Documentation_Capstone_Propensify

February 28, 2024

1 Introduction

This document explains the series of steps in training the model. The pipeline for the deployment is present in the source code file which utilizes the steps involved in this document. The document also explains the uses of the model built in this exercise to the company.

Import the required libraries

[48]:
```
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
```

Load the dataset and observe the shape of data frame

[49]:
```
#load dataset
train_propensify = pd.read_excel(r"C:\Users\HARI␣
↪CHARAN\Downloads\UPGRAD_ALL\Upgrad\train.xlsx")
train_propensify.shape
```

[49]:
```
(8240, 24)
```

Check if there are any unnecessary columns

[50]:
```
train_propensify.columns
```

[50]:
```
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')
```

The data is highly imbalanced, with around 88% of the customers are not responded while only 11% of them responded to the marketing campaign. Hence it is essential to address this imbalance of the target variable before building the model.

[51]:
```
# Calculate value counts
value_counts = train_propensify['responded'].value_counts()

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

# Display the result
print(percentages)
```

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

Keeping only those columns that are required for the analysis

[52]:
```
#Keeping only those columns that are required
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']

train_propensify = train_propensify[columns_to_keep]
train_propensify.shape
```

[52]: (8240, 22)

---

2 Treating Missing Values

Check if there are any missing values in the data

[53]:
```
missing_values = train_propensify.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
```

Age, day of the week and schooling have missing values that almost account for 25% of the entire dataset. Age can have significant impact on the response to the marketing campaign for insurance products as individuals belonging to different categories of age may have different needs (Young to old). Day of the week can influence the decision too as individuals tend to be free in weekends and busy in week days. Further, schooling represents the indiviudual's education level which can have significant impact on decision to get insured. Thus, dropping these variables is not the ideal thing to do. Hence, the missing values are to be imputed and this section discusses the imputation techniques used.

1. Imputing missing schooling values: Education can have impact on the employment type of the individual. Hence, this study checks education levels and the associated profession of the individual to cross-check the education-employment match argument. The following table acts as an evidence for the above argument. Considering the above argument the missing education values are imputed based on the indivisual's profession

[54]:
```
cross_tab = pd.crosstab(train_propensify['schooling'],␣
 ↪train_propensify['profession'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
 ↪yellow' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[54]:
```
<pandas.io.formats.style.Styler at 0x1e214be8d50>
```

[55]:
```
#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',
}

train_propensify['schooling'] = train_propensify['schooling'].
 ↪replace(schooling_category)
```

[56]:
```
cross_tab = pd.crosstab(train_propensify['schooling'],␣
 ↪train_propensify['profession'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
 ↪yellow' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[56]: <pandas.io.formats.style.Styler at 0x1e21500cd90>

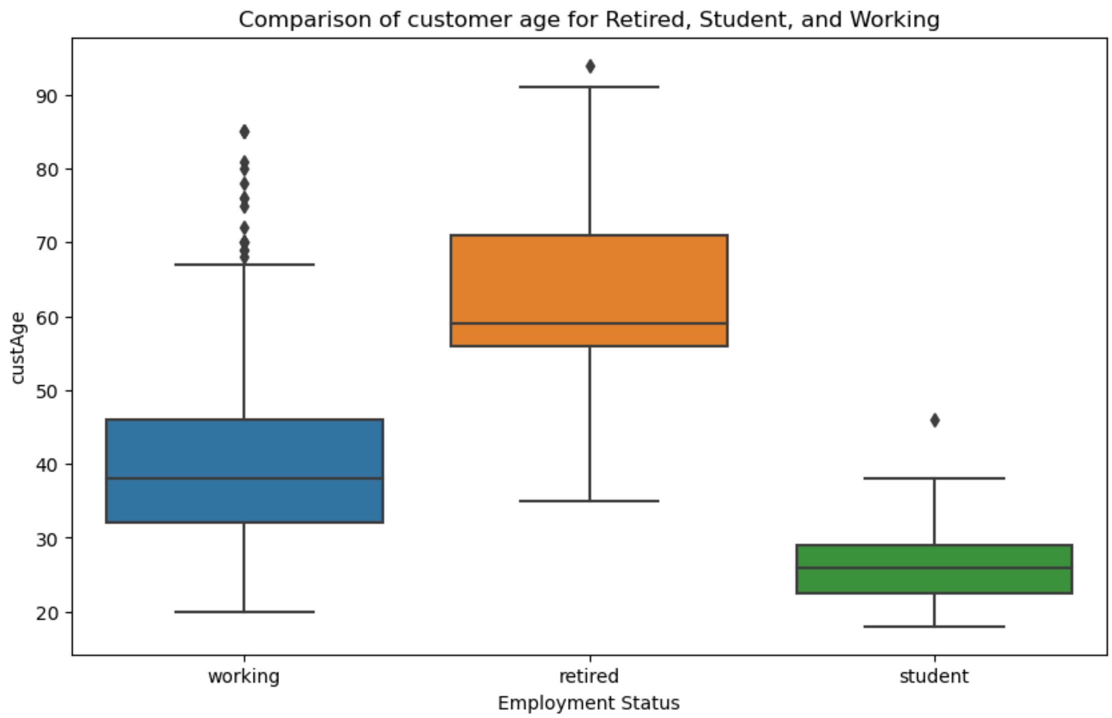
[57]:
```
# Imputation of missing values in education based on profession

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'
}
```

[58]:
```
train_propensify['schooling'] = train_propensify['schooling'].
 ↪combine_first(train_propensify['profession'].map(imputation_mapping))
```

2. Treating missing age values The age of an individual can have an impact on the working status of the individual. A student's age can be much lower as compared to a retired individual while a working individual's age can be expected to lie in between these two categories. Hence the age values are imputed based on the employment status (created from profession column) of the individual. The plot of comparision for customer age across retired, student and working individuals supports the above argument.

[59]:
```
#Profession & treating missing values of age
train_propensify['employment_status'] = train_propensify['profession'].
 ↪apply(lambda x: 'retired' if x == 'retired' else ('student' if x ==␣
 ↪'student' else 'working'))
```

[60]:
```python
#Age comparision w.r.t profession
plt.figure(figsize=(10, 6))
sns.boxplot(x='employment_status', y='custAge', data=train_propensify)
plt.title('Comparison of customer age for Retired, Student, and Working')
plt.xlabel('Employment Status')
plt.ylabel('custAge')
plt.show()
```



Imputing mean values for missing age values of retired and student categories and imputing with median for working category (As there are outliers in this category)

[61]:
```python
# Imputing age values
# Calculate mean and median values for each profession
mean_age_retired = train_propensify.loc[train_propensify['employment_status']␣
↪== 'retired', 'custAge'].mean()
mean_age_student = train_propensify.loc[train_propensify['employment_status']␣
↪== 'student', 'custAge'].mean()
median_age_working = train_propensify.loc[train_propensify['employment_status']␣
↪== 'working', 'custAge'].median()

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

```python
train_propensify['custAge'] = np.where((train_propensify['employment_status']␣
↪== 'student') & train_propensify['custAge'].isna(), mean_age_student,␣
↪train_propensify['custAge'])
train_propensify['custAge'] = np.where((train_propensify['employment_status']␣
↪== 'working') & train_propensify['custAge'].isna(), median_age_working,␣
↪train_propensify['custAge'])
```

3. Imputing day of week variable: The distribution of day of week plot can show that marketing campaign is equally distributed among all the days. Hence the missing values of day of the week are imputed based on random function.

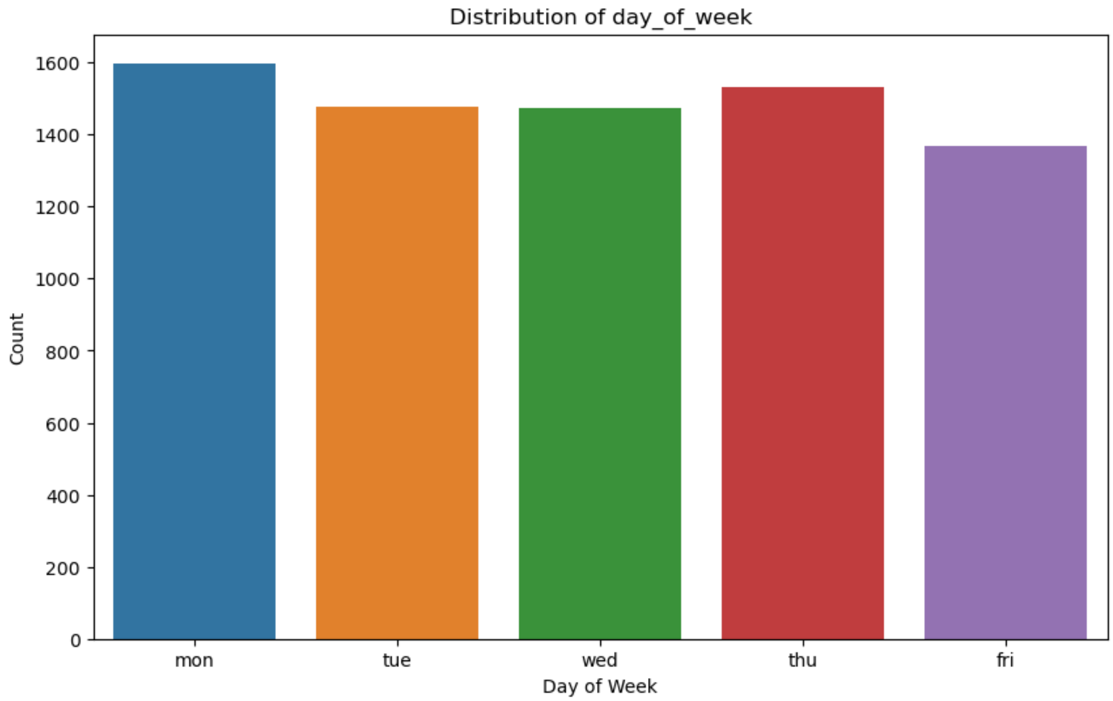
[62]:
```python
day_values = train_propensify['day_of_week'].value_counts()
print(day_values)
```

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

[63]:
```python
cross_tab = pd.crosstab(train_propensify['day_of_week'],␣
↪train_propensify['responded'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪yellow' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[63]: <pandas.io.formats.style.Styler at 0x1e214c2d250>

[64]:
```python
#day of week
plt.figure(figsize=(10, 6))
sns.countplot(x='day_of_week', data=train_propensify, order=['mon', 'tue',␣
↪'wed', 'thu', 'fri'])
plt.title('Distribution of day_of_week')
plt.xlabel('Day of Week')
plt.ylabel('Count')
plt.show()
```



[65]:
```
def impute_random_day(day):
    if pd.isna(day):
        return np.random.choice(['mon', 'tue', 'wed', 'thu', 'fri'])
    else:
        return day

# Apply the imputation function to the 'day_of_week' column
train_propensify['day_of_week'] = train_propensify['day_of_week'].
 ↪apply(impute_random_day)
```

[66]:
```
missing_values = train_propensify.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
```

Dropping the remaining missing values (which are minimal as compared to the data frame size)

[67]:
```python
#Now, dropping remaining missing values
train_propensify = train_propensify.dropna()
```

[68]:
```python
#cross check
missing_values = train_propensify.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
```

[69]:
```
train_propensify.shape
```

[69]:
```
(8051, 23)
```

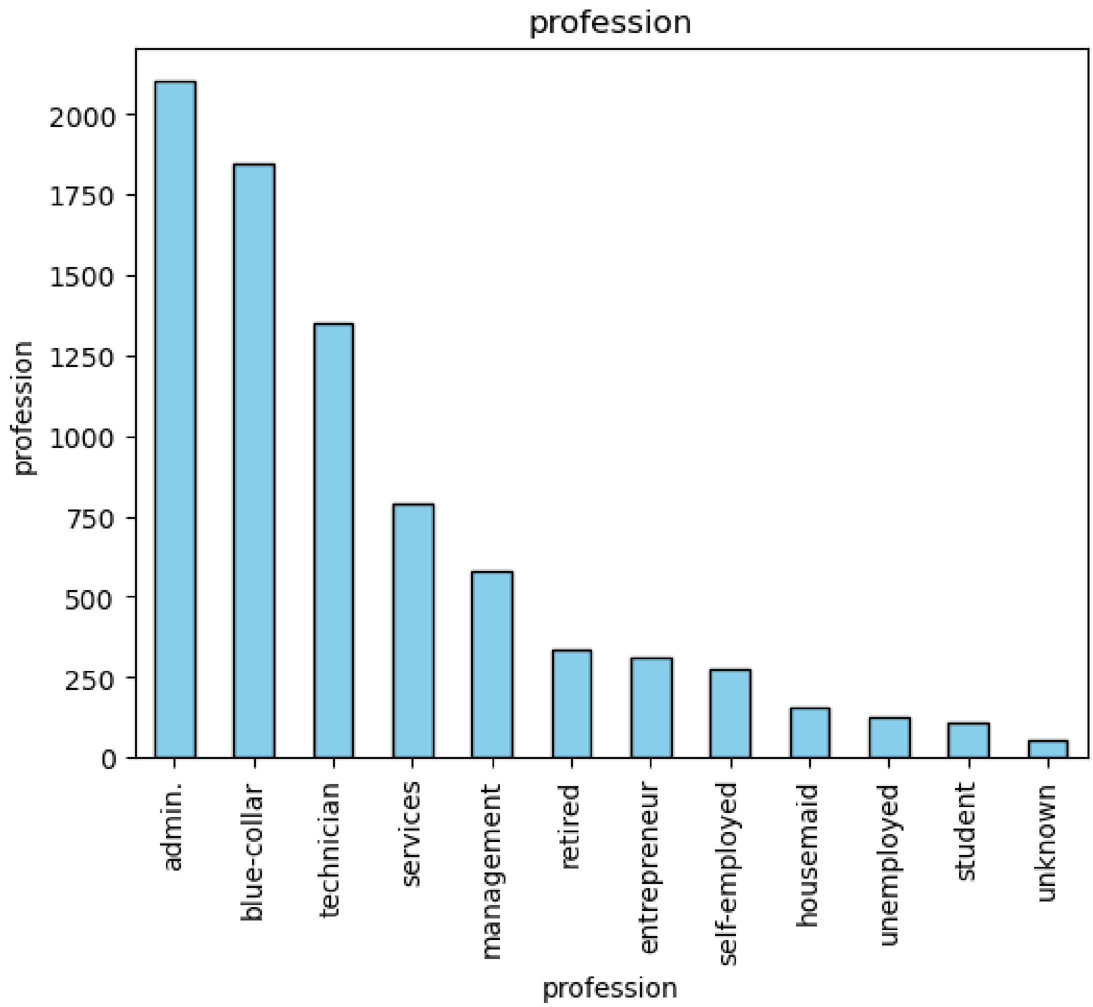
---

3 Feature Engineering

Feature engineering of categorical variables:

1. Profession: The profession can be label encoded whether an individual is dependent or working. Dependents insurance is in general taken care by the head of the family or by the state. Hence the label encoding is done accordingly.

[70]:
```
#1. Profession
train_propensify['profession'].value_counts().plot(kind='bar', color='skyblue', edgecolor='black')
plt.title('profession')
plt.xlabel('profession')
plt.ylabel('profession')
plt.show()
```



[71]:
```
cross_tab = pd.crosstab(train_propensify['profession'],␣
↪train_propensify['responded'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪yellow' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[71]: <pandas.io.formats.style.Styler at 0x1e214cd7d10>

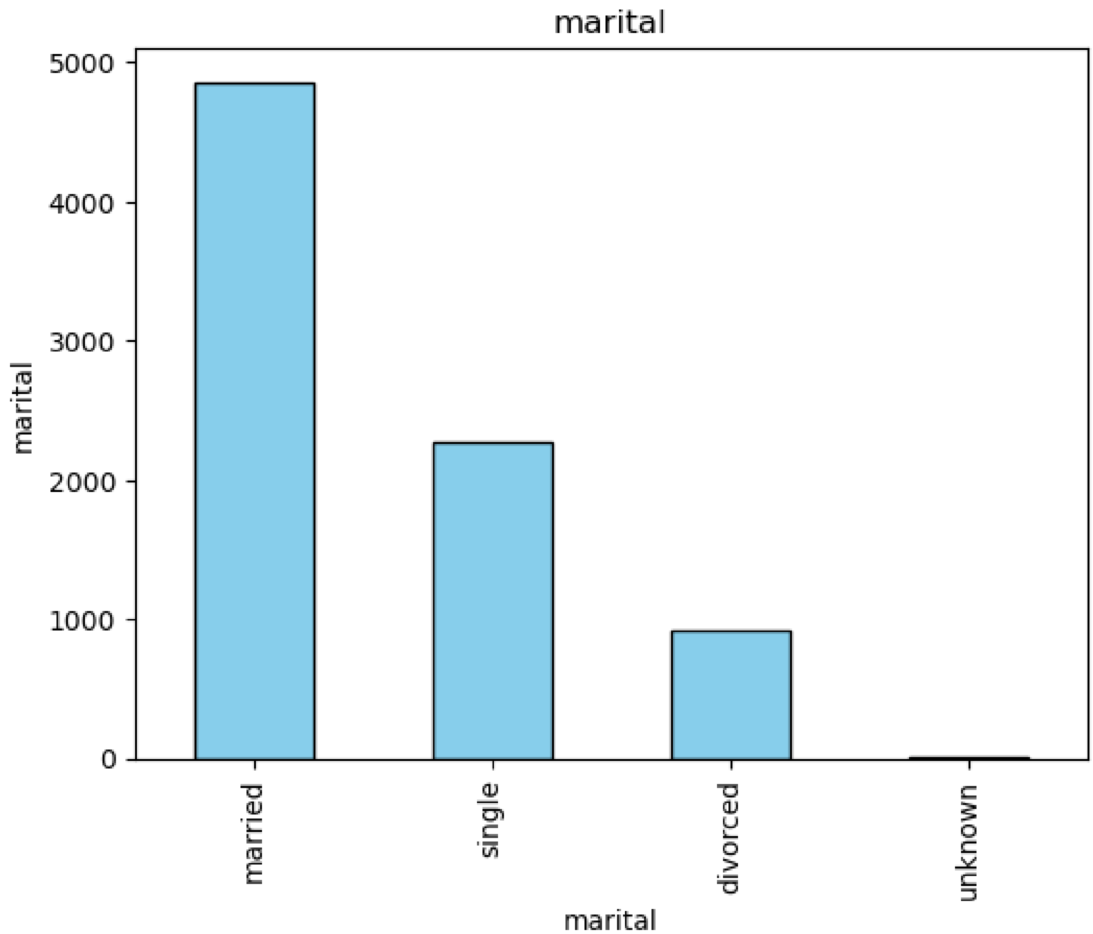
[72]:
```
#Label encoding
train_propensify['profession'] = train_propensify['profession'].map({'student':␣
↪'Dependents', 'retired': 'Dependents', 'unemployed': 'Unemployed&Unknown',␣
↪'unknown': 'Unemployed&Unknown',
                                                          'admin.':␣
↪'Working','blue-collar': 'Working','entrepreneur': 'Working','housemaid':␣
↪'Working',
```

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

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

[72]:
```
profession
Working               7427
Dependents             446
Unemployed&Unknown     178
Name: count, dtype: int64
```

2. Marital: Considering single and divorcee as a single caregory and keeping married and unknown as different categories

[73]:
```
#2. Marital
train_propensify['marital'].value_counts().plot(kind='bar', color='skyblue',␣
↪edgecolor='black')
plt.title('marital')
plt.xlabel('marital')
plt.ylabel('marital')
plt.show()
```



[74]:
```
cross_tab = pd.crosstab(train_propensify['marital'],␣
↪train_propensify['responded'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪yellow' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

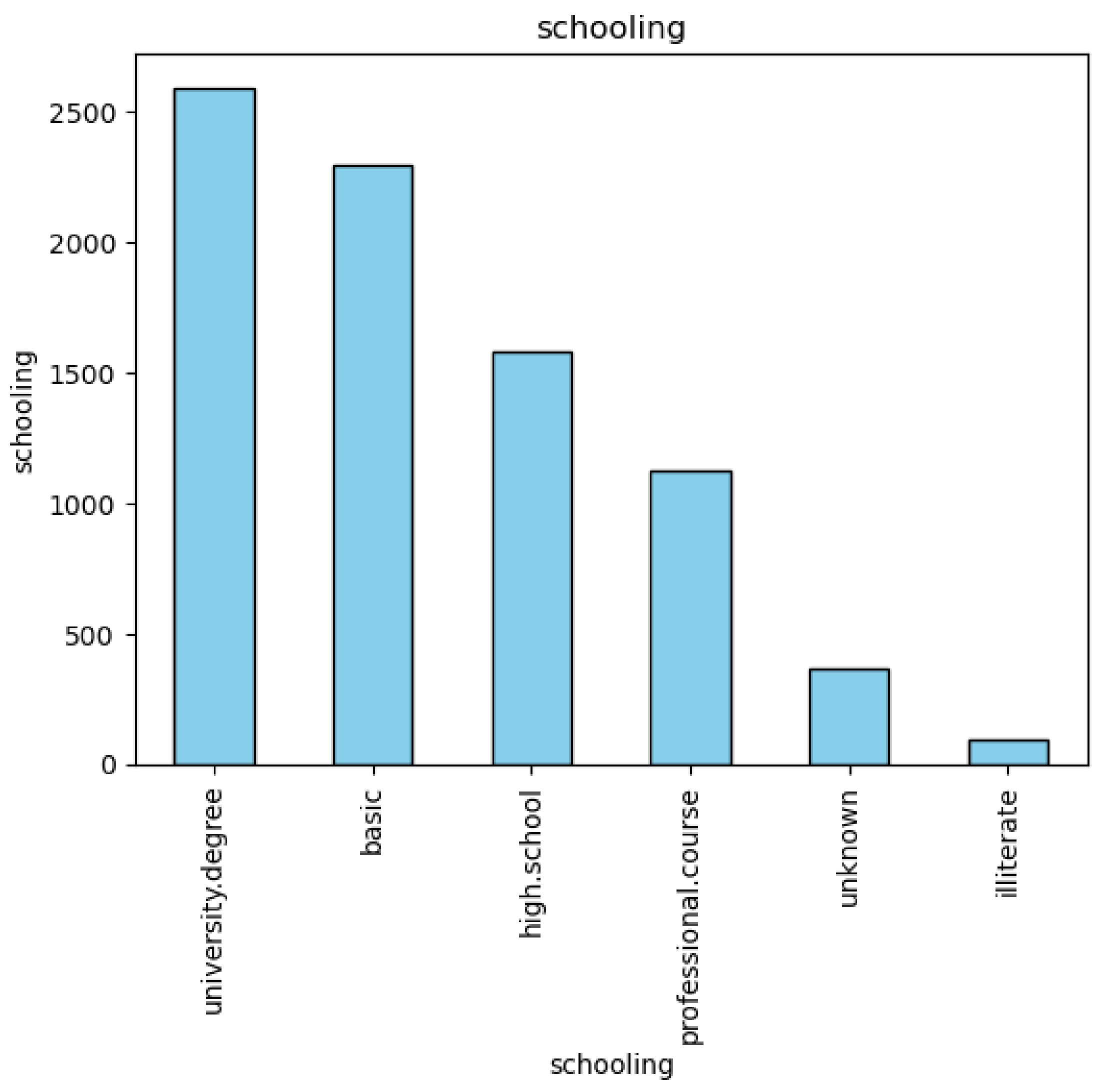
[74]: <pandas.io.formats.style.Styler at 0x1e214deb650>

[75]:
```
#Label encoding
train_propensify['marital'] = train_propensify['marital'].map({'single':␣
↪'Single&Divorced', 'divorced': 'Single&Divorced',
                                                                    'married':␣
↪'married', 'unknown': 'Unknown', })

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

[75]:
```
marital
married             4858
Single&Divorced     3184
Unknown                9
Name: count, dtype: int64
```

3. Schooling: An indiviudual's education can explain whether an indiidual is illiterate, or basic-educated or educated. Label encoding accordingly.

[76]:
```
#3. Schooling
train_propensify['schooling'].value_counts().plot(kind='bar', color='skyblue',␣
 ↪edgecolor='black')
plt.title('schooling')
plt.xlabel('schooling')
plt.ylabel('schooling')
plt.show()
```



[77]:
```
cross_tab = pd.crosstab(train_propensify['schooling'],
 ↪train_propensify['responded'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:
 ↪yellow' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

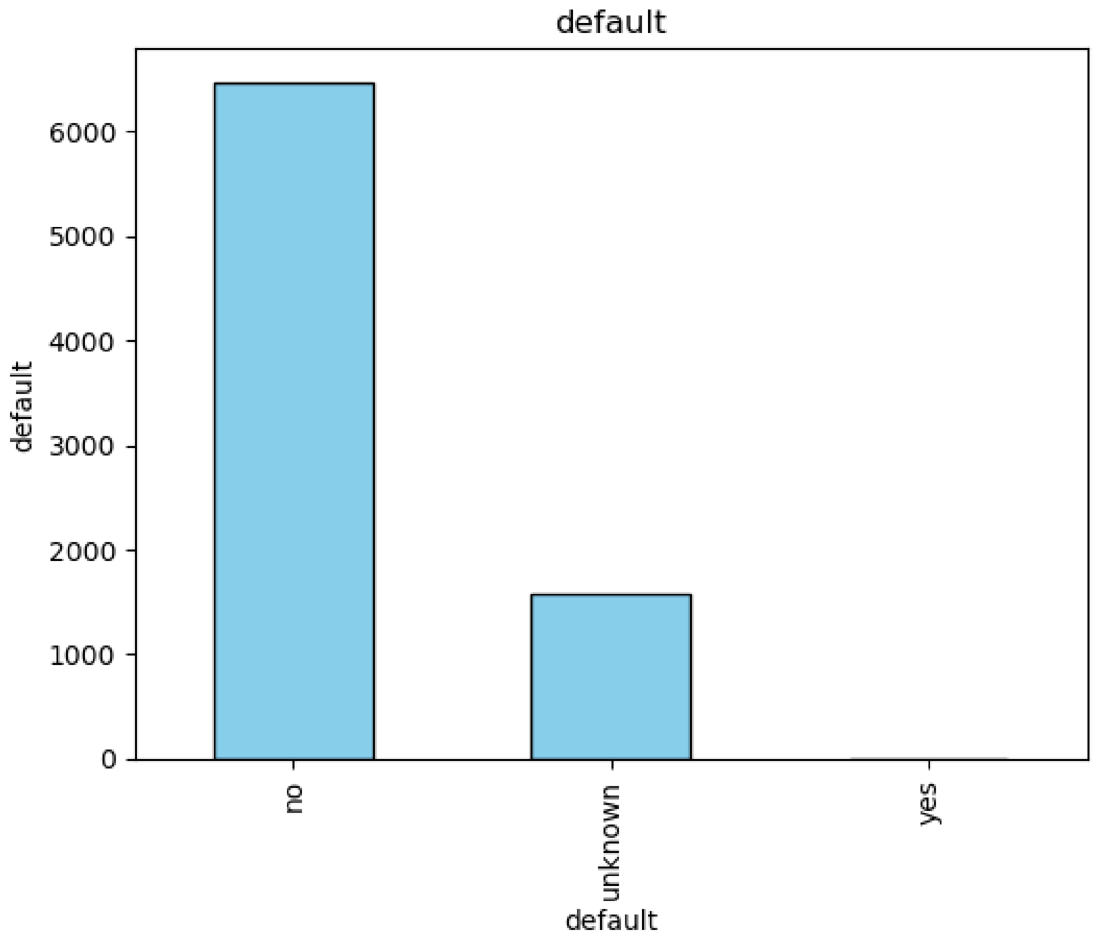
[77]: <pandas.io.formats.style.Styler at 0x1e214bb4d50>

[78]:
```
#Label encoding
train_propensify['schooling'] = train_propensify['schooling'].map({'basic':
 ↪'Uneducated&BasicEducation', 'high.school': 'Uneducated&BasicEducation',

 ↪'illiterate': 'Uneducated&BasicEducation',
                                                                      'unknown':
 ↪'Unknown',
                                                                     'professional.
 ↪course': 'Educated',
                                                                     'university.
 ↪degree': 'Educated',
                                                                     })

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

[78]:
```
schooling
Uneducated&BasicEducation    3968
Educated                     3715
Unknown                       368
Name: count, dtype: int64
```

4. Default: Yes and Unknown are grouped together and No is kept as a seperate category

[79]:
```
#Default
train_propensify['default'].value_counts().plot(kind='bar', color='skyblue',
 ↪edgecolor='black')
plt.title('default')
plt.xlabel('default')
plt.ylabel('default')
plt.show()
```



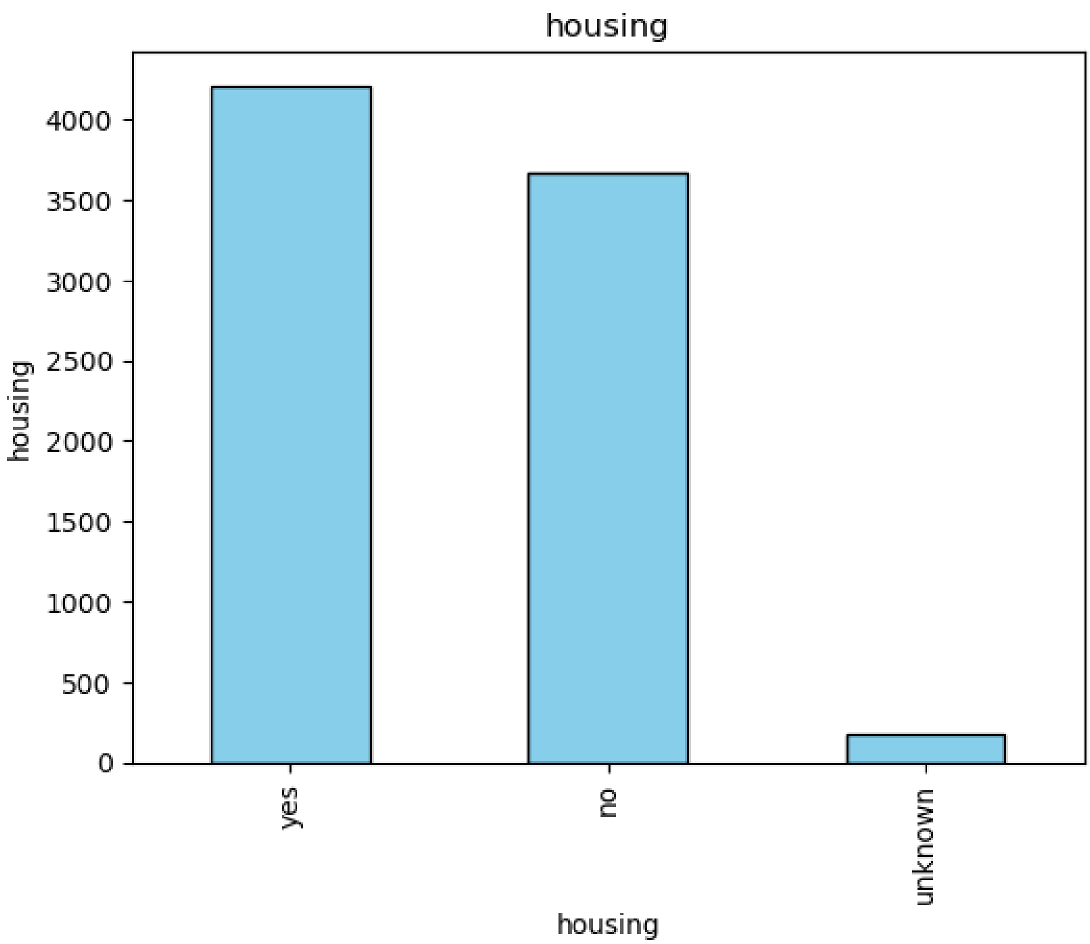
[80]:
```
#Label encoding
train_propensify['default'] = train_propensify['default'].map({'no': 'No',␣
↪'unknown': 'Yes&Unknown','yes':'Yes&Unknown' })

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

[80]:
```
default
No             6470
Yes&Unknown    1581
Name: count, dtype: int64
```

5. Housing is kept unchanged

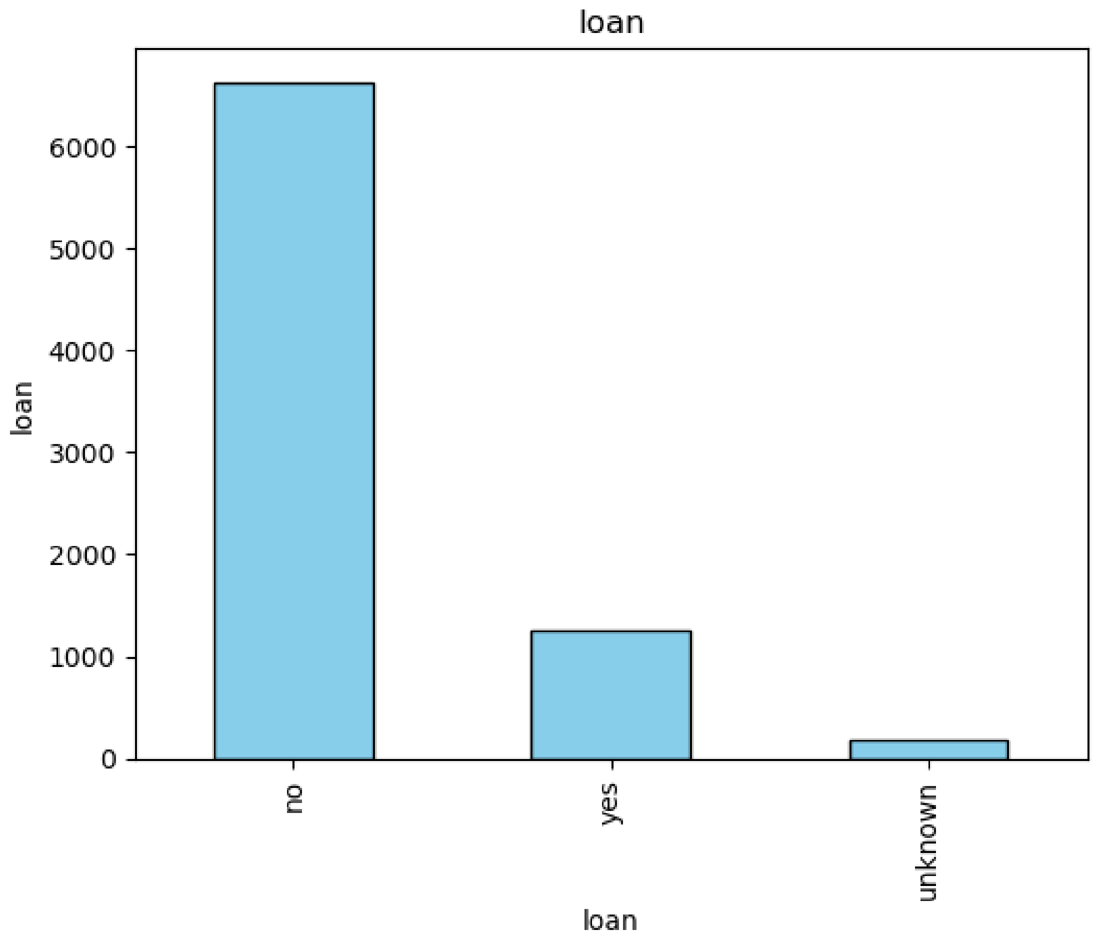
[81]:
```
#housing
train_propensify['housing'].value_counts().plot(kind='bar', color='skyblue',␣
↪edgecolor='black')
plt.title('housing')
```

```
plt.xlabel('housing')
plt.ylabel('housing')
plt.show()
```



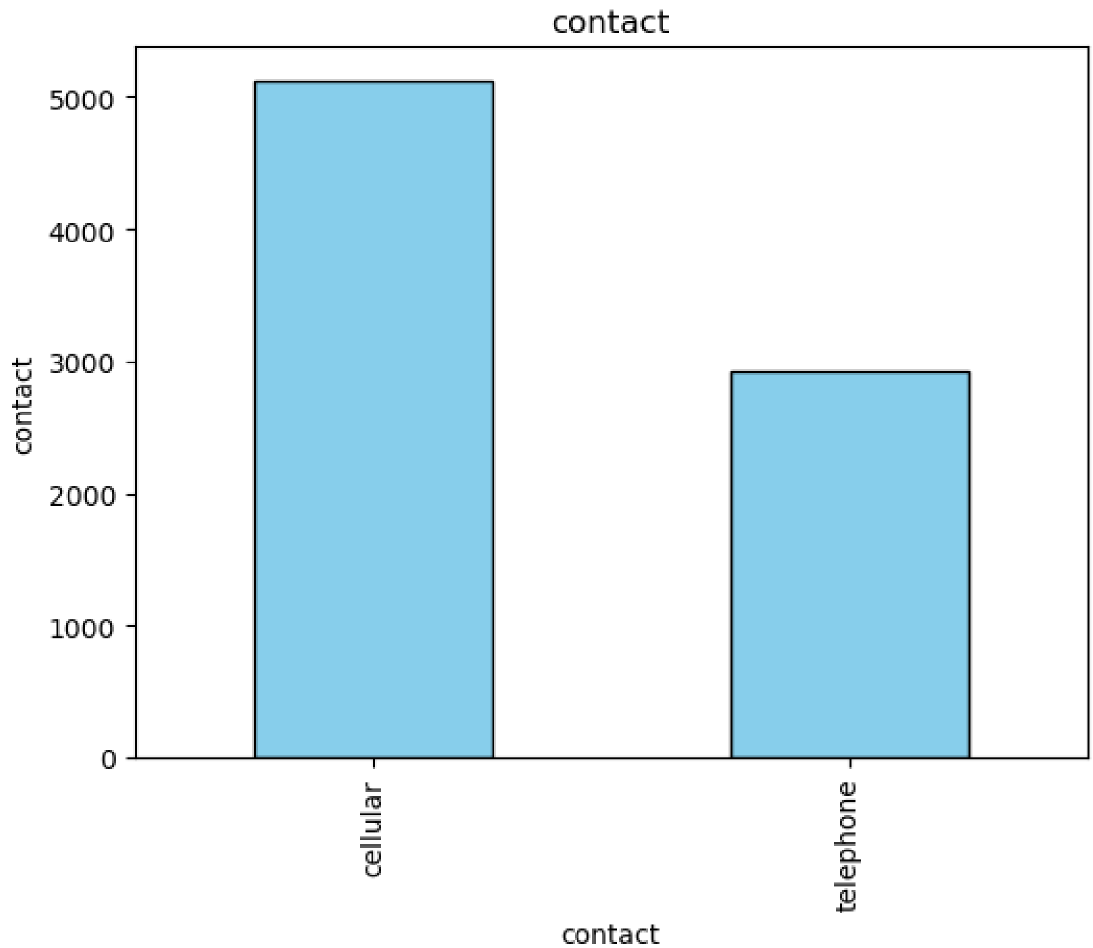
6. Loan is kept unchanged

[82]:
```
#loan
train_propensify['loan'].value_counts().plot(kind='bar', color='skyblue',␣
↪edgecolor='black')
plt.title('loan')
plt.xlabel('loan')
plt.ylabel('loan')
plt.show()
```



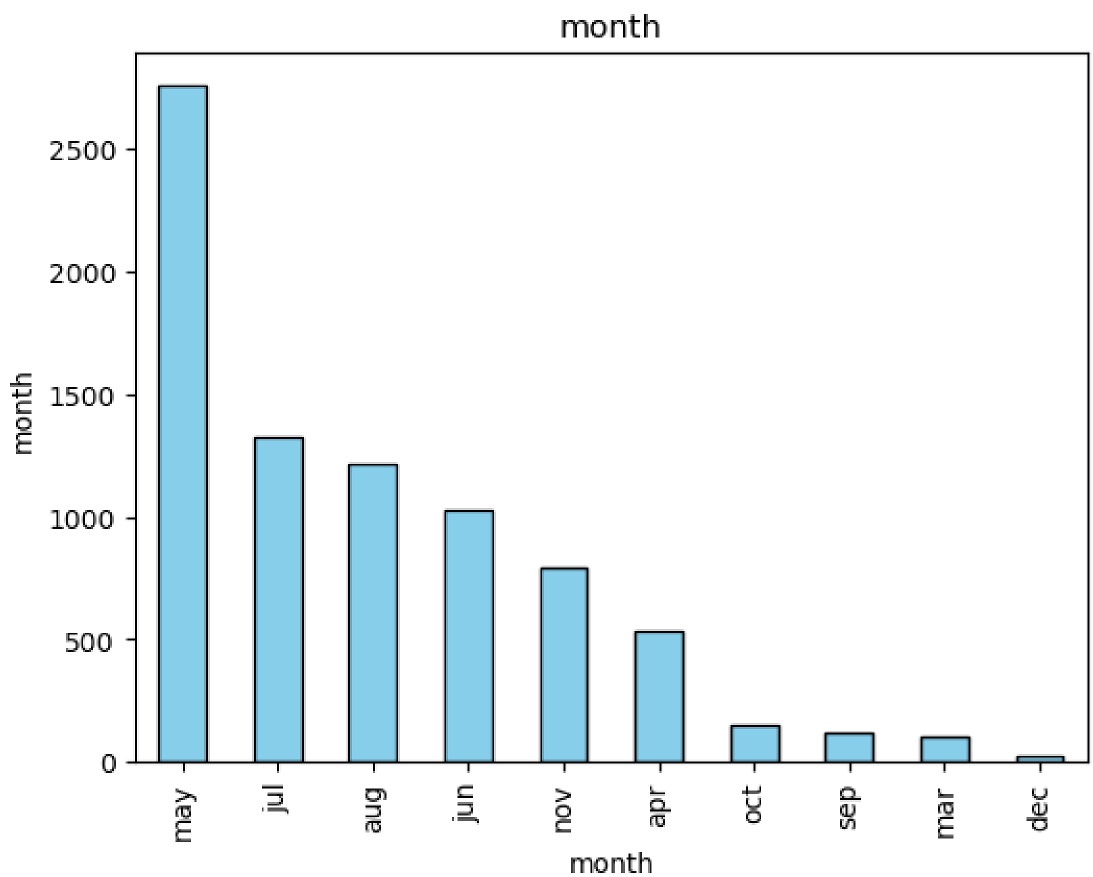
7. Contact is kept unchanged

[83]:
```
#contact
train_propensify['contact'].value_counts().plot(kind='bar', color='skyblue',␣
 ↪edgecolor='black')
plt.title('contact')
plt.xlabel('contact')
plt.ylabel('contact')
plt.show()
```



8. Month: Sales team tend to have sales pressure in quarter end hence there is a possibility to focus on marketing campaign on these months. Hence label encoding accordingly

[84]:
```
#month
train_propensify['month'].value_counts().plot(kind='bar', color='skyblue',␣
 ↪edgecolor='black')
plt.title('month')
plt.xlabel('month')
plt.ylabel('month')
plt.show()
```



[85]:
```
cross_tab = pd.crosstab(train_propensify['month'],␣
↪train_propensify['responded'],normalize = 'index')*100
highlighted_cross_tab = cross_tab.style.apply(lambda x: ['background-color:␣
↪yellow' if val == x.max() else '' for val in x], axis=1)
highlighted_cross_tab
```

[85]: <pandas.io.formats.style.Styler at 0x1e214a0f290>

[86]:
```
# Create a copy of the DataFrame to avoid modifying the original data
train_propensify_copy_c = train_propensify.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
train_propensify_copy_c['month_mapped'] = train_propensify_copy_c['month'].
↪replace(quarter_mapping)
```

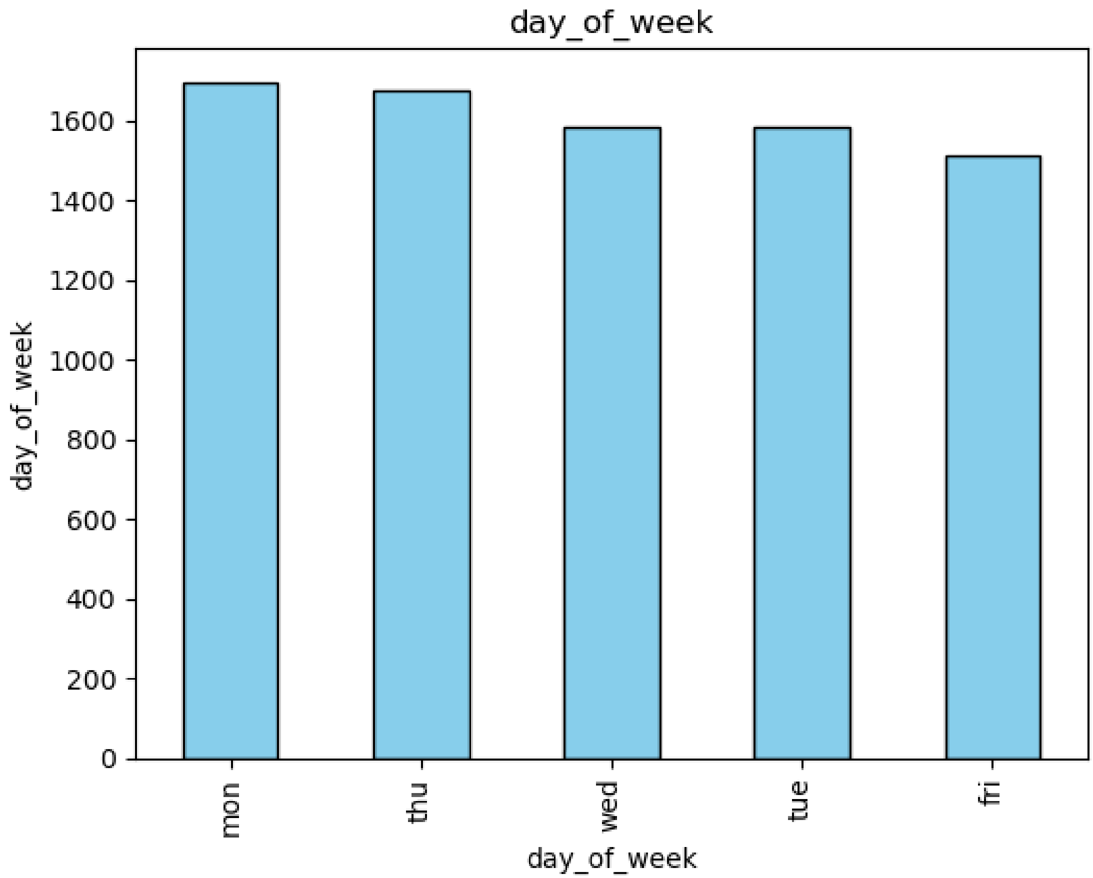
```
# Replace other months with 'others' in the copied DataFrame
train_propensify_copy_c['month_mapped'].
↪replace(to_replace=train_propensify_copy_c['month_mapped'][~train_propensify_copy_c['month_m
↪isin(['QuarterEnd'])].unique(), value='others', inplace=True)

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

train_propensify['month'] = train_propensify_copy_c['month_mapped']
train_propensify['month'].value_counts()
```

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

[86]:
```
month
others        6776
QuarterEnd    1275
Name: count, dtype: int64
```

9. Day of week: Considering the customer's leisure time availabilty to label encode day of week.

[87]:
```
#Day_of_week
train_propensify['day_of_week'].value_counts().plot(kind='bar',␣
↪color='skyblue', edgecolor='black')
plt.title('day_of_week')
plt.xlabel('day_of_week')
plt.ylabel('day_of_week')
plt.show()
```



[88]:
```
#Label encoding
train_propensify['day_of_week'] = train_propensify['day_of_week'].map({'mon':␣
 ↪'WeekBeginning', 'tue': 'WeekBeginning','wed':'WeekBeginning',
                                                                        'thu':
 ↪'WeekEnding','fri':'WeekEnding'})

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

[88]:
```
day_of_week
WeekBeginning    4862
WeekEnding       3189
Name: count, dtype: int64
```

10. Feature engineering pdays and pmonths by addressing 999

[89]:
```
# Feature engineering of other variables

#pdays
```

```
conditions = [
    (train_propensify['pdays'] == 999),
    (train_propensify['pdays'] < 5),
    ((train_propensify['pdays'] >= 5) & (train_propensify['pdays'] <= 10)),
    (train_propensify['pdays'] > 10)
]

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

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

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

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

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

[90]:
```
train_propensify.dtypes
```

[90]:
```
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
```

---

4 One hot encoding categoric features and normalizing continuous features

[91]:
```
# One hot encoding and normalization for appropriate variables
# Drop target and unnecessary columns
X = train_propensify.drop(['responded', 'pdays','pmonths','employment_status'],␣
↪axis=1)
y = train_propensify['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'
                       ]
```

[92]:
```
# Extract the continuous columns from X_encoded
X_continuous = X_encoded[continuous_columns]

# Instantiate 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
```

[93]:
```
X_encoded.columns
```

```
[93]: 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')
```

---

5 Choice of sampling:

Since the data is imbalanced there is a need to resample. The available options are undersampling, oversampling and mixed sampling. Since the data is highly imbalanced, oversampling could lead to create too much of synthetic data for the minority class and undersampling could lead to the loss of information. Hence mixed sampling is done using the SMOTE-NN method. It utilizes k-nearest neighbors to generate synthetic instances.

---

6 Choice of metrics and model:

Since the data is highly imbalanced machine learning algorithms tend to predict the majority class (Here "No" i.e., not responded is the majority class) and thus, models tend to have high overall accurancy.

However, since it is a propensity model, choosing not to market to an individual who could be potential customer will be costly to the company. Hence it is essential to improve the recall of minority class (Here "Yes" i.e., responded is minority class) is essential too.

If the model just focuses on accuracy (A RFC can achieve 89% accuracy even with out addressing the imbalnce in data, however, the recall of minority data will be nearly 20%), the company tend to not choose to do marketing to the potential customers, which could be a loss to the company.

On the other hand accuracy is important too, else marketing costs will drastically increase as the marketing will be done to those individuals who do not buy the product.

Thus, there is a need for balance. The metrics given in the project is an accurancy of above 85%. However, this report focuses on maximizing the accuracy and recall of minority class. That is the model tries the maximize the recall while trying to keep the accuracy above 85%.

To improve accuracy and recall, ensembling technique is used and the algorithms considered are Random Forest Classifier and Support Vector Machines.

---

7 Model

[95]:
```python
#Ensembling without gridsearchcv, using rbf for SVC

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


# 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=42)


y_train = np.array(y_train)
y_test = np.array(y_test)

# Apply SMOTEENN to the training data
smoteenn = SMOTEENN(random_state=42)
X_train_resampled, y_train_resampled = smoteenn.fit_resample(X_train, y_train)

# Create a Random Forest classifier
rf_classifier = RandomForestClassifier(random_state=42)

# Create a Linear Support Vector Machine (SVM) classifier
svm_classifier = SVC(kernel='rbf', probability=True, random_state=42)

# Ensemble the classifiers using a VotingClassifier
ensemble_classifier = VotingClassifier(estimators=[
    ('rf', rf_classifier),
    ('svm', svm_classifier)
], voting='hard')  # 'hard' for probability voting

# Fit the ensemble model on the resampled training data
ensemble_classifier.fit(X_train_resampled, y_train_resampled)

# Make predictions on the test set
y_pred = ensemble_classifier.predict(X_test)

# Evaluate the ensemble model
accuracy = accuracy_score(y_test, y_pred)
```

```python
print(f"Accuracy: {accuracy:.2f}")

# Display classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# 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()

# Display the confusion matrix
print("Confusion Matrix:")
print(conf_matrix)

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

```
Accuracy: 0.86
Classification Report:
              precision    recall  f1-score   support

          no       0.95      0.89      0.92      1431
         yes       0.40      0.60      0.48       180

    accuracy                           0.86      1611
   macro avg       0.67      0.74      0.70      1611
weighted avg       0.89      0.86      0.87      1611

Confusion Matrix:
[[1271  160]
 [  72  108]]
True Positives: 108
True Negatives: 1271
False Positives: 160
False Negatives: 72
```

8 Utility of the Model

It can be observed from the above results that the recall of minority class is maximized while keeping the accuracy above 85% as required by the project. Hence the model keeps the fine balance between accuracy and recall of minority class so that the company does not loose out too much on marketing cost and at the same time it tries to make sure that the most of the potential customers are treated with the marketing campaign so that the company does not loose out the potential customers.

```
[ ]:
```