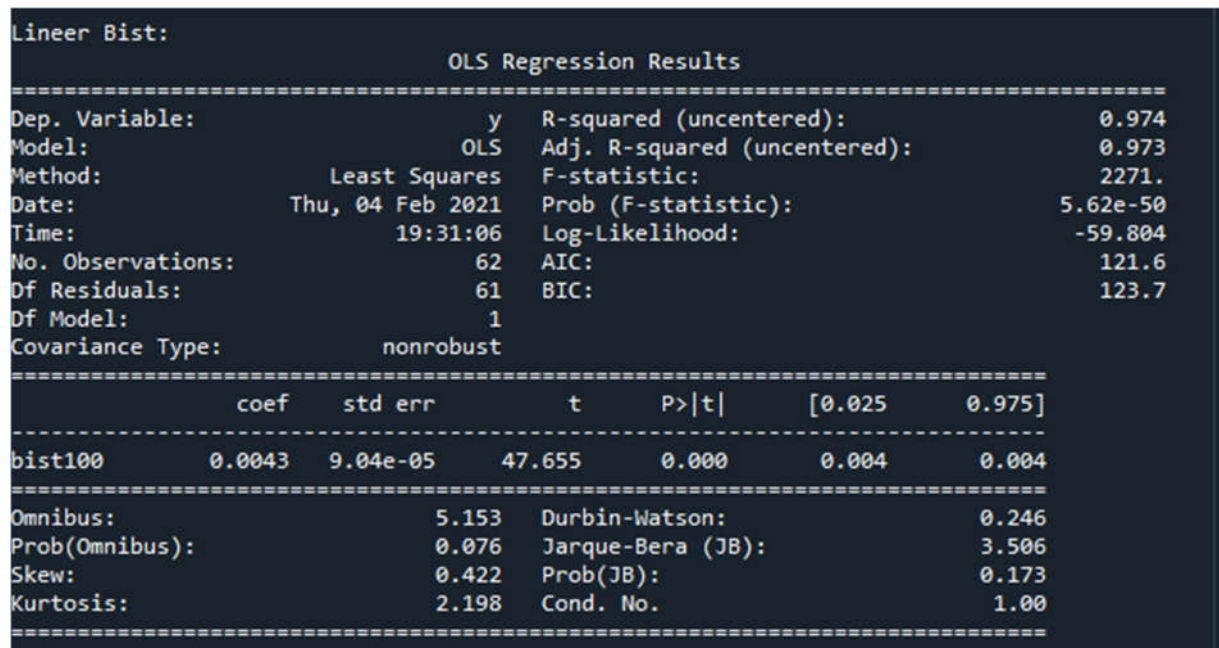
In our project, we first performed data collection. Based on the information given to us by the authorized person in Tüik, we find most of our data from the Central Bank of the Republic of Turkey Data Systems. We received this data monthly and started data processing. The range of data we collect is between 2013 and 2020. (Türkiye Cumhuriyeti Merkez Bankası, 2021)

Then we trained our project with some regression models using this data.

After that, we interpreted these models and decided which models are suitable for us.

After these models, we learned the NLP (natural language processing) steps and applied NLP prediction algorithms on our project using the data we got from Twitter.

In **gp_project.py**, we imported the libraries in order to use the data and algorithms necessary for the estimation we will do. Then, we uploaded our data. We split each data for training and testing. We have done the standardization process required for some algorithms. We found OLS regression results for each prediction algorithm. Finally, we analyzed the data distributions by visualization.



```
Linear Bist:
=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      0.974
Model:                  OLS    Adj. R-squared (uncentered):    0.973
Method:                 Least Squares    F-statistic:          2271.
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    5.62e-50
Time:                   19:31:06    Log-Likelihood:       -59.804
No. Observations:       62    AIC:                  121.6
Df Residuals:           61    BIC:                  123.7
Df Model:                1
Covariance Type:        nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
bistl00      0.0043    9.04e-05    47.655    0.000    0.004    0.004
=====
Omnibus:            5.153    Durbin-Watson:      0.246
Prob(Omnibus):      0.076    Jarque-Bera (JB):    3.506
Skew:               0.422    Prob(JB):            0.173
Kurtosis:           2.198    Cond. No.            1.00
=====
```

Figure 3.1: Linear Bist OLS Results

```

Linear Cari Açık:
                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared (uncentered):      0.357
Model:                        OLS      Adj. R-squared (uncentered):    0.346
Method:                      Least Squares      F-statistic:          33.85
Date:                        Thu, 04 Feb 2021      Prob (F-statistic):    2.36e-07
Time:                        19:31:07      Log-Likelihood:       -156.78
No. Observations:            62      AIC:                  315.6
Df Residuals:                61      BIC:                  317.7
Df Model:                    1
Covariance Type:             nonrobust
=====
                                coef      std err          t      P>|t|      [0.025      0.975]
-----
cari_acik      -0.0006      0.000      -5.818      0.000      -0.001      -0.000
=====
Omnibus:                7.065      Durbin-Watson:          0.352
Prob(Omnibus):          0.029      Jarque-Bera (JB):        6.341
Skew:                   0.753      Prob(JB):                0.0420
Kurtosis:               3.430      Cond. No.                 1.00
=====

```

Figure 3.2: Linear Cari Açık OLS Results

```

Linear Döviz Rezervi:
                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared (uncentered):      0.687
Model:                        OLS      Adj. R-squared (uncentered):    0.681
Method:                      Least Squares      F-statistic:          133.6
Date:                        Thu, 04 Feb 2021      Prob (F-statistic):    5.24e-17
Time:                        19:31:07      Log-Likelihood:       -138.64
No. Observations:            62      AIC:                  279.3
Df Residuals:                61      BIC:                  281.4
Df Model:                    1
Covariance Type:             nonrobust
=====
=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----
doviz_rezervi(milyon dolar)  3.62e-05  3.13e-06    11.559      0.000      2.99e-05
4.25e-05
=====
Omnibus:                7.374      Durbin-Watson:          0.057
Prob(Omnibus):          0.025      Jarque-Bera (JB):        7.319
Skew:                   0.841      Prob(JB):                0.0257
Kurtosis:               3.033      Cond. No.                 1.00
=====

```

Figure 3.3: Linear Döviz Rezervi OLS Results


```

Linear Para Arz1:

=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      1.000
Model:                  OLS    Adj. R-squared (uncentered):    1.000
Method:                 Least Squares    F-statistic:          1.542e+08
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    5.28e-197
Time:                   19:31:07    Log-Likelihood:       282.24
No. Observations:      62    AIC:                  -562.5
Df Residuals:          61    BIC:                  -560.4
Df Model:               1
Covariance Type:       nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
para_arzi(bin tl)  2.423e-09   1.95e-13   1.24e+04   0.000   2.42e-09   2.42e-09
=====
Omnibus:              8.923    Durbin-Watson:         0.011
Prob(Omnibus):         0.012    Jarque-Bera (JB):      9.421
Skew:                  0.955    Prob(JB):              0.00900
Kurtosis:              2.962    Cond. No.              1.00
=====

```

Figure 3.4: Linear Para Arz1 OLS Results

```

Linear Faiz:

=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      0.987
Model:                  OLS    Adj. R-squared (uncentered):    0.987
Method:                 Least Squares    F-statistic:          4809.
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    9.86e-60
Time:                   19:31:07    Log-Likelihood:       -35.248
No. Observations:      62    AIC:                  72.50
Df Residuals:          61    BIC:                  74.62
Df Model:               1
Covariance Type:       nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
faiz                  0.3010     0.004    69.345   0.000     0.292     0.310
=====
Omnibus:              13.692    Durbin-Watson:         0.210
Prob(Omnibus):         0.001    Jarque-Bera (JB):      15.429
Skew:                  -1.205    Prob(JB):              0.000446
Kurtosis:              3.399    Cond. No.              1.00
=====

```

Figure 3.5: Linear Faiz OLS Results

```

Linear Enflasyon:
=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      0.992
Model:                  OLS    Adj. R-squared (uncentered):    0.992
Method:                 Least Squares    F-statistic:          7718.
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    6.15e-66
Time:                   19:31:07    Log-Likelihood:       -21.668
No. Observations:      62    AIC:                  45.34
Df Residuals:          61    BIC:                  47.46
Df Model:              1
Covariance Type:       nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
enflasyon      0.3443      0.004      87.850      0.000      0.336      0.352
=====
Omnibus:          30.890    Durbin-Watson:      0.169
Prob(Omnibus):    0.000    Jarque-Bera (JB):    54.871
Skew:            -1.776    Prob(JB):            1.22e-12
Kurtosis:         5.936    Cond. No.            1.00
=====

```

Figure 3.6: Linear Enflasyon OLS Results

```

Linear İhracat:
=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      0.997
Model:                  OLS    Adj. R-squared (uncentered):    0.997
Method:                 Least Squares    F-statistic:          2.079e+04
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    5.35e-79
Time:                   19:31:07    Log-Likelihood:       11.153
No. Observations:      62    AIC:                  -20.31
Df Residuals:          61    BIC:                  -18.18
Df Model:              1
Covariance Type:       nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
ihracat      2.734e-07      1.9e-09      144.181      0.000      2.7e-07      2.77e-07
=====
Omnibus:          2.628    Durbin-Watson:      1.061
Prob(Omnibus):    0.269    Jarque-Bera (JB):    1.780
Skew:            0.341    Prob(JB):            0.411
Kurtosis:         3.474    Cond. No.            1.00
=====

```

Figure 3.7: Linear İhracat OLS Results

```

Linear İthalat:
=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      0.887
Model:                  OLS    Adj. R-squared (uncentered):    0.885
Method:                 Least Squares    F-statistic:          477.7
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    1.51e-30
Time:                   19:31:07    Log-Likelihood:       -103.41
No. Observations:       62    AIC:                  208.8
Df Residuals:           61    BIC:                  210.9
Df Model:                1
Covariance Type:        nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
ithalat      1.883e-07   8.62e-09    21.857    0.000    1.71e-07    2.06e-07
=====
Omnibus:                2.280    Durbin-Watson:        0.589
Prob(Omnibus):           0.320    Jarque-Bera (JB):      1.451
Skew:                   0.076    Prob(JB):              0.484
Kurtosis:               2.266    Cond. No.              1.00
=====

```

Figure 3.8: Linear İthalat OLS Results

```

Linear Dış Ticaret:
=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      0.607
Model:                  OLS    Adj. R-squared (uncentered):    0.601
Method:                 Least Squares    F-statistic:          94.21
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    5.51e-14
Time:                   19:31:07    Log-Likelihood:       -142.95
No. Observations:       62    AIC:                  287.9
Df Residuals:           61    BIC:                  290.0
Df Model:                1
Covariance Type:        nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
dis_ticaret_dengesi -5.202e-07   5.36e-08    -9.706    0.000    -6.27e-07    -4.13e-07
=====
Omnibus:                0.390    Durbin-Watson:        0.396
Prob(Omnibus):           0.823    Jarque-Bera (JB):      0.537
Skew:                   0.157    Prob(JB):              0.765
Kurtosis:               2.669    Cond. No.              1.00
=====

```

Figure 3.9: Linear Dış Ticaret OLS Results


```

Multilinear:

=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):          1.000
Model:                  OLS    Adj. R-squared (uncentered):        1.000
Method:                  Least Squares    F-statistic:          1.464e+05
Date:                    Thu, 04 Feb 2021    Prob (F-statistic):    3.37e-114
Time:                    19:31:07    Log-Likelihood:        134.61
No. Observations:        62    AIC:                    -253.2
Df Residuals:            54    BIC:                    -236.2
Df Model:                 8
Covariance Type:         nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
bist100                  -8.219e-05   5.05e-05     -1.629     0.109     -0.000     1.9e-05
cari_acik                -7.362e-07   2.84e-06     -0.259     0.797     -6.44e-06   4.96e-06
doviz_rezervi(milyon dolar) 2.024e-06   3.37e-07     6.012     0.000     1.35e-06   2.7e-06
para_arzi(bin tl)         2.195e-09   1.39e-11    157.938     0.000     2.17e-09   2.22e-09
ihracat                  6.162e-09   2.35e-09     2.627     0.011     1.46e-09   1.09e-08
ithalat                 -2.192e-08   1.71e-09    -12.806     0.000     -2.54e-08  -1.85e-08
dis_ticaret_dengesi       2.809e-08   2.53e-09    11.112     0.000     2.3e-08    3.32e-08
enflasyon                 0.0552      0.002      35.929     0.000     0.052     0.058
faiz                     0.0115      0.001       8.059     0.000     0.009     0.014
=====
Omnibus:                 4.891    Durbin-Watson:          0.939
Prob(Omnibus):            0.087    Jarque-Bera (JB):        3.932
Skew:                     -0.560    Prob(JB):                0.140
Kurtosis:                 3.517    Cond. No.                6.89e+17
=====

```

Figure 3.10: Multilinear OLS Results

```

Polinom Bist:

=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):          0.969
Model:                  OLS    Adj. R-squared (uncentered):        0.969
Method:                  Least Squares    F-statistic:          2866.
Date:                    Thu, 04 Feb 2021    Prob (F-statistic):    3.91e-71
Time:                    19:37:57    Log-Likelihood:        -98.254
No. Observations:        93    AIC:                    198.5
Df Residuals:            92    BIC:                    201.0
Df Model:                 1
Covariance Type:         nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
x1                      0.0043   7.99e-05    53.538     0.000     0.004     0.004
=====
Omnibus:                 152.109    Durbin-Watson:          0.320
Prob(Omnibus):            0.000    Jarque-Bera (JB):        9.614
Skew:                     0.267    Prob(JB):                0.00817
Kurtosis:                 1.518    Cond. No.                1.00
=====

```

Figure 3.11: Polynomial Bist OLS Results

```
Polinom CARİ AÇIK:
OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):      0.320
Model:                  OLS      Adj. R-squared (uncentered):    0.312
Method:                Least Squares      F-statistic:              43.25
Date:                  Thu, 04 Feb 2021      Prob (F-statistic):      2.87e-09
Time:                  19:57:18      Log-Likelihood:          -238.70
No. Observations:      93      AIC:                    479.4
Df Residuals:          92      BIC:                    481.9
Df Model:              1
Covariance Type:      nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
x1	-0.0006	9.41e-05	-6.577	0.000	-0.001	-0.000

```
=====
Omnibus:                13.212      Durbin-Watson:              0.263
Prob(Omnibus):          0.001      Jarque-Bera (JB):          14.104
Skew:                   0.892      Prob(JB):                  0.000866
Kurtosis:               3.673      Cond. No.                  1.00
=====
```

Figure 3.12: Polynomial Cari Açık OLS Results

```
Polinom Döviz Rezervi:
                                OLS Regression Results
=====
Dep. Variable:                  y    R-squared (uncentered):          0.695
Model:                        OLS    Adj. R-squared (uncentered):      0.692
Method:                      Least Squares    F-statistic:                209.9
Date:                        Thu, 04 Feb 2021    Prob (F-statistic):        1.81e-25
Time:                        19:37:57    Log-Likelihood:            -207.11
No. Observations:            93    AIC:                        416.2
Df Residuals:                92    BIC:                        418.7
Df Model:                    1
Covariance Type:              nonrobust
=====
                                coef    std err          t      P>|t|      [0.025    0.975]
-----
x1                3.659e-05    2.53e-06    14.487    0.000    3.16e-05    4.16e-05
=====
Omnibus:                    9.240    Durbin-Watson:              0.047
Prob(Omnibus):              0.010    Jarque-Bera (JB):           9.242
Skew:                      0.720    Prob(JB):                   0.00984
Kurtosis:                  2.445    Cond. No.                   1.00
=====
```

Figure 3.13: Polynomial Döviz Rezervi OLS Results

```

Polinom Para Arz1:
                                OLS Regression Results
=====
Dep. Variable:                  y    R-squared (uncentered):          0.997
Model:                        OLS    Adj. R-squared (uncentered):      0.997
Method:                      Least Squares    F-statistic:                3.376e+04
Date:                        Thu, 04 Feb 2021    Prob (F-statistic):         7.78e-120
Time:                        19:37:57    Log-Likelihood:             12.164
No. Observations:            93    AIC:                        -22.33
Df Residuals:                92    BIC:                        -19.80
Df Model:                    1
Covariance Type:              nonrobust
=====
                                coef    std err          t      P>|t|      [0.025    0.975]
-----
x1                2.443e-09    1.33e-11    183.748    0.000    2.42e-09    2.47e-09
=====
Omnibus:                    32.064    Durbin-Watson:              0.066
Prob(Omnibus):              0.000    Jarque-Bera (JB):           85.595
Skew:                      -1.170    Prob(JB):                   2.59e-19
Kurtosis:                   7.076    Cond. No.                    1.00
=====

```

Figure 3.14: Polynomial Para Arz1 OLS Results

```

Polinom Faiz:
                                OLS Regression Results
=====
Dep. Variable:                  y    R-squared (uncentered):          0.978
Model:                        OLS    Adj. R-squared (uncentered):      0.978
Method:                      Least Squares    F-statistic:                4137.
Date:                        Thu, 04 Feb 2021    Prob (F-statistic):         2.81e-78
Time:                        19:37:57    Log-Likelihood:             -79.803
No. Observations:            93    AIC:                        161.6
Df Residuals:                92    BIC:                        164.1
Df Model:                    1
Covariance Type:              nonrobust
=====
                                coef    std err          t      P>|t|      [0.025    0.975]
-----
x1                 0.2924    0.005    64.322    0.000    0.283    0.301
=====
Omnibus:                    45.783    Durbin-Watson:              0.366
Prob(Omnibus):              0.000    Jarque-Bera (JB):           101.848
Skew:                      -1.924    Prob(JB):                   7.66e-23
Kurtosis:                   6.388    Cond. No.                    1.00
=====

```

Figure 3.15: Polynomial Faiz OLS Results


```

Polinom Enflasyon:
                                OLS Regression Results
=====
Dep. Variable:                  y    R-squared (uncentered):          0.974
Model:                        OLS    Adj. R-squared (uncentered):      0.973
Method:                      Least Squares    F-statistic:                3383.
Date:                        Thu, 04 Feb 2021    Prob (F-statistic):        2.37e-74
Time:                        19:37:57    Log-Likelihood:            -90.782
No. Observations:              93    AIC:                        183.6
Df Residuals:                  92    BIC:                        186.1
Df Model:                      1
Covariance Type:               nonrobust
=====
                                coef    std err          t      P>|t|      [0.025    0.975]
-----
x1                            0.3369      0.006     58.163      0.000      0.325      0.348
=====
Omnibus:                      58.807    Durbin-Watson:              0.292
Prob(Omnibus):                 0.000    Jarque-Bera (JB):           228.201
Skew:                         -2.143    Prob(JB):                   2.80e-50
Kurtosis:                     9.365    Cond. No.                    1.00
=====

```

Figure 3.16: Polynomial Enflasyon OLS Results

```

Polinom İhracat:
                                OLS Regression Results
=====
Dep. Variable:                  y    R-squared (uncentered):          0.964
Model:                        OLS    Adj. R-squared (uncentered):      0.964
Method:                      Least Squares    F-statistic:                2499.
Date:                        Thu, 04 Feb 2021    Prob (F-statistic):        1.75e-68
Time:                        19:37:57    Log-Likelihood:            -101.97
No. Observations:              93    AIC:                        205.9
Df Residuals:                  92    BIC:                        208.5
Df Model:                      1
Covariance Type:               nonrobust
=====
                                coef    std err          t      P>|t|      [0.025    0.975]
-----
x1                           2.75e-07      5.5e-09     49.988      0.000      2.64e-07      2.86e-07
=====
Omnibus:                      50.368    Durbin-Watson:              1.529
Prob(Omnibus):                 0.000    Jarque-Bera (JB):           125.079
Skew:                         2.064    Prob(JB):                   6.91e-28
Kurtosis:                     6.904    Cond. No.                    1.00
=====

```

Figure 3.17: Polynomial İhracat OLS Results

```
Polinom İthalat:
```

```
OLS Regression Results
```

```
=====
```

Dep. Variable:	y	R-squared (uncentered):	0.905
Model:	OLS	Adj. R-squared (uncentered):	0.904
Method:	Least Squares	F-statistic:	877.4
Date:	Thu, 04 Feb 2021	Prob (F-statistic):	7.84e-49
Time:	19:37:57	Log-Likelihood:	-146.94
No. Observations:	93	AIC:	295.9
Df Residuals:	92	BIC:	298.4
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
x1	1.896e-07	6.4e-09	29.621	0.000	1.77e-07	2.02e-07

```
=====
```

Omnibus:	3.280	Durbin-Watson:	0.720
Prob(Omnibus):	0.194	Jarque-Bera (JB):	1.894
Skew:	-0.014	Prob(JB):	0.388
Kurtosis:	2.302	Cond. No.	1.00

```
=====
```

Figure 3.18: Polynomial İthalat OLS Results

Polinom Dış Ticaret:						
OLS Regression Results						
=====						
Dep. Variable:	y	R-squared (uncentered):	0.604			
Model:	OLS	Adj. R-squared (uncentered):	0.599			
Method:	Least Squares	F-statistic:	140.2			
Date:	Thu, 04 Feb 2021	Prob (F-statistic):	3.42e-20			
Time:	19:37:57	Log-Likelihood:	-215.38			
No. Observations:	93	AIC:	432.8			
Df Residuals:	92	BIC:	435.3			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

x1	-5.214e-07	4.4e-08	-11.839	0.000	-6.09e-07	-4.34e-07
=====						
Omnibus:	6.473	Durbin-Watson:	0.359			
Prob(Omnibus):	0.039	Jarque-Bera (JB):	3.605			
Skew:	0.273	Prob(JB):	0.165			
Kurtosis:	2.205	Cond. No.	1.00			
=====						

Figure 3.19: Polynomial Dış Ticaret OLS Results


```
multi polinom:
```

```
OLS Regression Results
```

```
=====
```

Dep. Variable:	y	R-squared:	0.941
Model:	OLS	Adj. R-squared:	0.937
Method:	Least Squares	F-statistic:	275.2
Date:	Thu, 04 Feb 2021	Prob (F-statistic):	9.81e-52
Time:	19:37:57	Log-Likelihood:	-35.881
No. Observations:	93	AIC:	83.76
Df Residuals:	87	BIC:	98.96
Df Model:	5		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	-1.365e-17	1.47e-17	-0.930	0.355	-4.28e-17	1.55e-17
x1	5.364e-17	5.64e-17	0.952	0.344	-5.84e-17	1.66e-16
x2	-3.454e-23	3.73e-23	-0.926	0.357	-1.09e-22	3.96e-23
x3	-2.197e-21	2.07e-21	-1.061	0.291	-6.31e-21	1.92e-21
x4	-4.554e-26	4.85e-26	-0.940	0.350	-1.42e-25	5.08e-26
x5	-1.45e-22	1.45e-22	-0.997	0.321	-4.34e-22	1.44e-22
x6	-7.619e-19	8.47e-19	-0.900	0.371	-2.44e-18	9.21e-19
x7	-1.012e-24	1.13e-24	-0.898	0.372	-3.25e-24	1.23e-24
x8	-4.34e-20	5.37e-20	-0.808	0.421	-1.5e-19	6.33e-20
x9	1.169e-15	2.71e-16	4.318	0.000	6.31e-16	1.71e-15
x10	-1.18e-20	1.26e-20	-0.934	0.353	-3.69e-20	1.33e-20
x11	1.164e-18	1.65e-19	7.034	0.000	8.35e-19	1.49e-18
x12	-1.481e-28	4.42e-29	-3.353	0.001	-2.36e-28	-6.03e-29
x13	-1.191e-28	1.25e-28	-0.951	0.344	-3.68e-28	1.3e-28
x14	-8.031e-28	7.48e-28	-1.074	0.286	-2.29e-27	6.83e-28
x15	-1.412e-26	1.17e-26	-1.206	0.231	-3.74e-26	9.15e-27
x16	-2.38e-28	2.5e-28	-0.953	0.343	-7.34e-28	2.58e-28
x17	-4.767e-27	4.94e-27	-0.966	0.337	-1.46e-26	5.05e-27
x18	-1.126e-25	1.17e-25	-0.967	0.336	-3.44e-25	1.19e-25
x19	-1.743e-22	1.87e-22	-0.932	0.354	-5.46e-22	1.97e-22
x20	-1.264e-15	1.35e-15	-0.934	0.353	-3.95e-15	1.43e-15
x21	6.134e-22	1.02e-22	6.043	0.000	4.12e-22	8.15e-22
x22	-2.556e-22	2.74e-22	-0.933	0.353	-8e-22	2.89e-22
x23	-2.716e-15	2.9e-15	-0.936	0.352	-8.48e-15	3.05e-15
x24	-4.114e-23	1.21e-22	-0.341	0.734	-2.81e-22	1.99e-22
x25	8.127e-23	8.69e-23	0.935	0.352	-9.15e-23	2.54e-22
x26	-3.303e-16	3.51e-16	-0.942	0.349	-1.03e-15	3.67e-16
x27	-1.384e-21	4.75e-22	-2.916	0.005	-2.33e-21	-4.41e-22

```
=====
```

Figure 3.20: Multipolynomial OLS Results

```
SVR rbf:
```

```

              OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):          0.992
Model:                  OLS    Adj. R-squared (uncentered):      0.991
Method:                 Least Squares    F-statistic:          1320.
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    9.96e-86
Time:                   19:37:57    Log-Likelihood:        95.750
No. Observations:      93    AIC:                   -175.5
Df Residuals:          85    BIC:                   -155.2
Df Model:              8
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
x1	0.0148	0.016	0.900	0.371	-0.018	0.048
x2	-0.0088	0.019	-0.475	0.636	-0.046	0.028
x3	-0.1268	0.040	-3.182	0.002	-0.206	-0.048
x4	0.6781	0.039	17.534	0.000	0.601	0.755
x5	0.0135	0.011	1.263	0.210	-0.008	0.035
x6	-0.0357	0.009	-3.909	0.000	-0.054	-0.018
x7	0.0471	0.013	3.724	0.000	0.022	0.072
x8	0.1383	0.018	7.694	0.000	0.103	0.174
x9	0.0396	0.015	2.721	0.008	0.011	0.068

```

=====
Omnibus:                0.980    Durbin-Watson:          1.067
Prob(Omnibus):          0.613    Jarque-Bera (JB):       1.077
Skew:                   0.218    Prob(JB):               0.584
Kurtosis:               2.704    Cond. No.                1.39e+15
=====

```

Figure 3.21: SVR rbf OLS Results

SVR linear:						
OLS Regression Results						
=====						
Dep. Variable:	y	R-squared (uncentered):	1.000			
Model:	OLS	Adj. R-squared (uncentered):	1.000			
Method:	Least Squares	F-statistic:	1.168e+05			
Date:	Thu, 04 Feb 2021	Prob (F-statistic):	2.61e-168			
Time:	19:37:57	Log-Likelihood:	301.36			
No. Observations:	93	AIC:	-586.7			
Df Residuals:	85	BIC:	-566.5			
Df Model:	8					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----+-----						
x1	-0.0188	0.002	-10.406	0.000	-0.022	-0.015
x2	0.0200	0.002	9.829	0.000	0.016	0.024
x3	-0.0796	0.004	-18.225	0.000	-0.088	-0.071
x4	0.7783	0.004	183.630	0.000	0.770	0.787
x5	0.0138	0.001	11.775	0.000	0.011	0.016
x6	-0.0297	0.001	-29.700	0.000	-0.032	-0.028
x7	0.0409	0.001	29.502	0.000	0.038	0.044
x8	0.1323	0.002	67.127	0.000	0.128	0.136
x9	0.0386	0.002	24.232	0.000	0.035	0.042
=====						
Omnibus:	3.010	Durbin-Watson:	0.000			
Prob(Omnibus):	0.222	Jarque-Bera (JB):	2.579			
Skew:	-0.201	Prob(JB):	0.275			
Kurtosis:	3.710	Cond. No.	1.39e+15			
=====						

Figure 3.22: SVR linear OLS Results

SVR poly:						
OLS Regression Results						
=====						
Dep. Variable:	y	R-squared (uncentered):	0.944			
Model:	OLS	Adj. R-squared (uncentered):	0.938			
Method:	Least Squares	F-statistic:	178.3			
Date:	Thu, 04 Feb 2021	Prob (F-statistic):	9.31e-50			
Time:	19:37:57	Log-Likelihood:	8.7966			
No. Observations:	93	AIC:	-1.593			
Df Residuals:	85	BIC:	18.67			
Df Model:	8					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

x1	0.0427	0.042	1.018	0.311	-0.041	0.126
x2	0.1104	0.047	2.338	0.022	0.017	0.204
x3	-0.3013	0.102	-2.968	0.004	-0.503	-0.099
x4	0.4368	0.098	4.435	0.000	0.241	0.633
x5	0.0030	0.027	0.110	0.913	-0.051	0.057
x6	-0.0112	0.023	-0.484	0.630	-0.057	0.035
x7	0.0140	0.032	0.435	0.664	-0.050	0.078
x8	0.0437	0.046	0.955	0.342	-0.047	0.135
x9	0.0947	0.037	2.556	0.012	0.021	0.168
=====						
Omnibus:	10.896	Durbin-Watson:	1.145			
Prob(Omnibus):	0.004	Jarque-Bera (JB):	14.370			
Skew:	-0.560	Prob(JB):	0.000758			
Kurtosis:	4.567	Cond. No.	1.39e+15			
=====						

Figure 3.23: SVR poly OLS Results

SVR sigmoid:						
OLS Regression Results						
=====						
Dep. Variable:	y	R-squared (uncentered):	0.296			
Model:	OLS	Adj. R-squared (uncentered):	0.230			
Method:	Least Squares	F-statistic:	4.468			
Date:	Thu, 04 Feb 2021	Prob (F-statistic):	0.000150			
Time:	19:37:57	Log-Likelihood:	-154.20			
No. Observations:	93	AIC:	324.4			
Df Residuals:	85	BIC:	344.7			
Df Model:	8					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

x1	-0.2446	0.242	-1.011	0.315	-0.726	0.236
x2	-0.0865	0.273	-0.318	0.752	-0.628	0.455
x3	-0.2429	0.586	-0.415	0.679	-1.408	0.922
x4	0.9202	0.568	1.619	0.109	-0.210	2.050
x5	0.1252	0.157	0.797	0.428	-0.187	0.438
x6	0.1889	0.134	1.409	0.163	-0.078	0.455
x7	-0.1202	0.186	-0.647	0.519	-0.490	0.249
x8	-0.0823	0.264	-0.311	0.756	-0.608	0.443
x9	-0.0982	0.214	-0.460	0.647	-0.523	0.327
=====						
Omnibus:	2.610	Durbin-Watson:	1.529			
Prob(Omnibus):	0.271	Jarque-Bera (JB):	2.370			
Skew:	0.391	Prob(JB):	0.306			
Kurtosis:	2.961	Cond. No.	1.39e+15			
=====						

Figure 3.24: SVR sigmoid OLS Results


```

Decision Tree:
=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):          0.999
Model:                  OLS    Adj. R-squared (uncentered):        0.999
Method:                 Least Squares    F-statistic:          9033.
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    4.36e-121
Time:                   19:37:57    Log-Likelihood:        50.994
No. Observations:      93    AIC:                   -85.99
Df Residuals:          85    BIC:                   -65.73
Df Model:              8
Covariance Type:       nonrobust
=====
                        coef      std err      t      P>|t|      [0.025      0.975]
-----
x1          -0.0002      0.000     -1.347      0.182     -0.001      0.000
x2          4.045e-06     1.17e-05      0.346      0.730     -1.92e-05     2.73e-05
x3          6.623e-07     1.3e-06      0.510      0.611     -1.92e-06     3.24e-06
x4          2.2e-09      5.48e-11     40.173      0.000     2.09e-09     2.31e-09
x5          9.333e-09     9.27e-09      1.007      0.317     -9.1e-09     2.78e-08
x6         -1.475e-08     6.36e-09     -2.317      0.023     -2.74e-08     -2.09e-09
x7          2.408e-08     1.01e-08      2.385      0.019      4e-09     4.42e-08
x8          0.0616      0.006     10.043      0.000      0.049      0.074
x9          0.0122      0.005      2.312      0.023      0.002      0.023
=====
Omnibus:              4.309    Durbin-Watson:          0.944
Prob(Omnibus):        0.116    Jarque-Bera (JB):        5.060
Skew:                 0.139    Prob(JB):                0.0797
Kurtosis:             4.108    Cond. No.                1.17e+18
=====

```

Figure 3.25: Decision Tree OLS Results

```

Random Forest:
=====
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared (uncentered):          0.999
Model:                  OLS    Adj. R-squared (uncentered):        0.999
Method:                 Least Squares    F-statistic:          9752.
Date:                   Thu, 04 Feb 2021    Prob (F-statistic):    1.69e-122
Time:                   19:37:58    Log-Likelihood:        54.529
No. Observations:      93    AIC:                   -93.06
Df Residuals:          85    BIC:                   -72.80
Df Model:              8
Covariance Type:       nonrobust
=====
                        coef      std err      t      P>|t|      [0.025      0.975]
-----
x1          -0.0003      0.000     -1.746      0.084     -0.001     4.29e-05
x2          7.99e-06     1.13e-05      0.710      0.480     -1.44e-05     3.04e-05
x3          6.533e-07     1.25e-06      0.523      0.603     -1.83e-06     3.14e-06
x4          2.226e-09     5.27e-11     42.210      0.000     2.12e-09     2.33e-09
x5          7.575e-09     8.92e-09      0.849      0.398     -1.02e-08     2.53e-08
x6         -1.237e-08     6.13e-09     -2.019      0.047     -2.46e-08     -1.89e-10
x7          1.995e-08     9.72e-09      2.052      0.043     6.19e-10     3.93e-08
x8          0.0603      0.006     10.207      0.000      0.049      0.072
x9          0.0121      0.005      2.385      0.019      0.002      0.022
=====
Omnibus:              0.752    Durbin-Watson:          1.059
Prob(Omnibus):        0.687    Jarque-Bera (JB):        0.459
Skew:                 0.166    Prob(JB):                0.795
Kurtosis:             3.092    Cond. No.                1.17e+18
=====

```

Figure 3.26: Random Forest OLS Results

Index	bist100	carı_acık	USD	EURO	ezervi(milyon dolar)	ara_arzi(bin t)	ihracat	ithalat	ticaret_deng	enflasyon	faiz
bist100	1	0.077145	0.714289	0.72501	-0.69801	0.742072	0.345939	0.00751576	0.218902	0.463531	0.468503
carı_acık	0.077145	1	0.432614	0.408851	-0.314877	0.330421	0.242996	-0.612348	0.815705	0.520746	0.445955
USD	0.714289	0.432614	1	0.992261	-0.96221	0.980027	0.271315	-0.432341	0.641362	0.685987	0.552043
EURO	0.72501	0.408851	0.992261	1	-0.95831	0.974551	0.312605	-0.362293	0.593377	0.702913	0.582934
doviz_rezervi(milyon dolar)	-0.69801	-0.314877	-0.96221	-0.95831	1	-0.956245	-0.188078	0.416034	-0.569276	-0.63899	-0.479047
para_arzi(bin t)	0.742072	0.330421	0.980027	0.974551	-0.956245	1	0.219917	-0.382837	0.554585	0.558143	0.451329
ihracat	0.345939	0.242996	0.271315	0.312605	-0.188078	0.219917	1	0.411776	0.21474	0.439803	0.476215
ithalat	0.00751576	-0.612348	-0.432341	-0.362293	0.416034	-0.382837	0.411776	1	-0.801601	-0.266717	-0.135516
dis_ticaret_dengesi	0.218902	0.815705	0.641362	0.593377	-0.569276	0.554585	0.21474	-0.801601	1	0.574393	0.457666
enflasyon	0.463531	0.520746	0.685987	0.702913	-0.63899	0.558143	0.439803	-0.266717	0.574393	1	0.723879
faiz	0.468503	0.445955	0.552043	0.582934	-0.479047	0.451329	0.476215	-0.135516	0.457666	0.723879	1

Figure 3.27: Correlation Results

In `nlp.py`, we imported the libraries. We downloaded the stopwords from corpus in the `nlk` library. Thanks to these downloaded words, we have removed the words that do not contain meaning in our data. We split each data for training and testing. Finally, we found the accuracy values of the algorithms we use with the confusion matrix.

```

Logistic
[[26 15]
 [11 43]]
*****

KNN
[[28 13]
 [29 25]]
*****

SVC
[[21 20]
 [ 9 45]]
*****

SVC linear
[[27 14]
 [14 40]]
*****

SVC poly
[[39  2]
 [42 12]]
*****

SVC sigmoid
[[25 16]
 [ 7 47]]
*****

GNB
[[24 17]
 [11 43]]
*****

DTC
[[22 19]
 [ 9 45]]
*****

DTC gini
[[21 20]
 [ 8 46]]
*****

RFC
[[22 19]
 [12 42]]
*****

RFC gini
[[30 11]
 [14 40]]

```

Figure 3.28: Confusion Matrix Results

In veri_çekmek.py, we imported the libraries. As a result of our research, we learned that we need to use the BeautifulSoup library to extract data from the internet, and using this library, we pulled data from Twitter. By doing an advanced search on Twitter, we took the link of the site and pasted it into our code. Keywords in these advanced searches are: economy, dollar, USA. There was an excessive repetition in the data we took. Using Excel, we deleted these repetitive tweets and made our data usable in our algorithms. Before using it in our algorithms, we marked our data. These markings affect the dollar rate (1) and not the dollar rate (0), and we used our data in algorithms. We showed the results we got from these algorithms in a table.

4. CONCLUSION

In summary, we have seen the importance of having a lot of data for machine learning. We saw that some algorithms learn 100% because our data is scarce. In fact, we noticed that the machine is overfitting. We know that this can be overcome by increasing data. We need to use a machine learning algorithm according to the state of the data. Since we do not know how the data will behave, we cannot know which algorithm to use. So we have to try algorithms. By comparing the results we got from this experiment, we can decide which algorithm is efficient.

In prediction algorithms, The adj. r-squared values were 1 in the prediction algorithms. Although these 1 values seem to work very efficiently, in fact, the values it predicts are not equal to the real values and we cannot decide the efficiency by looking only at this metric. Since we have little data, the probability of the system to be memorized is very high. Therefore, we cannot find the algorithm that is efficient in prediction algorithms at the moment. However, when we opened the value table and looked at it, we saw that the most efficient one was the random forest algorithm.

1	ALGORITHMS	ADJ.R-SQUARED
2	LINEAR BİST	0.973
3	LINEAR CARI_AÇIK	0.346
4	LINEAR DÖVİZ_REZERVİ	0.681
5	LINEAR PARA_ARZI	1
6	LINEAR FAİZ	0.987
7	LINEAR ENFLASYON	0.992
8	LINEAR İHRACAT	0.997
9	LINEAR İTHALAT	0.885
10	LINEAR DIŞ_TİCARET	0.601
11	MULTILINEAR	1
12	POLINOM BİST	0.969
13	POLINOM CARI_AÇIK	0.312
14	POLINOM DÖVİZ_REZERVİ	0.692
15	POLINOM PARA_ARZI	0.997
16	POLINOM FAİZ	0.978
17	POLINOM ENFLASYON	0.973
18	POLINOM İHRACAT	0.964
19	POLINOM İTHALAT	0.904
20	POLINOM DIŞ_TİCARET	0.599
21	MULTIPOLINOM	0.937
22	SVR RBF	0.991
23	SVR LINEAR	1
24	SVR POLY	0.938
25	SVR SIGMOID	0.230
26	DECISION TREE	0.999
27	RANDOM FOREST	0.999
28		

Figure 4.1: Table of Prediction Algorithms

In NLP algorithms, we can make comparisons in these algorithms because the tweet data we have taken from the internet is ideal. When we look at the accuracy values, we see that the most efficient algorithm is the SVC sigmoid algorithm. With a 76% success rate, it caught more accurate markups than other algorithms. We have seen and experienced that this is the most efficient algorithm for our data by creating the confusion matrix.

1	ALGORITHMS	ACCURACY	
2	LOGISTIC	73	
3	KNN	58	
4	SVC RBF	69	
5	SVC LINEAR	71	
6	SVC POLY	54	
7	SVC SIGMOID	76	
8	GNB	71	
9	DTC	66	
10	DTC GINI	65	
11	RFC	69	
12	RFC GINI	71	
13			

Figure 4.2: Table of NLP Algorithms

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