

Assignment₇

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1 7.1

```
#!/usr/bin/env python  
# coding: utf-8
```

```
# In[1]:
```

```
import numpy as np  
import pandas as pd  
import math  
import random  
import matplotlib.pyplot as plt  
from sklearn.model_selection import train_test_split
```

```
# In[2]:
```

```
def readTrainigData():  
  
    return pd.read_csv( './data/DWH-Training.csv' )
```

```
# In[3]:
```

```
def initializeParamteres():  
  
    numberOfNeuronsInHiddenLayer = 5  
    numberOfHiddenLayers = 2  
  
    np.random.seed(37)
```

```

# This will create a 5x2 matrix which are 10 weights of input layer to first
wHiddenLayer1 = np.random.uniform(low=0, high=1, size=(numberOfNeuronsInHidd
deltaHiddenLayer1 = np.random.uniform(low=0, high=1, size=(numberOfNeuronsIn

# This will create a 5x5 matrix which are 25 weights of first hidden layer t
wHiddenLayer2 = np.random.uniform(low=0, high=1, size=(numberOfNeuronsInHidd
deltaHiddenLayer2 = np.random.uniform(low=0, high=1, size=(numberOfNeuronsIn

# This is the weight of the ouput neuron.
wOutputLayer = np.random.uniform(low=0, high=1, size=(numberOfNeuronsInHidde
deltaOutputLayer = np.random.uniform(low=0, high=1, size=(numberOfNeuronsInH

# This is the bias for each layer
bHiddenLayer1 = bHiddenLayer2 = np.random.uniform(low=0,high=1,size=(numberO
bOutputLayer = np.random.uniform(low=0,high=1,size=(1,1))

# This is is the weighed sum from input layer to first hidden layer.
weightedSumH1 = np.zeros((len(wHiddenLayer1),1))

# This is the activation of the first hidden layer
activationH1 = np.zeros((len(wHiddenLayer1),1))

# This is is the weighed sum from first hidden layer to the second hidden la
weightedSumH2 = np.zeros((len(wHiddenLayer2),1))

# This is the activation of the second hidden layer
activationH2 = np.zeros((len(wHiddenLayer2),1))

# This the weighted sum from 2nd hidden layer to the output layer.
weightedSumOp = np.zeros((1,1))

    return wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, weightedSum
bHiddenLayer1, bHiddenLayer2, activationH1, activationH2, bOutputLayer, deltaHid
deltaHiddenLayer2, deltaOutputLayer

# In[4]:

def getTrainingSamples(trainingData):

    featureSet = np.zeros((len(trainingData),3))

    for index,row in trainingData.iterrows():

        featureSet[index][0] = row['Height']

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        featureSet[index][1] = row['Weight']

        # Here the labels that are originally [1,-1] are coveredd
to [1,0]
        if row['Gender'] != 1:
            featureSet[index][2] = 0
        else :
            featureSet[index][2] = 1

    return featureSet

# In [5]:

def getStandardizedFeatureSet(featureSet):

    totalHeight = meanCorrectedHeight = 0.0
    totalWeight = meanCorrectedWeight = 0.0

    sampleSize = len(featureSet)
    normalizedFeatureSet = np.zeros((len(featureSet),3))

    for row in featureSet:

        totalHeight += row[0]
        totalWeight += row[1]

    hMean = totalHeight/sampleSize
    wMean = totalWeight/sampleSize
    print("Height_mean: ",hMean)
    print("Weight_mean: ",wMean)
    for rowIndex in range(len(featureSet)):

        normalizedFeatureSet[rowIndex][0] += (featureSet[rowIndex][0] - hMean)
        normalizedFeatureSet[rowIndex][1] += (featureSet[rowIndex][1] - wMean)
        normalizedFeatureSet[rowIndex][2] = featureSet[rowIndex][2]

        meanCorrectedHeight += math.pow(normalizedFeatureSet[rowIndex][0],2)
        meanCorrectedWeight += math.pow(normalizedFeatureSet[rowIndex][1],2)

    sdHeight = math.sqrt((meanCorrectedHeight/sampleSize))
    sdWeight = math.sqrt((meanCorrectedWeight/sampleSize))
    print("Height_SD: ",sdHeight)
    print("Weight_SD: ",sdWeight)

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    for rowIndex in range(len(featureSet)):

        normalizedFeatureSet[rowIndex][0] = (normalizedFeatureSet[rowIndex][0] /
        normalizedFeatureSet[rowIndex][1] = (normalizedFeatureSet[rowIndex][1] /

    return normalizedFeatureSet

# In[6]:

def splitTrainingData(validationDataPercentage, featureSet):

    trainingSet, validationSet = train_test_split(featureSet, test_size=0.05)
    #print(validationSet.shape)
    return trainingSet, validationSet

# In[7]:

def applySigmoidActivation(weightedSum):

    activationOutput = np.zeros((len(weightedSum),1))

    for index in range(len(weightedSum)):

        activationOutput[index][0] = 1/(1+math.exp(-(weightedSum[index][0])))

    return activationOutput

# In[8]:

def computeError(output, label):

    # Log loss computation  $-(y*\log(output) + (1 - y)\log(1-output))$ 

    if label == 0:
        return -(math.log(1 - output))
    else:
        return -(math.log(output))

# In[9]:

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def feedForward(sample, wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1,
                weightedSumOp, bHiddenLayer1, bHiddenLayer2, activationH1, activa

    heightOfSample = sample[0]
    weightOfSample = sample[1]
    label = sample[2]

    for index in range(len(wHiddenLayer1)):

        weightedSumH1[index][0] = ((heightOfSample * wHiddenLayer1[index][0]) +
                                   (weightOfSample * wHiddenLayer1[index][1])
                                   ) + bHiddenLayer1[index][0]
        activationH1 = applySigmoidActivation(weightedSumH1)
        for rowIndex in range(len(wHiddenLayer2)):

            tempSum = 0
            for colIndex in range(len(wHiddenLayer2[rowIndex])):

                tempSum += (activationH1[colIndex][0] * wHiddenLayer2[rowIndex][colIndex])

            weightedSumH2[rowIndex][0] = tempSum
            activationH2 = applySigmoidActivation(weightedSumH2)
            tempSum = 0
            for rowIndex in range(len(activationH2)):
                tempSum += (activationH2[rowIndex][0] * wOutputLayer[rowIndex][0]) + bOutputLayer[rowIndex][0]
            weightedSumOp[0][0] = tempSum

            outPut = applySigmoidActivation(weightedSumOp)
            error = computeError(outPut[0][0], label)

    #return outPut[0][0], error
    return wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, weightedSumH2,
    activationH2, outPut[0][0], error

# In[10]:

def sigmoidDerivative(outputOfPreviousLayer):
    sigmoid = 1/(1+math.exp(-(outputOfPreviousLayer)))
    return ((sigmoid)*(1-sigmoid))

# In[11]:

```

```

def backPropagate(ouput, sample, wHiddenLayer1, wHiddenLayer2, wOutputLayer, weights,
                  bHiddenLayer1, bHiddenLayer2, activationH1, activationH2, bOutputLayer,
                  deltaHiddenLayer2, deltaOutputLayer):

    errorDerivative = (ouput - sample[2]) / (ouput - (ouput * ouput))
    outputLayerDerivative = []
    totalCalcDerivate = 0.0

    for rowIndex in range(len(wOutputLayer)):
        #Momentum Update
        outputLayerDerivative.append(errorDerivative * sigmoidDerivative(weights[rowIndex][0] *
                                     totalCalcDerivate + bOutputLayer[rowIndex][0]))
        totalCalcDerivate = outputLayerDerivative[rowIndex] * activationH2[rowIndex][0]
        deltaOutputLayer[rowIndex][0] = (psy * deltaOutputLayer[rowIndex][0]) + totalCalcDerivate
        wOutputLayer[rowIndex][0] -= (LR * deltaOutputLayer[rowIndex][0])
        bOutputLayer[0][0] -= (LR * totalCalcDerivate)

    hiddenLayerOutputDerivative = np.zeros((5, 5))

    for rowIndex in range(len(wHiddenLayer2)):
        deltaForBias = 0
        hiddenLayerOutputDerivative[rowIndex][0] = wOutputLayer[rowIndex][0] * sigmoidDerivative(
            weights[rowIndex][0] * totalCalcDerivate + bOutputLayer[rowIndex][0])
        for colIndex in range(len(wHiddenLayer2[rowIndex])):
            totalCalcDerivate = outputLayerDerivative[colIndex] * hiddenLayerOutputDerivative[rowIndex][0]
            deltaHiddenLayer2[colIndex][rowIndex] = (psy * deltaHiddenLayer2[colIndex][rowIndex]) + totalCalcDerivate
            deltaForBias += totalCalcDerivate
            wHiddenLayer2[colIndex][rowIndex] -= (LR * deltaHiddenLayer2[colIndex][rowIndex])

        bHiddenLayer2[rowIndex][0] -= (LR * deltaForBias)

    for rowIndex in range(len(wHiddenLayer1)):
        tempSum = 0.0
        deltaForBias = 0
        tempDerivative = sigmoidDerivative(weights[rowIndex][0] * totalCalcDerivate + bOutputLayer[rowIndex][0])
        for colIndex in range(len(wHiddenLayer1[rowIndex])):
            for elementIndex in range(len(hiddenLayerOutputDerivative)):
                tempSum += (hiddenLayerOutputDerivative[elementIndex][0] * wHiddenLayer1[elementIndex][colIndex])
            totalCalcDerivate = outputLayerDerivative[colIndex] * hiddenLayerOutputDerivative[rowIndex][0]
            tempSum * tempDerivative * sample[colIndex]
            deltaHiddenLayer1[rowIndex][colIndex] = (psy * deltaHiddenLayer1[rowIndex][colIndex]) + totalCalcDerivate
            deltaForBias += totalCalcDerivate
            wHiddenLayer1[rowIndex][colIndex] -= (LR * deltaHiddenLayer1[rowIndex][colIndex])

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        bHiddenLayer1[rowIndex][0] -= (LR * deltaForBias)

    return wHiddenLayer1, wHiddenLayer2, wOutputLayer, bHiddenLayer1, bHiddenLayer2,
    deltaHiddenLayer2, deltaOutputLayer

```

In [12]:

```

def startNNTraining(trainingSet, validationSet, standardizedTestSet):

    print("Neural_Network_Started")
    epochs = 50000
    threshold = 0.5
    prediction = None
    correctResult = None
    validationAccuracy = None
    trainingAccuracy = None

    wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, weightedSumH2, wOutputLayer,
    bHiddenLayer2, activationH1, activationH2, bOutputLayer, deltaHiddenLayer1, deltaHiddenLayer2,
    deltaOutputLayer = initializeParamteres()

    fwHiddenLayer1 = wHiddenLayer1
    fwHiddenLayer2 = wHiddenLayer2
    fwOutputLayer = wOutputLayer
    fbHiddenLayer1 = bHiddenLayer1
    fbHiddenLayer2 = bHiddenLayer2
    fbOutputLayer = bOutputLayer
    validationIterationCount = 0
    smallestValidationError = 100
    valList = []
    LRList = []
    PsyList = []
    for randLearnParam in range(5):
        psy = random.random()
        LR = random.uniform((np.divide(1, epochs)), (np.divide(10, epochs)))
        for iteration in range(epochs):
            randomIndicesForSGD = random.sample(range(0, len(trainingSet)), 50)
            validationIterationCount += 1
            if validationIterationCount == 250:

                correctResult = 0
                validationAccuracy = 0.0
                for sample in validationSet:

```

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        wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, w
feedForward(sample, wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, w
        weightedSumOp, bHiddenLayer1, bHiddenLayer2, activationH1, a

        if output >= threshold:
            prediction = 1.0
        else:
            prediction = 0.0

        if sample[2] == prediction:
            correctResult += 1

validationAccuracy = (correctResult / len(validationSet))*100

print("Validation accuracy after 250 iterations is", validationA

if (error < smallestValidationError):

    smallestValidationError = error

    fwHiddenLayer1 = wHiddenLayer1
    fwHiddenLayer2 = wHiddenLayer2
    fwOutputLayer = wOutputLayer
    fbHiddenLayer1 = bHiddenLayer1
    fbHiddenLayer2 = bHiddenLayer2
    fbOutputLayer = bOutputLayer

    validationIterationCount = 0
    #print('Smallest Val Error', smallestValidationError)
    #print('LR', LR)

else:
    correctResult = 0.0
    for randomIndex in randomIndicesForSGD:

        wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, w
activationH1, activationH2, output, error = feedForward(trainingSet[randomIndex]
        wOut
        bHid
        bOut

        if output >= threshold:
            prediction = 1.0
        else:
            prediction = 0.0

```



```

        if trainingSet[randomIndex][2] == prediction:
            correctResult += 1

        wHiddenLayer1, wHiddenLayer2, wOutputLayer, bHiddenLayer1, b
        deltaHiddenLayer1, deltaHiddenLayer2, deltaOutputLayer =
        backPropagate(output, trainingSet[randomIndex], wHiddenLayer1, wHiddenLayer2, wO
            weightedSumH1, weightedSumH2, weightedSumO
            activationH1, activationH2, bOutputLayer, L
            deltaHiddenLayer2, deltaOutputLayer)

    trainingAccuracy = (correctResult/50)*100

    if ((iteration +1) % 100 == 0):
        print("Training_Loss_after", iteration+1, "of", epochs, "is:", error
        print("Training_accuracy_after", iteration+1, "=", trainingAccuracy
    valList.append(smallestValidationError)
    LRList.append(LR)
    PsyList.append(psy)
    testModel(standardizedTestSet, fwHiddenLayer1, fwHiddenLayer2, fwOutputL
fbOutputLayer)
    return valList, LRList, PsyList, smallestValidationError

```

In[13]:

```

def readTestData():

    return pd.read_csv('./data/DWH_test.csv')

```

In[14]:

```

def testModel(standardizedTestSet, wHiddenLayer1, wHiddenLayer2, wOutputLayer, b
bOutputLayer):

    threshold = 0.5
    correctResult = 0
    # This is the activation of the first hidden layer
    activationH1 = np.zeros((len(wHiddenLayer1),1))

    # This is the activation of the second hidden layer
    activationH2 = np.zeros((len(wHiddenLayer2),1))

    # This the weighted sum from 2nd hidden layer to the output layer.

```

```

weightedSumOp = np.zeros((1,1))

# This is is the weighed sum from first hidden layer to the second hidden la
weightedSumH2 = np.zeros((len(wHiddenLayer2),1))

# This is is the weighed sum from first hidden layer to the second hidden la
weightedSumH1 = np.zeros((len(wHiddenLayer2),1))

for sample in standardizedTestSet:
    wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, weightedSumH2 =
weightedSumOp, activationH1, activationH2, output, error =
feedForward(sample, wHiddenLayer1, wHiddenLayer2, wOutputLayer, weightedSumH1, w
    weightedSumOp, bHiddenLayer1, bHiddenLayer2, activationH1, activationH2,

    #output, error = feedForward(sample, wHiddenLayer1, wHiddenLayer2, wOutp
    # weightedSumOp, bHiddenLayer1, bHiddenLayer2, activationH1, acti

    if output >= threshold:
        prediction = 1.0
    else:
        prediction = 0.0

    if sample[2] == prediction:
        correctResult += 1

testAccuracy = (correctResult / len(standardizedTestSet))*100
print("Test accuracy = ", testAccuracy, "%.")

# In [15]:

def main():

    print('Stats of Training Data')
    trainingData = readTrainigData()
    featureSet = getTrainingSamples(trainingData)
    standardizedFeatureSet = getStandardizedFeatureSet(featureSet)
    trainingSet, validationSet = splitTrainingData(5, standardizedFeatureSet)

    print('Stats of Testing Data')
    testData = readTestData()
    featureTestSet = getTrainingSamples(testData)
    standardizedTestSet = getStandardizedFeatureSet(featureTestSet)

```

```

valList , LRList , PsyList , BestValScore = startNNTraining(trainingSet , valida

#wHiddenLayer1 , wHiddenLayer2 , wOutputLayer , bHiddenLayer1 , bHiddenLayer2 , \
#      bOutputLayer , valList , LRList , BestValScore = startNNTraining(t

#testModel(standardizedTestSet , wHiddenLayer1 , wHiddenLayer2 , wOutputLayer ,
#      bOutputLayer)
print( 'Val_List: ' , valList)
print( 'LR_List: ' , LRList)
print( 'Psy_List: ' , PsyList)
print( 'Best_Validation_Score: ' , BestValScore)


fig , ax1 = plt.subplots()
ax1.set_xlabel( 'Learning_Rate' )
ax1.set_ylabel( 'Validation_Error' )
ax1.plot(LRList , valList , linestyle='-' , marker='o' , color = 'blue' )
ax1.tick_params(axis='y')
ax2 = ax1.twinx()

ax2.set_ylabel( 'Psy_Values' )
ax2.plot(LRList , PsyList , linestyle='-' , marker='o' , color = 'red' )
ax2.tick_params(axis='y')
fig.tight_layout()
#plt.plot(LRList , valList , linestyle='-' , marker='o' )
#plt.xlabel( 'Learning_Rate' )
#plt.ylabel( 'Validation_Error' )
plt.title( 'Learning_Rate_vs_Validation_Error_vs_Psy_Values' )
plt.show()


# In [16]:


if __name__ == '__main__':
    main()

```

INFERENCE: The momentum method helped in increasing the accuray of the model.

Best Validation Score: 0.016580560445184724

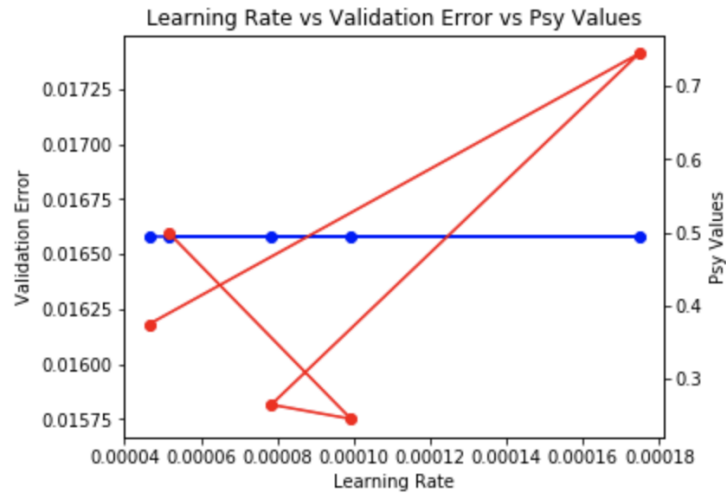


Figure 1: Learning Rate vs Validation Error vs Psy Values

```
Test accuracy = 80.0 %
Val List: [0.016580560445184724, 0.016580560445184724, 0.016580560445184724, 0.016580560445184724, 0.016580560445184724]
LR List: [5.162981092376697e-05, 9.929730046679222e-05, 7.843780861649396e-05, 0.00017467847286190062, 4.643303993907212e-05]
Psy List: [0.49890615887308953, 0.24465007414878592, 0.2641752849712331, 0.7442272536640275, 0.3742192823910755]
Best Validation Score: 0.016580560445184724
```

Figure 2: Other Results

2 7.2

a) With Momentum,
Method 1: Random uniform weight initialization

Best Validation Score: 0.2676784284234564

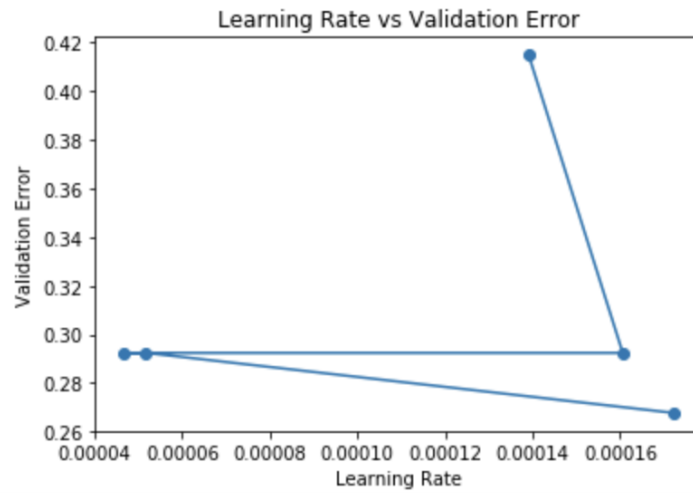


Figure 3: Learning Rate vs Validation Error (Method 1)

```
Test accuracy = 75.55555555555556 %.
Val List: [0.414895329797015, 0.2923732726401062, 0.2923732726401062, 0.2923732726401062, 0.2676784284234564]
LR List: [0.00013908576622578315, 0.00016057720164272486, 4.647224865380795e-05, 5.16916085242404e-05, 0.0001722119
9028597347]
Best Validation Score: 0.2676784284234564
```

Figure 4: Other Results (Method 1)

Method 2: Zero weight initialization

Best Validation Score: 0.1769086740814002

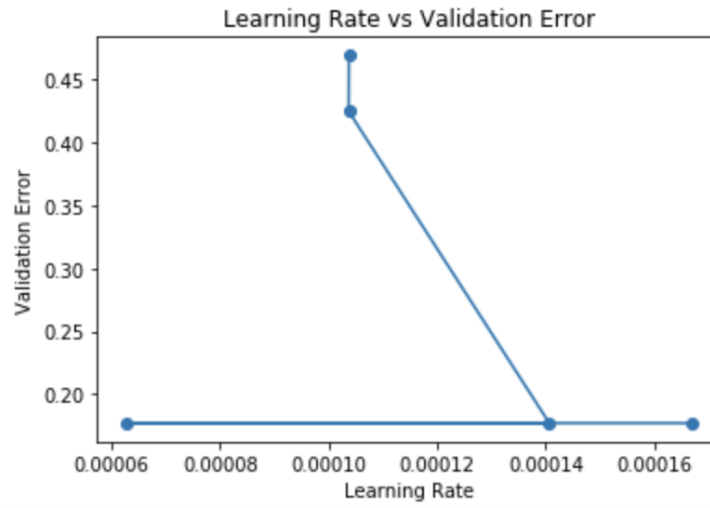


Figure 5: Learning Rate vs Validation Error (Method 2)

Test accuracy = 82.222222222221 %.
Val List: [0.46939566929004994, 0.4248829151476636, 0.1769086740814002, 0.1769086740814002, 0.1769086740814002]
LR List: [0.00010373643451990835, 0.00010368624105041301, 0.000140655230238908, 6.262157900426877e-05, 0.0001669189781983274]
Best Validation Score: 0.1769086740814002

Figure 6: Other Results (Method 2)

Method 3: Xavier weight initialization

Best Validation Score: 0.2794394189289825

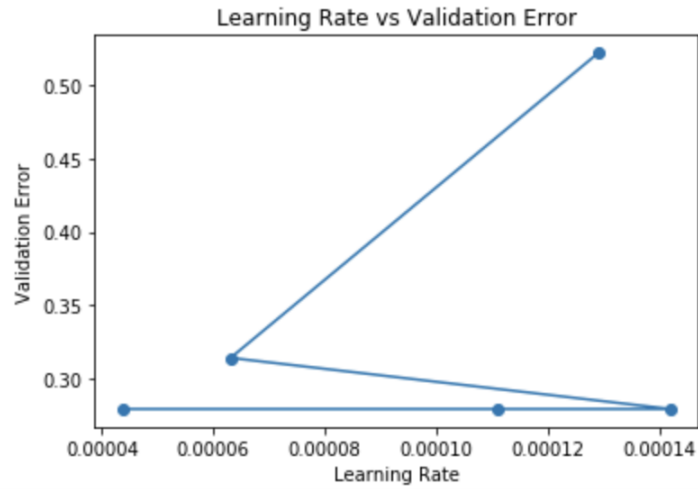


Figure 7: Learning Rate vs Validation Error (Method 3)

```
Test accuracy = 73.33333333333333 %.  
Val List: [0.5219772359396917, 0.31425338979319317, 0.2794394189289825, 0.2794394189289825, 0.2794394189289825]  
LR List: [0.00012911094290093633, 6.309237870325465e-05, 0.00014203999849697773, 0.00011101799368482724, 4.36042244  
0198492e-05]  
Best Validation Score: 0.2794394189289825
```

Figure 8: Other Results (Method 3)

b) Without Momentum,
Method 1: Random uniform weight initialization

Best Validation Score: 0.42947063776424066

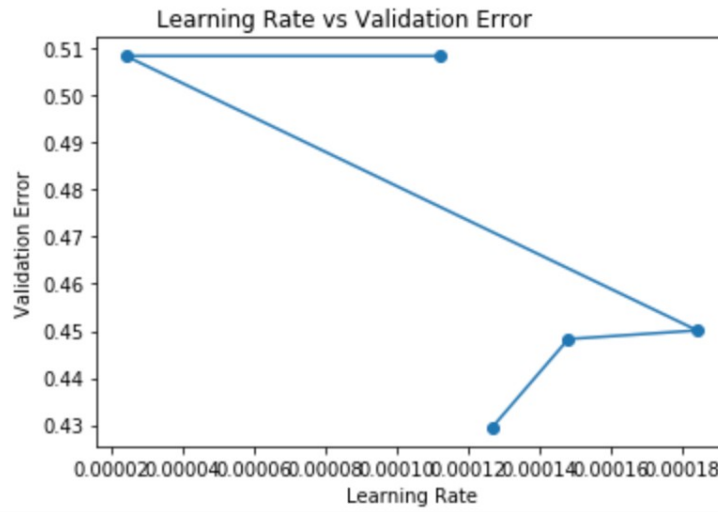


Figure 9: Learning Rate vs Validation Error (Method 1)

Test accuracy = 57.77777777777777 %.
Val List: [0.5084233355211298, 0.5084233355211298, 0.4501016273197388, 0.4482703367034948, 0.42947063776424066]
LR List: [0.00011220659808944273, 2.4089483225686756e-05, 0.0001844873851806272, 0.00014829773059012999, 0.00012688305173251063]
Best Validation Score: 0.42947063776424066

Figure 10: Other Results (Method 1)

Method 2: Zero weight initialization

Best Validation Score: 0.6277491176726115

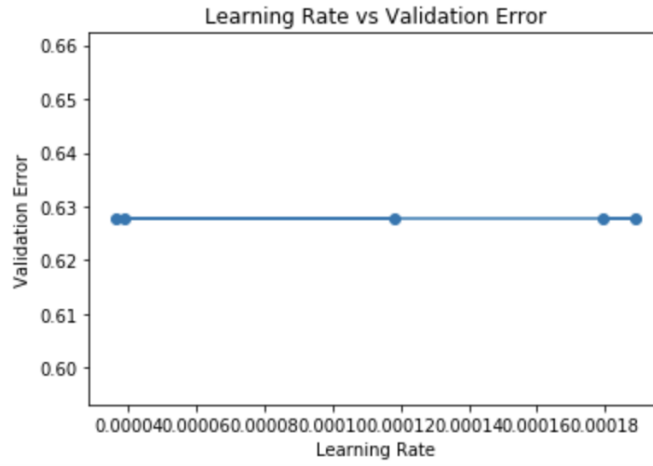


Figure 11: Learning Rate vs Validation Error (Method 2)

```
Test accuracy = 44.44444444444444 %.  
Val List: [0.6277491176726115, 0.6277491176726115, 0.6277491176726115, 0.6277491176726115, 0.6277491176726115]  
LR List: [0.0001793648770132244, 0.00018896752101655174, 3.6093696176431154e-05, 3.871468226154752e-05, 0.000118314  
76275157661]  
Best Validation Score: 0.6277491176726115
```

Figure 12: Other Results (Method 2)

Method 3: Xavier weight initialization

Best Validation Score: 0.12670178439978305

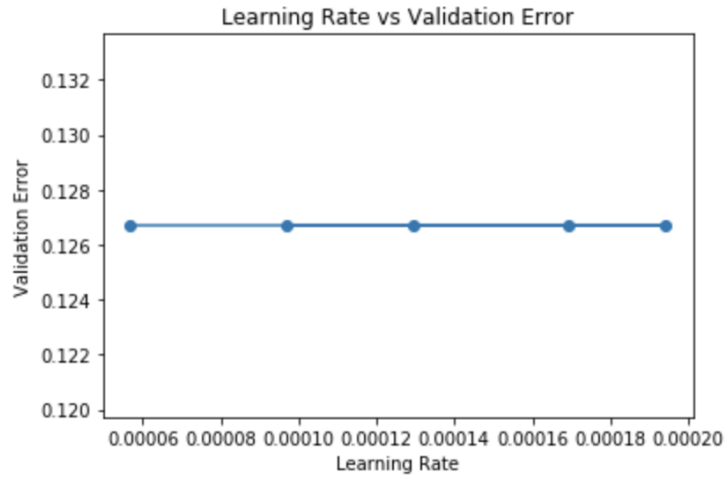


Figure 13: Learning Rate vs Validation Error (Method 3)

```
Test accuracy = 44.44444444444444 %.  
Val List: [0.12670178439978305, 0.12670178439978305, 0.12670178439978305, 0.12670178439978305, 0.12670178439978305]  
LR List: [5.6692424604767855e-05, 0.00019431403538870242, 9.68997344514569e-05, 0.00012957633364906279, 0.000169411  
0121895974]  
Best Validation Score: 0.12670178439978305
```

Figure 14: Other Results (Method 3)

c) INFERENCE: We saw that when we used momentum with the update rule, test accuracy was higher. The zero weight error has yielded us better accuracy than the Uniform weight initialization and Xavier initialization technique. Without the momentum the validation error was constant and also the test accuracy was low.

3 7.3

a) Iteration on 50 values for σ

```
import pandas as pd
import math
import numpy as np
from sklearn.svm import SVC
import statistics as stats
import matplotlib.pyplot as plt

# Module for training data set using RBF Kernel
def svmTrain(sigma, trainingData, trainingLabels):
    g = math.pow(2 * sigma, 1/2)
    clf = SVC(kernel='rbf', gamma=g)
    validationData, validationOutput, newTrainingData, newTrainingLabels = crossVal
    #print(newTrainingData)
    clf.fit(newTrainingData, newTrainingLabels)
    return svmValidate(clf, validationData, validationOutput), clf

# Module for normalizing training input values between 0 and 1
def normalizeDataSet(trainData):
    for i in range(0, len(trainData[0]) - 1):
        min1 = np.min(trainData[:, i])
        trainData[:, i] = trainData[:, i] - min1
        diff = np.max(trainData[:, i]) - np.min(trainData[:, i])
        trainData[:, i] = trainData[:, i] / diff
    return trainData

# Module for loading the data set
def prepareData(dataFrame):
    X = np.zeros((len(dataFrame), 2))
    Y = []
    X[:, 0] = dataFrame['height'].tolist()
    X[:, 1] = dataFrame['weight'].tolist()
    Y = dataFrame['gender'].tolist()
    Y[Y == -1] = 0
    return X, Y
```

```

# Module for validation using the best training weights
def svmValidate(clf, validationData, validationLabel):
    labels = []
    labels = clf.predict(validationData)
    print(labels)
    count = 0
    for i in range(0, len(labels)-1):
        if validationLabel[i] == labels[i]:
            count = count + 1
        else:
            continue
    return count/len(validationLabel)

# Module for measuring training accuracy using cross validation
def crossValidation(trainingData, trainingLabels, numFolds):
    foldSize = len(trainingData)//numFolds
    validationData = np.zeros((foldSize, 2))
    validationOutput = []
    newTrainingData = trainingData.copy()
    newTrainingLabels = trainingLabels.copy()
    for i in range(0, foldSize - 1):
        foldIndex = np.random.randint(0, len(newTrainingData))
        validationData[i, :] = trainingData[foldIndex, :]
        validationOutput.append(trainingLabels[foldIndex])
        newTrainingData = np.delete(newTrainingData, foldIndex, axis=0)
        newTrainingLabels.remove(trainingLabels[foldIndex])
    return validationData, validationOutput, newTrainingData, newTrainingLabels

def readDataFromCSV(fileName):
    return pd.read_csv(fileName)

# Main module: Entry Point of the code.
def main():
    trainFrame = readDataFromCSV('EX7data1.csv')
    trainingData, trainingLabels = prepareData(trainFrame)
    trainingData = normalizeDataSet(trainingData)
    validationFrame = readDataFromCSV('EX7data2.csv')
    validationData, validationLabels = prepareData(validationFrame)
    validationData = normalizeDataSet(validationData)

    trainAccuracy = []
    testAccuracy = []
    sigmaList = []
    trainAccuracyS = []
    testAccuracyS = []

```

```

sigmaListS = []

for i in range(50):
    sigma = np.random.randint(math.pow(10,-6),math.pow(10,6))
    sigmaList.append(sigma)
    ta, clf = svmTrain(sigma, trainingData, trainingLabels)
    trainAccuracy.append(ta)
    testAccuracy.append(svmValidate(clf, validationData, validationLabels))

for idx in np.argsort(sigmaList):
    sigmaListS.append(math.log(sigmaList[idx]))
    trainAccuracyS.append(trainAccuracy[idx])
    testAccuracyS.append(testAccuracy[idx])
plt.plot(sigmaListS, trainAccuracyS, 'red')
plt.plot(sigmaListS, testAccuracyS, 'blue')
plt.show()
if __name__ == '__main__':
    main()

```

b)

c)

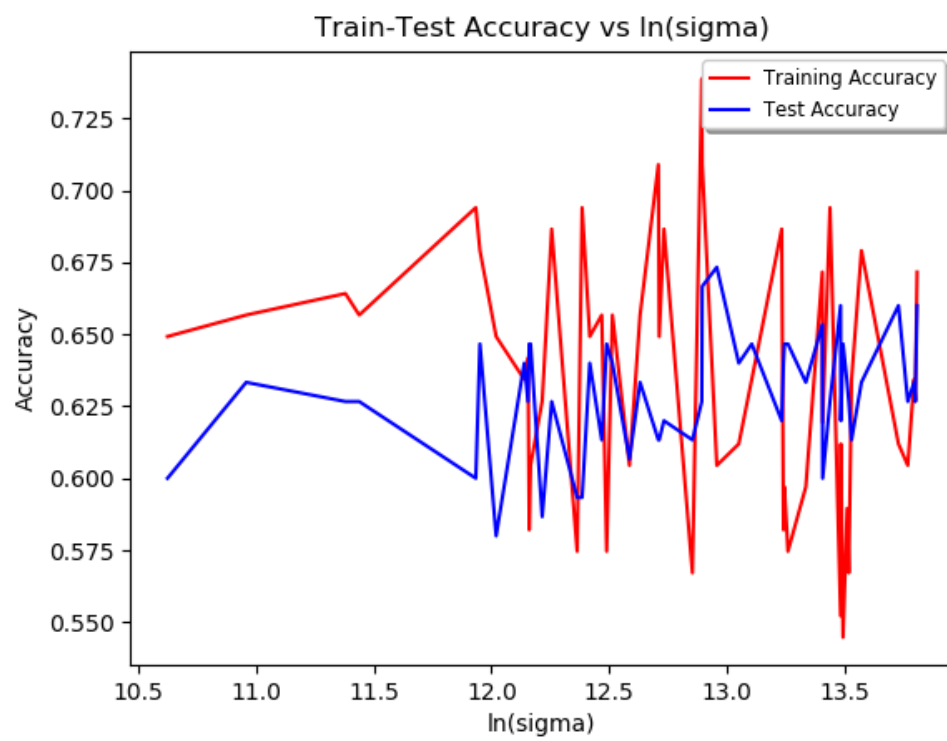


Figure 15: Plot of $\ln(\sigma)$ vs Training and Testing Accuracy

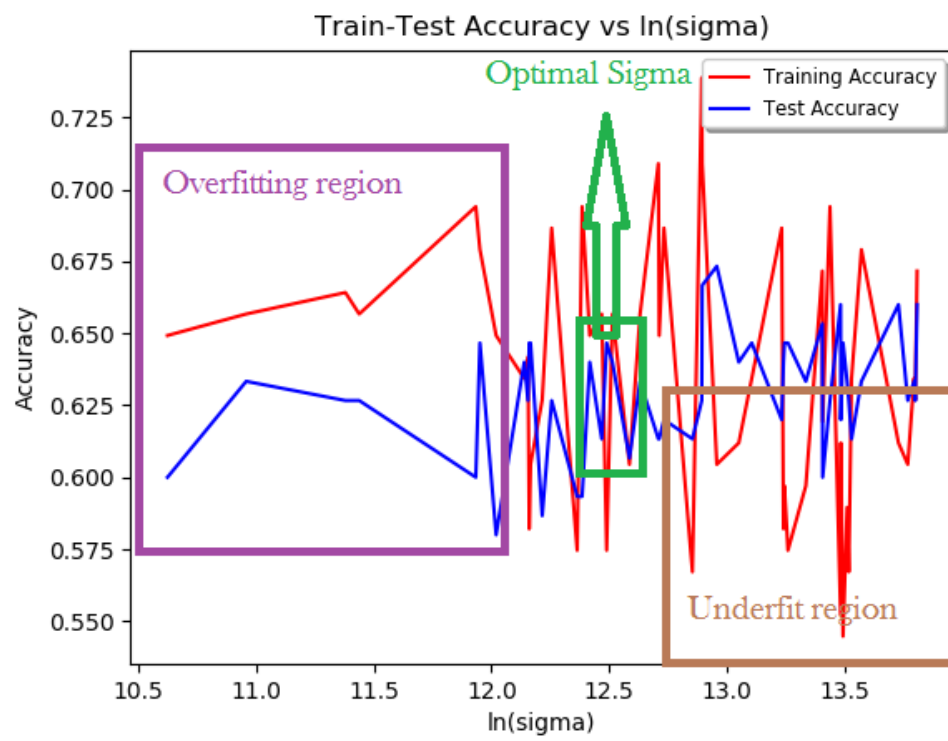


Figure 16: Overfitted, Underfitted and Optimal regions.