A Data-Driven Approach for Game Evaluation Using Latent Dirichlet Allocation Method Based on Players' Reviews

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Abstract

Garena is a global game developer and publisher. Garena provides users with access to popular and engaging online games for mobile and PC, developed, curated, and localized for each market. The Battle Royale genre is relatively new, and this research will evaluate Free Fire, one of the games in this genre made by Garena. Analyzing end-user reviews is considered important for evaluating software quality. Researchers need to understand which aspects need to be evaluated based on player reviews on Google Play and how the model's performance is generated using feedback from players who have played Free Fire. In this study, researchers use the Latent Dirichlet Allocation (LDA) method to model topics and generate clusters in discussions for each topic. LDA is a generative probabilistic model of a corpus. This research on topic modeling using Google Play reviews and LDA has identified the topics users are most concerned with. The research shows three main aspects: bugs, graphics and performance, and game rules/punishment policy, as aspects that need to be evaluated based on player reviews on Google Play.

Keywords: LDA, Garena, Data Mining, Gameplay, Free Fire, Google Play, Review, Topic Modeling.

Introduction

J.P. Morgan, in their report, said the lifecycle of games in the battle royale genre is relatively new and hard to evaluate. One way to evaluate the playability of a video game product is through the opinions of game players. Reviews are considered important for software quality evaluation (Sharma, 2019). One way of evaluating the playability of video game product is through opinions of the game players. Players give their opinions, feedback, and suggestions through the Google Play Store, its publication

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platform on Android. Google Play has a valuation feature that allows customers to give reviews on the advantages and disadvantages of using an app (Hermanto et al., 2020).

Garena is part of Sea integrated platform that provides services of many popular online mobile and PC games that are localized to each region (Sea Limited, 2021). Figure 1 depicts three Garena's core business areas: esports, games, and communities. Free Fire is one of the games being self-developed by Garena and it's one of the most successful in terms of revenue. According to the report, in several region, Free Fire has been topping the app store rank from March 2019 until June 2019 (Sharma, 2019).

Figure 1. Garena Core Business Area

Kwak et al (2020) identify critical topics for successful games in game reviews by using topic modeling analysis. Kwak et al (2020) used LDA to find 50 topics by crawling data from the game review site (www.metacritic.com/game). On the other hand, there is similar research from Lin et al. using multi-label text classification (MLTC) algorithms. The data evaluated were game reviews of Steam games. The research maps the result to three dimensions of playability: functionality, gameplay, and usability (Lin et al., 2019). The results showed that a review-data-driven method can effectively evaluate the perceived quality of video games, enumerating their merits and defects in terms of playability. Furthermore, the Google Play Store is also used as a data source in research discussing sentiment analysis of Google Play reviews using the Naïve Bayes Algorithm and SVM (Hermanto et al., 2020). The research includes preprocessing methods for data before it is processed by the model. The accuracy achieved in this research is reported to be quite high.

Kwak et al (2020), Li et al (2021), and Hermanto et al (2020) did not focus their research on a specific genre of game, such as the battle royale genre. According to a J.P. Morgan report, the battle royale genre is relatively new and hard to evaluate, especially using Google Play data as a data source. This gap needs to be addressed. The goal of this research is to understand which aspects need to be evaluated based on players' reviews on Google Play. This way, Garena will understand how to evaluate the playability of their video game based on players' reviews on Google Play. The method used in this research will be topic modeling using the LDA (Latent Dirichlet Allocation) method as a topic modeling analysis technique. LDA was first introduced in 2003 and has since become the de facto standard for information retrieval. Many studies have already shown that LDA performs well in document classification (Kim & Gil, 2019; Lee & Seo, 2020; Tan, 2020).

Literature Review

Text Mining with Google Play Review

Google Play, as Google's official store for Android apps, is a significant platform with over a million downloadable applications (Fuad et al., 2020). Google Play includes a feature that allows users to view reviews left by other app users (Hossain & Rahman, 2024). User reviews are frequently used as an effective and efficient resource for gathering information about a product or service (Kim & Lee, 2023) Recent research indicates that nearly 50% of internet users depend on word-of-mouth recommendations before trying a product, as user reviews offer current information (Aaputra et al., 2019).

Customer opinions written on social media or reviews on Google Play, to a lesser extent or a lot, will impact potential customers. However, monitoring public opinions does come with challenges. Opinions posted on social media are too numerous to process manually and therefore need a proper data analysis method to gain values from it (Aaputra et al., 2019). For this reason, a special method or technique is needed to categorize these reviews automatically into one topic that generally presents these reviews.

One method used to find patterns or information is called text mining. Text mining is the process of uncovering patterns from large amounts of text data which may be unstructured or semi-structured (Cai

& Sun, 2009). Text mining usually requires input data to be processed first using a set of parsing processes and other techniques (Hermanto et al., 2020).

Topic Modelling

Topic modelling is used to determine the most dominant topic among a big amount of data (Drus & Khalid, 2022). Topic modelling can be used on unstructured data by applying various clustering methods (Maryamah et al., 2019). In other words, topic modeling is a technique that can analyze large volumes of text without using labels. This is known as unsupervised learning, and its goal is to uncover hidden topics (Negara & Andryani, 2019). Topic modelling is an example of text mining.

Previously, Vukanti & Jose (2021) has described how topic modelling works. Firstly, data is collected in a big collection of documents of unstructured texts called Corpus. Afterwards, word-topics will be extracted through topic modelling methods which will result in a topic trend. Therefore, there are two main outputs of topic modelling, a collection of topics which are the most frequently occurred words and a list of documents that are associated with similar topics. Topic generated are supposedly unique.

Among the types of most used topic modelling, there are four types (Vukanti & Jose, 2021):

1. Latent Semantic Analysis (LSA): LSA takes advantage of vector-based representation
2. Probabilistic Latent Semantic Analysis (PLSA): PLSA uses probabilistic framework to construct semantic structure of a data
3. Latent Dirichlet Allocation (LDA): LDA measures the similarity of each provided documents with the acquired distribution of all documents
4. Correlated Topic Model (CTM): CTM makes use of logistic normal distribution to retrieve topics from documents.

LDA

Latent Dirichlet Allocation (LDA) is a popular topic modeling method used to identify hidden thematic patterns within a set of documents (Nawang Sari & Dwi Purnomo, 2022). LDA assumes that every document consists of a mix of multiple topics, and each topic is characterized by a distribution of words (Chen et al., 2017). Through the application of LDA, researchers can discover these underlying topics and their distribution throughout the document corpus, facilitating a more profound comprehension of the content and themes present (Yoshida et al., 2023). A significant benefit of LDA is its capability to automatically detect topics without requiring labeled data, which proves especially valuable in situations where manual annotation is either impractical or costly (Li et al., 2015).

The processes of LDA can be summarized like this (Goyal & Kashyap, 2022). The procedure begins with specifying the number of documents as m, the number of topics as t, and the vocabulary matrix as β. These elements are essential for initiating the topic modeling process using Latent Dirichlet Allocation (LDA). Then, these steps are done:

1. Select Topic Distribution: Choose the initial distribution of topics (α).
2. Assign Topics to Words: For each word W in every document d:
    a. Decide which topic t the word belongs to.
3. Calculate Probabilities:
    a. Estimate P(Topic t | Document d): Probability of topic t given document d.
    b. Compute P(word W | Topic t): Probability of word W given topic t.
4. Select Words for Topics: Use the distribution of words in β to select the specific words associated with each topic t.

Generally, LDA analyzes a single document and various input parameters to generate a model comprising weights that can be normalized into probabilities. These probabilities fall into two categories: (a) the likelihood that a specific document generates a particular topic, and (b) the likelihood that a specific topic generates a particular word from the vocabulary set (Goyal & Kashyap, 2022).

Methodology

This study consists of several phases to obtain accurate analytical results. In this study, researchers use the Latent Dirichlet Allocation (LDA) method to model topics and generate clustering in discussions for each topic. This research uses Google Play data crawled using a Python program. There are three major phases that consist of preparation and crawling, data preprocessing, and the LDA process itself.

Google Play Preparation and Data Crawling

Preparation

In this step, we do several research to understand more about how LDA algorithm works in a python program. In this stage, we setup the environment required to run the LDA model. The platform being used is Google Colab, a product developed by Google Research which enables anybody to write and execute python codes on browser. On preparation step, external libraries installed and imported. External libraries used are google-play-scraper, pyLDAvis, and Sastrawi.

Data Crawling

After installing required library, we crawl data from google play to used. The researchers use 'com.dts.freefireth' as identifier, id as language used and id as country origin. The researchers also add 200000 as number of data crawled for this research. The results of the data crawling that was carried out produced data with the following columns: reviewId, userName, userImage, content, score, thumbsUpCount, reviewCreatedVersion, at, replyContent, and repliedAt. The researchers will use the data retrieved in this process to be processed further in the next step.

Data Preprocessing

After data crawling process, we use NLTK's library to enable stopwords in Indonesian. Stopwords are used to remove word that doesn't have any meaning by itself, such as conjunctions, prepositions, and pronouns (Gustafson et al., 2008). In addition, we also use Sastrawi library to help with the stemming process. Stemming is a text processing method used to convert words in sentence to its basic form so it would be standardized and unified (Rao & Ranjana, 2020). After adding library's stopwords. The researchers extended several stopwords to improve quality. The researchers add 34 new stopwords into data set. The additional stopwords were obtained after conducting analysis, which identified these extra words as unnecessary for this research. By using stopwords, the text emphasizes the key terms and phrases that convey the main semantic content, which enhances the accuracy of subsequent analysis tasks (Amarasinghe et al., 2015).

To focus the dataset on points that need to be improved, researchers only use data with a rating below 3. Thus, this process also includes filtering data of reviews with above condition. Furthermore, during this step, there a function that transform a string (original review) to an array of words. Inside the function, there was some steps:

1. Escape the punctuation and white spaces: Such character is not relevant for text processing; therefore, punctuation needs to be removed from the review first.
2. Stemming: Stemming needs to be done to generalize words by converting it to original form. This step returns a sentence that has its words converted to base form.
3. Tokenizing: To make the review able to be processed, it needs to be in a form of array of string. Therefore, in this step, the sentence or in other words the string itself spoilt with single white space as separator then saved to an array.
4. Removing Stop Words: Stop words doesn't hold any meaning and could potentially affects the result of topic modelling in bad ways, therefore it needs to filter from the final array.

Afterwards, each data's content column will be mapped using previous function.

Latent Dirichlet Allocation

Determine Optimum Number of Topics

During this step, we will try out the possibilities for number of topics by simulating it using LDA model that is used in this research. For every number of topics, the one with the highest performance will be used as the final number of topics and be proceeded to the next step.

Topic Modeling with Latent Dirichlet Allocation (LDA)

On this step, we generate LDA model using Gensim library. The input used to generate the LDA model were corpus, dictionary of words, and number of topics. pyLDAvis is used to help the researchers visualize the result and gain clearer picture of each topic which includes its distribution and coherence. Furthermore, the coherence scores found in this study will be compared to existing research related to topic modeling in game reviews. Previous study has indicated that the average coherence score for game review topics is 0.470 (Li et al., 2021). This comparison will help in evaluating the effectiveness and reliability of our topic models in capturing coherent and meaningful themes within the game reviews.

Topic Interpretation

In this phase, the authors draw conclusions from the results and discussions made in the previous phase. The interpretation is done with Human-In-The-Loop approach, or HITL which refers to a methodology that integrates human expertise and intervention at various stages of the machine learning process (Abdel-Karim et al., 2020). The topic interpretation will be done using a human-in-the-loop approach, where the researchers will review the sets of words generated by the LDA model and assign meaningful themes to each topic based on their contextual understanding.

For more details, methodology captured in Figure 2 below.

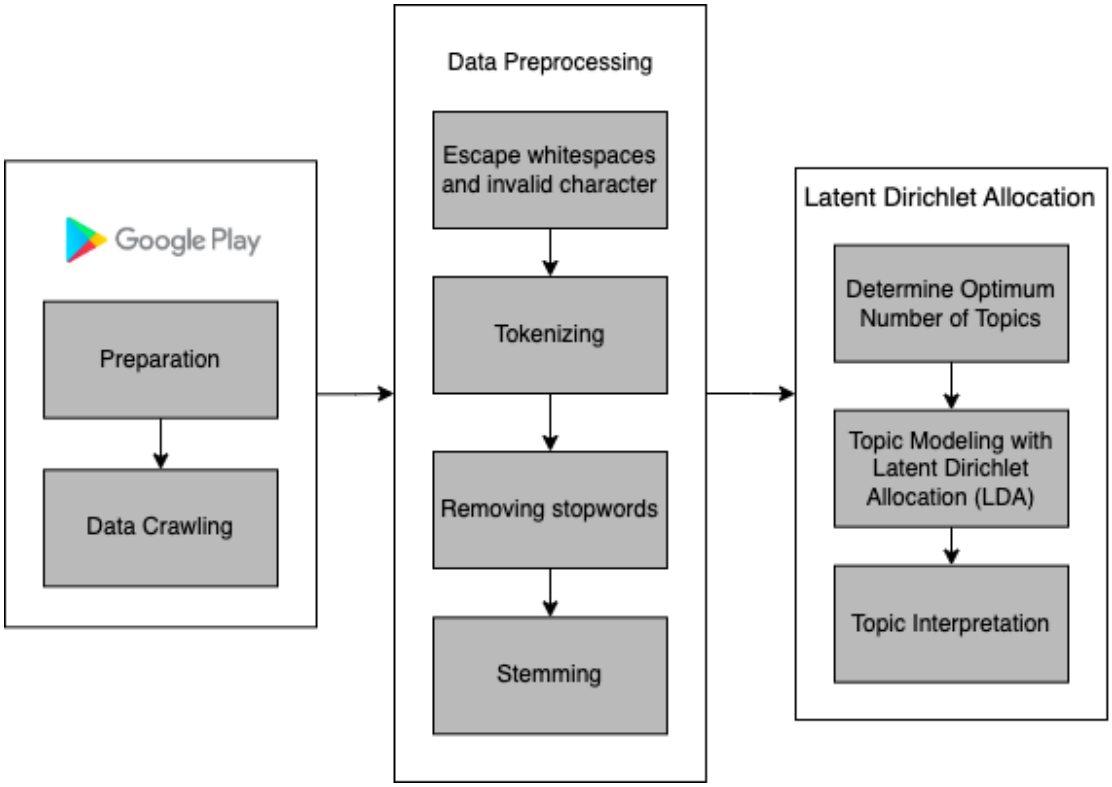

Figure 2. Methodology

Result

The process of deciding optimal number of topics is done through coherence score evaluation. Coherence scores describe how interpretable is a certain topic. Therefore, the higher the score the better because it means that detected topics are more interpretable. Figure 3 shows the result of evaluating number of topics with topic number (k) values that range from 1 until 9. The result shows that the highest score was obtained using k=3 with the value of 0.426, although six number of topics seems to be almost in par in terms of coherence score. Despite that, we have decided the number of topics used will be three because it has the highest score. Compared to previous research related to game reviews topic modeling, the coherence score is not far off from the average coherence score value retrieved, which shows a consistent level of topic coherence and suggests that our topic models are effectively capturing meaningful themes within the dataset (Li et al., 2021).

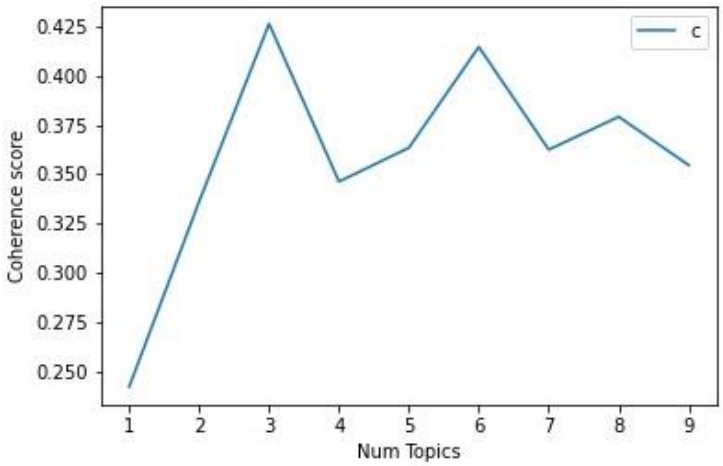

Figure 3. Number of Topics Evaluation

The result of the model using three number of topics has generated these most frequent terms. Table 1 shows the top twenty most frequent term for each topic with notes, that some of the words are being censored because it contains profanity.

Table 1. Topics and Most Frequent Term

Topic 1	Topic 2	Topic 3
garena	bu**k	ff
tolong	gem	akun
main	pintu	download
bug	hp	login
bagus	to**l	top
update	patah	up
sinyal	bit	pensi
jaring	geme	rusak
kasih	bocil	pake
free	epep	dm
fire	buruk	hapus
bintang	a**	orang

Topic 1	Topic 2	Topic 3
pas	mending	kena
jelek	mata	bang
player	bur**q	gara
mohon	grafik	lu
banget	bikin	suspend
seru	ram	main
suka	sakit	beli
masuk	ml	kaya

Discussion

The first topic can be interpreted as a complaint for player issues with bugs, as seen with words such as 'bug'. Furthermore, 'sinyal' and 'jaring' terms can be interpreted as player's inconvenience in terms of the game network performance. The same goes for 'jelek' which symbolizes some aspects of the game playability was not up to player standards or it may have some faulty features. In other words, many Free Fire player express their disappointments because of bugs that occurred in the game. Previous research shows that support team responsiveness related to technical errors are one of the factors that may affect player drop out on games (Lebres et al., 2018). These bugs can vary from graphical glitches that affect the visual quality of the game to more critical issues like crashes or game balance problems (Tufano et al., 2022).

The complexity of modern video games, with their vast worlds and intricate mechanics, makes manual bug detection increasingly challenging (Wilkins et al., 2020). Garena may need to look for the most important bugs that affects user's experience first. Visual bugs, such as graphical glitches that occur during GUI rendering, are common in graphically-rich applications like video games and can significantly impact the overall quality of the game (Chen et al., 2021). Detecting these visual bugs requires specialized approaches that combine visual and textual information to identify and understand issues reported by users effectively (Cooper et al., 2021). By leveraging techniques like deep reinforcement learning and anomaly detection, developers can augment automated testing processes to detect and address visual bugs more efficiently (Bergdahl et al., 2020; Wilkins et al., 2020).

As for the second topic, it mostly talks about graphics and performance issues. It's shown by word '*patah'* or stutter. Beside performance, in this topic, players also complain about the graphics of the game. One word, which is included in the list of profanity words also contain such complaint related to graphic. According to Lebres et al., performance issues are one of the factors on why player quit playing a game. erformance issues encompass a range of factors, including latency, rendering processes, memory allocation, graphical components, and real-time processing, all of which can affect the game's responsiveness and visual quality (Agrahari & Chimalakonda, 2020). These issues can lead to gameplay disruptions, such as lag, frame rate drops, stuttering, and overall sluggishness, detracting from the immersive experience that players expect (Agrahari & Chimalakonda, 2020). These further shows that those aspects of the game need to be improved although the effort may be huge.

Upon analysis, the third topic appears to represent the comments of individuals who have been suspended for engaging in illegal top-up activities, potentially without their knowledge of the illegality of such actions. Consequently, they have decided to retire ("pensi") from playing the game Free Fire. A lot of players express that their account got suspended or banned without strong reason behind it. Terms like 'suspend' prove this point. Technologies like real-time detection systems have been developed to identify and intervene in cases of harassment or rule-breaking during gameplay, enabling companies to issue warnings, mute players, or impose bans as necessary (Stoop et al., 2019). However, the effectiveness of such measures in influencing player behavior and ensuring compliance remains a

subject of ongoing evaluation (Xiao, 2023). Garena must evaluate the administrative action done related to player's account, whether this is a valid complaint or the opposite, it needs to be further investigated. In summary, the result of topics interpretation can be seen on Figure 4

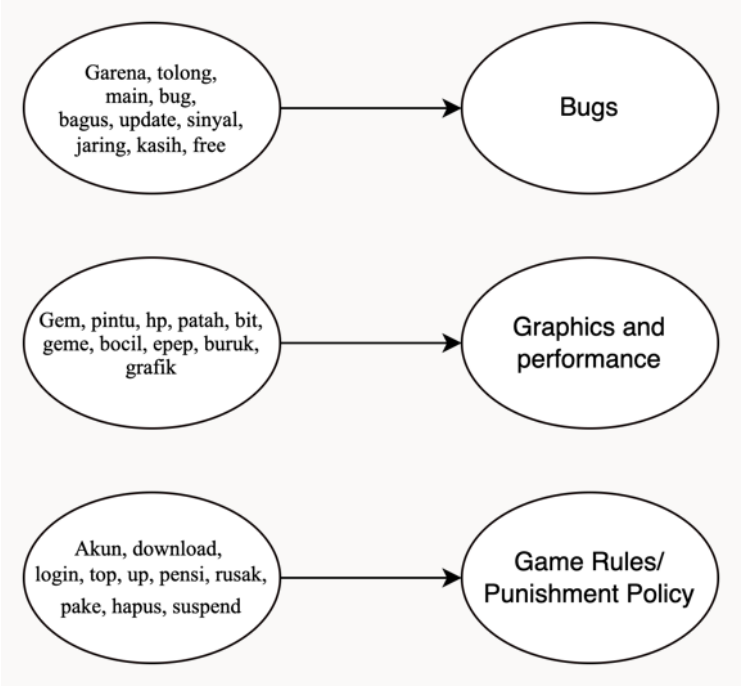

Figure 4. Topic Interpretation

Conclusion

This research on topic modeling using Google Play reviews and Latent Dirichlet Allocation (LDA) has gained a result of which aspects of the Free Fire game are users mostly concerned with. The three main topics that were generated from this research includes bugs, graphic and performance and game rules/punishment policy. The model generated from this research have a coherence score comparable to previous research and therefore considered to be quite interpretable.

The next step of this research is to further dive into each topic. Starting from bugs issue, Garena may need to strengthen their quality assurance process and find out what are the most common problems found by players. Next, in terms of performance, although the effort required to improve game performance is quite big, opinions from users show that it has quite an influence on player's experience. Garena need to make sure their games adapt well to lower-end devices, as many users has expressed their dissatisfaction toward in-game performance. Finally, related to punishment policy, Garena may have to conduct evaluation on their administrative action towards player's account to decide whether the current set of processes has accurately achieved its goal of preventing players misbehaving against the game rules.

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