Assignment_8_Rohit_Byas

March 7, 2021

1 CSL558: MachineLearning

Instructor : [Dr. Chandra Prakash]

For more information visit the class website (https://cprakash86.wordpress.com/ml/)

2 Assignment 8:

Due Date: 7-March-2021

Student Name: Rohit Byas sherwan

2.1 Assignment Instructions

You must save your as Assignment_NO_Yourname

2.1.1 Agenda for the Assignment 8

1.1Understand the working of the Linear Regression :

1.2Tradition Machine Learning Techniques :

Your source file will most likely end in .pynb if you are using a Jupyter notebook; however, it might also end in .py if you are using a Python script.

You have to add your name and roll no in the Google Colab Instructions section below and print it.

2.1.2 Google CoLab Instructions

The following code ensures that Google CoLab is running the correct version of TensorFlow.

[5]:

```
try:
from google.colab import drive
%tensorflow_version 2.x COLAB = True print("Assignment 8")
print("Note: using Google CoLab")
except: print("Assignment 8")
print("Note: not using Google CoLab")
```

```
COLAB = False
# Print your name and Roll No. print('rohit byas') print('181210043')
# Print the curent time
import datetime
print(datetime.datetime.now())
```

Assignment 8
Note: using Google CoLab
rohit byas
181210043
2021-03-06 22:10:39.2324836

[6]:
```
# importing required libraries
import numpy as np import pandas as pd
from sklearn.datasets import make_classification
import matplotlib.pyplot as plt import seaborn as sns
```

2.2 Part A: Linear Regression from scratch

2.2.1 Task 1: Derive the equations for regression on the slide no 29,Regression.pdf Upload your handwritten file as PDF

[7]:
```
## Submission Status over Microsoft [ Yes/No]
print('Yes')
```

Yes

[14]:
```
# Write a function for the caluclate the cost
def calculate_cost(slope, intercept, data):
# from data extract features and target values
X = np.array([i[0] for i in data]) y = np.array([i[1] for i in data]) m = X.shape[0]
h = X*slope + intercept
# calculate the final cost
total_cost = (1/(2*m))*(np.sum(np.square(h-y)))
return total_cost
```

[15]:
```
# Write a function for the caluclate the slope
def calculate_slope(slope, y_intercept, data,learning_rate):
# extract all the features and target values from data
```

```
X = np.array([i[0] for i in data]) y = np.array([i[1] for i in data]) m = X.shape[0]
h = X*slope + y_intercept
# Slope of the line is getting updated below
slope = slope - learning_rate*(1/m)* np.sum((h-y)*X)
# returning the updated slope
return slope
```

[16]:
```
# Write a function for the caluclate the slope
def calculate_intercept(slope, y_intercept, data,learning_rate):
# from data extracting features and target values
X = np.array([i[0] for i in data]) y = np.array([i[1] for i in data]) # size of data
m = X.shape[0]
# hypothesis
h = X*slope + y_intercept
# updating the y_intercept
y_intercept = y_intercept - learning_rate*(1/m)* np.sum((h-y))
return y_intercept
```

[17]:
```
# Generate data randomely
data=[]
for x in range(111): data.append((x,x))
slope=0 y_intercept=0
cost=calculate_cost(slope, y_intercept, data) print(cost)
```

```
2025.8333333333333
```

[20]:
```
learning_rate=0.00001 previous_cost=cost+1

# we can train data for 50 iteration
iterations = 50
while iterations>0 : #TODO:
iterations-=1

new_slope=calculate_slope(slope, y_intercept, data,learning_rate)
new_y_intercept=calculate_intercept(slope, y_intercept,data,learning_rate) previous_cost=cost
slope=new_slope y_intercept=new_y_intercept
```

```
cost=calculate_cost(slope, y_intercept, data) print('cost:',cost)
print('slope:',slope) print('y_intercept:',y_intercept)
```

```
cost: 0.001601595617498023
slope: 0.9989333295882401
y_intercept: 0.013555183320449 83
```

2.3 PART B : Logistic Regression

Logistic regression is used when the response variable is categorical in nature. The name is taken from the linear regression only. The logistic term is used because it uses the logistic function as tranfer function.

Linear regression is suitable for predicting output that is continuous value, such as predicting the price of a property. Its prediction output can be any real number, range from negative infinity to infinity. The regression line is generally a straight line.

Whereas logistic regression is for classification problems, which predicts a probability range between 0 to 1. For example, predict whether a customer will make a purchase or not. The regression line is a sigmoid curve.

Why linear regression is not suitable for Classification: - the predicted value is continuous, not probabilistic

- Sensitive to imbalance data when using linear regression for classification

Probalistic model in Linear regression is Gaussian while in Logistic regression is binomial distribu- tion

3 steps in Logistic Regression 1. Sigmoid Function 2. Cost Function / Loss function 3. Gradient Descent

[21]:
```
# 1. Sigmoid Function
def sigmoid(x):
return 1/(1 + np.exp(-x))
```

[22]:
```
#2 Cost Function - Write a function for the caluclate the cost
def compute_cost(X, y, theta):
# data size
m = X.shape[0]
# hypothesis function
h = sigmoid(X @ theta)
# final cost
cost = -1*(1/m)*(y.T@np.log(h)+(1-y).T@np.log(1-h))
```

```
return cost
```

[23]:
```
def gradient_descent(X, y, params, learning_rate, iterations): m = len(y)
cost_history = np.zeros((iterations,1))
# using for loops on iterations
for i in range(iterations):
params = params - (learning_rate/m) * (X.T @ (sigmoid(X @ params) -y)) cost_history[i] =
compute_cost(X, y, params)
return (cost_history, params)
```

[24]:
```
def predict(X, params):
return np.round(sigmoid(X @ params))
```

[25]:
```
?make_classification
```

[26]:
```
# Generating artificail data sets
X, y = make_classification(n_samples=500, n_features=2, n_redundant=0,
↪n_informative=1,
n_clusters_per_class=1, random_state=14)
y = y[:,np.newaxis]
```

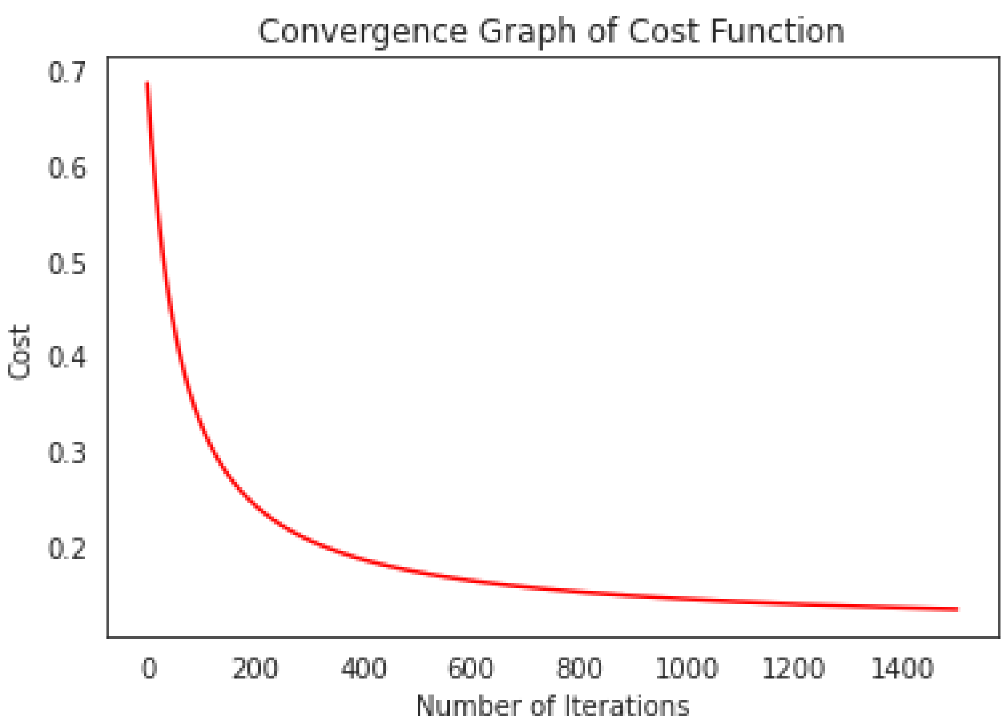
[27]:
```
m = len(y)

print(f"init shape of X {X.shape}") X = np.hstack((np.ones((m,1)),X))
n = np.size(X,1)
params = np.zeros((n,1))
print(f"after padding shape of X{X.shape}") print(f"shape of parms {params.shape}")
print(f"shape of y {y.shape}")
iterations = 1500
learning_rate = 0.03
initial_cost = compute_cost(X, y, params) print("Initial Cost is: {}\n".format(initial_cost))
(cost_history, params_optimal) = gradient_descent(X, y, params,learning_rate,
↪iterations)
print("Optimal Parameters are: \n", params_optimal, "\n") plt.figure()
```

```
sns.set_style('white') plt.plot(range(len(cost_history)), cost_history, 'r') plt.title("Convergence
Graph of Cost Function") plt.xlabel("Number of Iterations")
plt.ylabel("Cost") plt.show()
```

```
init shape of X (500, 2)
after padding shape of X (500, 3) shape of
parms (3, 1)
shape of y (500, 1)
Initial Cost is: [[0.69314718]]

Optimal Parameters are: [[-
  0.45293068]
  [ 3.26552327]
  [ 0.03334871]]
```

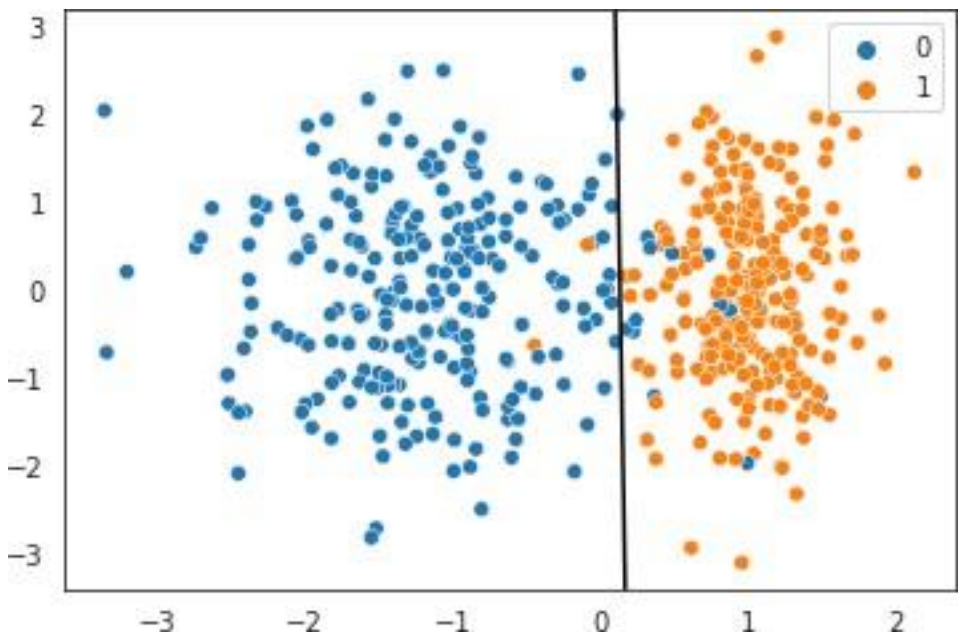


[28]:
```
y_pred = predict(X, params_optimal)
score = float(sum(y_pred == y))/ float(len(y)) print(score)
```

```
0.966
```

[29]: slope = -(params_optimal[1] / params_optimal[2]) intercept = -(params_optimal[0] / params_optimal[2]) sns.set_style('white') sns.scatterplot(X[:,1],X[:,2],hue=y.reshape(-1));
ax = plt.gca() ax.autoscale(False)
x_vals = np.array(ax.get_xlim()) y_vals = intercept + (slope * x_vals) plt.plot(x_vals, y_vals, c="k");

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments withoutan explicit keyword will result in an error or misinterpretation.
FutureWarning



2.4 PART C : Traditional ML Techniques over MNIT Gait Dataset

Take the filtered Gait Dataset from the Assignment 4. You need to apply the traditional ML techniques for the analysis of the this dataset.

Objective 1: Predict the age from the rest of features in the dataset in [Task 2] . Objective 2: Identify the gender from the rest of the features in the dataset in [Task 3]. Objective 3: Predict the knee angle for the next gait cycle [Task 4] .

2.4.1 Task 1: Data reading and package setup

1.1Read Analysis_MNIT_database.xlsx. and import the packages

[31]:

```
# importing general libraries for data analytics from sklearn.model_selection import
train_test_split from sklearn.preprocessing import StandardScaler from sklearn.linear_model
import LinearRegression from sklearn import metrics
from sklearn.linear_model importLogisticRegression from sklearn.metrics import
plot_confusion_matrix matplotlib inline
```

[33]:

```
%
# reading the dataset from Analysis_MNIT.xlsx df = pd.read_excel('Analysis_MNIT.xlsx')
df.drop(columns=[df.columns[0]], inplace=True)
df
```

[33]:

```
     Subject #   Age  (Year)   Height (m)   ...   Bi-illiac    width (m)     Gender_0
Gender_1
0           S21            30        1.740   ...                     0.79           0
1
1           S22            27        1.855   ...                     0.81           0
1
2           S23            27        1.570   ...                     0.87           1
0
3           S24            22        1.580   ...                     0.76           1
0
4           S25            20        1.740   ...                     0.87           0
1
..          ...           ...          ...   ...                 ...      ...
...
109        S130            25        1.670   ...                     0.81           0
1
110        S131            28        1.700   ...                     0.76           0
1
111        S132            55        1.670   ...                     0.81           0
1
112        S133            42        1.680   ...                     0.92           0
1
113        S134            53        1.780   ...                     0.94           0
1

[114 rows x 15 columns]
```

[51]:

```
# describing data set
```

[51]:

```
df.describe()Age (Year)    Height (m)   ...     Gender_0      Gender_1
count     114.000000    114.000000   ...   114.000000    114.000000
mean       28.096491      1.681886   ...     0.245614      0.754386
std         8.831730      0.110621   ...     0.432351      0.432351
min         4.000000      0.970000   ...     0.000000      0.000000
```

```
25%        23.000000      1.640000   ...     0.000000      1.000000
50%        27.000000      1.695000   ...     0.000000      1.000000
75%        31.000000      1.740000   ...     0.000000      1.000000
max        57.000000      1.930000   ...     1.000000      1.000000

[8 rows x 14 columns]
```

2.4.2 Task 2: Regression

Perform the Objective 1:

[35]:
```
# We need to create features and target array
X = df[df.columns[2:]].to_numpy() y = df[[df.columns[1]]].to_numpy()
```

[36]:
```
# Dataset are getting splitted into training and test dataset x_train, x_test, y_train, y_test =
train_test_split(X, y, t_size=0.2) x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

[36]: ((91, 13), (23, 13), (91, 1), (23, 1))

[52]:
```
# Crerating the regressor object of LinearRegression class
r=LinearRegression() r.fit(x_train,y_train)
```

[52]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,normalize=False) [53]:

```
# regressor's intercept and coeffcient
r.intercept_, r.coef_
```

[53]:
```
(array([-25.27270289]),
 array([[-44.40421244,     -0.21959502,      0.63534084,    77.50567941,
          10.03881382, -13.65059126,     -6.55436642, 106.91249275,
         -2.10666205,     -2.40775161, 152.12934878,     -4.41536348,
         4.41536348]]))
```

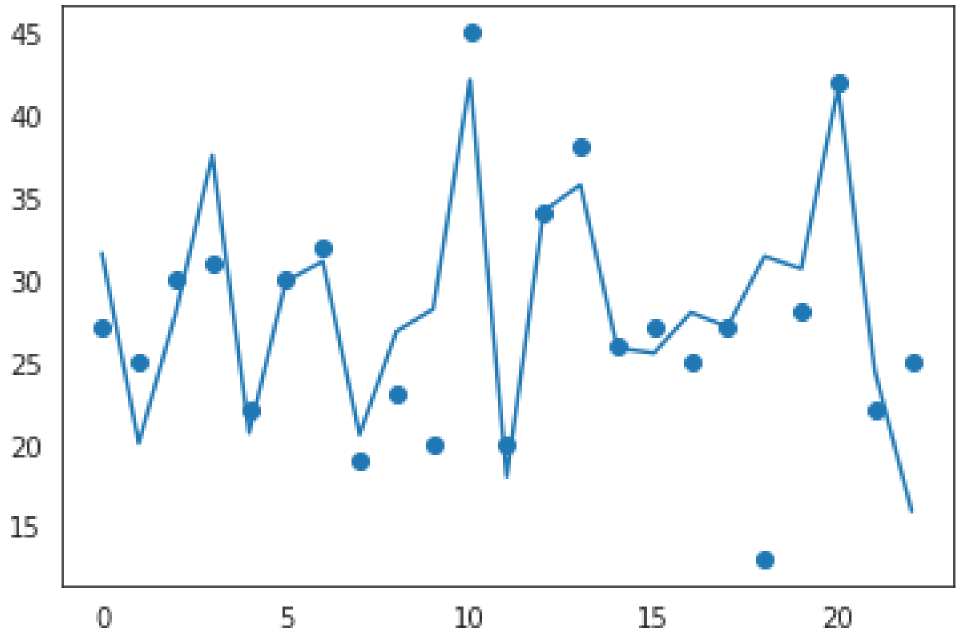
[39]:
```
# For Testing
y_predict=regressor.predict(x_test)
```

[40]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape,y_predict.shape
```

[40]: ((91, 13), (23, 13), (91, 1), (23, 1), (23, 1))

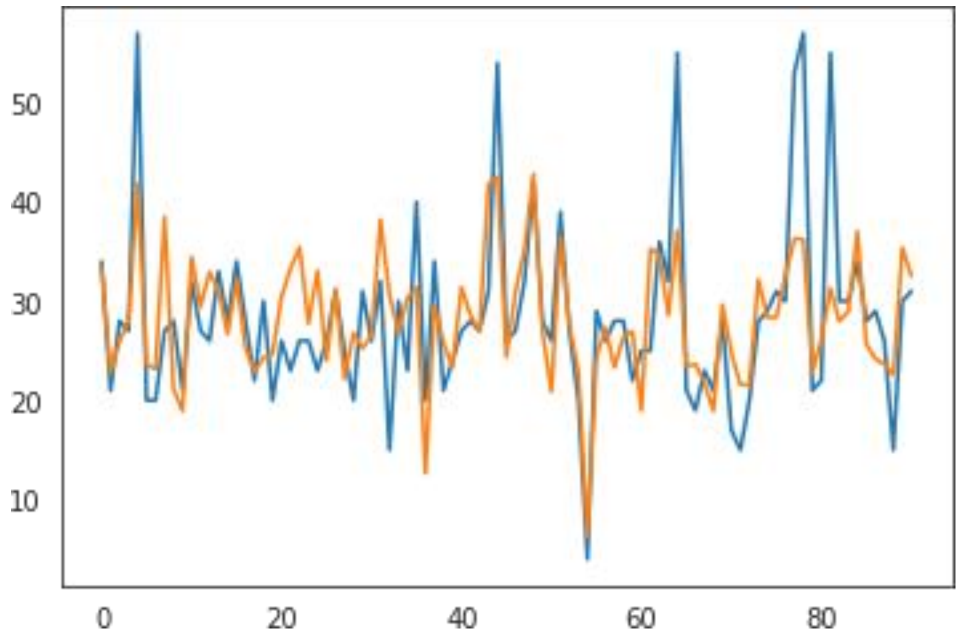
[41]: plt.scatter([i for i in range(len(x_test))], y_test) plt.plot(y_predict)

41 : [<matplotlib.lines.Line2D at 0x7f1e759e6c50>]



[42]: # ploting ytrain and xtrain plt.plot(y_train) plt.plot(r.predict(x_train))

42 : [<matplotlib.lines.Line2D at 0x7f1e759cc910>]



[43]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test,y_pred)) print('Mean Squared
Error:', metrics.mean_squared_error(y_test, y_pred)) print('Root Mean Squared Error:',
np.sqrt(metrics.
↪mean_squared_error(y_test,y_pred)))
```

```
Mean Absolute Error: 3.43953471218567 Mean
Squared Error: 27.91292312491641
Root Mean Squared Error: 5.283268223828543
```

2.4.3 Task 3: Logistic Regression

[44]:
```
X = df[df.columns[1:-2]].to_numpy()
y = df[[df.columns[-1]]].to_numpy().squeeze()
```

[45]:
```
train_data,t_data, train_label, t_lable =train_test_split(X,y,t_size=0.20)
```

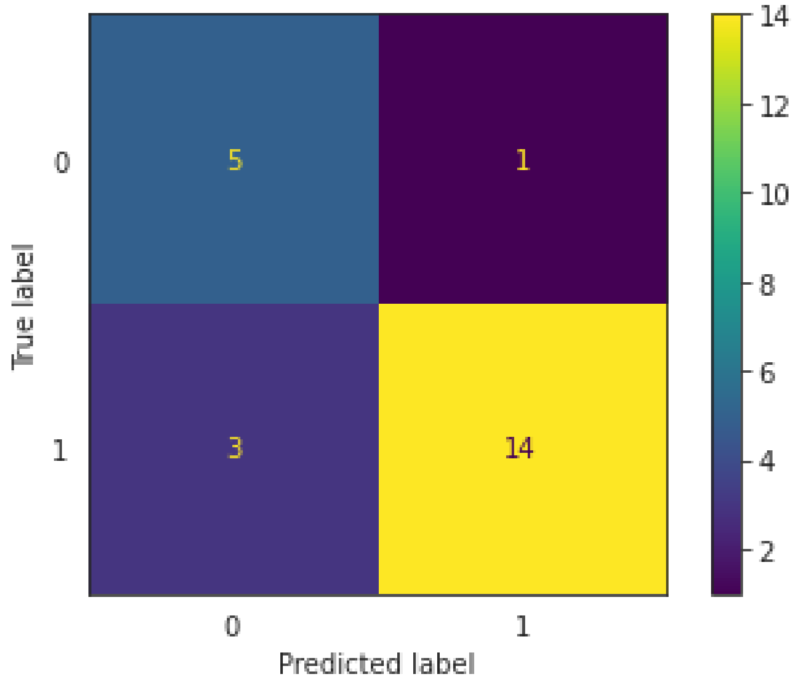
[46]:
```
# crerating the regressor object of LogisticRegression class with 500iteration
r= LogisticRegression(max_iter=500)
# fitting the model with data
r.fit(train_data, train_label)
# predicting model's performancce on test data
p_t_lable=r.predict(t_data)
```

[47]: confusion_matrix= metrics.confusion_matrix(t_lable,p_t_lable) confusion_matrix

[47]: array([[5, 1],
[3, 14]])

[48]: plot_confusion_matrix(regressor, t_data,t_lable)

[48]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f1e75974c50>



[50]:
```
print("Accuracy:",metrics.accuracy_score(t_lable, p_t_lable))
print("Precision:",metrics.precision_score(t_lable,p_t_lable))
print("Recall:",metrics.recall_score(t_lable, p_t_lable))
```

Accuracy: 0.8260869565217391
Precision: 0.9333333333333333
Recall: 0.8235294117647058

Observations: 1. Learnt about Linear and Multiple regression 2. Learnt about different types of errors and their usage 3. Learnt why we use logistic reasoning 4. Learnt about importance of precision and recall value in confusion matrix