

October 16, 2020

Question 1)

a)

```
[1]: import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.datasets import load_iris
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from scipy.io import loadmat
import warnings
warnings.filterwarnings('ignore')
```

Import and read in the iris dataset

```
[2]: iris = load_iris()
iris_df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
convert_species = np.vectorize(lambda x : "setosa" if x==0 else ("versicolor"
    ↳if x==1 else "virginica"))
iris_unnamed = iris_df
iris_df["target"] = convert_species(iris.target)
iris_unnamed["target"] = iris.target
```

```
[3]: iris_unnamed.head()
```

```
[3]:   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1                3.5                1.4                0.2
1                4.9                3.0                1.4                0.2
2                4.7                3.2                1.3                0.2
3                4.6                3.1                1.5                0.2
4                5.0                3.6                1.4                0.2

   target
0       0
1       0
2       0
```

```
3      0
4      0
```

```
[4]: iris_df.head()
```

```
[4]:   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0              5.1             3.5             1.4             0.2
1              4.9             3.0             1.4             0.2
2              4.7             3.2             1.3             0.2
3              4.6             3.1             1.5             0.2
4              5.0             3.6             1.4             0.2
```

```
      target
0         0
1         0
2         0
3         0
4         0
```

Import and read in the indian pines dataset

```
[5]: indian = loadmat(os.path.join(os.getcwd(), "indianR.mat"))
data = np.array(indian["X"]).T
targets = np.array(indian["gth"])[0]
indian_df = pd.DataFrame(data=data)
indian_df["target"] = targets
```

```
[6]: np.unique(indian_df["target"], return_counts=True)
```

```
[6]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16],
      dtype=uint8),
      array([10776,   46, 1428,   830,   237,   483,   730,    28,   478,
            20,   972, 2455,   593,   205, 1265,   386,    93],
      dtype=int64))
```

```
[7]: iris_df.head()
```

```
[7]:   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0              5.1             3.5             1.4             0.2
1              4.9             3.0             1.4             0.2
2              4.7             3.2             1.3             0.2
3              4.6             3.1             1.5             0.2
4              5.0             3.6             1.4             0.2

      target
0         0
1         0
```

```
2      0
3      0
4      0
```

```
[8]: indian_df.describe()
```

```
[8]:
```

	0	1	2	3	4 \
count	21025.000000	21025.000000	21025.000000	21025.000000	21025.000000
mean	3341.313103	4091.957765	4277.523662	4170.075672	4516.685375
std	212.254014	227.885060	257.819760	280.381316	346.041777
min	2632.000000	3477.000000	3649.000000	3578.000000	3840.000000
25%	3179.000000	3889.000000	4066.000000	3954.000000	4214.000000
50%	3343.000000	4107.000000	4237.000000	4126.000000	4478.000000
75%	3510.000000	4247.000000	4479.000000	4350.000000	4772.000000
max	4536.000000	5744.000000	6361.000000	6362.000000	7153.000000

	5	6	7	8	9 \
count	21025.000000	21025.000000	21025.000000	21025.000000	21025.000000
mean	4790.607134	4848.334269	4714.739073	4668.916528	4439.259453
std	414.386445	469.244664	491.731609	533.233484	539.486030
min	4056.000000	4004.000000	3865.000000	3775.000000	3560.000000
25%	4425.000000	4421.000000	4263.000000	4173.000000	3940.000000
50%	4754.000000	4808.000000	4666.000000	4632.000000	4404.000000
75%	5093.000000	5198.000000	5100.000000	5084.000000	4860.000000
max	7980.000000	8284.000000	8128.000000	8194.000000	7928.000000

	...	193	194	195	196 \
count	...	21025.000000	21025.000000	21025.000000	21025.000000
mean	...	1060.238383	1063.299215	1050.072913	1040.227539
std	...	38.694237	41.906116	34.232348	26.447967
min	...	999.000000	999.000000	993.000000	990.000000
25%	...	1024.000000	1024.000000	1019.000000	1016.000000
50%	...	1052.000000	1054.000000	1043.000000	1033.000000
75%	...	1098.000000	1104.000000	1083.000000	1066.000000
max	...	1289.000000	1315.000000	1258.000000	1201.000000

	197	198	199	200	201 \
count	21025.000000	21025.000000	21025.000000	21025.000000	21025.000000
mean	1043.391011	1030.223496	1015.600856	1008.513864	1006.791011
std	29.788944	20.872378	11.437696	7.052013	6.995153
min	992.000000	989.000000	986.000000	981.000000	980.000000
25%	1016.000000	1012.000000	1006.000000	1004.000000	1003.000000
50%	1037.000000	1026.000000	1014.000000	1009.000000	1005.000000
75%	1072.000000	1050.000000	1024.000000	1014.000000	1010.000000
max	1245.000000	1167.000000	1076.000000	1037.000000	1034.000000

target

```
count    21025.000000
mean       4.224923
std        5.281972
min         0.000000
25%         0.000000
50%         0.000000
75%        10.000000
max        16.000000
```

[8 rows x 203 columns]

```
[9]: indexDrop = indian_df[indian_df["target"] == 0].index
      indian_df.drop(indexDrop, inplace=True)
      indian_df.reset_index(inplace=True)
```

```
[10]: indian_df.describe()
```

```
[10]:
```

	index	0	1	2	3 \
count	10249.000000	10249.000000	10249.000000	10249.000000	10249.000000
mean	9322.297200	3382.435847	4152.747292	4355.246073	4257.888184
std	5218.036087	210.366658	224.041937	256.879124	281.800019
min	0.000000	2640.000000	3491.000000	3739.000000	3601.000000
25%	5016.000000	3196.000000	3990.000000	4137.000000	4029.000000
50%	8723.000000	3358.000000	4130.000000	4394.000000	4270.000000
75%	13560.000000	3526.000000	4264.000000	4510.000000	4431.000000
max	20214.000000	4536.000000	5526.000000	6080.000000	6139.000000

	4	5	6	7	8 \
count	10249.000000	10249.000000	10249.000000	10249.000000	10249.000000
mean	4630.182750	4930.287931	5010.664357	4887.468241	4859.082349
std	348.119919	417.197677	473.771399	497.665315	539.681324
min	3911.000000	4123.000000	4138.000000	3997.000000	3883.000000
25%	4327.000000	4536.000000	4560.000000	4415.000000	4337.000000
50%	4661.000000	4993.000000	5091.000000	4976.000000	4958.000000
75%	4881.000000	5202.000000	5335.000000	5234.000000	5227.000000
max	7070.000000	7809.000000	8000.000000	7980.000000	8106.000000

	...	193	194	195	196 \
count	...	10249.000000	10249.000000	10249.000000	10249.000000
mean	...	1078.458874	1083.158845	1066.017855	1052.516928
std	...	38.994331	42.108992	34.516822	26.723702
min	...	1000.000000	999.000000	993.000000	995.000000
25%	...	1039.000000	1040.000000	1031.000000	1026.000000
50%	...	1093.000000	1099.000000	1078.000000	1062.000000
75%	...	1110.000000	1117.000000	1094.000000	1074.000000
max	...	1163.000000	1180.000000	1141.000000	1110.000000

	197	198	199	200	201 \
count	10249.000000	10249.000000	10249.000000	10249.000000	10249.000000
mean	1057.192799	1039.704459	1020.304322	1010.365499	1008.517416
std	30.055980	21.030831	11.539938	7.034534	7.080302
min	992.000000	989.000000	986.000000	985.000000	985.000000
25%	1027.000000	1020.000000	1010.000000	1005.000000	1004.000000
50%	1067.000000	1045.000000	1022.000000	1010.000000	1009.000000
75%	1081.000000	1055.000000	1029.000000	1015.000000	1014.000000
max	1130.000000	1088.000000	1048.000000	1037.000000	1034.000000

	target
count	10249.000000
mean	8.667089
std	4.327987
min	1.000000
25%	5.000000
50%	10.000000
75%	11.000000
max	16.000000

[8 rows x 204 columns]

Both indian and iris datasets have successfully been loaded. Now, we need to setup PCA and LDA. First is PCA. PCA needs to scale the data first and then deconstruct the data into its principal components.

```
[11]: def scale(df, scaler="MinMax"):
    inputs = df.iloc[:, :-1].to_numpy()
    if scaler == "MinMax":
        scale = MinMaxScaler()
    elif scaler == "Standard":
        scale = StandardScaler()
    else:
        raise ValueError(f"Unsupported scaler {scaler}")
    scale.fit(inputs.astype(float))
    inputs = scale.transform(inputs)

    scaled_df = pd.DataFrame(data=inputs)

    scaled_df["target"] = df["target"]

    return scaled_df
```

```
[12]: def fit_pca(df, **kwargs):
    n_components = kwargs.get("n_components", len(df.columns)-1)
    plot_variance = kwargs.get("plot_variance", True)
```

```

inputs = df.iloc[:, :-1].to_numpy()

pca = PCA(n_components=n_components)
pc = pca.fit(inputs)

return pc

```

```

[13]: def transform_pca(df, pc):
    inputs = df.iloc[:, :-1].to_numpy()
    transformed_df = pd.DataFrame(data=pc.transform(inputs))
    transformed_df.columns = [*map(lambda y : f"PC-{y}", list(range(1, pc.
↪n_components + 1)))]
    transformed_df["target"] = df["target"]
    return transformed_df

```

```

[55]: def plot_variance(pc, n_components=None):
    pc_cols = lambda x : [*map(lambda y : f"PC-{y}", list(range(1, x+1)))]

    n_comps = n_components if n_components is not None else pc.n_components

    plt.figure(figsize=(18,12))
    plt.style.use("ggplot")
    plt.rcParams.update({'font.size': 18})
    plt.bar(pc_cols(n_comps), pc.explained_variance_ratio_[:n_comps])
    plt.title("Explained Variance Ratio vs. Principal Component")
    plt.ylabel("Explained Variance Ratio")
    plt.xlabel("Principal Component")
    plt.ylim([0, 1])

    return

```

```

[15]: def plot_pca_lda(df, **kwargs):
    title = kwargs.get("title", "Plot of Data With First Two Components")
    xlabel = kwargs.get("xlabel", "First Component")
    ylabel = kwargs.get("ylabel", "Second Component")
    eigens = kwargs.get("eigens", None)
    alpha = kwargs.get("alpha", 0.75)

    labels = np.unique(df["target"])

    fig = plt.figure(figsize=(18,12))
    plt.style.use("ggplot")
    plt.rcParams.update({'font.size': 18})
    #fig, ax = plt.subplots(1,1, figsize=(18,12), style="ggplot")
    ax = fig.add_subplot(111)
    ax.set_xlabel(xlabel)
    ax.set_ylabel(ylabel)

```

```

ax.set_title(title)

colors = ['r', 'g', 'b', 'y', 'm', 'c', 'k', 'r', 'g', 'b', 'y', 'm', 'c', 'k',
↳ 'k', 'r', 'g', 'b']
markers = ['o', 'o', 'o', 'o', 'o', 'o', '*', '*', '*', '*', '*', '*', '+', '
↳ '+', '+', '+', '+']

for i, label in enumerate(labels):
    first_two = df.loc[df["target"] == label].iloc[:, 0:2].to_numpy()
    ax.scatter(first_two[:, 0], first_two[:, 1], label=label, alpha=alpha,
↳ color=colors[i], marker=markers[i])

    if eigens is not None:
        eig_vec = eigens[0][:2]
        eig_val = eigens[1][:2]
        for vec, val in zip(eig_vec, eig_val.T):
            ax.plot([0, np.sqrt(vec)*val[0]], [0, np.sqrt(vec)*val[1]], "k-",
↳ lw=2)

ax.legend()

return

```

```

[16]: def get_eigens(df):
    inputs = df.iloc[:, :-1].to_numpy()
    cov = np.cov(inputs.T)
    eig_vec, eig_val = np.linalg.eig(cov)

    print(f"Eigen Values:\n{eig_val}")
    print(f"Eigen Vectors:\n{eig_vec}")

    return eig_vec, eig_val

```

```

[17]: def perform_pca(df, **kwargs):

    df_scaled = scale(df)
    pc = fit_pca(df_scaled, **kwargs)
    df_pca = transform_pca(df_scaled, pc)

    return df_pca

```

Now to create the same functionality for LDA.

```

[98]: def perform_lda(df, **kwargs):
    n_components = kwargs.get("n_components", len(np.unique(df["target"].
↳ values))-1)

    inputs = df.iloc[:, :-1].to_numpy()

```

```

targets = np.array(df["target"].values)

lda = LinearDiscriminantAnalysis(n_components=n_components)
transform_df = pd.DataFrame(data=lda.fit(inputs, targets).transform(inputs))
transform_df["target"] = df["target"]

return transform_df

```

```

[56]: plot_pca_lda(iris_df, title="Iris with First Two Components")
iris_scaled = scale(iris_df)
pc = fit_pca(iris_scaled)
print(f"Explained Variance Ratio:\n{pc.explained_variance_ratio_}")
plot_variance(pc)
iris_pc = transform_pca(iris_scaled, pc)
eigens = get_eigens(iris_pc)
plot_pca_lda(iris_pc, title="Iris with First Two PCA Components")

```

Explained Variance Ratio:

```
[0.84136038 0.11751808 0.03473561 0.00638592]
```

Eigen Values:

```

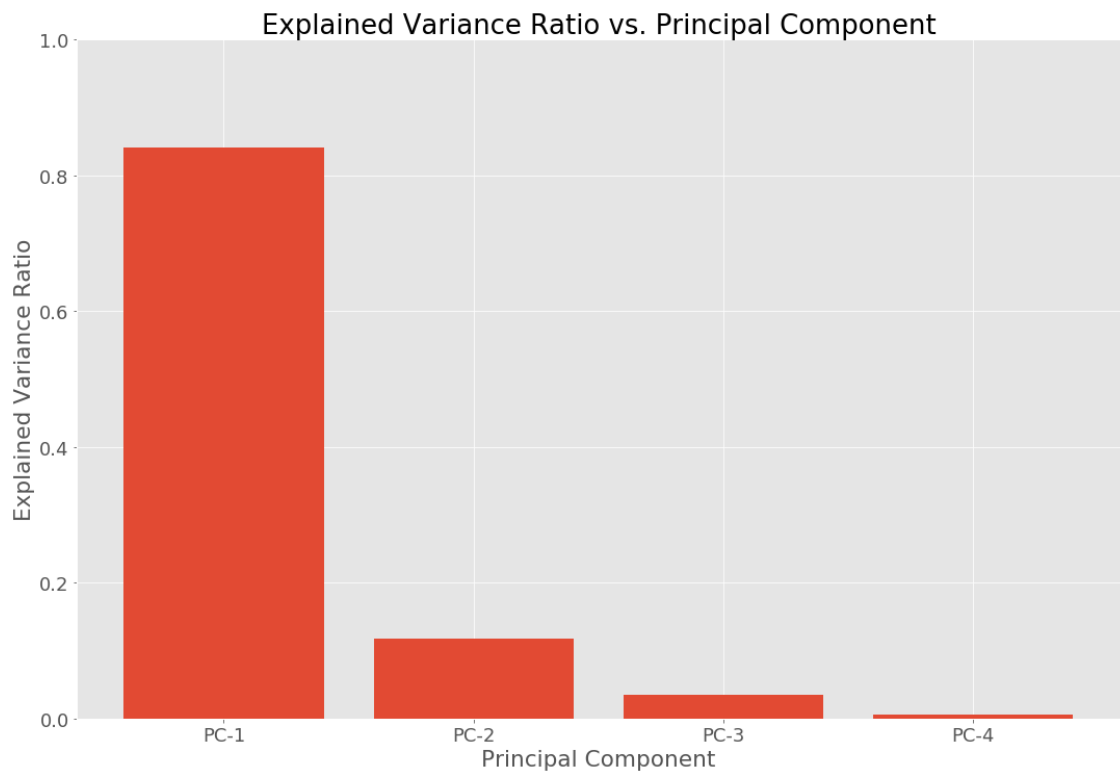
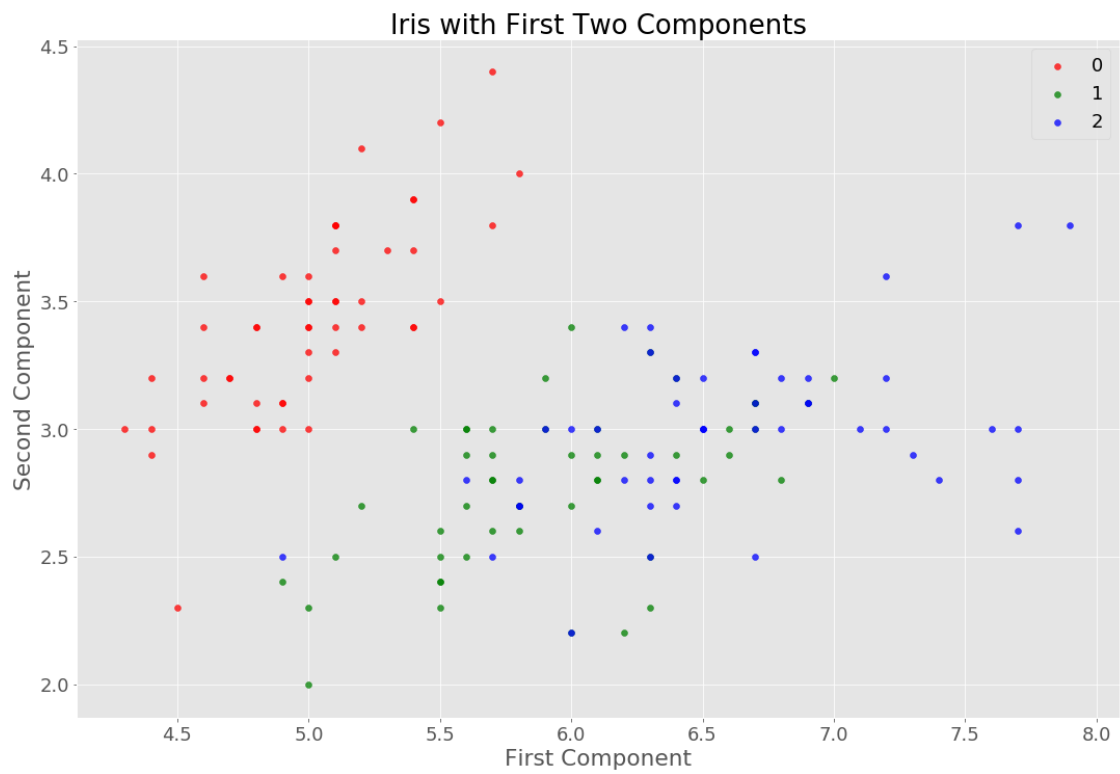
[[ 1.00000000e+00  2.27117367e-16  1.58067971e-16  8.17929707e-17]
 [ 0.00000000e+00  1.00000000e+00 -3.34545298e-16 -3.45648222e-17]
 [ 0.00000000e+00  3.46217222e-16  1.00000000e+00  8.87035040e-17]
 [ 0.00000000e+00  4.27653296e-17 -1.11519743e-16  1.00000000e+00]]

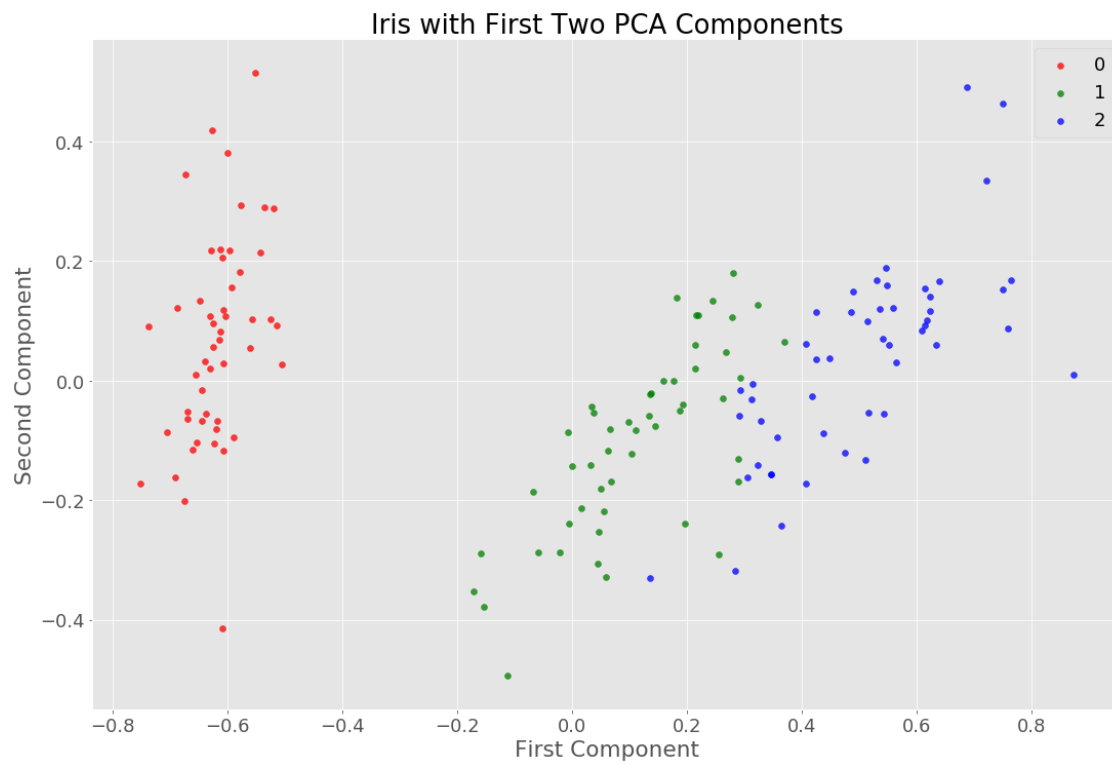
```

Eigen Vectors:

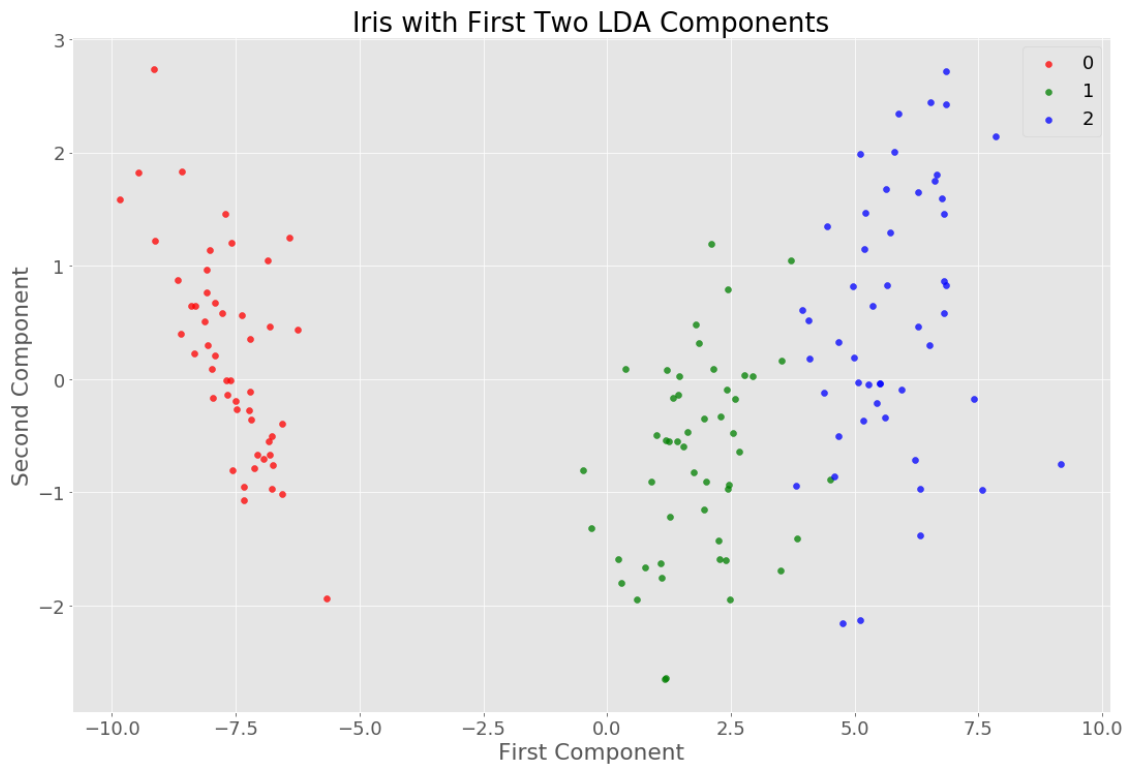
```
[0.23245325 0.0324682 0.00959685 0.00176432]
```







```
[99]: iris_lda = perform_lda(iris_df)
      plot_pca_lda(iris_lda, title="Iris with First Two LDA Components")
```



```
[57]: plot_pca_lda(indian_df, title="Indian Pines with First Two Components")
indian_scaled = scale(indian_df, scaler="MinMax")
pc = fit_pca(indian_scaled, n_components=10)
print(f"Explained Variance Ratio:\n{pc.explained_variance_ratio_}")
plot_variance(pc)
plot_variance(pc, n_components=10)
indian_pc = transform_pca(indian_scaled, pc)
eigens = get_eigens(indian_pc)
plot_pca_lda(indian_pc, title="Indian Pines with First Two PCA Components")
```

Explained Variance Ratio:

```
[0.84769736 0.0979396  0.01467606 0.00926067 0.00496592 0.00250275
 0.00205987 0.00193326 0.00187837 0.00145054]
```

Eigen Values:

```
[[-1.00000000e+00 -1.10880946e-14 -1.40330785e-16  4.85082057e-16
 -5.21843460e-17  7.91244887e-18  1.77887767e-17  4.99162322e-18
 -1.18330066e-17  6.43894374e-18]
 [ 1.09451092e-14 -1.00000000e+00 -2.64710375e-15 -4.82564896e-17
 -1.79793213e-17 -1.88014807e-18  2.17592495e-17 -7.42968871e-17
 -1.69549214e-17  1.06717568e-16]
 [ 1.40298725e-16  2.60253373e-15 -1.00000000e+00 -2.49253600e-15
 3.55477068e-16 -6.68949838e-17 -2.55609923e-17 -1.68382381e-17
 -2.00112835e-17  5.60125718e-17]
```

```

[ 4.85045236e-16 -8.59690482e-17 -2.27078014e-15  1.00000000e+00
 5.88837499e-16  2.33399434e-17 -4.54690348e-15 -2.30954762e-16
-3.68794125e-16  3.39257181e-16]
[-5.21836566e-17 -1.83984740e-17 -7.68094097e-17 -8.51038433e-16
 1.00000000e+00 -5.18415414e-15 -3.04761817e-13 -1.10657704e-14
-2.22272638e-14  2.42962006e-14]
[-7.91244474e-18  8.93207144e-19  4.36666978e-17 -3.17809477e-17
-5.03406042e-15 -1.00000000e+00 -1.05699219e-10 -8.48933554e-12
-1.68542306e-11  1.06431567e-11]
[ 4.99162301e-18 -7.35152431e-17 -5.13873478e-17  2.33400125e-16
 1.11017702e-14 -8.48958110e-12 -1.24637505e-09  1.00000000e+00
-5.05969454e-10  2.45900340e-10]
[ 1.18330067e-17  1.79452390e-17  3.62878280e-17 -3.32106266e-16
-2.23725540e-14  1.68533959e-11  3.88778810e-09 -5.05968335e-10
-1.00000000e+00 -1.94585398e-09]
[-6.43894382e-18 -1.07635194e-16 -4.21677319e-17  3.08769410e-16
 2.43087216e-14 -1.06429512e-11 -3.28060483e-09  2.45900736e-10
 1.94585304e-09 -1.00000000e+00]
[ 1.77887718e-17  2.47380815e-17 -1.16363735e-16  4.60422907e-15
 3.05012776e-13 -1.05698449e-10  1.00000000e+00  1.24637467e-09
 3.88778805e-09 -3.28060503e-09]]

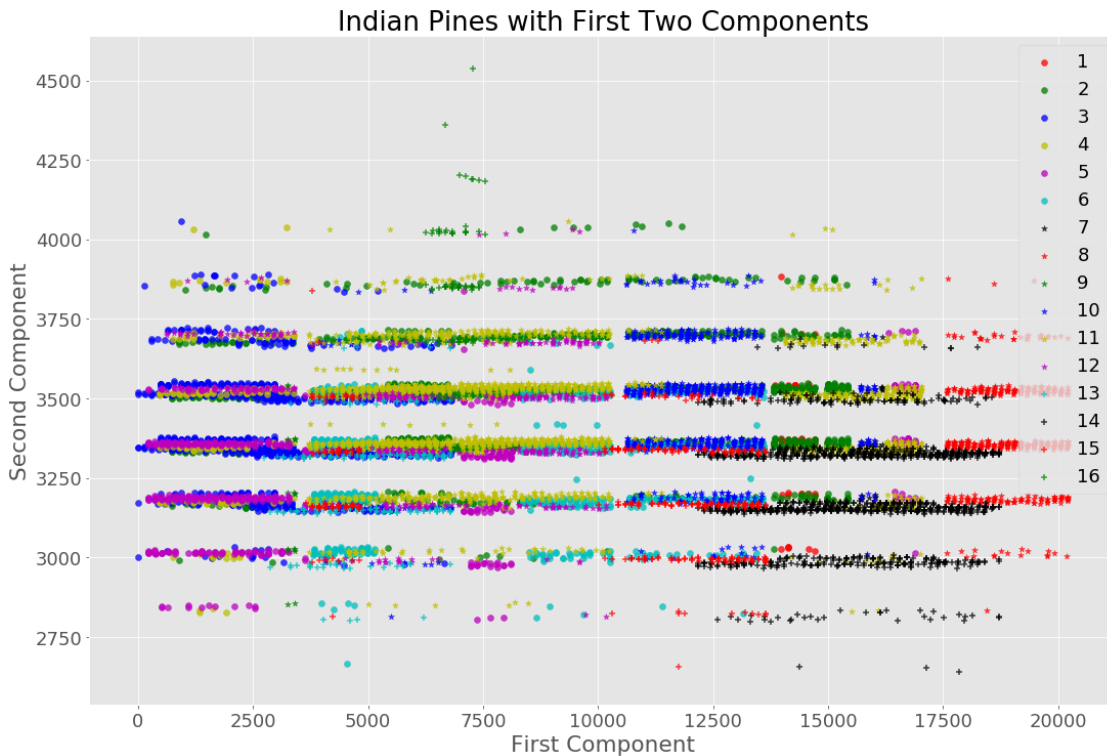
```

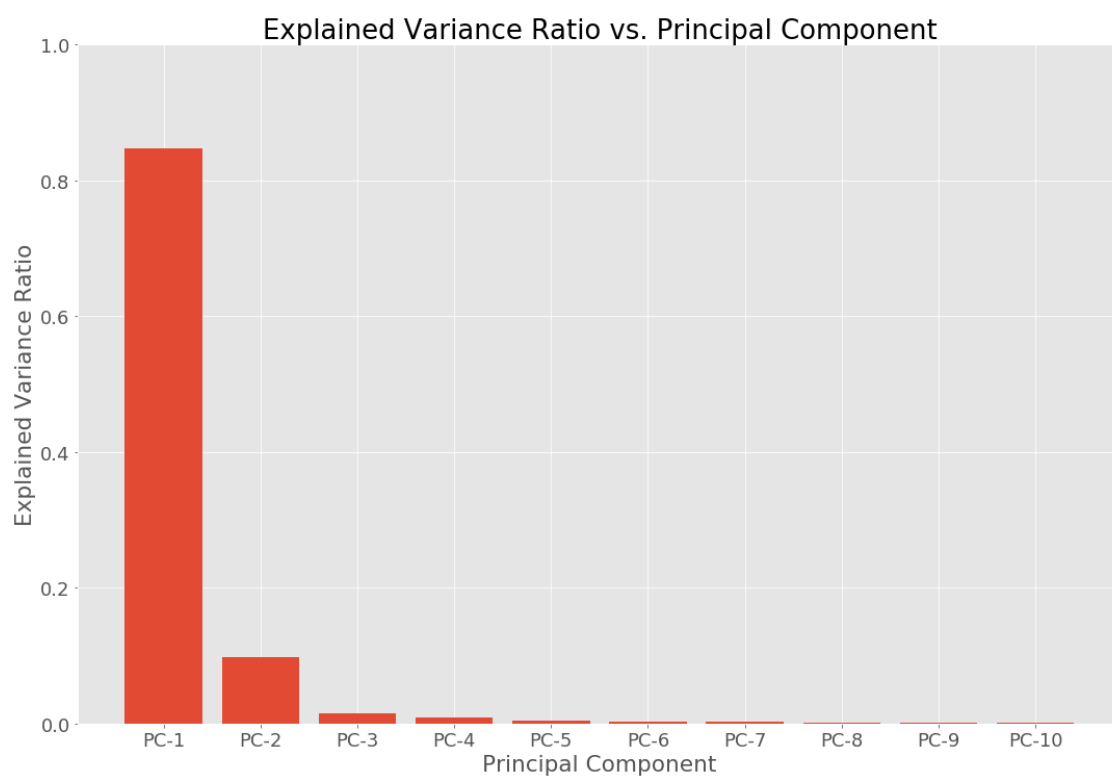
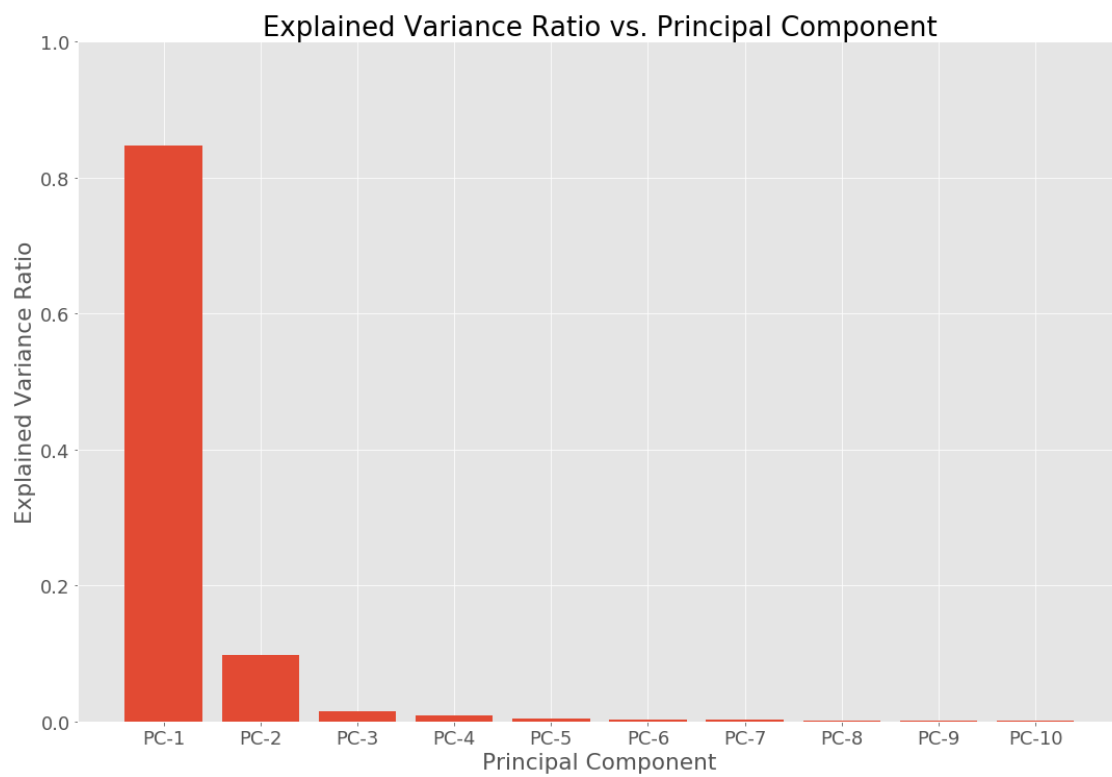
Eigen Vectors:

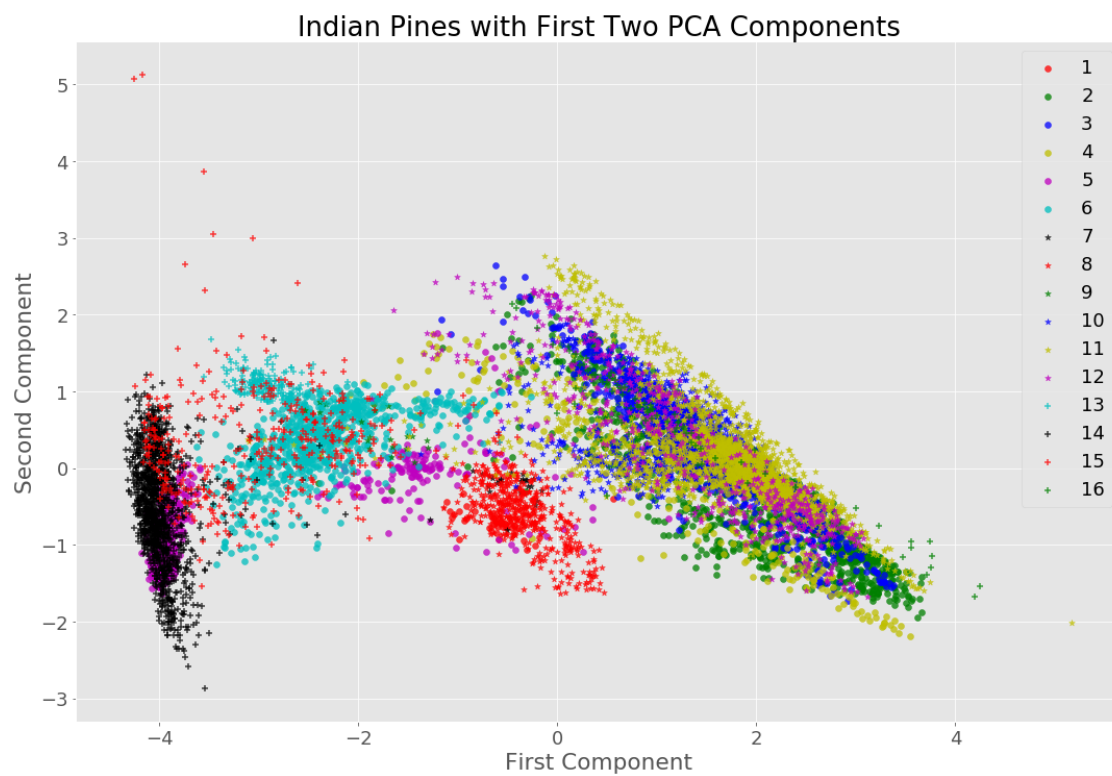
```

[5.49293297  0.63463172  0.09509832  0.06000752  0.03217833  0.01621739
 0.00939925  0.01334759  0.0125272  0.01217151]

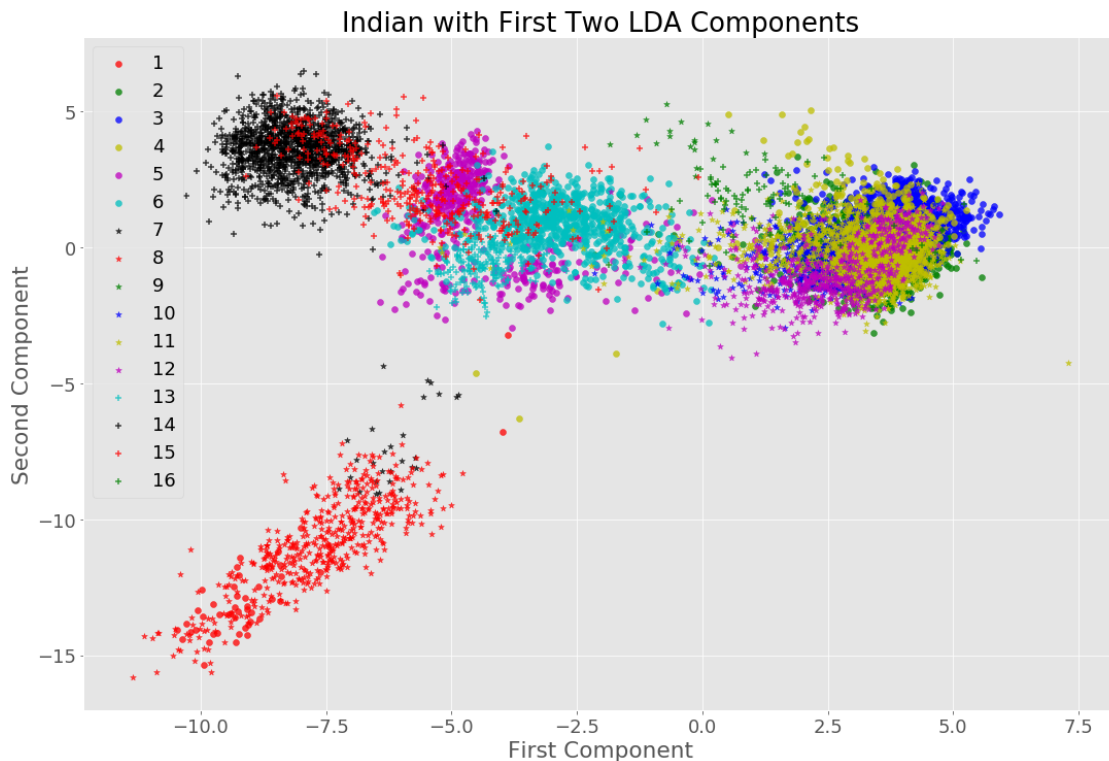
```







```
[105]: indian_lda = perform_lda(indian_df, n_components=2)
       plot_pca_lda(indian_lda, title="Indian with First Two LDA Components")
```



b)

- i) The three plots of the first two components with no, pca and lda dimensionality reduction for both the iris and indian datasets demonstrate the usefulness of dimensionality reduction and preprojection. First, with the iris, with no projection there is a lot of overlap between the first and second classes. It is not clear how to delineate between the two. After performing either LDA or PCA, the separability became much clearer and easier. This separation also only requires two components/dimensions to be readily apparent. This is further supported by the variances plot which shows that the first two principal components contain over 90% of the iris' data variance.

Looking at the indian pines dataset and plots we see a similar pattern. The first plot shows no dimensionality reduction or projection. There is a lot of overlap between classes. Note that this plot just shows the first two components of the data, and not the best two. The PCA's and LDA's first two components do a much better job of separating the classes. There is still overlap between classes in the plot but we are starting to separate the classes out. It is not surprising that there is still some overlap between the data since we are only taking 2 of 202 components to try and separate all the data. However, the first two components show significant improvement and could make things much better once including several more components. From the variance plot, we see once again that the first two principal components are able to capture over 90% of the indian's data variance. This suggests we can severely decrease the number of components from 202 to a much more reasonable number. This should greatly reduce runtimes of learners on the data (as demonstrated later in question two).

The number of principal components to use for the classifiers seems to suggest 2 for the iris dataset,

and possibly around 5-10 for the indian. We only need two for the iris because we can already see the three classes are separated in its plot. However, the indian dataset, while improved, would still need more components since the classes are not able to be completely separated with just the first two components. The same could be said for the LDA analyses.

The LDA and PCA worked about the same for the iris dataset. Most likely since it is a simple dataset and the variance does a good job of explaining the data's separate classes. The LDA appears to perform better on the indian dataset. PCA still works but there appears to still be significant overlap in some regions. The explained variance plot also shows that minimal variance is explained by principal components greater than 2, but we can see from our plot that we will need more than just two principal components to explain the data. LDA seems to perform slightly better. This is most likely because it is able to take the classes into consideration when finding the best basis for projection to increase separability. PCA can sometimes struggle because it looks for overall variances, and does not consider intra- and inter- class means and variances.

Question 2)

a)

```
[60]: from sklearn.model_selection import train_test_split, StratifiedKFold
      from sklearn.neighbors import KNeighborsClassifier
      from sklearn.naive_bayes import GaussianNB
      from sklearn.svm import SVC
      import time

[24]: def perform_classification(df_data, model, test_size):
      def split_data(df, test_size):
          X = df.iloc[:, :-1].to_numpy()
          y = df["target"].to_numpy()
          return train_test_split(X, y, test_size=test_size, random_state=42,
      ↪shuffle=True)

      X_train, X_test, Y_train, Y_test = split_data(df_data, test_size)

      model.fit(X_train, Y_train)
      predict_train = model.predict(X_train)

      predict_test = model.predict(X_test)

      return {"predict_train": predict_train,
              "predict_test": predict_test,
              "train": Y_train,
              "test": Y_test
            }

[74]: def perform_performance(classifications):
      def get_spec_sens(confusion_matrix):
          specificities = []
```



```

sensitivities = []

for iLabel in list(range(len(confusion_matrix))):
    tp, tn, fn, fp = 0, 0, 0, 0
    for i in range(len(confusion_matrix)):
        for j in range(len(confusion_matrix)):
            if j == iLabel and i == j:
                tp += confusion_matrix[i, j]
            elif j == iLabel:
                fp += confusion_matrix[i, j]
            elif iLabel == i:
                fn += confusion_matrix[i, j]
            else:
                tn += confusion_matrix[i, j]
        sensitivity = tp / (tp+fn)
        specificity = tn / (tn+fp)
        sensitivities.append( sensitivity)
        specificities.append( specificity)

    return specificities, sensitivities

def get_score(actual, predictions):
    correct = 0
    for i in range(len(actual)):
        if actual[i] == predictions[i]:
            correct += 1
    return correct / len(actual)

def confusion_matrix(actual, predict, targets):
    def get_target_index(target):
        for i in range(len(targets)):
            if targets[i] == target:
                found = True
                break
        if found == False:
            raise ValueError(f"Target {target} not found in targets_
↪{targets}")
        return i

    conf_mat = np.zeros((len(targets), len(targets)), dtype=int)
    for i in range(len(actual)):
        iActual = get_target_index(actual[i])
        iPredict = get_target_index(predict[i])
        conf_mat[iActual, iPredict] += 1

    return conf_mat

```

```

    performance = {}
    targets = np.unique(list(np.unique(classifications["train"])) + list(np.
→unique(classifications["test"])))
    performance["conf_mat_train"] = confusion_matrix(classifications["train"],
→classifications["predict_train"], targets)
    performance["specificity_train"], performance["sensitivity_train"] =
→get_spec_sens(performance["conf_mat_train"])
    performance["accuracy_train"] = get_score(classifications["train"],
→classifications["predict_train"])

    performance["conf_mat_test"] = confusion_matrix(classifications["test"],
→classifications["predict_test"], targets)
    performance["specificity_test"], performance["sensitivity_test"] =
→get_spec_sens(performance["conf_mat_test"])
    performance["accuracy_test"] = get_score(classifications["test"],
→classifications["predict_test"])

    return performance

```

```

[26]: def print_conf_mat(conf_mat, labels):
    spacer=4
    width = " "*spacer
    print("Act /\n" + "      Predictions\n")

    line = width
    for label in labels:
        line += " | " + label
    print(line)
    for i, label in enumerate(labels):
        line = label
        for j in range(len(conf_mat)):
            line += f" | {conf_mat[i,j]:<4}"
        print(line)

```

```

[27]: def get_targets(dataset, targets):
    def convert(val):
        if val == 0:
            ret = "Seto"
        elif val == 1:
            ret = "Vers"
        else:
            ret = "Virg"
        return ret

    ret_targets = np.empty(len(targets), dtype=object)
    if dataset == "iris":

```

```

        for i in range(len(targets)):
            ret_targets[i] = convert(targets[i])
    else:
        for i in range(len(targets)):
            ret_targets[i] = str(targets[i]).ljust(4)
    return ret_targets

```

```

[28]: def run_model(dataset, df, model, testing_sizes):
    def get_training_sizes(testing_sizes):
        training_sizes = []
        for i in range(len(testing_sizes)):
            training_size = np.round((1-testing_sizes[i])*10)/10
            training_sizes.append(training_size)
        return training_sizes

    output = {}
    start = time.time()
    output["targets"] = get_targets(dataset, np.unique(df.target))
    output["specs_train"] = np.zeros((len(testing_sizes),
    ↪len(output["targets"])))
    output["senss_train"] = np.zeros((len(testing_sizes),
    ↪len(output["targets"])))
    output["specs_test"] = np.zeros((len(testing_sizes),
    ↪len(output["targets"])))
    output["senss_test"] = np.zeros((len(testing_sizes),
    ↪len(output["targets"])))
    output["train_scores"] = []
    output["test_scores"] = []
    output["training_sizes"] = get_training_sizes(testing_sizes)

    for i, size in enumerate(testing_sizes):
        print(size)
        classifications = perform_classification(df, model, size)
        performance = perform_performance(classifications)

        output["test_scores"].append(performance["accuracy_test"])
        output["train_scores"].append(performance["accuracy_train"])
        output["specs_train"][i, :] = performance["specificity_train"]
        output["senss_train"][i, :] = performance["sensitivity_train"]
        output["specs_test"][i, :] = performance["specificity_test"]
        output["senss_test"][i, :] = performance["sensitivity_test"]
        if size == 0.7:
            output["conf_mat_train"] = performance["conf_mat_train"]
            output["conf_mat_test"] = performance["conf_mat_test"]
    output["runtime"] = time.time() - start
    return output

```

Now loop over all possible cases, and run the models.

```
[61]: testing_sizes = np.array([*range(90, 0, -10)])/100
models = {}
models["svm_rbf"] = SVC(kernel="rbf", gamma="auto")
models["svm_poly"] = SVC(kernel="poly", gamma="auto")
models["svm_linear"] = SVC(kernel="linear", gamma="auto")
models["knn"] = KNeighborsClassifier()
models["naive_bayes"] = GaussianNB()
dim_recs = [("PCA", 3), ("LDA", 6), (None, None)]

[88]: iris_pca = perform_pca(iris_unnamed, n_components=2)
iris_lda = perform_lda(iris_unnamed, n_components=2)
indian_pca = perform_pca(indian_df, n_components=4)
indian_lda = perform_lda(indian_df, n_components=15)
dfs = {"iris_PCA_2": iris_pca,
      "iris_LDA_2": iris_lda,
      "iris_None_None": iris_unnamed,
      "indian_PCA_4": indian_pca,
      "indian_LDA_15": indian_lda,
      "indian_None_None": indian_df
      }

[89]: total_output = {}
for key, df in dfs.items():
    data, dim_red, dim_num = key.split("_")
    output_classifier = {}
    for classifier, model in models.items():
        print(f"==== {data} - {classifier} - {dim_red} ====")
        output_classifier[classifier] = run_model(data, df, model,
        ↪testing_sizes)
    total_output[key] = output_classifier

print("finished")
```

```
==== iris - svm_rbf - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - svm_poly - PCA ====
0.9
0.8
```

```

0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - svm_linear - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - knn - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - naive_bayes - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - svm_rbf - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - svm_poly - LDA ====

```

```

0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - svm_linear - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - knn - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - naive_bayes - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - svm_rbf - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2

```

```

0.1
==== iris - svm_poly - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - svm_linear - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - knn - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== iris - naive_bayes - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - svm_rbf - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4

```

```

0.3
0.2
0.1
==== indian - svm_poly - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - svm_linear - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - knn - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - naive_bayes - PCA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - svm_rbf - LDA ====
0.9
0.8
0.7
0.6

```



```

0.5
0.4
0.3
0.2
0.1
==== indian - svm_poly - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - svm_linear - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - knn - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - naive_bayes - LDA ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - svm_rbf - None ====
0.9
0.8

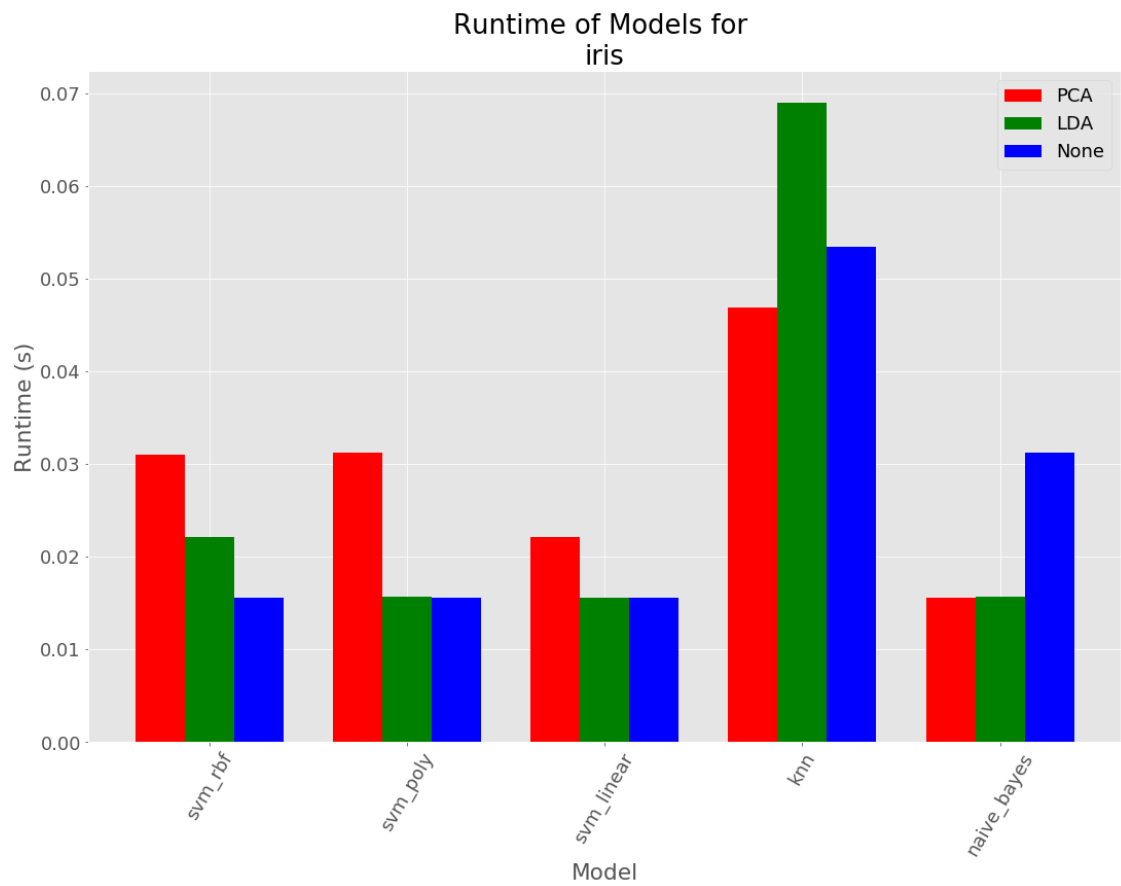
```

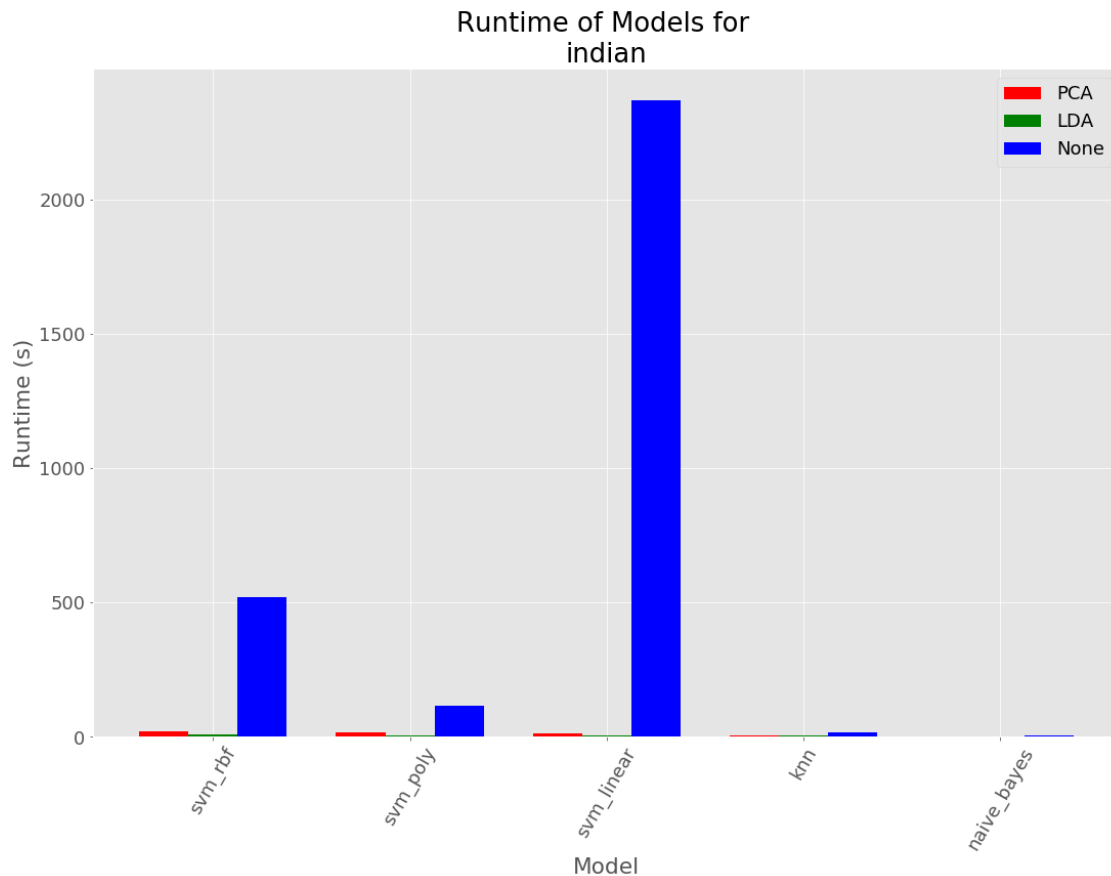
```
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - svm_poly - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - svm_linear - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - knn - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
==== indian - naive_bayes - None ====
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
finished
```

```

[78]: for dataset in ["iris", "indian"]:
    count = 0
    fig = plt.figure(figsize=(18,12))
    ax = fig.add_subplot(111)
    ax.set_title(f"Runtime of Models for \n{dataset}")
    ax.set_xlabel("Model")
    ax.set_ylabel("Runtime (s)")
    colors = ["r", "g", "b"]
    for key, df in dfs.items():
        data, dim_red, dim_num = key.split("_")
        if data != dataset:
            continue
        runtimes = []
        classifiers = []
        for classifier, model in models.items():
            runtimes.append(total_output[key][classifier]["runtime"])
            classifiers.append(classifier)
        X = np.arange(len(classifiers))
        ax.bar(X - 0.25 + count*0.25, runtimes, color=colors[count], width=0.25,
        ↪label=dim_red)
        count += 1
        classifiers = [""] + classifiers
    ax.set_xticklabels(classifiers, Rotation=60)
    ax.legend()

```





```
[72]: def get_header(data, dim_red, dim_num, classifier, length):
    mid = f" {data} - {dim_red} - {dim_num} - {classifier} "
    excess = length - len(mid)
    if excess > 0:
        output = "=" * (excess // 2 + excess % 2)
        output += mid
        output += "=" * (excess // 2)
    else:
        output = mid
    return output
```

```
[90]: for dataset in ["iris", "indian"]:
    fig_scores, ax_scores = plt.subplots(3, 2, figsize=(24,18))
    fig_scores.suptitle(f"{dataset}\nTraining/Testing Scores vs. Training Size")
    fig_sens, ax_sens = plt.subplots(3, 2, figsize=(24,18))
    fig_sens.suptitle(f"{dataset}\nSensitivity vs Target for each Classifier")
    fig_specs, ax_specs = plt.subplots(3, 2, figsize=(24,18))
    fig_specs.suptitle(f"{dataset}\nSpecificity vs Target for each Classifier")

    for axes in [ax_scores, ax_sens, ax_specs]:
```

```

for axis, dim_reduction in zip(range(3), ["None", "PCA", "LDA"]):
    axes[axis, 0].set_title(f"{dim_reduction} Train")
    axes[axis, 1].set_title(f"{dim_reduction} Test")

for key, df in dfs.items():
    data, dim_red, dim_num = key.split("_")
    if data != dataset:
        continue
    if dim_red == "PCA":
        axis = 1
    elif dim_red == "LDA":
        axis = 2
    else:
        axis = 0

    senss_train = []
    senss_test = []
    specs_train = []
    specs_test = []
    classifiers = []
    for classifier, model in models.items():
        run_output = total_output[key][classifier]
        if True:
            print("=====")
            print(get_header(data, dim_red, dim_num, classifier, 44))
            print("=====")
            print(f"===== Train Size: 30% =====")
            print("---- Training Confusion Matrix ----")
            print_conf_mat(run_output["conf_mat_train"],
→run_output["targets"])
            print("---- Testing Confusion Matrix ----")
            print_conf_mat(run_output["conf_mat_test"],
→run_output["targets"])

            label = f"{classifier}"
            ax_scores[axis, 0].plot(run_output["training_sizes"],
                                   run_output["train_scores"], label=label)
            ax_scores[axis, 1].plot(run_output["training_sizes"],
                                   run_output["test_scores"], label=label)
            classifiers.append(classifier)
            senss_train.append(run_output["senss_train"][2,:])
            senss_test.append(run_output["senss_test"][2,:])
            specs_train.append(run_output["specs_train"][2,:])
            specs_test.append(run_output["specs_test"][2,:])

X = np.arange(1, len(run_output["targets"])+1)
if dataset == "indian":

```

```

        pass
        #breakpoint()
width = 1/(len(classifiers)+1)
offset = width*(len(classifiers)//2) + width*(len(classifiers)%2)/2
for iClassifier, classifier in enumerate(classifiers):
    ax_sens[axis, 0].bar(X+offset-width*iClassifier,
                        senss_train[iClassifier],
                        label=classifier,
                        width=width)
    ax_sens[axis, 1].bar(X+offset-width*iClassifier,
                        senss_test[iClassifier],
                        label=classifier,
                        width=width)
    ax_specs[axis, 0].bar(X+offset-width*iClassifier,
                        specs_train[iClassifier],
                        label=classifier,
                        width=width)
    ax_specs[axis, 1].bar(X+offset-width*iClassifier,
                        specs_test[iClassifier],
                        label=classifier,
                        width=width)

targets = [""] + run_output["targets"]
for i in range(3):
    for j in range(2):
        ax_sens[i, j].set_xticks(X)
        ax_specs[i, j].set_xticks(X)
        ax_sens[i, j].set_xticklabels(targets, Rotation=60)
        ax_specs[i, j].set_xticklabels(targets, Rotation=60)

for axes, yax, xax in [(ax_scores, " Score", "Training Size"),
                       (ax_sens, " Sensitivity", "Target Class"),
                       (ax_specs, " Specificity", "Target Class")]:
    for i in range(3):
        for j, te_tr in [(0, "Train"), (1, "Test")]:
            axes[i, j].set_ylim([0, 1.1])
            axes[i, j].legend(loc="lower right")
            axes[i, j].set_xlabel(xax)
            axes[i, j].set_ylabel(te_tr + yax)
for fig in [fig_scores, fig_sens, fig_specs]:
    fig.tight_layout()

```

```

=====
===== iris - PCA - 2 - svm_rbf =====
=====
=====      Train Size: 30%      =====
----      Training Confusion Matrix      ----
Act /      Predictions

```

	Seto	Vers	Virg
Seto	10	0	0
Vers	0	16	1
Virg	0	4	14

----- Testing Confusion Matrix -----

Act /	Predictions			
		Seto	Vers	Virg
Seto		40	0	0
Vers		0	32	1
Virg		0	8	24

===== iris - PCA - 2 - svm\_poly =====

===== Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions			
		Seto	Vers	Virg
Seto		0	0	10
Vers		0	0	17
Virg		0	0	18

----- Testing Confusion Matrix -----

Act /	Predictions			
		Seto	Vers	Virg
Seto		0	0	40
Vers		0	0	33
Virg		0	0	32

===== iris - PCA - 2 - svm\_linear =====

===== Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions			
		Seto	Vers	Virg
Seto		10	0	0
Vers		0	16	1
Virg		0	4	14

----- Testing Confusion Matrix -----

Act /	Predictions			
		Seto	Vers	Virg
Seto		40	0	0
Vers		0	32	1
Virg		0	5	27

===== iris - PCA - 2 - knn =====

===== Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions			
-------	-------------	--	--	--



	Seto	Vers	Virg
Seto	10	0	0
Vers	0	17	0
Virg	0	1	17

---- Testing Confusion Matrix ----

Act /	Predictions		
	Seto	Vers	Virg
Seto	40	0	0
Vers	0	30	3
Virg	0	1	31

=====

==== iris - PCA - 2 - naive\_bayes =====

=====

==== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions		
	Seto	Vers	Virg
Seto	10	0	0
Vers	0	15	2
Virg	0	2	16

---- Testing Confusion Matrix ----

Act /	Predictions		
	Seto	Vers	Virg
Seto	40	0	0
Vers	0	28	5
Virg	0	4	28

=====

==== iris - LDA - 2 - svm\_rbf =====

=====

==== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions		
	Seto	Vers	Virg
Seto	10	0	0
Vers	0	17	0
Virg	0	0	18

---- Testing Confusion Matrix ----

Act /	Predictions		
	Seto	Vers	Virg
Seto	40	0	0
Vers	0	29	4
Virg	0	0	32

=====

==== iris - LDA - 2 - svm\_poly =====

=====

==== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions		
-------	-------------	--	--

	Seto   Vers   Virg
Seto	10   0   0
Vers	0   17   0
Virg	0   0   18

----- Testing Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	40   0   0
Vers	0   29   4
Virg	0   0   32

=====

=====  
iris - LDA - 2 - svm\_linear  
=====

=====  
Train Size: 30%  
=====

----- Training Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	10   0   0
Vers	0   17   0
Virg	0   0   18

----- Testing Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	40   0   0
Vers	0   30   3
Virg	0   0   32

=====

=====  
iris - LDA - 2 - knn  
=====

=====  
Train Size: 30%  
=====

----- Training Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	10   0   0
Vers	0   17   0
Virg	0   0   18

----- Testing Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	40   0   0
Vers	0   31   2
Virg	0   0   32

=====

=====  
iris - LDA - 2 - naive\_bayes  
=====

=====  
Train Size: 30%  
=====

----- Training Confusion Matrix -----

Act /	Predictions
-------	-------------

	Seto   Vers   Virg
Seto	10   0   0
Vers	0   17   0
Virg	0   0   18

----- Testing Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	40   0   0
Vers	0   30   3
Virg	0   1   31

=====

=====  
iris - None - None - svm\_rbf  
=====

=====  
Train Size: 30%  
=====

----- Training Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	10   0   0
Vers	0   17   0
Virg	0   1   17

----- Testing Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	40   0   0
Vers	0   30   3
Virg	0   0   32

=====

=====  
iris - None - None - svm\_poly  
=====

=====  
Train Size: 30%  
=====

----- Training Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	10   0   0
Vers	0   17   0
Virg	0   0   18

----- Testing Confusion Matrix -----

Act /	Predictions
	Seto   Vers   Virg
Seto	40   0   0
Vers	0   29   4
Virg	0   0   32

=====

=====  
iris - None - None - svm\_linear  
=====

=====  
Train Size: 30%  
=====

----- Training Confusion Matrix -----

Act /	Predictions
-------	-------------

	Seto	Vers	Virg
Seto	10	0	0
Vers	0	17	0
Virg	0	0	18

----- Testing Confusion Matrix -----

Act /	Predictions			
	Seto	Vers	Virg	
Seto	40	0	0	
Vers	0	31	2	
Virg	0	0	32	

===== iris - None - None - knn =====

===== Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions			
	Seto	Vers	Virg	
Seto	10	0	0	
Vers	0	17	0	
Virg	0	2	16	

----- Testing Confusion Matrix -----

Act /	Predictions			
	Seto	Vers	Virg	
Seto	40	0	0	
Vers	0	31	2	
Virg	0	1	31	

===== iris - None - None - naive\_bayes =====

===== Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions			
	Seto	Vers	Virg	
Seto	10	0	0	
Vers	0	16	1	
Virg	0	1	17	

----- Testing Confusion Matrix -----

Act /	Predictions			
	Seto	Vers	Virg	
Seto	40	0	0	
Vers	0	29	4	
Virg	0	2	30	

===== indian - PCA - 4 - svm\_rbf =====

===== Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions			
-------	-------------	--	--	--

	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	0	0	0	0	0	0	0	14	0	0	1
0	0	0	0	0							
2	0	187	11	0	1	1	0	1	0	16	195
23	0	0	0	0							
3	0	10	151	1	0	0	0	0	0	1	70
9	0	0	0	0							
4	0	0	13	42	0	2	0	0	0	0	1
1	0	0	0	0							
5	0	0	0	2	140	7	0	4	0	0	0
0	0	0	1	0							
6	0	0	0	0	3	209	0	0	0	0	0
0	0	1	5	0							
7	0	0	0	0	1	0	0	8	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	154	0	0	0
0	0	0	0	0							
9	0	0	0	0	1	3	0	0	0	0	0
0	0	0	0	0							
10	0	6	0	0	0	1	0	1	0	212	70
15	0	0	0	0							
11	0	22	10	0	2	4	0	0	0	26	673
6	0	0	0	0							
12	0	47	7	0	0	1	0	0	0	9	40
58	0	0	0	0							
13	0	0	0	0	0	3	0	0	0	0	0
0	54	0	0	0							
14	0	0	0	0	1	1	0	0	0	0	0
0	0	370	2	0							
15	0	0	0	0	1	46	0	0	0	0	0
0	9	31	35	0							
16	0	0	0	0	0	0	0	0	0	2	0
0	0	0	0	19							

----- Testing Confusion Matrix -----											
Act /	Predictions										
	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	0	0	0	0	0	0	0	31	0	0	0
0	0	0	0	0							
2	0	391	20	0	1	1	0	2	0	36	454
88	0	0	0	0							
3	0	20	362	16	0	0	0	0	0	1	171
18	0	0	0	0							
4	1	0	48	118	0	7	0	0	0	1	1
2	0	0	0	0							
5	0	0	0	4	288	13	0	10	0	6	6
0	0	0	2	0							

6	0	0	0	0	5	484	0	0	0	0	4
0	1	0	18	0							
7	0	0	0	0	0	0	0	19	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	324	0	0	0
0	0	0	0	0							
9	0	0	0	0	1	15	0	0	0	0	0
0	0	0	0	0							
10	0	8	0	0	1	0	0	2	0	471	140
45	0	0	0	0							
11	0	55	21	1	7	11	0	0	0	68	
1529	20	0	0	0	0						
12	0	144	14	0	0	0	0	0	0	19	135
119	0	0	0	0							
13	0	0	0	0	0	12	0	0	0	0	1
0	135	0	0	0							
14	0	0	0	0	0	10	0	0	0	0	0
0	0	874	7	0							
15	0	0	0	0	8	116	0	0	0	3	2
2	10	61	62	0							
16	0	6	0	0	0	0	0	0	0	1	4
2	0	0	0	59							

=====

===== indian - PCA - 4 - svm\_poly =====

=====

=====	Train Size: 30%	=====									
----	Training Confusion Matrix	----									
Act /	Predictions										
	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	0	0	0	0	0	0	0	14	0	0	1
0	0	0	0	0							
2	0	159	15	0	0	1	0	0	0	10	241
9	0	0	0	0							
3	0	9	122	2	0	0	0	0	0	0	108
1	0	0	0	0							
4	0	1	8	18	0	2	0	0	0	1	29
0	0	0	0	0							
5	0	0	0	0	124	19	0	4	0	1	6
0	0	0	0	0							
6	0	0	0	0	3	196	0	0	0	0	9
0	0	0	10	0							
7	0	0	0	0	0	0	0	1	0	0	8
0	0	0	0	0							
8	0	0	0	0	0	0	0	144	0	0	10
0	0	0	0	0							
9	0	0	0	0	2	2	0	0	0	0	0
0	0	0	0	0							

10	0	0	0	0	0	0	0	0	0	181	114
10	0	0	0	0	0						
11	0	19	4	0	0	2	0	0	0	26	692
0	0	0	0	0	0						
12	0	19	17	0	0	5	0	0	0	3	79
39	0	0	0	0	0						
13	0	0	0	0	0	3	0	0	0	0	0
0	54	0	0	0	0						
14	0	0	0	0	0	1	0	0	0	0	0
0	0	366	7	0	0						
15	0	0	0	0	0	1	43	0	0	0	0
0	6	12	60	0	0						
16	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	21	0						

----- Testing Confusion Matrix -----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	0	0	0	0	0	0	0	29	0	0	2	
0	0	0	0	0	0							
2	0	334	32	0	1	2	0	0	0	14	583	
27	0	0	0	0	0							
3	0	15	317	20	0	0	0	0	0	1	231	
4	0	0	0	0	0							
4	0	7	23	83	0	11	0	1	0	2	51	
0	0	0	0	0	0							
5	0	0	1	1	246	43	0	8	0	2	28	
0	0	0	0	0	0							
6	0	0	0	0	11	455	0	0	0	0	17	
0	1	0	28	0	0							
7	0	0	0	0	0	0	0	1	0	0	18	
0	0	0	0	0	0							
8	0	0	0	0	0	0	0	293	0	0	31	
0	0	0	0	0	0							
9	0	0	0	0	6	10	0	0	0	0	0	
0	0	0	0	0	0							
10	0	0	0	0	1	0	0	0	0	415	222	
29	0	0	0	0	0							
11	0	29	10	0	0	11	0	0	0	75		
1585	2	0	0	0	0							
12	0	39	47	0	0	8	0	0	0	5	193	
139	0	0	0	0	0							
13	0	0	0	0	0	11	0	0	0	0	1	
0	136	0	0	0	0							
14	0	0	0	0	0	3	0	0	0	0	0	
0	0	863	25	0	0							
15	0	0	0	0	2	113	0	1	0	0	7	
0	8	31	102	0	0							

```

16 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 4
| 2 | 0 | 0 | 0 | 60
=====
===== indian - PCA - 4 - svm_linear =====
=====
===== Train Size: 30% =====
----- Training Confusion Matrix -----
Act / Predictions
      | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11
| 12 | 13 | 14 | 15 | 16
1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 13 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 0
2 | 0 | 166 | 25 | 0 | 1 | 1 | 0 | 1 | 0 | 17 | 210
| 14 | 0 | 0 | 0 | 0
3 | 0 | 2 | 160 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 76
| 0 | 0 | 0 | 0 | 0
4 | 0 | 0 | 13 | 45 | 0 | 1 | 0 | 0 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 0
5 | 3 | 0 | 0 | 1 | 134 | 15 | 0 | 0 | 0 | 0 | 1
| 0 | 0 | 0 | 0 | 0
6 | 0 | 0 | 0 | 0 | 15 | 192 | 0 | 0 | 0 | 0 | 0
| 0 | 0 | 0 | 11 | 0
7 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 8 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 0
8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 154 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 0
9 | 0 | 0 | 0 | 0 | 2 | 2 | 0 | 0 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 0
10 | 0 | 13 | 0 | 2 | 0 | 1 | 0 | 1 | 0 | 211 | 74
| 3 | 0 | 0 | 0 | 0
11 | 0 | 43 | 10 | 6 | 2 | 4 | 0 | 0 | 0 | 67 | 610
| 1 | 0 | 0 | 0 | 0
12 | 0 | 26 | 31 | 0 | 0 | 5 | 0 | 0 | 0 | 12 | 75
| 13 | 0 | 0 | 0 | 0
13 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0
| 0 | 54 | 0 | 0 | 0
14 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0
| 0 | 0 | 370 | 3 | 0
15 | 0 | 0 | 0 | 0 | 9 | 38 | 0 | 0 | 0 | 0 | 0
| 0 | 9 | 28 | 38 | 0
16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0
| 0 | 0 | 0 | 0 | 20
----- Testing Confusion Matrix -----
Act / Predictions
      | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11
| 12 | 13 | 14 | 15 | 16
1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 31 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 0

```



2	0	331	87	0	3	1	0	0	0	33	524
14	0	0	0	0							
3	0	5	398	18	0	0	0	0	0	0	164
3	0	0	0	0							
4	0	6	48	114	1	4	0	0	0	1	0
4	0	0	0	0							
5	4	1	0	3	264	42	0	5	0	5	2
3	0	0	0	0							
6	0	0	0	0	54	418	0	0	0	2	1
0	2	0	35	0							
7	0	0	0	0	0	0	0	19	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	324	0	0	0
0	0	0	0	0							
9	0	0	0	0	8	8	0	0	0	0	0
0	0	0	0	0							
10	0	30	0	0	0	1	1	1	0	444	186
4	0	0	0	0							
11	0	62	11	7	10	8	0	0	0	175	
1425	14	0	0	0	0						
12	0	63	111	0	0	7	0	0	0	31	174
45	0	0	0	0							
13	0	0	0	1	0	9	0	0	0	0	0
0	138	0	0	0							
14	0	0	0	0	2	3	0	0	0	0	0
0	0	880	6	0							
15	0	0	0	0	26	97	0	0	0	1	0
3	17	59	61	0							
16	0	7	0	0	0	0	0	0	0	5	1
1	0	0	0	58							

=====

===== indian - PCA - 4 - knn =====

=====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	14	0	0	0	0	0	0	0	0	1	0	
0	0	0	0	0	0							
2	0	361	10	0	1	2	0	1	0	8	42	
10	0	0	0	0								
3	0	11	196	4	0	0	0	0	0	1	24	
6	0	0	0	0								
4	0	0	8	47	0	2	0	0	0	1	0	
1	0	0	0	0								
5	1	0	0	2	148	0	1	2	0	0	0	
0	0	0	0	0								

6	0	0	0	0	3	211	0	0	0	0	0
0	0	1	3	0							
7	0	0	0	0	1	0	6	2	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	154	0	0	0
0	0	0	0	0							
9	0	0	0	0	1	3	0	0	0	0	0
0	0	0	0	0							
10	0	6	2	1	0	2	0	1	0	280	10
3	0	0	0	0							
11	0	19	11	1	2	3	0	0	0	28	673
6	0	0	0	0							
12	0	30	4	0	0	0	0	0	0	8	18
101	0	0	1	0							
13	0	0	0	0	0	2	0	0	0	0	0
0	55	0	0	0							
14	0	0	0	0	1	1	0	0	0	0	0
0	1	366	5	0							
15	0	0	0	0	1	37	0	0	0	0	0
0	7	11	66	0							
16	0	0	0	0	0	0	0	0	0	0	1
1	0	0	0	19							

----- Testing Confusion Matrix -----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	27	0	0	0	0	0	0	4	0	0	0	
0	0	0	0	0								
2	0	731	35	1	3	1	1	0	0	25	148	
48	0	0	0	0								
3	0	35	431	26	1	0	0	0	0	8	69	
18	0	0	0	0								
4	1	2	20	129	2	7	0	0	0	13	4	
0	0	0	0	0								
5	5	0	0	6	298	5	0	3	0	9	3	
0	0	0	0	0								
6	0	0	0	0	12	476	0	0	0	0	0	
1	3	3	17	0								
7	0	0	0	0	0	0	14	5	0	0	0	
0	0	0	0	0								
8	0	0	0	0	0	0	0	324	0	0	0	
0	0	0	0	0								
9	0	0	0	0	2	11	0	0	2	0	1	
0	0	0	0	0								
10	0	12	2	0	1	2	5	0	0	573	49	
23	0	0	0	0								
11	0	79	32	2	8	8	0	0	0	118		
1443	22	0	0	0	0							

12	0	103	15	0	3	1	0	0	0	28	64
217	0	0	0	0							
13	0	0	0	0	0	6	0	0	0	0	1
0	141	0	0	0							
14	0	0	0	0	2	6	0	0	0	0	0
0	0	870	13	0							
15	0	0	0	0	6	103	0	0	0	4	0
2	11	37	101	0							
16	0	5	0	0	0	0	0	0	0	1	5
1	0	0	0	60							

=====

===== indian - PCA - 4 - naive\_bayes =====

=====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act / Predictions		1	2	3	4	5	6	7	8	9	10	11
		12	13	14	15	16						
1	14	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0							
2	0	179	19	2	0	1	0	0	0	0	26	199
9	0	0	0	0	0							
3	0	22	132	16	0	0	0	0	0	0	0	68
4	0	0	0	0	0							
4	0	8	13	29	0	1	0	0	0	0	0	7
1	0	0	0	0	0							
5	1	2	0	1	107	26	1	0	0	0	1	0
5	0	0	10	0								
6	0	0	0	0	12	196	0	0	0	0	4	0
0	0	0	6	0								
7	0	0	0	0	0	0	9	0	0	0	0	0
0	0	0	0	0								
8	1	0	0	0	0	0	3	150	0	0	0	0
0	0	0	0	0								
9	0	0	0	0	0	1	0	0	3	0	0	0
0	0	0	0	0								
10	0	36	0	0	0	0	0	0	0	0	172	82
15	0	0	0	0								
11	0	67	26	0	0	6	0	0	0	0	32	588
24	0	0	0	0								
12	0	37	33	0	0	3	0	0	0	0	2	66
20	0	0	1	0								
13	0	0	0	0	0	1	0	0	0	0	0	0
0	55	0	1	0								
14	0	0	0	0	0	0	0	0	0	0	0	0
0	0	359	15	0								
15	0	0	0	0	5	35	0	0	0	0	0	0
0	4	38	40	0								

16	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	20								

----- Testing Confusion Matrix -----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	31	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0								
2	0	382	54	0	1	2	0	0	0	66	453	
35	0	0	0	0								
3	0	53	341	30	0	0	0	0	0	0	154	
10	0	0	0	0								
4	0	34	46	78	0	4	0	0	0	0	9	
7	0	0	0	0								
5	4	8	3	2	214	57	4	0	0	3	0	
9	0	0	24	1								
6	0	0	0	0	38	442	0	0	0	7	1	
3	1	1	19	0								
7	0	0	0	0	0	0	18	1	0	0	0	
0	0	0	0	0								
8	0	0	0	0	0	0	8	316	0	0	0	
0	0	0	0	0								
9	0	0	0	0	1	3	0	0	12	0	0	
0	0	0	0	0								
10	0	83	4	0	0	1	2	0	0	369	179	
29	0	0	0	0								
11	0	144	60	1	0	15	0	0	0	84		
1342	66	0	0	0	0							
12	0	126	62	0	0	4	0	0	0	3	163	
71	0	0	1	1								
13	0	0	0	0	0	1	0	0	0	0	0	
1	141	0	5	0								
14	0	0	0	0	1	1	0	0	0	0	0	
0	0	857	32	0								
15	0	0	0	0	14	88	0	0	0	2	0	
4	5	69	80	2								
16	0	10	0	0	0	0	0	0	0	0	0	
1	0	0	0	61								

=====  
===== indian - LDA - 15 - svm\_rbf =====  
=====

=====  
Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	15	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0								

2	0	410	5	0	0	0	0	0	0	7	12
1	0	0	0	0							
3	0	9	219	2	0	0	0	0	0	0	11
1	0	0	0	0							
4	0	0	1	58	0	0	0	0	0	0	0
0	0	0	0	0							
5	0	0	0	0	152	1	0	0	0	0	0
1	0	0	0	0							
6	0	0	0	0	0	218	0	0	0	0	0
0	0	0	0	0							
7	0	0	0	0	0	0	9	0	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	154	0	0	0
0	0	0	0	0							
9	0	0	0	0	0	0	0	0	4	0	0
0	0	0	0	0							
10	0	1	0	0	0	0	0	0	0	289	15
0	0	0	0	0							
11	0	15	0	0	1	0	0	0	0	12	715
0	0	0	0	0							
12	0	1	4	0	0	0	0	0	0	0	0
157	0	0	0	0							
13	0	0	0	0	0	0	0	0	0	0	0
0	57	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0
0	0	374	0	0							
15	0	0	0	0	0	0	0	0	0	0	0
0	0	5	117	0							
16	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	21							

----- Testing Confusion Matrix -----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	31	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0								
2	0	889	11	5	0	0	0	0	0	24	56	
7	0	0	1	0								
3	0	34	488	15	0	0	0	0	0	1	46	
4	0	0	0	0								
4	0	5	24	141	4	0	0	0	0	0	2	
0	0	0	2	0								
5	0	0	0	0	316	3	0	0	0	0	4	
3	0	0	3	0								
6	0	0	0	0	0	504	0	0	0	3	0	
0	0	1	4	0								
7	0	0	0	0	0	0	18	0	0	0	0	
0	0	0	1	0								

8	0	0	0	0	0	0	0	0	324	0	0	0
	0	0	0	0	0							
9	0	0	0	0	0	0	0	0	0	16	0	0
	0	0	0	0	0							
10	0	8	0	0	0	2	0	0	0	0	587	68
	2	0	0	0	0							
11	0	45	13	0	12	0	0	0	0	0	55	
1579	6	0	0	2	0							
12	0	9	38	0	0	0	0	0	0	0	1	5
	377	0	0	1	0							
13	0	0	0	0	0	0	0	0	0	0	0	1
	0	147	0	0	0							
14	0	0	0	0	0	1	0	0	0	0	0	0
	0	0	882	8	0							
15	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	10	254	0							
16	0	2	0	0	0	0	0	0	0	0	0	3
	0	0	0	20	47							

=====

===== indian - LDA - 15 - svm\_poly =====

=====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act / Predictions

	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	15	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0						
2	0	418	2	0	0	0	0	0	0	5	9
	1	0	0	0	0						
3	0	4	231	0	0	0	0	0	0	0	7
	0	0	0	0	0						
4	0	0	0	59	0	0	0	0	0	0	0
	0	0	0	0	0						
5	0	0	0	0	153	0	0	0	0	0	0
	1	0	0	0	0						
6	0	0	0	0	0	218	0	0	0	0	0
	0	0	0	0	0						
7	0	0	0	0	0	0	9	0	0	0	0
	0	0	0	0	0						
8	0	0	0	0	0	0	0	154	0	0	0
	0	0	0	0	0						
9	0	0	0	0	0	0	0	0	4	0	0
	0	0	0	0	0						
10	0	1	0	0	0	0	0	0	0	296	8
	0	0	0	0	0						
11	0	9	1	0	0	0	0	0	0	10	723
	0	0	0	0	0						

12	0	1	0	0	0	0	0	0	0	0	0	0
161	0	0	0	0	0							
13	0	0	0	0	0	0	0	0	0	0	0	0
0	57	0	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0	0
0	0	374	0	0								
15	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	122	0								
16	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	21								

```

-----      Testing Confusion Matrix      -----
Act /      Predictions
      | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      | 10     | 11
| 12   | 13   | 14   | 15   | 16
1      | 31   | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0
| 0      | 0      | 0      | 0      | 0
2      | 0      | 887   | 18     | 2      | 0      | 0      | 0      | 0      | 0      | 30     | 51
| 4      | 0      | 0      | 1      | 0
3      | 0      | 40     | 492   | 13     | 0      | 0      | 0      | 0      | 0      | 3       | 34
| 6      | 0      | 0      | 0      | 0
4      | 0      | 7      | 35     | 129   | 4      | 0      | 0      | 0      | 0      | 2       | 0
| 1      | 0      | 0      | 0      | 0
5      | 0      | 1      | 0      | 0      | 303   | 4      | 0      | 0      | 0      | 13     | 3
| 4      | 0      | 0      | 1      | 0
6      | 0      | 0      | 0      | 0      | 6      | 501   | 0      | 0      | 0      | 4       | 0
| 0      | 0      | 0      | 1      | 0
7      | 0      | 0      | 0      | 0      | 0      | 0      | 19     | 0      | 0      | 0       | 0
| 0      | 0      | 0      | 0      | 0
8      | 1      | 0      | 0      | 0      | 0      | 0      | 0      | 323   | 0      | 0       | 0
| 0      | 0      | 0      | 0      | 0
9      | 0      | 0      | 0      | 1      | 2      | 0      | 0      | 0      | 13     | 0       | 0
| 0      | 0      | 0      | 0      | 0
10     | 0      | 14     | 1      | 0      | 0      | 3      | 0      | 0      | 0      | 585    | 63
| 1      | 0      | 0      | 0      | 0
11     | 0      | 50     | 22     | 0      | 6      | 0      | 0      | 0      | 0      | 91     |
1536  | 6      | 0      | 0      | 1      | 0
12     | 0      | 13     | 24     | 0      | 0      | 0      | 0      | 0      | 0      | 5       | 3
| 385   | 0      | 0      | 0      | 1
13     | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0       | 2
| 0      | 146   | 0      | 0      | 0
14     | 0      | 0      | 0      | 0      | 0      | 1      | 0      | 0      | 0      | 0       | 0
| 0      | 0      | 869   | 21     | 0
15     | 0      | 1      | 0      | 0      | 1      | 7      | 0      | 0      | 0      | 2       | 0
| 4      | 0      | 13     | 236   | 0
16     | 0      | 4      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0       | 1
| 4      | 0      | 0      | 0      | 63
=====
===== indian - LDA - 15 - svm_linear =====

```

```

=====
=====      Train Size: 30%      =====
-----      Training Confusion Matrix      -----
Act /      Predictions
      | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      | 10     | 11
      | 12     | 13     | 14     | 15     | 16
1      | 15     | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0
      | 0      | 0      | 0      | 0      | 0
2      | 0      | 382    | 12     | 1      | 0      | 0      | 0      | 0      | 0      | 17     | 21
      | 2      | 0      | 0      | 0      | 0
3      | 0      | 12     | 210    | 5      | 0      | 0      | 0      | 0      | 0      | 0      | 11
      | 4      | 0      | 0      | 0      | 0
4      | 0      | 0      | 1      | 58     | 0      | 0      | 0      | 0      | 0      | 0      | 0
      | 0      | 0      | 0      | 0      | 0
5      | 0      | 0      | 0      | 0      | 0      | 152    | 1      | 0      | 0      | 0      | 0
      | 1      | 0      | 0      | 0      | 0
6      | 0      | 0      | 0      | 0      | 0      | 0      | 218    | 0      | 0      | 0      | 0
      | 0      | 0      | 0      | 0      | 0
7      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 9      | 0      | 0      | 0
      | 0      | 0      | 0      | 0      | 0
8      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 154    | 0      | 0
      | 0      | 0      | 0      | 0      | 0
9      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 4      | 0
      | 0      | 0      | 0      | 0      | 0
10     | 0      | 12     | 1      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 246    | 46
      | 0      | 0      | 0      | 0      | 0
11     | 0      | 51     | 5      | 0      | 0      | 3      | 0      | 0      | 0      | 0      | 30     | 654
      | 0      | 0      | 0      | 0      | 0
12     | 0      | 1      | 6      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 3
      | 152    | 0      | 0      | 0      | 0
13     | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0
      | 0      | 57     | 0      | 0      | 0
14     | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0
      | 0      | 0      | 371    | 3      | 0
15     | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0
      | 0      | 0      | 3      | 119    | 0
16     | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0
      | 0      | 0      | 0      | 0      | 21
-----      Testing Confusion Matrix      -----
Act /      Predictions
      | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      | 10     | 11
      | 12     | 13     | 14     | 15     | 16
1      | 31     | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0
      | 0      | 0      | 0      | 0      | 0
2      | 0      | 862    | 29     | 6      | 0      | 0      | 0      | 0      | 0      | 35     | 53
      | 7      | 0      | 0      | 1      | 0
3      | 0      | 40     | 493    | 17     | 0      | 0      | 0      | 0      | 0      | 0      | 31
      | 7      | 0      | 0      | 0      | 0

```



4	0	4	15	154	3	0	0	1	0	0	0
1	0	0	0	0							
5	0	1	0	2	317	3	0	0	0	3	1
1	0	0	1	0							
6	0	0	0	0	12	498	0	0	0	1	0
0	0	0	1	0							
7	0	0	0	0	0	0	19	0	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	324	0	0	0
0	0	0	0	0							
9	0	0	0	0	0	0	0	0	16	0	0
0	0	0	0	0							
10	0	24	1	0	0	2	0	0	0	517	122
1	0	0	0	0							
11	0	86	36	1	14	0	0	0	0	76	
1496	3	0	0	0	0						
12	0	6	45	1	0	0	0	0	0	5	10
363	0	0	0	1							
13	0	0	0	0	0	0	0	0	0	0	1
0	147	0	0	0							
14	0	0	0	0	0	1	0	0	0	0	0
0	0	876	14	0							
15	0	0	0	0	4	6	0	0	0	1	1
3	0	13	236	0							
16	0	3	0	0	0	0	0	0	0	0	0
4	0	0	0	65							

===== indian - LDA - 15 - knn =====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	12	0	0	0	1	0	0	2	0	0	0	
0	0	0	0	0								
2	0	399	4	0	0	0	0	0	0	14	15	
3	0	0	0	0								
3	0	13	201	5	0	0	0	0	0	1	19	
3	0	0	0	0								
4	0	1	7	51	0	0	0	0	0	0	0	
0	0	0	0	0								
5	0	0	0	0	150	3	0	0	0	0	0	
1	0	0	0	0								
6	0	0	0	0	0	218	0	0	0	0	0	
0	0	0	0	0								
7	0	0	0	0	0	0	9	0	0	0	0	
0	0	0	0	0								

8	0	0	0	0	0	0	0	0	154	0	0	0
	0	0	0	0	0							
9	0	0	0	0	0	0	0	0	0	4	0	0
	0	0	0	0	0							
10	0	4	0	0	0	1	0	0	0	0	274	26
	0	0	0	0	0							
11	0	18	2	0	3	1	0	0	0	0	17	702
	0	0	0	0	0							
12	0	4	5	0	0	0	0	0	0	0	0	7
	145	0	0	1	0							
13	0	0	0	0	0	0	0	0	0	0	0	0
	0	57	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0	0
	0	1	372	1	0							
15	0	0	0	0	0	2	0	0	0	0	0	0
	0	1	8	111	0							
16	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	21							

----- Testing Confusion Matrix -----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	30	0	0	0	0	0	0	1	0	0	0	
	0	0	0	0	0							
2	0	856	18	4	0	1	0	0	0	24	87	
	3	0	0	0	0							
3	0	37	467	13	0	0	0	0	0	1	65	
	5	0	0	0	0							
4	0	11	38	123	3	0	0	1	0	0	2	
	0	0	0	0	0							
5	0	1	1	0	311	6	0	0	0	5	1	
	3	0	0	1	0							
6	0	0	0	0	1	511	0	0	0	0	0	
	0	0	0	0	0							
7	0	0	0	0	0	0	19	0	0	0	0	
	0	0	0	0	0							
8	0	0	0	0	0	0	0	324	0	0	0	
	0	0	0	0	0							
9	0	0	0	0	0	0	0	0	16	0	0	
	0	0	0	0	0							
10	0	16	1	0	0	4	0	0	0	567	79	
	0	0	0	0	0							
11	0	64	12	0	13	0	0	0	0	79		
	1537	7	0	0	0							
12	0	11	48	0	0	0	0	0	0	2	15	
	354	0	0	0	1							
13	0	0	0	0	0	0	0	0	0	0	1	
	0	147	0	0	0							

14	0	0	0	0	0	1	0	0	0	0	0	0
	0	0	878	12	0							
15	0	0	0	0	5	9	0	0	0	0	0	0
	1	1	17	231	0							
16	0	5	0	0	0	0	0	0	0	0	0	2
	1	0	0	0	64							

=====

===== indian - LDA - 15 - naive\_bayes =====

=====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	13	0	0	0	0	0	0	1	0	0	0	
	0	0	0	1	0							
2	0	370	16	1	0	0	0	0	0	20	23	
	3	0	0	1	1							
3	0	17	196	6	0	0	0	0	0	0	20	
	3	0	0	0	0							
4	0	0	4	55	0	0	0	0	0	0	0	
	0	0	0	0	0							
5	0	0	0	2	142	4	0	0	0	0	1	
	2	0	0	3	0							
6	0	0	0	0	0	215	0	0	0	0	0	
	0	0	0	3	0							
7	0	0	0	0	0	0	9	0	0	0	0	
	0	0	0	0	0							
8	0	0	0	0	0	0	0	154	0	0	0	
	0	0	0	0	0							
9	0	0	0	0	0	0	0	0	4	0	0	
	0	0	0	0	0							
10	0	8	1	0	0	1	0	0	0	251	38	
	3	0	0	1	2							
11	0	61	4	0	4	1	0	0	0	42	624	
	1	0	0	6	0							
12	0	3	17	0	0	0	0	0	0	0	4	
	135	0	0	1	2							
13	0	0	0	0	0	0	0	0	0	0	0	
	0	57	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0	
	0	0	363	11	0							
15	0	0	0	0	1	0	0	0	0	0	0	
	0	0	21	100	0							
16	0	0	0	0	0	0	0	0	0	0	0	
	0	0	0	0	21							

---- Testing Confusion Matrix ----

Act / Predictions

	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	31	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0							
2	0	852	37	11	0	1	0	0	0	39	44
6	0	0	1	2							
3	0	44	471	16	0	0	0	0	0	0	55
2	0	0	0	0							
4	0	4	34	132	0	0	0	0	0	0	0
2	0	0	6	0							
5	0	0	0	2	277	21	0	0	0	1	0
6	0	0	22	0							
6	0	0	0	0	2	500	0	0	0	3	0
0	0	0	7	0							
7	0	0	0	0	0	0	19	0	0	0	0
0	0	0	0	0							
8	1	0	0	0	0	0	0	323	0	0	0
0	0	0	0	0							
9	0	0	0	4	0	1	0	0	8	0	0
0	0	0	3	0							
10	0	15	2	0	0	2	0	0	0	518	126
3	0	0	0	1							
11	0	116	38	0	11	1	0	0	0	96	
1430	15	0	0	4	1						
12	0	5	79	1	0	0	0	0	0	0	7
338	0	0	0	1							
13	0	0	0	0	1	0	0	0	0	0	0
0	147	0	0	0							
14	0	0	0	0	3	1	0	0	0	0	0
0	0	863	24	0							
15	0	0	0	0	0	6	0	0	0	0	0
0	0	28	229	1							
16	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	64							

=====  
===== indian - None - None - svm\_rbf =====  
=====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act / Predictions

	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	15	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0							
2	0	435	0	0	0	0	0	0	0	0	0
0	0	0	0	0							
3	0	0	242	0	0	0	0	0	0	0	0
0	0	0	0	0							

4	0	0	0	59	0	0	0	0	0	0	0
	0	0	0	0	0						
5	0	0	0	0	0	154	0	0	0	0	0
	0	0	0	0	0						
6	0	0	0	0	0	0	218	0	0	0	0
	0	0	0	0	0						
7	0	0	0	0	0	0	0	9	0	0	0
	0	0	0	0	0						
8	0	0	0	0	0	0	0	0	154	0	0
	0	0	0	0	0						
9	0	0	0	0	0	0	0	0	0	4	0
	0	0	0	0	0						
10	0	0	0	0	0	0	0	0	0	0	305
	0	0	0	0	0						
11	0	0	0	0	0	0	0	0	0	0	743
	0	0	0	0	0						
12	0	0	0	0	0	0	0	0	0	0	0
	162	0	0	0	0						
13	0	0	0	0	0	0	0	0	0	0	0
	0	57	0	0	0						
14	0	0	0	0	0	0	0	0	0	0	0
	0	0	374	0	0						
15	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	122	0						
16	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	21						

----- Testing Confusion Matrix -----

Act /	Predictions										
	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	0	0	0	0	0	0	0	0	0	0	31
	0	0	0	0	0						
2	0	0	0	0	0	0	0	0	0	0	993
	0	0	0	0	0						
3	0	0	0	0	0	0	0	0	0	0	588
	0	0	0	0	0						
4	0	0	0	0	0	0	0	0	0	0	178
	0	0	0	0	0						
5	0	0	0	0	0	0	0	0	0	0	329
	0	0	0	0	0						
6	0	0	0	0	0	0	0	0	0	0	512
	0	0	0	0	0						
7	0	0	0	0	0	0	0	0	0	0	19
	0	0	0	0	0						
8	0	0	0	0	0	0	0	0	0	0	324
	0	0	0	0	0						
9	0	0	0	0	0	0	0	0	0	0	16
	0	0	0	0	0						

10	0	0	0	0	0	0	0	0	0	0	0	667
	0	0	0	0	0							
11	0	0	0	0	0	0	0	0	0	0	0	
1712	0	0	0	0	0							
12	0	0	0	0	0	0	0	0	0	0	0	431
	0	0	0	0	0							
13	0	0	0	0	0	0	0	0	0	0	0	148
	0	0	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0	891
	0	0	0	0	0							
15	0	0	0	0	0	0	0	0	0	0	0	264
	0	0	0	0	0							
16	0	0	0	0	0	0	0	0	0	0	0	72
	0	0	0	0	0							

=====

===== indian - None - None - svm\_poly =====

=====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	15	0	0	0	0	0	0	0	0	0	0	
	0	0	0	0	0							
2	0	435	0	0	0	0	0	0	0	0	0	
	0	0	0	0	0							
3	0	0	242	0	0	0	0	0	0	0	0	
	0	0	0	0	0							
4	0	0	0	59	0	0	0	0	0	0	0	
	0	0	0	0	0							
5	0	0	0	0	154	0	0	0	0	0	0	
	0	0	0	0	0							
6	0	0	0	0	0	218	0	0	0	0	0	
	0	0	0	0	0							
7	0	0	0	0	0	0	9	0	0	0	0	
	0	0	0	0	0							
8	0	0	0	0	0	0	0	154	0	0	0	
	0	0	0	0	0							
9	0	0	0	0	0	0	0	0	4	0	0	
	0	0	0	0	0							
10	0	0	0	0	0	0	0	0	0	305	0	
	0	0	0	0	0							
11	0	0	0	0	0	0	0	0	0	0	743	
	0	0	0	0	0							
12	0	0	0	0	0	0	0	0	0	0	0	
162	0	0	0	0	0							
13	0	0	0	0	0	0	0	0	0	0	0	
	0	57	0	0	0							

14	0	0	0	0	0	0	0	0	0	0	0	0
0	0	374	0	0								
15	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	122	0								
16	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	21								

----- Testing Confusion Matrix -----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	31	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0								
2	0	937	10	2	2	0	0	0	0	14	23	
4	0	0	1	0								
3	0	28	524	13	0	0	0	0	0	0	15	
8	0	0	0	0								
4	0	1	5	171	0	0	0	0	0	0	0	
1	0	0	0	0								
5	0	0	0	0	312	2	5	0	0	6	1	
3	0	0	0	0								
6	0	0	0	0	6	502	0	0	0	0	0	
0	0	0	4	0								
7	0	0	0	0	0	0	19	0	0	0	0	
0	0	0	0	0								
8	0	0	0	0	0	0	0	324	0	0	0	
0	0	0	0	0								
9	0	0	0	0	0	0	0	0	16	0	0	
0	0	0	0	0								
10	0	19	1	0	0	1	0	0	0	600	44	
2	0	0	0	0								
11	0	58	19	0	3	0	0	0	0	56		
1570	2	0	0	4	0							
12	0	4	21	0	0	0	0	0	0	2	2	
402	0	0	0	0								
13	0	0	0	0	0	0	0	0	0	1	0	
0	147	0	0	0								
14	0	0	0	0	0	1	0	0	0	0	0	
0	0	881	9	0								
15	0	0	0	0	0	8	0	0	2	3	0	
10	1	4	236	0								
16	0	0	0	0	0	0	0	0	0	1	0	
7	0	0	0	64								

=====

===== indian - None - None - svm\_linear =====

=====

===== Train Size: 30% =====

----- Training Confusion Matrix -----

Act /	Predictions											
-------	-------------	--	--	--	--	--	--	--	--	--	--	--

	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	15	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0							
2	0	417	0	0	0	0	0	0	0	0	18
0	0	0	0	0							
3	0	0	242	0	0	0	0	0	0	0	0
0	0	0	0	0							
4	0	0	0	59	0	0	0	0	0	0	0
0	0	0	0	0							
5	0	0	0	0	154	0	0	0	0	0	0
0	0	0	0	0							
6	0	0	0	0	0	218	0	0	0	0	0
0	0	0	0	0							
7	0	0	0	0	0	0	9	0	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	154	0	0	0
0	0	0	0	0							
9	0	0	0	0	0	0	0	0	4	0	0
0	0	0	0	0							
10	0	2	0	0	1	0	0	0	0	280	22
0	0	0	0	0							
11	0	37	2	0	2	0	0	0	0	32	670
0	0	0	0	0							
12	0	0	0	0	0	0	0	0	0	0	0
162	0	0	0	0							
13	0	0	0	0	0	0	0	0	0	0	0
0	57	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0
0	0	374	0	0							
15	0	0	0	0	0	0	0	0	0	0	0
0	0	0	122	0							
16	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	21							

Testing Confusion Matrix											
Act /	Predictions										
	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	31	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0							
2	0	848	22	2	3	0	0	0	0	25	82
11	0	0	0	0							
3	0	29	520	16	0	0	0	0	0	0	13
10	0	0	0	0							
4	0	1	6	169	0	0	0	0	0	0	0
2	0	0	0	0							
5	0	1	0	0	312	5	4	0	0	3	1
3	0	0	0	0							



6	0	0	0	0	4	499	0	0	0	4	0
0	0	0	5	0							
7	0	0	0	0	0	0	19	0	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	324	0	0	0
0	0	0	0	0							
9	0	0	0	0	0	0	0	0	16	0	0
0	0	0	0	0							
10	0	47	2	0	1	0	0	0	0	497	118
2	0	0	0	0							
11	0	179	29	0	13	0	0	1	0	132	
1347	8	0	0	3	0						
12	0	5	21	0	1	5	0	0	0	5	3
391	0	0	0	0							
13	0	0	0	0	0	0	0	0	0	1	0
0	147	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0
0	0	882	9	0							
15	0	2	0	0	4	12	0	0	1	4	0
6	0	6	229	0							
16	0	2	0	0	0	0	0	0	0	0	0
7	0	0	0	63							

=====

===== indian - None - None - knn =====

=====

===== Train Size: 30% =====

---- Training Confusion Matrix ----

Act /	Predictions											
	1	2	3	4	5	6	7	8	9	10	11	
12	13	14	15	16								
1	14	0	0	0	0	0	0	0	0	1	0	
0	0	0	0	0	0							
2	0	387	13	0	0	1	0	0	0	3	25	
6	0	0	0	0	0							
3	0	7	222	6	0	0	0	0	0	2	4	
1	0	0	0	0	0							
4	0	0	3	56	0	0	0	0	0	0	0	
0	0	0	0	0	0							
5	0	0	0	0	153	0	0	0	0	1	0	
0	0	0	0	0	0							
6	0	0	0	0	1	215	0	0	0	0	0	
0	0	0	2	0								
7	0	0	0	0	1	0	8	0	0	0	0	
0	0	0	0	0	0							
8	0	0	0	0	0	0	0	154	0	0	0	
0	0	0	0	0	0							
9	0	0	0	0	0	3	0	0	1	0	0	
0	0	0	0	0	0							

10	0	5	4	0	1	0	0	0	0	286	7
2	0	0	0	0							
11	0	17	8	0	1	3	0	0	0	8	706
0	0	0	0	0							
12	0	10	2	0	0	1	0	0	0	2	14
133	0	0	0	0							
13	0	0	0	0	0	1	0	0	0	0	0
0	56	0	0	0							
14	0	0	0	0	0	0	0	0	0	0	0
0	0	369	5	0							
15	0	0	0	0	0	20	0	0	0	0	2
0	5	4	91	0							
16	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	21							

----- Testing Confusion Matrix -----

Act /	Predictions										
	1	2	3	4	5	6	7	8	9	10	11
12	13	14	15	16							
1	31	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0							
2	0	822	55	0	3	0	0	0	0	1	81
31	0	0	0	0							
3	0	30	485	22	0	0	0	0	0	6	35
10	0	0	0	0							
4	0	0	16	162	0	0	0	0	0	0	0
0	0	0	0	0							
5	0	0	0	2	307	3	1	0	0	13	3
0	0	0	0	0							
6	0	0	0	0	5	495	0	0	0	0	0
0	0	0	12	0							
7	1	0	0	0	0	0	18	0	0	0	0
0	0	0	0	0							
8	0	0	0	0	0	0	0	324	0	0	0
0	0	0	0	0							
9	0	0	0	0	0	10	0	0	5	0	0
0	1	0	0	0							
10	0	7	8	0	0	3	5	0	0	618	23
3	0	0	0	0							
11	0	42	28	1	8	9	0	0	0	25	
1590	9	0	0	0	0						
12	0	58	12	0	0	1	0	0	0	2	50
308	0	0	0	0							
13	0	0	0	0	0	2	0	0	0	1	1
0	144	0	0	0							
14	0	0	0	0	0	1	0	0	0	0	0
0	0	873	17	0							
15	0	5	2	0	0	65	0	0	0	2	3
3	3	10	171	0							

```

16 | 0 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3
| 0 | 0 | 0 | 0 | 60
=====

```

```

==== indian - None - None - naive_bayes ====
=====

```

```

===== Train Size: 30% =====

```

```

----- Training Confusion Matrix -----

```

```

Act / Predictions
      | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11
| 12 | 13 | 14 | 15 | 16
1 | 13 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0
| 1 | 0 | 0 | 0 | 0
2 | 0 | 226 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | 107 | 75
| 24 | 0 | 0 | 0
3 | 0 | 46 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 104 | 58
| 31 | 0 | 0 | 0
4 | 0 | 20 | 6 | 12 | 0 | 3 | 0 | 0 | 0 | 5 | 3
| 10 | 0 | 0 | 0
5 | 0 | 0 | 0 | 6 | 4 | 33 | 0 | 3 | 0 | 0 | 0
| 1 | 0 | 106 | 1 | 0
6 | 0 | 0 | 0 | 1 | 9 | 176 | 0 | 0 | 3 | 0 | 0
| 6 | 1 | 0 | 22 | 0
7 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 1 | 0 | 0 | 0
| 0 | 0 | 0 | 0
8 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 152 | 0 | 0 | 0
| 0 | 0 | 0 | 0
9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0
| 0 | 0 | 0 | 0
10 | 0 | 27 | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 174 | 67
| 34 | 0 | 0 | 0
11 | 0 | 150 | 4 | 8 | 0 | 2 | 0 | 0 | 0 | 211 | 312
| 55 | 0 | 0 | 1 | 0
12 | 0 | 54 | 3 | 1 | 0 | 4 | 0 | 0 | 0 | 39 | 10
| 51 | 0 | 0 | 0
13 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0
| 0 | 53 | 0 | 1 | 0
14 | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0
| 0 | 0 | 362 | 6 | 0
15 | 0 | 0 | 0 | 0 | 11 | 32 | 0 | 0 | 0 | 0 | 0
| 0 | 9 | 37 | 33 | 0
16 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 19

```

```

----- Testing Confusion Matrix -----

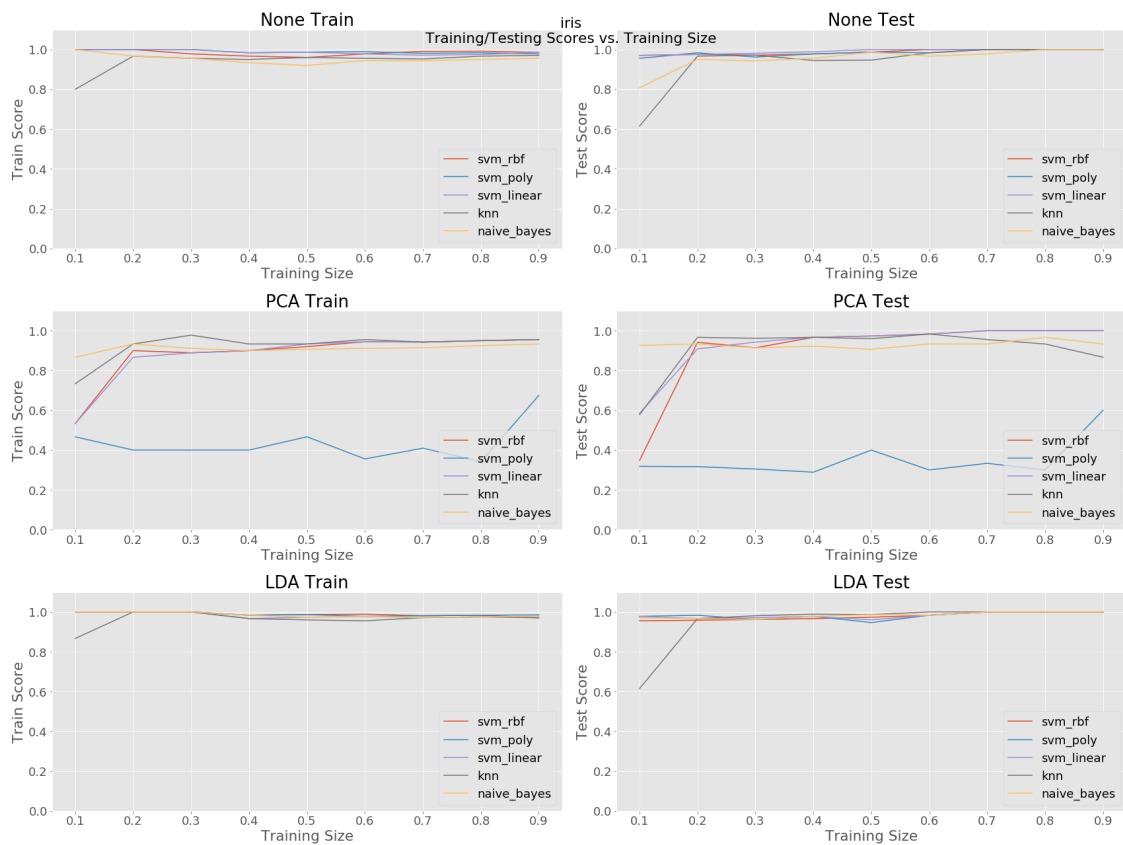
```

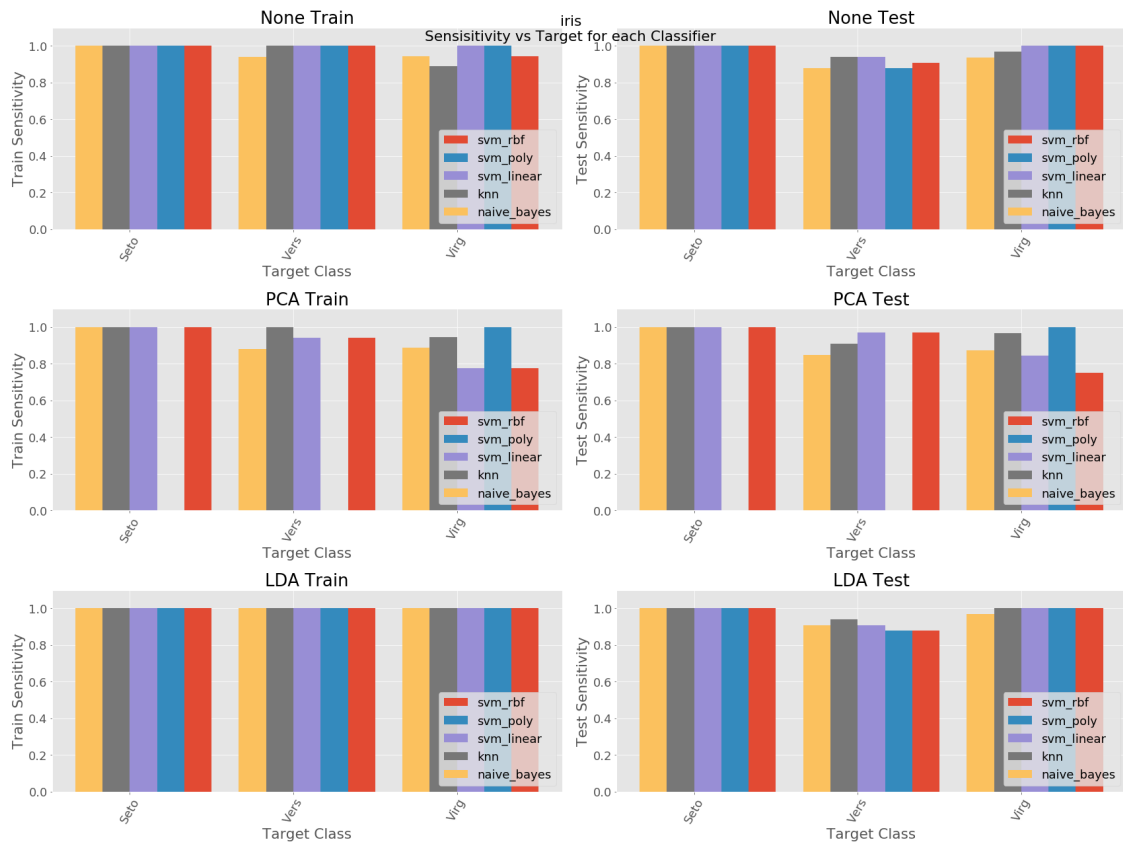
```

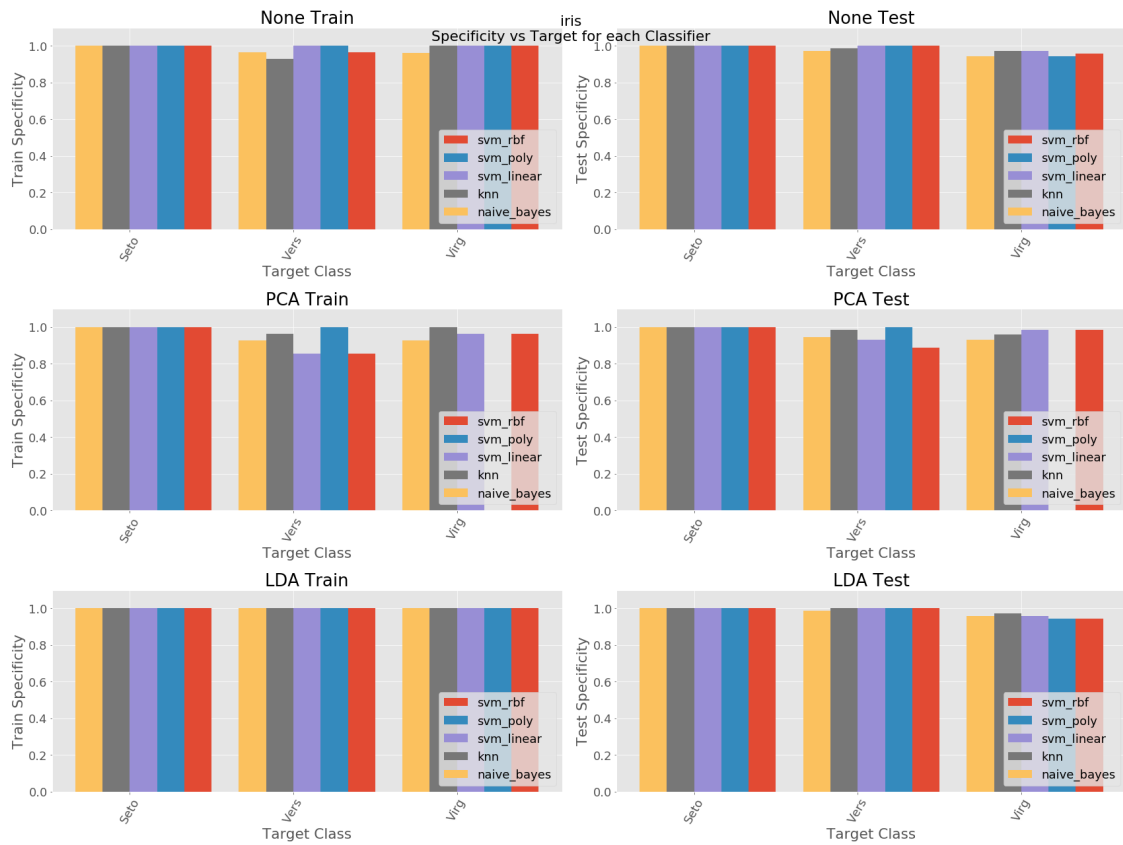
Act / Predictions
      | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11
| 12 | 13 | 14 | 15 | 16
1 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0
| 0 | 0 | 0 | 0 | 0

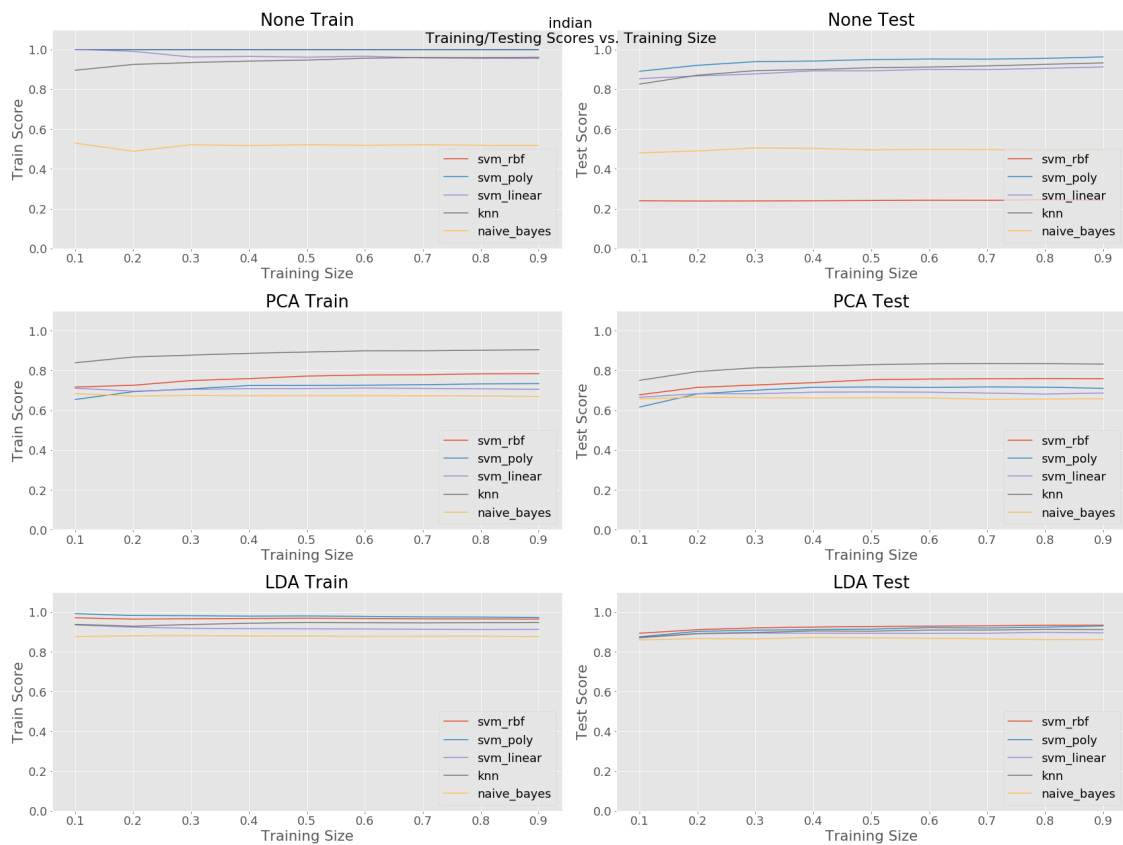
```

2	0	509	0	2	0	2	0	2	0	234	161
83	0	0	0	0							
3	0	131	4	5	0	1	0	0	0	269	126
52	0	0	0	0							
4	0	91	4	28	0	12	0	0	0	21	12
10	0	0	0	0							
5	1	1	0	24	14	62	1	10	0	1	0
4	0	210	1	0							
6	0	0	0	1	31	385	0	0	1	0	0
14	6	1	73	0							
7	1	0	0	0	0	0	18	0	0	0	0
0	0	0	0	0							
8	1	0	0	0	0	0	2	320	0	0	0
1	0	0	0	0							
9	0	0	0	0	0	0	0	0	16	0	0
0	0	0	0	0							
10	0	65	0	1	0	1	2	4	0	382	144
68	0	0	0	0							
11	0	390	8	17	0	10	0	2	0	466	694
123	0	0	2	0							
12	0	168	1	0	0	5	0	0	0	121	29
106	0	0	1	0							
13	0	0	0	1	0	10	0	0	1	0	0
0	134	0	2	0							
14	0	0	0	0	11	2	0	0	0	0	0
0	0	864	14	0							
15	0	0	0	3	20	82	0	0	3	0	0
8	11	66	71	0							
16	0	12	0	4	0	0	0	0	0	0	0
5	0	0	0	51							

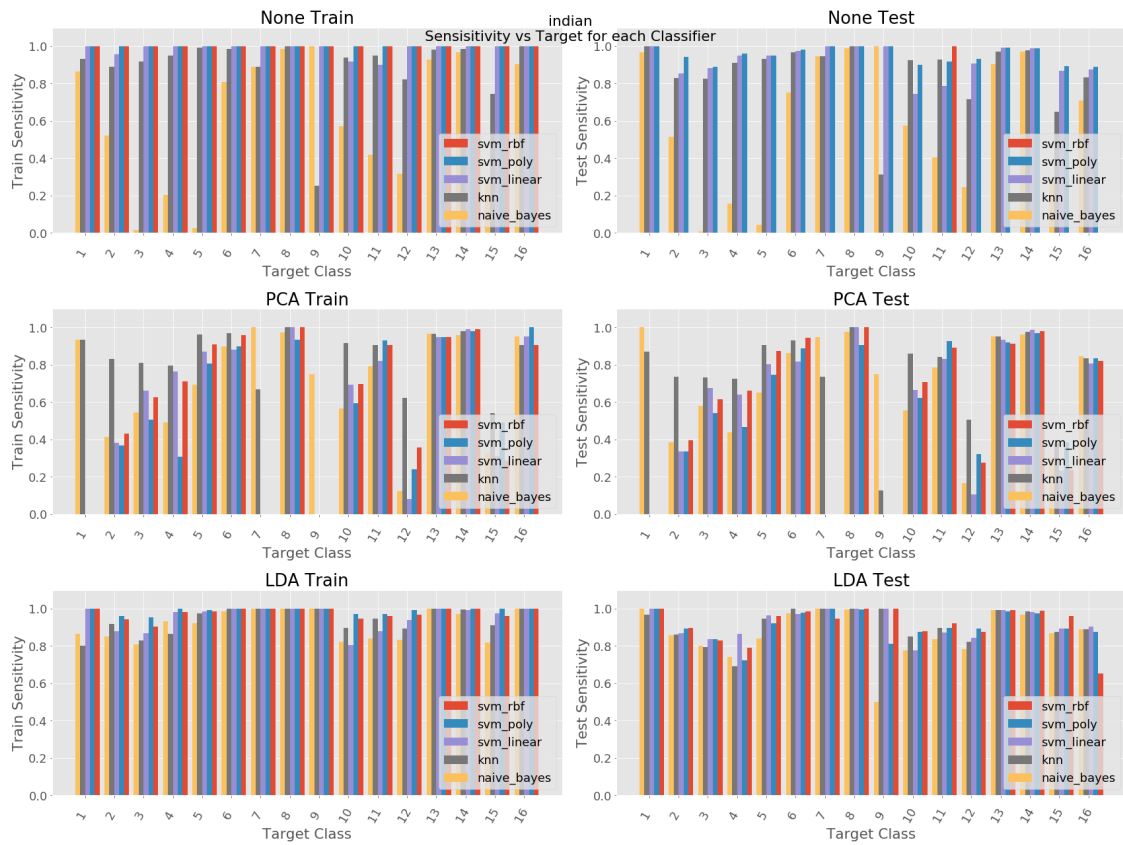


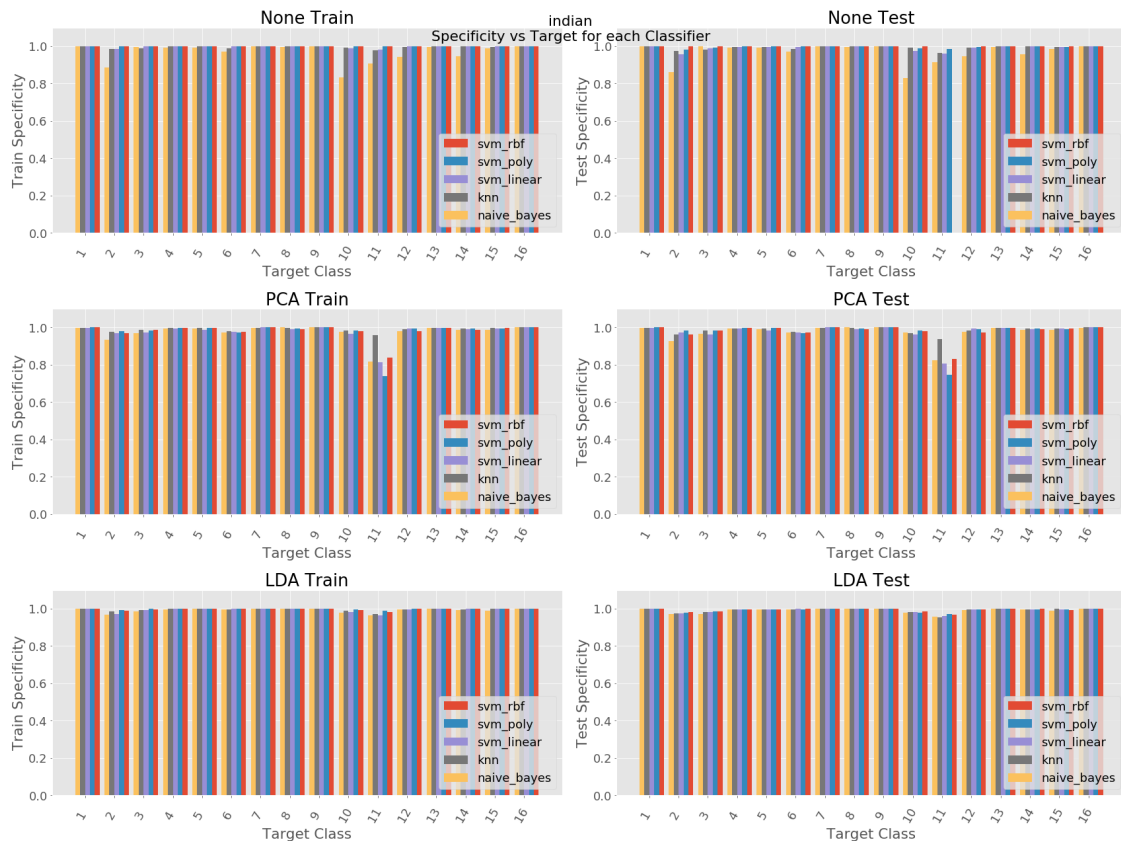












b) iris) A PCA of 2 components and LDA of 2 components were chosen based on the information from question 1.

With the iris dataset, there is not a huge difference in performances and runtimes with and without data reduction (apart from the svm-poly on pca data). As long as the train size is over 20%, the performance reaches above 95%. In the end, it is up to personal preference on which learning method to use. Personally, I would choose LDA with 2 dimensions and use a simple knn model to predict. It is simple, easy to understand, fast and highly accurate for the iris dataset. The svm-poly dataset is completely failing with pca and I cannot determine quite determine why. It appears to select everything as Virginica (based on the confusion matrix). All the others perform adequately enough that I do not feel that it is necessary to alter the methods much to improve performance.

indian) Initially I used a PCA and LDA of only 4 components, but the results were not impressive so I upped the number of components to 10, then 15. The PCA has minimal improvement with increased components, so I stuck with 4 (which is what would be expected based on the results from question 1). The LDA saw about 5-10% improvement with increased components from 4 to 15. I ended up choosing 15 components as that uses all of the classes for LDA, and its runtime is still quite fast.

With the indian dataset, we see a much more noticable difference in performance and runtime based on dimensionality reduction. Without dimensionality reduction, the runtimes for the svm learners on the dataset are quite intensive. I would not use any of the svms on the unreduced data. The learners sensitivity versus target appear much improved with LDA vs PCA or no dimensionality

reduction. The specificity seems to excel in most cases, except for the svm rbf and naive bayes with no dimensionality reduction in certain classes (class 11 being a bad instance) and svm poly appears to struggle in specificity with the PCA data. Based on the plots, PCA is not a good approach for the indian dataset for most learners (though it does seem to do quite well with knn). Most likely, there is significant overlap in the data (which is shown in the first question), and merely using variances to determine principal components is not enough. LDA is able to perform better because it takes into account target classes to try and maximize the inter- and intra- class means. LDA appears to be the right approach as it has drastically faster runtimes and comparable performance with using the whole dataset. The best classifier in terms of classification accuracy is svm\_rbf, but they all perform about the same. Looking at specificity and sensitivity, they all seem to do similar as well. Each learner seems to have one or two classes it particularly struggles with (ie. naive bayes struggles with class 9). An ensemble majority vote learner using knn, naive bayes and svm\_rbf might be an interesting and more fruitful approach to combat this dilemma.