Research Statement of Xiuying Chen

Artificial Intelligence Generated Content (AIGC) aims to revolutionize content creation by generating customized content that aligns with user-specified requirements. AIG text is an essential step towards this goal, as ideas, information, and communication are conveyed through text. Though text generation has achieved enormous progress with pretrained language models and advanced algorithms, generating contextually relevant text that meets human standards and expectations is a long, arduous, and expensive journey. Hence it is highly in demand for AI models to gain the capability of understanding human language, generating high-quality text, and ultimately benefit human society. I have been motivated during my master and Ph.D. training by this goal, and working on the design of new fundamental algorithms for better AIG text. Principally, my efforts go towards the following aims:

- **Aim 1**: How can AI-generated text be *accurate*?
- **Aim 2**: How can AI-generated text be *trustworthy*?

Next, I briefly introduce the main contributions of my research to fulfill the Aim 1 to Aim 2, and illustrate the future plan.

1 Past & Current Research

1.1 Aim 1: Enhancement of Accurate Text Generation

The first step towards artificial intelligent text generation is to generate accurate text that prioritizes precision and correctness of the generated content. Accuracy serves as a fundamental requirement to ensure that the generated text is reliable and useful in various applications, ultimately enhancing the overall performance and usability of AI-powered text generation systems.

Multi-task To enhance the understanding of the given context and generate faithful text, our proposed approach utilizes reading comprehension aside from text generation task [AAAI’21]. We examine whether the encoder fully comprehends the input document by evaluating its ability to answer questions regarding key information within the input. Furthermore, we introduce a max-margin loss, which is defined based on the difference between the language model and the task-specific model, i.e., summarization model [NeurIPS'22]. This loss aims to prevent the language model from becoming overconfident in its generated output, ensuring more reliable and accurate text generation.

Refinement Drawing inspiration from the observation that humans often need to read an article multiple times to fully comprehend and summarize its content, we propose a refinement model in [EMNLP'18]. This model employs an iterative approach to refine the document representation through multiple passes over the document, improving its understanding and summarization capabilities. In addition to the model aspect refinement, we also explore data aspect refinement. In [AAAI’23], we propose to select representative and beneficial data samples for augmentation, which are then utilized to further train the model.

1.2 Aim 2: Development of Trustworthy Text Generation

While accuracy is the first step towards effective AI text generation, it's important to note that it's only one piece of the puzzle. To truly provide value, these systems must not only generate accurate text, but also earn the trust of their users. This is where the concept of trustworthy text generation comes into play, setting a higher standard for the quality and reliability of AI-generated content. However, existing text generation systems face challenges such as vulnerability to imperceptible attacks, lack of transparency, and significant environmental impact.

Robustness A trustworthy and robust text generation system should be able to capture the gist of the document, regardless of the specific word choices or noise in the input. In [ACL’23], we first show that state-of-the-art summarization models have a significant decrease in performance on adversarial and noisy test sets. Correspondingly, we propose a dual-augmentation method for improving the robustness, which generates discrete and virtual training cases in the same meaning but with various expression formats.

Explainability Generating text from scratch is challenging as it requires understanding, planning, and organizing content in a logical order. This process is often seen as a black-box, making it difficult to analyze and interpret how the text is generated. However, using prototype templates can alleviate the difficulty, as the generated text can be directly attributed to the underlying template, enhancing transparency and interpretability. In [EMNLP'19] and [TOIS'21], we applied this prototype template theory to text generation tasks. Through human evaluation, we observed that nearly 90% of the selected prototype templates significantly aided in understanding the generated text. This finding highlights the potential of using prototype templates as a valuable technique to enhance text generation and improve its interpretability.

Environmental Well-being The pursuit of larger models in deep learning is leading to considerable carbon emissions and increased resource consumption, underscoring the need for sustainability in AIG text systems. In [SIGIR'23], we introduce a unified-modal summarization framework with side information. This framework leverages side information from diverse modalities and covers various aspects, thus reduces the necessity for scenario-specific model retraining, enhancing overall efficiency. Building upon this, in our [submission'23], we take a step further by proposing a parameter-efficient unified summarization model. This model can effectively handle input text from different domains using a hierarchical expert structure, expanding its applicability to a wide range of text summarization tasks.

2 Future Research

Given the vast terrain of AI and the immense complexity of AIG-T, the aforementioned four questions remain largely unaddressed. Therefore, I plan to delve deeper into this core aspect of AIG-T in my future endeavors.

2.1 Advancing Explainable Capabilities in AIG-T

Despite the remarkable achievements of AIG-T in general domains, its application in high-stakes domains remains challenging. Domains like science discovery and healthcare demand a greater emphasis on accuracy, reliability, transparency, and minimal fault tolerance. Inaccurate medical diagnoses could have severe consequences for patients, while misleading scientific conclusions can misdirect research efforts. To address these concerns, generative models in high-stakes applications should incorporate confidence scores, explaination abilities, and source information alongside the generated results. This approach ensures that decision-makers have the necessary context and information to make informed judgments, minimizing the potential risks and maximizing the benefits of AIGT in these critical domains.

2.2 Harnessing the Power of AIG-T for social goods

I intend to explore the use of advanced generative models, including GANs, VAEs, and large language models, to address key social challenges. My focus will be on creating algorithms that not only push the boundaries of these models but also incorporate fairness and explainability, ensuring their ethical application in societal contexts. Leveraging my background in adversarial ML and statistical learning theory, I plan to integrate differential privacy into these models, enhancing data security in sensitive applications. This series of works aim to demonstrate the positive societal impact of AI technologies, marrying technical innovation with a commitment to social responsibility, a core aspect of my research ambitions.

2.3 Environmentally-Friendly Continual Learning for AIG-T

In today's world, knowledge keeps expanding and new challenges continuously emerge. This underscores the importance of enabling language models to acquire new knowledge. However, the considerable costs associated with training large language models can't be ignored. Therefore, it's crucial to develop language models that are efficient in terms of resource use and environmentally friendly, while maintaining their ability to adapt and learn new things. A promising initial step could be to synergize software enhancement with hardware development.

Reference

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