Graph-based Self-Adaptive Conversational Agent

Lan Zhang
Auckland University of Technology
Auckland, New Zealand
xth6271@autuni.ac.nz

Weihua Li
Auckland University of Technology
Auckland, New Zealand
weihua.li@aut.ac.nz

Quan Bai
University of Tasmania
Hobart, Australia
quan.bai@utas.edu.au

Edmund Lai
Auckland University of Technology
Auckland, New Zealand
edmund.lai@aut.ac.nz

ABSTRACT

Conversational agents have been widely adopted in dialogue systems for various business purposes. Many existing conversational agents are rule-based and require significant human intervention to adapt the knowledge and conversational flow. In this paper, we propose a graph-based adaptive conversational agent model which is capable of learning knowledge from human beings and adapting the knowledge-base according to human-agent interactions. Studies to evaluate the proposed model are conducted and presented, which compare the responses from the proposed adaptive agent model and a conventional agent.

KEYWORDS

self-adaptive, conversational agents, knowledge graph

ACM Reference Format:
Lan Zhang, Weihua Li, Quan Bai, and Edmund Lai. 2021. Graph-based Self-Adaptive Conversational Agent. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), London, UK, May 3–7, 2021*, IFAAMAS, 3 pages.

1 INTRODUCTION

Nowadays, the conversational agents have been widely adopted by many businesses for a wide range of applications, including intelligent tutoring for improving learning and teaching, chatbots offering 24/7 supporting services and personalized conversation agents in health care [1, 3–5, 7, 9].

Most existing intelligent conversational agents (named as *"agents"* for the sake of brevity) can be categorized as goal-driven and non-goal-driven agents[6, 13, 14]. In the former, with a predefined service target, agents participate in a Question-and-Answer (Q/A) system by providing domain-specific services to address the problems in a specific sector. In other words, agents are equipped with a set of fixed rules involved in a particular field's services, such as customer support, ticket booking, etc. While, in the latter, the service target and conversational scope are not predefined. Non-goal-driven agents are capable of handling a variety of problems by leveraging various information and ontology in the universe. Such agents can be adopted in an open field, such as entertainment.

However, the advent limitations of these agents are presented. First, the knowledge curation of agents relies on manual inputs from domain experts. Agents themselves have very limited capabilities of retaining and recalling knowledge obtained from the conversations [2]. Second, the current state-of-the-art approaches for designing agents are based on sequence-to-sequence variants, enabling the automatically adaptive skill of the conversational agents. Whereas, such approaches generally suffer from an inability to bring memory and knowledge to bear and fail to consider the time-series context [10–12]. Third, agents' responses may appear out of control when the models are black-box. Specifically, for those agents trained using neural networks, the model turns out to be untransparent, and it is a non-trivial task to revise the agents' knowledge base without re-training.

To address the challenging issues mentioned above, in this paper, we propose a novel conversational agent model, named Graph-based Self-adaptive Conversational Agent (GSCA). The proposed model enables the agents to learn from the human-agent interactions, continuously enriching the knowledge base. We represent agents' knowledge base as a dynamic and transparent knowledge graph, where the nodes denote key entities and links that describes the semantic relationship. On top of that, to obtain appropriate responses, we develop a temporal-based triple extraction algorithm for GSCA, where Google T5 [8] has been utilized for text generation.

2 THE GSCA FRAMEWORK

The GSCA framework supports agents to learn and adapt the knowledge through conversations with end-users. Figure 1 demonstrates the overall picture of the framework.

A User can communicate with an agent by sending text. Semantic triples will be extracted using information extraction techniques. Triples $F = \{f_1, f_2, ..., f_n\}, n \in \mathbb{N}$ can be represented as a collection of facts, and each fact comprises three entities ε, i.e., $f_x = (h_x, r_x, t_x), f_x \in F$, where h_x, r_x and t_x represent head, relation and tail of f_x, respectively.

In GSCA, each entity $\varepsilon \in \{h, r, t\}$, has been granted with enriched features, including the last accessed time τ_ε, frequency of being visited ω_ε and attention degree η_ε. The agent is capable of inferring the user's update-to-date preferences according to these features. Specifically, the attention degree of any entity η_ε can be derived by using a time decay function, i.e., $\eta_\varepsilon = e^{-\alpha \Delta\tau}, \alpha > 0$, where $\Delta\tau = \tau_\varepsilon - \tau_{now}$ and α describes a constant controlling the degree of decay. Having the entities with enriched features, the agent utilizes extracted triples to match and enhance the contents of the existing knowledge base.

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, London, UK.

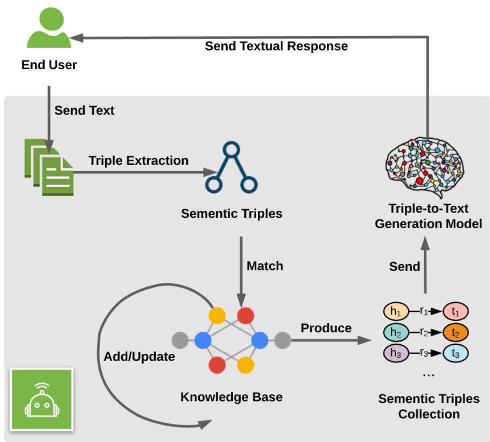

Figure 1: GSCA Framework

We propose a novel algorithm, named the Temporal-based Triple Retrieval (TTR), to effectively identify the most relevant triples with a confidence score, where both temporal features and user preferences are taken into consideration. Our algorithm involves three major steps. ***First***, the entities of a fact are vectorized, $f_x' = (v(h_x), v(r_x), v(t_x))$, where $v(.)$ indicates a function, converting a token into a vector. There are two reasons why the translate models for KG, e.g., TransE, are not adopted. (1) Such algorithms vectorize the entire triple, but GSCA intends to match entities for obtaining a sub-graph. (2) GSCA facilities self-adaptive framework; thus, it is a non-trivial task to keep training and updating the vectors in a dynamic environment. ***Second***, we estimate the distance between the hypothesis triple and existing triples, i.e., $dis(f_i, f_j) = \sum_{\varepsilon \in \{h,r,t\}} w_\varepsilon \cdot sim(v(\varepsilon_i), v(\varepsilon_j))$. where $sim(\varepsilon_i, \varepsilon_j)$ denotes the cosine similarity between ε_i and ε_j, having $sim(\varepsilon_i, \varepsilon_j) = \frac{v(\varepsilon_i) \cdot v(\varepsilon_j)}{\|v(\varepsilon_i)\| \times \|v(\varepsilon_j)\|}$, While w_ε balances the trade-off among h, r and t with a restriction of $\sum_{\varepsilon \in \{h,r,t\}} w_\varepsilon = 1$. ***Third***, the agent identifies potential answer triples with extracted triples and the connected siblings. Given hypothesis triple f_i, the confidence score of an identified triple $f_j = (h_j, r_j, t_j)$ can be derived from distance $dis(f_i, f_j)$, normalized frequency of being accessed $\hat{\omega_\varepsilon}$ and attention degree of the entity η_ε, where $\varepsilon \in \{h_j, r_j, t_j\}$.

According to the confidence score, the triples are selected and become the inputs of the Triple-to-Text model for response generation. However, if the score appears below a certain threshold, the agent treats these triples as new knowledge and resolves them internally. On top of that, the agent can proactively initiate conversations with users. Without any inputs from the users, the agent can periodically trigger a semantic triples recommendation using the TTR algorithm, which dynamically produces up-to-date triples according to the recent conversations and preferences of the user. Another novelty of our model can be reflected as the capability of joining a variety of KGs produced by multiple users, forming a global KG for supporting the ongoing conversation.

3 EXPERIMENTS

Two experiments have been conducted to evaluate the performance of GSCA. We simulate two virtual end-users, i.e., Lindsay and Jason, who communicate with the agent based on two topics, i.e., food and artist.

Table 1: Conversation examples

Topic	Input Sentence	Retrieved Triple	Reply Text
Artist	Aaron turner is a friend of Billy.	"aaron turner" "be friend of" "aaron deer"	Aaron turner was a friend of Aaron Deer.
Artist	Hip hop music is very popular.	"hip hop music" "be genre of" "rap music"	Hip hop music is a genre of rap music.
Artist	Billy performs rap music.	"Billy" "perform" "hip hop music."	Billly performs hip hop music.
Food	Almond is brown colour	"almond" "be" "flowering plant"	Almond is a flowering plant.
Food	Almond has colour	"Almonds" "be from" "rosaceae family"	Almonds are from the rosaceae family.
Food	Almonds is food.	"sandwich" "be" "food"	The sandwich is a food.

Experiment 1 aims to evaluate the agent's self-adaptive capabilities, having the users' preference and attention degree considered. Table 1 illustrates only a few conversation examples, but it is obvious that the agent responses by extending user's input.

The proposed TTR algorithm determines the selection of triples for response generation. For evaluation purpose, we intentionally increase the access frequency ω_ε and refresh the last visiting time stamp η_ε of node "hip hop music" via mentioning it a few times to the agent. We find that the agent is more inclined to use this node for generating responses.

We conduct 60 rounds of conversations covering the topics of both artist and food. After varying both ω_ε and η_ε through the interactive conversations, the experimental results show that 73% of the responses are adapted and appear reasonable. There is around 17% chances for a user to receive a response without knowledge adaptation, and merely 10% turn out to be unreasonable. This is due to the limited knowledge obtained by the agent.

Experiment 2 evaluates the knowledge augmentation capability of the agent. Though the knowledge base keeps increasing through agent-human interactions, the knowledge may still appear insufficient to handle all the user's inputs, especially in the early stage. The agent intends to borrow the knowledge obtained from other users for a reply.

We further initiate 30 rounds of conversation using user Lindsay. The agent properly handles 70% of the inputs through the TTR algorithm, matching the triples and generating responses. 30% is missing from the knowledge base, but new triples are retained. It is worth noting that 10% of the responses utilize the knowledge of both users, Lindsay and Jason. This implies the agent is capable of effectively augmenting a user's knowledge by using others.

4 CONCLUSION AND FUTURE WORK

Based on the experimental results, we can conclude that our proposed GSAC framework enables agents to learn, adapt and augment knowledge through the interactions. In the future, we plan to enhance the existing framework by resolving conflict knowledge learnt from multiple users, where truth discovery will be applied.

REFERENCES

[1] Gopi Battineni, Nalini Chintalapudi, and Francesco Amenta. 2020. AI Chatbot Design during an Epidemic Like the Novel Coronavirus. In *Healthcare*, Vol. 8. Multidisciplinary Digital Publishing Institute, 154.

[2] Chayan Chakrabarti and George F Luger. 2015. Artificial conversations for customer service chatter bots: Architecture, algorithms, and evaluation metrics. *Expert Systems with Applications* 42, 20 (2015), 6878–6897.

[3] Ulrich Gnewuch, Stefan Morana, and Alexander Maedche. 2017. Towards Designing Cooperative and Social Conversational Agents for Customer Service.. In *ICIS*.

[4] Alice Kerlyl, Phil Hall, and Susan Bull. 2006. Bringing chatbots into education: Towards natural language negotiation of open learner models. In *International Conference on Innovative Techniques and Applications of Artificial Intelligence*. Springer, 179–192.

[5] Liliana Laranjo, Adam G Dunn, Huong Ly Tong, Ahmet Baki Kocaballi, Jessica Chen, Rabia Bashir, Didi Surian, Blanca Gallego, Farah Magrabi, Annie YS Lau, et al. 2018. Conversational agents in healthcare: a systematic review. *Journal of the American Medical Informatics Association* 25, 9 (2018), 1248–1258.

[6] Varvara Logacheva, Valentin Malykh, Aleksey Litinsky, and Mikhail Burtsev. 2020. ConvAI2 dataset of non-goal-oriented human-to-bot dialogues. In *The NeurIPS'18 Competition*. Springer, 277–294.

[7] Vânia Mendonça, Francisco S Melo, Luísa Coheur, and Alberto Sardinha. 2017. A conversational agent powered by online learning. In *Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems*. 1637–1639.

[8] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. *arXiv preprint arXiv:1910.10683* (2019).

[9] Hedieh Ranjbartabar, Deborah Richards, Ayse Aysin Bilgin, Cat Kutay, and Samuel Mascarenhas. 2020. User-Models to Drive an Adaptive Virtual Advisor. In *Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems*. 2117–2119.

[10] Iulian Vlad Serban, Ryan Lowe, Laurent Charlin, and Joelle Pineau. 2016. Generative deep neural networks for dialogue: A short review. *arXiv preprint arXiv:1611.06216* (2016).

[11] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*. 3104–3112.

[12] Oriol Vinyals and Quoc Le. 2015. A neural conversational model. *arXiv preprint arXiv:1506.05869* (2015).

[13] Rui Yan. 2018. " Chitty-Chitty-Chat Bot": Deep Learning for Conversational AI.. In *IJCAI*, Vol. 18. 5520–5526.

[14] Qi Zhu, Zheng Zhang, Yan Fang, Xiang Li, Ryuichi Takanobu, Jinchao Li, Baolin Peng, Jianfeng Gao, Xiaoyan Zhu, and Minlie Huang. 2020. Convlab-2: An open-source toolkit for building, evaluating, and diagnosing dialogue systems. *arXiv preprint arXiv:2002.04793* (2020).