In [2]: data=pd.read_csv("D:/Sem 5/ML/ex1data1.txt", header=None) data.head() Out[2]: 1 **0** 6.1101 17.5920 **1** 5.5277 9.1302 2 8.5186 13.6620 **3** 7.0032 11.8540 **4** 5.8598 6.8233 data.describe() In [3]: Out[3]: 0 1 count 97.000000 97.000000 8.159800 5.839135 mean 3.869884 5.510262 std 5.026900 -2.680700 min 5.707700 25% 1.986900 6.589400 4.562300 8.578100 75% 7.046700 max 22.203000 24.147000 In [4]: data.columns = ['Population', 'Profit'] #assigning column names In [5]: data.isnull().sum() Out[5]: Population Profit dtype: int64 In [6]: plt.scatter(data['Population'], data['Profit']) plt.xticks(np.arange(5,30,step=5)) plt.yticks(np.arange(-5,30,step=5)) plt.xlabel('Population (in 10,000s)') plt.ylabel('Profit (in 10,000\$)') plt.title('Profit vs Population') Out[6]: Text(0.5, 1.0, 'Profit vs Population') Profit vs Population 25 20 Profit (in 10,000\$) 0 20 15 25 10 Population (in 10,000s) Cost Function $J(\theta)$ In [7]: def computeCost(X,y,theta): Take in a numpy arary X, y, theta and get cost function using theta as parameter in a linear regression model m = len(y)predictions = X.dot(theta) $square_err = (predictions - y)**2$ return 1/(m)*np.sum(square_err) In [8]: data['x0'] = 1In [9]: data_val = data.values $m = len(data_val[:-1])$ X = data[['x0', 'Population']].iloc[:-1].values y = data['Profit'][:-1].values.reshape(m,1) theta = np.zeros((2,1))m, X.shape, y.shape, theta.shape Out[9]: (96, (96, 2), (96, 1), (2, 1)) In [10]: $\# h(\theta) = x0\theta0 + x1\theta1 \dots (x0 = 1)$ In [11]: computeCost(X,y,theta) Out[11]: 64.80968355754062 **Gradient Descent** In [12]: def gradientDescent(X,y,theta,alpha,num_iters): Take numpy array for X, y, theta and update theta for every iteration of gradient steps Return theta and the list of cost of theta during each iteration m = len(y)J_history = [] for i in range(num_iters): predictions = X.dot(theta) error = np.dot(X.transpose(), (predictions-y)) descent = alpha * 1/m * error theta-=descent J_history.append(computeCost(X,y,theta)) return theta, J_history In [13]: theta, J_history = gradientDescent(X,y,theta,0.001, 2000) In [14]: $print(f"h(x) = \{str(round(theta[0,0],2))\} + \{str(round(theta[1,0],2))\}x$ h(x) = -1.11 + 0.92x1In [15]: from mpl_toolkits.mplot3d import Axes3D #Generating values for theta0, theta1 and the resulting cost value theta0_vals=np.linspace(-10,10,100) theta1_vals=np.linspace(-1,4,100) J_vals=np.zeros((len(theta0_vals),len(theta1_vals))) for i in range(len(theta0_vals)): for j in range(len(theta1_vals)): t=np.array([theta0_vals[i], theta1_vals[j]]) J_vals[i,j]=computeCost(X,y,t) #Generating the surface plot fig = plt.figure() ax = fig.add_subplot(111, projection='3d') surf=ax.plot_surface(theta0_vals, theta1_vals, J_vals, cmap="coolwarm") fig.colorbar(surf, shrink=0.5, aspect=5) ax.set_xlabel("\$\Theta_0\$") ax.set_ylabel("\$\Theta_1\$") ax.set_zlabel("\$J(\Theta)\$") #rotate for better angle ax.view_init(30,120) 140000 150000 120000 100000@ 100000 †80000≅† 60000 40000 50000 20000 -10 In [16]: plt.plot(J_history) plt.xlabel("Iteration") plt.ylabel("\$J(\Theta)\$") plt.title("Cost function using Gradient Descent") Out[16]: Text(0.5, 1.0, 'Cost function using Gradient Descent') Cost function using Gradient Descent 50 40 <u>(e)</u> 30 20 10 750 1000 1250 1500 1750 2000 Iteration In [17]: plt.scatter(data['Population'], data['Profit']) $x_value = [x for x in range(25)]$ $y_value = [x*theta[1] + theta[0]$ **for** x **in** $x_value]$ plt.plot(x_value, y_value, color = 'r') plt.xticks(np.arange(5,30,step=5)) plt.yticks(np.arange(-5,30,step=5)) plt.xlabel('Population (in 10,000s)') plt.ylabel('Profit (in 10,000\$)') plt.title('Profit vs Population') Out[17]: Text(0.5, 1.0, 'Profit vs Population') Profit vs Population 25 20 Profit (in 10,000\$) 15 10 0 -5 10 15 20 25 Population (in 10,000s) In [18]: def predict(x, theta): Takes in numpy array x and theta and returns predicted value of ypredictions = np.dot(theta.transpose(),x) return predictions[0] In [19]: | data.tail(1) Out[19]: Population Profit x0 5.4369 0.61705 1 predict1 = predict(data[['x0', 'Population']].iloc[-1].values, theta)*100 In [20]: print(f'For a population of 6170 the predicted profit is \${predict1}') For a population of 6170 the predicted profit is \$38686.246103378166 **TODO: Configure code for multivariate linear** regression In [21]: hw = pd.read_csv("D:/Sem 5/ML/ex1data2.txt", header=None) hw.head() Out[21]: 0 1 **0** 2104 3 399900 **1** 1600 3 329900 **2** 2400 3 369000 **3** 1416 2 232000 **4** 3000 4 539900 In [22]: hw.columns = ["Size", "Num_bedrooms", "Price"] hw.head(1)Out[22]: Size Num_bedrooms Price **0** 2104 3 399900 In [23]: hw.describe() Out[23]: Size Num_bedrooms Price 47.000000 47.000000 47.000000 count 3.170213 340412.659574 2000.680851 mean 794.702354 0.760982 125039.899586 std min 852.000000 1.000000 169900.000000 **25**% 1432.000000 3.000000 249900.000000 1888.000000 3.000000 299900.000000 **75%** 2269.000000 4.000000 384450.000000 max 4478.000000 5.000000 699900.000000 In [24]: hw.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 47 entries, 0 to 46 Data columns (total 3 columns): Non-Null Count Dtype Column 47 non-null Size 1 Num_bedrooms 47 non-null int64 47 non-null Price int64 dtypes: int64(3) memory usage: 1.2 KB In [25]: | hw.isnull().sum() Out[25]: Size 0 Num_bedrooms 0 0 Price dtype: int64 Price vs Size of house and Price vs No. of bedrooms plt.scatter(hw['Size'], hw['Price']) plt.xticks(np.arange(500,500,step=500)) plt.yticks(np.arange(100000,800000,step=50000)) plt.xlabel('Size') plt.ylabel('Price') plt.title('Price vs Size') Out[26]: Text(0.5, 1.0, 'Price vs Size') Price vs Size 750000 700000 650000 600000 550000 500000 450000 400000 350000 300000 250000 200000 150000 100000 In [27]: plt.scatter(hw['Num_bedrooms'], hw['Price']) plt.xticks(np.arange(0,6,step=1)) plt.yticks(np.arange(-5,30,step=5)) plt.xlabel('Num_bedrooms') plt.ylabel('Price') plt.title('Price vs Num_bedrooms') Out[27]: Text(0.5, 1.0, 'Price vs Num_bedrooms') Price vs Num_bedrooms Num_bedrooms Scaling the column "Size" In [28]: from sklearn.preprocessing import MinMaxScaler col = ["Size", "Price"] scaler = MinMaxScaler() hw[col] = pd.DataFrame(scaler.fit_transform(hw[col]),columns = hw[col].c olumns) **Defining X and y** In [29]: X = np.array(hw.drop("Price", axis =1)[:-1])y = np.array(hw["Price"][:-1])X.shape, y.shape Out[29]: ((46, 2), (46,)) In [30]: y = y.reshape(y.shape[0],1) $X = np.c_{np.ones}(X.shape[0]), X$ X.shape, y.shape Out[30]: ((46, 3), (46, 1)) **Defining functions** In [31]: def computeCost(X,y,theta): Take in a numpy arary X, y, theta and get cost function using theta as parameter in a linear regression model m = y.sizeh_theta = np.dot(X,theta) #Predictions error = (h_theta - y) cost = (1/(2*m))*np.dot(error.T, error)return cost In [32]: def gradientDescent(X,y,theta,alpha,num_iters): Take numpy array for X, y, theta and update theta for every iteration of gradient steps Return theta and the list of cost of theta during each iteration m = len(y)past_cost = [] $past_theta = [theta]$ for i in range(num_iters): $h_{t} = np.dot(X, theta)$ error = (h_theta-y) past_cost.append(computeCost(X,y,theta)) descent = alpha * 1/m *np.dot(X.T,error) theta-=descent past_theta.append(theta) return past_theta, past_cost,i In [45]: def predict(x, theta): Takes in numpy array x and theta and returns predicted value of ypredictions = np.dot(theta.T,x) return predictions[0] Declaring θ and α and number of iterations In [34]: np.random.seed(1111) theta = np.random.rand(X.shape[1],1) alpha = 0.01 $num_iters = 5000$ **Performing regression** In [35]: import time start = time.time() past_theta, past_cost, stop = gradientDescent(X, y, theta, alpha, num_iters) timeTaken = time.time() -start In [36]: best_theta = past_theta[-1] best_cost = past_cost[-1] In [37]: | print(f'The model performed {stop} iterations out of {num_iters}.') print(f'Best Theta: {best_theta}') print(f'Best cost: {best_cost}') The model performed 4999 iterations out of 5000. Best Theta: [[0.06027362] [0.93572888] [-0.01125156]] Best cost: [[0.00743669]] In [53]: print(f'h(theta) = {str(round(best_theta[0,0],5))} + {str(round(best_theta[0,0],5))} ta[0,0],5))x1 + {str(round(best_theta[0,0],5))}x2') print(f'Time taken: {timeTaken}') print(f'Accuracy: {round(r2_score(y,predict(X,best_theta),4))*100}%') h(theta) = 0.06027 + 0.06027x1 + 0.06027x2Time taken: 0.05385303497314453 Traceback (most recent call la ValueError st) <ipython-input-53-fe1c492f4b65> in <module> 1 print(f'h(theta) = {str(round(best_theta[0,0],5))} + {str(round (best_theta[0,0],5))}x1 + {str(round(best_theta[0,0],5))}x2') 2 print(f'Time taken: {timeTaken}') ----> 3 print(f'Accuracy: {round(r2_score(y,predict(X,best_theta),4))*10 0}%') <ipython-input-45-e8c352d812f8> in predict(x, theta) Takes in numpy array x and theta and returns predicted value of y predictions = np.dot(theta.T,x) return predictions[0] <_array_function__ internals> in dot(*args, **kwargs) ValueError: shapes (1,3) and (46,3) not aligned: 3 (dim 1) != 46 (dim 0) **Plotting cost** In [40]: cost = np.asarray(past_cost).reshape((len(past_cost),1)) cost.shape Out[40]: (5000, 1) In []: In [41]: plt.plot(cost) plt.show Out[41]: <function matplotlib.pyplot.show(*args, **kw)> 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0.0 3000 5000 1000 2000 4000 **Predicting price for test data** In [42]: hw.tail(1) Out[42]: Size Num_bedrooms Price 3 0.131321 **46** 0.096801 In [47]: **from sklearn.metrics import** r2_score prediction = predict(X[-1], best_theta)*1000000 print(f'For house of size 968 sq.ft the predicted price is :\${str(predic tion)}') For house of size 968 sq.ft the predicted price is :\$273328.3006931557 Traceback (most recent call la ValueError st) <ipython-input-47-1456dc3b3729> in <module> 2 prediction = predict(X[-1], best_theta)*1000000 3 print(f'For house of size 968 sq.ft the predicted price is :\${st r(prediction)}') ----> 4 print(f'Accuracy: {round(r2_score(y,predict(X,theta),4))*100}%') <ipython-input-45-e8c352d812f8> in predict(x, theta) Takes in numpy array x and theta and returns predicted value of y ---> 5 predictions = np.dot(theta.T,x) return predictions[0] <_array_function__ internals> in dot(*args, **kwargs) ValueError: shapes (1,3) and (46,3) not aligned: 3 $(\dim 1) != 46 (\dim 0)$ **Comparing the parameters** In [44]: print(f'Parameters from StatsModels: {sm.OLS(y,X).fit().params()}')

print(f'Parameters from ScikitLearn: {LinearRegression().fit(X,y).coef

print(f'Parameters from GradientDescent: {best_theta.reshape((3,))}')

----> 1 print(f'Parameters from StatsModels: {sm.OLS(y,X).fit().params

2 print(f'Parameters from ScikitLearn: {LinearRegression().fit(X,

3 print(f'Parameters from GradientDescent: {best_theta.reshape

<ipython-input-44-d9eb5f790d7c> in <module>

TypeError: 'numpy.ndarray' object is not callable

TypeError

y).coef_}')

((3,))}')

In []:

Traceback (most recent call la

In [1]: %matplotlib inline

import time

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt

import statsmodels.api as sm

from sklearn.metrics import r2_score

from sklearn.linear_model import LinearRegression

Univariate Linear Regression