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TUTORIAL

Preventing and Detecting Misinformation Generated by Large Language Models

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Preventing and Detecting Misinformation Generated by Large Language Models

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ABSTRACT

As large language models (LLMs) become increasingly capable and widely deployed, the risk of them generating misinformation poses a critical challenge. Misinformation from LLMs can take various forms, from factual errors due to hallucination to intentionally deceptive content, and can have severe consequences in high-stakes domains.This tutorial covers comprehensive strategies to prevent and detect misinformation generated by LLMs. We first introduce the types of misinformation LLMs can produce and their root causes. We then explore two broad categories: **Preventing misinformation generation**: a) AI alignment training techniques to reduce LLMs' propensity for misinformation and refuse malicious instructions during model training. b) Training-free mitigation methods like prompt guardrails, retrieval-augmented generation (RAG), and decoding strategies to curb misinformation at inference time. **Detecting misinformation after generation**, including a) using LLMs themselves to detect misinformation through embedded knowledge or retrieval-enhanced judgments, and b) distinguishing LLM-generated text from human-written text through black-box approaches (e.g., classifiers, probability analysis) and white-box approaches (e.g., watermarking). We also discuss the challenges and limitations of detecting LLM-generated misinformation.

CCS CONCEPTS

• **Computing methodologies** → *Natural language processing*; • **Security and privacy** → **Social aspects of security and privacy**.

KEYWORDS

Large Language Models, Misinformation, Hallucination

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1 INTENDED AUDIENCE

This tutorial is intended for researchers, practitioners, and policymakers interested in understanding and addressing the challenges of misinformation generated by large language models (LLMs). Attendees should have a basic understanding of natural language processing and large language models. The tutorial will be accessible to a broad audience, including researchers and practitioners from academia and industry, as well as policymakers and journalists. Attendees will gain a comprehensive understanding of the types of misinformation LLMs can produce, the root causes of misinformation, and the state-of-the-art strategies to prevent and detect misinformation generated by LLMs.

2 PRESENTERS

Aiwei Liu[1] is a Ph.D. student at the School of Software, Tsinghua University, supervised by Prof. Lijie Wen. He received his Bachelor's degree from the Software Institute, Nanjing University in 2020. His research interests focus on large language models, particularly in the areas of security and trustworthiness, including red-teaming, secure alignment, and watermarking techniques for large models. He has published numerous papers in top-tier conferences and journals, such as ICLR, SIGKDD, ACL, EMNLP, SIGIR, and TKDE. Additionally, he serves as a reviewer for several prestigious conferences, including ACL, EMNLP, EACL, and WWW.

Qiang Sheng[2] is an Assistant Professor at the Media Synthesis and Forensics Lab, Institute of Computing Technology, Chinese Academy of Sciences. He received his Ph.D. from the University of Chinese Academy of Sciences under the supervision of Prof. Juan Cao. His research interests include fake news detection, fact-checking, natural language understanding, social media mining, and AI safety. He has published in top-tier conferences and journals such as ACL, AAAI, SIGIR, WWW, and TKDE. He has served as an area chair, reviewer, or PC member for conferences including MM, AAAI, ACL, EMNLP, IJCAI, KDD, and WWW, and as a reviewer for journals such as ACM TOIS, IEEE TASLP, and IP&M.

Xuming Hu[3] is an Assistant Professor at the Hong Kong University of Science and Technology (Guangzhou). He obtained his Ph.D. from the School of Software at Tsinghua University in 2024. His research interests encompass trustworthy large language models, multimodal large language models, and AI for science. His work has been published in numerous top-tier international conferences, such as SIGIR, SIGKDD, ACL, EMNLP, ICLR, NAACL, and TKDE.

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[2] https://scholar.google.com/citations?user=8BEUQ9UAAAAJ
[3] https://scholar.google.com/citations?user=dbBKbXoAAAAJ

Furthermore, he serves as an Area Chair for prestigious conferences, including ACL, NAACL, and EACL.

3 TOPIC AND RELEVANCE

3.1 Motivation

The rapid development of large language model technologies has led to the emergence of increasingly powerful models, including open-source ones like LLaMA [51], Falcon [2], and Mixtral [29], as well as commercial products such as GPT-4 [1], Claude [3], and Gemini [45]. These models have not only made tremendous progress in traditional NLP tasks like question answering [48], translation [42], and information extraction [55] but have also demonstrated new capabilities in areas such as code generation [43]. Some researchers even refer to GPT-4 as an early version of Artificial General Intelligence (AGI) [8]. As more and more text on the internet is generated by LLMs, concerns about the credibility and authenticity of LLM-generated content have grown [16, 53, 62]. On one hand, LLMs themselves suffer from hallucination [27, 44], which can lead to the unintentional generation of false information. Some studies suggest that hallucination in large models may even be inevitable [59]. On the other hand, due to the strong instruction-following capabilities of LLMs [17], malicious users can manipulate them to generate false information through carefully crafted prompts [41]. Research has shown that fake information generated by LLMs is more difficult for both humans and detectors to identify [10], suggesting that LLM-generated misinformation may have a more deceptive style and potentially cause greater harm.

Therefore, mitigating the harm caused by LLM-generated misinformation is a crucial issue. In this tutorial, we will discuss two main aspects: how to prevent LLMs from generating misinformation and how to detect misinformation generated by LLMs.

- Prevention strategies: Current research on prevention strategies focus more on how to mitigate the hallucination phenomenon in LLMs [50, 61], enabling them to generate more accurate and reliable information. This can be achieved by modifying the input prompts of LLMs, including retrieving information from external knowledge bases to guide LLMs in generating more accurate and reliable content, known as the Retrieval-Augmented Generation (RAG) method [15, 52, 57]. Additionally, designing appropriate prompting strategies can also guide LLMs to generate more accurate and reliable content [14, 28]. Furthermore, research on LLMs' decoding strategies can help generate more accurate content [13]. Moreover, some studies focus on aligning LLMs during the training phase to ensure that the content generated by LLMs better aligns with human values and preferences [5]. This not only mitigates the hallucinations generated by LLMs [60] but also enables LLMs to refuse some malicious instructions to generate misinformation [6]. However, it is important to note that for intentionally generated misinformation, prevention strategies cannot guarantee complete prevention of LLMs from generating misinformation [10, 59]. Therefore, we also need detection strategies to identify misinformation.
- Detection strategies: We will discuss the detection strategies for LLM-generated misinformation from two perspectives. The first perspective focuses on whether we can detect text generated by LLMs [49]. This can be achieved through black-box approaches, such as training a classifier to distinguish between LLM-generated and human-written text [26] or exploring the probabilities assigned by LLMs to the generated text [40]. Alternatively, white-box approaches can be employed, such as incorporating watermarks into the text generation process of LLMs to facilitate detection [30, 36]. The second perspective is to attempt to use LLMs themselves to detect misinformation [19, 20, 25]. This can be done by utilizing the knowledge embedded within the LLMs to make judgments [10, 56] or by employing retrieval methods to leverage external knowledge bases for retrieval-enhanced judgments [11, 12]. Lastly, some works openly discuss whether misinformation generated by LLMs can be detected at all [10]. This is an important consideration, as the increasing sophistication of LLMs may make it challenging to distinguish between genuine and misleading content.

In this tutorial, we aim to provide a comprehensive overview of the current progress in both prevention and detection strategies for misinformation generated by LLMs.

Necessity and timely of this tutorial. Mitigating and detecting misinformation generated by large language models (LLMs) is a relatively new topic that has become particularly important recently as the quality of LLM-generated text continues to improve. In recent years, a significant number of relevant papers have been published at top international conferences (such as ACL, ICML, NeurIPS, SIGIR, EMNLP, etc.), with one paper receiving the ICML Outstanding Paper Award [30]. We believe that more valuable work will emerge in this field in the future. This tutorial is highly necessary to provide a comprehensive understanding to researchers, practitioners, and decision-makers in this field, helping them better carry out relevant work.

3.2 Objectives

The objective of this tutorial is to provide a comprehensive overview of the current strategies for preventing and detecting misinformation generated by large language models. It aims to equip attendees with the knowledge and skills needed to develop and implement effective techniques to mitigate the harm caused by LLM-generated misinformation. Furthermore, this tutorial seeks to foster discussion, raise awareness, inspire new research directions, and contribute to the responsible development and deployment of LLM technologies in various domains.

3.3 Relevance

This tutorial is highly relevant to the SIGIR community, as information retrieval and large language models have become closely intertwined fields that can significantly benefit from each other. Previous tutorials at SIGIR 2022 [9] and ACL 2023 [4] have discussed retrieval-augmented generation and the generative capabilities of LLMs. Additionally, tutorials at EMNLP 2023 [32, 58] have discussed the potential harms associated with LLMs.

What sets our tutorial apart is its specific focus on mitigating the harm caused by misinformation generated by LLMs, which presents a more targeted and challenging problem. Retrieval techniques play a crucial role in this context, and with the increasing application of LLMs in the retrieval domain, this tutorial offers a valuable opportunity for SIGIR attendees to gain a deeper understanding of how LLMs are being utilized in their field.

3.4 Format and Schedule

This tutorial will be held offline, and all speakers will present it on site. The tentative schedule of this half-day tutorial (3 hours plus breaks) is as follows:

- 9:00-9:30: Introduction
  - Large Language Models (LLMs) and their capabilities [1–3, 29, 45, 51]
  - Misinformation generated by LLMs
    - Unintentional generated misinformation. (Hallucination) [27, 44, 59]
    - Intentional generated misinformation. [10, 41]
  - Overview of prevention and detection strategies
- 9:30-10:30: Prevention strategies
  - Retrieval augmented generation (RAG) [15, 52, 57]
  - Prompting techniques [14, 28]
  - Decoding based methods [13]
  - LLM alignment training [5, 6, 60]
- 10:30-11:00: Coffee break
- 11:00-12:10: Detection strategies
  - LLM generated text detection
    - Black-box detection [26, 40]
    - White-box detection [30, 36]
  - Misinformation detection with LLMs [10–12, 19, 25, 31, 56]
  - Could LLM-Generated Misinformation be Detected? [10]
- 12:10-12:25: Open problems, future directions and conclusions
  - Misinformation in Multimedia Content
  - Transferability of Solutions
  - Policy and Governance
  - Conclusions
- 12:25-12:30: Q&A

3.5 Qualification of presenters

We have been working on preventing and detecting Misinformation generated by large language models for a long time and have published a series of related works in top-tier conferences [7, 18, 20–24, 34, 35, 37–39, 46, 47, 63], including ICLR 2024, AAAI 2024, SIGIR 2023, EMNLP 2022, TKDE, MM 2023, ACL 2022, SIGIR 2022 and ACL 2020. These studies range from research on hallucinations in large models [22], to retrieval-augmented approaches[24], to alignment techniques [33], and to using large models for misinformation detection [7, 20, 21, 46, 47, 63] and retrieval of text generated by large models [35, 36]. We are very familiar with both lines of research on this topic and have contributed surveys on knowledge retrieval for LLM [54] as well as watermarking techniques for LLMs [37].

4 TURORIAL MATERIALS

- **Duration:** The tutorial is planned as a 3-hour tutorial.
- **Interaction style:** This is a lecture-style tutorial.
- **Turorial materials:** The slides will be released at https://sigir24-llm-misinformation.github.io/.
- **Organization details:** The tutorial can be conducted through both in-person and online formats, with all presenters intending to be physically present and lead the tutorial. If needed, we can offer a pre-recorded lecture as well. Additionally, with permission, we can also live-stream the tutorial using well-known video streaming platforms.

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