Exploring BERT Synonyms and Quality Prediction for Argument Retrieval

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Task: Argument Retrieval

Respond to user queries with a set of relevant and high quality arguments.

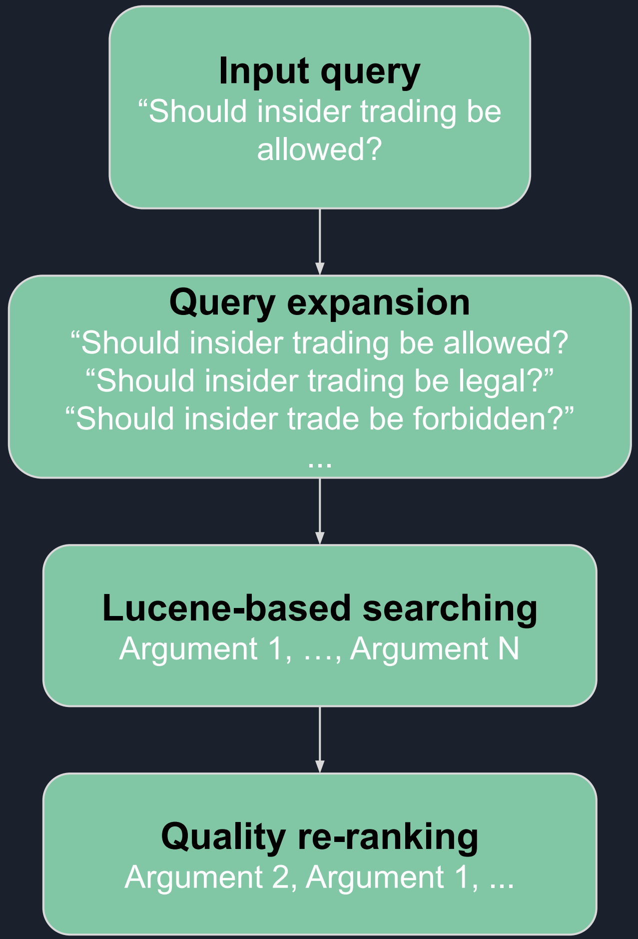
Argument: “A conclusion (claim) supported by premises (reasons)”

Example of user query: “Should insider trading be allowed?”

Our approach

After indexing, given a user query:

1. Expand user query: try to expand query scope
2. Search for each expanded query and merge retrieved arguments
3. Run argument quality re-ranking: boost arguments with higher “quality”



Indexing: Args.me arguments

We considered the following properties for each document, i.e. argument:

```
{
    "id": "abc-123",
        "text": "I think climate change is fake because I feel cold during winter",
        "stance": "CON",
        "context": {
            "discussionTitle": "Is climate change real?"
        }
}
```

Indexing: Args.me arguments

A few documents were discarded due to:

- **Empty body** (text field): no reason to include them

- **Repeated ID**: the argument IDs are computed hashing the argument's body (plus other things), therefore same ID means same argument

Original dataset size: **8.2 GB**

Final index size: **457 MB**

Indexing: analyzer

We used to following filters (for title and argument body):

- Standard tokenizer
- Lower case filter

We tried and removed:

- Stop words filter: slightly lower score
- Stemming filter: any kind of stemmer significantly downgraded the performance
- English possessive filter: slightly reduced performance

Searching: similarity

- **Similarity**: we used **LMDirichletSimilarity** which almost doubled the score obtained with BM25

- **Baseline nDCG@5 score: 0.8279**
  (using the corrected .qrels file)

Searching: query parser

Idea: the “discussionTitle” should briefly describe the topic of the argument, therefore we tried to match the query terms both in the body and title of the arguments.

We used **MultiFieldQueryParser**:

- Run the same boolean query on more fields (title and body)
- Assign a boost to each field

Parametrizing the boost given to a match of a query term with a title term, we found that the higher was the title boost the lower was the final score.

Possible reason: “bad” arguments may be pushed up in the final rank just because they inherit the discussion title.

Query Expansion: definition

- Query Expansion consists in enriching a user query:
  - to increase its effectiveness in the search process.
  - to improve the recall of the retrieval system.

- Transformer-based models -> Masked Language Model -> BERT [1]
  - generates substitute terms depending on context of the query.

- No labelled data or external resources (e.g. WordNet)

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[1] J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding, 2019.

Query Expansion: our approach

Sounds like a job for me!

1. Tokenization and PoS tagging.
2. Replace specific tokens with BERT's [MASK] .
3. Generate the best 10 tokens that fit in place of each [MASK]
   -> exploit BERT's bidirectional attention mechanism.
4. Compute the BERT embeddings of these 10 tokens and compare them, using cosine similarity, to the embedding of the original token.
5. Perform a two-phase screening: if generated tokens are not good enough
   -> use BERT again to generate new candidates.
6. Compose all the possible new queries and take a set of 10 random queries.

Query Expansion: some examples

- “Should insider trading be <allowed>?”

permitted (+)
tolerated (+)
forbidden (-)
illegal (-)

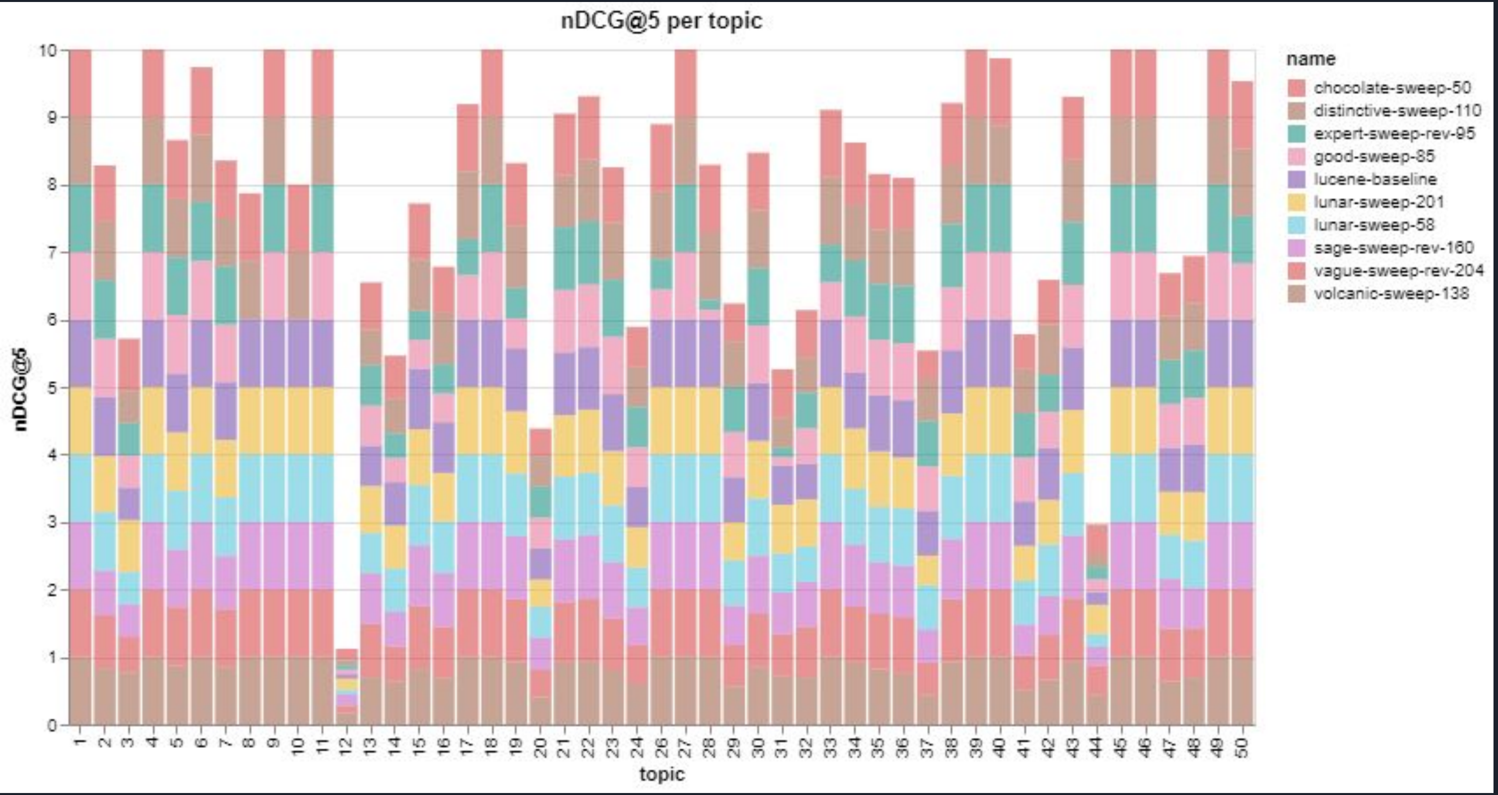
- “Is homework beneficial?”

“Is homework acceptable?”
“Is homework great?”
“Is homework appropriate?”

- “Is vaping with <e-cigarettes> safe?”

e-book
half-readers
mini-com (?)
z-commerce (?)

Query Expansion: hardest topics



Query Expansion: hardest topics

- Topic 8: “Should abortion be legal?”
  - it is a very short topic.
  - “abortion” and “divorce” are very similar according to BERT.
  - bias in BERT’s pre-training dataset.

- Topic 10: “Should any vaccines be required for children?”
  - “required” is equally replaced with “mandatory” and “recommended”.
  - there are contexts where lexical nuances make the difference.

Argument Quality re-ranking

- Objective: provide the user with relevant but also “good” arguments
- What makes an argument good? We can distinguish between[1]
  - Logical quality
  - Rhetorical quality
  - Dialectical quality

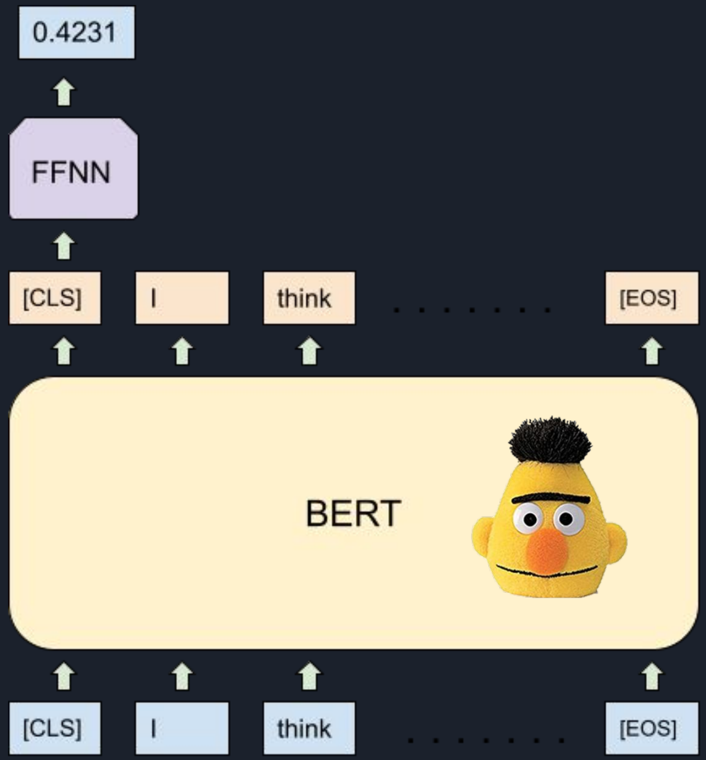
[1] Wachsmuth, Henning, et al. “Computational Argumentation Quality Assessment in Natural Language.” Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, vol. 1, 2017, pp. 176–187.

The Argument Quality Dataset

- To train our models, we used the Argument Quality Dataset
- It contains 1271 arguments from *args.me*, each having:
    - Relevance Score
    - Rhetorical Quality
    - Logical Quality
    - Dialectical Quality
    - Combined Quality

BERT for Argument Quality Prediction

- Idea: use models from the BERT family to have an argument quality regressor
- Explored 4 different models[1]:
  - BERT
  - DistilBERT
  - RoBERTa
  - ALBERT



[1] *huggingface.co/models*

Ranking Functions

- Normalization Function

$$R(q,d) = (1-\alpha)\, r_{norm} + \alpha\, q_{norm}$$

- Sigmoid Function

$$R(q,d) = (1-\alpha)\, \sigma(\beta\, r(d)) + \alpha\, \sigma(\beta\, q(d))$$

- Hybrid Function

$$R(q,d) = (1-\alpha)\, r_{norm} + \alpha\, \sigma(\beta\, q(d))$$

Parameter Space

- α: regulates the importance of quality for the re-ranking
- β: controls sigmoid steepness
- n_{rerank} : number of documents that are re-ranked according to quality
- *Query expansion*: boolean value to activate QE
- *Quality model*: BERT, DistilBERT, ALBERT and RoBERTa.
- *R(q,d)*: ranking function

Hyperparameter Study and Results

- We studied several combination of parameters using Weights and Biases[1]
- We selected 10 runs, 5 of which were sent to Touchè

Run	AQE	α	β	n_{rerank}	quality model	$R(q,d)$	nDCG@5
lunar-sweep-201	no	0.75	-	5	BERT	normalize	**0.8279**
chocolate-sweep-50	no	0.1	2	5	BERT	sigmoid	0.8273
volcanic-sweep-138	no	0.5	0.8	5	BERT	sigmoid	0.8271
swordsman baseline	no	-	-	-	-	-	0.8266
lunar-sweep-58	no	0.1	0.2	5	RoBERTa	hybrid	0.8230
vague-sweep-rev-204	no	0.75	1.1	5	ALBERT	sigmoid	0.8229
lucene-baseline	no	0	-	-	-	normalize	0.8224
sage-sweep-rev-160	no	0.5	1.5	5	RoBERTa	sigmoid	0.8093
distinctive-sweep-110	no	0.1	0.8	15	ALBERT	hybrid	0.7992
good-sweep-85	yes	0.1	0.3	15	DistilBERT	hybrid	0.6857
expert-sweep-rev-95	yes	0.1	0.3	20	RoBERTa	hybrid	0.6801

[1] wandb.ai