Esports Game Updates and Player Perception: Data Analysis of PUBG Steam Reviews

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Abstract—Game updates are essential because they usually contain critical patches to improve the players’ experience. Compared with traditional online games, esports games abandon the storyline and emphasize the players’ competitive motivation. As a result, esports games need to be updated more frequently to extend the game development life cycle. Meanwhile, developers get feedback from players’ reviews on esports games to improve the game experience, services, or adjust operating strategies. However, there has been little research conducted on the influence of esports game updates on player reviews. In this study, we aim to determine the influence of the monthly update on the player community by carrying out an analysis of PUBG, one of the representatives of esports games, via topic modeling. In total, we collect approximately 300,000 reviews on Steam. Our contributions in this paper are: (i) we use the LDA model to infer and group reviews into 14 topics, (ii) we analyze the influence from esports game updates on topics prevalence over time, and (iii) we conduct sentiment analysis to reveal players’ satisfaction levels with each topic.

Index Terms—esports reviews, Steam, topic modeling, player sentiment

I. INTRODUCTION

Video games have increased in popularity over time and have become one of the most popular entertainment activities. Gaming can both be entertainment as well as competition. This professional and competitive video gaming in the form of competitions has been termed esports (electronic sports). Compared with the traditional video game mode that emphasizes graphics and storylines, esports games advocate PVP (Player vs. Player) more. Esports is a monthly factor in the video game industry by effectively boosting players’ competitive motivation and continuously updating new contents. Many game developers were actively designing and providing funding for tournaments and other events. A recent global esports market report (Newzoo 2021) indicates that global esports revenues will grow from $947.1 million in 2020 to $1.084 million in 2021 on year-on-year growth of 14.5%. The global esports games live-streaming audience will reach 728.8 million in 2021, growing 10.0% from 2020¹. Online digital distribution platforms partly enabled this increasing popularity for games, such as Steam.

¹https://newzoo.com/insights/trend-reports/newzoos-global-esports-live-streaming-market-report-2021-free-version

The Steam platform is the most prominent digital distribution platform for PC gaming. Steam has more than 120 million monthly active users and a catalog of over 50 thousand games². In addition to being a platform for purchasing and playing games, it is also a place where players can write game reviews and share their opinions. Players can label the game as recommend or not recommend when commenting. An overall summary of the proportion of positive reviews is prominently reported on a game’s Steam store page [1] and game reviews are the most valuable feedback to reflect the preferences and problems of esports enthusiasts. Players are more inclined to seek peer reviews or expert recommendations when purchasing games, rather than relying on unilateral game information provided by the company, because players are more willing to search for as much information as possible to reduce the risk of finding games. Therefore, game reviews have a significant impact on businesses and play a pivotal role in decision-making by players [2]. Similarly, game reviews are rich and varied in terms of themes and topics covered and offer developers advice on improving the quality of games. Hence, much research conducted on player’s behavior have benefited from Steam’s powerful review system [3], [4].

In addition to communicating directly with players in the community, game updates are crucial for game developers to interact with and respond to players. Game updates are creating new content, adding new items, play modes, ranking systems, and so forth. It is an indispensable part of online games because it sustains players’ attraction and motivation in playing games [5]. In many cases, developers use the online game community for advertising their games’ new updates to reach the game players. The reviews also include players’ opinions on the update. In order to make the best use of game updates to increase the popularity and profitability of the game, the player’s comments offer valuable insights for game developers. Hyong et al. [6] empirically analyzed the actual changes of individual players’ gameplay before and after updates in online games.

In this study, we choose a particular game, PlayerUnknown’s Battlegrounds (PUBG). As an online multiplayer battle
royale game on Steam, PUBG is one of the most played, highest-grossing, and best-selling esports games. Since PUBG was first launched on Steam, the game has been widely supported by many players. As an esports game, PUBG ensures the frequency of game updates at least once a month\(^3\). Therefore, online reviews are essential for developers to receive players’ feedbacks and opinions. There are many aspects that players pay attention to, which makes it complicated to find the topics most concerned by players. The solution to this problem can be found by studying their opinions and comments. The result might enable us to understand the meaning behind the player’s choice of the game. The study focuses on understanding the game experience’s crucial features by analyzing game reviews on the Steam platform. We collect player’s reviews from games available on Steam and apply text mining techniques based on machine learning to analyze the collected data. We extract meaningful topics and their sentiment in the player reviews and infer the relationship between these topics and updates.

In the following section, we introduce the related work on the topic modeling and previous research in game reviews. Next, we describe the methodological details of data collection, analysis methods, and processing. Then we summarize the experiment results. Finally, we discuss limitations and draw future research directions with practical implications.

II. RELATED WORK

In this study, we choose one of the simplest and most popular topic models, Latent Dirichlet Allocation (LDA) [7], by considering the computational complexity of inference in topic models [8]. The LDA model is arguably one of the most important probabilistic models widely used today. It is a powerful generative probabilistic topic model tool for exploring large datasets and inferring document content [7]. The idea of LDA is that every document contains potential topics, and these topics determine the distribution of words. For example, Stefan et al. [9] addressed the problem of automatically identifying the underlying topics of news releases by using the LDA method. Tran et al. [10] pointed out the sentiment of customers towards many hotel aspects from a large number of hotel reviews by running an online LDA algorithm. Putri et al. [11] interpreted the general trend of travel reviews into certain topics by using LDA method. Yu et al. [12] detected esports players’ favorite topics by using the LDA method. Chen et al. [13] proposed to apply LDA to cluster hotel reviews into multiple topics to improve the comprehensibility of visualization.

Game reviews can be defined as product evaluations generated by peers published on a company or third-party website [14]. Game reviews provide information about a product from the players’ perspective, which helps users reduce their uncertainty about purchasing gaming products. From the viewpoint of developers, review analysis can help verify defects in the products they develop [15]. As for game reviews, many researchers have chosen the Steam online reviews to catch up with such trends related to games. It is because game communities created by users have a broad range of data in various forms. Kang et al. [2] analyzed community data in the games domain available on Steam, using Classification and Regression Tree. There are few restrictions on game reviews, resulting in poor quality of review data and invalid expressions. Game reviews could contain invalid information, such as special characters or spam messages. Therefore, it is more difficult to get high-quality reviews from gaming reviews compared to other platforms. Busurkina et al. [1] found how people evaluate their game experience based on reviews on the Steam platform.

Although many studies have been conducted on online games, few studies analyze the effect of updates on player behaviors. Therefore, through topic modeling, we aim to explore the concerned topic of esports players from the Steam community reviews. By visualizing the sentiment of players’ reviews, we examine the effectiveness of updates reflected via players’ thoughts.

III. METHODOLOGY

A. Proposed Framework

Fig. 1 shows the workflow of the proposed framework that perform topic discovering and a topic prevalence analysis task for PUBG reviews.

![Fig. 1. Proposed framework](image)

First, we collect the PUBG reviews dataset from Steam. Second, we apply text preprocessing, including crucial information detection and extraction (e.g., user’s SteamID, updated date, number of helpful and funny, language tag, reviews), language detection and filtration, noise removal to get the processed review dataset. The processed reviews will be fed into the topic model to extract topic words that reflect players’ concerns. Simultaneously, we implement a data analysis approach combining topic words discovered from the topic model and review text to discover topic prevalence and players’ overall

\(^3\)https://steamdb.info/depot/578081/history/
satisfaction. In this step, we calculate the topic positive rate and frequency with the following equations [3]:

\[
\text{positive rate} = \frac{\text{recommended reviews contain the topic}}{\text{all reviews}} \quad (1)
\]

\[
\text{frequency} = \frac{\text{reviews contain the topic}}{\text{all reviews}} \quad (2)
\]

Then we use the topic frequency to plot a heatmap for better monitoring the trend over time. Finally, we draw a conclusion for the whole dataset based on the achieved results.

### B. Latent Dirichlet Allocation (LDA) for Topic modeling

In this study, we apply Latent Dirichlet Allocation (LDA) [7], a widely used topic modeling method, to discover the underlying topics from the review text. LDA is a generative probabilistic model, which assumes that each document in the corpus is represented as a random mixture of potential topics, and the feature of each topic is the distribution of words in a vocabulary. Algorithm 1 shows the LDA generative process:

**Algorithm 1:** Generative Process of LDA [7]

1: for each topic \( k \in [1, K] \) do
2: \hspace{1em} sample mixture components \( \phi_k \sim \text{Dir}(\beta) \)
3: end for
4: for each document \( d \in [1, D] \) do
5: \hspace{1em} sample mixture proportion \( \theta_d \sim \text{Dir}(\alpha) \)
6: \hspace{1em} for each word \( n \in [1, N_d] \) do
7: \hspace{2em} sample topic index \( z_{d,n} \sim \text{Mult}(\theta_d) \)
8: \hspace{2em} sample a term for word \( w_{d,n} \sim \text{Mult}(\phi_{z_{d,n}}) \)
9: end for
10: end for

### IV. EXPERIMENTAL RESULTS

#### A. Dataset

We analyze community data in the PUBG by using the API\(^4\) provided by Steam to obtain a new dataset. Totally 324,722 PUBG reviews were collected from March 2017 (early access) to May 2021. The features of the data include a unique id of the recommendation, user ID, review publication & updated date, the recommend/not recommend tag for the review, language tag, review text, the number of people who rated the review as helpful, and the number of people who rated the review as funny, and so forth.

Before we apply LDA topic modeling, basic text processing will be implemented for data such as stopwords removal, stemming and tokenization. The purpose of text processing is to eliminate non-English words, emoticons or characters that are insignificant meaning for information extraction. Stopword removal is a process to eliminating words that likely unimportant for information extraction such as “a”, “the”, “are”, “in”, and “with”. The next text process is tokenization. It separates sentences into words, also called tokens, so that they can be processed by our model. The last processing is stemming, reducing inflected words to their word base form. After three steps of text processing, there are 258,790 reviews were left for further topic modeling and data analysis.

#### B. Topic Modeling and Grouping with LDA

For finding the optimal number of topics, we calculate and analyze the coherence score (\( u_{\text{mass}} \)) [16] of PUBG, which is a measure used to evaluate a topic model [17]. Fig. 2 shows the number of topics from 3 to 100 with their coherence value, from that we choose the optimal number of topics as 14 as the coherence scores are flattened out.

![Coherence scores of PUBG](Fig. 2)

In addition, we present some representative topics for PUBG inferred through LDA using WordCloud in Fig. 3. The size of each word corresponds to its probability in a topic.

![Topics discovered by LDA](Fig. 3)

We validate the inferred topics of the LDA model by reading the most weighted keywords of each topic and original review text to avoid implicit expressions or forum spam. For example, topic 6 could be inferred with “cheating”, while topic 5 is named by reading the sentences where keywords exist. Table I lists the topics we summarized from PUBG reviews.

#### C. Topic Prevalence and Semantic Analysis

In this stage, we feed those 14 topics inferred from the LDA model into a data analysis approach to infer the influence of esports game updates on topics’ popularity and satisfaction levels and then summarize.

Fig. 4 shows the interaction between PUBG players’ concern topics with time. The horizontal axis displays the date

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\(^4\)https://partner.Steamgames.com/doc/store/getreviews
Fig. 4. Topics prevalence over time

TABLE I
TOPICS AND RELATED KEYWORDS

<table>
<thead>
<tr>
<th>index</th>
<th>inferred topic</th>
<th>keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>character</td>
<td>0.006*&quot;man&quot; + 0.001*&quot;skin&quot;...</td>
</tr>
<tr>
<td>2</td>
<td>gameplay</td>
<td>0.005*&quot;gameplay&quot; + 0.002*&quot;survival&quot;...</td>
</tr>
<tr>
<td>3</td>
<td>server</td>
<td>0.040*&quot;server&quot; + 0.033*&quot;update&quot;...</td>
</tr>
<tr>
<td>4</td>
<td>optimization</td>
<td>0.045*&quot;bug&quot; + 0.016*&quot;crash&quot;...</td>
</tr>
<tr>
<td>5</td>
<td>matchmaking</td>
<td>0.015*&quot;hour&quot; + 0.005*&quot;match&quot;...</td>
</tr>
<tr>
<td>6</td>
<td>teamwork</td>
<td>0.034*&quot;friend&quot; + 0.008*&quot;team&quot;...</td>
</tr>
<tr>
<td>7</td>
<td>cheating</td>
<td>0.055*&quot;cheater&quot; + 0.019*&quot;hacker&quot;...</td>
</tr>
<tr>
<td>8</td>
<td>price</td>
<td>0.019*&quot;money&quot; + 0.003*&quot;price&quot;...</td>
</tr>
<tr>
<td>9</td>
<td>community</td>
<td>0.015*&quot;people&quot; + 0.003*&quot;relationship&quot;...</td>
</tr>
<tr>
<td>10</td>
<td>graphics</td>
<td>0.031*&quot;pc&quot; + 0.008*&quot;fps&quot;...</td>
</tr>
<tr>
<td>11</td>
<td>skill</td>
<td>0.004*&quot;recoil&quot; + 0.002*&quot;headshot&quot;...</td>
</tr>
<tr>
<td>12</td>
<td>learning curve</td>
<td>0.023*&quot;time&quot; + 0.001*&quot;tryhard&quot;...</td>
</tr>
<tr>
<td>13</td>
<td>maps</td>
<td>0.023*&quot;map&quot; + 0.006*&quot;snapground&quot;...</td>
</tr>
<tr>
<td>14</td>
<td>region</td>
<td>0.056*&quot;lock&quot; + 0.052*&quot;region&quot;...</td>
</tr>
</tbody>
</table>

of topics. The vertical axis is our inferred topic words. Each block on the heatmap corresponding to their frequency in that month. The higher the frequency of the keyword, the redder the color. On the contrary, lower frequency leads to dark blue. It can be observed from the heatmap that the frequency of topic “server”, “optimization” and “cheating” is larger than 0.2 in most time, while “price”, “player skills” and “learning curve” are less than 0.1. In other words, topics of “server”, “optimization” and “cheating” were most widely discussed in PUBG’s community, and PUBG players are more sensitive in these aspects during the monthly update, compared to the less attention paid to “player skills” and “learning curve”.

In addition, to explore PUBG players’ satisfaction levels for each specific topic, we summary the positive rates of our inferred topics during the entire period and present the result in Table II. These topics related to “server”, “optimization”, and “cheating” occupied approximately 62.63% of all aspect terms mentioned on the reviews. PUBG players and reviewers usually pay more attention to these topics because they are significant for the game experience. Besides, topics for cheating and optimization were expressed predominantly along with negative.

TABLE II
SENTIMENT DISTRIBUTION OF TOPICS

<table>
<thead>
<tr>
<th>Topics</th>
<th>#Positive</th>
<th>#Negative</th>
<th>Positive(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>character</td>
<td>5,699</td>
<td>7,357</td>
<td>43.65%</td>
</tr>
<tr>
<td>gameplay</td>
<td>6,295</td>
<td>6,222</td>
<td>50.29%</td>
</tr>
<tr>
<td>server</td>
<td>14,984</td>
<td>34,996</td>
<td>29.98%</td>
</tr>
<tr>
<td>optimization</td>
<td>21,932</td>
<td>34,311</td>
<td>39.00%</td>
</tr>
<tr>
<td>matchmaking</td>
<td>4,062</td>
<td>5,434</td>
<td>42.78%</td>
</tr>
<tr>
<td>teamwork</td>
<td>7,440</td>
<td>2,130</td>
<td>77.74%</td>
</tr>
<tr>
<td>cheating</td>
<td>12,821</td>
<td>34,450</td>
<td>22.39%</td>
</tr>
<tr>
<td>price</td>
<td>1,017</td>
<td>1,739</td>
<td>50.29%</td>
</tr>
<tr>
<td>community</td>
<td>2,554</td>
<td>3,328</td>
<td>43.42%</td>
</tr>
<tr>
<td>graphics</td>
<td>5,078</td>
<td>4,323</td>
<td>54.02%</td>
</tr>
<tr>
<td>player skills</td>
<td>1,787</td>
<td>1,370</td>
<td>56.60%</td>
</tr>
<tr>
<td>learning curve</td>
<td>1,189</td>
<td>482</td>
<td>71.15%</td>
</tr>
<tr>
<td>maps</td>
<td>7,855</td>
<td>9,904</td>
<td>44.23%</td>
</tr>
<tr>
<td>region</td>
<td>3,721</td>
<td>8,564</td>
<td>30.29%</td>
</tr>
</tbody>
</table>

Fig. 5 shows the trend of positive aspects for each topic of PUBG from March 2017 to May 2021 (by percent), which reveals how PUBG players’ satisfaction levels have changed over time. For instance, the overall satisfaction level of topic 6 “cheating” is lower than 50%, indicating that the game update does not solve the problem of cheating. Besides, bug and crash problems (optimization) also annoy PUBG players. The result shows that PUBG players were dissatisfied with fundamental problems such as anti-cheating or optimization even though new contents were added, which means that the developers
did not solve them properly.

Moreover, the genre of esports games was limited. Other representative esports games such as CS:GO were not analyzed, which might affect our recognition of emerging opinions where esports players concern. Additionally, those implicitly expressed topic words are not examined, leading to bias in our conclusions.

As future work, the scope of our research objects can be expanded to other esports games with non-English reviews to make our results more representative. Apart from LDA, more methods of topic modeling can be added to better analyze latent topics from reviews, such as Latent Semantic Analysis (LSA) or Correlated Topic Model (CTM). Moreover, aspect-based sentiment analysis can be applied to discover the sentiment in the reviews for implicitly expressed topic words.

REFERENCES
