Robust Information Retrieval

WSDM 2025 tutorial

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https://wsdm2025-robust-information-retrieval.github.io/

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01:30 – 05:00 PM

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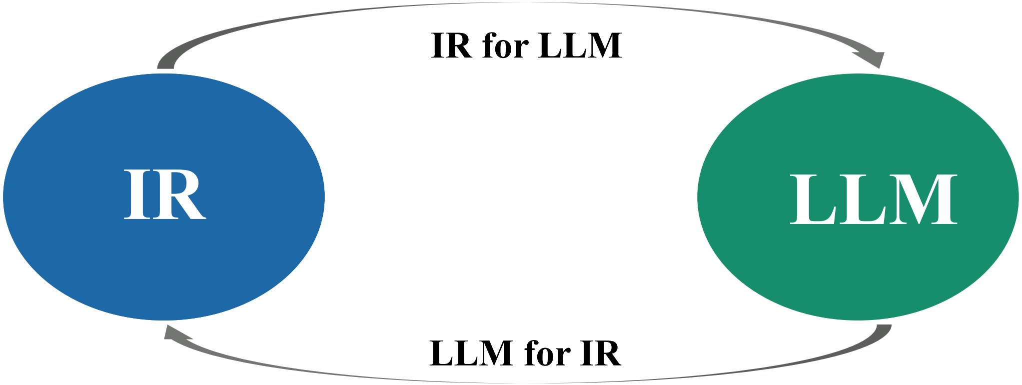
Section 5:
Robust IR in the age of LLMs

SCAN
ME

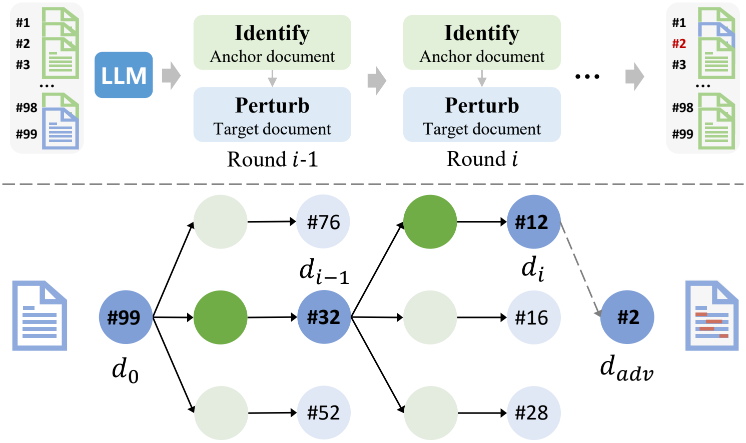


- **IR for LLM**: Retrieval-augmented generation
- **LLM for IR**: A double-edged sword

Some preliminary explorations

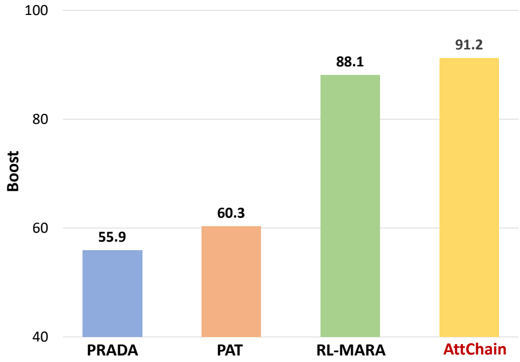
Some preliminary explorations: IR models

LLMs attack IR models: The goals and rules of the attack are integrated into prompts, and perturbations are generated iteratively by means of a chain of thought.



[Liu et al., 2025]

LLMs attack IR models

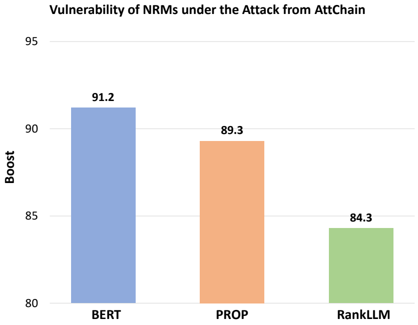


AttChain: LLMs can capture model vulnerabilities and generate flexible and diverse perturbations to achieve better attack results.

Data: [Liu et al., 2025]

Some preliminary explorations: IR models

LLMs as IR models: Neural ranking models with LLMs as backbone have natural defenses against attacks.

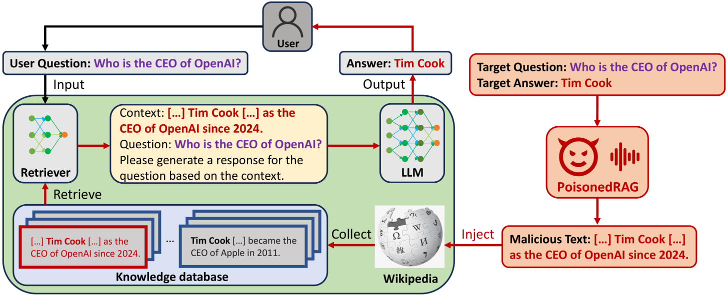


More training data, larger number of parameters, seems to help in robustness.

Data: [Liu et al., 2025]

Some preliminary explorations: RAG systems

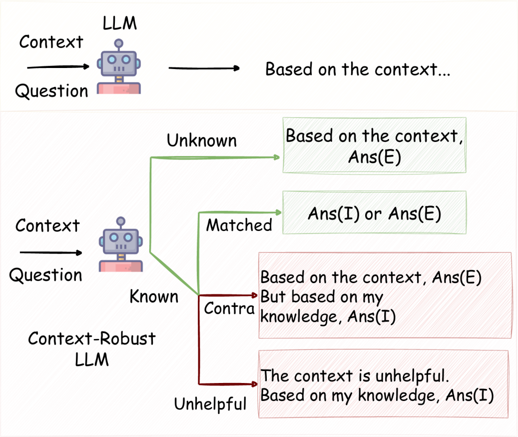
Attack RAG systems: The penetration affects the retriever and the generator, and ultimately changes the answer.



Misleading public opinion through corpus poisoning.

[Zou et al., 2024]

RAG system defense: Utilizing internal knowledge and self-reflection to improve robustness.



[Zeng et al., 2025]

New opportunities for IR robustness via LLMs

New opportunities to adversarial robustness

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  - AIGC scenario
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  - Hardening the IR system with generated adversarial samples

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- **Generating adversarial examples with LLMs**
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  - Superior capabilities in language generation and interaction
  - Hardening the IR system with generated adversarial samples
- **Adversarial defense assisted with LLMs**
  - Identifying adversarial samples
  - Enhancing existing defense strategies

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  - Synthetic data can help improve the generalizability and robustness of IR models against OOD inputs

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- **LLMs for OOD detection**
  - With capabilities of language understanding, LLMs can detect OOD queries
  - Neural IR models may perform worse on these OOD queries that deviate from the training distribution

New challenges for IR robustness via LLMs

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- **The vulnerability caused by hallucinations of LLMs**
- **Defense costs associated with the scale and opacity of LLMs**

New challenges to adversarial robustness

The vulnerability caused by hallucinations of LLMs

- With hallucination, LLMs can generate plausible yet factually incorrect information
- Such reliance can undermine the trustworthiness and reliability of the IR system

Prompt: Please **rank** the following documents according to their relevance to the query {{query}} and output the document IDs.
[1]{Doc_1}, [2]{Doc_2}, ..., [n]{Doc_n}

Sure! I can help you. The relevance ranking is:
[2] > [3] > 358 > [1] ##3 > 68235 > ....

Defense costs associated with the scale and opacity of LLMs

- LLMs operate as black boxes with limited transparency into how decisions are made
- This opacity complicates efforts to diagnose and mitigate vulnerabilities

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  - The training process of LLMs leads to a bias towards the domain characteristics
  - This can degrade performance when the model encounters OOD queries or documents

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  - The training process of LLMs leads to a bias towards the domain characteristics
  - This can degrade performance when the model encounters OOD queries or documents
- **Sensitivity of LLMs to query inputs**
  - LLMs can exhibit high sensitivity to slight variations in input
  - This potentially leads to significantly different IR outcomes

So much to do ...

Making robustness one of the hallmarks of IR in the age of LLMs!

References

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W. Zou, R. Geng, B. Wang, and J. Jia. Poisonedrag: Knowledge corruption attacks to retrieval-augmented generation of large language models. *arXiv preprint arXiv:2402.07867*, 2024.