PRACTICAL TECHNICAL ASSESMENT

MUHAMMED HIDASH
ADIT22AP02601

Activity

1. Load the dataset and apply necessary preprocessing steps.
2. Perform exploratory data analysis (EDA) to understand the dataset.
3. Implement classification models and evaluate them using a confusion matrix and
cross-validation.
4. Implement regression models and evaluate them using R-squared, MSE, and crossvalidation.
5. Visualize the confusion matrix for at least one classification model.
6. Report and interpret the results of each model.

Requirements

- PC / Laptop
- VS code with python installed
- Dataset (data.csv)

Procedure

Data Preprocessing

- Load the dataset using pd.read_csv('data.csv')

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# Load the dataset
data = pd.read_csv('data.csv')

# Display the first few rows of the dataset
print(data.head())
```

✓ 0.0s

- Handle missing values.

```
# Check for missing values
print(data.isnull().sum())

# Drop rows with missing values
data = data.dropna()
```

✓ 0.0s

- Encode categorical variables.

```
# Encode categorical variables
label_encoder = LabelEncoder()
df['target'] = label_encoder.fit_transform(df['target'])
```

✓ 0.0s

- Scale/normalize the features.

```
# Scale/normalize the features
scaler = StandardScaler()
df[['feature1', 'feature2', 'feature3', 'feature4']] = scaler.fit_transform(df[['feature1', 'feature2', 'feature3', 'feature4']])
```

✓ 0.0s

Result:

	feature1	feature2	feature3	feature4	target
0	5.1	3.5	1.4	0.2	Class1
1	4.9	3.0	1.4	0.2	Class1
2	4.7	3.2	1.3	0.2	Class1
3	4.6	3.1	1.5	0.2	Class1
4	5.0	3.6	1.4	0.2	Class1

```
feature1    0
feature2    0
feature3    0
feature4    0
target      0
dtype: int64
```

Exploratory Data Analysis (EDA)

- Provide statistical summaries of the dataset.

```python
# Exploratory Data Analysis (EDA)
import matplotlib.pyplot as plt
import seaborn as sns


# Statistical summaries
print(df.describe())
```

✓ 0.0s

- Visualize the data distribution and relationships between features using plots.

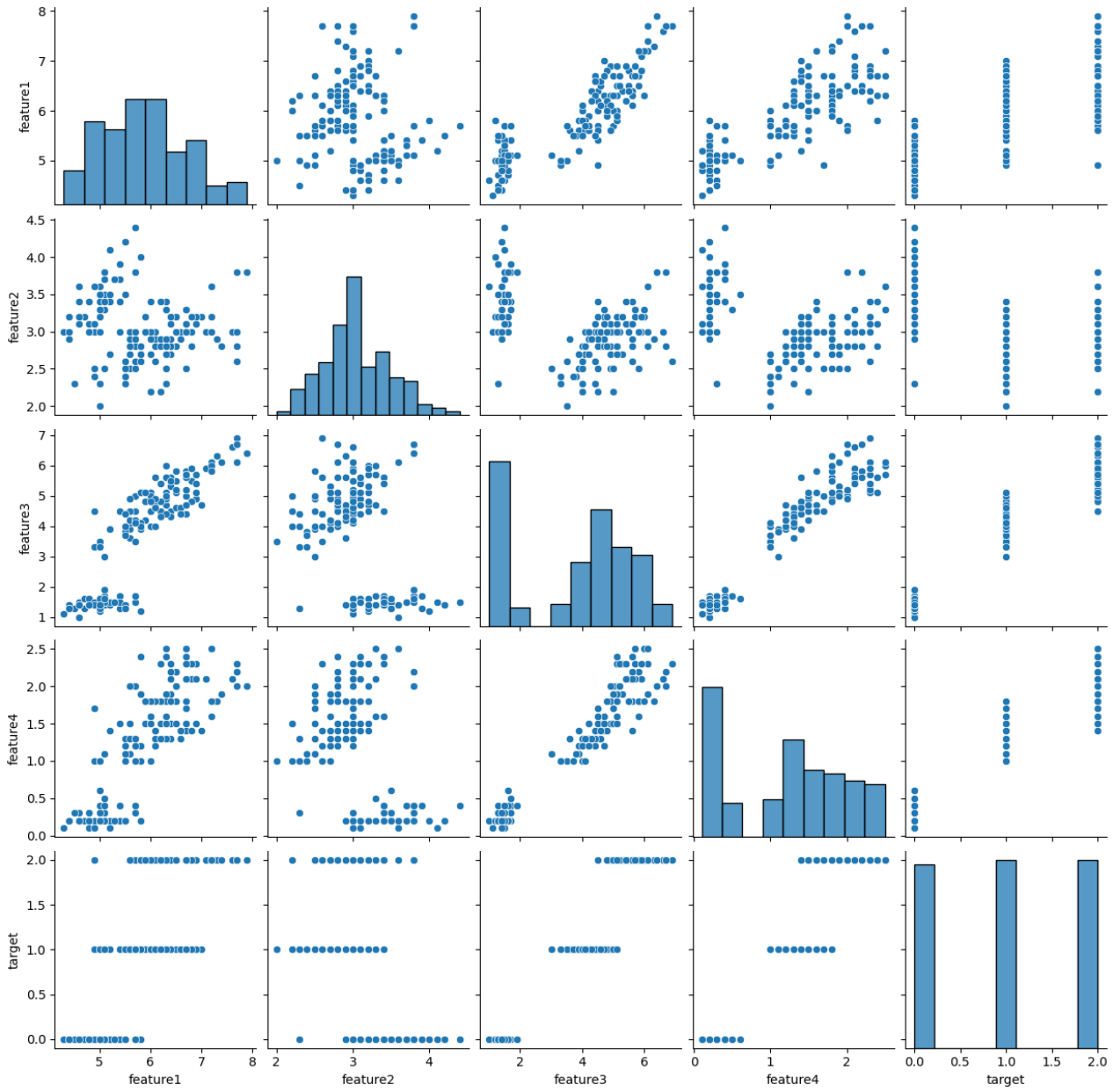
```python
# Visualize the data distribution and relationships
plt.figure(figsize=(1, 0.5))
sns.pairplot(df)
plt.show()
```

✓ 3.9s

Result:

	feature1	feature2	feature3	feature4	target
count	1.490000e+02	1.490000e+02	1.490000e+02	1.490000e+02	149.000000
mean	-1.430623e-16	-3.099683e-16	4.768743e-17	-1.430623e-16	1.006711
std	1.003373e+00	1.003373e+00	1.003373e+00	1.003373e+00	0.817847
min	-1.882359e+00	-2.425614e+00	-1.575313e+00	-1.456862e+00	0.000000
25%	-9.110290e-01	-5.863444e-01	-1.234147e+00	-1.193264e+00	0.000000
50%	-6.111554e-02	-1.265269e-01	3.579562e-01	1.247222e-01	1.000000
75%	6.673817e-01	5.631992e-01	7.559821e-01	7.837155e-01	2.000000
max	2.488625e+00	3.092195e+00	1.779477e+00	1.706306e+00	2.000000

+ Code + Markdown



Classification

- Apply Logistic Regression, Decision Tree, and Random Forest classifiers.
- Use a confusion matrix to evaluate the performance of each classifier.
- Perform cross-validation to assess the model stability.

```
# Classification
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score
```

```
# Split the dataset into features (X) and target (y)
X = df[['feature1', 'feature2', 'feature3', 'feature4']]
y = df['target']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Logistic Regression
lr = LogisticRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)

# Confusion Matrix for Logistic Regression
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)
print("Logistic Regression:")
print("Confusion Matrix:\n", conf_matrix_lr)

# Accuracy for Logistic Regression
print("Accuracy:", accuracy_score(y_test, y_pred_lr))

# Precision, Recall, F1 Score for Logistic Regression
average_method = 'weighted'  # or 'micro', 'macro', depending on your requirement

print("Precision:", precision_score(y_test, y_pred_lr, average=average_method))
print("Recall:", recall_score(y_test, y_pred_lr, average=average_method))
print("F1 Score:", f1_score(y_test, y_pred_lr, average=average_method))

# Decision Tree Classifier
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)
```

```
conf_matrix_dt = confusion_matrix(y_test, y_pred_dt)
print("\nDecision Tree Classifier:")
print("Confusion Matrix:\n", conf_matrix_dt)

# Accuracy for Decision Tree Classifier
print("Accuracy:", accuracy_score(y_test, y_pred_dt))

# Precision, Recall, F1 Score for Decision Tree Classifier
print("Precision:", precision_score(y_test, y_pred_dt, average=average_method))
print("Recall:", recall_score(y_test, y_pred_dt, average=average_method))
print("F1 Score:", f1_score(y_test, y_pred_dt, average=average_method))

# Random Forest Classifier
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)

# Confusion Matrix for Random Forest Classifier
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
print("\nRandom Forest Classifier:")
print("Confusion Matrix:\n", conf_matrix_rf)

# Accuracy for Random Forest Classifier
print("Accuracy:", accuracy_score(y_test, y_pred_rf))

# Precision, Recall, F1 Score for Random Forest Classifier
print("Precision:", precision_score(y_test, y_pred_rf, average=average_method))
print("Recall:", recall_score(y_test, y_pred_rf, average=average_method))
print("F1 Score:", f1_score(y_test, y_pred_rf, average=average_method))
```

Result:

```
Logistic Regression:
Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
Accuracy: 0.9
Precision: 0.9214285714285714
Recall: 0.9
F1 Score: 0.896

Decision Tree Classifier:
Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
Accuracy: 0.9
Precision: 0.9214285714285714
Recall: 0.9
F1 Score: 0.896

Random Forest Classifier:
Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
Accuracy: 0.9
Precision: 0.9214285714285714
Recall: 0.9
F1 Score: 0.896
```

Regression

- Apply Linear Regression and Decision Tree Regressor.
- Evaluate the models using R-squared and Mean Squared Error (MSE).
- Perform cross-validation to assess the model stability.

```python
# Regression
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import r2_score, mean_squared_error


# Linear Regression
lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)
r2_lr = r2_score(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
print("\nLinear Regression:")
print("R-squared:", r2_lr)
print("Mean Squared Error:", mse_lr)

# Decision Tree Regressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
y_pred_dtr = dtr.predict(X_test)
r2_dtr = r2_score(y_test, y_pred_dtr)
mse_dtr = mean_squared_error(y_test, y_pred_dtr)
print("\nDecision Tree Regressor:")
print("R-squared:", r2_dtr)
print("Mean Squared Error:", mse_dtr)
```

Result:

```
Linear Regression:
R-squared: 0.9165749856447737
Mean Squared Error: 0.0583048155882637

Decision Tree Regressor:
R-squared: 0.8569157392686804
Mean Squared Error: 0.1
```

Confusion Matrix

For classification tasks, plot the confusion matrix and compute the following metrics:

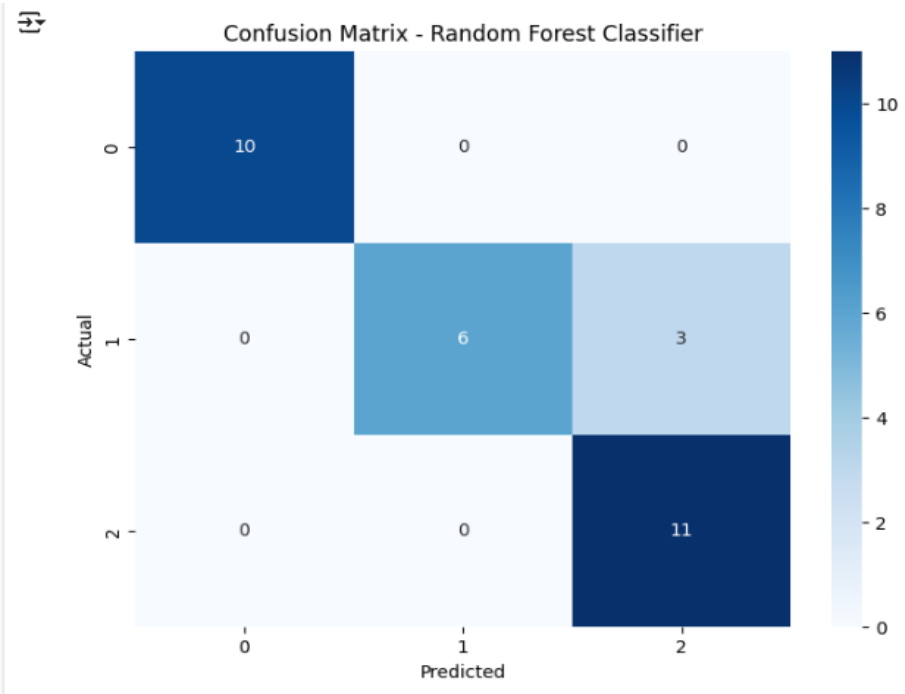
- Accuracy
- Precision
- Recall
- F1 Score

```python
# Confusion Matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Plot the confusion matrix for the Random Forest Classifier
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_rf, annot=True, cmap='Blues', fmt='g')
plt.title('Confusion Matrix - Random Forest Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

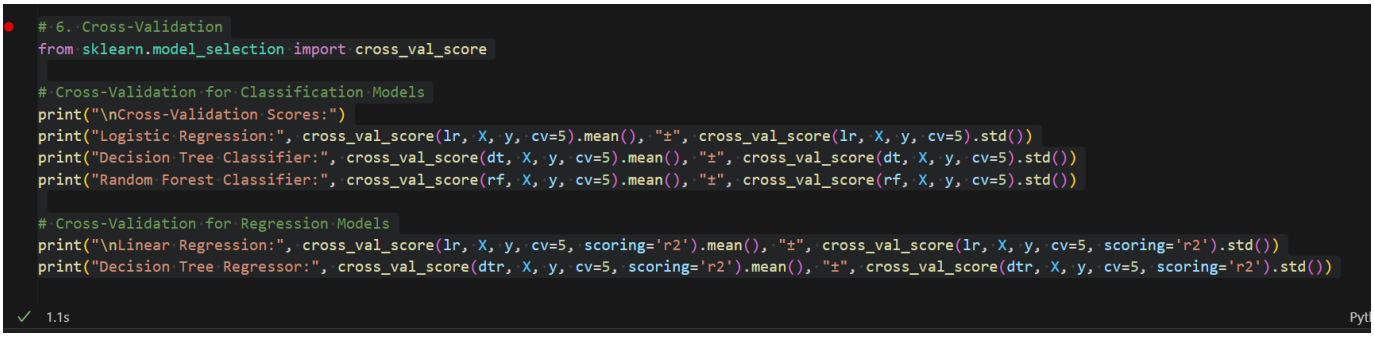
✓ 0.1s

Result:



Cross-Validation

- Implement k-fold cross-validation for both classification and regression models.
- Report the mean and standard deviation of the cross-validation scores.



```python
# 6. Cross-Validation
from sklearn.model_selection import cross_val_score

# Cross-Validation for Classification Models
print("\nCross-Validation Scores:")
print("Logistic Regression:", cross_val_score(lr, X, y, cv=5).mean(), "±", cross_val_score(lr, X, y, cv=5).std())
print("Decision Tree Classifier:", cross_val_score(dt, X, y, cv=5).mean(), "±", cross_val_score(dt, X, y, cv=5).std())
print("Random Forest Classifier:", cross_val_score(rf, X, y, cv=5).mean(), "±", cross_val_score(rf, X, y, cv=5).std())

# Cross-Validation for Regression Models
print("\nLinear Regression:", cross_val_score(lr, X, y, cv=5, scoring='r2').mean(), "±", cross_val_score(lr, X, y, cv=5, scoring='r2').std())
print("Decision Tree Regressor:", cross_val_score(dtr, X, y, cv=5, scoring='r2').mean(), "±", cross_val_score(dtr, X, y, cv=5, scoring='r2').std())
```

✓ 1.1s

Result:

```
Cross-Validation Scores:
Logistic Regression: 0.3211297123381488 ± 0.3948011769951609
Decision Tree Classifier: 0.9600000000000002 ± 0.03265986323710903
Random Forest Classifier: 0.9533333333333334 ± 0.024944382578492935

Linear Regression: 0.3211297123381488 ± 0.3948011769951609
Decision Tree Regressor: 0.5077998025366446 ± 0.42663328635961273
```

Conclusion

This documentation outlines the process of loading and preprocessing a dataset, performing exploratory data analysis (EDA), implementing classification and regression models, evaluating the models using various metrics, and visualizing results. The dataset used is assumed to have numerical and categorical features, with a target variable for prediction.