جامعة الملك سعود
King Saud University

Machine Learning HW4

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DATA SET DESCRIPTION:

The Iris dataset is a foundational dataset in machine learning and statistics, comprising measurements of 150 iris flowers, equally divided among three species: setosa, versicolor, and virginica. For each flower, four features are recorded: sepal length, sepal width, petal length, and petal width, all in centimeters. The dataset's primary purpose is to classify iris flowers into their respective species based on these features.

Clear screenshots of the code, evaluations and outputs:

Import Necessary Libraries

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

Part1: Dataset Loading, Exploration & Preprocessing

```
# 1. Load the Iris dataset.
iris = load_iris()
iris_df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
iris_df['target'] = iris.target

# Display the first 10 rows.
print(iris_df.head(10))

# 2. Check for missing values.
print(iris_df.isnull().sum())
# imputation for numerical features:
for column in iris_df.select_dtypes(include=np.number).columns:
    iris_df[column] = iris_df[column].fillna(iris_df[column].mean())

# imputation for categorical features:
for column in iris_df.select_dtypes(include=['object']).columns:
    iris_df[column] = iris_df[column].fillna(iris_df[column].mode()[0])
```

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```
# 3. Select target as the target variable (y) and all other columns as the input features (X).
X = iris_df.drop('target', axis=1)
y = iris_df['target']

# 4. Scale the input features using StandardScaler class from sklearn library.
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 5. Split the data into training and testing sets.
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2
5                5.4               3.9                1.7               0.4
6                4.6               3.4                1.4               0.3
7                5.0               3.4                1.5               0.2
8                4.4               2.9                1.4               0.2
9                4.9               3.1                1.5               0.1

   target
0       0
1       0
2       0
3       0
4       0
5       0
6       0
7       0
8       0
9       0
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
target               0
dtype: int64
```

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Part2: Linear Kernel SVM

```
# 1. Implement a Support Vector Machine classifier using the linear kernel.
svm_classifier = SVC(kernel='linear')


# 2. Fit the model to the training data.
svm_classifier.fit(X_train, y_train)


# 3. Predict the target values for the test set.
y_pred = svm_classifier.predict(X_test)


# 4. Calculate and display the accuracy and confusion matrix for the model.
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)


# 5. Visualize the confusion matrix.
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Purples',
            xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Linear Kernel SVM')
plt.show()
```

```
Accuracy: 0.9666666666666667
Confusion Matrix:
```

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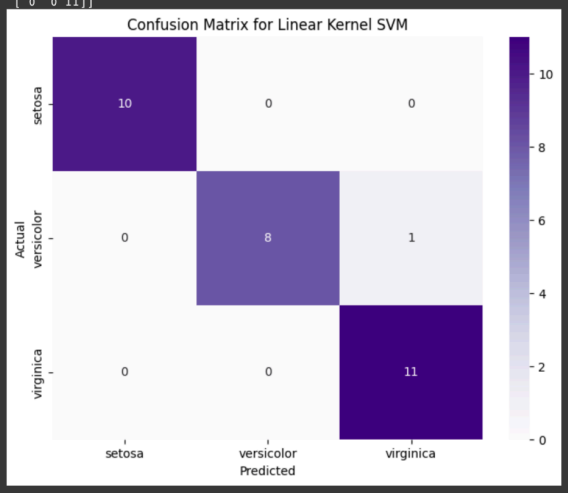
```
Accuracy: 0.9666666666666667
Confusion Matrix:
[[10  0  0]
 [ 0  8  1]
 [ 0  0 11]]
```



Part3: RBF Kernel SVM

Part3: RBF Kernel SVM

```python
# 1. Implement an SVM with the radial basis function (RBF) kernel.
svm_rbf_classifier = SVC(kernel='rbf')

# 2. Fit the model to the training data.
svm_rbf_classifier.fit(X_train, y_train)

# 3. Predict the target values for the test set.
y_pred_rbf = svm_rbf_classifier.predict(X_test)

# 4. Calculate and display the accuracy and confusion matrix for the model.
accuracy_rbf = accuracy_score(y_test, y_pred_rbf)
print(f"Accuracy (RBF Kernel): {accuracy_rbf}")
conf_matrix_rbf = confusion_matrix(y_test, y_pred_rbf)
print("Confusion Matrix (RBF Kernel):")
print(conf_matrix_rbf)

# 5. Visualize the confusion matrix for RBF kernel.
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_rbf, annot=True, fmt='d', cmap='Greens',
            xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for RBF Kernel SVM')
plt.show()


# 6. Compare the performance of the linear and RBF kernels.
print("Classification Report (Linear Kernel):")
print(classification_report(y_test, y_pred))

print("Classification Report (RBF Kernel):")
print(classification_report(y_test, y_pred_rbf))

print(f"Accuracy (Linear Kernel): {accuracy}")
```

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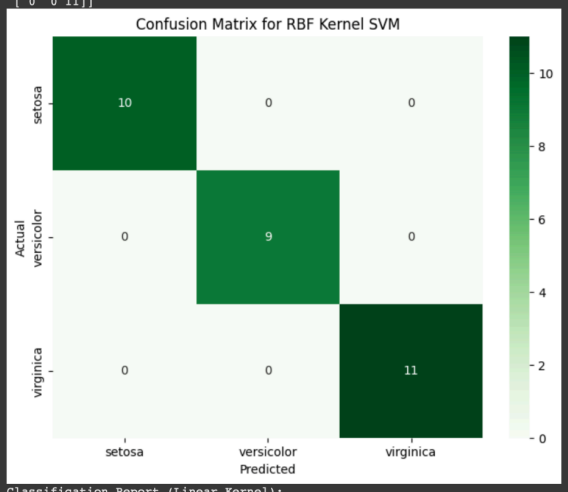
```python
print(f"Accuracy (Linear Kernel): {accuracy}")
print(f"Accuracy (RBF Kernel): {accuracy_rbf}")

if accuracy > accuracy_rbf:
  print("Linear kernel performs better than RBF kernel in this case.")
else:
  print("RBF kernel performs better than the Linear kernel in this case.")
```

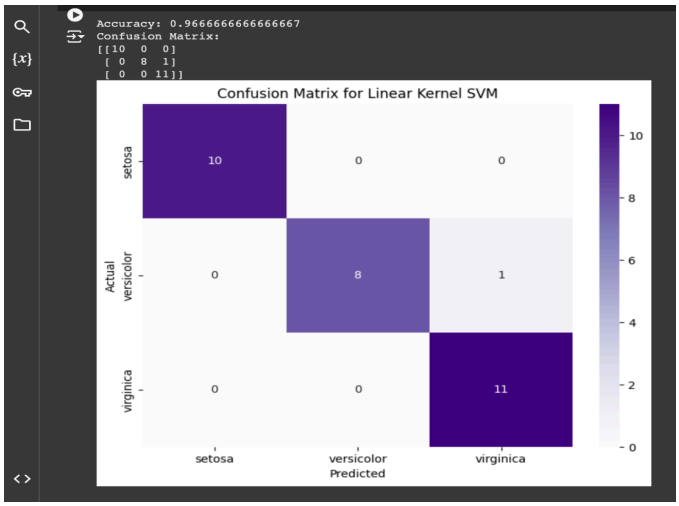
```
Accuracy (RBF Kernel): 1.0
Confusion Matrix (RBF Kernel):
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```



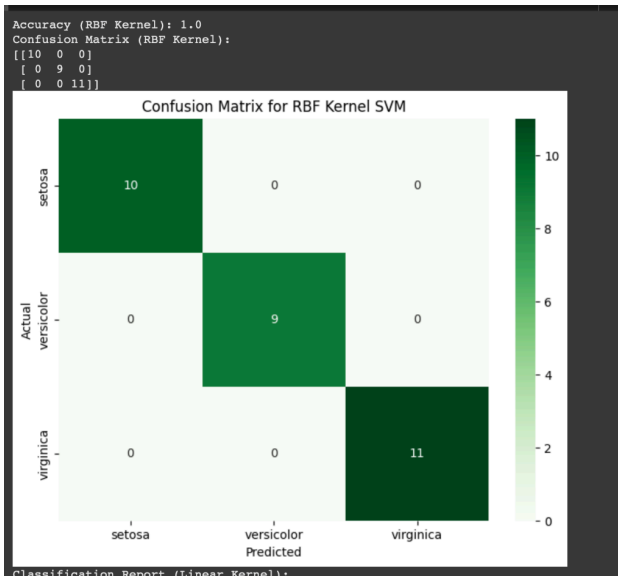

```
Classification Report (Linear Kernel):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      0.89      0.94         9
           2       0.92      1.00      0.96        11

    accuracy                           0.97        30
   macro avg       0.97      0.96      0.97        30
weighted avg       0.97      0.97      0.97        30

Classification Report (RBF Kernel):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         9
           2       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Accuracy (Linear Kernel): 0.9666666666666667
Accuracy (RBF Kernel): 1.0
RBF kernel performs better than the Linear kernel in this case.
```

A table displaying printed results (e.g., model parameters and/or predicted values):

Results of linear kernel SVM:



Results of RBF kernel SVM:



Reported results for both :

```
Classification Report (Linear Kernel):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      0.89      0.94         9
           2       0.92      1.00      0.96        11

    accuracy                           0.97        30
   macro avg       0.97      0.96      0.97        30
weighted avg       0.97      0.97      0.97        30

Classification Report (RBF Kernel):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         9
           2       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Accuracy (Linear Kernel): 0.9666666666666667
Accuracy (RBF Kernel): 1.0
RBF kernel performs better than the Linear kernel in this case.
```

1.Compare the performance of the linear and RBF kernels. Discuss which kernel performs better and why, with reference to the data:

While both kernels performed very well on the test set , the **RBF kernel performed better** than the linear kernel, achieving **100% accuracy** compared to 96.67% for the linear kernel.

Linear Kernel Confusion Matrix:

- The linear kernel SVM model achieved an accuracy of 0.967, indicating that it correctly classified 29 out of 30 instances in the test set.
- There was one misclassification, where an instance of 'virginica' was incorrectly classified as 'versicolor'.

RBF Kernel Confusion Matrix:

- The RBF kernel SVM model achieved an accuracy of 1.0, indicating that it correctly classified all 30 instances in the test set. The model perfectly classified 'setosa', 'versicolor', and 'virginica' instances.

Comparison:

- The linear kernel SVM had a minor misclassification, highlighting a potential limitation in its ability to capture complex decision boundaries compared to the RBF kernel.
- Both models showed good performance in classifying 'setosa' and 'versicolor' instances, suggesting that these classes are **relatively well-separated** in the feature space.

Reasons for RBF's better Performance:

Although the Iris dataset is mostly linearly separable, there might be subtle non-linear relationships between features that the RBF kernel is better able to capture . These subtle relationships could account for the misclassifications made by the linear kernel.