Day53_Support_Vector_Machine_(SVM)_Classifier

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Support Vector Machine (SVM) Classifier

Understanding SVM

- Suppose we have **two classes**, like A and B.
- SVM tries to find a line called the hyperplane that best separates these two classes.
- The points closest to the decision boundary are called **support vectors**.
- The distance between these support lines is called **marginal distance**.
- SVM tries to maximize the margin which means better generalization and fewer errors.

Linear vs Non-linear SVM

- Linear SVM: Can separate classes using a straight line.
- Non-linear SVM: When data is not linearly separable, it uses a **kernel function** to project data into higher dimensions.
- This way, SVM converts a **non-linear problem** into a **linear one** in higher-dimensional space.

Examples:

- $1D \rightarrow 2D$
- $2D \rightarrow 3D$

Important SVM Concepts

- **Kernel function** helps move data to higher dimensions to make it separable.
- Maximum margin = better generalization (small errors can be adjusted, leading to more accuracy).
- Common kernels: linear, rbf, poly.

Now, let's implement an SVM Classifier in Python using scikit-learn!

1 Import Libraries

```
[2]: # Step 1: Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix,__

classification_report
```

2 Load and Prepare Data

```
[3]: # Step 2: Load Dataset
dataset = pd.read_csv(r"C:\Users\Lenovo\Downloads\logit classification.csv") #_\(\pi\)
\[ \times adjust path if needed \]
dataset.head()
```

```
[3]:
        User ID Gender Age EstimatedSalary Purchased
    0 15624510
                                     19000
                Male
                        19
    1 15810944
                  Male
                                                   0
                        35
                                     20000
    2 15668575 Female 26
                                     43000
                                                   0
    3 15603246 Female
                       27
                                     57000
                                                   0
    4 15804002
                  Male
                                     76000
                       19
```

3 Feature Selection & Train-Test Split

```
[4]: # Step 3: Select Features and Target
X = dataset[["Age", "EstimatedSalary"]].values
y = dataset["Purchased"].values
```

```
[5]: # Split into train-test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,_
Grandom_state=0)
```

4 Feature Scaling

```
[6]: # Step 4: Scale Features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

5 Train SVM Classifier

```
[7]: # Step 5: Train the SVM model

svm_model = SVC(kernel='rbf', C=1.0, gamma='scale') # Try 'linear' or 'poly'

as well

svm_model.fit(X_train_scaled, y_train)
```

[7]: SVC()

6 Model Evaluation

```
[8]: # Step 6: Make Predictions and Evaluate
     y_pred_svm = svm_model.predict(X_test_scaled)
     print("SVM Classifier Results")
     print("Accuracy:", accuracy_score(y_test, y_pred_svm))
     print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_svm))
     print("Classification Report:\n", classification_report(y_test, y_pred_svm))
    SVM Classifier Results
    Accuracy: 0.93
    Confusion Matrix:
     [[64 	4]
     [ 3 29]]
    Classification Report:
                   precision
                                 recall f1-score
                                                     support
               0
                        0.96
                                  0.94
                                            0.95
                                                         68
                        0.88
                                  0.91
               1
                                            0.89
                                                         32
        accuracy
                                            0.93
                                                        100
       macro avg
                        0.92
                                  0.92
                                            0.92
                                                        100
    weighted avg
                        0.93
                                  0.93
                                            0.93
                                                        100
```

7 Future Prediction

Once the model is trained, you can pass new user data (like Age and Estimated Salary) for prediction:

Example:

```
new_data = [[30, 87000]]
scaled_data = scaler.transform(new_data)
svm_model.predict(scaled_data)
```

8 Predicting from Future Data CSV

	User ID	Gender	Age	EstimatedSalary
0	1674381	Male	29	39000
1	1674382	Female	14	34500
2	1674383	Male	28	40000
3	1674384	Female	58	56490
4	1674385	Female	80	59000
5	1674386	Male	90	41000
6	1674387	Male	100	23000
7	1674388	Female	45	20000
8	1674389	Male	37	33000
9	1674390	Female	48	23000
10	1674391	Female	59	64000
11	1674392	Male	60	33000
12	1674393	Male	61	23000
13	1674394	Female	62	45000

9 Scale the future data using the same scaler used during training

```
[16]: future_scaled = scaler.transform(future_data[["Age", "EstimatedSalary"]])
```

10 Predict using trained SVM model

```
[17]: future_predictions = svm_model.predict(future_scaled)
```

11 Append predictions to the DataFrame

```
[18]: future_data["Predicted_Purchase"] = future_predictions

print("\n Future Predictions:\n")
print(future_data)
```

Future Predictions:

	User ID	Gender	Age	EstimatedSalary	Predicted_Purchase
0	1674381	Male	29	39000	0
1	1674382	Female	14	34500	0
2	1674383	Male	28	40000	0
3	1674384	Female	58	56490	1
4	1674385	Female	80	59000	1
5	1674386	Male	90	41000	1
6	1674387	Male	100	23000	1
7	1674388	Female	45	20000	1
8	1674389	Male	37	33000	0
9	1674390	Female	48	23000	1
10	1674391	Female	59	64000	1
11	1674392	Male	60	33000	1
12	1674393	Male	61	23000	1
13	1674394	Female	62	45000	1

Future Prediction Summary (SVM Classifier)

- Goal: Predict if a user will purchase based on Age and EstimatedSalary.
- Output: Predicted_Purchase = 1 (Will buy), 0 (Will not buy)

Key Insights:

- Older users (Age 58+) are mostly predicted as buyers, even with lower salaries.
- Younger users (<30) are predicted as non-buyers, especially with average income.
- Model prioritizes **Age** more than **Salary** when making predictions.

Example:

Age	Salary	Prediction
29	39000	No
58	56490	Yes
90	41000	Yes

This helps companies target real buyers and reduce marketing costs.

12 Real-Time Use Case Explanation

How Does SVM Work in Real-Time Product Predictions?

Imagine a company like **Amazon** or **Flipkart** wants to predict whether a user will buy a product or not.

Here's how this real-time prediction happens using models like SVM:

Step-by-Step Real-Time Flow

1. User visits the website

The system captures user features like:

- Age
- Estimated salary
- Location, device, or browsing history

2. Features are passed to a trained model

The features are scaled using the same scaler used during model training.

3. Model gives prediction

The model outputs:

- 1 (User is likely to purchase)
- 0 (User is not likely to purchase)

4. Personalization kicks in

- If the user is likely to buy → show targeted offers, add-to-cart prompts, urgency messages like "Only 1 left!"
- If unlikely \rightarrow offer discounts, alternative recommendations, etc.

Example

A user with:

Age	Estimated Salary
30	87,000

The system passes this to the model:

model.predict([[30, 87000]])

If result = 1, the product page shows:

"Special deal just for you!"

Business Impact

- Increases conversion rate
- Improves customer experience
- Reduces ad wastage by targeting the right users

13 Final Reflection

In this notebook, I explored how **Support Vector Machines (SVM)** can be used not just as a mathematical model, but as a **real-world decision-making tool**.

From training on historical data to making predictions on unseen users, this project shows how machine learning can:

- Improve business efficiency
- Personalize user experiences
- Reduce marketing costs
- Increase product conversions

This is just one use case. The same logic applies to finance, healthcare, e-commerce, and more.

This project boosted my understanding of:

- Classification models
- Real-time prediction systems
- Data preprocessing (scaling, splitting)
- Model evaluation and deployment thinking

[&]quot;A model is only as good as the data and questions we ask of it."