Analysis Support System of Open-ended Questionnaires Based on Atypical and Typical Opinions Classification

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Abstract: This paper proposes a support system for analyzing answers to open-ended questions supplied by users as mobile game content evaluation when they unsubscribe the services. The answers include useful, unexpected opinions (atypical opinions) and expected opinions (typical opinions). It is inefficient to read them all during analysis. Therefore, we propose a support system for analysis of questionnaire data related to unsubscribing. The main function of the support system is classifying the answers into typical opinions and atypical opinions, and presenting them with user interfaces. In order to grasp user tendency, typical opinions are presented as a graph showing the number of transitions. Atypical opinions are presented as cards placement on 2-dimensional plane in order to grasp opinion groups with their content.

Keywords: Classification system, natural language processing, typical pattern, questionnaire

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1. Introduction

Mobile phones and the Internet are frequently and increasingly used as marketing mediums. Users of a mobile game content system respond to a questionnaire that is intended to improve contents when they stop their subscription to the services. The questionnaire consists of multiple-choice and open-ended questions that appear on the screen of their cellular phones. Using multiple-choice questions, the questionnaire asks users to choose from some possible answers and responses that can be statistically analyzed.

Answers to the multiple-choice questions, however, are completely standardized and known from the service provider's perspective. To tap into unexpected ideas, answers to open-ended questions must be analyzed.

There are no restrictions on open-ended questions and they are generally answered with natural language. Therefore, the answers include an enormous amount of text data for the questionnaire analyst, and some support methods for analysis by text mining have been proposed [1][2][3][4]. However, since answers are input through cellular phones, they often include many symbols that are dependent on various kinds of terminals and grammatical mistakes, which can make them hard to understand. Additionally, since most answers are included in multiple-choice questionnaires and do not need to be read, there are a few useful opinions. Based on our previous research, a method of classifying opinions as typical or atypical is proposed [5][6], and a support system that presents two interfaces for analyzing each opinion group is designed [7].

The interface that supports the analysis of typical opinions has bar graphs that present the trend in the number of opinions in each category that includes the same opinion content. However, since the number of categories increases along with the number of opinions, the graph gets complicated. Therefore, it is necessary to freely group some categories. The function allows an analyst to discover a subscriber's reason for unsubscribing.

The interface that supports the analysis of atypical opinions presents opinions on screen as cards in order to grasp the opinion content intuitively. Especially, this paper proposes a support system for discovering correlations between a subscriber's properties and the singularity of their opinions.

2. Questionnaire Analysis Problem

Questionnaire for unsubscribing services

The questionnaire is given to consumers who unsubscribe from a game service consists of multiple-choice and open-ended questions. In the multiple-choice questions, the questionnaire asks consumers to choose from a limited number of predefined answers. In the open-ended questions, consumers are able to freely write their opinions.

- Multiple-choice questions: In questions about reasons for unsubscribing, the following 11 items are listed and users can choose any item. For instance, some examples include "stopped playing the game", "There are not enough incentives to continue", and "I could not win a prize".
- Open-ended questions: The open-ended questions are as follows;
  - Improvement demands
  - Other opinions.

Consumers are able to freely write their opinions for each question. Nearly 10% of customers who unsubscribe write opinions for each question.

Analysis of open-ended questionnaire

The answers from consumers include important remarks related to dissatisfaction that cannot be grasped in the multiple-choice questions. The answers also include impressions or demands that the provider may not expect. Open-ended questions are analyzed as shown in Figure 1. If similar opinions are frequently appeared, they are included in the multiple-choice questions. Additionally, frequent dissatisfaction and demands opinions motivate improvements to the service. However, useful opinions comprise only about 5% of all the opinions. Most answers reflect opinions already known by the provider or duplicate the meaning of other answers.

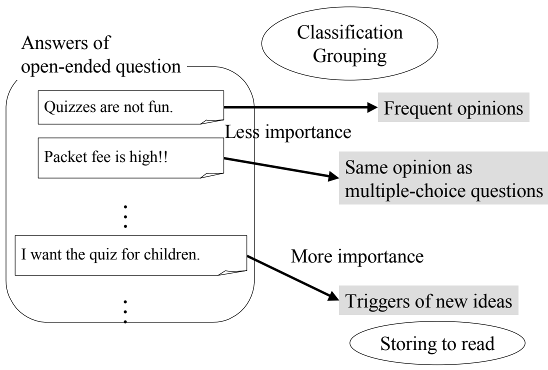

Figure 1. Analysis of open-ended questionnaires data

To grasp unexpected opinions, our system tries to classify the opinions of open-ended questionnaire data into typical and atypical opinions. The definition of typical and atypical opinions is as follows:

- Typical opinions
  - Opinions that echo the meaning of items included in the multiple-choice questions. (e.g.: The packet charge is too expensive.)
  - Frequently appeared opinions that the provider already knows. (e.g.: My knowledge increased.)
  - Irrelevant opinions. (e.g.: I had a baby!)

- Atypical opinions
  - Opinions that are not typical. (e.g.: Quizzes are for kids)

However, the boundary between the atypical and the typical is very ambiguous and the distinction differs according to an analyst's background knowledge. An atypical opinion might change to a typical opinion when the provider reads many opinions.

The proposed system classifies open-ended questions into typical or atypical opinions according to the above definition, and supports their analysis.

Analysis support function

Since an analyst does not carefully read all typical opinions, they need to be grouped by each opinion and the number of them as output. Since an analyst needs to read all sentences in atypical opinions, a support system is needed that provides a user interface that makes it easy to grasp opinion contents. To this end, typical opinions are grouped when open-ended questions are classified into typical or atypical opinions. Additionally, since the classification differs to the analyst's background knowledge, the system needs to provide a framework that reflects an analyst's background knowledge into the classification.

The following three support functions are needed for the support system as shown in Figure 2;

- Classification into typical or atypical opinions that reflects an analyst's background knowledge
- User interface that supports the analysis of typical opinions
- User interface that supports the analysis of atypical opinions

3. Questionnaire Analysis Support System

Outline of the support system

Our system aims to support to analyze open-ended questions that are answered by users when they unsubscribe the service, and provides the following functions based on the support functions mentioned in the previous chapter. Not all opinions need to be read by an analyst, and the system enables an analyst to read only useful opinions. This makes analyzing typical opinions more efficient as it shows the transition of the number of grouped opinions. Moreover, it should enable the boundary between typical and atypical opinions to be flexibly changed by the analyst. Figure 3 shows the outline of this system. When new questionnaire data is input, opinions from the open-ended questions are extracted automatically.

Extracted opinions are processed by word lists and classified into typical or atypical opinions. During this classification process, typical opinions are grouped into categories for each opinion's content as defined set in advance.

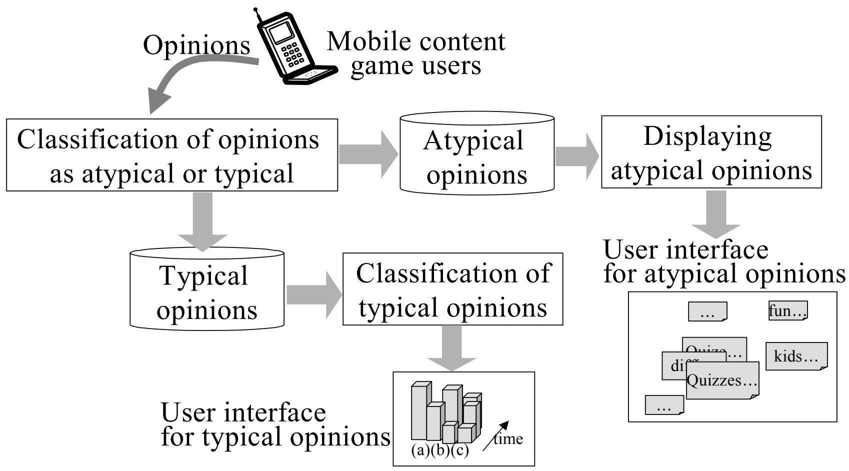

Figure 2. Overview of questionnaire analysis support

Atypical opinions are placed on the screen as cards, and analyst can grasp opinion content intuitively. Since the system shows typical opinions as a graph that represents the relationship between the number in each category and the date, an analyst can easily grasp the transitions among the number in each category.

The following sections describe the data input process, the classification method, and the user interface along with the operation procedure.

Data input part

Opinions from the open-ended questions extracted from questionnaire data are divided into word lists by morphological analysis with “ChaSen” [8], Japanese software. From the word lists, we extract nouns, independent adjectives, and independent verbs as the minimum words required for understanding a sentence. In Japanese, nouns are roughly divided into 14 types. There are also words that may constitute the keywords in context. Based on the morpheme connection and extraction rules, morphemes are transformed to keywords. For example, “packet” and “fee” are transformed to the keyword “packet fee” according to the rules.

Classification method

The system classifies into typical or atypical opinions by matching between the word lists of each opinion and word combinations that are stored beforehand in the typical word database. Figure 4 shows an example of an opinion “quizzes are interesting.” Generally “interesting” is not synonymous with “fun”, however, when “interesting” and “fun” are used with “quiz” in collected questionnaire data, they are considered to have the same meaning. As explained above, typical word database consists of two words combination that has each set of synonyms.

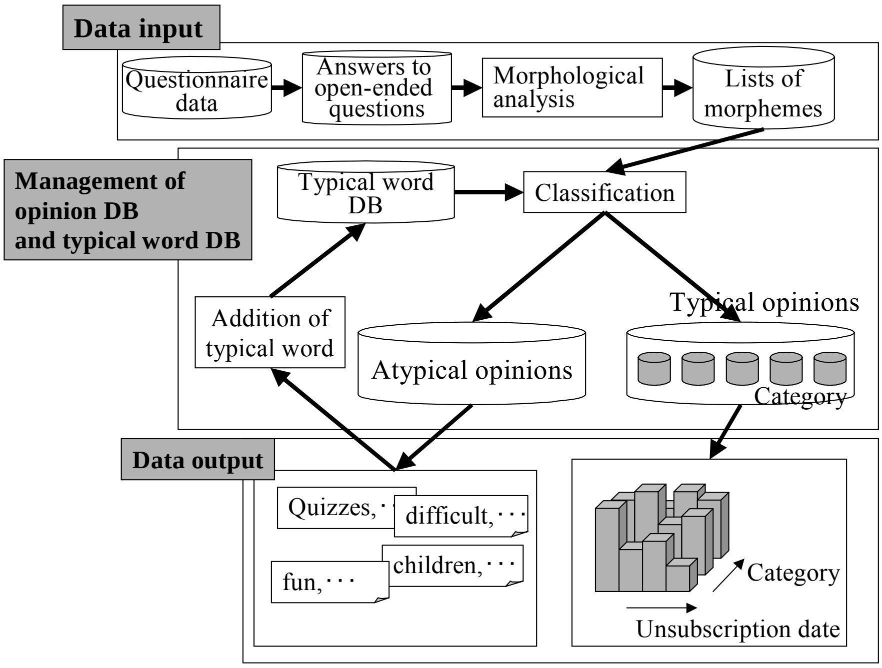

Figure 3. Outline of the analysis support system

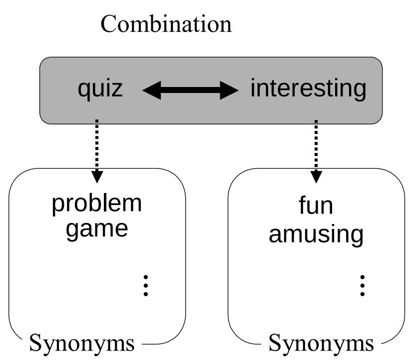

Figure 4. Typical word database

The longer the distance between the word combinations, the weaker their relationship is. Therefore the system defines a parameter *d* as the distance between the word combinations that can be considered to have a relationship. In other words, the word combination with a distance of "*d+1*" or more is considered to be unrelated.

When an opinion includes a combination of words found in the typical word database and the word distance is not more than "*d*", the combination of words is called a "typical element". If the ratio of typical elements to all keywords in an opinion is over a certain ratio, the opinion is classified as typical. If an opinion satisfies the following formula condition, it is classified as typical.

"The number of keywords in typical elements" + α × "The number of typical elements" □ "The number of all keywords"

Here, α shows how many other keywords are permitted to be included in a typical opinion for each typical element.

When the opinion consists of sentences with many keywords, the opinion includes many typical elements and a few atypical elements. Since the service provider needs atypical ideas, even if they are only a very small part of an opinion, the few atypical elements in an opinion must not be overlooked. To classify opinions without missing atypical elements, sentences in opinions should be divided according to the change in the meanings.

Since the target text data input through cellular phones often contains peculiar pictographs instead of punctuation marks or sentences are not delimited beforehand, it is difficult to delimit sentences to meaningful phrases. Consequently, the points where typical elements appear are regarded as the delimiters of the break points of meanings. Delimiters divide the sentences in opinions into phrases. The aforementioned condition is applied to each phrase. This means that the number of typical elements in a phrase is always 1. If an opinion includes at least one atypical phrase, the opinion is classified as atypical.

Figure 5 shows an example of classification using this method. This example includes four typical elements and is divided into four phrases. Since the fourth phrase does not satisfy the condition, the opinion is classified as an atypical opinion.

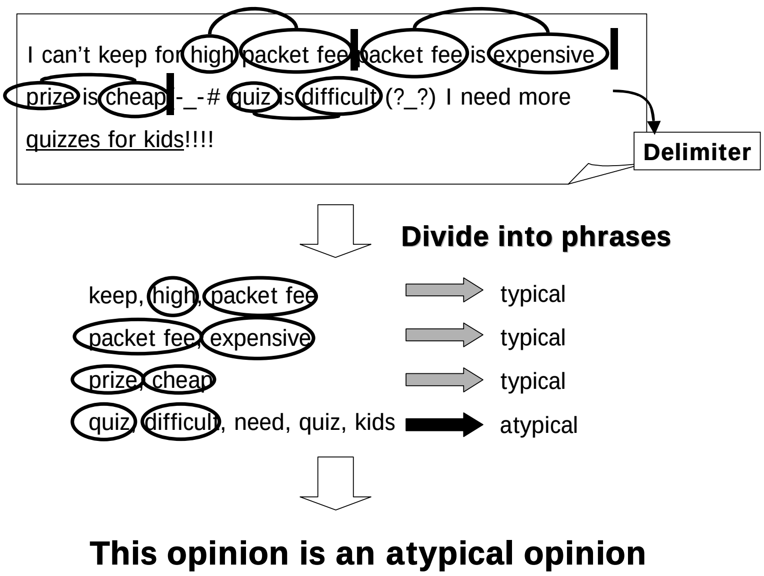

Figure 5. Classification method for typical/atypical phrases

When the opinions are classified as typical, they are immediately grouped by matching word combinations. For example, a sentence including the typical element "quiz-interesting" is grouped as the category "quizzes are interesting".

User interface

3.4.1 System startup

When the system starts, the window shown in Figure 6 launches. The number of typical and atypical opinions is shown as a table in the window. Additionally, an analyst can choose from the following five menus above the window; “Input of questionnaire data” to select the input questionnaire data; “Number of opinions” to launch the table of opinion numbers at the system start up; “Analysis of atypical opinions”, which is explained in the section 3.4.2. “Analysis of typical opinions” as explained in the section 3.4.3; and “Management” to adjust the parameters *d* and α.

Figure 6. System startup screen

subscriber's properties in order to filter atypical opinions that an analyst wants to analyze. Examples of subscriber's properties are the subscribing period, the number of months they used the service, age, job and so on. Using the example of filtering, the system can show only opinions provided by the users who use more than a constant frequency.

When an analyst changes the tab to the existing word tab pane, the list ordered by the word frequency in atypical opinions is shown in descending order. Then, when analyst chooses the word they want to read in the list, opinion cards appear in the opinion card area as shown in Figure 8. The opinion card shows the number of words and some of the words used in the opinion. When an analyst clicks a card, the opinion is shown at the bottom of the window and the word list is shown below that. Additionally, the subscriber's properties are shown at the lower right of the window in order to confirm what type of the subscriber expressed the opinion.

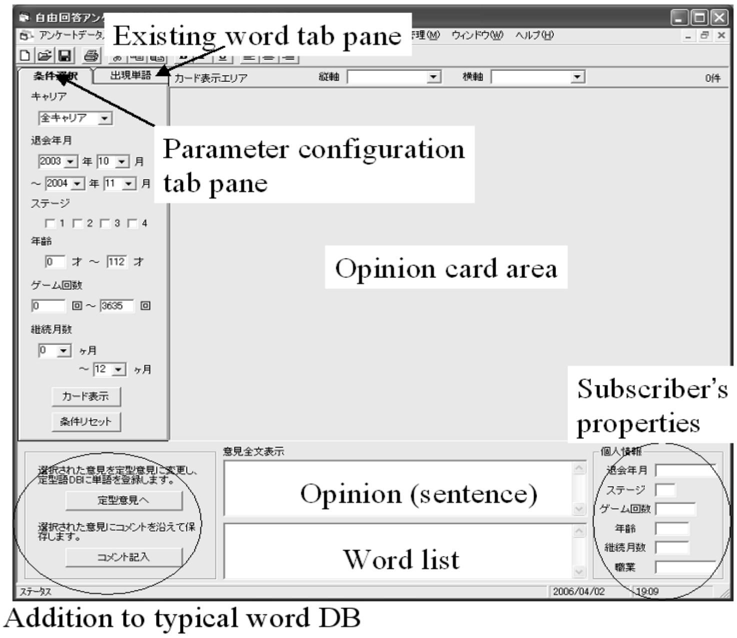

Figure 7. User interface for atypical opinions

3.4.2 Analysis of atypical opinions

When an analyst chooses “Analysis of atypical opinions” at the system start, the window launches so that atypical opinions can be analyzed as shown in Figure 7. In the parameter configuration tab pane at the left side of the window, an analyst can adjust the parameters of

An analyst can adjust the axes of the two-dimensional layout of the opinion card area at the top of the window. The vertical axis and horizontal axis can be changed based on the subscriber's properties and the singularity of the opinion. Singularity is the index that consists of the following three characteristics of atypical opinions:

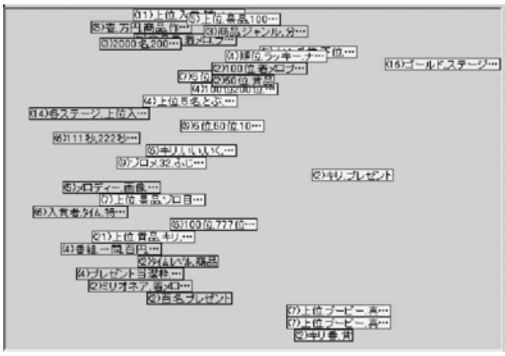

Figure 8. Displayed atypical opinion cards

- Degree of unexpected opinions
- Degree of opinions that should be classified into typical opinions
- Degree of opinions of dissatisfaction and opinions on improvement

Concretely, the more unexpected the opinion is, the larger singularity is, and the opinion in which singularity is small is opinion that should be classified into typical opinions. Additionally, opinions of dissatisfaction show negative singularity and opinions on improvement show positive singularity. In order to calculate singularity, words that are similar in atypical opinions are set into the similarity word database beforehand. Also, in order to distinguish between opinions of dissatisfaction and opinions of improvement, the words that represent dissatisfaction are set into the dissatisfaction word database beforehand. The singularity of opinion *i* is defined in the following condition;

$$S_i = \beta/n \times \sum_{j=1} F_j$$

$$F_j = 1/\text{ “Appearance frequency fo word}_j\text{”}$$

When the word included in the dissatisfaction word database is in the opinion, β is -1. Otherwise, it is 1. F_j is the inverse of the appearance frequency of word_j. If the word_j is included in the similarity word database, it is inverse of the sum of the appearance frequency of words that are included as set in the similarity word database. In other words, singularity represents the degree where words different from the others are included. If the opinion shows large singularity, it includes unique words.

Thus, when opinions from which singularity is calculated are laid in the area, unexpected improvement opinions are placed to the left side of it and unexpected opinions of dissatisfaction are placed at the right side. Additionally, frequent opinions that are grouped in atypical opinions are at middle of it, and they are the opinions that should be moved to the typical opinions category. Since the opinion cards that include similarity words or dissatisfaction words are distinguished by the card color, an analyst can grasp them easily.

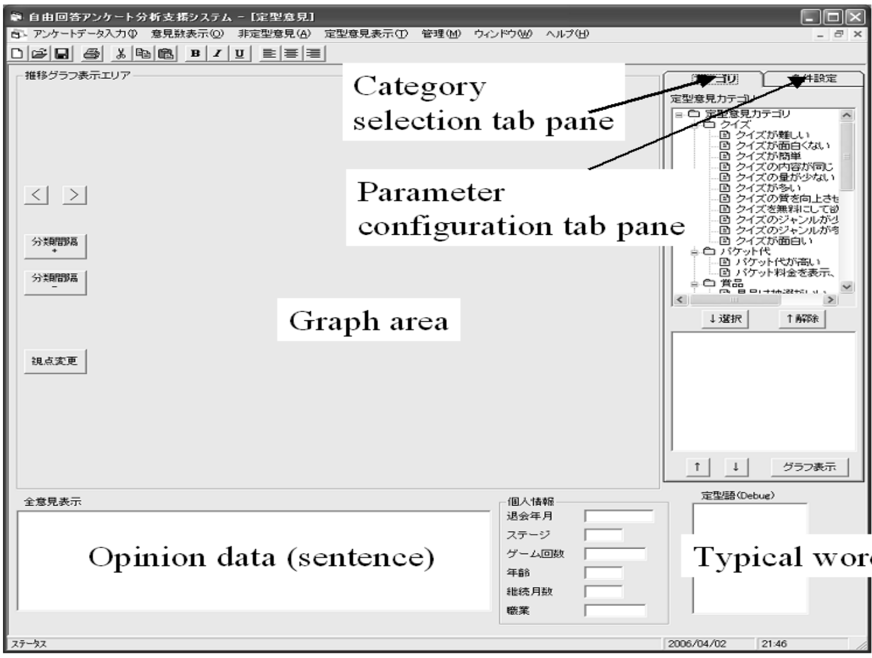

Figure 9. User interface for typical opinions

3.4.3. Analysis of typical opinions

When an analyst chooses "Analysis of typical opinions" at the system start, the window shown in Figure 9 launches to analyze typical opinions.

All typical opinions are categorized beforehand by matching words in the typical word database. The number of categories is 53 items for 13 months, and it will increase over time. Therefore, a function for grouping some categories is necessary to analyze in perspective. This system provides a function where, for example, some categories such as, "quizzes are not fun" and "quizzes are difficult", etc. are grouped under the group name, "Quiz".

All category names are shown as a list at the category tab pane at the right side of the window. In the category list, the category name and group name are shown. An analyst chooses categories or groups, whichever he/she wants. The names of chosen categories or groups are shown in the list box at the bottom in the tab pane. Additionally, when an analyst changes the tab to the parameter configuration tab pane, he can adjust the parameters of a subscriber's properties in order to filter the typical opinions that he/she wants to analyze. The transition history of chosen categories or groups is displayed as three-dimensional bar chart as shown in Figure 10.

Figure 10 shows the result when three items are chosen. The graph consists of three-dimensions, each category or group, the quit date, and the number of opinions, and it shows time-series transition by quit date. Five buttons are displayed at the left side of the window. The quit date axis can be moved back and forth using the top two buttons, which allows an analyst to analyze from the past data. The scale of the quit date can be changed using the middle two buttons. This supports an analysis of tendencies in perspective by changing scales to monthly, two-monthly, quarterly and half yearly. Clicking the bottom button can turn around the 3-dimensional view. An analyst can turn the graph around by clicking it.

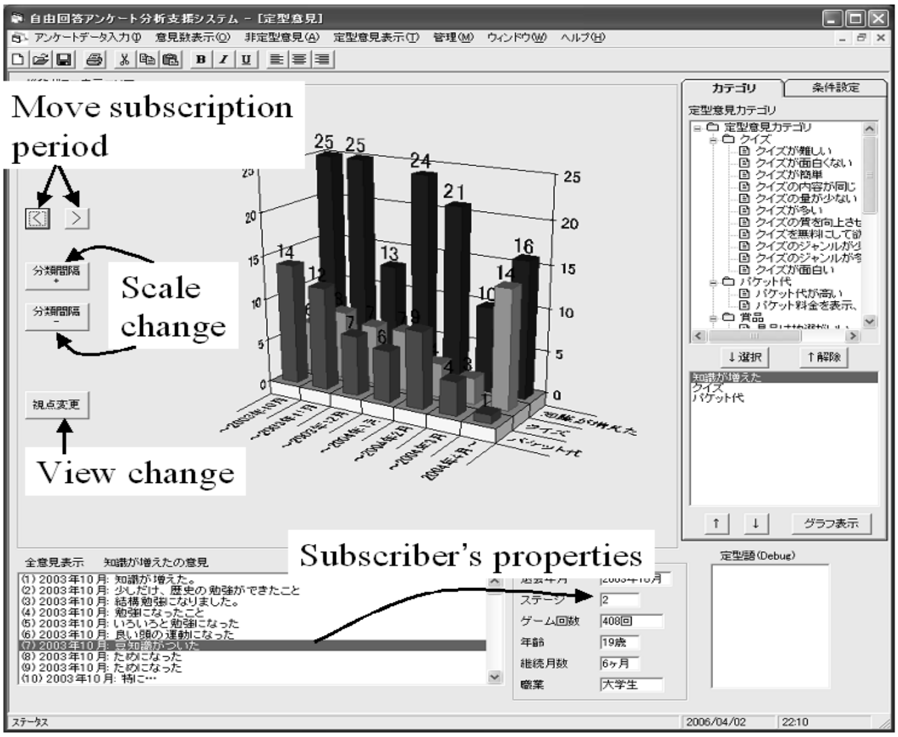

Figure 10. User interface for typical opinions statistics

The opinions that are included in the category or group are shown in the opinion data area by choosing a certain bar of the graph. Additionally, if a specific opinion is selected in it, the subscriber properties of the user who offered the opinion is shown in the lower right of the window.

4. Experimental Results

Since the vertical axis and horizontal axis can be adjusted freely from the subscriber's properties and singularity, an analyst can analyze in many ways. For example, as shown in Figure 11, in a case where the vertical axis is the subscribing period and the horizontal axis is singularity, since cards with low singularity are few at the square area in the figure, it is possible to analyze that users who subscribe long term offer more unexpected opinions. Therefore, by focusing on cards in this area, the service provider can consider a service strategy in which users who often quit early can be made to subscribe long term.

Figure 12 shows another analysis example in a case where the vertical axis is the unsubscribing date and the horizontal axis is the subscriber's age. From the card layout in

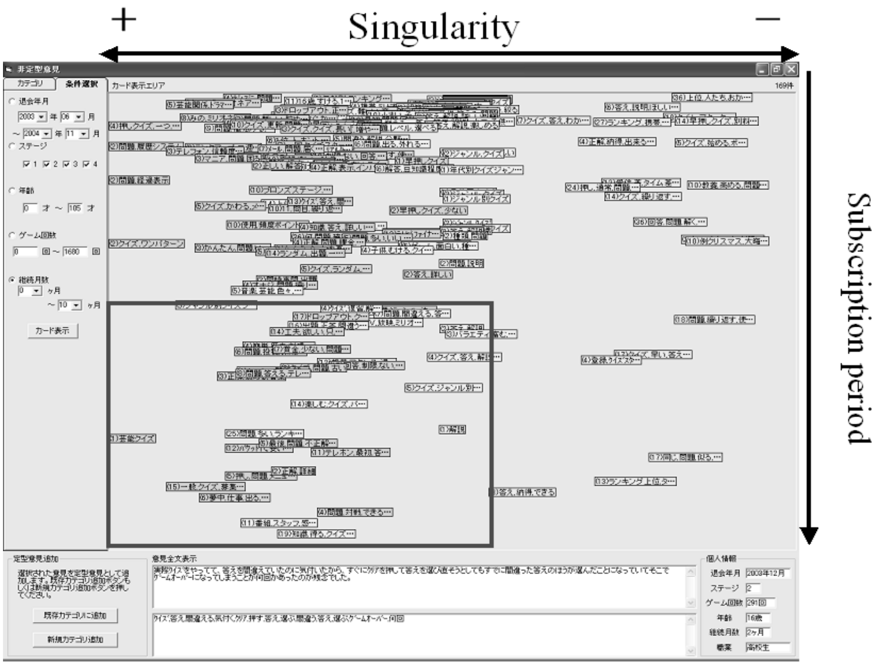

Figure 11. An analysis example of atypical opinions with “singularity” and “subscription period”

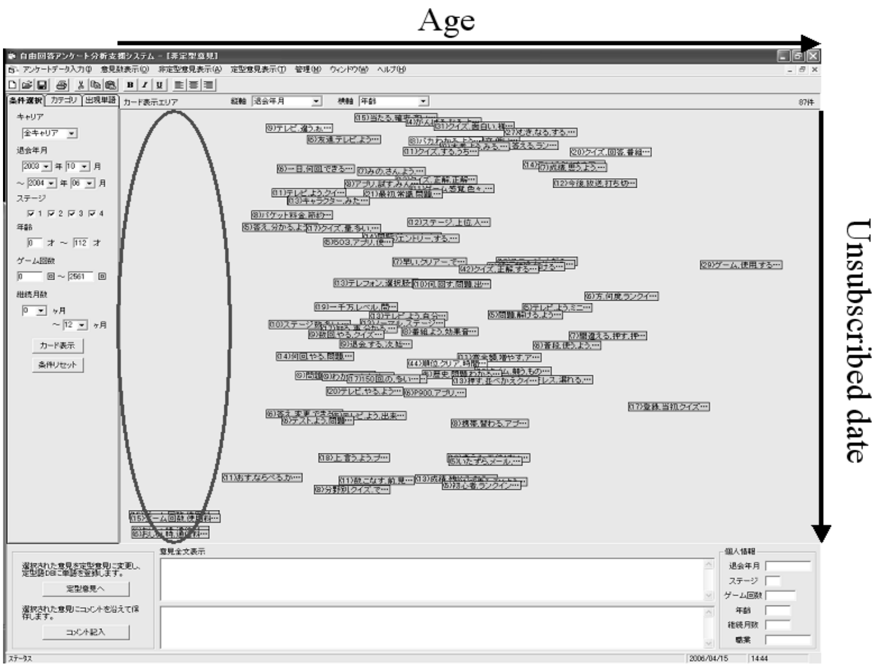

Figure 12. An analysis example of atypical opinions with “age” and “unsubscribed date”

the circle of Figure 12, an analyst can analyze that young users didn't answer for a long time but that they did offer opinions at some point in time. Then, the analyst can consider what is negative for young users when improving content.

5. Conclusion

This paper proposes a support system for analyzing answers to open-ended questions supplied by users as mobile game content evaluation when they unsubscribe the services. First, this system classifies user questionnaire into atypical opinions that are unknown opinions, and typical opinions that are known opinions. It then shows atypical opinions as cards in order to grasp them easily. Additionally, it supports the discovery of unexpected opinions or frequent opinions and to investigate relationships between a subscriber's properties and singularity. It shows typical opinions as a bar graph in order to analyze them statistically. Experimental result shows service strategy cane be obtained through the analysis of atypical opinions.

REFERENCES

1. YAMANISHI, K., H. LI, **Mining open answers in questionnaire data**, IEEE Intelligent Systems, vol.17, no. 5, 2002, pp.58-63.
2. ROMANO, N. C. Jr., BAUER, C., CHEN, H. and NUNAMAKER, J. F. Jr., **The mindmine comment analysis tool for collaborative attitude solicitation, analysis, sense-making and visualization**, in Proceedings of the 33rd Hawaii Int. Conf. on System Sciences (in CD-ROM), 2000.
3. CHEN, H., O TITKOVA, R. ORWIG, and NUNAMAKER, J. F. Jr., **Information visualization for collaborative computing**, IEEE Computer, vol. 31, no. 8, 1998, pp.75-82.
4. FRASCONI, P., M. GORI, and G. SODA, **Data categorization using decision trellises**, IEEE Tran. on Knowledge and Data Engineering, vol. 11, no. 5, 1999 pp.697-712.
5. HIRAMATSU, A., S. TAMURA, H. OISO and N. KOMODA, **Method for atypical opinion extraction from answers in open-ended questions**, in Proceedings of IEEE Int. Conf. on Computational Cybernetics (ICCC 2004) (in CD-ROM), 2004, pp.273-278.
6. HIRAMATSU, A., S. TAMURA, H. OISO, and N. KOMODA, **Support system for analyzing open-ended questionnaires data by culling typical opinions**, 2004 Int. Conf. on Systems, Man and Cybernetics (SMC2004), 2004, pp.1377-1382.
7. HIRAMATSU, A., H. OISO, T. SHOJIMA, and N. KOMODA, **Man-machine interface of a support system for analyzing open-ended questionnaires**, in Proceedings of IEA/AIE 2005, 2005, pp. 318-320.
8. MATSUMOTO, Y., A. KITAUCHI, T. YAMASHITA, Y. HIRANO, H. MATSUDA, K. TAKAOKA, and M. ASAHARA, **Japanese morphological analysis system ChaSen version 2.2.1**, http://chasen.aist-nara.ac.jp/chasen/doc/chasen-2.2.1.pdf, 2000