CSE4020 – Machine Learning Lab

Classification and Regression

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16BEC0789

F2

1. Consider a dataset from UCI repository. a. Create a Simple Linear Regression model using the training data set. b. Predict the scores on the test data and output RMSE and R Squared score. c. Include appropriate code snippets to visualize the model.

DATASET USED:

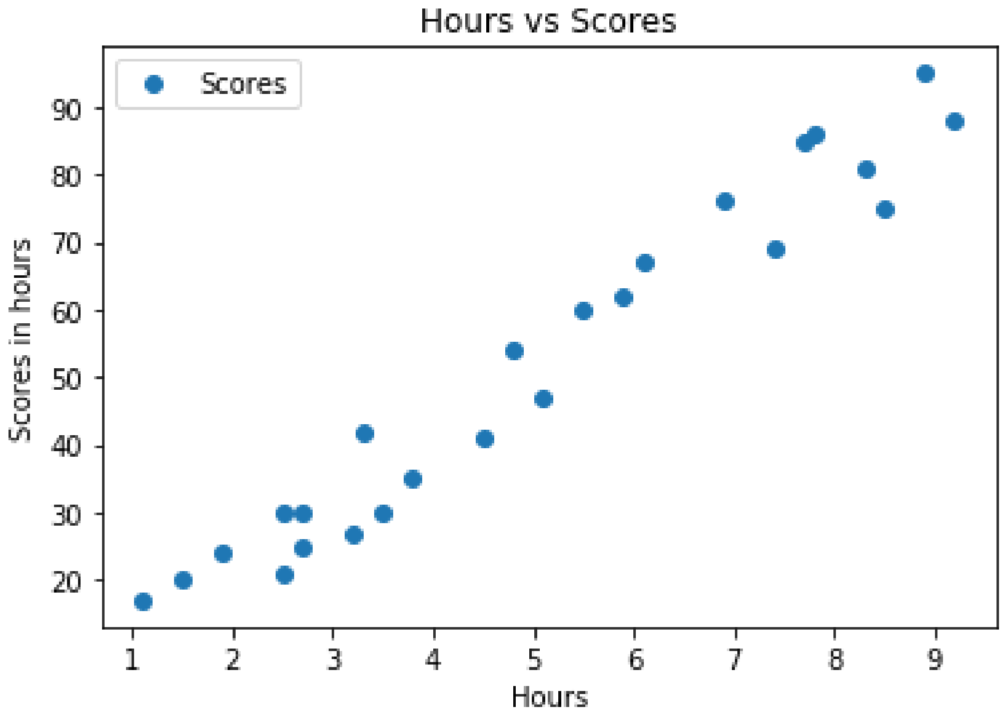
Hours	Scores
2.5	21
5.1	47
3.2	27
8.5	75
3.5	30
1.5	20
9.2	88
5.5	60
8.3	81
2.7	25
7.7	85
5.9	62
4.5	41
3.3	42
1.1	17
8.9	95
2.5	30
1.9	24
6.1	67
7.4	69
2.7	30
4.8	54
3.8	35

6.9	76
7.8	86

PYTHON PROGRAM:

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,  r2_score
scores = pd.read_csv('D:/Nikhil/Documents/scores.csv')
scores.plot(x='Hours',y='Scores',style='o')
plt.title('Hours vs Scores')
plt.xlabel('Hours')
plt.ylabel('Scores in hours')
plt.show()
x=scores.iloc[:,:-1].values
y=scores.iloc[:,1].values
regressionModel = LinearRegression()
regressionModel.fit(x,y)
y_predicted=regressionModel.predict(x)
print(y_predicted)

rmse=mean_squared_error(y,y_predicted)
r2=r2_score(y,y_predicted)

print('Slope',regressionModel.coef_)
print('Intercept:',regressionModel.intercept_)
print('Root mean square error',rmse)
print('R2 score:',r2)

plt.scatter(x,y,s=10)
plt.xlabel('x')
plt.ylabel('y')

plt.plot(x,y_predicted,color='r')
plt.show()
```

OUTPUT:



[26.92318188 52.3402707 33.76624426 85.57800223 36.69898527 17.14737849

92.4210646 56.25059205 83.62284155 28.87834256 77.75735951 60.16091341

46.47478866 34.74382459 13.23705714 89.48832358 26.92318188 21.05769985

62.11607409 74.8246185 28.87834256 49.40752968 39.63172629 69.9367168

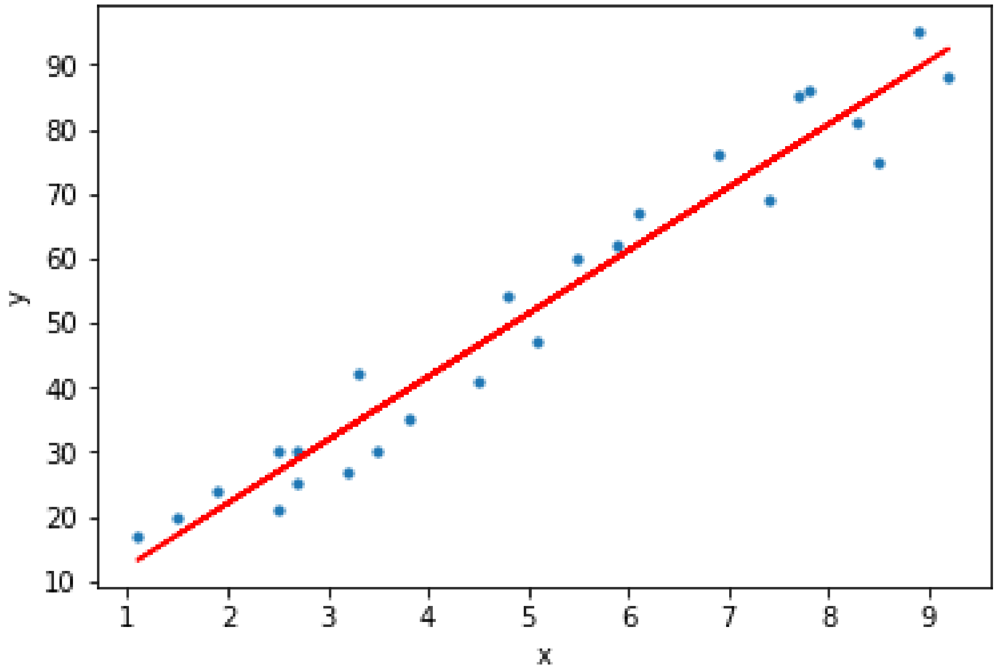
78.73493985]

Slope [9.77580339]

Intercept: 2.48367340537321

Root mean square error 28.882730509245466

R2 score: 0.9529481969048356



2. Implement Multiple Linear Regression using a dataset from UCI repository.

DATASET USED -

Year	Month	Interest_Rate	Unemployment_Rate	Stock_Index_Price
2017	12	2.75	5.3	1464
2017	11	2.5	5.3	1394
2017	10	2.5	5.3	1357
2017	9	2.5	5.3	1293
2017	8	2.5	5.4	1256
2017	7	2.5	5.6	1254
2017	6	2.5	5.5	1234
2017	5	2.25	5.5	1195
2017	4	2.25	5.5	1159
2017	3	2.25	5.6	1167
2017	2	2	5.7	1130
2017	1	2	5.9	1075
2016	12	2	6	1047
2016	11	1.75	5.9	965
2016	10	1.75	5.8	943
2016	9	1.75	6.1	958
2016	8	1.75	6.2	971
2016	7	1.75	6.1	949
2016	6	1.75	6.1	884
2016	5	1.75	6.1	866

2016	4	1.75	5.9	876
2016	3	1.75	6.2	822
2016	2	1.75	6.2	704
2016	1	1.75	6.1	719

PYTHON PROGRAM:

```
import matplotlib.pyplot as plt
from sklearn import linear_model
from sklearn.metrics import mean_squared_error,r2_score
import numpy as np
import pandas as pd

stock = pd.read_csv("D:/Nikhil/Documents/economy.csv")
df = pd.DataFrame(stock)
df.isnull().any()
df = df.fillna(method='ffill')
print(df)
Y = df['Stock_Index_Price']
X = df['Interest_Rate']

X=X.values.reshape(-1,1)
Y=Y.values.reshape(-1,1)

plt.scatter(X,Y,color='red')
plt.title('Stock Index Price Vs Interest Rate for All Data')
plt.xlabel('Interest Rate')
plt.ylabel('Stock Index Price')
plt.grid(True)
plt.show()

# Split the data into training/testing sets
X_train = X[0:18]
X_test = X[18:24]

# Split the targets into training/testing sets
Y_train = Y[0:18]
Y_test = Y[18:24]

# Plot outputs
plt.scatter(X_test,Y_test,color='red')
plt.title('Stock Index Price Vs Interest Rate for Test Data')
plt.xlabel('Interest Rate')
plt.ylabel('Stock Index Price')
plt.grid(True)

# Create linear regression object
regr = linear_model.LinearRegression()
```

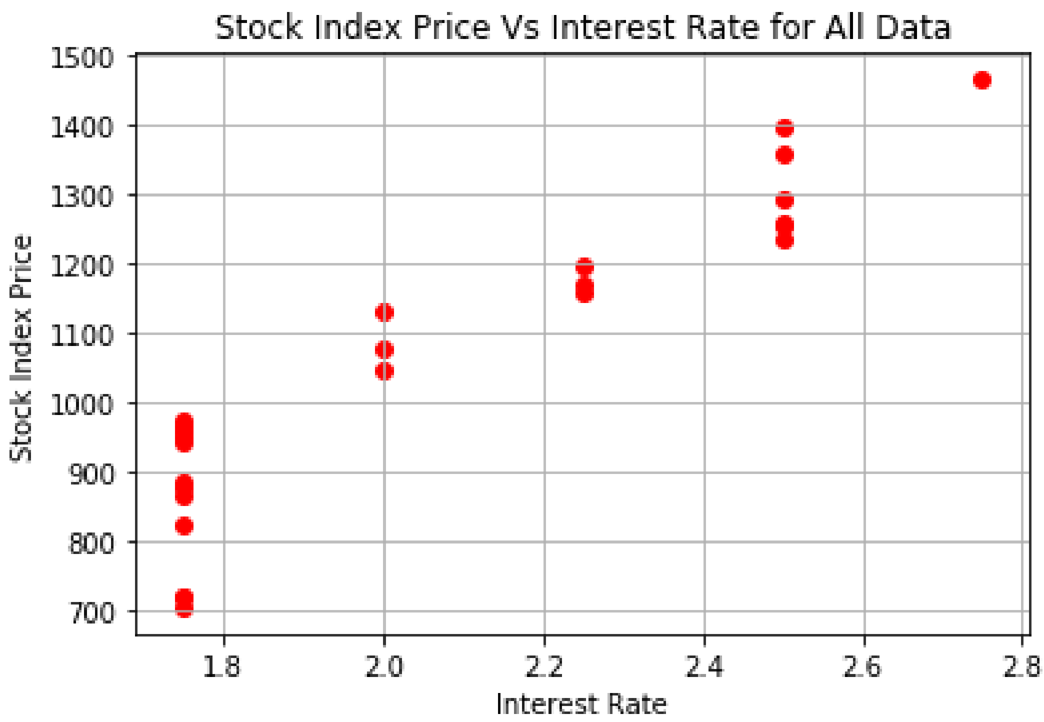
```python
# Train the model using the training sets
regr.fit(X_train,Y_train)

# Plot outputs
plt.plot(X_test, regr.predict(X_test), color='red',linewidth=3)
plt.show()

Y_predicted=regr.predict(X)
print(Y_predicted)

rmse=mean_squared_error(Y,Y_predicted)
r2=r2_score(Y,Y_predicted)

print('Slope',regr.coef_)
print('Intercept:',regr.intercept_)
print('Root mean square error:',rmse)
print('R2 score:',r2)
```

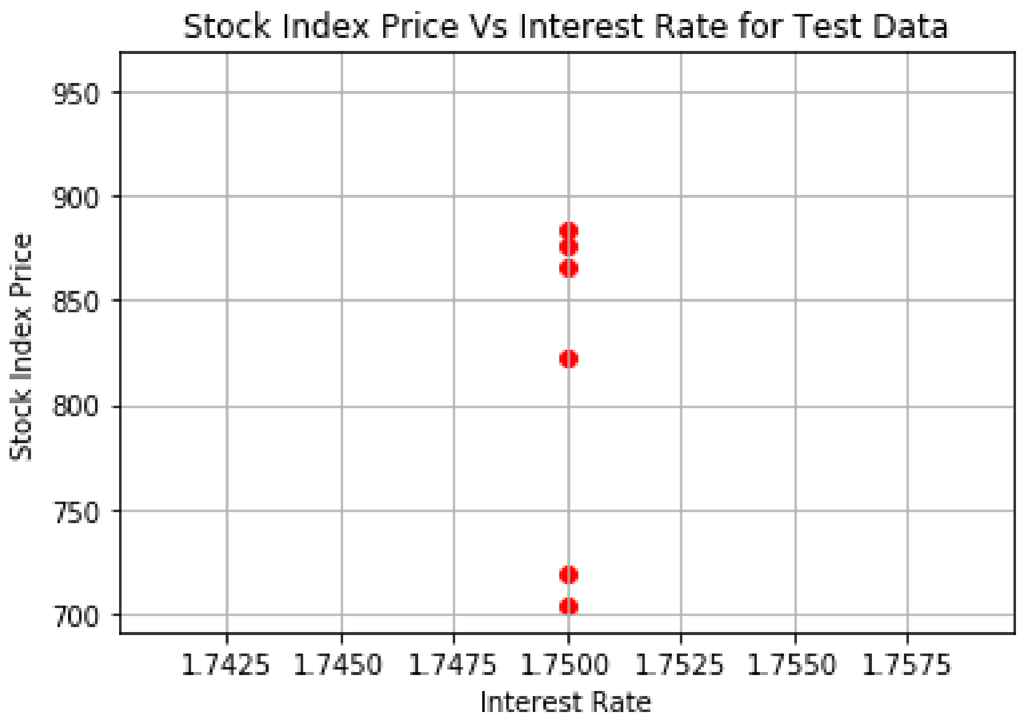
OUTPUT:

DATAFRAME -

	Year	Month	...	Unemployment_Rate	Stock_Index_Price
0	2017.0	12.0	...	5.3	1464.0
1	2017.0	11.0	...	5.3	1394.0
2	2017.0	10.0	...	5.3	1357.0
3	2017.0	9.0	...	5.3	1293.0
4	2017.0	8.0	...	5.4	1256.0
5	2017.0	7.0	...	5.6	1254.0
6	2017.0	6.0	...	5.5	1234.0
7	2017.0	5.0	...	5.5	1195.0
8	2017.0	4.0	...	5.5	1159.0
9	2017.0	3.0	...	5.6	1167.0
10	2017.0	2.0	...	5.7	1130.0
11	2017.0	1.0	...	5.9	1075.0
12	2016.0	12.0	...	6.0	1047.0
13	2016.0	11.0	...	5.9	965.0
14	2016.0	10.0	...	5.8	943.0

15	2016.0	9.0	...	6.1	958.0
16	2016.0	8.0	...	6.2	971.0
17	2016.0	7.0	...	6.1	949.0
18	2016.0	6.0	...	6.1	884.0
19	2016.0	5.0	...	6.1	866.0
20	2016.0	4.0	...	5.9	876.0
21	2016.0	3.0	...	6.2	822.0
22	2016.0	2.0	...	6.2	704.0
23	2016.0	1.0	...	6.1	719.0
24	2016.0	1.0	...	6.1	719.0





Y_Predicted :

[1420.8172232]

[1304.62917399]

[1304.62917399]

[1304.62917399]

[1304.62917399]

[1304.62917399]

[1304.62917399]

[1188.44112478]

[1188.44112478]

[1188.44112478]

[1072.25307557]

[1072.25307557]

[1072.25307557]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

[956.06502636]

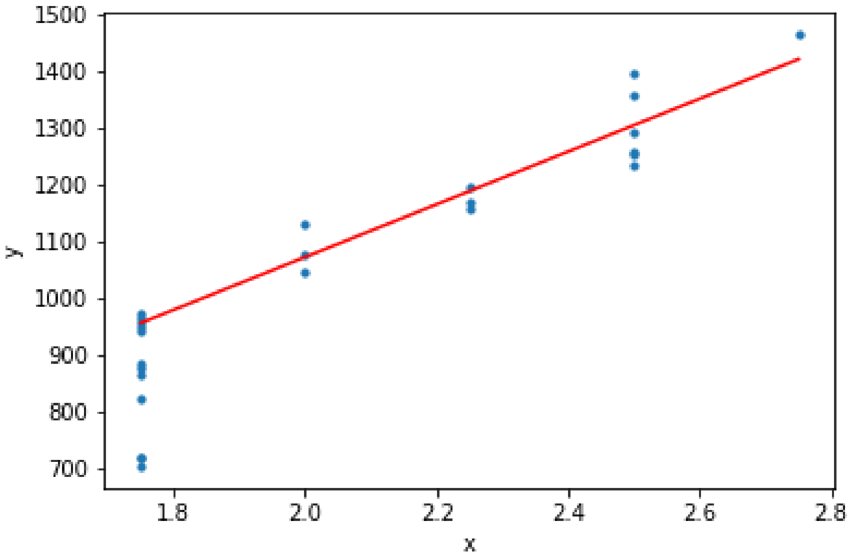
[956.06502636]]

Slope [[464.75219684]]

Intercept: [142.7486819]

Root mean square error: 9685.940305225162

R2 score: 0.7875414973270607



3. Implement logistic regression and test it using any dataset of your choice from UCI repository. The output should include Confusion Matrix, Accuracy, Error rate, Precision, Recall and F Measure.

Code:

```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd


# Importing the dataset
dataset = pd.read_csv('Social_Network_Ads.csv')
X = dataset.iloc[:, [2, 3]].values
y = dataset.iloc[:, 4].values

# Splitting the dataset into the Training set and Test set
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,
random_state = 0)

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)

# Visualising the Training set results
from matplotlib.colors import ListedColormap
X_set, y_set = X_train, y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:,
0].max() + 1, step = 0.01),
                     np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:,
1].max() + 1, step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape),
```

```python
             alpha = 0.75, cmap = ListedColormap(('red', 'green')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green'))(i), label = j)
plt.title('Logistic Regression (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()

# Visualising the Test set results
from matplotlib.colors import ListedColormap
X_set, y_set = X_test, y_test
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:,
0].max() + 1, step = 0.01),
                     np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:,
1].max() + 1, step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape),
             alpha = 0.75, cmap = ListedColormap(('red', 'green')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green'))(i), label = j)
plt.title('Logistic Regression (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()


#Confusion matrix
from sklearn.metrics import confusion_matrix
conf_matrics=confusion_matrix(y_test, y_pred)
print("Confusion Matrics===>")
print(conf_matrics)
print()

#Accuracy and error rate
from sklearn import metrics
accuracy = metrics.accuracy_score(y_test, y_pred)
error_rate = 1 - accuracy
print("Accuracy = {}".format(accuracy))
print("Error Rate = {}".format(error_rate))
print()
#classification report
```

```python
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

Output:

Confusion Matrics===>

[[65 3]

[8 24]]

Accuracy = 0.89

Error Rate = 0.10999999999999999

	precision	recall	f1-score	support
0	0.89	0.96	0.92	68
1	0.89	0.75	0.81	32
avg / total	0.89	0.89	0.89	100