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WHAT MAKES THE DIFFERENCE BETWEEN POPULAR GAMES AND UNPOPULAR GAMES? ANALYSIS OF ONLINE GAME REVIEWS FROM STEAM PLATFORM USING WORD2VEC AND BASS MODEL

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Abstract. *The product's popularity is playing a major role in the growing trend of the gaming industry. Therefore, it is important to ensure a game becomes popular among users. To identify the success factors of a game, we divided games in two categories, popular games and unpopular games, using the Bass diffusion model. The games and users' reviews were selected from Steam, the most popular gaming platform that leads to the growth of the game industry. Moreover, we proposed a few methods for text mining to analyze user reviews on Steam, such as Word2vec, PCA, K-means clustering, word cluster creation, and characterization, based on the Kano model. In this context, we suggest methods to analyze online customer reviews and identify success factors in the gaming industry using these methods.*
Keywords: Gaming industry, Steam platform, Online customer review, Text mining, Bass diffusion model, Word2vec, Kano model

1. **Introduction.** Over the last few years, technology advances have not only led to remarkable developments in PC performance but also to the popularization of PCs, given that the cost of PC hardware has fallen. The spread of mobile devices and the number of media devices have also increased, which has enabled the continued growth of the gaming industry. According to Newzoo's report [1], the gaming industry's overall market size is expected to grow by 6.6%, from \$91.8 billion in 2015 to \$118.6 billion in 2019. Valve Corporation's Steam platform is an example of a medium that has driven the growth of the gaming industry, especially PC games. There are about 7,400 products on Steam; some products are popular among consumers, whereas some products fail to be popular among consumers. For example, the North American video game industry witnessed a crisis in 1983. At that time, the home-use game machines that were launched by Atari in the US released program specifications, allowing anyone to freely develop and sell games. This may have played a positive role in terms of game diversity; however, it resulted in a loss of interest among consumers owing to the mass production of poor quality games. The mass production of these unpopular games has caused a long recession in the gaming industry [2]. To avoid repeating this "Atari shock", it is important to develop a popular game that consumers do not ignore, and to enhance games. Thus, identifying the key

success factors in game development is crucial not only to gain competitiveness in the gaming industry but also to avoid a second gaming market downturn.

In this paper, we examine a leading gaming platform, Steam, to identify the factors of success for games that can help drive industry growth in the future. We focus on Steam user reviews, which have not been investigated in previous studies, to identify the entertainment elements. We firstly classify the games distributed on Steam that have led to the growth of the gaming industry in two groups – popular games and unpopular games – using the Bass diffusion model. Then we propose a method to analyze online game reviews from Steam using Word2vec. Further, we evaluate the semantic features based on the Kano model, which is a guideline for understanding consumer requirements. We expect that our study makes an academic contribution by combining econometric analysis and text mining to perform semantic analysis in addition to numerical analysis. The results show that there are not only numerical differences but also semantic differences between the groups classified using the Bass diffusion model.

2. Literature Review.

2.1. **Steam platform.** Valve corporation's Steam is an integrated game distribution platform and social networking site. Steam allows users to purchase and store games made by various providers [3]. It is remarkable that users are actively involved with Steam, through user-defined tags for games, the Steam community, and Steam user reviews.

In terms of user-defined tags, users who have played a game can voluntarily tag the characteristics of the game. Windleharth et al. [4] said that this social tagging prevalent on Steam has been used on various websites since the early 2000s, also noting that in Steam's case, users are actively engaged in tagging their experiences and feelings about gaming products to characterize the game.

The Steam community connects all users of the game on the platform and enables them to communicate with the group. Becker et al. [5] analyzed the role of games and groups in the Steam community by representing the network of users as a connectivity graph.

The Steam user reviews section, which states "Read, Rate, and Discuss", comprises online customer reviews written by a plurality of users. Several previous studies have analyzed user participation on Steam using the "achievement system framework [6]", and performed cluster analysis on the basis of game characteristics [7]. However, there has been no study that has analyzed user reviews on Steam, which includes user-defined tags and the Steam community.

2.2. **Online review and text mining.** Online customer reviews can be defined as peer-generated product evaluations posted on company or third-party websites [8]. Online customer reviews provide information about a product from the user's perspective and not from the developers' and distributors' viewpoint. As this information helps users reduce their uncertainty about purchasing gaming products, it has a positive effect on users [9,10]. These features can also be seen in the case of Steam user reviews. From the viewpoint of developers, review analysis can help verify deficiencies in the products they develop; a typical method for analyzing such online customer reviews is text mining [11].

Text mining constitutes a series of processes for finding and extracting meaningful patterns and relationships in a document to formalize atypical data [12,13]. Research projects that use text mining techniques to analyze online customer reviews are currently active and ongoing. Cao et al. [14] analyzed online reviews of CNETDownload.com using the latent semantic analysis (LSA) technique, a text mining technique, to analyze the semantic characteristics of online reviews.

Recently, the Word2vec technique using neural networks was used in a study for text data analysis [25]. Word2vec is a deep learning-based text mining technique proposed by Google. It understands the context by vectorizing the distribution of words before and after specific words [15]. Zhang et al. [16] used Word2vec to learn about Chinese comments on clothing products and then clustered similar semantic features. Sharma et al. [17] used Word2vec to classify online review data from RateMDs.com, a doctor reviewing website. However, the abovementioned studies derived the semantic characteristics of only one group using online review analysis instead of classifying and comparing two groups on the basis of specific criteria.

2.3. **Bass diffusion model.** This study aims to compare the differences between the popular group and the unpopular group. Therefore, we have adopted the Bass diffusion model, which predicts the demand for new products and explains two primary ways of launching new products in the market. The Bass diffusion model is a forecasting model for new product demand that explains how new products are adopted [18]. Several studies have shown that there is a difference in the diffusion patterns of products, depending on the product group. Song et al. [7] reported a diffusion pattern difference between the popular group and the unpopular group on Steam. Kim and Hong [19] found that there was a diffusion pattern for each cluster in the case of clusters divided by the size and popularity of films. Clement et al. [20] demonstrated a comparative analysis of spread patterns for various hedonic products. However, the abovementioned studies have a limitation in that they only used qualitative methods. We believe that text mining techniques can enrich the analysis.

2.4. **Kano model.** This study aims to suggest factors that create popular games through text mining. The Kano model is a method used for clustering and evaluating the results of text mining. The Kano model represents a product planning theory related to product development that grasps the needs of consumers using what the consumer directly or indirectly speaks about the product [21]. It proposes factors that have a significant effect on customer satisfaction – "Must-be requirements (M)", "One-dimensional requirements (O)", and "Attractive requirements (A)". The Kano model has been used in various industries to identify the key factors that affect customer satisfaction. Von Dran et al. [22] used the Kano model to suggest a website framework with quality factors that affect consumer satisfaction. Basfirinci and Mitra [23] used the Kano model to find balance factors that help consumers obtain different levels of service in the aviation services industry.

3. **Research Methodology.** This study consists of three analysis steps. The first step comprises the application of the Bass diffusion model, based on monthly time-series data, to the average number of users of the game followed by the classification of this data in two groups: popular and unpopular. The second step involves the collection of data from Steam user reviews for each group, their evaluation using the Word2vec technique, and the construction of word clusters through principal component analysis (PCA) and K-means clustering. Finally, the word clusters are qualitatively evaluated using the Kano model. Figure 1 presents the overall research procedure.

3.1. **Data.** The data were collected from Steam's official website with the API provided by Steam; the Steam Chart site provided statistics on the number of users. The Steam Chart shows the top 750 gaming products based on the current number of users. The collected data comprise time-series data for the average number of users per month. Steam's official site includes a dataset of features that represents the characteristics of the game, such as the genre of games that share a primary key (called "game name"), user ratings, reviews, user-defined tags, and minimum system requirements to control the characteristics of the comparison group.

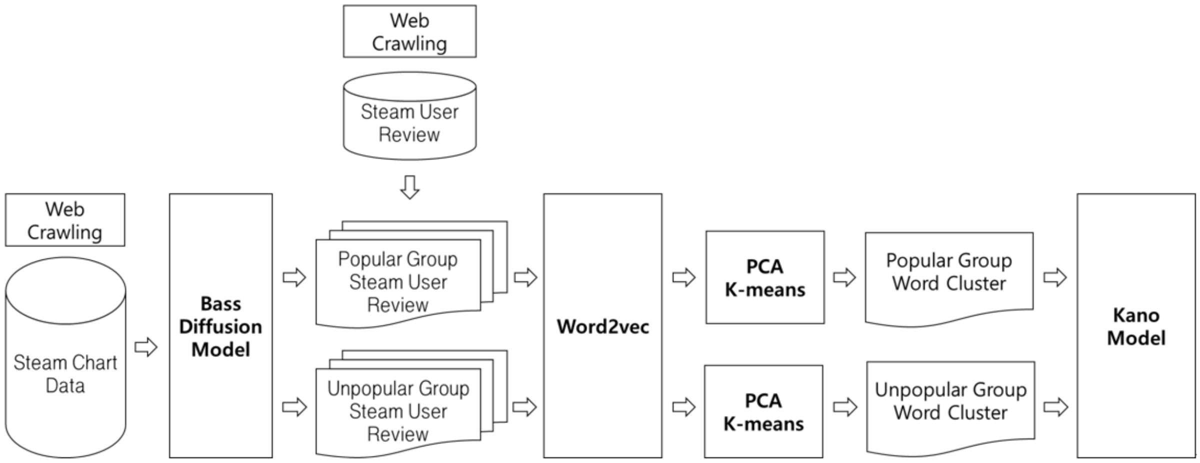

FIGURE 1. The overall research procedure

3.2. **Classification of games.** The coefficients that explain the process of adopting new products are the innovation factor (p) and the imitation factor (q) [18]. The innovation coefficient is an indicator of the external effect, which is the degree to which the increase in the number of adopters is influenced by changes in external factors, such as marketing or prices. On the other hand, the imitation coefficient is an indicator of the internal effect, which is the oral effect of the adopter. In this paper, we analyze the monthly average number of game users and compare them with the method used by Song et al. [7], which classifies gaming products into a popular group – having the imitation coefficient relatively higher than the innovation coefficient – and an unpopular group – having the innovation coefficient that is relatively higher than the imitation coefficient. In addition, we use the nonlinear least squares method, which is known to be most effective when using the Bass diffusion model [24]. Based on this method, we estimate p, q, and m that minimize the sum of squares error (SSE), which is the sum of the difference between the actual average number of users and the expected average number of users in the month. It can be expressed by the following equation:

$$\underset{p,q,m}{Min} \sum_{t=1}^{T} [X_t - (N(p,q,m,t) - N(p,q,m,t-1))]^2$$

where t is the number of months since the product has been released and X_t is the actual number of adopters at time t. $(N(p,q,m,t) - N(p,q,m,t-1))$ is the formula to calculate the number of predicted adopters at time t by subtracting the number of predicted cumulative adoption from t. The formula calculates the optimal values of p, q, and m which make a minimal SSE value. Thereafter, it is classified in two groups, the popular group and the unpopular group, by comparing the values of p and q. $q > p$ and $p > q$ refer to the popular group and the unpopular group, respectively. Table 1 shows the result of comparing two coefficients for each game. The initial value is set as the sum of the monthly average users for m; thus, 0.03 and 0.38 are used for p and q, respectively.

3.3. **Word2vec and clustering.** The games were classified in two groups in the previous step. The review data were extracted from each group, and the Word2vec method was used to extract semantic properties through user reviews. We used the skip-gram method instead of continuous bag of words (CBOW) because the meaning of individual words was required to be analyzed to create a word cluster. Typical parameters were used for size and window. PCA is a dimension reduction method that converts the word vectors into several major dimensions. In our study, we used PCA to reduce the projected word vectors created by Word2vec to only two dimensions. After the dimension reduction, word

Table 1. Result of Bass diffusion model

Title	t	m	p	q	type
Counter-Strike: Global Offensive	57	14533920	0.0015586	0.1079163	Popular
Call of Duty: Infinite Warfare	5	13059.941	0.1990427	0.0443014	Unpopular
Undertale	19	55380.033	0.0679691	0.0657168	Unpopular
Star Trek Online	57	138522.93	0.011833	0.0268691	Popular
APB Reloaded	57	134491.86	0.0198315	0.0224178	Popular
Football Manager Touch 2017	8	5359.3571	0.0447427	0.5945254	Popular
Age of Wonders III	52	39033.887	0.0077989	0.0860589	Popular
Lost Castle	14	10554.837	0.0153287	0.3638275	Popular
Stronghold Kingdoms	57	120703.08	0.0275833	0.0147132	Unpopular
Spintires	34	95177.281	0.0082328	0.0299501	Popular
Mad Max	37	51897.287	0.0132222	0.1152845	Popular
Marvel Heroes 2016	53	120483.5	0.0084414	0.0804896	Popular
Saints Row IV	44	97458.834	0.0256686	0.0193646	Unpopular
Project CARS	49	31981.597	0.0039571	0.1324893	Popular
Source Filmmaker	57	82415.986	0.0013965	0.0481226	Popular
Saints Row: The Third	57	116862.09	0.0310515	0.0045515	Unpopular

words	vec1	vec2	vec3	vec4	vec5	…
seem	0.63373	0.01896	-0.19616	0.173724	-0.37286	
comes	-0.29953	0.003891	-0.0624	0.226494	0.116782	
milk	0.247838	-0.18072	0.045772	0.022559	-0.01569	
picking	0.262812	0.101757	-0.08973	0.259249	0.090441	
series	-0.32727	-0.04375	0.11736	-0.17796	-0.01687	
rp	0.046984	0.051128	-0.11465	0.02856	0.040275	
hold	0.12135	0.065104	-0.07704	-0.31426	0.097007	
waste	1.61763	-0.3947	-0.12788	0.012306	-0.12081	
honestly	-0.06948	-0.0655	0.013071	-0.25558	-0.00113	
…						

words	PC1	PC2
seem	1.66829	-1.2323
comes	-0.42257	0.897333
milk	-0.51585	0.380838
picking	-1.55322	-0.24617
series	0.222833	0.162955
rp	-0.41155	-0.75902
hold	-1.67797	0.979591
waste	2.958073	1.932938
honestly	2.752241	0.932003
…		

Figure 2. Results of Word2vec analysis and PCA

clusters were produced through K-means clustering to segment words into groups. The results of PCA and K-means clustering for each group were the word clusters that were expected to describe the characteristics of each group. Figure 2 shows the results of the Word2vec analysis and PCA.

3.4. **Kano model.** This study is theoretically based on the Kano model for extracting the characteristics of the popular group's and unpopular group's gaming products in the generated word clusters. The Kano model defines the key success factor by associating the three main types of factors, M, O, and A, with the gaming industry. The factors are being studied by a research group led by Kent Thorén at the Royal Institute of Technology in Sweden. The following information is based on the research content of this study group.

The mandatory requirement, M, represents the Basic Attributes of the gaming product, and, if associated with the gaming product, can be categorized as technical functionality, motivator, and challenge. O, which is a proportional requirement, represents the Performance Attributes, an indicator of the product's performance level. Examples of performance attributes are price, audiovisual aesthetics, story and/or narrative, and gameplay. The attractive requirements, A, represent the Excitement Attributes and are properties of the condition that makes the consumer happy, that is, the situation in which the experience exceeds the expectations. Examples of such attributes are emotional connection and uniqueness.

We classify the word cluster based on the information about the attributes of these major factor types and classify the unclassified word cluster as indifferent (I) or reverse (R).

4. **Result.**

4.1. **Overview.**

The Steam user reviews used in the word cluster analysis of the popular and unpopular groups utilized "Counter-Strike: Global Offensive" and "Saints Row: The Third", respectively. The top five games of the popular group were Counter-Strike: Global Offensive, Arma 3, PAYDAY 2, Left 4 Dead 2, and Creativerse, while the top five games of the unpopular group were Saints Row: The Third, Alan Wake's American Nightmare, Just Cause 2, Deus Ex: Human Revolution Cut, and DRAGON BALL XENOVERSE. "Counter-Strike: Global Offensive" had 10010 user reviews, while "Saints Row: The Third" had 15947 user reviews. For fitting the Word2vec model with the reviews, we used 100 for the vector dimension, 10 for the window size, 10 for the minimum word count and 0.001 for the down sampling. As the K-means model clustering had five factor types explained in the PCA, the K value was set to 6 in consideration of the error. Table 2 shows the words that can best describe each factor type based on the three major types of factors presented in the Kano model.

Table 2. Words describing each factor type

M	Technical functionality	"bug", "bugs", "problem", "problems", "needs", "wants", "conflict"
	Motivator	"motivator", "achieve", "compete"
	Challenge	"challenge", "challenges", "difficult", "easy"
O	Price	"price"
	Audiovisual aesthetics	"audio", "music", "sound", "graphic", "visual"
	Story and/or narrative	"story", "storyline", "campaign"
	Gameplay	"gameplay", "gameplays"
A	Emotional connection	"positive", "negative", "emotional", "connection"
	Uniqueness	"unique", "uniqueness", "original"

Figure 3 shows the distribution of words describing factor types on the two-dimensional chart. This section is similar in the case of both the groups and can be explained as a result of the popular group. It can be seen that the three major types of factors are distributed in clusters 2, 4, 5, and 6. The attributes of types M, O, and A are not grouped together in one cluster, but are slightly mixed. However, it is noteworthy that these major factor attributes are not distributed in clusters 1 or 3.

Figure 4 shows clusters 1 and 3. In the upper cluster, the main game items such as "grenade", "bomb", and "knife", and characters such as "enemies" and "sniper" were dominant. These factors were found in other games of the same genre. Based on this, it can be seen that the satisfaction of cluster 1 is type I, which is not related to the satisfaction of the game. Next, we can see words such as "hacker" and "cheater" in cluster 3, and words such as "rank" in the same cluster. The words in this cluster mainly imply cheating, hacking, and other factors influencing game results, resulting in dissatisfaction with the game among the users. Therefore, we define this cluster as having elements of the R type.

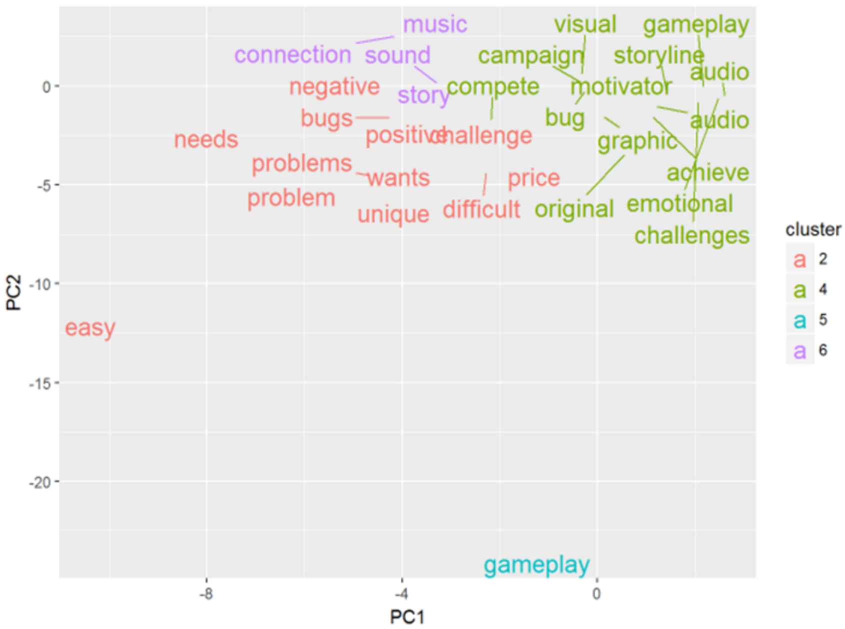

FIGURE 3. Distribution of words describing factor types

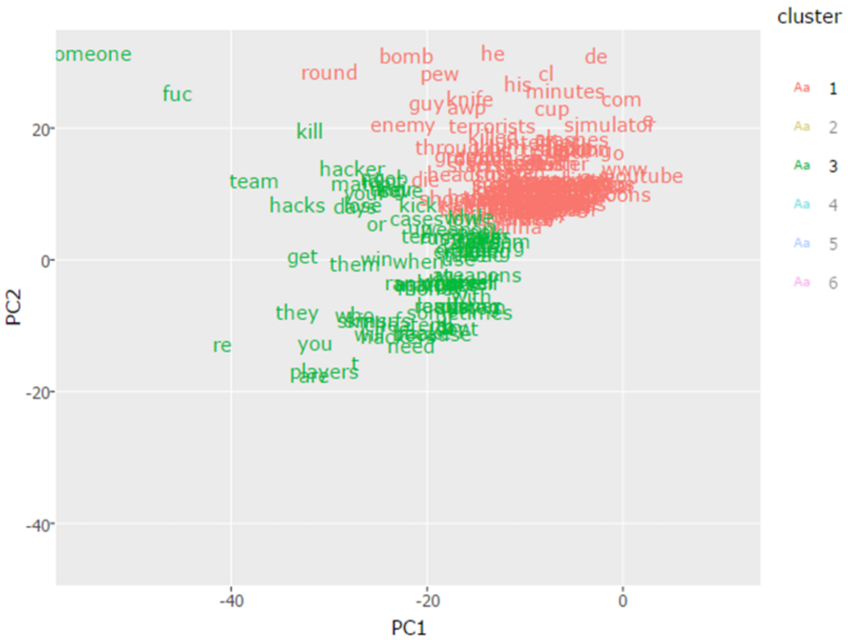

FIGURE 4. Word clusters 1 and 3

In this regard, Steam user reviews refer to all five types of product planning elements discussed in the Kano model. It is, therefore, important to evaluate the word clusters obtained from Steam user reviews based on the Kano model.

4.2. **Differences between two groups.** Because we use Word2vec, the closer the distance between the vectors is, the higher the correlation between them is. To find the differences between the two groups, we calculate the distances between two chosen words of each factor of the Kano model for each group as shown in Table 3.

Firstly, the distances between "bug" and "problem" associated with the "technical functionality" factor, which are 8.80 and 5.88 for the popular and unpopular groups, respectively, show that bugs are interpreted as a problem in the unpopular group. The distances between "campaign" and "easy" of the "Motivator and Challenge" factor, which

Table 3. Results of group differences

Kano Model Factor		Game Group	
		Popular Group	Unpopular Group
M	Technical functionality	8.80	5.88
	Motivator & Challenge	15.28	6.21
O	Price	3.28	10.65
	Audiovisual aesthetics	3.35	4.96
	Story and/or narrative	3.26	15.84
	Gameplay	11.25	20.45
A	Emotional connection	11.91	10.67
	Uniqueness	5.15	2.55

are 15.28 and 6.21 for the popular and unpopular groups, respectively, show that unpopular games are easier in the campaigns.

Secondly, the distances between "price" and "fair" of the "Price" factor, which are 3.28 and 10.65 for the popular and unpopular games, respectively, imply that the games of the popular group meet the consumer expectations in terms of pricing better than the games of the unpopular group. The distances between "original" and "storyline" of the "Story and/or narrative" factor, which are 3.26 and 15.84, for the popular and unpopular games, respectively, imply that the story is more original and well-organized in the case of popular games. Finally, the distances between "gameplay" and "fix" which are 11.25 and 20.45 respectively, for the popular and unpopular groups for the "Gameplay" factor show that popular games have more feedback on improvements.

Thirdly, the distances between "needs" and "unique" associated with the "unique" factor, which are 5.15 and 2.55 for the popular and unpopular games, respectively, show that the unpopular games are required to have more original elements.

5. **Conclusion and Limitation.** This study focuses on analyzing steam user reviews obtained from Valve Corporation's Steam platform, which is currently a leading gaming platform in the industry. First, we divided the games in the popular and unpopular categories using the Bass diffusion model and by comparing the innovation coefficient and the imitation coefficient. After converting Steam user reviews to vector form, we attempted to represent these word vectors in two dimensions using Word2vec and PCA and constructed word clusters through K-means clustering. Finally, we used the Kano model to compare the differences between the groups and presented the differences among the groups.

This study makes two major contributions. By classifying games in two groups and analyzing user reviews using Word2Vec, we could identify the semantic characteristics of the popular and unpopular clusters. We expect that our study will contribute academically to the integration of econometric analysis and text-mining techniques through the classification of groups using the Bass diffusion model and the identification of semantic differences of the groups using the Kano model. Our study is also expected to have practical implications for the gaming industry such as understanding the factors that are important in the development of a new game. Further, even after launching gaming products, our study can help suggest directions for improvements.

However, this study has some limitations. The first is the imbalance between the quality and quantity of the review data. We controlled the genre of games to enhance the quality; however, the number of reviews of each game may not be adequate to reach a generalized conclusion. The second is the incomplete word clusters. Each cluster may not contain enough number of words for the corresponding type. However, we expect that using a greater number of reviews will solve the problem of using Word2vec in the study.

REFERENCES

[1] Newzoo_Games, *2016 Global Games Market Report – An Overview of Trends & Insights Global Games Report*, https://newzoo.com/insights/articles/global-games-market-reaches-99-6-billion-2016-mobile-generating-37/, 2016.
[2] M. Ernkvist, Down many times, but still playing the game: Creative destruction and industry crashes in the early video game industry 1971-1986, *History of Insolvency and Bankruptcy*, vol.161, 2008.
[3] C.-U. Lim and D. F. Harrell, Modeling player preferences in avatar customization using social network data: A case-study using virtual items in Team Fortress 2, *IEEE Conference on the Computational Intelligence in Games (CIG)*, 2013.
[4] T. W. Windleharth, J. Jett, M. Schmalz and J. H. Lee, Full steam ahead: A conceptual analysis of user-supplied tags on steam, *Cataloging & Classification Quarterly*, vol.54, no.7, pp.418-441, 2016.
[5] R. Becker, Y. Chernihov, Y. Shavitt and N. Zilberman, An analysis of the steam community network evolution, *IEEE the 27th Convention of the Electrical & Electronics Engineers in Israel (IEEEI)*, 2012.
[6] J. Hamari and V. Eranti, Framework for designing and evaluating game achievements, *Proc. of DiGRA 2011: Think Design Play*, vol.115, no.115, pp.122-134, 2011.
[7] S. Song, N.-W. Cho and T. Kim, Success factors of game products by using a diffusion model and cluster analysis, *Journal of Korean Institute of Industrial Engineers*, vol.42, no.3, pp.222-230, 2016.
[8] S. M. Mudambi and D. Schuff, What makes a helpful online review? A study of customer reviews on Amazon.com, *MIS Quarterly*, vol.34, no.1, pp.185-200, 2010.
[9] L.-T. Bei, E. Y. Chen and R. Widdows, Consumers' online information search behavior and the phenomenon of search vs. experience products, *Journal of Family and Economic Issues*, vol.25, no.4, pp.449-467, 2004.
[10] J. A. Chevalier and D. Mayzlin, The effect of word of mouth on sales: Online book reviews, *Journal of Marketing Research*, vol.43, no.3, pp.345-354, 2006.
[11] M. Hu and B. Liu, Mining and summarizing customer reviews, *Proc. of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2004.
[12] P. Schulman, C. Castellon and M. E. Seligman, Assessing explanatory style: The content analysis of verbatim explanations and the attributional style questionnaire, *Behaviour Research and Therapy*, vol.27, no.5, pp.505-509, 1989.
[13] A.-H. Tan, Text mining: The state of the art and the challenges, *Proc. of the PAKDD 1999 Workshop on Knowledge Discovery from Advanced Databases*, 1999.
[14] Q. Cao, W. Duan and Q. Gan, Exploring determinants of voting for the "Helpfulness" of online user reviews: A text mining approach, *Decision Support Systems*, vol.50, no.2, pp.511-521, 2011.
[15] T. Mikolov, K. Chen, G. Corrado and J. Dean, Efficient estimation of word representations in vector space, *arXiv Preprint arXiv: 1301.3781*, 2013.
[16] D. Zhang, Y. Xu, H. Xu and Z. Su, Chinese comments sentiment classification based on word2vec and SVMperf, *Expert Systems with Applications*, vol.42, no.4, pp.1857-1863, 2015.
[17] R. D. Sharma, S. Tripathi, S. K. Sahu, S. Mittal and A. Anand, Predicting online doctor ratings from user reviews using convolutional neural networks, *International Journal of Machine Learning and Computing*, vol.6, no.2, p.149, 2016.
[18] F. M. Bass, A new product growth for model consumer durables, *Management Science*, vol.15, no.5, pp.215-227, 1969.
[19] T. Kim and J. Hong, Identifying the diffusion patterns of movies by opening strength and profitability, *Journal of Korean Institute of Industrial Engineers*, vol.39, no.5, pp.412-421, 2013.
[20] M. Clement, S. Fabel and C. Schmidt-Stolting, Diffusion of hedonic goods: A literature review, *The International Journal on Media Management*, vol.8, no.4, pp.155-163, 2006.
[21] N. Kano, N. Seraku, F. Takahashi and S. Tsuji, Attractive quality and must-be quality, *The Journal of the Japanese Society for Quality Control*, pp.39-48, 1984.
[22] G. von Dran, P. Zhang and R. Small, Quality websites: An application of the Kano model to website design, *Proc. of the 5th Americas Conference on Information Systems*, p.314, 1999.
[23] C. Basfirinci and A. Mitra, A cross cultural investigation of airlines service quality through integration of Servqual and the Kano model, *Journal of Air Transport Management*, vol.42, pp.239-248, 2015.
[24] J.-S. Hong, T.-G. Kim and H.-Y. Koo, A parameter estimation of Bass diffusion model by the hybrid of NLS and OLS, *Journal of Korean Institute of Industrial Engineers*, vol.37, no.1, pp.74-82, 2011.
[25] L. Worf, Y. Hanani, K. Bar and N. Dershowitz, Joint word2vec networks for bilingual semantic representations, *International Journal of Computational Linguistics and Applications*, vol.5, no.1, pp.27-44, 2014.