Answers

STEPS TO STEPS TO TAKE BEFORE STARTING ANY ANALYSIS:

1) The first step in data analysis is to clearly define your questions and goals,

- Similar to creating a hypothesis before an experiment, you should be asking a targeted question before searching the data for an answer. What problems are you trying to solve? Which parts of your business do you want more information about? Are you trying to solve an existing problem or predict how your company will perform based on determined factors? Clearly defining your goals will help guide the rest of the analysis process. For example, questions about overall performance can be open-ended and it can be hard to pinpoint which metrics are needed for analysis. Instead, it is more advantageous to ask questions such as “How have certain metrics changed over time?” and “Do these metrics correlate with others, and if so, how strongly?” These types of questions have a specific focus which will help determine the type of analysis needed and what data is the most relevant to include.

2) Now we need to COLLECT DATA as per our requirements

- Before you can start analyzing, there needs to be data available for use. Data can include sales records, customer demographics, lead tracking, net promoter scores, and more. When using a business intelligence tool, it is important to make sure that all of the data is accessible and the proper connections are set between your data warehouse and your BI tool of choice. Ultimately the volume of data required will depend on the question you wish to answer. Though you may only need a subset of the data collected, not having enough data can skew the results of your analysis

3) Cleaning the data or in terms DATA WRANGLING

- Now that you have all of your data in one place, it is important to clean the data before beginning the analysis portion of this process. A large part of the cleansing process includes making sure that the data is in a usable format. This entails searching for outliers, dealing with null values, and looking for data that may have been incorrectly input. Often this can be a lengthy and arduous process. A recent survey among Data Science professionals indicated that Data Analysts spend approximately 27% of their time cleansing data. While it may not be glamorous or the most enjoyable portion of the data analysis process, data cleansing is crucial to optimize the accuracy of your analysis.

WHAT WE NEED TO MAKE SURE OF BEFORE STARTING ANY ANALYSIS:

- Before starting any analysis we need to be sure of few things first of all we need to make sure that our data is corrected properly that we have got rid of all the redundant variables after getting rid of all the redundant variables and making sure that our data is in correct format we need to translate our data into readable format and you need to make sure of the inclusion and exclusion criteria .in basic terms we need to be sure of the term to include in analysis and terms which we need to exclude from analysis and this is a crucial step because we are defining the most important things in our data which are useful in defining the analysis and can provide us with useful insights. Based on the type of analysis which we are going to perform we need to make sure of the metrics. Well in this case since we are performing rfm analysis we need to be sure of how we need to calculate recency or frequency score and what is a good monetization threshold for our data.

WHAT COULD ENRICH OUR DATASET

- If we have age of each customer provided in the dataset we could perform an analysis based on age group and find out which age group is our strongest customer base and plan an action accordingly , for example launching new product specifically targeted for certain age group or planning our advertisement to attract certain age group.

RFM Analysis

Before starting with RFM we should know something about Customer Segmentation,

Customer segmentation is the process of dividing customers into groups based on common characteristics so companies can market to each group effectively and appropriately. A company might segment customers according to a wide range of factors, including but not limited to:

- Customer Demographics
- Transaction history
- Location

Why Segment Customers?

Segmentation allows marketers to better tailor their marketing efforts to various audience subsets. Those efforts can relate to both communications and product development. Specifically, segmentation helps a company,

- Select the best communication channel for the segment, which might be email, social media posts, radio advertising, or another approach, depending on the segment.
- Identify ways to improve products or new product or service opportunities.
- Establish better customer relationships.
- Test pricing options.
- Upsell and cross-sell other products and services.

How to Segment Customers?

Customer segmentation requires a company to gather specific information about customers and analyze it to identify patterns that can be used to create segments.Some of that can be gathered from the customers purchasing information such as Date of Purchase, geography, products purchased, etc. Some of it might be gleaned from how the customer entered your system. An online marketer working from an opt-in email list might segment marketing messages according to the opt-in offer that attracted the customer, Other information, however, including consumer demographics such as age and marital status, will need to be acquired in other ways.

For my analysis I have to used techinque called RFM analysis, where:

- R - Recency: Recency is how recently for the date of analysis did the customer make a purchase. Customers who have purchased recently are more likely to purchase again when compared to those who did not purchase recently.

- F - Frequency: Frequency is how often did the customer made purchases. The higher the frequency, the higher is the chances of these responding to the offers.

- M - Monetary: Monetary is the total revenue generated by the customer through thier purchases. Customers who have spent higher contribute more value to the business as compared to those who have spent less

In [ ]:

```
# importing all the neccessary libraries incase need to use , in most cases i will use 4 to 5 libra
import pandas as pd ## for feautre engineering
import numpy as np  ## for feautre engineering
import matplotlib as mpl ## for plot
import matplotlib.pyplot as plt ## for plot
import seaborn as sns  ## for plot
import datetime, nltk, warnings
```

```
import matplotlib.cm as cm
from sklearn.decomposition import NMF
import itertools
from pathlib import Path
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score
from sklearn import preprocessing, model_selection, metrics, feature_selection
from sklearn.decomposition import PCA
from sklearn.decomposition import SparsePCA
from IPython.display import display, HTML
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation
import matplotlib.pyplot as plt
import math
color = sns.color_palette()
warnings.filterwarnings("ignore")
plt.rcParams["patch.force_edgecolor"] = True
plt.style.use('fivethirtyeight')
mpl.rc('patch', edgecolor = 'dimgray', linewidth=1)
%matplotlib inline
```

In [5]:

```
# read the datafile

# Loading the dataset:
dataset = pd.read_excel("C:/Users/mk98s/Desktop/python scripts/test_msa_bb.xlsx")
display(dataset.shape) # this tell us what size is our data how many raws and columns

# Top 10 observations of our data:
display(dataset.head(10))
```

```
(300000, 19)
```

	email	phone	
0	5b31baf92171234adacc3aaf0ee5a14cf0b1adb35194	3567550f9cf51d6b9fe94cbbf17f8cf5da83677b20a6	be34ad33b31774d
1	b47a23dfa8a71dd52879e32b46b95d3b0673e6ea38b0	0ff8479f1516d3de1091624ded4b0eeb2a0144854801	e6d5c8867b7a46d
2	6929f69b848bb6ea80905aa169a80c962644f6e1ea89	09a7a47a69b67e1d65c4ce385ec430bf49397261f38c	208ad55e4c4200
3	c5c2d17bbf20b772ff72abfcb2f5021cf02cebe422d3	c15aa8b05de5ccd5816dc3f69e8babbff8b8998b0e64	f805bcb3efc982e
4	e60a1afac6a840b383ad8172de7304eb404348e72f66	f09585362157ce6813345220cc5de55cc72e01c9905f	09c12d01508bb6b
5	620c6031417106c60575a1b500b4a49ac92694436dd3	b7b92384a7a4ba7a7f3eb016873a382c8664e7ee2a2d	d70f47790f6894
6	609f7d8ce047d04f036537281797e86efb556e4701dd	ea93f73fbea0390fafb333c3899d49f207433d3d9d80	f51ab9d849938a4
7	5485bed91c1320b157961987bef8e7065caac91077e5	fd896e75c364cfdce3b60a9d6da34fa1613918228259	a79c356d145709bd
8	93e5d078ca75594f3ba172dca80a49b465cf3d94acbb	7a23221c9a68883eafbd95f12e43930762c62e128fdb	8d0cfd6182ef851
9	59cd89e6b93fed11b123b6111fccb8ca394360cb63de	5052a5146e1a95bcc5f2f3a3dfc3fd9321bb2b157b4b	cd71fa4239dac42

In [6]:

```
# Checking the stastics of the dataset
display(dataset.describe())
```

	state	birthday_year	gender	age	conversion_id	conversion_value	conversion_value_margin	handling_cost
count	0.0	0.0	0.0	0.0	300000.000000	300000.000000	300000.000000	300000.000000
mean	NaN	NaN	NaN	NaN	781250.550087	939.881778	268.354929	-61.902571
std	NaN	NaN	NaN	NaN	133699.604353	1506.028013	553.698287	38.519695
min	NaN	NaN	NaN	NaN	219371.000000	-341831.100000	-116096.530000	-274.100000
25%	NaN	NaN	NaN	NaN	661873.750000	507.000000	39.600000	-91.500000
50%	NaN	NaN	NaN	NaN	800083.000000	897.000000	237.820000	-76.500000

	state	birthday_year	gender	age	conversion_id	conversion_value	conversion_value_margin	handling_cost
75%	NaN	NaN	NaN	NaN	899629.250000	1365.000000	478.527500	-33.500000
max	NaN	NaN	NaN	NaN	982191.000000	341831.100000	116096.530000	803.500000

In [7]:

```
# converting conversion date to datetime
dataset['conversion_date'] = pd.to_datetime(dataset['conversion_date'])

#______________________________________________________________
# some info on columns types and find number of columns with null values
tab_info=pd.DataFrame(dataset.dtypes).T.rename(index={0:'column type'})
tab_info=tab_info.append(pd.DataFrame(dataset.isnull().sum()).T.rename(index={0:'null values (nb)'}
tab_info=tab_info.append(pd.DataFrame(dataset.isnull().sum()/dataset.shape[0]*100).T.
                         rename(index={0:'null values (%)'}))

# displaying the observations with missing values and thier percentage count
display(tab_info)
```

	email	phone	first_name	last_name	zip	city	state	country	birthday_year	gender	age	con
column type	object	object	object	object	object	object	float64	object	float64	float64	float64	
null values (nb)	0	0	0	0	0	10	300000	0	300000	300000	300000	
null values (%)	0.0	0.0	0.0	0.0	0.0	0.003333	100.0	0.0	100.0	100.0	100.0	

In [34]:

```
print('Duplicate Entries: {}'.format(dataset.duplicated().sum()))
dataset[(dataset.conversion_date == 2020-8-8) & (dataset.conversion_id == 918183) & (dataset.conver

# Our data is quite clean without any duplicate entries Incase if we have any we can drop them in t
```

```
Duplicate Entries: 0
```

Out[34]:

email	phone	first_name	last_name	zip	city	state	country	birthday_year	gender	age	conversion_name	conv

In [9]:

```
# dropping values with duplicate entries
dataset.drop_duplicates(inplace = True)

dataset.shape
```

Out[9]:

```
(291720, 19)
```

In [10]:

```
temp = dataset[['conversion_name', 'conversion_id', 'country']].groupby(['conversion_name', 'conver
temp = temp.reset_index(drop = False)
countries = temp['country'].value_counts()
print('The Online Retail Company covers : {} countries'.format(len(countries)))

# counting the countries in our dataset as it can be a crucial part of our analysis
```

```
The Online Retail Company covers : 26 countries
```

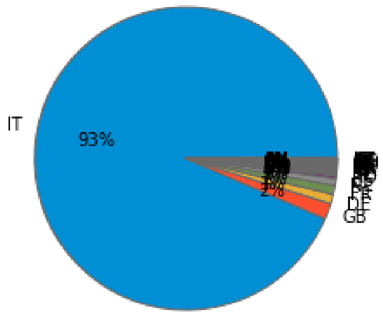
In [11]:

```
dataset['conversion_name'].value_counts()
# WOW, puchase rate's quite good for our data but anyway we need to get new customers
```

Out[11]:

```
Purchase          260173
Return             18803
Cancel              8556
ReturnToSender      4188
Name: conversion_name, dtype: int64
```

In [12]:
```
plt.pie(dataset.country.value_counts(),
        labels=dataset.country.value_counts().index,
        autopct='%.0f%%')
plt.show()
# Italia , here we go our 93% customer base is in italy,
# we could use a seperate analysis just for italia.
```



In [13]:
```
dataset_it = dataset[dataset.country == 'IT']
dataset_it.shape
# representing the dataset just for ITALIA
```

Out[13]:
```
(272729, 19)
```

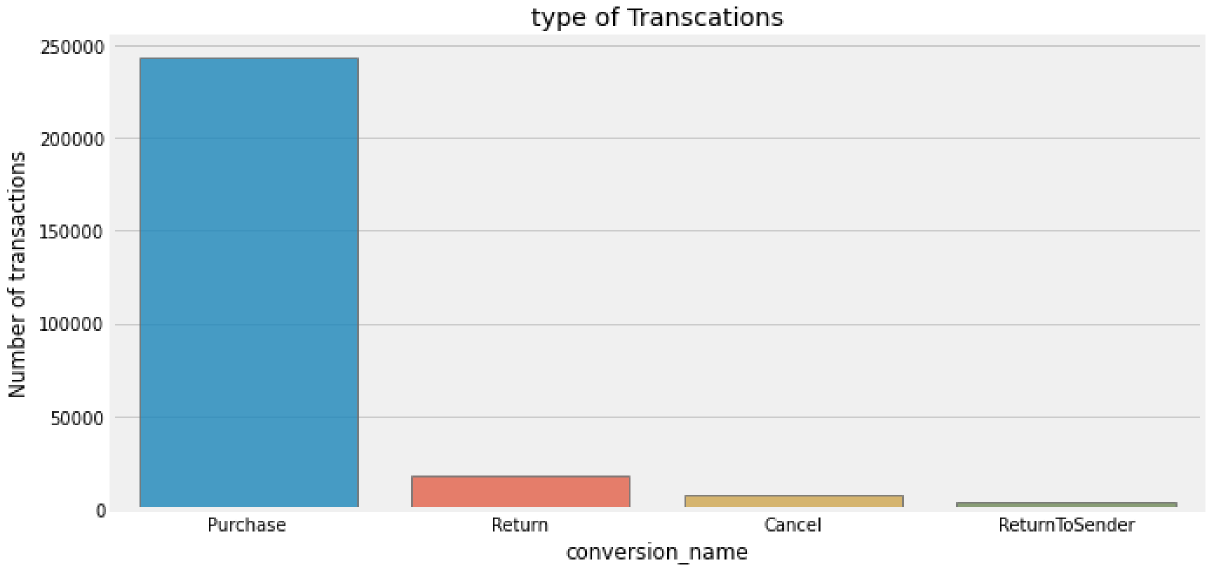
In [14]:
```
dataset_it['conversion_name'].value_counts()
```

Out[14]:
```
Purchase          242877
Return             17864
Cancel              7926
ReturnToSender      4062
Name: conversion_name, dtype: int64
```

In [15]:
```
# JUST MAKING SURE IF ITS CORRECT OR NOT
dataset_it.groupby('conversion_name').size()
```

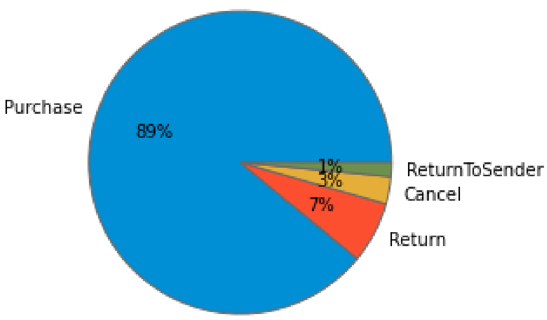
Out[15]:
```
conversion_name
Cancel              7926
Purchase          242877
Return             17864
ReturnToSender      4062
dtype: int64
```

In [16]:
```
# LETS REPRESENT OUR CONVERSIONS AND SEE HOW IT LOOKS VISUALLY

conversion_count  = dataset_it['conversion_name'].value_counts()
conversion_count = conversion_count[:5,]
plt.figure(figsize=(10,5))
sns.barplot(conversion_count.index, conversion_count.values, alpha=0.8)
plt.title('type of Transcations')
plt.ylabel('Number of transactions', fontsize=12)
plt.xlabel('conversion_name', fontsize=12)
plt.show()

# Here's our Leaning tower of purchase
```



In [17]:

```
plt.pie(dataset_it.conversion_name.value_counts(),
        labels=dataset_it.conversion_name.value_counts().index,
        autopct='%.0f%%')
plt.show()
# HERE WE CAN PLOT OUR CONVERSION PERCENTAGE WE CAN SEE THAT IN ITALY 89% PUCHASES WERE SUCCESSFULL
```



In [18]:

```
dataset_it['city'].value_counts()
```

Out[18]:

```
roma                              10032
milano                             7754
napoli                             3476
torino                             3000
bologna                            2038
                                  ...
san dorligo della valle-dolina        1
lucugnano di tricase                  1
firenze osmannoro                     1
riscone                               1
lido marini di ugento                 1
Name: city, Length: 13988, dtype: int64
```

In [19]:

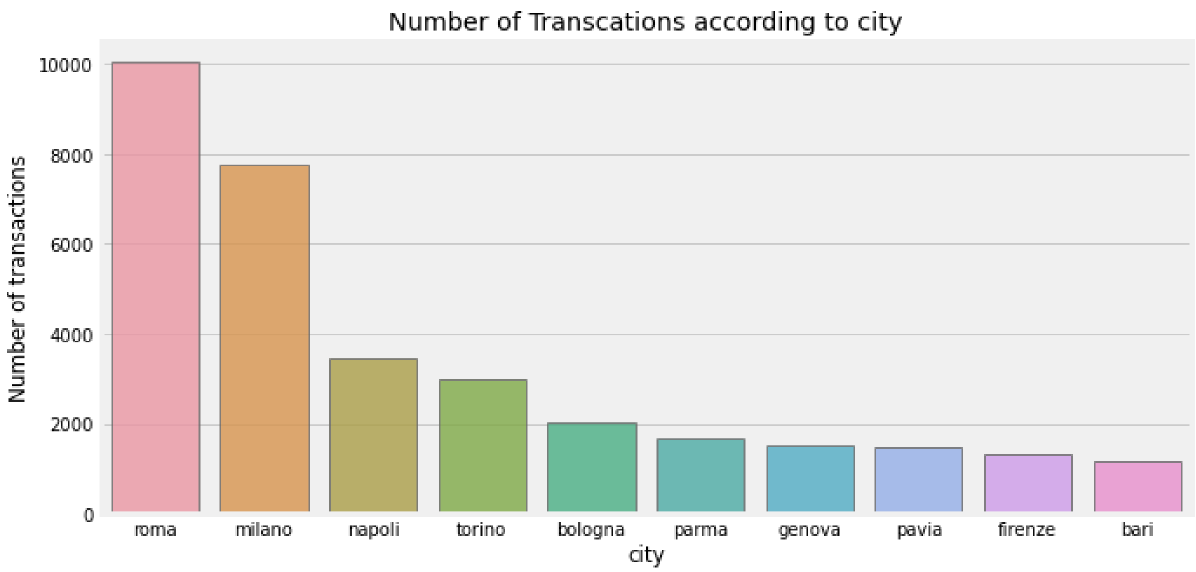
```
display(dataset_it.sort_values('conversion_date')[:10])

# just sorting the data based on date
```

	email	phone	
87387	7866162ba31eec860e6843f07fefceb7f665a1074076	aae9fbff852d6fce490b9f0d9667d84eac689e00d356	ffe138c168
18108	713753d111fff6fde430aba308a25f6a477782e31ba3	26264c0fb41bf3d2800968ec6b4910be891c4e16bff2	bb3625483b
225475	4f79ebda2dc87893942a5a5411be8fc21e4718977e26	dd7d330115c1d21d46e0cba238846e82ee688392e2d3	e4c2eed8a
140554	12ecb707fba5f5c4be6d999ab785d4904decce981c67	11a2cc92d1c59b041a3e1b5c20d81e0be704d7516680	4d462242da

	email	phone	
18101	8bc5c83b496db5b87ed4ba142f4736855aa94e5d6f92	307f71c42a99a8c6288f37ba7ebc6383d400987506c8	76151dc2a2
225383	8721248d281ff63b193f7b79ee220bd22d7ba237e532	7c773a34726b8ab0e41f320550d0b800793226912535	254835d73c
149799	0a3ea1291c2017571a870238375e29fd9792dedcd19b	5e405c36308777ca73299b6bb50b18248bc01ee0b1aa	208ad55e
82056	2563933e137b052a3435cc255d6a5e96a2605ccbb2b2	d9720a6c2cf73a0908a9792bc4fde1592e0ac04594e8	a66fad2bfc
38654	f9e5df8b3971798aa84187daa6c717ce400e76711bf0	d63a3ccd02f65fad5885a315ad6d697bdaa2536b278c	657543898
38631	942138a06704f0ea0d496c4fcdc8897d8e9c46cbaef7	e76b3b9a940b8bc9e7b74e18fa337c0adf411357654c	5e9286da8

In [39]:

```
city_count  = dataset_it['city'].value_counts()
city_count = city_count[:10,]
plt.figure(figsize=(10,5))
sns.barplot(city_count.index, city_count.values, alpha=0.8)
plt.title('Number of Transcations according to city')
plt.ylabel('Number of transactions', fontsize=12)
plt.xlabel('city', fontsize=12)
plt.show()
```



In [21]:

```
Cust_date_it=dataset_it[dataset_it['country']=='IT']
Cust_date_it=Cust_date_it[['conversion_name','conversion_date']].drop_duplicates()

# now if Needed we can do a seperate rfm analysis for ITALIA only but I will proceed with all the d
```

In [22]:

```
dataset_recency = dataset.groupby(by='email',
                        as_index=False)['conversion_date'].min()
dataset_recency.columns = ['email', 'LastPurchaseDate']
recent_date = dataset_recency['LastPurchaseDate'].min()
dataset_recency['Recency'] = dataset_recency['LastPurchaseDate'].apply(
    lambda x: (recent_date - x).days)
dataset_recency.head()

# starting off we calculate the recency
```

Out[22]:

	email	LastPurchaseDate	Recency
0	00001b2e4eb7289182f1834c7360e103a4bd0668aead	2019-02-14	-44
1	000070d28dd1463499ae00c25975526ee400790297a6	2020-06-05	-521
2	0000a860ea4b614addb407de1f5c0cd98ca487d80370	2019-06-20	-170

	email	LastPurchaseDate	Recency
3	0000b4a6700e0329a114c99ef3801e6b716080549210	2020-06-05	-521
4	0001160167ed97aa7f7ceac519ef53207561b0599308	2019-01-01	0

In [23]:
```
display(dataset_recency.sort_values('Recency')[:10])
```

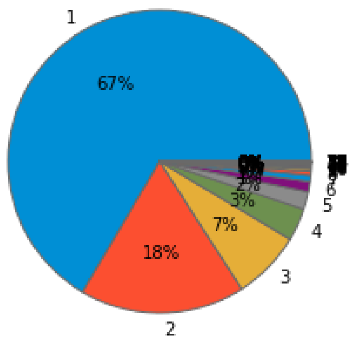
	email	LastPurchaseDate	Recency
140228	d6ed837eea6e60b73da0ee53f7cf037187c12585b6d3	2020-12-01	-700
65386	645b9499629bbfb448a6d0065b1b271dfdb4304f9ad7	2020-12-01	-700
144027	dcb1764245d4fae5153be2a3e42cfd870644c1b443ae	2020-12-01	-700
19125	1d2829f8fe46f06272d06976b512aaa1d6c2d31b56d8	2020-12-01	-700
68831	69c5381442eca176bc32e5a0df89f554469958ed5d4c	2020-12-01	-700
116246	b2104c0aa38dd90f8ea72b97e141aa165b714d785d4e	2020-12-01	-700
154682	ecf37d7708bb2bb7cfe3a6ab7963783e190b9ae59613	2020-12-01	-700
117384	b3e6b95f379a7405d5b17b182872b5d7ef0452bcceeb	2020-12-01	-700
4546	06b88834a71ffcd1ba16c44804c110286484852f8417	2020-12-01	-700
125199	bfce321737d9f580ff251b560ff41490cb027910a06f	2020-12-01	-700

In [24]:
```
frequency_dataset = dataset.drop_duplicates().groupby(
    by=['email'], as_index=False)['conversion_date'].count()
frequency_dataset.columns = ['email', 'Frequency']
frequency_dataset.head()

# now we calculate the frequency
```

Out[24]:

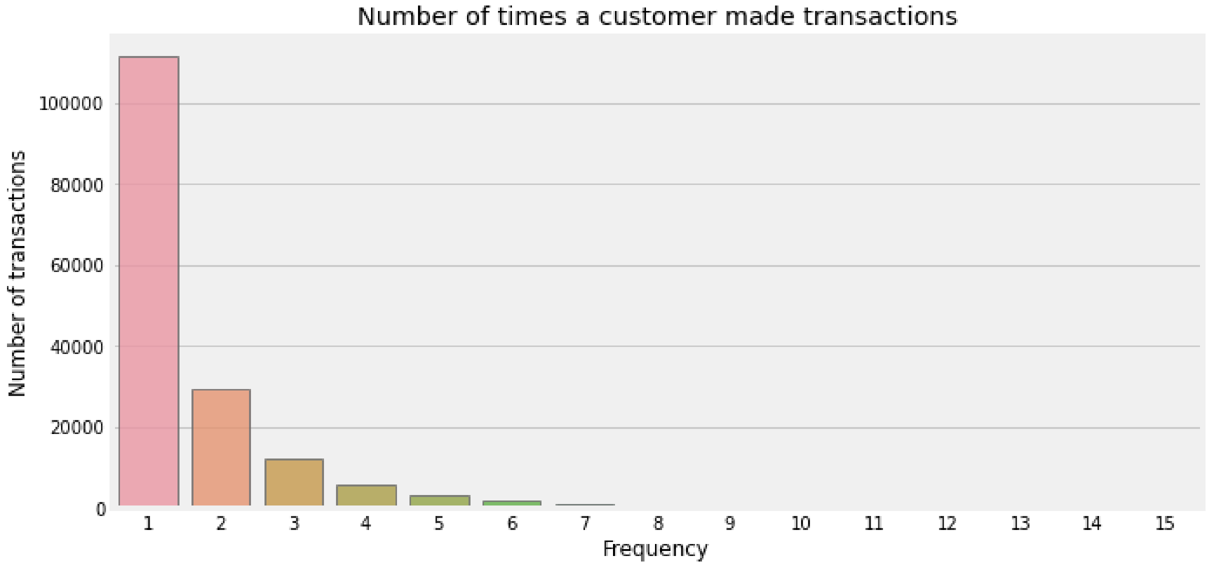
	email	Frequency
0	00001b2e4eb7289182f1834c7360e103a4bd0668aead	1
1	000070d28dd1463499ae00c25975526ee400790297a6	1
2	0000a860ea4b614addb407de1f5c0cd98ca487d80370	1
3	0000b4a6700e0329a114c99ef3801e6b716080549210	1
4	0001160167ed97aa7f7ceac519ef53207561b0599308	11

In [25]:
```
plt.pie(frequency_dataset.Frequency.value_counts(),
        labels=frequency_dataset.Frequency.value_counts().index,
        autopct='%.0f%%')
plt.show()
```



In [41]:
```
freq_count  = frequency_dataset['Frequency'].value_counts()
freq_count = freq_count[:15,]
```

```
plt.figure(figsize=(10,5))
sns.barplot(freq_count.index, freq_count.values, alpha=0.8)
plt.title('Number of times a customer made transactions')
plt.ylabel('Number of transactions', fontsize=12)
plt.xlabel('Frequency', fontsize=12)
plt.show()
```



In [27]:

```
display(frequency_dataset.sort_values('Frequency')[:10])
```

	email	Frequency
0	00001b2e4eb7289182f1834c7360e103a4bd0668aead	1
100163	99a30a3853c10d7b569d106efa141fbf3e700f989be4	1
100162	99a2d7f0a1589ff15e87e873b3bffa263864dbb4d9d8	1
100160	99a2317bf2b98b67054220ae5f9e94b2bea1f54a138b	1
100159	99a2022836cad5b9710181563944fc15b7cd499ad6fb	1
100158	99a16d983cc4c2fd4b7f1c63b7b87b0c704d4a26907c	1
100156	99a14d76a4c0543b4be8022c23b46ecc6a3efade54e0	1
100155	99a127f91268f01733374e0dd3138091e4f4420dc39d	1
100154	99a10c61485ff52120247087127d86870277a4c47a80	1
100152	999fa6fbfdfb958fbf54dbb56a67009ef02cc67ffb86	1

In [28]:

```
dataset['Total'] = dataset['conversion_value']+dataset['handling_cost']
monetary_dataset = dataset.groupby(by='email', as_index=False)['Total'].sum()
monetary_dataset.columns = ['email', 'Monetary']
monetary_dataset

# calculating the monetary value , here we can see the dataset getting reduced that
# means I have combined the customers who made two ore more transactins
```

Out[28]:

	email	Monetary
0	00001b2e4eb7289182f1834c7360e103a4bd0668aead	330.5
1	000070d28dd1463499ae00c25975526ee400790297a6	169.3
2	0000a860ea4b614addb407de1f5c0cd98ca487d80370	268.1
3	0000b4a6700e0329a114c99ef3801e6b716080549210	615.7
4	0001160167ed97aa7f7ceac519ef53207561b0599308	10106.9
...	...	...

	email	Monetary
167225	fffee6da05a8346478f60275454a510eedc6693ed09f	3736.0
167226	ffff447aa42252107b1181612d6a3c5d65f1248dd882	1610.5
167227	ffff721154544dfc09eb70ee87309631775da51c82ef	1143.5
167228	ffffac7d8e5f76e72616c5e7b7b15b7678767cb599da	591.0
167229	ffffb70cf1a4d3c43b10eaf8385055da6fc98d599261	-859.6

167230 rows × 2 columns

In [ ]:

In [29]:

```
# merging all the values together to represent customers all three ratings i.e R, F, and M
rf_dataset = dataset_recency.merge(frequency_dataset, on='email')
rfm_dataset = rf_dataset.merge(monetary_dataset, on='email').drop(
    columns='LastPurchaseDate')
rfm_dataset.head()
```

Out[29]:

	email	Recency	Frequency	Monetary
0	00001b2e4eb7289182f1834c7360e103a4bd0668aead	-44	1	330.5
1	000070d28dd1463499ae00c25975526ee400790297a6	-521	1	169.3
2	0000a860ea4b614addb407de1f5c0cd98ca487d80370	-170	1	268.1
3	0000b4a6700e0329a114c99ef3801e6b716080549210	-521	1	615.7
4	0001160167ed97aa7f7ceac519ef53207561b0599308	0	11	10106.9

In [ ]:

In [30]:

```
display(rfm_dataset.sort_values('Frequency')[:10])
```

	email	Recency	Frequency	Monetary
0	00001b2e4eb7289182f1834c7360e103a4bd0668aead	-44	1	330.50
100163	99a30a3853c10d7b569d106efa141fbf3e700f989be4	-309	1	709.30
100162	99a2d7f0a1589ff15e87e873b3bffa263864dbb4d9d8	-558	1	488.50
100160	99a2317bf2b98b67054220ae5f9e94b2bea1f54a138b	-635	1	972.00
100159	99a2022836cad5b9710181563944fc15b7cd499ad6fb	-36	1	1355.40
100158	99a16d983cc4c2fd4b7f1c63b7b87b0c704d4a26907c	-510	1	805.50
100156	99a14d76a4c0543b4be8022c23b46ecc6a3efade54e0	-689	1	480.00
100155	99a127f91268f01733374e0dd3138091e4f4420dc39d	-173	1	584.50
100154	99a10c61485ff52120247087127d86870277a4c47a80	-267	1	1715.50
100152	999fa6fbfdfb958fbf54dbb56a67009ef02cc67ffb86	-381	1	607.35

In [31]:

```
rfm_dataset.sort_values("Recency", axis = 0, ascending = True,
                 inplace = True, na_position ='first')

rfm_dataset
```

Out[31]:

	email	Recency	Frequency	Monetary
140228	d6ed837eea6e60b73da0ee53f7cf037187c12585b6d3	-700	1	654.70

	email	Recency	Frequency	Monetary
65386	645b9499629bbfb448a6d0065b1b271dfdb4304f9ad7	-700	1	343.50
144027	dcb1764245d4fae5153be2a3e42cfd870644c1b443ae	-700	1	1585.50
19125	1d2829f8fe46f06272d06976b512aaa1d6c2d31b56d8	-700	1	718.40
68831	69c5381442eca176bc32e5a0df89f554469958ed5d4c	-700	1	1975.50
...	...	...	...	...
38854	3b7d50dca83fdb24a39da9cfe367ef4fa29b0fed2032	0	2	2255.80
5284	07de073bef543387ec5112ad744a9e5c61c88cba8f99	0	2	1093.90
38731	3b4e6898e1a0fb818a91ebae6d3cecdcb6a19bb43265	0	1	1037.00
146740	e0b1c7e4528fec57cb9f71bfbbf3ec9b848a9787ec95	0	3	686.40
140706	d7b23a82effc1d01321a83bf3ba9eac2810bbc7b0b33	0	2	1276.25

167230 rows × 4 columns

In [45]:

```
# HERE I have ranked the customers based on R,F, and M
rfm_dataset['R_rank'] = rfm_dataset['Recency'].rank(ascending=True)
rfm_dataset['F_rank'] = rfm_dataset['Frequency'].rank(ascending=True)
rfm_dataset['M_rank'] = rfm_dataset['Monetary'].rank(ascending=True)

# normalizing the rank of the customers
rfm_dataset['R_rank_norm'] = (rfm_dataset['R_rank']/rfm_dataset['R_rank'].max())*100
rfm_dataset['F_rank_norm'] = (rfm_dataset['F_rank']/rfm_dataset['F_rank'].max())*100
rfm_dataset['M_rank_norm'] = (rfm_dataset['F_rank']/rfm_dataset['M_rank'].max())*100

rfm_dataset.drop(columns=['R_rank', 'F_rank', 'M_rank'], inplace=True)

rfm_dataset.head()
```

Out[45]:

	email	Recency	Frequency	Monetary	R_rank_norm	F_rank_norm
140228	d6ed837eea6e60b73da0ee53f7cf037187c12585b6d3	-700	1	654.7	0.222854	33.262274
65386	645b9499629bbfb448a6d0065b1b271dfdb4304f9ad7	-700	1	343.5	0.222854	33.262274
144027	dcb1764245d4fae5153be2a3e42cfd870644c1b443ae	-700	1	1585.5	0.222854	33.262274
19125	1d2829f8fe46f06272d06976b512aaa1d6c2d31b56d8	-700	1	718.4	0.222854	33.262274
68831	69c5381442eca176bc32e5a0df89f554469958ed5d4c	-700	1	1975.5	0.222854	33.262274

In [47]:

```
# scoring customers
rfm_dataset['RFM_Score'] = 0.15*rfm_dataset['R_rank_norm']+0.28 * \
    rfm_dataset['F_rank_norm']+0.57*rfm_dataset['M_rank_norm']
rfm_dataset['RFM_Score'] *= 0.05
rfm_dataset = rfm_dataset.round(2)
rfm_dataset[['email', 'RFM_Score']].head(7)
```

Out[47]:

	email	RFM_Score
140228	d6ed837eea6e60b73da0ee53f7cf037187c12585b6d3	1.42
65386	645b9499629bbfb448a6d0065b1b271dfdb4304f9ad7	1.42
144027	dcb1764245d4fae5153be2a3e42cfd870644c1b443ae	1.42
19125	1d2829f8fe46f06272d06976b512aaa1d6c2d31b56d8	1.42
68831	69c5381442eca176bc32e5a0df89f554469958ed5d4c	1.42
116246	b2104c0aa38dd90f8ea72b97e141aa165b714d785d4e	1.42
154682	ecf37d7708bb2bb7cfe3a6ab7963783e190b9ae59613	1.42

In [49]:

```
# segmenting customers based on the RFM ranking which eventually provides us with an insight which
rfm_dataset["Customer_segment"] = np.where(rfm_dataset['RFM_Score'] >
                                       4.5, "Top Customers",
                                       (np.where(
                                         rfm_dataset['RFM_Score'] > 4,
                                         "High value Customer",
                                         (np.where(
rfm_dataset['RFM_Score'] > 3,
                             "Medium Value Customer",
                             np.where(rfm_dataset['RFM_Score'] > 1.6,
                            'Low Value Customers', 'Lost Customers'))))))
rfm_dataset[['email', 'RFM_Score', 'Customer_segment']].head(20)
```

Out[49]:

	email	RFM_Score	Customer_segment
140228	d6ed837eea6e60b73da0ee53f7cf037187c12585b6d3	1.42	Lost Customers
65386	645b9499629bbfb448a6d0065b1b271dfdb4304f9ad7	1.42	Lost Customers
144027	dcb1764245d4fae5153be2a3e42cfd870644c1b443ae	1.42	Lost Customers
19125	1d2829f8fe46f06272d06976b512aaa1d6c2d31b56d8	1.42	Lost Customers
68831	69c5381442eca176bc32e5a0df89f554469958ed5d4c	1.42	Lost Customers
116246	b2104c0aa38dd90f8ea72b97e141aa165b714d785d4e	1.42	Lost Customers
154682	ecf37d7708bb2bb7cfe3a6ab7963783e190b9ae59613	1.42	Lost Customers
117384	b3e6b95f379a7405d5b17b182872b5d7ef0452bcceeb	1.42	Lost Customers
4546	06b88834a71ffcd1ba16c44804c110286484852f8417	1.42	Lost Customers
125199	bfce321737d9f580ff251b560ff41490cb027910a06f	1.42	Lost Customers
61447	5e329d744f8c53ad7473c4c25716d508ffc4a4ac4625	1.42	Lost Customers
46940	47ef78ee02684037abb1d76d82be71dd1df6d552c24f	1.42	Lost Customers
102041	9c7f5e9c442eb0b9df9e4c4e7f43c286330c31ddfd8f	1.42	Lost Customers
3913	05cb1eaf5c7ecaa58ccef6d82fe595da581cc5a8a28a	1.42	Lost Customers
103215	9e4d691503cd79af47a5020fa4aef3e5e010dd711b65	1.42	Lost Customers
123804	bda997cacad4c91409f6d4f66434876b5f6fffa48514	1.42	Lost Customers
144013	dcad98b1a500a31da46910e15d126dcd52dbca61f120	1.42	Lost Customers
56127	5615e675bfdaf153d3455b1a1ede2f7c4d9702b87798	1.42	Lost Customers
116094	b1d5eb21f28d113ccf8c38896a2bc6944e854fc89e27	1.42	Lost Customers
38832	3b75263b79b5c262b602d927586c4f0e416c7122457f	1.42	Lost Customers

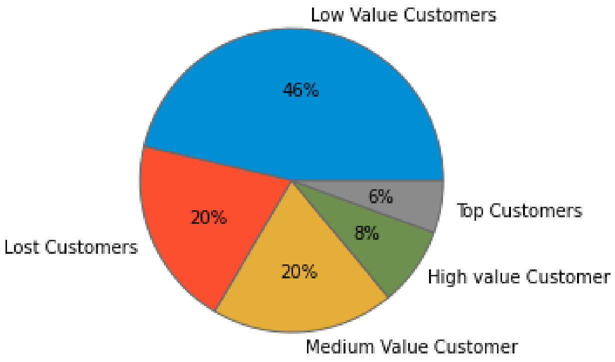
In [62]:

```
rfm_dataset.shape
```

Out[62]: (167230, 9)

In [50]:

```
plt.pie(rfm_dataset.Customer_segment.value_counts(),
        labels=rfm_dataset.Customer_segment.value_counts().index,
        autopct='%.0f%%')
plt.show()
```



FINAL REPRESENTATION OF CUSTOMERS

HERE WE CAN SEE FIVE GROUP OF CUSTOMERS

- TOP CUSTOMERS: THESE ARE THE CUSTOMER WHO HAVE MADE SEVERAL SUCCESFULL PURCHASES WITH REALLY HIGH PROFIT VALUE
- HIGH VALUE CUSTOMER: THESE ARE THE CUSTOMER WHO HAVE MADE TWO OR MORE SUCCESFULL PURCHASES WITH MODERATELY HIGH PROFIT VALUE
- MEDIUM VALUE CUSTOMERS : THESE ARE THE CUSTOMER WHO HAVE MADE AROUND ONE OR TWO SUCCESFULL PURCHASES WITH MODERATE PROFIT VALUE
- LOW VALUE CUSTOMERS : THESE ARE THE CUSTOMER WHO HAVE MADE SINGLE SUCCESFULL PURCHASES WITH LOW PROFIT VALUE
- LOST CUSTOMERS : THESE ARE THE CUSTOMER WHO HAVE CANCELLED OR RETURNED PRODUCTS POSSIBLY CAUSING LOSS

Alternative

- Clustering: Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups (clusters). This way we can form groups leading us to insights, groupinh high value customers or how many times a single cusomer made purhases. WE CAN ALSO USE SQL/EXCEL FOR THE ANALYSIS BUT OUR DATASET WOULD BE QUITE LARGE FOR EXCEL TO HANDLE

In [ ]: