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Research Article

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Answer planning based answer generation for cooking question answering system

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ABSTRACT

The rise of question answering (QA) research is mainly due to the demand of people that access to information quickly and accurately. Instead of returning "hits", as information retrieval systems do, QA systems respond to natural language questions with concise, precise answer. In this work, we addressed on generating an exact answer in natural language for cooking QA system. We first reviewed the previous work of question analysis. Then, we presented the annotation scheme for knowledge database. Finally, we proposed the answer planning methodology for answer generation. The method mainly includes two steps: answer content planning and answer surface realization. An evaluation has been conducted on natural language questions and the results showed that the proposed answer generation method is effective and can satisfy user's demand.

Key words: QA system, answer generation, answer planning, cooking domain

INTRODUCTION

Nowadays the popularization of computer and Internet technology raised the urgent need for the natural language processing (NLP), and some applications of NLP technologies have already moved toward practical use. Some researches have been done for computer-aided cooking. For example, a retrieval system for cooking recipes was developed in Ref.[1]. This system searches for recipes according to the search condition input by users, classifies the materials of recipes into food groups, and gives the suggested food menu that balanced necessary nutrition contained in different food groups. Ref.[2] described a user adaptive task model of cooking for a cooking navigation system. Ref.[3] present a method that improves search performance in cooking domain by adding the domain -specific keyword to the user's input query. Although the Web search engine can get useful information for users, satisfying much information searching requests, it is not efficient enough to provide the precise content required by people. People always need to do information filtering work manually on the result of search engine. One challenging problem is how to return the quick and precise answers to the user. The automatic question answering system is developed for resolving the problem, it involves the research areas including computational linguistics, information science and artificial intelligence, etc., and has been one of the hot topics of the computer applications. For enriching computer aided cooking service, we aim to establish an effective and robust question answering system.

General QA systems adhere to the pipeline architecture which mainly includes three parts: question analysis, information retrieval, and answer extraction (AE). Much research has been done about answer extraction for QA, they returned answer list by various similarity calculations, confidence score comparison and so on. However, how to generate a well-formed answer to complex questions is a difficult task,there's still no consensus method. Several systems have specifically addressed the task of answer generation or real application of text generation. For example, generating the intelligent numerical answer in a QA system, generating intensional answers in intelligent QA systems, generating weather forecast text, and generating approximate geographic description [4-8]. Our QA system is aiming at real application of the cooking domain. We can obtain rich structural cooking documents from the web and build an offline knowledge sources. After annotating the corpus with cooking attribute blocks, the answer information may extract directly from the knowledge database. Then, an exact answer in natural language can be generated.

OUR PREVIOUS WORK

To understand the answer generation method, which will be introduced in this paper, we briefly review our previous work. The service objects of our cooking QA system are the people who are interested in cooking and want to cook dishes by themselves. Our system will accept the natural language inquires as input, and directly returns the precise answer to the user.

At the beginning of work, we categorized the cooking domain questions into four types. The first type asks for raw material, the corresponding answer should be the main ingredients or the condiments of a dish. The second type asks for the cooking recipe, the answer of which should be about how to cook a dish step by step. The third type asks the dish name, the answer includes the dish recommendations according to the raw material or cooking form. The fourth type asks the cooking techniques, the answer of this type should be procedures of some basic cooking skills. On the basis of our question taxonomy, we collected and arranged the question instances of Chinese cuisine with a total of 522 from the Internet and obtained 453 effective questions. We have carried out question analysis to these instances. Fig.1 shows the architecture of question analysis module.

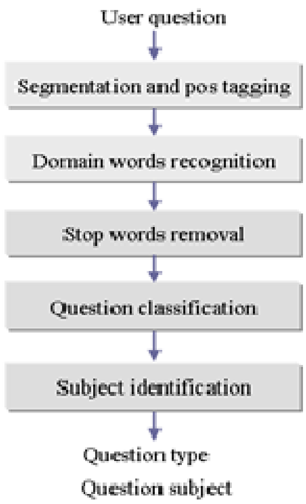

Fig.1: The architecture of question analysis

In question analysis module, user's questions were preprocessed at first, which is to do lexical analysis, create domain dictionary and remove stop words. Then, question type was classified. To use the domain knowledge effectively, we have increased five kinds of domain words (dish name, raw material, cooking form, cooking skill and taste type.) and added them to domain dictionary.

In QA system, question classification is very important, it has two major functions. One is to reduce the set of candidate answer and thus increase the accuracy of returned answer. The other is to decide the strategy of answer extraction. We have classified questions according to their expected answer type. In previous works, according to the question instances and the extracted classification features, the rule based classifier was constructed. Support vector machine (SVM) classifier was used for secondary classification to the questions which cannot be matched with rules. We have achieved a classification accuracy of 96.22% [9-10].

If let q be a user's question denotation, we use such as dish name (q), cooking skill (q), taste type (q) to express the domain words which are contained in the user's question. After analyzing the question sets which have been processed by question analysis module, we find that using the domain words can distinctively describe the subject of the question [11]. Table 1 lists the question subject and corresponding question type.

Table1. Question subjects corresponding to the question types.

Question type	Subject word
1. cooking material	dish name(q) + focus word(q)
2. dish recipe	dish name(q)
3. dish recommendation	main ingredient(q) or cooking form(q)
4. cooking technique	cooking skill(q) or taste type(q)

RESEARCHMETHOD

After analyzing user's questions, in this section we detail our answer generation method. This module solves the problem of generating answer from the off-line database. The inputs are question type and question subject which are generated by question analysis module. The output is well-formed exact answer.We consider that, an answer generation problem can be defined as a triplet (Q, A, S):

Q is the set of variables which represents the questions (Q = q_1, q_2, ...q_i, ...).
A is the set of variables which represents the answers (A = a_1, a_2, ...a_i, ...).
S is the set of constraints/system function.

Each constraint is the relation between a variable q_i and a_i, A solution assigns to each variable q_i with an answer value a_i. For a question, depending on the constraints, there may be one solution or there may be no solution.

3.1. Knowledge representation of domain document

The web is a valuable resource for QA system. The documents of cooking area, such as fundamental cooking techniques, raw materials, condiments, are relatively stable. Although new dishes may appear from time to time, the main menu is rarely changed completely, they don't need continuous updating. Therefore, we can obtain rich structural cooking documents from the web and build an off-line knowledge sources.As pointed by Ref. [12], Knowledge annotation is a question answering strategy that allows heterogeneous sources on the Web to be accessed as if it were a uniform database. To obtain the exact answer from the local database, we put further effective annotation on domain documents. In our work, we collected domain documents from the web and cooking book and created two different resources, namely, dish cooking documents and cooking technique documents. The dish cooking documents differ from the general text that they have been well-structured; while the cooking technique documents are similar to the texts in general which are narrated in paragraphs. The key point of our document collection is that they make it easy to find answer information [13].

3.1.1 Annotation scheme for dish cooking document

Dish cooking documents, whether be collected from the cooking website, blog, cook books, or magazines, have a good structure of the specific style. They generally consist of the information such as dish name, raw material, condiment, cooking steps. They may also provide the characteristics of cuisine, the nutrition of food and so on. In this work, the dish cooking corpus consists of 703 Sichuan cuisine recipes. To provide an effective mechanism for answering questions, we annotate dish cooking documents with four function blocks they are: (1) dish name block, (2) cooking form block, (3) raw material block, and (4) directions block. Where, the raw material block also consists of three sub-blocks, i.e.,(i) main ingredient sub-blocks, (ii) ingredient sub-blocks, and (iii)condiments sub-blocks.

3.1.2 Annotation scheme for cooking technique document

Our cooking technique corpus consists of 98 cooking skill and taste type items. The documents of cooking techniques are collected from the websites such as Wikipedia, Baidu, meishij. We also collected some cooking techniques from the cooking books [14]. The characteristic of this source is different from the dish cooking document. Generally, the explanation of cooking techniques is a paragraph constituted by several sentences, and in some situations, the sentences may not contain a domain attribute word. Therefore, the annotation scheme of cooking technique documents is very different from the dish cooking documents. We annotate them with two function blocks they are: (1) the subject of cooking technique, (2) the explanation of operating. The annotation does not involve any other modification of the original text.

By annotating the corpus with function blocks, the answer information can be extracted directly from the knowledge database. Then, an exact answer in natural language can be generated.

3.2. Answer Generation Based on Answer Planning Method

In natural language generation (NLG), discourse generation is not possible without text planning. The main purpose of the text planning is to make sure the generated content and the relationship between the contents. However, the planning content is dependent upon the user models. In this work, we propose answer planning based approach to generating answers for QA system in cooking domain. We exploit a two-stage strategy for answer generating. i.e, answer content planning and answer surface realization. The architecture of planning based answer generation is shown in Fig. 2.

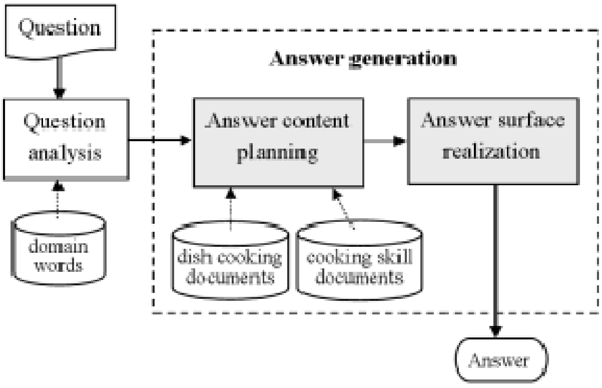

Fig. 2: Architecture of answer planning based answer generation

3.2.1 Answer content planning

Content planning decides what information must be communicated, namely, answercontent selection and ordering. As referred to in section 2, we categorized the cooking questions into four classes. According to question type and question subject (refer to Table 1), we can extract answer component from the related database. Fig.3 shows the flow chart of answer content planing.

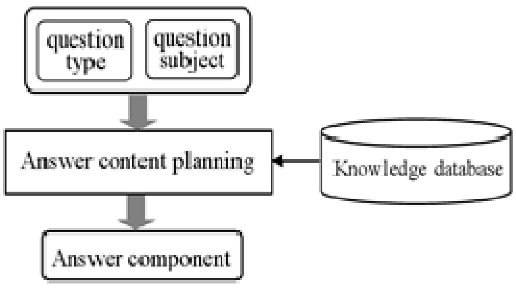

Fig. 3: Flowchart of answer content planning

Input		Related database	Output
type*(q)*	subject *(q)*		component *(a)*
1. raw material	dish name *(q)* & material concept word *(q)*	dish cooking	raw material *(a)* or main ingredient*(a)* or ingredient *(a)* or condiment *(a)*
2. cooking recipe	dish name *(q)*	dish cooking	raw material *(a)* & direction *(a)*
3. dish recommendation	main ingredient *(q)* or cooking form *(q)*	dish cooking	dish names *(a)*
4. cooking technique	cooking skill *(q)* or taste type *(q)*	cooking technique	explanation *(a)*

Note: type(*q*) → question type, subject(*q*) → question subject, component(*a*) → answer component(s)

Fig. 4: Representation of answer content planning

In our work, the answers which correspond with first, second and the third type of questions could be generated from dish cooking documents, the answer components are some function blocks which have been annotated. However, as the difference in domain characteristic, the answers corresponding the fourth type will be generated from the resources of cooking technique documents, and the answer component is an explanatory paragraph. Fig. 4 is a detailed description of content planning for the four types of question.

3.2.2 Answer surface realization

According to content planning, we can decide the answer content component from the related database. By answer surface realization, we can convert content components into actual answer. (e.g. Insert function words, order components, add punctuation, etc,.). As our system is aimed at answering frequently asked questions of users, we argue that a small number of predefined patterns can cover all the superficial variations in answer construction. In this work, the approach we proposed to answer surface realization is to use domain-specific language, and summarize the generic templates for answer sentences according to four question categories. Fig. 5 shows the workflow of the answer surface realization.

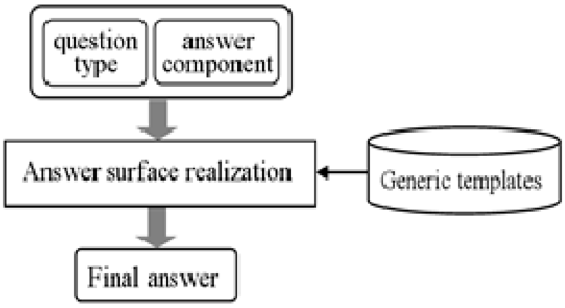

Fig. 5: Flowchart of answer surface realization

To use generic templates to represent answer, we denote a user's question as q, correspondingly, system's answer as a. Then we can use such as dish name (q), cooking form (q), cooking skill (q) to express the domain words in questions, use subject (q) to represent the subject in question. Similarly we use answer block (a), dish name (a), cooking skill (a) and so on to express the answer component. Supposing for a question q, the answer is a, then the answer for all questions consist of two parts. Namely, subject (q) and answer component (a). Accordance with the expressing way of cooking domain, the four type answer templates are summarized as Fig. 6 – Fig. 9.

The material concept word (q_i) of cooking dish name (q_i) is material block (a_i).

Fig. 6: Generic answer template of question type 1

The cooking procedure of dish name (q_i) is as follows: raw material (a_i). direction (a_i).

Fig. 7: Generic answer template of question type 2

Template 1. (the attribute of subject is main ingredient)
You can cook dish name1(a_i), dish name 2 (a_i) or dish name 3 (a_i) by using main ingredient(q_i).

Template 2. (the attribute of subject is cooking form)
You can cook cooking form (q_i) such as dish name 1(a_i), dish name 2(a_i) or dish name 3(a_i).

Note that: As the subject has two possible attribute values, the template has two possibilities.

Fig. 8: Generic answer template of question type 3

Template 1. (the attribute of subject is cooking skill)
The method of cooking skill (q_i): explanation (a_i).

Template 2. (the attribute of subject is taste type)
The method of cooking taste type (q_i): explanation (a_i).

Fig.9: Generic answer template of question type 4

No answer: When the answer component can be extracted from the knowledge database (regardless of being correct or incorrect), we can generate a certain answer. However we should give user a reply even if there is no answer in some cases. The reply template is shown in Fig.10.

Sorry, no answer for this question yet.

Fig. 10: Reply template for no answer

RESULTS AND DISCUSSION

Experiment sets
We evaluate our approach by applying our answer generating method to 53 questions which has been classified by our classifier, and we distinguish three cases:correct answer, incorrect answer, and no answer.The performance of AG module is evaluated by means of coverage and accuracy. Here coverage and accuracy are defined as follows: [15-16].

$$precision = \frac{number \quad of \quad correctly \quad classified \quad questions}{number \quad of \quad obtained \quad classified \quad questions}$$

$$recall = \frac{number \quad of \quad correctly \quad classified \quad questions}{number \quad of \quad questions}$$

Evaluation results
The result of evaluation is shown in Table 2. Where,
#QT: the type of question;
#Q: the number of questions;
#CA: the number of correct answers;
#ICA: the number of incorrect answers;
#NA: the number of no answer;
Cov: coverage;
Acc: accuracy.

Table 2. Evaluation of the answer generation

QT	#Q	#CA	#ICA	#NA	Cov(%)	Acc(%)
1	10	10	0	0	100	100
2	17	15	0	2	88.24	88.24
3	12	11	0	1	91.67	91.67
4	14	13	1	0	100	92.85
total	53	49	1	3	94.34	92.45

DISCUSSION

Our answer generation is based on the question classification. When the question has been wrongly classified, there are two kinds of situation: (1) we can not extract the answer component according to content planning. (2) we extract a wrong answer component.The system can evaluate the coverage automatically, however, the accuracy relies on human judgement. As seen in Table2, we achieve a high accuracy, but the coverage is somewhat low. From the application's point of view, it is better that there is no answer rather than a wrong one.

CONCLUSION

For the off-line QA strategy, we constructed the cooking QA-orientated corpus, the domain documents are annotated with function blocks. The answer planning methodology for answer generation was proposed, By answer content planning, question-answer relationships were captured and the answer component can be extracted from the related database. Generic syntactic templates for answers were summarized. We generate a succinct and explicit answer in natural language to return to user. Evaluation results show that combining with domain knowledge, natural language generating techniques can be used flexibly in the restricted domain QA system.

Text oriented QA has achieved great development ever since its inception. However, how to retrieve and answer the question for multimedia information is not only a challenge, but also a development opportunity for the QA technology. For the practice cooking domain, pictures and videos are more vivid and illustrative than the text information, to build a multimedia cooking QA system will be an interesting direction.

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