User Intention Recognition and Requirement Elicitation Method for Conversational AI Services

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Abstract—In recent years, chat-bot has become a new type of intelligent terminal to guide users to consume services. However, it is criticized most that the services it provides are not what users expect or most expect. This defect mostly due to two problems, one is that the incompleteness and uncertainty of user's requirement expression caused by the information asymmetry, the other is that the diversity of service resources leads to the difficulty of service selection. Conversational bot is a typical mesh device, so the guided multi-rounds Q&A is the most effective way to elicit user requirements. Obviously, complex Q&A with too many rounds is boring and always leads to bad user experience. Therefore, we aim to obtain user requirements as accurately as possible in as few rounds as possible. To achieve this, a user intention recognition method based on Knowledge Graph (KG) was developed for fuzzy requirement inference, and a requirement elicitation method based on Granular Computing was proposed for dialog policy generation. Experimental results show that these two methods can effectively reduce the number of conversation rounds, and can quickly and accurately identify the user intention.

Index Terms—Knowledge Graph; Uncertainty requirement Analysis; Multi-round dialogue; Cognitive Service Computing; chat-bots; Conversational AI Bot; Granular Computing.

I. INTRODUCTION

In recent years, Apple’s Siri, Microsoft Cortana, and other service products have become more and more popular. Conversational AI bot, such as Intelligent Voice AI Assistant, has been trained to understand voice commands and complete tasks for users in various application scenarios. The convenience of conversational AI bot makes the cognitive service computing system an inevitable trend in the future. We had developed this kind of Cognitive Service Robot, to help users to find appropriate services and construct coarse-grained service solutions [1]. According to the method referred in above, we perform domain validation predictions for user requirements. During the conversational AI bot development, we found that massive services with various functional and non-functional attributes make it very difficult for cognitive service to select the user expected services automatically and accurately. This problem requires the user requirements, including dominant or implicit, can be recognized automatically.

Understanding and feedback are two basic abilities for bots. However, they are great challenges for bots to achieve intelligence. Currently, there are three kinds of bots, Q&A bot, Task bot, and chat-bot. Most of the Q&A bot prefers to deal with single round conversations, rather than the complex ones with context. Task bot are specialized for one domain related mission, such as navigation, or any kinds of consulting. They might reject to provide service once the request beyond their ability, which is given by domain prior knowledge. Chat-bots are more like a pet, only responsible for entertainment-related matters.

Conversational AI bot can be considered as a cognitive mediator to lead users to the service world. The two methods proposed in this paper can help bots to adapt to more complex scenarios and deal with the intention contained in the user’s fuzzy and uncertain requirement expressions. Their accurate recognition results would further support bot to make service recommendation decisions by selecting different services from various domains (as shown in Fig. 1). In addition to the above tasks, these two methods also need to contribute on the following breakthroughs. So, the human-computer interaction of bot would be more natural and intelligent. Firstly, to minimize the formatting of system input, especially rule-based input. Secondly, to make the method of user intention understanding more flexible and intelligent. Last but not least, not to be single specific domain. Different from the traditional dialogue mode, when the user needs a housekeeping cleaning service, he doesn’t need to give the command “please make an appointment for housekeeping”. Instead, he may inadvertently say, “the kitchen is a little dirty”. The bot should automatically infer the user’s intention, and then clear the details of the service, such as price and time, through several rounds of inquiry.

Fig. 1. Challenge and Contribution

Generally, the multi-round conversation for eliciting user requirements is led by a knowledge graph based inference rather than the predefined domain rules. This knowledge graph is constructed based on the description of services from several domains by using our previous work [2]. The domain projection method mentioned in this work and the
**A. The status of chat-bot.**

Early chat-bots generally adopted a rule-based Q&A bot bases on a semantic template called an expert system. The system finds the best answer through the template matching paradigm. In recent years, the structure of the Q&A system has also transformed from a traditional template-based method to a knowledge-based approach. The system can use search, logical reasoning, and other ways to find answers to user questions. But it is limited to the scale of the knowledge graph when input requests are outside the scope of the knowledge graph, the stability of the answer drops distinctly.

Chat-bots used information retrieval technologies to achieve the best match between questions and answers since 1995. They are not prone to grammatical errors, but they may not be able to deal with scenes without pre-defined. After receiving the user data, bots use a specific method to create a sentence automatically. The benefit is that the bot can cover user questions on any topic as the response. But the disadvantage is that the quality of the response sentence generated may have problems. For example, the statement may not be fluent or has syntax errors and other low-level errors. The chat-bots can serve in the open domain or limited domain. In the open-domain environment, the user can chat with the bot about any content belonging to the open-domain category (still countable domain). In the limited field, the user can barely talk about the dialogues that are not preset within this specific domain.

As an open-source bot, ALICE built according to rules that receive input and generate output, but there are no automatic statements and questions and no response to user input. Google Now is a smart personal assistant software that answers questions and provides suggestions through a series of web services. It also predicts what information may be needed based on the user’s past search habits. This paper gives the comparison of various types of robots shows in TABLE I.

**B. Requirement acquisition and analysis**

Requirement acquisition and analysis is an essential part of accomplishing project tasks. Traditional methods use user records to identify intentions. Letizia and Lieberman proposed to represent documents of interest to users as keyword vectors, and calculated each keyword weight to establish a user demand model. Li el used weakly supervised learning methods to extract user-related information from Twitter social data. Venkatesan records user requirements by analyzing the user’s behavior log. Srinivasan and Batri conduct user requirements analysis by users’ search records on the server.

The traditional chat-bots obtain the query intention by directly matching the word list. At the same time, it can accurately solve the high-frequency words by adding categories that are relatively simple and have relatively concentrated query patterns. However, it requires more human participation, which is challenging to automate.

Ontology analysis is also a common method in traditional requirements analysis methods. In 2006, Kaiya and Saeki used ontology to build a domain knowledge base for requirement analysis. (For example, “today’s air ticket price from a to b” can be converted into [location] to [location][date][bus/air/trainticket] price.) This method of intention recognition by rules has better recognition accuracy for the requirement with strong regularity and can extract accurate information. However, the process of discovering and formulating rules also requires more human participation. Zhang and Wallace regard intention recognition as a classification problem and define different categories of requirement intention according to the characteristics of vertical products, and common words for each intention category can be counted. For the requirement input by the user, the probability of

### TABLE I

| Type of Bot                            | Attention                                | State                        | Benefit                                      | Weakness                                   |
|---------------------------------------|------------------------------------------|------------------------------|----------------------------------------------|--------------------------------------------|
| QA Bot based on Reading Comprehension | Confirm User Question and Answer         | Understand User Intention    | Pinpoint the answer to the question;          | Single dialogue;                                    |
|                                       |                                          |                              | Answer highly relevant;                       | Context free;                                |
| Task Bot based Dialogue System        | Take action and Extract keywords          | Clear the propose            | Pinpoint to the domain;                      | Resolving for a specific scenario           |
|                                       | Based Dialogue                           |                              | High probability of success in each round;   |                                            |
|                                       |                                          |                              | Multi-dialogue;                              |                                            |
| Chat-bots                             | Answer and Response                      | The History of Communication | Natural Interaction without limited domain;  | Unable to solve problem                     |
| KG Conversational AI Bot              | Understand User need and filter the possible service base on Multi-dialog System |                             | Accept unlimited input;                      |                                            |
| Method (Our Bot)                      |                                          |                              | Pinpoint the dialog domain;                  |                                            |
|                                       |                                          |                              | Clear the condition by Multi-dialogue;       |                                            |
|                                       |                                          |                              | Reasoning based on KG;                       |                                            |
|                                       |                                          |                              | Return the proper solutions;                 |                                            |
|                                       |                                          |                              |                                              |                                            |
each intention is calculated according to the statistical classification model, and finally, the intention of the requirement is given. Google proposed the Bidirectional Encoder Representation from Transformers Model (BERT), which significantly improved the ability to identify user intention in 2018 [14]. The BERT model is used to solve the Q&A and service recommendation problems based on the KG.

III. MOTIVATION AND PROBLEM DEFINITION

A. Motivation

In general, this study aims at proposing a human-like machine dialogue method. This method can lead users to express their requirements completely and accurately, step by step. Currently, most of the existing chat-bots work quite well with the requirement expression in a fixed format or trigger. However, this is not a human style, in which every single expression in a conversation could be full of metaphor, implication, and personalization. This would cause the incompleteness, diversity, or implication of the user requirement proposition. It means uncertainty that brings a huge challenge to the intention understanding of the bots. The partial semantic description and various expressions, especially for specific nouns and local dialects, extremely affect the accuracy of intention identification. Thus, it makes the original expression of user requirements difficult to be translated into machine understandable service objectives.

Artificial design of semantic slots is the most commonly used way for intention understanding of chat-bots. Traditional Q&A uses feature extraction and matching method to realize requirements understanding and identify requirements domain, which is based on rules, word embedding, or classifier (such as Bayes). However, it has a strong dependence on domain knowledge, which makes it difficult to switch between different domains in conversation semantic space and action space. Besides, most of the existing question understanding methods are focus on the questions of single sentence form, which also relies on a specific sentence structure. Therefore, to not only identify person, location, organization, and date but identify also much more fine-grained entity types, this paper use the BERT model to enhance the ability of recognition.

The traditional Q&A modes are always suffered from problems like inaccurate information retrieval, redundant Q&A information error, etc. Although big data and deep learning methods have greatly improved their accuracy, the number of samples substantially limits the personalization of the answers. However, different people will not always have the same requirement. Therefore, guided multi-round Q&A should be the most suitable way for requirements elicitation. This requires the method of requirement pruning to generate dialogue strategy.

The decision tree algorithm is one of the commonly used pruning methods. Typically, when the number of candidate service is small, this algorithm can correctly and efficiently classify the services. However, once the number of candidate service become larger and larger, the tree would become more complex with tremendous nodes. Then, this algorithm would not be possible to perform well as expected, no matter in accuracy or efficiency. While the granular computing [15] can deal with large-scale problems, many reasoning algorithms combined with rough set theory and granular computing theory, and form multi-granular and multilevel analysis and processing methods. Granular computing theory can perform granular analysis on the domain information represented by big data, and determine the number of possible granularity levels. The results of the analysis and its quality can affect the accuracy and efficiency of dialogue strategy generation. This paper selects suitable multi-granularity modeling for specific data to achieve support for specific GrC models that can better perform data analysis.

B. Problem Definition

Definition 1 (Service Knowledge Graph): Knowledge graph is a structured semantic knowledge base. Service knowledge graph $G \in (E, R, S)$, and $E = \{e_1, e_2, \ldots, e_{|E|}\}$ is the set of the entities in knowledge base, which includes $|E|$ different entities. Entities includes service entity nodes $sn_i$ and attribute nodes $Attribute_e$. $R = \{r_1, r_2, \ldots, r_{|R|}\}$ is the set of the relationships in knowledge base, which includes $|R|$ different relationships. Realationships in service KG are the labels of attributes $S \subseteq E \times R \times E$ represents the set of triples in the knowledge base. The semantic is “The $r_k$ of $sn_k$ is $Attribute_e$” ($k$ is any value).

Definition 2 (User Initial Intention): System accepts an initial user fuzzy requirement as input $S$. And the paper can get an analysis result $D$ of user intention, where $D$ includes lots of requirement concerns $D_1, D_2, \ldots, D_i, \ldots$. For every $D_i$, there are some restrict sets $H_{ij}$. Restrict set is a set of a label with some attributes. The label is the identified entity type by BERT model. The attributes of the label are the constraint conditions that the user proposes. The structure of $H_{ij}$ and $D_i$ are shown as below:

$$D_i = \{H_{i1}, H_{i2}, \ldots, H_{ij}, \ldots\}, \forall i, j > 0$$

(1)

$$H_{ij} = \text{label} : \{\text{Attribute}_1, \text{Attribute}_2, \ldots\}$$

(2)

Definition 3 (Requirement Pruning Strategy): This strategy aims at finding the mutually exclusive service attributes for individual requirement inquiry. Thus, all services need to be optimally clustered into $C = \{C_1, C_2, C_3, \ldots, C_k\}$ according to these different attributes. The optimization objective function of clustering algorithm is defined as equation $\mu_{ij}$ is the membership degree of service $sn_j$ and cluster $i$, as defined in equation $\mu_{ij}$ is a weighted value; $d_{ij}$ is the distance between the attribute vector of the service $sn_j$ and the cluster $i$ vector, which is recorded as $\sum_{t=1}^{N_a} (y_{it} - m_{it})^2$. Where $y_{it}$ and $m_{it}$ are the value mapping of the service $sn_j$ and centroid point $m_{it}$ on attribute $t$ ($m_{it}$ is the clustering center vector), $N_a$ is the number of attributes.

$$\mu_{ij} = \left( \sum_{t=1}^{c} \left( \frac{d_{it}}{d_{ij}} \right)^{m-1} \right)^{-1}$$

(3)

$$\text{Goal} = \sum_{j=1}^{n} \sum_{i=1}^{c} (\mu_{ij})^m (d_{ij})^2$$

(4)
IV. OUR METHOD OF SOLVING PLAN

A. Overview of the Framework

As shown in Fig. 2, the framework proposed in this paper consists of four major modules, NLU (Nature Language Understanding) module, Reasoning Module (RM), Dialogue Management Module (DMM), and NLG (Nature Language Generation) module. NLU identifies the domain that user requirement belongs to, and the intentions implied in the user expression. RM decides what the candidate services are. DMM requires the domain of one short sentence. This command is always a fuzzy text requirement. As mentioned in Definition 2, this command input contains user initial intentions $D$, which can be recognized by the fine-tuned BERT model. If $D$ is empty, this command would be regarded as a chatting command, which cannot trigger the follow-up rounds. Otherwise, the intention set $D$ would be transferred into the reasoning module. Meanwhile, the result $\beta$ of the module “domain identify” would be saved for follow-up rounds.

This fine-tuned BERT model is trained based on the google BERT model (https://storage.googleapis.com/bert_models/2018_11_03/chinese_L-12_H-768_A-12.zip) with domain-specific corpus.

2) Follow-up Rounds: The reasoning module with initial intention set $D$ can generate the first reply (the detail would be explained in the next section). According to this reply, the user reacts with a new command. It would enter the module “domain identify function as well. If its output does not equal the saved $\beta$, then the bot considers that it is a new dialogue. Otherwise, it is the follow-up round. It would repeat the tasks of the first round until the conversation ends. The user intention set $D$ would be filled up in every round. An example structure of $D$ and $H$ shows as follows:

\[ H_{11} = \text{pro}: \{\text{‘Housekeeper’}\}; H_{12} = \text{price}: \{\text{‘low’}\}; \]
\[ H_{13} = \text{gender}: \{\text{‘woman’}\}; H_{14} = \text{age}: \{\text{‘young’}\}; \]
\[ D_1 = \{H_{11}, H_{12}, H_{13}, H_{14}\}; \]
\[ D_{\text{result}} = \{D_1\} = \{\{\text{pro}: \{\text{‘housekeeper’}\}, \text{price}: \{\text{‘low’}\}, \text{gender}: \{\text{‘woman’}\}, \text{age}: \{\text{‘young’}\}\}\} \]

C. Reasoning Module

The Q&A method designed in this paper is quite similar to the process of information retrieval and knowledge reasoning. It is based on a service knowledge graph as defined in Definition 1. KG is responsible for searching or inferring the qualified candidate services according to the user requirements, so as to support the reply generation of each follow-up round. For example, “How about eating fried chicken at noon today?”. Obviously, “fried chicken” is the goal. KG has to help clarify this goal by identifying the following factors, timely store, satisfied price, proper delivery time, etc. These factors are the attribute nodes of the KG. Another example, “I prefer something warm to make my stomach comfortable.” In this case, the goal is missing. We have to firstly infer the goal with those presented attributes based on the KG. As shown in the Reasoning Module in Fig. 2, information retrieval was processed through the connections between entities in KG.

1) Mapping Concept to Knowledge Graph Entities:

As shown in Fig. 3, we match the concepts identified in $D_{\text{result}}$ to entities for reasoning in KG. The system generates lists of proper nouns when creating the KG. When restricts

![Fig. 2. Our framework of system](image)

**Table II**: Example of the first round system process based on KG

| Process | Explanation | The result of each process of the example |
|---------|-------------|------------------------------------------|
| Situational judgment | Determine whether the user chats or Q&A | A real need, not a chat |
| Domain identify | Judge possible domain, sort and record | {Housekeeping, Job...} |
| Named Entity Recognition | Extract entities from user requirements | \{ [pro: {‘Housekeeper’}, price: {‘low’}], [gender: {‘woman’}], age: {‘young’} \} |
| Search in KG | Find the point and correlation of user’s requirement | Corresponding service personnel with their attributes |
| Generate intermediate answer | The answer obtained by the query graph is processed by the prepared answer template and returned to the user | “What are the experience restricts?” |
whose label is pro are identified in D (Profession is the main entity intention in the demand of human services by default), reasoning module maps the “HouseKeeper” to the entity in KG by looking up the list and matching (purple, ID = 336).

2) Reasoning in Knowledge Graph:

Mapping entity concepts to services As step 2.1 shows in Fig. 3 the corresponding service entity (red, ID = 567) is found through the representational learning method, such as Trans [16], which can help to infer the entire connected entities (relevant services).

Tracing the services to service providers The set \( T \) obtained by step 2.2 is the set of entities connected with the entity (red) in the result of step 2.1. (Two Y entities in blue and One service entity E in black who may capable of providing this service A.)

1) Offline Before Dialogue Beginning: GrC method takes the various types of service combinations as the root data \( C \) for the pruning as Fig. 7. GrC divides data into optimal granules \( C = \{C_1, C_2, C_3, \ldots, C_p\} \) once the value of Goal defined in Definition 3 tends to be stable. The current granules clustering center \( m_i \). The system traverses every cluster class, depending on all available choices by users (different granules in GrC result), then processes the next round GrC with the result set after pruning in each round, until the number of leaf node elements clustered by GrC is less than a threshold value \( N \). The \( N \) is a parameter to be tuned, which determines the number of the most suitable leaves return to the user. \( N \) can’t be too small, because not all kinds of data sets can be of excellent particle size. But at the same time, \( N \) cannot be too large either, otherwise, it would lose the essence of service recommendation. The system generates \( N \) by algorithm 1.

X is the upper limit of Service Recommendation at a time, and \( \text{Res} \) is the GrC algorithm result array, which includes the number of services contained in each leaf node in the result of GrC pruning.

And for the selection of class clusters number \( p \), the system quotes \( fpc \) index. \( fpc \) is fuzzy partition coefficient, which is an index to evaluate the classification. It ranges from 0 to 1, and 1 works best. The algorithm sets \( p \) at \( 2 \leq p \leq \sqrt{N} \), tests \( fpc \) values under different \( p \), and selects \( p \) corresponding to the maximum \( fpc \) value as the default number of \( p \).

The dialog policy that means the inquiring attribute in every round is determined based on data. Dialog policy offline in DMM can avoid heavy computation online effectively and still speed up the dialogue process (Reduce the number of dialogue rounds).

2) Conversation Process Online: After dialog policy confirming the inquiring attribute of each round, user chooses proper granules \( C_i \) belongs to the result of the GrC pruning \( C = \{C_1, C_2, C_3, \ldots, C_p\} \). DMM accepts user feedback and determines the corresponding solution path in the GrC result tree until the candidate set \( T \) achieve a leaf node. DMM formulates a data-based dialog policy for the fastest and most efficient elicitation of user requirement services by the GrC method. The dialog policy in DMM can help the system elicit user requirements and accelerate conversation end in the least round.

E. NLG Module

The purpose of the NLG module is to improve the interactivity between users and the system. The module accepts input in a non-verbal format and converts it into human-readable format sentences. When conversational state receives the output data by the dialogue management module, it determines whether the output conforms to the termination state EndTag. If output meets the end conditions, the NLG module receives the DMM output data and transfers the human-readable sentences as the final result to the user; otherwise, the system would generate the intermediate results and return to the user, waiting for user’s feedback as the TABLE below.

1) Intermediate Q&A: When conversational state judges dialogue management module output does not satisfy the conditions that no attribute deserved to be classified or the number of the results is small enough, the system generates intermediate inquiry base on the template where templates and grammar are rule-based strategies to finish multi-round dialogue NLG module. The system displays the output through modules defined in advance. Take elderly services
Algorithm 1 Calculate N in GrC algorithm automatically

Input: Upper limit X; GrC algorithm result array Res
Output: N
1: Res_freq ← { }
2: for each different value in Res do
3: Res_freq ← Res_freq + (value, frequency)
4: end for
5: frequency_in_order ← sort each pair in Res_freq in value's ascending order
6: M ← The serial number of the median of the element in frequency_in_order, Candidate ← { }
7: for p = M → len(Res_freq) - 1 do
8: Candidate ← Candidate + frequency_in_order[p]
9: end for
10: max_pair ← the pair where have the max frequency in Candidate
11: while i < len(Candidate) and v < X do
12: v ← Candidate[i].value
13: if i = 0 then
14: ∆left ← infinite
15: ∆right ← Candidate[i].frequency − Candidate[i + 1].frequency
16: else if i = len(Candidate) - 1 then
17: ∆left ← infinite
18: ∆right ← Candidate[i].frequency − Candidate[i + 1].frequency
19: else
20: ∆right ← Candidate[i].frequency − Candidate[i − 1].frequency
21: ∆left ← Candidate[i].frequency − Candidate[i + 1].frequency
22: end if
23: δleft ← |∆left|, δright ← |∆right|
24: if ∆right < 0 and ∆left < 0 then
25: if δleft < δright then
26: v ← Candidate[i − 1].value
27: break
28: end if
29: else if ∆right > 0 and ∆left > 0 then
30: if δleft > δright then
31: break
32: end if
33: else if ∆right > 0 and ∆left < 0 then
34: if δleft > δright then
35: v ← Candidate[i − 1].value
36: end if
37: break
38: end if
39: i ← i + 1
40: end while
41: N ← v

tag set in 8:1:1.

as an example, and the sentence is dynamically changed
and generated by a predefined set of business rules (such
as the if/else loop statement). The return to user of first
line in table is an inquiring sentence based on module input
{Tag=\{\text{Price}\}; End_Tag=0; Quantity=1}.

2) Final Answer Generation: When the end conditions are
met, the system would execute the Answer Generation function.
Whatever N is in the final T, the system would return
the complete information of the first N possible solutions to the
user for selection in descending order of user matching finally.
As the example in TABLE III when End_Tag meets 1, NLG
generates readable return which is the detailed information
of service providers in Back-End input as the final result to the
user. If the quantity of the element in the set is more than N,
the return sentence would show the first N service providers
and point out there are no attributes left. Otherwise, NLG only
displays the corresponding information as the final result.

V. EXPERIMENTS AND RESULTS

A. Experiment Setup

Data Set One of the data sets is used to fine-tune
and validate the pretrained Google BERT model. This data set
has been divided into train_set, dev_set, and test_set in 8:1:1.
Finally, the accuracy of this model has achieved 89.5% based
on 1975 valid corpus, better than BiLSTM_Attention 84.7%.
Another data set is used to construct the service knowledge
graph. This data set contains 827 service providers. Every
service has more than 9 attributes. After removing the illegal
or missing data, the constructed KG has 9478 triples, which
includes 960 entities and 10 relationships.

Baseline and Evaluation The experiment defines the k-
means method as a traditional pruning strategy to simulate
the whole process of multi-round dialogue. And the system
uses FCM algorithm as an implementation of Grc method.
Within the scope of the knowledge graph information, user
requirement can be simulated as the generated user input to be
accepted by the system. The NLU module loaded BERT, and
the reasoning module would traverse and simulate all possible
valid multi-round dialogue process, record the path generated
by each decision. The experiment judges the accuracy of
the two methods by the hit_rate index. Users need and only
need the best 1 service by default. And hit_rate refers to
the probability that our best service target would appear in the
case of N recommended items at one time calculating through
conditional probability, such as equation [5] and i is the number
of elements in leaf node:

\[\text{Hit rate} = \frac{C_i^1C_{n-1}^{R_N}}{C_n^p} = \frac{C_i^{n-1}}{C_i^p}\] (5)

Then the experiment statistics the end round number R_N and
calculates the average round through \(\frac{\sum_r R_N}{r}\), r is the number
of test cases. The experiment result compares two methods
by hit_rate and average round. The two cluster results of 16
types of service combinations are shown in Fig. [4]

[4] https://github.com/tian231825/Conversational_AI_Bot/tree/master/project/BERT\_model\_data

[5] https://github.com/tian231825/Conversational_AI_Bot/tree/master/data

| TABLE III |
|----------|
| Back-End | End Tag | Element Quantity in Set | Return to User |
|----------|
| Tag=\{\text{Price}\} | 0 | 1 | No attributes left and we get a lot of services for you:  
\{1: \{\text{Name}: \text{"Fred"}, \text{Age}: 28, \text{Price}: \text{2400}\},  
2: \{\text{Name}: \text{"Rose"}, \text{Age}: 22, \text{Price}: \text{3500}\},  
3: \{\text{Name}: \text{"Lisa"}, \text{Age}: 25, \text{Price}: \text{2400}\};  
\} |
| Id=\{\text{‘386’,}  
\‘624’, \‘125’,  
\cdots \‘444’\} | 1 | 9 (≥8) | Prepare three services for you:  
\{1: \{\text{Name}: \text{"Fred"}, \text{Age}: 28, \text{Price}: \text{2700}\},  
2: \{\text{Name}: \text{"Rose"}, \text{Age}: 22, \text{Price}: \text{2400}\},  
3: \{\text{Name}: \text{"Lisa"}, \text{Age}: 25, \text{Price}: \text{2600}\};  
\} |
| Id=\{\text{‘586’,}  
\‘633’, \‘636’\} | 1 | 3 (≤8) | |
Fig. 4. The pruning effect of Two Cluster Method

B. Result and Analysis

In TABLE IV, the experimental results indicate that the recommendation accuracy decreases with the decrease of rounds. In practical application, the paper is more inclined to make the dialogue rounds and final candidate set accuracy both achieve better results, not just one to achieve the optimal. We believe that a 36.1% decreasing in the average rounds would make the conversational AI bot user experience better than a 1% decreasing in accuracy.

| Method                  | HIT rate (%) | Avg Round |
|-------------------------|--------------|-----------|
| Traditional Cluster     | 95.06        | 8.391     |
| Granular Computing      | 94.79        | 5.357     |

Fig. 4 also shows the pruning strategy efficiency of all service types based on granular computing. The experiment result can get a conclusion from the figure: the GrC method is universal and not only valid for certain types of data. In contrast to the figure of the traditional cluster method, you can see that the GrC method is indeed effective in decreasing the round of each type of service screening process.

Fig. 5. Example of GrC solution space

At the same time, the paper is pleased to find that GrC method solves the problem of the fuzzy boundary of continuous variables. For example, continuous “price” can be classified according to data automatically rather than manual operation. As shown in Fig. 5, the system can accept the fuzzy requirement like “low price” in TABLE IV. Traditional methods are disadvantageous for dealing with such fuzzy requirements. If the price is between 0 and 4000, and what does “expensive” mean? Artificial can define more than a particular value means “expensive”, such as “3000”. But it’s hard to say “2999” or “2998” is medium or cheap although they are lower than “3000”. GrC method can solve this, and after data divided into several general categories, the system only needs to get the entities in the corresponding solution space according to user requirement. Fig. 5 shows that two requirements for the staff.

Fig. 6. Service PBCE pruning process in the system.

The six graphs in Fig. 6 are the granular calculation steps in the dialog process that simulates the service type PBCE (nursery teacher). The experiment normalized the service price, service provider educational background, and service area to display better in the results. In Fig. 6(a)(b),(d),(e),(f), we can notice that the Y-axis in the figure has no value because the figures uses a two-dimensional projection to make the overlapping part of the granules visible. And the service set is constantly dismembered until the end of Fig. 6(f) in the process. It took up at most seven rounds dialogue (the elicitation of the service type is seen as one round dialogue). The red path in Fig. 7 has shown the process of Fig. 6. Furthermore, Fig. 6(a) shows the second round result, it can be observed that the age-based division is such that the data set can aggregate into two granularity with distinct boundaries. And the same situation in Fig. 6(b), the system gathered the overlapping parts of the classification results as a single granularity. In the two results in Fig. 6(c) and Fig. 6(e), since the separate attribute belongs to discrete non-continuous variables, the figures show that the data set coincide at some points, and the algorithm automatically divides the granules according to the result. In the fourth round results Fig. 6(c), the granular calculations divide the data into several categories in 1 round dialogue through multidimensional attributes, which is why the total round number of the GrC method is much lower than the traditional cluster method. Divided by more than one attribute also occurs at the green point in Fig. 7. And the paper marks the longest dialog path with red points.

The Fig. 8 shows that the k-means algorithm early-round hit ratio is 100. This is because the strategy system adopted is to stop clustering until the leaf node is less than 8 ($N = 8$). If the leaf node is more than 8, the system would continue to the next round. Therefore, there would be no leaves greater than 8 (the available attributes are no longer available) until the 10th round, resulting in a hit ratio below 100. The actual comparison should be the hit ratio of the two methods when the available attributes are no longer available. That is, the hit
to data, even the crossover domains data, are further required to remain or enhance the intelligence and effectiveness of this conversational service delivery method. Honestly, base on the method proposed in this paper, underlying more in-depth requirements would not be recognized very clearly such as the requirements need to elicited by multi-hop in the text, and we still need to make the pruning strategy offline before the process, and we hope to be able to make it online in real-time in the future. These issues mentioned above would be our future works.

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