```
[ ] from google.colab import drive
    drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
[ ] #unzip the dataset folder
    !unzip /content/drive/MyDrive/thesisproject/data.csv.zip
```

```
Archive:  /content/drive/MyDrive/thesisproject/data.csv.zip
  inflating: data.csv
```

- https://www.kaggle.com/mustafacicek/detailed-marketing-cohort-pareto-rfm-forecast?scriptVersionId=78275259

1. Overview and understanding of data

Install libraries

```
[ ] !pip install squarify
```

```
Collecting squarify
  Downloading squarify-0.4.3-py3-none-any.whl (4.3 kB)
Installing collected packages: squarify
Successfully installed squarify-0.4.3
```

Load libraries

```
[ ] # Importing Libraries
    import pandas as pd
    import matplotlib.pyplot as plt
    import numpy as np
    import seaborn as sns
    import warnings
    import plotly.express as px

    from random import sample
    from numpy.random import uniform
    from math import isnan
    from sklearn.cluster import KMeans
    from sklearn.metrics import silhouette_score
    from sklearn.neighbors import NearestNeighbors
    from sklearn.cluster import AgglomerativeClustering
    from scipy.cluster.hierarchy import linkage
    from scipy.cluster.hierarchy import dendrogram
    from scipy.cluster.hierarchy import cut_tree
    from matplotlib.ticker import PercentFormatter
    %matplotlib inline

    pd.set_option("display.max_rows", None,"display.max_columns", None)

    warnings.simplefilter(action='ignore')
    plt.style.use('seaborn')
    sns.set_style("darkgrid")
```

reading the dataset

```
[ ] # Importing data.csv
    df = pd.read_csv('/content/data.csv', sep=",", encoding="unicode_escape", header=0)
    df.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

understanding the dataset

```
[ ] # basics of the df
    df.info()
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   InvoiceNo    541909 non-null  object 
 1   StockCode    541909 non-null  object 
 2   Description  540455 non-null  object 
 3   Quantity     541909 non-null  int64  
 4   InvoiceDate  541909 non-null  object 
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object 
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

[ ]
```
df.isnull().sum()
```

```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

[ ]
```
print("We have {} observations.".format(df.shape[0]))

df.dropna(inplace=True)

print("We have {} observations after removing null values.".format(df.shape[0]))
```

```
We have 541909 observations.
We have 406829 observations after removing null values.
```

We are done with systematically missing values. But lets go deeper.

Sometimes, missing values are filled with some denotations. "NAN", "na", "?", "Unknown", and so on. Let's check them.

[ ]
```
df[df.Description.str.len() < 5]
```

InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country

Nothing!

Lets check invoiceNo!

[ ]
```
df.InvoiceNo.value_counts()
```

```
576339    540
579196    527
580727    522
578270    440
573576    432
567656    417
567183    398
575607    373
571441    361
570488    351
572552    348
568346    331
547063    293
569246    283
562031    277
554098    264
543040    259
570672    259
569897    237
572103    222
562046    218
566290    217
578233    212
574328    207
556484    204
571653    200
577504    198
579470    193
574481    189
575491    189
561894    186
578041    183
580956    183
581405    182
569866    181
572913    178
565150    178
560504    177
552039    175
540372    168
562688    168
537224    167
563613    167
```

```
563357    166
579167    163
545901    163
569220    163
537781    161
574700    160
579516    158
573300    157
548714    157
560209    157
571883    157
573904    156
547358    155
572703    154
540247    153
564342    153
```

InvoiceNo has coded with 6 digit numeric characters. We can see that some InvoiceNo records starts with the letter C. This means cancellation.

```
[ ] df[df["InvoiceNo"].str.startswith("C")].head(5)
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
141	C536379	D	Discount	-1	12/1/2010 9:41	27.50	14527.0	United Kingdom
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	12/1/2010 9:49	4.65	15311.0	United Kingdom
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	12/1/2010 10:24	1.65	17548.0	United Kingdom
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	12/1/2010 10:24	0.29	17548.0	United Kingdom
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	12/1/2010 10:24	0.29	17548.0	United Kingdom

Cancelled invoices have negative quantity.

```
[ ] df["Cancelled"] = df["InvoiceNo"].apply(lambda x: 1 if x.startswith("C") else 0)
```

```
[ ] df = df[df.Cancelled == 0]
    df.shape
```

```
(397924, 9)
```

Stock Codes generally contains 5 digit numerical codes.

```
[ ] df[df.StockCode.str.contains("^[a-zA-Z]")].StockCode.value_counts()
```

```
POST            1099
M                290
C2               133
DOT               16
BANK CHARGES      12
PADS               4
Name: StockCode, dtype: int64
```

```
[ ] df[df.StockCode.str.contains("^[a-zA-Z]")].Description.value_counts()
```

```
POSTAGE                      1099
Manual                        290
CARRIAGE                      133
DOTCOM POSTAGE                 16
Bank Charges                   12
PADS TO MATCH ALL CUSHIONS      4
Name: Description, dtype: int64
```

It looks like data contains more than customer transactions. I will drop them.

```
[ ] df[df.StockCode.str.len() > 5].StockCode.value_counts()
```

```
85123A          2035
85099B          1618
82494L           820
85099F           664
85099C           659
84997D           429
84970S           415
47591D           401
15056N           382
84596B           379
47590B           363
47590A           356
85049E           347
84970L           338
84997B           330
84029E           328
84029G           326
47566B           317
84997C           309
85014B           306
84596F           304
15056BL          291
84030E           287
85049A           274
85014A           257
```

```
16161P          249
47559B          246
84406B          244
85049G          244
84997A          234
84536A          225
85049C          212
46000S          182
47504K          179
48173C          176
85199S          170
47503A          168
16156S          167
84596G          162
51014A          161
72351B          159
84510A          151
16169E          150
35471D          148
47599A          146
85034C          142
85184C          140
84509A          139
72351A          139
15056P          137
72760B          136
16161U          134
46000M          134
84032B          133
85040A          132
47567B          128
85132C          127
75049L          124
85061W          121
```

```
[ ] df[df.StockCode.str.len() > 5].Description.value_counts()
```

```
WHITE HANGING HEART T-LIGHT HOLDER     2028
JUMBO BAG RED RETROSPOT                1618
WOODEN FRAME ANTIQUE WHITE              820
JUMBO BAG STRAWBERRY                    664
JUMBO  BAG BAROQUE BLACK WHITE          659
HANGING HEART ZINC T-LIGHT HOLDER       415
PINK FAIRY CAKE CHILDRENS APRON         401
EDWARDIAN PARASOL NATURAL               382
SMALL DOLLY MIX DESIGN ORANGE BOWL      379
PINK HAPPY BIRTHDAY BUNTING             363
BLUE HAPPY BIRTHDAY BUNTING             356
SCANDINAVIAN REDS RIBBONS               347
SINGLE HEART ZINC T-LIGHT HOLDER        338
CHILDRENS CUTLERY POLKADOT PINK         328
RED WOOLLY HOTTIE WHITE HEART.          328
KNITTED UNION FLAG HOT WATER BOTTLE     326
TEA TIME PARTY BUNTING                  317
RED RETROSPOT UMBRELLA                  306
SMALL MARSHMALLOWS PINK BOWL            304
EDWARDIAN PARASOL BLACK                 291
ENGLISH ROSE HOT WATER BOTTLE           287
TRADITIONAL CHRISTMAS RIBBONS           274
BLACK/BLUE POLKADOT UMBRELLA            257
WRAP ENGLISH ROSE                       249
TEA TIME OVEN GLOVE                     246
CREAM CUPID HEARTS COAT HANGER          244
CHOCOLATE BOX RIBBONS                   244
CHILDRENS CUTLERY RETROSPOT RED         232
ENGLISH ROSE NOTEBOOK A7 SIZE           225
CHILDRENS CUTLERY POLKADOT BLUE         212
ROMANTIC PINKS RIBBONS                  212
POLYESTER FILLER PAD 40x40cm            182
ENGLISH ROSE GARDEN SECATEURS           179
DOORMAT BLACK FLOCK                     176
SMALL HANGING IVORY/RED WOOD BIRD       170
ASS FLORAL PRINT MULTI SCREWDRIVER      168
WRAP PINK FAIRY CAKES                   167
CHILDRENS CUTLERY POLKADOT GREEN        166
SMALL CHOCOLATES PINK BOWL              162
FEATHER PEN,HOT PINK                    161
SET/6 PINK  BUTTERFLY T-LIGHTS          159
SET OF 4 ENGLISH ROSE COASTERS          151
WRAP 50'S  CHRISTMAS                    150
SET OF 3 BIRD LIGHT PINK FEATHER        148
PINK PARTY BAGS                         146
3 ROSE MORRIS BOXED CANDLES             142
SET/6 TURQUOISE BUTTERFLY T-LIGHTS      139
SET OF 4 ENGLISH ROSE PLACEMATS         139
EDWARDIAN PARASOL PINK                  137
VINTAGE CREAM 3 BASKET CAKE STAND       136
POLYESTER FILLER PAD 45x45cm            134
WRAP SUKI AND FRIENDS                   134
CHARLIE + LOLA RED HOT WATER BOTTLE     133
S/4 PINK FLOWER CANDLES IN BOWL         132
TEA TIME KITCHEN APRON                  128
CHARLIE AND LOLA FIGURES TINS           127
LARGE CIRCULAR MIRROR MOBILE            124
WHITE JEWELLED HEART DECORATION         121
SMALL HEART FLOWERS HOOK                117
```

Some stock codes have a letter at the end of their codes. I don't know what they refers, so I will keep them.

```
[ ] df =  df[~ df.StockCode.str.contains("^[a-zA-Z]")]
    df.shape
```

```
(396370, 9)
```

```
[ ] df["Description"] = df["Description"].str.lower()
```

I just standardize descriptions with converting them to all lowercase characters.

Stock Codes - Description

```
[ ] df.groupby("StockCode")["Description"].nunique()[df.groupby("StockCode")["Description"].nunique() != 1]
```

```
StockCode
16156L    2
17107D    3
20622     2
20725     2
20914     2
21109     2
21112     2
21175     2
21232     2
21243     2
21507     2
21811     2
21818     2
21899     2
21928     2
22129     2
22134     2
22135     2
22179     2
22197     2
22199     2
22246     2
22268     2
22285     2
22286     2
22287     2
22383     2
22407     2
22416     2
22466     2
22502     2
22584     2
22595     2
22597     2
22602     2
22632     2
22776     3
22777     2
22778     2
22785     2
22804     2
22812     2
22813     2
22837     2
22847     2
22849     2
22896     2
22900     2
22932     2
22937     3
22939     2
22949     2
22950     2
22952     2
22953     2
22963     2
22965     2
22972     2
```

Some Stock codes have more than one description. Let's check some of them.

```
[ ] df[df.StockCode == "16156L"].Description.value_counts()
```

```
wrap carousel     14
wrap, carousel     4
Name: Description, dtype: int64
```

```
[ ] df[df.StockCode == "17107D"].Description.value_counts()
```

```
flower fairy,5 summer b'draw liners    25
flower fairy 5 drawer liners           21
flower fairy 5 summer draw liners       1
Name: Description, dtype: int64
```

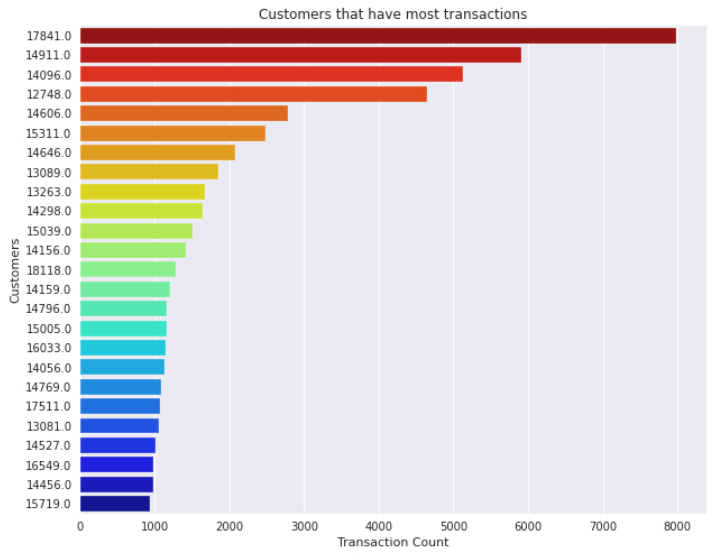
Seems we have just a litle differences between them, i.e. "," or "/"

```
[ ] df.CustomerID.value_counts()
```

```
17841.0    7838
14911.0    5591
14096.0    5095
12748.0    4580
14606.0    2697
15311.0    2379
14646.0    2064
```

```
13089.0    1818
13263.0    1672
14298.0    1637
15039.0    1502
14156.0    1387
18118.0    1278
14159.0    1203
14796.0    1140
16033.0    1137
15005.0    1118
14056.0    1106
14769.0    1089
13081.0    1028
16549.0     981
14527.0     971
14456.0     968
17511.0     963
15719.0     936
16931.0     898
15555.0     897
17811.0     850
14505.0     799
18283.0     754
17338.0     751
17757.0     740
12921.0     720
12415.0     715
15159.0     710
16904.0     708
16764.0     706
17675.0     705
13137.0     704
15547.0     702
17920.0     695
17735.0     690
16923.0     672
15529.0     671
16241.0     662
16360.0     662
16729.0     659
15856.0     644
13969.0     626
16713.0     624
14502.0     623
12681.0     616
13230.0     611
14415.0     590
14088.0     589
16686.0     585
14194.0     579
17611.0     576
14667.0     572
```

```
[ ] customer_counts = df.CustomerID.value_counts().sort_values(ascending=False).head(25)

    fig, ax = plt.subplots(figsize = (10, 8))

    sns.barplot(y = customer_counts.index, x = customer_counts.values, orient = "h",
                ax = ax, order = customer_counts.index, palette = "jet_r")

    plt.title("Customers that have most transactions")
    plt.ylabel("Customers")
    plt.xlabel("Transaction Count")

    plt.show()
```

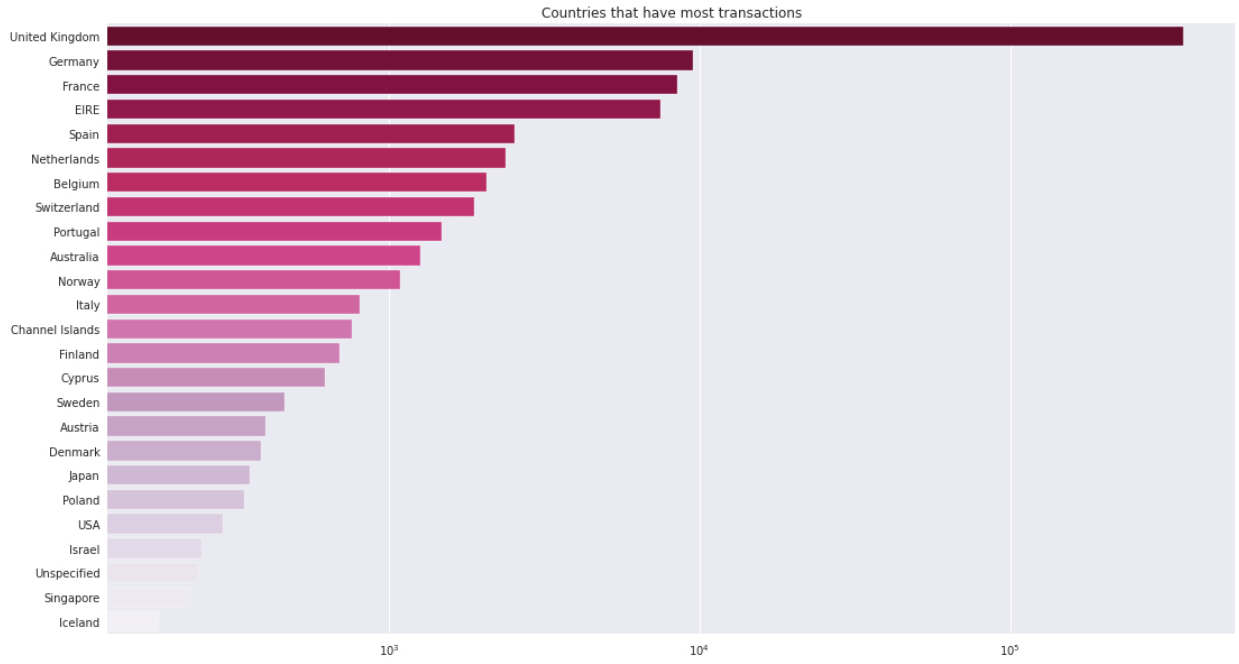



```
[ ] df.Country.value_counts()
```

```
United Kingdom          354005
Germany                   8659
France                    8034
EIRE                      7138
```

```
Spain                   2423
Netherlands             2326
Belgium                 1935
Switzerland             1811
Portugal                1425
Australia               1184
Norway                  1049
Channel Islands          744
Italy                    741
Finland                  647
Cyprus                   612
Sweden                   428
Austria                  384
Denmark                  367
Poland                   325
Japan                    321
Israel                   248
Unspecified              244
Singapore                215
Iceland                  182
USA                      179
Canada                   150
Greece                   142
Malta                    109
United Arab Emirates      67
European Community        57
RSA                       57
Lebanon                   45
Lithuania                 35
Brazil                    32
Czech Republic            24
Bahrain                   17
Saudi Arabia               9
Name: Country, dtype: int64
```

```
[ ] country_counts = df.Country.value_counts().sort_values(ascending=False).head(25)

    fig, ax = plt.subplots(figsize = (18, 10))

    sns.barplot(x = country_counts.values, y = country_counts.index, orient = "h",
                ax = ax, order = country_counts.index, palette = "PuRd_r")
    plt.title("Countries that have most transactions")
    plt.xscale("log")
    plt.show()
```




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

```
count    396370.000000
mean          2.867983
std           4.264566
min           0.000000
25%           1.250000
50%           1.950000
75%           3.750000
max         649.500000
Name: UnitPrice, dtype: float64
```

0 unit price?

```
[ ] df[df.UnitPrice == 0].head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Cancelled
9302	537197	22841	round cake tin vintage green	1	12/5/2010 14:02	0.0	12647.0	Germany	0

9302	537197	22841	round cake tin vintage green	1	12/5/2010 14:02	0.0	12647.0	Germany	0
33576	539263	22580	advent calendar gingham sack	4	12/16/2010 14:36	0.0	16560.0	United Kingdom	0
40089	539722	22423	regency cakestand 3 tier	10	12/21/2010 13:45	0.0	14911.0	EIRE	0
47068	540372	22090	paper bunting retrospot	24	1/6/2011 16:41	0.0	13081.0	United Kingdom	0
47070	540372	22553	plasters in tin skulls	24	1/6/2011 16:41	0.0	13081.0	United Kingdom	0

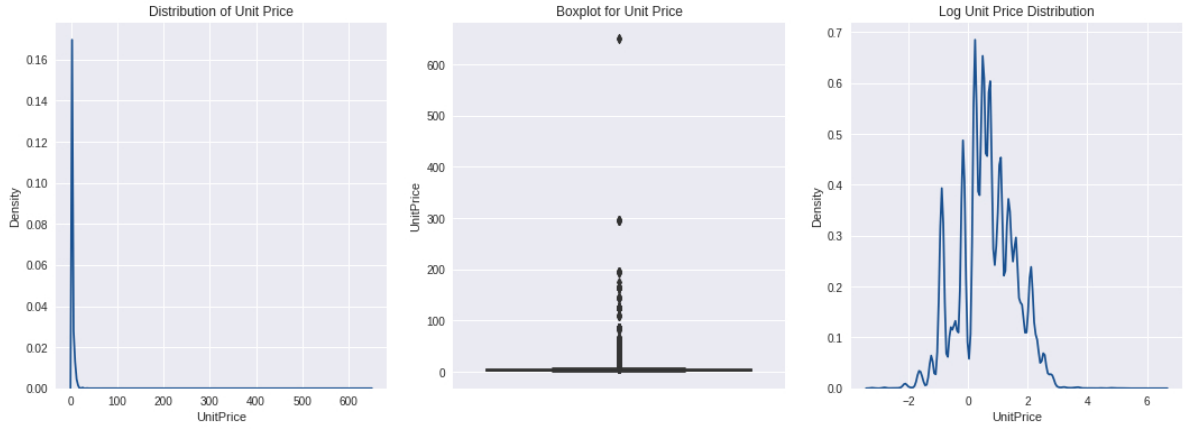
Data cleaning

I didn't find any pattern. So, I remove them.

```
print("We have {} observations.".format(df.shape[0]))

df = df[df.UnitPrice > 0]

print("We have {} observations after removing records that have 0 unit price.".format(df.shape[0]))
```

```
We have 396370 observations.
We have 396337 observations after removing records that have 0 unit price.
```

```
fig, axes = plt.subplots(1, 3, figsize = (18, 6))

sns.kdeplot(df["UnitPrice"], ax = axes[0], color = "#195190").set_title("Distribution of Unit Price")
sns.boxplot(y = df["UnitPrice"], ax = axes[1], color = "#195190").set_title("Boxplot for Unit Price")
sns.kdeplot(np.log(df["UnitPrice"]), ax = axes[2], color = "#195190").set_title("Log Unit Price Distribution")

plt.show()
```




```
print("Lower limit for UnitPrice: " + str(np.exp(-2)))
print("Upper limit for UnitPrice: " + str(np.exp(3)))
```

```
Lower limit for UnitPrice: 0.1353352832366127
Upper limit for UnitPrice: 20.085536923187668
```

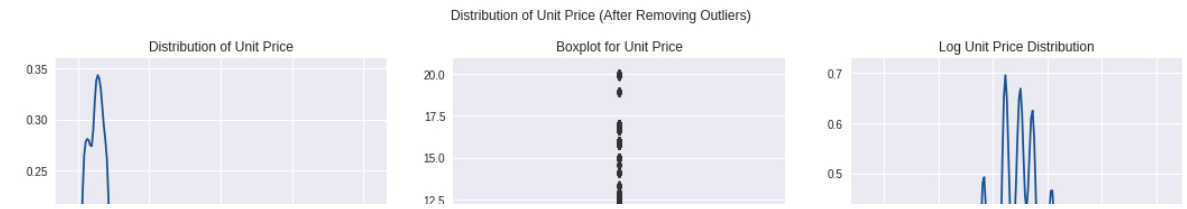
```
np.quantile(df.UnitPrice, 0.99)
```

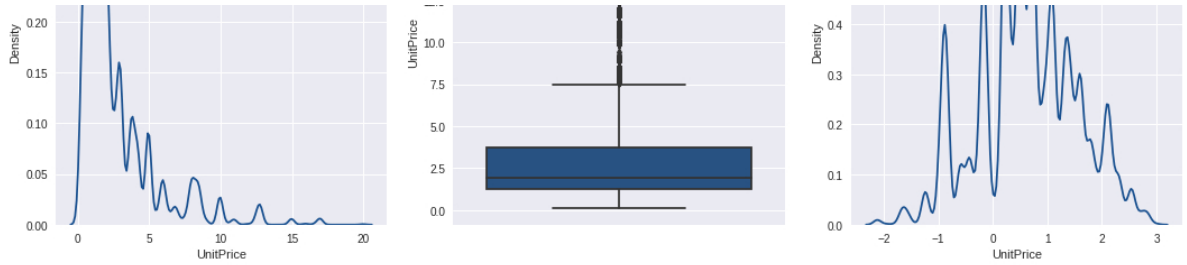
```
12.75
```

```
print("We have {} observations.".format(df.shape[0]))

df = df[(df.UnitPrice > 0.1) & (df.UnitPrice < 20)]

print("We have {} observations after removing unit prices smaller than 0.1 and greater than 20.".format(df.shape[0]))
```

```
We have 396337 observations.
We have 395385 observations after removing unit prices smaller than 0.1 and greater than 20.
```

```
fig, axes = plt.subplots(1, 3, figsize = (18, 6))

sns.kdeplot(df["UnitPrice"], ax = axes[0], color = "#195190").set_title("Distribution of Unit Price")
sns.boxplot(y = df["UnitPrice"], ax = axes[1], color = "#195190").set_title("Boxplot for Unit Price")
sns.kdeplot(np.log(df["UnitPrice"]), ax = axes[2], color = "#195190").set_title("Log Unit Price Distribution")

fig.suptitle("Distribution of Unit Price (After Removing Outliers)")
plt.show()
```






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

```
count    395385.000000
mean         12.946075
std         179.665683
min           1.000000
25%           2.000000
50%           6.000000
75%          12.000000
max       80995.000000
Name: Quantity, dtype: float64
```

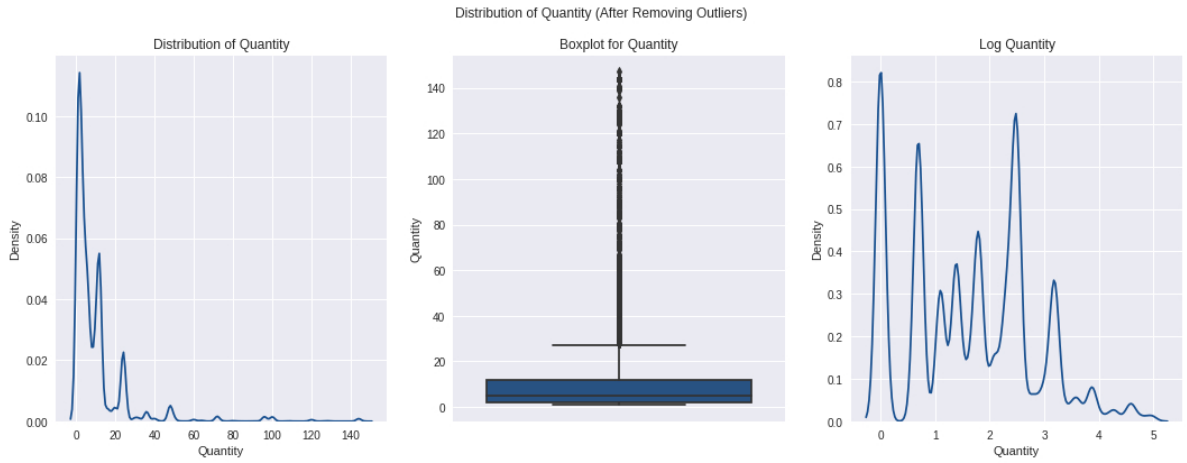
```
[ ] np.quantile(df.Quantity, 0.99)
```

```
120.0
```

```
[ ] print("We have {} observations.".format(df.shape[0]))

    df = df[(df.Quantity < 150)]

    print("We have {} observations after removing quantities greater than 150.".format(df.shape[0]))
```

```
We have 395385 observations.
We have 392735 observations after removing quantities greater than 150.
```

```
[ ] fig, axes = plt.subplots(1, 3, figsize = (18, 6))

    sns.kdeplot(df["Quantity"], ax = axes[0], color = "#195190").set_title("Distribution of Quantity")
    sns.boxplot(y = df["Quantity"], ax = axes[1], color = "#195190").set_title("Boxplot for Quantity")
    sns.kdeplot(np.log(df["Quantity"]), ax = axes[2], color = "#195190").set_title("Log Quantity")

    fig.suptitle("Distribution of Quantity (After Removing Outliers)")
    plt.show()
```



making additional columns

```
[ ] df["TotalPrice"] = df["Quantity"] * df["UnitPrice"]
    df['InvoiceDate2'] = df['InvoiceDate']
    df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
    df['InvoiceDate2'].head(5)
```

```
0    12/1/2010 8:26
1    12/1/2010 8:26
2    12/1/2010 8:26
3    12/1/2010 8:26
4    12/1/2010 8:26
Name: InvoiceDate2, dtype: object
```

```
[ ] df.drop("Cancelled", axis = 1, inplace = True)
    df.to_csv("/content/drive/MyDrive/thesisproject/online_retail_final.csv", index = False)
```

saving modified dataset

[ ] 4 1 cell hidden

2. Cohort Analysis

[ ] 4 35 cells hidden

3. RFM Analysis

Recency, frequency, monetary value is a marketing analysis tool used to identify a company's or an organization's best customers by using certain measures. The RFM model is based on three quantitative factors:

Recency: How recently a customer has made a purchase

Frequency: How often a customer makes a purchase

Monetary Value: How much money a customer spends on purchases

RFM analysis numerically ranks a customer in each of these three categories, generally on a scale of 1 to 5 (the higher the number, the better the result). The "best" customer would receive a top score in every category.

Let's perform RFM Analysis on our data.

Preparing RFM Table

```
[ ] print("Min date: {} \nMax date: {}".format(df.InvoiceDate.min(), df.InvoiceDate.max()))
```

```
Min date: 2010-12-01 08:26:00
Max date: 2011-12-09 12:50:00
```

```
[ ] last_day = df.InvoiceDate.max() + dt.timedelta(days = 1)
```

```
[ ] rfm_table = df.groupby("CustomerID").agg({"InvoiceDate": lambda x: (last_day - x.max()).days,
                                              "InvoiceNo": "nunique",
                                              "TotalPrice": "sum"})

    rfm_table.rename(columns = {"InvoiceDate": "Recency",
                                "InvoiceNo": "Frequency",
                                "TotalPrice": "Monetary"}, inplace = True)

    rfm_table.head()
```

CustomerID	Recency	Frequency	Monetary
12347.0	2	7	4060.40
12348.0	75	4	1437.24
12349.0	19	1	1417.60
12350.0	310	1	294.40
12352.0	36	7	1385.74

```
[ ] r_labels = range(5, 0, -1)
    fm_labels = range(1, 6)

    rfm_table["R"] = pd.qcut(rfm_table["Recency"], 5, labels = r_labels)
    rfm_table["F"] = pd.qcut(rfm_table["Frequency"].rank(method = 'first'), 5, labels = fm_labels)
    rfm_table["M"] = pd.qcut(rfm_table["Monetary"], 5, labels = fm_labels)

    rfm_table.head()
```

CustomerID	Recency	Frequency	Monetary	R	F	M
12347.0	2	7	4060.40	5	5	5
12348.0	75	4	1437.24	2	4	4
12349.0	19	1	1417.60	4	1	4
12350.0	310	1	294.40	1	1	2
12352.0	36	7	1385.74	3	5	4

```
[ ] rfm_table["RFM_Segment"] = rfm_table["R"].astype(str) + rfm_table["F"].astype(str) + rfm_table["M"].astype(str)
    rfm_table["RFM_Score"] = rfm_table[["R", "F", "M"]].sum(axis = 1)

    rfm_table.head()
```

CustomerID	Recency	Frequency	Monetary	R	F	M	RFM_Segment	RFM_Score

12347.0	2	7	4060.40	5	5	5	555	15
12348.0	75	4	1437.24	2	4	4	244	10
12349.0	19	1	1417.60	4	1	4	414	9
12350.0	310	1	294.40	1	1	2	112	4
12352.0	36	7	1385.74	3	5	4	354	12

RFM Segments

Champions: Bought recently, buy often and spend the most

Loyal customers: Buy on a regular basis. Responsive to promotions.

Potential loyalist: Recent customers with average frequency.

Recent customers: Bought most recently, but not often.

Promising: Recent shoppers, but haven't spent much.

Needs attention: Above average recency, frequency and monetary values. May not have bought very recently though.

About to sleep: Below average recency and frequency. Will lose them if not reactivated.

At risk: Some time since they've purchased. Need to bring them back!

Can't lose them: Used to purchase frequently but haven't returned for a long time.

Hibernating: Last purchase was long back and low number of orders. May be lost.

```
[ ]  segt_map = {
        r'[1-2][1-2]': 'Hibernating',
        r'[1-2][3-4]': 'At-Risk',
        r'[1-2]5': 'Cannot lose them',
        r'3[1-2]': 'About To Sleep',
        r'33': 'Need Attention',
        r'[3-4][4-5]': 'Loyal Customers',
        r'41': 'Promising',
        r'51': 'New Customers',
        r'[4-5][2-3]': 'Potential Loyalists',
        r'5[4-5]': 'Champions'
    }
    rfm_table['Segment'] = rfm_table['R'].astype(str) + rfm_table['F'].astype(str)
    rfm_table['Segment'] = rfm_table['Segment'].replace(segt_map, regex=True)
    rfm_table.head()
```

CustomerID	Recency	Frequency	Monetary	R	F	M	RFM_Segment	RFM_Score	Segment
12347.0	2	7	4060.40	5	5	5	555	15	Champions
12348.0	75	4	1437.24	2	4	4	244	10	At-Risk
12349.0	19	1	1417.60	4	1	4	414	9	Promising
12350.0	310	1	294.40	1	1	2	112	4	Hibernating
12352.0	36	7	1385.74	3	5	4	354	12	Loyal Customers

Visualizing RFM Grid

```
[ ]  rfm_coordinates = {"Champions": [3, 5, 0.8, 1],
                        "Loyal Customers": [3, 5, 0.4, 0.8],
                        "Cannot lose them": [4, 5, 0, 0.4],
                        "At-Risk": [2, 4, 0, 0.4],
                        "Hibernating": [0, 2, 0, 0.4],
                        "About To Sleep": [0, 2, 0.4, 0.6],
                        "Promising": [0, 1, 0.6, 0.8],
                        "New Customers": [0, 1, 0.8, 1],
                        "Potential Loyalists": [1, 3, 0.6, 1],
                        "Need Attention": [2, 3, 0.4, 0.6]}
```

```
[ ]  fig, ax = plt.subplots(figsize = (10, 15))

    ax.set_xlim([0, 5])
    ax.set_ylim([0, 5])

    plt.rcParams["axes.facecolor"] = "white"
    palette = ["#282828", "#04621B", "#971194", "#F1480F",  "#4C00FF",
               "#FF007B", "#9736FF", "#8992F3", "#B29800", "#80004C"]

    for key, color in zip(rfm_coordinates.keys(), palette[:10]):

        coordinates = rfm_coordinates[key]
        ymin, ymax, xmin, xmax = coordinates[0], coordinates[1], coordinates[2], coordinates[3]

        ax.axhspan(ymin = ymin, ymax = ymax, xmin = xmin, xmax = xmax, facecolor = color)
```

```
        users = rfm_table[rfm_table.Segment == key].shape[0]
        users_percentage = (rfm_table[rfm_table.Segment == key].shape[0] / rfm_table.shape[0]) * 100
        avg_monetary = rfm_table[rfm_table.Segment == key]["Monetary"].mean()

        user_txt = "\n\nTotal Users: " + str(users) + "(" +  str(round(users_percentage, 2)) + "%)"
        monetary_txt = "\n\n\n\nAverage Monetary: " + str(round(avg_monetary, 2))

        x = 5 * (xmin + xmax) / 2
        y = (ymin + ymax) / 2

        plt.text(x = x, y = y, s = key, ha = "center", va = "center", fontsize = 18, color = "white", fontweight = "bold")
        plt.text(x = x, y = y, s = user_txt, ha = "center", va = "center", fontsize = 14, color = "white")
        plt.text(x = x, y = y, s = monetary_txt, ha = "center", va = "center", fontsize = 14, color = "white")

        ax.set_xlabel("Recency Score")
        ax.set_ylabel("Frequency Score")

    sns.despine(left = True, bottom = True)
    plt.show()
```

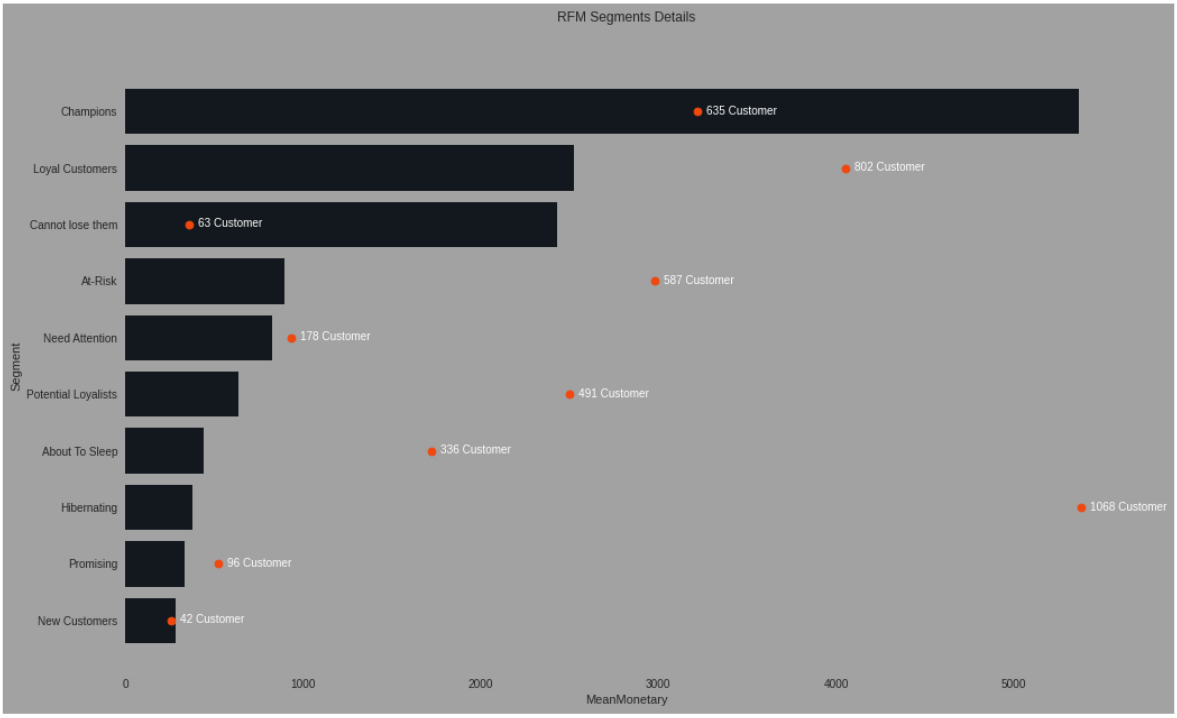
Visualizing RFM Segments

We can show table of descriptive statistics for RFM segments, but it is not best way. Using data visualization skills and creating great plots as important as finding great results.

```
[ ]  rfm_table2 = rfm_table.reset_index()

     rfm_monetary_size = rfm_table2.groupby("Segment").agg({"Monetary": "mean",
                                                            "CustomerID": "nunique"})

     rfm_monetary_size.rename(columns = {"Monetary": "MeanMonetary", "CustomerID": "CustomerCount"}, inplace = True)
     rfm_monetary_size = rfm_monetary_size.sort_values("MeanMonetary", ascending = False)
```

```
[ ]  plt.rcParams["axes.facecolor"] = "#A2A2A2"
     fig, ax = plt.subplots(figsize = (16, 10), facecolor = "#A2A2A2")

     sns.barplot(x = rfm_monetary_size.MeanMonetary, y = rfm_monetary_size.index, ax = ax, color = "#101820")
     ax2 = ax.twiny()
     sns.lineplot(x = rfm_monetary_size.CustomerCount, y = rfm_monetary_size.index, ax = ax2, marker = "o", linewidth = 0,
                  color = "#F1480F", markeredgecolor = "#F1480F")


     ax2.axis("off")
```

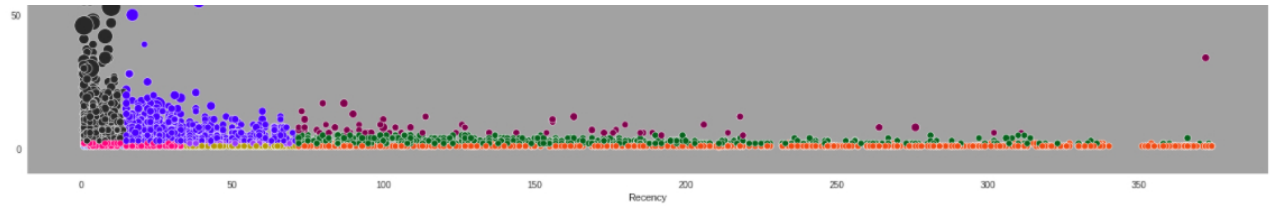
```
    for y, x in list(enumerate(rfm_monetary_size.CustomerCount)):
        ax2.text(x + 10, y + 0.05, str(x) + " Customer", color = "white", fontweight = "normal")

    plt.title("RFM Segments Details")
    sns.despine(left = True, right = True, bottom = True, top = True)
    plt.show()
```




```
[ ] rfm = rfm_table2.groupby("Segment").agg({"CustomerID": "nunique",
                                             "Recency": "mean",
                                             "Frequency": "mean",
                                             "Monetary": "mean"})
    rfm.rename(columns = {"CustomerID": "Segment Size"}, inplace = True)

    cm = sns.light_palette("#A2A2A2", as_cmap = True)

    rfm.T.style.background_gradient(cmap = cm, axis = 1)\
    .set_precision(2)\
    .highlight_min(axis = 1, color = "#195190")\
    .highlight_max(axis = 1, color = "#D60000")
```

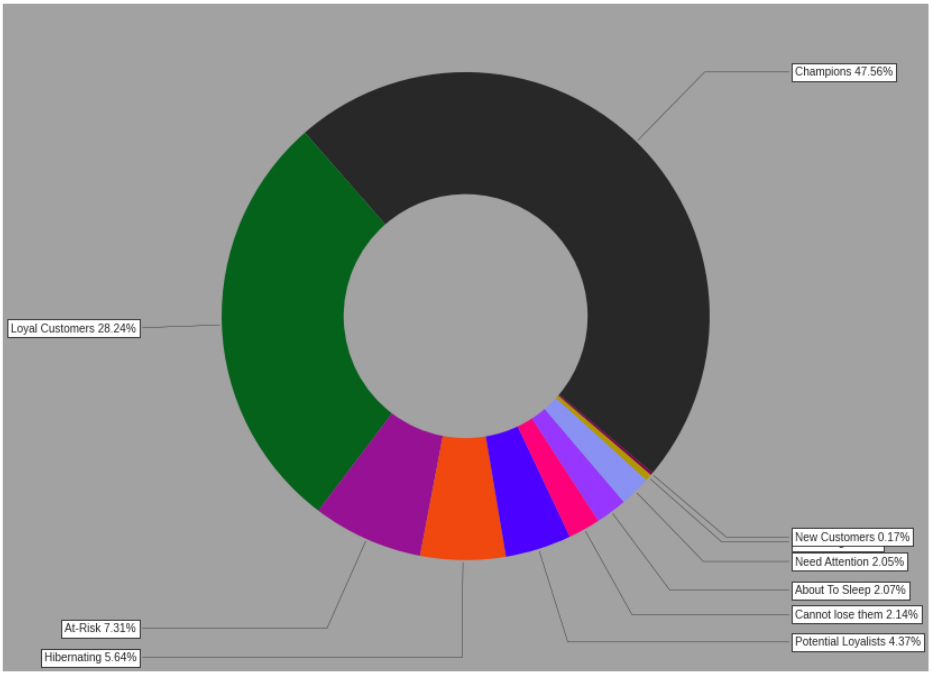
Segment	About To Sleep	At-Risk	Cannot lose them	Champions	Hibernating	Loyal Customers	Need Attention	New Customers	Potential Loyalists	Promising
Segment Size	336.00	587.00	63.00	635.00	1068.00	802.00	178.00	42.00	491.00	96.00
Recency	53.06	152.81	134.65	6.01	216.59	33.30	52.03	7.17	17.18	23.55
Frequency	1.14	2.85	8.30	12.04	1.09	6.39	2.30	1.00	1.99	1.00
Monetary	440.99	892.89	2429.75	5367.17	378.59	2523.46	824.97	283.17	638.41	335.18

```
[ ] plt.rcParams["axes.facecolor"] = "#A2A2A2"
    plt.rcParams["axes.grid"] = False

    sns.relplot(x = "Recency", y = "Frequency", hue = "Segment", size = "Monetary", data = rfm_table2, palette = palette,
                height = 10, aspect = 2, sizes = (50, 1000))

    plt.show()
```




```
[ ]  monetary_per_segment = (rfm_table2.groupby("Segment")["Monetary"].sum() /\
                             rfm_table2.groupby("Segment")["Monetary"].sum().sum()).sort_values(ascending = False)
```

```
[ ]  fig, ax = plt.subplots(figsize = (10, 10), facecolor = "#A2A2A2")

     wedges, texts = ax.pie(monetary_per_segment.values, wedgeprops=dict(width=0.5),
                            startangle=-40, colors = palette)

     bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
     kw = dict(arrowprops=dict(arrowstyle="-"),
               bbox=bbox_props, zorder=0, va="center")

     for i, p in enumerate(wedges):
         ang = (p.theta2 - p.theta1)/2. + p.theta1
         y = np.sin(np.deg2rad(ang))
         x = np.cos(np.deg2rad(ang))
         horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
         connectionstyle = "angle,angleA=0,angleB={}".format(ang)
         kw["arrowprops"].update({"connectionstyle": connectionstyle})
         ax.annotate(monetary_per_segment.index[i] + " " + str(round(monetary_per_segment[i] * 100, 2)) + "%", xy=(x, y),
                     xytext=(1.35*np.sign(x), 1.4*y),horizontalalignment=horizontalalignment, **kw)
     plt.show()
```

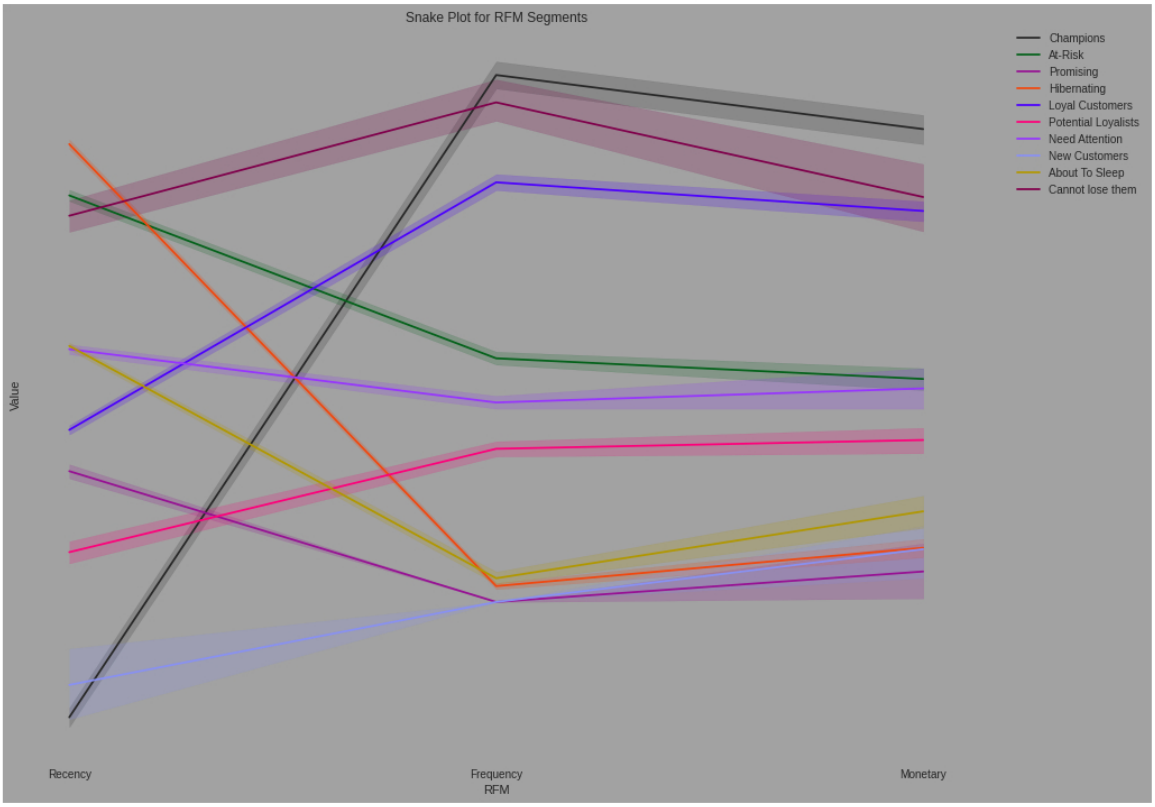


47.5% of total revenue comes from "Champions" segment, and 28% of total revenue comes from "Loyal Customers" segment. These two segments have 75% of company's total revenue.

```
[ ]  from sklearn.preprocessing import StandardScaler
```

```
[ ]  rfm_clustering = rfm_table2[["Recency", "Frequency", "Monetary", "Segment"]]

     for col in ["Recency", "Frequency", "Monetary"]:

         scaler = StandardScaler()
         rfm_clustering[col] = np.log(rfm_clustering[col])
         rfm_clustering[col] = scaler.fit_transform(rfm_clustering[col].values.reshape(-1, 1))

     rfm_melted = pd.melt(rfm_clustering, id_vars = "Segment", value_vars = ["Recency", "Frequency", "Monetary"],
                          var_name = "RFM", value_name = "Value")
```

```
[ ]  fig, ax = plt.subplots(figsize = (15, 12), facecolor = "#A2A2A2")
     ax.set_facecolor("#A2A2A2")

     sns.lineplot(x = "RFM", y = "Value", hue = "Segment", data = rfm_melted, palette = palette)
     ax.legend(bbox_to_anchor = (1.05, 1), loc = 2, borderaxespad = 0.)
     ax.set_yticks([])
     ax.set_title("Snake Plot for RFM Segments")
     plt.show()
```



3. Customer Segmentation with using RFM Metrics

```
[ ] # Calculating Monetary attribute
    cus_data = df.groupby('CustomerID')[['TotalPrice']].sum() # Total amount spent
    cus_data.rename(columns={'TotalPrice':'Monetary'},inplace=True)
    cus_data.head()
```

CustomerID	Monetary
12347.0	4060.40
12348.0	1437.24
12349.0	1417.60
12350.0	294.40
12352.0	1385.74

```
[ ] # Calculating frequency attribute
    cus_data['Frequency'] = df.groupby('CustomerID')['InvoiceNo'].count()
    cus_data.head()
```

CustomerID	Monetary	Frequency
12347.0	4060.40	181
12348.0	1437.24	27
12349.0	1417.60	71
12350.0	294.40	16
12352.0	1385.74	77

```
[ ] max_date = max(df['InvoiceDate'])
    max_date
```

```
Timestamp('2011-12-09 12:50:00')
```

```
[ ] df['diff'] = max_date - df['InvoiceDate']
    df.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	TotalPrice	InvoiceDate2	InvoiceMonth	CohortMonth	CohortIndex	di
0	536365	85123A	white hanging heart t-light holder	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	15.30	12/1/2010 8:26	2010-12-01	2010-12-01	1	3 da 04:24

1	536365	71053	white metal lantern	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	20.34	12/1/2010 8:26	2010-12-01	2010-12-01	1
2	536365	84406B	cream cupid hearts coat hanger	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	22.00	12/1/2010 8:26	2010-12-01	2010-12-01	1
3	536365	84029G	knitted union flag hot water bottle	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	20.34	12/1/2010 8:26	2010-12-01	2010-12-01	1
4	536365	84029E	red woolly hottie white heart.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	20.34	12/1/2010 8:26	2010-12-01	2010-12-01	1

```
[ ] # Adjust today:
    import datetime as dt
    today = dt.datetime(2012,1,1)
    # Recency and Monetary
    data_x = df.groupby('CustomerID').agg({'TotalPrice': lambda x: x.sum(),
                                           'InvoiceDate': lambda x: (today - x.max()).days})
    data_x.head()
```

CustomerID	TotalPrice	InvoiceDate
12347.0	4060.40	24
12348.0	1437.24	97
12349.0	1417.60	40
12350.0	294.40	332
12352.0	1385.74	58

```
[ ] cus_data['Recency'] = df.groupby('CustomerID')['diff'].min().dt.days
    cus_data = cus_data.reset_index()
    cus_data.head()
```

	CustomerID	Monetary	Frequency	Recency
0	12347.0	4060.40	181	1
1	12348.0	1437.24	27	74
2	12349.0	1417.60	71	18
3	12350.0	294.40	16	309
4	12352.0	1385.74	77	35

```
[ ] from datetime import datetime
    def toDtObject(value):
        return datetime.strptime(value,'%m/%d/%Y %H:%M')
```

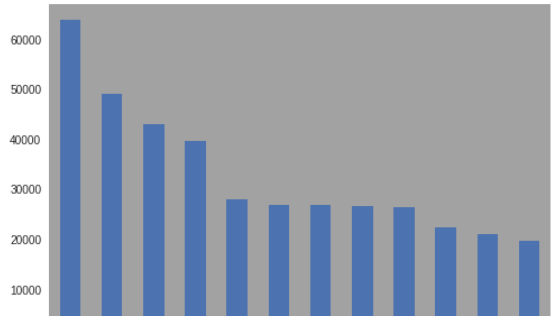
```
[ ] df['InvoiceDate2']=df['InvoiceDate2'].apply(toDtObject)
```

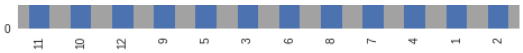
```
[ ] def getMonth(value):
        return int(value.strftime('%m'))
    def getDay(value):
        return int(value.strftime('%d'))
    def getYear(value):
        return int(value.strftime('%Y'))
    def getHour(value):
        return int(value.strftime('%H'))
```

```
[ ] df['month']=df['InvoiceDate2'].apply(getMonth)
    df['day']=df['InvoiceDate2'].apply(getDay)
    df['year']=df['InvoiceDate2'].apply(getYear)
    df['hour']=df['InvoiceDate2'].apply(getHour)
```

```
[ ] df.month.value_counts().plot(kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f881c1c3c10>
```

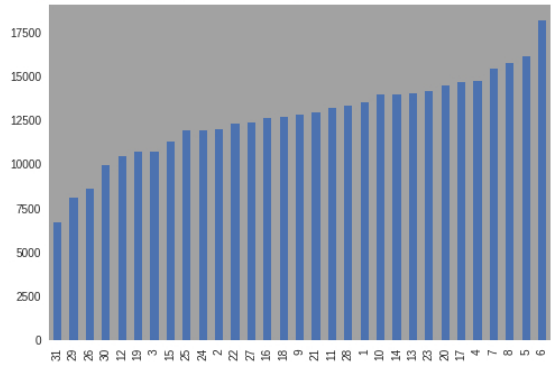




From the above graph we can conclude that most of sales happended in the last quarter of year

```
[ ] df.day.value_counts(ascending=True).plot(kind='bar')
```

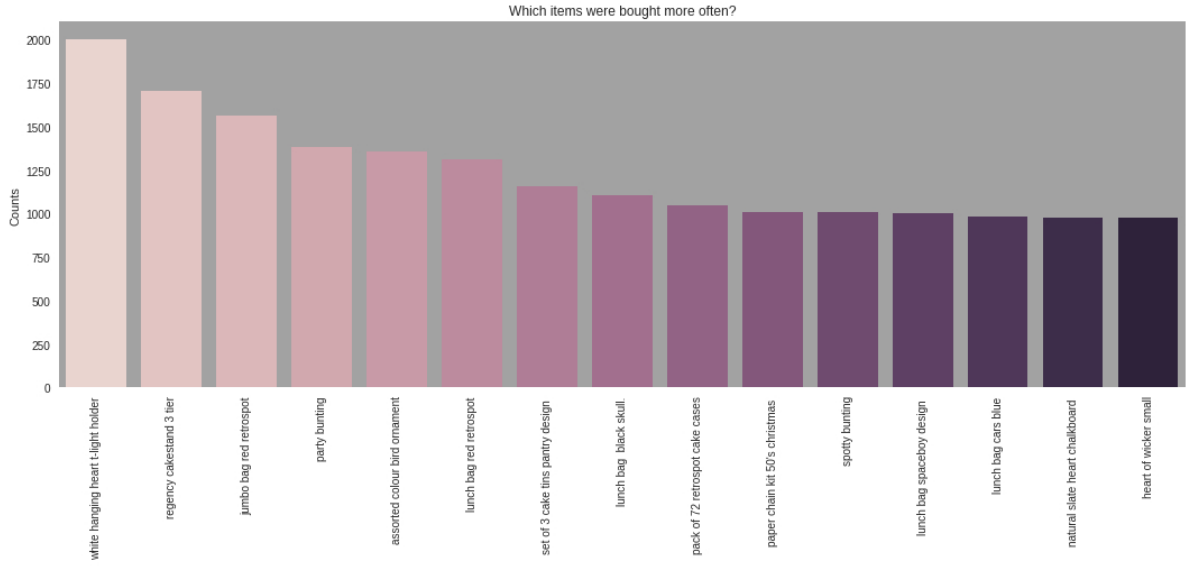
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f881b4a5810>
```




```
[ ] ##### Top 10 items most sales
    df.Description.value_counts()[:10]
```

```
white hanging heart t-light holder    2003
regency cakestand 3 tier              1708
jumbo bag red retrospot               1562
party bunting                         1384
assorted colour bird ornament         1355
lunch bag red retrospot               1312
set of 3 cake tins pantry design      1155
lunch bag  black skull.               1104
pack of 72 retrospot cake cases       1047
paper chain kit 50's christmas        1011
Name: Description, dtype: int64
```

```
[ ] item_counts = df['Description'].value_counts().sort_values(ascending=False).iloc[0:15]
    plt.figure(figsize=(18,6))
    sns.barplot(item_counts.index, item_counts.values, palette=sns.cubehelix_palette(15))
    plt.ylabel("Counts")
    plt.title("Which items were bought more often?");
    plt.xticks(rotation=90);
```

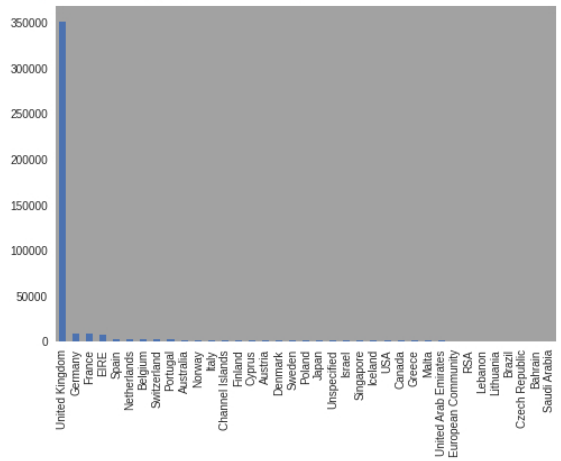



```
[ ] df[df['month']==11].groupby(['Description']).sum().sort_values(by='TotalPrice',ascending=False)[:5]
```

Description	Quantity	UnitPrice	CustomerID	TotalPrice	CohortIndex	month	day	year	hour
rabbit night light	7701	923.67	6821663.0	14807.41	3602	5027	7116	919027	5866
paper chain kit 50's christmas	4379	1041.81	5473927.0	12212.01	2885	3905	5857	713905	4551
regency cakestand 3 tier	940	2127.90	2552913.0	10964.40	1345	1870	2630	341870	2164
hot water bottle keep calm	1742	1312.80	4244709.0	8006.10	2240	2970	4310	542970	3440
paper chain kit vintage christmas	2821	701.06	3646274.0	7736.11	1895	2618	3830	478618	3095

```
[ ] df.Country.value_counts().plot(kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f880fefd250>
```



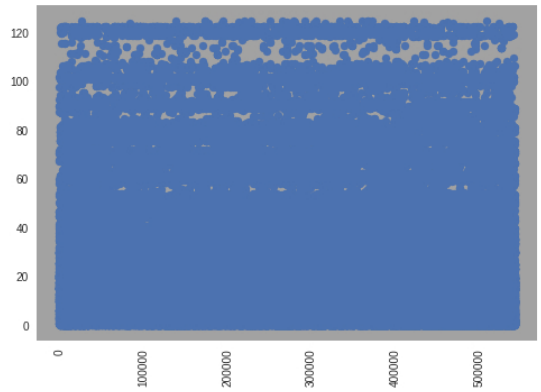
- United Kindom has most number of sales and remaining countries sales are very far less than it
- WHITE HANGING HEART T-LIGHT HOLDER and JUMBO BAG RED RETROSPOT product are in top positions
- Most sales happended in November month
- First week of every month has good sales count
- Huge sales are happening around 12 PM everyday
- Most sales happednd in the end of year and maybe it's because of christmas
- In those months christmas gifts related products should have more stock

```
[ ] df.quantile([0.05, 0.95, 0.98, 0.99, 0.999])
```

	Quantity	UnitPrice	CustomerID	TotalPrice	CohortIndex	month	day	year	hour
0.050	1.0	0.42	12637.0	1.25	1.0	1.0	2.0	2010.0	9.0
0.950	36.0	8.50	17908.0	59.80	12.0	12.0	29.0	2011.0	17.0
0.980	64.0	10.95	18121.0	102.00	12.0	12.0	30.0	2011.0	17.0
0.990	96.0	12.75	18212.0	165.00	13.0	12.0	31.0	2011.0	19.0
0.999	144.0	16.95	18283.0	367.20	13.0	12.0	31.0	2011.0	20.0

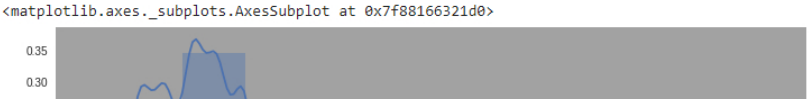
```
[ ] df_quantile = df[df['TotalPrice'] < 125]
    plt.scatter(x=df_quantile.index, y=df_quantile['TotalPrice'])
    plt.xticks(rotation=90)
```

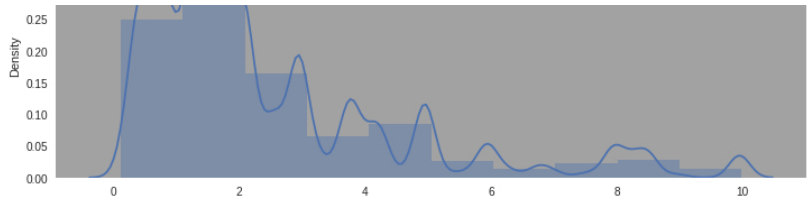
```
(array([-100000.,       0.,  100000.,  200000.,  300000.,  400000.,
         500000.,  600000.]), <a list of 8 Text major ticklabel objects>)
```

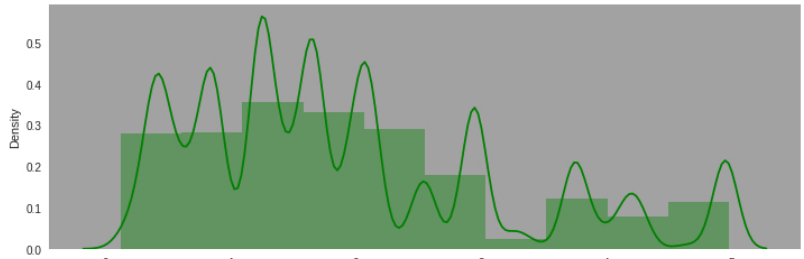


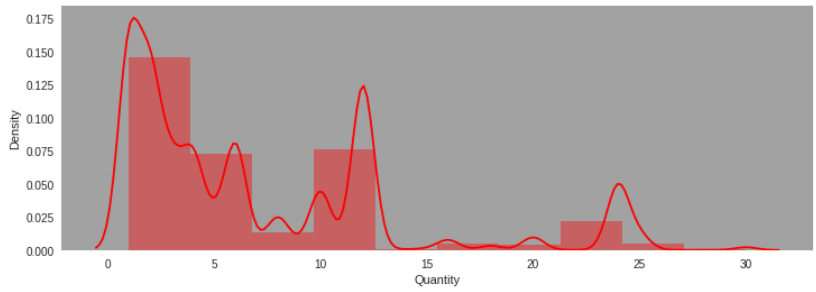

```
[ ] plt.figure(figsize=(12,4))
    sns.distplot(df_quantile[df_quantile['UnitPrice'] < 10]['UnitPrice'].values, kde=True, bins=10)
    plt.figure(figsize=(12,4))
    sns.distplot(df_quantile[df_quantile['UnitPrice'] < 5]['UnitPrice'].values, kde=True, bins=10, color='green')
    plt.figure(figsize=(12,4))
    sns.distplot(df_quantile[df_quantile['Quantity'] <= 30]['Quantity'], kde=True, bins=10, color='red')
    plt.figure(figsize=(12,4))
    sns.distplot(df_quantile[df_quantile['Quantity'] <= 15]['Quantity'], kde=True, bins=10, color='orange')
    plt.figure(figsize=(12,4))
    sns.distplot(df_quantile[df_quantile['TotalPrice'] < 60]['TotalPrice'], kde=True, bins=10, color='purple')
    plt.figure(figsize=(12,4))
    sns.distplot(df_quantile[df_quantile['TotalPrice'] < 30]['TotalPrice'], kde=True, bins=10, color='grey')
```

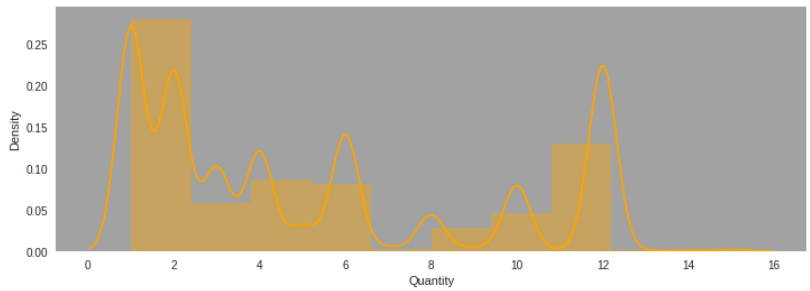
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f88166321d0>
```

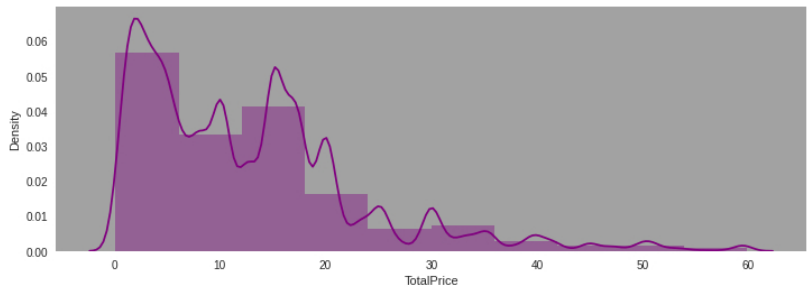








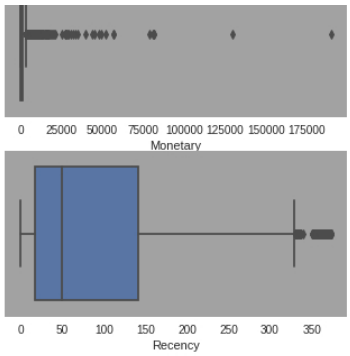




- From these histograms we that people bought normally 1-5 items or 10-12 - maybe there were some kind of offers for sets?
- From these histograms we can understand that majority of sales per order were in range 1-15 pounds each

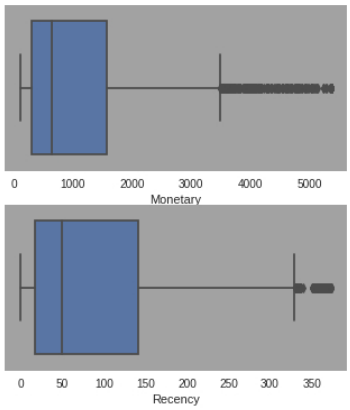
Treating Outliers

```
[ ]  num_features = cus_data.columns[1:]
     r = c = 0
     fig,ax = plt.subplots(2,2,figsize=(12,6))

     for n,i in enumerate(num_features):
         sns.boxplot(x=i, data=cus_data,ax=ax[r,c])
         c+=1
         if (n+1)%2==0:
             r+=1
             c=0
     ax[r,c].axis("off")
     plt.show()
```




```
[ ] h_cap = 0.95
    h_cap_val = cus_data['Monetary'].quantile(h_cap)
    cus_data['Monetary'][cus_data['Monetary'] > h_cap_val] = h_cap_val
    l_cap = 0.05
    l_cap_val = cus_data['Monetary'].quantile(l_cap)
    cus_data['Monetary'][cus_data['Monetary'] < l_cap_val] = l_cap_val
    cap = 0.95
    cap_val = cus_data['Frequency'].quantile(cap)
    cus_data['Frequency'][cus_data['Frequency'] > cap_val] = cap_val
```

```
[ ] num_features = cus_data.columns[1:]
    r = c = 0
    fig,ax = plt.subplots(2,2,figsize=(12,6))

    for n,i in enumerate(num_features):
        sns.boxplot(x=i, data=cus_data,ax=ax[r,c])
        c+=1
        if (n+1)%2==0:
            r+=1
            c=0
    ax[r,c].axis("off")
    plt.show()
```




```
[ ] from sklearn.pipeline import Pipeline
    from sklearn.preprocessing import MinMaxScaler
    from sklearn.decomposition import PCA

    preprocessor = Pipeline(
            [
                ("scaler", MinMaxScaler()),
                ("pca", PCA(n_components=2, random_state=42)),
            ]
        )
```

```
[ ] X = cus_data.drop('CustomerID',axis=1)
    X_scaled = pd.DataFrame(preprocessor.fit_transform(X),columns=['PC_1','PC_2'])
```

```
[ ] X_scaled.head()
```

	PC_1	PC_2
0	0.662820	0.071900
1	-0.049485	-0.076881
2	0.105706	-0.167020
3	-0.497690	0.398526
4	0.093001	-0.122535

Hopkins Test

The Hopkins statistic, is a statistic which gives a value which indicates the cluster tendency, in other words: how well the data can be clustered.

- If the value is between {0.01, ...,0.3}, the data is regularly spaced.
- If the value is around 0.5, it is random.
- If the value is between {0.7, ..., 0.99}, it has a high tendency to cluster.

```
[ ] def hopkins(X):
        d = X.shape[1]
        #d = len(vars) # columns
        n = len(X) # rows
        m = int(0.1 * n)
        nbrs = NearestNeighbors(n_neighbors=1).fit(X.values)

        rand_X = sample(range(0, n, 1), m)

        ujd = []
        wjd = []
        for j in range(0, m):
            u_dist, _ = nbrs.kneighbors(uniform(np.amin(X,axis=0),np.amax(X,axis=0),d).reshape(1, -1), 2, return_distance=True)
            ujd.append(u_dist[0][1])
            w_dist, _ = nbrs.kneighbors(X.iloc[rand_X[j]].values.reshape(1, -1), 2, return_distance=True)
            wjd.append(w_dist[0][1])

        H = sum(ujd) / (sum(ujd) + sum(wjd))
        if isnan(H):
            print(ujd, wjd)
            H = 0

        return H
```

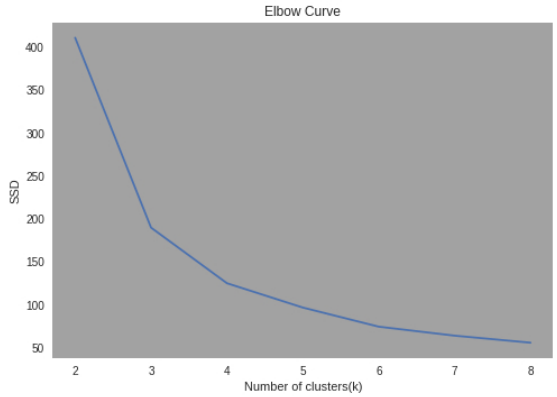
```
[ ] for i in range(5):
      print('Hopkins statistic value is:',round(hopkins(X_scaled),3))
```

```
Hopkins statistic value is: 0.964
Hopkins statistic value is: 0.962
Hopkins statistic value is: 0.968
Hopkins statistic value is: 0.967
Hopkins statistic value is: 0.967
```

Since the Hopkins test value hovers around 0.967, therefore given data have high clustering tendency.

Finding Optimal value of K (Clusters)

```
[ ] # elbow-curve/SSD
    # k means for scaled dataset
    ssd = []
    range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
    for num_clusters in range_n_clusters:
        kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
        kmeans.fit(X_scaled)
        ssd.append(kmeans.inertia_)

    plt.plot(range_n_clusters,ssd)
    plt.xlabel('Number of clusters(k)')
    plt.ylabel('SSD')
    plt.title('Elbow Curve')
    plt.show()
```




```
[ ] # silhouette analysis
    range_n_clusters = [2, 3, 4, 5, 6, 7, 8]

    for num_clusters in range_n_clusters:

        # intialise kmeans
        kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
        kmeans.fit(X_scaled)
```

```
        cluster_labels = kmeans.labels_

        # silhouette score
        silhouette_avg = silhouette_score(X_scaled, cluster_labels)
        print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, round(silhouette_avg,2)))
```

```
For n_clusters=2, the silhouette score is 0.54
For n_clusters=3, the silhouette score is 0.55
For n_clusters=4, the silhouette score is 0.52
For n_clusters=5, the silhouette score is 0.48
For n_clusters=6, the silhouette score is 0.46
For n_clusters=7, the silhouette score is 0.43
For n_clusters=8, the silhouette score is 0.42
```

Using silhouette analysis k=3 seems to be the optimal number of clusters.

```
[ ] # final model with k=3
    kmeans_new = KMeans(n_clusters=3, max_iter=50,random_state=1)
    kmeans_new.fit(X_scaled)
```

```
KMeans(max_iter=50, n_clusters=3, random_state=1)
```

```
[ ] # Adding cluster labels to master dataframe
    X_scaled['cluster_id'] = kmeans_new.labels_
    X['cluster_id'] = kmeans_new.labels_
    X.head(4)
```

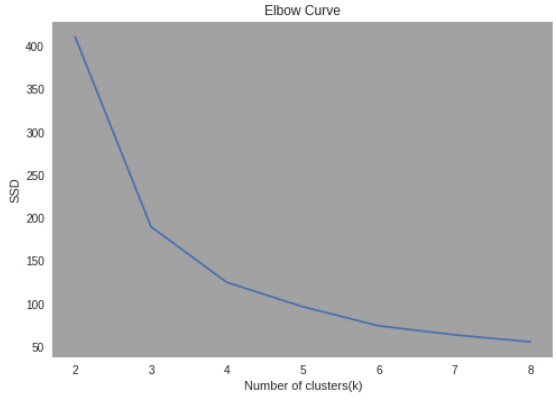
	Monetary	Frequency	Recency	cluster_id
0	4060.40	181.0	1	1
1	1437.24	27.0	74	0
2	1417.60	71.0	18	0
3	294.40	16.0	309	2

```
[ ] X2 = X.drop(columns=['cluster_id'])
    X2.head(5)
```

	Monetary	Frequency	Recency
0	4060.40	181.0	1
1	1437.24	27.0	74
2	1417.60	71.0	18
3	294.40	16.0	309
4	1385.74	77.0	35

k means for raw dataset

```
[ ] # k means for raw dataset
    ssd2 = []
    range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
    for num_clusters in range_n_clusters:
        kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
        kmeans.fit(X2)
        ssd2.append(kmeans.inertia_)

    plt.plot(range_n_clusters,ssd)
    plt.xlabel('Number of clusters(k)')
    plt.ylabel('SSD')
    plt.title('Elbow Curve')
    plt.show()
```




```
[ ] # silhouette analysis
    range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
```

```
for num_clusters in range_n_clusters:

    # intialise kmeans
    kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
    kmeans.fit(X2)

    cluster_labels = kmeans.labels_

    # silhouette score
    silhouette_avg = silhouette_score(X2, cluster_labels)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, round(silhouette_avg,2)))
```

```
For n_clusters=2, the silhouette score is 0.75
For n_clusters=3, the silhouette score is 0.67
For n_clusters=4, the silhouette score is 0.62
For n_clusters=5, the silhouette score is 0.57
For n_clusters=6, the silhouette score is 0.54
For n_clusters=7, the silhouette score is 0.51
For n_clusters=8, the silhouette score is 0.5
```

[ ]
```
# final model for raw dataset with k=3
kmeans_rfm = KMeans(n_clusters=3, max_iter=50,random_state=1)
kmeans_rfm.fit(X2)
```

```
KMeans(max_iter=50, n_clusters=3, random_state=1)
```

[ ]
```
X2['cluster_id'] = kmeans_rfm.labels_
```

[ ]
```
kmeans_rfm.predict([[200,80,40]])
```

```
array([0], dtype=int32)
```

Trying Agglomotative and DBSCAN clustering algorithms

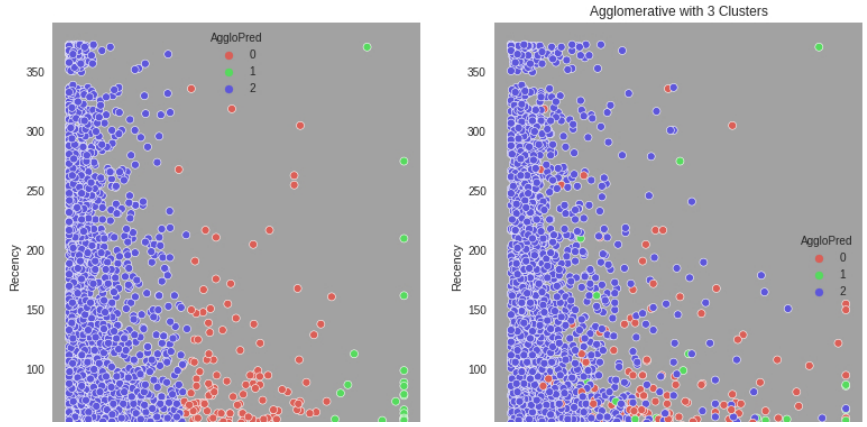
[ ]
```
aggX = X.drop(columns=['cluster_id'])
aggX_sc = X_scaled.drop(columns=['cluster_id'])

dbX = X.drop(columns=['cluster_id'])
dbX_sc = X_scaled.drop(columns=['cluster_id'])
```

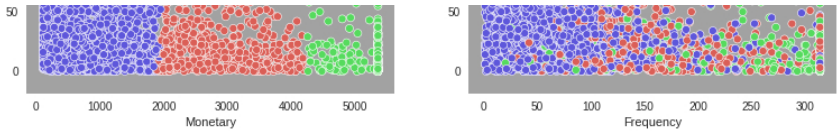
[ ]
```
aggX_sc.head(5)
```

	PC_1	PC_2
0	0.662820	0.071900
1	-0.049485	-0.076881
2	0.105706	-0.167020
3	-0.497690	0.398526
4	0.093001	-0.122535

[ ]
```
agglom = AgglomerativeClustering(n_clusters=3, linkage='average').fit(aggX)
aggX['AggloPred'] = agglom.labels_
```

[ ]
```
fig = plt.figure(figsize=[20,8])

plt.subplot(1,3,1)
sns.scatterplot(aggX['Monetary'], aggX['Recency'], hue=aggX['AggloPred'],
                palette=sns.color_palette('hls', 3))
plt.subplot(1,3,2)
sns.scatterplot(aggX['Frequency'], aggX['Recency'], hue=aggX['AggloPred'],
                palette=sns.color_palette('hls', 3))
plt.title('Agglomerative with 3 Clusters')
plt.show()
```



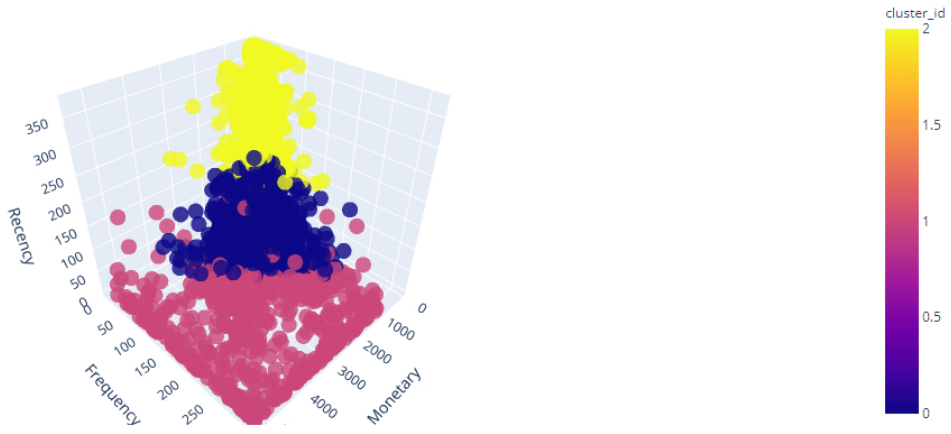


Customer distribution

```
[ ]  # Number of customers per cluster

     font_title = {
             'color':  '#104C6C',
             'weight': 'normal',
             'size': 16,
             }


     font_label = {
             'color':  '#104C6C',
             'weight': 'normal',
             'size': 13,
             }
     plt.figure(figsize=(8,6))
     ax = X_scaled['cluster_id'].value_counts().plot(kind='bar')
     ax.set_xticklabels(['Promising','Slipping','Loyal'])
     ax.set_ylabel('Number of Customers',font_label)
     ax.set_xlabel('Clusters',font_label)
     ax.set_title("Customer Distribution",font_title)
     plt.show()
```

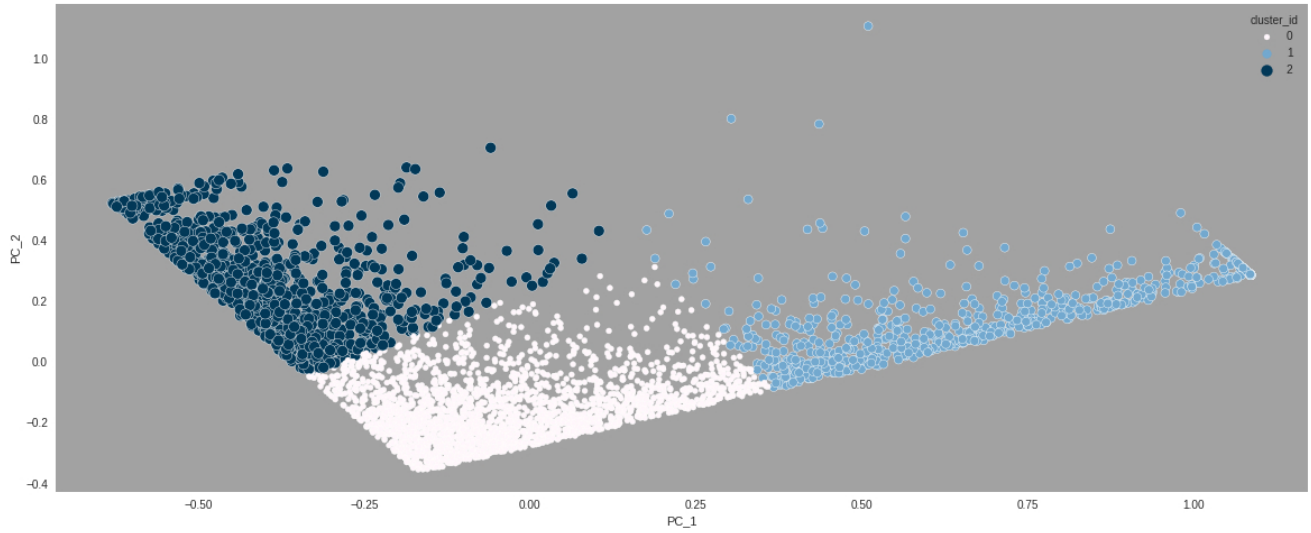

```
[ ]
```

```
[ ]  fig = plt.figure(figsize=[15,7])
     fig = px.scatter_3d(X, x = 'Monetary', y='Frequency', z='Recency',
                 color='cluster_id', opacity = 0.8,size_max=30)
     fig.show()
```




```
<Figure size 1080x504 with 0 Axes>
```

```
[ ] # Vusializing clusters using Principle Components
    fig = plt.figure(figsize=[20,8])
    sns.scatterplot(data=X_scaled,x="PC_1",y="PC_2",hue="cluster_id",size="cluster_id",palette="PuBu")
    plt.show()
```



Inference:

- Cluster 0 contains the customers who generate the least revenue and are not frequent, most likely because these were one-time customers. Hence they can be labeled as Slipping.
- Cluster 1 seems to have the most loyal customers, as they bring the most revenue and are often the most frequent customers.
- Cluster 2 customers seem promising as it consists of frequent buyers, however revenue generation is not as high as Loyal customers

5. Recommendations

- After segmenting customers into loyal, slipping, and promising it empowers businesses to run personalized, high-performing campaigns and preserves profit margin. Below are a few recommendations or targeted strategies for each customer segment:
- Loyal - Loyalty programs are effective for these repeat visitors. Advocacy programs and reviews are also common X1X strategies. Lastly, consider rewarding these customers with Free Shipping or other like benefits.
- Promising - Focus on increasing monetization through product recommendations based on past purchases and incentives tied to spending thresholds.
- Slipping - Customers leave for a variety of reasons. Depending on your situation price deals, new product launches, or other retention strategies.