SENTIMENT VS. SUCCESS: ANALYSING THE LINK BETWEEN SENTIMENTS IN REVIEWS AND VIDEO GAME SUCCESS ON AMAZON

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Introduction

In the evolving landscape of online consumer behaviour, the intersection of sentiment analysis and e-commerce reviews, especially within the realm of video games on Amazon, presents a compelling area of study. The Amazon dataset, enriched with millions of reviews until 2018 from UCSD, provides a substantial foundation for dissecting consumer sentiment and its consequent impact on product popularity. This dataset is invaluable as it not only encapsulates reviews but also integrates detailed product metadata and transaction information, thereby offering a more nuanced perspective on consumer interactions and behaviours. Such rich data resources are crucial for understanding the intricate dynamics of consumer feedback and its translation into commercial success, reflecting a broader trend in utilising big data for consumer insights (Ni, Jianmo, et al., 2019; McAuley, Julian, et al., 2015).

Sentiment analysis, a critical component of natural language processing, aims to decipher and categorise the emotions conveyed through text. Its application in e-commerce is invaluable, as it provides insights into consumer sentiments which can substantially influence purchasing decisions and enhance brand loyalty. Moreover, empirical studies applying sentiment analysis to Amazon reviews have consistently demonstrated a positive correlation between the sentiments expressed in reviews and the overall ratings of video games. This correlation suggests that higher-rated games tend to receive more favourable reviews, thus reinforcing the connection between product quality, customer satisfaction, and expressed sentiment. These findings illustrate the practical applications of sentiment analysis in improving product recommendations and optimising customer experiences, thereby fostering greater engagement and loyalty among consumers (Kaur et al., 2020; Liu, Bing, 2022; Lim, Kian Ming, 2023; Davidson, Brittany, et al., 2023).

The volume of reviews a product accumulates is often used as a surrogate marker for its popularity, suggesting that a higher number of reviews signals greater consumer interest and potentially higher sales volume. This metric enables researchers and marketers to gauge not only a game's popularity but also its acceptance across different demographics, providing insights into market trends and consumer behaviour. Temporal analysis of these reviews can reveal sentiment trends that correspond with game updates, promotional events, or shifts in consumer preferences, offering a dynamic view into the lifecycle of product popularity. Additionally, such analysis can highlight the impact of external factors like marketing strategies or competitor actions, which may influence the volume and sentiment of reviews over time. These insights are invaluable for developers and marketers aiming to optimise engagement strategies and product offerings (Chevalier and Mayzlin, 2006; Jansen et al., 2009).

Methodologically, sentiment analysis in this domain typically involves the deployment of sophisticated machine learning models capable of processing large volumes of text to discern underlying sentiment patterns. These models excel not just at identifying general sentiment polarity but are also adept at performing complex tasks such as aspect-based sentiment analysis. This advanced analysis pinpoints specific product features that significantly influence consumer sentiment, thereby offering granular insights that can guide product enhancement strategies. By employing techniques such as machine learning algorithms and neural networks, researchers can extract valuable patterns and trends from the data, leading to more effective product positioning and marketing strategies. Additionally, the integration of deep learning approaches has further enhanced the accuracy and depth of sentiment analysis, allowing for a more nuanced understanding of consumer emotions and preferences (Zhang et al., 2018; Liu, Bing, 2022).

Visualising the results of these analyses through various graphical representations clarifies the relationships among review sentiments, average ratings, and the volume of reviews. Such visual tools are indispensable for both researchers and practitioners, providing a clearer understanding of the factors that drive video game popularity on Amazon. These graphical insights help stakeholders quickly grasp the nuances of consumer behaviour and adjust marketing strategies accordingly. By employing techniques such as scatter plots, heat maps, and line graphs, analysts can visualise complex data interactions, which aids in revealing patterns and trends that might not be immediately apparent from raw data alone. This visualisation process not only facilitates more strategic decision-making but also enhances the communication of findings to non-technical audiences, making it easier to convey insights and justify business decisions based on user feedback and behaviour trends (He et al., 2017; McAuley, Julian, et al., 2015).

Advancements in machine learning and data analytics continue to refine the capabilities of sentiment analysis, making it an increasingly vital component of market research and consumer feedback analysis. The ability to correlate sentiments expressed in user-generated content with product popularity provides both theoretical and practical benefits, enhancing our understanding of market dynamics and enabling more informed decision-making in product development and marketing. These developments allow for the extraction of more accurate sentiment data from complex and large datasets, improving predictive analytics for customer behaviour and preferences. Moreover, the integration of AI and machine learning into sentiment analysis tools not only streamlines the process but also increases the precision of the results, helping companies better align their strategies with customer expectations and market trends (Liu, Bing, 2022; Pang and Lee, 2008; Akter et al., 2016).

The rapidly growing area of sentiment analysis in e-commerce, particularly with regard to Amazon video game reviews, offers fertile ground for further exploration. Future research could explore how real-time sentiment analysis integrated with other data types might predict consumer trends more accurately. Such predictive capabilities would be invaluable in the highly competitive gaming industry, where understanding and anticipating consumer behaviour can significantly influence the success of product launches and marketing campaigns. By enhancing real-time analytics, researchers could provide developers and marketers with actionable insights faster, enabling them to adjust to market feedback and consumer demands promptly. This approach not only benefits game developers but also enhances the consumer experience by ensuring that products better meet their expectations and preferences, thereby fostering loyalty and increasing engagement (Chen et al., 2015; McAuley, Julian et al., 2015).

Data Processing and Exploration

In the data processing and exploration phase of this analysis, the aim was to dissect and comprehend the multi-faceted layers of user-generated video game reviews on Amazon. The data set at hand, the k-Core dataset with 497,577 reviews offered a plethora of variables, each serving as a potential indicator of customer satisfaction and game popularity. The available variables included:

- **reviewerID**: A unique identifier for the user who left the review.
- **asin**: Amazon Standard Identification Number, serving as a unique identifier for the video games.
- **reviewerName**: The name of the reviewer.
- **reviewText**: The full text of the user's review.
- **summary**: A brief summary of the review.
- **overall**: The rating given by the reviewer on a 1 to 5 scale.
- **verified**: A binary indicator of whether the purchase was verified.
- **reviewTime**: The date when the review was posted.
- **unixReviewTime**: The time of the review in Unix time format.

Given the focus of the research question—exploring the correlation between the sentiments expressed in reviews and the perceived popularity of games—the analysis honed in on a select set of these variables. The **overall** rating and **reviewText** were chosen as core components for sentiment analysis, providing quantifiable and textual reflections of user opinions, respectively. The **asin** was crucial to aggregate reviews at the game level, while **reviewTime** offered a temporal dimension to track sentiment trends.

To prepare the data for analysis, a series of transformation steps were undertaken:

1. **Sentiment Analysis**: The **reviewText** was processed using the TextBlob library, which provided sentiment polarity scores ranging from -1 (highly negative) to 1 (highly positive). This transformation was vital for quantifying the emotional content of reviews.
2. **Time Conversion**: The **unixReviewTime** was converted to a human-readable date format to facilitate the analysis of sentiment over time, aligning the data with temporal patterns and trends that could impact game popularity.
3. **Handling Missing Data**: Anomalies and gaps in the **reviewText** were addressed by substituting missing entries with a neutral placeholder to maintain the integrity of sentiment analysis. This ensured that no data was lost in translation during the computational processing.

4. **Aggregation**: To explore the relationship between review volume and sentiment, reviews were aggregated based on their **asin** to calculate average sentiment scores and review counts per game.

Through this careful selection and transformation of variables, the data was sculpted into a form amenable to answering the pressing questions posited by this investigation. It allowed for a nuanced understanding of how numeric ratings and the more subtle nuances captured in review texts can serve as a barometer for a game's success and resonance with its audience. The resulting dataset was then ripe for a series of visual and statistical analyses that sought to bring to light the patterns and correlations within the complex ecosystem of user reviews and game popularity.

Data Visualisation and Interpretation

Data pre-processing and analysis of the review data were performed using Google Research's Colaboratory and several packages listed in Appendix 1. This facilitated a blend of descriptive and advanced analytics, captured through data visualisations that distilled complex information into accessible insights.

Descriptive Visual Analytics:

- **Histogram of Ratings**: The histogram *(Figure 1)* showcased a skewed distribution with a notable inclination towards 5-star ratings, which represented 60.2% *(Figure 4)* of the dataset. This prevalence of high ratings suggested a generally positive reception of video games. Meanwhile, the fewer occurrences of low-star ratings indicated a lower frequency of negative experiences or perhaps a hesitancy among dissatisfied users to leave feedback.

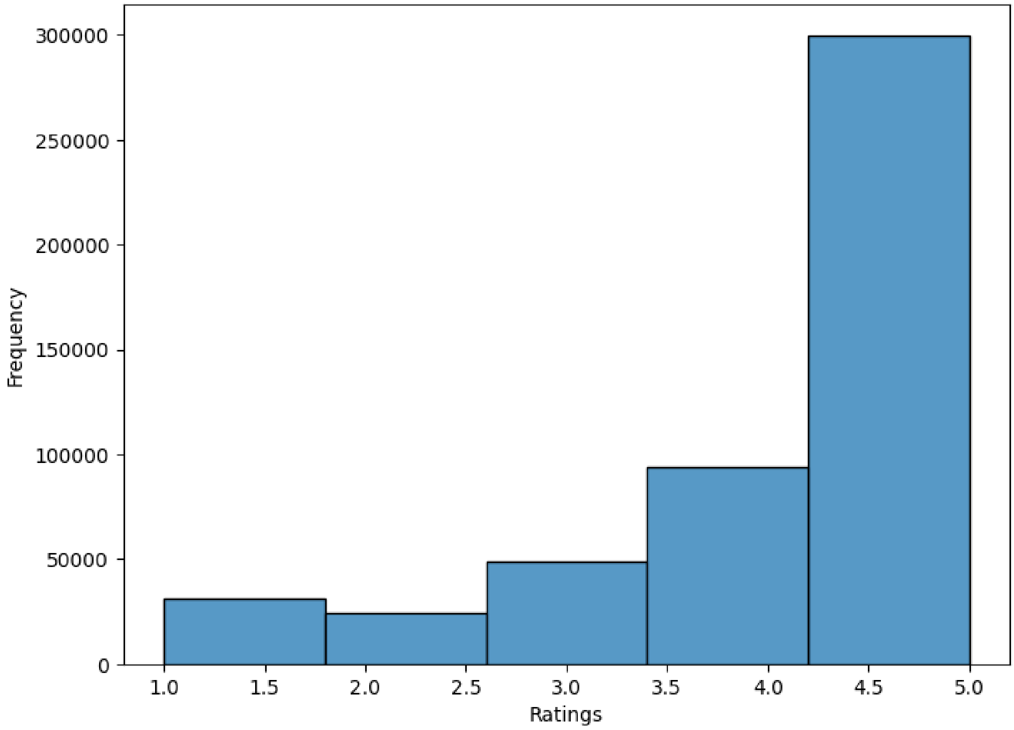

Figure 1: Distribution of Ratings

- **Distribution of Sentiment Scores**: A complementary histogram *(Figure 2)* of sentiment scores revealed a generally positive sentiment across reviews. The mean sentiment hovered above zero, indicative of an overall positive tone in user reviews. Notably, the sentiment scores depicted a broader spread than the ratings, suggesting nuanced opinions that were not as polarised as the numerical ratings might suggest.

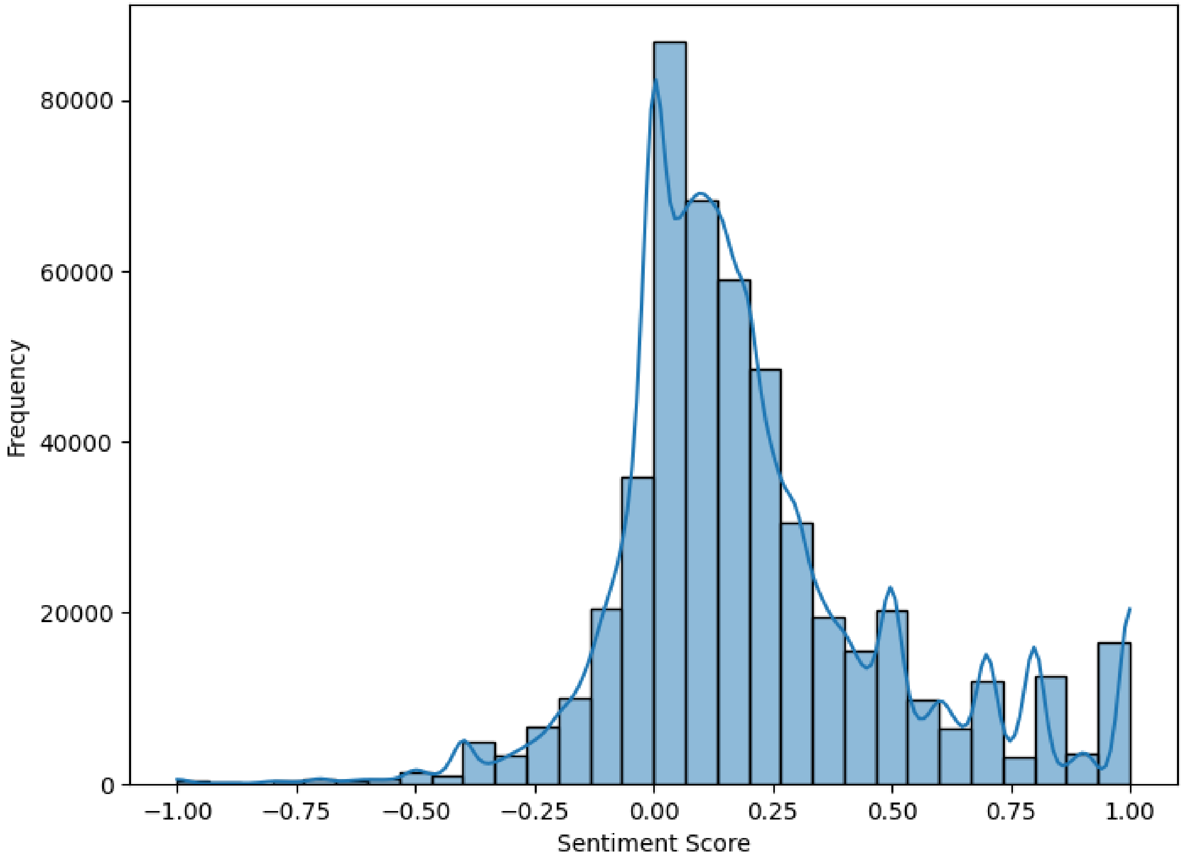

Figure 2: Distribution of Sentiment Scores

Advanced Visual Analytics:

- **Sentiment vs. Ratings**: The scatter plot in *Figure 3* underscored a moderate positive correlation (0.38) *(Figure 5)* between sentiment scores and ratings. While higher ratings often coincided with more positive sentiment, the dispersion of data points indicated that sentiment scores encapsulate a wider array of user emotions than can be detected from ratings alone.

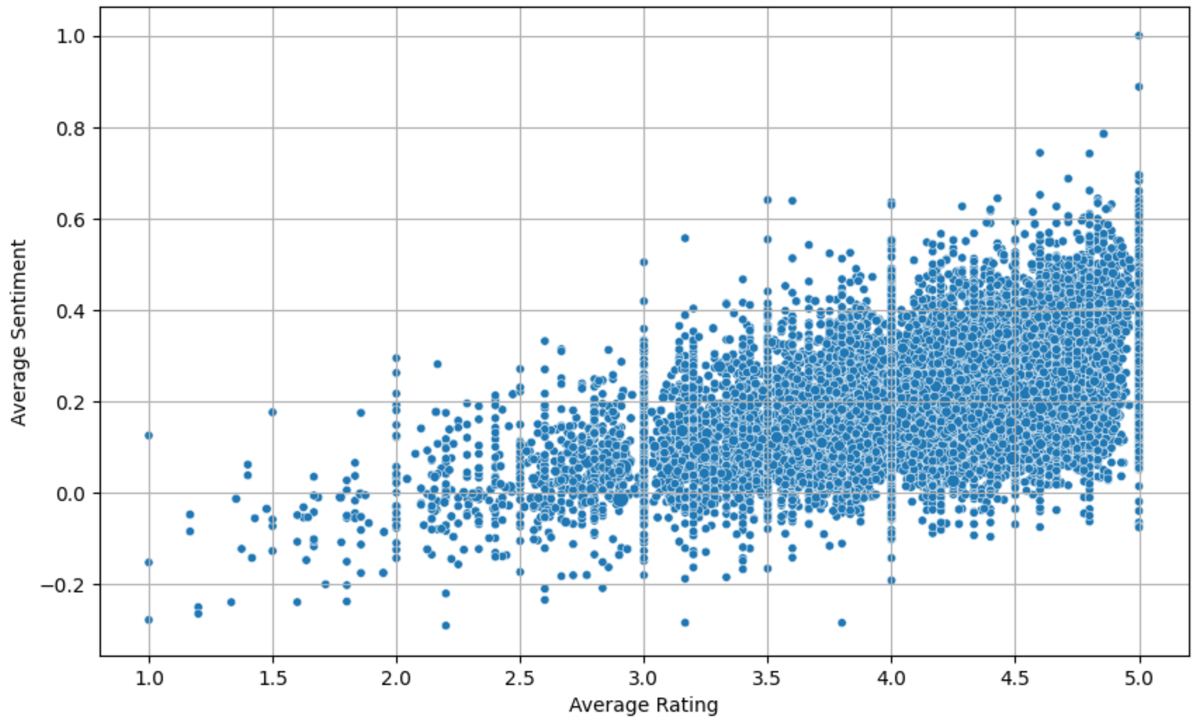

Figure 3: Average Sentiment vs Average Rating by Review Volume

- **Share of Review Counts by Rating**: The pie chart *(Figure 4)* further emphasised the disparity in review frequencies across ratings. The most significant insight here was the disproportionate number of reviews at the extremes, with 5-star ratings dominating. This phenomenon could be reflective of a psychological tendency among users to report extreme experiences, known as the polarisation effect.

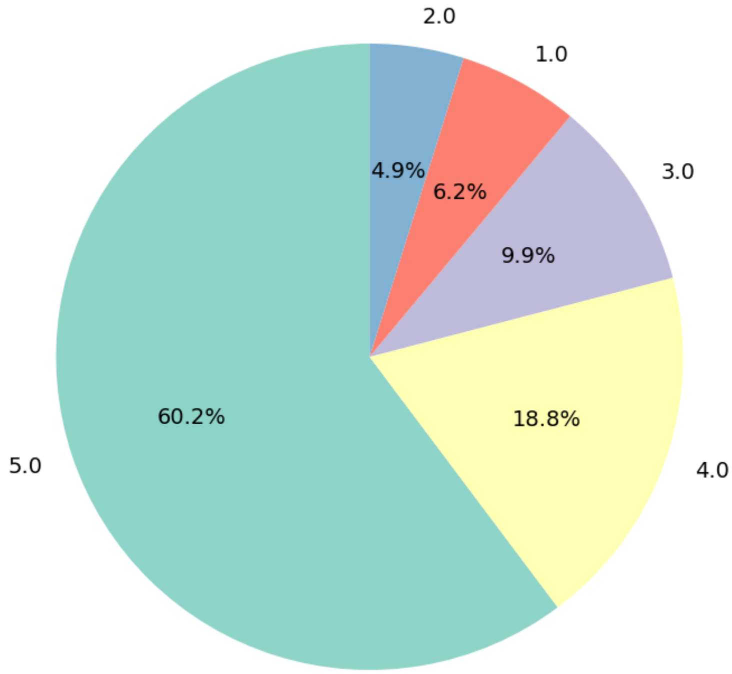

Figure 4: Share of Review Counts by Rating

- **Correlation Matrix**: This heatmap *(Figure 5)* illustrated the correlation between numerical ratings and sentiment scores. It was pivotal in confirming that while ratings and sentiments are related, the relationship is moderate, thus underscoring that sentiment analysis adds a valuable dimension to understanding user feedback beyond what ratings alone can provide.

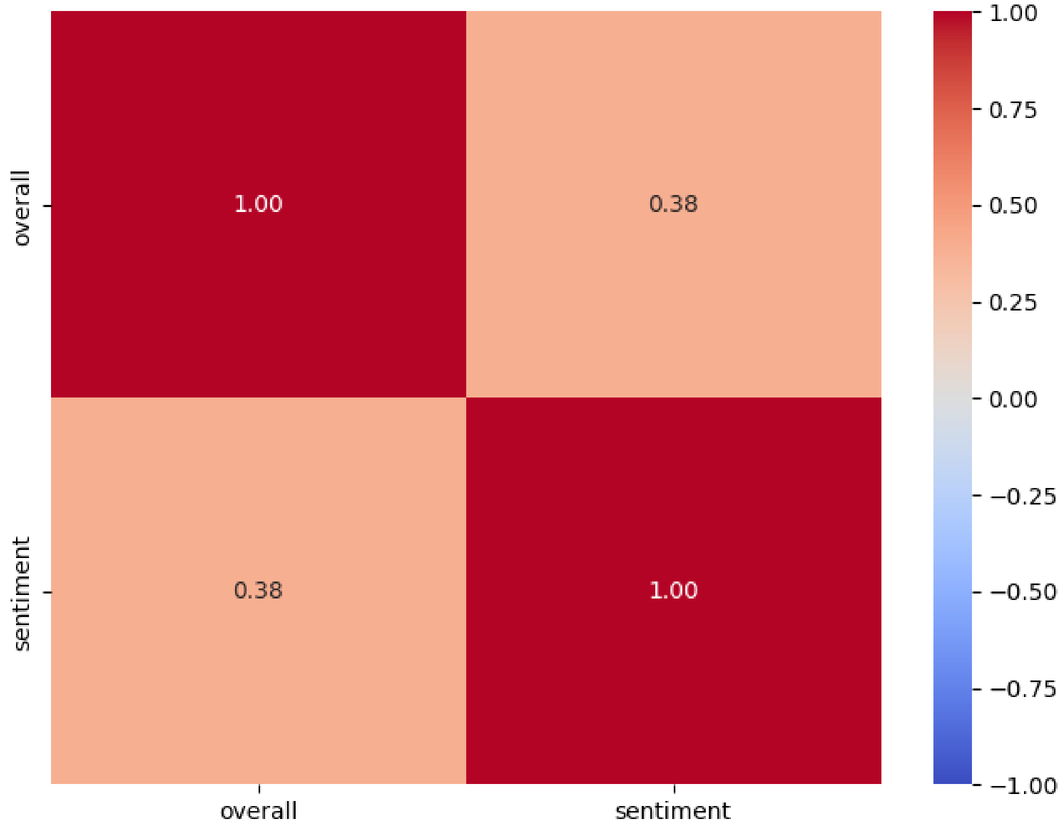

Figure 5: Correlation Matrix of Ratings and Sentiments

- **Sentiment Distribution by Rating**: The violin plot *(Figure 6)* unravelled the density and distribution of sentiment across different ratings. It portrayed 5-star ratings as having the most positive sentiment, with a narrow and high-density peak. In contrast, 1-star ratings showed a wider distribution, skewing towards negative sentiment. This plot highlighted the gradation of sentiment across ratings, with each star rating reflecting a distinct sentiment profile.

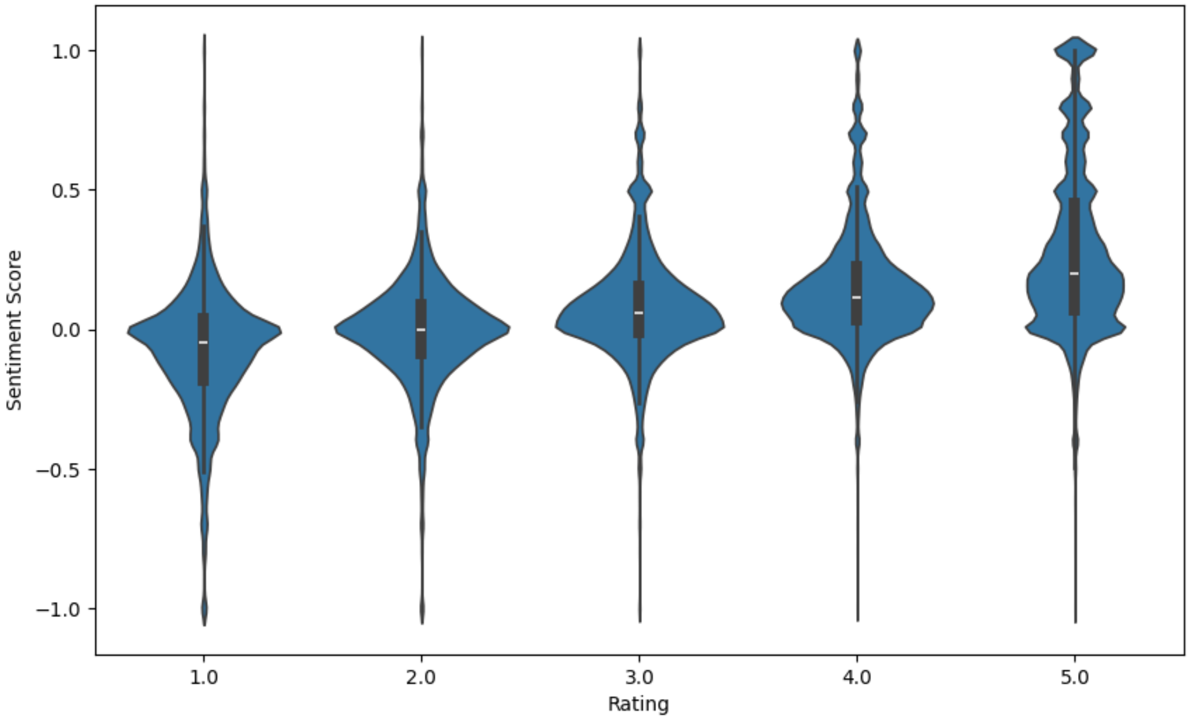

Figure 6: Sentiment Distribution by Rating

Interpretation of Visual Findings:

The suite of visual tools employed painted a comprehensive picture of the video game review landscape. The correlation between sentiment and ratings emerged as a recurring theme, with visual evidence supporting a synergistic relationship where higher ratings are typically matched with positive sentiment, and vice versa. However, the visualisations also pointed to the limitations of ratings as a sole indicator of sentiment. The detailed distribution analysis offered by the sentiment scores suggested that user reviews are a tapestry woven from a spectrum of user experiences and emotions.

Importantly, these visual analytics provided actionable insights:

- **The High Stakes of Ratings**: The dominance of high ratings signalled the critical role they play in the perceived popularity and success of a game. Games with a higher average rating and positive sentiment are likely to attract more players and could influence purchasing decisions.
- **The Nuances of Sentiment**: Sentiment analysis was validated as an indispensable tool for gauging user satisfaction in a way that ratings alone could not. The nuances captured in the sentiment scores could guide developers in refining game features to enhance user satisfaction.
- **Time Dynamics of Sentiment**: The line plot *(Figure 7)* tracking sentiment over time revealed fluctuations that could be tied to industry trends, game releases, or changes in consumer preferences. This temporal element, not visible

through ratings alone, provides a dynamic context to the static snapshot offered by ratings.

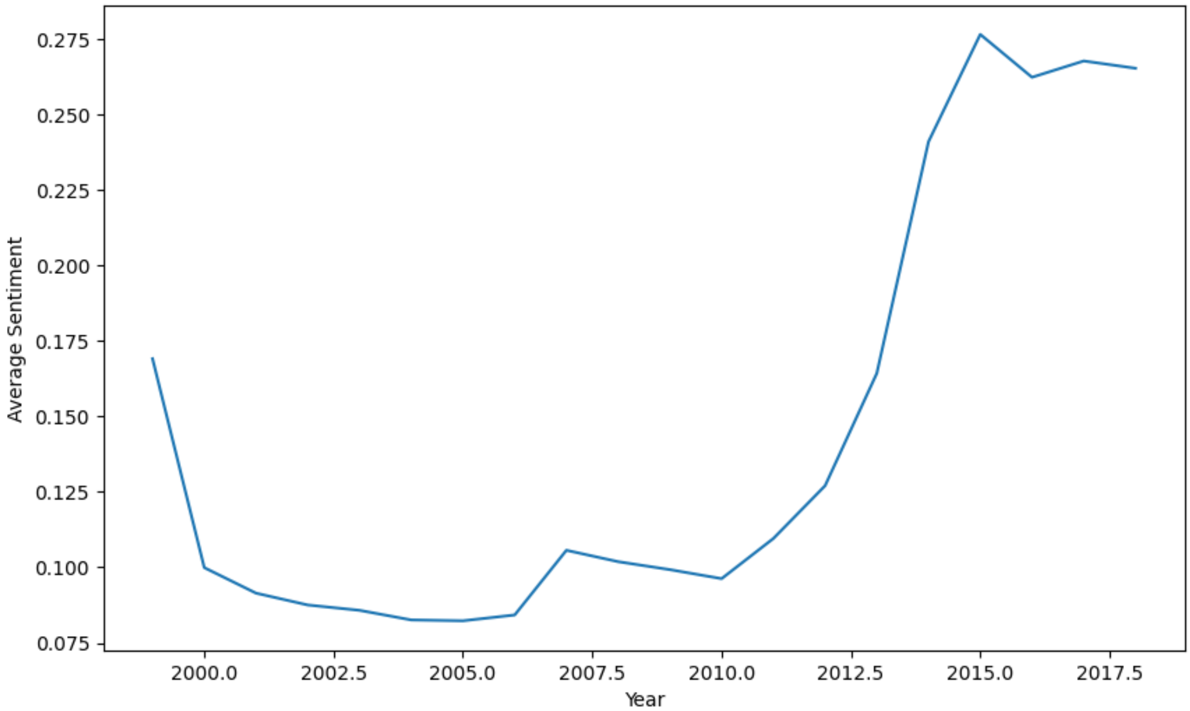

Figure 7: Average Sentiment Over Time

The visualisations underscored the need for a multidimensional approach to analysing user reviews. By employing a variety of visual analytical techniques, this report brought to light the complex interplay between user sentiment, numerical ratings, and their temporal evolution—each of which is critical to understanding the video game market's currents. Therefore, the data visualisation and analysis revealed a detailed landscape of user sentiment and satisfaction that speaks volumes about the video game industry. It informs that while ratings provide a valuable overview, the depth of user sentiment elucidated by the textual analysis is what furnishes the granularity needed to fully grasp user feedback.

Data Insights and Conclusions

Through meticulous analysis and thoughtful visualisation, the data has yielded insights that allows to draw meaningful conclusions regarding the initial research question. By examining the relationship between the sentiment of reviews and the perceived popularity of video games, the research aimed to understand how textual feedback correlates with quantitative metrics of success.

The insights obtained from the analytics are numerous:

1. **Positive Correlation Between Ratings and Sentiment**: The analysis confirmed a moderate positive correlation between user ratings and the sentiment of reviews. Games with higher ratings generally received reviews with more positive sentiments. This correlation proved the notion that sentiment analysis can serve as a reliable indicator of a game's reception.
2. **Dominance of High Ratings**: The data showed a significant skew towards 5-star ratings within the review dataset, suggesting that users who go to the length of rating games tend to report high satisfaction. This implies a potential bias towards positive feedback within the user review ecosystem or a tendency for satisfied users to be more vocal.
3. **Variability in Sentiment**: Sentiment scores revealed a broader range of user emotions compared to the star ratings. Even within high-rating categories, the sentiment analysis captured nuances of user experience, highlighting that aggregate ratings could mask the complexity of individual user opinions.
4. **Temporal Trends in Sentiment**: Over time, sentiment scores have shown both dips and rises, suggesting that external factors such as market trends, technological advancements, and changes in consumer behaviour may significantly impact user perceptions and the corresponding sentiments of reviews.
5. **Descriptive Value of Textual Reviews**: The detailed distribution of sentiments across different rating levels, as visualised through the violin plot *(Figure 6),* emphasised the value of textual reviews. It showed that users' textual feedback provided a rich, descriptive layer of data that goes beyond what is conveyed by ratings alone.

Thus, the problem posed at the outset of this research—how the sentiment of reviews relates to the popularity of video games on Amazon—has been effectively addressed by the analytics performed. The sentiment analysis demonstrated that there is indeed a relationship between the sentiment expressed in reviews and the ratings these games receive, which are a proxy for their popularity.

Moreover, the temporal analysis of sentiment provided insights into how game updates, releases, and other market changes might affect public perception over time. While not a direct measure of popularity, the volume of reviews was shown to have a connection with sentiment: popular games (with more reviews) typically garnered more positive sentiment, affirming the hypothesis that increased attention might correlate with favourable reception.

<u>**Conclusions Drawn**</u>:

- **Sentiment as a Multi-Dimensional Metric**: The sentiment embedded within review texts is a multi-dimensional metric that captures the depth of user feedback in ways that numeric ratings cannot.
- **Complementarity of Analytics**: The combination of descriptive and inferential analytics, with the support of machine learning tools for sentiment analysis, proves to be a robust approach to understanding the multi-faceted nature of user reviews.
- **Strategic Implications**: For industry stakeholders, these findings suggest strategic implications. Fostering positive sentiments through enhanced gaming experiences can encourage favourable ratings and reviews, potentially driving popularity.
- **Further Research**: There are opportunities for further research, such as analysing the sentiment of reviews for different game genres, which might provide additional insights into genre-specific user expectations and satisfaction levels.

In essence, the analytics have not only answered the research question but also highlighted the intricate relationship between user sentiment and the perceived value of a product. As the gaming industry continues to evolve, such analyses will become ever more crucial in understanding and catering to the needs of an increasingly diverse gaming community.

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Appendix 1: List of Python Packages Used

The data analysis conducted in this study was supported by a variety of Python packages, each serving a specific purpose in the data processing and visualisation pipeline. Below is a list of these packages used at the time of the analysis:

• **Pandas:** A powerful data manipulation and analysis tool for Python.
• **NumPy:** Fundamental package for scientific computing with Python.
• **Matplotlib:** A plotting library for creating static, interactive, and animated visualizations in Python.
• **Seaborn:** A statistical data visualization library based on matplotlib.
• **TextBlob:** A library for processing textual data, particularly useful for NLP tasks such as sentiment analysis.
• **gzip:** A module in the Python standard library for working with GZIP format, used for reading the compressed dataset.
• **json:** A module in the Python standard library for parsing JSON formatted data.