Report of Mini project on

“Prediction of profit value of company using ML”

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ABSTRACT

A company should always set a goal that should be achievable, otherwise, employees will not be able to work to their best potential if they find that the goal set by the company is unachievable. The task of profit prediction for a particular period is the same as setting goals. If you know how much profit you can make with the amount of R&D and marketing you do, then a business can make more than the predicted profit provided the predicted value is achievable. So in this project, I will be predicting profit of company using R&D Spend, Administration Cost and Marketing Spend of the company with machine learning using Python.

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CHAPTER 1
INTRODUCTION

In today's world, data are produced everywhere now and then. These information's are being used to provide a personalized environment to the user. It is true that these data are quite large, and they can't be processed by a single person or a team because their sources of production make them grow tremendously. Thus, Machine Learning makes use of AI. Hence, Machine Learning uses all these data and provides what people concept is used to predict the profit of a company as it is very difficult to determine or predict the profit of a company as there are many factors that influence it, such as the cost of R&D, marketing, and company standards. These increased factors that affects the profit of a company make things unpredictable by an average individual. Thus, based on the past profit record and administration costs of the companies, a model is created which recognizes a pattern via the factors affecting profit in order to better predict profit.

CHAPTER 2

EXISTING SYSTEM

By using a single independent variable such as the investment cost of a company's project, the value of the dependent variable i.e., the profit of the company by the means of that project is approximately predicted. Linear regression makes use of a single independent variable to predict the value of a dependent variable by developing a regression line along the given data and thereby predicting dependent variable using that regression line. There are some other techniques viz., the Classification tree and Random Forest that makes use of a lot of dependent variable to predict the value of the dependent variable and these techniques works best for some of the given values but not for all.

Disadvantages of the existing system

• Linear regression makes use of only one independent variable and so results are less accurate.

• Data are not completely consumed by a linear regression model.

CHAPTER 3

PROPOSED SYSTEM

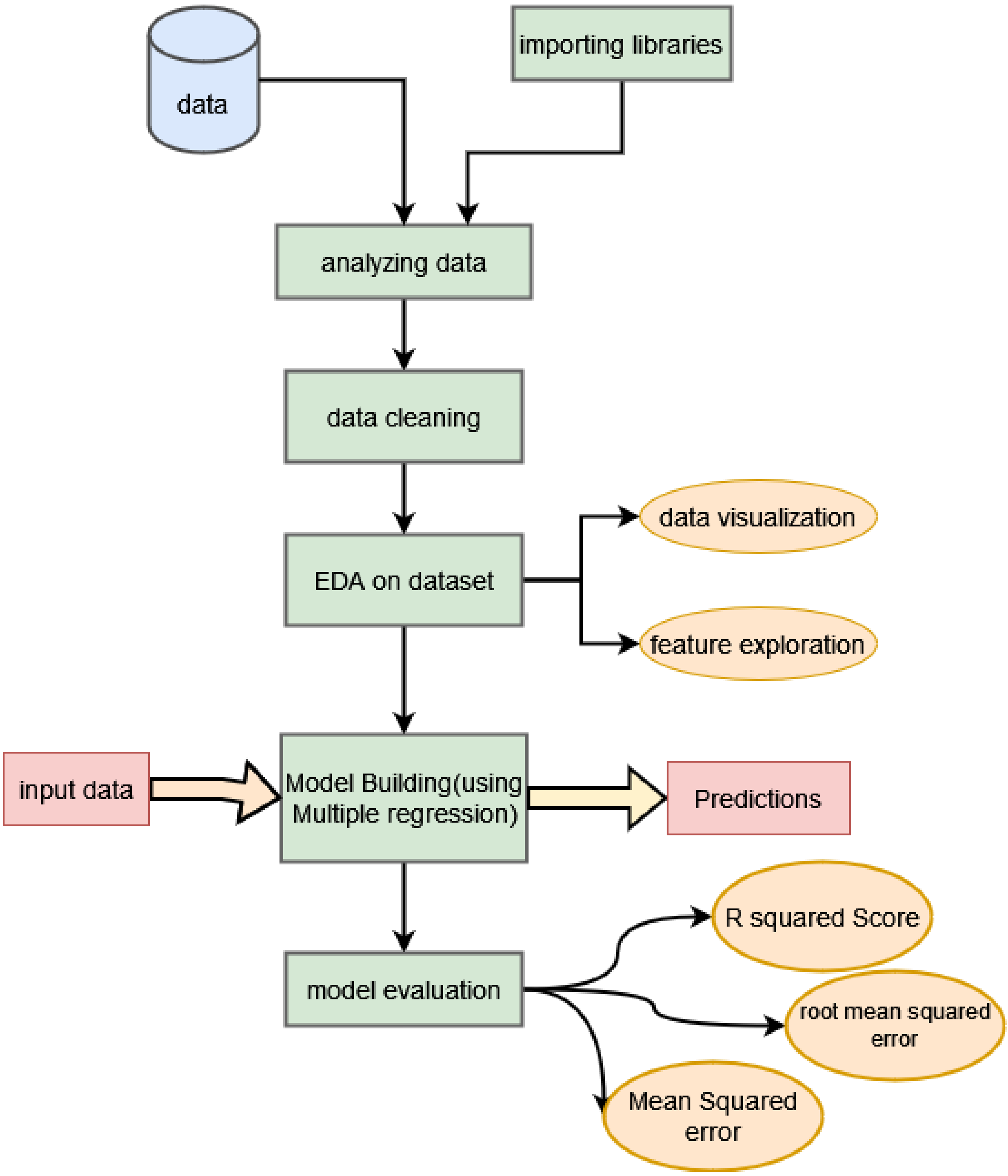


Fig – 3.1 process flow Diagram

The main intention is to predict the value of the dependent variable i.e., the value of the profit of the company based on the data of the company over the previous years. So, from all the techniques used before for the prediction of profit an average from all those predicted values of the dependent variable is computed and made as the predicted dependent variable.

Advantages of the proposed system

• It makes use of all the data given to it to predict the value of independent variable.

• Theoretically it is better than all the other existing algorithms

CHAPTER 4

METHODOLOGY

1. **Importing libraries**

   numpy for performing mathematical calculations behind ML algorithms

   matplotlib.pyplot for visualization

   pandas for handling and cleaning the dataset

   seaborn for visualization

   sklearn for model evaluation and development

2. **Analyzing the data**
   a. Looking for missing values.
   b. Replacing missing values with appropriate value.
   c. Converting string values to float
   d. Making data relational able.

3. **EDA on the dataset**
   1. Data Visualization
      a. Correlation matrix for summarizing data, as an input into a more advanced analysis, and as a diagnostic for advanced analyses.
      b. Outliers detection in the target variable.
   2. Feature exploration
      a. Histogram

4. Model development

The ML model development involves data acquisition from multiple trusted sources, data processing to make suitable for building the model, choose algorithm to build the model, build model, compute performance metrics and choose best performing model.

5. Model evaluation

a. **R2 score**: R2 score – R squared score. It is one of the statistical approaches by which we can find the variance or the spread of the target and feature data.
b. **MSE**: MSE – Mean Squared Error. By using this approach we can find that how much the regression best fit line is close to all the residual.
c. **RMSE**: RMSE – Root Mean Squared Error. This is similar to the Mean squared error (MSE) approach, the only difference is that here we find the root of the mean squared error i.e. root of the Mean squared error is equal to Root Mean Squared Error.

CHAPTER 5

IMPLEMENTATION

1. Importing libraries

```
In [1]: import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        import seaborn as sns
        import sklearn
```

2. Getting dataset

```
In [3]: dataset = pd.read_csv('50_Startups.csv')
```

```
In [5]: dataset.head(),dataset.tail()
```

```
Out[5]: (   R&D Spend  Administration  Marketing Spend     Profit
         0  165349.20       136897.80        471784.10  192261.83
         1  162597.70       151377.59        443898.53  191792.06
         2  153441.51       101145.55        407934.54  191050.39
         3  144372.41       118671.85        383199.62  182901.99
         4  142107.34        91391.77        366168.42  166187.94,
             R&D Spend  Administration  Marketing Spend     Profit
         45     1000.23       124153.04          1903.93   64926.08
         46     1315.46       115816.21        297114.46   49490.75
         47        0.00       135426.92             0.00   42559.73
         48      542.05        51743.15             0.00   35673.41
         49        0.00       116983.80         45173.06   14681.40)
```

```
In [7]: print('rows :',dataset.shape[0])
        print('columns :',dataset.shape[1])

        rows : 50
        columns : 4
```

3. Data cleaning and preprocessing

```
In [8]: #checking for repeated values in dataset
        dataset.duplicated().sum()

Out[8]: 0
```

```
In [9]: #checking for null values in dataset
        dataset.isnull().sum()

Out[9]: R&D Spend          0
        Administration     0
        Marketing Spend    0
        Profit             0
        dtype: int64
```

```
In [10]: #dataset schema
         dataset.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   Profit           50 non-null     float64
dtypes: float64(4)
memory usage: 1.7 KB
```

4. Using Correlation function

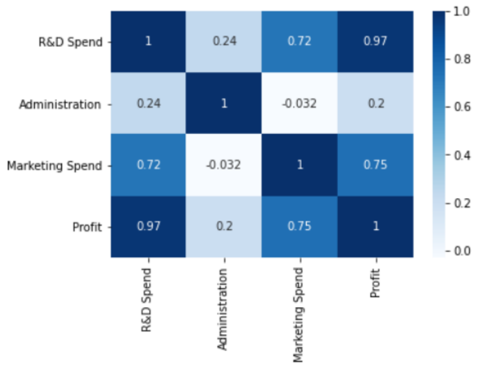
```
In [12]: #corr function
         #corr() is used to find the pairwise correlation of all columns in the dataframe. Any na values are automatically excluded. For
         c = dataset.corr()

In [13]: c
```

Out[13]:

	R&D Spend	Administration	Marketing Spend	Profit
R&D Spend	1.000000	0.241955	0.724248	0.972900
Administration	0.241955	1.000000	-0.032154	0.200717
Marketing Spend	0.724248	-0.032154	1.000000	0.747766
Profit	0.972900	0.200717	0.747766	1.000000

correlation matrix

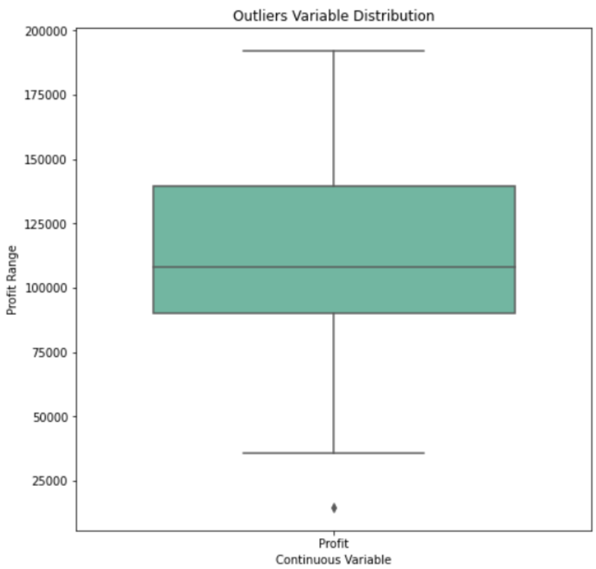
```
In [14]: sns.heatmap(c,annot=True,cmap='Blues')
         plt.show()
```



5. Outlier Detection

Outliers detection in the target variable

In [15]:
```
outliers = ['Profit']
plt.rcParams['figure.figsize'] = [8,8]
sns.boxplot(data=dataset[outliers], orient="v", palette="Set2" , width=0.7) # orient = "v" : vertical boxplot ,
                                                                            # orient = "h" : hotrizontal boxplot

plt.title("Outliers Variable Distribution")
plt.ylabel("Profit Range")
plt.xlabel("Continuous Variable")

plt.show()
```



6. Model preparation

model preparation

In [21]:
```
# spliting Dataset in Dependent & Independent Variables
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 3].values
```

In [24]:
```
from sklearn.preprocessing import LabelEncoder
```

In [26]:
```
#Label Encoder : Encode labels with value between 0 and n_classes-1.
labelencoder = LabelEncoder()
X[:, 2] = labelencoder.fit_transform(X[:, 2])
X1 = pd.DataFrame(X)
X1.head()
```

Out[26]:

	0	1	2
0	165349.20	136897.80	47.0
1	162597.70	151377.59	46.0
2	153441.51	101145.55	45.0
3	144372.41	118671.85	44.0
4	142107.34	91391.77	43.0

7. Splitting Data

split the data into training and testing data

In [27]:
```
split the data into training and testing data
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(X,y,train_size=0.7,random_state=0)
x_train
```

Out[27]:
```
array([[1.3029813e+05, 1.4553006e+05, 4.0000000e+01],
       [1.1994324e+05, 1.5654742e+05, 2.8000000e+01],
       [1.0002300e+03, 1.2415304e+05, 1.0000000e+00],
       [5.4205000e+02, 5.1743150e+04, 0.0000000e+00],
       [6.5605480e+04, 1.5303206e+05, 8.0000000e+00],
       [1.1452361e+05, 1.2261684e+05, 2.9000000e+01],
       [6.1994480e+04, 1.1564128e+05, 7.0000000e+00],
       [6.3408860e+04, 1.2921961e+05, 5.0000000e+00],
       [7.8013110e+04, 1.2159755e+05, 3.0000000e+01],
       [2.3640930e+04, 9.6189630e+04, 1.4000000e+01],
       [7.6253860e+04, 1.1386730e+05, 3.4000000e+01],
       [1.5505730e+04, 1.2738230e+05, 3.0000000e+00],
       [1.2054252e+05, 1.4871895e+05, 3.9000000e+01],
       [9.1992390e+04, 1.3549507e+05, 2.7000000e+01],
       [6.4664710e+04, 1.3955316e+05, 1.2000000e+01],
       [1.3187690e+05, 9.9814710e+04, 4.2000000e+01],
       [9.4657160e+04, 1.4507758e+05, 3.1000000e+01],
       [2.8754330e+04, 1.1854605e+05, 1.6000000e+01],
       [0.0000000e+00, 1.1698380e+05, 4.0000000e+00],
       [1.6259770e+05, 1.5137759e+05, 4.6000000e+01],
       [9.3863750e+04, 1.2732038e+05, 2.6000000e+01],
       [4.4069950e+04, 5.1283140e+04, 1.9000000e+01],
```

8. Model Training

In [31]:
```
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(x_train,y_train)
print('Model has been trained successfully')
```

```
Model has been trained successfully
```

9. Model Predictions

In [32]:
```
y_pred = model.predict(x_test)
y_pred
```

Out[32]:
```
array([103365.65430448, 132409.63159464, 133669.58924177,  71596.33493623,
        179574.8809234 , 114195.96899299,  65656.85292429,  97938.81018901,
        114412.29898539, 169772.36831918,  96050.9051499 ,  87515.25731045,
        110242.6075272 ,  90000.89195708, 127479.23515393])
```

In [33]:
```
testing_data_model_score = model.score(x_test, y_test)
print("Model Score/Performance on Testing data",testing_data_model_score)

training_data_model_score = model.score(x_train, y_train)
print("Model Score/Performance on Training data",training_data_model_score)
```

```
Model Score/Performance on Testing data 0.9324057207634493
Model Score/Performance on Training data 0.9506671824404848
```

In [34]:
```
df = pd.DataFrame(data={'Predicted value':y_pred.flatten(),'Actual Value':y_test.flatten()})
df
```

Out[34]:

	Predicted value	Actual Value
0	103365.654304	103282.38
1	132409.631595	144259.40
2	133669.589242	146121.95
3	71596.334936	77798.83
4	179574.880923	191050.39
5	114195.968993	105008.31
6	65656.852924	81229.06
7	97938.810189	97483.56
8	114412.298985	110352.25
9	169772.368319	166187.94
10	96050.905150	96778.92
11	87515.257310	96479.51
12	110242.607527	105733.54
13	90000.891957	96712.80

10. Model Evaluations

regression metrics

R2 score

In [35]:
```
from sklearn.metrics import r2_score
r2Score = r2_score(y_pred, y_test)
print("R2 score of model is :" ,r2Score*100)
```

```
R2 score of model is : 93.21346390789374
```

mean squared error

In [36]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_pred, y_test)
print("Mean Squarred Error is :" ,mse*100)
```

```
Mean Squarred Error is : 6524519362.317416
```

root Mean squared Error

In [37]:
```
rmse = np.sqrt(mean_squared_error(y_pred, y_test))
print("Root Mean Squarred Error is : ",rmse*100)
```

```
Root Mean Squarred Error is :  807744.9697966195
```

Mean absolute Error

In [38]:
```
from sklearn.metrics import mean_absolute_error

mae = mean_absolute_error(y_pred,y_test)
print("Mean Absolute Error is :" ,mae)
```

```
Mean Absolute Error is : 6603.238628961085
```

CHAPTER 6

CONCLUSION

This is how we can predict the profit of a company for a particular period by using machine learning algorithm. Such tasks can help a company to set a target that can be achieved and boost up revenue. In real life, it can be generalized as a universal template for all companies with the same financial form. For investors who prefer medium and long-term investment, it has certain reference significance.

REFRENCES

1. Understanding Multiple Regression (The fundamental basis)
2. https://towardsdatascience.com/understanding-multiple-regression-249b16bde83e.
3. Support Vector Regression Tutorial for Machine Learning,
4. https://www.analyticsvidhya.com/blog/2020/03/support-vector-regression-tutorial-for-machinelearning/ .
5. An introduction to support vector regression, https://towardsdatascience.com/an introduction-tosupport-vector-regression-svr-a3ebc1672c2