

Identifying Latent Similarities among Near-Miss Incident Records Using a Text-Mining Method and a Scenario-Based Approach

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Abstract. This research focuses on supporting an analyst's activity of interpreting the contents of existing incident reports. During this activity, analysts are always predicting *expected* scenarios of the incidents at hand in comparing that with the actual development of the incidents reported therein. In order to learn lessons from a particular prior experience, analysts should be aware of the latent similarities among the incidents and should experience a breakdown called "expectation-failure" to let that incident be surely printed in their memory. To let the human analysts experience this breakdown, our system introduces a theory of *Memory Organization Packets (MOPs)* as a framework for explaining the dynamic memory structure of the human. By utilizing this idea as a basis for *scenario-based expectation* of human analysts and by integrating this idea with a text-mining method, a system for supporting an incident analysis is developed for a domain of medical incidents. Results of the experiments using our proposing system are presented, where the subjects are nurses working for a hospital. Based on those results, effectiveness of the system is discussed from various viewpoints by investigating into the protocols gathered from the subjects of the experiments.

Keywords: Text-mining, knowledge management for safety, learning by failure, knowledge creation, semiosis.

1 Introduction

As recognized as "Year 2007 Problem" in Japan, decrease of opportunities for expertise/skill transfer in organization is a considerable social concern, and some urgent countermeasures to that problem are seriously requested, especially for the purpose of *safety management* in organizations. It is said that most of the troubles that organizations encounter could be avoided if the prior experiences concerning with the analogous troubles were shared by the members of the organization and generalized lessons were learned from those. For this purpose, many approaches have been attempted to construct a database that stores *failures* and/or *near-miss incidents* to let those be shared by the members of the community. However, this kind of databases has not been utilized in an effective way. This is due to the fact that accessibility to

the constructed database is not fitted to users' needs and utility of such a database depends much upon the user's ability of *interpreting* the items stored therein. To let this database be more actively utilized for enhancing the creation of knowledge for safety management, some more advanced support tool is essentially needed.

Generally speaking, what can be stored in such a database is restricted only to a little portion of know-how to be shared, and the transfer and sharing of most part of them are dependent upon the abilities of the individual analysts who make access to those storages. Once stored, items stored within a database are fixed and should be *true*, not allowed to vary in principle. However, what is more important therein is how to make the people interpret the pre-stored cases and discover their own *meanings* within those pre-stored cases. Whether they can obtain any lessons from past failures may depend much upon analysts' *proactive* commitment during this interpretation phase; lessons can only exist in relations with analysts' conceptions and with awareness about their sources. Wherein, the tools supporting this interpretation phase should be designed so that they can assist the analysts' "editing" process; to discover relations between what is known and what is not known, to find out latent relations among seemingly irrelevant items, and to reconstruct a new meaning based on information fragments that are newly recognized.

In the following of this article, we develop a system assisting such analysts' interpreting prior failures and/or near-miss incidents stored in the database. For this purpose, we introduce a theory of *Memory Organization Packets (MOPs)* as a framework for explaining the dynamic memory structure of the human, and by utilizing this idea as a basis for scenario-based expectation of human analysts and by integrating this idea with a text-mining method, we develop a conversation system in which active interactions between analysts and a incident database are assumed and analysts' learning from prior cases are more actively promoted.

2 Design Principles for Nurturing Safety Conceptions

2.1 Semiotics, Editorial Engineering and Breakdowns

In order to assist analysts' discovering meanings fitted to their current concerns of the targeted incidents, we propose that two technical issues should be resolved. One is to assist the phase of browsing prior incident reports including ambiguous and/or specific terminologies while subconsciously struggling to relate them with others. This subconscious effort inspires analysts to find ways of linking the factual fragments of the report into an original whole as well as into another analogous incident that is out of their expectation. The other is to assist the analysts' scenario formation concerning with how and why the incident occurred, since the actual chronology of events provides with the primary ways we construct meaning in general and is a human universal on the basis of which trans-cultural messages about the nature of a shared reality can be transmitted [1].

A motivation of introducing those two techniques is to promote analysts' learning. Especially we focus on the importance of "breakdowns" [2]. At the heart of learning theory lies the concept of breakdowns. When trying something for the first time we experience breakdowns in our usage of that, and we use these breakdowns to

experiment with reality. When something goes wrong we are given an opportunity to learn, as the breakdown reminds us of the discrepancy between our expectations and the actual reality. This is also true for the analysts of the incident reports; they can obtain lessons from prior incidents only when they expect what has occurred therein and experience the failure of that expectation in comparing that with the actual incident reported. This expectation failure does bring about a shift of focus of their analysis and promotes their learning on what they lack and what is missed in their prior knowledge.

2.2 Memory Organizing Packets (MOPs)

In order to realize such a learning environment, the system should have an ability to support the analysts' expectation formation as well as to support the analysts to recognize why and how their expectation fails. For the first purpose, we introduce the idea of Schank's memory structure of MOPs (Memory Organizing Packets). In 1977, Schank and Abelson proposed that our general knowledge about situations be recorded as *scripts* that allow us to set up expectations and perform inferences [3]. Schank then investigated the role that the memory of previous situations and situation patterns play in problem solving and learning [4]. The primary function of MOPs was to provide top-down expectations, and MOPs had additional advantages. They provided a method for sharing knowledge between structures that was lacking in earlier theories of scripts. Schank's model [4][5] of 'dynamic memory' also includes 'scenes' as the basic level of conceptual structure. Schank defined scenes as 'general structures that describe how and where a particular set of actions take place' [5]. Scenes are combined to form larger structures of MOPs and different versions of the same scene will be activated depending on the specific context.

In this work, we design a system with a function of generating a variety of MOPs based upon the accumulated incident reports, thus the system supports analysts' expectation formation. Then, the system lets analysts check whether their expectation matches with the actual incidents stored in the platform, while analysts may encounter expectation failures due to the existence of some unexpected events. In discovering this, to update their understanding, analysts try to create a new MOP that includes an expectation predicting what was previously the anomalous event. This process is iterated, and thus analysts' perspectives and knowledge are enlarged through a conversation with the system. People depend on top-down structures to understand the incidents. Thus, analysts' creativity is required to stretch those structures even for the cases in which they do not quite fit.

3 Text-Mining Method for Extracting Causal Relations

3.1 Swanson's ABC Model

Text mining usually involves the process of structuring the input text (e.g. *morphological analysis and parsing*), deriving patterns within the structured data, and finally evaluation and interpretation of the output. 'High quality' in text mining usually refers to some combination of relevance, novelty, and interestingness. Relevance among the documents is often evaluated using co-occurrence relations

among terms appearing in the documents. By way of definition, co-occurrence networks are the collective interconnection of terms based on their paired presence within a specified unit of text. Networks are generated by connecting pairs of terms using a set of criteria defining co-occurrence. For example, terms A and B may be said to “co-occur” if they both appear in a particular document. Another article may contain terms B and C. Linking A to B and B to C creates a co-occurrence network of these three terms. The text-mining methods have been adopted for the purpose of analyzing the incident reports.

Most of the text-mining methods extract indexing terms by usage of morphological analysis and represent individual documents as a collection of those terms. Since the written materials are broken into a collection of terms, such information like relations with the contexts and causalities existing in the original materials are lost during the processing. This limitation is critical for the purpose of our system, since a higher-level memory structures like MOPs is to represent some relatums of causality among events and is to be activated depending on the specific context. Thus, in order to utilize the text-mining methods to our purpose, we introduce an extended text-mining method that can extract relations among terms preserving the causalities among them and can lead to hypothesis generation.

The idea of the text-mining approach towards hypothesis generation, known as Swanson’s ABC model, consists of discovering complementary structures in disjoint journal articles. This model assumes that when one literature reports that agent A causes phenomenon B, and second literature reports that B influences C, we could propose that agent A might influence phenomenon C [6]. To find some published evidence leading to undiscovered knowledge, the A and C literatures should have few or no published articles in common. In such way, Swanson discovered, among others, several relationships that connected migraine and decreased levels of magnesium.

There are two approaches to discovery that we have defined as open and closed. The closed discovery starts with known A and C. This may an observed association, or an already generated hypothesis. The discovery in this situation concerns finding novel Bs that may explain the observation. The open discovery process starts in the knowledge structure in which the scientist takes part (A). The first step is to find potential B-connections. These will likely be found within the domain. The crucial step, however, is from B to C which is most likely outside the scientist’s scope, and might therefore be in any point of the knowledge space of science. In most cases, an open discovery concerns generating a hypothesis that is evaluated in a closed discovery process. Thus, for the purpose of our work, the open discovery is more appropriate for generating expectation structures like MOPs. On the other hand, the weakness of Swanson’s ABC model is that the discovered connections do not always represents the chronological causalities among the events. Our solutions to overcome this will be given in the next section.

3.2 Design of Assisting Tool for Analysts of Incident Reports

The original incident reports dealt with in this work are structured. For each incident, the report is described according to the following four progressive stages: “cause”, “situation”, “course” and “consequence”. We structure each incident at the chronological progression of a failure. That is, first the *cause* takes place, followed by

its inevitable effect, or result (*situation*). As a developing failure becomes evident as a failure, a person takes action to deal with the unfolding sequence of events (*course*). In addition, a variety of related developments take place that are described as *consequence*. Then, a text mining method is applied to a collection of descriptions that are gathered for each stage. Thus, the description of each stage making up an individual incident report is represented as a set of indexing terms. Next, co-occurrence relations existing in the same incident report are investigated between the indexing terms that appear in the chronologically neighboring stages; between the stages of “cause” and “situation”, “situation” and “course”, and “course” and “consequence”. For instance, as shown in Fig.1, an indexing term of “insufficient precaution” appearing in the cause stage co-occurs with another indexing term of “incorrect administration” appearing in the situation stage, thus chronological causality from “insufficient precaution” to “incorrect administration” can be inferred, though the reverse relation were not inferred between them. With the frequency of co-occurrence, the potential causal relationships can be extracted out of a collection of all incident reports with the degree of confirmation. These relationships are shown in diagrams as shown at the bottom of Fig.1.

The analyst first select a keyword from a repertoire of indexing terms appearing in the cause stage. Then, using the text-mining method the system extracts a set of

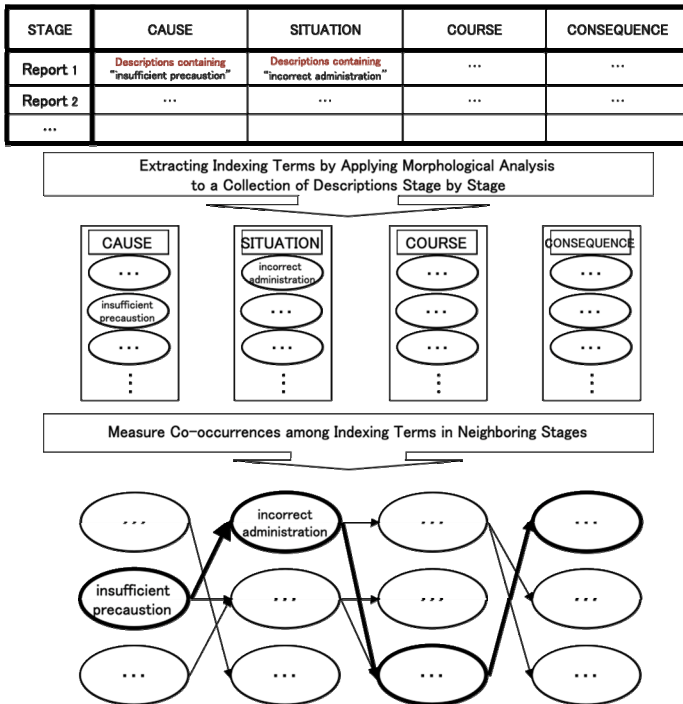


Fig. 1. Extracting chains of indexing terms as analysts' expectation structures

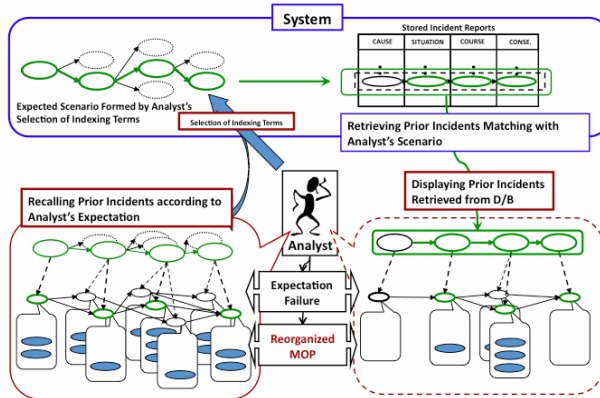


Fig. 2. An overview of the system

candidate indexing terms that are inferred as resultant situation caused by the selected indexing term. Herein, analysts are requested to choose one or more indexing terms from the candidate set, then the system processes in the same way and extracts a set of candidate indexing terms that are inferred as course triggered by the chosen indexing terms. This process is iterated, and the system provides the analysts with potential causal scenarios to be expected according to their specific concerns that are taught to the system through the selection of indexing terms at each stage. At the same time, analysts are assisted to stretch their expectations with the aid of the presented indexing terms. Since the entire set of incident reports are stored within the database of the system, the system at the same time presents the original incident reports that contain the selected causal relationships to the analysts. By comparing these actual incidents with what the analyst expected, they can recognize whether their expectation is right or not, and if they recognize it is wrong, the breakdown of the expectation occurs and they can investigate into why and how their expectation is violated by forming and checking other possible scenarios using the system. An overview of the system is shown in Fig.2.

In terms of MOPs, the chronological causalities extracted using the text mining method are the relations connecting the different chronological scenes making us a particular MOP. Note that the system can neither extract nor present a structure of the MOP itself, but only can make the analysts infer the MOP from the presented cues of indexing terms; MOP only exists within the analysts' mind. However, having this expectation in their mind, analysts are encouraged to proactively interpret the prior incident in a top-down way. Then, by looking at the actual incidents and comparing that with their expectation, they can recognize what knowledge for safety management is missed.

4 Experiments for Medical Incident Reports

4.1 Outline of the Experiments

Our system contains 3,690 incidents that actually occurred in a particular general hospital in Japan during 2002 and 2007 (for six years). Each of the original incident

reports is described in a structured way according to as many as 110 attributes, out of which we choose four important attributes corresponding to the four stages of cause, situation, course and consequence as mentioned in the previous section. The users of the system are analysts of the incidents (i.e., nurses and pharmacist) working for the hospital where the incidents are gathered. The providers of the original incident reports are different from these analysts, so analysts are requested to infer what and how the incidents occurred and progressed referring to the prior cases stored within the database. The details of the experiments are summarized as follows.

1. Subjects: Seven professional nurses and one pharmacist (all females) with different years of experience varying from 10 months to more than 20 years.
2. Tasks requested to the subjects: Subjects are requested to choose one or more indexing terms of the cause stage that is of their concern and to browse the incidents using the system (Fig.3). During the session, subjects are requested to utter the protocol on what incidents are expected from the indexing terms presented by the system at each of the stages, and those protocols are recorded. At the same time, subjects are instructed to refer to the actual incident reports stored in the database and to tell how their expectations are violated or right in comparing those with what they expected from the presented indexing terms.

In these experiments, the data were gathered during 17 sessions performed by eight subjects. During the sessions, the experimenter requested the subjects to select particular incident reports up to four cases that most attracts their interests and asked them why and how. The number of those protocols was 39 in total from 17 sessions. Each of the gathered protocols is transformed into a structured graphic representation using the method of gIBIS (graphical Issue-Based Information System) [7].

For the discussions on the results obtained in the experiments, we classify the subjects into Dreyfus's typology. Dreyfus and Dreyfus [8] developed a useful five-stage typology of developing expertise, with the characteristics of each stage: *Novice*, *Advanced Beginner*, *Competent*, *Proficient* and *Expert*. This model has been extremely influential, particularly in the field of nursing, thus we classify eight subjects into one of these typologies and discuss about the effectiveness of our system for different subjects having characteristics of expertise at each stage.

4.2 Results of the Experiments

New Knowledge Acquisition Triggered by Expectation Failures. The result obtained from subject 1 is illustrated. The protocol was obtained at the time when the subject has constructed some expectations (i.e., MOPs) in mind observing a chain of indexing terms that is displayed by the system. At this time, the subject referred to the actual incident reports stored in the database in which those indexing terms are present in their descriptions at each of the progressive stages. The expertise typology of this subject 1 has is "Proficient." From the presented chain of indexing terms, she thought of an incident in which carelessness simply caused oblivescence of administering intravenous drips to a patient. However, the actual incident report retrieved from the database was on the incident in which a nurse mixed up the kinds of the materials in making solutions for instillation; she made a solution with a wrong material of glucose, while the right material was normal saline. Finding this

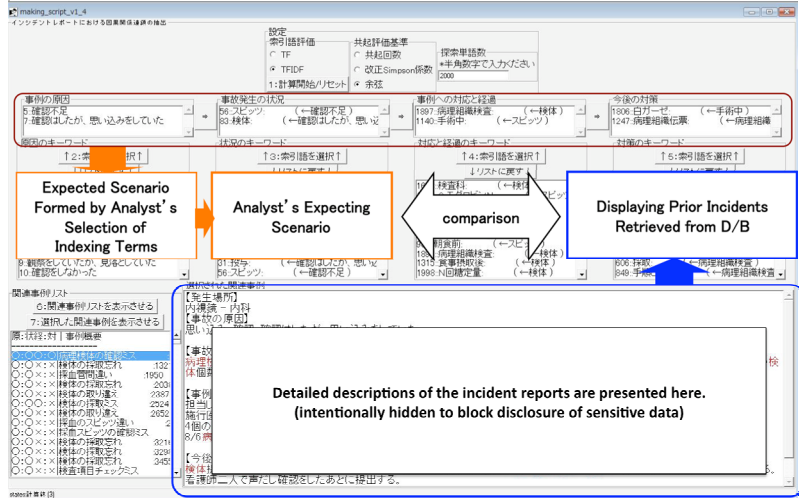


Fig. 3. A hard copy of the display presented to the analyst

unexpected incident, the subject explained why she could not think of such an incident. She said, “I have known the precaution of checking the material in making solutions for instillation, but I guessed other types of incidents caused by some wrong procedures, and it is really unexpected that such mixing up do occur in such a stage.” This shows that her expectation was formed from the indexing terms based upon her biased knowledge on her prior experiences, but the presented incident was out of her expectation. In other experiments, especially in the sessions by the subjects classified as Proficient and Expert, the subjects are very good at associating prior incidents with the presented indexing terms, but their associations were sometimes apt to be quite biased, which caused them to stretch their expectation towards a wrong way during their sessions. Wherein, the notice on their expectation failures by referring to the actual incident reports is really important and contributive to resetting and expanding their biased focus.

Missing of Expectation Failures. In another session, there occurred no expectation failure at all. This was observed in subject 3 who is classified as a typology of “Advanced Beginner” or “Competent.” Subjects with this proficiency are quite good at memorizing all the incidents, but this is simply due to rote learning, meaning that they cannot relate individuals with each other and they miss grasping any contextual factors affecting the incidents. In constructing their expectations through the conversation with the system, they apt to make up scenarios exhaustively by picking many indexing terms in many ways in their sessions. Consequently, the actual incident reports presented to the subject are all within the scope of their expectations, and no expectation failure has occurred.

Failures in Forming Expectations. The other typical observation in the experiments is that subjects failed in forming their expectations. This is mostly found in the sessions by the subjects (e.g. subject 8 and subject 7) classified as a typology of

“Novice” or “Advanced Beginner”. At the stage of stretching their expectations, subjects are demanded to select the appropriate indexing terms at each progressive stage. At this time, with the poor expertise they cannot imagine any possible scenarios from the displayed indexing terms, thus they fail in constructing any expected scenarios. With such incomplete expectations, even though the actual incident reports were presented to the subjects, they could not understand why they are presented therein, and comparison with what they expected cannot be made. As a result of this, they frequently give up continuing the session and no learning occurs at all.

4.3 Discussions on the Results of Experiments

The results of the experiments shown in the previous section reveal that the ways of interacting with the system do vary among the analysts depending upon their developing expertise. First, novice can be characterized by their rigid adherence to taught rules or plans, little situational perception and no discretionary judgment. For those analysts with less experience, our proposing system is less effective, since they fail in forming holistic scenarios. As the novice gains experience actually coping with real situations, he begins to note perspicuous examples of meaningful additional aspects of the situation. After seeing a sufficient number of examples, people of advanced beginner can learn to recognize these new aspects, but their situational perception is still limited and all attributes and aspects are treated separately and given equal importance. These characteristics are improved for competent people; with more experience, the number of potentially relevant elements that the learner is able to recognize becomes overwhelming. At this point, however, since a sense of what is important in any particular situation is missing, performance becomes exhausting. This fact is reflected in the results of the experiments for the analysts ranked as advanced beginner and competent; they could make up their expectation structures well and exhaustively, but fails in focusing their views, thus they could find many of the prior incident cases, but they are all within the scope of their expectations, so learning does not occur. At the stage of proficient, such an ability is drastically reconstructed; to cope with this overload and to achieve competence, people learn through experience to devise a plan or choose a perspective that then determines which elements of the situation are to be treated as important and which ones can be ignored. They can see situations *holistically* rather than in terms of aspects, and can see what is most important in a situation. This is typically observed in the results of the experiments in which expectation failures occurred and new knowledge acquisition is attained. Since they are able to perceive deviations from the normal pattern and to cope with those deviations by reorganizing the expectation structures of the MOP in an adaptive way even when they encounter expectation failures. Wherein, learning by expectation failure does occur in the most effective way.

5 Conclusions and Future Perspectives

Of immediate importance in our proposing system is the Peircian notion of semiosis in which the role of the interpreting instance and of the context in which this “interpretant” operates. The core of the analysts’ activity during the session with the

system is in the first place a “checking against” one's own foreknowledge, one's prior observations and experiences. During a conversational session of interacting with the system, existing knowledge that has been acquired before the session *interferes* with the information supplied *on the spot* by the system. And exactly this interference creates *meaning* within the analysts; meaning does not solely exist within the written materials of incident reports. Meaning then largely depends on the cognitive structure of the analysts and on the nature of their *expectations*.

The innovative design principle proposed in this article is the radical shift of the emphasis from the production side, where an incident report is required to be a coherent arrangement of elements, to the reception side of the communication schema, in which the viewing of the actual incident - and not the reading of a text - acts as the drive for interpretation by the analysts. Our proposing system does contribute to enhancing analysts' *sense-making* [9], i.e., placement of items into frameworks, comprehending, redressing surprise, constructing meaning, interacting in pursuit of deep understanding and patterning for safety management.

References

1. White, H.: The Content of the Form: Narrative Discourse and Historical Representation. Johns Hopkins UP, Baltimore (1987)
2. Winograd, T., Flores, F.: Understanding Computers and Cognition: A New Foundation for Design. Ablex Pub. Addison-Wesley (1987)
3. Schank, R., Abelcon, R.: Scripts, plans, goals, and understanding: An inquiry into human knowledge structures. Lawrence Erlbaum, Hillsdale (1977)
4. Schank, R.: Dynamic Memory: A theory of reminding and learning in computers and people. Cambridge University Press, New York (1982)
5. Schank, R.: Dynamic Memory Revisited. Cambridge University Press, New York (1999)
6. Swanson, D.R.: Fish Oil, Raynaud's Syndrome, and Undiscovered Public Knowledge. *Perspectives in Biology and Medicine* 30(1), 7–18 (1986)
7. Conklin, E.J., Begeman, M.L.: gIBIS: A Hypertext Tool for Exploratory Policy Discussion. In: *Proceedings of CSCW 1988*, pp. 140–152. ACM, New York (1988)
8. Dreyfus, H.L., Dreyfus, S.E.: *Mind over Machine: the power of human intuition and expertise in the era of the computer*. Basil Blackwell, Oxford (1986)
9. Weick, K.: *Sensemaking in Organizations*. Sage Publications, Thousand Oaks (1995)