jupyter Lab7_24_10_17 Last Checkpoint: 25 minutes ago

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Markdown JupyterLab Python 3 (ipykernel)

CISC3024 Lab 7

Create Synthetic Samples

Create a 3-class toy dataset, each sampled from a 2D Gaussian distribution.

[12]:
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (confusion_matrix, accuracy_score,
                             precision_score, recall_score,
                             f1_score, roc_auc_score,
                             roc_curve, precision_recall_curve,
                             average_precision_score)
from sklearn.preprocessing import label_binarize
from sklearn.metrics import ConfusionMatrixDisplay

# Random Seed for reproductability
np.random.seed(0)

# Hyper Parameters
n_train = 50
n_test = 30
n_classes = 3

# Means for gauss dists of each class
mean_0 = [0, 0]
mean_1 = [1, 1] # Close to class 0
mean_2 = [3, 3] # Far from class 0 and 1

cov = [[1, 0], [0, 1]] # Common, Identity covariate matrix (Euclidean Dist)

# Generate Training Data (Pseudo)
X_train_0 = np.random.multivariate_normal(mean_0, cov, n_train)
X_train_1 = np.random.multivariate_normal(mean_1, cov, n_train)
X_train_2 = np.random.multivariate_normal(mean_2, cov, n_train)

y_train_0 = np.zeros(n_train)
y_train_1 = np.ones(n_train)
y_train_2 = np.full(n_train, 2)

X_train = np.vstack([X_train_0, X_train_1, X_train_2])
y_train = np.concatenate([y_train_0, y_train_1, y_train_2])

# Generate Testing Data
X_test_0 = np.random.multivariate_normal(mean_0, cov, n_test)
X_test_1 = np.random.multivariate_normal(mean_1, cov, n_test)
X_test_2 = np.random.multivariate_normal(mean_2, cov, n_test)

y_test_0 = np.zeros(n_test)
y_test_1 = np.ones(n_test)
y_test_2 = np.full(n_test, 2)

X_test = np.vstack([X_test_0, X_test_1, X_test_2])
y_test = np.concatenate([y_test_0, y_test_1, y_test_2])
```

Train a Logistic Regression Model

[13]:
```python
# Initialize classifier
clf = LogisticRegression(multi_class='multinomial', solver='lbfgs')

# Train classifier
clf.fit(X_train, y_train)

# Predict
y_pred = clf.predict(X_test)

# Predict Probabilities
y_score = clf.predict_proba(X_test)
```

Accuracy, Precision, Recall and F_1 score

[19]:
```python
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

precision = precision_score(y_test, y_pred, average=None, labels=[0,1,2])
recall = recall_score(y_test, y_pred, average=None, labels=[0,1,2])
f1 = f1_score(y_test, y_pred, average=None, labels=[0,1,2])

for i in range(n_classes):
    print(f"Class {i}: Prec:{precision[i]:.2f}, Rec:{recall[i]:.2f}, F1:{f1[i]:.2f}")
```

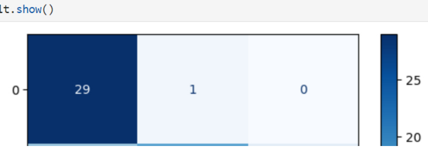
```
Accuracy: 0.79
Class 0: Prec:0.72, Rec:0.97, F1:0.83
Class 1: Prec:0.76, Rec:0.53, F1:0.63
Class 2: Prec:0.90, Rec:0.87, F1:0.88
```

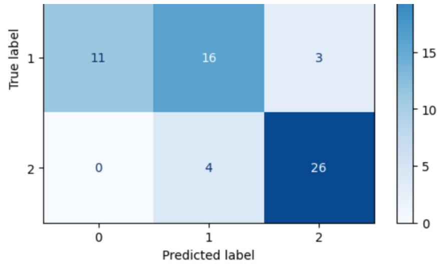
Plot Confusion Matrix

[20]:
```python
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print(f"Confusion Matirx:\n{cm}")
```

```
Confusion Matirx:
[[29  1  0]
 [11 16  3]
 [ 0  4 26]]
```

[21]:
```python
# Plot Confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[0,1,2])
disp.plot(cmap=plt.cm.Blues)
plt.show()
```





Plot ROC curve and compute ROC AUC

To compute ROC (Receiver Operating Characteristic), we need to first specify positive class using `label_binarize`.

[25]:
```
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])
y_test_bin[:5]
```

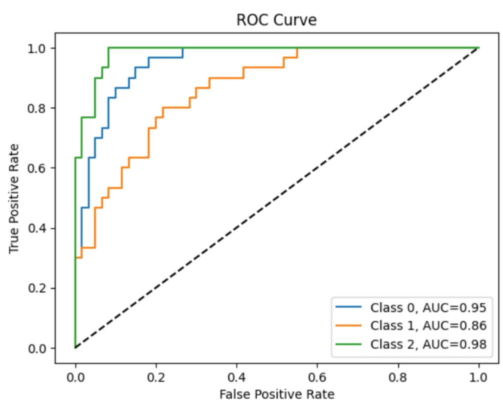
[25]:
```
array([[1, 0, 0],
       [1, 0, 0],
       [1, 0, 0],
       [1, 0, 0],
       [1, 0, 0]])
```

[27]:
```
# Compute ROC AUC for each class
roc_auc = dict()
for i in range(n_classes):
    roc_auc[i] = roc_auc_score(y_test_bin[:,i], y_score[:, i])
    print(f"Class {i}: ROC AUC: {roc_auc[i]:.2f}")
```

```
Class 0: ROC AUC: 0.95
Class 1: ROC AUC: 0.86
Class 2: ROC AUC: 0.98
```

[28]:
```
# Plot ROC Curves
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    plt.plot(fpr, tpr, label=f"Class {i}, AUC={roc_auc[i]:.2f}")

plt.plot([0, 1], [0, 1], 'k--') # Diagonal Line
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='best')
plt.show()
```

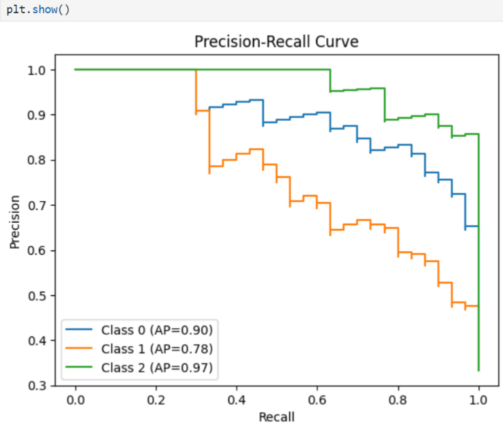


Plot Precision-Recall Curve

[32]:
```
for i in range(n_classes):
    precision_i, recall_i, _ = precision_recall_curve(y_test_bin[:, i], y_score[:, i])
    average_precision = average_precision_score(y_test_bin[:, i], y_score[:, i])
    plt.step(recall_i, precision_i, where="post", label=f"Class {i} (AP={average_precision:.2f})")

plt.xlabel("Recall")
plt.ylabel("Precision")

plt.title('Precision-Recall Curve')
plt.legend(loc='best')
plt.show()
```



Plot Decision Boundary

[34]:
```
x_min, x_max = X_train[:, 0].min() - 1, X_train[:, 0].max() + 1
```

```
y_min, y_max = X_train[:, 1].min() - 1, X_train[:, 1].max() + 1

xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02), np.arange(y_min, y_max, 0.02))
Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

plt.figure()
plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.RdYlBu)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=20, edgecolor='k',
cmap=plt.cm.RdYlBu)
plt.title('Decision Boundary')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()
```