CAPSTONE PROJECT: MARKETING AND RETAIL ANALYTICS

PROBLEM DEFINITION

- OList is a e-commerce company that has faced some losses recently and they want to manage their inventory very well so as to reduce any unnecessary costs that they might be bearing.
- Need to identify top products that contribute to the revenue and also use
 market basket analysis to analyse the purchase behaviour of individual
 customers to estimate with relative certainty, what items are more likely to be
 purchased individually or in combination with some other products.

DATA EXPLORATION AND CLEANING

- I have used Python notebook for data exploration and cleaning treatment.
- In order table we are interested in orders which are successfully delivered only. rest are not useful for analysis. Hence, filtered and created new data frame:

```
# creating new DF where the status of orders are delivered orders = orders[orders.order_status =='delivered']
```

Missing values are identified :

```
# checking missing values
orders.isna().sum().sort_values(ascending = False)
```

- order_approved_at and order_delivered_timestamp had missing values
- Missing values were filled with the values of:
- order_approved_at = order_purchase_timestamp
- order_delivered_timestamp = orders_estimated_delivery_dateMissing values are identified in table Products:

```
# checking missing values
products.isna().sum().sort_values(ascending = False)
```

- Below columns had missing values:
 - product_category_name & product_weight_g
 - product_length_cm & product_height_cm & product_width_cm

- Missing values were filled with the values of:
- product_category_name = products.product_category_name.mode()[0]
 - product_weight_g = product_weight_g.median()
 - product_length_cm = product_length_cm. median()
 - product_height_cm = product_height_cm. median()
 - product_width_cm = product_width_cm. median()
- In customers table I have found duplicates values.
- Duplicates values are identified:

 # looking for duplicates
 customers.customer_id.duplicated().sum()
- 3345 duplicates values were present which was removed:

 #dropping duplicates values
 customers.drop_duplicates(subset='customer_id', keep='first',inplace=True)
- Data set is now cleaned.

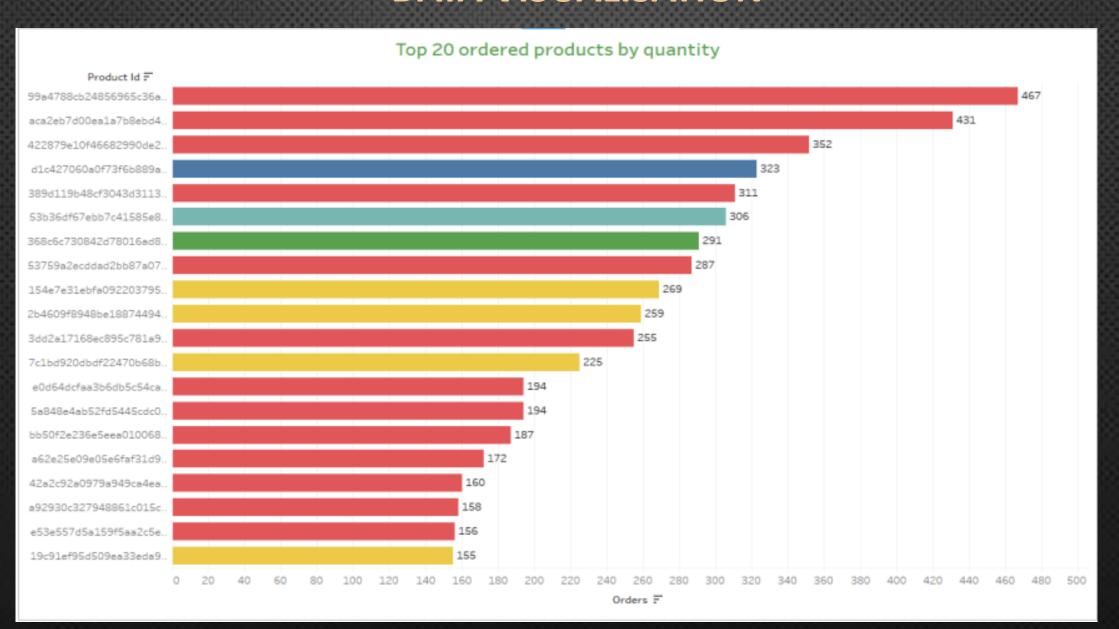
EXPORTING DATA SET

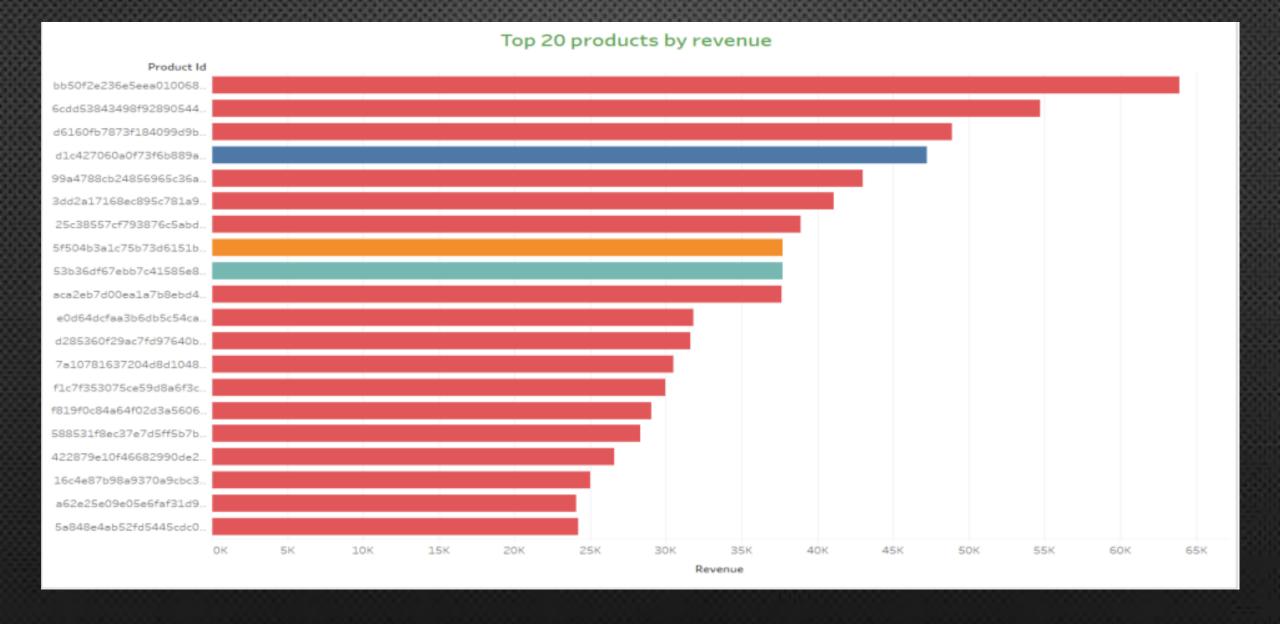
- Exporting to excel file named as "Retail_dataset_cleaned.xls"
- I have used pandas library writer function to export the data set to excel file:

```
writer = pd.ExcelWriter('Retail_dataset_cleaned.xlsx', engine='xlsxwriter')
```

- # Write each data frame to a different worksheet.
 orders.to_excel(writer, sheet_name='orders')
 order_items.to_excel(writer, sheet_name='order_items')
 customers.to_excel(writer, sheet_name='customers')
 payments.to_excel(writer, sheet_name='payments')
 products.to_excel(writer, sheet_name='products')
- # Close the Pandas Excel writer and output the Excel file. writer.save()

DATA VISUALISATION





Toys in the product categories contributes maximum towards revenue generation.

- Percentage Running total with Product ID, count of Order Items and Revenue has been broken down by Product ID.
- I have applied filter to see the TOP 20 products.
- Toys in the product categories contributes more than 80% in revenue generation.

Revenue Pareto

bb50f2e236e5eea010068 63,885 8,73% 195 6cdd53843498f92890544 54,730 7,48% 156 d6160fb7873f184099d9b 48,899 6,68% 35 d1c427060a0f73f6b889a 47,215 6,45% 343 99a4788cb24856965c36a 43,026 5,88% 488 3dd2a17168ec895c781a9 41,083 5,61% 274 25c3857cf793876c5abd 38,907 5,32% 38 5f504b3a1c75b73d6151b 37,734 5,16% 63 53b36df67ebb7c41585e8 37,683 5,15% 323 aca2eb7d00ea1a7b8ebd4 37,609 5,14% 527 e0d64dcfaa3b6db5c54ca 31,787 4,34% 194 d285360f29ac7fd97640b 31,624 4,32% 123 7a10781637204d8d1048 30,468 4,16% 143 f1c7f353075ce59d8a6f3c 29,997 4,10% 154 f819f0c84a64f02d3a560 29,024 3,97% 45 588531f8ec37e7d5ff5b7 28,292 3,87% 20 422879e10f46682990de2 26,577 3,63% 484 16c4e87b98a9370a9cbc3 25,034 3,42% 13 5a848e4ab55fd5445cdc0 24,229 3,31% 197	Product Id	Revenue_	% of Total Revenue	Count of Products
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422879e10f46682990de2 26,577 3.63% 484 16c4e87b98a9370a9cbc3 25,034 3.42% 13	f819f0c84a64f02d3a560	29,024	3.97%	45
16c4e87b98a9370a9cbc3 25,034 3.42% 13	588531f8ec37e7d5ff5b7	28,292	3.87%	20
2422	422879e10f46682990de2	26,577	3.63%	484
5a848e4ab52fd5445cdc0 24,229 3.31% 197	16c4e87b98a9370a9cbc3	25,034	3.42%	13
	5a848e4ab52fd5445cdc0	24,229	3.31%	197
a62e25e09e05e6faf31d9 24,051 3.29% 226	a62e25e09e05e6faf31d9	24,051	3.29%	226

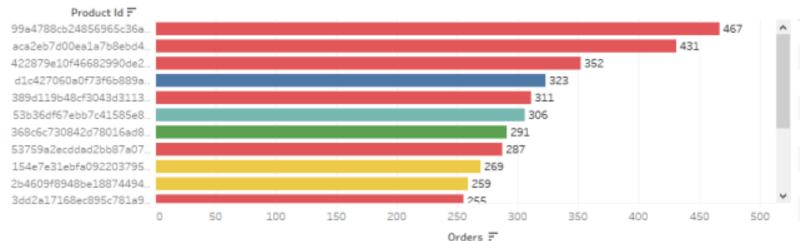
Category Wise order



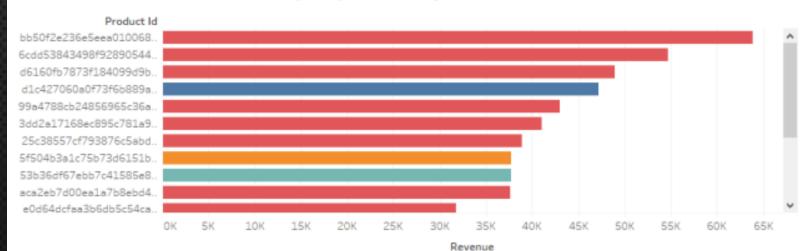
DASHBOARD

Top Products and Revenue Pareto

Top 20 ordered products by quantity



Top 20 products by revenue



Revenue Pareto

Product Id	Revenue_	% of Total Revenue	Count of Products
bb50f2e236e5	63,885	8.73%	195
6cdd53843498	54,730	7.48%	156
d6160fb7873f	48,899	6.68%	35
d1c427060a0f	47,215	6.45%	343
99a4788cb248	43,026	5.88%	488
3dd2a17168ec	41,083	5.61%	274
25c38557cf79	38,907	5.32%	38
5f504b3a1c75	37,734	5.16%	63
53b36df67ebb	37,683	5.15%	323
aca2eb7d00ea	37,609	5.14%	527
e0d64dcfaa3b	31,787	4.34%	194
d285360f29ac	31,624	4.32%	123
7a1078163720	30,468	4.16%	143
f1c7f353075ce	29,997	4.10%	154
f819f0c84a64f	29,024	3.97%	45
588531f8ec37	28,292	3.87%	20
422879e10f46	26,577	3.63%	484
16c4e87b98a9	25,034	3.42%	13
5a848e4ab52f	24,229	3.31%	197
a62e25e09e05	24,051	3.29%	226

MARKET BASKET ANALYSIS

This Treemap shows Product Categories which Are ordered more than 5 Times.



Combinations of product categories (ordered together)

Product Category Name

Product Cate \mp			ndustr	kitchen			music	musical.	office		y_s p				small_a	small_a	sports	station			toys	watche
toys	7	63			11	. 7	1	٤	8	18		32	23				62	30		30		73
bed_bath_table																					291	
furniture_decor																					153	
computers_acces																					103	
health_beauty																					81	
watches_gifts																					73	
sports_leisure																					62	
housewares																					63	
garden_tools																					45	
fashion_bags_acc.																					41	
auto																					39	
perfumery																					32	
telephony																					30	
stationery																					30	
cool_stuff																					25	
pet_shop																					23	
baby																					20	
office_furniture																					18	
construction_tool.	,=																				12	
luggage_accessor.	,-																				11	
costruction_tools.																					11	
home_construction	n																				7	
fashion_shoes																					8	
electronics																					8	
musical_instrume.																					8	
market_place																					7	
consoles_games																					6	
Null	33	1,371	49	65	183	87	7	170	0	469	11	714	435	38	141	15	1,965	537	65	1,043	72,020	1,390
	<																					>

Market Basket Analysis Dashboard

Combinations of product categories (ordered together)

Product Category Name Product Cate.. = .. signalin.. small_a.. small_a.. sports_.. station.. tablets.. telepho.. toys watche.. 30 73 291 153

bed_bath_table furniture_decor 103 computers_acces. health_beauty 81

toys

Null

73 watches_gifts sports_leisure 63 housewares 45 garden_tools

fashion_bags_acc.. 39 auto 32 perfumery

30 telephony 30 stationery cool_stuff 25 pet_shop 23

baby 20 office_furniture construction_tool.. 12 luggage_accessor.. costruction_tools.. 11

home_construction fashion_shoes electronics musical_instrume.. market_place consoles_games

1,965

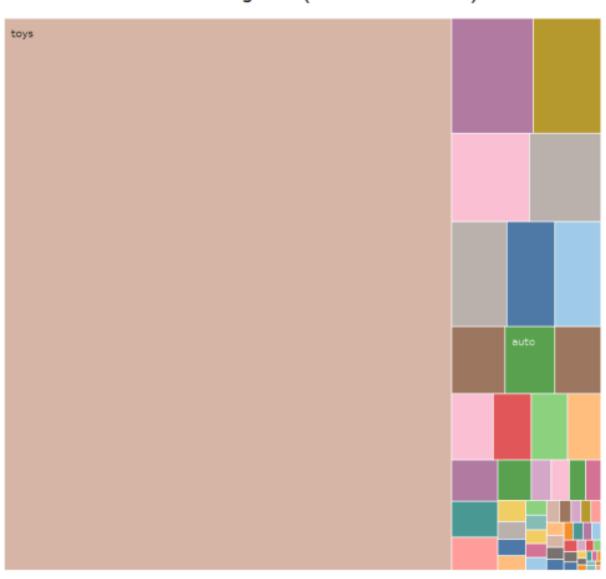
1,043

72,020

1,390

141

Product Categories (order More than 5)



INSIGHTS

- The category 'Toys' constitutes 20% of the products which generates 80% of revenue.
- It can be seen that even if the price of the certain products are high, it is still bought by the customer.
- The categories apart from Toys which are at least ordered 5 times are health_beauty, bed_bath_table, Sports_leisure, computer_accessories, furniture_decor, watches_gifts and have high order quantity.
- Hence, the combination of all these few categories with Toys and each other are frequently high.

RECOMMENDATIONS & BUSINESS IMPACT

- Company should focus on giving offers for the customers who are frequent buys to retain them.
- Since, there are many categories of products, company can reduce sub categories
 for ease of access and should cut down few of products which least contributing
 towards revenue generation.
- As Toys are most selling product company can target customers who are more likely to buy it like parents of newly born and young children.
- Company can given some good discounts or offers to gain new customers.