Models Accuracy

May 10, 2018

0.1 Overview:

This notebook will focus on shaping the data in ways that make it satisfactory for the machine learning process.

0.1.1 Scale the dataset

In general, learning algorithms benefit from standardization of the data set. If some outliers are present in the set, robust scalers or transformers are more appropriate. Standardization of datasets is a common requirement for many machine learning estimators implemented in scikit-learn.

```
In [1]: import pandas as pd
        import numpy as np
        import sys
        from sklearn.preprocessing import StandardScaler
        from sklearn.preprocessing import LabelEncoder
        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import cross_val_score
        import random

        import warnings
        warnings.filterwarnings('ignore')
```

```
In [2]: # START:OWN CODE
        sys.path.append('/Users/Kassi/Desktop/Gender_Recognition_by_Voice')
```

```
In [3]: path = '/Users/Kassi/Desktop/Gender_Recognition_by_Voice/voice.csv'
        voice_data = pd.read_csv(path)
        col_names = list(voice_data.columns.values)
        print("Total number of samples: {}".format(voice_data.shape[0]))
        print("Total number of male: {}".format(voice_data[voice_data.label == 'male'].shape[0
        print("Total number of female: {}".format(voice_data[voice_data.label == 'female'].sha
```

```
Total number of samples: 3168
Total number of male: 1584
Total number of female: 1584
```

Check if dataset contains NA's

```
In [4]: voice_data.isnull().any().any()

Out[4]: False
```

Fortunately, our dataset does not contain any missing values and therefore does not need cleaning.

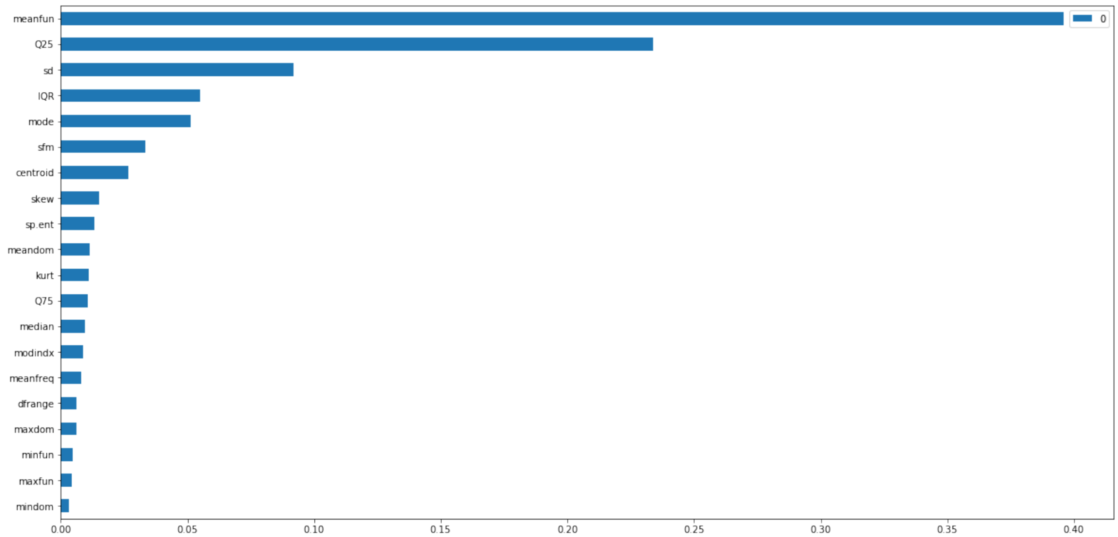
```
In [5]: voice_data = voice_data.values
        voices = voice_data[:, :-1]
        labels = voice_data[:, -1:]

In [6]: gender_encoder = LabelEncoder()
        labels = gender_encoder.fit_transform(labels)

In [7]: # 2 most significant features (IQR and meanfun)
        voices_two_features = voices[:,[5,12]]
        labels_two_features = labels

        # train_x_two_features.shape
        # labels_two_features.shape

In [8]: # Splitting the whole dataset into the Training set and Test set
        train_x, test_x, train_y, test_y = train_test_split(voices, labels, test_size=0.25, ran

        # Splitting the subset into the Training set and Test set
        train_x_two_features, test_x_two_features, train_y_two_features, test_y_two_features =

In [9]: # Feature Scaling (all features)
        # Learning algorithms benefit from standardization of the whole data set
        from sklearn.preprocessing import StandardScaler
        sc = StandardScaler()
        train_x = sc.fit_transform(train_x)
        test_x = sc.transform(test_x)

In [10]: # Feature Scaling (top 2 features)
         # Learning algorithms benefit from standardization of the subset
         sc = StandardScaler()
         train_x_two_features = sc.fit_transform(train_x_two_features)
         test_x_two_features = sc.transform(test_x_two_features)
```

0.1.2 Feature Importance

We used random forest to gain an insight on the importance of each feature. And again, we found that the IQR and Meanfun are two most significant features

```
In [11]: from sklearn.ensemble import RandomForestClassifier
         import matplotlib.pyplot as plt
         import seaborn as sns
```

```
from pandas.tools.plotting import scatter_matrix

clf = RandomForestClassifier()
clf.fit(voices, labels)
col_names = col_names[:-1]
#print(col_names)
importance = list(zip(clf.feature_importances_ , col_names))
#print(importance)
importance.sort()
pd.DataFrame(importance, index=[x for (_,x) in importance]).plot(kind = 'barh', figsi
plt.show()
```

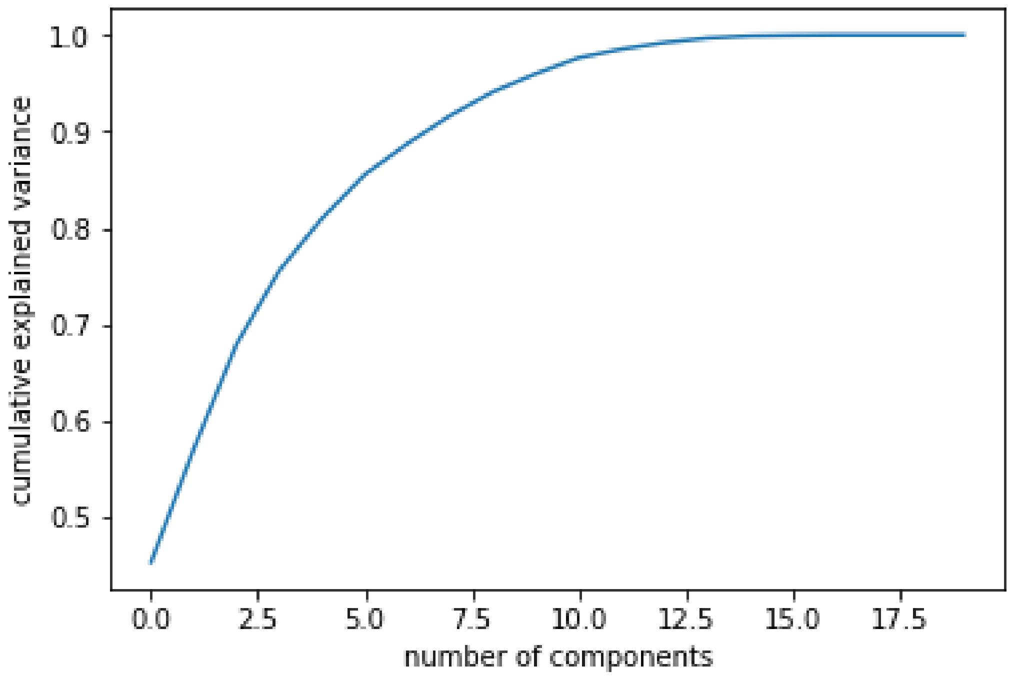


The plot above showed the top two features are still meanfun and IQR.

0.1.3 Principle Component Analysis(PCA)

The number of components is determined by looking at the cumulative explained variance ratio as a function of the number of components

```
In [12]: from sklearn.decomposition import PCA

         pca = PCA().fit(train_x)
         plt.plot(np.cumsum(pca.explained_variance_ratio_))
         plt.xlabel('number of components')
         plt.ylabel('cumulative explained variance');
         plt.show()
```



This curve quantifies how much of the total, 20-dimensional variance is contained within the first N components. For example, we see that with the digits the first 5 components contain approximately 85% of the variance, while we need around 10 components to describe close to 100% of the variance.

```
In [13]: pca = PCA(n_components = 10)
         pca.fit(train_x)
         pca_train_x = pca.transform(train_x)
         pca_test_x = pca.transform(test_x)
```

```
In [14]: # Store variables in the current directory and use it later
         %store train_x
         %store test_x
         %store train_y
         %store test_y

         %store voices
         %store labels

         %store train_x_two_features
         %store test_x_two_features
         %store train_y_two_features
         %store test_y_two_features

         %store pca_train_x
         %store pca_test_x
```

```
Stored 'train_x' (ndarray)
Stored 'test_x' (ndarray)
Stored 'train_y' (ndarray)
Stored 'test_y' (ndarray)
Stored 'voices' (ndarray)
Stored 'labels' (ndarray)
Stored 'train_x_two_features' (ndarray)
Stored 'test_x_two_features' (ndarray)
Stored 'train_y_two_features' (ndarray)
Stored 'test_y_two_features' (ndarray)
Stored 'pca_train_x' (ndarray)
Stored 'pca_test_x' (ndarray)
```

In [15]:
```
# Importing Jupyter Notebooks as Modules
# code get from http://jupyter-notebook.readthedocs.io/en/stable/examples/Notebook/Im

import io, os, sys, types
from IPython import get_ipython
from nbformat import read
from IPython.core.interactiveshell import InteractiveShell

def find_notebook(fullname, path=None):
    """find a notebook, given its fully qualified name and an optional path

    This turns "foo.bar" into "foo/bar.ipynb"
    and tries turning "Foo_Bar" into "Foo Bar" if Foo_Bar
    does not exist.
    """
    name = fullname.rsplit('.', 1)[-1]
    if not path:
        path = ['']
    for d in path:
        nb_path = os.path.join(d, name + ".ipynb")
        if os.path.isfile(nb_path):
            return nb_path
        # let import Notebook_Name find "Notebook Name.ipynb"
        nb_path = nb_path.replace("_", " ")
        if os.path.isfile(nb_path):
            return nb_path


class NotebookLoader(object):
    """Module Loader for Jupyter Notebooks"""
    def __init__(self, path=None):
        self.shell = InteractiveShell.instance()
        self.path = path
```

```
    def load_module(self, fullname):
        """import a notebook as a module"""
        path = find_notebook(fullname, self.path)

        print ("importing Jupyter notebook from %s" % path)

        # load the notebook object
        with io.open(path, 'r', encoding='utf-8') as f:
            nb = read(f, 4)


        # create the module and add it to sys.modules
        # if name in sys.modules:
        #    return sys.modules[name]
        mod = types.ModuleType(fullname)
        mod.__file__ = path
        mod.__loader__ = self
        mod.__dict__['get_ipython'] = get_ipython
        sys.modules[fullname] = mod

        # extra work to ensure that magics that would affect the user_ns
        # actually affect the notebook module's ns
        save_user_ns = self.shell.user_ns
        self.shell.user_ns = mod.__dict__

        try:
          for cell in nb.cells:
            if cell.cell_type == 'code':
                # transform the input to executable Python
                code = self.shell.input_transformer_manager.transform_cell(cell.source
                # run the code in themodule
                exec(code, mod.__dict__)
        finally:
            self.shell.user_ns = save_user_ns
        return mod


class NotebookFinder(object):
    """Module finder that locates Jupyter Notebooks"""
    def __init__(self):
        self.loaders = {}

    def find_module(self, fullname, path=None):
        nb_path = find_notebook(fullname, path)
        if not nb_path:
            return

        key = path
```

```
            if path:
                # lists aren't hashable
                key = os.path.sep.join(path)

            if key not in self.loaders:
                self.loaders[key] = NotebookLoader(path)
            return self.loaders[key]
```

```
In [16]: sys.meta_path.append(NotebookFinder())
```

```
In [17]: import SVM
         print("Run linear svm with all features(Built-in Algorithm):")
         SVM.run_linear_svm(train_x, test_x, train_y, test_y)
         print("------------------------------------------------------------")
         print("Run rbf svm with all features(Built-in Algorithm):")
         SVM.run_rbf_svm(train_x, test_x, train_y, test_y)
         print("============================================================")
         print("Run linear svm with dimensionality reduction using PCA(Built-in Algorithm)")
         SVM.run_linear_svm(pca_train_x, pca_test_x, train_y, test_y)
         print("------------------------------------------------------------")
         print("Run rbf svm with dimensionality reduction using PCA(Built-in Algorithm)")
         SVM.run_rbf_svm(pca_train_x, pca_test_x, train_y, test_y)
         print("============================================================")
         print("Run linear svm with top 2 features(Built-in Algorithm):")
         SVM.run_linear_svm(train_x_two_features, test_x_two_features, train_y_two_features, te
         print("============================================================")
         print("Run rbf svm with top 2 features(Built-in Algorithm):")
         SVM.run_rbf_svm(train_x_two_features, test_x_two_features, train_y_two_features, test_
```

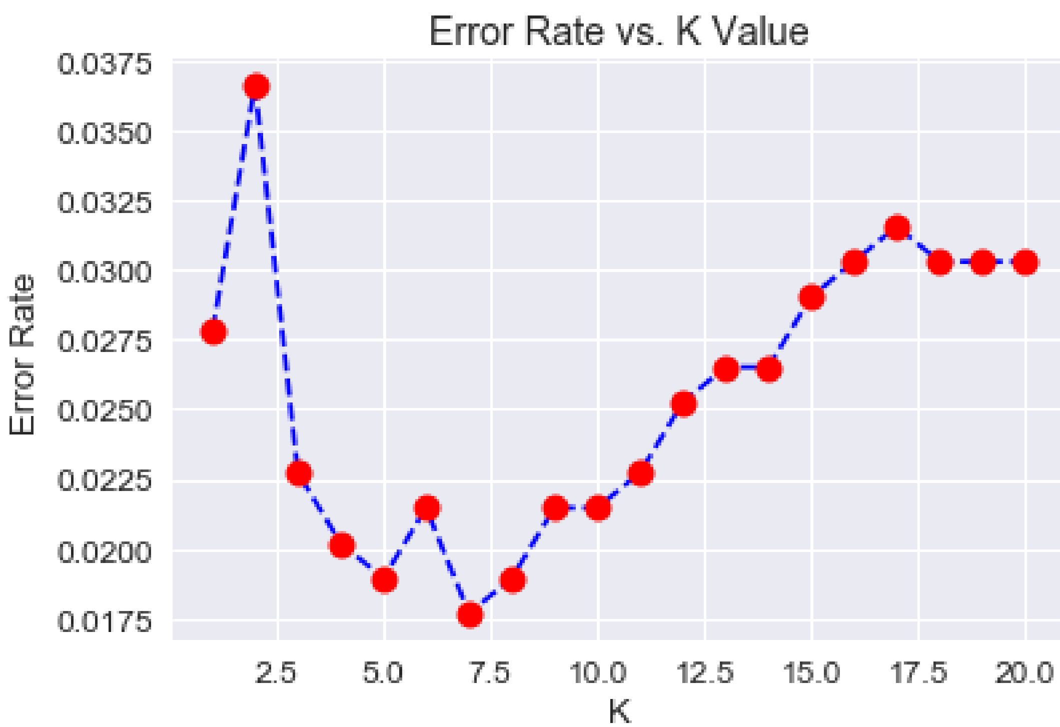
```
importing Jupyter notebook from SVM.ipynb
Run linear svm with all features(Built-in Algorithm):
In-sample accuracy for svm with Linear kernel: 0.9743290243
Out-of-sample accuracy for svm with Linear kernel: 0.9722076268
------------------------------------------------------------
Run rbf svm with all features(Built-in Algorithm):
In-sample accuracy for svm with RBF kernel: 0.9806448362
Out-of-sample accuracy for svm with RBF kernel: 0.9722235491
============================================================
Run linear svm with dimensionality reduction using PCA(Built-in Algorithm)
In-sample accuracy for svm with Linear kernel: 0.9751702488
Out-of-sample accuracy for svm with Linear kernel: 0.9734654884
------------------------------------------------------------
Run rbf svm with dimensionality reduction using PCA(Built-in Algorithm)
In-sample accuracy for svm with RBF kernel: 0.9781202858
Out-of-sample accuracy for svm with RBF kernel: 0.9633787119
============================================================
Run linear svm with top 2 features(Built-in Algorithm):
In-sample accuracy for svm with Linear kernel: 0.9629720840
```

```
Out-of-sample accuracy for svm with Linear kernel: 0.9709338428
============================================================
Run rbf svm with top 2 features(Built-in Algorithm):
In-sample accuracy for svm with RBF kernel: 0.9659132604
Out-of-sample accuracy for svm with RBF kernel: 0.9734654884
```

```
In [18]: import KNN
         print("with all features(Built-in Algorithm):")
         KNN.run_k_nearest_neighbour(train_x, test_x, train_y, test_y)
         print("============================================================")
         print("with all features(Self-Written Algorithm):")
         KNN.run_my_k_nearest_neighbour(train_x, test_x, train_y, test_y)
         print("============================================================")
         print("with top 2 features(Built-in Algorithm):")
         KNN.run_k_nearest_neighbour(train_x_two_features, test_x_two_features, train_y_two_fea
         print("============================================================")
         print("with top 2 features(Self-Written Algorithm):")
         KNN.run_my_k_nearest_neighbour(train_x_two_features, test_x_two_features, train_y_two_
         print("============================================================")
         print("with dimensionality reduction using PCA(Built-in Algorithm)")
         KNN.run_k_nearest_neighbour(pca_train_x, pca_test_x, train_y, test_y)
         print("============================================================")
         print("with dimensionality reduction using PCA(Self-Written Algorithm)")
         KNN.run_my_k_nearest_neighbour(pca_train_x, pca_test_x, train_y, test_y)
```

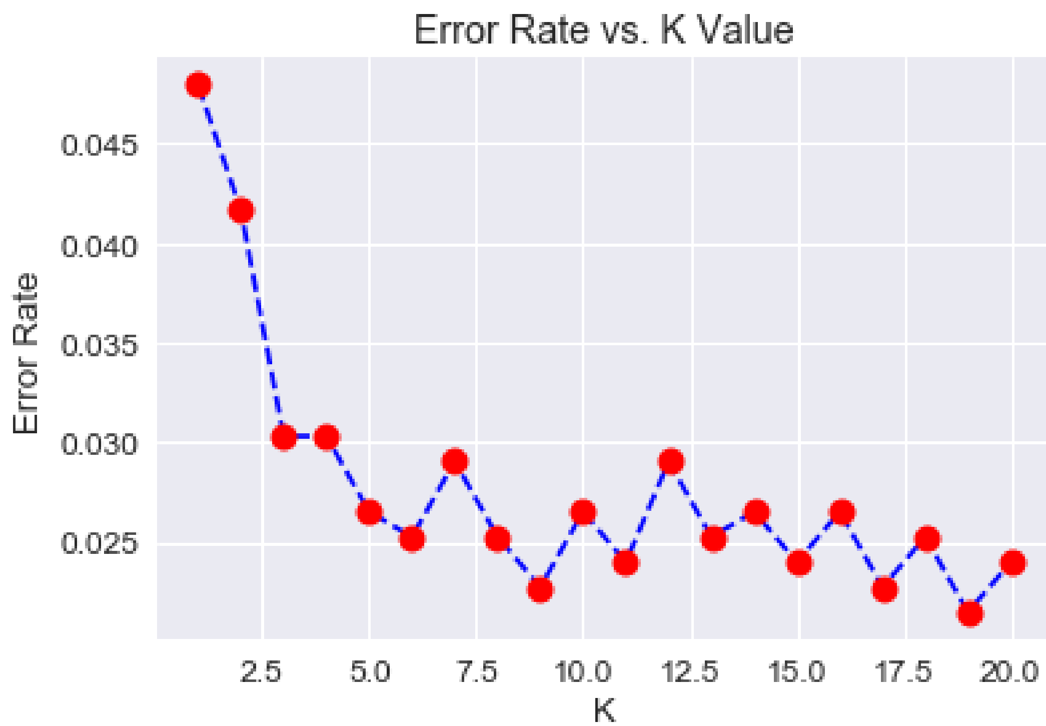
```
importing Jupyter notebook from KNN.ipynb

Use self-written KNeighbors Classifier:
Correct rate is 0.972222222222 when K = 1.
Correct rate is 0.963383838384 when K = 2.
Correct rate is 0.977272727273 when K = 3.
Correct rate is 0.979797979798 when K = 4.
Correct rate is 0.981060606061 when K = 5.
Correct rate is 0.978535353535 when K = 6.
Correct rate is 0.982323232323 when K = 7.
Correct rate is 0.981060606061 when K = 8.
Correct rate is 0.978535353535 when K = 9.
Correct rate is 0.978535353535 when K = 10.
Correct rate is 0.977272727273 when K = 11.
Correct rate is 0.974747474747 when K = 12.
Correct rate is 0.973484848485 when K = 13.
Correct rate is 0.973484848485 when K = 14.
Correct rate is 0.97095959596 when K = 15.
Correct rate is 0.969696969697 when K = 16.
Correct rate is 0.968434343434 when K = 17.
Correct rate is 0.969696969697 when K = 18.
Correct rate is 0.969696969697 when K = 19.
```

```
Highest correct rate 0.982323232323 occurs at K = 7.
with all features(Built-in Algorithm):
```



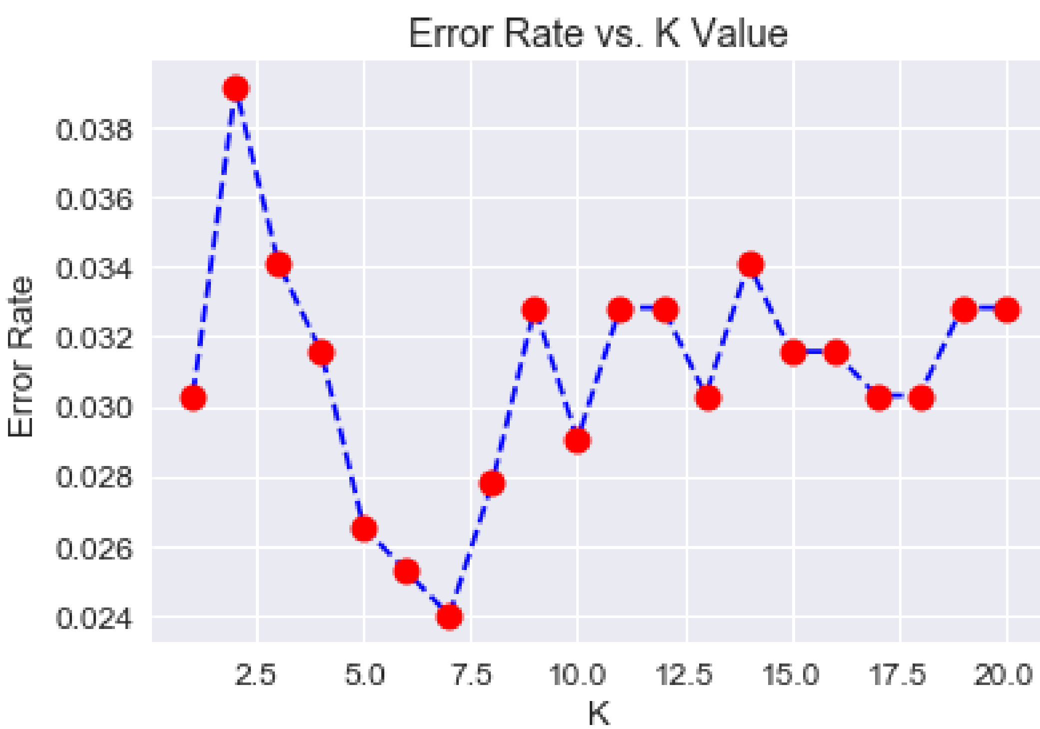

```
Lowest error is 0.0176767676768 occurs at k=7.
In-sample accuracy for KNN: 0.9696947768
Out-of-sample accuracy for KNN: 0.9507602898
===========================================================
with all features(Self-Written Algorithm):

Use self-written KNeighbors Classifier:
Correct rate is 0.972222222222 when K = 1.
Correct rate is 0.963383838384 when K = 2.
Correct rate is 0.977272727273 when K = 3.
Correct rate is 0.979797979798 when K = 4.
Correct rate is 0.981060606061 when K = 5.
Correct rate is 0.978535353535 when K = 6.
Correct rate is 0.982323232323 when K = 7.
Correct rate is 0.981060606061 when K = 8.
Correct rate is 0.978535353535 when K = 9.
Correct rate is 0.978535353535 when K = 10.
Correct rate is 0.977272727273 when K = 11.
Correct rate is 0.974747474747 when K = 12.
Correct rate is 0.973484848485 when K = 13.
```

```
Correct rate is 0.973484848485 when K = 14.
Correct rate is 0.97095959596 when K = 15.
Correct rate is 0.969696969697 when K = 16.
Correct rate is 0.968434343434 when K = 17.
Correct rate is 0.969696969697 when K = 18.
Correct rate is 0.969696969697 when K = 19.
Highest correct rate 0.982323232323 occurs at K = 7.
===========================================================
with top 2 features(Built-in Algorithm):
```




```
Lowest error is 0.0214646464646 occurs at k=19.
In-sample accuracy for KNN: 0.9654922078
Out-of-sample accuracy for KNN: 0.9633468673
===========================================================
with top 2 features(Self-Written Algorithm):

Use self-written KNeighbors Classifier:
Correct rate is 0.95202020202 when K = 1.
Correct rate is 0.958333333333 when K = 2.
Correct rate is 0.969696969697 when K = 3.
Correct rate is 0.969696969697 when K = 4.
Correct rate is 0.973484848485 when K = 5.
Correct rate is 0.974747474747 when K = 6.
```

```
Correct rate is 0.97095959596 when K = 7.
Correct rate is 0.974747474747 when K = 8.
Correct rate is 0.977272727273 when K = 9.
Correct rate is 0.973484848485 when K = 10.
Correct rate is 0.97601010101 when K = 11.
Correct rate is 0.97095959596 when K = 12.
Correct rate is 0.974747474747 when K = 13.
Correct rate is 0.973484848485 when K = 14.
Correct rate is 0.97601010101 when K = 15.
Correct rate is 0.973484848485 when K = 16.
Correct rate is 0.977272727273 when K = 17.
Correct rate is 0.974747474747 when K = 18.
Correct rate is 0.978535353535 when K = 19.
Highest correct rate 0.978535353535 occurs at K = 19.
============================================================
with dimensionality reduction using PCA(Built-in Algorithm)
```




```
Lowest error is 0.0239898989899 occurs at k=7.
In-sample accuracy for KNN: 0.9633816261
Out-of-sample accuracy for KNN: 0.9520181514
============================================================
with dimensionality reduction using PCA(Self-Written Algorithm)
```

```
Use self-written KNeighbors Classifier:
Correct rate is 0.969696969697 when K = 1.
Correct rate is 0.960858585859 when K = 2.
Correct rate is 0.965909090909 when K = 3.
Correct rate is 0.968434343434 when K = 4.
Correct rate is 0.973484848485 when K = 5.
Correct rate is 0.974747474747 when K = 6.
Correct rate is 0.97601010101 when K = 7.
Correct rate is 0.972222222222 when K = 8.
Correct rate is 0.967171717172 when K = 9.
Correct rate is 0.97095959596 when K = 10.
Correct rate is 0.967171717172 when K = 11.
Correct rate is 0.967171717172 when K = 12.
Correct rate is 0.969696969697 when K = 13.
Correct rate is 0.965909090909 when K = 14.
Correct rate is 0.968434343434 when K = 15.
Correct rate is 0.968434343434 when K = 16.
Correct rate is 0.969696969697 when K = 17.
Correct rate is 0.969696969697 when K = 18.
Correct rate is 0.967171717172 when K = 19.
Highest correct rate 0.97601010101 occurs at K = 7.
```

In [19]:
```python
import Random_Forest
print("Run random forest with all features(Built-in Algorithm):")
Random_Forest.run_random_forest_classifier(train_x, test_x, train_y, test_y)
print("=================================================================================
print("Run random forest with top 2 features(Built-in Algorithm):")
Random_Forest.run_random_forest_classifier(train_x_two_features, test_x_two_features,
print("=================================================================================
print("Run random forest with dimensionality reduction using PCA(Built-in Algorithm)")
Random_Forest.run_random_forest_classifier(pca_train_x, pca_test_x, train_y, test_y)
```

```
importing Jupyter notebook from Random_Forest.ipynb
Run random forest with all features(Built-in Algorithm):
```

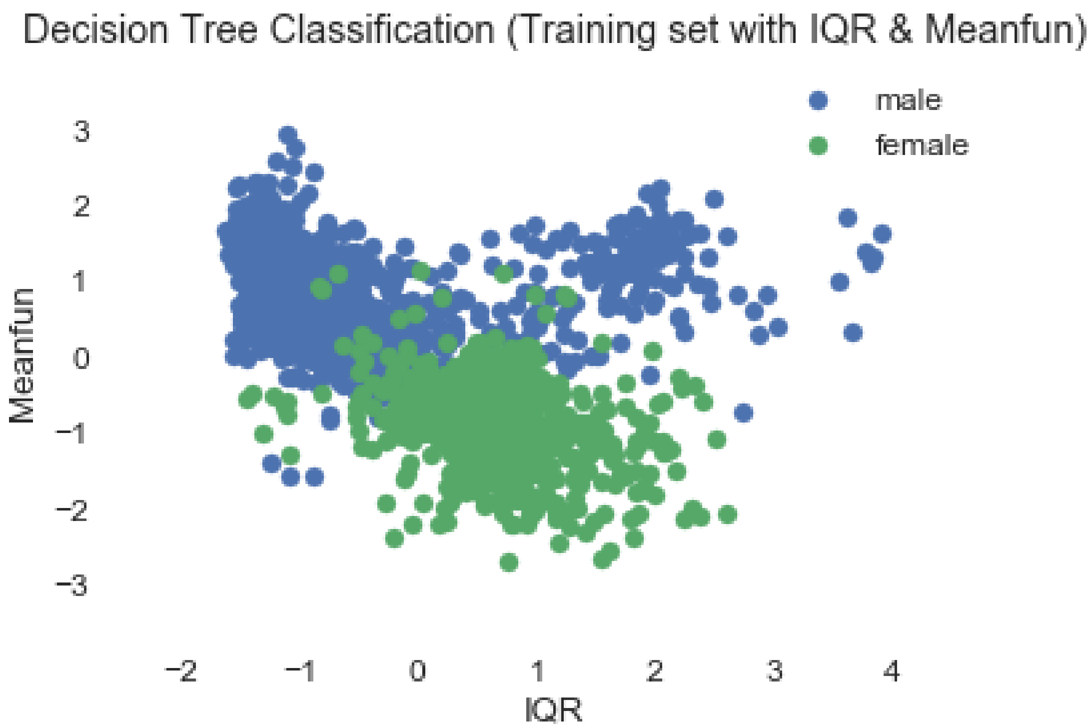

```
Lowest error of 0.0151515151515 occurs at n=241.
The highest in-sample accuracy in Random Forest is 0.984848484848 when n=241.
Out-of-sample accuracy in Random Forest:0.9671522968
================================================================================

Run random forest with top 2 features(Built-in Algorithm):
```

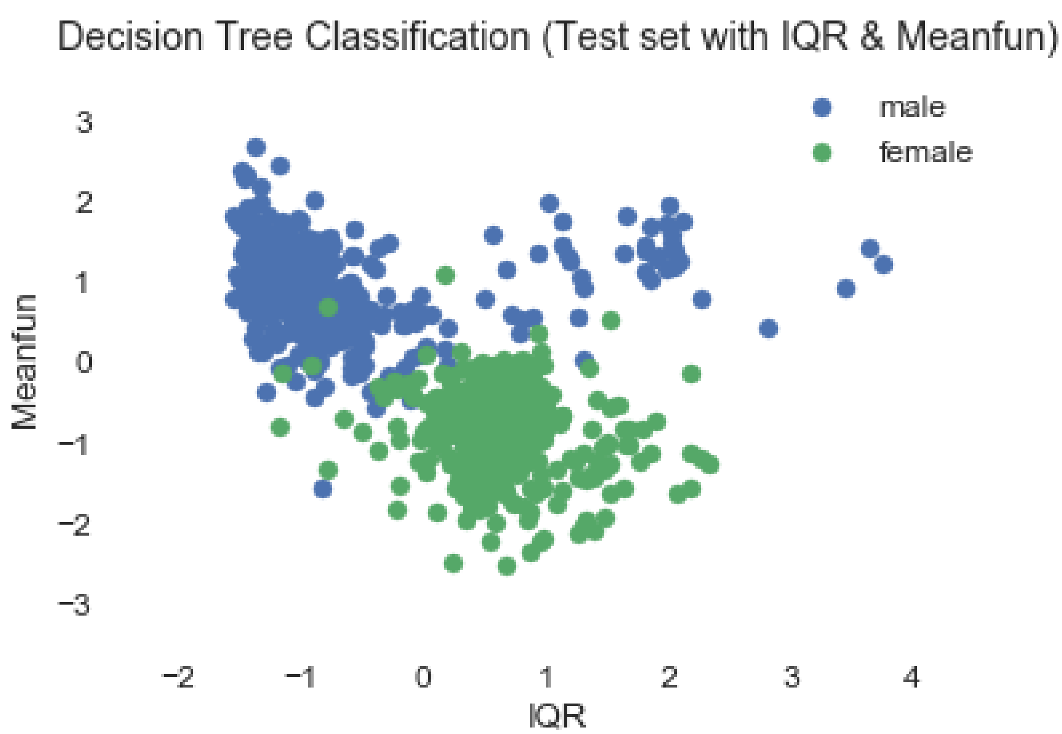

```
Lowest error of 0.030303030303 occurs at n=31.
The highest in-sample accuracy in Random Forest is 0.969696969697 when n=31.
Out-of-sample accuracy in Random Forest:0.9696839424
================================================================================

Run random forest with dimensionality reduction using PCA(Built-in Algorithm)
```


```
Lowest error of 0.030303030303 occurs at n=151.
The highest in-sample accuracy in Random Forest is 0.969696969697 when n=151.
Out-of-sample accuracy in Random Forest:0.9608629886
```

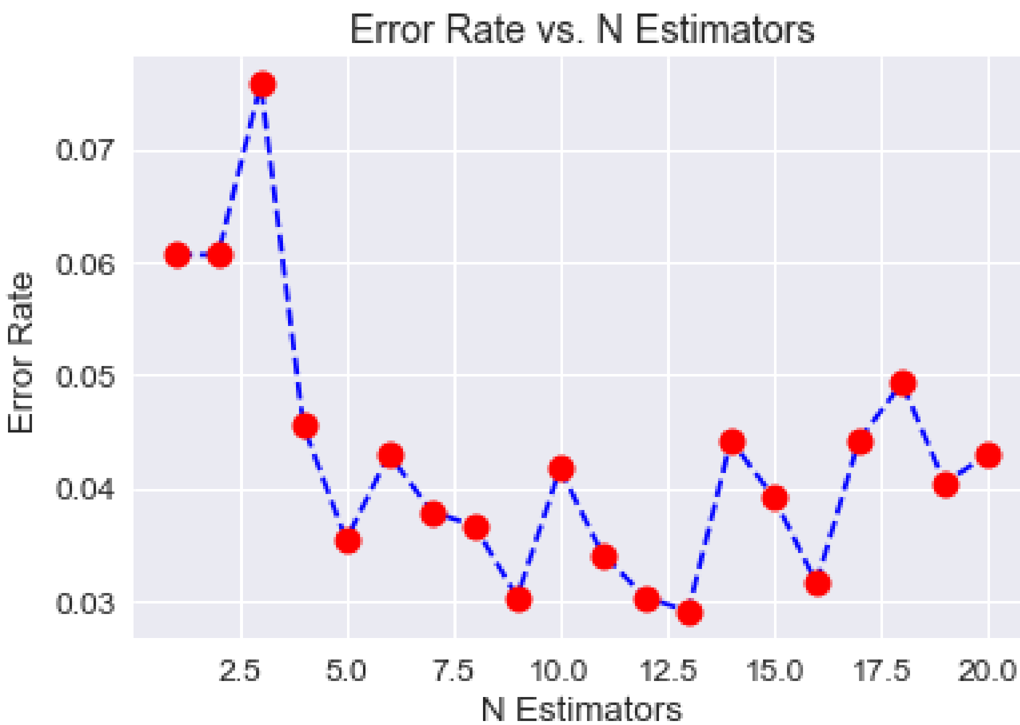
```
In [20]: import Decision_Tree
         print("Run decision tree with all features(Built-in Algorithm):")
         Decision_Tree.run_Decision_tree(train_x, test_x, train_y, test_y)
         print("==============================================================================
         print("Run decision tree with top 2 features(Built-in Algorithm):")
         Decision_Tree.run_Decision_tree(train_x_two_features, test_x_two_features, train_y_two
         print("==============================================================================
         print("Run decision tree with dimensionality reduction using PCA(Built-in Algorithm)")
         Decision_Tree.run_Decision_tree(pca_train_x, pca_test_x, train_y, test_y)
```

```
importing Jupyter notebook from Decision_Tree.ipynb
```

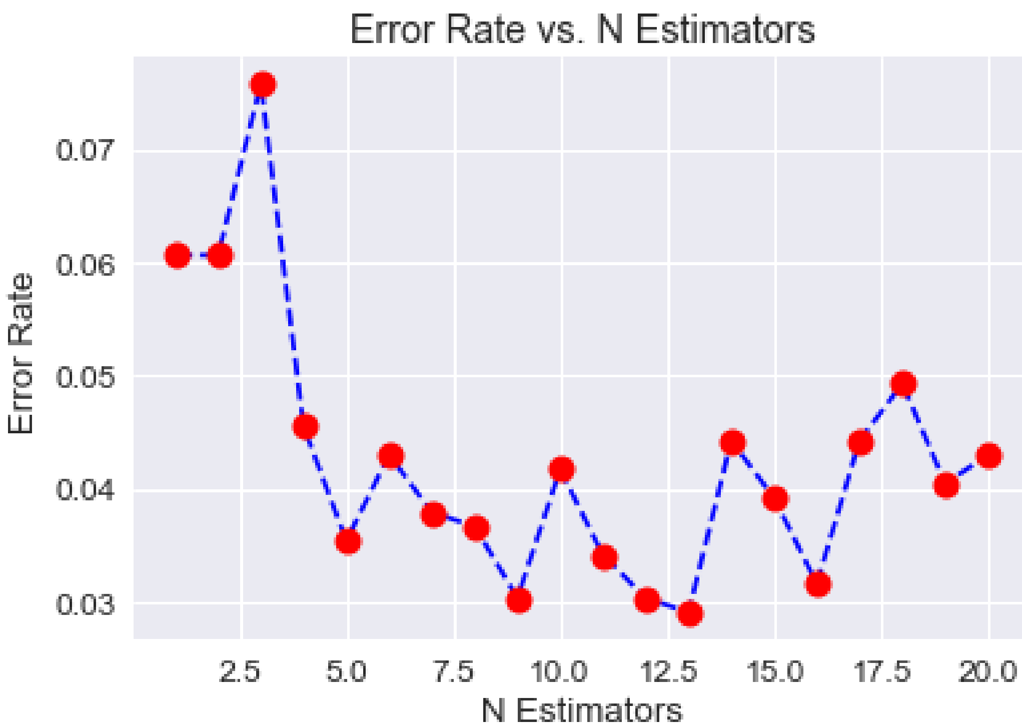

Decision Tree Classification (Training set with IQR & Meanfun)
male
female
Meanfun
IQR
3
2
1
0
−1
−2
−3
−2
−1
0
1
2
3
4


Decision Tree Classification (Test set with IQR & Meanfun)
male
female
Meanfun
IQR
3
2
1
0
−1
−2
−3
−2
−1
0
1
2
3
4

```
In-Sample Accuracy:100.0000%
Out-of-Sample Accuracy:95.8333%
```




```
Lowest error of 0.0290404040404 occurs at n=13.
In-Sample Accuracy:100.0000%
Out-of-Sample Accuracy:95.7071%

with all features(Built-in Algorithm):
```




```
Lowest error of 0.0290404040404 occurs at n=13.
In-Sample Accuracy:100.0000%
Out-of-Sample Accuracy:95.7071%
```

```
In [21]: from sklearn.linear_model import LogisticRegression
         import Logistic_Regression
         print("Run Logistic Regression with all features(Built-in Algorithm):")
         Logistic_Regression.run_Logistic_Regression(train_x,test_x,train_y,test_y)
         print("===============================================================================
         print("Run Logistic Regression with top 2 features(Built-in Algorithm):")
         Logistic_Regression.run_Logistic_Regression(train_x_two_features, test_x_two_features
         print("===============================================================================
         print("Run Logistic Regression with dimensionality reduction using PCA(Built-in Algor
         Logistic_Regression.run_Logistic_Regression(pca_train_x, pca_test_x, train_y, test_y)
```

```
importing Jupyter notebook from Logistic_Regression.ipynb
In-sample accuracy for Logistic Regression: 0.9718035894
Out-of-sample accuracy for Logistic Regression: 0.9747392724
Run Logistic Regression with all features(Built-in Algorithm):
In-sample accuracy for Logistic Regression: 0.9718035894
Out-of-sample accuracy for Logistic Regression: 0.9747392724
===============================================================================
```

```
Run Logistic Regression with top 2 features(Built-in Algorithm):
In-sample accuracy for Logistic Regression: 0.9633949132
Out-of-sample accuracy for Logistic Regression: 0.9696759812
===============================================================================

Run Logistic Regression with dimensionality reduction using PCA(Built-in Algorithm)
In-sample accuracy for Logistic Regression: 0.9726456947
Out-of-sample accuracy for Logistic Regression: 0.9747392724
```

```
In [28]: import Neural_Network
         print("Run Neural Network with all features(Built-in Algorithm):")
         Neural_Network.run_neural_network(train_x,train_y,test_x,test_y)
         print("===============================================================================
         print("Run Neural Network with all features(self-written Algorithm):")
         Neural_Network.run_my_neural_network(train_x,train_y,test_x,test_y)
```

```
Run Neural Network with all features(Built-in Algorithm):
In-sample accuracy in Neural Network using Keras package (with all features):1.0
Out-of-sample accuracy in Neural Network using Keras package (with 2 features):0.982323232323
===============================================================================

Run Neural Network with all features(self-written Algorithm):
Epoch 1: cost=0.7508
Epoch 2: cost=0.7387
Epoch 3: cost=0.7233
Epoch 4: cost=0.7041
Epoch 5: cost=0.6809
Epoch 6: cost=0.6547
Epoch 7: cost=0.6267
Epoch 8: cost=0.5983
Epoch 9: cost=0.5714
Epoch 10: cost=0.5464
Epoch 11: cost=0.5234
Epoch 12: cost=0.5027
Epoch 13: cost=0.4842
Epoch 14: cost=0.4680
Epoch 15: cost=0.4539
Epoch 16: cost=0.4414
Epoch 17: cost=0.4305
Epoch 18: cost=0.4210
Epoch 19: cost=0.4125
Epoch 20: cost=0.4051
Epoch 21: cost=0.3984
Epoch 22: cost=0.3924
Epoch 23: cost=0.3871
Epoch 24: cost=0.3823
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Epoch 25: cost=0.3780
Epoch 26: cost=0.3742
Epoch 27: cost=0.3707
Epoch 28: cost=0.3675
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Epoch 31: cost=0.3596
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In-sample accuracy in Neural Network: 0.99495
Out-of-sample accuracy in Neural Network: 0.97601
```

```
In [29]: import Gaussian_Naive_Bayes
         print("Run Gaussian Naive Bayes with all features(Built-in Algorithm):")
         Gaussian_Naive_Bayes.run_naive_bayes(train_x, test_x, train_y, test_y)
         print("================================================================================
         print("Run Gaussian Naive Bayes with all features(Self-Written Algorithm):")
         Gaussian_Naive_Bayes.run_my_gaussian_naive_bayes(train_x, test_x, train_y, test_y)
         print("================================================================================
         print("Run Gaussian Naive Bayes with top 2 features(Built-in Algorithm):")
         Gaussian_Naive_Bayes.run_naive_bayes(train_x_two_features, test_x_two_features, train_
         print("================================================================================
         print("Run Gaussian Naive Bayes with dimensionality reduction using PCA(Built-in Algo
         Gaussian_Naive_Bayes.run_naive_bayes(pca_train_x, pca_test_x, train_y, test_y)
```

```
importing Jupyter notebook from Gaussian_Naive_Bayes.ipynb
Correct rate is 0.900252525253
             precision    recall  f1-score   support

          0       0.89      0.90      0.89       367
          1       0.91      0.90      0.91       425

avg / total       0.90      0.90      0.90       792

Run Gaussian Naive Bayes with all features(Self-Written Algorithm):
Correct rate is 0.900252525253
             precision    recall  f1-score   support

          0       0.89      0.90      0.89       367
          1       0.91      0.90      0.91       425

avg / total       0.90      0.90      0.90       792

===============================================================================

Run Gaussian Naive Bayes with top 2 features(Built-in Algorithm):
In-sample accuracy for svm with Linear kernel: 0.9659123721
Out-of-sample accuracy for svm with Linear kernel: 0.9747313112
===============================================================================

Run Gaussian Naive Bayes with dimensionality reduction using PCA(Built-in Algorithm)
In-sample accuracy for svm with Linear kernel: 0.9482405343
Out-of-sample accuracy for svm with Linear kernel: 0.9507523286
Run Gaussian Naive Bayes with all features(Built-in Algorithm):
In-sample accuracy for svm with Linear kernel: 0.8943739953
Out-of-sample accuracy for svm with Linear kernel: 0.8711328716
===============================================================================

Run Gaussian Naive Bayes with all features(Self-Written Algorithm):
Correct rate is 0.900252525253
```

```
             precision    recall  f1-score   support

          0       0.89      0.90      0.89       367
          1       0.91      0.90      0.91       425

avg / total       0.90      0.90      0.90       792

===============================================================================

Run Gaussian Naive Bayes with top 2 features(Built-in Algorithm):
In-sample accuracy for svm with Linear kernel: 0.9659123721
Out-of-sample accuracy for svm with Linear kernel: 0.9747313112
===============================================================================

Run Gaussian Naive Bayes with dimensionality reduction using PCA(Built-in Algorithm)
In-sample accuracy for svm with Linear kernel: 0.9482405343
Out-of-sample accuracy for svm with Linear kernel: 0.9507523286
```

In [30]:
```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn import svm
def getModels(train_x, test_x, train_y, test_y):
    # KNN
    error_rate = []
    kvals = range(1,21)  # range of k parameters to test
    for i in kvals:
        knn = KNeighborsClassifier(n_neighbors=i)
        knn.fit(train_x,train_y)
        pred_y_i = knn.predict(test_x)
        error_rate.append(np.mean(pred_y_i != test_y))
    kloc = error_rate.index(min(error_rate))
    clf = KNeighborsClassifier(kvals[kloc], 'uniform')
    clf1 =clf.fit(train_x, train_y)

    # Decision Tree
    clf2 = tree.DecisionTreeClassifier()
    clf2 = clf2.fit(train_x, train_y)

    # Random Forest
    error_rate = []
    nvals = range(1,301,30)
    for i in nvals:
        clf = RandomForestClassifier(n_estimators=i)
        clf.fit(train_x,train_y)
        pred_y_i = clf.predict(test_x)
```

```python
                error_rate.append(np.mean(pred_y_i != test_y))
            nloc = error_rate.index(min(error_rate))
            clf3 = RandomForestClassifier(n_estimators= nvals[nloc])
            clf3 = clf3.fit(train_x, train_y)

            # SVM
            clf4 = svm.SVC()
            clf4 = clf4.fit(train_x, train_y)

            # Naive Bayes
            clf5 = GaussianNB()
            clf5 = clf5.fit(train_x, train_y)

            return [clf1, clf2, clf3, clf4, clf5]
```

In [31]:
```python
# Majority vote
def run_majority_voting(train_x, test_x, train_y, test_y):
    models = getModels(train_x, test_x, train_y, test_y);
    correct = 0;
    for i in range(len(test_x)):
        count = 0;
        for j in range(len(models)):
            if (models[j].predict(test_x[i].reshape(1,-1))[0] == test_y[i]):
                count = count + 1;
            else:
                count = count - 1;
        if (count > 0):
            correct = correct + 1;

    accuracy = (correct*1.0)/len(test_x)
    print("Majority vote accuracy : %.10f" % accuracy)
```

In [32]:
```python
print("Run majority voting with all features(Built-in Algorithm):")
run_majority_voting(train_x, test_x, train_y, test_y)
print("=======================================================================
print("Run majority voting with top 2 features(Built-in Algorithm):")
run_majority_voting(train_x_two_features, test_x_two_features, train_y_two_features, t
print("=======================================================================
print("Run majority voting with dimensionality reduction using PCA(Built-in Algorithm
run_majority_voting(pca_train_x, pca_test_x, train_y, test_y)
```

```
Run majority voting with all features(Built-in Algorithm):
Majority vote accuracy : 0.9823232323
===============================================================================
Run majority voting with top 2 features(Built-in Algorithm):
Majority vote accuracy : 0.9747474747
===============================================================================
Run majority voting with dimensionality reduction using PCA(Built-in Algorithm)
```

```
Majority vote accuracy : 0.9747474747
```

```
In [33]: # Our test data
         path = '/Users/Kassi/Desktop/Gender_Recognition_by_Voice/voice_test.csv'
         voice_data_test = pd.read_csv(path)
         print("Total number of samples: {}".format(voice_data_test.shape[0]))
         print("Total number of male: {}".format(voice_data_test[voice_data_test.label == 'male
         print("Total number of female: {}".format(voice_data_test[voice_data_test.label == 'fe
         print("Correlation between each feature")
```

```
Total number of samples: 460
Total number of male: 230
Total number of female: 230
Correlation between each feature
```

```
In [34]: #### Check if dataset contains NA's
         voice_data_test.isnull().any().any()
```

```
Out[34]: False
```

```
In [35]: voice_data_test = voice_data_test.values
         voices_test = voice_data_test[:, :-1]
         labels_test = voice_data_test[:, -1:]
```

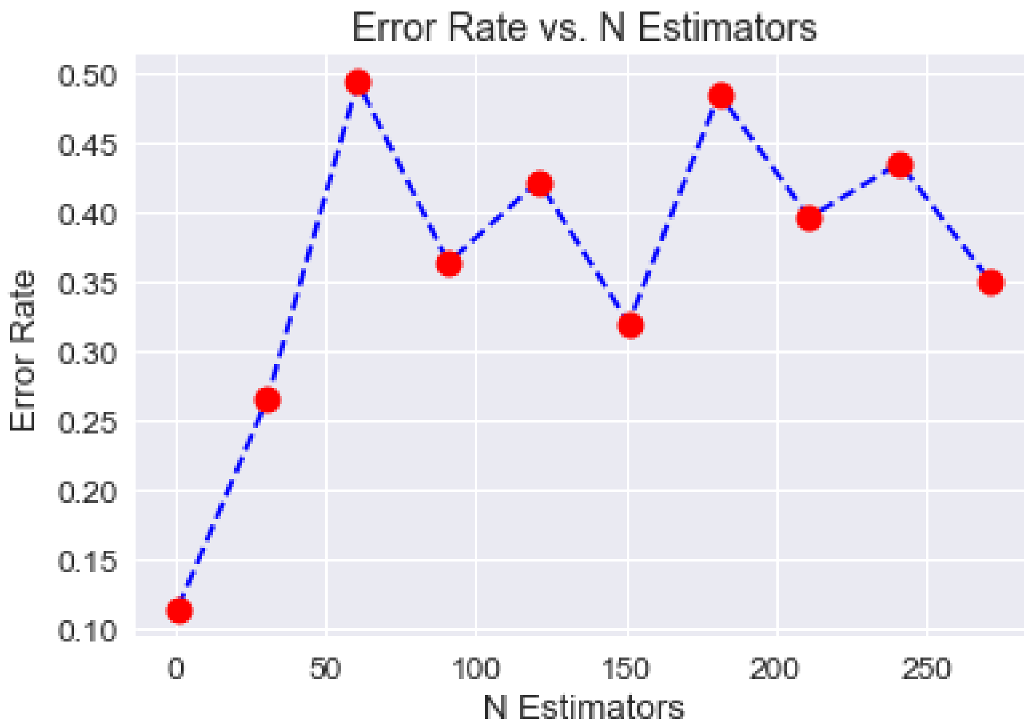
```
In [36]: gender_encoder = LabelEncoder()
         labels_test = gender_encoder.fit_transform(labels_test)
         # labels_test
```

```
In [37]: # randomly shuffle our data
         voices_tmp = []
         lables_tmp = []
         index_shuf = range(len(voices_test))
         random.shuffle(index_shuf)
         for i in index_shuf:
             voices_tmp.append(voices_test[i])
             lables_tmp.append(labels_test[i])
         voices_test = np.array(voices_tmp)
         labels_test = np.array(lables_tmp)
```

```
In [38]: print("Run random forest with all features(Built-in Algorithm):")
         Random_Forest.run_random_forest_classifier(train_x, voices_test, train_y,labels_test)
         print("=================================================================================
         print("Run majority voting with all features(Built-in Algorithm):")
         run_majority_voting(train_x, voices_test, train_y, labels_test)
         print("=================================================================================
         print("Run linear svm with all features(Built-in Algorithm):")
         SVM.run_linear_svm(train_x, voices_test, train_y, labels_test)
```

```
print("=================================================================================
print("Run rbf svm with all features(Built-in Algorithm):")
SVM.run_rbf_svm(train_x, voices_test, train_y, labels_test)
print("=================================================================================
print("with all features(Built-in Algorithm):")
KNN.run_k_nearest_neighbour(train_x, test_x, train_y, test_y)
```

```
Run random forest with all features(Built-in Algorithm):
```



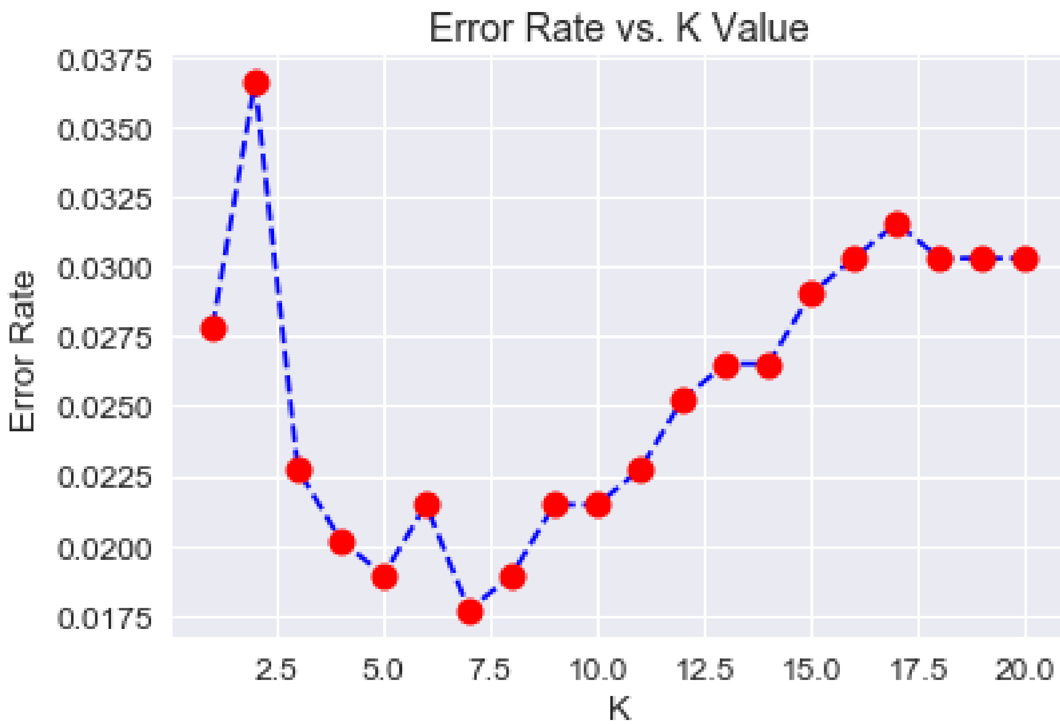

```
Lowest error of 0.113043478261 occurs at n=1.
The highest in-sample accuracy in Random Forest is 0.886956521739 when n=1.
Out-of-sample accuracy in Random Forest:0.7543478261
===============================================================================

Run majority voting with all features(Built-in Algorithm):
Majority vote accuracy : 0.6478260870
===============================================================================

Run linear svm with all features(Built-in Algorithm):
In-sample accuracy for svm with Linear kernel: 0.9743290243
Out-of-sample accuracy for svm with Linear kernel: 0.7913043478
===============================================================================
```

```
Run rbf svm with all features(Built-in Algorithm):
In-sample accuracy for svm with RBF kernel: 0.9806448362
Out-of-sample accuracy for svm with RBF kernel: 0.5847826087
================================================================================

with all features(Built-in Algorithm):
```




```
Lowest error is 0.0176767676768 occurs at k=7.
In-sample accuracy for KNN: 0.9696947768
Out-of-sample accuracy for KNN: 0.9507602898
```

```
In [ ]: # END:OWN CODE
```