prodigy-ds-03

December 19, 2023

Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository.

0.1 Decision Tree Terminologies

Root Node: Root node is from where the decision tree starts. It represents the entire dataset, which further gets divided into two or more homogeneous sets.

Leaf Node: Leaf nodes are the final output node, and the tree cannot be segregated further after getting a leaf node.

Splitting: Splitting is the process of dividing the decision node/root node into sub-nodes according to the given conditions.

Branch/Sub Tree: A tree formed by splitting the tree.

Pruning: Pruning is the process of removing the unwanted branches from the tree.

Parent/Child node: The root node of the tree is called the parent node, and other nodes are called the child nodes.

Step-1: Begin the tree with the root node, says S, which contains the complete dataset.

Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).

Step-3: Divide the S into subsets that contains possible values for the best attributes.

Step-4: Generate the decision tree node, which contains the best attribute.

Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

IMPORTING LIBRARIES

Setting up necessary libraries for use.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, accuracy_score,␣
 ↪classification_report
from mlxtend.plotting import plot_confusion_matrix
```

Loading the dataset

[2]:
```python
from google.colab import files
raw= files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving bank full.csv to bank full.csv
```

REVIEWING DATASET:

[51]:
```python
rdata= pd.read_csv('bank full.csv')
```

[52]:
```python
rdata
```

[52]:
```
       age           job   marital  education default  balance housing loan  \
0       58    management   married   tertiary      no     2143     yes   no
1       44    technician    single  secondary      no       29     yes   no
2       33  entrepreneur   married  secondary      no        2     yes  yes
3       47   blue-collar   married    unknown      no     1506     yes   no
4       33       unknown    single    unknown      no        1      no   no
…      …           …       …        …      …       …      …    …
45206   51    technician   married   tertiary      no      825      no   no
45207   71       retired  divorced    primary      no     1729      no   no
45208   72       retired   married  secondary      no     5715      no   no
45209   57   blue-collar   married  secondary      no      668      no   no
45210   37  entrepreneur   married  secondary      no     2971      no   no

         contact  day month  duration  campaign  pdays  previous poutcome    y
0        unknown    5   may       261         1     -1         0  unknown   no
1        unknown    5   may       151         1     -1         0  unknown   no
2        unknown    5   may        76         1     -1         0  unknown   no
3        unknown    5   may        92         1     -1         0  unknown   no
4        unknown    5   may       198         1     -1         0  unknown   no
…            …   …    …       …       …      …          …    …
45206   cellular   17   nov       977         3     -1         0  unknown  yes
45207   cellular   17   nov       456         2     -1         0  unknown  yes
45208   cellular   17   nov      1127         5    184         3  success  yes
45209  telephone   17   nov       508         4     -1         0  unknown   no
45210   cellular   17   nov       361         2    188        11    other   no
```

```
[45211 rows x 17 columns]
```

[53]:
```
data=rdata.copy()
```

1 *Exploratory data analysis*

Now, I will explore the data to gain insights about the data.

[54]:
```
# view dimensions of dataset
data.shape
```

[54]:
```
(45211, 17)
```

Preview of dataset

[55]:
```
data.head()
```

[55]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
3   47   blue-collar  married    unknown      no     1506     yes   no
4   33       unknown   single    unknown      no        1      no   no

   contact  day month  duration  campaign  pdays  previous poutcome   y
0  unknown    5   may       261         1     -1         0  unknown  no
1  unknown    5   may       151         1     -1         0  unknown  no
2  unknown    5   may        76         1     -1         0  unknown  no
3  unknown    5   may        92         1     -1         0  unknown  no
4  unknown    5   may       198         1     -1         0  unknown  no
```

[56]:
```
data.tail()
```

[56]:
```
       age           job   marital  education default  balance housing loan  \
45206   51    technician   married   tertiary      no      825      no   no
45207   71       retired  divorced    primary      no     1729      no   no
45208   72       retired   married  secondary      no     5715      no   no
45209   57   blue-collar   married  secondary      no      668      no   no
45210   37  entrepreneur   married  secondary      no     2971      no   no

         contact  day month  duration  campaign  pdays  previous poutcome    y
45206   cellular   17   nov       977         3     -1         0  unknown  yes
45207   cellular   17   nov       456         2     -1         0  unknown  yes
45208   cellular   17   nov      1127         5    184         3  success  yes
45209  telephone   17   nov       508         4     -1         0  unknown   no
45210   cellular   17   nov       361         2    188        11    other   no
```

[57]:
```python
data.info() #To display a brief DataFrame summary, use the 'info()' method. It␣
            #shows index and column data types, non-null values, and memory␣
↪usage
```

```
<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
```

[58]:
```python
data.duplicated().sum()  #to check the duplication in the instances
```

[58]: 0

[59]:
```python
data.describe().T #The 'describe()' method gives statistical insights for␣
                  #numerical columns in the DataFrame: count (non-empty), mean␣
↪(average), and␣
                  #more.
```

[59]:

	count	mean	std	min	25%	50%	75%	\
age	45211.0	40.936210	10.618762	18.0	33.0	39.0	48.0	
balance	45211.0	1362.272058	3044.765829	-8019.0	72.0	448.0	1428.0	
day	45211.0	15.806419	8.322476	1.0	8.0	16.0	21.0	
duration	45211.0	258.163080	257.527812	0.0	103.0	180.0	319.0	
campaign	45211.0	2.763841	3.098021	1.0	1.0	2.0	3.0	
pdays	45211.0	40.197828	100.128746	-1.0	-1.0	-1.0	-1.0	
previous	45211.0	0.580323	2.303441	0.0	0.0	0.0	0.0	

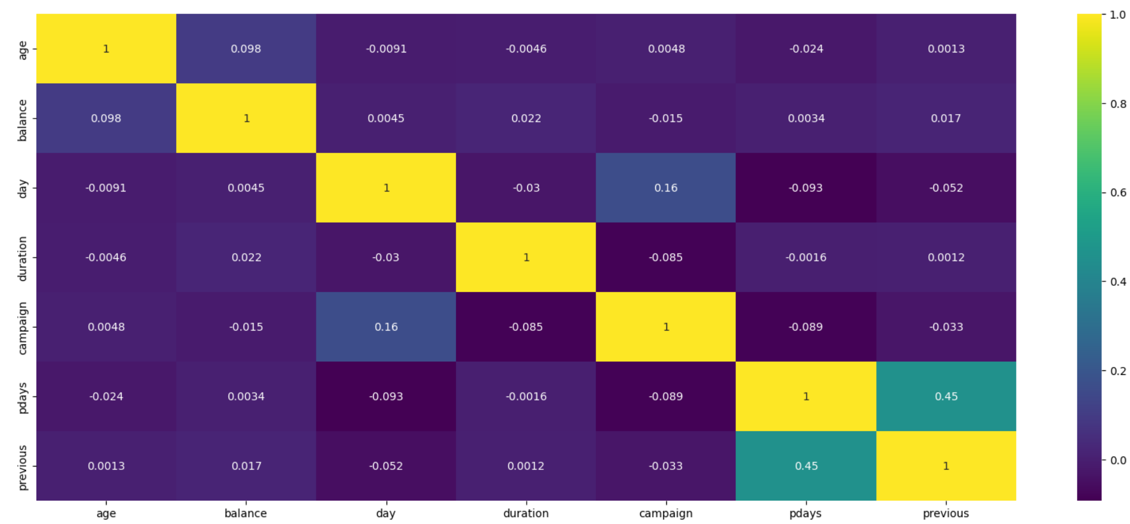
```
               max
age           95.0
balance   102127.0
day           31.0
duration    4918.0
campaign      63.0
pdays        871.0
previous     275.0
```

[60]:

```python
plt.figure(figsize=(20,8))
sb.heatmap(data=data.corr(), annot=True, cmap='viridis')

#plt.figure(figsize=(30, 8))
#sb.heatmap(data.corr() , annot = True, cmap = "Blues")
```

```
<ipython-input-60-e2eca7faf9df>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sb.heatmap(data=data.corr(), annot=True, cmap='viridis')
```

[60]: `<Axes: >`



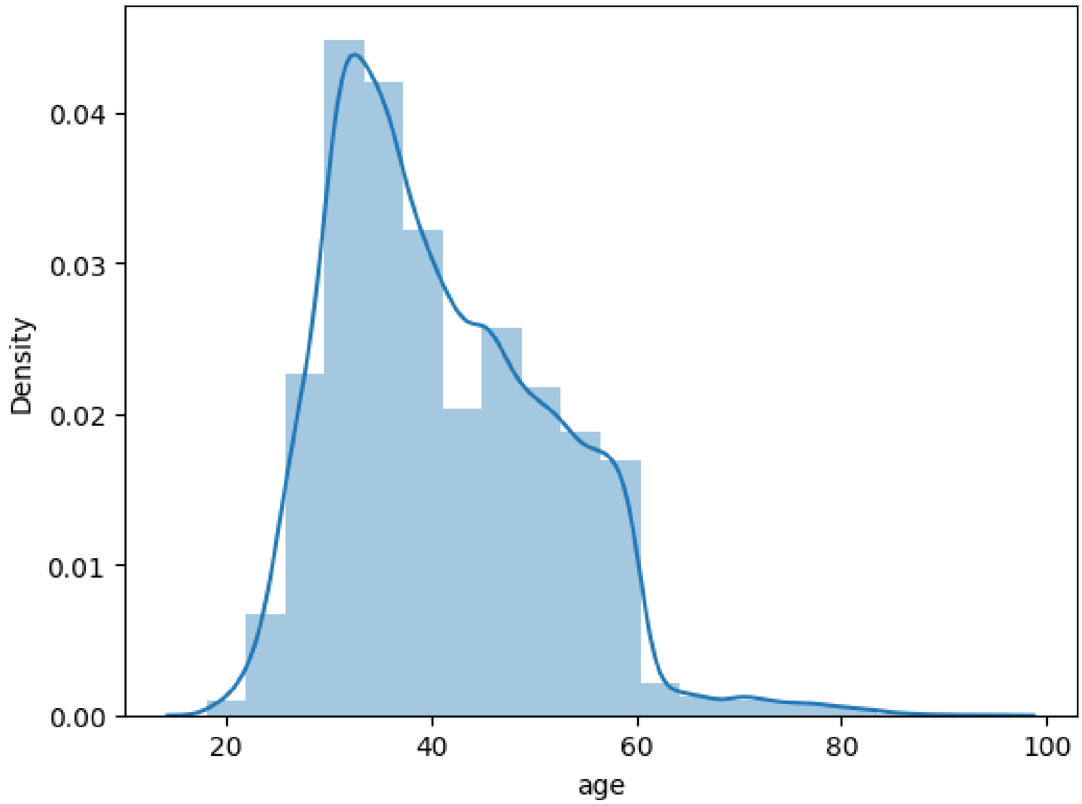
[61]:

```python
sb.distplot(data.age, bins = 20)
```

```
<ipython-input-61-3fb6461e9a12>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
```

```
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sb.distplot(data.age, bins = 20)
```

[61]:
```
<Axes: xlabel='age', ylabel='Density'>
```



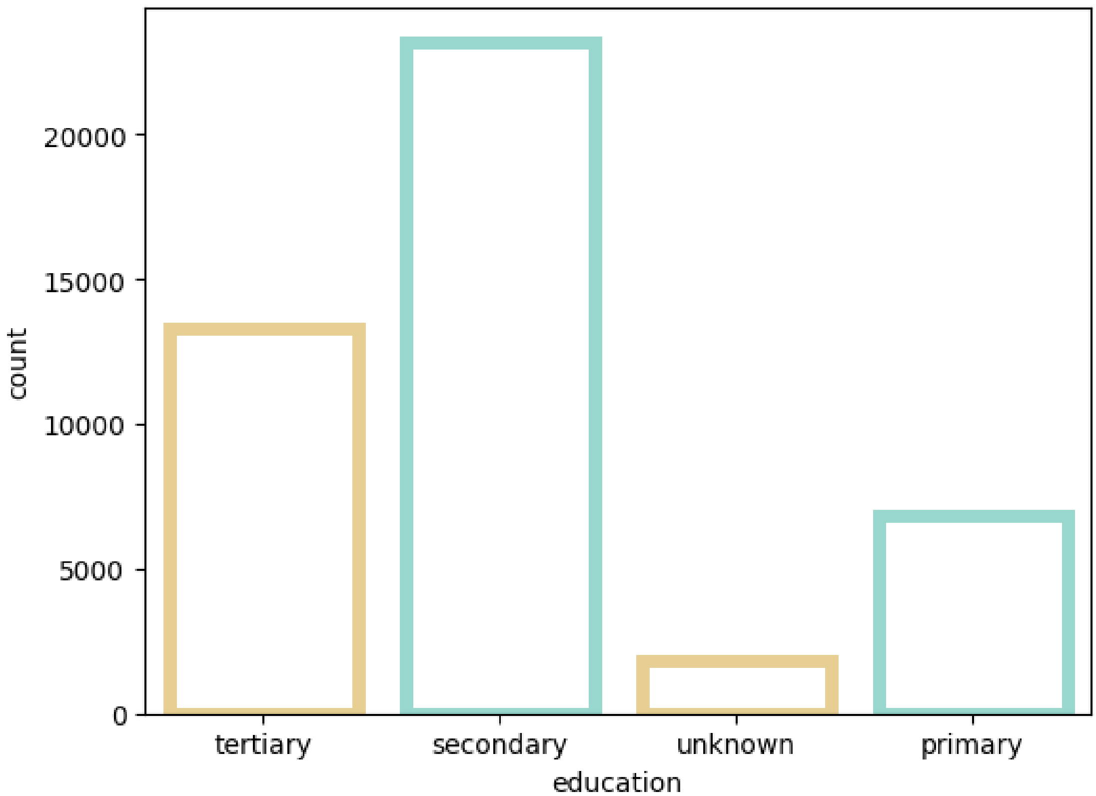
[62]:
```python
data.job.value_counts(dropna=False) #The 'value_counts() function tallies␣
↪unique values, presenting them in
                                     #descending order, with the most common value␣
↪listed first
```

[62]:
```
blue-collar      9732
management       9458
technician       7597
admin.           5171
services         4154
retired          2264
self-employed    1579
```

```
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64
```

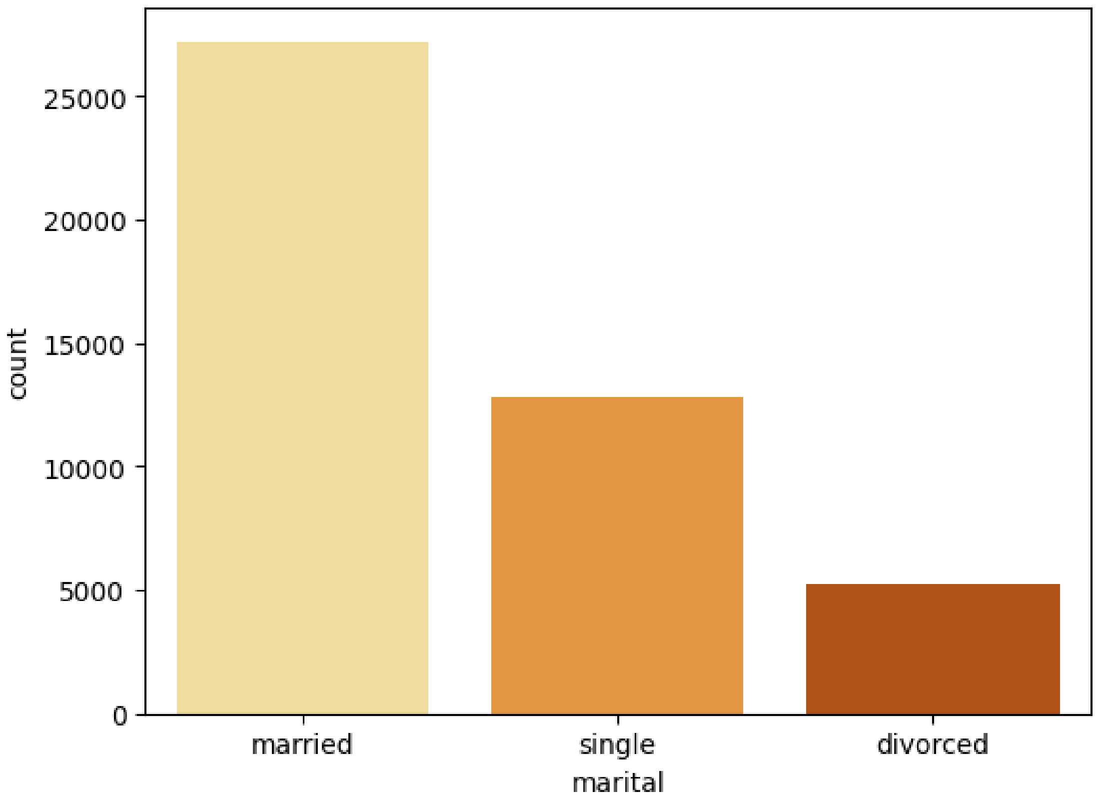
[63]:
```
data.education.value_counts(dropna=False)
sb.countplot(x ='education', data = data,color="salmon", facecolor=(0, 0, 0, 0),
                   linewidth=5,
                   edgecolor=sb.color_palette("BrBG", 2))
```

[63]:
```
<Axes: xlabel='education', ylabel='count'>
```



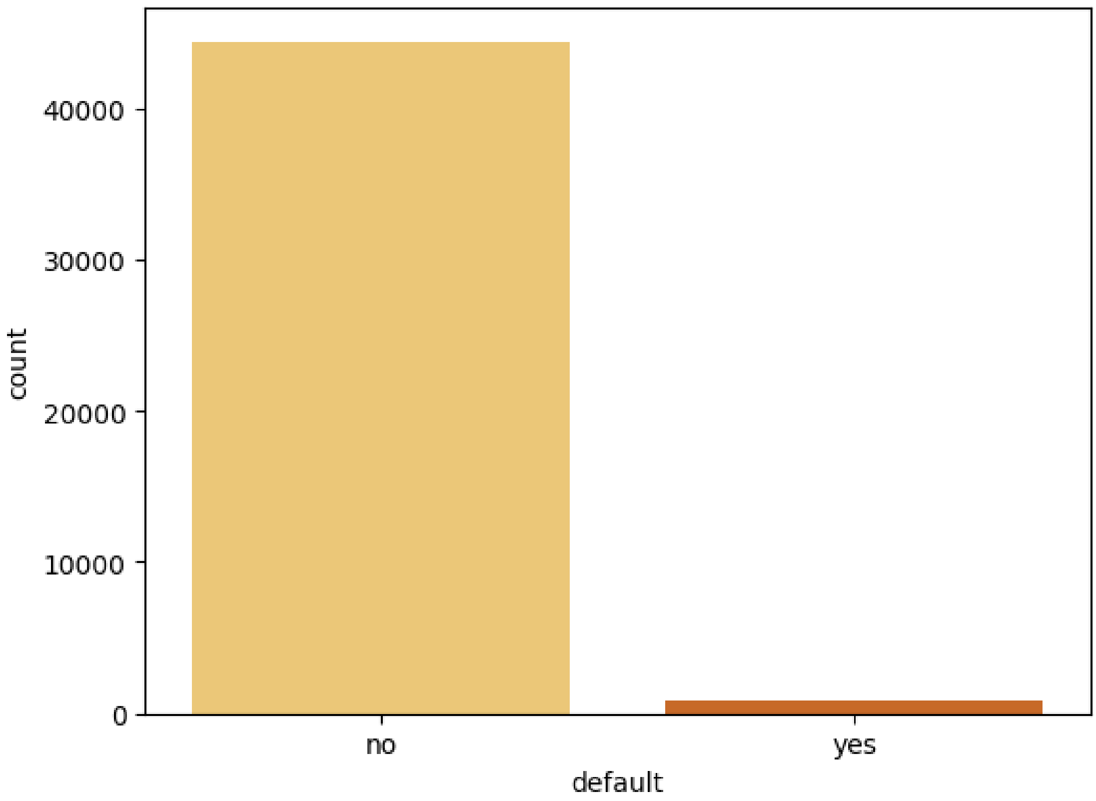
[64]:
```
data.marital.value_counts(dropna=False)
sb.countplot(x="marital", data=data, palette="YlOrBr")
```

[64]:
```
<Axes: xlabel='marital', ylabel='count'>
```



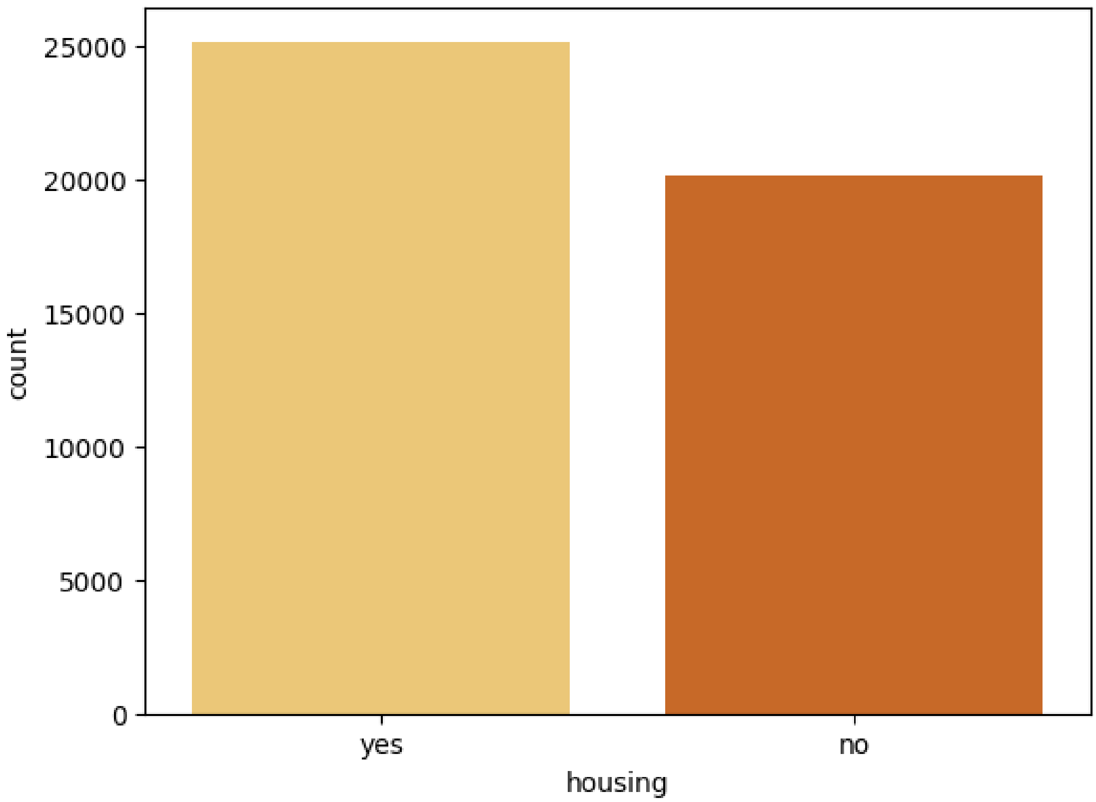
[65]:
```
data.default.value_counts(dropna=False)
sb.countplot(x="default", data=data, palette="YlOrBr")
```

[65]: <Axes: xlabel='default', ylabel='count'>




```
[66]: data.housing.value_counts(dropna=False)
      sb.countplot(x="housing", data=data, palette="YlOrBr")
```

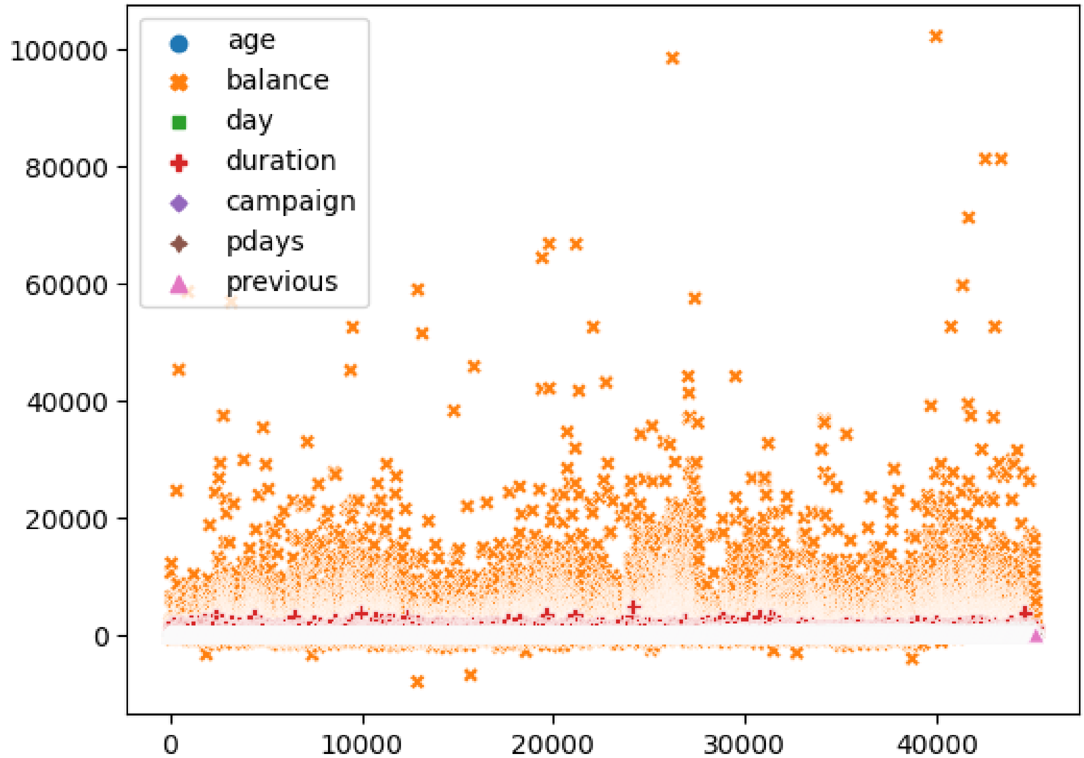
```
[66]: <Axes: xlabel='housing', ylabel='count'>
```



[67]:
```
sb.scatterplot(data)
```

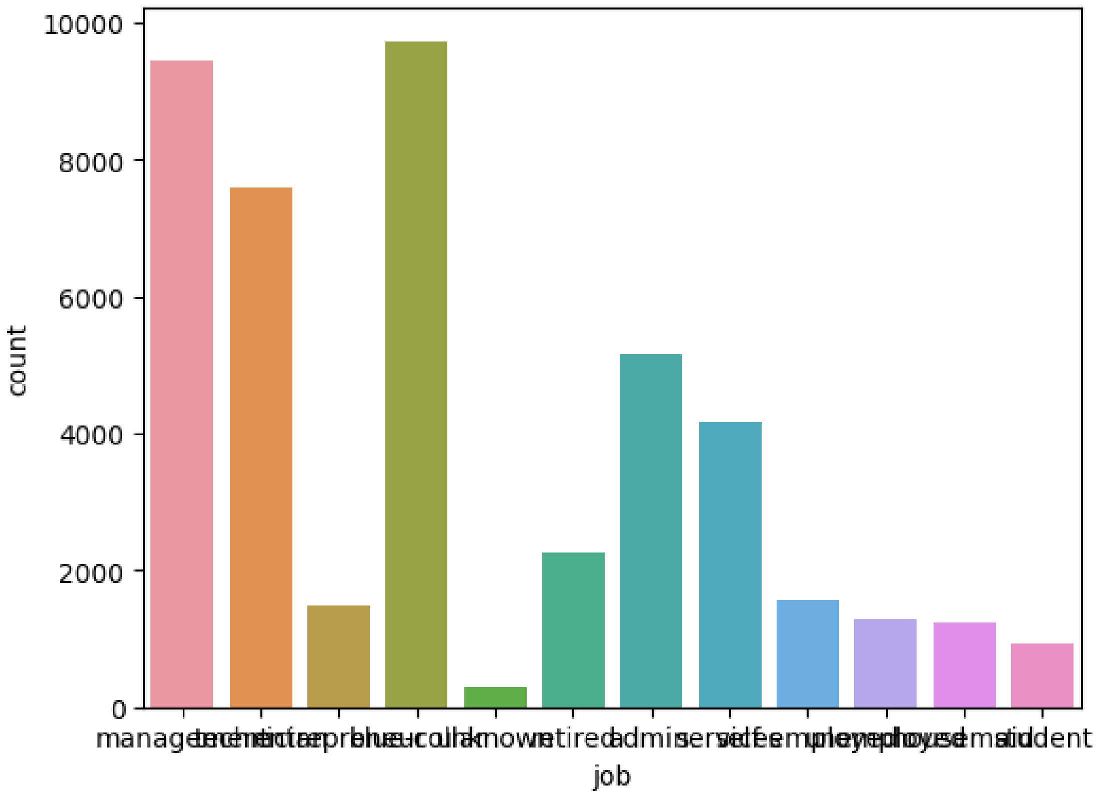
[67]: <Axes: >

```
/usr/local/lib/python3.10/dist-packages/IPython/core/events.py:89: UserWarning:
Creating legend with loc="best" can be slow with large amounts of data.
  func(*args, **kwargs)
/usr/local/lib/python3.10/dist-packages/IPython/core/pylabtools.py:151:
UserWarning: Creating legend with loc="best" can be slow with large amounts of
data.
  fig.canvas.print_figure(bytes_io, **kw)
```



[68]:
```
# Example: Distribution of the target variable
sb.countplot(x='job', data=data)
plt.figure(figsize=(12,9))
```

[68]: <Figure size 1200x900 with 0 Axes>




```
<Figure size 1200x900 with 0 Axes>
```

NULL VALUES:

[69]:
```
data.isnull().sum()
```

[69]:
```
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
```

DATA CLEANING: #Unecessary variables will be dropped in this section.

[70]:
```
data.columns
```

[70]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

[71]:
```
data.dtypes
```

[71]:
```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
y            object
dtype: object
```

ORDINAL ENCODING:

Converting categorical variables for improved prediction using ML algorithms.

[72]:
```
from sklearn.preprocessing import LabelEncoder
le= LabelEncoder() # Simple conversion of categorical data to numerical format␣
 ↪for analysis or ML models."
data['job']=le.fit_transform(data['job'])
data['marital']=le.fit_transform(data['marital'])
data['education']=le.fit_transform(data['education'])
data['default']=le.fit_transform(data['default'])
data['housing']=le.fit_transform(data['housing'])
data['loan']=le.fit_transform(data['loan'])
data['contact']=le.fit_transform(data['contact'])
data['month']=le.fit_transform(data['month'])
```

```
data['poutcome']=le.fit_transform(data['poutcome'])
data['y']=le.fit_transform(data['y'])
```

[73]:
```
data.dtypes
```

[73]:
```
age          int64
job          int64
marital      int64
education    int64
default      int64
balance      int64
housing      int64
loan         int64
contact      int64
day          int64
month        int64
duration     int64
campaign     int64
pdays        int64
previous     int64
poutcome     int64
y            int64
dtype: object
```

DATA PARTITIONING:

The dataset will be divided into 80% for training and 20% for testing.

[74]:
```
# Split data into train and test sets
from sklearn.model_selection import train_test_split
X = data.drop('y', axis=1)
y = data['y']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
 ↪random_state=1234)
```

[75]:
```
X.shape
```

[75]:
```
(45211, 16)
```

[76]:
```
y.shape
```

[76]:
```
(45211,)
```

STANDARDIZATION

Standardize features by removing the mean and scaling to unit variance.

Centering and scaling happen independently on each feature by computing the relevant statistics on the samples in the training set. Mean and standard deviation are then stored to be used on later data using transform.

Standardization of a dataset is a common requirement for many machine learning estimators: they might behave badly if the individual features do not more or less look like standard normally distributed data (e.g. Gaussian with 0 mean and unit variance).

StandardScaler is sensitive to outliers,

[77]:
```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
x_train = ss.fit_transform(X_train)
x_test = ss.transform(X_test)
```

MODELS:

[78]:
```
from sklearn.tree import DecisionTreeClassifier
```

[79]:
```
#Train
dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
```

[79]:
```
DecisionTreeClassifier()
```

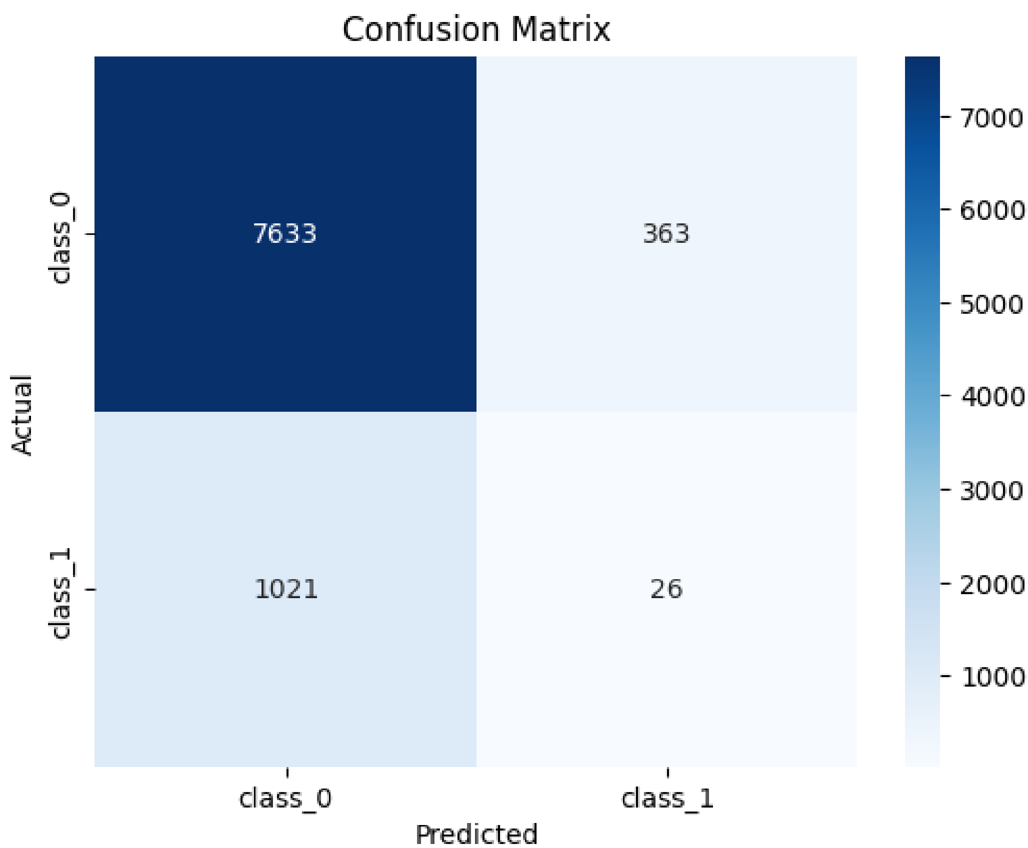
[80]:
```
y_pred_dtc = dtc.predict(x_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but DecisionTreeClassifier was fitted with feature
names
  warnings.warn(
```

[81]:
```
score_dtc = accuracy_score(y_test, y_pred_dtc)*100
score_dtc
```

[81]:
```
84.6953444653323
```

[82]:
```
# Print confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_dtc)
sb.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=['class_0', 'class_1'], yticklabels=['class_0', 'class_1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



[83]:
```
# Print classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_dtc))
```

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

           0       0.88      0.95      0.92      7996
           1       0.07      0.02      0.04      1047

    accuracy                           0.85      9043
   macro avg       0.47      0.49      0.48      9043
weighted avg       0.79      0.85      0.81      9043
```

[84]:
```
acs=accuracy_score(y_test, y_pred_dtc)*100
acs
```

[84]: 84.6953444653323

Advantages of the Decision Tree It is simple to understand as it follows the same process which a human follow while making any decision in real-life. It can be very useful for solving decision-related problems. It helps to think about all the possible outcomes for a problem. There is less requirement of data cleaning compared to other algorithms.

Disadvantages of the Decision Tree The decision tree contains lots of layers, which makes it complex. It may have an overfitting issue, which can be resolved using the Random Forest algorithm. For more class labels, the computational complexity of the decision tree may increase.