Training a Support Vector Machine (SVM) Model and Evaluating Its Performance

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Description

This lab guide demonstrates how to train a Support Vector Machine (SVM) model and evaluate its performance using popular evaluation metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC curve. SVM is a widely used supervised learning algorithm that works well for classification tasks.

Problem Statement

The objective of this lab is to guide you through the steps needed to train and evaluate an SVM model using Scikit-learn. By the end of this guide, you will be able to train an SVM model on a dataset, make predictions, and assess its performance.

Prerequisites

Completion of all previous lab guides (up to Lab Guide-08) is required before proceeding with Lab Guide-09.

Software Required

- **Python**: Python 3.11.9
- **Visual Studio Code (VSCode)**: A lightweight code editor that provides powerful features for Python development, including extensions for linting, debugging, and version control.
- **Libraries**: `NumPy`, `Pandas`, `Matplotlib`, `Seaborn`, `Scikit-learn`

Hardware Requirements

- Minimum 4GB RAM.
- At least 1GB of free disk space.
- A GPU (optional, but recommended for faster training).

Setup Instructions

Step 1: Install Python and Required Libraries

Install Python:

- Download and install Python 3.11.9 from the **official Python website**.

Install Visual Studio Code (VSCode):

- Download and install VSCode from the **official Visual Studio Code website**.

Install Required Libraries:

- Open a terminal and run the following command to install Scikit-learn and other libraries:

```
pip install numpy pandas matplotlib seaborn scikit-learn
```

```
PS C:\Users\Administrator\Desktop\AIML> pip install numpy pandas matplotlib seaborn scikit-learn

Collecting numpy
  Using cached numpy-2.1.2-cp311-cp311-win_amd64.whl.metadata (59 kB)
Collecting pandas
  Using cached pandas-2.2.3-cp311-cp311-win_amd64.whl.metadata (19 kB)
Collecting matplotlib
  Downloading matplotlib-3.9.2-cp311-cp311-win_amd64.whl.metadata (11 kB)
Collecting seaborn
  Downloading seaborn-0.13.2-py3-none-any.whl.metadata (5.4 kB)
Collecting scikit-learn
  Using cached scikit_learn-1.5.2-cp311-cp311-win_amd64.whl.metadata (13 kB)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\program files\python311\lib\site-pac
kages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\program files\python311\lib\site-packages (fro
m pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in c:\program files\python311\lib\site-packages (f
rom pandas) (2024.2)
Collecting contourpy>=1.0.1 (from matplotlib)
  Downloading contourpy-1.3.0-cp311-cp311-win_amd64.whl.metadata (5.4 kB)
Collecting cycler>=0.10 (from matplotlib)
  Using cached cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
Collecting fonttools>=4.22.0 (from matplotlib)
  Downloading fonttools-4.54.1-cp311-cp311-win_amd64.whl.metadata (167 kB)
     ---------------------------------------- 167.0/167.0 kB 1.7 MB/s eta 0:00:00
Collecting kiwisolver>=1.3.1 (from matplotlib)
  Downloading kiwisolver-1.4.7-cp311-cp311-win_amd64.whl.metadata (6.4 kB)
Collecting packaging>=20.0 (from matplotlib)
  Using cached packaging-24.1-py3-none-any.whl.metadata (3.2 kB)
Collecting pillow>=8 (from matplotlib)
  Downloading pillow-11.0.0-cp311-cp311-win_amd64.whl.metadata (9.3 kB)
Collecting pyparsing>=2.3.1 (from matplotlib)
  Using cached pyparsing-3.2.0-py3-none-any.whl.metadata (5.0 kB)
Requirement already satisfied: scipy>=1.6.0 in c:\program files\python311\lib\site-packages (fro
```

Support Vector Machine (SVM) Overview

What is SVM?

SVM is a powerful supervised learning algorithm used for classification tasks. It works by finding the optimal hyperplane that best separates the classes in a dataset. SVM can handle both linear and non-linear classification tasks.

Applications of SVM

- Text Classification
- Image Recognition
- Bioinformatics
- Handwriting Recognition

Training an SVM Model

- **Create a new python file**
  - Create a Python file named `SVM.py` and add the following code.

Step 1: Load and Preprocess the Dataset

For this example, we will use the **Iris dataset**, which is readily available in Scikit-learn.

```
from sklearn import datasets
from sklearn.preprocessing import StandardScaler
```

```
# Load the Iris dataset and standardize its features.
iris = datasets.load_iris()
X = iris.data  # Features
y = iris.target  # Target labels

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Step 2: Split the Dataset into Training and Test Sets

We will split the dataset into training (80%) and test (20%) sets.

```
from sklearn.model_selection import train_test_split

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

Step 3: Train the SVM Model

Now, we will train the SVM model using a linear kernel.

```
from sklearn.svm import SVC

# Initialize and train the SVM model with a linear kernel.
svm_model = SVC(kernel='linear', probability=True)
svm_model.fit(X_train, y_train)
print(svm_model)
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python SVM.py
```

```
PS C:\Users\Administrator\Desktop\AIML> python SVM.py
```

Output

```
PS C:\Users\Administrator\Desktop\AIML> python SVM.py
SVC(kernel='linear', probability=True)
```

Evaluating Model Performance

Accuracy, Precision, Recall, and F1-score

We will evaluate the model performance using key classification metrics.

```
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score

# Make predictions
y_pred = svm_model.predict(X_test)

# Calculate and print accuracy, precision, recall, and F1-score.
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='macro')
recall = recall_score(y_test, y_pred, average='macro')
f1 = f1_score(y_test, y_pred, average='macro')

print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1 Score: {f1:.2f}')
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python SVM.py
```

Output

```
PS C:\Users\Administrator\Desktop\AIML> python SVM.py
Accuracy: 0.97
Precision: 0.97
Recall: 0.96
F1 Score: 0.97
```

Confusion Matrix

A confusion matrix provides insights into how well the model is performing in terms of correct and incorrect predictions.

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Generate and plot the confusion matrix.
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 4))
```

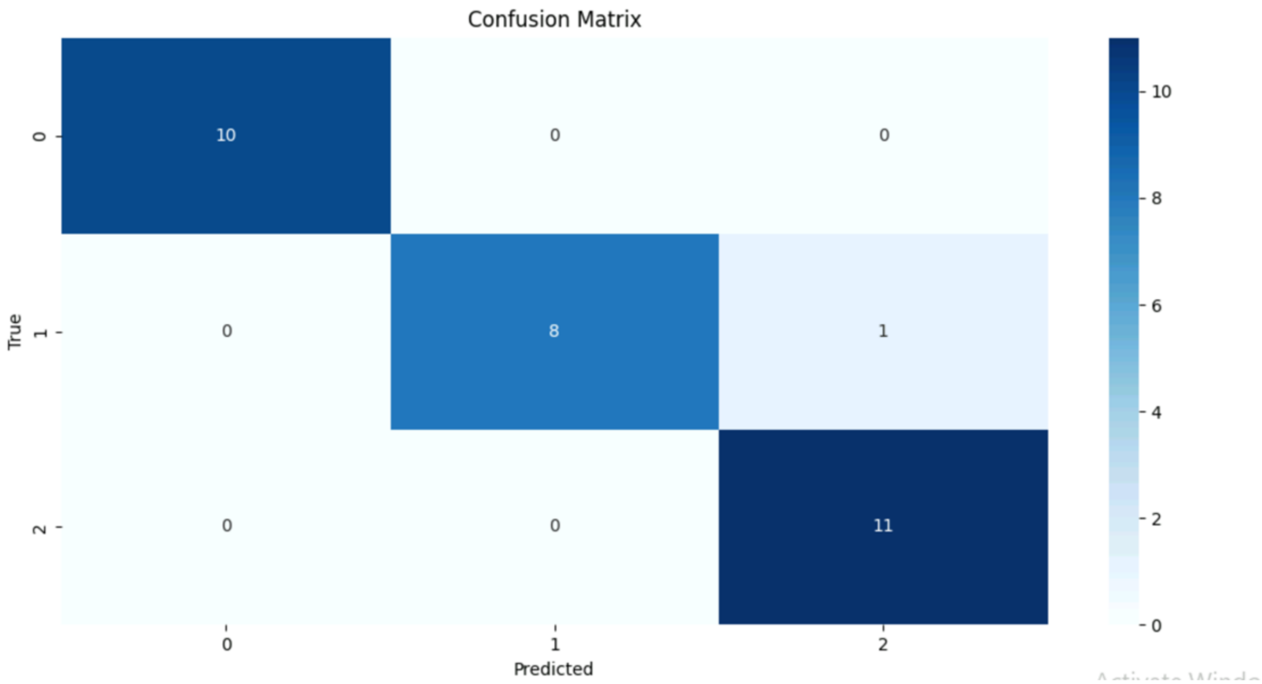
```
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python SVM.py
```

Output



ROC Curve and AUC

Although ROC curves are typically used for binary classification, we can apply it to one of the classes in the Iris dataset to visualize the performance.

```
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
import numpy as np

# Binarize the output (for class 1 vs rest binary classification)
y_test_binarized = label_binarize(y_test, classes=[0, 1, 2])
n_classes = y_test_binarized.shape[1]

# Decision function gives decision scores for each class
```

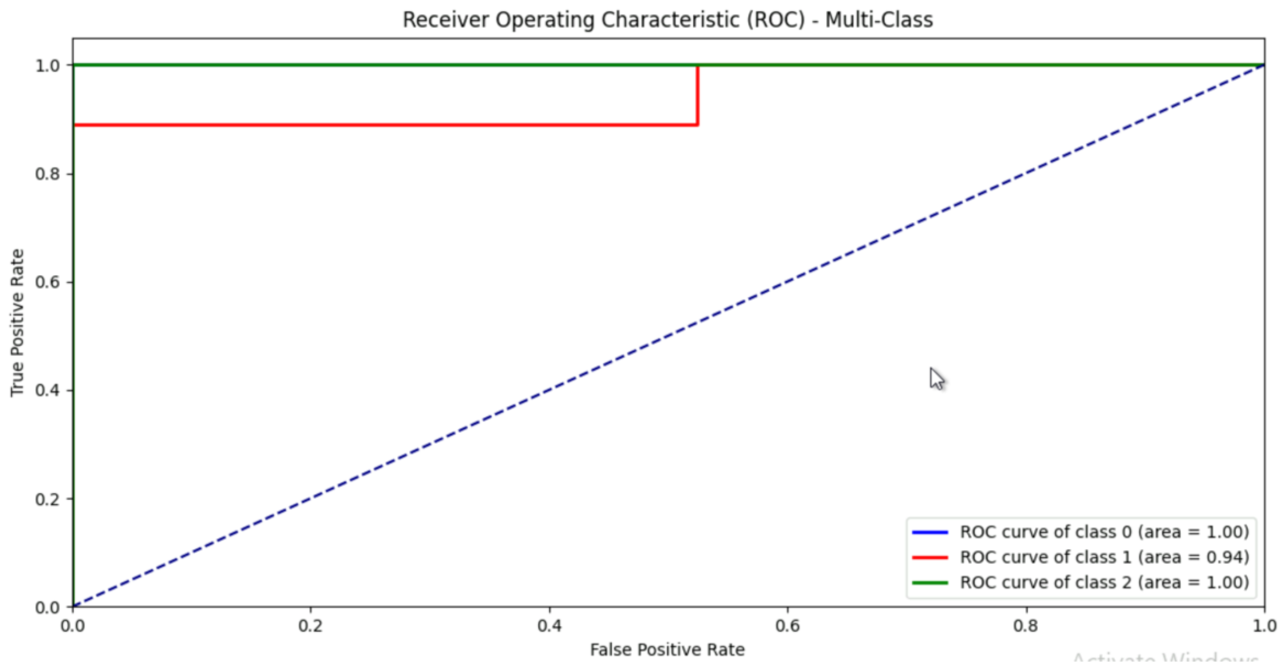
```
y_score = svm_model.decision_function(X_test)

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarized[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curve for each class
plt.figure(figsize=(8, 6))
colors = ['blue', 'red', 'green']
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f'ROC curve of class {i} (area = {roc_auc[i]:0.2f})')

plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.title('Receiver Operating Characteristic (ROC) - Multi-Class')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.show()
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python SVM.py
```

Output



References

- [Scikit-learn Documentation]
- [Understanding SVMs]