Introduction

In a world where businesses are growing tremendously, and cater to a large number of customers on a regular basis. It becomes very essential for businesses to categorize their customers. Customer segmentation is an effective tool for businesses to closely align their strategy and tactics with, and better target, their customers. Every customer is different and every customer journey is different so a single approach often isn't going to work for all. This is where customer segmentation becomes a valuable process.

Problem Description

To bulid RFM Value and categorize the customers for given Data set

This project has been completed in 5 steps :-

1. Data Cleaning

2. Exploratory Data Analysis (EDA)

3. Data Transformation

4. Clustering and segmentation

5. Data visulization

1) Importing the data and Cleaning

In [1]:
```
# Import Dependencies
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import missingno
import seaborn as sns
import datetime as dt
import numpy as np
import squarify
import plotly.express as px
import regex as re
import plotly.graph_objects as go
```

here we will read our data and go through the columns and rows for further development

In [2]:
```
df = pd.read_csv('sales_data.csv')
```

In [3]:
```
1 df.head(10)
```

Out[3]:

	CustomerID	TOTAL_ORDERS	REVENUE	AVERAGE_ORDER_VALUE	CARRIAGE_REVENUE	AVERAGESHIPPING	FIRST_ORDER_DATE
0	22	124	11986.54	96.67	529.59	4.27	30-Dec-16
1	29	82	11025.96	134.46	97.92	1.19	31-Mar-18
2	83	43	7259.69	168.83	171.69	3.99	30-Nov-17
3	95	44	6992.27	158.92	92.82	2.11	9-Apr-19
4	124	55	6263.44	113.88	179.04	3.26	23-Oct-20
5	153	49	5841.24	119.21	96.84	1.98	26-Jul-15
6	187	43	5470.27	127.22	128.77	2.99	14-Jan-19
7	219	54	5200.53	96.31	237.53	4.40	19-Nov-19
8	258	19	4967.06	261.42	51.91	2.73	3-Mar-21
9	308	21	4726.38	225.07	63.88	3.04	6-Jan-20

10 rows × 40 columns

In [4]:
```
1 df.columns
```

Out[4]:
```
Index(['CustomerID', 'TOTAL_ORDERS', 'REVENUE', 'AVERAGE_ORDER_VALUE',
       'CARRIAGE_REVENUE', 'AVERAGESHIPPING', 'FIRST_ORDER_DATE',
       'LATEST_ORDER_DATE', 'AVGDAYSBETWEENORDERS', 'DAYSSINCELASTORDER',
       'MONDAY_ORDERS', 'TUESDAY_ORDERS', 'WEDNESDAY_ORDERS',
       'THURSDAY_ORDERS', 'FRIDAY_ORDERS', 'SATURDAY_ORDERS', 'SUNDAY_ORDERS',
       'MONDAY_REVENUE', 'TUESDAY_REVENUE', 'WEDNESDAY_REVENUE',
       'THURSDAY_REVENUE', 'FRIDAY_REVENUE', 'SATURDAY_REVENUE',
       'SUNDAY_REVENUE', 'WEEK1_DAY01_DAY07_ORDERS',
       'WEEK2_DAY08_DAY15_ORDERS', 'WEEK3_DAY16_DAY23_ORDERS',
       'WEEK4_DAY24_DAY31_ORDERS', 'WEEK1_DAY01_DAY07_REVENUE',
       'WEEK2_DAY08_DAY15_REVENUE', 'WEEK3_DAY16_DAY23_REVENUE',
       'WEEK4_DAY24_DAY31_REVENUE', 'TIME_0000_0600_ORDERS',
       'TIME_0601_1200_ORDERS', 'TIME_1200_1800_ORDERS',
       'TIME_1801_2359_ORDERS', 'TIME_0000_0600_REVENUE',
       'TIME_0601_1200_REVENUE', 'TIME_1200_1800_REVENUE',
       'TIME_1801_2359_REVENUE'],
      dtype='object')
```

In [5]:
```
1 df.shape
```

Out[5]:
```
(5000, 40)
```

In [6]:
```
df.dtypes
```

Out[6]:
```
CustomerID                    int64
TOTAL_ORDERS                  int64
REVENUE                     float64
AVERAGE_ORDER_VALUE         float64
CARRIAGE_REVENUE            float64
AVERAGESHIPPING             float64
FIRST_ORDER_DATE             object
LATEST_ORDER_DATE            object
AVGDAYSBETWEENORDERS        float64
DAYSSINCELASTORDER            int64
MONDAY_ORDERS                 int64
TUESDAY_ORDERS                int64
WEDNESDAY_ORDERS              int64
THURSDAY_ORDERS               int64
FRIDAY_ORDERS                 int64
SATURDAY_ORDERS               int64
SUNDAY_ORDERS                 int64
MONDAY_REVENUE              float64
TUESDAY_REVENUE             float64
WEDNESDAY_REVENUE           float64
THURSDAY_REVENUE            float64
FRIDAY_REVENUE              float64
SATURDAY_REVENUE            float64
SUNDAY_REVENUE              float64
WEEK1_DAY01_DAY07_ORDERS      int64
WEEK2_DAY08_DAY15_ORDERS      int64
WEEK3_DAY16_DAY23_ORDERS      int64
WEEK4_DAY24_DAY31_ORDERS      int64
WEEK1_DAY01_DAY07_REVENUE   float64
WEEK2_DAY08_DAY15_REVENUE   float64
WEEK3_DAY16_DAY23_REVENUE   float64
WEEK4_DAY24_DAY31_REVENUE   float64
TIME_0000_0600_ORDERS         int64
TIME_0601_1200_ORDERS         int64
TIME_1200_1800_ORDERS         int64
TIME_1801_2359_ORDERS         int64
TIME_0000_0600_REVENUE      float64
TIME_0601_1200_REVENUE      float64
TIME_1200_1800_REVENUE      float64
TIME_1801_2359_REVENUE      float64
dtype: object
```

Different type of datatype in data set

Data Cleaning and handleing for missing value

- It is very important to clean the data and find the missing values as it may affect our model
- I am using an lib called missingo to verify the miising values in data sets
- It returns a graph as we can easily visualise the data set

In [7]:
```
df.describe()
```

Out[7]:

	CustomerID	TOTAL_ORDERS	REVENUE	AVERAGE_ORDER_VALUE	CARRIAGE_REVENUE	AVERAGESHIPPING	AVGDAYSB
count	5000.000000	5000.00000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	40709.227800	12.87040	1681.523840	136.537378	46.036376	3.592574	
std	49949.848017	12.67988	1998.618678	91.651569	47.879226	2.021360	
min	1.000000	1.00000	38.500000	10.680000	0.000000	0.000000	
25%	1687.500000	3.00000	315.097500	83.025000	9.980000	2.500000	
50%	13765.000000	8.00000	966.725000	113.160000	24.985000	3.660000	
75%	71891.500000	20.00000	2493.072500	160.272500	76.862500	4.790000	
max	277160.000000	156.00000	34847.400000	1578.880000	529.590000	35.990000	

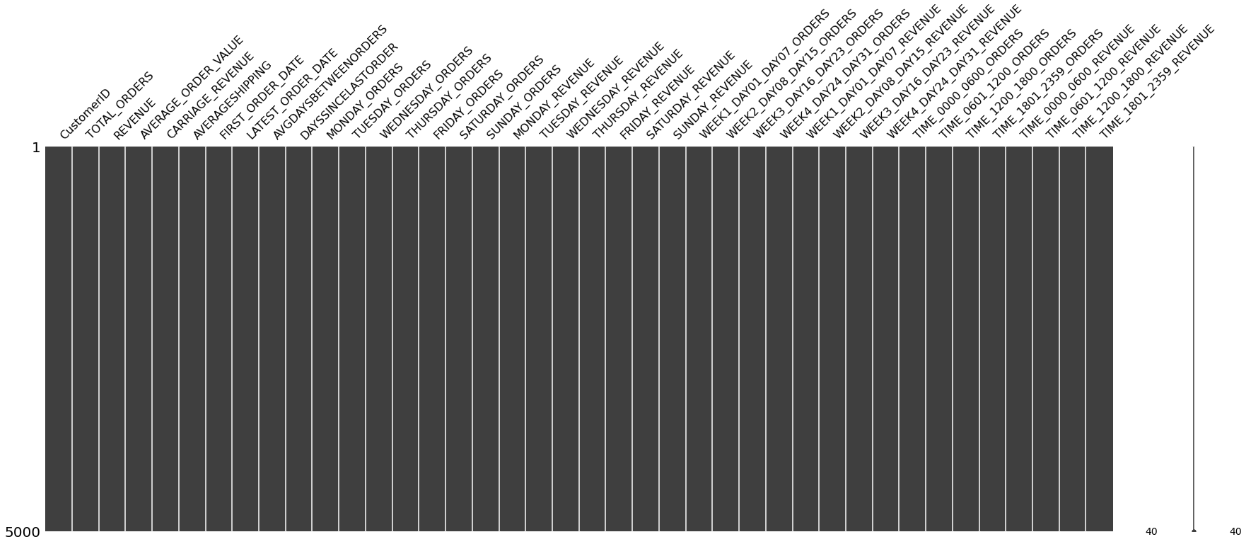
8 rows × 38 columns

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 40 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   CustomerID                 5000 non-null   int64
 1   TOTAL_ORDERS               5000 non-null   int64
 2   REVENUE                    5000 non-null   float64
 3   AVERAGE_ORDER_VALUE        5000 non-null   float64
 4   CARRIAGE_REVENUE           5000 non-null   float64
 5   AVERAGESHIPPING            5000 non-null   float64
 6   FIRST_ORDER_DATE           5000 non-null   object
 7   LATEST_ORDER_DATE          5000 non-null   object
 8   AVGDAYSBETWEENORDERS       5000 non-null   float64
 9   DAYSSINCELASTORDER         5000 non-null   int64
 10  MONDAY_ORDERS              5000 non-null   int64
 11  TUESDAY_ORDERS             5000 non-null   int64
 12  WEDNESDAY_ORDERS           5000 non-null   int64
 13  THURSDAY_ORDERS            5000 non-null   int64
```

In [9]:
```
missingno.matrix(df,figsize=(30,10))
```

Out[9]: <AxesSubplot:>



- **hear we can see the data set is clean and their is no missing value**

2) EDA

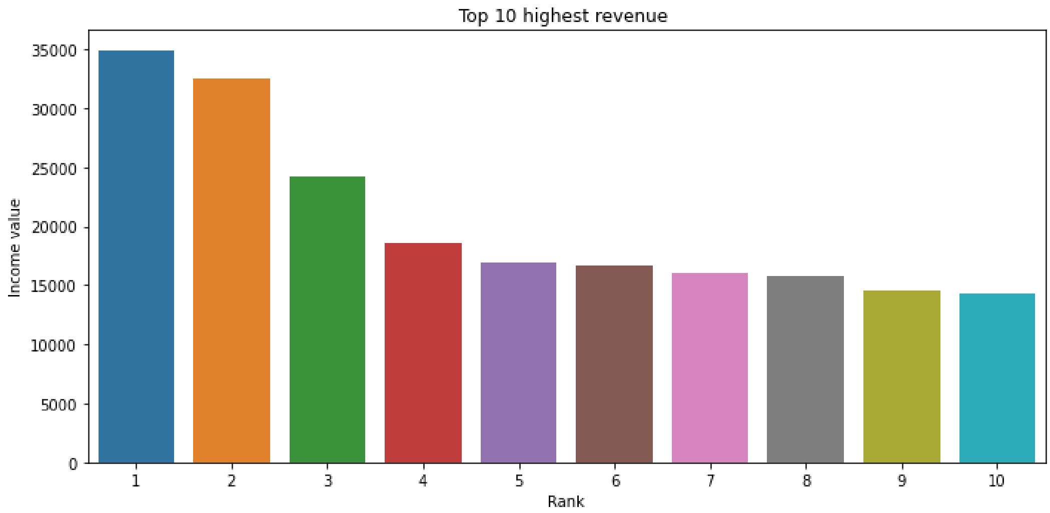
In EDA we are trying to figure out more about the data so you can build a model the best way you can.we usually do this when you first look at a dataset but it'll continually happen as you learn more. EDA is an iterative process. There's no one way to do it either. It'll vary with each new dataset

- the basic idea is
- 1) to make our RFM model based on customer Data
- 2) to Know on which day, week of month the customer is active so we can give special deals
- 3) this data set is clean and do not have any typo error

1)Top ten highest revenue

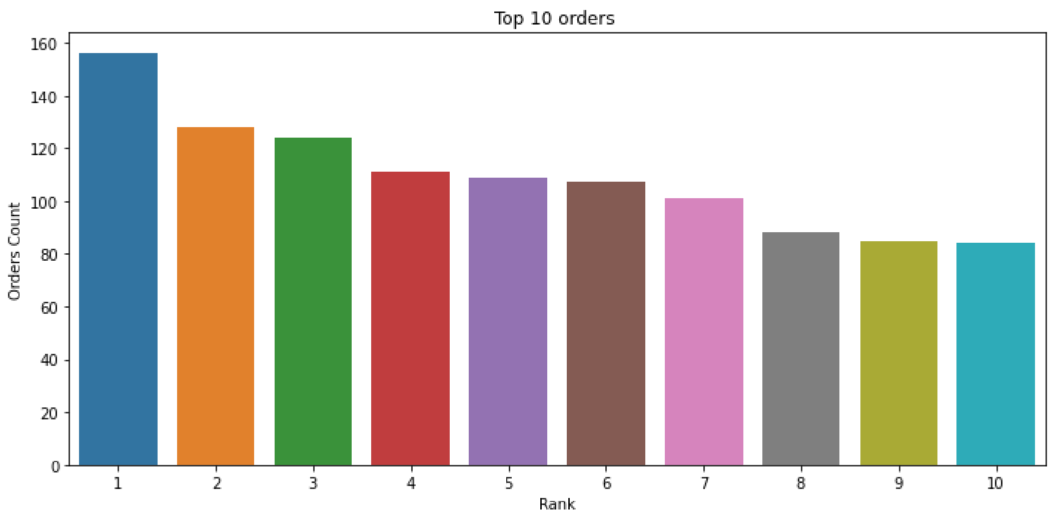
In [10]:
```
top_revenue = df['REVENUE'].sort_values(ascending = False)[:10]
```

In [11]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = [1,2,3,4,5,6,7,8,9,10], y = top_revenue)
plt.xlabel('Rank')
plt.ylabel('Income value')
plt.title('Top 10 highest revenue ')
plt.tight_layout()
```



2) Top ten highest orders

In [12]:
```
top_orders = df['TOTAL_ORDERS'].sort_values(ascending = False)[:10]
plt.figure(figsize = (10,5))
sns.barplot(x = [1,2,3,4,5,6,7,8,9,10], y = top_orders)
plt.xlabel('Rank')
plt.ylabel('Orders Count')
plt.title('Top 10 orders ')
plt.tight_layout()
```



3) Days of week

weekly purchaces

In [13]:
```
df_dates = df[['MONDAY_ORDERS', 'TUESDAY_ORDERS', 'WEDNESDAY_ORDERS',
       'THURSDAY_ORDERS', 'FRIDAY_ORDERS', 'SATURDAY_ORDERS', 'SUNDAY_ORDERS',
       'MONDAY_REVENUE', 'TUESDAY_REVENUE', 'WEDNESDAY_REVENUE',
       'THURSDAY_REVENUE', 'FRIDAY_REVENUE', 'SATURDAY_REVENUE',
       'SUNDAY_REVENUE']]
```

In [14]:
```
df_dates.head()
```

Out[14]:

	MONDAY_ORDERS	TUESDAY_ORDERS	WEDNESDAY_ORDERS	THURSDAY_ORDERS	FRIDAY_ORDERS	SATURDAY_ORDERS	SUNDA
0	13	13	29	25	19	15	
1	11	13	10	13	14	10	
2	5	4	3	5	5	8	
3	10	8	5	8	5	3	
4	2	3	8	8	12	10	

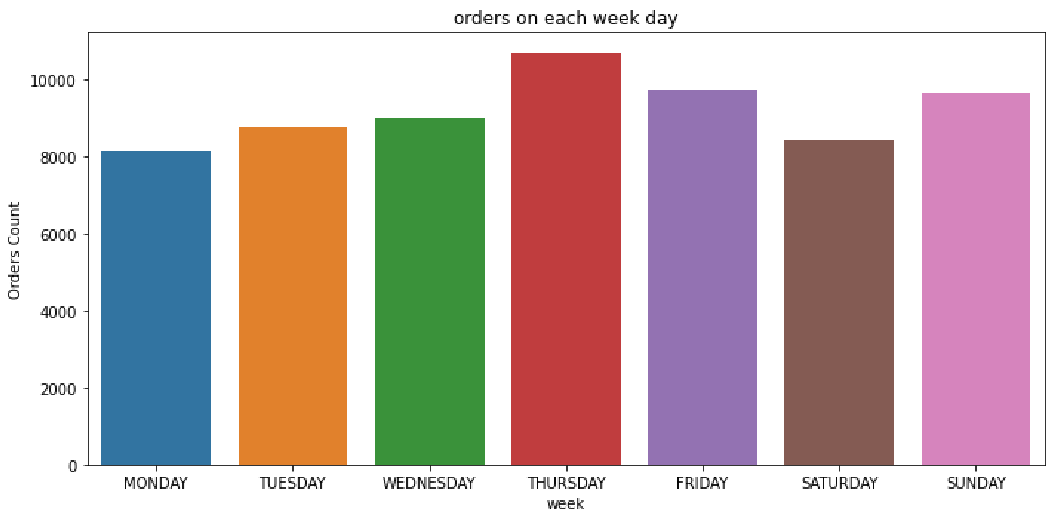
In [15]:
```
sum_of_orders = df_dates[['MONDAY_ORDERS', 'TUESDAY_ORDERS', 'WEDNESDAY_ORDERS',
       'THURSDAY_ORDERS', 'FRIDAY_ORDERS', 'SATURDAY_ORDERS', 'SUNDAY_ORDERS',
       'MONDAY_REVENUE', 'TUESDAY_REVENUE', 'WEDNESDAY_REVENUE',
       'THURSDAY_REVENUE', 'FRIDAY_REVENUE', 'SATURDAY_REVENUE',
       'SUNDAY_REVENUE']].sum()
```

In [16]:
```
sum_of_orders = pd.DataFrame(sum_of_orders)
```

Orders

In [17]:
```
# making number of order on any week day
orders_day = pd.DataFrame(sum_of_orders[:7] )
orders_day.reset_index(inplace = True)
orders_day.rename(columns = {'index':'Day',0:'NO_of_Orders'},inplace = True)
# removing "_"orders to make everything look clean
orders_day['Day']=orders_day['Day'].str.split('_').str[0]
```

In [18]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = orders_day['Day'], y = orders_day['NO_of_Orders'])
plt.xlabel('week')
plt.ylabel('Orders Count')
plt.title('orders on each week day')
plt.tight_layout()
```

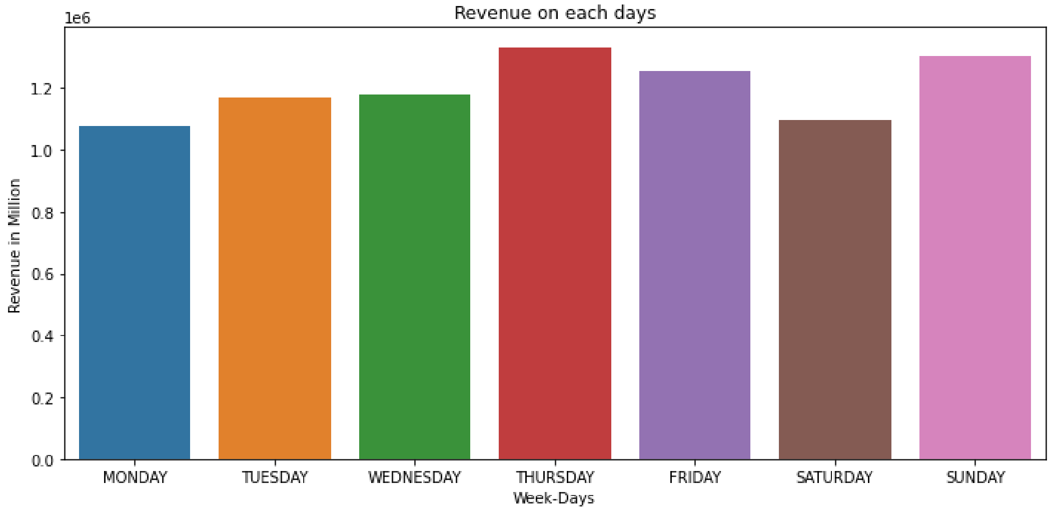


Revenue

In [19]:
```
# making total revenue on any week day
revenue_day = pd.DataFrame(sum_of_orders[7:])
revenue_day.reset_index(inplace = True)
revenue_day.rename(columns = {'index':'Day',0:'Sum_of_Revenue'},inplace = True)
```

In [20]:
```
# removing "_"orders to make everything look clean
revenue_day['Day']=revenue_day['Day'].str.split('_').str[0]
```

In [21]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = revenue_day['Day'], y = revenue_day['Sum_of_Revenue'])
plt.xlabel('Week-Days')
plt.ylabel('Revenue in Million')
plt.title('Revenue on each days')
plt.tight_layout()
```



From the plot for Weekly purchases it is seen that most of the purchases, occur in the Thursday Followed by Sunday and friday

- **now we got orders_day and revenue_day**

In [22]:
```
#combain to make it one df
revenue_day['NO_of_Orders'] = orders_day['NO_of_Orders']
```

In [23]:
```
# normalizing the revenue to make easy plot as revenue is in millions so dividing by 100 we will
# get in 10k range
revenue_day['Sum_of_Revenue_in_100'] = revenue_day['Sum_of_Revenue']/100
```

4) Week's in Month

total months can be calucalted form first_order and last order

In [24]:
```
df_Fday = pd.to_datetime(df['FIRST_ORDER_DATE'].min())
df_Lday = pd.to_datetime(df['LATEST_ORDER_DATE'].max())
```

In [25]:
```
# Finding to days years and months
total_days = (df_Lday-df_Fday).days
total_Year = total_days/365
total_month = total_Year*12
```

In [26]:

```
df_months = df[['WEEK1_DAY01_DAY07_ORDERS',
        'WEEK2_DAY08_DAY15_ORDERS', 'WEEK3_DAY16_DAY23_ORDERS',
        'WEEK4_DAY24_DAY31_ORDERS', 'WEEK1_DAY01_DAY07_REVENUE',
        'WEEK2_DAY08_DAY15_REVENUE', 'WEEK3_DAY16_DAY23_REVENUE',
        'WEEK4_DAY24_DAY31_REVENUE']]
rename =['WEEK1_ORDERS',
        'WEEK2_ORDERS', 'WEEK3_ORDERS',
        'WEEK4_ORDERS', 'WEEK1_REVENUE',
        'WEEK2_REVENUE', 'WEEK3_REVENUE',
        'WEEK4_REVENUE']
columns = ['WEEK1_DAY01_DAY07_ORDERS', 'WEEK2_DAY08_DAY15_ORDERS',
        'WEEK3_DAY16_DAY23_ORDERS', 'WEEK4_DAY24_DAY31_ORDERS',
        'WEEK1_DAY01_DAY07_REVENUE', 'WEEK2_DAY08_DAY15_REVENUE',
        'WEEK3_DAY16_DAY23_REVENUE', 'WEEK4_DAY24_DAY31_REVENUE']
df_months = pd.DataFrame(df_months)
# changing column names
k = {}
for i,(x,y) in enumerate(zip(columns,rename)):
    k[x] = y
df_months.rename(columns = k, inplace = True)
```

In [27]:

```
df_months
```

Out[27]:

	WEEK1_ORDERS	WEEK2_ORDERS	WEEK3_ORDERS	WEEK4_ORDERS	WEEK1_REVENUE	WEEK2_REVENUE	WEEK3_REVENUE
0	28	42	30	24	2685.37	4299.28	2592.18
1	18	19	19	26	1336.09	2776.02	2807.66
2	9	11	6	17	2299.93	1383.92	713.94
3	12	15	9	8	2317.95	2417.22	997.02
4	10	18	21	6	831.14	1938.18	2725.66
...	...	...	...	...	...	...	...
4995	1	0	0	0	117.49	0.00	0.00
4996	1	0	0	0	117.49	0.00	0.00
4997	1	0	0	0	117.49	0.00	0.00
4998	1	0	0	0	117.49	0.00	0.00
4999	1	0	0	1	44.19	0.00	0.00

5000 rows × 8 columns

In [28]:

```
df_months_ = df_months[['WEEK1_ORDERS',
        'WEEK2_ORDERS', 'WEEK3_ORDERS',
        'WEEK4_ORDERS', 'WEEK1_REVENUE',
        'WEEK2_REVENUE', 'WEEK3_REVENUE',
        'WEEK4_REVENUE']].sum()
df_months_=pd.DataFrame(df_months_)
```

Orders

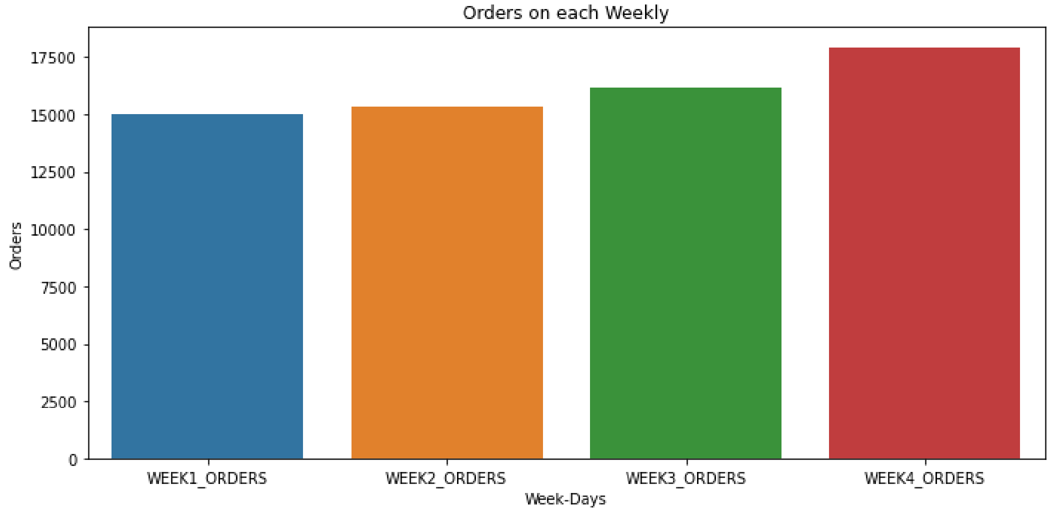
In [29]:

```
#month order
df_months_order = pd.DataFrame(df_months_[:4])
df_months_order.reset_index(inplace = True)
df_months_order.rename(columns = {'index':'Week_Num',0:'NUM_of_Orders'} , inplace = True)
df_months_order
```

Out[29]:

	Week_Num	NUM_of_Orders
0	WEEK1_ORDERS	14989.0
1	WEEK2_ORDERS	15313.0
2	WEEK3_ORDERS	16150.0
3	WEEK4_ORDERS	17900.0

In [30]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = df_months_order['Week_Num'], y = df_months_order['NUM_of_Orders'])
plt.xlabel('Week-Days')
plt.ylabel('Orders')
plt.title('Orders on each Weekly')
plt.tight_layout()
```



Revenue

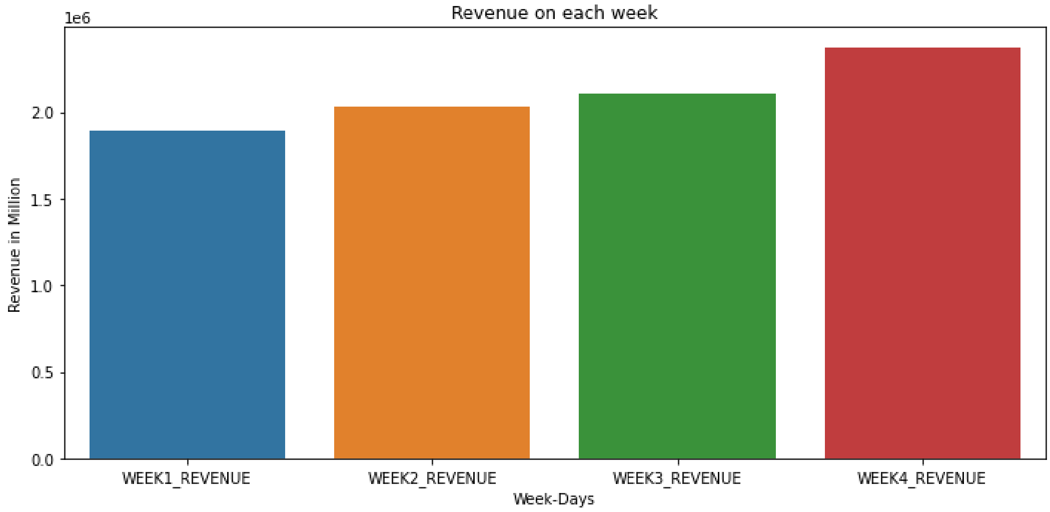
In [31]:
```

df_months_revenue = pd.DataFrame(df_months_[4:])
df_months_revenue.reset_index(inplace = True)
df_months_revenue.rename(columns = {'index':'Week_Num',0:'Revenue'} , inplace = True)
df_months_revenue
```

Out[31]:

	Week_Num	Revenue
0	WEEK1_REVENUE	1893191.73
1	WEEK2_REVENUE	2032978.67
2	WEEK3_REVENUE	2109134.54
3	WEEK4_REVENUE	2372314.26

In [32]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = df_months_revenue['Week_Num'], y = df_months_revenue['Revenue'])
plt.xlabel('Week-Days')
plt.ylabel('Revenue in Million')
plt.title('Revenue on each week')
plt.tight_layout()
```



From the Above plot's. it is seen that most of the purchases, occur in the Week-4

4) Time of Day

In [33]:
```
df_time = pd.DataFrame(df[['TIME_0000_0600_ORDERS',
       'TIME_0601_1200_ORDERS', 'TIME_1200_1800_ORDERS',
       'TIME_1801_2359_ORDERS', 'TIME_0000_0600_REVENUE',
       'TIME_0601_1200_REVENUE', 'TIME_1200_1800_REVENUE',
       'TIME_1801_2359_REVENUE']])
df_time_ = df_time[['TIME_0000_0600_ORDERS',
       'TIME_0601_1200_ORDERS', 'TIME_1200_1800_ORDERS',
       'TIME_1801_2359_ORDERS', 'TIME_0000_0600_REVENUE',
       'TIME_0601_1200_REVENUE', 'TIME_1200_1800_REVENUE',
       'TIME_1801_2359_REVENUE']].sum()
df_time_ = pd.DataFrame(df_time_)
```

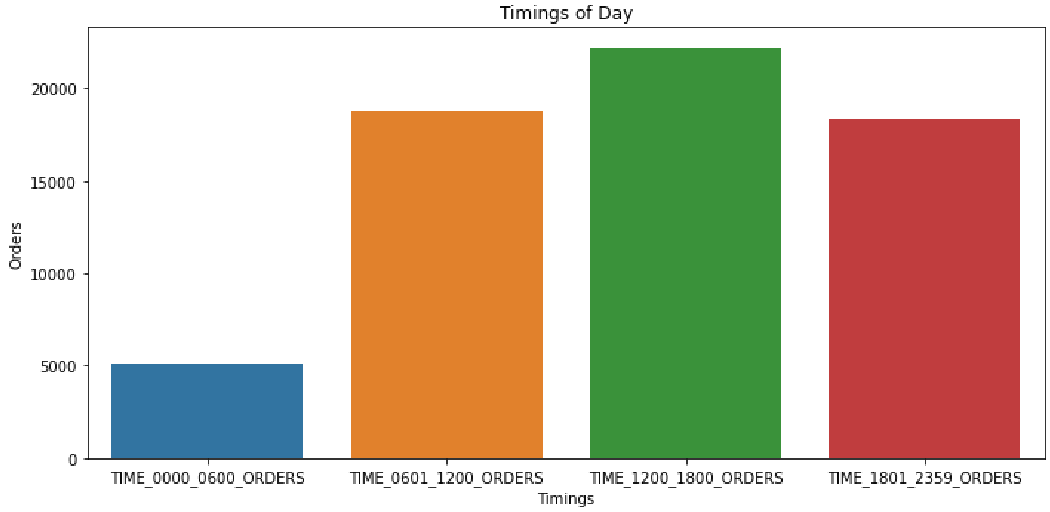
Orders

In [34]:
```
df_Time_order = pd.DataFrame(df_time_[:4])
df_Time_order.reset_index(inplace = True)
df_Time_order.rename(columns = {'index':'Timings',0:'NUM_of_Orders'} , inplace = True)
df_Time_order
```

Out[34]:

	Timings	NUM_of_Orders
0	TIME_0000_0600_ORDERS	5144.0
1	TIME_0601_1200_ORDERS	18731.0
2	TIME_1200_1800_ORDERS	22170.0
3	TIME_1801_2359_ORDERS	18307.0

In [35]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = df_Time_order['Timings'][:10], y = df_Time_order['NUM_of_Orders'][:10])
plt.xlabel('Timings')
plt.ylabel('Orders')
plt.title('Timings of Day')
plt.tight_layout()
```



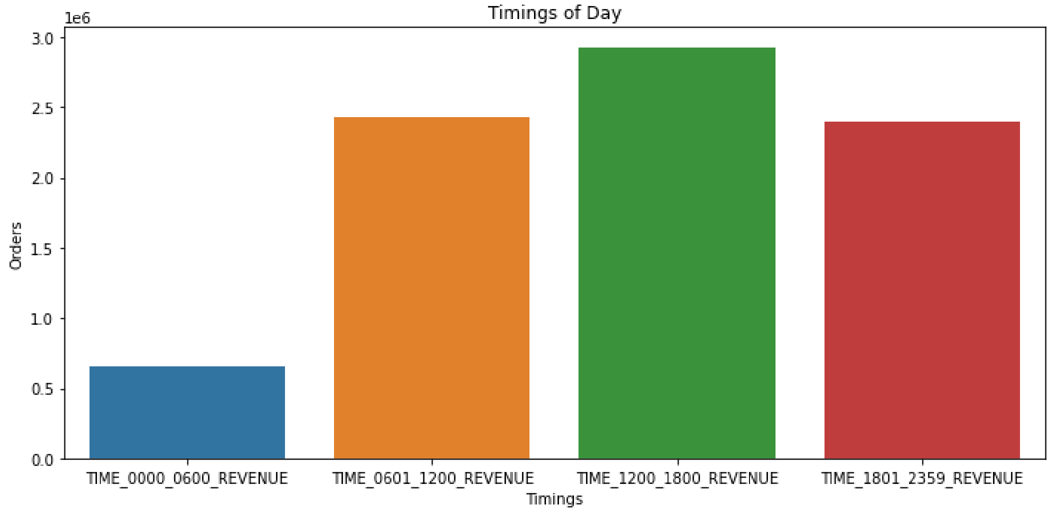
Revenue

In [36]:
```
df_Time_revenue = pd.DataFrame(df_time_[4:])
df_Time_revenue.reset_index(inplace = True)
df_Time_revenue.rename(columns = {'index':'Timings',0:'Revenue'} , inplace = True)
df_Time_revenue
```

Out[36]:

	Timings	Revenue
0	TIME_0000_0600_REVENUE	655313.18
1	TIME_0601_1200_REVENUE	2434319.34
2	TIME_1200_1800_REVENUE	2923658.13
3	TIME_1801_2359_REVENUE	2394328.55

In [37]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = df_Time_revenue['Timings'], y = df_Time_revenue['Revenue'])
plt.xlabel('Timings')
plt.ylabel('Orders')
plt.title('Timings of Day')
plt.tight_layout()
```



In [ ]:
```

```

5) Customer with high revenue and high order

In [38]:
```
df_customer = pd.DataFrame(df[['CustomerID','REVENUE','TOTAL_ORDERS']])
df_customer_revenue = pd.DataFrame(df[['CustomerID','REVENUE']])
df_customer_orders = pd.DataFrame(df[['CustomerID','TOTAL_ORDERS']])
```

Orders

In [39]:
```
df_customer_orders .sort_values(by =['TOTAL_ORDERS'],ascending=False,inplace = True)
df_customer_orders.reset_index(inplace = True)
df_customer_orders.drop(columns=['index'],inplace =True)
df_customer_orders.head(10)

```

Out[39]:

	CustomerID	TOTAL_ORDERS
0	26	156
1	28	128
2	22	124
3	47	111
4	88	109
5	48	107
6	23	101
7	107	88
8	180	85
9	4	84

Revenue

In [40]:
```
df_customer_revenue.sort_values(by =['REVENUE'],ascending=False,inplace = True)
df_customer_revenue.reset_index(inplace = True)
df_customer_revenue.drop(columns=['index'],inplace =True)
df_customer_revenue.head(10)
```

Out[40]:

	CustomerID	REVENUE
0	1	34847.40
1	2	32486.98
2	3	24178.97
3	4	18554.49
4	5	16884.99
5	6	16693.78
6	7	15999.94
7	8	15840.36
8	9	14526.72
9	10	14309.92

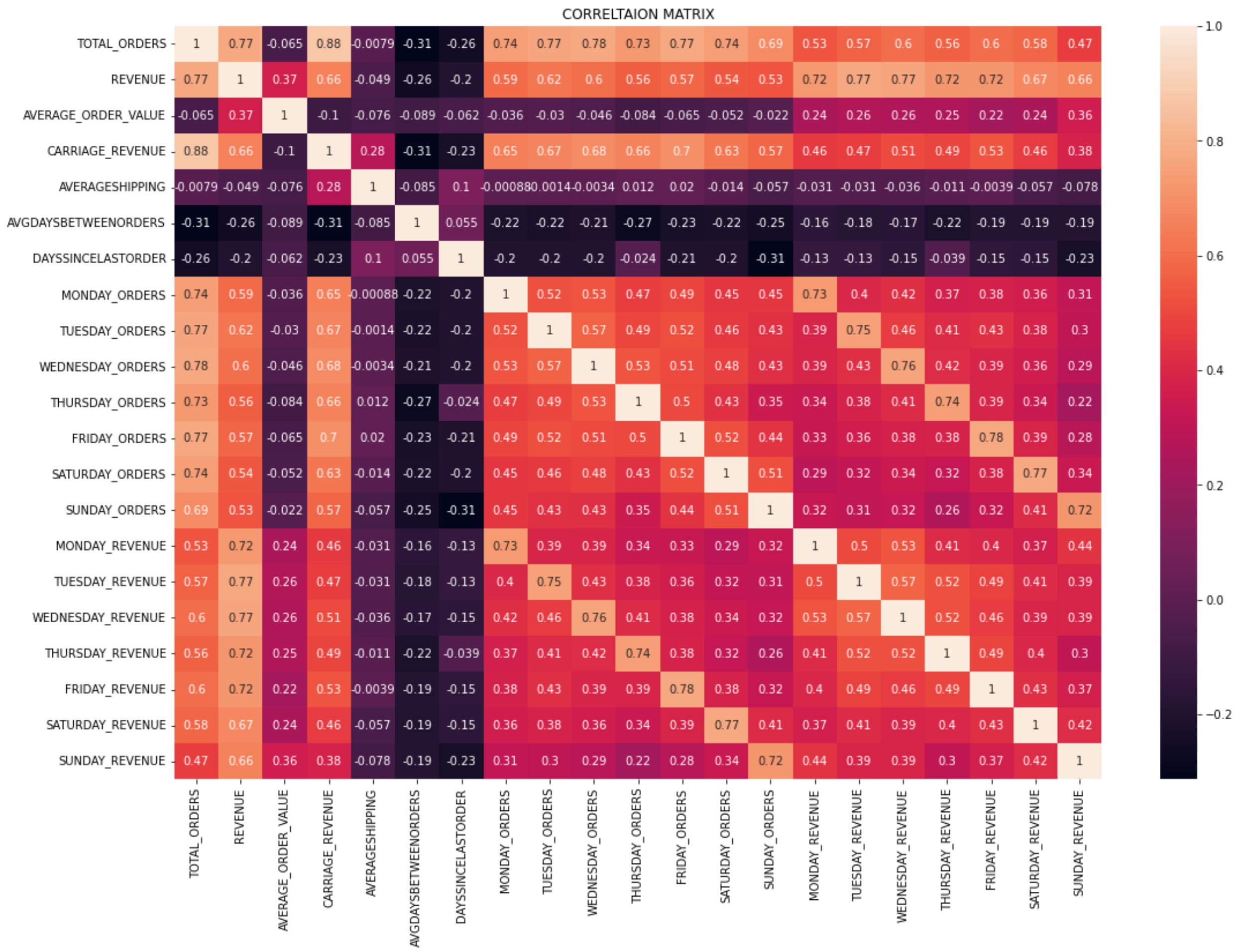
From above tables CustomerID 1 Has high Revenue and CustomerID 26 has high Order list

6) Correlation between variables

In [41]:
```
k = df.columns[1:24]
df1 = pd.DataFrame(df[k])
```

In [42]:
```
plt.figure(figsize = (18,12))
sns.heatmap(df1.corr(), annot = True)
plt.title('CORRELTAION MATRIX')
```

Out[42]: Text(0.5, 1.0, 'CORRELTAION MATRIX')



From the correaltion matrix, it is understood that most columns are not correlated to each other. Except for Day and weeks, they are highly correlated . Where as 'AVGdays' and 'Days since last order' are negatively correlated.

EDA Summary

From Above EDA Process we can assume that

- 156 is the Highest Ordes from a single person
- 34847 is the highest revenue from a single person
- Thursday and Sunday are the Highest in revenue and Order placed
- most Shopping happens at month End
- some People have less order but average cost of each item is high
- If person purchaced more than 3 times he tend's to shop more

2) Data Transformation

Performing RFM Segmentation and RFM Analysis

RFM model

* The idea is to divide the customer based on their Recency , Frequency , Monetary

* RFM model will be the best fit for this data

- Recency: How much time has elapsed since a customer’s last activity or transaction with the brand
- Frequency: How often has a customer transacted or interacted with the brand during a particular period of time
- Monetary: Also referred to as “monetary value,” this factor reflects how much a customer has spent with the brand during a particular period of time.

1) Recency

Recency factor is based on the notion that the more recently a customer has made a purchase with a company, the more likely they will continue to keep the business and brand in mind for subsequent purchases. This information can be used to remind recent customers to revisit the business soon to continue meeting their purchase needs.

now we calculate recency using our data set

In [43]:
```
df.head()
```

Out[43]:

	CustomerID	TOTAL_ORDERS	REVENUE	AVERAGE_ORDER_VALUE	CARRIAGE_REVENUE	AVERAGESHIPPING	FIRST_ORDER_DATE
0	22	124	11986.54	96.67	529.59	4.27	30-Dec-16
1	29	82	11025.96	134.46	97.92	1.19	31-Mar-18
2	83	43	7259.69	168.83	171.69	3.99	30-Nov-17
3	95	44	6992.27	158.92	92.82	2.11	9-Apr-19
4	124	55	6263.44	113.88	179.04	3.26	23-Oct-20

5 rows × 40 columns

In [44]:
```
# convert to date time
df['Date']= pd.to_datetime(df['LATEST_ORDER_DATE'])

```

In [45]:
```
# grouping the based on customerID and laste date of order
df_RFM = df.groupby(by='CustomerID',as_index=False)['Date'].max()
```

In [46]:
```
# recent date will be the latest order amoung all orders
recent_date = df_RFM['Date'].max()
```

In [47]:
```
# as defination Recency is latest order date - last date of that customer ordered
df_RFM['Recency'] = df_RFM['Date'].apply(lambda x: (recent_date - x).days)
```

In [48]:
```
df_RFM.head()
```

Out[48]:

	CustomerID	Date	Recency
0	1	2021-09-02	52
1	2	2021-07-23	93
2	3	2021-09-02	52
3	4	2021-10-20	4
4	5	2021-06-17	129

2) Frequency

The frequency of a customer's transactions may be affected by factors such as the type of product, the price point for the purchase, and the need for replenishment or replacement. Predicting this can assist marketing efforts directed at reminding the customer to visit the business again.

alredy we have total-order from each customer so the frequency will be easy to find

In [49]:
```
df_RFM['Frequency'] = df['TOTAL_ORDERS']
```

3) Monetary Value

Monetary value stems from how much the customer spends. A natural inclination is to put more emphasis on encouraging customers who spend the most money to continue to do so. While this can produce a better return on investment in marketing and customer service, it also runs the risk of alienating customers who have been consistent but may not spend as much with each transaction.

- in this data set we have carriage revenue
- we should minus this value from total revenue of customer to get our exact profit

In [50]:
```
df_RFM['Monetary'] = df['REVENUE'] - df['CARRIAGE_REVENUE']
```

In [51]:
```
df_RFM.drop('Date', inplace=True, axis=1)
```

In [52]:
```
df_RFM.head()
```

Out[52]:

	CustomerID	Recency	Frequency	Monetary
0	1	52	124	11456.95
1	2	93	82	10928.04
2	3	52	43	7088.00
3	4	4	44	6899.45
4	5	129	55	6084.40

In [53]:
```
plt.figure(figsize=(12,10))
# Plot distribution of R
plt.subplot(3, 1, 1); sns.distplot(df_RFM['Recency'])
# Plot distribution of F
plt.subplot(3, 1, 2); sns.distplot(df_RFM['Frequency'])
# Plot distribution of M
plt.subplot(3, 1, 3); sns.distplot(df_RFM['Monetary'])
# Show the plot
plt.show()
```

```
C:\Users\prajw\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a depr
ecated function and will be removed in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\prajw\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a depr
ecated function and will be removed in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\prajw\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a depr
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gure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```
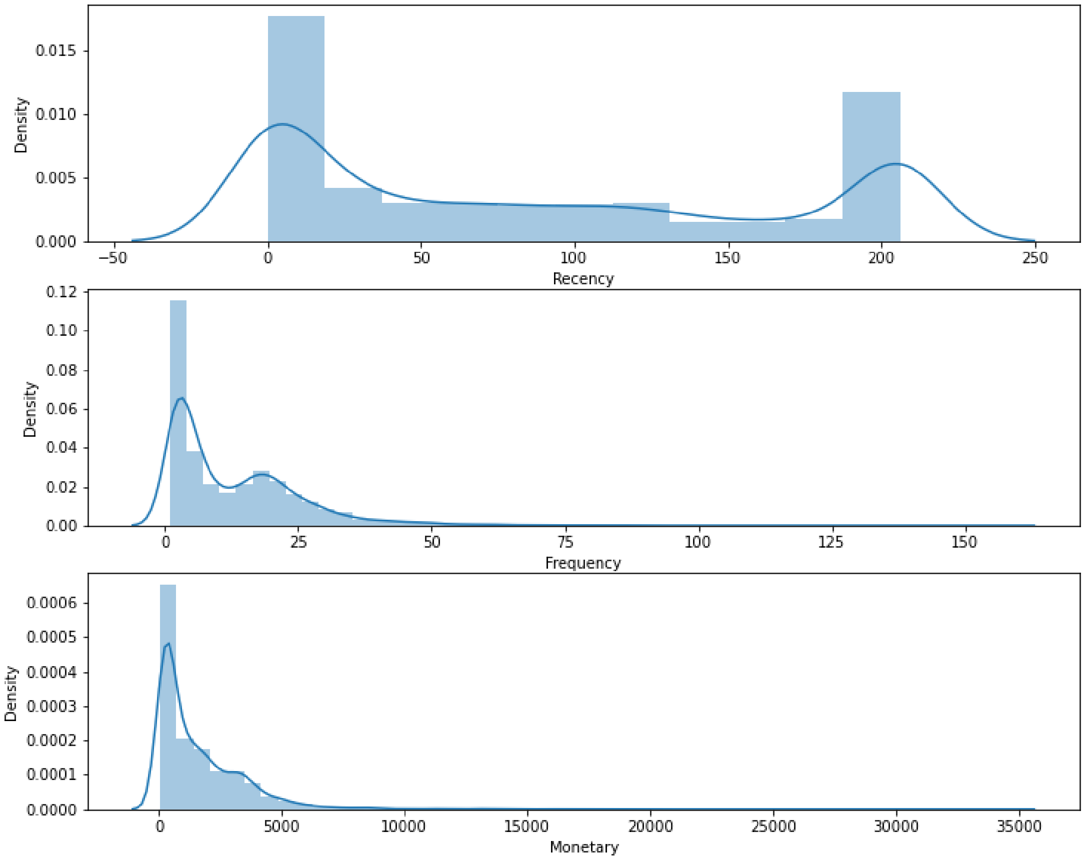
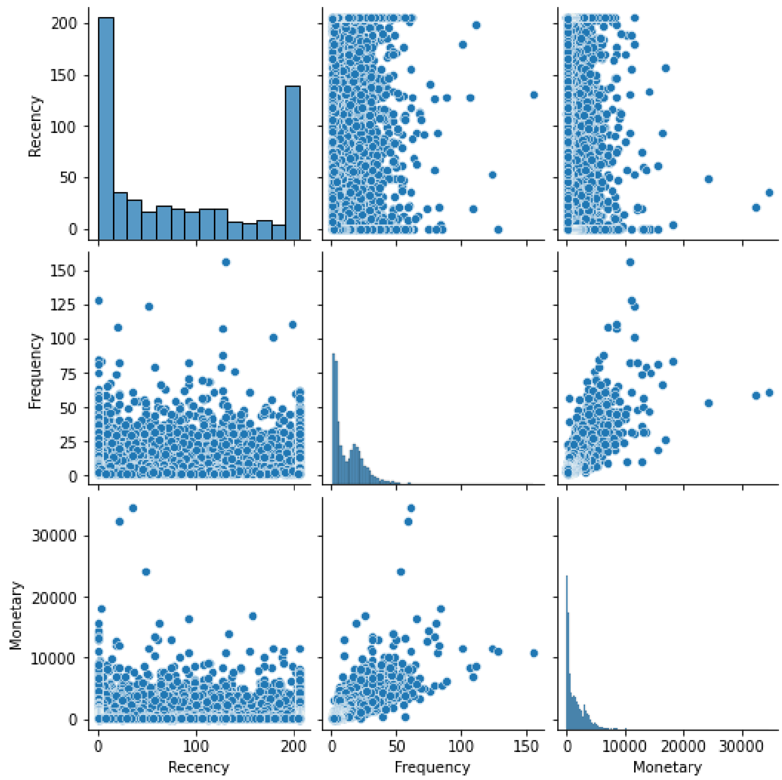



In [54]:
```
sns.pairplot(df_RFM[['Recency','Frequency','Monetary']])
```

Out[54]: <seaborn.axisgrid.PairGrid at 0x1ed4cd99a90>



By Analysing both plots we can say that

- we can see that in recency, that we have some regulars who are buying frequently as some customer who are we loseing at starting of graph and ending
- and we can see that higher the frequency higher is the revenue from customers
- There are many recent purchaces with higher monetary value than older purchases.
- Frequency and monetary variables have slight linear trend.

There are some customers who are potential outliers, but these cannot be removed because, for example there is a customerID 1 have high revenue but less order compared to customerID26. He could be vital to the business. There is also another customer who has frequently billed a high value. Hence, if these are removed, business could miss classifying their main customers, who could potentially be of high value in the future also.

In [55]:
```
from sklearn.preprocessing import StandardScaler, Normalizer
rfm_df_copy = df_RFM.copy()
rfm_df_copy.set_index('CustomerID', inplace= True)
```

In [56]:
```
scaler = StandardScaler()
normal = Normalizer()
scaled_data = scaler.fit_transform(rfm_df_copy)
scaled_data = normal.fit_transform(scaled_data)
rfm_scaled = pd.DataFrame(scaled_data, columns = ['Recency','Frequency','Monetary'])
rfm_scaled.set_index(rfm_df_copy.index, inplace=True)
```

In [57]:
```
rfm_scaled.describe()
```

Out[57]:

	Recency	Frequency	Monetary
count	5000.000000	5000.000000	5000.000000
mean	-0.060526	-0.072436	-0.097299
std	0.677550	0.543473	0.476845
min	-0.999823	-0.999237	-0.996170
25%	-0.704506	-0.521817	-0.463232
50%	-0.209647	-0.314139	-0.318324
75%	0.733205	0.438643	0.296378
max	0.999963	0.999533	0.996846

4) Clustering

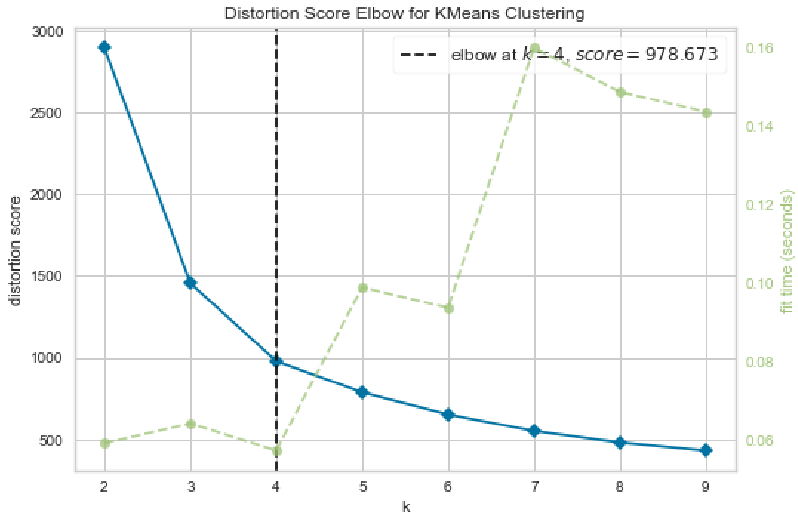
In [58]:
```
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer, SilhouetteVisualizer
from sklearn.metrics import silhouette_score
```

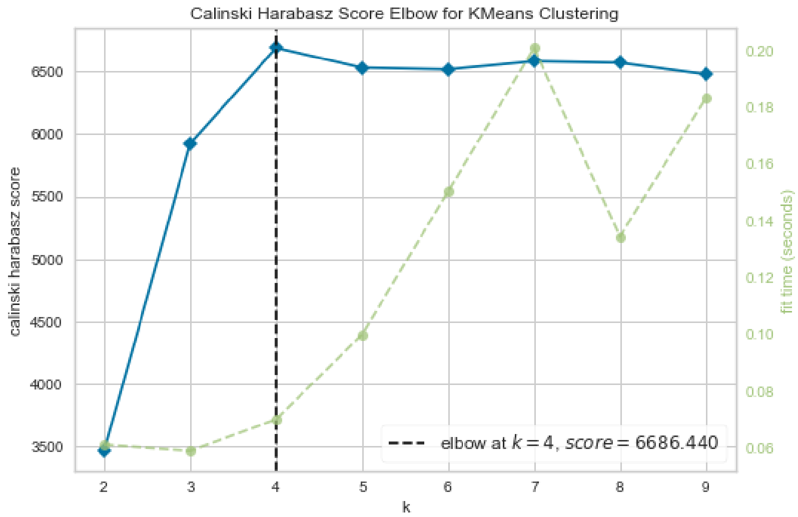
In [59]:
```
# Creating an kmeans model
kmeans = KMeans()
```

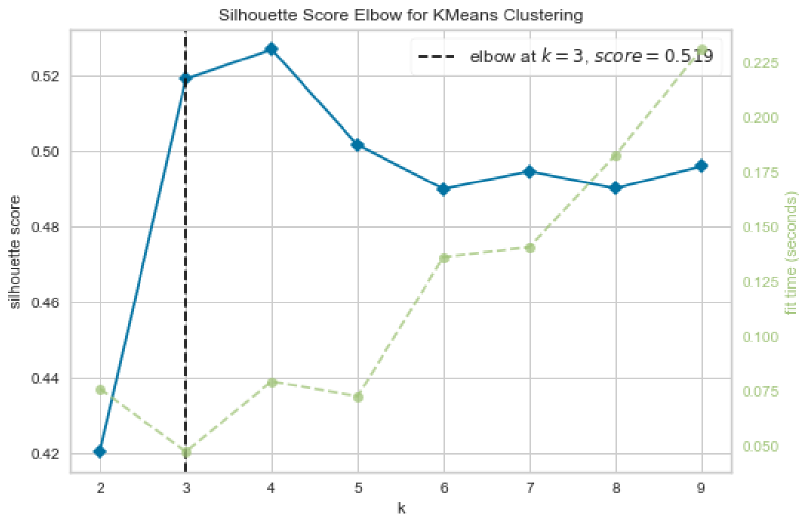
KMeans requires the number of clusters to be specified during the model building process. To know the right number of clusters, we use elbow method and silhouette analysis to get the number of optimal clusters

In [60]:
```
def elbow_method(X):


    metrics = ['distortion', 'calinski_harabasz', 'silhouette']

    for m in metrics:
        visualizer = KElbowVisualizer(kmeans, k = (2,10), metric = m)
        visualizer.fit(X)
        visualizer.poof()
```

In [61]:
```
# Using the elbow method function to understand optimum number of clusters
elbow_method(rfm_scaled)
```







From the elbow method it is clearly understood that, 4 clusters is performing the best. Hence, 4 clusters will be selected to build the KMeans model and

classify the customers.

In [62]:
```
kmeans = KMeans(n_clusters = 4, random_state=10)
```

In [63]:
```
kmeans.fit(rfm_scaled)
```

Out[63]: `KMeans(n_clusters=4, random_state=10)`

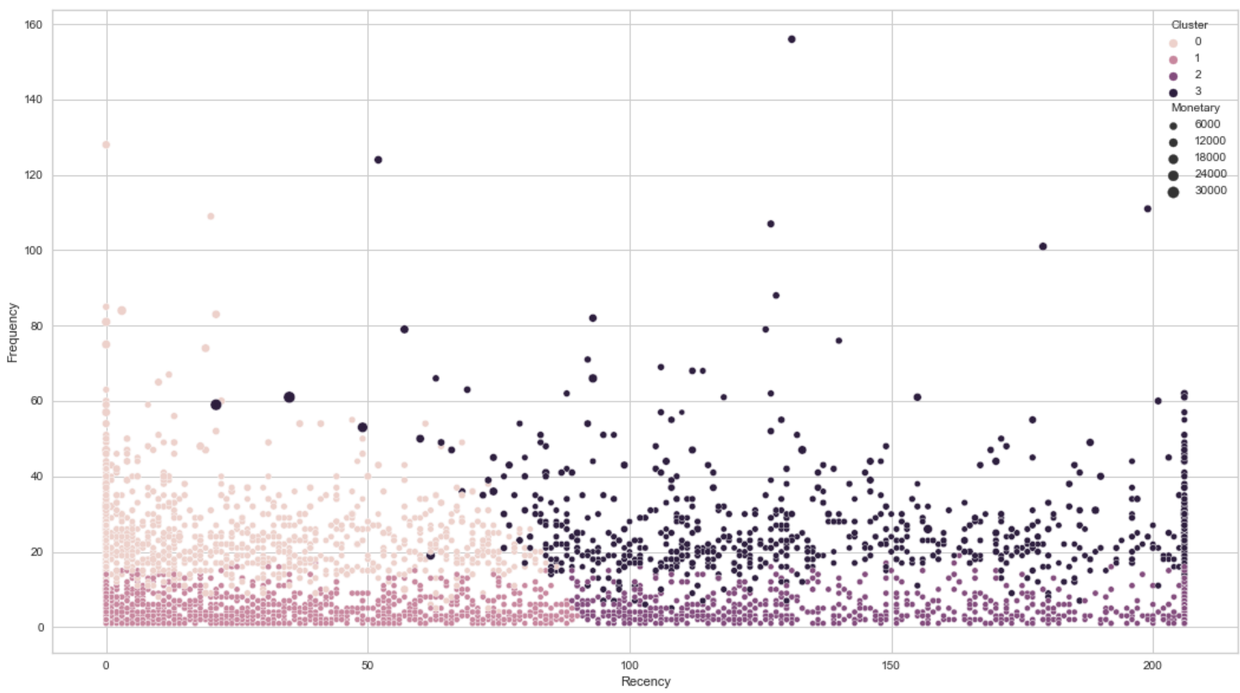
In [64]:
```
labels = kmeans.predict(rfm_scaled)
rfm_df_copy['Cluster'] = labels
rfm_df_copy.head(10)
```

Out[64]:

CustomerID	Recency	Frequency	Monetary	Cluster
1	52	124	11456.95	3
2	93	82	10928.04	3
3	52	43	7088.00	0
4	4	44	6899.45	0
5	129	55	6084.40	3
6	31	49	5744.40	0
7	115	43	5341.50	3
8	61	54	4963.00	0
9	111	19	4915.15	3
10	12	21	4662.50	0

In [65]:
```
plt.figure(figsize = (18,10))
sns.scatterplot(x = rfm_df_copy['Recency'], y = rfm_df_copy['Frequency'], size= rfm_df_copy['Monetary'], h
```

Out[65]: `<AxesSubplot:xlabel='Recency', ylabel='Frequency'>`



Making groups of Recency, Frequency, Monetary and Calculating Score

In [66]:
```
# Grouping by clusters to understand the profiles
rfm_df_copy.groupby('Cluster').mean()
```

Out[66]:

Cluster	Recency	Frequency	Monetary
0	19.139968	23.250000	3028.428163
1	23.205805	4.990106	541.483694
2	175.164029	4.393525	456.629554
3	151.264569	25.574592	3471.673368

In [67]:
```
# Number of customers belonging to each cluster
rfm_df_copy['Cluster'].value_counts()
```

Out[67]:
```
1    1516
2    1390
0    1236
3     858
Name: Cluster, dtype: int64
```

5) Segmentation

potential customer segmentation using RFM model and some meaningful insights from each segment.

Score 10 and above are "Champions" and there are in top 25%

Score 8 and above but below 10 are "Loyal" and there are in top 50%

Score 5 and above but below 8 are "Potential customers" and there are in top 75%

Score 4 and above but below 5 are "promising customers"

Score below 4 are Requires Attention

Champions and belongs to cluster 3

Loyal customers belongs to cluster 2

Potential customers belongs to cluster 1

Requires Attention belongs to cluster 0

In [68]:
```
df_RFM.head()
```

Out[68]:

	CustomerID	Recency	Frequency	Monetary
0	1	52	124	11456.95
1	2	93	82	10928.04
2	3	52	43	7088.00
3	4	4	44	6899.45
4	5	129	55	6084.40

In [69]:
```
#Calculating R and F groups
# Create labels for Recency and Frequency
r_labels = range(4, 0, -1);
f_labels = range(1, 5)
# Assign these labels to 4 equal percentile groups
r_groups = pd.qcut(df_RFM['Recency'], q=4, labels=r_labels)
# Assign these labels to 4 equal percentile groups
f_groups = pd.qcut(df_RFM['Frequency'], q=4, labels=f_labels)
# Create new columns R and F
df_RFM = df_RFM.assign(R = r_groups.values, F = f_groups.values)
# Create labels for Monetary
m_labels = range(1, 5)
# Assign these labels to three equal percentile groups
m_groups = pd.qcut(df_RFM['Monetary'], q=4, labels=m_labels)
# Create new column M
df_RFM = df_RFM.assign(M = m_groups.values)
df_RFM.head()
```

Out[69]:

	CustomerID	Recency	Frequency	Monetary	R	F	M
0	1	52	124	11456.95	3	4	4
1	2	93	82	10928.04	2	4	4
2	3	52	43	7088.00	3	4	4
3	4	4	44	6899.45	4	4	4
4	5	129	55	6084.40	2	4	4

In [70]:
```
def join_rfm(x): return x['R'] + x['F'] +x['M']
df_RFM['Score'] = df_RFM.apply(join_rfm, axis=1)
df_RFM.head()
```

Out[70]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	Score
0	1	52	124	11456.95	3	4	4	11.0
1	2	93	82	10928.04	2	4	4	10.0
2	3	52	43	7088.00	3	4	4	11.0
3	4	4	44	6899.45	4	4	4	12.0
4	5	129	55	6084.40	2	4	4	10.0

In [71]:
```
def customer_level(df):
    if df['Score'] >= 10:
        return 'Champions'
    elif ((df['Score'] >= 8) and (df['Score'] < 10)):
        return 'Loyal_customers'
    elif ((df['Score'] >= 5) and (df['Score'] < 8)):
        return 'Potential_customers'
    elif ((df['Score'] >= 0) and (df['Score'] < 5)):
        return 'Requires Attention'
```

In [72]:
```
df_RFM['Score_level'] = df_RFM.apply(customer_level,axis = 1)
```

In [73]:
```
df_RFM.head()
```

Out[73]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	Score	Score_level
0	1	52	124	11456.95	3	4	4	11.0	Champions
1	2	93	82	10928.04	2	4	4	10.0	Champions
2	3	52	43	7088.00	3	4	4	11.0	Champions
3	4	4	44	6899.45	4	4	4	12.0	Champions
4	5	129	55	6084.40	2	4	4	10.0	Champions

In [74]:
```
df['RFM_Score'] = df_RFM['Score']
```

In [75]:
```python
RFM_level_agg = df_RFM.groupby('Score_level').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'Monetary': ['mean', 'count']
}).round(1)
# Print the aggregated dataset
print(RFM_level_agg)
```

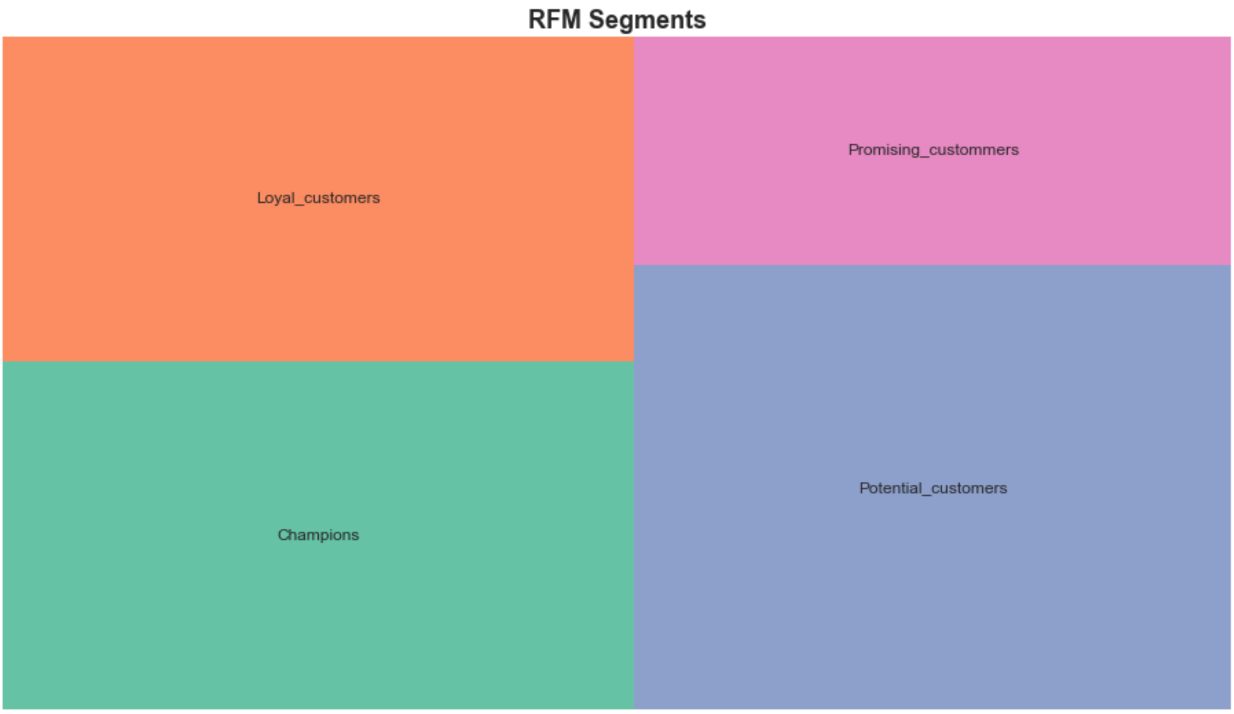
```
                    Recency Frequency Monetary      
                       mean      mean     mean count
Score_level                                         
Champions              31.4      25.9   3494.7  1331
Loyal_customers        86.8      15.9   1974.0  1241
Potential_customers    83.0       5.2    565.0  1602
Requires Attention    181.2       2.2    207.2   826
```

I made some data adjustment for data visulization

6) Data visulization

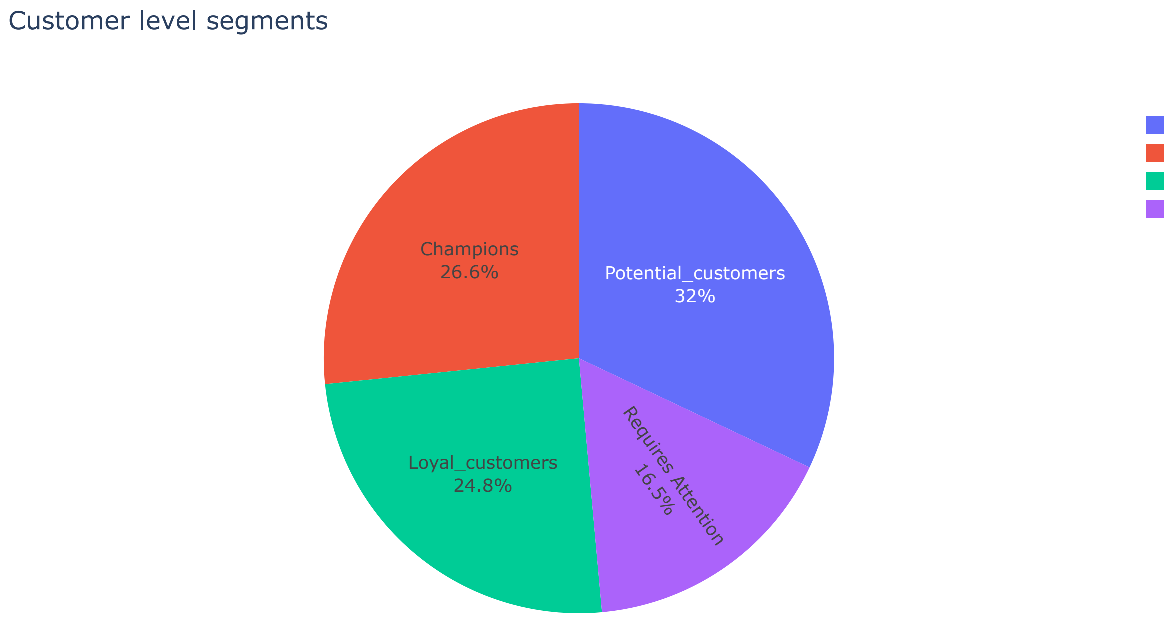
Customer Level

In [76]:
```python
RFM_level_agg.columns = ['RecencyMean','FrequencyMean','MonetaryMean', 'Count']
#Create our plot and resize it.
fig = plt.gcf()
ax = fig.add_subplot()
fig.set_size_inches(16, 9)
squarify.plot(sizes=RFM_level_agg['Count'],
              label=[
                     'Champions',
                     'Loyal_customers',
                     'Potential_customers',
                      'Promising_custommers',
                       'Requires Attention'], alpha=1,color=plt.cm.Set2.colors )
plt.title("RFM Segments",fontsize=18,fontweight="bold")
plt.axis('off')
plt.show()

```



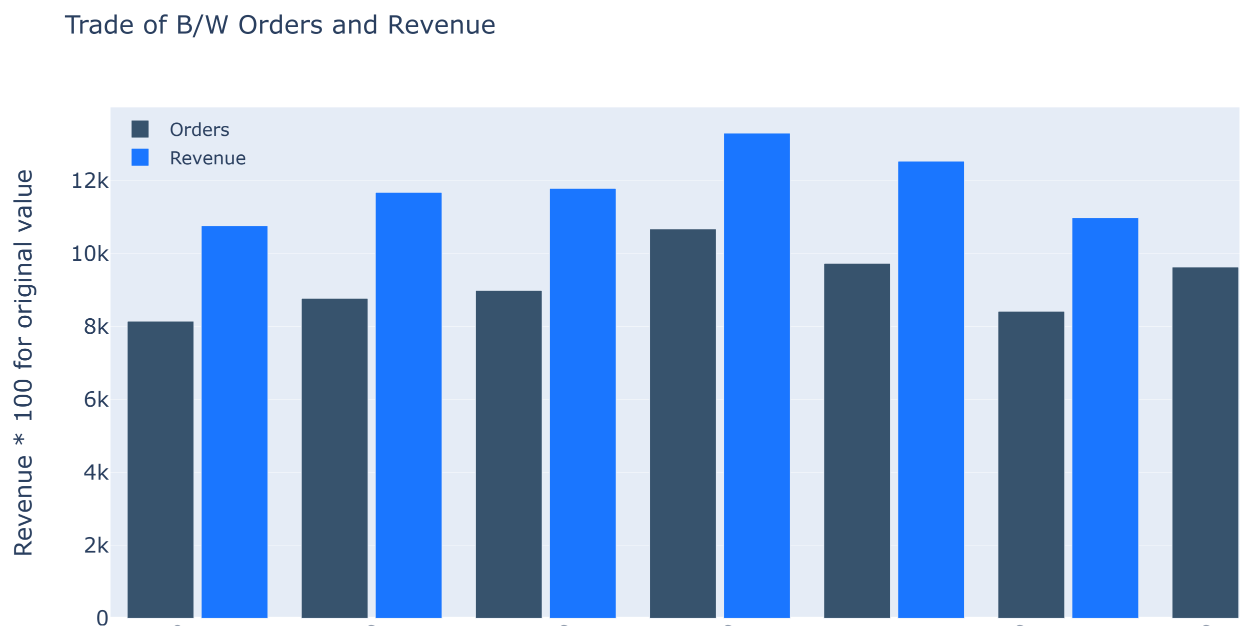
Pie chart of customer level

In [77]:
```
count = df_RFM.Score_level.value_counts()
name = df_RFM.Score_level.value_counts().index
fig = px.pie(df_RFM, values= count, names=name,
             title='Customer level segments',
              labels=name)
fig.update_traces(textposition='inside', textinfo='percent+label')
fig.show()
```



Trade of B/W Orders and Revenue

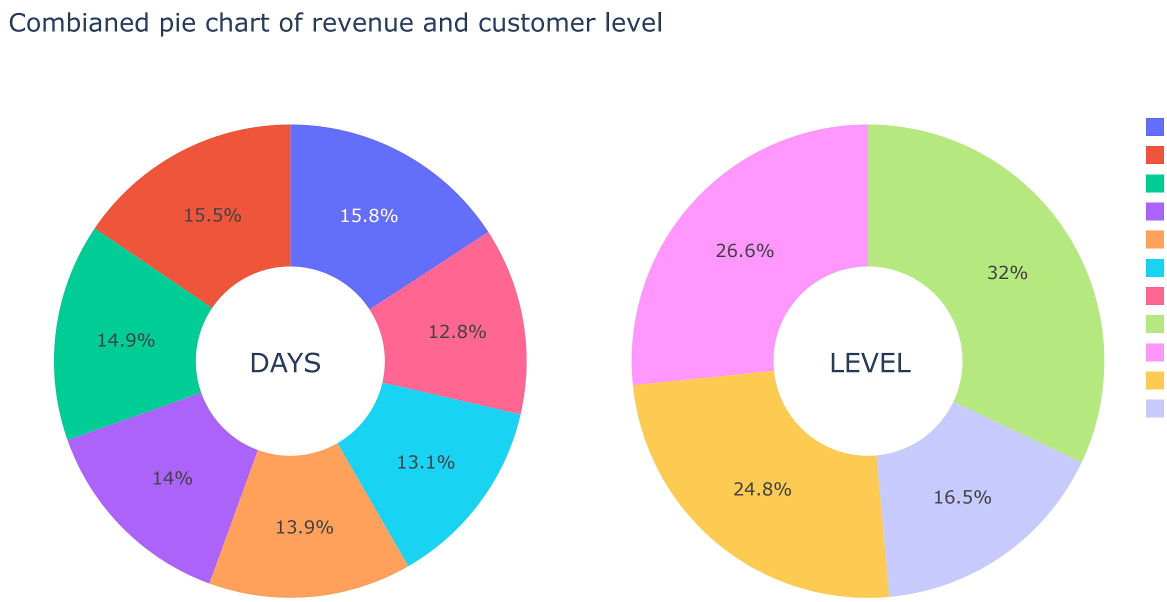
In [78]:
```
days = ['MONDAY', 'TUESDAY', 'WEDNESDAY', 'THURSDAY', 'FRIDAY', 'SATURDAY',
       'SUNDAY']
fig = go.Figure()
fig.add_trace(go.Bar(x=days,
                y=revenue_day['NO_of_Orders'],
                name='Orders',
                marker_color='rgb(55, 83, 109)'
                ))
fig.add_trace(go.Bar(x=days,
                y=revenue_day['Sum_of_Revenue_in_100'],
                name='Revenue',
                marker_color='rgb(26, 118, 255)'
                ))

fig.update_layout(
    title='Trade of B/W Orders and Revenue',
    xaxis_tickfont_size=14,
    yaxis=dict(
        title='Revenue * 100 for original value',
        titlefont_size=16,
        tickfont_size=14,
    ),
    legend=dict(
        x=0,
        y=1.0,
        bgcolor='rgba(255, 255, 255, 0)',
        bordercolor='rgba(255, 255, 255, 0)'
    ),
    barmode='group',
    bargap=0.15, # gap between bars of adjacent location coordinates.
    bargroupgap=0.1 # gap between bars of the same location coordinate.
)
fig.show()
```



- by observing the graph we can say that on monday we have less revenue than whole week
- Thursday has high Revenue and Orders of the whole week
- on Saturday We have low orders

Combianed pie chart of revenue and customer level

In [79]:
```python
import plotly.graph_objects as go
from plotly.subplots import make_subplots

labels = ['MONDAY', 'TUESDAY', 'WEDNESDAY', 'THURSDAY', 'FRIDAY', 'SATURDAY',
       'SUNDAY']

# Create subplots: use 'domain' type for Pie subplot
fig = make_subplots(rows=1, cols=2, specs=[[{'type':'domain'}, {'type':'domain'}]])
fig.add_trace(go.Pie(labels=labels, values=revenue_day['Sum_of_Revenue_in_100'], name="revenue"),
              1, 1)
fig.add_trace(go.Pie(labels=name, values=count, name="Custormers"),
              1, 2)

# Use `hole` to create a donut-like pie chart
fig.update_traces(hole=.4, hoverinfo="label+percent+name")

fig.update_layout(
    title_text="Combianed pie chart of revenue and customer level",
    # Add annotations in the center of the donut pies.
    annotations=[dict(text='DAYS', x=0.183, y=0.5, font_size=18, showarrow=False),
                 dict(text='LEVEL', x=0.82, y=0.5, font_size=18, showarrow=False)])
fig.show()
```



Conclusion

In this project, a translational dataset online store was used. The data set contained various columns. It contains data for almost a period of 7 year. The main aim of the project was to classify the customers into different segments. These segments will have a defining character of their own. This will help the business cater better to their customers which inturn could increase the profits.

1) data Cleaning :- the data set was clean we given

2) Exploratory Data Analysis (EDA)

***156 is the Highest Ordes from a single person**

*** 34847 is the highest revenue from a single person**

*** Thursday and Sunday are the Highest in revenue and Order placed**

* most Shopping happens at month End

* some People have less order but average cost of each item is high

* If person purchaced more than 3 times he tend's to shop more

3) Data Transformation

* In this section, a Recency, Frequency and Monetary analysis Model was developed for each customerID

4) Clustering and 5) segmentation

* In this section, the optimum number of clusters were chosen via elbow method It was found that 4 clusters would be the most optimum.

* A KMeans model with 4 clusters was developed.

* Each customer ID was clustered into one of the 4 clusters. and named based on their Score Champions , Loyal , Potential , Requires Attention

6) Data Data visulization :- Ploted some pie chart and barchart for further analysis

* On the basis of this analysis, the business can offer attractive deals to its Potential and low value customers and they can also treat their high value customers with special business offers such as loyalty points.

* they can even make spechial day on weekday's as monday to boost their revenue on monday

In [ ]:
```
1
```

In [ ]:
```
1
```

In [ ]:
```
1
```