

Relationships between nursing conversations and activities

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Abstract

In this paper, we determine the relationships between nursing activities and nursing conversations based on the principle of maximum entropy. For analysis of the features of nursing activities, we built nursing corpora from actual nursing conversation sets collected in hospitals that involve various information about nursing activities. Ex-nurses manually assigned nursing activity information to the nursing conversations in the corpora. Since it is inefficient and too expensive to attach all information manually, we introduced an automatic nursing activity determination method for which we built models of relationships between nursing conversations and activities. In this paper, we adopted a maximum entropy approach for learning. Even though the conversation data set is not large enough for learning, acceptable results were obtained.

1. Introduction

Recently, specialized tasks, for instance, in factories and hospitals have become too complex for general persons to understand. Accidents are caused by complicated procedures and the complex relationships between each task. If we cannot grasp the whole procedure, dealing with emergent changes and unpredictable, novel or less known events during tasks is difficult. In addition, accidents are also caused by communication errors during tasks. Human relationships have become complex. Thus accidents are usually caused by complex environmental and human factors. To remove or reduce accidents during tasks, the features of tasks must be analyzed from both environmental and human viewpoints. Therefore, risk management is introduced in various places.

For instance, hospitals usually have risk management departments to reduce medical accidents and minimize the costs of medical care, including insurance fees and financial losses. Of course, risk management can also save patients' lives. For actual managements, hospitals have their own accident/incident report databases. The Japan Council for Quality Health Care also collects such examples from registered hospitals to provide report databases (AIRD). Risk management experts can refer to such databases to generate generalized patterns of frequent accidents/incidents. Thus, compiling a textbook on nursing accidents/incidents is important to reduce or avoid them.

Analyzing nursing accident/incident reports is also crucial for reducing identical or similar accidents/incidents in the future. In addition, to share the acquired knowledge, analyzed data have been published such as a database of accident/incident reports (AIRD). Human risk management experts usually analyze those reports to generate necessary risk management knowledge. Since the number of reports is huge, recently a computational approach has been proposed to analyze the vast number of nursing accident/incident reports (Matsuoka et al. 2002; Park et al. 2002), but the approach remains unpopular.

In actual practices, many factors, such as environment, probably cause nursing accidents/incidents. Sometimes, dealing with changeable situations is difficult. Accordingly, dynamic risk management is necessary in actual situations (Abe et al. 2007). To achieve dynamic risk management, the features of nursing activities must be analyzed because it is necessary to infer nurses' situations by viewing their activities and determining their actions.

For the analysis of the features of nursing activities, we built nursing corpora from actual nursing conversation sets collected in hospitals that involve various information about nursing activities (Ozaku et al. 2005; Ozaku et al. 2006b; Ozaku et al. 2007). In fact, the corpora can be used for communication and error analyses (Abe et al. 2008). In the framework, for nursing task analysis, the relationships between conversation and tasks must be comprehended because conversation involves explicit and implicit information of the activity. Currently, in our experiments, ex-nurses manually assign nursing activity information to actual nursing conversations. Of course if we manually assign nursing activity information to nursing conversation sets, we can build perfect corpora. However, this solution is very expensive and requires long-term analysis by many professionals. After a considerable number of assignments, machine learning can generate general models of assignments. If we can obtain such models, assigning nursing activity information to nursing conversation data sets will be easy. We analyzed the features of terminologies in nursing activities and focused on the abbreviations and jargon frequently used in nursing conversations (Ozaku et al. 2006c). Since using such abbreviations and jargon helps nurses understand, we assumed that specialized words appear in conversations and that we can model the relationships between such words and nursing activities as well as general words.

In this paper, we propose a strategy to determine the relationships between nursing conversations and activities based on the principle of maximum entropy. First, instead of focusing on specialized words to model nursing

activities, we gradually changed the focus during analysis to improve it. Section 2 introduces the E-nightingale project, which develops a strategy for understanding nursing activities. Section 3 discusses a learning method for the automatic determination of nursing activities. Actually, C4.5 (Quinlan 1993) and the maximum entropy approach (Berger et al. 1996) are compared. Section 4 describes a nursing activities determination method based on the maximum entropy method. Finally, Section 5 concludes the paper.

2. E-nightingale project for understanding nursing activity

Kuwahara et al. proposed an integrated nursing activity monitoring system that couples ubiquitous apparatus with fixed apparatus (Kuwahara N. et al. 2004) in E-nightingale Project (Kogure 2006). The proposed system monitored all of the nursing activities. Nurses wore wearable sensors that recorded their conversations with other nurses and with themselves, their locations in a hospitals, the number of footsteps, body angles, etc. The data were simultaneously collected from many nurses in identical hospitals including several departments or floors.

In the E-nightingale Project, our main objective is to develop a system that includes the following functions:

- (1) Nursing activity record and analysis function
- (2) Just-in-time nursing advice function
- (3) Accident/incident video documentation function

We omit function (3), since its topic is rather different from this paper's. For the function (1), data were recorded by developing a wearable apparatus, and analysis has been conducted from several viewpoints (Abe et al. 2007; Naya et al. 2006; Ozaku et al. 2006a; Ozaku et al. 2006c; Sagara et al. 2006). For the function (2), it is necessary to understand nursing activities immediately after collecting their data. A system must be developed that can determine an exact activity feature by referring to the collected data in the real time. For that purpose, as shown above, we have conducted various types of analysis. Using Fisher Linear Discriminant Analysis statistically investigated such monitored data as location, body angle and footsteps to obtain patterns or models of nursing activities (Naya et al. 2006). The obtained results were unsatisfactory because we needed to guess and connect the name of the activities to the monitored data. To avoid such a symbol grounding problem, we must use the nursing conversation data in which they state the actual names of their activities¹.

For voice data analysis, speech recognition techniques are usually applied. To the collected voice data, however, it is sometimes difficult to simply apply speech recognition techniques. One reason is that we have not prepared adequate dictionaries to perform speech recognition of voice data involving terminologies specialized to nursing activities. Even if we could perform speech recognition, it is still

¹Even though stating the actual name of jobs during nursing activities is rather unusual, we asked the nurses to name their activities.

Table 1: Example of labeled conversation by nurses

Time	conversation	Job Category
11:01:00	I'm going to a short conference (meeting or handover).	18-106 conference
11:20:48	The short conference is finished.	18-106 conference
11:28:11	I'm going to prepare a drip infusion for XX.	13-63-6A0502 intravenous infusion
11:32:01	I have finished preparing the drip for XX.	13-63-6A0502 intravenous infusion

insufficient for our aims. Determining what nurses are doing by referring to their conversations is more significant. Simple speech recognition with automatic transcription is insufficient. We need to obtain more information from conversations. For instance, from "washing hands" we must infer "an activity before a surgery."

Accordingly, we built sets of nursing (interaction) corpora (Ozaku et al. 2005; Ozaku et al. 2006b) and extracted nursing workflow patterns by analyzing transcribed nursing conversations (Ozaku et al. 2006a). In addition, we manually added labels to authorized nursing jobs to the transcribed nursing conversations (Table 1 (Privacy is protected.)). The types of labels were determined by ex-nurses who referred to authorized job categories provided in the Classification of Nursing Practice (CNP) and in the Nursing Practice Classification Table (NPCT). They involve such labels as "conference (18-106)" and "intravenous infusion (13-63-6A0502)." Thus the corpora contain pair sets of conversation and nursing activities. By referring to the corpora, we can determine what nurses were doing when they said the sentence.

We have already tagged about 250 hours of data. Since it is inefficient and expensive to attach all tags manually, we must introduce an automatic nursing activity determination method.

3. Automatic determination of nursing activities

For the E-nightingale Project, it was necessary to understand nursing activities immediately after collecting their data. Nursing activities must be determined by referring to nursing conversations.

In the previous section, we manually assigned 250 hours of nursing activity data to nursing conversations. However, since it is inefficient and too expensive to attach all tags manually, we must introduce an automatic nursing activity determination method. Since no general method exists that assigns nursing activities to nursing conversations, we must model the relationships between them.

For such applications, a frequently used strategy is to introduce a machine learning or induction method. In general, machine learning or induction methods need positive/negative examples. However, in our applications, since data are collected in actual situations, preparing negative examples for learning is difficult. Accordingly, we adopt machine learning methods that do not require negative examples during the learning procedure. In this section, we compare C4.5 and the maximum entropy approach that do not require negative examples.

3.1. C4.5

C4.5 (Quinlan 1993) is a decision tree learner that does not require negative examples, is robust for noisy data, and can learn disjunctive expressions. We adopted C4.5 to obtain the relationships between nursing conversations and activities. Each conversation is divided into word sets by Chasen (Chasen), a popular and powerful tool for ordinary conversation parsing. Part of the used data after Chasen application is shown in Figure 1. They consist of time, shift information, job category, and word sets.

```
time,shift,job category,words
18:04:02,S-1,20-o-113,output,end,worksheet
14:32:44,S-1,33,n
13:50:19,S-1,33,medical ward,during,treat,now,emergent,...
14:34:18,S-1,33,avoid,words,medical accident,request,...
....
8:46:53,S-1,18-109,morning,prepare,for,meeting
8:48:05,S-1,18-109,inform,form,report,enter hospital,...
8:48:05,S-1,20-119,inform,form,report,enter hospital,...
8:48:05,S-1,29-150,inform,form,report,enter hospital,...
8:48:05,S-1,33-159,inform,form,report,enter hospital,...
....
22:49:50,S-3,18-109,now,medical records check
00:13:17,S-3,18-109,resume,medical records check
01:17:16,S-3,20-113,entry,Koxxx(name),medical record,Mr.
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Figure 1: Data used for analysis

We simply applied C4.5 to the above data. Some results are shown below and contain time and shift information, but no significant difference could be observed by analyzing them with time and shift information. In the following analyzed results, we display those without time and shift information:

- one word
 -
 - word = pillow: 10-44-3A0301 (1.2/0.2)
 - word = weak: 18-110 (3.5/2.5)
 - word = I: 33-156 (1.2/0.2)
 - word = alcohol: 22-122 (2.3/1.3)
 - word = gastrocamera: 31-153 (1.2/0.2)
 - word = medical office: 29-150 (2.3/1.3)
 - word = doctor order form: 17-101 (1.2/0.2)
 -
- two word baskets
 - ..
 - word = meal+please: 18-105 (2/1)
 - word = meal+wait: 28-142 (1)
 - word = Mr.+ADL: 5-24-1A0301 (23/14)
 - word = Mr.+AED: 18-110 (3/2)
 - word = Mr.+ATA: 34-162 (2/1)
 - word = doctor+Anamne: 18-108 (2/1)
 - ...
- three word baskets
 - ...
 - word = ward+during+treat: 18-110 (0)
 - word = meal+noon+disturb:
 - 4-20-1A0701 (1)
 - word = CALONAL+medical record+name:
 - 20-113 (1)
 - word = conference+operation room+Mr.:
 - 13-58 (6/5)
 -

In the above analyses, we reformed the data to conduct a method similar to basket analysis (Agrawal et al. 1993). For learning, we made all possible word combinations such as meal+please and ward+during+treat from the word sets in a sentence of the data. Acceptable results are obtained, but automatically determining meaningful data classification is rather difficult. We must introduce an additional mechanism to determine useful relationships.

3.2. Principle of maximum entropy

The principle of maximum entropy analyzed available qualitative information to determine a unique epistemic probability distribution. The least biased distribution that encodes certain given information is that which maximizes the information entropy. It was first expounded by Jaynes (Jaynes 1957) for a statistical analysis of thermodynamics. This deconvolution algorithm functions by minimizing a smoothness function (entropy) in data.

For natural language modeling, Berger adopted the principle of maximum entropy (Berger et al. 1996). An application of Berger is machine translation between English and French. For a statistical translation, the probability $p(F | E)$ that F is a translation of E is expressed as the sum over all possible alignments A between F of the probability of F and A given E :

$$p(F | E) = \sum_A p(F, A | E) \quad (1)$$

Next the proper parameters must be selected to maximize the entropy of $p(F | E)$. By adopting the maximum entropy approach, Berger obtained acceptable results.

If we introduce the maximum entropy approach to obtain statistical relationships, the results are shown as probability. The mechanism resembles Bayesian estimation. To obtain frequently appearing relationships between more than two events, it would be easier and more effective to adopt the maximum entropy approach than the other statistical methods or C4.5.

4. Nursing activity determination based on the principle of maximum entropy

As pointed out above, it would be effective to adopt the maximum entropy approach to obtain relationships between nursing activities and conversations. In the framework of the maximum entropy approach, our task selects proper parameters or word sets to maximize the entropy of $p(J | D)$, where J is a job category and D is a word set which are spoken by nurses.

4.1. Application of maximum entropy method

First, we applied the maximum entropy method to learn the 17,000 or 67,000 nursing conversation sets. 17,000 data involve data from one floor, and 67,000 data involve data from multiple floors. Two conversation sets are analyzed to determine the effect of data volume and multiple departments. In this analysis, we did not modify to the conversation sets. No words are generalized, for instance, "Aspirin, Warfarin, ... → medicine."

Data sets to be learned have the following structure; [conversation, job category, word(1), word(2), ... ,

$word(i)$

For $word(i)$, nouns and noun phrases are mainly selected. For $job\ category$, we adopted the authorized category set provided by the Japan Academy of Nursing Science. $Job\ category$ is roughly divided into 36 classifications (major classification; e.g. 18 (only the first number, that is, major classification)) or around 430 classifications (minor classification; e.g. 18-106). In fact, $job\ category$ can be assigned to a $conversation$ more than once, because a sentence sometimes contains information about more than one task. Nurses sometimes concurrently perform more than one tasks. A word set $\{word(1), word(2), \dots, word(i)\}$ are automatically generated or extracted from a $conversation$ by Chasen. Thus by machine learning, relationships between $Job\ category$ and variable length word set $\{word(1), word(2), \dots, word(i)\}$ can be obtained. Since for a $conversation$, more than one $job\ category$ can be assigned, a $conversation$ can have more than one answer or relationship. Accordingly, we analyzed the results from the two criteria: “all job categories are correctly assigned (All),” and “at least one job category is correctly assigned (Not all).”

We applied the models generated by the maximum entropy method to the other 173 nursing conversation sets to determine the “job category” of each conversation. The accuracy ratio of the results is shown below;

- for 17,000 nursing conversation sets

	All	Not all
major classification	48.55%	66.47%
minor classification	33.53%	56.07%

- for 67,000 nursing conversation sets

	All	Not all
major classification	52.02%	75.14%
minor classification	42.20%	70.52%

Accepting the results is rather difficult, but the accuracy ratio improved based on the increase of the example number for learning.

4.2. Application of maximum entropy method with word sets specialized to nursing activities

The above result is not sufficient for a job category determination system. We assumed that since the original Chasen dictionary does not include nursing specialized terminology such as medical, nursing and hospital jargon/abbreviations, conversation data could not be correctly parsed. They are usually treated as unknown words. Even if they are unknown, if these words are correctly extracted, no problem occurs during the learning. However, we found another more serious reason that we failed to consider. For the original dictionary, single words are divided (parsed) into small fragments. For instance, “**アミグランド点滴静注用** (Amigrand for IV injection)”, the name of a medicine, is parsed as **アミ/グランド/点滴/静/注/用** (mesh field drip silent pour utility). It should be parsed as one word. At least, it should be parsed as **アミグランド/点滴/静注用** (Amigrand drip intravenous). That is, since the original

dictionary does not have this specialized word, it is divided into more than one word and has different meanings. From a linguistic viewpoint, this situation is not good; small and different meaning words are easy to learn to superficially show better results. Therefore, we added such jargon to the Chasen dictionary and learned the word sets parsed by Chasen with a specialized dictionary. The accuracy ratio of the result is shown below:

- for 17,000 nursing conversation sets

	All	Not all
major classification	47.40%	65.90%
minor classification	36.99%	60.12%

- for 67,000 nursing conversation sets

	All	Not all
major classification	54.34%	78.03%
minor classification	43.35%	72.83%

For 17,000 conversation sets cases, the result unexpectedly deteriorated. For the minor classification, the result is rather improved. However, the difference is rather small and it is still insufficient. For the 67,000 conversation sets, the results also improved. However, the difference is small and still insufficient in the case of “All,” because little medical jargon appears in the conversations on the hospital wards. On the wards, nurses usually speak to patients, so they tend to avoid jargon. In fact, we observed few situations where jargon was used on the wards, it was frequently observed during meetings, suggesting that if we apply this strategy to data collected during meetings, better results might be obtained.

4.3. Application of maximum entropy method with generalized unit information

Variations of numerical information such as time and quantity of medicine are sometimes difficult to learn. For instance, 30 min. and 20 min. should be treated as the same pattern, but ordinary learning system cannot. Therefore, we removed such numerical information and replaced unit with general information. That is, 30 min. is converted to [time] and 10 ml or 10 mg is converted to [unit]. A result for the converted data sets is shown below:

- for 17,000 nursing conversation sets

	All	Not all
major classification	48.55%	66.47%
minor classification	35.84%	58.96%

- for 67,000 nursing conversation sets

	All	Not all
major classification	52.02%	74.57%
minor classification	42.77%	71.68%

Similar to the case where specialized words are added to the Chasen dictionary, no outstanding improvement was observed. Actually, since only 6% of the numerical information appears in the conversation data, the effect of conversion is small. In addition, 67,000 is still a small number to conduct proper machine learning to classify the entire medical space into 430 medical sub-spaces. More data must be collected to conduct additional plausible machine learning. For the 67,000 nursing conversation sets, we obtained 50% accuracy for the “All” cases, and more than 70% for the “Not all” cases, which are acceptable results for the first learning step.

4.4. Acceptable accuracy ratio in general use

In the above experiments, we obtained around 80% of accuracy ratio for “Not all” cases. For general use, the presentation of three or five candidates will be acceptable. Users can choose correct information from useful candidates that will serve as references when assigning nursing job information to nursing conversations. Therefore, we also analyzed the results from the above viewpoint.

We conducted experiments for three cases;

R1: Only the most possible result is shown.

R3: Top 3 of possible results are shown.

R5: Top 5 of possible results are shown.

For R1, the same situation as in the above experiments is applied. And Maj means major classification. Min means minor classification. On the other hands, for R3 and R5, the constraints are relaxed to display many possible relationships. Intuitively, for general use, R3 is acceptable.

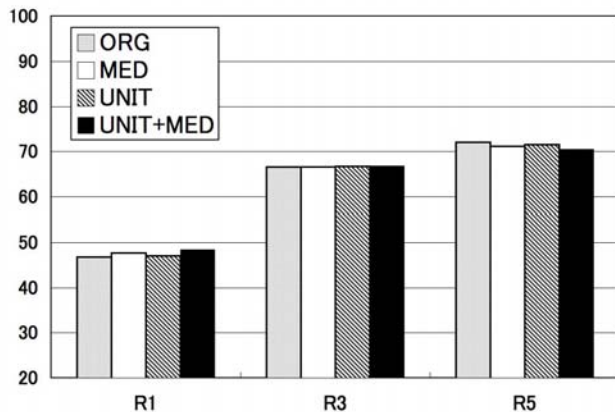


Figure 2: Accuracy ratio based on number of candidates (Maj: 17,000 nursing conversation sets).

Figure2–5 show the accuracy ratios of each strategy based on the number of candidates (1, 3, or 5). The ORG bars show the accuracy ratio for learning with the original Chasen dictionary. The MED bars show the learning with the original Chasen dictionary adding specialized terminology dictionary. The UNIT bars show the learning with the original Chasen dictionary with numerical data conversion. The UNIT+MED bars show the learning with the original

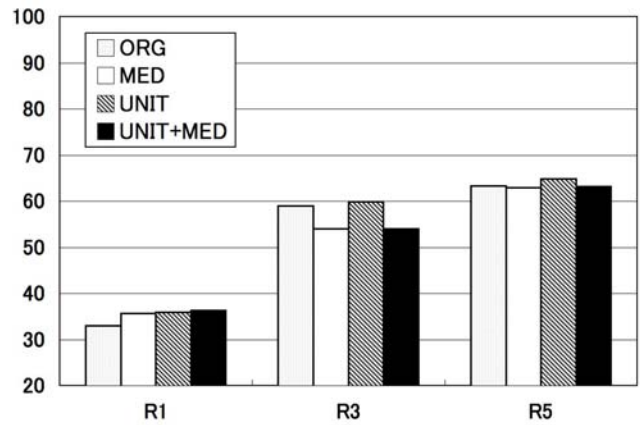


Figure 3: Accuracy ratio based on number of candidates (Min: 17,000 nursing conversation sets).

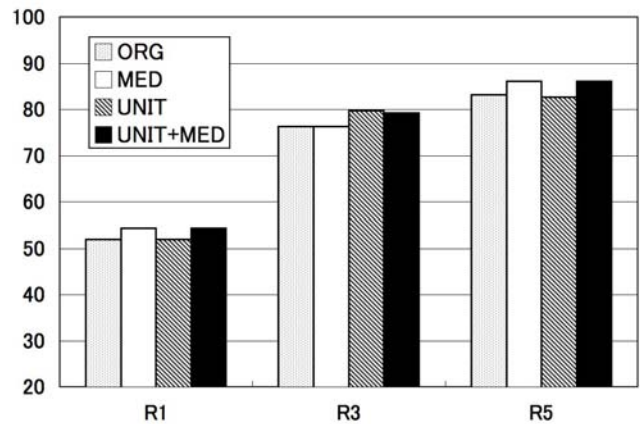


Figure 4: Accuracy ratio based on number of candidates (Maj: 67,000 nursing conversation sets).

Chasen dictionary adding specialized terminology dictionary with numerical data conversion.

Figure2–5 show similar tendencies. R5 is the upper band of the accuracy ratio in this application. The accuracy ratio for R3 is around 80% which seems acceptable for general use. From the above intuitive observation, R3 is the most acceptable situation for general use when we semi-automatically add nursing activity labels to nursing conversations.

5. Conclusions

In this paper, we proposed a strategy to determine the relationships between nursing activities and nursing conversations based on the principle of maximum entropy. First, after comparing C4.5 and the maximum entropy method, we adopted the maximum entropy method, since its results are more intuitive and understandable than those from C4.5. By applying the maximum entropy method, we obtained the relationship between nursing conversations and activities. In addition, we applied various strategies for conversation parsing, added nursing and medical jargon to Chasen’s dictionary, and generalized such information as time and unit (mg, ml etc.). Contrary to our expectations, we failed to obtain outstanding improvement when we applied the

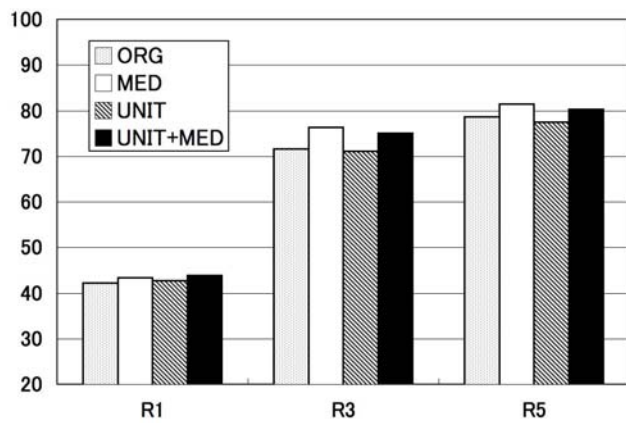


Figure 5: Accuracy ratio based on number of candidates (Min: 67,000 nursing conversation sets).

above strategies. Since few specialized words appear in conversations on hospital wards, we obtained similar results as the general strategies. However, if we apply the above strategies to the places where jargon is frequently used, we will improve our results.

Our results remain insufficient since we have not collected enough data. In addition, we must assign nursing activity information to nursing conversations. When ex-nurses assigned nursing activity information to conversations, they also consider the surrounding situations and context to make decisions. Such a technique is necessary for better assignment. For the 67,000 nursing conversation sets, without considering context, we obtained 50% accuracy for “All” cases, and more than 70% accuracy for the “Not all” cases, which are acceptable results for the first step of learning step.

Despite insufficient results, we showed the possibility of introducing machine learning to determine the relationships between nursing conversation and activities, that can be used in various situations such as automatic nursing activity reporting.

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