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A REVIEW ON TEXT DATA MINING OF CARE LIFE LOG USING KEY GRAPH

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ABSTRACT

Data Mining is a method that requires analyzing and exploring large blocks of data to glean meaningful trends and patterns. In today's period, every person on earth relies on allopathic treatments and medicines. Data mining techniques can be applied to medical databases that have a vast scope of opportunity for textual as well as visual data. Care Life Log is used to integrate and analyze the level of care required. There are five levels of care, with Level 1 vocabulary including recreation, toilet, morning, afternoon, etc. The level of care gradually increases from Level 1 to Level 5, which has vocabulary that includes tube, danger, treatment, removal, and discovery. The higher the level, the worse the health condition and therefore the greater care required. These levels allow for a clear analysis of a patient's condition. This analysis has led to an improvement in Quality of Life as well as a decrease in mismatches between the level of care required for patients and the level of care given by care takers. The qualitative analysis result of in-patient nursing records used a text data mining technique to achieve the initial goal: a visual record of such information. The analysis discovered vocabularies relating to proper treatment methods and concisely summarized their extracts from in-patient nursing records. Important vocabularies that characterize each nursing record were also revealed. The results of this research will contribute to nursing work evaluation and education. This research used a text data mining technique to extract useful information from nursing records within Electronic Medical Records.

KEYWORDS: Text Data Mining, Care Life Log, Nursing Records, Qualitative Analysis, Electronic Medical Records, Visualization.

1. INTRODUCTION

Text data mining resembles data mining because it extracts useful knowledge and information by analyzing the diversified viewpoints of written data.[1] Recently, interest has risen in text data mining because it uncovers useful knowledge buried in a large amount of accumulated documents.[2] Research has started to apply text data mining to medicine and healing.[3] In addition, the speed of electronic medical treatment data is accelerating because of the rapid informationization of medical systems, including EMRs. Recently, research on data mining in medical treatment that aims for knowledge and pattern extraction from a huge accumulated database is increasing. However, many medical documents, including EMRs that describe the treatment information of patients, are text information. Moreover, mining such information is complicated. The data arrangement and retrieval of such text parts become difficult because they are often described in a free format; the words, phrases, and expressions are too subjective and reflect each writer.[4] Perhaps in the future, the text data mining of documents will be used for lateral retrieval, even in the medical treatment world, not only by the numerical values of the inspection data but also by computerizing documents.[5] In this present study, to classify the vast amount of Care Life Log data that occurs in nursing in one Miyazaki Hospital Long-term Health Care Facility by level of care required, text data mining was carried out using Key Graph.

Then this information was visualized.

2. Care Life Log and the Level of Care Required

Care Life log records a period of 24 hours of the caregiver’s activity. It is also utilized as a long-term service content record. The recording itself is not the main purpose, but it transmits information to others, accumulates and analyzes data, and aims to connect the service to better care. The level of care required is categorized as Standard Support 1 and 2, and Essential Support 1, 2, 3, 4 and 5. Essential Support 1 indicates that a person can eat and use the restroom by themselves. Essential Support 5 indicates a person is mostly unable to do these things by themselves. Essential Support Levels are outlined below:

(1) Level 1: He or she needs care by others when performing complex actions or moving. There is a noticed decrease in physical and mental capabilities.

(2) Level 2: The same conditions as Level 1 with the addition of needing some assistance when eating or using the restroom.
(3) Level 3: The patient cannot use the restroom by themselves and needs assistance performing any action indicated by Level 2.
(4) Level 4: The patient can hardly use the restroom or perform any action indicated in Level 3.
(5) Level 5: The patient can hardly eat or use the restroom and needs assistance with almost all actions.

3. EMR

The text data in EMR consist of paper notations about inspection reports, in-patient care plans, nutrition management plans, bedsore-prevention plans, fall checks, operation notes, and summaries. The doctor fills in the passage record and the nurses fill in the nursing records, which include the life and inspection history of a patient. The care life log also has small notes about reservations etc. Since no guidelines exist about recording text, ambiguous feelings or impressions are sometimes included. Care workers remember or take notes about what their patients say while working and later input them into the EMR.

There are four recording categories:
(1) Subjective data (S): Information directly gleaned from patients.
(2) Objective data (O): Objective facts and observations about the patient's appearance or state by co-medicals.
(3) Assessment (A): Evaluations and judgments derived from this information and
(4) Plans (P): Future plans and care actually taken.

The care life log, which records the care activities practiced by nurses, contains many notes about nursing processes. It helps ensure high quality nursing and evaluates nursing practices.

4. Text Data Mining Applications to Medicine

Text data mining is roughly equivalent to text analytics that refers to the process of deriving high-quality information from texts. It usually structures the input text (often by parsing, adding derived linguistic features, removing others and insertion into a database), deriving patterns within the structured data and finally evaluating and interpreting the output. Fig. 1 shows the process of text data mining. Two particular aspects should be considered when applying text data mining to a medical context. Second, final decisions can be obtained regarding courses of treatment. One difficulty with applying text data mining to medicine is the entire process of identifying symptoms for understanding the associated risks while taking appropriate action.

Fig. 1: process of text data mining.

5. Key Graph

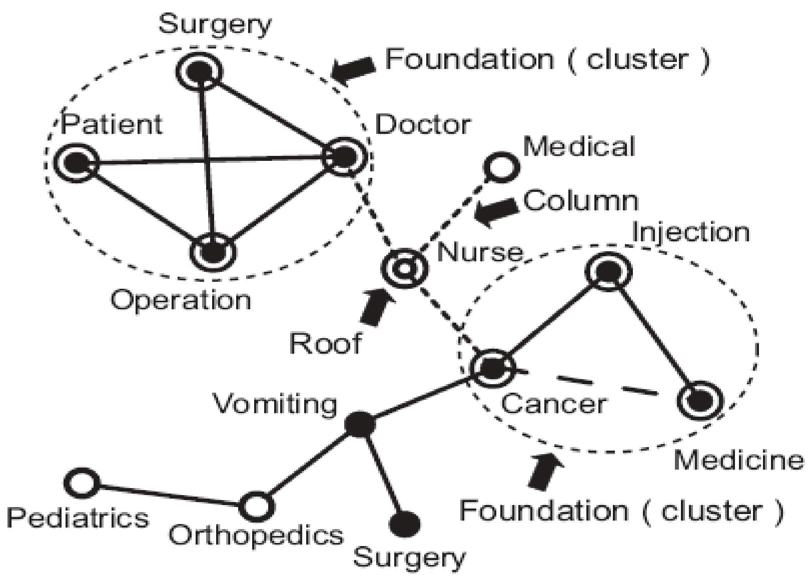
Key Graph is applied to the text data mining technique.[6,7] It is also applied for extracting key words.

Example of Key Graph Performance

Figure 2 shows an example when it is applied to text data.

(1) Black nodes indicate items that frequently occur in a data set.

(2) White nodes indicate the items that occur less frequently overall but frequently occur with black nodes in a data set.



●: High frequency terms

○: Connect high frequency “foundations”

◙: Keywords of ●

©: Keywords of ○

“Foundation (Cluster)”

: Mass of black nodes and links

“Roof”: Connect with the “foundation”

“Column”: ------------

: Significant “roofs” between “foundations”

Solid lines (-): Strongly correlated terms of “foundations”

-----------------: Strongly correlated terms

Fig. 2: Key Graph example when applied to text data.

(3)Double-circled nodes indicate items whose co-occurrence frequency with black nodes is especially high. Double-circled nodes are considered keywords.

(4)Links indicate that the connected item pair frequently co-occurs in a data set. (5)Solid lines form a foundation, which dotted lines connect. Foundations, which are circles of dotted lines, are obtained from the text data.

Key Graph consists of three major components derived from construction metaphors. Each component is described as follows:

1) Foundations: sub-graphs of highly associated and frequent terms that represent basic concepts in the data. A foundation is defined as a cluster that consists of black nodes linked by solid lines. The foundations are underlying common contexts because they are formed by a set of items that frequently co-occur in the data set.

2) Roofs: terms that is highly associated with foundations.

3) Columns: associations between foundations and roofs that are used for extracting keywords, i.e., the main concepts in the data. A column is a dotted line that connects foundations.

Concept of Key Graph Algorithm

Key Graph was originally an algorithm for extracting assertions based on the co-occurrence graph of terms from text data.

Its process consists of four phases:

1) Document preparation: Before processing document D, stop words [29] with little meaning are discarded from, the words in D are stemmed [30], and the phrases in D are specified [31]. Hereafter, a term means a word or a phrase n processed D.

2) Extracting foundations: Graph G for document D is made of nodes representing terms and links representing the co-occurrence (term-pairs that frequently occur in the same sentences throughout D). Nodes and links in G are defined as follows:

Nodes: Nodes in G represent high-frequency terms in D because they might appear frequently for expressing typical, basic concepts in the domain. High-frequency terms are a set of terms above the 30th highest frequency. This set is denoted by HF.

Links: nodes in HF are linked if the association between the corresponding terms is strong. The association of terms between wi and wj in D is defined as assoc (wi, wj) = $\sum_{s \in D} \min(|wi|s, |wj|s)$, (1)

Where |x|s denotes the count of x in sentence s. Pairs of high-frequency terms in HF are sorted by assoc and the pairs above the (number of nodes in G) -1th tightest association are represented in G by links between nodes.

Extracting columns: The probability that term w appears is defined as key (w), and key (w) is defined by

$$\text{Key}(w) = 1 - \Pi_{g \subset G} [1 - \text{based}(w, g) / \text{neighbors}(g)], \quad (2)$$

$$\text{Based}(w, g) = \Sigma_{s \in D} |w|_s \; |g - w|_s, \quad (3)$$

$$\text{Neighbors}(g) = \Sigma_{s \in D} \Sigma_{w \in s} |w|_s \; |g - w|_s. \quad (4)$$

$$|g - w|_s = \{|g|_s - |w|_s, w \in g, \quad (5)$$

$$\{|g|_s, w \,!\!\in g$$

Extracting roofs: The strength of a column between high key term wi and high-frequency term wj ⊂ HF is expressed as

$$\text{Column}(wi, wj) = \Sigma_{s \in D} \min(|wi|_s, |wj|_s). \quad (6)$$

Columns touching wi are sorted by column (wi, wj) for each high key term wi. Columns with the highest column values connecting term wi to two or more clusters are selected to create new links in G. Finally, the nodes in G are sorted by the sum of the column of the touched columns. Terms represented by the nodes of higher values than a certain threshold are extracted as the keywords for document D.

6. CONCLUSION

In this study, to categorize the huge amount of Care Life Log data that occurs in nursing in Long-term Health Care Facility by level of care required, text data mining was carried out using Key Graph. Sentences were analyzed into morphemes, and the relations between feature vocabularies were analyzed by a text data mining technique to visualize this information. In addition, this identified vocabularies relating to the proper methods of treatment, resulting in a concise summary of the vocabularies extracted from the care life log. Text data mining is expected to become a valuable technique in the analysis of care documents in the future.

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