Project: Bank Marketing (Campaign) -- Group Project

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Problem description:

One bank wants to sell its term deposit product to customers before launching the product. To save their resource and time, they want to know what kind of customers they should focus on, and then they can put more advertisements to these customers, who have more chances of buying the product. Thus, our problem is to pick up this kind of customer, based on customers' past interaction with this bank or other financial institutions. We are going to use the customers' data to build some machine learning models and then, select customers who most likely buy the product.

Data cleansing and transformation done on the data.

1. Load Data

In [24]:
```
# Import packages
import pandas as pd
from pandas import factorize
import numpy as np
import os, glob
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import seaborn as sb
plt.rcParams.update(plt.rcParamsDefault)
import calendar
```

In [25]:
```
# Define functions
def prob(x):
    x = round(x.div(len(data))*100, 2)
    return x
```

In [26]:
```
# load data
data = pd.read_csv("/Users/jinwen/Downloads/data_glacier_6-9/bank/bank-full
data.head()
```

Out[26]:

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

2. Explore Data

In [27]:
```
data.dtypes
```

Out[27]:
```
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
```

In [28]:
```
col = data.columns.tolist()
col_num = data.select_dtypes(include=np.number).columns.tolist()
```

In [29]:
```python
print("Number of unique values stat:")
data.nunique()
```

```
Number of unique values stat:
```

Out[29]:
```
age             77
job             12
marital          3
education        4
default          2
balance       7168
housing          2
loan             2
contact          3
day             31
month           12
duration      1573
campaign        48
pdays          559
previous        41
poutcome         4
y                2
dtype: int64
```

In [30]:
```python
x = prob(data.isnull().sum())
print("Percentage of null values in data: ")
x
```

```
Percentage of null values in data:
```

Out[30]:
```
age          0.0
job          0.0
marital      0.0
education    0.0
default      0.0
balance      0.0
housing      0.0
loan         0.0
contact      0.0
day          0.0
month        0.0
duration     0.0
campaign     0.0
pdays        0.0
previous     0.0
poutcome     0.0
y            0.0
dtype: float64
```

In [31]:
```
data.describe().applymap('{:,.0f}'.format)
```

Out[31]:

	age	balance	day	duration	campaign	pdays	previous
count	45,211	45,211	45,211	45,211	45,211	45,211	45,211
mean	41	1,362	16	258	3	40	1
std	11	3,045	8	258	3	100	2
min	18	-8,019	1	0	1	-1	0
25%	33	72	8	103	1	-1	0
50%	39	448	16	180	2	-1	0
75%	48	1,428	21	319	3	-1	0
max	95	102,127	31	4,918	63	871	275

2. Outliers Removal

In order to detect and remove outliers, here we use two statistical methods: Interquartile range(IQR) and Standard Deviation.

In [32]:
```python
# Outliers removal using Interquartile range(IQR) statistical method
def outliers_iqr(df, feature):
    Q1= df[feature].quantile(0.25)
    Q3 = df[feature].quantile(0.75)
    IQR = Q3 - Q1
    upper_limit = Q3 + 1.5 * IQR
    lower_limit = Q1 - 1.5 * IQR
    return upper_limit, lower_limit

for col in col_num:
    upper, lower = outliers_iqr(data, col)
    print(str(col)+":")
    print("Upper limit: ", upper)
    print("Lower limit: ", lower)
    if upper > lower:
        data_iqr = data[(data[col] > lower) & (data[col] < upper)]

data_iqr.describe().applymap('{:,.0f}'.format)
```

```
age:
Upper limit:  70.5
Lower limit:  10.5
balance:
Upper limit:  3462.0
Lower limit:  -1962.0
day:
Upper limit:  40.5
Lower limit:  -11.5
duration:
Upper limit:  643.0
Lower limit:  -221.0
campaign:
Upper limit:  6.0
Lower limit:  -2.0
pdays:
Upper limit:  -1.0
Lower limit:  -1.0
previous:
Upper limit:  0.0
Lower limit:  0.0
```

Out[32]:

	age	balance	day	duration	campaign	pdays	previous
count	40,856	40,856	40,856	40,856	40,856	40,856	40,856
mean	41	1,369	15	265	2	42	1
std	11	3,053	8	258	1	102	2
min	18	-8,019	1	0	1	-1	0
25%	33	76	8	109	1	-1	0
50%	39	455	15	187	2	-1	0
75%	48	1,440	21	326	3	-1	0
max	95	102,127	31	4,918	5	871	275

In [33]:
```python
# Outliers removal using Standard Deviation statistical method
def outlier_std(df, variable):
    upper_limit = df[variable].mean() + 3 * df[variable].std()
    lower_limit = df[variable].mean() - 3 * df[variable].std()
    return upper_limit, lower_limit

for col in col_num:
    upper_limit, lower_limit = outlier_std(data, col)
    print(str(col)+":")
    print("Upper limit: ", upper_limit)
    print("Lower Limit: ",lower_limit)
    data_std = data[(data[col] > lower_limit) & (data[col] < upper_limit)]

data_std.describe().applymap('{:,.0f}'.format)
```

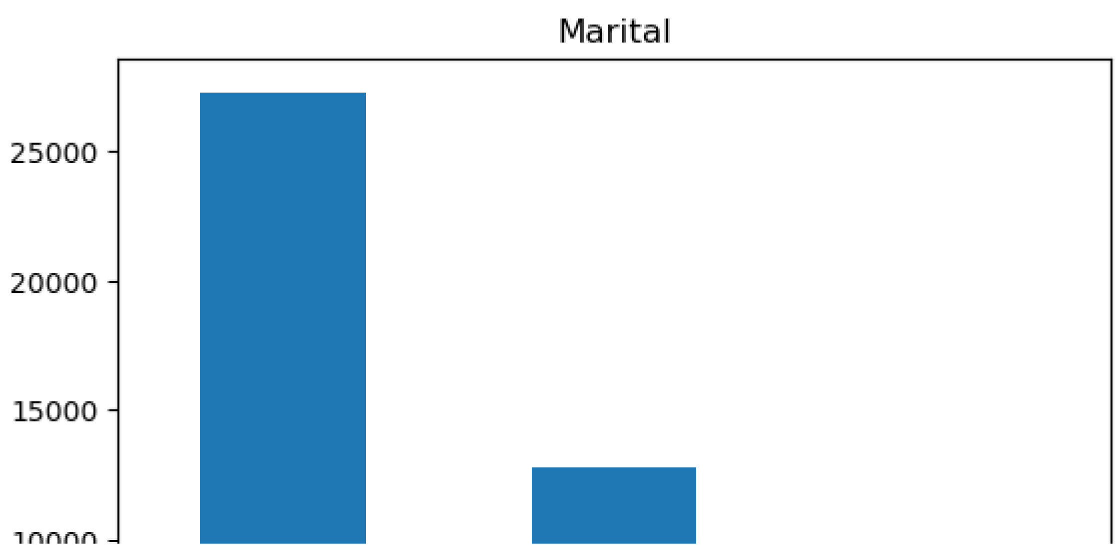
```
age:
Upper limit:  72.79249633725466
Lower Limit:  9.079924091402077
balance:
Upper limit:  10496.569545190878
Lower Limit:  -7772.025429820724
day:
Upper limit:  40.77384725101949
Lower Limit:  -9.161009667245626
duration:
Upper limit:  1030.746516576982
Lower Limit:  -514.4203570140437
campaign:
Upper limit:  12.057903308087548
Lower Limit:  -6.530221991593775
pdays:
Upper limit:  340.5840659340357
Lower Limit:  -260.18841000959253
previous:
```

3.Process of NA values

In [34]:

```
#Process of NA Values

plt.title('Job')
data.job.value_counts().plot(kind='bar')
plt.show()
plt.title('Marital')
data.marital.value_counts().plot(kind='bar')
plt.show()
plt.title('Education')
data.education.value_counts().plot(kind='bar')
plt.show()
plt.title('Default')
data.default.value_counts().plot(kind='bar')
plt.show()
plt.title('Housing')
data.housing.value_counts().plot(kind='bar')
plt.show()
plt.title('Loan')
data.loan.value_counts().plot(kind='bar')
plt.show()
plt.title('Contact')
data.contact.value_counts().plot(kind='bar')
plt.show()
plt.title('Poutcome')
data.poutcome.value_counts().plot(kind='bar')
plt.show()
plt.title('Y')
data.y.value_counts().plot(kind='bar')
plt.show()
```



In [35]:
```
# There is no null value. However there are unknown values as we can see ab
data.isnull().sum()
```

Out[35]:
```
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
```

In [36]:
```
#unknown values
strings = [x for x in data.columns if type(data[x].loc[data[x].first_valid_

for columns in strings:
  print(columns, ':', len(data[data[columns].str.contains('unknown')]))
```

```
job : 288
marital : 0
education : 1857
default : 0
housing : 0
loan : 0
contact : 13020
month : 0
poutcome : 36959
y : 0
```

In [37]:
```
data_copy=data
```

In [43]:
```
#There are 288 unknown in Job column, 1857 in education, 13020 in contact a
data['job'] = data['job'].replace(['unknown'],np.nan)
data['education'] = data['education'].replace(['unknown'],np.nan)
data['contact'] = data['contact'].replace(['unknown'],np.nan)
data['poutcome'] = data['poutcome'].replace(['unknown'],np.nan)
```

In [44]:
```
# method 1 for NA(drop NA)
data=data.dropna()
```

In [45]:
```
data.isnull().mean().sum()
```

Out[45]:
```
0.0
```

In [50]:
```
# method 2 for NA(using mode value to fill NA)
data_copy['job'].fillna(data_copy['job'].mode())
```

Out[50]:
```
0          management
1          technician
2        entrepreneur
3         blue-collar
4                 NaN
             ...
45206      technician
45207         retired
45208         retired
45209     blue-collar
45210    entrepreneur
Name: job, Length: 45211, dtype: object
```

In [49]:
```
data_copy['education'].fillna(data_copy['education'].mode())
```

Out[49]:
```
0         tertiary
1        secondary
2        secondary
3              NaN
4              NaN
           ...
45206     tertiary
45207      primary
45208    secondary
45209    secondary
45210    secondary
Name: education, Length: 45211, dtype: object
```

In [52]:
```
data_copy['contact'].fillna(data_copy['contact'].mode())
data_copy['poutcome'].fillna(data_copy['poutcome'].mode())
```

Out[52]:
```
0        failure
1            NaN
2            NaN
3            NaN
4            NaN
          ...
45206        NaN
45207        NaN
45208    success
45209        NaN
45210      other
Name: poutcome, Length: 45211, dtype: object
```

In [ ]: