

## ❖ **Day -7: Introduction to SVM**

### ❖ SVM:

Support Vector Machine (SVM) is a machine learning algorithm that finds the best hyperplane to separate classes in a data, with applications in classification and regression.

### ❖ Types:

- I. Linear SVM
- II. Non-linear SVM
- III. Binary SVM
- IV. Multiclass SVM
- V. Support Vector Regression

### ❖ Working:

➤ Support Vector Machines (SVMs) work by:

- 1.Training: Find the hyperplane that maximizes the margin between classes.
- 2.kernel Transformation: Handle non-linear patterns using kernel functions.
- 3.classification:Assign new data points to classes based on their position relative to the hyperplane.

### ❖ Advantage:

- Effective in high dimensions: performs well in dataset with many features.
- Versatile: handle linear and non-linear relationships using kernel functions.

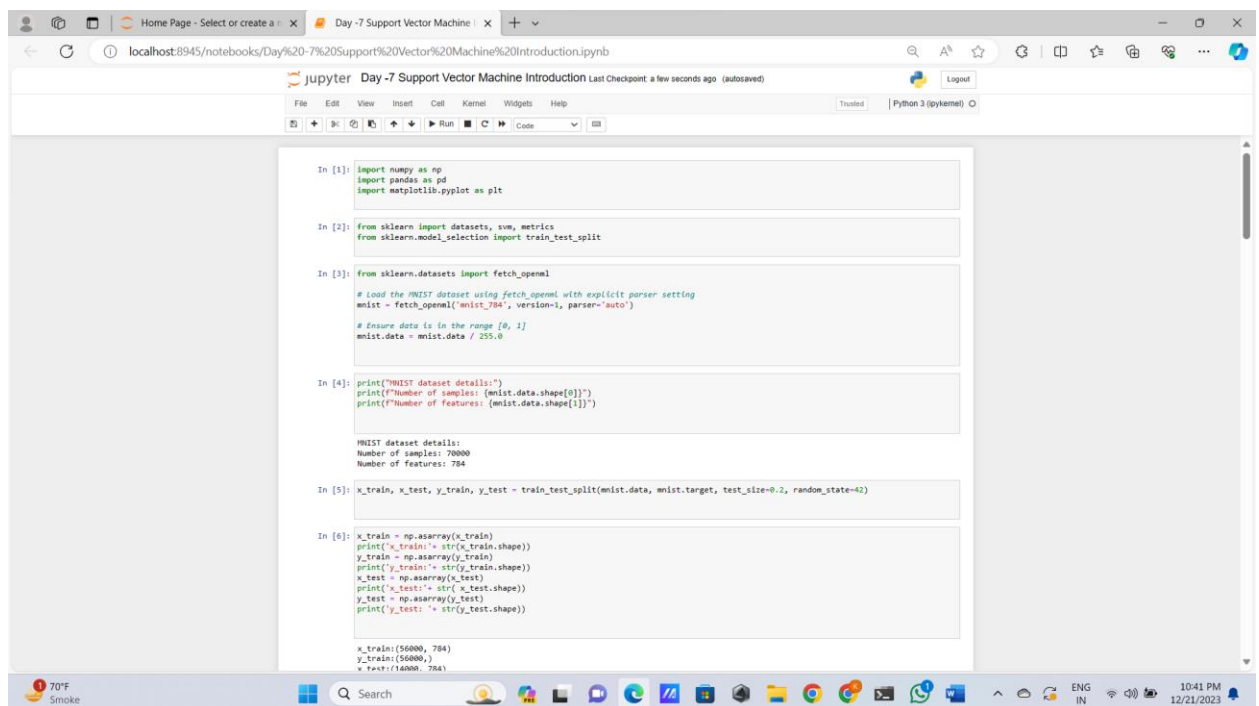
### ❖ Disadvantage:

- Computational intensity: High computational demand, especially for large datasets.

- **Memory Usage:** Substantial memory requirements, particularly with non-linear kernels.

### ❖Description:

I'm thrilled to apply this newfound knowledge to real-world scenarios, and the prospect of further honing these skills through the Skill Boost Internship Program adds an extra layer of excitement. Here's to the journey ahead and the exciting challenges awaiting in the Skill Boost Internship Program([www.Batweb.com](http://www.Batweb.com)).



```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

In [2]: from sklearn import datasets, svm, metrics
from sklearn.model_selection import train_test_split

In [3]: from sklearn.datasets import fetch_openml

# Load the MNIST dataset using fetch_openml with explicit parser setting
mnist = fetch_openml("mnist_784", version=3, parser="auto")

# Ensure data is in the range [0, 1]
mnist.data = mnist.data / 255.0

In [4]: print("MNIST dataset details:")
print(f"Number of samples: {mnist.data.shape[0]}")
print(f"Number of features: {mnist.data.shape[1]}")

MNIST dataset details:
Number of samples: 70000
Number of features: 784

In [5]: x_train, x_test, y_train, y_test = train_test_split(mnist.data, mnist.target, test_size=0.2, random_state=42)

In [6]: x_train = np.asarray(x_train)
print('x_train:', str(x_train.shape))
y_train = np.asarray(y_train)
print('y_train:', str(y_train.shape))
x_test = np.asarray(x_test)
print('x_test:', str(x_test.shape))
y_test = np.asarray(y_test)
print('y_test:', str(y_test.shape))

x_train: (56000, 784)
y_train: (56000,)
x_test: (14000, 784)
y_test: (14000,)
```

```
Day-7 Support Vector Machine Introduction Last Checkpoint: a few seconds ago (autosaved)

x_train=(56000, 784)
y_train=(56000,)
x_test=(14000, 784)
y_test=(14000,)

In [7]: # normalize and scale the data
x_train_flat=x_train/255.0
x_test_flat=x_test/255.0
x_train_flat=x_train.reshape(x_train.shape[0],-1)
x_test_flat=x_test.reshape(x_test.shape[0],-1)
x_train_flat=x_train_flat[0:100][:]
y_train_flat=y_train[0:100]

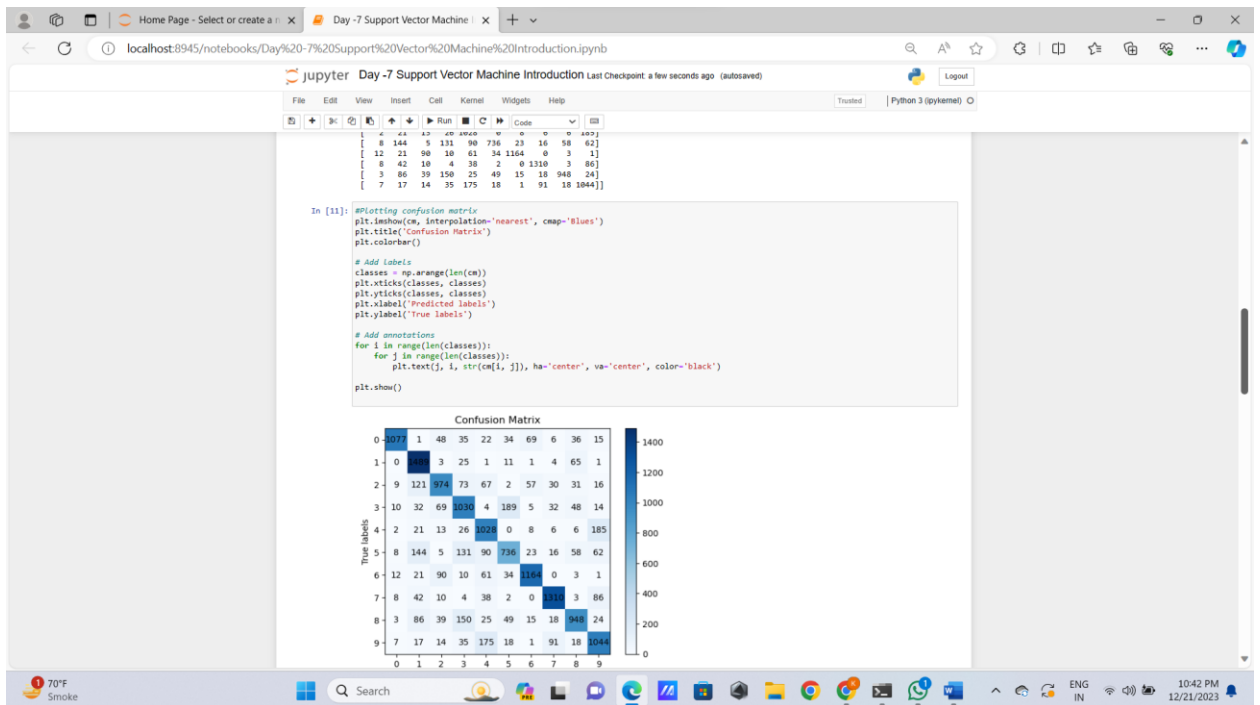
In [8]: # train model
from sklearn.svm import SVC
model_linear=SVC(kernel='linear')
model_linear.fit(x_train_flat,y_train)

Out[8]: SVC
SVC(kernel='linear')

In [9]: # get the accuracy
from sklearn import metrics
#predict
y_pred=model_linear.predict(x_test_flat)
#accuracy
print("accuracy",metrics.accuracy_score(y_test,y_pred),)
accuracy 0.7714285714285715

In [10]: #confusion matrix
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,y_pred)
print(cm)

[[1077  1  48  35  22  34  69  6  36  15]
 [  0 1489  3  25  1  11  1  4  65  1]
 [  9 121 974  73  67  2  57  30  31  16]
 [ 10  32  69 1030  4 189  5  32  46  14]
 [  2  21  13  26 1028  0  8  6  6 185]
 [  8 144  5 131  90  736 23 16 58  62]
 [ 12  21  90  10  61  34 1164  0  3  1]
 [  8  42  10  4  38  2  0 1310  3  86]
 [  3  86  39 150  25  49  15 18 948  24]
 [  7 17 14 35 175 18  1  91 18 1044]]
```




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```
In [12]: # Choose a random sample of images to plot
num_samples = 5
sample_indices = np.random.choice(mnist.data.shape[0], num_samples, replace=False)

# Plot the sampled images
plt.figure(figsize=(12, 4))
for i, index in enumerate(sample_indices, 1):
    plt.subplot(1, num_samples, i)
    plt.imshow(mnist.data.iloc[index].values.reshape(28, 28), cmap='gray') # Use .values to access Numpy array
    plt.title(f"Label: {mnist.target.iloc[index]}")
plt.axis('off')

plt.show()
```

Label: 0      Label: 7      Label: 8      Label: 3      Label: 2



```
In [13]: from sklearn.decomposition import PCA

In [14]: # Reduce dimensionality using PCA
pca = PCA(n_components=2)
mnist_2d = pca.fit_transform(mnist.data)

# Create a scatter plot
plt.figure(figsize=(10, 8))
scatter = plt.scatter(mnist_2d[:, 0], mnist_2d[:, 1], c=mnist.target.astype(int), cmap='viridis', alpha=0.5, edgecolors='w')

# Add colorbar
char = plt.colorbar(scatter)
char.set_label('Digit Label', rotation=270, labelpad=15)

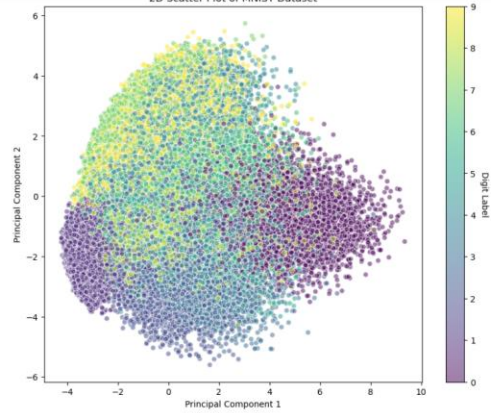
plt.title('2D Scatter Plot of MNIST Dataset')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()
```

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```
In [15]: from sklearn import datasets, svm, metrics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

In [18]: # Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.2, random_state=42)
# Ensure that X_train and X_test are NumPy arrays
```

2D Scatter Plot of MNIST Dataset



```
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In [18]: # Split the dataset into training and testing sets
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```
X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.2, random_state=42)

# Ensure that X_train and X_test are NumPy arrays
X_train_np = X_train.values.reshape(X_train.shape[0], -1)
X_test_np = X_test.values.reshape(X_test.shape[0], -1)

# Standardize the features (important for SVM)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_np)
X_test_scaled = scaler.transform(X_test_np)

# Create an SVM classifier
classifier = svm.SVC(gamma=0.001)

# Fit the classifier on the training data
classifier.fit(X_train_scaled, y_train)

# Make predictions on the test data
y_pred = classifier.predict(X_test_scaled)

# Print classification report
print("Classification report for SVM classifier:\n%s" % (metrics.classification_report(y_test, y_pred)))
```

Classification report for SVM classifier:

	precision	recall	f1-score	support
0	0.98	0.98	0.98	1343
1	0.97	0.99	0.98	1600
2	0.96	0.95	0.96	1300
3	0.96	0.95	0.95	1433
4	0.95	0.96	0.96	1295
5	0.96	0.95	0.96	1273
6	0.97	0.98	0.97	1396
7	0.93	0.97	0.95	1503
8	0.96	0.94	0.95	1357
9	0.96	0.93	0.94	1420
accuracy			0.96	14000
macro avg	0.96	0.96	0.96	14000
weighted avg	0.96	0.96	0.96	14000

70°F Smoke

Search

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