Dialogue System for Automatic Cognitive Task Analysis

Junyi Du
University of Southern California
junyidu@usc.edu

Abstract

Cognitive task analysis (CTA) is a type of analysis in applied psychology aimed at capture the procedural knowledge domain experts. In CTA, often heavy human labor is involved to interview domain experts and convert the transcript into structured knowledge, e.g., flowchart. To reduce human efforts and scale the process, In this paper, we design a chatbot system to extract the procedural knowledge from experts automatically. The chatbot asks questions to experts about the procedures of a task, then extracts procedural knowledge from the answers and asks new questions based on the extracted knowledge on-the-fly. Equipped with natural language understanding features and off-the-shelf text-to-speech / speech-to-text, the chatbot can interview human expert in spoken language.

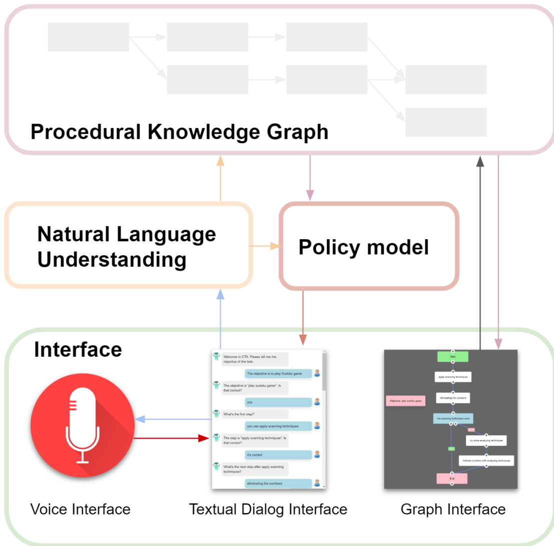


Figure 1: Overview of the dialogue system

1 Introduction

Cognitive task analysis (CTA) is a tool for training, instructional design, and development of expert systems focusing on extracting the knowledge from domain experts. CTA requires interviews with domain experts and parsing the interview transcript into structured text describing processes, which both require heavy human labor, and become the major hurdles of scaling up CTA. Therefore, automated approach to extract structured knowledge from domain experts is important.

To automate the CTA process, we develop a dialogue system to interview domain experts. The system consist of 4 parts: 1) Human interface, including textual dialog interface, voice interface, and graph interface; 2) Natural Language Understanding (NLU); 3) Policy model and 4) Procedural knowledge graph. Please refer to Fig. 1 for a general view.

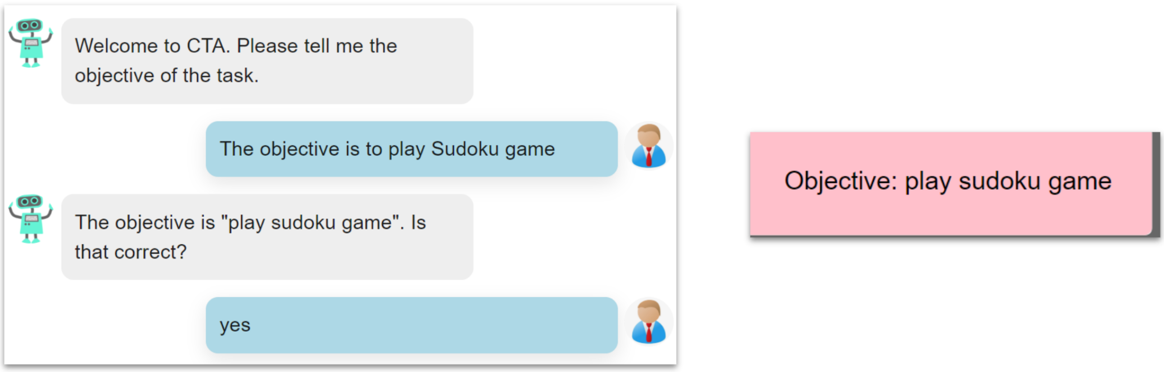
More specifically, NLU understands answers from experts, extract user's intentions and filling the slots, and updates the procedural knowledge graph; policy model generates new questions based on user's intentions, slots and the procedural knowledge graph. The goal of the dialogue system is to complete the procedural knowledge graph by interviewing human domain experts.

We present our dialogue system demo and show it could conduct CTA interview with domain experts automatically and collect procedural knowledge within the dialog.

2 Related Work

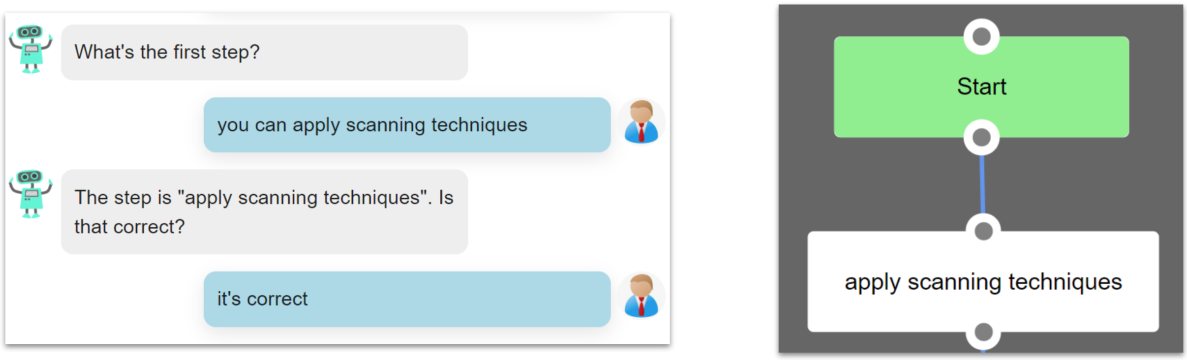
Our work is closely related to procedural extraction, however we focus on dialog which is a interactive setting.

Cognitive task analysis. Cognitive task analysis is a powerful tool for extracting knowledge and thought processes of experts widely used in different domains (Schraagen et al., 2000; Seamster and Redding, 2017). Yet, it is time-consuming and not scalable. Recent years, with the development of natural language processing, techniques are in-



(a) Textual Dialog Interface (b) Graph Interface

Figure 2: User answers system's question about objective



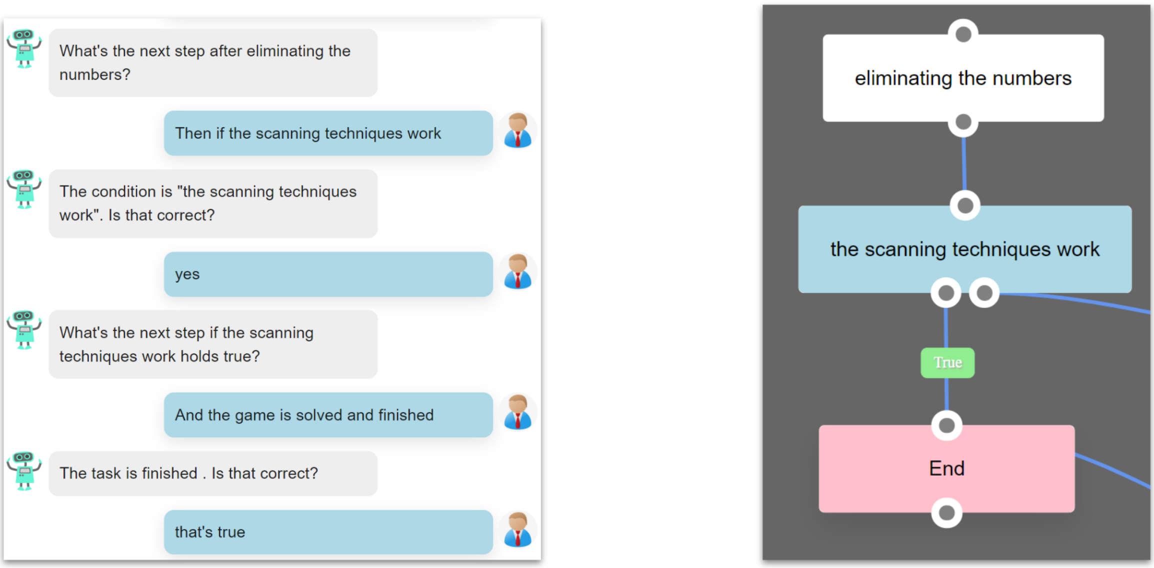
(a) Textual Dialog Interface (b) Graph Interface

Figure 3: User answers system's question about step

troduced to aid human expertise (Zhong et al., 2015; Roose et al., 2018). Li et al.(2013) used learning agent to discover cognitive model in specific domains. Chaplot et al.(2018) explored modeling cognitive knowledge in well-defined tasks with neural models. However, for the most general setting that extract cognitive processes from interviews, we still need substantial expertise to interpret the interview transcript.

Procedural extraction. Recent advances in machine reading comprehension, textual entailment (Devlin et al., 2018) and relation extraction (Zhang et al., 2017) shows the contemporary NLP models have the capability of capturing causal relations in some degree. However, it is still an open problem to extract procedural information from text. There were some attempts to extract similar procedural information on well-structured instructional text from how-to community. Park and Motahari Nezhad (2018) treated procedural extraction as a relation extraction problem on sentence pair extracted by pattern matching. They used `OpenIE` for pattern extraction and hierarchical LSTM to classify relation labels of sentence pairs.

Goal-oriented Dialogue System Goal-oriented systems aim to assist the user to complete certain tasks (e.g. finding products, and booking accommodations and restaurants). The widely applied approaches to goal-oriented systems are to treat the dialogue response as a pipeline that first understand the message given by human, represent it as a internal state, then take some actions according to the policy with respect to the dialogue state, and finally the action is transformed to its surface form as a natural language. Though language understanding is processed by statistical models, most deployed dialogue systems still use manual features or handcrafted rules for the state and action space representations, intent detection,



(a) Textual Dialog Interface (b) Graph Interface

Figure 4: User tells a branching condition and a ending criteria for the task

and slot filling.

Our dialogue system is not a traditional goal-oriented dialogue system, since it has infinite number of states and goals. Our dialogue system asks new questions continually with the policy model, based on the extracted knowledge, until the procedural knowledge graph is completed.

Dialogue System with External Knowledge Recently, researchers began to incorporate external knowledge to enhance reply generation of dialogue systems, for example, filling reply templates using text retrieved from external knowledge graph. However, our dialogue system is more advanced: it is updating the knowledge graph based on the conversation.

3 Framework

The system consist of 4 parts: 1) Human interface; 2) Natural Language Understanding (NLU); 3) Policy model and 4) Procedural knowledge graph. Please refer to Fig. 1 for a general view.

3.1 Human interface

We provides 3 interfaces for users: voice interface, textual dialog interface and graph interface. Voice input would first interpreted into transcript, then treated as text input; Graph interface display and manipulate procedural knowledge graph directly and is easy for visualization and debugging.

3.2 Natural Language Understanding (NLU)

There are 2 components in NLU: intent detection and slot-filling. For text input from user, the two components would be executed to understand user's input and parsed them into structured information, then we can update the procedural knowledge graph and generate new questions with these information.

3.3 Policy Model

To conduct interview like human, our dialogue system need to ask question with intelligent instead of fixed templates. Here we adopt a policy model which could generate new questions based on NLU parsing results and procedural knowledge graph on-the-fly.

3.4 Procedural knowledge graph

Procedural knowledge graph helps our dialogue system to track the state of interview. It's a infinite space of states and the transitions could be updated during the conversations, which is the distinguishing property of our dialogue system.

4 Demonstration

In this section we present screenshots of our demo system with a CTA interview case on Sudoku game:

5 Conclusion

In this paper, we demonstrate our dialogue system for automated CTA interview, which asks questions to experts about the procedures of a task, then extracts procedural knowledge from the answers and asks new questions based on the extracted knowledge on-the-fly. Screenshots shows it's user friendly, could conduct CTA interview with domain experts automatically, and collect procedural knowledge within the dialog.

References

Devendra Singh Chaplot, Christopher MacLellan, Ruslan Salakhutdinov, and Kenneth R. Koedinger. 2018. Learning cognitive models using neural networks. *CoRR*, abs/1806.08065.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805.

Nan Li, Eliane Stampfer, William Cohen, and Kenneth Koedinger. 2013. General and efficient cognitive model discovery using a simulated student. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 35.

Hogun Park and Hamid Reza Motahari Nezhad. 2018. Learning procedures from text: Codifying how-to procedures in deep neural networks. In *Companion Proceedings of the The Web Conference 2018*, WWW '18, pages 351–358, Republic and Canton of Geneva, Switzerland. International World Wide Web Conferences Steering Committee.

Kaitlyn Roose, Elizabeth Veinott, and Shane Mueller. 2018. The tracer method: The dynamic duo combining cognitive task analysis and eye tracking.

Jan Maarten Schraagen, Susan F Chipman, and Valerie L Shalin. 2000. *Cognitive task analysis*. Psychology Press.

Thomas L Seamster and Richard E Redding. 2017. *Applied cognitive task analysis in aviation*. Routledge.

Yuhao Zhang, Victor Zhong, Danqi Chen, Gabor Angeli, and Christopher D Manning. 2017. Position-aware attention and supervised data improve slot filling. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 35–45.

Chen Zhong, John Yen, Peng Liu, Rob Erbacher, Renee Etoty, and Christopher Garneau. 2015. An integrated computer-aided cognitive task analysis method for tracing cyber-attack analysis processes. In *Proceedings of the 2015 Symposium and Bootcamp on the Science of Security*, HotSoS '15, pages 9:1–9:11, New York, NY, USA. ACM.

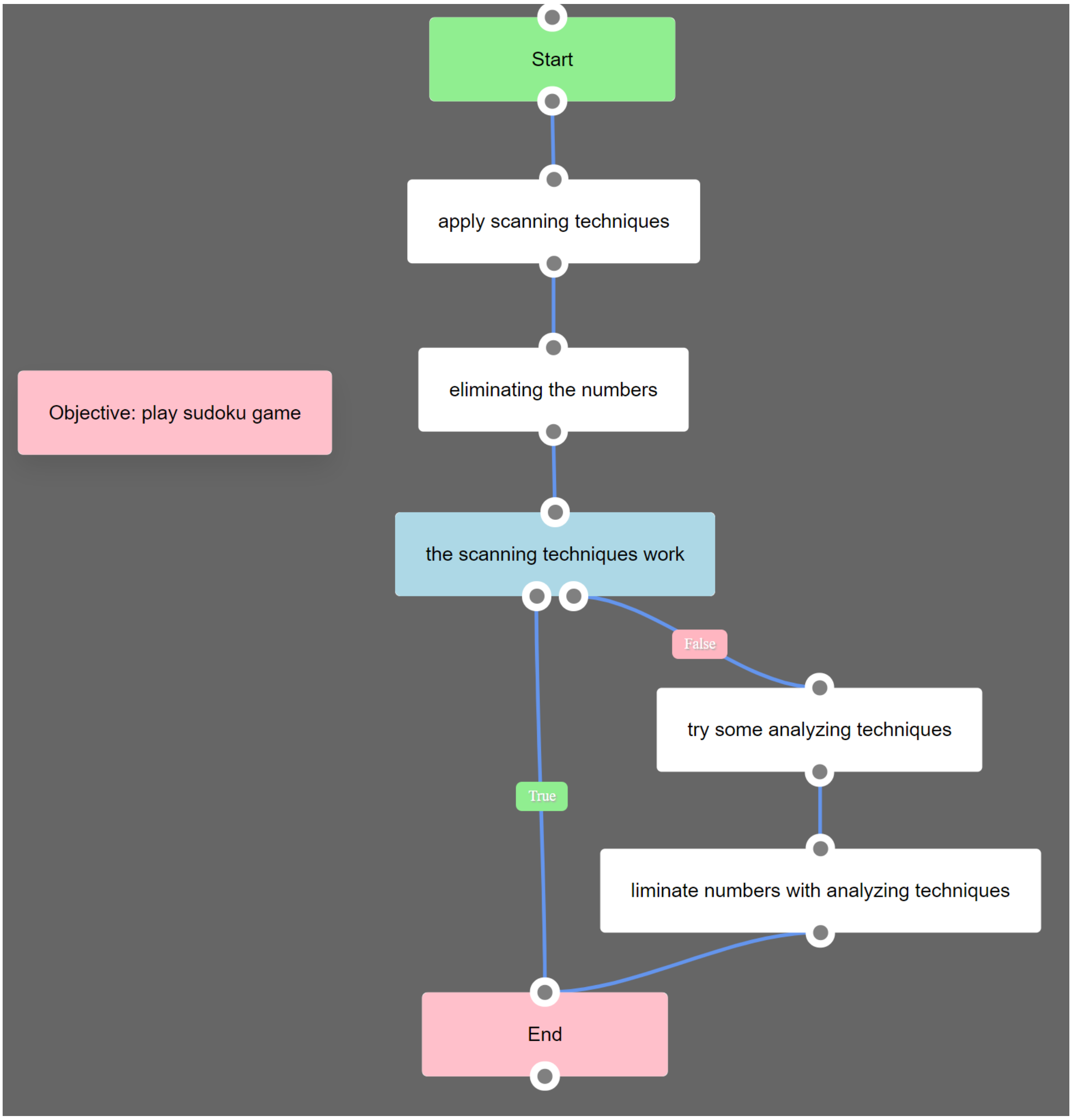


Figure 5: The over all procedural knowledge graph