Bayes Risk-based Optimization of Dialogue Management for Document Retrieval System with Speech Interface

Teruhisa Misu and Tatsuya Kawahara

School of Informatics, Kyoto University,
Sakyo-ku, Kyoto 606-8501, Japan
misu@ar.media.kyoto-u.ac.jp

Abstract

We propose an efficient dialogue management for an information navigation system based on a document knowledge base. It is expected that incorporation of appropriate N-best candidates of ASR and contextual information will improve the system performance. The system also has several choices in generating responses or confirmations. In this paper, this selection is optimized as minimization of Bayes risk based on reward for correct information presentation and penalty for redundant turns. We have evaluated this strategy with our spoken dialogue system "Dialogue Navigator for Kyoto City", which also has question-answering capability. Effectiveness of the proposed framework was confirmed in the success rate of retrieval and the average number of turns for information access.

Index Terms: spoken dialogue system, dialogue management, Bayes risk

10.21437/Interspeech.2007-710

1. Introduction

The target of spoken dialogue systems is being extended from simple databases such as flight information to general documents including manuals and newspaper articles[1]. In such systems, the automatic speech recognition (ASR) result of the user utterance is matched against a set of target documents using the vector space model, and documents with high matching scores are presented to the user. These kinds of applications are expected to be useful especially when retrieving information with keyboardless devices such as a PDA, a tablet PC and a car navigation system. We have developed "Dialogue Navigator for Kyoto City", which can make interactive guidance by incorporating the question-answering (QA) function as well as general document retrieval.

In these systems, making confirmation is needed to eliminate misunderstandings caused by ASR errors, but so many redundant confirmations are bothersome to users. There have been many studies that deal with efficient dialogue management to make confirmation[2, 3, 4]. However, most of them are designed for relational database (RDB) query tasks, which have a definite set of keywords, and they are not directly applicable to document retrieval tasks, in which every word is used in matching. In document retrieval tasks, therefore, it is more reasonable to make confirmation considering the confidence score of retrieval.

In addition, our system classifies user utterances to queries and questions, and generates appropriate responses for respective inputs. Unlike conventional QA tasks, such as TREC QA Track[5], it is not obvious whether the utterance is a query or a question. In addition, an exact answer for a question does not necessarily exist in the document sets. Therefore, it is not always optimal to respond the question with its answer alone.

U1:	Please explain the Golden Pavilion.
S1:	The Golden Pavilion is one of the buildings in the Rokuon-ji in Kyoto, and is the main attraction of the temple sites. The entire pavilion except the basement floor is covered with pure gold leaf.
U2:	When was it built?
S2:	The Golden Pavilion was originally built in 1397 to serve as a retirement villa for Shogun Ashikaga Yoshimitsu.
U3:	Then, please tell me its history.
.....	

Figure 1: Example dialogue of Dialogue Navigator for Kyoto City

In this paper, we address the extension of conventional optimization methods of dialogue management, to be applicable to general document retrieval tasks with QA function. Specifically, we propose a dialogue management that optimizes the choices in response generation by minimizing Bayes risk, based on reward for correct information presentation and penalty for redundant turns, which are defined by the score of document retrieval and answer extraction.

2. Dialogue management and response generation in document retrieval system

The "Dialogue Navigator for Kyoto City" is a document retrieval system with a spoken dialogue interface. The system can retrieve information from a document set about sightseeing spot of Kyoto City. The KBs of this system are Wikipedia documents concerning Kyoto and the official tourist information of Kyoto city (810 docments, 220K words in total). This system is also capable of handling user's specific question, such as "Who built this shrine?" using QA techniques. An example dialogue of the system is shown in Figure 1.

2.1. Choices in generating responses

We have conducted a field trial for about three months at Kyoto University museum[6], and analyzed the collected dialogue sessions. We found that we could achieve a higher success rate by handling following issues.

1. **Use of N-best hypotheses of ASR**
   There have been many studies that used N-best hypotheses (or word graph) of ASR for robust interpretation of a user utterance in RDB query tasks[7]. In our previous study of the document retrieval system, use of all nouns in the 3-best hypotheses contributed the improvement of the retrieval, compared with using only the first hypothesis. However, the analysis also showed that some failures of retrieval were caused by extraneous nouns included in erroneous hypotheses, and a higher success rate could be achieved by selecting the optimal hypothesis[6]. As a related study, Akiba[8] proposed a rescoring method of N-best hypotheses considering the matching score of retrieval.
2. **Incorporation of contextual information**
   In interactive query systems, users tend to make queries that include anaphoric expressions. In these cases, it is impossible to extract the correct answer using the current query alone. For example, "When was it built?" makes no sense being used by itself. In our previous study, we have handled this problem by concatenating the contextual information or keywords from the user's previous utterances to generate a query. However, this may add inappropriate context when the user changes the topic. Therefore, it is preferable to judge whether to use contextual information query by query. In fact, we have also confirmed that we could achieve a higher success rate by setting an optimal context length[6].
3. **Choices in generating responses or confirmations**
   To avoid presentation of inappropriate documents, making confirmation is indespensable, especilly when the score of retrieval is low. This decision is also affected by 1. and 2. Also, presentation of the whole document may be "safer" rather than presenting the specific answer to the user's question, when the score of answer extraction is low.

In this work, we formulate the optimization of the abovementioned choices under minimization of Bayes risk.

2.2. Overview of proposed method

The proposed dialogue management is realized by comparing and selecting from possible responses hypothesized by changing conditions of query generation and the manner of response.

The manners of response using the document D consist of following three actions. One is presentation ($Pres(D)$) of the document D, which is made by summarizing the document. Another is confirmation ($Conf(D)$) for presenting the document D. The other is answering $Ans(D)$ for user's specific question, which is generated by extracting specific one sentence from the document D.

For these response candidates, we define Bayes risk based on reward for success, penalty for failure, and the probability of success (approximated by confidence measure). Then, we select the candidate with the minimum Bayes risk. The system flow of these processes is summarized below and also shown in Figure 2.

1. Make search queries $q_i (i = 1, \ldots, 8)$ using 1st, 2nd, 3rd hypothesis of ASR, and all of them, with/without contextual information.
2. Retrieve from the KB and obtain a candidate document D_i and its confidence measure $P(D_i)$.

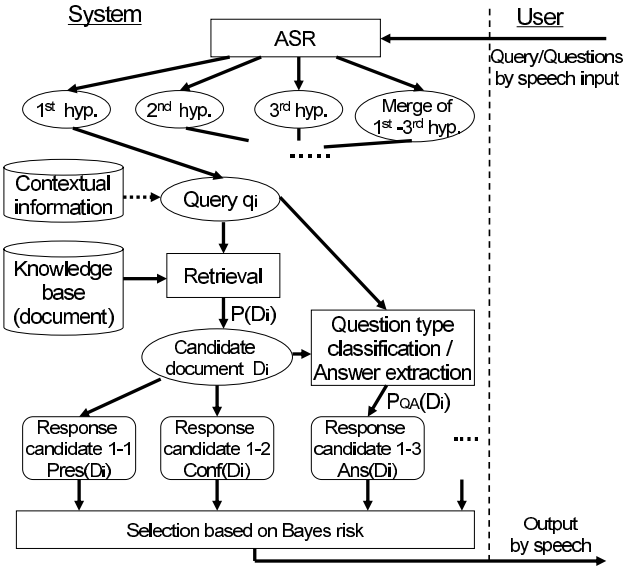

Figure 2: Overview of proposed method

3. Generate response candidates of Presentation $Pres(D_i)$, Confirmation $Conf(D_i)$, and Answering $Ans(D_i)$ using the document D_i.
4. Calculate Bayes risk for 25 response candidates, which are combination of 4 (N-best hypotheses) $\times$ 2 (use of contextual information) $\times$ 3 (choice in response generation) + 1 (rejection).
5. Select the optimal rseponse candidate that has the minimum Bayes risk.

3. Generation of response candidates

3.1. Document retrieval

We adopt an orthodox vector space model to calculate the matching score (degree of similarity) between a user query and the document in the KB. That is, the vector D of the document is made based on the occurrence counts of nouns in the document by section unit. The vector q for the user query is also made using the ASR result of the current utterance. When incorporating contextual information, the user's previous utterances concerning the current topic are added to the vector q_i. We also use the ASR confidence measure (CM) as a weight for the nouns. The matching score $Product(q, D)$ is calculated by the product of these two vectors. We then transform the product to a confidence measure $P(D)$ using a sigmoid function.

$$P(D) = \frac{1}{1 + \alpha * \exp\{-1 * (Product(q, D) - \beta)\}}$$

Here, α and β are constants.

3.2. Response generation for user's retrieval query

Presentation of the document $Pres(D)$ is generated by extracting important sentences, considering user's easiness of comprehension.

A confirmation $Conf(D)$ may be generated using the title or the section title of documents, such as "Do you want to know the Golden Pavilion?".

3.3. Answer extraction for user's question

We have implemented an answer extraction module. For each named entity (NE) in the retrieved document that matches the question type (who, when, ...), a score is calculated using the following features.

- Number of matched nouns in the sentence including the NE.
- Number of matched nouns included in the clause that depend on/depended by the clause that includes the NE.

The system then selects the NE with the highest score as an answer to the question. A confidence measure of answering $P_{QA}(D)$ is calculated using the ASR confidence measure of base word for question type classification and the above score of answer extraction.

4. Response candidate selection based on Bayes risk

Then, we define Bayes risk for selection of response candidates. The risk is calculated based on reward for presenting an appropriate response and penalty for a confirmation or an inappropriate response. That is, a reward is given according to the manner of response, when the system presented an appropriate response. On the other hand, a penalty is given based on the number of extraneous turns required for uttering the rephrasal, when the system presented an incorrect response. The penalty is zero for appropriate responses, otherwise has a positive value. For example, the penalty for a confirmation is 2 turns {system's confirmation + user's approval}, and presenting incorrect information is 5 {presentation + user's correction + system's apology + request for rephrasing/confirmation + user's rephrasing/approval}.

The Bayes risk for response candidates is formulated as follows using the confidence measure $P(D)$ of retrieval, the confidence measure $P_{QA}(D)$ of answer extraction, reward Rwd_{Ret}, and Rwd_{QA} ($Rwd_{Ret} < Rwd_{QA}$) for successful presentation as well as $Penalty$ for inappropriate actions or rejection.

- Presentation of document D (without confirmation)

$$\begin{aligned} Risk(Pres(D)) \;=\; & -Rwd_{Ret} * P(D) \\ & +(5 * Penalty) * (1 - P(D)) \end{aligned}$$

- Confirmation for presenting document D

$$\begin{aligned} Risk(Conf(D)) \;=\; & (-Rwd_{Ret} + 2 * Penalty) * P(D) \\ & +(3 * Penalty) * (1 - P(D)) \end{aligned}$$

- Answering user's question using document D

$$\begin{aligned} Risk(Ans(D)) \;=\; & -Rwd_{QA} * P_{QA}(D) * P(D) \\ & -\frac{1}{2} * Rwd_{Ret} * (1 - P_{QA}(D)) * P(D) \\ & +5 * Penalty * (1 - P(D)) \end{aligned}$$

- Rejection

$$Risk(Rej) \;=\; 2 * Penalty$$

User utterance: When the shogun ordered to build the temple?
(Previous query:) Tell me the the Silver Pavilion.
Response candidates:
* Without context:
$\rightarrow P(\text{Golden Pavilion history}) = 0.2$
$\rightarrow P_{QA}(\text{Golden Pavilion history}) = 0.5$: In 1397
- $Risk(Pres(\text{Golden Pavilion history}))$
$= -0.8 + 4.0 = 3.2$
- $Risk(Conf(\text{Golden Pavilion history}))$
$= -0.4 + 2.4 = 2.0$
- $Risk(Ans(\text{Golden Pavilion history}; \text{In1397}))$
$= -0.8 - 0.2 - 4.0 = 3.0$
* With context:
$\rightarrow P(\text{Silver Pavilion history}) = 0.4$
$\rightarrow P_{QA}(\text{Silver Pavilion history}) = 0.2$: In 1485 ?
- $Risk(Pres(\text{Silver Pavilion history}))$
$= -1.6 + 3.0 = 1.4$
- $\mathbf{Risk(Conf(Silver\ Pavilion\ history))}$
$\mathbf{= -0.8 + 1.8 = 1.0}$
- $Risk(Ans(\text{Silver Pavilion history}; \text{In1485}))$
$= -0.64 - 0.64 + 3.0 = 1.72$
...
* Rejection
- $Risk(Rej) = 2.0$
↓
Response: Confiarmation [Silver Pavilion history]
"Do you want to know the history of the Silver Pavilion?"

Figure 3: Example of calculating Bayes risk

A half of the ordinal reward $-\frac{1}{2} * Rwd_{Ret}$ is given when the system responds the user's question by simply presenting the retrieved document rather than directly answering it. This is because the answer for the question may be included in the summary, even if the system fails to present the answer alone.

Figure 3 shows an example of calculating Bayes risk (where $Penalty = 1$, $Rwd_{Ret} = 4$, $Rwd_{QA} = 8$). In this example, an appropriate document is retrieved by incorporating previous user's query. However, since the answer of user's question does not exist in the KB, the score of answer extraction is low. Therefore, the system selected confirmation for presenting the whole document.

5. Evaluation of the proposed method

We have evaluated the proposed dialogue strategy using the user utterances collected in the field trial of "Dialogue Navigator for Kyoto City". We transcribed in-domain 1,416 utterances (1,084 queries and 332 questions) and labeled their correct documents/NEs by hand.

We adopted evaluation measures of the success rate and the number of turns for information access. We regarded a retrieval as successful if the system presented (or confirmed) the appropriate document/NE for the query. The number of turns for information access was calculated as an expected turns assuming the probability of success by rephrasal was 60%[1]. We then de-

[1]Based on the success rate of the baseline method

termined the value of $Penalty$ and Rwd by 2-fold cross validation by splitting the test set into two (set-1 & set-2), that is, set-1 was used as a development set to estimate $Penalty$ and Rwd for evaluation of set-2, and vice versa. The result of the evaluation is shown in Table 1.

We compared the proposed method with following conventional methods. Note that the method 1 is the baseline method and the method 2 was adopted in the original "Dialogue Navigator for Kyoto City" and used in the field trial.

Method 1 (baseline)

- Make a search query using the 1st hypothesis of ASR.
- Incorporate contextual information related to the current topic.
- Make a confirmation when the ASR confidence of the pre-defined topic word is low.
- Answer the question when the user query is judged as a question.

Method 2 (original system)

- Make a search query using all nouns in the 1st-3rd hypotheses of ASR.
- Other conditions are same as the method 1.

The comparison with these conventional methods are shown in Table 2. The improvement compared with the baseline method 1 is 6% in the response success rate and about one turn in the number of turns for information access. The breakdown of the selected response candidates by the proposed method is shown in Table 3. Many of the responses were generated using a single hypothesis from the N-best list of ASR. Most of the confirmations were generated using the 1st hypothesis of ASR. Answers of questions were often generated from search queries with contextual information. The result suggests that appropriate contextual information was incorporated to the question, when users used anaphoric expressions.

6. Conclusion

We have proposed a dialogue framework to generate an optimal response based on Bayes risk in the document retrieval system with a spoken dialogue interface. Experimental evaluations by real user utterances demonstrated that the proposed method achieved a higher success rate of information access with less number of turns.

Although we have formulated the Bayes risk using penalty based on the number of turns, the quality (content) of a turn is not taken into account. In actual dialogues, however, the quality of a turn is not necessarily uniform. For example, there is a large difference in time for presentation and amount of information between confirmation and document presentation. Therefore, we will extend the framework reflecting the quality of the turn on the reward and penalty in the future work. We also plan to investigate online learning of the reward and penalty.

Table 1: Result by proposed method

	Succes rate	# turns for presentation
Retrieval	67.4%	4.35
QA	57.8%	4.95
Total	65.2%	4.49

Table 2: Comparison with conventional methods

	Succes rate	# turns for presentation
Method 1 (baseline)	59.2%	5.44
Method 2 (original)	63.4%	5.07
Proposed method	65.2%	4.49

Table 3: Breakdown of selected response candidates

	w/o context			with context		
	Pres	Conf	Ans	Pres	Conf	Ans
1st hyp.	260	108	62	0	129	2
2nd hyp.	146	38	29	0	1	6
3rd hyp.	222	38	44	2	2	5
merge all	78	8	3	41	0	90
rejection	50					

7. References

[1] E. Chang, F. Seide, H. M. Meng, Z. Chen, Y. Shi, and Y. C. Li. A system for spoken query information retrieval on mobile devices. *IEEE Trans. on Speech and Audio Processing*, 10(8):531–541, 2002.

[2] Y. Niimi and Y. Kobayashi. A dialog control strategy based on the reliability of speech recognition. In *Proc. ICSLP*, 1996.

[3] D. J. Litman, M. S. Kearns, S. Singh, and M. A. Walker. Automatic optimization of dialogue management. In *Proc. COLING*, pages 502–508, 2000.

[4] K. Dohsaka, N. Yasuda, and K. Aikawa. Efficient spoken dialogue control depending on the speech recognition rate and system's database. In *Proc. Eurospeech*, 2003.

[5] NIST and DARPA. The twelfth Text REtrieval Conference (TREC 2003). In *NIST Special Publication SP 500–255*, 2003.

[6] T. Misu and T. Kawahara. Speech-based interactive information guidance system using question-answering technique. In *Proc. IEEE-ICASSP*, 2007.

[7] C. Raymond, Y. Esteve, F. Bechet, R. De Mori, and G. DamnatiK. Belief confirmation in spoken dialog systems using confidence measures. In *Proc. ASRU*, 2003.

[8] T. Akiba and H. Abe. Exploiting passage retrieval for N-best rescoring of spoken questions. In *Proc. Interspeech*, 2005.