

Introduction

- Sephora is a well-known multinational beauty retailer that offers a wide range of cosmetic, skincare, haircare, and fragrance products.
- Sephora carries an extensive selection of products from various renowned brands, as well as its own private label products.
- They provide a wide range of products suitable for diverse skin tones, hair textures, and personal preferences. Sephora also emphasizes clean beauty, offering products that are formulated without certain ingredients, cruelty-free, or vegan.
- Sephora has both physical retail stores and an online platform, making it convenient for customers to explore and purchase products. Sephora also offers beauty services such as makeovers, consultations, and classes to enhance the overall shopping experience
- The store features a diverse range of cosmetics, including foundations, concealers, blushes, eye shadows, lipsticks, and more. Skincare products available at Sephora cater to different skin types and concerns, such as cleansers, moisturizers, serums, masks, and sunscreens.
- Sephora offers Haircare products for various hair types and Fragrances for both men and women are also part of their product offerings, featuring perfumes, colognes, and body sprays.



Problem Statement

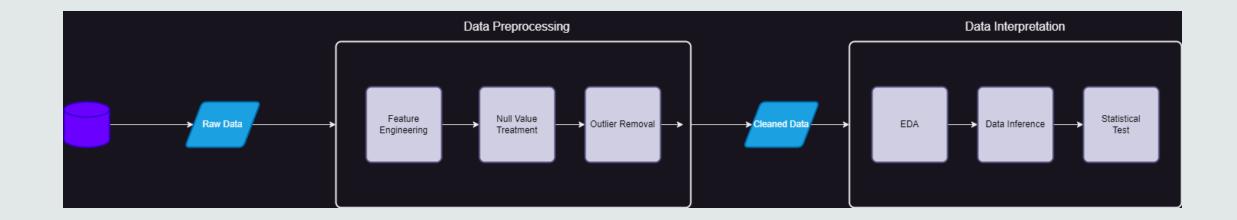
- As we seen they offer various products Sephora Collection, and includes beauty products such as cosmetics, skincare, body, fragrance, nail color, beauty tools, body lotions and haircare
- They often provide detailed product descriptions, customer reviews, and tutorials to help customers make informed decisions.
- As a Data Scientist we need to explore the data, and find popular brand name and what are all their main category of product, subsequently find their total worth of their products in Sephora.
- Find out Sephora exclusive product and most loved products and brand name among customers based on reviews and ratings
- Perform analysis of customer recommendation about products and other features based on skin tone, eye color, skin type



. About Datasets

- There are two different datasets provided for our analysis of Sephora products
- One dataset is about Overview of Sephora products, which has 8494 rows and 27 columns
- Other dataset is about detailed review of each author about their product they purchased is around 808855 rows and 19 columns. This dataset is a concatenation of two datasets
- Information about all beauty products from the Sephora online store, including product and brand names, prices, ingredients, ratings, and all features.
- User reviews of all products from the Skincare category, including user appearances, and review ratings by other users
- Kaggle Sephora Products and Skin care reviews

Flow Diagram



Contents

- Data Display
- Feature Engineering
- Null value of Each column and its visualization
- Data Cleaning
 - Imputing Null value using KNN Imputer
 - Imputing Null value using Decision Tree Imputer
- Cleaned Data
- EDA
 - Numeric Analysis
 - Univariate Analysis
 - Bivariate Analysis
 - Outlier Detection and Removal of Outlier
 - Correlation Analysis



Contents

Asking Questions to Data and Getting Insights from Data

Working with Main dataset

- 1. Which brand is popular among user and loved ones based on reviews and ratings?
- 2. What is the total worth of price value for Each Brand respective to their Category?
- 3. Which size is most preferred by user based on primary category?
- 4. Which popular brand owns sephora exclusive and does not have physical shop?
- 5. Which new product cost high price and average ratings by user for that product?
- 6. Show visualization of total price shared by primary category

Working with reviews dataset

- 1. Which product is most recommended by user and its skin tone?
- 2. Analyse the Positive feedback count for each brand and other features
- 3. Number of ratings given on Each date



. Display Data

Products Data

5] pro	duct_df.head	0																	
	product_id	product_name	brand_id	brand_name lov	ves_count r	rating r	eviews siz	e variation_type	variation_value	online_	only out_of_st	ck sephora_exclusi	ve highlights	primary_category	secondary_category	tertiary_category	child_count	child_max_pric	e child_min_pri
0	P473671	Fragrance Discovery Set	6342	19-69	6320	3.6364	11.0 Na	N NaN	NaN		1	0	['Unisex, Genderless O Scent', 'Warm &Spic, Scen	Fragrance	Value & Gift Sets	Perfume Gift Sets	0	Nal	N Na
1	P473668	La Habana Eau de Parfum	6342	19-69	3827	4.1538	3. 13.0 0. m	Z/ Size + O Concentration +			1	0	('Unisex Genderless O Scent' 'Layerable Scent'	Fragrance	Women	Perfume	2	85.	0 30
2	P473662	Rainbow Bar Eau de Parfum	6342	19-69	3253	4.2500	3. 16.0 0. m	4 Size + z/ 0 Concentration + L Formulation			1	0	['Unisex Genderless 0 Scent' 'Layerable Scent'	Fragrance	Women	Perfume	2	75.	0 30
3	P473660	Kasbah Eau de Parfum	6342	19-69	3018	4.4762	3. 21.0 0. m	4 Size + z/ 0 Concentration + L Formulation			1	0	['Unisex, Genderless 0 Scent', 'Layerable Scent'	Fragrance	Women	Perfume	2	75.	0 30
4	P473658	Purple Haze Eau de Parfum	6342	19-69	2691	3.2308	3. 13.0 10 m				1	0	['Unisex Genderless 0 Scent' 'Layerable Scent'	Fragrance	Women	Perfume	2	75.	0 30

. Display Data

Reviews Data

rev	iew_df.he	ad(3)																		
	Unnamed:	author_i	d rating	is_recommende	ed helpfuln	ess total_feedback_co	unt total_neg_feedback_co	unt total_pos_feedback_	_count su	ubmission_time	review_text	review_title	skin_tone	eye_color	skin_type	hair_color	product_id	product_name	brand_name	price_u
5	5	4280256915	4 4	1.	.0	1.00	1	0	1	2023-03-19	The scent isn't my favourite but it works grea	Great!	lightMedium	brown	normal	brown	P420652	Lip Sleeping Mask Intense Hydration with Vitam		24
6	6	694188380	8 2	0.	.0).25	8	6	2	2023-03-19		Dried my lips out and clogged my pores		blue	combination	brown	P420652	Lip Sleeping Mask Intense Hydration with Vitam		2.
8	8	765679172	6 5	1.	.0	1.00	1	0	1	2023-03-18	I love this stuff. I first had the sample size	Must have.	light	blue	normal	blonde	P420652	Lip Sleeping Mask Intense Hydration with Vitam		2

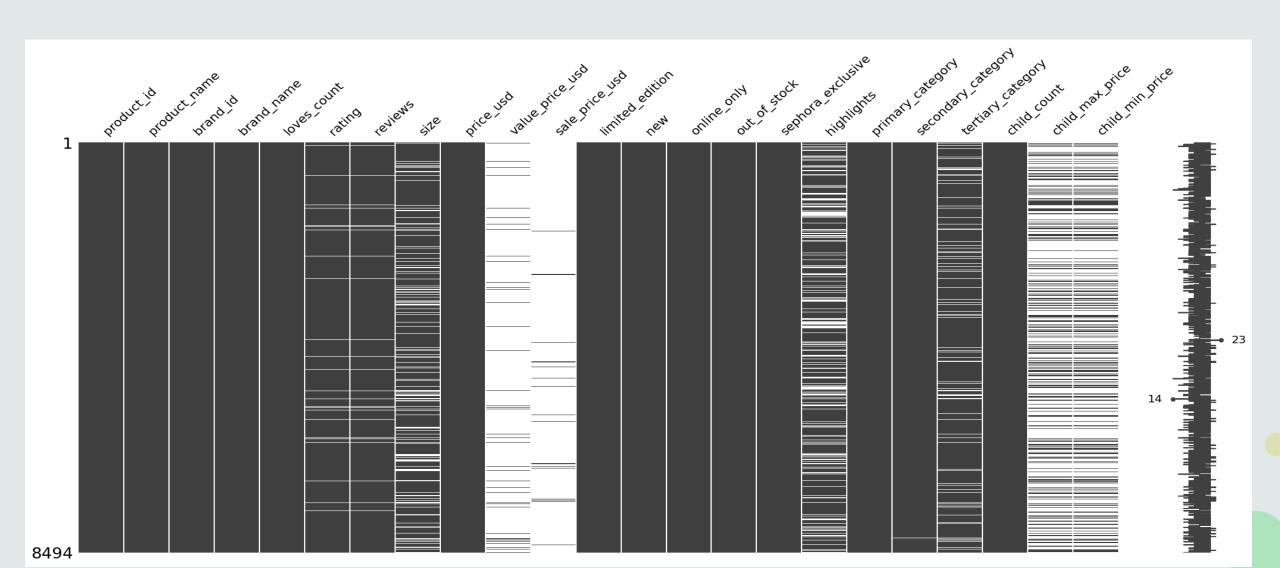
Feature Engineering

- The "Size" columns is dirty data which a mixture of *numeric* and *categorical* data.
- Numeric points has 60% and Categorical points is around 40% of "Size" feature
- So, We performed feature engineering process to convert "Size" feature numeric datapoints into bins for categorical points

brand_id	brand_name	loves_count	rating	reviews	size	v
6342	19-69	6320	3.6364	11.0	NaN	
6342	19-69	3827	4.1538	13.0	3.4 oz/ 100 mL	
6342	19-69	3253	4.2500	16.0	3.4 oz/ 100 mL	
6342	19-69	3018	4.4762	21.0	3.4 oz/ 100 mL	
6342	19-69	2691	3.2308	13.0	3.4 oz/ 100 mL	

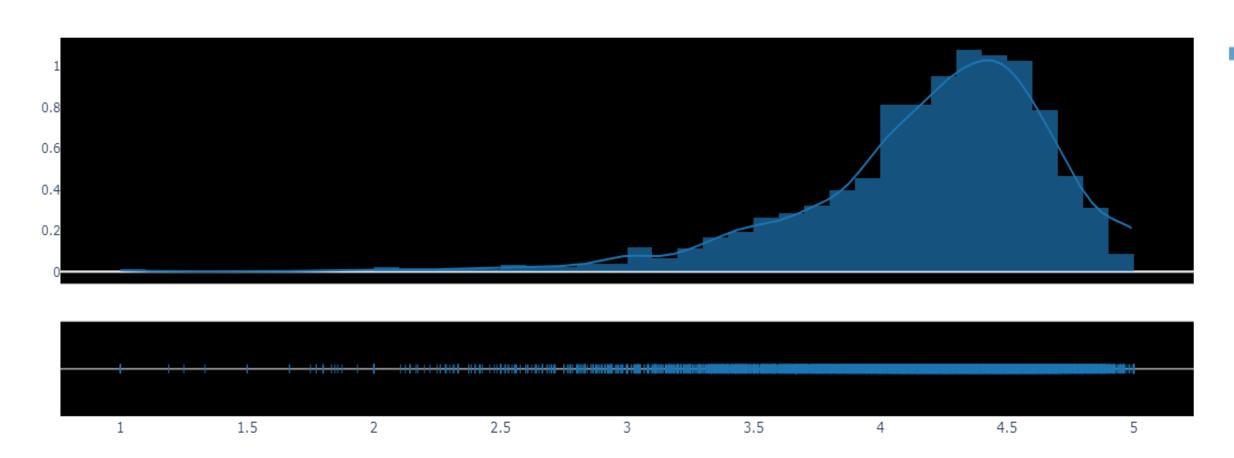
	size	loves_count	rating
0	125-175 ML	6320.0	3.6364
1	75-100 ML	3827.0	4.1538
2	75-100 ML	3253.0	4.2500
3	75-100 ML	3018.0	4.4762
4	75-100 ML	2691.0	3.2308

Null value Visualize



Numerical Analysis

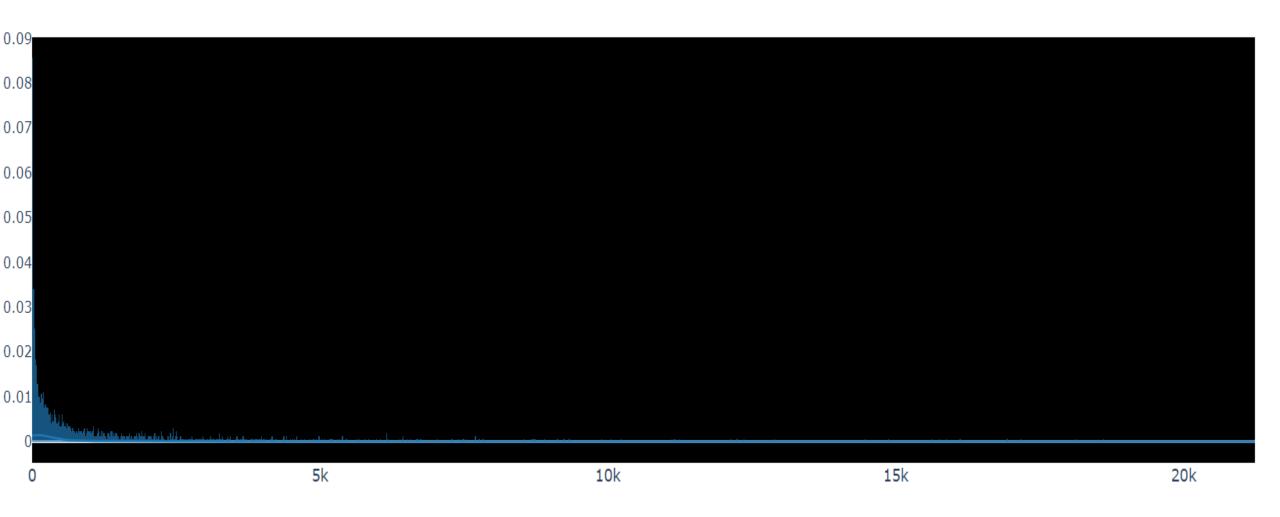
Numerical Distribution of Rating



Numerical Analysis

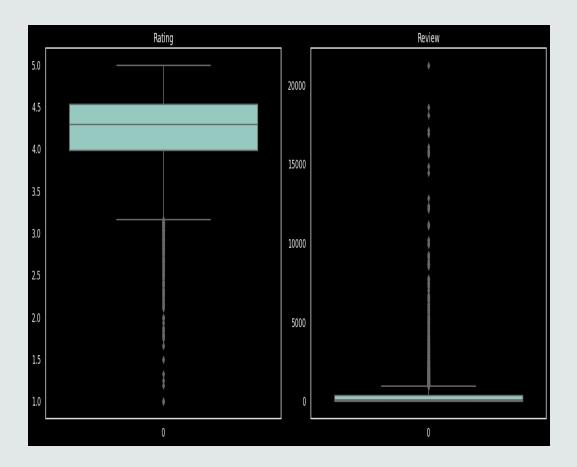
Numerical Distribution of Reviews

Download plot as a png

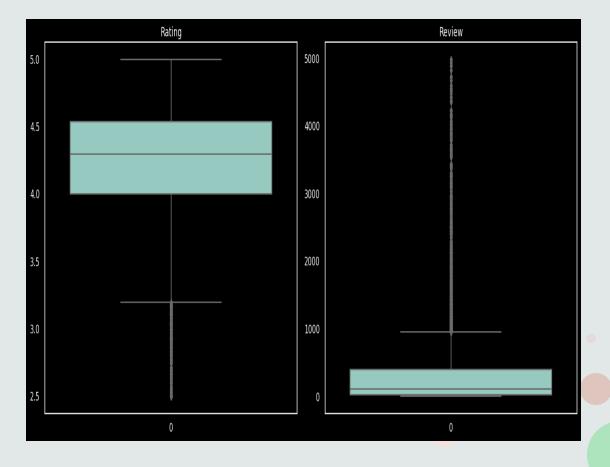


. Outlier Detection and Removal

Outlier Detection



Removal of Outlier

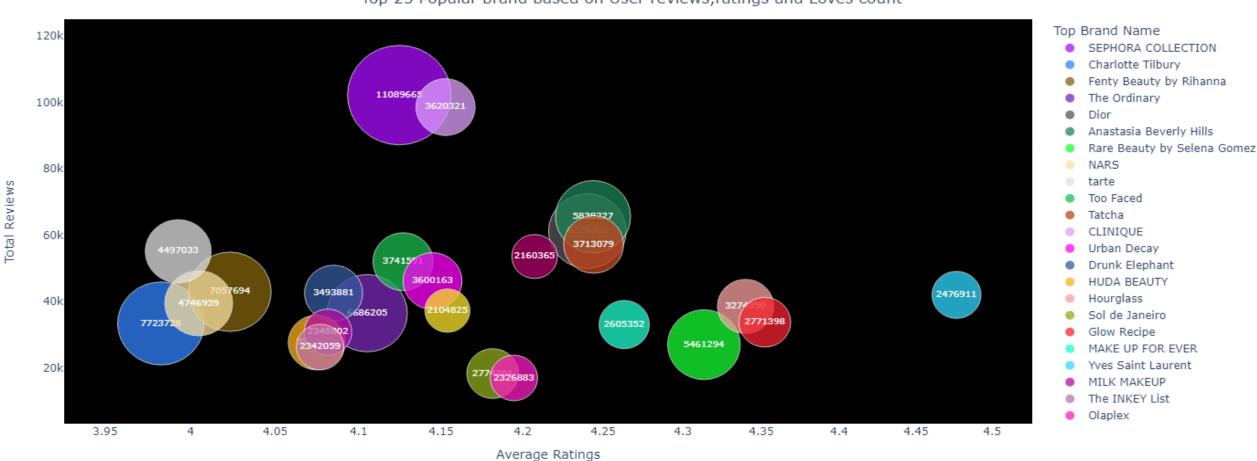


. Correlation Analysis

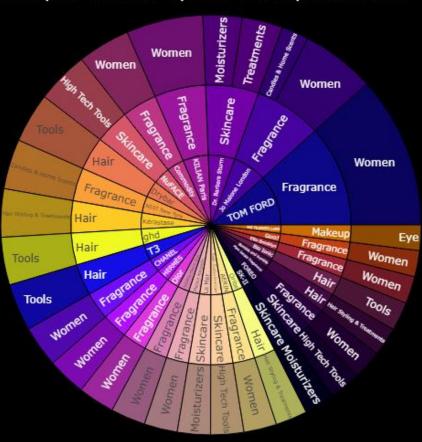
loves_count	1	0.015	0.59	-0.097	-0.07	-0.08	-0.17	-0.052	0.061	- 1.0
rating	0.015	1	0.078	0.054	-0.016	0.12	0.019	-0.039	0.023	- 0.8
reviews	0.59	0.078	1	-0.059	-0.11	-0.076	-0.18	-0.074	-0.017	
price_usd	-0.097	0.054	-0.059	1	0.045	0.028	0.093	-0.023	-0.14	- 0.6
limited_edition	-0.07	-0.016	-0.11	0.045	1	0.16	0.055	0.16	0.068	- 0.4
new	-0.08	0.12	-0.076	0.028	0.16	1	0.042	0.015	0.066	
online_only	-0.17	0.019	-0.18	0.093	0.055	0.042	1	0.0042	-0.1	- 0.2
out_of_stock	-0.052	-0.039	-0.074	-0.023	0.16	0.015	0.0042	1	0.023	- 0.0
sephora_exclusive	0.061	0.023	-0.017	-0.14	0.068	0.066	-0.1	0.023	1	
	loves_count	rating	reviews	price_usd	limited_edition	new	online_only	out_of_stock	sephora_exclusive	

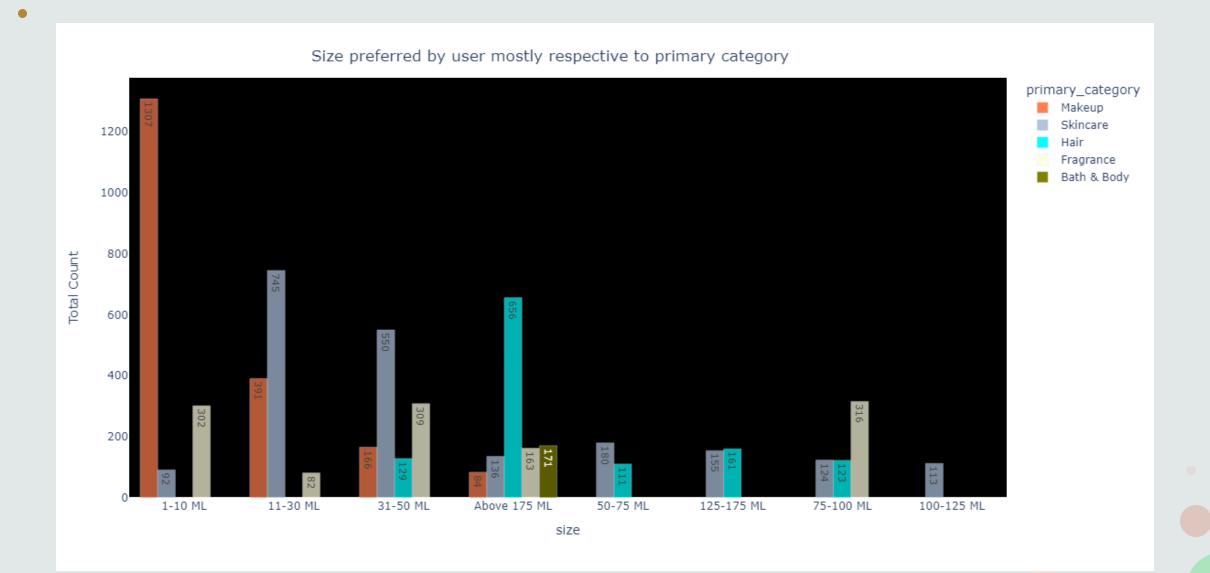
. Custom Analysis

Top 25 Popular brand based on User reviews, ratings and Loves count

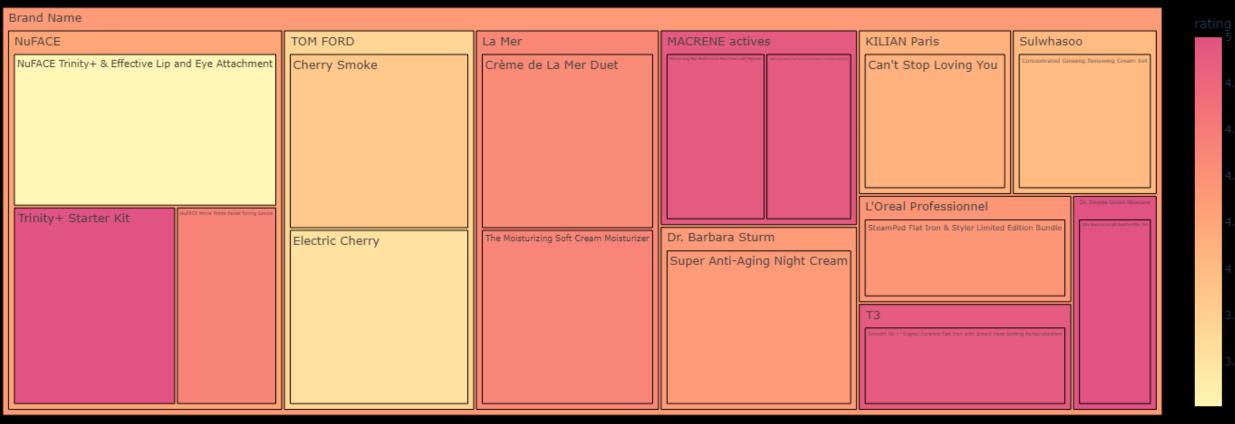


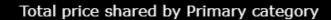


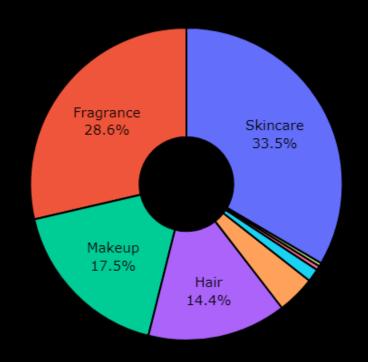




Product with High cost price and their Average ratings with their Brand Name







Skincare
Fragrance
Makeup
Hair

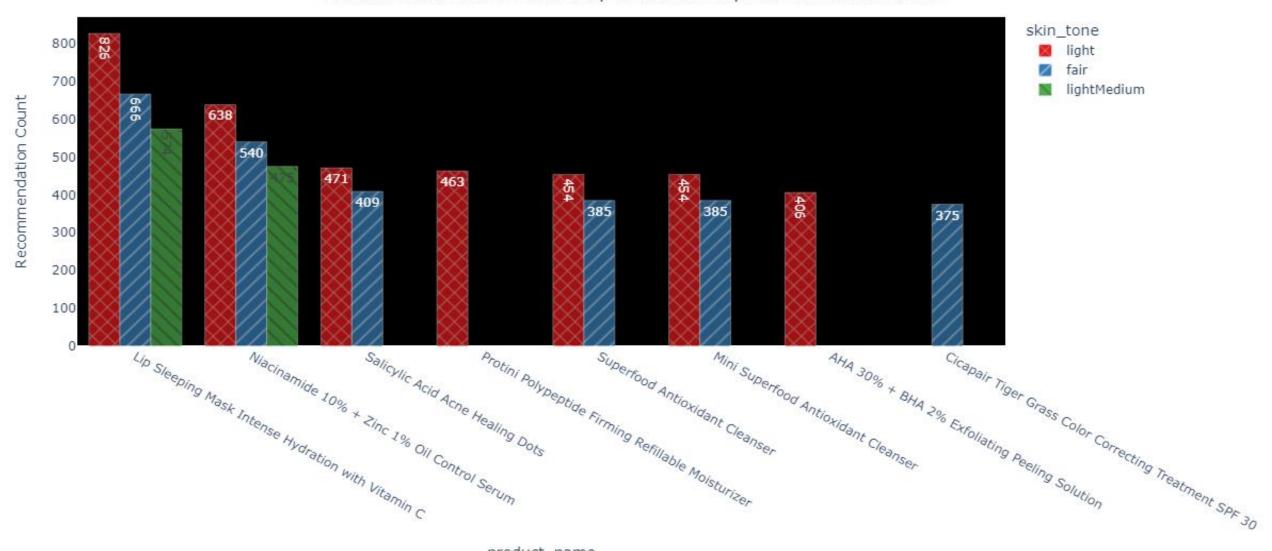
Bath & Body

Tools & Brushes

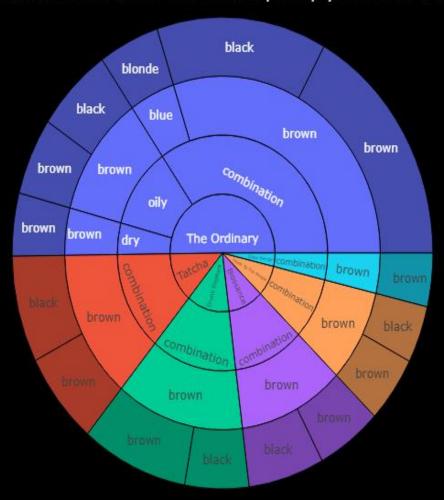
Mini Size

Men

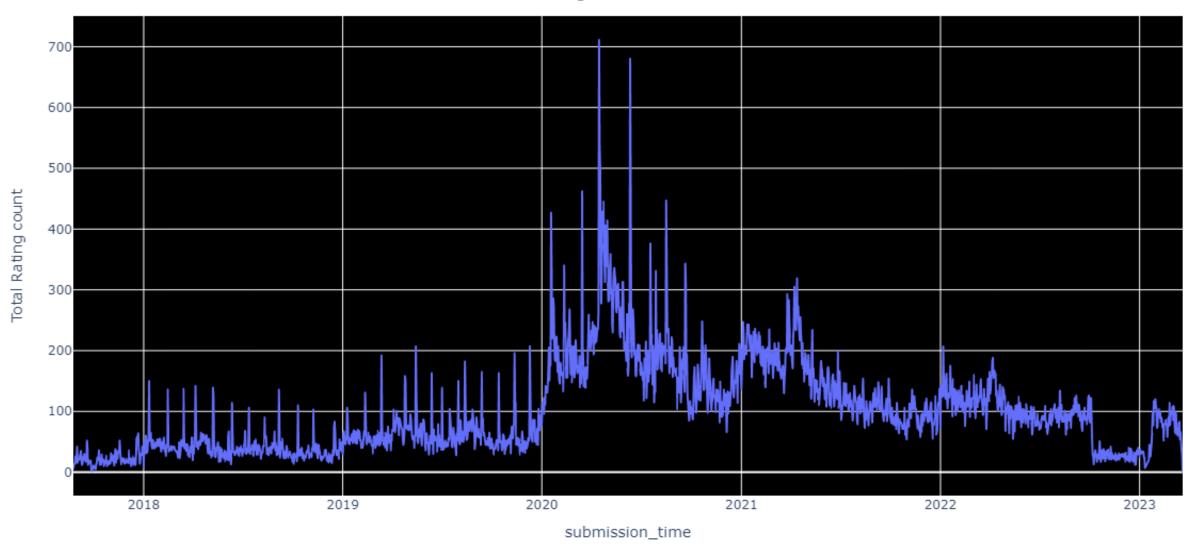




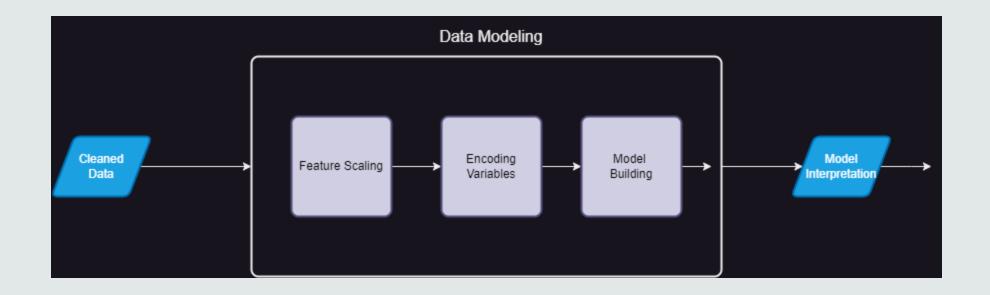
Total Positive feedback for Brand Name, Skin, Eye and Hair features



Number of ratings Submitted on Each Date



Data Modeling



- We build Model to Predict a Price of Product
- We Further perform Feature Scaling using Standard Scalar Method
- We done Encoding using One Hot Encoding
- We build a Model using Linear Regression, Lasso Regression, Decision Tree Regression, XGBOOST Regression
- Once Model is built, we performed data interpretation from model to check its accuracy of model

Linear Regression Modeling

```
linear_model = LinearRegression()
linear model.fit(X train, y train)
 ▼ LinearRegression
 LinearRegression()
# Make predictions on the training set
y train pred = linear model.predict(X train)
# Make predictions on the test set
y_test_pred = linear model.predict(X test)
# Calculate mean squared error (MSE) for training and test data
mse train = mean squared error(y train, y train pred)
mse test = mean squared error(y test, y test pred)
# Calculate R-squared (coefficient of determination) for training and test data
r2 train = r2 score(y train, y train pred)
r2 test = r2 score(y test, y test_pred)
print("MSE - Training Data:", mse train)
print("MSE - Test Data:", mse test)
print("R-squared - Training Data:", r2 train)
print("R-squared - Test Data:", r2 test)
MSE - Training Data: 2117.707814566357
MSE - Test Data: 1741.2426426634333
R-squared - Training Data: 0.284180407548297
R-squared - Test Data: 0.3242229016496214
```

Lasso Regression Modeling

```
lasso model = Lasso(alpha=0.1)
lasso model.fit(X train, y train)
       Lasso
Lasso(alpha=0.1)
# Make predictions on the training set
y train pred = lasso model.predict(X train)
# Make predictions on the test set
y test pred = lasso model.predict(X test)
# Calculate mean squared error (MSE) for training and test data
mse train = mean squared error(y train, y train pred)
mse test = mean squared error(y test, y test pred)
# Calculate R-squared (coefficient of determination) for training and test data
r2 train = r2 score(y train, y train pred)
r2 test = r2 score(y test, y test pred)
print("MSE - Training Data:", mse train)
print("MSE - Test Data:", mse test)
print("R-squared - Training Data:", r2 train)
print("R-squared - Test Data:", r2_test)
MSE - Training Data: 2118.731451131079
MSE - Test Data: 1739.0521579582098
R-squared - Training Data: 0.28383440178511377
R-squared - Test Data: 0.32507302980626507
```

Decision Tree Regression Modeling

```
# Create and train the Decision Tree regression model
   tree model = DecisionTreeRegressor()
   tree model.fit(X train, y train)
    ▼ DecisionTreeRegressor
   DecisionTreeRegressor()
] # Make predictions on the training set
   y train pred = tree model.predict(X train)
   # Make predictions on the test set
   y test pred = tree model.predict(X test)
   # Calculate mean squared error (MSE) for training and test data
   mse train = mean squared error(y train, y train pred)
   mse test = mean squared error(y test, y test pred)
   # Calculate R-squared (coefficient of determination) for training and test data
   r2 train = r2 score(y train, y train pred)
   r2_test = r2_score(y_test, y_test_pred)
   print("MSE - Training Data:", mse_train)
   print("MSE - Test Data:", mse test)
   print("R-squared - Training Data:", r2_train)
   print("R-squared - Test Data:", r2 test)
   MSE - Training Data: 7.365939893930465e-05
   MSE - Test Data: 3822.718686042403
   R-squared - Training Data: 0.9999999751019283
   R-squared - Test Data: -0.48359894145025084
```

XGBOOST Regression Modeling

```
# Create and train the XGBoost regression model
xg boost model = XGBRegressor()
xg_boost_model.fit(X_train, y_train)
                                  XGBRegressor
XGBRegressor(base score=None, booster=None, callbacks=None,
              colsample bylevel=None, colsample bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable categorical=False, eval metric=None, feature types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max cat threshold=None, max cat to onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n estimators=100, n jobs=None, num parallel tree=None,
              predictor=None, random_state=None, ...)
# Make predictions on the training set
y train pred = xg boost model.predict(X train)
# Make predictions on the test set
y_test_pred = xg_boost_model.predict(X_test)
# Calculate mean squared error (MSE) for training and test data
mse train = mean squared error(y train, y train pred)
mse_test = mean_squared_error(y_test, y_test_pred)
# Calculate R-squared (coefficient of determination) for training and test data
r2 train = r2 score(y train, y train pred)
r2_test = r2_score(y_test, y_test_pred)
```

MSE - Training Data: 341.30385509068924 MSE - Test Data: 2377.797073953913 R-squared - Training Data: 0.8846337607233885 R-squared - Test Data: 0.07717582390199496

print("R-squared - Training Data:", r2_train)
print("R-squared - Test Data:", r2_test)

print("MSE - Training Data:", mse_train)
print("MSE - Test Data:", mse test)

Statistical Test



We perform Statistical Test to infer from the data and get the interpretation from it



We used Independent t-test, Chi Squared test, One way Annova, Pearson Correlation Coefficient Test

Independent t-test:

The independent t-test **compares the means** of two **independent groups** to determine if there is a significant difference between them

Group1= The ratings of Skincare from Primary category

Group2= The ratings of Makeup from Primary category

Inference Results:

T-statistic: 5.913358400426621

p-value: 3.5848167759449255e-09

• There is a significant difference in the mean 'rating' between 'Skincare' and 'Makeup'

Chi-squared test:

The chi-squared test is used to determine if there is a significant **association between two categorical** variables

Category var1=Primary category

Category var2=Size

Inference Results:

Chi-squared statistic: 9903.90445683496

p-value: 0.0

• There is a significant difference in the mean 'rating' between 'Size' and 'Primary category'

One-way Annova:

One-Way ANOVA is used to compare the **means of two or more groups** to determine if there are any significant differences

Group1= The ratings of Women from Secondary category

Group2= The ratings of Eye from Secondary category

Group3= The ratings of Face from Secondary category

Inference Results:

F-statistic: 29.65235576069065

p-value: 1.9476949111852175e-13

• There is a significant difference in the mean 'rating' among the 'Women', 'Eye', and 'Face' categories.

Pearson Correlation Coefficient:

The Pearson correlation coefficient measures the **linear relationship between two continuous variables**. It assesses how strongly they are linearly correlated

Numerical var1=Loves Count

Numerical var2=Reviews

Inference Results:

Pearson Correlation Coefficient: 0.6832004791644654

p-value: 0.0

• There is a strong linear relationship between 'loves_count' and 'reviews'

