Analysis of users' events from an eCommerce website

Clara Villalba

Abstract

- In this project we will use a dataset containing users' events from an eCommerce website to find out some metrics and to create a model to predict the next purchase date of a product

Motivation

- All companies wants more customers, more orders, more revenue, more signups, more efficiency.
- To do that we need to find out metrics that best captures the core value that products delivered to customers
- We this on mind, we will analyze a dataset containing users' events from an eCommerce website and we will try to discover this metrics
- Finally we will train some ML algorithms to predict the next purchase day of a product.

Dataset Used

- eCommerce Events History in Cosmetics Shop
- This dataset contains 20M users' events from eCommerce website
- Contains behavior data for 5 months (Oct 2019 – Feb 2020) from a medium cosmetics online store
- https://www.kaggle.com/mkechinov/ecommerce-events-history-in-cosmetics-shop

Data Preparation and Cleaning

- The Dataset contains behavior data for 5 months (Oct 2019 – Feb 2020) from a medium cosmetics online store but for the purpose of this analysis only the data from **December 2019** and **January 2020** were used.
- Each row in the file represents an event. All events are related to products and users. Each event is like many-to-many relation between products and users.
- Semantic of the datasets:
  - User **userid** during session **usersession** added to shopping cart (property **eventtype** is equal **cart**) product **productid** of brand **brand** of category **categorycode** (categorycode) with price **price** at **event_time**
- There were missing values, we dropped them in the cleaning process

Research Questions

- How many purchases we have in each month?
- What was the Monthly Revenue?
- What was the number of Monthly Active Customers?
- Who were the main buyers in each month?
- Which brands were the top 10 sellers in each month?
- Which products were the top 10 sellers in each month?
- How was the distribution of events each month?
- Can we predicting the Next Purchase Day of a product?

Methods

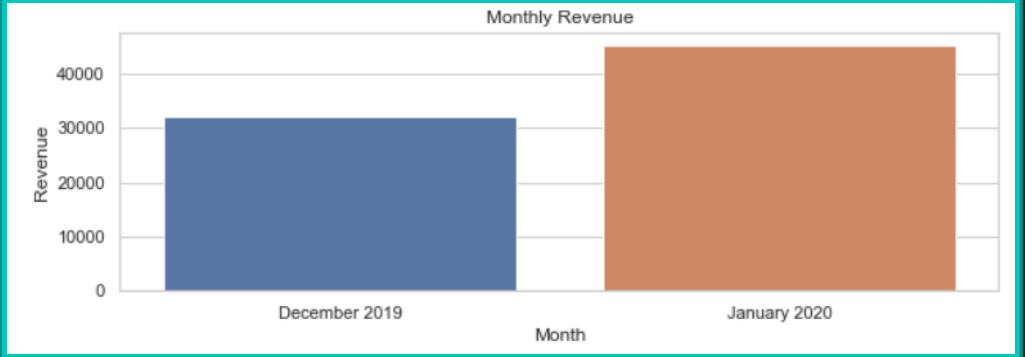
- To analyze the data we use Jupyter Notebooks
- We first did some basis Data Cleaning Steps
- Later, we did some Data Analysis and found some metrics witch were useful to answer the research questions
- Finally, we applied Machine Learning algorithms to try to predict when a product will be next purchased based in the purchases it had.

Findings

How many purchases we have in each month?

Purchases in December: 2111
Purchases in January: 3160

We can see that there were more purchases in January 2020 and therefore the revenue were higher

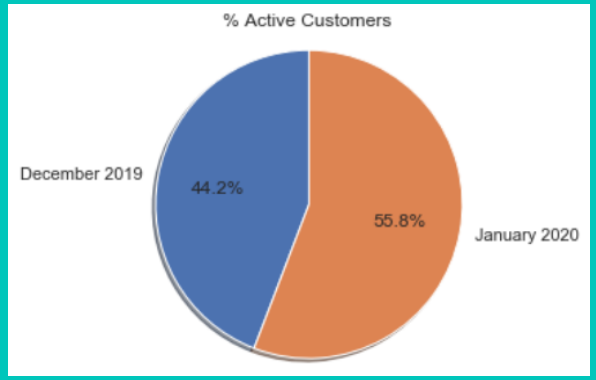


What was the Monthly Revenue?

The revenue increase from 32125.35 in December 2019 to 45313.29 in January 2020

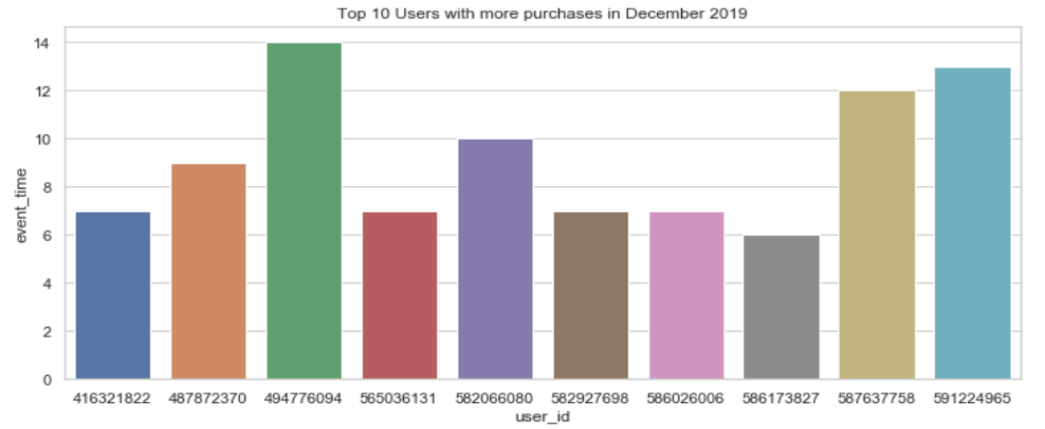
Findings

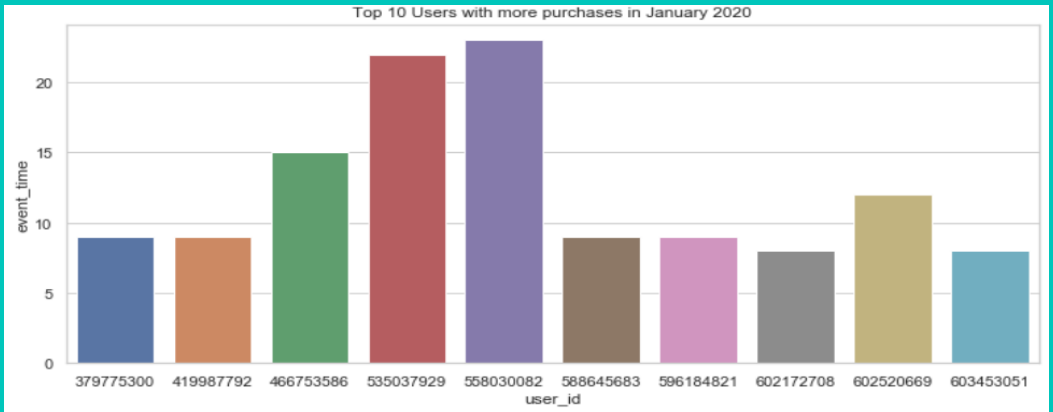
What was the number of Monthly Active Customers?



In January 2020 the number of active customers went up from 13318 in December 2019 to 16832

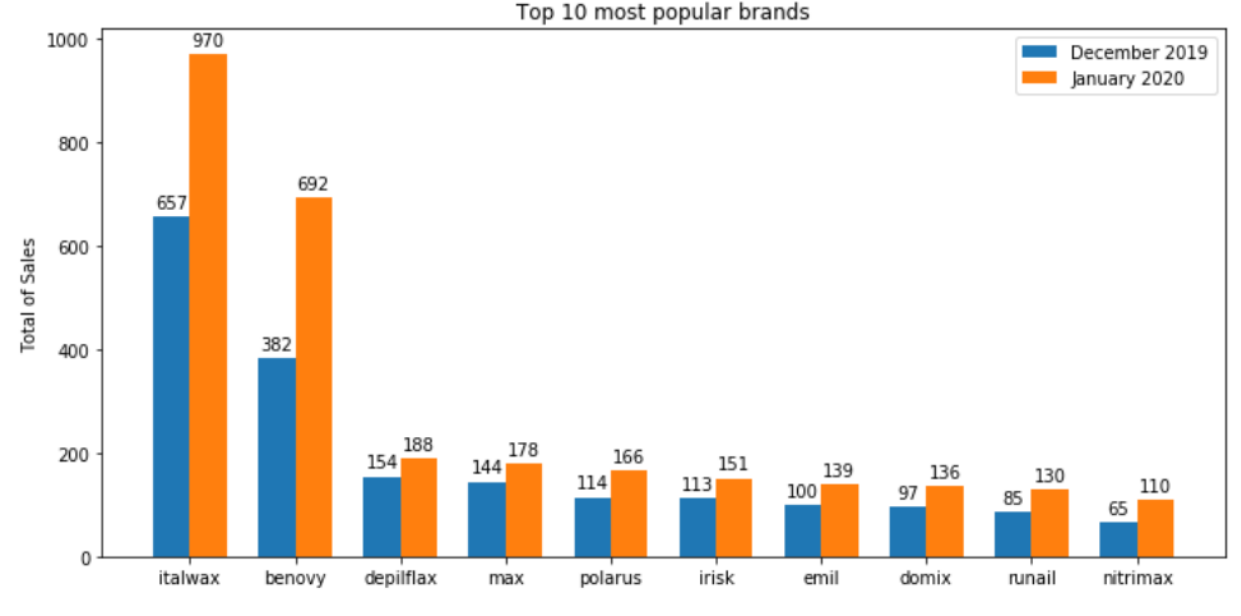
Who were the main buyers in each month?





Findings

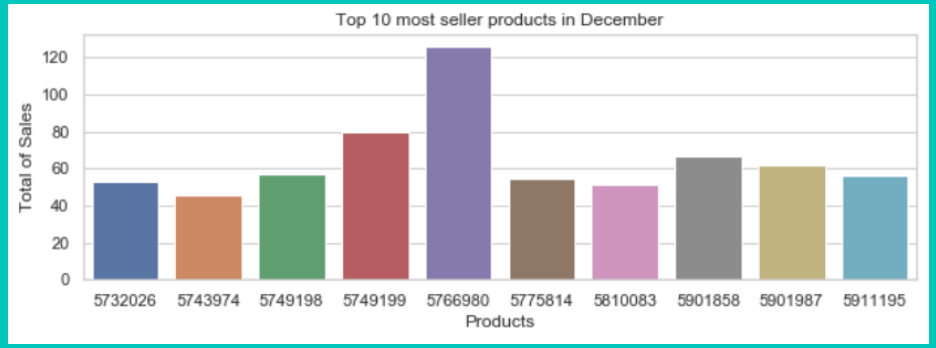
Which brands were the top 10 sellers in each month?

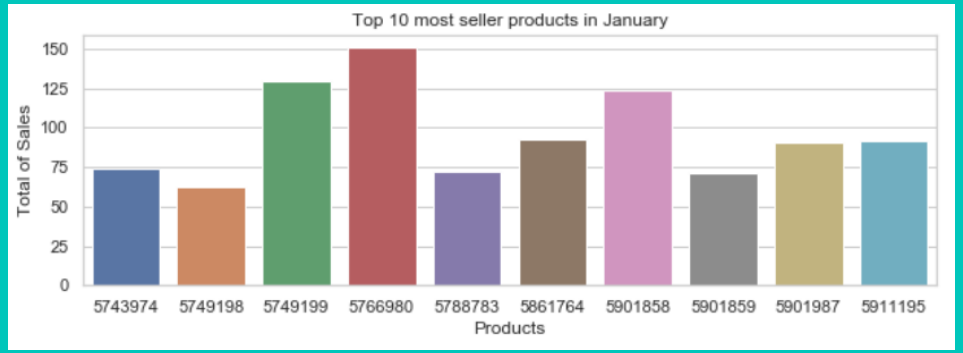


As we can see in the bar chart above, there were more sales in January 2020 than December 2019 for the same top 10 brands

Findings

Which products were the top 10 sellers in each month?





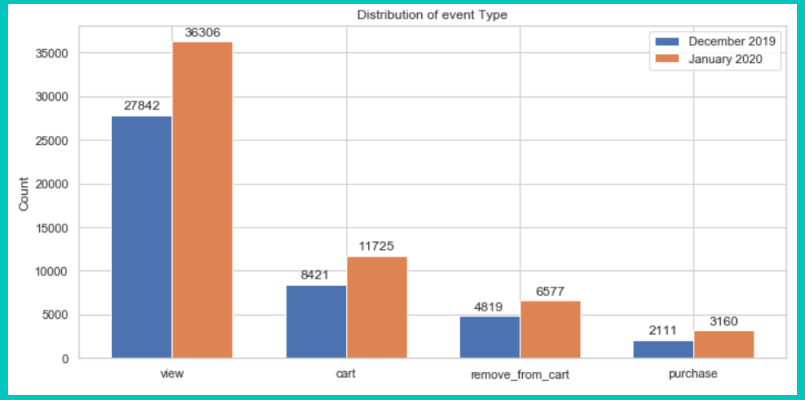
We can see that the top seller product was 5766980 in both months

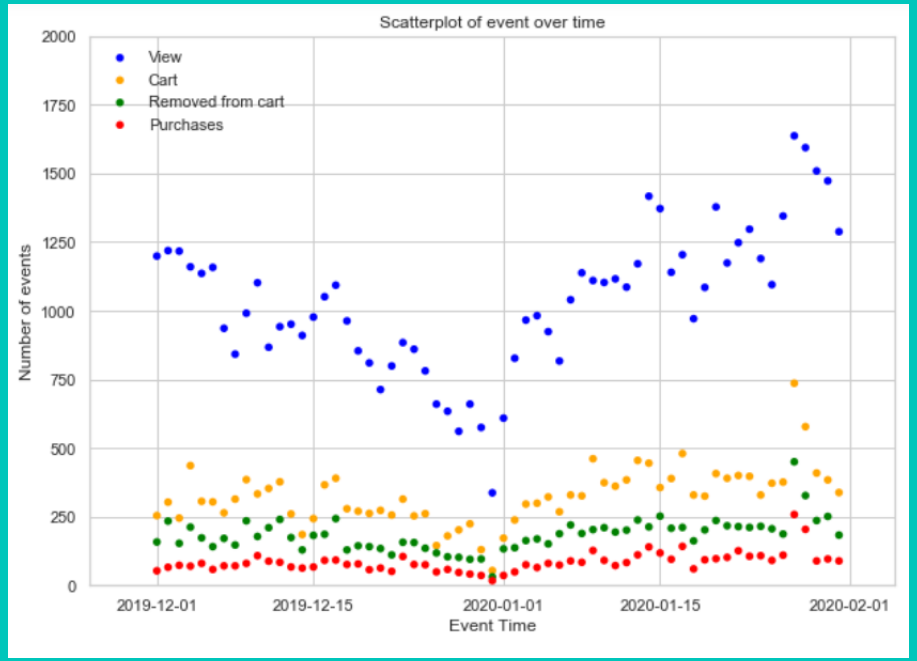
Findings

How was the distribution of events each month?

There are 4 types of event

- View
- Cart
- Purchase
- Remove_from_cart





A normal flow in a session should be:

Start >> VIEW >> CART >> REMOVE/PURCHASE

We can see clearly that there were more view events

Findings

Can we predicting the Next Purchase Day of a product?

- To answer this we used Machine Learning Classification algorithms
- Before that to convert to a Classification Task, we did some data preparation:
  - We concatenated both files to work with only unified dataset
  - We left only the data of the event type: purchased
  - To create our features we calculate the days between last purchase and first purchase:

	product_id	MaxPurchaseDate	MinPurchaseDate	NextPurchaseDay
0	5395	2020-01-28 17:56:55	2019-12-14 14:19:26	45
1	8372	2020-01-13 08:44:00	2019-12-06 08:00:56	38
2	8373	2020-01-28 07:27:43	2020-01-28 07:27:43	0
3	24330	2020-01-28 16:17:51	2019-12-05 08:44:04	54
4	24331	2020-01-29 15:39:10	2019-12-02 19:57:58	57

  - We got the last 3 purchase dates of each product
  - We calculated the difference in days for each product purchase date

Findings

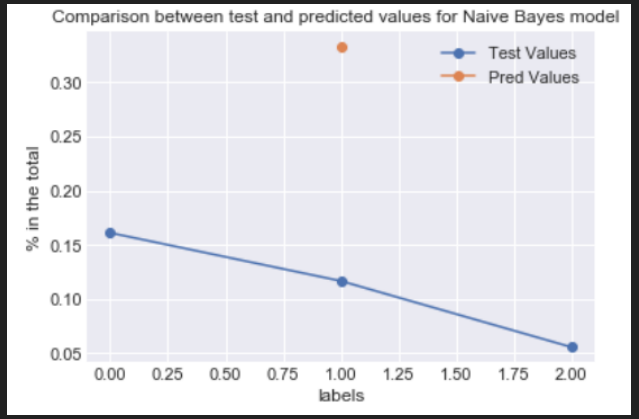
Can we predicting the Next Purchase Day of a product?

- We calculated the difference in days for each product purchase date
- We find out the mean and standard deviation of the difference between purchases in days and convert them to categorical values
- Finally our features are:

	product_id	NextPurchaseDay	DayDiff	DayDiff2	DayDiff3	DayDiffMean	DayDiffStd
0	5873430	58	1.0	2.0	4.0	1.870968	1.765256
1	5861766	54	7.0	8.0	13.0	6.750000	7.146428
2	5889695	61	3.0	6.0	7.0	2.033333	1.496740
3	5889696	60	1.0	2.0	3.0	2.857143	2.988072
4	5746974	61	2.0	3.0	4.0	3.388889	2.872566

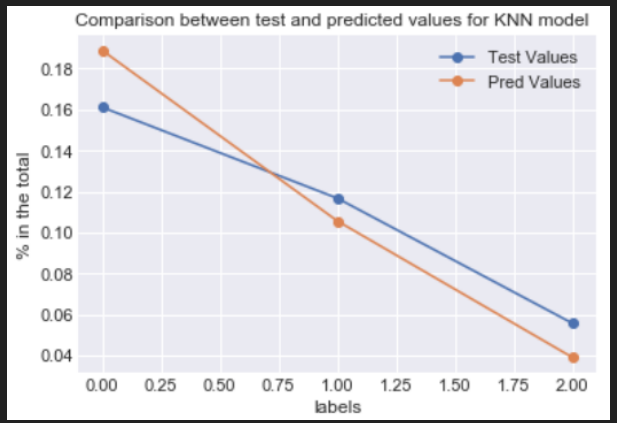
- For the labels we decided this boundaries:
  - 0-40: class_name = 2
  - 41-55: class_name = 1
  - >= 55: class_name = 0

So our labels will be 0, 1 and 2



Acc = 0.35

Acc = 0.57



Acc = 0.65

Findings

We trained 3 algorithms:

- **Naïve Bayes:** we get an accuracy of 0.35 but as we can see in the plot it only predict the label 1 class
- **Decision Tree Classifier:** we get an accuracy of 0,57 but as we can see in the plot it only predict the label 0 and 1 classes
- **Kneighbors Classifier:** it is our best model with an accuracy of 0.65 and it predicted the 3 classes

Conclusions

- In this study of the dataset of eCommerce Events History in Cosmetics Shop we got some metrics that could be useful to have knowledge about the events in December 2019 compared to the events in January 2020
- On the other hand, we trained a model to predict the Next Purchase Day of a product we an accuracy of 0.65, which is a very good score.

Acknowledgements

https://www.kaggle.com/mkechinov/ecommerce-events-history-in-cosmetics-shop

https://matplotlib.org/3.1.1/index.html

http://seaborn.pydata.org/

TP-Final

June 24, 2020

Analysis of users events from an eCommerce website

[ ]:
```
#Importing the Necessary Libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

Ecommerce Cosmetics Shop Data Description

[2]:
```
#import the dataset info a dataframe
data_Dec = pd.read_csv('C:/Users/clara.o.villalba/Documents/Curso EDX/
↪Week-9-ExampleNotebooks/TP/eCommerce_Cosmetics_ Shop_Inputs/2019-Dec.csv')
data_Jan = pd.read_csv('C:/Users/clara.o.villalba/Documents/Curso EDX/
↪Week-9-ExampleNotebooks/TP/eCommerce_Cosmetics_ Shop_Inputs/2020-Jan.csv')
```

Semantic of the datasets: User **userid** during session **usersession** added to shopping cart (property **eventtype** is equal **cart**) product **productid** of brand **brand** of category **categorycode** (categorycode) with price **price** at **event_time**

Each row in the file represents an event. All events are related to products and users. Each event is like many-to-many relation between products and users.

[3]:
```
data_Dec.head()
```

[3]:

	event_time	event_type	product_id	category_id	category_code	brand	price	user_id	user_session
0	2019-12-01 00:00:00 UTC	remove_from_cart	5712790	1487580005268456287	NaN	f.o.x	6.27	576802932	
1	2019-12-01 00:00:00 UTC	view	5764655	1487580005411062629	NaN	cnd	29.05	412120092	
2	2019-12-01 00:00:02 UTC	cart	4958	1487580009471148064	NaN	runail	1.19	494077766	
3	2019-12-01 00:00:05 UTC	view	5848413	1487580007675986893	NaN	freedecor	0.79	348405118	
4	2019-12-01 00:00:07 UTC	view	5824148	1487580005511725929	NaN	NaN	5.56	576005683	

[4]:
```
data_Dec.describe()
```

[4]:

	product_id	category_id	price	user_id
count	3.533286e+06	3.533286e+06	3.533286e+06	3.533286e+06
mean	5.473054e+06	1.555023e+18	8.871856e+00	5.223318e+08
std	1.331331e+06	1.689262e+17	1.986474e+01	8.494819e+07
min	3.752000e+03	1.487580e+18	-7.937000e+01	1.180452e+06
25%	5.726191e+06	1.487580e+18	2.060000e+00	4.866830e+08
50%	5.811429e+06	1.487580e+18	4.210000e+00	5.566496e+08
75%	5.859462e+06	1.487580e+18	7.140000e+00	5.828019e+08
max	5.917178e+06	2.235524e+18	3.277800e+02	5.954145e+08

[5]:
```
data_Dec.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3533286 entries, 0 to 3533285
Data columns (total 9 columns):
event_time       object
event_type       object
product_id       int64
category_id      int64
category_code    object
brand            object
price            float64
user_id          int64
user_session     object
dtypes: float64(1), int64(3), object(5)
memory usage: 242.6+ MB
```

[6]:
```
data_Jan.head()
```

[6]:

	event_time	event_type	product_id	category_id	category_code	brand	price	user_id	user_session
0	2020-01-01 00:00:00 UTC	view	5809910	1602943681873052386	NaN	grattol	5.24	595414620	
1	2020-01-01 00:00:09 UTC	view	5812943	1487580012121948301	NaN	kinetics	3.97	595414640	
2	2020-01-01 00:00:19 UTC	view	5798924	1783999068867920626	NaN	NaN			
3	2020-01-01 00:00:24 UTC	view	5793052	1487580005754995573	NaN	NaN			
4	2020-01-01 00:00:25 UTC	view	5899926	2115334439910245200	NaN	NaN			

0.0.1 Data Cleaning Steps

As we can see there are some nulls in our data, let's do some cleaning

[190]:
```
data_Dec_clean = data_Dec.dropna()
print(data_Dec.shape)
print(data_Dec_clean.shape)
```

```
(3533286, 9)
(43193, 9)
```

As we can see, now we have less rows. Just let's check if there is any missing null value...

[9]:
```
data_Dec_clean.isnull().any(axis=1)
```

[9]:
```
33         False
52         False
90         False
112        False
138        False
           ...
3532871    False
3532874    False
3533061    False
3533221    False
3533226    False
Length: 43193, dtype: bool
```


As we see there is no null values any more. Now lets do the same with the data_Jan Dataset..

[191]:
```
data_Jan_clean = data_Jan.dropna()
print(data_Jan.shape)
print(data_Jan_clean.shape)
```

```
(4264752, 9)
(57768, 9)
```

[11]:
```
data_Jan_clean.isnull().any(axis=1)
```

[11]:
```
359        False
380        False
487        False
907        False
987        False
           ...
4264525    False
4264534    False
4264594    False
4264721    False
4264738    False
Length: 57768, dtype: bool
```

0.0.2 Data Analysis

1- How many diferents categories we have, and how many values for each one?

[186]:
```
print("Unique Categories in December = ",len(data_Dec_clean['category_code'].
 ↪value_counts()))
print('-' * 50)
print(data_Dec_clean['category_code'].value_counts())
print('-' * 50)
print('-' * 50)
print("Unique Categories in Jan = ",len(data_Jan_clean['category_code'].
 ↪value_counts()))
print('-' * 50)
print(data_Jan_clean['category_code'].value_counts())
```

```
Unique Categories in December =  9
```

```
--------------------------------------------------
appliances.environment.vacuum              23084
stationery.cartrige                         8410
apparel.glove                               5825
furniture.bathroom.bath                     2775
furniture.living_room.cabinet               1583
accessories.bag                              867
accessories.cosmetic_bag                     301
appliances.personal.hair_cutter              273
appliances.environment.air_conditioner        75
Name: category_code, dtype: int64
--------------------------------------------------
--------------------------------------------------
Unique Categories in Jan =  10
--------------------------------------------------
appliances.environment.vacuum              28979
stationery.cartrige                        10392
apparel.glove                               9958
furniture.bathroom.bath                     4350
furniture.living_room.cabinet               2249
accessories.bag                              780
appliances.personal.hair_cutter              517
accessories.cosmetic_bag                     377
appliances.environment.air_conditioner       102
appliances.personal.massager                  64
Name: category_code, dtype: int64
```

We have 9 categories in December 2019 and 10 categories in January 2020. This last have the category appliances.personal.massager that is not in December

2- How many differents brands we have? and How many rows for each?

[270]:
```
unique_dec_brands = data_Dec_clean['brand'].value_counts()
unique_jan_brands = data_Jan_clean['brand'].value_counts()
print("Unique brands in December = ",len(unique_dec_brands))
print('-' * 32)
print(unique_dec_brands.head())
print('-' * 32)
print("Unique brands in January = ",len(unique_jan_brands))
print('-' * 32)
print(unique_jan_brands.head())
```

```
Unique brands in December =  38
--------------------------------
italwax    6490
max        5961
polarus    4938
runail     4191
emil       3969
Name: brand, dtype: int64
--------------------------------
Unique brands in January =  38
--------------------------------
italwax    8472
max        7125
benovy     6465
polarus    6430
emil       5595
Name: brand, dtype: int64
```

We have 38 brands in each month

3- Do we have negative prices? Let's check if we have negative values in the prices

[14]:
```
print(data_Dec_clean.loc[data_Dec_clean['price']<0][['product_id','price']].
 ↪drop_duplicates())
print(data_Jan_clean.loc[data_Jan_clean['price']<0][['product_id','price']].
 ↪drop_duplicates())
```

```
Empty DataFrame
Columns: [product_id, price]
Index: []
Empty DataFrame
Columns: [product_id, price]
Index: []
```

As we can see we don't have negative prices

4- How many purchases we have in each month?

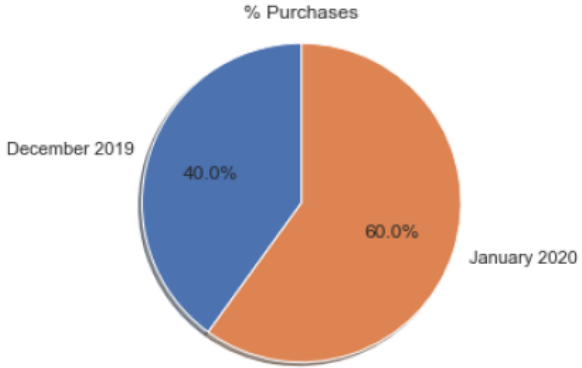
[15]:
```
# Get only purchases
dec_purchases = data_Dec_clean.loc[data_Dec_clean.event_type == 'purchase']
#print(dec_purchases.head())
jan_purchases = data_Jan_clean.loc[data_Jan_clean.event_type == 'purchase']
#print(jan_purchases.head())
```

[16]:
```
print("Purchases in December: ",len(dec_purchases))
print("Purchases in January: ", len(jan_purchases))
```

```
Purchases in December:  2111
Purchases in January:  3160
```

[180]:
```
# Pie chart of % purchases
labels = 'December 2019', 'January 2020'
sizes = [2111, 3160]

fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=labels, autopct='%1.1f%%',
```

```
        shadow=True, startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
ax1.set_title('% Purchases')

plt.show()
```



We have more purchases in January

5- What was the Monthly Revenue? We now can calcule the revenue in each month

[17]:
```
revenue_dec = dec_purchases['price'].sum()
revenue_jan = jan_purchases['price'].sum()
print('December Revenue: ', revenue_dec)
print('January Revenue: ',revenue_jan)
```

```
December Revenue:  32125.35
January Revenue:  45313.29
```

[181]:
```
import seaborn as sns
sns.set(style="whitegrid")
f, ax = plt.subplots(figsize=(10, 3))
ax.set_ylabel('Revenue')
ax.set_xlabel('Month')
ax.set_title('Monthly Revenue')
labels = ['December 2019', 'January 2020']
y_values = [revenue_dec, revenue_jan]
```

```
ax = sns.barplot(x=labels, y=y_values)
```

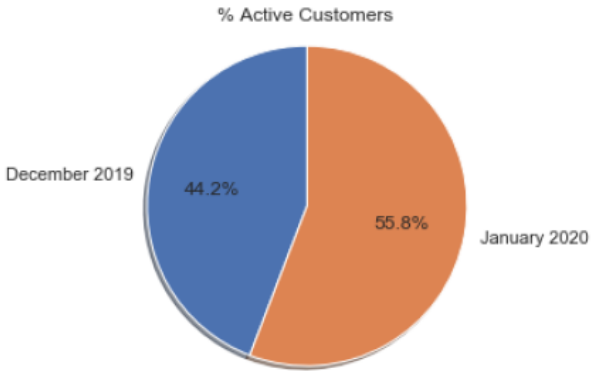
The revenue increase from 32125.35 in December 2019 to 45313.29 in January 2020

6- What was the number of Monthly Active Customers?

[18]:
```
#counting unique users IDs
customers_dec = data_Dec_clean['user_id'].nunique()
customer_jan = data_Jan_clean['user_id'].nunique()
print('Active Custumers in December: ' , customers_dec)
print('Active Custumers in January : ' ,customer_jan)
```

```
Active Custumers in December:  13318
Active Custumers in January :  16832
```

[183]:
```
# Pie chart of % active customers
labels = 'December 2019', 'January 2020'
sizes = [13318, 16832]

fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=labels, autopct='%1.1f%%',
        shadow=True, startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
ax1.set_title('% Active Customers')

plt.show()
```



In January 2020 the number of active customers went up from 13318 in December 2019 to 16832

0.0.3 Calculate some metrics

1- Which brands were the top 10 sellers in each month?

[19]:
```
#first we look for the top sellers brands of each month
dec_top_sellers = dec_purchases.groupby('brand').brand.agg([len]).
 ↪sort_values(by='len', ascending=False)
dec_top_sellers= dec_top_sellers.reset_index()
dec_top_sellers_top10 = dec_top_sellers[:10]
#print(dec_top_sellers)
#print('-' * 20)
jan_top_sellers = jan_purchases.groupby('brand').brand.agg([len]).
 ↪sort_values(by='len', ascending=False)
jan_top_sellers = jan_top_sellers.reset_index()
jan_top_sellers_top10 = jan_top_sellers[:10]
#print(jan_top_sellers)
```

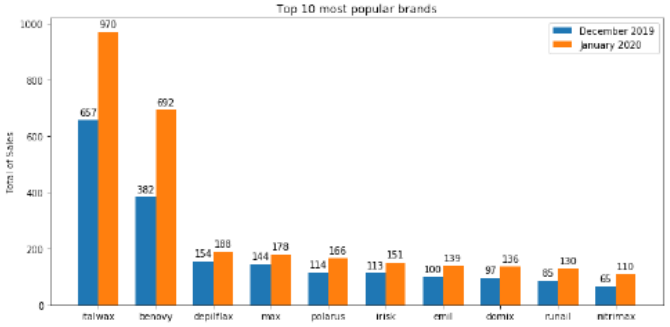
Now let's create a grouped bar chart to compare the top 10 total sales in both months. To do that I used matplotlib documentation: https://matplotlib.org/3.1.1/gallery/lines_bars_and_markers/barchart.html

[20]:
```
labels = dec_top_sellers_top10['brand'].values.tolist()
labels2 = jan_top_sellers_top10['brand'].values.tolist()
print(labels)
print(labels2)
```

```
['italwax', 'benovy', 'depilflax', 'max', 'polarus', 'irisk', 'emil', 'domix',
'runail', 'nitrimax']
['italwax', 'benovy', 'emil', 'max', 'polarus', 'domix', 'irisk', 'depilflax',
'nitrimax', 'runail']
```

As we can see we have the same top 10 brands, we are using them like labels

[21]:
```
labels = dec_top_sellers_top10['brand'].values.tolist()
dec_values = dec_top_sellers_top10['len'].values.tolist()
jan_values = jan_top_sellers_top10['len'].values.tolist()

x = np.arange(len(labels))  # the label locations
width = 0.35  # the width of the bars

fig, ax = plt.subplots(figsize=(10, 5))
rects1 = ax.bar(x - width/2, dec_values, width, label='December 2019')
rects2 = ax.bar(x + width/2, jan_values, width, label='January 2020')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Total of Sales')
ax.set_title('Top 10 most popular brands')
ax.set_xticks(x)
ax.set_xticklabels(labels)
ax.legend()


def autolabel(rects):
    """Attach a text label above each bar in *rects*, displaying its height."""
    for rect in rects:
        height = rect.get_height()
        ax.annotate('{}'.format(height),
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')
autolabel(rects1)
autolabel(rects2)

fig.tight_layout()

plt.show()
```



As we can see in the bar chart above, there were more sales in January 2020 than December 2019 for the same top 10 brands

2- Which products were the top 10 sellers in each month?

[22]:
```
#the 10 top sellers products id of each month
dec_top_prod_sellers = dec_purchases.groupby('product_id').brand.agg([len]).
 ↪sort_values(by='len', ascending=False)[:10]
dec_top_prod_sellers= dec_top_prod_sellers.reset_index()
print(dec_top_prod_sellers)
print('-' * 25)
jan_top_prod_sellers = jan_purchases.groupby('product_id').brand.agg([len]).
 ↪sort_values(by='len', ascending=False)[:10]
jan_top_prod_sellers = jan_top_prod_sellers.reset_index()
print(jan_top_prod_sellers)
```

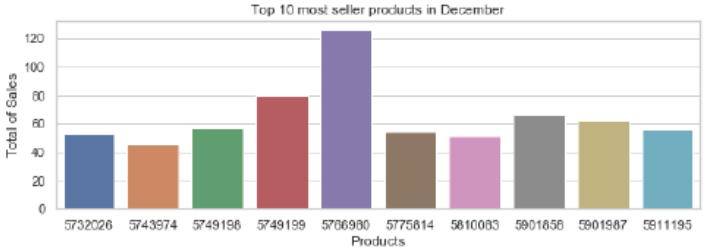
```
   product_id  len
0     5766980  126
1     5749199   80
2     5901858   67
3     5901987   62
4     5749198   57
5     5911195   56
6     5775814   55
7     5732026   53
8     5810083   51
9     5743974   46
-------------------------
   product_id  len
0     5766980  151
1     5749199  130
2     5901858  124
3     5861764   93
4     5911195   92
5     5901987   91
6     5743974   74
7     5788783   72
8     5901859   71
9     5749198   63
```

Let's create a grouped bar chart to compare the top 10 total sales in both months

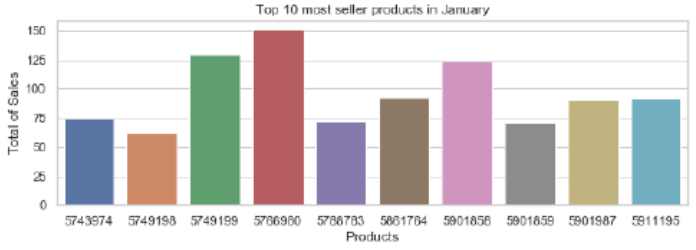
[23]:
```
labels_prod_dec = dec_top_prod_sellers['product_id'].values.tolist()
labels_prod_jan = jan_top_prod_sellers['product_id'].values.tolist()
print(labels_prod_dec)
print(labels_prod_jan)
dec_values_prod = dec_top_prod_sellers['len'].values.tolist()
jan_values_prod = jan_top_prod_sellers['len'].values.tolist()
print(dec_values)
print(jan_values)
```

```
[5766980, 5749199, 5901858, 5901987, 5749198, 5911195, 5775814, 5732026,
5810083, 5743974]
[5766980, 5749199, 5901858, 5861764, 5911195, 5901987, 5743974, 5788783,
5901859, 5749198]
[657, 382, 154, 144, 114, 113, 100, 97, 85, 65]
[970, 692, 188, 178, 166, 151, 139, 136, 130, 110]
```

[24]:
```
import seaborn as sns
sns.set(style="whitegrid")
f, ax = plt.subplots(figsize=(10, 3))
ax.set_ylabel('Total of Sales')
ax.set_xlabel('Products')
ax.set_title('Top 10 most seller products in December')
ax = sns.barplot(x=labels_prod_dec, y=dec_values_prod)
```



[25]:
```
sns.set(style="whitegrid")
f, ax = plt.subplots(figsize=(10, 3))
ax.set_ylabel('Total of Sales')
ax.set_xlabel('Products')
ax.set_title('Top 10 most seller products in January')
ax = sns.barplot(x=labels_prod_jan, y=jan_values_prod)
```



We can see that the top seller product was 5766080 in both months

3- Who user was the top buyer in each month? We need to find the total number purchases orders for each customer

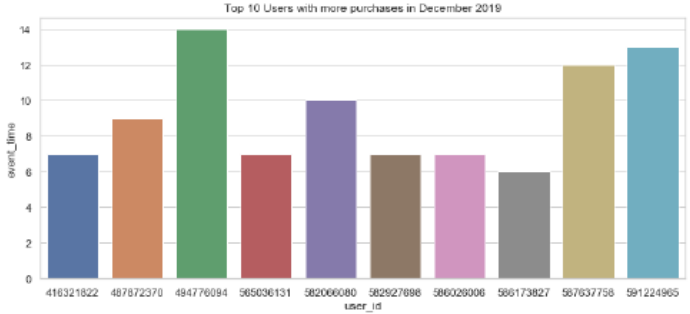
[26]:
```
dec_purchase_frequency = dec_purchases.groupby('user_id').event_time.count().
↪reset_index()
dec_purchase_frequency = dec_purchase_frequency.sort_values(by='event_time',␣
↪ascending=False)[:10]
print(dec_purchase_frequency)
print('-' * 30)
jan_purchase_frequency = jan_purchases.groupby('user_id').event_time.count().
↪reset_index()
jan_purchase_frequency = jan_purchase_frequency.sort_values(by='event_time',␣
↪ascending=False)[:10]
print(jan_purchase_frequency)
```

	user_id	event_time
438	494776094	14
1374	591224965	13
1273	587637758	12
1081	582066080	10
408	487872370	9
1222	586026006	7
1112	582927698	7
183	416321822	7
837	565036131	7
1229	586173827	6

---

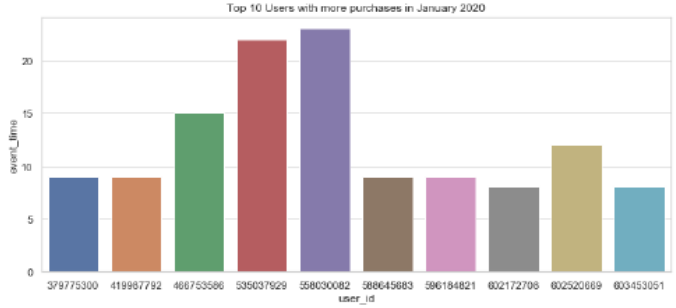
	user_id	event_time
1028	558030082	23
838	535037929	22
473	466753586	15
1798	602520669	12
1458	596184821	9
1346	588645683	9
296	419987792	9
184	379775300	9
1768	602172708	8
1839	603453051	8

[34]:
```
sns.set(style="whitegrid")
f, ax = plt.subplots(figsize=(12, 5))
plt.ylabel('Total of purchases')
plt.xlabel('User ID')
ax.set_title('Top 10 Users with more purchases in December 2019')
ax = sns.barplot(x=dec_purchase_frequency['user_id'],␣
↪y=dec_purchase_frequency['event_time'])
```



[33]:
```
sns.set(style="whitegrid")
f, ax = plt.subplots(figsize=(12, 5))
plt.ylabel('Total of purchases')
plt.xlabel('User ID')
ax.set_title('Top 10 Users with more purchases in January 2020')
```

```
ax = sns.barplot(x=jan_purchase_frequency['user_id'],
↪y=jan_purchase_frequency['event_time'])
```



We can see that the top buyer in December was the user 494776094 with 14 purchases and in January was the user 558030082 with 23 purchases

4- Normal flow There are 4 types of event * View * Cart * Purchase * Remove_from_cart

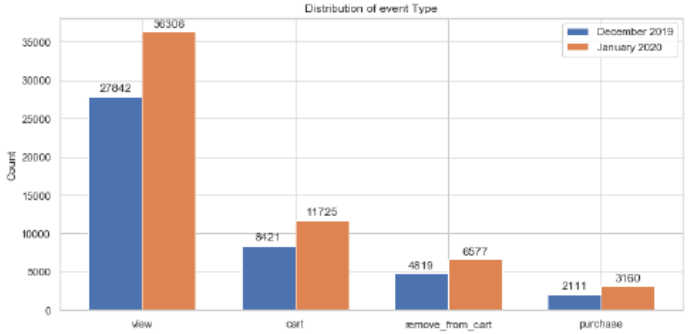
A normal flow in a session should be:

Start >> VIEW >> CART >> REMOVE/PURCHASE We can see the distribution of the events type in each month in a bar chart

[187]:
```
events_count_dec= data_Dec_clean['event_type'].value_counts()
events_count_dec=events_count_dec.reset_index()
events_count_jan= data_Jan_clean['event_type'].value_counts()
events_count_jan=events_count_jan.reset_index()
print(events_count_dec)
print(events_count_jan)
```

```
              index  event_type
0              view       27842
1              cart        8421
2  remove_from_cart        4819
3          purchase        2111
              index  event_type
0              view       36306
1              cart       11725
2  remove_from_cart        6577
3          purchase        3160
```

[36]:
```
labels = events_count_dec['index'].values.tolist()
dec_values_type = events_count_dec['event_type'].values.tolist()
jan_values_type = events_count_jan['event_type'].values.tolist()

x = np.arange(len(labels))  # the label locations
width = 0.35  # the width of the bars

fig, ax = plt.subplots(figsize=(10, 5))
rects1 = ax.bar(x - width/2, dec_values_type, width, label='December 2019')
rects2 = ax.bar(x + width/2, jan_values_type, width, label='January 2020')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Count')
ax.set_title('Distribution of event Type')
ax.set_xticks(x)
ax.set_xticklabels(labels)

ax.legend()
autolabel(rects1)
autolabel(rects2)

fig.tight_layout()

plt.show()
```



[205]:
```
#we transform the event_time to the event day
data_Dec_clean_copy = data_Dec_clean.copy()
data_Dec_clean_copy['event_time'] = pd.
↪to_datetime(data_Dec_clean_copy['event_time'],infer_datetime_format=True)
```

```
data_Dec_clean_copy['event_time_day'] = data_Dec_clean_copy['event_time'].dt.
 ↪date
#---
data_Jan_clean_copy = data_Jan_clean.copy()
data_Jan_clean_copy['event_time'] = pd.
 ↪to_datetime(data_Jan_clean_copy['event_time'],infer_datetime_format=True)
data_Jan_clean_copy['event_time_day'] = data_Jan_clean_copy['event_time'].dt.
 ↪date
#---
x_dec = pd.to_datetime(data_Dec_clean_copy['event_time_day'], format='%Y/%m/%d')
x_jan = pd.to_datetime(data_Jan_clean_copy['event_time_day'], format='%Y/%m/%d')
print(x_dec)
print(x_jan)
```

```
33         2019-12-01
52         2019-12-01
90         2019-12-01
112        2019-12-01
138        2019-12-01
              ...
3532871    2019-12-31
3532874    2019-12-31
3533061    2019-12-31
3533221    2019-12-31
3533226    2019-12-31
Name: event_time_day, Length: 43193, dtype: datetime64[ns]
359        2020-01-01
380        2020-01-01
487        2020-01-01
907        2020-01-01
987        2020-01-01
              ...
4264525    2020-01-31
4264534    2020-01-31
4264594    2020-01-31
4264721    2020-01-31
4264738    2020-01-31
Name: event_time_day, Length: 57768, dtype: datetime64[ns]
```

[231]:
```
#we group by event_time_day and event_type
events_dec = pd.DataFrame(data_Dec_clean_copy.
 ↪groupby(['event_time_day','event_type']).event_time_day.agg([len]).
 ↪sort_values(by='len', ascending=False))
events_dec = events_dec.reset_index()
#print(events_dec)
```

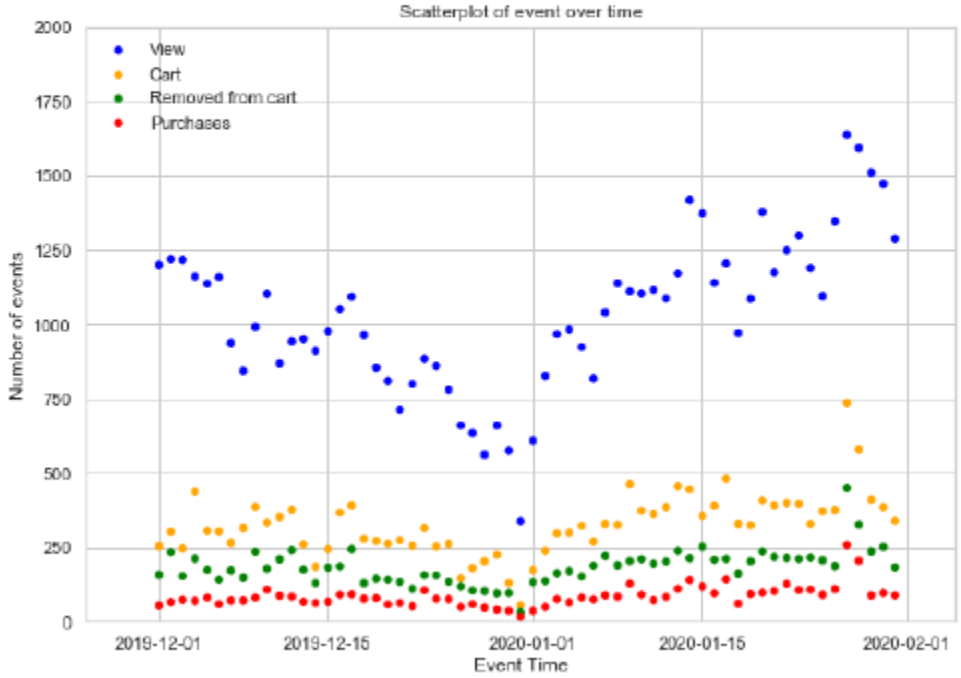
```
events_jan = pd.DataFrame(data_Jan_clean_copy.
 ↪groupby(['event_time_day','event_type']).event_time_day.agg([len]).
 ↪sort_values(by='len', ascending=False))
events_jan = events_jan.reset_index()
#print(events_jan)

#we concat the dataframes
events= pd.concat([events_dec, events_jan])
print(events)
```

```
    event_time_day event_type   len
0       2019-12-02       view  1219
1       2019-12-03       view  1217
2       2019-12-01       view  1199
3       2019-12-04       view  1160
4       2019-12-06       view  1158
..             ...        ...   ...
119     2020-01-11   purchase    72
120     2020-01-04   purchase    65
121     2020-01-18   purchase    60
122     2020-01-02   purchase    49
123     2020-01-01   purchase    36

[248 rows x 3 columns]
```

[233]:
```
#we filtered for each type of event
views = events[events.event_type == 'view']
carts = events[events.event_type == 'cart']
removes = events[events.event_type == 'remove_from_cart']
purchs = events[events.event_type == 'purchase']
#print(purch_dec)
```

[273]:
```
#we plot a scatter plot to show the number of event types over the time.
fig, ax = plt.subplots()
ax.scatter(views['event_time_day'],views['len'], edgecolors = 'none', label =␣
 ↪'View', s = 30, c= 'blue')
ax.scatter(carts['event_time_day'],carts['len'], edgecolors = 'none', label =␣
 ↪'Cart', s = 30, c='orange')
ax.scatter(removes['event_time_day'],removes['len'], edgecolors = 'none', label␣
 ↪= 'Removed from cart', s = 30, c= 'green')
ax.scatter(purchs['event_time_day'],purchs['len'], edgecolors = 'none', label =␣
 ↪'Purchases', s = 30, c='red')

plt.axis(['2019-11-25','2020-02-05',0,2000])
fig.set_size_inches(10,7)
ax.grid(True)
```

```
plt.xlabel('Event Time')
plt.ylabel('Number of events')
plt.title('Scatterplot of event over time', fontsize =12)
plt.legend()
plt.show()
```



Convert to a Classification Task

Knowing the next purchase day for a product is a good indicator for predicting sales ### Can we predicting the Next Purchase Day of a product?

Now we are going to prepare the data to applied some machine learning algorithm for classification.

[274]:
```
#First we are going to join both datasets
data_concat = pd.concat([data_Dec_clean, data_Jan_clean])
print(data_Dec_clean.shape)
print(data_Jan_clean.shape)
print(data_concat.shape)
```

```
(43193, 9)
(57768, 9)
(100961, 9)
```

[275]:
```
#change the event_time to datetime
data_concat['event_time'] = pd.
↪to_datetime(data_concat['event_time'],infer_datetime_format=True)
```


First, we only take the purchases

[276]:
```
#we only take the purchases
data_concat_purch = data_concat.loc[data_concat["event_type"].
↪isin(["purchase"])]

data_concat_purch = data_concat_purch.reset_index()
data_concat_purch.head()
#print(data_concat_purch.loc[data_concat_purch.user_id == 494776094])
```

[276]:

	index	event_time	event_type	product_id	category_id	\
0	2402	2019-12-01 01:18:32	purchase	5873430	2007399943458784057	
1	3221	2019-12-01 02:09:57	purchase	5861766	1487580006350586771	
2	11617	2019-12-01 06:26:22	purchase	5889695	2007399943458784057	
3	11618	2019-12-01 06:26:22	purchase	5889696	2007399943458784057	
4	15905	2019-12-01 07:26:17	purchase	5746974	2193074740686488401	

	category_code	brand	price	user_id	\
0	apparel.glove	benovy	7.46	356011474	
1	appliances.environment.vacuum	emil	1.75	443163709	
2	apparel.glove	nitrile	9.52	557560536	
3	apparel.glove	nitrile	9.52	557560536	
4	furniture.bathroom.bath	irisk	52.70	534305618	

[277]:
```
#create a dataframe with User_id, product_id and event_time Date
tx_day_order = data_concat_purch[['user_id','event_time','product_id']]
tx_day_order.head()
#print(tx_day_order.loc[tx_day_order.user_id == 494776094])
```

[277]:

	user_id	event_time	product_id
0	356011474	2019-12-01 01:18:32	5873430
1	443163709	2019-12-01 02:09:57	5861766
2	557560536	2019-12-01 06:26:22	5889695
3	557560536	2019-12-01 06:26:22	5889696
4	534305618	2019-12-01 07:26:17	5746974

Next we need to calculate our labels (days between last purchase and first purchase after that) and the features

[278]:
```
#first we created un new dataframe with the distints products id
tx_product = pd.DataFrame(data_concat_purch['product_id'].unique())
```



```
tx_product.columns = ['product_id']
#tx_product
```

[279]:
```
# next create a dataframe with product_id and first purchase date
tx_next_first_purchase = data_concat_purch.groupby('product_id').event_time.
↪min().reset_index()
tx_next_first_purchase.columns = ['product_id','MinPurchaseDate']
tx_next_first_purchase.head()
```

[279]:

	product_id	MinPurchaseDate
0	5395	2019-12-14 14:19:26
1	8372	2019-12-06 08:00:56
2	8373	2020-01-28 07:27:43
3	24330	2019-12-05 08:44:04
4	24331	2019-12-02 19:57:58

[280]:
```
#next create a dataframe with customer id and last purchase date
tx_last_purchase = data_concat_purch.groupby('product_id').event_time.max().
↪reset_index()
tx_last_purchase.columns = ['product_id','MaxPurchaseDate']
tx_last_purchase.head()
```

[280]:

	product_id	MaxPurchaseDate
0	5395	2020-01-28 17:56:55
1	8372	2020-01-13 08:44:00

[281]:
```
#merge two dataframes
tx_purchase_dates = pd.
↪merge(tx_last_purchase,tx_next_first_purchase,on='product_id',how='left')
tx_purchase_dates.head()
```

[281]:

	product_id	MaxPurchaseDate	MinPurchaseDate
0	5395	2020-01-28 17:56:55	2019-12-14 14:19:26
1	8372	2020-01-13 08:44:00	2019-12-06 08:00:56
2	8373	2020-01-28 07:27:43	2020-01-28 07:27:43
3	24330	2020-01-28 16:17:51	2019-12-05 08:44:04
4	24331	2020-01-29 15:39:10	2019-12-02 19:57:58

[282]:
```
#calculate the time difference in days:
tx_purchase_dates['NextPurchaseDay'] = (tx_purchase_dates['MaxPurchaseDate'] -␣
↪tx_purchase_dates['MinPurchaseDate']).dt.days
tx_purchase_dates.head()
```


[282]:

	product_id	MaxPurchaseDate	MinPurchaseDate	NextPurchaseDay
0	5395	2020-01-28 17:56:55	2019-12-14 14:19:26	45
1	8372	2020-01-13 08:44:00	2019-12-06 08:00:56	38
2	8373	2020-01-28 07:27:43	2020-01-28 07:27:43	0
3	24330	2020-01-28 16:17:51	2019-12-05 08:44:04	54
4	24331	2020-01-29 15:39:10	2019-12-02 19:57:58	57

[283]:
```
#merge with tx_product
tx_product = pd.merge(tx_product,␣
↪tx_purchase_dates[['product_id','NextPurchaseDay']],on='product_id',how='left')
#fill NA values with 999
tx_product = tx_product.fillna(999)
tx_product.head()
```

[283]:

	product_id	NextPurchaseDay
0	5873430	58
1	5861766	54
2	5889695	61
3	5889696	60
4	5746974	61

Back to the tx_day_order dataframe:

[284]:
```
#convert event time to day
tx_day_order['PurchaseDay'] = data_concat_purch['event_time'].dt.date
tx_day_order = tx_day_order.sort_values(['product_id','event_time'])
#print(tx_day_order.loc[tx_day_order.product_id == 5766980 ].head())

#drop duplicates
#Then we will remove the duplicates since customers can do multiple purchases␣
↪of the same product in a day
tx_day_order = tx_day_order.
↪drop_duplicates(subset=['PurchaseDay','product_id'],keep='first')
#print(tx_day_order.loc[tx_day_order.product_id == 5766980 ].head())
tx_day_order.head()
```

Now we need to get the last 3 dates the product was purchased, to do that we use the shift() function

[285]:
```
#shifting last 3 purchase dates of each product
tx_day_order['PrevPurchaseDate'] = tx_day_order.
↪groupby(['product_id'])['PurchaseDay'].shift(1)
tx_day_order['T2PurchaseDate'] = tx_day_order.
↪groupby(['product_id'])['PurchaseDay'].shift(2)
tx_day_order['T3PurchaseDate'] = tx_day_order.
↪groupby(['product_id'])['PurchaseDay'].shift(3)
tx_day_order.head()
#tx_day_order.loc[tx_day_order.product_id == 5766980]
```

[285]:

	user_id	event_time	product_id	PurchaseDay	PrevPurchaseDate	\
997	568407203	2019-12-14 14:19:26	5395	2019-12-14	NaN	
1609	450923816	2019-12-23 04:03:22	5395	2019-12-23	2019-12-14	
1732	585040980	2019-12-24 09:23:23	5395	2019-12-24	2019-12-23	
2038	562973122	2019-12-29 14:01:58	5395	2019-12-29	2019-12-24	
2067	586595889	2019-12-30 06:37:42	5395	2019-12-30	2019-12-29	

	T2PurchaseDate	T3PurchaseDate
997	NaN	NaN
1609	NaN	NaN
1732	2019-12-14	NaN
2038	2019-12-23	2019-12-14
2067	2019-12-24	2019-12-23

Now we are going to caculate the difference in days for each product purchase date

[286]:
```
tx_day_order['DayDiff'] = (tx_day_order['PurchaseDay'] -␣
↪tx_day_order['PrevPurchaseDate']).dt.days
tx_day_order['DayDiff2'] = (tx_day_order['PurchaseDay'] -␣
↪tx_day_order['T2PurchaseDate']).dt.days
tx_day_order['DayDiff3'] = (tx_day_order['PurchaseDay'] -␣
↪tx_day_order['T3PurchaseDate']).dt.days
tx_day_order
#tx_day_order.loc[tx_day_order.product_id == 5766980].head(20)
```

[286]:

	user_id	event_time	product_id	PurchaseDay	PrevPurchaseDate	\
997	568407203	2019-12-14 14:19:26	5395	2019-12-14	NaN	
1609	450923816	2019-12-23 04:03:22	5395	2019-12-23	2019-12-14	
1732	585040980	2019-12-24 09:23:23	5395	2019-12-24	2019-12-23	

For each product ID, we utilize .agg() method to find out the mean and standard deviation of the difference between purchases in days

[91]:
```
tx_day_diff = tx_day_order.groupby('product_id').agg({'DayDiff':␣
↪['mean','std']}).reset_index()
tx_day_diff.columns = ['product_id', 'DayDiffMean','DayDiffStd']
tx_day_diff.head()
tx_day_diff.shape
#tx_day_diff.loc[tx_day_diff.product_id == 5766980]
```

[91]: (245, 3)

[92]:
```
#drop duplicated and keep the last
tx_day_order_last = tx_day_order.
↪drop_duplicates(subset=['product_id'],keep='last')
tx_day_order_last.loc[tx_day_order.product_id == 24331]
tx_day_order_last.shape
```

[92]: (245, 10)

[93]:
```
#Drop NAN values
tx_day_order_last = tx_day_order_last.dropna()
tx_day_order_last.head()
```


[93]:

	user_id	event_time	product_id	PurchaseDay	PrevPurchaseDate	\
4844	607103363	2020-01-28 08:56:21	5395	2020-01-28	2020-01-27	
3064	530311269	2020-01-13 08:44:00	8372	2020-01-13	2020-01-05	
4934	600569855	2020-01-28 16:17:51	24330	2020-01-28	2020-01-25	
5044	577514838	2020-01-29 15:39:10	24331	2020-01-29	2020-01-26	
4189	605133120	2020-01-23 16:43:41	24332	2020-01-23	2020-01-13	

	T2PurchaseDate	T3PurchaseDate	DayDiff	DayDiff2	DayDiff3
4844	2020-01-26	2020-01-23	1.0	2.0	5.0
3064	2019-12-28	2019-12-24	8.0	16.0	20.0
4934	2020-01-22	2020-01-21	3.0	6.0	7.0
5044	2020-01-23	2020-01-22	3.0	6.0	7.0
4189	2020-01-07	2019-12-25	10.0	16.0	29.0

[94]:
```
#Merge dataframes
tx_day_order_last = pd.merge(tx_day_order_last, tx_day_diff, on='product_id')
tx_day_order_last.head()
```

Merge tx_day_order_last dataframes with tx_product and apply .get_dummies() for converting categorical values:

[95]:
```
tx_product = pd.merge(tx_product,␣
↪tx_day_order_last[['product_id','DayDiff','DayDiff2','DayDiff3','DayDiffMean','DayDiffStd']
↪on='product_id')
#create tx_class as a copy of tx_user before applying get_dummies
tx_class = tx_product.copy()
```



```
tx_class = pd.get_dummies(tx_class)
tx_class.head()
```

[95]:

	product_id	NextPurchaseDay	DayDiff	DayDiff2	DayDiff3	DayDiffMean	\
0	5873430	58	1.0	2.0	4.0	1.870968	
1	5861766	54	7.0	8.0	13.0	6.750000	
2	5889695	61	3.0	6.0	7.0	2.033333	
3	5889696	60	1.0	2.0	3.0	2.857143	
4	5746974	61	2.0	3.0	4.0	3.388889	

	DayDiffStd
0	1.765256
1	7.146428
2	1.496740
3	2.988072
4	2.872566

Our feature set is ready for building a classification model. Now we need to define our labels. To do that fisrt:

[96]:
```
tx_product.NextPurchaseDay.describe()
```

[96]:
```
count    180.000000
mean      48.461111
std       13.008963
min        7.000000
25%       43.000000
50%       54.000000
75%       58.000000
max       61.000000
Name: NextPurchaseDay, dtype: float64
```

Considering the information adove we decide this boundaries:

- 0-40: class_name = 2
- 41-55: class_name = 1
- />55: class_name = 0 So our labels will be 0, 1 and 2

[97]:
```
tx_class['NextPurchaseDayRange'] = 2
tx_class.loc[tx_class.NextPurchaseDay>40,'NextPurchaseDayRange'] = 1
tx_class.loc[tx_class.NextPurchaseDay>55,'NextPurchaseDayRange'] = 0
tx_class
```

[97]:

	product_id	NextPurchaseDay	DayDiff	DayDiff2	DayDiff3	DayDiffMean	\
0	5873430	58	1.0	2.0	4.0	1.870968	
1	5861766	54	7.0	8.0	13.0	6.750000	
2	5889695	61	3.0	6.0	7.0	2.033333	
3	5889696	60	1.0	2.0	3.0	2.857143	

4	5746974	61	2.0	3.0	4.0	3.388889	
..	...	...	...	...	...	...	
175	5892335	8	4.0	5.0	9.0	3.000000	
176	5710610	9	1.0	4.0	10.0	3.333333	
177	5889693	13	2.0	3.0	12.0	3.250000	
178	5885589	7	3.0	7.0	8.0	2.666667	
179	5921389	8	2.0	3.0	9.0	3.000000	

	DayDiffStd	NextPurchaseDayRange
0	1.765256	0
1	7.146428	1
2	1.496740	0
3	2.988072	0
4	2.872566	0
..	...	...
175	1.732051	2
176	2.516611	2
177	3.862210	2
178	1.527525	2
179	2.645751	2

[180 rows x 8 columns]

We can see the porcentage of each we have in our dataset

Now we need to separate Target and features:

[101]:
```
features=␣
↪['product_id','DayDiff','DayDiff2','DayDiff3','DayDiffMean','DayDiffStd']
y= tx_class[['NextPurchaseDayRange']].copy()
X =tx_class[features].copy()
y.columns
```

[101]:
```
Index(['NextPurchaseDayRange'], dtype='object')
```

[102]:
```
#train & test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
↪random_state=324)
y_train.head()
```

[102]:

	NextPurchaseDayRange
151	2
134	2
41	0
162	2
175	2

[146]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.metrics import accuracy_score
gnb = GaussianNB()
y_pred = gnb.fit(X_train, y_train).predict(X_test)
print(accuracy_score(y_test, y_pred))

print("Number of mislabeled points out of a total %d points : %d" % (X_test.
↪shape[0], (y_test['NextPurchaseDayRange'].values.tolist() != y_pred).sum()))
```



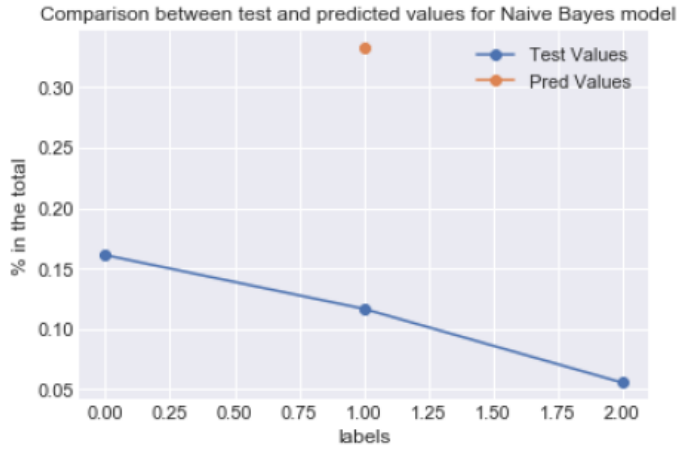
```
#print(classification_report(y_test, y_pred))
```

```
0.35
Number of mislabeled points out of a total 60 points : 39
```

[148]:
```
print(y_test.NextPurchaseDayRange.value_counts()/len(tx_product))
test_values_NB = (y_test.NextPurchaseDayRange.value_counts()/len(tx_product)).
↪tolist()
y_pred_df = pd.DataFrame(y_pred)
y_pred_df.columns = ['NextPurchaseDayRange']
print(y_pred_df.NextPurchaseDayRange.value_counts()/len(tx_product))
pred_values_NB = (y_pred_df.NextPurchaseDayRange.value_counts()/
↪len(tx_product)).tolist()
```

```
0    0.161111
1    0.116667
2    0.055556
Name: NextPurchaseDayRange, dtype: float64
1    0.333333
Name: NextPurchaseDayRange, dtype: float64
```

[149]:
```
# Initialize the figure
plt.style.use('seaborn-darkgrid')
# line 1 points
x1 = [0,1,2]
y1 = test_values_NB
# plotting the line 1 points
plt.plot(x1, y1, label = "Test Values",marker='o')
# line 2 points
x2 = [1]
y2 = pred_values_NB
# plotting the line 2 points
plt.plot(x2, y2, label = "Pred Values",marker='o')
plt.xlabel('labels')
# Set the y axis label of the current axis.
plt.ylabel('% in the total')
# Set a title of the current axes.
plt.title('Comparison between test and predicted values for Naive Bayes model ␣
↪')
# show a legend on the plot
plt.legend()
# Display a figure.
```

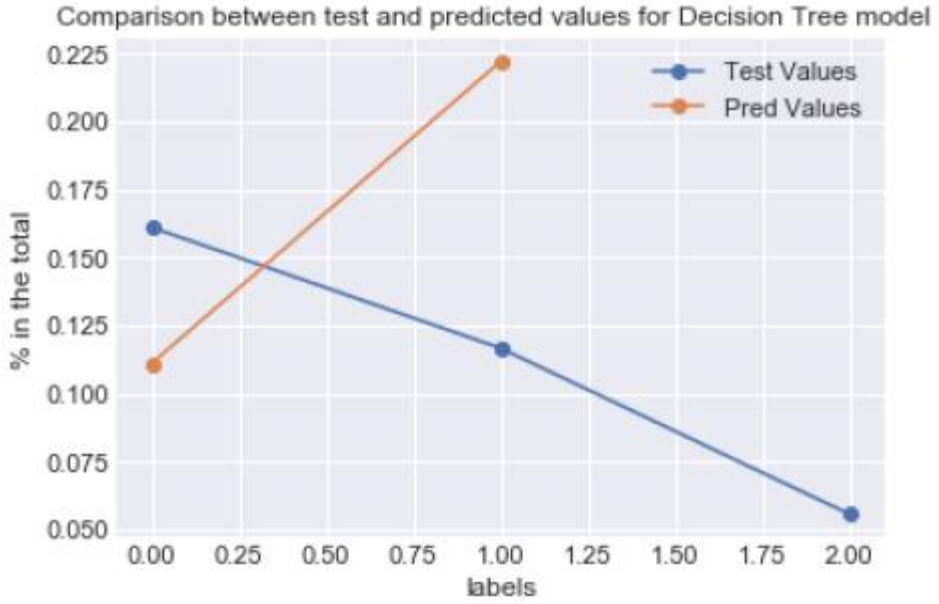


[104]:
```
from sklearn.tree import DecisionTreeClassifier
train_classifier = DecisionTreeClassifier(max_leaf_nodes=2, random_state=0)
v = train_classifier.fit(X_train, y_train)
y_pred2 = v.predict(X_test)
print(accuracy_score(y_test, y_pred2))

print("Number of mislabeled points out of a total %d points : %d" % (X_test.
 ↪shape[0], (y_test['NextPurchaseDayRange'].values.tolist() != y_pred2).sum()))
#print(classification_report(y_test, y_pred))
```

```
0.5666666666666667
Number of mislabeled points out of a total 60 points : 26
```

[140]:
```
print(y_pred2)
print((y_test.NextPurchaseDayRange.value_counts()/len(tx_product)))
test_values_DT = (y_test.NextPurchaseDayRange.value_counts()/len(tx_product)).
 ↪tolist()
y_pred_df = pd.DataFrame(y_pred2)
y_pred_df.columns = ['NextPurchaseDayRange']
print((y_pred_df.NextPurchaseDayRange.value_counts()/len(tx_product)))
pred_values_DT =(y_pred_df.NextPurchaseDayRange.value_counts()/len(tx_product)).
 ↪tolist()
```

[142]:
```
# Initialize the figure
plt.style.use('seaborn-darkgrid')
# line 1 points
x1 = [0,1,2]
y1 = test_values_DT
# plotting the line 1 points
plt.plot(x1, y1, label = "Test Values",marker='o')
# line 2 points
x2 = [1,0]
y2 = pred_values_DT
# plotting the line 2 points
plt.plot(x2, y2, label = "Pred Values",marker='o')
plt.xlabel('labels')
# Set the y axis label of the current axis.
plt.ylabel('% in the total')
# Set a title of the current axes.
plt.title('Comparison between test and predicted values for Decision Tree model␣
 ↪ ')
# show a legend on the plot
plt.legend()
# Display a figure.
plt.show()
```



[123]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
y_pred = knn.fit(X_train, y_train).predict(X_test)
print(accuracy_score(y_test, y_pred))
print("Number of mislabeled points out of a total %d points : %d" % (X_test.
 ↪shape[0], (y_test['NextPurchaseDayRange'].values.tolist() != y_pred).sum()))
#print(classification_report(y_test, y_pred))
```

```
0.65
Number of mislabeled points out of a total 60 points : 21
```

From this result, we see that KNeighborsClassifier is the best performing one (~65% accuracy).

[126]:
```
test_values = (y_test.NextPurchaseDayRange.value_counts()/len(tx_product)).
↪tolist()
#y_test
y_pred_df = pd.DataFrame(y_pred)
y_pred_df.columns = ['NextPurchaseDayRange']
```



```
#y_pred_df
pred_values = (y_pred_df.NextPurchaseDayRange.value_counts()/len(tx_product)).
↪tolist()
print(test_values)
print(pred_values)
```

```
[0.16111111111111112, 0.11666666666666667, 0.05555555555555555]
[0.18888888888888888, 0.10555555555555556, 0.03888888888888889]
```

[153]:
```
import matplotlib.pyplot as plt
# Initialize the figure
plt.style.use('seaborn-darkgrid')
# line 1 points
x1 = [0,1,2]
y1 = test_values
# plotting the line 1 points
plt.plot(x1, y1, label = "Test Values",marker='o')
# line 2 points
x2 = [0,1,2]
y2 = pred_values
# plotting the line 2 points
plt.plot(x2, y2, label = "Pred Values",marker='o')
plt.xlabel('labels')
# Set the y axis label of the current axis.
plt.ylabel('% in the total')
# Set a title of the current axes.
plt.title('Comparison between test and predicted values for KNN model  ')
# show a legend on the plot
plt.legend()
# Display a figure.
plt.show()
```