Lab 4 (30-01-2024)

This lab experiments help you master how to do linear regression and multiple linear regression.

We will be using real estate database provided in lab2.

In [ ]:
```
Registration_Number = "22011103010"
Name = "Deepthi"

# Python Program to Get IP Address
import socket
hostname = socket.gethostname()
IPAddr = socket.gethostbyname(hostname)

print("My name is " + Name + " and my roll no : " + Registration_Number)
print("Computer IP Address is: " + IPAddr)
```

```
My name is Deepthi and my roll no : 22011103010
Computer IP Address is: 192.168.29.104
```

Experiment 1 - Predicting House prise using the area of the house using Linear regression

Load real estate dataset Split the dataset into

1. Split the dataset into train (90%) and test (10%) using scikit learn
2. Fill the cost function
3. Fill the liner regression fit function
4. Fill the routine for Gradient descent

In [ ]:
```
# split the dataset into test and train
import numpy as np
import pandas as pd
from sklearn.datasets import load_diabetes
diabetes = load_diabetes(as_frame=True,scaled=True)
dataset_dia = diabetes.data

X = dataset_dia['age'].to_numpy()
y = diabetes.target.to_numpy()

diabetes
```

Out[ ]:
```
{'data':           age       sex       bmi        bp        s1        s2
s3  \
 0    0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
 1   -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
 2    0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
 3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
 4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
 ..        ...       ...       ...       ...       ...       ...       ...
 437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
 438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
 439  0.041708  0.050680 -0.015906  0.017293 -0.037344 -0.013840 -0.024993
 440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
 441 -0.045472 -0.044642 -0.073030 -0.081413  0.083740  0.027809  0.173816

            s4        s5        s6
 0   -0.002592  0.019907 -0.017646
 1   -0.039493 -0.068332 -0.092204
 2   -0.002592  0.002861 -0.025930
 3    0.034309  0.022688 -0.009362
 4   -0.002592 -0.031988 -0.046641
 ..        ...       ...       ...
 437 -0.002592  0.031193  0.007207
 438  0.034309 -0.018114  0.044485
 439 -0.011080 -0.046883  0.015491
 440  0.026560  0.044529 -0.025930
 441 -0.039493 -0.004222  0.003064

 [442 rows x 10 columns],
 'target': 0      151.0
 1       75.0
 2      141.0
 3      206.0
 4      135.0
        ...
 437    178.0
 438    104.0
 439    132.0
 440    220.0
 441     57.0
 Name: target, Length: 442, dtype: float64,
 'frame':           age       sex       bmi        bp        s1        s2
s3  \
 0    0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
 1   -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
 2    0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
 3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
 4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
 ..        ...       ...       ...       ...       ...       ...       ...
 437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
 438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
 439  0.041708  0.050680 -0.015906  0.017293 -0.037344 -0.013840 -0.024993
 440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
 441 -0.045472 -0.044642 -0.073030 -0.081413  0.083740  0.027809  0.173816

            s4        s5        s6  target
 0   -0.002592  0.019907 -0.017646   151.0
 1   -0.039493 -0.068332 -0.092204    75.0
 2   -0.002592  0.002861 -0.025930   141.0
 3    0.034309  0.022688 -0.009362   206.0
 4   -0.002592 -0.031988 -0.046641   135.0
```

```
..         ...        ...        ...      ...
437 -0.002592  0.031193  0.007207   178.0
438  0.034309 -0.018114  0.044485   104.0
439 -0.011080 -0.046883  0.015491   132.0
440  0.026560  0.044529 -0.025930   220.0
441 -0.039493 -0.004222  0.003064    57.0

 [442 rows x 11 columns],
 'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n----------------\n\nTen b
aseline variables, age, sex, body mass index, average blood\npressure, and six
blood serum measurements were obtained for each of n =\n442 diabetes patients,
as well as the response of interest, a\nquantitative measure of disease progres
sion one year after baseline.\n\n**Data Set Characteristics:**\n\n  :Number of
Instances: 442\n\n  :Number of Attributes: First 10 columns are numeric predict
ive values\n\n  :Target: Column 11 is a quantitative measure of disease progres
sion one year after baseline\n\n  :Attribute Information:\n      - age     age
in years\n      - sex\n      - bmi     body mass index\n      - bp      average
blood pressure\n      - s1      tc, total serum cholesterol\n      - s2      ld
l, low-density lipoproteins\n      - s3      hdl, high-density lipoproteins\n
- s4      tch, total cholesterol / HDL\n      - s5      ltg, possibly log of se
rum triglycerides level\n      - s6      glu, blood sugar level\n\nNote: Each o
f these 10 feature variables have been mean centered and scaled by the standard
deviation times the square root of `n_samples` (i.e. the sum of squares of each
column totals 1).\n\nSource URL:\nhttps://www4.stat.ncsu.edu/~boos/var.select/d
iabetes.html\n\nFor more information see:\nBradley Efron, Trevor Hastie, Iain J
ohnstone and Robert Tibshirani (2004) "Least Angle Regression," Annals of Stati
stics (with discussion), 407-499.\n(https://web.stanford.edu/~hastie/Papers/LAR
S/LeastAngle_2002.pdf)\n',
 'feature_names': ['age',
  'sex',
  'bmi',
  'bp',
  's1',
  's2',
  's3',
  's4',
  's5',
  's6'],
 'data_filename': 'diabetes_data_raw.csv.gz',
 'target_filename': 'diabetes_target.csv.gz',
 'data_module': 'sklearn.datasets.data'}
```

In [ ]:

```
# Experiment 1 - Linear regression with one variable
# Fill following functions
# Linear regression one variable
def cost_function(weight,bias,X,y):
  J = 0.0
  n = len(y)
  for i in range(0,n):
    J += (weight*X[i]+bias-y[i])**2
  J /= (2*n)
  return J

def get_gradients(weight,bias,X,y):
  dJ_dw = 0.0
  dJ_db = 0.0
  n = len(y)
  for i in range(0,n):
    dJ_dw += (weight*X[i] + bias -y[i])*X[i]
    dJ_db += weight*X[i]+bias-y[i]
```

```
  dJ_dw /= (n)
  dJ_db /= (n)
  return dJ_dw, dJ_db

def gradient_descent(X, y, weight=1.0, bias=1.0, learning_rate=0.9,threshold=0.1
  isConverged = False
  weight_ = weight
  bias_ = bias
  iter_count = 0
  while(not isConverged):
    iter_count += 1
    dw, db = get_gradients(weight_,bias_,X,y)
    weight_ -= learning_rate*dw
    bias_ -= learning_rate*db
    if(abs(learning_rate*dw)<threshold and abs(learning_rate*db)<threshold):
      isConverged = True
    # print(weight_, bias_)
    weight = weight_
    bias = bias_
  print("Converged in " , iter_count,  "iterations...")
  return weight_, bias_
```

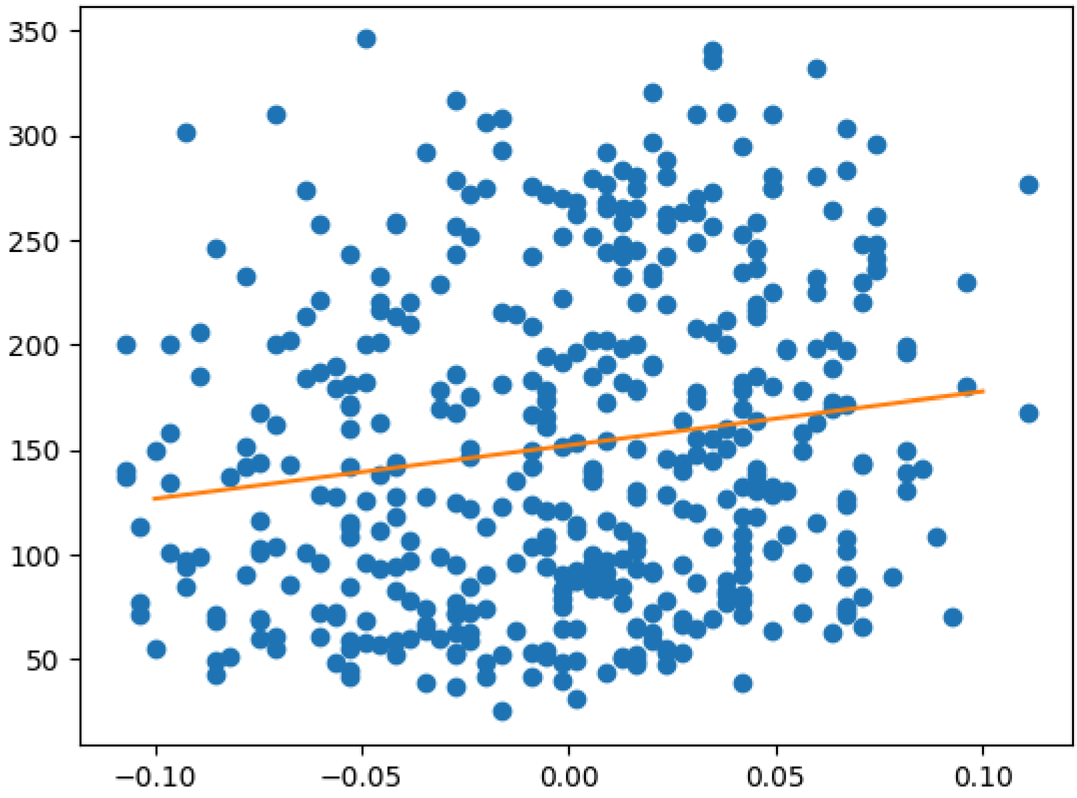
In [ ]:

```
w,b = gradient_descent(X,y)

import matplotlib.pyplot as plt

plt.plot(X, y, 'o')
zx = np.linspace(-0.1, 0.1, 100)
zy = w*zx + b
plt.plot(zx,zy)
plt.show()
```

```
Converged in  895 iterations...
```



Experminent 2 - Multiple linear regression

use more features and modify the code for more than 1 features

In [ ]:
```
import numpy as np
import pandas as pd
from sklearn.datasets import load_diabetes

diabetes = load_diabetes(as_frame=True, scaled=True)
dataset_dia = diabetes.data

X = dataset_dia[['age', 'bmi']].to_numpy()
y = diabetes.target.to_numpy()
```

In [ ]:
```
def cost_function(weight, bias, X, y):
    J = 0.0
    n = len(y)
    for i in range(0, n):
        J += (np.dot(weight, X[i]) + bias - y[i]) ** 2
    J /= (2 * n)
    return J

def get_gradients(weight, bias, X, y):
    dJ_dw = np.zeros_like(weight)
    dJ_db = 0.0
    n = len(y)
    for i in range(0, n):
        dJ_dw += (np.dot(weight, X[i]) + bias - y[i]) * X[i]
        dJ_db += np.dot(weight, X[i]) + bias - y[i]
    dJ_dw /= n
    dJ_db /= n
    return dJ_dw, dJ_db

def gradient_descent(X, y, weight=None, bias=None, learning_rate=0.9, threshold=
    if weight is None:
        weight = np.ones(X.shape[1])
    if bias is None:
        bias = 1.0
    isConverged = False
    weight_ = weight
    bias_ = bias
    iter_count = 0
    while not isConverged:
        iter_count += 1
        dw, db = get_gradients(weight_, bias_, X, y)
        weight_ -= learning_rate * dw
        bias_ -= learning_rate * db
        if np.all(abs(learning_rate * dw) < threshold) and abs(learning_rate * d
            isConverged = True
    print("Converged in", iter_count, "iterations...")
    return weight_, bias_
```

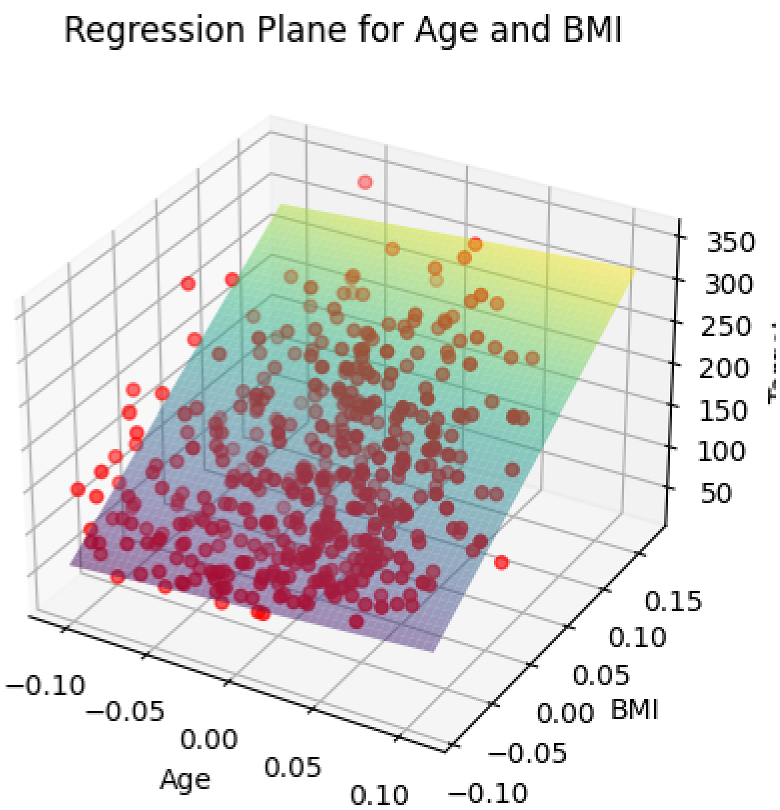
In [ ]:
```
# Perform gradient descent
w, b = gradient_descent(X, y)
```

```
# Creating meshgrid for age and bmi
age_range = np.linspace(X[:, 0].min(), X[:, 0].max(), 100)
bmi_range = np.linspace(X[:, 1].min(), X[:, 1].max(), 100)
age_mesh, bmi_mesh = np.meshgrid(age_range, bmi_range)

# Predicting target variable for each point on meshgrid
predictions = w[0] * age_mesh + w[1] * bmi_mesh + b

# Plotting
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X[:, 0], X[:, 1], y, c='r', marker='o', label='Data Points')
ax.plot_surface(age_mesh, bmi_mesh, predictions, alpha=0.5, cmap='viridis', labe
ax.set_xlabel('Age')
ax.set_ylabel('BMI')
ax.set_zlabel('Target')
ax.set_title('Regression Plane for Age and BMI')
plt.show()
```

```
Converged in 1438 iterations...
```



Experiment 3 - Polynomial Linear Regression

In [ ]:

```
import numpy as np
import pandas as pd
from sklearn.datasets import load_diabetes
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
import matplotlib.pyplot as plt
```

```
# Load the diabetes dataset
diabetes = load_diabetes()
X = dataset_dia[['age', 'bmi','s1']].to_numpy()
y = diabetes.target

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,

# Function to add polynomial features
def add_polynomial_features(X, degree):
    poly_features = PolynomialFeatures(degree=degree, include_bias=True)
    X_poly = poly_features.fit_transform(X)
    return X_poly

# Cost function for polynomial regression
def cost_function(weight, bias, X_poly, y):
    """
    Calculates the mean squared error for polynomial regression.
    """
    n = len(y)
    predictions = np.dot(X_poly, weight) + bias
    J = np.sum((predictions - y) ** 2) / (2 * n)
    return J

# Gradients for polynomial regression
def get_gradients(weight, bias, X_poly, y):
    """
    Calculates the gradients of the cost function for polynomial regression.
    """
    n = len(y)
    predictions = np.dot(X_poly, weight) + bias
    error = predictions - y
    dJ_dw = np.dot(X_poly.T, error) / n
    dJ_db = np.sum(error) / n
    return dJ_dw, dJ_db

# Manual implementation of gradient descent
def gradient_descent(X_poly, y, weight, bias, learning_rate=0.01, num_iterations
    """
    Performs gradient descent to train the polynomial regression model.
    """
    for _ in range(num_iterations):
        dJ_dw, dJ_db = get_gradients(weight, bias, X_poly, y)
        weight -= learning_rate * dJ_dw
        bias -= learning_rate * dJ_db
        if np.max(np.abs(learning_rate * dJ_dw)) < threshold and np.abs(learning
            break
    return weight, bias

# Experiment - Perform polynomial linear regression with degree 2
degree = 2
x_train_trans = add_polynomial_features(x_train, degree)
x_test_trans = add_polynomial_features(x_test, degree)

# Initialize weights and bias
weight = np.random.randn(x_train_trans.shape[1])
```

```
bias = np.random.randn(1)

# Train the model using gradient descent
weight, bias = gradient_descent(x_train_trans, y_train, weight, bias)

# Make predictions on the test set
y_pred = np.dot(x_test_trans, weight) + bias

# Visualize the predictions
plt.scatter(x_test[:, 0], y_test, color='blue', label='Original Data')
sorted_indices = np.argsort(x_test[:, 0])
plt.plot(x_test[sorted_indices, 0], y_pred[sorted_indices], color='red', label='
plt.xlabel('Age')
plt.ylabel('Target')
plt.legend()
plt.title('Polynomial Linear Regression (Degree {})'.format(degree))
plt.show()
```