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 2: Preliminaries

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Information retrieval task

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The goal of an IR system is to employ the ranking function f to generate a score $f(q, d)$ for any query-document pair (q, d), reflecting the relevance degree between them, and produce a relevance permutation $\pi_f(q, D)$ according to the predicted score:

$$f(q, d) = g\left(\psi(q), \phi(d), \eta(q, d)\right),$$

where ψ, ϕ, and η return representations of q, d, and a relevance score

Neural IR model

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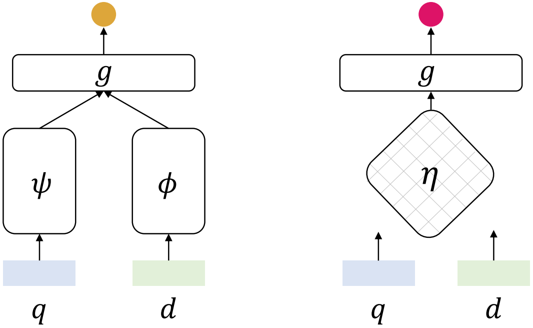

Image source: [Guo et al., 2020]

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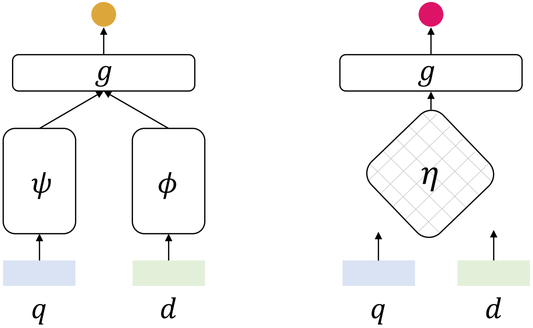

Dense retrieval model **efficiently** recalls document candidates with **dual-encoder**

Neural ranking model **effectively** generates the final ranked list with **cross-encoder**

Image source: [Guo et al., 2020]

Evaluation of IR model

In IR, we mainly focus on the top-K ranking result. Given:

- A metric M focus on the top-K ranking results, e.g., NDCG@K and MRR@K;
- A test dataset $\mathcal{D}_{\text{test}}$ with ground truth Y;

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The ranking performance $\mathcal{R}_M$ of the IR model is usually evaluated by

$$\mathcal{R}_M(f; \mathcal{D}_{\text{test}}, K) = \frac{1}{|\mathcal{D}_{\text{test}}|} \sum_{(q,D,Y)\in\mathcal{D}_{\text{test}}} M(f; (q, D, Y), K).$$

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M includes a mapping function h related to ranking and an indicator function $\mathbb{I}\{\cdot\}$:

$$M(f; (q, D, Y), K) = \sum_{(d, y_d) \in (D, Y)} y_d \cdot h(\pi_f(q, d)) \cdot \mathbb{I}\{\pi_f(q, d) \leq K\}.$$

Definition (Top-K robustness in information retrieval)

Let $\delta \geq 0$ denote an acceptable error threshold. Given an IR model $f_{\mathcal{D}_{\text{train}}}$ trained on training dataset $\mathcal{D}_{\text{train}}$ with a corresponding testing dataset $\mathcal{D}_{\text{test}}$, an unseen test dataset $\mathcal{D}^*_{\text{test}}$, for the top-$K$ ranking result, if

$$\left|\mathcal{R}_M\left(f_{\mathcal{D}_{\text{train}}}; \mathcal{D}_{\text{test}}, K\right) - \mathcal{R}_M\left(f_{\mathcal{D}_{\text{train}}}; \mathcal{D}^*_{\text{test}}, K\right)\right| \leq \delta,$$

we consider the model $f_{\mathcal{D}_{\text{train}}}$ to be Top-K-robust for metric M.

Adversarial robustness in IR: Definition

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Definition (Adversarial robustness in information retrieval)

Given an IR model $f_{\mathcal{D}_{\text{train}}}$ trained on training dataset $\mathcal{D}_{\text{train}}$ with a corresponding testing dataset $\mathcal{D}_{\text{test}}$, a new document set D_{adv} containing adversarial examples, and an acceptable error threshold δ, for the top-K ranking result, if

$$\left|\mathcal{R}_M\left(f_{\mathcal{D}_{\text{train}}}; \mathcal{D}_{\text{test}}, K\right) - \mathcal{R}_M\left(f_{\mathcal{D}_{\text{train}}}; \mathcal{D}'_{\text{test}}, K\right)\right| \leq \delta \text{ such that } \mathcal{D}'_{\text{test}} \leftarrow \mathcal{D}_{\text{test}} \cup D_{\text{adv}},$$

where $\mathcal{D}_{\text{test}} \cup D_{\text{adv}}$ denotes injecting the set of all generated adversarial examples D_{adv} into the original test dataset, and then model f is considered δ-robust against adversarial examples for metric M.

Out-of-distribution robustness: Definition

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Definition (Out-of-distribution robustness of information retrieval)

Given an IR model $f_{\mathcal{D}_{\text{train}}}$, an original dataset with training and test data, $\mathcal{D}_{\text{train}}$ and $\mathcal{D}_{\text{test}}$, drawn from the original distribution $\mathcal{G}$, along with a new test dataset $\tilde{\mathcal{D}}_{\text{test}}$ drawn from the new distribution $\tilde{\mathcal{G}}$, and an acceptable error threshold δ, for the top-K ranking result, if

$$\left|\mathcal{R}_M\left(f_{\mathcal{D}_{\text{train}}};\mathcal{D}_{\text{test}},K\right)-\mathcal{R}_M\left(f_{\mathcal{D}_{\text{train}}};\tilde{\mathcal{D}}_{\text{test}},K\right)\right|\leq\delta \text{ where } \mathcal{D}_{\text{train}},\mathcal{D}_{\text{test}}\sim\mathcal{G},\tilde{\mathcal{D}}_{\text{test}}\sim\tilde{\mathcal{G}},$$

the model f is considered δ-robust against out-of-distribution data for metric M.

Performance variance: Definition

A robust neural IR model should not only have good performance over the entire query set, but also ensure that the performance on individual queries is not too bad.

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Definition (Performance variance of information retrieval)

Given an IR model $f_{\mathcal{D}_{\text{train}}}$ trained on training dataset $\mathcal{D}_{\text{train}}$ with a corresponding testing dataset $\mathcal{D}_{\text{test}}$, and an acceptable error threshold δ, for the top-K ranking result, if

$$\text{Var}\left(\left\{M\left(f_{\mathcal{D}_{\text{train}}}; (q, D, Y), K\right) \mid (q, D, Y) \in \mathcal{D}_{\text{test}}\right\}\right) \leq \delta,$$

where $\mathrm{Var}(\cdot)$ is the variance of the ranking performance of the IR model $f_{\mathcal{D}_{\text{train}}}$ on $\mathcal{D}_{\text{test}}$, then the model f is considered δ-robust in terms of performance variance for metric M.

Robustness in IR: Taxonomy

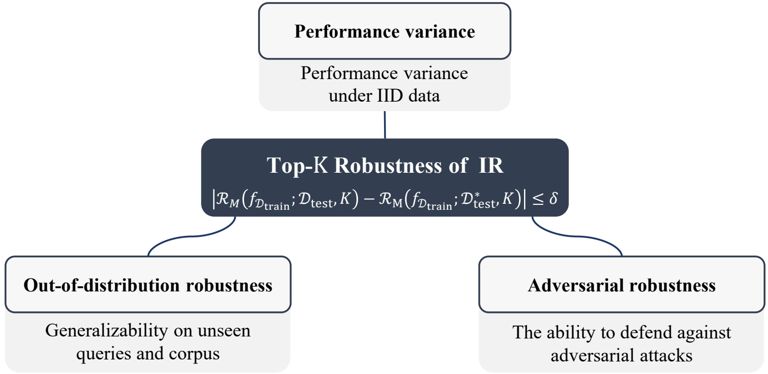

Image source: [Liu et al., 2024]

We will address adversarial robustness in Section 3 and OOD robustness in Section 4!

References

References i

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Y.-A. Liu, R. Zhang, J. Guo, M. de Rijke, Y. Fan, and X. Cheng. Robust neural information retrieval: An adversarial and out-of-distribution perspective. *arXiv preprint arXiv:2407.06992*, 2024.