What do you like in boardgames

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Abstract

The project mainly focuses on the sentiment analysis performed on the comments of the users from the website BoardGameGeek (BGG). It focuses on some particular aspects of the game and provides the sentiment label as positive, negative or neutral along with the sentiment score. A pre-trained model is used from the BERT and used for Aspect-Based Sentiment Analysis on the dataset of the comments of one of the top 10 games.

1 Introduction

Aspect-Based Sentiment Analysis (ABSA) is an advanced Natural Language Processing (NLP) technique that extends traditional sentiment analysis by identifying and evaluating sentiment towards specific aspects of a given text. Unlike general sentiment analysis, which provides an overall sentiment score for an entire text, ABSA breaks down user comments to determine how they feel about particular attributes. This approach is especially useful in product reviews, social media analysis, and user feedback interpretation.

In this study, ABSA is applied to board game reviews from BoardGameGeek (BGG), focusing on predefined aspects such as **luck, bookkeeping, downtime, interaction, complexity**, and more. By analyzing these aspects separately, we aim to provide deeper insights into how each element of a game is perceived by players.

2 Methodology

2.1 Goal

In the project we aim to extract the sentiment from the comments of the users on a predefined aspect. We are further visualising and analysing the data provided on BGG for the ranking and filtering out the top 10 board games and comparing them based on their ratings by the users . We download the comments of these top 10 games to perform the sentiment analysis and Aspect-Based Sentiment Analysis providing each comment with a label of positive, negative or neutral and visualising the distribution of different aspects, which are luck, bookkeeping, downtime, interaction, bash the leader, complex and complicated.

2.2 Data

The data for the project was downloaded from the BoardgameGeek website api. The dataset for the ranking is downloaded in a csv file directly from the website consisting of 162340 games and 16 columns manually after they are analysed based on rating distribution. The Bayesian average provides a more stable estimate of the average rating by incorporating the number of ratings. It helps in mitigating the effect of outliers or sparsely rated items. Top 10 games are ranked and compared with that of the actual ranking on the website. By sorting games based on Bayesian average, we are identifying games that not only have good ratings but also have enough data to back up those ratings, avoiding the bias of outliers or games with very few ratings. (Figure1) The comments for the top10 games are according to the website as they are the most famous games rated by the community is downloaded which consist of more than 52k comments . The comments are further visualised based on the various languages (Figure 2) they are written in, the data is further cleaned, and only English-language comments are included, which came down to 45k comments.

Board Game Rank ▲		Title	Your Rating	Geek Rating	Avg Rating	Num Voters
1		**Brass: Birmingham** (2018) Build networks, grow industries, and navigate the world of the Industrial Revolution.	N/A	8.406	8.58	50275
2		**Pandemic Legacy: Season 1** (2015) Mutating diseases are spreading around the world - can your team save humanity?	N/A	8.370	8.52	55006
3		**Ark Nova** (2021) Plan and build a modern, scientifically managed zoo to support conservation projects.	N/A	8.343	8.53	49870
4		**Gloomhaven** (2017) Vanquish monsters with strategic cardplay. Fulfill your quest to leave your legacy!	N/A	8.334	8.57	64157
5		**Twilight Imperium: Fourth Edition** (2017) Build an intergalactic empire through trade, research, conquest and grand politics.	N/A	8.232	8.58	25433
6		**Dune: Imperium** (2020) Influence, intrigue, and combat in the universe of Dune.	N/A	8.228	8.43	50555
7		**Terraforming Mars** (2016) Compete with rival CEOs to make Mars habitable and build your corporate empire.	N/A	8.204	8.35	104264
8		**War of the Ring: Second Edition** (2011) The Fellowship and the Free Peoples clash with Sauron over the fate of Middle-earth.	N/A	8.192	8.55	22748
9		**Star Wars: Rebellion** (2016) Strike from your hidden base as the Rebels—or find and destroy it as the Empire.	N/A	8.169	8.42	33920
10		**Spirit Island** (2017) Island Spirits join forces using elemental powers to defend their home from invaders.	N/A	8.144	8.34	55700

	id	name	yearpublished	rank	bayesaverage	average	usersrated
105075	247030	Terraforming Mars: Prelude	2018	0	8.40978	8.84707	16106
0	224517	Brass: Birmingham	2018	1	8.40655	8.58340	50192
1	161936	Pandemic Legacy: Season 1	2015	2	8.37032	8.52021	54987
2	342942	Ark Nova	2021	3	8.34254	8.53492	49741
3	174430	Gloomhaven	2017	4	8.33433	8.57124	64118
138518	363622	The Castles of Burgundy: Special Edition	2023	0	8.31470	9.15260	7886
4	233078	Twilight Imperium: Fourth Edition	2017	5	8.23113	8.58243	25403
5	316554	Dune: Imperium	2020	6	8.22822	8.42701	50463
6	167791	Terraforming Mars	2016	7	8.20412	8.35197	104174
7	115746	War of the Ring: Second Edition	2011	8	8.19200	8.54693	22718

Fig. 1 Comparison of top 10 games based on Bayes ranking and ranking on BGG website.

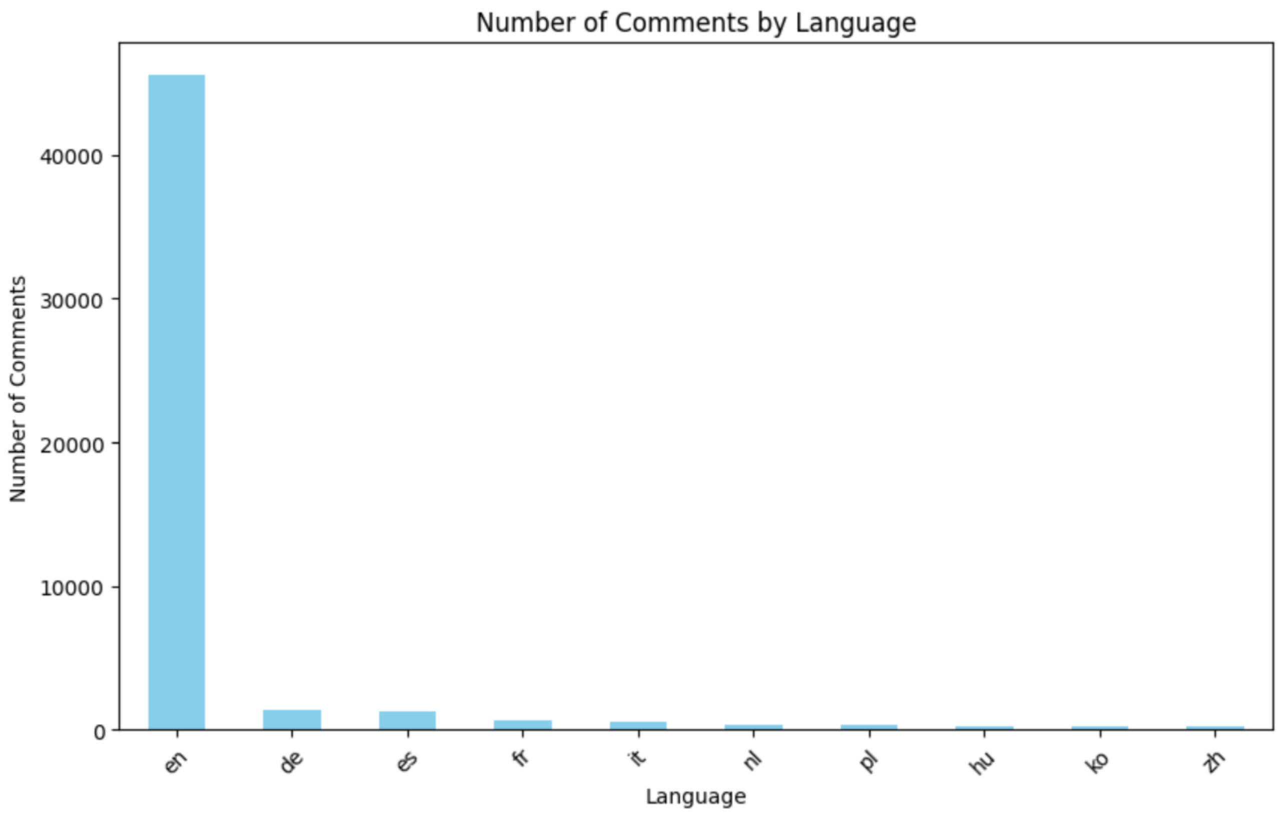

Fig. 2 comments in different Languages

2.3 Models

2.3.1 CardiffNLP Twitter RoBERTa Model (cardiffnlp/twitter-roberta-base-sentiment-latest)

This **RoBERTa-based** model is trained on **Twitter sentiment data**, making it effective for analyzing **social media-style comments**. The model is **fine-tuned** specifically for **sentiment classification**, assigning labels as **positive, neutral, or negative** with a confidence score. It excels in handling **slang, abbreviations, and informal expressions** often found in user-generated reviews.

2.3.2 ABSA (yangheng/deberta-v3-base-absa-v1.1)

Aspect-Based Sentiment Analysis (ABSA) with DeBERTa-v3

DeBERTa-v3 is an advanced transformer model fine-tuned for **Aspect-Based Sentiment Analysis (ABSA)**. Unlike traditional sentiment analysis, which classifies an entire comment, ABSA allows us to extract **sentiments related to specific aspects** within a review. This makes it highly effective for **understanding fine-grained opinions on individual board game mechanics.**

2.3.3 VADER-Sentiment Analysis

VADER (Valence Aware Dictionary and sentiment Reasoner) is a lexicon and rulebased sentiment analysis tool that is specifically attuned to sentiments expressed in social media. Unlike traditional sentiment analysis tools, VADER is designed to handle the informal, abbreviated, and emotive language commonly found in social media posts, tweets, product reviews, etc. It is particularly effective at analyzing sentiment in short texts, where machine learning-based models may struggle.

3 Results

3.1 Sentiment Analysis V/S Aspect-Based sentiment analysis:

While sentiment analysis provides an overall understanding of how people feel about a product, it falls short in uncovering why those feelings exist. This is where aspectbased sentiment analysis (ABSA) becomes crucial. Sentiment analysis offers a broad picture of whether the overall sentiment is positive, negative, or neutral. However, it doesn't tell us what specific aspects of the product are driving that sentiment. ABSA allows us to break down the overall sentiment into specific categories, such as ”bookkeeping,” ”complex” etc This helps in identifying what exactly is causing positive or negative reactions.Below are the compared results of ABSA (Fig 3) and sentiment analysis (Fig 4) for Brass Birmingham (game-id 224517).

	username	rating	value	boardgame_id	LANGUAGE	PROBABILITY	sentiment_label	sentiment_score
0	07734	10.0	Main	224517	en	0.169462	neutral	0.598183
1	1 Family Meeple	NaN	SLEEVED[IMG]https://cf.geekdo-static.com/mbs/m...	224517	en	1.000000	neutral	0.904020
2	13inha	NaN	G	224517	en	0.169462	neutral	0.475218
3	1bez	10.0	Great game, full controllo of your strategy th...	224517	en	1.000000	positive	0.894109
4	1x0r	8.5	Location: MSK	224517	en	0.169462	neutral	0.890108

Fig. 3 Aspect-Based Sentiment Analysis

	value	sentiment_label
0	Main	neutral
1	SLEEVED[IMG]https://cf.geekdo-static.com/mbs/m...	neutral
2	G	neutral
3	Great game, full controllo of your strategy th...	positive
4	Location: MSK	neutral
...	...	...
52657	Love this game! Haven't explored all of this g...	positive
52658	1	neutral
52659	Amazing game, with huge replayability. Have pl...	positive
52660	The undisputed king of my boardgame collection...	positive
52661	OA1-3	neutral

Fig. 4 Sentiment analysis

3.2 ABSA on Top 10 Board Games

For each game and aspect, a sentiment score **S** was calculated as follows:

$$S(game, aspect) = \frac{\#Positive - \#Negatives}{\#Reviews}$$

- A **score close to 0** indicates a **neutral sentiment**.
- A **score near -1 or 1** signifies a **strongly negative or strongly positive sentiment**.

The Aspect based analysis performed on all top 10 games on the predefined list of aspects given in the task (Table 1), which extracts the sentiment towards each aspect from comments. Some aspects did not return any sentiment score for some games. This can be due to the length of some comments, they had to be truncated to fit the model's input size. When comments are shortened, important contextual information related to specific aspects might be lost, leading to certain aspects not being identified or assigned a sentiment value. Also, some comments in the dataset are general in nature and do not mention any explicit aspect (e.g., ”Great game!” or ”Not worth the money”). These types of comments are difficult for Aspect-Based Sentiment Analysis (ABSA) models to process because they don’t focus on specific features or attributes of the product.

aspect game_id	BASH THE LEADER	BOOKKEEPING	COMPLEX	COMPLICATED	DOWNTIME	INTERACTION	LUCK
115746	NaN	NaN	-0.359455	-0.558704	0.130616	0.246035	-0.037419
161936	NaN	-0.704486	-0.112262	-0.317575	0.719961	0.975588	-0.198350
162886	NaN	-0.637781	-0.062874	-0.528871	0.303960	0.447259	0.141527
167791	-0.193153	0.011038	-0.198023	-0.437873	-0.524343	-0.235566	-0.023446
174430	NaN	-0.475967	-0.110227	-0.460587	-0.059197	0.100361	-0.104765
187645	NaN	-0.906832	-0.163251	-0.523608	0.284850	0.557191	-0.159391
224517	NaN	NaN	-0.159855	-0.459253	-0.152831	0.804205	0.008525
233078	-0.332175	-0.363805	-0.248086	-0.527748	-0.166143	0.621739	-0.126795
316554	NaN	NaN	-0.013212	-0.139640	0.291078	0.544670	-0.141087
342942	NaN	-0.339100	-0.205878	-0.673293	-0.301490	-0.489559	-0.106315

Table 1 Results obtained from ABSA on top 10

-The average sentiment score of the aspects of the top 10 games (Fig:5) are mostly in the range on -0.5 to 0.3 indicating strong negative sentiments. When ABSA is performed on one game for all aspects indicating sentiment distribution for different aspect.

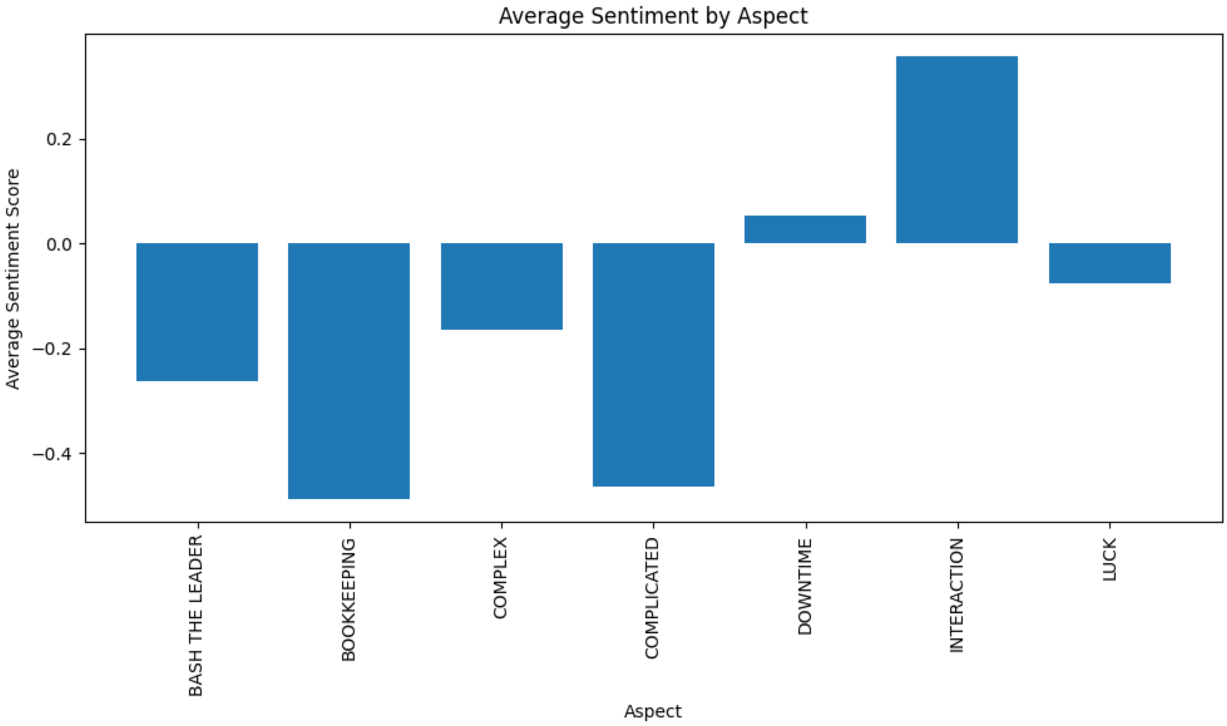

Fig. 5 average sentiment score on the aspects the top 10

3.3 Aspects term extraction using VADER

The goal of this task is to extract from each comment 10 positive and negative aspect for the top 10 games. The aspects have been filtered based on the frequent positive and negative term aspects (Table 3).Words like "great," "good," "fun," "best," and "play" appear frequently, suggesting that players generally have a positive experience with these games. These terms reflect satisfaction with gameplay, quality, and enjoyment. Games such as those with IDs 233078, 115746, and 167791 received specific praise for aspects like "friends," "fan," and "favorite," suggesting strong community or fandom support for these titles. Several games (e.g., 174430, 233078, 187645) are frequently associated with words like "combat," "war," and "battle," which may indicate that players feel these games are too focused on conflict and which is also true as all of these games are related to war and triumph in war or combat based scenarios.

	boardgame_id	top_positive	top_negative
0	224517	[good, great, fun, original, play, best, bette...	[hard, difficult, bad, demand, boring, tense, ...
1	161936	[great, fun, good, best, play, amazing, intere...	[bad, difficult, difficulty, hard, risk, borin...
2	342942	[good, great, fun, play, plays, luck, best, in...	[bad, hard, negative, difficult, problem, frus...
3	174430	[great, fun, good, best, play, interesting, am...	[combat, hard, repetitive, bad, enemies, diffi...
4	233078	[great, fun, good, best, play, better, friends...	[combat, hard, bad, war, battles, difficult, p...
5	316554	[good, great, fun, play, best, luck, interesti...	[combat, conflict, bad, battle, tense, tension...
6	167791	[good, great, fun, play, best, better, plays, ...	[bad, hard, poor, boring, problem, low, diffic...
7	115746	[great, best, good, play, fun, fan, amazing, p...	[war, combat, hard, tense, difficult, bad, bat...
8	187645	[great, fun, good, play, best, fan, original, ...	[combat, wars, rebels, rebel, rebellion, war, ...
9	162886	[great, fun, good, best, play, spirit, plays, ...	[difficulty, difficult, hard, adversaries, bad...

Table 3 Boardgame Positive Negative Aspects

4 Conclusion

Sentiment analysis results can vary based on specific aspects, with some generally neutral or negative aspects being perceived positively in certain games. Extracting positive and negative aspects highlights what the community values and what needs improvement.

To enhance accuracy:

- Model Performance: Pre-trained models may not be optimal for this dataset.
- Expanded Analysis: Analyzing more than the top 10 games across different complexities and themes can provide broader insights.
- Domain-Specific Fine-Tuning: Adapting PyABSA models with board game terminology and custom lexicons (e.g., "dice rolling," "worker placement") can improve sentiment classification.

References

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