

# WEEK 8 : DELIVERABLES

## BANK MARKETING CAMPAIGN

### ‘DATA SCIENCE’

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## PROBLEM DESCRIPTION :

ABC Bank wants to sell its term deposit product to customers and before launching the product they want to develop a model which helps them in understanding whether a particular customer will buy their product or not.

To achieve this task they have consulted an analytics consultancy to automate the process of classification.

The Analytics company has to come up with an ML model to shortlist the customers whose chances to buy the product is higher. This will lead marketing team to target on the given lead.

## **BUSINESS UNDERSTANDING :**

There's been a revenue decline for the ABC bank and to overcome that they want to come up with the actions needed to be taken. With analysis they came to know that customers are not depositing as frequently as before. Banks make investments from the investment made by customers to make high profits.

Banks also urge customers to buy other products such as insurance and Different kind of deposits. They want to check the customers from existing data they pursue and filter the customers having higher chances of buying any new schemes or products from the bank.

## **DATA UNDERSTANDING :**

Data belongs to a banking organisation and corresponds to marketing campaigns. These campaigns are based on phone calls. More than one call to the same client tells whether the bank term deposit (product) was subscribed by client or not.

There are four datasets provided for this classification problem. We are having 2 pairs of test and train datasets.

Bank.csv and Bank\_full.csv are one pair having 16 features and Bank\_additional.csv and Bank\_additional\_full.csv are having 20 features. Bank.csv is the older version of bank\_additional.csv.

Below are the details of all four datasets:

File	Dataset Type	Description
Bank.csv	Test	4521 observations(10% of train data) and 16 features
Bank_full.csv	Train	45211 observations and 16 features
Bank_additional.csv	Test	4111 observations(10% of train data) and 20 features
Bank_additional_full.csv	Train	41118 observations and 20 features

## Datatype and Description of columns:

Data columns (total 21 columns):

#	Column	Dtype	Description
0	age	int64	Age of Client.
1	job	object	Type of Job.
2	marital	object	Marital Status.
3	education	object	Level of Education.
4	default	object	Has credit in default?
5	housing	object	Has housing loan?
6	loan	object	Has personal loan?
7	contact	object	How client has been communicated?
8	month	object	last contacted month.
9	day_of_week	object	last contacted day.
10	duration	int64	duration of communication(seconds).
11	campaign	int64	number of contacts performed in Campaign.
12	pdays	int64	number of days passed after contact.
13	previous	int64	number of total contacts performed.
14	poutcome	object	outcome of the previous campaign.
15	emp.var.rate	float64	Employment variation rate.
16	cons.price.idx	float64	Consumer price index.
17	cons.conf.idx	float64	Consumer confidence index.
18	euribor3m	float64	Euribor 3 months rate.
19	nr.employed	float64	number of employees.
20	y	object	has the client subscribed product.

dtypes: float64(5), int64(5), object(11)

- First 7 features are the client information.
- Features 8-11 are last contact information.

- Features 12-15 are other important details regarding contact.
- Features 16-20 are economic and social features.
- The 21<sup>st</sup> feature is the target variable(dependent).

## **Data Problems :**

## Missing Attribute:

None of the dataset contains any missing value.

```
#Checking null values
bank_add_full.isnull().sum()

age          0
job           0
marital      0
education    0
default      0
housing      0
loan         0
contact      0
month        0
day_of_week  0
duration     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
y            0
dtype: int64
```

```
#Checking null values
bank_add.isnull().sum()

age          0
job           0
marital      0
education    0
default      0
housing      0
loan         0
contact      0
month        0
day_of_week  0
duration     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
y            0
dtype: int64
```

```
#Checking null values
bank_full.isnull().sum()

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
```

```
#Checking null values
bank.isnull().sum()

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
```

## Value Counts :

Some of the variables consists of value counts as “Unknown” which is significantly high. **So we assume “Unknown” as another category for these variables.**

```
admin.          10422
blue-collar     9254
technician      6743
services        3969
management      2924
retired         1720
entrepreneur    1456
self-employed   1421
housemaid       1060
unemployed      1014
student         875
unknown         330
Name: job, dtype: int64
```

```
-----
married         24928
single          11568
divorced        4612
unknown         80
Name: marital, dtype: int64
```

```
-----
university.degree  12168
high.school        9515
basic.9y           6045
professional.course 5243
basic.4y           4176
basic.6y           2292
unknown            1731
illiterate         18
Name: education, dtype: int64
```

```
-----
no              32588
unknown         8597
yes              3
Name: default, dtype: int64
```

```
-----
yes            21576
no             18622
unknown        990
Name: housing, dtype: int64
```

```
-----
no              33950
yes             6248
unknown         990
Name: loan, dtype: int64
```

### **Duplicate Counts :**

```
In [70]: #Checking the count of duplicates in bank_add_full dataset
print(f'There are {bank_add_full.duplicated().sum()} duplicates in bank_addition_full.')
bank_add_full.drop_duplicates(inplace=True, keep='first')

There are 12 duplicates in bank_addition_full.
```

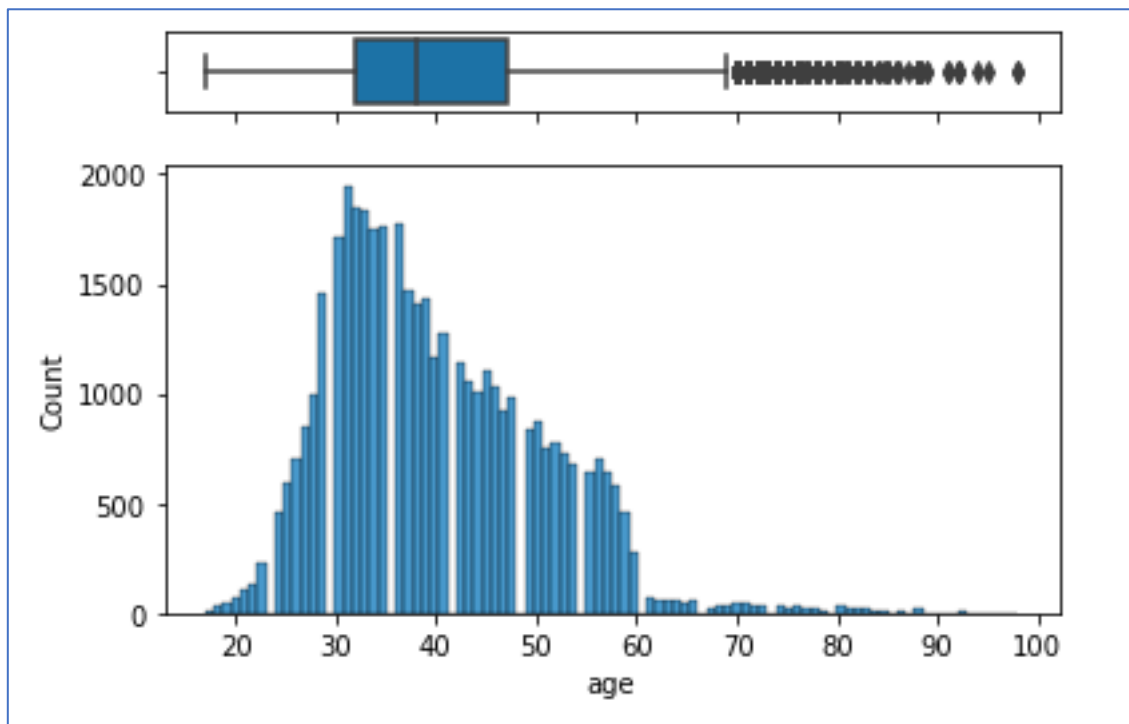
There are 12 duplicates present in the bank additional full dataset, we will remove the duplicates using drop\_duplicates function.

## Outliers :

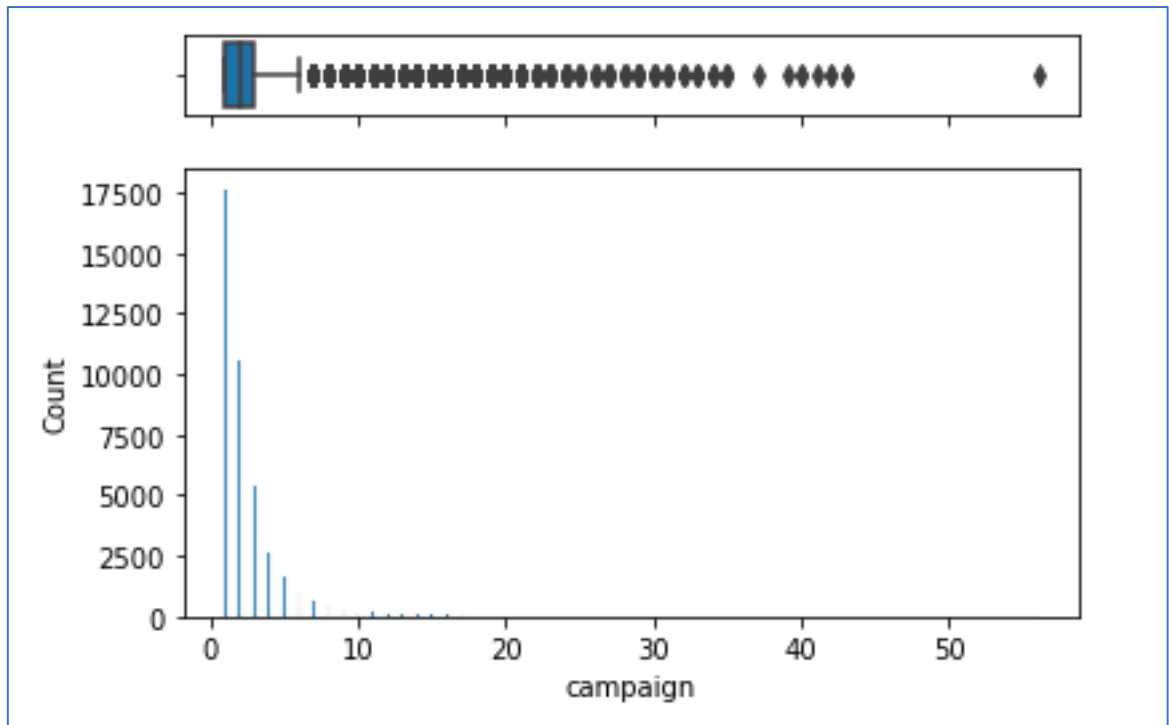
Outliers are the values which lie at above 3 standard deviation distance from the other Values in normal distribution.

It might occur due to improper collection of the data. . Outliers can disturb our analysis by changing the mean on normal distribution graph. Following variables consists of significant outliers.

- 'Age' Feature :



- 'Campaign Feature :



*The maximum value for 'age' variable is 98 and that of 'campaign' variable is 56 and both are significant values.*

Since model is needed to be generalized to reflect the real world data we are not going to remove these outliers as these seems to be realistic value

### Skewness and Kurtosis:

Skewness is a **measure of symmetry**, or more precisely, the **lack of symmetry**. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.



```
#Checking skewness
```

```
import warnings
```

```
warnings.filterwarnings('ignore')
```

```
bank_add_full.skew(axis=0, skipna=True)
```

```
age                0.784560
duration           3.262808
campaign           4.762044
pdays            -4.921386
previous           3.831396
emp.var.rate      -0.724061
cons.price.idx    -0.230853
cons.conf.idx      0.302876
euribor3m         -0.709194
nr.employed       -1.044317
dtype: float64
```

```
bank_add_full.kurt(axis=0, skipna=True)
```

```
age                0.791113
duration           20.243771
campaign           36.971857
pdays            22.221553
previous           20.102164
emp.var.rate      -1.062698
cons.price.idx    -0.829851
cons.conf.idx     -0.359097
euribor3m         -1.406791
nr.employed       -0.003540
dtype: float64
```

GITHUB LINK : [https://github.com/AbhimanyuGangani/Week\\_7\\_Bank\\_Marketing/tree/main/Week\\_8\\_Bank\\_Marketing](https://github.com/AbhimanyuGangani/Week_7_Bank_Marketing/tree/main/Week_8_Bank_Marketing)