COM6101 - Final Project Report

Olist’s Third Anniversary Celebration

Module code: COM6101

Group[3] member:

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Project Introduction

1. Background

We used the Brazilian E-Commerce Public Dataset by Olist data source, found at: https://www.kaggle.com/datasets/olistbr/brazilian-ecommerce/data.

This data belongs to Olist and was released by them.

The Brazilian E-Commerce Public Dataset by Olist offers a comprehensive view of the e-commerce landscape in Brazil from 2016 to 2018.

It encompasses data from 100,000 orders across multiple marketplaces within the country, providing a detailed perspective on various dimensions of online retail.

The dataset includes information on order status, pricing, payment methods, shipping performance, customer locations, product attributes, and customer reviews.

Notably, it has been anonymized, ensuring privacy and security while retaining the integrity of the commercial data.

2. Objectives

I. In this project, we became managers of different departments in the company. Our goal is to help Olist discover what their customers care about from multiple perspectives and what can affect customer satisfaction, and to try to provide solutions to improve satisfaction.

II. Firstly, the marketing department conducted exploratory analysis (EDA) on the dataset using various charts, attempting to discover some interesting patterns and provide direction for our future exploration.

III. Next, the product development department will analyze the product dataset and use joint tables and rules to help us better understand user consumption habits.

IV. Subsequently, the customer service department applied natural language processing (NLP) to gain insights from customer comments. The reason for choosing NLP is that it can help Olist better understand consumer feedback and evaluations. Allowing Olist to improve products and services, enhance user experience, and increase user satisfaction will increase sales and customer loyalty.

V. Finally, the business department will summarize the previous findings and propose solutions.

3. Dataset

The entire dataset consists of 8 CSV files with 50 features and 1,551,016 records in total. There were no duplicates, but some values were missing. If more than half of the data in a column was missing, the column was dropped.

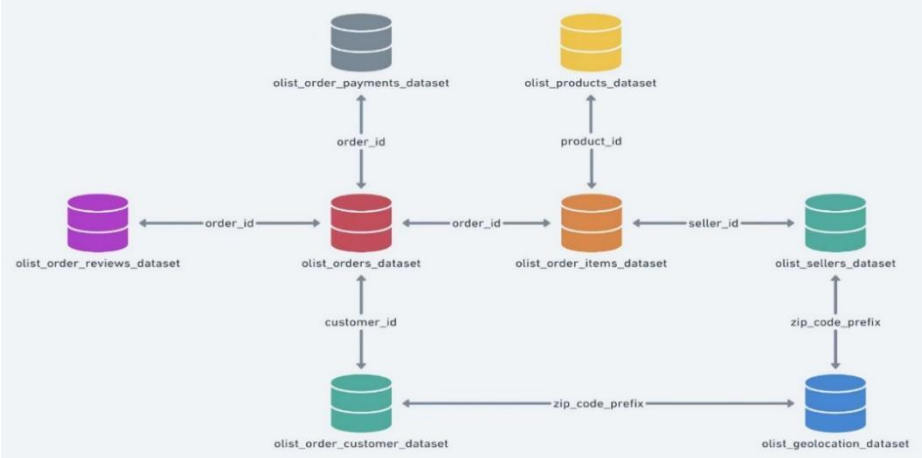
The data includes information about:

- Orders, payment, and delivery related dates.
- Customer and seller related information, including their location.
- Products related information such as category, size, and weight.
- Customers' reviews in text for and as a 1-5 score.
- Due to the large number of tables, the tables used in each section will be processed separately according to the requirements, and there will be intermediate transition tables generated during the analysis process for further analysis.
- And more.

Basic information of original files

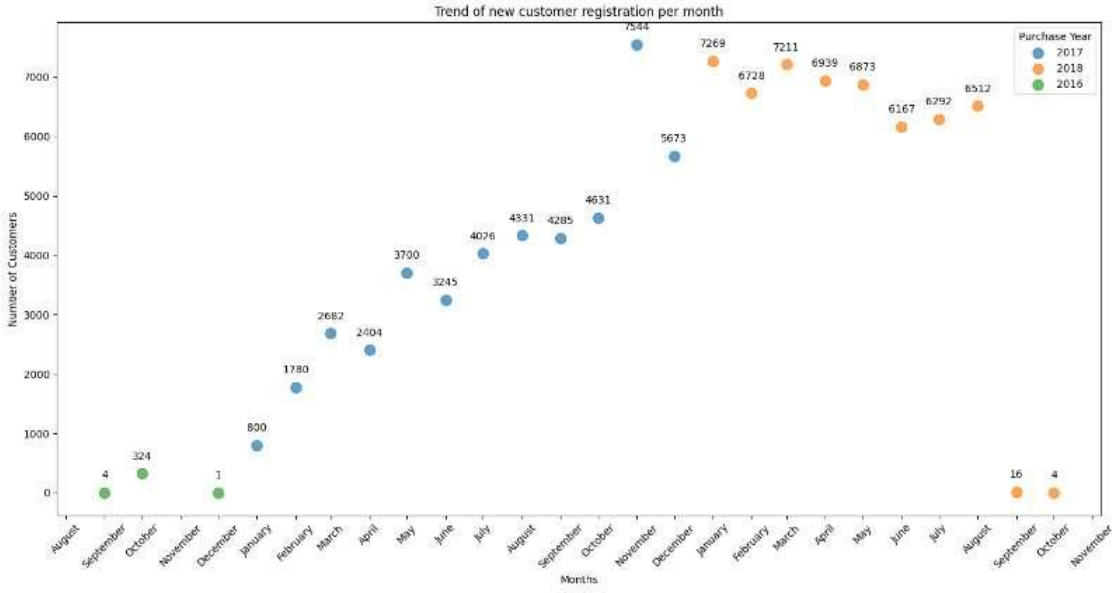
	dataset	nrows	ncols	names_of_null_cols	num_null_cols
0	products_df	32340	9		0
1	order_items_df	112650	7		0
2	olist_orders_df	99441	8	order_approved_at, order_delivered_carrier_dat...	3
3	order_reviews_df	100000	7	review_comment_title, review_comment_message	2
4	olist_customers_df	99441	5		0
5	order_payments_df	103886	5		0
6	sellers_df	3095	4		0
7	geolocation_df	1000163	5		0

Logic and connections for all files



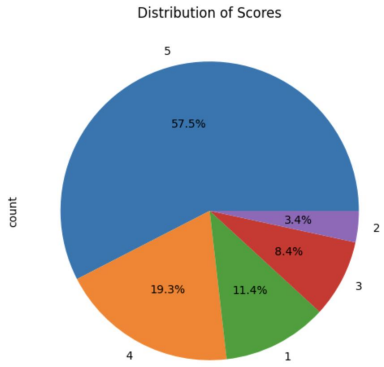
4. EDA

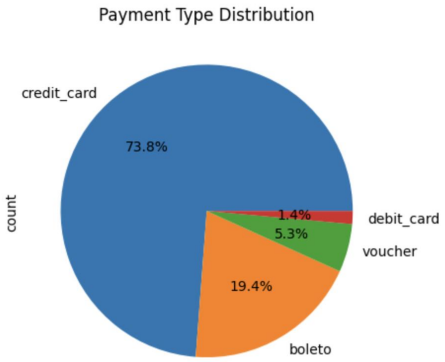
From 16/8 to 2017, there was continuous and significant explosive growth. In 2018, it was basically on the right track, with steady growth every month, and the number of new users was more than 6,000. The future goal is to increase customer satisfaction and repurchase rate on the basis of stable monthly user growth.



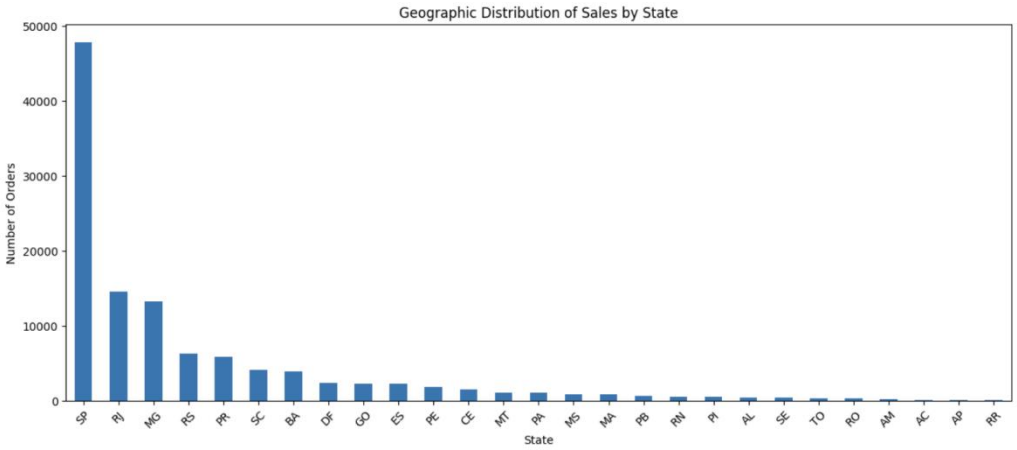
The main payment method is credit card. More than 70% of users pay with credit card, and nearly 20% use boleto. We will develop more credit card categories and partners. Influence of Payment Types on Purchases: Enhancing the checkout process to increase conversion rates. Sales Trends Over Time: Identifying periods of high demand to inform inventory and marketing strategies.

According to customer feedback, 57.5%, more than half, scored 5 points, and nearly 20% scored 4 points. In the future, we will work with the customer service department to improve satisfaction.



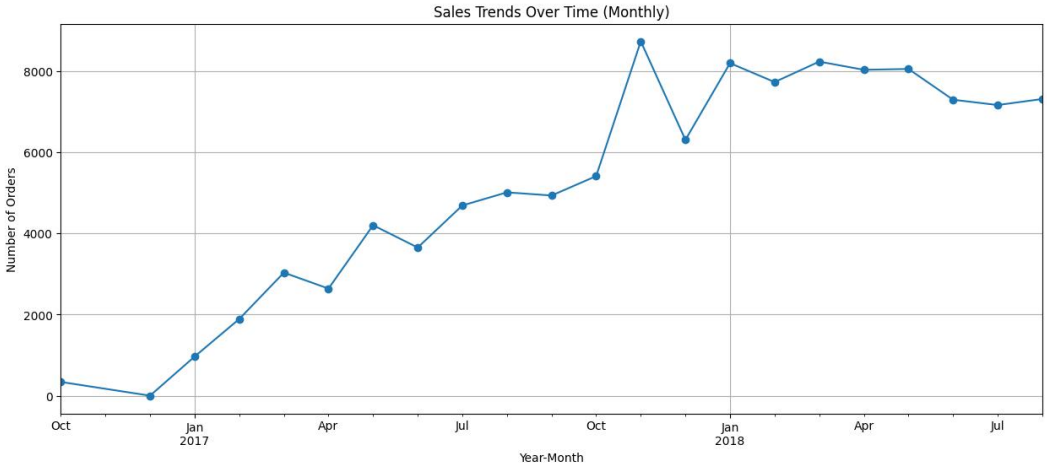


The regions with the highest number of orders are SP and RJ.



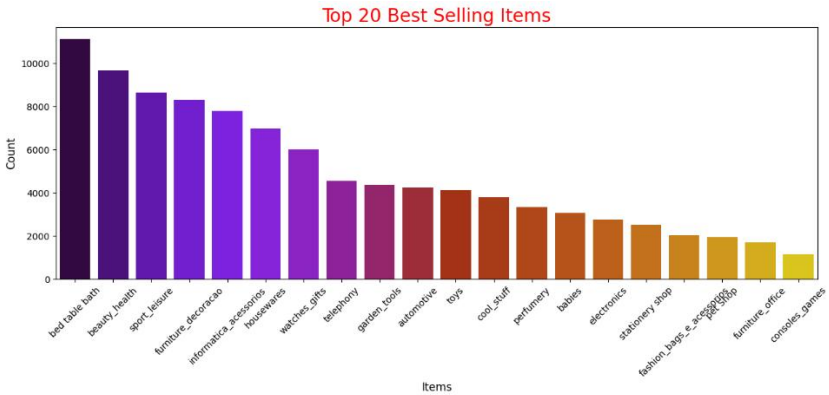
There appears to be peaks in sales around the beginning and middle of the year, which might correlate with holiday seasons or seasonal shopping behaviors. Despite some fluctuations, the general direction of the trend is upward, indicating growth in business activity over the observed period.

There is an overall upward trend in the number of orders starting from October 2017. There are notable peaks in January and March of 2018, with the peak in March nearing 8,000 orders. These peaks could indicate seasonal demands or the effects of specific marketing campaigns.

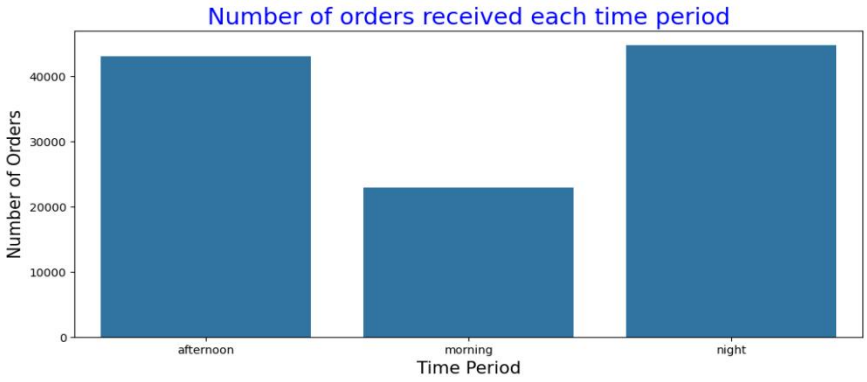


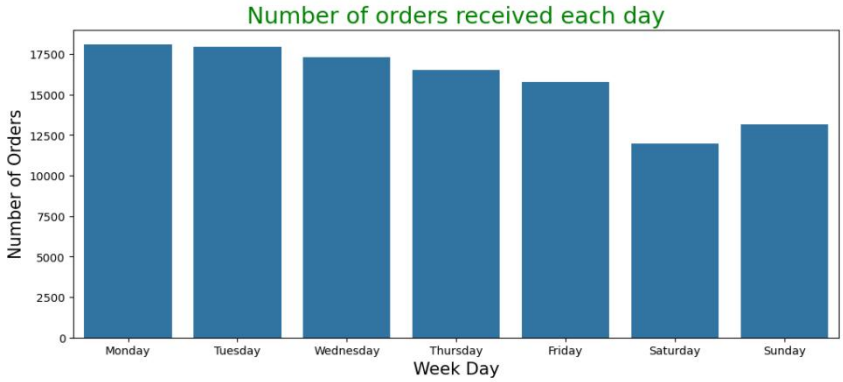
5. Product

From the chart of the top 20 best-selling products, the consumption of daily necessities, healthcare, sports and leisure, and home products ranks first, indicating that residents have a healthier lifestyle. In the future, product development will continue to focus on the health and home categories. Prioritize inventory and marketing work.

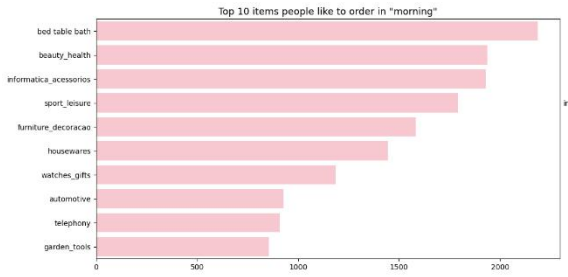


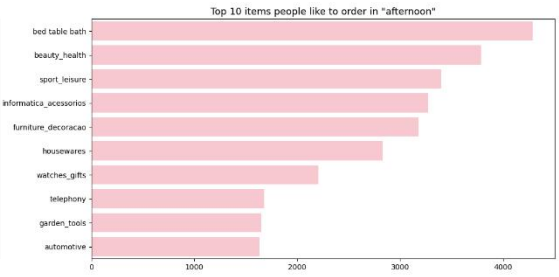
Most orders are confirmed in the evening, and there are relatively more orders in the afternoon. As the week progresses, the order volume has decreased. Most transactions occur in the afternoon and evening, with Monday being the peak and orders gradually decreasing during the week.

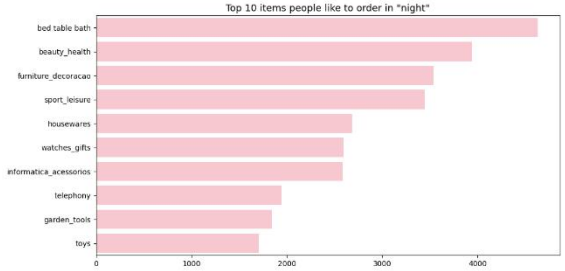




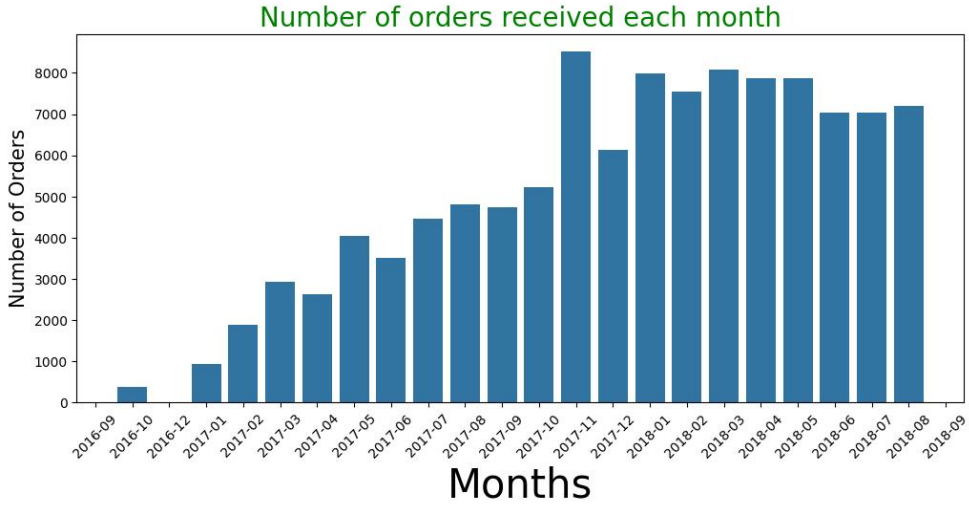
Bedside baths and beauty and health products are people's top choices at any time of the day. Communication products, leisure activities in the morning and afternoon, and home decoration in the evening. This confirms the majority of customers who purchase household and beauty products. Marketers can utilize these findings to effectively adjust their activities and marketing efforts.







E-commerce in Brazil has indeed been showing a growing trend. We can see some seasonal peaks in specific months, but overall, we can clearly see that customers are more inclined to shop online than before.

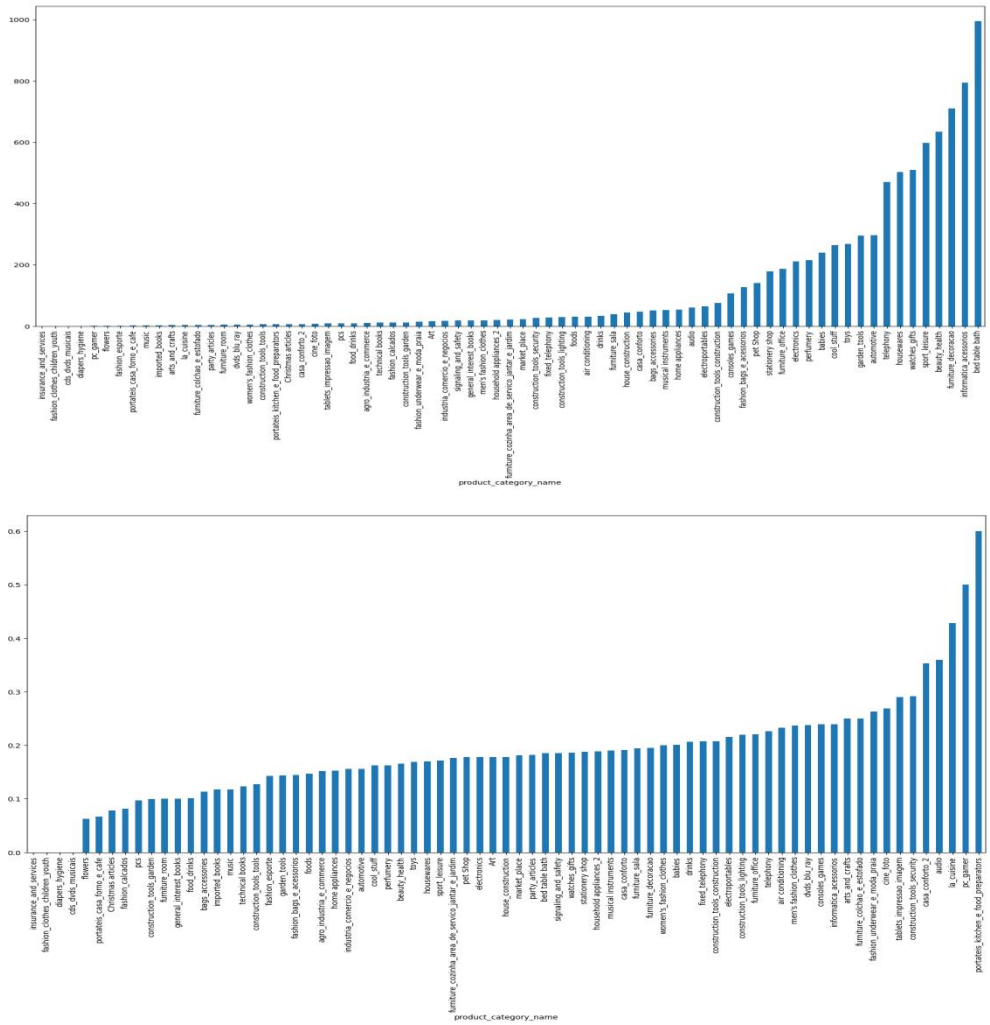


In this dataset, it is rare for the same user to purchase multiple products, and the probability of purchasing multiple products at the same time is also low. In addition, there are also fewer cases of purchasing products at the same time, and large combination lifts are basically the target products with sparse sales in most cases.

```
rules = association_rules(frequent_items_sort,metric='lift',min_threshold=1)
rules.sort_values('lift',ascending=False,inplace=True)
rules.head(5)
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
71	(perfumery, bed table bath)	(market_place)	0.000010	0.002886	0.00001	1.000000	346.546429	0.00001	inf	0.997125
74	(market_place)	(perfumery, bed table bath)	0.002886	0.000010	0.00001	0.003571	346.546429	0.00001	1.003574	1.000000
79	(cine_foto)	(cool_stuff, telephony)	0.000670	0.000062	0.00001	0.015385	248.802564	0.00001	1.015562	0.996648
78	(cool_stuff, telephony)	(cine_foto)	0.000062	0.000670	0.00001	0.166667	248.802564	0.00001	1.199196	0.996042
24	(musical instruments)	(fashion_bags_e_acessorios, automotive)	0.006472	0.000010	0.00001	0.001592	154.511146	0.00001	1.001585	1.000000

Due to the high total sales volume, the total number of negative reviews for bed and table baths is high, which does not indicate the problem. However, in terms of negative reviews per unit product, kitchen food has the highest, followed by PC gamer and la cuisine. This is due to the high perishable rate of food, which cannot match the inventory turnover rate.



Through language model analysis, we learned common words for negative comments in this dataset. Statistics have found that negative words and phrases appear most frequently in comments on portateis_kitchen_efood_preparators, and further analysis will be conducted by printing out the final comments.

```
bad_words_toanalyze.groupby(['product_category_name']).sum()[(bad_words_toanalyze.groupby(['product_category_name']).sum()).index=='portateis_kitchen_e_food_preparators']
```

product_category_name	terrible	bad	delay	not	defective	late	broken	estimate	slow
portateis_kitchen_e_food_preparators	0.0	0.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0

```
bad_words_toanalyze.groupby(['product_category_name']).count()[(bad_words_toanalyze.groupby(['product_category_name']).count()).index=='portateis_kitchen_e_food_preparators']
```

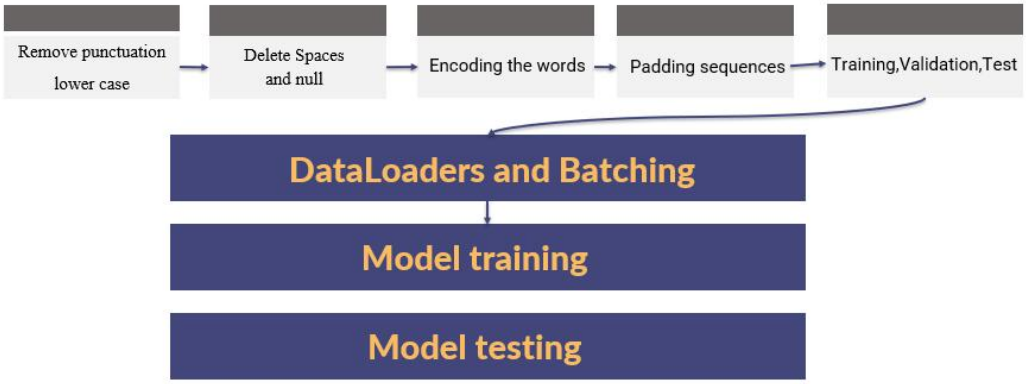
product_category_name	terrible	bad	delay	not	defective	late	broken	estimate	slow
portateis_kitchen_e_food_preparators	10	10	10	10	10	10	10	10	10

```
for i in bad_words_products[bad_words_products['product_category_name']=='portateis_kitchen_e_food_preparators']['review_comment_message'].dropna():
    print(i)
```

```
the cup is not exactly as it is in the photo despite saying that it is made of semitransparent plastic it is also said that the lid is black and contrary to that the lid is white
great well before the deadline perfect
 excellent
i bought the crystal clear glass and the milky one arrived it works but i didnt like it because it was of inferior quality
unfortunately the main information regarding the product is not clearly found on the lannister page i bought a machine to extract oil with 220 voltage i will return it
good evening the only problem was that the invoice did not show payment for shipping which should have been paid grateful gilson
the invoice was missing which did not arrive with the product and is not in the email which states that it has already been issued and i have not received one at all i am waiting
ive always bought from americascom and orders arrived before the expected date but this one hasnt arrived yet and they havent even sent an email notifying me of anything
product looks like it has already been used ugly everything dirty and scratched
product looks like it has already been used ugly everything dirty and scratched
```

6. NLP

Training processing:



6.1 Remove punctuation and lower

There are many punctuation marks in the original comment data, and even words connected to punctuation marks need to be deleted.

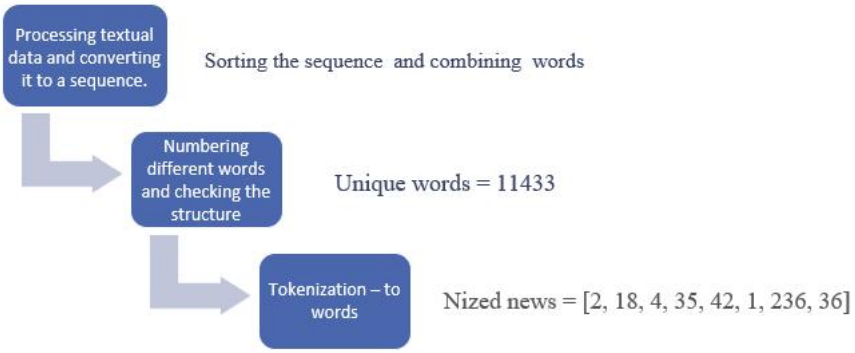
There are comments with only spaces in the original comments, which cannot be recognized in the isna() and dropna() methods and need to be processed separately.

```
data['review_comment_message'] =
data['review_comment_message'].str.lower().str.replace('[{}]'.format(string.punctuation), '')
```

```
data = data[data['review_comment_message'].str.strip().astype(bool)]
```

6.2 Encoding the words and padding sequences

By converting different words in the comments into codes, we obtained 11433 unique words and paired them back into the original sentence. Due to the short original comment, there is no need to do too much length processing.



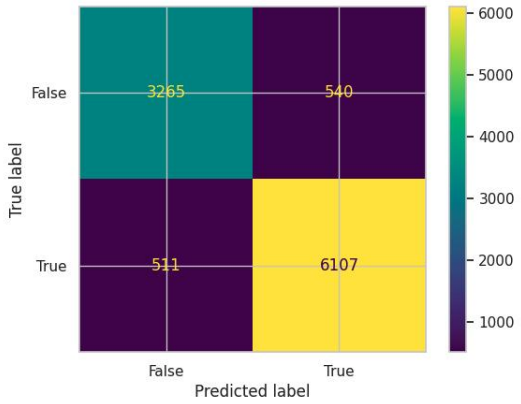
In order to handle text of different lengths, we use 0 for padding

```
[ [ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 325 425 16 1 90 1 404 9 1 425 11 1601 26]]
```

6.3 Remove punctuation and lower

6.1 Remove punctuation and lower

We then performed TF-IDF and Logistic Regression which is suitable for binary classification. The reviews were vectorized, shuffled (with controlled randomness), and then split into 75% training data and 25% test data (Geeks for Geeks, 2022; Saturn Cloud, 2023).



	precision	recall	f1-score	support
0	0.86	0.86	0.86	3805
1	0.92	0.92	0.92	6618
accuracy			0.90	10423
macro avg	0.89	0.89	0.89	10423
weighted avg	0.90	0.90	0.90	10423

Results

Overall model sentiment analysis accuracy was 90%, an improvement from the 75% we previously got.

5.3 Recurrent Neural Network (RNN)

RNN is a family of neural networks that is ideal for text classification tasks due to its ability to capture sequential dependencies in data (Geeks for Geeks, 2024; Thomas, 2019).

5.3.1 Data Preprocessing

- Tokenization - removed all punctuations and separated each review into individual words, (0-41,752 items, 548,213 words).
- Encoded them, which resulted in 9,665 unique words.
- Padding -we added padding to ensure the encoding was the same size - Length= 50.
- Split the data to 80% - training, 10% - test, and 10% - validation.

  {Feature Shapes: Train set: (33295, 50); Validation set: (4162, 50); Test set: (4162, 50)}

5.3.2 Select and Train model (Sentiment Network with PyTorch)

Defined network with the following layers:

1. An embedding layer that converts our word tokens (integers) into embeddings of a specific size.
2. An LSTM layer that is defined by a hidden state size and number of layers.
3. A fully connected output layer that maps the LSTM layer outputs to a desired output size.
4. A sigmoid activation layer that turns all outputs into a value 0-1; returns only the last sigmoid output as the output of this network.

The Embedding Layer

We need to add an embedding layer because there are over 9,000 words in our vocabulary. It is inefficient to one-hot encode that many classes therefore, we can have an embedding layer and use it as a lookup table. Just make a new layer, use it for dimensionality reduction only, and let the network learn the weights (PyTorch, n.d.a).

The LSTM Layer(s)

We've created an LSTM layer(s) to use in our recurrent network, which takes in an input size, a hidden dim, several layers, a dropout probability (for dropout between multiple layers), and a batch first parameter (PyTorch, n.d.b).

Usually, a network will have better performance with more layers which enables it to learn complex relationships. We used 2.

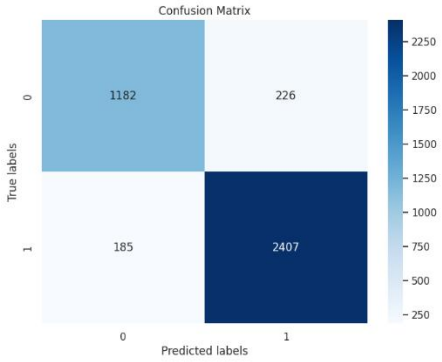
Set hyperparameters and define lr scheduler

BCELoss, or Binary Cross Entropy Loss, is designed to work with a single Sigmoid output. It applies cross-entropy loss to a single value between 0 and 1.

- lr: learning rate for our optimizer.
- epochs: number of times to iterate through the training dataset.
- clip: the maximum gradient value to clip at (to prevent exploding gradients).

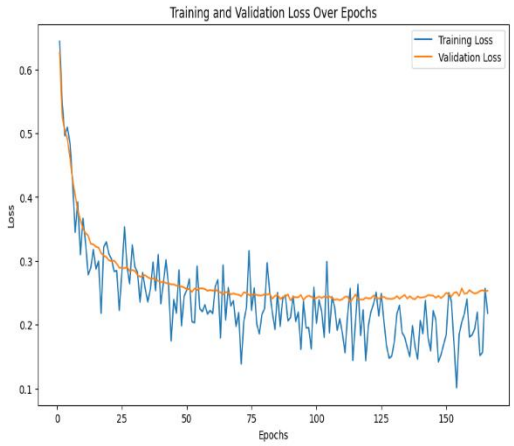
5.3.3 Performance

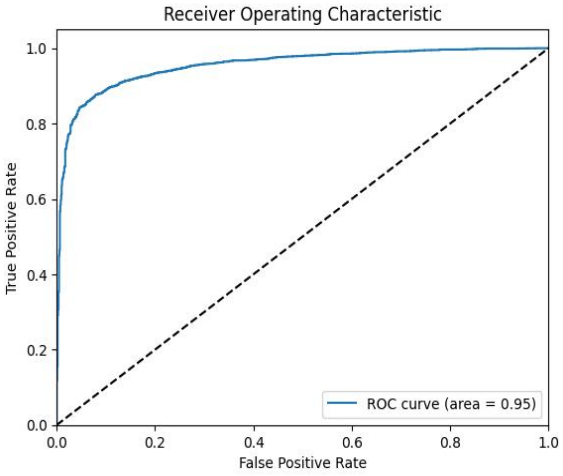
as can be seen below, that the model is well-trained.



Evaluation on Testing

	precision	recall	f1-score	support
0	0.86	0.84	0.85	1408
1	0.91	0.93	0.92	2592
accuracy			0.90	4000
macro avg	0.89	0.88	0.89	4000
weighted avg	0.90	0.90	0.90	4000





5.3.4 Testing (inference on user-generated data):

We also tested the model by entering two reviews that we created and reviewed the qualitatively accurate results. Below are the detailed results:

```
test_review_neg = 'So bad, left me with only bad effects, will not come again.'  → (0.011665682308375835, 0.0)
test_review_pos = 'Very good personal service, I was very impressed. It will come again next time.'  → (0.5842257738113403, 1.0)
```

5.3.5 Results

The model also revealed that some words were related to a low satisfaction score as below:

	words	prediction	sentiment	Frequency
86	not	0.185101	0.0	5873
63	terrible	0.219538	0.0	271
509	poor	0.255759	0.0	264
455	bad	0.268946	0.0	306
483	defective	0.366252	0.0	284
106	delay	0.369741	0.0	541
272	break	0.387206	0.0	339
354	wait	0.399479	0.0	1291
372	didnt	0.403751	0.0	2284
1349	late	0.445502	0.0	205
589	low	0.451298	0.0	139
1875	offices	0.454110	0.0	28
61	disappoint	0.462625	0.0	328
1120	lack	0.463513	0.0	236
1511	turn	0.474624	0.0	83

This helped us decide that we should further explore deliveries, as delay was an important word for dissatisfaction.

6 XGBoost

For Timeseries

The data had some issues that needed to be addressed.

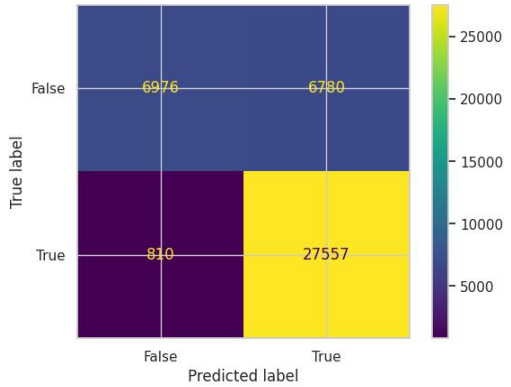
Remove Outliers

There were several mistakes with various timestamps. For example, for one record estimated delivery date was 3 years after the order date. For such a problem, we decided to delete the data received before delivery. The delay rate (transit time/estimated time) has been screened by the IQR to ensure the transit time is not too long or too short.

XGBoost is a gradient lift tree algorithm that can be applied to text data to learn patterns and correlations in the text and map them to predicted results. We created an XGBoost model for training and used the trained model to make predictions on the test set. Depending on the size of the predicted value, we marked the predicted value as 0 or 1. Then the confusion matrix was used to evaluate the classification performance of the model.

We choose to use XGBoost as it has benefits such as:

- Regularization - helps in reducing overfitting.
- Parallel Processing - XGBoost implements parallel processing and is much faster compared to GBM.
- Handling missing values - it has an in-built routine to handle missing values.
- Built-in cross-validation - allows the user to run cross-validation at each iteration of the boosting process.



	precision	recall	f1-score	support
0	0.90	0.51	0.65	13756
1	0.80	0.97	0.88	28367
accuracy			0.82	42123
macro avg	0.85	0.74	0.76	42123
weighted avg	0.83	0.82	0.80	42123

XGBoost had lower accuracy than previous methods.

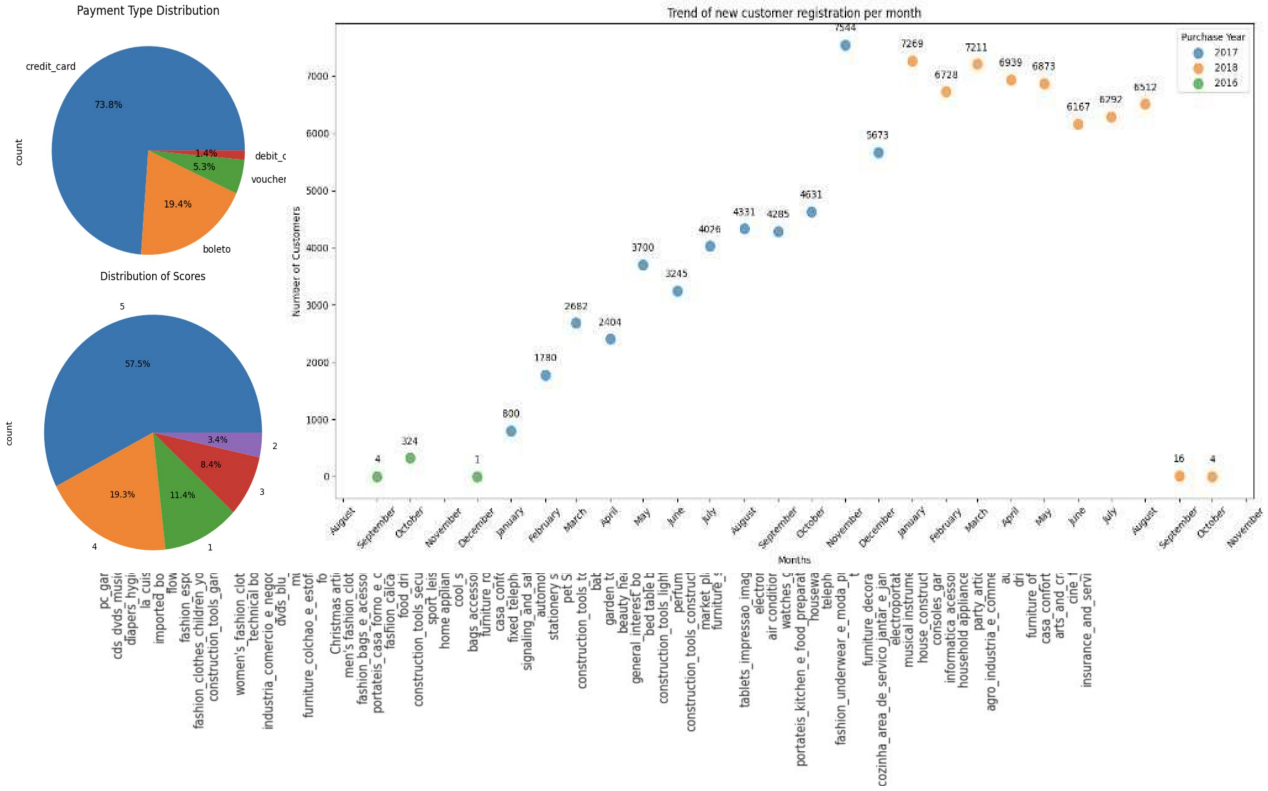
7 Business Analysis

For this part of the analysis, date columns were updated to data type “datetime” and new features were created. In total, we used 113,782 records and 49 features for analyzing customers, sellers, orders, and product information. On top of that, geographical data was also used.

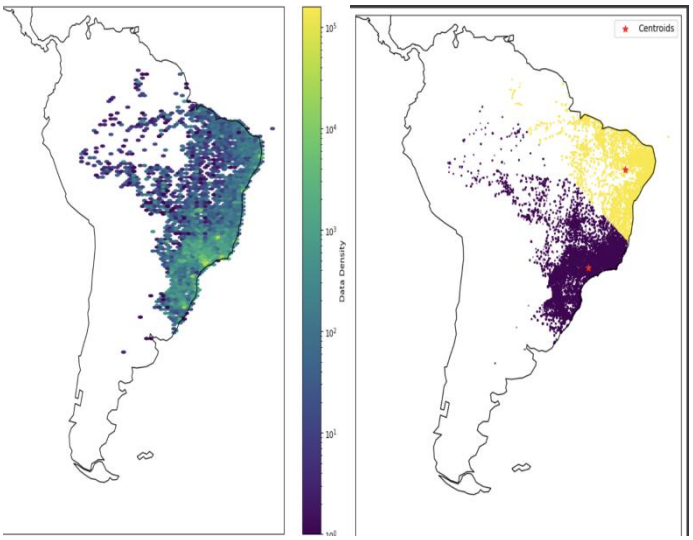
Kmeans was used as it is more suitable for unbalanced data than KNN.

1. More than 70% of users pay with credit cards, and nearly 20% use boleto.
2. 57.5%, more than half, scored 5 points, and nearly 20% scored 4 points.
3. E-commerce in Brazil is growing. We can see some seasonality with peaks at specific months, February, March and November, December. But in general, customers are more prone to buy things online than before.
4. The following categories had the highest ranking: life items, health care, sports and leisure, and home products.
5. Products in the following categories: bed, tables, and bath, had the most negative reviews, but it may be due to the large quantity purchased.
6. Most of the high delay regions are inland or at the northeast edge of the country.

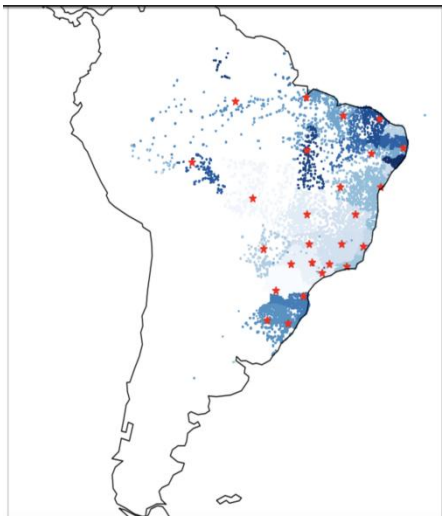
Negative word analysis for product *['delay']>0) | ['slow']>0)) | ['late']>0)]*



Normal orders location with heatmap



Map of delay rates region



8 Improvement Suggestions

We analyzed the data to learn what our customers care about, and we focused on the dissatisfaction that is associated with delays in shipment. From the information we learned, we have the following suggestion for Olist.

As we discovered, **certain regions in the country suffer more from delays,** we offer the below three improvement suggestions:

1. Short-term - increase delivery time on the website
2. Mid-term - find an additional courier company
3. Long-term - build a logistical center closer to that area

During high-selling **months there are more delays**:

1. Short-term - increase delivery time on the website
2. Mid-term - find an additional courier company and offer pre-sale, which could be a premium service

Oversized or heavy products:

1. Short-term - increase delivery time on the website
2. Mid-term - find a specialized courier company or build with courier partners to build this capacity

On top of that, Olist needs to work with sellers who are consistently delayed in approving orders and shipping them.

Finally, as Olist wishes to expand out of Brazil, Amazon services such as Translate, Lex, and Lambda, can help the company localize its services and offer better customer support.

9AWS Applied

An S3 bucket was used to store the data. AWS Simple Cloud Storage or S3 will enable various parties to easily access and work with the data while maintaining security.

10 Summary for ML Model

- It is important to choose a suitable direction and target at the beginning.

- Hyperparameter settings should be constantly tried, compared, and improved for tuning.
- Trying newer models to improve the accuracy of review predictions is still needed.

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