E-commerce Customers Clustering | Sentiment and Sales Analysis

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Objective: The rise of the Internet has caused most of the people are more willing to shop through the Internet, so there is no doubt that e-commerce platforms are one of the most powerful ways for any kind of business to communicate with each other. E-commerce has grown at an incredible rate in the past decades, so the competition between the online marketplaces to become the best one is increasing. Since customers play a significant role in this industry, it is important to have a better understanding of them. There are some potential aspects that with working on them may help companies to have a better perspective about customers.

Golas: In this project we are going to see the unspurevised customers clustering based on their payment information from a Brizillian e-commerce dataset. In the following, we have an observation on the sales during a year to see in what time of the year the online marketpalce sold most, and at the end we train a model to predict whether the customers' reviews have a good or bad sentimnet.

Dataset: The dataset is taken from *kaggle.com*. The dataset has information of 100k orders from 2016 to 2018. We have a variety of information about customers, sellers, products, orders, and geolocations.

Let's start with grabbing some libraries.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import plotly.graph_objects as go
import plotly.express as px
```

In [2]:
```
# Read all csv files into the separate dataframe:

customers_df = pd.read_csv('olist_customers_dataset.csv')
geolocations_df = pd.read_csv('olist_geolocation_dataset.csv')
order_items_df = pd.read_csv('olist_order_items_dataset.csv')
order_payments_df = pd.read_csv('olist_order_payments_dataset.csv')
order_reviews_df = pd.read_csv('olist_order_reviews_dataset.csv')
orders_df = pd.read_csv('olist_orders_dataset.csv')
products_df = pd.read_csv('olist_products_dataset.csv')
sellers_df = pd.read_csv('olist_sellers_dataset.csv')
product_category_name_translation_df = pd.read_csv('product_category_name_transl
```

Data Cleaning

In this part, we are going to have a look at each dataframe. The steps are taken:

- View some rows of the dataframe
- View the shape (number of rows and columns)
- Looking for any NaN values
- Looking for any duplicated rows
- Looking at the information of each dataframe

Customers Data

In [3]:
```
customers_df.head()
```

Out[3]:

	customer_id	customer_unique_id	customer_zip_code_prefi:
0	06b8999e2fba1a1fbc88172c00ba8bc7	861eff4711a542e4b93843c6dd7febb0	1440!
1	18955e83d337fd6b2def6b18a428ac77	290c77bc529b7ac935b93aa66c333dc3	979(
2	4e7b3e00288586ebd08712fdd0374a03	060e732b5b29e8181a18229c7b0b2b5e	115
3	b2b6027bc5c5109e529d4dc6358b12c3	259dac757896d24d7702b9acbbff3f3c	877!
4	4f2d8ab171c80ec8364f7c12e35b23ad	345ecd01c38d18a9036ed96c73b8d066	1305(

In [4]:
```
# We have 99441 customers and 5 columns which our features about customers
customers_df.shape
```

Out[4]:
```
(99441, 5)
```

In [5]:
```
# No NAN values
customers_df_nan_values = customers_df.isna().sum()
customers_df_nan_values[customers_df_nan_values > 0]
```

Out[5]:
```
Series([], dtype: int64)
```

In [6]:
```
# No duplicated rows
duplicated_rows_customers_df = customers_df[customers_df.duplicated()]
duplicated_rows_customers_df
```

Out[6]:

customer_id	customer_unique_id	customer_zip_code_prefix	customer_city	customer_state

In [7]:
```
customers_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99441 entries, 0 to 99440
Data columns (total 5 columns):
customer_id                 99441 non-null object
customer_unique_id          99441 non-null object
customer_zip_code_prefix    99441 non-null int64
customer_city               99441 non-null object
customer_state              99441 non-null object
dtypes: int64(1), object(4)
memory usage: 3.8+ MB
```

In [8]:
```
customers_df.describe(include = 'all')
```

Out[8]:

	customer_id	customer_unique_id	customer_zip_code_pr
count	99441	99441	99441.000
unique	99441	96096	N
top	120dd4afde62b0c8dfe915a1597950bd	8d50f5eadf50201ccdcedfb9e2ac8455	N
freq	1	17	N
mean	NaN	NaN	35137.474
std	NaN	NaN	29797.938
min	NaN	NaN	1003.000
25%	NaN	NaN	11347.000
50%	NaN	NaN	24416.000
75%	NaN	NaN	58900.000
max	NaN	NaN	99990.000

In [9]:
```
customers_df['customer_id'].unique().shape
```

Out[9]: (99441,)

Sellers Data

In [10]:
```
sellers_df.head()
```

Out[10]:

	seller_id	seller_zip_code_prefix	seller_city	seller_state
0	3442f8959a84dea7ee197c632cb2df15	13023	campinas	SP
1	d1b65fc7debc3361ea86b5f14c68d2e2	13844	mogi guacu	SP
2	ce3ad9de960102d0677a81f5d0bb7b2d	20031	rio de janeiro	RJ
3	c0f3eea2e14555b6faeea3dd58c1b1c3	4195	sao paulo	SP
4	51a04a8a6bdcb23deccc82b0b80742cf	12914	braganca paulista	SP

In [11]:
```python
# We have 3095 sellers and 4 columns which our features about sellers
sellers_df.shape
```

Out[11]: (3095, 4)

In [12]:
```python
# No NAN values
sellers_df_nan_values = sellers_df.isna().sum()
sellers_df_nan_values[sellers_df_nan_values > 0]
```

Out[12]: Series([], dtype: int64)

In [13]:
```python
# No duplicated rows
duplicated_rows_sellers_df = sellers_df[sellers_df.duplicated()]
duplicated_rows_sellers_df
```

Out[13]:

seller_id	seller_zip_code_prefix	seller_city	seller_state

In [14]:
```python
sellers_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3095 entries, 0 to 3094
Data columns (total 4 columns):
seller_id                 3095 non-null object
seller_zip_code_prefix    3095 non-null int64
seller_city               3095 non-null object
seller_state              3095 non-null object
dtypes: int64(1), object(3)
memory usage: 96.8+ KB
```

In [15]:
```python
sellers_df.describe(include = 'all')
```

Out[15]:

	seller_id	seller_zip_code_prefix	seller_city	seller_state
count	3095	3095.000000	3095	3095
unique	3095	NaN	611	23
top	8a43128d7f9a3db592b866e6861a6cce	NaN	sao paulo	SP
freq	1	NaN	694	1849
mean	NaN	32291.059451	NaN	NaN
std	NaN	32713.453830	NaN	NaN
min	NaN	1001.000000	NaN	NaN
25%	NaN	7093.500000	NaN	NaN
50%	NaN	14940.000000	NaN	NaN
75%	NaN	64552.500000	NaN	NaN
max	NaN	99730.000000	NaN	NaN

Products Data

In [16]:
```
products_df.head()
```

Out[16]:

	product_id	product_category_name	product_name_lenght	product_descr
0	1e9e8ef04dbcff4541ed26657ea517e5	perfumaria	40.0	
1	3aa071139cb16b67ca9e5dea641aaa2f	artes	44.0	
2	96bd76ec8810374ed1b65e291975717f	esporte_lazer	46.0	
3	cef67bcfe19066a932b7673e239eb23d	bebes	27.0	
4	9dc1a7de274444849c219cff195d0b71	utilidades_domesticas	37.0	

In [17]:
```
# We have 32951 products and 9 columns which our features about products
products_df.shape
```

Out[17]:
```
(32951, 9)
```

In [18]:
```
# We have some NAN values in our products dataset
# The most reasonable decision is to get rid of those rows contains NAN values, l
products_df_nan_values = products_df.isna().sum()
products_df_nan_values[products_df_nan_values > 0]
```

Out[18]:
```
product_category_name         610
product_name_lenght           610
product_description_lenght    610
product_photos_qty            610
product_weight_g                2
product_length_cm               2
product_height_cm               2
product_width_cm                2
dtype: int64
```

In [19]:
```
products_df.dropna(inplace = True)
```

In [20]:
```
# There is no NAN anymore
products_df_nan_values = products_df.isna().sum()
products_df_nan_values[products_df_nan_values > 0]
```

Out[20]:
```
Series([], dtype: int64)
```

In [21]:
```
# No duplicated rows
duplicated_rows_products_df = products_df[products_df.duplicated()]
duplicated_rows_products_df
```

Out[21]:

product_id	product_category_name	product_name_lenght	product_description_lenght	product_ph

In [22]:
```
products_df_nan_values = products_df.isna().sum()
products_df_nan_values[products_df_nan_values > 0]
```

Out[22]:
```
Series([], dtype: int64)
```

In [23]:
```
products_df.shape
```

Out[23]:
```
(32340, 9)
```

Now we need to translate product name to english using translation dataset.

In [24]:
```
portuguese_to_english = list(zip(product_category_name_translation_df.product_ca
                                 product_category_name_translation_df.product_ca

for word in portuguese_to_english:
    product_category_name_mask = products_df['product_category_name'].str.contai
    products_df['product_category_name'][product_category_name_mask] = word[1]
```

```
C:\Users\Mona\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: SettingWithC
opyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydat
a.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y)
```

In [25]:
```
# Add a new column named volume_cubed_cm which is a volume calculation of each pı
products_df['volume_cubed_cm'] = products_df['product_length_cm'] * \
                                 products_df['product_width_cm'] * \
                                 products_df['product_height_cm']
```

In [26]:
```
products_df.head()
```

Out[26]:

	product_id	product_category_name	product_name_lenght	product_descr
0	1e9e8ef04dbcff4541ed26657ea517e5	perfumery	40.0	
1	3aa071139cb16b67ca9e5dea641aaa2f	art	44.0	
2	96bd76ec8810374ed1b65e291975717f	sports_leisure	46.0	
3	cef67bcfe19066a932b7673e239eb23d	baby	27.0	
4	9dc1a7de274444849c219cff195d0b71	housewares	37.0	

In [27]:
```
products_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32340 entries, 0 to 32950
Data columns (total 10 columns):
product_id                    32340 non-null object
product_category_name         32340 non-null object
product_name_lenght           32340 non-null float64
product_description_lenght    32340 non-null float64
product_photos_qty            32340 non-null float64
product_weight_g              32340 non-null float64
product_length_cm             32340 non-null float64
product_height_cm             32340 non-null float64
product_width_cm              32340 non-null float64
volume_cubed_cm               32340 non-null float64
dtypes: float64(8), object(2)
memory usage: 2.7+ MB
```

In [28]:
```
products_df.describe(include = 'all')
```

Out[28]:

	product_id	product_category_name	product_name_lenght	product_c
count	32340	32340	32340.000000	
unique	32340	65	NaN	
top	18297d6ba9247aa8fb22c28df54bbcd4	bed_bath_table	NaN	
freq	1	3029	NaN	
mean	NaN	NaN	48.476592	
std	NaN	NaN	10.245699	
min	NaN	NaN	5.000000	
25%	NaN	NaN	42.000000	
50%	NaN	NaN	51.000000	
75%	NaN	NaN	57.000000	
max	NaN	NaN	76.000000	

Orders Data

In [29]:
```
orders_df.head()
```

Out[29]:

	order_id	customer_id	order_status	order_purcl
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	201
1	53cdb2fc8bc7dce0b6741e2150273451	b0830fb4747a6c6d20dea0b8c802d7ef	delivered	201
2	47770eb9100c2d0c44946d9cf07ec65d	41ce2a54c0b03bf3443c3d931a367089	delivered	201
3	949d5b44dbf5de918fe9c16f97b45f8a	f88197465ea7920adcdbec7375364d82	delivered	201
4	ad21c59c0840e6cb83a9ceb5573f8159	8ab97904e6daea8866dbdbc4fb7aad2c	delivered	201

In [30]:
```
orders_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99441 entries, 0 to 99440
Data columns (total 8 columns):
order_id                         99441 non-null object
customer_id                      99441 non-null object
order_status                     99441 non-null object
order_purchase_timestamp         99441 non-null object
order_approved_at                99281 non-null object
order_delivered_carrier_date     97658 non-null object
order_delivered_customer_date    96476 non-null object
order_estimated_delivery_date    99441 non-null object
dtypes: object(8)
memory usage: 6.1+ MB
```

We define a function that convert any data types into date time:

In [31]:
```
def to_datetime(df, column_names):
    for name in column_names:
        df[name] = pd.to_datetime(df[name])
```

In [32]:
```
to_datetime(orders_df, ['order_purchase_timestamp',
                        'order_approved_at',
                        'order_delivered_carrier_date',
                        'order_delivered_customer_date',
                        'order_estimated_delivery_date'])
```

In [33]:
```
orders_df.shape
```

Out[33]:
```
(99441, 8)
```

In [34]:
```
# We have some NAN values in our products dataset
# The most reasonable decision is to get rid of those rows contains NAN values, l
orders_df_nan_values = orders_df.isna().sum()
orders_df_nan_values[orders_df_nan_values > 0]
```

Out[34]:
```
order_approved_at                 160
order_delivered_carrier_date     1783
order_delivered_customer_date    2965
dtype: int64
```

In [35]:
```
orders_df.dropna(how = 'any', inplace = True)
```

In [36]:
```
# No duplicated rows
duplicated_rows_orders_df = orders_df[orders_df.duplicated()]
duplicated_rows_orders_df
```

Out[36]:

order_id	customer_id	order_status	order_purchase_timestamp	order_approved_at	order_delivere

Order Items Data

In [37]:
```
order_items_df.head()
```

Out[37]:

	order_id	order_item_id	product_id	
0	00010242fe8c5a6d1ba2dd792cb16214	1	4244733e06e7ecb4970a6e2683c13e61	48436dad
1	00018f77f2f0320c557190d7a144bdd3	1	e5f2d52b802189ee658865ca93d83a8f	dd7ddc04
2	000229ec398224ef6ca0657da4fc703e	1	c777355d18b72b67abbeef9df44fd0fd	5b51032e
3	00024acbcdf0a6daa1e931b038114c75	1	7634da152a4610f1595efa32f14722fc	9d7a1d34a
4	00042b26cf59d7ce69dfabb4e55b4fd9	1	ac6c3623068f30de03045865e4e10089	df560393

In [38]:
```
# We have no NAN values in our order items dataset
order_items_df_nan_values = order_items_df.isna().sum()
order_items_df_nan_values[order_items_df_nan_values > 0]
```

Out[38]:
```
Series([], dtype: int64)
```

In [39]:
```
order_items_df.shape
```

Out[39]:
```
(112650, 7)
```

In [40]:
```
# No duplicated rows
duplicated_rows_orders_df = order_items_df[order_items_df.duplicated()]
duplicated_rows_orders_df
```

Out[40]:

order_id	order_item_id	product_id	seller_id	shipping_limit_date	price	freight_value

In [41]:
```
order_items_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112650 entries, 0 to 112649
Data columns (total 7 columns):
order_id               112650 non-null object
order_item_id          112650 non-null int64
product_id             112650 non-null object
seller_id              112650 non-null object
shipping_limit_date    112650 non-null object
price                  112650 non-null float64
freight_value          112650 non-null float64
dtypes: float64(2), int64(1), object(4)
memory usage: 6.0+ MB
```

In [42]:
```
to_datetime(order_items_df, ['shipping_limit_date'])
```

Order Payments Data

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

Out[43]:

	order_id	payment_sequential	payment_type	payment_installments	pa
0	b81ef226f3fe1789b1e8b2acac839d17	1	credit_card	8	
1	a9810da82917af2d9aefd1278f1dcfa0	1	credit_card	1	
2	25e8ea4e93396b6fa0d3dd708e76c1bd	1	credit_card	1	
3	ba78997921bbcdc1373bb41e913ab953	1	credit_card	8	
4	42fdf880ba16b47b59251dd489d4441a	1	credit_card	2	

In [44]:
```
order_payments_df.shape
```

Out[44]: (103886, 5)

In [45]:
```
# We have no NAN values in our order payment dataset
order_items_df_nan_values = order_payments_df.isna().sum()
order_items_df_nan_values[order_items_df_nan_values > 0]
```

Out[45]: Series([], dtype: int64)

In [46]:
```
# No duplicated rows
duplicated_rows_orders_df = order_payments_df[order_payments_df.duplicated()]
duplicated_rows_orders_df
```

Out[46]:

order_id	payment_sequential	payment_type	payment_installments	payment_value

In [47]:
```
order_payments_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103886 entries, 0 to 103885
Data columns (total 5 columns):
order_id                103886 non-null object
payment_sequential      103886 non-null int64
payment_type            103886 non-null object
payment_installments    103886 non-null int64
payment_value           103886 non-null float64
dtypes: float64(1), int64(2), object(2)
memory usage: 4.0+ MB
```

Order Reviews Data

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

Out[48]:

	review_id	order_id	review_score	review_co
0	7bc2406110b926393aa56f80a40eba40	73fc7af87114b39712e6da79b0a377eb	4	
1	80e641a11e56f04c1ad469d5645fdfde	a548910a1c6147796b98fdf73dbeba33	5	
2	228ce5500dc1d8e020d8d1322874b6f0	f9e4b658b201a9f2ecdecbb34bed034b	5	
3	e64fb393e7b32834bb789ff8bb30750e	658677c97b385a9be170737859d3511b	5	
4	f7c4243c7fe1938f181bec41a392bdeb	8e6bfb81e283fa7e4f11123a3fb894f1	5	

Geolocations Data

In [49]:
```
geolocations_df.head()
```

Out[49]:

	geolocation_zip_code_prefix	geolocation_lat	geolocation_lng	geolocation_city	geolocation_state
0	1037	-23.545621	-46.639292	sao paulo	SP
1	1046	-23.546081	-46.644820	sao paulo	SP
2	1046	-23.546129	-46.642951	sao paulo	SP
3	1041	-23.544392	-46.639499	sao paulo	SP
4	1035	-23.541578	-46.641607	sao paulo	SP

In [50]:
```
geolocations_df['geolocation_city'].value_counts()
```

Out[50]:
```
sao paulo                          135800
rio de janeiro                      62151
belo horizonte                      27805
são paulo                           24918
curitiba                            16593
                                    ...  
jardim abc de goias                     1
antunes (igaratinga)                    1
praia grande (fundão) - distrito        1
campinal                                1
socorro do piaui                        1
Name: geolocation_city, Length: 8011, dtype: int64
```

From the code above, we can get that the importance of the cities based on the amount of the purchases. The first top 3 cities that most customers buy products are Saou Paulo, Rio De Janeiro, and Belo Horizonte. So, in the next step we are going to keep the information of these 3 cities and do the analysis based on these cities.

In [51]:
```
cities = ['sao paulo', 'rio de janeiro', 'belo horizonte']
city_mask_ = geolocations_df['geolocation_city'].isin(cities)
```

In [52]:
```
geolocations_df['geolocation_city'] = geolocations_df['geolocation_city'][city_ma
```

In [53]:
```
geolocations_df['geolocation_city'].value_counts()
```

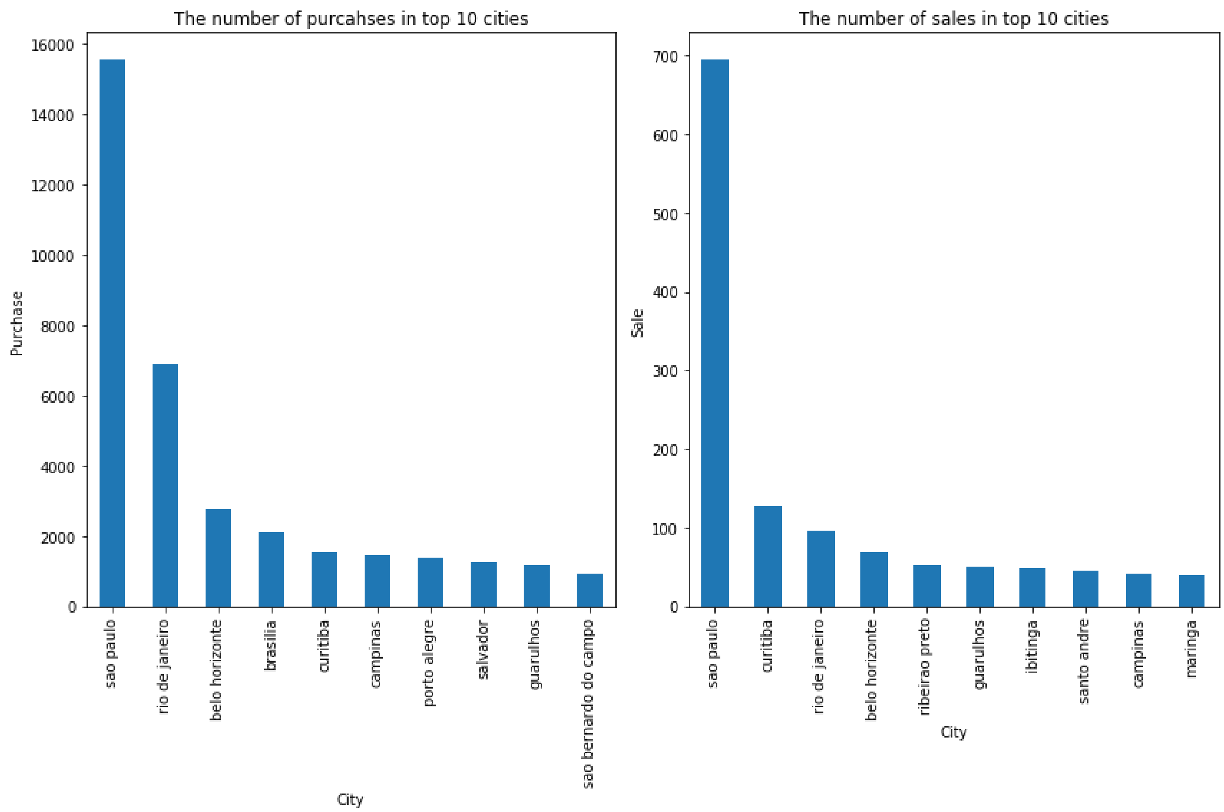
Out[53]:
```
sao paulo         135800
rio de janeiro     62151
belo horizonte     27805
Name: geolocation_city, dtype: int64
```

Visuliazation

In this part we are going to visulize the top 10 cities that most of the purchase and sales are made:

Customers vs Sellers

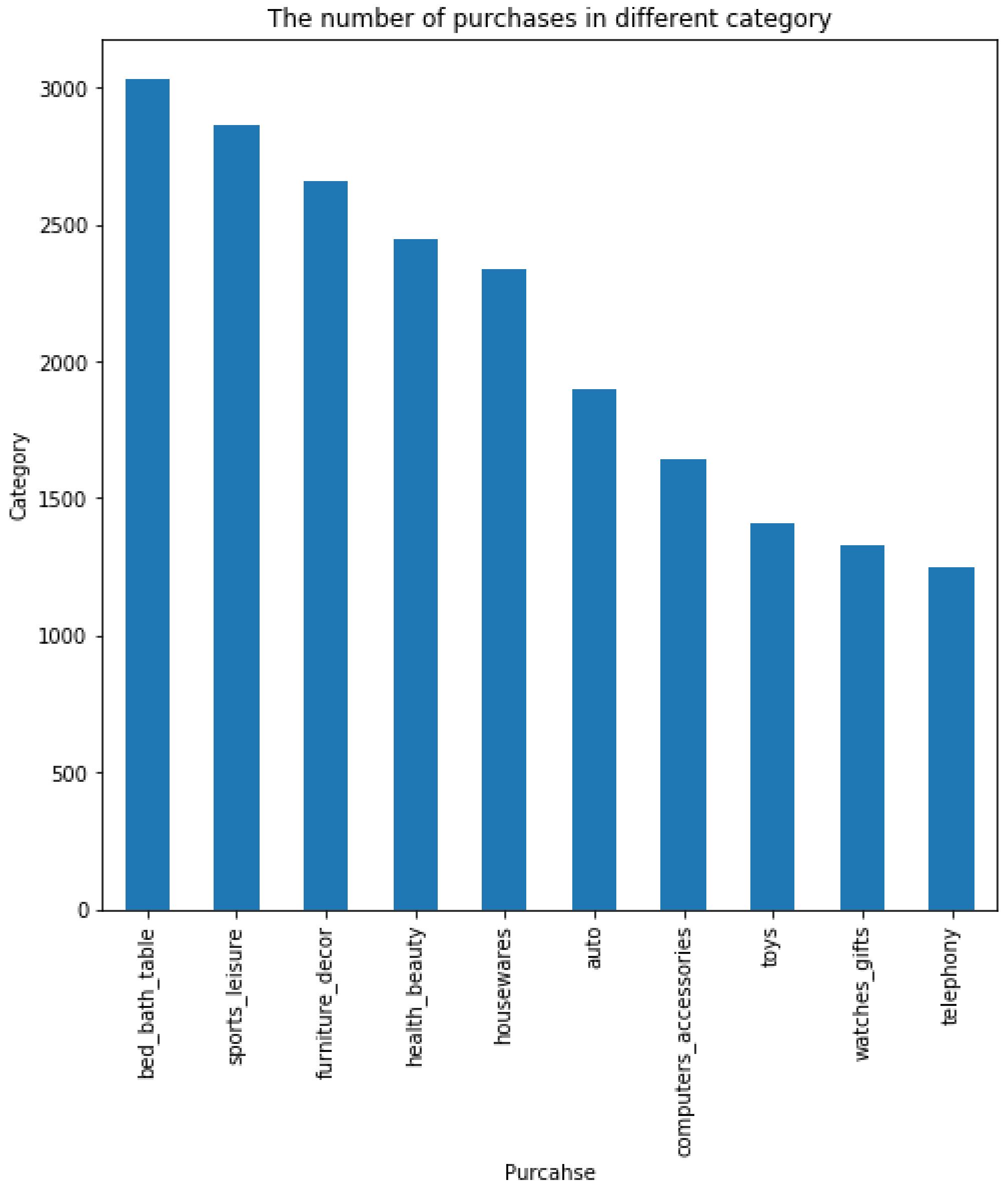
In [54]:
```
plt.subplots(1, 2)
plt.subplot(1, 2, 1)
customers_df['customer_city'].value_counts()[:10].plot(kind = 'bar', figsize = (
plt.xlabel('City')
plt.ylabel('Purchase')
plt.title('The number of purcahses in top 10 cities')
plt.subplot(1 ,2 ,2)
sellers_df['seller_city'].value_counts()[:10].plot(kind = 'bar', figsize = (12, 
plt.xlabel('City');
plt.ylabel('Sale');
plt.title('The number of sales in top 10 cities');
plt.tight_layout()
```



Products

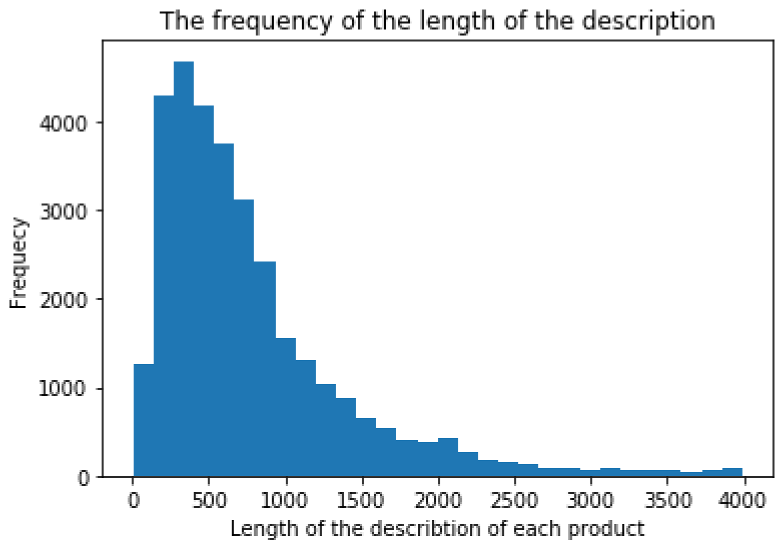
Now, let's look at the top 10 categories that are most popular among customers:

In [55]:
```
products_df['product_category_name'].value_counts()[:10].plot(kind = 'bar', figs
plt.xlabel('Purcahse');
plt.ylabel('Category');
plt.title('The number of purchases in different category');
```



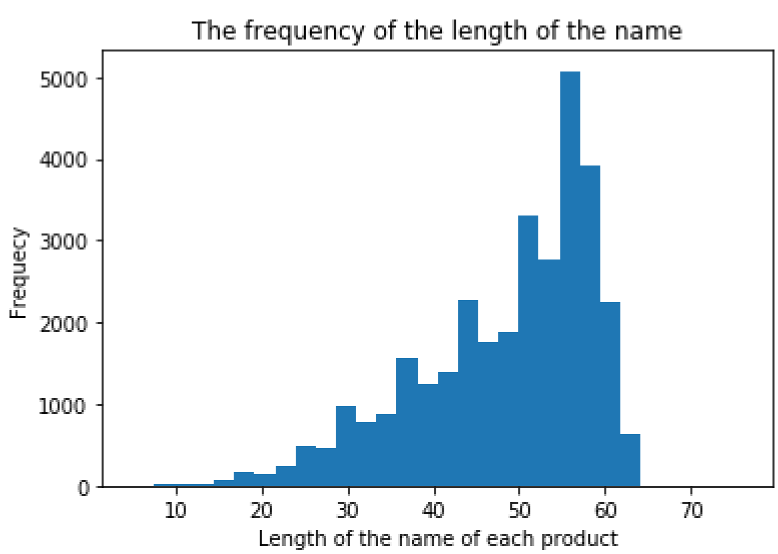
In this part we have an observation on the description and the name of the each products:

In [56]:
```
plt.figure()
plt.hist(products_df['product_description_lenght'], bins = 30)
plt.xlabel('Length of the describtion of each product');
plt.ylabel('Frequecy');
plt.title('The frequency of the length of the description');
```



From the histogram above, we can see that most of the products' description are written around 500 to 700 characters.

In [57]:
```
plt.figure()
plt.hist(products_df['product_name_lenght'], bins = 30)
plt.xlabel('Length of the name of each product');
plt.ylabel('Frequecy');
plt.title('The frequency of the length of the name');
```



The length of the name of each product is around 45 characters.

Keep top 3 cities information:

In this project we are going to focus on the top 3 cities in which customers come from.

In [58]:
```
cities = ['sao paulo', 'rio de janeiro', 'belo horizonte']
city_mask = customers_df['customer_city'].isin(cities)
city_mask
```

Out[58]:
```
0        False
1        False
2         True
3        False
4        False
         ...
99436     True
99437    False
99438    False
99439    False
99440    False
Name: customer_city, Length: 99441, dtype: bool
```

In [59]:
```
customers_df['customer_city'] = customers_df['customer_city'][city_mask]
```

Now, we have a dataframe contains customers information from the top 3 cities. But, we get a lot of NaN values from the cities not include the top 3, so we are going to remove those rows from our dataframe.

In [60]:
```
customers_df.head()
```

Out[60]:

	customer_id	customer_unique_id	customer_zip_code_prefi
0	06b8999e2fba1a1fbc88172c00ba8bc7	861eff4711a542e4b93843c6dd7febb0	1440
1	18955e83d337fd6b2def6b18a428ac77	290c77bc529b7ac935b93aa66c333dc3	979
2	4e7b3e00288586ebd08712fdd0374a03	060e732b5b29e8181a18229c7b0b2b5e	115
3	b2b6027bc5c5109e529d4dc6358b12c3	259dac757896d24d7702b9acbbff3f3c	877
4	4f2d8ab171c80ec8364f7c12e35b23ad	345ecd01c38d18a9036ed96c73b8d066	1305

In [61]:
```python
customers_df.dropna(how = 'any', inplace = True)
```

In [62]:
```python
customers_df.head()
```

Out[62]:

	customer_id	customer_unique_id	customer_zip_code_pre
2	4e7b3e00288586ebd08712fdd0374a03	060e732b5b29e8181a18229c7b0b2b5e	11
6	fd826e7cf63160e536e0908c76c3f441	addec96d2e059c80c30fe6871d30d177	45
9	4b7139f34592b3a31687243a302fa75b	9afe194fb833f79e300e37e580171f22	305
11	5aa9e4fdd4dfd20959cad2d772509598	2a46fb94aef5cbeeb850418118cee090	202
13	eabebad39a88bb6f5b52376faec28612	295c05e81917928d76245e842748184d	57

In [63]:
```python
customers_df.shape
```

Out[63]: (25195, 5)

In [64]:
```python
customers_df.customer_city.unique()
```

Out[64]: array(['sao paulo', 'belo horizonte', 'rio de janeiro'], dtype=object)

Gather information (merging dataframes):

Orders

In [65]:
```python
df = orders_df.merge(order_items_df, on = 'order_id')
```

In [66]:
```python
orders_item_payments = df.merge(order_payments_df, on = 'order_id')
```

In [67]:
```python
orders_item_payments.head()
```

Out[67]:

	order_id	customer_id	order_status	order_purc
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	201
1	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	201
2	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	201
3	53cdb2fc8bc7dce0b6741e2150273451	b0830fb4747a6c6d20dea0b8c802d7ef	delivered	201
4	47770eb9100c2d0c44946d9cf07ec65d	41ce2a54c0b03bf3443c3d931a367089	delivered	201

In [68]:
```
orders_item_payments.shape
```

Out[68]:
```
(115018, 18)
```

Products and Orders

In [69]:
```
products_orders_df = orders_item_payments.merge(products_df, on = 'product_id')
```

In [70]:
```
products_orders_df.head()
```

Out[70]:

	order_id	customer_id	order_status	order_purc
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
1	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
2	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
3	128e10d95713541c87cd1a2e48201934	a20e8105f23924cd00833fd87daa0831	delivered	20
4	0e7e841ddf8f8f2de2bad69267ecfbcf	26c7ac168e1433912a51b924fbd34d34	delivered	20

5 rows × 27 columns

Products, Orders, and Customers

In [71]:
```
products_orders_customers_df = products_orders_df.merge(customers_df, on = 'custo
```

In [72]:
```
pd.set_option('display.max_columns', 40)
products_orders_customers_df.head()
```

Out[72]:

	order_id	customer_id	order_status	order_purc
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
1	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
2	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
3	128e10d95713541c87cd1a2e48201934	a20e8105f23924cd00833fd87daa0831	delivered	20
4	0e7e841ddf8f8f2de2bad69267ecfbcf	26c7ac168e1433912a51b924fbd34d34	delivered	20

In [73]:
```
products_orders_customers_df.shape
```

Out[73]:
```
(28824, 31)
```

In [74]:
```
# No duplicated rows
duplicated_rows_customers_df = products_orders_customers_df[products_orders_cust
products_orders_customers_df = products_orders_customers_df.drop_duplicates()
```

In [75]:
```
products_orders_customers_df['payment_type'].unique()
```

Out[75]:
```
array(['credit_card', 'voucher', 'boleto', 'debit_card'], dtype=object)
```

In [76]:
```
# translate boleto in english
products_orders_customers_df['payment_type'] = \
                                            np.where(products_orders_customers_
                                            'boleto', 'billet', products_orders_
```

In [77]:
```
products_orders_customers_df['payment_type'].value_counts()
```

Out[77]:
```
credit_card    21795
billet          4970
voucher         1571
debit_card       488
Name: payment_type, dtype: int64
```

In [78]:
```
products_orders_customers_df['product_category_name'].value_counts()
```

Out[78]:
```
bed_bath_table               3356
health_beauty                2607
sports_leisure               2214
furniture_decor              2211
housewares                   2102
                             ...
party_supplies                  7
la_cuisine                      5
fashion_sport                   5
fashion_childrens_clothes       4
pc_gamer                        1
Name: product_category_name, Length: 64, dtype: int64
```

By looking at the code above, we can see that there are a lot of categories some of which are related to each other, but they are in different category. In this part we are going to define some main categories that include all related categories.

In [79]:

```
def name_mask (df, column_name, list_of_tuples_str_contains_and_desired_name):
    '''
    This fuction gets 3 parameters to change the names in whatever column's conte
    '''
    for i, j in list_of_tuples_str_contains_and_desired_name:
        mask = df[column_name].str.contains(i)
        df[column_name][mask] = j
```

In [80]:

```
# We define a list pf tuples that contains the old name and the desired one:

old_and_new_names = [
                    ('game', 'computers'), ('food', 'food'),
                    ('appliance', 'appliances'), ('fashio', 'fashion'),
                    ('computer', 'electronics'), ('security', 'security'),
                    ('furniture', 'furniture'), ('construction', 'construction')
                    ('book', 'book'), ('housewares', 'furniture'),
                    ('bed_bath_table', 'furniture'), ('costruction_tools_tools',
                    ('dvds_blu_ray', 'electronics'), ('tablets_printing_image',
                    ('market_place', 'sports_leisure'), ('garden_tools', 'garden
                    ('flowers', 'garden'), ('party_supplies', 'cool_stuff'),
                    ('la_cuisine', 'sports_leisure'), ('books_general_interest',
                    ('diapers_and_hygiene', 'baby'), ('toys', 'baby'),
                    ('christmas_supplies', 'cool_stuff'), ('watches_gifts', 'coo
                    ('home_confort', 'appliances'), ('luggage_accessories', 'spo
                    ('perfumery', 'health_beauty'), ('commerce', 'industry_comme
                    ('drink', 'food'), ('air_conditioning', 'appliances'),
                    ('cine_photo', 'electronics'), ('audio', 'electronics')
                    ]

name_mask(products_orders_customers_df, 'product_category_name', old_and_new_nam
```

```
C:\Users\Mona\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: SettingWithC
opyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydat
a.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y)
```

In [81]:
```
products_orders_customers_df.product_category_name.value_counts()
```

Out[81]:
```
furniture           8517
health_beauty       3476
electronics         3193
sports_leisure      2545
cool_stuff          2277
baby                1946
telephony           1008
garden               999
auto                 863
appliances           703
fashion              623
stationery           619
construction         530
pet_shop             499
food                 400
book                 197
music                191
industry_commerce    118
security              61
art                   59
Name: product_category_name, dtype: int64
```

In this project are going to keep categories that their popularity are more than 10% of the other one.

In [82]:
```
my_list = ['food',
          'music',
          'security',
          'art',
          'book',
          'industry_commerce',
          'construction',
          'fashion',
          'appliances',
          'stationery',
          'pet_shop']

for i in my_list:
    products_orders_customers_df = \
    products_orders_customers_df[~products_orders_customers_df['product_category_
```

In [83]:
```
products_orders_customers_df.drop_duplicates()
```

Out[83]:

	order_id	customer_id	order_status	order_
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	
1	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	
2	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	
3	128e10d95713541c87cd1a2e48201934	a20e8105f23924cd00833fd87daa0831	delivered	
4	0e7e841ddf8f8f2de2bad69267ecfbcf	26c7ac168e1433912a51b924fbd34d34	delivered	
...	...	...	...	
28819	add4f182072426430ee6c993eab97efe	b87639f5efd3e2316dca5dec5e2f88f4	delivered	
28820	f6f9344efc918f1e00ab84c014aa21d7	166478efeed4f9a861164b4ff5acfe8b	delivered	
28821	87b4c933f31145a28413b39d880ad6c3	ddfdf5e9b2659e1fbd073404c9b762e0	delivered	
28822	e8fd20068b9f7e6ec07068bb7537f781	609b9fb8cad4fe0c7b376f77c8ab76ad	delivered	
28823	e8fd20068b9f7e6ec07068bb7537f781	609b9fb8cad4fe0c7b376f77c8ab76ad	delivered	

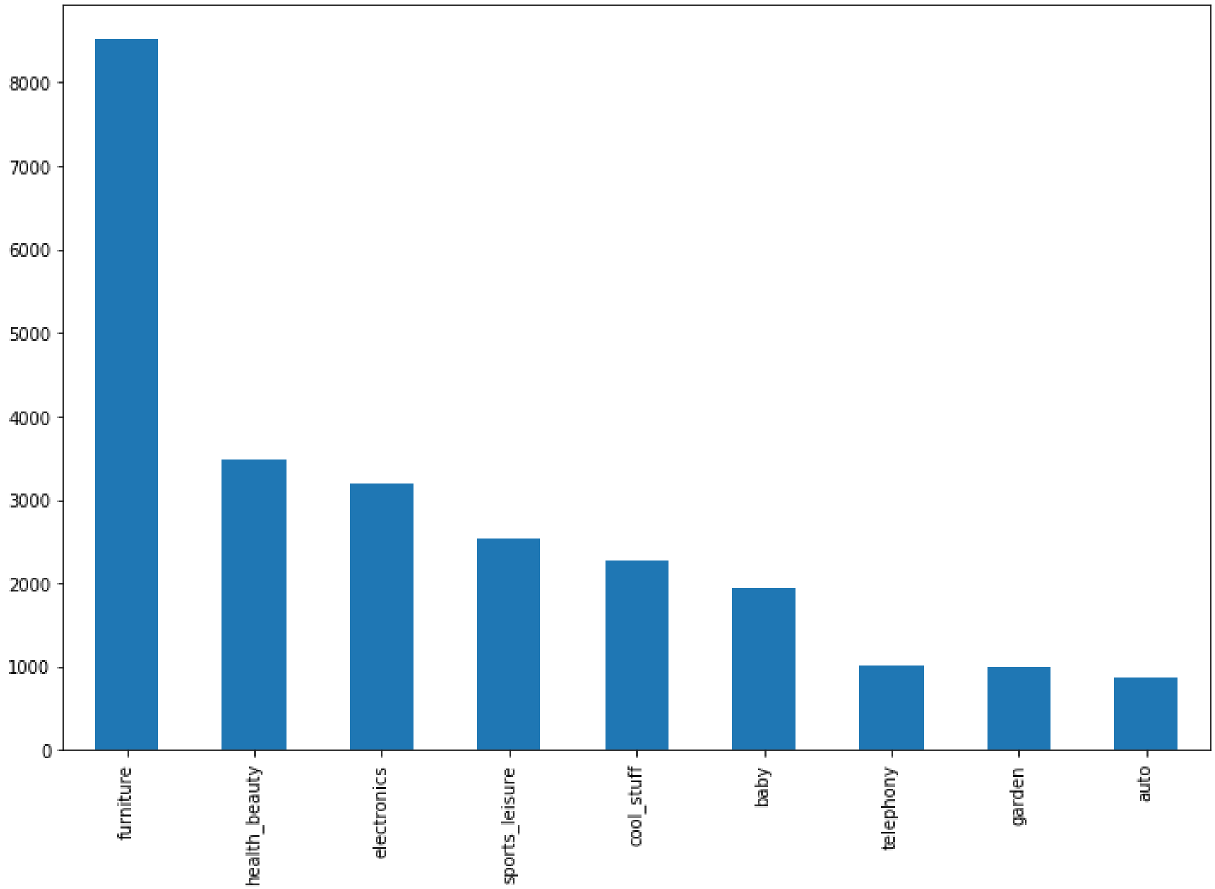
24824 rows × 31 columns

Now, let's see the top 9 most favorite category among customers:

In [84]:
```
products_orders_customers_df['product_category_name'].value_counts()
```

Out[84]:
```
furniture         8517
health_beauty     3476
electronics       3193
sports_leisure    2545
cool_stuff        2277
baby              1946
telephony         1008
garden             999
auto               863
Name: product_category_name, dtype: int64
```

In [85]:
```
plt.figure(figsize = (8, 8))
products_orders_customers_df['product_category_name'].value_counts().plot(kind =
```



Sales Analysis

> We are going to see the time stamp as customers did their purchase, to find the amount of purchase during a year.

In [86]:
```
from matplotlib.dates import DateFormatter
import matplotlib.dates as mdates
```

In [87]:
```
orders_df['order_purchase'] = orders_df['order_purchase_timestamp'].dt.date
```

In [88]:
```
purchase_year = orders_df.groupby('order_purchase')['customer_id'].count()
purchase_year.head()
```

Out[88]:
```
order_purchase
2016-09-15     1
2016-10-03     8
2016-10-04    54
2016-10-05    35
2016-10-06    41
Name: customer_id, dtype: int64
```

In [89]:
```
purchase_year.index = pd.to_datetime(purchase_year.index)
purchase_year.head()
```

Out[89]:
```
order_purchase
2016-09-15     1
2016-10-03     8
2016-10-04    54
2016-10-05    35
2016-10-06    41
Name: customer_id, dtype: int64
```

In [90]:
```
purchase_year_df = pd.DataFrame(purchase_year)
purchase_year_df.index = pd.to_datetime(purchase_year_df.index)
purchase_year_df.head()
```

Out[90]:

	customer_id
order_purchase	
2016-09-15	1
2016-10-03	8
2016-10-04	54
2016-10-05	35
2016-10-06	41

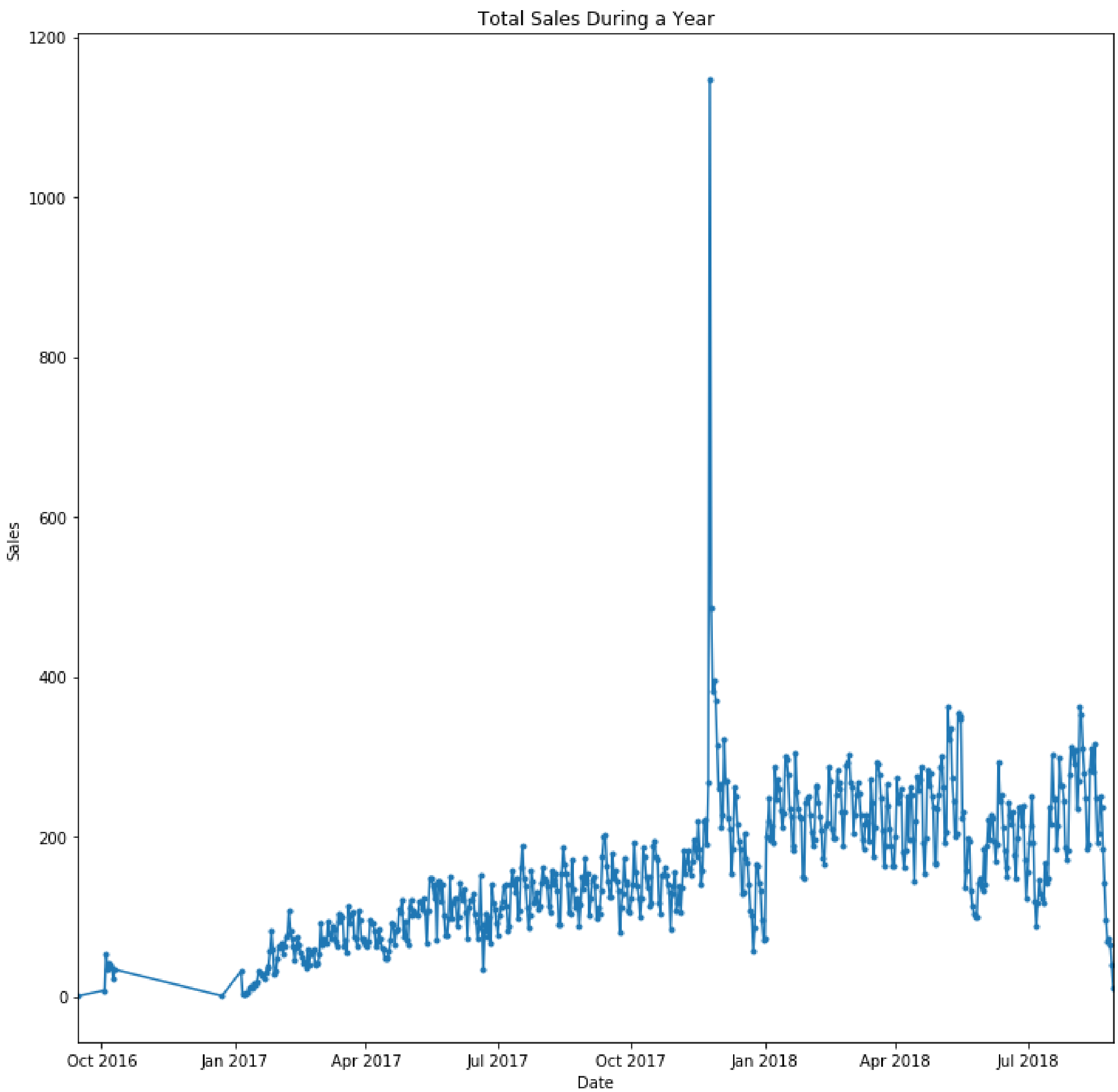
In [91]:
```
purchase_year_df = purchase_year_df.reset_index()
purchase_year_df.head()
```

Out[91]:

	order_purchase	customer_id
0	2016-09-15	1
1	2016-10-03	8
2	2016-10-04	54
3	2016-10-05	35
4	2016-10-06	41

In [92]:

```
plt.figure(figsize=(12,12))
ax = plt.gca()
plt.plot(purchase_year, marker='.')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Total Sales During a Year')
ax.autoscale(enable=True, axis='x', tight=True)
ax.xaxis.set_major_formatter(DateFormatter("%b %Y"))
plt.show();
```



As the plot above shows, there was a huge peak between December and January. It means that, around this time more customers are going to buy something. Which is expected to see that because this time is near holidays.

In this part the facbook prophet is used to have a better observation on sales.

In [95]:
```
from fbprophet import Prophet
```

In [96]:
```
purchase_year_df.set_axis(['ds', 'y'], axis=1, inplace = True)
purchase_year_df.head()
```

Out[96]:

	ds	y
0	2016-09-15	1
1	2016-10-03	8
2	2016-10-04	54
3	2016-10-05	35
4	2016-10-06	41

In [97]:
```
# Split the data into train and test
test_size = 100
test = purchase_year_df.iloc[-test_size:]
train = purchase_year_df.iloc[:-test_size]
```

In [98]:
```
fig_time_sales = go.Figure()
fig_time_sales.add_trace(go.Scatter(x=train['ds'], y=train['y'].values,
                    mode='lines+markers', name='train', line = dict(color='royall
                    ))
fig_time_sales.add_trace(go.Scatter(x=test['ds'], y=test['y'].values,
                    mode='lines+markers', name='test', line = dict(color='red', w
                    ))
fig_time_sales.update_layout(
    xaxis_title="Date",
    yaxis_title="Sales",
    font=dict(
        family="Courier New, monospace",
        size=18,
        color="#7f7f7f"
    )
)

fig_time_sales.show()
```

Set a holiday variable which is contains the important date from December to January. It will use as a input for holiday argument.

In [99]:
```
holiday = pd.DataFrame({
  'holiday': 'christmas',
  'ds': pd.to_datetime(['2018-12-01', '2018-12-02', '2018-12-08',
                        '2018-12-09', '2018-12-13', '2018-12-15',
                        '2018-12-16', '2018-12-22', '2018-12-23',
                        '2018-12-24', '2018-12-25', '2018-12-26',
                        '2018-12-27', '2018-12-28']),

})
```

In [100]:
```
model = Prophet(interval_width=0.95, holidays=holiday)
model.fit(train)
```

```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with yearly_seasonalit
y=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonality=
True to override this.
```

Out[100]:
```
<fbprophet.forecaster.Prophet at 0x14c2d4e6c08>
```

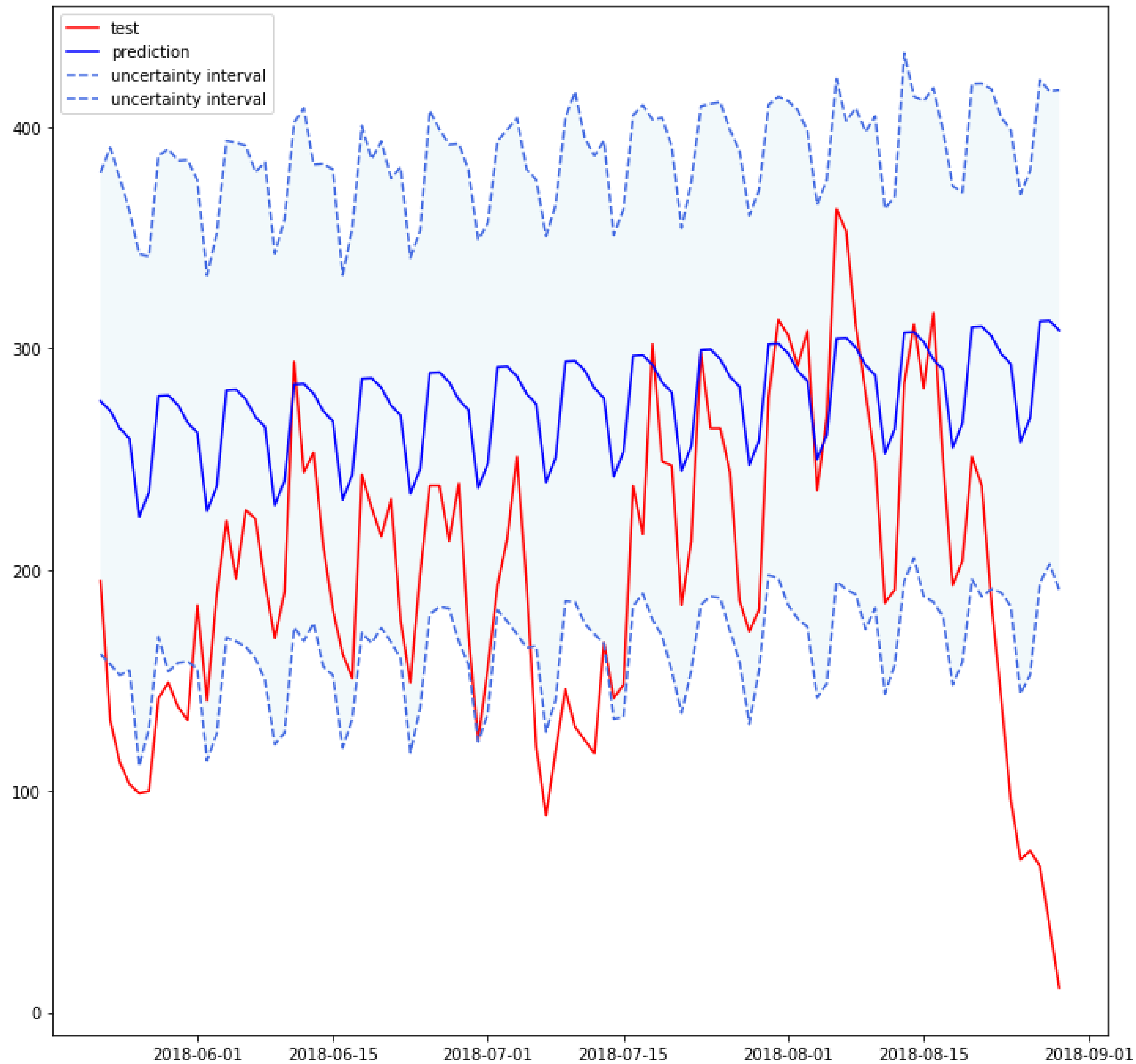
In [101]:
```
future = model.make_future_dataframe(periods=test_size, freq='D' ,include_histor
```

In [102]:
```
# We need to have a dataframe for the predict method, it must also contain a ds c
forecast = model.predict(future)
forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].head()
```

Out[102]:

	ds	yhat	yhat_lower	yhat_upper
0	2018-05-22	276.235817	161.965935	379.465560
1	2018-05-23	271.824133	157.201068	390.821944
2	2018-05-24	263.878875	152.375159	376.880191
3	2018-05-25	259.328649	154.517369	362.120562
4	2018-05-26	223.943489	111.248945	342.686285

In [103]:
```
plt.figure(figsize = (12, 12))
plt.plot(test['ds'], test['y'].values, c="red", label="test")
plt.plot(test['ds'], forecast['yhat'].values, c="blue", label="prediction")
plt.plot(test['ds'], forecast['yhat_lower'].values, c="royalblue", label="uncerta
plt.plot(test['ds'], forecast['yhat_upper'].values, c="royalblue", label="uncerta
ax = plt.gca()
ax.fill_between(test['ds'],  forecast['yhat_lower'], forecast['yhat_upper'], face
plt.legend()
plt.show();
```



From the plot above, red line is the actual values and blue trend is the prediction. In some areas, the prediction has a good match with the actual datapoints, but the blue line followed a patternal trend. It seems that there is a need to set more arguments with specific values to see the changes in prediction trend and come up with the best result. However, in this part we don't want to deep into the time-series analysis.

Machine Learning:

The methodologies we are going to use in this project are taken from scikit learn library as you can seen from below:

Machine Learning Part

In [104]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA
from sklearn.mixture import GaussianMixture
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import TfidfTransformer # Sentiment analysi

# Libraries for visualizing
import plotly.graph_objects as go
import plotly.express as px
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```

Unsupervised Clustering

Before define our fetures, we need to come up with features that are in categorical values. To do this we used get dummies method to convert the values from categorical to numerical.

K-means

In [105]:
```
products_orders_customers_df = pd.get_dummies(products_orders_customers_df, colu
                                              ['payment_type',
                                               'product_category_name'
                                               ])
```

In [106]:
```
products_orders_customers_df.head()
```

Out[106]:

	order_id	customer_id	order_status	order_purc
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
1	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
2	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	20
3	128e10d95713541c87cd1a2e48201934	a20e8105f23924cd00833fd87daa0831	delivered	20
4	0e7e841ddf8f8f2de2bad69267ecfbcf	26c7ac168e1433912a51b924fbd34d34	delivered	20

5 rows × 42 columns

In [107]:
```
products_orders_customers_df.columns
```

Out[107]:
```
Index(['order_id', 'customer_id', 'order_status', 'order_purchase_timestamp',
       'order_approved_at', 'order_delivered_carrier_date',
       'order_delivered_customer_date', 'order_estimated_delivery_date',
       'order_item_id', 'product_id', 'seller_id', 'shipping_limit_date',
       'price', 'freight_value', 'payment_sequential', 'payment_installments',
       'payment_value', 'product_name_lenght', 'product_description_lenght',
       'product_photos_qty', 'product_weight_g', 'product_length_cm',
       'product_height_cm', 'product_width_cm', 'volume_cubed_cm',
       'customer_unique_id', 'customer_zip_code_prefix', 'customer_city',
       'customer_state', 'payment_type_billet', 'payment_type_credit_card',
       'payment_type_debit_card', 'payment_type_voucher',
       'product_category_name_auto', 'product_category_name_baby',
       'product_category_name_cool_stuff', 'product_category_name_electronics',
       'product_category_name_furniture', 'product_category_name_garden',
       'product_category_name_health_beauty',
       'product_category_name_sports_leisure',
       'product_category_name_telephony'],
      dtype='object')
```

Specify which features is more related to customers in terms of how they can affect customers' behaviour:

In [108]:
```
products_orders_customers_df.corr()
```

Out[108]:

	order_item_id	price	freight_value	payment_sequential	pa
order_item_id	1.000000	-0.056880	-0.041255	0.014946	
price	-0.056880	1.000000	0.378731	-0.019066	
freight_value	-0.041255	0.378731	1.000000	0.027728	
payment_sequential	0.014946	-0.019066	0.027728	1.000000	
payment_installments	0.048832	0.267361	0.169339	-0.082231	
payment_value	0.243399	0.627341	0.247549	-0.053524	
product_name_lenght	-0.030251	0.019749	0.016693	0.006432	
product_description_lenght	-0.032286	0.198124	0.092657	-0.023336	
product_photos_qty	-0.042324	0.058946	0.014916	0.004514	
product_weight_g	-0.008880	0.305167	0.683016	0.029072	
product_length_cm	0.001781	0.125347	0.370563	0.050815	
product_height_cm	0.019031	0.213782	0.434759	0.037589	
product_width_cm	-0.031266	0.146001	0.366519	0.031045	
volume_cubed_cm	-0.003692	0.277266	0.641821	0.028187	
customer_zip_code_prefix	-0.021184	0.026803	0.227744	-0.021339	
payment_type_billet	0.052932	-0.036424	-0.012561	-0.057510	
payment_type_credit_card	-0.036028	0.049602	-0.000671	-0.216958	
payment_type_debit_card	-0.002752	-0.017529	-0.020764	-0.014079	
payment_type_voucher	-0.018253	-0.023297	0.033618	0.511239	
product_category_name_auto	-0.026648	0.009658	-0.011931	-0.018417	
product_category_name_baby	-0.043523	0.005910	0.005349	-0.016459	
product_category_name_cool_stuff	-0.049940	0.135391	-0.047197	-0.029291	
product_category_name_electronics	0.016304	0.011480	-0.038925	-0.035047	
product_category_name_furniture	0.079011	-0.089734	0.128773	0.103696	
product_category_name_garden	0.010076	-0.015894	0.047182	-0.013473	
product_category_name_health_beauty	-0.004119	0.019159	-0.086800	-0.035389	
product_category_name_sports_leisure	-0.034275	0.001659	0.012434	-0.013542	
product_category_name_telephony	-0.010781	-0.039050	-0.084384	-0.011185	

In [109]:
```
features_to_include = [
                      'product_weight_g',
                      'price',
                      'product_photos_qty',
                      'freight_value',
                      'volume_cubed_cm',
                      'payment_sequential',
                      'payment_installments',
                      'payment_value',
                      'payment_type_billet',
                      'payment_type_credit_card',
                      'payment_type_debit_card',
                      'payment_type_voucher',
                      'product_category_name_auto',
                      'product_category_name_baby',
                      'product_category_name_cool_stuff',
                      'product_category_name_electronics',
                      'product_category_name_furniture',
                      'product_category_name_garden',
                      'product_category_name_health_beauty',
                      'product_category_name_sports_leisure',
                      'product_category_name_telephony'
                      ]
```

In [110]:
```
scaler = StandardScaler()
scaler.fit(products_orders_customers_df[features_to_include])
X = scaler.transform(products_orders_customers_df[features_to_include])
```

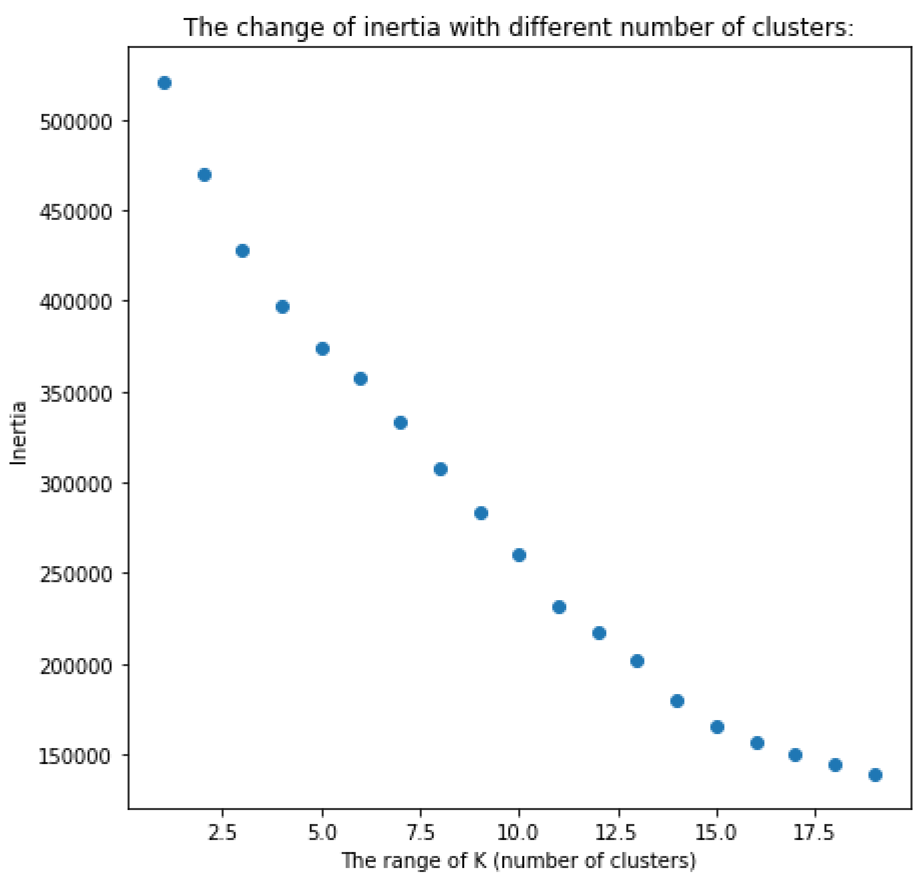
In [111]:
```
X.shape
```

Out[111]:
```
(24824, 21)
```

At this stage by looking at the inertia value, we are going to see how many clusters would be better to have in the k-means clustering:

In [112]:
```
k_range = np.arange(1,20)

inertia_list = []

for k in k_range :

    #Specify the model
    k_means_model = KMeans(n_clusters = k, random_state = 1)
    k_means_model.fit(X)

    inertia_list.append(k_means_model.inertia_)
    print(k, end = '\r')

plt.figure(figsize = (7,7))
plt.scatter(k_range, inertia_list)
plt.title('The change of inertia with different number of clusters:')
plt.xlabel('The range of K (number of clusters)')
plt.ylabel('Inertia')
plt.show()
```

19



As we can see from the scatter plot above, the amount of inertia is extremely high, so we couldn't decide on the number of clusters that we need for our model. So, the next step would be decreasing the dimensional of our features to 2 features:

PCA

In [113]:
```
# Build and fit a PCA model
my_pca = PCA(n_components = 2, random_state = 1)

#Transform the data
X_PCA = my_pca.fit_transform(X)
```

In [114]:
```
my_pca.components_
```

Out[114]:
```
array([[ 4.88650312e-01,  3.43701353e-01,  2.59674377e-02,
         4.61304183e-01,  4.77355014e-01,  1.76398716e-03,
         2.28711336e-01,  2.80330726e-01, -7.98974557e-02,
         9.04427943e-02, -4.23267782e-02, -1.43946494e-02,
        -6.45939622e-03,  1.51101488e-02, -8.14680782e-03,
        -9.46709224e-02,  1.68535778e-01,  1.58588415e-02,
        -9.54120271e-02, -7.01140432e-03, -8.47325091e-02],
       [ 1.39867160e-01, -9.32358209e-02, -1.10981981e-02,
         1.05206440e-01,  1.48346384e-01,  2.92406177e-01,
        -3.40377856e-01, -8.58289765e-02,  4.24224772e-01,
        -5.94546297e-01,  9.41546733e-02,  3.64342773e-01,
        -1.19989330e-02, -1.17262672e-02, -1.11421267e-01,
        -1.31979812e-02,  1.68009936e-01,  2.32401822e-02,
        -1.13390026e-01,  4.88411159e-04, -1.62145541e-02]])
```

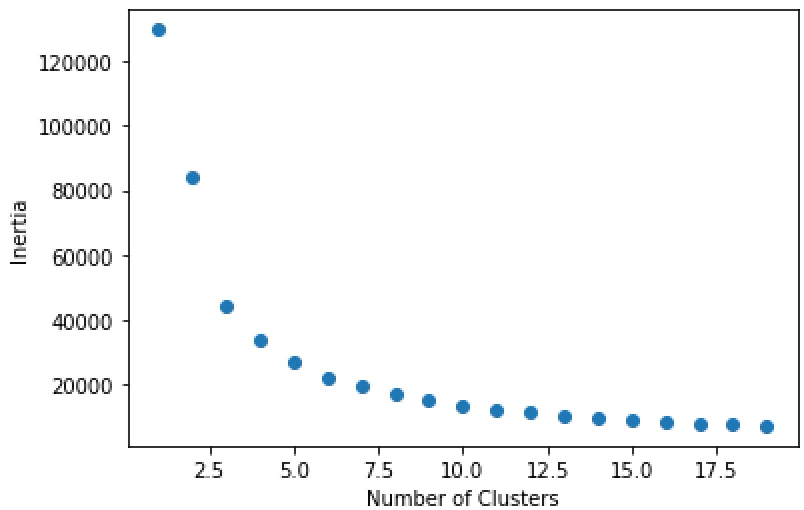
In [115]:
```
#PCA_model = PCA().fit(X_PCA)
```

In [116]:
```
X_PCA.shape
```

Out[116]:
```
(24824, 2)
```

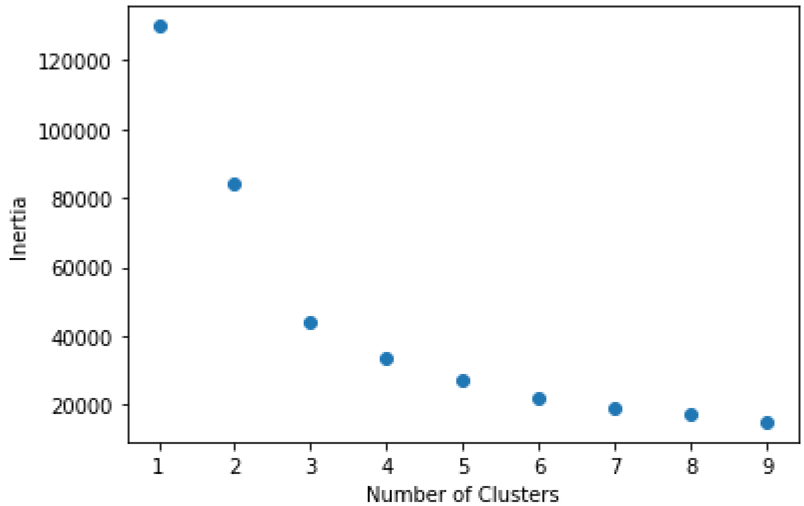
In [117]:
```
k_range = np.arange(1,20)

inertia_list = []

for k in k_range :

    #Specify the model
    k_means_model = KMeans(n_clusters = k, random_state = 1)
    k_means_model.fit(X_PCA)

    inertia_list.append(k_means_model.inertia_)
    print(k, end = '\r')
plt.scatter(k_range,inertia_list)
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show()
```

19



In [118]:
```
#len(inertia_list)
```

In [119]:
```
plt.figure()
plt.scatter(range(1,10),inertia_list[0:9])
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show();
```

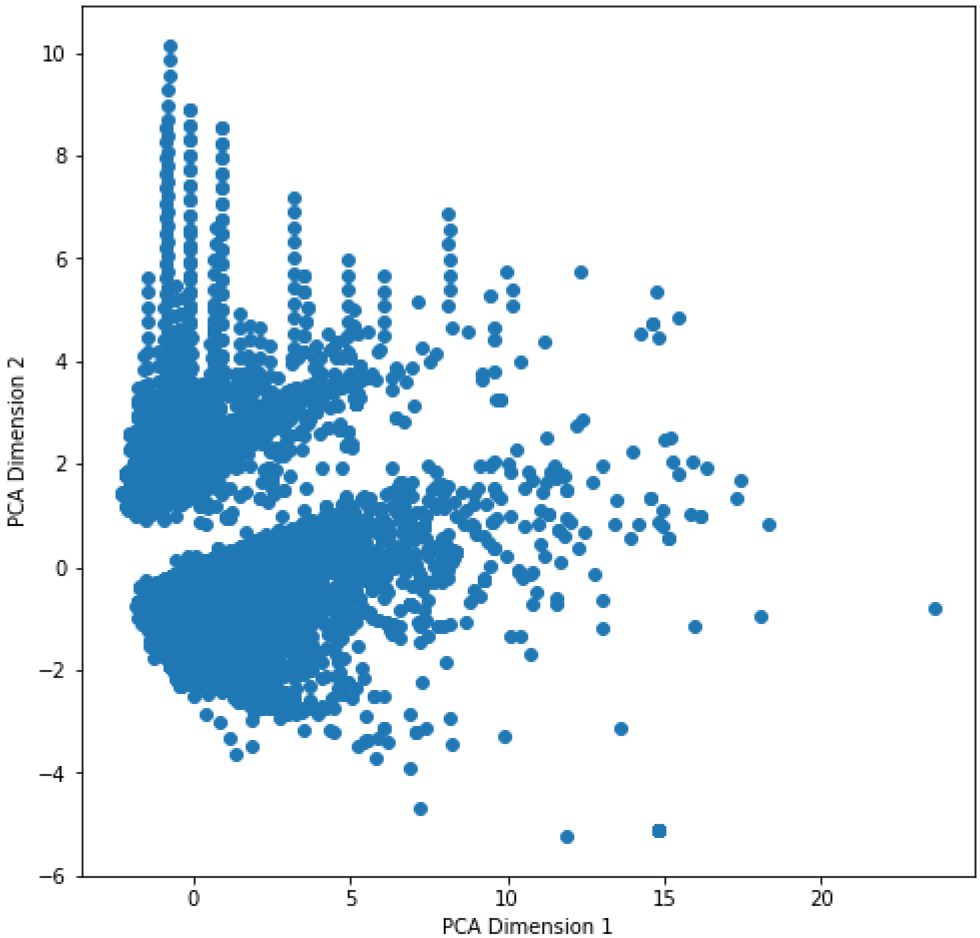


By reducing the dimension of the features using PCA, the amount of the inertia has changed in a good way. By looking at the plot above, it seems that if we have 2 to 5 clusters would be fine for our model.

Let's try the different number of clusters and visualize the clusters to decide on the final number of clusters.

In [120]:
```
plt.figure(figsize=(8, 8))
plt.scatter(X_PCA[:,0],X_PCA[:,1])

plt.xlabel("PCA Dimension 1")
plt.ylabel("PCA Dimension 2")
```

Out[120]: Text(0, 0.5, 'PCA Dimension 2')



In [121]:
```
k2_means_model = KMeans(n_clusters = 2, random_state = 1)
#Fit the model to the data
k2_means_model.fit(X_PCA);

k3_means_model = KMeans(n_clusters = 3, random_state = 1)
#Fit the model to the data
k3_means_model.fit(X_PCA);

k4_means_model = KMeans(n_clusters = 4, random_state = 1)
#Fit the model to the data
k4_means_model.fit(X_PCA);

k5_means_model = KMeans(n_clusters = 5, random_state = 1)
#Fit the model to the data
k5_means_model.fit(X_PCA);
```

In [122]:
```
k2_means_model.labels_
pred_labels2 = k2_means_model.labels_

k3_means_model.labels_
pred_labels3 = k3_means_model.labels_

k4_means_model.labels_
pred_labels4 = k4_means_model.labels_

k5_means_model.labels_
pred_labels5 = k5_means_model.labels_
```

> Now check the silhoutte score of different using number of clustering. It seems that having 3 clusters gives a better score on silhouette score, but visually having 2 clusters is more practical.

In [123]:
```
print(silhouette_score(X_PCA, pred_labels2))
print(silhouette_score(X_PCA, pred_labels3))
print(silhouette_score(X_PCA, pred_labels4))
print(silhouette_score(X_PCA, pred_labels5))
```

```
0.5422998929540715
0.6042094828374953
0.5176052974847161
0.466834715299024
```

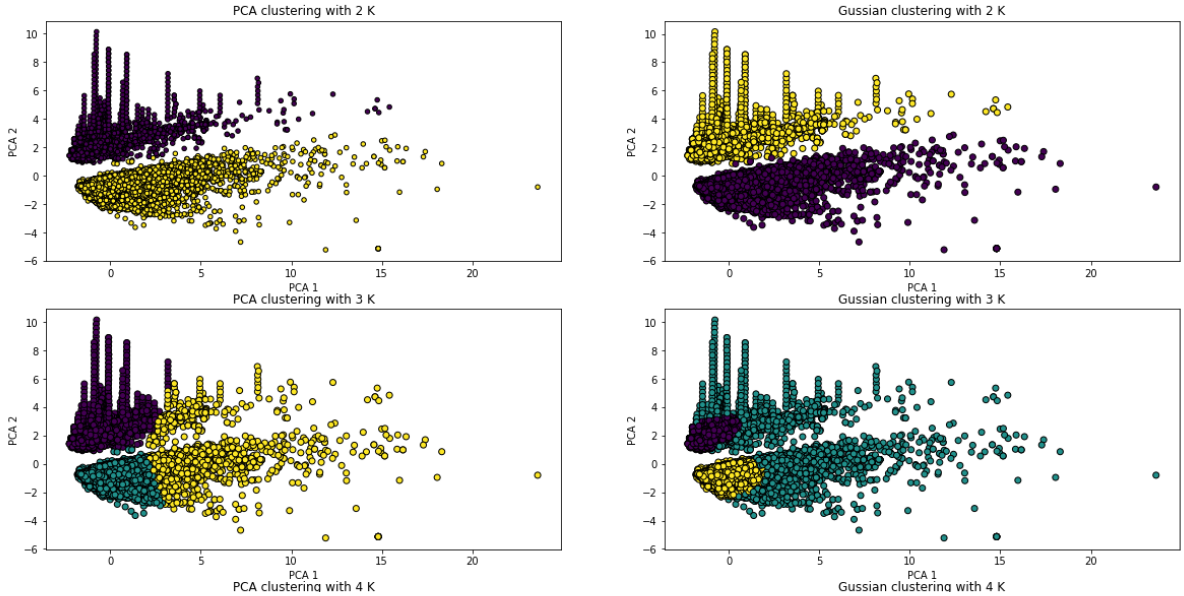
In [124]:
```
my_gmm2 = GaussianMixture(n_components = 2, covariance_type='full')
my_gmm2.fit(X_PCA)
#Getting the labels
pred_labels_gmm2 = my_gmm2.predict(X_PCA)

my_gmm3 = GaussianMixture(n_components = 3, covariance_type='full')
my_gmm3.fit(X_PCA)
#Getting the labels
pred_labels_gmm3 = my_gmm3.predict(X_PCA)

my_gmm4 = GaussianMixture(n_components = 4, covariance_type='full')
my_gmm4.fit(X_PCA)
#Getting the labels
pred_labels_gmm4 = my_gmm4.predict(X_PCA)

my_gmm5 = GaussianMixture(n_components = 5, covariance_type='full')
my_gmm5.fit(X_PCA)
#Getting the labels
pred_labels_gmm5 = my_gmm5.predict(X_PCA)
```

In [125]:

```
fig_clustering = go.Figure()
#pca = px.data.X_PCA
fig_clustering = px.scatter(x=X_PCA[:,0], y=X_PCA[:,1], color=pred_labels2,
           color_continuous_scale=px.colors.sequential.Viridis, render_mode="webg

fig_clustering.update_layout(
    xaxis_title="PCA 1",
    yaxis_title="PCA 2",
    font=dict(
        family="Courier New, monospace",
        size=18,
        color="#7f7f7f"
    )
)
fig_clustering.show()
```

In [126]:
```
plt.rcParams['figure.figsize'] = (20, 20)
plt.subplots(4, 2)
plt.subplot(4, 2, 1)
#Plot the data:
plt.subplot(4, 2, 1)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels2, s=20, edgecolor='k')
plt.title('PCA clustering with 2 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')

plt.subplot(4, 2, 2)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels_gmm2, edgecolor='k')
plt.title('Gussian clustering with 2 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')


plt.subplot(4, 2, 3)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels3, edgecolor='k')
plt.title('PCA clustering with 3 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')

plt.subplot(4, 2, 4)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels_gmm3, edgecolor='k')
plt.title('Gussian clustering with 3 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')


plt.subplot(4, 2, 5)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels4, s=20, edgecolor='k')
plt.title('PCA clustering with 4 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')

plt.subplot(4, 2, 6)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels_gmm4, edgecolor='k')
plt.title('Gussian clustering with 4 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')


plt.subplot(4, 2, 7)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels5, s=20, edgecolor='k')
plt.title('PCA clustering with 5 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')

plt.subplot(4, 2, 8)
plt.scatter(X_PCA[:,0], X_PCA[:,1], c=pred_labels_gmm5, edgecolor='k')
plt.title('Gussian clustering with 5 K')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
```

Out[126]:
```
Text(0, 0.5, 'PCA 2')
```



It seems that from the plots above, our model does the best clustering with having 2 clusters. The data points are devided into two seperate groups beautifully. But, how we can interpret our model in terms of each cluster?

In the following part, we are going to add the lables which are related to each cluster into the dataframe consists of all features that we included to find any relation between each cluster and the features.

In [127]:
```
poc_fetures_to_include_df = products_orders_customers_df[features_to_include]
```

In [128]:
```
k2_labels = k2_means_model.labels_
```

In [129]:
```
poc_fetures_to_include_df['labels_k2'] = k2_labels
```

In [130]:
```
poc_fetures_to_include_df.head()
```

Out[130]:

	product_weight_g	price	product_photos_qty	freight_value	volume_cubed_cm	payment_sequen
0	500.0	29.99	4.0	8.72	1976.0	
1	500.0	29.99	4.0	8.72	1976.0	
2	500.0	29.99	4.0	8.72	1976.0	
3	500.0	29.99	4.0	7.78	1976.0	
4	500.0	29.99	4.0	7.78	1976.0	

In [131]:
```
labels_group = poc_fetures_to_include_df.groupby('labels_k2').sum()
labels_group
```

Out[131]:

	product_weight_g	price	product_photos_qty	freight_value	volume_cubed_cm	pay
labels_k2						
0	12197851.0	549463.47	12487.0	100235.61	91257411.0	
1	37652774.0	2194042.03	39703.0	313940.66	276959696.0	

In [132]:
```
poc_fetures_to_include_df.labels_k2.value_counts()
```

Out[132]:
```
1    18802
0     6022
Name: labels_k2, dtype: int64
```

In [133]:
```
poc_fetures_to_include_df.corrwith(poc_fetures_to_include_df.labels_k2 == 0)
```

Out[133]:
```
product_weight_g                        0.002673
price                                  -0.068708
product_photos_qty                     -0.010002
freight_value                          -0.001855
volume_cubed_cm                         0.007824
payment_sequential                      0.217441
payment_installments                   -0.377797
payment_value                          -0.044731
payment_type_billet                     0.800757
payment_type_credit_card               -0.997376
payment_type_debit_card                 0.225458
payment_type_voucher                    0.426148
product_category_name_auto             -0.006851
product_category_name_baby             -0.016809
product_category_name_cool_stuff       -0.036913
product_category_name_electronics       0.023136
product_category_name_furniture         0.035212
product_category_name_garden            0.016572
product_category_name_health_beauty    -0.034729
product_category_name_sports_leisure   -0.004457
product_category_name_telephony         0.010700
labels_k2                              -1.000000
dtype: float64
```

In [134]:
```
poc_fetures_to_include_df.corrwith(poc_fetures_to_include_df.labels_k2 == 1)
```

Out[134]:
```
product_weight_g                      -0.002673
price                                  0.068708
product_photos_qty                     0.010002
freight_value                          0.001855
volume_cubed_cm                       -0.007824
payment_sequential                    -0.217441
payment_installments                   0.377797
payment_value                          0.044731
payment_type_billet                   -0.800757
payment_type_credit_card               0.997376
payment_type_debit_card               -0.225458
payment_type_voucher                  -0.426148
product_category_name_auto             0.006851
product_category_name_baby             0.016809
product_category_name_cool_stuff       0.036913
product_category_name_electronics     -0.023136
product_category_name_furniture       -0.035212
product_category_name_garden          -0.016572
product_category_name_health_beauty    0.034729
product_category_name_sports_leisure   0.004457
product_category_name_telephony       -0.010700
labels_k2                              1.000000
dtype: float64
```

From the information above, we see that there are correlation between customers and their payment information. Now, let's visulize the payment methods and clusters.

In [135]:
```
poc_fetures_to_include_df
```

Out[135]:

	product_weight_g	price	product_photos_qty	freight_value	volume_cubed_cm	payment_se
0	500.0	29.99	4.0	8.72	1976.0	
1	500.0	29.99	4.0	8.72	1976.0	
2	500.0	29.99	4.0	8.72	1976.0	
3	500.0	29.99	4.0	7.78	1976.0	
4	500.0	29.99	4.0	7.78	1976.0	
...	...	...	...	...	...	
28819	300.0	369.90	2.0	10.78	1936.0	
28820	30000.0	399.99	2.0	82.70	201600.0	
28821	350.0	57.99	1.0	27.26	2964.0	
28822	2800.0	356.00	1.0	18.12	14812.0	
28823	2800.0	356.00	1.0	18.12	14812.0	

24824 rows × 22 columns

In [136]:
```
billet_labels_sum = poc_fetures_to_include_df.groupby('labels_k2').sum()['paymen
```

In [137]:
```
voucher_labels_sum = poc_fetures_to_include_df.groupby('labels_k2').sum()['payme
```

In [138]:
```
debit_labels_sum = poc_fetures_to_include_df.groupby('labels_k2').sum()['payment_
```

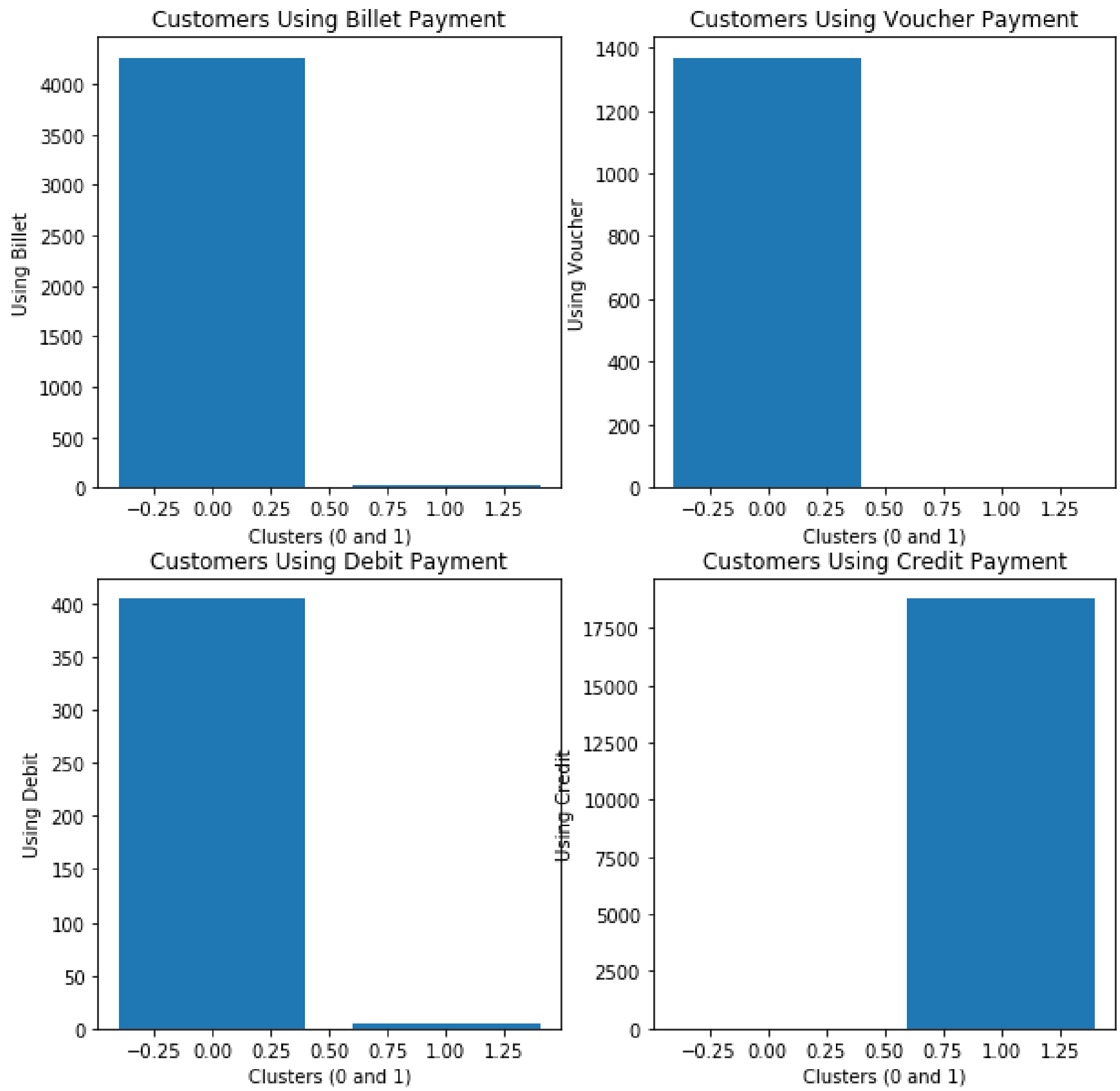
In [139]:
```
credit_labels_sum = poc_fetures_to_include_df.groupby('labels_k2').sum()['paymen
```

In [140]:

```
plt.rcParams['figure.figsize'] = (10, 10)
plt.subplots(4, 2)
plt.subplot(2, 2, 1)
#Plot the data:

plt.subplot(2, 2, 1)
plt.bar(billet_labels_sum.index,
        billet_labels_sum.values)
plt.title('Customers Using Billet Payment')
plt.xlabel('Clusters (0 and 1)')
plt.ylabel('Using Billet')

plt.subplot(2, 2, 2)
plt.bar(voucher_labels_sum.index,
        voucher_labels_sum.values)
plt.title('Customers Using Voucher Payment')
plt.xlabel('Clusters (0 and 1)')
plt.ylabel('Using Voucher')


plt.subplot(2, 2, 3)
plt.bar(debit_labels_sum.index,
        debit_labels_sum.values)
plt.title('Customers Using Debit Payment')
plt.xlabel('Clusters (0 and 1)')
plt.ylabel('Using Debit')

plt.subplot(2, 2, 4)
plt.bar(credit_labels_sum.index,
        credit_labels_sum.values)
plt.title('Customers Using Credit Payment')
plt.xlabel('Clusters (0 and 1)')
plt.ylabel('Using Credit')
```

Out[140]:

```
Text(0, 0.5, 'Using Credit')
```



From the information above, we can group the customers into two groups. First, who are willing to use more cashy methods like debit card and voucher, second group are willing to use more credit card.

Sentiment Analysis

In this part we want to make a sentiment prediction based on the customers' reviews using review scores. But, in this project the goal is make a prediction in a binary form (good or bad sentiment).

For training model, we used random forest.

In [141]:
```
order_reviews_df.head()
```

Out[141]:

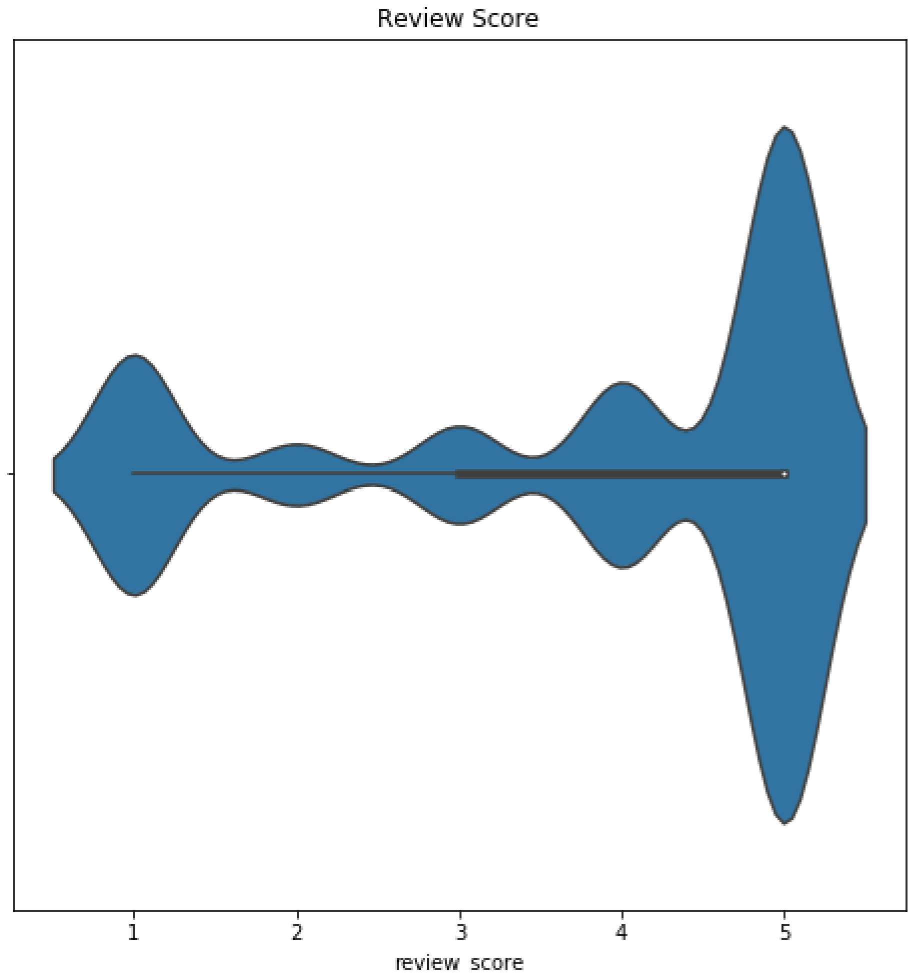
	review_id	order_id	review_score	review_co
0	7bc2406110b926393aa56f80a40eba40	73fc7af87114b39712e6da79b0a377eb	4	
1	80e641a11e56f04c1ad469d5645fdfde	a548910a1c6147796b98fdf73dbeba33	5	
2	228ce5500dc1d8e020d8d1322874b6f0	f9e4b658b201a9f2ecdecbb34bed034b	5	
3	e64fb393e7b32834bb789ff8bb30750e	658677c97b385a9be170737859d3511b	5	
4	f7c4243c7fe1938f181bec41a392bdeb	8e6bfb81e283fa7e4f11123a3fb894f1	5	

In [142]:
```
order_reviews_df.dropna(how = 'any', inplace = True)
```

In [143]:
```
order_reviews_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9986 entries, 9 to 99975
Data columns (total 7 columns):
review_id                  9986 non-null object
order_id                   9986 non-null object
review_score               9986 non-null int64
review_comment_title       9986 non-null object
review_comment_message     9986 non-null object
review_creation_date       9986 non-null object
review_answer_timestamp    9986 non-null object
dtypes: int64(1), object(6)
memory usage: 624.1+ KB
```

In [144]:
```
plt.figure(figsize = (8, 8))
sns.violinplot(order_reviews_df['review_score'])
plt.title("Review Score")
plt.show()
```



As we can see, most of the review score are above 3 stars. So we can change the rating more than 3 to 1 and the less than 3 to 0.

In [145]:
```
# define a new column to show us how long the review messages are:
order_reviews_df['review_length'] = order_reviews_df['review_comment_message'].ap
order_reviews_df.head()
```

Out[145]:

	review_id	order_id	review_score	review_c
9	8670d52e15e00043ae7de4c01cc2fe06	b9bf720beb4ab3728760088589c62129	4	
15	3948b09f7c818e2d86c9a546758b2335	e51478e7e277a83743b6f9991dbfa3fb	5	Sup
19	373cbeecea8286a2b66c97b1b157ec46	583174fbe37d3d5f0d6661be3aad1786	1	Nã
22	d21bbc789670eab777d27372ab9094cc	4fc44d78867142c627497b60a7e0228a	5	
34	c92cdd7dd544a01aa35137f901669cdf	37e7875cdce5a9e5b3a692971f370151	4	

Let's see the distribution of the review messeges length to see an average of the length of the reviews written by the customers for each purchase.

In [146]:
```
fig_len = px.histogram(order_reviews_df, x="review_length", nbins = 100, width =
fig_len.show()
```

> The plot above, shows a distribution of length of the reviews written by the customers. Most of the reviews are short that is about 2 to 10 words longer. Some people write more than 50 words, but they are few.

In [147]:
```
from sklearn.feature_extraction.text import CountVectorizer
```

In [148]:
```
cv = CountVectorizer(stop_words = 'english')
words = cv.fit_transform(order_reviews_df['review_comment_message']) #learn a voc
words_sum = words.sum(axis=0)


words_freq = [(word, words_sum[0, index]) for word, index in cv.vocabulary_.item
words_freq = sorted(words_freq, key = lambda x: x[1], reverse = True)
words_frequency = pd.DataFrame(words_freq, columns=['word', 'frequency'])
```

In [149]:
```
words_frequency.head()
```

Out[149]:

	word	frequency
0	produto	4573
1	não	2401
2	muito	2079
3	prazo	2064
4	que	2007

In [150]:
```
words_frequency.frequency.values[:10]
```

Out[150]:
```
array([4573, 2401, 2079, 2064, 2007, 1566, 1534, 1477, 1355, 1182],
      dtype=int64)
```

In [151]:
```
# The tranlation in this part is done manually for the first top 10 words
top_10_words_English = ['product', 'not', 'very', 'term','what','delivery','with

fig_10_words = go.Figure()

fig_10_words = px.bar(x = top_10_words_English,
             y = words_frequency.frequency.values[:10], width = 500, height = 50(

fig_10_words.update_layout(
    xaxis_title="word",
    yaxis_title="frequency",
    font=dict(
        family="Courier New, monospace",
        size=18,
        color="#7f7f7f"
             )
                 )
fig_10_words.show()
```

First, we train the model based on the review score from 1 to 5:

In [152]:

```
import spacy
import string
import re
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords

!python -m spacy download en_core_web_md

stopwords = stopwords.words('english')
punctuations = string.punctuation
nlp = spacy.load('en_core_web_sm')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Mona\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping corpora\stopwords.zip.


Collecting en_core_web_md==2.2.5 from https://github.com/explosion/spacy-model
s/releases/download/en_core_web_md-2.2.5/en_core_web_md-2.2.5.tar.gz#egg=en_cor
e_web_md==2.2.5 (https://github.com/explosion/spacy-models/releases/download/en
_core_web_md-2.2.5/en_core_web_md-2.2.5.tar.gz#egg=en_core_web_md==2.2.5)
  Downloading https://github.com/explosion/spacy-models/releases/download/en_co
re_web_md-2.2.5/en_core_web_md-2.2.5.tar.gz (https://github.com/explosion/spacy
-models/releases/download/en_core_web_md-2.2.5/en_core_web_md-2.2.5.tar.gz) (9
6.4MB)
Requirement already satisfied: spacy>=2.2.2 in c:\users\mona\anaconda3\lib\site
-packages (from en_core_web_md==2.2.5) (2.2.3)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in c:\users\mona\anaco
nda3\lib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (1.0.0)
Requirement already satisfied: catalogue<1.1.0,>=0.0.7 in c:\users\mona\anacond
a3\lib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (0.0.8)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in c:\users\mona\anaconda3\l
ib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (2.0.3)
Requirement already satisfied: wasabi<1.1.0,>=0.4.0 in c:\users\mona\anaconda3
\lib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (0.4.2)
Requirement already satisfied: setuptools in c:\users\mona\anaconda3\lib\site-p
ackages (from spacy>=2.2.2->en_core_web_md==2.2.5) (41.4.0)
Requirement already satisfied: requests<3.0.0,>=2.13.0 in c:\users\mona\anacond
a3\lib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (2.22.0)
Requirement already satisfied: thinc<7.4.0,>=7.3.0 in c:\users\mona\anaconda3\l
ib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (7.3.0)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in c:\users\mona\anaconda3
\lib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (3.0.2)
Requirement already satisfied: numpy>=1.15.0 in c:\users\mona\anaconda3\lib\sit
e-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (1.16.5)
Requirement already satisfied: blis<0.5.0,>=0.4.0 in c:\users\mona\anaconda3\li
b\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (0.4.1)
Requirement already satisfied: plac<1.2.0,>=0.9.6 in c:\users\mona\anaconda3\li
b\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (0.9.6)
Requirement already satisfied: srsly<1.1.0,>=0.1.0 in c:\users\mona\anaconda3\l
ib\site-packages (from spacy>=2.2.2->en_core_web_md==2.2.5) (0.2.0)
Requirement already satisfied: importlib-metadata>=0.20; python_version < "3.8"
in c:\users\mona\anaconda3\lib\site-packages (from catalogue<1.1.0,>=0.0.7->spa
cy>=2.2.2->en_core_web_md==2.2.5) (0.23)
```

```
Requirement already satisfied: idna<2.9,>=2.5 in c:\users\mona\anaconda3\lib\si
te-packages (from requests<3.0.0,>=2.13.0->spacy>=2.2.2->en_core_web_md==2.2.5)
(2.8)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in c:\us
ers\mona\anaconda3\lib\site-packages (from requests<3.0.0,>=2.13.0->spacy>=2.2.
2->en_core_web_md==2.2.5) (1.24.2)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\mona\anaconda3\li
b\site-packages (from requests<3.0.0,>=2.13.0->spacy>=2.2.2->en_core_web_md==2.
2.5) (2019.9.11)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in c:\users\mona\anaconda3
\lib\site-packages (from requests<3.0.0,>=2.13.0->spacy>=2.2.2->en_core_web_md=
=2.2.5) (3.0.4)
Requirement already satisfied: tqdm<5.0.0,>=4.10.0 in c:\users\mona\anaconda3\l
ib\site-packages (from thinc<7.4.0,>=7.3.0->spacy>=2.2.2->en_core_web_md==2.2.
5) (4.36.1)
Requirement already satisfied: zipp>=0.5 in c:\users\mona\anaconda3\lib\site-pa
ckages (from importlib-metadata>=0.20; python_version < "3.8"->catalogue<1.1.0,
>=0.0.7->spacy>=2.2.2->en_core_web_md==2.2.5) (0.6.0)
Requirement already satisfied: more-itertools in c:\users\mona\anaconda3\lib\si
te-packages (from zipp>=0.5->importlib-metadata>=0.20; python_version < "3.8"->
catalogue<1.1.0,>=0.0.7->spacy>=2.2.2->en_core_web_md==2.2.5) (7.2.0)
Building wheels for collected packages: en-core-web-md
  Building wheel for en-core-web-md (setup.py): started
  Building wheel for en-core-web-md (setup.py): finished with status 'done'
  Created wheel for en-core-web-md: filename=en_core_web_md-2.2.5-cp37-none-an
y.whl size=98051308 sha256=46c096160443e1c9b8d125ab9d12f1b1effeb15de059063f6b12
56be0dbce48b
  Stored in directory: C:\Users\Mona\AppData\Local\Temp\pip-ephem-wheel-cache-g
k4dykp2\wheels\df\94\ad\f5cf59224cea6b5686ac4fd1ad19c8a07bc026e13c36502d81
Successfully built en-core-web-md
Installing collected packages: en-core-web-md
Successfully installed en-core-web-md-2.2.5
[+] Download and installation successful
You can now load the model via spacy.load('en_core_web_md')
```

Define a function does cleaning our text and preparing for training:

In [153]:
```
def cleanup_text(docs, logging=False):
    texts = []
    counter = 1
    table = str.maketrans({key: None for key in string.punctuation})

    for doc in docs:
        if counter % 1000 == 0 and logging:
            print("Processed %d out of %d documents." % (counter, len(docs)))
        counter += 1
        doc = nlp(doc, disable=['parser', 'ner'])
        ###Convert text to lowercase, strip whitespace and remove personal prono
        tokens = [tok.lemma_.lower().strip() for tok in doc if tok.lemma_ != '-PI
        ###Remove stopwords
        tokens = [tok.translate(table) for tok in tokens if tok not in stopwords
        tokens = ' '.join(tokens)
        #Remove extra whitespace
        tokens = ' '.join(tokens.split())
        texts.append(tokens)
    return pd.Series(texts)
```

In [154]:
```
X = cleanup_text(order_reviews_df["review_comment_message"], logging=True)
```

```
Processed 1000 out of 9986 documents.
Processed 2000 out of 9986 documents.
Processed 3000 out of 9986 documents.
Processed 4000 out of 9986 documents.
Processed 5000 out of 9986 documents.
Processed 6000 out of 9986 documents.
Processed 7000 out of 9986 documents.
Processed 8000 out of 9986 documents.
Processed 9000 out of 9986 documents.
```

In [155]:
```
y = order_reviews_df['review_score'].values
```

In [156]:
```
from sklearn.feature_extraction.text import CountVectorizer
counter_vectorizer_model = CountVectorizer(max_features=4000, min_df=5, max_df=0
X_cv = counter_vectorizer_model.fit_transform(X).toarray()
```

In [157]:
```
#training and testing
X_train_cv, X_test_cv, y_train_cv, y_test_cv = train_test_split(X_cv, y, test_si

print(X_train_cv.shape)
print(y_train_cv.shape)
print(X_test_cv.shape)
print(y_test_cv.shape)
```

```
(7988, 1555)
(7988,)
(1998, 1555)
(1998,)
```

In [158]:
```
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train_cv, y_train_cv)

y_pred_cv = random_forest_model.predict(X_test_cv)

print("Training Accuracy using Counter Vectorizer :", random_forest_model.score(X
print("Testing Accuracy using Counter Vectorizer:", random_forest_model.score(X_t

conf_matrix = confusion_matrix(y_test_cv, y_pred_cv)
print(conf_matrix)
```

```
Training Accuracy using Counter Vectorizer : 0.9496745117676515
Testing Accuracy using Counter Vectorizer: 0.6526526526526526
[[294  10   7  10  37]
 [ 65   5   2   3  16]
 [ 68   5  12  14  47]
 [ 42   2  14  36 217]
 [ 52   1  10  72 957]]
```

We set the max_features parameter to 4000, which means that we want to use 4000 most occurring words (half of the whole datapoints) as features for training our classifier. Because the words that have a very low frequency of occurrence are not a good parameter for classifying documents. min_df is corresponding to the minumum number of documents that should contain this feature and max_df means that we should include only those words that occur in a maximum of 70% of all the documents.

> **TFIDF** Now we are going to use the TFIDF model to convert text documents into numerical data:

In [159]:
```
from sklearn.feature_extraction.text import TfidfTransformer
tfidfconverter = TfidfTransformer()
X_tfidf = tfidfconverter.fit_transform(X_cv).toarray()
```

In [160]:
```
#training and testing
X_train_tfidf, X_test_tfidf, y_train_tfidf, y_test_tfidf = train_test_split(X_tfi

print(X_train_tfidf.shape)
print(y_train_tfidf.shape)
print(X_test_tfidf.shape)
print(y_test_tfidf.shape)
```

```
(7988, 1555)
(7988,)
(1998, 1555)
(1998,)
```

In [161]:
```
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train_tfidf, y_train_tfidf)

y_pred_tfidf = random_forest_model.predict(X_test_tfidf)

print("Training Accuracy using TFIDF :", random_forest_model.score(X_train_tfidf
print("Testing Accuracy using TFIDF:", random_forest_model.score(X_test_tfidf, y_

conf_matrix = confusion_matrix(y_test_tfidf, y_pred_tfidf)
print(conf_matrix)
```

```
Training Accuracy using TFIDF : 0.9508012018027041
Testing Accuracy using TFIDF: 0.6756756756756757
[[ 304    5   14    3   32]
 [   58    6    4    3   20]
 [   72    1   10   11   52]
 [   46    2   11   23  229]
 [   42    1    7   35 1007]]
```

Let's see if we convert review score in a binary form (from 0 to 1) as opposed to 1 to 5, what happen to our model in terms of testing accuracy score. We set 0 if the review score is below than 3 otherwise is set to 1.

In [162]:
```
order_reviews_df['rating_binary'] = np.where(order_reviews_df['review_score'] >=
```

Now, set the y variable to the binary form and fit the model again to see the new results:

In [163]:
```
y_binary = order_reviews_df['rating_binary']
```

In [164]:
```
#training and testing
X_train_cv, X_test_cv, y_train_cv, y_test_cv = train_test_split(X_cv, y_binary, 

print(X_train_cv.shape)
print(y_train_cv.shape)
print(X_test_cv.shape)
print(y_test_cv.shape)
```

```
(7988, 1555)
(7988,)
(1998, 1555)
(1998,)
```

In [165]:
```
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train_cv, y_train_cv)

y_pred_cv = random_forest_model.predict(X_test_cv)

print("Training Accuracy using Counter Vectorizer :", random_forest_model.score(X
print("Testing Accuracy using Counter Vectorizer:", random_forest_model.score(X_t
```

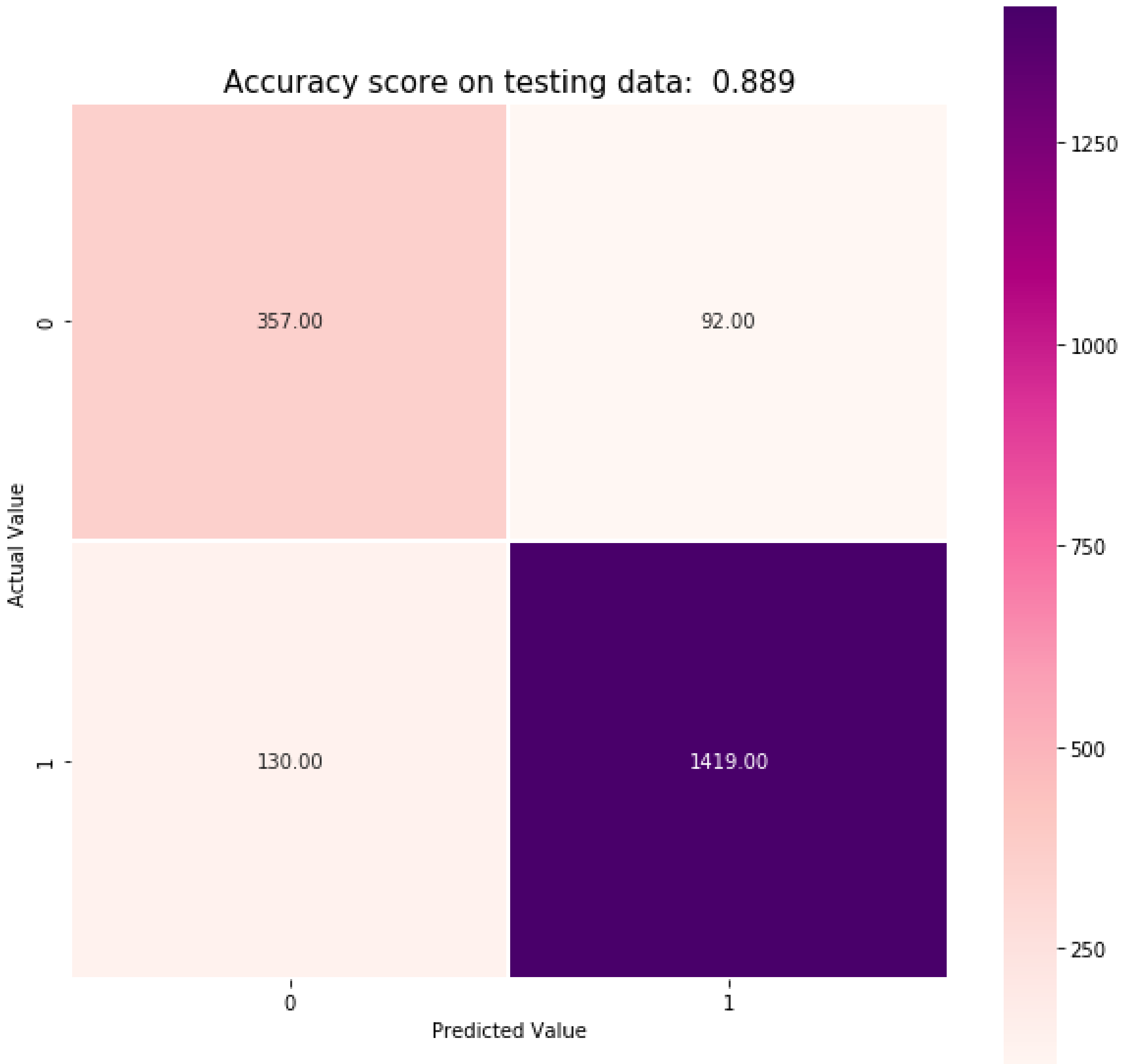
```
Training Accuracy using Counter Vectorizer : 0.991862794191287
Testing Accuracy using Counter Vectorizer: 0.8888888888888888
```

In [166]:
```
conf_matrix = confusion_matrix(y_test_cv, y_pred_cv)
print(conf_matrix)
```

```
[[ 357   92]
 [ 130 1419]]
```

In [167]:

```python
plt.figure(figsize = (10, 10));
ax = sns.heatmap(conf_matrix, annot = True, fmt = '.2f', linewidths = 1, square =
plt.xlabel('Predicted Value');
plt.ylabel('Actual Value');
plt.title(f"Accuracy score on testing data: {random_forest_model.score(X_test_cv,
bottom, top = ax.get_ylim();
ax.set_ylim(bottom + 0.5, top - 0.5);
```



In [168]:

```python
#training and testing
X_train_tfidf, X_test_tfidf, y_train_tfidf, y_test_tfidf = train_test_split(X_tf

print(X_train_tfidf.shape)
print(y_train_tfidf.shape)
print(X_test_tfidf.shape)
print(y_test_tfidf.shape)
```

```
(7988, 1555)
(7988,)
(1998, 1555)
(1998,)
```

In [169]:
```
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train_tfidf, y_train_tfidf)

y_pred_tfidf = random_forest_model.predict(X_test_tfidf)

print("Training Accuracy using TFIDF :", random_forest_model.score(X_train_tfidf
print("Testing Accuracy using TFIDF :", random_forest_model.score(X_test_tfidf, y
```

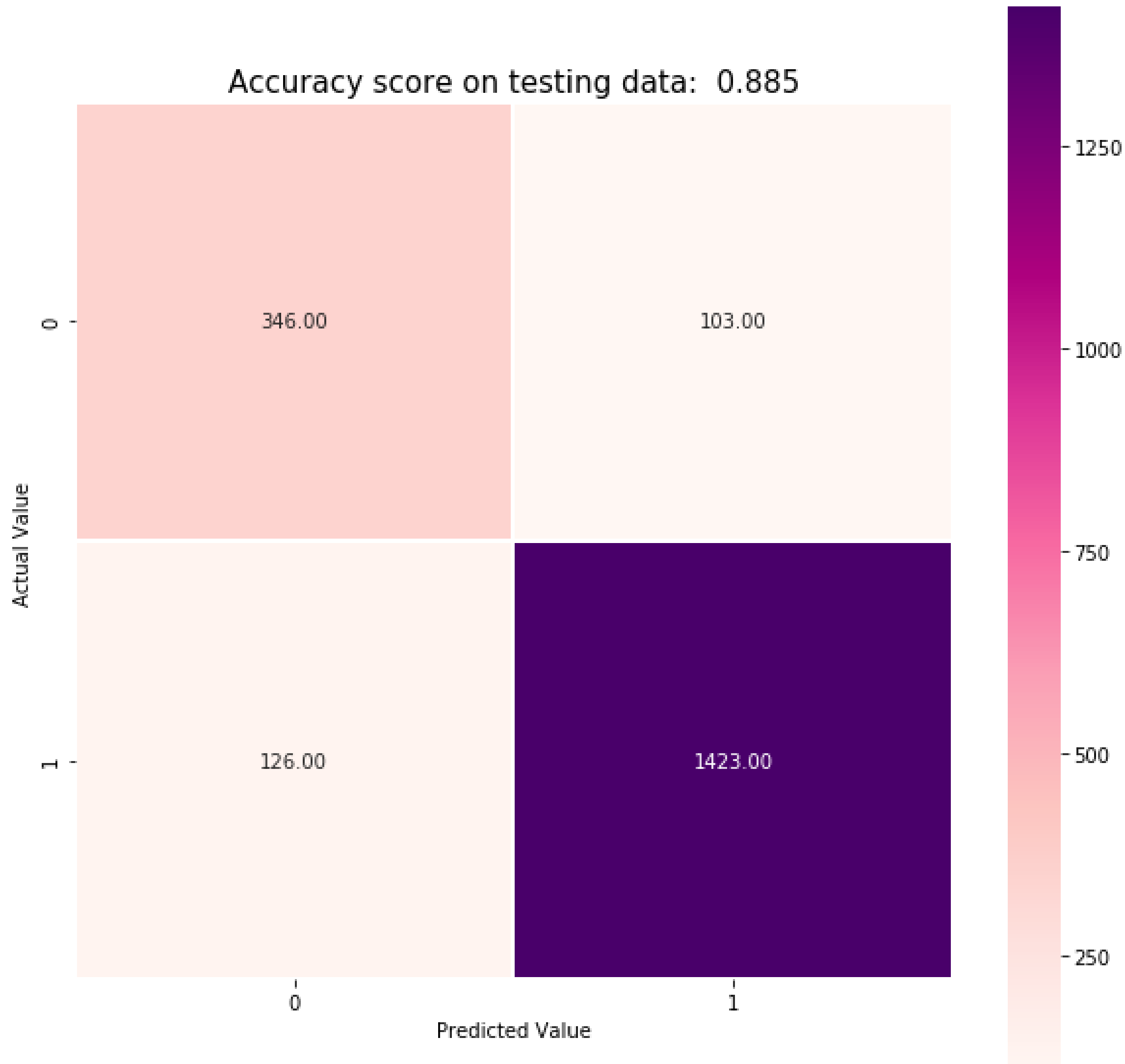
```
Training Accuracy using TFIDF : 0.9902353530295444
Testing Accuracy using TFIDF : 0.8853853853853854
```

In [170]:
```
conf_matrix = confusion_matrix(y_test_tfidf, y_pred_tfidf)
print(conf_matrix)
```

```
[[ 346  103]
 [ 126 1423]]
```

In [171]:

```
plt.figure(figsize = (10, 10));
ax = sns.heatmap(conf_matrix, annot = True, fmt = '.2f', linewidths = 1, square =
plt.xlabel('Predicted Value');
plt.ylabel('Actual Value');
plt.title(f"Accuracy score on testing data: {random_forest_model.score(X_test_tf
bottom, top = ax.get_ylim();
ax.set_ylim(bottom + 0.5, top - 0.5);
```



New results are extremely better than the previous model using 5 labels. So, we can have a prediction on reviews as a good or bad (0 or 1) review with 88% of accuracy.