	Machine Learning Assignment Aditya Gavankar (J072) Exp 3 :- Linear Regression / Gradient Descent
In [1]:	<pre>%matplotlib inline import numpy as np import pandas as pd import matplotlib.pyplot as plt Univariate Linear Regression</pre>
<pre>In [2]: Out[2]:</pre>	<pre>data=pd.read_csv("ex1data1.txt", header=None) data.head()</pre>
In [3]:	2 8.5186 13.6620 3 7.0032 11.8540 4 5.8598 6.8233 data.describe()
Out[3]:	count 97.000000 97.000000 mean 8.159800 5.839135 std 3.869884 5.510262
	min 5.026900 -2.680700 25% 5.707700 1.986900 50% 6.589400 4.562300 75% 8.578100 7.046700 max 22.203000 24.147000
<pre>In [4]: Out[4]:</pre>	<pre>data.columns = ['Population', 'Profit'] data.head() Population Profit 0 6.1101 17.5920</pre>
	1 5.5277 9.1302 2 8.5186 13.6620 3 7.0032 11.8540 4 5.8598 6.8233
<pre>In [5]: Out[5]:</pre>	<pre>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')</pre> Text(0.5, 1.0, 'Profit vs Population')
	Profit vs Population 25 - 20 - \$\hat{\frac{3}{5}}\$ 15 -
	15 - 10 - 15 - 10 - 15 - 20 - 25 Population (in 10,000s)
In [6]:	Cost function J(θ) 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 """
In [7]:	<pre>m = len(y) predictions = X.dot(theta) square_err = (predictions - y) **2 return 1/(m) *np.sum(square_err) data['x0'] = 1</pre>
In [8]:	<pre>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))</pre>
	m, X.shape, y.shape, theta.shape $(96, (96, 2), (96, 1), (2, 1))$ $h(\theta) = x0\theta0 + x1\theta1 + (x0 = 1)$
	<pre>computeCost(X,y,theta) 64.80968355754062 data.tail() Population Profit x0</pre>
ouc[10].	92 5.8707 7.20290 1 93 5.3054 1.98690 1 94 8.2934 0.14454 1 95 13.3940 9.05510 1 96 5.4369 0.61705 1
In [11]:	Gradient Descent def gradientDescent(X,y,theta,alpha,num_iters): """ Take numpy array for X,y,theta and update theta for every iteration of gradient steps
	<pre>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)</pre>
In [12]:	<pre>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 theta, J history = gradientDescent(X,y,theta,0.001, 2000)</pre>
In [13]:	
	<pre>#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</pre>
	<pre>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</pre>
	ax.view_init(30,120) 150000 12500 100000 100000
	10 5 0 0 -5 -10 4 50000
In [15]: Out[15]:	<pre>plt.plot(J_history) plt.xlabel("Iteration") plt.ylabel("\$J(\Theta)\$") plt.title("Cost function using Gradient Descent") Text(0.5, 1.0, 'Cost function using Gradient Descent')</pre>
	Cost function using Gradient Descent 50 - 40 - 60 - 30
	30 - 20 - 20 - 250 500 750 1000 1250 1500 1750 2000 Iteration
In [16]:	<pre>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)')</pre>
Out[16]:	plt.ylabel('Profit (in 10,000\$)') plt.title('Profit vs Population') Text(0.5, 1.0, 'Profit vs Population') Profit vs Population 25
	20 - (\$\frac{5}{15} - \frac{10}{10} - \frac{1}{10}
In [17]:	def predict(x, theta):
In [18]:	<pre>takes in numpy array x and theta and returns predicted value of y """ predictions = np.dot(theta.transpose(),x) return predictions[0] data.tail(1)</pre>
Out[18]: In [19]:	<pre>Population Profit x0 96 5.4369 0.61705 1 predict1 = predict(data[['x0', 'Population']].iloc[-1].values, theta)*10000 print(f'For a population of 6170 the predicted profit is \${predict1}')</pre>
In [20]:	For a population of 6170 the predicted profit is \$38686.246103378166 Multivariate Linear Regression import statsmodels.api as sm
In [21]: Out[21]:	<pre>from sklearn.linear_model import LinearRegression np.random.seed(123) df=pd.read_csv("exldata2.txt", header=None) df.head()</pre>
	 0 2104 3 399900 1 1600 3 329900 2 2400 3 369000 3 1416 2 232000 4 3000 4 539900
In [22]: Out[22]:	df.describe() 0 1 2 count 47.000000 47.000000 47.000000
	mean 2000.680851 3.170213 340412.659574 std 794.702354 0.760982 125039.899586 min 852.000000 1.000000 169900.00000 25% 1432.000000 3.000000 249900.00000 50% 1888.000000 3.000000 299900.000000
In [23]:	75% 2269.000000 4.000000 384450.000000 max 4478.000000 5.000000 699900.000000 df.columns = ['Size of House(in sq.ft)', 'No. of BHK','Price'] df.head()
Out[23]:	Size of House(in sq.ft) No. of BHK Price 0 2104 3 399900 1 1600 3 329900 2 2400 3 369000 3 1416 2 232000
In [24]: Out[24]:	4 3000 4 539900 df.isnull().sum() Size of House(in sq.ft) 0 No. of BHK 0
In [25]:	Price 0 dtype: int64 Cost Function J(0) def normalize(dataframe): dft = dataframe.copy()
In [26]:	<pre>for col in dft.columns: dft[col] = (dft[col] - dft[col].mean()) / dft[col].std() return dft normalized_df = normalize(df) normalized_df.head()</pre>
Out[26]:	Size of House(in sq.ft) No. of BHK Price 0 0.130010 -0.223675 0.475747 1 -0.504190 -0.223675 -0.084074 2 0.502476 -0.223675 0.228626 3 -0.735723 -1.537767 -0.867025
In [27]:	<pre>X = normalized_df.iloc[:,:-1].values y = normalized_df.iloc[:,-1].values m = y.size n = df.shape[1]</pre>
In [28]: Out[28]: In [29]:	y.shape (47,)
In [29]: Out[29]: In [30]:	<pre>ones = np.ones((m,1)) X1 = np.concatenate((ones,X),axis=1)</pre>
Out[30]:	<pre>x1[:5] array([[1.</pre>
In [31]: In [32]:	theta = np.random.rand(n,1) epoch = 10000
.⊍∠]:	<pre>def GD(X1, y, theta, epoch, alpha, decimals=5): past_cost = [] past_theta = [theta] m = y.size n = X1.shape[1] for i in range(epoch): h_theta = np.dot(X1, theta) error = h_theta - y cost = np.dot(error.T, error)/(2*m)</pre>
	<pre>cost = np.dot(error.T,error)/(2*m) past_cost.append(cost[0][0]) diff=np.dot(X1.T,error)/m theta=theta-(alpha*diff) past_theta.append(theta) if np.equal(np.round(past_theta[i],decimals=decimals),np.round(past_theta[i+1],decimals=decimals)).sum</pre>
In [33]: In [34]:	<pre>pastCost, pastTheta, stop_epoch = GD(X1=X1, y=y, theta=theta, epoch=epoch, alpha=alpha) print(f'Our model performed {stop_epoch} epochs out of {epoch} epochs before converging') Our model performed 1320 epochs out of 10000 epochs before converging plt.plot(pastCost)</pre>
Out[34]:	[<matplotlib.lines.line2d 0x28f29a59b20="" at="">] 0.50 -</matplotlib.lines.line2d>
	0.30 - 0.25 - 0.20 - 0.15 -
In [35]:	0 200 400 600 800 1000 1200 new_theta = np.array(pastTheta[-1]).reshape(n,) print(new_theta) [1.20603184e-06 8.83291779e-01 -5.17046112e-02]
In [36]:	<pre>print(f'Parameters from StatsModels == {sm.OLS(y,X1).fit().params}') print(f'Parameters from SciKitLearn == {LinearRegression().fit(X1,y).coef_}') Parameters from StatsModels == [-9.71445147e-17 8.84765988e-01 -5.31788197e-02] Parameters from SciKitLearn == [[0.</pre>