Name: Shubham Jha
Div: D15C
Roll No:19

EXP 1

Aim:

- Load data in Pandas.
- Description of the dataset.
- Drop columns that aren't useful.
- Drop rows with maximum missing values.
- Take care of missing data.
- Create dummy variables.
- Find out outliers (manually)
- standardization and normalization of columns

Data preprocessing

Data preprocessing is the process of transforming raw data into an understandable format. It is also an important step in data mining as we cannot work with raw data. The quality of the data should be checked before applying machine learning or data mining algorithms.

Why is Data Preprocessing important?

Preprocessing of data is mainly to check the data quality. The quality can be checked by the following:

- Accuracy: To check whether the data entered is correct or not.
- Completeness: To check whether the data is available or not recorded.
- Consistency: To check whether the same data is kept in all the places that do or do not match.

- Timeliness: The data should be updated correctly.
- Believability: The data should be trustable.

Interpretability: The understandability of the data.

Dataset: SuperMarket Dataset

1) Loading Data in Pandas

```
import pandas as pd

df = pd.read_csv('ssc.csv')

df.head()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gros incom
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.141
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.820
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.215
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.288
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.208

2)Description of the dataset.

Attribute/Column Name	Data Type	Description
Invoice ID	String	Unique identifier for each transaction/invoice.
Branch	String	Branch identifier for the supermarket (`A`, `B`, or `C`).
City	String	City where the supermarket branch is located.
Customer type	String	Type of customer (`Member` or `Normal`).
Gender	String	Gender of the customer (`Male` or `Female`).
Product line	String	Category of products purchased (`Health and beauty`, `Electronic accessories`, etc.).
Unit price	Float	Price per unit of the product.
Quantity	Integer	Number of units purchased.
Tax 5%	Float	5% tax on the total amount for the purchase.
Total	Float	Total bill amount, including tax.
Date	DateTime	Date of the purchase transaction.
Time	String	Time of the purchase transaction.
Payment	String	Payment method used (`Cash`, `Credit card`, or `Ewallet`).
cogs (Cost of Goods Sold)	Float	Total cost of goods sold before tax.
gross margin %	Float	Percentage of gross margin fixed at 4.76%.
gross income	Float	Profit made from the transaction.
Rating	Float	Customer's rating of their experience (range: 1 to 10).

`df.info()`: Provides an overview of the dataset, including:

- Number of rows and columns.
- Data types of each column (e.g., int, float, object).
- Number of non-null (non-missing) values in each column.

`df.describe()`: Generates summary statistics for numeric columns, such as:

- `count`: Number of non-missing values.
- `mean`: Average value.
- `std`: Standard deviation.
- `min`, `25%`, `50%` (median), `75%`, and `max`: Percentile values.

```
print(df.info())


print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Invoice ID               1000 non-null   object
 1   Branch                   1000 non-null   object
 2   City                     1000 non-null   object
 3   Customer type            1000 non-null   object
 4   Gender                   1000 non-null   object
 5   Product line             1000 non-null   object
 6   Unit price               1000 non-null   float64
 7   Quantity                 1000 non-null   int64
 8   Tax 5%                   1000 non-null   float64
 9   Total                    1000 non-null   float64
 10  Date                     1000 non-null   object
 11  Time                     1000 non-null   object
 12  Payment                  1000 non-null   object
 13  cogs                     1000 non-null   float64
 14  gross margin percentage  1000 non-null   float64
 15  gross income             1000 non-null   float64
 16  Rating                   1000 non-null   float64
dtypes: float64(7), int64(1), object(9)
memory usage: 132.9+ KB
None
        Unit price     Quantity       Tax 5%        Total        cogs  \
count  1000.000000  1000.000000  1000.000000  1000.000000  1000.00000
mean     55.672130     5.510000    15.379369   322.966749   307.58738
std      26.494628     2.923431    11.708825   245.885335   234.17651
min      10.080000     1.000000     0.508500    10.678500    10.17000
25%      32.875000     3.000000     5.924875   124.422375   118.49750
50%      55.230000     5.000000    12.088000   253.848000   241.76000
75%      77.935000     8.000000    22.445250   471.350250   448.90500
max      99.960000    10.000000    49.650000  1042.650000   993.00000
```

3) Drop columns that aren't useful: Columns like Invoice ID may not contribute to analysis (it's often just an identifier). Removing irrelevant columns reduces complexity.

```
[ ] df = df.drop(['Invoice ID'], axis=1)

    df.head()
```

	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating
0	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1
1	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6
2	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4
3	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4
4	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3

```
[ ] df.info()
```

4)Drop rows with maximum missing values.

`df.dropna(thresh=int(0.5 * len(df.columns)))`:

- Drops rows where more than half the columns have missing (NaN) values.
- `thresh=int(0.5 * len(df.columns))`: Ensures that a row must have at least 50% non-null values to remain.

`df = ...`: Updates the DataFrame after dropping rows.
`print(df.info())`: Confirms that rows with excessive missing values have been removed.

```
[ ] df = df.dropna(thresh=int(0.5 * len(df.columns)))

    df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Branch                   1000 non-null   object
 1   City                     1000 non-null   object
 2   Customer type            1000 non-null   object
 3   Gender                   1000 non-null   object
 4   Product line             1000 non-null   object
 5   Unit price               1000 non-null   float64
 6   Quantity                 1000 non-null   int64
 7   Tax 5%                   1000 non-null   float64
 8   Total                    1000 non-null   float64
```

5)Take care of missing data.

`df.fillna(df.mean())`: Replaces missing values (NaN) in numeric columns with the mean of that column.

```
print(df.isnull().sum())
# to check null values..this is like boolean ..if Nan ? true:false ..then adds all bolean values.....finally 0 matlab false....this dataset has no null or NaN values.
```

```
Branch                    0
City                      0
Customer type             0
Gender                    0
Product line              0
Unit price                0
Quantity                  0
Tax 5%                    0
Total                     0
Date                      0
Time                      0
Payment                   0
cogs                      0
gross margin percentage   0
```

6)Create dummy variables.

`pd.get_dummies()`: Converts categorical variables into dummy variables (binary indicators: 0 or 1).

- Example: The `Gender` column becomes `Gender_Male` (1 if Male, 0 otherwise).

`columns=['...']`: Specifies which columns to convert.
`drop_first=True`: Avoids the "dummy variable trap" by dropping one dummy variable to prevent multicollinearity.

```
df = pd.get_dummies(df, columns=['Gender', 'City'], drop_first=True)
```

```
[ ] df.head()
```

	Branch	Customer type	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating	Gender_Male	City_Naypyitaw	City_Yangon
0	A	Member	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1	False	False	True
1	C	Normal	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6	False	True	False
2	A	Normal	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4	True	False	True
3	A	Member	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4	True	False	True
4	A	Normal	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3	True	False	True

7)Find out outliers (manually)

```
def detect_outliers(col):
    Q1 = df[col].quantile(0.25)  # First quartile (25th percentile)
    Q3 = df[col].quantile(0.75)  # Third quartile (75th percentile)
    IQR = Q3 - Q1               # Interquartile range
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[col] < lower_bound) | (df[col] > upper_bound)]
```

```
outliers = detect_outliers('Total')
print(outliers)
if outliers.empty:
    print("No outliers detected.")
else:
    print(f"Outliers detected:\n{outliers}")

print(f"Number of outliers: {len(outliers)}")
```

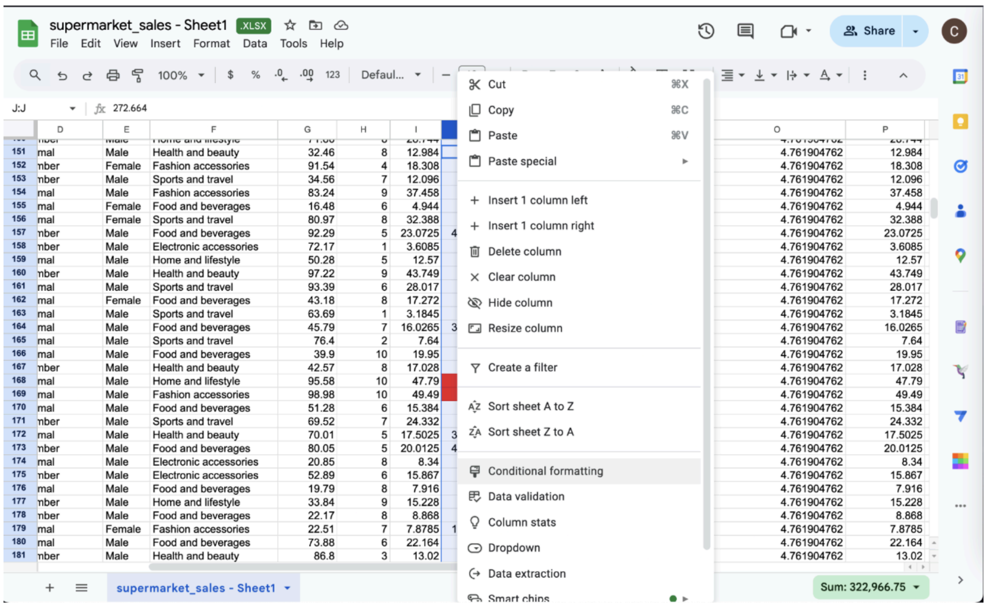
```
    Branch Customer type         Product line  Unit price  Quantity  Tax 5%  \
166      C        Normal   Home and lifestyle       95.58        10  47.790
167      A        Normal  Fashion accessories       98.98        10  49.490
350      C        Member  Fashion accessories       99.30        10  49.650
357      C        Normal    Sports and travel       95.44        10  47.720
422      C        Member  Fashion accessories       97.21        10  48.605
557      C        Member   Food and beverages       98.52        10  49.260
699      C        Normal   Home and lifestyle       97.50        10  48.750
792      B        Normal   Home and lifestyle       97.37        10  48.685
996      B        Normal   Home and lifestyle       97.38        10  48.690

        Total       Date   Time      Payment   cogs  gross margin percentage  \
166  1003.590  1/16/2019  13:32         Cash  955.8                 4.761905
167  1039.290   2/8/2019  16:20  Credit card  989.8                 4.761905
350  1042.650  2/15/2019  14:53  Credit card  993.0                 4.761905
357  1002.120   1/9/2019  13:45         Cash  954.4                 4.761905
422  1020.705   2/8/2019  13:00  Credit card  972.1                 4.761905
557  1034.460  1/30/2019  20:23      Ewallet  985.2                 4.761905
699  1023.750  1/12/2019  16:18      Ewallet  975.0                 4.761905
792  1022.385  1/15/2019  13:48  Credit card  973.7                 4.761905
996  1022.490   3/2/2019  17:16      Ewallet  973.8                 4.761905

     gross income  Rating  Gender_Male  City_Naypyitaw  City_Yangon
166        47.790     4.8         True            True        False
167        49.490     8.7         True           False         True
```

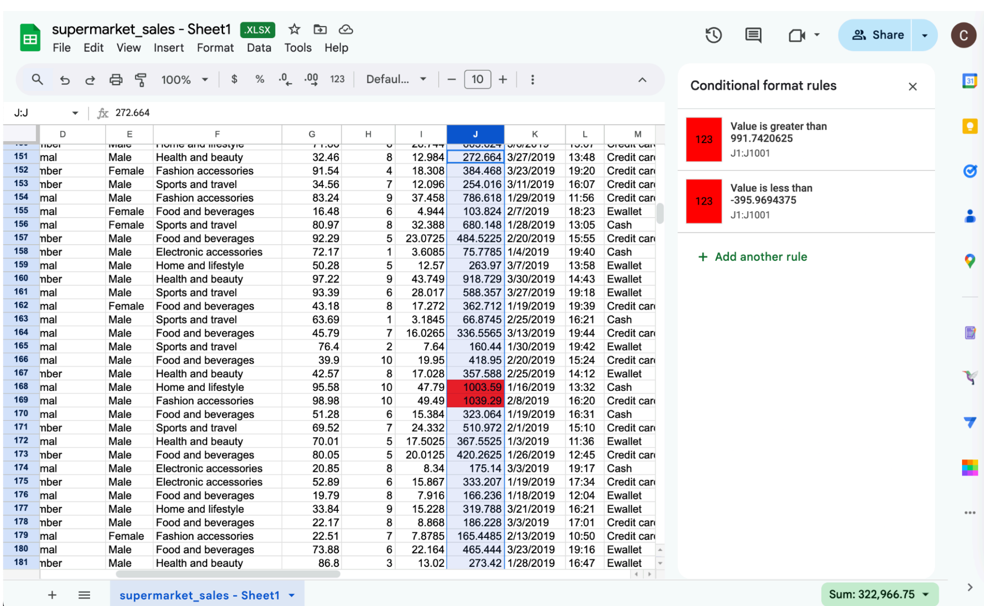
```
        Total       Date   Time      Payment   cogs  gross margin percentage  \
166  1003.590  1/16/2019  13:32         Cash  955.8                 4.761905
167  1039.290   2/8/2019  16:20  Credit card  989.8                 4.761905
350  1042.650  2/15/2019  14:53  Credit card  993.0                 4.761905
357  1002.120   1/9/2019  13:45         Cash  954.4                 4.761905
422  1020.705   2/8/2019  13:00  Credit card  972.1                 4.761905
557  1034.460  1/30/2019  20:23      Ewallet  985.2                 4.761905
699  1023.750  1/12/2019  16:18      Ewallet  975.0                 4.761905
792  1022.385  1/15/2019  13:48  Credit card  973.7                 4.761905
996  1022.490   3/2/2019  17:16      Ewallet  973.8                 4.761905

     gross income  Rating  Gender_Male  City_Naypyitaw  City_Yangon
166        47.790     4.8         True            True        False
167        49.490     8.7         True           False         True
350        49.650     6.6        False            True        False
357        47.720     5.2        False            True        False
422        48.605     8.7        False            True        False
557        49.260     4.5        False            True        False
699        48.750     8.0         True            True        False
792        48.685     4.9        False           False        False
996        48.690     4.4        False           False        False
Number of outliers: 9
```

Using custom format rules functionality in excel to color all the outliers present in the dataset

Eg -

1. Lower bound = -395.96 -> Coloring values less than Lower Bound
2. Upper bound = 991.74 -> Coloring values greater than Upper Bound





8) standardization and normalization of columns

Standardization is another scaling technique where the values are centered around the mean with a unit standard deviation. This means that the mean of the attribute becomes zero and the resultant distribution has a unit standard deviation.

Standardization equation

$$X' = \frac{X - \mu}{\sigma}$$

To standardize your data, we need to import the StandardScalar from the sklearn library and apply it to our dataset.

Normalization is a scaling technique in which values are shifted and rescaled so that they end up ranging between 0 and 1. It is also known as Min-Max scaling.

Normalization equation

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Here, Xmax and Xmin are the maximum and the minimum values of the feature respectively.

- When the value of X is the minimum value in the column, the numerator will be 0, and hence X' is 0
- On the other hand, when the value of X is the maximum value in the column, the numerator is equal to the denominator and thus the value of X' is 1
- If the value of X is between the minimum and the maximum value, then the value of X' is between 0 and 1

To normalize your data, you need to import the MinMaxScalar from the sklearn library and apply it to our dataset.

```
from sklearn.preprocessing import StandardScaler
# mean 0 karega and sd 1..this is standardization
scaler = StandardScaler()
df[['Unit price', 'Total']] = scaler.fit_transform(df[['Unit price', 'Total']])
```

```
[ ] from sklearn.preprocessing import MinMaxScaler
# this is normaliztion.....helps to scale data between 0-1
normalizer = MinMaxScaler()
df[['Unit price', 'Total']] = normalizer.fit_transform(df[['Unit price', 'Total']])
```

```
[ ] df.head()
```

	Branch	Customer type	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating	Gender_Male	City_Naypyitaw	City_Yangon
0	A	Member	Health and beauty	0.718847	7	26.1415	0.521616	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1	False	False	True
1	C	Normal	Electronic accessories	0.057855	5	3.8200	0.067387	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6	False	True	False
2	A	Normal	Home and lifestyle	0.403316	7	16.2155	0.319628	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4	True	False	True
3	A	Member	Health and beauty	0.535603	8	23.2880	0.463549	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4	True	False	True
4	A	Normal	Sports and travel	0.848131	7	30.2085	0.604377	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3	True	False	True

```
[ ] df.describe()
```

	Unit price	Quantity	Tax 5%	Total	cogs	gross margin percentage	gross income	Rating
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1.000000e+03	1000.000000	1000.00000
mean	0.507256	5.510000	15.379369	0.302613	307.58738	4.761905e+00	15.379369	6.97270
std	0.294778	2.923431	11.708825	0.238268	234.17651	6.131498e-14	11.708825	1.71858
min	0.000000	1.000000	0.508500	0.000000	10.17000	4.761905e+00	0.508500	4.00000
25%	0.253616	3.000000	5.924875	0.110220	118.49750	4.761905e+00	5.924875	5.50000
50%	0.502336	5.000000	12.088000	0.235636	241.76000	4.761905e+00	12.088000	7.00000
75%	0.754951	8.000000	22.445250	0.446400	448.90500	4.761905e+00	22.445250	8.50000
max	1.000000	10.000000	49.650000	1.000000	993.00000	4.761905e+00	49.650000	10.00000

Conclusion:

Thus we have understood how to perform data preprocessing which can further be taken into exploratory data analysis and further in the Model preparation sequence.