# PRODUCT DEMAND PREDICTION WITH MACHINE LEARNING

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PHASE 2 SUBMISSION DOCUMENT

## INTRODUCTION:

A product company plans to offer discounts on its product during the upcoming holiday season. The company wants to find the price at which its product can be a better deal compared to its competitors. For this task, the company provided a dataset of past changes in sales based on price changes. You need to train a model that can predict the demand for the product in the market with different price segments.

The **dataset** that we have for this task contains data about:

1. the product id;
2. store id;
3. total price at which product was sold;
4. base price at which product was sold;
5. Units sold (quantity demanded);

### Product Demand Prediction using Python:

**Example:**

```
import pandas as pd
import numpy as np
import plotly.express as px
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor

data =
pd.read_csv("https://raw.githubusercontent.com/amankharwal/Website-data/master/demand.csv")
data.head()
```

**Output:**

| | ID | Store ID | Total Price | Base Price | Units Sold |
|---|---|---|---|---|---|
| 0 | 1 | 8091 | 99.0375 | 111.8625 | 20 |
| 1 | 2 | 8091 | 99.0375 | 99.0375 | 28 |
| 2 | 3 | 8091 | 133.9500 | 133.9500 | 19 |
| 3 | 4 | 8091 | 133.9500 | 133.9500 | 44 |
| 4 | 5 | 8091 | 141.0750 | 141.0750 | 52 |

## Content:

Consider incorporating time series forecasting techniques like ARIMA or Prophet to capture temporal patterns in demand data.

## Data source:

To predict the future, statistics utilize data from the past. That's why statistical forecasting is often called *historical*. The common recommendation is collecting data on sales for at least two years.

**DatasetLink:** **https://www.kaggle.com/datasets/chakradharmattapalli/product-demand-prediction-with-machine-learning**

| ID | Store ID | Total Price | Base Price | Units Sold |
|---|---|---|---|---|
| 1 | 8091 | 99.0375 | 111.8625 | 20 |
| 2 | 8091 | 99.0375 | 99.0375 | 28 |
| 3 | 8091 | 133.95 | 133.95 | 19 |
| 4 | 8091 | 133.95 | 133.95 | 44 |
| 5 | 8091 | 141.075 | 141.075 | 52 |
| 9 | 8091 | 227.2875 | 227.2875 | 18 |
| 10 | 8091 | 327.0375 | 327.0375 | 47 |
| 13 | 8091 | 210.9 | 210.9 | 50 |

| | | | | |
|---|---|---|---|---|
| 14 | 8091 | 190.2375 | 234.4125 | 82 |
| 17 | 8095 | 99.0375 | 99.0375 | 99 |
| 18 | 8095 | 97.6125 | 97.6125 | 120 |
| 19 | 8095 | 98.325 | 98.325 | 40 |
| 22 | 8095 | 133.2375 | 133.2375 | 68 |
| 23 | 8095 | 133.95 | 133.95 | 87 |
| 24 | 8095 | 139.65 | 139.65 | 186 |
| 27 | 8095 | 236.55 | 280.0125 | 54 |
| 28 | 8095 | 214.4625 | 214.4625 | 74 |
| 29 | 8095 | 266.475 | 296.4 | 102 |
| 30 | 8095 | 173.85 | 192.375 | 214 |

| | | | | |
|---|---|---|---|---|
| 31 | 8095 | 205.9125 | 205.9125 | 28 |
| 32 | 8095 | 205.9125 | 205.9125 | 7 |
| 33 | 8095 | 248.6625 | 248.6625 | 48 |
| 34 | 8095 | 200.925 | 200.925 | 78 |
| 35 | 8095 | 190.2375 | 240.825 | 57 |
| 37 | 8095 | 427.5 | 448.1625 | 50 |
| 38 | 8095 | 429.6375 | 458.1375 | 62 |
| 39 | 8095 | 177.4125 | 177.4125 | 22 |
| 42 | 8094 | 87.6375 | 87.6375 | 109 |
| 43 | 8094 | 88.35 | 88.35 | 133 |
| 44 | 8094 | 85.5 85.5 11 | | |

| | | | | |
|---|---|---|---|---|
| 45 | 8094 | 128.25 | 180.975 | 9 |
| 47 | 8094 | 127.5375 | 127.5375 | 19 |
| 48 | 8094 | 123.975 | 123.975 | 33 |
| 49 | 8094 | 139.65 | 164.5875 | 49 |
| 50 | 8094 | 235.8375 | 235.8375 | 32 |
| 51 | 8094 | 234.4125 | 234.4125 | 47 |
| 52 | 8094 | 235.125 | 235.125 | 27 |
| 53 | 8094 | 227.2875 | 227.2875 | 69 |
| 54 | 8094 | 312.7875 | 312.7875 | 49 |

## **Data collection and preprocessing:**

- Data Collection: Data collection is the process of gathering and measuring information on variables of interest, in an established systematic fashion that enables one to answer stated research questions, test hypotheses, and evaluate outcomes.

- Data preprocessing: A component of data preparation, describes any type of processing performed on raw data to prepare it for another data processing procedure. It has traditionally been an important preliminary step for the data mining process.

## MODEL SELECTION:

There are some regression algorithms are present

- Linear regression
- Random forest
- XG boost

## FEATURE ENGINEERING:

Create new features or transform existing ones to capture valuable information.

- **Enhanced Model Performance**
- **Improved Interpretability**

- **Handling Non-linearity**

**Time-based features**: These features capture trends and patterns over time. Examples include day of the week, month, year, and holidays.

**Store-based features**: These features capture pharmacy-specific characteristics. Examples include the location of the pharmacy, the size of the pharmacy, and the customer demographics.

## ADVANCED REGRESSION TECHNIQUES:

- Linear : Linear regression analysis is used to predict the value of a variable based on the value of another variable
- Logistic : This type of statistical model (also known as logit model) is often used for classification and predictive analytics. Logistic regression estimates the probability of an event occurring, such as voted or didn't vote, based on a given dataset of independent variables.

- Polynomial : Polynomial regression is a form of Linear regression where only due to the Non-linear relationship between dependent and independent variables.

- Stepwise : Stepwise regression is the step-by-step iterative construction of a regression model that involves the selection of independent variables to be used in a final model.

- Ridge : Ridge regression is a model tuning method that is used to analyse any data that suffers from multicollinearity.

- Lasso : LASSO regression, also known as L1 regularization, is a popular technique used in statistical modeling and machine learning to estimate the relationships between variables and make predictions.

- Elastic Net Regression : Elastic net linear regression uses the penalties from both the lasso and ridge techniques to regularize regression models.

ARIMA technique:

ARIMA is a method for forecasting or predicting future outcomes based on a historical time series. It is based on the statistical concept of serial correlation, where past data points influence future data points.

## Why is ARIMA good for forecasting?

## Advantages of ARIMA models:

ARIMA models can account for various patterns, such as linear or nonlinear trends, constant or varying volatility, and seasonal or non-seasonal fluctuations.

ARIMA Time-series Forecasting Methods:

Autoregressive integrated moving average (ARIMA) forecasting methods were popularized by G. E. P. Box and G. M. Jenkins in the 1970s. These techniques, often called the Box-Jenkins forecasting methodology, have the following steps:

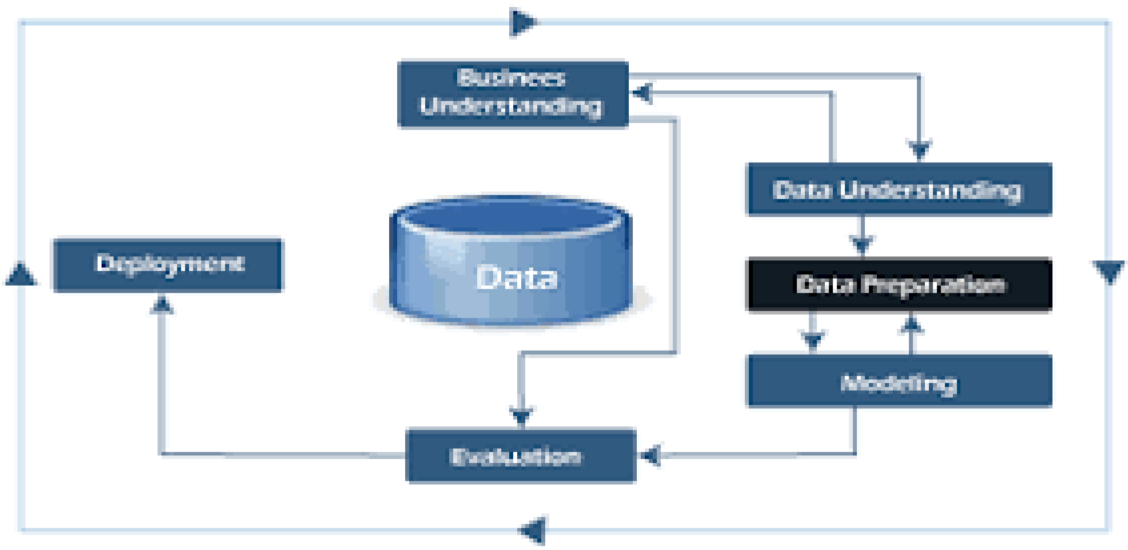
6. Model identification and selection
7. Estimation of autoregressive (AR), integration or differencing (I), and moving average (MA) parameters
8. Model checking

ARIMA is a univariate process. Current values of a data series are correlated with past values in the same series to produce the AR component, also known as *p*. Current values of a random error term are correlated with past values to produce the MA component, *q*. Mean and variance values of current and past data are assumed to be stationary, unchanged over time. If necessary, an I component (symbolized by *d*) is added to correct for a lack of stationarity through differencing.

In a nonseasonal ARIMA(*p*,*d*,*q*) model, *p* indicates the number or order of AR terms, *d* indicates the number or order of differences, and *q* indicates the number or order of MA terms. The *p*, *d*, and *q* parameters are integers equal to or greater than 0.

Data wrangling technique:

- Merging several data sources into one data-set for analysis.
- Identifying gaps or empty cells in data and either filling or removing them.
- Deleting irrelevant or unnecessary data.
- Identifying severe outliers in data and either explaining the inconsistencies or deleting them to facilitate analysis.




- SARIMA (Seasonal ARIMA):

Extends ARIMA to handle seasonal patterns in data.

- Exponential Smoothing Methods:

These include Holt-Winters for capturing trends and seasonality.

- Prophet:

Developed by Facebook, Prophet is useful for data with daily observations, holidays, and seasonality.

- Deep Learning Models (e.g., LSTM and GRU):

Suitable for capturing complex temporal patterns, but they may require more data and computational resources.

Model Training:

Train the selected time series forecasting model using historical demand data. This involves estimating model parameters and seasonal components, if applicable.

Data:

1. ID Store ID Total Price Base Price Units Sold
2. 1 8091 99.0375 111.8625 20
3. 2 8091 99.0375 99.0375 28
4. 3 8091 133.95 133.95 19
5. 4 8091 133.95 133.95 44
6. 5 8091 141.075 141.075 52
7. 9 8091 227.2875 227.2875 18
8. 10 8091 327.0375 327.0375 47
9. 13 8091 210.9 210.9 50
10. 14 8091 190.2375 234.4125 82

| | | | | | |
|---|---|---|---|---|---|
| 11. | 17 | 8095 | 99.0375 | 99.0375 | 99 |
| 12. | 18 | 8095 | 97.6125 | 97.6125 | 120 |
| 13. | 19 | 8095 | 98.325 | 98.325 | 40 |
| 14. | 22 | 8095 | 133.2375 | 133.2375 | 68 |
| 15. | 23 | 8095 | 133.95 | 133.95 | 87 |
| 16. | 24 | 8095 | 139.65 | 139.65 | 186 |
| 17. | 27 | 8095 | 236.55 | 280.0125 | 54 |
| 18. | 28 | 8095 | 214.4625 | 214.4625 | 74 |
| 19. | 29 | 8095 | 266.475 | 296.4 | 102 |
| 20. | 30 | 8095 | 173.85 | 192.375 | 214 |
| 21. | 31 | 8095 | 205.9125 | 205.9125 | 28 |

| | | | | | |
|---|---|---|---|---|---|
| 22. | 32 | 8095 | 205.9125 | 205.9125 | 7 |
| 23. | 33 | 8095 | 248.6625 | 248.6625 | 48 |
| 24. | 34 | 8095 | 200.925 | 200.925 | 78 |
| 25. | 35 | 8095 | 190.2375 | 240.825 | 57 |
| 26. | 37 | 8095 | 427.5 | 448.1625 | 50 |
| 27. | 38 | 8095 | 429.6375 | 458.1375 | 62 |
| 28. | 39 | 8095 | 177.4125 | 177.4125 | 22 |
| 29. | 42 | 8094 | 87.6375 | 87.6375 | 109 |
| 30. | 43 | 8094 | 88.35 | 88.35 | 133 |
| 31. | 44 | 8094 | 85.5 | 85.5 | 11 |
| 32. | 45 | 8094 | 128.25 | 180.975 | 9 |

| | | | | | |
|---|---|---|---|---|---|
| 33. | 47 | 8094 | 127.5375 | 127.5375 | 19 |
| 34. | 48 | 8094 | 123.975 | 123.975 | 33 |
| 35. | 49 | 8094 | 139.65 | 164.5875 | 49 |
| 36. | 50 | 8094 | 235.8375 | 235.8375 | 32 |
| 37. | 51 | 8094 | 234.4125 | 234.4125 | 47 |
| 38. | 52 | 8094 | 235.125 | 235.125 | 27 |
| 39. | 53 | 8094 | 227.2875 | 227.2875 | 69 |
| 40. | 54 | 8094 | 312.7875 | 312.7875 | 49 |

PROGRAM:

Product Demand Prediction:

Import pandas as pd

```
Import numpy as np

Import plotly.express as px

Import seaborn as sns

Import matplotlib.pyplot as plt

From sklearn.model_selection import train_test_split

From sklearn.tree import DecisionTreeRegressor



Data=pd.read_csv("C:\Users\mabir\AppData\Local\Microsoft\Windows\INetCache\IE\AHLGJQP8\archive[1].zip ")

Data.head()
```

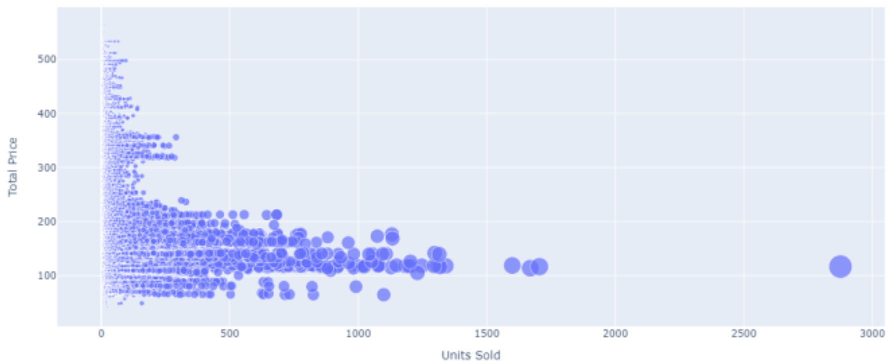
Relationship between price and demand for the product:

```
Fig = px.scatter(data, x="Units Sold", y="Total Price",
```

Size='Units Sold')

Fig.show()

Output:




Correlation between the features of the dataset:

Print(data.corr())

Output:

| | ID | Store ID | Total Price | Base Price | Units Sold |
|---|---|---|---|---|---|
| ID | 1.000000 | 0.007464 | 0.008473 | 0.018932 | -0.010616 |
| Store ID | 0.007464 | 1.000000 | -0.038315 | -0.038848 | -0.004372 |
| Total Price | 0.008473 | -0.038315 | 1.000000 | 0.958885 | -0.235625 |
| Base Price | 0.018932 | -0.038848 | 0.958885 | 1.000000 | -0.140032 |
| Units Sold | -0.010616 | -0.004372 | -0.235625 | -0.140032 | 1.000000 |

1

Correlations = data.corr(method='pearson')

2

Plt.figure(figsize=(15, 12))

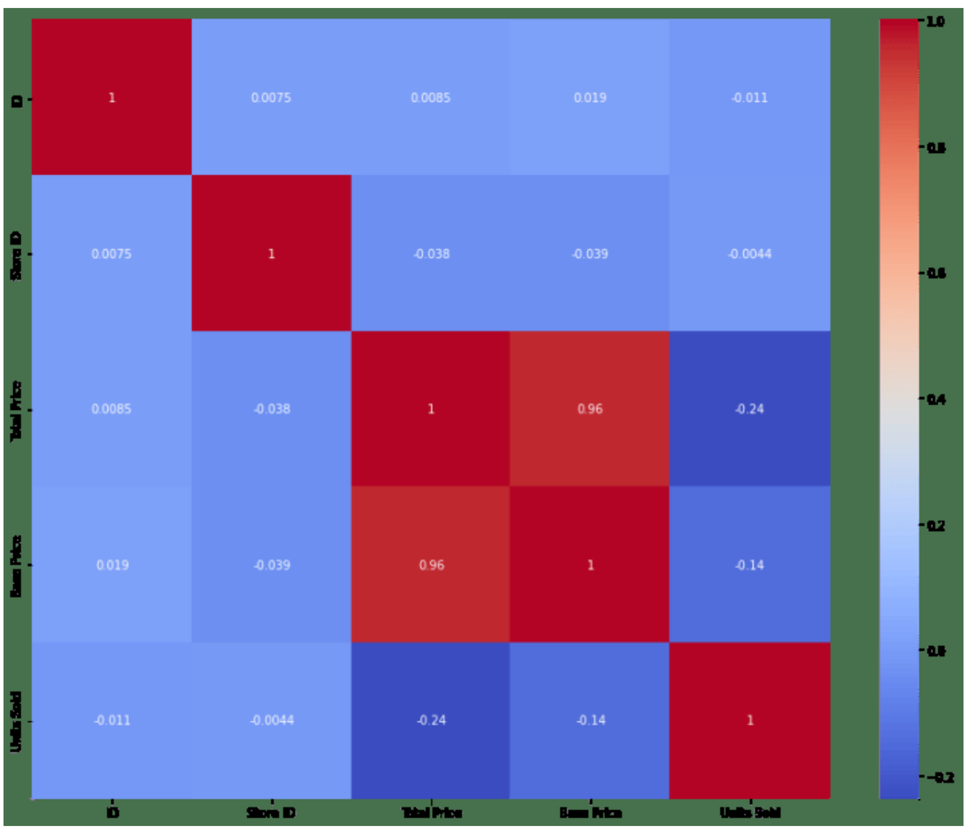
3

Sns.heatmap(correlations, cmap=”coolwarm”, annot=True)

4

Plt.show()

Output:



```
# fit an ARIMA model and plot residual errors

From pandas import datetime

From pandas import read_csv

From pandas import DataFrame

From statsmodels.tsa.arima.model import ARIMA

From matplotlib import pyplot

# load dataset
```

```
Def parser(x):

        Return datetime.strptime('190'+x, '%Y-%m')

Series = read_csv('shampoo-sales.csv', header=0, index_col=0,
parse_dates=True, squeeze=True, date_parser=parser)

Series.index = series.index.to_period('M')

# fit model

Model = ARIMA(series, order=(5,1,0))

Model_fit = model.fit()

# summary of fit model

Print(model_fit.summary())
```

```
# line plot of residuals

Residuals = DataFrame(model_fit.resid)

Residuals.plot()

Pyplot.show()

# density plot of residuals

Residuals.plot(kind='kde')

Pyplot.show()

# summary stats of residuals
```

```
Print(residuals.describe())
```

Output:

SARIMAX Results

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Dep. Variable: Sales No. Observations:
36

Model: ARIMA(5, 1, 0) Log Likelihood -
198.485

Date: Thu, 10 Dec 2020 AIC
408.969

Time: 09:15:01 BIC 418.301

Sample: 01-31-1901 HQIC 412.191

- 12-31-1903

Covariance Type: opg

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| Ar.L1 | -0.9014 | 0.247 | -3.647 | 0.000 | -1.386 | -0.417 |
| Ar.L2 | -0.2284 | 0.268 | -0.851 | 0.395 | -0.754 | 0.298 |
| Ar.L3 | 0.0747 | 0.291 | 0.256 | 0.798 | -0.497 | 0.646 |
| Ar.L4 | 0.2519 | 0.340 | 0.742 | 0.458 | -0.414 | 0.918 |

Ar.L5 0.3344 0.210 1.593 0.111 -0.077 0.746

Sigma2 4728.9608 1316.021 3.593 0.000 2149.607 7308.314

---

Ljung-Box (L1) (Q): 0.61 Jarque-Bera (JB): 0.96

Prob(Q): 0.44 Prob(JB): 0.62

Heteroskedasticity (H): 1.07 Skew: 0.28

Prob(H) (two-sided): 0.90 Kurtosis: 2.41

Prophet:

# make an in-sample forecast

from pandas import read_csv

```
from pandas import to_datetime
from pandas import DataFrame
from fbprophet import Prophet
from matplotlib import pyplot
# load data

path =
'https://raw.githubusercontent.com/jbrownlee/Datasets/master/m
onthly-car-sales.csv'
df = read_csv(path, header=0)
# prepare expected column names

df.columns = ['ds', 'y']
df['ds']= to_datetime(df['ds'])
# define the model

model = Prophet()
# fit the model

model.fit(df)
# define the period for which we want a prediction

future = list()
for i in range(1, 13):
```

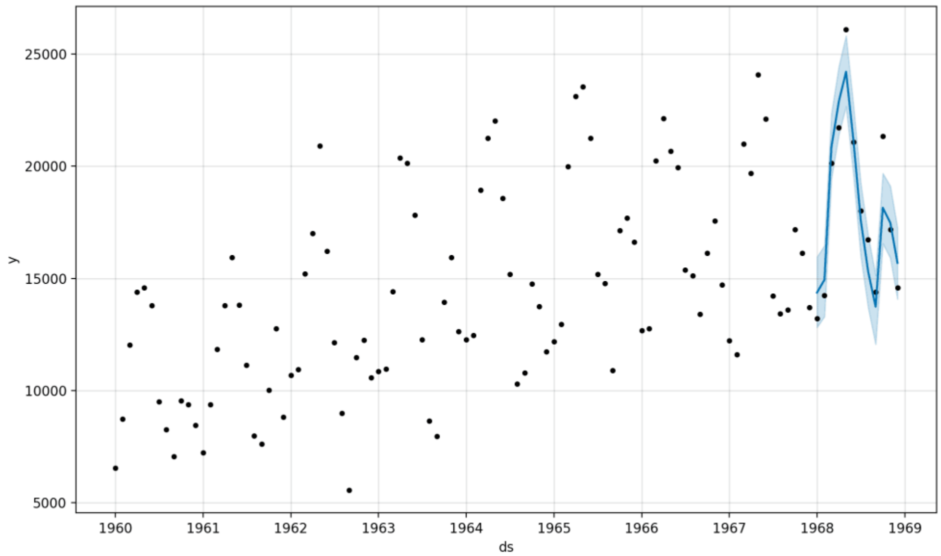
```
date = '1968-%02d' % i
future.append([date])
future = DataFrame(future)
future.columns = ['ds']
future['ds']= to_datetime(future['ds'])
# use the model to make a forecast

forecast = model.predict(future)
# summarize the forecast

print(forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].head())
# plot forecast

model.plot(forecast)
pyplot.show()
```

Running the example forecasts the last 12 months of the dataset.

The first five months of the prediction are reported and we can see that values are not too different from the actual sales values in the dataset(output).

| | ds | yhat | yhat_lower | yhat_upper |
|---|---|---|---|---|
| 0 | 1968-01-01 | 14364.866157 | 12816.266184 | 15956.555409 |
| 1 | 1968-02-01 | 14940.687225 | 13299.473640 | 16463.811658 |
| 2 | 1968-03-01 | 20858.282598 | 19439.403787 | 22345.747821 |

| | | | | |
|---|---|---|---|---|
| 3 | 1968-04-01 | 22893.610396 | 21417.399440 | 24454.642588 |
| 4 | 1968-05-01 | 24212.079727 | 22667.146433 | 25816.191457 |




EVALUATION:

- Mean Absolute Error(MAE) is the mean size of the mistakes in collected predictions. We know that an error basically is the absolute difference between the actual or true values and the values that are predicted. The absolute difference means that if the result has a negative sign, it is ignored.

# What is Mean Squared Error or MSE

- The Mean Absolute Error is the squared mean of the difference between the actual values and predictable values.