Data Analysis - Forma AI

Data Description There are three tables involved in this question: `transactions` , `segments` and `products` , which simulate a simplified retail data schema. Here is a semantic description of the tables:

- `transactions` : contains detailed information about each product a customer has purchased. A transaction consists of one or more products purchased by a customer indexed by a unique transaction id.
  - `trans_id` : the transaction id
  - `cust_id` : the customer id
  - `prod_id` : the product id
  - `item_qty` : the quantity of the product that is being purchased
  - `item_price` : the per unit price of the product (NOTE: the total revenue for a product is `item_qty * item_price`)
- `products` : contains detailed attributes about each product.
  - `prod_id` : the product id (same meaning as in `transactions`)
  - `prod_name` : the product name
  - `brand` : the brand of the product
  - `category` : the category of the product
- `segments` : contains a history of customer segmentation labelling for each customer. Segments are computed periodically for all current customers and appended to the table after each computation. The current (most up to date) active segment for each customer is specified by `active_flag = 'Y'` column.
  - `cust_id` : the customer id (same meaning as in `transactions`)
  - `seg_name` : the segment of this customer
  - `update_dt` : the date when this segment was updated
  - `active_flag` : whether or not this segment is the active segment for this customer

Steps -

1. Joined the 3 tables from the database using the following code -
```
 select t.trans_id, t.trans_dt, t.cust_id, t.prod_id, t.item_qty,
t.item_price,
 s.seg_name, s.update_at, s.active_flag, p.prod_name, p.brand, p.category
 from transactions t
 join segments s
 on t.cust_id =  s.cust_id
 join products p
 on t.prod_id = p.prod_id
```
2. Saved it as a csv file called *insights.csv*.

   - Visually assessed the data in Microsoft Excel
3. In Jupyter Notebook, read the csv file to a dataframe called 'df'.
4. Assessed and Cleaned the dataframe.
   - Checked for Nulls.

- Checked for Duplicates.
- Inspected dataframe for data discrepencies.
- Found the unique values and top count for number or rows in the dataframe.
- Converted *trans_dt* and *update_at* to datetime datatype.
- Converted *trans_id, cust_id and prod_id* to categorical datatype.
- Extracted months from trans_dt and made a new column called *trans_month*.
- Verified the changes made to the dataframe at various stages.

5. Exploratary analysis done by visualizing the data, searching for insights.
6. Based on the findings, summarized the insights.
7. Explanatory analysis presented in powerpoint to provide results.

In [647]:
```
#import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb

%matplotlib inline
```

Gather Data

In [648]:
```
#read csv data into the dataframe 'df'
df = pd.read_csv('insights.csv')
```

Assess and Clean Data

In [649]:
```
#display few rows of the dataframe
df.head()
```

Out[649]:

	trans_id	trans_dt	cust_id	prod_id	item_qty	item_price	seg_name	update_at	active_flag	pr
0	1	2016-01-02 10:06:00	9085146	223029	1	42.99	GONE AWAY	2015-11-01 00:00:00	N	
1	1	2016-01-02 10:06:00	9085146	223029	1	42.99	INACTIVE	2014-09-01 00:00:00	N	
2	1	2016-01-02 10:06:00	9085146	223029	1	42.99	INACTIVE	2016-01-01 00:00:00	N	
3	1	2016-01-02 10:06:00	9085146	223029	1	42.99	LAPSED	2014-01-01 00:00:00	N	
4	1	2016-01-02 10:06:00	9085146	223029	1	42.99	LAPSED	2014-03-01 00:00:00	N	

In [650]:
```
#display number of rows and columns of the dataframe
df.shape
```

Out[650]:
```
(18097, 12)
```

The original dataframe has **18097 rows** and **12 columns**

In [651]:
```
#summary of dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18097 entries, 0 to 18096
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   trans_id     18097 non-null  int64
 1   trans_dt     18097 non-null  object
 2   cust_id      18097 non-null  int64
 3   prod_id      18097 non-null  int64
 4   item_qty     18097 non-null  int64
 5   item_price   18097 non-null  float64
 6   seg_name     18097 non-null  object
 7   update_at    18097 non-null  object
 8   active_flag  18097 non-null  object
 9   prod_name    18097 non-null  object
 10  brand        18097 non-null  object
 11  category     18097 non-null  object
dtypes: float64(1), int64(4), object(7)
memory usage: 1.7+ MB
```

In [652]:
```
#Check for null values
df.isnull().sum()
```

Out[652]:
```
trans_id       0
trans_dt       0
cust_id        0
prod_id        0
item_qty       0
item_price     0
seg_name       0
update_at      0
active_flag    0
prod_name      0
brand          0
category       0
dtype: int64
```

No Null values are found

In [653]:
```
#check for duplicate values
df.duplicated().sum()
```

Out[653]: 2

Dataframe seems to have duplicates

In [654]:
```
#display the the duplicated rows
df[df.duplicated()]
```

Out[654]:

	trans_id	trans_dt	cust_id	prod_id	item_qty	item_price	seg_name	update_at	active_flag
9880	1620	2016-01-02 11:02:00	9960002	223909	1	31.99	GONE AWAY	2015-06-01 00:00:00	N
9881	1620	2016-01-02 11:02:00	9960002	223909	1	31.99	ONE-OFFS	2016-02-01 00:00:00	Y

In [655]:
```
#drop duplicates, keeping the last record because the active_flag = Y
df.drop_duplicates(inplace = True)
```

In [656]:
```
#verify the duplicates have been dropped
df.duplicated().sum(), df.shape
```

Out[656]: (0, (18095, 12))

In [657]:
```
df[df['trans_id'] == 1620]
```

Out[657]:

	trans_id	trans_dt	cust_id	prod_id	item_qty	item_price	seg_name	update_at	active_flag
9878	1620	2016-01-02 11:02:00	9960002	223909	1	31.99	GONE AWAY	2015-06-01 00:00:00	N
9879	1620	2016-01-02 11:02:00	9960002	223909	1	31.99	ONE-OFFS	2016-02-01 00:00:00	Y

The duplicates (row - 9880 and 9881) have been dropped, now we have 18095 entries

In [658]:
```
#description of quntitative data
df.describe()
```

Out[658]:

	trans_id	cust_id	prod_id	item_qty	item_price
count	18095.000000	1.809500e+04	1.809500e+04	18095.000000	18095.000000
mean	1418.033987	8.705213e+06	7.344467e+07	1.050014	37.366029
std	777.953111	5.132218e+06	1.113840e+08	0.274736	26.949988
min	1.000000	4.402000e+03	1.999220e+05	1.000000	0.400000
25%	747.000000	4.134518e+06	2.507560e+05	1.000000	19.990000
50%	1483.000000	8.468925e+06	4.082950e+05	1.000000	31.990000
75%	2105.000000	1.307541e+07	1.382621e+08	1.000000	49.990000
max	2666.000000	2.123399e+07	4.078207e+08	4.000000	215.950000

In [659]:
```
df[(df['active_flag'] == 'N') & (df['seg_name'] == 'VIP')]
```

311	62	01-02 15:51:00	14225812	261117	1	15.99	VIP	01 00:00:00
312	62	2016-01-02 15:51:00	14225812	261117	1	15.99	VIP	2015-05-01 00:00:00
317	62	2016-01-02 15:51:00	14225812	268232	1	15.99	VIP	2014-01-01 00:00:00
...	...	...	...	...	...	...	...	...
18073	2662	2016-06-18 10:00:00	3649704	364872356	1	41.99	VIP	2015-01-01 00:00:00
18074	2662	2016-06-18 10:00:00	3649704	364872356	1	41.99	VIP	2015-05-01 00:00:00
18075	2662	2016-06-18 10:00:00	3649704	364872356	1	41.99	VIP	2015-08-01 00:00:00

In [660]:
```
df[(df['active_flag'] == 'N') & (df['seg_name'] == 'LOYAL')]
```

Out[660]:

	trans_id	trans_dt	cust_id	prod_id	item_qty	item_price	seg_name	update_at	active_
47	9	2016-01-02 11:55:00	5904487	258744	1	38.99	LOYAL	2014-05-01 00:00:00	
48	9	2016-01-02 11:55:00	5904487	258744	1	38.99	LOYAL	2014-06-01 00:00:00	
49	9	2016-01-02 11:55:00	5904487	258744	1	38.99	LOYAL	2014-12-01 00:00:00	
78	17	2016-01-02 12:35:00	2591778	223453	1	49.99	LOYAL	2015-05-01 00:00:00	
79	17	2016-01-02 12:35:00	2591778	223453	1	49.99	LOYAL	2015-09-01 00:00:00	
...	...	...	...	...	...	...	...	...	
18057	2662	2016-06-18 10:00:00	3649704	365543537	1	30.99	LOYAL	2014-12-01 00:00:00	
18068	2662	2016-06-18 10:00:00	3649704	364872356	1	41.99	LOYAL	2014-12-01 00:00:00	
18085	2665	2016-06-18 17:51:00	4095901	277123	1	89.99	LOYAL	2014-05-01 00:00:00	
18086	2665	2016-06-18 17:51:00	4095901	277123	1	89.99	LOYAL	2014-10-01 00:00:00	
18087	2665	2016-06-18 17:51:00	4095901	277123	1	89.99	LOYAL	2015-03-01 00:00:00	

2793 rows × 12 columns

Checkout different series in the dataframe -

In [661]:
```
df.seg_name.value_counts()
```

Out[661]:
```
INFREQUENT    5013
VIP           4858
LOYAL         3632
ONE-OFFS      2359
LAPSED        1138
INACTIVE       485
NEW            387
GONE AWAY      223
Name: seg_name, dtype: int64
```

In [662]:
```
df.category.value_counts()
```

Out[662]:
```
Women          8360
Make up        6493
Men            2069
Accessoires     866
Sun             307
Name: category, dtype: int64
```

In [663]:
```
df.active_flag.value_counts()
```

Out[663]:
```
N    14237
Y     3858
Name: active_flag, dtype: int64
```

In [664]:
```
df.cust_id.nunique(), df.prod_id.nunique(), df.trans_id.nunique()
```

Out[664]:
```
(971, 1863, 1491)
```

In [665]:

```
#changing the trans_dt, updated_at datatype to datetime object
df["trans_dt"] = pd.to_datetime(df["trans_dt"])
df["update_at"] = pd.to_datetime(df["update_at"])
#verify changes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18095 entries, 0 to 18096
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   trans_id     18095 non-null  int64
 1   trans_dt     18095 non-null  datetime64[ns]
 2   cust_id      18095 non-null  int64
 3   prod_id      18095 non-null  int64
 4   item_qty     18095 non-null  int64
 5   item_price   18095 non-null  float64
 6   seg_name     18095 non-null  object
 7   update_at    18095 non-null  datetime64[ns]
 8   active_flag  18095 non-null  object
 9   prod_name    18095 non-null  object
 10  brand        18095 non-null  object
 11  category     18095 non-null  object
dtypes: datetime64[ns](2), float64(1), int64(4), object(5)
memory usage: 1.8+ MB
```

In [666]:

```
#Change the columns to categorical types because we won't manipulate or perf
#They are considered as label groups even though they are integers
#df[['trans_id', 'cust_id', 'prod_id']].apply(lambda x: x.astype('category')

for col in ['trans_id', 'cust_id', 'prod_id']:
    df[col] = df[col].astype('category')
```

In [667]:

```
#Extracting month from datetime object
df['trans_month'] = df['trans_dt'].dt.month_name()
#Verify the new coloumn
df.head()
```

Out[667]:

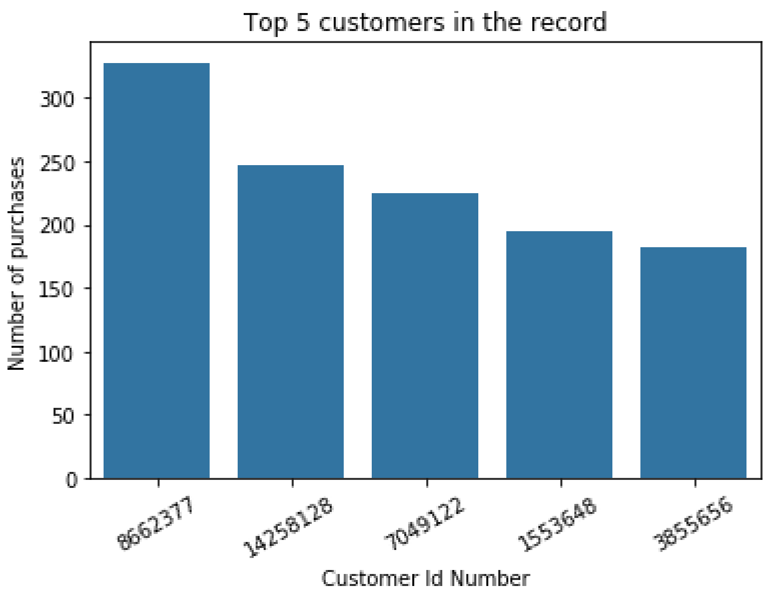
	trans_id	trans_dt	cust_id	prod_id	item_qty	item_price	seg_name	update_at	active_flag	pr
0	1	2016-01-02 10:06:00	9085146	223029	1	42.99	GONE AWAY	2015-11-01	N	
1	1	2016-01-02 10:06:00	9085146	223029	1	42.99	INACTIVE	2014-09-01	N	
2	1	2016-01-02 10:06:00	9085146	223029	1	42.99	INACTIVE	2016-01-01	N	
3	1	2016-01-02 10:06:00	9085146	223029	1	42.99	LAPSED	2014-01-01	N	
4	1	2016-01-02 10:06:00	9085146	223029	1	42.99	LAPSED	2014-03-01	N	

Visualization - Exploratory Analysis

Question: Who are the top 5 most valuable customers in the record?

In [668]:

```
#create plot
base_color = sb.color_palette()[0]
customers_id = df.cust_id.value_counts()[:5].index
#sb.barplot(x=df.cust_id.value_counts()[:5].index, y=df.cust_id.value_counts
sb.countplot(data=df , x='cust_id', color=base_color, order=df.cust_id.value
plt.xlabel('Customer Id Number')
plt.xticks(rotation = 30)
plt.ylabel('Number of purchases')
plt.title('Top 5 customers in the record');
```

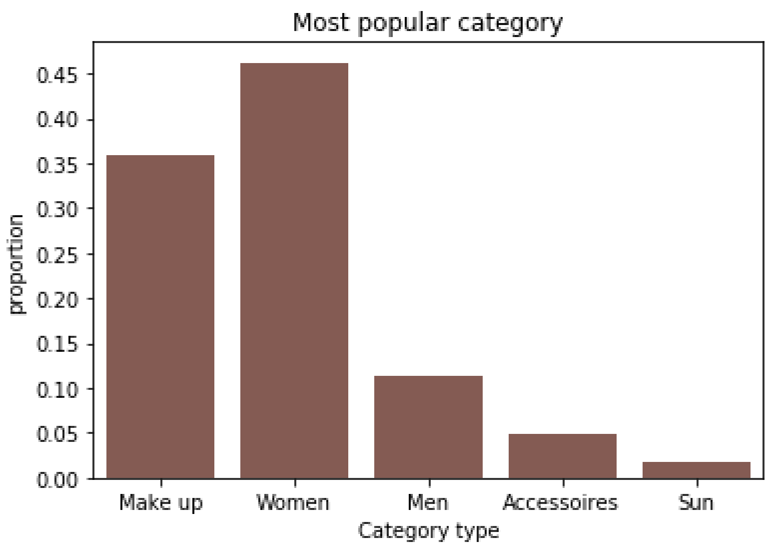


> Customer with id = **8662377** has the most number of transcations(over 300) in the lifetime followed by customer id **14258128** and **7049122**.

Question : What is the top selling category?

In [669]:

```
#generate proportion
n_points = df.shape[0]
max_count = df['category'].value_counts().max()
max_prop = max_count/n_points

#generate tick mark location and names
tick_props = np.arange(0, max_prop, 0.05)
tick_names = ['{:0.2f}'.format(v) for v in tick_props]

#create plot
sb.countplot(data=df, x='category', color=sb.color_palette()[5])
plt.yticks(tick_props * n_points, tick_names)
plt.ylabel('proportion')
plt.xlabel('Category type')
plt.title('Most popular category');
```



'Women' category is close to 50% of purchases, hence it is the most popular item that people like to buy.

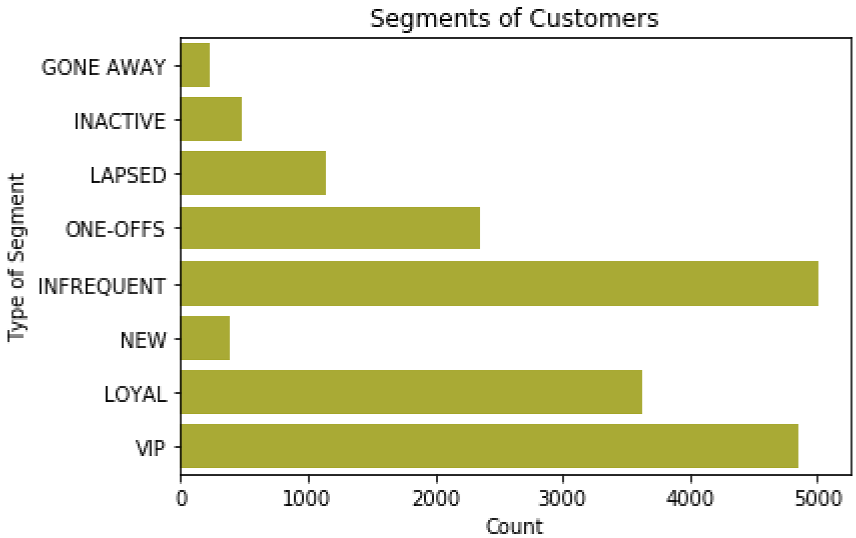
'Women' and 'Make up' together are dominant selling products.

'Men', 'Accessories', and 'Sun' are not doing well. 'Accessories' and 'Sun' make up only 5% of sales. These products needs to be reconsidered.

Visualizing different Segments of cusomters

In [670]:

```
sb.countplot(data=df, y='seg_name', color=sb.color_palette()[8])
plt.ylabel('Type of Segment')
plt.xlabel('Count')
plt.title('Segments of Customers');
```



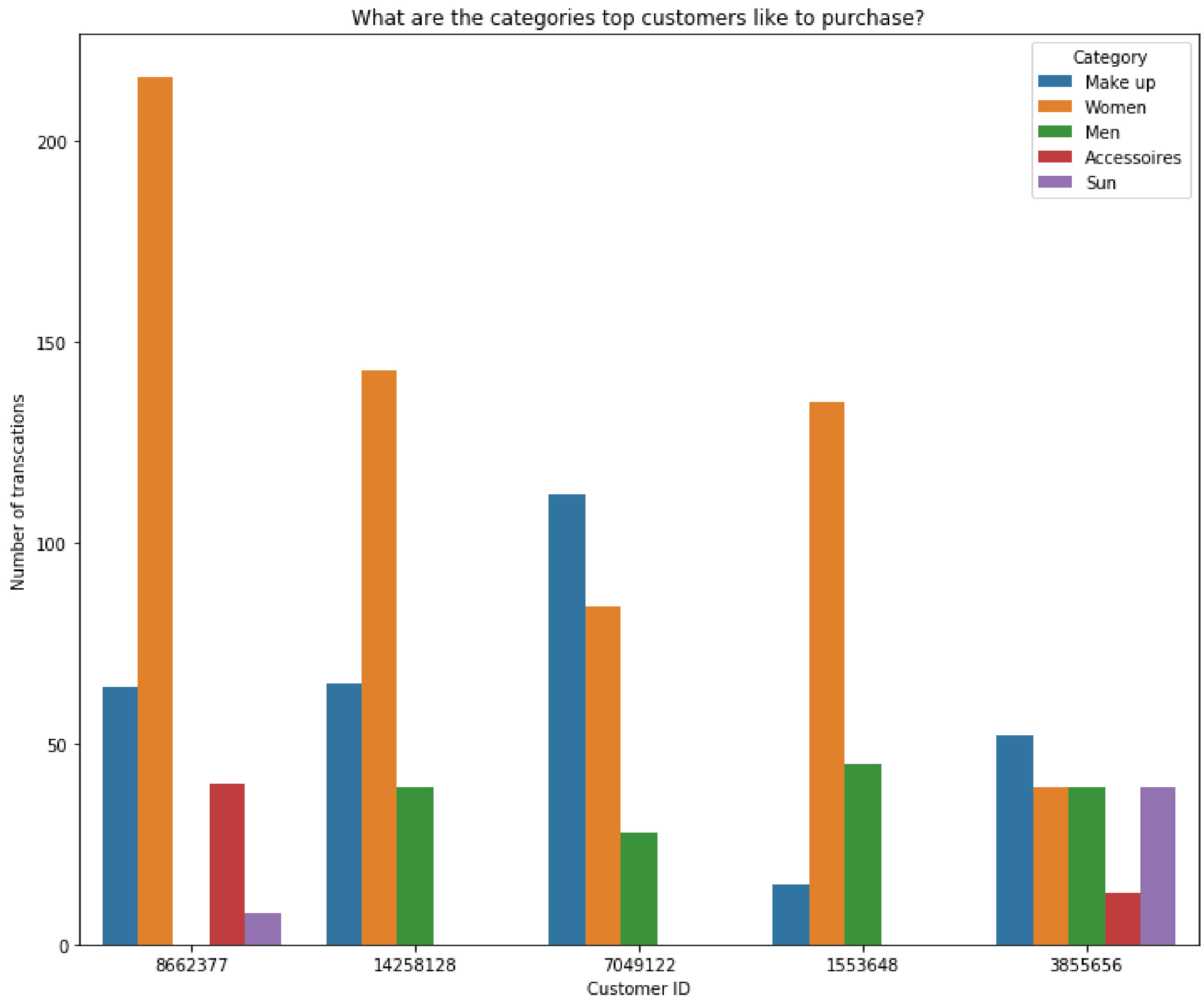
Few 'New' segments of customers are introduced in year of 2016. Looks like company is not interested in bringing new consumers or the efforts are not up to the mark.

It would be great to convert loyal customers to become VIP.

Question : What is the purchase pattern of loyal customers based on the current category offerings?

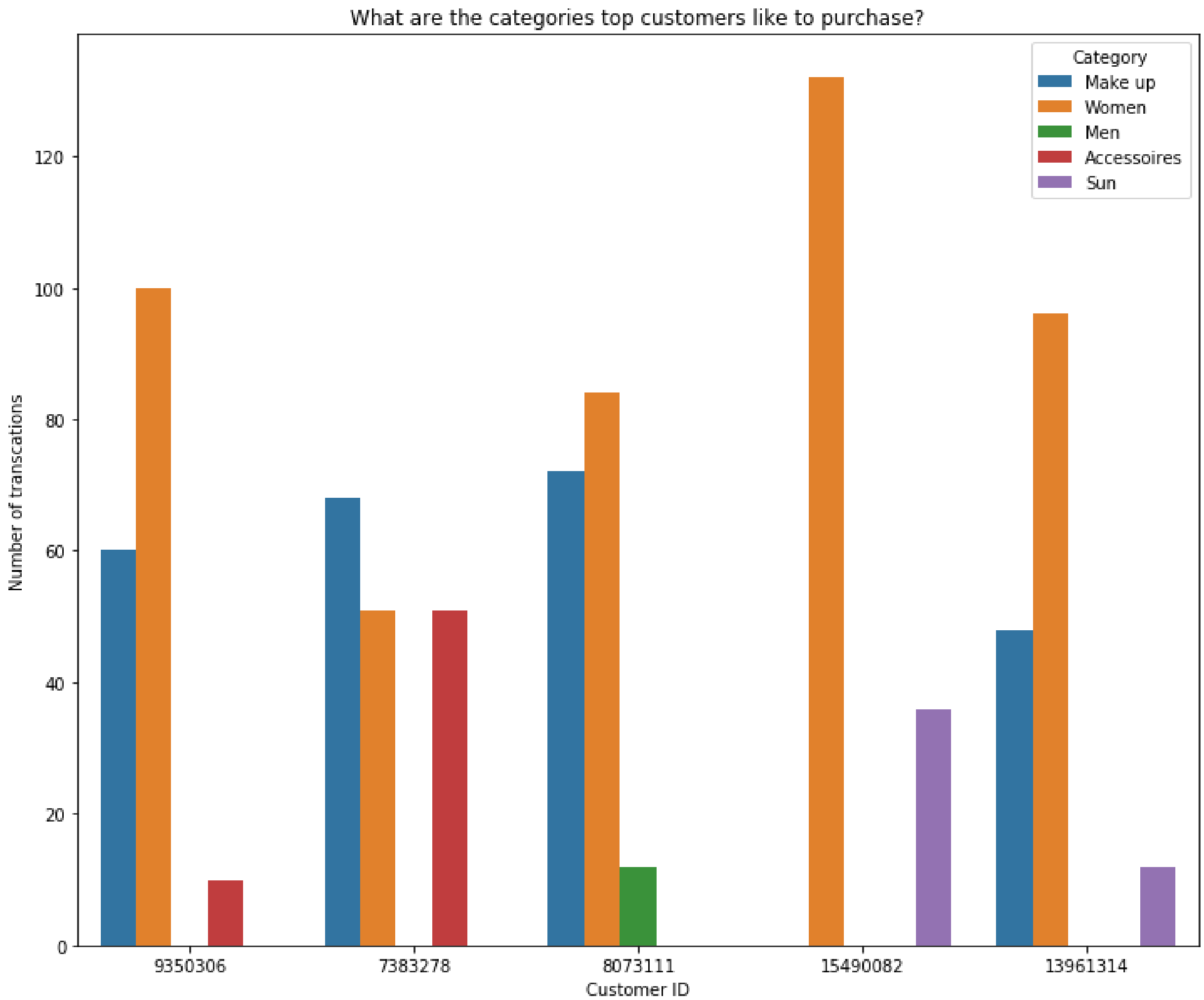
In [671]:

```
#Visualization of the purchases of top 10 customers in the dataframe
#create plot - Top 5 ranked Customers
plt.figure(figsize=[12, 10])
sb.countplot(data=df, x='cust_id' , hue='category', order=df.cust_id.value_c
plt.title('What are the categories top customers like to purchase?')
plt.ylabel('Number of transcations')
plt.xlabel('Customer ID')
plt.legend(title = 'Category');
```



In [672]:

```
#create plot- Ranked 5-10 Customers
plt.figure(figsize=[12, 10])
sb.countplot(data=df, x='cust_id' , hue='category', order=df.cust_id.value_c
plt.title('What are the categories top customers like to purchase?')
plt.ylabel('Number of transcations')
plt.xlabel('Customer ID')
plt.legend(title = 'Category');
```



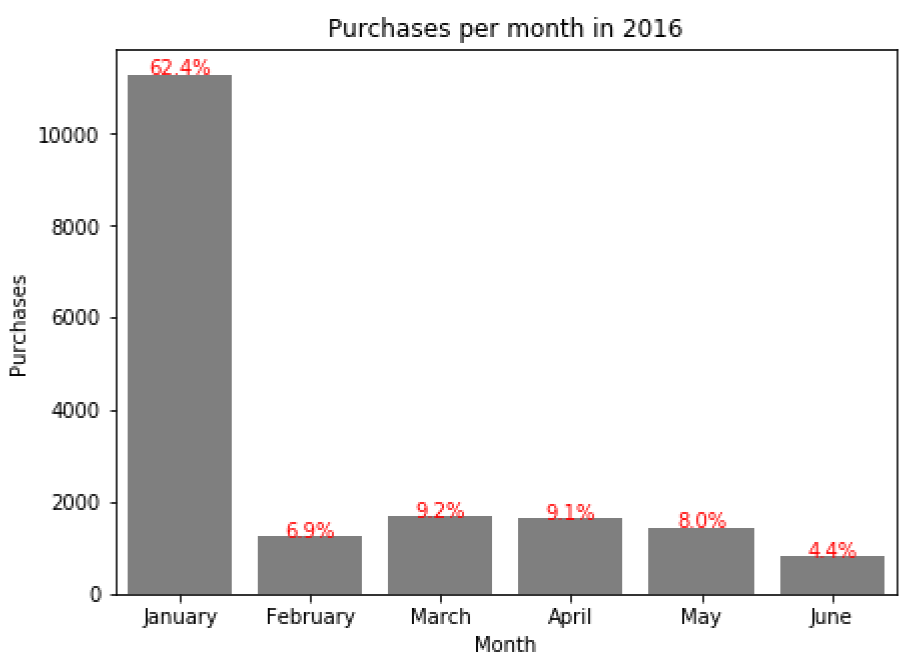
As we expected: 'Women' and 'Make up' are the top purchases for the customers.

Some customers have bought more 'Make up' over 'Women' products.

These customers have atleast bought 2 type of items.

Question: What month was the most profitable?

In [680]:
```
plt.figure(figsize =(7,5))
sb.countplot(data=df, x='trans_month', color = sb.color_palette()[7]);
plt.title('Purchases per month in 2016')
plt.ylabel('Purchases')
plt.xlabel('Month');

#add annotations
n_points = df.shape[0]
cat_counts = df.trans_month.value_counts()
locs, labels = plt.xticks() # get the current tick locations and labels

#loop through each pair of locations and labels
for loc, label in zip(locs, labels):

    count = cat_counts[label.get_text()]
    pct_string = '{:0.1f}%'.format(100*count/n_points)

    plt.text(loc, count-8, pct_string, ha = 'center', color = 'r')

```



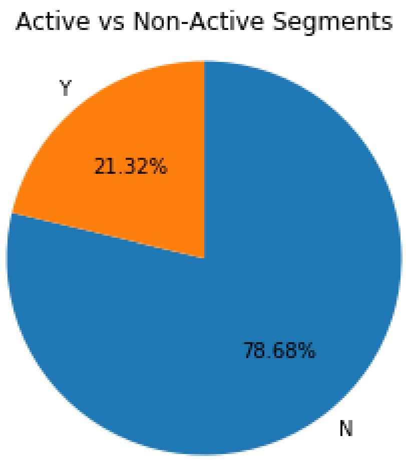
In the given dataframe, January (62.4%) was the most profitable month of the year 2016. I am assuming there is a new year sale in this month.

March - May seems to be consistent with sales.

Lowest number of sales in June (4.4%).

Question : What is the distribution of the active segments?

In [674]:
```
sorted_counts = df.active_flag.value_counts()
plt.pie(sorted_counts, labels = sorted_counts.index, startangle=90, autopct=
plt.axis('square')
plt.title('Active vs Non-Active Segments');
```

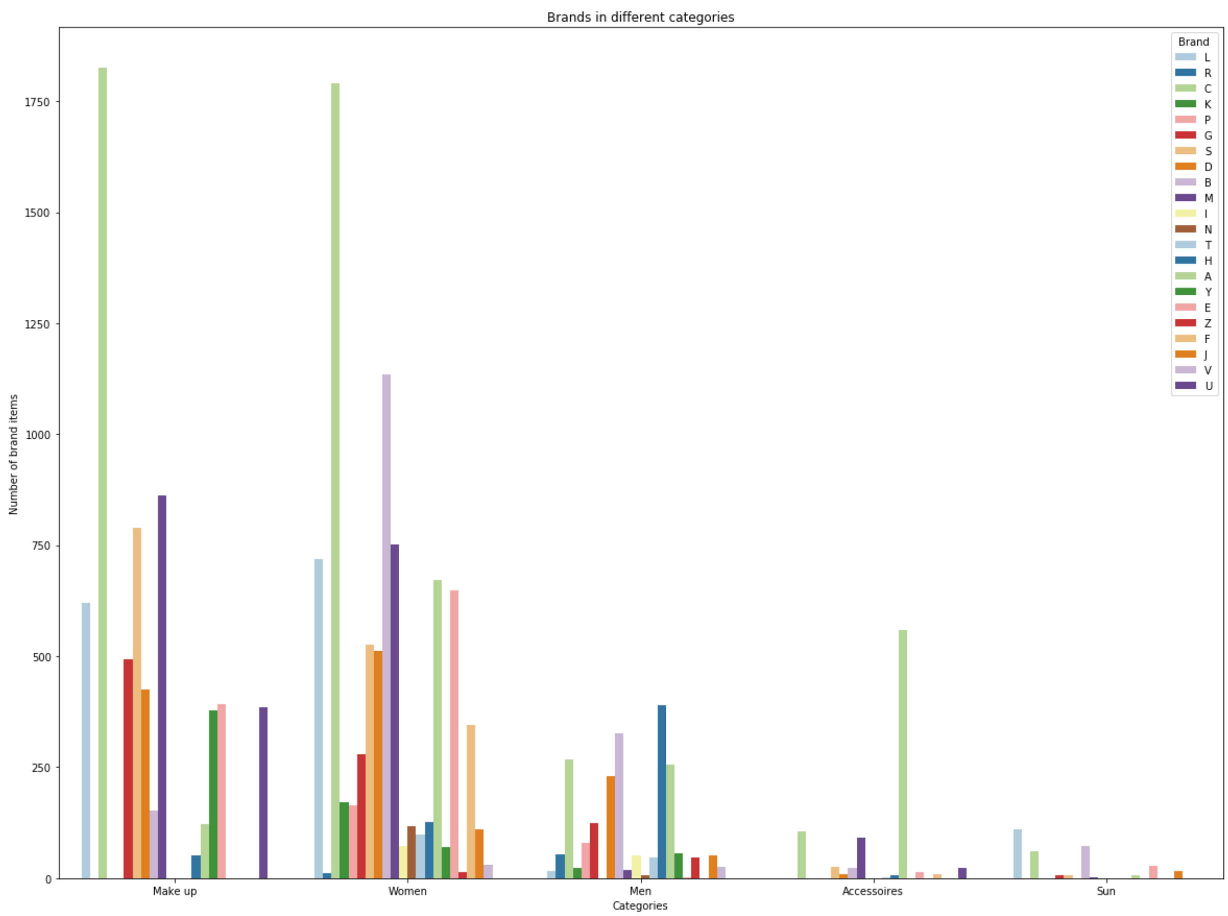


Seems like flag is not active the majority of the current customers.

Question : How are labels associated with the categories

In [675]:

```
#createplot
plt.figure(figsize =[20,15])
pal = sb.color_palette("Paired") #color palette is friendly for colorblind i
sb.countplot(data=df, x='category', hue='brand', palette = pal)
plt.legend(title = 'Brand', loc='upper right')
plt.xlabel('Categories')
plt.ylabel('Number of brand items')
plt.title('Brands in different categories');
```



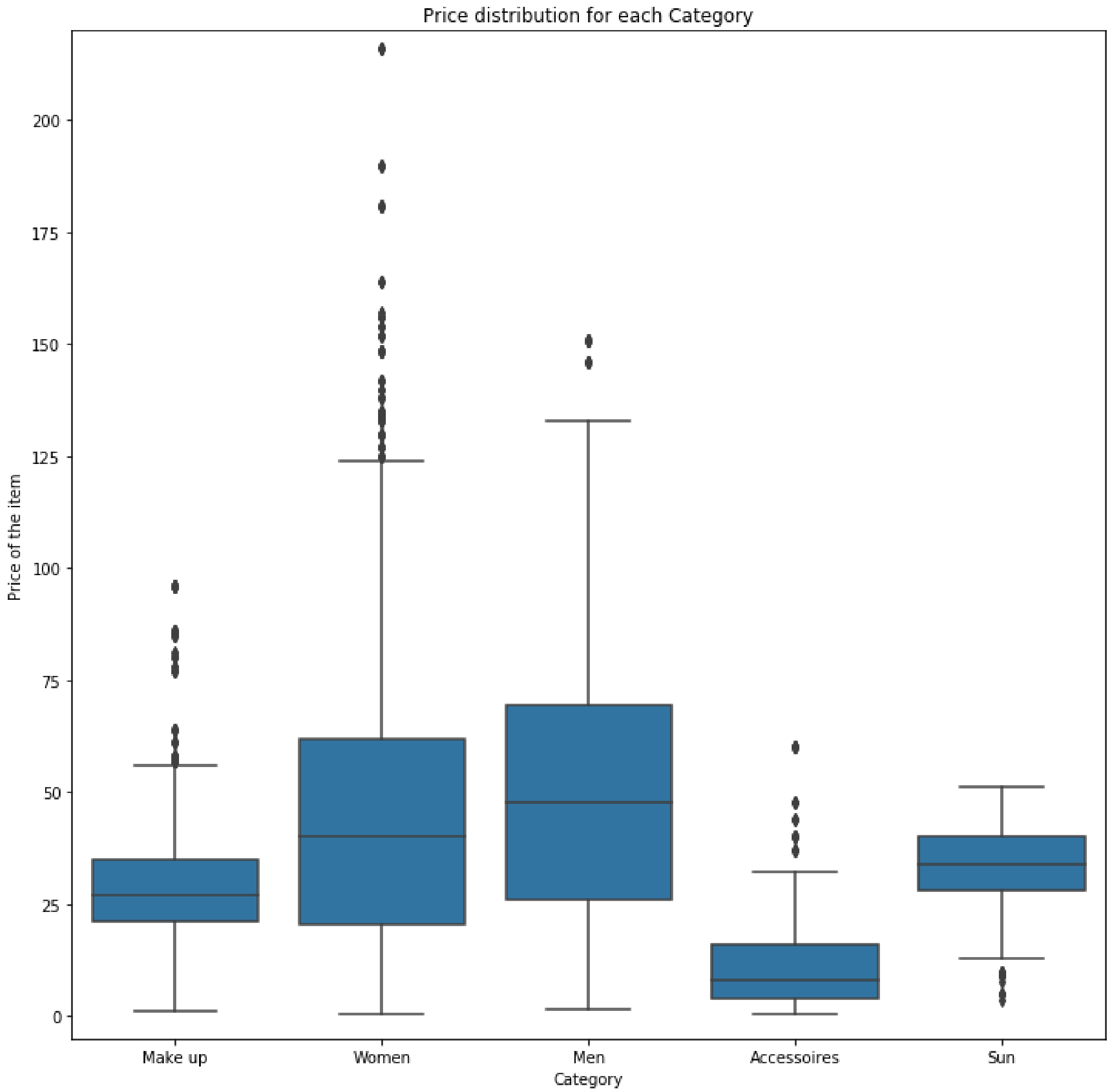
All the categories have different types of brand selections,

Some brands are limited to specific categories. For example - Brand 'I' can be only seen in 'Women' and 'Men'.

Brand 'C' is the most favored.

Question : Show the relation of price for each category

In [676]:
```
plt.figure(figsize =[12,12])
sb.boxplot(data=df, x='category', y='item_price', color=base_color)
plt.ylim(-5, 220)
plt.title('Price distribution for each Category')
plt.xlabel('Category')
plt.ylabel('Price of the item');
```



High variance is seen in 'Women' followed by 'Men' category. Hence, 'Women' has the most expensive items present in the inventory.

Central Line in each plot shows indicates the median of the distribution. Top and bottom line represents the third and first quartile of the price respectively.

Max range is set by whisker length. Although, we can see points above the highest whisker in 'Make up', 'Women', 'Men', and 'Accessories' category. This indicates there are many outliers for these categories which are higher than the third quartile.

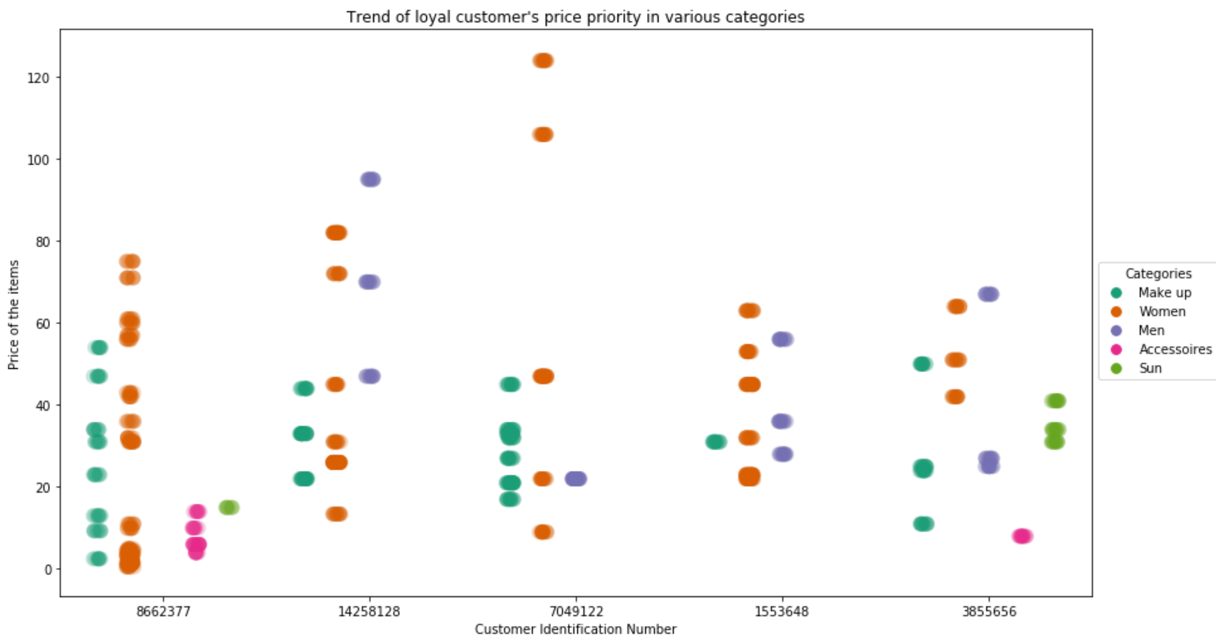
In [677]:

```
#most_occurring_values = df['cust_id'].value_counts().head(3).index
#cars_subset = df[df['cust_id'].isin(most_occurring_values)]
#sb.stripplot(data = cars_subset, x = 'category', y = 'item_price', hue='cus
#             jitter = 0.35, dodge = True, palette='Dark2')
```

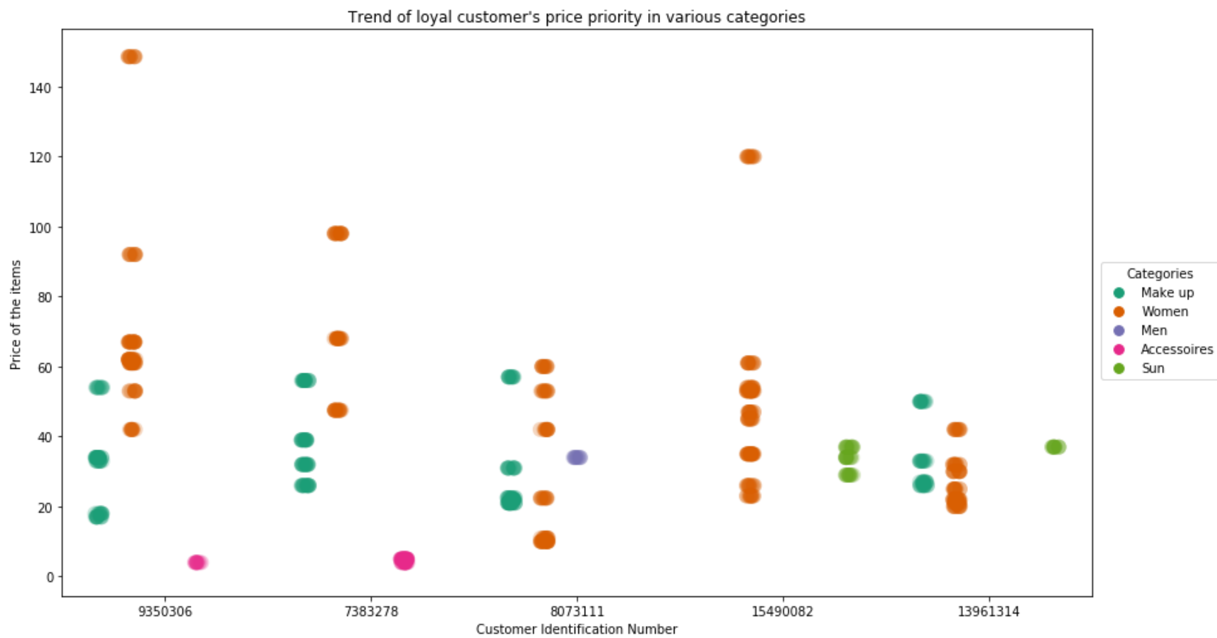
Showing the trend of loyal customers in respect to price and categories

In [678]:

```
plt.figure(figsize=[14.70, 8.27])
sb.stripplot(x = 'cust_id', y = 'item_price',hue='category', data = df, orde
                 jitter=True, dodge = True,size=12, edgecolor='gray',alpha=.25,
plt.title("Trend of loyal customer's price priority in various categories")
plt.legend(title = 'Categories', bbox_to_anchor=(1,0.6) )
plt.xlabel('Customer Identification Number')
plt.ylabel('Price of the items');
```



In [679]:
```
plt.figure(figsize=[14.70, 8.27])
sb.stripplot(x = 'cust_id', y = 'item_price',hue='category', data = df, orde
                jitter=True, dodge = True,size=12, edgecolor='gray',alpha=.25,
plt.title("Trend of loyal customer's price priority in various categories")
plt.legend(title = 'Categories', bbox_to_anchor=(1.13,0.6) )
plt.xlabel('Customer Identification Number')
plt.ylabel('Price of the items');
```



> Previously, in the box plots we realized the 'Women' category had the 2nd highest median. The trend of most valuable customers shows us that these folks tend to buy items under the Interquartile Range (Approx Item Price: 25-75).

Insights

Overall the original dataset has been very well maintained and didn't require much cleaning.

1. Major revenue comes from products which are under **'Women'** and **'Makeup'** Category. It seems like the company has a target market for females.
2. There are large number of **Loyal** customers who have not been categorized as VIP. Incentives can be provided to the Loyal customers to lure them to VIP section.
3. Majority of the purchases are made during the month of **January**. Assuming the 'New Year' sales plays a major factor.
4. There is a huge catalog for brand presented by the company. Selling **22** different brands across various categories.
5. The customers prefer to buy items whose price falls under a specific range. For 'Women' category there are many outliers.
6. Brand 'C' is very popular amongst the top 2 categories.
7. Active Segments can be utilized more to understand the behavior of customers, it's not being used efficiently. The active flag has been set to 'N' for

- 3652 VIP customers
- 2793 LOYAL customers

8. Customer 8662377 is has the most transcations in the system.