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ML - Experiment 8 - SVM

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ML - Experiment 8 - SVM

Aim: To implement Support Vector Machine (SVM)

Theory: SVM can solve both linear & non-linear problems and work well for many practical problems. The idea of SVM is simple - it creates a line / hyperplane which separates data into classes. At first, what SVM do is to find a separating line (or hyperplane) btw data of classes. SVM is an algo that takes the data as input & outputs a line that separate those classes if possible. These points are called support vectors & distance is called margin. Our goal is to maximize the margin. The hyperplane for which the margin is maximum is the optimal hyperplane. Thus, SVM tries to decide boundary in such a way that the separation btw 2 classes is as wide as possible. For non-linear data, we can classify the data by adding an extra dimension to it so that it becomes linearly separable & then projecting the decision boundary back to orignal dimensions using mathemical transformation. SVM has several advantages over other classification algorithms such as logistic regression, decision trees & random forests. It can handle high dimensional data efficiently, has a strong theoritical foundation & can be used for both classification & regression tasks. SVM can also handle non-linear data efficiently using kernel functions.

In SVM, kernels are used to transform the input data into a higher dimensional space where it becomes easier to separate the classes linearly. Each kernel has its own characteristics & is suitable for different kinds of data.

① Linear kernel — Linear kernel is the simplest kernel & is used when the data is linearly separable. It computes the dot product of input vectors, which is equivalent to the original feature space

Math Expression : $K(x, y) = x^T \cdot y$

② Polynomial kernel — It is used to handle non-linearly separable data by mapping the data into higher dimensional space using a polynomial function.

Math. Expression : $K(x, y) = (x^T \cdot y + c)^d$

where c — constant

d — degree of polynomial.

③ Radial Basis Function (RBF) kernel — Commonly used for non-linear data. It maps data into ∞ dimensional space using Gaussian Radial Basis Function.

Math. Expression :- $K(x, y) = e^{-\gamma(x-y)^2}$

γ — parameter that defines spread of kernel

④ Sigmoid kernel — It is based on Sigmoid function & maps data into higher-dimensional space.

Math. Expression :- $K(x, y) = \tanh(\alpha x^T y + c)$

α — Scaling parameter

c — constant.

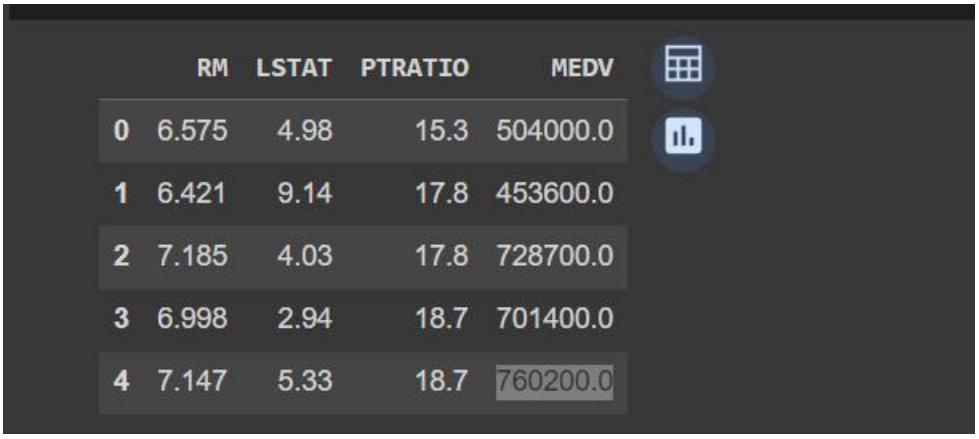
(Conclusion) : It was found that different kernels performed better depending on the dataset. RBF generally performed well, indicating its versatility for various datasets. Linear kernel worked effectively for cancer dataset; while polynomial kernel showed mixed results.

```
from google.colab import drive
drive.mount('/content/gdrive')

import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot as plt
from sklearn.preprocessing import KBinsDiscretizer
```

LINEAR

DATASET

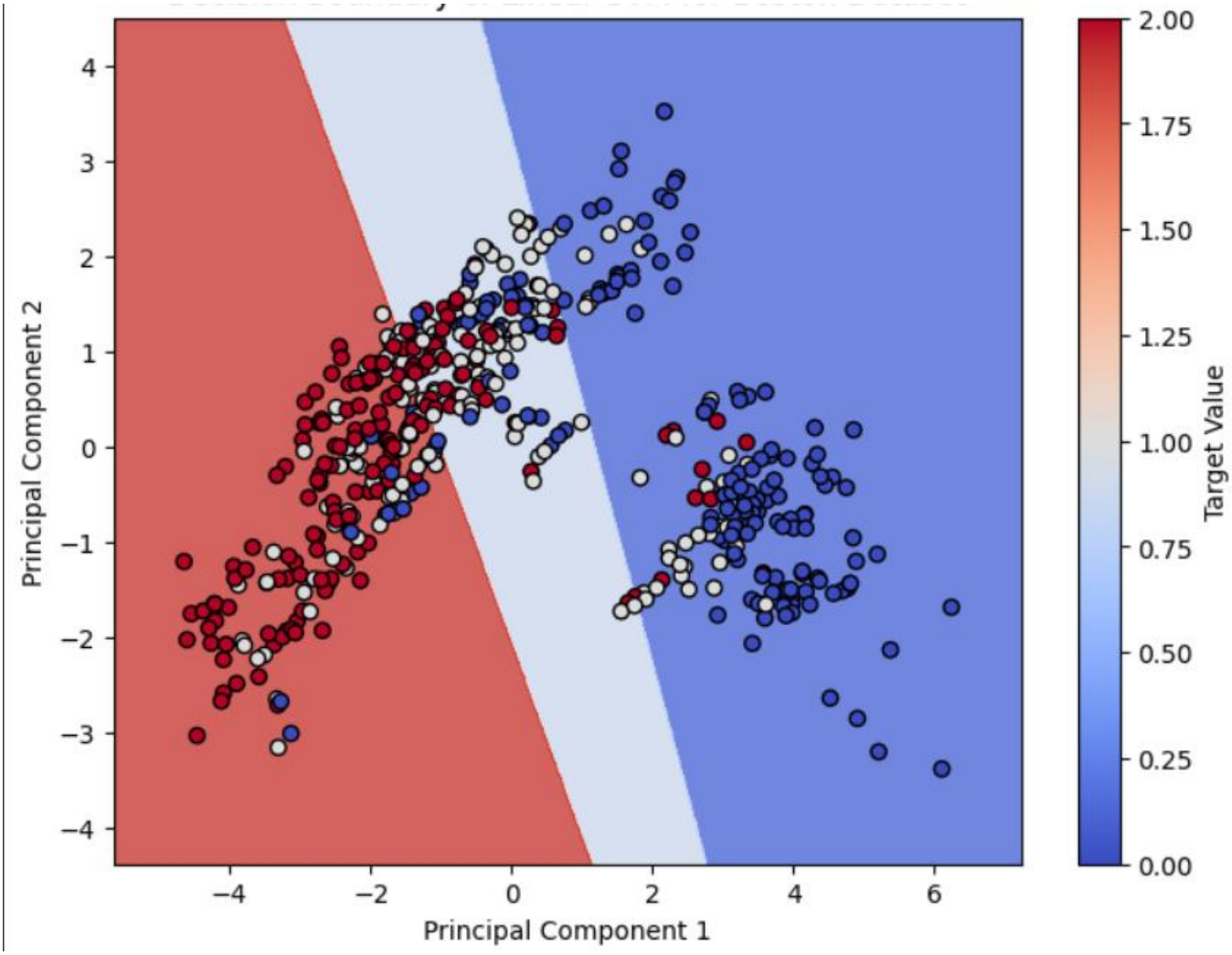
```
# Load the dataset
dataset_path = '/content/gdrive/MyDrive/ML/california.csv'
data = pd.read_csv(dataset_path)
data.head()
```



	RM	LSTAT	PTRATIO	MEDV
0	6.575	4.98	15.3	504000.0
1	6.421	9.14	17.8	453600.0
2	7.185	4.03	17.8	728700.0
3	6.998	2.94	18.7	701400.0
4	7.147	5.33	18.7	760200.0

```
X = data.drop(columns=['medv'])  # Features
y = data['medv']  # Target variable

kbins = KBinsDiscretizer(n_bins=3, encode='ordinal', strategy='quantile')
y_discrete = kbins.fit_transform(y.values.reshape(-1, 1))

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

svm = SVC(kernel='linear')
svm.fit(X_pca, y_discrete)

plt.figure(figsize=(8, 6))

h = .02
x_min, x_max = X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1
```

```
y_min, y_max = X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])

Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap='coolwarm', alpha=0.8)

plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y_discrete, cmap='coolwarm', marker='o', edgecolors='k')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Target Value')
plt.show()
```




```
data = pd.read_csv('/content/gdrive/MyDrive/ML/california.csv')

bins = [0, 453600.0, 760200.0, float('inf')]
labels = ['low', 'medium', 'high']
data['medv_category'] = pd.cut(data['MEDV'], bins=bins, labels=labels)

X = data.drop(columns=['MEDV', 'medv_category'])
y = data['medv_category']


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

kernels = ['linear', 'poly', 'rbf', 'sigmoid']
```

```
for kernel in kernels:

    svm = SVC(kernel=kernel)
    svm.fit(X_train, y_train)
    y_pred = svm.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)
    confusion_mat = confusion_matrix(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)

    print(f"Kernel: {kernel}")
    print("Accuracy:", accuracy)
    print("Confusion Matrix:\n", confusion_mat)
    print("Classification Report:\n", class_report)
     print()
```

OUTPUT

```
Kernel: linear
Accuracy: 0.8367346938775511
Confusion Matrix:
 [[ 2  0  0]
 [ 0 52 10]
 [ 0  6 28]]
Classification Report:
              precision    recall  f1-score   support

        high       1.00      1.00      1.00         2
         low       0.90      0.84      0.87        62
      medium       0.74      0.82      0.78        34

    accuracy                           0.84        98
   macro avg       0.88      0.89      0.88        98
weighted avg       0.84      0.84      0.84        98
```

```
Kernel: poly
Accuracy: 0.8163265306122449
Confusion Matrix:
 [[ 2  0  0]
 [ 0 51 11]
 [ 0  7 27]]
Classification Report:
              precision    recall  f1-score   support

        high       1.00      1.00      1.00         2
         low       0.88      0.82      0.85        62
      medium       0.71      0.79      0.75        34

    accuracy                           0.82        98
   macro avg       0.86      0.87      0.87        98
weighted avg       0.82      0.82      0.82        98
```

```
Kernel: rbf
Accuracy: 0.8163265306122449
Confusion Matrix:
 [[ 0  0  2]
 [ 0 53  9]
 [ 0  7 27]]
Classification Report:
              precision    recall  f1-score   support

        high       0.00      0.00      0.00         2
         low       0.88      0.85      0.87        62
      medium       0.71      0.79      0.75        34

    accuracy                           0.82        98
   macro avg       0.53      0.55      0.54        98
weighted avg       0.81      0.82      0.81        98
```

```
Kernel: sigmoid
Accuracy: 0.6326530612244898
Confusion Matrix:
 [[ 0  2  0]
 [ 0 62  0]
 [ 0 34  0]]
Classification Report:
              precision    recall  f1-score   support

        high       0.00      0.00      0.00         2
         low       0.63      1.00      0.78        62
      medium       0.00      0.00      0.00        34

    accuracy                           0.63        98
   macro avg       0.21      0.33      0.26        98
weighted avg       0.40      0.63      0.49        98
```

NON - LINEAR

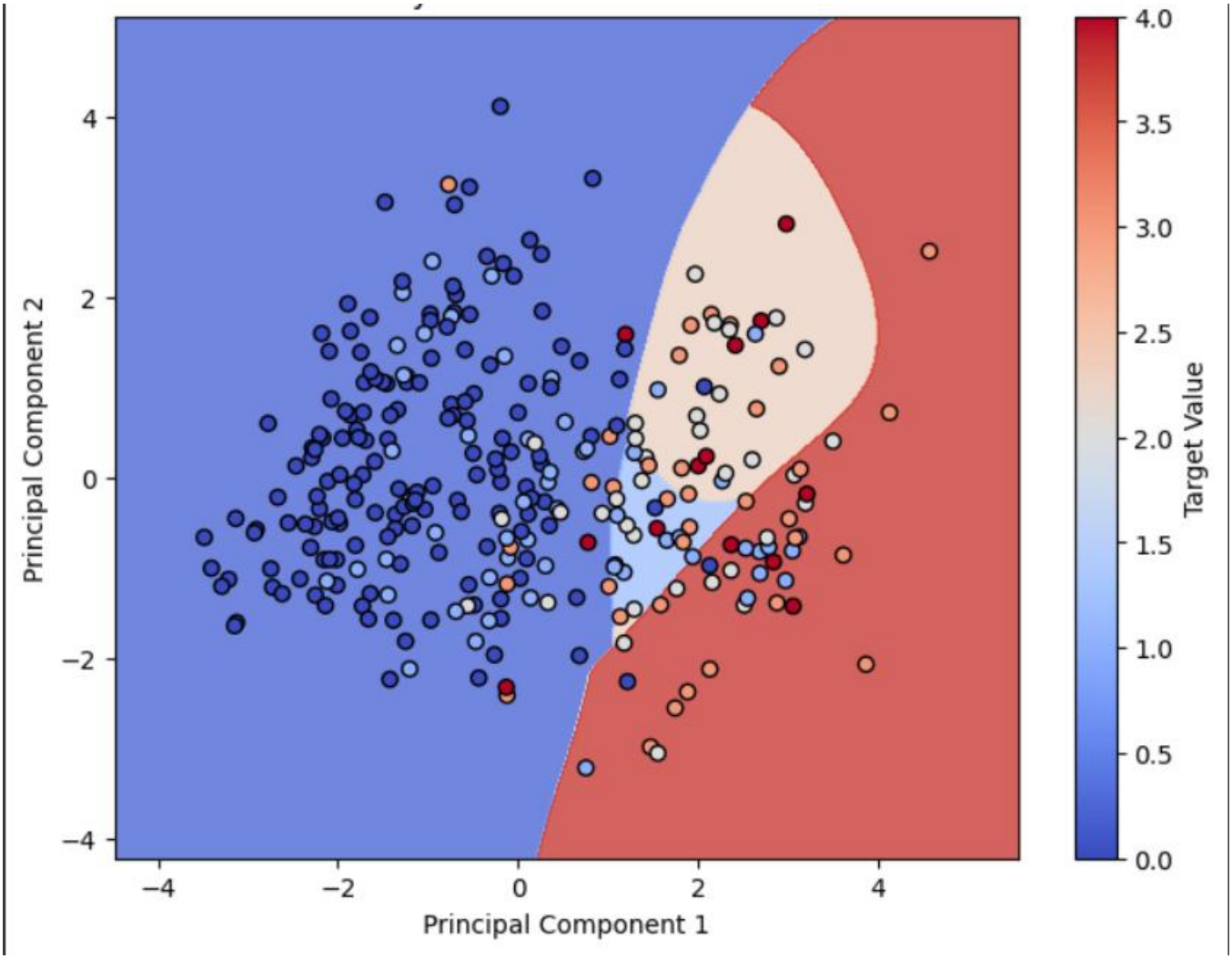
DATASET

```
df = pd.read_csv('/content/gdrive/MyDrive/ML/heart.csv')
df.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

```
dataset_url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/heart-disease/processed.cleveland.data'
names = ['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg',
         'thalach', 'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target']
data = pd.read_csv(dataset_url, names=names)
data.replace('?', np.nan, inplace=True)
data.dropna(inplace=True)

X = data.drop(columns=['target'])
y = data['target']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

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

svm = SVC(kernel='rbf', gamma='scale')
svm.fit(X_train, y_train)

plt.figure(figsize=(8, 6))

h = .02  # step size in the mesh
x_min, x_max = X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1
y_min, y_max = X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap='coolwarm', alpha=0.8)

plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='coolwarm', marker='o', edgecolors='k')
plt.title('Decision Boundary of Non-linear SVM for Heart Disease')
plt.xlabel('Principal Component 1')
```

```
plt.ylabel('Principal Component 2')
plt.colorbar(label='Target Value')
plt.show()
```




```
dataset_url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/heart-
disease/processed.cleveland.data'
names = ['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg',
        'thalach', 'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target']
data = pd.read_csv(dataset_url, names=names)
data.replace('?', np.nan, inplace=True)
data.dropna(inplace=True)
X = data.drop(columns=['target'])
y = data['target']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_state=42)
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
results = {}
```

```
for kernel in kernels:
    svm = SVC(kernel=kernel, gamma='scale')
    svm.fit(X_train, y_train)
    y_pred = svm.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    cm = confusion_matrix(y_test, y_pred)
    report = classification_report(y_test, y_pred)
    results[kernel] = {'accuracy': accuracy, 'confusion_matrix': cm, 'classification_report': report}

for kernel, result in results.items():
    print(f"Kernel: {kernel}")
    print(f"Accuracy: {result['accuracy']}")
    print("Confusion Matrix:")
    print(result['confusion_matrix'])
    print("Classification Report:")
    print(result['classification_report'])
    print()
```

OUTPUT

```
Kernel: linear
Accuracy: 0.6666666666666666
Confusion Matrix:
[[35  0  1  0  0]
 [ 5  1  1  2  0]
 [ 1  1  1  2  0]
 [ 2  0  2  3  0]
 [ 2  0  0  1  0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.97      0.86        36
           1       0.50      0.11      0.18         9
           2       0.20      0.20      0.20         5
           3       0.38      0.43      0.40         7
           4       0.00      0.00      0.00         3

    accuracy                           0.67        60
   macro avg       0.37      0.34      0.33        60
weighted avg       0.60      0.67      0.61        60
```

```
Kernel: poly
Accuracy: 0.6333333333333333
Confusion Matrix:
[[35  0  1  0  0]
 [ 6  1  1  1  0]
 [ 2  2  0  1  0]
 [ 2  2  1  2  0]
 [ 2  0  0  1  0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.74      0.97      0.84        36
           1       0.20      0.11      0.14         9
           2       0.00      0.00      0.00         5
           3       0.40      0.29      0.33         7
           4       0.00      0.00      0.00         3

    accuracy                           0.63        60
   macro avg       0.27      0.27      0.26        60
weighted avg       0.52      0.63      0.57        60
```

```
Kernel: rbf
Accuracy: 0.6666666666666666
Confusion Matrix:
[[35  0  1  0  0]
 [ 5  1  1  2  0]
 [ 1  1  2  1  0]
 [ 2  1  2  2  0]
 [ 2  0  0  1  0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.97      0.86        36
           1       0.33      0.11      0.17         9
           2       0.33      0.40      0.36         5
           3       0.33      0.29      0.31         7
           4       0.00      0.00      0.00         3

    accuracy                           0.67        60
   macro avg       0.36      0.35      0.34        60
weighted avg       0.58      0.67      0.61        60
```

```
Kernel: sigmoid
Accuracy: 0.6333333333333333
Confusion Matrix:
[[32  4  0  0  0]
 [ 4  3  2  0  0]
 [ 0  3  2  0  0]
 [ 3  1  2  1  0]
 [ 1  1  1  0  0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.89      0.84        36
           1       0.25      0.33      0.29         9
           2       0.29      0.40      0.33         5
           3       1.00      0.14      0.25         7
           4       0.00      0.00      0.00         3

    accuracy                           0.63        60
   macro avg       0.47      0.35      0.34        60
weighted avg       0.66      0.63      0.61        60
```