

```
In [243]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
In [244]: #create linear regression model

#IMPORTANT NOTICE!
'''
#####
This is taken from Homework 2 assignment
#####
'''
def sums(x, y):
    '''
    This function creates all the necessary sums for the linear regression equations
    Inputs:
        x (np array) data that will be used to make predictions
        y (np array) data that will be used to check predictions
    Outputs:
        sum_x (float) sum of all the x values
        sum_y (float) sum of all the y values
        sum_x2 (float) sum of all the squared x values
        sum_xy (float) sum of all the x values multiplied by their respective y value
    '''
    sum_x = np.sum(x)
    sum_y = np.sum(y)
    sum_x2 = np.sum(x**2)
    sum_xy = np.sum(x*y)
    return sum_x, sum_y, sum_x2, sum_xy
```

```
In [245]: #Also from Homework 2
def B_i(x,y):
    '''
    This function calculates the slope (B_1) and intercept (B_0) of the regression
    Inputs:
        x (np array) data that will be used to make predictions
        y (np array) data that will be used to check predictions
    Outputs:
        B1 (float) slope of the regression
        B0 (float) intercept for the regression
    '''
    sum_x, sum_y, sum_x2, sum_xy = sums(x,y)
    numerator = ((len(x) * sum_xy) - (sum_x * sum_y))
    denominator = ((len(x) * sum_x2) - (sum_x**2))
    B1 = numerator/denominator
    B0 = (sum_y - (B1 * sum_x)) / len(x)
    return B1, B0
```

```
In [246]: #The ridge regression is based on the gradient descent from homework 4
#It works on matrices so that if you wanted more predictors it would be easy to expand
def ridge_regression(x, y, Lr=0.1, penalty=0.1, epochs=10000):
    '''
    This function does a gradient descent for ridge regression.
```

```

input:
    x: np array, predictor values
    y: np array, target values
    lr: float, learning rate
    lambda: float, ridge regularization strength
    epochs: int, number of iterations
output:
    B: array with floats, Contains both the slopes and intercept after the gradient descent
    ...

m, n = x.shape #m = number of samples, n = number of features
slope = []
intercept = []
#My B_i fxn is meant for only one predictor so if i want to expand it to a matrix
for i in range(n):
    B1, B0 = B_i(x[:,i], y[i]) #Apply B_i for each row of x
    slope.append(B1)
    intercept.append(B0)
B = np.zeros((n+1, 1)) #Initialize weights
B[0] = intercept #The first row is for intercepts
B[1:] = np.array(slope).reshape(-1, 1) #The rest are for slopes

#need a column in X of ones to account for B having the intercept
x_B = np.ones((m,n+1))
x_B[:,1:] = x #now x_B has x as well as a column to account to intercepts

for epoch in range(epochs):
    Y_pred = np.dot(x_B, B) #calculate predicted y vals
    err = Y_pred - y #find residuals

    B_pen = np.copy(B) #Creating a copy of B to not interfere with updating it
    B_pen[0] = 0 #set the intercept to 0

    dB = (1/m) * (np.dot(x_B.T, err) + penalty * B_pen) #calculate change
    B -= Lr * dB #apply changes to B

return B

```

[https://www.kaggle.com/code/ninjaac/lasso-and-ridge-regression-from-scratch?utm_source=chatgpt.com]

Assisted in building the ridge regression model.. it is kind of hard to follow along with this because it uses a class. I think I managed to apply my old functions into this method fairly well.

```

In [247]: #Now clean the data as in step 2
data = pd.read_csv('FY_2025_Hospital_Readmissions_Reduction_Program_Hospital.csv')
data = data.drop(columns = ['Footnote'])
data = data[data['Measure Name'] == 'READM-30-AMI-HRRP']
#I forgot to only include heart attack patients in the first upload so I'll have to r
data = data.dropna()
data['Number of Readmissions'] = data['Number of Readmissions'].astype(float)
print(data.head())
print(data.columns)

```

	Facility Name	Facility ID	State	Measure Name \
0	SOUTHEAST HEALTH MEDICAL CENTER	10001	AL	READM-30-AMI-HRRP
14	NORTH ALABAMA MEDICAL CENTER	10006	AL	READM-30-AMI-HRRP
31	ST. VINCENT'S EAST	10011	AL	READM-30-AMI-HRRP
47	SHELBY BAPTIST MEDICAL CENTER	10016	AL	READM-30-AMI-HRRP
77	BAPTIST MEDICAL CENTER SOUTH	10023	AL	READM-30-AMI-HRRP

	Number of Discharges	Excess Readmission Ratio \
0	296.0	0.9483
14	315.0	0.9704
31	148.0	0.9675
47	77.0	1.0186
77	194.0	1.0485

	Predicted Readmission Rate	Expected Readmission Rate \
0	13.0146	13.7235
14	11.8750	12.2373
31	11.8541	12.2521
47	14.4337	14.1707
77	14.2860	13.6247

	Number of Readmissions	Start Date	End Date
0	36.0	07/01/2020	06/30/2023
14	36.0	07/01/2020	06/30/2023
31	16.0	07/01/2020	06/30/2023
47	12.0	07/01/2020	06/30/2023
77	30.0	07/01/2020	06/30/2023

```
Index(['Facility Name', 'Facility ID', 'State', 'Measure Name',
      'Number of Discharges', 'Excess Readmission Ratio',
      'Predicted Readmission Rate', 'Expected Readmission Rate',
      'Number of Readmissions', 'Start Date', 'End Date'],
      dtype='object')
```

```
In [248]: #Make new column and pull out data to be used
data['Read_Dis_ratio'] = data['Number of Readmissions'] / data['Number of Discharges']
X_both = data['Read_Dis_ratio']
X = data['Number of Discharges']
Y = data['Excess Readmission Ratio']
```

```
In [249]: #Having trouble with the regression working forgot to normalize data
mean_X = np.mean(X)
std_dev_X = np.std(X)
normal_X = (X-mean_X)/std_dev_X
```

```
In [250]: normal_X = np.array(normal_X).reshape(-1,1)
Y = np.array(Y).reshape(-1,1)
print(normal_X.shape, Y.shape)
print(normal_X)
```

```
(1244, 1) (1244, 1)
[[ 0.46130755]
 [ 0.58904711]
 [-0.53371636]
 ...
 [-0.4059768 ]
 [-0.95727383]
 [-0.61439397]]
```

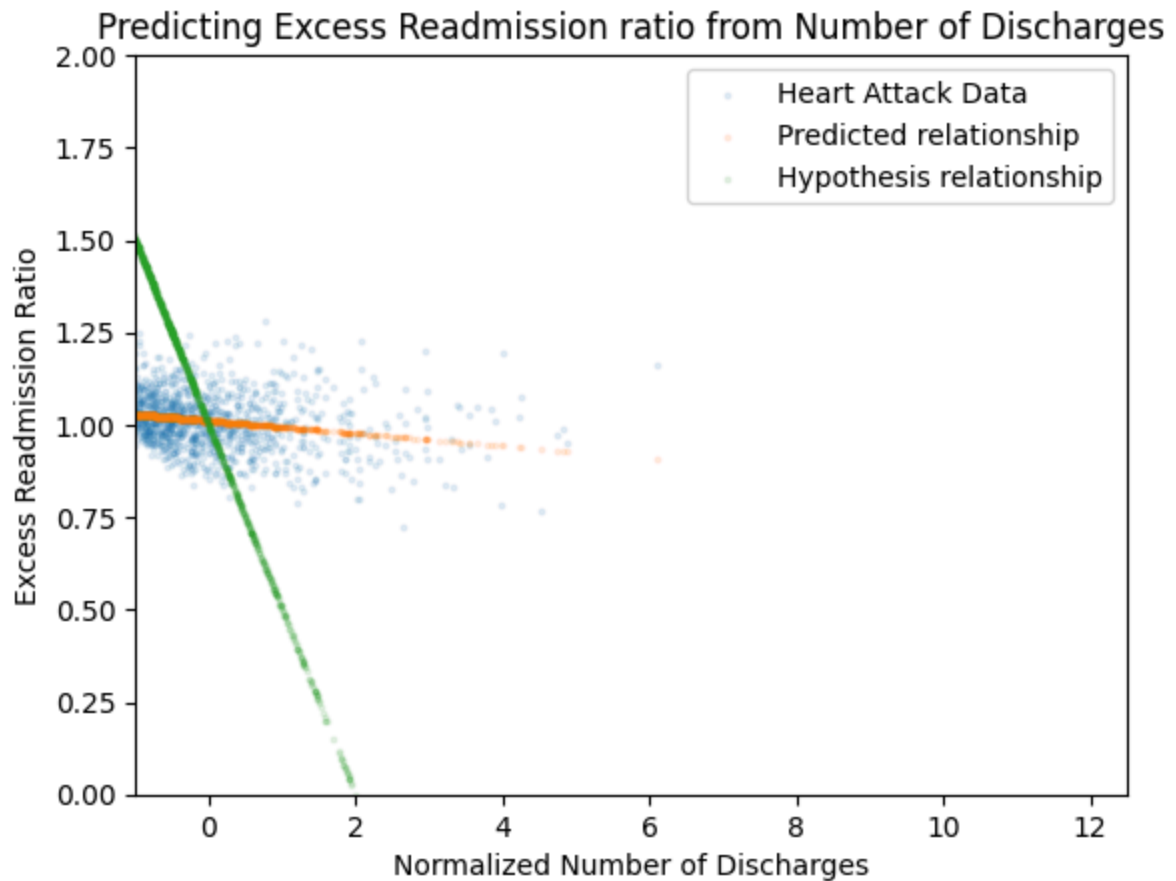
In [251]: *#Testing to see how different param effect the output*

```
B = ridge_regression(normal_X,Y,epochs=300)
print(B)
B = ridge_regression(normal_X,Y,epochs=1000)
print(B)
```

```
[[ 1.0115168 ]
 [-0.01707499]]
[[ 1.0115168 ]
 [-0.01707499]]
```

In [252]:

```
Y_pred = B[0] + B[1]*normal_X
Y_hypo = 1. - 0.5*normal_X
plt.scatter(normal_X, Y, s=3, alpha=0.1, label='Heart Attack Data')
plt.scatter(normal_X, Y_pred, s=3, alpha=0.1, label='Predicted relationship')
plt.scatter(normal_X, Y_hypo, s=3, alpha=0.1, label='Hypothesis relationship')
plt.ylim(0,2)
plt.xlim(-1,12.5)
plt.ylabel('Excess Readmission Ratio')
plt.xlabel('Normalized Number of Discharges')
plt.title('Predicting Excess Readmission ratio from Number of Discharges')
plt.legend()
plt.show()
```

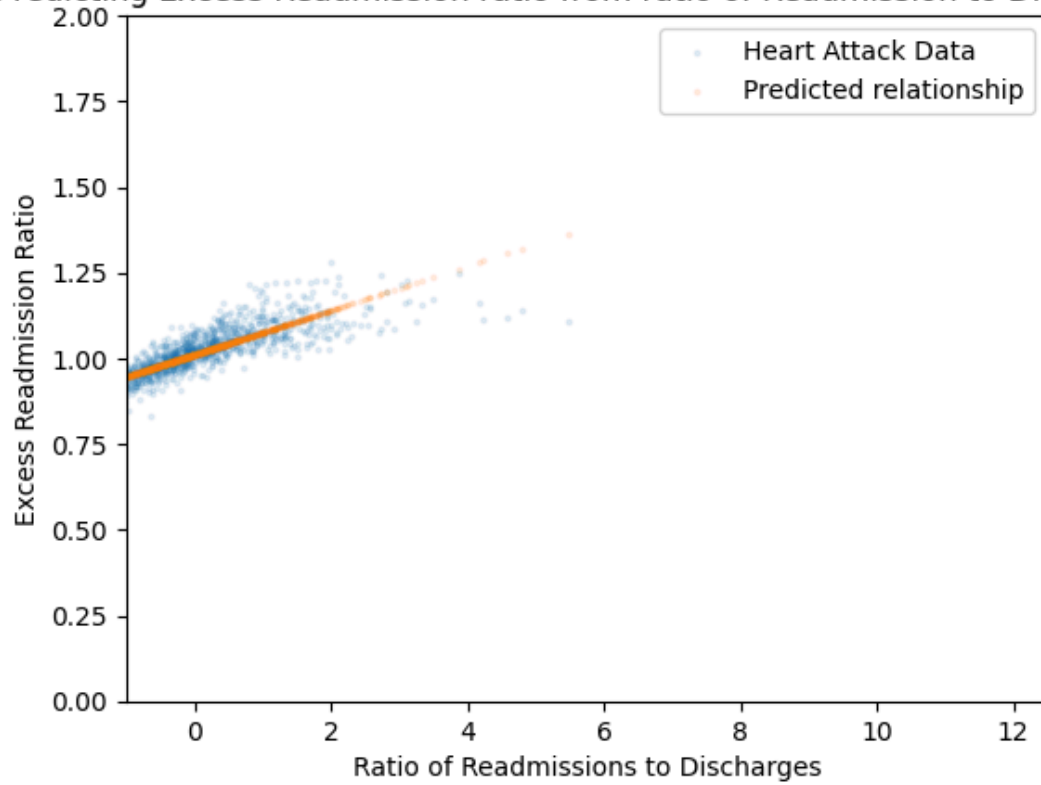


It looks like the models results are not as extreme as my hypothesis but it still gives credit to the hypothesis by having a negative slope. Out of curiosity (one of the other questions I wanted to look at was how the ratio of readmissions to discharges relates to excess readmission ratio. I can do this easily with the model already built)

```
In [253]: mean_X_both = np.mean(X_both)
std_dev_X_both = np.std(X_both)
normal_X_both = (X_both-mean_X_both)/std_dev_X_both
normal_X_both = np.array(normal_X_both).reshape(-1,1)
B = ridge_regression(normal_X_both,Y)
```

```
In [254]: Y_pred_both = B[0] + B[1]*normal_X_both
plt.scatter(normal_X_both, Y, s=3, alpha=0.1, label='Heart Attack Data')
plt.scatter(normal_X_both, Y_pred_both, s=3, alpha=0.1, label='Predicted relationship')
plt.ylim(0,2)
plt.xlim(-1,12.5)
plt.ylabel('Excess Readmission Ratio')
plt.xlabel('Ratio of Readmissions to Discharges')
plt.title('Predicting Excess Readmission ratio from ratio of Readmission to Discharge')
plt.legend()
plt.show()
```

Predicting Excess Readmission ratio from ratio of Readmission to Discharges



This relationship makes total sense.. It wouldn't make sense to really consider this as a question. Both are measures of how often people are readmitted.