2023aiml554-miniproject

June 13, 2024

1 1- Library Import

[18]:
```
# importing required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sbn
import warnings as wrn
from datetime import datetime
wrn.filterwarnings('ignore')
```

2 2- Read dataSet

[19]:
```
# Defining dataSet csv path
filePath="C:\\Users\\ASUS\\jupyterworkspace\\Assignment\\2\\Dataset - Mini␣
↪Project.csv"
# Loading dataSet
dataSet=pd.read_csv(filePath)
# Checking dataframe shape
print(dataSet.shape)
# checking dataframe type
print(type(dataSet))
```

```
(159, 6)
<class 'pandas.core.frame.DataFrame'>
```

3 3- EDA

3.1 3.1- Incpect the data

[20]:
```
# Checking quick overview of the dataSet
print(dataSet.head())
# Checking descriptive statistic of the dataSet
print(dataSet.describe())
#checking summary of the dataSet
print(dataSet.info())
```

```
    Cost  Weight  Weight1  Length   Height   Width
0  242.0    23.2     25.4    30.0  11.5200  4.0200
1  290.0    24.0     26.3    31.2  12.4800  4.3056
2  340.0    23.9     26.5    31.1  12.3778  4.6961
3  363.0    26.3     29.0    33.5  12.7300  4.4555
4  430.0    26.5     29.0    34.0  12.4440  5.1340
              Cost      Weight     Weight1      Length      Height       Width
count   159.000000  159.000000  159.000000  159.000000  159.000000  159.000000
mean    398.326415   26.247170   28.415723   31.227044    8.970994    4.417486
std     357.978317    9.996441   10.716328   11.610246    4.286208    1.685804
min       0.000000    7.500000    8.400000    8.800000    1.728400    1.047600
25%     120.000000   19.050000   21.000000   23.150000    5.944800    3.385650
50%     273.000000   25.200000   27.300000   29.400000    7.786000    4.248500
75%     650.000000   32.700000   35.500000   39.650000   12.365900    5.584500
max    1650.000000   59.000000   63.400000   68.000000   18.957000    8.142000
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159 entries, 0 to 158
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Cost     159 non-null    float64
 1   Weight   159 non-null    float64
 2   Weight1  159 non-null    float64
 3   Length   159 non-null    float64
 4   Height   159 non-null    float64
 5   Width    159 non-null    float64
dtypes: float64(6)
memory usage: 7.6 KB
None
```

3.2 3.2- Check for missing , duplicates & unique values

[21]:
```
#Calculating the number of missing values in each column
print(dataSet.isnull().sum())
# Handeling missing values
print(dataSet.dropna())
# Dropping Duplicates if exists
dataSet_duplicate = dataSet.drop_duplicates()
print(dataSet_duplicate.shape)
# Checking unique values columswise
print(dataSet.nunique())
```

```
Cost       0
Weight     0
Weight1    0
Length     0
Height     0
Width      0
```

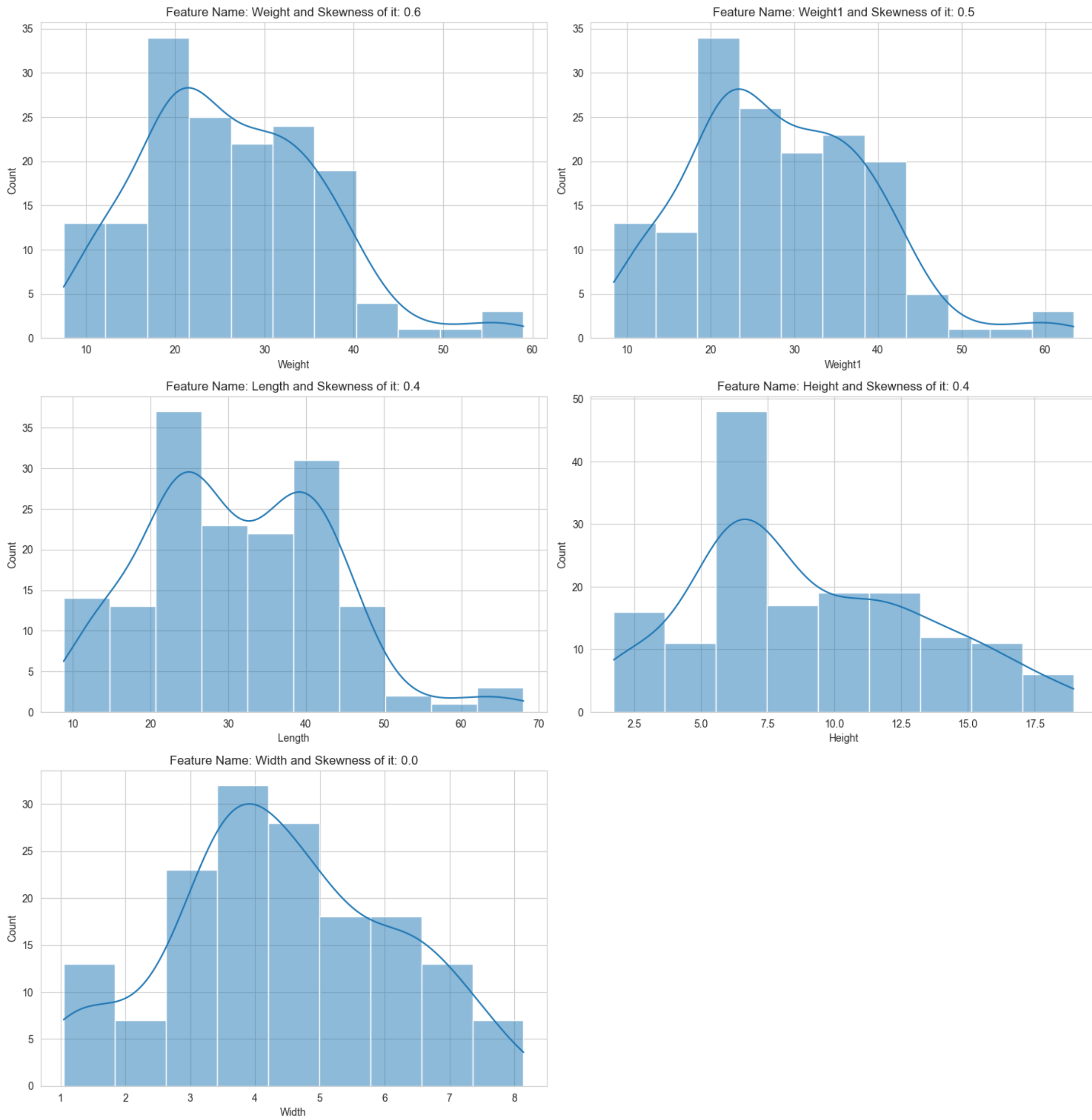
```
dtype: int64
      Cost  Weight  Weight1  Length   Height   Width
0    242.0    23.2     25.4    30.0  11.5200  4.0200
1    290.0    24.0     26.3    31.2  12.4800  4.3056
2    340.0    23.9     26.5    31.1  12.3778  4.6961
3    363.0    26.3     29.0    33.5  12.7300  4.4555
4    430.0    26.5     29.0    34.0  12.4440  5.1340
..     …       …      …       …      …       …
154   12.2    11.5     12.2    13.4   2.0904  1.3936
155   13.4    11.7     12.4    13.5   2.4300  1.2690
156   12.2    12.1     13.0    13.8   2.2770  1.2558
157   19.7    13.2     14.3    15.2   2.8728  2.0672
158   19.9    13.8     15.0    16.2   2.9322  1.8792

[159 rows x 6 columns]
(159, 6)
Cost       101
Weight     116
Weight1     93
Length     124
Height     154
Width      152
dtype: int64
```

3.3 3.3- Univirate analysis

3.3.1 3.3.1- Histogram Plot

[22]:
```
# Set the parameters that control the general style of the plots.
sbn.set_style(style="whitegrid")
#dropping dependent feature column
X=dataSet.drop('Cost',axis=1)
# Selecting all independent feature columns names
columns=X.columns
#Building Histogram plot for each independent features
plt.figure(figsize=(15, 30) )
for index, columns_name in enumerate(columns, 1):
    plt.subplot(6, 2,index)
    sbn.histplot(X[columns_name], kde=True)
    skewness = round(X[columns_name].skew(),1)
    plt.title("Feature Name: {} and Skewness of it: {}".
 ↪format(columns_name,skewness))
plt.tight_layout()
plt.show()
print("skewness and histogram shows that except Widht column all the columns␣
 ↪are skewed \ & do not follow perfectly normal distribution ")
```

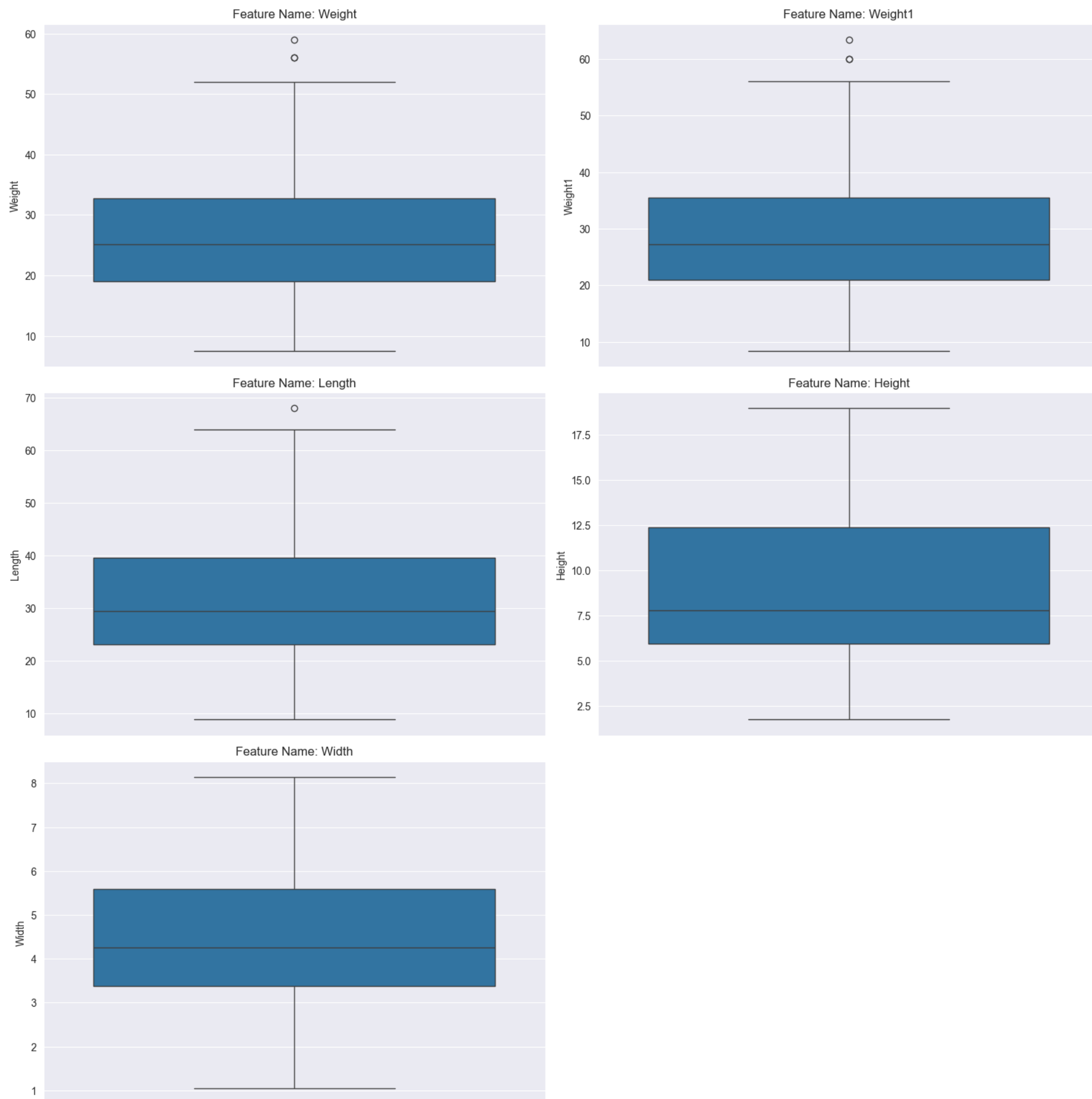


skewness and histogram shows that except Widht column all the columns are skewed \ & do not follow perfectly normal distribution

3.3.2 3.3.2- Box Plot

[23]:
```
# Set the parameters that control the general style of the plots.
sbn.set_style("darkgrid")
#dropping dependent feature column
X=dataSet.drop('Cost',axis=1)
# Selecting all independent feature columns names
columns=X.columns
#Building Box plot for each independent features
plt.figure(figsize=(15, 30) )
```

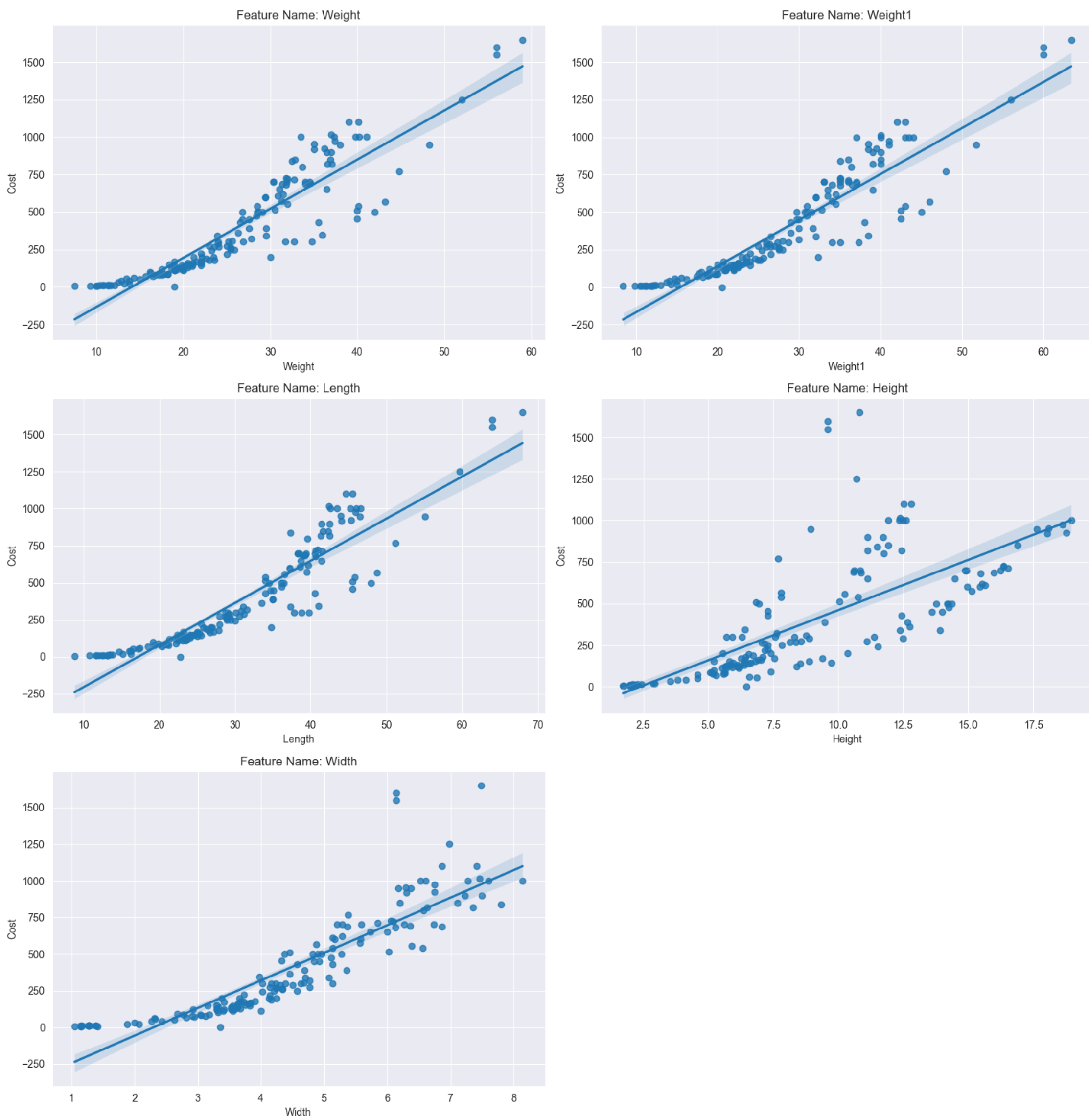
```
for index, columns_name in enumerate(columns, 1):
    plt.subplot(6, 2, index)
    sbn.boxplot(X[columns_name])
    plt.title("Feature Name: {}".format(columns_name))
plt.tight_layout()
plt.show()
```



3.4 3.4- Bivariate Analysis - Scatter Plot with Regression Line

[24]:
```
# Set the parameters that control the general style of the plots.
sbn.set_style("darkgrid")
#dropping dependent feature column
```

```
X=dataSet.drop('Cost',axis=1)
# Selecting all independent feature columns names
columns=X.columns
#Building Box plot for each independent features
plt.figure(figsize=(15, 30) )
for index, columns_name in enumerate(columns, 1):
    plt.subplot(6, 2, index)
    # draw regplot
    sbn.regplot(data=dataSet,x=dataSet[columns_name],y='Cost')
    plt.title("Feature Name: {}".format(columns_name))
plt.tight_layout()
# show the plot
plt.show()
```



3.5 3.5- Multivariate Analysis - Correaltion

[25]:
```
plt.figure(figsize=(8, 5))
# Using Seaborn to create a heatmap
sbn.heatmap(dataSet.corr(method='pearson'), annot=True, fmt='.3f',␣
 ↪cmap='YlGnBu', linewidths=2)
plt.title('Correlation Heatmap')
plt.show()
dataSet.corr(method='pearson')
```

[25]:

	Cost	Weight	Weight1	Length	Height	Width
Cost	1.000000	0.915712	0.918618	0.923044	0.724345	0.886507
Weight	0.915712	1.000000	0.999517	0.992031	0.625378	0.867050
Weight1	0.918618	0.999517	1.000000	0.994103	0.640441	0.873547
Length	0.923044	0.992031	0.994103	1.000000	0.703409	0.878520
Height	0.724345	0.625378	0.640441	0.703409	1.000000	0.792881
Width	0.886507	0.867050	0.873547	0.878520	0.792881	1.000000

3.6 3.6- Detecting Outlier and Treatment using Inter Quantile Range

[26]:
```
outliers = []
var1 = sorted(dataSet['Length'])
q1 = np.percentile(dataSet['Length'], 25)
q3 = np.percentile(dataSet['Length'], 75)
IQR = q3 - q1
upper_IQR = q3 + (1.5 * IQR)
lower_IQR = q1 - (1.5 * IQR)

for i in dataSet['Length']:
    if i < lower_IQR or i > upper_IQR:
        outliers.append(i)
print(outliers)
arr = np.where(dataSet['Length'].isin(outliers))[0]
print(arr)
# deleting rows where there is outlier
dataSet.drop(index=arr, inplace=True)
print(dataSet.shape)
dataSet.describe()
```

```
[68.0]
[144]
(158, 6)
```

[26]:

	Cost	Weight	Weight1	Length	Height	Width
count	158.00000	158.000000	158.000000	158.000000	158.000000	158.000000
mean	390.40443	26.039873	28.194304	30.994304	8.959342	4.398103
std	344.85164	9.679323	10.379127	11.268932	4.297309	1.673296
min	0.00000	7.500000	8.400000	8.800000	1.728400	1.047600
25%	120.00000	19.025000	21.000000	23.125000	5.940600	3.380625
50%	272.50000	25.100000	27.150000	29.350000	7.733000	4.248050
75%	642.50000	32.650000	35.000000	39.575000	12.371850	5.577375
max	1600.00000	56.000000	60.000000	64.000000	18.957000	8.142000

4 4- Model Building

4.1 4.1 Split data in to features & target

[27]:
```
# importing required package
from sklearn.model_selection import train_test_split
#Dropping all columns except length
X=dataSet.drop(['Cost','Weight','Weight1','Width'],axis=1)
#Dropping all columns except Cost
Y=dataSet['Cost']
#Splitting train & test data
```

```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.
↪28,random_state=42)
```

4.2 4.2- Standard Scalling

[28]:
```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
X_train_scaled=scaler.fit_transform(X_train)
X_test_scaled=scaler.transform(X_test)
```

[29]:
```
Y_train=Y_train.reset_index(drop=True)
```

4.3 4.3- Linear Regression Model using OLS

[30]:
```
from sklearn.linear_model import LinearRegression
# Fit the model
start_time = datetime.now()
model = LinearRegression()
model.fit(X_train_scaled, Y_train)
OLS_time = datetime.now() - start_time
print(f'Time Taken : {datetime.now() - start_time}')
# Predict on the test set
# Checking  the score & Coef
# on Train Data
print("****On Train Data****")
score = model.score(X_train_scaled, Y_train)
model_Coef=model.coef_
model_Intercept=model.intercept_
print("Model Score: {}".format(score))
print("Model Coef: {}".format(model_Coef))
print("Model Intercept: {}".format(model_Intercept))
Y_pred1 = model.predict(X_train_scaled)
Y_train_data_list = list(Y_train)
# Squared error Calculation
se_sum_train = 0
for i, j in zip( Y_train_data_list, list(Y_pred1)):
  se_sum_train = se_sum_train +  (i - j)**2
OLS_mse_train = se_sum_train/len(Y_train_data_list)
OLS_rmse_train = (se_sum_train / len(Y_train_data_list)) ** .5
print("Model MSE: {}".format(OLS_mse_train))
print("Model RMSE: {}".format(OLS_rmse_train))
# on Test Data
print("****On Test Data****")
Y_pred2 = model.predict(X_test_scaled)
Y_test_data_list = list(Y_test)
# Squared error Calculation
```

```
se_sum_test = 0
for i, j in zip( Y_test_data_list, list(Y_pred2)):
  se_sum_test = se_sum_test +  (i - j)**2
OLS_mse_test = se_sum_test/len(Y_test_data_list)
OLS_rmse_test = (se_sum_test / len(Y_test_data_list)) ** .5
print("Model MSE: {}".format(OLS_mse_test))
print("Model RMSE: {}".format(OLS_rmse_test))
```

```
Time Taken : 0:00:00.002052
****On Train Data****
Model Score: 0.8576087246820725
Model Coef: [296.58599234  34.45291988]
Model Intercept: 391.1159292035397
Model MSE: 17258.93000889855
Model RMSE: 131.37324692987744
****On Test Data****
Model MSE: 17689.505287412085
Model RMSE: 133.00189956317197
```

5 5- Evaluate Normal/Batch Gradient Descent

[31]:
```
from sklearn.metrics import r2_score
class GDesc:
    def __init__(self,lr=0.01,loops=100):
        self.coef_ = None
        self.intercept_ = None
        self.lr = lr
        self.loops = loops
    def fit_gdesc(self,X_train,y_train):
        # Initialization of Intercept and Coeffient
        # intercept is defined as 0 at first and all coefficient are defined as␣
↪1 using numpy.ones
        start_time = datetime.now()
        self.intercept = 0
        self.coef = np.ones(X_train.shape[1])
        for i in range(self.loops):
            # intercept and coefficient modified here
            y_pred = np.dot(X_train,self.coef) + self.intercept
            intercept_derivative = -2 * np.mean(y_train - y_pred)
            self.intercept = self.intercept - (self.lr * intercept_derivative)

            coef_derivative = -2 * np.dot((y_train - y_pred),X_train)/X_train.
↪shape[0]
            self.coef = self.coef - (self.lr * coef_derivative)
        print(f'Time Taken : {datetime.now() - start_time}')
        time_taken = datetime.now() - start_time
```

```
        return self.intercept,self.coef,time_taken
    def predict_gdesc(self,data):
        #  predicting result
        return np.dot(data,self.coef) + self.intercept
# On Training␣
 ↪Data-------------------------------------------------------------------------------------
# Class Object initialization (Learning Rate and number of epochs defined)
gd_obj = GDesc(loops=2000,lr=0.01)
# Model Fit
coef,intercept,GD_time = gd_obj.fit_gdesc(X_train_scaled,Y_train)
# Train Data Prediction
y_pred_train_gd = gd_obj.predict_gdesc(X_train_scaled)
# Model Score
GD_score = r2_score(Y_train,y_pred_train_gd)
print('----On Training Data----')
print(f"Model score: {GD_score}")
print(f"Model X Coef :  {coef} ")
print(f"Model Intercept :  {intercept} ")
y_train_data_list = list(Y_train)
# Squared error Calculation
se_sum_train = 0
for i, j in zip( y_train_data_list, list(y_pred_train_gd)):
  se_sum_train = se_sum_train +  (i - j)**2
GD_mse_train = se_sum_train/len(y_train_data_list)
GD_rmse_train = (se_sum_train / len(y_train_data_list)) ** .5
print(f"Model MSE : {GD_mse_train}")
print(f"Model RMSE :  {GD_rmse_train} ")
# On Test␣
 ↪Data-------------------------------------------------------------------------------------
print('----On Test Data----')
y_pred_test_gd = gd_obj.predict_gdesc(X_test_scaled)
y_test_data_list = list(Y_test)
# Squared error Calculation
se_sum_test = 0
for i, j in zip( y_test_data_list, list(y_pred_test_gd)):
  se_sum_test = se_sum_test +  (i - j)**2
GD_mse_test = se_sum_test/len(y_test_data_list)
GD_rmse_test = (se_sum_test / len(y_test_data_list)) ** .5
print(f"Model MSE : {GD_mse_test}")
print(f"Model RMSE :  {GD_rmse_test} ")
```

```
Time Taken : 0:00:00.315115
----On Training Data----
Model score: 0.8576087246629392
Model X Coef :  391.11592920353837
Model Intercept :  [296.58394218  34.45497005]
Model MSE : 17258.930011217653
```

```
Model RMSE :  131.37324693870383
----On Test Data----
Model MSE : 17689.270593382404
Model RMSE :  133.00101726446456
```

6 6- Stochastic Gradient Descent

[32]:
```
from sklearn.metrics import r2_score
class SGDesc:
    def __init__(self,lr=0.01,loops=100):
        self.coef = None
        self.intercept = None
        self.lr = lr
        self.loops = loops
    def fit_sgdesc(self,X_train,y_train):
        # initialize your coeffienct and intercept
        # intercept is defined as 0 at first and all coefficient are defined as␣
 ↪1 using numpy.ones
        start_time = datetime.now()
        self.intercept = 0
        self.coef = np.ones(X_train.shape[1])
        for i in range(self.loops):
            for j in range(X_train.shape[0]):
                indx = np.random.randint(0,X_train.shape[0])
                # intercept and coefficient modified here
                y_hat = np.dot(X_train[indx],self.coef) + self.intercept
                intercept_der = -2 * (y_train[indx] - y_hat)
                self.intercept = self.intercept - (self.lr * intercept_der)
                coef_der = -2 * np.dot((y_train[indx] - y_hat),X_train[indx])
                self.coef = self.coef - (self.lr * coef_der)
        print(f'Time Taken : {datetime.now() - start_time}')
        time_taken = datetime.now() - start_time
        return self.intercept,self.coef,time_taken
    def predict_sgdesc(self,X_test):
        return np.dot(X_test,self.coef) + self.intercept
# On Training␣
 ↪Data-----------------------------------------------------------------------------
# Class Object initialization (Learning Rate and number of epochs defined)
sgd_obj = SGDesc(loops=30,lr=0.01)
# Model Fit
coef,intercept,SGD_time = sgd_obj.fit_sgdesc(X_train_scaled,Y_train)
# Train Data Prediction
y_pred_train_sgd = sgd_obj.predict_sgdesc(X_train_scaled)
# # Model Score
SGD_score = r2_score(Y_train,y_pred_train_sgd)
print('----On Training Data----')
print(f"Model score: {SGD_score}")
```

```
print(f"Model X Coef :  {coef} ")
print(f"Model Intercept :  {intercept} ")
y_train_data_list = list(Y_train)
# # Squared error Calculation
se_sum_train = 0
for i, j in zip( y_train_data_list, list(y_pred_train_sgd)):
  se_sum_train = se_sum_train +  (i - j)**2
SGD_mse_train = se_sum_train/len(y_train_data_list)
SGD_rmse_train = (se_sum_train / len(y_train_data_list)) ** .5
print(f"Model MSE : {SGD_mse_train}")
print(f"Model RMSE :  {SGD_rmse_train} ")
# On Test␣
 ↪Data-------------------------------------------------------------------------------------
print('----On Test Data----')
y_pred_test_sgd = sgd_obj.predict_sgdesc(X_test_scaled)
y_test_data_list = list(Y_test)
# Squared error Calculation
se_sum_test = 0
for i, j in zip( y_test_data_list, list(y_pred_test_sgd)):
  se_sum_test = se_sum_test +  (i - j)**2
SGD_mse_test = se_sum_test/len(y_test_data_list)
SGD_rmse_test = (se_sum_test / len(y_test_data_list)) ** .5
print(f"Model MSE : {SGD_mse_test}")
print(f"Model RMSE :  {SGD_rmse_test} ")
```

```
Time Taken : 0:00:00.058856
----On Training Data----
Model score: 0.8458908155677587
Model X Coef :  402.2175254978517
Model Intercept :  [315.87226256  53.95567847]
Model MSE : 18679.231728951436
Model RMSE :  136.67198589671344
----On Test Data----
Model MSE : 21108.59992429165
Model RMSE :  145.28798960785318
```

7 7- Mini Batch Gradient Descent

[33]:
```
import random
class MBGD:
    def __init__(self,batch_size,lr=0.01,loops=100):
        self.coef_ = None
        self.intercept_ = None
        self.lr = lr
        self.loops = loops
        self.batch_size = batch_size
    def MBGDfit(self,X_train,y_train):
```

```
        # initialize  your coeffient and intercept
        # intercept is defined as 0 at first and all coefficient are defined as␣
 ↪1 using numpy.ones
        start_time = datetime.now()
        print(start_time)
        self.intercept = 0
        self.coef = np.ones(X_train.shape[1])
        for i in range(self.loops):
            for j in range(int(X_train.shape[0]/self.batch_size)):
                idx = random.sample(range(X_train.shape[0]),self.batch_size)
                # intercept and coefficient modified here
                y_hat = np.dot(X_train[idx],self.coef) + self.intercept
                intercept_der = -2 * np.mean(y_train[idx] - y_hat)
                self.intercept = self.intercept - (self.lr * intercept_der)
                coef_der = -2 * np.dot((y_train[idx] - y_hat),X_train[idx])
                self.coef = self.coef - (self.lr * coef_der)
        print(f'Time Taken : {datetime.now() - start_time}')
        time_taken = datetime.now() - start_time
        return self.intercept,self.coef,time_taken
    def MBGDpredict(self,X_test):
        return np.dot(X_test,self.coef) + self.intercept
# On Training␣
 ↪Data-----------------------------------------------------------------------------------
# Class Object initialization (Learning Rate and number of epochs defined)
mbr = MBGD(batch_size=int(X_train_scaled.shape[0]/20),lr=0.01,loops=110)
# Model Fit
coef,intercept,MBGD_time = mbr.MBGDfit(X_train_scaled,Y_train)
# Train Data Prediction
y_pred_train_mbgd = mbr.MBGDpredict(X_train_scaled)
# # Model Score
MBGD_score = r2_score(Y_train,y_pred_train_mbgd)
print('----On Training Data----')
print(f"Model score: {MBGD_score}")
print(f"Model X Coef :  {coef} ")
print(f"Model Intercept :  {intercept} ")
y_train_data_list = list(Y_train)
# # Squared error Calculation
se_sum_train = 0
for i, j in zip( y_train_data_list, list(y_pred_train_mbgd)):
  se_sum_train = se_sum_train +  (i - j)**2
MBGD_mse_train = se_sum_train/len(y_train_data_list)
MBGD_rmse_train = (se_sum_train / len(y_train_data_list)) ** .5
print(f"Model MSE : {MBGD_mse_train}")
print(f"Model RMSE :  {MBGD_rmse_train} ")
# On Test␣
 ↪Data-----------------------------------------------------------------------------------
print('----On Test Data----')
```

```
y_pred_test_mbgd = mbr.MBGDpredict(X_test_scaled)
y_test_data_list = list(Y_test)
# Squared error Calculation
se_sum_test = 0
for i, j in zip( y_test_data_list, list(y_pred_test_mbgd)):
  se_sum_test = se_sum_test +  (i - j)**2
MBGD_mse_test = se_sum_test/len(y_test_data_list)
MBGD_rmse_test = (se_sum_test / len(y_test_data_list)) ** .5
print(f"Model MSE : {MBGD_mse_test}")
print(f"Model RMSE :  {MBGD_rmse_test} ")
```

```
2024-06-13 21:36:27.291720
Time Taken : 0:00:02.024972
----On Training Data----
Model score: 0.8572375285610967
Model X Coef :  384.9793088761508
Model Intercept :  [297.66929144  31.06548422]
Model MSE : 17303.92186571838
Model RMSE :  131.54437223126797
----On Test Data----
Model MSE : 17849.49251465542
Model RMSE :  133.6019929292053
```

8 Final Result Summary

[34]:
```
results = {
    "Model": ["SGD", "Mini Batch", "Batch", "Normal Equation"],
    "MSE": [SGD_mse_test, MBGD_mse_test, GD_mse_test, OLS_mse_test],
    "RMSE": [SGD_rmse_test, MBGD_rmse_test, GD_rmse_test, OLS_rmse_test],
    "R2 Score": [SGD_score, MBGD_score, GD_score, score],
    "Time Taken in Seconds": [SGD_time.total_seconds(),MBGD_time.
 ↪total_seconds(),GD_time.total_seconds(),OLS_time.total_seconds()]
}
results_df = pd.DataFrame(results)
results_df
```

[34]:

	Model	MSE	RMSE	R2 Score	Time Taken in Seconds
0	SGD	21108.599924	145.287990	0.845891	0.058856
1	Mini Batch	17849.492515	133.601993	0.857238	2.024972
2	Batch	17689.270593	133.001017	0.857609	0.315115
3	Normal Equation	17689.505287	133.001900	0.857609	0.001031

9 Observation & Explanation :

1- All 4 regression models are performing similarly and has similar R^2 scores.

2- OLS method is performing little better and also taking lesser time than other models.

3- OLS and Normal Gradient descent have lesser RMSE and MSE than other two models.

4- From the Box Plot, outliers have been found for Length, Weight and weigh1 variables.

5- From the correlation heatmap, it is noticed that Length has more association with Cost or target variable than other independent variables and
Length is inter correlated with Weight, Weight1, Width very strongly.

6- Hence, Length and Height have been taken as final model features to predict Cost.

[ ]:

```

```