

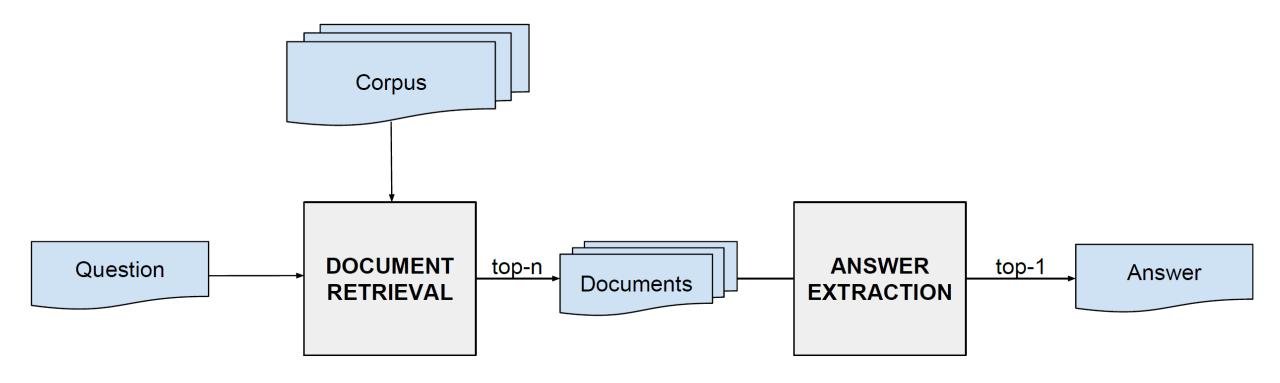


Adaptive Document Retrieval for Deep Question **Answering**

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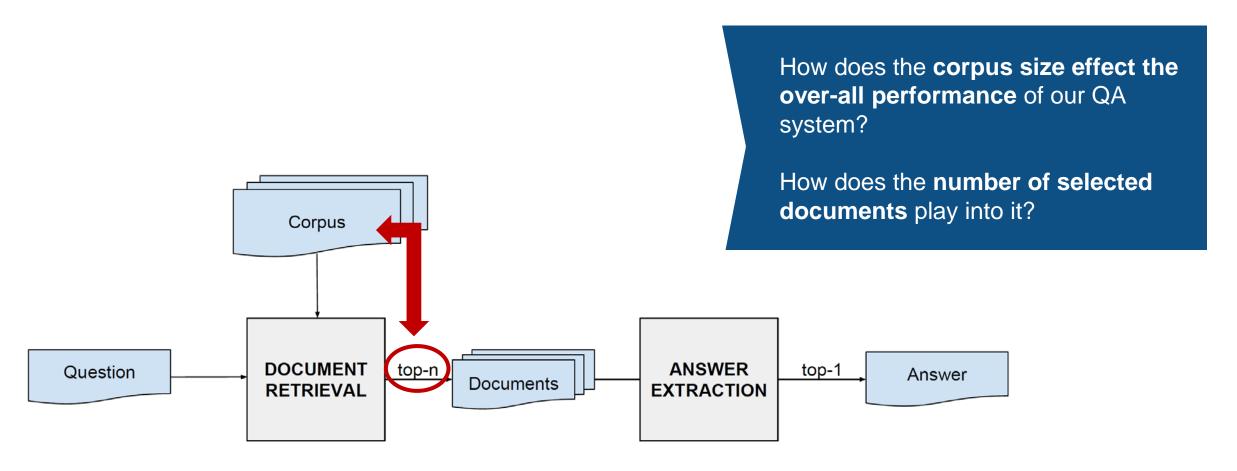
Empirical Methods in Natural Language Processing (EMNLP) 2018

Content based QA systems with neural answer extraction



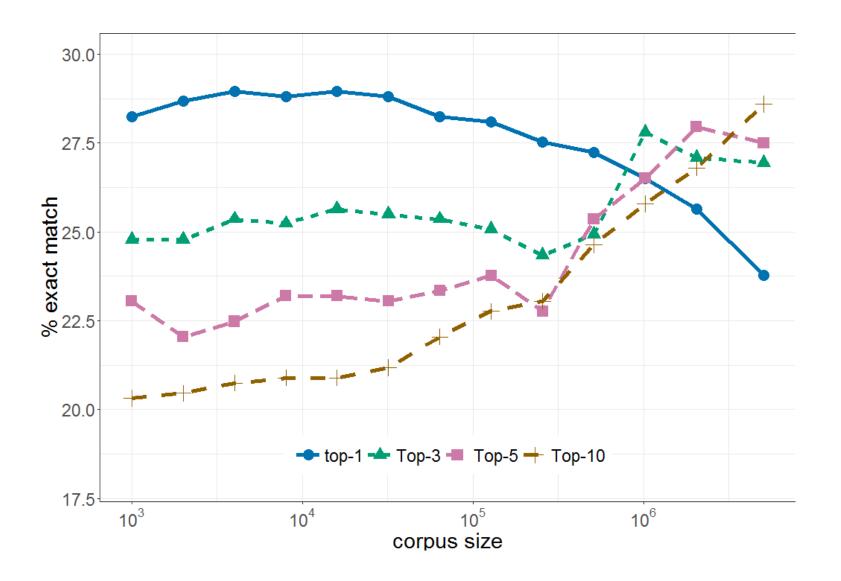


How does top-*n* document retrieval influence the performance of neural QA systems?





Varying top-*n* retrieval under a dynamic corpus



Findings

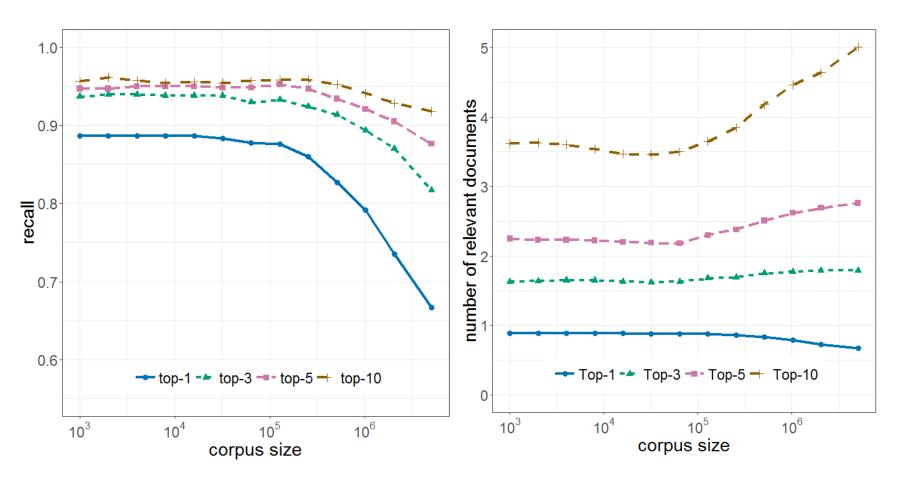
- For small corpora, a top-1 system outperforms any other configuration
- For bigger corpora, a top-n system preforms better than any top-1

Experiments based on DrQA System:

Chen, Danqi, et al. "Reading Wikipedia to Answer Open-Domain Questions." Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (2017)



Document retrieval under a dynamic corpus



Findings

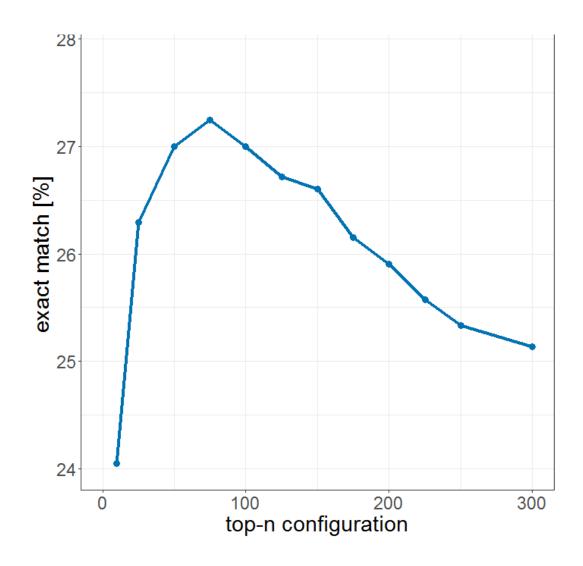
- The recall@1 is very volatile when the corpus grows
- Top-*n* retrieval results in a higher density of information

Experiments based on DrQA System:

Chen, Danqi, et al. "Reading Wikipedia to Answer Open-Domain Questions." Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics



Varying top-*n* retrieval under a static corpus

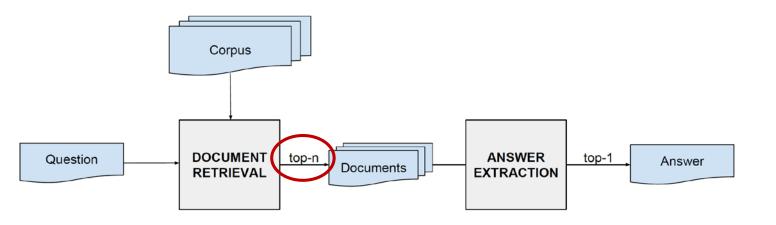


Findings

- In the beginning, selecting more paragraphs results in higher performance
- Selecting too many paragraphs results in a performance loss



The noise information trade-off in neural question answering



Noise-information trade-off

- Pick a query dependent number of documents to select
- Select enough documents to answer the question → but not too many to select a wrong candidate answer



A threshold baseline for adaptive retrieval

Number of documents is determined independently for every query

$$n_i = \max_k \sum_{j=1}^k s_i^{(j)} < \theta$$

 $s_i^{(j)}$ score of document j, in query i

• The Idea: The more confident we are, the less documents we want to select

A ordinal regression model for adaptive retrieval

We model the **number of top-***n* **documents** by

$$y_i = f([s_i^{(1)}, \dots, s_i^{(\tau)}]) = \lceil s_i^T \beta \rceil$$

The Idea: Learn the cut-off point by minimizing

$$\mathcal{L} = \| [X\beta] - y\|_1 + \lambda \|\beta\|_2$$

For prediction, we use an additional off-set

$$\hat{n}_i = \lceil s'_i^T \hat{\beta} \rceil + b$$

Results on the full Wikipedia corpus

	SQuAD	TREC	WebQuestions	WikiMovies
DrQA (Chen et al., 2017) [†]	29.3	27.5	18.5	36.6
Threshold-based ($\theta = 0.75$)	29.8	28.7	19.2	38.6
Ordinal regression ($b = 1$) Ordinal regression ($b = 3$)	29.7 29.6	28.1 29.3	19.4 19.6	38.0 38.4
R^3 (Wang et al., 2018)	29.1	28.4	17.1	38.8

^{†:} Numbers vary slightly from those reported in the original paper, as the public repository was optimized for runtime performance.

Experiment

- [DrQA] system #1
- Corpus: Full Wikipedia

Experiment

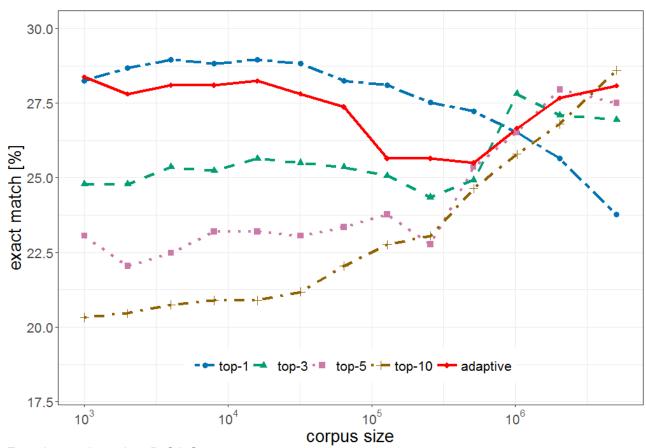
- Paragraph system #2
- Corpus: Full Wikipedia

	SQuAD	TREC	WebQuestions	WikiMovies
Top-50 System	27.0	23.5	15.1	24.4
Top-80 System	27.2	25.9	14.9	26.0
Threshold-based ($\theta=0.75, \tau=100$)	27.2	27.1	15.4	26.3
Ordinal regression ($b=3, \tau=250$)	27.3	27.1	16.7	26.5

Chen, Dangi, et al. "Reading Wikipedia to Answer Open-Domain Questions." Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (2017) Wang, Shuohang, et al. "R3: Reinforced Reader-Ranker for Open-Domain Question Answering." Conference on Artificial Intelligence AAAI (2018).



Results under varying corporas



The adaptive approach remains the most robust

It's the 'safest' bet in terms of regret \rightarrow i.e. when the corpus grows/shrinks over time

Experiments based on DrQA System:

Chen, Danqi, et al. "Reading Wikipedia to Answer Open-Domain Questions." Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (2017)



Thank you very much!

Questions?

Feel free to reach out to us: bkratzwald@ethz.ch