1 DT-Classi ier- Day - Outlook - Temp - Humidity - Wind - Play

Tennis as Classifier

[1]:
```
# Importing necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪ConfusionMatrixDisplay
```

[2]:
```
# Load the dataset
data = pd.read_csv('DT.csv')
```

[4]:
```
data
```

[4]:

	Day	Outlook	Temp	Humidity	Wind	PlayTennis	Unnamed: 6
0	D1	sunny	hot	high	weak	No	NaN
1	D2	sunny	hot	high	strong	No	NaN
2	D3	overcast	hot	high	weak	Yes	NaN
3	D4	rain	mild	high	weak	Yes	NaN
4	D5	rain	cold	normal	weak	Yes	NaN
5	D6	rain	cold	normal	strong	No	NaN
6	D7	overcast	cold	normal	strong	Yes	NaN
7	D8,	sunny	mild	high	weak	No	NaN
8	D9	sunny	cold	normal	weak	Yes	NaN
9	D10	rain	mild	normal	weak	Yes	NaN
10	D11	sunny	mild	normal	strong	Yes	NaN
11	D12	overcast	mild	high	strong	Yes	NaN
12	D13	overcast	hot	normal	weak	Yes	NaN
13	D14	rain	mild	high	strong	No	NaN
14	D15	sunny	hot	normal	weak	No	NaN

[6]:
```
# Encoding categorical variables
label_encoders = {}
for column in data.columns[1:]:  # Ignore 'Day' as it's an identifier
    le = LabelEncoder()
```

```
    data[column] = le.fit_transform(data[column])
    label_encoders[column] = le
```

[7]:
```
# Separating features and target variable
X = data[['Outlook', 'Temp', 'Humidity', 'Wind']]  # Feature columns
y = data['PlayTennis']  # Target column
```

[8]:
```
# Split the data 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)
```

[9]:
```
# Train the Decision Tree classifier
model = DecisionTreeClassifier(random_state=42)
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)
```

[10]:
```
y_pred
```

[10]:
```
array([1, 1, 0])
```

[11]:
```
y_test
```

[11]:
```
9     1
11    1
0     0
Name: PlayTennis, dtype: int32
```

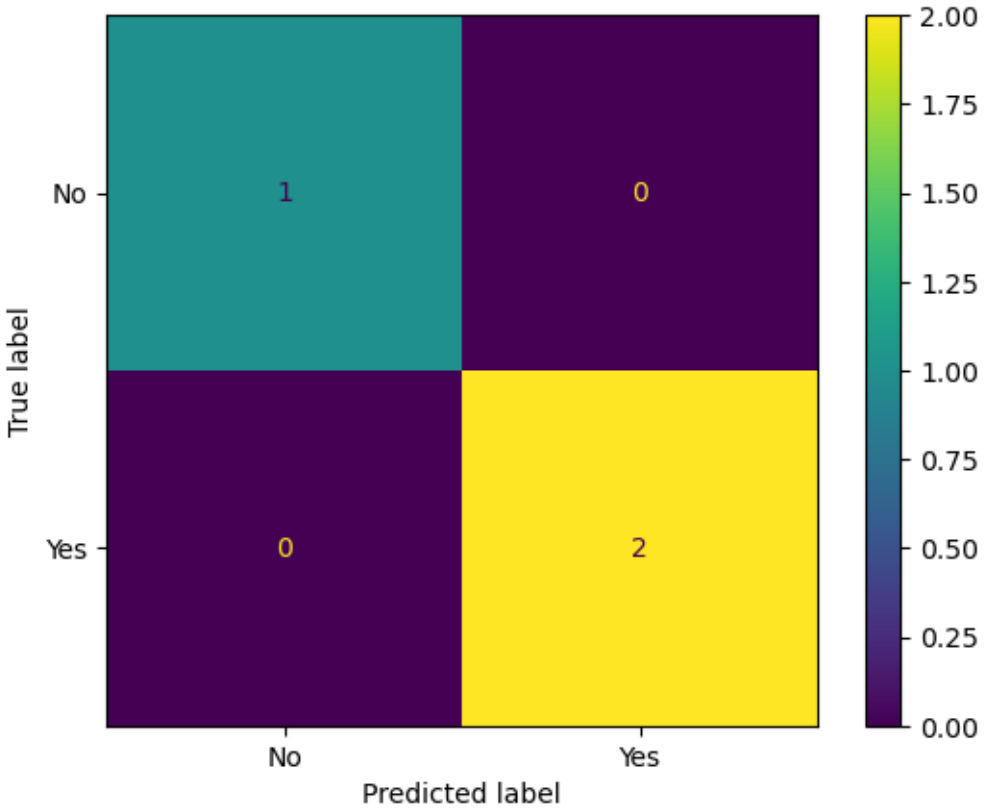
[12]:
```
# Calculate and print accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Model accuracy:", accuracy)
```

```
Model accuracy: 1.0
```

[13]:
```
# Display confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(conf_matrix)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred,␣
 ↪display_labels=label_encoders['PlayTennis'].classes_)
```

```
Confusion Matrix:
[[1 0]
 [0 2]]
```

[13]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x28921e31cd0>



[14]:
```
# Show actual vs predicted values for each test sample
print("\nActual vs Predicted:")
for actual, predicted in zip(y_test, y_pred):
    print(f"Actual: {label_encoders['PlayTennis'].
 ↪inverse_transform([actual])[0]}, "
          f"Predicted: {label_encoders['PlayTennis'].
 ↪inverse_transform([predicted])[0]}")
```

```
Actual vs Predicted:
Actual: Yes, Predicted: Yes
Actual: Yes, Predicted: Yes
Actual: No, Predicted: No
```

[15]:
```
# Example prediction for new input {rain, mild, high, strong}
input_data = pd.DataFrame({
    'Outlook': [label_encoders['Outlook'].transform(['rain'])[0]],
    'Temp': [label_encoders['Temp'].transform(['mild'])[0]],
    'Humidity': [label_encoders['Humidity'].transform(['high'])[0]],
```

```
    'Wind': [label_encoders['Wind'].transform(['strong'])[0]]
})
```

[16]:
```
# Predict whether to play tennis
prediction = model.predict(input_data)
result = label_encoders['PlayTennis'].inverse_transform(prediction)
print("\nPrediction for input {rain, mild, high, strong}: Play Tennis =",␣
 ↪result[0])
```

```
Prediction for input {rain, mild, high, strong}: Play Tennis = No
```

1 Decision tree from Dataset to predict as a Regressor

[53]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

[54]:
```
# Load the dataset
data = pd.read_csv('house_data_DT.csv')
```

[55]:
```
# Ensure all column names are stripped of whitespace
data.columns = data.columns.str.strip()
# Check if 'Location' exists
if 'Location' not in data.columns:
    raise KeyError("'Location' column is missing!")

# Convert all values in the 'Location' column to strings and strip whitespace
data['Location'] = data['Location'].astype(str).str.strip()

# Encode the 'Location' column
data['Location'] = data['Location'].map({'Suburb': 0, 'City': 1})

# Check for missing or unmapped values
if data['Location'].isnull().any():
    print("Warning: Some rows in 'Location' have unmapped or invalid values!")
    print(data[data['Location'].isnull()])
    data = data.dropna()  # Drop rows with unmapped values if necessary
```

[56]:
```
# Define features (X) and target (y)
X = data[['Rooms', 'Area', 'Location']]
y = data['Price']

# Split the data 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)
```

[57]:
```
# Train the Decision Tree Regressor
regressor = DecisionTreeRegressor(random_state=42)
regressor.fit(X_train, y_train)
```

[57]:
```
DecisionTreeRegressor(random_state=42)
```

[58]:
```
# Make predictions on the test set
y_pred = regressor.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")
```

```
Mean Squared Error: 2500000000.0
R^2 Score: -10.11111111111111
```

[59]:
```
# Function to predict price based on user input
def predict_price(rooms, area, location):
    # Encode the location input to match training data encoding
    location_encoded = 0 if location.lower() == 'suburb' else 1
    # Prepare the input data
    input_data = pd.DataFrame({
        'Rooms': [rooms],
        'Area': [area],
        'Location': [location_encoded]
    })

# Make the prediction
    predicted_price = regressor.predict(input_data)
    print("\nPredicted Price for input (Rooms: {}, Area: {}, Location: {}): ${:
 ↪,.2f}".format(rooms, area, location, predicted_price[0]))

    # Example prediction
predict_price(rooms=3, area=75, location='Suburb')
predict_price(rooms=4, area=95, location='City')
```

```
Predicted Price for input (Rooms: 3, Area: 75, Location: Suburb): $320,000.00

Predicted Price for input (Rooms: 4, Area: 95, Location: City): $450,000.00
```

confusion-matrix-print

October 2, 2024

1 Confusion Matrix

[18]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix , classification_report
```

[19]:
```
def plot_confusion_matrix(conf_matrix, class_names):
    df_cm = pd.DataFrame(conf_matrix, index=class_names, columns=class_names)
    plt.figure(figsize=(8, 6))
    sns.heatmap(df_cm, annot=True, fmt='d', cmap='Blues')
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.show()
```

Here is an explanation of each line in the `plot_confusion_matrix` function:

1. Function Definition

def plot_confusion_matrix(conf_matrix, class_names):

- This defines a function named `plot_confusion_matrix` that takes two parameters:
  - `conf_matrix`: The confusion matrix, which is typically a 2D array (like a NumPy array) containing the number of predictions for each class.
  - `class_names`: A list of class names corresponding to the labels in the confusion matrix (e.g., ["Dog", "Not a dog"]).

2. Creating a DataFrame

df_cm = pd.DataFrame(conf_matrix, index=class_names, columns=class_names)

- This line converts the confusion matrix (`conf_matrix`) into a Pandas DataFrame. Using a DataFrame makes it easier to visualize the matrix with labeled rows and columns.
- `index=class_names` and `columns=class_names` set the row and column labels of the DataFrame using the list `class_names`, making the matrix easier to interpret.

3. Creating a Plot Figure

plt.figure(figsize=(8, 6))

- This line creates a new figure for the plot with a specified size (`8` inches wide and `6` inches tall). This sets up the area where the heatmap will be drawn.

4. Drawing the Heatmap

sns.heatmap(df_cm, annot=True, fmt='d', cmap='Blues')

- This line uses Seaborn's `heatmap` function to create a visual representation of the confusion matrix (`df_cm`):
  - `df_cm`: The DataFrame to be visualized.
  - `annot=True`: Displays the values in each cell of the matrix.
  - `fmt='d'`: Formats the annotations as integers.
  - `cmap='Blues'`: Specifies the color scheme for the heatmap. The 'Blues' color palette is used to differentiate between higher and lower values visually.

5. Adding Axis Labels

plt.ylabel('Actual') plt.xlabel('Predicted') "`- These lines set the labels for the y-axis (Actual) and x-axis (Predicted`') of the plot. This indicates that the rows represent the actual classes, and the columns represent the predicted classes.

6. Displaying the Plot

plt.show()

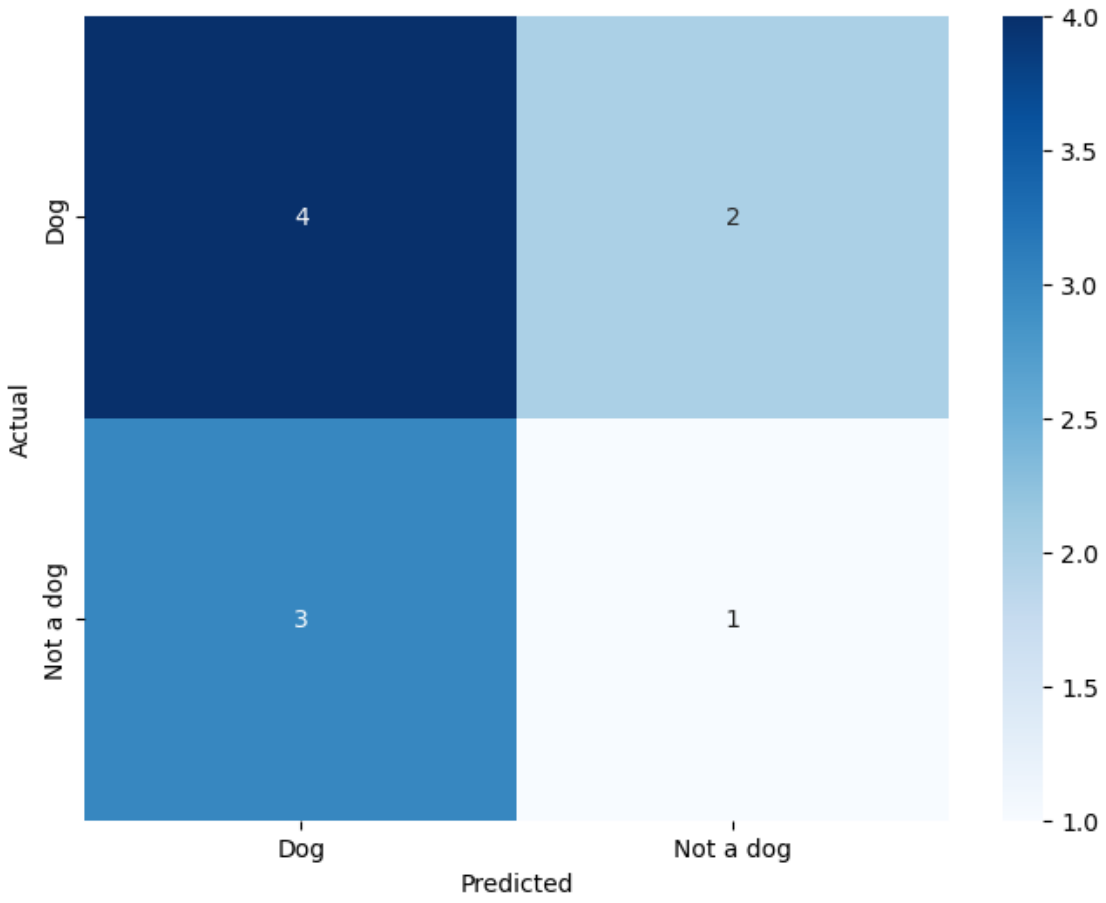
- This line displays the heatmap plot. Without this line, the plot might not render, especially in some interactive environments like Jupyter Notebooks.

Summary The `plot_confusion_matrix` function takes a confusion matrix and a list of class names, then creates a heatmap using Seaborn to visualize the matrix. It labels the rows and columns, uses a color gradient to represent values, and annotates each cell with the corresponding numbers for easy interpretation. This is helpful for understanding the performance of a classification model by showing how many instances were correctly or incorrectly classified.

[20]:
```
truth =      ["Dog","Not a dog","Dog","Dog",      "Dog", "Not a dog", "Not a␣
 ↪dog", "Dog",       "Dog", "Not a dog"]
prediction = ["Dog","Dog",      "Dog","Not a dog","Dog", "Not a dog", "Dog",  ␣
 ↪   "Not a dog", "Dog", "Dog"]
```

[21]:
```
from sklearn.metrics import confusion_matrix

# Assuming 'truth' and 'prediction' are defined earlier in your code
cm = confusion_matrix(truth, prediction)
plot_confusion_matrix(cm, ["Dog", "Not a dog"])
```



[22]:
```
print(classification_report(truth, prediction))
```

```
              precision    recall  f1-score   support

         Dog       0.57      0.67      0.62         6
     Not a dog       0.33      0.25      0.29         4

    accuracy                           0.50        10
   macro avg       0.45      0.46      0.45        10
weighted avg       0.48      0.50      0.48        10
```

2 f1 score for "Dog" class

[23]:
```
2*(0.57*0.67/(0.57+0.67))
```

[23]: 0.6159677419354839

3 f1 score for “not a Dog” class

[24]:
```
2*(0.33*0.25/(0.33+0.25))
```

[24]:
```
0.2844827586206896
```