Code with Execution Procedure

Import Libraries

import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.metrics import mean_absolute_error, mean_squared_error

from sklearn.preprocessing import MinMaxScaler

from sklearn.preprocessing import StandardScaler

from sklearn.tree import export_text

from sklearn.ensemble import AdaBoostRegressor

from sklearn.tree import DecisionTreeRegressor

from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import mean_squared_error

from sklearn.metrics import accuracy_score

- These lines import necessary libraries and modules for data manipulation, machine learning modeling, and evaluation.

Read Dataset

data = pd.read_csv("C:\\jupyter-notebook\\cocomo81.csv")

- Reads the CSV file named "cocomo81.csv" into a pandas DataFrame called `data`.

Obtain No. of rows and columns

```
num_rows, num_columns = data.shape
print("Number of rows:", num_rows)
print("Number of columns:", num_columns)
print("Column names:", data.columns)
```

- Obtains the number of rows and columns in the dataset and prints them, along with the column names.

Apply Normalization

```
scaler = MinMaxScaler()
data_scaled = scaler.fit_transform(data)
data_scaled_df = pd.DataFrame(data_scaled, columns=data.columns)
```

- Initializes a MinMaxScaler object to scale the data between 0 and 1. Fits the scaler to the data and transforms it. Finally, creates a DataFrame `data_scaled_df` with the scaled data.

Drop Effort

data_scaled_df.columns = data_scaled_df.columns.str.strip()

- Removes leading and trailing whitespaces from the column names.

```
target_column = 'Effort1'
```

- Defines the target column name.

```
X = data_scaled_df.drop(columns=['Effort1'])
```

Y = data_scaled_df['Effort1']

Split the Data

- Splits the DataFrame into features (X) and the target variable (Y).

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

- Splits the data into training and testing sets with 80% for training and 20% for testing, using a random state for reproducibility.

Initialize Decision Tree Regressor

```
dt_model = DecisionTreeRegressor(random_state=42)
dt_model.fit(X_train, Y_train)
Y_pred = dt_model.predict(X_test)
```

- Initializes a Decision Tree Regressor model, fits it to the training data, and predicts the target variable for the test data.

```
tree_regressor = DecisionTreeRegressor(max_depth=20, min_samples_split=2,
random_state=42)
tree_regressor.fit(X_train, Y_train)
Y_pred = tree_regressor.predict(X_test)
```

Calculate MSE & RMSE for Decision Tree

```
mse = np.mean((Y_test - Y_pred)**2)
rmse = np.sqrt(np.mean((Y_test - Y_pred)**2))
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```

- Calculates mean squared error (MSE) and root mean squared error (RMSE) between the predicted and actual values, then prints them.

Initialize AdaBoost Technique

```
base_regressor = DecisionTreeRegressor(max_depth=5, random_state=42)
adaboost_regressor = AdaBoostRegressor(base_regressor, n_estimators=1, random_state=42)
Y_train = Y_train.ravel()
adaboost_regressor.fit(X_train, Y_train)
y_pred_boosted = adaboost_regressor.predict(X_test)
```

- Initializes a base Decision Tree Regressor and an AdaBoost Regressor using it. Fits the AdaBoost model to the training data and predicts the target variable for the test data.

Calculate MSE & RMSE for AdaBoost

```
mse = np.mean((Y_test - y_pred_boosted)**2)
rmse = np.sqrt(np.mean((Y_test - y_pred_boosted)**2))
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```

- Calculates MSE and RMSE between the predicted and actual values for the AdaBoost model, then prints them.

Initialize Pruned Decision Tree

```
pruned_dt_regressor = DecisionTreeRegressor(max_depth=2 ,random_state=42)
pruned_dt_regressor.fit(X_train, Y_train)
Y pred pruned = pruned dt regressor.predict(X test)
```

Initializes and fits a pruned Decision Tree Regressor with specified hyperparameters to the training data and predicts the target variable for the test data.

Calculate MSE & RMSE for Pruned Decision Tree

```
mse = np.mean((Y_test - Y_pred_pruned)**2)
rmse = np.sqrt(np.mean((Y_test - Y_pred_pruned)**2))
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```

Calculates MSE and RMSE between the predicted and actual values for the pruned Decision Tree model, then prints them.

The provided code performs regression analysis on software effort estimation data using decision tree-based models. It first preprocesses the data, scales it, and splits it into training and testing sets. Three decision tree regressors are trained: one with default parameters, one with boosted AdaBoost, and one pruned for simplicity. The code evaluates each model's performance using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics. Finally, it prints the MSE and RMSE values for each model. Overall, the code demonstrates the application of decision tree regressors and their variants in software effort estimation, comparing their performance.

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[63 rows x 17 columns]
X = data_scaled_df.drop(columns=['Effort1'])
Y= data_scaled_df['Effort1']
#print(Y)
X train, X test, Y train, Y test = train test split(X, Y, test size=0.2, random state=42)
```

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       Name: Effort1, Length: 63, dtype: float64
      dt_model = DecisionTreeRegressor(random_state=42)
[13]:
       dt model.fit(X train, Y train)
      Y pred = dt model.predict(X test)
       #print(Y_pred)
[14]: tree_regressor = DecisionTreeRegressor(max_depth=20, min_samples_split=2, random_state=42)
      tree regressor.fit(X train, Y train)
[14]:
                      DecisionTreeRegressor
      DecisionTreeRegressor(max depth=20, random state=42)
[15]: Y_pred = tree_regressor.predict(X_test)
       print(Y_pred)
       print(Y test)
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      Name: Effort1, dtype: float64
      mse = np.mean((Y test - Y pred)**2)
[18]:
      rmse = np.sqrt(np.mean((Y test - Y pred)**2))
      print(f"MSE: {mse}")
      print(f"RMSE: {rmse}")
      MSE: 0.0026035678653477047
      RMSE: 0.05102516893992321
      base regressor = DecisionTreeRegressor(max depth=5, random state=42)
[21]:
      adaboost_regressor = AdaBoostRegressor(base_regressor, n_estimators=1, random_state=42)
      Y train = Y train.ravel()
      adaboost regressor.fit(X train, Y train)
      y_pred_boosted = adaboost_regressor.predict(X_test)
      #print(y pred boosted)
      mse = np.mean((Y test - y pred boosted)**2)
[12]:
      rmse = np.sqrt(np.mean((Y test - y pred boosted)**2))
      print(f"MSE: {mse}")
      print(f"RMSE: {rmse}")
      MSE: 0.0018943267009220099
      RMSE: 0.04352386357990304
      pruned dt regressor = DecisionTreeRegressor(max depth=2 ,random state=42)
[13]:
      pruned_dt_regressor.fit(X_train, Y_train)
      Y pred pruned = pruned dt regressor.predict(X test)
      mse = np.mean((Y test - Y pred pruned)**2)
[12]:
      rmse = np.sqrt(np.mean((Y_test - Y_pred_pruned)**2))
      print(f"MSE: {mse}")
      print(f"RMSE: {rmse}")
      MSE: 0.002504062444789234
      RMSE: 0.05004060795782995
```