Effortless Integration of Memory Management into Open-Domain Conversation Systems

Eunbi Choi¹* Kyoung-Woon On² Gunsoo Han² Sungwoong Kim³

Daniel Wontae Nam² Daejin Jo² Seung Eun Rho² Taehwan Kwon² Minjoon Seo¹

¹KAIST AI ²Kakao Brain ³Korea University

{eunbi,minjoon}@kaist.ac.kr

{kloud.ohn,coco.han,dwtnam,daejin.jo}@kakaobrain.com

swkim01@korea.ac.kr seungeun07@snu.ac.kr kwonth0315@gmail.com

Abstract

Open-domain conversation systems integrate multiple conversation skills into a single system through a modular approach. One of the limitations of the system, however, is the absence of management capability for external memory. In this paper, we propose a simple method to improve BLENDERBOT3 by integrating memory management ability into it. Since no training data exists for this purpose, we propose an automating dataset creation for memory management. Our method 1) requires little cost for data construction, 2) does not affect performance in other tasks, and 3) reduces external memory. We show that our proposed model BLENDERBOT3-M[^]3, which is multitask trained with memory management, outperforms BLENDERBOT3 with a relative 4% performance gain in terms of F1 score.

1 Introduction

Open-domain conversation, which refers to conversing without any constraints on topic (e.g., chitchat), has been the subject of active research in recent years (Shuster et al., 2022b; Roller et al., 2020; Thoppilan et al., 2022; Freitas et al., 2020). A good open-domain conversational agent is expected to be engaging, knowledgeable, up-to-date, and personalized by remembering the user. Therefore it is key to seamlessly blend all desirable skills into a conversation system.

To address this, previous works utilized separate modules for internet search (Shuster et al., 2022a; Komeili et al., 2022) or memory generation (Zhong et al., 2022; Xu et al., 2022b,a). Recently, there have been studies aimed at unifying various conversation abilities into a single language model based on the modular approach (Shuster et al., 2022a,b). One notable recent work is BLENDERBOT3 (Shuster et al., 2022b), a modular system where a single transformer model is served for all modules. Recently, there is a trend of providing personalized conversation experiences by memorizing individual user information (Xu et al., 2022b; Lu et al., 2022; Bae et al., 2022; Mazaré et al., 2018). However, as shown in Figure 1, the agent may encounter problems when the conversation lasts long, as information about a person is not static and changes over time. Therefore, managing memory based on the current state is one of key abilities for a good open domain conversational agent (Bae et al., 2022).

In this paper, we propose an effortless method to improve BLENDERBOT3 by integrating memory management capability into it. Since no general data exists for this purpose, we formally define a new task for memory management and present an automated method to create memory management datasets. Our method has following advantages:

- Require little cost for data construction.
- Do not affect BLENDERBOT3's performance in other tasks.
- Need no additional costs for the external memory and model parameters, but rather reduces the costs.

We leverage publicly available datasets to construct memory management data, which can be easily scaled up and extended to other domains. Additionally, we report performance in other tasks of BLENDERBOT3 and external memory efficiency of our model.

Experimental results show that our proposed model BLENDERBOT3-M³, which is multi-task trained with memory management, outperforms BLENDERBOT3 with a relative 4% performance gain in terms of F1 score. In addition, across all 67 tasks where BLENDERBOT3 is trained, we observe that the average PPL score of BLENDERBOT3-M³ increases 0.05 from the PPL of BLENDERBOT3, demonstrating the seamless integration of the new

^{*}Work done during internship at Kakao Brain.

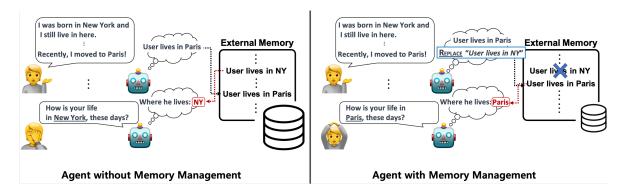


Figure 1: Illustrative examples of open-domain conversation with an agent with/without memory management. *Left*: Without memory management, an agent cannot handle the situation of changing user's information. Also, the size of the memory is monotonically increased during the conversation. *Right*: With memory management, the agent can replaces the out-dated information with the new one. In addition, the size of the memory also tend to be suppressed.

memory management task. Through these explorations, we demonstrate that the overall conversation performance is effortlessly, yet successfully improved by incorporating the memory management capability into the conversational agent.

2 Related Work

2.1 Unified Conversation Systems

Recently, there have been studies for unifying different conversation skills, such as being engaging, factual, empathetic, civil and knowledgeable, into a single language model based on modular approach (Smith et al., 2020; Shuster et al., 2022a,b; Ung et al., 2021; Kim et al., 2022). Therefore, it is crucial to incorporate all desirable skills into a conversation system seamlessly. BLENDER-BOT3 (Shuster et al., 2022b) shows that equipping a single transformer model with all skills through multi-task training can be a promising direction.

2.2 Personalized Conversation Systems with Memory

Providing personalized conversation experiences to users has been improved by memorizing their information. Conversational agents either keep the user's profile (Zhang et al., 2018) or extracted user information from conversation history (Xu et al., 2022b; Lu et al., 2022; Bae et al., 2022) to generate personalized response. Especially, Xu et al. (2022b) extract and store user information dynamically during conversation, allowing the agents to remember the user in long-term conversations.

2.3 Memory in Long-term Conversation Systems

Xu et al. (2021) and Xu et al. (2022b) have tackled long-term conversation problem and released MSC and DuLeMon datasets, respectively. In MSC (Xu et al., 2021) dataset, sessions are annotated with summaries of previous sessions that may be useful in current conversations. It is intended to refer to the previous conversation with memory in longterm. However, MSC does not aim to reflect the dynamic feature of personal information.

Work of Bae et al. (2022) represents the first attempt to address this problem, presenting the memory management task. However, since their approach classifies relationship of sentence pairs to compute memory management operation, the inference time increases as the length of memory increases.

3 Approach

We improve BLENDERBOT3 by equipping it with memory management capability, which requires data of memory management for multi-task training along with other tasks. Since no general data exists for this purpose, we define a new task for memory management and present an effortless way to create the memory management dataset, which can be easily scaled up. In this paper, we apply this method to open-domain conversations, but it is generally extendable to memory management in other tasks.

3.1 Memory Management Task Definition

During conversation, a conversational agent maintains natural language memory sentences $M_t = \{m_1, m_2, \cdots, m_n\}$ which consists of user

information abstracted from the previous utterances. At time step t, we are given the memory M_t and user information p_t generated from utterance u_t , each of which could be either user's utterance or bot's utterance. At the end of each turn, we aim to predict memory management operation op. We define the management operation set as $O = \{APPEND, PASS, REPLACE m_i\}$ where m_i is an entry of the memory M_t and define this task as $Model(M_t, p_t) \rightarrow op$ where $op \in O$. Consequently, the model is required to determine whether to add p_t , not add p_t , or replace m_i with p_t by considering all memory M_t and p_t holistically.

3.2 Memory Management Data Curation

For memory management training, we need $\langle M_t, p_t, op \rangle$ triples. As there is no existing dataset providing the triple, we construct it in an automated way with existing datasets. We reinterpret publicly available DNLI (Welleck et al., 2018) dataset, that is designed for detecting textual entailment in dialogs, for memory management operations. Given a DNLI triple $\langle s_1, s_2, relationship \rangle$, we utilize s1 as a memory sentence to be part of all memory M_t and s_2 as p_t , newly generated information that is to be added or not. Then, we reinterpret the relationship labels as memory operations as below:

- **Positive** means s₁ and s₂ share relevant information. However, the relationship between s₁ and s₂ can be either s₁ entails s₂, s₂ entails s₁, or almost identical, depending on the amount of information. We classify DNLI data with positive labels into the three categories above and label them as PASS, REPLACE s₁, and APPEND operations, respectively.
- Negative means s_1 and s_2 are contradictory. We make up REPLACE s_1 operations with those data.
- Neutral means s₁ and s₂ are not related. We construct data with APPEND operation using neutral data.

Then, random memory sentences are collected to construct the memory M' of various lengths. We append s_1 to M' to comprise the entire memory M and finally obtain $\langle M, s2, op \rangle$ triples where $M = M' \cup \{s1\}.$

4 Experiments

In this section, we describe the experimental setups in detail and show results of our model BLENDERBOT3-M³, which is multi-task trained with memory management data.

4.1 Implementation Details

We leverage self-reproduced BLENDERBOT3 based on huggingface library as the LM backbone. The proposed model BLENDERBOT3-M³ is multi-task trained with constructed memory management data along with data for other conversation skills, starting from the r2c2 checkpoint. We use the Adam optimizer (Kingma and Ba, 2014) with a cosine learning rate 5e-5 and batch size 64. For comparison purposes, we additionally fine-tuned BLENDERBOT3 on the memory management dataset. Experiments are performed with BLENDERBOT3 3B, BLENDERBOT3 3B + MM fine-tuning, and BLENDERBOT3-M³ 3B.

4.2 Training Dataset

In addition to the existing 67 training datasets of 11 particular tasks to train BLENDERBOT3, Memory Management (MM) dataset is built following the creation method introduced in Section 3.2. The created MM dataset consists of 90,000 examples, and its operation labels (PASS, APPEND, REPLACE m_i) are equally distributed.

4.3 Evaluation Dataset

The baseline model and proposed models are evaluated on Multi Session Chat (MSC) in an end-to-end manner for measuring overall conversation ability in long-term conversation, and on all 67 datasets corresponding to the training datasets for measuring performance of each task (module).

4.4 Experimental Results

End-to-End Evaluation The comparison of overall conversation ability on MSC dataset which has long dialogues is shown in Table 1. Models are evaluated in an end-to-end manner. As shown in Table 1, throughout all sessions, we observe an overall increase in performance of BLENDERBOT3-M³ compared to BLENDER-BOT3, indicating a successful integration of the memory management capability followed by an improvement in overall conversation capability. Specifically, BLENDERBOT3-M³ outperforms BLENDERBOT3 with a relative 4% performance gain in terms of F1 score (average result from all sessions). It demonstrates that keeping memory up-to-date through memory management improves

	Session 2	Session 3	Session 4	Session 5	All Sessions	Memory		
	F1 (†)	# of entries (\downarrow)						
BLENDERBOT3	0.1791	0.1747	0.1528	0.149	0.164	117.7		
BLENDERBOT3 + MM fine-tuning	0.1732	0.1681	0.1443	0.1376	0.1558	<u>85.7</u>		
BLENDERBOT3-M ³ (OURS)	0.1882	0.1828	0.1583	0.1536	0.1708	70.3		

Table 1: End-to-end evaluation for measuring overall conversation ability on MSC dataset. BLENDERBOT3-M³, multi-task trained with memory management data, outperforms BLENDERBOT3 and BLENDERBOT3+ MM fine-tuning across all sessions.

	Decision		Generation		Knowledge		Dialogue			All	Management		
	Search	Memory	Query	Memory	Search	Memory	Entity	Search	Memory	Entity	Vanilla		Memory
	PPI	L (↓)	PPI	L (↓)		PPL (↓))		PPI	L (↓)		PPL (↓)	PPL (↓)
BLENDERBOT3	1.028	1.003	5.847	2.522	1.759	1.247	5.010	2.729	9.115	10.218	11.260	3.144	-
BlenderBot3-M^3 (ours)	1.028	1.003	5.627	2.567	1.798	1.257	5.405	2.781	9.181	10.371	11.485	3.196	1.735

Table 2: Modular performance (PPL) for other conversation capabilities are shown. There is no significant differences between BLENDERBOT3 and BLENDERBOT3-M[^]3.

general conversation performance in long-term conversations, which further can be a cornerstone of lifelong conversations.

Additionally, the numbers of entries in memory per every 100 turns is reported in Table 1, showing that memory management can effectively reduce external memory usage.

Evaluation in other tasks One may consider that in exchange for the memory management ability, other existing abilities might be compromised. To deal with this concern, we directly measure the task performance of each module, which can be also inferred from Table 1 Perplexity of each module is reported in Table 2. Across all tasks, we observe that the average PPL score of BLENDERBOT3-M³ increases 0.05 from the PPL of BLENDERBOT3.

The above explorations show that the overall conversational performance has been improved by successfully incorporating the new memory management capability into conversational agents.

5 Conclusion

In this paper, we propose an effortless way to improve open-domain conversation systems by integrating memory management into them. It is effortless in that we fully leverage existing data to construct memory management data in an automated way which can be easily scaled up. Our proposed method does not affect BB3's performance in other tasks, and does not require additional costs for the external memory and model parameters, but rather reduces the costs. We show that in end-to-end conversation evaluation, our proposed model BLENDERBOT3-M^3, which is multi-task trained with memory management, outperforms BLENDERBOT3 with a relative 4% performance gain in terms of F1 score. To deal with lifelong conversations where conversation histories and memories are accumulated endlessly, keeping memory up-to-date compactly via memory management can be a promising direction.

Limitations and Future Work While constructing memory management dataset, we comprise memories with randomly selected user information sentences. This may cause inconsistent memories and different distributions from those encountered in the actual conversation flows. Therefore, a careful design of the memory could be a potential avenue for further improving model performance.

Even with management, memory will constantly increase. Accumulated large memory is not suitable for the input of LM and occupies storage. However, our experiments only assume long conversations where the length of maximum memory is predetermined and fixed.

Ethical Considerations

Since the purpose of the conversation system is to interact with human, it is important to build reliable and controllable system. Also, as the proposed system stores the information of the user, protecting privacy is also important. Lastly, we will release the dataset and code for research purpose only to prevent from unintended usage of our product.

References

- Sanghwan Bae, Donghyun Kwak, Soyoung Kang, Min Young Lee, Sungdong Kim, Yuin Jeong, Hyeri Kim, Sang-Woo Lee, Woo Chul Park, and Nako Sung. 2022. Keep me updated! memory management in long-term conversations. *ArXiv*, abs/2210.08750.
- Daniel De Freitas, Minh-Thang Luong, David R. So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, and Quoc V. Le. 2020. Towards a human-like opendomain chatbot. ArXiv, abs/2001.09977.
- Hyunwoo Kim, Youngjae Yu, Liwei Jiang, Ximing Lu, Daniel Khashabi, Gunhee Kim, Yejin Choi, and Maarten Sap. 2022. Prosocialdialog: A prosocial backbone for conversational agents. *ArXiv*, abs/2205.12688.
- Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980.
- Mojtaba Komeili, Kurt Shuster, and Jason Weston. 2022. Internet-augmented dialogue generation. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 8460–8478, Dublin, Ireland. Association for Computational Linguistics.
- Hongyuan Lu, Wai leung William. Lam, Hong Cheng, and Helen Meng. 2022. Partner personas generation for dialogue response generation. In *NAACL*.
- Pierre-Emmanuel Mazaré, Samuel Humeau, Martin Raison, and Antoine Bordes. 2018. Training millions of personalized dialogue agents. In *Conference on Empirical Methods in Natural Language Processing*.
- Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Kurt Shuster, Eric Michael Smith, Y.-Lan Boureau, and Jason Weston. 2020. Recipes for building an open-domain chatbot. In *Conference of the European Chapter of the Association for Computational Linguistics*.
- Kurt Shuster, Mojtaba Komeili, Leonard Adolphs, Stephen Roller, Arthur Szlam, and Jason Weston. 2022a. Language models that seek for knowledge: Modular search & generation for dialogue and prompt completion. *arXiv preprint arXiv:2203.13224*.

- Kurt Shuster, Jing Xu, Mojtaba Komeili, Da Ju, Eric Michael Smith, Stephen Roller, Megan Ung, Moya Chen, Kushal Arora, Joshua Lane, et al. 2022b. Blenderbot 3: a deployed conversational agent that continually learns to responsibly engage. *arXiv preprint arXiv:2208.03188*.
- Eric Michael Smith, Mary Williamson, Kurt Shuster, Jason Weston, and Y-Lan Boureau. 2020. Can you put it all together: Evaluating conversational agents' ability to blend skills. In *Annual Meeting of the Association for Computational Linguistics*.
- Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam M. Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, Yaguang Li, Hongrae Lee, Huaixiu Zheng, Amin Ghafouri, Marcelo Menegali, Yanping Huang, Maxim Krikun, Dmitry Lepikhin, James Qin, Dehao Chen, Yuanzhong Xu, Zhifeng Chen, Adam Roberts, Maarten Bosma, Yanqi Zhou, Chung-Ching Chang, I. A. Krivokon, Willard James Rusch, Marc Pickett, Kathleen S. Meier-Hellstern, Meredith Ringel Morris, Tulsee Doshi, Renelito Delos Santos, Toju Duke, Johnny Hartz Søraker, Ben Zevenbergen, Vinodkumar Prabhakaran, Mark Díaz, Ben Hutchinson, Kristen Olson, Alejandra Molina, Erin Hoffman-John, Josh Lee, Lora Aroyo, Ravindran Rajakumar, Alena Butryna, Matthew Lamm, V. O. Kuzmina, Joseph Fenton, Aaron Cohen, Rachel Bernstein, Ray Kurzweil, Blaise Aguera-Arcas, Claire Cui, Marian Croak, Ed Huai hsin Chi, and Quoc Le. 2022. Lamda: Language models for dialog applications. ArXiv, abs/2201.08239.
- Megan Ung, Jing Xu, and Y-Lan Boureau. 2021. Saferdialogues: Taking feedback gracefully after conversational safety failures. In *Annual Meeting of the Association for Computational Linguistics*.
- Sean Welleck, Jason Weston, Arthur D. Szlam, and Kyunghyun Cho. 2018. Dialogue natural language inference. In *Annual Meeting of the Association for Computational Linguistics*.
- Jing Xu, Arthur Szlam, and Jason Weston. 2022a. Beyond goldfish memory: Long-term open-domain conversation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics* (*Volume 1: Long Papers*), pages 5180–5197, Dublin, Ireland. Association for Computational Linguistics.
- Jing Xu, Arthur D. Szlam, and Jason Weston. 2021. Beyond goldfish memory: Long-term open-domain conversation. In *Annual Meeting of the Association for Computational Linguistics*.
- Xinchao Xu, Zhibin Gou, Wenquan Wu, Zheng-Yu Niu, Hua Wu, Haifeng Wang, and Shihang Wang. 2022b. Long time no see! open-domain conversation with long-term persona memory. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2639–2650, Dublin, Ireland. Association for Computational Linguistics.

- Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur D. Szlam, Douwe Kiela, and Jason Weston. 2018. Personalizing dialogue agents: I have a dog, do you have pets too? In Annual Meeting of the Association for Computational Linguistics.
- Hanxun Zhong, Zhicheng Dou, Yutao Zhu, Hongjin Qian, and Ji-Rong Wen. 2022. Less is more: Learning to refine dialogue history for personalized dialogue generation. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 5808–5820, Seattle, United States. Association for Computational Linguistics.