Assignment2

February 19, 2022

Complete each problem below and print to pdf. Submit the pdf.
You will need to work with the three datasets attached to this assignment:

- poverty.csv
- poverty_2.csv
- real_estate.csv

1 Problem 1: Univariate Linear Regression

1.1 1) import the libraries you will need:

numpy pandas matplotlab.pyplot statsmodels.api

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
from google.colab import files
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

1.2 2) Import the date poverty.csv dataset

[3]:
```
url = 'https://raw.githubusercontent.com/nnguyen09/Machine-Learning-/master/
 ↪assignment2/poverty.csv'
df = pd.read_csv(url)
df.head()
```

[3]:

	Location	PovPct	Brth15to17	Brth18to19	ViolCrime	TeenBrth
0	Alabama	20.1	31.5	88.7	11.2	54.5
1	Alaska	7.1	18.9	73.7	9.1	39.5
2	Arizona	16.1	35.0	102.5	10.4	61.2
3	Arkansas	14.9	31.6	101.7	10.4	59.9
4	California	16.7	22.6	69.1	11.2	41.1

1.3 3) Print the dataset indexed upon the location column.

[4]:
```
df['Location']
```

[4]:
```
0                   Alabama
1                    Alaska
2                   Arizona
3                  Arkansas
4                California
5                  Colorado
6               Connecticut
7                  Delaware
8     District_of_Columbia
9                   Florida
10                  Georgia
11                   Hawaii
12                    Idaho
13                 Illinois
14                  Indiana
15                     Iowa
16                   Kansas
17                 Kentucky
18                Louisiana
19                    Maine
20                 Maryland
21            Massachusetts
22                 Michigan
23                Minnesota
24              Mississippi
25                 Missouri
26                  Montana
27                 Nebraska
28                   Nevada
29            New_Hampshire
30               New_Jersey
31               New_Mexico
32                 New_York
33           North_Carolina
34             North_Dakota
35                     Ohio
36                 Oklahoma
37                   Oregon
38             Pennsylvania
39             Rhode_Island
40           South_Carolina
41             South_Dakota
42                Tennessee
43                    Texas
```

```
44                   Utah
45                Vermont
46               Virginia
47             Washington
48          West_Virginia
49              Wisconsin
50                Wyoming
Name: Location, dtype: object
```

1.4 4) Get useful descriptive statistial data on the dataset.

Hint: this is a single line, data._____

[5]:
```
df.describe()
```

[5]:
```
          PovPct  Brth15to17  Brth18to19  ViolCrime   TeenBrth
count  51.000000   51.000000   51.000000  51.000000  51.000000
mean   13.117647   22.282353   72.019608   7.854902  42.243137
std     4.277228    8.043499   18.975563   8.914131  12.318511
min     5.300000    8.100000   39.000000   0.900000  20.000000
25%    10.250000   17.250000   58.300000   3.900000  33.900000
50%    12.200000   20.000000   69.400000   6.300000  39.500000
75%    15.800000   28.100000   87.950000   9.450000  52.600000
max    25.300000   44.800000  104.300000  65.000000  69.100000
```

1.5 5) Print the columns

[6]:
```
df.columns
```

[6]:
```
Index(['Location', 'PovPct', 'Brth15to17', 'Brth18to19', 'ViolCrime',
       'TeenBrth'],
      dtype='object')
```

1.6 6) Create a regression line based upon the dependent and independent variables:

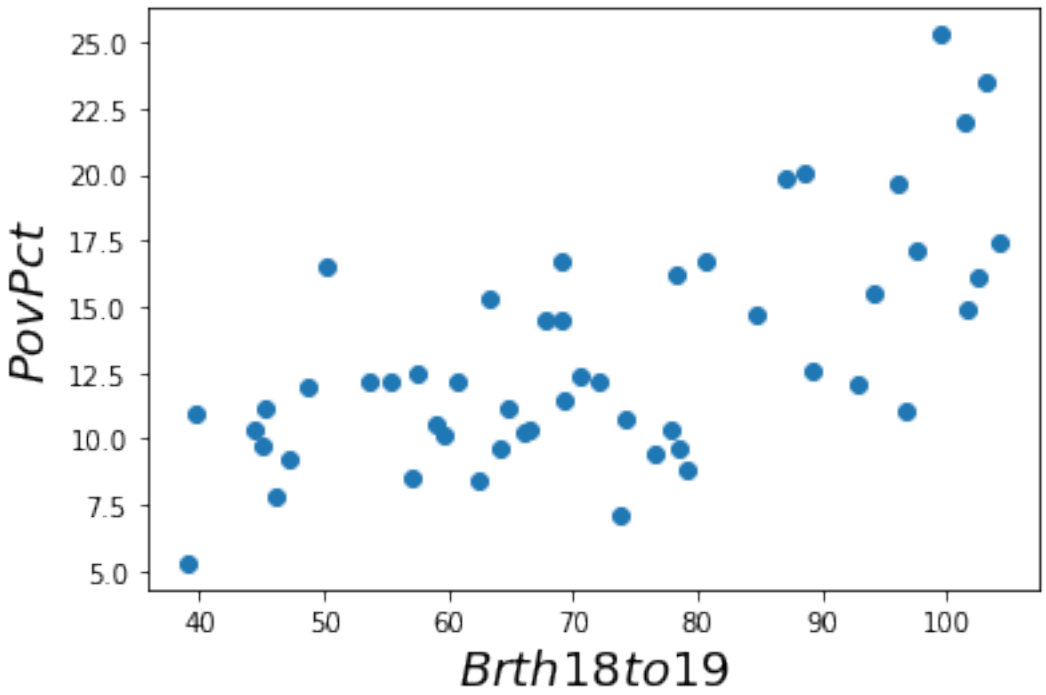
PovPct Brth18to19

In this step only create a scatterplot of the two variables, simply plotting the data.

Note: The variable PovPct is the percent of a state's population in 2000 living in households with incomes below the federally defined poverty level.

[64]:
```
y=df['PovPct']
x=df['Brth18to19']
plt.ylabel("$PovPct$", fontsize = 18)
plt.xlabel("$Brth18to19$", fontsize = 18)
plt.scatter(x, y)
```

[64]:
```
<matplotlib.collections.PathCollection at 0x7f61d3e8a3d0>
```



1.7 7) Lets create a new variable, x1, as well as the results variable:

Example would be 1. x1 = sm.add_constant(x) 2. results = sm.OLS(y, x1).fit() 3. results.summary()

This gives you the OLS Regression results, the coefficients table, and some additional tests. The data that you are interested in is the coefficient values. This is the value for the constant you created is b0, and birth19to19 is b1 in the regression equation.

[73]:
```
x1 = sm.add_constant(x)
result = sm.OLS(y,x1).fit()
print(result.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PovPct   R-squared:                       0.422
Model:                            OLS   Adj. R-squared:                  0.410
Method:                 Least Squares   F-statistic:                     35.78
Date:                Sat, 19 Feb 2022   Prob (F-statistic):           2.50e-07
Time:                        04:06:59   Log-Likelihood:                -132.00
No. Observations:                  51   AIC:                             268.0
Df Residuals:                      49   BIC:                             271.9
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
```

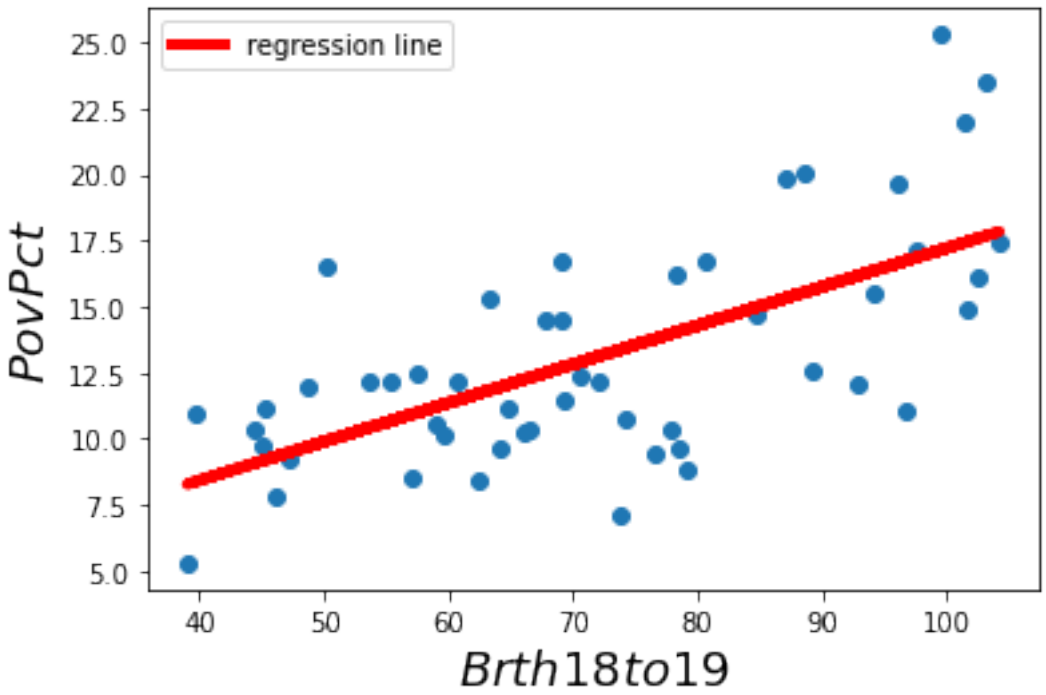
```
------------------------------------------------------------------------------
const          2.5712      1.822      1.411      0.165      -1.090       6.233
Brth18to19     0.1464      0.024      5.982      0.000       0.097       0.196
==============================================================================
Omnibus:                        0.886   Durbin-Watson:                   2.265
Prob(Omnibus):                  0.642   Jarque-Bera (JB):                0.944
Skew:                           0.283   Prob(JB):                        0.624
Kurtosis:                       2.647   Cond. No.                         295.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:117:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

1.8 8) Taking the coeffient values for the new constant and the Y variable, create a scatterplot:

e.g. yhat = 0.1464*x + 0.25712 fig = plt.plot(x, yhat, lw=4, c='red', label = 'regression line')

[74]:
```
yhat = 0.1464*x + 2.5712
plt.ylabel("$PovPct$", fontsize = 18)
plt.xlabel("$Brth18to19$", fontsize = 18)
plt.scatter(x, y)
fig = plt.plot(x, yhat,lw=4, c= 'red',label = 'regression line')
plt.legend(loc='upper left')
```

[74]:
```
<matplotlib.legend.Legend at 0x7f61d1806e10>
```

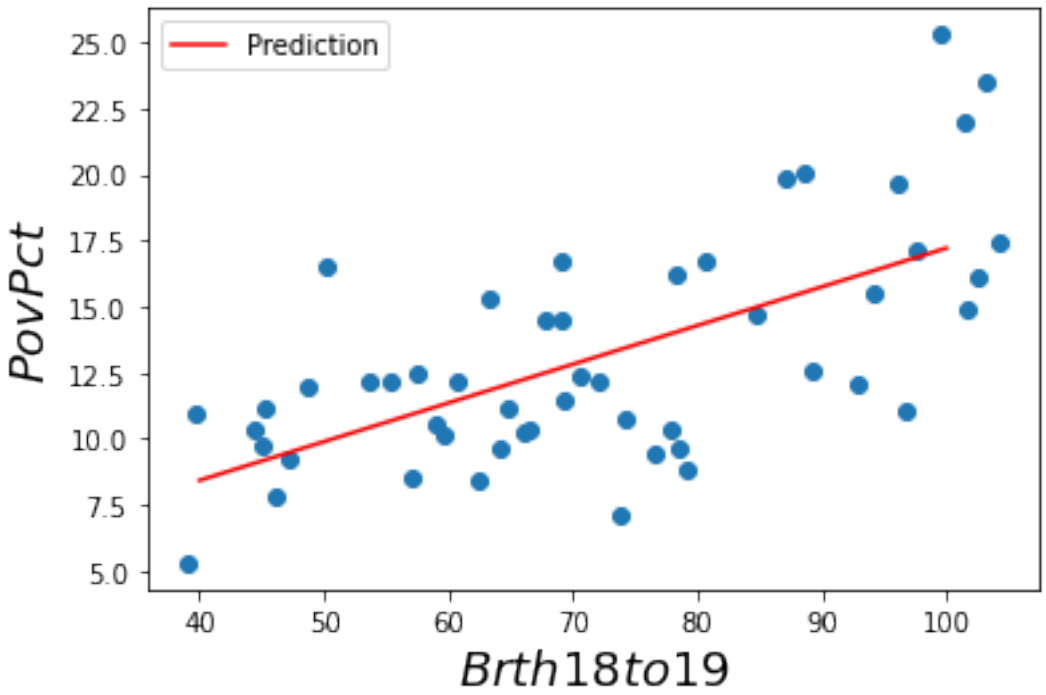


2 Problem 2: Implement code from lecture

2.1 1) Perform linear regression using the normal equation, as done in slides.

[75]:
```
plt.ylabel("$PovPct$", fontsize = 18)
plt.xlabel("$Brth18to19$", fontsize = 18)
plt.scatter(x,y)
X_b = np.c_[np.ones((x.size,1)),x] #add x0 = 1 to each instance
theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)
theta_best
X_new= np.array([[40],[100]])
X_new_b = np.c_[np.ones((2,1)), X_new] #add x0 = 1 to each instance
y_predict = X_new_b.dot(theta_best)
y_predict
plt.plot(X_new, y_predict, c="red", label = "Prediction")
plt.legend(loc = "upper left")
```

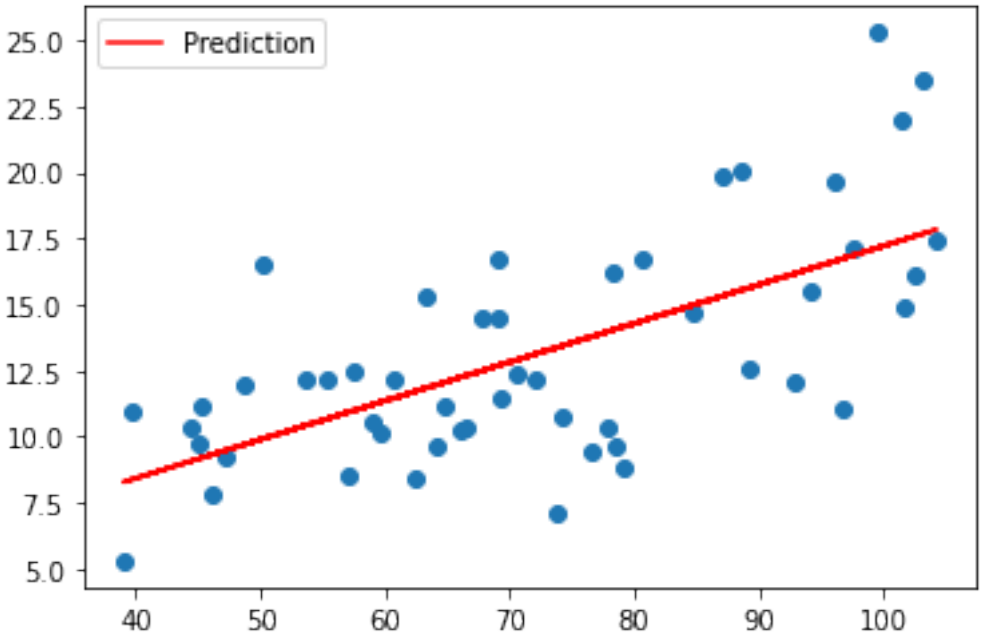
[75]:
```
<matplotlib.legend.Legend at 0x7f61d1761b10>
```



2.2 2) Perform linear regression using Scikit-Learn, as done in the slides.

[68]:
```
from sklearn.linear_model import LinearRegression
plt.scatter(x,y)
x_new = np.c_[x]
y_new = np.c_[y]

lin_reg = LinearRegression()
lin_reg.fit(x_new,y_new)
lin_reg.intercept_, lin_reg.coef_

plt.plot(x_new, lin_reg.coef_*x_new + lin_reg.intercept_, c='red',␣
 ↪label='Prediction')
plt.legend(loc = 'upper left')
```

[68]:
```
<matplotlib.legend.Legend at 0x7f61d3d8f090>
```



3 Problem 3: Multivariate Linear Regression

In this problem we will continue using the poverty dataset. Do poverty and violent crimes affect teen pregnancy?

3.1 1) import the libraries you will need:

numpy pandas matplotlab.pyplot statsmodels.api

[76]:
```
import numpy as np
import pandas as pd
from sklearn.preprocessing import normalize
```

3.2 2) Import the dataset, poverty_2.csv, and print it.

[77]:
```
url_2 = 'https://raw.githubusercontent.com/nnguyen09/Machine-Learning-/master/
 ↪assignment2/poverty_2.csv'
data= pd.read_csv(url_2)
print(data)
```

```
    PovPct  ViolCrime  TeenBrth
0     20.1       11.2      54.5
1      7.1        9.1      39.5
2     16.1       10.4      61.2
3     14.9       10.4      59.9
```

4	16.7	11.2	41.1
5	8.8	5.8	47.0
6	9.7	4.6	25.8
7	10.3	3.5	46.3
8	22.0	65.0	69.1
9	16.2	7.3	44.5
10	12.1	9.5	55.7
11	10.3	4.7	38.2
12	14.5	4.1	39.1
13	12.4	10.3	42.2
14	9.6	8.0	44.6
15	12.2	1.8	32.5
16	10.8	6.2	43.0
17	14.7	7.2	51.0
18	19.7	17.0	58.1
19	11.2	2.0	25.4
20	10.1	11.8	35.4
21	11.0	3.6	23.3
22	12.2	8.5	34.8
23	9.2	3.9	27.5
24	23.5	12.9	64.7
25	9.4	8.8	44.1
26	15.3	3.0	36.4
27	9.6	2.9	37.0
28	11.1	10.7	53.9
29	5.3	1.8	20.0
30	7.8	5.1	26.8
31	25.3	8.8	62.4
32	16.5	8.5	29.5
33	12.6	9.4	52.2
34	12.0	0.9	27.2
35	11.5	5.4	39.5
36	17.1	12.2	58.0
37	11.2	4.1	36.8
38	12.2	6.3	31.6
39	10.6	3.3	35.6
40	19.9	7.9	53.0
41	14.5	1.8	38.0
42	15.5	10.6	54.3
43	17.4	9.0	64.4
44	8.4	3.9	36.8
45	10.3	2.2	24.2
46	10.2	7.6	37.6
47	12.5	5.1	33.0
48	16.7	4.9	45.5
49	8.5	4.3	32.3
50	12.2	2.1	39.9

3.3 3) We need to normalize the input variables.

[78]:
```
from sklearn.preprocessing import normalize
data = normalize(data, axis=0)
```

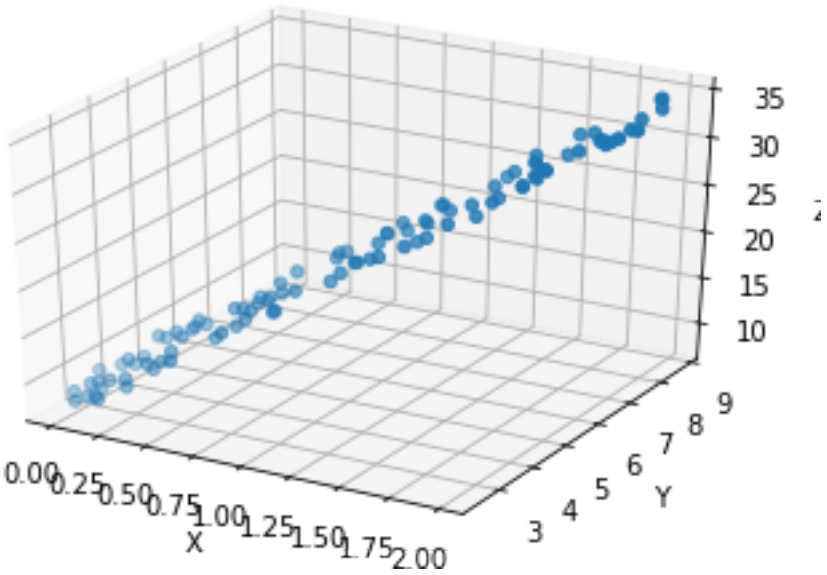
3.4 4) Split the data into input variables, X, and the output variable, Y.

[79]:
```
X=data[:,0:2]
Y=data[:,2:]
```

3.5 5) Graph the dataset with a seed of 42.

Replace the FILLINTHESEVALUES fields.

[80]:
```
np.random.seed(42)

fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

xs = 2*np.random.rand(100,1)
ys = 2+3*xs+np.random.rand(100,1)
zs = 4*xs+3*ys+np.random.rand(100,1)

ax.scatter(xs, ys, zs)

ax.set_xlabel('X')
ax.set_ylabel('Y')
ax.set_zlabel('Z')


plt.show()
```



3.6 6) Implement Gradient Descent.

This section has be provided. Please run and understand the code.

[81]:
```
# hyperparameters
learning_rate = 0.05
max_iteration = 500

#parameters
theta = np.zeros((data.shape[1], 1))
```

[82]:
```
def hypothesis (theta, X) :
  tempX = np.ones((X.shape[0], X.shape[1] + 1))
  tempX[:,1:] = X
  return np.matmul(tempX, theta)
```

[83]:
```
def loss (theta, X, Y) :
  return np.average(np.square(Y - hypothesis(theta, X))) / 2
```

[84]:
```
def gradient (theta, X, Y) :
  tempX = np.ones((X.shape[0], X.shape[1] + 1))
  tempX[:,1:] = X
  d_theta = - np.average((Y - hypothesis(theta, X)) * tempX, axis= 0)
  d_theta = d_theta.reshape((d_theta.shape[0], 1))
  return d_theta
```

[85]:
```
def gradient_descent (theta, X, Y, learning_rate, max_iteration, gap) :
  cost = np.zeros(max_iteration)
  for i in range(max_iteration) :
```

```
    d_theta = gradient (theta, X, Y)
    theta = theta - learning_rate * d_theta
    cost[i] = loss(theta, X, Y)
    if i % gap == 0 :
      print ('iteration : ', i, ' loss : ', loss(theta, X, Y))
  return theta, cost
```

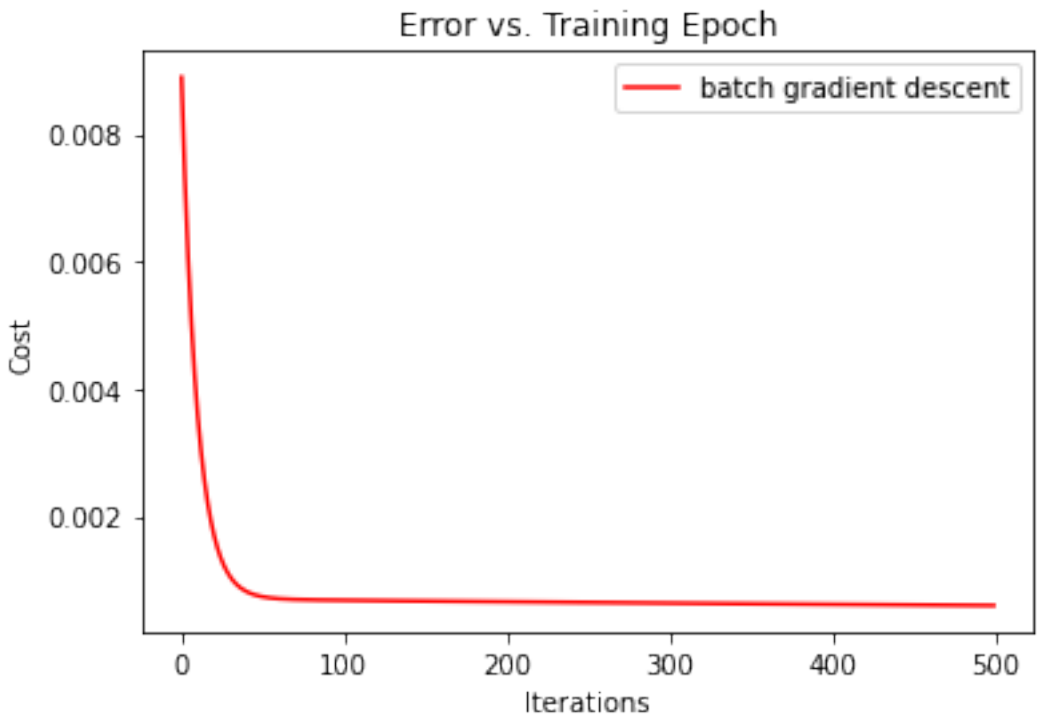
[86]:
```
# Training model
theta, cost = gradient_descent (theta, X, Y, learning_rate, max_iteration, 100)
```

```
iteration :  0  loss :  0.008893757788504215
iteration :  100  loss :  0.0006811106575134702
iteration :  200  loss :  0.0006573219302696655
iteration :  300  loss :  0.0006360731168287809
iteration :  400  loss :  0.0006169026951758099
```

[87]:
```
#optimal value is :
theta
```

[87]:
```
array([[0.12381477],
       [0.04264512],
       [0.05698502]])
```

[88]:
```
#plot cost
fig, ax = plt.subplots()
ax.plot(np.arange(max_iteration), cost, 'r')
ax.legend(loc='upper right', labels=['batch gradient descent'])
ax.set_xlabel('Iterations')
ax.set_ylabel('Cost')
ax.set_title('Error vs. Training Epoch')

plt.show()
```



3.7 7) Implement Stochastic Gradient Descent. Please run.

[90]:
```
def stochastic_gradient_descent (theta, X, Y, learning_rate, max_iteration,␣
↪gap) :
 cost = np.zeros(max_iteration)
 for i in range(max_iteration) :
   for j in range(X.shape[0]):
     d_theta = gradient (theta, X[j,:].reshape(1, X.shape[1]), Y[j,:].
↪reshape(1, 1))
     theta = theta - learning_rate * d_theta

   cost[i] = loss(theta, X, Y)
   if i % gap == 0 :
     print ('iteration : ', i, ' loss : ', loss(theta, X, Y))
 return theta, cost
```

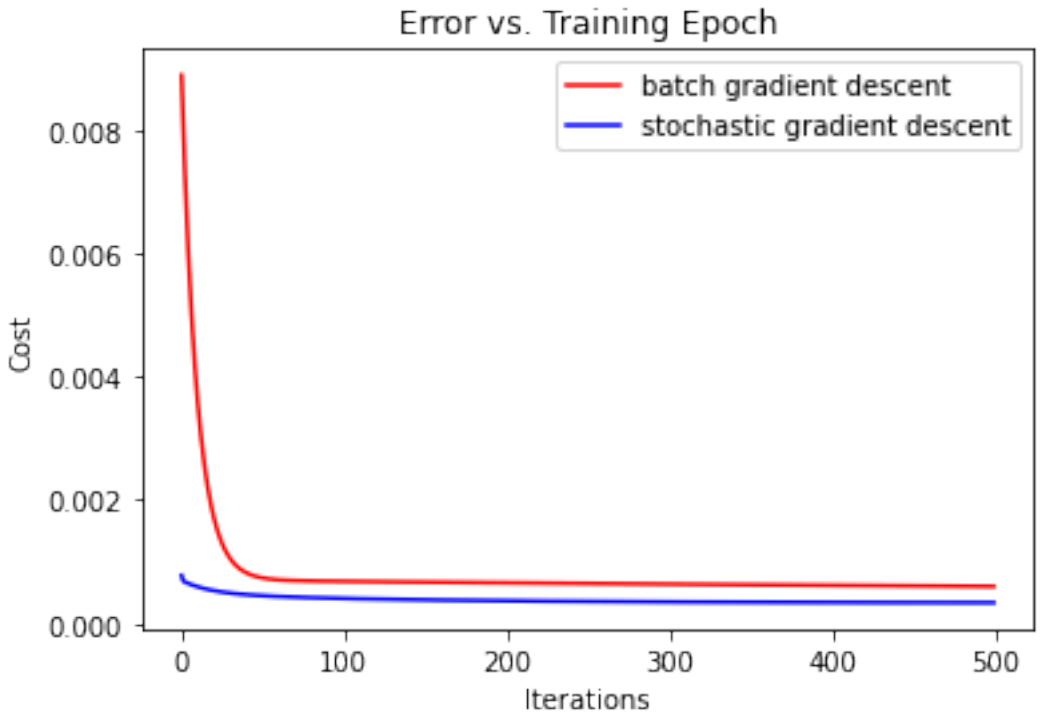
[91]:
```
theta_stoc = np.zeros((data.shape[1], 1))
```

[92]:
```
theta_stoc, cost_stoc = stochastic_gradient_descent (theta_stoc, X, Y,␣
↪learning_rate, max_iteration, 100)
```

```
iteration :  0  loss :  0.0007764556902156442
iteration :  100  loss :  0.0004037848207345314
iteration :  200  loss :  0.00036553095210465356
```

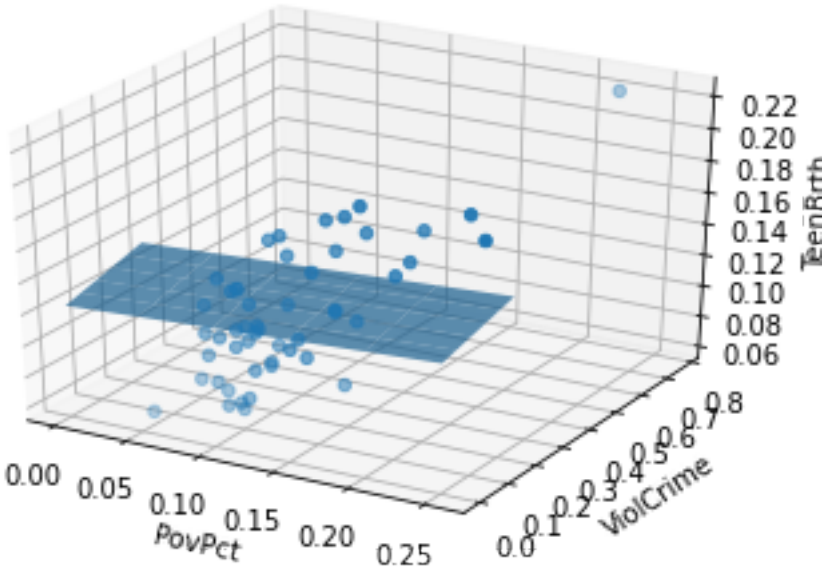
```
iteration :  300  loss :  0.0003478477587442 26
iteration :  400  loss :  0.00033956148785195
```

[93]:
```
#plot the cost
fig, ax = plt.subplots()
ax.plot(np.arange(max_iteration), cost, 'r')
ax.plot(np.arange(max_iteration), cost_stoc, 'b')
#ax.plot(np.arange(max_iteration), mb_cost, 'g')
ax.legend(loc='upper right', labels=['batch gradient descent', 'stochastic␣
 ↪gradient descent'])#, 'mini-batch gradient descent'])
ax.set_xlabel('Iterations')
ax.set_ylabel('Cost')
ax.set_title('Error vs. Training Epoch')

plt.show()
```



[94]:
```
np.random.seed(42)

fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

xs = X[:, 0]
ys = X[:, 1]
zs = Y
```

```
ax.scatter(xs, ys, zs)

ax.set_xlabel('PovPct')
ax.set_ylabel('ViolCrime')
ax.set_zlabel('TeenBrth')

# new
x = y = np.arange(0, 0.3, 0.05)
xp, yp = np.meshgrid(x, y)
z = np.array([hypothesis(theta, np.array([[x,y]]))[0, 0] for x,y in zip(np.
 ↪ravel(xp), np.ravel(yp))])
zp = z.reshape(xp.shape)

ax.plot_surface(xp, yp, zp, alpha=0.7)

plt.show()
```



4 Problem 4, predict house price.

- import real_estate.csv
- Are there any null values in the dataset? Drop any missing data if exist.
- Create X as a 1-D array of the distance to the nearest MRT station, and y as the housing price
- What is the number of samples in the data set? To do this, you can look at the "shape" of X and y
- Split the data into train and test sets using sklearn's train_test_split, with test_size = 1/3

- Find the line of best fit using a Linear Regression and show the result of coefficients and intercept (you can use sklearn's linear regression)
- Using the predict method, make predictions for the test set and evaluate the performance (e.g., MSE or other metrics).

[95]:
```
#import real_estate.csv
url_3 = 'https://raw.githubusercontent.com/nnguyen09/Machine-Learning-/master/
 ↪assignment2/real_estate.csv'
data_real_estate = pd.read_csv(url_3)

print(data_real_estate.columns)

#Are there any null values in the dataset? Drop any missing data if exist.
data_real_estate.dropna(axis = 0, how = 'any')

#Create X as a 1-D array of the distance to the nearest MRT station, and y as␣
 ↪the housing price
X=data_real_estate['X3 distance to the nearest MRT station'].array
print(X)
Y=data_real_estate['Y house price of unit area'].array
print(Y)

#What is the number of samples in the data set? To do this, you can look at the␣
 ↪"shape" of X and y
print('Number of sample in data set is: ' , X.shape, Y.shape)
```

```
Index(['No', 'X1 transaction date', 'X2 house age',
       'X3 distance to the nearest MRT station',
       'X4 number of convenience stores', 'X5 latitude', 'X6 longitude',
       'Y house price of unit area'],
      dtype='object')
<PandasArray>
[84.87882, 306.5947, 561.9845, 561.9845, 390.5684,  2175.03, 623.4731,
 287.6025, 5512.038,  1783.18,
 ...
 289.3248, 130.9945, 372.1386, 2408.993, 2175.744, 4082.015, 90.45606,
 390.9696, 104.8101, 90.45606]
Length: 414, dtype: float64
<PandasArray>
[37.9, 42.2, 47.3, 54.8, 43.1, 32.1, 40.3, 46.7, 18.8, 22.1,
 ...
 41.2, 37.2, 40.5, 22.3, 28.1, 15.4, 50.0, 40.6, 52.5, 63.9]
Length: 414, dtype: float64
Number of sample in data set is:  (414,) (414,)
```

[96]:
```
#Split the data into train and test sets using sklearn's train_test_split, with␣
 ↪test_size = 1/3
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

X_train, X_test, y_train, y_test = train_test_split(X,Y,test_size = 1/3)

X_train = X_train.reshape(-1, 1)
y_train = y_train.reshape(-1, 1)
X_test = X_test.reshape(-1,1)
y_test = y_test.reshape(-1,1)
```

[97]:
```
#Find the line of best fit using a Linear Regression and show the result of␣
 ↪coefficients and intercept (you can use sklearn's linear regression)
lin_reg = LinearRegression()
lin_reg.fit(X_train,y_train)
print(lin_reg.intercept_, lin_reg.coef_)
```

```
[46.68201581] [[-0.00764843]]
```

[98]:
```
#Using the predict method, make predictions for the test set and evaluate the␣
 ↪performance (e.g., MSE or other metrics).
y_predict = lin_reg.predict(X_test)

print(mean_squared_error(y_test, y_predict))
print(lin_reg.score(X_test,y_test))
```

```
91.52078612852627
0.42585247237704293
```