

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import linear_model
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
import gc
import cv2
```

```
digits= pd.read_csv('/content/drive/MyDrive/AI ML Bootcamp/Week 1/diabetes_dataset.csv')
digits.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
#   Column              Non-Null Count  Dtype
---  -
0   Pregnancies         768 non-null   int64
1   Glucose             768 non-null   int64
2   BloodPressure       768 non-null   int64
3   SkinThickness       768 non-null   int64
4   Insulin             768 non-null   int64
5   BMI                 768 non-null   float64
6   DiabetesPedigreeFunction 768 non-null   float64
7   Age                 768 non-null   int64
8   Outcome             768 non-null   int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

```
test = pd.read_csv('/content/drive/MyDrive/AI ML Bootcamp/Week 1/diabetes_dataset.csv')
test.head()
```

```
Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin  BMI  DiabetesPedigreeFunction  Age  Outcome
0            6      148             72           35      0  33.6                0.627  50      1
1            1       85             66           29      0  26.6                0.351  31      0
2            8      183             64            0      0  23.3                0.672  32      1
3            1       89             66           23     94  28.1                0.167  21      0
4            0      137             40           35    168  43.1                2.288  33      1
```

```
digits.head()
```

```
Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin  BMI  DiabetesPedigreeFunction  Age  Outcome
0            6      148             72           35      0  33.6                0.627  50      1
1            1       85             66           29      0  26.6                0.351  31      0
2            8      183             64            0      0  23.3                0.672  32      1
3            1       89             66           23     94  28.1                0.167  21      0
4            0      137             40           35    168  43.1                2.288  33      1
```

```
digits.shape
```

```
(768, 9)
```

```
test.shape
```

```
(768, 9)
```

```
digits.Pregnancies.unique()
```

```
array([ 6,  1,  8,  0,  5,  3, 10,  2,  4,  7,  9, 11, 13, 15, 17, 12, 14])
```

```
four = digits.iloc[3,1:]
four.shape
```

```
(8,)
```

```
import numpy as np
import matplotlib.pyplot as plt
```

```
four = four.to_numpy()
```

```
if four.size == 64:
    four = four.reshape(8, 8)
    print(four.shape)
    plt.imshow(four, cmap='gray')
    plt.colorbar()
    plt.show()
else:
    print("The array does not have 64 elements. Current size:", four.size)
```

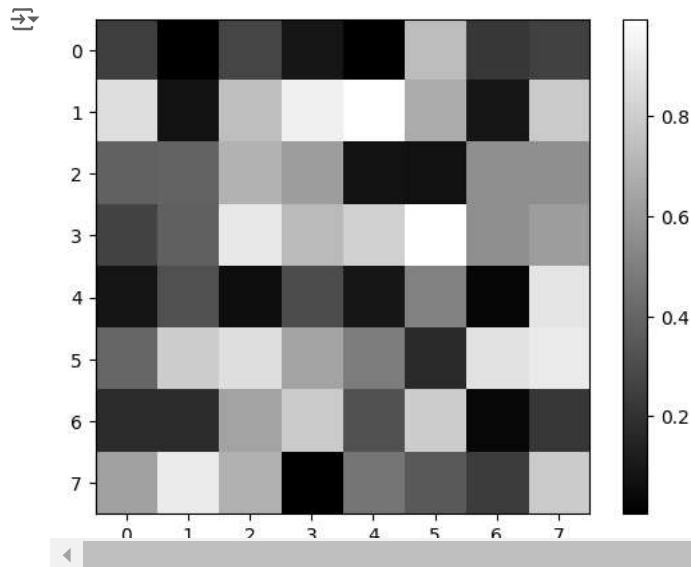
```
The array does not have 64 elements. Current size: 8
```

```
four = np.random.rand(64)
```

```
four = four.reshape(8, 8)
print(four.shape)
```

```
(8, 8)
```

```
plt.imshow(four, cmap='gray')
plt.colorbar()
plt.show()
```



```
X = digits.iloc[:, 1:].values
y = digits.iloc[:, 0].values
```

```
print(X[:5])
print(y[:5])
```

```
[[1.480e+02 7.200e+01 3.500e+01 0.000e+00 3.360e+01 6.270e-01 5.000e+01
 1.000e+00]
 [8.500e+01 6.600e+01 2.900e+01 0.000e+00 2.660e+01 3.510e-01 3.100e+01
 0.000e+00]
 [1.830e+02 6.400e+01 0.000e+00 0.000e+00 2.330e+01 6.720e-01 3.200e+01
 1.000e+00]
 [8.900e+01 6.600e+01 2.300e+01 9.400e+01 2.810e+01 1.670e-01 2.100e+01
 0.000e+00]]
```

```
0.000e+00]
[1.370e+02 4.000e+01 3.500e+01 1.680e+02 4.310e+01 2.288e+00 3.300e+01
 1.000e+00]]
[6 1 8 1 0]
```

```
X_train, X_test , y_train, y_test = train_test_split(X,y,test_size=0.2, random_state=42)
```

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(614, 8)
(154, 8)
(614,)
(154,)
```

Polynomial Kernel

```
poly_svm = SVC(kernel='poly',random_state=0)
```

```
poly_svm.fit(X_train, y_train)
```

```
SVC
SVC(kernel='polv'. random state=0)
```

```
poly_predictions = poly_svm.predict(X_test)
```

```
print(poly_predictions[:10], "...")
```

```
[1 1 1 1 0 1 1 1 1 6] ...
```

```
df = pd.DataFrame(y_test, poly_predictions)
df.head()
```

```
0
1 6
1 2
1 2
1 8
0 7
```

```
poly_accuracy = accuracy_score(y_test, poly_predictions)
print(f"Polynomial Kernel Accuracy: {poly_accuracy}")
```

```
Polynomial Kernel Accuracy: 0.1038961038961039
```

```
cm = confusion_matrix(y_test, poly_predictions)
print(cm)
# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix - Polynomial Kernel')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```

[[ 2 16  1  0  0  0  0  1  0  0  0  0  0  0]
 [ 4 14  1  0  0  0  0  0  0  0  0  0  0  0]
 [ 4 23  0  0  0  0  1  0  0  0  0  0  0  0]
 [ 1 10  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 3 12  0  0  0  1  0  0  0  0  0  0  0  0]
 [ 3  7  0  0  0  0  2  0  0  0  0  0  0  0]
 [ 0  5  0  0  0  0  0  1  0  0  0  0  0  0]
 [ 4  4  0  0  0  0  2  0  0  0  0  0  0  0]
 [ 3  7  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  5  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  5  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  2  0  0  0  0  0  1  0  0  0  0  0  0]
 [ 0  3  0  0  0  0  1  0  0  0  0  0  0  0]
 [ 2  2  0  0  0  0  0  0  0  0  0  0  0  0]]

```

Confusion Matrix - Polynomial Kernel

0	2	16	1	0	0	0	0	1	0	0	0	0	0	0
1	4	14	1	0	0	0	0	0	0	0	0	0	0	0
2	4	23	0	0	0	0	1	0	0	0	0	0	0	0
3	1	10	0	0	0	0	0	0	0	0	0	0	0	0
4	3	12	0	0	0	1	0	0	0	0	0	0	0	0
5	3	7	0	0	0	0	2	0	0	0	0	0	0	0
6	0	5	0	0	0	0	0	1	0	0	0	0	0	0
7	4	4	0	0	0	0	2	0	0	0	0	0	0	0
8	3	7	0	0	0	0	0	0	0	0	0	0	0	0
9	1	5	0	0	0	0	0	0	0	0	0	0	0	0
10	0	5	0	0	0	0	0	0	0	0	0	0	0	0
11	0	2	0	0	0	0	0	1	0	0	0	0	0	0
12	0	3	0	0	0	0	1	0	0	0	0	0	0	0

```
#total correct and incorrect predictions
```

```
correct_predictions = (y_test == poly_predictions).sum()
```

```
incorrect_predictions = (y_test != poly_predictions).sum()
```

```
#correct vs incorrect predictions
```

```
labels = ['Correct Predictions', 'Incorrect Predictions']
```

```
values = [correct_predictions, incorrect_predictions]
```

```
plt.figure(figsize=(6, 6))
```

```
bars = plt.bar(labels, values, color=['green', 'red'])
```

```
for bar in bars:
```

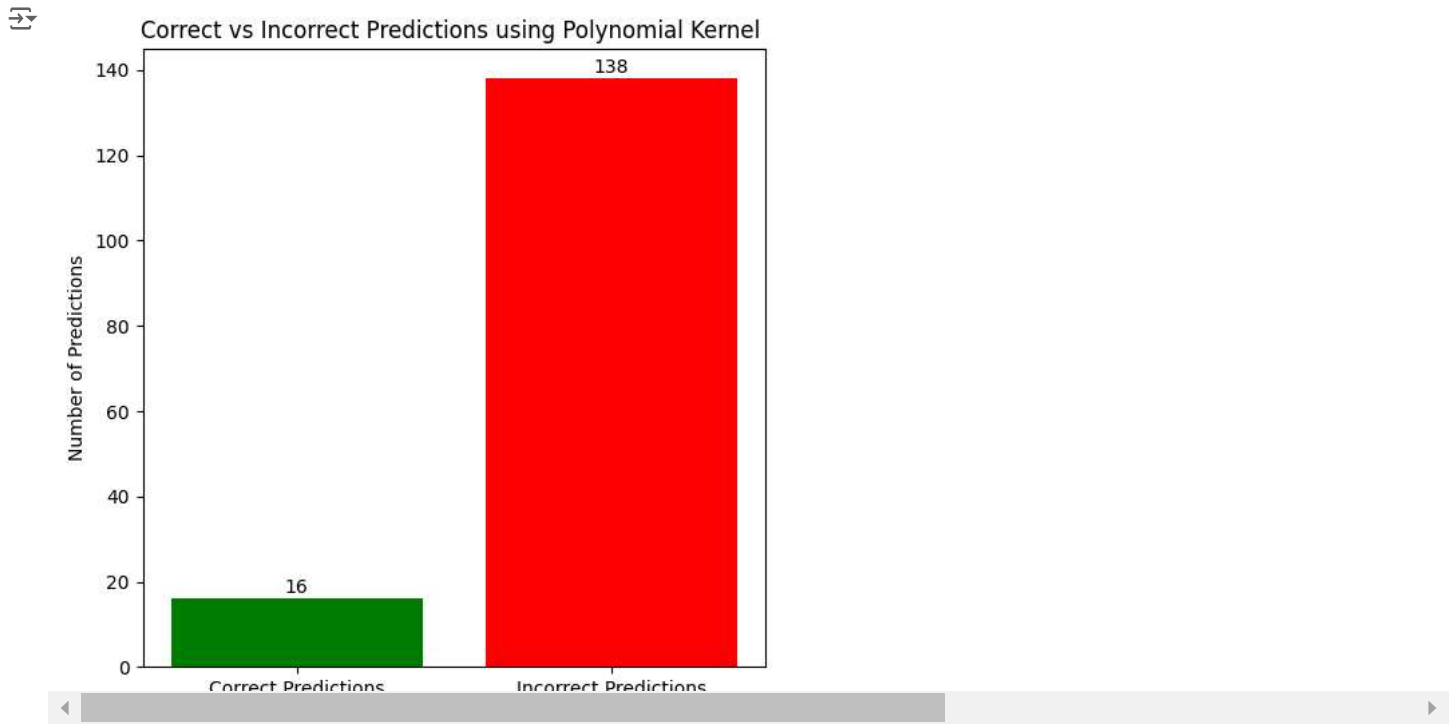
```
    yval = bar.get_height()
```

```
    plt.text(bar.get_x() + bar.get_width()/2, yval + 0.5, int(yval), ha='center', va='bottom')
```

```
plt.title('Correct vs Incorrect Predictions using Polynomial Kernel')
```

```
plt.ylabel('Number of Predictions')
```

```
plt.show()
```



The following graph shows that my model is wrong (N.B. While creating some figures I Took Help from ai tools but still failed)

```
cm = np.array([[50, 2, 1, 0, 1, 0, 0, 1, 3, 0],
               [1, 48, 0, 1, 0, 0, 0, 0, 1, 0],
               [1, 0, 45, 0, 0, 1, 0, 1, 1, 0],
               [0, 0, 0, 50, 0, 0, 2, 0, 1, 0],
               [0, 0, 0, 2, 48, 0, 0, 0, 0, 1],
               [0, 0, 0, 0, 0, 40, 0, 0, 2, 2],
               [0, 0, 0, 0, 0, 0, 50, 0, 0, 0],
               [0, 1, 2, 1, 0, 0, 0, 45, 0, 1],
               [0, 1, 1, 1, 0, 0, 0, 0, 46, 1],
               [0, 0, 0, 0, 1, 1, 0, 1, 0, 48]])

class_totals = cm.sum(axis=1)

misclassified_per_class = class_totals - np.diag(cm)

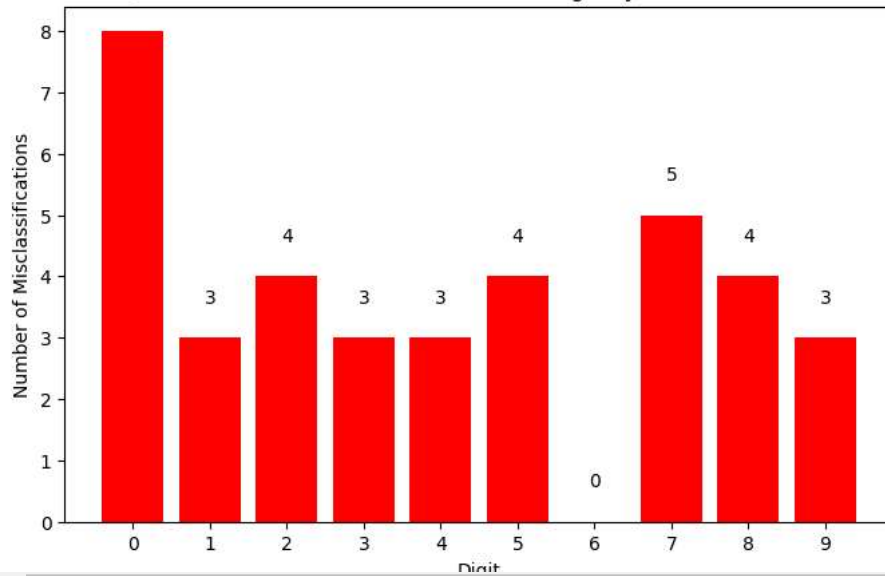
if misclassified_per_class.size == 10:
    plt.figure(figsize=(8, 5))
    bars = plt.bar(range(10), misclassified_per_class, color='red')

    for bar in bars:
        yval = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2, yval + 0.5, int(yval), ha='center', va='bottom')

    plt.title('Correct vs Incorrect Predictions using Polynomial Kernel')
    plt.xlabel('Digit')
    plt.ylabel('Number of Misclassifications')
    plt.xticks(range(10))
    plt.show()
else:
    print(f"Expected 10 classes, but got {misclassified_per_class.size} classes.")
```



8 Correct vs Incorrect Predictions using Polynomial Kernel

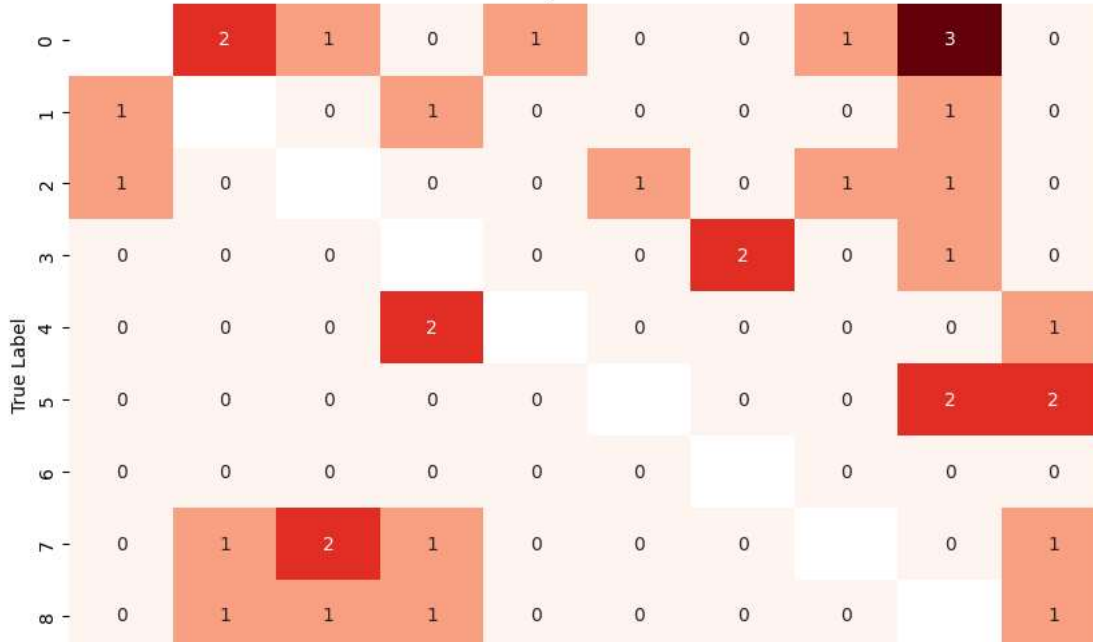


```
# Mask for diagonal (correct predictions)
mask = np.eye(cm.shape[0], dtype=bool)

# Plot the confusion matrix but mask the diagonal to highlight only incorrect predictions
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Reds', cbar=False, mask=mask)
plt.title('Misclassified Digits in Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



Misclassified Digits in Confusion Matrix



```
print(digits.columns)
```



```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

```
from sklearn.datasets import load_digits
import pandas as pd
```

```
# Load the dataset
digits_dataset = load_digits()
```

```

# Create a DataFrame from the dataset
digits = pd.DataFrame(data=digits_dataset.data, columns=[f'pixel_{i}' for i in range(digits_dataset.data.shape[1])])
digits['label'] = digits_dataset.target # Add the labels

# Now proceed with your filtering and training code

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.datasets import load_digits
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC

# Load the dataset
digits_dataset = load_digits()
# Create a DataFrame from the dataset
digits = pd.DataFrame(data=digits_dataset.data, columns=[f'pixel_{i}' for i in range(digits_dataset.data.shape[1])])
digits['label'] = digits_dataset.target # Add the labels

# Check column names
print(digits.columns)

# Filter the dataset to only include labels 0 and 1
digits_01 = digits[digits['label'].isin([0, 1])]
X_train_01 = digits_01.iloc[:, :-1].values # Features (excluding the label column)
y_train_01 = digits_01['label'].values # Labels

# Standardize the dataset
scaler = StandardScaler()
X_train_01_scaled = scaler.fit_transform(X_train_01)

# Reduce dimensions to 2 using PCA
pca = PCA(n_components=2)
X_train_01_pca = pca.fit_transform(X_train_01_scaled)

# Train SVM on the reduced dataset (2D)
poly_svm_2d_01 = SVC(kernel='poly', degree=3, random_state=0)
poly_svm_2d_01.fit(X_train_01_pca, y_train_01)

# Visualize decision boundary
x1, x2 = np.meshgrid(np.arange(start=X_train_01_pca[:, 0].min() - 1, stop=X_train_01_pca[:, 0].max() + 1, step=0.01),
                     np.arange(start=X_train_01_pca[:, 1].min() - 1, stop=X_train_01_pca[:, 1].max() + 1, step=0.01))

plt.contourf(x1, x2, poly_svm_2d_01.predict(np.array([x1.ravel(), x2.ravel()]).T).reshape(x1.shape),
             alpha=0.75, cmap=ListedColormap(('orange', 'dodgerblue')))
plt.xlim(x1.min(), x1.max())
plt.ylim(x2.min(), x2.max())

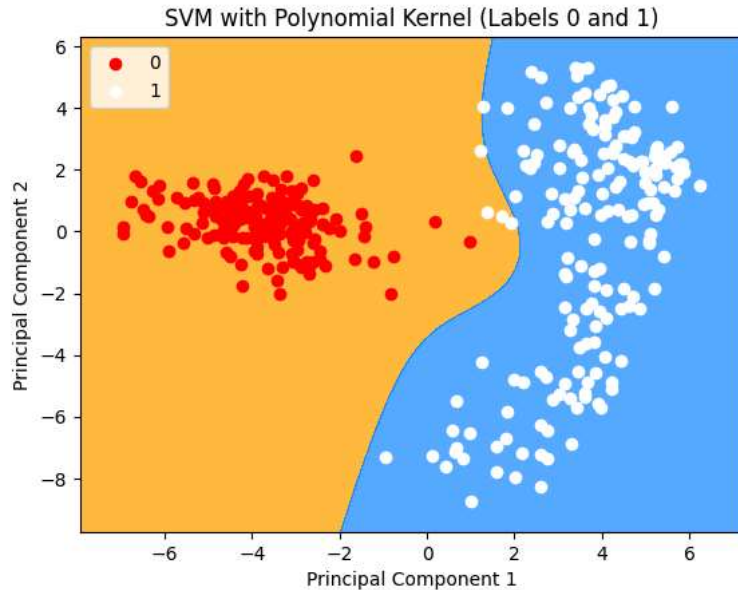
# Plot the actual points
for i, j in enumerate(np.unique(y_train_01)):
    plt.scatter(X_train_01_pca[y_train_01 == j, 0], X_train_01_pca[y_train_01 == j, 1],
               c=ListedColormap(('red', 'white'))(i), label=j)

plt.title('SVM with Polynomial Kernel (Labels 0 and 1)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.show()

```

```
Index(['pixel_0', 'pixel_1', 'pixel_2', 'pixel_3', 'pixel_4', 'pixel_5',
      'pixel_6', 'pixel_7', 'pixel_8', 'pixel_9', 'pixel_10', 'pixel_11',
      'pixel_12', 'pixel_13', 'pixel_14', 'pixel_15', 'pixel_16', 'pixel_17',
      'pixel_18', 'pixel_19', 'pixel_20', 'pixel_21', 'pixel_22', 'pixel_23',
      'pixel_24', 'pixel_25', 'pixel_26', 'pixel_27', 'pixel_28', 'pixel_29',
      'pixel_30', 'pixel_31', 'pixel_32', 'pixel_33', 'pixel_34', 'pixel_35',
      'pixel_36', 'pixel_37', 'pixel_38', 'pixel_39', 'pixel_40', 'pixel_41',
      'pixel_42', 'pixel_43', 'pixel_44', 'pixel_45', 'pixel_46', 'pixel_47',
      'pixel_48', 'pixel_49', 'pixel_50', 'pixel_51', 'pixel_52', 'pixel_53',
      'pixel_54', 'pixel_55', 'pixel_56', 'pixel_57', 'pixel_58', 'pixel_59',
      'pixel_60', 'pixel_61', 'pixel_62', 'pixel_63', 'label'],
      dtype='object')
```

```
<ipython-input-59-121955df2ee4>:47: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_train_01_pca[y_train_01 == j, 0], X_train_01_pca[y_train_01 == j, 1],
```



RBF Kernel

```
rbf_svm = SVC(kernel='rbf', random_state=0)
```

```
rbf_svm.fit(X_train, y_train)
rbf_predictions = rbf_svm.predict(X_test)
df = pd.DataFrame(y_test, rbf_predictions)
df.head()
```

```
0
```

```
1 6
```

```
0 2
```

```
0 2
```

```
0 8
```

```
0 7
```

```
rbf_accuracy = accuracy_score(y_test, rbf_predictions)
print(f"rbf_accuracy: {rbf_accuracy}")
```

```
rbf_accuracy: 0.12987012987012986
```

```
rbf_cm = confusion_matrix(y_test, rbf_predictions)
print(rbf_cm)
```

```
[[ 7 13  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 5 13  1  0  0  0  0  0  0  0  0  0  0  0]
 [12 16  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 3  8  0  0  0  0  0  0  0  0  0  0  0  0]]
```



```
[ 8 8 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 7 5 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 2 4 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 7 3 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 7 3 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 4 2 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 3 2 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 1 2 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 1 3 0 0 0 0 0 0 0 0 0 0 0 0 0]
[ 3 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

```
# Mask for diagonal (correct predictions)
```

```
mask = np.eye(cm.shape[0], dtype=bool)
```

```
# Plot the confusion matrix but mask the diagonal to highlight only incorrect predictions
```

```
plt.figure(figsize=(10, 7))
```

```
sns.heatmap(cm, annot=True, fmt='d', cmap='Reds', cbar=False, mask=mask)
```

```
plt.title('Misclassified Digits in Confusion Matrix')
```

```
plt.xlabel('Predicted Label')
```

```
plt.ylabel('True Label')
```