

# Customer Segmentation in E-commerce

W6W7W8 - Python Advanced Assignment

by Annita

RevoU FSDA Section Madrid - Team 5





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# 01

# **BUSINESS OVERVIEW**

Describing business problem and project objectives





## **OVERVIEW PROBLEM**

An e-commerce startup based in Brazil recently opened an online website to sell their product. They launch the website when the Covid-19 hits and making them grow faster than ever. But, the startup is still not using targeted marketing which hurts their marketing budget as only a fraction of their user comes back to their website.

### **OBJECTIVES**

The goal is to increase their marketing conversion rate by doing customer segmentation analysis to understand the customer's behaviour and planning targeted marketing strategy so that it will not hurt the budget anymore.







02

**EDA** 

Understanding current business performance

## **DELIVERY TIME**









#### **Customer made purchase**

It takes around 2 ~ 3 days in general for the e-commerce to process the customer's order before they hand it to carrier.

#### Carrier is on its way

It takes around one week in general for the carrier to deliver the order to customer's address.

#### The order is finally delivered

In general, it takes around 9 ~ 10 days since customer's purchase date until the order arrive to the customer's address. Based on estimation time, it takes around 23 days to finish an order.

However, there is still around 7.98% overdue delivered orders.

## **BUSINESS PERFORMANCE**

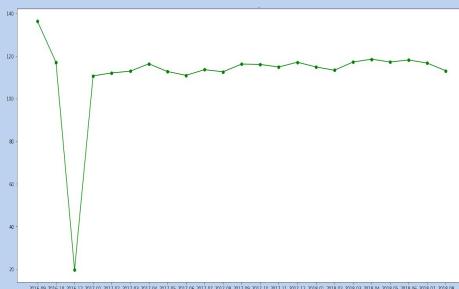


#### Total Orders in Sept 2016 to Aug 2018

2016-09 2016-10 2016-12 2017-01 2017-02 2017-03 2017-04 2017-05 2017-06 2017-07 2017-08 2017-09 2017-10 2017-11 2017-12 2018-01 2018-02 2018-03 2018-04 2018-05 2018-06 2018-07 2018-08 2018-09 2018-0

From Sept 2016 to Nov 2017, number of order tend to increase. Largest increment happened from Oct 2017 to Nov 2017 (need investigation), but it decreases in Dec 2017. Start from Jan 2018, number of order increases from last month, but until Aug 2018, they tend to decrease slowly.

#### **AOV in Sept 2016 to Aug 2018**



2016-09 2016-10 2016-12 2017-01 2017-02 2017-03 2017-04 2017-05 2017-06 2017-07 2017-08 2017-09 2017-10 2017-12 2018-01 2018-02 2018-03 2018-04 2018-05 2018-06 2018-07 2018-07 2018-08 2018-07 2018-08 2018-09 2018-0

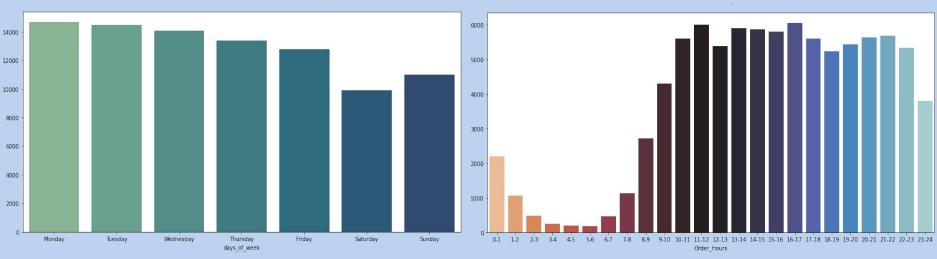
Average Order Value is quite stable for each month (around 110). AOV in Sept 2016 and Dec 2016 are fluctuate because total non-canceled or unavailable order is only one order.

## **BUSINESS PERFORMANCE**



#### **Busiest Day in A Week**

### **Busiest Hour in A Day**



From 2016 to 2018, total order in weekday (Monday - Friday) is greater than weekend (Saturday & Sunday). Which means that the customer tend to buy in weekday rather than weekend. Besides, Monday and Tuesday become the busiest days in a week for three years.

From 2016 to 2018, most of the customers do purchase in 10 AM to 11 PM. Highest total orders happened in 11-12 and 16-17.

**OUR CUSTOMER** 

**Top 10 States with Most Customer** 

#### São Paulo

(42.56% of customer, ARPC = 107)

#### Rio de Janeiro

(12.91% of customer, ARPC = 120.52)

#### **Minas Gerais**

(11.76% of customer, ARPC = 121.06)

#### **Rio Grande do Sul**

(5.5% of customer, ARPC = 121.88)

#### Paraná

(5.06% of customer, ARPC = 116.6)

#### Santa Catarina

(3.64% of customer, ARPC = 124.64)

#### **Bahia**

(3.34% of customer, ARPC = 124.49)

#### **Distrito Federal**

(2.16% of customer, ARPC = 118.63)

#### **Espírito Santo**

(2.06% of customer, ARPC = 119.02)

#### Goiás

(2.01% of customer, ARPC = 121.6)



Our customers come from **27** different states, but **91**% of our customers come from **Top 10 States** above. Although São Paulo has the biggest percentage of customers, the Average Revenue per Country is the lowest among the other 26 states.

There are 4 payment methods, but most of our customers love to pay with credit card and boleto. (The others are voucher and debit card)

# RECOMMENDATIONS



#### Based on results of Exploratory Data Analysis, there are several recommendations that can be given:

- In order to increase Average Order Value, we can try cross sell complementary product and upsell our products or even provide bundle deals, this will encourage customers to buy more complete products (and more expensive of course), thus increasing our average order value.
- For efficiency cost and human resources, we can create an effective working schedule to allocate more workers on weekdays, especially Monday and Tuesday, and allocate less workers on weekend.
- We can run limited-time offers to boost sales in several busiest hours.
- For increasing Average Revenue per Country, we can create order minimums for free shipping. This will
  encourage customers to add more products to their carts, and if their amount of order surpasses certain
  amount, they will get free shipping coupon.
- Most of our customers are credit card or boleto users, we can reward our existing customers by giving discount or cashback for selected payment method. Not only that, we should pay more attention to our security and customer service in order to minimize payment failure and payment fraud.



03

# **CLUSTER ANALYSIS**

Do cluster analysis for better targeting customer



# **CLUSTERING PROCESS**





#### **Data Preparation**

Prepare the datasets for cluster analysis



#### **Cluster Analysis**

Determine cluster number and fit the data to model



# Interpreting Results

See the behaviour for each cluster



# **Business Recommendations**

Give recommendations for improve business

# Data Preprocessing

Checking outliers and scaling the numbers

## **DATA PREPARATION**

















#### **Import Datasets**

Import three datasets that are going to be used in this project.

#### Clean & Merge

Handling unlogical, missing, duplicates, typos and outliers values for each datasets and merged them become one dataset.

#### **Removing Data**

Removing unused rows and columns.

#### **Create Table**

Create RFM Table for doing Cluster Analysis

# **CREATE RFM TABLE**



### Recency

It shows time since last order from customer.

	customer_unique_id	recency
(	0000366f3b9a7992bf8c76cfdf3221e2	160
00	000b849f77a49e4a4ce2b2a4ca5be3f	163
00	000f46a3911fa3c0805444483337064	585
00	000f6ccb0745a6a4b88665a16c9f078	369
0	0004aac84e0df4da2b147fca70cf8255	336
		47.
	fffbf87b7a1a6fa8b03f081c5f51a201	293
ff	ffea47cd6d3cc0a88bd621562a9d061	310
f	ffff371b4d645b6ecea244b27531430a	617
	ffff5962728ec6157033ef9805bacc48	168
f	ffffd2657e2aad2907e67c3e9daecbeb	532

First, find the last date purchase for each customers. Then, calculate recency since last date purchase made in the e-commerce.

### <u>Frequency</u>

It shows total number of transactions purchased by customer.

order_id	customer_unique_id	
1	0000366f3b9a7992bf8c76cfdf3221e2	0
1	0000b849f77a49e4a4ce2b2a4ca5be3f	1
1	0000f46a3911fa3c0805444483337064	2
1	0000f6ccb0745a6a4b88665a16c9f078	3
1	0004aac84e0df4da2b147fca70cf8255	4
1	fffbf87b7a1a6fa8b03f081c5f51a201	87417
1	fffea47cd6d3cc0a88bd621562a9d061	87418
1	ffff371b4d645b6ecea244b27531430a	87419
1	ffff5962728ec6157033ef9805bacc48	87420
1	ffffd2657e2aad2907e67c3e9daecbeb	87421

Find total number of transactions purchased by each customer.

## **Monetary**

It shows transaction value that customer spends in total.

payment_value	customer_unique_id	
141.90	0000366f3b9a7992bf8c76cfdf3221e2	0
27.19	0000b849f77a49e4a4ce2b2a4ca5be3f	1
86.22	0000f46a3911fa3c0805444483337064	2
43.62	0000f6ccb0745a6a4b88665a16c9f078	3
196.89	0004aac84e0df4da2b147fca70cf8255	4
167.32	fffbf87b7a1a6fa8b03f081c5f51a201	87417
84.58	fffea47cd6d3cc0a88bd621562a9d061	87418
112.46	ffff371b4d645b6ecea244b27531430a	87419
133.69	ffff5962728ec6157033ef9805bacc48	87420
71.56	ffffd2657e2aad2907e67c3e9daecbeb	87421

Calculate total transaction value that customer spends in the e-commerce.

## **MERGE RFM TABLE**



### Recency

It shows time since last order from customer.

## **Frequency**

It shows total number of transactions purchased by customer.

## **Monetary**

It shows transaction value that customer spends in total.

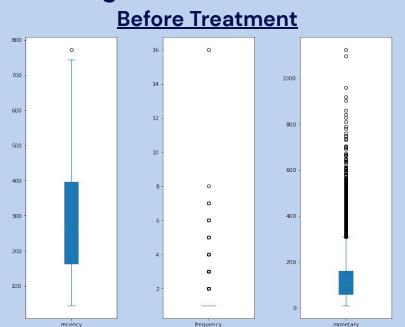
	customer_unique_id	recency	frequency	monetary
0	0000366f3b9a7992bf8c76cfdf3221e2	160	1	141.90
1	0000b849f77a49e4a4ce2b2a4ca5be3f	163	1	27.19
2	0000f46a3911fa3c0805444483337064	585	1	86.22
3	0000f6ccb0745a6a4b88665a16c9f078	369	1	43.62
4	0004aac84e0df4da2b147fca70cf8255	336	1	196.89
		***		***
87417	fffbf87b7a1a6fa8b03f081c5f51a201	293	1	167.32
87418	fffea47cd6d3cc0a88bd621562a9d061	310	1	84.58
87419	ffff371b4d645b6ecea244b27531430a	617	1	112.46
87420	ffff5962728ec6157033ef9805bacc48	168	1	133.69
87421	ffffd2657e2aad2907e67c3e9daecbeb	532	1	71.56

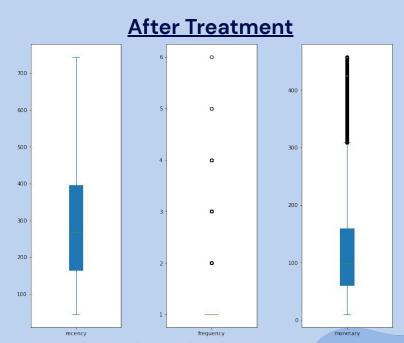
```
# Join all the tables
RFM_table = pd.merge(pd.merge(df_recency,
df_frequency, how='inner'), df_monetary,
how='inner')
# Rename the column name
RFM_table.rename(columns={'order_id':'freq
uency',
'payment_value':'monetary'},inplace =
True)
RFM_table
```

## DATA PREPROCESSING



## **Checking Outliers**





For recency column, the outliers will be removed by Lower & Upper Inner Bound method (1.5\*IQR). For frequency column, the outliers are simply removed for frequency greater than 7. For monetary column, the outliers will be removed by Lower & Upper Outer Bound method (3\*IQR).

Total rows :  $87422 \text{ rows} \rightarrow 87257 \text{ rows}$ 

## DATA PREPROCESSING



## **Scaling The Numbers**

Since each of numerical columns have different scale, so all of numerical values will be scaled by using MinMaxScaler method.

	recency	frequency	monetary
customer_unique_id			
0000366f3b9a7992bf8c76cfdf3221e2	0.165714	0.0	0.295361
0000b849f77a49e4a4ce2b2a4ca5be3f	0.170000	0.0	0.039289
0000f46a3911fa3c0805444483337064	0.772857	0.0	0.171064
0000f6ccb0745a6a4b88665a16c9f078	0.464286	0.0	0.075967
0004aac84e0df4da2b147fca70cf8255	0.417143	0.0	0.418118
Stee			
fffbf87b7a1a6fa8b03f081c5f51a201	0.355714	0.0	0.352107
fffea47cd6d3cc0a88bd621562a9d061	0.380000	0.0	0.167403
ffff371b4d645b6ecea244b27531430a	0.818571	0.0	0.229641
ffff5962728ec6157033ef9805bacc48	0.177143	0.0	0.277034
ffffd2657e2aad2907e67c3e9daecbeb	0.697143	0.0	0.138338

```
# Import Library
from sklearn.preprocessing import MinMaxScaler

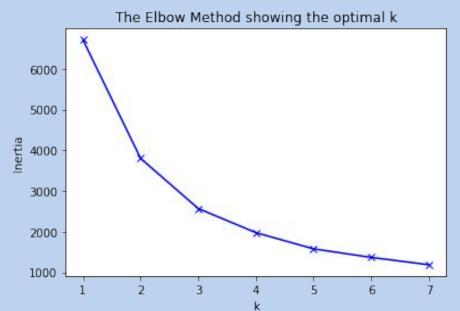
numerical_column = ['recency', 'frequency',
    'monetary']
# Scale DataFrame by using MinMaxScaler
scaler = MinMaxScaler()
RFM_scale[numerical_column] =
scaler.fit_transform(RFM_scale[numerical_column])
RFM_scale
```

**MinMax** Scaler will shrinks the data within the given range, in this project, range from 0 to 1 will be used.



#### **Determine Number of Cluster**

Elbow Method and Silhouette Analysis will be used for determining optimal number of cluster.



#### **Elbow Method**

```
# Create Elbow Plot for Determining Number of Cluster
distortions = []
K = range(1,8)
for k in K:
    kmeanModel = cluster.KMeans(n_clusters=k)
    kmeanModel.fit(RFM_scale)
    distortions.append(kmeanModel.inertia_)

plt.figure(figsize= £5,10))
plt.figure()
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Inertia')
plt.title('The Elbow Method showing the optimal k)'
plt.show()
```

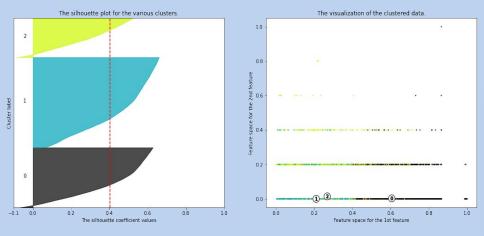
From the graph above, it is clear that number of k = 2 or 3 will be the optimal for number of cluster. But for more accurate analysis, Silhouette Analysis will be performed.



#### **Determine Number of Cluster**

Elbow Method and Silhouette Analysis will be used for determining optimal number of cluster.

#### Silhouette analysis for KMeans clustering on sample data with n\_clusters = 3



# For n\_clusters = 2 The average silhouette\_score is : 0.3967991279610512 For n\_clusters = 3 The average silhouette\_score is : 0.404201834304504 For n\_clusters = 4 The average silhouette\_score is : 0.36158892503002943 For n\_clusters = 5 The average silhouette\_score is : 0.3733258747477178

## Silhouette Analysis

```
# Import Library from silhoutte import silhoutte_analysis

# Perform silhouette analysis for determine the number of cluster silhoutte_analysis(RFM_scale,[2,3,4,5])
```

From the Silhouette Score and Silhouette plot, k = 3 will be chosen as number of cluster because average silhouette score reach the highest when number of cluster is 3.



#### Fit Data Into Model

After determining the number of cluster, the next step is fit the data into cluster model.

	recency	frequency	monetary	cluster
customer_unique_id				
0000366f3b9a7992bf8c76cfdf3221e2	0.165714	0.0	0.295361	1
0000b849f77a49e4a4ce2b2a4ca5be3f	0.170000	0.0	0.039289	1
0000f46a3911fa3c0805444483337064	0.772857	0.0	0.171064	2
0000f6ccb0745a6a4b88665a16c9f078	0.464286	0.0	0.075967	2
0004aac84e0df4da2b147fca70cf8255	0.417143	0.0	0.418118	0
···	****		***	***
fffbf87b7a1a6fa8b03f081c5f51a201	0.355714	0.0	0.352107	0
fffea47cd6d3cc0a88bd621562a9d061	0.380000	0.0	0.167403	1
ffff371b4d645b6ecea244b27531430a	0.818571	0.0	0.229641	2
ffff5962728ec6157033ef9805bacc48	0.177143	0.0	0.277034	1
ffffd2657e2aad2907e67c3e9daecbeb	0.697143	0.0	0.138338	2

```
# Import Library
from sklearn import cluster

cluster_model =
cluster.KMeans(n_clusters=3,random_state=2)
cluster_model.fit(RFM_fitmodel)
cluster_label = cluster_model.labels_
RFM_fitmodel['cluster'] = cluster_label
RFM_fitmodel
```

In this project, K-Means Clustering Method will be used.



## **Bring The Cluster To Data**

After determining the number of cluster and fit them into the model, finally bring the cluster to the original data.

	customer_unique_id	recency	frequency	monetary	cluster
0	0000366f3b9a7992bf8c76cfdf3221e2	160	1	141.90	1
1	0000b849f77a49e4a4ce2b2a4ca5be3f	163	1	27.19	1
2	0000f46a3911fa3c0805444483337064	585	1	86.22	2
3	0000f6ccb0745a6a4b88665a16c9f078	369	1	43.62	2
4	0004aac84e0df4da2b147fca70cf8255	336	1	196.89	0
	xxx		***	02.5	
87252	fffbf87b7a1a6fa8b03f081c5f51a201	293	1	167.32	0
87253	fffea47cd6d3cc0a88bd621562a9d061	310	1	84.58	1
87254	ffff371b4d645b6ecea244b27531430a	617	1	112.46	2
87255	ffff5962728ec6157033ef9805bacc48	168	1	133.69	1
87256	ffffd2657e2aad2907e67c3e9daecbeb	532	1	71.56	2

By having the cluster information, the next step is interpreting the descriptive statistics for each columns to understand the clusters' behaviour.

# **INTERPRETING RESULTS**



### **Descriptive Statistics**

By performing descriptive analysis, each clusters' behaviour will be interpreted in order to give suitable recommendations.

	count mean std min 25% 50% 75% max mean std min 25% 50% 75% max mean std median sum min max																				
	count	mean	std	min	25%	50%	75%	max	mean	std	min	25%	50%	75%	max	mean	std	median	sum	min	max
cluster Recency						Frequency					Monetary										
0	18025.0	234.694591	104.137087	44.0	156.0	232.0	314.0	615.0	1.085936	0.306742	1.0	1.0	1.0	1.0	5.0	228.022478	57.616154	214.13	4110105.16	138.16	457.55
1	41703.0	190.403568	82.566276	49.0	119.0	190.0	259.0	343.0	1.012517	0.113948	1.0	1.0	1.0	1.0	3.0	80.930355	37.119192	75.25	3375038.60	9.59	173.70
2	27529.0	468.119002	87.369095	320.0	396.0	460.0	532.0	744.0	1.018962	0.145416	1.0	1.0	1.0	1.0	6.0	102.708697	58.071210	90.28	2827467.73	10.07	350.97

#### From the table above, it can be concluded that:

- Cluster 0 is customer's cluster who made purchase a quite long time ago, they only come one time but they spent highest amount of money among the others. Although their population is the smallest, they contribute the most sales in e-commerce.
- Cluster 1 is customer's cluster who spend lowest amount of money but they are most recent purchasers but also one-time buyers. They dominate most of our customer population.
- Cluster 2 is customer's cluster who made only one purchase and hasn't been back for very long time, but they spent moderate amount of money.

Most of our customers are one-time purchasers.

## NAMING THE CLUSTERS





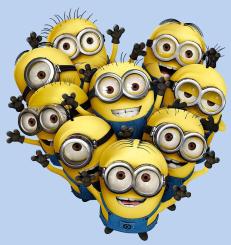
# Loyalist Squarepants!

They only come one time and haven't been back for a quite long time, but they spend much amount of money as long as they happy. They spend the highest amount among the others.



## Sleeping Snorlax ~

They spend moderate amount of money, also come only one time but they made their purchase long long time ago.



#### Minions on Shopping:D

47.79% of customers

They are recent purchasers who dominate the customer population, but they spend less money and also come only one time. They spend the lowest among the others.

# **BUSINESS RECOMMENDATIONS**

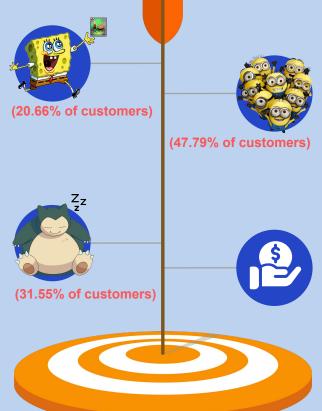


#### **Loyalist Squarepants**

Giving special new product introductions based on their purchase product history. We can also try add cross/up-sells strategy such as bundling in order to increase their AOV. Sending special voucher on special day will make them feel special too!

### **Sleeping Snorlax**

Bring them back with Reactivation campaign or promotions (not too often), and run e-mail surveys to find out the reasons why customers didn't come back. If possible, we can try giving discounts, but we need to consider our marketing budget.



Minions on Shopping
Giving welcome discount with small

rate or amount will make them feel welcome to our e-commerce. Build a promote referrals/review program is also recommended, so we can turn them into our advocates while acquiring new customers and gain positive image to our customers.

#### **Overall Customers**

Build a membership programs where customers get certain points for every purchase they make that can be encashed during the next purchase. Also create VIP programs with exclusive offers specifically for high-contribute customers. This will encourage new customers to shop/spend more and join the group.



# Customer Segmentation in E-commerce

W6W7W8 - Python Advanced Assignment

by Annita

Revol FSDA Section Madrid - Team 5

