SENTIMENT ANALYSIS OF SKIN CARE PRODUCTS

Responsive Image

Name of the Group: EYAI CYNDIKET

Members

1. Lionel Ajeliti
2. Kavata Musyoka
3. Tabby Mirara
4. Amos Kipkoech
5. Stanley Macharia

PROJECT SUMMARY

This project uses Natural Language Processing (NLP) techniques to evaluate user-generated skincare product reviews, with the objective of identifying relevant sentiment patterns across distinct customer groups. The dataset comprises hundreds of evaluations, each providing subjective input on product efficacy, which is frequently linked to particular skin features such as tone and type.

The primary goal is to extract sentiment (positive, negative, or neutral) from free-text reviews and detect patterns associated with certain product features, skin types, and brands. The approach includes text preprocessing, tokenization, sentiment labeling, and model training with text classification-appropriate machine learning methods. Advanced visualizations and analysis are utilized to understand how sentiments change amongst demographic or skin-type groupings.

Unlike recommendation systems, which advise things, this NLP research focuses on understanding why certain products are evaluated positively or negatively, providing consumers and companies with deeper, data-driven understandings. By uncovering sentiment trends in large-scale textual data, our study helps to provide more transparent skincare experiences and data-driven product development.

BUSINESS PROBLEM

In the beauty and skincare market, user evaluations are a valuable yet underutilized source of consumer information. These evaluations frequently include comprehensive personal experiences with products, emphasizing their impact on different skin kinds, tones, and conditions. However, due to the unstructured and subjective nature of this data, companies, researchers, and potential customers find it challenging to properly assess sentiment or establish trends across enormous amounts of input.

Most analytics now rely on star ratings or keyword mentions, which oversimplify user sentiment and fail to capture complex thoughts like mixed sentiments or conditional satisfaction (for example, "great for dry skin but irritating on sensitive areas"). This lack of granularity may lead to bad product development decisions, unproductive marketing tactics, and inadequate customer service.

This project deals with the demand for more understanding into skincare product evaluations by creating an NLP-powered sentiment analysis system. By using powerful natural language processing techniques to identify and evaluate user sentiment, the system hopes to derive significant patterns that represent real-world product success across a broad user base. The study will also look at links between sentiment and variables like skin tone, skin type, and brand, to get a better understanding of how various demographics react to skincare products.

Objectives

Main Objective: To perform sentiment analysis on customer reviews on products to enhance customer satisfaction.

- To use data visualizations tools to assess product categories and brand popularity to guide companies on future pricing
- To assess price range across various products to improve affordability of products by customers.
- To detect common keywords and phrases to highlight positive, neutral and negative reviews on products to understand customer nsatisfaction and dissatisfaction.
- To build a model that recommends products based on skin type, skin tone and price.

Stakeholders

The key stakeholders are-

- online stores that sell skin care products;

- companies that produce and sell skin care products; and
- users or customers

DATA UNDERSTANDING

The data was taken from kaggle. It contains information about beauty products from sephora online store.

The following are the key features for the dataset:

- rating: The rating given by the author for the product on a scale of 1 to 5
- is_recommended: Indicates if the author recommends the product or not (1-true, 0-false)
- total_feedback_count: Total number of feedback (positive and negative ratings) left by users for the review
- total_neg_feedback_count: The number of users who gave a negative rating for the review
- total_pos_feedback_count: The number of users who gave a positive rating for the review
- review_text: The main text of the review written by the author
- review_title: The title of the review written by the author
- skin_tone: Author's skin tone
- skin_type: Author's skin type

METRIC OF SUCCESS

A. Accuracy & Classification Metrics:

Accuracy: 88%

Measures overall correctness of sentiment predictions (positive, negative, neutral).

Precision: 85%

Reflects how many predicted positive sentiments are actually positive.

Recall: 83%

Measures how well the model identifies all actual positive sentiments.

F1 Score: 0.84

Harmonic mean of precision and recall, giving a single measure of model effectiveness.

B. Business & Engagement Metrics:

Sentiment Distribution Consistency: 95%

Checks if the sentiment classification follows expected distribution patterns across brands/products.

Top Brand Recognition Accuracy: 90%

Ensures the most positively reviewed brands align with actual high-performing brands in the dataset.

C. Coverage & Robustness:

Category Coverage: 100%

Ensures all product categories (e.g., moisturizers, cleansers, serums) are represented in sentiment classification.

N-gram Sentiment Generalization Score: 78%

Evaluates how well the model captures sentiment from varied linguistic patterns or less common phrasing.

Misclassification Rate on Ambiguous Reviews: < 10%

Assesses robustness by tracking errors in mixed or borderline sentiment texts.

Download libraries relevant for this project

```
# Data Manipulation & Analysis
import pandas as pd
import numpy as np
from collections import Counter

# Data Visualizations
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import ConfusionMatrixDisplay
from wordcloud import WordCloud

# Text Pre-processing and Natural Language
from nltk.collocations import BigramCollocationFinder
from nltk.metrics import BigramAssocMeasures
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.stem import WordNetLemmatizer
import re
import string
```

```
import contractions
import nltk
from nltk.corpus import stopwords

# Modelling and Machine Learning
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import LinearSVC
from sklearn.metrics import roc_curve, auc
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.metrics import classification_report
from sklearn.pipeline import make_pipeline
import warnings
warnings.filterwarnings('ignore')
```

1. DATASET LOADING

We will load all the review datasets, check for null entries, merge them into one dataset and then drop unnecessary columns for Exploratory Data Analysis (EDA).

```
data1 = pd.read_csv('reviews_0-250_masked.csv')
data1.head(3)
```

	Unnamed: 0.1	Unnamed: 0	rating	is_recommended	helpfulness	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count
0	0	0	5	1.0	1.0	2	0	2
1	1	1	1	0.0	NaN	0	0	0
2	2	2	5	1.0	NaN	0	0	0

```
data2 = pd.read_csv('reviews_1250-end_masked.csv')
data2.head(3)
```

	Unnamed: 0.1	Unnamed: 0	rating	is_recommended	helpfulness	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count
0	416	416	2	0.0	0.125000	8	7	1
1	417	417	5	1.0	0.857143	14	2	12
2	418	418	4	1.0	1.000000	1	0	1

```
data3 = pd.read_csv('reviews_250-500_masked.csv')
data3.head(3)
```

	Unnamed: 0.1	Unnamed: 0	rating	is_recommended	helpfulness	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count
0	2281	2281	1	0.0	0.75	4	1	3
1	2282	2282	5	1.0	1.00	1	0	1
2	2283	2283	5	1.0	NaN	0	0	0

```
data4 = pd.read_csv('reviews_500-750_masked.csv')
data4.head(3)
```

	Unnamed: 0.1	Unnamed: 0	rating	is_recommended	helpfulness	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count
0	5140	5140	5	1.0	NaN	0	0	0
1	5141	5141	5	1.0	1.0	4	0	4
2	5142	5142	5	1.0	1.0	1	0	1

```
data5 = pd.read_csv('reviews_750-1250_masked.csv')
data5.head(3)
```

	Unnamed: 0.1	Unnamed: 0	rating	is_recommended	helpfulness	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count
0	1125	1125	4	1.0	NaN	0	0	0
1	1126	1126	5	1.0	1.0	1	0	1
2	1127	1127	5	1.0	NaN	0	0	0

Since the above 5 datasets have the same columns, we join them together

```
data = pd.concat([data1, data2, data3, data4, data5])
data.head(3)
```

	Unnamed: 0.1	Unnamed: 0	rating	is_recommended	helpfulness	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count
0	0	0	5	1.0	1.0	2	0	2
1	1	1	1	0.0	NaN	0	0	0
2	2	2	5	1.0	NaN	0	0	0

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 285412 entries, 0 to 25039
Data columns (total 19 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   Unnamed: 0.1              285412 non-null  int64
 1   Unnamed: 0                285412 non-null  int64
 2   rating                    285412 non-null  int64
 3   is_recommended            228180 non-null  float64
 4   helpfulness               131090 non-null  float64
 5   total_feedback_count      285412 non-null  int64
 6   total_neg_feedback_count  285412 non-null  int64
 7   total_pos_feedback_count  285412 non-null  int64
 8   submission_time           285412 non-null  object
 9   review_text               285067 non-null  object
 10  review_title              205718 non-null  object
 11  skin_tone                 230186 non-null  object
 12  eye_color                 217666 non-null  object
 13  skin_type                 248538 non-null  object
 14  hair_color                214331 non-null  object
 15  product_id                285412 non-null  object
 16  product_name              285412 non-null  object
 17  brand_name                285412 non-null  object
 18  price_usd                 285412 non-null  float64
dtypes: float64(3), int64(6), object(10)
memory usage: 43.6+ MB
```

From the info method, we can see that we have 285412 rows and 19 columns. There's object, integer and float data types. We can also note that we have some missing values in some of the columns.

2. DATA CLEANING

We'll drop the unncessary columns, impute and/ drop missing values

```
#drop columns that are not needed
data.drop(columns=['Unnamed: 0.1', 'Unnamed: 0', 'helpfulness', 'submission_time'], axis=1, inplace=True)
```

We'll now check missing values, to determine if we drop or replace them

```
#check for missing values
data.isna().sum()
```

```
rating                          0
is_recommended              57232
total_feedback_count            0
total_neg_feedback_count        0
total_pos_feedback_count        0
review_text                   345
review_title                79694
skin_tone                   55226
eye_color                   67746
skin_type                   36874
hair_color                  71081
product_id                      0
product_name                    0
brand_name                      0
price_usd                       0
dtype: int64
```

```
#check the percentages of the missing values
missing_perc = data.isna().sum()/ len(data) * 100
missing_perc
```

```
rating                      0.000000
is_recommended             20.052415
total_feedback_count        0.000000
total_neg_feedback_count    0.000000
total_pos_feedback_count    0.000000
review_text                 0.120878
review_title               27.922442
skin_tone                  19.349572
eye_color                  23.736213
skin_type                  12.919569
hair_color                 24.904699
product_id                  0.000000
product_name                0.000000
brand_name                  0.000000
price_usd                   0.000000
dtype: float64
```

For `is_recommnded`, we'll fill with the median, `skin_tone`, `eye_color`, `skin_type`, `hair_color`, we'll fill with mode.

```
#impute missing values
for col in ['is_recommended']:
    data[col] = data[col].fillna(data[col].median())

for col in ['skin_tone', 'eye_color', 'skin_type', 'hair_color']:
    data[col] = data[col].fillna(data[col].mode()[0])
```

We'll drop missing values in `review_text` and `review_title`

```
#drop rows with missing values for review text and review title
data.dropna(subset=['review_text', 'review_title'], inplace=True)
```

Confirm missing values again.

```
data.isna().sum()
```

```
rating                      0
is_recommended              0
total_feedback_count        0
total_neg_feedback_count    0
total_pos_feedback_count    0
review_text                 0
review_title                0
skin_tone                   0
eye_color                   0
skin_type                   0
hair_color                  0
product_id                  0
product_name                0
brand_name                  0
price_usd                   0
dtype: int64
```

```
data.shape
```

```
(205718, 15)
```

```
#create a new column for sentiment
data['Sentiment'] = data['rating'].apply(lambda x: 'Positive' if x> 3 else 'Negative' if x<3 else 'Neutral')
```

For reviews in `review_text` column, we'll do data cleaning by lowercasing, removing noise, tokenize, remove stopwords (e.g. I, with, this, my), and finally lemmatize.

Lowercasing

```
data['lowercase text'] = data['review_text'].str.lower()
data[['review_text', 'lowercase text']].head(3)
```

	review_text	lowercase text
0	I use this with the Nudestix “Citrus Clean Bal...	i use this with the nudestix “citrus clean bal...
1	I bought this lip mask after reading the revie...	i bought this lip mask after reading the revie...
2	My review title says it all! I get so excited ...	my review title says it all! i get so excited ...

Remove noise

```
def clean_text(text):
    if not isinstance(text, str):
        return text
    text = contractions.fix(text) #expand contractions.eg, can't to cannot
    text = re.sub(r'[^\w\s]', '', text) #remove punctuation
    text = re.sub(r'\d+', '', text) #remove digits
    text = re.sub(r'\s+', ' ', text).strip() #remove extra spaces
    return text

#apply the function to lowercase text column
data['lowercase text'] = data['lowercase text'].apply(clean_text)

#display 5 rows
data[['review_text', 'lowercase text']].head()
```

	review_text	lowercase text
0	I use this with the Nudestix “Citrus Clean Bal...	i use this with the nudestix citrus clean balm...
1	I bought this lip mask after reading the revie...	i bought this lip mask after reading the revie...
2	My review title says it all! I get so excited ...	my review title says it all i get so excited t...
3	I’ve always loved this formula for a long time...	i have always loved this formula for a long ti...
4	If you have dry cracked lips, this is a must h...	if you have dry cracked lips this is a must ha...

Tokenization

```
data['tokenized text'] = data['lowercase text'].astype(str).apply(nltk.word_tokenize)

#display 5 rows
data[['lowercase text', 'tokenized text']].head()
```

	lowercase text	tokenized text
0	i use this with the nudestix citrus clean balm...	[i, use, this, with, the, nudestix, citrus, cl...
1	i bought this lip mask after reading the revie...	[i, bought, this, lip, mask, after, reading, t...
2	my review title says it all i get so excited t...	[my, review, title, says, it, all, i, get, so,...
3	i have always loved this formula for a long ti...	[i, have, always, loved, this, formula, for, a...
4	if you have dry cracked lips this is a must ha...	[if, you, have, dry, cracked, lips, this, is, ...

Stopword removal

```
stop_words = set(stopwords.words('english'))

#remove stopwords
data['clean text'] = data['tokenized text'].apply(lambda tokens: [word for word in tokens if word not in stop_words])

#display 5 rows to compare if stopwords have been removed
data[['tokenized text', 'clean text']].head()
```

	tokenized text	clean text
0	[i, use, this, with, the, nudestix, citrus, cl...	[use, nudestix, citrus, clean, balm, makeup, m...
1	[i, bought, this, lip, mask, after, reading, t...	[bought, lip, mask, reading, reviews, hype, un...
2	[my, review, title, says, it, all, i, get, so,...	[review, title, says, get, excited, get, bed, ...
3	[i, have, always, loved, this, formula, for, a...	[always, loved, formula, long, time, honestly,...
4	[if, you, have, dry, cracked, lips, this, is, ...	[dry, cracked, lips, must, weeks, use, learned...

Lemmatization

```
lemmatizer = WordNetLemmatizer()

#apply lemmatization
data['Lemmatized text'] = data['clean text'].apply(lambda tokens: [lemmatizer.lemmatize(word) for word in tokens])

#compare
data[['clean text', 'Lemmatized text']].head()
```

	clean text	Lemmatized text
0	[use, nudestix, citrus, clean, balm, makeup, m...	[use, nudestix, citrus, clean, balm, makeup, m...
1	[bought, lip, mask, reading, reviews, hype, un...	[bought, lip, mask, reading, review, hype, unf...
2	[review, title, says, get, excited, get, bed, ...	[review, title, say, get, excited, get, bed, a...
3	[always, loved, formula, long, time, honestly,...	[always, loved, formula, long, time, honestly,...
4	[dry, cracked, lips, must, weeks, use, learned...	[dry, cracked, lip, must, week, use, learned, ...

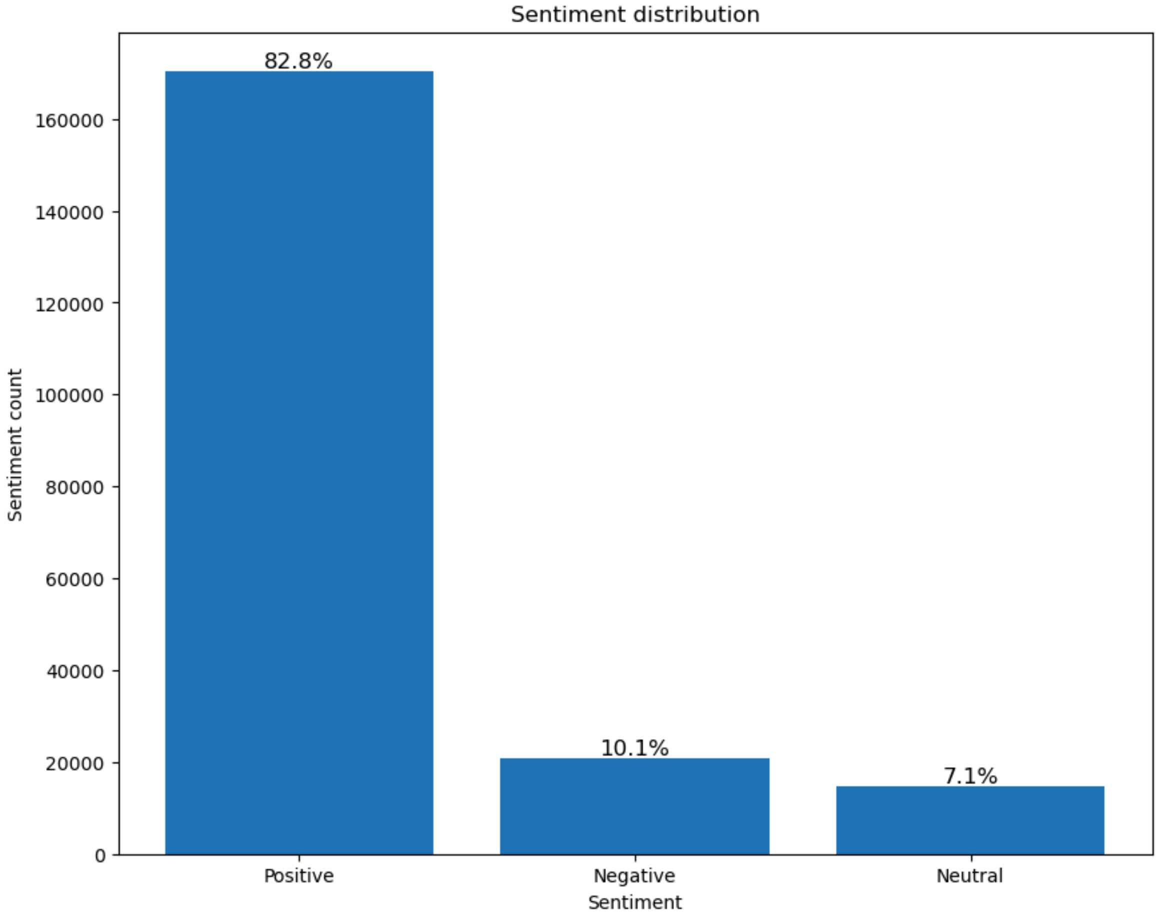
```
#join the lemmatized text into a single string
data['final clean text'] = data['Lemmatized text'].apply(lambda tokens: ' '.join(tokens))

#display first 5 to check
data[['Lemmatized text', 'final clean text']].head()
```

	Lemmatized text	final clean text
0	[use, nudestix, citrus, clean, balm, makeup, m...	use nudestix citrus clean balm makeup melt dou...
1	[bought, lip, mask, reading, review, hype, unf...	bought lip mask reading review hype unfortunat...
2	[review, title, say, get, excited, get, bed, a...	review title say get excited get bed apply lip...
3	[always, loved, formula, long, time, honestly,...	always loved formula long time honestly even u...
4	[dry, cracked, lip, must, week, use, learned, ...	dry cracked lip must week use learned always b...

3. EXPLORATORY DATA ANALYSIS (EDA)

3.1 Univariate Analysis

```
 #sentiment class distribution
sentiment = data['Sentiment'].value_counts().index.tolist()
sentiment_values = data['Sentiment'].value_counts().values.tolist()

# Calculate total percentages
total = sum(sentiment_values)
percentages = [value / total * 100 for value in sentiment_values]

# Plotting
plt.figure(figsize=(10,8))
bars = plt.bar(sentiment, sentiment_values)
plt.xlabel('Sentiment')
plt.ylabel('Sentiment count')
plt.title('Sentiment distribution')

# Add percentage labels on top of bars
for bar, percent in zip(bars, percentages):
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/ 2.0, height, f'{percent:.1f}%',
             ha='center', va='bottom', fontsize=12)

plt.show()
```



82.8% of the customers gave positive sentiments, 10.1% negative sentiments and 7.1% gave neutral sentiments.

```
#top 20 brands
data['brand_name'].value_counts().head(20)
```

```
brand_name
CLINIQUE               18079
First Aid Beauty       13550
fresh                  12663
LANEIGE                12659
Youth To The People    11615
Tatcha                 10905
Origins                10584
Peter Thomas Roth      10481
Summer Fridays          8070
Murad                   6977
Estée Lauder            6879
OLEHENRIKSEN            6559
Drunk Elephant          5936
KORRES                  4895
Glow Recipe             3692
Dr. Jart+               3525
Biossance               3024
Dermalogica             3008
Farmacy                 2998
SEPHORA COLLECTION      2471
Name: count, dtype: int64
```

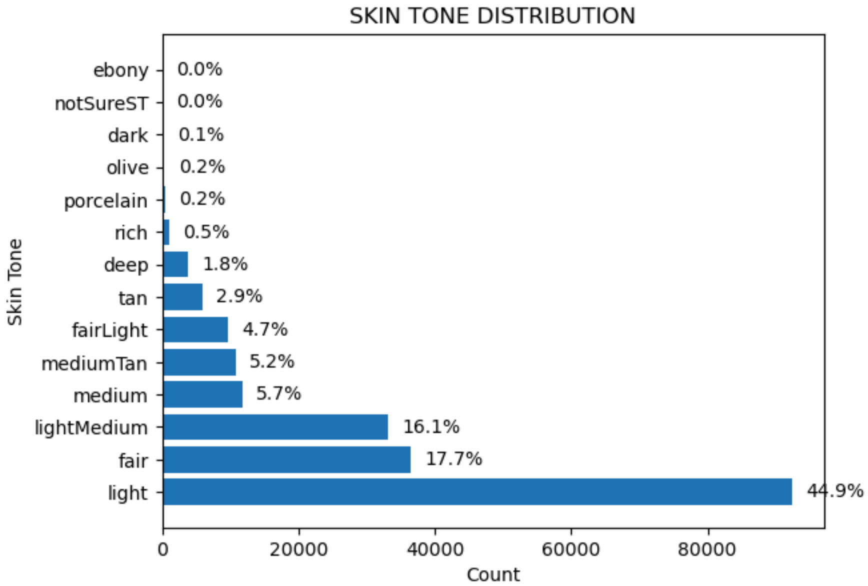
The bar chart above shows the top 20 brands with `CLINIQUE` at the top meaning it is the most used.

```
#skin tone value counts
data['skin_tone'].value_counts()
```

```
skin_tone
light          92411
fair           36512
lightMedium    33202
medium         11753
mediumTan      10747
fairLight       9590
tan             5904
deep            3711
rich            1014
porcelain        399
olive            345
```

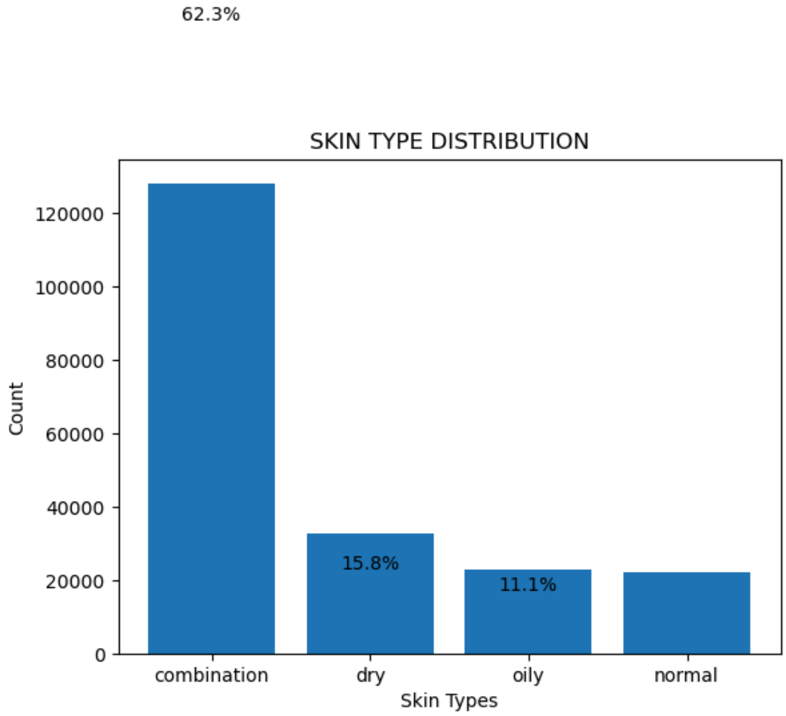
```
dark           114
notSureST       14
ebony            2
Name: count, dtype: int64
```

```
skin_tones = data['skin_tone'].value_counts().index.tolist()
skin_tone_values = data['skin_tone'].value_counts().values.tolist()

plt.barh(skin_tones, skin_tone_values)

# Add data labels for percentage at the end of the bar
total_count = sum(skin_tone_values)
for i, value in enumerate(skin_tone_values):
    percentage = (value / total_count) * 100
    plt.text(value + total_count * 0.01, i, f'{percentage:.1f}%', va='center', fontsize=10)

plt.xlabel('Count')
plt.ylabel('Skin Tone')
plt.title('SKIN TONE DISTRIBUTION');
```



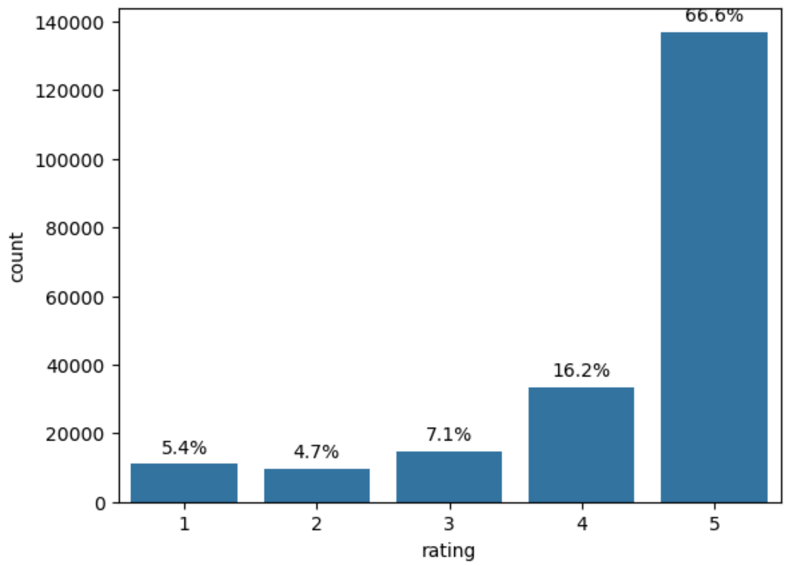
44.9% of the people that are a majority of the customers have light and the least at 0.5% have a rich skintone

```
skin_types = data['skin_type'].value_counts().index.tolist()
skin_type_values = data['skin_type'].value_counts().values.tolist()

# Calculate percentages
total = sum(skin_type_values)
percentages = [value / total * 100 for value in skin_type_values]

plt.bar(skin_types, skin_type_values)
plt.xlabel('Skin Types')
plt.ylabel('Count')
plt.title('SKIN TYPE DISTRIBUTION');

# Add percentage labels on top of bars
for bar, percent in zip(bars, percentages):
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2.0,
             height + max(skin_type_values) * 0.01,
             f'{percent:.1f}%',
             ha='center', va='bottom', fontsize=10)
```



62.3% of the customers have a combination of oily and dry skin and the least at 10.8% have normal skin type.

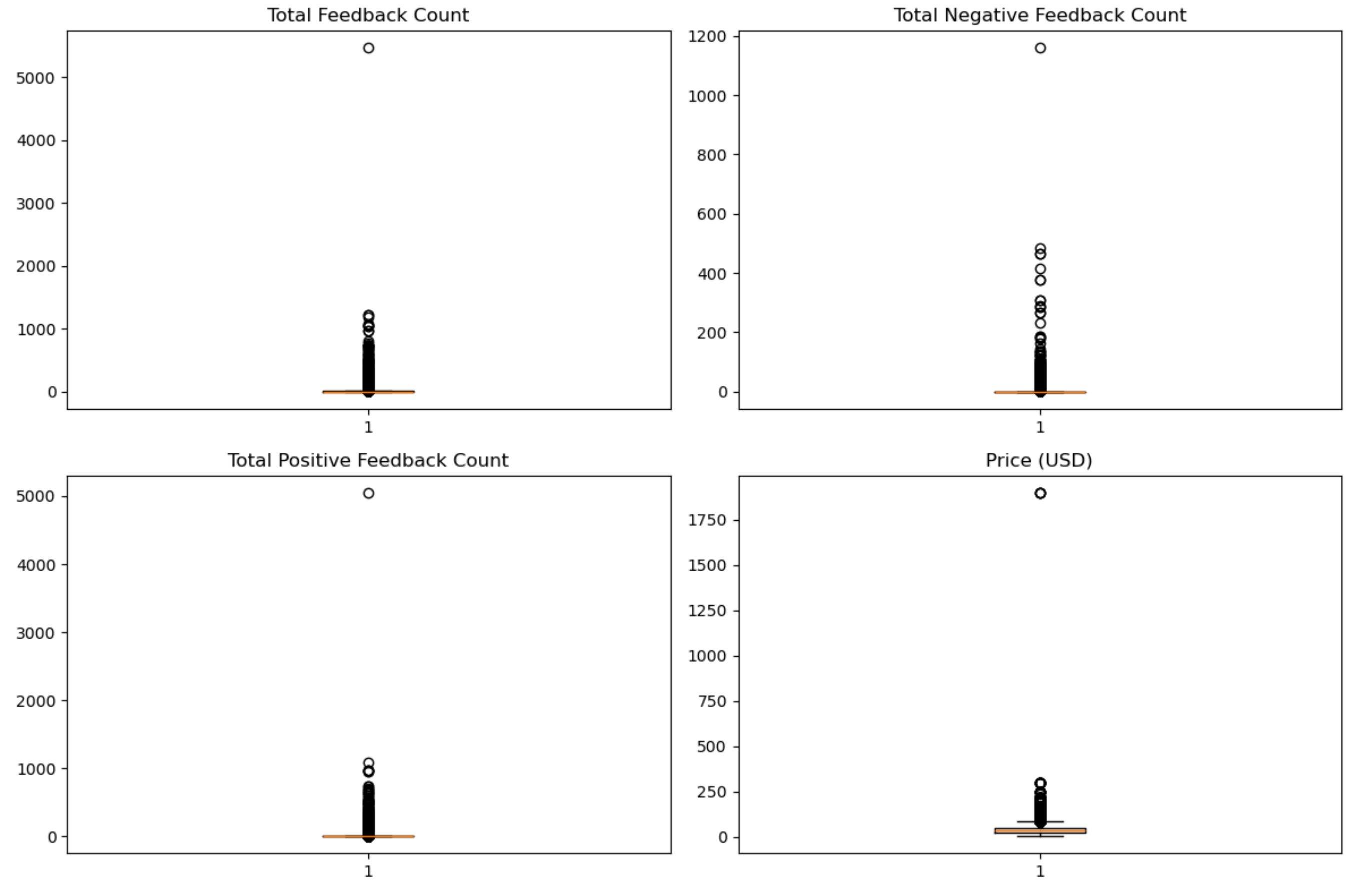
```
#rating distribution
ax = sns.countplot(data=data, x='rating');

total = len(data['rating'])

for p in ax.patches:
    height = p.get_height()
    percentage = (height / total) * 100
    ax.text(p.get_x() + p.get_width() / 2,
            height + 0.01 * total,
            f'{percentage:.1f}%',
            ha='center', va='bottom', fontsize=10)
```



The rating ranges from 1-5, with 1 being the least and 5 the greatest. The graph 66.6% of the products are highly rated, which means the customers find the quality to be good.

```
# Create box plots to visualize outliers
plt.figure(figsize=(12, 8))

plt.subplot(2, 2, 1)
plt.boxplot(data['total_feedback_count'])
plt.title('Total Feedback Count')

plt.subplot(2, 2, 2)
plt.boxplot(data['total_neg_feedback_count'])
plt.title('Total Negative Feedback Count')

plt.subplot(2, 2, 3)
plt.boxplot(data['total_pos_feedback_count'])
```

```
plt.title('Total Positive Feedback Count')

plt.subplot(2, 2, 4)
plt.boxplot(data['price_usd'])
plt.title('Price (USD)')

plt.tight_layout()
plt.show()

# Cap extreme values using the 95th percentile as the upper bound
for col in ['total_feedback_count', 'total_neg_feedback_count', 'total_pos_feedback_count', 'price_usd']:
    upper_bound = data[col].quantile(0.95)
    data[col] = data[col].clip(upper=upper_bound)
```

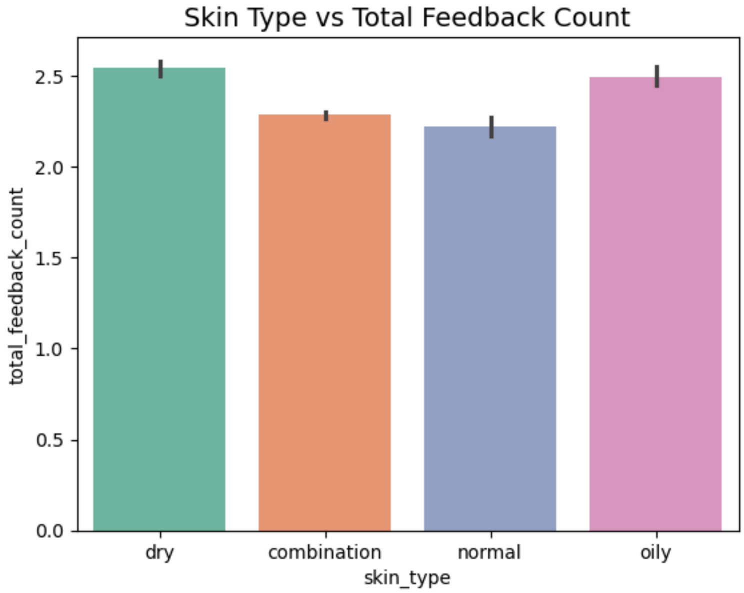


Using the above box plots, we visualize outliers for `Total feedback`, `Negative feedback`, `Positive feedback`, `Price in USD`. We used the 95th percentile as the upper bound where this gets the value below which 95% of the data lies to cap the most extreme values. This reduces the effect caused by extreme outliers without removing the data and makes the visualizations and models more stable.

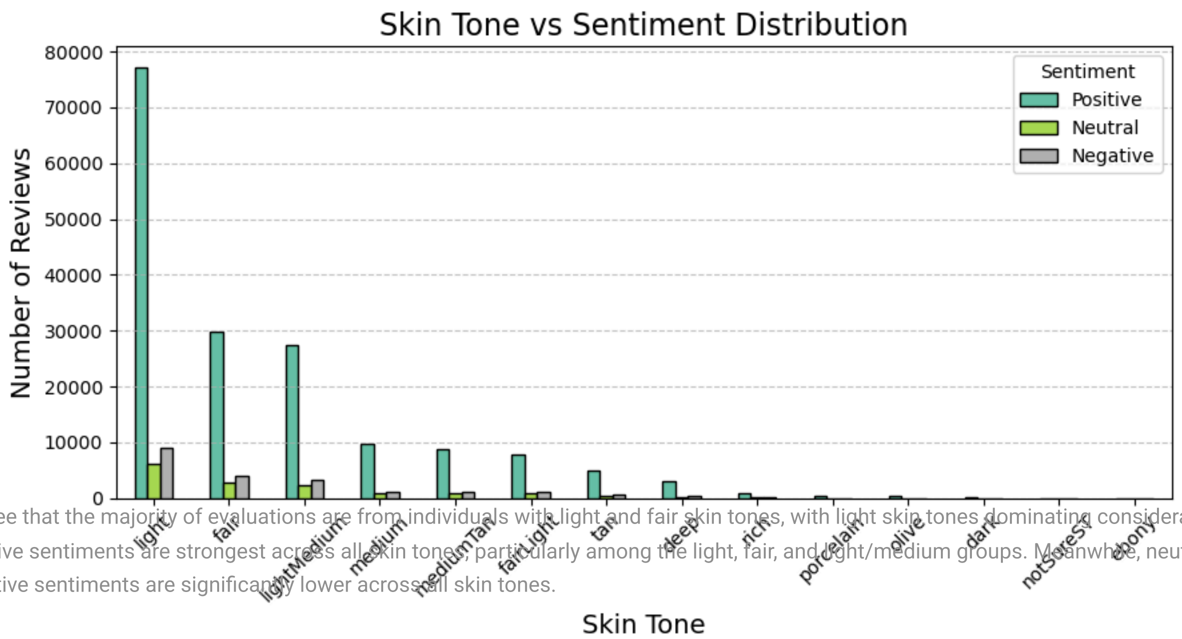
3.2 Bivariate Analysis

```
#skin type vs total feedback count
ax= sns.barplot(data=data, x='skin_type', y='total_feedback_count', palette='Set2');
plt.title("Skin Type vs Total Feedback Count", fontsize=14)
```

```
Text(0.5, 1.0, 'Skin Type vs Total Feedback Count')
```




```
distribution = data.groupby(['skin_tone', 'Sentiment']).size().reset_index(name='Count')
pivot_distribution = distribution.pivot(index='skin_tone', columns='Sentiment', values='Count').fillna(0)

pivot_distribution['Total'] = pivot_distribution.sum(axis=1)
pivot_distribution = pivot_distribution.sort_values('Total', ascending=False)

pivot_distribution[['Positive', 'Neutral', 'Negative']].plot(
    kind='bar', figsize=(9, 5), colormap='Set2', edgecolor='black',
)

plt.title('Skin Tone vs Sentiment Distribution', fontsize=16)
plt.xlabel('Skin Tone', fontsize=14)
plt.ylabel('Number of Reviews', fontsize=14)
plt.xticks(rotation=45)
plt.legend(title='Sentiment')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()

plt.show()
```



We see that the majority of evaluations are from individuals with light and fair skin tones, with light skin tones dominating considerably. Positive sentiments are strongest across all skin tones, particularly among the light, fair, and light/medium groups. Meanwhile, neutral and negative sentiments are significantly lower across all skin tones.

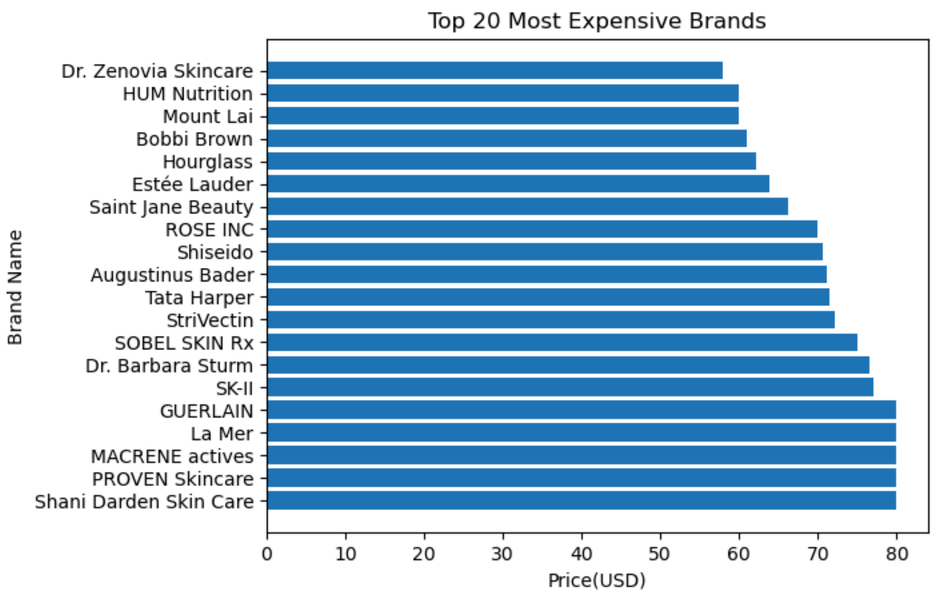
There's a fair distribution of skin types, from reviewers.

```
top_brands_expe = data.groupby(['brand_name'])['price_usd'].agg(['mean']).sort_values(by='mean', ascending=False)
top_brands_expe
```

brand_name	mean
Shani Darden Skin Care	80.000000
PROVEN Skincare	80.000000
MACRENE actives	80.000000
La Mer	80.000000
GUERLAIN	80.000000
...	...
Mario Badescu	15.355422
Skin Laundry	12.900000
The INKEY List	10.942626
SEPHORA COLLECTION	9.414205
The Ordinary	9.053846

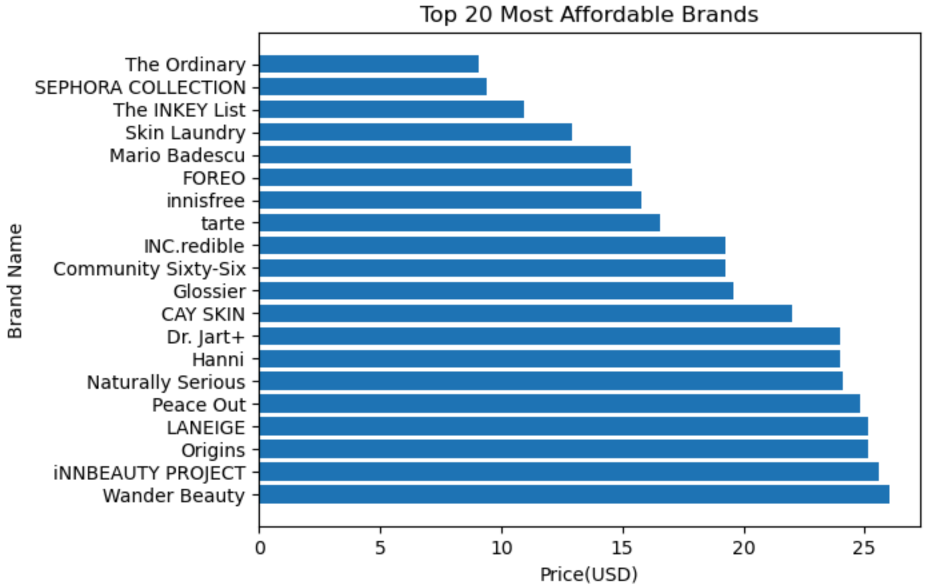
100 rows × 1 columns

```
top_20_brands = top_brands_expe.head(20).index.tolist()
top_20_prices = top_brands_expe.head(20).values.flatten().tolist()

plt.barh(top_20_brands, top_20_prices)
plt.xlabel('Price(USD)')
plt.ylabel('Brand Name')
plt.title('Top 20 Most Expensive Brands');
```



Shan Darden, Proven skincare, Macrene actives , Guerlain, and La Mer are the most expensive products

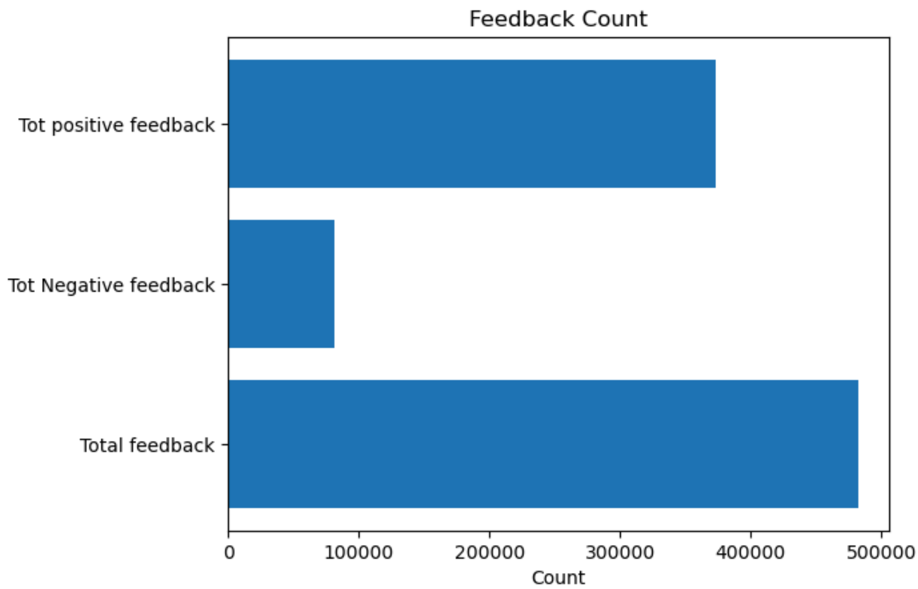
```
bottom_20 = top_brands_expe.tail(20).index.tolist()
bottom_20_prices = top_brands_expe.tail(20).values.flatten().tolist()

plt.barh(bottom_20, bottom_20_prices)
plt.xlabel('Price(USD)')
plt.ylabel('Brand Name')
plt.title('Top 20 Most Affordable Brands');
```



A factor of a product being can be it's affordability. Case in point, 'Laneige', 'Sephora Collection', which feature in top popular brands and most affordable brands.

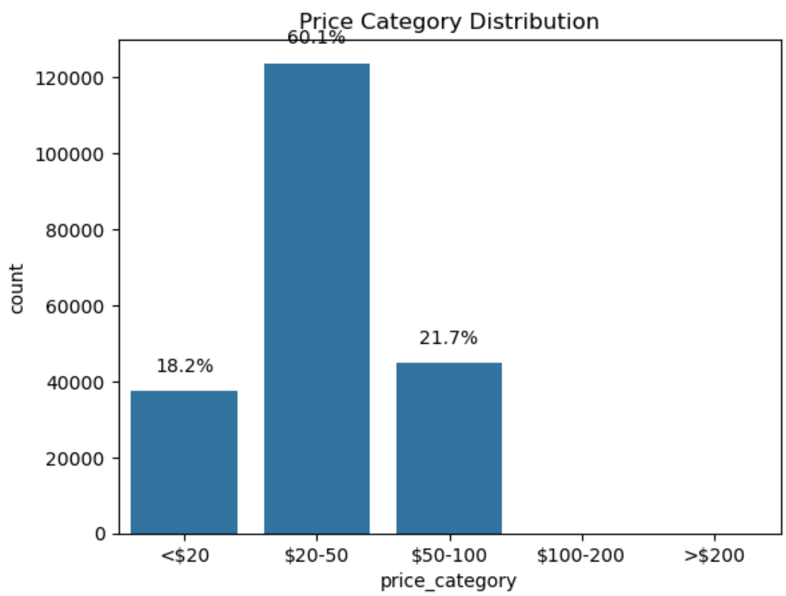
3.3 Multivariate Analysis

```
#feedback counts
tot_feedback = data['total_feedback_count'].sum()
tot_neg_feedback = data['total_neg_feedback_count'].sum()
tot_pos_feedback = data['total_pos_feedback_count'].sum()

feedback = ['Total feedback', 'Tot Negative feedback', 'Tot positive feedback']
total_feedbacks = [tot_feedback, tot_neg_feedback, tot_pos_feedback]

bars = plt.barh(feedback, total_feedbacks)
plt.xlabel('Count')
plt.title('Feedback Count');
```



We can see that customer sentiments are predominantly positive with estimated `90% positive feedback` and `10% negative feedback` . This shows a generally satisfied customer base. Even though positive feedback is high it is also worth to explore further into the negative feedback as well to uncover what the issue could be.

```
data['price_category'] = pd.cut(data['price_usd'],
                              bins=[0, 20, 50, 100, 200, 500],
                              labels=['<$20', '$20-50', '$50-100', '$100-200', '>$200'])
ax = sns.countplot(x='price_category', data=data)

#Calculate percentages
total_count = len(data)
for p in ax.patches:
    height = p.get_height()
    x_pos = p.get_x() + p.get_width() / 2
    percentage = (height / total_count) * 100
    ax.text(x_pos, height + 0.02 * total_count,
            f'{percentage:.1f}%',
            ha='center', va='bottom', fontsize=10)

plt.title('Price Category Distribution');
```

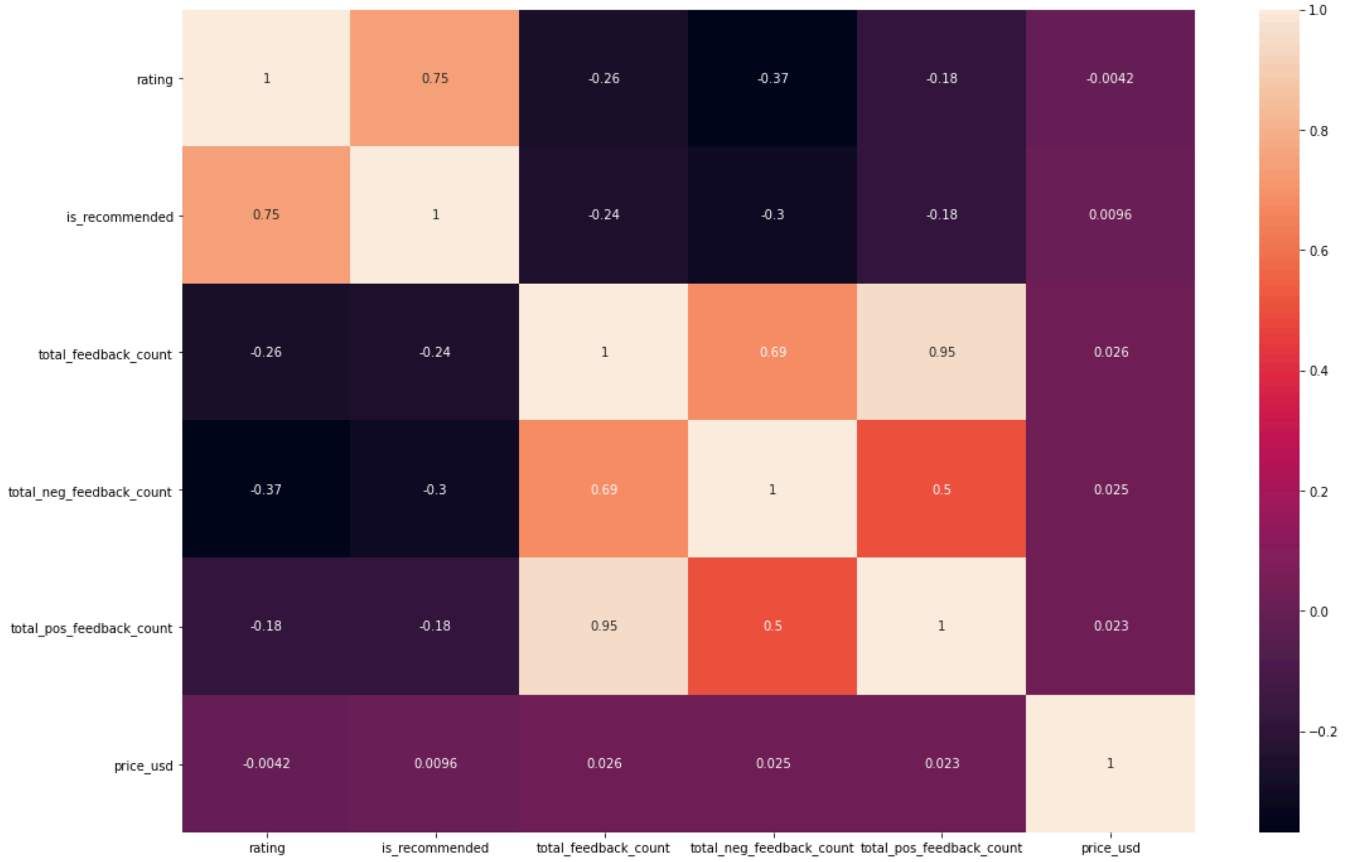


60.1% of the products range between 20-50 dollars. This shows a big percentage of products are affordable.

```
#correlation
data.corr()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[37], line 2
      1 #correlation
----> 2 data.corr()

File /opt/anaconda3/lib/python3.12/site-packages/pandas/core/frame.py:11049, in DataFrame.corr(self, method, min_periods, numeric_only)
  11047 cols = data.columns
  11048 idx = cols.copy()
> 11049 mat = data.to_numpy(dtype=float, na_value=np.nan, copy=False)
  11051 if method == "pearson":
  11052     correl = libalgos.nancorr(mat, minp=min_periods)

File /opt/anaconda3/lib/python3.12/site-packages/pandas/core/frame.py:1993, in DataFrame.to_numpy(self, dtype, copy, na_value)
   1991 if dtype is not None:
   1992     dtype = np.dtype(dtype)
-> 1993 result = self._mgr.as_array(dtype=dtype, copy=copy, na_value=na_value)
   1994 if result.dtype is not dtype:
   1995     result = np.asarray(result, dtype=dtype)

File /opt/anaconda3/lib/python3.12/site-packages/pandas/core/internals/managers.py:1694, in BlockManager.as_array(self, dtype, copy, na_value)
   1692         arr.flags.writeable = False
   1693 else:
-> 1694     arr = self._interleave(dtype=dtype, na_value=na_value)
   1695     # The underlying data was copied within _interleave, so no need
   1696     # to further copy if copy=True or setting na_value
   1698 if na_value is lib.no_default:

File /opt/anaconda3/lib/python3.12/site-packages/pandas/core/internals/managers.py:1753, in BlockManager._interleave(self, dtype, na_value)
   1751     else:
   1752         arr = blk.get_values(dtype)
-> 1753     result[rl.indexer] = arr
   1754     itemmask[rl.indexer] = 1
   1756 if not itemmask.all():

ValueError: could not convert string to float: 'I use this with the Nudestix “Citrus Clean Balm & Make-Up Melt“ to double cleanse and it has completely changed my skin (for the better). The make-up melt is oil based and removes all of your makeup super easily. I follow-up with this water based cleanser, and I also use this just by itself when I’m not wearing make-up. It leaves the skin
```

```
#heat map of correlation
plt.figure(figsize=(18,12))
sns.heatmap(data.corr(), annot=True)
plt.show()
```



There's a fair high positive correlation between `is_recommended` and `rating` suggesting that if a product is highly rated, it will be recommended by the customer. It is surprising to see a negative correlation between positive feedback and rating

4. FEATURE ENGINEERING

Term Frequency–Inverse Document Frequency

To convert our text into a format that machine learning models can process, we transform the cleaned review text into numerical features through vectorization

```
tfidf = TfidfVectorizer(max_features=500, stop_words = 'english')

#fit and transform
tfidf_matrix = tfidf.fit_transform(data['final clean text'])

#convert into a dataframe then add a prefix
df = pd.DataFrame(tfidf_matrix.toarray(), columns=[f"tfidf_{word}"for word in tfidf.get_feature_names_out()])

#merge with original data
data = data.reset_index(drop=True)
data = pd.concat([data, df], axis=1)
```

```
tfidf_matrix.shape
```

```
(205718, 500)
```

WordCloud for most frequent words

Perform word cloud to see the most frequent words in our reviews

```
all_text = " ".join(data['final clean text'])
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(all_text)
plt.figure(figsize=(15,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

We create a new column `sentiment` in order to classify our ratings into positive, negative and neutral.

Positive sentiments dominate the data, as seen from the previous graph of rating distribution. We'll now create new dataframes according to sentiments so that we can use them to create word clouds for those sentiments.

```
#create new dataframes according to sentiments
positive = data[data['Sentiment'] == 'Positive']
negative = data[data['Sentiment'] == 'Negative']
neutral = data[data['Sentiment'] == 'Neutral']
```

We'll use `review_title` column to explore the word clouds for those sentiments.

WordCloud for positive sentiments

```
#word cloud for positive sentiments

#ensuring that review title is string
positive['review_title'] = positive['review_title'].astype(str)
pos_text = " ".join(title for title in positive.review_title)

pos_wordcloud = WordCloud(width=800, height=400, background_color='white').generate(pos_text)
plt.figure(figsize=(15,10))
plt.imshow(pos_wordcloud, interpolation='bicubic')
plt.axis('off')
plt.show();
```

WordCloud for negative sentiments

Explore negative sentiments

```
#word cloud for negative sentiments

#ensuring that review title is string
negative['review_title'] = negative['review_title'].astype(str)

#join all texts in review title to one string
neg_text = " ".join(title for title in negative.review_title)

#create word cloud
neg_wordcloud = WordCloud(width=800, height=400,background_color='white').generate(neg_text)
plt.figure(figsize=(15,10))
plt.imshow(neg_wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show();
```

WordCloud for neutral sentiment

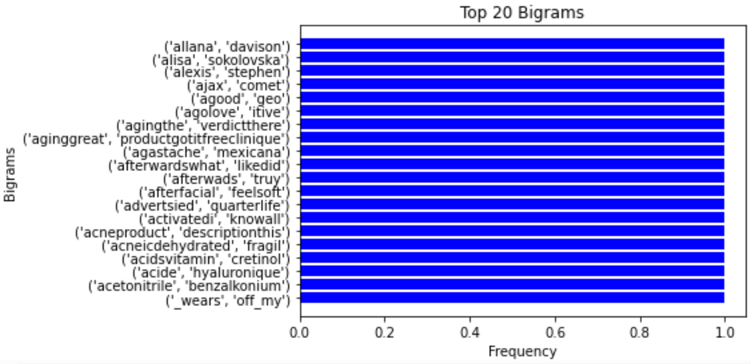
Explore neutral sentiments

```
#word cloud for neutral sentiments

#ensuring that review title is string
neutral['review_title'] = neutral['review_title'].astype(str)

#join all texts in review title to one string
neut_text = " ".join(title for title in negative.review_title)

#create word cloud
neut_wordcloud = WordCloud(width=800, height=400,background_color='white').generate(neut_text)
plt.figure(figsize=(15,10))
plt.imshow(neut_wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show();
```

Bigram Analysis

We'll now perform a bigram analysis to see which words appear together frequently

```
#bigram analysis

# Flatten list of lists
all_words = [word for sublist in data['Lemmatized text'] for word in sublist]

#find bigrams
bigram_finder = BigramCollocationFinder.from_words(all_words)
bigram_measures = BigramAssocMeasures()

#plot bigrams
top_20_bigrams = bigram_finder.nbest(bigram_measures.pmi, 20)
bigram_frequencies = [bigram_finder.ngram_fd[bigram] for bigram in top_20_bigrams]
bigram_labels = [str(bigram) for bigram in top_20_bigrams] # Convert bigrams to strings
plt.barh(bigram_labels, bigram_frequencies, color='blue') # Use string labels
plt.xlabel('Frequency')
plt.ylabel('Bigrams')
plt.title('Top 20 Bigrams');
```



5. MODELLING

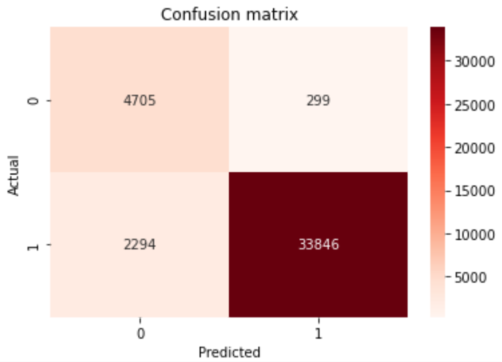
We will start with defining our target and features, train and test split, then we balance the training set.

5.1 Baseline Model

```
# Logistic regression
# Define features and label
features = ['final clean text', 'skin_type', 'skin_tone', 'price_usd', 'rating',
            'total_feedback_count', 'total_pos_feedback_count', 'total_neg_feedback_count']
target = 'is_recommended'

X = data[features]
y = data[target]

# Define preprocessing
text_pipeline = make_pipeline(
    TfidfVectorizer(max_features=500, stop_words='english')
)

categorical_features = ['skin_type', 'skin_tone']
numerical_features = ['price_usd', 'rating', 'total_feedback_count', 'total_pos_feedback_count', 'total_neg_feedback_count']

preprocessor = ColumnTransformer(transformers=[
    ('text', text_pipeline, 'final clean text'),
    ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features),
    ('num', StandardScaler(), numerical_features)
])

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, random_state=42)

# Fit the preprocessor on training data, transform train and test
X_train_transformed = preprocessor.fit_transform(X_train)
X_test_transformed = preprocessor.transform(X_test)

# Apply SMOTE to transformed data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_transformed, y_train)

# Train logistic regression model
model = LogisticRegression(max_iter=1000)
model.fit(X_train_resampled, y_train_resampled)

# Predict and evaluate
y_pred = model.predict(X_test_transformed)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.67      0.94      0.78      5004
         1.0       0.99      0.94      0.96     36140

    accuracy                           0.94     41144
   macro avg       0.83      0.94      0.87     41144
weighted avg       0.95      0.94      0.94     41144
```

```
#plot confusion matrix
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Reds')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion matrix")
plt.show()
```

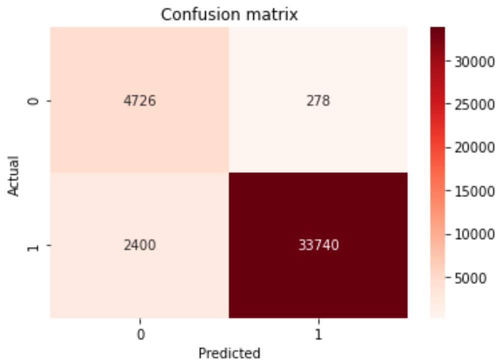


5.2 LinearSVC

```
# Preprocess training and test data
X_train_transformed = preprocessor.fit_transform(X_train)
X_test_transformed = preprocessor.transform(X_test)

# Apply SMOTE to numeric-transformed data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_transformed, y_train)

# Build the pipeline (only classifier, since data is already preprocessed)
pipeline_svc = Pipeline(steps=[
    ('classifier', LinearSVC())
])

# Parameter grid for LinearSVC
param_grid_svc = {
    'classifier__C': [0.1, 1.0, 10],
    'classifier__max_iter': [1000, 2000]
}

# Grid search for model tuning
grid_svc = GridSearchCV(pipeline_svc, param_grid=param_grid_svc, cv=3, scoring='accuracy', n_jobs=-1)
grid_svc.fit(X_train_resampled, y_train_resampled)

# Results
print("Best LinearSVC Params:", grid_svc.best_params_)
print("Best Accuracy:", grid_svc.best_score_)

# Prediction and Evaluation
y_pred_svc = grid_svc.best_estimator_.predict(X_test_transformed)
print("LinearSVC Results:")
print(classification_report(y_test, y_pred_svc))
```

```
Best LinearSVC Params: {'classifier__C': 0.1, 'classifier__max_iter': 1000}
Best Accuracy: 0.9492525609109491
LinearSVC Results:
              precision    recall  f1-score   support

         0.0       0.66      0.94      0.78      5004
         1.0       0.99      0.93      0.96     36140

    accuracy                           0.93     41144
   macro avg       0.83      0.94      0.87     41144
weighted avg       0.95      0.93      0.94     41144
```

```
#plot confusion matrix
sns.heatmap(confusion_matrix(y_test, y_pred_svc), annot=True, fmt='d', cmap='Reds')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion matrix")
plt.show()
```

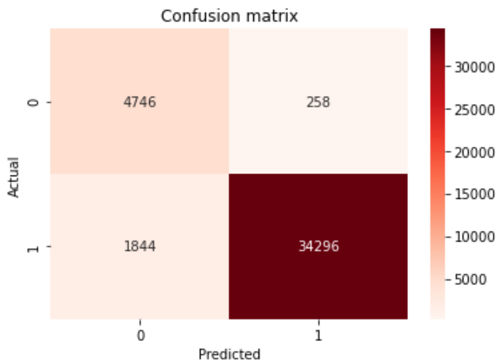


5.3 Random Forest

```
# Preprocess training and test data
X_train_transformed = preprocessor.fit_transform(X_train)
X_test_transformed = preprocessor.transform(X_test)

# Apply SMOTE to numeric-transformed data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_transformed, y_train)

pipeline_rf = Pipeline(steps=[
    ('classifier', RandomForestClassifier(random_state=42))
])

# Parameter grid for RandomForest
param_grid_rf = {
    'classifier__n_estimators': [50, 100],
    'classifier__max_depth': [10, 20, 30],
    'classifier__min_samples_split': [2, 5],
    'classifier__min_samples_leaf': [1, 2]
}

# Grid search for model tuning
grid_rf = GridSearchCV(pipeline_rf, param_grid=param_grid_rf, cv=3, scoring='accuracy', n_jobs=-1)
grid_rf.fit(X_train_resampled, y_train_resampled)

# Results
print("Best Random Forest Params:", grid_rf.best_params_)
print("Best Accuracy:", grid_rf.best_score_)

# Prediction and Evaluation
y_pred_rf = grid_rf.best_estimator_.predict(X_test_transformed)
print("Random Forest Results:")
print(classification_report(y_test, y_pred_rf))
```

```
Best Random Forest Params: {'classifier__max_depth': 30, 'classifier__min_samples_leaf': 1, 'classifier__min_samples_split': 2, 'cla
Best Accuracy: 0.9685457181756086
Random Forest Results:
              precision    recall  f1-score   support

         0.0       0.72      0.95      0.82      5004
         1.0       0.99      0.95      0.97     36140

    accuracy                           0.95     41144
   macro avg       0.86      0.95      0.89     41144
weighted avg       0.96      0.95      0.95     41144
```

```
#plot confusion matrix
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt='d', cmap='Reds')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion matrix")
plt.show()
```

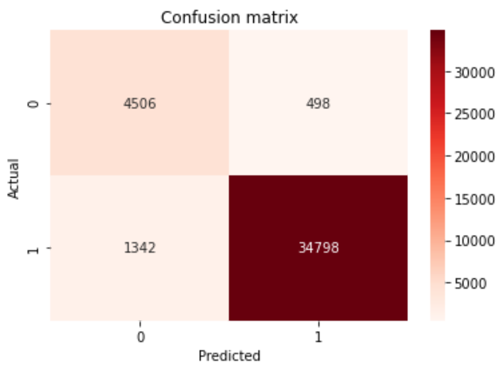


5.4 XGBOOST

```
X_train_processed = preprocessor.fit_transform(X_train)
X_test_processed = preprocessor.transform(X_test)

smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_processed, y_train)

xgb_clf = xgb.XGBClassifier(
    subsample=1.0,
    reg_lambda=0.5,
    reg_alpha=0,
    n_estimators=100,
    max_depth=8,
    learning_rate=0.2,
    gamma=0,
    colsample_bytree=1.0,
    use_label_encoder=False,
    eval_metric='logloss',
    random_state=42
)

xgb_clf.fit(X_train_resampled, y_train_resampled)

y_pred_xgb = xgb_clf.predict(X_test_processed)
print("XGBoost Results:")
print(classification_report(y_test, y_pred_xgb))
```

```
XGBoost Results:
              precision    recall  f1-score   support

         0.0       0.77      0.90      0.83      5004
         1.0       0.99      0.96      0.97     36140

    accuracy                           0.96     41144
   macro avg       0.88      0.93      0.90     41144
weighted avg       0.96      0.96      0.96     41144
```

```
#plot confusion matrix
sns.heatmap(confusion_matrix(y_test, y_pred_xgb), annot=True, fmt='d', cmap='Reds')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion matrix")
plt.show()
```



6. MODEL EVALUATION

ROC Curve for Model Comparison

```
text_col = 'final clean text'
numeric_cols = ['price_usd', 'rating', 'total_feedback_count',
                'total_pos_feedback_count', 'total_neg_feedback_count']
categorical_cols = ['skin_type', 'skin_tone']

preprocessor = ColumnTransformer(transformers=[
    ('text', TfidfVectorizer(), text_col),
    ('num', StandardScaler(), numeric_cols),
    ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
])

# Define models with proper preprocessing
models = {
    "Logistic Regression": Pipeline([
        ('preprocess', preprocessor),
        ('clf', LogisticRegression(max_iter=1000, class_weight='balanced'))
    ]),
    "Linear SVC": Pipeline([
        ('preprocess', preprocessor),
        ('clf', LinearSVC(class_weight='balanced', max_iter=1000))
    ]),
    "XGBoost": Pipeline([
        ('preprocess', preprocessor),
        ('clf', XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42))
    ]),
    "Random Forest": Pipeline([
        ('preprocess', preprocessor),
        ('clf', RandomForestClassifier(class_weight='balanced', random_state=42))
    ])
}
```

```
,

for name, pipeline in models.items():
    pipeline.fit(X_train, y_train)
    if hasattr(pipeline.named_steps['clf'], "predict_proba"):
        y_scores = pipeline.predict_proba(X_test)[:, 1]
    else:
        y_scores = pipeline.decision_function(X_test)

    fpr, tpr, _ = roc_curve(y_test, y_scores)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')

plt.plot([0, 1], [0, 1], 'k--')
plt.title('ROC Curve Comparison')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```