practical_file

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1 Machine Learning sem 5 Practical File

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1. Extract the data from the database using python

[ ]:
```
# extract OBostonHousing and store in a dataframe

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import matplotlib

dataframe0 = pd.read_csv(os.path.join(os.getcwd(),'datasets', 'BostonHousing.
↪csv'))
dataframe0.head()
```

[ ]:
```
      crim    zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296     15.3
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222     18.7

        b  lstat  medv
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90   5.33  36.2
```

2. Write a program to implement linear and logistic regression

[ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import mean_squared_error, accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.exceptions import ConvergenceWarning
```

```
import warnings


linear_features = dataframe0.drop('medv', axis=1)
linear_target = dataframe0['medv']

logistic_features = dataframe0.drop('chas', axis=1)
logistic_target = dataframe0['chas']

linear_features_train, linear_features_test, linear_target_train, 
 ↪linear_target_test = train_test_split(
    linear_features, linear_target, test_size=0.2, random_state=42
)

logistic_features_train, logistic_features_test, logistic_target_train, 
 ↪logistic_target_test = train_test_split(
    logistic_features, logistic_target, test_size=0.2, random_state=42
)

scaler = StandardScaler()
linear_features_train_scaled = scaler.fit_transform(linear_features_train)
linear_features_test_scaled = scaler.transform(linear_features_test)

linear_model = LinearRegression()
linear_model.fit(linear_features_train_scaled, linear_target_train)

linear_predictions = linear_model.predict(linear_features_test_scaled)

linear_mse = mean_squared_error(linear_target_test, linear_predictions)
print(f"Linear Regression Mean Squared Error: {linear_mse}")

with warnings.catch_warnings():
    warnings.filterwarnings("ignore", category=ConvergenceWarning)

    logistic_scaler = StandardScaler()
    logistic_features_train_scaled = logistic_scaler.
 ↪fit_transform(logistic_features_train)
    logistic_features_test_scaled = logistic_scaler.
 ↪transform(logistic_features_test)

    logistic_model = LogisticRegression(max_iter=1000)
    logistic_model.fit(logistic_features_train_scaled, logistic_target_train)

logistic_predictions = logistic_model.predict(logistic_features_test_scaled)

logistic_accuracy = accuracy_score(logistic_target_test, logistic_predictions)
print(f"Logistic Regression Accuracy: {logistic_accuracy}")
```

```
Linear Regression Mean Squared Error: 24.29111947497352
Logistic Regression Accuracy: 0.9411764705882353
```

3. Write a program to implement the naïve Bayesian classifier for a sample training data set stored as a CSV file. Compute the accuracy of the classifier, considering few test data sets.

a. naïve Bayesian classifier On BostonHousing dataset

[ ]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB

dataframe0 = pd.read_csv(os.path.join(os.getcwd(),'datasets', 'BostonHousing.
↪csv'))

dataframe0['target'] = (dataframe0['medv'] > dataframe0['medv'].median()).
↪astype(int)
dataframe0 = dataframe0.drop('medv', axis=1)

X = dataframe0.drop('target', axis=1)
y = dataframe0['target']

label_encoder = LabelEncoder()
for column in X.columns:
    if X[column].dtype == 'object':
        X[column] = label_encoder.fit_transform(X[column])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

nb_classifier = GaussianNB()
nb_classifier.fit(X_train, y_train)

y_pred = nb_classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Naive Bayes Classifier Accuracy: {accuracy}")
```

```
Naive Bayes Classifier Accuracy: 0.7647058823529411
```

b. naïve Bayesian classifier on adult dataset ("Census Income" dataset)

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```python
dataframe1 = pd.read_csv(os.path.join(os.getcwd(),'datasets', 'adult.csv'))
col_names = ['age', 'workclass', 'fnlwgt', 'education', 'education_num',␣
 ↪'marital_status', 'occupation', 'relationship',
             'race', 'sex', 'capital_gain', 'capital_loss', 'hours_per_week',␣
 ↪'native_country', 'income']
dataframe1.columns = col_names
dataframe1.head()
```

[ ]:

```
   age         workclass  fnlwgt   education  education_num  \
0   50  Self-emp-not-inc   83311   Bachelors             13
1   38           Private  215646     HS-grad              9
2   53           Private  234721        11th              7
3   28           Private  338409   Bachelors             13
4   37           Private  284582     Masters             14

       marital_status         occupation   relationship   race     sex  \
0  Married-civ-spouse    Exec-managerial        Husband  White    Male
1            Divorced  Handlers-cleaners  Not-in-family  White    Male
2  Married-civ-spouse  Handlers-cleaners        Husband  Black    Male
3  Married-civ-spouse     Prof-specialty           Wife  Black  Female
4  Married-civ-spouse    Exec-managerial           Wife  White  Female

   capital_gain  capital_loss  hours_per_week native_country income
0             0             0              13  United-States  <=50K
1             0             0              40  United-States  <=50K
2             0             0              40  United-States  <=50K
3             0             0              40           Cuba  <=50K
4             0             0              40  United-States  <=50K
```

[ ]:

```python
label_encoder = LabelEncoder()
for col in dataframe1.columns:
    if dataframe1[col].dtype == 'object':
        dataframe1[col] = label_encoder.fit_transform(dataframe1[col])

X = dataframe1.drop('income', axis=1)
y = dataframe1['income']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

naive_bayes = GaussianNB()
naive_bayes.fit(X_train, y_train)

y_pred = naive_bayes.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the Naive Bayes classifier: {accuracy:.2f}")
```

```
Accuracy of the Naive Bayes classifier: 0.80
```

4. Write a program to implement k-nearest neighbors (KNN) and Support Vector Machine (SVM) Algorithm for classification

[ ]:
```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler

dataframe1 = pd.read_csv(os.path.join("datasets", "adult.csv"), names=['age',␣
 ↪'workclass', 'fnlwgt', 'education', 'education_num', 'marital_status',␣
 ↪'occupation', 'relationship',
                                                 'race', 'sex', 'capital_gain',␣
 ↪'capital_loss', 'hours_per_week', 'native_country', 'income'])

label_encoder = LabelEncoder()
for col in dataframe1.columns:
    if dataframe1[col].dtype == 'object':
        dataframe1[col] = label_encoder.fit_transform(dataframe1[col])

X = dataframe1.drop('income', axis=1)
y = dataframe1['income']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

knn_classifier = KNeighborsClassifier(n_neighbors=5)
knn_classifier.fit(X_train, y_train)
y_pred_knn = knn_classifier.predict(X_test)
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print(f"Accuracy of KNN classifier: {accuracy_knn:.2f}")

svm_classifier = make_pipeline(StandardScaler(), SVC())
svm_classifier.fit(X_train, y_train)
y_pred_svm = svm_classifier.predict(X_test)
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print(f"Accuracy of SVM classifier: {accuracy_svm:.2f}")
```

```
Accuracy of KNN classifier: 0.78
Accuracy of SVM classifier: 0.85
```

5. Implement classification of a given dataset using random forest

[ ]:
```python
from sklearn.ensemble import RandomForestClassifier
```

```
dataframe1 = pd.read_csv(os.path.join("datasets","adult.csv"), names=['age',␣
↪'workclass', 'fnlwgt', 'education', 'education_num', 'marital_status',␣
↪'occupation', 'relationship',
                                             'race', 'sex', 'capital_gain',␣
↪'capital_loss', 'hours_per_week', 'native_country', 'income'])

label_encoder = LabelEncoder()
for col in dataframe1.columns:
    if dataframe1[col].dtype == 'object':
        dataframe1[col] = label_encoder.fit_transform(dataframe1[col])

X = dataframe1.drop('income', axis=1)
y = dataframe1['income']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
random_forest_classifier = RandomForestClassifier(n_estimators=100,␣
↪random_state=42)
random_forest_classifier.fit(X_train, y_train)

y_pred = random_forest_classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of Random Forest classifier: {accuracy:.2f}")
```

```
Accuracy of Random Forest classifier: 0.86
```

6. Build an Artificial Neural Network (ANN) by implementing the Back propagation algorithm and test the same using appropriate data sets.

[ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix

import tensorflow as tf

dataframe2 = pd.read_csv(os.path.join('datasets', 'Churn_Modelling.csv'))
dataframe2 = dataframe2.drop(['RowNumber', 'CustomerId', 'Surname'], axis=1)
dataframe2 = pd.get_dummies(dataframe2, columns=['Geography', 'Gender'],␣
↪drop_first=True)

X = dataframe2.drop('Exited', axis=1)
y = dataframe2['Exited']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
model = tf.keras.Sequential([
    tf.keras.layers.Dense(64, activation='relu', input_shape=(X_train.
 ↪shape[1],)),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.1)
# y_pred = model.predict_classes(X_test)

y_pred_prob = model.predict(X_test)
y_pred = np.argmax(y_pred_prob, axis=1)


accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

print(f'Test Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
2023-12-01 01:49:39.125608: I tensorflow/core/util/port.cc:113] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2023-12-01 01:49:39.147133: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI AVX512_BF16 FMA,
in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

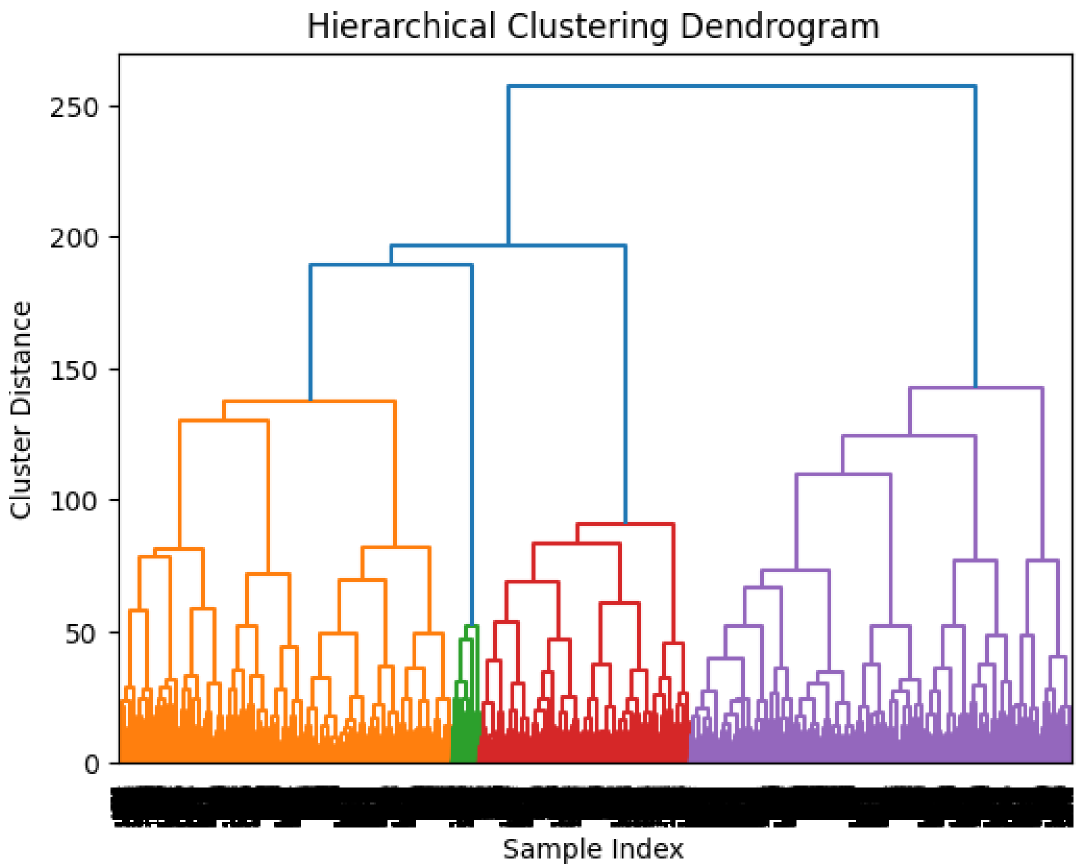
```
Epoch 1/10
225/225 [==============================] - 0s 926us/step - loss: 0.4961 -
accuracy: 0.7749 - val_loss: 0.4089 - val_accuracy: 0.8288
Epoch 2/10
225/225 [==============================] - 0s 578us/step - loss: 0.4184 -
accuracy: 0.8200 - val_loss: 0.3853 - val_accuracy: 0.8525
Epoch 3/10
225/225 [==============================] - 0s 575us/step - loss: 0.3961 -
accuracy: 0.8347 - val_loss: 0.3684 - val_accuracy: 0.8550
Epoch 4/10
225/225 [==============================] - 0s 589us/step - loss: 0.3762 -
accuracy: 0.8450 - val_loss: 0.3580 - val_accuracy: 0.8537
Epoch 5/10
225/225 [==============================] - 0s 562us/step - loss: 0.3635 -
accuracy: 0.8497 - val_loss: 0.3475 - val_accuracy: 0.8537
Epoch 6/10
```

```
225/225 [==============================] - 0s 514us/step - loss: 0.3554 -
accuracy: 0.8553 - val_loss: 0.3436 - val_accuracy: 0.8612
Epoch 7/10
225/225 [==============================] - 0s 548us/step - loss: 0.3503 -
accuracy: 0.8589 - val_loss: 0.3411 - val_accuracy: 0.8612
Epoch 8/10
225/225 [==============================] - 0s 563us/step - loss: 0.3460 -
accuracy: 0.8596 - val_loss: 0.3401 - val_accuracy: 0.8550
Epoch 9/10
225/225 [==============================] - 0s 549us/step - loss: 0.3442 -
accuracy: 0.8581 - val_loss: 0.3385 - val_accuracy: 0.8600
Epoch 10/10
225/225 [==============================] - 0s 544us/step - loss: 0.3424 -
accuracy: 0.8599 - val_loss: 0.3383 - val_accuracy: 0.8575
63/63 [==============================] - 0s 402us/step
Test Accuracy: 80.35%
Confusion Matrix:
[[1607    0]
 [ 393    0]]
```

7. Apply k-Means algorithm k-Means algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using the heirarcial clustering. Compare the results of these two algorithms and comment on the quality of clustering. You can add Python ML library classes in the program.

[ ]:
```
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
from scipy.cluster.hierarchy import dendrogram, linkage

dataset_path = os.path.join('datasets', 'bike-share.csv')
dataframe3 = pd.read_csv(dataset_path)
numeric_cols = dataframe3.drop(['instant', 'dteday'], axis=1)
scaler = StandardScaler()
data_scaled = scaler.fit_transform(numeric_cols)
kmeans = KMeans(n_clusters=2, random_state=42)
kmeans_labels = kmeans.fit_predict(data_scaled)
agg_clustering = AgglomerativeClustering(n_clusters=2)
agg_labels = agg_clustering.fit_predict(data_scaled)
kmeans_silhouette = silhouette_score(data_scaled, kmeans_labels)
agg_silhouette = silhouette_score(data_scaled, agg_labels)
linked = linkage(data_scaled, 'ward')
dendrogram(linked, orientation='top', distance_sort='descending',␣
 ↪show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Sample Index')
plt.ylabel('Cluster Distance')
```

```python
plt.show()

print(f'K-Means Silhouette Score: {kmeans_silhouette:.4f}')
print(f'Hierarchical Silhouette Score: {agg_silhouette:.4f}')
```

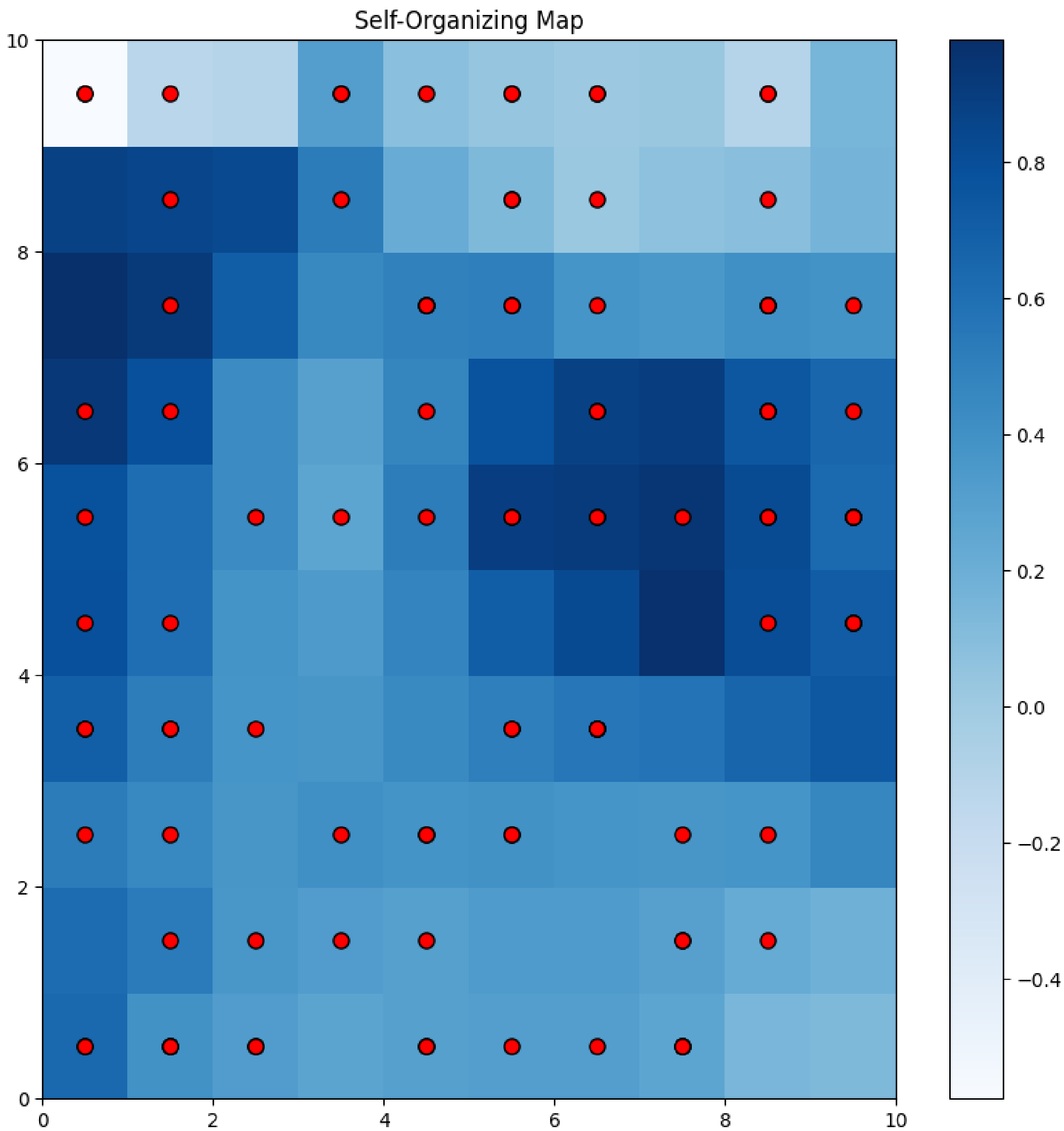



```
K-Means Silhouette Score: 0.1617
Hierarchical Silhouette Score: 0.1179
```

8. Write a program to implement Self-Organizing Map (SOM)

[ ]:
```python
from minisom import MiniSom

np.random.seed(42)
data = np.random.rand(100, 2)  # 100 samples with 2 features

data = (data - data.min(axis=0)) / (data.max(axis=0) - data.min(axis=0))

som_size = (10, 10)  # SOM grid size
learning_rate = 0.5
sigma = 1.0
```

```python
som = MiniSom(som_size[0], som_size[1], data.shape[1], sigma=sigma,␣
 ↪learning_rate=learning_rate)
som.train_random(data, 1000)
weights = som.get_weights()
winning_neurons = np.array([som.winner(x) for x in data])

plt.figure(figsize=(10, 10))
plt.pcolor(weights[:, :, 0], cmap='Blues')  # Display the first feature of the␣
 ↪weights
plt.colorbar()

for i, j in winning_neurons:
    plt.plot(i + 0.5, j + 0.5, 'ro', markeredgecolor='k', markersize=8)

plt.title('Self-Organizing Map')
plt.show()
```

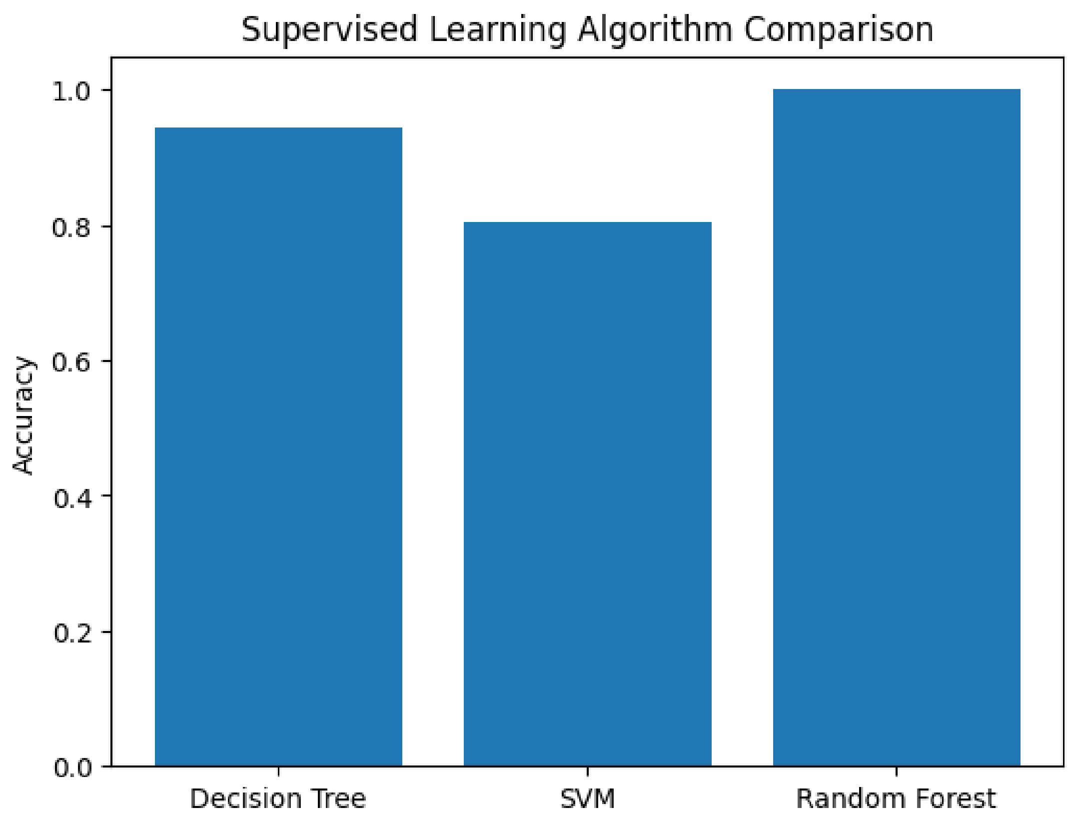


9. Write a program for empirical comparison of different supervised learning algorithms

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_wine
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

```python
wine = load_wine()
X, y = wine.data, wine.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

classifiers = {
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'SVM': SVC(random_state=42),
    'Random Forest': RandomForestClassifier(random_state=42)
}

results = {}
for name, clf in classifiers.items():
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    results[name] = accuracy
    print(f'{name} Accuracy: {accuracy:.4f}')

fig, ax = plt.subplots()
ax.bar(results.keys(), results.values())
ax.set_ylabel('Accuracy')
ax.set_title('Supervised Learning Algorithm Comparison')
plt.show()
```

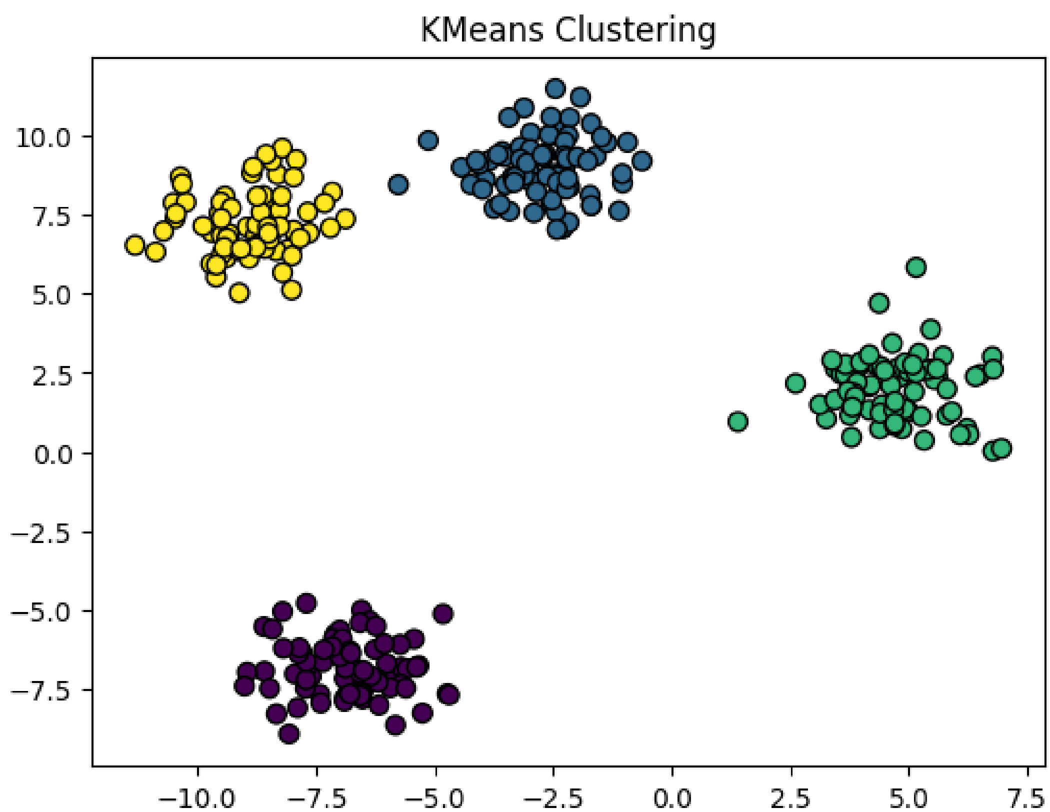
```
Decision Tree Accuracy: 0.9444
SVM Accuracy: 0.8056
Random Forest Accuracy: 1.0000
```



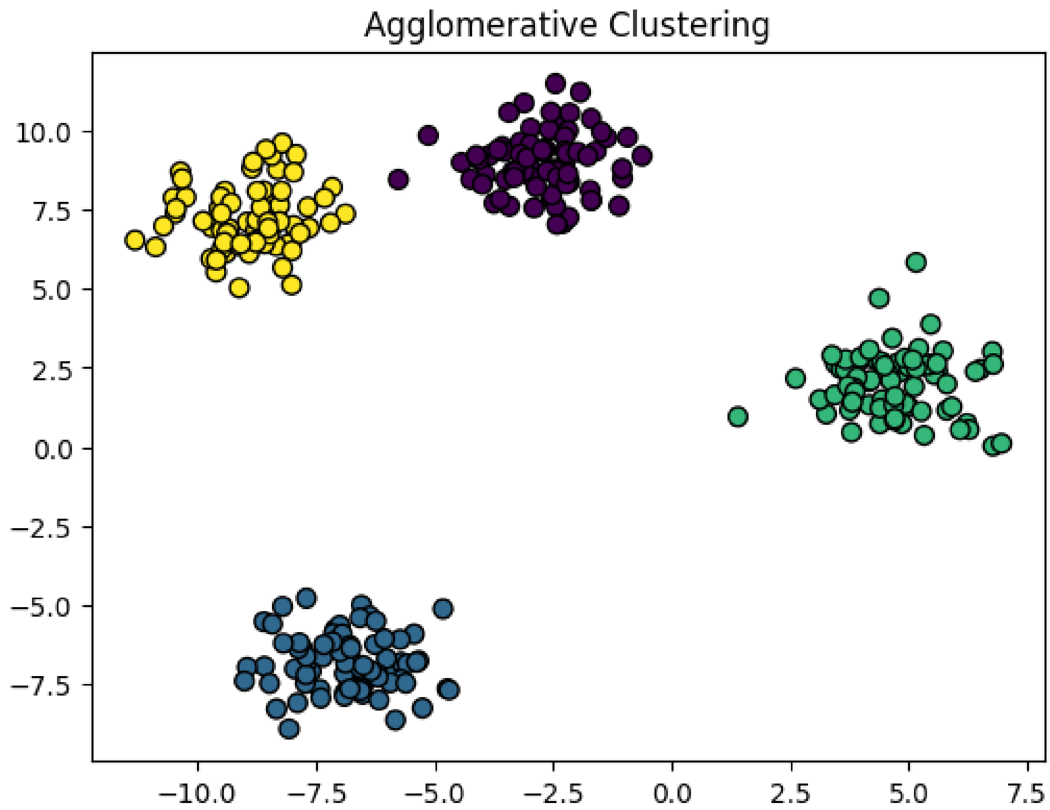
10. Write a program for empirical comparison of different unsupervised learning algorithms

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
from sklearn.metrics import silhouette_score

X, _ = make_blobs(n_samples=300, centers=4, random_state=42) # Generate some␣
↪data

algorithms = {
    'KMeans': KMeans(n_clusters=4),
    'Agglomerative': AgglomerativeClustering(n_clusters=4),
    'DBSCAN': DBSCAN(eps=0.5, min_samples=5)
}

for name, algorithm in algorithms.items():
    algorithm.fit(X)
    labels = algorithm.labels_
```

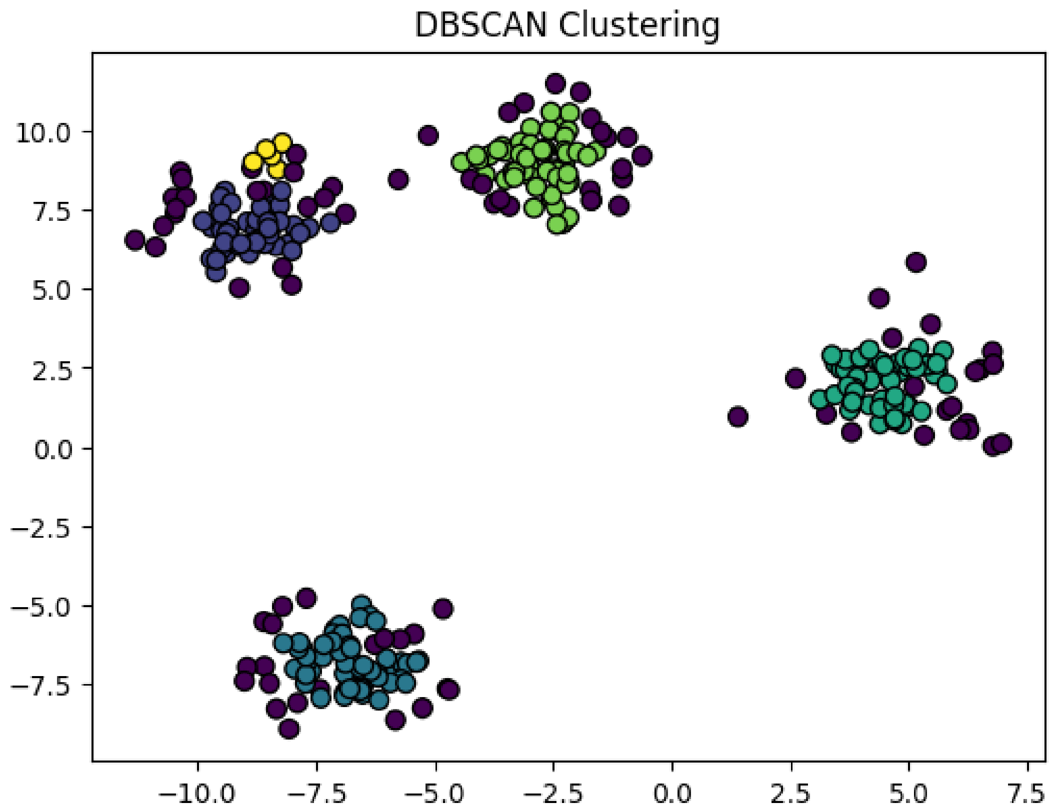
```
    plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis', edgecolors='k',␣
↪s=50)
    plt.title(f'{name} Clustering')
    plt.show()

    silhouette_avg = silhouette_score(X, labels)
    print(f'{name} Silhouette Score: {silhouette_avg:.3f}\n')
```




```
KMeans Silhouette Score: 0.792
```




```
Agglomerative Silhouette Score: 0.792
```

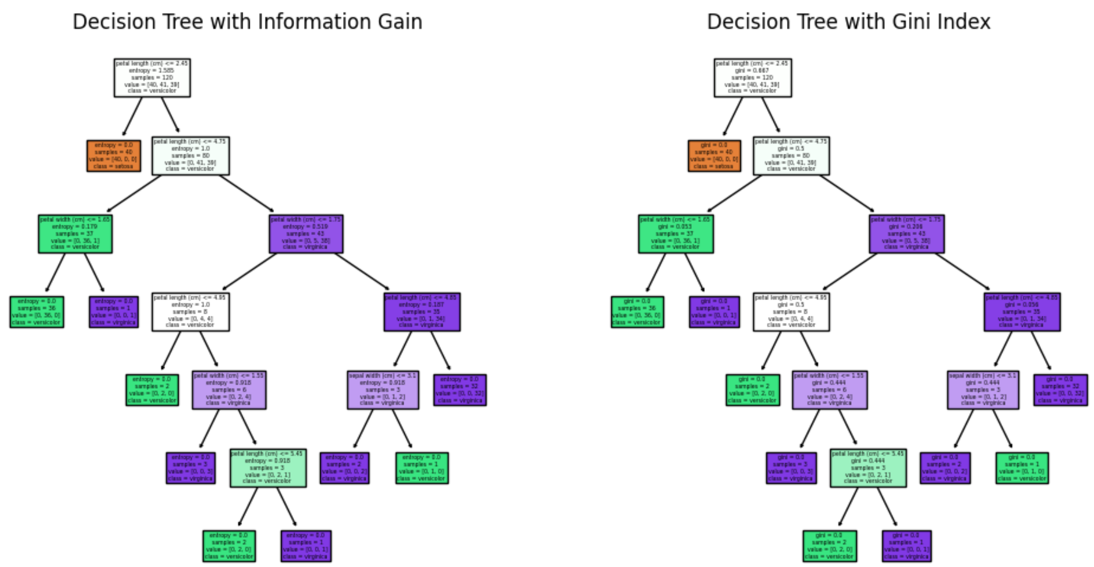



```
DBSCAN Silhouette Score: 0.325
```

11. Write a program to build Decision Trees using i) Information Gain, and ii) Gini Index methods using the appropriate dataset. Visualize the trees and compare all the performance metrics.

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

iris = load_iris()
X, y = iris.data, iris.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

dt_info_gain = DecisionTreeClassifier(criterion='entropy', random_state=42)
dt_info_gain.fit(X_train, y_train)
```

```python
dt_gini = DecisionTreeClassifier(criterion='gini', random_state=42)
dt_gini.fit(X_train, y_train)

plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
plot_tree(dt_info_gain, feature_names=iris.feature_names, class_names=iris.
 ↪target_names, filled=True)
plt.title('Decision Tree with Information Gain')

plt.subplot(1, 2, 2)
plot_tree(dt_gini, feature_names=iris.feature_names, class_names=iris.
 ↪target_names, filled=True)
plt.title('Decision Tree with Gini Index')

plt.show()

def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred, target_names=iris.
 ↪target_names)
    return accuracy, report

accuracy_info_gain, report_info_gain = evaluate_model(dt_info_gain, X_test,␣
 ↪y_test)
print("Decision Tree with Information Gain:")
print(f"Accuracy: {accuracy_info_gain:.3f}")
print("Classification Report:\n", report_info_gain)

accuracy_gini, report_gini = evaluate_model(dt_gini, X_test, y_test)
print("\nDecision Tree with Gini Index:")
print(f"Accuracy: {accuracy_gini:.3f}")
print("Classification Report:\n", report_gini)
```




```
Decision Tree with Information Gain:
Accuracy: 1.000
Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30


Decision Tree with Gini Index:
Accuracy: 1.000
Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

12. Implement all the steps of Data Preprocessing on the appropriate dataset. Include handling missing data, encoding categorical data, and feature scaling in addition to the basic steps.

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

df = pd.read_csv("datasets/train.csv")

print("Initial Dataset:")
print(df.head())

columns_with_missing = df.columns[df.isnull().any()].tolist()

print("\nStep 1: Handling Missing Data")
print("Columns with Missing Values:", columns_with_missing)

numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns.
 ↪tolist()
categorical_columns = df.select_dtypes(include=['object']).columns.tolist()

numerical_imputer = SimpleImputer(strategy='median')
df[numerical_columns] = numerical_imputer.fit_transform(df[numerical_columns])

categorical_imputer = SimpleImputer(strategy='most_frequent')  # You can also␣
 ↪use a constant value or a different strategy
df[categorical_columns] = categorical_imputer.
 ↪fit_transform(df[categorical_columns])

print("Missing Values Imputed.")
print(df.head())

print("\nStep 2: Encoding Categorical Data")
print("Categorical Columns:", categorical_columns)

encoder = OneHotEncoder(drop='first', sparse=False)
df_encoded = pd.DataFrame(encoder.fit_transform(df[categorical_columns]))
df_encoded.columns = encoder.get_feature_names_out(categorical_columns)

df = pd.concat([df, df_encoded], axis=1)
df = df.drop(categorical_columns, axis=1)

print("Categorical Data Encoded.")
print(df.head())
```

```
print("\nStep 3: Feature Scaling")
print("Numerical Columns for Scaling:", numerical_columns)

scaler = StandardScaler()
df[numerical_columns] = scaler.fit_transform(df[numerical_columns])

print("Numerical Features Scaled.")
print(df.head())

X = df.drop("SalePrice", axis=1)  # Features
y = df["SalePrice"]  # Target variable
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

print("\nStep 4: Dataset Splitting")
print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)
```

```
Initial Dataset:
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]

Step 1: Handling Missing Data
Columns with Missing Values: ['LotFrontage', 'Alley', 'MasVnrType',
'MasVnrArea', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
'BsmtFinType2', 'Electrical', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
'GarageFinish', 'GarageQual', 'GarageCond', 'PoolQC', 'Fence', 'MiscFeature']
```

```
Missing Values Imputed.
    Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0  1.0        60.0       RL         65.0   8450.0   Pave  Grvl      Reg
1  2.0        20.0       RL         80.0   9600.0   Pave  Grvl      Reg
2  3.0        60.0       RL         68.0  11250.0   Pave  Grvl      IR1
3  4.0        70.0       RL         60.0   9550.0   Pave  Grvl      IR1
4  5.0        60.0       RL         84.0  14260.0   Pave  Grvl      IR1

  LandContour Utilities  … PoolArea PoolQC  Fence MiscFeature MiscVal  \
0         Lvl    AllPub  …      0.0     Gd  MnPrv        Shed     0.0
1         Lvl    AllPub  …      0.0     Gd  MnPrv        Shed     0.0
2         Lvl    AllPub  …      0.0     Gd  MnPrv        Shed     0.0
3         Lvl    AllPub  …      0.0     Gd  MnPrv        Shed     0.0
4         Lvl    AllPub  …      0.0     Gd  MnPrv        Shed     0.0

  MoSold  YrSold  SaleType  SaleCondition  SalePrice
0    2.0  2008.0        WD         Normal   208500.0
1    5.0  2007.0        WD         Normal   181500.0
2    9.0  2008.0        WD         Normal   223500.0
3    2.0  2006.0        WD        Abnorml   140000.0
4   12.0  2008.0        WD         Normal   250000.0

[5 rows x 81 columns]

Step 2: Encoding Categorical Data
Categorical Columns: ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour',
'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1',
'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'Heating',
'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Functional',
'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond',
'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature', 'SaleType', 'SaleCondition']
Categorical Data Encoded.
    Id  MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
0  1.0        60.0         65.0   8450.0          7.0          5.0     2003.0
1  2.0        20.0         80.0   9600.0          6.0          8.0     1976.0
2  3.0        60.0         68.0  11250.0          7.0          5.0     2001.0
3  4.0        70.0         60.0   9550.0          7.0          5.0     1915.0
4  5.0        60.0         84.0  14260.0          8.0          5.0     2000.0

   YearRemodAdd  MasVnrArea  BsmtFinSF1  …  SaleType_ConLI  SaleType_ConLw  \
0        2003.0       196.0       706.0  …             0.0             0.0
1        1976.0         0.0       978.0  …             0.0             0.0
2        2002.0       162.0       486.0  …             0.0             0.0
3        1970.0         0.0       216.0  …             0.0             0.0
4        2000.0       350.0       655.0  …             0.0             0.0
```

```
   SaleType_New  SaleType_Oth  SaleType_WD  SaleCondition_AdjLand  \
0           0.0           0.0          1.0                    0.0
1           0.0           0.0          1.0                    0.0
2           0.0           0.0          1.0                    0.0
3           0.0           0.0          1.0                    0.0
4           0.0           0.0          1.0                    0.0

   SaleCondition_Alloca  SaleCondition_Family  SaleCondition_Normal  \
0                   0.0                   0.0                   1.0
1                   0.0                   0.0                   1.0
2                   0.0                   0.0                   1.0
3                   0.0                   0.0                   0.0
4                   0.0                   0.0                   1.0

   SaleCondition_Partial
0                    0.0
1                    0.0
2                    0.0
3                    0.0
4                    0.0

[5 rows x 246 columns]

Step 3: Feature Scaling
Numerical Columns for Scaling: ['Id', 'MSSubClass', 'LotFrontage', 'LotArea',
'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea',
'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',
'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSold',
'YrSold', 'SalePrice']
Numerical Features Scaled.
         Id  MSSubClass  LotFrontage   LotArea  OverallQual  OverallCond  \
0 -1.730865    0.073375    -0.220875 -0.207142     0.651479    -0.517200
1 -1.728492   -0.872563     0.460320 -0.091886    -0.071836     2.179628
2 -1.726120    0.073375    -0.084636  0.073480     0.651479    -0.517200
3 -1.723747    0.309859    -0.447940 -0.096897     0.651479    -0.517200
4 -1.721374    0.073375     0.641972  0.375148     1.374795    -0.517200

   YearBuilt  YearRemodAdd  MasVnrArea  BsmtFinSF1  …  SaleType_ConLI  \
0   1.050994      0.878668    0.514104    0.575425  …             0.0
1   0.156734     -0.429577   -0.570750    1.171992  …             0.0
2   0.984752      0.830215    0.325915    0.092907  …             0.0
3  -1.863632     -0.720298   -0.570750   -0.499274  …             0.0
4   0.951632      0.733308    1.366489    0.463568  …             0.0

   SaleType_ConLw  SaleType_New  SaleType_Oth  SaleType_WD  \
```

```
0            0.0            0.0            0.0           1.0
1            0.0            0.0            0.0           1.0
2            0.0            0.0            0.0           1.0
3            0.0            0.0            0.0           1.0
4            0.0            0.0            0.0           1.0

   SaleCondition_AdjLand  SaleCondition_Alloca  SaleCondition_Family  \
0                    0.0                   0.0                   0.0
1                    0.0                   0.0                   0.0
2                    0.0                   0.0                   0.0
3                    0.0                   0.0                   0.0
4                    0.0                   0.0                   0.0

   SaleCondition_Normal  SaleCondition_Partial
0                   1.0                    0.0
1                   1.0                    0.0
2                   1.0                    0.0
3                   0.0                    0.0
4                   1.0                    0.0

[5 rows x 246 columns]

Step 4: Dataset Splitting
Training set shape: (1168, 245)
Testing set shape: (292, 245)
```