Artificial intelegence

ASSIGNMENT #3



Submitted by: Muhammad Umar

Reg no. : 712

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Submitted To: Mr. Zubair

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1. Accuracy Metrics Calculation:

```
import pandas as pd
from sklearn.model selection import train test split
from sklearn.linear model import LogisticRegression
from sklearn.metrics import accuracy score, precision score, recall score,
fl score
# Load dataset (replace 'your dataset.csv' with your actual file)
data = pd.read csv('your dataset.csv')
# Separate features (X) and target variable (y)
X = data.drop('target column', axis=1) # Replace 'target column' with your
target column name
y = data['target column']
# Train-test split (80% train, 20% test)
X train, X test, y train, y test = train test split(X, y, test size=0.2,
random state=42)
# Model training
model = LogisticRegression()
model.fit(X train, y train)
# Prediction
y_pred = model.predict(X_test)
# Metric calculation
accuracy = accuracy score(y test, y pred)
precision = precision score(y test, y pred, average='weighted')
recall = recall score(y test, y pred, average='weighted')
f1 = f1 score(y test, y pred, average='weighted')
# Print and interpret results
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1)
```

2. Confusion Matrix Interpretation:

```
# Generate confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Print and interpret
print("Confusion Matrix:\n", cm)
print("TP:", cm[0][0]) # True Positives
print("FP:", cm[0][1]) # False Positives
print("TN:", cm[1][1]) # True Negatives
print("FN:", cm[1][0]) # False Negatives
# Analyze the matrix to identify potential issues
# ... (Add your analysis here based on the confusion matrix values)
```

3. ROC/AUC Calculation:

```
from sklearn.metrics import roc curve, roc auc score
import matplotlib.pyplot as plt
# Get ROC curve data
fpr, tpr, = roc curve(y test, model.predict proba(X test)[:, 1])
# Plot ROC curve
plt.plot(fpr, tpr, label='ROC Curve (area = %0.2f)' % roc auc score(y test,
model.predict proba(X_test)[:, 1]))
plt.plot([0, \overline{1}], [0, \overline{1}], 'k--') # Plot perfect classification line
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
# Calculate AUC
auc = roc auc score(y test, model.predict proba(X test)[:, 1])
# Interpret results
print("AUC:", auc)
# ... (Explain the AUC value in the context of your model)
4. Cross-Validation Reporting:
from sklearn.model selection import KFold
# K-Fold cross-validation
kfold = KFold(n splits=5, shuffle=True, random state=42)
cv scores = []
# Iterate through folds
for train index, test index in kfold.split(X):
    X train, X test = X.iloc[train index], X.iloc[test index]
    y train, y test = y.iloc[train index], y.iloc[test index]
    # Train model on current fold
    model.fit(X train, y train)
    # Evaluate on hold-out set
    y pred = model.predict(X test)
    accuracy = accuracy_score(y_test, y_pred)
    cv scores.append(accuracy)
# Calculate mean and standard deviation
mean accuracy = np.mean(cv scores)
std dev = np.std(cv
```

Sources

- 1. <u>medium.com/mlearning-ai/how-to-manage-an-end-to-end-machine-learning-project-with-mlflow-part-1-ff2e70d81789</u>
- 2. github.com/AlbertoBarbado/mbti-text-classifier
- 3. stats.stackexchange.com/questions/490048