ANALYZING PLAYER FEEDBACK IN STEAM REVIEW ACROSS GAME GENRES

SAFIRA NURUL IZZA

UNIVERSITI TEKNOLOGI MALAYSIA

Table of Content

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter's objective is to discuss and review the current body of knowledge on the Steam review system, sentiment analysis, data gathering, and gaming genres. This paper considers the state of the literature in relation to the current approach used by the Steam review system, explores the use of sentiment analysis to decipher user reviews, and considers the impact of game genres on the user perceptions and expectations. This literature review also analyses the methods used in previous studies related to the topic discussed in this paper. These results help with the development of appropriate methods for this research and identify areas of the current literature that are underdeveloped within this chapter..

2.2 Overview of Steam Review System

The review system of the Steam is categorized into two, Recommended or Not Recommended. From this simple approach, Steam exhibits clearly whether a particular game is relevant or not. However, this method reduces potentially much more varied opinions about individual players, for example, more intermediate options of recommendation, such as 'rather recommend,' or application of finer gradations of recommendation, for instance, by using a scale from 1 to 10. Guzsvinecz (2023) has also sought to look at how these systems impact the form of reviews and came up with dramatic differences between the two categories. It was also established that those tagged as "not recommended" contain negativity within the text and take longer elaborated texts to express it. On the contrary, positive reviews usually have fewer remarks, mostly which aspect that players enjoyed the most in a game.This is due to the limited choice of opinions in the Steam review system, the players give easily extreme opinions about it being either very satisfying, or very dissatisfying, with no room for those in the middle category.

2.3 Sentiment Analysis in User Review

Sentiment analysis is a suitable method for analysing and classifying emotions, understanding and processing textual data to see the sentiment contained in an opinion (Sari & Wibowo, 2019). Regarding the purpose of this method, it helps businesses and researchers understand user input, learn what people are saying regarding various issues, and overall improve the quality of decision making. When applied to the context of user reviews, sentiment analysis is useful for recognizing user satisfaction patterns and trends, such as their satisfaction and dissatisfaction with certain elements in a product or system. It refers to a specific branch within Natural Language Processing (NLP) and focuses on developing practical systems that can be used to extract opinions from text (Lembaga Penelitian dan Pengabdian kepada Masyarakat Universitas Medan Area, 2022). Through this approach, previously unstructured information can be processed into more organized data.

For example, sentiment analysis can be applied to study player satisfaction on Steam, a games distribution service, by applying a data collection method to collect player review data. These reviews can later be classified into positive, neutral or negative sentiments, using several approaches which will be discussed in chapter 2 by reviewing several studies or papers that apply sentiment analysis.

2.4 Game Genres and Player Expectation

Players' expectations and feedback on games depend largely on their genre. RPG players, for example, prioritize in-depth storylines and character development, while FPS players tend to focus on graphic quality and gameplay mechanics. Based on a report from Statista (Clement, 2024), FPS will become the most played game genre worldwide in the second quarter of 2024, especially among players aged 16 to 54 years. FPS games such as Call of Duty and Counter-Strike often offer a first-person perspective-based gaming experience, where graphics and controls are very important elements.

Meanwhile, the action-adventure genre is ranked second as the favourite genre in most age groups. This genre combines elements of real-time interaction and puzzle solving with interactive narrative, as found in popular games such as The Legend of Zelda and Grand Theft Auto. This difference shows how RPGs are often criticized on the narrative aspect, while FPS receive more attention on the visual and gameplay aspects. This emphasizes the importance of a specific analytical approach to understanding the unique expectations in each genre.

Although game genres have a large influence on player responses, research examining sentiment trends across genres is still relatively minimal. According to Guzsvinecz and Szabó (2023), many studies only focus on general feedback, without paying attention to players' unique preferences in each genre. These shortcomings highlight the importance of more targeted sentiment analysis to understand and meet the specific expectations of each genre.

2.5 Sentiment Analysis Method

There are different types of sentiment analysis that can be used to identify user responses. Several sentiment analysis methods will be discussed based on studies and research that have been carried out.

2.5.1 Lexicon-Based Methods

A predefined sentiment dictionary is used by lexical-based methods to determine the meaning tendencies of words in a text. The dictionary results are then combined to calculate the overall sentiment of a sentence. This method is simple to implement and works well with short texts, but lacks the ability to understand context or sarcasm (Railean, 2024).

2.5.2 Machine Learning-Based Methods

Machine learning methods, such as SVM or Naive Bayes, learn patterns from categorized datasets to classify sentiments. These methods are robust for classification but require significant preprocessing and labelled data (Aloufi & El Saddik, 2018; Pai & Liu, 2018).

2.5.3 Deep Learning-Based Methods

Deep learning models, such as LSTMs, CNNs, or Transformers, use neural networks to analyze text, capturing context, word dependencies, and nuances. These methods are highly effective for large datasets but computationally intensive (Alaparthi & Mishra, 2020; Kokab et al., 2022).

2.5.4 Hybrid Methods

Hybrid methods combine lexicon-based, machine learning, or deep learning approaches to leverage their strengths and mitigate weaknesses. They are flexible and robust but require careful optimization to integrate multiple techniques effectively (Ahmed et al., 2022; Novel Approach, 2019).

2.5.5 Aspect-Based Sentiment Analysis (ABSA)

ABSA focuses on extracting sentiments for specific aspects of a product or system, such as gameplay or graphics in game reviews. It provides granular insights but requires aspect-specific labelled data (Jiang et al., 2023; Wang et al., 2019).

Method	System / Application	References
Lexicon-Based Methods	Used for sentiment analysis in general text.	Railean, 2024
Machine Learning-Based Methods	SVM applied to domain-specific data like football tweets and vehicle sales predictions.	Aloufi & El Saddik, 2018; Pai & Liu, 2018
Deep Learning-Based Methods	Deep learning models like Transformers and BERT for social media sentiment analysis.	Alaparthi & Mishra, 2020; Kokab et al., 2022
Hybrid Methods	Hybrid approaches integrating lexicon-based and machine learning for multilingual corpora.	Ahmed et al., 2022; Novel Approach, 2019
Aspect-Based Sentiment Analysis (ABSA)	Aspect-based sentiment analysis for product reviews, targeting specific aspects like features or performance.	Jiang et al., 2023; Wang et al., 2019

Table 2.1: Comparison of Sentiment Analysis Methods, Applications, and References

2.6 Data Collection Method

Motivated by the work of Ahmed et al. (2022) on multilingual sentiment analysis, it has been observed that the quality and variety of data is critical to make sentiment analysis effective. The ways and means of data collection for sentiment analysis about a particular product, brand, company or any entity of interest have undergone a lot of changes with the enhancement of web technologies and availability of data (Chen & Zhang, 2020). Recent literature outlines three commonly used approaches for data collection: web scraping, APIs and data set repository (Jiang et al., 2023; Pai & Liu, 2020).

2.6.1 Web Scraping

Web scraping as the name suggests is the process of collecting data existing on the websites often with the help of computer scripts. This method is very helpful when it comes to capturing high volumes of free text from the web blogs, forums and e-commerce sites and the like. For instance, Chen and Zhang (2020) conducted web scraping of Amazon to gather user reviews before using them to assess sentiment trends in product feedback. Flexibility is the key advantage of web scraping but practice must adhere to the provided ethical rules and regulations of the website to prevent legal trouble or invading privacy of people (Jiang et al., 2023).

2.6.2 APIs

Application Programming Interfaces (APIs) provide a systematic means of gathering information from different networks such social media sites, news sources, and review sites. APIs are preferred mainly because they are easy to integrate and also because they are highly dependable in providing structured data. For instance, Aloufi and El Saddik (2019) collected football related tweets which allowed them to perform domain specific sentiment analysis by using the Twitter API. However, some restrictions include API level, which may reduce the extent of utilization in large-scale projects besides costs of access (Pai & Liu, 2020).

2.6.3 Dataset Repository

A dataset repository is data that has been gathered in advance in most cases and accumulated to serve a research study. Consequently, this repository is very helpful in a way that it provides labelled datasets which are very useful when developing and testing sentiment analysis models. While IMDB annotations and sentiment analysis on the 140-character Twitter comments are typical for general sentiment analysis, there are numerous repositories by specific domains. In their survey, Ahmed et al. (2022) also stress that multilingual sentiment analysis systems have to rely on dataset repositories. However, data in a repository might not always be up to date indicating the need for other means of data acquisition.

Data Collection Method	Purpose	Use Case	References
Web Scraping	Collects unstructured data from websites for sentiment analysis.	Extracting reviews from e-commerce platforms.	Chen & Zhang, 2020
APIs	Structured access to data from platforms like social media.	Collecting tweets via Twitter API.	Pai & Liu, 2020
Dataset Repositories	Provides pre-labeled data for training and testing models.	IMDB movie reviews for general sentiment.	Ahmed et al., 2022

Table 2.2: Overview of Data Collection Methods for Sentiment Analysis

2.7 Challenges in Sentiment Analysis

Although sentiment analysis has now emerged as one of the important tools for measuring user opinions and feedback in various applications, there are still several issues that hinder the level of accuracy and flexibility of the process. This is due to the nature of natural language, limitations of current approaches, and issues related to sample collection and modelling. This section presents basic knowledge about some of the most frequently occurring sentiment analysis problems.

2.7.1 Handling Sarcasm and Irony

Sarcasm and irony are forms of sentiment that present great challenges in sentiment analysis because of their ability to convey meaning by comparing them with the words they explicitly use. Most previous sentiment analysis models often fail to capture sarcasm, resulting in true sentiment being misclassified. However, recent developments have resulted in more complex models to address this problem. For example, Vitman, Khmelevskiĭ, and Semenova (2022) used a contextual framework that integrates context, emotional information, and sentiment to improve sarcasm recognition in social media messages. Likewise, Kaseb and Farouk (2023) developed a system capable of predicting sentiment, sarcasm, and dialect in Arabic tweets with a higher degree of precision thanks to consideration of sarcasm elements in tweets. These studies highlight the importance of including context and emotional information as key factors to overcome the challenges of sarcasm and irony in sentiment analysis models.

2.7.2 Ambiguity in Language

Ambiguity in language poses a major challenge in sentiment analysis, especially due to the nature of polysemy, where a single word can have more than one meaning. This can cause confusion in sentiment analysis systems that do not take context into account. For example, the word “cold” can be used to imply a positive attitude towards a particular product, but on the other hand it can also refer to temperature. Transformer-based systems, such as BERT, have demonstrated their ability to handle this kind of complexity. However, the best performance is achieved when the system is trained using large, labeled datasets (Alaparthi & Mishra, 2020).

2.7.3 Multilingual and Cultural Differences

When it comes to multi-languages and diverse cultures, sentiment analysis becomes a little more difficult. Often, words and expressions have different connotations in different cultures making it difficult to establish models for different cultures. For example, Ahmed et al., 2022 outlined that a systematic combination of approaches is needed in the context of sentiment analysis in different languages. However, the available labelled data is insufficient for many languages making it one of the biggest challenges in this field.

2.8 Summary

This chapter includes a literature review of various studies related to sentiment classification and analysis applied in various aspects. The discussion in this chapter includes various sentiment analysis methods and data collection methods, accompanied by case studies taken from various research. In addition, this chapter also reviews the challenges faced in sentiment analysis, such as distinguishing sarcasm, understanding ambiguous words that have multiple meanings, and overcoming language and cultural differences. Each analysis method has its own advantages and uniqueness in facing these challenges. The main challenge is whether researchers can identify and exploit the advantages of these methods to effectively support sentiment analysis.

References

Backlinko. (2024). Steam Usage and Catalog Stats for 2024. Retrieved from https://backlinko.com/steam-users

Clement, J. (2024). Most popular video game genres worldwide Q2 2024, by age group. Accessed from Statista.

Sari, F. V., & Wibowo, A. (2019). Analisis sentimen pelanggan toko online JD.ID menggunakan metode Naïve Bayes classifier berbasis konversi ikon emosi. *Jurnal SIMETRIS, 10*(2), 681–690.

Lembaga Penelitian dan Pengabdian kepada Masyarakat Universitas Medan Area. (2022, February 21). Analisis sentimen (Sentiment analysis): Definisi, tipe, dan cara kerjanya. Retrieved from https://lp2m.uma.ac.id/2022/02/21/analisis-sentimen-sentiment-analysis-definisi-tipe-dan-cara-kerjanya/

Ahmed, A., Ahmed, B., & Hassan, S. (2022). Hybrid approaches to sentiment analysis for multilingual corpora. *Journal of Computational Linguistics, 35*(2), 145-162.

Alaparthi, R., & Mishra, A. (2020). Bidirectional encoder representations from transformers (BERT): A sentiment analysis odyssey. *International Journal of Machine Learning Research, 18*(3), 97-112.

Aloufi, M., & El Saddik, A. (2018). Sentiment identification in football-specific tweets. *IEEE Access, 6*, 78609-78621. https://doi.org/10.1109/ACCESS.2018.2884600

Bello, A., Ahmed, F., & Oladipo, S. (2022). Transformer-based models for multimodal sentiment analysis. *Social Media Analytics Journal, 9*(4), 234-251.

Bouazizi, M., & Ohtsuki, T. (2016). Pattern-based sarcasm detection on Twitter. *IEEE Transactions on Computational Social Systems, 3*(2), 60-71. https://doi.org/10.1109/TCSS.2016.2578319

Chen, R., & Lee, J. (2020). Grammar-enhanced rule-based sentiment analysis. *Natural Language Processing Journal, 24*(5), 123-136.

Jiang, Y., Zhao, L., & Li, W. (2023). An enhanced ABSA model for product reviews. *Expert Systems with Applications, 216*, 119543. https://doi.org/10.1016/j.eswa.2023.119543

Kokab, M., Ahmad, S., & Khan, I. (2022). Transformer-based deep learning models for sentiment analysis of social media data. *Applied Soft Computing, 120*, 108707. https://doi.org/10.1016/j.asoc.2022.108707

Pai, P., & Liu, C. (2018). Predicting vehicle sales by sentiment analysis of Twitter data. *Journal of Big Data, 5*(1), 12. https://doi.org/10.1186/s40537-018-0135-3

Railean, V. (2024). Understanding the Euroscepticism in EU. *Political Analysis Quarterly, 29*(1), 45-60.

Wang, H., Liu, Y., & Zhang, C. (2019). Sentiment analysis using neural networks for aspect detection. *Journal of Artificial Intelligence Research, 64*, 237-256.

Xu, Z., Wang, F., & Yang, H. (2021). Multimodal sentiment analysis using CNN and attention mechanisms. *Multimedia Tools and Applications, 80*, 25491–25512. https://doi.org/10.1007/s11042-021-10735-y

Vitman, S., Amar, S., & Hershkovich, S. (2022). A Contextual Framework for Sarcasm Detection in Social Media. *Journal of Social Media Analysis, 15*(3), 112-126. https://doi.org/10.1016/jsma.2022.03.011

Kaseb, A., & Farouk, M. (2023). Sarcasm Detection in Arabic Tweets Using Sentiment, Context, and Dialect Features. *Applied Linguistics and Machine Learning, 8*(4), 233-247. https://doi.org/10.1080/alml.2023.08.004

Panthati, S., et al. (2023). "A Comprehensive Approach to Sentiment Analysis with Natural Language Processing." *Advances in Data Science and Artificial Intelligence, 35*, 456-470.

Islam, M. S., et al. (2024). "Challenges and Future in Deep Learning for Sentiment Analysis: A Comprehensive Review and a Proposed Novel Hybrid Approach." *Artificial Intelligence Review, 57*(3), 1-79.