Machine Learning Lab (PMCA507P)

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Exercise 10 : Hierarchical clustering

Collab url : https://colab.research.google.com/drive/1HK-FQPz1ngNORohkkjWMTO7eEUPSaMD1?usp=sharing

Import necessary libraries

```
import pandas as pd
import numpy as np
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree
from sklearn.ensemble import RandomForestClassifier
```

Load the dataset

```
data = pd.read_csv('/content/StudentsPerformance.csv')
data.info();
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   gender                   1000 non-null   object
 1   race                     1000 non-null   object
 2   parental_education       1000 non-null   object
 3   lunch                    1000 non-null   object
 4   test_preparation_course  1000 non-null   object
 5   math_score               1000 non-null   int64
 6   reading_score            1000 non-null   int64
 7   writing_score            1000 non-null   int64
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
```

```
data
```

	gender	race	parental_education	lunch	test_preparation_course	math_s
0	female	group B	bachelor's degree	standard	none	
1	female	group C	some college	standard	completed	
2	female	group B	master's degree	standard	none	
3	male	group A	associate's degree	free/reduced	none	
4	male	group C	some college	standard	none	
...	...	...	...	...	...	
995	female	group E	master's degree	standard	completed	
996	male	group C	high school	free/reduced	none	

Next steps: Generate code with data | View recommended plots

Data preprocessing

Encode categorical variables

```
label_encoders = {}
```

```python
for column in ['gender', 'race', 'parental_education', 'lunch', 'test_preparation_course']:
    label_encoders[column] = LabelEncoder()
    data[column] = label_encoders[column].fit_transform(data[column])

# Feature selection
features = ['gender', 'race', 'parental_education', 'lunch', 'test_preparation_course',
            'math_score', 'reading_score', 'writing_score']
X = data[features]
y = data['math_score']  # Predicting math scores, we can change this to reading_score or writing_score

# 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)

# Model training
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Model evaluation
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse)
print("R^2 Score:", r2)
```

```
Mean Squared Error: 1.1386555
R^2 Score: 0.9953206912677982
```

```python
# Define grading criteria
def get_grade(score):
    if score >= 90:
        return 'A'
    elif score >= 80:
        return 'B'
    elif score >= 70:
        return 'C'
    elif score >= 60:
        return 'D'
    else:
        return 'F'

# Apply grading criteria to predicted scores
predicted_grades = [get_grade(score) for score in y_pred]

# Get actual grades from the test set
actual_grades = [get_grade(score) for score in y_test]

# Compare predicted grades with actual grades
correct_predictions = sum(1 for pred, actual in zip(predicted_grades, actual_grades) if pred == actual)
total_predictions = len(predicted_grades)

# Calculate accuracy
accuracy = correct_predictions / total_predictions
print("Accuracy:", accuracy)
```

```
Accuracy: 0.99
```

```python
# Define a function to calculate the score based on groups
def calculate_group_score(group):
    group_data = data[data['race'] == group]
    score = group_data[['math_score', 'reading_score', 'writing_score']].mean(axis=0)
    return score.mean()

# Calculate scores for each group
group_scores = {}
for group in data['race'].unique():
    group_scores[group] = calculate_group_score(group)

# Print the scores for each group
for group, score in group_scores.items():
    print(f"Group {group}: {score}")
```

```
Group 1: 65.46842105263157
Group 2: 67.13166144200626
Group 0: 62.99250936329588
Group 3: 69.1793893129771
Group 4: 72.75238095238096
```

```
# Calculate total score for each student
data['total_score'] = data['math_score'] + data['reading_score'] + data['writing_score']

# Define grading criteria based on total marks
def get_grade(total_score):
    if total_score >= 240:
        return 'A'
    elif total_score >= 180:
        return 'B'
    elif total_score >= 120:
        return 'C'
    else:
        return 'D'

# Assign grades to students based on total marks
data['grade'] = data['total_score'].apply(get_grade)

# Print the grades for each student
print(data[['gender', 'race', 'parental_education', 'lunch', 'test_preparation_course', 'total_score', 'grade']])
```

```
     gender  race  parental_education  lunch  test_preparation_course  \
0         0     1                   1      1                        1
1         0     2                   4      1                        0
2         0     1                   3      1                        1
3         1     0                   0      0                        1
4         1     2                   4      1                        1
..      ...   ...                 ...    ...                      ...
995       0     4                   3      1                        0
996       1     2                   2      0                        1
997       0     2                   2      0                        0
998       0     3                   4      1                        0
999       0     3                   4      0                        1

     total_score grade
0            218     B
1            247     A
2            278     A
3            148     C
4            229     B
..           ...   ...
995          282     A
996          172     C
997          195     B
998          223     B
999          249     A

[1000 rows x 7 columns]
```

```
# Define grading criteria based on total marks
def get_grade(total_score):
    if total_score >= 240:
        return 'A'
    elif total_score >= 180:
        return 'B'
    elif total_score >= 120:
        return 'C'
    else:
        return 'D'

# Calculate total score for each student
data['total_score'] = data['math_score'] + data['reading_score'] + data['writing_score']

# Assign grades to students based on total marks
data['grade'] = data['total_score'].apply(get_grade)

# Function to get grade based on index number
def get_grade_by_index(index_no):
    student_row = data.iloc[index_no]  # Retrieve the row corresponding to the index number
    return student_row['grade']  # Retrieve the grade from the 'grade' column

# Example usage:
index_no = 10  # Example index number
grade = get_grade_by_index(index_no)
print(f"Grade of student at index {index_no}: {grade}")
```

```
Grade of student at index 10: C
```

Check for missing values in the dataset

```
missing_values = data.isnull().sum()
print("Missing Values:")
print(missing_values)
```

```
Missing Values:
gender                     0
race                       0
parental_education         0
lunch                      0
test_preparation_course    0
math_score                 0
reading_score              0
writing_score              0
total_score                0
grade                      0
dtype: int64
```

```
# Mapping numeric values to categories
data['gender'] = data['gender'].map({0: 'female', 1: 'male'})

# Check unique values in the 'gender' column after mapping
unique_genders = data['gender'].unique()
print("Unique Genders:", unique_genders)
```

```
Unique Genders: ['female' 'male']
```

```
# Calculate average scores for male and female students
male_avg_scores = data[data['gender'] == 'male'][['math_score', 'reading_score', 'writing_score']].mean()
female_avg_scores = data[data['gender'] == 'female'][['math_score', 'reading_score', 'writing_score']].mean()

# Print average scores for male and female students
print("Average Scores for Male Students:")
print(male_avg_scores)
print("\nAverage Scores for Female Students:")
print(female_avg_scores)
```

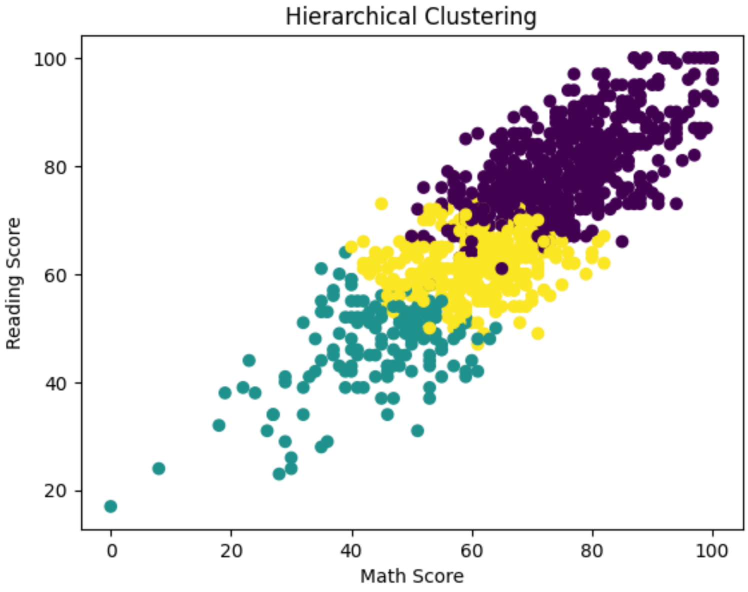
```
Average Scores for Male Students:
math_score       68.728216
reading_score    65.473029
writing_score    63.311203
dtype: float64

Average Scores for Female Students:
math_score       63.633205
reading_score    72.608108
writing_score    72.467181
dtype: float64
```

Hierarchial Clustering

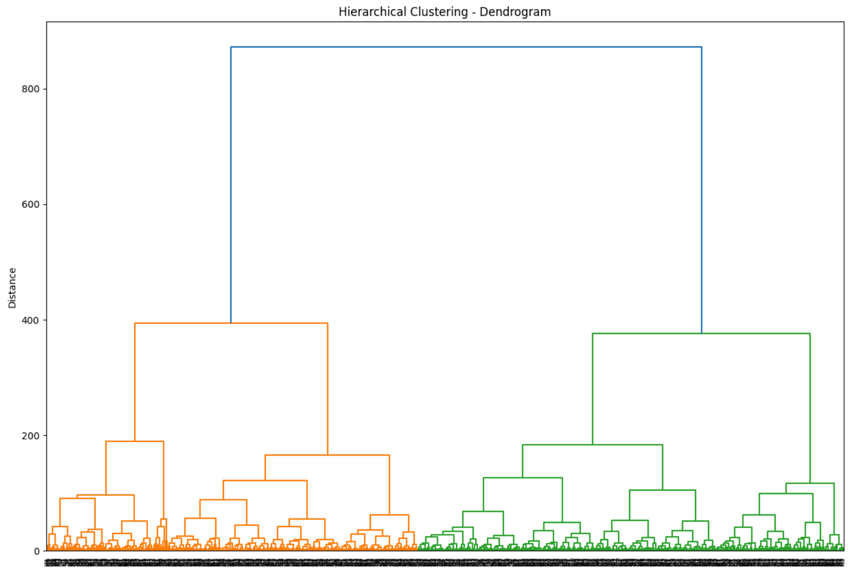
```
from sklearn.cluster import AgglomerativeClustering
import matplotlib.pyplot as plt
from sklearn.metrics import silhouette_score, davies_bouldin_score

# Define features (math, reading, writing scores)
features = ['math_score', 'reading_score', 'writing_score']
X = data[features]

# Choose the number of clusters (k)
k = 3  # we can choose any number of clusters based on our requirements

# Create AgglomerativeClustering model
hierarchical_clustering = AgglomerativeClustering(n_clusters=k)

# Fit the model to the data
hierarchical_clustering.fit(X)

# Get cluster labels
cluster_labels = hierarchical_clustering.labels_

# Add cluster labels to the dataset
data['cluster'] = cluster_labels

# Visualize the clusters (for 2D representation)
plt.scatter(X['math_score'], X['reading_score'], c=cluster_labels, cmap='viridis')
plt.xlabel('Math Score')
plt.ylabel('Reading Score')
plt.title('Hierarchical Clustering')


# Print the number of students in each cluster
print("Number of students in each cluster:")
print(data['cluster'].value_counts())

# Calculate silhouette score
silhouette = silhouette_score(X, cluster_labels)

# Calculate Davies-Bouldin index
```

```
davies_bouldin = davies_bouldin_score(X, cluster_labels)

print("Silhouette Score:", silhouette)
print("Davies-Bouldin Index:", davies_bouldin)

plt.show()
```

```
Number of students in each cluster:
cluster
0    534
2    314
1    152
Name: count, dtype: int64
Silhouette Score: 0.35242898815984935
Davies-Bouldin Index: 0.8487755692543697
```




```
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage

# Define features (math, reading, writing scores)
features = ['math_score', 'reading_score', 'writing_score']
X = data[features]

# Choose the number of clusters (k)
k = 3  # we can choose any number of clusters based on our requirements

# Create AgglomerativeClustering model
hierarchical_clustering = AgglomerativeClustering(n_clusters=k)

# Fit the model to the data
hierarchical_clustering.fit(X)

# Get cluster labels
cluster_labels = hierarchical_clustering.labels_

# Add cluster labels to the dataset
data['cluster'] = cluster_labels

# Plot the dendrogram
plt.figure(figsize=(15, 10))
plt.title('Hierarchical Clustering - Dendrogram')
plt.xlabel('Data Points')
plt.ylabel('Distance')
dendrogram(linkage(X, method='ward'), orientation='top', distance_sort='descending')
plt.show()
```



Visualize the clusters (for 2D representation)

```
plt.figure(figsize=(10, 7))
plt.scatter(X['math_score'], X['reading_score'], c=cluster_labels, cmap='viridis')
plt.xlabel('Math Score')
plt.ylabel('Reading Score')
plt.title('Hierarchical Clustering - Scatter Plot')
plt.show()
```