Step by step procedure to implement bank task

1. Understand the Goal

- **We want to predict whether a customer will subscribe to a term deposit (`y` column in the dataset), based on demographic and behavioral features using a Decision Tree Classifier.**

🛠️ Step-by-Step Implementation

- Step 1: Load and Explore the Dataset
- You can use pandas to load and inspect the data.

In [4]:
```
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns, os
```

In [5]:
```
bank_df=pd.read_csv(r"C:\Users\seenu\Desktop\prodigy\bank\bank.csv",sep=';')
bank_df
```

Out[5]:

	age	job	marital	education	default	balance	housing	loan	contact	da
0	30	unemployed	married	primary	no	1787	no	no	cellular	
1	33	services	married	secondary	no	4789	yes	yes	cellular	
2	35	management	single	tertiary	no	1350	yes	no	cellular	
3	30	management	married	tertiary	no	1476	yes	yes	unknown	
4	59	blue-collar	married	secondary	no	0	yes	no	unknown	
...	...	...	...	...	...	...	...	...	...	
4516	33	services	married	secondary	no	-333	yes	no	cellular	
4517	57	self-employed	married	tertiary	yes	-3313	yes	yes	unknown	
4518	57	technician	married	secondary	no	295	no	no	cellular	
4519	28	blue-collar	married	secondary	no	1137	no	no	cellular	
4520	44	entrepreneur	single	tertiary	no	1136	yes	yes	cellular	

4521 rows × 17 columns

In [6]:
```
bank_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4521 entries, 0 to 4520
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        4521 non-null   int64 
 1   job        4521 non-null   object
 2   marital    4521 non-null   object
 3   education  4521 non-null   object
 4   default    4521 non-null   object
 5   balance    4521 non-null   int64 
 6   housing    4521 non-null   object
 7   loan       4521 non-null   object
 8   contact    4521 non-null   object
 9   day        4521 non-null   int64 
 10  month      4521 non-null   object
 11  duration   4521 non-null   int64 
 12  campaign   4521 non-null   int64 
 13  pdays      4521 non-null   int64 
 14  previous   4521 non-null   int64 
 15  poutcome   4521 non-null   object
 16  y          4521 non-null   object
dtypes: int64(7), object(10)
memory usage: 600.6+ KB
```

Step 2: Preprocess the Data

2.1 seperate the **categorical_column** and **numerical_column**

In [8]:
```
cat_col= bank_df.select_dtypes(include='object').columns
num_col=bank_df.select_dtypes(exclude='object').columns
```

In [9]:
```
cat_col
```

Out[9]:
```
Index(['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact',
       'month', 'poutcome', 'y'],
      dtype='object')
```

In [10]:
```
num_col
```

Out[10]:
```
Index(['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous'], dtyp
e='object')
```

2.2 Handle categorical variables using One-Hot Encoding or Label Encoding.

- Check for null values and handle them.
- Convert the target variable (y) into binary (Yes → 1, No → 0).

In [12]:
```
from sklearn.preprocessing import LabelEncoder

# Encode target variable
bank_df['y'] = bank_df['y'].map({'yes': 1, 'no': 0})

# Convert categorical columns using one-hot encoding
df_encoded = pd.get_dummies(bank_df.drop('y', axis=1), drop_first=True)

# Final dataset
X = df_encoded
y = bank_df['y']
```

In [13]:
```
X
```

Out[13]:

	age	balance	day	duration	campaign	pdays	previous	job_blue-collar	job_entrepreneu
0	30	1787	19	79	1	-1	0	False	Fals
1	33	4789	11	220	1	339	4	False	Fals
2	35	1350	16	185	1	330	1	False	Fals
3	30	1476	3	199	4	-1	0	False	Fals
4	59	0	5	226	1	-1	0	True	Fals
...	...	...	...	...	...	...	...	...	
4516	33	-333	30	329	5	-1	0	False	Fals
4517	57	-3313	9	153	1	-1	0	False	Fals
4518	57	295	19	151	11	-1	0	False	Fals
4519	28	1137	6	129	4	211	3	True	Fals
4520	44	1136	3	345	2	249	7	False	Tru

4521 rows × 42 columns

In [14]:
```
y
```

Out[14]:
```
0       0
1       0
2       0
3       0
4       0
       ..
4516    0
4517    0
4518    0
4519    0
4520    0
Name: y, Length: 4521, dtype: int64
```

Step 3: Train-Test Split

- Split the dataset to evaluate model performance.

In [16]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

In [17]:
```
X_train
```

Out[17]:

	age	balance	day	duration	campaign	pdays	previous	job_blue-collar	job_entrepreneu
4153	42	440	3	13	5	-1	0	False	Fals
2085	33	-77	28	151	3	-1	0	True	Fals
1891	32	656	20	148	2	-1	0	False	Fals
3611	28	389	11	15	7	-1	0	False	Fals
4015	36	5902	23	219	4	-1	0	False	Fals
...	...	...	...	...	...	...	...	...	
4426	41	1536	4	54	2	-1	0	False	Fals
466	34	-370	21	748	1	-1	0	False	Fals
3092	46	523	6	105	4	366	2	False	Fals
3772	47	440	21	71	4	-1	0	False	Fals
860	58	309	19	156	2	-1	0	True	Fals

3164 rows × 42 columns

In [18]:
```
X_test
```

Out[18]:

	age	balance	day	duration	campaign	pdays	previous	job_blue-collar	job_entreprene
2398	51	-2082	28	123	6	-1	0	False	Tru
800	50	2881	5	510	2	2	5	False	Fals
2288	50	1412	6	131	3	-1	0	False	Fals
2344	37	0	3	247	13	-1	0	False	Fals
3615	31	757	3	343	2	-1	0	False	Fals
...	...	...	...	...	...	...	...	...	
2600	45	959	18	74	1	-1	0	False	Fals
554	43	11269	29	92	1	-1	0	False	Fals
1159	31	62	18	175	1	293	5	False	Fals
1213	49	2576	15	64	6	-1	0	False	Fals
1498	51	837	30	41	2	-1	0	True	Fals

1357 rows × 42 columns

In [19]:

```
y_train
```

Out[19]:

```
4153    0
2085    0
1891    0
3611    0
4015    0
       ..
4426    0
466     0
3092    0
3772    0
860     0
Name: y, Length: 3164, dtype: int64
```

In [20]:

```
y_test
```

Out[20]:
```
2398    0
800     0
2288    0
2344    0
3615    0
       ..
2600    0
554     0
1159    0
1213    0
1498    0
Name: y, Length: 1357, dtype: int64
```

Step 4: Train a Decision Tree Classifier

In [22]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

model = DecisionTreeClassifier(random_state=42)
model.fit(X_train, y_train)
```

Out[22]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

Step 5: Evaluate the Model

In [24]:
```python
y_pred = model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8695652173913043
[[1113   92]
 [  85   67]]
              precision    recall  f1-score   support

           0       0.93      0.92      0.93      1205
           1       0.42      0.44      0.43       152

    accuracy                           0.87      1357
   macro avg       0.68      0.68      0.68      1357
weighted avg       0.87      0.87      0.87      1357
```

1. Accuracy

- **Accuracy: 0.8695652173913043**
- This means that approximately **87% of predictions were correct**.

2. Confusion Matrix

- [[1113 92]
- [85 67]]

Confusion Matrix

	Predicted No (0)	Predicted Yes (1)
Actual No (0)	1113 (True Neg)	92 (False Pos)
Actual Yes (1)	85 (False Neg)	67 (True Pos)

- **True Negatives (1113)**: Correctly predicted as "No".
- **False Positives (92)**: Predicted as "Yes" but actually "No".
- **False Negatives (85)**: Predicted as "No" but actually "Yes".
- **True Positives**: Correctly predicted as "Yes".

📊 3. Classification Report

Class	Precision	Recall	F1-score	Support
0	0.93	0.92	0.93	1205
1	0.42	0.44	0.43	

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- ➤ **Precision**:
- Of all predicted "Yes", how many were correct?
  - For class 1: 42% were actually Yes.
- ➤ **Recall**:
- Of all actual "Yes", how many were predicted correctly?
  - For class 1: 44% were captured corectly.
- ➤ **F1-score**:
- A harmonic mean of precision and recall.
  - For class 1: 0.43 (indicating the model struggles with positive class prediction).
- ➤ **Support**:
- The actual count of each class in test data:
  - 1205 were No, and 152 . |

|

Conclusion:

- The model is doing very well at predicting class 0 (No), but poorly at class 1 (Yes).
- This usually happens in imbalanced datasets, where one class dominates.
- **If Our business goal is to identify customers who are likely to buy (Yes), this model needs improvement**.

Step 6: Visualize the Decision Tree

In [ ]:
```
from sklearn.tree import plot_tree

plt.figure(figsize=(20,10))
plot_tree(model, filled=True, feature_names=X.columns, class_names=["No", "Yes"])
plt.show()
```

we need to fine tune our model

In [ ]:
```
from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=42)
X_resampled, y_resampled = sm.fit_resample(X, y)

print("Before:", y.value_counts())
print("After:", y_resampled.value_counts())
```

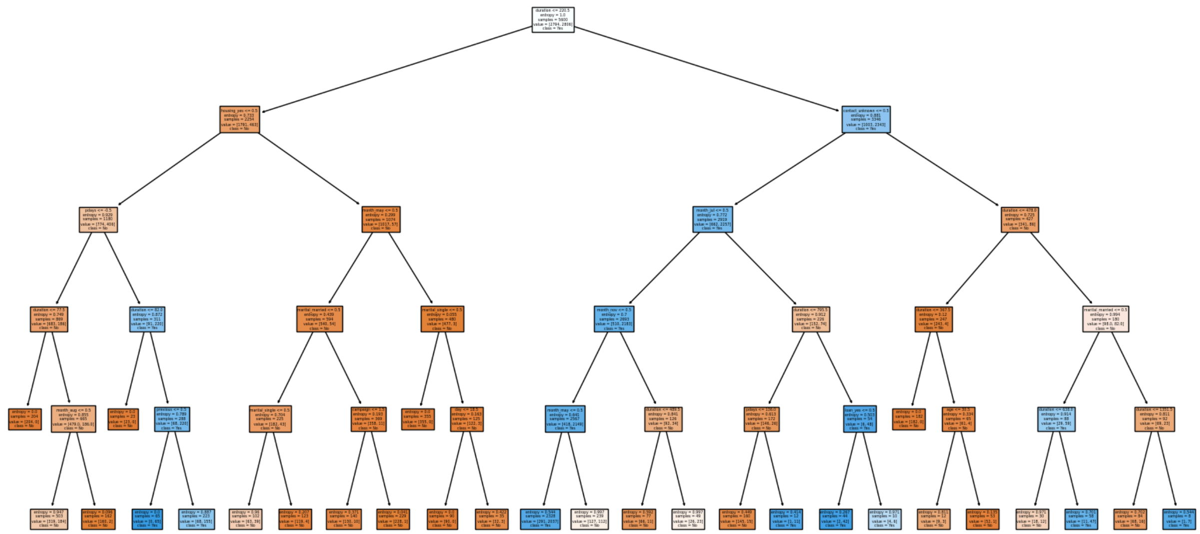
In [50]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Split balanced data
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_

# Train a tuned decision tree
model = DecisionTreeClassifier(max_depth=5, min_samples_split=10, criterion='entrop
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8533333333333334
[[1042  164]
 [ 188 1006]]
              precision    recall  f1-score   support

           0       0.85      0.86      0.86      1206
           1       0.86      0.84      0.85      1194

    accuracy                           0.85      2400
   macro avg       0.85      0.85      0.85      2400
weighted avg       0.85      0.85      0.85      2400
```

In [52]:
```python
from sklearn.metrics import classification_report, confusion_matrix

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[1042  164]
 [ 188 1006]]

Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.86      0.86      1206
           1       0.86      0.84      0.85      1194

    accuracy                           0.85      2400
   macro avg       0.85      0.85      0.85      2400
weighted avg       0.85      0.85      0.85      2400
```

In [54]:
```python
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 10))
plot_tree(model, filled=True, feature_names=X.columns, class_names=['No', 'Yes'])
plt.show()
```



In [56]:
```
import joblib
joblib.dump(model, 'decision_tree_bank_model.pkl')
```

Out[56]:
```
['decision_tree_bank_model.pkl']
```

✅ Conclusion

After applying SMOTE to balance the dataset and training a Decision Tree Classifier, we achieved:

- Accuracy: **85.3%**
- Balanced precision and recall for both classes
- Improved performance on minority class (Yes)

This shows that Decision Trees, combined with data balancing, can effectively predict customer purchase behavior from demographic and behavioral features.