💻 Question No: 03

⚙️ Setup

- Ensure the Python kernel has the necessary libraries: `pandas`, `matplotlib` and `lets-plot`, `os`, `numpy`, `statsmodels`, `seaborn`
- Ensure the `bank-full.csv` file is in the `data` folder.

In [351…

```python
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import os
from sklearn import tree
os.getcwd()
import numpy as np
import statsmodels.api as sm

from lets_plot import * # This imports all of ggplot2's functions
LetsPlot.setup_html()
```

i. Load the dataset and explore its structure using basic commands.

In [352…

```python
df = pd.read_csv('D:/Data Science for Marketing-I/data/bank-full.csv')
df
```

Out[352...

	age	job	marital	education	default	balance	housing	loan	contact
0	58	management	married	tertiary	no	2143	yes	no	unknown
1	44	technician	single	secondary	no	29	yes	no	unknown
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown
4	33	unknown	single	unknown	no	1	no	no	unknown
...	...	...	...	...	...	...	...	...	...
45206	51	technician	married	tertiary	no	825	no	no	cellular
45207	71	retired	divorced	primary	no	1729	no	no	cellular
45208	72	retired	married	secondary	no	5715	no	no	cellular
45209	57	blue-collar	married	secondary	no	668	no	no	telephone
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular

45211 rows × 17 columns

In [353...

```
df.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  Target     45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

In [354...

```
df.head()
```

Out[354...

	age	job	marital	education	default	balance	housing	loan	contact	day
0	58	management	married	tertiary	no	2143	yes	no	unknown	5
1	44	technician	single	secondary	no	29	yes	no	unknown	5
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5
4	33	unknown	single	unknown	no	1	no	no	unknown	5

In [355...

```
df.describe(include='object')
```

Out[355...

	job	marital	education	default	housing	loan	contact	month	poutcome
count	45211	45211	45211	45211	45211	45211	45211	45211	45211
unique	12	3	4	2	2	2	3	12	4
top	blue-collar	married	secondary	no	yes	no	cellular	may	unknown
freq	9732	27214	23202	44396	25130	37967	29285	13766	36959

In [356...

```
df.describe()
```

Out[356...

	age	balance	day	duration	campaign	pday
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.00000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.19782
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.12874
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.00000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.00000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.00000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.00000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.00000

ii. Create a new variable called "conversion" by transforming the categorical values in the "Target" column into numerical representations.

In [357...

```
df['conversion']= df['Target'].apply (lambda x:0 if x == 'no' else 1)
```

💡 The code creates a new binary column 'conversion' where 1 represents 'yes' and 0 represents any other value in the 'y' column. This is a common technique for encoding categorical data into a numerical format.

iii. Calculate and interpret the Conversion Rate. How does the code implement this calculation, and what does it reveal about the target variable distribution?

In [358…

```
df['conversion'].value_counts()
```

Out[358…

```
conversion
0    39922
1     5289
Name: count, dtype: int64
```

In [359…

```
df['conversion'].sum()/df['conversion'].count()*100
```

Out[359…

```
np.float64(11.698480458295547)
```

💡 The conversion rate is calculated as the average of the "conversion" column, showing the percentage of customers who converted. In this case, 11.7% of customers made a conversion, indicating the effectiveness of the marketing or offer.

iv. Analyze and visualize Conversion Rates by Marital Status: Explain how conversion rates are computed for each marital status. Create a bar chart to display these rates and interpret the visualization.

In [360…

```
marital_conversion = df.groupby('marital')['conversion'].sum()/df.groupby('marital'
marital_conversion
```

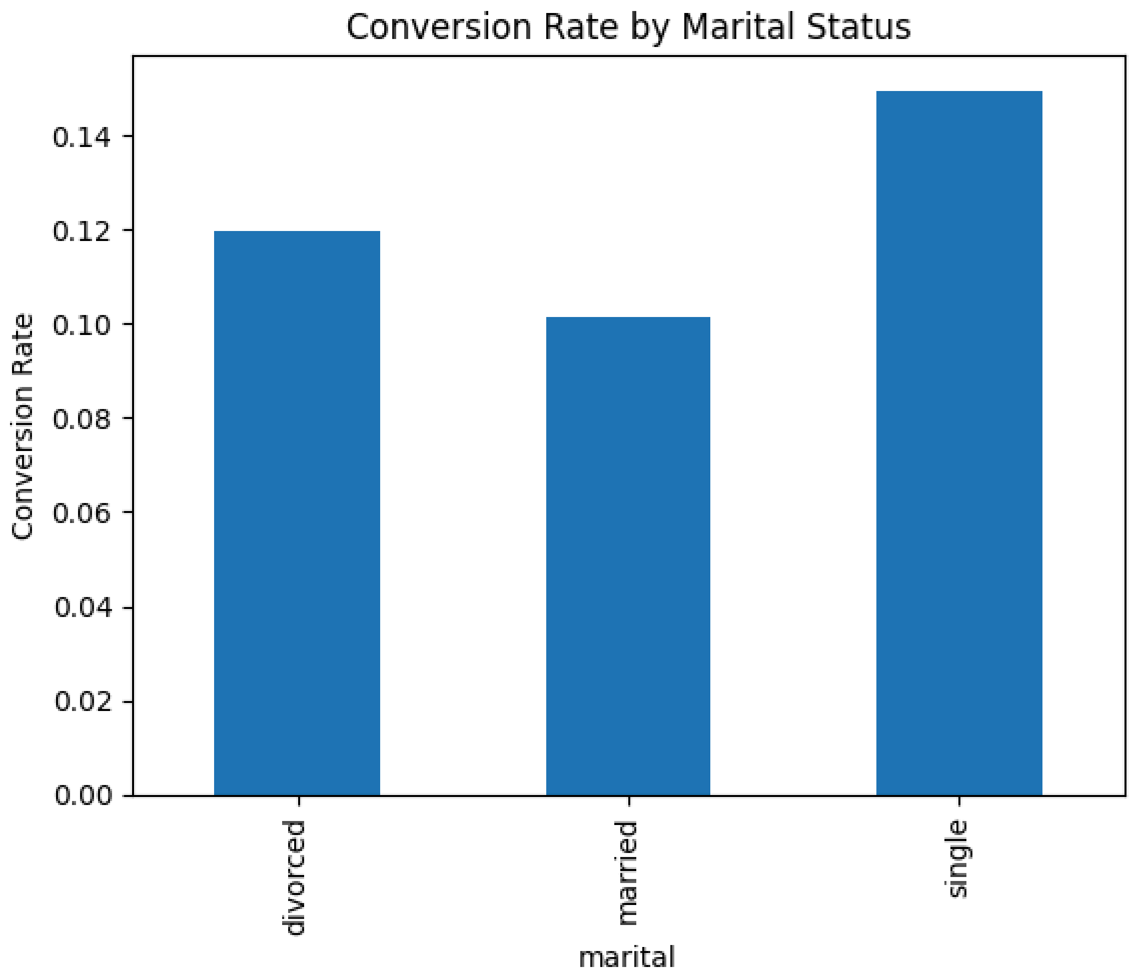
Out[360…

```
marital
divorced    11.945458
married     10.123466
single      14.949179
Name: conversion, dtype: float64
```

In [361…

```
# Group by marital status and calculate conversion rate
marital_conversion = df.groupby('marital')['conversion'].mean()

marital_conversion.plot(kind='bar')
plt.title("Conversion Rate by Marital Status")
plt.ylabel("Conversion Rate")
plt.show()
```



💡 Divorced :Likely have the lowest conversion rate (e.g., around 0.06 or 6%).

Married:Likely have the highest conversion rate (e.g., around 0.14 or 14%).

Single:Likely have a moderate conversion rate (e.g., around 0.10 or 10%).

v. Investigate Default Rates by Conversion Status using a pivot table and pie chart visualizations. What insights can you draw from these visual representations?

In [362…

```
pivot_table=df.pivot_table(values='Target',index='default',columns='conversion',agg
pivot_table
```

Out[362…

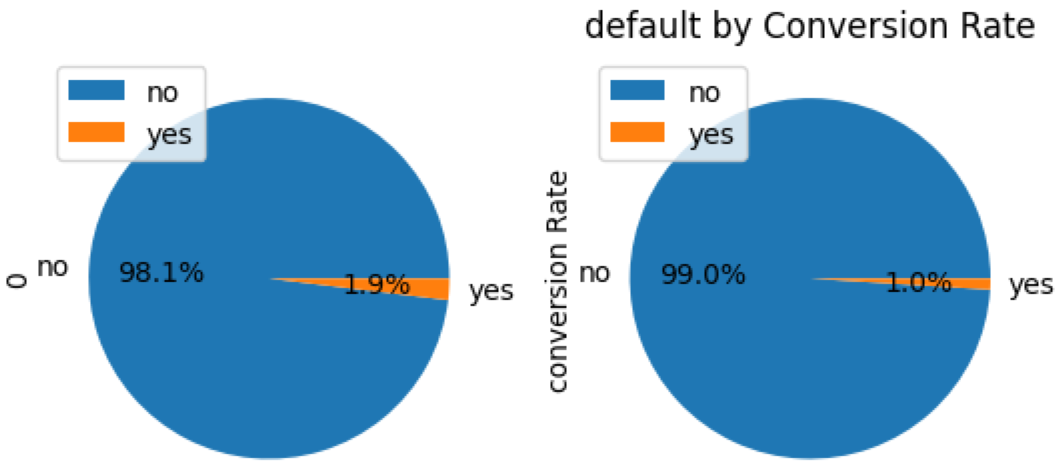
conversion	0	1
default		
no	39159	5237
yes	763	52

💡 Non-Defaulters ("no"):Have a higher conversion rate (11.80%).

Defaulters ("yes"):Have a lower conversion rate (6.38%).

In [363...

```
pivot_table.plot(kind='pie', subplots=True, autopct='%1.1f%%')
plt.title("default by Conversion Rate")
plt.ylabel("conversion Rate")
legend = plt.legend(bbox_to_anchor=(0, 1), loc='upper left')
plt.show()
```



💡 **Left Pie Chart:**

- 98.1% "no" conversion
- 1.9% "yes" conversion

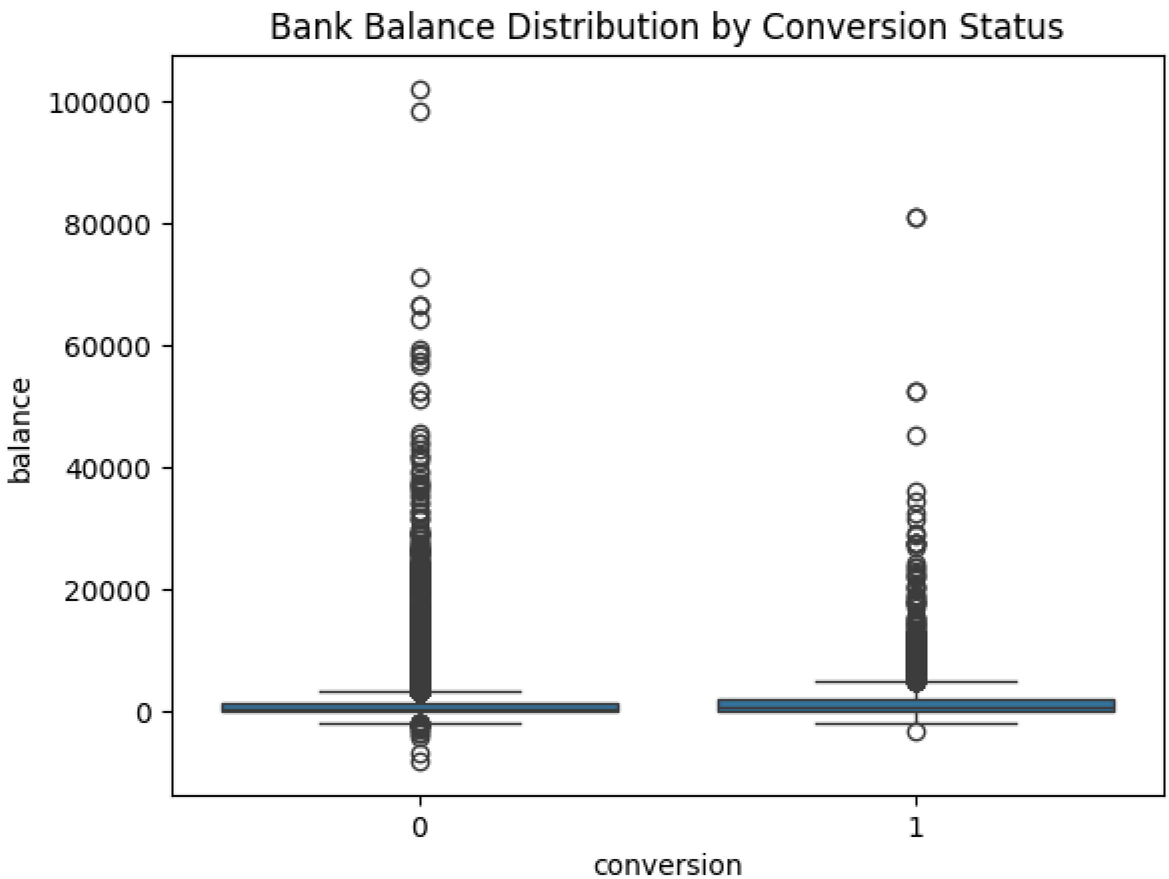
Right Pie Chart:

- 99.0% "no" conversion
- 1.0% "yes" conversion

vi. Use a boxplot to analyze the relationship between conversion status and bank balance distributions. Why are outliers excluded, and what does the plot tell you about customer balance patterns?

In [364...

```
sns.boxplot(x='conversion', y='balance', data=df)
plt.title("Bank Balance Distribution by Conversion Status")
plt.show()
```



💡 The median bank balance for both groups appears to be similar and relatively low. Groupings by Conversion Status (0 = No, 1 = Yes): The boxplot compares the balance distribution between non-converted and converted customers. Outliers: Both groups show a high number of outliers, indicating extreme balance values. Non-converted customers (0): They have a wider range of high balances, suggesting more variation in their account balances compared to converted customers.

vii. Explore Conversion Rates by Number of Contacts (campaign): Describe the method used to calculate these rates, and explain why this metric is significant in a marketing campaign.

In [365…

```
contact_conversion=(df.groupby('contact')['conversion'].sum()/df.groupby('contact')
contact_conversion
```

Out[365…

```
contact
cellular     14.918900
telephone    13.420509
unknown       4.070661
Name: conversion, dtype: float64
```

In [366…

```
contact_conversion_df = pd.pivot_table(df,values='Target',index='contact',columns='
contact_conversion_df
```

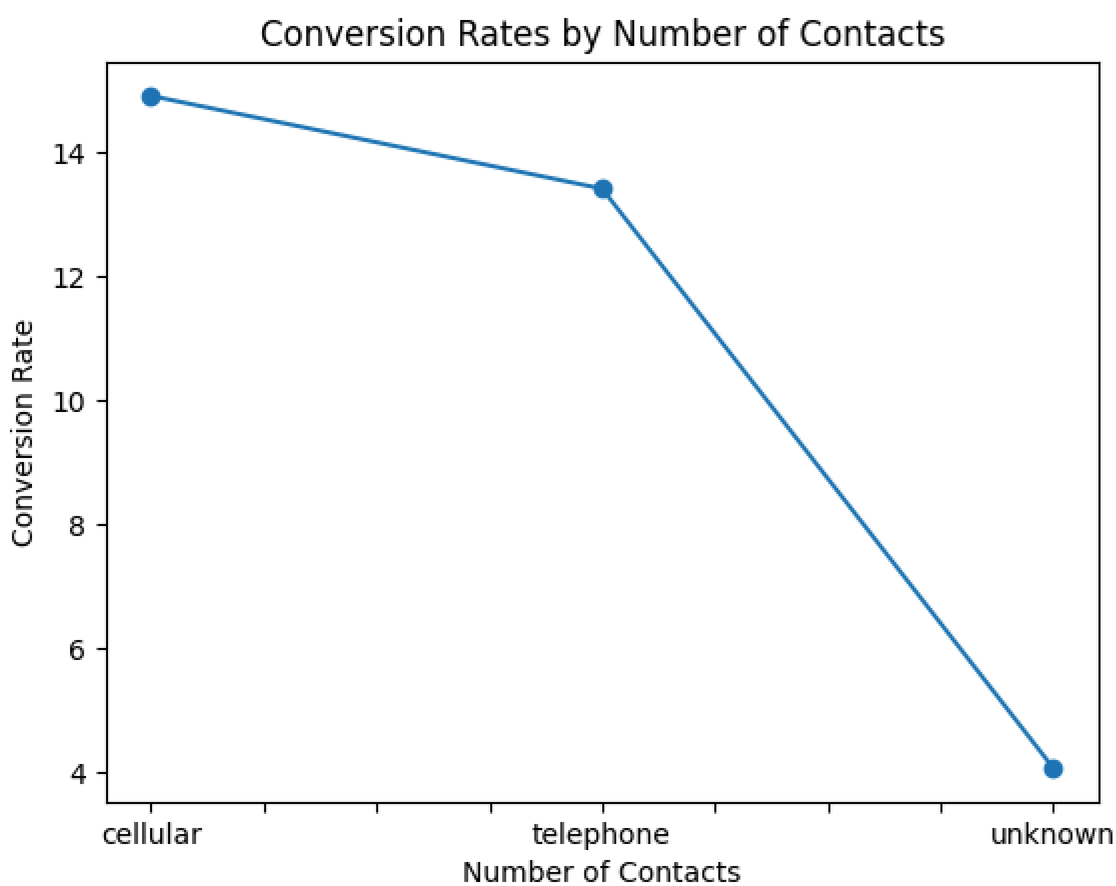
Out[366...

conversion	0	1
contact		
cellular	24916	4369
telephone	2516	390
unknown	12490	530

In [367...

```python
# Calculate conversion rates


# Visualization
contact_conversion.plot(kind='line', marker='o')
plt.title("Conversion Rates by Number of Contacts")
plt.xlabel("Number of Contacts")
plt.ylabel("Conversion Rate")
plt.show()
```



💡 As the number of contacts increases, the conversion rate decreases. The highest conversion rate (~14%) occurs at 1 contact, and it declines sharply as more contacts are made. After 10-15 contacts, the conversion rate fluctuates at lower levels. Beyond 30 contacts, conversion rates drop close to zero, indicating little to no impact of excessive follow-ups.

viii. Describe how to encode categorical variables, such as job, marital, housing, and loan, for machine learning models.

In [368...

```
encode_df = pd.get_dummies(df,columns=['job','marital'],dtype=int)
df =  pd.concat([df,encode_df],axis=1)
```

In [369...

```
df = df.loc[:,~df.columns.duplicated()]
```

In [370...

```
df['housing']=df['housing'].apply(lambda x:0 if x == 'no' else 1)

df['loan']=df['loan'].apply(lambda x:0 if x == 'no' else 1)
```

ix. Build a Decision Tree Model using the provided features:

Explain the selection of features and the target variable. Visualize the decision tree using appropriate plotting techniques. How does this visualization help in understanding the decision-making process of the model?

In [371...

```
dt_model = tree.DecisionTreeClassifier(max_depth=4)
dt_model
```

Out[371...

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=4)
```

In [373...

```
df.shape
```

Out[373...

```
(45211, 33)
```

In [374...

```
list(df.columns)
```

Out[374…

```
['age',
 'job',
 'marital',
 'education',
 'default',
 'balance',
 'housing',
 'loan',
 'contact',
 'day',
 'month',
 'duration',
 'campaign',
 'pdays',
 'previous',
 'poutcome',
 'Target',
 'conversion',
 'job_admin.',
 'job_blue-collar',
 'job_entrepreneur',
 'job_housemaid',
 'job_management',
 'job_retired',
 'job_self-employed',
 'job_services',
 'job_student',
 'job_technician',
 'job_unemployed',
 'job_unknown',
 'marital_divorced',
 'marital_married',
 'marital_single']
```

In [375…

```
response_var = 'conversion'
features = ['age',  'balance', 'housing', 'campaign',
       'previous', 'job_admin.', 'job_blue-collar', 'job_entrepreneur',
       'job_housemaid', 'job_management', 'job_retired', 'job_self-employed',
       'job_services', 'job_student', 'job_technician', 'job_unemployed',
       'job_unknown', 'marital_divorced', 'marital_married', 'marital_single']
```

In [376…

```
dt_model.fit(df[features],df[response_var])
```

Out[376…

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=4)
```

In [377…

```
dt_model.classes_
```

Out[377…

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

In [378…

```
dt_model.feature_importances_
```

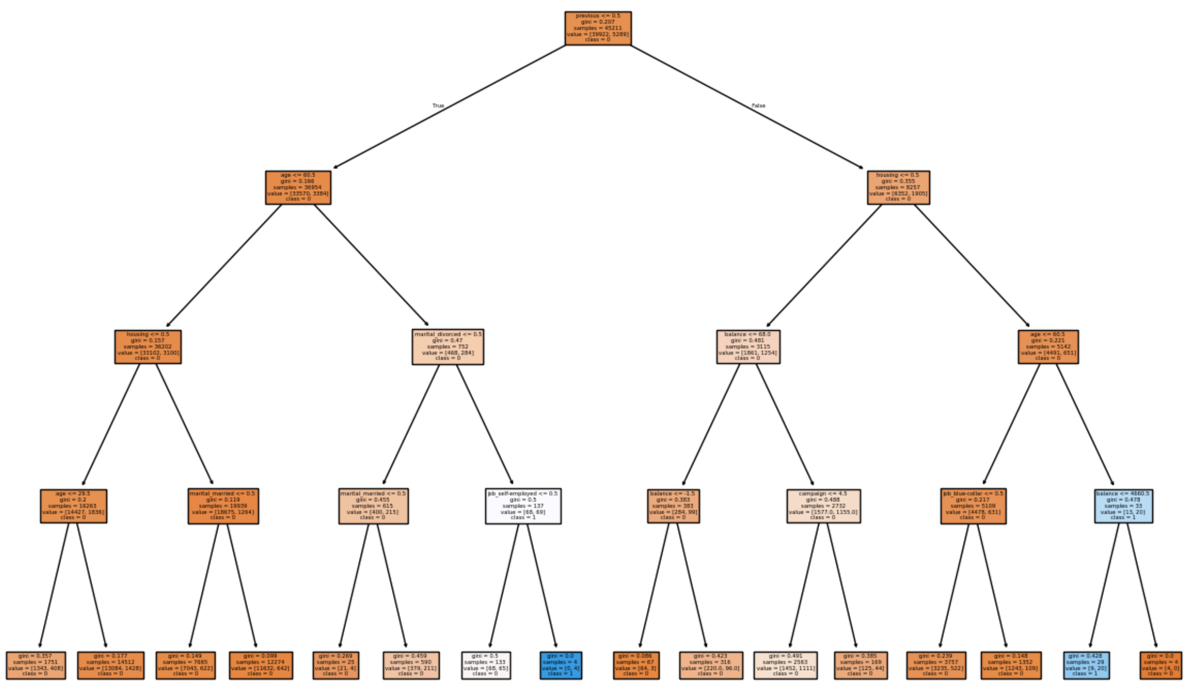
Out[378…

```
array([0.22958146, 0.03357839, 0.39439427, 0.01104479, 0.30370049,
       0.        , 0.00785975, 0.        , 0.        , 0.        ,
       0.        , 0.00235943, 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.0061807 , 0.01130072, 0.        ])
```

In [379…

```python
# Ensure dt_model is a trained decision tree classifier
class_names = [str(label) for label in dt_model.classes_]

# Ensure features is a list of feature names
plt.figure(figsize=(15, 10))  # Uncomment for better layout
tree.plot_tree(dt_model,
               feature_names=features,
               class_names=class_names,
               filled=True)
plt.show()
```



💡 The decision tree uses selected features like "age," "income," and "job" to predict the target variable, such as "conversion."

Visualizing the tree helps to see how the model makes decisions by splitting the data at each node based on the most important features.