DTSA 5510 Final

June 6, 2025

0.1 Goal of the Project

The goal of this project is to create a product recommender system for Sephora based on customer ratings/reviews. This will be an unsupervised machine learning problem to attempt to predict how customers will like a given product. The approach will be to clean the data and perform some exploratory data analysis to get a high-level understanding of the data elements and the relationships between them. I will then create unsupervised learning models using collaborative filtering and NMF to predict ratings. I will also create an unsupervised model using K-nearest neighbors to provide recommendations to Sephora customers about products they may enjoy based on their highest rated product.

This project has been published to GitHub at https://github.com/cmis1/MSDS/tree/main/DTSA%205510. I did not push the data files to the GitHub directory because they are large and also available at https://www.kaggle.com/datasets/nadyinky/sephora-products-and-skincare-reviews.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline

from scipy.sparse import coo_matrix, csr_matrix
from sklearn.decomposition import NMF
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import train_test_split
from sklearn.neighbors import NearestNeighbors, KNeighborsRegressor

import warnings
warnings.filterwarnings('ignore')
```

0.2 Data Understanding

The dataset author collected review and product information for Sephora (a beauty and skin care retailer) via a Python scraper in March 2023.

0.2.1 Data Citation in APA Format

Inky, N. (2023). Sephora Products and Skincare Reviews. Version 1. [Data set]. Retrieved from https://www.kaggle.com/datasets/nadyinky/sephora-products-and-skincare-reviews.

0.2.2 Data Description

Users The user dataset contains 1,094,411 rows and 18 columns, which I will narrow down to the following columns of interest for this project:

Column	Data Type	Description
author_id	string	Unique identifier for the user
rating	int	1-5 rating for the product
skin_tone	string	User's skin tone (e.g. fair, tan, etc.)
eye_color	string	User's eye color (e.g. brown, green, etc.)
skin_type	string	User's skin type (e.g. combination, oily, etc.)
hair_color	string	User's hair color (e.g. brown, auburn, etc.)
product_id	string	Unique alphanumeric identifier for the product

Products The product dataset contains 8494 rows and 27 columns, which I will narrow down to the following columns of interest for this project:

Column	Data Type	Description
product_id	string	Unique alphanumeric identifier for the product
product_name	string	Full name of the product
brand_name	string	Full name of the brand
price_usd	float	Price of the product in U.S. dollars
limited_edition	int	Indicates whether the product is a limited edition (1-yes, 0-no)
online_only	int	Indicates whether the product only available online (1-yes, 0-no)
sephora_exclusive	int	Indicates whether the product is exclusive to Sephora (1-yes, 0-no)
primary_category	string	First level of product categorization

0.2.3 Load the Data

Users and Ratings I load the reviews data from the muliple CSV files provided by the dataset author and combine them together into a single dataframe. I then separate that dataframe into two dataframes, one for the user's attributes noted above (e.g., eye color) and another for the ratings (i.e., author ID, product ID, and rating).

[2]:
```
df1 = pd.read_csv('reviews_0-250.csv', index_col=0)
df2 = pd.read_csv('reviews_250-500.csv', index_col=0)
df3 = pd.read_csv('reviews_500-750.csv', index_col=0)
df4 = pd.read_csv('reviews_750-1250.csv', index_col=0)
```

```python
df5 = pd.read_csv('reviews_1250-end.csv', index_col=0)

df_users = pd.concat([df1, df2, df3, df4, df5])
df_users.head()
```

```
[2]:      author_id  rating  is_recommended  helpfulness  total_feedback_count  \
     0   1741593524       5             1.0          1.0                     2
     1  31423088263       1             0.0          NaN                     0
     2   5061282401       5             1.0          NaN                     0
     3   6083038851       5             1.0          NaN                     0
     4  47056667835       5             1.0          NaN                     0

        total_neg_feedback_count  total_pos_feedback_count submission_time  \
     0                         0                         2      2023-02-01
     1                         0                         0      2023-03-21
     2                         0                         0      2023-03-21
     3                         0                         0      2023-03-20
     4                         0                         0      2023-03-20

                                              review_text  \
     0  I use this with the Nudestix "Citrus Clean Bal…
     1  I bought this lip mask after reading the revie…
     2  My review title says it all! I get so excited …
     3  I've always loved this formula for a long time…
     4  If you have dry cracked lips, this is a must h…

                          review_title skin_tone eye_color    skin_type  \
     0  Taught me how to double cleanse!       NaN     brown          dry
     1                      Disappointed       NaN       NaN          NaN
     2               New Favorite Routine     light     brown          dry
     3   Can't go wrong with any of them       NaN     brown  combination
     4                    A must have !!!     light     hazel  combination

       hair_color product_id                                       product_name  \
     0      black    P504322                   Gentle Hydra-Gel Face Cleanser
     1        NaN    P420652  Lip Sleeping Mask Intense Hydration with Vitam…
     2     blonde    P420652  Lip Sleeping Mask Intense Hydration with Vitam…
     3      black    P420652  Lip Sleeping Mask Intense Hydration with Vitam…
     4        NaN    P420652  Lip Sleeping Mask Intense Hydration with Vitam…

       brand_name  price_usd
     0   NUDESTIX       19.0
     1    LANEIGE       24.0
     2    LANEIGE       24.0
     3    LANEIGE       24.0
     4    LANEIGE       24.0
```

[3]:
```
df_users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1094411 entries, 0 to 49976
Data columns (total 18 columns):
 #   Column                    Non-Null Count    Dtype
---  ------                    --------------    -----
 0   author_id                 1094411 non-null  object
 1   rating                    1094411 non-null  int64
 2   is_recommended            926423 non-null   float64
 3   helpfulness               532819 non-null   float64
 4   total_feedback_count      1094411 non-null  int64
 5   total_neg_feedback_count  1094411 non-null  int64
 6   total_pos_feedback_count  1094411 non-null  int64
 7   submission_time           1094411 non-null  object
 8   review_text               1092967 non-null  object
 9   review_title              783757 non-null   object
 10  skin_tone                 923872 non-null   object
 11  eye_color                 884783 non-null   object
 12  skin_type                 982854 non-null   object
 13  hair_color                867643 non-null   object
 14  product_id                1094411 non-null  object
 15  product_name              1094411 non-null  object
 16  brand_name                1094411 non-null  object
 17  price_usd                 1094411 non-null  float64
dtypes: float64(3), int64(4), object(11)
memory usage: 158.6+ MB
```

[4]:
```
df_ratings = df_users[['author_id', 'product_id', 'rating']]
df_users = df_users[['author_id', 'skin_tone', 'eye_color', 'skin_type',␣
 ↪'hair_color']]
df_users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1094411 entries, 0 to 49976
Data columns (total 5 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   author_id   1094411 non-null  object
 1   skin_tone   923872 non-null   object
 2   eye_color   884783 non-null   object
 3   skin_type   982854 non-null   object
 4   hair_color  867643 non-null   object
dtypes: object(5)
memory usage: 50.1+ MB
```

[5]:
```
df_users.head()
```

[5]:

```
      author_id skin_tone eye_color    skin_type hair_color
0    1741593524       NaN     brown          dry      black
1   31423088263       NaN       NaN          NaN        NaN
2    5061282401     light     brown          dry     blonde
3    6083038851       NaN     brown  combination      black
4   47056667835     light     hazel  combination        NaN
```

[6]:

```
df_ratings.head()
```

[6]:

```
      author_id product_id  rating
0    1741593524    P504322       5
1   31423088263    P420652       1
2    5061282401    P420652       5
3    6083038851    P420652       5
4   47056667835    P420652       5
```

Products I now load the product dataset and filter to the columns of interest listed above.

[7]:

```
df_products = pd.read_csv('product_info.csv')
df_products.head()
```

[7]:

```
  product_id               product_name  brand_id brand_name  loves_count  \
0    P473671    Fragrance Discovery Set      6342      19-69         6320
1    P473668    La Habana Eau de Parfum      6342      19-69         3827
2    P473662  Rainbow Bar Eau de Parfum      6342      19-69         3253
3    P473660       Kasbah Eau de Parfum      6342      19-69         3018
4    P473658  Purple Haze Eau de Parfum      6342      19-69         2691

   rating  reviews            size                    variation_type  \
0  3.6364     11.0             NaN                               NaN
1  4.1538     13.0  3.4 oz/ 100 mL  Size + Concentration + Formulation
2  4.2500     16.0  3.4 oz/ 100 mL  Size + Concentration + Formulation
3  4.4762     21.0  3.4 oz/ 100 mL  Size + Concentration + Formulation
4  3.2308     13.0  3.4 oz/ 100 mL  Size + Concentration + Formulation

  variation_value  … online_only out_of_stock  sephora_exclusive  \
0             NaN  …           1            0                  0
1  3.4 oz/ 100 mL  …           1            0                  0
2  3.4 oz/ 100 mL  …           1            0                  0
3  3.4 oz/ 100 mL  …           1            0                  0
4  3.4 oz/ 100 mL  …           1            0                  0

                                          highlights  primary_category  \
0  ['Unisex/ Genderless Scent', 'Warm &Spicy Scen…         Fragrance
1  ['Unisex/ Genderless Scent', 'Layerable Scent'…         Fragrance
2  ['Unisex/ Genderless Scent', 'Layerable Scent'…         Fragrance
3  ['Unisex/ Genderless Scent', 'Layerable Scent'…         Fragrance
```

```
4  ['Unisex/ Genderless Scent', 'Layerable Scent'…        Fragrance

   secondary_category  tertiary_category  child_count  child_max_price  \
0   Value & Gift Sets  Perfume Gift Sets            0              NaN
1               Women            Perfume            2             85.0
2               Women            Perfume            2             75.0
3               Women            Perfume            2             75.0
4               Women            Perfume            2             75.0

   child_min_price
0              NaN
1             30.0
2             30.0
3             30.0
4             30.0

[5 rows x 27 columns]
```

[8]:
```
df_products.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8494 entries, 0 to 8493
Data columns (total 27 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   product_id          8494 non-null   object
 1   product_name        8494 non-null   object
 2   brand_id            8494 non-null   int64
 3   brand_name          8494 non-null   object
 4   loves_count         8494 non-null   int64
 5   rating              8216 non-null   float64
 6   reviews             8216 non-null   float64
 7   size                6863 non-null   object
 8   variation_type      7050 non-null   object
 9   variation_value     6896 non-null   object
 10  variation_desc      1250 non-null   object
 11  ingredients         7549 non-null   object
 12  price_usd           8494 non-null   float64
 13  value_price_usd     451 non-null    float64
 14  sale_price_usd      270 non-null    float64
 15  limited_edition     8494 non-null   int64
 16  new                 8494 non-null   int64
 17  online_only         8494 non-null   int64
 18  out_of_stock        8494 non-null   int64
 19  sephora_exclusive   8494 non-null   int64
 20  highlights          6287 non-null   object
 21  primary_category    8494 non-null   object
 22  secondary_category  8486 non-null   object
```

```
 23  tertiary_category   7504 non-null   object
 24  child_count         8494 non-null   int64
 25  child_max_price     2754 non-null   float64
 26  child_min_price     2754 non-null   float64
dtypes: float64(7), int64(8), object(12)
memory usage: 1.7+ MB
```

[9]:
```
df_products = df_products[['product_id', 'product_name',
                           'brand_name',  'price_usd',
                           'limited_edition', 'online_only',
                           'sephora_exclusive', 'primary_category']]
```

[10]:
```
df_products.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8494 entries, 0 to 8493
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   product_id         8494 non-null   object
 1   product_name       8494 non-null   object
 2   brand_name         8494 non-null   object
 3   price_usd          8494 non-null   float64
 4   limited_edition    8494 non-null   int64
 5   online_only        8494 non-null   int64
 6   sephora_exclusive  8494 non-null   int64
 7   primary_category   8494 non-null   object
dtypes: float64(1), int64(3), object(4)
memory usage: 531.0+ KB
```

0.3 Data cleaning

0.3.1 Data Types

The author id had some dummy values that were not numeric. Casting the column to a number replaces the invalid values with NaNs.

[11]:
```
df_ratings['author_id'] = pd.to_numeric(df_ratings['author_id'],␣
 ↪errors='coerce')
df_users['author_id'] = pd.to_numeric(df_users['author_id'], errors='coerce')
```

0.3.2 Handle missing values

Ratings I removed the 60 rows with missing IDs (i.e., the author_ids that had invalid values when converting the column to an integer).

[12]:
```
print(df_ratings.isna().sum())
max_na = max(df_ratings.isna().sum())
print(f"{max_na*100/len(df_ratings):.2f}% of rows have missing value")
```

```
print(df_ratings.shape)
```

```
author_id     64
product_id     0
rating         0
dtype: int64
0.01% of rows have missing value
(1094411, 3)
```

[13]:
```
df_ratings = df_ratings.dropna()
print(df_ratings.isna().sum())
print(df_ratings.shape)
```

```
author_id     0
product_id    0
rating        0
dtype: int64
(1094347, 3)
```

Users The user information has missing values in at least 20% of the rows. However, each user can submit multiple reviews which may allow me to copy any missing values from another review submitted by that same user.

[14]:
```
print(df_users.isna().sum())
max_na = max(df_users.isna().sum())
print(f"At least {max_na*100/len(df_users):.2f}% of rows have missing value")
print(df_users.shape)
```

```
author_id         64
skin_tone     170539
eye_color     209628
skin_type     111557
hair_color    226768
dtype: int64
At least 20.72% of rows have missing value
(1094411, 5)
```

[15]:
```
''' Create a dictionary for each of the columns with missing values using the␣
↪author_id as the key
    and the first value for the column in question (e.g,. skin_tone) as the␣
↪value in the dictionary.
    Then map the values from the dictionary into the rows missing those values.
'''

skin_tone_dict = df_users.dropna(subset=['skin_tone']).
↪groupby('author_id')['skin_tone'].first().to_dict()
df_users['skin_tone'] = df_users['author_id'].map(skin_tone_dict).
↪fillna(df_users['skin_tone'])
```

```
eye_color_dict = df_users.dropna(subset=['eye_color']).
 ↪groupby('author_id')['eye_color'].first().to_dict()
df_users['eye_color'] = df_users['author_id'].map(skin_tone_dict).
 ↪fillna(df_users['eye_color'])

skin_type_dict = df_users.dropna(subset=['skin_type']).
 ↪groupby('author_id')['skin_type'].first().to_dict()
df_users['skin_type'] = df_users['author_id'].map(skin_tone_dict).
 ↪fillna(df_users['skin_type'])

hair_color_dict = df_users.dropna(subset=['hair_color']).
 ↪groupby('author_id')['hair_color'].first().to_dict()
df_users['hair_color'] = df_users['author_id'].map(skin_tone_dict).
 ↪fillna(df_users['hair_color'])
```

I cut the percentage of rows with missing values almost in half. Given the data set contains over one million users, I am just going to drop the rows that contain a missing value. This left 969,071 rows in the dataset.

[16]:
```
print(df_users.isna().sum())
max_na = max(df_users.isna().sum())
print(f"At least {max_na*100/len(df_users):.2f}% of rows have missing value")
print(df_users.shape)
```

```
author_id         64
skin_tone     116184
eye_color     108376
skin_type      76126
hair_color    111621
dtype: int64
At least 10.62% of rows have missing value
(1094411, 5)
```

[17]:
```
df_users = df_users.dropna()
print(df_users.isna().sum())
print(df_users.shape)
```

```
author_id     0
skin_tone     0
eye_color     0
skin_type     0
hair_color    0
dtype: int64
(978178, 5)
```

The users dataframe contains duplicate rows now that I populated the missing values, so I removed the duplicates. This left over 400,000 unique users with no missing attributes.

[18]:
```
df_users = df_users.drop_duplicates()
print(df_users.shape)
```

```
(419679, 5)
```

Products There are no missing values in the products dataset, which contains over 8,000 records.

[19]:
```
print(df_products.isna().sum())
max_na = max(df_products.isna().sum())
print(f"{max_na*100/len(df_products):.2f}% of rows have missing value")
print(df_products.shape)
```

```
product_id           0
product_name         0
brand_name           0
price_usd            0
limited_edition      0
online_only          0
sephora_exclusive    0
primary_category     0
dtype: int64
0.00% of rows have missing value
(8494, 8)
```

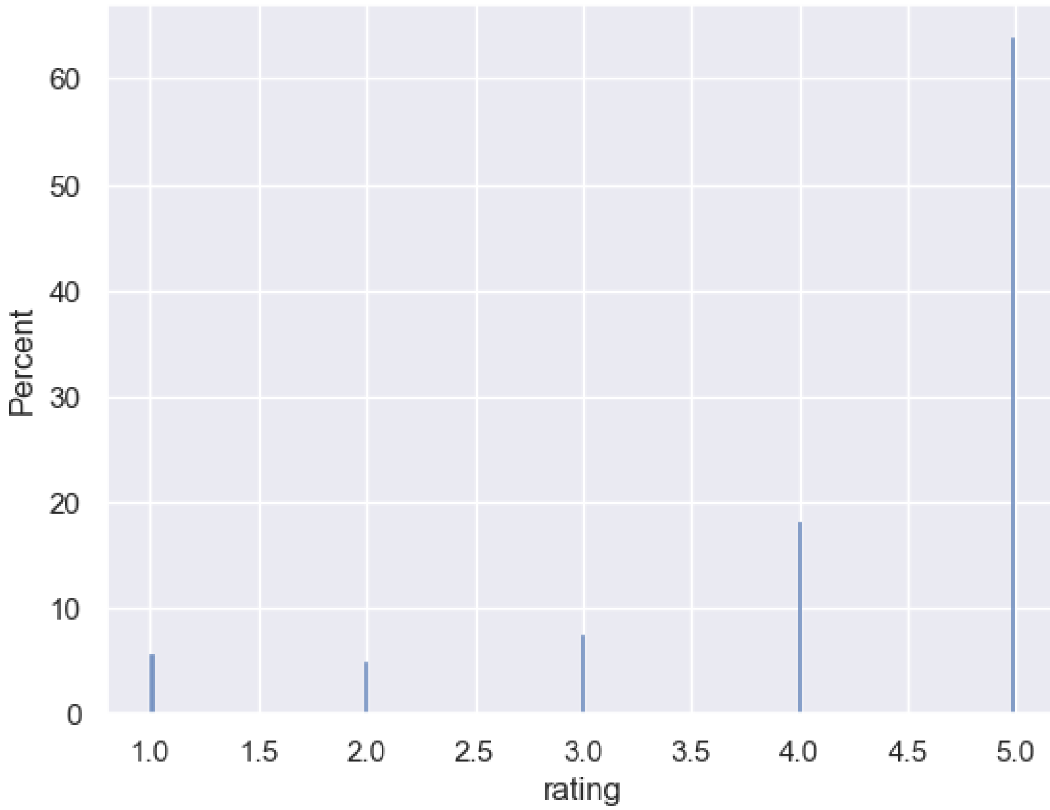
0.4 EDA

0.4.1 Distribution of Data

Ratings The ratings are on a 1-5 scale and contains a majority of 5 ratings.

[20]:
```
sns.histplot(data=df_ratings, x="rating", stat="percent")
```

[20]:
```
<Axes: xlabel='rating', ylabel='Percent'>
```

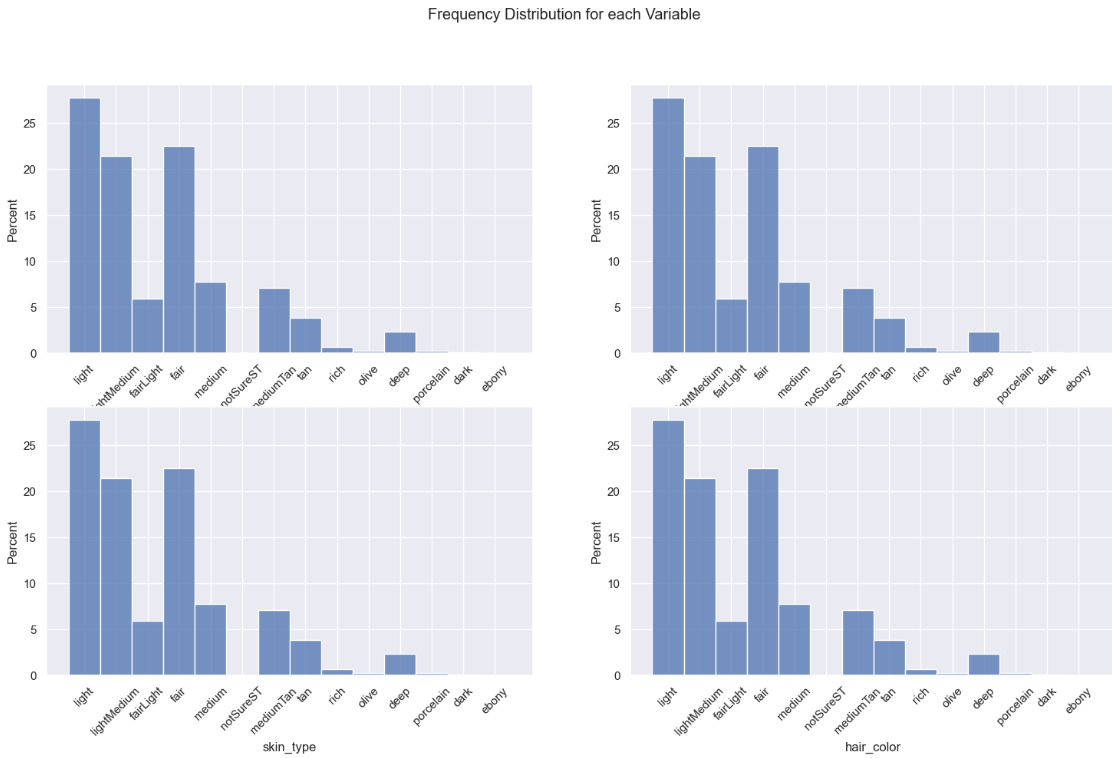


Users The users dataset is skewed toward users with lighter skin, eyes, and hair, so the model will likely have difficulty predicting for users with darker features.

[21]:
```
fig, axes = plt.subplots(2, 2, figsize=(18, 10))
fig.suptitle('Frequency Distribution for each Variable')
axes[0,0].tick_params(axis='x', labelrotation=45)
axes[0,1].tick_params(axis='x', labelrotation=45)
axes[1,0].tick_params(axis='x', labelrotation=45)
axes[1,1].tick_params(axis='x', labelrotation=45)

sns.histplot(ax=axes[0, 0], data=df_users, x='skin_tone', stat="percent")
sns.histplot(ax=axes[0, 1], data=df_users, x='eye_color', stat="percent")
sns.histplot(ax=axes[1, 0], data=df_users, x='skin_type', stat="percent")
sns.histplot(ax=axes[1, 1], data=df_users, x='hair_color', stat="percent")
```

[21]: <Axes: xlabel='hair_color', ylabel='Percent'>

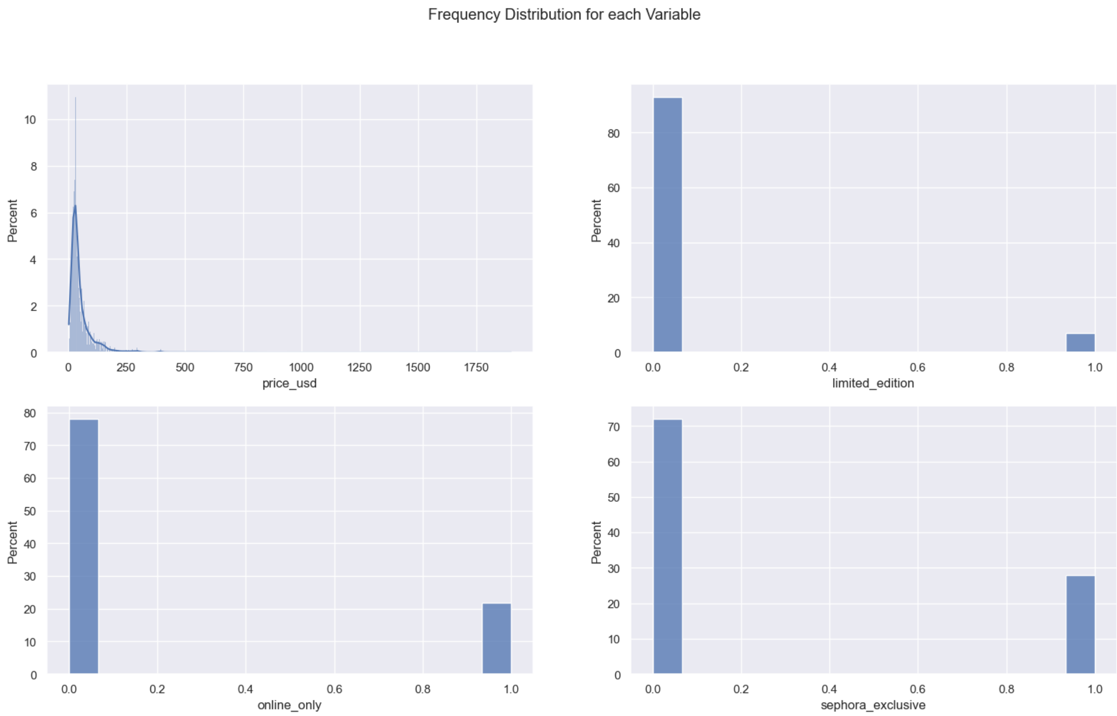


Products The binary factors (limited edition, online only, and sephora exclusive) have values of 0 and 1 and are heavily skewed toward the 0 (not) value.

[22]:
```
fig, axes = plt.subplots(2, 2, figsize=(18, 10))
fig.suptitle('Frequency Distribution for each Variable')

sns.histplot(ax=axes[0, 0], data=df_products, x='price_usd', kde=True,␣
  ↪stat="percent")
sns.histplot(ax=axes[0, 1], data=df_products, x='limited_edition',␣
  ↪stat="percent")
sns.histplot(ax=axes[1, 0], data=df_products, x='online_only', stat="percent")
sns.histplot(ax=axes[1, 1], data=df_products, x='sephora_exclusive',␣
  ↪stat="percent")
```

[22]:
```
<Axes: xlabel='sephora_exclusive', ylabel='Percent'>
```

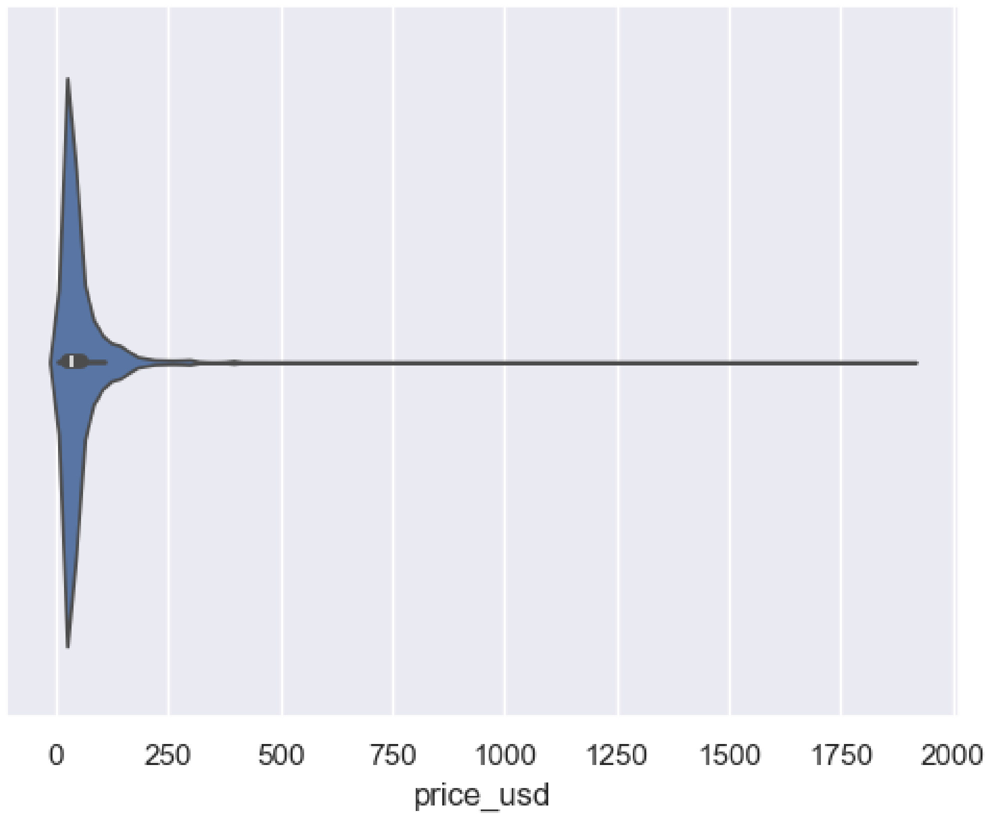


0.4.2 Outliers in Price

Price has some significant outliers given the third quartile at \$58 and a max value of \$1900. Removing outliers outside of 4 standard deviations will eliminate the significant outliers and leave 8113 rows in the dataset that follow a roughly normal distribution with a right skew.

[23]:
```
sns.violinplot(data=df_products, x='price_usd')
```

[23]:
```
<Axes: xlabel='price_usd'>
```



[24]:
```
df_products['price_usd'].describe()
```

[24]:
```
count    8494.000000
mean       51.655595
std        53.669234
min         3.000000
25%        25.000000
50%        35.000000
75%        58.000000
max      1900.000000
Name: price_usd, dtype: float64
```

[25]:
```
total = len(df_products['price_usd'])
z_scores = np.abs((df_products['price_usd'] - df_products['price_usd'].mean()) /
 ↪ df_products['price_usd'].std())

for i in range(3,7):
    count = len(df_products['price_usd'][z_scores >  i])
    print(f"Outliers outside {i} standard deviations: {count} ({count*100/total:
 ↪.2f}% of dataset)")
```

```
Outliers outside 3 standard deviations: 163 (1.92% of dataset)
Outliers outside 4 standard deviations: 98 (1.15% of dataset)
Outliers outside 5 standard deviations: 37 (0.44% of dataset)
Outliers outside 6 standard deviations: 31 (0.36% of dataset)
```

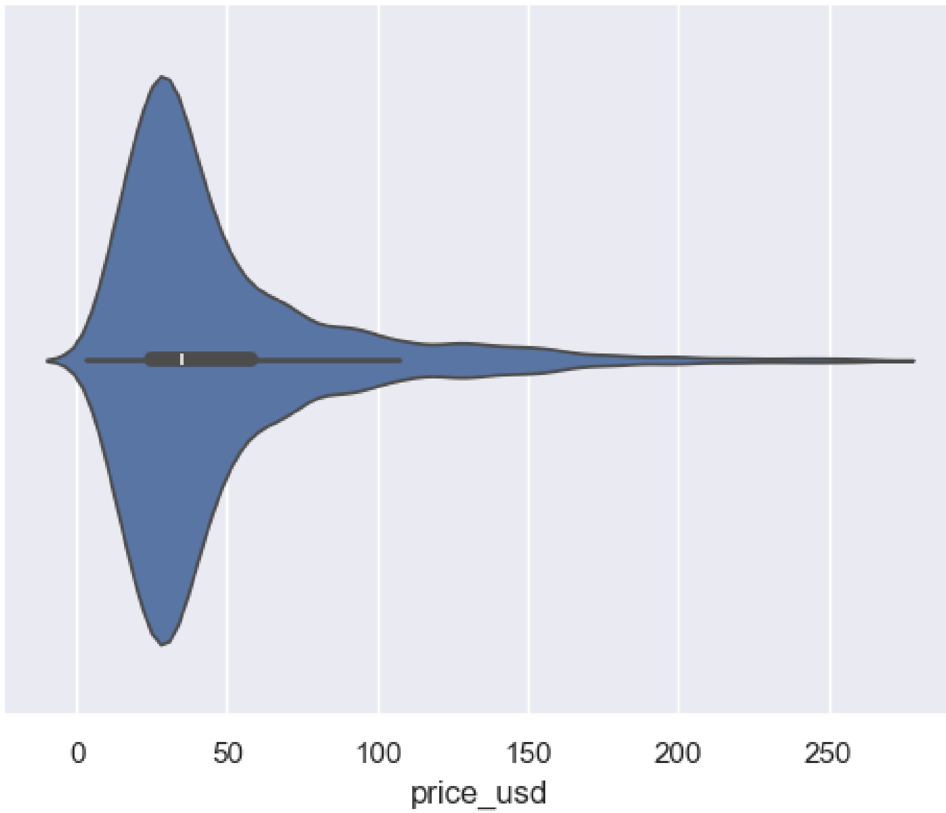
[26]:
```
#Filter out rows with prices outside of 4 standard deviations from the mean
df_products = df_products[z_scores <= 4]
df_products['price_usd'].describe()
```

[26]:
```
count    8396.000000
mean       48.209578
std        39.456292
min         3.000000
25%        25.000000
50%        35.000000
75%        58.000000
max       265.000000
Name: price_usd, dtype: float64
```

After removing the significant outliers, the price still has a right skew. However, the remaining outliers are less severe.

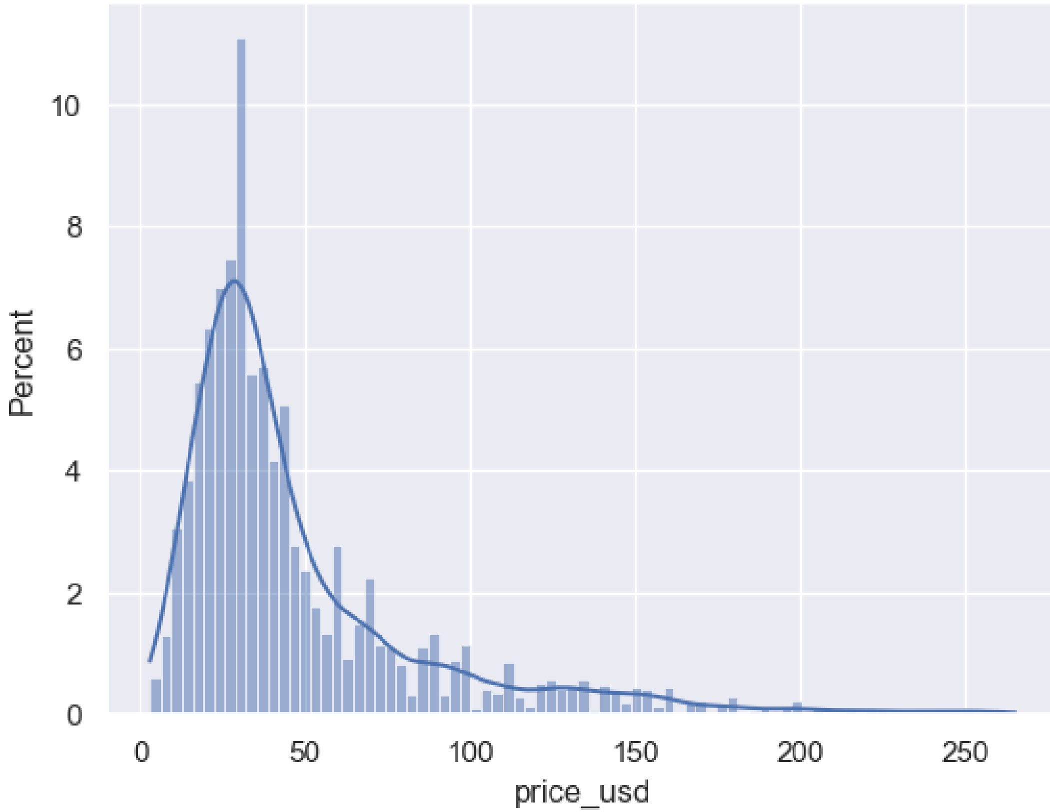
[27]:
```
sns.violinplot(data=df_products, x='price_usd')
```

[27]:
```
<Axes: xlabel='price_usd'>
```



[28]:
```
sns.histplot(data=df_products, x="price_usd", kde=True, stat="percent")
```

[28]: <Axes: xlabel='price_usd', ylabel='Percent'>



0.4.3 Correlation Analysis

Correlation analysis of the numerical columns shows little to no correlation between the factors. The strongest correlation is between the price and Sephora exclusive factors at a -0.14, which is still a weak correlation.

[29]:
```
df_corr = df_products[['price_usd', 'limited_edition', 'online_only',␣
↪'sephora_exclusive']]
```

[30]:
```
df_corr.corr()
```

[30]:

	price_usd	limited_edition	online_only	sephora_exclusive
price_usd	1.000000	0.055505	0.084031	-0.163157
limited_edition	0.055505	1.000000	0.060368	0.065669
online_only	0.084031	0.060368	1.000000	-0.101281
sephora_exclusive	-0.163157	0.065669	-0.101281	1.000000

[31]:
```
fig, ax = plt.subplots(figsize=(7, 4))
#Plot a heatmap using correlation matrix
sns.heatmap(df_corr.corr(), annot=True, fmt=".2f", linewidth=.1, cmap="RdBu_r",␣
↪ax=ax)
```

```python
plt.show()
```

0.4.4 Sync up Rating, User, and Product Datasets

I removed a number of rows from the user and product datasets, so I need to ensure that any rows remaining in the rating dataset have author_id and product_id values that exist in the user and product datasets, respectively.

[32]:
```python
df_ratings = df_ratings[df_ratings['author_id'].isin(df_users['author_id']) &␣
↪df_ratings['product_id'].isin(df_products['product_id'])]
```

[33]:
```python
df_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 973072 entries, 2 to 49976
Data columns (total 3 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   author_id    973072 non-null  float64
 1   product_id   973072 non-null  object
 2   rating       973072 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 29.7+ MB
```

0.5 Modeling

I first split the rating data into a training and test set. I filtered the test set to ensure that the users and products were in the training set, which left me with I then create a sparse matrices to hold the ratings for all users and products. This left a training set of 778,457 rows and a test set of 140,659 rows.

[34]:
```
x_train, x_test = train_test_split(df_ratings, test_size=.2, random_state=42)
x_train.shape
```

[34]:
```
(778457, 3)
```

[35]:
```
x_test.shape
```

[35]:
```
(194615, 3)
```

[36]:
```
x_test = x_test[x_test['author_id'].isin(x_train['author_id'])]
x_test.shape
```

[36]:
```
(140664, 3)
```

[37]:
```
x_test = x_test[x_test['product_id'].isin(x_train['product_id'])]
x_test.shape
```

[37]:
```
(140659, 3)
```

[38]:
```
df_ratings.head()
```

[38]:

	author_id	product_id	rating
2	5.061282e+09	P420652	5
3	6.083039e+09	P420652	5
4	4.705667e+10	P420652	5
5	4.280257e+10	P420652	4
6	6.941884e+09	P420652	2

0.5.1 Create Sparse Rating Matrices

[39]:
```
user_count = len(df_ratings['author_id'].unique())
prod_count = len(df_ratings['product_id'].unique())

# Map Ids to indices
user_id_to_idx = dict(zip(np.unique(df_ratings["author_id"]),
 ↪list(range(user_count))))
prod_id_to_idx = dict(zip(np.unique(df_ratings["product_id"]),
 ↪list(range(prod_count))))

# Map indices to IDs
prod_idx_to_id = dict(zip(list(range(prod_count)), np.
 ↪unique(df_ratings["product_id"])))

user_index = [user_id_to_idx[i] for i in x_train['author_id']]
prod_index = [prod_id_to_idx[i] for i in x_train['product_id']]
```

```
rating_matrix_csr = csr_matrix((x_train["rating"], (prod_index, user_index)),␣
↪shape=(prod_count, user_count))
rating_matrix_coo = np.array(coo_matrix((list(x_train['rating']), (user_index,␣
↪prod_index)), shape=(user_count, prod_count)).toarray())
```

0.5.2 Predict Ratings Using Collaborative Similarity

I created an unsupervised learning model to predict user-product ratings. The model used both cosine and jaccard similarity measures.

[40]:
```
def predict_from_sim(userID, prodID, sim_matrix, rat_matrix):
    #1. Get index of the provided user id
    index_userID = user_id_to_idx[userID]

    #2. Get all the user ratings for the user using index_userID
    ratings_index_userID = rat_matrix[index_userID]

    #3. Get index of the provided product id
    index_prodID = prod_id_to_idx[prodID]

    #4. Get all the similarity scores using index_prodID
    prod_sims = sim_matrix[index_prodID]

    #5. Take the **averaged** dot product.
    valid_ratings = (ratings_index_userID != 0)

    num = np.dot(ratings_index_userID, prod_sims)
    den = np.dot(prod_sims, valid_ratings)
    return num / den

def predict(sim_matrix, rat_matrix):
    test_preds = []
    for i in range(len(x_test)):
        userID = x_test.iloc[i]['author_id']
        prodID = x_test.iloc[i]['product_id']
        test_preds.append(predict_from_sim(userID, prodID, sim_matrix,␣
↪rat_matrix))
    return np.array(test_preds)

def cossim(xr):
    #Algorithm:
    #1. Compute **averaged** product ratings for all users␣
↪(prod_ratings_allUsers)
    #Calcs mean of each row
    prod_ratings_allUsers = xr.sum(axis=1) / np.count_nonzero(xr, axis=1)
```

```
    #2. Create a sparse matrix for operating cosine on its values:
    prod_ratings_array = np.repeat(np.expand_dims(prod_ratings_allUsers, axis=1), xr.shape[1], axis=1)

    #3. Take care of all the zero ratings (missing value/itentionally we don't know):
    prod_ratings_array_adjusted = xr + (xr==0)*prod_ratings_array - prod_ratings_array

    #4. Average all the ratings: divide by its magnitude!
    rating_avg = prod_ratings_array_adjusted/np.sqrt((prod_ratings_array_adjusted**2).sum(axis=0))

    #5. Put a Boundary check # 1: since dividing by magnitude may produce inf, zeros, etc. Set nans to 0.
    rating_avg = np.nan_to_num(rating_avg, 0)

    #6. Perform an item-item cosine similarity using: np.dot(matrix.T, matrix)
    similarity = np.dot(rating_avg.T, rating_avg)

    #7. Put a Boundary check # 2: Covariance/correlation values for np.dot([M.T, M]) matrix should have
    #   diagonal set to 1.
    np.fill_diagonal(similarity, 1)

    #8. Normalized Cosine Formula:
    similarity = np.multiply(similarity, 0.5) + 0.5

    return similarity

def jacsim(Xr):
    # Return a sim matrix by calculating item-item similarity for all pairs of items using Jaccard similarity
    # Jaccard Similarity: J(A, B) = |A B| / |A B|
    n = Xr.shape[1]
    maxr = int(Xr.max())

    nz_inter = np.zeros((n,n)).astype(int)
    for i in range(1, maxr+1):
        csr = csr_matrix((Xr==i).astype(int))
        nz_inter = nz_inter + np.array(csr.T.dot(csr).toarray()).astype(int)

    # Formula JS:
    A = (Xr>0).astype(bool)
    rowsum = A.sum(axis=0)
    rsumtile = np.repeat(rowsum.reshape((n,1)),n,axis=1)
```

```
    union = rsumtile.T + rsumtile - nz_inter

    # Perform the two boundary checks:-
    #  - since dividing by magnitude may produce inf, zeros, etc. Set nans to 0.
    #  - Covariance/correlation values for np.dot([M.T, M]) matrix should have
    #    diagonal set to 1.

    union = np.nan_to_num(union, 0)
    intersection = np.nan_to_num(nz_inter, 0)

    similarity = np.divide(intersection, union, out=np.zeros_like(intersection,␣
↪dtype=float), where=union!=0)
    np.fill_diagonal(similarity, 1)
    return similarity

def rmse(yp):
    yp[np.isnan(yp)]=3 #In case there is nan values in prediction, it will␣
↪impute to 3.
    yt=np.array(x_test['rating'])
    return np.sqrt(((yt-yp)**2).mean())
```

[41]:
```
sim_matrix = cossim(rating_matrix_coo)
```

[42]:
```
yp = predict(sim_matrix, rating_matrix_coo)
print(rmse(yp))
```

```
1.0881795275262927
```

[43]:
```
jacsim_matrix = jacsim(rating_matrix_coo)
```

[44]:
```
yp = predict(jacsim_matrix, rating_matrix_coo)
print(rmse(yp))
```

```
1.1191216782108373
```

0.5.3 Predict Using Non-Negative Matrix Factorization (NMF)

I created an unsupervised model to predict user-product ratings using Non-Negative Matrix Factorization (NMF).

[45]:
```
def predict_nmf(all_preds):
    """
    Predict ratings in the test data. Returns predicted rating in a numpy array␣
↪of size (# of rows in testdata,)
    """
    test_preds = []
    for i, row in x_test.iterrows():
        index_userID = user_id_to_idx[row['author_id']]
```

```
        index_prodID = prod_id_to_idx[row['product_id']]
        rating = all_preds[index_prodID][index_userID]
        test_preds.append(rating)
    return np.array(test_preds)
```

[46]:
```
model = NMF(n_components=5)
W = model.fit_transform(rating_matrix_csr)
H = model.components_
pred_ratings = np.dot(W, H)

y_pred = predict_nmf(pred_ratings)
rmse(y_pred)
```

[46]: 4.328119360439703

0.5.4 Recommendation System Using K-Nearest Neighbors

Now that I've implemented rating prediction, I enhanced the solution by building a recommender system. I used k-nearest neighbors to return the recommendations for a given user. The recommendations are centered around the user's favorite (highest-rated) product. Using two different distance metrics for the neighbor calculations provided different recommendations for the same user, as shown below.

[47]:
```
def find_similar_products(target_prod_id, rating_matrix, k, metric='cosine'):
    neighbor_ids = []

    product_to_match = prod_id_to_idx[target_prod_id]
    prod_vector = rating_matrix[product_to_match]
    k += 1  #Increase by one because the target product will be included by␣
 ↪NearestNeighbors

    kNN = NearestNeighbors(n_neighbors=k, metric=metric)
    kNN.fit(rating_matrix)
    neighbor = kNN.kneighbors(prod_vector, return_distance=False)

    for i in range(0, k):
        n = neighbor.item(i)
        neighbor_ids.append(prod_idx_to_id[n])

    neighbor_ids.pop(0)  # Remove the target product from the final list
    return neighbor_ids
```

[48]:
```
def recommend_prods_for_user(user_id, rating_matrix, metric, k=5):
    df = df_ratings[df_ratings['author_id'] == user_id]

    # Find the user's highest-rated product and k-nearest neighbors
    fav_prod_id = df[df['rating'] == max(df['rating'])]['product_id'].iloc[0]
```

```
    similar_ids = find_similar_products(fav_prod_id, rating_matrix, k,␣
↪metric=metric)

    # Map product IDs to product names
    prod_names = dict(zip(df_products['product_id'],␣
↪df_products['product_name']))

    print(f"Since you liked {prod_names[fav_prod_id]}, you might also like:")

    for i in similar_ids:
        if i in prod_names:
            print(f"* {prod_names[i]}")
```

[49]:
```
user_id = 6047267707
recommend_prods_for_user(user_id, rating_matrix_csr, metric='cosine')
```

```
Since you liked Greek Yoghurt Foaming Cream Cleanser, you might also like:
* Extra Illuminating Moisture Balm
* Greek Yoghurt Nourishing Probiotic Gel-Cream
* POWER Recharging Night Pressed Serum
* Pep-Start Eye Cream
* Advanced Night Repair Synchronized Multi-Recovery Complex Duo
```

[50]:
```
user_id = 6047267707
recommend_prods_for_user(user_id, rating_matrix_csr, metric='euclidean')
```

```
Since you liked Greek Yoghurt Foaming Cream Cleanser, you might also like:
* ExfoliKate All Over Glow Kit
* Big Break Soap Set
* 3 Step Intro Kit Type II
* Break from the Burnout Skin Wellness Set
* Glow Facial Set
```

0.6 Results and Analysis

0.6.1 Model Comparison

The cosine similarity model performed better than the jaccard similarity and NMF models based on root mean squared error. The NMF likely did not perform well because of the sparsity of the training data (i.e., the training data was missing ratings for most user-product combinations). Using a zero for the missing data would skew the predictions because the 0 value falls outside of the valid range of 1-5.

Method	RMSE
Collaborative, cosine	1.09
Collaborative, jaccard	1.12
NMF, 5	4.33
NMF, 15	4.23

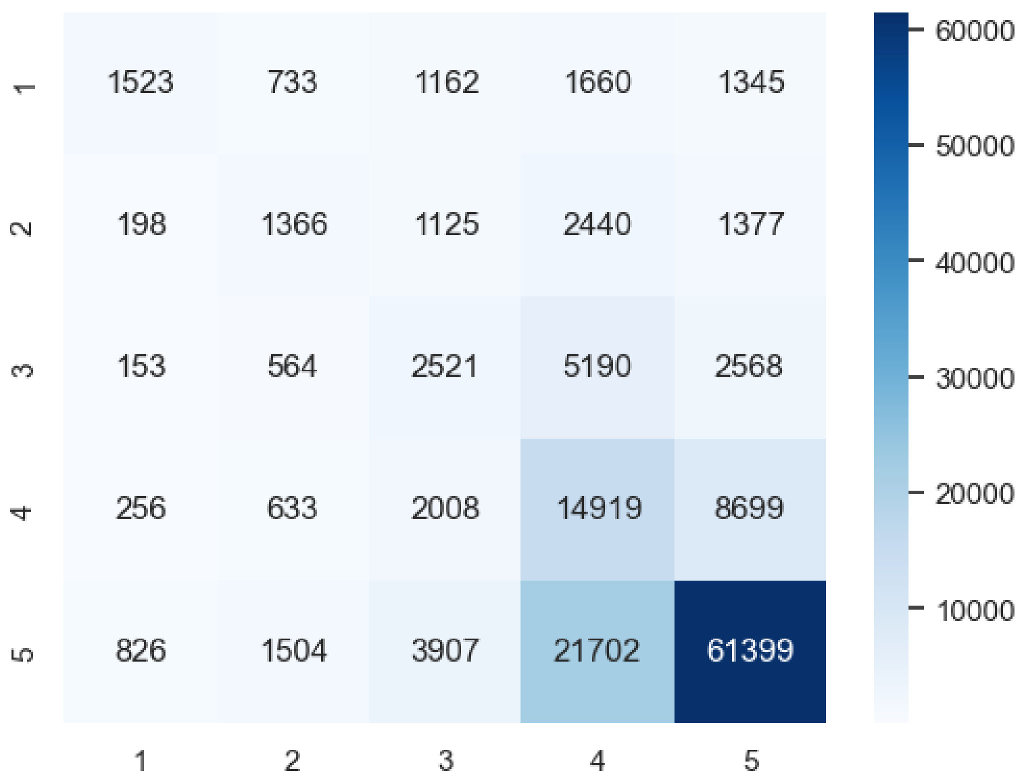
Method	RMSE
NMF, 25	4.15
NMF, 50	4.07

I plotted the confusion matrix of the cosine similarity model, which had the lowest RMSE of the models I built. The training data was heavily skewed toward high ratings, which also show up in the predicted test ratings in terms of both accurate and inaccurate predictions.

[51]:
```
y_pred = predict(sim_matrix, rating_matrix_coo)
y_pred_rounded = np.round(y_pred, decimals=0, out=None)
```

[52]:
```
cm = confusion_matrix(x_test['rating'], y_pred_rounded, labels=[1,2,3,4,5])
sns.heatmap(cm, annot=True, cmap='Blues', fmt='g', xticklabels=[1,2,3,4,5],␣
↪yticklabels=[1,2,3,4,5])
```

[52]: <Axes: >



0.6.2 Improving Performance Through Hypertuning Parameters

I adjusted the number of components to see if I could improve the performance of the NMF model. The RMSE improved as the number of components increased, but the RMSE was still significantly above that of the collaborative similarity models.

[ ]:
```python
components = [5, 15, 25, 50]
for n in components:
    model = NMF(n_components=n)
    W = model.fit_transform(rating_matrix_csr)
    H = model.components_
    pred_ratings = np.dot(W, H)
    y_pred = predict_nmf(pred_ratings)
    error = rmse(y_pred)
    print(f"{n} components RMSE: {error:.2f}")
```

```
5 components RMSE: 4.33
```

0.7 Discussion and Conclusion

0.7.1 Learnings and Takeaways

Understanding and cleaning the data is incredibly important to creating a useful and accurate model. There is a delicate balance between eliminating noise in the data and inadvertantly skewing the data, so it is important to repeatedly inspect the data for bias.

0.7.2 Things that Did Not Go as Planned

The NMF prediction did not perform as well as collaborative models. This could be due to the sparseness of the ratings in the training set (i.e., users did not rate all movies). Increasing the number of components or imputing missing values to make the matrix less sparse could improve the RMSE. Note that when imputing missing values, it would be better to use something other than zero (e.g., use the user's average rating) because filling in missing values as zero falls outside of the "valid" ratings of 1-5.

0.7.3 Ways to Improve

Ideally, the dataset would be more balanced between user and product features. This would allow for a more accurate model with less bias. The models would also have benefitted from more user-product ratings to make the rating matrix less sparse.

0.8 References

1. https://scikit-learn.org/stable/modules/neighbors.html
2. https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.NMF.html
3. https://www.geeksforgeeks.org/recommendation-system-in-python/

[ ]:
```python

```