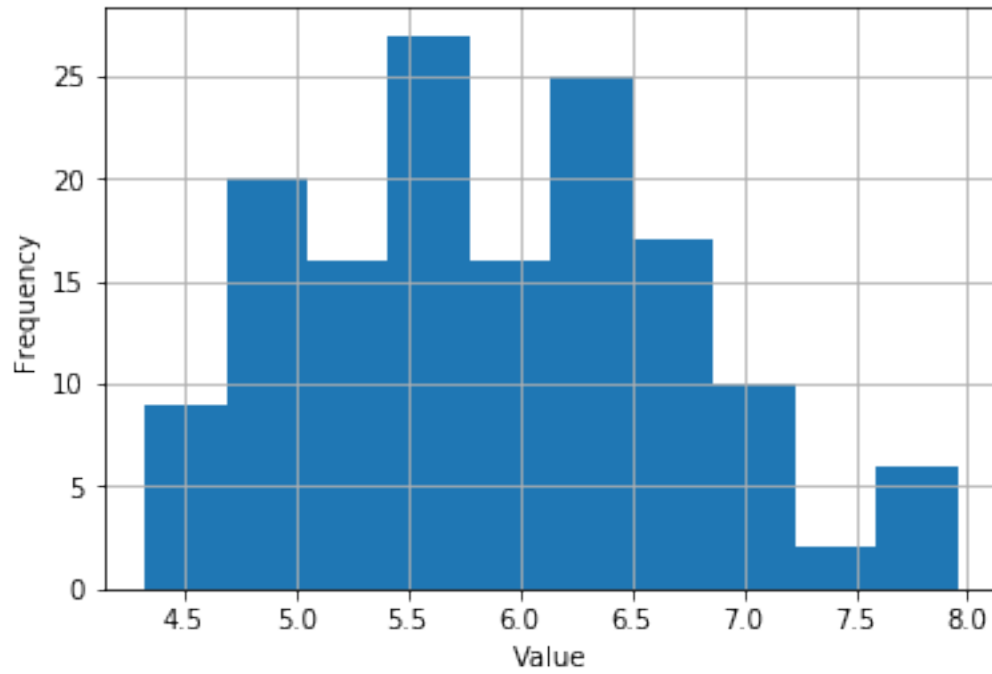


hw1

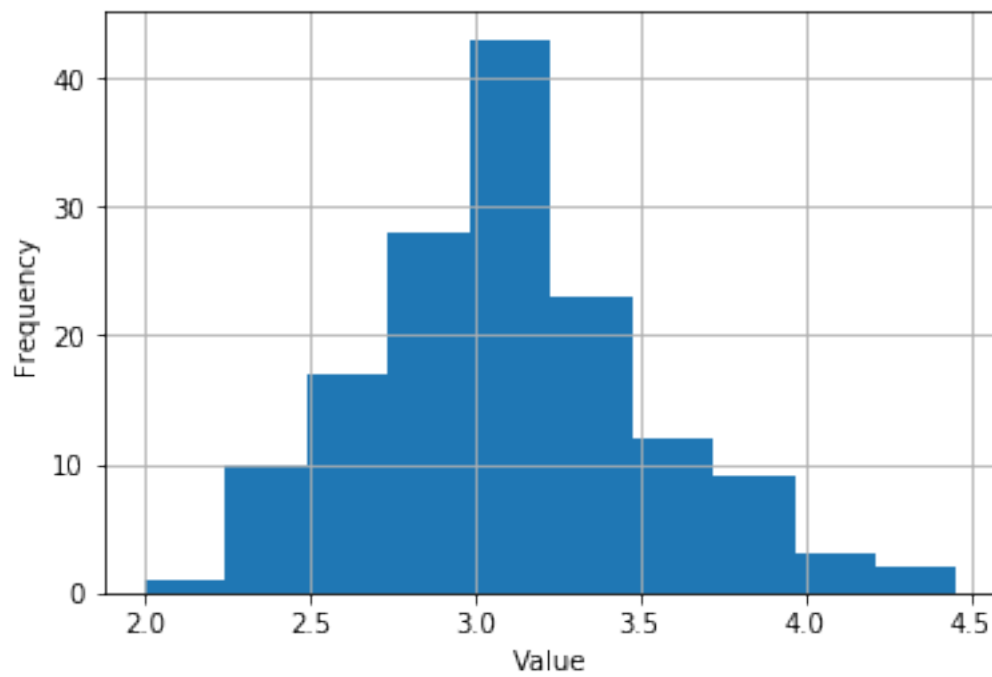
April 19, 2018

Problem 1 : Python and Data Exploration

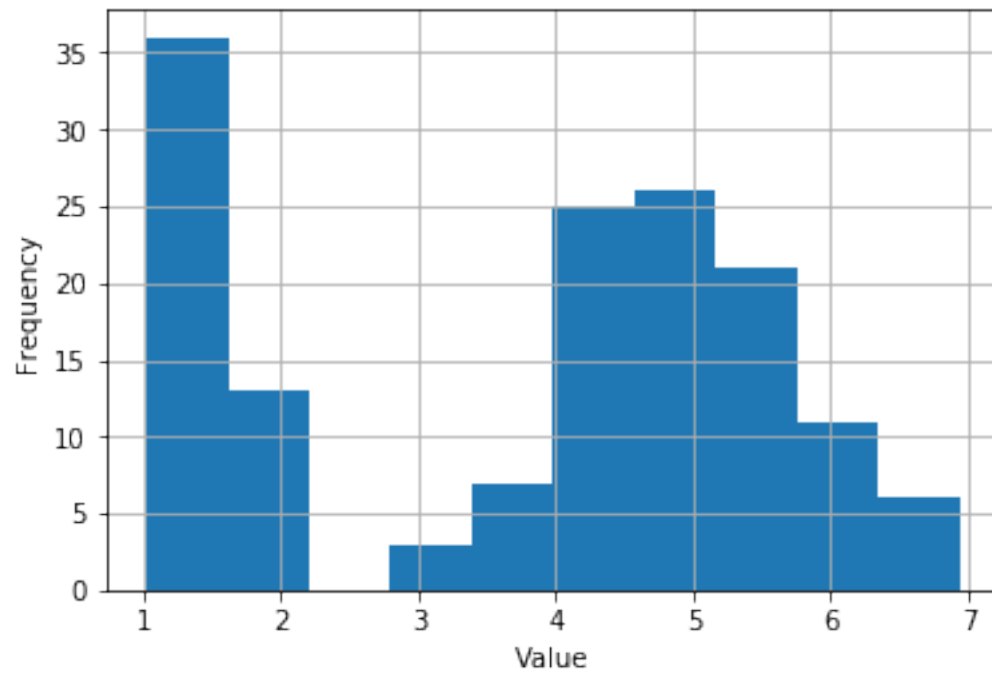
```
In [3]: import numpy as np
import matplotlib.pyplot as plt
import mltools as ml
np.random.seed(0)
if __name__ == "__main__":
    iris=np.genfromtxt("data/iris.txt",delimiter=None)
    Y=iris[:,-1]
    X=iris[:,0:-1]
    numDataPoints=X.shape[0]
    numFeatures=X.shape[1]
    count=0
    while (count<numFeatures):
        x=X[:,count] # get count'th column
        plt.hist(x)
        plt.xlabel("Value")
        plt.ylabel("Frequency")
        plt.grid(True)
        plt.show()
        mean=np.mean(x)
        std=np.std(x)
        print('Mean: ',mean,' Standard Deviation: ',std)
        count+=1
```



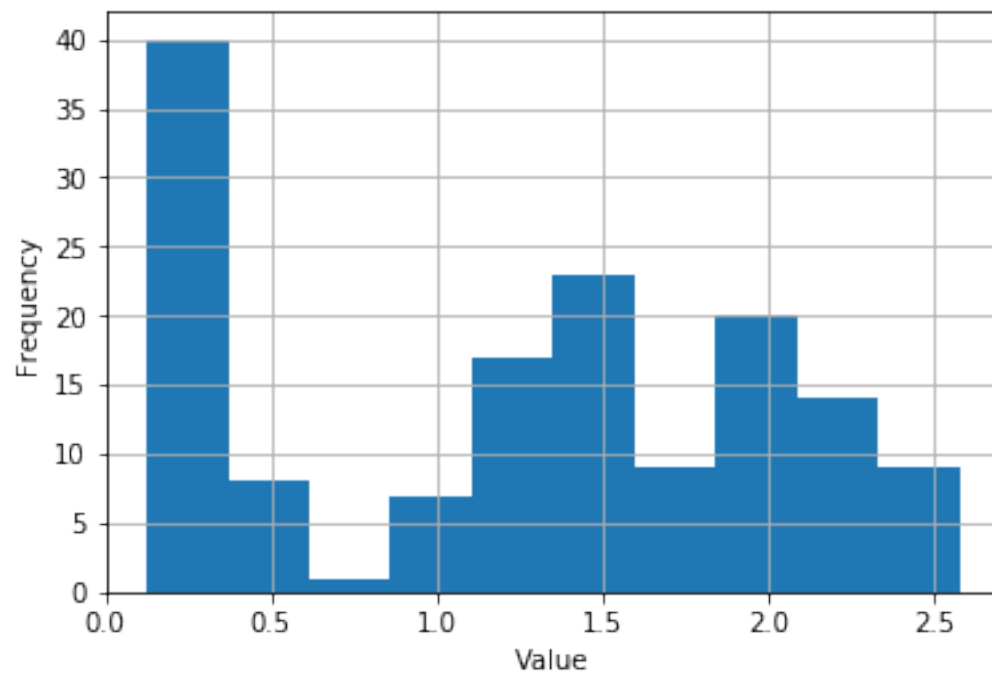
Mean: 5.900103764189188 Standard Deviation: 0.833402066774894



Mean: 3.098930916891892 Standard Deviation: 0.43629183800107685



Mean: 3.8195548405405404 Standard Deviation: 1.7540571093439352

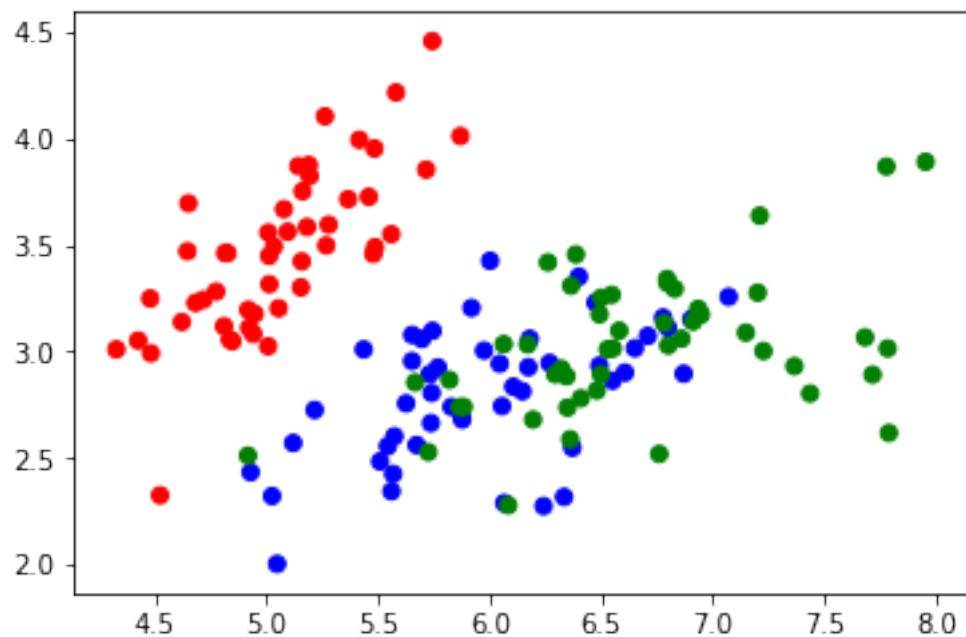


Mean: 1.2525554845945945 Standard Deviation: 0.7587724570263247

```
In [4]: #Assign colors to classes
        colors=[]
        for y in Y:
            if y==0:
                colors.append('r');
            elif y==1:
                colors.append('b');
            else:
                colors.append('g');
```

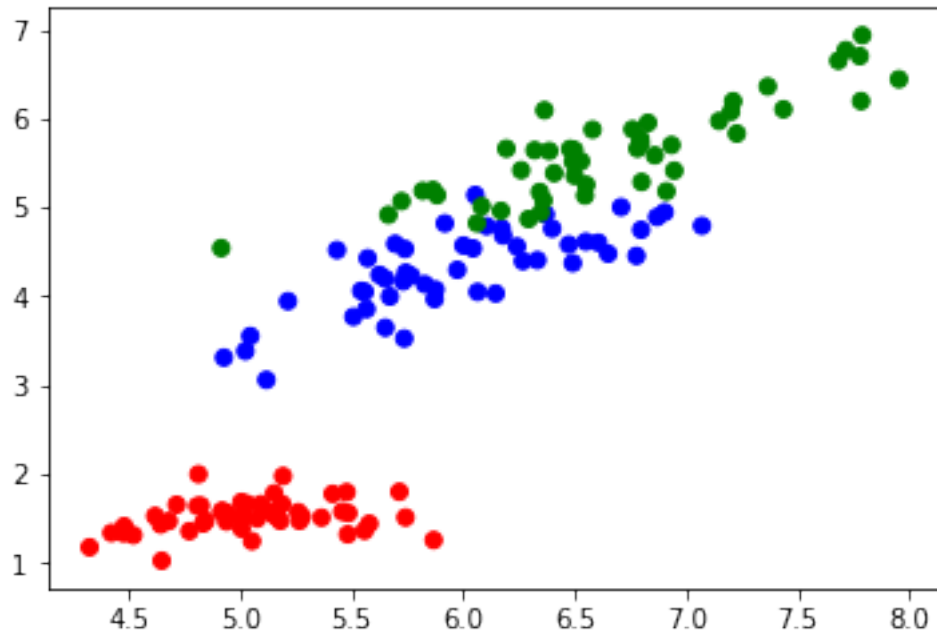
```
In [5]: #Pairwise features scatter plot
        #Different colors for different classes
        f1=X[:,0]
        f2=X[:,1]
        plt.scatter(f1,f2,c=colors)
```

Out[5]: <matplotlib.collections.PathCollection at 0x1066d1208>



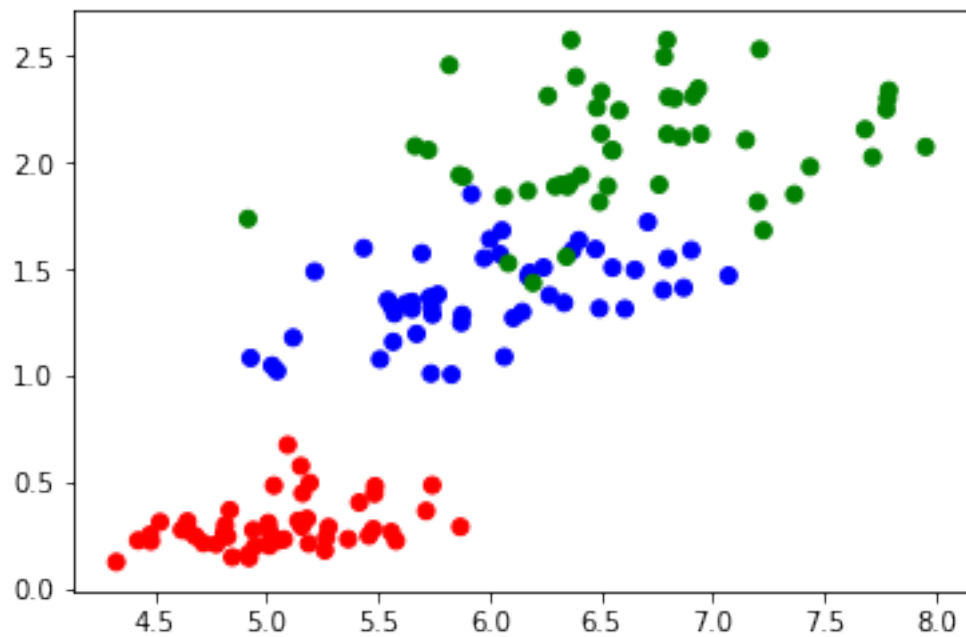
```
In [6]: f1=X[:,0]
        f3=X[:,2]
        plt.scatter(f1,f3,c=colors)
```

Out[6]: <matplotlib.collections.PathCollection at 0x106736198>



```
In [7]: f1=X[:,0]
        f4=X[:,3]
        plt.scatter(f1,f4,c=colors)
```

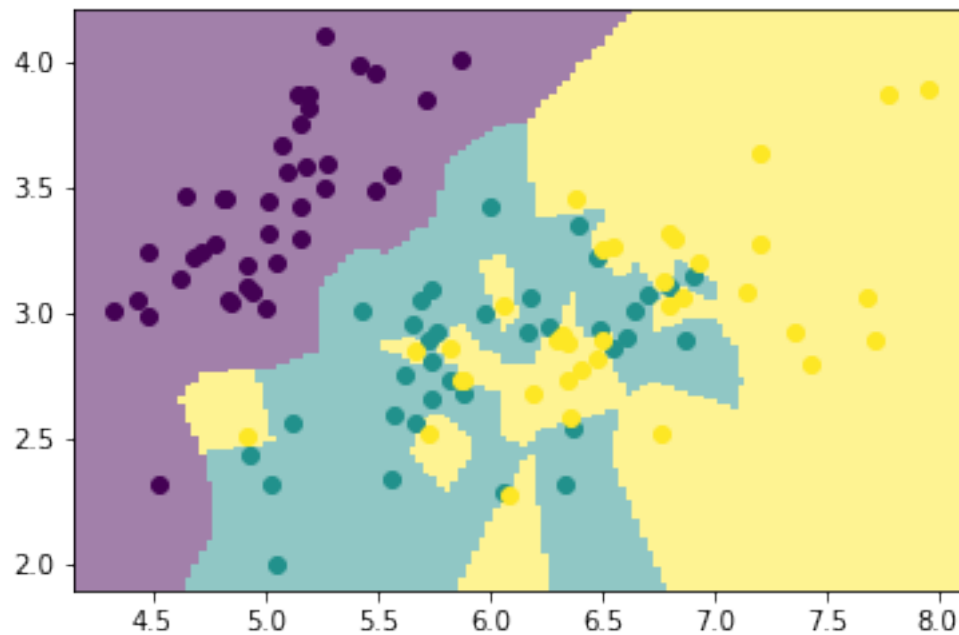
Out[7]: <matplotlib.collections.PathCollection at 0x106836cc0>



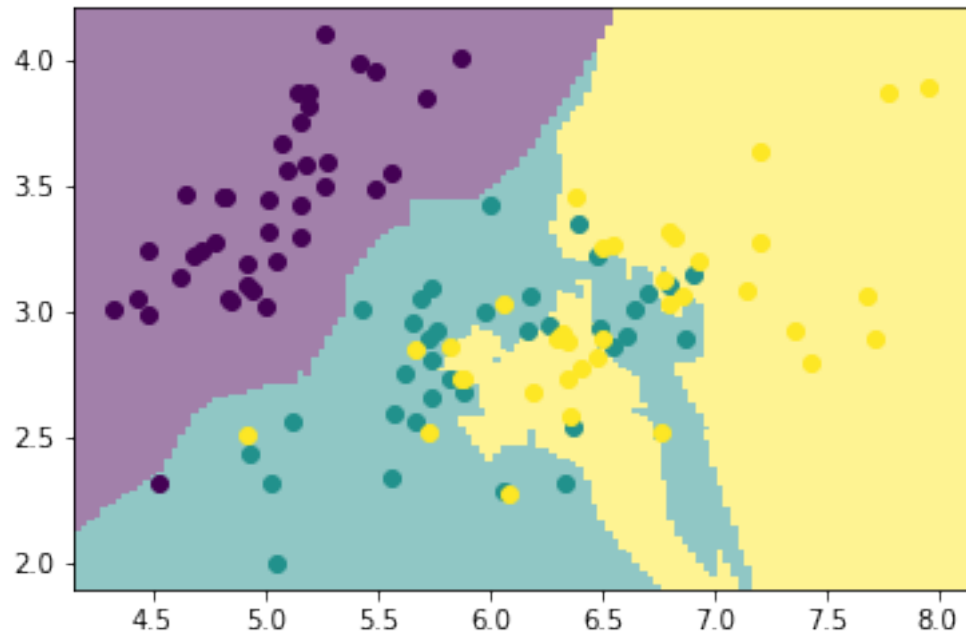
Problem 2: KNN Predictions

```
In [8]: X,Y = ml.shuffleData(X,Y);  
Xtr,Xva,Ytr,Yva = ml.splitData(X[:,0:2],Y, 0.75);
```

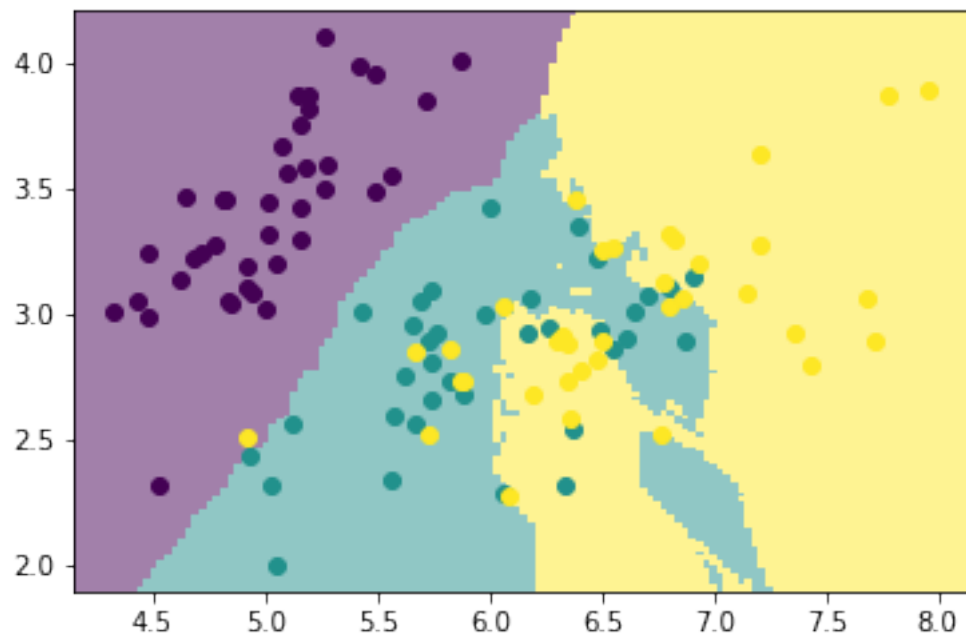
```
In [9]: knn = ml.knn.knnClassify()  
knn.train(Xtr, Ytr, 1)  
YvaHat = knn.predict(Xva)  
ml.plotClassify2D( knn, Xtr, Ytr );
```



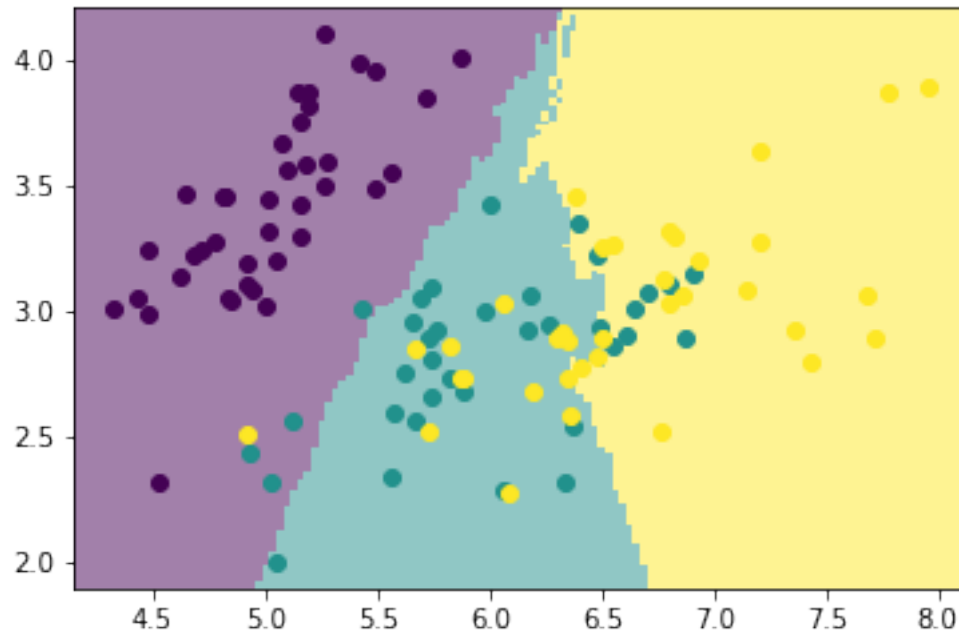
```
In [10]: knn = ml.knn.knnClassify()  
knn.train(Xtr, Ytr, 5)  
YvaHat = knn.predict(Xva)  
ml.plotClassify2D( knn, Xtr, Ytr );
```



```
In [11]: knn = ml.knn.knnClassify()
knn.train(Xtr, Ytr, 10)
YvaHat = knn.predict(Xva)
ml.plotClassify2D( knn, Xtr, Ytr );
```



```
In [12]: knn = ml.knn.knnClassify()
knn.train(Xtr, Ytr, 50)
YvaHat = knn.predict(Xva)
ml.plotClassify2D( knn, Xtr, Ytr );
```

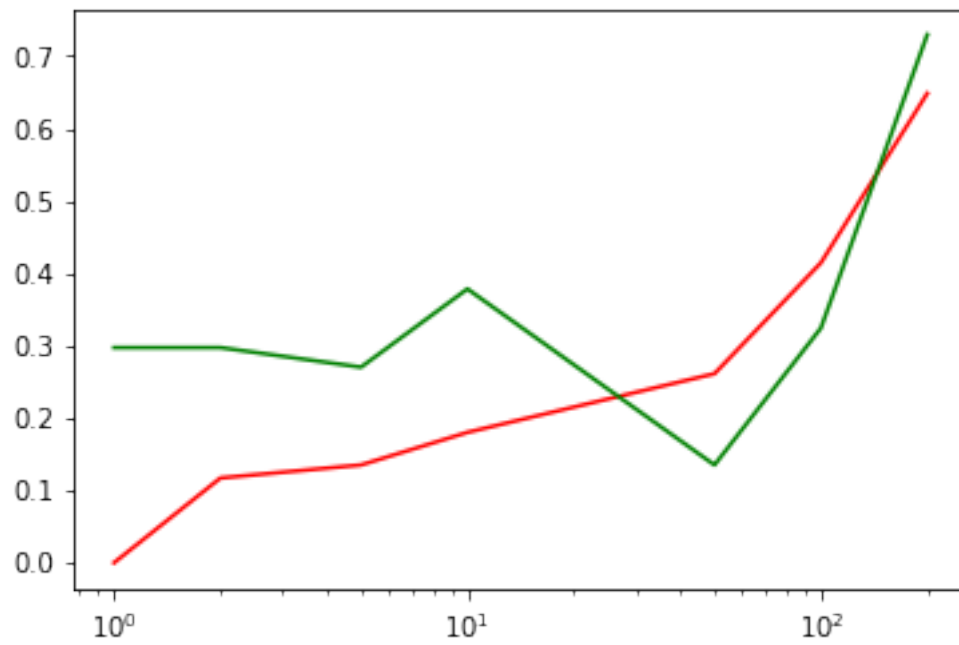


```
In [13]: K=[1,2,5,10,50,100,200];
errTrain=[]
errVal=[]
for k in K:
    learner1=ml.knn.knnClassify()
    learner1.train(Xtr, Ytr, k)
    Yhat = learner1.predict(Xtr)
    differenceCounter=0
    for t in range(0,len(Yhat)):
        if Yhat[t]!=Ytr[t]:
            differenceCounter=differenceCounter+1
    errTrain.append(differenceCounter/len(Yhat))
    Yval=learner1.predict(Xva)
    differenceCounter=0
    for t in range(0,len(Yval)):
        if(Yval[t]!=Yva[t]):
            differenceCounter=differenceCounter+1
    errVal.append(differenceCounter/len(Yval))

plt.semilogx(K,errTrain,'r')
```



```
plt.semilogx(K,errVal,'g')  
plt.show()
```



Value of K I would recommend is 50, since training error is minimum at this point.

Problem 3:

a)

$$P(x_1=1 | y=1) = 3/4$$

$$P(x_1=1 | y=-1) = 1/2$$

$$P(x_1=0 | y=1) = 1/4$$

$$P(x_1=0 | y=-1) = 1/2$$

$$P(x_2=1 | y=1) = 0$$

$$P(x_2=1 | y=-1) = 5/6$$

$$P(x_2=0 | y=1) = 4/4 = 1$$

$$P(x_2=0 | y=-1) = 1/6$$

$$P(x_3=1 | y=1) = 3/4$$

$$P(x_3=1 | y=-1) = 4/6$$

$$P(x_3=0 | y=1) = 1/4$$

$$P(x_3=0 | y=-1) = 2/6$$

$$P(x_4=1 | y=1) = 2/4$$

$$P(x_4=1 | y=-1) = 5/6$$

$$P(x_4=0 | y=1) = 2/4$$

$$P(x_4=0 | y=-1) = 1/6$$

$$P(x_5=1 | y=1) = 1/4$$

$$P(x_5=1 | y=-1) = 2/6$$

$$P(x_5=0 | y=1) = 3/4$$

$$P(x_5=0 | y=-1) = 4/6$$

b)

$$X = (0 \ 0 \ 0 \ 0 \ 0)$$

$$\text{Naïve Bayesian rule: } P(y|X) = P(x_1|y) * P(x_2|y) * P(x_3|y) * P(x_4|y) * P(x_5|y) * P(y)$$

For $y=1$,

$$\begin{aligned} P(y=1 | X = (0 \ 0 \ 0 \ 0 \ 0)) &= (1/4) * 1 * (1/4) * (1/2) * (3/4) * (4/10) \\ &= 0.009375 \end{aligned}$$

$$\begin{aligned} P(y=-1 | X = (0 \ 0 \ 0 \ 0 \ 0)) &= (1/2) * (1/6) * (2/6) * (1/6) * (4/6) * (6/10) \\ &= 0.001851 \end{aligned}$$

Class predicted for $X = (0 \ 0 \ 0 \ 0 \ 0)$ is $Y=1$.

$$X = (1 \ 1 \ 0 \ 1 \ 0)$$

For $y=1$,

$$\begin{aligned} P(y=1 | X = (1 \ 1 \ 0 \ 1 \ 0)) &= (3/4) * (0) * \dots \\ &= 0 \end{aligned}$$

For $y=-1$,

$$P(y=-1 | X = (1 \ 1 \ 0 \ 1 \ 0)) = (1/2) * (5/6) * (1/3) * (5/6) * (4/6) * (6/10) \\ = 0.04629$$

Class predicted for $X = (1 \ 1 \ 0 \ 1 \ 0)$ is $Y = -1$

c)

$$P(y=1 | x=11010) = P(x=11010 | y=1) * P(y=1) / P(x=11010) \\ = 0$$

d)

We should not use a Joint Bayes classifier, in contrast to Naïve Bayes classifier, because in Joint Bayes classifier, we shall have 5 features, each having 2 possible values, hence, $2^5=32$ independent probabilities to estimate classification probability. Whereas in Naïve Bayes classifier, we have 4 and 6 data points. For both the cases, we have only 10 observations and thus, Bayes classifier using Joint probability would be uncertain to generalize well with new data.

e) There is no need to re-train the model, as in Naïve Bayes classifier, classification is done based on each feature individually, and the features are independent of each other.