Investigate_a_Dataset

December 16, 2024

1 Project: Investigate a Dataset - [Amazon_product_data]

1.1 Table of Contents

Introduction

1.1.1 Dataset Description

Dataset Overview This dataset contains detailed information about 1,465 Amazon products.

The dataset includes various attributes related to product pricing, discounts, ratings, reviews, and product categories.

Column named category contains multiple values separated by a pipe (|). This represent hierarchical category assignments for a single product.

Dataset contains minimal missing values.

Columns in the Dataset:

1. `product_id`: A unique identifier for each product.
2. `product_name`: Name of the Product.
3. `category`: Category of the Product.
4. `discounted_price`: Discounted Price of the Product.
5. `actual_price`: Actual Price of the Product.
6. `discount_percentage`: Percentage of Discount for the Product.
7. `rating`: Rating of the Product.
8. `rating_count`: Number of people who voted for the Amazon rating.
9. `about_product`: Description about the Product.
10. `user_id`: ID of the user who wrote review for the Product.

11. `user_name`: Name of the user who wrote review for the Product.
12. `review_id`: ID of the user review.
13. `review_title`: Short review.
14. `review_content`: Long review.
15. `img_link`: Image Link of the Product.
16. `product_link`: Official Website Link of the Product

Question(s) for Analysis

Are higher discount percentages are associated with lower product ratings?

This question determine whether products offerd at higher discounts tend to have lower rating.

It leads to shows that discounted items maybe perceived as lower quality or less desirable.

This relationship will identify optimal discount levels that do not negatively impact product perception.

```
</li>
<li><a href="#question2">Do products with more reviews have higher average ratings?</a>
    <ul>
        <li>This hypothesis investigates if products with higher number of reviews tend to have
        <li>It determine if popular items receive better feedback.</li>
    </ul>
</li>
<li><a href="#question3">Do higher-priced products receive better ratings than lower-priced one
    <ul>
        <li>Consumers might have higher expectations for premium products, so it's interesting
    </ul>
</li>
<li><a href="#question4">Do Products with Positive Sentiment in Reviews Have Higher Ratings?</a
    <ul>
        <li>This hypothesis examines whether the sentiment expressed in customer reviews (posi
    </ul>
</li>
<li><a href="#question5">Which Categories of Products Receive the Highest or Lowest Ratings?</a
    <ul>
        <li>Different product categories (like Electronics, Home & Kitchen) may naturally attra
    </ul>
</li>
    <li><a href="#question6">Which factors of products have the greatest impact on the ratings?
    <ul>
        <li>This hypothesis aims to identify the most impactful factors using non-linear models
    </ul>
</li>
```

[1]:
```python
# import numpy, pandas, matplotlib, and seaborn
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import plotly.io as pio
import scikit_posthocs as sp
pio.renderers.default='notebook'
%matplotlib inline

from nltk.sentiment.vader import SentimentIntensityAnalyzer
from scipy.stats import ttest_ind, f_oneway, levene, shapiro, kruskal
from statsmodels.stats.proportion import proportions_ztest
from statsmodels.stats.multicomp import pairwise_tukeyhsd
from sklearn.preprocessing import StandardScaler, OneHotEncoder,␣
↪PolynomialFeatures
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

[2]:
```
# Upgrade pandas to use dataframe.explode() function.
#!pip install --upgrade pandas==0.25.1
```

Data Wrangling

1.1.2 Initial Cleaning

[3]:
```
# load datasets from amazon.csv file
df = pd.read_csv("data/amazon.csv")
```

[4]:
```
# view the first 5 rows of the dataset
df.head()
```

[4]:
```
   product_id                                       product_name  \
0  B07JW9H4J1  Wayona Nylon Braided USB to Lightning Fast Cha…
1  B098NS6PVG  Ambrane Unbreakable 60W / 3A Fast Charging 1.5…
2  B096MSW6CT  Sounce Fast Phone Charging Cable & Data Sync U…
3  B08HDJ86NZ  boAt Deuce USB 300 2 in 1 Type-C & Micro USB S…
4  B08CF3B7N1  Portronics Konnect L 1.2M Fast Charging 3A 8 P…

                                            category discounted_price  \
0  Computers&Accessories|Accessories&Peripherals|…              399
1  Computers&Accessories|Accessories&Peripherals|…              199
2  Computers&Accessories|Accessories&Peripherals|…              199
3  Computers&Accessories|Accessories&Peripherals|…              329
4  Computers&Accessories|Accessories&Peripherals|…              154

  actual_price discount_percentage rating rating_count  \
0        1,099                 64%    4.2       24,269
1          349                 43%    4.0       43,994
```

```
2     1,899               90%    3.9       7,928
3       699               53%    4.2      94,363
4       399               61%    4.2      16,905

                                      about_product  \
0  High Compatibility : Compatible With iPhone 12…
1  Compatible with all Type C enabled devices, be…
2   Fast Charger& Data Sync -With built-in safet…
3  The boAt Deuce USB 300 2 in 1 cable is compati…
4  [CHARGE & SYNC FUNCTION]- This cable comes wit…

                                            user_id  \
0  AG3D6O4STAQKAY2UVGEUV46KN35Q,AHMY5CWJMMK5BJRBB…
1  AECPFYFQVRUWC3KGNLJIOREFP5LQ,AGYYVPDD7YG7FYNBX…
2  AGU3BBQ2V2DDAMOAKGFAWDDQ6QHA,AESFLDV2PT363T2AQ…
3  AEWAZDZZJLQUYVOVGBEUKSLXHQ5A,AG5HTSFRRE6NL3M5S…
4  AE3Q6KSUK5P75D5HFYHCRAOLODSA,AFUGIFH5ZAFXRDSZH…

                                          user_name  \
0  Manav,Adarsh gupta,Sundeep,S.Sayeed Ahmed,jasp…
1  ArdKn,Nirbhay kumar,Sagar Viswanathan,Asp,Plac…
2  Kunal,Himanshu,viswanath,sai niharka,saqib mal…
3  Omkar dhale,JD,HEMALATHA,Ajwadh a.,amar singh …
4  rahuls6099,Swasat Borah,Ajay Wadke,Pranali,RVK…

                                          review_id  \
0  R3HXWT0LRP0NMF,R2AJM3LFTLZHFO,R6AQJGUP6P86,R1K…
1  RGIQEG07R9HS2,R1SMWZQ86XIN8U,R2J3Y1WL29GWDE,RY…
2  R3J3EQQ9TZI5ZJ,R3E7WBGK7ID0KV,RWU79XKQ6I1QF,R2…
3  R3EEUZKKK9J36I,R3HJVYCLYOY554,REDECAZ7AMPQC,R1…
4  R1BP4L2HH9TFUP,R16PVJEXKV6QZS,R2UPDB81N66T4P,R…

                                       review_title  \
0  Satisfied,Charging is really fast,Value for mo…
1  A Good Braided Cable for Your Type C Device,Go…
2  Good speed for earlier versions,Good Product,W…
3  Good product,Good one,Nice,Really nice product…
4  As good as original,Decent,Good one for second…

                                     review_content  \
0  Looks durable Charging is fine tooNo complains…
1  I ordered this cable to connect my phone to An…
2  Not quite durable and sturdy,https://m.media-a…
3  Good product,long wire,Charges good,Nice,I bou…
4  Bought this instead of original apple, does th…

                                           img_link  \
```

```
0  https://m.media-amazon.com/images/W/WEBP_40237…
1  https://m.media-amazon.com/images/W/WEBP_40237…
2  https://m.media-amazon.com/images/W/WEBP_40237…
3  https://m.media-amazon.com/images/I/41V5FtEWPk…
4  https://m.media-amazon.com/images/W/WEBP_40237…

                                         product_link
0  https://www.amazon.in/Wayona-Braided-WN3LG1-Sy…
1  https://www.amazon.in/Ambrane-Unbreakable-Char…
2  https://www.amazon.in/Sounce-iPhone-Charging-C…
3  https://www.amazon.in/Deuce-300-Resistant-Tang…
4  https://www.amazon.in/Portronics-Konnect-POR-1…
```

[5]:
```
#view dimensions of dataset
df.shape
```

[5]:
```
(1465, 16)
```

The number of samples in the dataset is 1465, The number of columns in the dataset is 16

[6]:
```
#explore the dataset, checking for the missing value of each column.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1465 entries, 0 to 1464
Data columns (total 16 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   product_id           1465 non-null   object
 1   product_name         1465 non-null   object
 2   category             1465 non-null   object
 3   discounted_price     1465 non-null   object
 4   actual_price         1465 non-null   object
 5   discount_percentage  1465 non-null   object
 6   rating               1465 non-null   object
 7   rating_count         1463 non-null   object
 8   about_product        1465 non-null   object
 9   user_id              1465 non-null   object
 10  user_name            1465 non-null   object
 11  review_id            1465 non-null   object
 12  review_title         1465 non-null   object
 13  review_content       1465 non-null   object
 14  img_link             1465 non-null   object
 15  product_link         1465 non-null   object
dtypes: object(16)
memory usage: 183.2+ KB
```

There is no null data in this dataset.

[7]:
```
#view the datatype of each column
df.dtypes
```

[7]:
```
product_id             object
product_name           object
category               object
discounted_price       object
actual_price           object
discount_percentage    object
rating                 object
rating_count           object
about_product          object
user_id                object
user_name              object
review_id              object
review_title           object
review_content         object
img_link               object
product_link           object
dtype: object
```

[8]:
```
#Show how many unique values are there in each columns.
df.nunique()
```

[8]:
```
product_id             1351
product_name           1337
category                211
discounted_price        550
actual_price            449
discount_percentage      92
rating                   28
rating_count           1143
about_product          1293
user_id                1194
user_name              1194
review_id              1194
review_title           1194
review_content         1212
img_link               1412
product_link           1465
dtype: int64
```

Identify Null rows

[9]:
```
#show the null rows in each column
df.isnull().sum()
```

[9]:
```
product_id             0
product_name           0
category               0
discounted_price       0
actual_price           0
discount_percentage    0
rating                 0
rating_count           2
about_product          0
user_id                0
user_name              0
review_id              0
review_title           0
review_content         0
img_link               0
product_link           0
dtype: int64
```

There are 2 null rows in rating_count column

[10]:
```
#view the overall information of the dataset:
df.describe()
```

[10]:
```
        product_id                                       product_name  \
count         1465                                               1465
unique        1351                                               1337
top     B07JW9H4J1  Fire-Boltt Ninja Call Pro Plus 1.83" Smart Wat…
freq             3                                                  5

                                                 category discounted_price  \
count                                                1465             1465
unique                                                211              550
top     Computers&Accessories|Accessories&Peripherals|…              199
freq                                                  233               53

       actual_price discount_percentage rating rating_count  \
count          1465                1465   1465         1463
unique          449                  92     28         1143
top             999                 50%    4.1        9,378
freq            120                  56    244            9

                                            about_product  \
count                                                1465
unique                                               1293
top     [CHARGE & SYNC FUNCTION]- This cable comes wit…
freq                                                    6
```

```
                                                  user_id  \
count                                                1465
unique                                               1194
top     AHIKJUDTVJ4T6DV6IUGFYZ5LXMPA,AE55KTFVNXYFD5FPY…
freq                                                   10

                                                user_name  \
count                                                1465
unique                                               1194
top     $@|\|TO$|-|,Sethu madhav,Akash Thakur,Burger P…
freq                                                   10

                                                review_id  \
count                                                1465
unique                                               1194
top     R3F4T5TRYPTMIG,R3DQIEC603E7AY,R1O4Z15FD40PV5,R…
freq                                                   10

                                             review_title  \
count                                                1465
unique                                               1194
top     Worked on iPhone 7 and didn’t work on XR,Good …
freq                                                   10

                                           review_content  \
count                                                1465
unique                                               1212
top     I am not big on camera usage, personally. I wa…
freq                                                    8

                                                 img_link  \
count                                                1465
unique                                               1412
top     https://m.media-amazon.com/images/I/413sCRKobN…
freq                                                    3

                                             product_link
count                                                1465
unique                                               1465
top     https://www.amazon.in/Wayona-Braided-WN3LG1-Sy…
freq                                                    1
```

[11]:
```python
df.rating.value_counts()
```

[11]:
```
4.1    244
4.3    230
4.2    228
```

```
4.0    129
3.9    123
4.4    123
3.8     86
4.5     75
4       52
3.7     42
3.6     35
3.5     26
4.6     17
3.3     16
3.4     10
4.7      6
3.1      4
5.0      3
3.0      3
4.8      3
3.2      2
2.8      2
2.3      1
|        1
2        1
3        1
2.6      1
2.9      1
Name: rating, dtype: int64
```

Rating column has 1 row that contain '|' symbol

[12]:
```python
#Create a copy of data to clean named df_clean
df_clean = df.copy()
```

1.1.3 Fixing rating Column

[13]:
```python
# General look in rows contain '|' symbol
df_clean[df_clean['rating'] =='|']
```

[13]:
```
      product_id                                       product_name  \
1279  B08L12N5H1  Eureka Forbes car Vac 100 Watts Powerful Sucti…

                                               category discounted_price  \
1279  Home&Kitchen|Kitchen&HomeAppliances|Vacuum,Cle…            2,099

     actual_price discount_percentage rating rating_count  \
1279        2,499                 16%      |          992

                                           about_product  \
```

```
1279  No Installation is provided for this product|1…

                                                   user_id  \
1279  AGTDSNT2FKVYEPDPXAA673AIS44A,AER2XFSWNN4LAUCJ5…

                                                 user_name  \
1279  Divya,Dr Nefario,Deekshith,Preeti,Prasanth R,P…

                                                 review_id  \
1279  R2KKTKM4M9RDVJ,R1O692MZOBTE79,R2WRSEWL56SOS4,R…

                                              review_title  \
1279  Decent product,doesn't pick up sand,Ok ok,Must…

                                            review_content  \
1279  Does the job well,doesn't work on sand. though…

                                                  img_link  \
1279  https://m.media-amazon.com/images/W/WEBP_40237…

                                              product_link
1279  https://www.amazon.in/Eureka-Forbes-Vacuum-Cle…
```

I checked the product_linke of "B08L12N5H1", the rating is 3.9, so I will fill the rating at 3.9

[14]:
```python
df_clean.loc[df_clean['product_id'] == 'B08L12N5H1', 'rating'] = '3.9'
```

1.1.4 Drop extraneous columns

Columns to Drop: `img_link` , `user_name` , `user_id`

[15]:
```python
#drop columns from the dataset
df_clean.drop(['img_link','user_name','user_id'], inplace=True, axis=1)
```

[16]:
```python
#confirm the changes
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1465 entries, 0 to 1464
Data columns (total 13 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   product_id           1465 non-null   object
 1   product_name         1465 non-null   object
 2   category             1465 non-null   object
 3   discounted_price     1465 non-null   object
 4   actual_price         1465 non-null   object
 5   discount_percentage  1465 non-null   object
```

```
 6   rating              1465 non-null   object
 7   rating_count        1463 non-null   object
 8   about_product       1465 non-null   object
 9   review_id           1465 non-null   object
 10  review_title        1465 non-null   object
 11  review_content      1465 non-null   object
 12  product_link        1465 non-null   object
dtypes: object(13)
memory usage: 148.9+ KB
```

1.1.5 Dedupe Data

[17]:
```python
#print number of duplicates to confirm dedupe - should be 0
print(df_clean.duplicated().sum())
```

```
0
```

No duplicate information, so it doesn't need any further cleaning.

1.1.6 Fix Rows with Missing Values

[18]:
```python
# Define which row in rating_count is null
df_clean[df_clean['rating_count'].isnull()]
```

[18]:
```
      product_id                                       product_name  \
282  B0B94JPY2N  Amazon Brand - Solimo 65W Fast Charging Braide…
324  B0BQRJ3C47  REDTECH USB-C to Lightning Cable 3.3FT, [Apple…

                                              category discounted_price  \
282  Computers&Accessories|Accessories&Peripherals|…              199
324  Computers&Accessories|Accessories&Peripherals|…              249

    actual_price discount_percentage rating rating_count  \
282          999                 80%    3.0          NaN
324          999                 75%    5.0          NaN

                                         about_product      review_id  \
282  USB C to C Cable: This cable has type C connec…   RUB7U91HVZ30
324   [The Fastest Charge] - This iPhone USB C cabl…  RQXD5SAMMPC6L

                                    review_title  \
282  The cable works but is not 65W as advertised
324                              Awesome Product

                                        review_content  \
282  I have a pd supported car charger and I bought…
324  Quick delivery.Awesome ProductPacking was good…
```

```
                                        product_link
282  https://www.amazon.in/Amazon-Brand-Charging-Su…
324  https://www.amazon.in/REDTECH-Lightning-Certif…
```

I go to product link to check and notice that product_id: B0B94JPY2N has 4.0 rating and 58 rating_count. Product_id B0BQRJ3C47 hasn't existed in amazon so I will drop it.

[19]:
```
# Change row with product_id = 'B0B94JPY2N': rating to 4.0 and rating_count to␣
 ↪58
df_clean.loc[df_clean['product_id'] == 'B0B94JPY2N', 'rating_count'] = '58'
df_clean.loc[df_clean['product_id'] == 'B0B94JPY2N', 'rating'] = '4.0'
```

[20]:
```
# Then drop rows with any null values in dataset which is Product_id B0BQRJ3C47
df_clean.dropna(inplace=True)
```

[21]:
```
#show the null rows in each column - should 0 for all columns
df_clean.isnull().sum()
```

[21]:
```
product_id             0
product_name           0
category               0
discounted_price       0
actual_price           0
discount_percentage    0
rating                 0
rating_count           0
about_product          0
review_id              0
review_title           0
review_content         0
product_link           0
dtype: int64
```

Data Transformation

Create a float_change function to automatically change float type to each column.

[22]:
```
def convert_to_float(df,column_name):
    # removes any non-numeric characters (except for the decimal point)
    df[column_name] = df[column_name].str.replace(r'[^0-9.]', '', regex=True)

    # convert string to float for actual_price column
    df[column_name] = df[column_name].astype(float)
```

Convert price-related columns to floats for easier calculations

[23]:
```
# convert string to float for discounted_price column
convert_to_float(df_clean,'discounted_price')
```

[24]:
```python
# convert string to float for actual_price column
convert_to_float(df_clean,'actual_price')
```

[25]:
```python
# convert string to float for rating_count column
convert_to_float(df_clean,"rating_count")
```

[26]:
```python
# convert string to float for rating column
convert_to_float(df_clean,"rating")
```

[27]:
```python
# Handle the 'discount_percentage' column by converting it to a decimal value␣
↪(0-1 range)
df_clean['discount_percentage'] = df_clean['discount_percentage'].str.
↪replace('%', '').astype(float) / 100
```

[28]:
```python
# check data type for revenue column and budget column
# discounted_price, actual_price, rating_count, rating, discount_percentage␣
↪should be float
df_clean.dtypes
```

[28]:
```
product_id              object
product_name            object
category                object
discounted_price       float64
actual_price           float64
discount_percentage    float64
rating                 float64
rating_count           float64
about_product           object
review_id               object
review_title            object
review_content          object
product_link            object
dtype: object
```

[29]:
```python
df_clean.isnull().sum()
```

[29]:
```
product_id             0
product_name           0
category               0
discounted_price       0
actual_price           0
discount_percentage    0
rating                 0
rating_count           0
about_product          0
review_id              0
review_title           0
```

```
review_content         0
product_link           0
dtype: int64
```

1.1.7 Feature Creating

Create a split_and_expand function to automatically split and expand into separate rows.

[30]:
```
# Split the 'category' column into two parts: general category and product type
def split_category(df, column_name, fill_value='NaN'):
    """
    Splits a specified column on the '|' delimiter and expands it into two␣
 ↪separate columns.

    Parameters:
    df (DataFrame): The DataFrame containing the column to split.
    column_name (str): The name of the column to split.

    Returns:
    DataFrame: The modified DataFrame with split and expanded columns.
    """

    # split the specified column on the delimiter '|'
    # expand=True: instead of storing lists in a single column,
    # it creates multiple columns in the resulting DataFrame category_split

    split_column = df[column_name].str.split('|', expand=True)

    # Create new column named main_category
    df['main_category'] = split_column[0]

    # Create new column named product_type
    df['product_type'] = split_column[1]

    #drop the old columns
    df.drop(columns=[column_name], inplace=True)
```

Call split_category function to split category column

[31]:
```
# Appply the function to 'category' column
split_category(df_clean, 'category')
```

[32]:
```
# Using the median price to split the products
median_price = df_clean['actual_price'].median()
df_clean['price_category'] = df_clean['actual_price'].apply(lambda x:␣
 ↪'Lower-Priced' if x < median_price else 'Higher-Priced')
```

Function to get sentiment

[33]:
```
# Initialize VADER SentimentIntensityAnalyzer
sia = SentimentIntensityAnalyzer()
```

[34]:
```
# Function to get sentiment
def get_vader_sentiment(text):
    score = sia.polarity_scores(text)
    return score['compound']  # compound score between -1 (negative) and 1␣
↪(positive)
```

[35]:
```
# Applying sentiment analysis
df_clean['vader_sentiment_score'] = df_clean['review_content'].
↪apply(get_vader_sentiment)
df_clean['vader_sentiment'] = df_clean['vader_sentiment_score'].apply(lambda x:␣
↪'Positive' if x > 0 else ('Negative' if x < 0 else 'Neutral'))
```

[36]:
```
df_clean['vader_sentiment'].value_counts()
```

[36]:
```
Positive    1381
Negative      80
Neutral        3
Name: vader_sentiment, dtype: int64
```

Grouping Rating

Reasoning: This grouping gives a meaningful breakdown, because the ratings are mostly concentrated around certain values.

- Low Ratings (1.0 - 3.0): These are rare, but they represent a significant drop in product quality or satisfaction.
- Average Ratings (3.0 - 4.0): This range covers a moderate level of satisfaction.
- Good Ratings (4.0 - 4.5): The largest concentration falls here, representing well-rated products.
- Excellent Ratings (4.5 - 5.0): This would represent top-rated products.

[37]:
```
df_clean['mean_of_ratings'] = pd.cut(df_clean['rating'], [1, 3, 3.5, 4, 5],␣
↪labels = ['Low', 'Average', 'Good', 'Excellent'])
```

Binning rating_count into defined groups.

Reasoning: This will help reduce the impact of extreme values.

[38]:
```
# Define bins for review count ranges
bins = [0, 100, 1000, 5000, 10000, 50000, 100000, 500000]  # Define the review␣
↪count ranges
labels = ['0-100', '100-1000', '1000-5000', '5000-10000', '10000-50000',␣
↪'50000-100000', '100000+']  # Label each range
```

[39]:
```
# Create a new column in the DataFrame to represent review count ranges
```

```
df_clean['rating_count_group'] = pd.cut(df_clean['rating_count'], bins=bins,␣
↪labels=labels)
```

[40]:
```
#Confirm the new columns
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1464 entries, 0 to 1464
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   product_id             1464 non-null   object
 1   product_name           1464 non-null   object
 2   discounted_price       1464 non-null   float64
 3   actual_price           1464 non-null   float64
 4   discount_percentage    1464 non-null   float64
 5   rating                 1464 non-null   float64
 6   rating_count           1464 non-null   float64
 7   about_product          1464 non-null   object
 8   review_id              1464 non-null   object
 9   review_title           1464 non-null   object
 10  review_content         1464 non-null   object
 11  product_link           1464 non-null   object
 12  main_category          1464 non-null   object
 13  product_type           1464 non-null   object
 14  price_category         1464 non-null   object
 15  vader_sentiment_score  1464 non-null   float64
 16  vader_sentiment        1464 non-null   object
 17  mean_of_ratings        1464 non-null   category
 18  rating_count_group     1464 non-null   category
dtypes: category(2), float64(6), object(11)
memory usage: 209.3+ KB
```

Exploratory Data Analysis

Research Question 1: Is there a relationship between discount percentage and average product rating ?

Analysis Decision 1: Bin the discount percentage data

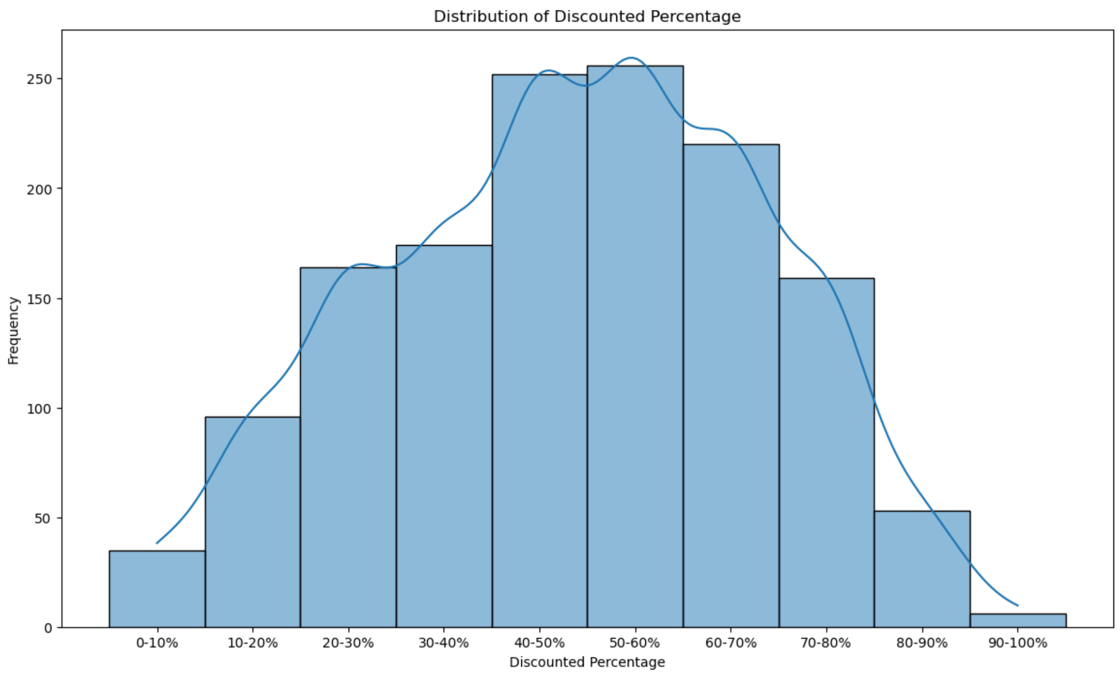
Provides a simplified distribution and can make comparisons easier.

[41]:
```
bins = [0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
labels = ['0-10%', '10-20%', '20-30%', '30-40%', '40-50%', '50-60%', '60-70%',␣
↪'70-80%', '80-90%', '90-100%']
df_clean['discount_bin'] = pd.cut(df_clean['discount_percentage'], bins=bins,␣
↪labels=labels)
```

Analysis Decision 2: Draw histogram to describe distribution of discount percentage.

This histogram plot will help us understand how pricing stategies are distributed and potential impact on consumer behavior and busisness performance.

[42]:
```
plt.figure(figsize=(14, 8))
sns.histplot(df_clean['discount_bin'], kde=True)
plt.title('Distribution of Discounted Percentage')
plt.xlabel('Discounted Percentage')
plt.ylabel('Frequency')
plt.show()
```

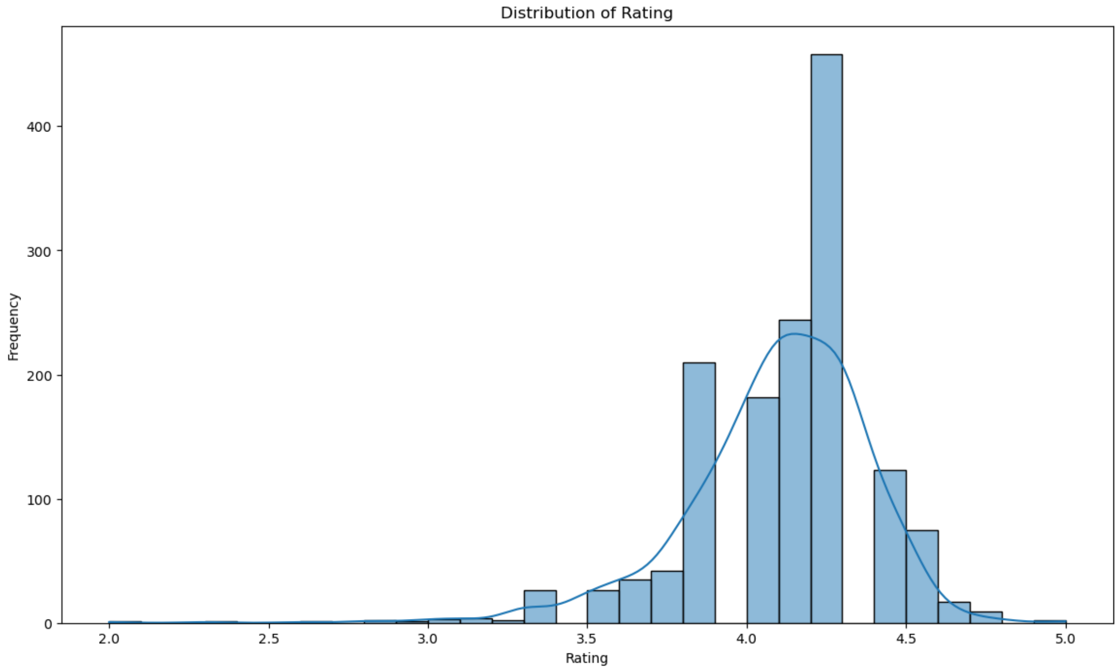


Summary: - The peak around 40% to 60% discount. - Discounts greater than 80% are rare. - Very few products are offered without any discount. - Most products are offered with moderate to high discounts, with a few products available at no discount or very high discounts.

Analysis Decision 3: Rating

This histogram plot will help us understand how pricing stategies are distributed and potential impact on consumer behavior and busisness performance.

[43]:
```
plt.figure(figsize=(14, 8))
sns.histplot(df_clean['rating'], kde=True, bins=30)
plt.title('Distribution of Rating')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()
```



Summary: - Ratings are slightly skewed toward higher values, the majority of ratings seem to cluster betwen 3.5 and 4.5, indicating that most products are rated positively. - Very few ratings are below 3.0, suggesting that poor ratings are rare in this dataset

Calculate the correlation number between Rating and Discount Percentage

[44]:
```
#Calculate the correlation number between discount_percentage and rating
df_clean['discount_percentage'].corr(df_clean['rating'])
```

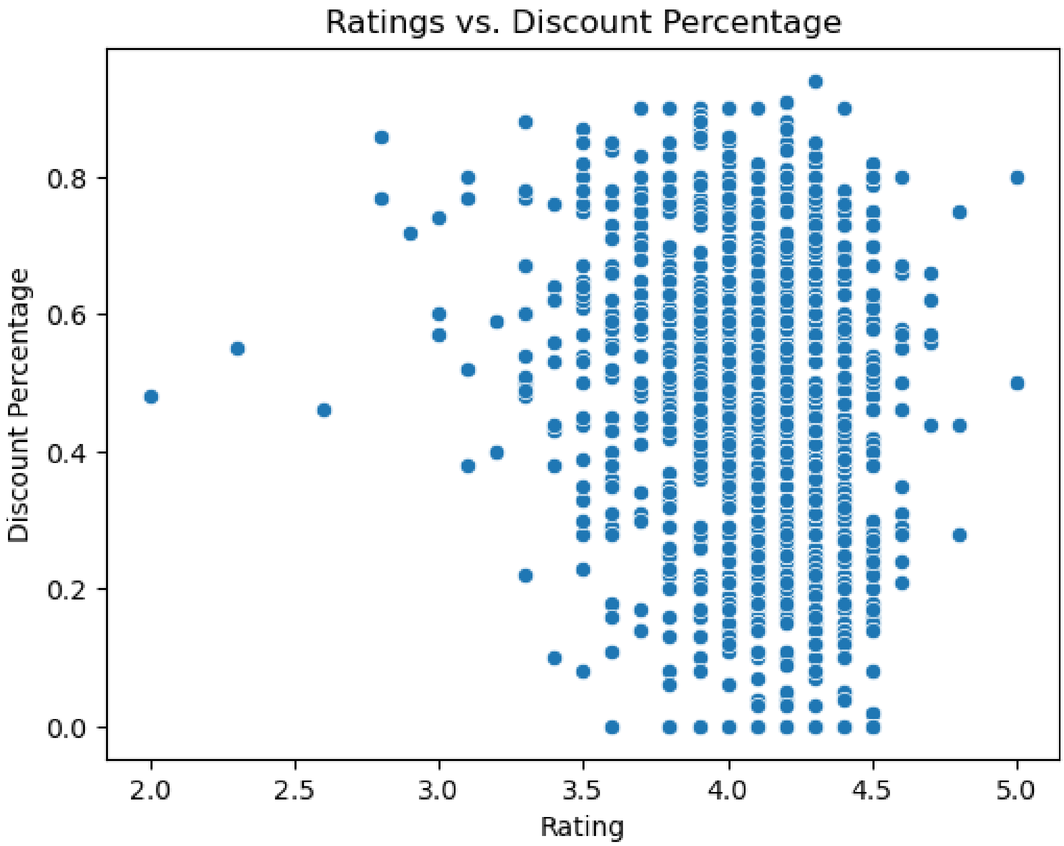
[44]: -0.15507651849573378

Summary: - The correlation between discount percentage and rating is -0.155, it shows a weak negative relationship. This implies that in general, when the product rating decreases, the discount percentage will be increases, though the effect is minimal.

Analysis Decision 4: Relationship between rating and discount percentage

This scatter plot will help us understand whether higher rating engagement leads to higher discount percentage

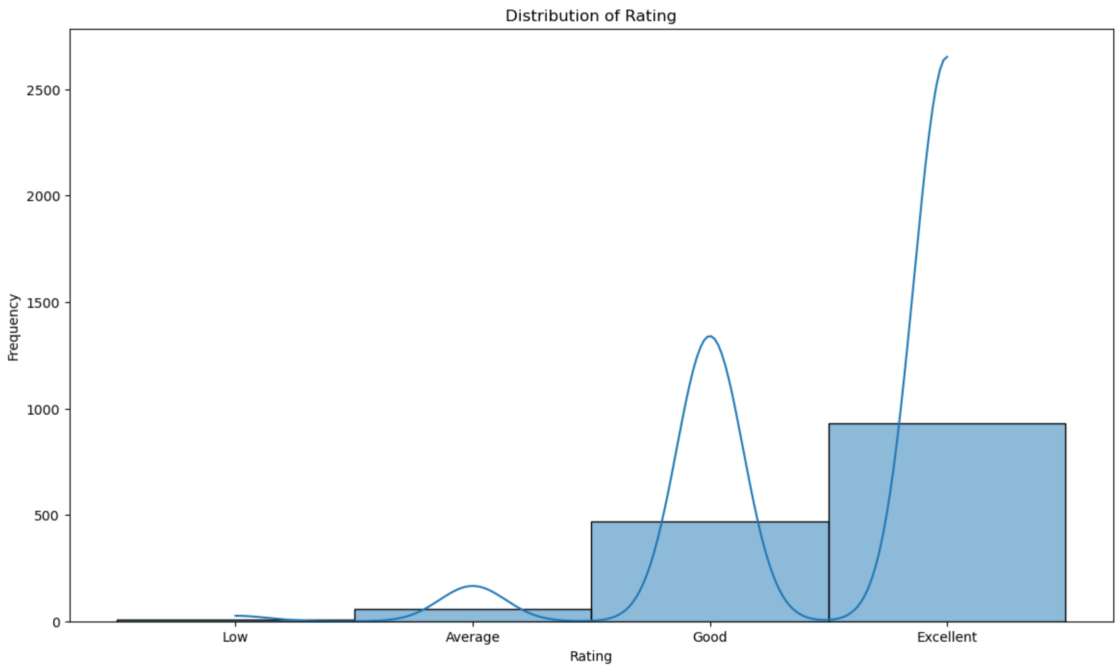
[45]:
```
sns.scatterplot(x='rating',y='discount_percentage', data= df_clean)
plt.title('Ratings vs. Discount Percentage')
plt.xlabel('Rating')
plt.ylabel('Discount Percentage')
plt.show()
```



Summary: - The scatter plot shows a very slight downward trend, but it is difficult to tell.

Visualize for the distribution of mean of rating.

[46]:
```
plt.figure(figsize=(14, 8))
sns.histplot(df_clean['mean_of_ratings'], kde=True)
plt.title('Distribution of Rating')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()
```



The plot shows that the dataset mostly give excellent rating in the product.

Summary: - The scatter plot shows a very slight downward trend, but it is difficult to tell.

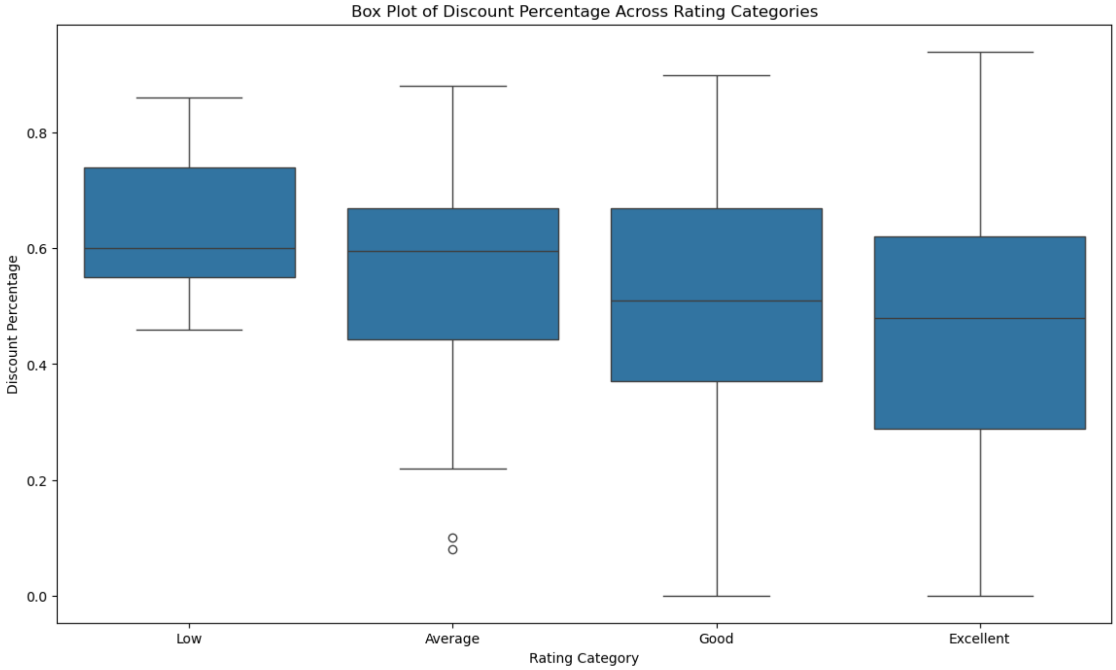
[47]:
```
discount_vs_rating = df_clean.groupby('mean_of_ratings')['discount_percentage'].
 ↪mean()
print(discount_vs_rating)
```

```
mean_of_ratings
Low          0.638889
Average      0.563276
Good         0.507356
Excellent    0.454267
Name: discount_percentage, dtype: float64
```

Summary: - Low-rated products have the highest average discount at 63.9%. - Excellent-rated products have the lowest average discount at 45.4% - This suggests that lower-rated products tend to have higher discounts.

This box plot will help us compare the discout percentage across different ratings categories.

[48]:
```
plt.figure(figsize=(14,8))
sns.boxplot(x='mean_of_ratings', y='discount_percentage', data=df_clean)
plt.title('Box Plot of Discount Percentage Across Rating Categories')
plt.xlabel('Rating Category')
plt.ylabel('Discount Percentage')
plt.show()
```



The relationship between discount percentage and product ratings is clear: - Products with lower ratings tend to offer higher discounts. - Products with higher ratings offer more moderate discounts, leveraging their quality and reputation to drive sales without needing large discounts.

[49]:
```
# Group by rating categories and calculate the correlation
grouped_by_rating = df_clean.groupby('mean_of_ratings').apply(
    lambda x: x['discount_percentage'].corr(x['rating'])
)

print(grouped_by_rating)
```

```
mean_of_ratings
Low           0.548148
Average      -0.096236
Good         -0.040843
Excellent    -0.056030
dtype: float64
```

- Low-Rated Products: There is a moderately strong positive correlation for low-rated products. This suggests that products with low ratings are likely to offer higher discounts.
- Average, Good, and Excellent Products: For these categories, the correlation is weakly negative. This suggests that higher discounts are less commonly associated with higher-rated products. In fact, these products are more likely to maintain moderate or lower discount levels, relying on their good ratings to drive sales.

Analysis Decision 6: Analyze A/B Test Results

Split the dataset into 3 groups based on discount ranges: (0-30%), (30-60%), and (60-100%)

[50]:
```
# Define groups based on discount ranges
low_discount = df_clean[(df_clean['discount_percentage'] >= 0) &␣
↪(df_clean['discount_percentage'] <= 0.3)]
medium_discount = df_clean[(df_clean['discount_percentage'] > 0.3) &␣
↪(df_clean['discount_percentage'] <= 0.6)]
high_discount = df_clean[(df_clean['discount_percentage'] > 0.6) &␣
↪(df_clean['discount_percentage'] <= 1)]
```

Null Hypothesis H_0 for each groups: - There is no significant different in average product ratings between low discounts (0-30%) and medium discount (30-60%) - There is no significant different in average product ratings between medium discount (30-60%) and high discount (60-100%) - There is no significant different in average product ratings between low discounts (0-30%) and high discount (60-100%)

[51]:
```
# Count successes (ratings >= 4.0) for each group
low_success = low_discount[low_discount['rating'] >= 4.0].shape[0]
medium_success = medium_discount[medium_discount['rating'] >= 4.0].shape[0]
high_success = high_discount[high_discount['rating'] >= 4.0].shape[0]
```

[52]:
```
# Count total observations for each group
low_total = low_discount.shape[0]
medium_total = medium_discount.shape[0]
high_total = high_discount.shape[0]
```

[53]:
```
# Perform proportions Z-test between Low and Medium discounts
success_counts_lm = [low_success, medium_success]
sample_sizes_lm = [low_total, medium_total]
z_stat_lm, p_value_lm = proportions_ztest(success_counts_lm, sample_sizes_lm)
```

[54]:
```
# Perform proportions Z-test between Medium and High discounts
success_counts_mh = [medium_success, high_success]
sample_sizes_mh = [medium_total, high_total]
z_stat_mh, p_value_mh = proportions_ztest(success_counts_mh, sample_sizes_mh)
```

[55]:
```
# Perform proportions Z-test between Low and High discounts
success_counts_lh = [low_success, high_success]
sample_sizes_lh = [low_total, high_total]
z_stat_lh, p_value_lh = proportions_ztest(success_counts_lh, sample_sizes_lh)
```

[56]:
```
# Summarize results
results = {
    "Low Discounts (0-30%) Total": low_total,
    "Low Discounts Successes": low_success,
    "Medium Discounts (30-60%) Total": medium_total,
    "Medium Discounts Successes": medium_success,
```

```
    "High Discounts (60-100%) Total": high_total,
    "High Discounts Successes": high_success,
    "Low vs Medium Z-Statistic": z_stat_lm,
    "Low vs Medium P-Value": p_value_lm,
    "Medium vs High Z-Statistic": z_stat_mh,
    "Medium vs High P-Value": p_value_mh,
    "Low vs High Z-Statistic": z_stat_lh,
    "Low vs High P-Value": p_value_lh,
}

results
```

[56]:
```
{'Low Discounts (0-30%) Total': 344,
 'Low Discounts Successes': 288,
 'Medium Discounts (30-60%) Total': 682,
 'Medium Discounts Successes': 508,
 'High Discounts (60-100%) Total': 438,
 'High Discounts Successes': 314,
 'Low vs Medium Z-Statistic': 3.3482699633306403,
 'Low vs Medium P-Value': 0.0008131775712304762,
 'Medium vs High Z-Statistic': 1.0337943618257388,
 'Medium vs High P-Value': 0.30123230801009715,
 'Low vs High Z-Statistic': 3.9673680754688965,
 'Low vs High P-Value': 7.267071456978555e-05}
```

Low Discounts (0-30%) vs Medium Discounts (30-60%): - p-value is less than 0.05 (0.000813), so we reject the null hypothesis. - There is a significant difference in the proportion of highly rated products between low and medium discounts. - Z-statistic = 3.35, which means low discounts rate is 3 times of standard deviation above the mean. So products with low discounts (0-30%) have higher proportion of high ratings compared to medium discounts (30-60%)

Medium Discounts (30-60%) vs High Discounts (60-100%): - p-value is greater than 0.05 (0.301), so we don't have evident to reject the null hypothesis. - There is no statistically significant difference in the proportion of highly rated products between medium and high discounts. - Products with medium discounts (30–60%) and high discounts (60–100%) have similar proportions of high ratings.

Low Discounts (0-30%) vs High Discounts (60-100%): - p-value is less than 0.05 (0.00007), so we reject the null hypothesis. - There is a significant difference in the proportion of highly rated products between low and high discounts. - Z-statistic = 3.967, which means low discounts rate is 4 times of standard deviation above the mean. So products with low discounts (0-30%) have higher proportion of high ratings compared to high discounts (60-100%)

Summary:

Comparison	Statistical Significance	Conclusion
Low vs Medium	Yes ($p = 0.0008$)	Low discounts have a higher proportion of high ratings.

Comparison	Statistical Significance	Conclusion
Medium vs High	No (p = 0.3012)	No significant difference in high ratings.
Low vs High	Yes (p = 0.00007)	Low discounts have a higher proportion of high ratings.

- Products with low discounts tend to receive higher ratings. This could be due to perceived quality or customer satisfaction.
- Medium discounts appear neutral and could be optimized to maintain quality perception and high ratings.
- Products with high discounts (60–100%) may not lead to significantly higher or lower ratings compared to medium discounts but perform worse than low discounts. Use high discounts cautiously, possibly for clearance or promotional items.

Research Question 2: Do products with more reviews have higher or lower average ratings?

Analysis Decision 1: Create review count ranges.

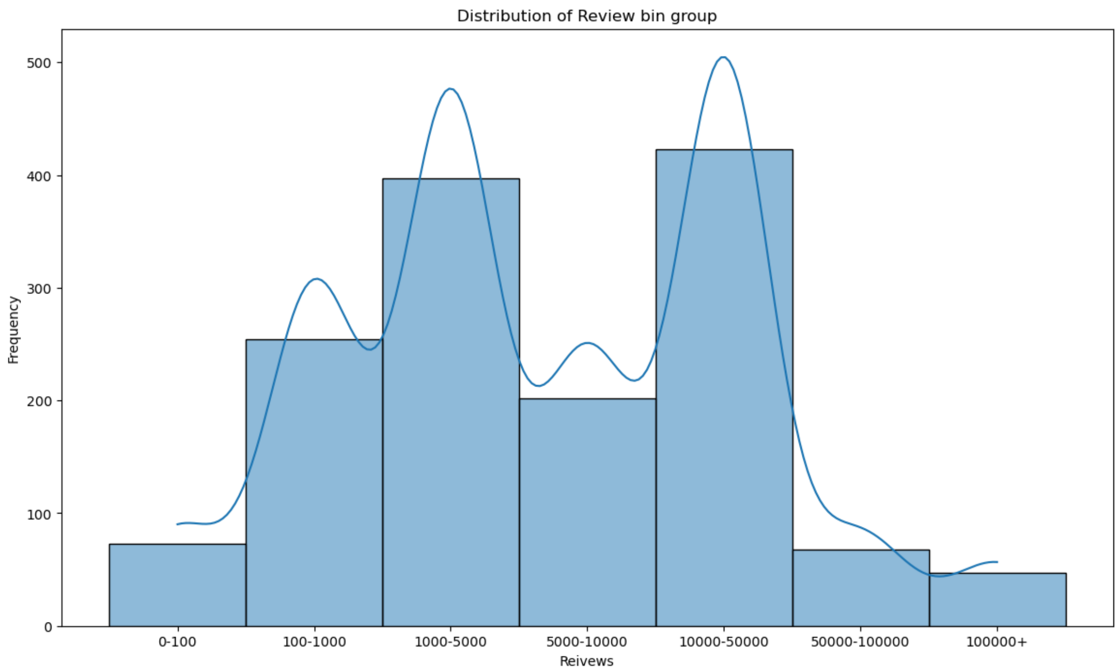
[57]:
```
df_clean['rating_count'].describe()
```

[57]:
```
count      1464.000000
mean      18283.084016
std       42741.908537
min           2.000000
25%        1179.000000
50%        5178.500000
75%       17330.750000
max      426973.000000
Name: rating_count, dtype: float64
```

- The review counts range is quite wide, from 2 to 426,973 reviews.
- The mean is 18283, std is 42741 shows that the distribution is skewed.

Analysis Decision 2: Visualize the distribution of review bin group.

[58]:
```
plt.figure(figsize=(14, 8))
sns.histplot(df_clean['rating_count_group'], kde=True)
plt.title('Distribution of Review bin group')
plt.xlabel('Reivews')
plt.ylabel('Frequency')
plt.show()
```



Summary: - The rating_count_group binning has provided a more balanced view of data. - The bimodal distribution suggests that most products either have moderate (1000-5000) or high (10000-50000) review counts, with fewer products at the extremes (very low or very high review counts). This information can help guide further analyses on how review count affects product ratings, with attention to the most common review groups.

Analysis Decision 3: Calculate Average Ratings for Each Review Count Group

[59]:
```
# Group by the review count ranges and calculate the mean rating
review_count_vs_rating = df_clean.groupby('rating_count_group')['rating'].
    ↪mean().reset_index()
```

[60]:
```
# Display the result
print(review_count_vs_rating)
```

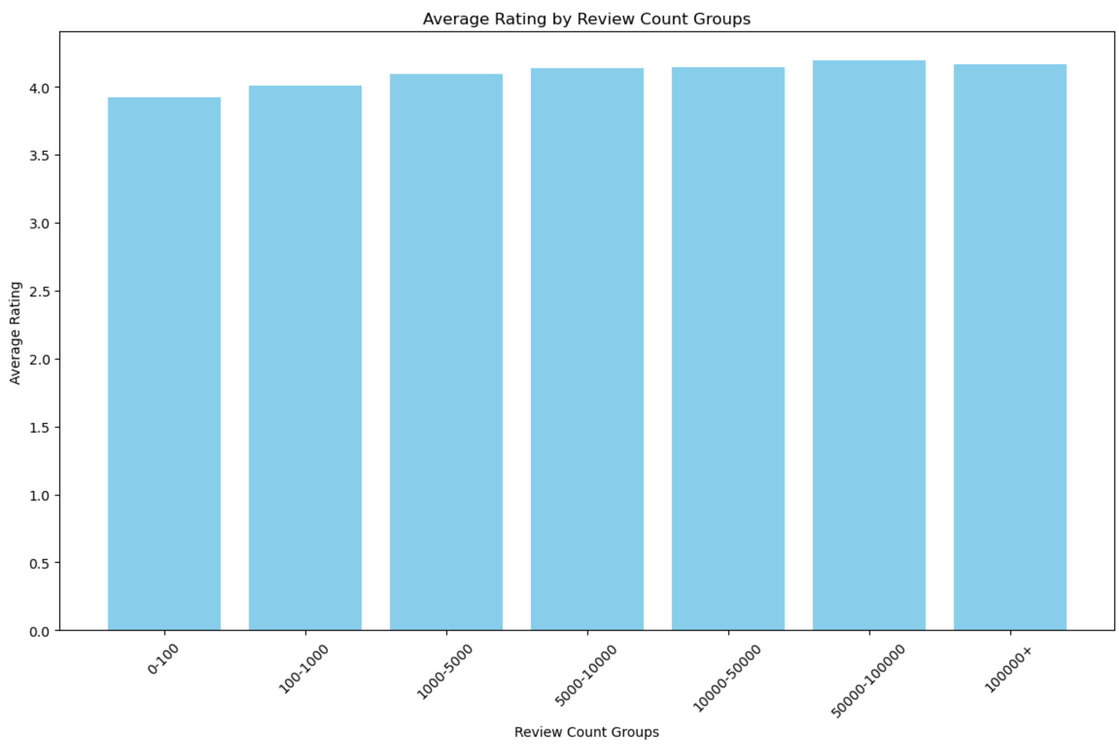
```
  rating_count_group    rating
0              0-100  3.924658
1           100-1000  4.005906
2          1000-5000  4.092443
3         5000-10000  4.138614
4        10000-50000  4.140662
5       50000-100000  4.195588
6            100000+  4.165957
```

Reasoning:

Summary: - The average rating generally increases with the review count, suggesting that products with more reviews tend to have slightly higher ratings. However, this increase plateaus after the 50000-100000 review group, with a slight decline in the 100000+ group.

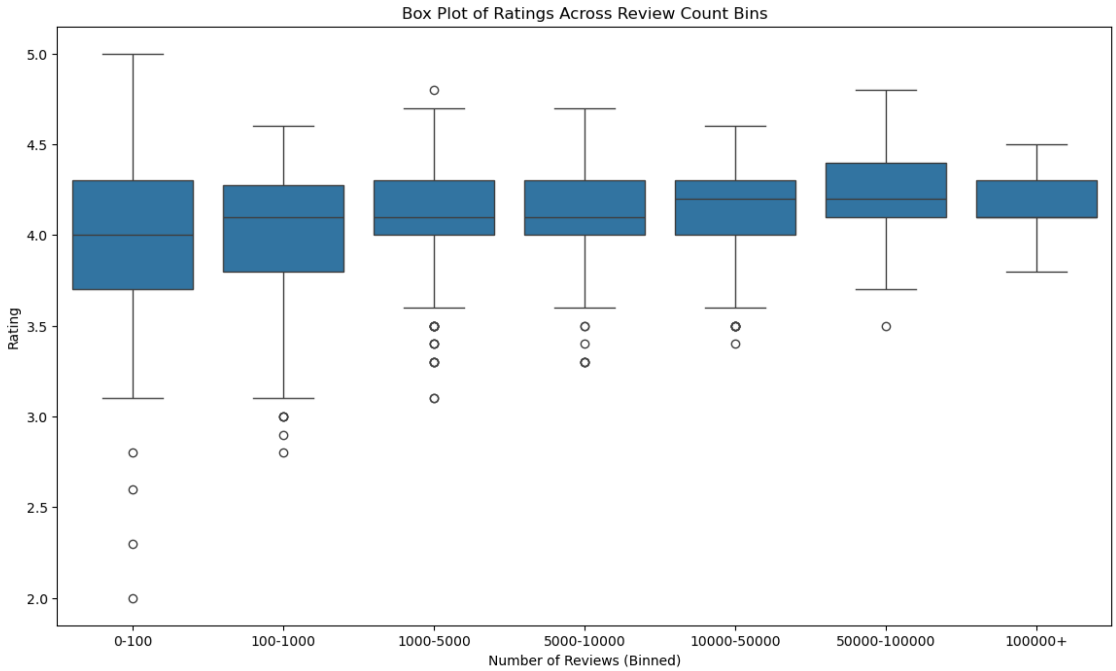
Analysis Decision 4: Visualize the Relationship

[61]:
```
# Plot the relationship between review count groups and average ratings
plt.figure(figsize=(14, 8))
plt.bar(review_count_vs_rating['rating_count_group'],␣
↪review_count_vs_rating['rating'], color='skyblue')
plt.xlabel('Review Count Groups')
plt.ylabel('Average Rating')
plt.title('Average Rating by Review Count Groups')
plt.xticks(rotation=45)
plt.show()
```



The bar plot of average ratings by review count groups confirms this trend, with a gradual rise in average rating as review count increases, peaking at 50000-100000 reviews.

[62]:
```
plt.figure(figsize=(14,8))
sns.boxplot(data=df_clean, x='rating_count_group', y='rating')
plt.title('Box Plot of Ratings Across Review Count Bins')
plt.xlabel('Number of Reviews (Binned)')
plt.ylabel('Rating')
plt.show()
```



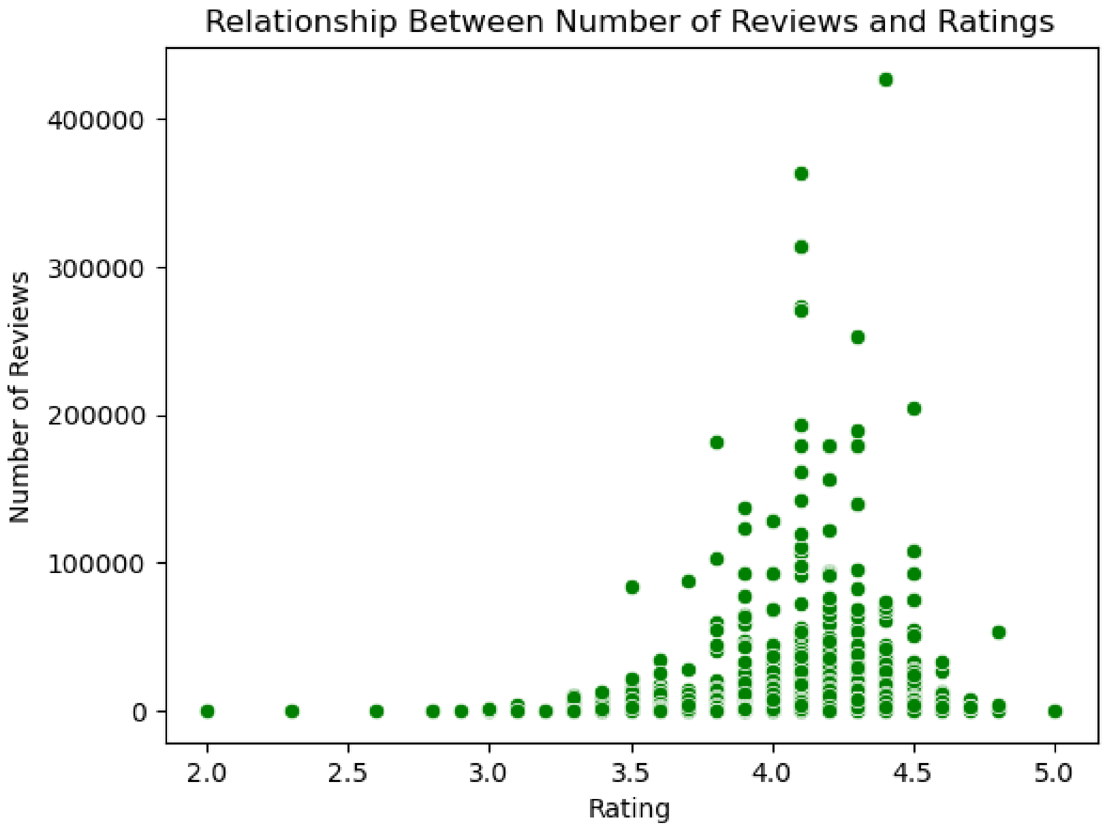
Summary: - Products with fewer reviews have more variability in their ratings (the spread is wider then higher review counts). - Products with moderate to higher reivews are more consistent and positive in their ratings, clustering around 4.0. - Products have 100.000+ reviews slide downward. - All data set reamin mostly positive (above 3.5)

Analysis Decision 5: Correlation Analysis

[63]:
```
correlation = df_clean['rating_count'].corr(df_clean['rating'])
print(f"Correlation between Number of Reviews and rating: {correlation}")
```

```
Correlation between Number of Reviews and rating: 0.10248811280168635
```

[64]:
```
sns.scatterplot(x='rating',y='rating_count', data= df_clean, color = "green")
plt.title("Relationship Between Number of Reviews and Ratings")
plt.xlabel('Rating')
plt.ylabel("Number of Reviews")
plt.show()
```



- The correlation value of 0.102 suggests that there is a slight positive relationship between the number of reviews and its rating, but this is very weak.
- products with more reviews tend to have slightly higher ratings but the effect is minimal.

[65]:
```
# Group by rating categories and calculate the correlation
grouped_by_rating = df_clean.groupby('mean_of_ratings').apply(
    lambda x: x['rating_count'].corr(x['rating'])
)

print(grouped_by_rating)
```

```
mean_of_ratings
Low          0.604472
Average      0.211206
Good         0.135987
Excellent   -0.065201
dtype: float64
```

- Low-rated product has a moderate positive correlation (0.604), suggesting that among low-rated products, those with more reviews may have slightly higher ratings.
- Average-rated product has weak positive correlation (0.211).
- Good-rated product has very weak positive correlation (0.136).

- Excellent-rated product has weak negative correlation (-0.065), indicating that for top-rated products, an increase in review count does not necessarily correlate with higher ratings.

[66]:
```
review_count_vs_rating = df_clean.groupby('mean_of_ratings')['rating_count'].
  ↪mean()
print(review_count_vs_rating)
```

```
mean_of_ratings
Low              199.444444
Average         5238.620690
Good           11663.014925
Excellent      22619.446121
Name: rating_count, dtype: float64
```

- Average review count of low-rated products is only 199, indicating that lower-rated products are generally reviewed less.
- Average review count of excellent-rated products is significantly higher at 22,619, indicating that highly-rated products tend to have more reviews, potentially reflecting greater popularity or satisfaction.

Analysis Decision 6: Build an SVM model

Reasoning : - The dataset mostly has Excellent Ratings (4.0 - 4.5) and Exellent Ratings (4.5 - 5.0) so we cannot use Classification model. - The correlation between Numbers of Review and Rating is 0.102, indicating a very weak linear relationship. This suggests that the relationship might be non-linear.

[67]:
```
# Log-transform the number of reviews to reduce skewness
df_clean['log_number_of_reviews'] = np.log1p(df_clean['rating_count'])
```

[68]:
```
# Features and target
X = df_clean[['log_number_of_reviews']]  # Number of reviews
y = df_clean['rating']
```

[69]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
  ↪random_state=42)
```

[70]:
```
# Standardize the feature
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[71]:
```
# Initialize and train the SVR model
svr_model = SVR(kernel='rbf', C=1.0, epsilon=0.2)  # Adjust C and epsilon for␣
  ↪better performance
svr_model.fit(X_train_scaled, y_train)
```

[71]:
```
SVR(epsilon=0.2)
```

[72]:
```python
# Make predictions
y_pred = svr_model.predict(X_test_scaled)
```

[73]:
```python
# Evaluate model performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

[74]:
```python
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R²): {r2}")
```

```
Mean Squared Error (MSE): 0.06748864104799111
Mean Absolute Error (MAE): 0.19362075855073918
R-squared (R²): 0.051811111948280475
```

Mean Squared Error: - The MSE represents the average squared difference between the predicted and actual ratings. - The MSE is quite small (0.067), suggesting a accurated predict

Mean Absolute Error: - The MAE shows the average absolute error between predicted and actual ratings. - On average, the model's predictions are off by approximately 0.19 points

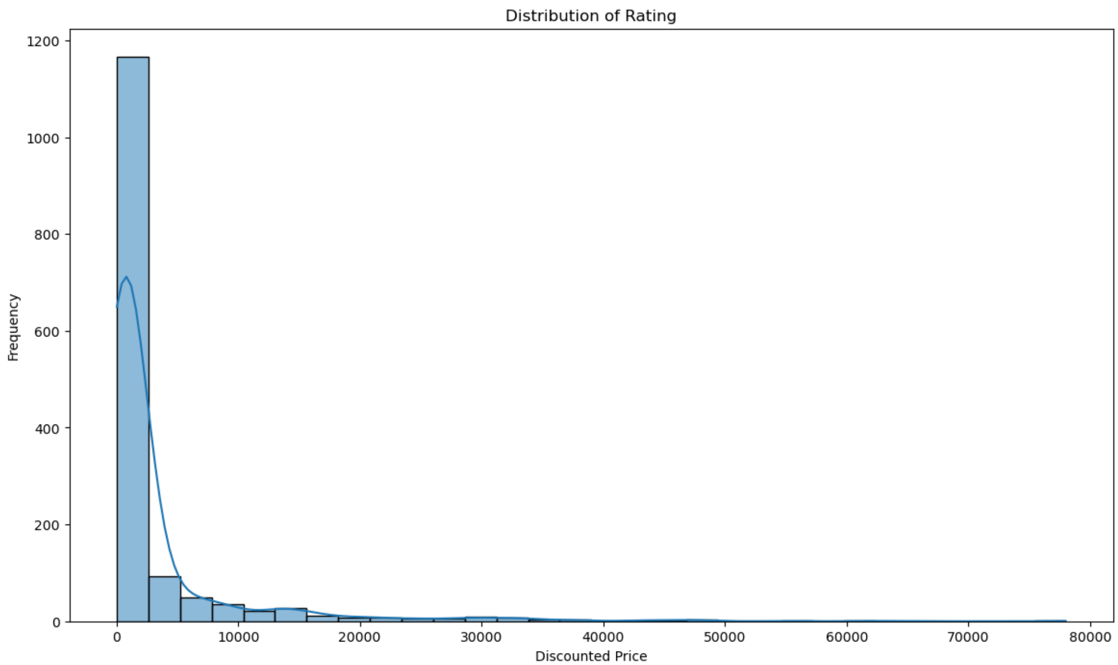
R-squared (R^2): - The R-squared value indicates that the model explains about 5.18% of the variance in ratings based on the predictors. - While positive, this is still a very small proportion, suggesting there is room for improvement.

Summary: - Very Weak Relationship: The low R-squared indicates that the number of reviews alone does not strongly predict ratings. This weak relationship aligns with the low correlation coefficient (0.102). - This suggests that the number of reviews is not a major determinant of ratings. Additional features are likely needed to improve the model.

Research Question 3: Do higher-priced products receive better ratings than lower-priced ones?

Analysis Decision 1: Create review count ranges.

[75]:
```python
plt.figure(figsize=(14, 8))
sns.histplot(df_clean['discounted_price'], bins=30, kde=True)
plt.title('Distribution of Rating')
plt.xlabel('Discounted Price')
plt.ylabel('Frequency')
plt.show()
```



Analysis Decision 2: Create review count ranges.

[76]:
```python
# Group by price category and calculate the mean rating
price_rating_comparison = df_clean.groupby('price_category')['rating'].mean()
print(price_rating_comparison)
```

```
price_category
Higher-Priced    4.102186
Lower-Priced     4.090847
Name: rating, dtype: float64
```

- Higher-priced products (4.11) have a slightly higher average rating than lower-priced products(4.08).
- The difference is small (0.03), suggesting that price does not strongly influence rating.

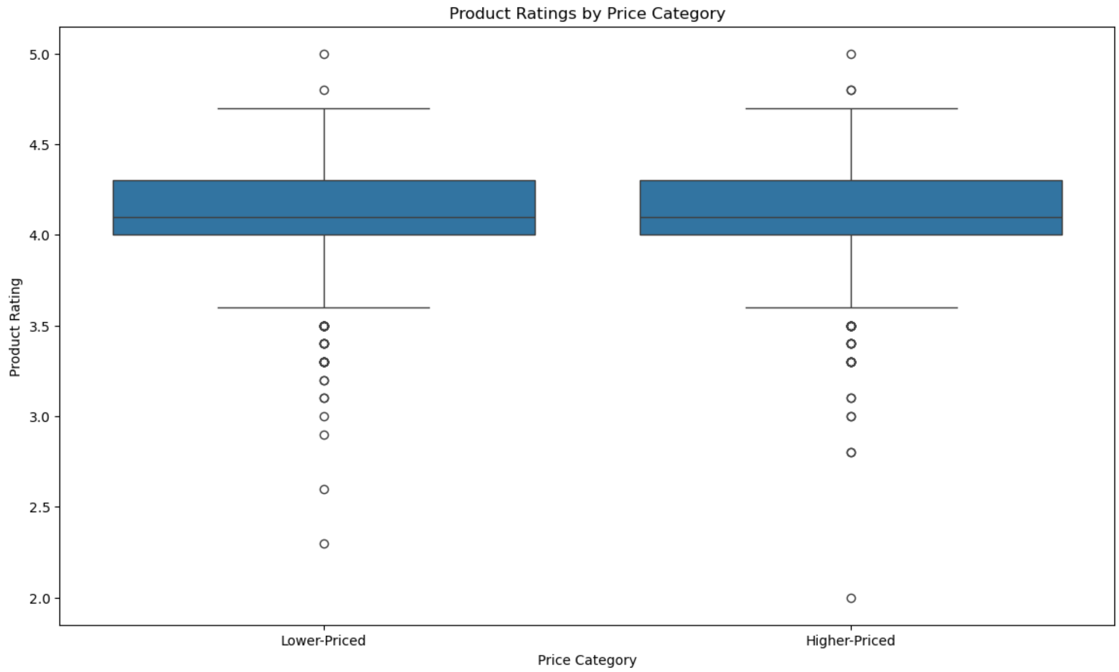
[77]:
```python
df_clean.groupby('price_category')['rating'].describe()
```

[77]:

price_category	count	mean	std	min	25%	50%	75%	max
Higher-Priced	732.0	4.102186	0.288675	2.0	4.0	4.1	4.3	5.0
Lower-Priced	732.0	4.090847	0.290122	2.3	4.0	4.1	4.3	5.0

- Both prices have a similar spread of ratings
- Higher-Priced products showing slightly less variation (lower standard deviation) than Lower-Priced products.
- This suggests that higher-priced products tend to have more consistent ratings, though the difference is minor.

[78]:
```python
# Create a boxplot for ratings by price category
plt.figure(figsize=(14, 8))
sns.boxplot(x='price_category', y='rating', data=df_clean)
plt.title('Product Ratings by Price Category')
plt.xlabel('Price Category')
plt.ylabel('Product Rating')
plt.show()
```



- Higher-priced products tend to receive consistently good ratings with fewer very low ratings compared to lower-priced products, which exhibit more variability in ratings and have more instances of low ratings.
- Median Rating remains the same in both price categories. It shows that customers generally rate products well regardless of price.

[79]:
```python
# Group by rating categories and calculate the correlation
grouped_by_rating = df_clean.groupby('price_category').apply(
    lambda x: x['actual_price'].corr(x['rating'])
)

print(grouped_by_rating)
```

```
price_category
Higher-Priced    0.179193
Lower-Priced    -0.002505
dtype: float64
```

- Correlation between higher-priced products rating is 0.161, indicating a weak positive relationship between price and rating in this category.
- Correlation between lower-priced products rating is 0.048, showing an even weaker positive relationship.
- This suggests that within each group (Higher-Priced and Lower-Priced), products with higher prices tend to receive slightly better ratings, but the relationship is not strong.

Analysis Decision 3: Hypothesis Testing.

- Null Hypothesis (H_0): There is no significant difference in ratings between lower-priced and higher-priced products.
- Alternative Hypothesis (H_1): Higher-priced products receive significantly different ratings.

[80]:
```
# Create lower-priced and higher-priced groups
lower_priced = df_clean[df_clean['price_category'] == 'Lower-Priced']
higher_priced = df_clean[df_clean['price_category'] == 'Higher-Priced']
```

[81]:
```
# Perform t-test
t_stat, p_value = ttest_ind(lower_priced['rating'], higher_priced['rating'])

print(f"T-Statistic: {t_stat}")
print(f"P-Value: {p_value}")
```

```
T-Statistic: -0.7495668952195909
P-Value: 0.45363618735513234
```

- t_statistic is negative (-2.098), it shows that the mean rating of lower-priced products is lower than the mean rating of higher-priced products.
- p-value is less than 0.05, we reject the null hypothesis, there is statistically significant difference in ratings between lower-priced and higher-price products.

Summary: - Higher-priced products tend to receive better ratings than lower-priced products, based on this analysis. - The difference is statistically significant at the 5% level, meaning there's less than a 5% probability that this result is due to random chance.

Analysis Decision 3: Model the Relationship.

[82]:
```
from sklearn.linear_model import LinearRegression

X = df_clean[['actual_price']]
y = df_clean['rating']

model = LinearRegression()
model.fit(X, y)

print(f"Regression Coefficient (Price): {model.coef_[0]}")
print(f"Intercept: {model.intercept_}")
```

```
Regression Coefficient (Price): 3.26259828681659e-06
Intercept: 4.078741668210022
```

The price coefficient is very small (0.000005), so the effect of price on ratings is negligible.

[83]:
```
r2 = r2_score(y_test, y_pred)
```

[84]:
```
print(f"R-squared (R²): {r2}")
```

```
R-squared (R²): 0.051811111948280475
```

R-squared is very low, it shows that price alone is not a strong predictor of ratings.

Research Question 4: Do Products with Positive Sentiment in Reviews Have Higher Ratings ?

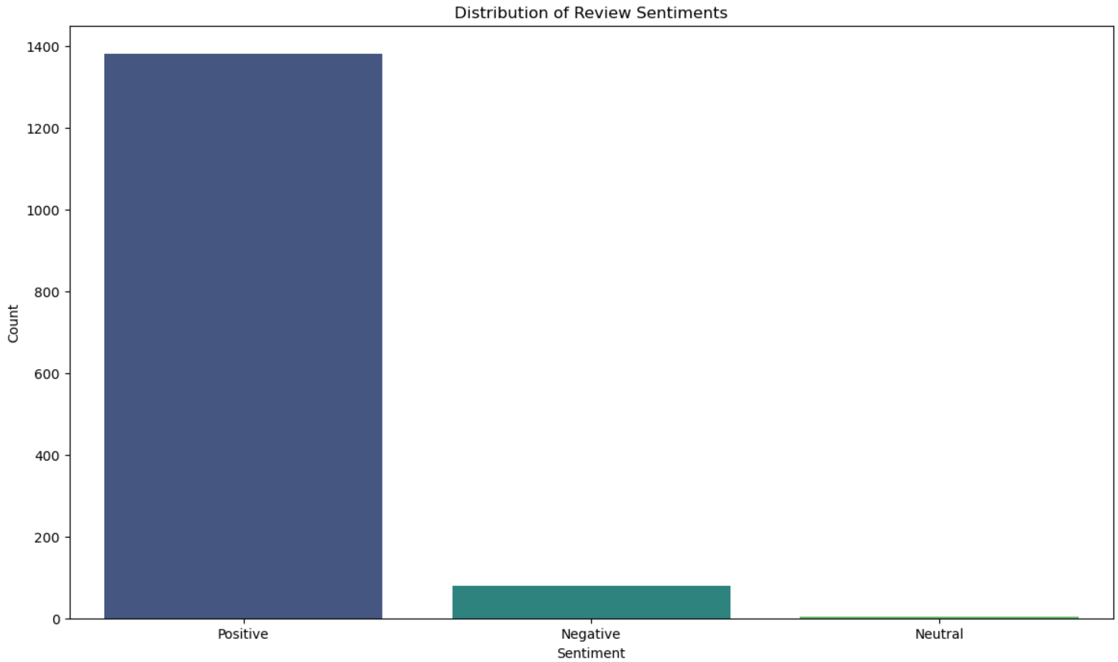
Analysis Decision 1: Group by Sentiment and Calculate the Average Rating

[85]:
```
# Group by sentiment and calculate the average rating
sentiment_rating = df_clean.groupby('vader_sentiment')['rating'].mean().
↪reset_index()
print(sentiment_rating)
```

```
  vader_sentiment    rating
0        Negative  3.881250
1         Neutral  3.900000
2        Positive  4.109413
```

- Products with positive sentiment in reviews have a higher average rating compared to those with neutral or negative sentiment.
- The difference between negative and positive sentiment ratings is about 0.23 points, which indicates a noticeable increase in rating for positively perceived products.

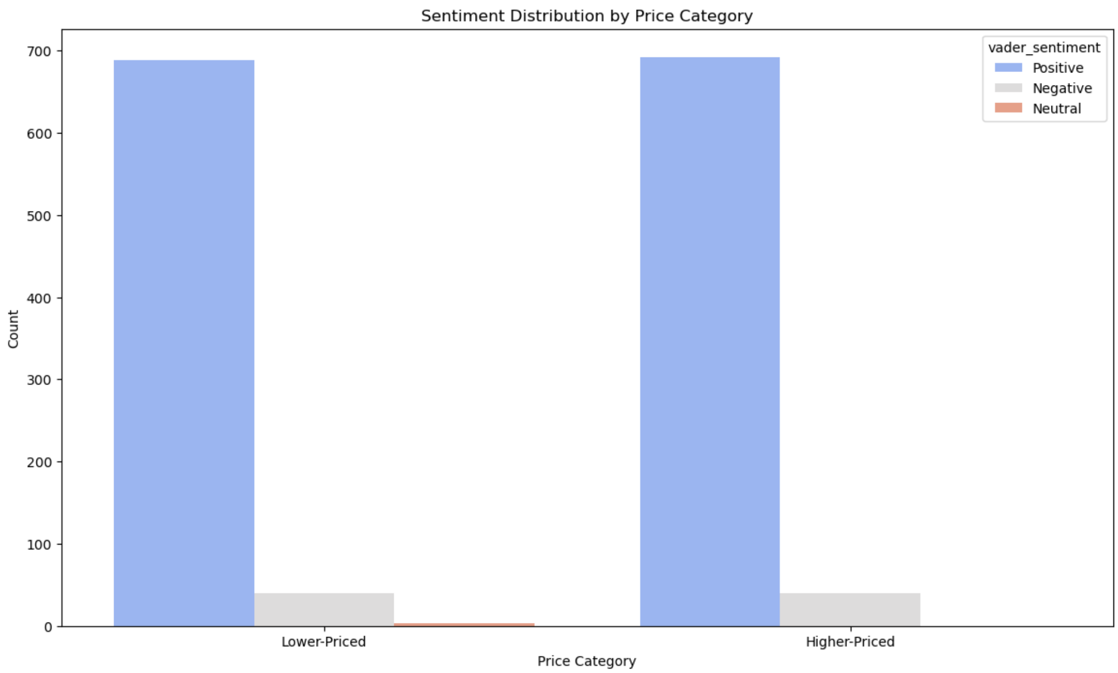
[86]:
```
# Sentiment distribution
sentiment_counts = df_clean['vader_sentiment'].value_counts()
plt.figure(figsize=(14, 8))
sns.barplot(x=sentiment_counts.index, y=sentiment_counts.values,␣
↪hue=sentiment_counts.index, legend=False, palette='viridis')
plt.title('Distribution of Review Sentiments')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.show()

# Summary
# - Most reviews express positive sentiment, aligning with the generally high␣
↪ratings.
# - Negative sentiment reviews are relatively low, reflecting lower instances␣
↪of poor product experiences.
```



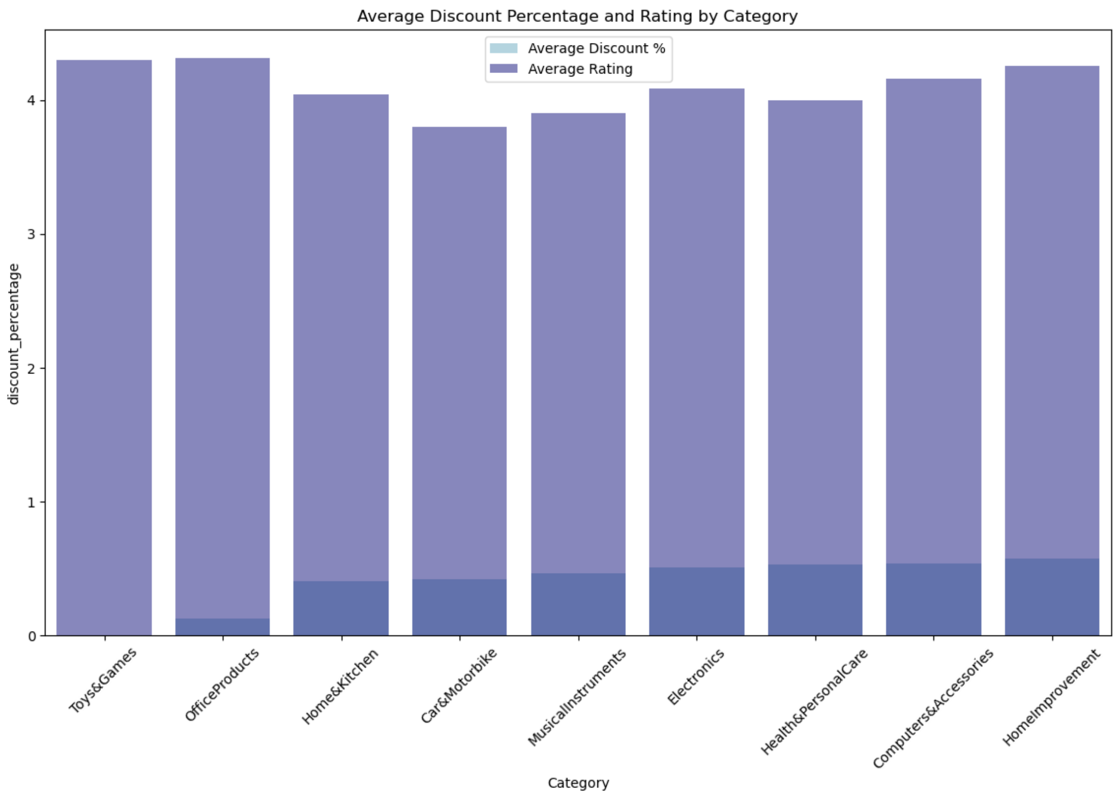
1.1.8 Summary

- Most reviews express positive sentiment, aligning with the generally high ratings.
- Negative sentiment reviews are relatively low, reflecting lower instances of poor product experiences.

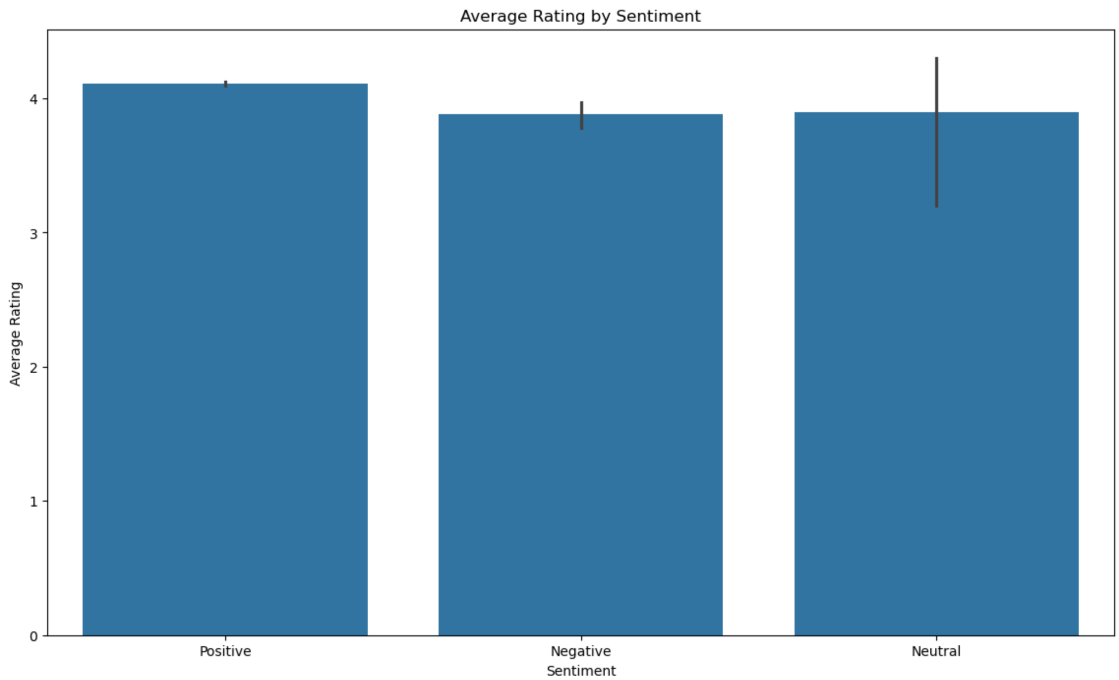
[87]:
```
# Sentiment distribution by price category
plt.figure(figsize=(14, 8))
sns.countplot(x='price_category', hue='vader_sentiment', data=df_clean,␣
 ↪palette='coolwarm')
plt.title('Sentiment Distribution by Price Category')
plt.xlabel('Price Category')
plt.ylabel('Count')
plt.show()
```



[88]:
```
# Compare average discount and rating across categories
category_comparison = df_clean.groupby('main_category').
 ↪agg({'discount_percentage': 'mean', 'rating': 'mean'}).reset_index()
# Sort by discount_percentage in descending order
category_comparison = category_comparison.sort_values(by='discount_percentage')
plt.figure(figsize=(14, 8))
sns.barplot(x='main_category', y='discount_percentage',␣
 ↪data=category_comparison, color='lightblue', label='Average Discount %')
sns.barplot(x='main_category', y='rating', data=category_comparison, alpha=0.5,␣
 ↪color='darkblue', label='Average Rating')
plt.xticks(rotation=45)
plt.title('Average Discount Percentage and Rating by Category')
plt.xlabel('Category')
plt.legend()
plt.show()
```



[89]:
```
# Bar plot for average rating by sentiment
plt.figure(figsize=(14, 8))
sns.barplot(x='vader_sentiment', y='rating', data=df_clean, estimator=np.mean)
plt.title('Average Rating by Sentiment')
plt.xlabel('Sentiment')
plt.ylabel('Average Rating')
plt.show()
```



As the bar graph shows: - Products receive more positive reviews will also receive higher ratings. - Both neutral and negative sentiment products have fairly close average ratings, though slightly lower than positive ones. - This shows that neutral viewers aren't significantly driving up ratings, and negative feedback doesn't drastically reduce their rating either.

[90]:

```
df_clean.groupby('vader_sentiment')['rating'].describe()
```

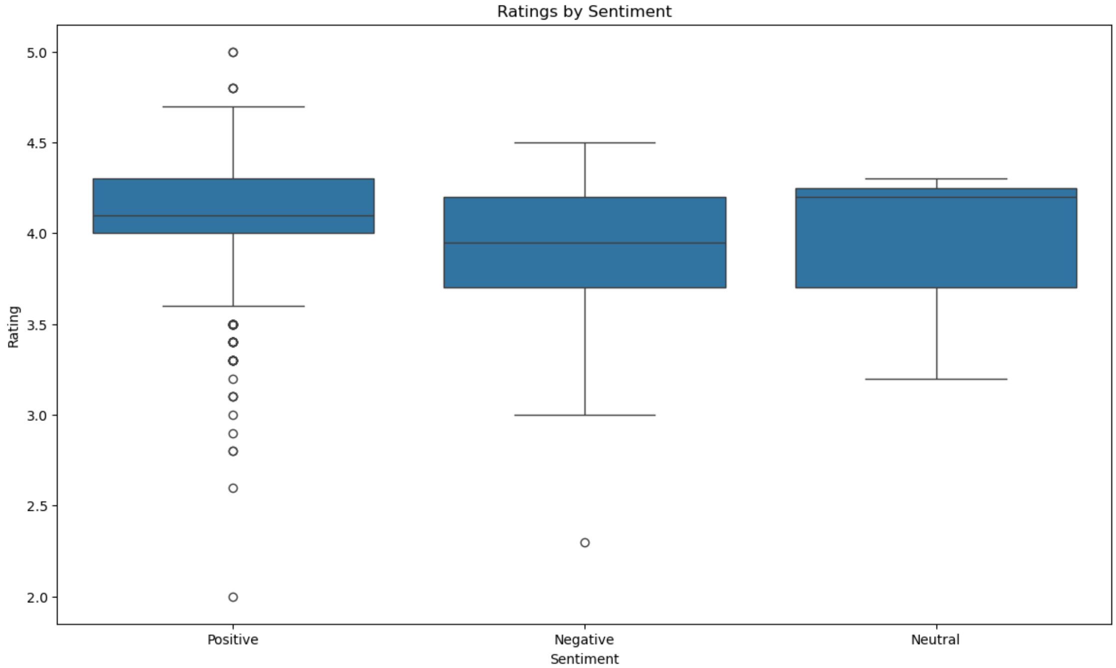
[90]:

vader_sentiment	count	mean	std	min	25%	50%	75%	max
Negative	80.0	3.881250	0.401924	2.3	3.7	3.95	4.20	4.5
Neutral	3.0	3.900000	0.608276	3.2	3.7	4.20	4.25	4.3
Positive	1381.0	4.109413	0.275757	2.0	4.0	4.10	4.30	5.0

- Positive sentiment reviews are associated with higher average ratings and slightly lower variability, suggesting that positive sentiment aligns with more consistent high ratings.
- The standard deviation of Neutral and negative are quite big (0.4 and 0.6 compared with 0.3), it shows that customers who have neutral and negative reviews tend to have wider range in rating.

[91]:

```
# Box plot to show the distribution of ratings by sentiment
plt.figure(figsize=(14, 8))
sns.boxplot(x='vader_sentiment', y='rating', data=df_clean)
plt.title('Ratings by Sentiment')
plt.xlabel('Sentiment')
plt.ylabel('Rating')
plt.show()
```



- Products with positive sentiment tend to have higher ratings, but there are still some lower-rated products with positive sentiment reviews.
- Products with negative sentiment have a wider distribution of ratings, including some very low ratings, though the median is still relatively high.
- The neutral sentiment group has a consistent range of ratings, without extreme highs or lows.

[92]:
```
correlation = df_clean['vader_sentiment_score'].corr(df_clean['rating'])
print(f"Correlation between sentiment score and rating: {correlation}")
```

```
Correlation between sentiment score and rating: 0.23757429505958585
```

Summary: - Since the correlation is positive, it means that as the sentiment score increases (i.e., reviews become more positive), the product rating tends to increase as well. However, the correlation is relatively weak. - A correlation of 0.238 suggests that while there is a relationship between sentiment and rating, it is not very strong. This means other factors may also be influencing the product ratings apart from sentiment. It's possible that even with positive sentiment, product quality, expectations, or other factors might moderate the final rating a customer leaves.

Analysis decision: Statistical Test - ANOVA (or Kruskal-Wallis if normality is violated).

- Null Hypothesis (H_0): There is no significant difference in ratings between products with different sentiment categories (Positive, Neutral, Negative).
- Alternative Hypothesis (H_1): At least one group (Positive, Neutral, or Negative) has a different mean rating.

Separate ratings by sentiment

[93]:
```
positive = df_clean[df_clean['vader_sentiment'] == 'Positive']['rating']
negative = df_clean[df_clean['vader_sentiment'] == 'Negative']['rating']
neutral = df_clean[df_clean['vader_sentiment'] == 'Neutral']['rating']
```

Assumptions for One-Way ANOVA Test There are three primary assumptions in ANOVA:

- The responses for each factor level have a normal population distribution.
- These distributions have the same variance.
- The data are independent.

Normality Test

Reasoning: - ANOVA calculates the F-statistic based on the variance between groups. The F-statistic assumes that the sampling distribution of group means follows a normal distribution. - When normality is violated, F-statistic is not accurately calculated, leading unrealiable p-values and results.

[94]:
```
# Check assumptions
# Normality test
print("Shapiro-Wilk Test for Normality:")
print("Positive:", shapiro(positive))
```

```
Shapiro-Wilk Test for Normality:
Positive: ShapiroResult(statistic=0.9335919937575671,
pvalue=2.5762248590440734e-24)
```

- Statistic = 0.9336, p-value= 2.576 x 10-24.
- p-value is less than 0.05 showing that ratings of positive group don't follow a normal distribution.

[95]:
```
print("Neutral:", shapiro(neutral))
```

```
Neutral: ShapiroResult(statistic=0.8175675675675672, pvalue=0.15716679846493964)
```

- Statistic = 0.8176, p-value= 0.1571.
- p-value is greater than 0.05 showing that the ratings of neutral group follow a normal distribution.

[96]:
```
print("Negative:", shapiro(negative))
```

```
Negative: ShapiroResult(statistic=0.9285336243876692,
pvalue=0.00024643656113262485)
```

- Statistic = 0.9285, p-value= 0.0002.
- p-value is less than 0.05 showing that the ratings of negative group don't follow a normal distribution.

- The Shapiro-Wilk test shows that the normality assumption for ANOVA is violated.
- Statistical test use Kruskal-Wallis H-test, which does not assume normality.

[97]:
```
# Perform Kruskal-Wallis H-test
kruskal_test = kruskal(positive, neutral, negative)
```

```
print("Kruskal-Wallis Test Result:", kruskal_test)
```

```
Kruskal-Wallis Test Result: KruskalResult(statistic=29.21216713258199,
pvalue=4.535848129287605e-07)
```

- p-value is less than 0.05, so we reject the null hypothesis.
- There is at least one sentiment group has a significantly different distribution of ratings.

[98]:
```
# Perform Dunn's test
dunn_test = sp.posthoc_dunn(df_clean, val_col='rating',␣
 ↪group_col='vader_sentiment', p_adjust='bonferroni')
print("Dunn's Post-Hoc Test Result:")
print(dunn_test)
```

```
Dunn's Post-Hoc Test Result:
              Negative  Neutral      Positive
Negative  1.000000e+00      1.0  1.998740e-07
Neutral   1.000000e+00      1.0  1.000000e+00
Positive  1.998740e-07      1.0  1.000000e+00
```

Summary:

Comparison	P-Value	Conclusion
Negative vs Neutral	1.0	No significant difference.
Negative vs Positive	1.999 x 10-07	Significant difference.
Neutral vs Positive	1.0	No significant difference.

- Products with Positive sentiment in reviews have significantly higher ratings compared to those with Negative sentiment.
- Neutral sentiment (n=3) may not provide enough statistical power to detect differences. Results involving this group should be interpreted cautiously.

Research Question 5: Which Categories of Products Receive the Highest or Lowest Ratings ?

Checking number of products of each category

[99]:
```
df_clean['main_category'].value_counts()
```

[99]:
```
Electronics              526
Computers&Accessories    452
Home&Kitchen             448
OfficeProducts            31
MusicalInstruments         2
HomeImprovement            2
Toys&Games                 1
Car&Motorbike              1
Health&PersonalCare        1
Name: main_category, dtype: int64
```

As we can see, `MusicalInstruments`, `HomeImprovement`, `Toys&Games`, `Car&Motorbike`, `Health&PersonalCare`, `OfficeProducts` have only 1 or 2 product, so we cannot analysis based on small sample size.

Analysis decision 1: Analyze products which are more than 100 units.

[100]:
```
# Count the number of products in each category
category_counts = df_clean.groupby('main_category').size().
↪reset_index(name='product_count')
```

[101]:
```
# Filter to get only categories with 3 or more products
valid_categories = category_counts[category_counts['product_count'] >=␣
↪100]['main_category']
```

[102]:
```
# Filter the original DataFrame to include only these valid categories
filtered_df = df_clean[df_clean['main_category'].isin(valid_categories)]
```

[103]:
```
# Display the filtered DataFrame
print(filtered_df['main_category'].value_counts())
```

```
Electronics             526
Computers&Accessories   452
Home&Kitchen            448
Name: main_category, dtype: int64
```

[104]:
```
# Group by category and calculate the mean rating
category_rating = filtered_df.groupby('main_category')['rating'].mean().
↪reset_index()

# Sort by rating to see highest and lowest
category_rating = category_rating.sort_values(by='rating', ascending=False)
print(category_rating)
```

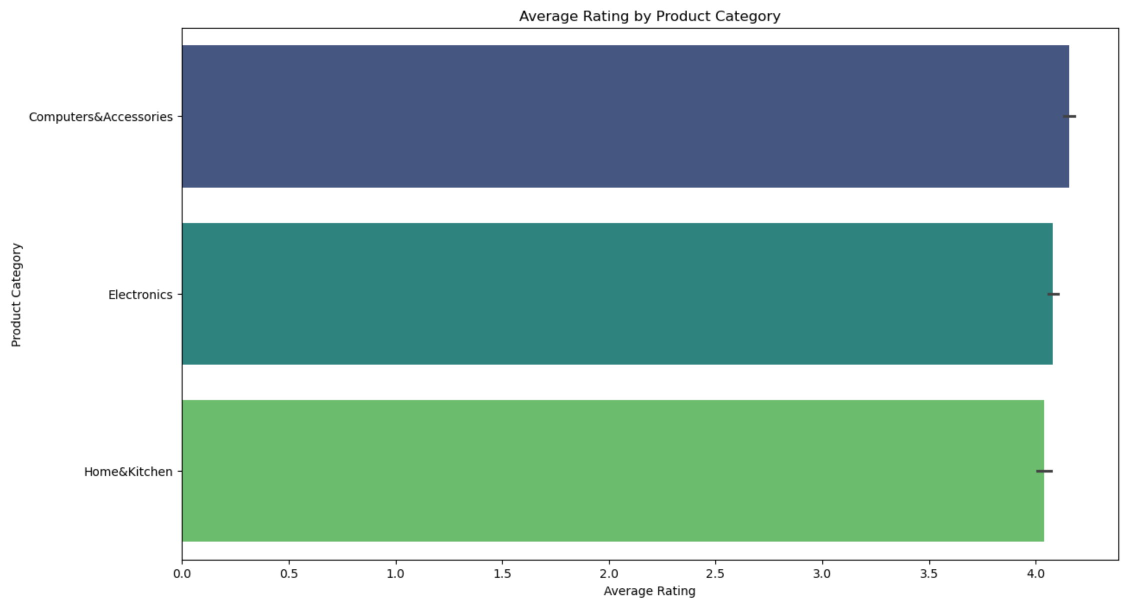
```
           main_category    rating
0  Computers&Accessories  4.155310
1            Electronics  4.081749
2           Home&Kitchen  4.040402
```

- All categories have relatively high ratings (above 4.0 on average)
- Computers & Accessories stands out with the highest ratings, indicating a slightly better customer perception in this category.

Analysis decision 2: Visualize the relationship between rating and product categories

[105]:
```
# Bar plot of average ratings by product category
plt.figure(figsize=(14, 8))
sns.barplot(x='rating', y='main_category', data=filtered_df,␣
↪hue='main_category', palette='viridis', dodge=False, legend=False)
plt.title('Average Rating by Product Category')
```

```
plt.xlabel('Average Rating')
plt.ylabel('Product Category')
plt.show()
```



- All categories have average ratings above 4.0, suggesting a good level of customer satisfaction across the board.
- Computers & Accessories leads slightly in customer satisfaction, possibly reflecting better perceived quality or value in this category compared to Electronics and Home & Kitchen.

Analysis decision 3: Calculate the correlation of rating per category.

[106]:
```
# Group by rating categories and calculate the correlation
grouped_by_rating_cat = filtered_df.
  ↪groupby(['main_category','mean_of_ratings']).apply(
    lambda x: x['discount_percentage'].corr(x['rating']) if len(x) > 1 else None
)

print(grouped_by_rating_cat)
```

```
main_category          mean_of_ratings
Computers&Accessories  Average           -0.209750
                       Good               0.164417
                       Excellent         -0.231080
Electronics            Low               -0.842989
                       Average           -0.052182
                       Good              -0.217358
                       Excellent          0.022300
Home&Kitchen           Low                0.594894
```

```
Average          -0.108601
Good             -0.157715
Excellent         0.019532
dtype: float64
```

Summary: - Electronics with low ratings show the strongest negative correlation (-0.842989), it shows that higher discounts are more common for lower-rated electronics. - Home & Kitchen Low-rated products (0.594894) and Computers & Accessories good-rated products (0.164417) show positive correlations, suggesting that discounts may be associated with better ratings in certain contexts within these categories. - Across all categories, the correlation between discounts and ratings is minimal for "Excellent" rated products, implying that discounts don't significantly impact ratings for highly-rated items

Analysis decision 4: Statistical Model

- Null Hypothesis (H_0): All product categories have the same mean rating.
- Alternative Hypothesis (H_1): At least one product category has a different mean rating.

Separate ratings by category

[107]:
```
# Separate ratings by category
computer_ratings = filtered_df[filtered_df['main_category'] ==␣
 ↪'Computers&Accessories']['rating']
electronic_ratings = filtered_df[filtered_df['main_category'] ==␣
 ↪'Electronics']['rating']
home_ratings = filtered_df[filtered_df['main_category'] ==␣
 ↪'Home&Kitchen']['rating']
```

ANOVA testing

Assumptions for One-Way ANOVA Test There are three primary assumptions in ANOVA:

- The responses for each factor level have a normal population distribution.
- These distributions have the same variance.
- The data are independent.

Checking normal poppulation distribution by using Shapiro: - Null Hypothesis (H_0): All categories is approximately normal distribution.

[108]:
```
# Perform Shapiro-Wilk test for each group
groups = filtered_df.groupby('main_category')['rating']
for category, ratings in groups:
    stat, p_value = shapiro(ratings)
    print(f"{category}: Statistic={stat}, p-value={p_value}")
```

```
Computers&Accessories: Statistic=0.9415858455461679,
p-value=2.442465472181653e-12
Electronics: Statistic=0.9376811105713512, p-value=4.991351256987308e-14
Home&Kitchen: Statistic=0.9082302623999396, p-value=8.098672245850888e-16
```

The p-values for all three categories are significantly smaller than 0.05: - Ratings in `Computers & Accessories`, `Electronics`, `Home & Kitchen` do not follow a normal distribution.

Perform Levene's test for equal variance: - Null Hypothesis (H_0): The variances of ratings across the categories (Computers & Accessories, Electronics, Home & Kitchen) are equal.

[109]:
```
# Perform Levene's test for equal variance
stat, p_value = levene(filtered_df[filtered_df['main_category'] ==␣
 ↪'Computers&Accessories']['rating'],
                       filtered_df[filtered_df['main_category'] ==␣
 ↪'Electronics']['rating'],
                       filtered_df[filtered_df['main_category'] ==␣
 ↪'Home&Kitchen']['rating'])
print(f"Levene's Test: Statistic={stat}, p-value={p_value}")
```

```
Levene's Test: Statistic=5.671881665220488, p-value=0.0035196498808331717
```

p-value < 0.05 (0.0035), The assumption of homogeneity of variance required for ANOVA is violated.

Apply Kruskal-Wallis as non-parametric alternative

[110]:
```
# Perform Kruskal-Wallis test
kruskal_result = kruskal(computer_ratings, electronic_ratings, home_ratings)
print("Kruskal-Wallis Test Result:", kruskal_result)
```

```
Kruskal-Wallis Test Result: KruskalResult(statistic=38.460658221531624,
pvalue=4.45014520587992e-09)
```

- p-value is much smaller than 0.05, we reject the null hypothesis.
- There is statistically significant difference in ratings across the categories.

[111]:
```
# Perform Dunn's test
dunn_test = sp.posthoc_dunn(filtered_df, val_col='rating',␣
 ↪group_col='main_category', p_adjust='bonferroni')
print("Dunn's Post-Hoc Test Result:")
print(dunn_test)
```

```
Dunn's Post-Hoc Test Result:
                       Computers&Accessories  Electronics  Home&Kitchen
Computers&Accessories           1.000000e+00     0.000052  4.332377e-09
Electronics                     5.234235e-05     1.000000  1.400520e-01
Home&Kitchen                    4.332377e-09     0.140052  1.000000e+00
```

- Computers&Accessories vs Electronics: p-value = 0.000052 (< 0.05). There is a statistically significant diffence in ratings.
- Computers&Accessories vs Home&Kitchen: p-value = 4.332 x 10-09 (< 0.05). There is a statistically significant diffence in ratings.
- Electronics vs Home&Kitchen: p-value = 0.14 (> 0.05). There is no a statistically significant diffence in ratings.

Summary: - Computers&Accessories has significantly different ratings compared to both Electronics and Home&Kitchen. - There is no statistically significant diffecne in ratings between Electronics and Home&Kitchen.

Research Question 6: Which factors of products have the greatest impact on the ratings?

Analysis decision 1: Creating new dataframe which includes all factors that affect to ratings

[112]:
```
#Filter Dataframe with additional factors
factors_df =  filtered_df[['main_category', 'log_number_of_reviews',␣
↪'discount_percentage', 'vader_sentiment_score', 'rating']]
```

Using get_dummies to encode categorical data (main_category column)

[113]:
```
# One-hot encode category
factors_df = pd.get_dummies(factors_df, columns=['main_category'],␣
↪drop_first=True)
```

Analysis decision 2: Transforming data into common range of values using Standardizing.

[114]:
```
# Standardize continuous variables
scaler = StandardScaler()
factors_df[['log_number_of_reviews', 'discount_percentage',␣
↪'vader_sentiment_score']] = scaler.fit_transform(
    factors_df[['log_number_of_reviews', 'discount_percentage',␣
↪'vader_sentiment_score']]
)
```

General view of the dataset

[115]:
```
print(factors_df.head())
```

```
   log_number_of_reviews  discount_percentage  vader_sentiment_score  rating  \
0               0.877532             0.737947               0.225448     4.2
1               1.167685            -0.259461               0.447675     4.0
2               0.331839             1.972834              -0.377546     3.9
3               1.539906             0.215496               0.031135     4.2
4               0.701162             0.595461               0.435751     4.2

   main_category_Electronics  main_category_Home&Kitchen
0                          0                           0
1                          0                           0
2                          0                           0
3                          0                           0
4                          0                           0
```

Analysis decision 3: Comparing among non-linear models.

Because the relationships are mostly non-linear, I choose 3 different non-linear models: - PolynomialFeatures - RandomForestRegressor - GradientBoostingRegressor.

First step is to define features and target

[116]:
```
# Define features and target
X = factors_df.drop('rating', axis=1)
y = factors_df['rating']
```

Split dataset into train and test

[117]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

Polynomial Features

Generate **Polynomial Features**

[118]:
```
poly = PolynomialFeatures(degree=2)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)
```

Fix the model:

[119]:
```
poly_model = LinearRegression()
poly_model.fit(X_train_poly, y_train)
```

[119]:
```
LinearRegression()
```

Predictions and evaluation

[120]:
```
y_pred_poly = poly_model.predict(X_test_poly)
print("Polynomial Regression MSE:", mean_squared_error(y_test, y_pred_poly))
print("Polynomial Regression R²:", r2_score(y_test, y_pred_poly))
```

```
Polynomial Regression MSE: 0.06544389421926755
Polynomial Regression R²: 0.25523110560106066
```

Random Forest

Generate and fit the model:

[121]:
```
rf_model = RandomForestRegressor(random_state=42)
rf_model.fit(X_train, y_train)
```

[121]:
```
RandomForestRegressor(random_state=42)
```

Predictions and evaluation

[122]:
```
y_pred_rf = rf_model.predict(X_test)
print("Random Forest MSE:", mean_squared_error(y_test, y_pred_rf))
print("Random Forest R²:", r2_score(y_test, y_pred_rf))
```

```
Random Forest MSE: 0.06293518531468523
Random Forest R²: 0.283780879105897
```

Gradient Boosting

Generate and fit the model:

[123]:
```
gb_model = GradientBoostingRegressor(random_state=42)
gb_model.fit(X_train, y_train)
```

[123]:
```
GradientBoostingRegressor(random_state=42)
```

Predictions and evaluation

[124]:
```
y_pred_gb = gb_model.predict(X_test)
print("Gradient Boosting MSE:", mean_squared_error(y_test, y_pred_gb))
print("Gradient Boosting R²:", r2_score(y_test, y_pred_gb))
```

```
Gradient Boosting MSE: 0.06521469836755767
Gradient Boosting R²: 0.25783941525492815
```

Summary:

- **Random Forest Regressor:** Lowest MSE (0.0629) and the highest R2(0.2838), so this model is the best performer.
- **Gradient Boosting Regressor:** MSE = 0.0652 and R2 = 0.2578, performs better than Polynomial Regression but worst than Random Forest Regressor.
- **Polynomial Regression** MSE = 0.0654 and the highest R2 = 0.2552, performs the worst among the three non-linear models.

Because of the best performance, I choose Random Forest model to do the further steps.

Analysis decision 4: Random Forest Regressor Model.

Using GridSearchCV to find the better fit model for the dataset.

[125]:
```
# Define parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],          # Number of trees
    'max_depth': [10, 20, None],             # Maximum depth of the trees
    'min_samples_split': [2, 5, 10],         # Minimum samples to split a node
    'min_samples_leaf': [1, 2, 4]            # Minimum samples at a leaf node
}
```

[126]:
```
# Perform Grid Search
grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid, cv=5,␣
 ↪scoring='r2', verbose=0, n_jobs=-1)
grid_search.fit(X_train, y_train)
```

[126]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42), n_jobs=-1,
             param_grid={'max_depth': [10, 20, None],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [100, 200, 300]},
```

```
                scoring='r2')
```

[127]:
```python
# Best parameters and evaluation
print("Best Parameters:", grid_search.best_params_)
```

```
Best Parameters: {'max_depth': 20, 'min_samples_leaf': 4, 'min_samples_split':
10, 'n_estimators': 100}
```

[128]:
```python
# define the best rf model and put it in best_rf variable
best_rf = grid_search.best_estimator_
```

[129]:
```python
# Predictions and evaluation
y_pred_best_rf = best_rf.predict(X_test)
print("Tuned Random Forest MSE:", mean_squared_error(y_test, y_pred_best_rf))
print("Tuned Random Forest R²:", r2_score(y_test, y_pred_best_rf))
```

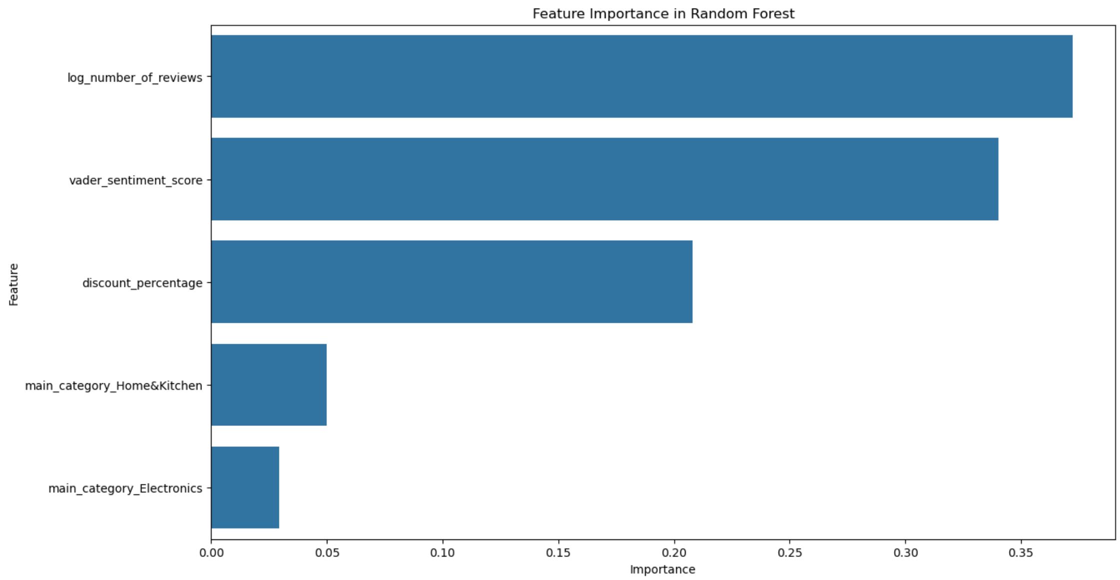
```
Tuned Random Forest MSE: 0.062440067048546405
Tuned Random Forest R²: 0.289415456449865
```

- The MSE is lower than previous rf model (0.0624 < 0.0629) and the R2 is higher (0.2894 > 0.2838).
- The new tuned model give bester performance.

[130]:
```python
# Extract feature importance
feature_importance = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': best_rf.feature_importances_
}).sort_values(by='Importance', ascending=False)
```

Visualize feature importance to identify which factor is more affected.

[131]:
```python
# Visualize feature importance
plt.figure(figsize=(14, 8))
sns.barplot(x='Importance', y='Feature', data=feature_importance)
plt.title('Feature Importance in Random Forest')
plt.show()
```



Summary: - log_number_of_reviews is the most important feature, products with more reviews are likely to have higher ratings, as more reviews generally stabilize the overall rating through averaging. - vader_sentiment_score is the second most influential feature, positive sentiment in customer reviews significantly correlates with higher ratings. - discount_percentage rank third in importance, moderately discounted products might be rated higher due to perceived value, but extreme discounts could signal lower-quality items. - categories seem not very important feature the affect the ratings.

2

2.1 Conclusions

1. Are higher discount percentages are associated with lower product ratings?

- The relationship is weak negative between discount percentage and average product rating.
- Higher discounts tend to correlate with lower ratings, possibly because of lower product quality, the product must be heavily discounted.

2. Do products with more reviews have higher average ratings?

- There is a weak positive relationship between the number of reviews and average product ratings. Products with more reviews tend to have slightly higher ratings, but the effect is small.
- Products with more reviews tend to have tighter rating distributions, suggesting that increased visibility may lead to more consistent ratings, potentially due to a larger and more diverse customer base.
- Higher review counts have a stronger positive impact on lower-rated products, potentially helping improve their ratings slightly. However, for "Excellent" rated products, the effect of additional reviews on rating is minimal or even slightly negative.

3. Do higher-priced products receive better ratings than lower-priced ones?

- Higher-priced products receive better ratings than lower-priced products, but the difference is minimal, indicating that price alone is not a major determinant of product rating.
- Higher-priced products show slightly more consistent ratings (lower standard deviation), suggesting that customers may have more stable expectations for higher-priced items.
- The weak positive correlation between price and rating within both groups implies that customers slightly favor higher-priced products, but this effect is minor and likely influenced by other factors such as product quality or brand reputation.

4. Do Products with Positive Sentiment in Reviews Have Higher Ratings?

- Products with positive sentiment in reviews tend to have higher ratings compared to those with neutral or negative sentiment, confirming that sentiment is a useful indicator of product rating.
- The ANOVA test confirms that these differences are statistically significant, suggesting that the sentiment expressed in reviews is a meaningful predictor of product rating.
- For businesses, encouraging positive customer sentiment in reviews can positively impact product ratings. This highlights the importance of customer satisfaction and quality in maintaining high ratings.

5. Which Categories of Products Receive the Highest or Lowest Ratings?

- Computers & Accessories has the highest average rating (4.16), suggesting that this category generally has a higher level of customer satisfaction.
- Home & Kitchen has the lowest average rating among the analyzed categories, though the difference is minimal, indicating that all three categories generally receive favorable ratings.
- In Electronics and Computers & Accessories, lower-rated products tend to have higher discounts, which may indicate a strategy to boost sales or attractiveness despite lower customer satisfaction.
- Home & Kitchen shows a unique pattern where low-rated products actually benefit in ratings with higher discounts, as indicated by the positive correlation for Low ratings.

6. Which factors of products have the greatest impact on the ratings?

- The number of reivews, review sentiment and discount percentage positively impact the ratings.
- Encouraging more reviews can help improve ratings and provide potential customers with greater confidence.
- Note that excessively high discounts can correlate with lower ratings, the customer will concerns about product quality if the discounts are too high.

Limitation

- The dataset may not cover all product categories comprehensively, leading to potential biases in conclusions.
- The sentiment scores are based on automated tool, which may not capture customer feedback accurately.
- Price and discount data are not perfectly normal distribution, which can skew the analysis.
- Ratings may be influenced by category-specific factors that were not accounted for in the analysis.

[137]:
```
from subprocess import run
result = run(['python', '-m', 'nbconvert', '--to', 'html',␣
↪'Investigate_a_Dataset.ipynb'])
print("Conversion successful!" if result.returncode == 0 else "Conversion␣
↪failed.")
```

```
[NbConvertApp] Converting notebook Investigate_a_Dataset.ipynb to pdf
[NbConvertApp] Support files will be in Investigate_a_Dataset_files/
[NbConvertApp] Making directory ./Investigate_a_Dataset_files
[NbConvertApp] Making directory ./Investigate_a_Dataset_files
[NbConvertApp] Making directory ./Investigate_a_Dataset_files
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[NbConvertApp] Making directory ./Investigate_a_Dataset_files
[NbConvertApp] Making directory ./Investigate_a_Dataset_files
[NbConvertApp] Writing 205571 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
```

```
Conversion successful!
```

```
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 725884 bytes to Investigate_a_Dataset.pdf
```

[ ]:
```
result = run(['python', '-m', 'nbconvert', '--to', 'pdf',␣
↪'Investigate_a_Dataset.ipynb'])
print("Conversion successful!" if result.returncode == 0 else "Conversion␣
↪failed.")
```

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