ANALYZING PLAYER FEEDBACK IN STEAM REVIEW

ACROSS GAME GENRES

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# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Introduction

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. This method is effective for processing data on a large scale, but involves a complex calculation process that requires large computing resources. (Alaparthi & Mishra, 2020; Kokab et al., 2022).

### 2.5.4 Hybrid Methods

Hybrid methods combine lexicon-based methods, machine learning or deep learning and utilize the advantages of each method to achieve a specific goal. Although this method is flexible and powerful, it still requires careful adjustments so that all methods can work well (Ahmed et al., 2022; Novel Approach, 2019).

### 2.5.5 Aspect-Based Sentiment Analysis (ABSA)

Aspect-Based Sentiment Analysis or ABSA is an attempt to determine sentiment towards aspects of a product or system, for example game play or graphics in game reviews. This approach offers more information, but labelled data relating to each aspect must be used (Jiang et al., 2023; Wang et al., 2019).

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

| 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 |

## 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 ecommerce 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 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.

Table 2.2: Overview of Data Collection Methods for Sentiment Analysis

| 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 |

## 2.7 Tools and Platforms

Google Colaboratory and Jupyter Notebook are two widely used tools for data analysis and machine learning. Their features and limitations are summarized in the table 2.3.

Table 2.3: Comparison of Google Colaboratory and Jupyter Notebook

| Feature | Google Colaboratory | Jupyter Notebook |
|---|---|---|
| Platform | Cloud-based, accessed via a web browser. | Local or server-based installation. |

| | | |
|---|---|---|
| Setup | Pre-configured with libraries like TensorFlow, Keras, PyTorch, and OpenCV. | Requires manual installation of libraries. |
| Hardware Resources | Provides free access to GPUs and TPUs. | Relies on user hardware. Can integrate with GPUs if available. |
| Performance | Suitable for GPU-centric tasks, less efficient for CPU-based operations due to limited cores. | Performance depends on local machine specs; scales with better hardware. |
| Runtime Limitations | Session lasts up to 12 hours, with GPU usage potentially restricted after extended use. | Unlimited runtime, contingent on local hardware capabilities. |
| Cost | Free of charge with Google Drive integration. | Cost depends on user hardware and maintenance. |
| Collaboration | Integrated sharing via Google Drive; supports real-time collaboration. | Limited sharing options; third-party tools required for collaboration. |
| Data Handling | Seamless integration with Google Drive. | File handling depends on the local environment or additional setups. |
| Offline Access | Not available, requires internet connection. | Fully functional offline. |

| Use Case | Ideal for quick prototyping, education, and projects requiring GPU access without dedicated hardware. | Preferred for projects needing full control over the environment or long-term computations. |
| --- | --- | --- |

Both tools have their strengths and serve different user needs. Google Colaboratory is great for users with limited resources or those needing quick setup and GPU support. Jupyter Notebook is better for advanced users who want more control and offline access. Using both tools together can create an efficient workflow. This summary is based on Carneiro et al. (2024).

## 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

Sarcasm is a form of sentiment and is the most complicated factor in sentiment analysis because it requires comparing the hidden meaning with the words written explicitly. In most previous sentiment analysis models, sarcasm is an aspect that often goes unnoticed, resulting in misinterpretation of words. However, much recent research has led to the development of complex models to solve this problem. For example, Vitman, Khmelevskiĭ, and Semenova (2022) proposed a contextual framework, which leverages context, affective information, and sentiment to improve sarcasm detection for SM messages. In addition, Kaseb and Farouk (2023) proposed a more accurate system in

terms of sentiment, sarcasm, and dialect for Arabic tweets because it considers the elements of sarcasm in tweets. These studies have revealed that the context and emotional information combined play a role as key factors to help eliminate the difficulties associated with sarcasm in sentiment analysis models.

## 2.7.2 Ambiguity in Language

One of the major obstacles in sentiment analysis comes from the use of words with multiple meanings, in other words, polysemy. This can be confusing to sentiment analysis systems that does not factor in context into the equation. For instance, the word 'cool' within the context of a text may be viewed to mean something positive, but on the other hand, it can also refer to temperature. Another benefit of the model is handling such feature complexity, and other similar systems include the BERT transformer. Yet, the most favorable performance is reached when working with large datasets that comprehensively labelled (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 Conclusion

This chapter includes a review of the literature, different research on sentiment analysis and analysis applied in various fields. This chapter highlights various sentiment analysis methods, and data collection methods followed by examples from different studies. Apart from that, this literature review also presents the difficulties experienced in doing

sentiment analysis, for example, how to differentiate between sarcasm, handle figures of speech with varying meanings, or overcome the barriers of different languages and cultures. When applied to these challenges, each analysis method has different benefits and approaches. However, a major concern is whether researchers can recognize and utilize such techniques to facilitate the sentiment analysis process.