

Generating Helpful Responses for Intelligent Tech Support

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Abstract

This is a three-page paper that describes a new kind of Complex QA task, its datasets and new challenges in the RCQA workshop’s focused area. The task is to generate helpful responses for intelligent technical support. Tech support forums (e.g., IBM DeveloperWorks, Microsoft TechNet, Sony Community) are widely available on the Internet, where users can report their technical issues and seek for solutions. However, it is expensive and often impossible to obtain timely and helpful responses. Compared with traditional answer generation tasks (e.g., SQuAD, MS-MARCO), response generation in the tech support domain has three unique challenges to AI and NLP technologies. First, questions and responses are often long-text of irrelevant information with the real problem. Second, responses are in different semantic spaces from the questions and need knowledge from external sources of the domain (e.g., user guide, manuals) to generate. Third, a thread of discussion starts from a question post and follows with a series of responses (and helpfulness signals) and follow-up questions, which is more complex than a question-answer pair. New technologies are needed to address the challenges.

Introduction

Tech companies such as IBM, Microsoft, and Sony have developed and actively maintained tech support discussion forums (e.g., IBM DeveloperWorks, Microsoft TechNet, and Sony Community) where their users can post technical issues and seek for advice and solution from peers and experts. The companies train employees to have professional communication skills and technical knowledge that are needed to respond users’ questions. However, it is sometimes expensive, or even impossible, to obtain *timely* and *helpful* responses from these forums. There are two main reasons for this. First, the users (peers) often have limited domain-specific knowledge to describe their problems, so it would be difficult to figure out the core problem and give helpful advice. It is common that the questioners added additional information, forming an interactive discussion of a long series of posts, which is actually very time consuming. Second, unlike the traditional reading comprehension tasks, helpful responses do not come from a given piece of contextual information, but rather require the respondent to

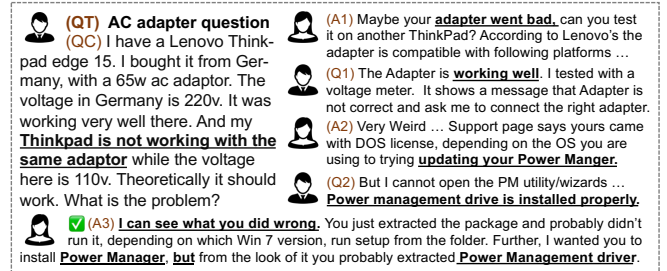


Figure 1: Discussion thread on Lenovo forum: An example

have in-depth background knowledge or have solved similar problems. Therefore, it is highly desirable to generate correct responses from tech support forums. If developed, such technologies can be used to develop intelligent applications, such as real-time tech support dialogue systems.

Figure 1 gives an example from the Lenovo forum.¹ Questions on the forum has two parts: question title (QT) and question content (QC). The question title summarizes the main content of the problem (e.g, battery problem, adapter problem). The question content describes the detailed information of the problem. Additionally, users usually give information of their products (e.g, device model, configurations, purchase year). Due to the limited background knowledge of peer users, it is difficult to generate a response (A) of high quality as a good solution. Therefore, a series of discussion (A1, Q1, A2, Q2, etc.) enrich the contexts and eventually come to a solution-level response (A3).

Difference from existing tasks/models: The traditional QA task is to read a passage (or a set of passages) and generate the answer given a question. The open access of the Stanford Question Answering Dataset (SQuAD) (Rajpurkar et al. 2016) and the Microsoft MACHine Reading COMprehension Dataset (MS-MARCO) (Nguyen et al. 2016) provides large-scale manually created datasets for model training and testing for this task. There are two differences. First, SQuAD constrains the answer to be an exact sub-span in the passage, while answer words are not necessary in the passages of MS-MARCO. Second, SQuAD only has one passage

¹<https://forums.lenovo.com/t5/ThinkPad-11e-Windows-13-E-and/AC-adapter-question-Edge-15/td-p/341079>

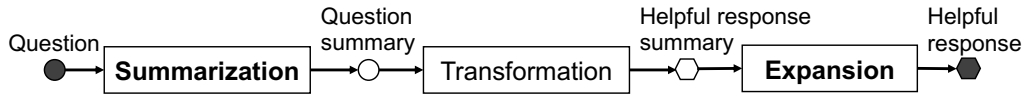


Figure 2: A summarization-expansion framework may address the *length* challenge (long-text question, response).

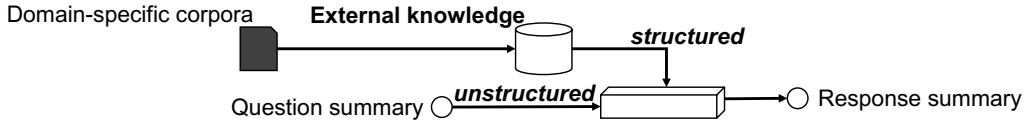


Figure 3: Responses are in a different space from questions and need external, specialized knowledge to be generated.

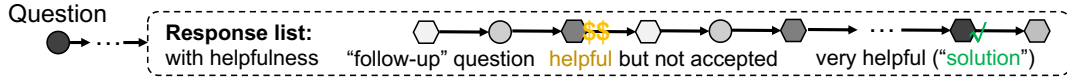


Figure 4: Beyond question-answer pairs: Modeling response sequences and helpfulness signals for generating the best solution.

for a question, while MS-MARCO has multiple passages. From the perspective of models, sequence-to-sequence models (Sutskever, Vinyals, and Le 2014) have demonstrated good performance in a wide range of natural language processing tasks including natural answer sentences generation. Besides, the application of attention mechanism (Vaswani et al. 2017) enabled attempts to learn sentence varieties from the memory and training data. Here, we are facing three unique challenges: (1) the text of questions and responses are of great length, (2) responses are in very different semantic spaces from questions and need external knowledge to complete, and (3) methods cannot directly be applied to create long-text content of correct semantics.

Related Work

Long-text Generation. Although there are no related works on the generation of long-text questions and responses, the long-text generations of story, news and paper abstract have been extensively researched (Liang et al. 2017; Fan, Lewis, and Dauphin 2018; Wang et al. 2019). (Li, Luong, and Jurafsky 2015) proposed a hierarchical neural encoder-decoder for paragraph generation, which arranges tokens, sentences and paragraphs in a hierarchical structure, with different levels of encoder-decoder to capture their compositionality. In contrast, dividing generation into two steps, (Wang et al. 2018) designed a novel writing-editing network that can attend to both the title and the previously generated abstract drafts and then iteratively revise and polish the abstract.

Knowledge Driven Generation. Modeling knowledge as a graph to improve generation results has been proved successfully on several tasks such as amr-to-text (Song et al. 2018), machine translation (Beck, Haffari, and Cohn 2018) and question generation (Chen, Wu, and Zaki 2020). Recently, (Koncel-Kedziorski et al. 2019) introduced a novel graph transforming encoder which can leverage the relational structure of knowledge graphs without imposing linearization or hierarchical constraints.

Datasets

Tech support forums are widely available on the Internet. After a user asked a question, peers and experts could make

responses. Two but not limited to these examples of datasets can be used for performing and evaluating the proposed task. For each of the data domains, user guide or developer documentation can serve as external knowledge sources (though unstructured). We are organizing the datasets (and collecting more datasets) and making documentation of them.

LenovoForum.² This dataset is consisted of 86,394 question posts (threads) and 334,387 response posts. 17,952 (20.8%) threads have one response post labeled as “solution” by the questioner. The average length (i.e., #words) of questions and responses are 103 and 52, respectively.

AskUbuntu.³ It has more than 332,914 question posts. Over 219,756 (66.0%) questions have a “solution” response. The average length of questions and responses are 51 and 37, respectively. They are relatively shorter than the Lenovo’s.

Challenges and Potential Ideas

Generating long-text questions and responses

Questions and responses (including solutions) on the tech support forums are often long-text of irrelevant information with the real problem. For example, the question posts often have greeting words to general audience, appreciation words to thank for replies in advance, and some *too* detailed information of the device model or configurations. The response posts may have greeting words to the questioner, redundant content (like direct quotes) from the question posts, or describe similar experience (which could be a long story). The solution posts may have itemized, suggested actions in steps. The less relevant information could distort the representation of posts and hurt the quality of generated responses. A basic idea to address it is to add question summary and response summary as bridges to connect the long-text question post and response post (see Figure 2). Then the main task is reduced down to generate response summary from question summary of reasonable length; but a summarization module and an expansion module must be added to the framework.

²<https://forums.lenovo.com>

³<https://askubuntu.com>

Generating responses with external knowledge

Unfortunately, there is no “passage” (like in SQuAD) in the tech support data that contains both the question context and answer. Responses are in different semantic spaces from the questions and need knowledge from external sources of the domain (e.g., user guide, manuals) to generate. The idea is to utilize the massive *unstructured* domain-specific corpora (e.g., user guide or developer documents) as external knowledge sources (see Figure 3). Knowledge bases and/or graphs can be constructed using information extraction technologies (Zeng et al. 2019; Yu et al. 2020a) and then be used for generating responses of rich, relevant semantics.

Learning helpfulness from response series

Problem solving on technical support forums is an interactive process. A thread of discussion starts from a question post and follows with a series of responses (and helpfulness signals). During the process, the questioner can describe the problem with additional information (“follow-up questions”). The forums often have mechanisms to motivate helpful responses. For example, on the Lenovo forum, questioners can give “Kudo” points to the responses they like and label no more than one response as a “solution” (with a green mark). This is more complex than traditional inputs - question-answer pairs only. To generate helpful responses, the basic idea is to learn helpfulness signals by modeling the series of response sentences (Ouyang et al. 2019; Yu et al. 2020b), which could improve the quality of response generation process (see Figure 4).

References

- [Beck, Haffari, and Cohn 2018] Beck, D.; Haffari, G.; and Cohn, T. 2018. Graph-to-sequence learning using gated graph neural networks. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 273–283.
- [Chen, Wu, and Zaki 2020] Chen, Y.; Wu, L.; and Zaki, M. J. 2020. Reinforcement learning based graph-to-sequence model for natural question generation. In *The International Conference on Learning Representations*.
- [Fan, Lewis, and Dauphin 2018] Fan, A.; Lewis, M.; and Dauphin, Y. 2018. Hierarchical neural story generation. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 889–898.
- [Koncel-Kedziorski et al. 2019] Koncel-Kedziorski, R.; Bekal, D.; Luan, Y.; Lapata, M.; and Hajishirzi, H. 2019. Text generation from knowledge graphs with graph transformers. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 2284–2293.
- [Li, Luong, and Jurafsky 2015] Li, J.; Luong, T.; and Jurafsky, D. 2015. A hierarchical neural autoencoder for paragraphs and documents. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 1106–1115.
- [Liang et al. 2017] Liang, X.; Hu, Z.; Zhang, H.; Gan, C.; and Xing, E. P. 2017. Recurrent topic-transition gan for visual paragraph generation. In *Proceedings of the IEEE International Conference on Computer Vision*, 3362–3371.
- [Nguyen et al. 2016] Nguyen, T.; Rosenberg, M.; Song, X.; Gao, J.; Tiwary, S.; Majumder, R.; and Deng, L. 2016. Ms marco: A human-generated machine reading comprehension dataset.
- [Ouyang et al. 2019] Ouyang, W.; Zhang, X.; Li, L.; Zou, H.; Xing, X.; Liu, Z.; and Du, Y. 2019. Deep spatio-temporal neural networks for click-through rate prediction. *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*.
- [Rajpurkar et al. 2016] Rajpurkar, P.; Zhang, J.; Lopyrev, K.; and Liang, P. 2016. Squad: 100,000+ questions for machine comprehension of text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, 2383–2392.
- [Song et al. 2018] Song, L.; Zhang, Y.; Wang, Z.; and Gildea, D. 2018. A graph-to-sequence model for amr-to-text generation. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 1616–1626.
- [Sutskever, Vinyals, and Le 2014] Sutskever, I.; Vinyals, O.; and Le, Q. V. 2014. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, 3104–3112.
- [Vaswani et al. 2017] Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention is all you need. In *Advances in neural information processing systems*, 5998–6008.
- [Wang et al. 2018] Wang, Q.; Zhou, Z.; Huang, L.; Whitehead, S.; Zhang, B.; Ji, H.; and Knight, K. 2018. Paper abstract writing through editing mechanism. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, 260–265.
- [Wang et al. 2019] Wang, Q.; Huang, L.; Jiang, Z.; Knight, K.; Ji, H.; Bansal, M.; and Luan, Y. 2019. PaperRobot: Incremental draft generation of scientific ideas. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 1980–1991. Florence, Italy: Association for Computational Linguistics.
- [Yu et al. 2020a] Yu, W.; Peng, W.; Shu, Y.; Zeng, Q.; and Jiang, M. 2020a. Experimental evidence extraction in data science with hybrid table features and ensemble learning. In *The World Wide Web Conference*. ACM.
- [Yu et al. 2020b] Yu, W.; Yu, M.; Zhao, T.; and Jiang, M. 2020b. Identifying referential intention with heterogeneous contexts. In *The World Wide Web Conference*. ACM.
- [Zeng et al. 2019] Zeng, Q.; Yu, M.; Yu, W.; Xiong, J.; Shi, Y.; and Jiang, M. 2019. Faceted hierarchy: A new graph type to organize scientific concepts and a construction method. In *Proceedings of the Thirteenth Workshop on Graph-Based Methods for Natural Language Processing (TextGraphs-13)*.