
Neural Document Expansion with User Feedback

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Motivation

User clicks provide strong relevance signals

- Benefit query disambiguation and user intent understanding



microsoft github



Microsoft · GitHub

<https://github.com/microsoft> ▼

The Microsoft Bot Framework provides what you need to build and connect intelligent bots that interact naturally wherever your users are talking, from text/sms to Skype, Slack, Office 365 mail and other popular services.

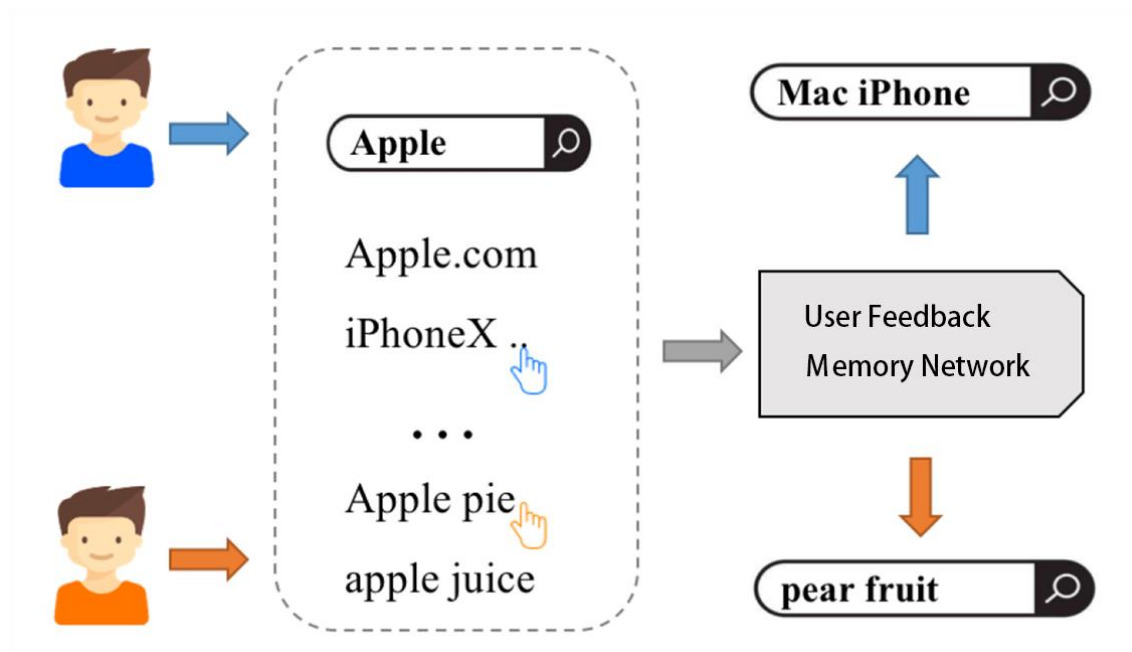
Microsoft to acquire GitHub for \$7.5 billion | Stories

<https://news.microsoft.com/2018/06/04/microsoft-to-a>

Jun 04, 2018 · Acquisition will empower developers, accelerate **GitHub's** growth and advance **Microsoft** services with new audiences From left: Chris Wanstrath, **Github** CEO and co-founder; Satya Nadella, **Microsoft** CEO; and Nat Friedman, **Microsoft** corporate vice president, Developer Services REDMOND, Wash. — June 4, 2018 — **Microsoft** ...

Motivation

External user feedback could enhance document representation



Wu et al. Query Suggestion with Feedback Memory Network. WWW 2018

However, user clicks are not always well leveraged in neural rankers.

Our Goal

Better document representation:

- Enrich document representation with user clicks
- Estimate term importance with Attention Mechanism

Better search performance:

- Using the better document representation
- Disambiguate current query with previous clicked queries

Expansion Terms Selection

Document Title	Clicked Queries	Expansion Terms
On-line Calculator	On-line Computer Application	On-line Computer Application Calculator Computing Use
	On-line Calculator Computing	
	Use On-line Calculator	
	Calculator	
	Computer	

Treat clicked queries as document expansion field

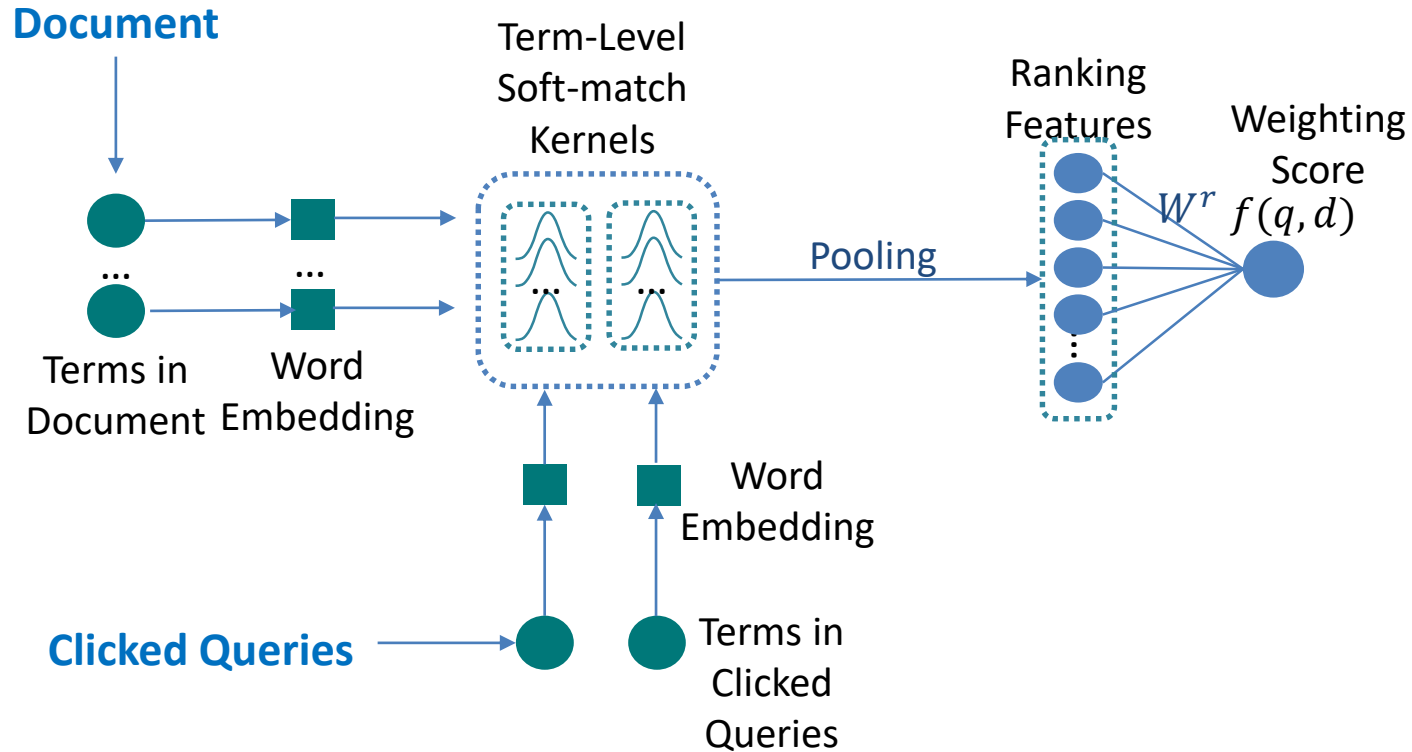
- Match document expansion with original query

Select terms from clicked queries of a document

$$C_d = \{c_i | click(c_i, d) = \text{True}\}$$

$$T_d = \{t_j | \exists c_i : t_j \in c_i, c_i \in C_d\}$$

Expansion Terms Weighting



Xiong et al. End-to-End Neural Ad-hoc Ranking with Kernel Pooling. SIGIR 2017

Based on the connections between original document and expansions

- Match clicked queries and document content with Self Attention

$$m(c_i, d) = \text{K-NRM}(\text{Self-ATT}(c_i), \text{Self-ATT}(d); w_c)$$

Model Training

Joint Learning:

- Match original document with original query
- Match document expansion with original query
- Linear combine the two match scores

$$f_{\text{NeuDEF}}(q, d) = \alpha f(q, d) + \beta f'(q, de)$$

End-to-end Training:

- Train on click model generated relevance labels (DCTR)
- Test on click model labels (TACM->Testing-DIFF) and raw user click labels (Testing-RAW), in 3 scenarios (Head, Torso, Tail)
- Pairwise loss

$$\sum_{d^+, d^- \in D^{+, -}} \max(0, 1 - f_{\text{NeuDEF}}(q, d^+) + f_{\text{NeuDEF}}(q, d^-))$$

Experimental Methodology

Dataset:

- Commercial search engine (Sogou) query log
- Both private(Sogou-KNRM) and public(Sogou-QCL) samples
- Both document title and body text

User Feedback:

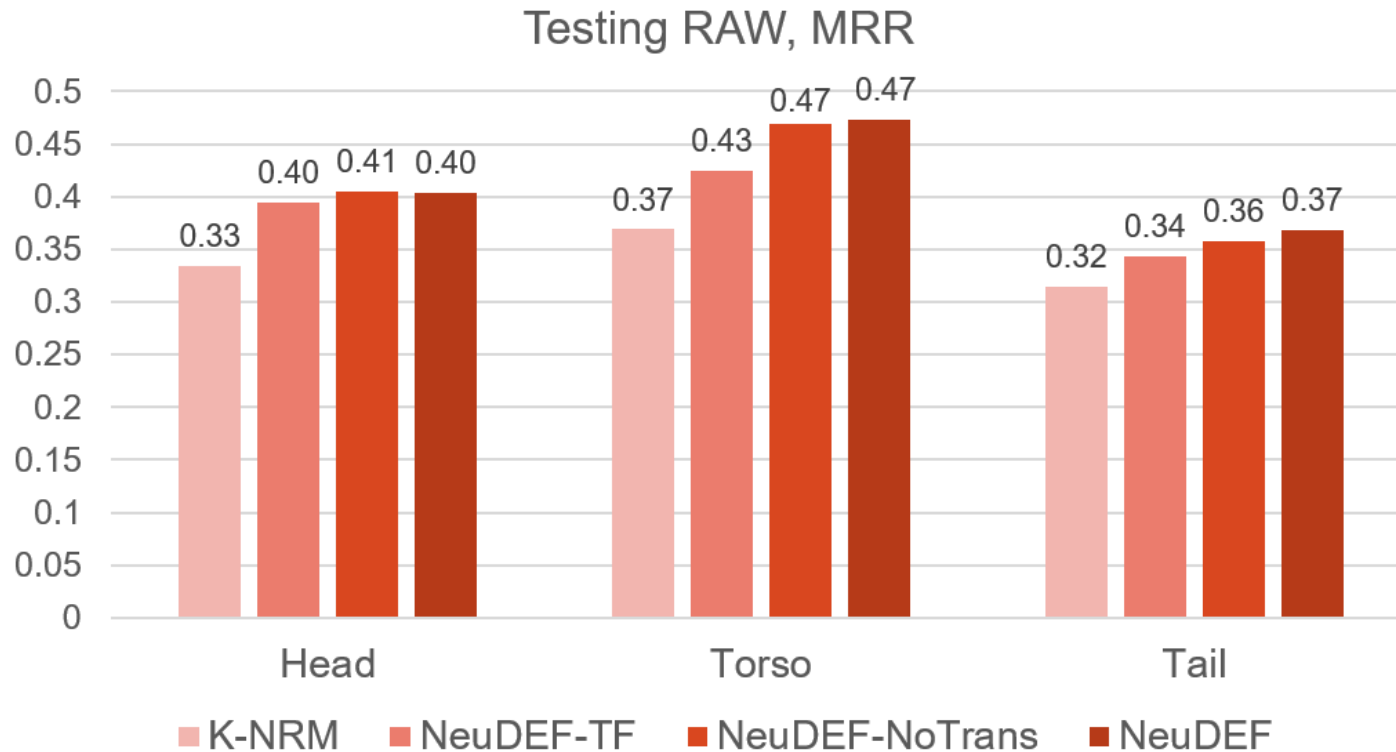
- Click signal and corresponding queries for each document

Evaluation Metrics:

- Traditional metrics: NDCG, MRR
- Document level metric: Delta Reciprocal Rank(ΔRR)

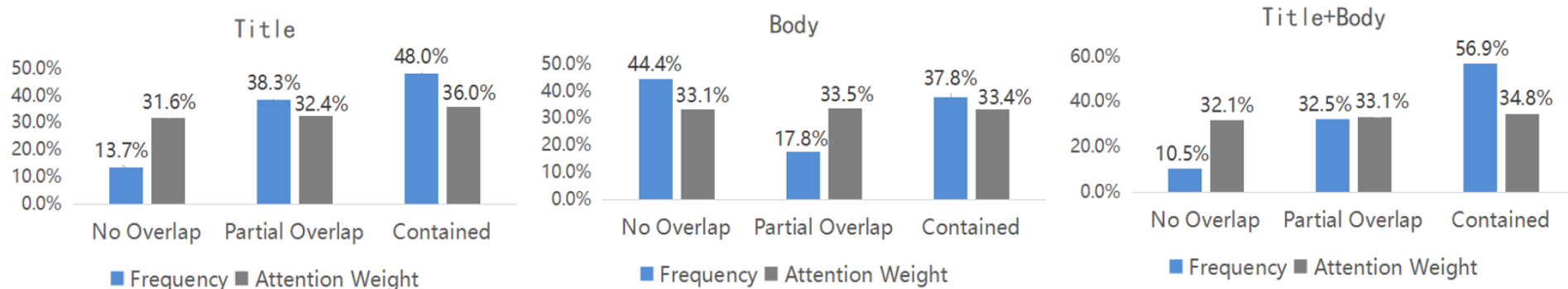
$$\Delta RR_{f_1 \rightarrow f_2}(d) = \sum_q y(q, d) \{RR_{f_2}(q, d) - RR_{f_1}(q, d)\}$$

Overall Performance



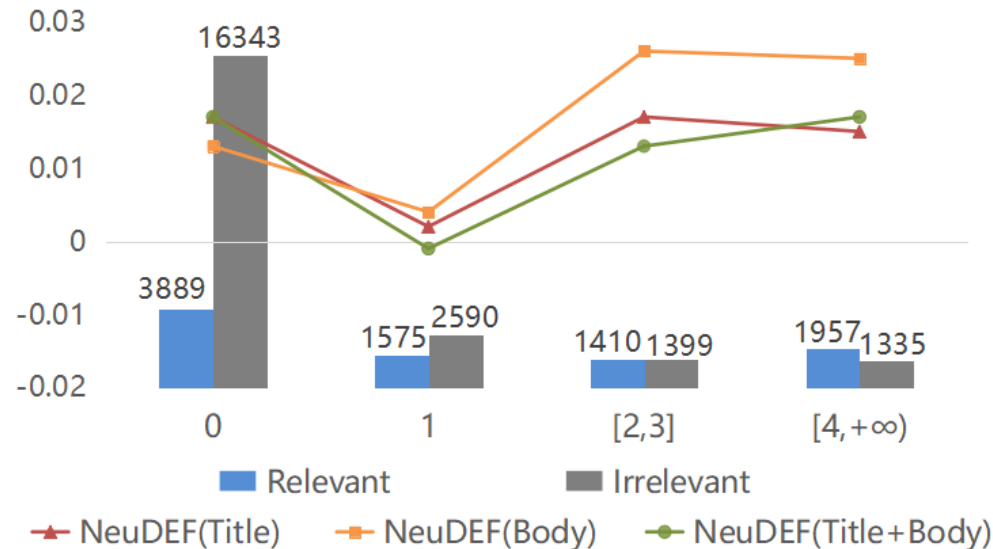
- NeuDEF significantly outperforms base ranker in all scenarios
- Attention Mechanism learns effective expansion weights

Frequent Distribution and Attention Weights



- Three groups of expansion terms divided by their frequent distribution:
 - Those from clicked queries that have No Overlap with document content
 - Those have Partial Overlaps
 - Those Contained by the document
- Analysis:
 - Expansion terms not in document still receive lots of weights
 - NeuDEF may leverage extra information

Document Level Performance



Performance on documents with different number of clicked queries:

- X-axis is the number of clicked queries
- Histograms are the number of documents.
- Plots and Y-axis are average ΔRR compared to K-NRM; higher is better.

Analysis:

- User clicks heavily favor popular document
- Documents with more click queries are more likely to be relevant

Case Study

Good Case:

Document	Clicked Queries
Train Schedule Inquiry	Train Schedule
	Train Ticket
	Railway Network
	Plane Ticket

- Synonym
- Alternative/competing query

Bad Case:

Document	Clicked Queries
4399 Games	Seer
	Naruto
	Aura Star

- 'Portal' websites can serve many possible clicked queries
- Sparse distribution of clicked queries

Conclusion

- **Designed User Feedback based Neural Ranker**
 - Enriches document representation for neural rankers via user feedback
- **Implemented End-to-end Training with User Clicks**
 - A data-driven combination of click signal and neural information retrieval
- **Demonstrated Effectiveness and Generalization Ability**
 - Show greater advantage on hard and short queries
 - Improve performances on all testing scenarios

Code & Paper

Code & Slides: <https://github.com/thunlp/NeuDEF>



Paper: <https://arxiv.org/pdf/1908.02938.pdf>



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