Learning to Attend On Essential Terms: An Enhanced Retriever-Reader
Model for Open-domain Question Answering

Jianmo Ni, Chenguang Zhu, Weizhu Chen, Julian McAuley
UC San Diego, Microsoft Speech and Dialogue Research Group

Introduction
- Open-domain QA on large-scale corpus is framed as machine reading comprehension based on evidence retrieved from corpus by search engines.
- Answer quality highly depends on retrieval results.
- Previous work uses question+choice as search query, which may return irrelevant results.
- Finding essential terms within questions can help improve quality.

Our Model

Enhanced Reader
- Propose a retriever that learns to attend on essential terms
- Identifies important words in a question
- Reformulates the query
- Searches for related evidence

Essential Term Selector
- Given a question Q and K answer choices C₁,...,Cₖ
- Predict a binary variable yᵢ for each word wᵢ in the question Q, where yᵢ=1 means wᵢ is an essential term and 0 otherwise
- Use BILSTM to learn each term’s yᵢ based on a supervised dataset

Enhanced Reader
- Input layer
  - Question Q = \{wᵢ\}ᵢ∈₁₉
  - K choices Cₖ = \{wᵢ\}ᵢ∈₁₉
  - K retrieved passages Pₓ = \{wᵢ\}ᵢ∈₁₉
- Use a mix of embeddings including output from essential term selector

Output Layer
- Attention layer
  - Cross attention between choices and retrieved passages
- Sequence Modeling Layer
  - Fusion layer
    - Attention over hᵢ, hᵢ, hᵢ
    - Inter-choice attention
    - cᵢ = Maxpool(\{hᵢ− cᵢ− Σᵢ hᵢ\})
- Generate scores for each (question, passage, choice) tuple

Results

Essential Term Selector: ET-Net
- We use the public dataset from Khashabi et al. (2017) which contains 2,223 questions, each accompanied by four answer choices.
- Labels about essential terms are available

ET-RR Performance

Impact of Essential term selection
- ET-RR outperforms other baselines using concatenation and TF-IDF, given different numbers of retrievals K.

Conclusion
- Retriever-reader model ET-RR for open-domain QA. Strong performance on various datasets.
- For future work, we plan to explore multi-hop query and end-to-end retriever-reader model via reinforcement learning.

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