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1 Research interests

In the modern field of Natural Language Processing (NLP), large language models (LLMs), such as GPT-4 (OpenAI, 2023), have become the key technologies that potentially break the traditional boundaries. These models can generate idiomatic high-quality text, successfully addressing many of the NLP challenges and drive rapid technological advancements. Within the context of LLMs, my research interests are: (1) utilizing the powerful text generation capabilities of the LLMs in terms of **customized dialogue data augmentation** in data-scarce tasks, and (2) applying the LLMs to the **psychological counseling dialogues**. Moreover, I hope to combine these two themes in the future.

1.1 Customized dialogue data augmentation

Spoken dialogue systems (SDSs) often rely on the interaction data between real humans for training. However, different people have different speaking styles and strategies, influenced by factors such as the dialogue topic, age, regional and local language variation, context, identity, preferences, and personality of the speaker, among others. In real life human conversations, individuals may adjust their responses based on the other party's strategy, such as seeking clarification when the other party speaks unclearly. For SDS, those with unique dialogue strategies form a minority group, resulting in relatively scarce dialogue data. Consequently, the SDS cannot adapt to the speaking strategies of others as effectively as humans, particularly when encountering individuals with unique speaking styles.

The scarcity of the annotated data and the challenge of data imbalance are persistent issues in various artificial intelligence domains (Shi et al., 2020; Ahmad et al., 2021; Hedderich et al., 2021). To address those effectively, various data augmentation techniques have been employed, as demonstrated in prior research on different tasks (Feng et al., 2021; Bayer et al., 2022; Kim et al., 2023). For instance, Schick and Schütze (2021) generated text similarity datasets from scratch by instructing a large pre-trained language model (PLM). Similarly, Liu et al. (2022) and Chen and Yang (2021) enhanced the data by manipulating individual utterances within dialogues—in ways such as adding, deleting, changing their order, or regenerating them—while preserving the original meaning, which improved the model's performance in the dialogue summarization tasks.

My research focuses on the dialogues that involve users of different age groups. Inaba et al. (2024a) have found that speakers of various age group exhibit distinct speaking strategies. For example, compared to other age groups, minor interlocutors are less likely to express their opinions. Consequently, the other speaker often seeks confirmation or asks additional questions to make the conversation flowing smoothly. Considering the unique speaking styles of minors and the inherent difficulties in obtaining data from them (Aydin et al., 2021), my recent research employs a framework that combine the LLM and PLM. This approach customizes the generation of dialogue data for minors, enhancing the performance of SDS in situations when data from minors is scarce.

1.2 Psychological counseling using LLM

Mental health is one of the critical issues in today's society. According to the World Health Organization (WHO), nearly 1 billion people worldwide suffer from mental disorders, yet 70% of them do not receive any treatment, such as counseling[1]. There is a significant gap between the existing mental health support and the needs of patients. In recent years, the emergence of online counseling platforms, such as 7cups[2] has made psychological counseling more accessible. However, due to the lack of experience of some counselors, the effectiveness of these services is not always ideal. Additionally, training professional counselors requires considerable effort.

In recent years, AI research related to psychological counseling has been increasing. Inaba et al. (2024b) collected counseling dialogue data using role-playing methods, and the evaluations by professional counselors indicated that the responses generated by GPT-4 were competitive compared to those generated by human counselors. Zhang et al. (2024) enriched the counseling dialogue dataset by using LLM to generate dialogues based on reports from online counseling platforms. Young et al. (2024) investigated the popularity of human and LLM-generated responses across various counseling top-

[1] https://news.un.org/zh/story/2022/06/1104712
[2] https://www.7cups.com/

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ics. Their results showed that LLM responses were more popular for topics like interpersonal relationships and physical health, while human responses were preferred for topics related to suicide.

Those studies indicate that LLMs can play the role of counselors, generating high-quality psychological counseling dialogues. However, due to the uncontrollable nature of their generated content, there is a potential risk when interacting with users who have suicidal tendencies or extreme emotions. Consequently, the aim of related research is not to have AI act as counselors directly but to use their powerful text generation capabilities to assist counselors with dialogues. Sharma et al. (2022) developed HAILEY using PLM to help peer supporters on online counseling platforms provide more empathetic responses. Similarly, Hsu et al. (2023) used PLMs to offer real-time response strategies and sentences during counseling dialogues, assisting counselors in their work. This approach mitigates safety and ethical risks while also helping inexperienced counselors develop their professional skills.

My research interest lies in utilizing LLMs to assist counselors with psychological counseling dialogues. Specifically, this study employs LLM to provide various forms of real-time support for the mental health counselors during their sessions with their patients, in terms of dialogue strategies, example responses, and refinement of drafted replies. Ultimately, the usefulness of the support system and the most preferred type of support by counselors will be analyzed through a questionnaire survey.

2 Spoken dialogue system (SDS) research

I believe that future SDSs need to have the ability to adapt to different individuals. For example, people's personalities vary; some enjoy engaging in conversation, while others are better listeners and appreciate different aspects of the dialogue. Additionally, some people are comfortable answering any questions, while others may be more restrained and prefer not to be asked very personal questions. The goal is for SDS to infer the users' personalities through various potential multimodal cues during conversations and adapt their responses accordingly. This adaptability would significantly enhance the evaluation of dialogue systems.

I also hope that SDSs will become increasingly active in the field of psychological counseling. The number of people suffering from psychological problems is enormous, and most of them do not receive adequate support due to a lack of someone to talk to, among other reasons. This situation needs improvement. The powerful capabilities of LLMs can provide significant help in psychological counseling.

Ultimately, applying the user adaptability to psychological counseling will enable SDSs to create more flexible and effective counseling dialogues when interacting with different users.

3 Suggested topics for discussion

I suggest discussing the following topics:

- **Multimodal Dialogue Systems for Individuals with Disabilities**: As multimodal dialogue systems evolve, more information becomes available for dialogue generation. Can we leverage these technologies to facilitate daily life activities for individuals with disabilities? What are the key technologies when building such dialogue systems, and what considerations should be made?

- **LLM's Personality Adaptation**: Humans typically exhibit a single personality type, possibly engaging comfortably in conversations with only a few other personality types. In contrast, LLMs are trained on extensive textual data from conversations involving various personality types. Thus, LLMs can theoretically adapt to any personality, potentially enhancing the conversational experience for all of the users by adopting different conversational styles to match the user's personality.

- **How long can the trend of LLMs last? What are the key technologies for future SDS?**

References

Tanveer Ahmad, Dongdong Zhang, Chao Huang, Hongcai Zhang, Ningyi Dai, Yonghua Song, and Huanxin Chen. 2021. Artificial intelligence in sustainable energy industry: Status quo, challenges and opportunities. *Journal of Cleaner Production* 289:125834.

Selami Aydin, Leyla Harputlu, Özgehan Uştuk, Şeyda Savran Çelik, and Serhat Güzel. 2021. Difficulties in collecting data from children aged 7–12. *International Journal of Teacher Education and Professional Development (IJTEPD)* 4(1):89–101.

Markus Bayer, Marc-André Kaufhold, and Christian Reuter. 2022. A survey on data augmentation for text classification. *ACM Comput. Surv.* 55(7). https://doi.org/10.1145/3544558.

Jiaao Chen and Diyi Yang. 2021. Simple conversational data augmentation for semi-supervised abstractive dialogue summarization. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Online and Punta Cana, Dominican Republic, pages 6605–6616. https://doi.org/10.18653/v1/2021.emnlp-main.530.

Steven Y. Feng, Varun Gangal, Jason Wei, Sarath Chandar, Soroush Vosoughi, Teruko Mitamura, and Eduard Hovy. 2021. A survey of data augmentation approaches for NLP. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*. Association for Computational Linguistics, Online, pages 968–988. https://doi.org/10.18653/v1/2021.findings-acl.84.

Michael A. Hedderich, Lukas Lange, Heike Adel, Jannik Strötgen, and Dietrich Klakow. 2021. A survey on recent approaches for natural language processing in low-resource scenarios. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Association for Computational Linguistics, Online, pages 2545–2568. https://doi.org/10.18653/v1/2021.naacl-main.201.

Shang-Ling Hsu, Raj Sanjay Shah, Prathik Senthil, Zahra Ashktorab, Casey Dugan, Werner Geyer, and Diyi Yang. 2023. Helping the helper: Supporting peer counselors via ai-empowered practice and feedback.

Michimasa Inaba, Yuya Chiba, Zhiyang Qi, Ryuichiro Higashinaka, Kazunori Komatani, Yusuke Miyao, and Takayuki Nagai. 2024a. Travel agency task dialogue corpus: A multimodal dataset with age-diverse speakers. *ACM Trans. Asian Low-Resour. Lang. Inf. Process.* https://doi.org/10.1145/3675166.

Michimasa Inaba, Mariko Ukiyo, and Keiko Takamizo. 2024b. Can large language models be used to provide psychological counselling? an analysis of gpt-4-generated responses using role-play dialogues. In *The 14th International Workshop on Spoken Dialogue Systems Technology*. https://arxiv.org/abs/2402.12738.

Hyunwoo Kim, Jack Hessel, Liwei Jiang, Peter West, Ximing Lu, Youngjae Yu, Pei Zhou, Ronan Bras, Malihe Alikhani, Gunhee Kim, Maarten Sap, and Yejin Choi. 2023. SODA: Million-scale dialogue distillation with social commonsense contextualization. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Singapore, pages 12930–12949. https://doi.org/10.18653/v1/2023.emnlp-main.799.

Yongtai Liu, Joshua Maynez, Gonçalo Simões, and Shashi Narayan. 2022. Data augmentation for low-resource dialogue summarization. In *Findings of the Association for Computational Linguistics: NAACL 2022*. Association for Computational Linguistics, Seattle, United States, pages 703–710. https://doi.org/10.18653/v1/2022.findings-naacl.53.

OpenAI. 2023. Gpt-4 technical report.

Timo Schick and Hinrich Schütze. 2021. Generating datasets with pretrained language models. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Online and Punta Cana, Dominican Republic, pages 6943–6951. https://doi.org/10.18653/v1/2021.emnlp-main.555.

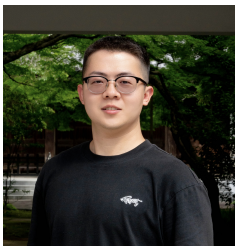
Ashish Sharma, Inna W. Lin, Adam S. Miner, David C. Atkins, and Tim Althoff. 2022. Human-ai collaboration enables more empathic conversations in text-based peer-to-peer mental health support.

Wenzhong Shi, Min Zhang, Rui Zhang, Shanxiong Chen, and Zhao Zhan. 2020. Change detection based on artificial intelligence: State-of-the-art and challenges. *Remote Sensing* 12(10). https://doi.org/10.3390/rs12101688.

Jordyn Young, Laala M Jawara, Diep N Nguyen, Brian Daly, Jina Huh-Yoo, and Afsaneh Razi. 2024. The role of ai in peer support for young people: A study of preferences for human- and ai-generated responses. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, CHI '24. https://doi.org/10.1145/3613904.3642574.

Chenhao Zhang, Renhao Li, Minghuan Tan, Min Yang, Jingwei Zhu, Di Yang, Jiahao Zhao, Guancheng Ye, Chengming Li, and Xiping Hu. 2024. Cpsycoun: A report-based multi-turn dialogue reconstruction and evaluation framework for chinese psychological counseling.

Biographical sketch



Zhiyang Qi is currently pursuing a PhD at The University of Electro-Communications in Japan, within the Graduate School of Informatics and Engineering. Associate Professor Michimasa Inaba is his advisor. Qi is interested in dialogue system competitions and dialogue systems for the Werewolf game. He enjoys playing board games, with his favorite being Catan.