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CosMovis: Semantic Network Visualization by Using Sentiment Words of Movie Review Data

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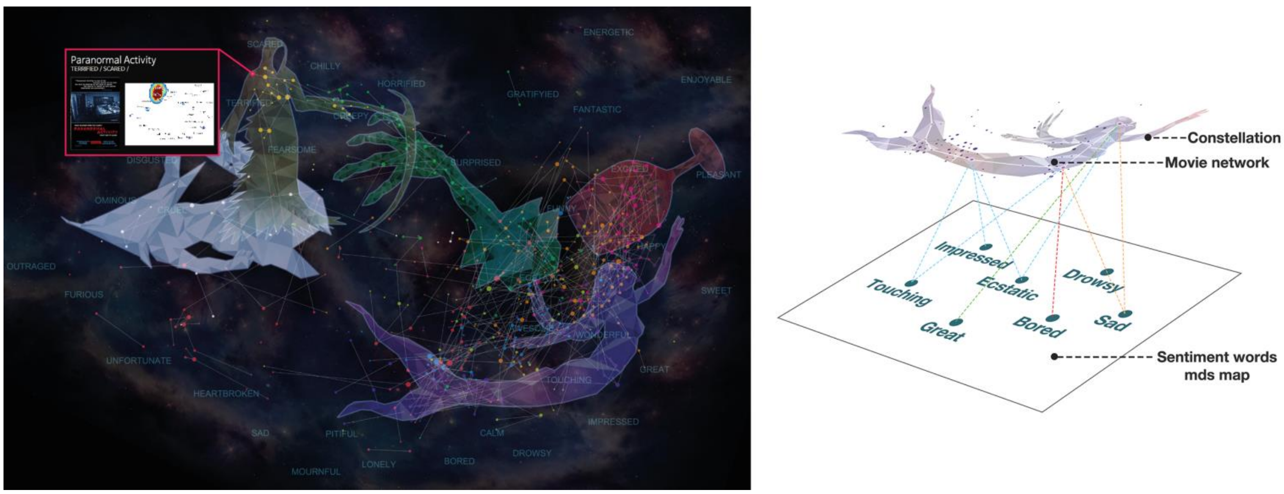

Figure 1. (a) Comprehensive CosMovis constellation map of sentiment word based movies
(b) Basic structure of the Sentiment-Movie

***Abstract*—This paper facilitates the understanding of each node's features through Heatmap visualization in creating network visualization, and suggests a clustering of nodes by connecting the sentiment words MDS Map and Social Network. This study on network visualization aims to design an efficient network analysis which enables users to discover a movie based on sentiment words. Movie review data from online resources were applied in this research, and the process is as follows:**

1) Calculated a frequency of sentiment words from each movie review.

2) Designed a Heatmap visualization to effectively discover the main emotions on each online movie review.

3) Formed a Sentiment-Movie Network combining the MDS Map and Social Network in order to fix the movie network topology, while creating a network graph to enable the clustering of similar nodes.

4) Applied the asterism graphic in order to impart the meaning in accordance with the characteristics of clustering for better cognitive interpretation.

5) Progressed pilot test: a cognition level pilot test varying with whether the sentiment words asterism is fixed.

Keywords- Empirical theory discussion, Review data mining, Semantic networks, Sentiment word analysis.

I. INTRODUCTION

Social Network Analysis (SNA) performs a significant role in understanding and finding solutions of society-functional problems by examining the original structure and relationships of network. Therefore, SNA Visualization is applied in extensive fields, including Network Analysis, based on data similarity, Network Analysis about social-scientific situation, Graph Theory. Force-directed, a standard layout algorithm designing network graph, is considered highly useful since it enables related nodes to form a cluster [1]. The location of the node, however, varies each time the graph is formed if using Force-directed since the entry value of the node's location is random and the eventual position is determined by the relative connections between nodes. Therefore, a notable drawback is found that users must repeat to learn the system if SNA, based on Force-directed, is used as a recommendation system since the absolute location information is not fixed.

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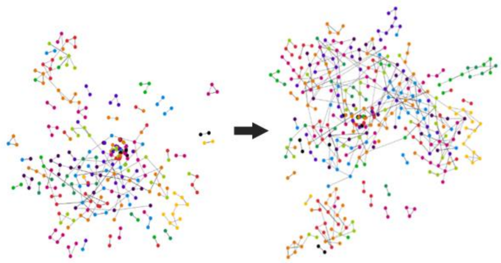

Figure 2. Force-directed layout Network (Left: 300 nodes Right: 400 nodes): The location of nodes continues to change, whenever the data is added or modified

This As an approach to find solutions for those difficulties, we proposed several methods. One strategy is to discover the correlations between keywords through 'Multidimensional Scaling: MDS' and reflect the analysis result in a two-dimensional distribution map, to distribute nodes in semantic positions when designing network visualization based on similarities. As each node is influenced by the semantic points depending on its attribute value, the absolute positions of nodes were designed to reflect the attributes of node [2]. We also tried to enable users to easily grasp the frequency of sentiment words on each movie, through sentiment words Heatmap Graph based upon the distribution map [3].

For a second strategy, we applied a constellation map formed upon nodes and edges of a network clustering structure to label the characteristics of each cluster, when the nodes in a network structure show clustering on a two-dimensional keyword distribution map.

We focused on 'movie data' to implement the 2 proposals noted above and found the sentiment word frequency level of 678 movie reviews by matching the words with sentiment word dictionary. Since this leads to a clustering structure in which nodes are arranged in appropriate positions according to the frequency of affective words in movies, it allows more effective analysis, although the network contains a great number of data nodes. This method is also expected to give effective insights in terms of cognitive SNA by overlapping the constellation graphics showing the characteristics of sentiment words in each clustering with network.

Pilot test was conducted to verify whether visualization method, the purpose of this research, can be related to cognition improvement for users.

This test focused on the comparison between the user awareness levels, varying with whether the network visualization is fixed on the sentiment words distribution map.

II. Related Work

A. Sentiment Words

'An Emotion Scanning System on Text Documents' by MyungKyu Kim, JungHo Kim, MyungHoon Cha and Soo-Hoan Cha covered the sentiment words shown in online postings [4]. 'The Perceived Lexical Space for Haptic Adjective based on Visual Texture aroused form Need for Touch' by JoungYeon Sung and KwangSu Cho (2013) illustrated the adjectives to describe the texture of Haptic, and indicated the relations between adjectives on MDS(Multi-Dimensional Scaling: MDS) [5].

B. Network Visualization and Layouts

Studies on network visualization methods have been done, including several recent studies regarding user's perception. 'Motif Simplification: Improving Network Visualization Readability with Fan, Connector, and Clique Glyphs' by Cody Dunne and Ben Shneiderman (2013) introduce a technique called motif simplification, in which common patterns of nodes and links are replaced with compact and meaningful glyphs, leading users to easily analyze network visualization [6].

Whereas this method identifies maximal motif in a faster and more accurate way, even enabling to estimate the size through glyph and interaction, there are several difficulties for ordinary users, such as the fact that users must put considerable efforts to learn the concepts of motif and to interpret glyph, in addition to the difficulty to discover the optimal set of motifs.

Another study 'Knot: an Interface for the Study of Social Networks in the Humanities' by Giorgio Uboldi, Giorgio Caviglia and Nicole Coleman, S´ebastien Heymann, Glauco Mantegari, and Paolo Ciuccarelli (2013) presented a tool called 'Knot', aiming to analyze the multi-dimensional and heterogeneous data, while focusing on interface design and information visualization on multidisciplinary research context[7].

Furthermore, 'Improving the Readability of Clustered Social Networks using Node Duplication' by Nathalie Henry, Anastasia Bezerianos and Jean-Daniel Fekete (2008) suggested the methods to solve the clustering ambiguity and increase readability in network visualization [8]. This paper said major challenges facing social network visualization and analysis include the lack of readability of the resulting large graphs and the often ambiguous assignment of actors shared among multiple communities to a single community. They proposed using actor duplication in social networks in order to assign actors to multiple communities without greatly affecting the readability. Duplications significantly improve community-related tasks but sometimes interfere with other graph readability tasks.

Also, although this research gives meaningful insights on how central actors bridge the community, it also leaves confusions when distinguishing the duplicated nodes when analyzing visualizations that are larger than a certain size since node duplications can artificially distort visualization.

The three studies mentioned above all aim to improve network visualization from the perspective of the user, particularly focusing on settling the challenges of visualization distortion and existing network through users' learning of new technologies. Our research may correspond with previous studies in that it fixed the network data based upon sentiment words, and was designed to minimize users' learning and prevent distorted interpretation, by applying the metaphor based on the characteristics of nodes in the network.

III. Data Processing

A. Sentiment Words Collection

We selected 100 sentiment words after filtering from 834 sentiment words based on the research by Doug Woong Hahn and Hye Ja Kang (2000), in order to create a sentiment word distribution map [9]. Further survey of 30 subjects aged from 20 to 29 determined the most frequently used words among these 100. After basic instruction on the concept of sentiment words during the movies, we investigated to what degree of the emotion represented in each sentiment word can be drawn from watching the movies. The survey began with the question ‘Describe how much you feel as in each sentiment words after watching the movies with following genres, based on your previous experience’; the questionnaire used a 7-point Likert Scale from “Strongly irrelevant’ to ‘Strongly relevant’. After eliminating 32 sentiment words relatively under the average, 68 sentiment words were finally selected [2].

B. Sentiment Words Refinement

To select the final sentiment words used on the two-dimensional distribution map from among the 68 sentiment words from the user survey, we collected and compared the sentiment word data in existing movie reviews, eliminating the words rarely used. This procedure consisted of three phases as follows:

1) Crawling: Movie review data used in this research were collected from the movie information service in NAVER [10], a web portal site with largest number of users in Korea. We designed a web crawler to automate the sentiment word collection from movie reviews. This crawler covered three stages: collecting the unrefined movie reviews and tags in NAVER movie web page, refining the collected data suitable for the research, and extracting the sentiment words based on the analysis of refined data. As a result, we obtained 4,107,605 reviews on 2289 movies from 2004 to 2013.

2) Establishing sentiment word dictionary: We divided the text data into morphemes collected through the crawling process, by using mecab-ko-lucene-analyzer, and further extracted the sentiment morphemes. A total of 133 morpheme clusters were selected through several text mining processes [11]. Each selected emotion morpheme was classified by 68 kinds of detailed sentiment word categories and a sentiment word dictionary, classified by chosen sentiment word, was established. Extracting emotion morphemes and classifying then by category was conducted with the consultation of Korean linguists.

3) Applying TF-IDF: We eliminated less influential sentiment word clusters after matching them with actual movie review data, in order to produce more accurate results.

We calculated the Term (w) Frequency (tf: Term Frequency) of each sentiment word cluster (t) suggested by this formula.

$$tf(t,d) = \sum_{i=0}^{j} f(w_i, d) \tag{1}$$

j = number of words in sentimental group t

Then Inverse Document Frequency (idf) was also drawn from this formula, so that the weight of the general sentiment word group would be lowered.

$$idf(t,D) = log(\frac{D}{d \in D : t \in d}) \tag{2}$$

The TF-IDF score of sentiment word clusters on each movie was calculated with the formula as follows.

$$TFIDF(t,d,D) = tf(t,d) * idf(t,D) \tag{3}$$

We next considered the maximum TF-IDF score that can appear from each sentiment word to decrease the number of sentiment words. For example, a word ‘Aghast’ shows the TF-IDF score of no more than 0.8% in every movie whereas ‘Sweet’ scored 42% on at least one movie. We eliminated the sentiment words of which the TF-IDF score was less than 10%, and eventually selected 36 sentiment words. This sentiment word clusters were broadly divided into ‘Happy’, ‘Surprise’, ‘Boring’, ‘Sad’, ‘Anger’, ‘Disgust’ and ‘Fear’, as shown in Table 1.

TABLE I. FINAL SENTIMENT WORDS

Clustering Characteristics	Sentiment Words
Happy	Happy, Sweet, Funny, Excited, Pleasant, Fantastic, Gratified, Enjoyable, Energetic
Surprise	Surprised, Ecstatic, Awesome, Wonderful, Great, Touched, Impressed
Boring	Calm, Drowsy, Bored
Sad	Pitiful, Lonely, Mournful, Sad, Heartbroken, Unfortunate
Anger	Outraged, Furious
Disgust	Ominous, Cruel, Disgusted
Fear	Scared, Chilly, Horrified, Terrified, Creepy, Fearsome

C. Movie Data Collection

Movie samples used in network visualization were also collected from NAVER movie service in accordance with movie review data [10]. Based on 2289 movie samples from 2004 to 2013 registered in the NAVER movie service, movies with more than 1000 emotion morphemes were used to filter the emotion level. As a result, 678 movie samples were selected and utilized as network sample data.

IV. VISUALIZATION PROPOSAL

We propose three methods to solve the problems of existing social network visualization layouts as follows.

A. Heatmap Visualization

Heat map is a visualizing method consisting of rectangular tiling shaded in scaled color [12]. It is used to search patterns of anomaly of data metrics like Robert Gove's research [13], as well as to comprehend convergences like Y.S. Jeong, Y.J. Chung, J.H. Park.'s research [14]. In this research, we showed the TF-IDF size frequency of sentiment words into Heatmap, utilizing coordinate space in 2-dimensional distribution map of each sentiment word for visualizing a sentimental distribution graphic of each movie node. The detailed research process is as follows.

First, we measured space among the selected 36 sentiment words and analyzed correlations to design a two-dimensional sentiment word distribution map, and then we conducted Multi-Dimensional Scaling (MDS). We conducted a survey on semantic distance among 36 sentiment words among 20 college students majoring in Digital Media Technology. The 36 sentiment words were on both axis (36X36) and the distance between words was scored by giving plus/minus 3 points, considering their emotional distance. We utilized UNICET to facilitate a variety of network analysis methods based on the data from 20 survey participants, and created Metric MDS as shown in Fig. 3, based on semantic distance among the movie review semantic words.

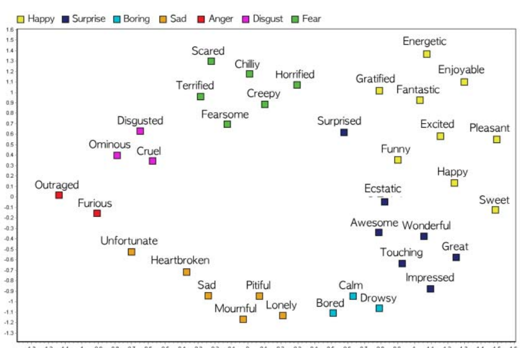

Figure 3. 36 Sentiment words MDS Map

As a result, positive emotions such as "Happy" and "Surprise" were distributed on the right side of the X-axis and negative feelings such as "Anger" and "Disgust" were distributed on the left side. Active emotions which generally arouse exaggerated gestures such as "Fear" and "Surprise" were distributed on the top of the Y-axis, and static emotions such as "Sad" and "Boring" were on the bottom. Also, each type of sentiment words was clustered concretely based on particular characteristics like 'Happy', 'Surprise', 'Boring', 'Sad', 'Anger', 'Disgust', and 'Fear' on the two-dimensional distribution map, and it showed that cluster characteristic "Surprise" can be divided into "Happy" and "Fear" clusters. It implies that both overflowing joy and sudden fright is dominant in particular movies.

After that, a Heat Map Visualization was designed based on two-dimensional sentiment word distribution map and the frequency of the 36 sentiment words, which consisted of two-dimensional distribution map, one optional movie was needed to design the Heat Map. We measured the frequency of the sentiment words on each movie by contrasting sentiment words in the movie review data obtained through data construction process and the sentiment words in the morphological dictionary. Also, we measured numerical values by calculating TF-IDF score to lower the weight of particular sentiment words, which frequently emerge regardless of the typical characteristics of the movie. Therefore, TF-IDF scores on each sentiment word could be interpreted as a numerical value reflected on the Heat Map Visualization Graph for target movies. The final heat map graph consisted of a two-dimensional distribution map with sentiment words and tiny triangular cells. Every cell was initialized in numerical value, 0, and the value increased depending on the TF-IDF score of the sentiment word located in the pertinent cell. As the numerical value of cell increased, the color of the cells changed, making it easy to discover the value of the TF-IDF score of the pertinent sentiment word. Also, as high valued cells influenced the values of surrounding cells, the heat map graph became gradually significant.

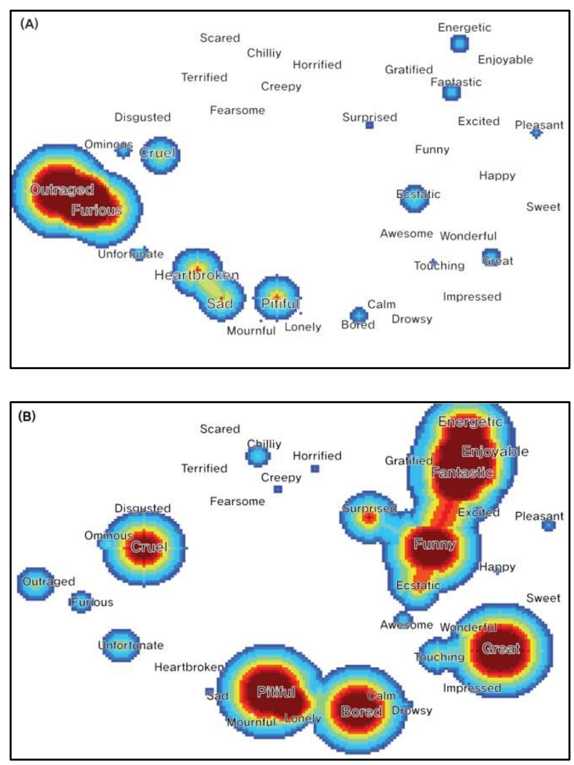

Figure 4. (A) Heat Map of 'Don't Cry Mommy' which shows single emotion (Furious, Outraged) (B) Heat Map of 'Snowpiercer' which shows various emotions (Cruel, Pitiful, Lonely, Bored, Funny, Great, And Energetic) : One Heatmap Present One Movie

Fig. 4 (B) is a heat map graph that represents the distribution map of sentiment words from movie reviews written by spectators of the movie 'Snowpiercer'. In this Graph, spectator shows high frequency of emotion such as 'Pitiful and boring' as well as 'Funny and great'. One of the reviews note that "This movie was very well directed until the middle phase and, especially, the scene that shows someone running forward with a torch was one of the greatest scenes reflected the director's taste. However, the plot drastically got bored and the tension maintained the surrounding became loose, and then it ended in vain like showing situation inside and outside of train uselessly."

As this review shows, it can be interpreted that there were various spectators with different emotions about this movie, includes disappointments.

Therefore, a Heatmap which shows movie sentiment words can be divided into two cases. One indicated that only one characteristic showed high frequency among several sentiment words including 'Happy', 'Surprise', 'Boring', 'Sad', 'Anger', 'Disgust', and 'Fear' (Fig. 4 (A)). The other indicated that more than two characteristic showed high frequency among several sentiment words. (Fig. 4 (B)) As the second case was more frequent, it is shown by the Heatmap that people are able to feel more than two combined sentiments. Furthermore, using the Heatmap made it possible to easily compare movie nodes which have contrasting or similar sentiment words.

B. *Sentiment-Movie Network*

In this chapter, we aim to explain the basic structure of suggested graphs and examples and that the location of nodes can be altered depending on the main sentiment word from the movie review. The suggested graph is similar to the Artefact Actor Network which is a type of Multi-Layered Social Network. The Artefact Actor Network connects between Artefact Network and Social Network using Semantic Connection, so it expresses Semantic Relation between two networks [15]. In our proposed graph, we connected Sentiment Words on 2-Dimensional Scaling Map with Movie Network. In this paper, we called this network Sentiment-Movie Network. Fig. 5 shows our basic structure of the Sentiment-Movie Network.

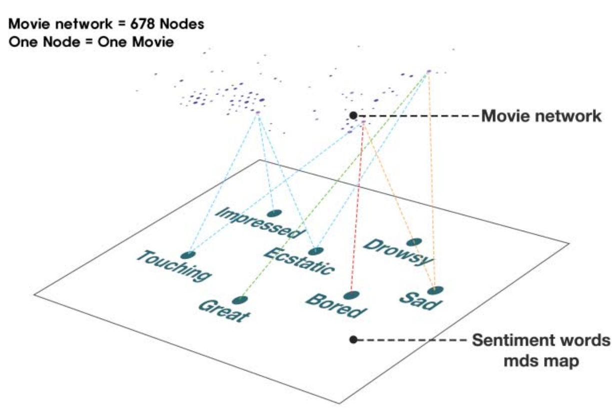

Figure 5. Basic Structure of the Sentiment Movie Network

Like Fig. 5, the suggested graph is comprised of two Layers. The First Layer is called The Semantic Layer and it consists of Semantic Points based on the 36 sentiment words. The Semantic Point of the sentiment word is located at an initially set value and it stays immovable. The Second Layer is called the Network Layer, which includes the nodes that comprise the movie network. Each movie node forms the edge of other movie nodes based on similarities and also forms imaginary edges with the sentiment word in the two-dimensional distribution map based on sentiment word that the pertinent node connotes. Nodes connected by edges have both attractive force and repulsive forces based on a forced-directed algorithm. On the other hand, semantic points of sentiment words are immovable, solely leaving the attractive force. For edge composition between nodes we calculated cosine similarity between movies based on the TF-IDF score of the 36 sentiment words. The Similarity between movie A and movie B, SIM(A, B), is as follows.

$$SIM(A, B) = \frac{\sum_{i=0}^{n} A_i * B_i}{\sqrt{\sum_{i=0}^{n} (A_i)^2} * \sqrt{\sum_{i=0}^{n} (B_i)^2}} \quad (4)$$

The edge between each node and Semantic Point sets up fixed threshold value, and generates an edge by designating sentiment word with a value that is greater than a threshold value as Semantic Feature.

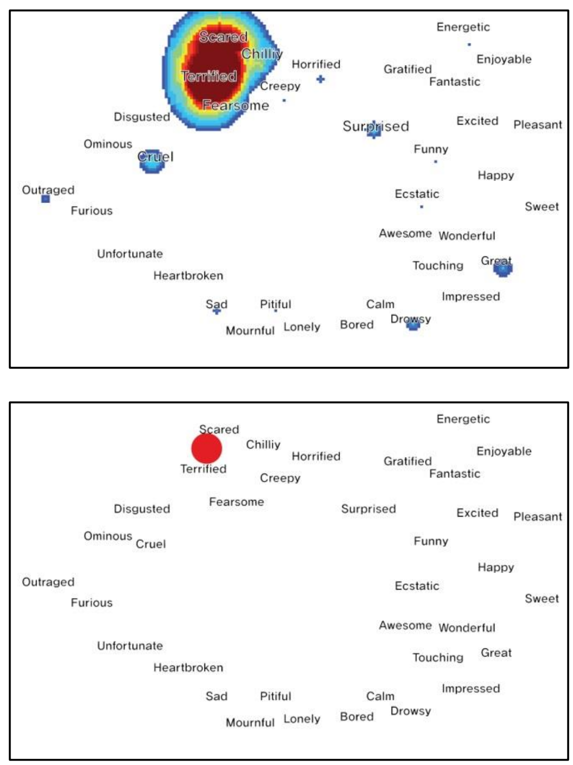

Figure 6. Heatmap Visualization and positioning on the Sentiment-Movie Network (One point position) in case of "Paranormal Activity"

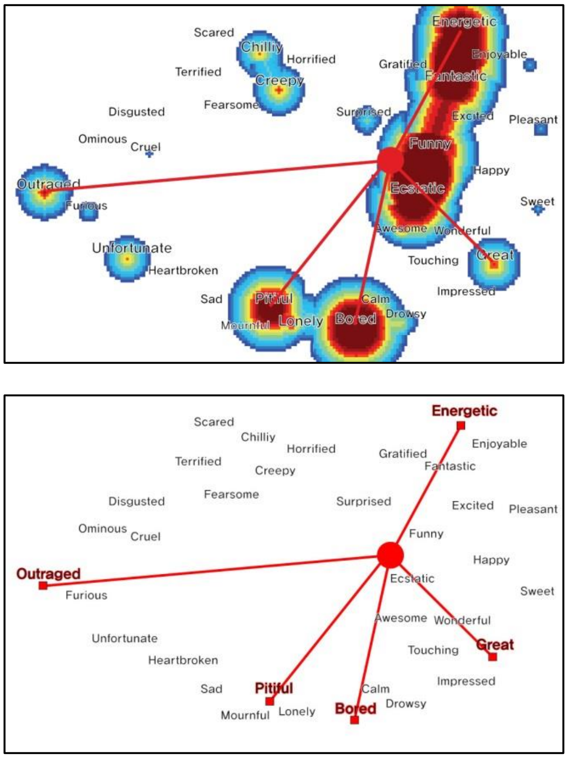

Figure 7. Heatmap Visualization and positioning on the Sentiment-Movie Network (More than two point position) in case of "Jack Reacher"

Although Fig. 6 and Fig. 7 show the example that the location of a node on the graph can be altered depending on the frequency of sentiment word indicated in the Heatmap Visualization. Fig. 6 show the node is located in the space of the sentiment word with overwhelmingly high frequency. Fig. 7 indicates a node is located in the middle of the space of several sentiment words. As every node connected by the network made up of suggested methods is located in the graph, clustering is formed by combined similar movies in the space of sentiment word with high frequency considering connections between movies and between related sentiment words. Fig. 8 shows the extreme position of a node and cluster. Finally, k-means clustering operation using cosine similarity value for classifying cluster characteristics of each node was conducted. The number of clusters was considered from 9 to 12, and the final cluster number was chosen to be 11 as the node number of each cluster was evenly distributed and various characteristics were well clustered. Also, each node was colored for the purpose of classifying each node group based on the 11 clusters.

C. *Constellation Visualization*

This chapter facilitates a cognitive understanding of the process to design constellation image visualization, based upon specific nodes and edges with significant sentiment word frequency to clarify the semantic parts of each clustering

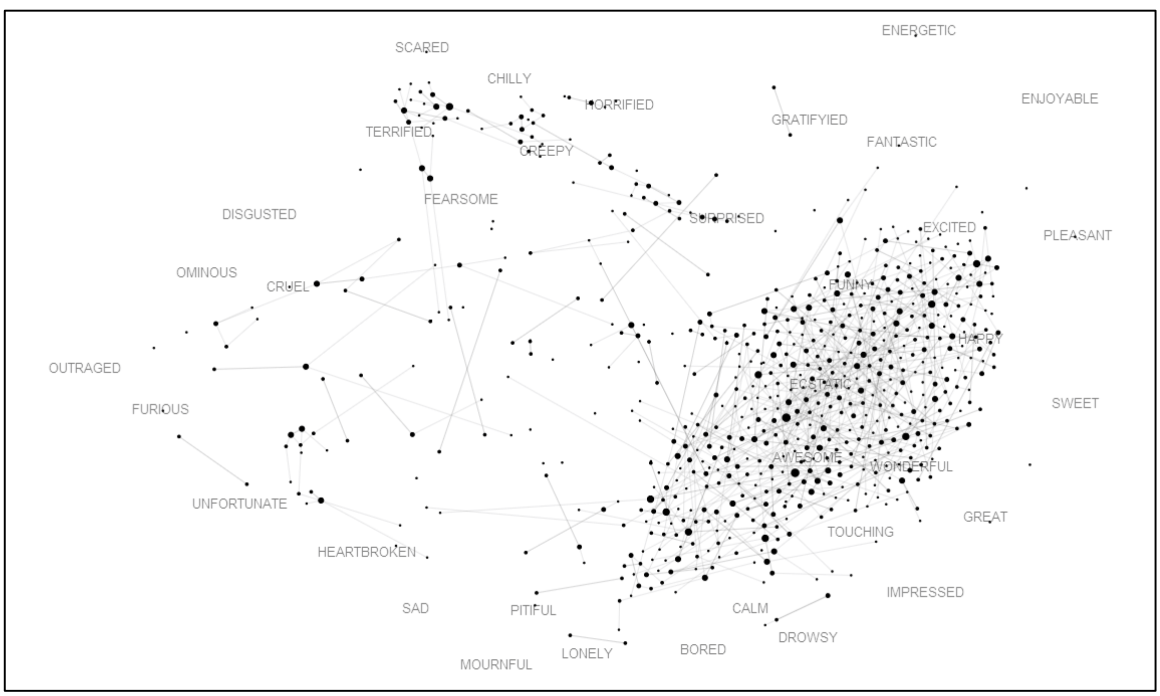

Figure 8. Sentiment Movie Network

We created an asterism graphic of each cluster network, considering the significant sentiment words, information on movies, and synopses in each cluster. In order to realize asterism images, we referred to the labeling data of the 11 different clusters yielded from k-means clustering, most dominant categories of sentiment words in each cluster, and their following information on movies and synopsis.

This 2-dimensional distribution map also attempted to better analyze emotions by varying the font sizes of 36 sentiment words according to the frequency of node in each cluster.

Below, Table 2 shows the main emotions and movie examples that each cluster has, and the motives for choosing each asterism name.

TABLE II. DEFINITION OF CONSTELLATION VISUALIZATION

Cluster Name	Movie Examples	Asterism Name	Movies for Each Name
Cruel and dreadful	Final Destination 3 Piranha 3D	**Red pyramid**	Symbolized the cruelly murdering character in a movie <Silent Hill>
Dramatic Emotional	Pride& Prejudice, The Notebook	**Whale**	Inspired from the scene when grampus appears in a movie <Life of Pi>, which aroused dramatic and emotional image simultaneously
Dynamic mood change	Snowpiercer ,Trans- formers	**Persona mask**	Persona masks are supposed to express various emotions, which is similar to movies with dynamic mood changes
Thrilling and horrifying	Resident Evil, War Of The Worlds	**Alien**	Aliens arouse fear and suspense in unrealistic situations
Surprising	Saw, A Perfect Getaway	**Jack in the Box**	Symbolized an object popping out of the box to express surprising moments
Pleasing and exciting	Iron Man Avatar	**Gambit**	Relevant to the magician character of a movie <X-men>, who is fun and surprising
Authentic fear	Paranormal Activity The Conjuring	**Reaper**	Symbolized as a reaper to show the authentic and intrinsic fear
Generally Monotonou s	127 Hours, Changeling	**Sloth**	Originated from the idea that sloths are boring and mundane
Fun and cheerful	Hairspray The Spy: Undercover Operation	**Wine Glass**	Wine glass is a symbol of romantic and festive atmosphere
Sweet and cute	Despicable Me Puss In Boots	**Ginger- bread Cookie**	Gingerbread men cookies represent cute and sweet sensations
Sad and touching	Million Dollar Baby, Man on fire	**Mermaid**	The story of little mermaid shows touching, magical and sad ambience at the same time

A comprehensive network map based on the information in this table is shown in Fig. 1 (a), while Fig. 1 (b) involves the asterism graphic examples of each cluster. Fig. 1 (b) also indicates that it is much easier to semantically analyze the network visualization with overlapping asterism images on each sentiment word and symbolic nodes with the connection structure of edges.

V. DISCUSSION

We aim to verify if the network visualization suggested in this study has actually contributed to user awareness improvement in an empirical way. 1 pilot test was conducted.

A. Pilot Test: Awareness and Usability experiment depending on sentiment word map fixations on network

This experiment aimed to verify the effects on user's awareness and usability of the network with fixed locations of nodes based on the sentiment word map, compared to the map with unfixed location of nodes. 10 subjects were divided into 2 groups (group A and B) and were asked to answer the movie sample in the order of a-a-a` questionnaire set such as the flow "Find the movie 'If Only' on the screen.", "Refresh the screen, and find the movie 'If Only' again", "Refresh the screen, and find the movie 'The Notebook' similar with 'If Only'." Movie samples in each questionnaire set were selected in the same clustering. Group A was asked to answer 2 sets first in the fixed network followed by 2 more sets in the unfixed network, group B was asked in the other order. After answering 2 questionnaire sets, they were required to make plural choices on the 68 sentiment words list to find out if they inferred the right characteristics of clustering, based on the classified sentiment word data considered through the previous survey. We measured the reaction time for the participants to infer the characteristics of each clustering, after letting the subjects learn freely. Every participant evaluated the decision making process and network usability during oral interviews, after the experiment.

Furthermore, information contained in the web tool was minimized, so it wouldn't affect the original purpose of this experiment, and also contained an additional function on reaction time outputs each time users clicked the nodes, for more accurate measurement. 2 test tools had same external conditions such as background colors or line thickness, and are shown as Fig. 9.

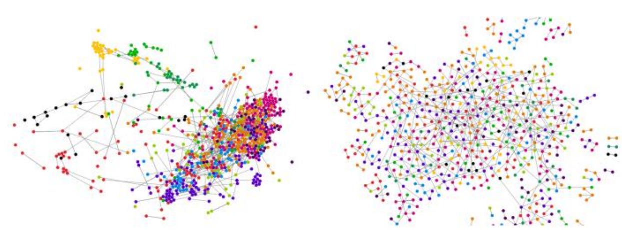

Figure 9. Sentiment words fixed network (Left) and unfixed network (Right) used in Pilot test

Result: The average reaction time was 143.07 seconds in the fixed network during the initial attempt (a-a-a'), which was about 1 minute faster than in the unfixed network, (213.1 seconds on average). In the same way, the second attempt (a-a-a') showed as average reaction time of 10.98 seconds in the fixed network and 74.77 seconds in the unfixed network, still approximately 1 minute faster. We further discovered from the interview and figure results that the participants were more easily able to predict the location of movies due to the learning effect when using a fixed network. Participant responses on the characteristics of clustering showed more than 60% match rates, and learning time to respond is as follows: While the learning time in group A has been increased from 101 seconds in the fixed network to 199 seconds in the unfixed network, Group B showed decreased learning time in the fixed network (57 seconds) compared to 66 seconds in the unfixed network. This may be because group A tends to discover the similar number of samples even in the unfixed network, affected by the unconscious criteria learned from the previously discovered fixed network. It was apparent in the interviews that participants in both groups had to discover the nodes from a certain number of movies initially in order to infer the characteristics of clustering.

VI. CONCLUSIONS

In order to efficient analyze network visualization, this research proposed Heatmap visualization to understand the characteristics of each node, a method to describe the network nodes based upon a two-dimensional sentiment word map and asterism graphic for the semantic interpretation of clustering, followed by pilot test to verify the suggestions.

As a result, we discovered that sentiment word-based network serves as a useful learning method, as proven in the second pilot test, as participants showed a faster reaction time when identifying the movies through a fixed network of sentiment words. In addition, we took extra test that contains user awareness experiment on network structure. Consequently, the extra test revealed that the participants understand the sentiment word distribution structure on the Sentiment-Movie Network Graph and its emotion locations of nodes.

This study, however, might be improved because users may take time predicting the sentiment words solely from the location of nodes in certain cases, since movie nodes with several frequent sentiment words is located in the middle of two-dimensional distribution map. We also did not consider the relation between color tones and emotions when designing the colors of the 11 clusters, leading to the difficulty in satisfying the users' possible needs to connect the node's color with emotions. We hope for further research on defining the network on movies with various sentiment words and the relation between colors and emotions, embracing the current challenges mentioned above. And we plan to do one more pilot test. It will include awareness and usability comparison experiment depending on asterism graphic metaphor applications. This research is expected to be adopted in another network system since our method is applicable regardless of the number of review data, and even to other media contents such as web-based cartoons, music, and books, using assorted constellation images related to target field.

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