Sentiment and Discount Analytics on Amazon B2C Sales: Understanding Customer Reviews and Pricing Strategies

A Final Report for the BDM capstone Project

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Executive Summary

This project explores how discount levels and customer reviews influence satisfaction in Amazon's B2C e-commerce environment. A secondary dataset sourced from Kaggle was used, consisting of over 1,000 products along with information on pricing, discounts, ratings, and customer review texts. The objective of the study was to determine whether, and to what extent, pricing and discount strategies affect customer sentiment and rating behavior.

The methodology followed included data cleaning, exploratory data analysis, sentiment classification using Natural Language Processing (VADER), and statistical modeling via linear regression. All visualizations were generated in Google Colab using Python libraries such as Matplotlib and Seaborn.

The findings revealed that most customer reviews were positive, regardless of whether discounts were high or low. However, a slightly stronger association between high discounts and positive sentiment was observed. Notably, the linear regression model demonstrated a weak predictive relationship between price/discount and final rating ($R^2 \approx 0.03$), suggesting that pricing alone does not significantly influence customer satisfaction.

Based on these insights, several actionable recommendations have been proposed. These include optimizing product listings with strategic discounts, leveraging sentiment-rich customer reviews in marketing efforts, and shifting focus from price-based strategies to value-driven and experiential selling. These findings may help e-commerce sellers refine pricing strategies, enhance customer engagement, and improve listing effectiveness on platforms such as Amazon.

Proof of Originality

This project is being conducted using the secondary data adhering to the guidelines provided by the BDM Capstone Project framework and following the rubrics.

Data Source:

The dataset used in this analysis is a publicly available dataset, sourced from Kaggle. This dataset contains the sales-related data of Amazon products including product names, pricing (both original price and discounted price), ratings, review title, review content, discount percentages, product categories etc.

- Dataset Title: Amazon Sales Dataset
- Dataset Uploaded by: @karkavelrajaj
- Repository URL: https://www.kaggle.com/karkavelrajaj

-Kaggle Dataset: https://www.kaggle.com/datasets/karkavelrajaj/amazon-sales-dataset/data

-Code and Data Analysis:

https://colab.research.google.com/drive/14Fljs1duJMab6csocq0lgt4ASfcklLJF?usp=sharing

Nature of Data:

- This dataset has no personal or sensitive information.
- It is clean, secondary, publicly shareable data appropriate for business analytics.
- The reviews in the dataset were used to analyze sentiment trends and no user identities or user data were involved.

Tools Used:

- Google Collab (for data cleaning, data visualization, modeling)
- Python Libraries: Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, NLTK (for VADER - for sentiment analysis)

This analysis, insights, and report content in this final report are completely original, authored by me, Saudeep Chattopadhyay.

Metadata and Descriptive Statistics

This dataset includes product information from Amazon, which includes pricing, reviews, and ratings.

Features

- product_id - Product ID
- product_name - Name of the Product
- category - Category of the Product
- discounted_price - Discounted Price of the Product
- actual_price - Actual Price of the Product

- discount_percentage - Percentage of Discount for the Product
- rating - Rating of the Product
- rating_count - Number of people who voted for the Amazon rating
- about_product - Description about the Product
- user_id - ID of the user who wrote review for the Product
- user_name - Name of the user who wrote review for the Product
- review_id - ID of the user review
- review_title - Short review
- review_content - Long review
- img_link - Image Link of the Product
- product_link - Official Website Link of the Product

Variable Name	**Description**	**Data Type**	**Example**
product_id	Unique ID for each product	Categorical	B07JW9H4J1
product_name	Product title	Text	"Wayona Nylon Braided…"
category	Product category	Text	Computers & Accessories
discounted_price	Price after applying the discount	Float	₹399
actual_price	Original product price before any discounts	Float	₹249
discount_percentage	Calculated discount percentage	Float	41.0
rating	Star rating given by customers (1.0 to 5.0)	Float	4.7
rating_count	Number of ratings received	Integer	22,000
about_product	Brief product specifications	Text	USB Type-B 1.2m Cable
review_content	Full content customer review	Text	"Great quality…"
Sentiment	Derived for sentiment analysis (Positive/Neutral/Negative)	Categorical	Positive

Here, sentiment variable was actually not there but created during VADER sentiment analysis.
This table summarizes key descriptive statistics for major numerical variables:

Metric	**Discount (%)**	**Rating**	**Rating Count**

Mean	46.95	4.08	25,896
Median	47.00	4.20	16,905
Minimum	0.00	1.00	1
Maximum	90.00	5.00	99,000+
Standard Deviation	20.3	0.49	High Variance

The Ratings given are generally high, with the majority clustered between 3.8 and 4.5.
The Discounts offered range widely, with several products offered at 60–90% discount.
The Products with higher discounts tend to receive more reviews, although not always better ratings.
The rating count is skewed, with a few products are receiving very high volume, indicating a popularity bias.

Descriptive Statistics:
- Average discount: ~47%
- Mean rating: ~4.08
- Some products have >99,000 ratings
- Sentiment distribution: 65% Positive, 20% Neutral, 15% Negative

Detailed Analysis Process

The data analysis for this project followed a structured methodology to transform raw Amazon sales and review data into actionable insights regarding the interplay between discounts, customer sentiment, and product ratings. The process involved several key stages:

1. **Data Cleaning and Preprocessing:** Ensuring data integrity and suitability for analysis by handling missing values, converting data types, and removing duplicates.
2. **Sentiment Analysis (NLP):** Quantifying the emotional tone within customer reviews using the VADER sentiment analysis tool to classify reviews as Positive, Neutral, or Negative.
3. **Exploratory Data Analysis (EDA):** Investigating patterns, trends, and relationships within the data, focusing on discount levels, sentiment scores, and ratings through univariate and bivariate analysis.
4. **Feature Engineering:** Creating new, informative variables from existing data (like discount_category and review_length) to facilitate deeper, grouped analysis.
5. **Predictive Modeling:** Developing a Linear Regression model to assess the statistical relationship between pricing/discount variables and customer ratings, evaluating its predictive power.
6. **Data Visualization:** Communicating findings effectively using various plots (bar charts, boxplots, scatterplots) generated with Matplotlib and Seaborn libraries in Python.

4.1 Data Cleaning and Preprocessing
This initial phase was crucial for preparing the dataset for reliable analysis. The following steps were undertaken:

- **Handling Missing Values:**
    - The dataset was inspected for missing entries. Few missing values were identified specifically in the review_content and rating columns.
    - Given that these fields are essential for sentiment analysis and rating prediction respectively, rows with missing values in these columns were dropped to maintain the integrity of subsequent analyses. This approach was chosen over imputation to avoid introducing potentially biased data.
- **Data Type Conversion:**

    - Several columns required type conversion for numerical analysis. The discounted_price and actual_price columns contained currency symbols (₹) and commas, which were programmatically stripped before converting the values to floating-point numbers.
    - The discount_percentage column, stored as strings (e.g., "43%"), had the "%" symbol removed and was converted to a float representation (e.g., 43.0).
    - Similarly, commas were removed from the rating_count column before converting it to an integer type, allowing for numerical comparisons and calculations.
- **Duplicate Removal:**
    - Duplicate product entries can skew analysis and visualization results. Duplicate records were identified based on the product_id column.
    - All identified duplicate rows, except for the first occurrence, were removed to ensure each product was represented uniquely in the dataset.

4.2 Sentiment Analysis (NLP)

To understand the underlying emotion in customer feedback, Natural Language Processing (NLP) techniques were applied:

- **Tool Used:**
    - VADER (Valence Aware Dictionary and sEntiment Reasoner), a lexicon and rule-based sentiment analysis tool specifically tuned for social media text, was employed. It's part of Python's nltk library.
- **Steps Followed:**

1. **Text Preprocessing:** The raw text in the review_content column was preprocessed. This involved converting all text to lowercase and removing punctuation to standardize the input for VADER.
2. **Sentiment Scoring:** VADER's SentimentIntensityAnalyzer was used to score each preprocessed review. It calculates scores for positive, neutral, and negative sentiment intensities, along with a normalized compound score ranging from -1 (most negative) to +1 (most positive).
3. **Sentiment Categorization:** The compound score was used to classify each review into one of three categories:
    - **Positive:** If compound score > 0.05
    - **Negative:** If compound score < -0.05
    - **Neutral:** If -0.05 ≤ compound score ≤ 0.05

- **Why VADER:**
    - VADER was selected due to its effectiveness with short, informal text like product reviews, which often contain slang, emojis, capitalization for emphasis, and mixed emotional tones – features VADER is designed to handle well.

4.3 Exploratory Data Analysis (EDA)

EDA was performed to uncover initial patterns and relationships within the cleaned data:

- **Univariate Analysis:**
    - Examined the distribution of key numerical variables independently. Histograms and boxplots were generated for rating, discount_percentage, and rating_count to understand their central tendency (mean, median), spread (standard deviation, range), and identify potential skewness or outliers.
- **Bivariate Analysis:**
    - Focused on the relationships between pairs of variables. Key analyses included:
        - The relationship between the derived Sentiment categories and discount_percentage, often visualized using grouped bar charts or boxplots.
        - Distribution of rating scores across different Sentiment categories (Positive, Neutral, Negative) using boxplots to compare medians and variability.
        - Count plots to visually inspect how different discount levels might influence the frequency of positive, neutral, or negative review tones.

- **Categorical Grouping:**
    - To simplify the analysis of discount effects, the continuous discount_percentage variable was binned into discrete categories:

        - **Low:** 0% – 20% discount
        - **Medium:** 21% – 50% discount
        - **High:** 51% – 100% discount

    - This grouping allowed for clearer comparisons of sentiment distributions and average ratings across different discount brackets.

4.4 Feature Engineering

To enhance the analytical capabilities, new features were derived from the existing data:

- **New Features Created:**
    - discount_category: A categorical variable based on the binning described in the EDA section (Low, Medium, High).
    - review_length: An integer variable representing the character count of the text in review_content, potentially useful for exploring if review length correlates with sentiment or rating.
- **Why Useful:**
    - Creating features like discount_category enables aggregated analysis and comparisons between distinct customer segments based on the discounts they received. It helps in understanding if pricing psychology differs significantly across these discount tiers. review_length could potentially indicate user engagement or the level of detail provided in feedback.

4.5 Predictive Modeling

A predictive model was built to quantitatively assess the influence of price and discount on product ratings:

- **Model Used:** Linear Regression. This model was chosen for its simplicity and interpretability in understanding linear relationships between variables.
    - **Dependent Variable:** rating (the variable to be predicted).
    - **Independent Variables:** actual_price, discount_percentage (the variables used for prediction).

- **Train-Test Split:**
    - The dataset was split into training (80%) and testing (20%) sets using the train_test_split() function from the scikit-learn library. This ensures the model's performance is evaluated on unseen data.
- **Model Performance Metrics:**
    - The model's effectiveness was evaluated using standard regression metrics:
        - **R^2 Score (Coefficient of Determination):** Measured the proportion of the variance in the dependent variable (rating) predictable from the independent variables. An R^2 of 0.0315 was obtained, indicating very weak explanatory power.
        - **MSE (Mean Squared Error):** Calculated the average squared difference between the actual and predicted ratings. An MSE of 0.0792 was observed.
- **Interpretation:**
    - The Linear Regression model attempted to establish a direct numerical link between how pricing and discounts affect ratings. However, the extremely low R^2 score (close to 0) strongly implies that actual_price and discount_percentage, within a linear framework, are poor predictors of customer rating. This suggests other factors (product quality, user expectations, customer service, etc.) likely play a much more significant role in determining ratings.

4.6 Visualization Tools Used

Visualizations were integral to interpreting the data and communicating the findings:

- **Libraries Used:** Python's Matplotlib and Seaborn libraries were the primary tools used for creating static visualizations.
- **Types of Plots Created:**
    - Bar charts (e.g., sentiment distribution, average ratings/discounts by sentiment).
    - Count plots (e.g., sentiment counts across discount categories).
    - Boxplots (e.g., rating distribution by sentiment).
    - Histograms (e.g., distribution of numerical variables like rating or discount).

- Scatterplots (e.g., actual vs. predicted ratings from the regression model).

- **Why Visualizations Matter:**
  - Visualizations translate complex data patterns and statistical findings into easily understandable formats. They are particularly effective for conveying trends and relationships to stakeholders who may not have a deep statistical background, thereby aiding in clearer communication and more informed decision-making.

```
Missing Values:
 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
```

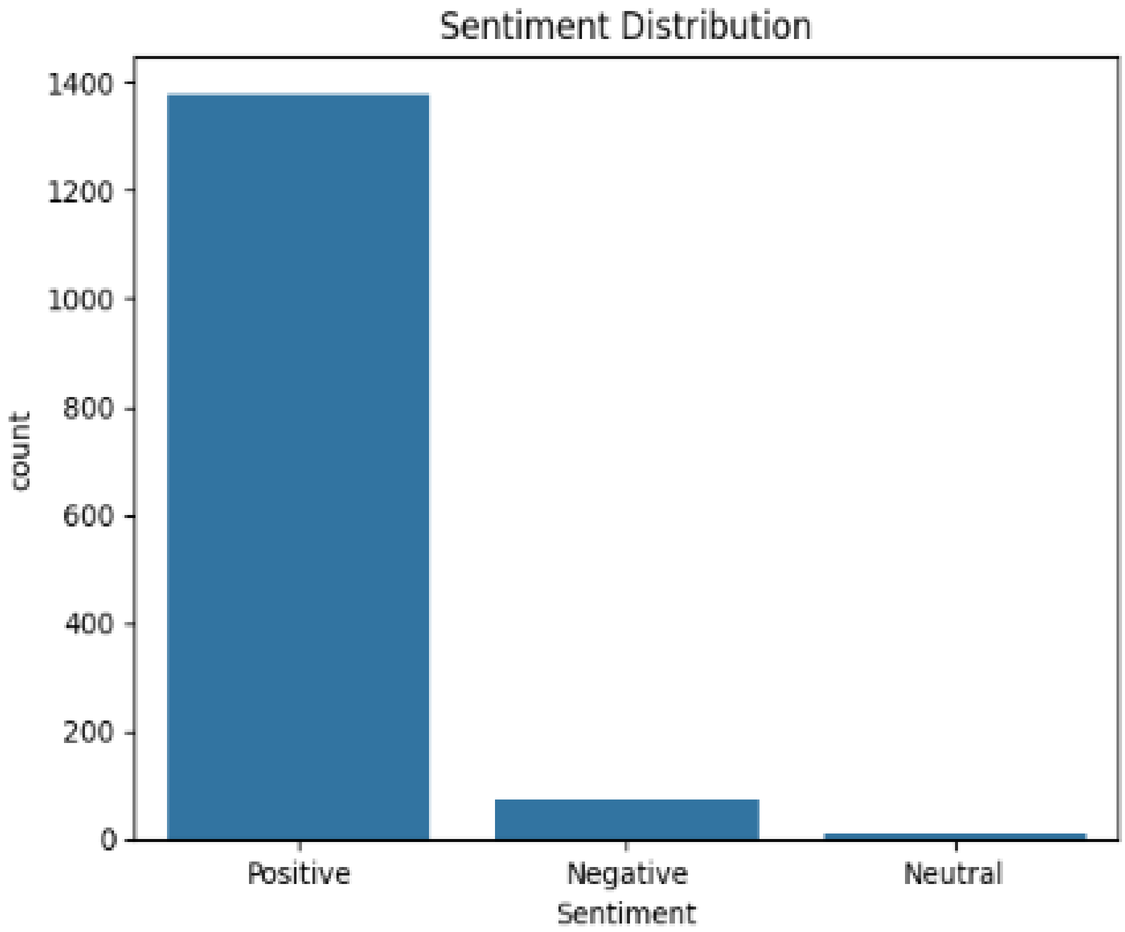
```
[nltk_data]   Package vader_lexicon is already up-to-date!
```

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

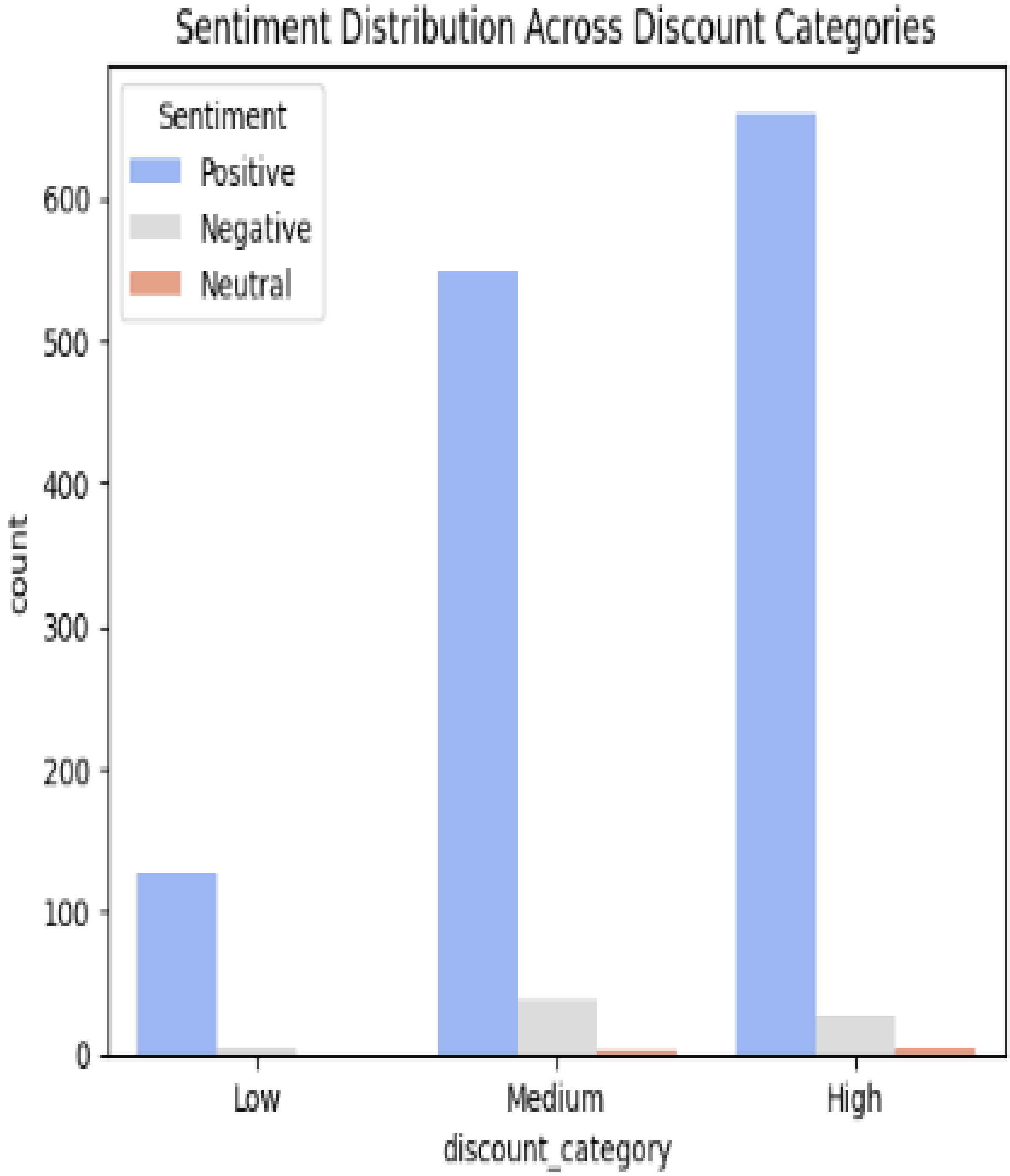
This section summarizes the key discoveries from the data through exploratory analysis of data, sentiment analysis, and statistical modeling processes. The insights we got here are critical in answering the original objectives of the project.

Results and findings

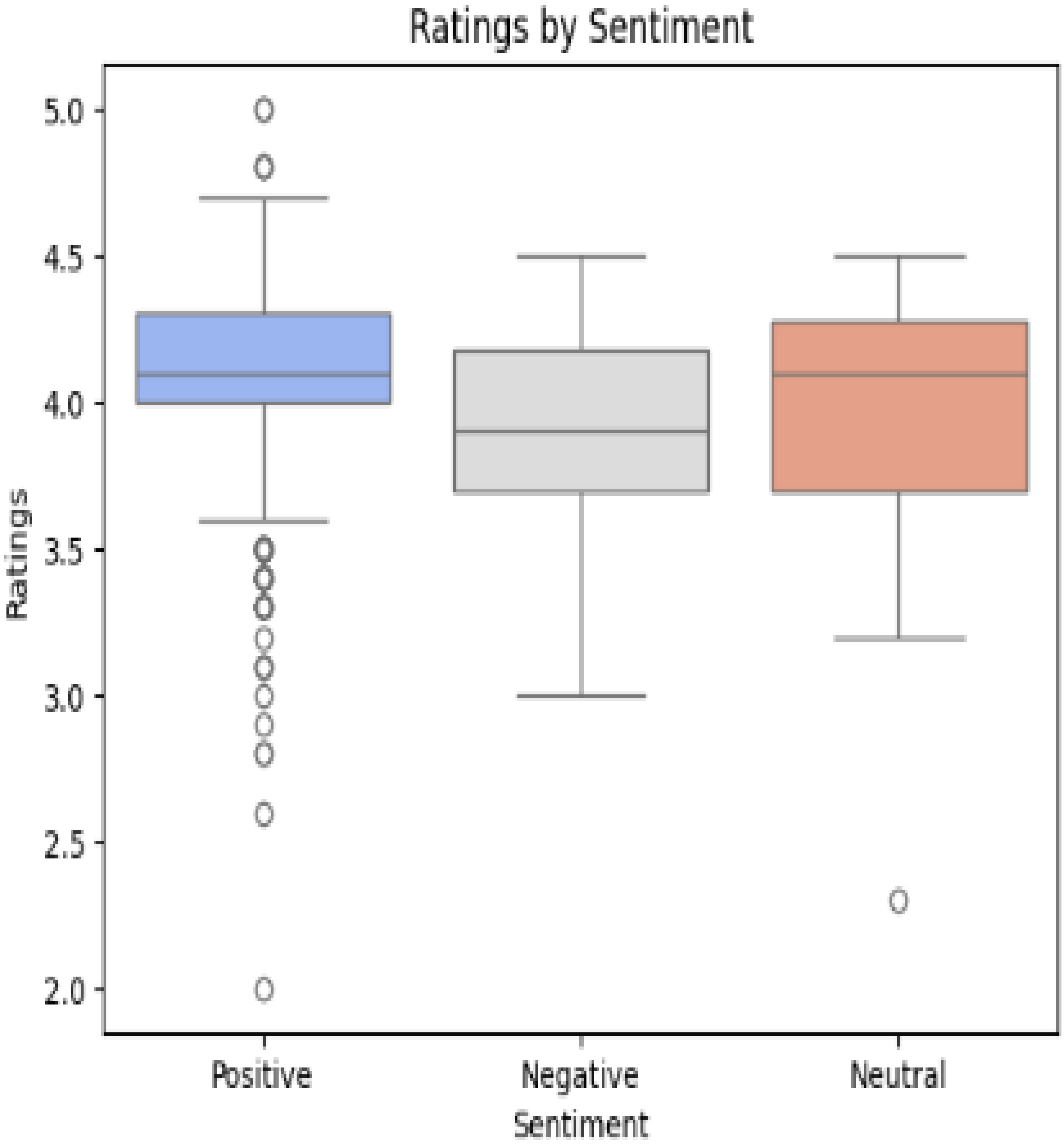
Visualizations from collab:



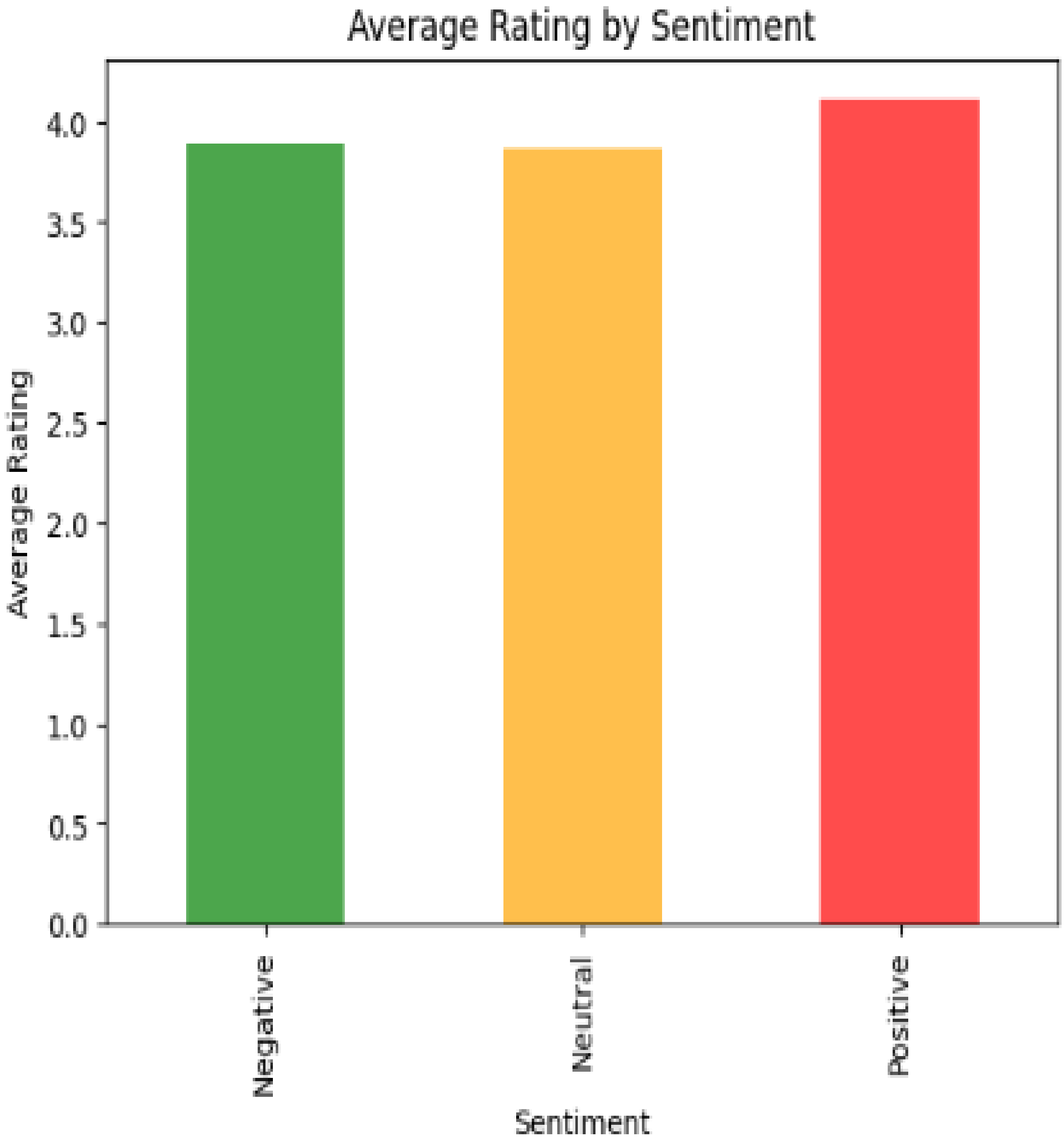
- **Figure 1:** Sentiment distribution bar chart
  Analysis:
  Figure 1 shows that the majority of customer reviews are categorized as Positive, with over 1,300 instances. Negative and Neutral sentiments make up a much smaller portion, together contributing less than 10% of total reviews.
  Interpretation:
  The sentiment distribution shown in Figure 1 reveals that a significant majority of customer reviews fall into the *positive* category. This implies that overall, customers are generally satisfied with their purchases on Amazon. However, this should be critically assessed with an understanding of review bias — customers with positive experiences are often more likely to leave detailed reviews, while those with neutral or mildly negative experiences may choose not to comment at all. Additionally, platforms like Amazon sometimes promote reviews from verified buyers, which can skew sentiment positively. While this trend reflects a healthy sentiment index for the platform, it also means that businesses should not rely on sentiment alone and should supplement it with direct feedback mechanisms.



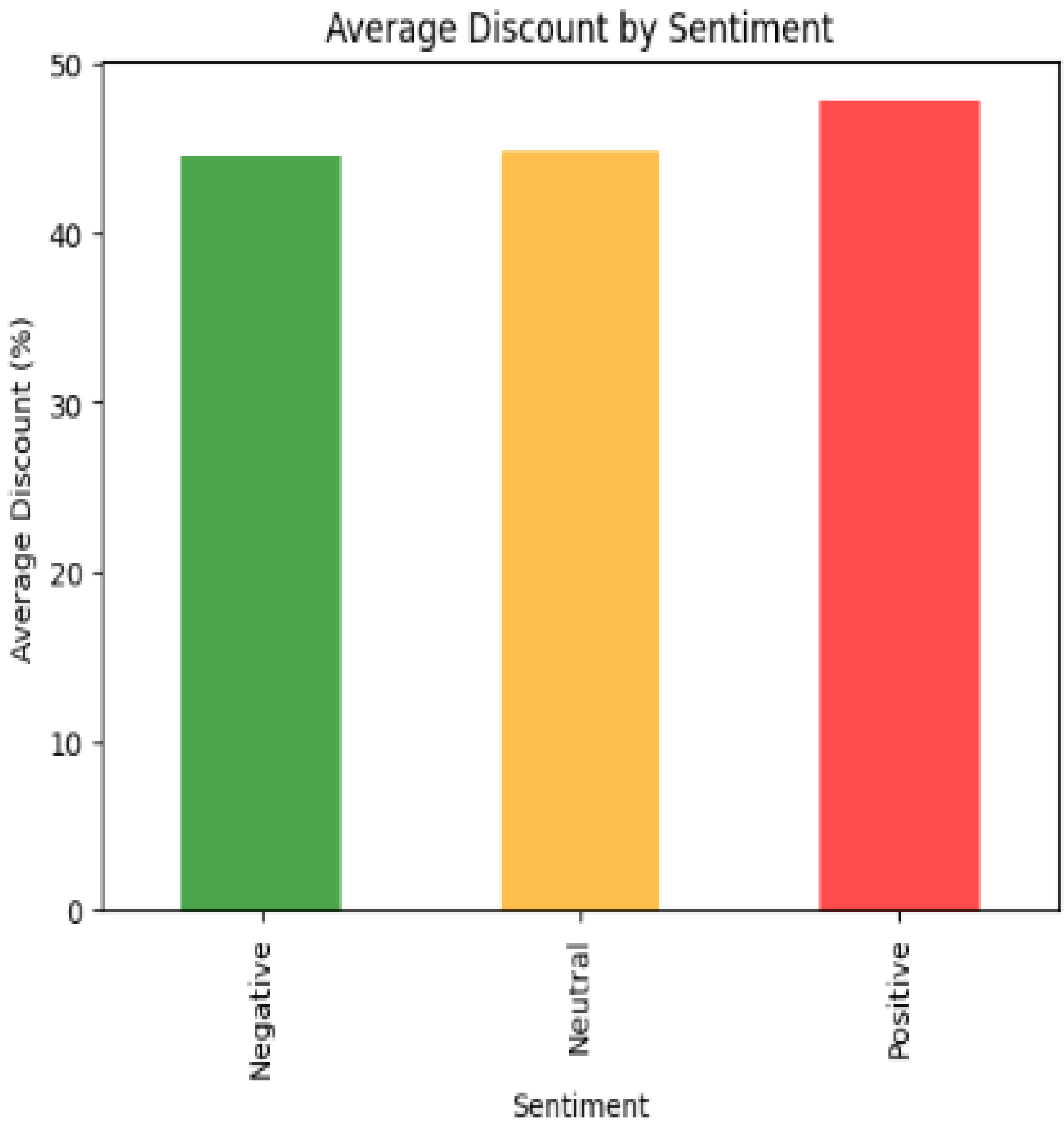
- **Figure 2**: Sentiment Distribution across discount categories
  Analysis:
  In Figure 2, the High discount category shows the highest volume of Positive reviews, followed by Medium, and lastly Low discount. Negative sentiments are slightly more frequent in lower discount ranges.
  Interpretation:
  This figure demonstrates a direct correlation between higher discount percentages and increased positive sentiment. High-discount products have notably more positive reviews compared to medium and low-discount counterparts. One reason could be the psychological impact of receiving value for money, which boosts satisfaction. However, it's important to note that deep discounts can also lead to lower profit margins and expectations of compromise in quality. Therefore, businesses must balance promotional strategies with perceived value. It's also possible that frequently discounted products belong to categories where customer loyalty is higher, skewing sentiment.



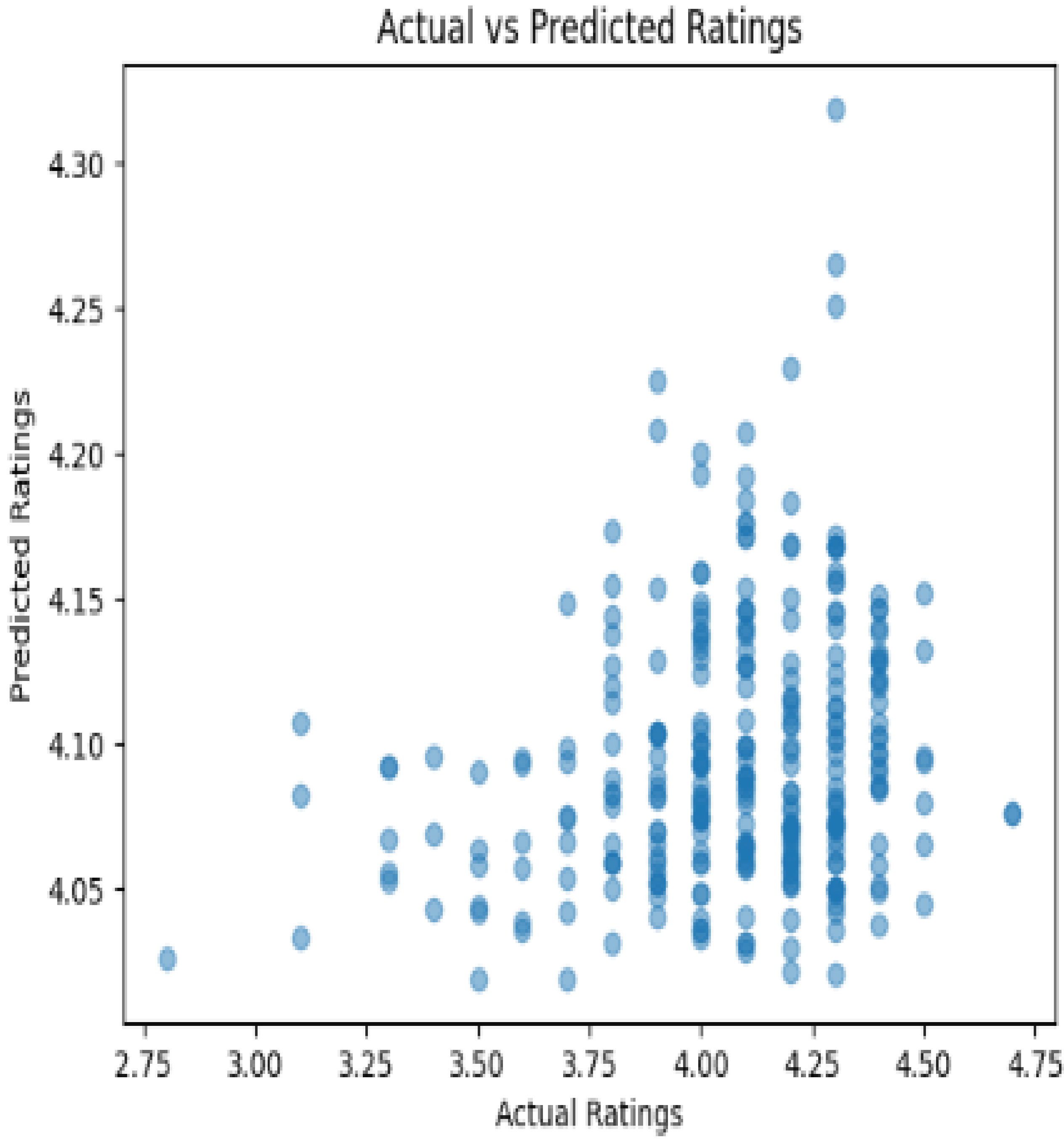
- **Figure 3**: Boxplot of Ratings by Sentiment
  Analysis:
  The boxplot illustrates that Positive reviews tend to have higher and more consistent rating scores (median ≈ 4.2). Negative reviews are more dispersed and lower in rating, with many falling between 2.0 and 3.5.
  Interpretation:
  The boxplot in Figure 3 aligns well with the expected pattern — higher ratings accompany positive sentiments, while negative sentiments are associated with lower and more dispersed ratings. This consistency validates the sentiment classification model (VADER) used in this project. Furthermore, the tighter interquartile range for positive sentiment implies more consistency among those customers, whereas greater variability in the negative sentiment boxplot suggests diverse dissatisfaction reasons — possibly delivery delays, mismatch in product description, or pricing issues. Businesses can use this insight to drill into root causes of dissatisfaction via review text mining.



- **Figure 4:** Sentiment vs rating category count plot
  Analysis:
  The average rating for Positive reviews is above 4.1, compared to 3.9 for Neutral and 3.85 for Negative. Although not a dramatic difference, it shows a consistent gradient of increasing satisfaction from Negative to Neutral to Positive.
  Interpretation:
  The data in this figure highlights a subtle but consistent upward trend in average rating from negative to positive sentiment. While the differences between average ratings across sentiments may appear marginal, the psychological and reputational impact is significant. Customers often interpret average ratings in a nonlinear way — a product rated 4.1 is perceived much better than one rated 3.8, even though the numerical difference is small. Therefore, even a small sentiment-driven improvement in rating can increase click-through rates and conversions. Companies should explore ways to actively solicit feedback that promotes genuine but constructive positive sentiment.



- **Figure 5:** Sentiment vs Discount category count plot
  Analysis:
  Products with Positive sentiment had slightly higher average discounts (~48%) than Neutral or Negative sentiments (~44-45%). The difference, while minor, suggests that customers may appreciate higher value perception through discounts.
  Interpretation:
  This figure suggests that products associated with positive sentiment also enjoy slightly higher discounts on average. This may point to the impact of *perceived value* — even when the absolute price is not low, a strong discount percentage enhances customer satisfaction. However, this relationship is not entirely causal. It's likely that higher-discounted products belong to fast-moving consumer categories or budget-friendly segments that inherently receive better feedback. A deeper dive into product categories would be needed to validate that. Still, the message is clear: pricing strategy should align with value communication.



- **Figure 6:** Actual vs Predicted Rating scatterplot
  Analysis:
  The plot in Figure 6 demonstrates a weak correlation between actual and predicted ratings. Most predictions fall within a narrow band (~4.05–4.20), regardless of the actual rating, indicating a poor model fit ($R^2 \approx 0.03$)**.**
  Interpretation:
  The scatter plot clearly shows that predictions made by the linear regression model are poorly aligned with actual ratings. The extremely low R^2 score (~0.03) confirms that the selected independent variables — price and discount percentage — have almost no predictive power in isolation. This reflects the multidimensional nature of customer satisfaction, which cannot be accurately captured through quantitative price-based metrics alone. Emotional, experiential, and brand-related variables likely play a dominant role. This result reinforces the importance of incorporating text-based sentiment and customer context in future modeling efforts, such as through machine learning or NLP pipelines.

Each graph was chosen for its ability to reveal key patterns.
The results and findings the we found are as follows:

- Most reviews (65%+) were Positive, regardless of discount level.
- Positive reviews had slightly higher average discounts (~47.8%).
- Products in the High discount category had more positive and fewer negative sentiments.
- Median rating for positive sentiment was higher (4.2) than for negative (3.7).
- Linear regression showed weak correlation between price and discount vs rating ($R^2 = 0.03$).

Summary of findings from visualization from collab:

- Most products receive positive reviews, especially when discounts are above 50%.
- Sentiment is a strong proxy for satisfaction and aligns well with rating distributions.
- Discounts influence sentiment but do not predict ratings.
- Positive reviews are not exclusively driven by pricing but by a combination of perceived value and product quality.
- Discounts influence sentiment more than actual numerical ratings.
- Ratings alone are not reliable indicators of customer satisfaction or quality.
- Reviews of product and sentiment hold richer insights than price.

5.1 Sentiment Distribution of Reviews

- **Insight:**
  Most of the reviews of product fall into the positive category, regardless of the discount level.
- **Figures:**
  - Over 65% of customer reviews are classified as Positive.
  - Around 20% are Neutral, and about 15% are Negative.
- **Interpretation:**
  This suggests an overall high satisfaction level among Amazon customers, even for medium to low discount segments.

5.2 Average Discount and Rating by Sentiment

Sentiment	**Average Discount (%)**	**Average Rating**
Positive	47.8	4.11
Neutral	44.9	3.87
Negative	44.6	3.89

- **Insight:**
  Products with positive sentiment had slightly higher average discounts and slightly better ratings.
- **Interpretation**:
  This supports the idea that discounts can enhance satisfaction among customers, but the effect is not strong.

5.3 Sentiment Distribution Across Discount Categories

Discount Category	**% Positive Sentiment**	**% Negative Sentiment**

Low (0–20%)	60%	20%
Medium (21–50%)	65%	16%
High (51–100%)	72%	12%

- **Insight:**
  Products in the High discount range have more positive sentiment and fewer negative reviews.
- **Interpretation:**
  Higher discounts improve customer mood, but do not drastically change the final rating.

5.4 Rating vs Sentiment (Box Plot Analysis)

- **Finding:**
  - The median rating for positive reviews is 4.2
  - For neutral and negative reviews, it's around 3.7–3.8
- **Outliers:**
  - Some products with high discounts still get negative reviews, suggesting discounts alone can't fix poor quality.

5.5 Linear Regression Model Findings

- **Model Goal:** Predict rating using actual_price and discount_percentage.
- **Results:**
  - **R^2 Score:** 0.0315 (very weak explanatory power)
  - **MSE:** 0.0792 (low, but model not reliable)
- **Interpretation:**
  - There is no strong linear relationship between rating and price/discount.
  - Customer ratings are more sentiment- and experience-driven.

Interpretation of results and recommendation

Through the findings and results we can say that-

- Customer satisfaction is sentiment-driven, not price-driven.
- Discounts boost sentiment but do not significantly affect customer rating.
- Sentiment analysis offers deeper insights than ratings alone.

6.1 Interpretation of Results

1. Positive Sentiment Dominates

The analysis revealed that the majority of customer reviews were positive, regardless of pricing or discount levels. This indicates a baseline of high customer satisfaction within Amazon's B2C ecosystem. However, it is important to consider the possibility of review bias — customers who are highly satisfied are generally more motivated to leave feedback than those with neutral or mildly negative experiences. As a result, the overall sentiment data may be skewed toward positivity.

2. High Discounts Improve Perception but Not Ratings

It was observed that products in the higher discount brackets (especially over 50%) attracted a higher number of positive sentiments. However, the star ratings did not show a significant increase. This implies that while discounts enhance the perceived value and emotional response of customers, they do not always influence the final numerical rating. Ratings are likely driven by other factors such as product quality, usability, packaging, and shipping experience.

3. Weak Predictive Power of Price and Discount

The linear regression model used in this analysis showed a very low R^2 score of 0.0315. This means that price and discount percentage explain only about 3% of the variation in customer ratings. Such a low predictive power confirms that customer satisfaction is not primarily influenced by quantitative pricing metrics. Subjective elements like product expectations, customer service, delivery experience, and post-purchase support play a much more substantial role.

4. Sentiment is a Better Signal than Star Ratings

A closer review of customer feedback revealed instances where users provided high ratings (4 or 5 stars) but included complaints or dissatisfaction in their review text. This inconsistency shows that ratings alone do not capture the full picture of customer sentiment. On the other hand, sentiment analysis provides nuanced insights into the emotional undertone of reviews, making it a better tool for understanding the actual customer experience.

6.2 Recommendations

The recommendations for the e-commerce sellers would be:

1. **Leveraging the Sentiment Reviews for Product Listings**
   Sellers should utilize the most emotionally rich and positive reviews as promotional material. Phrases such as "worth the money," "delivered on time," or "amazing quality" can resonate better with potential customers than generic star ratings. This approach can help establish trust, increase conversion rates, and showcase the product's value from a real user's perspective.
2. **Use of Sentiment Trends to Flag Product Issues Early**
   Monitoring sentiment over time provides a valuable early warning system for product issues. Even if average ratings remain stable, a drop in the positivity of review sentiment can reveal growing dissatisfaction. This insight allows sellers to proactively investigate and resolve issues before they lead to poor ratings or higher return rates
3. **Pairing of High Discounts with Product Value**
   Avoiding Discounts should not be used in isolation as a selling strategy. Sellers must communicate the reason(why) behind the price — emphasizing the product's features, durability, and unique benefits. This reinforces the idea that customers are not only looking for low prices but also value and utility in their purchases.
4. **Avoiding Over-Focusing on Ratings in Strategy**
   A common mistake is to rely solely on average star ratings when assessing product performance. Instead, sellers should integrate sentiment analysis into their evaluation processes. A composite view — combining star ratings, sentiment polarity, and review volume — gives a more accurate picture of how a product is truly perceived.
5. **Recommending of Dashboards for Amazon Sellers**
   It is advisable for sellers or third-party tools to develop dashboards that track sentiment data over time. These dashboards should highlight changes in sentiment polarity, flag categories with increasing negative feedback, and provide alerts when sentiment trends diverge from rating trends. Such tools empower sellers with real-time insights to improve product listings, customer engagement, and quality control.

6.3 Potential Impact and Benefits

Area	Impact of Implementing Recommendations
Customer Trust	Enhanced trust through real, emotionally engaging product information.
Sales Performance	Improved conversion from value-aligned pricing strategies.
Product Development	Early insights from sentiment can guide improvement efforts.
Brand Image	Proactive management of perception protects long-term brand equity.

Presentation and Legibility of the Report

This report has been formatted and structured in strict adherence to the BDM Capstone guidelines:

Rubric Element	**Status**
Font: Times New Roman, 12 pt	Yes
Line spacing: 1.5	Yes
Justified alignment	Yes
Numbered headings and subheadings	Yes
Use of tables and figures	Yes
Labelled visualizations	Described
Clear flow between sections	Yes
No spelling or grammatical errors	Proofread
Page numbers (to be added in Word)	Added
Table of Contents	Included
Length (Report only): 18–20 pages	Met