Machine Learning Lab LR

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Machine Learning Exercise 1 - Simple Linear Regression

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[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

0.0.1 Question 1 :

```
Create a random 2-D numpy array with 1500 values. Simulate different
lines of fit using 1000 values from the array and find the errors for each of
these lines. Find the line with the least error among these lines and store
it as the line of best fit. Using this line of best fit, predict the target variable
for the other 500 values.
```

0.0.2 Class Native to The given Question

```
Essentially Create A Random 2-D Array with NOT Normal Distribution Of random Function
So I Used Triangular Distribution . The Normal Distribution of Random Numbers is not
suitable for Linear Fit As such So Triangular Dist. is the closest to a nice data set
for a fit
```

PreProcessPipeline:

```
Perform The required pre-processing by
```

Initializing 2-d matrix (750x2)->1500 val

Convert to a DataFrame to work with and Rename columns

[2]:
```
'''
    Pre Processing is not Generic Though I have made it Generic to THIS Problem
'''
class PreProcessPipeline():
    def __init__(self):
        dataFrame=pd.DataFrame(np.random.triangular(-50,0,50,size=(750,2)))
        dataFrame=dataFrame.rename(columns={0:"X",1:"Y"})
```

```
        self.dataframe=dataFrame
        self._shuffle_data()
    def _shuffle_data(self):
        self.dataframe= self.dataframe.sample(frac=1).reset_index(drop=True)
    def X(self):
        return self.dataframe.iloc[:,:-1]["X"]
    def Y(self):
        return self.dataframe.iloc[:,-1]
pp=PreProcessPipeline()
x=pp.X()
y=pp.Y()
pp.dataframe
```

[2]:

```
             X          Y
0    15.057165  -8.169659
1    43.533611 -21.400248
2    -6.072795 -42.972982
3   -21.381086  13.919916
4     8.790788  -0.668049
..         …          …
745 -16.602356   1.681381
746 -16.612151  24.436824
747  11.036708  11.858102
748  -5.278104  -0.467222
749 -20.953278 -15.158881

[750 rows x 2 columns]
```

0.0.3 Class To Perform Train Test Split

[3]:

```
class Train_Test_Split:
    def __init__(self,x,y,split_size=0.667):
        self.x=x
        self.y=y
        self.split_size=split_size
    def split(self):
        return (x[:round(self.x.size*self.split_size)],x[round(self.x.size*self.
 ↪split_size):],y[:round(self.y.size*self.split_size)],y[round(self.y.
 ↪size*self.split_size):])
```

[4]:

```
x_train,x_test,y_train,y_test=Train_Test_Split(x,y).split()
```

0.0.4 Simulation Model

This Class Performs Multiple Random Line Fits By Altering its
weight (m) and Bias (_intercept) and we select the best parameters
based on the Error computed.

[5]:
```python
class LinearFitSimulation():
    def __init__(self,x_train,x_test,y_train,y_test,epochs=500):
        self.epochs=epochs
        self.x_train=x_train
        self.x_test=x_test
        self.y_train=y_train
        self.y_test=y_test
    def predict(self):
        best_err=np.inf
        best_line=None
        for i in range(self.epochs):
            m=np.random.randn()
            c=np.random.randn()
            y_pred=m*self.x_train+c
            err= Error_Suite(self.y_train,y_pred).mse()
        if err<best_err:
            best_err=err
            best_line=(m,c)
        return (best_line,best_err,x_test*best_line[0]+best_line[-1])
```

0.0.5 Error Suite Class

Essentially A Generic Class To compute Various Error Metrics
from (y_test,y_pred) for sake of conveinience

[6]:
```python
class Error_Suite:
    def __init__(self,y_test,y_pred):
        self.y_test=y_test
        self.y_pred=y_pred
        self.size=y_test.size
    def mse(self):
        return(np.mean((self.y_test-self.y_pred)**2))
    def mae(self):
        return (abs(self.y_test-self.y_pred).sum()/self.size)
    def mape(self):
        return (abs((self.y_test-self.y_pred)/self.y_test)).sum()*100/self.size
    def rmse(self):
        return self.mse()**0.5
```

0.0.6 Plot Function

Again For convenience sake and Code Reusablity . I wrote down this fn.

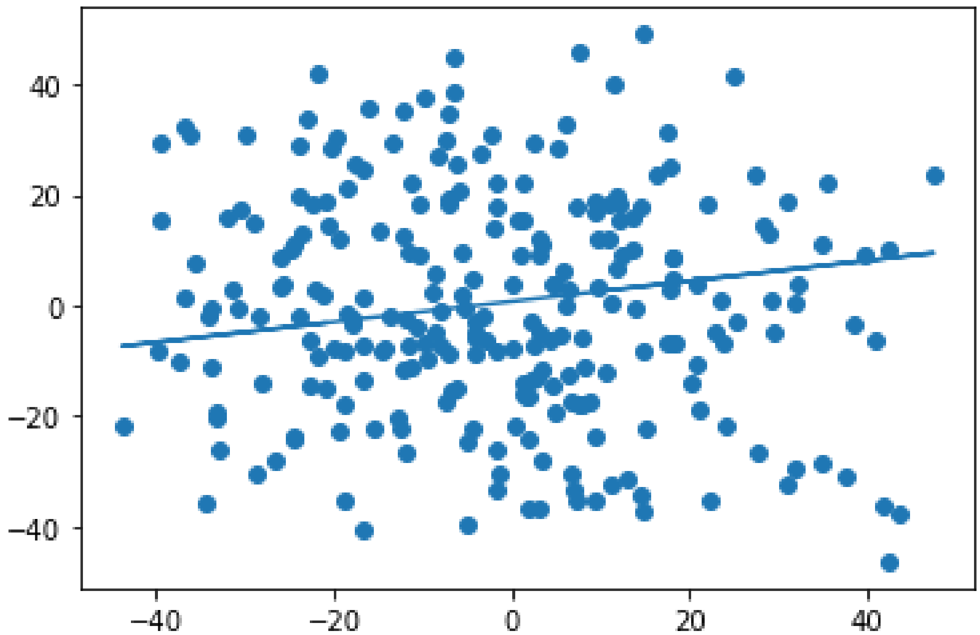
[7]:
```python
class Plot():
    def __init__(self,x_test,y_test,y_pred):
        self.x_test=x_test
        self.y_test=y_test
        self.y_pred=y_pred
```

```
        plt.scatter(x_test,y_test)
        plt.plot(x_test,y_pred)
```

[10]:
```
l=LinearFitSimulation(x_train,x_test,y_train,y_test,epochs=1000).predict()
(y_test,l[-1])
```

[10]:
```
(500    16.713255
 501    -8.110374
 502     0.974025
 503    -8.181004
 504    -0.984421
           …
 745     1.681381
 746    24.436824
 747    11.858102
 748    -0.467222
 749   -15.158881
 Name: Y, Length: 250, dtype: float64,
 500    2.476358
 501    3.463479
 502    6.165586
 503   -6.596648
 504   -0.706523
          …
 745   -2.322694
 746   -2.324505
 747    2.786670
 748   -0.229290
 749   -3.127006
 Name: X, Length: 250, dtype: float64)
```

[11]:
```
z=Plot(x_test,y_test,l[-1])
```



0.0.7 Interpretation

The Given Data or the data that I had Used is A Triangular Distribution (-50,0,50) which follows Somewhat Linear Ascent till Mode And Descent from Mode to the right . So the Fit May Not be Exact since the distribution peaks around 0 and descends around [0,50)

0.0.8 Question 2:

Use the data1.csv to build a simple linear regression from scratch without using sklearn libraries and print the RMSE and mean absolute error values. Use both the equations available in the slides (in theory page) to build the model and compare the intercept and coefficient values

0.0.9 Simple Linear Regression Model

This Class Essentially Performs Linear Regression using Least Squares Method.

[52]:
```
class SimpleLRModel():
    def __init__(self,x_train,x_test,y_train,y_test):
        self.x_train=x_train.flatten()
        self.x_test=x_test.flatten()   # This is necessary because without␣
 ↪flattening each element in x_test/train will be a sub array then being a 2-d␣
 ↪array messing up the computation
        self.y_train=y_train
        self.y_test=y_test
        self._slope=0
        self._intercept=0
```

```
    def fit(self):
        n=len(self.x_train)
        m_n=n*((self.x_train*self.y_train).sum())-(self.x_train.sum()*(self.
↪y_train.sum()))
        m_d=n*((self.x_train**2).sum())-((self.x_train).sum())**2
        self._slope=m_n/m_d
        self._intercept=((self.y_train.sum())-self._slope*(self.x_train.sum()))/
↪n
        return (self._slope,self._intercept)

    def predict(self):
        return self._slope*x_test+self._intercept
```

0.0.10 Simple Linear Regression Model Using Pearson Coeffiecient

[51]:
```
class SimpleLRModel_Pearson():
    def __init__(self,x_train,x_test,y_train,y_test):
        self.x_train=x_train.flatten()
        self.x_test=x_test.flatten()   # This is necessary because without␣
↪flattening each element in x_test/train will be a sub array then being a 2-d␣
↪array messing up the computation
        self.y_train=y_train
        self.y_test=y_test
        self._slope=0
        self._intercept=0


    def fit(self):
        x_mean=self.x_train.mean()
        y_mean=self.y_train.mean()
        x_std=np.sqrt(((self.x_train-x_mean)**2).sum()/len(self.x_train))
        y_std=np.sqrt(((self.y_train-y_mean)**2).sum()/len(self.y_train))
        #z_x=(self.x_train-x_mean)/x_std
        #z_y=(self.y_train-y_mean)/y_std
        #r=(z_x*z_y).sum()/len(self.x_train)-1
        r=((self.x_train-x_mean)*(self.y_train-y_mean)).sum()/np.sqrt(((self.
↪x_train-x_mean)**2).sum()*((self.y_train-y_mean)**2).sum())

        b1=r*(y_std/x_std)

        b0=y_mean-b1*x_mean
        self._slope =b1
```

```
        self._intercept=b0
        return (b1,b0)

    def predict(self):
        return self._slope*x_test+self._intercept
```

0.0.11 Data Pre processing

[48]:
```
data=pd.read_csv(r"D:\data1.csv")
x=data.iloc[:,:-1].values
y=data.iloc[:,-1].values
```

[56]:
```
x_train,x_test,y_train,y_test=Train_Test_Split(x,y).split()
```

0.0.12 Model Training (Least Squares)

[57]:
```
lrm=SimpleLRModel(x_train,x_test,y_train,y_test)
lrm.fit()
```

[57]:
```
(3.1792452830188678, 30.10377358490566)
```

0.0.13 Model prediction (Least Squares)

[58]:
```
y_pred=lrm.predict().flatten()
(y_pred,y_test)
```

[58]:
```
(array([84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396,
        84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396,
        84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396,
        84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396]),
 array([94, 73, 59, 80, 93, 85, 66, 79, 77, 91, 94, 73, 59, 80, 93, 85, 66,
        79, 77, 91, 94, 73, 59, 80, 93, 85, 66, 79, 77, 91, 94, 73, 59, 80,
        93, 85, 66, 79, 77, 91], dtype=int64))
```

0.0.14 Model Error Metrics (Least Squares)

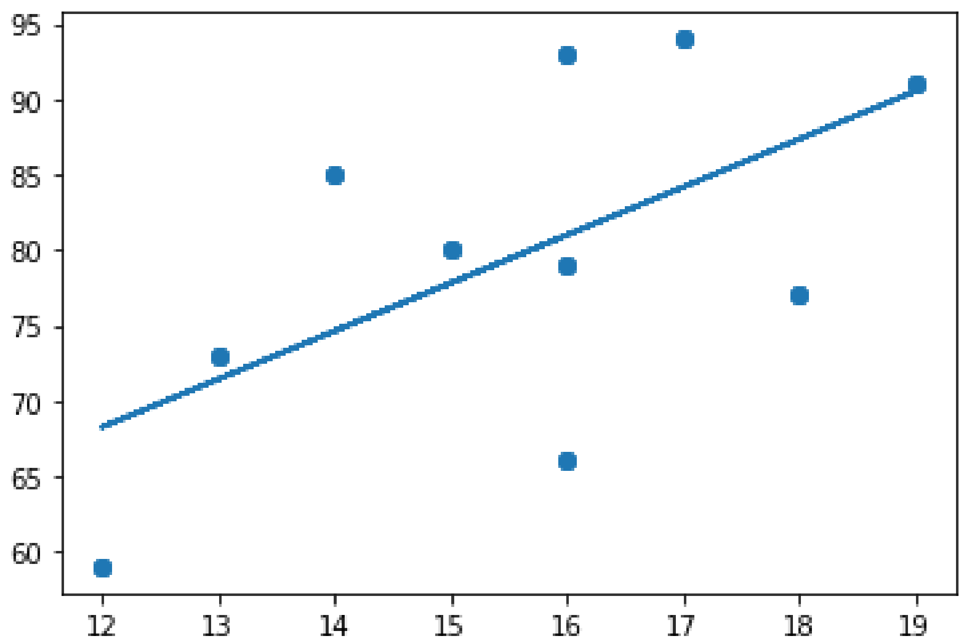
[59]:
```
mse=Error_Suite(y_test,y_pred).mse()
rmse=Error_Suite(y_test,y_pred).rmse()
mape=Error_Suite(y_test,y_pred).mape()
mae=Error_Suite(y_test,y_pred).mae()
```

```
print(f"Mean Squared Error :{mse}\nRoot Mean Squared Error:{rmse}\nMean␣
↪Percentage Error:{mape}\nMean AbsoluteError:{mae}\n")
```

```
Mean Squared Error :77.75377358490566
Root Mean Squared Error:8.817810022046611
Mean Percentage Error:9.535691016912438
Mean AbsoluteError:7.30566037735849
```

[60]:
```
plt.scatter(x_test,y_test)
plt.plot(x_test,y_pred)
```

[60]: [<matplotlib.lines.Line2D at 0x1bee3dbf4f0>]



0.0.15 Model Fit Using Pearson Correlation

[61]:
```
reg=SimpleLRModel_Pearson(x_train,x_test,y_train,y_test)
reg.fit()
```

[61]: (3.179245283018868, 30.10377358490566)

[62]:
```
y_pred_pearson=reg.predict()
(y_test,y_pred_pearson.flatten())
```

[62]:
```
(array([94, 73, 59, 80, 93, 85, 66, 79, 77, 91, 94, 73, 59, 80, 93, 85, 66,
        79, 77, 91, 94, 73, 59, 80, 93, 85, 66, 79, 77, 91, 94, 73, 59, 80,
```

```
        93, 85, 66, 79, 77, 91], dtype=int64),
 array([84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396,
        84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396,
        84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396,
        84.1509434 , 71.43396226, 68.25471698, 77.79245283, 80.97169811,
        74.61320755, 80.97169811, 80.97169811, 87.33018868, 90.50943396]))
```

0.0.16 Model Error metrics (Pearson Correlation)

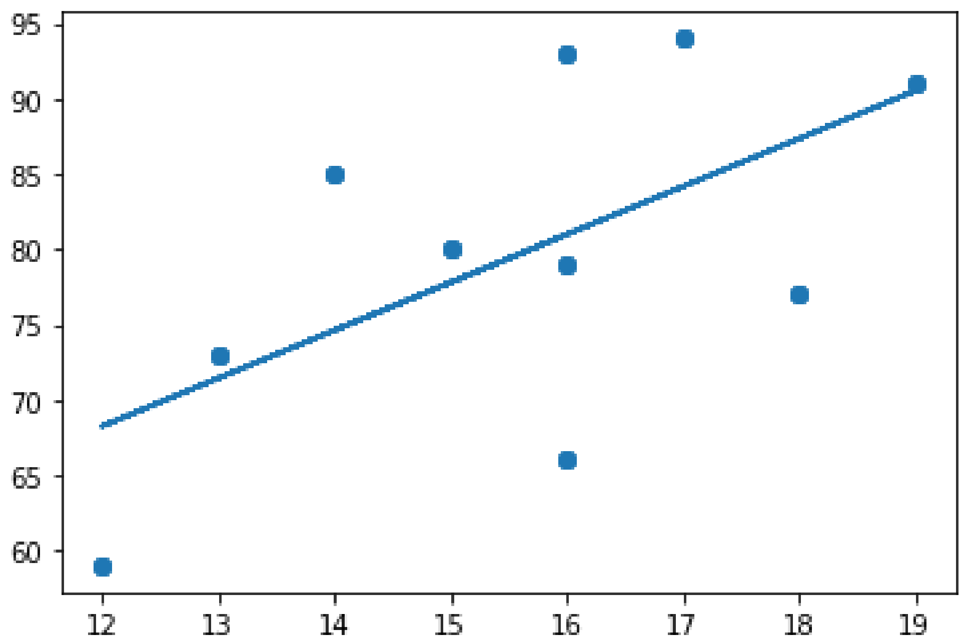
[64]:
```
mse=Error_Suite(y_test,y_pred_pearson.flatten()).mse()
rmse=Error_Suite(y_test,y_pred_pearson.flatten()).rmse()
mape=Error_Suite(y_test,y_pred_pearson.flatten()).mape()
mae=Error_Suite(y_test,y_pred_pearson.flatten()).mae()

print(f"Mean Squared Error :{mse}\nRoot Mean Squared Error:{rmse}\nMean␣
 ↪Percentage Error:{mape}\nMean AbsoluteError:{mae}\n")
```

```
Mean Squared Error :77.75377358490564
Root Mean Squared Error:8.81781002204661
Mean Percentage Error:9.535691016912434
Mean AbsoluteError:7.305660377358488
```

0.0.17 Regression Line Plot

[46]:
```
plt.scatter(x_test,y_test)
plt.plot(x_test,y_pred_pearson)
```

[46]:
```
[<matplotlib.lines.Line2D at 0x1bee41189a0>]
```



0.0.18 Inference

Thus the equations obtained are the same and the Errors obtained are comparably similar in magnitude.