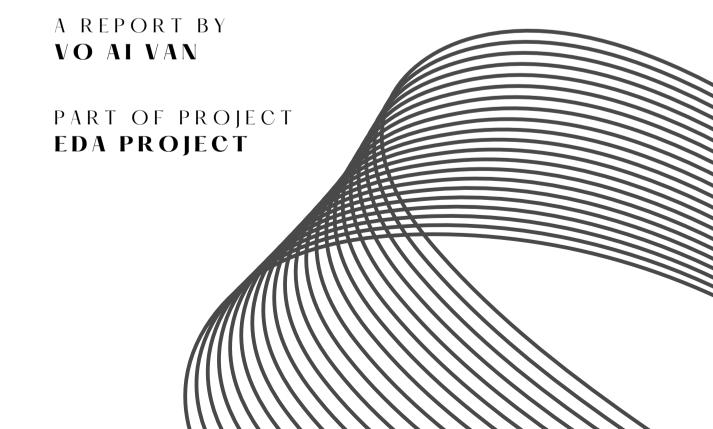
EDA with python



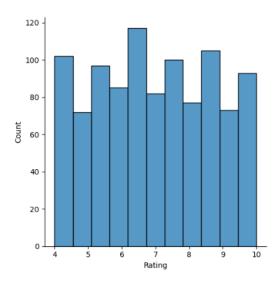


Figure 1: Plot on distribution of customer rating: sns.distplot(df['Rating']) plt.show()

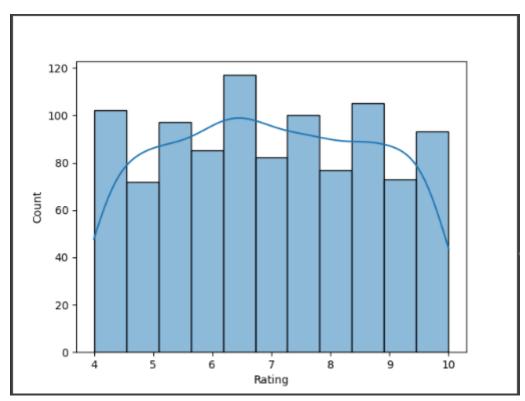


Figure 2: After adding a kernel density estimate to smooth the histogram and provide complementary information about the shape of the distribution. This distribution looks like a uniform distribution which means none of the rating number particularly spike out: sns.histplot (df['Rating'],kde=True)

plt.show()

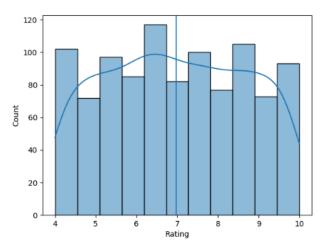


Figure 3: Mean rating in the graph: sns.histplot(df['Rating'], kde= True) plt.axvline(x=np.mean(df['Rating'])) plt.show()

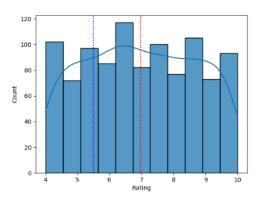


Figure 4: Percentile plot the line can be formatted in different support such as '-', '--', '-.', ':', 'None', '', ", 'solid', 'dashed', 'dashed', 'dotted' (25 percentile):

sns.histplot(df['Rating'],kde= True)
plt.axvline(x=np.mean(df['Rating']),c='red',ls=':')
plt.axvline(x=np.percentile(df['Rating'],25),c='blue',ls=':')
plt.show()

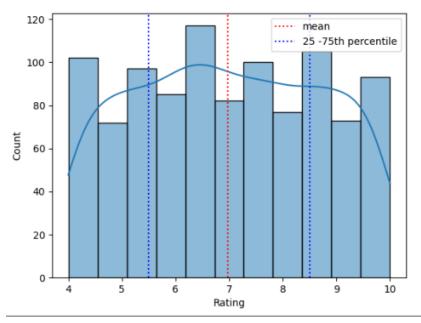


Figure 5: same function as *figure 4* but now we can also add label to the graph to indicate the line better:

```
sns.histplot(df['Rating'], kde= True)
plt.axvline(x=np.mean(df['Rating']),c='red',ls=':',label='mean')
plt.axvline(x=np.percentile(df['Rating'],25),c='blue',ls=':',label='25 -75th percentile')
plt.axvline(x=np.percentile(df['Rating'],75),c='blue',ls=':')
plt.legend()
plt.show()
```

Conclusion: from the graph, we can conclude that there is no skewed in left and right direction

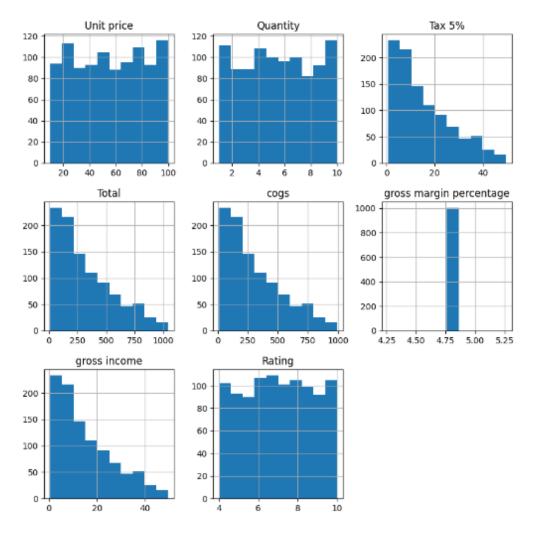


Figure 6: getting all the plot available for the dataset with figure size to avoid messed up plots:

df.hist(figsize=(10,10))
 plt.show()

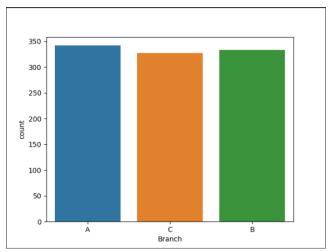
Conclusion:

uniform distributed: unit price, quantity, rating

tax: most of the tax collected fall between 0 and 20, some are at 40

constant value: gross margin percentage

fall precisely the same: total + gross income + cogs



350 - 300 - 250 - 250 - 150 - 100 - 50 - 100 - Ewallet Cash Payment Credit card

Figure 8: plot number of users for each type of payment: sns.countplot(df['Payment']) plt.show() df['Payment'].value_counts()

```
>>> df['Payment'].value_counts()

Ewallet 346

Cash 346

Credit card 311

Name: Payment, dtype: int64
```

Figure 9: show precise number for number of users on different type of payment

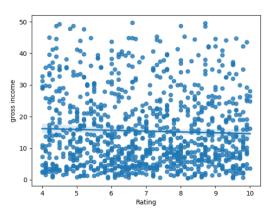
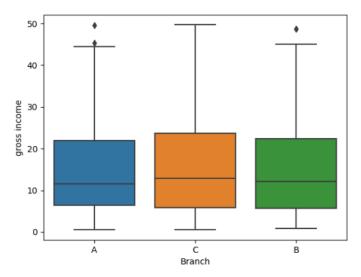


Figure 10: to know the relationship between gross margin and customer rating we use the following code. From that we can see the trend line seems to be very flat → there is no relation between them:

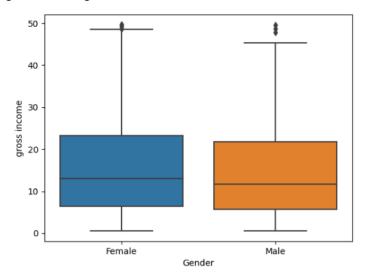
Similarly: we can also learn about the relationship between: branches and income:



sns.boxplot(x=df['Branch'],y=df['gross income'])
plt.show()

 \rightarrow Looking at $\,$ branch A, for instance, gross income is around 10 .And not much of variation between branches and gross income

gender and gross income:



sns.boxplot(x=df['Gender'],y=df['gross income'])
plt.show()

- → ON AVERAGE, both gender spend approximately the same
- → at 50th percentile women spend more than men

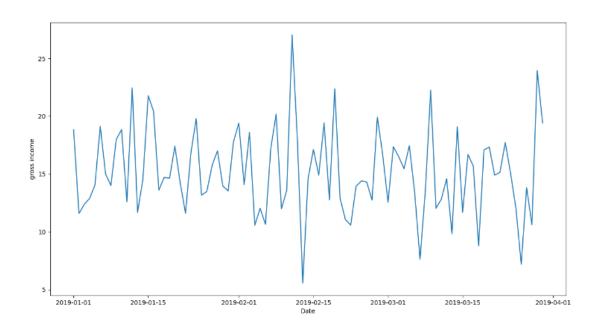


Figure 11: the graph shows lineplot for gross income each day:

plt.figure(figsize=(15,8))

sns.lineplot(x=df.groupby(df.index).mean().index,

y=df.groupby(df.index).mean()['gross income'])

plt.show()

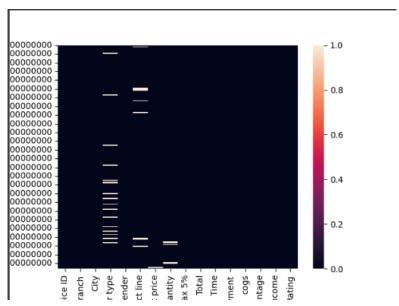


Figure 12: the heatmap indicating missing data: sns.heatmap(df.isnull(),cbar=False) # cbar is the color indicator plt.show()

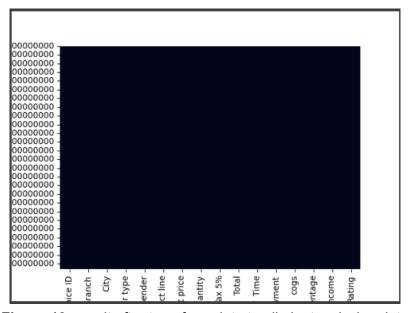


Figure 13: result after transform data to eliminate missing data

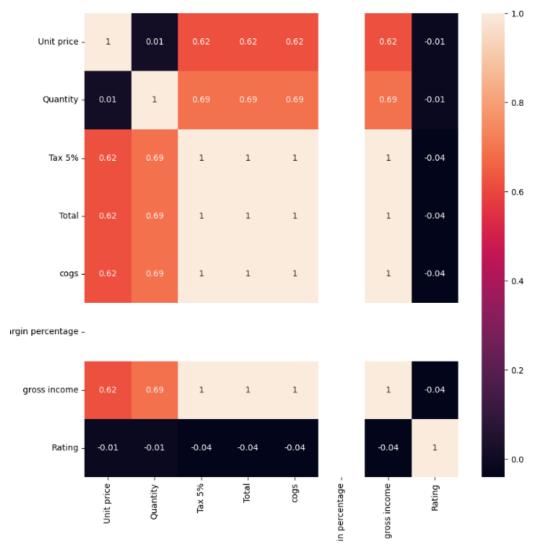


Figure 14: Correlation analysis
np.corrcoef(df['gross income'],df['Rating'])
round(np.corrcoef(df['gross income'],df['Rating']) [1][0],2) # pick and rounded to 2nd decimal
correlation matrix
round(df.corr(),2)

plt.figure(figsize=(10,10)) # resize the figure size in plots sns.heatmap(round(df.corr(),2),annot=True) plt.show()