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CharacterBERT and Self-Teaching for Improving the Robustness of Dense Retrievers on Queries with Typos

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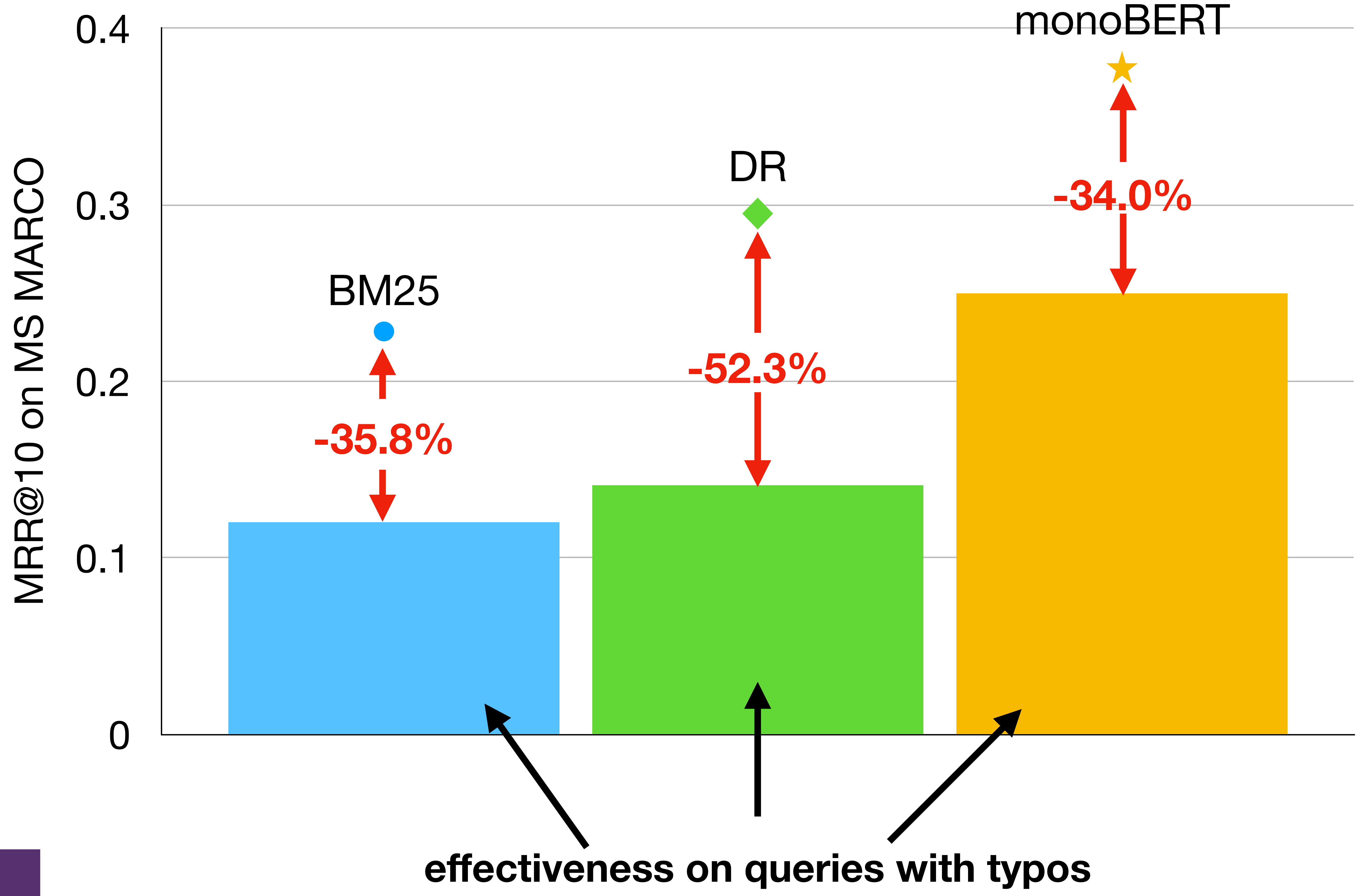
BERT-based rankers cannot deal with queries with typos



Both DR and monoBERT perform poorly on queries with typos

Zhuang, Zuccon, *"Dealing with Typos for BERT-based Passage Retrieval and Ranking*", EMNLP 2021

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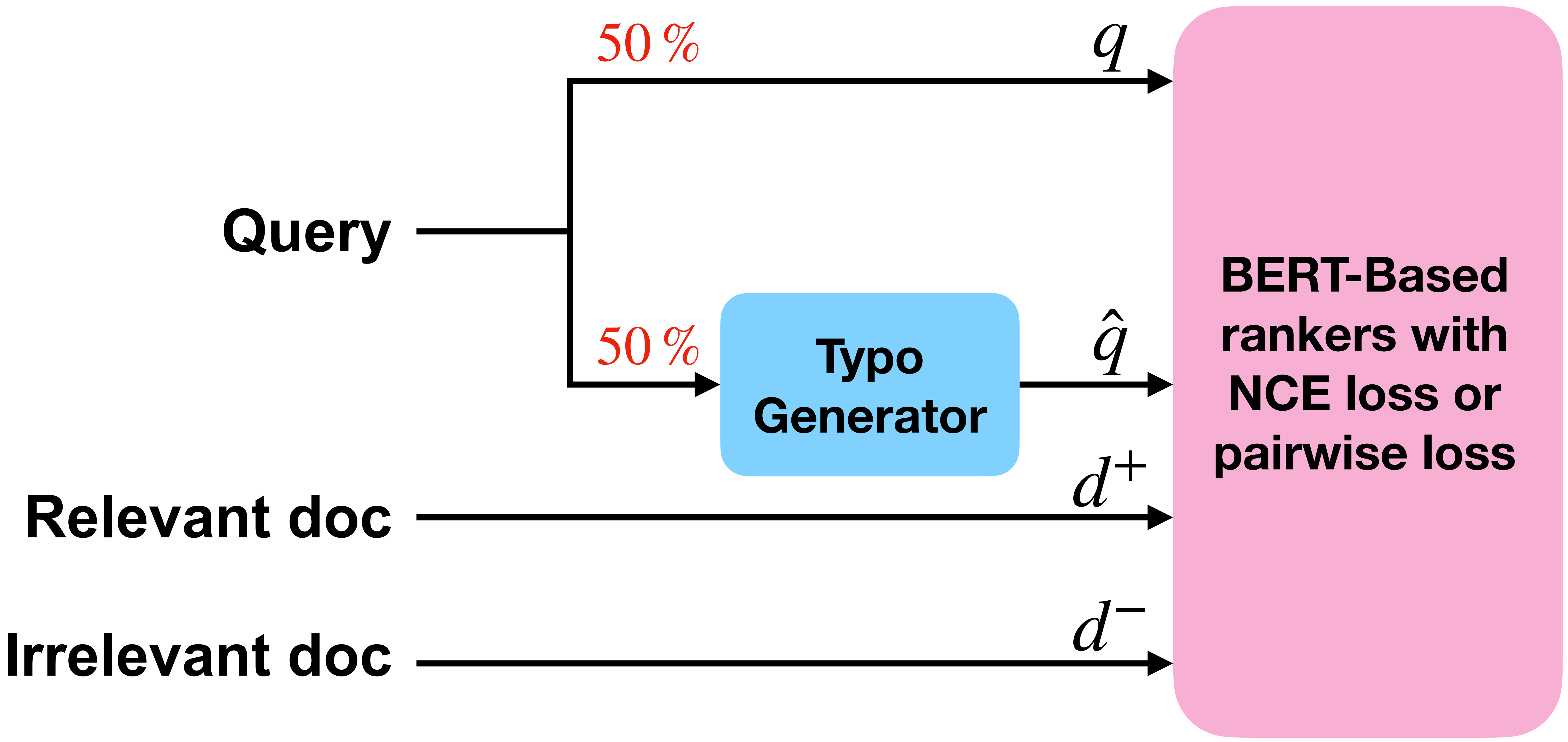
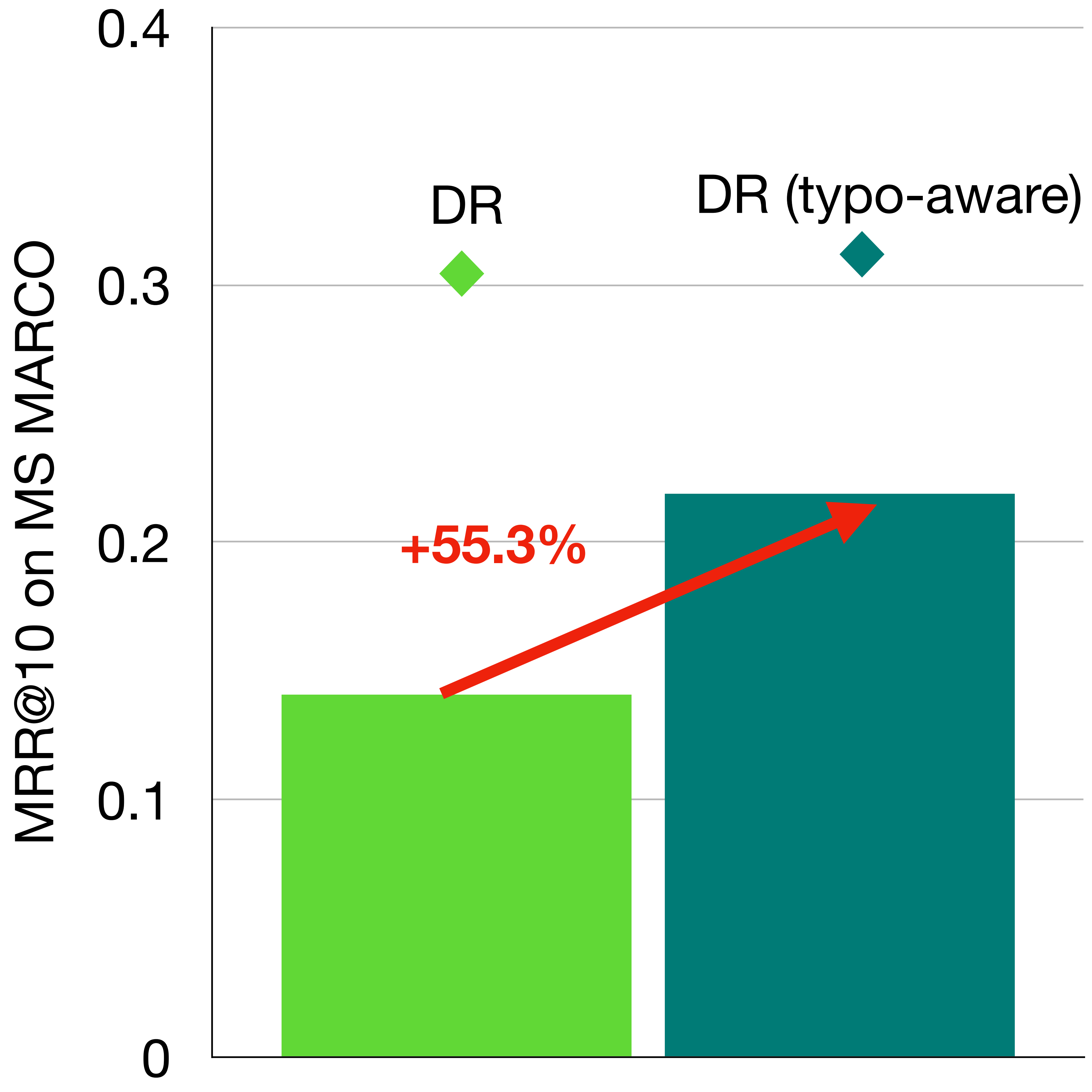
Prior work: Typos-aware training



Data Augmentation strategy: inject typos in training queries

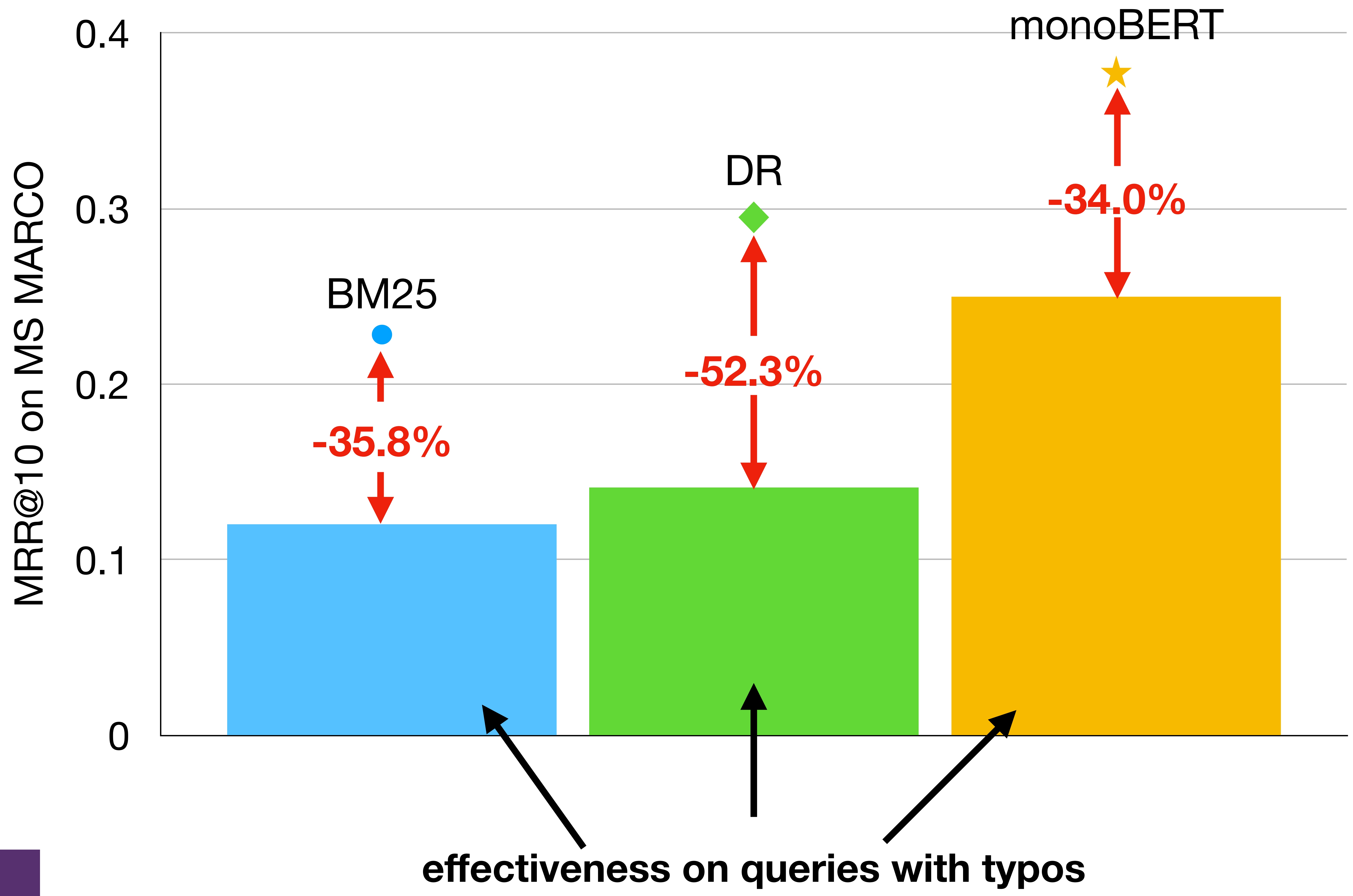
Zhuang, Zuccon, *"Dealing with Typos for BERT-based Passage Retrieval and Ranking*", EMNLP 2021

Prior work: Typos-aware training



- Data Augmentation improves effectiveness
  - Typo-aware training as effective as traditional training on queries without typos
  - Typo-aware training more effective on queries with typos

In this paper…



- Focus on **Dense Retrievers**
- **Why** Dense Retrievers cannot deal with typos in queries?
- **How** can we **improve** Dense Retriever's robustness to typos in queries?

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Why BERT-based DRs cannot deal with queries with typos?

- BERT is pre-trained on curated text, and MS MARCO dataset has no or very few queries with typos.
- WordPiece Tokenization based on small vocabulary which contains common terms + common subtokens
- What is the difference in output from the WordPiece Tokenization in presence of a typo?

‘information retrieval’ $\xrightarrow{\text{tokenize}}$ **[‘information’, ‘retrieval’]** $\xrightarrow{\text{input\_ids}}$ **[2592, 26384]**

‘infromation retrieval’ $\xrightarrow{\text{tokenize}}$ **[‘in’, ‘fr’, ‘oma’, ‘tion’, ‘retrieval’]** $\xrightarrow{\text{input\_ids}}$ **[1999, 19699, 9626, 3508, 26384]**

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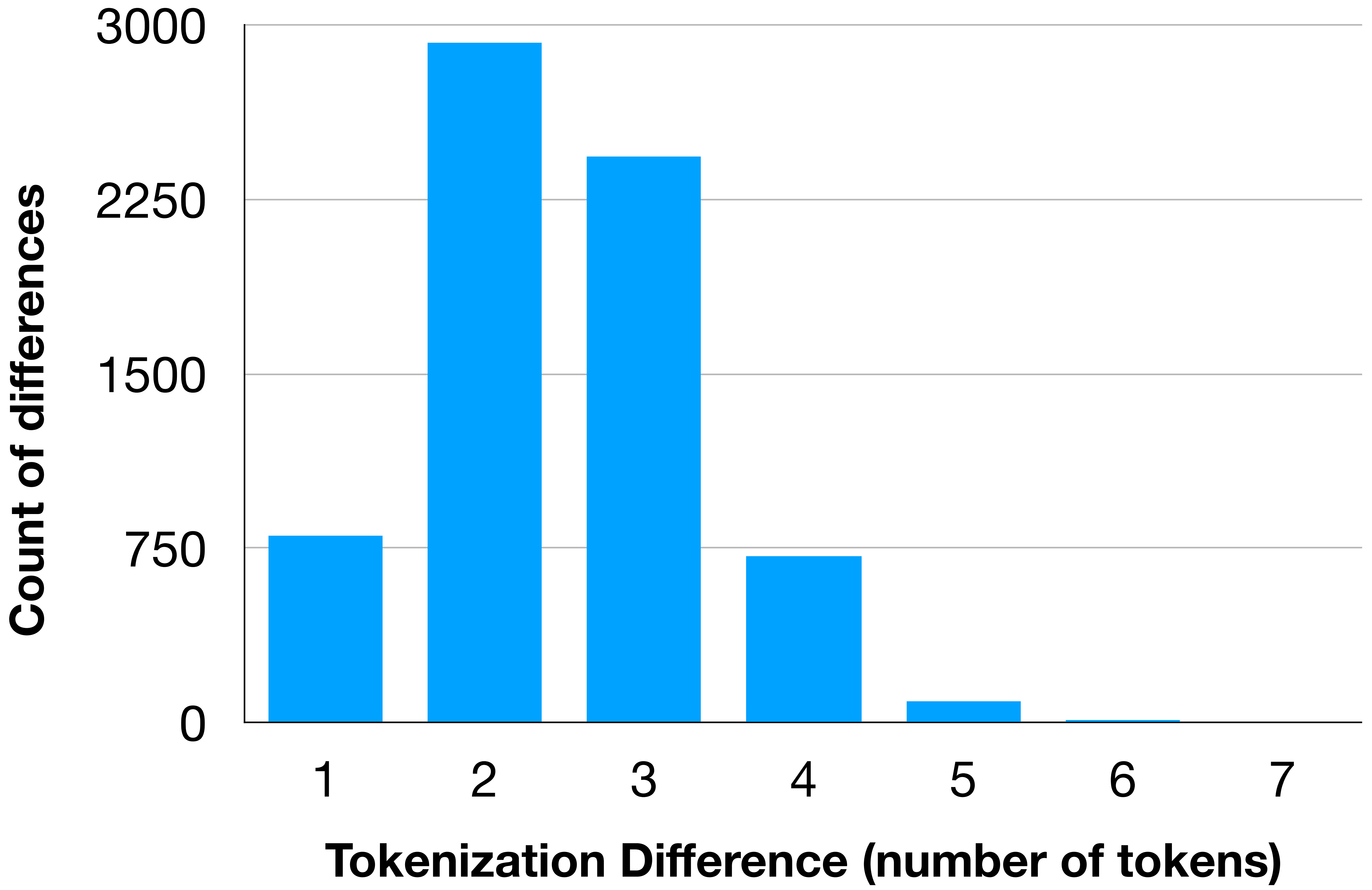
A typo resulted in the query being represented by 4 additional tokens (and lost 1)

How large are the tokenization differences caused by typos in queries?



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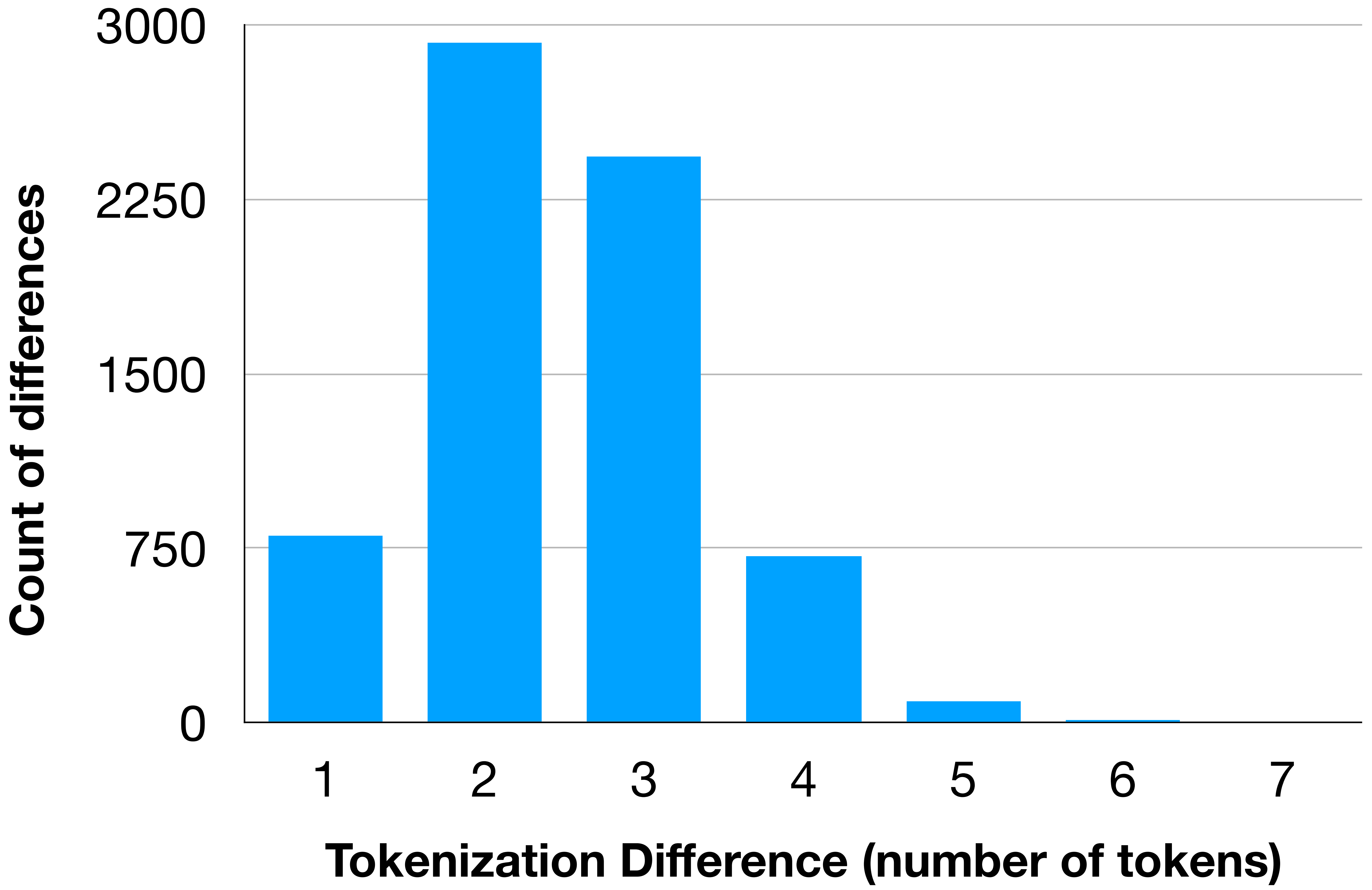
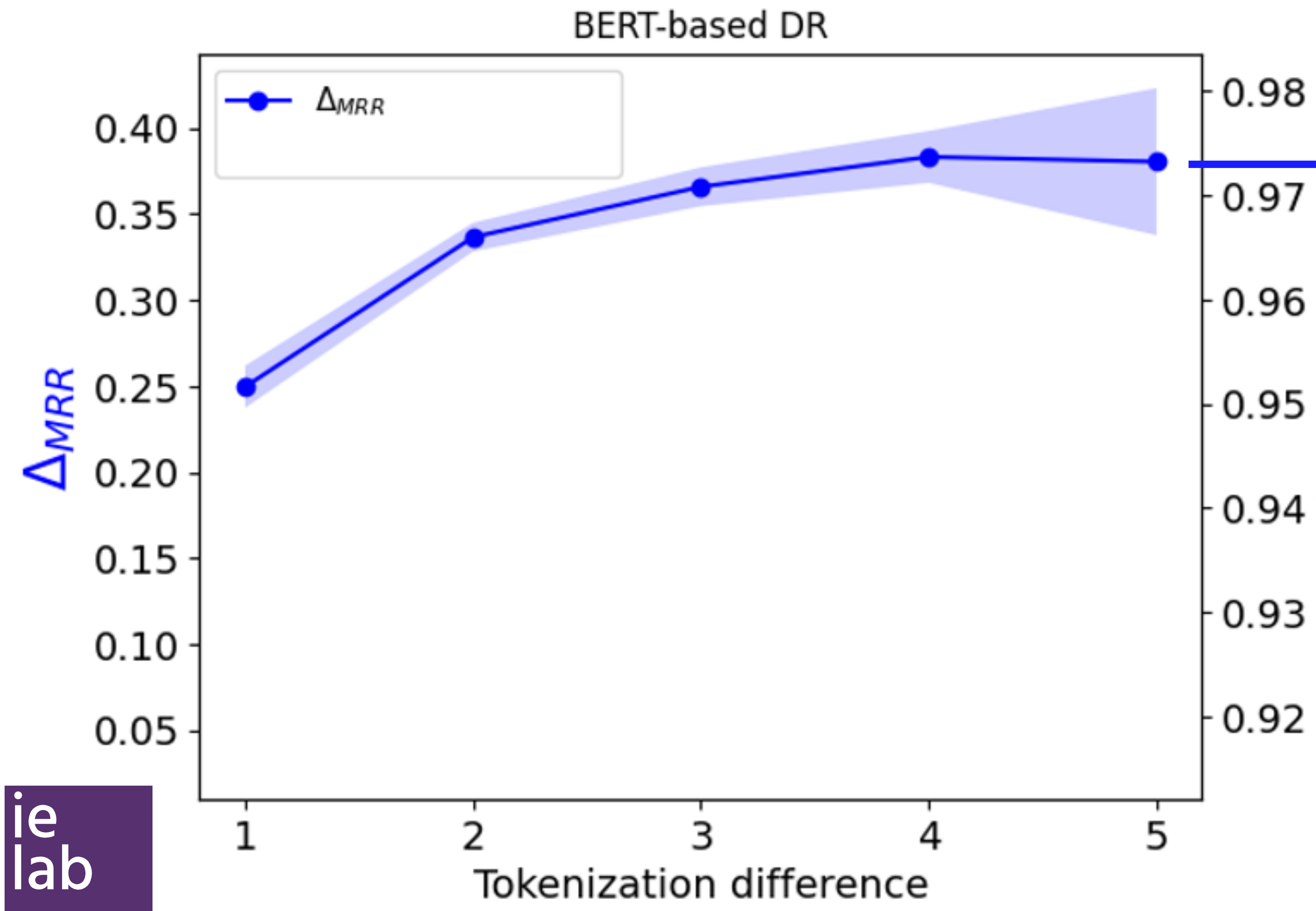


What are the effects of such tokenization difference?

Tokenization Difference produces effectiveness losses



Effectiveness drops

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The higher the loss, the worse the DR does on typos

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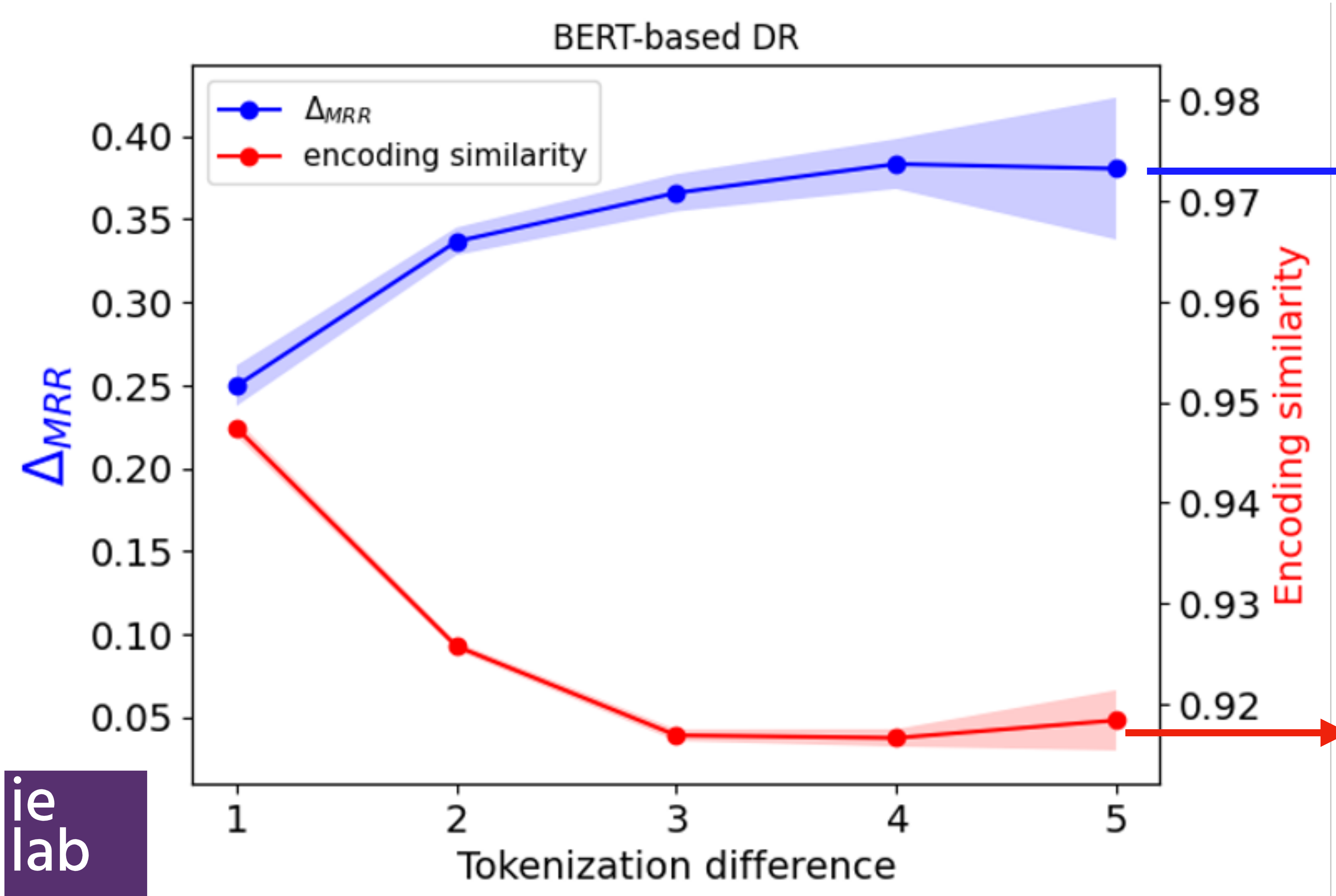
Tokenization Difference produces effectiveness losses & encodings different from query without typo



Effectiveness drops

Representation with typos diverges from original

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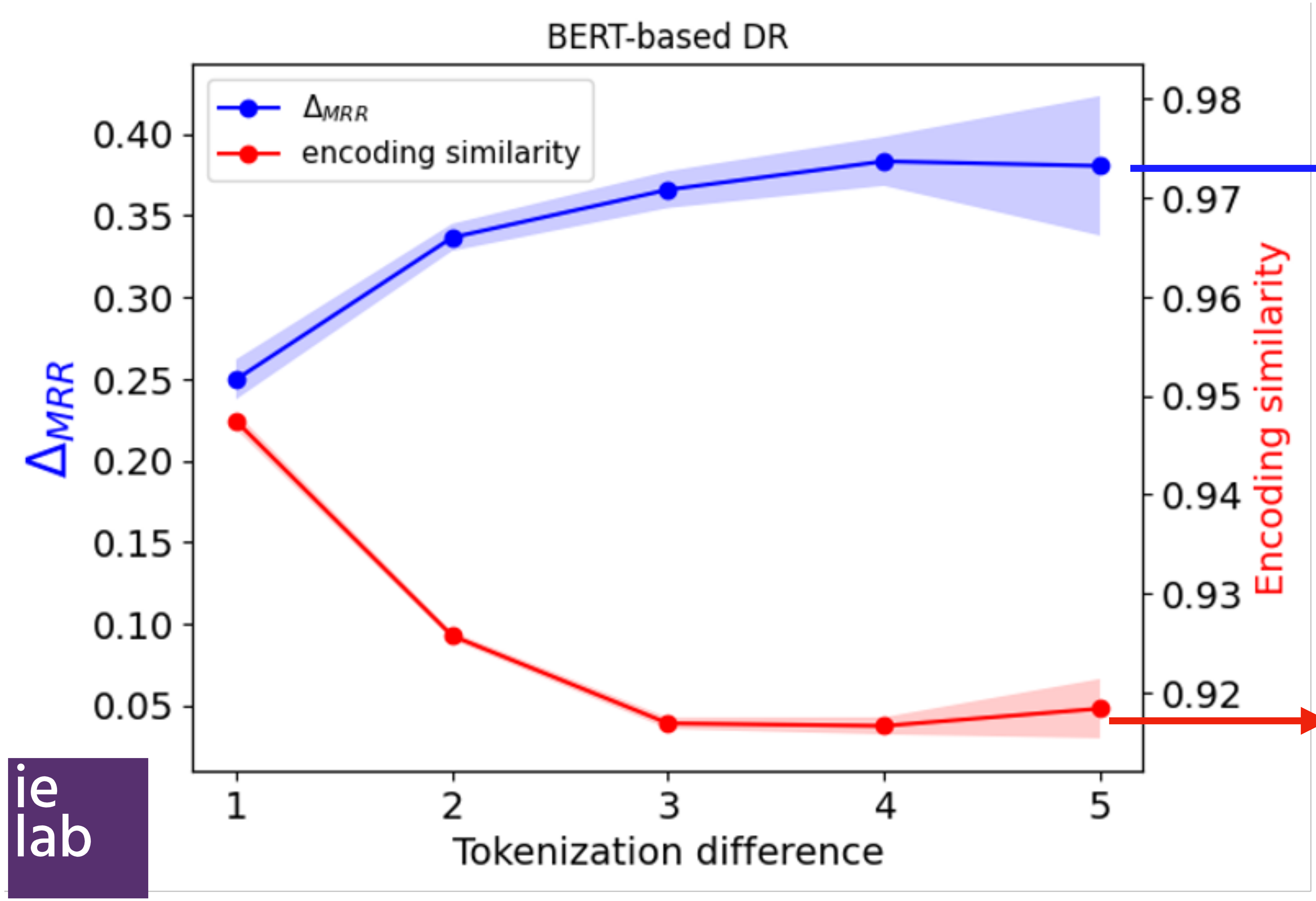
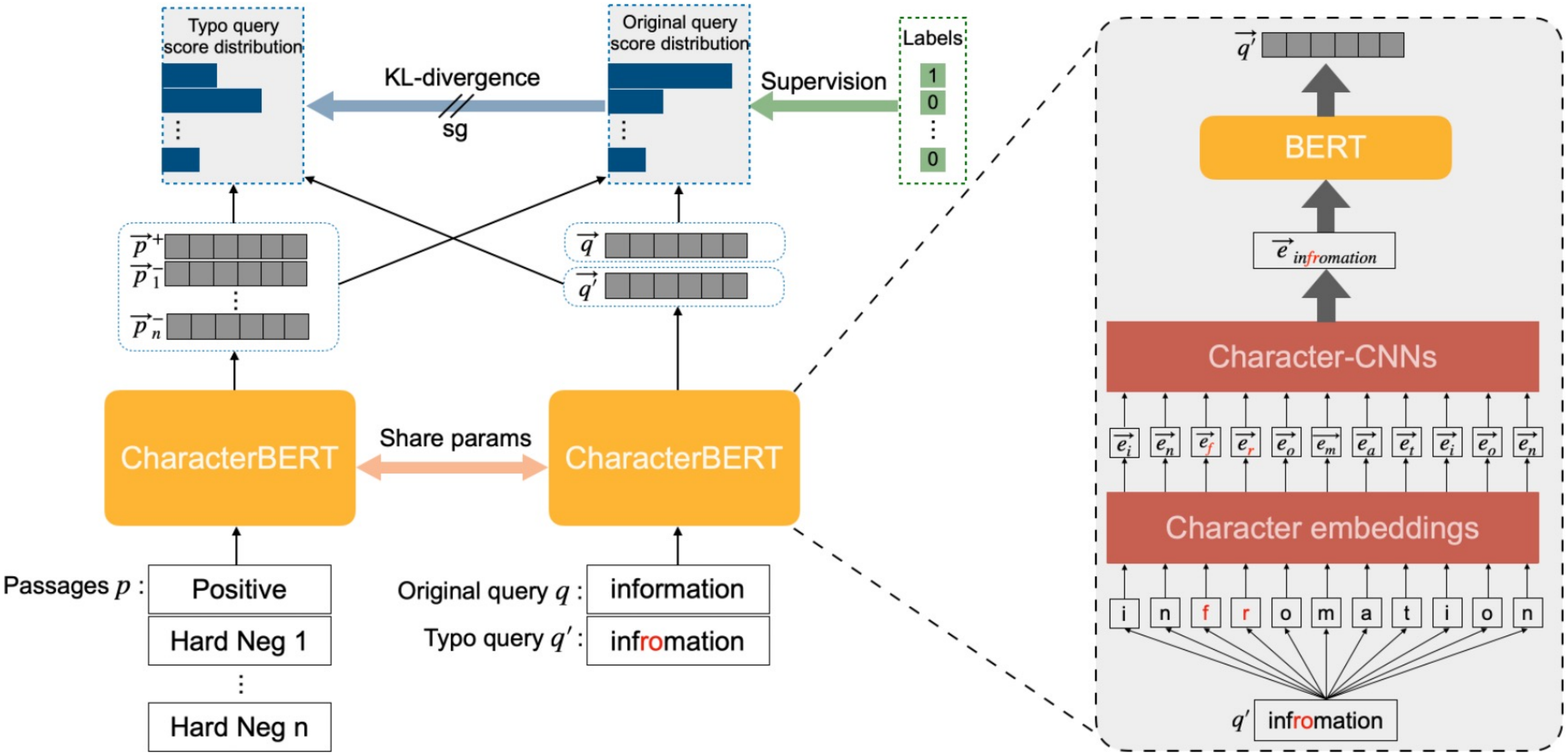


Effectiveness drops

Can we make representations that are invariant to the presence of typos?

Representation with typos diverges from original

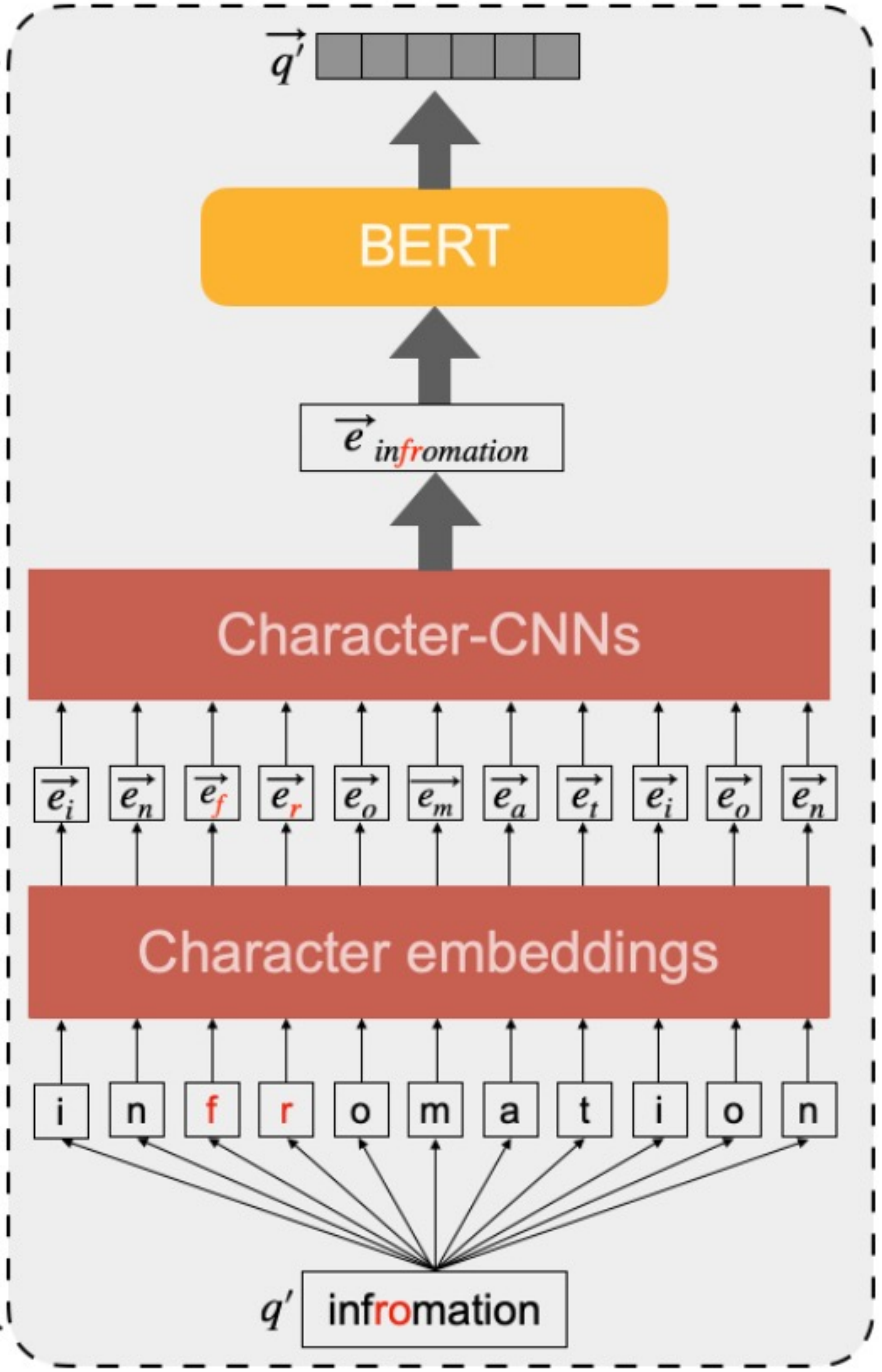
CharacterBERT-DR + Self-Teaching



CharacterBERT-DR + Self-Teaching

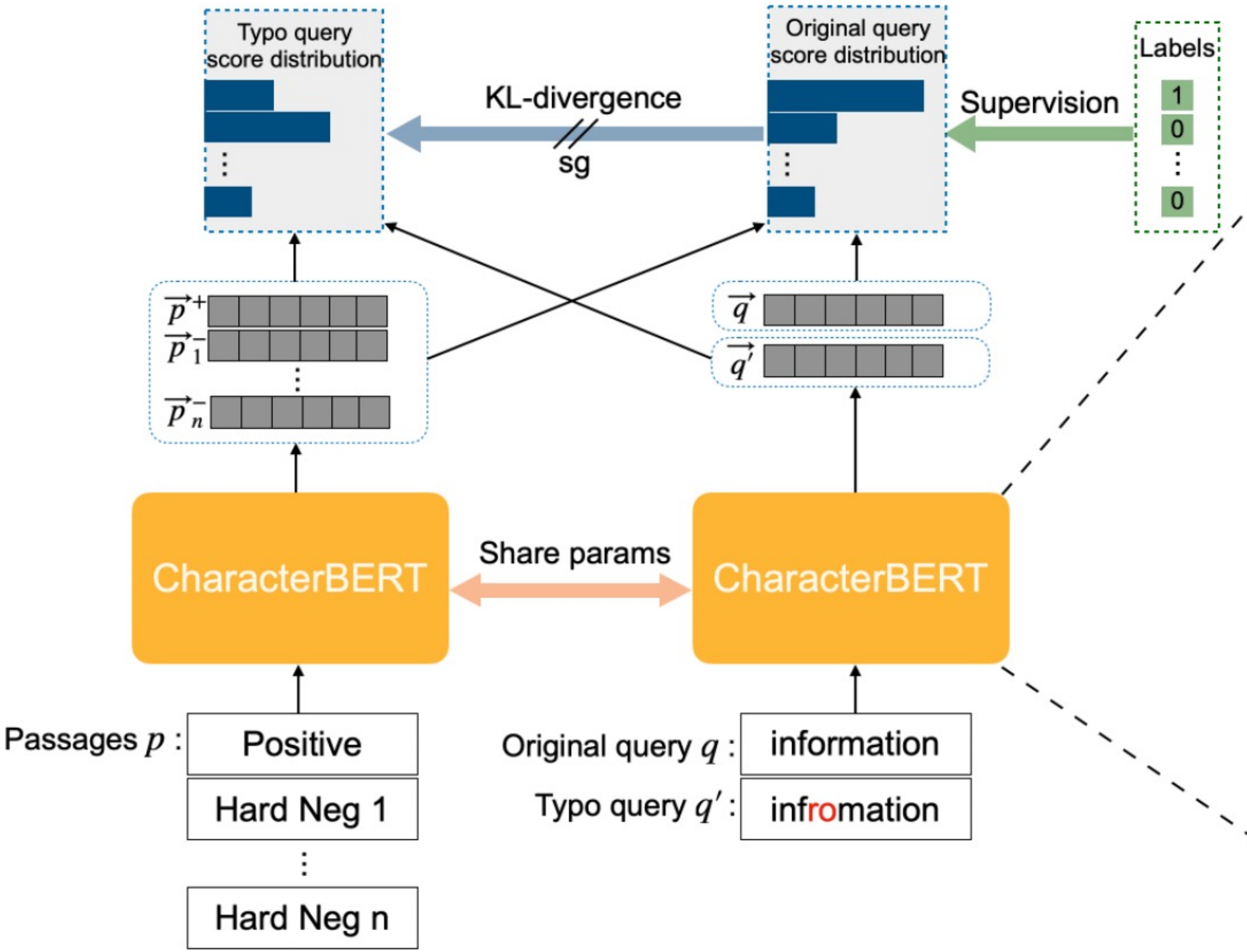
- Replace BERT WordPiece Tokenizer with CharacterBERT [2] to create query and passages embeddings.

- Does not rely on WordPiece vocabulary: any word will be represented by a single word embedding.



[2] CharacterBERT: Reconciling ELMo and BERT for Word-Level Open-Vocabulary Representations From Characters, Hicham et al, COLING 2020

CharacterBERT-DR + Self-Teaching



1. Make a typo augmentation during training.

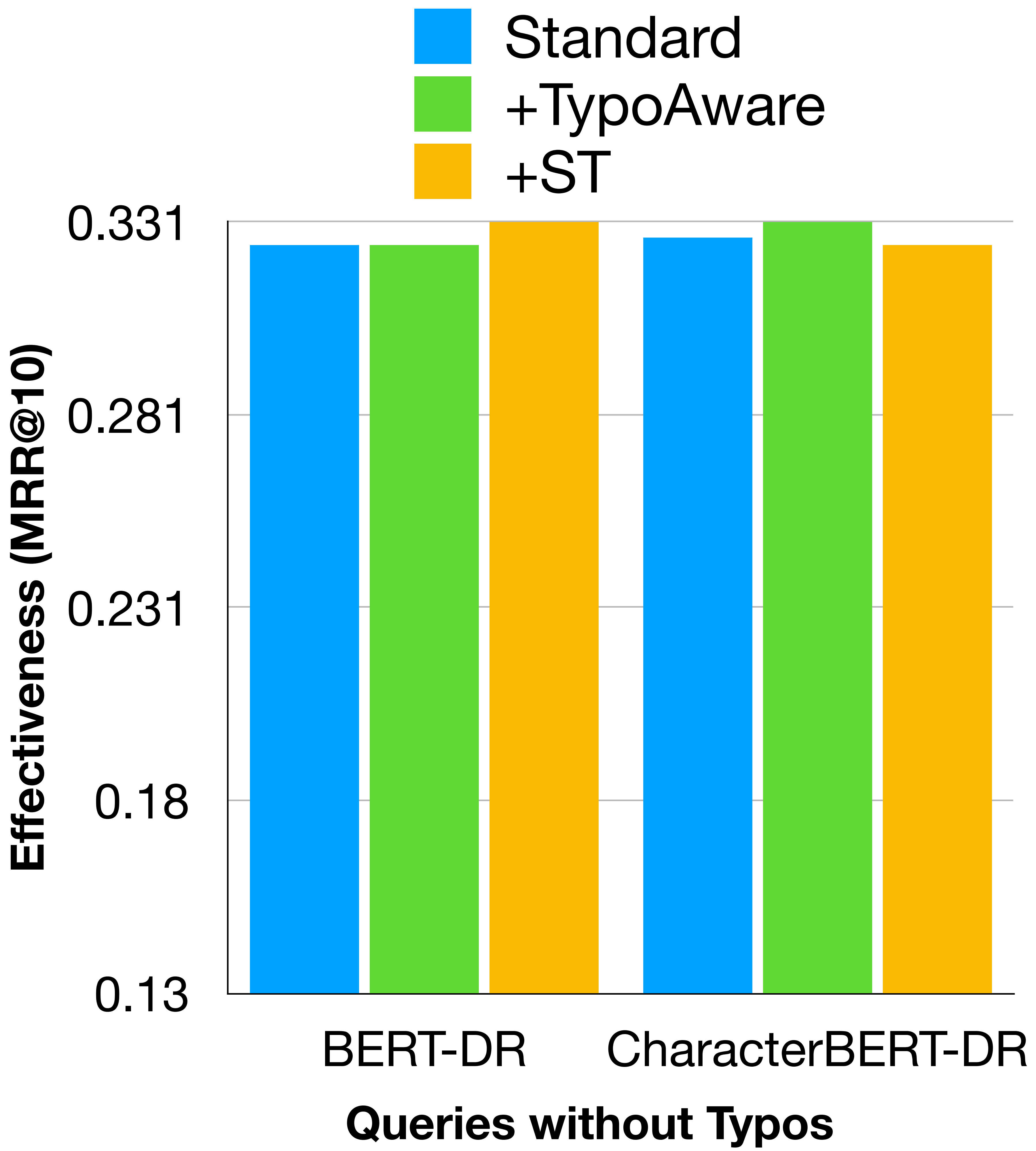
2. Self-Teaching: minimize score distribution difference b/w original query & query with typos:

$$\mathcal{L}_{KL}(\tilde{s}_{q'}, \tilde{s}_q) = \tilde{s}_{q'}(q', p) \cdot \log \frac{\tilde{s}_{q'}(q', p)}{\tilde{s}_q(q, p)}$$

3. Supervised contrastive loss:

$$\mathcal{L}_{CE}(s_q) = -\log \frac{e^{s_q(q,p^+)}}{e^{s_q(q,p^+)} + \sum_{p^-} e^{s_q(q,p^-)}}$$

Does CharacterBERT+ST produce unwanted effect on queries w/o typos?



- TypoAware, ST do not provide significant differences on queries without typos: **no risk to use them**

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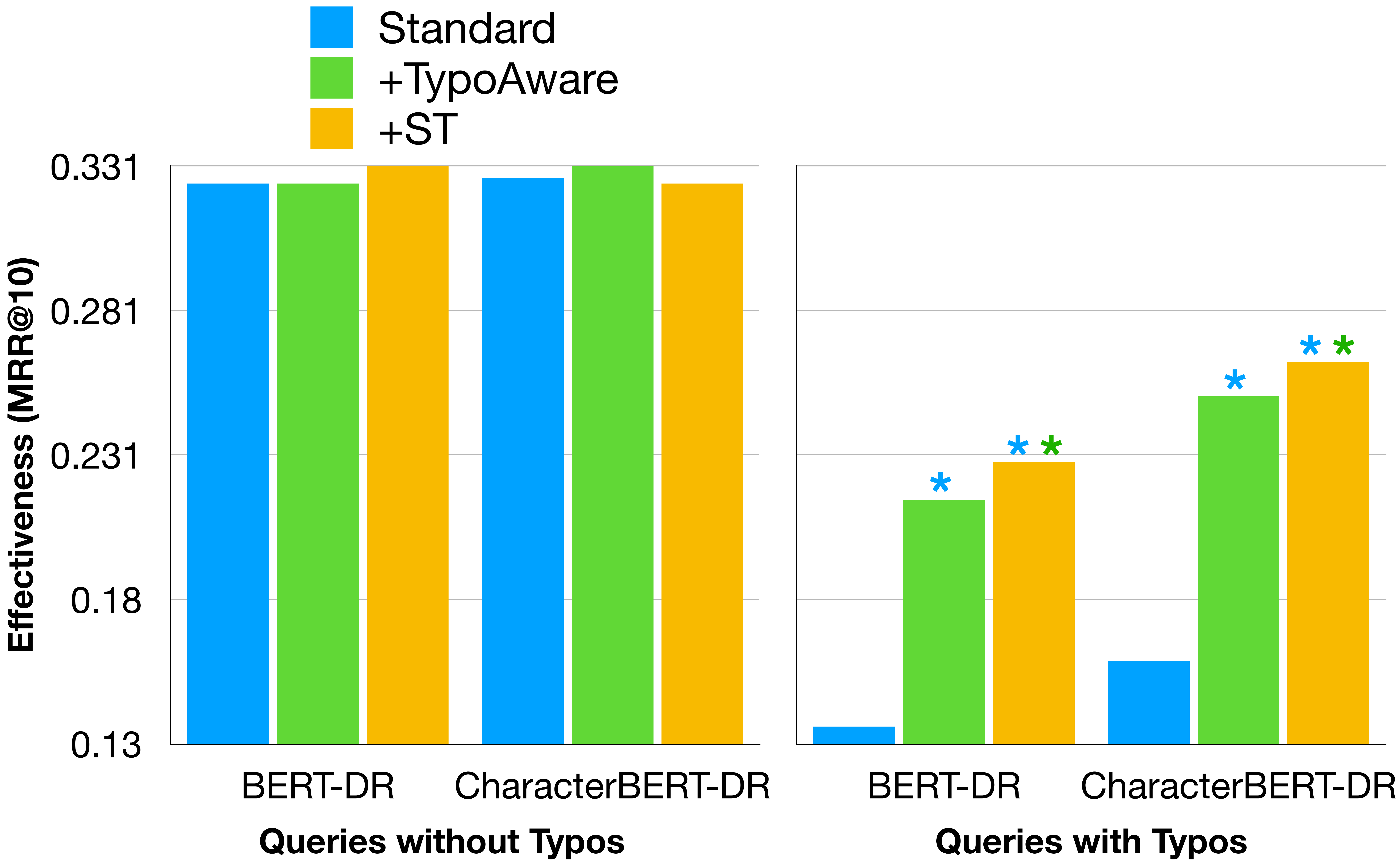
Does CharacterBERT+ST produce improvements on queries with typos?



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- **ST provides largest gains** on queries with typos

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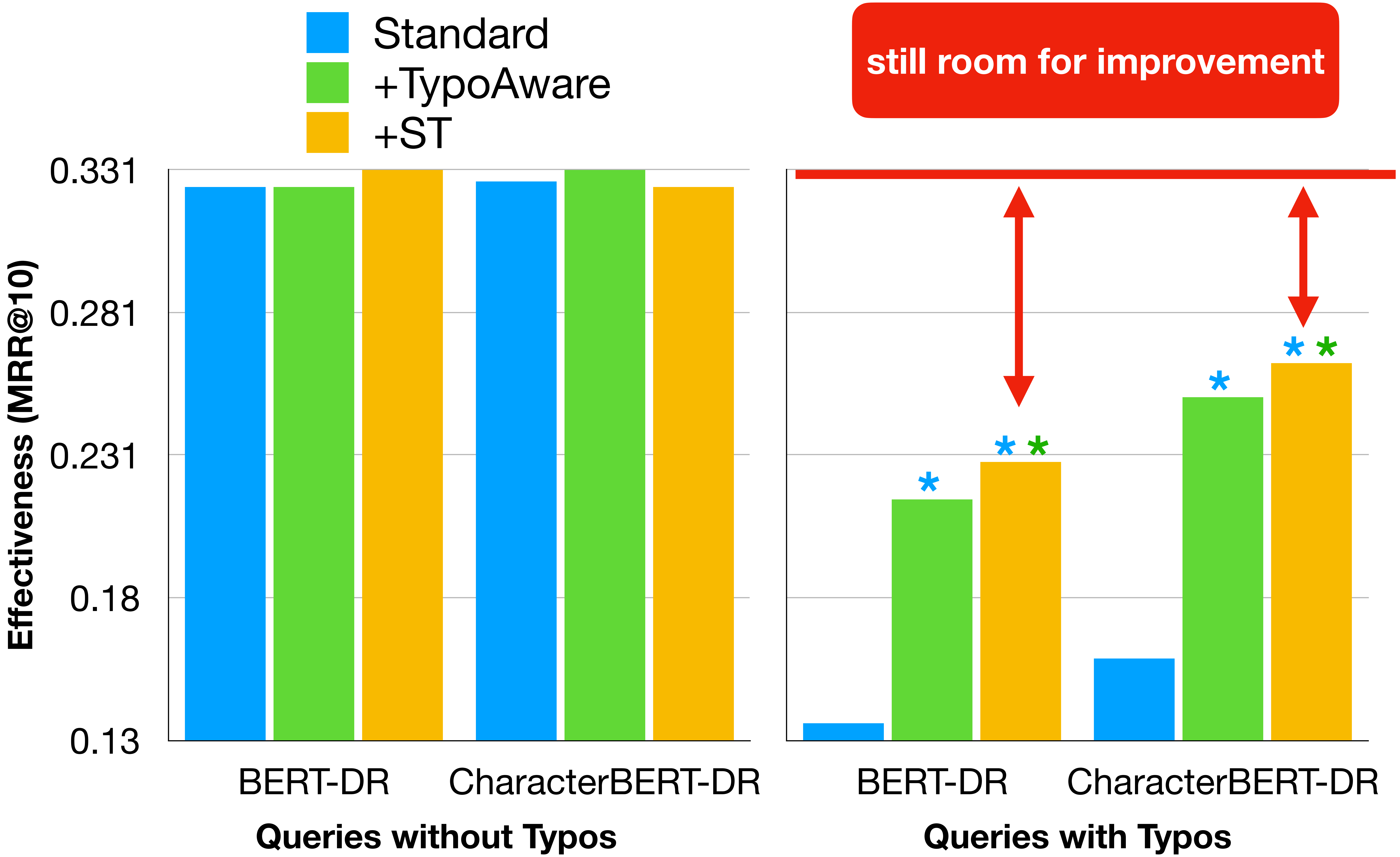

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What about using Spell Checkers instead?

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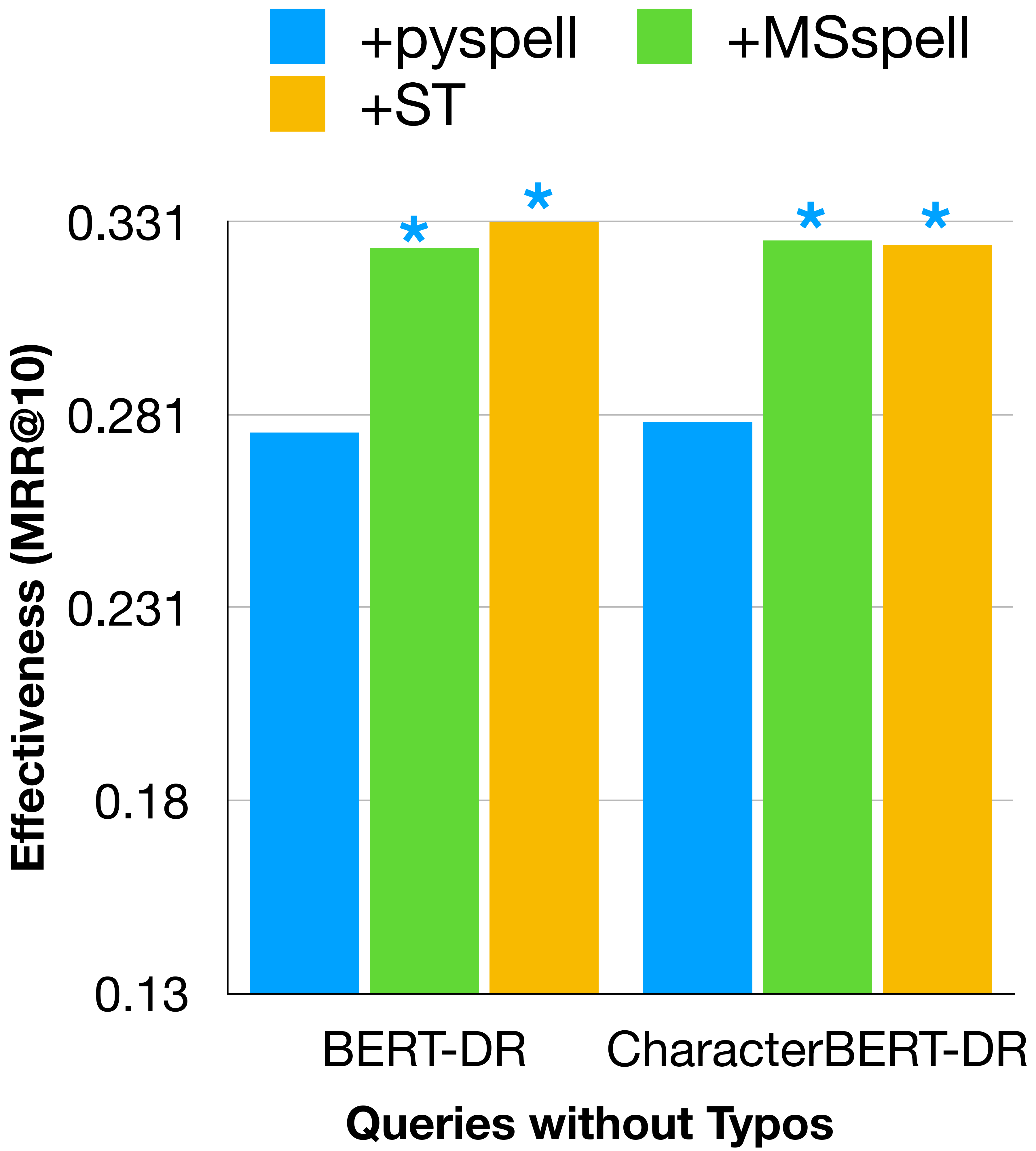

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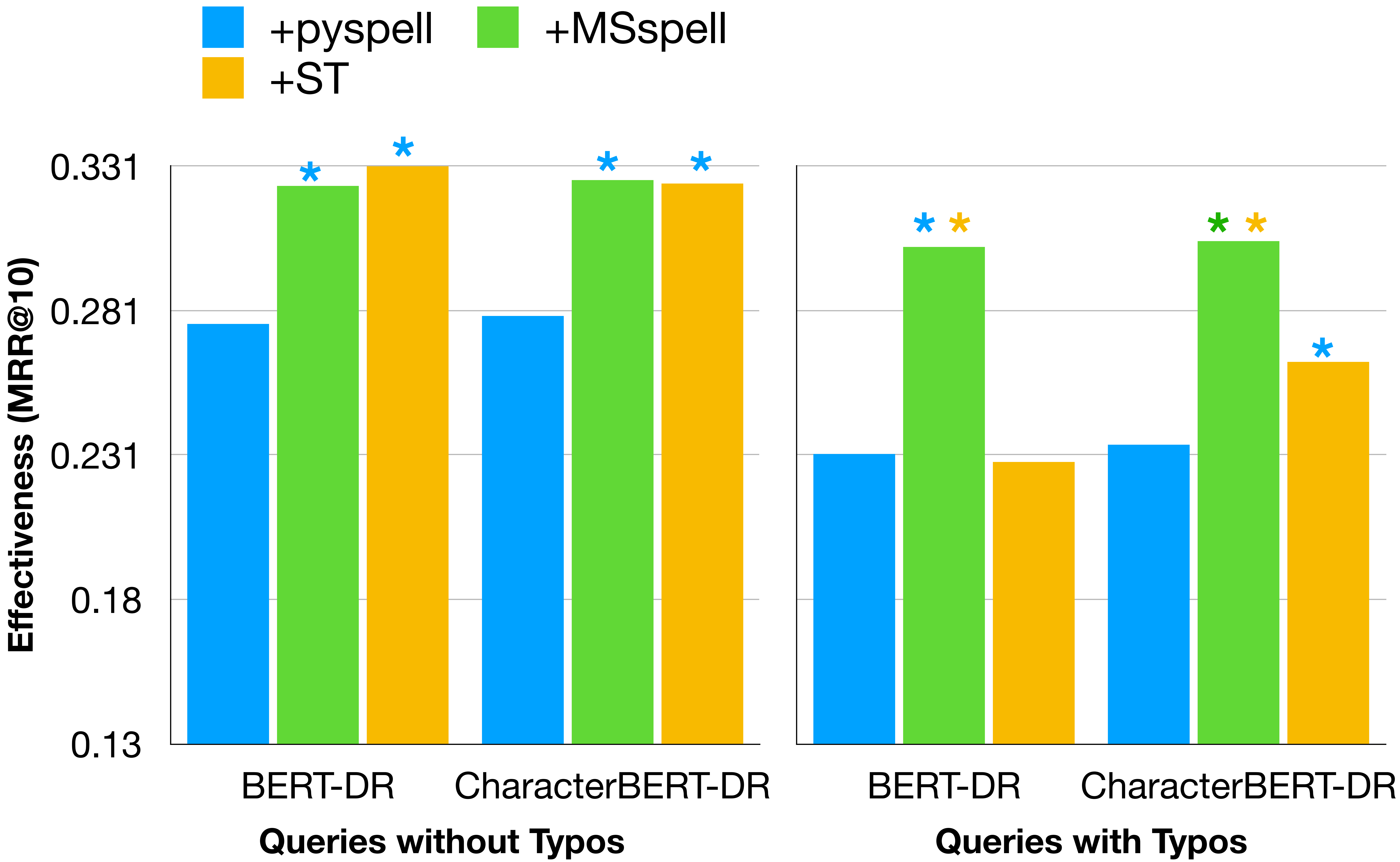

- MSspell provides significantly higher effectiveness
  - Most likely leverages extensive training data
- CharacterBERT+ST better than rule-based spell checker (pyspell)
- Engineering advantages in end-to-end DR pipeline rather than additional spell checker

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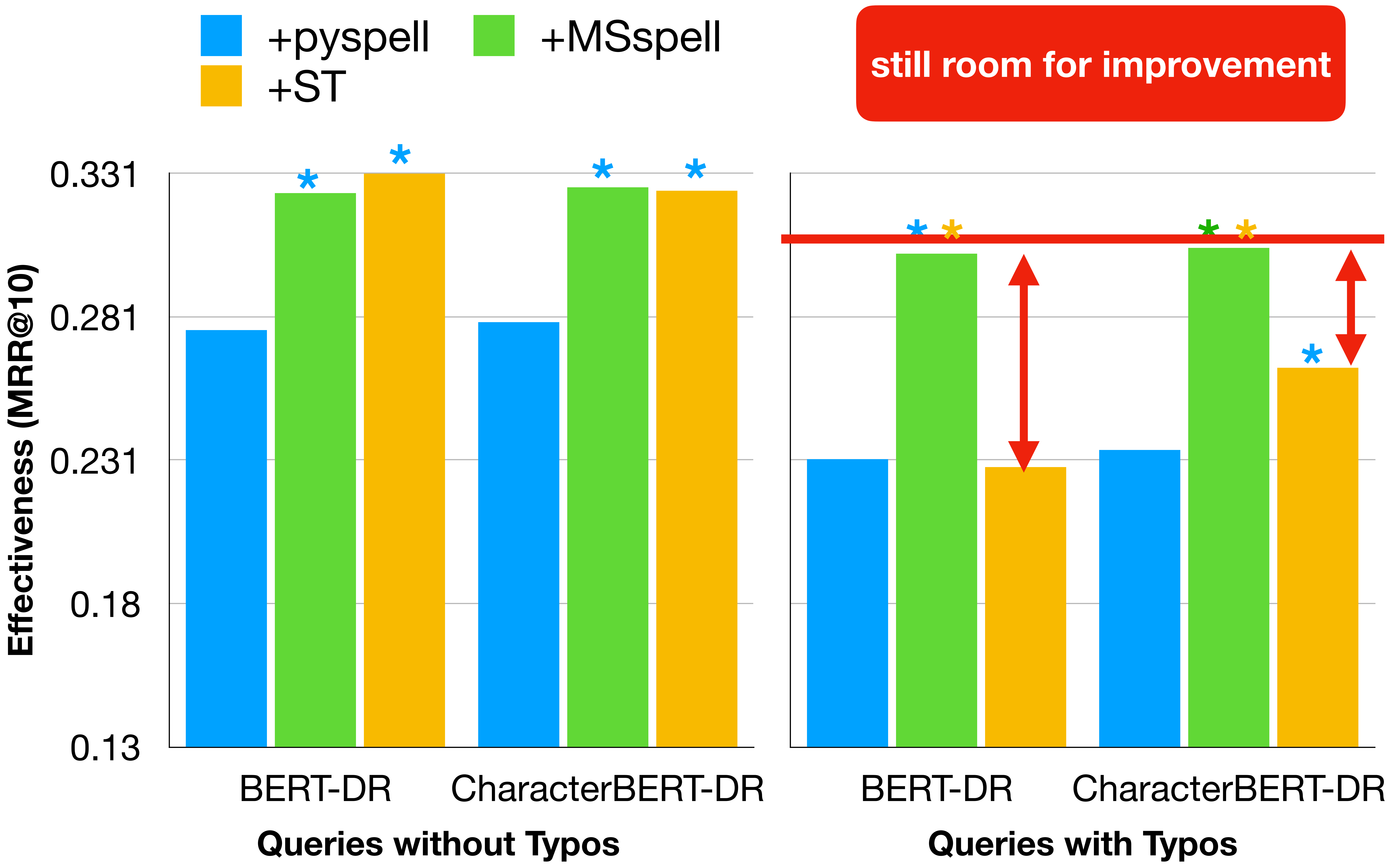

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Take-aways

- Typical Dense Retrievers do not perform well on queries with typos. Augmentation at training (EMNLP 2021) only goes so far
- The **key issue is in how a word with typos vs. without-typo is represented**
  - Bringing these two representations closer improves effectiveness
  - BERT’s Tokenizer major source for representation differences
- Replacing tokenizer with CharacterBERT encoder and using ST to further bring representations close drastically improves robustness of Dense Retrievers
- We also provide a **new dataset** for evaluation with real queries with typos

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Additional Material

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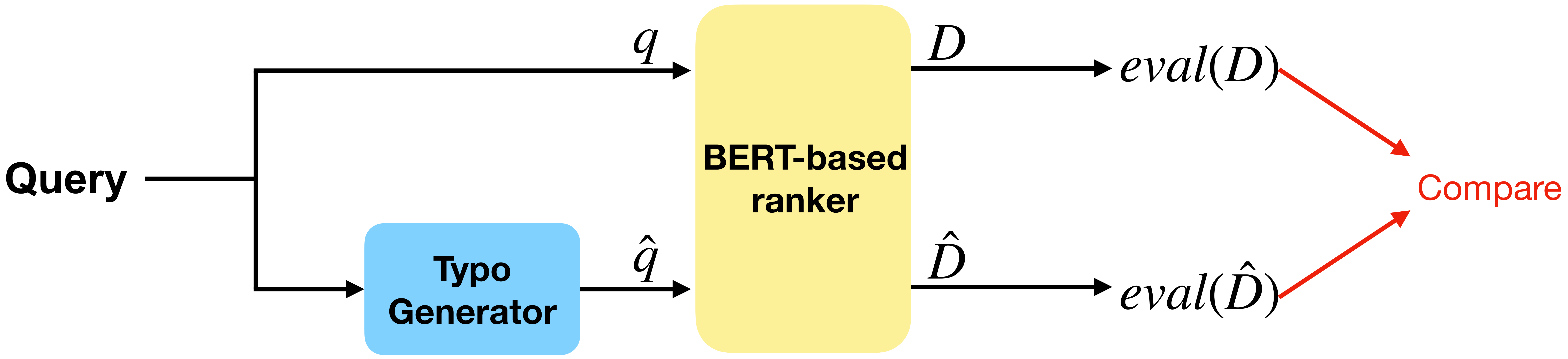
Evaluation with typo generator



Typo query generation

- Synthetic Typo generation for MS MARCO queries
  - Random character Insertion: ‘typo’ -> ‘tyapo’
  - Random character deletion: ‘typo’ -> ‘tyo’
  - Random character substitution: ‘typo’ -> ‘type’
  - Swap neighbour character: ‘typo’ -> ‘tyop’
  - Swap adjacent keyboard character: ‘typo’ -> ‘typi’
- These are common typos in real-world user queries [1]

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[1] Matthias Hagen, Martin Potthast, Marcel Gohsen, Anja Rathgeber, and Benno Stein. 2017. A large-scale query spelling correction corpus. SIGIR

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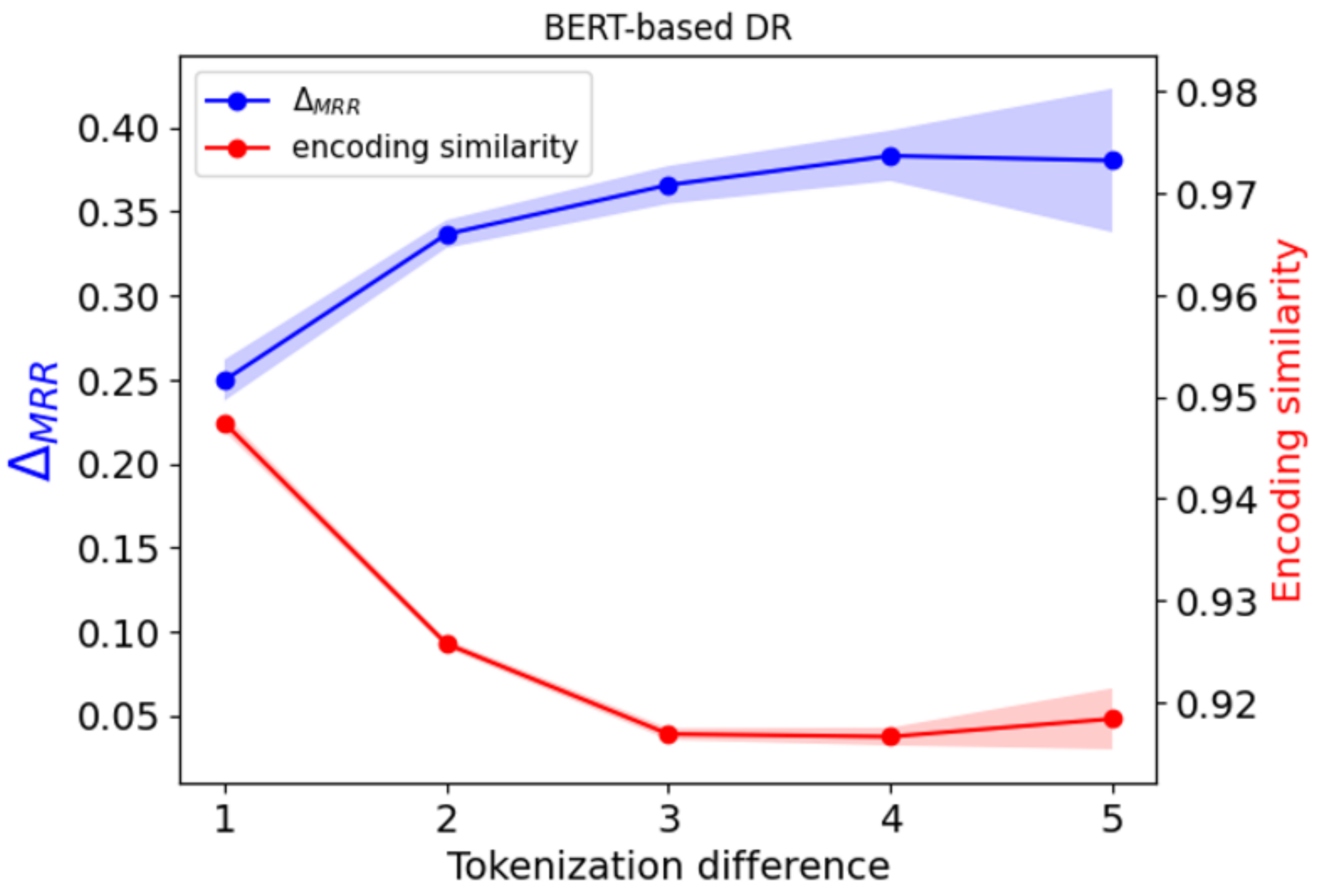
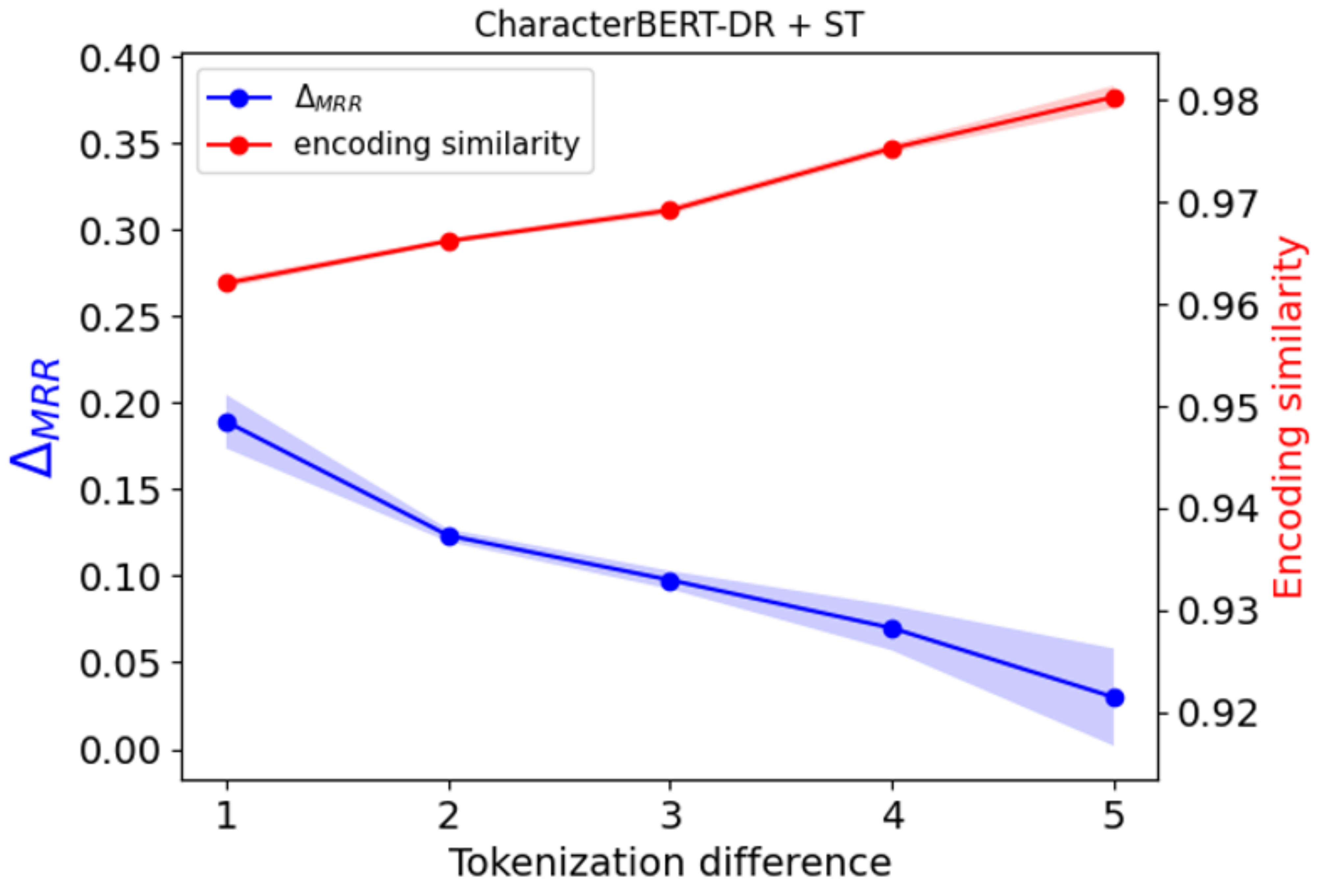
CharacterBERT-based DR behaves differently





Similar trends in other datasets

- We experimented with **MS MARCO** (dev queries), **TREC 2019** and **2020**
- We created a **new dataset**, DL-typo
  - 60 queries with typos from AOL query log
    Human spelling corrections
  - Relevance assessments following TREC DL relevance criteria
    On average 63.52 judgements per query (relevant: 25.7)