Virtual Internship (Data Science)

Data Intake Report

Group Name: Project Group 1

Members:

No	Name	Email	Country	College/company	Specialization
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Name: Bank Marketing (Campaign)

Report date: 26-04-2023

Internship Batch: LISUM19

Data intake by:

Data intake reviewer: Data Glacier

Data storage location:

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 to understand whether a particular customer will buy their product or not (based on the customer's past interaction with the bank or other Financial Institution). This is an application of the company's marketing data.

Business Understanding :

The goal is to build a Machine Learning model that helps in predicting the outcomes of each customer's marketing campaign and analyzing which features have an impact on the outcomes will help the company to understand how to make the campaign more effective. Additionally, categorizing the customer group that subscribed to the term deposit helps to determine who is more likely to purchase the product in the future, thereby developing more targeted marketing campaigns.

This can be accomplished by using an ML model that shortlists the customers whose possibility of purchasing the product is higher. So, marketing such as telemarketing, SMS or email marketing can concentrate only on those customers. It will save time and resources by doing this.

Project Lifecycle

Deadline (Date/week)	Plan and Deliverables
19 April 2023(Week 7)	• Problem statement • Business understanding • Dataset collection
26 April 2023(Week 8)	• Data understanding • Data analysis - finding null values, and outliers. • Data processing
2 May 2023(Week 9)	Data cleaning and transformation
9 May 2023(Week 10)	EDA and Model Recommendation
16 May 2023(Week 11)	EDA Presentation and Proposed Modeling Technique

23 May 2023(Week 12)	Model Selection and Building the Model
30 May 2023(Week 13)	Final project report and code submission

Tabular data details:

File 1: bank_additional_full.csv

Total number of observations	41189
Total number of files	2
Total number of features	21
Base format of the file	.csv
Size of the data	5.56MB

File 2: bank_additional.csv

Total number of observations	4120
Total number of files	2
Total number of features	21

Exploratory Data Analysis

1. The data covers the period from May 2008 to November 2010.

2. There are 2 datasets, the second dataset is a sample of the first dataset. So, we are not taking the second dataset.

3. There are 10 integers and 11 categorical variables.

4. The missing values in the dataset are presented by an "unknown" string. We changed it to NaN.

5. There are missing values in six variables: job, marital status, education, default, housing, and loan. This will be imputed using various methods.

6. There are 12 duplicates in the first dataset and no duplicates in the sample dataset, this will be dropped since they are minimal and will not affect our analysis

Assumptions

We assume the data provided is correct and up to date.

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Run Code

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [5]:
```
data = pd.read_csv("bank-additional-full.csv")
print(data.head(5))
```

```
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week  ...  campaign  pdays  previous     poutcome emp.var.rate  \
0   may         mon  ...         1    999         0  nonexistent          1.1
1   may         mon  ...         1    999         0  nonexistent          1.1
2   may         mon  ...         1    999         0  nonexistent          1.1
3   may         mon  ...         1    999         0  nonexistent          1.1
4   may         mon  ...         1    999         0  nonexistent          1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0          93.994          -36.4      4.857       5191.0  no
1          93.994          -36.4      4.857       5191.0  no
2          93.994          -36.4      4.857       5191.0  no
3          93.994          -36.4      4.857       5191.0  no
4          93.994          -36.4      4.857       5191.0  no

[5 rows x 21 columns]
```

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Run Code

```
4          93.994          -36.4       4.857       5191.0  no

[5 rows x 21 columns]
```

In [6]:

```python
print(data.dtypes)
```

```
age                 int64
job                object
marital            object
education          object
default            object
housing            object
loan               object
contact            object
month              object
day_of_week        object
duration            int64
campaign            int64
pdays               int64
previous            int64
poutcome           object
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
y                  object
dtype: object
```

In [7]:

```python
data.isna().sum()
```

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Run Code

In [7]:

```python
data.isna().sum()
```


Out[7]:

```
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
```

In [9]:

```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
```

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In [9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

Week 8 Assignment:

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Checking duplicate and null values

In the dataset, first, we must check duplicate and null values. Our dataset has 12 duplicate values. But we have no null values in the columns. So, we must handle duplicate values.

In [5]:
```
#Find the duplicates
print(data.duplicated().sum())

#Find null values
print(data.isnull().sum())
```

```
12
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
```

In [6]:
```
data.replace("unknown", np.nan, inplace=True)
```

In [7]:
```
# Drop duplicated
data.drop_duplicates(inplace=True)
data.shape
```

Out[7]:
```
(41176, 21)
```

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If we set 'Unknown' to null, then our dataset having null values. Below, we can see which feature contains null values.

In [8]:
```
# data.isna().sum()
print(data.isnull().sum())
```

```
age                  0
job                330
marital             80
education         1730
default           8596
housing            990
loan               990
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
```

In [9]:
```
null_percentage = data.isnull().mean()*100
null_percentage
```

Out[9]:
```
age                0.000000
job                0.801438
marital            0.194288
education          4.201477
default           20.876239
housing            2.404313
loan               2.404313
contact            0.000000
month              0.000000
day_of_week        0.000000
duration           0.000000
```

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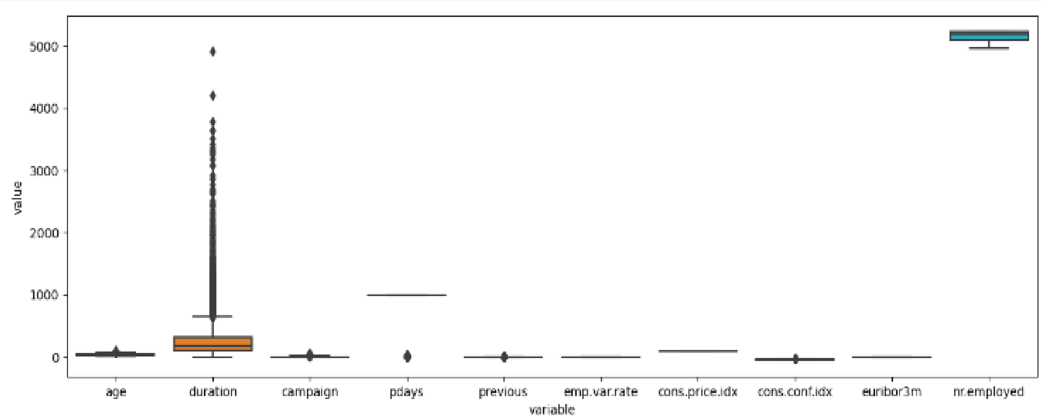
```
poutcome           0.000000
emp.var.rate       0.000000
cons.price.idx     0.000000
cons.conf.idx      0.000000
euribor3m          0.000000
nr.employed        0.000000
y                  0.000000
dtype: float64
```

Outliers in the dataset

In [10]:
```
data_1 = data[['age','duration','campaign','pdays','previous','emp.var.rate','cons.price.idx','cons.conf.idx','euribor3m','nr.em
```

In [11]:
```
fig, ax = plt.subplots(figsize=(15, 5))
sns.boxplot(x="variable", y="value", data=pd.melt(data_1))
plt.figure(figsize=(20,5))
plt.show()
```




```
<Figure size 2000x500 with 0 Axes>
```

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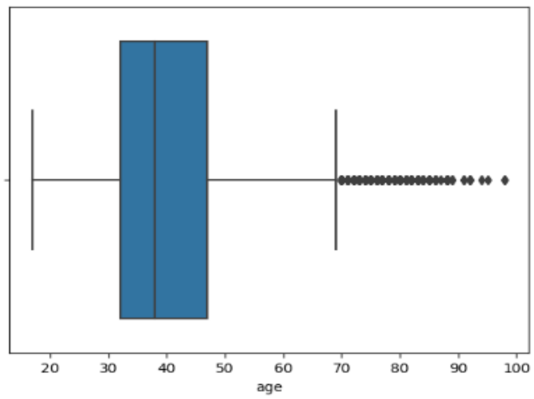
Run Code

In [12]:
```
sns.boxplot(x = data_1['age'])
plt.show()
```



In [13]:
```
fig, axs = plt.subplots(5, 2, figsize=(8, 8))
sns.histplot(data=data_1, x="age", kde=True, color="skyblue",ax=axs[0, 0])
sns.histplot(data=data_1, x="duration", kde=True, color="olive",ax=axs[0, 1])
sns.histplot(data=data_1, x="campaign", kde=True, color="gold", ax=axs[1, 0])
sns.histplot(data=data_1, x="pdays", kde=True, color="teal", ax=axs[1, 1])
sns.histplot(data=data_1, x="previous", kde=True, color="skyblue", ax=axs[2, 0])
sns.histplot(data=data_1, x="emp.var.rate", kde=True, color="olive", ax=axs[2, 1])
sns.histplot(data=data_1, x="cons.price.idx", kde=True, color="gold", ax=axs[3, 0])
sns.histplot(data=data_1, x="cons.conf.idx", kde=True, color="teal", ax=axs[3, 1])
sns.histplot(data=data_1, x="euribor3m", kde=True, color="olive", ax=axs[4, 0])
sns.histplot(data=data_1, x="nr.employed", kde=True, color="gold", ax=axs[4, 1])
```

Out[13]: <Axes: xlabel='nr.employed', ylabel='Count'>

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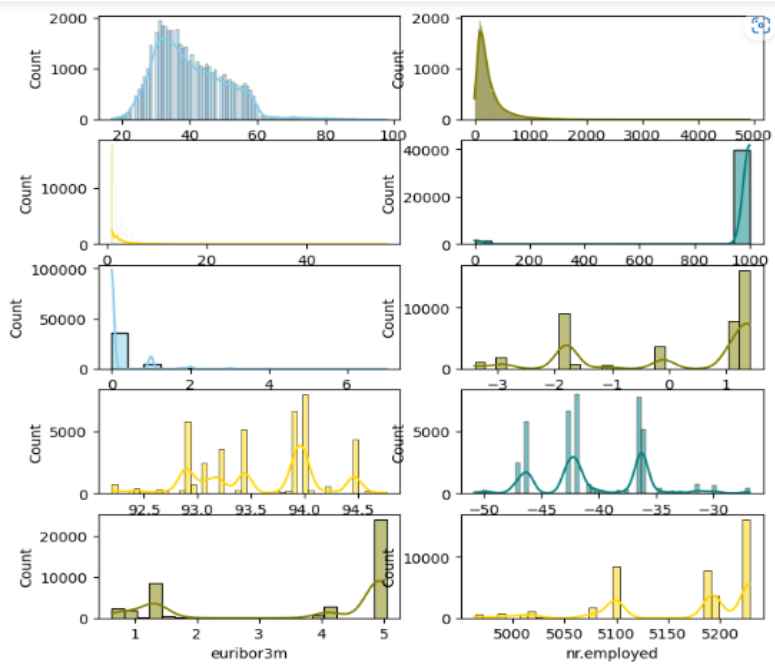
Run Code



In [14]:
```
sns.distplot(data_1['age'], bins = 15, kde = True)
plt.show()
```

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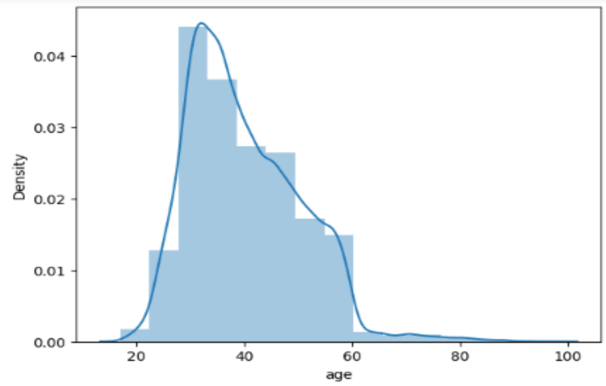

Handling the outliers in the Age column

The interquartile range (IQR) is a statistical measure used to determine the variability in a dataset by subtracting the 25th percentile (Q1) from the 75th percentile (Q3). Outliers are values that fall outside of a certain range, which is typically calculated as Q1−1.5IQR to Q3+1.5IQR.

In [15]:
```
data_1[['age']].describe()
```

Out[15]:

	age
count	41176.00000
mean	40.02380
std	10.42068
min	17.00000

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In [16]:
```
data_1['age'].quantile(0.25)
```

Out[16]: 32.0

In [17]:
```
data_1['age'].quantile(0.75)
```

Out[17]: 47.0

In [18]:
```
Q1 = data_1['age'].quantile(0.25)
Q3 = data_1['age'].quantile(0.75)
IQR = Q3-Q1
IQR
```

Out[18]: 15.0

In [19]:
```
lower_lim = Q1-1.5*IQR
upper_lim = Q1+1.5*IQR
print(lower_lim)
print(upper_lim)
```

```
9.5
54.5
```

In [20]:
```
outliers_15_low = (data_1['age']<lower_lim)
# print(outliers_15_low)
outliers_15_up = (data_1['age']>upper_lim)
# print(outliers_15_up)
```

In [21]:
```
len(data_1['age']) - (len(data_1['age'][outliers_15_low])+len(data_1['age'][outliers_15_up]))
```

Out[21]: 36948

In [22]:
```
data_1['age'][(outliers_15_low|outliers_15_up)]
```

Out[22]:
```
0        56
1        57
4        56
6        59
13       57
         ..
41178    62
41179    64
```

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Run Code

```
3        40
5        45
7        41
8        24
         ..
41180    36
41181    37
41182    29
41184    46
41186    44
Name: age, Length: 36948, dtype: int64
```

In [24]:

```
data_1 = data_1[~(outliers_15_low|outliers_15_up)]
data_1
```

Out[24]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
2	37	226	1	999	0	1.1	93.994	-36.4	4.857	5191.0
3	40	151	1	999	0	1.1	93.994	-36.4	4.857	5191.0
5	45	198	1	999	0	1.1	93.994	-36.4	4.857	5191.0
7	41	217	1	999	0	1.1	93.994	-36.4	4.857	5191.0
8	24	380	1	999	0	1.1	93.994	-36.4	4.857	5191.0
...	...	...	...	...	...	...	...	...	...	...
41180	36	254	2	999	0	-1.1	94.767	-50.8	1.028	4963.6
41181	37	281	1	999	0	-1.1	94.767	-50.8	1.028	4963.6
41182	29	112	1	9	1	-1.1	94.767	-50.8	1.028	4963.6
41184	46	383	1	999	0	-1.1	94.767	-50.8	1.028	4963.6
41186	44	442	1	999	0	-1.1	94.767	-50.8	1.028	4963.6

36948 rows × 10 columns

In [25]:

```
sns.boxplot(x = data_1['age'])
plt.show()
```

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Run Code

computing the frequency distribution.

Distribution on the basis of skewness value:

Skewness = 0: Then normally distributed.

Skewness > 0: Then more weight in the left tail of the distribution.

Skewness < 0: Then more weight in the right tail of the distribution.

In [27]:

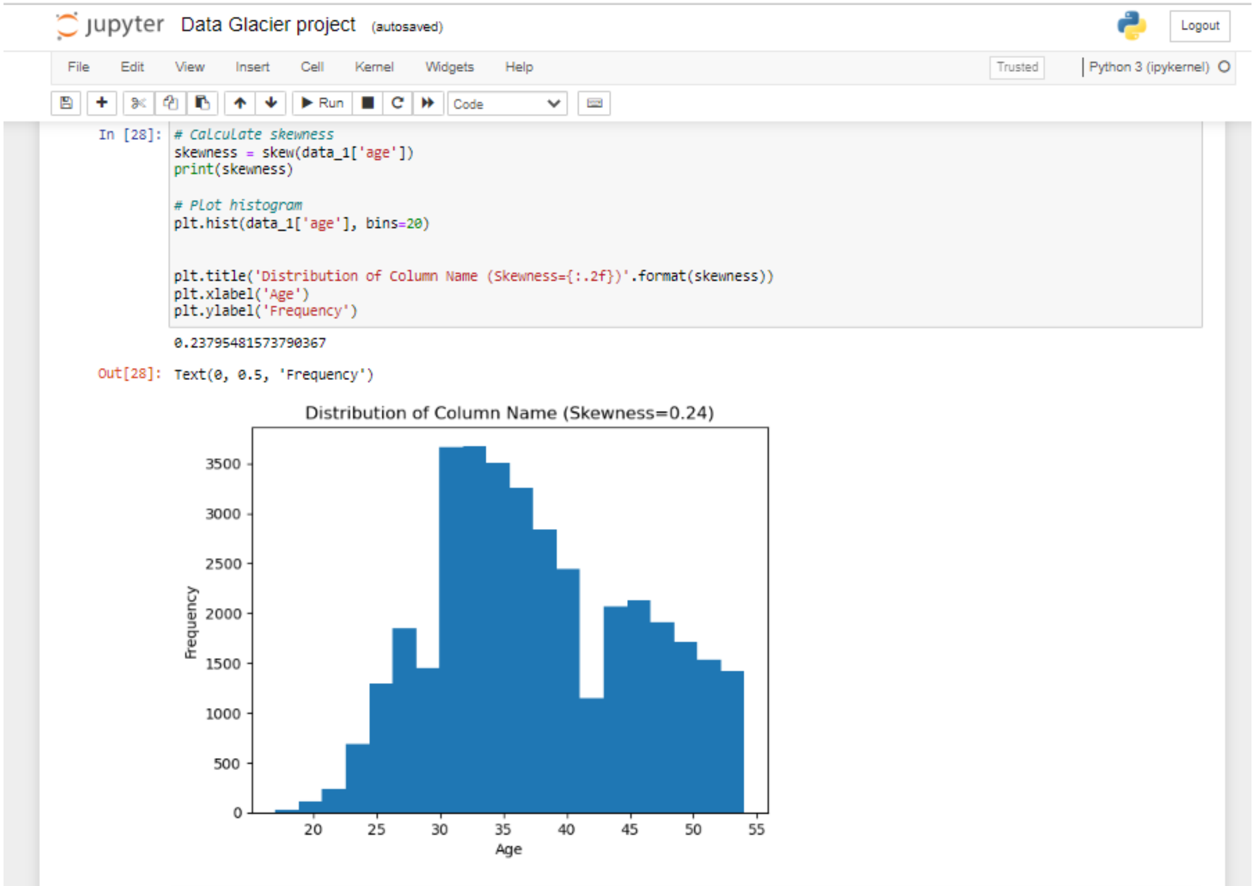
```
from scipy.stats import skew
# Calculate Pearson's skewness coefficient
skewness1 = skew(data_1)

# Calculate moment coefficient of skewness
skewness2 = np.mean((data_1 - np.mean(data_1)) ** 3) / (np.std(data_1) ** 3)

print("Pearson's skewness coefficient: ", skewness1)
print("Moment coefficient of skewness:\n", skewness2)
```

```
Pearson's skewness coefficient:  [ 0.23795482  3.3107468   4.79008024 -5.28224096  3.90406112 -0.74646063
 -0.19884943  0.27784703 -0.75398964 -1.08125485]
Moment coefficient of skewness:
 age             0.237955
duration        3.310747
campaign        4.790080
pdays          -5.282241
previous        3.904061
emp.var.rate   -0.746461
cons.price.idx -0.198849
cons.conf.idx   0.277847
euribor3m      -0.753990
nr.employed    -1.081255
dtype: float64
```

```
C:\ProgramData\Anaconda3\lib\site-packages\numpy\core\fromnumeric.py:3430: FutureWarning: In a future version, DataFrame.mean(a
xis=None) will return a scalar mean over the entire DataFrame. To retain the old behavior, use 'frame.mean(axis=0)' or just 'fr
ame.mean()'
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
C:\ProgramData\Anaconda3\lib\site-packages\numpy\core\fromnumeric.py:3430: FutureWarning: In a future version, DataFrame.mean(a
xis=None) will return a scalar mean over the entire DataFrame. To retain the old behavior, use 'frame.mean(axis=0)' or just 'fr
ame.mean()'
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
```



Week 9 Assignment:

Handling missing values is an essential step in data cleaning and preprocessing. There are several methods to handle missing values, and choosing the right method depends on the nature of the data and the missing values.

Filling missing values using value_counts method

value_counts(): This method is useful when the missing values are represented as NaN. The value_counts() method returns a series containing counts of unique values, excluding NaN values. It can be used to determine the most frequent value in a column and impute the missing values with that value.

This column('marital') has 80 missing values. So, we can use the value_counts method to fill these values.

Forward or backward fill:

This method involves filling missing values with the previous (forward fill) or next (backward fill) known value. This method is useful when dealing with time series data where the missing value is expected to be like the previous or next value.

Mode imputation:

The mode is the most frequent value in a column. Mode imputation involves replacing the missing values with the mode of the column. This method is useful when the missing values are few compared to the total number of observations and the mode is a reasonable representation of the missing values.

Interpolation:

Interpolation is a statistical technique that involves estimating missing values based on the pattern observed in the data. Linear interpolation is commonly used to estimate missing values. This method is useful when dealing with continuous data and the missing values are not frequent.

In [29]:
```
data_1['age'].fillna(data_1['age'].mean(), inplace=True)
```

In [30]:
```
data_1['age'].describe()
```

Out[30]:
```
count    36948.000000
mean        37.731731
std          8.032715
min         17.000000
25%         31.000000
50%         37.000000
75%         44.000000
max         54.000000
Name: age, dtype: float64
```

In [31]:
```
data_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36948 entries, 2 to 41186
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             36948 non-null  int64
 1   duration        36948 non-null  int64
 2   campaign        36948 non-null  int64
 3   pdays           36948 non-null  int64
 4   previous        36948 non-null  int64
 5   emp.var.rate    36948 non-null  float64
 8   euribor3m       36948 non-null  float64
 9   nr.employed     36948 non-null  float64
dtypes: float64(5), int64(5)
memory usage: 3.1 MB
```

In [32]:
```
# data[['age','duration','campaign','pdays','previous','emp.var.rate','cons.price.idx','cons.conf.idx',
```

Handling missing values in the dataset

Handling missing values is an essential step in data cleaning and preprocessing. There are several methods to handle missing values, and choosing the right method depends on the nature of the data and the missing values.

Filling missing values using value_counts method

value_counts(): This method is useful when the missing values are represented as NaN. The value_counts() method returns a series containing counts of unique values, excluding NaN values. It can be used to determine the most frequent value in a column and impute the missing values with that value.

This column('marital') has 80 missing values. So, we can use the value_counts method to fill these values.

In [33]:
```
data['marital'].fillna(data['marital'].value_counts().index[0], inplace = True)
```

Fill missing values with forward or backward fill:

Forward or backward fill: This method involves filling missing values with the previous (forward fill) or next (backward fill) known value. This method is useful when dealing with time series data where the missing value is expected to be similar to the previous or next value.

In [34]:
```
data['housing'] = data['housing'].fillna(method='ffill')
data['default'] = data['default'].fillna(method='bfill')
```

Fill missing values with mode:

Mode imputation: The mode is the most frequent value in a column. Mode imputation involves replacing the missing values with the mode of the column. This method is useful when the missing values are few compared to the total number of observations and the mode is a reasonable representation of the missing values.

In [35]:
```
data['loan'] = data['loan'].fillna(data['loan'].mode().iloc[0])
```

Interpolation:

Interpolation: Interpolation is a statistical technique that involves estimating missing values based on the pattern observed in the data. Linear interpolation is commonly used to estimate missing values. This method is useful when dealing with continuous data and the missing values are not frequent.

In [36]:
```
data['job'] = data['job'].interpolate()
```

In [37]:
```
data.isna().sum()
```

Out[37]:
```
age                0
job              330
marital            0
education       1730
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
```