Bank Marketing Dataset - Decision Tree Prediction

Performing prediction on a sample customer from the Bank Marketing dataset using a trained Decision Tree classifier, with label encoding for categorical features.

1 - Import libraries

```
# Core
import pandas as pd
import numpy as np

# Viz
import matplotlib.pyplot as plt
import seaborn as sns

# ML
from sklearn import tree
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, StandardScaler
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, ConfusionMatrixDisplay
```

2 - Load the dataset

```
data = pd.read_csv('bank-full.csv', sep=';')
data.head()
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	p
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	u
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	u
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	u
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	u
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	u

Next steps: Generate code with data | View recommended plots | New interactive sheet

3 - Data Inspection & Cleaning

```
# Shape of dataset (rows, columns)
print("Dataset shape:", data.shape)
```

```
Dataset shape: (45211, 17)
```

```
# Preview first 5 rows
print("\nFirst 5 rows:")
display(data.head())
```

```
First 5 rows:
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	p
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	u
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3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	u
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	u

```
# Data types and non-null count
print("\nData Info:")
print(data.info())
```

```
Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64 
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64 
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64 
 12  campaign   45211 non-null  int64 
 13  pdays      45211 non-null  int64 
 14  previous   45211 non-null  int64 
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
None
```

```
# Check for missing values
print("\nMissing values in each column:")
print(data.isnull().sum())
```

```
Missing values in each column:
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

```
# Basic statistics for numeric columns
print("\nStatistical Summary (Numeric Columns):")
display(data.describe())
```

Statistical Summary (Numeric Columns):

	age	balance	day	duration	campaign	pdays	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

```
# Check unique values for each column
print("\nUnique values per column:")
for col in data.columns:
    print(f"{col}: {data[col].nunique()} unique values")
```

```
Unique values per column:
age: 77 unique values
job: 12 unique values
marital: 3 unique values
```

```
education: 4 unique values
default: 2 unique values
balance: 7168 unique values
housing: 2 unique values
loan: 2 unique values
contact: 3 unique values
day: 31 unique values
month: 12 unique values
duration: 1573 unique values
campaign: 48 unique values
pdays: 559 unique values
previous: 41 unique values
poutcome: 4 unique values
y: 2 unique values
```

4 - Preprocessing (Encoding + Splitting)

```
# Copy dataset to avoid modifying original
df = data.copy()


# Encode all categorical columns using LabelEncoder
label_encoders = {}
for col in df.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le


# Separate features (X) and target (y)
X = df.drop('y', axis=1)  # 'y' is the target column
y = df['y']


# Train-test split (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)


print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)
```

```
Training set shape: (36168, 16)
Testing set shape: (9043, 16)
```

5 - Model Training

```
# Initialize the Decision Tree model
dt_model = DecisionTreeClassifier(
    criterion='entropy',  # use information gain
    max_depth=None,       # let the tree grow fully
    random_state=42
)


# Train the model
dt_model.fit(X_train, y_train)

print("Model training complete!")
```

```
Model training complete!
```

6 - Train the Decision Tree Classifier

```
# Create the Decision Tree model
clf = DecisionTreeClassifier(random_state=42)

# Train the model
clf.fit(X_train, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

7 - Model Evaluation

After training, we evaluate the model on the test data (X_test, y_test). We'll calculate:

Accuracy — percentage of correct predictions.

Classification Report — precision, recall, F1-score.

Confusion Matrix — to visualize correct vs. incorrect predictions.

```
# Predictions on test data
y_pred = dt_model.predict(X_test)
```

```
# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
```

```
Accuracy: 0.8758
```

```
# Classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.93      0.93      7952
           1       0.49      0.49      0.49      1091

    accuracy                           0.88      9043
   macro avg       0.71      0.71      0.71      9043
weighted avg       0.88      0.88      0.88      9043
```

```
# Confusion matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Confusion Matrix:
[[7389  563]
 [ 560  531]]
```

8 - Visualizing the Decision Tree

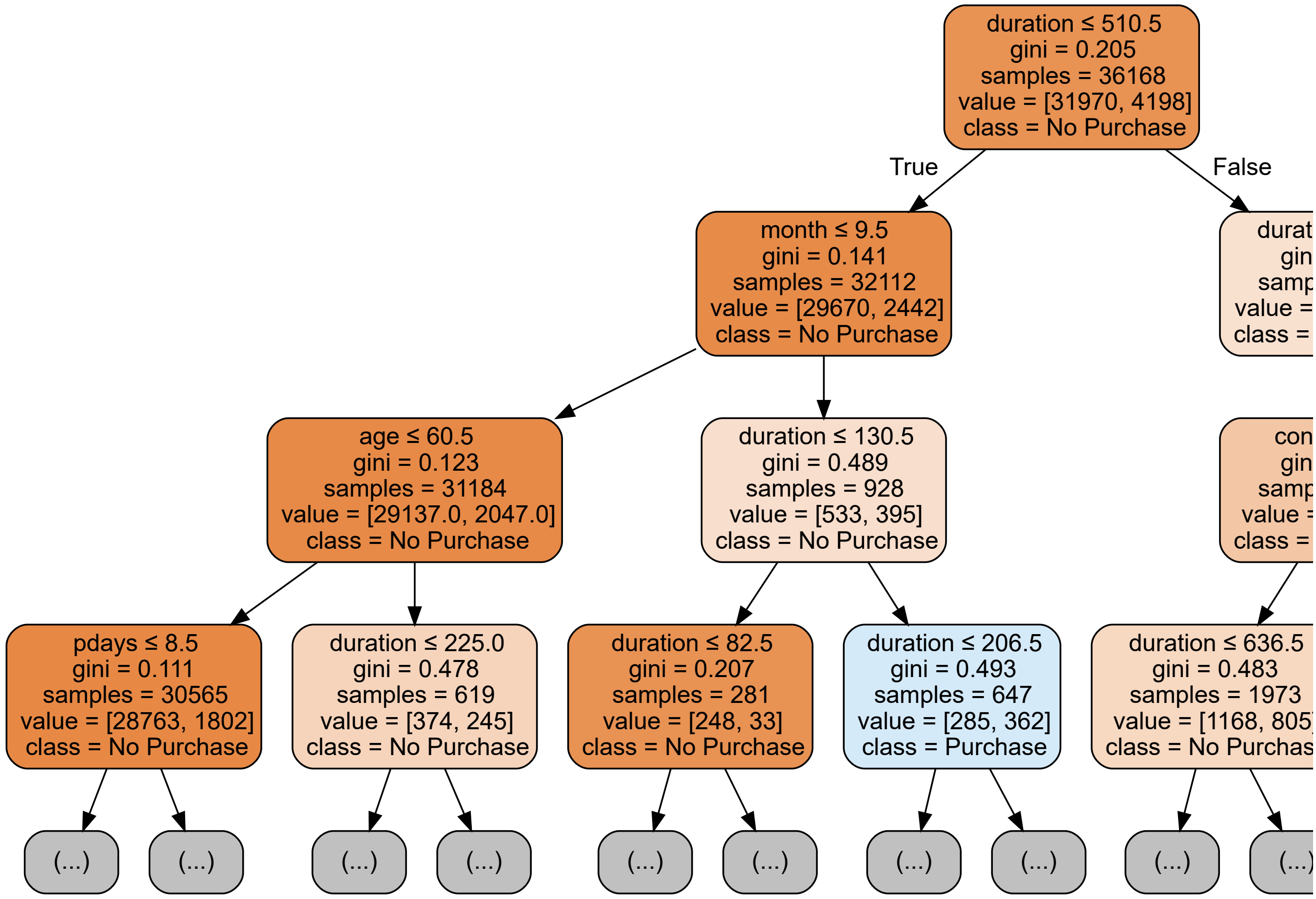
```
!pip install graphviz
```

```
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages (0.21)
```

```
!apt-get install -y graphviz
```

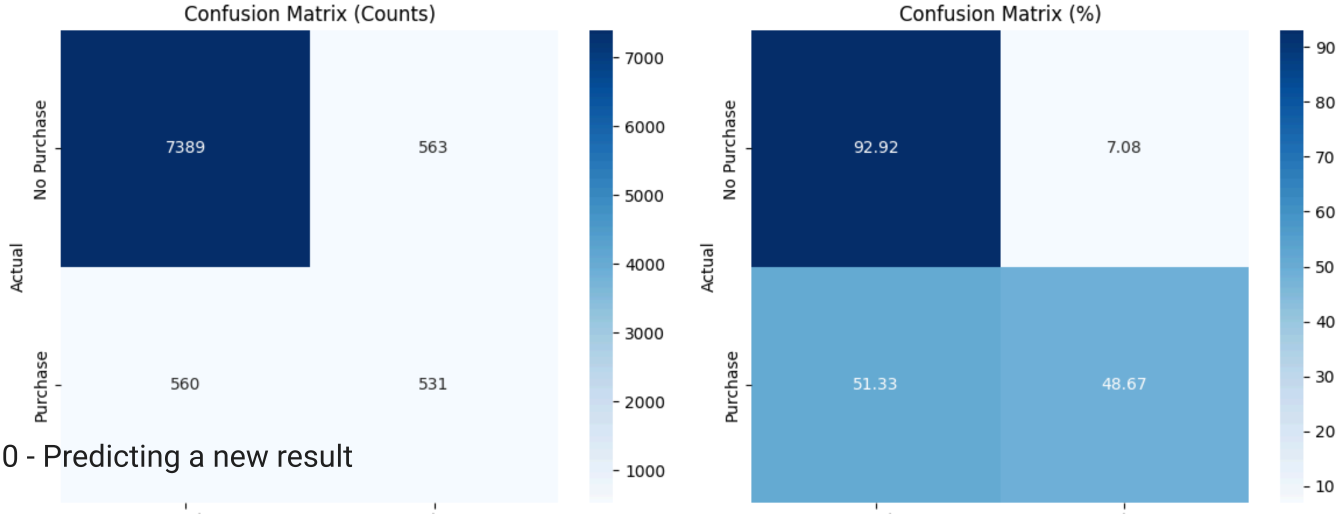
```
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
graphviz is already the newest version (2.42.2-6ubuntu0.1).
0 upgraded, 0 newly installed, 0 to remove and 35 not upgraded.
```

```
from sklearn.tree import export_graphviz
import graphviz

dot_data = export_graphviz(
    clf,
    out_file=None,
    feature_names=X.columns,
    class_names=['No Purchase', 'Purchase'],
    filled=True,
    rounded=True,
    special_characters=True,
    max_depth=3,  # Limit the depth of the tree for better visualization
)

graph = graphviz.Source(dot_data)
graph
```



9 - Confusion Matrix Visualization (Counts + Percentages)

```
# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)


# Create percentage version
cm_percent = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis] * 100


# Create side-by-side plots
fig, ax = plt.subplots(1, 2, figsize=(12, 5))

# --- Left: Raw counts ---
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", ax=ax[0],
            xticklabels=['No Purchase', 'Purchase'],
            yticklabels=['No Purchase', 'Purchase'])
ax[0].set_title("Confusion Matrix (Counts)")
ax[0].set_xlabel("Predicted")
ax[0].set_ylabel("Actual")

# --- Right: Percentages ---
sns.heatmap(cm_percent, annot=True, fmt=".2f", cmap="Blues", ax=ax[1],
            xticklabels=['No Purchase', 'Purchase'],
            yticklabels=['No Purchase', 'Purchase'])
ax[1].set_title("Confusion Matrix (%)")
ax[1].set_xlabel("Predicted")
ax[1].set_ylabel("Actual")

# Adjust layout & show
plt.tight_layout()
plt.show()
```



10 - Predicting a new result

```
# Define the sample customer data
new_data_dict = {
    'age': [36],
    'job': [label_encoders['job'].transform(['technician'])[0]],
    'marital': [label_encoders['marital'].transform(['married'])[0]],
    'education': [label_encoders['education'].transform(['secondary'])[0]],
    'default': [label_encoders['default'].transform(['no'])[0]],
    'balance': [368],
    'housing': [label_encoders['housing'].transform(['yes'])[0]],
    'loan': [label_encoders['loan'].transform(['yes'])[0]],
    'contact': [label_encoders['contact'].transform(['unknown'])[0]],
    'day': [6],
    'month': [label_encoders['month'].transform(['may'])[0]],
    'duration': [1597],
    'campaign': [2],
    'pdays': [-1],
    'previous': [0],
    'poutcome': [label_encoders['poutcome'].transform(['unknown'])[0]]
}

# Convert to DataFrame
new_data_df = pd.DataFrame(new_data_dict)

# Predict using the trained Decision Tree model
prediction = dt_model.predict(new_data_df)[0]
probability = dt_model.predict_proba(new_data_df)[0][1]  # Probability of positive class

# Decode the prediction back to original class names
predicted_class = label_encoders['y'].inverse_transform([prediction])[0]

# Display results
print(f"Prediction: {predicted_class}")
print(f"Probability of Purchase: {probability:.2%}")
```

```
Prediction: yes
Probability of Purchase: 100.00%
```