Assignment 1 - CS284A

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In [88]:
```
import numpy as np
import matplotlib.pyplot as plt
```

Iris data representsflowers classified by type of iris flower. Iris classes include:

- Setosa
- Versicolor
- Virginica

Additional continuous data is included that can be used to predict the class:

- Sepal Length (cm): The length of the sepal.
- Sepal Width (cm): The width of the sepal.
- Petal Length (cm): The length of the petal.
- Petal Width (cm): The width of the petal.

In [89]:
```
# load the data
iris = np.genfromtxt("data/iris.txt",delimiter=None)
```

In [90]:
```
# split data into Iris class and predictor variables
Y = iris[:, -1]
X = iris[:,0:-1]
```

Flower class labels have been converted to numeric:

In [91]:
```
# Y
```

Predictive variables are in unlabelled columns:

In [92]:
```
# X
```

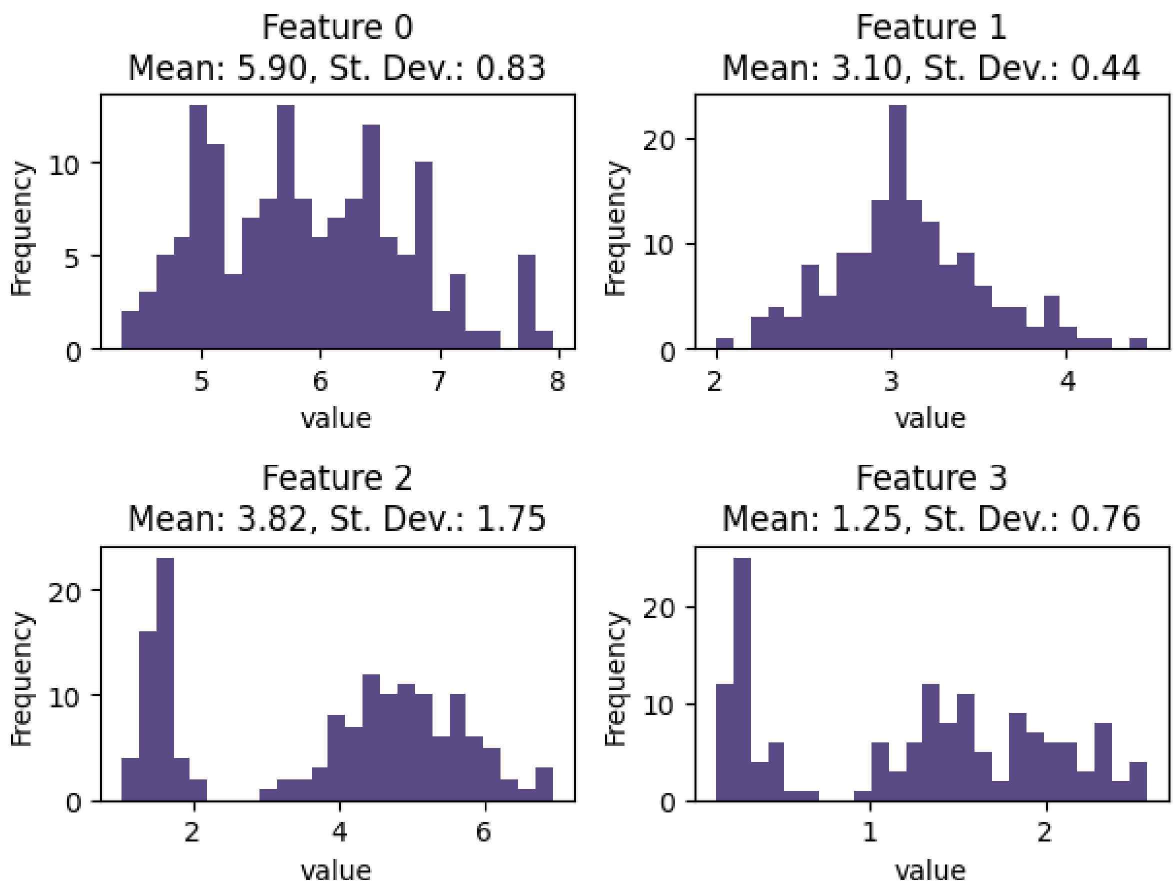
There are 148 data points with 4 features.

In [93]:
```
X.shape
```

Out[93]:
```
(148, 4)
```

In [94]:
```
for i in range(X.shape[1]):
    plt.subplot(2,2,i+1)
    plt.hist(X[:,i], bins=25, color='#5E4B8A')
    mean = np.mean(X[:, i])
```

```
    std = np.std(X[:, i])

    plt.title(f"Feature {i}\nMean: {mean:.2f}, St. Dev.: {std:.2f}", fontsiz
    plt.xlabel('value')
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```



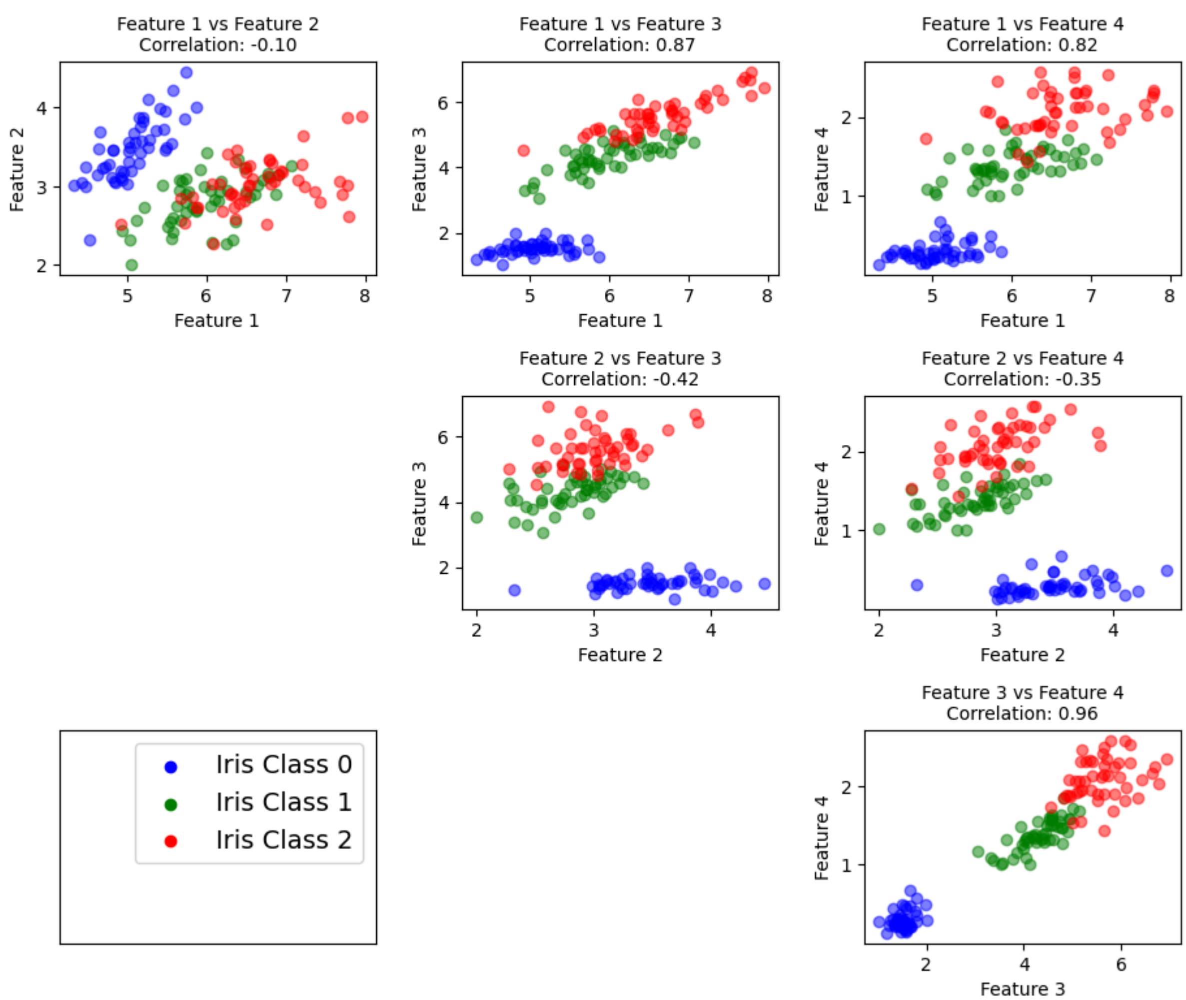
From these plots we see that the first 2 features (Feature 0 and Feature 1 in the charts) have fairly normal distributions.

However the next 2 features (Feature 2 and 3) are bimodal, with gaps in the middle of the distributions.

There are no significant outliers.

In [95]:
```
feature_names = ['Feature 1', 'Feature 2', 'Feature 3', 'Feature 4']
colors = {0: 'blue', 1: 'green', 2: 'red'}

plt.figure(figsize=(12, 10))

for i in range(X.shape[1]):
    for j in range(X.shape[1]):
        if i < j:
            plt.subplot(4, 4, i * 4 + j + 1)
```

```
            for class_label, color in colors.items():
                plt.scatter(X[Y == class_label, i], X[Y == class_label, j],
                            color=color, alpha=0.5, label=f'Class {class_lab

            correlation = np.corrcoef(X[:, i], X[:, j])[0, 1]

            plt.title(f'{feature_names[i]} vs {feature_names[j]}\nCorrelatic
            plt.xlabel(feature_names[i])
            plt.ylabel(feature_names[j])

# Hacky way to show the legend once for all plots
plt.subplot(4,4,10)
for class_label, color in colors.items():
    plt.scatter([], [], color=color, label=f'Iris Class {class_label}')
plt.xticks([])
plt.yticks([])
plt.legend(fontsize=14)

plt.tight_layout()
plt.show()
```



Scatterplots show significant clustering by Iris flower class.

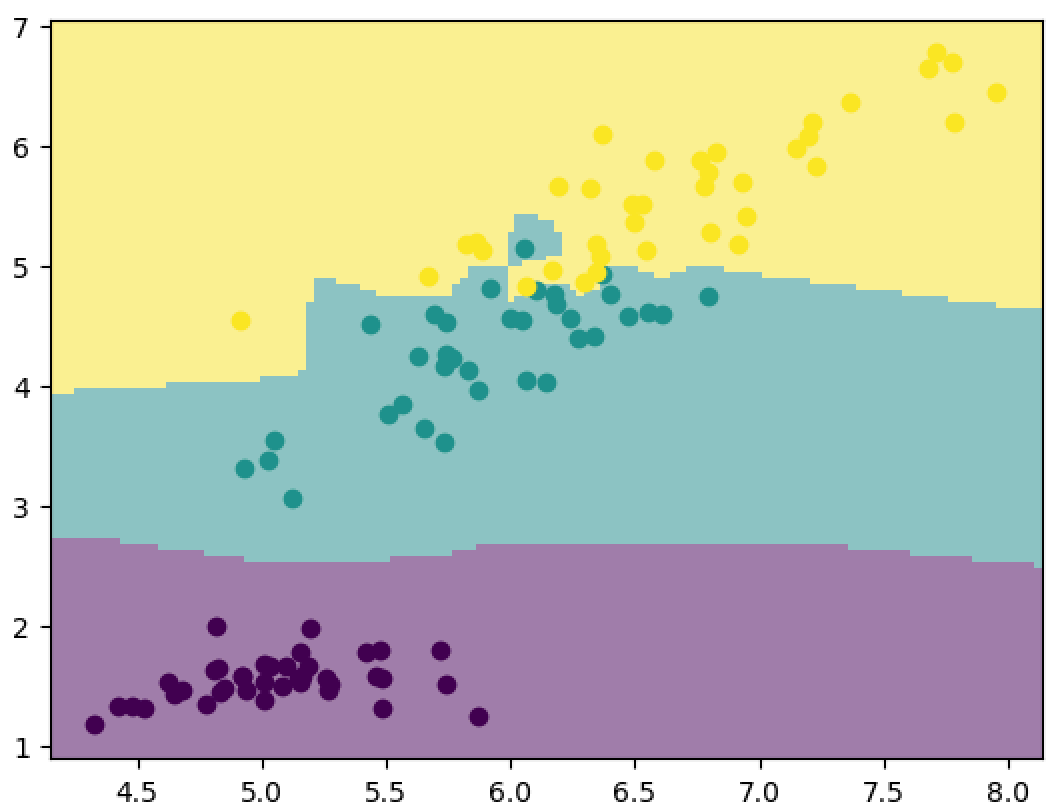
- Features 1, 3, 4 are highly correlated, and also appear to be predictive of Iris class

- Feature 2 combines with features 3 and 4 to create clear clusters of Iris class
- Iris class 0 has very clear cluster, separate from other classes
    - Class 2 and 3 are also clustered, but have less distinct boundary

KNN Clustering Problem

In [96]:
```
import mltools as ml

# reload data to make notebook stateless
Y = iris[:, -1]
X = iris[:,0:-1]

# shuffle data before splitting into train and test
np.random.seed(43)
X,Y = ml.shuffleData(X,Y)
X_small = X[:, [0,2]]
Xtr,Xva,Ytr,Yva = ml.splitData(X_small,Y, 0.75)
```

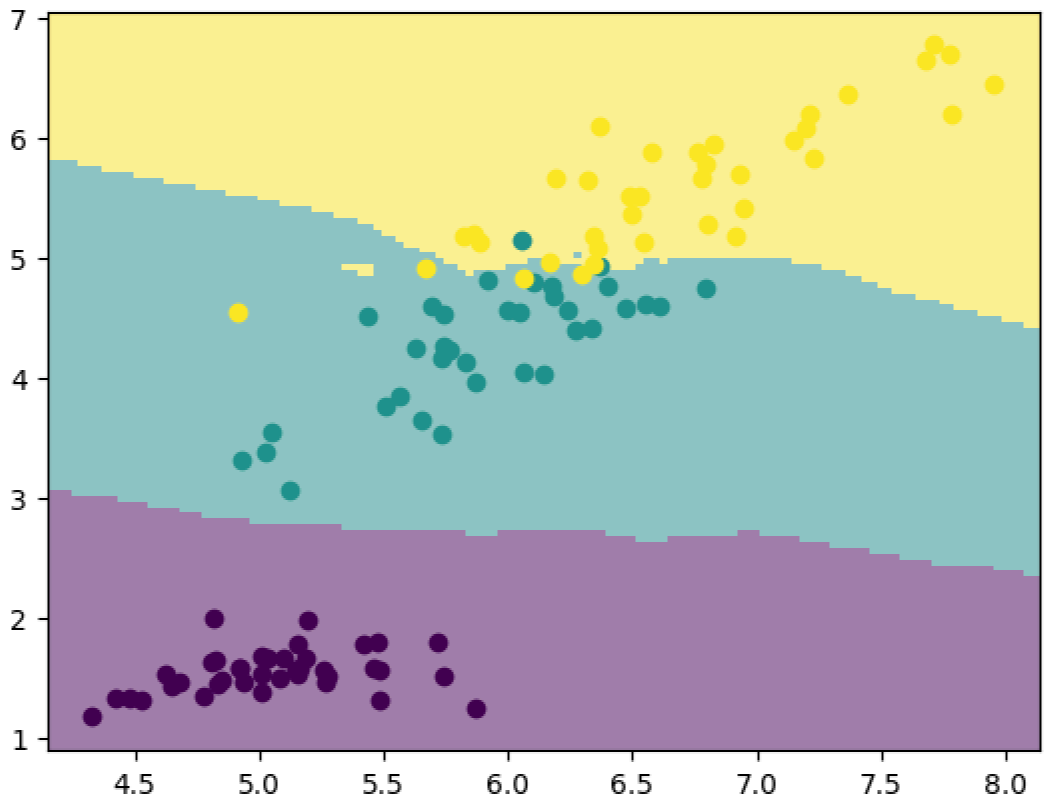
In [97]:
```
K = 1
knn = ml.knn.knnClassify()
knn.train(Xtr, Ytr, K)
YvaHat = knn.predict(Xva)
ml.plotClassify2D( knn, Xtr, Ytr )
```



K=1

Model has perfect accuracy with K = 1. The boundaries are pretty clean, but there are some unusual edges between yellow and green.

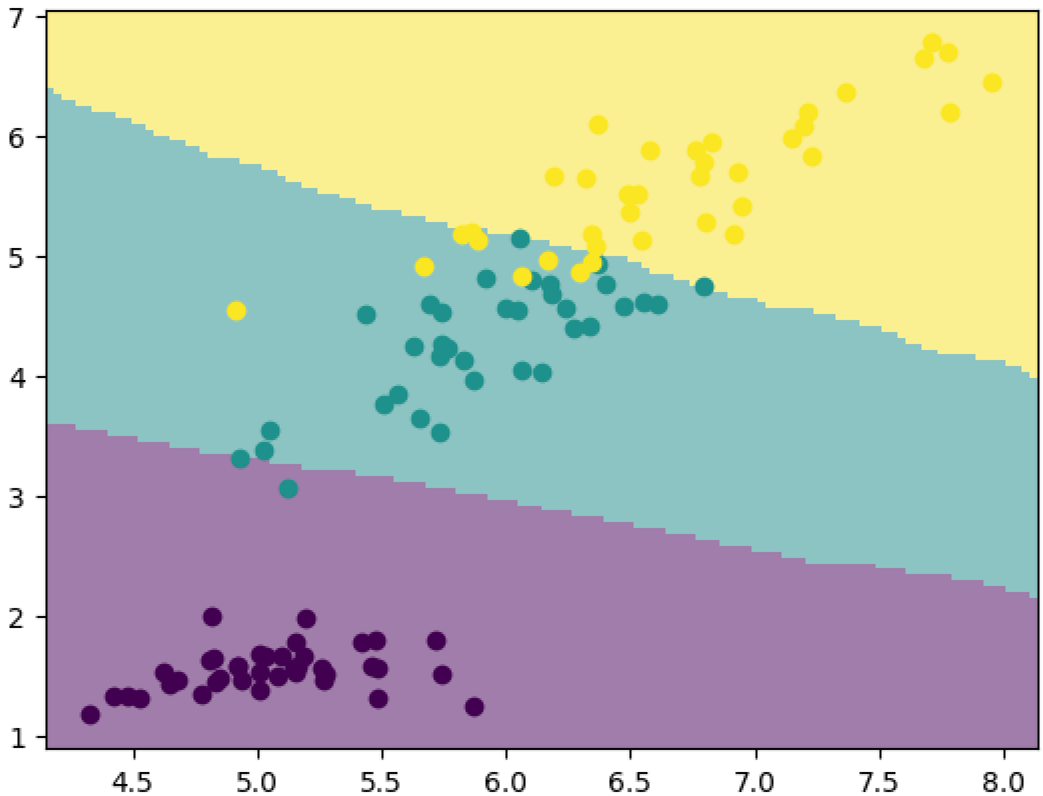
In [98]:
```
K = 10
knn = ml.knn.knnClassify()
knn.train(Xtr, Ytr, K)
YvaHat = knn.predict(Xva)
ml.plotClassify2D( knn, Xtr, Ytr )
```



K=10

Model still appears fairly accurate, but we can see some clear errors. Boundaries are cleanre, but still a little messy between yellow and green.

In [99]:
```
K = 50
knn = ml.knn.knnClassify()
knn.train(Xtr, Ytr, K)
YvaHat = knn.predict(Xva)
ml.plotClassify2D( knn, Xtr, Ytr )
```

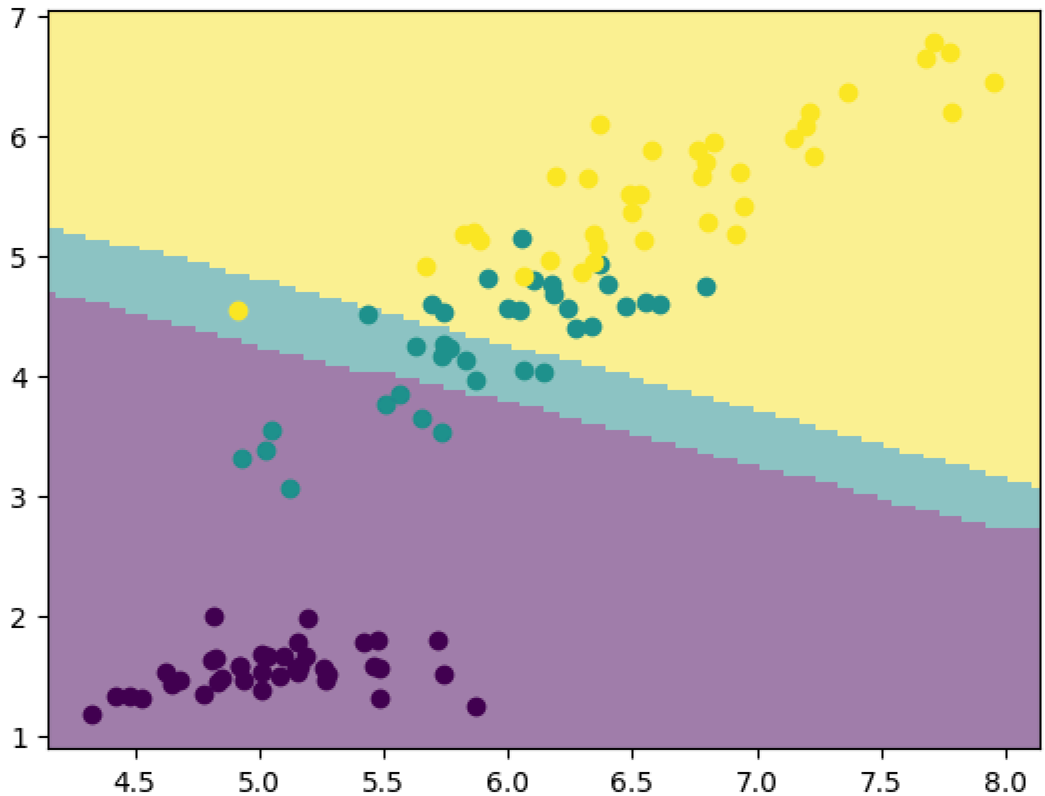


K=50

Boundaries are very clean, but the model is starting to lose some accuracy. Visually, we can see a clear distinction between the cluster of purple and green points. But we some some green points that are misclassified in the purple region, because K is getting too big.

In [100…

```
K = 100
knn = ml.knn.knnClassify()
knn.train(Xtr, Ytr, K)
YvaHat = knn.predict(Xva)
ml.plotClassify2D( knn, Xtr, Ytr )
```



K=100

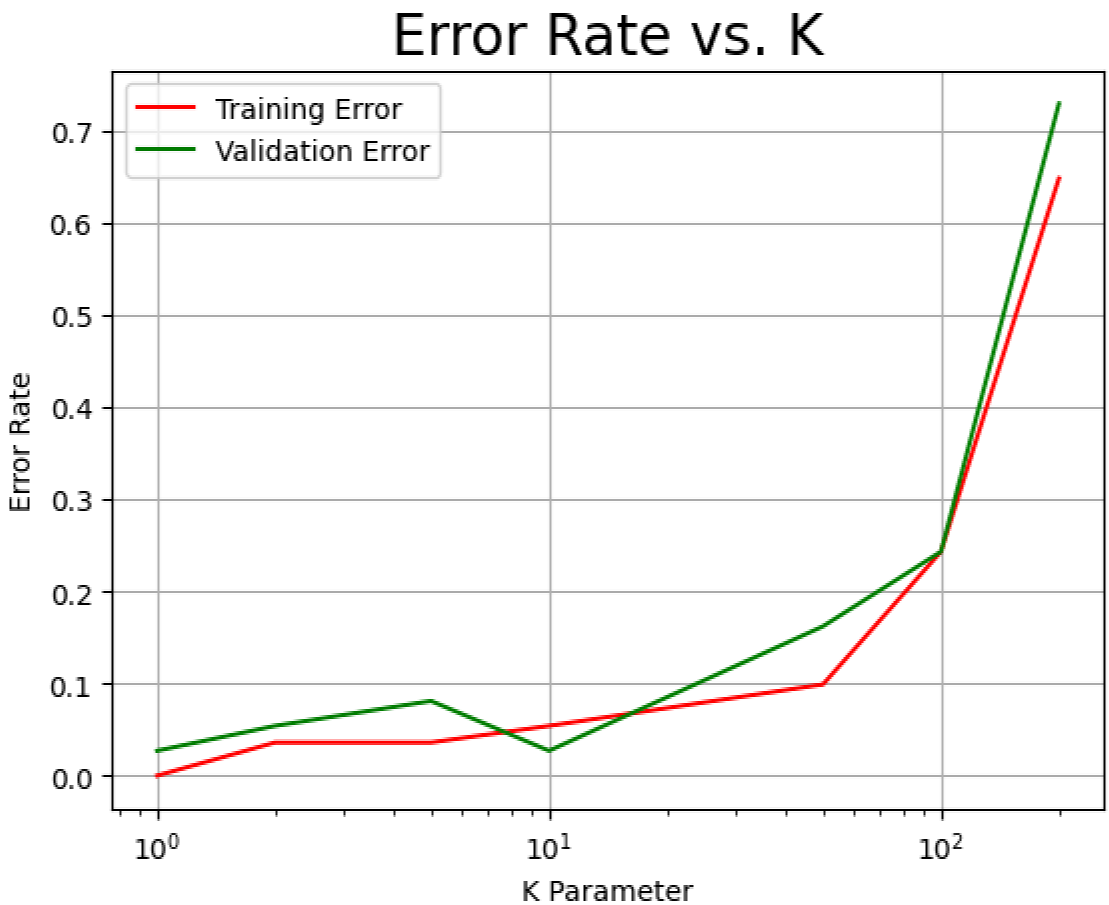
Now we see a lot of errors, becausae of the very large K. Notably, the green area has become very small, because these points are in the middle of the distribution and it is a very small area where the majority of the 100 nearest neighbors are green. It is interesting that accuracy of the model varies by class.

Part 2)

In [101…

```
K=[1,2,5,10,50,100,200]
errTrain = np.zeros(len(K))
errValidate = np.zeros(len(K))

for i,k in enumerate(K):
    learner = ml.knn.knnClassify()
    learner.train(Xtr, Ytr, k)
    Yhat = learner.predict(Xtr)
    errTrain[i] = np.mean(Yhat != Ytr)
    Yhatva = learner.predict(Xva)
    errValidate[i] = np.mean(Yhatva != Yva)

plt.semilogx(K, errTrain, color='red', label='Training Error')
plt.semilogx(K, errValidate, color='green', label='Validation Error')

plt.title('Error Rate vs. K', fontsize=20)
plt.xlabel('K Parameter')
plt.ylabel('Error Rate')
```

```
plt.legend()
plt.grid(True)

plt.show()
```



Results

Based on this plot, I think the best value of K is 10.

We expect low values of K to perform better on the training data than on the validation data, which is true here. However the validation error rate is very low for K=1, and K=1 is tied with K=10 for the lowest validation error rates. I am breaking the tie and choosing K=10 based on class lectures and prior knowledge. I think it is common for low values of K to result in overfitting, and indeed the error rate is higher for K=2 and K=5 than it is at K=10. K=10 is also the only K value for which the validation error rate is lower than the training error rate. In general, I expect to see more of a U-shape in the validation error rates, so I choose K=10 over K=1.

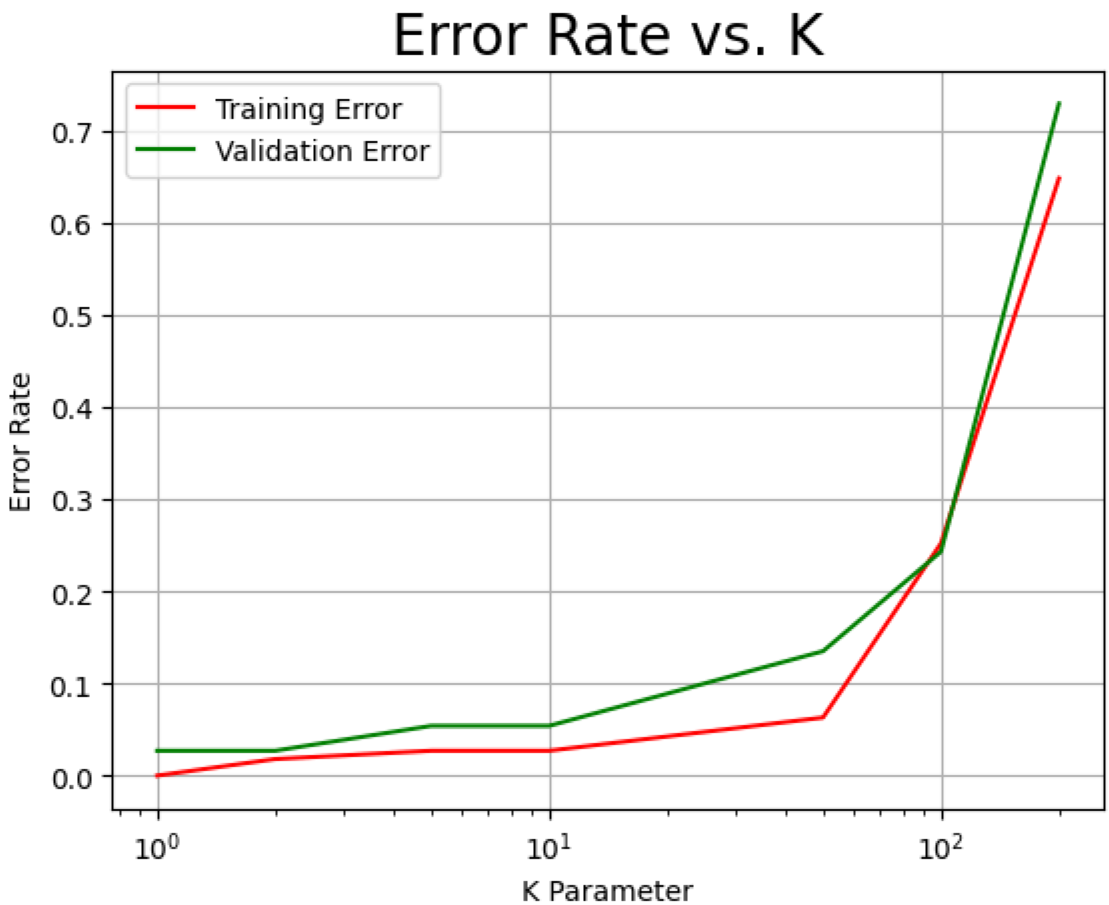
In [102…
```
errValidate
```

Out[102]:
```
array([0.02702703, 0.05405405, 0.08108108, 0.02702703, 0.16216216,
       0.24324324, 0.72972973])
```

Part 3)

In [103…

```
# Reset the data using all 4 features in X
Xtr,Xva,Ytr,Yva = ml.splitData(X,Y, 0.75)

K=[1,2,5,10,50,100,200]
errTrain = np.zeros(len(K))
errValidate = np.zeros(len(K))

for i,k in enumerate(K):
    learner = ml.knn.knnClassify()
    learner.train(Xtr, Ytr, k)
    Yhat = learner.predict(Xtr)
    errTrain[i] = np.mean(Yhat != Ytr)
    Yhatva = learner.predict(Xva)
    errValidate[i] = np.mean(Yhatva != Yva)

plt.semilogx(K, errTrain, color='red', label='Training Error')
plt.semilogx(K, errValidate, color='green', label='Validation Error')

plt.title('Error Rate vs. K', fontsize=20)
plt.xlabel('K Parameter')
plt.ylabel('Error Rate')
plt.legend()
plt.grid(True)

plt.show()
```



Results

When using all data features, the plot looks fairly similar to the previous plot based only on 2 of the data features. A notable difference is that the validation error is clearly smallest at K=1. This does change my anser and I now think that K=1 is the best choice.

Statement of Collaboration

I did not discuss the details of this assignment with anyone from class, and I did not share or discuss code with anyone. I followed the wuestions on Ed Discussion, but I did not finish the assignment in time to respond and participate in Ed Discussion.