OPEN ACCESS
J DATA SCI APPL, VOL. 1, NO. 1, PP.001-010, JULY 2018

E-ISSN 2614-7408
DOI: 10.21108/JDSA.2018.1.9

JOURNAL OF DATA SCIENCE AND ITS APPLICATIONS

Classifying Electronic Word of Mouth and Competitive Position in Online Game Industry

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Received on 27-04-2018, revised on 09-07-2018, accepted on 20-07-2018

Abstract

The number of online review in online game industry growing significantly along with growing rate of internet adoption. With abundant number of data, one can acquire limitless insight, for example, information regarding of electronic word-of-mouth (e-WOM) whom greatly affecting consumer behavior and business performance. Knowledge of e-WOM can act as competitive intelligence to deal with industrial competition. Therefore, this research answers how to classify e-WOM, what are e-WOM aspects emerge in massive multiplayer online first-person-shooter (MMOFPS) game, and how does comparison of e-WOM positivity between the three MMOFPS Game used as research objects. Dataset constructed from Review page of Steam website for respective games with total 499 reviews used as sample data. Then the analysis conducted using Orange and Indico API as tools. Therefore, we found several noun words frequently used as opinion target and we also found out that in aspect-level comparison, Game 2 gain the highest e-WOM positivity value in community aspect and Game 1 gain the highest e-WOM positivity value in general aspect. Thus, each respective game developer can manage to develop their strategies from the information of their competitive position in the industry.

Keywords: Aspect-based Sentiment Analysis, Competitive Comparison, Electronic Word-Of-Mouth, Online Game

I. INTRODUCTION

With growing rate of internet adoption across the globe, there is significant growth in number of consumer giving online reviews [1]. The phenomenon also occurring in online game industry. The abundant data should generate useful insight, if mined properly. One insight, which are available from the data, is knowledge regarding electronic word-of-mouth (e-WOM). E-WOM known for having significant influence towards consumer behavior [1] [2] [3]. E-WOM communication framework shows the direct relation and influence of e-WOM adoption towards consumer buying intentions [2]. Moreover, empirical study shows e-WOM influence towards business performance, which measured by offline or online sales [1] [3].

Understanding insight within e-WOM means knowing the appraisal from customer about product or service they were using [4]. The appraisal of product or service quality by customer usually based on comparison between client's expectations and the service performance [5]. However, in the case of online services, it is difficult to know in advance the expectations of customers because, according to [6], customers of online services, in many cases, do not have well-defined expectations about the service. Therefore, knowing the sentiment of the customers after the service delivery can be of great help for evaluating their satisfaction regarding the services [7]. Especially in online game industry, online game is different from video game because it is not only selling games as product but also conduct service for player to be able to play the game. However, tremendous amount of information in e-WOM makes it difficult to obtain information [8]. The content of e-WOM is characterized by text format, oversimplified or exaggerating expression, and newly coined phrases.

Thus, creating abundant information, which overwhelms collection and analysis effort if done manually. For e-WOM analysis to be done efficiently, tools are needed to summarize customer e-WOM so that it can generate purposeful insights.

Sentiment analysis, also called opinion mining, is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes [9]. In general, sentiment analysis investigated in three levels, which are document level, sentence level, and entity or aspect level. Aspect level perform finer-grained analysis, resulting a structured summary of opinions about entities and their aspect [9]. Sentiment analysis able to extract and summarize opinion/information exist in huge volume of opinion text. Thus, using aspect-based sentiment analysis, information regarding positive or negative appraisal for product or service and the specific aspect/attribute of the appraisal can be extracted from consumer's e-WOM [4].

After gaining knowledge of organization's own performance, the next step is to compare it with competitors, which done through competitive analysis. Competitive analysis is a management tool designed to track one's organization against itself over time across several organizational performance measures, as a part of a continuous improvement strategy [10]. The effort produces further value if these performance measures can be scaled against the competition, thereby identifying gaps that management should address [11].

Based on the problem explained above, we found it interesting to conduct research in classifying e-WOM and competitive position in online game industry. Because analyzing e-WOM in online game is not a frequent topic in research, also we expect it would be helpful for developer/game companies to understand how their player appraises their game and know the target aspect of their opinion. The limited number of research in online game industry, especially in studying the e-WOM, could also become one point of novelty of this research.

Due to nature of online game industry, which is very vast with game genre and many in number, we limit the object of this research into three top MMOFPS (Massive Multiplayer Online First-Person-Shooter) games. The research aim to answer several research question, which are:

1. How do we classify players' e-WOM in the three MMOFPS games?
2. What are important aspects, as opinion target, in the players' e-WOM of the three MMOFPS games?
3. How do we identify the three MMOFPS games' competitive position through its' aspect-based e-WOM positivity?

II. LITERATURE REVIEW

A. *Electronic Word of Mouth (e-WOM)*

Electronic word-of-mouth (e-WOM) defined as online sharing activity comprising vast amounts of consumer information on opinion and recommendation on vendors / products from experienced consumer [12].

Prior studies identified two types of e-WOM according to their source, which are organic or intrinsic e-WOM and amplified or extrinsic e-WOM (also called as exogenous e-WOM) [13] [14]. The difference between the two is that organic e-WOM occurs spontaneously by the costumer, while amplified e-WOM occurs when the company stimulate consumer to hasten the spread of e-WOM. Cheung and Thadani (2012) [2] also identify types of e-WOM based on the platform e-WOM are delivered. The types are online discussion forum (e.g. zapak.com), online consumer review sites (e.g. eopinions.com), blogs (e.g. blogspot.com), social networking sites (e.g. facebook.com), and online brand/shopping sites (e.g. amazon.com).

Empirical study confirms the impact of e-WOM towards consumer behavior and company performance, for example:

1. E-WOM have significant impact towards consumer purchasing intent [15].
2. E-WOM directly influencing consumers' purchasing decision [2].
3. E-WOM have significant impact towards sales [3].

However, study of e-WOM that connected to online games is still scarce. For example, in prior study [16] claim that it is the first study that relate e-WOM with social network games (SNG). Social network games are online games played through social network site (SNS). Another recent study, which relate e-WOM with online games, conducted in 2017. In [17], e-WOM connected with animations, comics, and games, with popular mobile online game as the product. Other that those two, we found that most of e-WOM related studies are done with SNS, online forums, blogs, and microblogs as their objects.

B. Aspect-based Sentiment Analysis

Sentiment analysis, also called opinion mining, is a process of identifying polarity of an opinion [18]. Opinion polarity obtained by filtering words, phrases, or sentence unrelated to opinion polarity, then extracting the remaining subjective information. Moreover, sentiment analysis also defined as the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes [9]. In general, sentiment analysis investigated in three levels, which are document level, sentence level, and entity or aspect level.

Aspects defined as attributes that describe the object [19]. For example, in review sentence "The online game has awesome graphic, but the control is terrible!" evaluate two aspects, which are 'graphic' and 'control' of 'online game' entity. The sentiment on online game's 'graphic' is positive, while the 'control' is negative. Aspect-level sentiment analysis perform finer-grained analysis, resulting a structured summary of opinions about entities and their aspect [9]. Aspect-level analysis based on the idea that an opinion consists of sentiment and target. Realizing the importance of opinion target will help understanding sentiment analysis problem. In general, there are two steps in aspect-based sentiment analysis, which are aspect detection and sentiment scoring [19].

C. Competitive Analysis

Competitive analysis is a management tool designed to track one's organization against itself over time across many organizational performance measures, as a part of a continuous improvement strategy [10].Then, the measuring result can furtherly be used in competition within industry. Through comparing performance with competitor, management can identify performance gap to develop continuous strategy. Competitive analysis could also be the method to find firm's own position within the competition. For example in [10], firm's competitive position determined through analysis of travel blog narratives, while in [11], competitive firm's competitive position determined through benchmarking its' performance with competitor.

III. RESEARCH METHOD

In this research, data collected for analysis from Steam®[1] website as the marketplace of the three online games. Dataset collected from the website resulting in 499 reviews for each respective games used as sample data. Then the analysis conducted using Orange [12] and Indico[2] API as tools.

Aspect-based sentiment analysis can follow different kind of methods or algorithm and use different kind of techniques. However, there are two core tasks in aspect-based sentiment analysis, namely aspect extraction and aspect sentiment classification [9]. Below is the explanation of algorithm to do the two aforementioned tasks in this research.

A. Aspect Extraction

Figure 1 gives an overview of the algorithm used for aspect extraction from each database. Firstly, corpus created for each database and data in the corpus were pre-processed. Pre-processing include lemmatization, stopwords, and tokenization. Then, wordcloud generated from the corpus, resulting in groups of words and its frequency. Noun words from 20 most frequent words in wordcloud kept as keywords. Lastly, aspects for dataset are determined from keywords semantic similarity.

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[1] https://store.steampowered.com/

[2] https://indico.io/

```
FOR each dataset
    Generate corpus
    FOR each data in dataset
        Perform tokenization
        Erase stopwords
        Perform lemmatization
    END FOR
    Generate wordcloud
    FOR each word in wordcloud
        Get 20 most frequent words
        IF noun,
                THEN keywords
                ELSE null
        Generate aspects from keywords
    END FOR
END FOR
```

Fig. 1 Algorithm for Aspect Extraction

B. Aspect Sentiment Classification

Figure 2 gives an overview of the algorithm used for aspect-based sentiment classification for each database. The algorithm is adapted from [20].Firstly, we created a set of keywords related to Community and General aspects. The set of keywords influenced by aspect-related keywords found during aspect extraction. Then, data were broken into several sentences then generate keywords from the sentence. Next, aspect for each sentence determined based on its similiarity with the set of keywords created before. Lastly, sentiment score for each and multiple aspect was calculated. The result of this step were visualized and discussed in the next section.

```
FOR each data
    Assume keywords of Community Aspects
    Assume keywords of General Aspects
    Break data into sentences
    FOR each sentence in data
        Generate keywords
        Determine aspect by keywords
        Calculate sentiment score (single aspect)
    END FOR
    Calculate sentiment score (multiple aspects)
END FOR
```

Fig. 2 Algorithm for Aspect Sentiment Classification

IV. RESULTS AND DISCUSSION

A. Aspect Extraction

Table 1 shows extracted aspects from databases. From the dataset of Game 1, obtained aspects are Download-able Content (DLC), Community, and Time. From the dataset of Game 2, obtained aspects are Display and Community. Lastly, from dataset of Game 3, obtained aspects are Theme, Community, DLC, and Time.

TABLE I.
ASPECT EXTRACTION RESULT

Dataset	Frequent Noun Words or Phrase	Extracted Aspects & Keywords
Game 1	*Community, player, team, people, skin, time*	**Download-able Content** ***Keywords***: *skin*
		Community ***Keywords***: *community, player, team, people*

		Time ***Keywords***: *time*
Game 2	*Operator, fps, team, friend, player*	**Display** ***Keywords***: *fps*
		Community ***Keywords***: *operator, team, friend, player*
Game 3	*Mod, time, military, friend*	**Theme** ***Keywords***: *military*
		Download-able Content ***Keywords***: *mod*
		Community ***Keywords***: *friend*
		Time ***Keywords***: *time*

Download-able Content (DLC) aspect represent the additional content outside the main feature of online game. These additional contents can vary depend on the developer intention in giving add-ons to their game. Community aspect represent the interaction between players in online game. Interaction between within online game community might improve or reduce player's experience in playing the game. In this research, big portion of the review talks mostly about the player's experience in interacting with fellow players inside the game and/or in game's online community. Time aspect represent the playing duration of players. Display aspect represent the graphic quality of online game visual assets. Graphic quality of games is one of vital key elements in determining game quality as a product [20]. While, Theme aspect represent theme or setting from the game which enjoyed by the players

In all database the common extracted aspect is Community. This caused by frequent noun words occurring in dataset 1 mostly can be related to community aspects defined in this research. It shows that players' review mostly talks about the online game social environment. Online game community is important in making successful games and game developers are putting their effort in support and nourishing the community actively [21]. Furthermore, this finding supports the statement that players also consider community aspect in spreading their positive or negative experience in online game.

B. Aspect-based Sentiment Analysis

In general, Table 2 shows guideline for identifying aspect from dataset. The guidelines were adapted from [19]. In the second column of the table contains keywords which having the similarity or contextually represent the aspect in data. For example, in sentence, "*Good game if you play it with friends*", the word 'friends' included in the list of keywords regarding Community aspect, therefore the sentence identified containing Community aspect. Another example from sentence "*Game 1 definitely better than Game 3*", this sentence identified containing General aspect, because it is having name of other game in context of overall comparison. After all data in dataset were categorized by their aspect, we then know the total number of data of Community and General aspect for each dataset and the number of data identified not having any aspects.

TABLE II.
ASPECT IDENTIFICATION

Keywords	Aspect	Issue Handled by Aspect
'team'; 'friends'; 'vac' (valve anti-cheat); 'cheaters'; 'enemy'; 'people'; 'streamers'; 'players'; 'competitive'; 'teamwork'; 'teammates'; 'cheat'; 'comrade'; 'newbie'; 'beginners'; nationality (Russian, Asian, etc.)	Community	• Player interaction • Degree of fairness • Fairness system
'game'; 'gameplay'; technical phrases (e. g. shooter, DLC, patch, mission, servers), name of other games	General	• Overall value of game • Specific judgement of certain feature • Comparison with other games

The next step in aspect-based sentiment analysis, after aspect identification, is to give sentiment score for each data in dataset. This process utilizes the Sentiment HQ tools deployed from Indico API. It analyzes the input data and return positivity value as a result. The value scale from 0 to 1. Positivity value over 0,9 indicating very positive sentiment, value between 0,75 to 0,9 indicating positive sentiment, value between 0,25 to 0,75 indicating neutral sentiment, value between 0,1 to 0,25 indicating negative sentiment, while value under 0,1 indicating very negative sentiment (Fig.3).

Very Negative	**Negative**	**Neutral**	**Positive**	**Very Positive**
0	0,1	0.25 0.75	0.9	1

FIG. 3. POSITIVITY VALUE SCALE

Table 3 shows the summary of aspect-based sentiment scoring of the three online games. Game 1 and Game 3 receive the average positivity value of 0.67 and 0.70 in *Community* aspect. Therefore, players' e-WOM of Game 1 and 3 classified as having *Neutral* sentiment in it. It means that players are appraising the quality of player interaction, degree of fairness and fairness system of Game 1 and 3 with balanced value of positive and negative opinion. Although, based on the value it indicates tendency towards positive opinion. As for Game 3, it receive the highest score of average positivity value of 0.80. It means that players are appraising the quality of player interaction, degree of fairness and fairness system of Game 2 with positive opinion in their e-WOM.

While in *General* aspect, Game 1 receive the highest average positivity value of 0.83. As for Game 1 and 2, both earning average positivity value 0.76 and 0.79. Therefore, players' e-WOM of the three games classified as having *Positive* sentiment in it. It means that players are appraising the overall quality of the three games with positive opinion in their e-WOM. Although, Game 1 receive a slightly more positive opinion compared to the other two.

TABLE III.
ASPECT-BASED SENTIMENT SCORING SUMMARY

Aspects	Dataset	Average Positivity Value	Positivity
Community	Game 1	0.67	Neutral
	Game 2	**0.80**	**Positive**
	Game 3	0.70	Neutral
General	Game 1	**0.83**	**Positive**
	Game 2	0.76	Positive
	Game 3	0.79	Positive

C. *Competitive Comparison*

The aspect-based sentiment scoring comparison shows that Game 2 receive highest score of average positivity value in *Community* aspect compared to the other two (shown by highlighted value). The comparison method for the figure is that superior value in figure 3 indicate superior performance of the game in certain aspect or factor [10]. Specifically, it indicates better performance in managing game fairness, matchmaking fairness, players' interaction and communication control. Because, based on observation towards the data, most positive opinion are targeted to 'friends' or 'team' keywords, while negative opinion mostly targeted to 'cheaters' keyword. Thus, based on Fig. 4, Game 2 perform better in maintaining fairness and controlling players' interaction and communication compared to the other two games.

While in non-specific aspect, namely the *General* aspect, Game 1 perform better than the other two games (shown by highlighted value), based on the sentiment scoring comparison result in Fig. 4. The result indicates that Game 1 still able to perform better in overall point, even though Game 1 receive more negative opinion for their *Community* aspect. Based on observation towards the data, the result might be caused by the ability of Game 1 to give better gameplay compared to the other two. Because most of the positive opinion in *General* aspect for Game 1 were targeted to 'gameplay' and 'game' keywords.

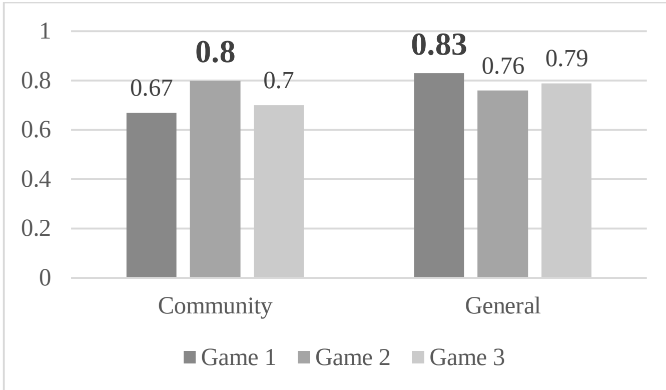

FIG. 4. ASPECT-BASED SENTIMENT COMPARISON

V. CONCLUSION

From the research conducted, we can draw conclusion in these several points:

- There are several aspects obtained from the datasets of the three online games, which are Community, DLC, Display, Theme, and Time. These aspects may suggest the opinion target frequently occur in online game domain.
- In Community aspect, Game 2 gain the most positive sentiment for their e-WOM compared with the other two online games. While in General aspect, Game 1 is the leading party in gaining positive sentiment for their e-WOM.

VI. SUGGESTION

From the findings of this research, we also suggest these several points for other researchers that might be interested in deepening the knowledge regarding aspect-based sentiment of e-WOM in online game industry:

- Pay heed for sarcasm context in sentence, for it might affecting the sentiment scoring, especially in document-level sentiment analysis.
- Further research and discussion about to confirm whether the aspects found in this research are suitable in online game sentiment domain or not might be needed. Furthermore, continuation mining is needed to find more aspects in online game domain, which might occur with different datasets.

As for the game developers, the practitioner in online game industry, several points that we can suggest based on the research results are:

- Consider the degree of fairness in matching system of the games. Because what cause negative opinion towards *Community* aspect is the degree of fairness during gameplay. Players mostly complain about how they frequently meet cheaters during game, which reducing the quality of their gameplay experience. With proper anti-cheat system implemented in online game, players could enjoy their gameplay experience thoroughly and increasing the chance of them giving positive e-WOM to the game.
- Developer should have control and preventive measure to ensure good interaction between players in online game. Because, bad conduct such as verbal abuse and flaming during game might affect players' gameplay experience. Chat filters and players reporting system are examples of preventive measure that developer could implement towards their game.

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