



Sephora Insights:

from web scraping
to EDA and NLP-ML reviews analysis



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Link to the full project

<https://github.com/nadyinky/sephora-analysis>

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01.

Purpose and objectives

What are the main purpose and objectives of this project?





Project purpose

Demonstrate proficiency in data analysis, programming languages such as Python and SQL, and machine learning techniques to inform and improve business decisions using large datasets



Scraping data from the Sephora website, **cleaning** and **storing** it in a SQL database



Performing exploratory **data analysis** (EDA) to identify trends and patterns



Applying **natural language processing** (NLP) and **machine learning** techniques to analyze consumer reviews of skincare products



02. Telling a story with data

Data collection results and
highlights from exploratory data
analysis and review analysis

Data scraping: result in numbers

0

**products
without reviews**

Every product in this store has at least one review and a non-zero rating

5

minutes

The average time it takes a scraper to gather information about products

8494

products

These are all the products of the online store at the time of data collection. That's more than 300 brands

1 mln +

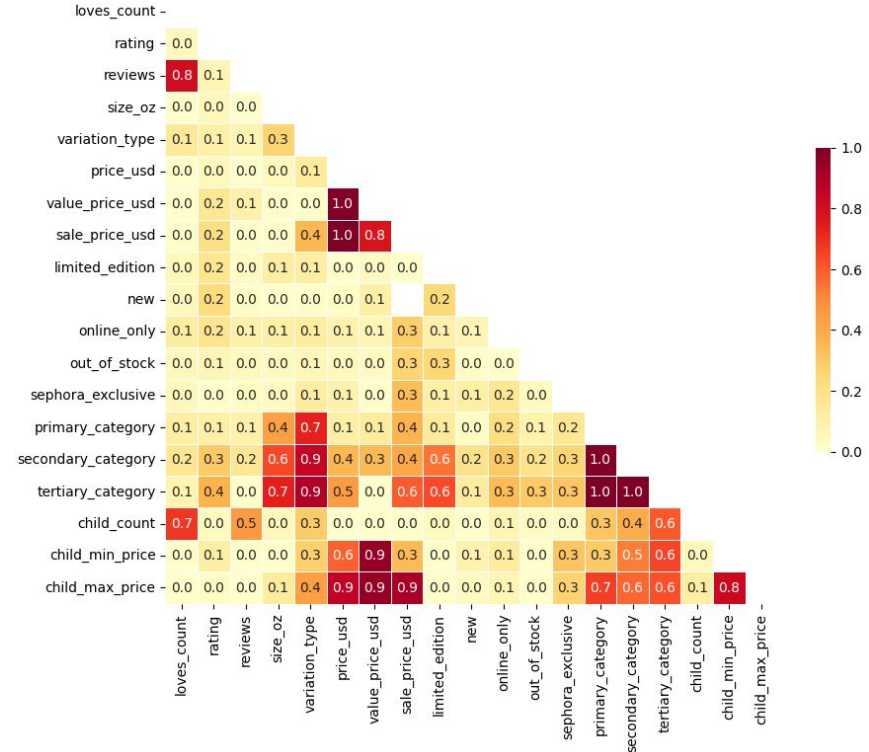
reviews

This is how many customer reviews from the Skincare category have been collected. These are all customer reviews for this category.

Correlation analysis

of Pearson's and Phik (ϕ_k) matrices

- The **correlation analysis** showed no meaningful significant correlations between prices and any of the collected data
- The most interesting thing seems to be the correlation between the number of **reviews** and **likes**, which at the same time is *not related* to the rating
- Reviews remain the most eloquent for a potential customer



Phik correlation matrix

Researching tags and labels

Single tags:

the tags reflect well the most important request for **safety**, **environmental friendliness** and **hydration**

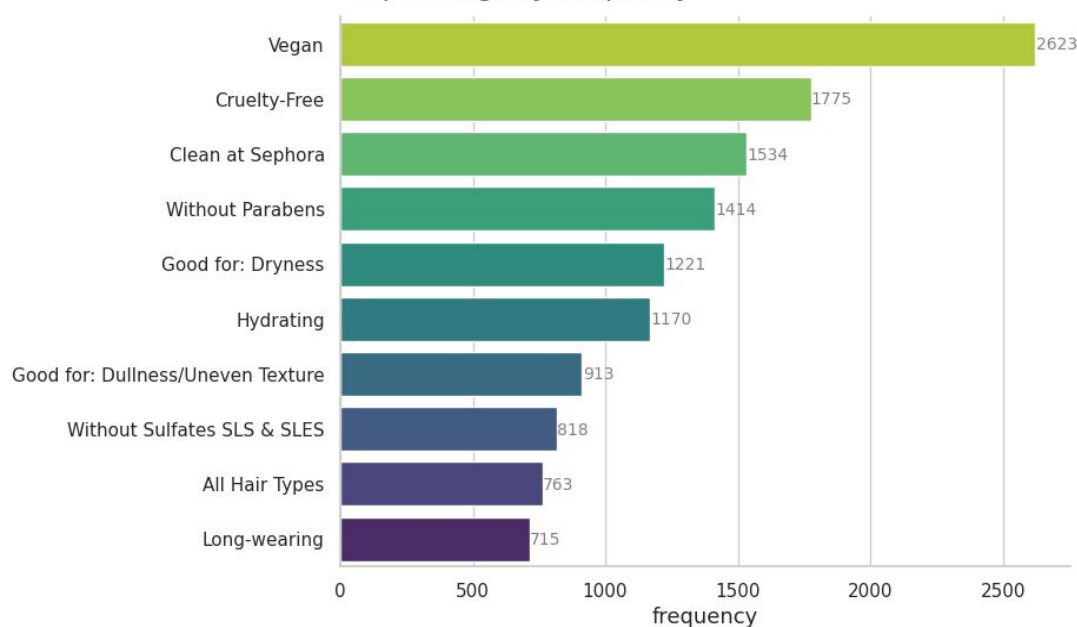
Tag pairs:

it is worth paying attention to **perfume tags** to enhance the shopping experience

The strong correlation between the **"limited edition" label** of products and the category is confirmed:

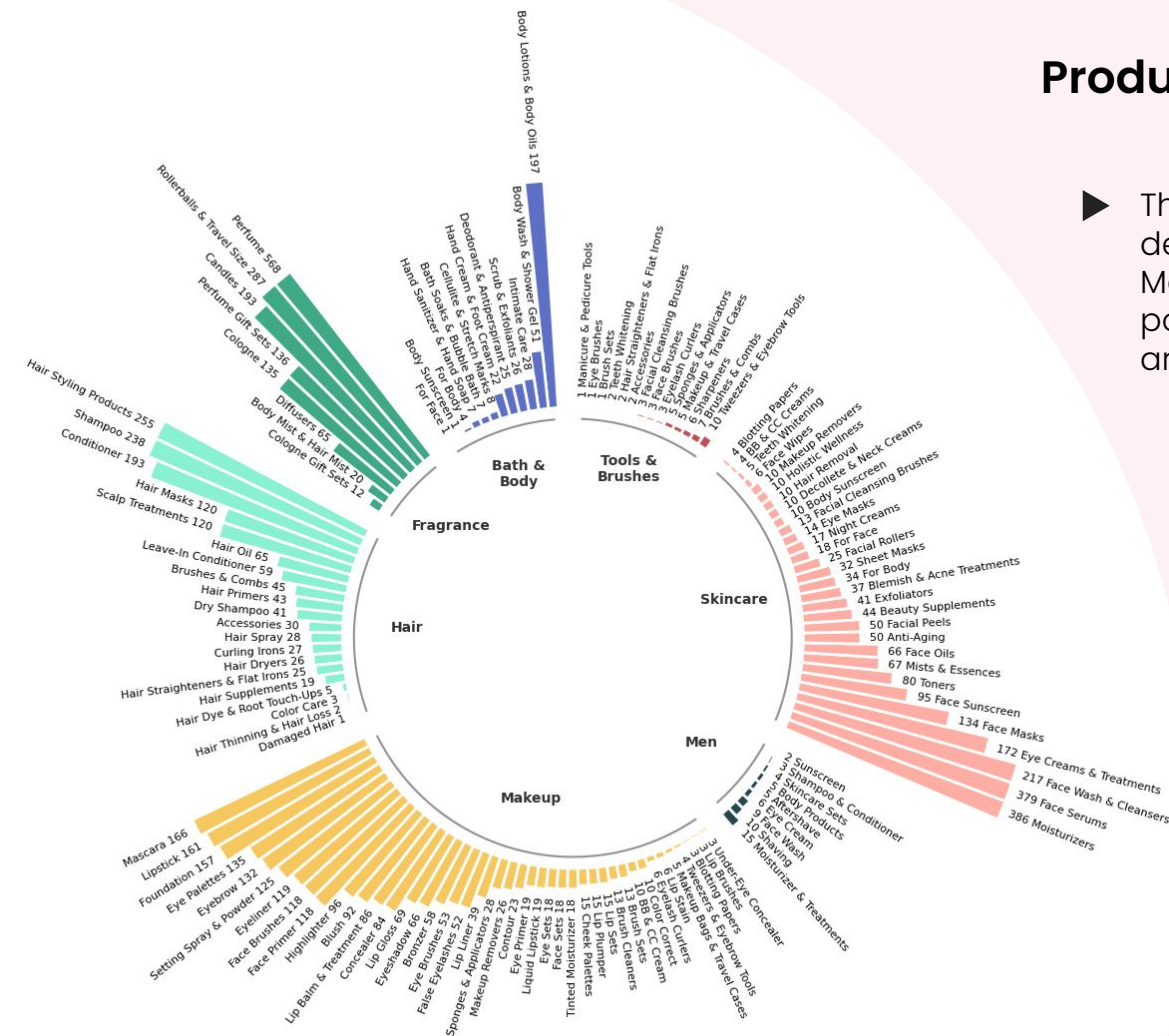
- almost 50% in the Values & Gift Sets category
- Candles and Eyes have another 15% each in the category

Top 10 Tags by Frequency



► The **assortment follows** the distribution of demand in the **global beauty market**: Skincare, Makeup, Hair and Fragrance take the leading positions. Although the **Hair** group shows an area of **potential improvement**

- *full-size visualization in a notebook

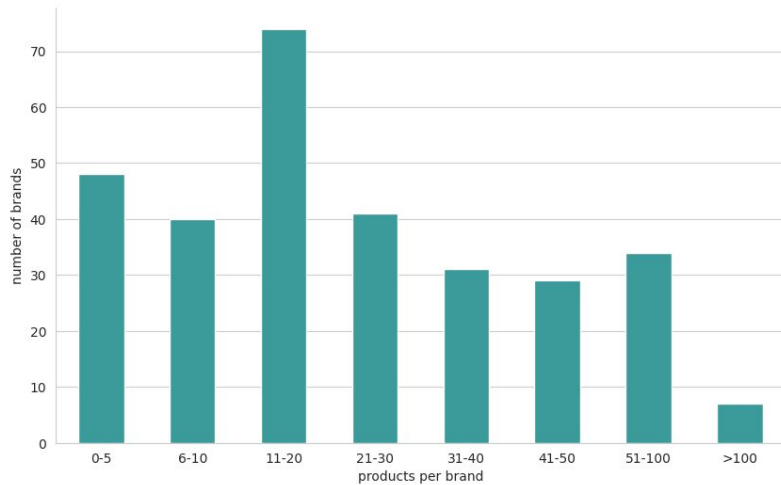


Price analysis: distribution by category



- The most widely represented **Makeup** category has an average item value of **\$32.8**, which is almost **half of the \$60.5** average value of the second largest category, **Skincare**
- The **Fragrance and Hair** categories have almost equal numbers of products, but the average product cost of **\$87.3** of the former **is twice as much** as the latter **\$42.8**

How Many Products do Brands have?



Average number of products per brand

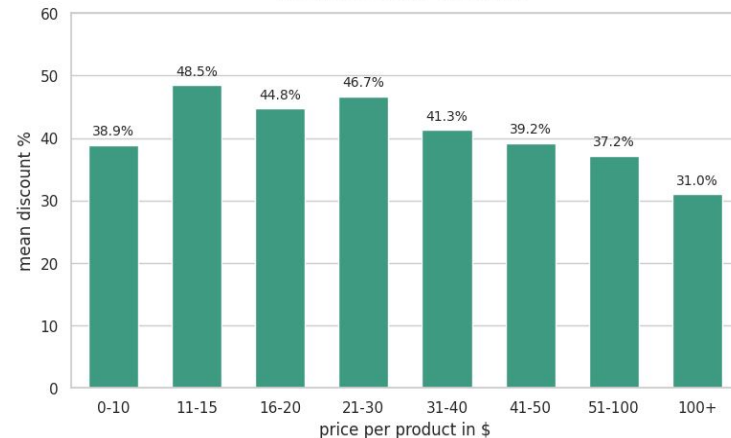
The largest number of brands has **between 11 and 20** products. Sephora also has many brands with as few as 5 products

Item price ranges with the highest discount

\$11-\$15 and **\$16-\$20** products have the highest average discount value



Mean Discount Percentage



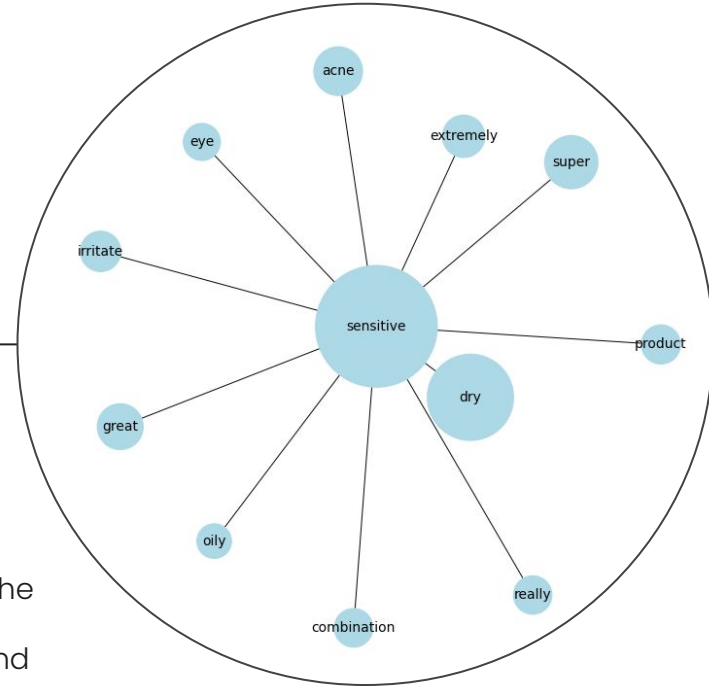
N-gram analysis: process and result

text
cleaning

- Getting rid of extraneous characters, punctuation, words with possible misprints, and 'stopwords'
- Using the **lemmatization** technique: Caring -> Care

tokenize
&
visualize

- Word **tokenization**
- Identify and visualize the most frequent **unigrams**, **bigrams**, and **trigrams**



bigram visualization

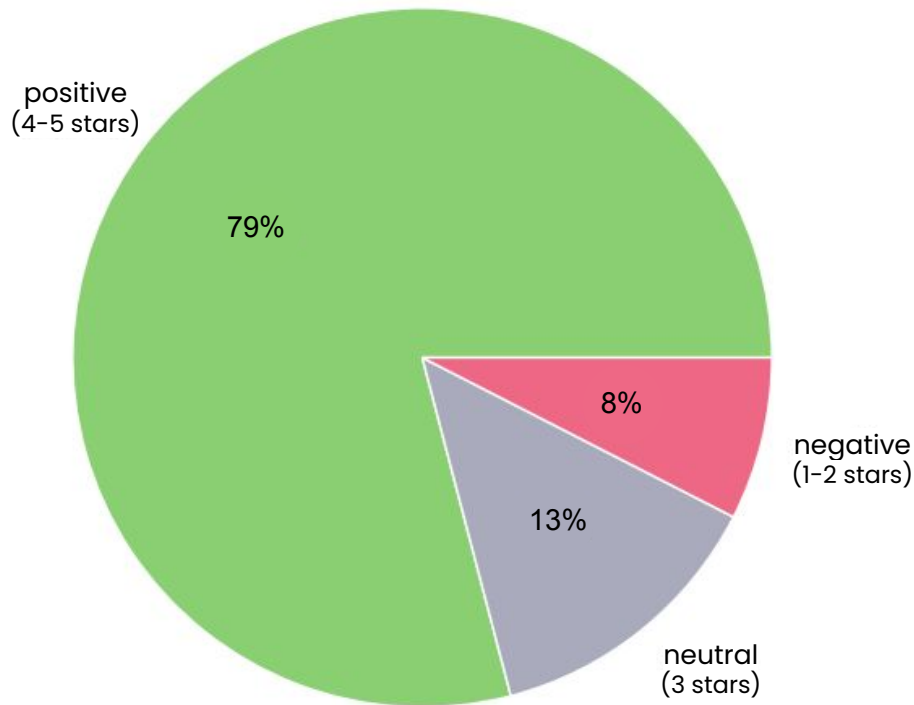


Sentiment prediction model: overcoming class imbalance

To create a **model predicting review sentiment**, I reduced the training dataset dimensionality from 50k to 12k reviews and employed undersampling to address the **class imbalance**.

In addition, I conducted tests on multiple models, carefully selected the **most suitable** one, and fine-tuned its **hyperparameters** to achieve optimal performance.

Sentiment Distribution



Sentiment prediction model: error analysis and result

```
ml_predict("Do not waste your money!  
This product did nothing for me.")
```

```
>>> 'negative', 0.99
```

demonstration of a real
example of classification

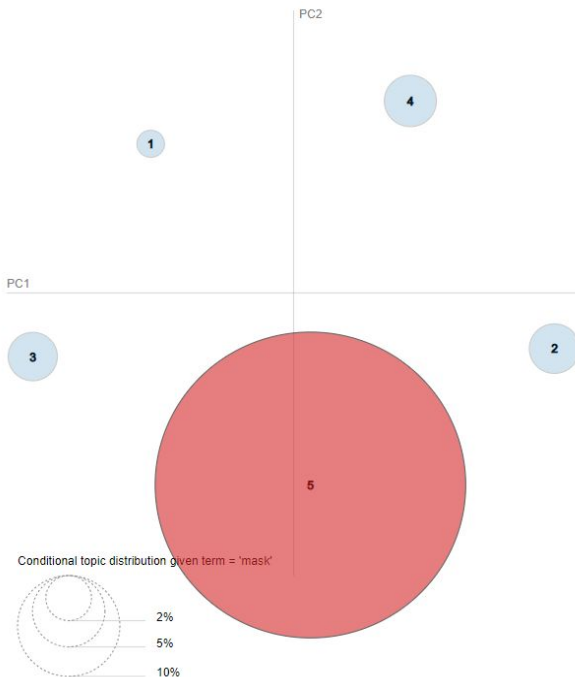
The completed model **takes in a review** and outputs both its corresponding **sentiment class and** the corresponding **probability** with which it is classified.

Error analysis showed that the **accuracy** of classification **is 81%**, the classification of positive and negative reviews is slightly better (85%), and neutral reviews slightly worse (77%)

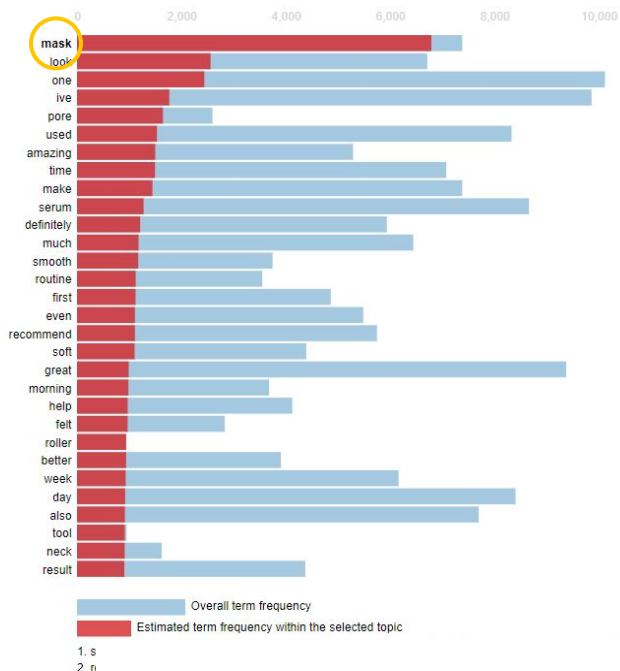


Topic modeling

Intertopic Distance Map (via multidimensional scaling)



Top-30 Most Relevant Terms for Topic 5 (16% of tokens)



- I pre-processed text and used **unsupervised machine learning** technique that helps **identify clusters** of words (topics)
- These topics **cover** five **main product types**, like mask, lip, etc. You can research words by generated topics and discover **hidden trends** or **characteristics** of each group (topic)

*Screenshot of **interactive** visualization from notebook: group n.5 is "Mask"



03. Conclusion

Summarizing the project, stages,
and tools



Conclusion

Created **concurrent scrapers** to collect **product** information and customer **reviews**.

Scraped data saved in **PostgreSQL** database and CSV files



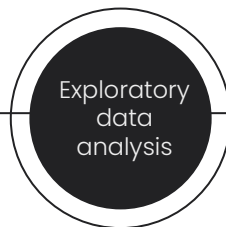
BeautifulSoup



Requests

Pydantic

An **in-depth analysis** was conducted that provided insight into products, prices, and trends



pandas

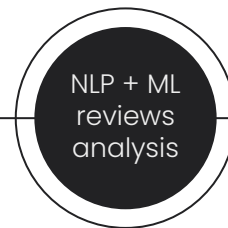
colab



matplotlib

seaborn

Reviews from the Skincare category were analyzed, a **sentiment prediction** model was created and **topic modeling** was performed



Natural Language Toolkit

NLTK





Thanks!



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