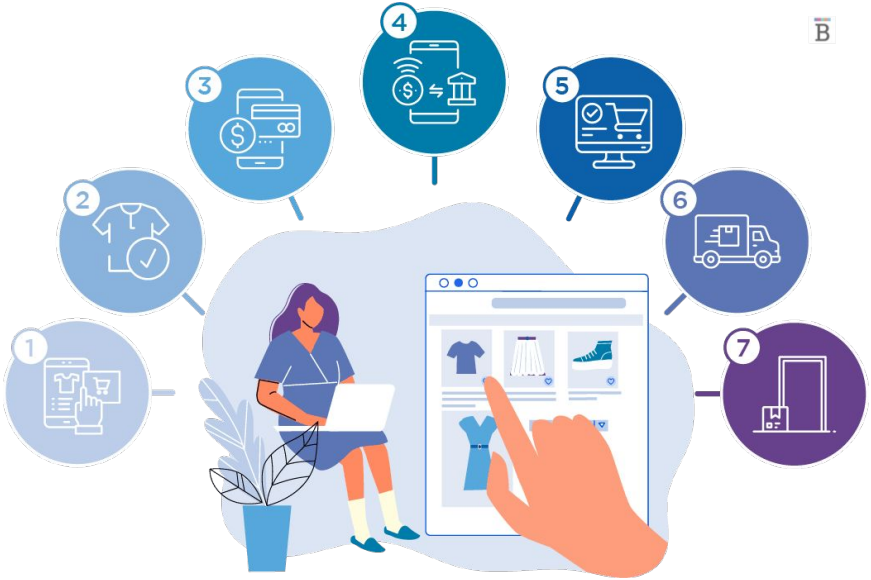
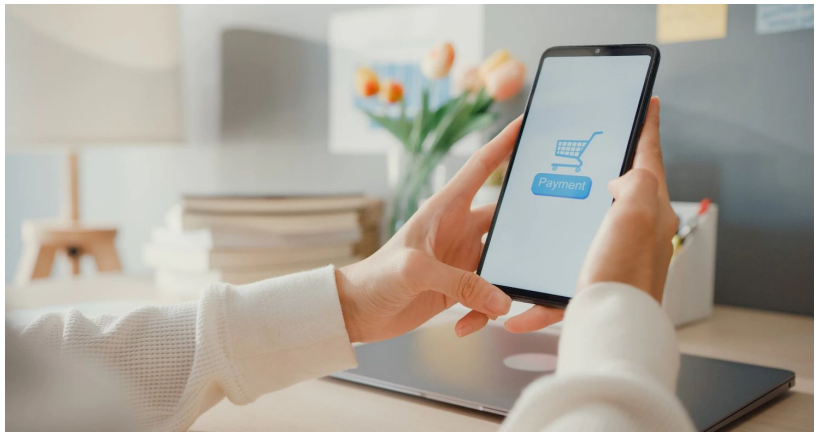
Keystone Project

Customer Satisfaction Prediction in E-commerce



Team C: Carol Wang, Yue Qiu, Jihua Chen, Yujie Zhang, Zinan Li



Keystone Project

- Problem & Objectives
- EDA
- Feature Engineering
- Models
- Evaluation

Problem definition

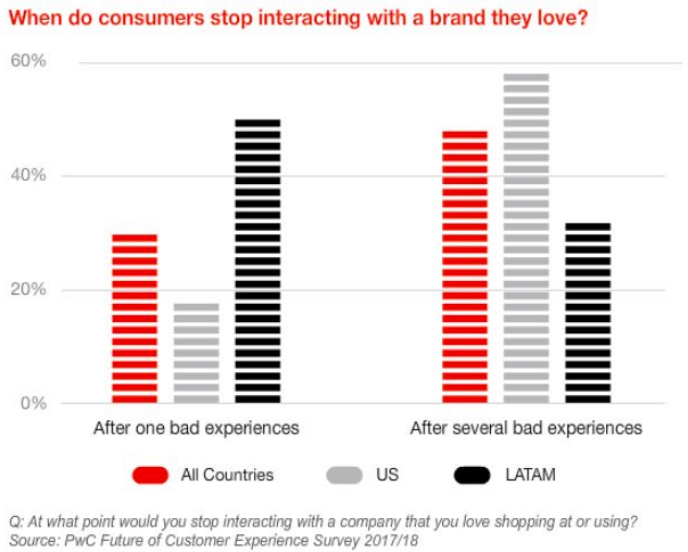
The scale of online retail business is constantly expanding with customers' increasing demand for online shopping. However, some customers did not leave a review which is challenging for the ecommerce company to keep track of each product of each seller.

Objectives

Build a customer satisfaction classifier to help the ecommerce company to predict a review score

- Long term: To optimize the strategy with business and marketing team with top important features for a greater service and user experience
- Short term: To accurately predict the review score when a customer did not leave one; some measures may be implemented in a timely manner to reduce the bad reviews before customers give one.

Why does customer satisfaction matter?



Q: At what point would you stop interacting with a company that you love shopping at or using?
Source: PwC Future of Customer Experience Survey 2017/18

Business impact:

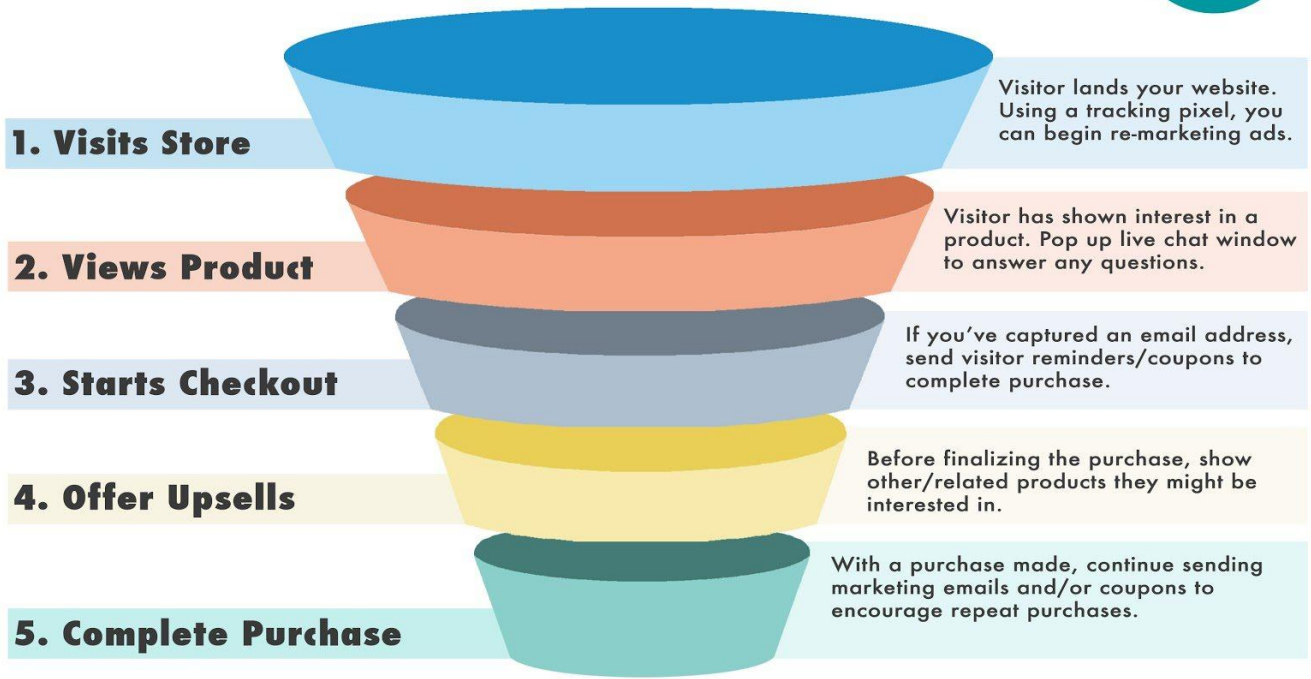
- 17% personal consumption is buying online
- $33.8 B online spending in 2021
- $315 spending per consumer per year

Project goal:

- Prediction on customer behavior
- Improve bottlenecks
- Optimize inventory and supply chain

Ecommerce Sales Funnel

A generalized sales cycle for ecommerce stores



FitSmallBusiness.com
Get Your Business Into Shape

https://straydigital.com/the-ultimate-guide-to-ecommerce-conversion-funnel-optimization/

TOC of EDA Section

1. Single Distribution

1. Correlation: Time
2. Correlation: Revenue
3. Correlation: Score
4. Correlation: Geo

1. Threshold for Satisfaction

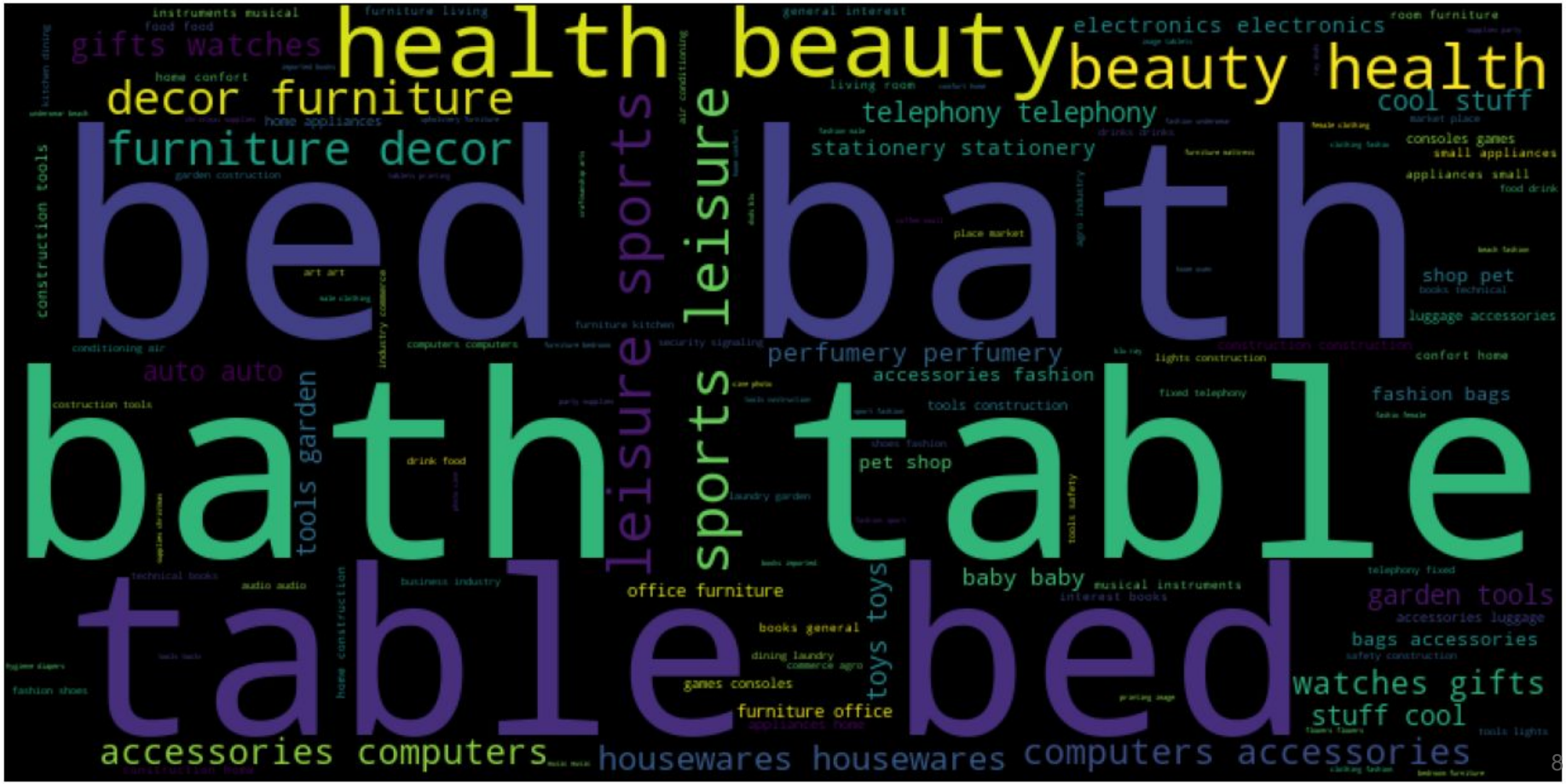
1.Single Distributions

Score and Order Status

Seller State

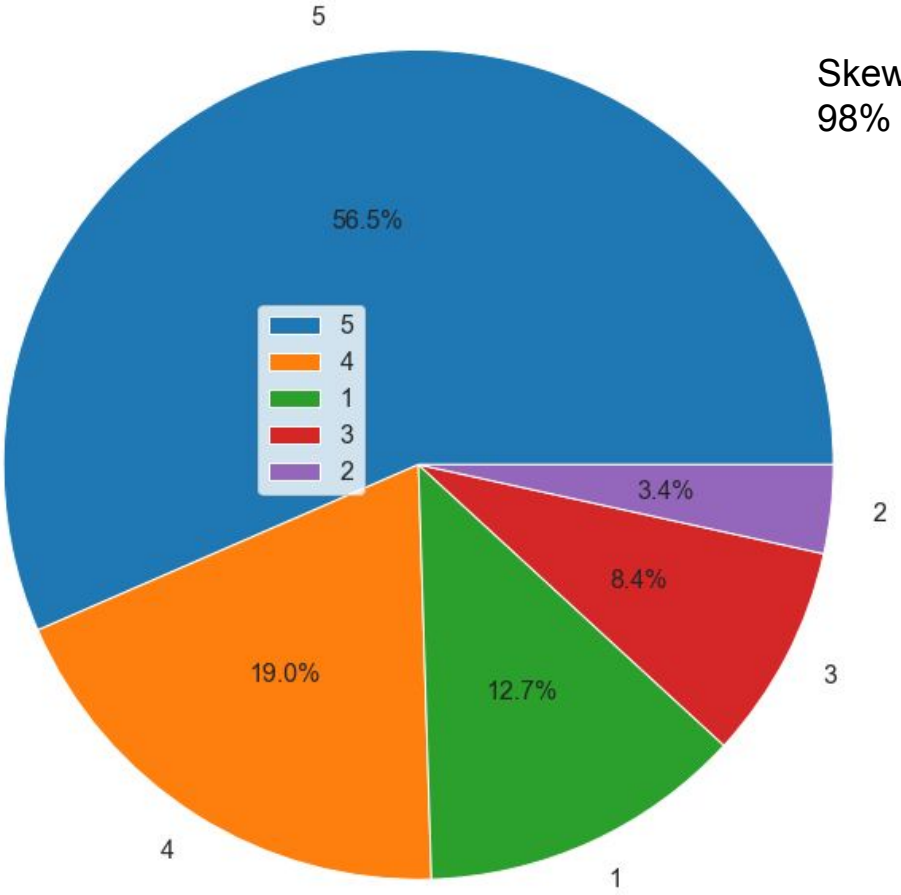
Many other features are discussed last time

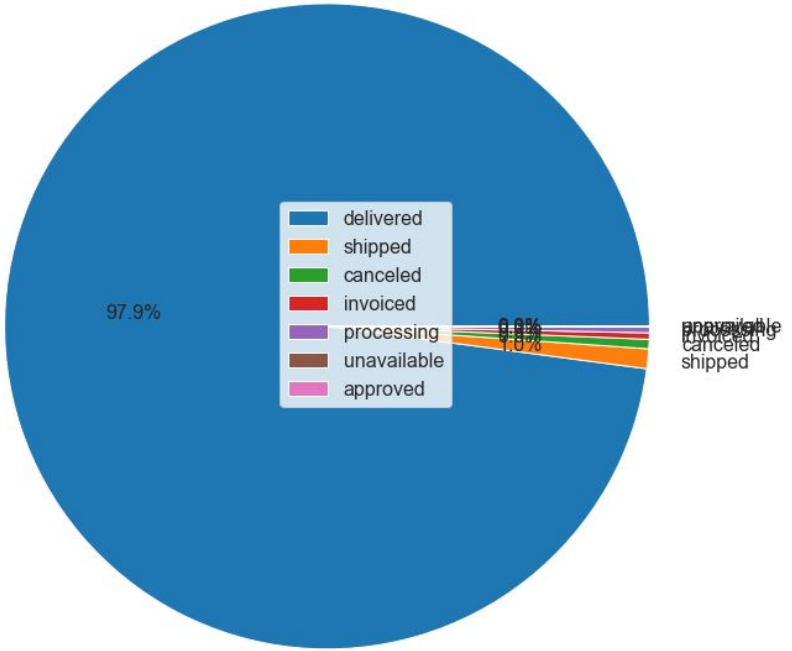
Word Cloud of Product Category



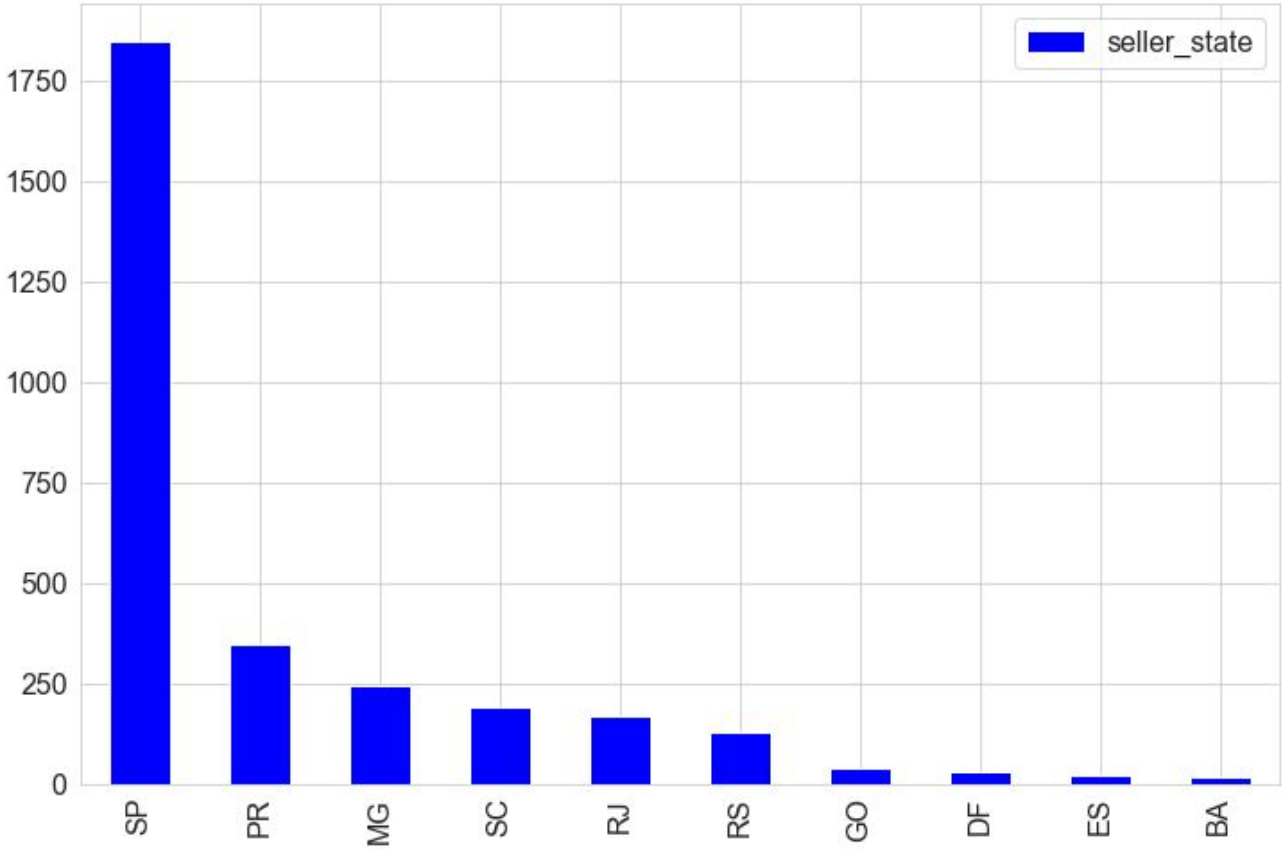
Rating and Order Status

Skewed data with low ratings.
98% order delivery rate.





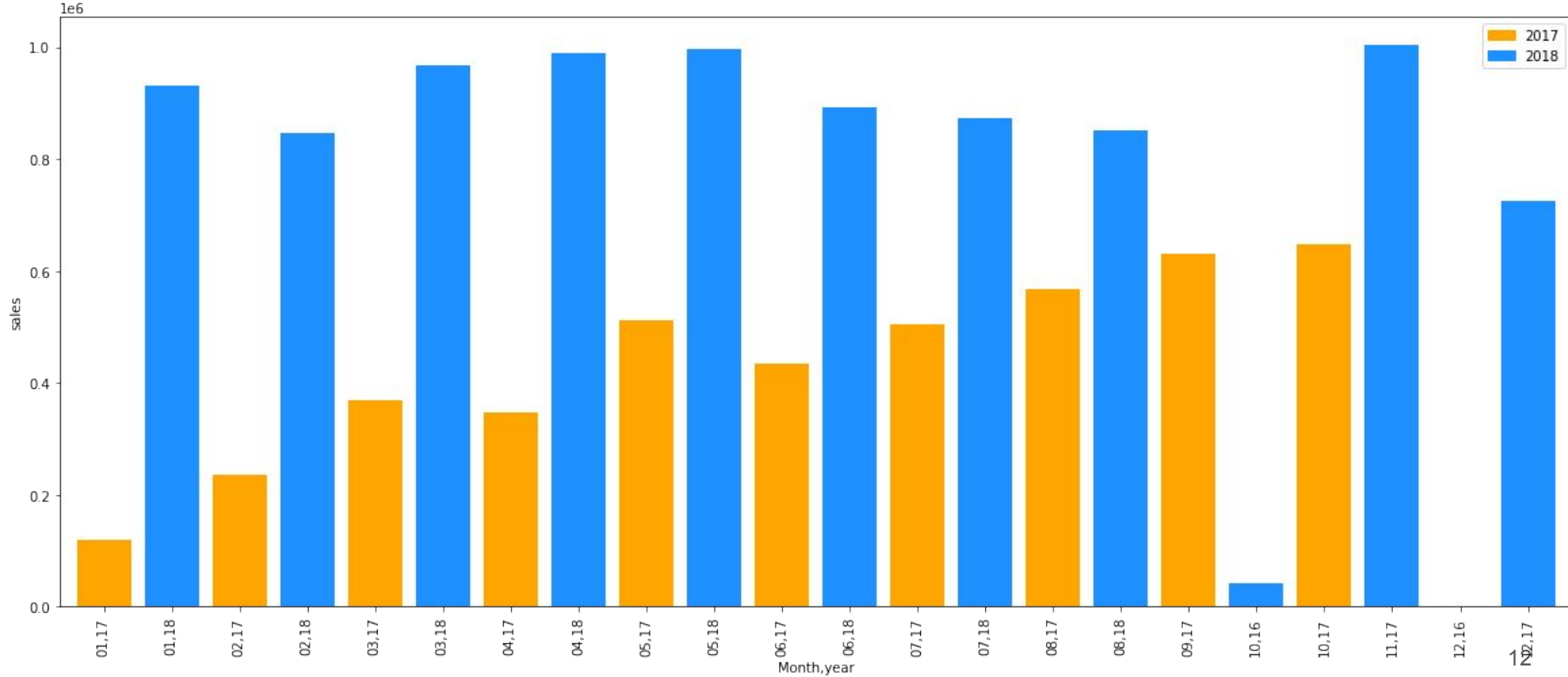
Seller Count vs State



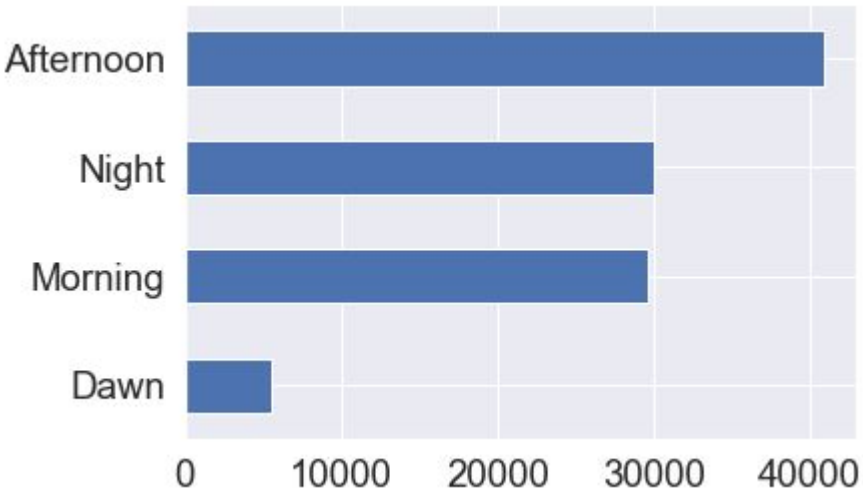
2. Correlations: Time

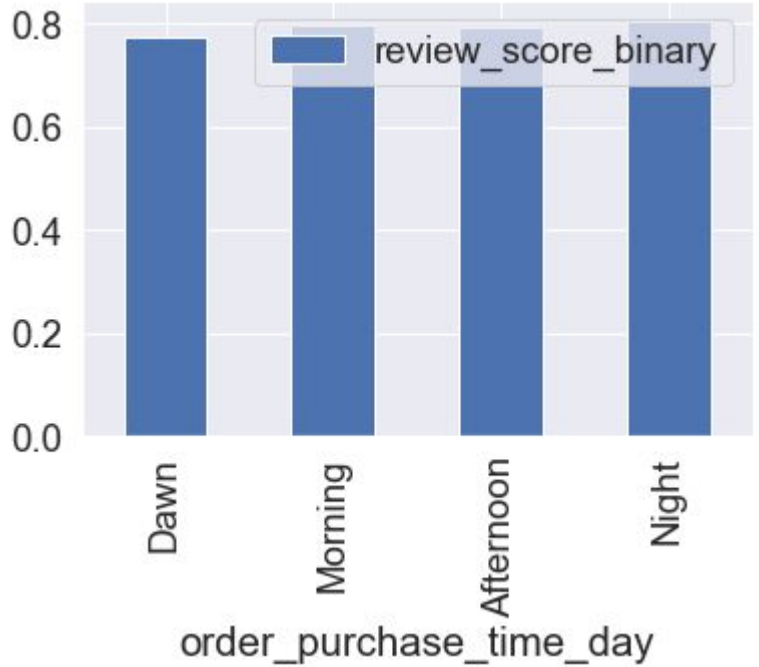
Sales: 2017 vs. 2018
Order Time vs State
Order vs. Hours
Order vs. Month and Weekday
Score vs. Est. Time
Score vs. Act. Time
Score vs. Diff btw Est. & Act. Time
Score vs. Diff btw Purch. & Approv.
Score vs. Diff btw Purch. & CXR.

Sales: 2017 vs 2018 Monthly Data

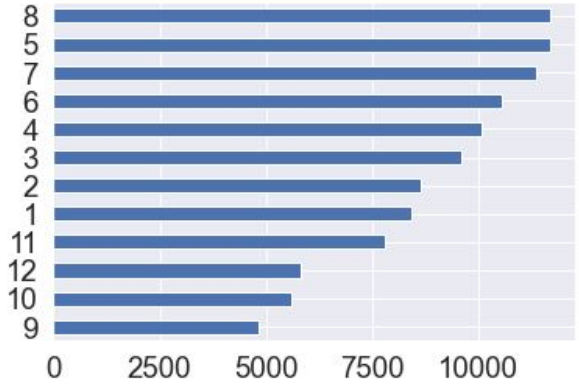


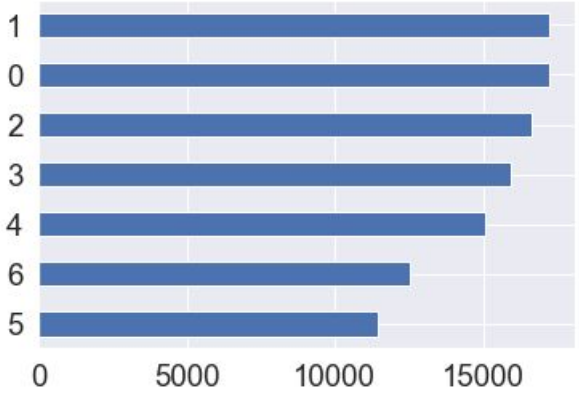
Order vs. Hours



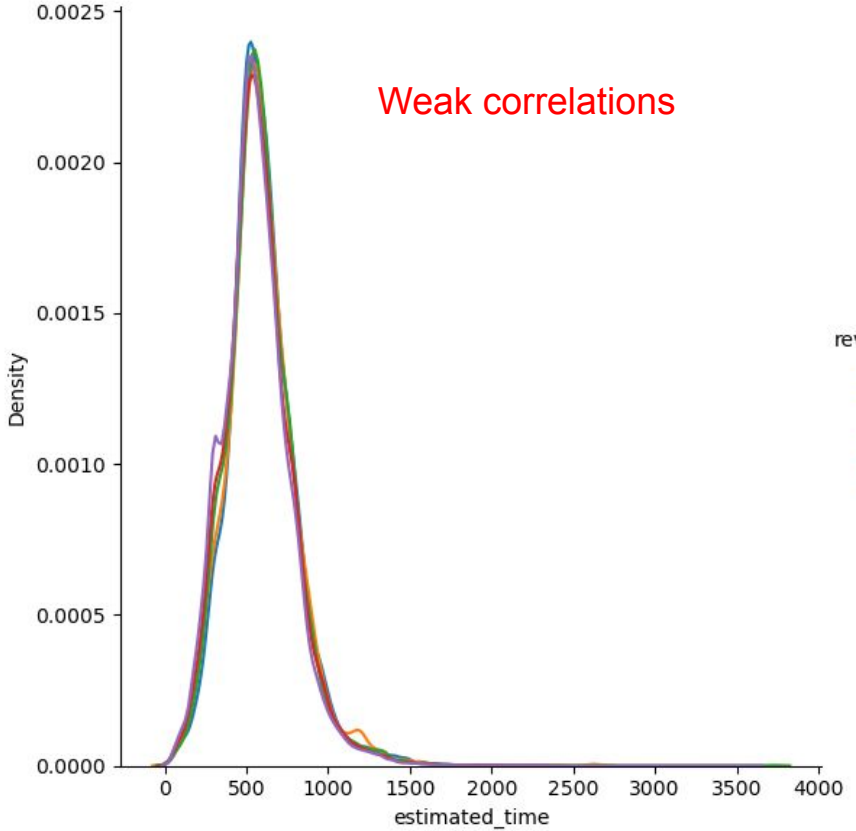


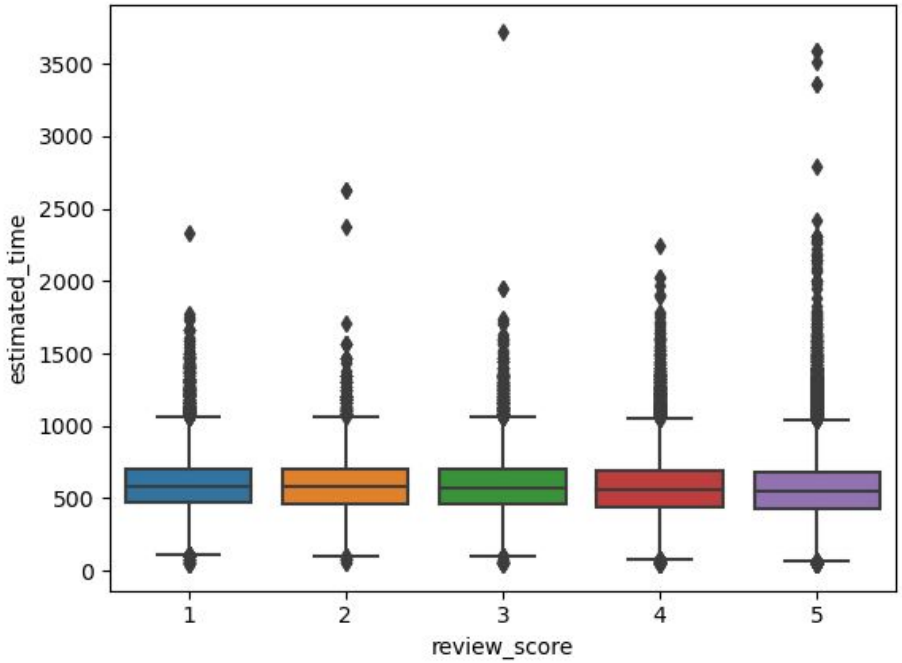
Order vs. Month and Weekday



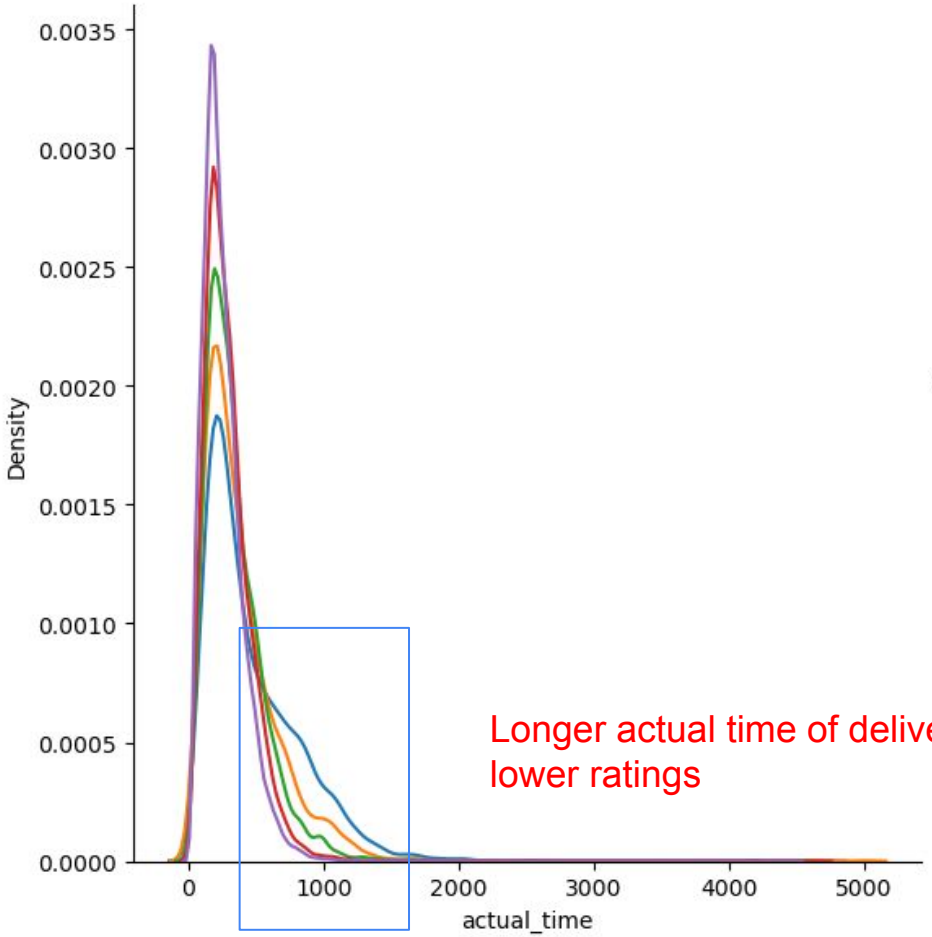


Review Score by Estimated Delivery Time

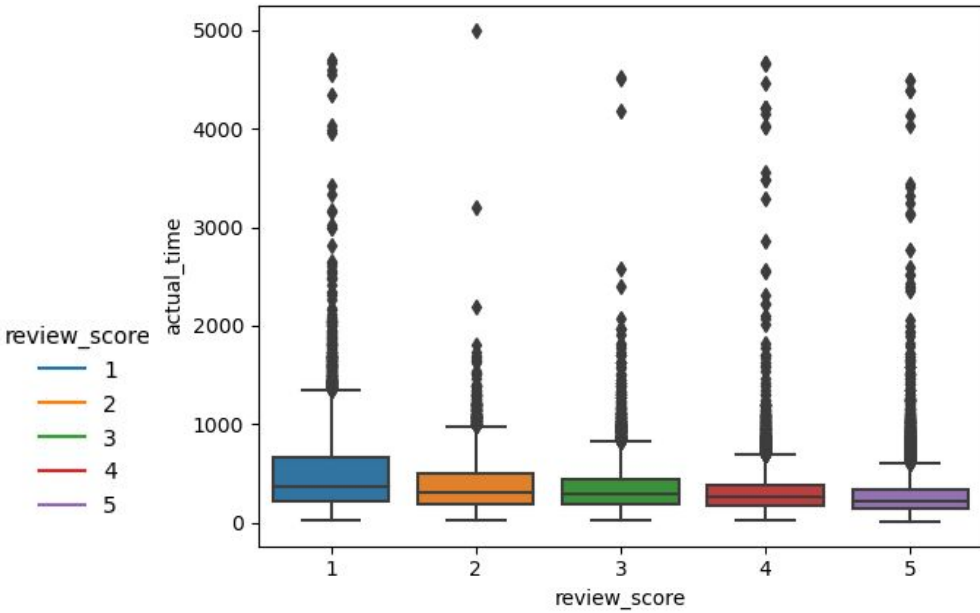




Review Score by Actual Delivery Time



Longer actual time of delivery yields lower ratings



3. Correlations: Revenue

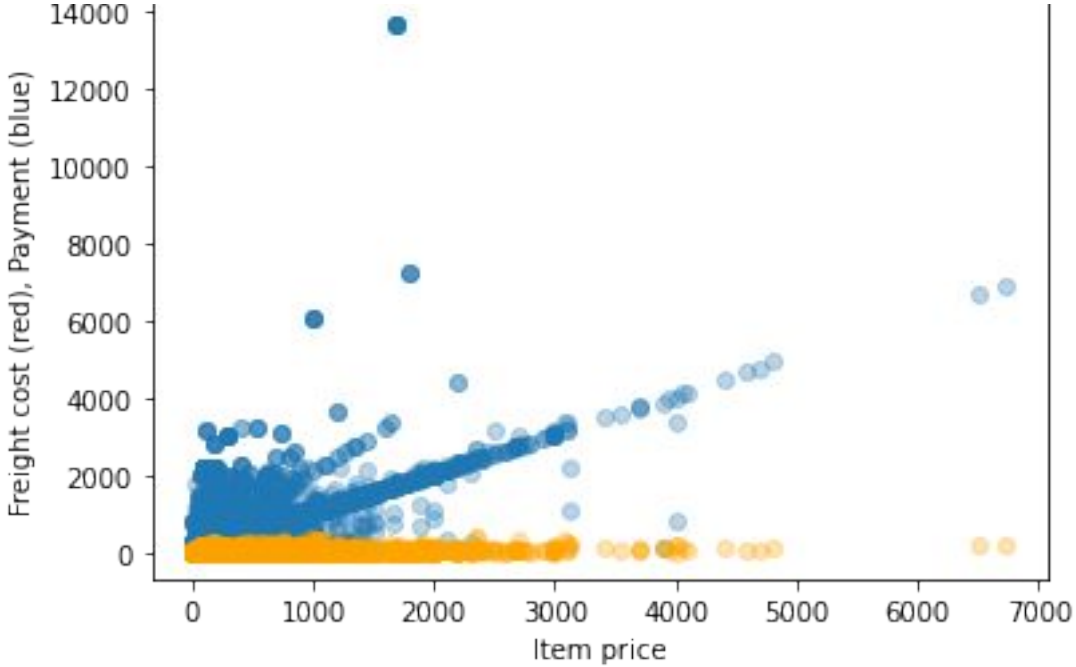
Price vs Freight cost and Payment

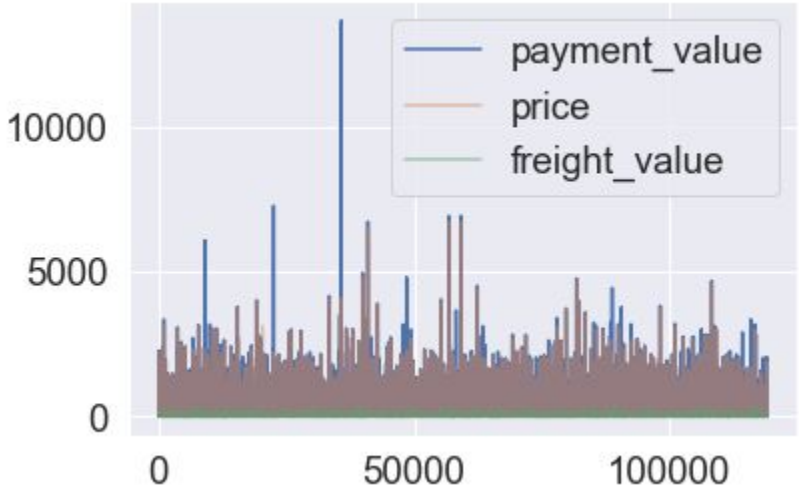
Category by counts or revenue

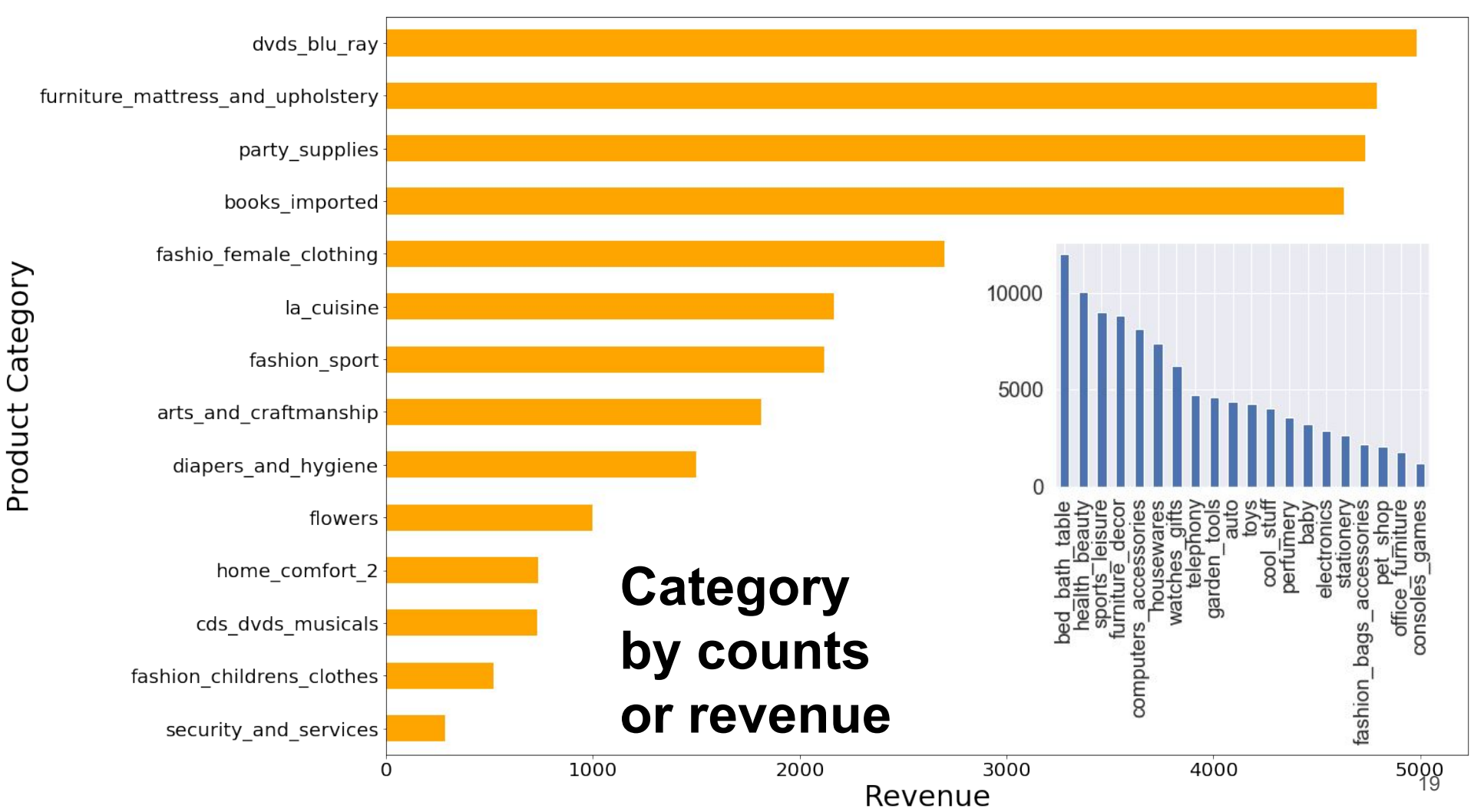
Freight Value vs. Product Weight

Score by Price

Price vs Freight cost and Payment






dvds_blu_ray
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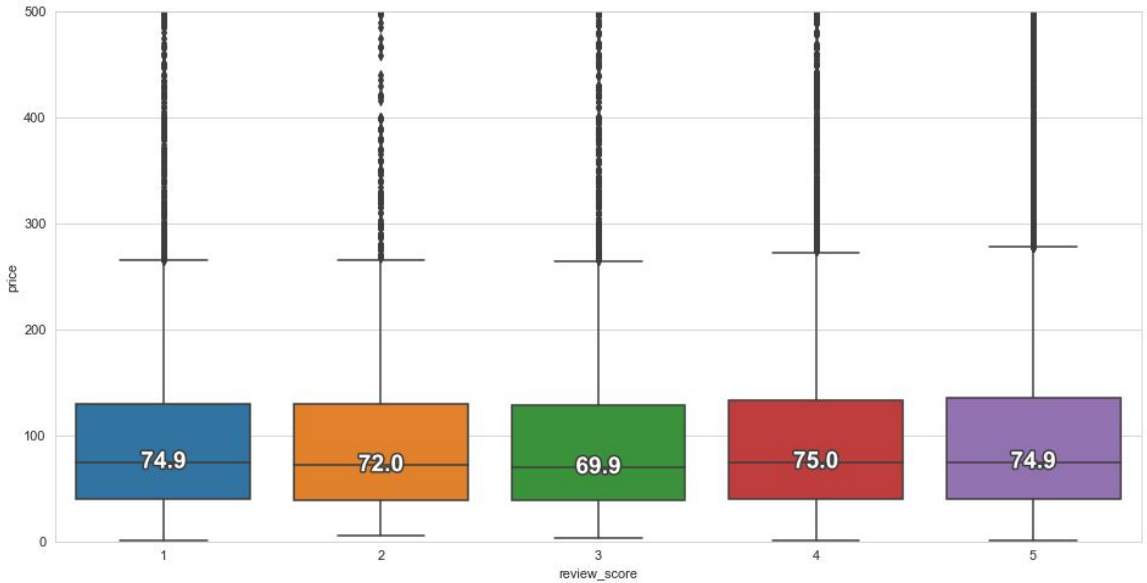
party_supplies
books_imported
fashio_female_clothing
la_cuisine
fashion_sport
arts_and_craftmanship
diapers_and_hygiene
flowers
home_comfort_2
cds_dvds_musicals
fashion_childrens_clothes
security_and_services
Product Category
0
1000
2000
3000
4000
5000
Revenue
Category by counts or revenue
10000
5000
0
bed_bath_table
health_beauty
sports_leisure
furniture_decor
computers_accessories
housewares
watches_gifts
telephony
garden_tools
auto
toys
cool_stuff
perfumery
baby
electronics
stationery
fashion_bags_accessories
pet_shop
office_furniture
consoles_games

4. Correlations: Score

Score vs. Price
Score vs. Customer State
Score vs. Payment
Score vs. Payment Installments
Score vs. Payment Sequential
Score vs. Category and Status
Score vs. Description and Name

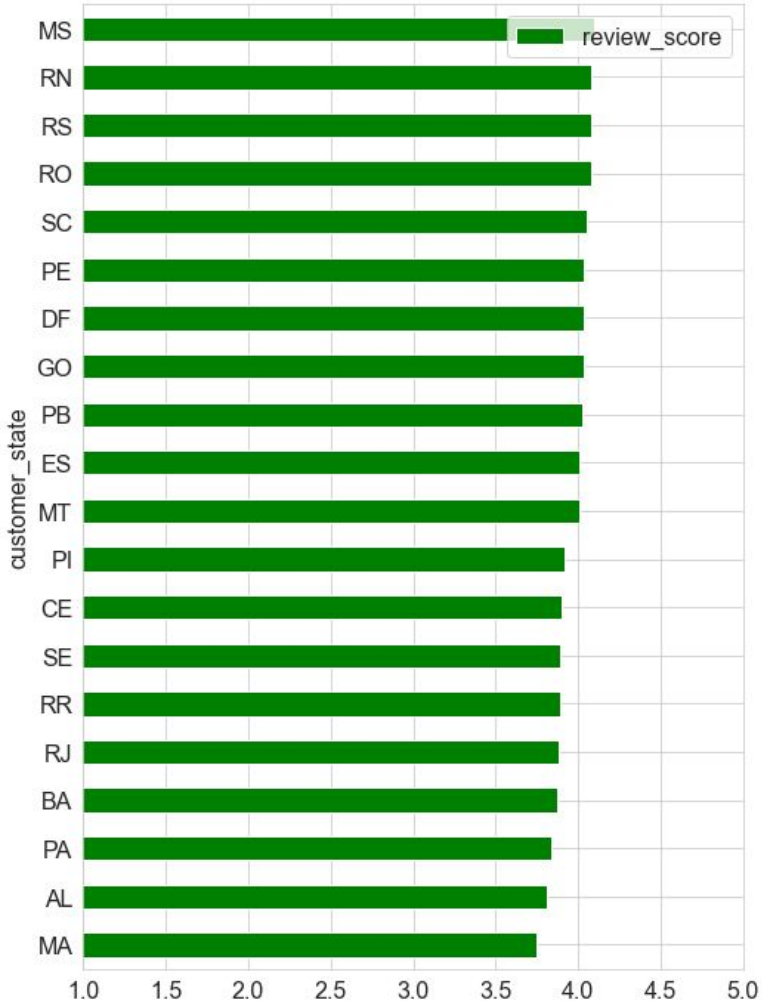
Score by price



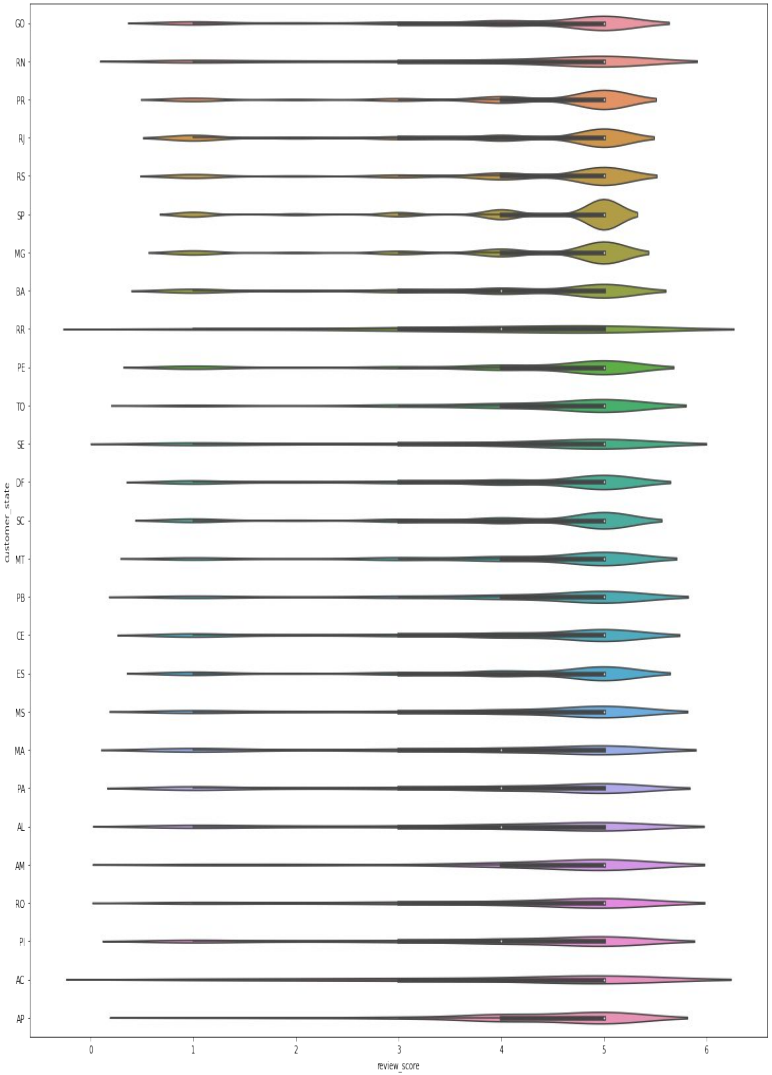
Weak correlations

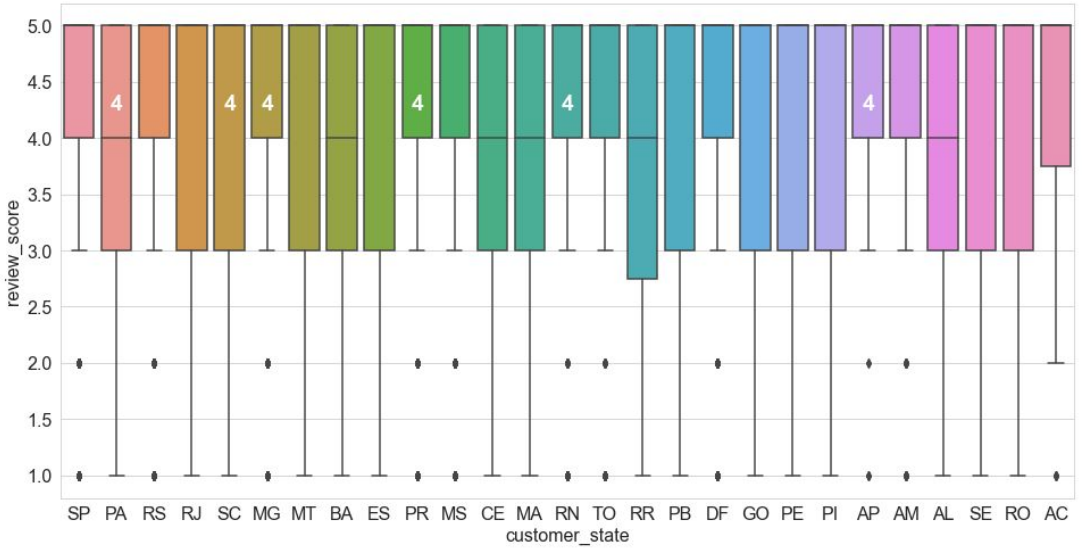
Score vs. Customer State

Some correlations to the customer state



Score vs. Customer State

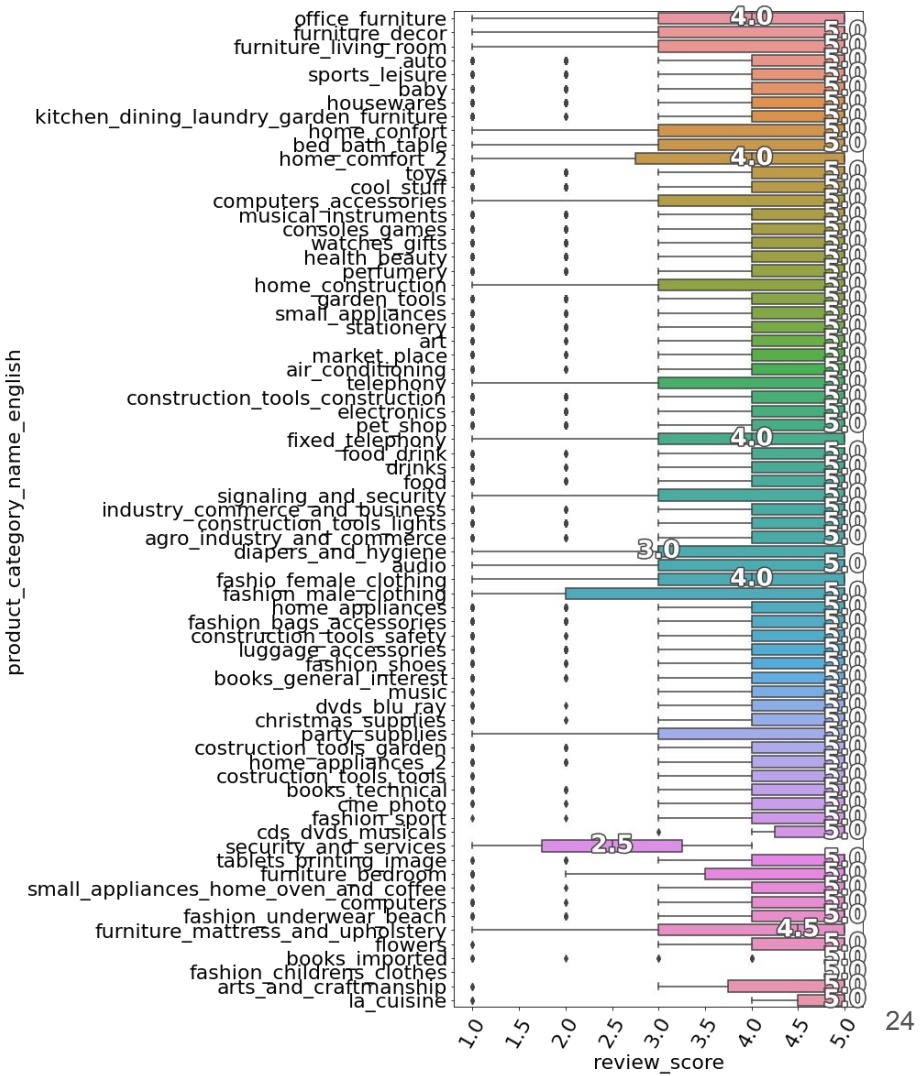




Score vs. Category

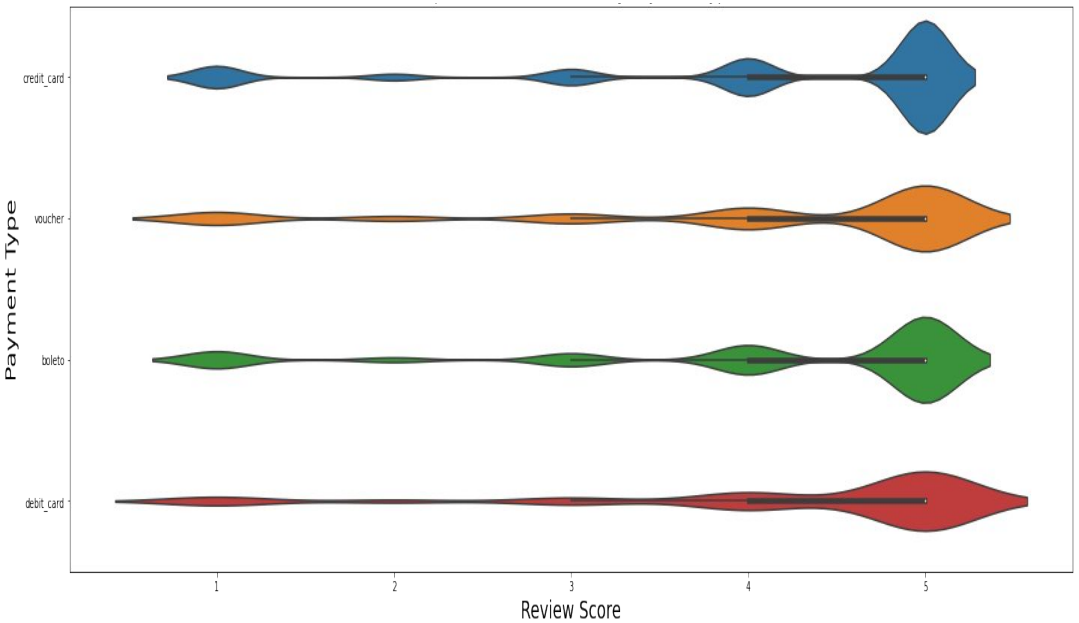
Certain product category has lower review scores in general

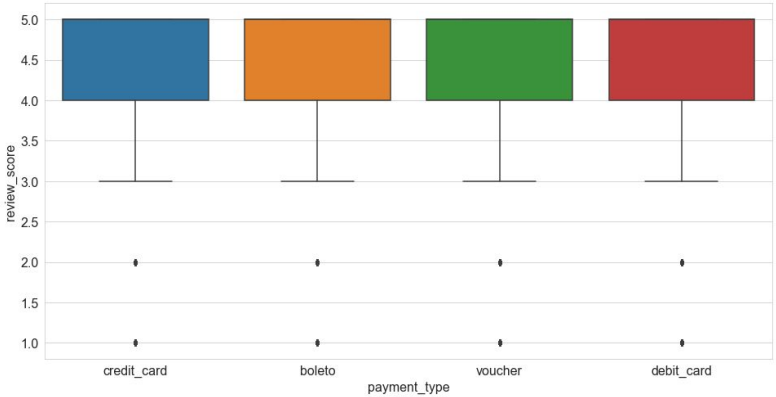
- Diapers and hygiene
- Security and services
- Fashion-male clothing



Score vs. Payment Type

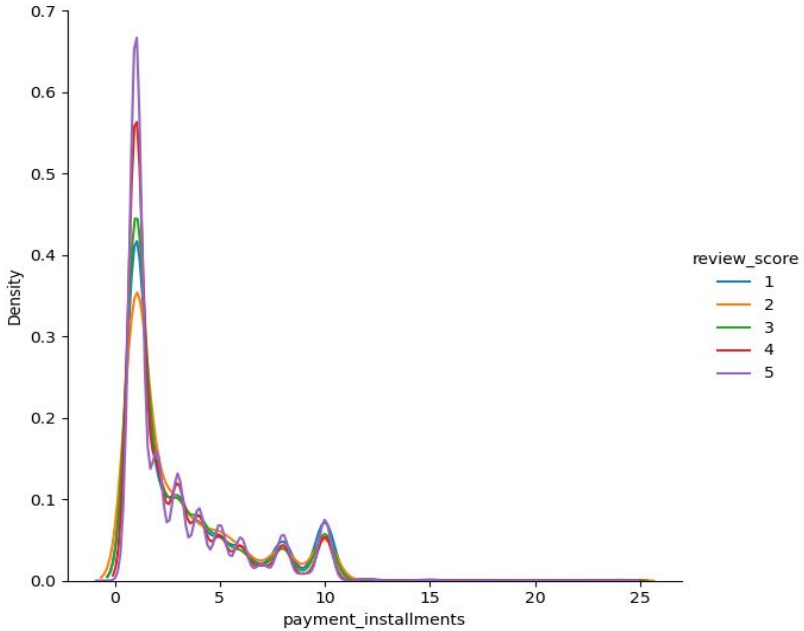
More concentrated 5 for two of the payment.

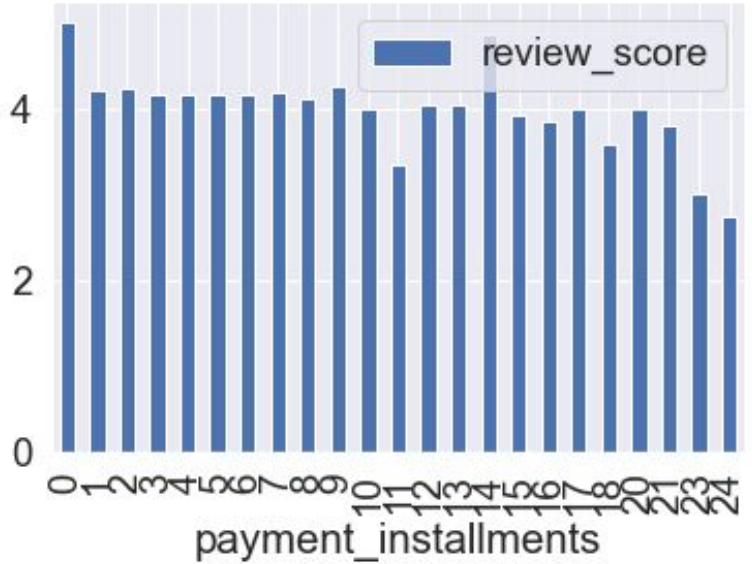




Score vs. Payment Installment

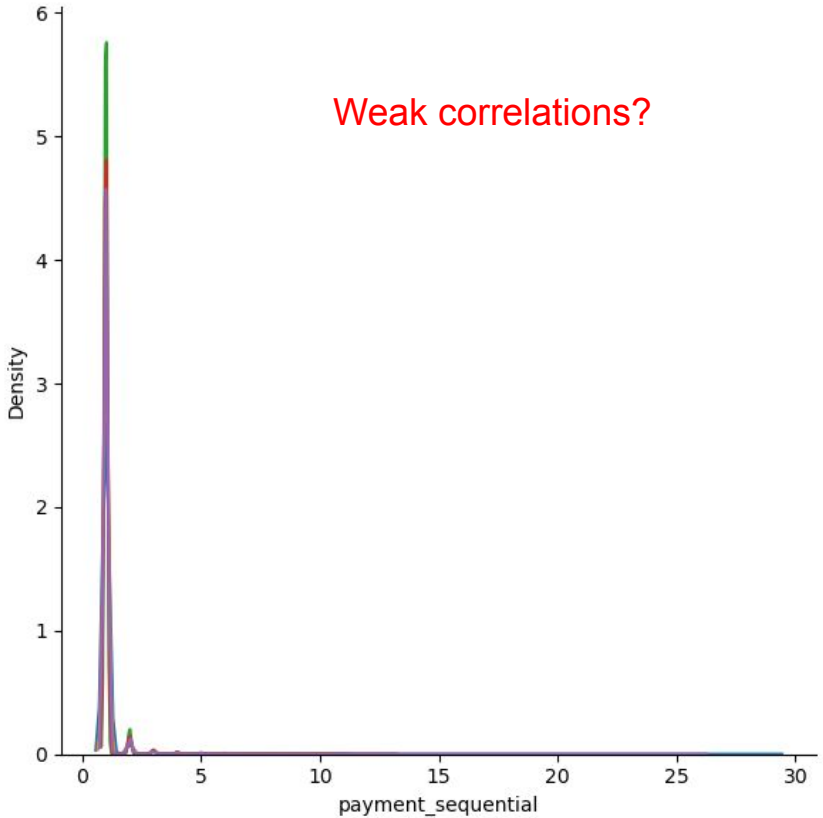
Generally weak correlatoin
When installment > 20, score trends towards the lower end

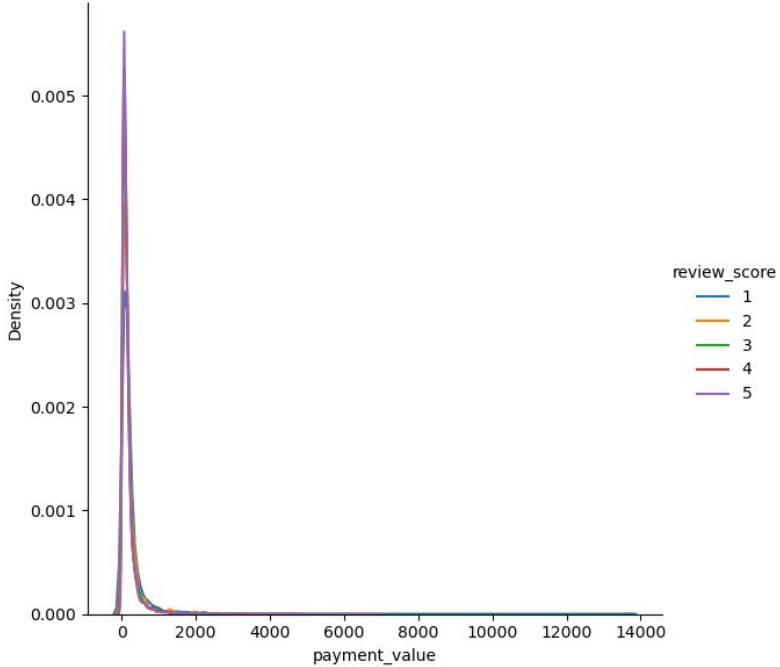




Score vs. Payment Sequential

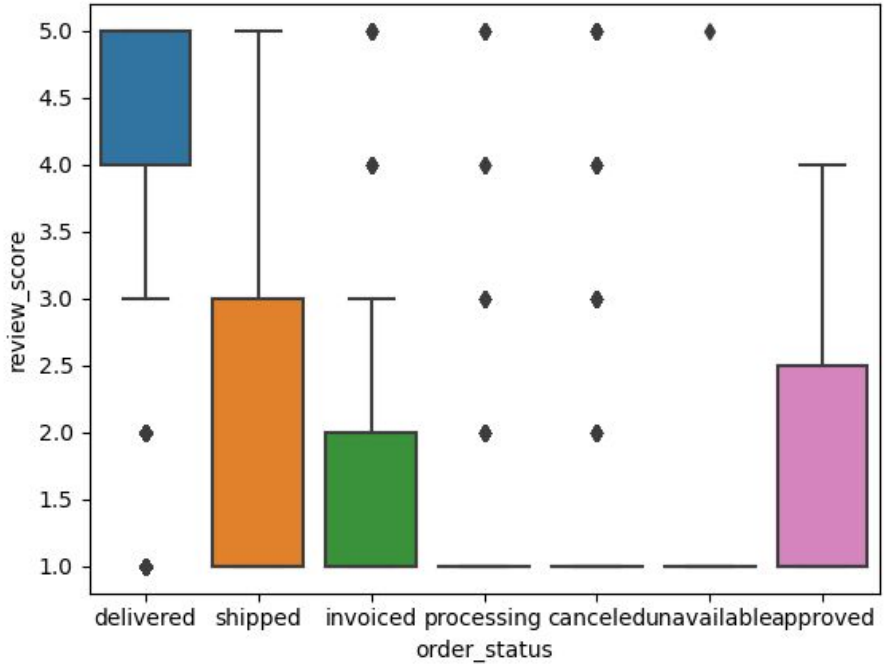
Weak correlations?





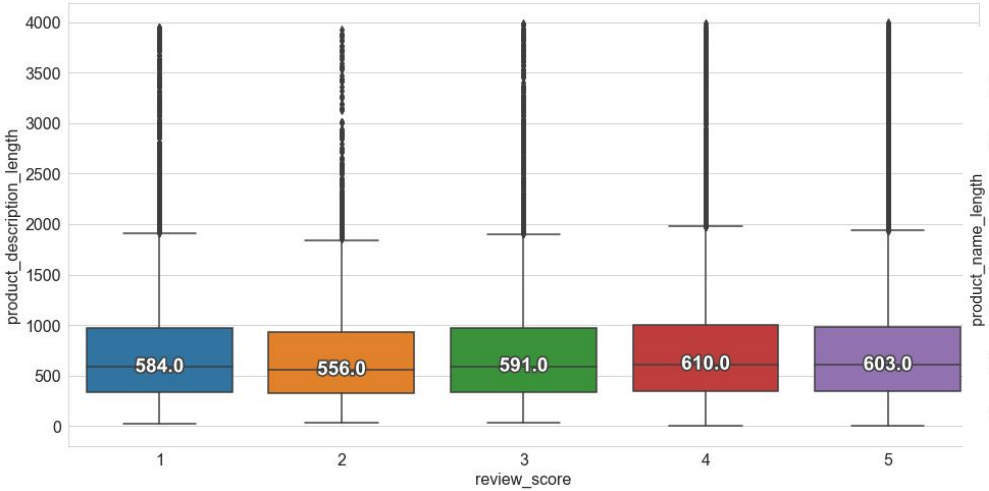
Score vs. Order Status

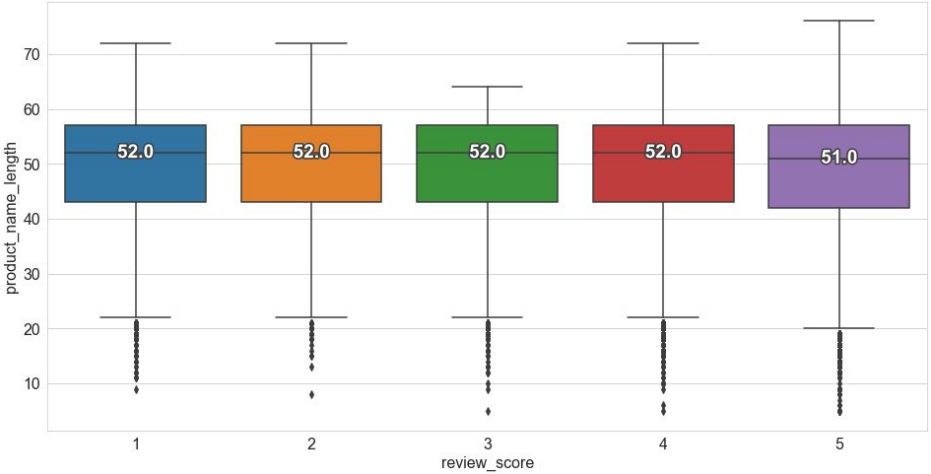
Strong Correlations!



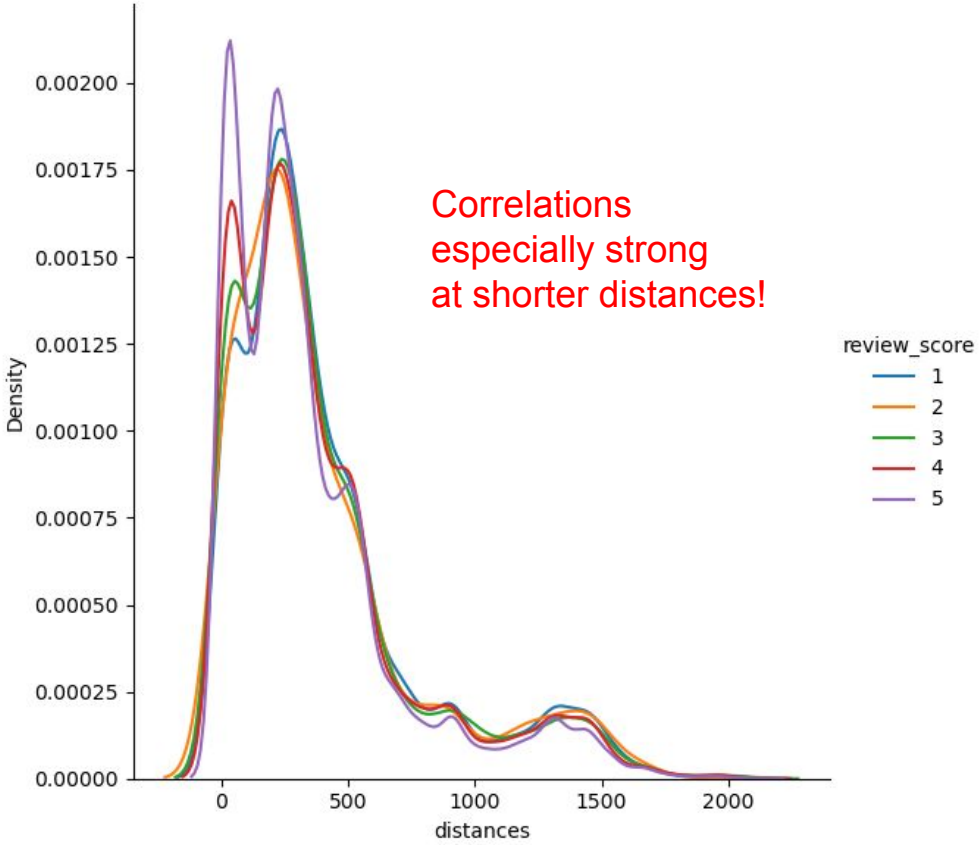
Score vs. Description and Name

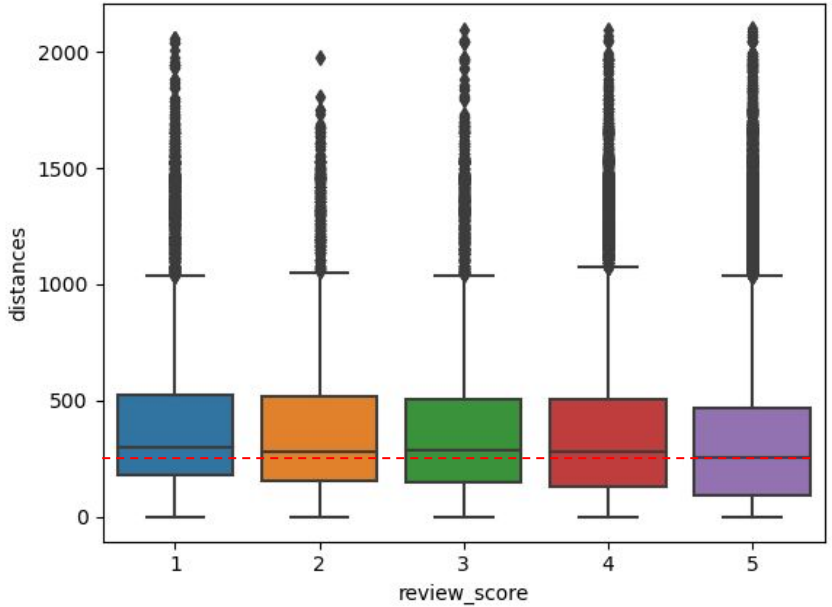
- Longer description has higher frequency of score 4 and 5.
- Product name length has no correlation with score



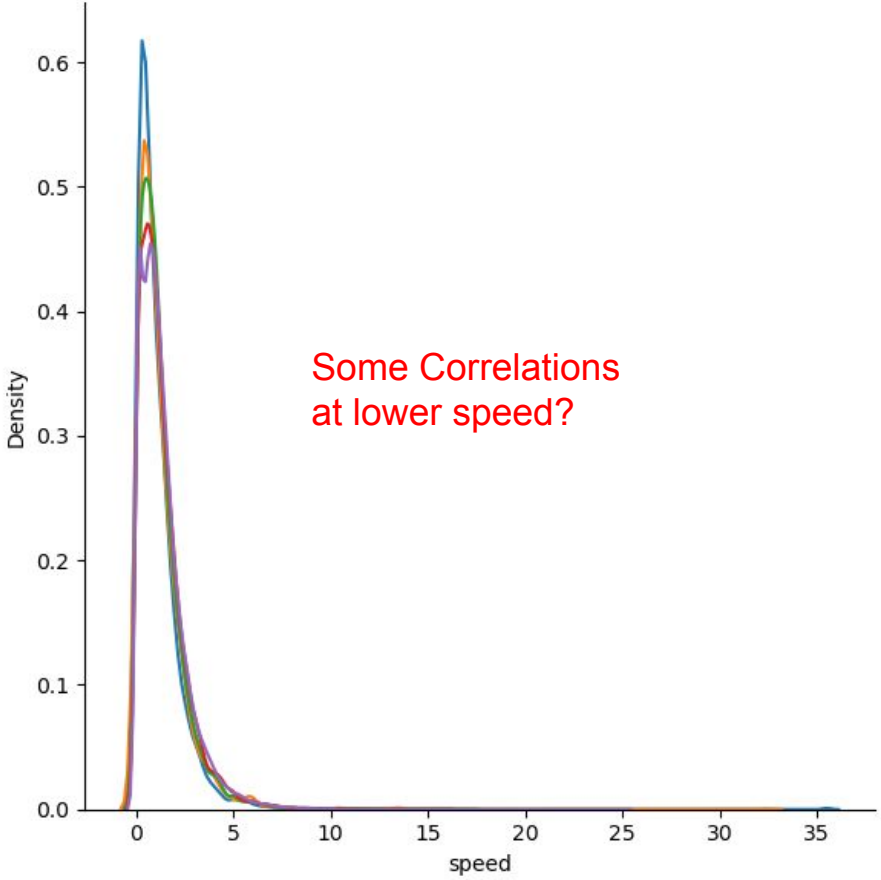


Score by distance

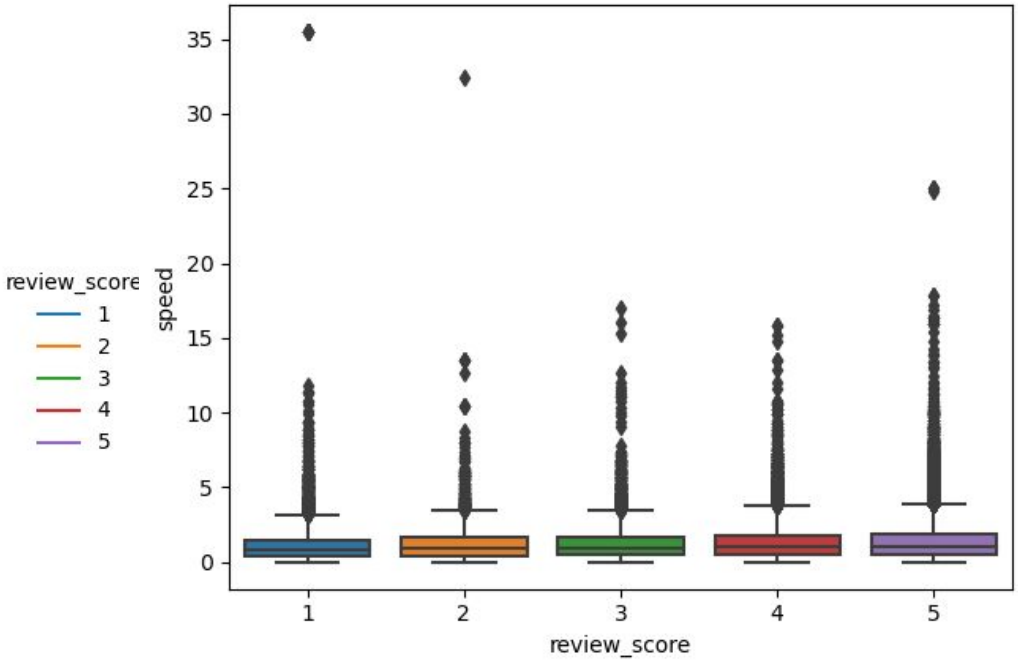




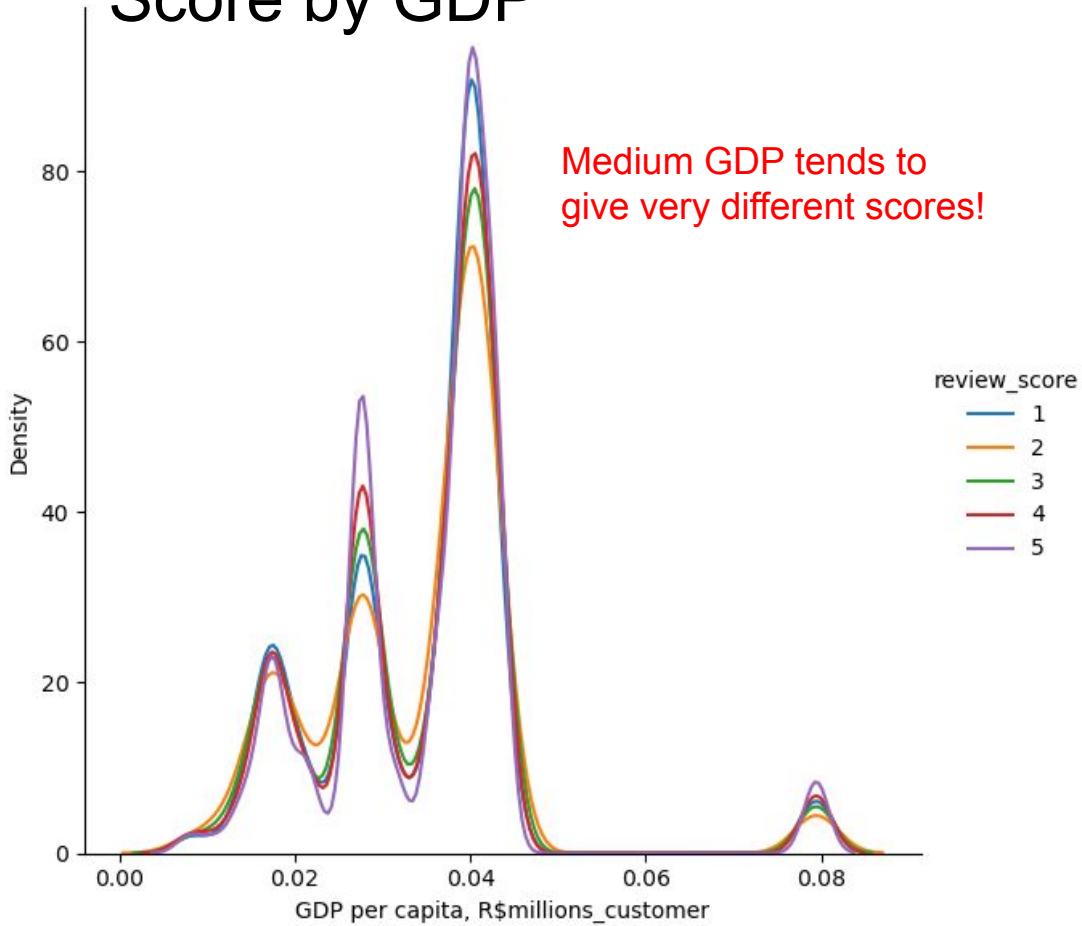
Score by speed



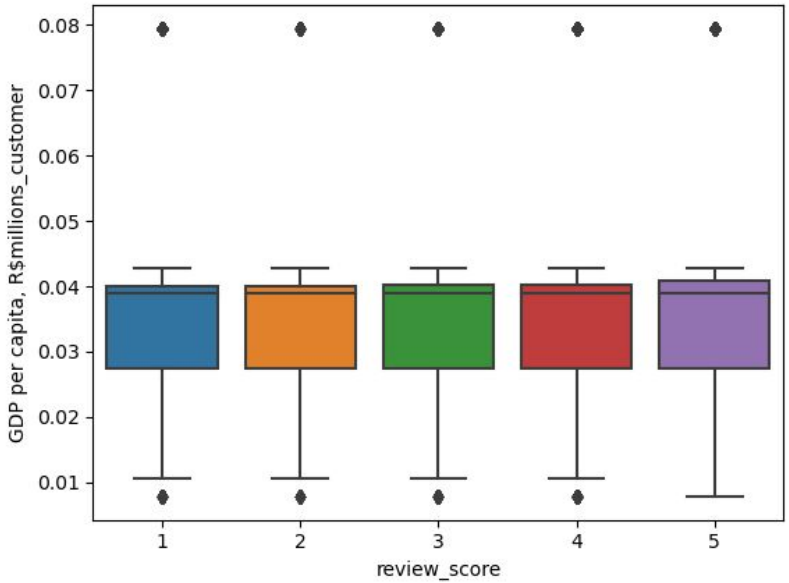
Some Correlations
at lower speed?



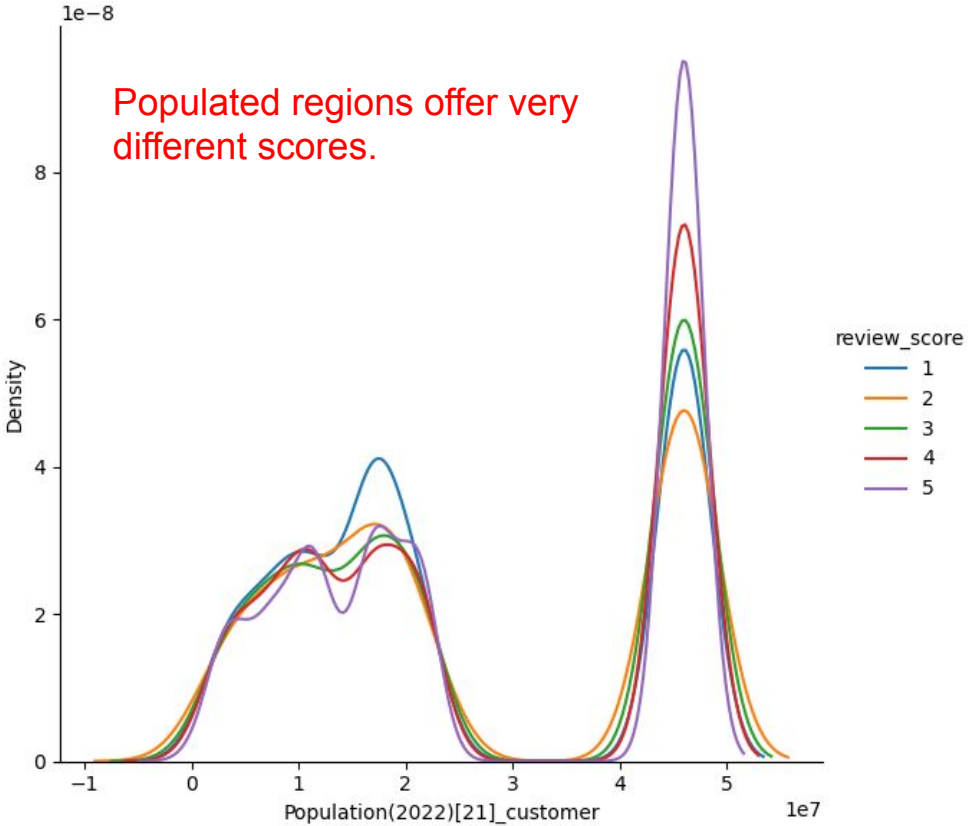
Score by GDP

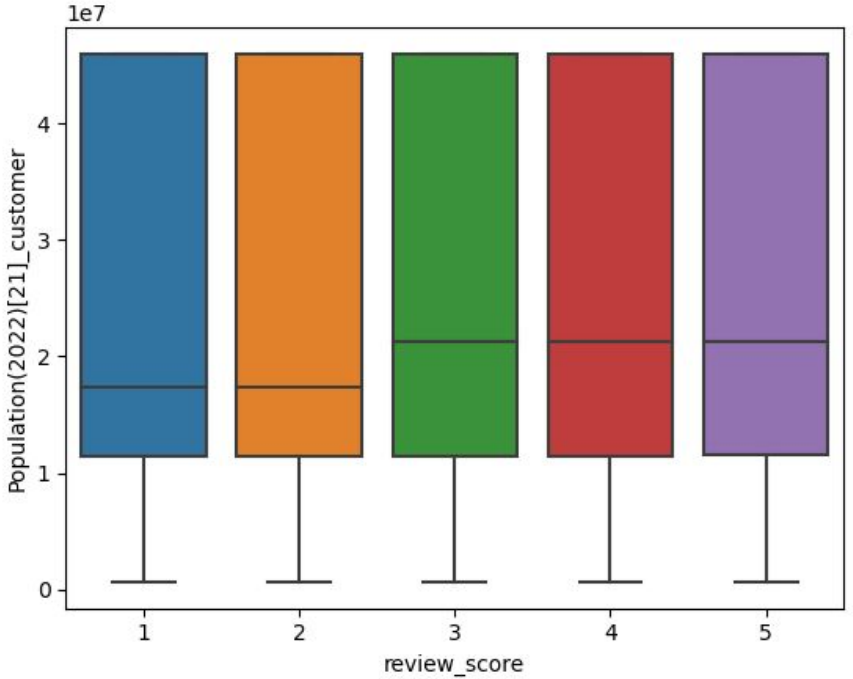


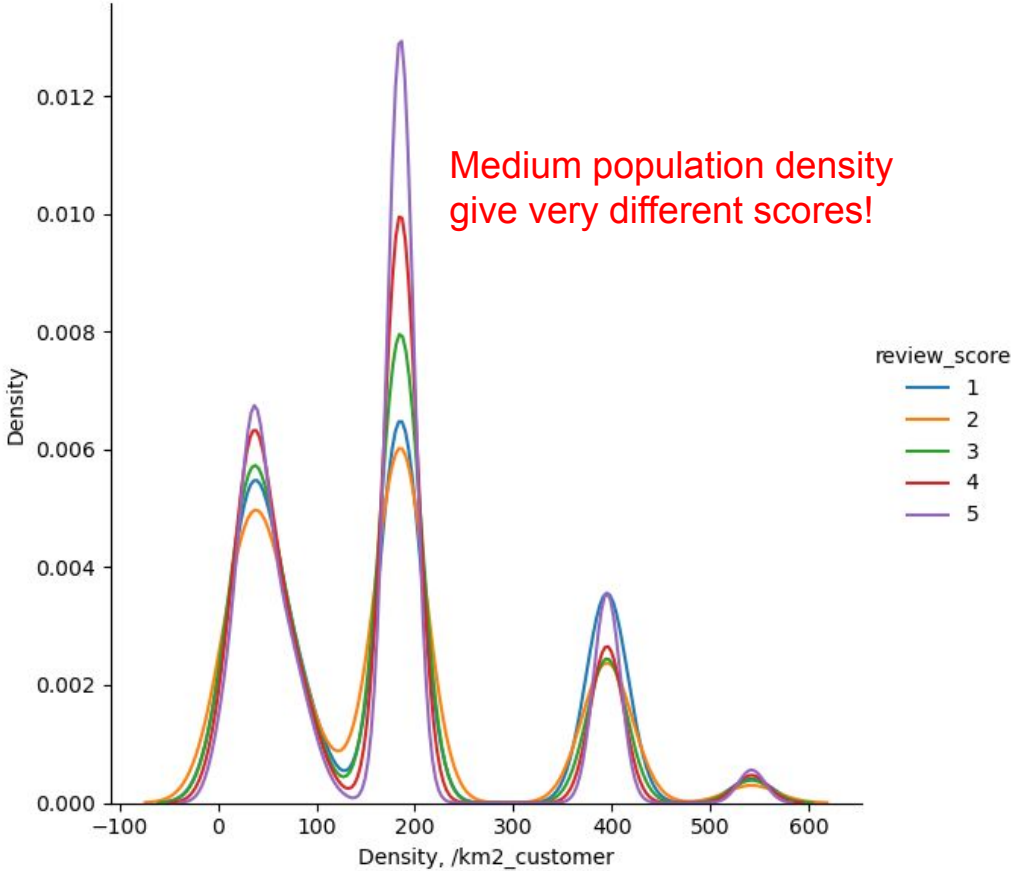
Medium GDP tends to
give very different scores!

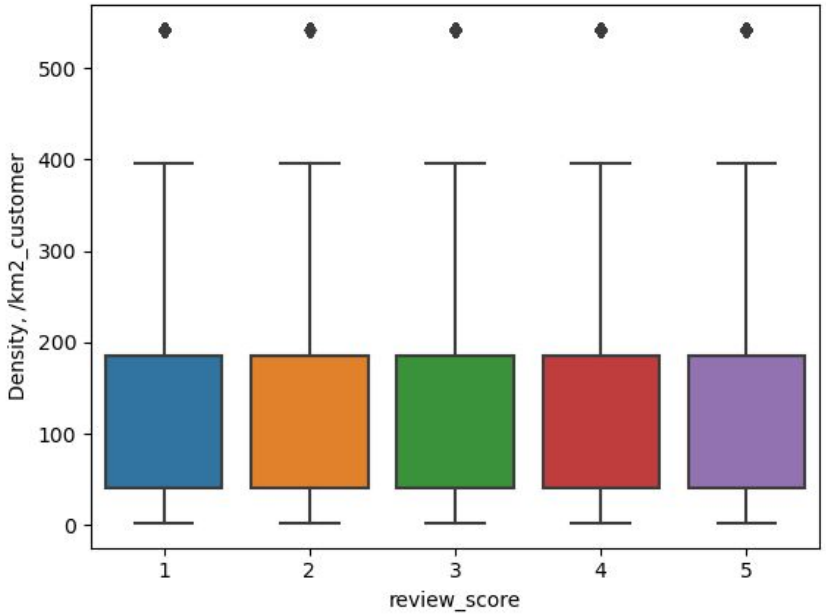


Score by Population





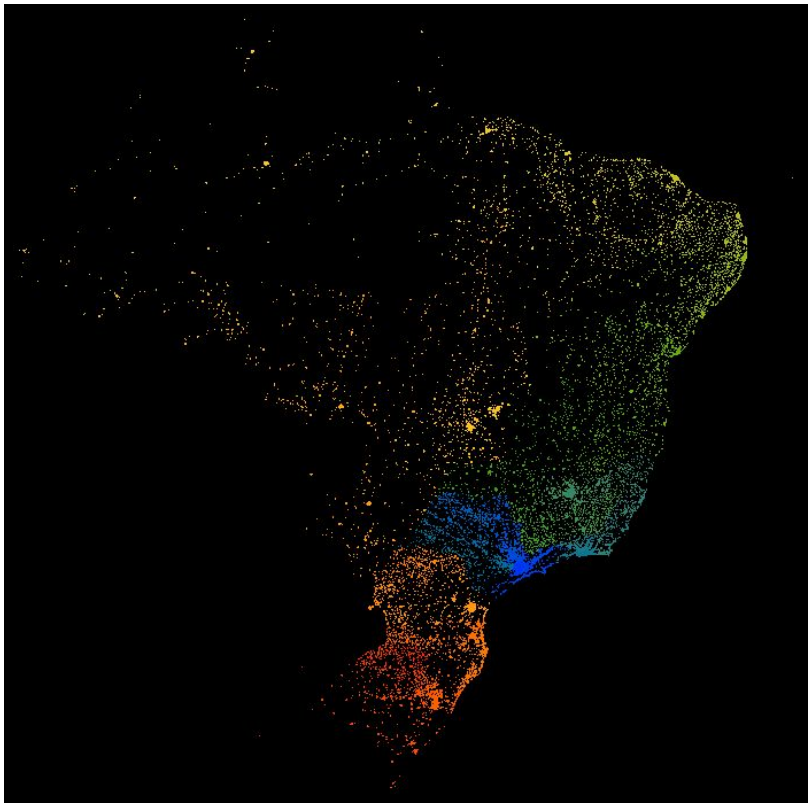

Medium population density
give very different scores!
Density
0.012
0.010
0.008
0.006
0.004
0.002
0.000
−100
0
100
200
300
400
500
600
Density, /km2_customer
review_score
1
2
3
4
5

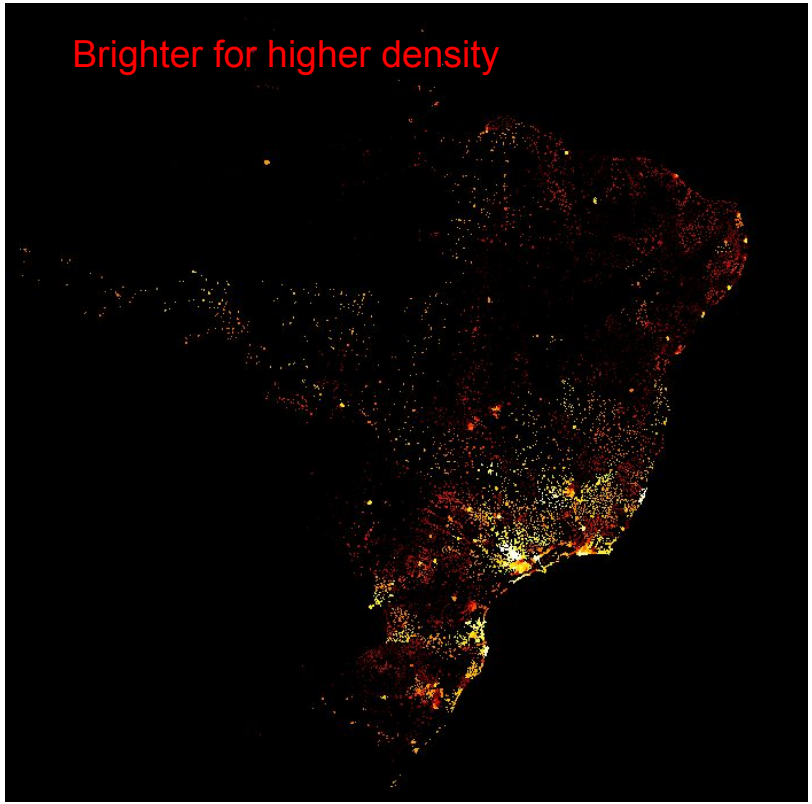

Density, /km2_customer
500
400
300
200
100
0
1
2
3
4
5
review_score

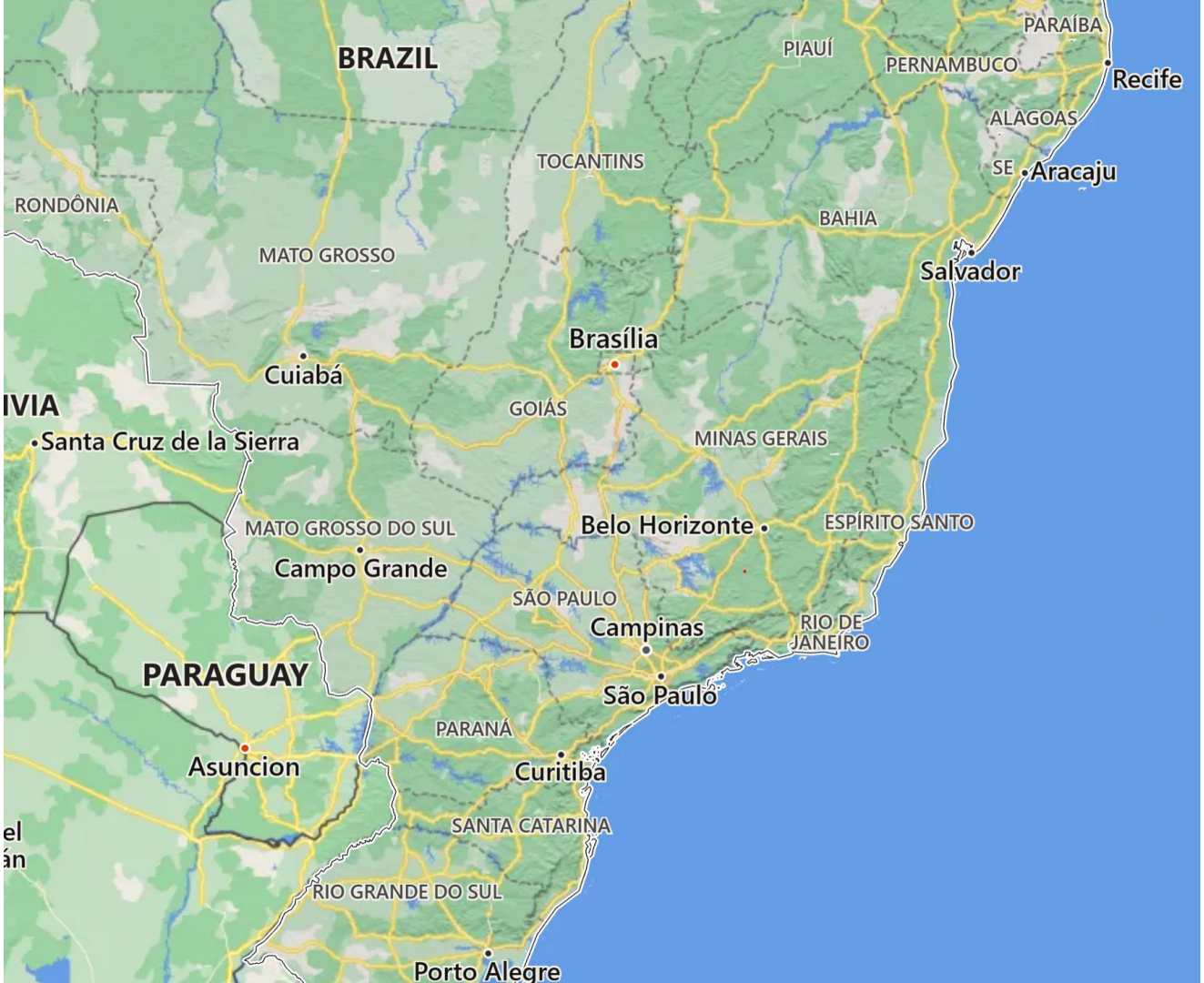
5. Correlations: Geo

Zip Code and Revenue
Average Ticket and Freight Ratio
Deliver Time and Delay
Average and Individual Review Score

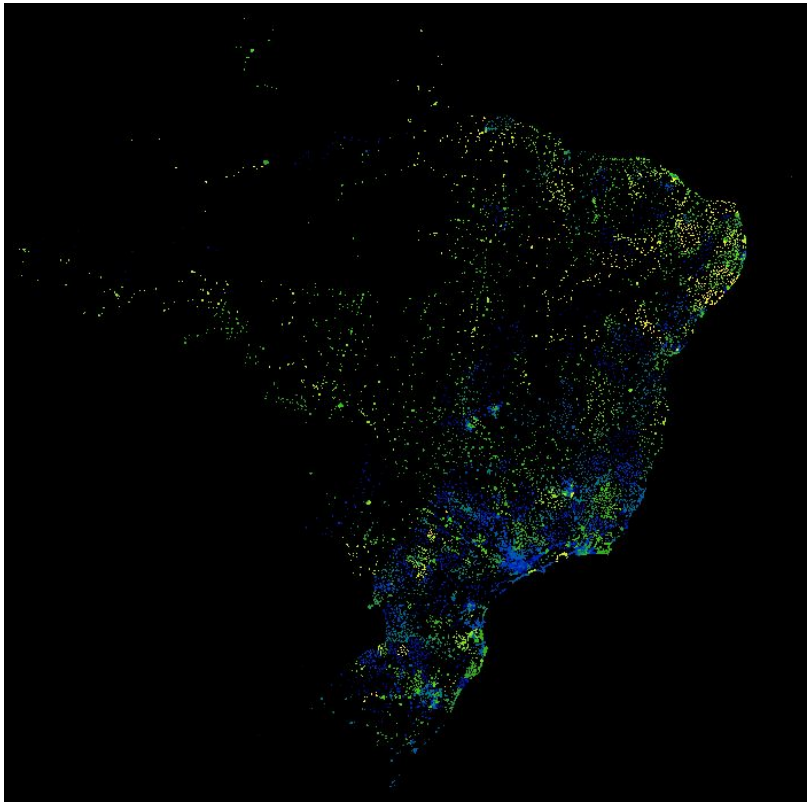
Zip code and Revenue

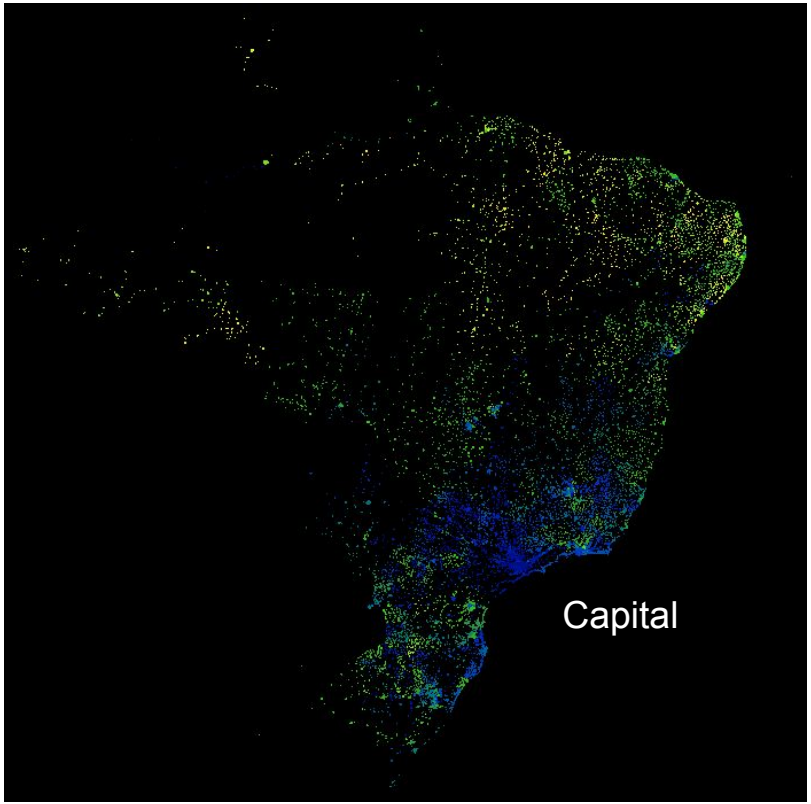




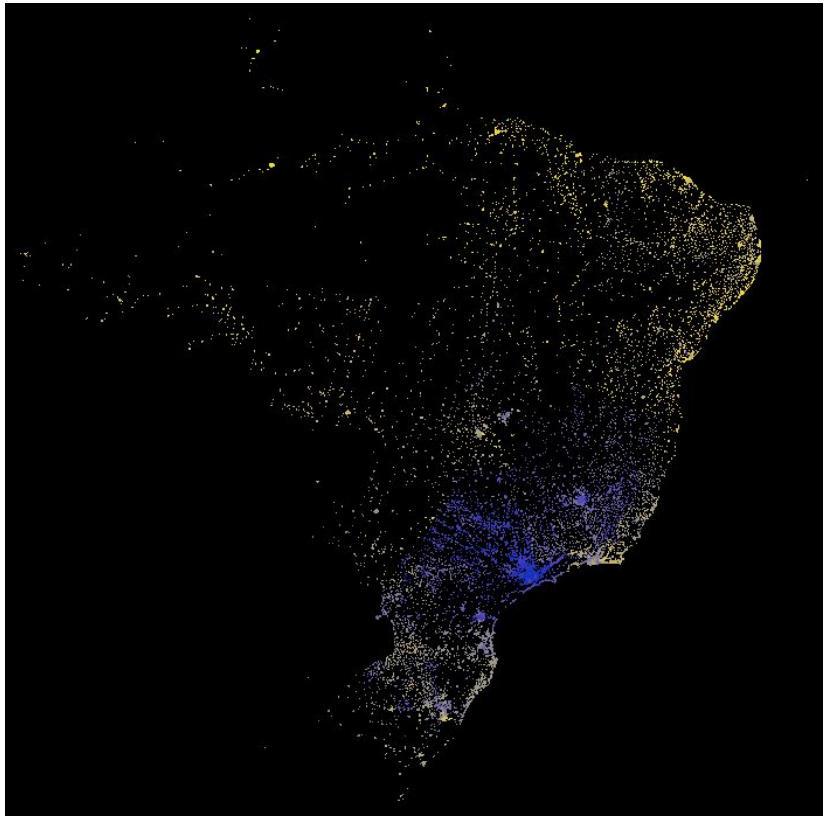

BRAZIL
PIAUÍ
PARAÍBA
PERNAMBUCO
Recife
ALAGOAS
SE
Aracaju
TOCANTINS
RONDÔNIA
BAHIA
MATO GROSSO
Salvador
Brasília
Cuiabá
GOIÁS
MINAS GERAIS
Santa Cruz de la Sierra
MATO GROSSO DO SUL
Belo Horizonte
ESPÍRITO SANTO
Campo Grande
SÃO PAULO
Campinas
RIO DE JANEIRO
PARAGUAY
São Paulo
PARANÁ
Asuncion
Curitiba
SANTA CATARINA
RIO GRANDE DO SUL
Porto Alegre

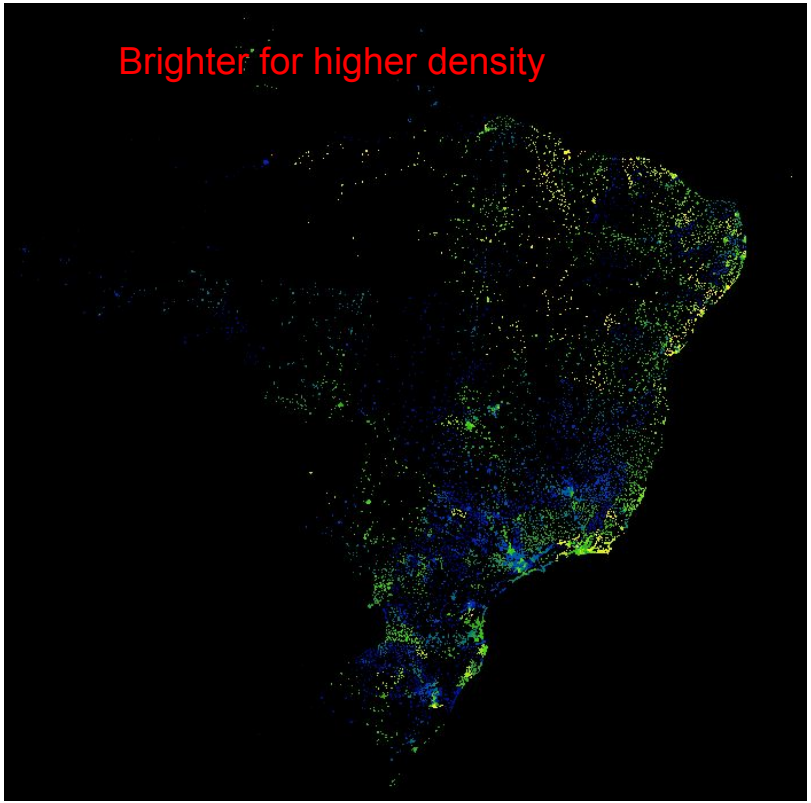
Average Ticket and Freight Ratio



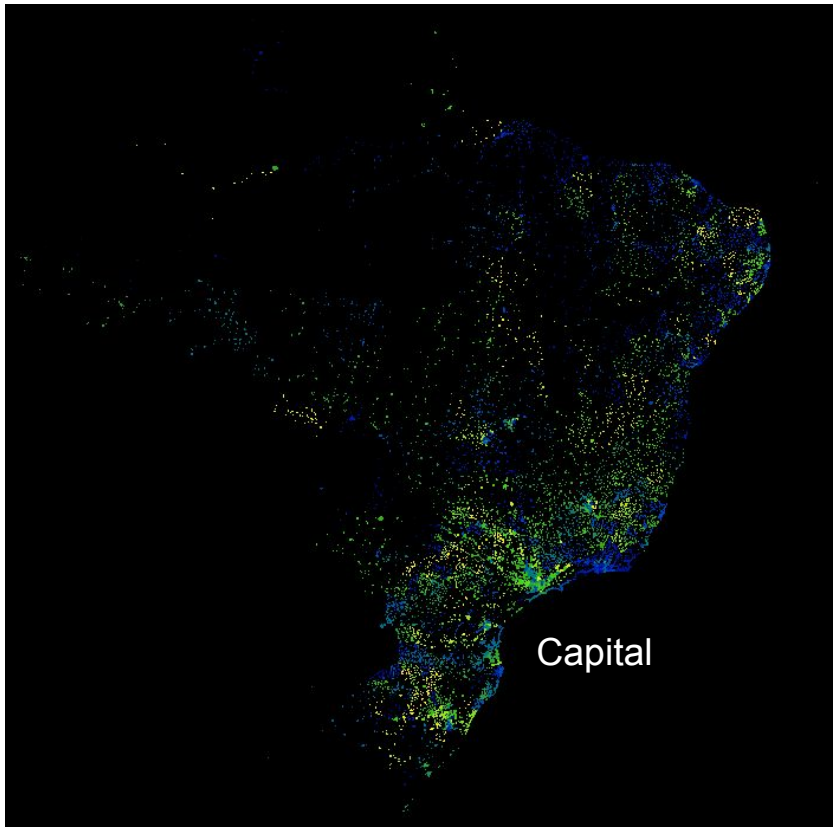


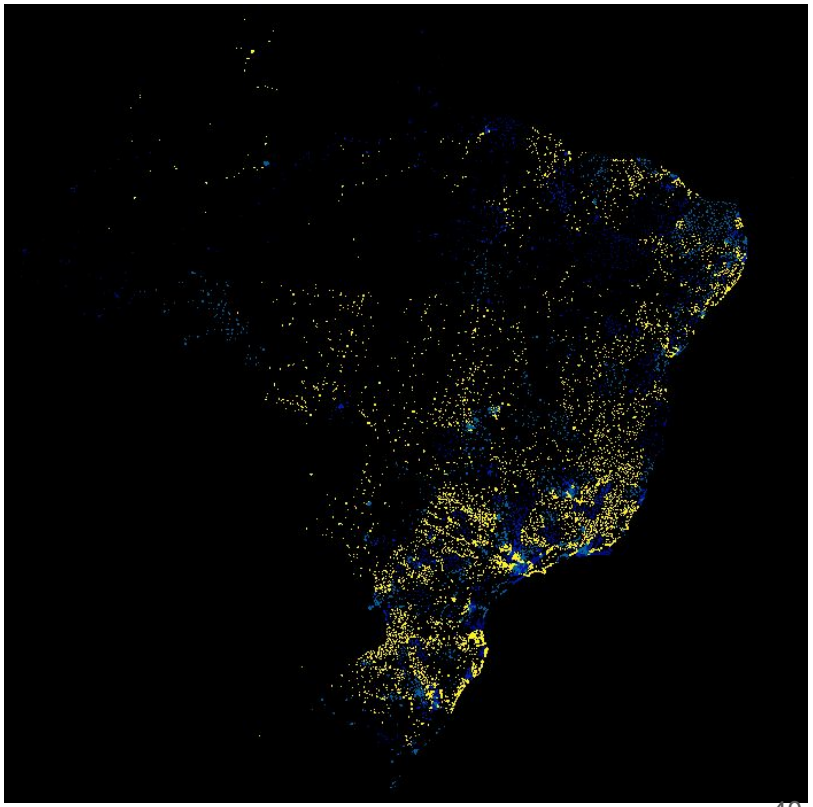
Deliver Time and Delay



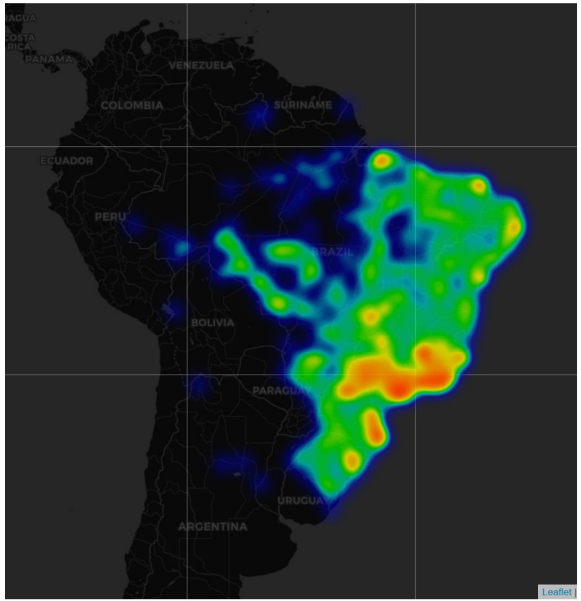


Average and Individual Review Score





Folium for time lapse and map

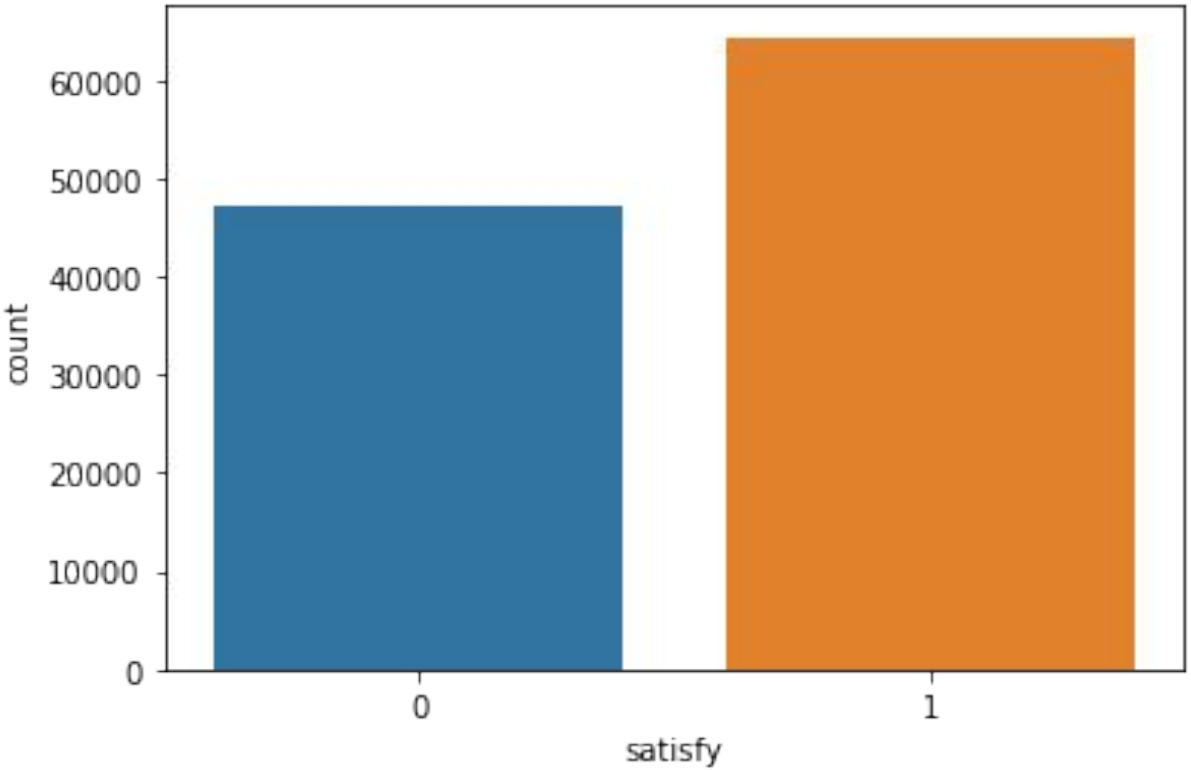


Youtube Link: https://www.youtube.com/watch?v=0xSW-_N7-OA

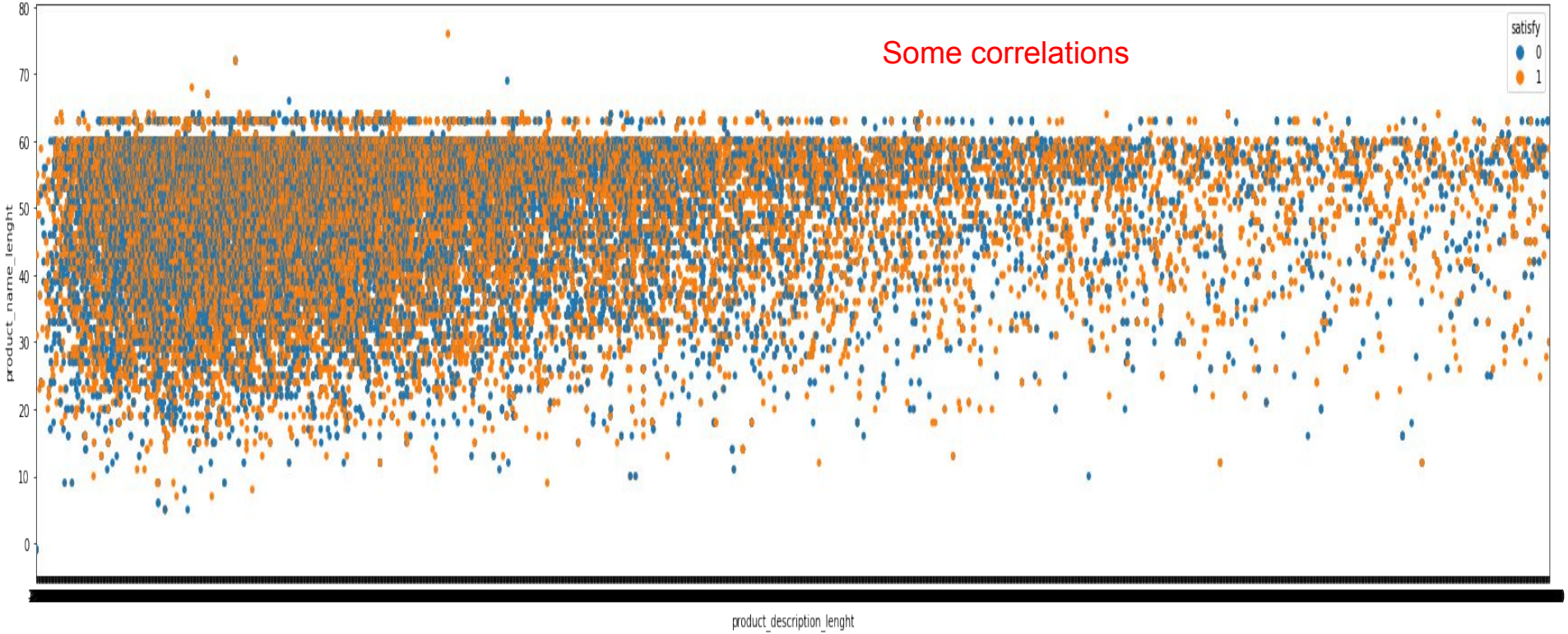
Reference: E-Commerce Sentiment Analysis: EDA + Viz + NLP ✍ | Kaggle

6. Threshold for Satisfaction

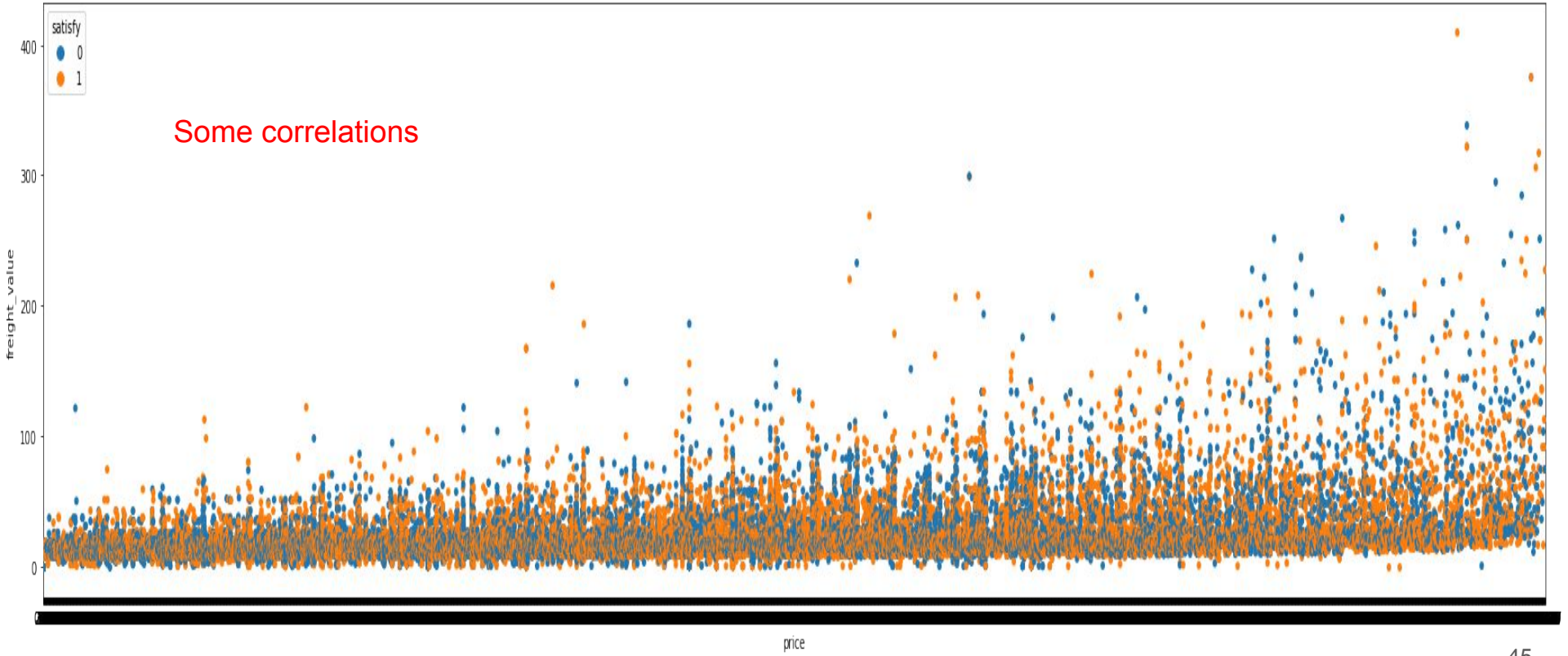
Target Distribution (Threshold =4)

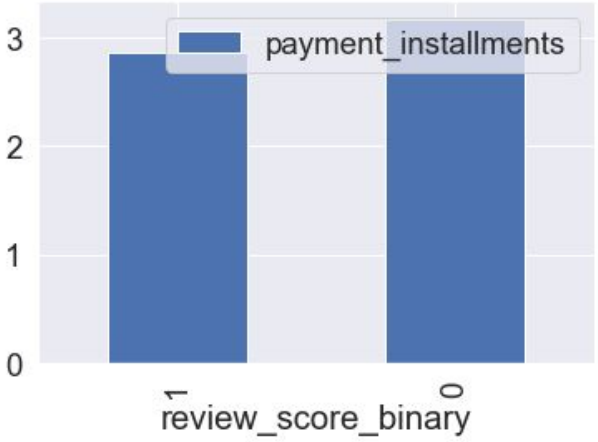


Satisfaction by length of product name and description

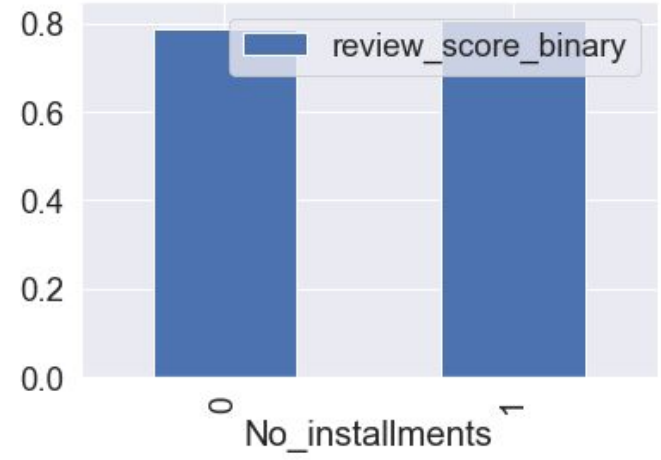


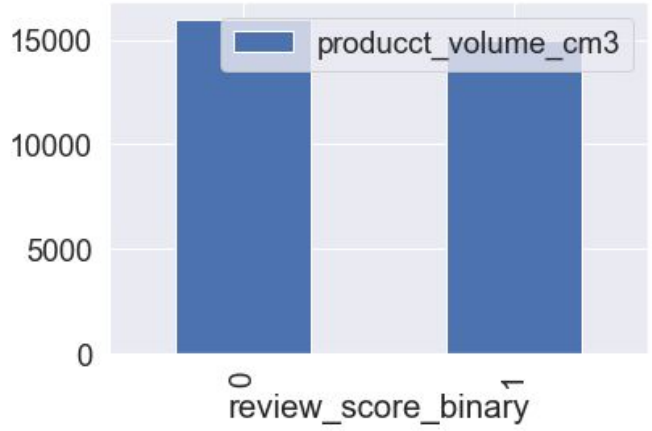
Satisfaction by price and freight value



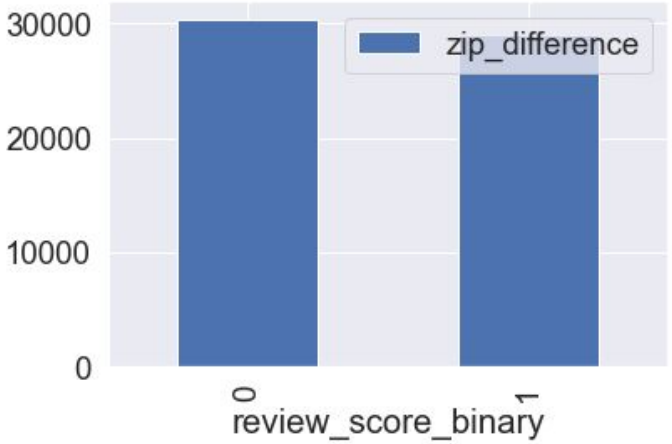


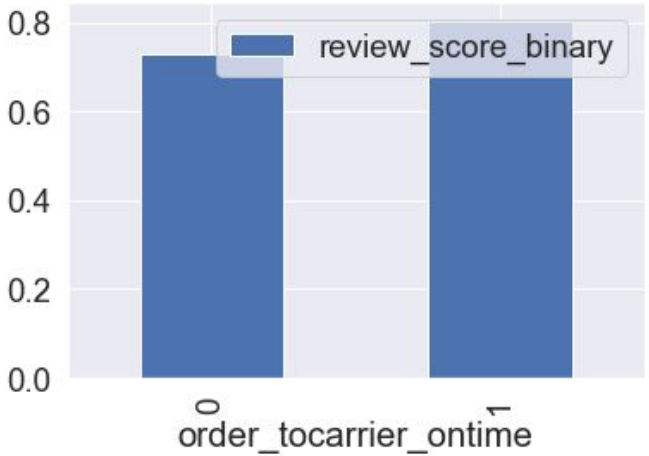
Satisfaction distribution for payment_installment, product volume

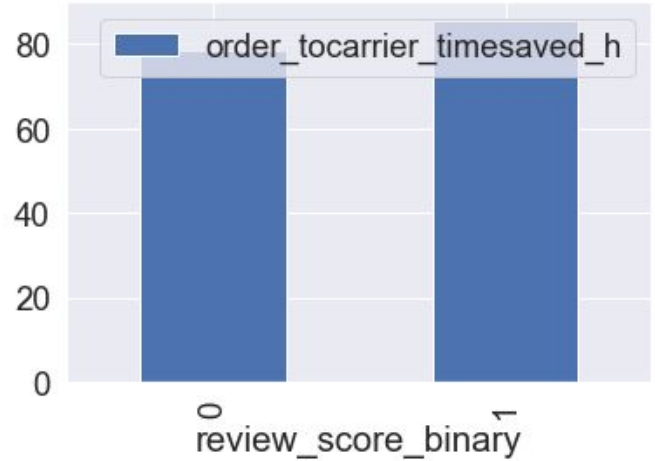


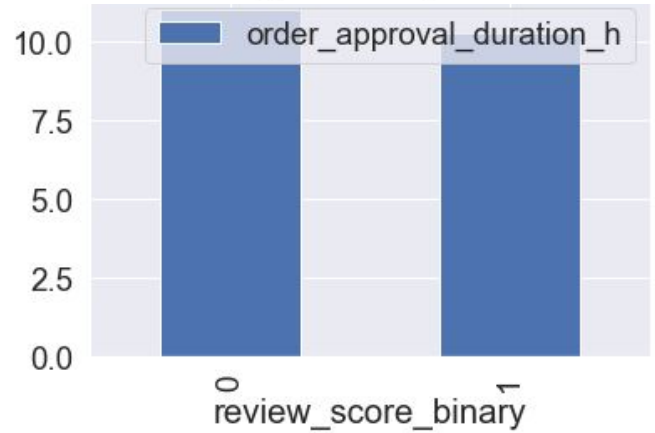


Even satisfaction distribution for other features









Feature Selection

Data Cleaning

1.Drop ID related feature

2. Make new features for time

3. Drop missing (110k to 90k)

4. CountVectorizer for categorical

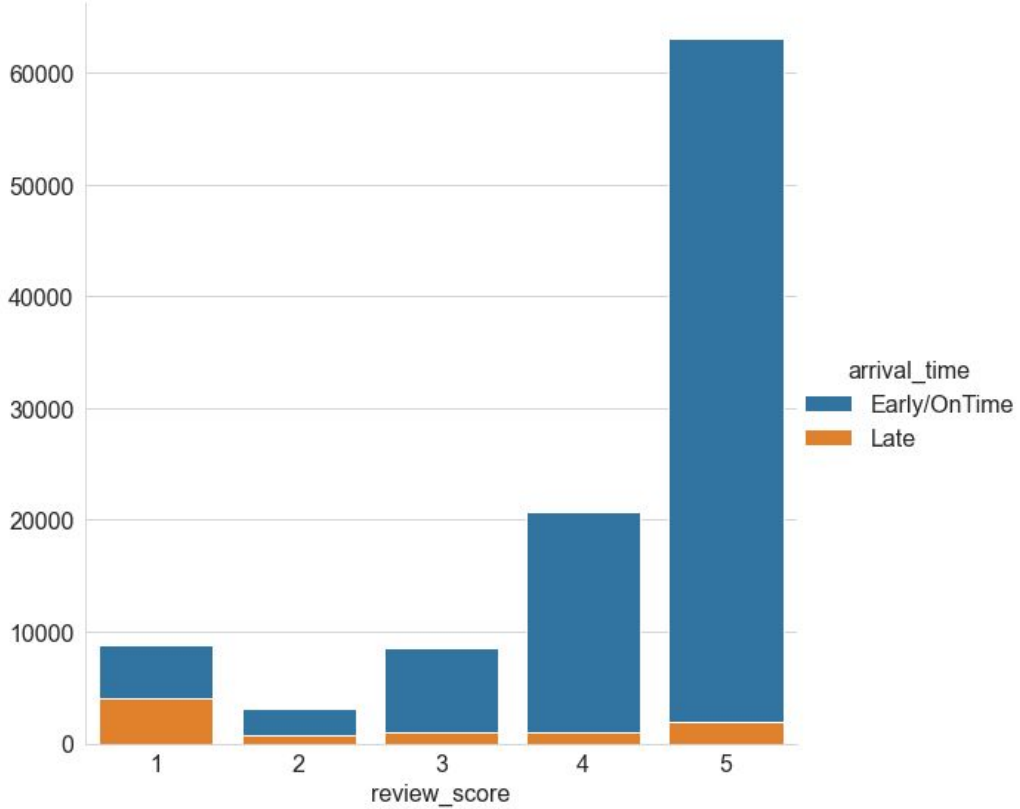
5. Dropped outliers such as 60-day delivery

6. Drop timestamps after new time-difference feature generated

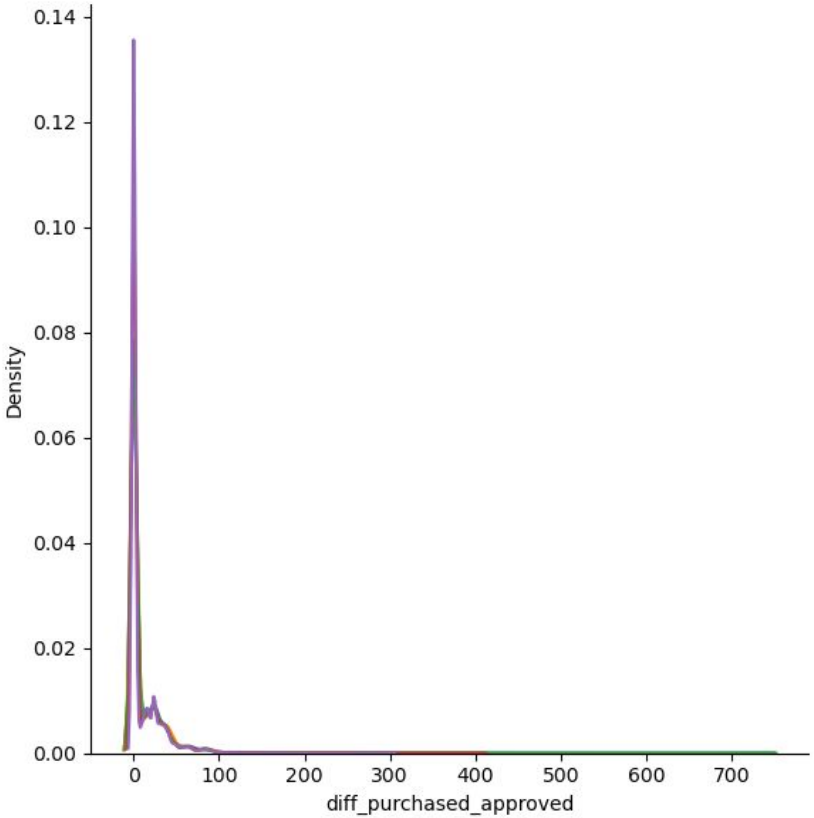
Other dropped features for high F1 models

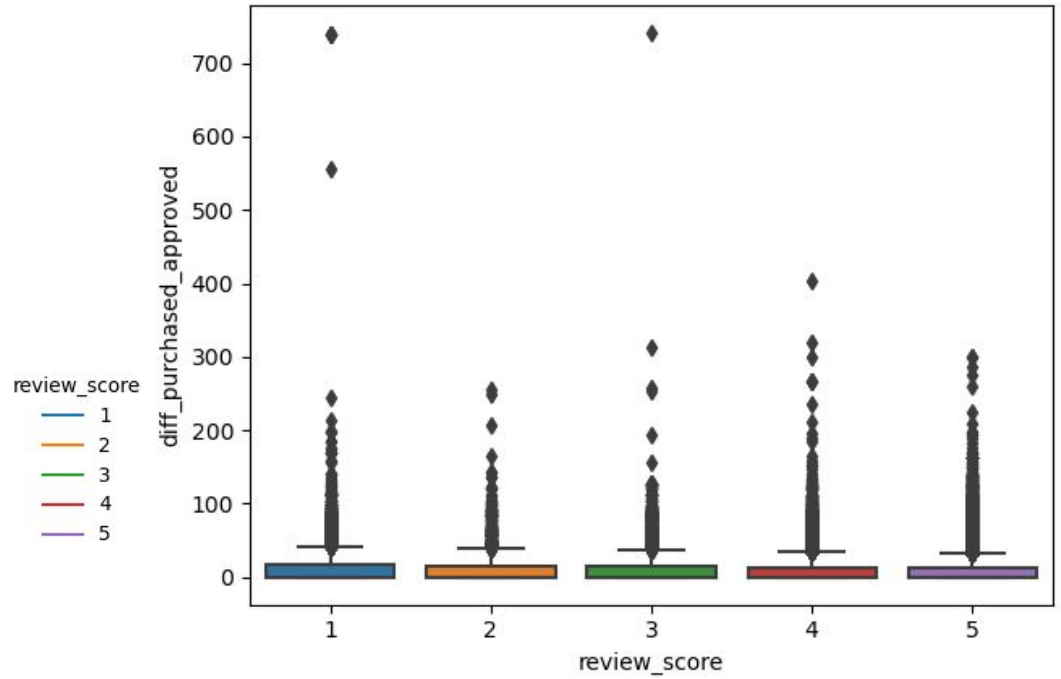
```
['review_comment_title','review_comment_message','product_category_name','product_weight_g','review_creation_date',

'product_length_cm','product_height_cm','product_width_cm','seller_city','review_answer_timestamp',

'geolocation_lat_y','geolocation_lng_y','geolocation_city_y','geolocation_state_y','review_id','order_approved_at','order_status',

'order_id','customer_id','order_item_id','geolocation_lat_x',

'geolocation_lng_x','geolocation_city_x','geolocation_state_x']
```

New Time Feature: delivery time

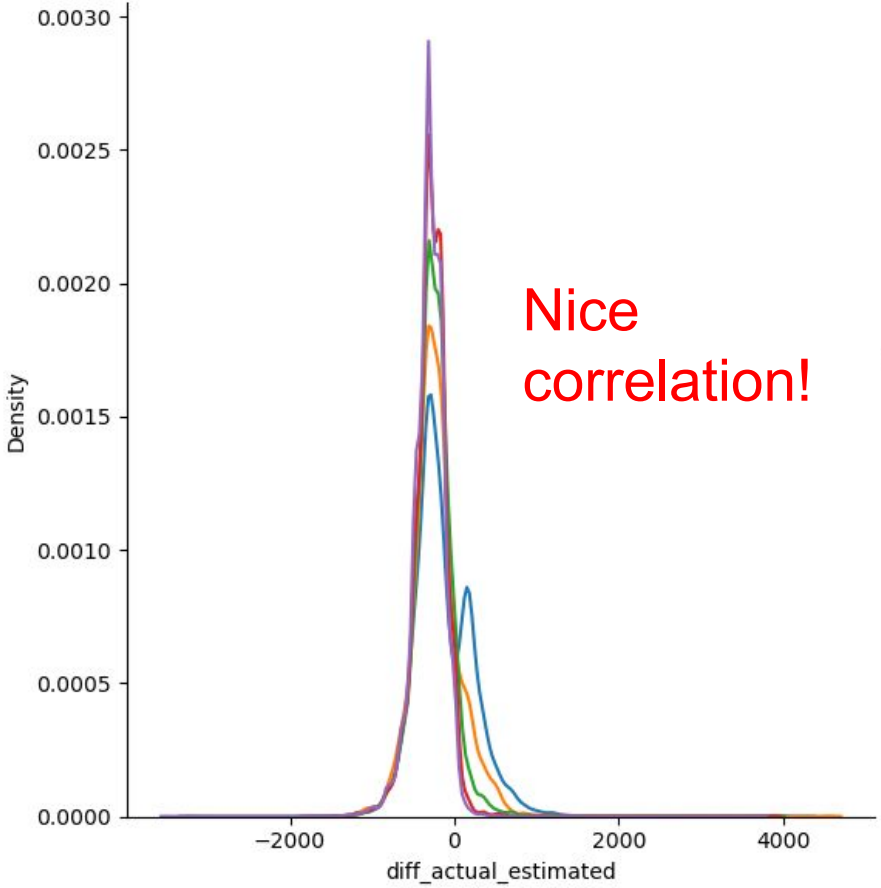


New Time Feature 2

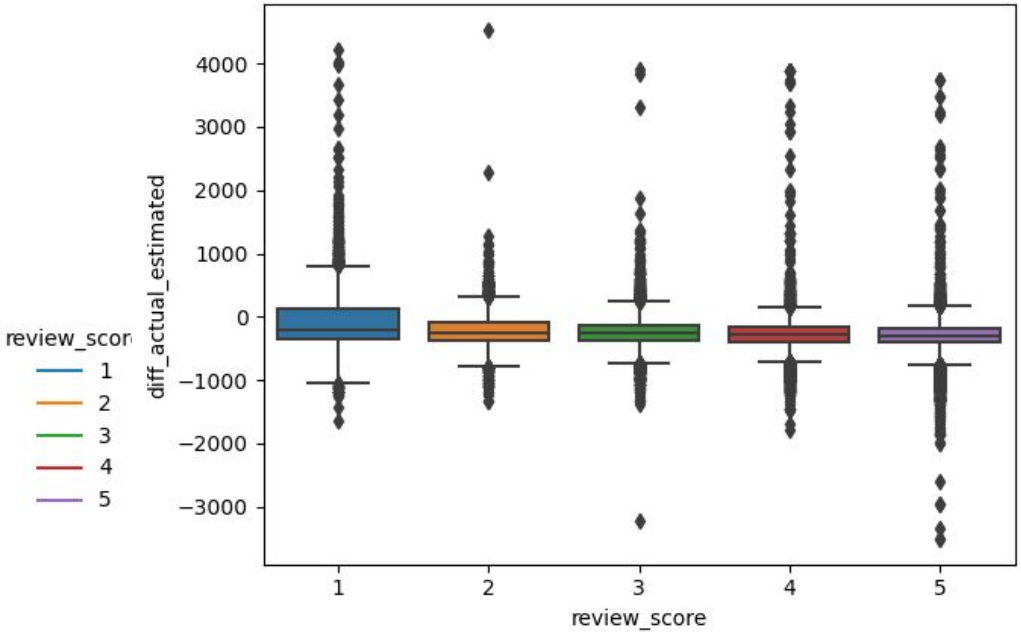




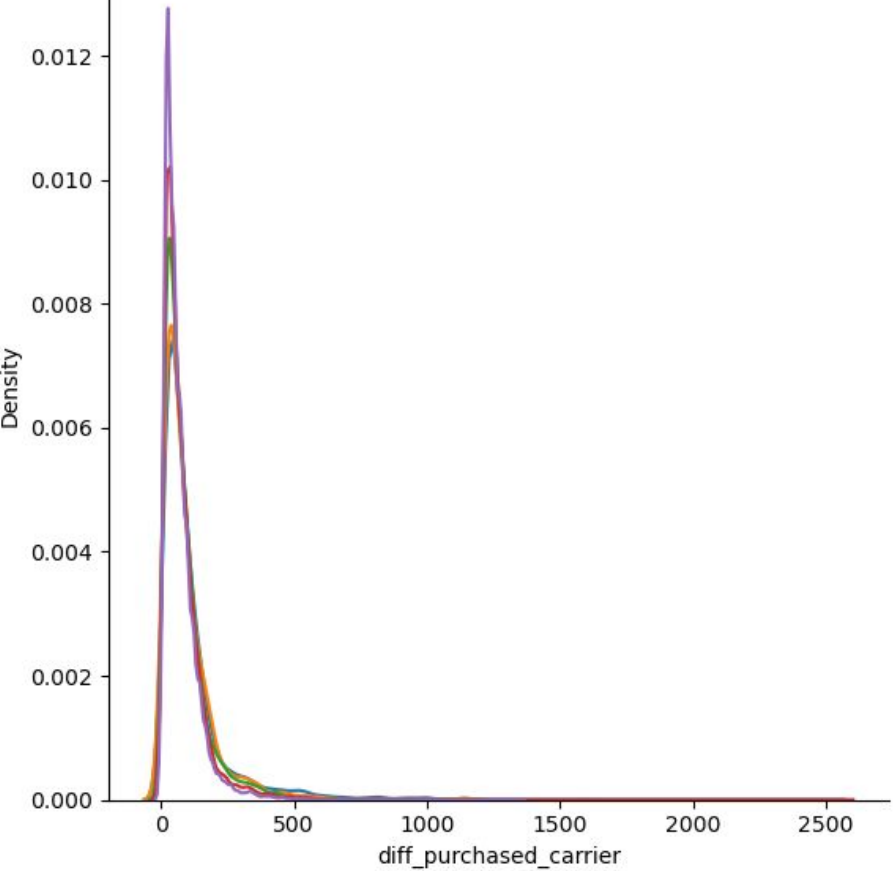
New Time Feature 3

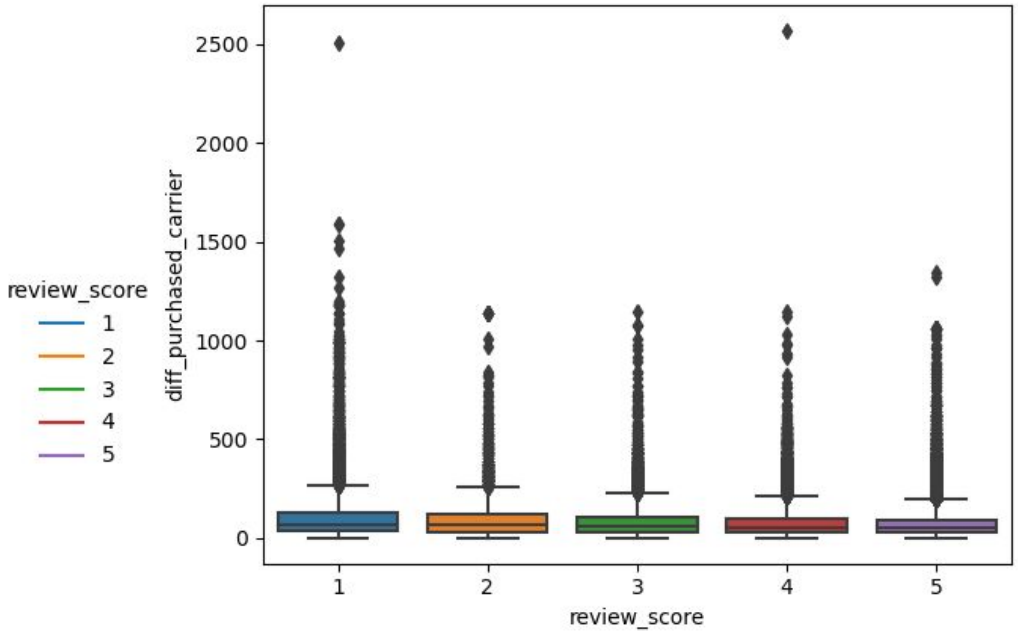


Nice correlation!

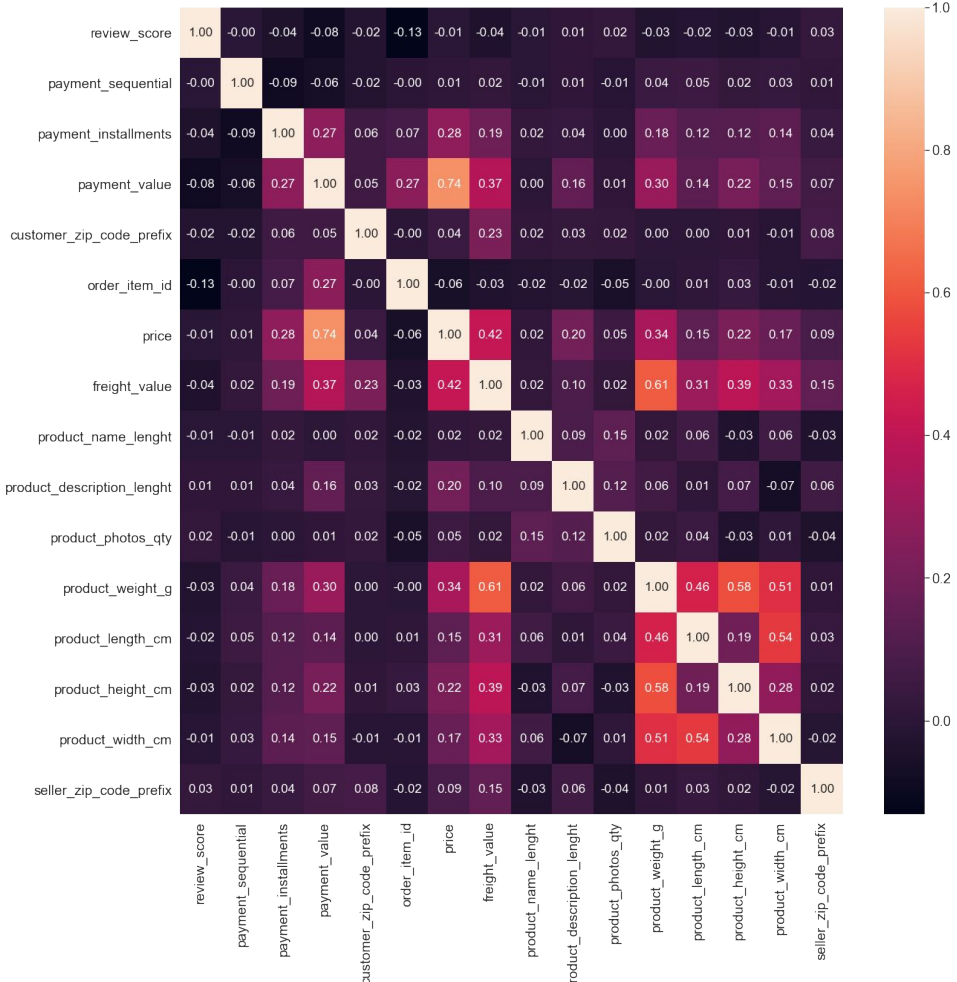


New Time Feature 4

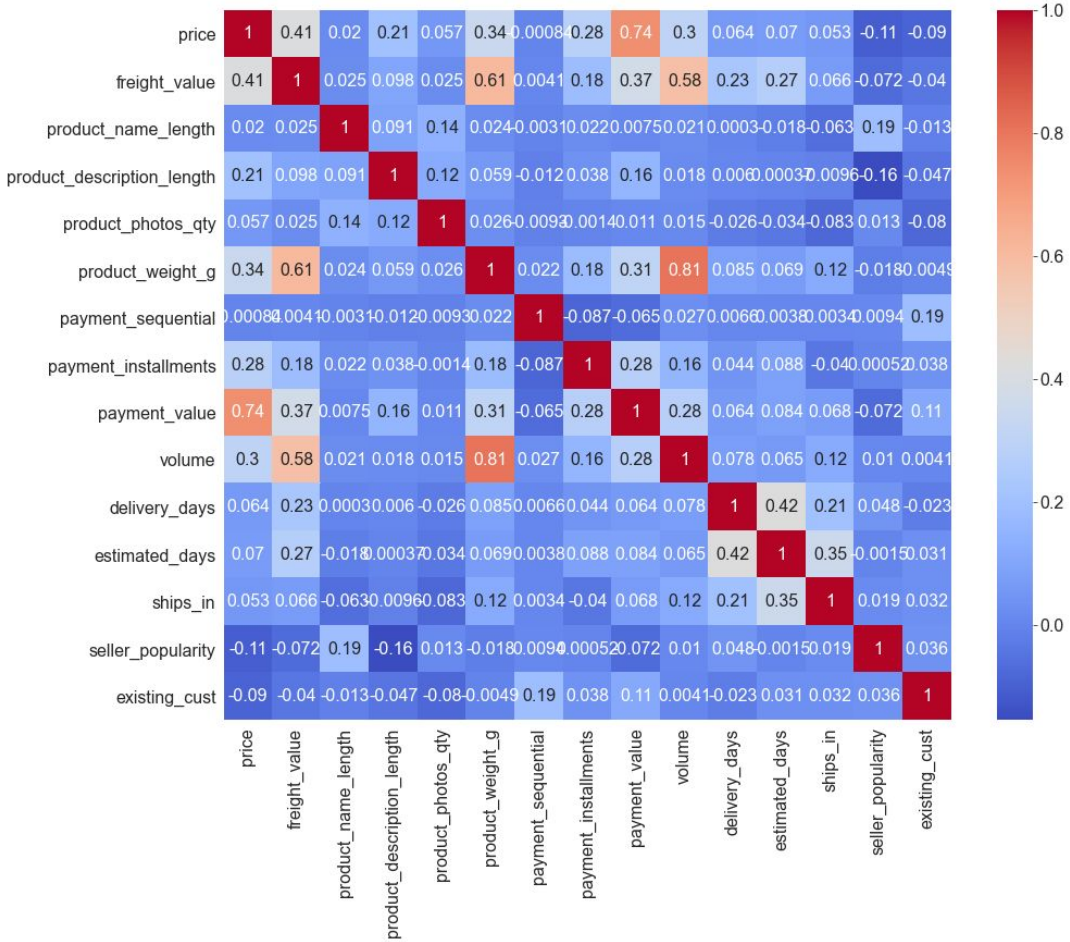




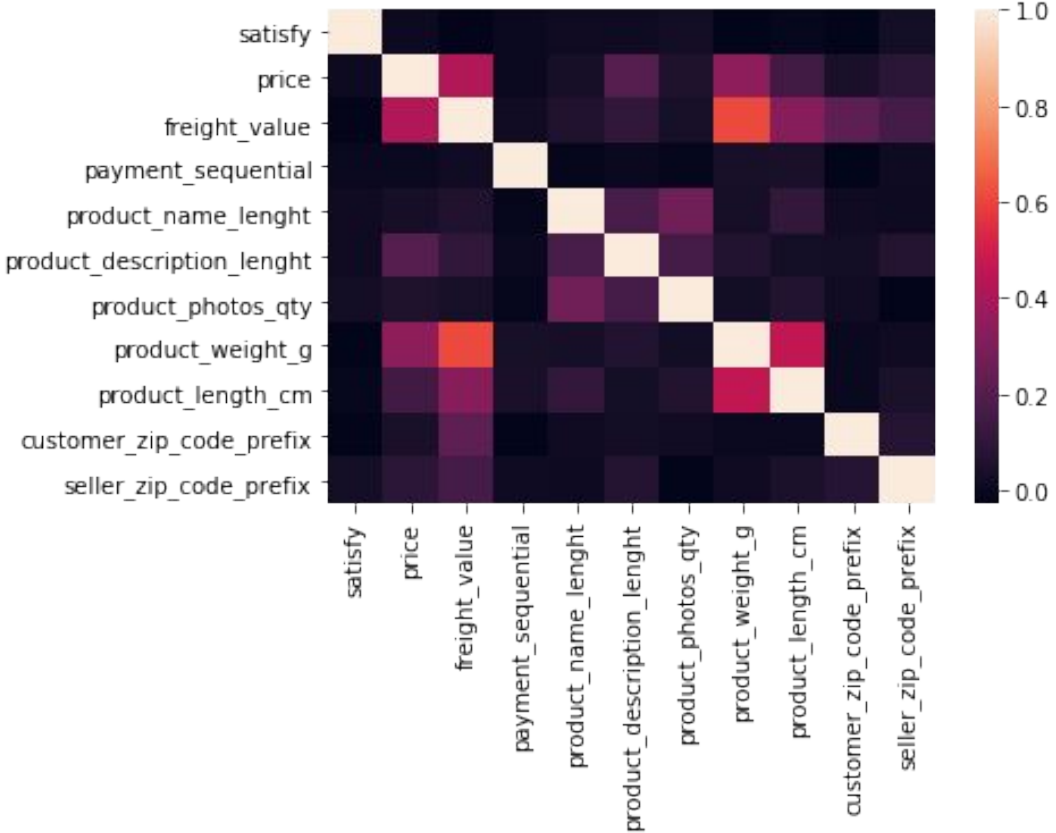
Numerical Features before feature engineering (w/o target)



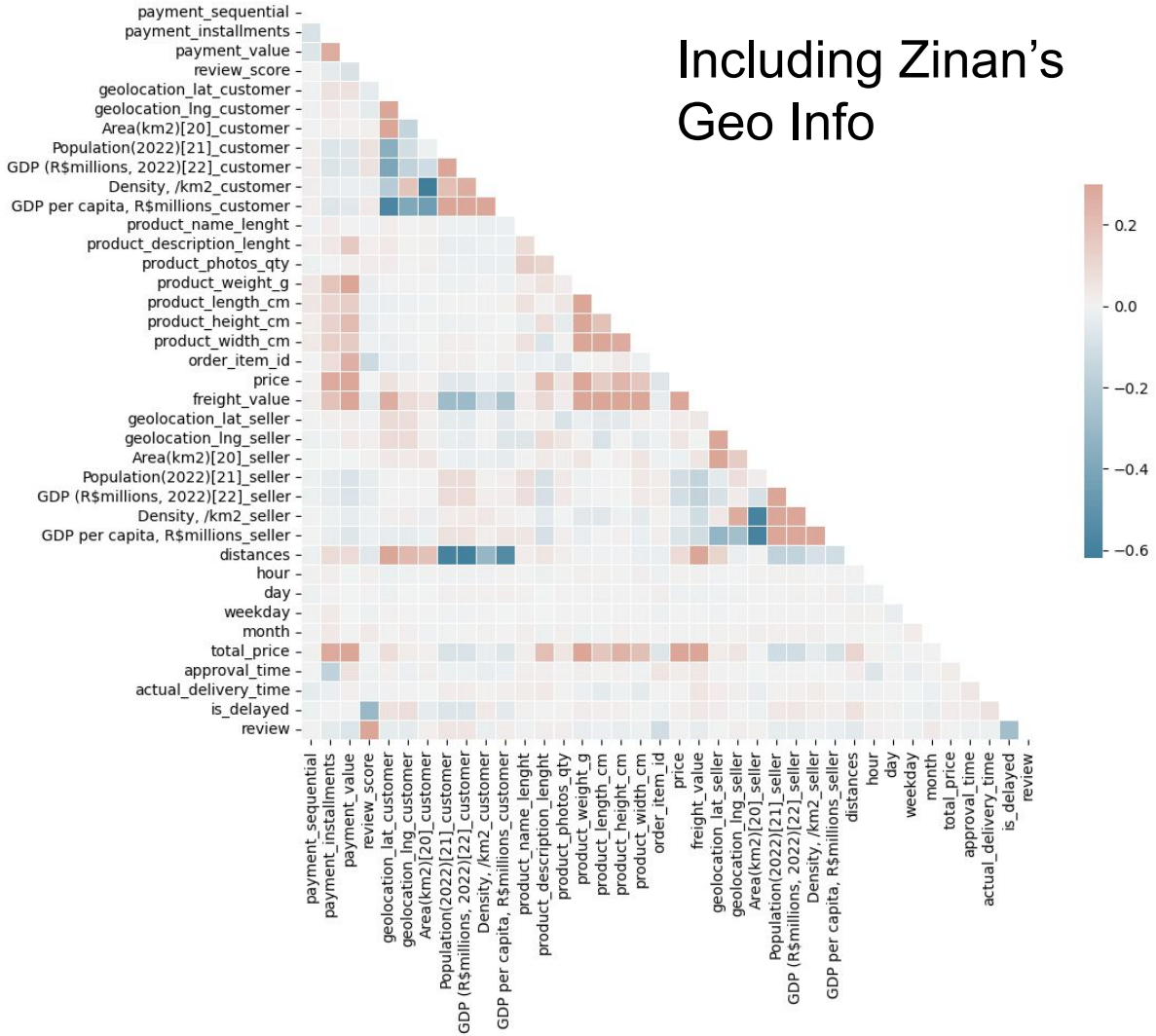
after adding seller popularity and existing customer

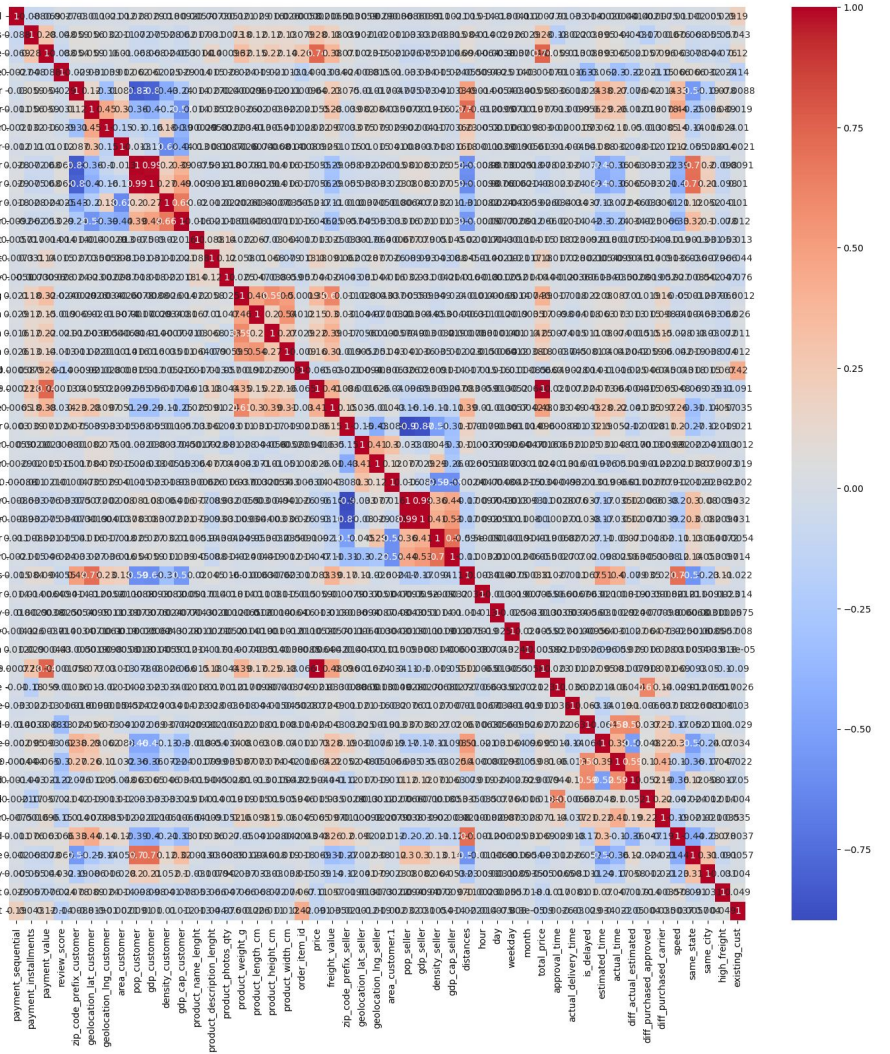


Numerical Features before feature engineering (with target)



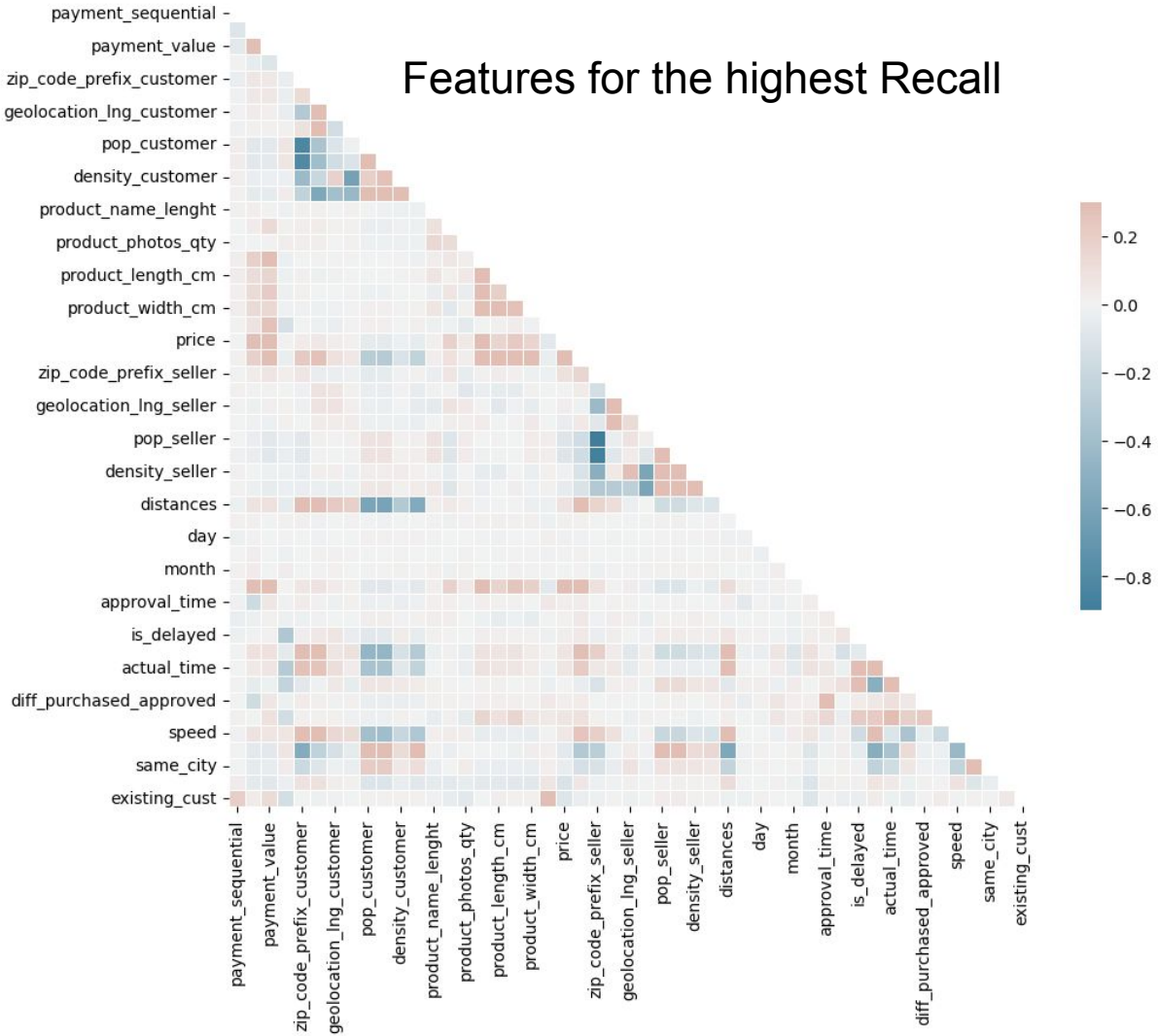
Including Zinan's Geo Info



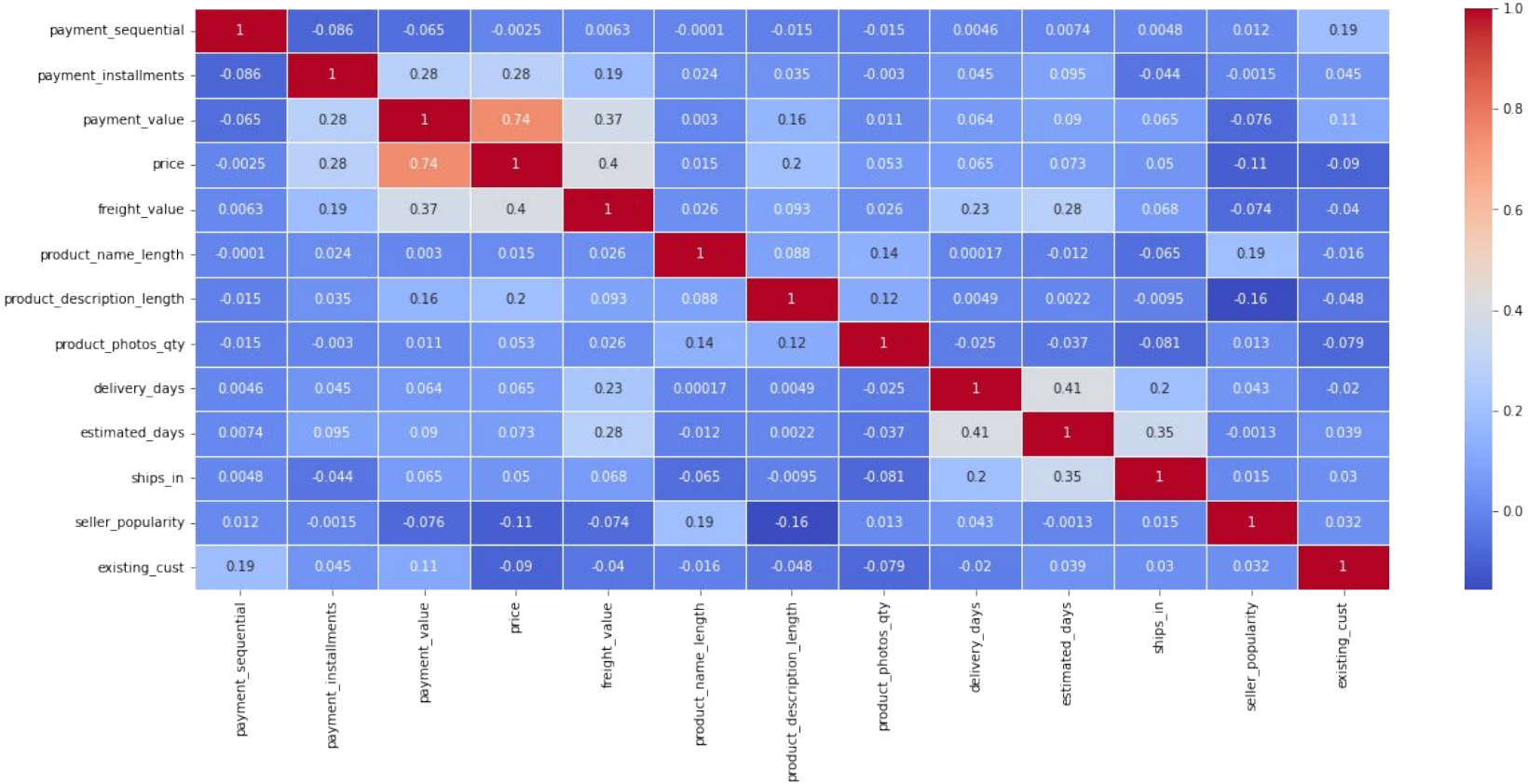


Zinan's Mega Features

Features for the highest Recall



Features for the highest AUC and F1



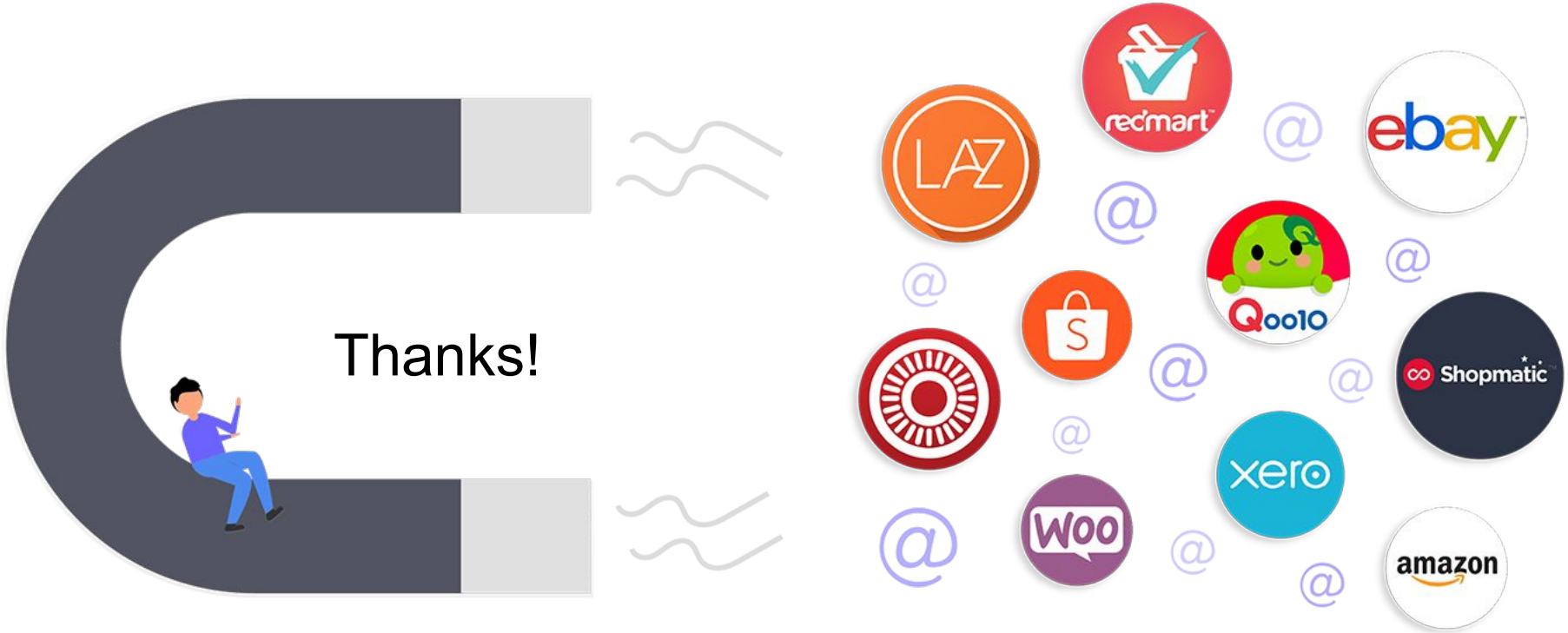
Threshold	Metric	Logistic Regression	Naive Bayes	DecisionTree	Random Forest	GBoost	XGBoost
4.0	F1_score	0.85	0.78	0.77	0.81	0.86	0.85
	AUC_score	0.68	0.67	0.68	0.68	0.71	0.72
Dropped Payment Value, 4.5	F1_new	0.74	0.68	0.68	0.70	0.74	0.73
	AUC_new	0.63	0.62	0.63	0.63	0.65	0.66
SMOTE w/ Tomek Link, 4.0	F1_smt	0.77	0.78	0.79	0.82	0.83	0.84
	AUC_smt	0.68	0.67	0.67	0.68	0.70	0.68

	0	Naive Bayes	Logistic Regression	LogisticRegression (balanced)	DecisionTree	Random Forest	GBoost
0	AUC_score	0.653	0.663	0.663	0.669	0.674	0.696
1	F1_score	0.71	0.75	0.71	0.70	0.74	0.76

	0	Naive Bayes	Logistic Regression	LogisticRegression (balanced)	DecisionTree	Random Forest	GBoost	XGBoost
0	Recall (0)	0.57	0.22	0.57	0.51	0.55	0.23	0.22
1	F1_score	0.75	0.88	0.78	0.81	0.80	0.88	0.88
2	AUC_score	0.68	0.69	0.68	0.69	0.69	0.7	0.70

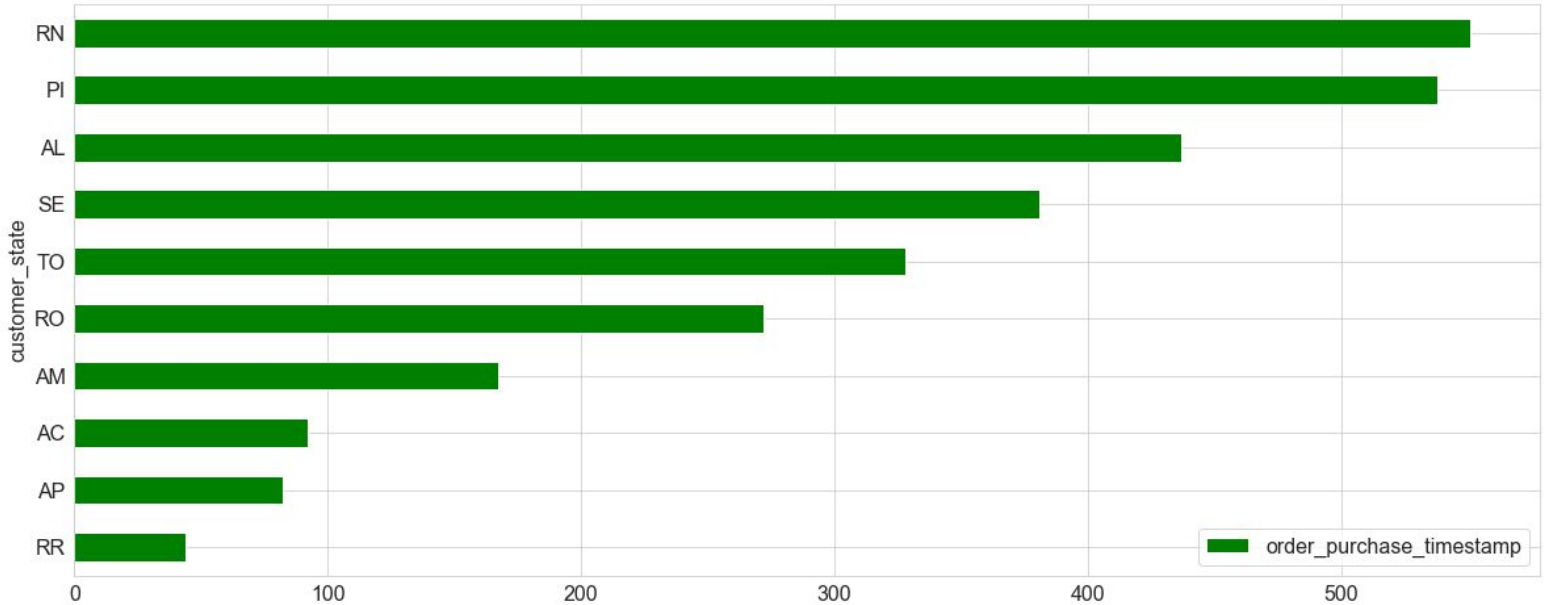
Possible actions to improve satisfaction

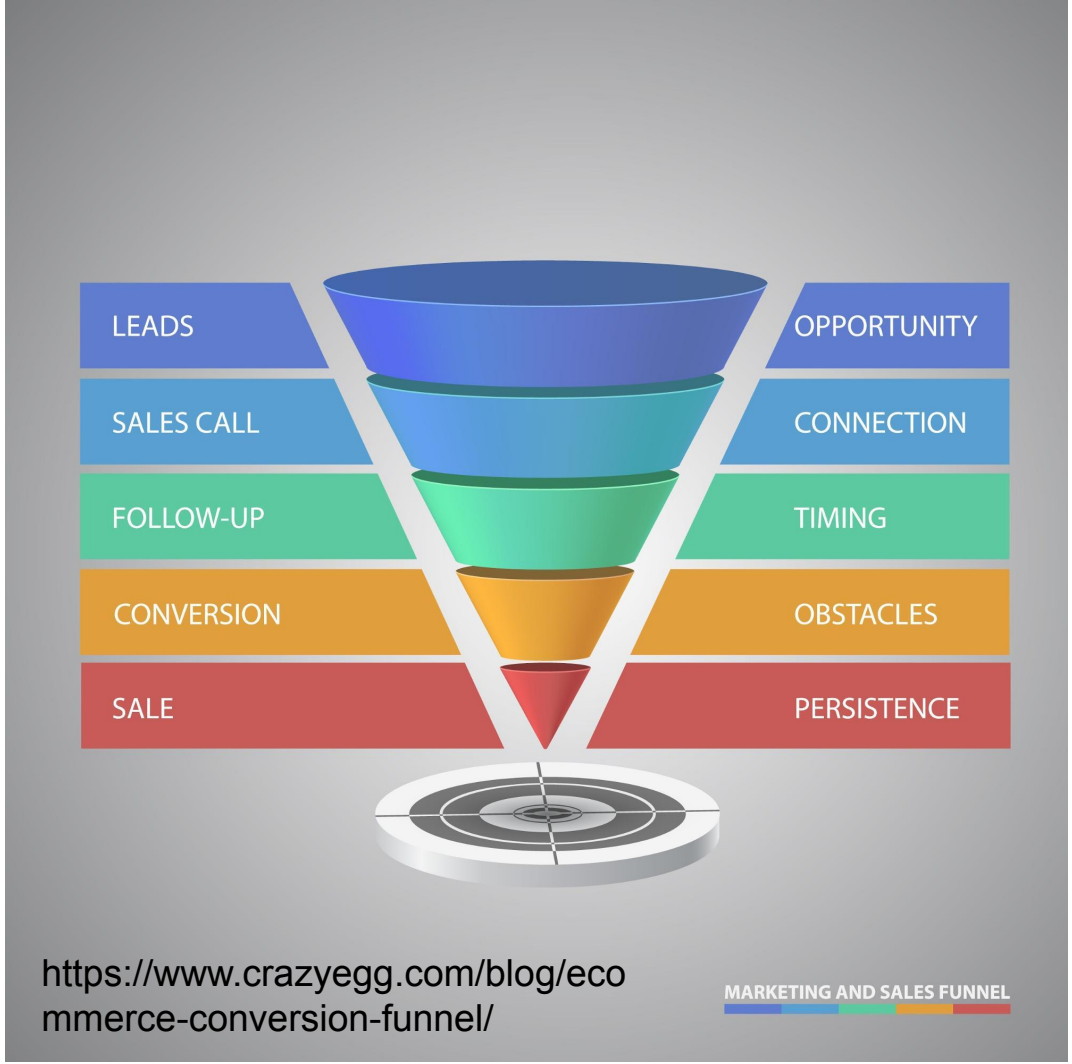
1. Coupon
2. Refund
3. New item or exchange
4. Improve other aspects for future customers


Thanks!
LAZ
redmart
ebay
Qoo10
Shopmatic
xero
Woo
amazon

backup

Order time by state





https://www.crazyegg.com/blog/ecommerce-conversion-funnel/