LAB 3 DATE:26 AUG 2025 NAME:AAYUSH SUTHAR
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~ Lab Report: Decision Tree for Housing Classification

~ Objective:

Train a Decision Tree model to classify houses as Expensive or Cheap based on features like area and number of bedrooms.

1 To build a Decision Tree Regression model to predict housing prices.
2 To understand the impact of outliers and feature scaling on model performance.
3 To visualize decision trees and interpret predictions.

~ Observations:

1 The tree splits based on the most informative features first (area or bedrooms).
2 Maximum depth = 3 ensures the tree doesn't overfit.
3 Accuracy depends on the dataset; small datasets may give perfect accuracy but not generalize well.
4 Feature selection affects the interpretability and performance of the tree.

~ Learning Outcomes:

1 Understand the concept and components of decision trees.
2 Prepare and split data for training and testing.
3 Train a Decision Tree model using scikit-learn.
4 Evaluate model performance with accuracy and confusion matrix.
5 Visualize the decision tree to interpret decisions.
6 Understand effects of tree depth and feature selection on performance.

~ Conclusion:

Decision Trees are easy to interpret and visualize. They can handle non-linear data relationships. Pruning (max_depth, min_samples_split) is important to prevent overfitting.

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'''Lab Report: Decision Tree for Housing Classification

Objective:
Train a Decision Tree Classifier to classify houses as Expensive or
Cheap.
Evaluate performance using accuracy, confusion matrix, and
classification report.
Visualize the Decision Tree and feature importance.'''

# 1. Import Libraries
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
from sklearn.datasets import fetch_california_housing

# 2. Load Dataset
california = fetch_california_housing(as_frame=True)
df = california.frame
# Display first 5 rows
df.head()

print("First 5 rows of dataset:\n", df.head())

# 3. Create Target Variable: Expensive / Cheap
df['PriceCategory'] = df['MedHouseVal'].apply(lambda x: 'Expensive' if
x > 2.0 else 'Cheap')

# 4. Select only the top 3 features for simplicity
X = df[['MedInc', 'AveRooms', 'HouseAge']]
y = df['PriceCategory']

# 5. Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42, stratify=y)

# 6. Train small Decision Tree
dt_small = DecisionTreeClassifier(random_state=42, max_depth=3,
min_samples_leaf=100)
dt_small.fit(X_train, y_train)

# 7. Predict
y_pred = dt_small.predict(X_test)

# 8. Evaluate Model
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
cr = classification_report(y_test, y_pred)

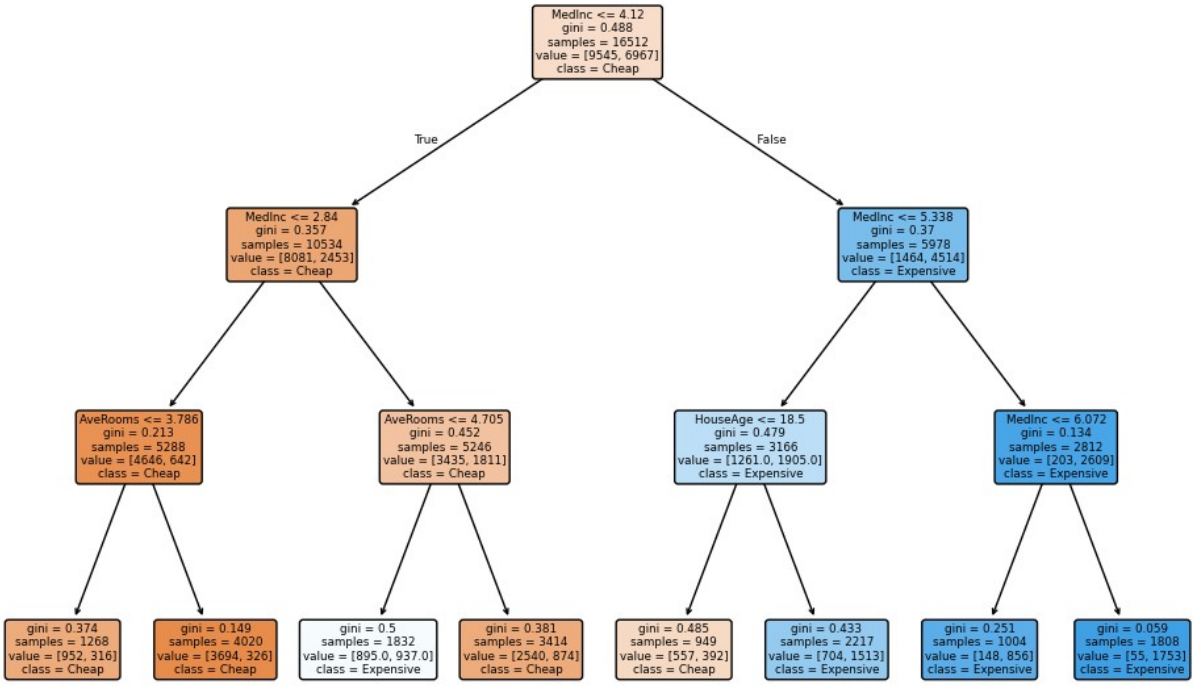
print("Accuracy:", accuracy)
print("\nConfusion Matrix:\n", cm)
print("\nClassification Report:\n", cr)

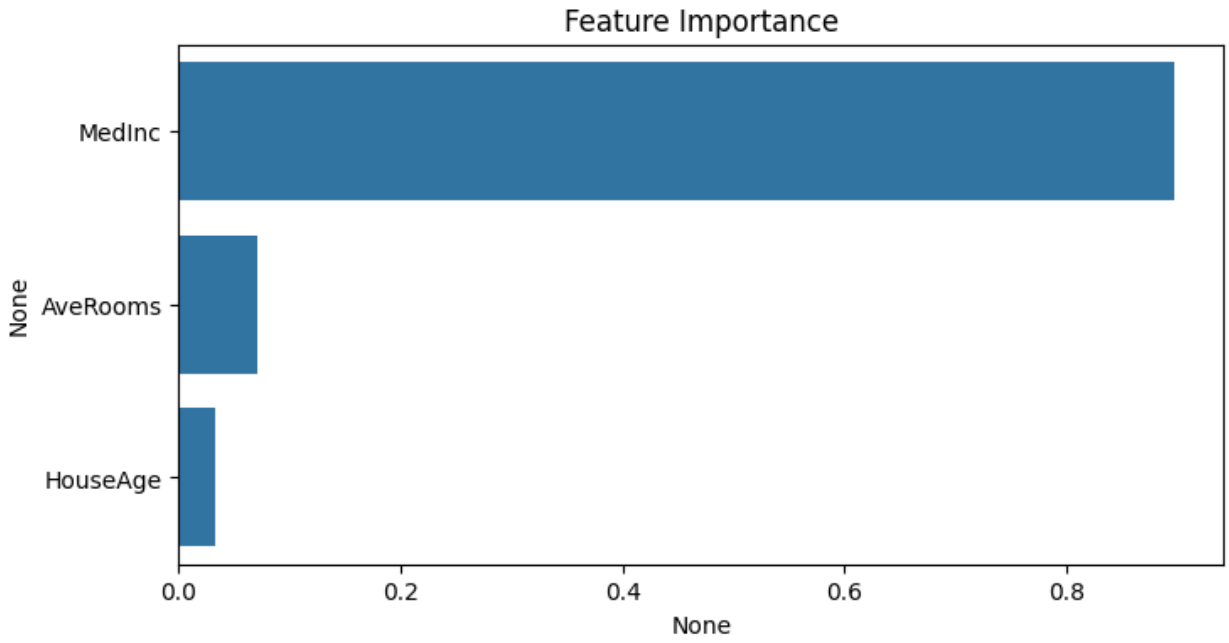
# 9. Visualize Tree
plt.figure(figsize=(12,8))
plot_tree(dt_small, feature_names=X.columns,
class_names=dt_small.classes_, filled=True, rounded=True)
plt.show()
```

```python
# 10. Feature Importance
importance = pd.Series(dt_small.feature_importances_,
index=X.columns).sort_values(ascending=False)
plt.figure(figsize=(8,4))
sns.barplot(x=importance, y=importance.index)
plt.title('Feature Importance')
plt.show()

# ------------------------------------------------------
# Note:
# If you face any issues or have questions regarding this lab,
# please contact the author:
# Name: Aayush Suthar
# Reg. No: 23FE10CAI00275
# Email: aayushsuthar5115@gmail.com
# ------------------------------------------------------
```

```
First 5 rows of dataset:
    MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup
Latitude  \
0  8.3252      41.0  6.984127   1.023810       322.0  2.555556
37.88
1  8.3014      21.0  6.238137   0.971880      2401.0  2.109842
37.86
2  7.2574      52.0  8.288136   1.073446       496.0  2.802260
37.85
3  5.6431      52.0  5.817352   1.073059       558.0  2.547945
37.85
4  3.8462      52.0  6.281853   1.081081       565.0  2.181467
37.85

   Longitude  MedHouseVal
0    -122.23        4.526
1    -122.22        3.585
2    -122.24        3.521
3    -122.25        3.413
4    -122.25        3.422
Accuracy: 0.7657461240310077

Confusion Matrix:
 [[1923  463]
 [ 504 1238]]

Classification Report:
              precision    recall  f1-score   support

       Cheap       0.79      0.81      0.80      2386
   Expensive       0.73      0.71      0.72      1742
```

```
    accuracy                           0.77      4128
   macro avg       0.76      0.76      0.76      4128
weighted avg       0.77      0.77      0.77      4128
```






```
'''
Lab 3: Decision Tree for Iris Classification
Date: 26 AUG 2025
Name: Aayush Suthar
Reg. No: 23FE10CAI00275

Objective:
1. Train a Decision Tree Classifier to classify Iris flowers into 3
species: setosa, versicolor, virginica.
2. Evaluate model performance using accuracy, confusion matrix, and
classification report.
3. Visualize the Decision Tree and feature importance.
'''

# 1. Import required libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

# 2. Load the Iris dataset
iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)  # Feature
columns
df['Species'] = iris.target                               # Target
```

```
column (0,1,2)
df['Species'] = df['Species'].map({0:'setosa', 1:'versicolor',
2:'virginica'})  # Map numeric to species names

# Preview dataset
print("First 5 rows of dataset:\n", df.head())

# 3. Prepare Features and Target
X = df[iris.feature_names]  # Features
y = df['Species']           # Target

# 4. Split dataset into training and testing sets (80% train, 20%
test)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# 5. Train Decision Tree Classifier
# - max_depth=3 ensures tree is small and interpretable
# - min_samples_leaf=5 avoids tiny splits and overfitting
dt = DecisionTreeClassifier(random_state=42, max_depth=3,
min_samples_leaf=5)
dt.fit(X_train, y_train)

# 6. Make Predictions on Test Set
y_pred = dt.predict(X_test)

# 7. Evaluate Model
accuracy = accuracy_score(y_test, y_pred)               # Overall
accuracy
cm = confusion_matrix(y_test, y_pred)                  # Confusion
matrix
cr = classification_report(y_test, y_pred)            # Precision,
Recall, F1-score

print("\nAccuracy:", accuracy)
print("\nConfusion Matrix:\n", cm)
print("\nClassification Report:\n", cr)

# 8. Visualize the Decision Tree
plt.figure(figsize=(12,8))
plot_tree(
    dt,
    feature_names=iris.feature_names,
    class_names=dt.classes_,
    filled=True,
    rounded=True
)
plt.title("Decision Tree for Iris Classification")
plt.show()
```

```python
# 9. Feature Importance
importance = pd.Series(dt.feature_importances_,
index=iris.feature_names).sort_values(ascending=False)
plt.figure(figsize=(8,4))
sns.barplot(x=importance, y=importance.index)
plt.title('Feature Importance')
plt.show()

# 10. Note for Users
# If you face any issues or have questions regarding this lab,
# please contact the author:
# Name: Aayush Suthar
# Reg. No: 23FE10CAI00275
# Date: 26 AUG 2025
```

```
First 5 rows of dataset:
    sepal length (cm)  sepal width (cm)  petal length (cm)  petal
width (cm)  \
0                5.1               3.5                1.4
0.2
1                4.9               3.0                1.4
0.2
2                4.7               3.2                1.3
0.2
3                4.6               3.1                1.5
0.2
4                5.0               3.6                1.4
0.2

  Species
0  setosa
1  setosa
2  setosa
3  setosa
4  setosa

Accuracy: 0.9333333333333333

Confusion Matrix:
 [[10  0  0]
 [ 0  9  1]
 [ 0  1  9]]

Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       0.90      0.90      0.90        10
   virginica       0.90      0.90      0.90        10
```

```
    accuracy                           0.93        30
   macro avg       0.93      0.93      0.93        30
weighted avg       0.93      0.93      0.93        30
```