What do you like in boardgames?

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Abstract

This project aims to utilize sentiment analysis models to analyze comments about board games, with the goal of identifying the positive, neutral and negative aspects of these games. This study aims to explore board game data to uncover insights regarding user preferences and factors contributing to game popularity. By leveraging sentiment analysis, particularly through BERT-based models, we classified user comments into sentiment categories and further analyzed these sentiments with respect to specific aspects of the games.

Keywords: Board games, Aspects, Sentiment Analysis, Aspect-Based Sentiment Analysis, top 10

1 Introduction

Sentiment analysis[1], or opinion mining, is the process of analyzing large volumes of text to determine whether the sentiment expressed is positive, negative, or neutral. Nowadays companies have access to more data about their customers than ever before, which presents both opportunities and challenges. With vast amounts of textual data available from emails and tweets to online survey responses, customer service chats, comments and reviews—extracting meaningful insights to guide business decisions is crucial.

While traditional sentiment analysis provides a broad overview of customer opinions, it often lacks the specificity needed to understand how particular aspects of a product or service are perceived. This is where Aspect-based sentiment analysis (ABSA) comes in. ABSA enables a more detailed understanding by focusing on specific features or attributes of a product or service. This approach allows you to analyze customer sentiment at a granular level, revealing insights about particular aspects—like the length of a board game—that might be driving overall satisfaction or dissatisfaction. The process typically begins with Aspect Term Extraction (ATE), where key aspects are automatically identified from textual data. Following this, Aspect Polarity Classification (APC) is applied to determine the sentiment associated with each aspect, whether positive, negative, or neutral. By understanding the specific features that customers love or dislike, you can enhance your products and services, deliver stronger customer experiences, and ultimately improve your product and brand reputation.

2 The Methodology

2.1 Goal

The primary objective of this project is to conduct a comprehensive analysis of reviews/comments related to board games. The analysis is focused on extracting sentiments from user comments related to predefined aspects of the games, such as luck, bookkeeping, downtime, interaction, bash the leader, complexity, and complication. Furthermore, to contextualize our analysis, we begin by visualizing and analyzing the overall data provided on BGG, including game rankings and user ratings. From this data, we filter out the top 10 board games (Figure 1), which are then used as the primary focus of our sentiment analysis and aspect based sentiment analysis.

	id	name	yearpublished	rank	bayesaverage	average	usersrated	is_expansion	abstracts_rank	cgs_rank	childrensgames_rank	familygames_rank
0	224517	Brass: Birmingham	2018	1	8.41442	8.59490	47004	0	NaN	NaN	NaN	NaN
1	161936	Pandemic Legacy: Season 1	2015	2	8.37725	8.52521	53863	0	NaN	NaN	NaN	NaN
2	174430	Gloomhaven	2017	3	8.34878	8.58415	62679	0	NaN	NaN	NaN	NaN
3	342942	Ark Nova	2021	4	8.33524	8.53450	44939	0	NaN	NaN	NaN	NaN
4	233078	Twilight Imperium: Fourth Edition	2017	5	8.23836	8.59733	24206	0	NaN	NaN	NaN	NaN
5	316554	Dune: Imperium	2020	6	8.23010	8.43435	46714	0	NaN	NaN	NaN	NaN
6	167791	Terraforming Mars	2016	7	8.20961	8.35659	100265	0	NaN	NaN	NaN	NaN
7	115746	War of the Ring: Second Edition	2011	8	8.18741	8.54189	21690	0	NaN	NaN	NaN	NaN
8	187645	Star Wars: Rebellion	2016	9	8.17001	8.41828	32857	0	NaN	NaN	NaN	NaN
9	291457	Gloomhaven: Jaws of the Lion	2020	10	8.15881	8.42990	34903	0	NaN	NaN	NaN	NaN

Fig. 1 Top 10 Board games.

2.2 Data

2.2.1 Data source

The board game review data was downloaded using the BoardGameGeek (BGG) website. The dataset was downloaded in a .csv file from the website.

There are more than one hundred and fifty thousands board games in the .csv file and the dataset included the following key columns: ID (A unique identifier for each board game.), Name (The name of the board game.), Rank (The rank of the game based on user ratings.), Bayesaverage (The Bayesian average rating.), Average (The average user rating.), Usersrated (The number of users who have rated the game.) and the Yearpublished (The year the game was published.)

Since there are more than one hundred and fifty thousand games in the file, only the top 10 games were considered for the analysis. For each game, the full set of reviews/comments was downloaded and used as the initial dataset. The initial dataset contains more than sixty nine thousand reviews/comments.

2.2.2 Data preparation

The downloaded comments need to be processed to make the dataset easier to analyze and generate more meaningful results.

After downloading the comments, the dataset was inspected for missing values and inconsistencies. URLs, extra spaces, and anything inside brackets were also removed.

Furthermore, the comments were filtered based on language (using langdetect library [2]) to keep only reviews in English so that the results can be interpreted more easily.

After the processing, there were around 49 thousand reviews remaining, which will be used for aspect extraction and sentiment analysis tasks.

2.3 Models

2.3.1 BERT[3]

BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained transformer model. It is designed to understand the context of a word in a sentence by looking at the words that come before and after it, making it a powerful tool for natural language processing (NLP) tasks. BERT set new standards for performance on a wide range of NLP tasks, such as sentiment analysis, question answering, and named entity recognition. BERT is conceptually simple and empirically powerful and it provides state-of-the-art performance on a wide range of NLP tasks without the need for task-specific architecture changes.

2.3.2 BERT-Base Multilingual Uncased Sentiment (nlptown/bert-base-multilingual-uncased-sentiment model)[4]

The BERT-Base Multilingual Uncased Sentiment model is a versatile language model fine-tuned specifically for sentiment analysis of product reviews across six languages: English, Dutch, German, French, Spanish, and Italian. This model predicts the sentiment of a review on a scale from 1 to 5 stars, providing a numerical representation of user sentiment. Designed for direct application in sentiment analysis tasks, this model is well-suited for analyzing product reviews in any of the aforementioned languages. Additionally, it can be further fine-tuned for related sentiment analysis tasks, making it a valuable tool for developers and researchers looking to enhance their NLP capabilities.

2.3.3 DistilBERT(distilbert-base-uncased-finetuned-sst-2-english)[5]

DistilBERT (a distilled version of BERT) is a smaller, faster, cheaper and lighter version of BERT, designed to preserve 95 percent of BERT's performance while being more efficient. It has 40 percent fewer parameters than google-bert/bert-base-uncased and runs 60 percent faster. It is a lightweight and efficient version of the BERT model, fine-tuned for sentiment analysis. This model has been implemented and made available on multiple platforms, including Hugging Face [6] and Gitee [7].

2.4 SpaCy [8]

spaCy is an open-source library for advanced natural language processing (NLP) in Python. It is designed for performance and usability, making it easy to integrate into production systems and providing robust tools for various NLP tasks. It is used for tasks such as sentiment analysis, aspect extraction, entity recognition, text classification, part of speech tagging and more. The model is an excellent choice for applications that prioritize efficiency, as it offers a lightweight alternative without compromising too much on performance.

3 Results

We first identified the top 10 board games based on user rankings and collected user comments for these games. After cleaning the data, we used the TextBlob library to conduct sentiment analysis, assigning polarity scores ranging from -1 (negative) to 1 (positive), with 0 representing neutral sentiment. The sentiment distribution was visualized in Figure 2, providing insights into the overall sentiment expressed by users.

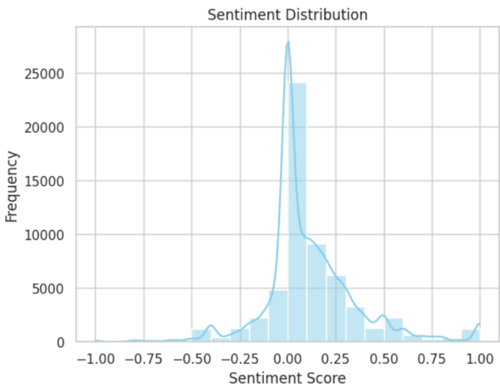

Fig. 2 Sentiment distribution on the comments(cleaned) of Top 10 board games.

3.1 Aspect Frequency Analysis

Next, we analyzed the frequency of predefined aspects within the comments, focusing on common board game topics such as Luck, Bookkeeping, Downtime, Interaction, Bash the Leader, and Complexity. The results, shown in Figure 3, highlight which aspects were most frequently mentioned by users.

	0
luck	3462
bookkeeping	792
downtime	3123
interaction	2361
bash_the_leader	8
complexity	5729

dtype: int64

Fig. 3 Frequency of aspects in comments(cleaned).

3.2 Aspect-Based Sentiment Analysis

After completing the initial sentiment and aspect frequency analysis using advanced NLP models. We focused on the English and employed DistilBERT, SpaCy, and the nlptown/bert-base-multilingual-uncased-sentiment model. We extracted specific aspects from the comments. This enabled a deeper aspect-based sentiment analysis, revealing sentiment trends tied to particular game features.

3.2.1 Sentiment Analysis Using DistilBERT

The analysis was conducted in six parts, with Parts 2, 5, and 6 utilizing the DistilBERT-base-uncased-finetuned-sst-2-english model for sentiment analysis on English comments. In Part 2, we applied the model to classify each comment as either positive or negative, ensuring truncation to fit the 512-token limit. The sentiment results, along with their confidence scores, were stored in a DataFrame and visualized in a bar plot, showing the distribution of positive and negative comments.(Figure 4)

	truncated_comment	sentiment	score
0	sleeved deluxe edition with clay coins	NEGATIVE	0.713939
2	great game, full controllo of your strategy th...	POSITIVE	0.999805
3	location : msk	NEGATIVE	0.954082
4	very clever game, enjoyable overall. plus poin...	NEGATIVE	0.988579
5	brilliant! fits right into my wheelhouse all a...	POSITIVE	0.999817

Fig. 4 Sentiment analysis on english comments.

3.2.2 Aspect-Based Sentiment Analysis on Top 10 Games using DistilBERT

Part 5 was Aspect-Based Sentiment Analysis on Top 10 Games. We defined specific keywords for six key aspects, such as "luck" and "complexity." For each comment, we checked for the presence of these aspect-related keywords. When a keyword was detected, we used the DistilBERT model to perform sentiment analysis, recording the sentiment and confidence score for that particular aspect within the comment. The results were then visualized, showing the sentiment distribution for each aspect across different board games. (Figure 5)

```
   boardgame_id                                            comment  \
0        224517  very clever game, enjoyable overall. plus poin...
1        224517  very clever game, enjoyable overall. plus poin...
2        224517  very clever game, enjoyable overall. plus poin...
3        224517  brilliant! fits right into my wheelhouse all a...
4        224517  the game itself is not interesting enough to l...

        aspect sentiment     score
0     downtime  NEGATIVE  0.988579
1  interaction  NEGATIVE  0.988579
2   complexity  NEGATIVE  0.988579
3  interaction  POSITIVE  0.999817
4  interaction  NEGATIVE  0.990829
```

Fig. 5 Aspect-Based Sentiment Analysis on Top 10 Games.

3.2.3 Game-Specific Aspect Sentiment Analysis

Part 6 was Game-Specific Aspect Sentiment Analysis. In this part, we defined game-specific aspects for each of the top 10 board games (e.g., "strategy," "theme," and "mechanics"). We then applied the DistilBERT model to analyze the sentiment for these specific aspects within the user comments. The results were stored and visualized to show how different aspects of each game were perceived by users, providing more granular insights into user opinions. (Figure6

```
   boardgame_id                                            comment     aspect  \
0        224517  absolutely brilliant! i never played the origi...  mechanics
1        224517  after walking away from it several times due t...      theme
2        224517  this is more or less the same game as the orig...  mechanics
3        224517  december 2022 - 10 - 8 + plays + excellent gam...   gameplay
4        224517  i can see why this game is so popular, even th...      theme

  sentiment     score
0  POSITIVE  0.999643
1  NEGATIVE  0.995838
2  NEGATIVE  0.985356
3  POSITIVE  0.997901
4  NEGATIVE  0.954900
```

Fig. 6 Game-specific Aspect Sentiment Analysis.

3.3 ABSA using nlptown/bert-base-multilingual-uncased-sentiment

In Part 3, we used the BERT-based model to perform ABSA on the cleaned English comments for the top board games. The sentiment analysis model outputs star ratings (e.g., "1 star," "2 stars") instead of traditional sentiment labels like "positive," "negative," or "neutral." Here 1 or 2 stars denote negative sentiments, 3 stars denote negative sentiments and 4 or 5 stars positive sentiments. (Figure7)

```
                                                comment      aspect  \
0     Very clever game, enjoyable overall. Plus poin...    downtime
1     Brilliant! Fits right into my wheelhouse all a...  interaction
2     This is a near-perfect board game because... T...  interaction
3     While it might be a heretical opinion to some,...        luck
4     December 2022 - 10 - 8+ plays + Excellent game...  complexity
...                                                 ...         ...
4138  Not exactly disappointing, but not particularl...    downtime
4139  X2 Yum, yum! This game set out to be a streaml...  complexity
4140  I like the game, but it's not my favorite craw...  complexity
4141  This fixed many problems that I found with Mag...  complexity
4142  It really is astounding that people are able t...  complexity

     sentiment     score
0      4 stars  0.498068
1      5 stars  0.960988
2      4 stars  0.589286
3      5 stars  0.615758
4      5 stars  0.496295
...        ...       ...
4138   3 stars  0.771739
4139   3 stars  0.472439
4140   3 stars  0.714700
4141   4 stars  0.463822
4142   4 stars  0.661779

[4143 rows x 4 columns]
```

Fig. 7 Aspect-Based Sentiment Analysis using nlptown/bert-base-multilingual-uncased-sentiment.

3.4 Model Comparison

We employed three different models for sentiment analysis and aspect extraction: TextBlob, DistilBERT-base-uncased-finetuned-sst-2-english, and nlptown/bert-base-multilingual-uncased-sentiment. Each model offered unique insights:

1. TextBlob: Provided an overall sentiment score for each comment. While effective for general sentiment analysis, it lacked detail in aspect-specific sentiment (Figure 2).

2. DistilBERT: This model allowed us to perform aspect-based sentiment analysis with higher precision. It identified both general and game-specific aspects and provided sentiment classifications with confidence scores (Figures 4, 5, 6).

3. nlptown/bert-base-multilingual-uncased-sentiment: This BERT-based model output star ratings (1–5) instead of traditional sentiment labels, offering a more detailed view of user sentiments, particularly in multilingual contexts (Figure 7).

3.4.1 Aspect Extraction using SpaCy

In Part 4, we used the spaCy library to extract aspects (nouns) from user comments about different board games. We grouped the extracted aspects by each game, counted their frequency, and identified the top 10 most common aspects for each game. Using the TextBlob library, we then analyzed the sentiment for each aspect by checking the sentences in which the aspect appeared, calculating an average sentiment score. Finally, we visualized the sentiment scores for each game, plotting the average sentiment for the most frequently mentioned aspects to better understand users' opinions on specific game features. (Figure 8)

	boardgame_id	sorted_aspects	aspect_sentiments
0	115746	[(game, 2911), (time, 522), (games, 417), (rul...	{'game': 0.051275894949258057, 'time': 0.11192...
1	161936	[(game, 6638), (games, 1433), (experience, 127...	{'game': 0.015054743792370165, 'legacy': 0.122...
2	167791	[(game, 12509), (cards, 3843), (player, 1959),...	{'cards': 0.08063151602611263, 'player': 0.073...
3	174430	[(game, 9293), (time, 2056), (campaign, 1343),...	{'game': 0.025440635685341703, 'time': 0.06397...
4	187645	[(game, 4281), (time, 690), (player, 685), (co...	{'game': 0.02374639086696151, 'player': 0.1272...
5	224517	[(game, 4115), (players, 791), (player, 658), ...	{'game': 0.05834133041797925, 'strategy': 0.16...
6	233078	[(game, 4002), (time, 883), (players, 663), (g...	{'game': 0.005641948409128686, 'games': 0.1582...
7	291457	[(game, 2648), (scenarios, 684), (time, 502), ...	{'game': 0.05138623152708084, 'scenario': 0.13...
8	316554	[(game, 5089), (cards, 1678), (deck, 1609), (w...	{'game': 0.02350117871739706, 'cards': 0.08516...
9	342942	[(game, 5456), (cards, 1838), (card, 911), (ga...	{'game': 0.023209817691680217, 'cards': 0.0950...

Fig. 8 Aspect extraction using spaCy.

4 Conclusion

This project successfully applied sentiment analysis to board game data, providing insights into what players value the most. The results indicate that user sentiment, particularly concerning specific aspects, plays a crucial role in determining a game's success. Future work could involve:

- Increase the Scope of Analysis: Expand the dataset which will be analyzed by including a larger number of games and reviews to gain more comprehensive insights.
- Domain-Specific Fine-Tuning: Fine-tune the sentiment analysis models using domain-specific data to explore potential improvements in their accuracy and effectiveness.
- Model Performance Evaluation: Create a test set from the existing comments and reviews to evaluate the performance of the sentiment analysis models used.

References

[1] IBM: Sentiment analysis. IBM. Accessed: 2024-09-05 (n.d.). https://www.ibm.com/topics/sentiment-analysis

[2] W3Schools: Language Detection in Python. [Accessed: 10-Sep-2024] (2024). https://www.w3schools.in/python/examples/language-detection

[3] Devlin, J., Chang, M.-W., Lee, K., Toutanova, K.: Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2019)

[4] Hugging Face: BERT: A multilingual model for sentiment analysis (2020). https://huggingface.co/nlptown/bert-base-multilingual-uncased-sentiment

[5] Hugging Face: DistilBERT. Transformers documentation (2024). https://huggingface.co/docs/transformers/model_doc/distilbert

[6] Hugging Face: DistilBERT: A distilled version of BERT for natural language understanding (2020). https://huggingface.co/distilbert/distilbert-base-uncased-finetuned-sst-2-english

[7] Hugging Face: DistilBERT: A distilled version of BERT for natural language understanding. Gitee (2020). https://gitee.com/hf-models/distilbert-base-uncased-finetuned-sst-2-english

[8] Hugging Face: spaCy. Hugging Face documentation (2024). https://huggingface.co/docs/hub/spacy