Importing the data and necessary libraries

In [10]:
```python
from sklearn.datasets import load_digits
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:
```python
digit_data = load_digits()
```

In [4]:
```python
digit_data.keys()
```

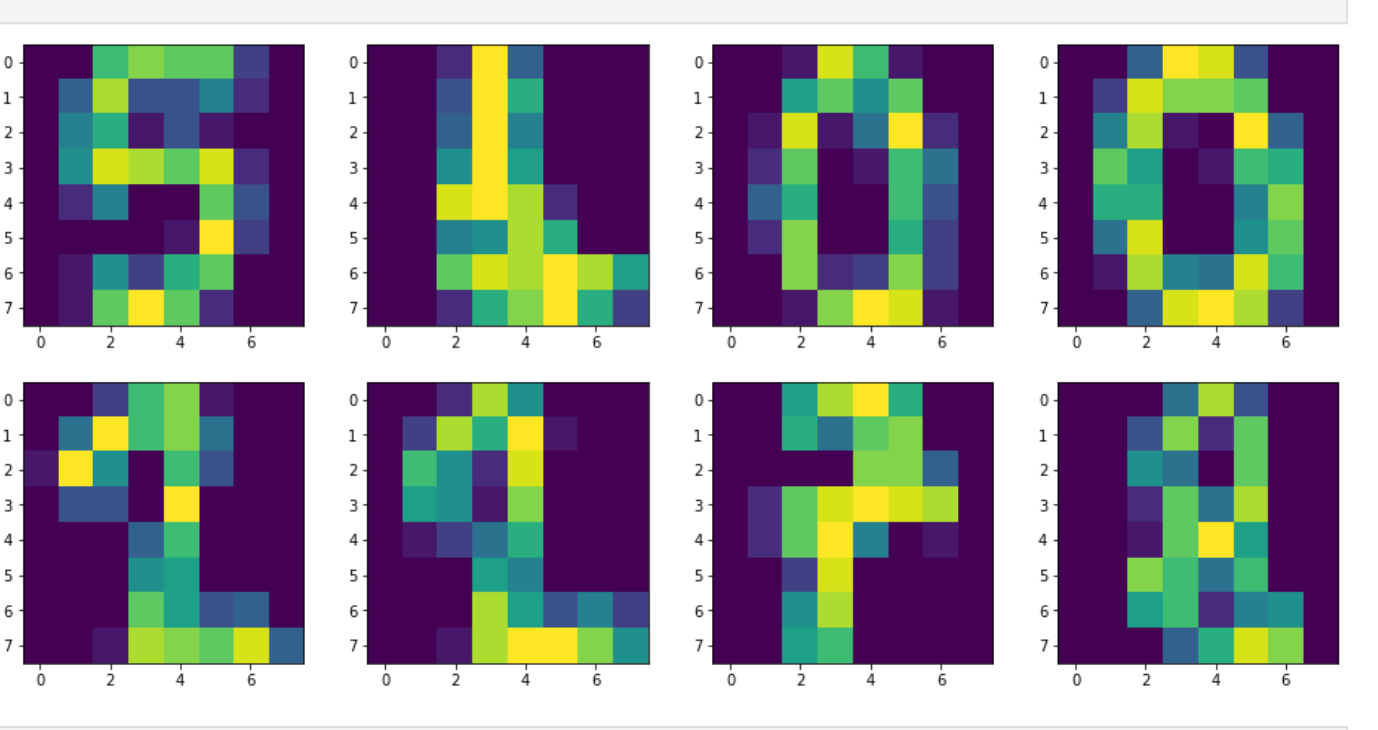
Out[4]:
```
dict_keys(['data', 'target', 'frame', 'feature_names', 'target_names', 'images', 'DESCR'])
```

In [5]:
```python
for i in digit_data.keys():
    try:
        print("Shape of", i, ":", digit_data[i].shape)
    except:
        try:
            print("Length of", i, ":", len(digit_data[i]))
        except:
            print("Data of", i, ":", digit_data[i])
```

```
Shape of data : (1797, 64)
Shape of target : (1797,)
Data of frame : None
Length of feature_names : 64
Shape of target_names : (10,)
Shape of images : (1797, 8, 8)
Length of DESCR : 2027
```

Displaying 8 random images in order

In [8]:
```python
import random
n = random.randint(0, 1796)

nrows = 4
ncols = 4
fig = plt.gcf()
fig.set_size_inches(ncols * 4, nrows * 4)


for i, img in enumerate(digit_data.images[n:n+8]):
    sp = plt.subplot(nrows, ncols, i + 1)
#     sp.axis('Off')
    plt.imshow(img.reshape([8, 8]))

plt.show()
```



In [7]:
```python
X, y = digit_data.data, digit_data.target

X[0, :].reshape([8, 8])
```

Out[7]:
```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]])
```

Checking if the data is linearly separable

Principal Component Analysis (PCA) is applied on the data to reduce it to 2 and 3 dimensions.

In [19]:
```python
df = pd.DataFrame(digit_data.data, columns=digit_data.feature_names)
df['Target'] = pd.DataFrame(digit_data.target)
print("Shape of original Dataset: ", df.shape)
df.head()
```

```
Shape of original Dataset:  (1797, 65)
```

Out[19]:

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	pixel_0_6	pixel_0_7	pixel_1_0	pixel_1_1	...
0	0.0	0.0	5.0	13.0	9.0	1.0	0.0	0.0	0.0	0.0	...
1	0.0	0.0	0.0	12.0	13.0	5.0	0.0	0.0	0.0	0.0	...
2	0.0	0.0	0.0	4.0	15.0	12.0	0.0	0.0	0.0	0.0	...
3	0.0	0.0	7.0	15.0	13.0	1.0	0.0	0.0	0.0	8.0	...
4	0.0	0.0	0.0	1.0	11.0	0.0	0.0	0.0	0.0	0.0	...

5 rows × 65 columns

Applying PCA (2 components)

In [50]:
```python
labels = df['Target'].unique()
labels
```

Out[50]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [20]:
```python
from sklearn.decomposition import PCA
```

In [228...
```python
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(X)
pca1 = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
pcadf1 = pd.concat([pca1, df[['Target']]], axis = 1)
print("Shape of the dataset after being reduced to 2 features: ", pca1.shape)
pcadf1.head(10)
```

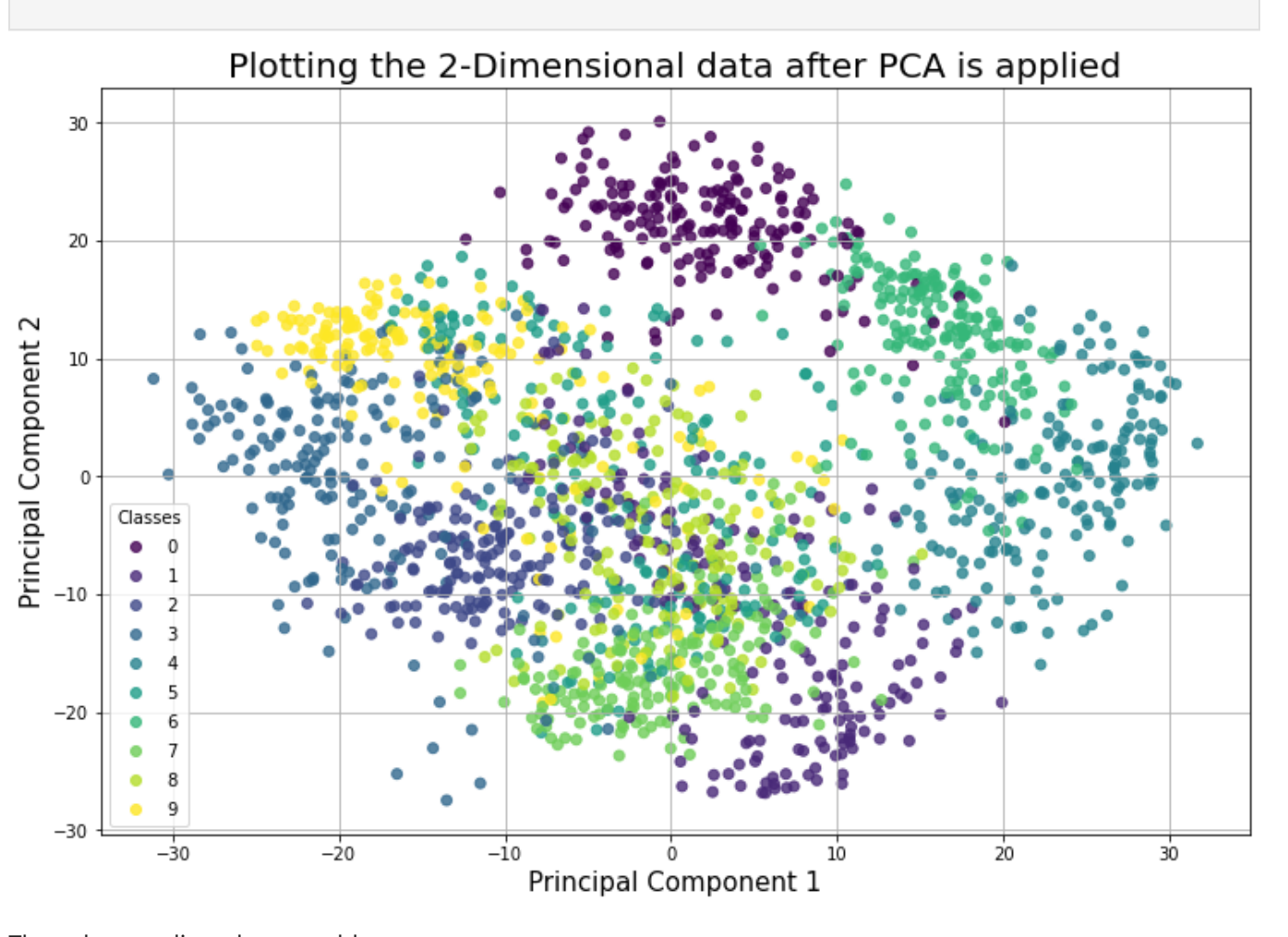
```
Shape of the dataset after being reduced to 2 features:  (1797, 2)
```

Out[228...

	principal component 1	principal component 2	Target
0	-1.259472	21.274894	0
1	7.957607	-20.768690	1
2	6.991929	-9.956001	2
3	-15.906106	3.332470	3
4	23.306865	4.269060	4
5	-14.087086	7.914449	5
6	21.363408	5.288340	6
7	-2.952599	-21.071685	7
8	-5.255142	1.183367	8
9	-5.480204	8.076329	9

Plotting the two dimensions

In [66]:
```python
fig, ax = plt.subplots(figsize=(12, 8))
scatter = ax.scatter(pca1['principal component 1'],
                     pca1['principal component 2'],
                     c = df['Target'], alpha=0.8)
plt.title('Plotting the 2-Dimensional data after PCA is applied', fontsize = 20)
plt.xlabel('Principal Component 1', fontsize = 15)
plt.ylabel('Principal Component 2', fontsize = 15)
plt.legend(*scatter.legend_elements(), loc="best", title="Classes")
ax.plot([])
ax.grid()
plt.show()
```



Thus, they are linearly separable to some extent

In [69]:
```python
pca.explained_variance_ratio_
```

Out[69]:
```
array([0.14890594, 0.13618771])
```

Applying PCA (3 components)

In [71]:
```python
pca = PCA(n_components=3)
principalComponents = pca.fit_transform(X)
pca2 = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2',
                          'principal component 3'])
print("Shape of the dataset after being reduced to 3 features: ", pca2.shape)
pca2.head(10)
```

```
Shape of the dataset after being reduced to 3 features:  (1797, 3)
```

Out[71]:

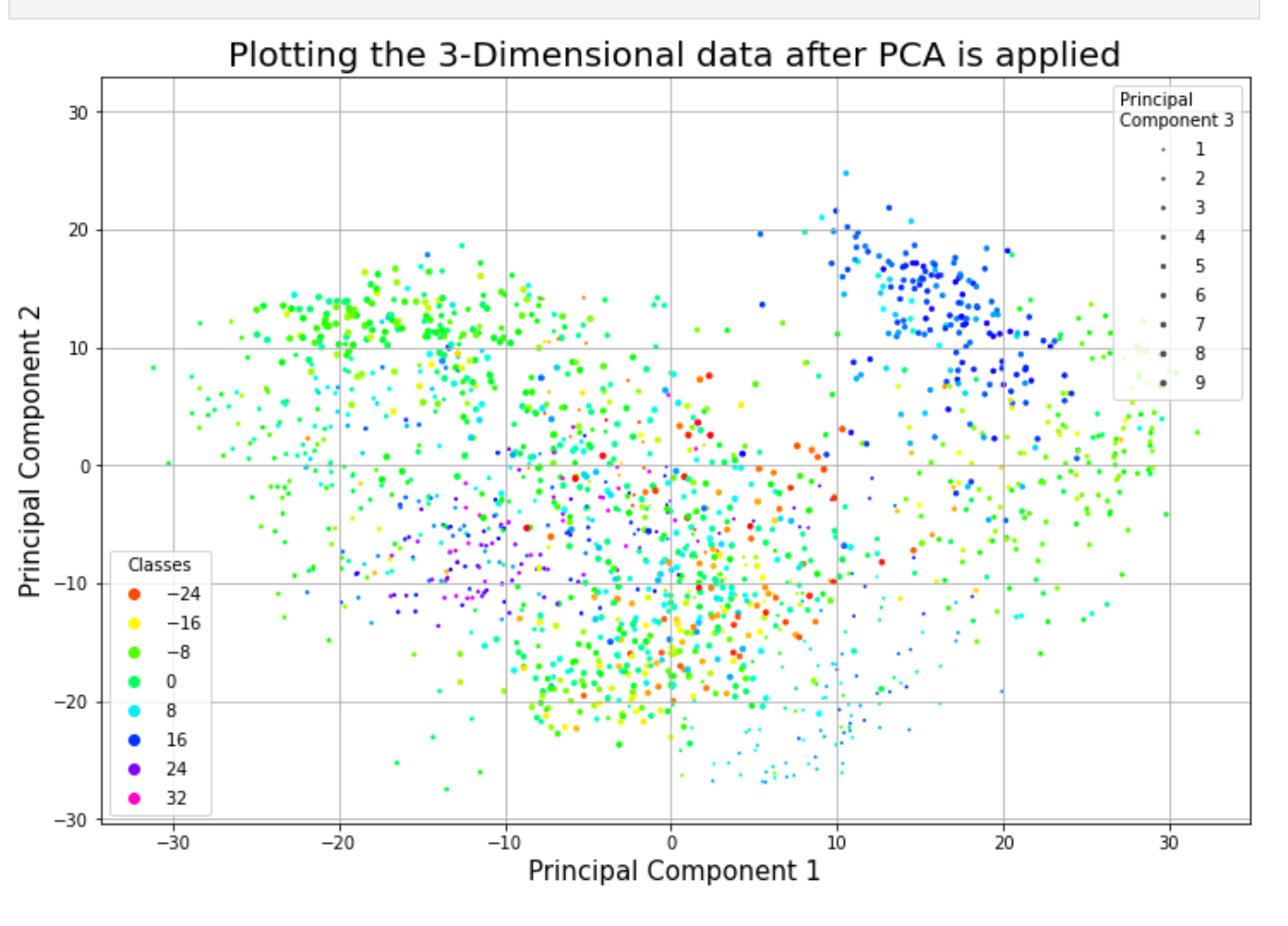
	principal component 1	principal component 2	principal component 3
0	-1.259467	21.274882	-9.463042
1	7.957611	-20.768699	4.439530
2	6.991923	-9.955985	2.958535
3	-15.906106	3.332464	9.824390
4	23.306868	4.269062	-5.675138
5	-14.087086	7.914447	0.392492
6	21.363410	5.288340	15.087400
7	-2.952606	-21.071663	-12.282940
8	-5.255134	1.183360	5.796237
9	-5.480199	8.076321	-5.028078

In [112...
```python
pca.explained_variance_ratio_
```

Out[112...
```
array([0.14890594, 0.13618771, 0.11794594])
```

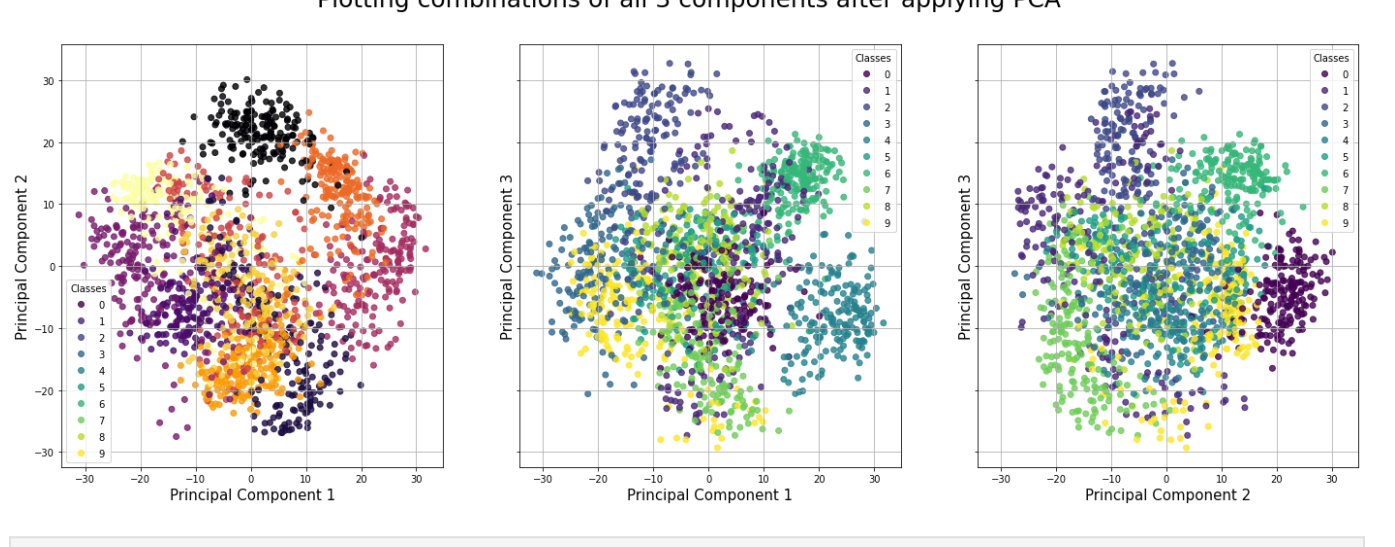
Plotting the 3 dimensions

In [105...
```python
fig, ax = plt.subplots(figsize=(12, 8))
scatter = ax.scatter(pca2['principal component 1'],
                     pca2['principal component 2'],
                     c = pca2['principal component 3'] ,
                     s = df['Target'],
                    cmap = 'gist_rainbow')
plt.title('Plotting the 3-Dimensional data after PCA is applied', fontsize = 20)
plt.xlabel('Principal Component 1', fontsize = 15)
plt.ylabel('Principal Component 2', fontsize = 15)
legend1 = ax.legend(*scatter.legend_elements(),
                    loc="lower left", title="Classes")
ax.add_artist(legend1)
handles, labels = scatter.legend_elements(prop="sizes", alpha=0.6)
legend2 = ax.legend(handles, labels, loc="upper right", title="Principal\nComponent 3")
ax.grid()
plt.show()
```



Plotting in groups of 2 components out of 3

In [141...
```python
fig, ax = plt.subplots(1, 3, sharex = True, sharey = True, figsize=(24, 8))
plt.suptitle("Plotting combinations of all 3 components after applying PCA", fontsize

ax[0].scatter(pca2['principal component 1'],
              pca2['principal component 2'],
              c = df['Target'], alpha=0.8,
              cmap = "inferno")
ax[0].set_xlabel('Principal Component 1', fontsize = 15)
ax[0].set_ylabel('Principal Component 2', fontsize = 15)
ax[0].legend(*scatter.legend_elements(), loc="best", title="Classes")
ax[0].grid()

scatter = ax[1].scatter(pca2['principal component 1'],
                        pca2['principal component 3'],
                        c = df['Target'], alpha=0.8,
                        cmap = "inferno")
ax[1].set_xlabel('Principal Component 1', fontsize = 15)
ax[1].set_ylabel('Principal Component 3', fontsize = 15)
ax[1].legend(*scatter.legend_elements(), loc="best", title="Classes")
ax[1].grid()

scatter = ax[2].scatter(pca2['principal component 2'],
                        pca2['principal component 3'],
                        c = df['Target'], alpha=0.8,
                        cmap = "inferno")
ax[2].set_xlabel('Principal Component 2', fontsize = 15)
ax[2].set_ylabel('Principal Component 3', fontsize = 15)
ax[2].legend(*scatter.legend_elements(), loc="best", title="Classes")
ax[2].grid()

plt.show()
```



In [140...
```python
pca.explained_variance_ratio_
```

Out[140...
```
array([0.14890594, 0.13618771, 0.11794594])
```

Building the model with different kernels

In [165...
```python
from sklearn import datasets, svm, metrics
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix, classificatio

# flatten the images
n_samples = len(digit_data.images)
data = digit_data.images.reshape((n_samples, -1))
```

In [166...
```python
# Use 80% of samples as training data size
X_train, X_test, y_train, y_test = train_test_split(data, digit_data.target, test_size
```

Making models with different kernels (without applying PCA)

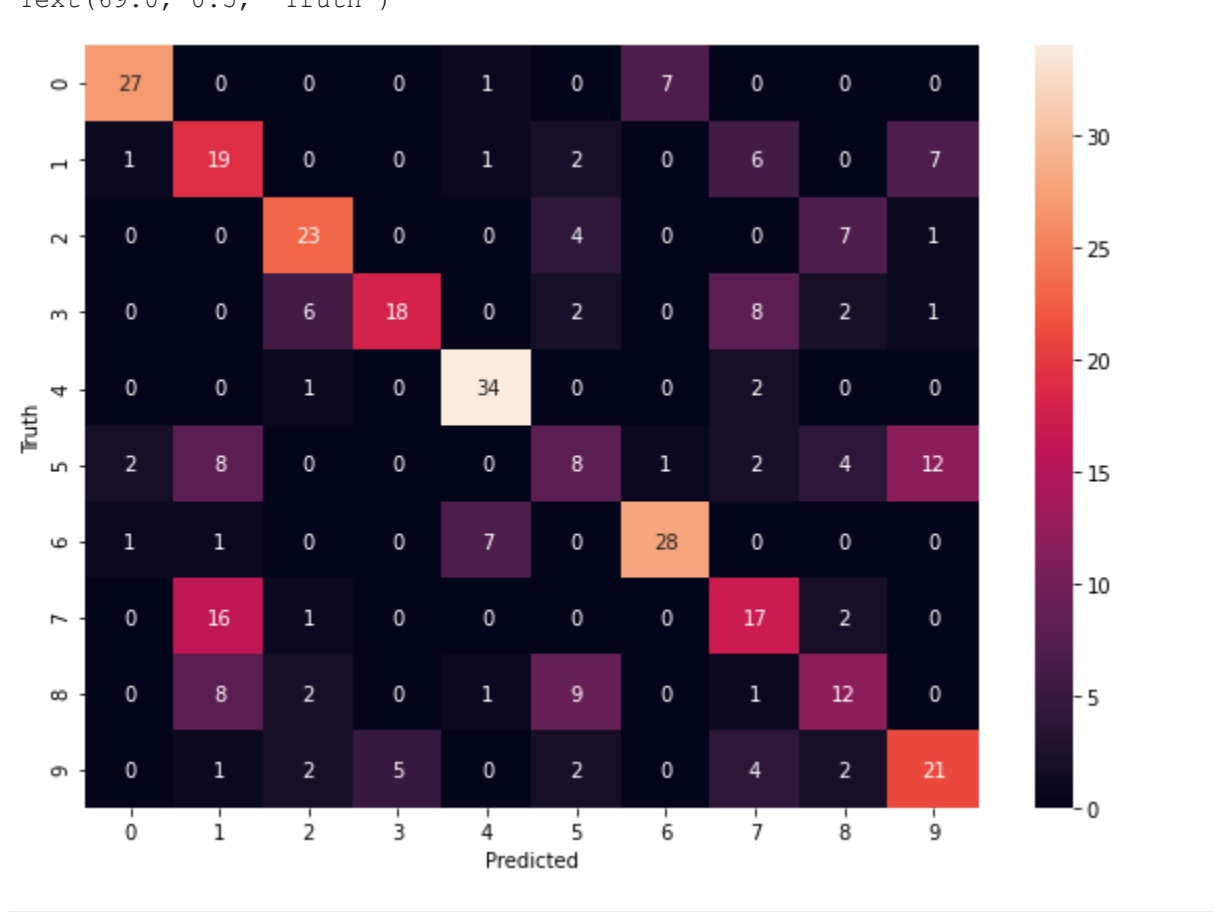
1. linear kernel

In [237...
```python
# linear kernel classifier
linear = svm.SVC(kernel = "linear")
linear.fit(X_train, y_train)
predicted = linear.predict(X_test)

print(" accuracy = ", accuracy_score(y_test, predicted), "\n")
print(" f1_score = ", f1_score(y_test, predicted, average='micro'), "\n")
print("Confusion Matrix: \n\n", confusion_matrix(y_test, predicted), "\n")
print("Classification Report: \n\n", classification_report(y_test, predicted))
```

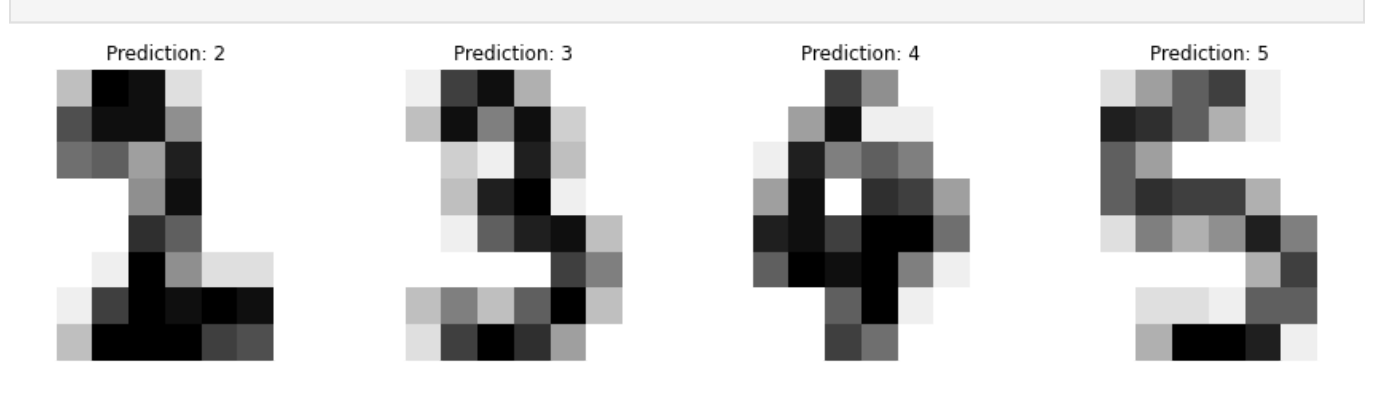
```
 accuracy =  0.575

 f1_score =  0.575

Confusion Matrix:

 [[27  0  0  0  1  0  7  0  0  0]
 [ 1 19  0  0  1  2  0  6  0  7]
 [ 0  0 23  0  0  4  0  0  7  1]
 [ 0  0  6 18  0  2  0  8  2  1]
 [ 0  0  1  0 34  0  0  2  0  0]
 [ 2  8  0  0  0  8  1  2  4 12]
 [ 1  1  0  0  7  0 28  0  0  0]
 [ 0 16  1  0  0  0  0 17  2  0]
 [ 0  8  2  0  1  9  0  1 12  0]
 [ 0  1  2  5  0  2  0  4  2 21]]

Classification Report:

              precision    recall  f1-score   support

           0       0.87      0.77      0.82        35
           1       0.36      0.53      0.43        36
           2       0.66      0.66      0.66        35
           3       0.78      0.49      0.60        37
           4       0.77      0.92      0.84        37
           5       0.30      0.22      0.25        37
           6       0.78      0.76      0.77        37
           7       0.42      0.47      0.45        36
           8       0.41      0.36      0.39        33
           9       0.50      0.57      0.53        37

    accuracy                           0.57       360
   macro avg       0.59      0.57      0.57       360
weighted avg       0.59      0.57      0.57       360
```

In [238...
```python
import seaborn as sns
plt.figure(figsize = (10,7))
sns.heatmap(confusion_matrix(y_test, predicted), annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[238...
```
Text(69.0, 0.5, 'Truth')
```



In [174...
```python
_, axes = plt.subplots(nrows=1, ncols=4, figsize=(15, 10))
for ax, image, prediction in zip(axes, X_test, predicted):
    ax.set_axis_off()
    image = image.reshape(8, 8)
    ax.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    ax.set_title(f'Prediction: {prediction}')
```



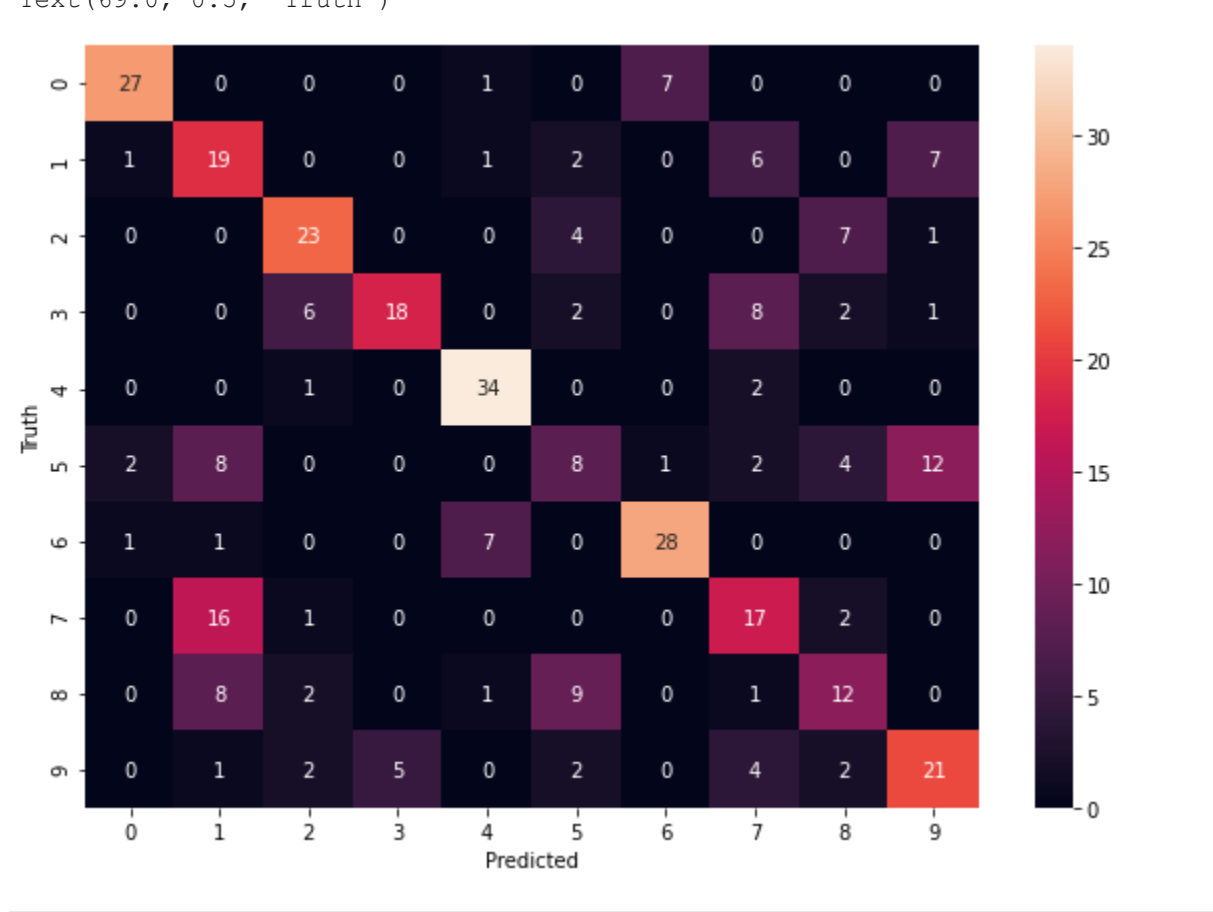
2. rbf kernel

In [209...
```python
# rbf kernel classifier
rbf = svm.SVC(gamma=0.001, C = 3, kernel = "rbf")
rbf.fit(X_train, y_train)
predicted = rbf.predict(X_test)

print(" accuracy = ", accuracy_score(y_test, predicted), "\n")
print(" f1_score = ", f1_score(y_test, predicted, average='micro'), "\n")
print("Confusion Matrix: \n\n", confusion_matrix(y_test, predicted), "\n")
print("Classification Report: \n\n", classification_report(y_test, predicted))
```

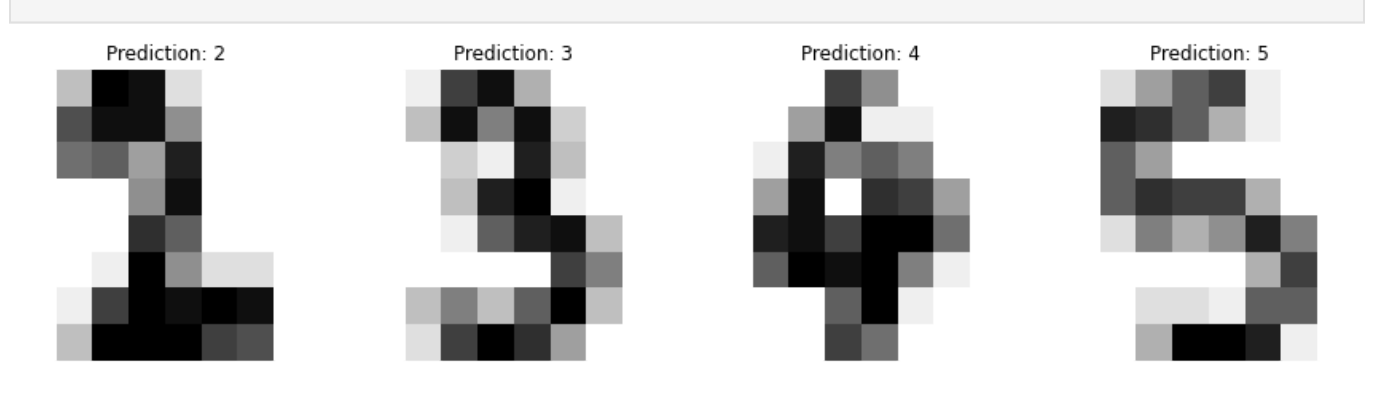
```
 accuracy =  0.9638888888888889

 f1_score =  0.9638888888888889

Confusion Matrix:

 [[34  0  0  0  1  0  0  0  0  0]
 [ 0 36  0  0  0  0  0  0  0  0]
 [ 0  0 35  0  0  0  0  0  0  0]
 [ 0  0  0 31  0  2  0  0  4  0]
 [ 0  0  0  0 34  0  0  0  0  3]
 [ 0  0  0  0  0 37  0  0  0  0]
 [ 0  0  0  0  0  0 37  0  0  0]
 [ 0  0  0  0  0  0  0 36  0  0]
 [ 0  1  0  0  0  0  0  0 32  0]
 [ 0  0  0  0  0  1  0  0  1 35]]

Classification Report:

              precision    recall  f1-score   support

           0       1.00      0.97      0.99        35
           1       0.97      1.00      0.99        36
           2       1.00      1.00      1.00        35
           3       1.00      0.84      0.91        37
           4       0.97      0.92      0.94        37
           5       0.93      1.00      0.96        37
           6       1.00      1.00      1.00        37
           7       1.00      1.00      1.00        36
           8       0.86      0.97      0.91        33
           9       0.92      0.95      0.93        37

    accuracy                           0.96       360
   macro avg       0.97      0.96      0.96       360
weighted avg       0.97      0.96      0.96       360
```

In [239...
```python
import seaborn as sns
plt.figure(figsize = (10,7))
sns.heatmap(confusion_matrix(y_test, predicted), annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[239...
```
Text(69.0, 0.5, 'Truth')
```



In [175...
```python
_, axes = plt.subplots(nrows=1, ncols=4, figsize=(15, 10))
for ax, image, prediction in zip(axes, X_test, predicted):
    ax.set_axis_off()
    image = image.reshape(8, 8)
    ax.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    ax.set_title(f'Prediction: {prediction}')
```



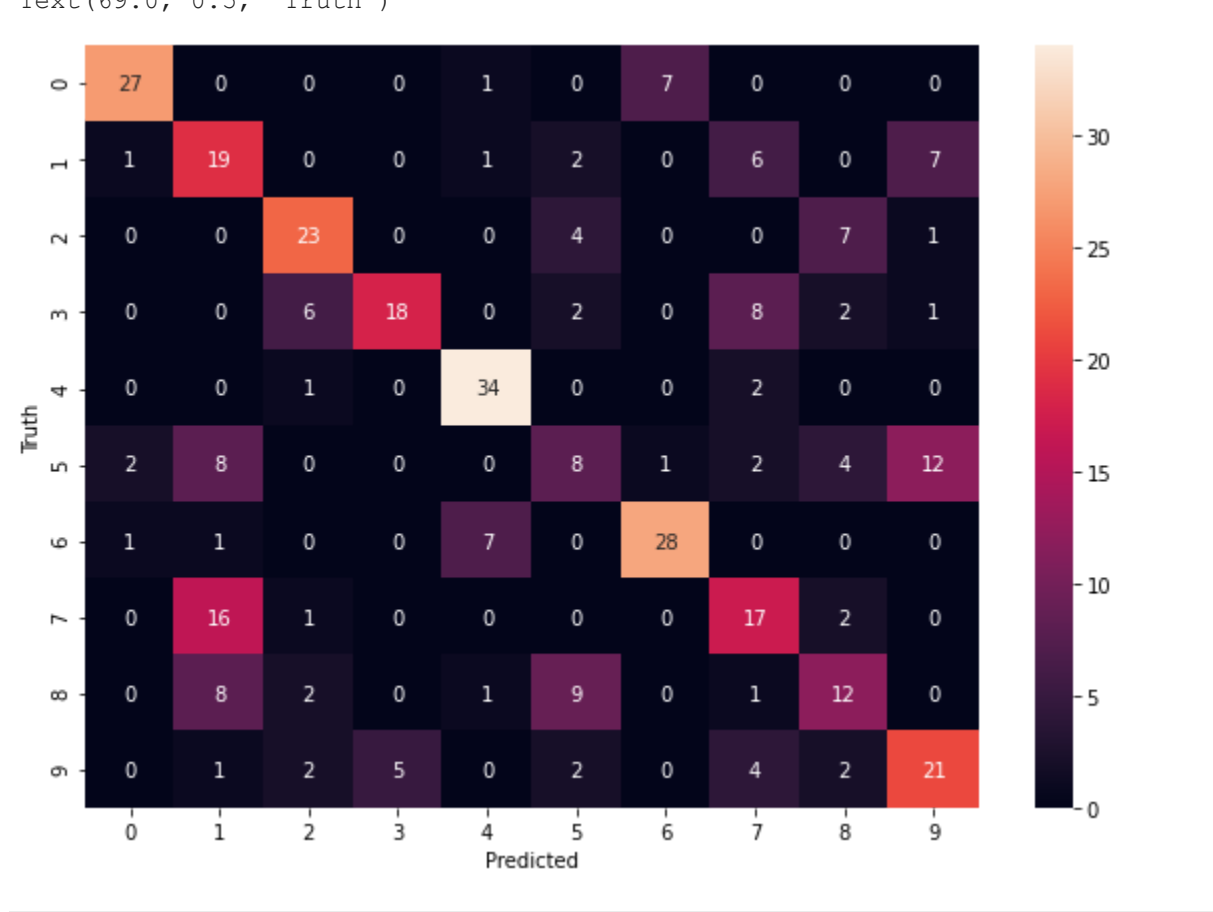
3. poly kernel

In [215...
```python
# poly kernel classifier
poly = svm.SVC(gamma=0.001, C = 10, kernel = "poly")
poly.fit(X_train, y_train)
predicted = poly.predict(X_test)

print(" accuracy = ", accuracy_score(y_test, predicted), "\n")
print(" f1_score = ", f1_score(y_test, predicted, average='micro'), "\n")
print("Confusion Matrix: \n\n", confusion_matrix(y_test, predicted), "\n")
print("Classification Report: \n\n", classification_report(y_test, predicted))
```

```
 accuracy =  0.9527777777777777

 f1_score =  0.9527777777777777

Confusion Matrix:

 [[33  0  0  0  1  0  1  0  0  0]
 [ 0 36  0  0  0  0  0  0  0  0]
 [ 0  0 35  0  0  0  0  0  0  0]
 [ 0  0  0 31  0  2  0  1  3  0]
 [ 0  0  0  0 34  0  0  0  0  3]
 [ 0  0  0  0  0 37  0  0  0  0]
 [ 0  1  0  0  0  0 36  0  0  0]
 [ 0  0  0  0  0  0  0 36  0  0]
 [ 0  1  0  0  0  0  0  1 31  0]
 [ 0  0  0  0  0  1  0  1  1 34]]

Classification Report:

              precision    recall  f1-score   support

           0       1.00      0.94      0.97        35
           1       0.95      1.00      0.97        36
           2       1.00      1.00      1.00        35
           3       1.00      0.84      0.91        37
           4       0.97      0.92      0.94        37
           5       0.93      1.00      0.96        37
           6       0.97      0.97      0.97        37
           7       0.92      1.00      0.96        36
           8       0.89      0.94      0.91        33
           9       0.92      0.92      0.92        37

    accuracy                           0.95       360
   macro avg       0.95      0.95      0.95       360
weighted avg       0.95      0.95      0.95       360
```

In [240...
```python
import seaborn as sns
plt.figure(figsize = (10,7))
sns.heatmap(confusion_matrix(y_test, predicted), annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[240...
```
Text(69.0, 0.5, 'Truth')
```



In [176...
```python
_, axes = plt.subplots(nrows=1, ncols=4, figsize=(15, 10))
for ax, image, prediction in zip(axes, X_test, predicted):
    ax.set_axis_off()
    image = image.reshape(8, 8)
    ax.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    ax.set_title(f'Prediction: {prediction}')
```