Tasks

- linear kernel SVC
- non-linear kernel SVC
- linear SVC with OvR (One-vs-Rest)

1.Import libraries

```
# Import necessary libraries
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
```

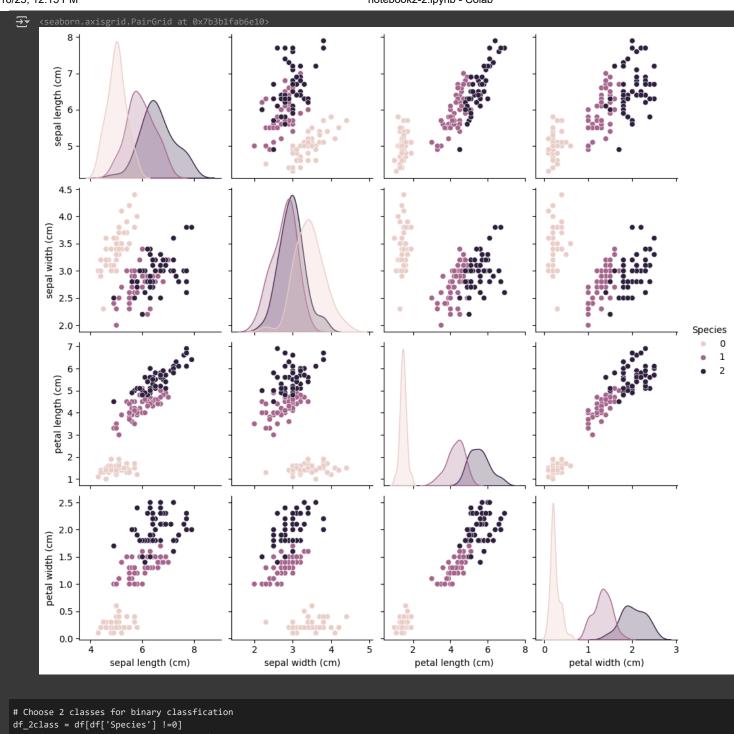
2.Load dataset

```
# Load the Iris dataset
iris = load_iris()
X = iris.data # Features
y = iris.target # Labels
# Display the first 5 rows of the dataset
df = pd.DataFrame(X, columns=iris.feature_names)
df['Species'] = y
print("First 5 rows of the Iris dataset:")
print(df.head())
First 5 rows of the Iris dataset:
        sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)
                                                                           0.2
                     5.1
                     4.9
                                       3.0
                                                         1.4
                                                                           0.2
                     4.7
                                                         1.3
                                                                           0.2
                                                                           0.2
                     5.0
                                       3.6
                                                          1.4
                                                                           0.2
        Species
```

df['Species'].value_counts()

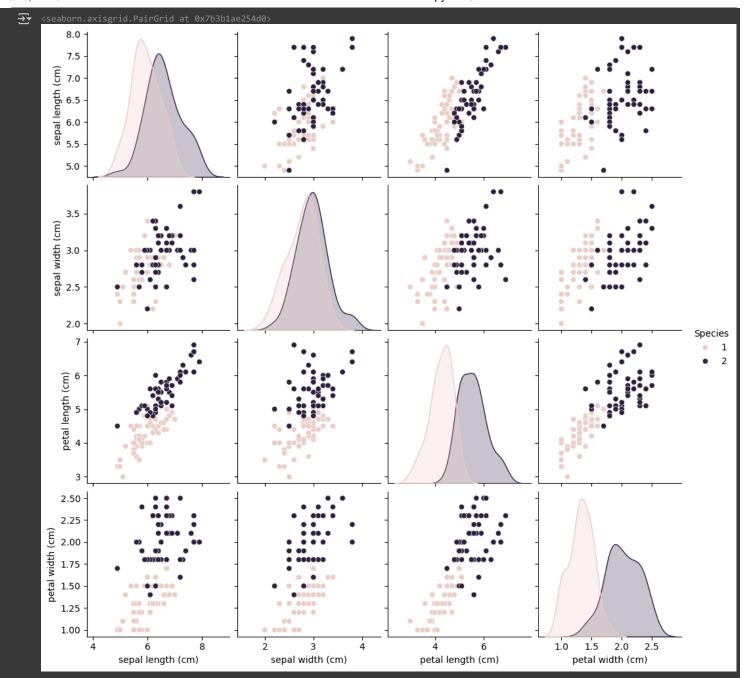


sns.pairplot(data = df, hue = 'Species')



```
# Choose 2 classes for binary classfication
df_2class = df[df['Species'] !=0]
X = df_2class.drop('Species', axis = 1)
y = df_2class['Species']

sns.pairplot(data = df_2class, hue = 'Species')
```



3. Preprocess dataset

 $\label{lem:https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html $$ $$ $$ https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html $$ $$ $$ $$ $$ $$$

```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Standardize the features (important for SVM and Logistic Regression)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

4.SVM for Classification (SVC)

```
# Train and evaluate SVM
print("\nSupport Vector Machine (SVM):")
svm = SVC(kernel='linear', random_state=42) # Use a linear kernel for simplicity
svm.fit(X_train, y_train)
# Predict on the test set
y_pred_svm = svm.predict(X_test)
# Evaluate accuracy
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print(f"Accuracy of SVM: {accuracy_svm:.2f}")
# Display SVM parameters
print("\nSVM Parameters:")
print(f"Support Vectors: {svm.support_vectors_.shape}")
print(f"Number of Support Vectors: {len(svm.support_)}")
₹
     Support Vector Machine (SVM):
     Accuracy of SVM: 0.90
     SVM Parameters:
     Support Vectors: (9, 4)
     Number of Support Vectors: 9
# Classification report
print("\nClassification Report for SVM:")
print(classification_report(y_test, y_pred_svm, target_names=iris.target_names[1:3]))
₹
     Classification Report for SVM:
                  precision recall f1-score support
      versicolor
                       1.00
                               0.82
                                           0.90
       virginica
                       0.81
                                 1.00
                                           0.90
                                           0.90
                                                       30
        accuracy
                       0.91
                                 0.91
                                           0.90
                                                       30
        macro avg
     weighted avg
                       0.92
                                 0.90
                                           0.90
                                                       30
  5.Non-linear kernel for SVM
Use a non-linear kernel (e.g. rbf)
# Train SVM with RBF kernel
print("\nTraining SVM with RBF kernel...")
svm_rbf = SVC(kernel='rbf', gamma='scale', C=1.0, random_state=42) # RBF kernel
svm_rbf.fit(X_train, y_train)
# Predict on the test set
y_pred = svm_rbf.predict(X_test)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy of SVM with RBF kernel: {accuracy:.2f}")
# Classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=iris.target_names[1:3]))
₹
     Training SVM with RBF kernel...
     Accuracy of SVM with RBF kernel: 0.87
     Classification Report:
                               recall f1-score support
                  precision
       versicolor
                       0.84
                                 0.94
                                           0.89
       virginica
```

0.83

0.77

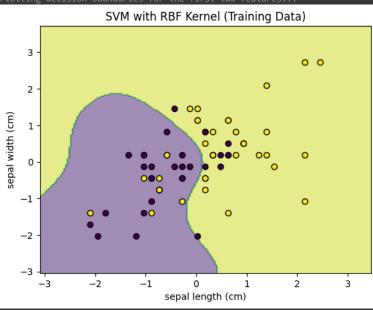
0.91

```
macro avg
                         0.88
                                    0.86
                                              0.86
                                                           30
                         0.87
                                    0.87
     weighted avg
                                              0.86
# Visualize decision boundaries (for 2D visualization)
from sklearn.inspection import DecisionBoundaryDisplay
def plot_decision_boundaries(X, y, model, title):
    feature_1, feature_2 = 0, 1 # Use the first two features for visualization
    X_2d = X[:, [feature_1, feature_2]]
    model.fit(X_2d, y) # Retrain the model on the 2D subset
    disp = DecisionBoundaryDisplay.from_estimator(
        model, X_2d, response_method="predict",
        xlabel=iris.feature_names[feature_1], ylabel=iris.feature_names[feature_2],
        alpha=0.5, grid_resolution=200
    \label{eq:disp.ax_scatter} disp.ax\_.scatter(X\_2d[:, 0], X\_2d[:, 1], c=y, edgecolor="k")
    plt.title(title)
    plt.show()
```

Plot decision boundaries for the first two features print("\nPlotting decision boundaries for the first two features...") plot_decision_boundaries(X_train, y_train, svm_rbf, "SVM_with RBF Kernel (Training Data)")

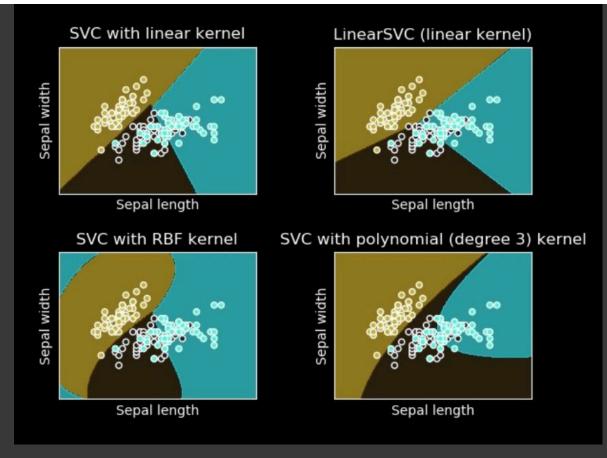


Plotting decision boundaries for the first two features...



Your work

Use SVM algorithm with linear and non-linear kernels (poly, rbf, sigmoid) for all the 3 classes in Iris dataset. Plot the data pionts and decision boundaries for each kernel. Take the sepal length as X-axis and the sepal width as y-axis.



Complete the remaining steps and send the notebook to zwu009@citymail.cuny.edu by 5:00 pm Feb 13, 2025.

```
import matplotlib.pyplot as plt
from sklearn import datasets, svm
from sklearn.inspection import DecisionBoundaryDisplay
iris = load_iris()
X = iris.data[:, :2]
y = iris.target
models = (
    svm.SVC(kernel='linear', random_state=42),
    svm.SVC(kernel="poly", degree=3, gamma="auto", C=1.0),
    svm.SVC(kernel='rbf', gamma='scale', C=1.0, random_state=42),
    svm.SVC(kernel="sigmoid", gamma='scale', coef0=0),
models = (clf.fit(X, y) for clf in models)
titles = (
    "SVC with linear kernel",
    "SVC with polynomial (degree 3) kernel",
    "SVC with RBF kernel",
    "SVC with sigmoid kernel",
fig, sub = plt.subplots(2, 2)
plt.subplots_adjust(wspace=0.5, hspace=0.5)
X0, X1 = X[:, 0], X[:, 1]
for clf, title, ax in zip(models, titles, sub.flatten()):
    disp = DecisionBoundaryDisplay.from_estimator(
        response_method="predict",
        cmap=plt.cm.YlGnBu,
        alpha=0.8,
        ax=ax,
        xlabel=iris.feature_names[0],
        ylabel=iris.feature_names[1],
```

