

## LAB 6

### SVN:

```
In [2]: import pandas as pd
from sklearn.datasets import load_digits
digits = load_digits()

digits.target

dir(digits)

digits.target_names

df = pd.DataFrame(digits.data,digits.target)
df.head()

df['target'] = digits.target
df.head(20)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.drop('target',axis='columns'), df.target, test_size=0.3)

"""Using RBF kernel"""

from sklearn.svm import SVC
rbf_model = SVC(kernel='rbf')

len(X_train)

len(X_test)

rbf_model.fit(X_train, y_train)

rbf_model.score(X_test,y_test)

"""Using Linear kernel"""

linear_model = SVC(kernel='linear')
linear_model.fit(X_train,y_train)
```

Out[2]: 0.9814814814814815

```
In [4]: #iris
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import tkinter as tk
from tkinter import filedialog
from google.colab import files
# Upload the CSV file
uploaded = files.upload()
# Read the CSV file into a pandas DataFrame
iris_df = pd.read_csv(next(iter(uploaded))) # Load the first uploaded file
print(iris_df.head())

# Feature columns and target
X = iris_df.drop("species", axis=1)
y = iris_df["species"]

# Split into training and test set (80/20)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Function to train and evaluate an SVM model
def train_evaluate_svm(kernel_type='linear'):
    model = SVC(kernel=kernel_type)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
```

```
acc = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)

print(f"\n--- SVM with {kernel_type} kernel ---")
print(f"Accuracy: {acc:.2f}")
print("Confusion Matrix:")
print(cm)

# Plot confusion matrix
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=model.classes_, yticklabels=model.classes_)
plt.title(f'Confusion Matrix ({kernel_type} kernel)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

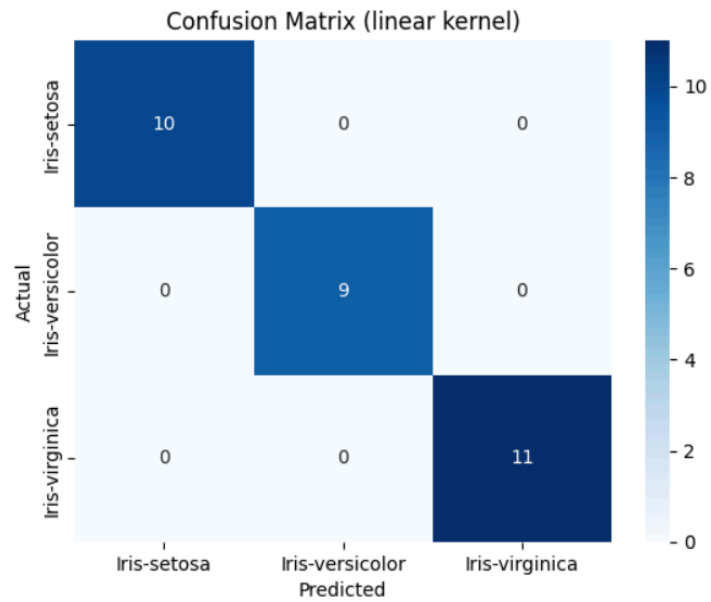
# Train and evaluate models
train_evaluate_svm(kernel_type='linear')
train_evaluate_svm(kernel_type='rbf')
```

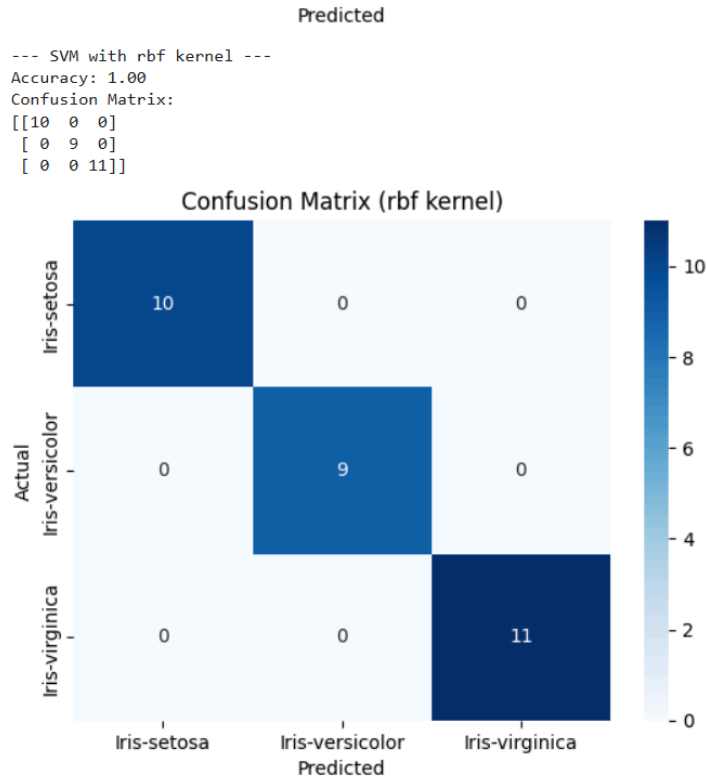
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Saving iris (1).csv to iris (1).csv

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

```
--- SVM with linear kernel ---
Accuracy: 1.00
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```





```
In [3]: #letter-recognition

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score, roc_curve
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
import matplotlib.pyplot as plt
import seaborn as sns
import tkinter as tk
from tkinter import filedialog
import numpy as np
from google.colab import files
# Upload the CSV file
uploaded = files.upload()
# Read the CSV file into a pandas DataFrame
df = pd.read_csv(next(iter(uploaded))) # Load the first uploaded file
print(df.head())

# Features and Labels
X = df.drop("letter", axis=1)
y = df["letter"]

# Binarize labels for ROC and AUC
classes = sorted(y.unique())
y_bin = label_binarize(y, classes=classes)

# Train-test split
X_train, X_test, y_train, y_test, y_bin_train, y_bin_test = train_test_split(
    X, y, y_bin, test_size=0.2, random_state=42
)

# SVM model (One-vs-Rest for multi-class ROC using LinearSVC)
svm_model = OneVsRestClassifier(LinearSVC())
```

```

# SVM model (One-vs-Rest for multi-class ROC using LinearSVC)
svm_model = OneVsRestClassifier(LinearSVC())
svm_model.fit(X_train, y_bin_train)

# For predictions:
y_pred_bin = svm_model.predict(X_test)
y_pred_labels = y_pred_bin.argmax(axis=1)
predicted_letters = [classes[i] for i in y_pred_labels]

# Accuracy
y_test_labels = y_test.reset_index(drop=True)
accuracy = accuracy_score(y_test_labels, predicted_letters)
print(f"\nAccuracy Score: {accuracy:.2f}")

# Confusion Matrix
cm = confusion_matrix(y_test_labels, predicted_letters, labels=classes)
plt.figure(figsize=(12, 10))
sns.heatmap(cm, annot=False, cmap="Blues", xticklabels=classes, yticklabels=classes)
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# ROC Curve & AUC Score using decision_function
y_score = svm_model.decision_function(X_test)
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(len(classes)):
    fpr[i], tpr[i], _ = roc_curve(y_bin_test[:, i], y_score[:, i])
    roc_auc[i] = roc_auc_score(y_bin_test[:, i], y_score[:, i])

# Plot ROC for a few classes (First 5 for simplicity)
plt.figure(figsize=(10, 8))
for i in range(5): # show first 5 classes for simplicity
    plt.plot(fpr[i], tpr[i], label=f'Class {classes[i]} (AUC = {roc_auc[i]:.2f})')
plt.plot([0, 1], [0, 1], 'k--')

```

```

# Plot ROC for a few classes (First 5 for simplicity)
plt.figure(figsize=(10, 8))
for i in range(5): # show first 5 classes for simplicity
    plt.plot(fpr[i], tpr[i], label=f'Class {classes[i]} (AUC = {roc_auc[i]:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve (First 5 Classes)")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.grid()
plt.show()

# Average AUC
mean_auc = np.mean(list(roc_auc.values()))
print(f"Average AUC Score (macro-average over classes): {mean_auc:.2f}")

```

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Saving letter-recognition.csv to letter-recognition (4).csv

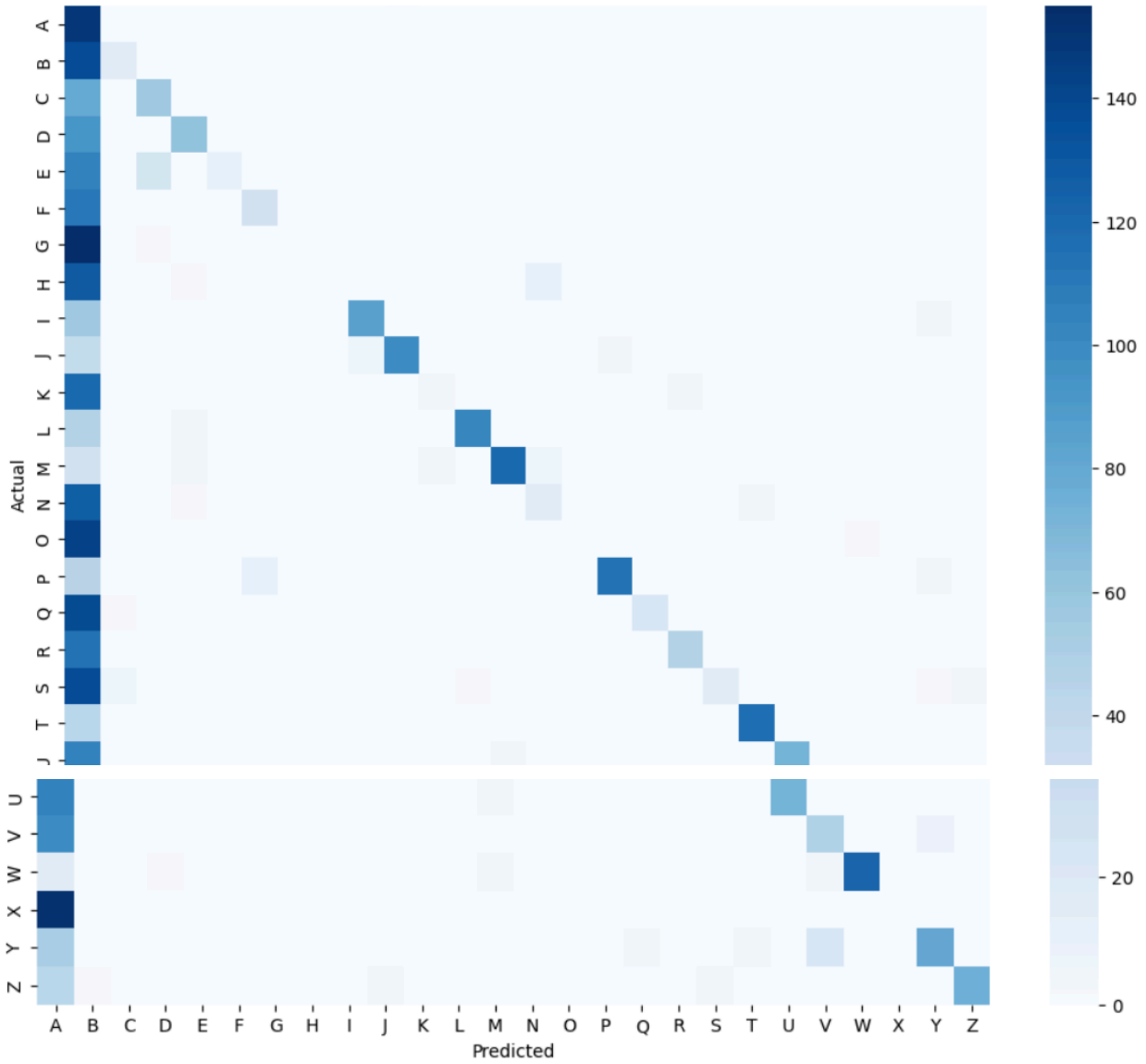
	letter	xbox	ybox	width	height	onpix	xbar	ybar	x2bar	y2bar	\
0	T	2	8	3	5	1	8	13	0	6	
1	I	5	12	3	7	2	10	5	5	4	
2	D	4	11	6	8	6	10	6	2	6	
3	N	7	11	6	6	3	5	9	4	6	
4	G	2	1	3	1	1	8	6	6	6	

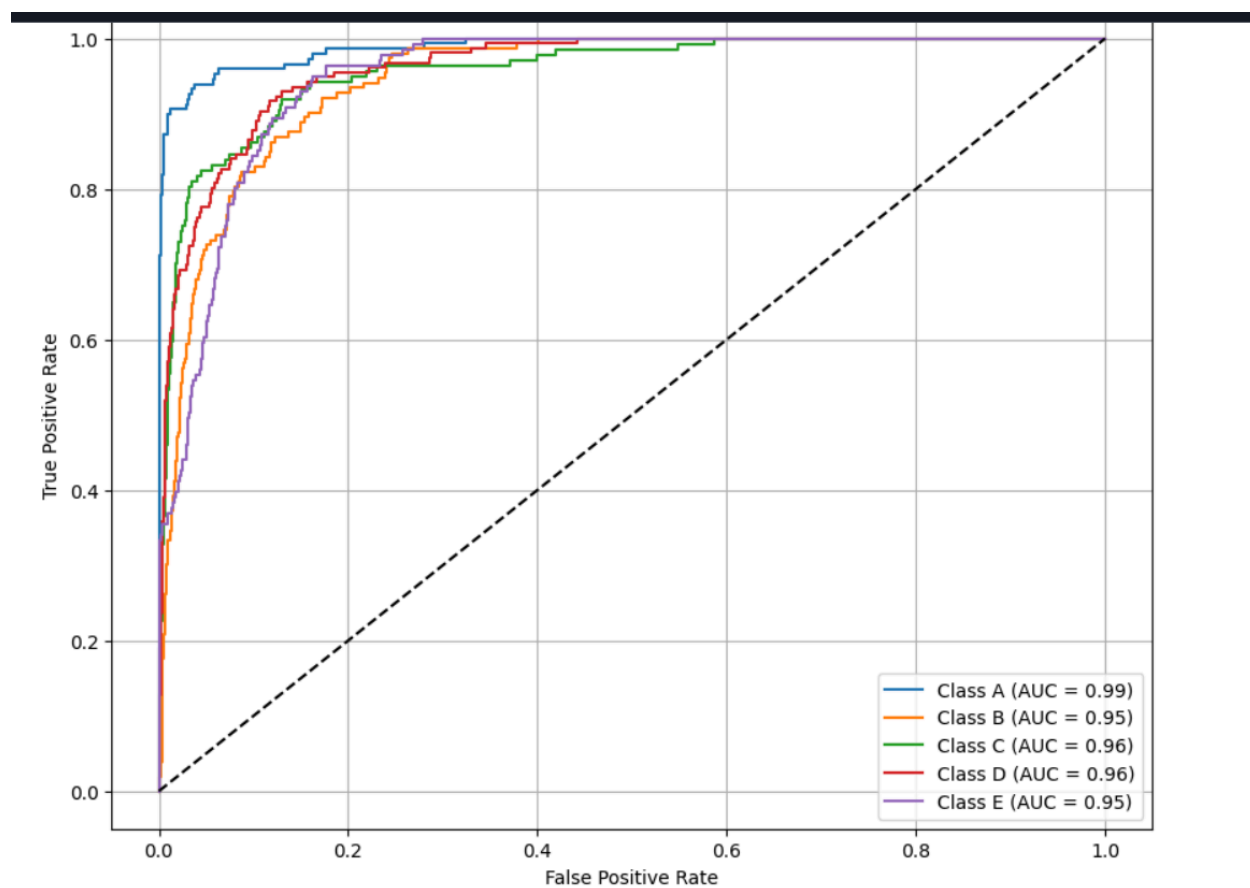
  

	xybar	x2ybar	xy2bar	xedge	xedgey	yedge	yedgey
0	6	10	8	0	8	0	8
1	13	3	9	2	8	4	10
2	10	3	7	3	7	3	9
3	4	4	10	6	10	2	8
4	6	5	9	1	7	5	10

Accuracy Score: 0.37

A confusion matrix for a 26-class classification task, where the classes are the letters of the alphabet (A-Z). The matrix is displayed as a heatmap with 'Actual' on the y-axis and 'Predicted' on the x-axis. The color scale ranges from 0 (lightest blue) to 140 (darkest blue). The diagonal elements, representing correct classifications, are the most prominent, with the highest counts (darkest blue) for letters A, G, and X. Off-diagonal elements represent misclassifications, with some notable concentrations, such as 'Actual A' being predicted as 'B' or 'C', and 'Actual X' being predicted as 'A' or 'B'.



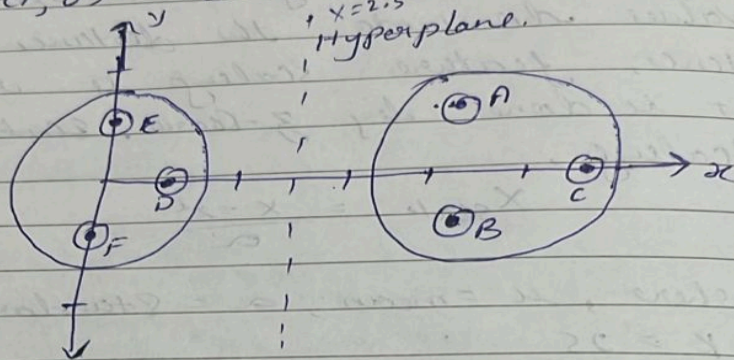


21/4/25  
Monday

## LAB-6 SVM

(14)

14 Positive class points :-  
 $A = (4, 1)$   $B = (4, -1)$   $C = (6, 0)$   
negative class points :-  
 $D = (1, 0)$   $E = (0, 1)$   $F = (0, -1)$



$$w_1 x + w_2 y + b = 0$$

Shortest dist is between  $x = 1$  and  $x = 4$

$$x = \frac{1+4}{2} = 2.5$$

optimal hyperplane equation,  $x = 2.5$

## 15 Test dataset

Accuracy using linear kernel is 1.00  
Accuracy using rbf kernel is also 1.00 as both models achieved 100% accuracy, it cannot be defined which is better. But by characteristics, rbf performs better and is stronger, as it can work on complex non-linear patterns.



37 Yes, specific letters are frequently confused with others, most letters are confused as A. ACU score : 0.94, indicating higher performance.

$$S_1 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \quad S_2 = \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} \quad S_3 = \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix}$$

$$\alpha_1 S_1 \cdot S_1 + \alpha_2 S_2 \cdot S_2 + \alpha_3 S_3 \cdot S_1 = -1$$

$$\Rightarrow \alpha_1 \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} + \alpha_2 \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} + \alpha_3 \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} = -1$$

$$\Rightarrow 2\alpha_1 + 5\alpha_2 + 5\alpha_3 = -1 \quad \rightarrow (1)$$

$$\alpha_1 S_1 \cdot S_2 + \alpha_2 S_2 \cdot S_2 + \alpha_3 S_3 \cdot S_2 = +1$$

$$\Rightarrow \alpha_1 \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} + \alpha_2 \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} + \alpha_3 \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix} \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} = +1$$

$$\Rightarrow 5\alpha_1 + 18\alpha_2 + 16\alpha_3 = -1 \quad \rightarrow (2)$$

$$\alpha_1 S_1 \cdot S_3 + \alpha_2 S_2 \cdot S_3 + \alpha_3 S_3 \cdot S_3 = +1$$

$$\Rightarrow \alpha_1 \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix} + \alpha_2 \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix} + \alpha_3 \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix} \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix} = +1$$

$$\Rightarrow 5\alpha_1 + 16\alpha_2 + 18\alpha_3 = 1 \quad \rightarrow (3)$$

$$\alpha_1 = \frac{-1237}{504}, \quad \alpha_2 = \frac{11}{28}, \quad \alpha_3 = \frac{7}{18} = 0.39$$

$$w = \sum \alpha_i S_i = 2.45 \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} + 0.39 \begin{pmatrix} 4 \\ 1 \\ 1 \end{pmatrix} + 0.39 \begin{pmatrix} 4 \\ -1 \\ 1 \end{pmatrix}$$

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$$y = wx + b$$

$$w = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad b = +2.5$$