# APPLICATION OF TASK-ORIENTED DIALOGUE IN OPERATIONS FOR FUTURE NETWORKS TO BUSINESS

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***Abstract*** *– At present, the network operation services provided by operators for to business (toB) customers have customer friendliness issues mostly affected by manual input. The limitations are reflected in four aspects: time consumption and understanding differences in the process of customer intention communication, waiting time and lack of process transparency. Therefore, in order to provide a more automatic, standard, concise and user-engaged method on operations for future networks in the toB field, this paper proposes applying a task-oriented dialogue system to the network operation task processing. The most significant advantage is that it makes possible for industry customers to participate directly in and facilitate their task completion process together with the system by several turns of dialogue. The conventional pipeline structure which combines both neural networks and rules is appropriate for meeting the above requirements for providing unified natural language understanding of intent, tracking dialogue state and generating actions of reply or command. With the help of a knowledge database and a network management system, the dialogue system provides users with more detailed operation information, which directly promotes user participation and transparency of the whole service process.*

**Keywords** – Artificial intelligence, customer friendliness, knowledge question & answer (Q&A), task-oriented human-machine dialogue, operations for future network services to business

## 1. INTRODUCTION

Task-oriented human-machine dialogue systems are applied to help users complete specific tasks in a certain field, such as ordering food, checking the weather, booking air tickets, etc. [1-2]. The typical pipeline structure is composed of six modules: Automatic Speech Recognition (ASR), Text To Speech (TTS), Natural Language Understanding (NLU), Dialogue State Tracking (DST), Dialogue Policy Learning (DPL) and Natural Language Generation (NLG), which are mainly responsible for functions that support understanding a user's intention, tracking dialogue state and generating decision-making actions (reply to the dialogue or call external APIs to complete a concrete operation) in each turn of the dialogue [3]. Deep learning technologies, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Hierarchical Recurrent Encoder-Decoder (HRED), attention networks, transformer, reinforcement learning, knowledge graph and augmented neural networks, have been used to tackle various tasks involved in the above-mentioned modules. For tasks of domain classification, intent detection and slot filling in NLU, there are many works aiming at combining multitasks into a joint learning framework [4-6]. For DST and DPL modules, some of the implementations are based on handcrafted rules [7-8], more and more methods reliant on deep learning have also emerged. Minimal belief span or Bert have been proposed to optimize the performance in state tracking [9-10] and reinforcement learning or supervised learning have also started to be used for dialogue policy learning [11-12].

Above all, while the rapid growth of deep learning has promoted the performance of dialogue systems, traditional rule-based dialogue systems are still of great value in industry domains. In this paper, task-oriented dialogue technology is applied to the field of network intelligence by integrating it with the traditional original network operating system called Operating and Supporting System (OSS) for networks. The new system creatively supports network business operation completion by human-computer dialogues with a focus on real-time voice or text interaction with the users. In expectation of increasing operational transparency, it is also possible for the dialogue system to provide customers with sufficient knowledge Questions & Answers (Q&A), knowledge introduction and details display, so that customers can have a deeper understanding of what actions or steps are included in the whole service process. Deep learning and rules methods are both effective for the dialogue function modules in the proposed network operating system. In these modules, definitions contain structural semantics and training data of the deep learning model, action types and mapping rules with the state, as well as a natural language reply template in the dialogue.

Compared with existing technology, this method has the advantages of a unified intention analysis standard, fast service response, deeper user participation and transparent operating process. It may solve the problem of customer friendliness in the current network operation service to business provided by operators to a certain extent.

## 2. DIALOGUE SYSTEM FOR OPERATIONS ON FUTURE NETWORKS TO BUSINESS

The dialogue system for operations on future networks to business is composed of ASR, TTS, NLU, DST, DPL and NLG modules in a pipeline structure. It has the abilities of supporting the understanding of a user's intent, tracking dialogue status and generating decision-making actions (reply to the dialogue or invoke external APIs) in each turn of the dialogue, to continuously promote the completion of the network operation objective. It is distinguished from any other traditional system since constant user intent tracking can be achieved by interactions with users. Nevertheless, it is correlated to the original network operating system by the way of merging into a new service system, the network operating system based on task-oriented human-machine dialogue (as shown in Fig. 1).

Fig. 1 also shows the data transfer relationships between the internal modules or with the external environments for a Dialogue System (DS), which is also consistent with the regular pipeline dialogue system. The coloured lines and other information in Fig. 1 refer to the following:

Black lines: internal interactions

$X_n$: text utterance

$U_n$: user action

$S_n$: current new state according to the dialogue

$A_n$: decision-making system actions

$Y_n$: system response

Red lines: external interactions with the user and other systems such as Knowledge Base (KB)

In addition to the system architecture overview, specific functions of NLU, DST, DPL, NLG modules and interactive interfaces are given in the following sections.

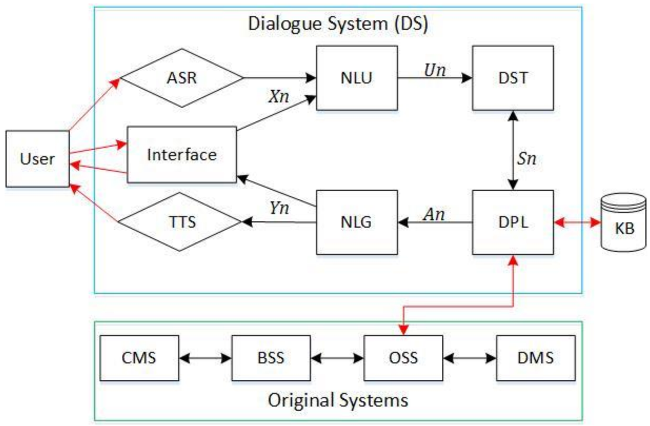


**Figure 1** – Network operating system based on task-oriented human-machine dialogue

### 2.1 NLU module

#### *2.1.1 Training module*

The NLU module needs to accomplish intent recognition and slot filling, which are text classification and sequence labelling tasks respectively. An attention-based bidirectional RNN model [4] with a shared encoder and independent decoders for joint intent detection and slot filling is adopted considering the module simplicity.

#### *2.1.2 Training data*

On the basis of model pre-training, the annotated data converted from historical toB network order data can be used for model fine-tuning and supervised deep learning.

The input data of the bidirectional RNN model can directly use the customer-oriented natural language text corresponding to the historical work order before sales. When the training text data is insufficient, the existing structured work order data is appropriate for generating natural language text to simulate customers' requirements, which belongs to data-to-text or attribute-based text generation tasks which can be achieved using LLMs such as GPT.

For example, when using real work order data to fine-tune GPT, three steps are required basically. Firstly, the training data should be determined. It is possible to obtain input data through extracting all the {Key,Value}s from real work orders provided by customers covering the predefined network operation intentions and slots both in NLU, and use the corresponding real order pre-sales text (can be translated manually if not available) as output data. Then, fine-tune GPT to obtain a model responsible for converting structured data to natural text. Finally, in order to simulate different customers' requirements, values of the keys are combined as much as possible as input of the reasoning, and the corresponding output text can be used for supplementary input data of the RNN model training.

The output data of the bidirectional RNN model is transformed from real or simulated structured order data according to the predefined semantic structure. The definitions of semantic structure include the value range of intention and slot. There are two kinds of user intentions defined in the dialogue system for network operation tasks. One is to operate networks such as 5G private network creation or dedicated Internet access modification, the other is to obtain knowledge related to network operations. The target slots for each network operation intention are defined equal to the keywords corresponding to all the specific processing in the workflow. The actual value of intention and slots related to the customer requirements corresponding to each existing order can be automatically recognized almost directly according to specific keywords. For instance, extract values of keywords "business type" and "order operation type" and combine them to express the value of intention. The way of extracting slot values is similar to intention.

## 2.2 DST&DPL module

In the dialogue system, DST and DPL cooperate closely to drive the progress of the task all the time. DST is responsible for tracking the dialogue state and synthesizing the new dialogue state according to the current input of the dialogue, historical dialogue state, and interactions with external systems. DPL decides the actions and strategies of the current turn of dialogue according to the output dialogue state of DST [13].

A method implementing action decision processes for each turn of dialogue is proposed based on definitions on actions (Table 1) and decision-making rules (Fig. 2). Table 1 shows six actions respectively with different meanings and oriented objects. Fig. 2 depicts mapping between current dialogue state and actions derived by a question sequence. The action execution results (output) will fill in the template predefined in the NLG module to support reply.

**Table 1** – Action interpretation

| Abbr | Meaning | Oriented Objects | Output (Content filling in the template) |
|---|---|---|---|
| RB | roll back performed for the last intention | OSS | null |
| CI | confirm intention | user | unsure user intention |
| C | confirm slot value | user | unsure slot values |
| O&PI | invoke APIs of OSS | OSS&user | task progress |
| R | require slot value | user | missing slot values for next operation |
| E&R | explore knowledge and reply to the user | KB&user | knowledge provided for the user |

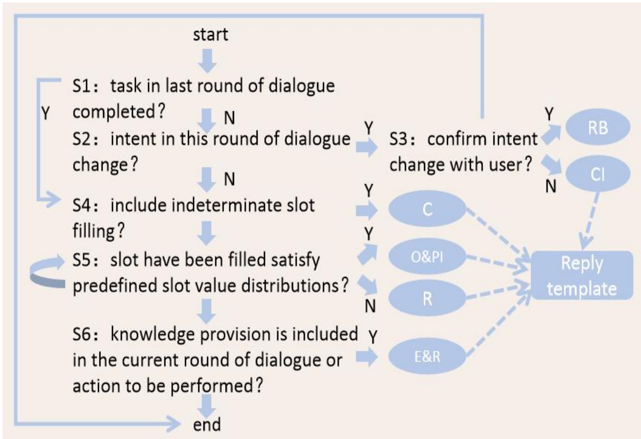


**Figure 2** – Mapping of state in DST and action in DPL of the dialogue system

The designed decision-making process may include six steps, more or less. In order to determine whether an action is needed for the current turn of dialogue state, we first define the state as follows:

$$Sn = \{G_n,\ U_n,\ H_n\} \quad (1)$$

$$Hn = \{U_0,\ A_0,\ U_1,\ A_1,\ \dots,\ U_{n-1},\ A_{n-1}\} \quad (2)$$

The parameter $G_n$, $U_n$, $H_n$ represents the meaning of distribution of current slot filling, semantic user action and historical states. The historical state $H_n$ consists of history output of NLU and all the actions performed before.

Then, the network operation intentions, semantic slots and network operation actions are predefined in NLU and DPL modules in the correct order. In order to enable NLU to identify according to the expected network operation intention, some intentions are required to be defined in advance, such as 5G private network creation, Internet private line modification, and so on. Similarly, in order to determine whether a network operation action should be called according to the dialogue state to promote the task progress, network operation actions and semantic slots are also predefined. The network operation actions for each intention are predefined as all the processing and calculations of the existing network operation order corresponding to the intention, such as network topology designing, network element instance selection, network service data configuration. The universal target slot set corresponding to each intention is defined as all the business keywords needed to realize all the actions of the intention. Each action corresponds to a slot value distribution $\mathrm{G_m}$ when it is triggered to be executed, so that the network operation task can be converted into a target semantic slot filling process in the dialogue system.

The complete action decision-making process in each turn of the dialogue is as follows:

S1: Once the decision process starts, first confirm whether the network operation task in the last turn of dialogue has ended.

S2: If the task is not finished, confirm whether the intention of the network operation in this turn of dialogue has changed compared with the last turn.

S3: If the intention of this turn has changed, it is determined whether the change intention has been confirmed with the user. If confirmed, the dialogue system will call OSS interfaces to roll back all the network operations of the previous intention task. Otherwise, confirm intention change with the user and the decision process is ended.

S4: If the intention is unchanged or the last turn of dialogue task has ended, it will determine whether the filled semantic slot values of the current turn of dialogue contain uncertain slot values with low credibility. In this case, the system will actively request the user for the uncertain slot values.

S5: If the semantic filled slot values (Gn for example) transformed by NLU of this turn of dialogue satisfies the slot value distribution of a predefined action (Gm for example), this action belonging to O&PI type will be executed. After that, DST updates the state, and determines whether the execution condition of some of another action of the O&PI type is satisfied according to the slot value distribution in the new state, and circulates it. When Gn matches Gm which symbolizes the end of the network service operation, it also marks the end of the task in the dialogue. If the intent is unchanged after the current action has been performed but the current slot values are not sufficient for any predefined slot value distribution of network operation action, the customer is asked for the missing slot values compared to the next predefined distribution.

S6: If the intention content of the dialogue includes knowledge questioning or the condition that any one of action types C, R or O&PI involves introductions of professional knowledge, the dialogue system interacts with the knowledge database to obtain professional knowledge data and replies to the user.

## 2.3 NLG module

For the other five action types C, CI, O&PI, R and E&RA, a unified reply template is adopted. The template content is transformed to generate natural language that users can understand for reply.

The reply template can be defined as follows:

{

business: (task progress),

require slot value: (missing slot values),

confirm slot fill: (unsure slot values),

confirm intention: (unsure intention),

information: (professional knowledge)

}

The knowledge originates from knowledge databases which use mapping knowledge domains based on attributed graphs or RDF.

## 2.4 Interactive interface

To assist the speech dialogue, the human-computer interaction interface provides several other interaction forms with the user. While the user hopes to provide requirements describing network operations through text (including text file), voice file or image way, the interface can support uploading. Knowledge Q&A window plays a role in solving users' questions in a timely and efficient way through text. Meanwhile, when the dialogue system determines to guide the user to provide more requirements for promoting the progress of the task or help the user understand more about the professional terms involved in the operation process actively, the dialogue system displays the natural language text generated by NLG on the interface for the user. In addition, the dialogue system displays task progress throughout the entire process and displays the complete operation information containing actual network topology after the task is completed.

## 3. APPLICATION METHOD

The interaction relationships of the new architecture based on task-oriented dialogue systems are shown in Fig. 3. The interaction functions of data configuration, card management, accounting and some others between the OSS and Business Supporting System (BSS), the OSS and Data Management System (DMS) and between the BSS and Card Management System (CMS) still work as usual unchanged therefore not emphasized here.

Three parts of interaction are added to the new architecture with the dialogue system regarded as the core. The added interactions including the horizontal between the DS and user and between the DS and knowledge database, and the vertical between the DS and OSS contribute to the restructure of the new network operation method based on the task-oriented human-machine dialogue.

A network operation task involves multiple turns of dialogues with the user. In each turn of dialogue, the user talks about requirements or asks questions about network knowledge to the business, and interacts with the DS or interface through real-time voice, text or both files (interaction1). The dialogue system decides the action according to the decision process shown in Fig. 2. When the decision action is to obtain expertise to reply to the user (E&R), the dialogue system interacts with the knowledge database (interaction2). When the decision action is to execute a specific network operation (O&PI), the dialogue system interacts with the OSS (interaction3). Interaction1 also includes generating natural language responses to the user through real-time text or voice based on reply templates (content includes confirming intention or slot values, requiring slot values, progress informing and providing knowledge). When action type OA&PI generated by the DS is the last one in the predefined action set, the interactive interface displays complete operated business information, actual complete networking topology and other information.

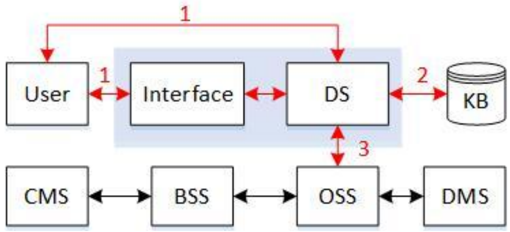


**Figure 3** – Interactions in network operating systems based on task-oriented human-machine dialogue

## 4. APPLICATION EXAMPLE

Next, 5G network slicing is taken as an example to illustrate the network service operation process based on task-oriented human-machine multi-turn dialogue.

Assume that the predefined semantic structure of the 5G private network creation operations is as follows:

{

Intention: 5G private network,

Slot: {

Package type (A, AA, AAA),

Park location,

UPF deploy location (park, country, city, province),

If base station exclusive (Y/N),

Base station count exclusive (0-100),

DNN networking mode (dedicated transmission, internet tunnel),

DNN tunnel access mode (GRE, L2TP, IPSEC),

AN resource instance,

TN resource instance,

CN resource instance,

If operation successful (Y/N)

}

}

Also assume the predefined network operation actions are as follows:

OA1: query Access Network (AN), Transmission Network (TN) and Core Network (CN) network resource instances

OA2: create AN, TN and CN subnetwork in parallel

OA3: create DNN

The actions are triggered by condition1-3 (satisfied slot value distribution).

If the dialogue can progress successfully, the process may be as follows:

**First turn:**

S1: The text recognized by ASR is related to the dedicated 5G network creation, including words similar to park location and base station exclusive. The content may be “Hello, I would like to request a 5G private network in the park of location PL, where the base station is exclusive”.

S2: The result transformed by NLU is as follows:

$I_1$: 5G private network creation

$G_1$ : {Package type: AAA, Park location: PL, UPF deploy location: ?, If base station exclusive: Y, Base station count exclusive: ?, DNN networking mode: ?, DNN tunnel access mode: ?, AN resource instance: ?, TN resource instance: ?, CN resource instance: ?, If operation successful: ?}

S3: $S_1 = G_1$. Condition1 is not satisfied. As a result, DPL decides action A1 includes three types of sub-actions. In order to meet state1, it is necessary to ask the customer the number of base stations exclusive (R type action), and confirm whether the deployment level of core network User Plane Function (UPF) is park level (C type action). Interacting with the knowledge base to obtain professional terms and knowledge related to the content of this turn of dialogue, such as package service introduction, suggestions on the number of base stations and conveying this information to the user (E&R type action) is also meaningful.

S4: NLG embeds the decided actions into the reply template as shown below.

{

business: (started processing),

require slot value: (base station count exclusive),

confirm slot fill: (if UPF deploy location is park level),

information: (package service introduction, suggestions on the number of base stations)

}

The corresponding natural language content may be like “OK. Your requested business has started to be processed. Could you please provide us more information about your requirements? The deployment level of core network UPF is hoped to be further confirmed and the number of wireless base stations exclusive is hoped to be provided according to our advice. AAA package business service can provide more isolated level resource in the access network. We advise you the base station count can range from 5 to 10.”.

**Second turn:**

S1: The text recognized by ASR confirms the question in the last turn of dialogue, including confirming the UPF deploy location is park level and required base station count is approximately 6.

S2: The result transformed by NLU is as follows:

$I_2$: 5G private network creation

$G_2$: {...UPF deploy location: park, Base station count exclusive: 6...}

S3: $S_2 = \{S_1, A_1, G_2\}$ . Condition1 is satisfied. DPL decides action A2 OA1.

S4: NLG embeds the decided actions into the reply template as shown below.

{

business: (querying access, transmission and core network resource instances)

}

**Third turn:**

S1: After the end of the second turn, the user does not initiate a new dialogue. As a consequence, after receiving the success notification of the operation from the OSS, DS directly updates the status to $S_3$.

S2: The result transformed by NLU is as follows:

$I_3$: 5G private network creation

$G_3$ : {...AN resource instance: ListAN, TN resource instance: ListTN, CN resource instance: ListCN...}

S3: $S_3 = \{S_2, A_2, G_3\}$ . Condition2 is satisfied. DPL decides action A3 includes three types of sub-actions. Firstly, predefined action OA2 is to be operated through interaction with the OSS. In order to meet state3, it is necessary to ask the customer DNN networking and tunnel access mode (R type action). It is required to interact with the knowledge base to obtain professional terms related to the content of this round of dialogue, such as DNN, DNN networking mode and DNN tunnel access mode (E&R type action).

S4: NLG embeds the decided actions into the reply template as shown below.

{

business: (creating AN, TN and CN subnetwork in parallel),

require slot value: (DNN networking mode, DNN tunnel access mode),

information: (DNN networking mode, DNN tunnel access mode)

}

The corresponding natural language content may be like “Three subnetworks are being created in parallel for you. Please wait patiently. Could you please provide us more information about the requirements about the DNN networking and tunnel access mode you expected? DNN refers to a private data network in our 5G private network creation service. The networking modes of DNN include transmission line, public network tunnel and tunnel access modes include GRE, IPSEC, and L2TP.”.

**Fourth turn:**

S1: The text recognized by ASR confirms the question in the last turn of dialogue, choosing transmission line mode GRE tunnel according to the provided range.

S2: The result transformed by NLU is as follows:

$I_4$: 5G private network creation

$G_4$ : {...DNN networking mode: transmission line, DNN tunnel access mode: GRE...}

S3: $S_4 = \{S_3, A_3, G_4\}$ . Condition3 is satisfied. DPL decides action A4 OA3.

S4: NLG embeds the decided actions into the reply template as shown below.

{

business: (creating DNN),

}

**Fifth turn:**

S1: After the end of the fourth turn, the user does not initiate a new dialogue. As a consequence, after receiving the success notification of the operation from the OSS, DS directly updates the status to $S_5$.

S2: The result transformed by NLU is as follows:

$I_4$: 5G private network creation

$G_4$: {...If operation successful: Y}

S3: $S_5 = \{S_4, A_4, G_5\}$ . The condition representing the end of the task is satisfied. By the time, all the slots have been filled. DPL decides action A5 only needs to inform the user of the operational result of the task.

S4: NLG embeds the decided actions into the reply template as shown below.

{

business: (operation finished successfully),

}

The corresponding language content may be like “Your task request has been operated successfully. Thank you for your trust”.

## 5. EXPERIMENT RESULTS

To verify the effects of the proposed network operating system based on task-oriented human-machine dialogue, the system was implemented by connecting the module DPL in a dialogue system with the original network operating system and a knowledge base with professional terms and knowledge. At the same time, an experiment was designed especially. 15 testers participated in the experiment. They were assigned the same typical network operation task. They described requirements in distinguishing natural language style. For comparison, everyone completed two communications, one with the dialogue system and the other with the customer managers in the traditional workflow. The testers also provided evaluation results subjectively after each task completed.

Statistical data was collected and calculated from four concerned indicators, with comparison results which could mainly reflect the system advantages (Table 2).

**Table 2** – Indicator statistics

| Indicator | Calculation Method | Statistics Comparison | |
|---|---|---|---|
| | | proposed | Traditional |
| Intention Similarity | count of task with similar intent recognition result /task amount | 86% | 73% |
| Average Task Completion Time | task completion time amount /task amount | 192 minutes | 206 minutes |
| User Participation Satisfaction | subjectively satisfied task count /task amount | 93% | 53% |
| Transparency of Operation Process | count of task with subjectively transparent operation process /task amount | 93% | 27% |

Compared to the statistics of traditional methods of network operating systems, the performance of the system based on task-oriented human-machine dialogue has mostly proved its expected effects. The system basically worked well as expected. The two objective indicators Intention Similarity and Average Task Completion Time performed better 13% and 7% approximately than the traditional way of work order. The other two subjective indicators, User Participation Satisfaction and Transparency of Operation Process were 40% and 66% higher than the traditional way respectively, also proving absolute advantage in customer friendliness. Most testers acknowledged they had obtained more details about the operations.

## 6. CONCLUSION

This paper proposes to apply the task-oriented dialogue system to the network operation in the field to industry business which promotes the completion of tasks in the process of in-depth interaction with the customer. It provides sufficient knowledge Q&A, knowledge introduction and details display in the service process, so that customers can have a deeper understanding of them.

Compared with traditional methods, the human-machine dialogue has the advantages of a unified intention resolution standard, fast service response, deeper user participation and a transparent operational process. It can solve the problems of customer friendliness existing in the current network operation service provided by operators to industry business. At the same time, it is possible to relieve the pressure of the original service bearer system and customer managers to a certain extent. Therefore, it is suitable for operators to innovate in network product ordering and operation modes for industry customers, supporting users to deeply participate in network operation processes and increase customer trust naturally.

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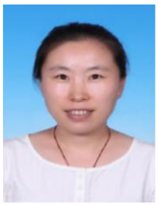

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