Ganesh_Propensity

April 2, 2024

1 Introduction

This project is aimed at building a propensity model to identify potential customers. The insurance company has provided you with a historical data set (train.csv). The company has also provided you with a list of potential customers to whom to market (test.csv).

[201]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score
from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings("ignore")
```

[202]:
```
# Load historical data
df_train = pd.read_excel(r"C:\Users\Zimm\Downloads\Propensify\train.xlsx")

# Load potential customer data
df_test = pd.read_excel(r"C:\Users\Zimm\Downloads\Propensify\test.xlsx")
```

[203]:
```
df_train.shape
```

[203]:
```
(8240, 24)
```

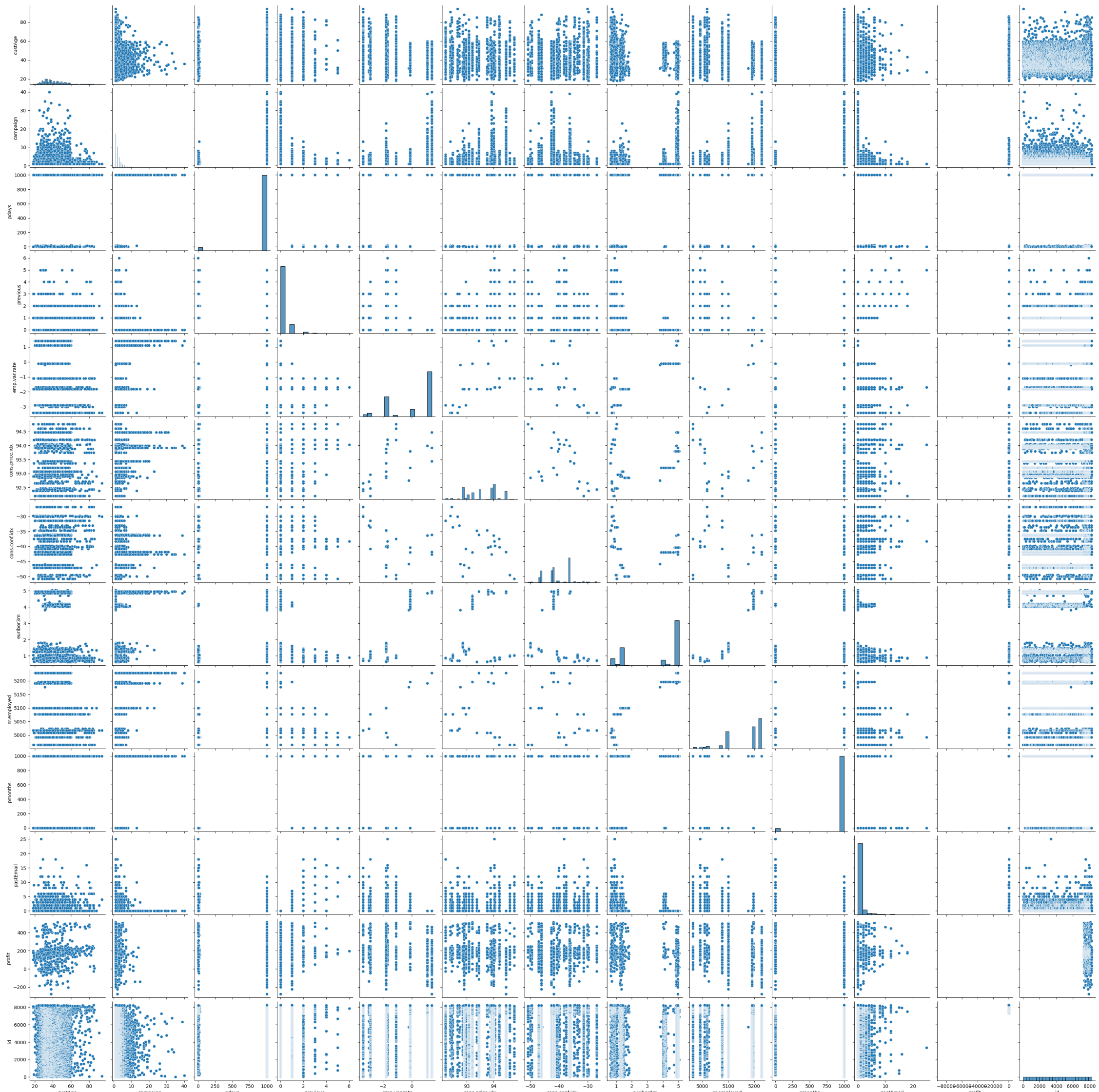
[204]:
```
# Checking the columns in dataset
df_train.columns
```

[204]:
```
Index(['custAge', 'profession', 'marital', 'schooling', 'default', 'housing',
       'loan', 'contact', 'month', 'day_of_week', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'pmonths', 'pastEmail',
       'responded', 'profit', 'id'],
      dtype='object')
```

[205]:
```python
df_train.describe()
```

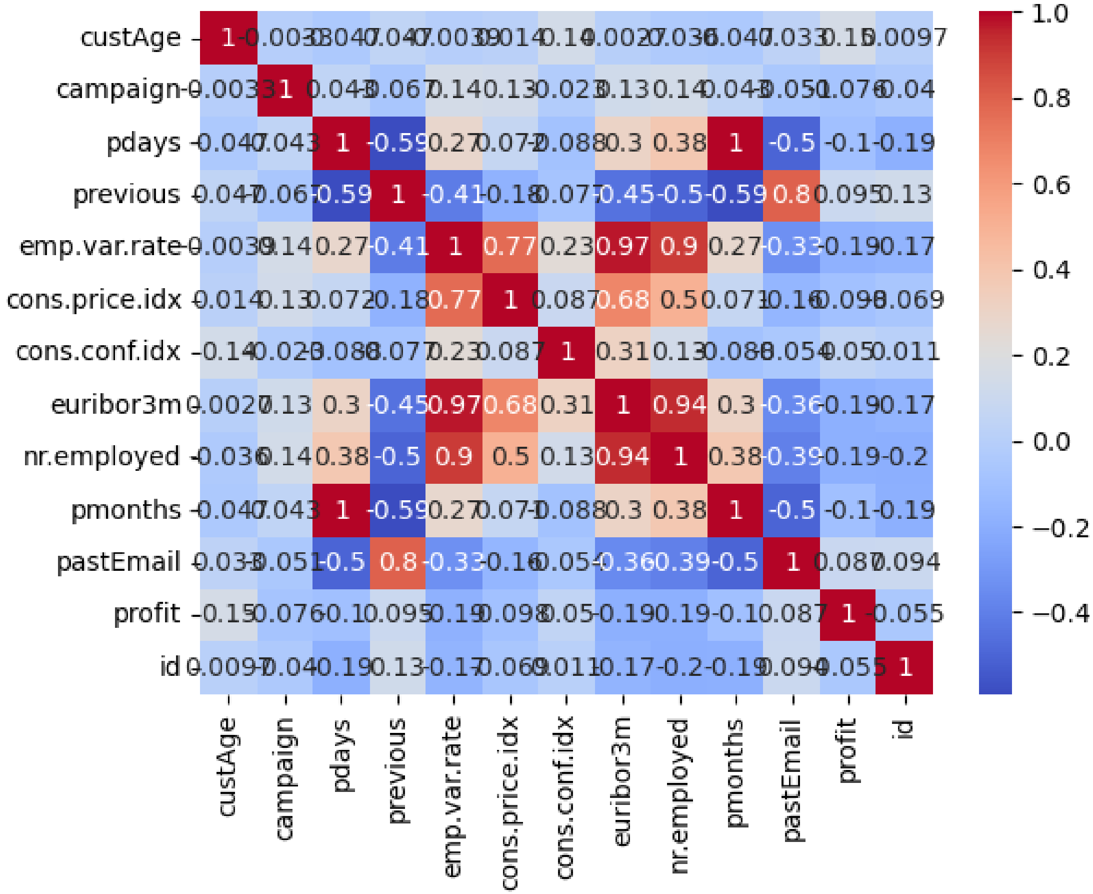
[205]:
```
          custAge     campaign        pdays     previous  emp.var.rate  \
count 6224.000000  8238.000000  8238.000000  8238.000000   8238.000000
mean    39.953728     2.531682   960.916606     0.183054      0.056397
std     10.540516     2.709773   190.695054     0.514209      1.566550
min     18.000000     1.000000     0.000000     0.000000     -3.400000
25%     32.000000     1.000000   999.000000     0.000000     -1.800000
50%     38.000000     2.000000   999.000000     0.000000      1.100000
75%     47.000000     3.000000   999.000000     0.000000      1.400000
max     94.000000    40.000000   999.000000     6.000000      1.400000

       cons.price.idx  cons.conf.idx    euribor3m  nr.employed      pmonths  \
count     8238.000000    8238.000000  8238.000000  8238.000000  8238.000000
mean        93.570977     -40.577907     3.586929  5165.575965   960.687436
std          0.578782       4.650101     1.742784    72.727423   191.841012
min         92.201000     -50.800000     0.634000  4963.600000     0.000000
25%         93.075000     -42.700000     1.334000  5099.100000   999.000000
50%         93.444000     -41.800000     4.857000  5191.000000   999.000000
75%         93.994000     -36.400000     4.961000  5228.100000   999.000000
max         94.767000     -26.900000     5.045000  5228.100000   999.000000

          pastEmail        profit           id
count   8238.000000    930.000000  8238.000000
mean       0.365501     77.709677  4119.500000
std        1.294101   2881.768500  2378.250092
min        0.000000 -87622.112070     1.000000
25%        0.000000    124.000000  2060.250000
50%        0.000000    170.000000  4119.500000
75%        0.000000    213.000000  6178.750000
max       25.000000    515.000000  8238.000000
```

[206]:
```python
# Data visualization
# Pairplot to visualize relationships between numerical variables
sns.pairplot(df_train)
plt.show()
```

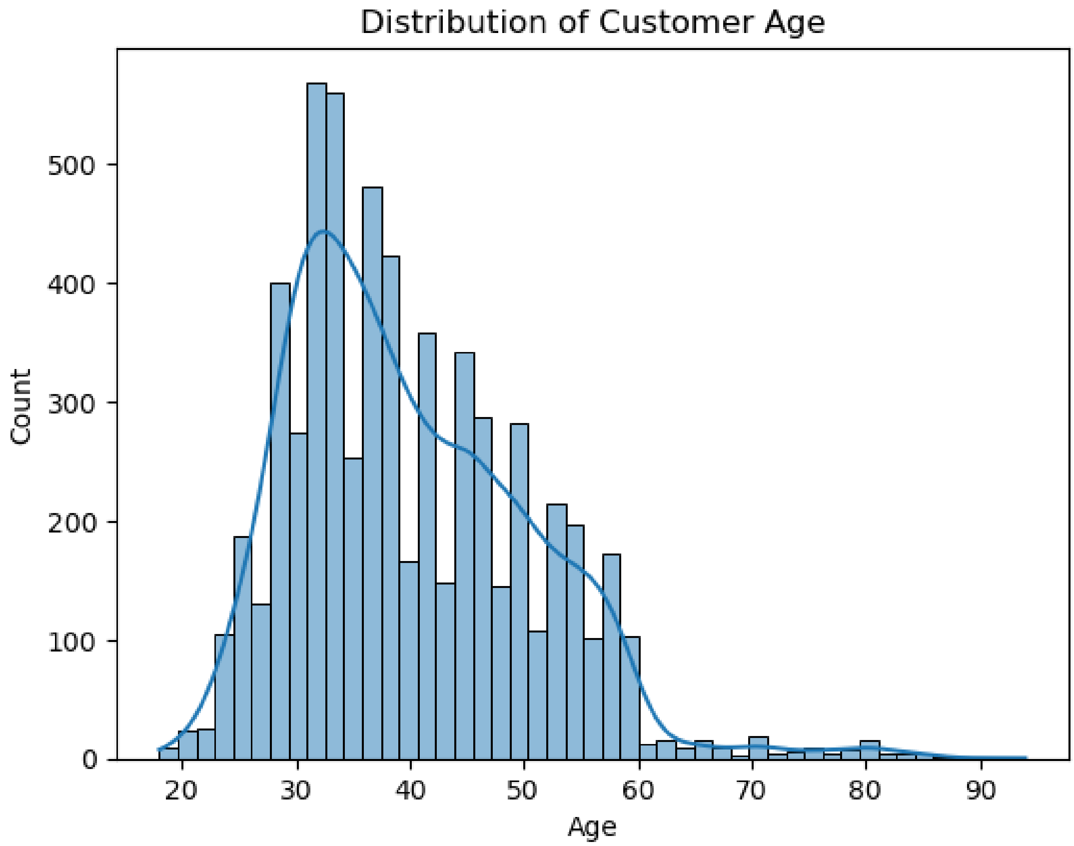


[207]:

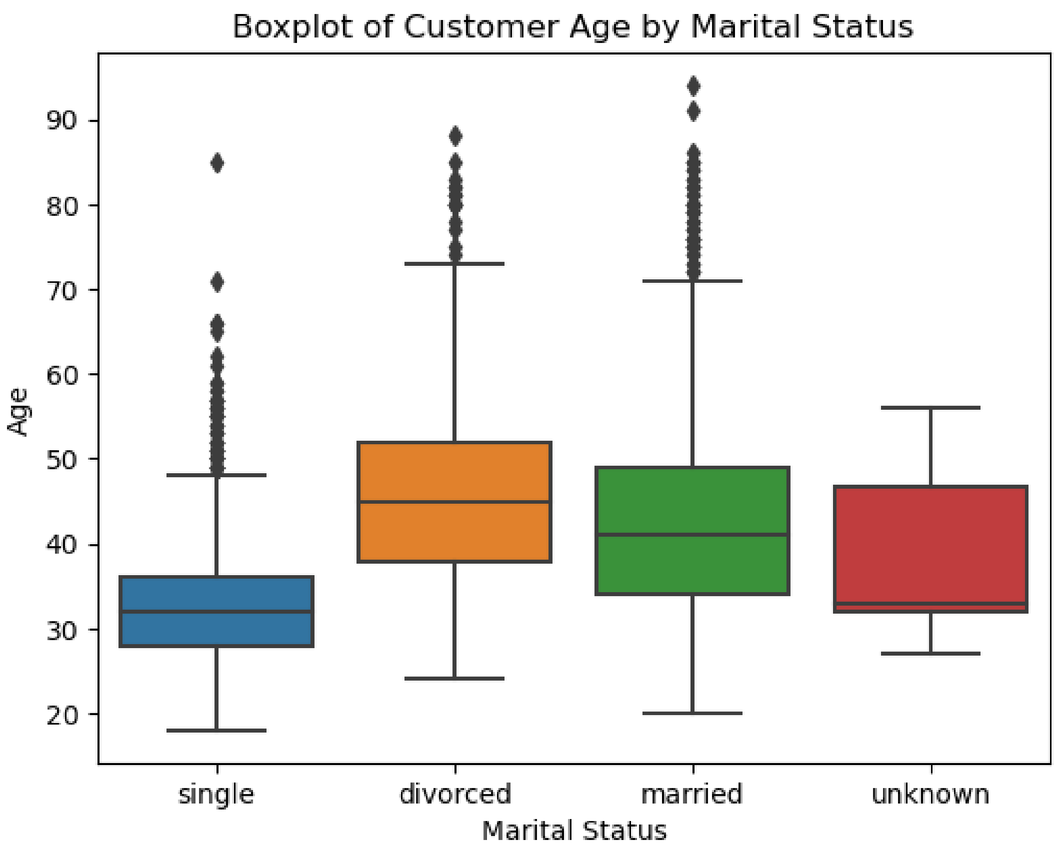
```python
# Correlation heatmap to identify relationships between variables
correlation_matrix = df_train.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```



[208]:
```python
# Distribution of a numerical variable
sns.histplot(df_train['custAge'], kde=True)
plt.title('Distribution of Customer Age')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



[209]:
```
# Boxplot to identify outliers and distribution of a numerical variable
sns.boxplot(x='marital', y='custAge', data=df_train)
plt.title('Boxplot of Customer Age by Marital Status')
plt.xlabel('Marital Status')
plt.ylabel('Age')
plt.show()
```

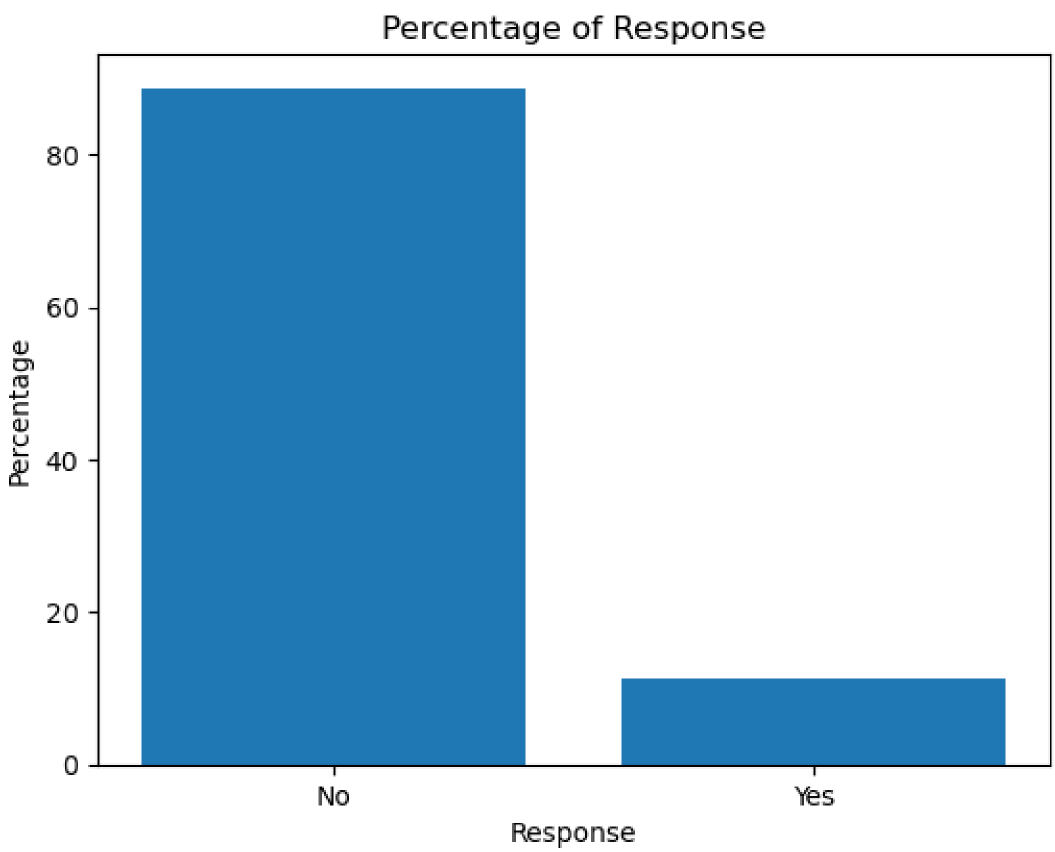


[210]:
```
# Calculate value counts
value_counts = df_train['responded'].value_counts()

# Calculate percentages
percentages = value_counts / len(df_train) * 100


# Display the result
print(percentages)
```

```
no     88.713592
yes    11.262136
Name: responded, dtype: float64
```

[211]:
```
# Create a bar plot
plt.bar(percentages.index, percentages.values)
plt.xlabel('Response')
plt.ylabel('Percentage')
plt.title('Percentage of Response')
```

```
plt.xticks([0, 1], ['No', 'Yes'])  # Assuming 0 represents 'No' and 1␣
↪represents 'Yes'
plt.show()
```



[212]:
```
# Keep only required columns
columns_to_keep = ['custAge', 'profession', 'marital', 'schooling', 'default',␣
↪'housing',
                   'loan', 'contact', 'month', 'day_of_week', 'campaign',␣
↪'pdays', 'previous',
                   'poutcome', 'emp.var.rate', 'cons.price.idx', 'cons.conf.
↪idx',
                   'euribor3m', 'nr.employed', 'pmonths', 'pastEmail',␣
↪'responded']

df_train = df_train[columns_to_keep]
df_train.shape
```

[212]: (8240, 22)

2 Data Cleaning

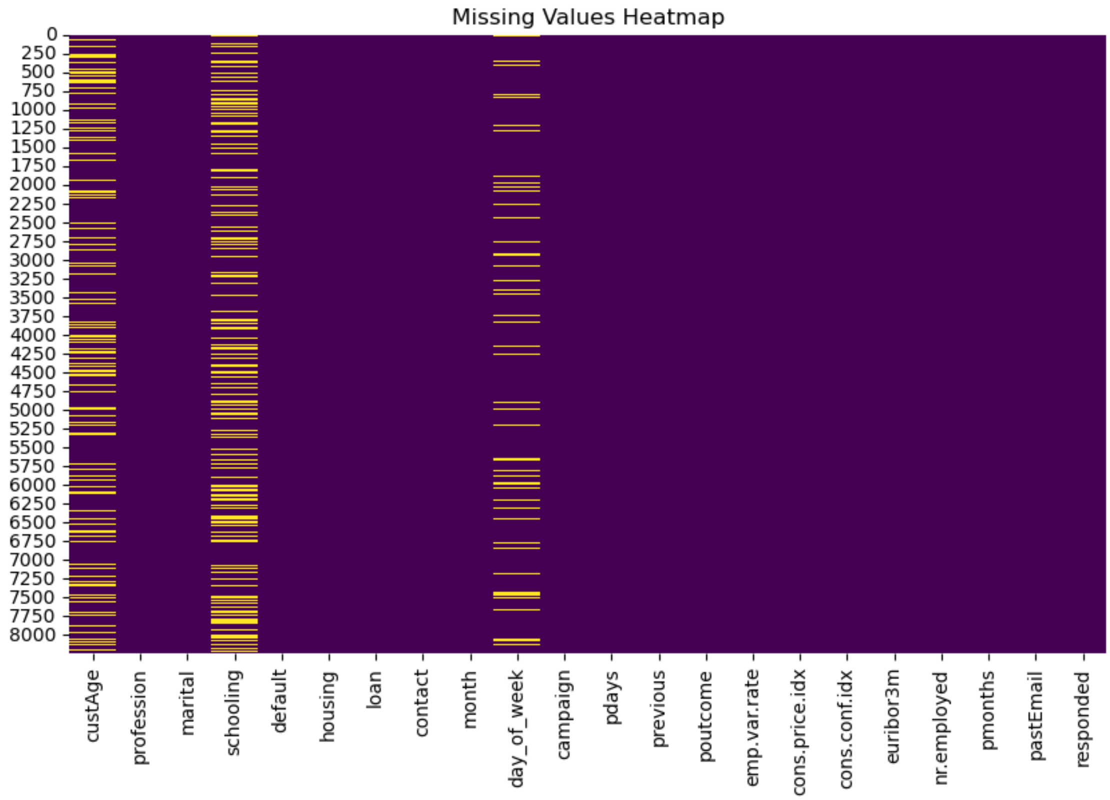
3 Dealing with Imbalanced data

This might include standardization, handling the missing values and outliers in the data This data set is highly imbalanced. The data should be balanced using the appropriate methods before moving onto model building.

[213]:
```
# Check for missing values
missing_values = df_train.isnull().sum()
print("Number of missing values in each column:")
print(missing_values)
```

```
Number of missing values in each column:
custAge           2016
profession           2
marital              2
schooling         2408
default              2
housing              2
loan                 2
contact              2
month                2
day_of_week        789
campaign             2
pdays                2
previous             2
poutcome             2
emp.var.rate         2
cons.price.idx       2
cons.conf.idx        2
euribor3m            2
nr.employed          2
pmonths              2
pastEmail            2
responded            2
dtype: int64
```

[214]:
```
# Create a heatmap to visualize missing values
plt.figure(figsize=(10, 6))
sns.heatmap(df_train.isnull(), cmap='viridis', cbar=False)
plt.title('Missing Values Heatmap')
plt.show()
```



[215]:
```
# Checking duplicate values
print(df_train.duplicated().value_counts())
```

```
False    8203
True       37
dtype: int64
```

[ ]:
```

```

[216]:
```
# Imputing missing values of schooling
cross_tab = pd.crosstab(df_train['schooling'], df_train['profession'],normalize␣
↪= 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪pink' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[216]:
```
<pandas.io.formats.style.Styler at 0x2865a2c9a10>
```

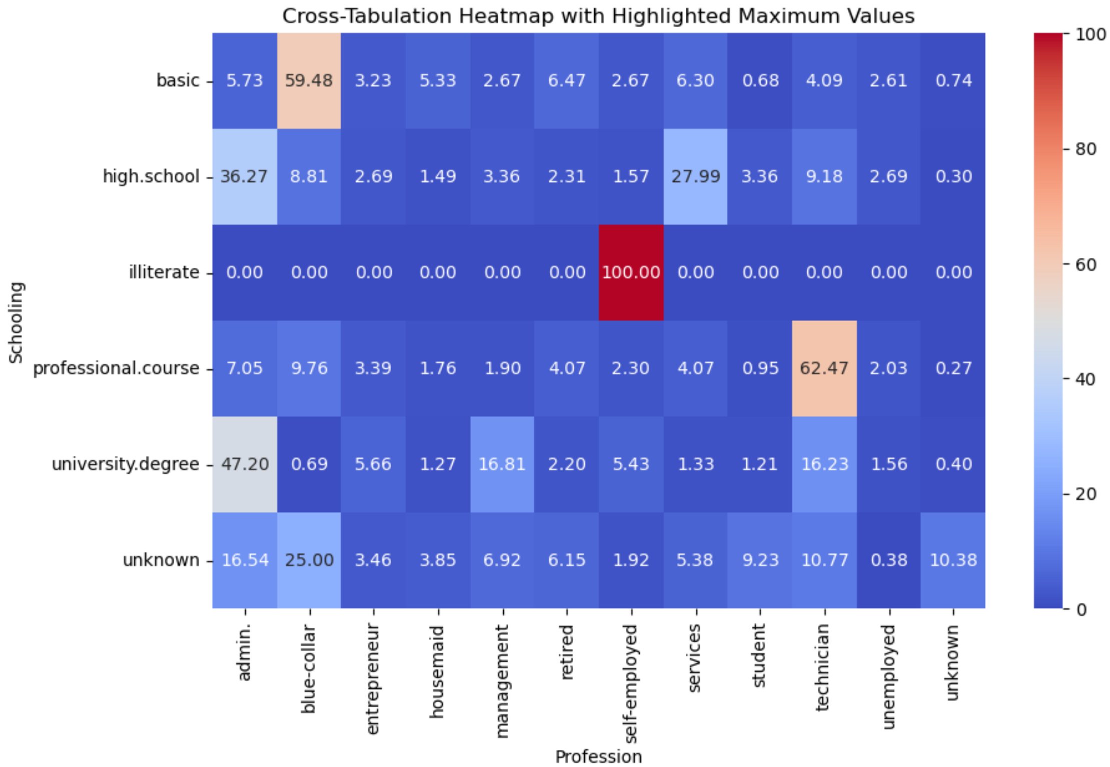
[217]:
```
# Feature engineering for schooling
schooling_category = {
    'basic.4y' : 'basic',
    'basic.6y' : 'basic',
```

```
    'basic.9y' : 'basic',
    'high.school': 'high.school',
    'illiterate':'illiterate',
    'professional.course': 'professional.course',
    'university.degree':'university.degree',
    'unknown':'unknown',
}

df_train['schooling'] = df_train['schooling'].replace(schooling_category)
```

[218]:
```
cross_tab = pd.crosstab(df_train['schooling'], df_train['profession'],normalize␣
 ↪= 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
 ↪pink' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[218]: <pandas.io.formats.style.Styler at 0x2865ae7f050>

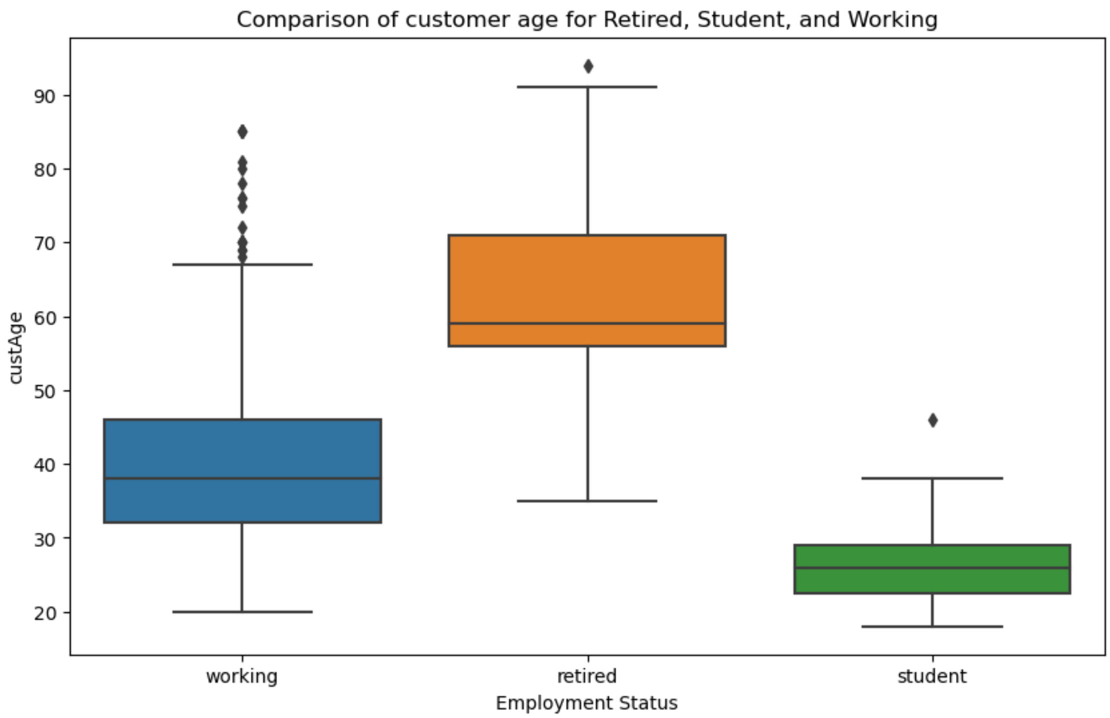
[219]:
```
# Create the cross-tabulation with normalization
cross_tab = pd.crosstab(df_train['schooling'], df_train['profession'],␣
 ↪normalize='index') * 100

# Create a heatmap with highlighted maximum values
plt.figure(figsize=(10, 6))
sns.heatmap(cross_tab, cmap='coolwarm', annot=True, fmt=".2f")
plt.title('Cross-Tabulation Heatmap with Highlighted Maximum Values')
plt.xlabel('Profession')
plt.ylabel('Schooling')
plt.show()
```



[220]:
```
# Imputing missing values in education based on profession

imputation_mapping = {
    'blue-collar' : 'basic',
    'self-employed': 'illiterate',
    'technician'   : 'professional.course',
    'admin.'        : 'university.degree',
    'services'      : 'high.school',
    'management'    : 'university.degree',
    'retired'       : 'unknown',
    'entrepreneur'  : 'university.degree'
}

df_train['schooling'] = df_train['schooling'].
 ↪combine_first(df_train['profession'].map(imputation_mapping))
```

[221]:
```
# Treating the missing values of profession
df_train['employment_status'] = df_train['profession'].apply(lambda x:␣
 ↪'retired' if x == 'retired' else ('student' if x == 'student' else␣
 ↪'working'))
```

[222]:
```python
# Age comparision of Retired, Student and Working
plt.figure(figsize=(10, 6))
sns.boxplot(x='employment_status', y='custAge', data=df_train)
plt.title('Comparison of customer age for Retired, Student, and Working')
plt.xlabel('Employment Status')
plt.ylabel('custAge')
plt.show()
```



[ ]:

[223]:
```python
# Imputing age values
# Calculate mean and median values for each profession
mean_age_retired = df_train.loc[df_train['employment_status'] == 'retired',␣
 ↪'custAge'].mean()
mean_age_student = df_train.loc[df_train['employment_status'] == 'student',␣
 ↪'custAge'].mean()
median_age_working = df_train.loc[df_train['employment_status'] == 'working',␣
 ↪'custAge'].median()

# Fill missing values based on profession-specific mean or median
df_train['custAge'] = np.where((df_train['employment_status'] == 'retired') &␣
 ↪df_train['custAge'].isna(), mean_age_retired, df_train['custAge'])
```

```
df_train['custAge'] = np.where((df_train['employment_status'] == 'student') &
    df_train['custAge'].isna(), mean_age_student, df_train['custAge'])
df_train['custAge'] = np.where((df_train['employment_status'] == 'working') &
    df_train['custAge'].isna(), median_age_working, df_train['custAge'])
```

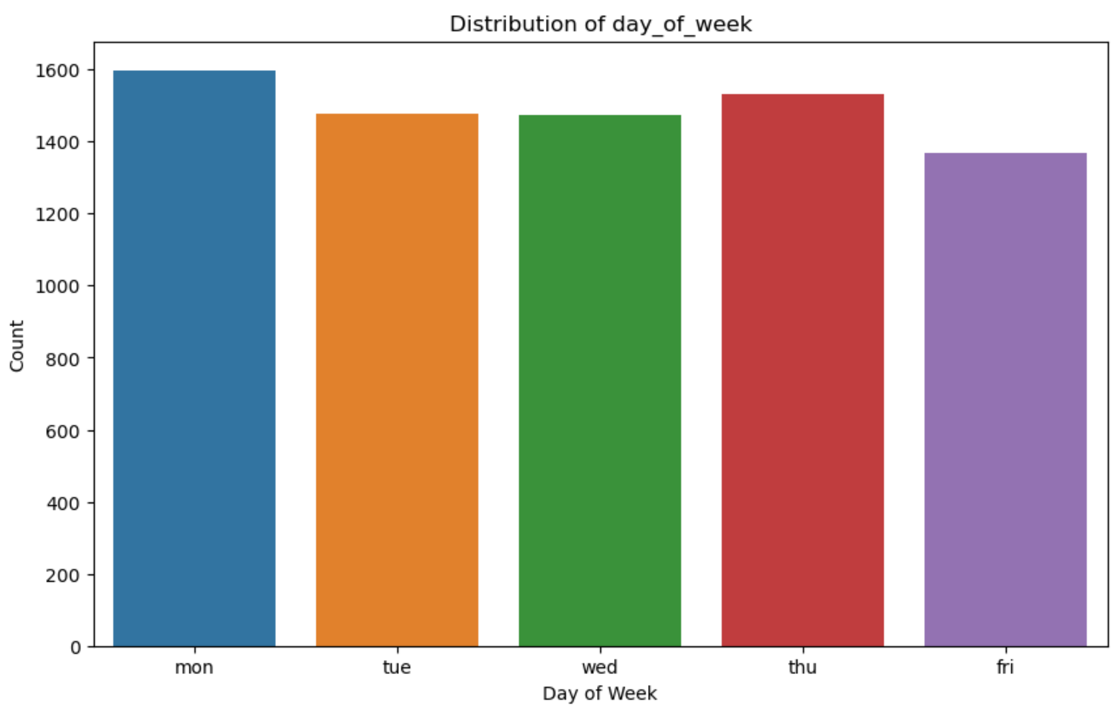
[224]:

```
# Imputing day of week variables which is based on random function
day_values = df_train['day_of_week'].value_counts()
print(day_values)
```

```
mon    1598
thu    1533
tue    1478
wed    1473
fri    1369
Name: day_of_week, dtype: int64
```

[225]:

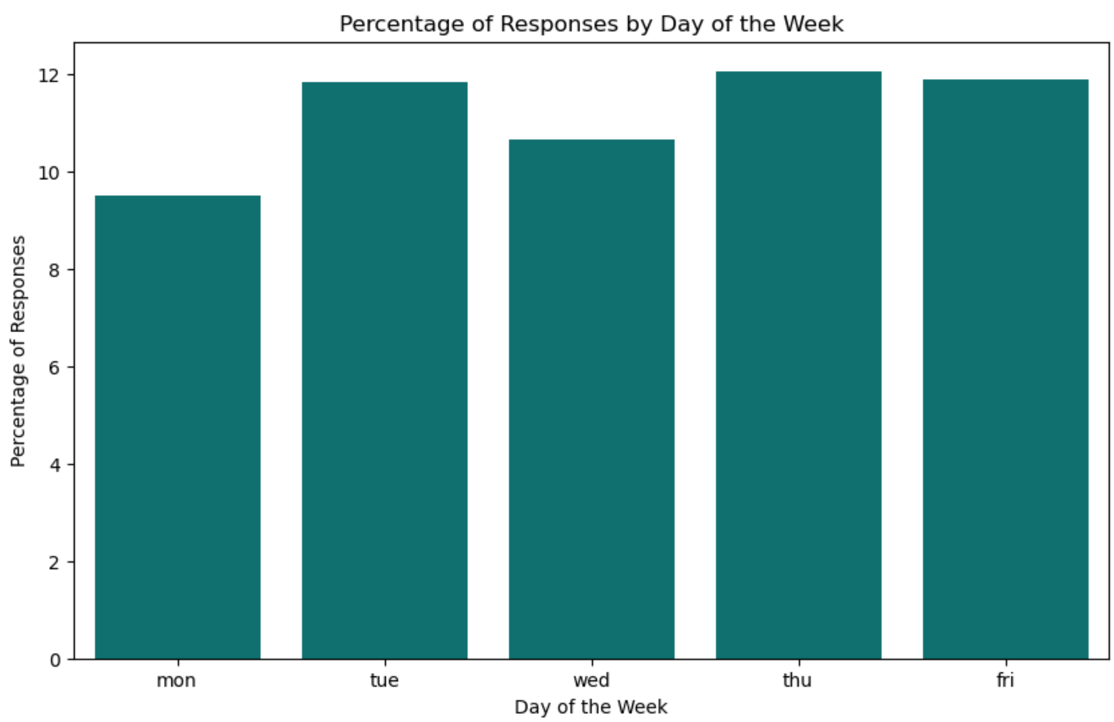
```
# Day of week
plt.figure(figsize=(10, 6))
sns.countplot(x='day_of_week', data=df_train, order=['mon', 'tue', 'wed',
    'thu', 'fri'])
plt.title('Distribution of day_of_week')
plt.xlabel('Day of Week')
plt.ylabel('Count')
plt.show()
```



[226]:
```
cross_tab = pd.crosstab(df_train['day_of_week'],␣
↪df_train['responded'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪pink' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[226]: <pandas.io.formats.style.Styler at 0x28665d9d650>

[227]:
```
# Extracting the DataFrame from styled DataFrame object
cross_tab = pd.crosstab(df_train['day_of_week'], df_train['responded'],␣
↪normalize='index') * 100

# Plotting the bar plot using Seaborn
plt.figure(figsize=(10, 6))
sns.barplot(data=cross_tab, x=cross_tab.index, y='yes', color='teal',␣
↪order=['mon', 'tue', 'wed', 'thu', 'fri'])
plt.title('Percentage of Responses by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Percentage of Responses')
plt.show()
```



[228]:
```
def impute_random_day(day):
    if pd.isna(day):
```

```
        return np.random.choice(['mon', 'tue', 'wed', 'thu', 'fri'])
    else:
        return day

# Imputation function to the 'day_of_week' column
df_train['day_of_week'] = df_train['day_of_week'].apply(impute_random_day)
```

[229]:
```
# Treat missing values
missing_values = df_train.isnull().sum()
print("Number of missing values in each column:")
print(missing_values)
```

```
Number of missing values in each column:
custAge                0
profession             2
marital                2
schooling            189
default                2
housing                2
loan                   2
contact                2
month                  2
day_of_week            0
campaign               2
pdays                  2
previous               2
poutcome               2
emp.var.rate           2
cons.price.idx         2
cons.conf.idx          2
euribor3m              2
nr.employed            2
pmonths                2
pastEmail              2
responded              2
employment_status      0
dtype: int64
```

[230]:
```
# Now dropping remaining missing values which is minimal
df_train = df_train.dropna()
```

[231]:
```
# Re-check the missing values
missing_values = df_train.isnull().sum()
print("Number of missing values in each column:")
print(missing_values)
```

```
Number of missing values in each column:
custAge              0
```

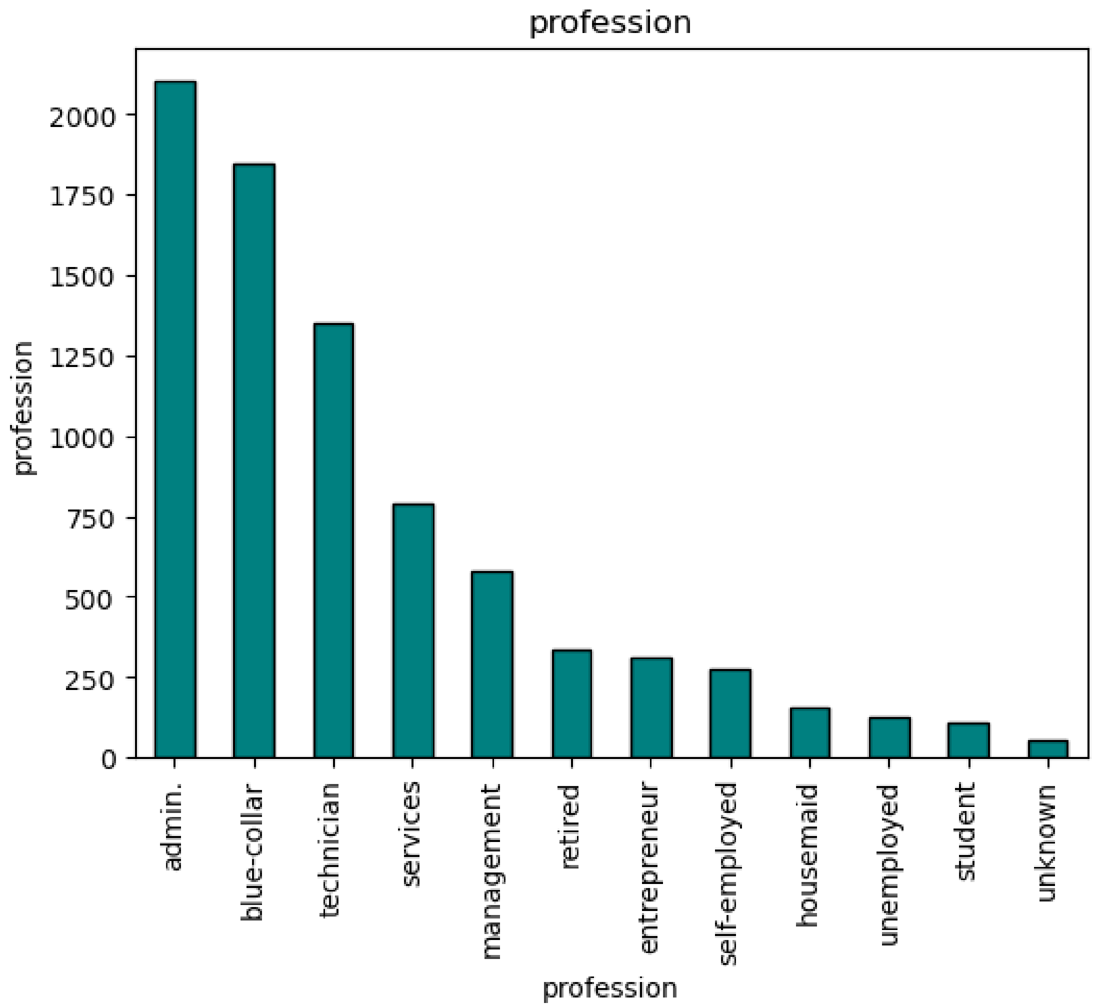
```
profession           0
marital              0
schooling            0
default              0
housing              0
loan                 0
contact              0
month                0
day_of_week          0
campaign             0
pdays                0
previous             0
poutcome             0
emp.var.rate         0
cons.price.idx       0
cons.conf.idx        0
euribor3m            0
nr.employed          0
pmonths              0
pastEmail            0
responded            0
employment_status    0
dtype: int64
```

[232]:
```
df_train.shape
```

[232]:
```
(8051, 23)
```

4 Feature engineering of categorical variables:

[233]:
```
#1. Profession
df_train['profession'].value_counts().plot(kind='bar', color='teal',␣
 ↪edgecolor='black')
plt.title('profession')
plt.xlabel('profession')
plt.ylabel('profession')
plt.show()
```



[234]:
```
cross_tab = pd.crosstab(df_train['profession'], df_train['responded'],normalize␣
↪= 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪pink' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

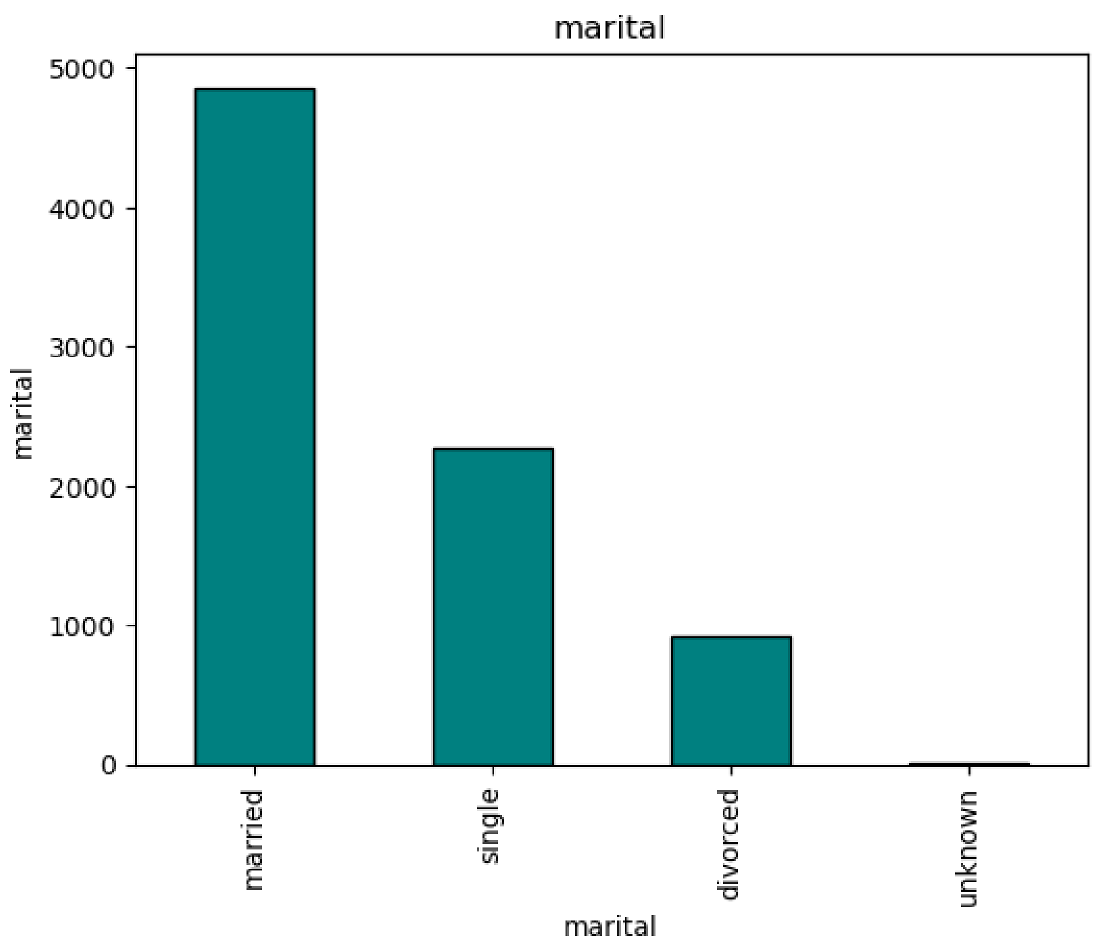
[234]: <pandas.io.formats.style.Styler at 0x28659c8a450>

[235]:
```
# Label encoding
df_train['profession'] = df_train['profession'].map({'student': 'Dependents',␣
↪'retired': 'Dependents', 'unemployed': 'Unemployed&Unknown', 'unknown':␣
↪'Unemployed&Unknown',
                                                    'admin.':␣
↪'Working','blue-collar': 'Working','entrepreneur': 'Working','housemaid':␣
↪'Working',
```

```
                                                   'management':␣
 ↪'Working','self-employed': 'Working','services': 'Working','technician':␣
 ↪'Working'})

# Display the updated DataFrame
df_train['profession'].value_counts()
```

[235]:
```
Working               7427
Dependents             446
Unemployed&Unknown     178
Name: profession, dtype: int64
```

[236]:
```
# Analyze Marital
df_train['marital'].value_counts().plot(kind='bar', color='teal',␣
 ↪edgecolor='black')
plt.title('marital')
plt.xlabel('marital')
plt.ylabel('marital')
plt.show()
```



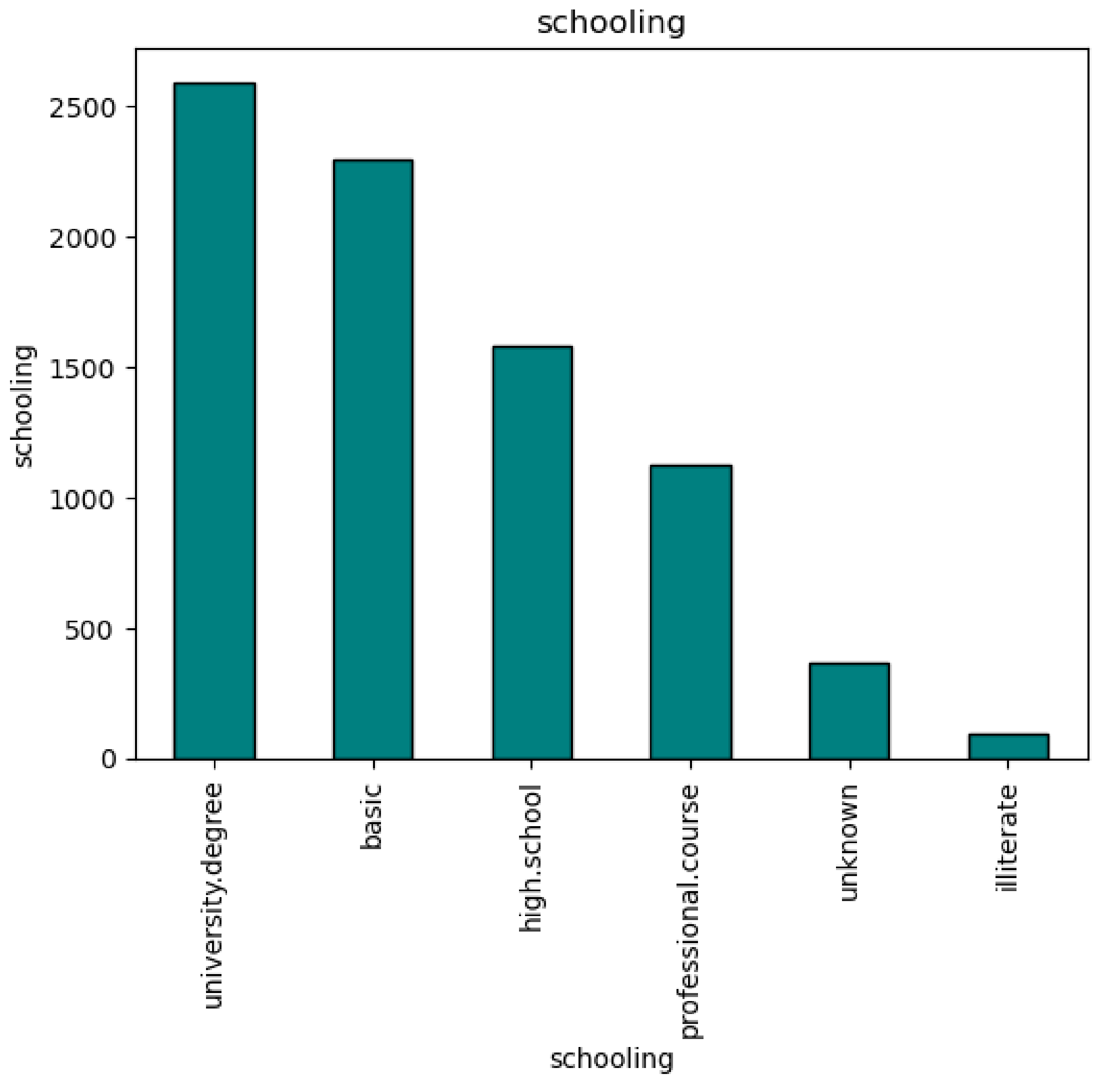
[237]:
```
cross_tab = pd.crosstab(df_train['marital'], df_train['responded'],normalize =␣
 ↪'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
 ↪pink' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[237]: <pandas.io.formats.style.Styler at 0x286598d4950>

[238]:
```
# Label encoding
df_train['marital'] = df_train['marital'].map({'single': 'Single&Divorced',␣
 ↪'divorced': 'Single&Divorced',
                                                                    'married':␣
 ↪'married', 'unknown': 'Unknown', })

# Display the updated DataFrame
df_train['marital'].value_counts()
```

[238]:
```
married            4858
Single&Divorced    3184
Unknown               9
Name: marital, dtype: int64
```

[239]:
```
# Schooling
df_train['schooling'].value_counts().plot(kind='bar', color='teal',␣
 ↪edgecolor='black')
plt.title('schooling')
plt.xlabel('schooling')
plt.ylabel('schooling')
plt.show()
```



[240]:
```
cross_tab = pd.crosstab(df_train['schooling'], df_train['responded'],normalize␣
↪= 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪pink' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

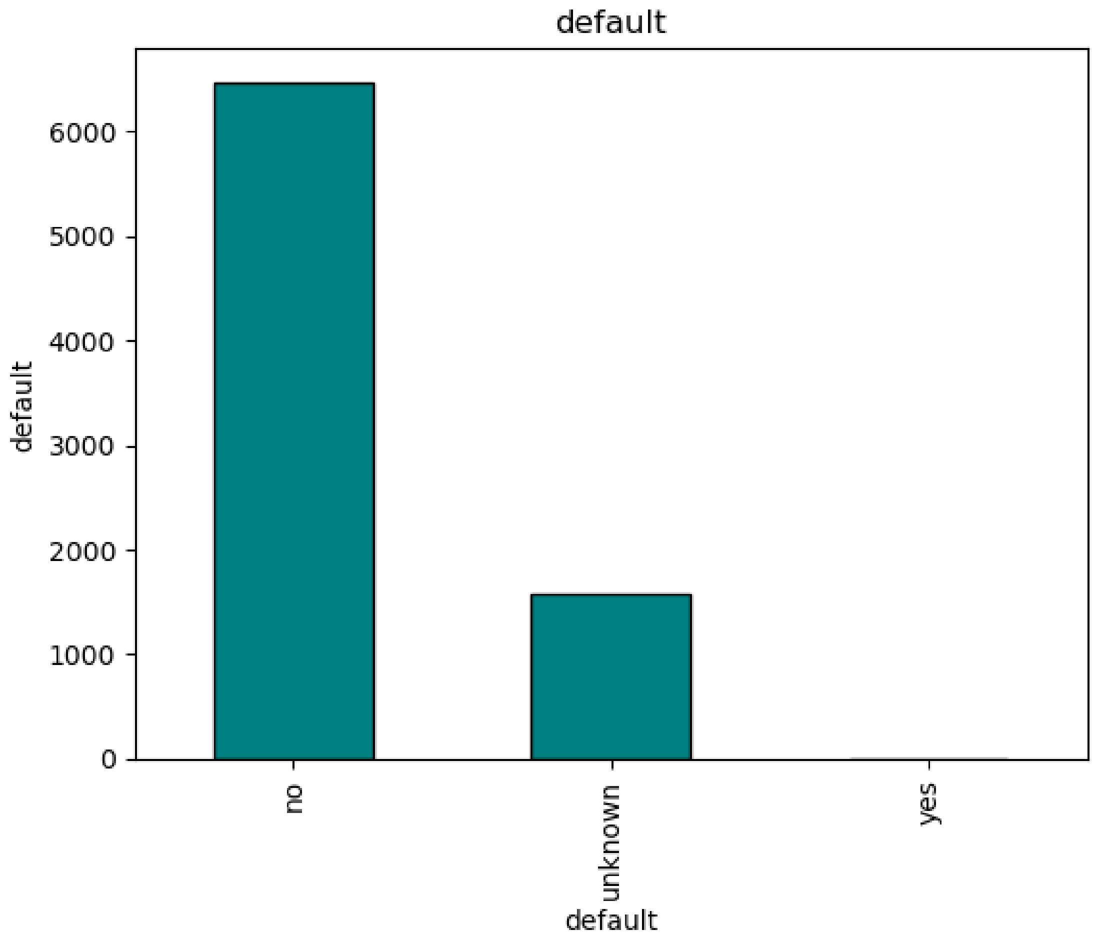
[240]: <pandas.io.formats.style.Styler at 0x28669ad8710>

[241]:
```
# Label encoding
df_train['schooling'] = df_train['schooling'].map({'basic':␣
↪'Uneducated&BasicEducation', 'high.school': 'Uneducated&BasicEducation',
                                                                          ␣
↪'illiterate': 'Uneducated&BasicEducation',
```

```
                                                                   'unknown':␣
 ↪'Unknown',
                                                                  'professional.
 ↪course': 'Educated',
                                                                  'university.
 ↪degree': 'Educated',
                                                                  })

# Display the updated DataFrame
df_train['schooling'].value_counts()
```

[241]:
```
Uneducated&BasicEducation    3968
Educated                     3715
Unknown                       368
Name: schooling, dtype: int64
```

[242]:
```
# Default
df_train['default'].value_counts().plot(kind='bar', color='teal',␣
 ↪edgecolor='black')
plt.title('default')
plt.xlabel('default')
plt.ylabel('default')
plt.show()
```

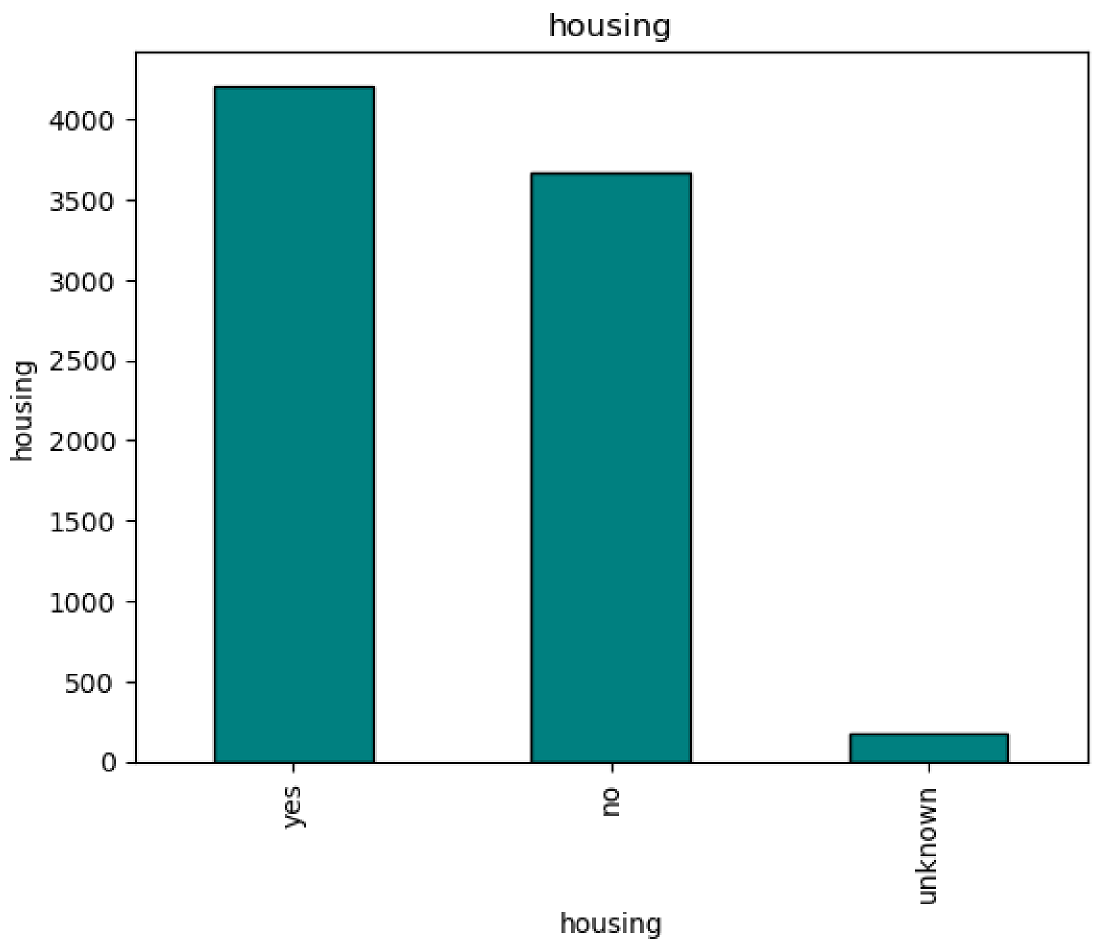


[243]:
```
# Label encoding
df_train['default'] = df_train['default'].map({'no': 'No', 'unknown':␣
↪'Yes&Unknown','yes':'Yes&Unknown' })

# Display the updated DataFrame
df_train['default'].value_counts()
```

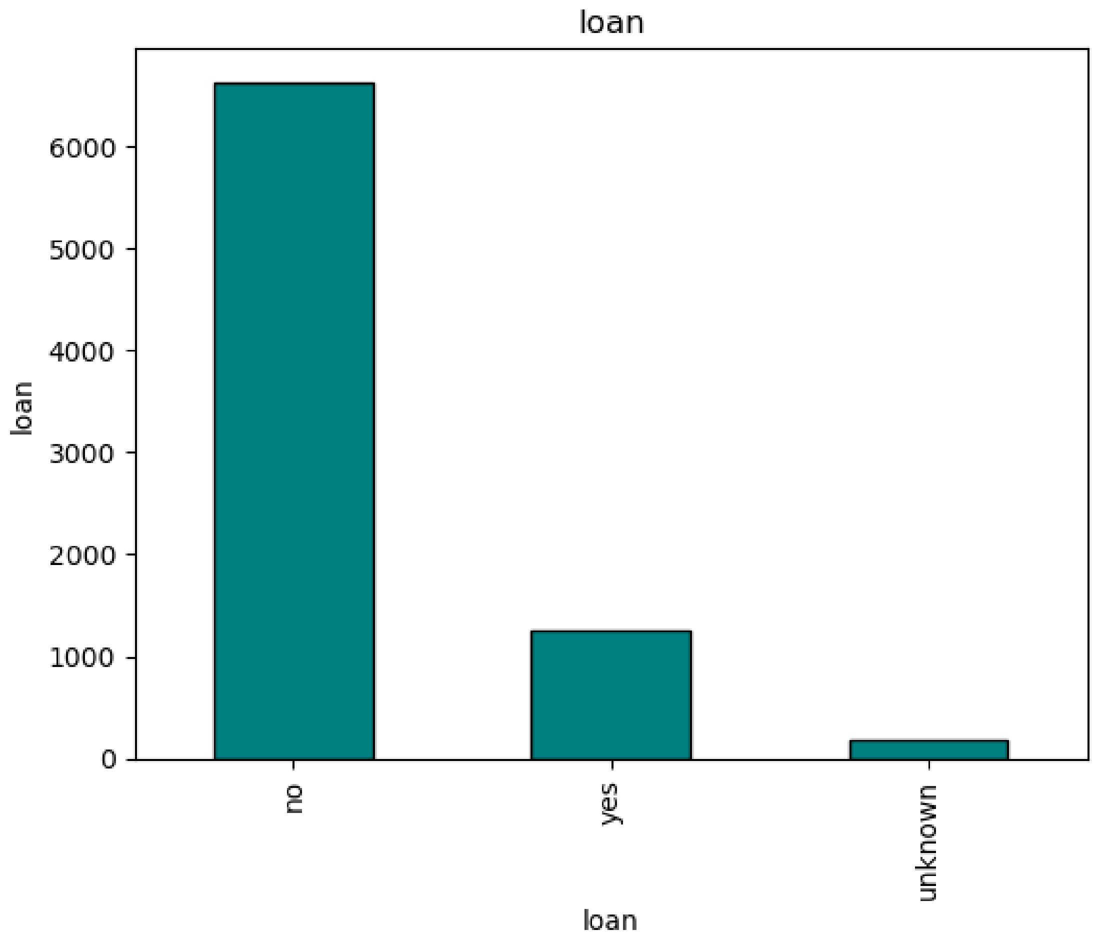
[243]:
```
No             6470
Yes&Unknown    1581
Name: default, dtype: int64
```

[244]:
```
# Analyze Housing
df_train['housing'].value_counts().plot(kind='bar', color='teal',␣
↪edgecolor='black')
plt.title('housing')
plt.xlabel('housing')
plt.ylabel('housing')
```

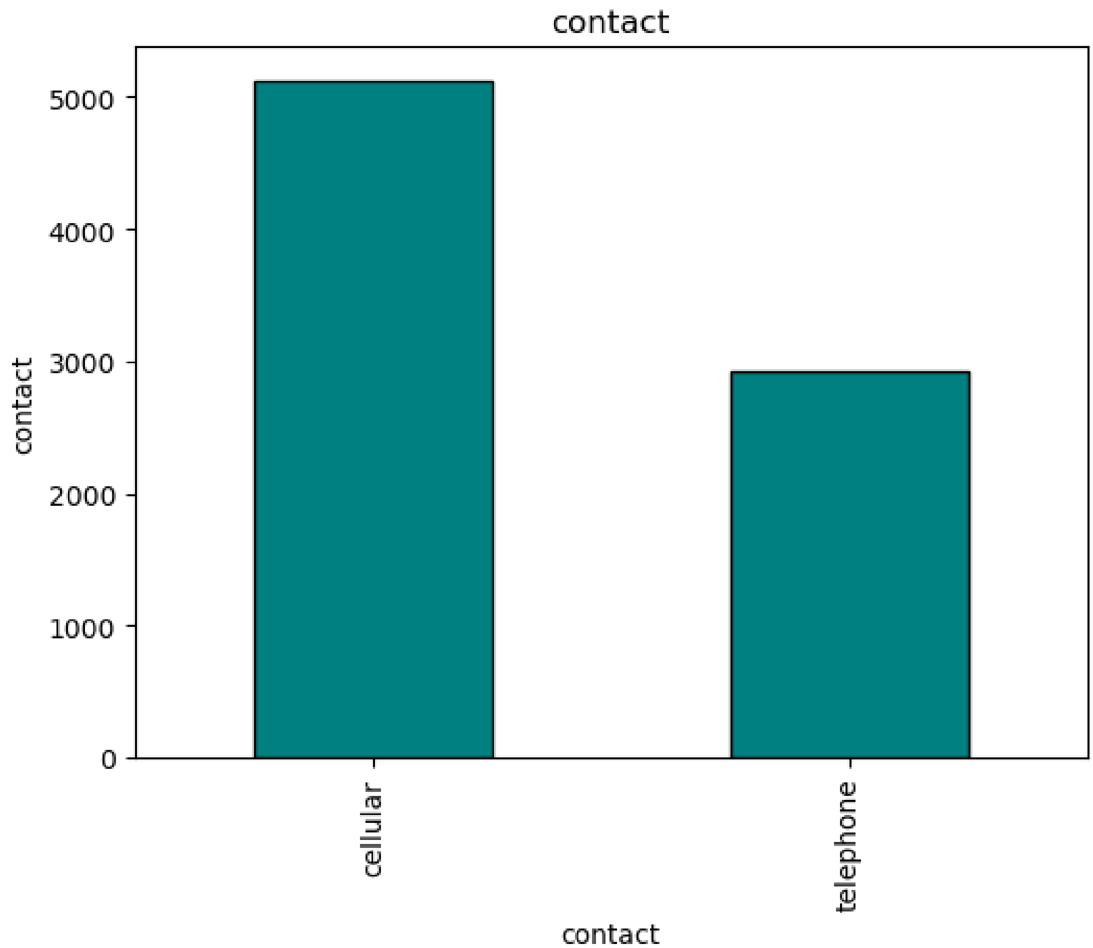
```
plt.show()
```



[245]:
```
# Analyze loan
df_train['loan'].value_counts().plot(kind='bar', color='teal',␣
↪edgecolor='black')
plt.title('loan')
plt.xlabel('loan')
plt.ylabel('loan')
plt.show()
```



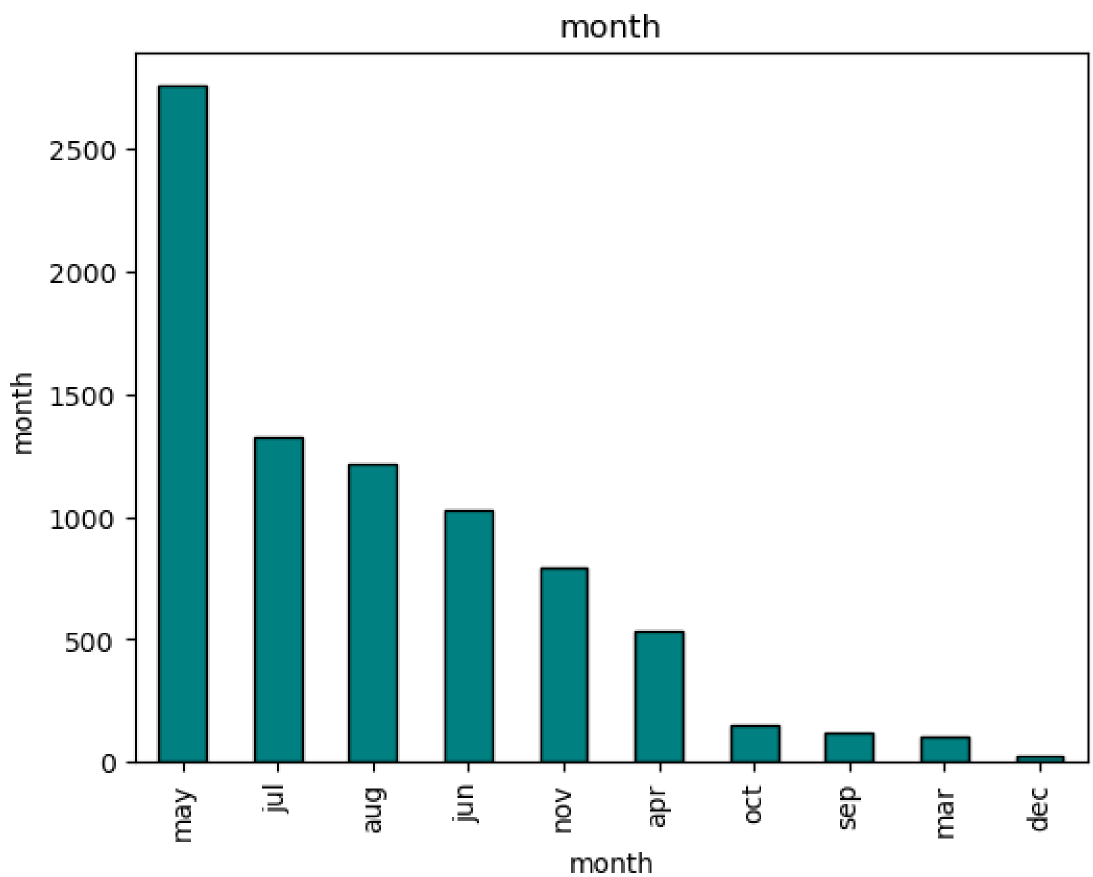
[246]:
```
# Analyze contact
df_train['contact'].value_counts().plot(kind='bar', color='teal',␣
    ↪edgecolor='black')
plt.title('contact')
plt.xlabel('contact')
plt.ylabel('contact')
plt.show()
```



[247]:
```
cross_tab = pd.crosstab(df_train['month'], df_train['responded'],normalize =␣
  ↪'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
  ↪pink' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[247]:
```
<pandas.io.formats.style.Styler at 0x28659c65c90>
```

[248]:
```
# Analyze Month
df_train['month'].value_counts().plot(kind='bar', color='teal',␣
  ↪edgecolor='black')
plt.title('month')
plt.xlabel('month')
plt.ylabel('month')
plt.show()
```



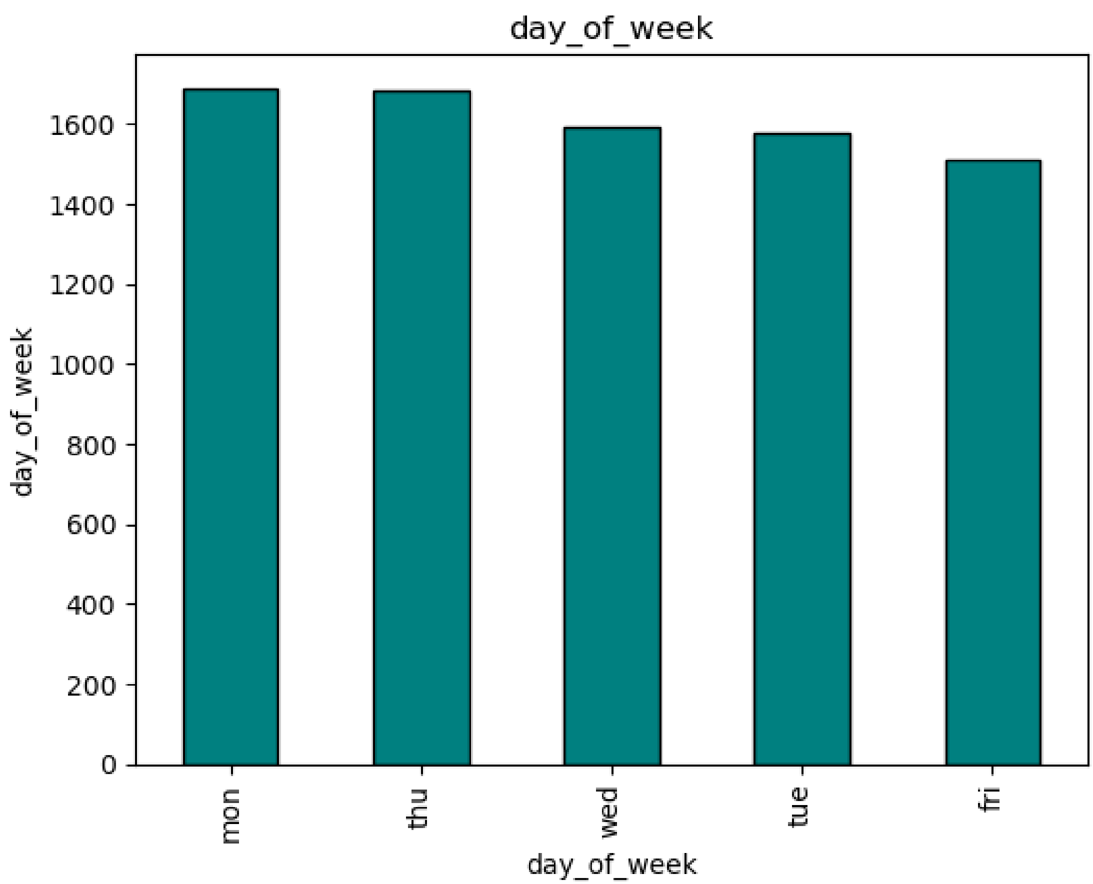
[249]:
```
# Create a copy of the DataFrame to avoid modifying the original data
df_train_copy_c = df_train.copy()

# Define a mapping for specific months
quarter_mapping = {'dec': 'QuarterEnd', 'sep': 'QuarterEnd', 'jun':␣
↪'QuarterEnd', 'mar': 'QuarterEnd'}

# Replace specified months with 'QuarterEnd' in the copied DataFrame
df_train_copy_c['month_mapped'] = df_train_copy_c['month'].
↪replace(quarter_mapping)

# Replace other months with 'others' in the copied DataFrame
df_train_copy_c['month_mapped'].
↪replace(to_replace=df_train_copy_c['month_mapped'][~df_train_copy_c['month_mapped'].
↪isin(['QuarterEnd'])].unique(), value='others', inplace=True)

# Display the value counts of the new variable
print(df_train_copy_c['month_mapped'].value_counts())
```

```
df_train['month'] = df_train_copy_c['month_mapped']
df_train['month'].value_counts()
```

```
others        6776
QuarterEnd    1275
Name: month_mapped, dtype: int64
```

[249]:
```
others        6776
QuarterEnd    1275
Name: month, dtype: int64
```

[250]:
```
# Day_of_week
df_train['day_of_week'].value_counts().plot(kind='bar', color='teal',␣
 ↪edgecolor='black')
plt.title('day_of_week')
plt.xlabel('day_of_week')
plt.ylabel('day_of_week')
plt.show()
```



[251]:
```python
# Label encoding
df_train['day_of_week'] = df_train['day_of_week'].map({'mon': 'WeekBeginning',␣
↪'tue': 'WeekBeginning','wed':'WeekBeginning',
                                                                        'thu':
↪'WeekEnding','fri':'WeekEnding'})

# Display the updated DataFrame
df_train['day_of_week'].value_counts()
```

[251]:
```
WeekBeginning    4859
WeekEnding       3192
Name: day_of_week, dtype: int64
```

[252]:
```python
# Feature engineering of other variables

# pdays
conditions = [
    (df_train['pdays'] == 999),
    (df_train['pdays'] < 5),
    ((df_train['pdays'] >= 5) & (df_train['pdays'] <= 10)),
    (df_train['pdays'] > 10)
]

choices = ['first visit', 'less than 5 days', '5 to 10 days', 'greater than 10␣
↪days']

# Create the 'pduration' column based on conditions
df_train['pduration'] = np.select(conditions, choices, default='unknown')

# pmonths
conditions = [
    (df_train['pmonths'] == 999),
    (df_train['pmonths'] <= 0.2),
    (df_train['pmonths'] > 0.2)
]

choices = ['first visit', 'less than 2 months',  'greater than 2 months']

# Create the 'pduration' column based on conditions
df_train['pduration_m'] = np.select(conditions, choices, default='unknown')
```

[253]:
```python
df_train.dtypes
```

[253]:
```
custAge                  float64
profession                object
marital                   object
schooling                 object
```

```
default                object
housing                object
loan                   object
contact                object
month                  object
day_of_week            object
campaign              float64
pdays                 float64
previous              float64
poutcome               object
emp.var.rate          float64
cons.price.idx        float64
cons.conf.idx         float64
euribor3m             float64
nr.employed           float64
pmonths               float64
pastEmail             float64
responded              object
employment_status      object
pduration              object
pduration_m            object
dtype: object
```

5 One-hot encode for categorical columns and continues features

[254]:
```
# One hot encoding and normalization of appropriate variables

X = df_train.drop(['responded', 'pdays','pmonths','employment_status'], axis=1)
y = df_train['responded']

# One-hot encode categorical columns
X_encoded = pd.get_dummies(X, columns=['loan', 'marital', 'schooling',␣
 ↪'default', 'housing', 'day_of_week',
                                       'poutcome',␣
 ↪'pduration','pduration_m','profession','month','contact' ],drop_first=True)

# Identify continuous columns for normalization
continuous_columns = ['custAge','campaign','previous', 'emp.var.rate','cons.
 ↪price.idx','cons.conf.idx',
                      'euribor3m','nr.employed','pastEmail'
                       ]
```

[255]:
```
# Extracting the continuous columns from X_encoded
X_continuous = X_encoded[continuous_columns]

# StandardScaler
```

```
scaler = StandardScaler()

# Fit and transform the scaler on the continuous data
X_continuous_normalized = scaler.fit_transform(X_continuous)

# Replace the original continuous columns in X_encoded with the normalized ones
X_encoded[continuous_columns] = X_continuous_normalized
```

[256]:
```
X_encoded.columns
```

[256]:
```
Index(['custAge', 'campaign', 'previous', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'pastEmail',
       'loan_unknown', 'loan_yes', 'marital_Unknown', 'marital_married',
       'schooling_Uneducated&BasicEducation', 'schooling_Unknown',
       'default_Yes&Unknown', 'housing_unknown', 'housing_yes',
       'day_of_week_WeekEnding', 'poutcome_nonexistent', 'poutcome_success',
       'pduration_first visit', 'pduration_greater than 10 days',
       'pduration_less than 5 days', 'pduration_m_greater than 2 months',
       'pduration_m_less than 2 months', 'profession_Unemployed&Unknown',
       'profession_Working', 'month_others', 'contact_telephone'],
      dtype='object')
```

6 Model Selection, Model Training, Model Validation

Choosing the most appropriate model that can be used for this project. Split the data into train & test sets and use the train set to estimate the best model parameters. Evaluate the performance of the model on data that was not used during the training process. The goal is to estimate the model'sability to generalize to new, unseen data and to identify any issues with the model, such as overfitting.

Data is highly imbalanced need to mixed sampling it by using the SMOTE-NN method.

[279]:
```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
from imblearn.combine import SMOTEENN
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
from sklearn.model_selection import GridSearchCV
```

[280]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.
 ↪2, random_state=78)
```

Using the GridSearchCV for hyperparameter tuning for the accuracy

[334]:
```
# Define parameter grid for Random Forest
param_grid = {
    'n_estimators': [10, 20, 30],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
```

[335]:
```
rf = RandomForestClassifier()
```

[336]:
```
# Perform GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1)
grid_search.fit(X_train, y_train)
```

[336]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'max_depth': [None, 10, 20],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [10, 20, 30]})
```

[337]:
```
# Print best parameters and best score
print("Best parameters found: ", grid_search.best_params_)
print("Best score: ", grid_search.best_score_)
```

```
Best parameters found:  {'max_depth': 10, 'min_samples_leaf': 4,
'min_samples_split': 2, 'n_estimators': 30}
Best score:  0.9
```

[338]:
```
# Evaluate the model performance (accuracy)
from sklearn.metrics import accuracy_score

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

```
Accuracy: 0.8603351955307262
```

Using ensemble classifier with random forest, rbf for SVC and hard probability voting for display classification report

[339]:
```
y_train = np.array(y_train)
y_test = np.array(y_test)
```

[340]:
```
# Apply SMOTEENN to the training data
smoteenn = SMOTEENN(random_state=78)
X_train_resampled, y_train_resampled = smoteenn.fit_resample(X_train, y_train)
```

[341]:
```
# Create a Random Forest classifier
rf = RandomForestClassifier(random_state=78)
```

[342]:
```
# Create a Linear Support Vector Machine (SVM) classifier
svm_classifier = SVC(kernel='rbf', probability=True, random_state=78)
```

[343]:
```
# Ensemble the classifiers using a Voting Classifier
 # Hard for probability voting
ensemble_classifier = VotingClassifier(estimators=[
    ('rf', rf),
    ('svm', svm_classifier)
], voting='hard')
```

[344]:
```
# Fit the ensemble model on the resampled training data
ensemble_classifier.fit(X_train_resampled, y_train_resampled)
```

[344]:
```
VotingClassifier(estimators=[('rf', RandomForestClassifier(random_state=78)),
                             ('svm', SVC(probability=True, random_state=78))])
```

[345]:
```
# Make predictions on the test set
y_pred = ensemble_classifier.predict(X_test)
```

[346]:
```
# Evaluate the ensemble model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
```

```
Accuracy: 0.86
```

[347]:
```
# Display classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

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

          no       0.94      0.90      0.92      1426
         yes       0.42      0.53      0.47       185

    accuracy                           0.86      1611
   macro avg       0.68      0.72      0.69      1611
weighted avg       0.88      0.86      0.87      1611
```

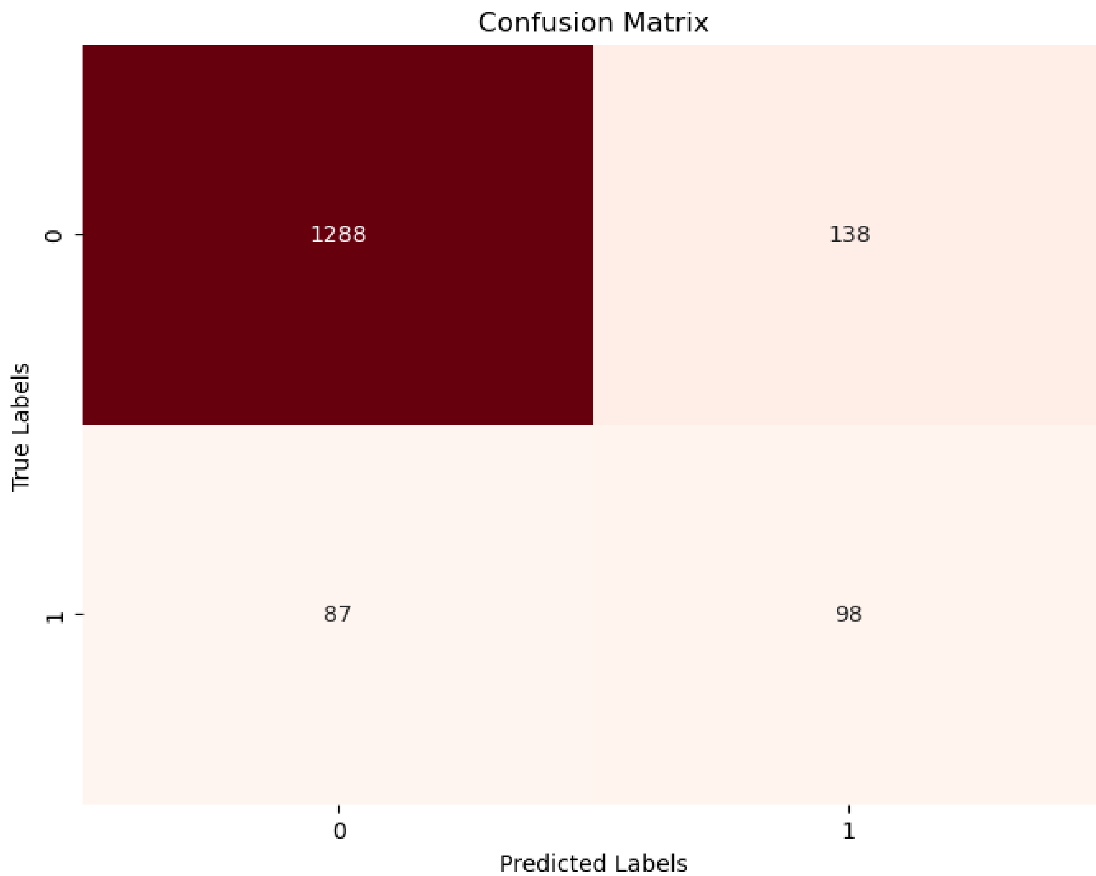
[348]:
```
# Get the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Extract values from the confusion matrix
tn, fp, fn, tp = conf_matrix.ravel()
```

[349]:
```
# Display the confusion matrix
print("Confusion Matrix:")
```

```
print(conf_matrix)
```

```
Confusion Matrix:
[[1288  138]
 [  87   98]]
```

[350]:
```
# Create a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, cmap='Reds', fmt='g', cbar=False)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()
```



[351]:
```
# Display number of true positives, true negatives, false positives, and false␣
↪negatives
print(f"True Positives: {tp}")
print(f"True Negatives: {tn}")
print(f"False Positives: {fp}")
```

```python
print(f"False Negatives: {fn}")
```

```
True Positives: 98
True Negatives: 1288
False Positives: 138
False Negatives: 87
```

Improved marketing campaign targeting, leading to higher conversion rates. Reduced marketing costs by focusing efforts on more likely customers. Data-driven decision making for customer acquisition strategies. achieving this balance, the model optimizes the allocation of marketing resources, ensuring that the company maximizes its return on investment while efficiently reaching out to potential customers. This human-centered approach considers both the company's financial objectives and its goal of engaging with as many potential customers as possible, ultimately contributing to the company's growth and success.

In summary, comprehensive and well-maintained documentation is a cornerstone of operational excellence, supporting compliance, risk management, efficiency, knowledge sharing, and continuous improvement within a company. This ultimately supports operational excellence and long-term success.

[ ]:
```python

```