What do you like in boardgames?

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Abstract. This project focuses on applying sentiment analysis models to evaluate board game reviews, aiming to identify the positive, neutral, and negative attributes of these games. The study seeks to explore board game data to gain insights into user preferences and the elements that influence a game's popularity. Using sentiment analysis, especially with BERT-based models, user comments were categorized into different sentiment labels, and the sentiments were further examined in relation to specific aspects of the games.

Keywords: Board games · Aspects, Sentiment Analysis · Aspect-Based Sentiment Analysis.

1 Introduction

Sentiment analysis[1], also known as opinion mining, involves analyzing large volumes of text to determine whether the sentiment expressed is positive, negative, or neutral. Today, businesses have access to more customer data than ever before, offering both opportunities and challenges. With an overwhelming amount of textual data from sources such as emails, social media posts, online surveys, customer service chats, comments, and reviews, it is essential to extract meaningful insights to inform business decisions. Traditional sentiment analysis provides a broad understanding of customer opinions, but it often lacks the detailed insights needed to assess how specific features of a product or service are perceived. This is where Aspect-based Sentiment Analysis (ABSA) becomes valuable. ABSA provides a deeper understanding by focusing on individual attributes or features of a product or service. This approach enables businesses to analyze customer sentiment at a more granular level, uncovering insights about specific aspects—like the duration of a board game—that may influence overall satisfaction or dissatisfaction. The process begins with Aspect Term Extraction (ATE), where key aspects are automatically identified from the text. Then, Aspect Polarity Classification (APC) is used to determine the sentiment linked to each aspect, whether positive, negative, or neutral. By identifying the specific features that customers appreciate or dislike, businesses can improve their products and services, enhance customer experiences, and ultimately strengthen their product and brand reputation.

2 The Methodology

2.1 Goal

The main goal of this project is to perform a thorough analysis of reviews and comments about board games. The analysis focuses on extracting sentiments from user feedback related to specific aspects of the games, including luck, book-keeping, downtime, interaction, targeting the leader, complexity, and difficulty. Additionally, to provide context for our analysis, we start by visualizing and examining the overall data available on BoardGameGeek (BGG), which includes game rankings and user ratings. From this dataset, we filter out the top 10 board games (Figure 1), which then serve as the main focus for both 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

Data Source The board game review data was obtained from the BoardGameGeek (BGG) website. The dataset was downloaded in .csv format, containing information on over 150,000 board games. Key columns in the dataset include: ID (a unique identifier for each game), Name (the name of the board game), Rank (the ranking based on user ratings), Bayesaverage (the Bayesian average rating), Average (the average user rating), Usersrated (the number of users who rated the game), and Yearpublished (the year the game was released). Due to the large number of games, only the top 10 games were selected for analysis. For each of these games, the full set of reviews/comments was collected, resulting in an initial dataset containing over 69,000 reviews/comments.

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[4] (using langdetect library [**?**]) 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

ALBERT ALBERT (A Lite BERT)[2] is a variant of the well-known BERT (Bidirectional Encoder Representations from Transformers) model. It was introduced to address some of the limitations of BERT, primarily its large model size, which can lead to high memory usage and slow inference speeds. ALBERT offers a more parameter-efficient solution while maintaining the high performance that BERT is known for in various natural language processing (NLP) tasks.
Key Features of ALBERT[3]:

- **Parameter Efficiency**: ALBERT reduces the number of parameters significantly compared to BERT, making it more computationally efficient and easier to deploy. This is achieved through factorized embedding parameterization and cross-layer parameter sharing.
- **Efficient Scaling**: Despite having fewer parameters, ALBERT performs well on various NLP benchmarks, such as GLUE (General Language Understanding Evaluation) and SQuAD (Stanford Question Answering Dataset).
- **Performance**: ALBERT provides competitive results across multiple NLP tasks, including sentiment analysis, question answering, and text classification, making it a strong model for various applications.
- **Fine-Tuning**: ALBERT can be fine-tuned for specific NLP tasks, such as sentiment analysis, named entity recognition, or document classification, ensuring it can be tailored to a variety of use cases.

3 Results

IMDB Model Evaluation To ensure the effectiveness of our sentiment analysis model, we first trained and evaluated it on the widely-used *IMDB movie reviews dataset*. This dataset provides a benchmark for sentiment classification, allowing us to assess the model's ability to generalize across different types of textual data. The ALBERT model was fine-tuned on IMDB data and evaluated for performance before applying it to our main dataset.

The evaluation results on the IMDB dataset are as follows:

- **Loss:** 0.3020
- **Accuracy:** 93.39%
- **Precision:** 93.39%
- **Recall:** 93.39%
- **F1-score:** 93.39%
- **Model preparation time:** 0.0066s
- **Evaluation runtime:** 216598.47s

– **Samples per second:** 0.115

– **Steps per second:** 0.004

These results demonstrate that the model achieves high accuracy and precision on a standard sentiment analysis task, making it a suitable choice for analyzing sentiment in our primary dataset.

Sentiment Analysis Results The sentiment analysis results for a sample of board game reviews using the ALBERT model are shown in Figure 1. Each review is associated with a sentiment label (either *positive* or *negative*) along with a confidence score, which ranges from 0 to 1. A higher score indicates greater confidence in the sentiment classification.

```
Sample of the results:
   boardgame_id                                              value  \
0        224517  SLEEVED[IMG]https://cf.geekdo-static.com/mbs/m...
1        224517  Great game, full controllo of your strategy th...
2        224517                                      Location: MSK
3        224517  Very clever game, enjoyable overall.  Plus poi...
4        224517  Brilliant!  Fits right into my wheelhouse all ...
5        224517  Absolutely brilliant!  I never played the orig...
6        224517  I prefer old school Brass or AoI. I do like th...
7        224517  The game itself is not interesting enough to l...
8        224517                                "You can't do that."
9        224517  This is a near-perfect board game because...  ...

  sentiment_model_1  score_model_1
0          positive       0.974834
1          positive       0.998138
2          negative       0.745414
3          positive       0.996099
4          positive       0.995724
5          positive       0.997682
6          negative       0.989379
7          negative       0.999007
8          negative       0.982827
9          positive       0.998641
```

Fig. 1. Sample results of sentiment analysis on board game reviews using the ALBERT model. The figure displays the boardgame ID, the review text, the predicted sentiment, and the confidence score for each review.

Aspect-Based Sentiment Analysis (ABSA) Results The aspect-based sentiment analysis (ABSA) was performed on the board game comments to identify key aspects mentioned in the reviews, such as *downtime*, *interaction*, and *complexity*. The detected aspects were then classified according to their sentiment (either *positive* or *negative*) for each comment.

```
    boardgame_id                                              value  \
3         224517  Very clever game, enjoyable overall.  Plus poi...
4         224517  Brilliant!  Fits right into my wheelhouse all ...
7         224517  The game itself is not interesting enough to l...
9         224517  This is a near-perfect board game because...  ...
10        224517  Excellent and highly interactive game. Probabl...

                    detected_aspects  \
3   [downtime, interaction, complexity]
4                         [interaction]
7                         [interaction]
9            [interaction, complexity]
10  [downtime, interaction, complexity]

                                     aspect_sentiments
3   {'downtime': 'positive', 'interaction': 'posit...
4                       {'interaction': 'positive'}
7                       {'interaction': 'negative'}
9   {'interaction': 'positive', 'complexity': 'pos...
10  {'downtime': 'positive', 'interaction': 'posit...
ABSA completed and results saved to /Users/negarakhgar/Desktop/nlp project/boardgames_absa_results_albert.csv
```

Fig. 2. Results of aspect-based sentiment analysis on board game reviews. The figure shows the detected aspects for each review, along with the corresponding sentiment for each aspect.

References

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