

# Task graph based task-oriented dialogue system using dialogue map for second language learning

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**Abstract.** This paper presents a rule-based task-oriented dialogue system for second language learning and a knowledge extraction method which automatically extracts the training data for Natural Language Understanding (NLU) and dialogue rules for dialogue management from a Dialogue Map (DM). The DM consists of turn-by-turn utterances between the system and the learner. Therefore, the proposed method can automatically extend a new dialogue domain by constructing a dialogue map with a simple format. We constructed two dialogue maps for English and Korean, respectively, and implemented English and Korean task-oriented dialogue systems using the DMs. In the experiments, although the turn success rates are relatively low (78.1% in English and 78.76% in Korean), the task success rates are 90.83% in English and 99.17% in Korean. The systems constructed by the proposed method should enable learners to communicate successfully in the topic despite some mistakes in the system responses.

**Keywords:** knowledge extraction method, task-oriented dialogue system, second language learning, dialogue map.

## 1. Introduction

Speech dialogue system technology is a promising tool to use in Computer-Assisted second Language Learning (CALL). Through dialogue with the system, we expect to improve learners' second language skills. Generally, the dialogue system suitable for CALL can be viewed as a Task-oriented Dialogue System (TDS) rather than a chatbot system, as it is necessary to be able to converse with the subject in a

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specific situation (Johnson & Valente, 2009). Most TDSs are implemented as a slot-filling dialogue model which is not suitable for language learning because a slot-filling dialogue consists of only simple request and response pairs.

We already proposed a Task Graph Dialogue Model (TGDM) that enables topic conversation in various situations (Choi, Kwon, Kim, & Lee, 2016). The model can divide a complex topic task into smaller subtasks and define the order between them. In TGDM, subtasks are defined as nodes and the order as edges. We also suggested a DM based on TGDM, which can be constructed by educators who do not know the dialogue systems (Choi et al., 2016).

In this paper, we introduce a knowledge extraction method platform that automatically convert a DM into the knowledge of a TGDM-based TDS to create a dialogue system for a new topic.

## 2. Automatic knowledge extraction for TGDM-based TDS

### 2.1. TGDM

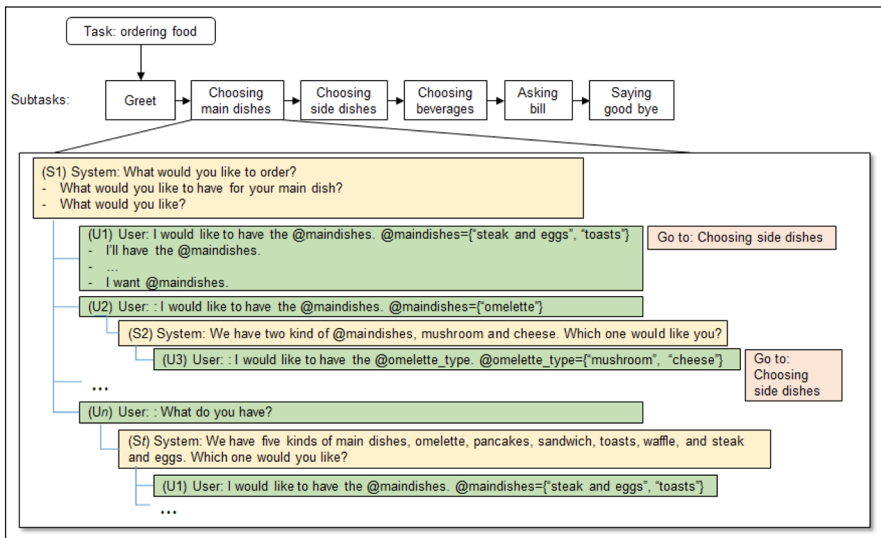
TDS needs a dialogue model that enables dialogue between learners and the system to perform a specific task. The dialogue model defines the dialogue strategy and response of the system to a learner's utterance on the dialogue context. In the model, the utterances and the dialogue context are represented by dialogue acts and slots. A dialogue act is a function of utterance and a slot is a semantic concept in the conversation. For example, in 'ordering food task', the utterance *I want to have a coffee* is represented by *want\_a\_food(beverage='coffee')*, which consists of the dialogue act *want\_a\_food*, as well as the beverage slot and its value *coffee*.

The proposed TGDM divides a complex task into small subtasks and places order constraints amongst the subtasks. TGDM is similar to finite-state transition models. Dialogue models of individual subtasks are implemented as a hybrid dialogue model of a slot-filling and information state. Therefore, TGDM is hybridised with different models, where expression ability of TGDM is more powerful than other models. Also, TGDM can (1) have the advantage that subtasks can be used for other tasks and (2) analyse learner's utterance and generate its system response according to subtasks.

## 2.2. DM for TGDM

DM is a method of expressing TGDM in a dialogue script manner. Figure 1 shows the ordering food task in the snack bar as DM. The ordering food task is divided into six subtasks that consist of turn-by-turn dialogue. The diversity of the conversation flow is made by the learner's various responses to a system utterance. In DM, each terminal turn of the subtask contains the next subtask information (for further details of DM, see Choi et al., 2016).

Figure 1. An example of DM for 'ordering food task'



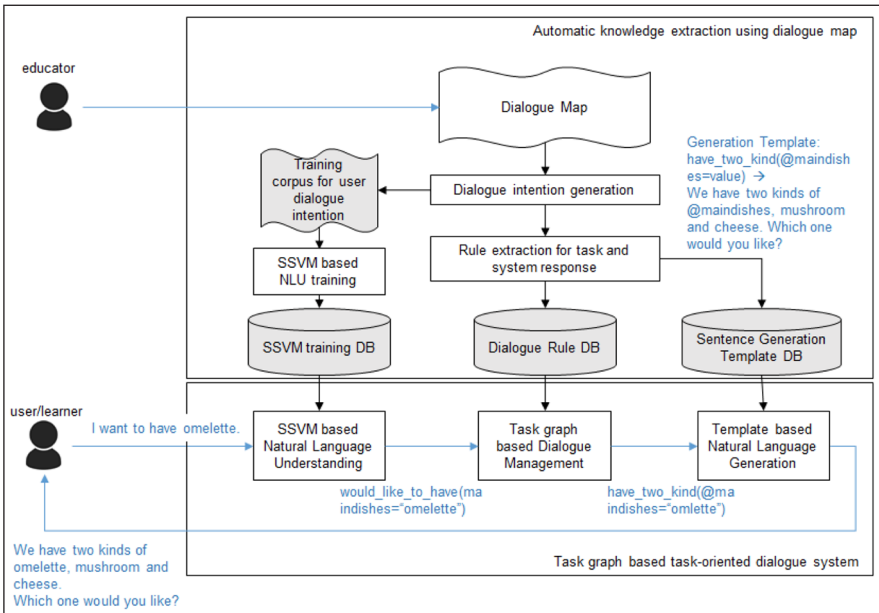
## 2.3. Automatic knowledge extraction using DMs

In this section, we introduce a method that can build a dialogue system for a new task by writing a machine readable DM. Figure 2 shows an overview of our TDS and also the procedures of automatic knowledge extraction method which automatically extracts the knowledge needed by our TDS from the DM.

Our TDS consists of a Structured Support Vector Machine (SSVM) based NLU (Kwon, Lee, Kim, & Lee, 2015), task graph-based dialogue management, and a generation template based Natural Language Generation (NLG). First, SSVM-based NLU analyses the learner utterance and determines the intention using

SSVM training data. Then, task graph-based dialogue management locates the appropriate system response for the learner intention on the context using dialogue rules and updates the context. Finally, NLG generates the system utterance from a template of the selected system response.

Figure 2. Automatic knowledge extraction for TGDM-based TDS using DM



Automatic knowledge extraction methods using DMs consist of dialogue intention generation, SSVM based NLU training, and rule extraction. Dialogue intention generation automatically makes the intention for each utterance in DMs using its predicate and object, which are analysed by shallow parser. If the utterance has no object or the object is a slot, it sets the dialogue act with the predicate, otherwise, with a combination of the predicate and object. For example, Utterances U1, U2, and U3 of Figure 1 have the same predicate *would like to have*, but have different objects. So, the intention generation makes the intention *would\_like\_to\_have(@maindishes='value')* for U1 and U2, and the intention *would\_like\_to\_have(@omelette\_type='value')* for U3.

SSVM training data consists of triples of user sentences of DMs, slot-annotated sentences, and its intentions automatically generated by dialogue intention generation. The SSVM-based NLU training module trains slot classification using

sentences and their slot-annotated sentences, as well as intention classification using sentences and their intentions.

Dialogue rules are generated after dialogue intention generation. The rules are divided into subtask movement rules and turn-by-turn rules. Subtask movement rules consist of a movement condition and a subtask information for the current subtask and the next subtask. The movement condition is defined as the terminal utterance's intention and/or all slots and their values as appear in the path from the initial utterance to the terminal utterance.

Turn-by-turn rules consist of activating the condition and the action to be performed when the condition is satisfied. The rules are extracted from each turn-by-turn utterance. Its condition is constructed by the subtask information, previous intention, and its talker (system or user/learner), and its action is current intention and its talker. From the rules, we may determine a proper system response intention to the user/learner's input on the context, and also proper utterances of the next user/learner's turn to current system response.

Sentence generation templates are easily generated from the utterance pattern of the DM. The templates are classified by the intention and the subtask.

### **3. Preliminary experiments and discussion**

We implemented English and Korean TDSs. The language educators constructed two DMs and implemented two TDSs using the DMs through the proposed knowledge extraction method for each language. To evaluate the performance, we recruited 20 second language learners for each language. The learners freely talked on the given task and conducted four conversations with each other topic on each task.

Table 1 shows the experiment results. The turn success rates to evaluate whether the system responded correctly to learners' utterances are 78.1% in English and 78.76% in Korean, and the task success rates to evaluate whether learners completed the conversation with the system in the topics are 90.83% in English and 99.17% in Korean. There were little differences in the performance depending on the number of learners' conversation attempts. According to these preliminary results, we believe the systems constructed by writing DMs may have the performance to communicate successfully with learners in the topic despite a rather low success rate; this will be further explored.

Table 1. The experiment results

Language	Task	Task success rate %	Turn success rate %
English	ordering food	88.33	78.74
	city tour ticketing	93.33	77.45
	both	90.83	78.10
Korean	ordering Korean food	100	81.41
	clothes shopping	98.33	75.65
	both	99.17	78.76

Task success rate (%) = (number of task completed dialogue) / (total number of dialogue) x 100

Turn success rate (%) = (number of correct system's responses to learners' utterances) / (total number of learners' utterances) x 100

## 4. Conclusions

This paper describes an automatic knowledge extraction method developing TDS using the DM. Through the experiments, the performance of the TDS constructed by writing a DM showed that second language learners could successfully practice conversations on a given topic. With the proposed automatic knowledge extraction method, we expect that anyone could construct dialogue systems for language learning. In future research, we will investigate whether educators can build DMs quickly and easily and collect more data to further improve the system's success rate.

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