Data Cleaning

Data cleaning includes processes such as filling in missing values and handling inconsistencies. It detects corrupt data and replaces or modifies it.

Missing Values

The concept of missing values is important to understand if you want to master the skill of successful management and understanding of data. Let's take a look at the following figure:

Removing Missing Data

***we will be loading the Banking_Marketing.csv dataset into the pandas DataFrame and handling the missing data. ***

```
import pandas as pd

dataset = '/content/Banking_Marketing.csv'

#reading the data into the dataframe into the object data

df = pd.read_csv(dataset, header=0)
```

Once you have fetched the dataset, print the datatype of each column. To do so, use the dtypes attribute from the pandas DataFrame:

df.dtypes

```
df.dtypes
```

```
age                float64
job                 object
marital             object
education           object
default             object
housing             object
loan                object
contact             object
month               object
day_of_week         object
duration           float64
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                    int64
dtype: object
```

Now we need to find the missing values for each column. In order to do that, we use the isna() function provided by pandas:

df.isna().sum()

```
df.isna().sum()
```

```
age               2
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           6
month             0
day_of_week       0
duration          7
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
```

Once you have figured out all the missing details, we remove all the missing rows from the DataFrame. To do so, we use the dropna() function:

removing Null values

```
df = df.dropna()
```

To check whether the missing vales are still present, use the isna() function:

```
df.isna().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
```

second method of dealing with missing data, which uses imputation.

Mean/Median/Mode Imputation

In the case of numerical data, we can compute its mean or median and use the result to replace missing values. In the case of the categorical (non-numerical) data, we can compute its mode to replace the missing value. This is known as imputation.

** Imputing Missing Data**

```
import pandas as pd

dataset = '/content/Banking_Marketing.csv'

df = pd.read_csv(dataset, header=0)
```

Impute the numerical data of the age column with its mean. To do so, first find the mean of the age column using the mean() function of pandas, and then print it:

```
mean_age = df.age.mean()

print(mean_age)
```

```
40.023812413525256
```

Once this is done, impute the missing data with its mean using the fillna() function. This can be done with the following code:

```
df.age.fillna(mean_age, inplace=True)
```

Now we impute the numerical data of the duration column with its median. To do so, first find the median of the duration column using the median() function of the pandas. Add the following code to do so:

```
median_duration = df.duration.median()

print(median_duration)
```

```
180.0
```

Impute the missing data of the duration with its median using the fillna() function.

```
df.duration.fillna(median_duration,inplace=True)
```

Impute the categorical data of the contact column with its mode. To do so, first, find the mode of the contact column using the mode() function of pandas. Add the following code to do this:

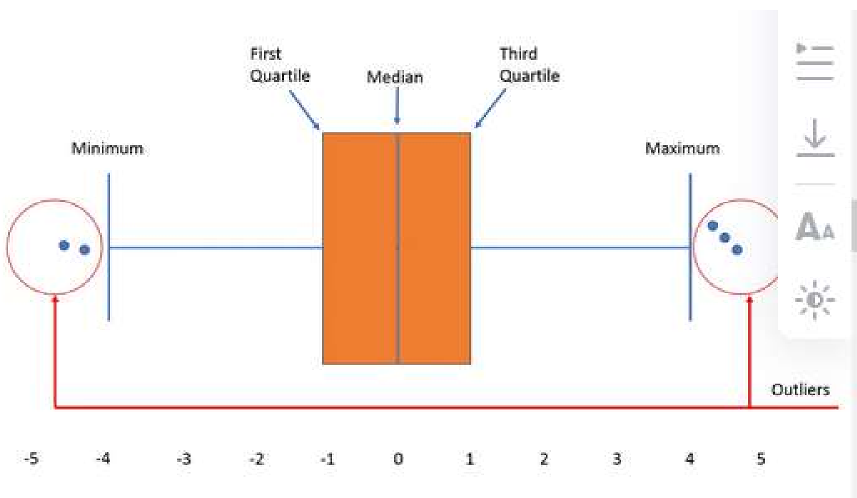
```
mode_contact = df.contact.mode()[0]

print(mode_contact)

     cellular
```

Impute the missing data of the contact column with its mode using the fillna() function. Add the following code to do this:

```
df.contact.fillna(mode_contact,inplace=True)
```

Outliers

Outliers are values that are very large or very small with respect to the distribution of the other data. We can only find outliers in numerical data. Box plots are one good way to find the outliers in a dataset, as you can see in the following figure: **bold text bold text**




```
Let's learn how to find outliers using a simple example. Consider a sample dataset of temperatures from a place a

71, 70, 90, 70, 70, 60, 70, 72, 72, 320, 71, 69

We can now do the following:

    First, we'll sort the data:

    60,69, 70, 70, 70, 70, 71, 71, 72, 72, 90, 320
    Next, we'll calculate the median (Q2). The median is the middle data after sorting.

    Here, the middle terms are 70 and 71 after sorting the list.

    The median is (70 + 71) / 2 = 70.5
    Then we'll calculate the lower quartile (Q1). Q1 is the middle value (median) of the first half of the datase

    First half of the data = 60, 69, 70, 70, 70, 70

    Points 3 and 4 of the bottom 6 are both equal to 70
```

```
Points 3 and 4 of the bottom 6 are both equal to 70.

The average is (70 + 70) / 2 = 70

Q1 = 70
Then we calculate the upper quartile (Q3).

Q3 is the middle value (median) of the second half of the dataset.
second half of the dataset.

Second half of the data = 71, 71, 72, 72, 90, 320

Points 3 and 4 of the upper 6 are 72 and 72.

The average is (72 + 72) / 2 = 72

Q3 = 72
Then we find the interquartile range (IQR).

IQR = Q3 – Q1 = 72 – 70

IQR = 2
Next, we find the upper and lower fences.

Lower fence = Q1 – 1.5 (IQR) = 70 – 1.5(2) = 67

Upper fence = Q3 + 1.5 (IQR) = 71.5 + 1.5(2) = 74.5

Boundaries of our fences = 67 and 74.5
```

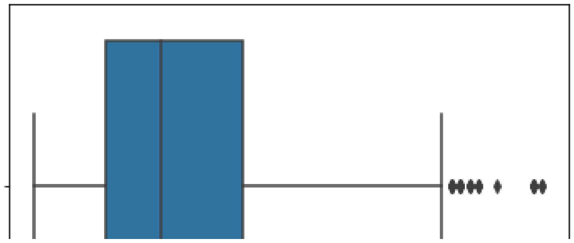
```
Any data points lower than the lower fence and greater than the upper fence are outliers. Thus, the outliers fror
```

```
import pandas as pd

import numpy as np

%matplotlib inline

import seaborn as sbn

dataset = '/content/german_credit_data.csv'

#reading the data into the dataframe into the object data

df = pd.read_csv(dataset, header=0)
```

This dataset contains an Age column. Let's plot a boxplot of the Age column. To do so, use the boxplot() function from the seaborn library:

```
sbn.boxplot(df['Age'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following var
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fb6a1abffd0>
```



```
Q1 = df["Age"].quantile(0.25)

Q3 = df["Age"].quantile(0.75)

IQR = Q3 - Q1

print(IQR)
```

```
15.0
```

```
Lower_Fence = Q1 - (1.5 * IQR)

Upper_Fence = Q3 + (1.5 * IQR)

print(Lower_Fence)

print(Upper_Fence)
```

```
4.5
64.5
```

```
df[((df["Age"] < Lower_Fence) |(df["Age"] > Upper_Fence))]
```

	Unnamed: 0	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose
0	0	67	male	2	own	NaN	little	1169	6	radio/TV
75	75	66	male	3	free	little	little	1526	12	car
137	137	66	male	1	own	quite rich	moderate	766	12	radio/TV
163	163	70	male	3	free	little	moderate	7308	10	car
179	179	65	male	2	own	little	little	571	21	car
186	186	74	female	3	free	little	moderate	5129	9	car
187	187	68	male	0	free	little	moderate	1175	16	car

```
df = df[~((df ["Age"] < Lower_Fence) |(df["Age"] > Upper_Fence))]
```

```
df
```

	Unnamed: 0	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose
1	1	22	female	2	own	little	moderate	5951	48	radio/TV
2	2	49	male	1	own	little	NaN	2096	12	education
3	3	45	male	2	free	little	little	7882	42	furniture/equipment
4	4	53	male	2	free	little	little	4870	24	car
5	5	35	male	1	free	NaN	NaN	9055	36	education
...	...	...	...	...	...	...	...	...	...	...
995	995	31	female	1	own	little	NaN	1736	12	furniture/equipment
996	996	40	male	3	own	little	little	3857	30	car
997	997	38	male	2	own	little	NaN	804	12	radio/TV
998	998	23	male	2	free	little	little	1845	45	radio/TV
999	999	27	male	2	own	moderate	moderate	4576	45	car

977 rows × 10 columns