

## MACHINE LEARNING ASSIGNMENT 02

## **NAME:**

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**REG. NO:** 

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**CLASS:** 

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**SUBMITTED TO:** 

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**DATE:** 

10-APR-2023

## Part 1: Linear Regression

- 1. Implement linear regression using gradient descent to predict the MEDV. Your implementation should include the following:
  - o A function to calculate the cost function.
  - o A function to perform gradient descent.
  - o A function to predict the MEDV given a set of input features.

```
# A function to calculate the cost function
import numpy as np
def cost(features, target, theta):
   total number of samples = len(target)
   predictions = features.dot(theta)
   cost = 1/(2 * total number of samples) *
np.sum(np.square(predictions - target))
   return cost
# A function to perform gradient descent.
import numpy as np
def gradient descent (features, target, theta, alpha,
number of iterations):
   total number of samples = len(target)
   cost history = np.zeros(number of iterations)
   for i in range(number of iterations):
        predictions = features.dot(theta)
        loss = predictions - target
       theta = theta - alpha * (1 / \text{total number of samples}) *
(features.T.dot(loss))
        cost history[i] = cost(features, target, theta)
   return theta, cost history
# A function to predict the MEDV given a set of input features.
def predict medv(features, theta):
    predictions = features.dot(theta)
    return predictions
```

2. Split the dataset into a training set and a test set. Use 80% of the data for training and the remaining 20% for testing.

```
# Downlaod the `Boston Housing Dataset`
!wget
https://raw.githubusercontent.com/selva86/datasets/master/BostonHousing
.csv
import pandas as pd
from sklearn.model_selection import train_test_split
df = pd.read_csv('BostonHousing.csv')
features = df.drop(['medv'], axis=1)
```

```
target = df['medv']
features train, features test, target train, target test =
train test split(features,
target,
test size=0.2)
len(features train), len(features test), len(target train),
len(target test)
--2023-04-12 20:12:43-- https://raw.githubusercontent.com/selva86/datasets/master/BostonHousing.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.111.133, 185.199.108.133, 185.199.110.133, ...
HTTP request sent, awaiting response... 200 OK
Length: 35735 (35K) [text/plain]
Saving to: 'BostonHousing.csv.13'
BostonHousing.csv.1 100%[=========] 34.90K --.-KB/s in 0.003s
2023-04-12 20:12:43 (11.2 MB/s) - 'BostonHousing.csv.13' saved [35735/35735]
(404, 102, 404, 102)
```

3. Train your linear regression model on the training set and evaluate its performance on the test set using the mean squared error (MSE) metric. Report the MSE value.

```
from sklearn.metrics import mean squared error
# Normalize to get the same scale of all values
features train normalize = (features train - np.mean(features train,
axis=0))/np.std(features train, axis=0)
features train normalize =
np.hstack((np.ones((features train normalize.shape[0],1)), features trai
n normalize))
theta = np.zeros(features train normalize.shape[1])
theta, cost hist = gradient descent(features train normalize,
                                    target train,
                                    theta,
                                    alpha=0.01,
                                    number of iterations=1000)
# Mean Squared Error
features test normalize = (features test - np.mean(features train,
axis=0))/np.std(features train, axis=0)
features test normalize =
np.hstack((np.ones((features test normalize.shape[0],1)), features test
normalize))
target predictions = features test normalize.dot(theta)
mean squared error = mean squared error (target test,
target predictions)
print('Mean Squared Error: ', mean squared error)
```

4. Plot the predicted values vs. the actual values on the test set in a scatter plot.

```
import matplotlib.pyplot as plt

# Plot the predicted values versus the actual values on the test set
plt.scatter(target_test, target_predictions)
plt.plot(target_test, target_test, color='red')
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual versus Predicted Values")
plt.show()
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## Part 2: Logistic Regression

1. Implement logistic regression using gradient descent to predict whether a suburb has a high or low MEDV. To do this, you will need to binarize the MEDV column by setting a threshold value. If the MEDV is greater than or equal to the threshold value, the suburb is classified as having a high MEDV, otherwise it is classified as having a low MEDV.

```
threshold = 21.2
target_train = (target_train >= threshold).astype(int)
target_test = (target_test >= threshold).astype(int)
threshold, len(target_train), len(target_test)
```

2. Split the dataset into a training set and a test set. Use 80% of the data for training and the remaining 20% for testing.

```
# Downland the `Boston Housing Dataset`
!wget
https://raw.githubusercontent.com/selva86/datasets/master/BostonHousing.csv
import pandas as pd
from sklearn.model_selection import train_test_split
df = pd.read_csv('BostonHousing.csv')
```

```
features = df.drop(['medv'], axis=1)
target = df['medv']
features train, features test, target train, target test =
train test split(features,
target,
test size=0.2)
len(features train), len(features test), len(target train),
len(target test)
 --2023-04-12 20:12:43-- https://raw.githubusercontent.com/selva86/datasets/master/BostonHousing.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.111.133, 185.199.108.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com) | 185.199.111.133 | :443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 35735 (35K) [text/plain]
Saving to: 'BostonHousing.csv.13'
BostonHousing.csv.1 100%[=======>] 34.90K --.-KB/s
2023-04-12 20:12:43 (11.2 MB/s) - 'BostonHousing.csv.13' saved [35735/35735]
(404, 102, 404, 102)
```

3. Train your logistic regression model on the training set and evaluate its performance on the test set using the accuracy metric. Report the accuracy value.

```
import numpy as np
def sigmoid(z):
  return 1/(1 + np.exp(-z))
NUMBER OF ITERATIONS = 1000
ALPHA = 0.01
total number of samples = len(target)
# Normalize to get the same scale of all values
features train normalize = (features train - np.mean(features train,
axis=0))/np.std(features train, axis=0)
features train normalize =
np.hstack((np.ones((features train normalize.shape[0],1)),features trai
n normalize))
for i in range(NUMBER OF ITERATIONS):
  z = np.dot(features train normalize, theta)
  h = sigmoid(z)
  gradient = np.dot(features train normalize.T, (h - target train)) /
total number of samples
  theta -= ALPHA * gradient
features test normalize = (features test - np.mean(features train,
axis=0))/np.std(features train, axis=0)
features test normalize =
np.hstack((np.ones((features test normalize.shape[0],1)),features test
```

```
normalize))
z_test = np.dot(features_test_normalize, theta)
h_test = sigmoid(z_test)
target_predictions = (h_test >= 0.5).astype(int)

from sklearn.metrics import accuracy_score, confusion_matrix
accuracy = accuracy_score(target_test, target_predictions)
print("Accuracy: ", accuracy)

Accuracy: 0.5392156862745098
```

4. Plot the decision boundary of your logistic regression model in a scatter plot that shows the data points with different colors for high and low MEDV.

```
import matplotlib.pyplot as plt

# Plot the predicted values versus the actual values on the test set
plt.scatter(z_test, target_predictions)
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual versus Predicted Values")
plt.show()
```

