CS 178 HW 4

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1.1 Problem 1: Decision Trees

```
In [1]: import numpy as np
        import matplotlib.pyplot as plt
        import mltools as ml

        # 1 Decision Trees

        # 1a) Entropy of Y = 6/10log(10/6) + 4/10log(10/4)
        #       0.44218 + 0.52877 = 0.97095 bits

        # 1b) Information gain for each variable Xi.
        #   X1 =  0.97095 - (4/10(3/4log(4/3)+1/4log(4))
        #              + 6/10(1/2log(2) + 1/2log(2)))
        #      = 0.97095 - (0.32451 +0.6) = 0.04644 bits
        #   X2 = 0.97095 - (5/10(1/5log(5)+4/5log(5/4))
        #              + 5/10(6log6 + 0log0))
        #      = 0.97095 -  (0.36096 + 0) = 0.60999 bits
        #   X3 = 0.97095 - (3/10(2/3log(3/2)+1/3log(3)) + 7/10(4/7log(7/4)
        #              + 3/7log(7/3 )
        #      = 0.97095 - (0.27548 + 0.68965) = 0.00582
        #   X4 = 0.97095 - (3/10(1/3log(3)+2/3log(3/2))
        #              +7/10(5/7log(7/5)+2/7log(7/2)))
        #      = 0.97095 - (0.27548 + 0.60418) = 0.09129
        #   X5 = 0.97095 - (7/10(4/7log(7/4)+3/7log(7/3))
        #              +3/10(2/3log(3/2)+1/3log(3)))
        #      = 0.97095 - (0.68965 + 0.27548) = 0.00582

        # 1c)  Draw Complete Decision Tree
        #                              (X2)
        #                           /        \
        #                         0           1
        #                     (X1)           [Y=-1]
        #                  /      \
        #                 0        1
        #               (X4)       [Y=1]
        #             /         \
        #           0            1
        #       [Y=1]            [Y=-1]
```

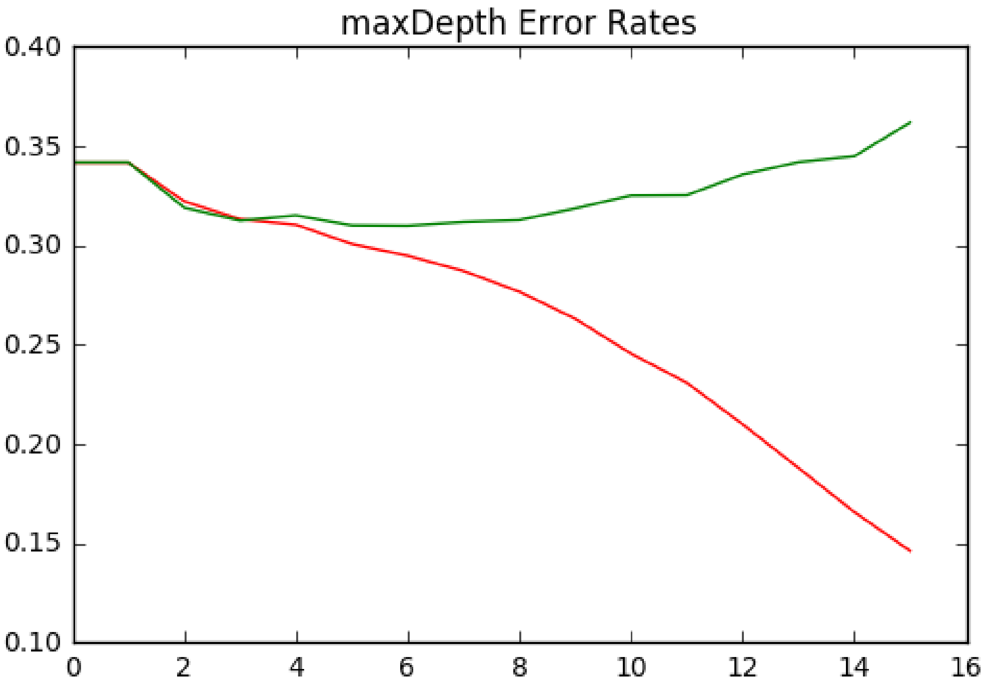
1.2 Problem 2: Decision Trees on Kaggle

```
In [2]: # 2 Decision Trees on Kaggle
        # Part A Load Data and Validation Set

        dataX = np.genfromtxt("X_train.txt",delimiter=None)
        dataY = np.genfromtxt("Y_train.txt",delimiter=None)

        # Take first 10,000 as training data.
        Xtr = dataX[0:10000,:]     # not sure if should do "0:2" or ":", plotclassi
        #print("2d = ",np.atleast_2d(Xtr).shape[1])
        Ytr = dataY[0:10000:]

        # Take second 10,000 as test/validation set.
        Xte = dataX[10000:20000,:]
        Yte = dataY[10000:20000:]

        # Part B Learn a decision tree classifier
        learnerTR = ml.dtree.treeClassify(Xtr,Ytr,maxDepth=50)

        mseTR = learnerTR.err(Xtr,Ytr)
        mseTE = learnerTR.err(Xte,Yte)

        print("maxDepth = 50 | Error of Training Data = "+str(mseTR)
            +" | Error of Test Data = "+str(mseTE))
```

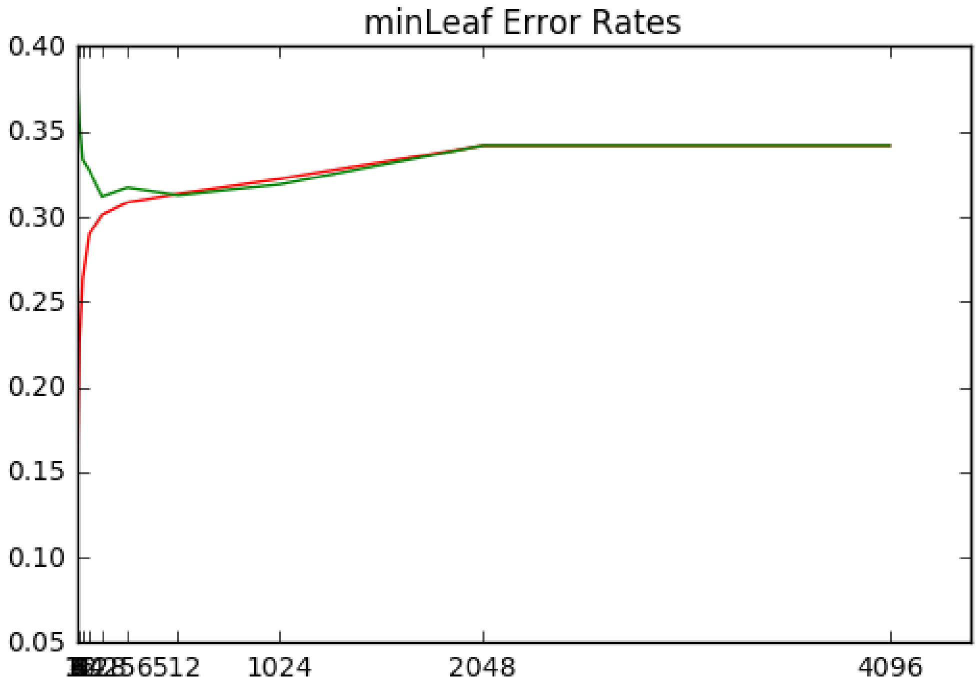
```
maxDepth = 50 | Error of Training Data = 0.0047 | Error of Test Data = 0.3779
```

```
In [3]: # Part C Test with Depths 0:15
        mseTRL = []
        mseTEL = []
        for i in range(0,16):
            learner2TR = ml.dtree.treeClassify(Xtr,Ytr,maxDepth=i)

            mseTR2 = learner2TR.err(Xtr,Ytr)
            mseTE2 = learner2TR.err(Xte,Yte)
            mseTRL.append(mseTR2)
            mseTEL.append(mseTE2)
            print("maxDepth = "+str(i)+ " | Error of Training Data = "
                  +str(mseTR2)+" | Error of Test Data = "+str(mseTE2))

        _,axis = plt.subplots()
        plt.title("maxDepth Error Rates")
        axis.plot(mseTRL, c='red')
        axis.plot(mseTEL, c='green')
        plt.show()

        # Complexity increases as depth increases. The most ideal depth is
        # a depth of 6 because it has the lowest test data error. Depth lower
        # than 6 is underfitting while depth over 6 is overfitting. MaxDepth = 6
        # is the optimal depth because it is right before the learner starts to
        # overfit.

        print("")
```

```
maxDepth = 0 | Error of Training Data = 0.3418 | Error of Test Data = 0.3419
maxDepth = 1 | Error of Training Data = 0.3418 | Error of Test Data = 0.3419
maxDepth = 2 | Error of Training Data = 0.3223 | Error of Test Data = 0.3191
maxDepth = 3 | Error of Training Data = 0.3133 | Error of Test Data = 0.3126
maxDepth = 4 | Error of Training Data = 0.3105 | Error of Test Data = 0.3152
maxDepth = 5 | Error of Training Data = 0.3008 | Error of Test Data = 0.3102
maxDepth = 6 | Error of Training Data = 0.2949 | Error of Test Data = 0.31
maxDepth = 7 | Error of Training Data = 0.2872 | Error of Test Data = 0.3119
maxDepth = 8 | Error of Training Data = 0.2768 | Error of Test Data = 0.3129
maxDepth = 9 | Error of Training Data = 0.2632 | Error of Test Data = 0.3187
maxDepth = 10 | Error of Training Data = 0.2456 | Error of Test Data = 0.3252
maxDepth = 11 | Error of Training Data = 0.2309 | Error of Test Data = 0.3254
maxDepth = 12 | Error of Training Data = 0.21 | Error of Test Data = 0.3358
maxDepth = 13 | Error of Training Data = 0.188 | Error of Test Data = 0.342
maxDepth = 14 | Error of Training Data = 0.1658 | Error of Test Data = 0.345
maxDepth = 15 | Error of Training Data = 0.1462 | Error of Test Data = 0.362
```



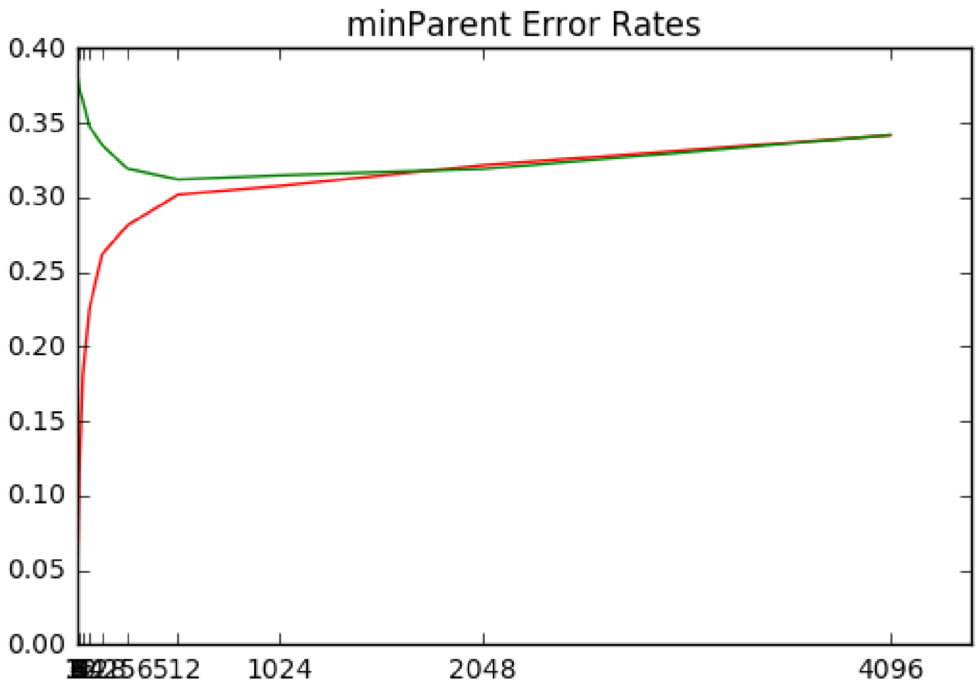
```
In [4]: # Part D Test with minLeaf 2^[2:12]
        mseTRL = []
        mseTEL = []
        for j in range(2,13):
            learnerTR = ml.dtree.treeClassify(Xtr,Ytr,maxDepth=50,minLeaf=2**j)
            mseTR2 = learnerTR.err(Xtr,Ytr)
            mseTE2 = learnerTR.err(Xte,Yte)
            mseTRL.append(mseTR2)
            mseTEL.append(mseTE2)
            print("minLeaf = "+str(2**j)+ " | Error of Training Data = "
                  +str(mseTR2)+" | Error of Test Data = "+str(mseTE2))

        _,axis = plt.subplots()
        plt.title("minLeaf Error Rates")
        axis.plot([4,8,16,32,64,128,256,512,1024,2048,4096],mseTRL, c='red')
        axis.plot([4,8,16,32,64,128,256,512,1024,2048,4096],mseTEL, c='green')
        axis.set_xticks([4,8,16,32,64,128,256,512,1024,2048,4096])
        plt.show()

        # Complexity decreases as the minLeaf increases because the training
        # data error continues to increase with higher minLeaf. The most ideal
        # minLeaf is 128 because thats where the test data error is the lowest.
        # minLeaf lower than 128 is overfitting the model while minLeaf higher
        # is underfitting.

        print("")

minLeaf = 4 | Error of Training Data = 0.0951 | Error of Test Data = 0.3815
minLeaf = 8 | Error of Training Data = 0.1691 | Error of Test Data = 0.3749
minLeaf = 16 | Error of Training Data = 0.2262 | Error of Test Data = 0.3549
minLeaf = 32 | Error of Training Data = 0.2637 | Error of Test Data = 0.3335
minLeaf = 64 | Error of Training Data = 0.2899 | Error of Test Data = 0.3274
minLeaf = 128 | Error of Training Data = 0.3012 | Error of Test Data = 0.3119
minLeaf = 256 | Error of Training Data = 0.3085 | Error of Test Data = 0.3172
minLeaf = 512 | Error of Training Data = 0.3135 | Error of Test Data = 0.3127
minLeaf = 1024 | Error of Training Data = 0.3223 | Error of Test Data = 0.3191
minLeaf = 2048 | Error of Training Data = 0.3418 | Error of Test Data = 0.3419
minLeaf = 4096 | Error of Training Data = 0.3418 | Error of Test Data = 0.3419
```



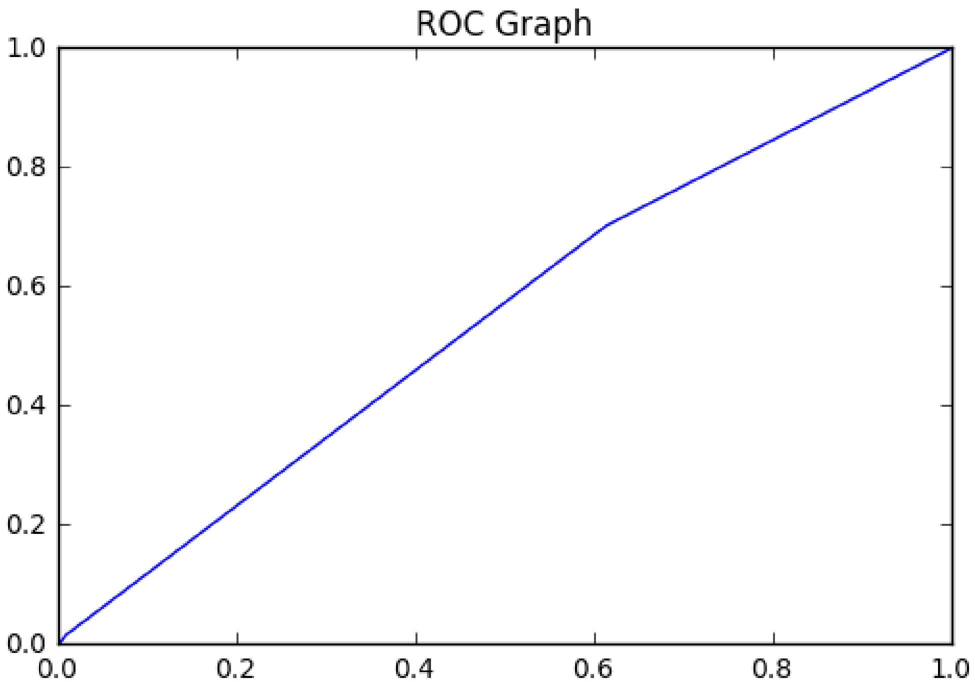
```
In [5]: # Part E Test with minParent 2^[2:12]
        mseTRL = []
        mseTEL = []
        for j in range(2,13):
```

```
        learnerTR = ml.dtree.treeClassify(Xtr,Ytr,maxDepth=50,minParent=2**j)
        mseTR2 = learnerTR.err(Xtr,Ytr)
        mseTE2 = learnerTR.err(Xte,Yte)
        mseTRL.append(mseTR2)
        mseTEL.append(mseTE2)
        print("minParent = "+str(2**j)+ " | Error of Training Data = "
              +str(mseTR2)+" | Error of Test Data = "+str(mseTE2))
    _,axis = plt.subplots()
    plt.title("minParent Error Rates")
    axis.plot([4,8,16,32,64,128,256,512,1024,2048,4096],mseTRL, c='red')
    axis.plot([4,8,16,32,64,128,256,512,1024,2048,4096],mseTEL, c='green')
    axis.set_xticks([4,8,16,32,64,128,256,512,1024,2048,4096])
    plt.show()
```

```
minParent = 4 | Error of Training Data = 0.0235 | Error of Test Data = 0.3749
minParent = 8 | Error of Training Data = 0.0641 | Error of Test Data = 0.38
minParent = 16 | Error of Training Data = 0.1203 | Error of Test Data = 0.3721
minParent = 32 | Error of Training Data = 0.1808 | Error of Test Data = 0.3653
minParent = 64 | Error of Training Data = 0.2248 | Error of Test Data = 0.348
minParent = 128 | Error of Training Data = 0.2618 | Error of Test Data = 0.3354
minParent = 256 | Error of Training Data = 0.2814 | Error of Test Data = 0.3194
minParent = 512 | Error of Training Data = 0.302 | Error of Test Data = 0.3121
minParent = 1024 | Error of Training Data = 0.3078 | Error of Test Data = 0.3149
minParent = 2048 | Error of Training Data = 0.3218 | Error of Test Data = 0.3192
minParent = 4096 | Error of Training Data = 0.3418 | Error of Test Data = 0.3419
```



```
In [6]: # Part F ROC Curve and AUC for maxDepth=50
        learnerTR = ml.dtree.treeClassify(Xtr,Ytr,maxDepth=50)
        ROC = learnerTR.roc(Xte,Yte)
        plt.plot(ROC[0],ROC[1])
        plt.title("ROC Graph")
        plt.show()
        AUC = learnerTR.auc(Xte,Yte)
        print("AUC for maxDepth=50 = "+str(AUC))
        print("")
```



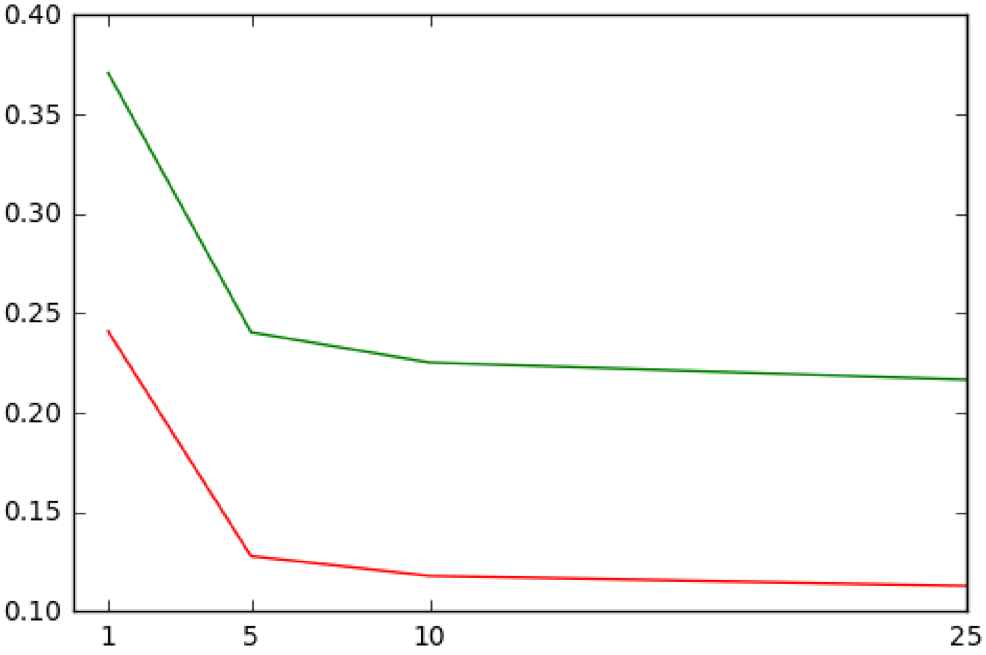
```
AUC for maxDepth=50 = 0.583537925638
```

```
In [7]: # Part G ROC Curve and AUC for best settings.
        # maxdepth=8 minLeaf=256 minParent512
        nXte = np.genfromtxt("X_test.txt",delimiter=None)
        learnerTR = ml.dtree.treeClassify(Xtr,Ytr,maxDepth=8,minLeaf=256
                                          ,minParent=512)
        Ypred = learnerTR.predictSoft(nXte)
        np.savetxt('Yhat_dtree.txt',
        np.vstack( (np.arange(len(Ypred)) , Ypred[:,1]) ).T,
        '%d, %.2f',header='ID,Prob1',comments='',delimiter=',');
```

1.3 Problem 3: Random Forests

```
In [8]: # Problem 3: Random Forests

        # Part A
        ensemble = [0]*25
        Ytrhat = np.zeros((np.size(Ytr),25))
        Ytehat = np.zeros((np.size(Yte),25))

        # Evaluate for up to 25 learners.
        for i in range(25):
            Xb,Yb = ml.bootstrapData(Xtr,Ytr)
            ensemble[i] = ml.dtree.treeClassify(Xb,Yb,maxDepth=15
                        ,minLeaf=4,nFeatures=60)
            Ytrhat[:,i] = ensemble[i].predict(Xtr)
            Ytehat[:,i] = ensemble[i].predict(Xte)

        # Write down mseTR and mseTE for learners [1,5,10,25]
        mseTR = []
        mseTE = []
        for index, value in enumerate([1,5,10,25]):
            mseTR.append(np.mean( (Ytr-np.mean(Ytrhat[:,0:value],1))**2 ))
            mseTE.append(np.mean( (Yte-np.mean(Ytehat[:,0:value],1))**2 ))
            print(str(value)+" Ensemble Members: mseTR = "
                  +str(mseTR[index])+" | mseTE = "+str(mseTE[index]))

        _,axis = plt.subplots()

        axis.plot([1,5,10,25],mseTR, c='red')
        axis.plot([1,5,10,25],mseTE, c='green')
        axis.set_xticks([1,5,10,25])
        plt.show()
```

```
1 Ensemble Members: mseTR = 0.2409 | mseTE = 0.3709
5 Ensemble Members: mseTR = 0.127908 | mseTE = 0.240512
10 Ensemble Members: mseTR = 0.11798 | mseTE = 0.225298
25 Ensemble Members: mseTR = 0.11296304 | mseTE = 0.21663328
```



```
In [9]: # Part B
        ensemble2 = [0]*25
        Xte = np.genfromtxt("X_test.txt",delimiter=None)
        Ypred2 = np.zeros((np.size(Xte,0),1))
        for i in range(25):
            Xb,Yb = ml.bootstrapData(Xtr,Ytr)
            ensemble2[i] = ml.dtree.treeClassify(Xb,Yb,maxDepth=8
                    ,minLeaf=256,nFeatures=60,minParent=512)
            Ypred2 = Ypred2 + ensemble2[i].predictSoft(Xte)
        Ypred2 = Ypred2/25
        print("AUC after 25 learners = " + str(ensemble2[24].auc(Xb,Yb)))
        np.savetxt('Ypred2.txt',
        np.vstack( (np.arange(len(Ypred2)) , Ypred2[:,1]) ).T,
        '%d, %.2f',header='ID,Prob1',comments='',delimiter=',');
```

```
AUC after 25 learners = 0.687753023516
```