CSCI547 Machine Learning
Homework 2

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1 Support Vector Machine

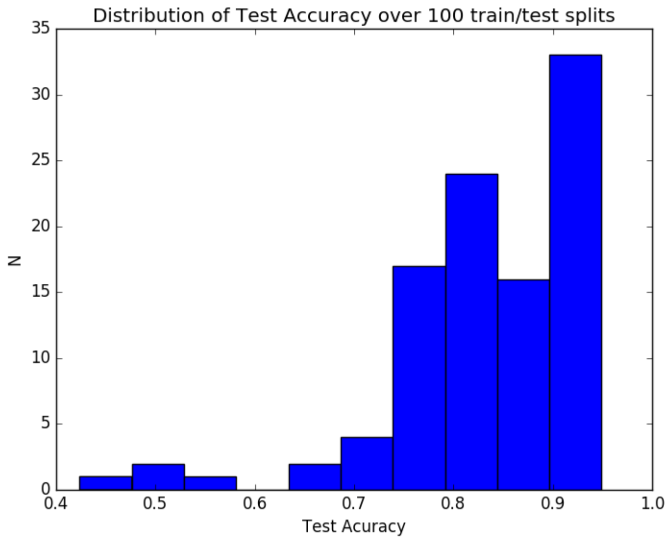
1A

```
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn import svm

if __name__ == '__main__':
        DATAFILE = 'wine.data'

        df = pd.read_csv(DATAFILE,header=None)
        X = df.iloc[:, 1:]
        y = df.iloc[:, 0]

        X,X_test,y,y_test = train_test_split(X,y,test_size=0.33)

        clf = svm.LinearSVC()

        clf.fit(X, y)

        train_accuracy = clf.score(X, y)
        test_accuracy = clf.score(X_test, y_test)

        print("training accuracy: {}".format(train_accuracy))
        print("test accuracy: {}".format(test_accuracy))
```

training accuracy: 0.8571428571428571
test accuracy: 0.847457627118644

1B

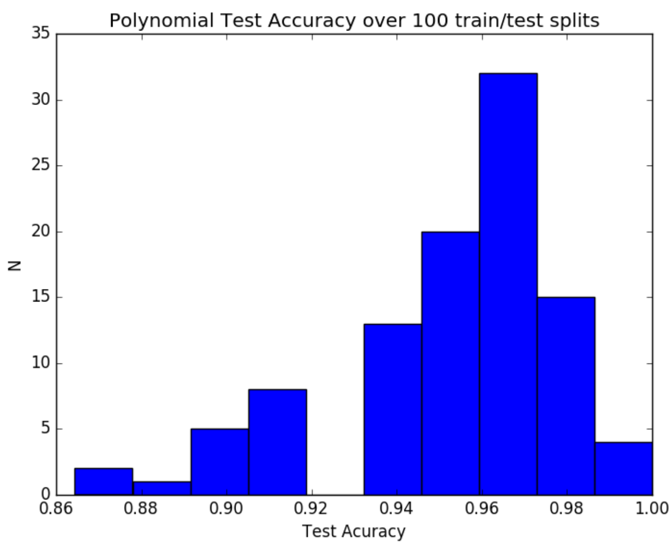
```
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn import svm

import matplotlib.pyplot as plt

if __name__ == '__main__':
        DATAFILE = 'wine.data'

        df = pd.read_csv(DATAFILE,header=None)
        X_df = df.iloc[:, 1:]
        y_df = df.iloc[:, 0]

        train_accuracies = []
        test_accuracies = []

        for i in range(100):
                X,X_test,y,y_test = train_test_split(X_df,y_df,test_size
                    =0.33)

                clf = svm.LinearSVC()

                clf.fit(X, y)

                train_accuracy = clf.score(X, y)
                test_accuracy = clf.score(X_test, y_test)

                train_accuracies.append(train_accuracy)
                test_accuracies.append(test_accuracy)

        plt.hist(test_accuracies)
        plt.xlabel('Test Acuracy')
        plt.ylabel('N')
        plt.title('Distribution of Test Accuracy over 100 train/test splits'
            )
        plt.show()
```

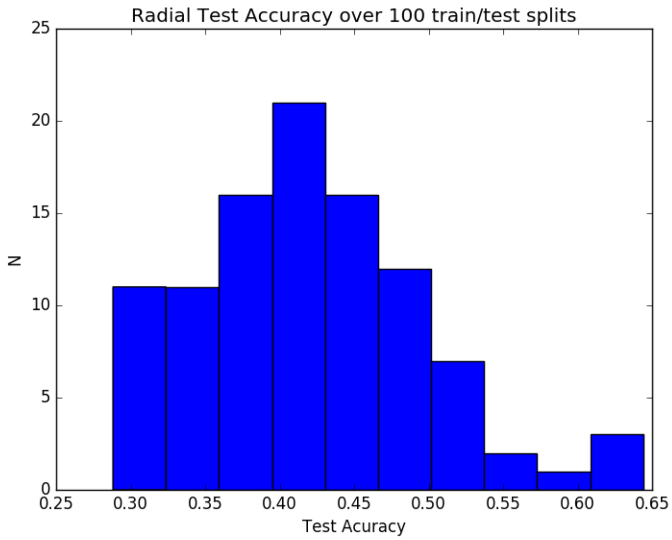


1C

```
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn import svm

import matplotlib.pyplot as plt

if __name__ == '__main__':
        DATAFILE = 'wine.data'

        df = pd.read_csv(DATAFILE,header=None)
        X_df = df.iloc[:, 1:]
        y_df = df.iloc[:, 0]

        poly_test_accuracies = []
        radial_test_accuracies = []

        for i in range(100):
                X,X_test,y,y_test = train_test_split(X_df,y_df,test_size
                    =0.33)

                clf_poly = svm.SVC(kernel='poly')
                clf_radial = svm.SVC(kernel='rbf')

                clf_poly.fit(X, y)
                clf_radial.fit(X, y)

                poly_test_accuracy = clf_poly.score(X_test, y_test)
```

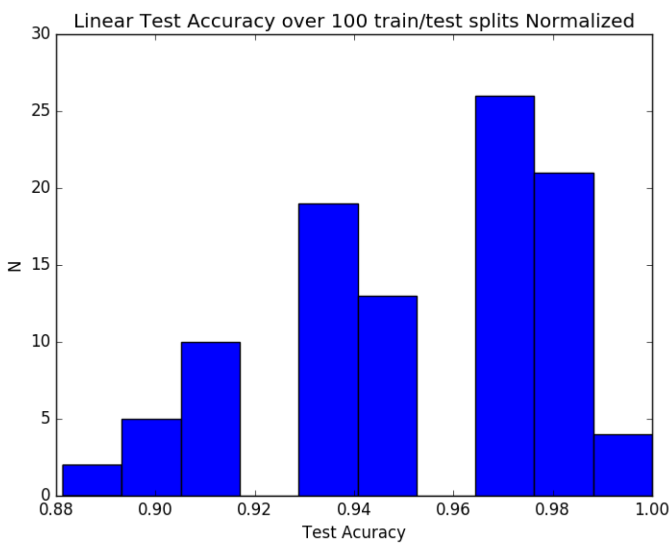
```
            radial_test_accuracy = clf_radial.score(X_test, y_test)

            poly_test_accuracies.append(poly_test_accuracy)
            radial_test_accuracies.append(radial_test_accuracy)

    plt.hist(poly_test_accuracies)
    plt.xlabel('Test Acuracy')
    plt.ylabel('N')
    plt.title('Polynomial Test Accuracy over 100 train/test splits')
    plt.show()

    plt.hist(radial_test_accuracies)
    plt.xlabel('Test Acuracy')
    plt.ylabel('N')
    plt.title('Radial Test Accuracy over 100 train/test splits')
    plt.show()
```

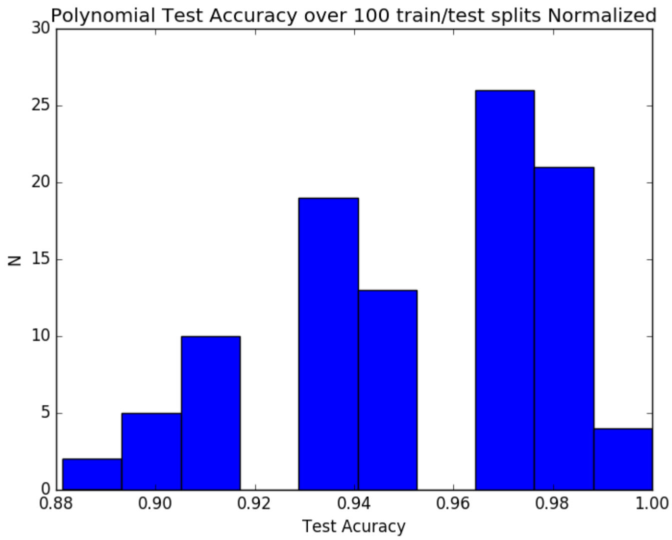


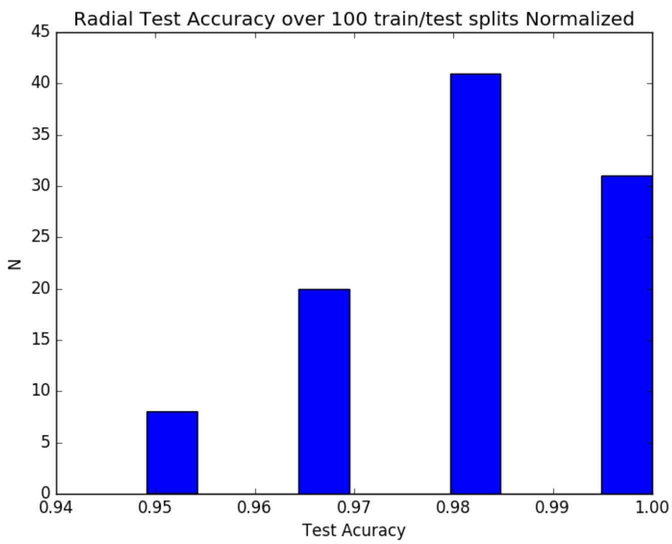


The polynomial kernel seems to clearly be the most robust for this dataset.

1D





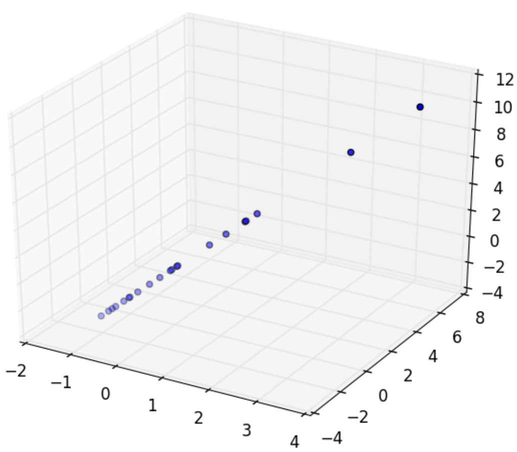


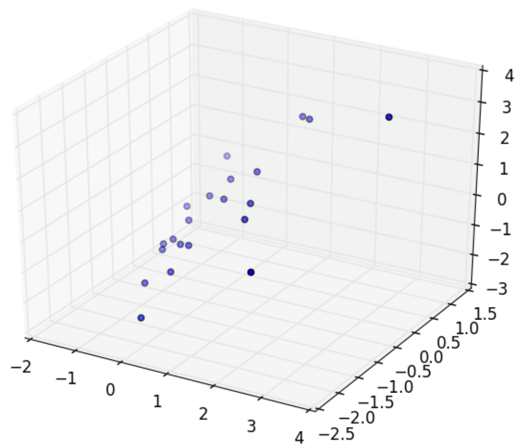
The normalization makes the performance of the radial basis go from poor to better than the polynomial or linear which had performed rather well without normalization.

2 Principal Component Analysis 1

2A

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

if __name__ == '__main__':
        DATAFILE1 = 'pca1.npy'
        DATAFILE2 = 'pca2.npy'

        data1 = np.load(DATAFILE1)
        data2 = np.load(DATAFILE2)

        fig = plt.figure()
        ax1 = fig.add_subplot(111, projection='3d')
        x,y,z = data1.T
        ax1.scatter(x,y,z)
        plt.show()

        fig = plt.figure()
        ax2 = fig.add_subplot(111, projection='3d')
        x,y,z = data2.T
        ax2.scatter(x,y,z)
        plt.show()
```





For the first dataset, it is pretty clear that all of the variance lies over a single axis. It is less clear with the second dataset but panning around, it appears that the variance can be explained with 2 of the 3 features.

2B

```
import numpy as np
import pandas as pd

from sklearn.decomposition import PCA

if __name__ == '__main__':
        DATAFILE1 = 'pca1.npy'
        DATAFILE2 = 'pca2.npy'

        data1 = np.load(DATAFILE1)
        data2 = np.load(DATAFILE2)

        pca1 = PCA()
        pca1.fit(data1)

        pca2 = PCA()
        pca2.fit(data2)

        print("for {}:".format(DATAFILE1))
        print (np.cumsum(pca1.explained_variance_ratio_))

        print("for {}:".format(DATAFILE2))
        print (np.cumsum(pca2.explained_variance_ratio_))
```

for pca1.npy:
[1. 1. 1.]
for pca2.npy:
[0.73936844 1. 1.]
For the first dataset, all of the variance is explained by the first feature. For the second dataset, all of the variance is explained by the first 2 features.

3 Principal Component Analysis 2

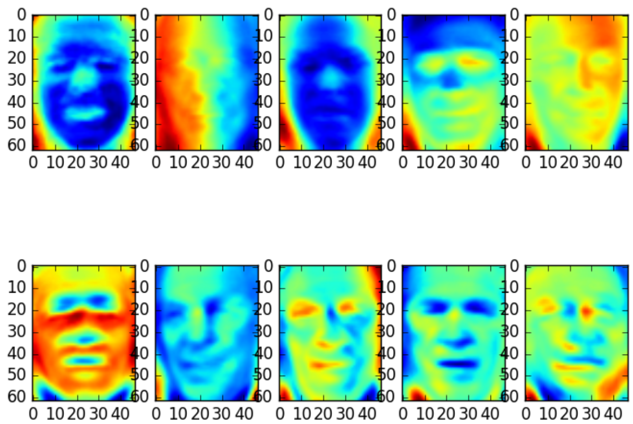
3A

```
from sklearn import datasets

if __name__ == "__main__":
        datasets.fetch_lfw_people(min_faces_per_person=50,resize=0.5)

        print("Done!")
```

3B

```
import numpy as np
import pandas as pd

from sklearn.decomposition import PCA
from sklearn import datasets
import matplotlib.pyplot as plt

if __name__ == '__main__':
        lfw_people = datasets.fetch_lfw_people(min_faces_per_person=50,
            resize=0.5)

        X = lfw_people.data
        y = lfw_people.target

        pca = PCA(n_components=100,copy=True,whiten=False)
        pca.fit(X)
        X = pca.transform(X)

        print (np.cumsum(pca.explained_variance_ratio_))

        fig,axs = plt.subplots(nrows=2,ncols=5)
        counter = 0
        for r in axs:
                for ax in r:
                        ax.imshow(pca.components_[counter,:].reshape((62,47)
                            ))
```

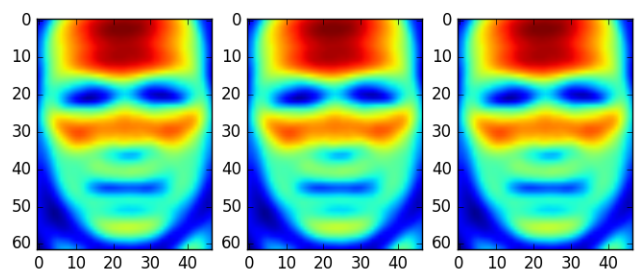
```
                        counter+=1
        plt.show()
```



3C

```
import numpy as np
import pandas as pd

from sklearn.decomposition import PCA
from sklearn import datasets
import matplotlib.pyplot as plt

if __name__ == '__main__':
        lfw_people = datasets.fetch_lfw_people(min_faces_per_person=50,
            resize=0.5)

        X = lfw_people.data
        y = lfw_people.target

        pca1 = PCA(n_components=1,copy=True,whiten=False)
        X1 = pca1.fit_transform(X)

        pca10 = PCA(n_components=10,copy=True,whiten=False)
        X10 = pca10.fit_transform(X)

        pca100 = PCA(n_components=100,copy=True,whiten=False)
        X100 = pca100.fit_transform(X)

        X1_reconstructed = 0
        for c,l in zip(pca1.components_,X1[42]):
        X1_reconstructed += c*l
```

```
        X1_reconstructed += pca1.mean_
        X1_reconstructed = X1_reconstructed.reshape((62,47))

        X10_reconstructed = 0
        for c,l in zip(pca1.components_,X10[42]):
        X10_reconstructed += c*l
        X10_reconstructed += pca10.mean_
        X10_reconstructed = X10_reconstructed.reshape((62,47))

        X100_reconstructed = 0
        for c,l in zip(pca1.components_,X100[42]):
        X100_reconstructed += c*l
        X100_reconstructed += pca100.mean_
        X100_reconstructed = X100_reconstructed.reshape((62,47))

        fig,axs = plt.subplots(nrows=1,ncols=3)
        axs[0].imshow(X1_reconstructed)
        axs[1].imshow(X10_reconstructed)
        axs[2].imshow(X100_reconstructed)
        plt.show()
```



I feel like I should be seeing some convergence here but am not and am not sure why.

3D*

```
import numpy as np
import pandas as pd

from sklearn.decomposition import PCA
from sklearn import datasets
```

```python
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.metrics import confusion_matrix

if __name__ == '__main__':
        lfw_people = datasets.fetch_lfw_people(min_faces_per_person=50,
            resize=0.5)

        X = lfw_people.data
        y = lfw_people.target

        pca = PCA(n_components=100,copy=True,whiten=True)
        X = pca.fit_transform(X)

        print (np.cumsum(pca.explained_variance_ratio_))

        X,X_test,y,y_test = train_test_split(X,y,test_size=0.33)

        clf = svm.LinearSVC()

        y_pred = clf.fit(X, y).predict(X_test)

        train_accuracy = clf.score(X, y)
        test_accuracy = clf.score(X_test, y_test)

        print("training accuracy: {}".format(train_accuracy))
        print("test accuracy: {}".format(test_accuracy))

        cnf_matrix = confusion_matrix(y_test, y_pred)
        print(cnf_matrix)
```

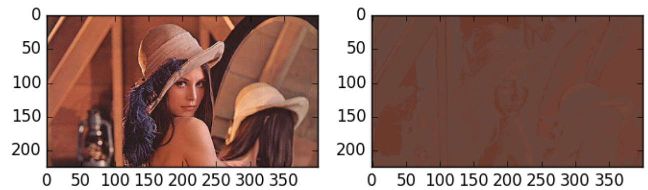
training accuracy: 0.9559808612440192
test accuracy: 0.7339805825242719

$$\begin{bmatrix}
14 & 2 & 1 & 4 & 1 & 0 & 2 & 1 & 2 & 0 & 0 & 0 \\
1 & 59 & 0 & 3 & 1 & 2 & 1 & 1 & 2 & 0 & 0 & 0 \\
2 & 2 & 23 & 7 & 4 & 0 & 0 & 0 & 2 & 0 & 1 & 0 \\
4 & 5 & 5 & 146 & 4 & 2 & 1 & 0 & 2 & 0 & 3 & 4 \\
0 & 3 & 1 & 2 & 22 & 1 & 0 & 1 & 2 & 0 & 0 & 1 \\
0 & 1 & 0 & 1 & 2 & 18 & 0 & 0 & 0 & 1 & 2 & 1 \\
1 & 1 & 0 & 3 & 2 & 0 & 2 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 2 & 1 & 0 & 0 & 1 & 9 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 2 & 2 & 0 & 0 & 1 & 12 & 1 & 0 & 4 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 22 & 0 & 0 \\
1 & 2 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 11 & 0 \\
0 & 2 & 2 & 3 & 6 & 0 & 1 & 1 & 0 & 1 & 0 & 40
\end{bmatrix}$$

4 K-mean/Gaussian Mixture Models/Expectation Maximization

4A

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from sklearn.cluster import KMeans

if __name__ == '__main__':
        IMAGEFILE = 'lenna.jpg'
        img=mpimg.imread(IMAGEFILE)
        lenna = np.array(img, dtype=np.float64) / 255

        w, h, d = original_shape = tuple(lenna.shape)
        assert d == 3
        image_array = np.reshape(lenna, (w * h, d))

        kmeans = KMeans(n_clusters=8).fit(image_array)
        labels = kmeans.predict(image_array)

        image = np.zeros((w, h, d))
        label_idx = 0
        for i in range(w):
        for j in range(h):
        image[i][j] = image_array[labels[label_idx]]
        label_idx += 1

        fig,axs = plt.subplots(nrows=1,ncols=2)
        axs[0].imshow(lenna)
        axs[1].imshow(image)
        plt.show()
```



0
50
100
150
200
0 50 100 150 200 250 300 350
0
50
100
150
200
0 50 100 150 200 250 300 350

4B*

. . .