HW2_1

October 30, 2018

```
In [68]: import numpy as np
         import matplotlib.pyplot as plt
         from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
         from sklearn.svm import SVC
         from sklearn.metrics import confusion_matrix
         from sklearn.neighbors import KNeighborsClassifier


         #part1a
         sigma=1
         rho=0.2
         u1=np.array([0,0])
         u2=np.array([1,1])
         cov=np.array([[sigma**2,rho*sigma**2],[rho*sigma**2,sigma**2]])
         print('cov',cov)

         nlist=np.linspace(20,100,num=9)

         test_error=np.zeros(len(nlist))
         err_lda=np.zeros(len(nlist))

         count=0
         score_avg=np.zeros([len(nlist),3])
         for train_n in range(0,len(nlist)) :
             score=[0,0,0]
             conf_matrix=np.float64(([0,0],[0,0])*3)
             for rep_i in range(0,1000):

                 #import pdb; pdb.set_trace()
                 #create sample two guassian distributions for each mean training data
                 x1_train=np.random.multivariate_normal(u1,cov,int(nlist[train_n]/2))
                 y1_train=np.zeros(int(nlist[train_n]/2))
                 for i in range (0,int(nlist[train_n]/2)):
                     y1_train[i]=0
                 x2_train=np.random.multivariate_normal(u2,cov,int(nlist[train_n]/2))
                 y2_train=np.zeros(int(nlist[train_n]/2))
                 for i in range (0,int(nlist[train_n]/2)):
                     y2_train[i]=1
```

```
X_train=np.concatenate((x1_train,x2_train),axis=0)
Y_train=np.concatenate((y1_train,y2_train),axis=0)

# generate test set
x1_test=np.random.multivariate_normal(u1,cov,200)
y1_test=np.zeros(200)
for i in range (0,200):
    y1_test[i]=0
x2_test=np.random.multivariate_normal(u2,cov,200)
y2_test=np.zeros(200)
for i in range (0,200):
    y2_test[i]=1

X_test=np.concatenate((x1_test,x2_test),axis=0)
Y_test=np.concatenate((y1_test,y2_test),axis=0)

#model1
model1 = LinearDiscriminantAnalysis()
model1.fit(X_train, Y_train)
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
solver='svd', store_covariance=False, tol=0.0001)
Y_pred1=model1.predict(X_test)

#model2
model2 = SVC(gamma='auto')
model2.fit(X_train, Y_train)
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
max_iter=-1, probability=False, random_state=None, shrinking=True,
tol=0.001, verbose=False)
Y_pred2=model2.predict(X_test)

#model2
model3 = KNeighborsClassifier(n_neighbors=3)
model3.fit(X_train, Y_train)
KNeighborsClassifier(...)
Y_pred3=model3.predict(X_test)


#acccuracy for this iteration
score[0]+=model1.score(X_test,Y_test)
score[1]+=model2.score(X_test,Y_test)
score[2]+=model3.score(X_test,Y_test)
conf_matrix[0:2][0:2]+=np.divide(confusion_matrix(Y_test, Y_pred1),200)
conf_matrix[2:4][0:2]+=np.divide(confusion_matrix(Y_test, Y_pred2),200)
conf_matrix[4:6][0:2]+=np.divide(confusion_matrix(Y_test, Y_pred3),200)
```

```python
        #average the accuracy and conf matrix
        for modelcount in range (0,3):
            print(score)
            score_avg[count,modelcount]=score[modelcount]/1000

            print('scoreavg',modelcount,score_avg[count,modelcount])
        count+=1
            #np.append(conf_matrix_avg[modelcount],np.divide(conf_matrix[modelcount],1000
```

```
cov [[1.  0.2]
 [0.2 1. ]]
[714.0849999999974, 688.6650000000003, 673.0324999999997]
scoreavg 0 0.7140849999999974
[714.0849999999974, 688.6650000000003, 673.0324999999997]
scoreavg 1 0.6886650000000003
[714.0849999999974, 688.6650000000003, 673.0324999999997]
scoreavg 2 0.6730324999999997
[722.9525000000006, 703.9200000000001, 679.7474999999995]
scoreavg 0 0.7229525000000006
[722.9525000000006, 703.9200000000001, 679.7474999999995]
scoreavg 1 0.7039200000000001
[722.9525000000006, 703.9200000000001, 679.7474999999995]
scoreavg 2 0.6797474999999995
[727.6049999999984, 709.5599999999994, 678.8874999999991]
scoreavg 0 0.7276049999999984
[727.6049999999984, 709.5599999999994, 678.8874999999991]
scoreavg 1 0.7095599999999994
[727.6049999999984, 709.5599999999994, 678.8874999999991]
scoreavg 2 0.6788874999999991
[732.2525000000014, 715.4950000000007, 681.3250000000003]
scoreavg 0 0.7322525000000014
[732.2525000000014, 715.4950000000007, 681.3250000000003]
scoreavg 1 0.7154950000000007
[732.2525000000014, 715.4950000000007, 681.3250000000003]
scoreavg 2 0.6813250000000003
[732.3200000000002, 718.3600000000005, 683.1699999999997]
scoreavg 0 0.7323200000000002
[732.3200000000002, 718.3600000000005, 683.1699999999997]
scoreavg 1 0.7183600000000004
[732.3200000000002, 718.3600000000005, 683.1699999999997]
scoreavg 2 0.6831699999999997
[734.3250000000002, 721.4550000000013, 685.4149999999996]
scoreavg 0 0.7343250000000001
[734.3250000000002, 721.4550000000013, 685.4149999999996]
scoreavg 1 0.7214550000000013
[734.3250000000002, 721.4550000000013, 685.4149999999996]
scoreavg 2 0.6854149999999997
[734.8600000000004, 723.68, 685.2775]
```

```
scoreavg 0 0.7348600000000004
[734.8600000000004, 723.68, 685.2775]
scoreavg 1 0.72368
[734.8600000000004, 723.68, 685.2775]
scoreavg 2 0.6852775
[735.1024999999997, 723.8874999999998, 683.3574999999998]
scoreavg 0 0.7351024999999998
[735.1024999999997, 723.8874999999998, 683.3574999999998]
scoreavg 1 0.7238874999999998
[735.1024999999997, 723.8874999999998, 683.3574999999998]
scoreavg 2 0.6833574999999998
[735.9074999999998, 725.9024999999997, 684.205]
scoreavg 0 0.7359074999999998
[735.9074999999998, 725.9024999999997, 684.205]
scoreavg 1 0.7259024999999997
[735.9074999999998, 725.9024999999997, 684.205]
scoreavg 2 0.6842050000000001
```

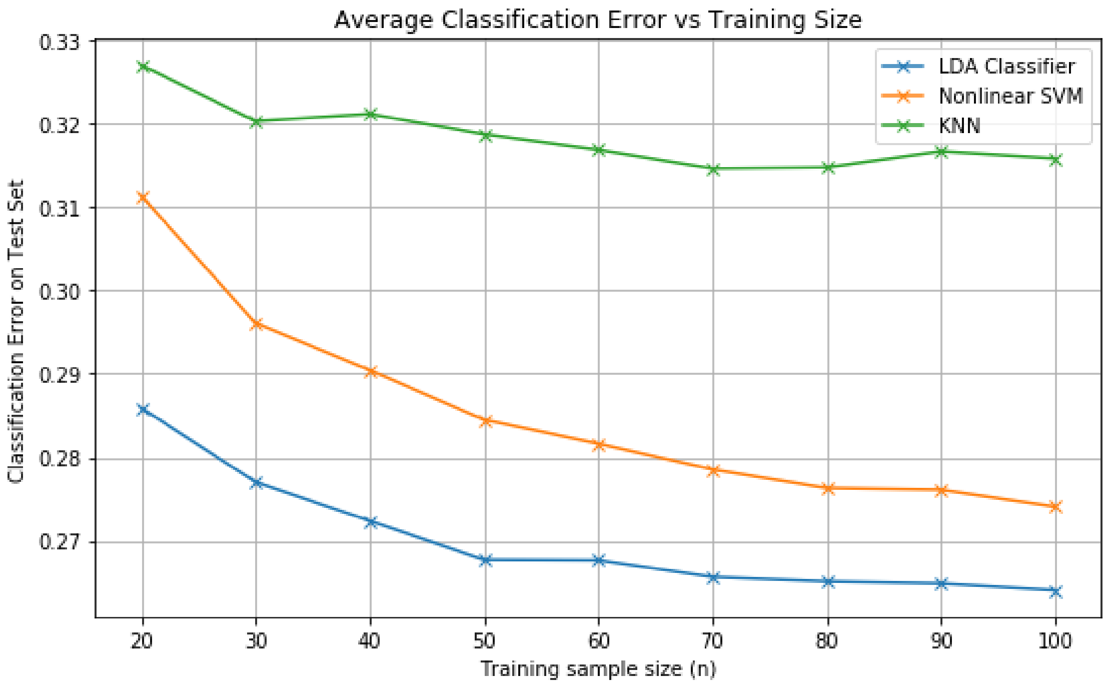
In [67]:
```
conf_matrix=np.float64(([0,0],[0,0])*3)
score_avg.shape
```

Out[67]:
```
(9, 3)
```

In [69]:
```
#plot error vs n
fig, ax = plt.subplots(figsize=[8,5])
plt.plot(nlist,1-score_avg[:,0],marker='x',label='LDA Classifier')
plt.plot(nlist,1-score_avg[:,1],marker='x',label='Nonlinear SVM')
plt.plot(nlist,1-score_avg[:,2],marker='x',label='KNN')
plt.hold(True)
plt.title('Average Classification Error vs Training Size')
plt.ylabel('Classification Error on Test Set')
plt.xlabel('Training sample size (n)')
fig.tight_layout()
ax.legend()
plt.grid(True)
plt.show
fig.savefig('hw2_1a.png')
```

```
C:\Users\aksha\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: MatplotlibDeprecationWarni
    Future behavior will be consistent with the long-time default:
    plot commands add elements without first clearing the
    Axes and/or Figure.

C:\Users\aksha\Anaconda3\lib\site-packages\matplotlib\__init__.py:911: MatplotlibDeprecationWa
  mplDeprecation)
C:\Users\aksha\Anaconda3\lib\site-packages\matplotlib\rcsetup.py:156: MatplotlibDeprecationWarn
  mplDeprecation)
```



In [70]:
```
#part1a
sigma=2
rho=0.2
u1=np.array([0,0])
u2=np.array([1,1])
cov=np.array([[sigma**2,rho*sigma**2],[rho*sigma**2,sigma**2]])
print('cov',cov)

nlist=np.linspace(20,100,num=9)

test_error=np.zeros(len(nlist))
err_lda=np.zeros(len(nlist))

count=0
score_avg=np.zeros([len(nlist),3])
for train_n in range(0,len(nlist)) :
    score=[0,0,0]
    conf_matrix=np.float64(([0,0],[0,0])*3)
    for rep_i in range(0,1000):

        #import pdb; pdb.set_trace()
        #create sample two guassian distributions for each mean training data
        x1_train=np.random.multivariate_normal(u1,cov,int(nlist[train_n]/2))
        y1_train=np.zeros(int(nlist[train_n]/2))
        for i in range (0,int(nlist[train_n]/2)):
```

```
    y1_train[i]=0
x2_train=np.random.multivariate_normal(u2,cov,int(nlist[train_n]/2))
y2_train=np.zeros(int(nlist[train_n]/2))
for i in range (0,int(nlist[train_n]/2)):
    y2_train[i]=1

X_train=np.concatenate((x1_train,x2_train),axis=0)
Y_train=np.concatenate((y1_train,y2_train),axis=0)

# generate test set
x1_test=np.random.multivariate_normal(u1,cov,200)
y1_test=np.zeros(200)
for i in range (0,200):
    y1_test[i]=0
x2_test=np.random.multivariate_normal(u2,cov,200)
y2_test=np.zeros(200)
for i in range (0,200):
    y2_test[i]=1

X_test=np.concatenate((x1_test,x2_test),axis=0)
Y_test=np.concatenate((y1_test,y2_test),axis=0)

#model1
model1 = LinearDiscriminantAnalysis()
model1.fit(X_train, Y_train)
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
solver='svd', store_covariance=False, tol=0.0001)
Y_pred1=model1.predict(X_test)

#model2
model2 = SVC(gamma='auto')
model2.fit(X_train, Y_train)
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
max_iter=-1, probability=False, random_state=None, shrinking=True,
tol=0.001, verbose=False)
Y_pred2=model2.predict(X_test)

#model2
model3 = KNeighborsClassifier(n_neighbors=3)
model3.fit(X_train, Y_train)
KNeighborsClassifier(...)
Y_pred3=model3.predict(X_test)


#acccuracy for this iteration
score[0]+=model1.score(X_test,Y_test)
score[1]+=model2.score(X_test,Y_test)
```

```
            score[2]+=model3.score(X_test,Y_test)
            conf_matrix[0:2][0:2]+=np.divide(confusion_matrix(Y_test, Y_pred1),200)
            conf_matrix[2:4][0:2]+=np.divide(confusion_matrix(Y_test, Y_pred2),200)
            conf_matrix[4:6][0:2]+=np.divide(confusion_matrix(Y_test, Y_pred3),200)

        #average the accuracy and conf matrix
        for modelcount in range (0,3):
            print(score)
            score_avg[count,modelcount]=score[modelcount]/1000

            print('scoreavg',modelcount,score_avg[count,modelcount])
        count+=1
            #np.append(conf_matrix_avg[modelcount],np.divide(conf_matrix[modelcount],1000
```

```
cov [[4.  0.8]
 [0.8 4. ]]
[583.6624999999991, 542.4375000000008, 555.1675]
scoreavg 0 0.5836624999999991
[583.6624999999991, 542.4375000000008, 555.1675]
scoreavg 1 0.5424375000000008
[583.6624999999991, 542.4375000000008, 555.1675]
scoreavg 2 0.5551675
[598.1074999999998, 552.5524999999999, 559.8300000000002]
scoreavg 0 0.5981074999999998
[598.1074999999998, 552.5524999999999, 559.8300000000002]
scoreavg 1 0.5525524999999999
[598.1074999999998, 552.5524999999999, 559.8300000000002]
scoreavg 2 0.5598300000000002
[606.775, 559.5799999999997, 562.0499999999997]
scoreavg 0 0.606775
[606.775, 559.5799999999997, 562.0499999999997]
scoreavg 1 0.5595799999999997
[606.775, 559.5799999999997, 562.0499999999997]
scoreavg 2 0.5620499999999997
[612.0074999999998, 566.1625000000001, 563.8750000000005]
scoreavg 0 0.6120074999999998
[612.0074999999998, 566.1625000000001, 563.8750000000005]
scoreavg 1 0.5661625000000001
[612.0074999999998, 566.1625000000001, 563.8750000000005]
scoreavg 2 0.5638750000000005
[613.5049999999989, 566.4575, 560.2950000000003]
scoreavg 0 0.6135049999999989
[613.5049999999989, 566.4575, 560.2950000000003]
scoreavg 1 0.5664575
[613.5049999999989, 566.4575, 560.2950000000003]
scoreavg 2 0.5602950000000003
[616.275, 569.5699999999999, 562.4374999999993]
scoreavg 0 0.616275
```

```
[616.275, 569.5699999999999, 562.4374999999993]
scoreavg 1 0.5695699999999999
[616.275, 569.5699999999999, 562.4374999999993]
scoreavg 2 0.5624374999999994
[616.5199999999999, 571.7, 561.1224999999995]
scoreavg 0 0.6165199999999998
[616.5199999999999, 571.7, 561.1224999999995]
scoreavg 1 0.5717000000000001
[616.5199999999999, 571.7, 561.1224999999995]
scoreavg 2 0.5611224999999995
[617.9774999999993, 574.2150000000001, 559.8374999999993]
scoreavg 0 0.6179774999999993
[617.9774999999993, 574.2150000000001, 559.8374999999993]
scoreavg 1 0.5742150000000001
[617.9774999999993, 574.2150000000001, 559.8374999999993]
scoreavg 2 0.5598374999999993
[619.0825000000006, 576.3650000000006, 560.0925000000001]
scoreavg 0 0.6190825000000005
[619.0825000000006, 576.3650000000006, 560.0925000000001]
scoreavg 1 0.5763650000000006
[619.0825000000006, 576.3650000000006, 560.0925000000001]
scoreavg 2 0.5600925000000001
```

In [71]:
```
#plot error vs n
fig, ax = plt.subplots(figsize=[8,5])
plt.plot(nlist,1-score_avg[:,0],marker='x',label='LDA Classifier')
plt.plot(nlist,1-score_avg[:,1],marker='x',label='Nonlinear SVM')
plt.plot(nlist,1-score_avg[:,2],marker='x',label='KNN')
plt.hold(True)
plt.title('Average Classification Error vs Training Size')
plt.ylabel('Classification Error on Test Set')
plt.xlabel('Training sample size (n)')
fig.tight_layout()
ax.legend()
plt.grid(True)
plt.show
fig.savefig('hw2_11a.png')
```

```
C:\Users\aksha\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: MatplotlibDeprecationWarni
    Future behavior will be consistent with the long-time default:
    plot commands add elements without first clearing the
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C:\Users\aksha\Anaconda3\lib\site-packages\matplotlib\__init__.py:911: MatplotlibDeprecationWa
  mplDeprecation)
C:\Users\aksha\Anaconda3\lib\site-packages\matplotlib\rcsetup.py:156: MatplotlibDeprecationWarn
  mplDeprecation)
```
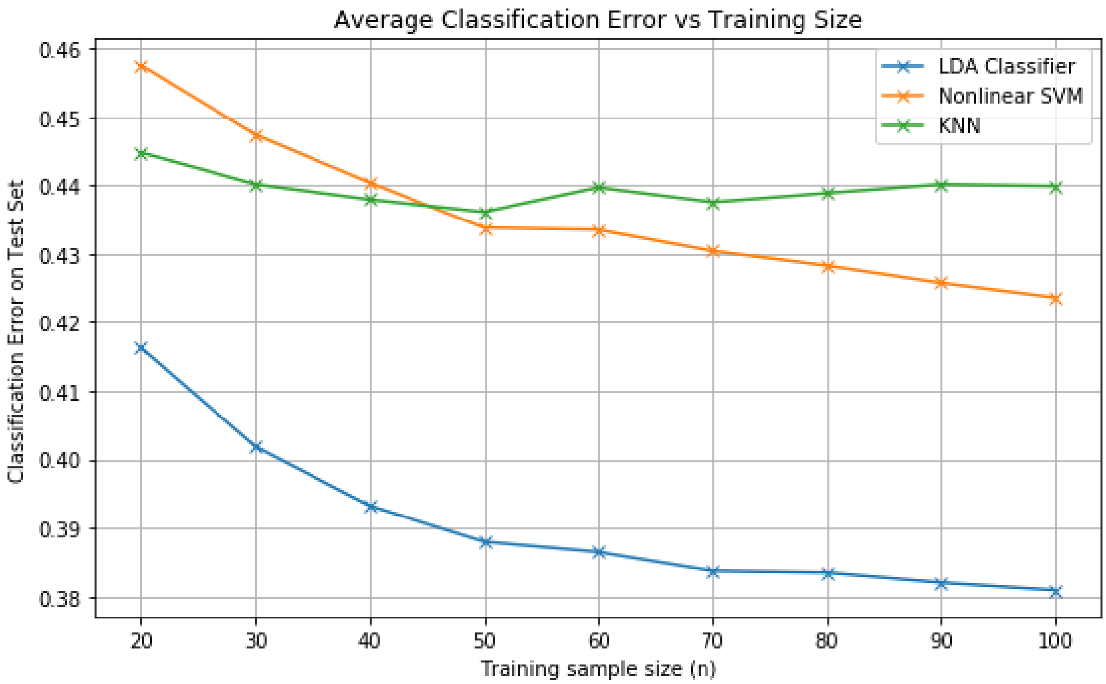




```
In [106]: from sklearn.model_selection import LeaveOneOut
          from sklearn.model_selection import KFold

          #part1a
          sigma=1
          rho=0.2
          u1=np.array([0,0])
          u2=np.array([1,1])
          cov=np.array([[sigma**2,rho*sigma**2],[rho*sigma**2,sigma**2]])
          print('cov',cov)

          nlist=np.linspace(20,100,num=9)

          test_error=np.zeros(len(nlist))
          err_lda=np.zeros(len(nlist))

          count=0
          score_avg=np.zeros([len(nlist),3])
          score_avgkf=np.zeros([len(nlist),3])
          score_avgloo=np.zeros([len(nlist),3])
          score_avgcl=np.zeros([len(nlist),3])
          for train_n in range(0,len(nlist)) :
              scorekf=[0,0,0]
              scoreloo=[0,0,0]
              score=[0,0,0]
```

```
score_cl=[0,0,0]
#import pdb; pdb.set_trace()
for rep_i in range(0,1000):

    #import pdb; pdb.set_trace()
    #create sample two guassian distributions for each mean training data
    x1_train=np.random.multivariate_normal(u1,cov,int(nlist[train_n]/2))
    y1_train=np.zeros(int(nlist[train_n]/2))
    for i in range (0,int(nlist[train_n]/2)):
        y1_train[i]=0
    x2_train=np.random.multivariate_normal(u2,cov,int(nlist[train_n]/2))
    y2_train=np.zeros(int(nlist[train_n]/2))
    for i in range (0,int(nlist[train_n]/2)):
        y2_train[i]=1

    X_train=np.concatenate((x1_train,x2_train),axis=0)
    Y_train=np.concatenate((y1_train,y2_train),axis=0)

    # generate test set
    x1_test=np.random.multivariate_normal(u1,cov,200)
    y1_test=np.zeros(200)
    for i in range (0,200):
        y1_test[i]=0
    x2_test=np.random.multivariate_normal(u2,cov,200)
    y2_test=np.zeros(200)
    for i in range (0,200):
        y2_test[i]=1

    X_test=np.concatenate((x1_test,x2_test),axis=0)
    Y_test=np.concatenate((y1_test,y2_test),axis=0)

    #kfold validation error estimate
    kf = KFold(n_splits=5)
    kf.get_n_splits(X_train)
    KFold(n_splits=5, random_state=None, shuffle=True)
    for train_index, test_index in kf.split(X_train):
        X_trainkf, X_testkf = X_train[train_index], X_train[test_index]
        Y_trainkf, Y_testkf = Y_train[train_index], Y_train[test_index]

        #model1
        model1 = LinearDiscriminantAnalysis()
        model1.fit(X_trainkf, Y_trainkf)
        LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None
        solver='svd', store_covariance=False, tol=0.0001)
        Y_pred1=model1.predict(X_testkf)

        #model2
        model2 = SVC(gamma='auto')
```

```
    model2.fit(X_trainkf, Y_trainkf)
    SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
    Y_pred2=model2.predict(X_testkf)

    #model2
    model3 = KNeighborsClassifier(n_neighbors=3)
    model3.fit(X_trainkf, Y_trainkf)
    KNeighborsClassifier(...)
    Y_pred3=model3.predict(X_testkf)

    #acccuracy for this iteration
    scorekf[0]+=model1.score(X_testkf,Y_testkf)
    scorekf[1]+=model2.score(X_testkf,Y_testkf)
    scorekf[2]+=model3.score(X_testkf,Y_testkf)

#import pdb; pdb.set_trace()


# leave one out error estimate
loo = LeaveOneOut()
loo.get_n_splits(X_train)

LeaveOneOut()
for train_index, test_index in loo.split(X_train):
    X_trainloo, X_testloo = X_train[train_index], X_train[test_index]
    Y_trainloo, Y_testloo = Y_train[train_index], Y_train[test_index]

    #model1
    model1 = LinearDiscriminantAnalysis()
    model1.fit(X_trainloo, Y_trainloo)
    LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
    solver='svd', store_covariance=False, tol=0.0001)
    Y_pred1=model1.predict(X_testloo)

    #model2
    model2 = SVC(gamma='auto')
    model2.fit(X_trainloo, Y_trainloo)
    SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
    Y_pred2=model2.predict(X_testloo)

    #model2
    model3 = KNeighborsClassifier(n_neighbors=3)
```

```
    model3.fit(X_trainloo, Y_trainloo)
    KNeighborsClassifier(...)
    Y_pred3=model3.predict(X_testloo)

    #acccuracy for this iteration
    scoreloo[0]+=model1.score(X_testloo,Y_testloo)
    scoreloo[1]+=model2.score(X_testloo,Y_testloo)
    scoreloo[2]+=model3.score(X_testloo,Y_testloo)


# average apparent error
#model1
model1 = LinearDiscriminantAnalysis()
model1.fit(X_train, Y_train)
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
solver='svd', store_covariance=False, tol=0.0001)
Y_pred1=model1.predict(X_test)

#model2
model2 = SVC(gamma='auto')
model2.fit(X_train, Y_train)
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
max_iter=-1, probability=False, random_state=None, shrinking=True,
tol=0.001, verbose=False)
Y_pred2=model2.predict(X_test)

#model2
model3 = KNeighborsClassifier(n_neighbors=3)
model3.fit(X_train, Y_train)
KNeighborsClassifier(...)
Y_pred3=model3.predict(X_test)


#acccuracy for this iteration
score[0]+=model1.score(X_train,Y_train)
score[1]+=model2.score(X_train,Y_train)
score[2]+=model3.score(X_train,Y_train)

# average classification error
#model1
model1 = LinearDiscriminantAnalysis()
model1.fit(X_train, Y_train)
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
solver='svd', store_covariance=False, tol=0.0001)
Y_pred1=model1.predict(X_test)

#model2
```

```
        model2 = SVC(gamma='auto')
        model2.fit(X_train, Y_train)
        SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
        decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
        max_iter=-1, probability=False, random_state=None, shrinking=True,
        tol=0.001, verbose=False)
        Y_pred2=model2.predict(X_test)

        #model2
        model3 = KNeighborsClassifier(n_neighbors=3)
        model3.fit(X_train, Y_train)
        KNeighborsClassifier(...)
        Y_pred3=model3.predict(X_test)


        #acccuracy for this iteration
        score_cl[0]+=model1.score(X_test,Y_test)
        score_cl[1]+=model2.score(X_test,Y_test)
        score_cl[2]+=model3.score(X_test,Y_test)

    #average across k folds
    scorekf=np.divide(scorekf,5)
    #average leave one out error estimate
    scoreloo=np.divide(scoreloo,int(nlist[train_n]))

    #average the accuracy for kf,loo,and average classification error
    for modelcount in range (0,3):
        score_avgkf[count,modelcount]=scorekf[modelcount]/1000
        score_avgloo[count,modelcount]=scoreloo[modelcount]/1000
        score_avg[count,modelcount]=score[modelcount]/1000
        score_avgcl[count,modelcount]=score_cl[modelcount]/1000

    count+=1
    print ('count of n',count)
    print ('score kf',score_avgkf)
    print('score loo',score_avgloo)
    print('score avg',score_avg)
    print('score avg',score_avgcl)

#plot error curves for LDA
fig, ax = plt.subplots(figsize=[8,5])
plt.plot(nlist,1-score_avgkf[:,0],marker='x',label='Average K fold validation error E
plt.plot(nlist,1-score_avgloo[:,0],marker='x',label='Average Leave One Out Error Esti
plt.plot(nlist,1-score_avg[:,0],marker='x',label='Average Apparent Error')
plt.plot(nlist,1-score_avgcl[:,0],marker='x',label='Average Classification Error')
plt.title('Average Classification Error and Error Estimates vs Training Size for LDA
plt.ylabel('Error Rate')
plt.xlabel('Training sample size (n)')
```

```
    fig.tight_layout()
    ax.legend()
    plt.grid(True)
    plt.show
    fig.savefig('hw2_14b.png')

    #plot error curves for SVM
    fig, ax = plt.subplots(figsize=[8,5])
    plt.plot(nlist,1-score_avgkf[:,1],marker='x',label='Average K fold validation error E
    plt.plot(nlist,1-score_avgloo[:,1],marker='x',label='Average Leave One Out Error Esti
    plt.plot(nlist,1-score_avg[:,1],marker='x',label='Average Apparent Error')
    plt.plot(nlist,1-score_avgcl[:,1],marker='x',label='Average Classification Error')
    plt.title('Average Classification Error and Error Estimates vs Training Size for SVM
    plt.ylabel('Error Rate')
    plt.xlabel('Training sample size (n)')
    fig.tight_layout()
    ax.legend()
    plt.grid(True)
    plt.show
    fig.savefig('hw2_15b.png')

    #plot error curves for KNN
    fig, ax = plt.subplots(figsize=[8,5])
    plt.plot(nlist,1-score_avgkf[:,2],marker='x',label='Average K fold validation error E
    plt.plot(nlist,1-score_avgloo[:,2],marker='x',label='Average Leave One Out Error Esti
    plt.plot(nlist,1-score_avg[:,2],marker='x',label='Average Apparent Error')
    plt.plot(nlist,1-score_avgcl[:,2],marker='x',label='Average Classification Error')
    plt.title('Average Classification Error and Error Estimates vs Training Size for KNN
    plt.ylabel('Error Rate')
    plt.xlabel('Training sample size (n)')
    fig.tight_layout()
    ax.legend()
    plt.grid(True)
    plt.show
    fig.savefig('hw2_16b.png')
```

```
cov [[1.  0.2]
 [0.2 1. ]]
count of n 1
score kf [[0.59785 0.48825 0.56155]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]]
```

```
score loo [[0.6925 0.6485 0.6521]
 [0.     0.     0.    ]
 [0.     0.     0.    ]
 [0.     0.     0.    ]
 [0.     0.     0.    ]
 [0.     0.     0.    ]
 [0.     0.     0.    ]
 [0.     0.     0.    ]
 [0.     0.     0.    ]]
score avg [[0.76935 0.8246  0.8184 ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 2
score kf [[0.59785    0.48825    0.56155   ]
 [0.60053333 0.5233     0.568     ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
```

```
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 3
score kf [[0.59785    0.48825    0.56155   ]
 [0.60053333 0.5233     0.568     ]
 [0.6065     0.536825   0.576625  ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.712125   0.689325   0.66595   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
 [0.749025   0.7915     0.819825  ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.729005  0.711005  0.680395 ]
 [0.        0.        0.       ]
```

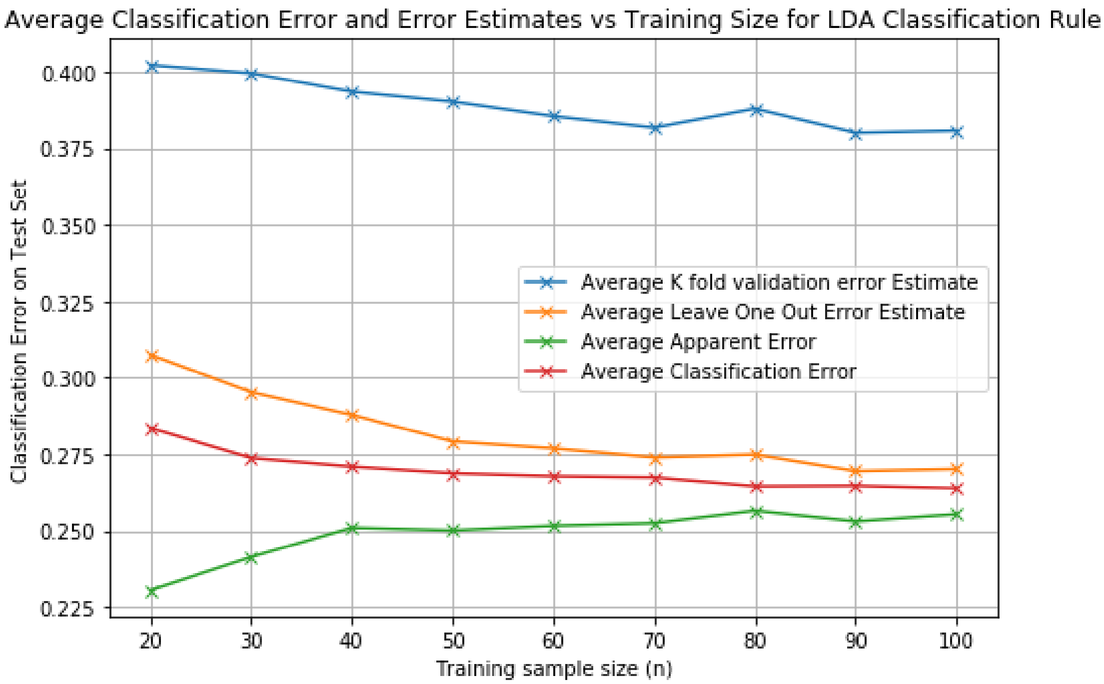
```
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
count of n 4
score kf [[0.59785    0.48825    0.56155   ]
 [0.60053333 0.5233     0.568     ]
 [0.6065     0.536825   0.576625  ]
 [0.60976    0.5474     0.57588   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.712125   0.689325   0.66595   ]
 [0.72078    0.69972    0.66722   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
 [0.749025   0.7915     0.819825  ]
 [0.74988    0.78326    0.82206   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.729005  0.711005  0.680395 ]
 [0.7311475 0.71515   0.6807675]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 5
score kf [[0.59785    0.48825    0.56155   ]
 [0.60053333 0.5233     0.568     ]
 [0.6065     0.536825   0.576625  ]
 [0.60976    0.5474     0.57588   ]
 [0.6145     0.55973333 0.58565   ]
```

```
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.712125   0.689325   0.66595   ]
 [0.72078    0.69972    0.66722   ]
 [0.72305    0.7092     0.67575   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
 [0.749025   0.7915     0.819825  ]
 [0.74988    0.78326    0.82206   ]
 [0.74835    0.77993333 0.82425   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.729005  0.711005  0.680395 ]
 [0.7311475 0.71515   0.6807675]
 [0.7321125 0.7175    0.6814625]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 6
score kf [[0.59785    0.48825    0.56155   ]
 [0.60053333 0.5233     0.568     ]
 [0.6065     0.536825   0.576625  ]
 [0.60976    0.5474     0.57588   ]
 [0.6145     0.55973333 0.58565   ]
 [0.61821429 0.56921429 0.58587143]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.712125   0.689325   0.66595   ]
 [0.72078    0.69972    0.66722   ]
 [0.72305    0.7092     0.67575   ]
 [0.72601429 0.71288571 0.67862857]
 [0.         0.         0.        ]
```

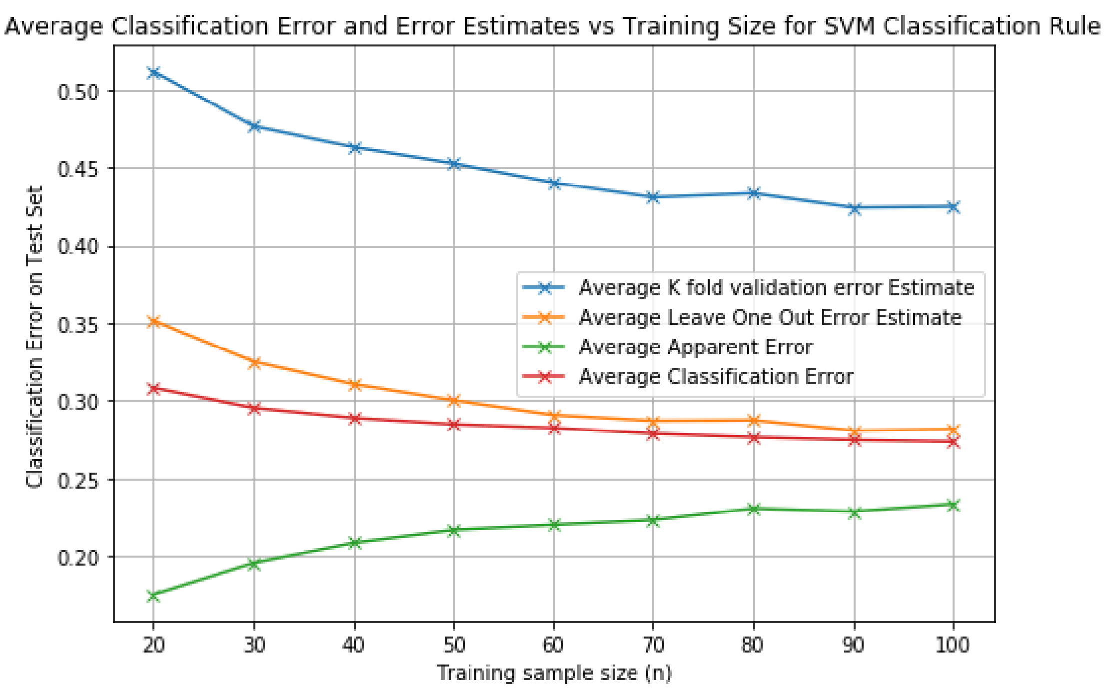
```
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
 [0.749025   0.7915     0.819825  ]
 [0.74988    0.78326    0.82206   ]
 [0.74835    0.77993333 0.82425   ]
 [0.7475     0.77681429 0.82478571]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.729005  0.711005  0.680395 ]
 [0.7311475 0.71515   0.6807675]
 [0.7321125 0.7175    0.6814625]
 [0.7325075 0.721205  0.6837525]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 7
score kf [[0.59785    0.48825    0.56155   ]
 [0.60053333 0.5233     0.568     ]
 [0.6065     0.536825   0.576625  ]
 [0.60976    0.5474     0.57588   ]
 [0.6145     0.55973333 0.58565   ]
 [0.61821429 0.56921429 0.58587143]
 [0.6120625  0.5665875  0.5811    ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.712125   0.689325   0.66595   ]
 [0.72078    0.69972    0.66722   ]
 [0.72305    0.7092     0.67575   ]
 [0.72601429 0.71288571 0.67862857]
 [0.7250625  0.712475   0.67545   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
 [0.749025   0.7915     0.819825  ]
 [0.74988    0.78326    0.82206   ]
 [0.74835    0.77993333 0.82425   ]
 [0.7475     0.77681429 0.82478571]
 [0.74345    0.7692875  0.8226    ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
```

```
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.729005  0.711005  0.680395 ]
 [0.7311475 0.71515   0.6807675]
 [0.7321125 0.7175    0.6814625]
 [0.7325075 0.721205  0.6837525]
 [0.7354    0.72361   0.6849825]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 8
score kf [[0.59785    0.48825    0.56155   ]
 [0.60053333 0.5233     0.568     ]
 [0.6065     0.536825   0.576625  ]
 [0.60976    0.5474     0.57588   ]
 [0.6145     0.55973333 0.58565   ]
 [0.61821429 0.56921429 0.58587143]
 [0.6120625  0.5665875  0.5811    ]
 [0.61988889 0.57577778 0.58855556]
 [0.         0.         0.        ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.712125   0.689325   0.66595   ]
 [0.72078    0.69972    0.66722   ]
 [0.72305    0.7092     0.67575   ]
 [0.72601429 0.71288571 0.67862857]
 [0.7250625  0.712475   0.67545   ]
 [0.73046667 0.71924444 0.68096667]
 [0.         0.         0.        ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
 [0.749025   0.7915     0.819825  ]
 [0.74988    0.78326    0.82206   ]
 [0.74835    0.77993333 0.82425   ]
 [0.7475     0.77681429 0.82478571]
 [0.74345    0.7692875  0.8226    ]
 [0.74691111 0.77128889 0.8257    ]
 [0.         0.         0.        ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.729005  0.711005  0.680395 ]
 [0.7311475 0.71515   0.6807675]
 [0.7321125 0.7175    0.6814625]
 [0.7325075 0.721205  0.6837525]
 [0.7354    0.72361   0.6849825]
 [0.7352425 0.725385  0.685275 ]
 [0.        0.        0.       ]]
count of n 9
score kf [[0.59785    0.48825    0.56155   ]
```

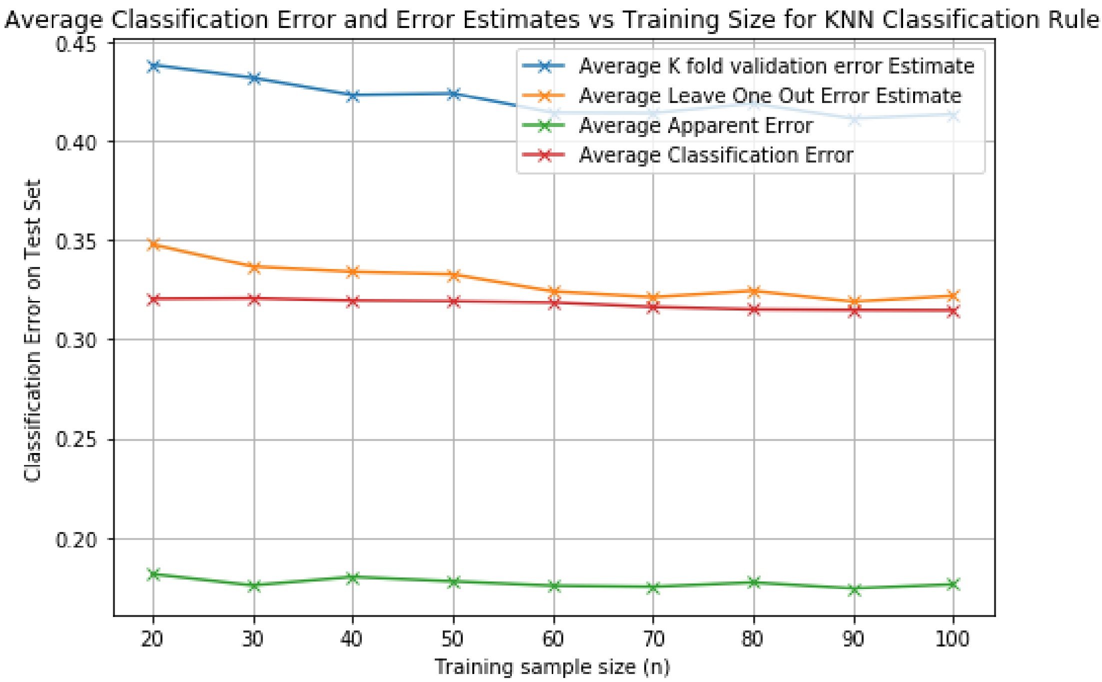
```
 [0.60053333 0.5233     0.568     ]
 [0.6065     0.536825   0.576625  ]
 [0.60976    0.5474     0.57588   ]
 [0.6145     0.55973333 0.58565   ]
 [0.61821429 0.56921429 0.58587143]
 [0.6120625  0.5665875  0.5811    ]
 [0.61988889 0.57577778 0.58855556]
 [0.61918    0.57506    0.58643   ]]
score loo [[0.6925     0.6485     0.6521    ]
 [0.70466667 0.67476667 0.6633    ]
 [0.712125   0.689325   0.66595   ]
 [0.72078    0.69972    0.66722   ]
 [0.72305    0.7092     0.67575   ]
 [0.72601429 0.71288571 0.67862857]
 [0.7250625  0.712475   0.67545   ]
 [0.73046667 0.71924444 0.68096667]
 [0.72978    0.71831    0.67796   ]]
score avg [[0.76935    0.8246     0.8184    ]
 [0.75853333 0.8045     0.82406667]
 [0.749025   0.7915     0.819825  ]
 [0.74988    0.78326    0.82206   ]
 [0.74835    0.77993333 0.82425   ]
 [0.7475     0.77681429 0.82478571]
 [0.74345    0.7692875  0.8226    ]
 [0.74691111 0.77128889 0.8257    ]
 [0.74458    0.76644    0.82358   ]]
score avg [[0.716375  0.6917125 0.6794275]
 [0.72618   0.7045625 0.6791725]
 [0.729005  0.711005  0.680395 ]
 [0.7311475 0.71515   0.6807675]
 [0.7321125 0.7175    0.6814625]
 [0.7325075 0.721205  0.6837525]
 [0.7354    0.72361   0.6849825]
 [0.7352425 0.725385  0.685275 ]
 [0.7360875 0.7264575 0.6854525]]
```



Average Classification Error and Error Estimates vs Training Size for LDA Classification Rule
Classification Error on Test Set
Training sample size (n)
0.400
0.375
0.350
0.325
0.300
0.275
0.250
0.225
20
30
40
50
60
70
80
90
100
Average K fold validation error Estimate
Average Leave One Out Error Estimate
Average Apparent Error
Average Classification Error



Average Classification Error and Error Estimates vs Training Size for SVM Classification Rule
Classification Error on Test Set
Training sample size (n)
0.50
0.45
0.40
0.35
0.30
0.25
0.20
20
30
40
50
60
70
80
90
100
Average K fold validation error Estimate
Average Leave One Out Error Estimate
Average Apparent Error
Average Classification Error



In [107]:
```
from sklearn.model_selection import LeaveOneOut
from sklearn.model_selection import KFold

#part1a
sigma=2
rho=0.2
u1=np.array([0,0])
u2=np.array([1,1])
cov=np.array([[sigma**2,rho*sigma**2],[rho*sigma**2,sigma**2]])
print('cov',cov)

nlist=np.linspace(20,100,num=9)

test_error=np.zeros(len(nlist))
err_lda=np.zeros(len(nlist))

count=0
score_avg=np.zeros([len(nlist),3])
score_avgkf=np.zeros([len(nlist),3])
score_avgloo=np.zeros([len(nlist),3])
score_avgcl=np.zeros([len(nlist),3])
for train_n in range(0,len(nlist)) :
    scorekf=[0,0,0]
    scoreloo=[0,0,0]
    score=[0,0,0]
```

```
score_cl=[0,0,0]
#import pdb; pdb.set_trace()
for rep_i in range(0,1000):

    #import pdb; pdb.set_trace()
    #create sample two guassian distributions for each mean training data
    x1_train=np.random.multivariate_normal(u1,cov,int(nlist[train_n]/2))
    y1_train=np.zeros(int(nlist[train_n]/2))
    for i in range (0,int(nlist[train_n]/2)):
        y1_train[i]=0
    x2_train=np.random.multivariate_normal(u2,cov,int(nlist[train_n]/2))
    y2_train=np.zeros(int(nlist[train_n]/2))
    for i in range (0,int(nlist[train_n]/2)):
        y2_train[i]=1

    X_train=np.concatenate((x1_train,x2_train),axis=0)
    Y_train=np.concatenate((y1_train,y2_train),axis=0)

    # generate test set
    x1_test=np.random.multivariate_normal(u1,cov,200)
    y1_test=np.zeros(200)
    for i in range (0,200):
        y1_test[i]=0
    x2_test=np.random.multivariate_normal(u2,cov,200)
    y2_test=np.zeros(200)
    for i in range (0,200):
        y2_test[i]=1

    X_test=np.concatenate((x1_test,x2_test),axis=0)
    Y_test=np.concatenate((y1_test,y2_test),axis=0)

    #kfold validation error estimate
    kf = KFold(n_splits=5)
    kf.get_n_splits(X_train)
    KFold(n_splits=5, random_state=None, shuffle=True)
    for train_index, test_index in kf.split(X_train):
        X_trainkf, X_testkf = X_train[train_index], X_train[test_index]
        Y_trainkf, Y_testkf = Y_train[train_index], Y_train[test_index]

        #model1
        model1 = LinearDiscriminantAnalysis()
        model1.fit(X_trainkf, Y_trainkf)
        LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None
        solver='svd', store_covariance=False, tol=0.0001)
        Y_pred1=model1.predict(X_testkf)

        #model2
        model2 = SVC(gamma='auto')
```

```
    model2.fit(X_trainkf, Y_trainkf)
    SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
    Y_pred2=model2.predict(X_testkf)

    #model2
    model3 = KNeighborsClassifier(n_neighbors=3)
    model3.fit(X_trainkf, Y_trainkf)
    KNeighborsClassifier(...)
    Y_pred3=model3.predict(X_testkf)

    #acccuracy for this iteration
    scorekf[0]+=model1.score(X_testkf,Y_testkf)
    scorekf[1]+=model2.score(X_testkf,Y_testkf)
    scorekf[2]+=model3.score(X_testkf,Y_testkf)

#import pdb; pdb.set_trace()


# leave one out error estimate
loo = LeaveOneOut()
loo.get_n_splits(X_train)

LeaveOneOut()
for train_index, test_index in loo.split(X_train):
    X_trainloo, X_testloo = X_train[train_index], X_train[test_index]
    Y_trainloo, Y_testloo = Y_train[train_index], Y_train[test_index]

    #model1
    model1 = LinearDiscriminantAnalysis()
    model1.fit(X_trainloo, Y_trainloo)
    LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None
    solver='svd', store_covariance=False, tol=0.0001)
    Y_pred1=model1.predict(X_testloo)

    #model2
    model2 = SVC(gamma='auto')
    model2.fit(X_trainloo, Y_trainloo)
    SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
    Y_pred2=model2.predict(X_testloo)

    #model2
    model3 = KNeighborsClassifier(n_neighbors=3)
```

```
    model3.fit(X_trainloo, Y_trainloo)
    KNeighborsClassifier(...)
    Y_pred3=model3.predict(X_testloo)

    #acccuracy for this iteration
    scoreloo[0]+=model1.score(X_testloo,Y_testloo)
    scoreloo[1]+=model2.score(X_testloo,Y_testloo)
    scoreloo[2]+=model3.score(X_testloo,Y_testloo)


# average apparent error
#model1
model1 = LinearDiscriminantAnalysis()
model1.fit(X_train, Y_train)
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
solver='svd', store_covariance=False, tol=0.0001)
Y_pred1=model1.predict(X_test)

#model2
model2 = SVC(gamma='auto')
model2.fit(X_train, Y_train)
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
max_iter=-1, probability=False, random_state=None, shrinking=True,
tol=0.001, verbose=False)
Y_pred2=model2.predict(X_test)

#model2
model3 = KNeighborsClassifier(n_neighbors=3)
model3.fit(X_train, Y_train)
KNeighborsClassifier(...)
Y_pred3=model3.predict(X_test)


#acccuracy for this iteration
score[0]+=model1.score(X_train,Y_train)
score[1]+=model2.score(X_train,Y_train)
score[2]+=model3.score(X_train,Y_train)

# average classification error
#model1
model1 = LinearDiscriminantAnalysis()
model1.fit(X_train, Y_train)
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
solver='svd', store_covariance=False, tol=0.0001)
Y_pred1=model1.predict(X_test)

#model2
```

```
            model2 = SVC(gamma='auto')
            model2.fit(X_train, Y_train)
            SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
            decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
            max_iter=-1, probability=False, random_state=None, shrinking=True,
            tol=0.001, verbose=False)
            Y_pred2=model2.predict(X_test)

            #model2
            model3 = KNeighborsClassifier(n_neighbors=3)
            model3.fit(X_train, Y_train)
            KNeighborsClassifier(...)
            Y_pred3=model3.predict(X_test)


            #acccuracy for this iteration
            score_cl[0]+=model1.score(X_test,Y_test)
            score_cl[1]+=model2.score(X_test,Y_test)
            score_cl[2]+=model3.score(X_test,Y_test)

        #average across k folds
        scorekf=np.divide(scorekf,5)
        #average leave one out error estimate
        scoreloo=np.divide(scoreloo,int(nlist[train_n]))

        #average the accuracy for kf,loo,and average classification error
        for modelcount in range (0,3):
            score_avgkf[count,modelcount]=scorekf[modelcount]/1000
            score_avgloo[count,modelcount]=scoreloo[modelcount]/1000
            score_avg[count,modelcount]=score[modelcount]/1000
            score_avgcl[count,modelcount]=score_cl[modelcount]/1000

        count+=1
        print ('count of n',count)
        print ('score kf',score_avgkf)
        print('score loo',score_avgloo)
        print('score avg',score_avg)
        print('score avg',score_avgcl)
```

```
cov [[4.  0.8]
 [0.8 4. ]]
count of n 1
score kf [[0.37915 0.2659  0.4081 ]
 [0.      0.      0.      ]
 [0.      0.      0.      ]
 [0.      0.      0.      ]
 [0.      0.      0.      ]
 [0.      0.      0.      ]
```

```
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]]
score loo [[0.51465 0.45365 0.51855]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]]
score avg [[0.66725 0.87095 0.75975]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]
 [0.      0.      0.     ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 2
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.51465    0.45365    0.51855    ]
 [0.54993333 0.50176667 0.53506667]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
```

```
 [0.         0.         0.        ]]
score avg [[0.66725    0.87095    0.75975   ]
 [0.65463333 0.84006667 0.76326667]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.5980475 0.550245  0.556865 ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 3
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
 [0.373475   0.302225   0.42015   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.51465    0.45365    0.51855   ]
 [0.54993333 0.50176667 0.53506667]
 [0.573375   0.52335    0.539675  ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.66725    0.87095    0.75975   ]
 [0.65463333 0.84006667 0.76326667]
 [0.65005    0.8131     0.76875   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.5850225 0.5435975 0.5558825]
```

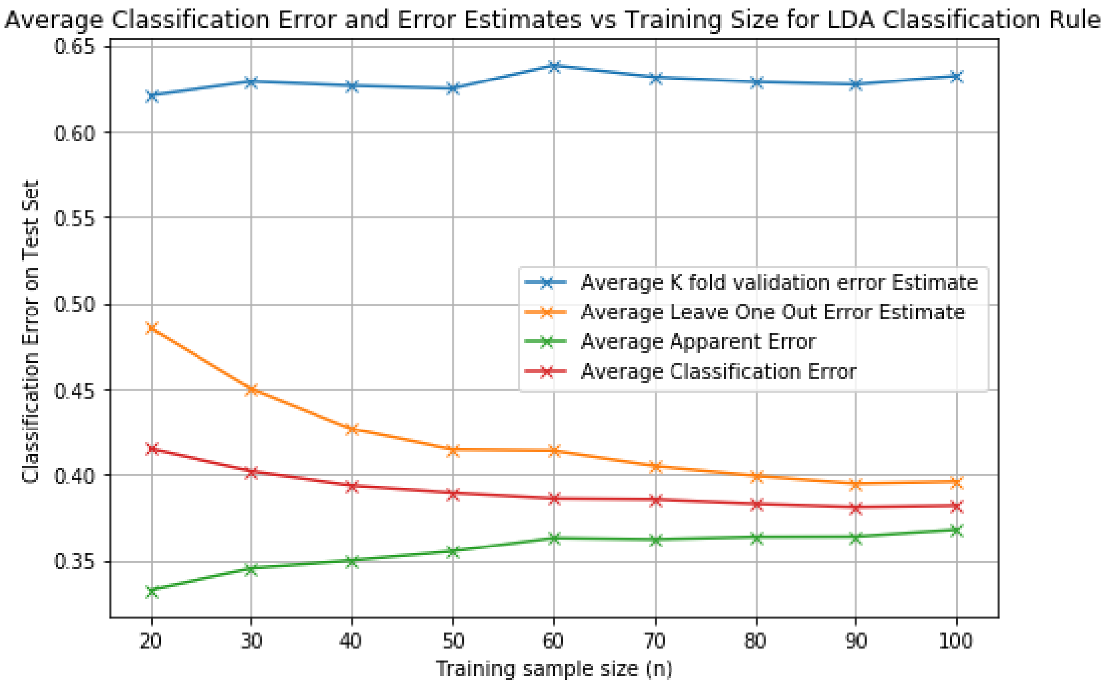
```
 [0.5980475 0.550245  0.556865 ]
 [0.6064025 0.55752   0.559835 ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 4
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
 [0.373475   0.302225   0.42015   ]
 [0.37512    0.31006    0.42372   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.51465    0.45365    0.51855   ]
 [0.54993333 0.50176667 0.53506667]
 [0.573375   0.52335    0.539675  ]
 [0.5855     0.53636    0.54992   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.66725    0.87095    0.75975   ]
 [0.65463333 0.84006667 0.76326667]
 [0.65005    0.8131     0.76875   ]
 [0.64464    0.79598    0.7696    ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.5980475 0.550245  0.556865 ]
 [0.6064025 0.55752   0.559835 ]
 [0.610645  0.5624775 0.5620175]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 5
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
```

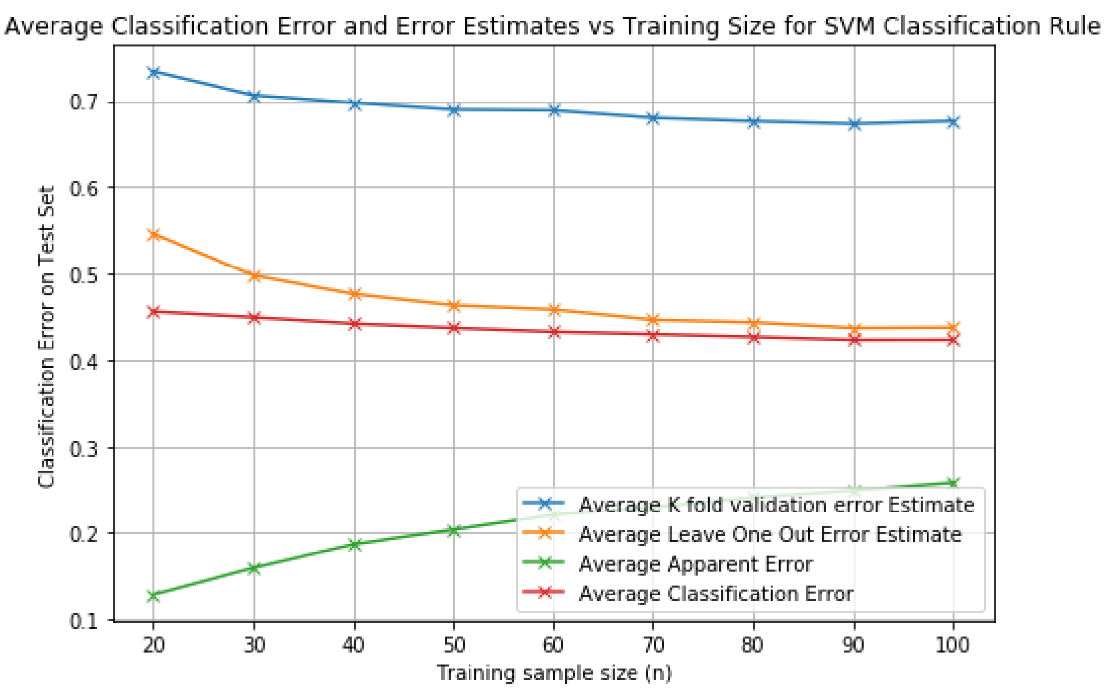
```
 [0.373475   0.302225   0.42015   ]
 [0.37512    0.31006    0.42372   ]
 [0.3615     0.31091667 0.42218333]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.51465    0.45365    0.51855   ]
 [0.54993333 0.50176667 0.53506667]
 [0.573375   0.52335    0.539675  ]
 [0.5855     0.53636    0.54992   ]
 [0.58616667 0.5413     0.54758333]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.66725    0.87095    0.75975   ]
 [0.65463333 0.84006667 0.76326667]
 [0.65005    0.8131     0.76875   ]
 [0.64464    0.79598    0.7696    ]
 [0.63685    0.77876667 0.76825   ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.5980475 0.550245  0.556865 ]
 [0.6064025 0.55752   0.559835 ]
 [0.610645  0.5624775 0.5620175]
 [0.6139225 0.566785  0.56079  ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 6
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
 [0.373475   0.302225   0.42015   ]
 [0.37512    0.31006    0.42372   ]
 [0.3615     0.31091667 0.42218333]
 [0.36842857 0.31951429 0.42804286]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.51465    0.45365    0.51855   ]
 [0.54993333 0.50176667 0.53506667]
 [0.573375   0.52335    0.539675  ]
 [0.5855     0.53636    0.54992   ]
```

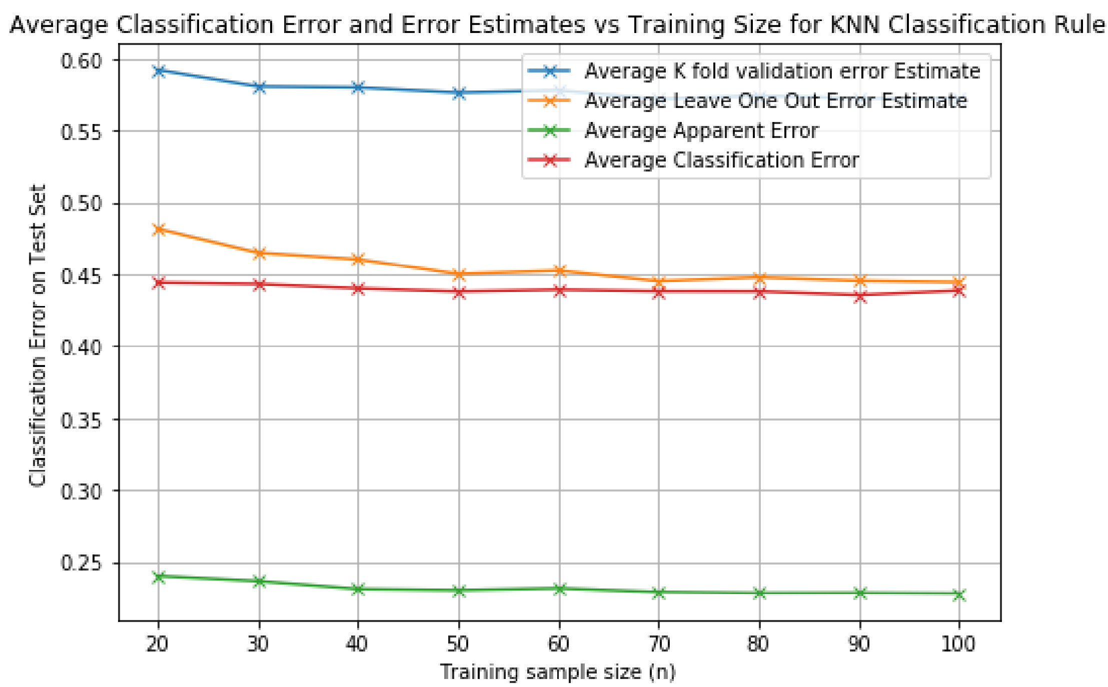
```
 [0.58616667 0.5413     0.54758333]
 [0.59504286 0.55318571 0.55492857]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.66725    0.87095    0.75975   ]
 [0.65463333 0.84006667 0.76326667]
 [0.65005    0.8131     0.76875   ]
 [0.64464    0.79598    0.7696    ]
 [0.63685    0.77876667 0.76825   ]
 [0.63767143 0.7699     0.7709    ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.5980475 0.550245  0.556865 ]
 [0.6064025 0.55752   0.559835 ]
 [0.610645  0.5624775 0.5620175]
 [0.6139225 0.566785  0.56079  ]
 [0.6144275 0.569565  0.5618625]
 [0.        0.        0.       ]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 7
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
 [0.373475   0.302225   0.42015   ]
 [0.37512    0.31006    0.42372   ]
 [0.3615     0.31091667 0.42218333]
 [0.36842857 0.31951429 0.42804286]
 [0.371225   0.3233625  0.4258625 ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score loo [[0.51465    0.45365    0.51855   ]
 [0.54993333 0.50176667 0.53506667]
 [0.573375   0.52335    0.539675  ]
 [0.5855     0.53636    0.54992   ]
 [0.58616667 0.5413     0.54758333]
 [0.59504286 0.55318571 0.55492857]
 [0.600725   0.5561     0.5523125 ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.66725    0.87095    0.75975   ]
 [0.65463333 0.84006667 0.76326667]
 [0.65005    0.8131     0.76875   ]
 [0.64464    0.79598    0.7696    ]
 [0.63685    0.77876667 0.76825   ]
 [0.63767143 0.7699     0.7709    ]
```

```
 [0.6362     0.75865    0.771625  ]
 [0.         0.         0.        ]
 [0.         0.         0.        ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.5980475 0.550245  0.556865 ]
 [0.6064025 0.55752   0.559835 ]
 [0.610645  0.5624775 0.5620175]
 [0.6139225 0.566785  0.56079  ]
 [0.6144275 0.569565  0.5618625]
 [0.6170375 0.57271   0.5619425]
 [0.        0.        0.       ]
 [0.        0.        0.       ]]
count of n 8
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
 [0.373475   0.302225   0.42015   ]
 [0.37512    0.31006    0.42372   ]
 [0.3615     0.31091667 0.42218333]
 [0.36842857 0.31951429 0.42804286]
 [0.371225   0.3233625  0.4258625 ]
 [0.37271111 0.32636667 0.42763333]
 [0.         0.         0.        ]]
score loo [[0.51465    0.45365    0.51855    ]
 [0.54993333 0.50176667 0.53506667]
 [0.573375   0.52335    0.539675  ]
 [0.5855     0.53636    0.54992   ]
 [0.58616667 0.5413     0.54758333]
 [0.59504286 0.55318571 0.55492857]
 [0.600725   0.5561     0.5523125 ]
 [0.60526667 0.5625     0.55468889]
 [0.         0.         0.        ]]
score avg [[0.66725    0.87095    0.75975    ]
 [0.65463333 0.84006667 0.76326667]
 [0.65005    0.8131     0.76875   ]
 [0.64464    0.79598    0.7696    ]
 [0.63685    0.77876667 0.76825   ]
 [0.63767143 0.7699     0.7709    ]
 [0.6362     0.75865    0.771625  ]
 [0.63604444 0.75071111 0.77153333]
 [0.         0.         0.        ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.5980475 0.550245  0.556865 ]
 [0.6064025 0.55752   0.559835 ]
 [0.610645  0.5624775 0.5620175]
 [0.6139225 0.566785  0.56079  ]
 [0.6144275 0.569565  0.5618625]
 [0.6170375 0.57271   0.5619425]
 [0.61893   0.5761625 0.5644725]
```

```
 [0.         0.         0.        ]]
count of n 9
score kf [[0.37915    0.2659     0.4081    ]
 [0.37093333 0.2935     0.41946667]
 [0.373475   0.302225   0.42015   ]
 [0.37512    0.31006    0.42372   ]
 [0.3615     0.31091667 0.42218333]
 [0.36842857 0.31951429 0.42804286]
 [0.371225   0.3233625  0.4258625 ]
 [0.37271111 0.32636667 0.42763333]
 [0.36773    0.32323    0.4276    ]]
score loo [[0.51465    0.45365    0.51855    ]
 [0.54993333 0.50176667 0.53506667]
 [0.573375   0.52335    0.539675  ]
 [0.5855     0.53636    0.54992   ]
 [0.58616667 0.5413     0.54758333]
 [0.59504286 0.55318571 0.55492857]
 [0.600725   0.5561     0.5523125 ]
 [0.60526667 0.5625     0.55468889]
 [0.60404    0.56197    0.5556    ]]
score avg [[0.66725    0.87095    0.75975    ]
 [0.65463333 0.84006667 0.76326667]
 [0.65005    0.8131     0.76875   ]
 [0.64464    0.79598    0.7696    ]
 [0.63685    0.77876667 0.76825   ]
 [0.63767143 0.7699     0.7709    ]
 [0.6362     0.75865    0.771625  ]
 [0.63604444 0.75071111 0.77153333]
 [0.63198    0.74166    0.77189   ]]
score avg [[0.5850225 0.5435975 0.5558825]
 [0.5980475 0.550245  0.556865 ]
 [0.6064025 0.55752   0.559835 ]
 [0.610645  0.5624775 0.5620175]
 [0.6139225 0.566785  0.56079  ]
 [0.6144275 0.569565  0.5618625]
 [0.6170375 0.57271   0.5619425]
 [0.61893   0.5761625 0.5644725]
 [0.61806   0.5760975 0.5614225]]
```

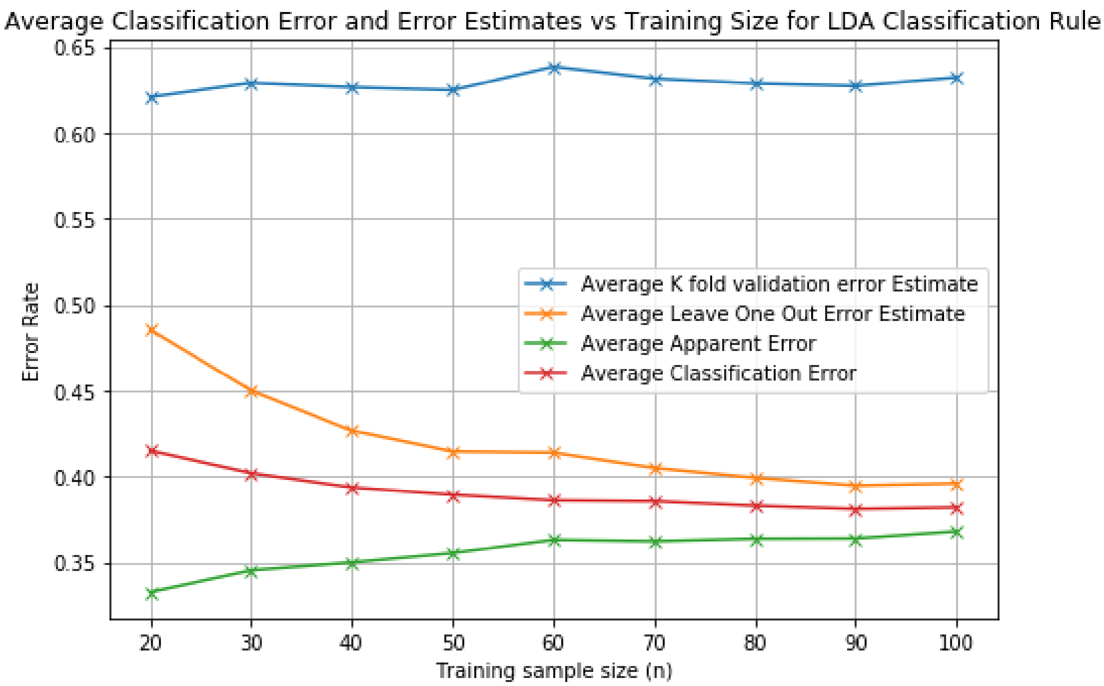

Average Classification Error and Error Estimates vs Training Size for LDA Classification Rule
Classification Error on Test Set
Training sample size (n)
Average K fold validation error Estimate
Average Leave One Out Error Estimate
Average Apparent Error
Average Classification Error
0.65
0.60
0.55
0.50
0.45
0.40
0.35
20
30
40
50
60
70
80
90
100

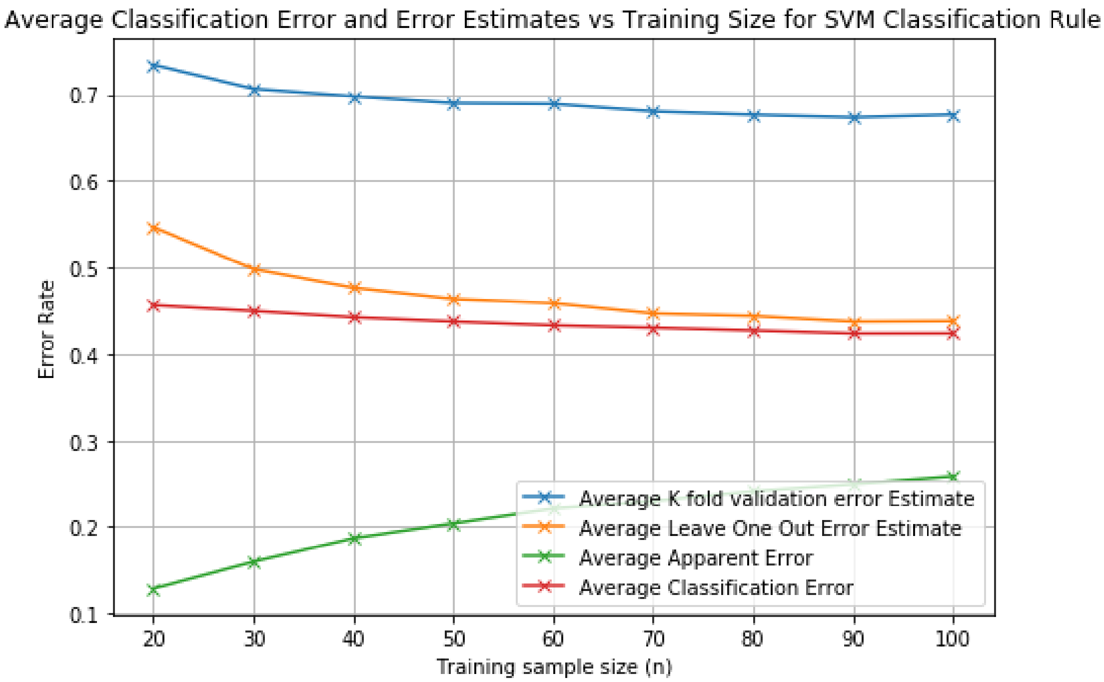

Average Classification Error and Error Estimates vs Training Size for SVM Classification Rule
Classification Error on Test Set
Training sample size (n)
Average K fold validation error Estimate
Average Leave One Out Error Estimate
Average Apparent Error
Average Classification Error
0.7
0.6
0.5
0.4
0.3
0.2
0.1
20
30
40
50
60
70
80
90
100

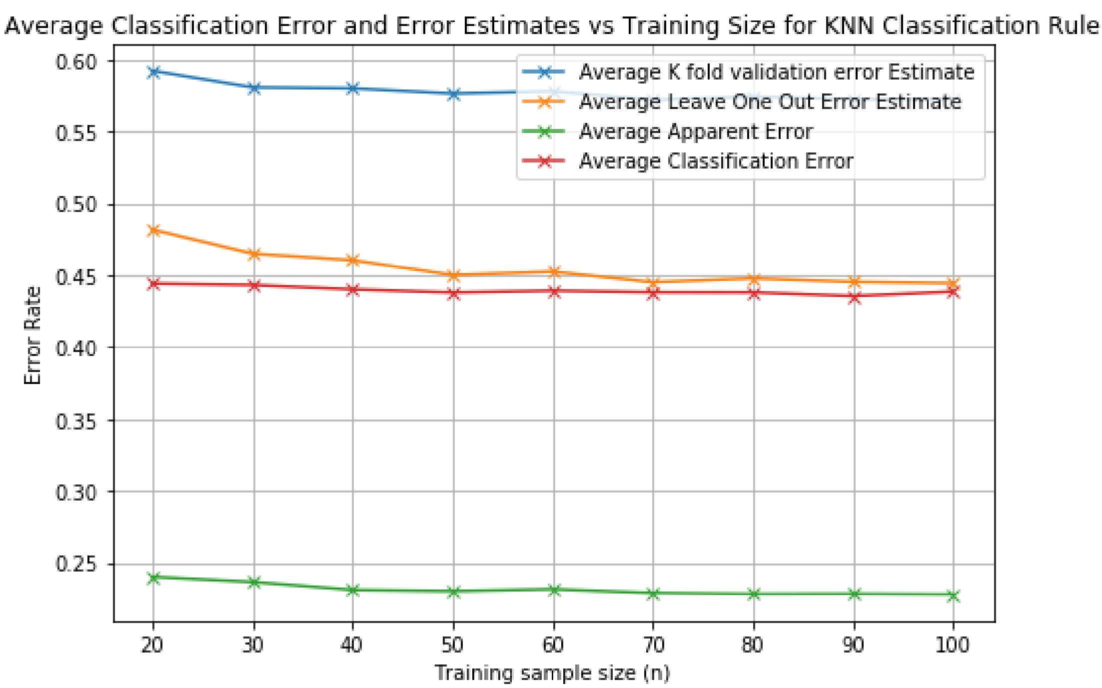


In [108]:
```
#plot error curves for LDA
fig, ax = plt.subplots(figsize=[8,5])
plt.plot(nlist,1-score_avgkf[:,0],marker='x',label='Average K fold validation error E
plt.plot(nlist,1-score_avgloo[:,0],marker='x',label='Average Leave One Out Error Esti
plt.plot(nlist,1-score_avg[:,0],marker='x',label='Average Apparent Error')
plt.plot(nlist,1-score_avgcl[:,0],marker='x',label='Average Classification Error')
plt.title('Average Classification Error and Error Estimates vs Training Size for LDA
plt.ylabel('Error Rate')
plt.xlabel('Training sample size (n)')
fig.tight_layout()
ax.legend()
plt.grid(True)
plt.show
fig.savefig('hw2_17b.png')

#plot error curves for SVM
fig, ax = plt.subplots(figsize=[8,5])
plt.plot(nlist,1-score_avgkf[:,1],marker='x',label='Average K fold validation error E
plt.plot(nlist,1-score_avgloo[:,1],marker='x',label='Average Leave One Out Error Esti
plt.plot(nlist,1-score_avg[:,1],marker='x',label='Average Apparent Error')
plt.plot(nlist,1-score_avgcl[:,1],marker='x',label='Average Classification Error')
plt.title('Average Classification Error and Error Estimates vs Training Size for SVM
plt.ylabel('Error Rate')
plt.xlabel('Training sample size (n)')
fig.tight_layout()
```

```
ax.legend()
plt.grid(True)
plt.show
fig.savefig('hw2_18b.png')

#plot error curves for KNN
fig, ax = plt.subplots(figsize=[8,5])
plt.plot(nlist,1-score_avgkf[:,2],marker='x',label='Average K fold validation error E
plt.plot(nlist,1-score_avgloo[:,2],marker='x',label='Average Leave One Out Error Esti
plt.plot(nlist,1-score_avg[:,2],marker='x',label='Average Apparent Error')
plt.plot(nlist,1-score_avgcl[:,2],marker='x',label='Average Classification Error')
plt.title('Average Classification Error and Error Estimates vs Training Size for KNN
plt.ylabel('Error Rate')
plt.xlabel('Training sample size (n)')
fig.tight_layout()
ax.legend()
plt.grid(True)
plt.show
fig.savefig('hw2_19b.png')
```




Average Classification Error and Error Estimates vs Training Size for SVM Classification Rule
Error Rate
0.7
0.6
0.5
0.4
0.3
0.2
0.1
20
30
40
50
60
70
80
90
100
Training sample size (n)
Average K fold validation error Estimate
Average Leave One Out Error Estimate
Average Apparent Error
Average Classification Error


Average Classification Error and Error Estimates vs Training Size for KNN Classification Rule
Error Rate
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
20
30
40
50
60
70
80
90
100
Training sample size (n)
Average K fold validation error Estimate
Average Leave One Out Error Estimate
Average Apparent Error
Average Classification Error