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

Sentiment Analysis is a sub-field of NLP and together with the help of machine learning, it tries to identify and extract the insights from the data. The ML model for sentiment analysis takes a huge corpus of data having user reviews, and then finds a pattern and comes up with the conclusion based on real evidence rather than assumptions made on small sample of data Traditional sentiment analysis methods treat a text as a whole and assign it a single sentiment label (e.g., positive, negative, or neutral). This is adequate for many tasks, but there are also many situations where it would be useful to know the sentiment of a text with respect to a specific aspect and there comes Aspect-Based Sentiment Analysis into picture, often referred to as fine-grained opinion mining, is the process of assessing a text's emotion for a certain element. The shortcomings of conventional sentiment analysis techniques have given rise to a relatively new area of study called aspect-based sentiment analysis.

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 157074 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 68k 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 59k comments

2.3 Models

2.3.1 DistilBERT (distilbert-base-uncased-finetuned-sst-2-english)

is a distilled version of BERT that retains much of BERT's accuracy while being faster and less resource-intensive.The model is pre-trained and fine-tuned specifically for sentiment analysis, making it ideal for extracting sentiment labels (positive/negative/neutral) and scores from textual comments, assigning a confidence score to each sentiment label, which provides an indication of how strongly the model feels about its classification

2.3.2 ABSA

Aspect-Based Sentiment Analysis (ABSA) extends sentiment analysis by breaking down text into specific aspects or features and analyzing the sentiment towards each aspect independently. This approach provides a more nuanced understanding of how different components of a product or service are perceived, enabling targeted improvements and more precise insights. The objective of this ABSA analysis is to evaluate customer comments to understand sentiments associated with different aspects, by identifying which aspects are praised or criticized, the analysis aims to provide actionable insights for product enhancement and customer satisfaction.

	id	name	yearpublished	rank	bayesaverage	average	usersrated
0	224517	Brass: Birmingham	2018	1	8.41479	8.59552	46799
104127	247030	Terraforming Mars: Prelude	2018	0	8.40603	8.84660	15374
1	161936	Pandemic Legacy: Season 1	2015	2	8.37768	8.52593	53788
2	174430	Gloomhaven	2017	3	8.34962	8.58507	62580
3	342942	Ark Nova	2021	4	8.33519	8.53477	44675
4	233078	Twilight Imperium: Fourth Edition	2017	5	8.24000	8.59945	24139
5	316554	Dune: Imperium	2020	6	8.23076	8.43514	46480
137817	363622	The Castles of Burgundy: Special Edition	2023	0	8.21430	9.15168	6513
6	167791	Terraforming Mars	2016	7	8.21008	8.35695	100058
7	115746	War of the Ring: Second Edition	2011	8	8.18601	8.54119	21621

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	8.414	8.59	46905
2		**Pandemic Legacy: Season 1** (2015) Mutating diseases are spreading around the world - can your team save humanity?	N/A	8.377	8.53	53836
3		**Gloomhaven** (2017) Vanquish monsters with strategic cardplay. Fulfill your quest to leave your legacy!	N/A	8.349	8.58	62638
4		**Ark Nova** (2021) Plan and build a modern, scientifically managed zoo to support conservation projects.	N/A	8.335	8.53	44823
5		**Twilight Imperium: Fourth Edition** (2017) Build an intergalactic empire through trade, research, conquest and grand politics.	N/A	8.239	8.60	24169
6		**Dune: Imperium** (2020) Influence, intrigue, and combat in the universe of Dune.	N/A	8.230	8.43	46595
7		**Terraforming Mars** (2016) Compete with rival CEOs to make Mars habitable and build your corporate empire.	N/A	8.210	8.36	100175
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	8.186	8.54	21652
9		**Star Wars: Rebellion** (2016) Strike from your hidden base as the Rebels—or find and destroy it as the Empire.	N/A	8.170	8.42	32824
10		**Gloomhaven: Jaws of the Lion** (2020) Vanquish monsters with strategic cardplay in a 25-scenario Gloomhaven campaign.	N/A	8.160	8.43	34837

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

2.3.3 VADER-Sentiment Analysi

VADER (Valence Aware Dictionary and sentiment Reasoner) is a lexicon and rule-based 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. 6. Limitations

3 Results

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

While sentiment analysis [1] provides an overall understanding of how people feel about a product, it falls short in uncovering why those feelings exist. This is where aspect-based sentiment analysis (ABSA) becomes crucial. Sentiment analysis offers a broad

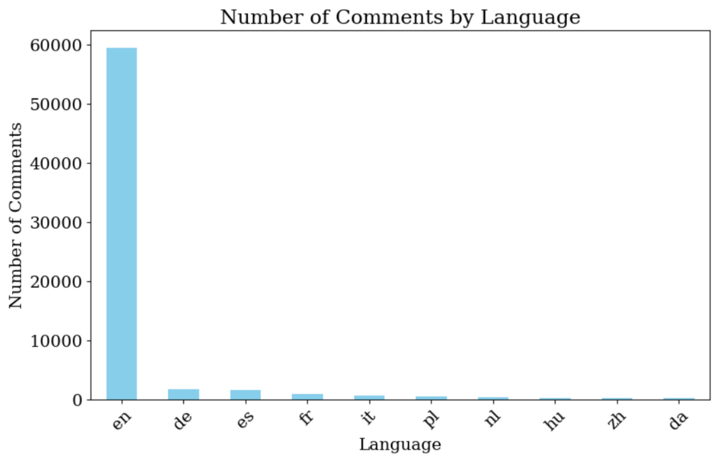

Fig. 2 comments in different Languages

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 war of the ring: second edition.

value	boardgame_id	LANGUAG	PROBABIL	(	overall_sentin	overall_sent
-0,5 for too soft plastic figures. They are disappointment!!!	115746	en	1		negative	0.966725
Organized; FoldedSpace.	115746	en	0.800493		neutral	0.6616355
BGG Spring 2019 VFM (trade)	115746	en	0.362988		neutral	0.9369762
Great strategy game but slightly biased against the Free Peoples I think.	115746	en	1		negative	0.602986
One of the best thematic implementations... you realy fight the war of the ring. Great!	115746	en	1		positive	0.8557879

Fig. 3 Aspect-Based Sentiment Analysis

```
                                                value sentiment_label
0     -0,5 for too soft plastic figures.  They are d...        NEGATIVE
1                               Organized; FoldedSpace.        NEGATIVE
2                           BGG Spring 2019 VFM (trade)        NEGATIVE
3     Great strategy game but slightly biased agains...        POSITIVE
4     One of the best thematic implementations... yo...        POSITIVE
```

Fig. 4 Sentiment analysis

3.2 ABSA on Top 10

For each pair (game, aspect) a score is calculated to gauge the polarity of the sentiment towards the aspect for that game, as follows:

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

A score S close to zero means that the positive and negative classifications balance themselves out so the overall sentiment is neutral, a score closer to the extremes, -1 and 1, means that the overall sentiment is, respectively, mostly negative or mostly positive. 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.

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.

Table 1 Results obtained from ABSA on top 10

Game Id	Game	Luck	Bookkeeping	Downtime	Interaction
224517	Brass: Birmingham	-0.04	-	-0.44	0.77
161936	Pandemic Legacy: Season 1	-0.21	-0.63	0.39	0.70
17440	Gloomhaven	0.01	-0.56	-0.15	0.16
342942	Ark Nova	-0.16	-0.65	-0.22	-0.44
233078	Twilight Imperium: 4th Edition	-0.13	-0.36	-0.24	0.65
316554	Dune: Imperium	-0.18	-	0.008	0.57
167791	Terraforming Mars	-0.15	-0.37	-0.42	-0.27
1154746	War of the Ring: 2nd Edition	-0.01	-	0.08	0.23
187645	Star Wars: Rebellion	-0.14	-0.91	0.24	0.61
291457	Gloomhaven: Jaws of the Lion	0.43	-0.38	-0.19	0.32

Table 2 Results obtained from ABSA on top 10

Game Id	Game	Bash the leader	Complicated	Complex
224517	Brass: Birmingham	-	-0.54	-
161936	Pandemic Legacy: Season 1	-	-0.41	-0.09
174430	Gloomhaven	-	-0.48	-0.16
342942	Ark Nova	-	-0.67	-0.24
233078	Twilight Imperium: 4th Edition	-0.41	-0.52	-0.24
316554	Dune: Imperium	-	-0.20	0.08
167791	Terraforming Mars	-0.23	-0.54	-0.107
115746	War of the Ring: 2nd Edition	-	-0.55	-0.33
187645	Star Wars: Rebellion	-	-0.54	-0.11
291457	Gloomhaven: Jaws of the Lion	-	-0.52	-0.29

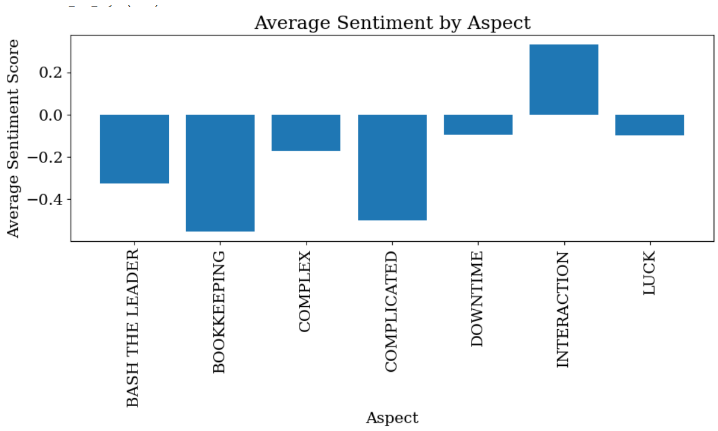

Fig. 5 average sentiment score on the aspects the top 10

3.3 Aspects term extraction using VADER

[2] 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 3.3).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

4 Conclusion

The results obtained show that the sentiment analysis results can indeed vary when done as per the aspects. Also, some aspects which may be seen as neutral or negative in average can be positive for some specific games. The extraction of positive and negative aspects clearly highlights what is being loved and liked by the community and what are the things which to be worked on.

There were things that could have been improved

- since the models were pre-trained the result might not perform the best for this particular dataset.
- Increase the number of games analyzed beyond the top 10. Analyzing games across different complexity levels, themes, and popularity can help generalize your findings and identify broader trends across the board game industry.
- Fine-tuning PyABSA [3] models with domain-specific data, such as board game terminology or phrases commonly used in the BGG community. Custom lexicons or

Index	Boardgame ID	Top Positive	Top Negative
0	224517	good, great, play, best, original, fun, interesting, better, plays, excellent	hard, difficult, bad, demand, boring, tense, wrong, limited, problem, tension
1	161936	great, fun, good, best, amazing, play, interesting, plays, better, original	bad, difficult, hard, tension, difficulty, risk, tense, boring, problem, wrong
2	174430	great, fun, good, best, play, interesting, amazing, better, friends, worth	combat, hard, repetitive, bad, enemies, difficult, difficulty, attack, boring, battle
3	342942	good, great, fun, play, luck, plays, best, interesting, better, nice	bad, hard, negative, problem, difficult, low, limited, frustrating, boring, lack
4	233078	great, good, fun, best, play, better, friends, worth, amazing, interesting	combat, hard, bad, battles, war, difficult, problem, battle, risk, boring
5	316554	good, great, fun, play, best, interesting, luck, better, plays, nice	combat, conflict, bad, tense, tension, battle, hard, limited, battles, conflicts
6	167791	great, good, fun, play, best, better, interesting, luck, plays, favorite	bad, hard, poor, problem, low, difficult, boring, terrible, ugly, negative
7	115746	great, good, best, play, fun, fan, amazing, plays, better, favorite	war, combat, hard, tense, difficult, bad, battle, risk, battles, tension
8	187645	great, fun, good, play, best, fan, original, amazing, interesting, plays	combat, wars, rebels, rebel, rebellion, war, battles, tension, hard, bad
9	291457	great, good, fun, original, best, better, play, easy, interesting, easier	combat, hard, repetitive, bad, enemies, difficult, difficulty, enemy, boring, damage

Table 3 Boardgame Positive Negative Aspects

dictionaries can be created to include specific terms (e.g., "dice rolling," "worker placement," "replayability") that are relevant to the board game context. Fine-tuning with this information can lead to more accurate aspect extraction and sentiment classification.

References

[1] D., A.: Introduction to BERT and Its Application in Sentiment Analysis. https://medium.com/analytics-vidhya/introduction-to-bert-and-its-application-in-sentiment-analysis-9c593e955560. Accessed: 2024-09-04 (2020)

[2] Hutto, C.J., Gilbert, E.: VADER: A parsimonious rule-based model for sentiment analysis of social media text. In: Proceedings of the Eighth International Conference on Weblogs and Social Media (ICWSM-14), Ann Arbor, MI (2014)

[3] Joulin, A., Grave, E., Bojanowski, P., Mikolov, T.: Bag of Tricks for Efficient Text Classification (2016). https://arxiv.org/abs/1607.01759