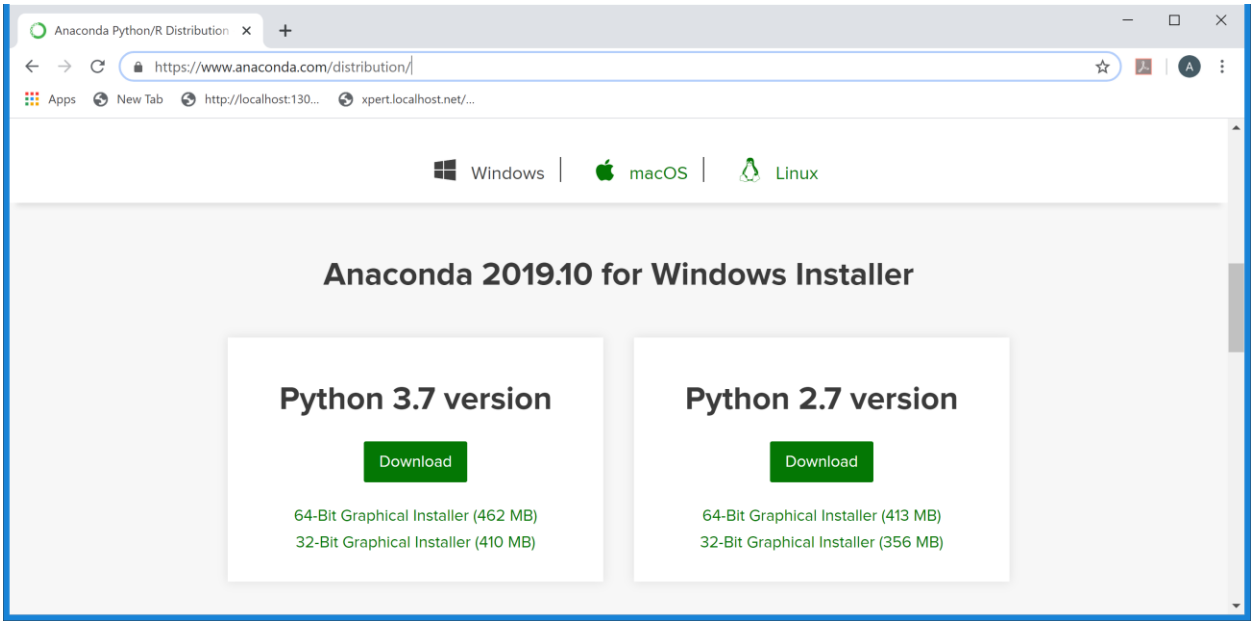
Programming Logistic Regression Using Python

This handout shows the Logistic Regression Python code under Visual Studio. If you wanted to use some other Python development environment, then the code is still valid. If you are new to Python, then first make sure that yu have Visual Studio 2019 Community edition installed (it is a free download), and also make sure when you install Visual Studio, you choose the Python development option along with other options.

Setting up the Python Environment:

Download the latest Python version (3.7 as of this writing) from the following url: https://www.anaconda.com/distribution/



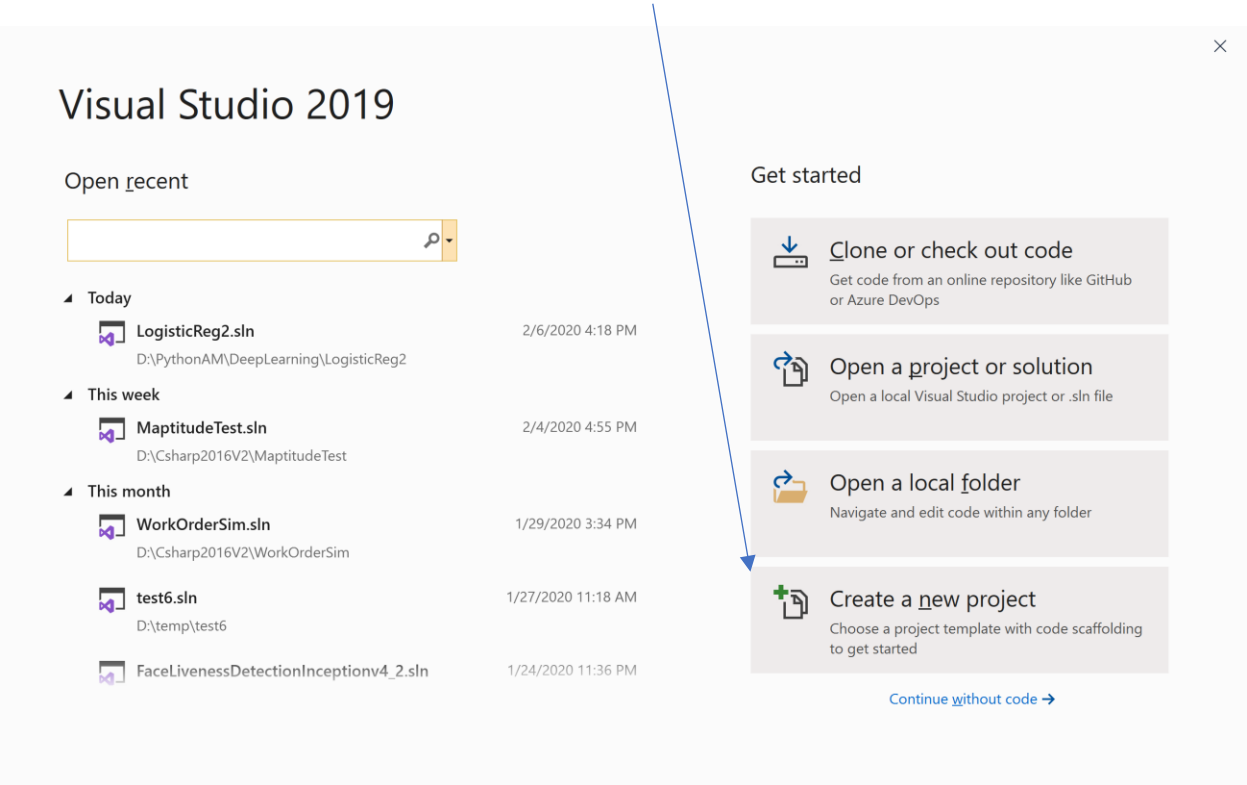
As you install Python, it will give you an option to set the path to the python environment, make sure you check this checkbox even if it gives you a warning.

Then launch command prompt as an administrator and type the following commands (one at a time):

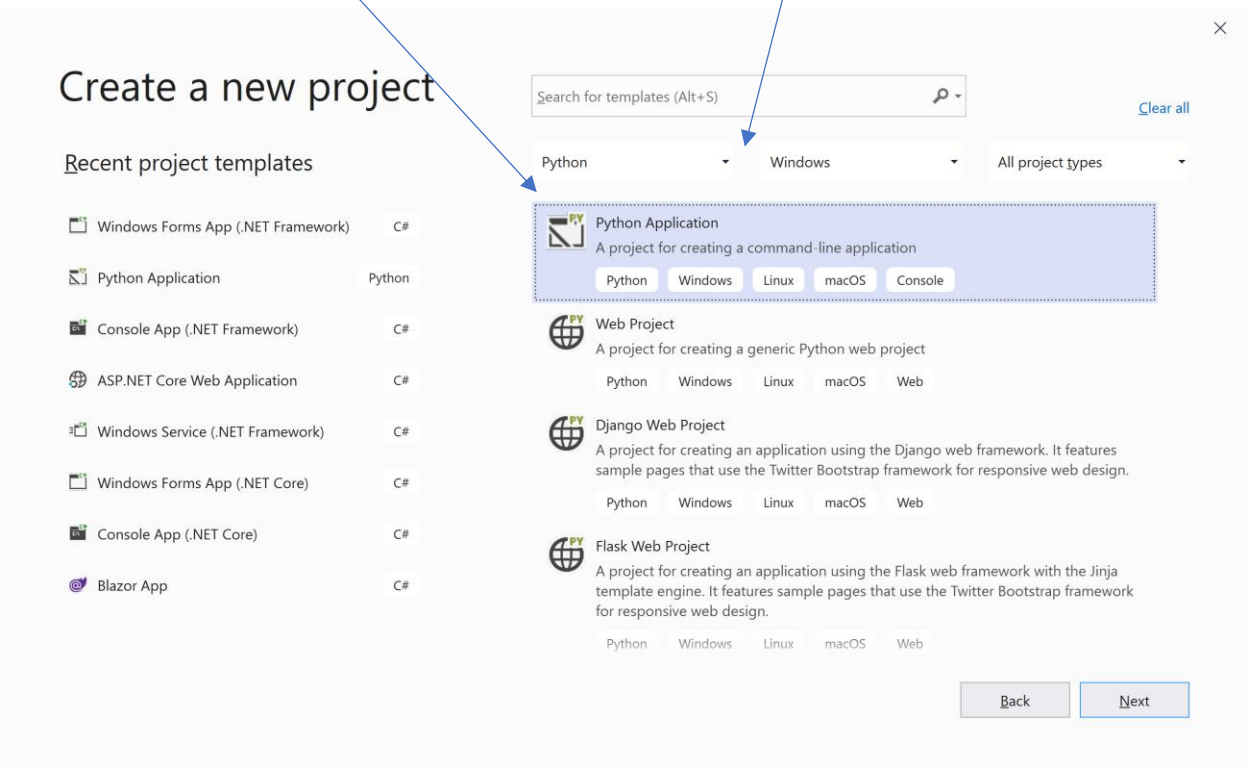
```
python -m pip install --upgrade pip
conda create -n tensorflow2cpu pip python=3.7
activate tensorflow2cpu
pip install --upgrade tensorflow
```

If the above commands run successfully, your Python environment is ready with the latest Tensorflow library.

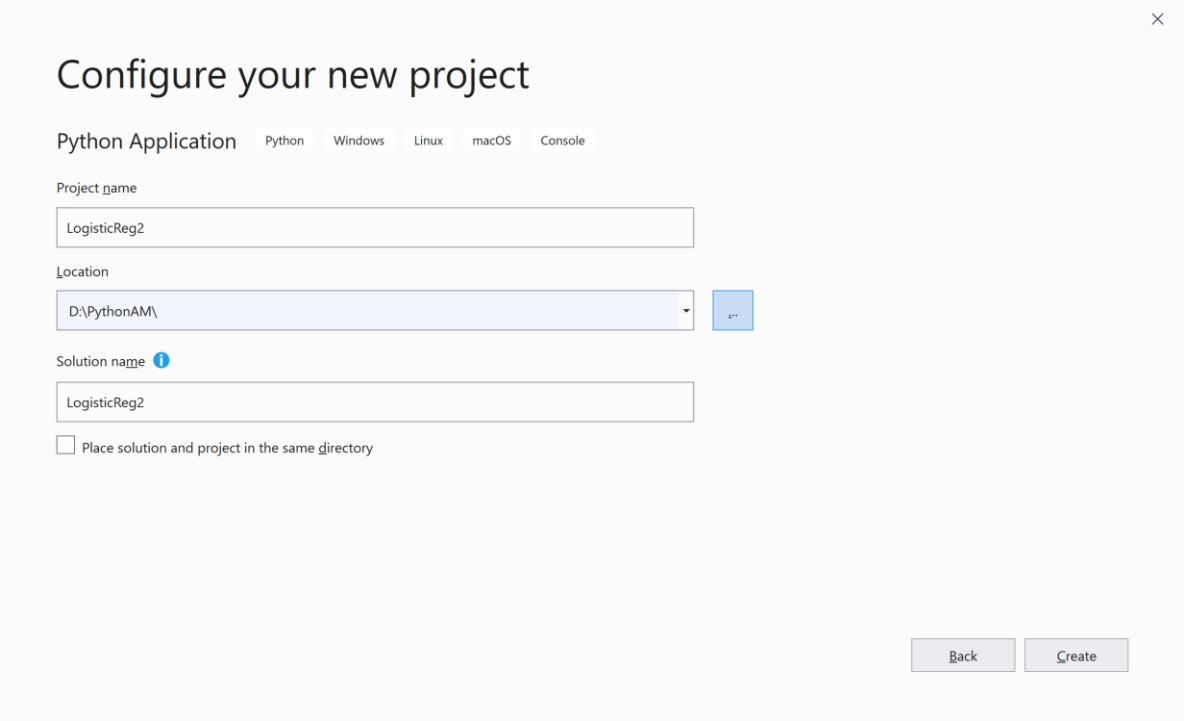
Launch Visual studio and create a new project as shown below.



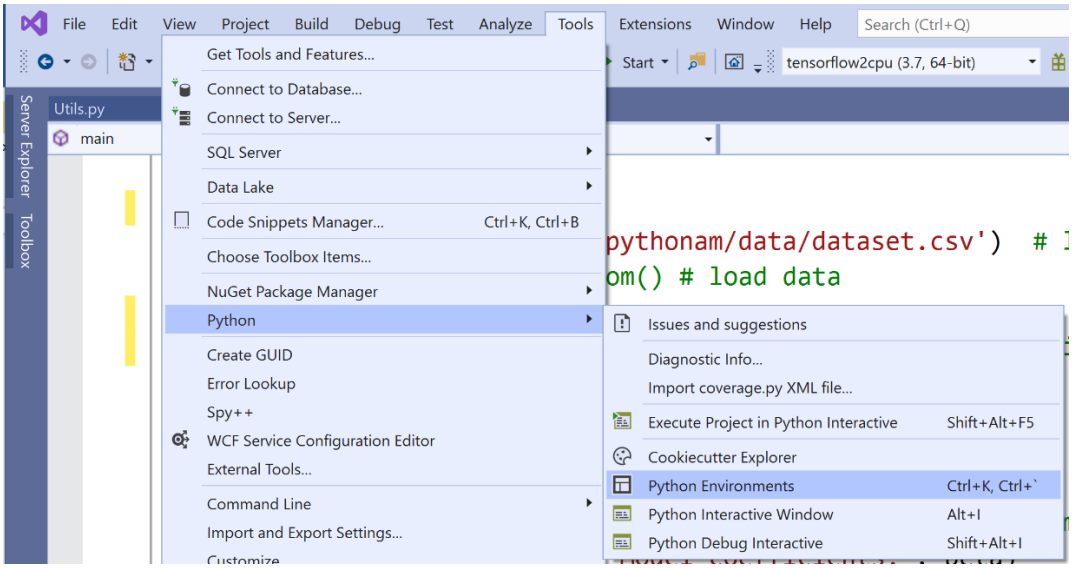
Choose the following on the next screen (select Python from the dropdown), then click Next:



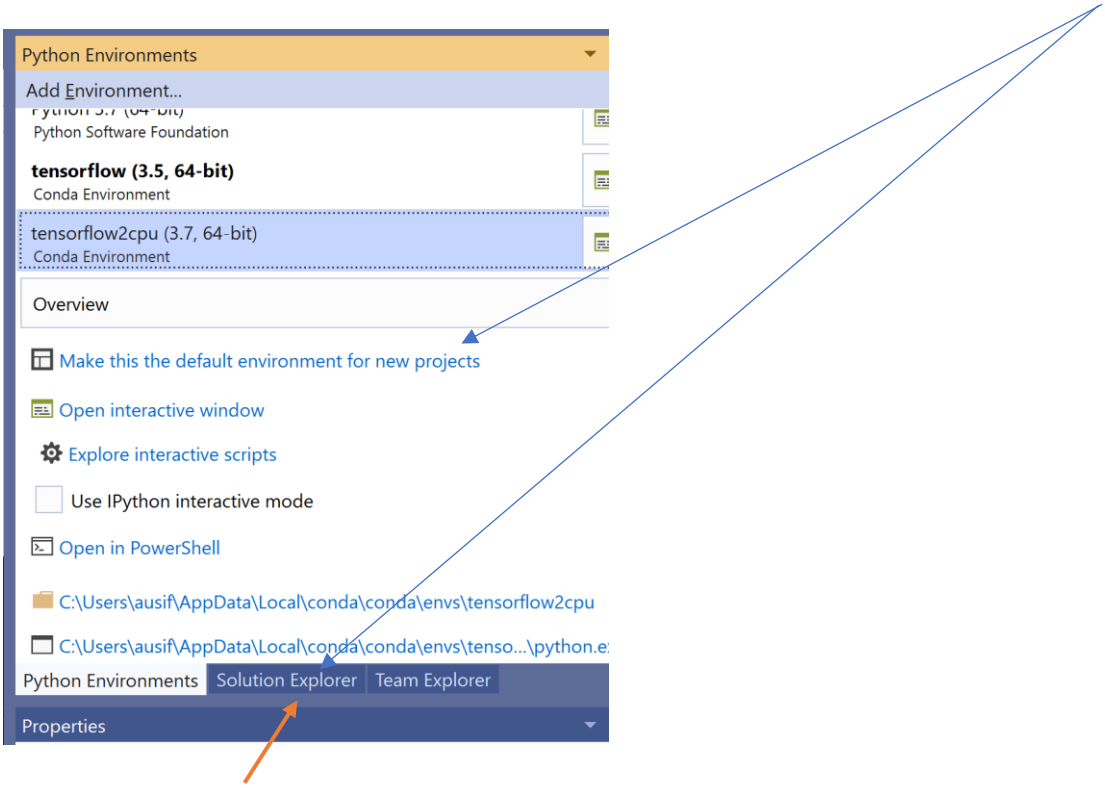
Give a project name of LogisticReg2, and select the directory where you would like the project to be created. Then click on the Create button as shown below



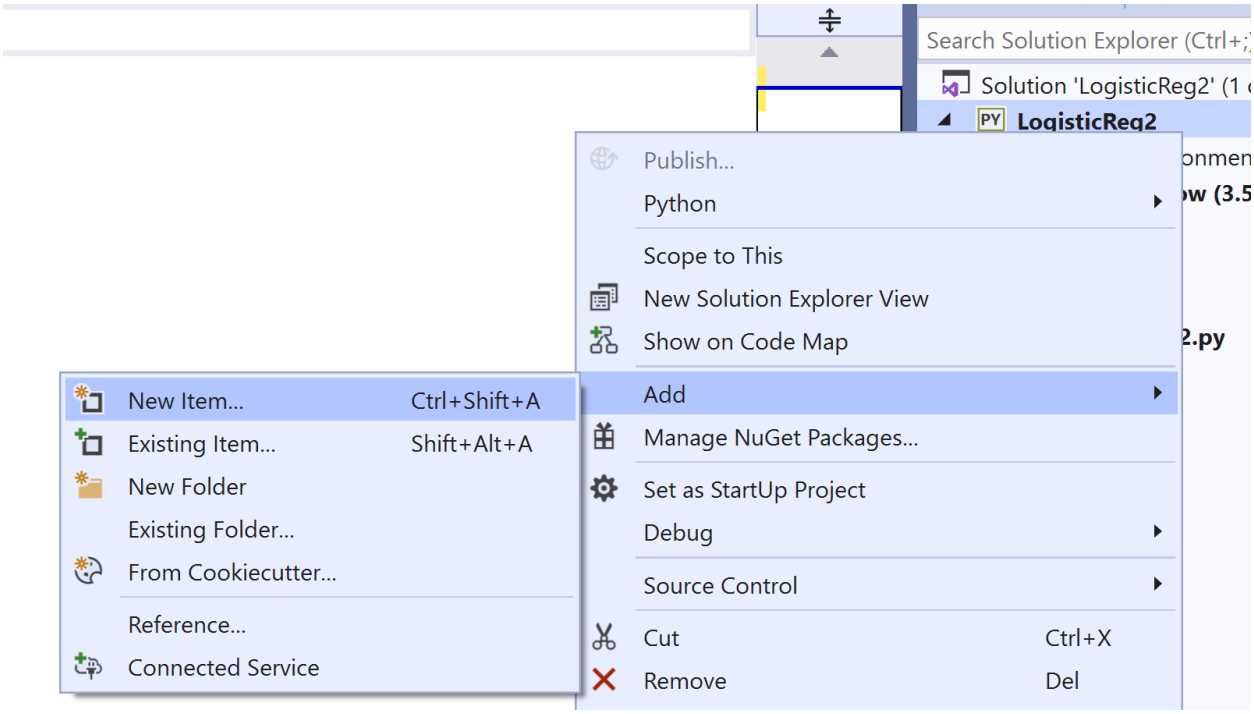
From the Tools menu, select Python-> Python Environments.



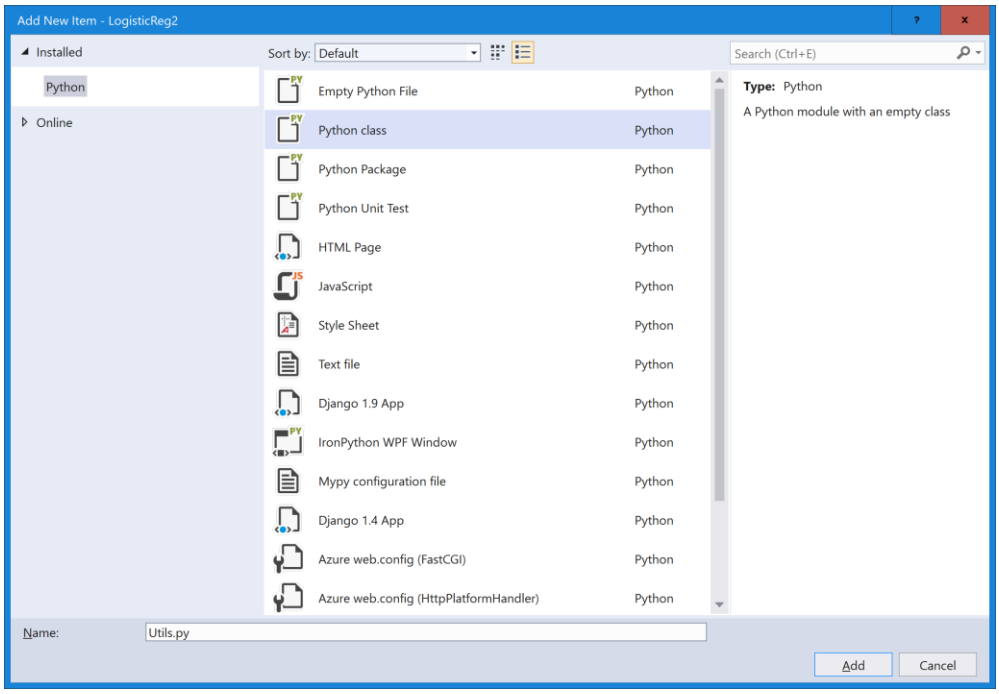
Then make the Tensorflow2cpu as the default environment for running Python, as shown below.



Then click on Solution Explorer tab, and right click on the project name, and choose Add Python class.



Then choose Python class as shown below. Name the class Utils.py.

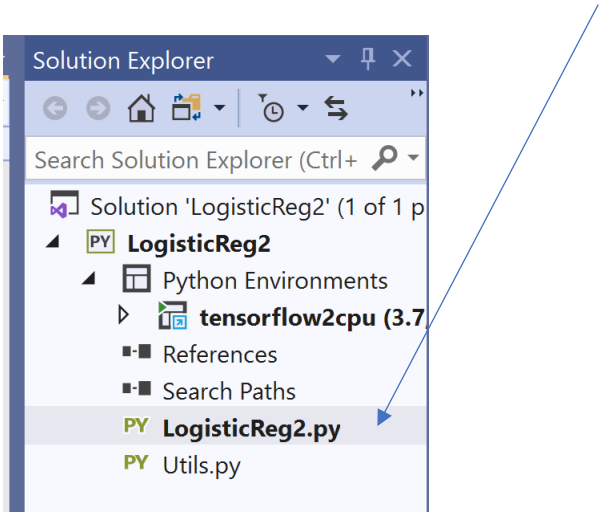


Type the following code in Utils.py.

```
import csv
import numpy as np
import matplotlib.pyplot as plt

class Utils(object):
	def readData(self,filename): # return as numpy array
		with open(filename,"r") as csvfile:
			lines = csv.reader(csvfile)
			data = list(lines)
			for i in range(len(data)): # convert data to float
				data[i] = [float(x) for x in data[i]]
		return np.array(data)

	def readDataRandom(self):
		np.random.seed(12)
		num_observations = 50
		x1 = np.random.multivariate_normal([1.5, 4], [[1, .75],[.75, 1]],
num_observations)
		print(x1.shape)
		x2 = np.random.multivariate_normal([1, 2], [[1, .75],[.75, 1]],
num_observations)
		data = np.vstack((x1, x2)).astype(np.float32)
		print(data.shape)
		labels = np.hstack((np.zeros(num_observations), np.ones(num_observations)))
		print(labels.shape)
		dataWithLabels = np.hstack((data,labels.reshape(labels.shape[0],1)))
		#print(dataWithLabels.shape)
		#print(labels.shape)
		plt.figure(figsize=(12,8))
		plt.scatter(data[:, 0], data[:, 1], c = labels, alpha = .4)
		plt.show()
```

```
            return dataWithLabels

        def normalizeData(self,X):
            min = np.min(X, axis = 0)
            max = np.max(X, axis = 0)
            normX = 1 - ((max - X)/(max-min))
            return normX

        def plot_result(self,X, y, beta):
            x_0 = X[np.where(y == 0.0)]
            x_1 = X[np.where(y == 1.0)]

            # plot the data points
            plt.scatter([x_0[:, 1]], [x_0[:, 2]], c='b', label='y = 0')
            plt.scatter([x_1[:, 1]], [x_1[:, 2]], c='r', label='y = 1')

            # plot the decision boundary
            x1 = np.arange(0, 1, 0.1)
            x2 = -(beta[0,0] + beta[0,1]*x1)/beta[0,2]
            plt.plot(x1, x2, c='g', label='reg line')

            plt.xlabel('x1')
            plt.ylabel('x2')
            plt.legend()
            plt.show()
```

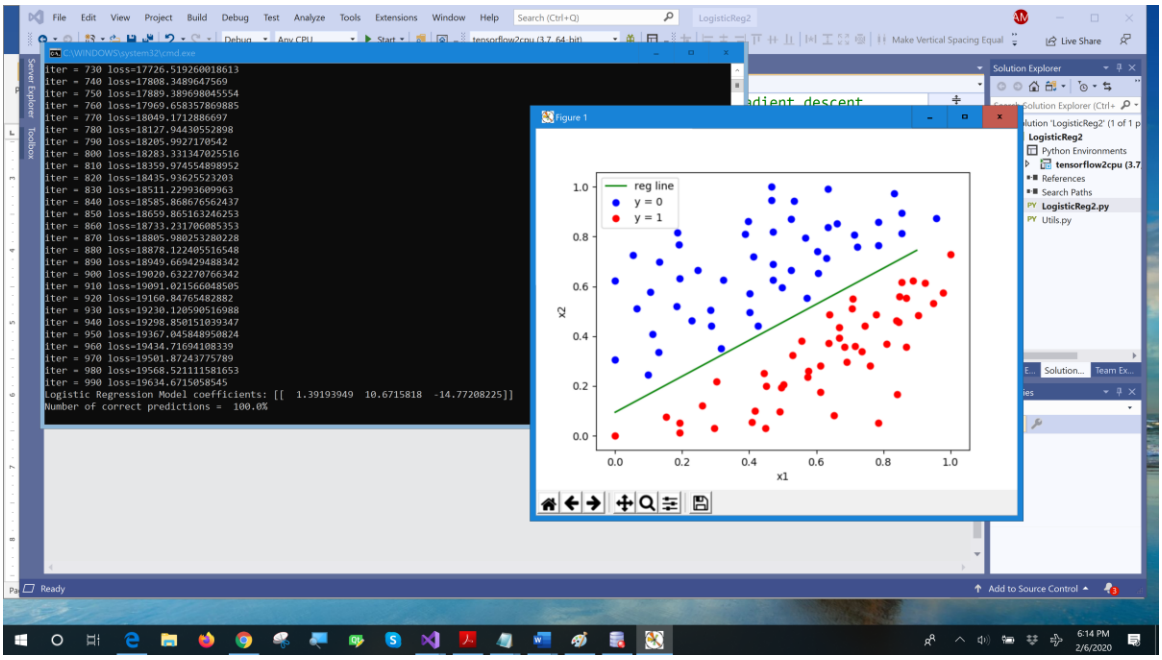
From the solution explorer, double click on the LogisticReg2.py and type the following code in it.




```
import sys
from Utils import Utils
import numpy as np

def sigmoid(beta, X):  # logistic function
        return 1.0/(1 + np.exp(-np.dot(X, beta.T)))

def gradientBeta(beta, X, y):   # dL/dbeta
        a = sigmoid(beta, X)
        part1 = a - y.reshape(X.shape[0], 1)
        grad = np.dot(part1.T, X)
        return grad
```

```
def logLoss(beta, X, y):
	a = sigmoid(beta, X) # actual output
	loss = -(y * np.log(a)  + (1 - y) * np.log(1 - a))
	return np.sum(loss)

def trainUsingGradientDescent(X, y, beta, num_iter, alpha = .01):
	loss = logLoss(beta, X, y)
	for i in range (num_iter):
		beta = beta - (alpha * gradientBeta(beta, X, y))
		loss = logLoss(beta, X, y)
		if (i%10 == 0):
			print('iter = ' + str(i) + ' loss=' + str(loss))
	return beta


def classifyData(beta, X):  # 0 or 1
	a = sigmoid(beta, X) # actual output
	decision = np.where(a >= .5, 1, 0)
	return decision


def main():
	utils = Utils()

	data = utils.readData('d:/pythonam/data/dataset.csv')  # load data
	#data = utils.readDataRandom() # load data

	X = utils.normalizeData(data[:,0:2])  # or [:,:-1] normalize data - scale between
0-1
	X = np.hstack((np.ones((1,X.shape[0])).T, X))   # add 1's column to data

	Y = data[:, -1] # expected output, -1 means last column
	beta = np.zeros((1,X.shape[1]))  # (1,3) in this example
	beta = trainUsingGradientDescent(X, Y, beta,1000)  # optimize using gradient
descent
	print("Logistic Regression Model coefficients:", beta)

	y_predicted = classifyData(beta, X)  # predictions by the trained model
	#print(y_predicted.shape)
	print("Number of correct predictions = ", str(np.sum(Y ==
y_predicted.reshape(Y.shape[0]))/len(X)*100) + '%')

	utils.plot_result(X, Y, beta) # plot results

if __name__ == "__main__":
    sys.exit(int(main() or 0))
```

From the Debug menu, choose Start without Debugging. The output will appear as:


iter = 730 loss=17726.519260018613
iter = 740 loss=17808.3489647569
iter = 750 loss=17889.389698045554
iter = 760 loss=17969.658357869885
iter = 770 loss=18049.1712886697
iter = 780 loss=18127.94430552898
iter = 790 loss=18205.9927170542
iter = 800 loss=18283.331347025516
iter = 810 loss=18359.974554898952
iter = 820 loss=18435.93625523203
iter = 830 loss=18511.229036089063
iter = 840 loss=18585.868676562437
iter = 850 loss=18659.865163246253
iter = 860 loss=18733.231706085353
iter = 870 loss=18805.980253280228
iter = 880 loss=18878.122405516548
iter = 890 loss=18949.669429488342
iter = 900 loss=19020.632270766342
iter = 910 loss=19091.021566048505
iter = 920 loss=19160.84765482882
iter = 930 loss=19230.120590516988
iter = 940 loss=19298.850151039347
iter = 950 loss=19367.045848950824
iter = 960 loss=19434.71694108339
iter = 970 loss=19501.872432775789
iter = 980 loss=19568.521111581653
iter = 990 loss=19634.6715058545
Logistic Regression Model coefficients: [[1.39193949 10.6715818 -14.77208225]]
Number of correct predictions = 100.0%
Figure 1
reg line
y = 0
y = 1
x1
x2
Solution Explorer
LogisticReg2
Python Environments
References
Search Paths
LogisticReg2.py
Utils.py
Ready
Add to Source Control
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