eda

October 28, 2023

0.1 Data Exploration and Preprocessing

Importing Necessary Libraries

[122]:
```
import pandas as pd
import numpy as np
import missingno
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
warnings.filterwarnings('ignore')
```

Reading the Data

[123]:
```
data = pd.read_csv("bank.csv")
data.head()
```

[123]:
```
   age         job  marital  education default  balance housing loan  contact  \
0   59      admin.  married  secondary      no     2343     yes   no  unknown
1   56      admin.  married  secondary      no       45      no   no  unknown
2   41  technician  married  secondary      no     1270     yes   no  unknown
3   55    services  married  secondary      no     2476     yes   no  unknown
4   54      admin.  married   tertiary      no      184      no   no  unknown

   day month  duration  campaign  pdays  previous poutcome deposit
0    5   may      1042         1     -1         0  unknown     yes
1    5   may      1467         1     -1         0  unknown     yes
2    5   may      1389         1     -1         0  unknown     yes
3    5   may       579         1     -1         0  unknown     yes
4    5   may       673         2     -1         0  unknown     yes
```

EXPLORATORY DATA ANALYSIS:

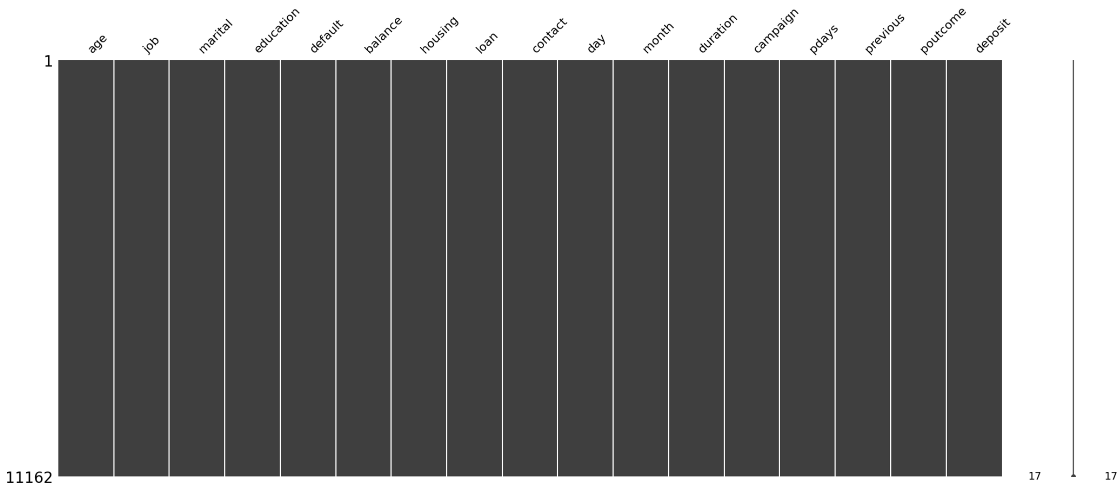
[124]:
```
print("Shape of the dataset: ", data.shape)
```

```
Shape of the dataset:  (11162, 17)
```

[125]:

```
missingno.matrix(data)
```

[125]: <Axes: >



[126]:

```
data.info()
```

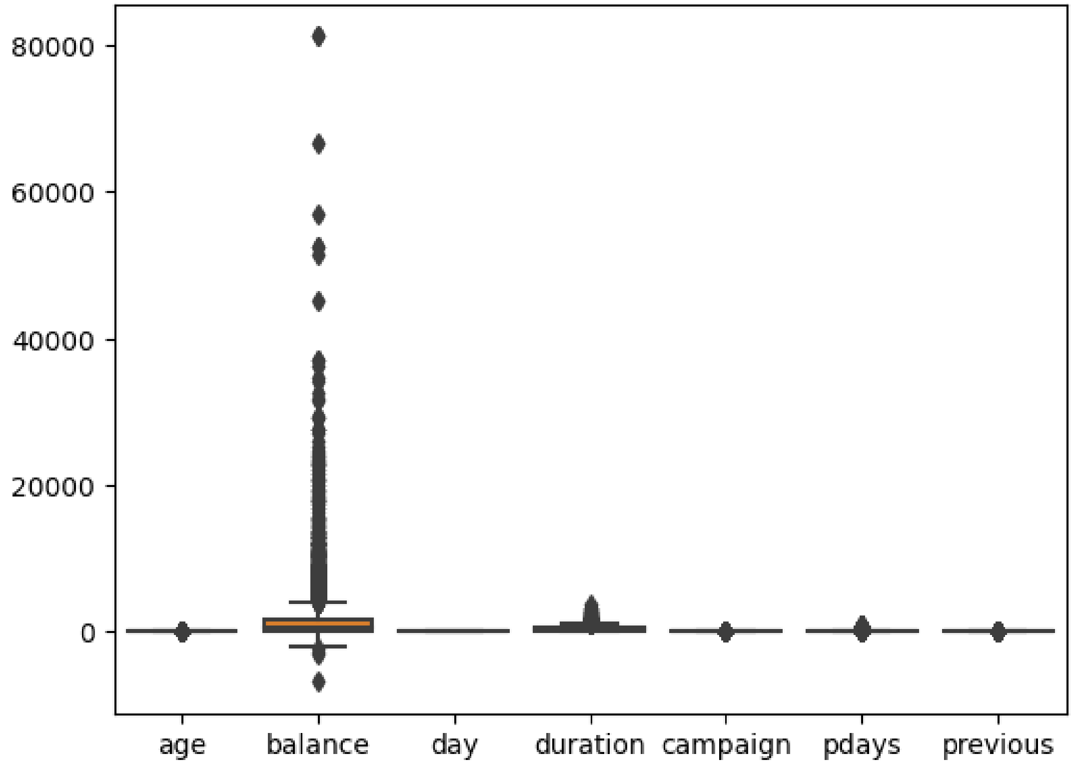
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        11162 non-null  int64
 1   job        11162 non-null  object
 2   marital    11162 non-null  object
 3   education  11162 non-null  object
 4   default    11162 non-null  object
 5   balance    11162 non-null  int64
 6   housing    11162 non-null  object
 7   loan       11162 non-null  object
 8   contact    11162 non-null  object
 9   day        11162 non-null  int64
 10  month      11162 non-null  object
 11  duration   11162 non-null  int64
 12  campaign   11162 non-null  int64
 13  pdays      11162 non-null  int64
 14  previous   11162 non-null  int64
 15  poutcome   11162 non-null  object
 16  deposit    11162 non-null  object
dtypes: int64(7), object(10)
memory usage: 1.4+ MB
```

[127]:
```
data.describe()
```

[127]:
```
                age       balance           day      duration      campaign  \
count  11162.000000  11162.000000  11162.000000  11162.000000  11162.000000
mean      41.231948   1528.538524     15.658036    371.993818      2.508421
std       11.913369   3225.413326      8.420740    347.128386      2.722077
min       18.000000  -6847.000000      1.000000      2.000000      1.000000
25%       32.000000    122.000000      8.000000    138.000000      1.000000
50%       39.000000    550.000000     15.000000    255.000000      2.000000
75%       49.000000   1708.000000     22.000000    496.000000      3.000000
max       95.000000  81204.000000     31.000000   3881.000000     63.000000

              pdays      previous
count  11162.000000  11162.000000
mean      51.330407      0.832557
std      108.758282      2.292007
min       -1.000000      0.000000
25%       -1.000000      0.000000
50%       -1.000000      0.000000
75%       20.750000      1.000000
max      854.000000     58.000000
```

[128]:
```
sns.boxplot(data=data)
```

[128]:
```
<Axes: >
```



AGE:

[129]:
```
data['age'].info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 11162 entries, 0 to 11161
Series name: age
Non-Null Count  Dtype
--------------  -----
11162 non-null  int64
dtypes: int64(1)
memory usage: 87.3 KB
```

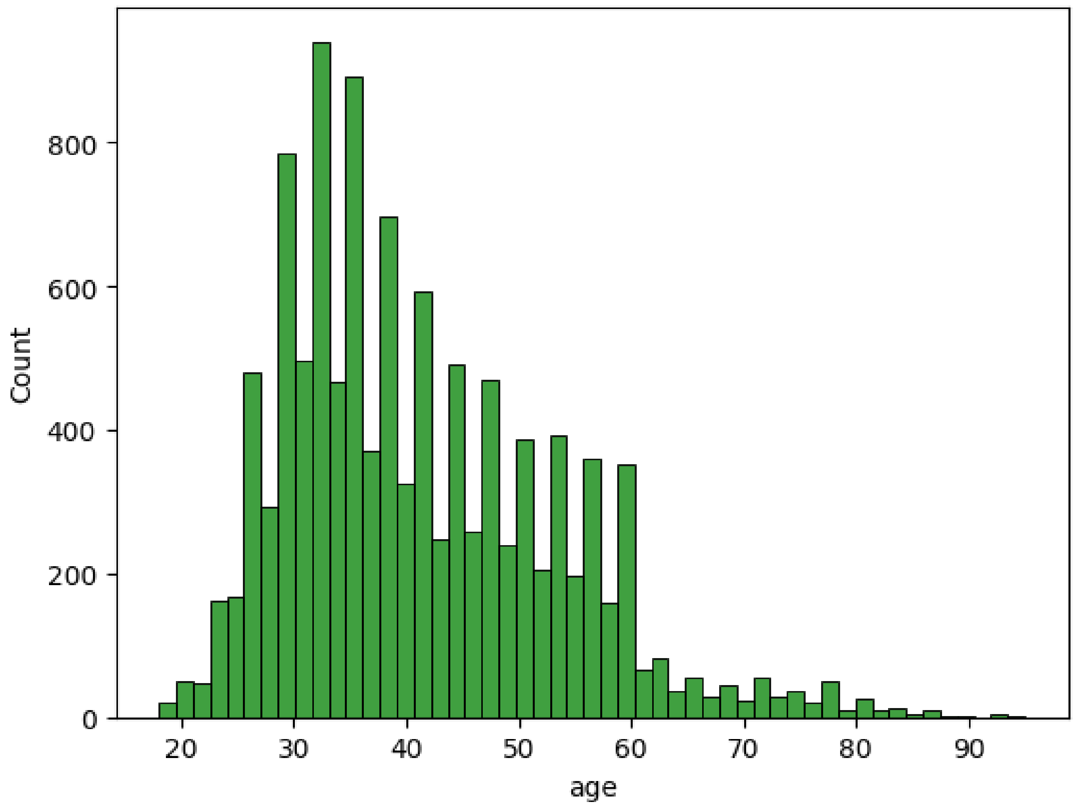
[130]:
```
data['age'].value_counts().head(10)
```

[130]:
```
age
31    496
32    477
34    466
33    464
35    461
30    456
36    432
```

```
37     370
38     353
39     343
Name: count, dtype: int64
```

[131]:
```
sns.histplot(x='age', data=data, color='green')
```

[131]:
```
<Axes: xlabel='age', ylabel='Count'>
```



JOB:

[132]:
```
data['job'].describe()
```

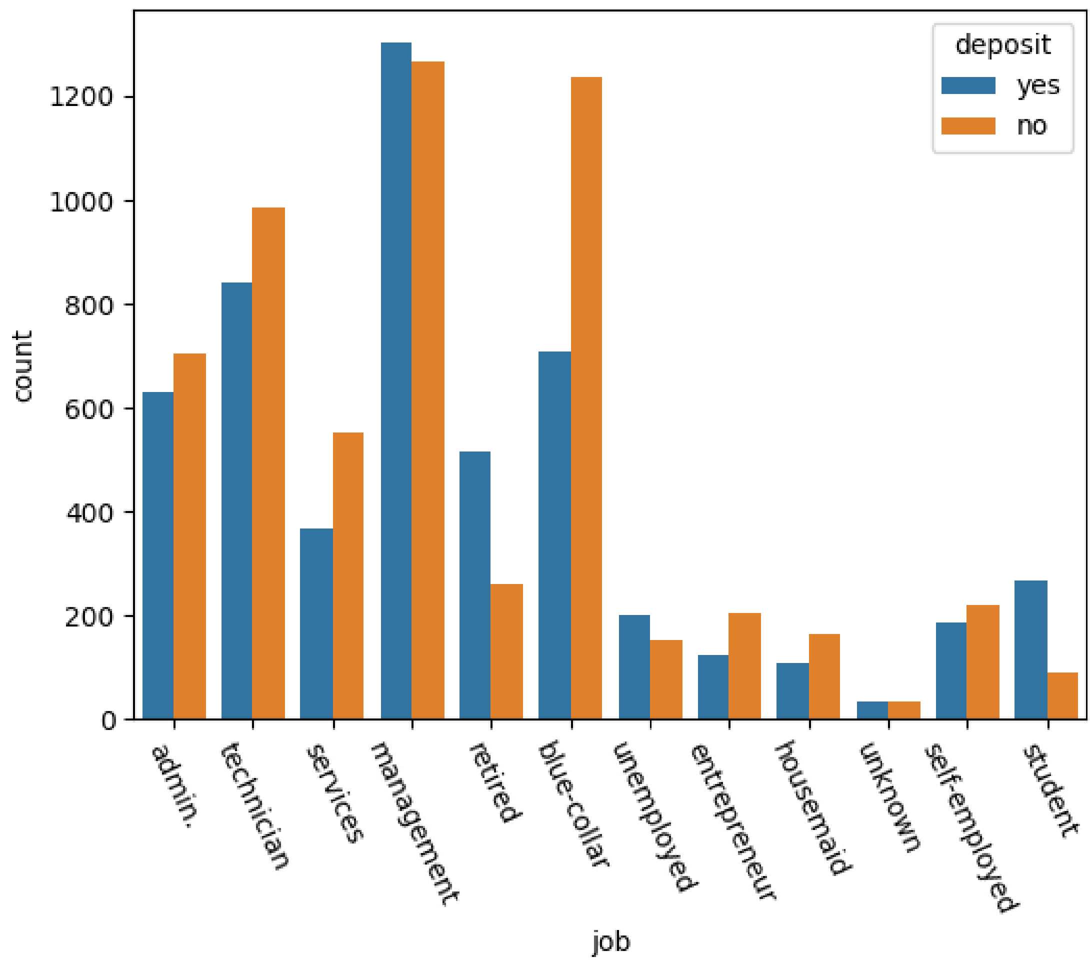
[132]:
```
count          11162
unique            12
top       management
freq            2566
Name: job, dtype: object
```

[133]:
```
data['job'].value_counts()
```

[133]:
```
job
management       2566
blue-collar      1944
technician       1823
admin.           1334
services          923
retired           778
self-employed     405
student           360
unemployed        357
entrepreneur      328
housemaid         274
unknown            70
Name: count, dtype: int64
```

[134]:
```
px.pie(data, values=np.ones(11162), names='job',␣
↪title='job',color_discrete_sequence=px.colors.sequential.Brwnyl)
```

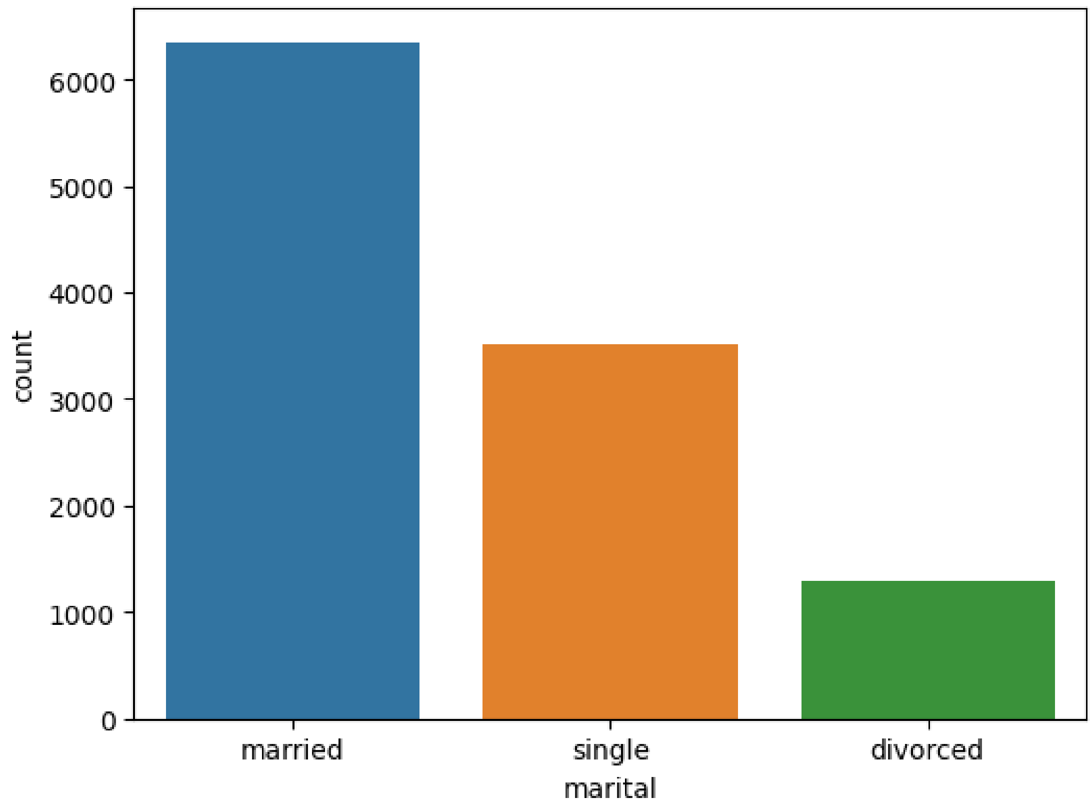
[135]:
```
sns.countplot(x='job', data=data, hue='deposit')
plt.xticks(rotation=-65)
plt.show()
```



MARITAL:

[136]:
```
sns.countplot(x="marital", data=data)
```

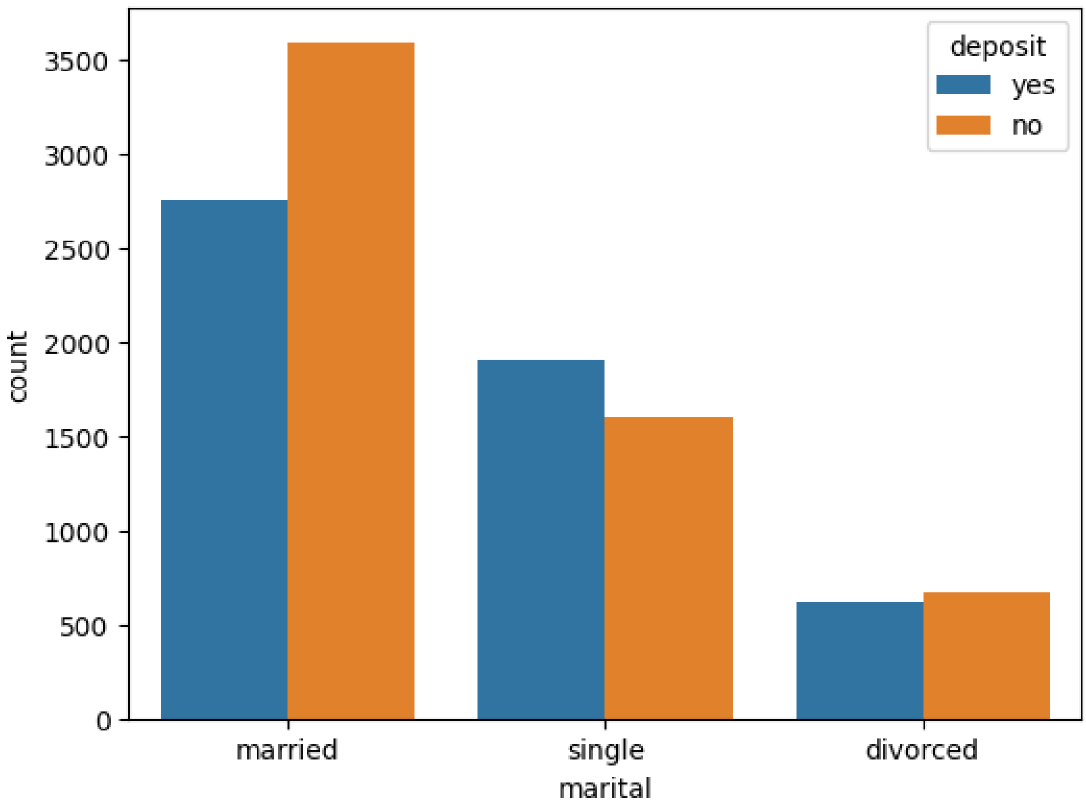
[136]: <Axes: xlabel='marital', ylabel='count'>



[137]:
```
fig = px.pie(data, values=np.ones(11162), names='marital',␣
 ↪title='marital',color_discrete_sequence=px.colors.sequential.Brwnyl)
fig.show()
```

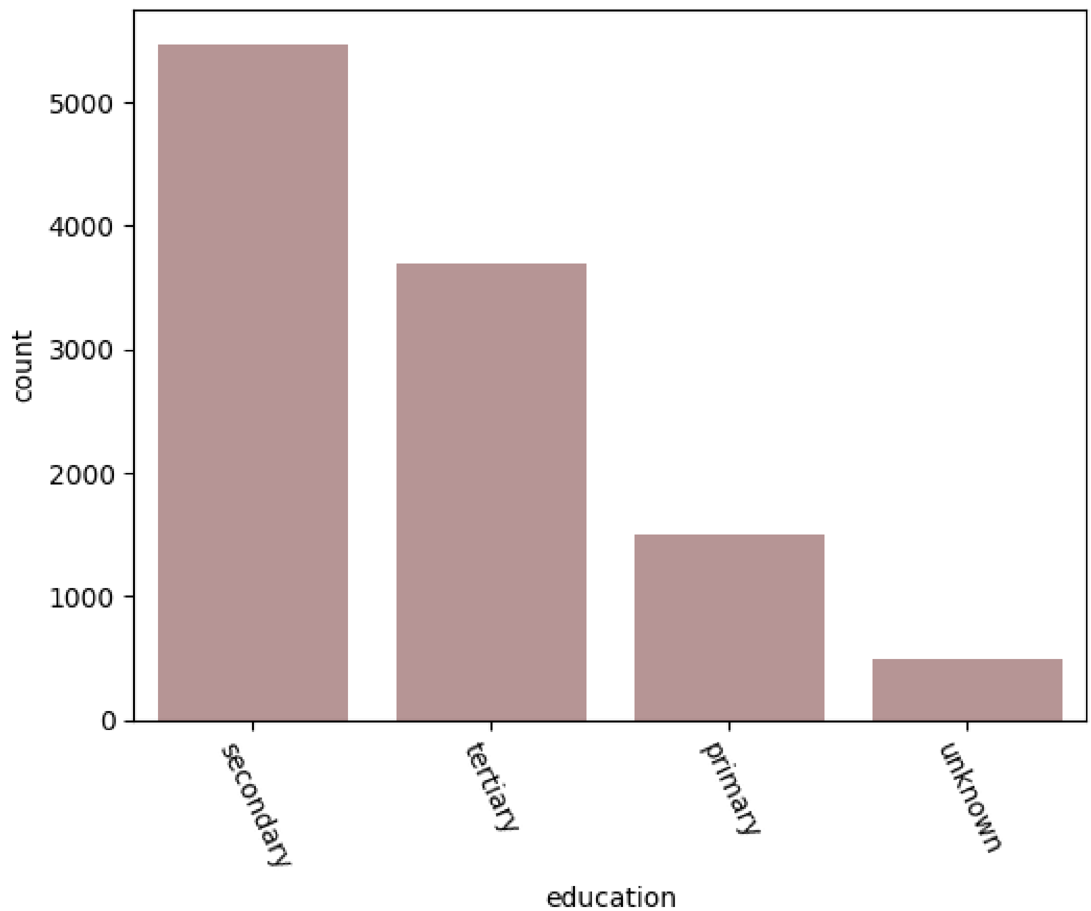
[138]:
```
sns.countplot(x="marital", data=data, hue="deposit")
```

[138]:
```
<Axes: xlabel='marital', ylabel='count'>
```



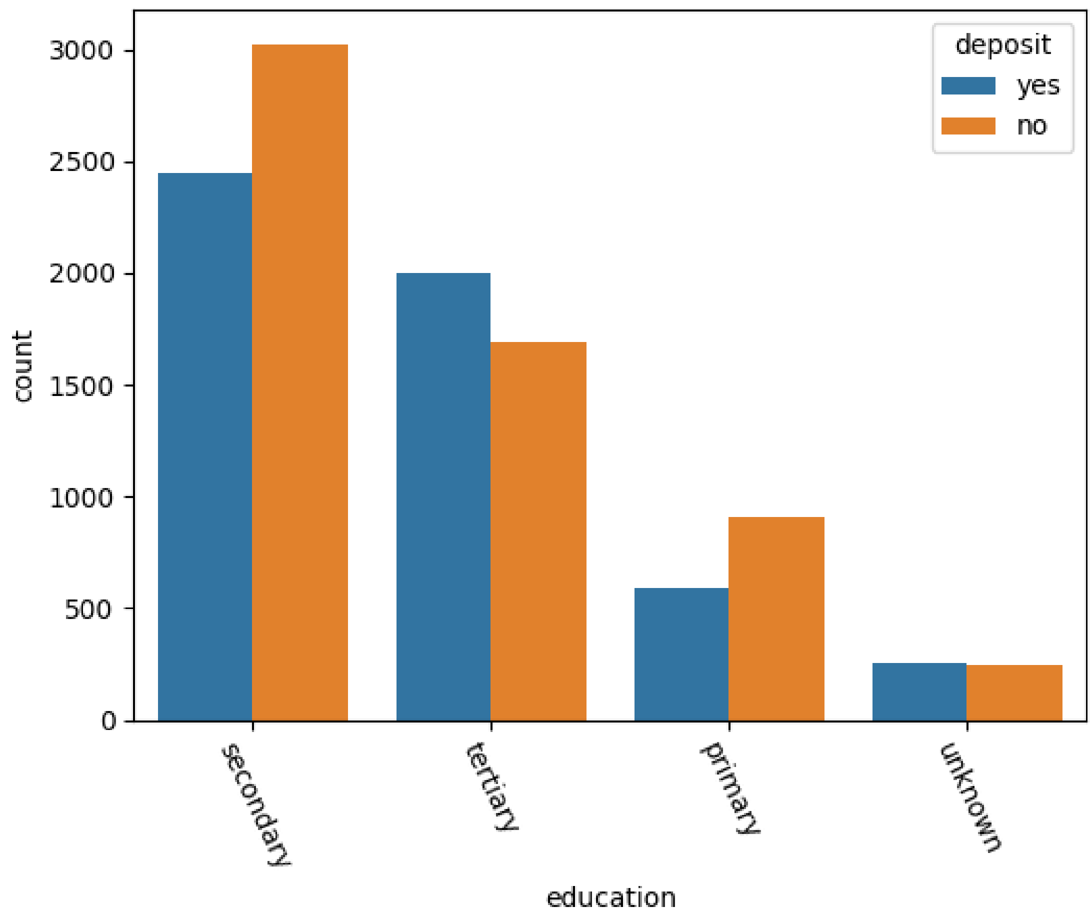
EDUCATION:

[139]:
```
sns.countplot(x="education", data=data, color='rosybrown')
plt.xticks(rotation=-65)
plt.show()
```



[140]:

```
sns.countplot(x="education", data=data, hue="deposit")
plt.xticks(rotation=-65)
plt.show()
```

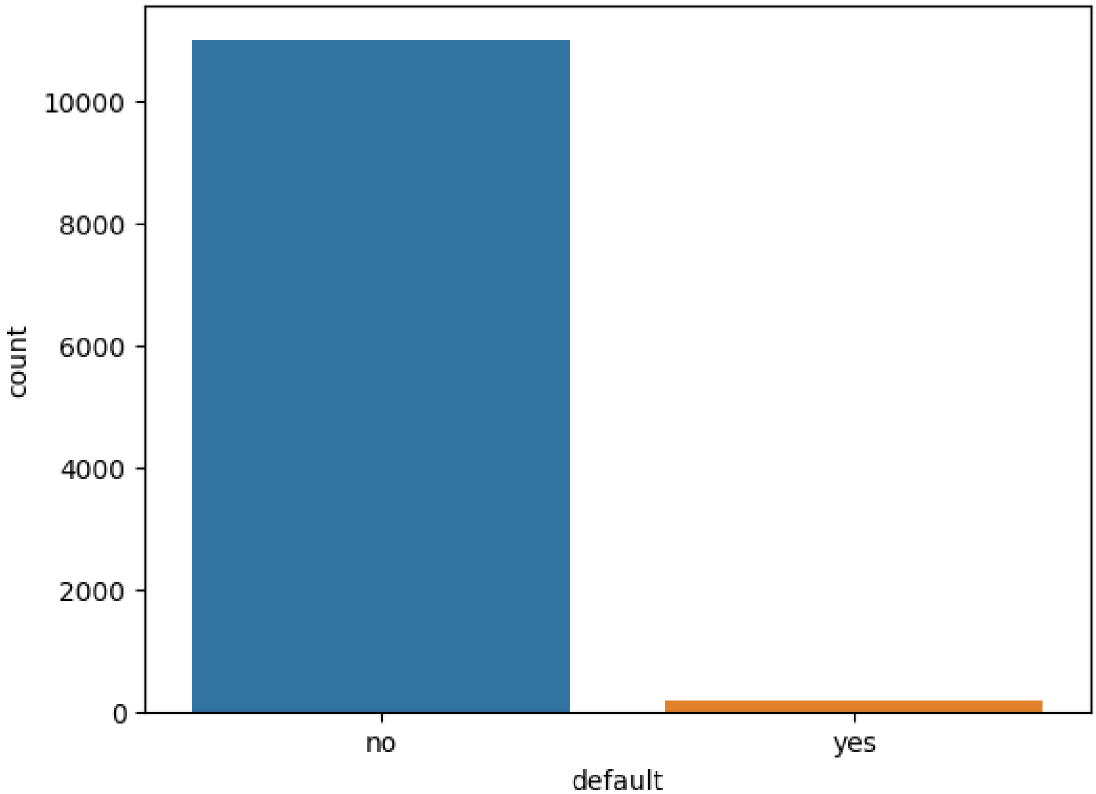


[141]:
```
fig = px.pie(data, values=np.ones(11162), names='education',␣
↪title='education',color_discrete_sequence=px.colors.sequential.Brwnyl)
fig.show()
```

DEFAULT:

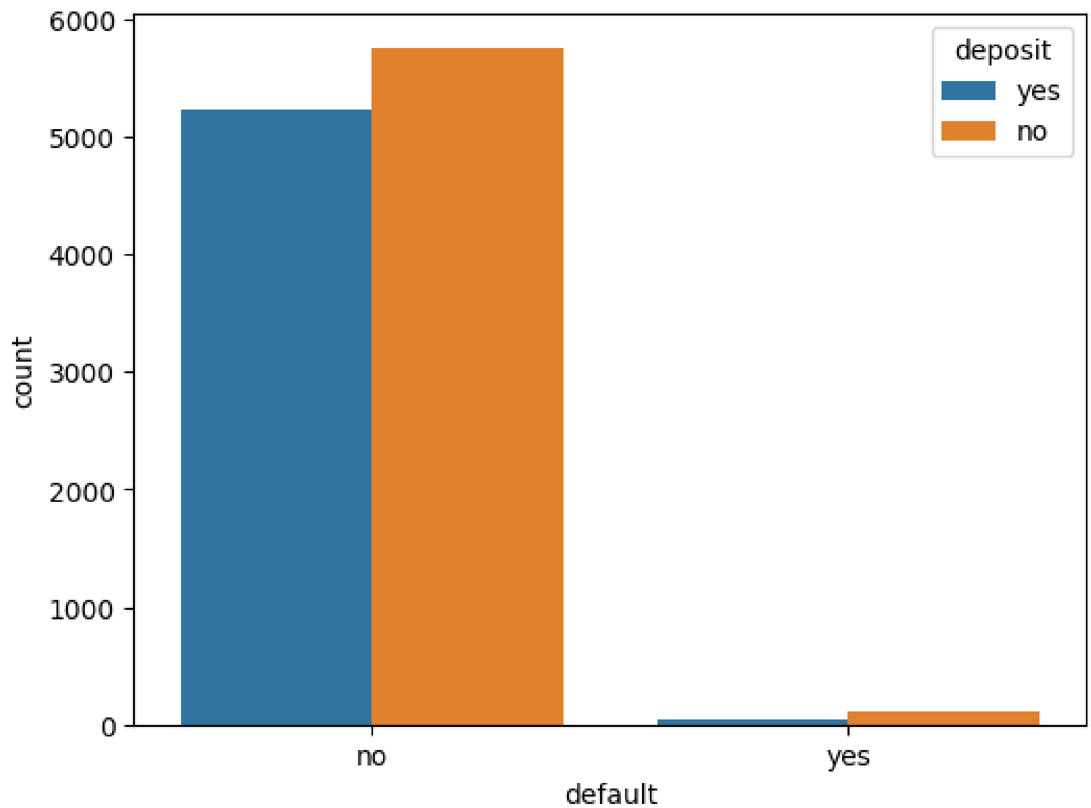
[142]:
```
sns.countplot(x="default", data=data)
```

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



[143]:
```
sns.countplot(x="default", data=data, hue="deposit")
```

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

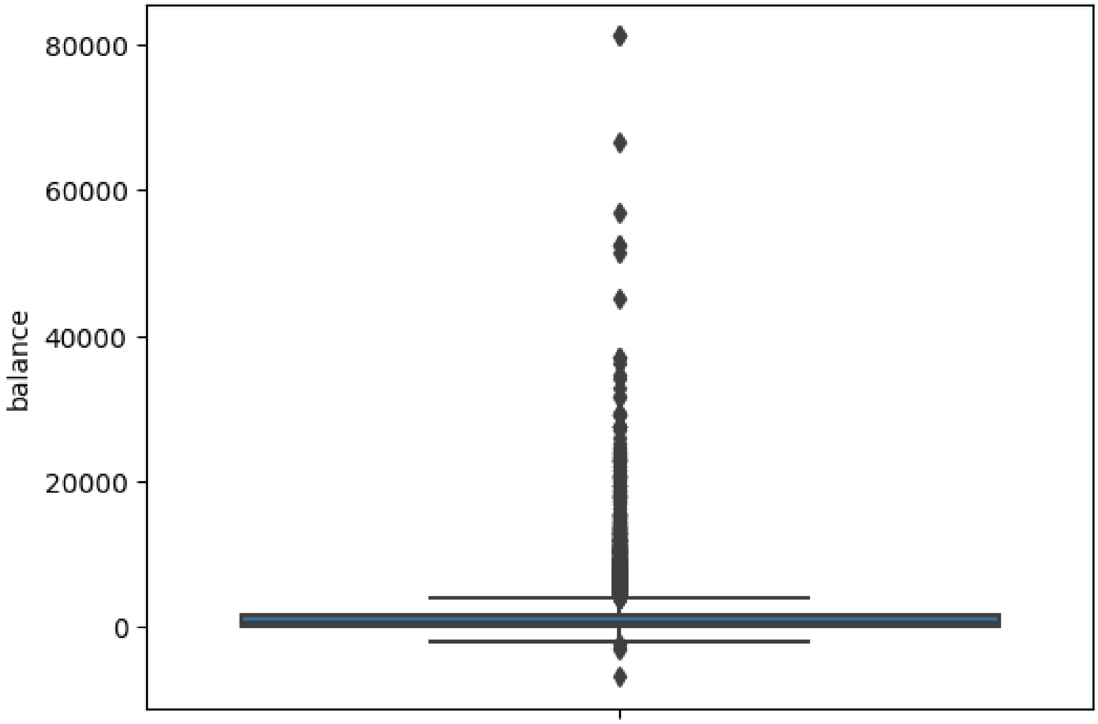


[144]:
```
fig = px.pie(data, values=np.ones(11162), names='default',␣
↪title='default',color_discrete_sequence=px.colors.sequential.Brwnyl)
fig.show()
```

BALANCE:

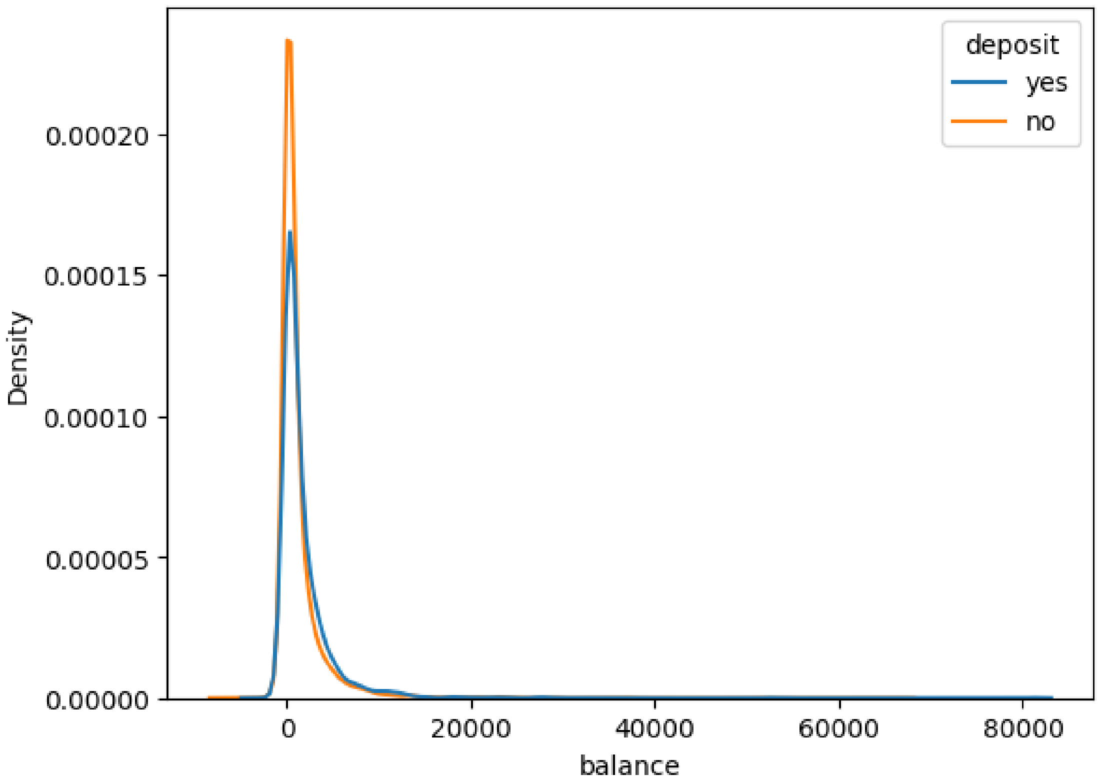
[145]:
```
sns.boxplot(y="balance",data=data)
```

[145]: <Axes: ylabel='balance'>



[146]:
```
sns.kdeplot(x="balance",data =data,hue="deposit")
```

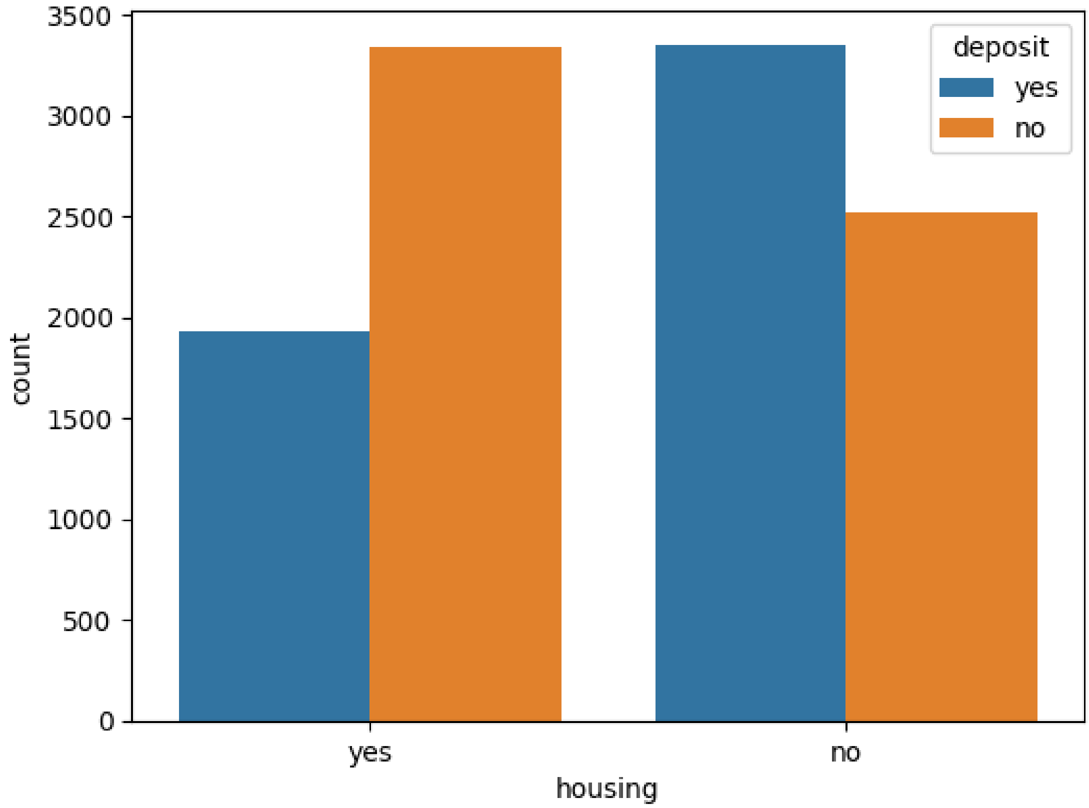
[146]: <Axes: xlabel='balance', ylabel='Density'>



HOUSING:

[147]:
```
sns.countplot(x="housing", data=data, hue="deposit")
```

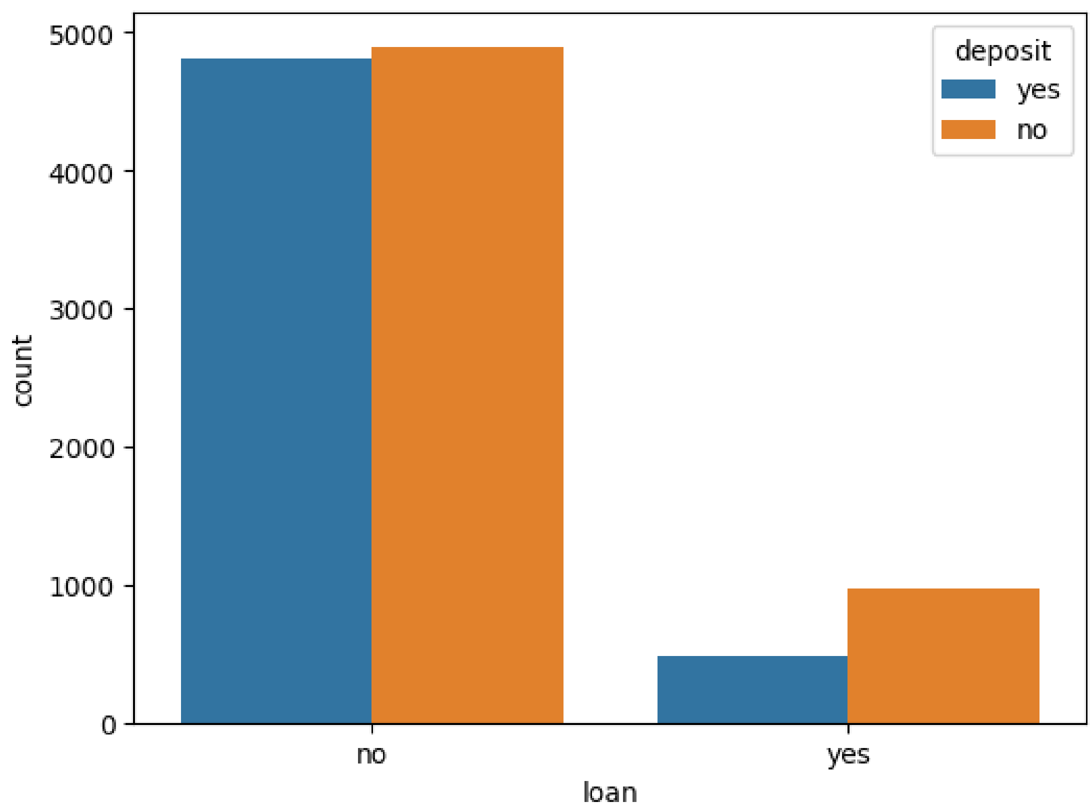
[147]: <Axes: xlabel='housing', ylabel='count'>



LOAN:

[148]:
```
sns.countplot(x="loan", data=data, hue="deposit")
```

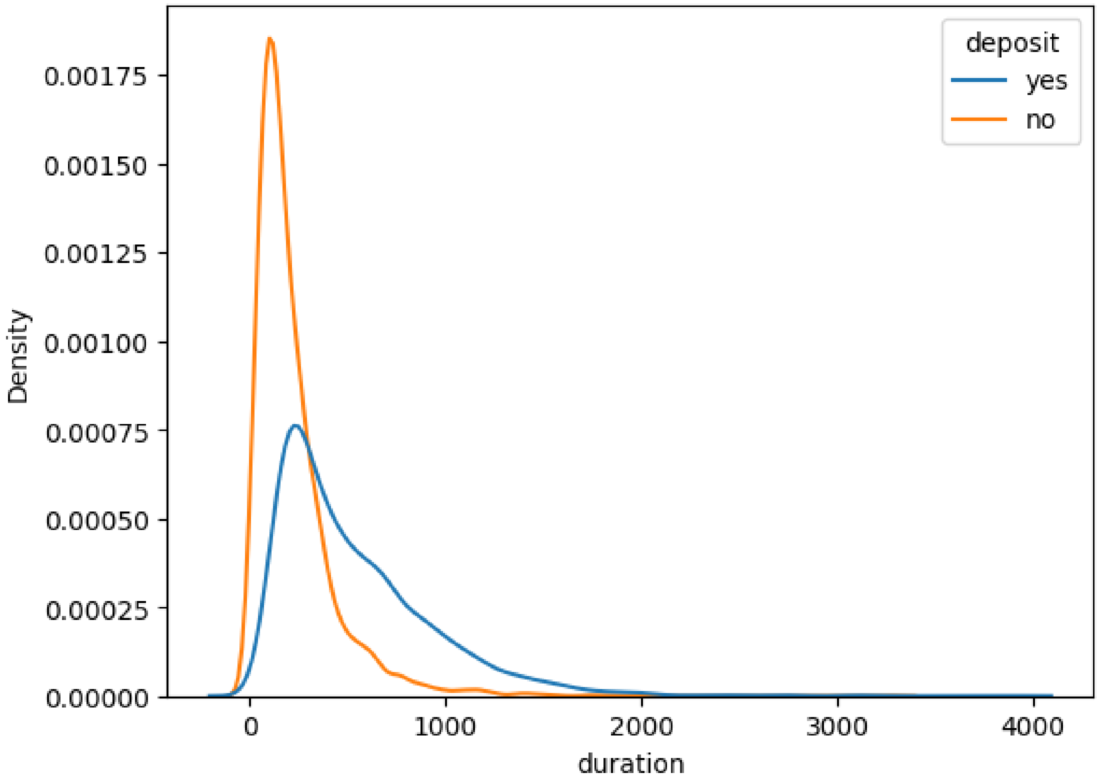
[148]: `<Axes: xlabel='loan', ylabel='count'>`



DURATION:

[149]:
```
sns.kdeplot(x="duration",data =data,hue ="deposit")
```

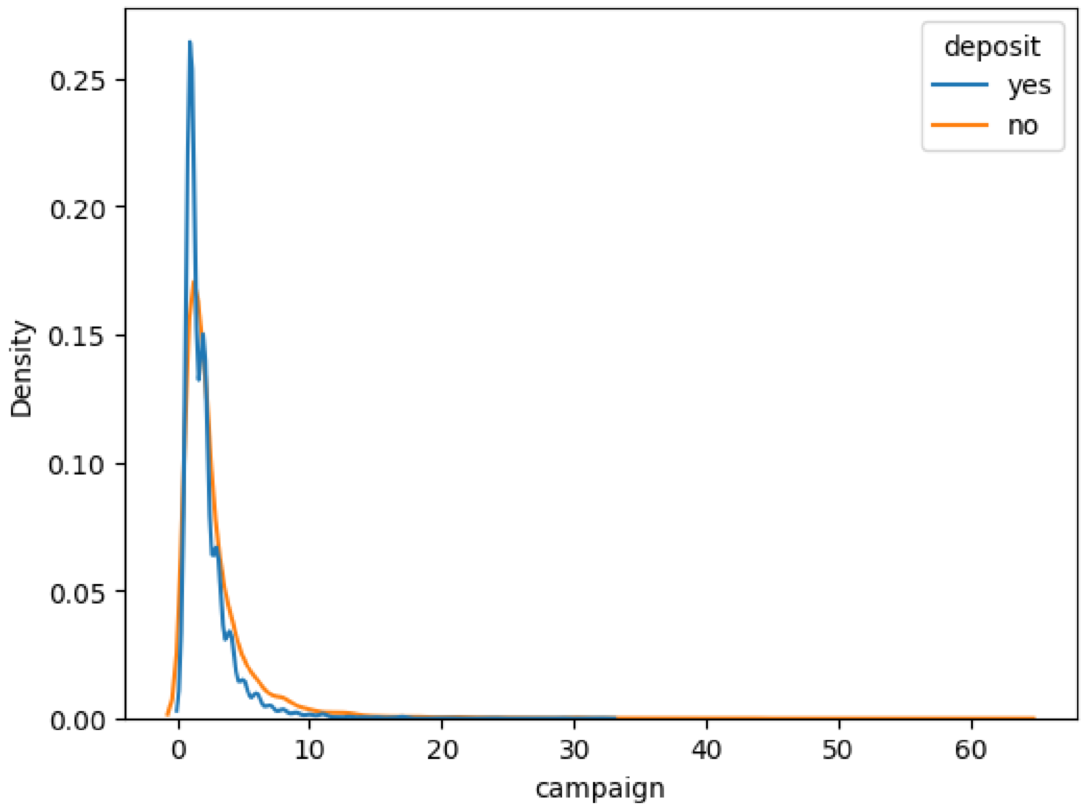
[149]: <Axes: xlabel='duration', ylabel='Density'>



CAMPAIGN:

[150]:
```
sns.kdeplot(data=data,x="campaign",hue="deposit")
```

[150]: <Axes: xlabel='campaign', ylabel='Density'>

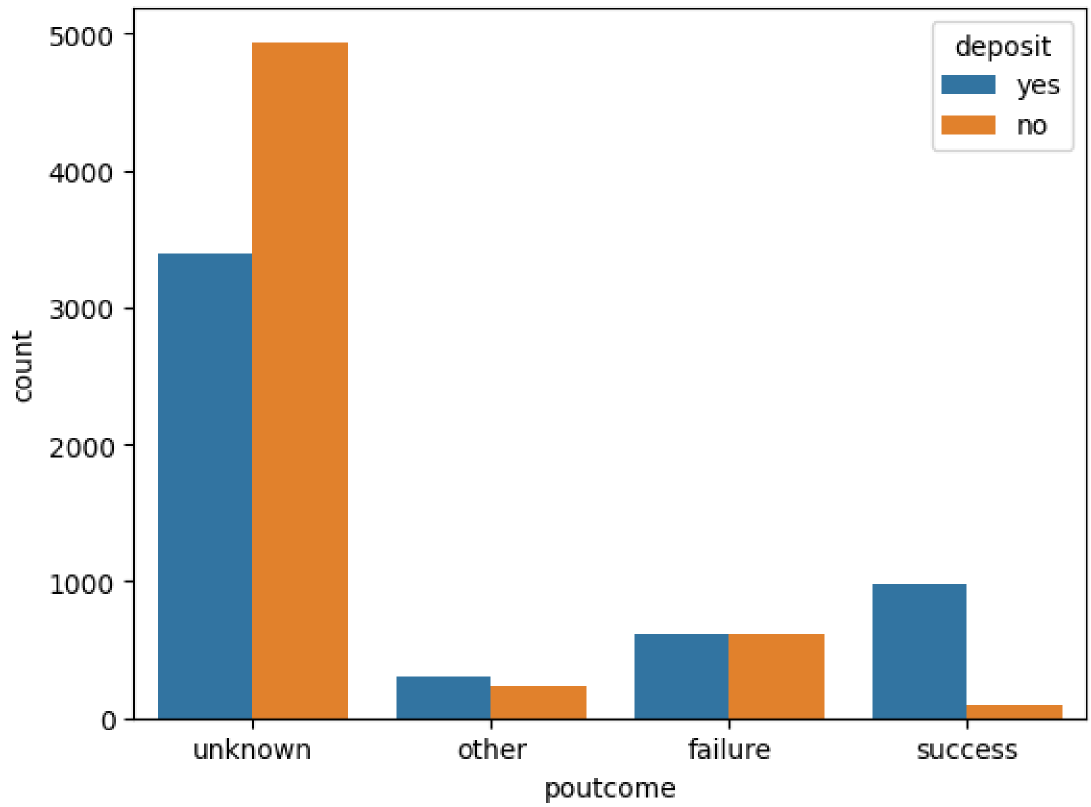


POUTCOME:

[151]:
```
fig = px.pie(data, values=np.ones(11162), names='poutcome',␣
  ↪title='poutcome',color_discrete_sequence=px.colors.sequential.Brwnyl)
fig.show()
```

[152]:
```
sns.countplot(x="poutcome", data=data, hue="deposit")
```

[152]:
```
<Axes: xlabel='poutcome', ylabel='count'>
```



DEPOSIT:

[153]:
```python
fig = px.pie(data, values=np.ones(11162), names='deposit',␣
    ↪title='deposit',color_discrete_sequence=px.colors.sequential.Brwnyl)
fig.show()
```

CORRELATION:

[154]:
```python
num = data.select_dtypes('int64')
num
```

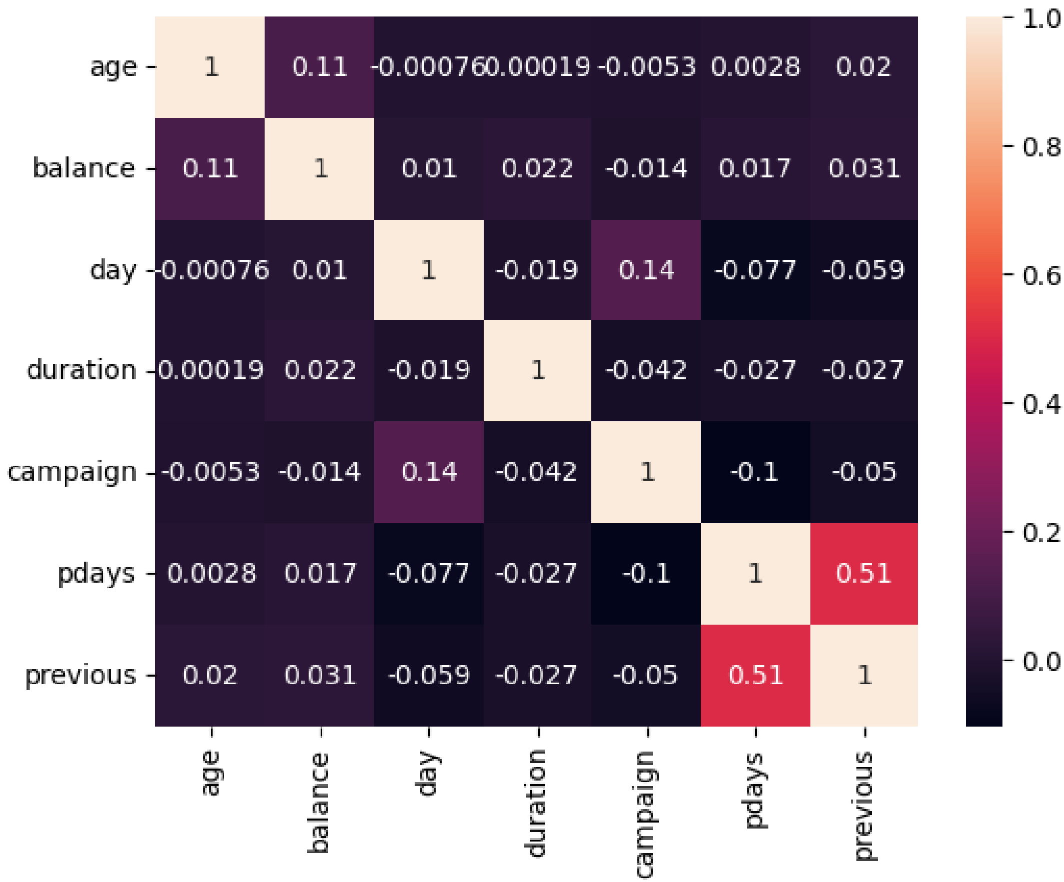
[154]:

	age	balance	day	duration	campaign	pdays	previous
0	59	2343	5	1042	1	-1	0
1	56	45	5	1467	1	-1	0
2	41	1270	5	1389	1	-1	0
3	55	2476	5	579	1	-1	0
4	54	184	5	673	2	-1	0
…	…	… …	…	…	…	…	
11157	33	1	20	257	1	-1	0
11158	39	733	16	83	4	-1	0
11159	32	29	19	156	2	-1	0
11160	43	0	8	9	2	172	5

```
11161   34          0    9        628           1      -1           0

[11162 rows x 7 columns]
```

[155]:
```python
sns.heatmap(num.corr(),annot =True)
```

[155]: `<Axes: >`



DATA PREPROCESSING:

LABEL ENCODING:

[156]:
```python
data.head()
```

[156]:
```
   age          job  marital  education default  balance housing loan  contact  \
0   59       admin.  married  secondary      no     2343     yes   no  unknown
1   56       admin.  married  secondary      no       45      no   no  unknown
2   41   technician  married  secondary      no     1270     yes   no  unknown
3   55     services  married  secondary      no     2476     yes   no  unknown
4   54       admin.  married   tertiary      no      184      no   no  unknown
```

```
   day month  duration  campaign  pdays  previous poutcome deposit
0    5   may      1042         1     -1         0  unknown     yes
1    5   may      1467         1     -1         0  unknown     yes
2    5   may      1389         1     -1         0  unknown     yes
3    5   may       579         1     -1         0  unknown     yes
4    5   may       673         2     -1         0  unknown     yes
```

[157]:

```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler

le = LabelEncoder()

for i in data.select_dtypes('object').columns:
    data[i] = le.fit_transform(data[i])
```

[158]:

```
data
```

[158]:

```
       age  job  marital  education  default  balance  housing  loan  contact  \
0       59    0        1          1        0     2343        1     0        2
1       56    0        1          1        0       45        0     0        2
2       41    9        1          1        0     1270        1     0        2
3       55    7        1          1        0     2476        1     0        2
4       54    0        1          2        0      184        0     0        2
…     …   …      …          …        …       …      …     …    …       …
11157   33    1        2          0        0        1        1     0        0
11158   39    7        1          1        0      733        0     0        2
11159   32    9        2          1        0       29        0     0        0
11160   43    9        1          1        0        0        0     1        0
11161   34    9        1          1        0        0        0     0        0

       day  month  duration  campaign  pdays  previous  poutcome  deposit
0        5      8      1042         1     -1         0         3        1
1        5      8      1467         1     -1         0         3        1
2        5      8      1389         1     -1         0         3        1
3        5      8       579         1     -1         0         3        1
4        5      8       673         2     -1         0         3        1
…     …    …       …        …       …     …        …       …         …
11157   20      0       257         1     -1         0         3        0
11158   16      6        83         4     -1         0         3        0
11159   19      1       156         2     -1         0         3        0
11160    8      8         9         2    172         5         0        0
11161    9      5       628         1     -1         0         3        0

[11162 rows x 17 columns]
```

[159]:

```
data.columns
```

[159]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'deposit'],
      dtype='object')
```

[167]:
```
x = data.drop([ 'contact', 'day', 'month','pdays','previous','deposit'],axis =1)
x
```

[167]:
```
       age  job  marital  education  default  balance  housing  loan  \
0       59    0        1          1        0     2343        1     0
1       56    0        1          1        0       45        0     0
2       41    9        1          1        0     1270        1     0
3       55    7        1          1        0     2476        1     0
4       54    0        1          2        0      184        0     0
…      …   …      …        …      …       …       …     …
11157   33    1        2          0        0        1        1     0
11158   39    7        1          1        0      733        0     0
11159   32    9        2          1        0       29        0     0
11160   43    9        1          1        0        0        0     1
11161   34    9        1          1        0        0        0     0

       duration  campaign  poutcome
0          1042         1         3
1          1467         1         3
2          1389         1         3
3           579         1         3
4           673         2         3
…           …        …        …
11157       257         1         3
11158        83         4         3
11159       156         2         3
11160         9         2         0
11161       628         1         3

[11162 rows x 11 columns]
```

[168]:
```
y=data["deposit"]
```

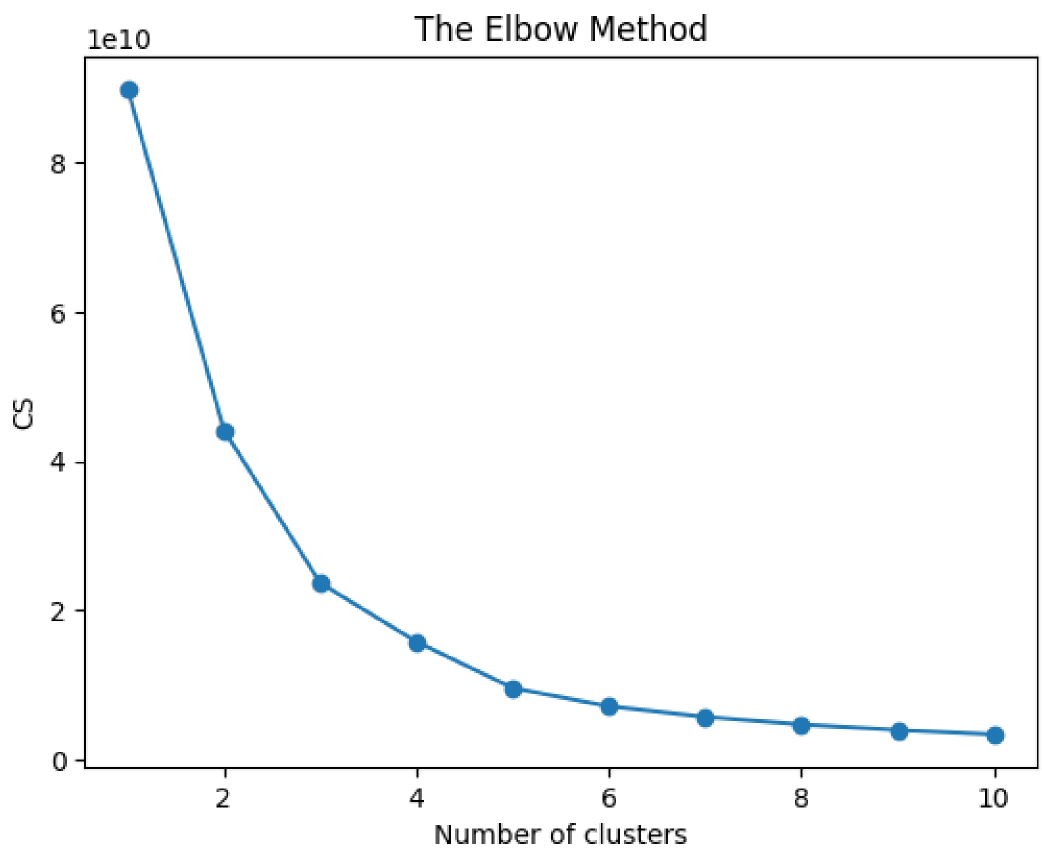
CUSTOMER SEGMENTATION AND MODELLING:

[172]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
↪random_state = 32)
```

[169]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
```

```
ms = MinMaxScaler()

X_scaled = ms.fit_transform(x)
```

[173]:
```
cs = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init␣
↪= 10, random_state = 0)
    kmeans.fit(X_train)
    cs.append(kmeans.inertia_)
plt.plot(range(1, 11), cs,marker='o')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('CS')
plt.show()
```



[174]:
```
kmeans = KMeans(n_clusters = 2, init = 'k-means++', max_iter = 300, n_init =␣
↪10, random_state = 0)
kmeans.fit(x)
```

[174]: KMeans(n_clusters=2, n_init=10, random_state=0)

[177]:
```
correct_labels = sum(y== kmeans.labels_)
print("Result: %d out of %d samples were correctly labeled." % (correct_labels,␣
↪y.size))
print('Accuracy score: {0:0.2f}'. format(correct_labels/float(y.size)))
```

```
Result: 5221 out of 11162 samples were correctly labeled.
Accuracy score: 0.47
```

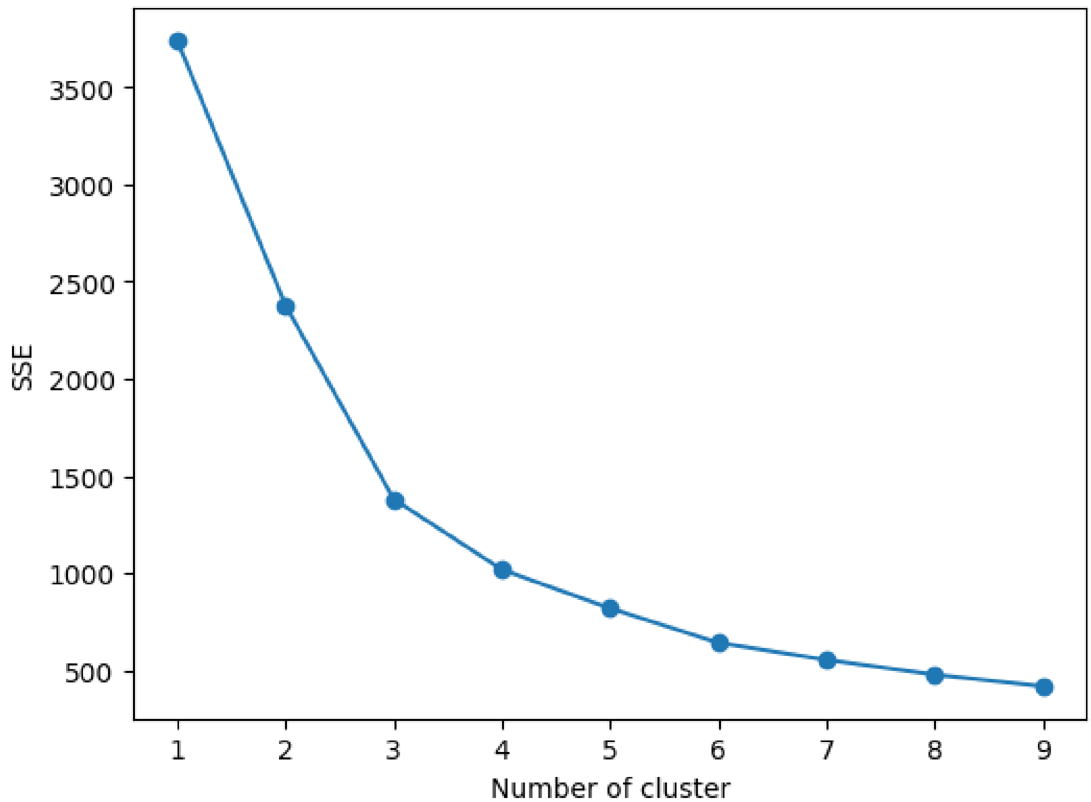
[178]:
```
# Using PCA:

from sklearn.preprocessing import StandardScaler, normalize
from sklearn.decomposition import PCA
```

[179]:
```
# Standardize data
scaler = StandardScaler()
scaled_df = scaler.fit_transform(x)

# Normalizing the Data
normalized_df = normalize(scaled_df)

# Converting the numpy array into a pandas DataFrame
normalized_df = pd.DataFrame(normalized_df)

# Reducing the dimensions of the data
pca = PCA(n_components = 2)
X_principal = pca.fit_transform(normalized_df)
X_principal = pd.DataFrame(X_principal)
X_principal.columns = ['P1', 'P2']

X_principal.head(2)
```

[179]:

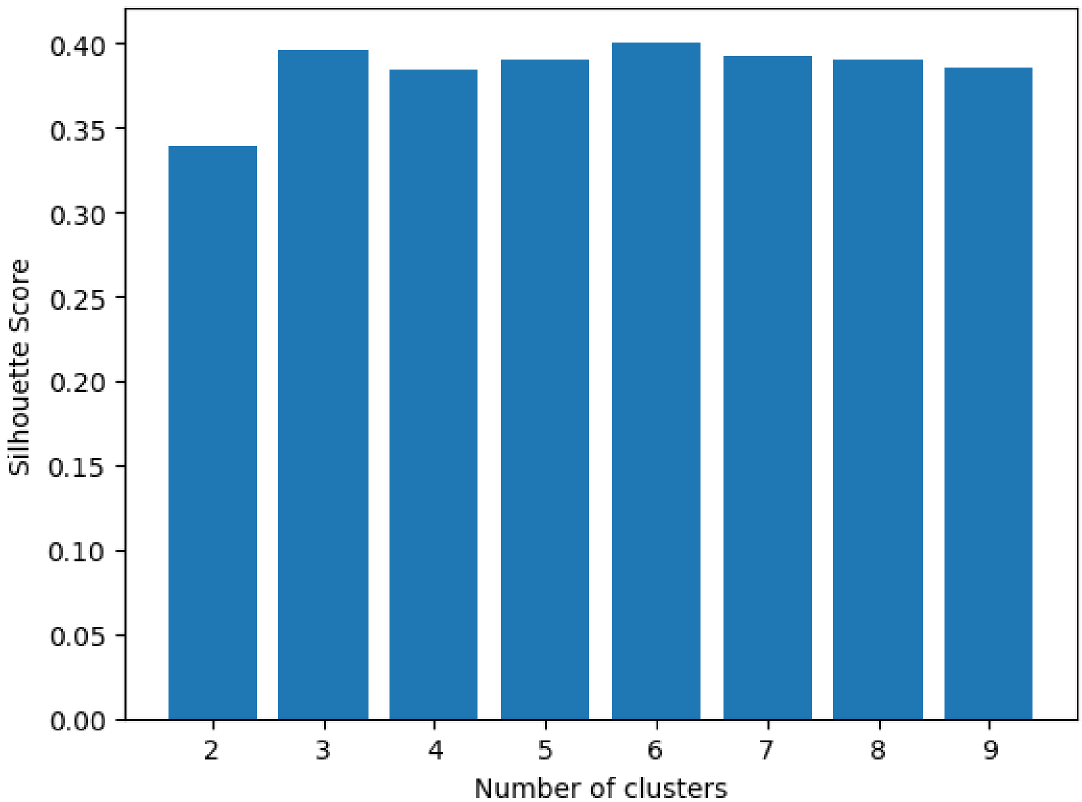
	P1	P2
0	0.608737	0.173193
1	0.343215	-0.189492

[180]:
```
sse = {} #sum of squared  errors
for k in range(1, 10):
    kmeans = KMeans(n_clusters=k, max_iter=1000).fit(X_principal)
    sse[k] = kmeans.inertia_ # Inertia: Sum of distances of samples to their␣
↪closest cluster center
plt.figure()
plt.plot(list(sse.keys()), list(sse.values()),marker='o')
plt.xlabel("Number of cluster")
plt.ylabel("SSE")
plt.show()
```



[181]:
```
# Silhoutte coefficient method:

from sklearn.metrics import silhouette_score
```

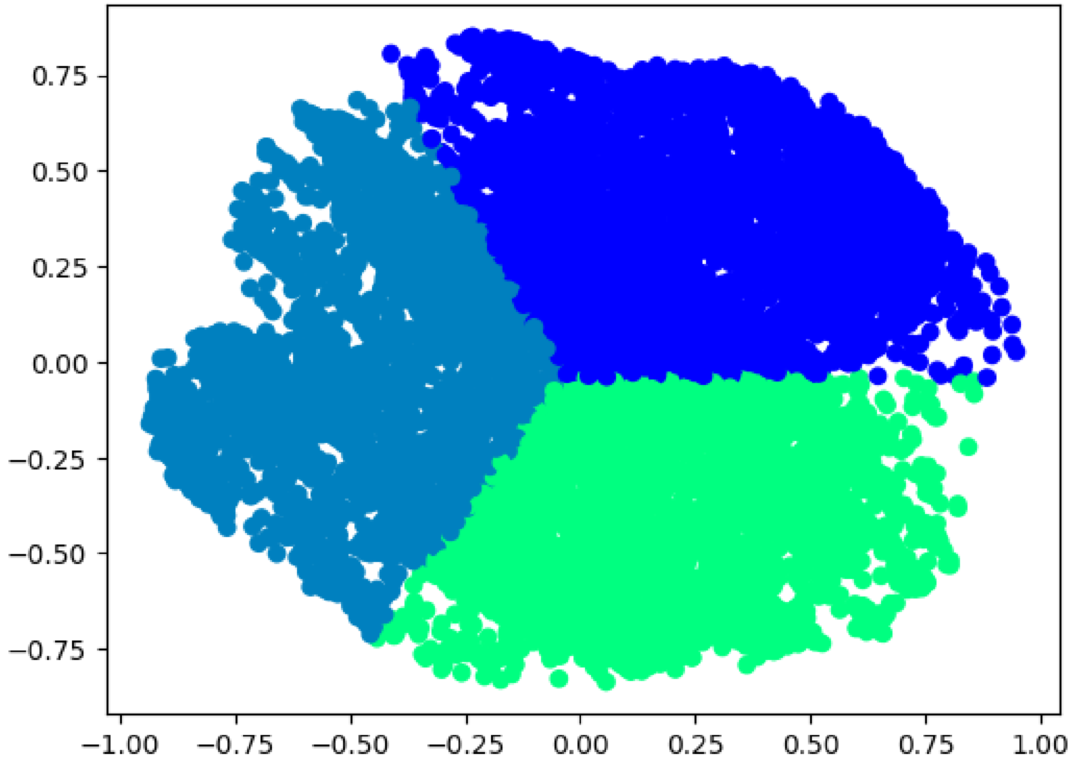
[182]:
```
silhouette_scores = []

for n_cluster in range(2, 10):
    silhouette_scores.append(
        silhouette_score(X_principal, KMeans(n_clusters = n_cluster).
 ↪fit_predict(X_principal)))

# Plotting a bar graph to compare the results
k = [2, 3, 4, 5, 6,7,8,9]
plt.bar(k, silhouette_scores)
plt.xlabel('Number of clusters', fontsize = 10)
plt.ylabel('Silhouette Score', fontsize = 10)
plt.show()
```



[183]:
```
# k=3:

kmeans = KMeans(n_clusters=3)
kmeans.fit(X_principal)
```

[183]: KMeans(n_clusters=3)

[184]:
```
# Visualizing the clustering
plt.scatter(X_principal['P1'], X_principal['P2'],
           c = KMeans(n_clusters = 3).fit_predict(X_principal), cmap =plt.cm.
 ↪winter)
plt.show()
```



[185]:
```
# Hierarchial Agglomerative Clustering:

from sklearn.cluster import AgglomerativeClustering

ac = AgglomerativeClustering(n_clusters=2, linkage='ward',␣
 ↪compute_full_tree=False)
model_ac = ac.fit(X_train)
train_predicted = model_ac.fit_predict(X_train)
test_predicted = model_ac.fit_predict(X_test)
print(train_predicted.shape, y_train.shape)
print(test_predicted.shape, y_test.shape)
```

```
(8929,) (8929,)
(2233,) (2233,)
```

[187]:
```
# Accuracy:

from sklearn.metrics import accuracy_score
train_accuracy = accuracy_score(y_train, train_predicted)
test_accuracy = accuracy_score(y_test, test_predicted)

from sklearn.metrics import classification_report
```

```
print("Train: ",classification_report(y_train,train_predicted))
print("Test: ", classification_report(y_test,test_predicted))
```

```
Train:                 precision    recall  f1-score   support

           0       0.53      0.99      0.69      4687
           1       0.56      0.01      0.02      4242

    accuracy                           0.53      8929
   macro avg       0.54      0.50      0.35      8929
weighted avg       0.54      0.53      0.37      8929

Test:                 precision    recall  f1-score   support

           0       0.41      0.03      0.06      1186
           1       0.46      0.95      0.62      1047

    accuracy                           0.46      2233
   macro avg       0.44      0.49      0.34      2233
weighted avg       0.44      0.46      0.32      2233
```

[189]:

```
# DBSCAN:

from sklearn.cluster import DBSCAN

dbs = DBSCAN(eps=3, min_samples=500)

model_dbs = dbs.fit(X_train)
predicted_train = list(map(lambda x: x+1, model_dbs.fit_predict(X_train)))
predicted_test = list(map(lambda x: x+1, model_dbs.fit_predict(X_test)))
```

[190]:

```
from sklearn.metrics import accuracy_score
train_accuracy = accuracy_score(y_train, predicted_train)
test_accuracy = accuracy_score(y_test, predicted_test)


print("Train: \n",classification_report(y_train,predicted_train))
print("Test: \n",classification_report(y_test,predicted_test))
```

```
Train:
               precision    recall  f1-score   support

           0       0.52      1.00      0.69      4687
           1       0.00      0.00      0.00      4242

    accuracy                           0.52      8929
```

```
   macro avg       0.26      0.50      0.34      8929
weighted avg       0.28      0.52      0.36      8929

Test:
              precision    recall  f1-score   support

           0       0.53      1.00      0.69      1186
           1       0.00      0.00      0.00      1047

    accuracy                           0.53      2233
   macro avg       0.27      0.50      0.35      2233
weighted avg       0.28      0.53      0.37      2233
```

[ ]: