CASE STUDY-1

1. Introduction

1.1 Business Problem

In the present system, the e-commerce platform will send a feedback mail to customers after the product is delivered. The customers can give ratings out of 5, also can write down some comments/reviews about the product that he/she has purchased. Using these reviews and ratings, e-commerce platform will rate the products, which helps other people to get the insights about the quality of the product. But according to seller perspective, these reviews will play crucial role to improve the business. But many times, customers would not give any ratings or reviews. How to predict the review score that a customer could give? This is the problem in e-commerce business. Also, the problem can be extended as “Is it possible to predict the review rating that a customer could give before actually he gives the rating?”. If this problem is solved, then it is also possible to predict the rating for which customer had not given any rating. In this case study, my objective is to try to solve this problem, that is Predicting the e-commerce customer satisfaction.

For this case study, I have taken the dataset given by Olist, which is an e-commerce platform in Brazil. Olist connects small businesses all over Brazil to customers with a single contract. Olist has provided over 100k order information that were placed between 2016 to 2018. Similar to all other e-commerce platforms, Olist also send feedback form to customers after the estimated delivery date to get the reviews and ratings. Now, Olist wants to improve the business as well as provide the better service to customers by using the customer satisfaction information. For that it needs to predict the review ratings before the user will give actual ratings. So, my approach is to address this business problem using data science, which is a scientific way to solve this business problem.

1.2 ML formulation of business problem:

To solve the business problem using data science, it is needed to pose that problem as classical machine learning problem. First of all, since the data has target variable, it is supervised ML problem. Further we need to predict the satisfaction of customers, that is predicting the ratings. Ratings are discrete ranging from 1 to 5. Hence it is a multi-class classification problem. We have 5 class labels, So, we can treat the problem as 5-class classification ML problem. Our goal is to predict the rating before the user give the rating/review. Hence, we should not consider data regarding review message, comments, etc as features.

1.3 Business constraints:

```
- There is no strict low latency requirement. But model should not take too much time for predicting, Since
 we should get the prediction before the user give.

- Low ratings like 1,2,3 are very important with respect to business improvement. So, misclassification of l
ow ratings would cost loss of customers. Hence misclassifications are crucial.

- Since low ratings are crucial, if we get the interpretations of the output, that will be better.
```

1.4 Performance Metrics: (possible)

- Multi-class confusion matrix
- Micro F1 score
- Precision Recall curve for each class
- Multi-class log loss
- Balanced accuracy score

1.5 Research-Papers/Solutions/Architectures/Kernels

- Existing solution: https://www.kaggle.com/andresionek/predicting-customer-satisfaction (https://www.kaggle.com/andresionek/predicting-customer-satisfaction)
- Repeat buyer prediction for e-commerce https://www.kdd.org/kdd2016/papers/files/adf0160-liuA.pdf (https://www.kdd.org/kdd2016/papers/files/adf0160-liuA.pdf)
- LightGBM Classifier: https://papers.nips.cc/paper/2017/file/6449f44a102fde848669bdd9eb6b76fa-Paper.pdf (https://papers.nips.cc/paper/2017/file/6449f44a102fde848669bdd9eb6b76fa-Paper.pdf)
- SMOTE technique: https://arxiv.org/pdf/1106.1813.pdf (https://arxiv.org/pdf/1106.1813.pdf)
- Blog on undersampling, oversampling, SMOTE, ensemble models: https://xang1234.github.io/louvain/ (https://xang1234.github.io/louvain/)
- https://imbalanced-learn.org/stable/references/generated/imblearn.over_sampling.SMOTE.html (https://imbalanced-learn.org/stable/references/generated/imblearn.over_sampling.SMOTE.html)
- https://machinelearningmastery.com/random-oversampling-and-undersampling-for-imbalanced-classification/ (https://machinelearningmastery.com/random-oversampling-and-undersampling-for-imbalanced-classification/)
- https://towardsdatascience.com/using-data-science-to-predict-negative-customer-reviews-2abbdfbf3d82 (https://towardsdatascience.com/using-data-science-to-predict-negative-customer-reviews-2abbdfbf3d82)

In [ ]:

2. Exploratory Data Analysis

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import folium

import datetime
```

2.1 Loading the data files

In [2]:

```
#loading all csv files
customer     = pd.read_csv("olist_customers_dataset.csv")
geo_location = pd.read_csv("olist_geolocation_dataset.csv")
items        = pd.read_csv("olist_order_items_dataset.csv")
payments     = pd.read_csv("olist_order_payments_dataset.csv")
reviews      = pd.read_csv("olist_order_reviews_dataset.csv")
orders       = pd.read_csv("olist_orders_dataset.csv")
products     = pd.read_csv("olist_products_dataset.csv")
sellers      = pd.read_csv("olist_sellers_dataset.csv")
translation  = pd.read_csv("product_category_name_translation.csv")
```

In [3]:

```
def overview(dataframe):
    """This function will return the overview of the dataframe"""

    print("Shape of the dataframe is : {}".format(dataframe.shape))
    print("**"*30)
    print("Information about features : ",dataframe.info())
    print("**"*30)
    print("Total number of null values : \n ",dataframe.isnull().sum())
    print("**"*30)

    return dataframe.head(3)
```

2.2 Overview of all data

In [4]:
```
overview(customer)
```

```
Shape of the dataframe is : (99441, 5)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99441 entries, 0 to 99440
Data columns (total 5 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   customer_id               99441 non-null  object
 1   customer_unique_id        99441 non-null  object
 2   customer_zip_code_prefix  99441 non-null  int64 
 3   customer_city             99441 non-null  object
 4   customer_state            99441 non-null  object
dtypes: int64(1), object(4)
memory usage: 3.8+ MB
Information about features :  None
************************************************************
Total number of null values :
  customer_id                 0
customer_unique_id          0
customer_zip_code_prefix    0
customer_city               0
customer_state              0
dtype: int64
************************************************************
```

Out[4]:

	customer_id	customer_unique_id	customer_zip_code_prefix	customer_city	customer_s
0	06b8999e2fba1a1fbc88172c00ba8bc7	861eff4711a542e4b93843c6dd7febb0	14409	franca	
1	18955e83d337fd6b2def6b18a428ac77	290c77bc529b7ac935b93aa66c333dc3	9790	sao bernardo do campo	
2	4e7b3e00288586ebd08712fdd0374a03	060e732b5b29e8181a18229c7b0b2b5e	1151	sao paulo	

In [5]:
```
overview(geo_location)
```

```
Shape of the dataframe is : (1000163, 5)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000163 entries, 0 to 1000162
Data columns (total 5 columns):
 #   Column                       Non-Null Count    Dtype  
---  ------                       --------------    -----  
 0   geolocation_zip_code_prefix  1000163 non-null  int64  
 1   geolocation_lat              1000163 non-null  float64
 2   geolocation_lng              1000163 non-null  float64
 3   geolocation_city             1000163 non-null  object 
 4   geolocation_state            1000163 non-null  object 
dtypes: float64(2), int64(1), object(2)
memory usage: 38.2+ MB
Information about features :  None
************************************************************
Total number of null values :
  geolocation_zip_code_prefix    0
geolocation_lat                0
geolocation_lng                0
geolocation_city               0
geolocation_state              0
dtype: int64
************************************************************
```

Out[5]:

	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

In [6]:
```
overview(items)
```

```
Shape of the dataframe is : (112650, 7)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112650 entries, 0 to 112649
Data columns (total 7 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   order_id             112650 non-null  object 
 1   order_item_id        112650 non-null  int64  
 2   product_id           112650 non-null  object 
 3   seller_id            112650 non-null  object 
 4   shipping_limit_date  112650 non-null  object 
 5   price                112650 non-null  float64
 6   freight_value        112650 non-null  float64
dtypes: float64(2), int64(1), object(4)
memory usage: 6.0+ MB
Information about features :  None
************************************************************
Total number of null values :
  order_id               0
order_item_id          0
product_id             0
seller_id              0
shipping_limit_date    0
price                  0
freight_value          0
dtype: int64
************************************************************
```

Out[6]:

	order_id	order_item_id	product_id	seller_id	sh
0	00010242fe8c5a6d1ba2dd792cb16214	1	4244733e06e7ecb4970a6e2683c13e61	48436dade18ac8b2bce089ec2a041202	2
1	00018f77f2f0320c557190d7a144bdd3	1	e5f2d52b802189ee658865ca93d83a8f	dd7ddc04e1b6c2c614352b383efe2d36	2
2	000229ec398224ef6ca0657da4fc703e	1	c777355d18b72b67abbeef9df44fd0fd	5b51032eddd242adc84c38acab88f23d	2

In [7]:
```
overview(payments)
```

```
Shape of the dataframe is : (103886, 5)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103886 entries, 0 to 103885
Data columns (total 5 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   order_id              103886 non-null  object 
 1   payment_sequential    103886 non-null  int64  
 2   payment_type          103886 non-null  object 
 3   payment_installments  103886 non-null  int64  
 4   payment_value         103886 non-null  float64
dtypes: float64(1), int64(2), object(2)
memory usage: 4.0+ MB
Information about features :  None
************************************************************
Total number of null values :
  order_id                0
payment_sequential      0
payment_type            0
payment_installments    0
payment_value           0
dtype: int64
************************************************************
```

Out[7]:

	order_id	payment_sequential	payment_type	payment_installments	payment_value
0	b81ef226f3fe1789b1e8b2acac839d17	1	credit_card	8	99.33
1	a9810da82917af2d9aefd1278f1dcfa0	1	credit_card	1	24.39
2	25e8ea4e93396b6fa0d3dd708e76c1bd	1	credit_card	1	65.71

In [8]:
```
overview(reviews)
```

```
Shape of the dataframe is : (100000, 7)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 7 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   review_id                100000 non-null  object
 1   order_id                 100000 non-null  object
 2   review_score             100000 non-null  int64
 3   review_comment_title     11715 non-null   object
 4   review_comment_message   41753 non-null   object
 5   review_creation_date     100000 non-null  object
 6   review_answer_timestamp  100000 non-null  object
dtypes: int64(1), object(6)
memory usage: 5.3+ MB
Information about features :  None
************************************************************
Total number of null values :
  review_id                      0
order_id                       0
review_score                   0
review_comment_title       88285
review_comment_message     58247
review_creation_date           0
review_answer_timestamp        0
dtype: int64
************************************************************
```

Out[8]:

	review_id	order_id	review_score	review_comment_title	review_comment_
0	7bc2406110b926393aa56f80a40eba40	73fc7af87114b39712e6da79b0a377eb	4	NaN	
1	80e641a11e56f04c1ad469d5645fdfde	a548910a1c6147796b98fdf73dbeba33	5	NaN	
2	228ce5500dc1d8e020d8d1322874b6f0	f9e4b658b201a9f2ecdecbb34bed034b	5	NaN	

In [9]:
```
overview(orders)
```

```
Shape of the dataframe is : (99441, 8)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99441 entries, 0 to 99440
Data columns (total 8 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   order_id                       99441 non-null  object
 1   customer_id                    99441 non-null  object
 2   order_status                   99441 non-null  object
 3   order_purchase_timestamp       99441 non-null  object
 4   order_approved_at              99281 non-null  object
 5   order_delivered_carrier_date   97658 non-null  object
 6   order_delivered_customer_date  96476 non-null  object
 7   order_estimated_delivery_date  99441 non-null  object
dtypes: object(8)
memory usage: 6.1+ MB
Information about features :  None
************************************************************
Total number of null values :
  order_id                           0
customer_id                        0
order_status                       0
order_purchase_timestamp           0
order_approved_at                160
order_delivered_carrier_date     1783
order_delivered_customer_date    2965
order_estimated_delivery_date      0
dtype: int64
************************************************************
```

Out[9]:

	order_id	customer_id	order_status	order_purchase_timestamp	order_approv
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	2017-10-02 10:56:33	2017 11
1	53cdb2fc8bc7dce0b6741e2150273451	b0830fb4747a6c6d20dea0b8c802d7ef	delivered	2018-07-24 20:41:37	2018 03
2	47770eb9100c2d0c44946d9cf07ec65d	41ce2a54c0b03bf3443c3d931a367089	delivered	2018-08-08 08:38:49	2018 08

In [10]:
```
overview(products)
```

```
Shape of the dataframe is : (32951, 9)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32951 entries, 0 to 32950
Data columns (total 9 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   product_id                  32951 non-null  object 
 1   product_category_name       32341 non-null  object 
 2   product_name_lenght         32341 non-null  float64
 3   product_description_lenght  32341 non-null  float64
 4   product_photos_qty          32341 non-null  float64
 5   product_weight_g            32949 non-null  float64
 6   product_length_cm           32949 non-null  float64
 7   product_height_cm           32949 non-null  float64
 8   product_width_cm            32949 non-null  float64
dtypes: float64(7), object(2)
memory usage: 2.3+ MB
Information about features :  None
************************************************************
Total number of null values :
  product_id                      0
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
************************************************************
```

Out[10]:

	product_id	product_category_name	product_name_lenght	product_description_lenght	product_photos
0	1e9e8ef04dbcff4541ed26657ea517e5	perfumaria	40.0	287.0	
1	3aa071139cb16b67ca9e5dea641aaa2f	artes	44.0	276.0	
2	96bd76ec8810374ed1b65e291975717f	esporte_lazer	46.0	250.0	

In [11]:
```
overview(sellers)
```

```
Shape of the dataframe is : (3095, 4)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3095 entries, 0 to 3094
Data columns (total 4 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   seller_id               3095 non-null   object
 1   seller_zip_code_prefix  3095 non-null   int64 
 2   seller_city             3095 non-null   object
 3   seller_state            3095 non-null   object
dtypes: int64(1), object(3)
memory usage: 96.8+ KB
Information about features :  None
************************************************************
Total number of null values :
  seller_id                 0
seller_zip_code_prefix    0
seller_city               0
seller_state              0
dtype: int64
************************************************************
```

Out[11]:

	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

In [12]:
```
overview(translation)
```

```
Shape of the dataframe is : (71, 2)
************************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71 entries, 0 to 70
Data columns (total 2 columns):
 #   Column                         Non-Null Count  Dtype 
---  ------                         --------------  ----- 
 0   product_category_name          71 non-null     object
 1   product_category_name_english  71 non-null     object
dtypes: object(2)
memory usage: 1.2+ KB
Information about features :  None
************************************************************
Total number of null values :
  product_category_name            0
product_category_name_english    0
dtype: int64
************************************************************
```

Out[12]:

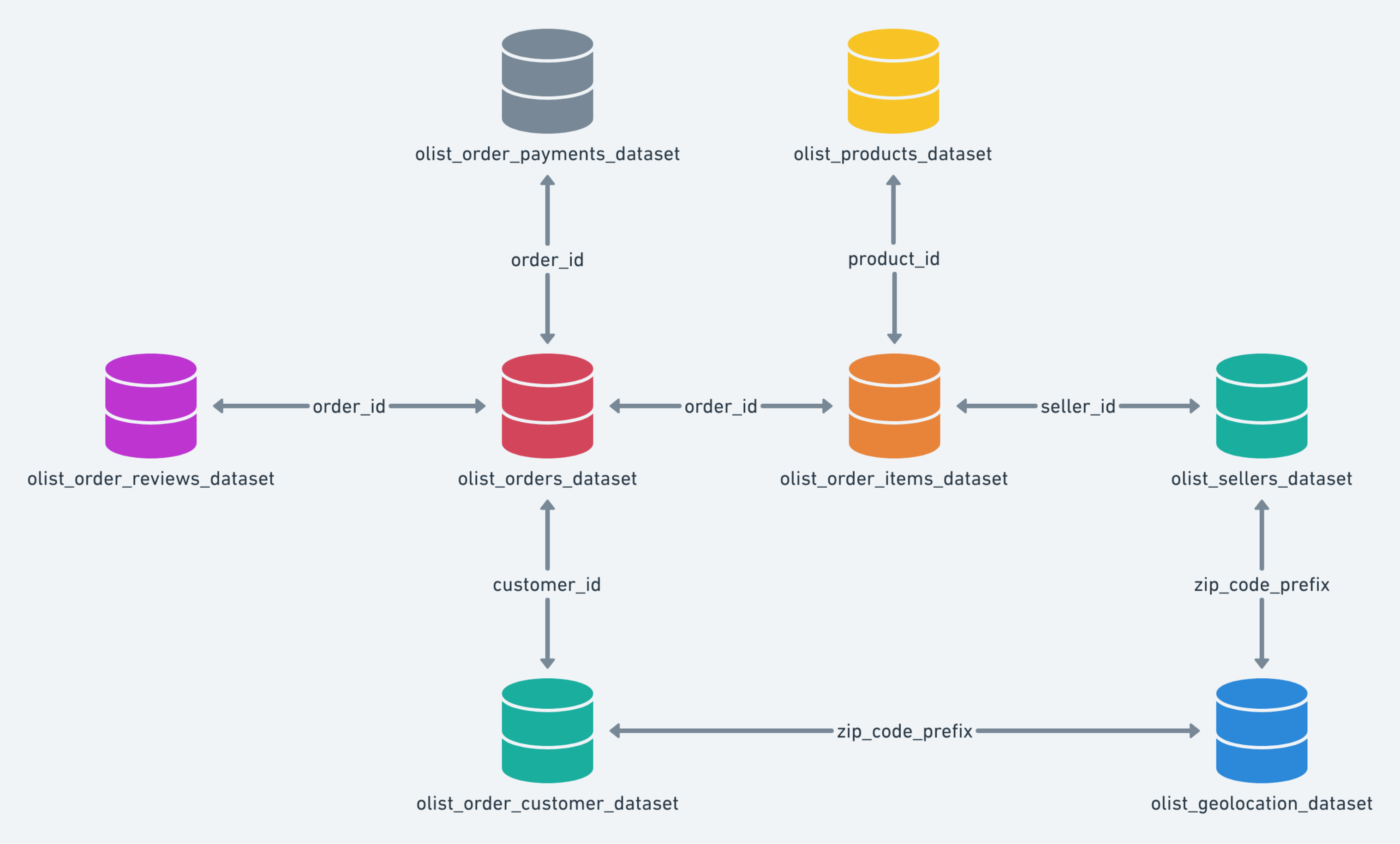
	product_category_name	product_category_name_english
0	beleza_saude	health_beauty
1	informatica_acessorios	computers_accessories
2	automotivo	auto

Observations:

```
* There are null values present in reviews data, orders data, product data. Rest of the dataframes do not ha
ve any null values.
* Translation data has the product category names in english, i.e. english version of product categories. So
we can use this to get the product category names in english.
* geo_location data has 1000163 data points, which seems very large compare to the data points of other data
frames. There is possibility of duplicate points present in geo_locations.
* To get the complete informations, we need to merge these sub dataframes to get single dataframe. Merging s
hould be done according to the data schema that is given below.
```

2.3 Merge the dataframes

Data schema



In [13]:
```
#zip_code_prefix column has different names in customer,geo_location,sellers dataframes
#Change these names to zip_code_prefix

customer.rename(columns = {"customer_zip_code_prefix":"zip_code_prefix"},inplace=True)
geo_location.rename(columns = {"geolocation_zip_code_prefix":"zip_code_prefix"},inplace=True)
sellers.rename(columns = {"seller_zip_code_prefix":"zip_code_prefix"},inplace=True)
```

In [14]:
```
#drop the duplicate values in geo_location (zip_code_prefix)

print("Number of rows before dropping duplicates in geo_location : ",geo_location.shape[0])
geo_location.drop_duplicates(subset="zip_code_prefix",keep="first",inplace=True)
print("Number of rows after dropping duplicates in geo_locations : ",geo_location.shape[0])
```

```
Number of rows before dropping duplicates in geo_location :  1000163
Number of rows after dropping duplicates in geo_locations :  19015
```

In [ ]:

In [15]:
```
#customer merging with geo_location (left join to preserve customer info)
geo_customer     = pd.merge(customer,geo_location,how="left",on="zip_code_prefix")

#sellers merging with geo_locations (left join to preserve sellers info)
geo_seller       = pd.merge(sellers,geo_location,how="left",on="zip_code_prefix")

#payment merging with order
payment_order    = pd.merge(payments,orders,on="order_id")

#product merging with item
product_item     = pd.merge(products,items,on="product_id")

#payment_order merging with reviews
pay_order_review = pd.merge(payment_order,reviews,on="order_id")

#pay_order_review merging with geo_customer
review_customer  = pd.merge(pay_order_review,geo_customer,on="customer_id")

#prod_item merging with geo_seller
prod_item_seller = pd.merge(product_item,geo_seller,on="seller_id")

#Finally review_customer with prod_item_seller
data             = pd.merge(review_customer,prod_item_seller,on="order_id",suffixes=("_customer","_sell
er"))
```

In [16]:
```
num_tot_rows = data.shape[0]
print("Shape of the final dataframe (data) is : ",data.shape)
```

```
Shape of the final dataframe (data) is :  (118315, 47)
```

In [ ]:

2.4 Data Cleaning

In [17]:
```
print("All the column names in the data : \n",data.columns)
```

```
All the column names in the data :
 Index(['order_id', 'payment_sequential', 'payment_type',
       'payment_installments', 'payment_value', 'customer_id', 'order_status',
       'order_purchase_timestamp', 'order_approved_at',
       'order_delivered_carrier_date', 'order_delivered_customer_date',
       'order_estimated_delivery_date', 'review_id', 'review_score',
       'review_comment_title', 'review_comment_message',
       'review_creation_date', 'review_answer_timestamp', 'customer_unique_id',
       'zip_code_prefix_customer', 'customer_city', 'customer_state',
       'geolocation_lat_customer', 'geolocation_lng_customer',
       'geolocation_city_customer', 'geolocation_state_customer', 'product_id',
       'product_category_name', 'product_name_lenght',
       'product_description_lenght', 'product_photos_qty', 'product_weight_g',
       'product_length_cm', 'product_height_cm', 'product_width_cm',
       'order_item_id', 'seller_id', 'shipping_limit_date', 'price',
       'freight_value', 'zip_code_prefix_seller', 'seller_city',
       'seller_state', 'geolocation_lat_seller', 'geolocation_lng_seller',
       'geolocation_city_seller', 'geolocation_state_seller'],
      dtype='object')
```

We should only use the informations which are upto the product delivery. We don't use the review text, comment,review creation date like features for the prediction. Hence it is better to drop these columns now.

In [18]:
```
data.drop(['review_id','review_comment_title', 'review_comment_message',
          'review_creation_date','review_answer_timestamp'],axis=1,inplace=True)
```

In [19]:
```
#Checking for nul values
data.isnull().sum()
```

Out[19]:
```
order_id                            0
payment_sequential                  0
payment_type                        0
payment_installments                0
payment_value                       0
customer_id                         0
order_status                        0
order_purchase_timestamp            0
order_approved_at                  15
order_delivered_carrier_date     1254
order_delivered_customer_date    2588
order_estimated_delivery_date       0
review_score                        0
customer_unique_id                  0
zip_code_prefix_customer            0
customer_city                       0
customer_state                      0
geolocation_lat_customer          317
geolocation_lng_customer          317
geolocation_city_customer         317
geolocation_state_customer        317
product_id                          0
product_category_name            1709
product_name_lenght              1709
product_description_lenght       1709
product_photos_qty               1709
product_weight_g                   20
product_length_cm                  20
product_height_cm                  20
product_width_cm                   20
order_item_id                       0
seller_id                           0
shipping_limit_date                 0
price                               0
freight_value                       0
zip_code_prefix_seller              0
seller_city                         0
seller_state                        0
geolocation_lat_seller            265
geolocation_lng_seller            265
geolocation_city_seller           265
geolocation_state_seller          265
dtype: int64
```

In [20]:
```
data["order_status"].value_counts()
```

Out[20]:
```
delivered      115728
shipped          1255
canceled          570
invoiced          376
processing        376
unavailable         7
approved            3
Name: order_status, dtype: int64
```

In [21]:
```
not_delivered = data[data["order_status"]!="delivered"]["order_status"].value_counts().sum()

print("Total number of orders which are not delivered : ",not_delivered)
print("percentage of orders which are not delivered : ", (not_delivered*100/data.shape[0]).round(3),"%"
)
```

```
Total number of orders which are not delivered :  2587
percentage of orders which are not delivered :  2.187 %
```

In [22]:
```
#We are interested in products that are delivered.
#We don't need the products which are not delivered yet/ cancelled. hence let's consider only delivered orders.
# Also there are only 2.2% of data which are not delivered.

data = data[data["order_status"]=="delivered"]
```

In [23]:
```
#Since we cannot impute datetime, lets drop the rows which has null values in order_approved_at,order_delivered_carrier_date,order_delivered_customer_date
#These columns has very little number of null values.
data.dropna(subset=["order_approved_at","order_delivered_carrier_date","order_delivered_customer_date"],axis=0,inplace=True)
```

In [24]:
```
data.isnull().sum()
```

Out[24]:
```
order_id                          0
payment_sequential                0
payment_type                      0
payment_installments              0
payment_value                     0
customer_id                       0
order_status                      0
order_purchase_timestamp          0
order_approved_at                 0
order_delivered_carrier_date      0
order_delivered_customer_date     0
order_estimated_delivery_date     0
review_score                      0
customer_unique_id                0
zip_code_prefix_customer          0
customer_city                     0
customer_state                    0
geolocation_lat_customer        303
geolocation_lng_customer        303
geolocation_city_customer       303
geolocation_state_customer      303
product_id                        0
product_category_name          1637
product_name_lenght            1637
product_description_lenght     1637
product_photos_qty             1637
product_weight_g                 20
product_length_cm                20
product_height_cm                20
product_width_cm                 20
order_item_id                     0
seller_id                         0
shipping_limit_date               0
price                             0
freight_value                     0
zip_code_prefix_seller            0
seller_city                       0
seller_state                      0
geolocation_lat_seller          261
geolocation_lng_seller          261
geolocation_city_seller         261
geolocation_state_seller        261
dtype: int64
```

In [ ]:

There are 261 rows in which seller location informations are null. Similarly 303 rows in which customer locatons are null.
We cannot impute these values, also these numbers are small, Hence we can drop these.

In [25]:
```
data.dropna(subset=["geolocation_lng_seller","geolocation_state_customer"],axis=0,inplace=True)
```

In [26]:
```
data.isnull().sum()
```

Out[26]:
```
order_id                             0
payment_sequential                   0
payment_type                         0
payment_installments                 0
payment_value                        0
customer_id                          0
order_status                         0
order_purchase_timestamp             0
order_approved_at                    0
order_delivered_carrier_date         0
order_delivered_customer_date        0
order_estimated_delivery_date        0
review_score                         0
customer_unique_id                   0
zip_code_prefix_customer             0
customer_city                        0
customer_state                       0
geolocation_lat_customer             0
geolocation_lng_customer             0
geolocation_city_customer            0
geolocation_state_customer           0
product_id                           0
product_category_name             1631
product_name_lenght               1631
product_description_lenght        1631
product_photos_qty                1631
product_weight_g                    20
product_length_cm                   20
product_height_cm                   20
product_width_cm                    20
order_item_id                        0
seller_id                            0
shipping_limit_date                  0
price                                0
freight_value                        0
zip_code_prefix_seller               0
seller_city                          0
seller_state                         0
geolocation_lat_seller               0
geolocation_lng_seller               0
geolocation_city_seller              0
geolocation_state_seller             0
dtype: int64
```

In [ ]:

In [27]:
```
data.dropna(subset=["product_photos_qty","product_width_cm"],axis=0,inplace=True)
```

In [28]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 113509 entries, 0 to 118314
Data columns (total 42 columns):
 #   Column                         Non-Null Count   Dtype  
---  ------                         --------------   -----  
 0   order_id                       113509 non-null  object 
 1   payment_sequential             113509 non-null  int64  
 2   payment_type                   113509 non-null  object 
 3   payment_installments           113509 non-null  int64  
 4   payment_value                  113509 non-null  float64
 5   customer_id                    113509 non-null  object 
 6   order_status                   113509 non-null  object 
 7   order_purchase_timestamp       113509 non-null  object 
 8   order_approved_at              113509 non-null  object 
 9   order_delivered_carrier_date   113509 non-null  object 
 10  order_delivered_customer_date  113509 non-null  object 
 11  order_estimated_delivery_date  113509 non-null  object 
 12  review_score                   113509 non-null  int64  
 13  customer_unique_id             113509 non-null  object 
 14  zip_code_prefix_customer       113509 non-null  int64  
 15  customer_city                  113509 non-null  object 
 16  customer_state                 113509 non-null  object 
 17  geolocation_lat_customer       113509 non-null  float64
 18  geolocation_lng_customer       113509 non-null  float64
 19  geolocation_city_customer      113509 non-null  object 
 20  geolocation_state_customer     113509 non-null  object 
 21  product_id                     113509 non-null  object 
 22  product_category_name          113509 non-null  object 
 23  product_name_lenght            113509 non-null  float64
 24  product_description_lenght     113509 non-null  float64
 25  product_photos_qty             113509 non-null  float64
 26  product_weight_g               113509 non-null  float64
 27  product_length_cm              113509 non-null  float64
 28  product_height_cm              113509 non-null  float64
 29  product_width_cm               113509 non-null  float64
 30  order_item_id                  113509 non-null  int64  
 31  seller_id                      113509 non-null  object 
 32  shipping_limit_date            113509 non-null  object 
 33  price                          113509 non-null  float64
 34  freight_value                  113509 non-null  float64
 35  zip_code_prefix_seller         113509 non-null  int64  
 36  seller_city                    113509 non-null  object 
 37  seller_state                   113509 non-null  object 
 38  geolocation_lat_seller         113509 non-null  float64
 39  geolocation_lng_seller         113509 non-null  float64
 40  geolocation_city_seller        113509 non-null  object 
 41  geolocation_state_seller       113509 non-null  object 
dtypes: float64(14), int64(6), object(22)
memory usage: 37.2+ MB
```

In [29]:
```
data.shape
```

Out[29]:
```
(113509, 42)
```

In [30]:
```
# % of data that we have drooped
print("Percentage of data that we have dropped is : ",round((num_tot_rows-data.shape[0])*100/num_tot_ro
ws,3),"%")
```

```
Percentage of data that we have dropped is :  4.062 %
```

So we have lost roughly 4% of data, which is not bad. Because we have 96% of data which don't have nul values.

In [31]:
```
data[data.duplicated()==True]
```

Out[31]:

	order_id	payment_sequential	payment_type	payment_installments	payment_value	
4	ba78997921bbcdc1373bb41e913ab953	1	credit_card	8	107.78	7a5d8efa
66	c0db7d31ace61fc360a3eaa34dd3457c	1	credit_card	5	65.71	80c0276f
74	95442deb81a5d91c97c0df96b431634a	1	boleto	1	368.98	daddb54
75	95442deb81a5d91c97c0df96b431634a	1	boleto	1	368.98	daddb54
188	14d9794bbb53614d12cc2df6a045f82b	1	boleto	1	116.70	666a4eb7
...	...	...	...	...	...	
116252	b9eb9fbcca54dfce1d087c752d0f4b35	1	boleto	1	35.01	38243190
117353	f7c5c5ff5045e13c98901bbbf8e871d4	1	credit_card	10	231.27	1d5f730
117453	169ab175fb915582d84c0c5c95bb0fe3	1	credit_card	10	741.10	fe02528a
117624	03515a836bb855b03f7df9dee520a8fc	1	credit_card	10	106.38	153e6d88
117883	c88b1d1b157a9999ce368f218a407141	1	credit_card	4	42.77	ae0fb7b

401 rows × 42 columns

In [32]:
```
#remove the duplicates
data.drop_duplicates(keep="first",inplace=True)
```

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

Out[33]: (113108, 42)

In [34]:
```
#lets change the datetime features to correct format
data["order_purchase_timestamp"] = pd.to_datetime(data["order_purchase_timestamp"])
data["order_approved_at"] = pd.to_datetime(data["order_approved_at"])
data["order_delivered_carrier_date"] = pd.to_datetime(data["order_delivered_carrier_date"])
data["order_delivered_customer_date"] = pd.to_datetime(data["order_delivered_customer_date"])
data["order_estimated_delivery_date"] = pd.to_datetime(data["order_estimated_delivery_date"])
data["shipping_limit_date"] = pd.to_datetime(data["shipping_limit_date"])
```

I found some problem with seller_city, seller_state information in sellers dataframe.

In [35]:
```
data[data["geolocation_state_seller"]!=data["seller_state"]]
```
Out[35]:

	order_id	payment_sequential	payment_type	payment_installments	payment_value	
53	1dcf0c8cd36ffaf57784fbdc90079310	1	credit_card	3	157.15	34955e04
238	591083bc42b589c7052118aa83118e76	5	voucher	1	20.00	276df8ef
240	591083bc42b589c7052118aa83118e76	3	voucher	1	20.00	276df8ef
242	591083bc42b589c7052118aa83118e76	2	voucher	1	20.00	276df8ef
244	591083bc42b589c7052118aa83118e76	6	voucher	1	15.21	276df8ef
...	...	...	...	...	...	
117074	d3037ef55ee7f4d6c892da7493f4912f	1	credit_card	5	154.47	a92c7dc3
117345	15cd24278cb6a373aa6bb2ca34837e16	1	boleto	1	24.60	61a5483
117599	cab69d0a36811c4945aec2d4f744c8b5	1	credit_card	10	230.19	2468eac8
117658	652dd239023471248957a1a2d5173b60	1	credit_card	3	140.44	35cc89fc7
117984	6e9583ad9400699e091e33534fa84aa4	1	credit_card	3	236.29	89fe9585

653 rows × 42 columns

There are 653 record in which seller_state and geo_location_state_seller are not matching. So, let us look deeply about this issue.

In [36]:
```
geo_location[(geo_location["geolocation_state"]=="SC") & (geo_location["geolocation_city"]=="itajai")]
```
Out[36]:

	zip_code_prefix	geolocation_lat	geolocation_lng	geolocation_city	geolocation_state
909293	88310	-26.891052	-48.701608	itajai	SC
909296	88309	-26.895500	-48.687952	itajai	SC
909297	88306	-26.935823	-48.627747	itajai	SC
909300	88311	-26.877642	-48.705441	itajai	SC
909307	88302	-26.920172	-48.657852	itajai	SC
909318	88317	-26.876740	-48.750403	itajai	SC
909319	88308	-26.928509	-48.700390	itajai	SC
909322	88303	-26.912429	-48.677381	itajai	SC
909332	88304	-26.899380	-48.679729	itajai	SC
909374	88312	-26.908691	-48.703615	itajai	SC
909405	88316	-26.945308	-48.718467	itajai	SC
910010	88318	-27.037284	-48.861505	itajai	SC
912083	88313	-26.971308	-48.683232	itajai	SC

In [37]:
```
geo_location[(geo_location["geolocation_state"]=="SP") & (geo_location["geolocation_city"]=="itajai")]
```
Out[37]:

zip_code_prefix	geolocation_lat	geolocation_lng	geolocation_city	geolocation_state

In [38]:
```
sellers[(sellers["seller_state"]=="SP") & (sellers["seller_city"]=="itajai")]
```

Out[38]:

	seller_id	zip_code_prefix	seller_city	seller_state
1303	0bae85eb84b9fb3bd773911e89288d54	88301	itajai	SP
1449	52b53f7061969fe471d119b6195da864	88301	itajai	SP

In [ ]:

So, I googled the actual city of itajai, Brazil. Actually state is SC (Santa Catarina). Not SP (São Paulo).
So,sellers data contains wrong information about this.

geo_location is accurate.

Hence it is better to drop seller_state, seller_city, since we have the correct information in geolocation data.i.e. geolocation_state_seller, geo_location_city_seller.

Since seller data has some wrong info, let us check customer data also.

In [39]:
```
data[data["geolocation_state_customer"]!=data["customer_state"]]
```

Out[39]:

order_id	payment_sequential	payment_type	payment_installments	payment_value	customer_id	order_status	order_purchase

0 rows × 42 columns

In [40]:
```
data[data["geolocation_city_customer"]!=data["customer_city"]][["geolocation_city_customer","customer_c
ity"]]
```

Out[40]:

	geolocation_city_customer	customer_city
57	jaguariúna	jaguariuna
58	guaraí	guarai
59	guaraí	guarai
60	guaraí	guarai
76	são lourenço	sao lourenco
...	...	...
118147	picuí	picui
118157	brasília	brasilia
118250	são paulo	sao paulo
118273	maringá	maringa
118291	são paulo	sao paulo

8254 rows × 2 columns

We can see that customer_state and geolocation_customer_state are same.
But in city names, customer_city names are in english. But geolocation_city_customer has different notation. But names are same.
Here we shall drop customer_city, since geolocation_city_customer has same notations as all seller_city has.

In [41]:
```
data.drop(["seller_state","seller_city","customer_city","customer_state"],axis=1,inplace=True)

data.rename(columns =
                    {"geolocation_state_seller":"seller_state","geolocation_city_seller":"seller_city",
                    "geolocation_lng_seller":"lng_seller","geolocation_lat_seller":"lat_seller",
                    "geolocation_lng_customer":"lng_customer","geolocation_lat_customer":"lat_customer"
,
                    "geolocation_city_customer":"customer_city","geolocation_state_customer":"customer_
state"}
            ,inplace=True)
```

**There are 3 records in the data, which has 0 installment. This is weird. Also these 3 records present in rating 5.
Let us drop these 3 records with installment = 0.**

In [42]:
```
data[data["payment_installments"]==0]
```

Out[42]:

	order_id	payment_sequential	payment_type	payment_installments	payment_value	
56288	744bade1fcf9ff3f31d860ace076d422	2	credit_card	0	58.69	5e5794da
91637	1a57108394169c0b47d8f876acc9ba2d	2	credit_card	0	129.94	48ebb06cf!
91638	1a57108394169c0b47d8f876acc9ba2d	2	credit_card	0	129.94	48ebb06cf!

3 rows × 38 columns

In [43]:
```
data.drop(data.index[[53769,87577,87578]],axis=0,inplace=True)
```

In [44]:
```
data[data["payment_installments"]==0]
```

Out[44]:

order_id	payment_sequential	payment_type	payment_installments	payment_value	customer_id	order_status	order_purchase

0 rows × 38 columns

map the product_category translation to data

In [45]:
```
data = pd.merge(data,translation,how="left",on="product_category_name")
```

In [46]:
```
data[data["product_category_name_english"].isnull()==True]["product_category_name"].value_counts()
```

Out[46]:
```
portateis_cozinha_e_preparadores_de_alimentos    14
pc_gamer                                          9
Name: product_category_name, dtype: int64
```

In [47]:
```
translation[translation["product_category_name"]=="portateis_cozinha_e_preparadores_de_alimentos"]
```

Out[47]:

product_category_name	product_category_name_english

**Translation data deos not has portateis_cozinha_e_preparadores_de_alimentos, pc_gamer.
portateis_cozinha_e_preparadores_de_alimentos english translation is kitchen_laptops_and_food_preparators**

pc_gamer is pc_gamer.

Let us fill the null values in english translation by these values.

In [48]:
```
null_1 = data[data["product_category_name"]=="portateis_cozinha_e_preparadores_de_alimentos"]["product_
category_name_english"]
null_2 = data[data["product_category_name"]=="pc_gamer"]["product_category_name_english"]
```

In [49]:
```
data.loc[null_1.index,"product_category_name_english"] = "kitchen_laptops_and_food_preparators"
data.loc[null_2.index,"product_category_name_english"] = "pc_gamer"
```

In [50]:
```
data.drop("product_category_name",inplace=True,axis=1)
data.rename(columns={"product_category_name_english":"product_category_name"},inplace=True)
```

In [ ]:
```

```

In [51]:
```
#let us save the data as final_data.csv, so that we do not need to run the above cells again.
data.to_csv("final_data.csv")
```

In [ ]:

Exploratory Data Analysis

In [52]:
```
#load the data
data = pd.read_csv("final_data.csv")
data.drop("Unnamed: 0",axis=1,inplace=True)
```

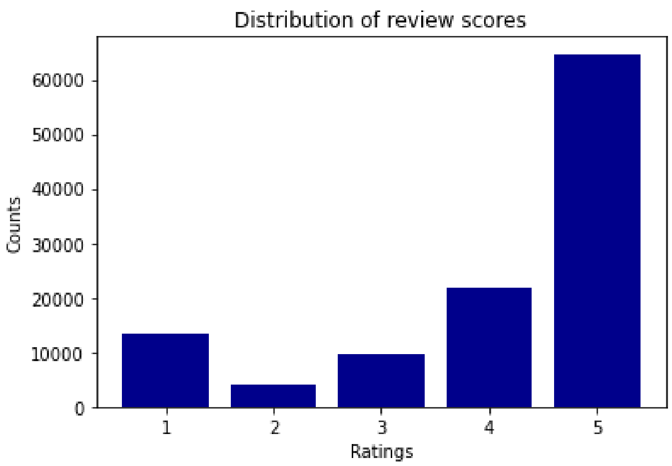
In [53]:
```
#info about the data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113105 entries, 0 to 113104
Data columns (total 38 columns):
 #   Column                         Non-Null Count   Dtype  
---  ------                         --------------   -----  
 0   order_id                       113105 non-null  object 
 1   payment_sequential             113105 non-null  int64  
 2   payment_type                   113105 non-null  object 
 3   payment_installments           113105 non-null  int64  
 4   payment_value                  113105 non-null  float64
 5   customer_id                    113105 non-null  object 
 6   order_status                   113105 non-null  object 
 7   order_purchase_timestamp       113105 non-null  object 
 8   order_approved_at              113105 non-null  object 
 9   order_delivered_carrier_date   113105 non-null  object 
 10  order_delivered_customer_date  113105 non-null  object 
 11  order_estimated_delivery_date  113105 non-null  object 
 12  review_score                   113105 non-null  int64  
 13  customer_unique_id             113105 non-null  object 
 14  zip_code_prefix_customer       113105 non-null  int64  
 15  lat_customer                   113105 non-null  float64
 16  lng_customer                   113105 non-null  float64
 17  customer_city                  113105 non-null  object 
 18  customer_state                 113105 non-null  object 
 19  product_id                     113105 non-null  object 
 20  product_name_lenght            113105 non-null  float64
 21  product_description_lenght     113105 non-null  float64
 22  product_photos_qty             113105 non-null  float64
 23  product_weight_g               113105 non-null  float64
 24  product_length_cm              113105 non-null  float64
 25  product_height_cm              113105 non-null  float64
 26  product_width_cm               113105 non-null  float64
 27  order_item_id                  113105 non-null  int64  
 28  seller_id                      113105 non-null  object 
 29  shipping_limit_date            113105 non-null  object 
 30  price                          113105 non-null  float64
 31  freight_value                  113105 non-null  float64
 32  zip_code_prefix_seller         113105 non-null  int64  
 33  lat_seller                     113105 non-null  float64
 34  lng_seller                     113105 non-null  float64
 35  seller_city                    113105 non-null  object 
 36  seller_state                   113105 non-null  object 
 37  product_category_name          113105 non-null  object 
dtypes: float64(14), int64(6), object(18)
memory usage: 32.8+ MB
```

Let us check the distribution of class label to understand the class balance

In [54]:
```
# checking the balance of the data
print("Counts :\n ",data["review_score"].value_counts())
print("**"*30)
print("Percentage distribution :\n ",100*data["review_score"].value_counts(normalize=True))
print("**"*30)

plt.bar(data["review_score"].value_counts().index,data["review_score"].value_counts(),color="darkblue")

plt.xlabel("Ratings")
plt.ylabel("Counts")
plt.title("Distribution of review scores")
plt.show()
```

```
Counts :
  5    64637
4    21725
1    13241
3     9573
2     3929
Name: review_score, dtype: int64
************************************************************
Percentage distribution :
  5    57.147783
4    19.207816
1    11.706821
3     8.463817
2     3.473763
Name: review_score, dtype: float64
************************************************************
```



We can see that review scores distributed in J like shape. This is the typical distribution of e-commerce review scores. Very high number of rating 5 followed by 4 and then rating 1, rating 2 and 3 are less compared to other ratings.

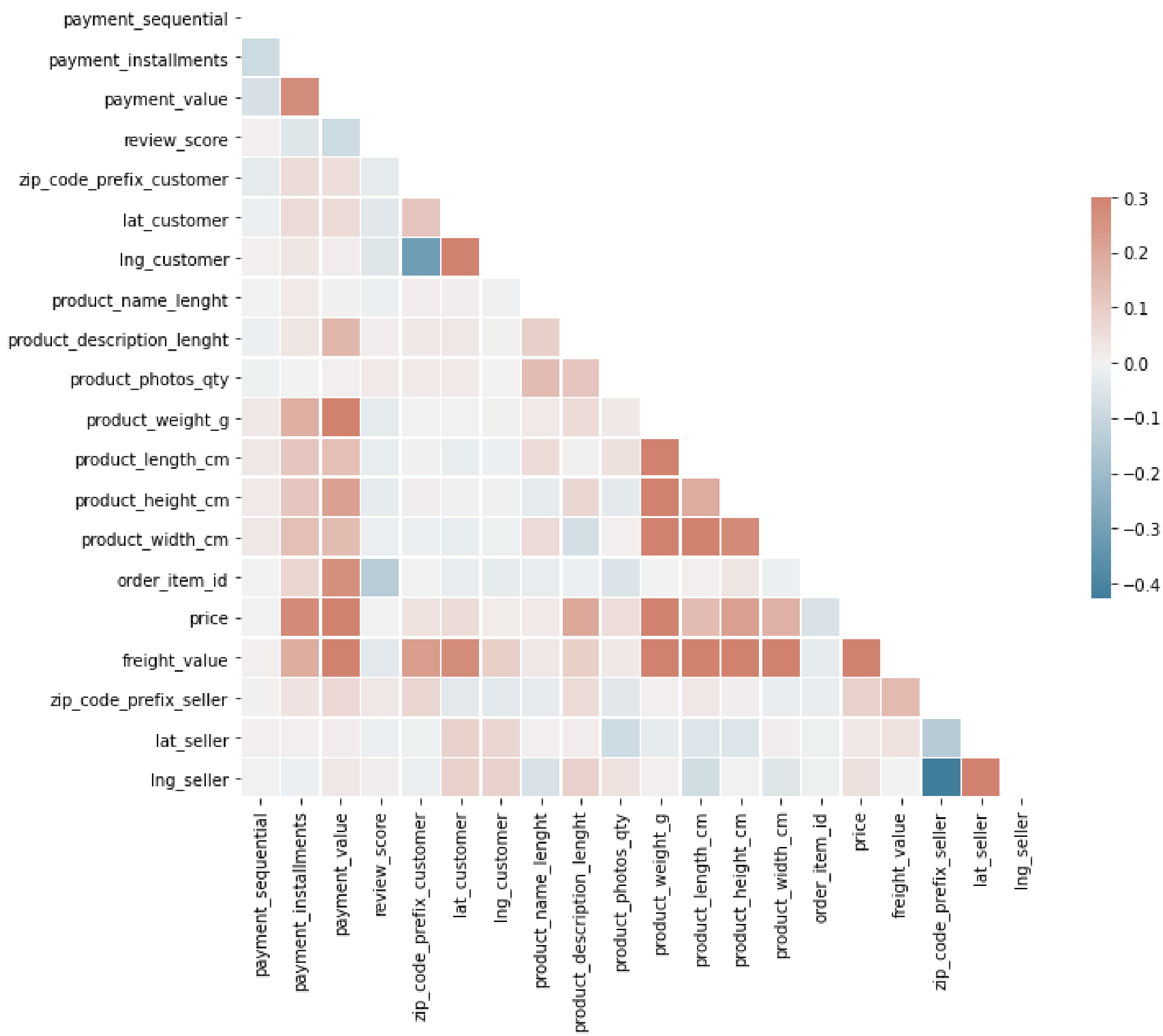
The dataset is highly imbalanced.
There are only 3.5% datapoints which belongs to rating 2.

**About 57% of datapoints belongs to rating 5. **

Correlation between features

In [55]:

```
#Reference documentation: https://seaborn.pydata.org/examples/many_pairwise_correlations.html

correlation = data.corr()
#mask the above triangle
mask = np.triu(np.ones_like(correlation,dtype='bool'))
f, ax = plt.subplots(figsize=(11, 9))
#colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)
#heatmap using seaborn
sns.heatmap(correlation, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```



We are interested in correlation of features with (target variable) review_score

In [56]:
```
data.corr()["review_score"]
```

Out[56]:
```
payment_sequential             0.007774
payment_installments          -0.043959
payment_value                 -0.083140
review_score                   1.000000
zip_code_prefix_customer      -0.027236
lat_customer                  -0.037309
lng_customer                  -0.042775
product_name_lenght           -0.013654
product_description_lenght     0.014226
product_photos_qty             0.021811
product_weight_g              -0.027676
product_length_cm             -0.020965
product_height_cm             -0.023773
product_width_cm              -0.012380
order_item_id                 -0.138087
price                          0.002252
freight_value                 -0.034503
zip_code_prefix_seller         0.026792
lat_seller                    -0.009388
lng_seller                     0.012411
Name: review_score, dtype: float64
```

It seems that none of the existing numerical features are highly correlated with the target variable.

Surprisingly price is very very less correlated with the review scoring. Similarly freight value.

2.4 Univariate analysis

In [57]:
```
#let us split the data with respect to review rating.
```

In [58]:
```
rate_1 = data[data["review_score"]==1]
rate_2 = data[data["review_score"]==2]
rate_3 = data[data["review_score"]==3]
rate_4 = data[data["review_score"]==4]
rate_5 = data[data["review_score"]==5]
```

2.4.1 payment_type analysis with review_score

In [59]:
```
#let us check some relation in type and sequential and installments
```

In [60]:
```
data[(data["payment_type"]!="voucher") & (data["payment_sequential"]>3)]
```

Out[60]:

order_id	payment_sequential	payment_type	payment_installments	payment_value	customer_id	order_status	order_purchase

0 rows × 38 columns

In [61]:
```
data[(data["payment_sequential"]>3) & (data["payment_installments"]>1)]
```

Out[61]:

order_id	payment_sequential	payment_type	payment_installments	payment_value	customer_id	order_status	order_purchase

0 rows × 38 columns

In [62]:
```
data[(data["payment_type"]=="voucher") & (data["payment_installments"]>1)]
```

Out[62]:

order_id	payment_sequential	payment_type	payment_installments	payment_value	customer_id	order_status	order_purchase

0 rows × 38 columns

- For payment sequential more than 3, all the payment methods are voucher.
- payment installments more than 1 present for payment_sequential 1, 2, 3. For payment_sequential more than 3, there is only one installment.
- For all voucher payment methods, installment is 1.

In [66]:
```
print(data["payment_type"].value_counts(normalize=True))
```

```
credit_card    0.737854
boleto         0.194580
voucher        0.053225
debit_card     0.014341
Name: payment_type, dtype: float64
```

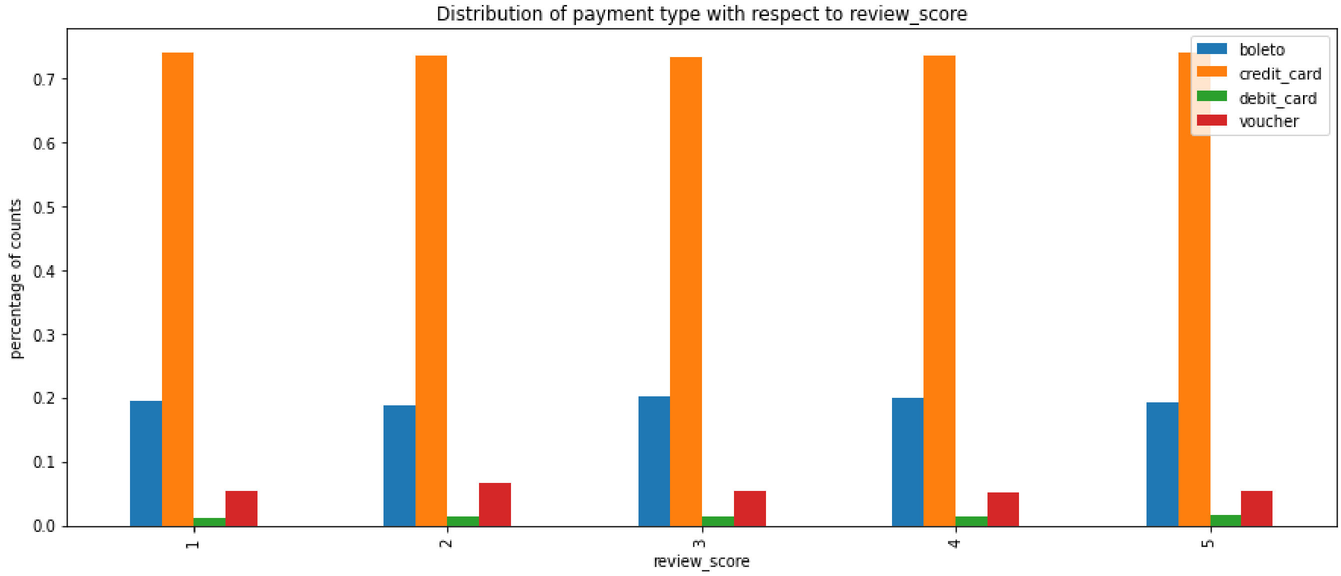
In [67]:
```
#payment_type grouped by review_score
pay_type_score = data.groupby("review_score")["payment_type"].value_counts(normalize=True)
pay_type_score.unstack()
```

Out[67]:

payment_type review_score	boleto	credit_card	debit_card	voucher
1	0.195227	0.740427	0.011253	0.053093
2	0.186561	0.734284	0.013489	0.065666
3	0.201922	0.731954	0.012744	0.053379
4	0.198113	0.736110	0.013763	0.052014
5	0.192661	0.739004	0.015456	0.052880

Distribution of different payment types in each review rating is almost same as in the original data.
Each of the ratings has nearly 74% of credit card payment. Roughly 1.2%-1.4% debit card payment.

In [68]:
```
pay_type_score.unstack().plot.bar(figsize=(15,6)).legend(loc="best")
plt.ylabel("percentage of counts")
plt.title("Distribution of payment type with respect to review_score")
plt.show()
```



From the plot also we can see that, the distribution is same

Let us test statistically, whether payment_type and review_score dependent or independent.

Chi-square test with significance level alpha=0.05

Null hypothesis : payment_type and review_score are not related i.e. independent
Althernative hypothesis: payment_type and review_score are related i.e. dependent

In [69]:
```
#reference: https://machinelearningmastery.com/chi-squared-test-for-machine-learning/
from scipy.stats import chi2_contingency,chi2

#creating contengency table
table = pd.crosstab(data["payment_type"],data["review_score"],margins=False)

#chi_square test using scipy.stats library
chi_2,p_value,dof,expected = chi2_contingency(table)
```

In [70]:
```
alpha = 0.05
print("Level of significance : ",alpha)
print("p-value is : ",p_value)

if p_value < alpha:
    print("Reject null hypothesis")
else:
    print("Failed to reject null hypothesis")
print("*"*30)
#interpreting test statistic
prob=0.95
critical = chi2.ppf(prob, dof)

print("Critical value is : ",critical)
print("chi2(test statistic) value is : ",chi_2)

if chi_2>=critical:
    print("Reject null hypothesis")
else:
    print("Failed to reject null hypothesis")
```

```
Level of significance :  0.05
p-value is :  0.00027649502286312483
Reject null hypothesis
******************************
Critical value is :  21.02606981748307
chi2(test statistic) value is :  36.42753432616247
Reject null hypothesis
```

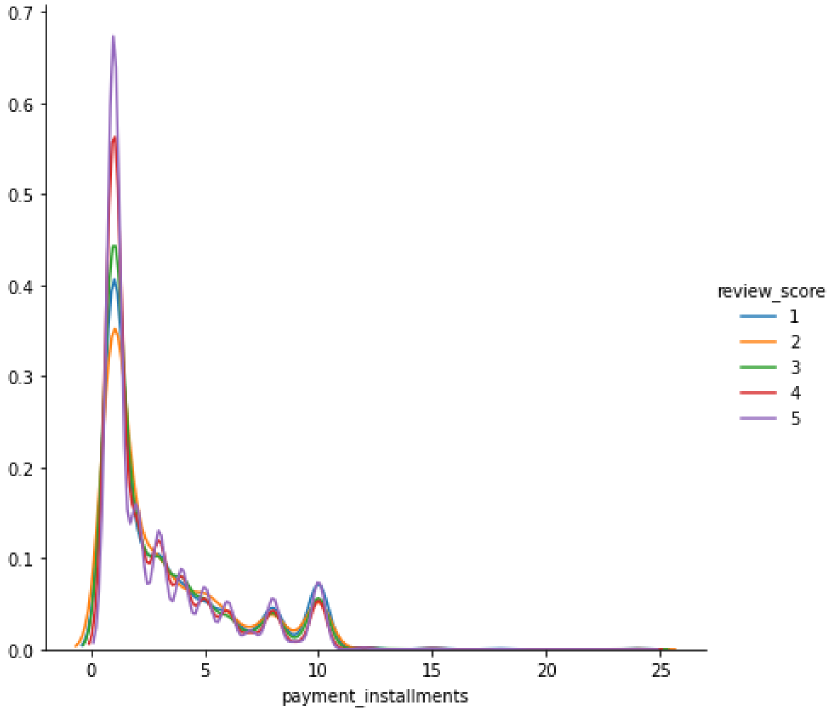
Hence we can conclude that dependence of review_score on payment_type is statistically significant

In [ ]:

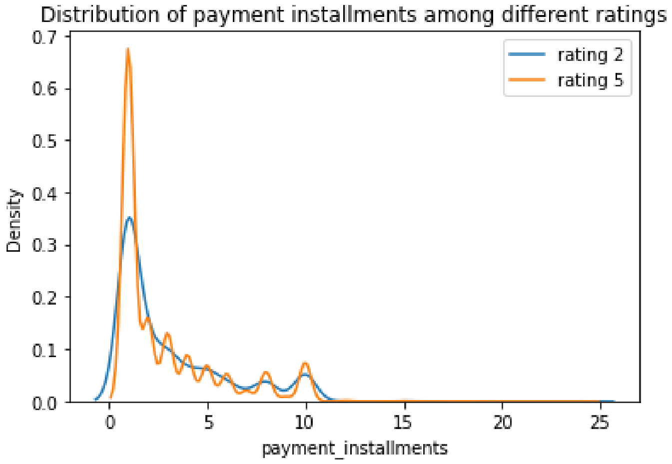
In [ ]:

2.4.2 payment_installments analysis with review_score

In [71]:
```
#plotting density plot of installments wrt each ratings
sns.FacetGrid(data,hue="review_score",height=6)\
    .map(sns.kdeplot,"payment_installments")\
    .add_legend()
plt.show()
```

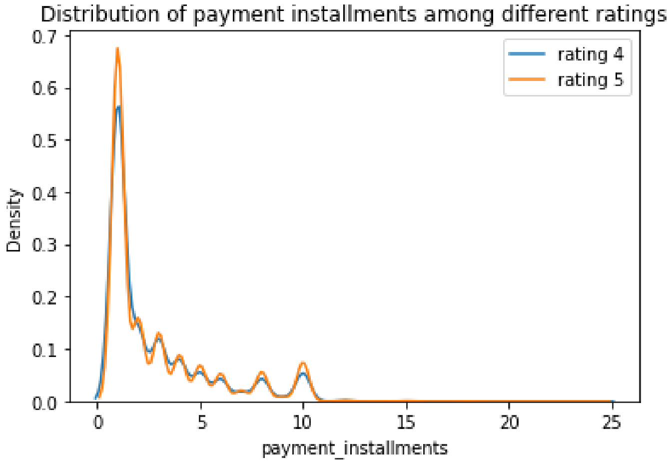


In [72]:
```
#distribution between rating 2 and rating 5
sns.kdeplot(rate_2["payment_installments"],label="rating 2")
sns.kdeplot(rate_5["payment_installments"],label="rating 5")

plt.title("Distribution of payment installments among different ratings")
plt.legend()
plt.show()
```



- **Distributions are not separable.**
- **Density is peak at installments 1 for rating 5 compared to rating 2.**

In [73]:
```
#distribution between rating 4 and rating 5
sns.kdeplot(rate_4["payment_installments"],label="rating 4")
sns.kdeplot(rate_5["payment_installments"],label="rating 5")

plt.title("Distribution of payment installments among different ratings")
plt.legend()
plt.show()
```

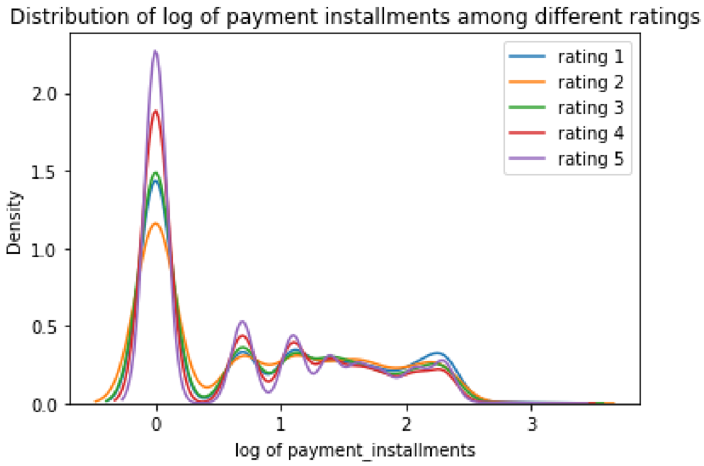


- **Installment distribution of rating 4 is highly overlapping with the same of rating 5**

- **From the density distribution of installments we can see that, ratings are not separable using installments alone.**
- **Distribution plots are highly overlapped.**

Since this distributon looks like follow power law, let us consider log scale.

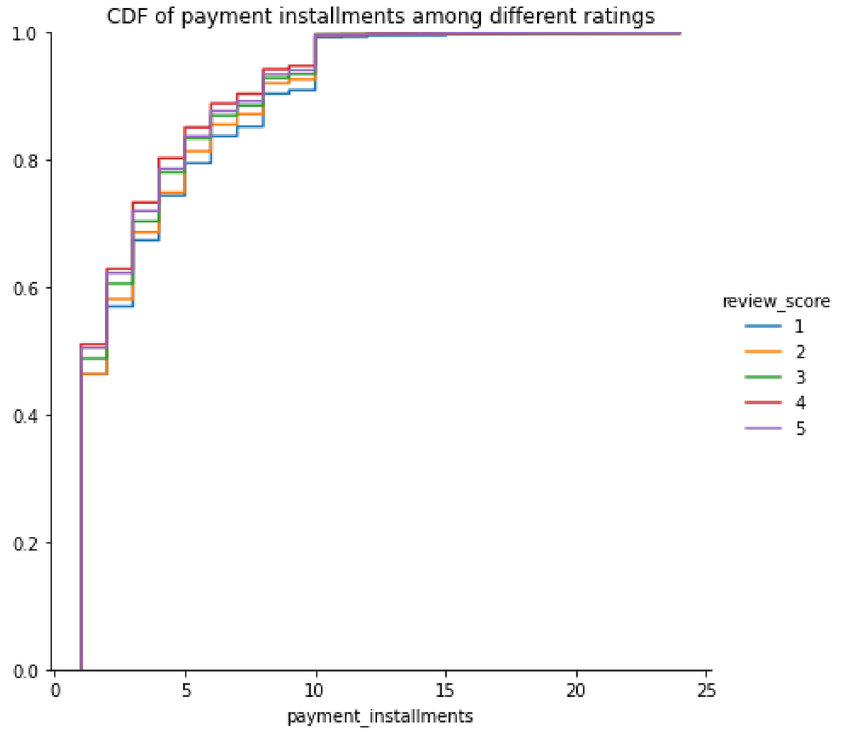
In [74]:
```
sns.kdeplot(np.log(rate_1["payment_installments"]),label="rating 1")
sns.kdeplot(np.log(rate_2["payment_installments"]),label="rating 2")
sns.kdeplot(np.log(rate_3["payment_installments"]),label="rating 3")
sns.kdeplot(np.log(rate_4["payment_installments"]),label="rating 4")
sns.kdeplot(np.log(rate_5["payment_installments"]),label="rating 5")

plt.title("Distribution of log of payment installments among different ratings")
plt.xlabel("log of payment_installments")
plt.legend()
plt.show()
```



In [ ]:
```

```

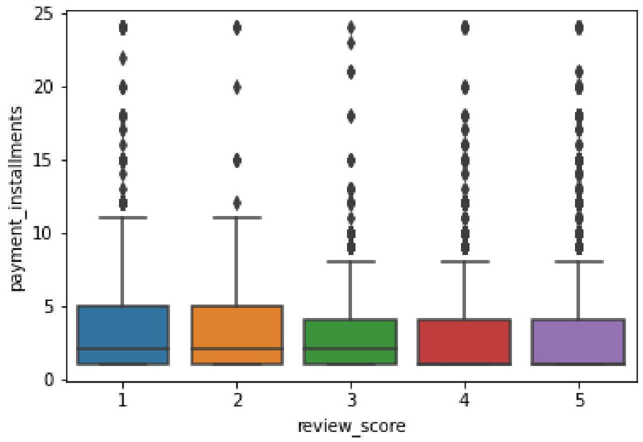
- **Most of the installments = 1 in all ratings.**
- **Distribution of installments is almost similar among all the ratings.**
- **payment_installment alone cannot distinguish among the ratings.**

In [75]:
```
#plotting cdf
sns.FacetGrid(data,hue="review_score",height=6)\
    .map(sns.ecdfplot,"payment_installments")\
    .add_legend()


plt.title("CDF of payment installments among different ratings")
plt.xlabel("payment_installments")
plt.show()
```



- **We cannot say anything more from cdf also.**
- **Plots are overlapped. payment_installment is discrete value. At each value the percentage of data lies below is almost same for all ratings.**

In [76]:
```
#boxplot
sns.boxplot(y="payment_installments",x="review_score",data=data)
plt.show()
```



In [77]:
```
#mean installments
data.groupby("review_score")["payment_installments"].mean()
```

Out[77]:
```
review_score
1    3.292425
2    3.149147
3    2.982451
4    2.807089
5    2.898294
Name: payment_installments, dtype: float64
```

In [78]:
```
#99.9% installments
data.groupby("review_score")["payment_installments"].apply(lambda x: np.percentile(x,99.9))
```

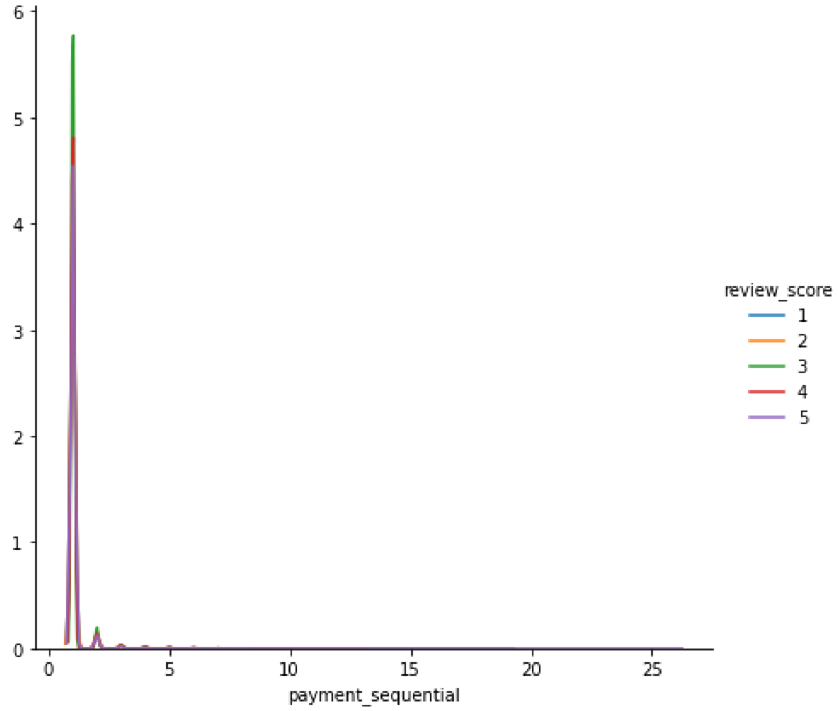
Out[78]:
```
review_score
1    24.00
2    15.36
3    15.00
4    15.00
5    15.00
Name: payment_installments, dtype: float64
```

- **Obviously the first observation is box plot of all ratings overlapped.**
- **There are outliers in the payment_installments.**
- **becuase, from the boxplot we can see that 75% of data lies below payment_installments less than 5.**
- **There are very very less datapoints which have installments greater than 10 in each ratings.**
- **Median of rating 1,2,3 are almost same that is equal to 2. Whereas for rating 4 and 5, median is 1.**
- **Most of the datapoints (75%) which has rating 3, 4 or 5, have installments below 4. The same for rating 2 and 1, is 5.**
- **Average payment installments for rating 1 and 2 are slightly high compared to rating 3,4,5. But the difference is not significant.**
- **99.9% of data points are below installments = 15 in case of ratings 2,3,4,5. Where is 99.9 percentile of rating 1 is 24.**

In [ ]:

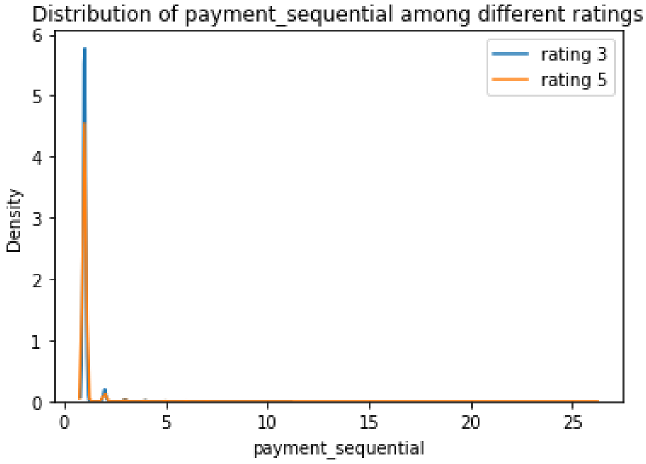
2.4.3 payment_sequential analysis with review_score

In [79]:
```
#plotting density plot of installments wrt each ratings
sns.FacetGrid(data,hue="review_score",height=6)\
    .map(sns.kdeplot,"payment_sequential")\
    .add_legend()
plt.show()
```



it seems that density of payment_sequential of rating 3 is high at payment_sequential = 1 compared to other ratings. But let us check this

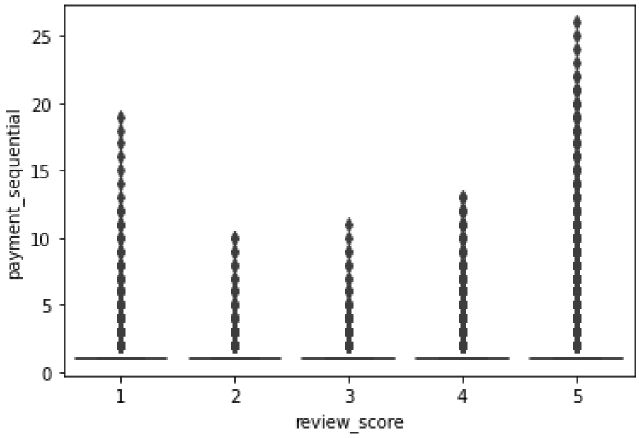
In [80]:
```
sns.kdeplot((rate_3["payment_sequential"]),label="rating 3")
sns.kdeplot((rate_5["payment_sequential"]),label="rating 5")

plt.title("Distribution of payment_sequential among different ratings")
plt.xlabel("payment_sequential")
plt.legend()
plt.show()
```



Yes!! Density of rating 3 at payment_sequential=1 is peaked comapared to the same of rating 5.

Distribution of payment_sequential is highly overlapped in all the ratings data. From this we can clearly see that we cannot distinguish among the ratings.
Here also we cannot get any helpful information from payment_sequential alone

In [81]:
```
sns.boxplot(y="payment_sequential",x="review_score",data=data)
plt.show()

#mean installments
print("Mean \n",data.groupby("review_score")["payment_sequential"].mean())

#99.9% installments
print("99.9 percentile \n",data.groupby("review_score")["payment_sequential"].apply(lambda x: np.percen
tile(x,95)))
```

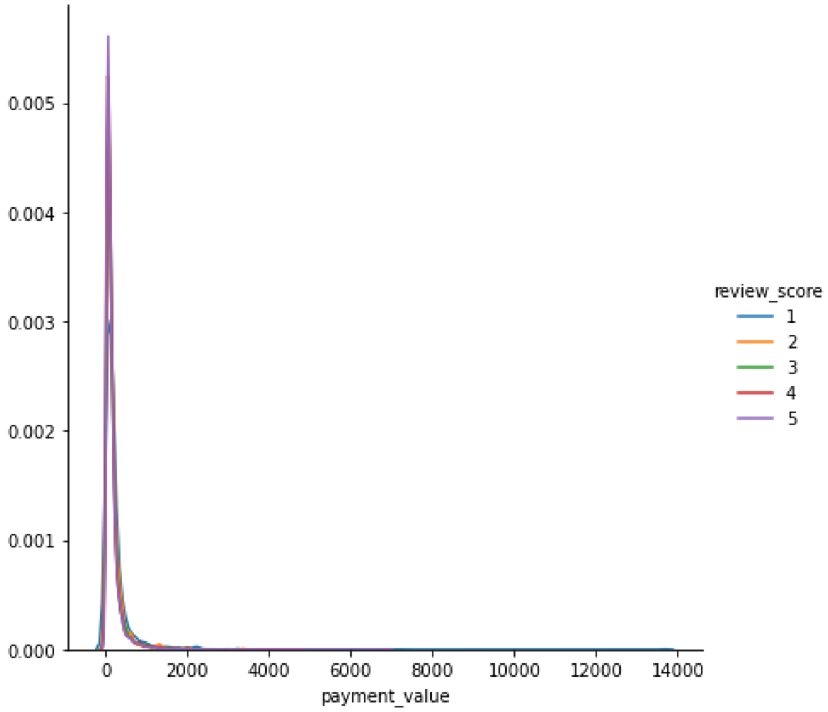



```
Mean
 review_score
1    1.085945
2    1.095444
3    1.062572
4    1.085432
5    1.096787
Name: payment_sequential, dtype: float64
99.9 percentile
 review_score
1    1.0
2    2.0
3    1.0
4    1.0
5    1.0
Name: payment_sequential, dtype: float64
```

- **payment_sequential is also discrete feature. Its value is ranging between 1 to 26.**
- **From the boxplot we can see that, there are very less values of sequential greater than 1 in each rating. So these are considered as outliers in the boxplot.**
- **Mean value for each rating is almost same. There is no difference among the mean values.**
- **From 99.9 percentile value, we can clearly say that, 99.9% of data points contains sequential = 1 for all ratings except for rating 2(sequential is 2)**
- **It is clear that payment_sequential alone cannot give any information to distinguish among ratings. Than means it does not has significant effect on review_rating.**

2.4.4 payment_value analysis with review_score

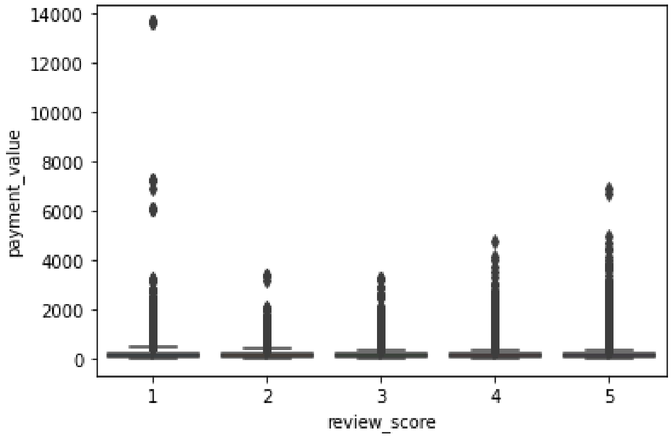
In [82]:
```
#plotting density plot of installments wrt each ratings
sns.FacetGrid(data,hue="review_score",height=6)\
    .map(sns.kdeplot,"payment_value")\
    .add_legend()
plt.show()
```



In [83]:
```
#above density plot is overlapped. So we cannot get much insight from this. let us have a look at numbe
rs.
```

In [ ]:

In [84]:
```
sns.boxplot(y="payment_value",x="review_score",data=data)
plt.show()

#mean payment_value
print("Mean \n",data.groupby("review_score")["payment_value"].mean())

#90% payment_value
print("90 percentile \n",data.groupby("review_score")["payment_value"].apply(lambda x: np.percentile(x,
90)))
```




```
Mean
 review_score
1    238.378781
2    185.442909
3    168.537174
4    164.140398
5    161.243232
Name: payment_value, dtype: float64
99.9 percentile
 review_score
1    464.890
2    372.840
3    334.414
4    323.900
5    317.850
Name: payment_value, dtype: float64
```

- **Mean values of payment_values of rating 5,4,3 are much less compared to the same of rating 1.**
- **But from the boxplot we can see that there are outliers with high payment values in rating 1. So this might pull the mean value of rating 1 towards higher value.**
- **90th percentile value is also high for rating 1 compared to other.**

In [85]:
```
rate_1[rate_1["payment_value"]>12000]
```

Out[85]:

	order_id	payment_sequential	payment_type	payment_installments	payment_value	
59174	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357
59175	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357
59176	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357
59177	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357
59178	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357
59179	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357
59180	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357
59181	03caa2c082116e1d31e67e9ae3700499	1	credit_card	1	13664.08	1617b1357

8 rows × 38 columns

- **Now we can see that one customer purchased same item 8 units in the sam time. The payment value is 13664.08.**
- **He gave 1 rating for all this product. This high value affects the mean value of payment value.**

We need to check more percentile values.

In [86]:
```
for i in range(95,100):
    print("{}th percentile \n {}".format(i,data.groupby("review_score")["payment_value"].apply(lambda x
: np.percentile(x,i))))
    print("*"*40)
```

```
95th percentile
 review_score
1    738.570
2    557.068
3    508.304
4    483.392
5    468.000
Name: payment_value, dtype: float64
****************************************
96th percentile
 review_score
1    854.1020
2    622.2800
3    581.2500
4    567.2632
5    545.1400
Name: payment_value, dtype: float64
****************************************
97th percentile
 review_score
1    1014.0200
2     696.9852
3     682.8300
4     660.4096
5     637.4604
Name: payment_value, dtype: float64
****************************************
98th percentile
 review_score
1    1342.98
2     939.72
3     835.55
4     838.97
5     783.00
Name: payment_value, dtype: float64
****************************************
99th percentile
 review_score
1    1853.0000
2    1308.1800
3    1076.7600
4    1150.0428
5    1071.1200
Name: payment_value, dtype: float64
****************************************
```

- **From 95 to 99 percentile, payment value of rating 5,4,3 is significantly less rating 1.**
- **For 95th percentile, rating 5 has less payment value compared to rating 1.**

Since there are some very larger values in each rating, lets check other percentiles.

In [87]:
```
lst=[50,75,80,85]     #let us check these percentile values
for i in lst:
    print("{}th percentile \n {}".format(i,data.groupby("review_score")["payment_value"].apply(lambda x
: np.percentile(x,i))))
    print("*"*40)
```

```
50th percentile
 review_score
1    137.57
2    119.29
3    107.78
4    104.61
5    104.43
Name: payment_value, dtype: float64
****************************************
75th percentile
 review_score
1    241.22
2    212.32
3    188.34
4    182.29
5    180.16
Name: payment_value, dtype: float64
****************************************
80th percentile
 review_score
1    284.550
2    247.640
3    218.270
4    208.632
5    207.278
Name: payment_value, dtype: float64
****************************************
85th percentile
 review_score
1    350.220
2    297.950
3    260.140
4    249.670
5    244.806
Name: payment_value, dtype: float64
****************************************
```

- **Median payment value is also high incase of rating 1 compared to other ratings.**

From these observations, We can say, payment value has effect on review_score.
Customers who bought products of very high values most likely to give low ratings.

But this does not prove causation.

This is the insights we got from the above numbers.