Multi-Granularity Guided Fusion-in-Decoder



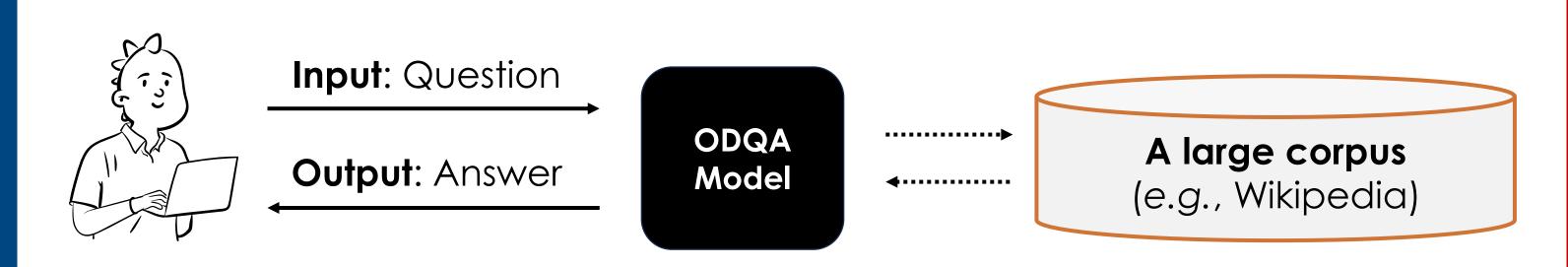


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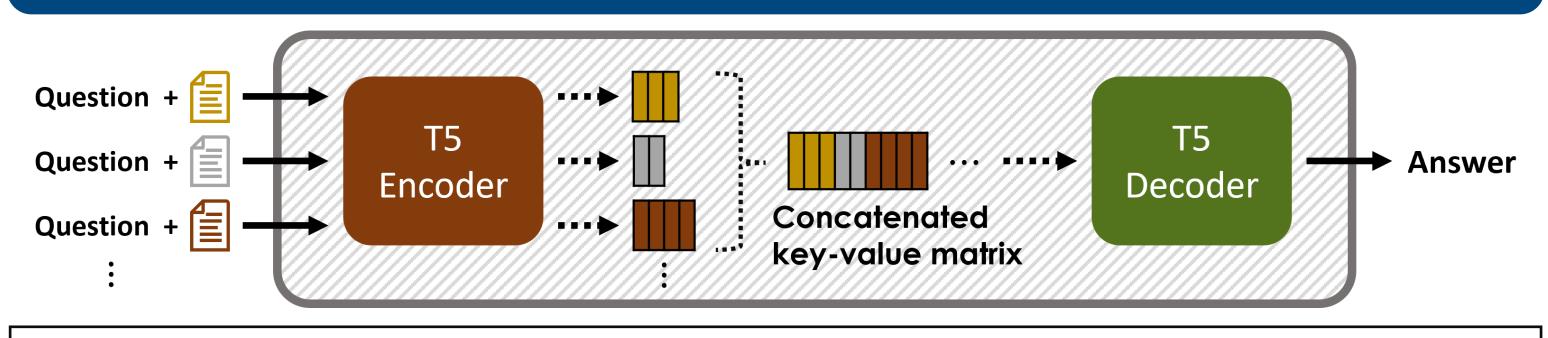
Task: Open-Domain Question Answering



Open-Domain Question Answering (ODQA) requires <u>answering factual</u> <u>questions</u> with reference to <u>a large corpus</u>.

- ✓ One of the Knowledge-Intensive Language Tasks (KILTs) that a human is unlikely to perform without access to an external knowledge source
- Impractical to examine every single document in the corpus
- → Retrieve-then-Read pipeline

Fusion-in-Decoder (FiD)



Fusion-in-Decoder (FiD) is a notable method which concatenates multiple encoder outputs and feeds them as a key-value matrix to the decoder, which we define as a **Multi-document Reader**.

✓ Aggregating evidence across multiple passages

Takeaways

- ✓ Multi-granularity-based evidentiality for the FiD architecture
- ✓ LLM generated pseudo-labels for supportive passages
 - filtering out spurious ones that contain the answer span
- Reusing multi-granularity contexts for accuracy and efficiency
- an anchor vector for the decoder
- threshold-based passage pruning

Challenges in Multi-document Readers

Question: who played in the most world series games **Answer**: the New York Yankees

Retrieved passage: World Series television ratings The highest average rating for an entire World Series is tied between the 1978 Series featuring the New York Yankees and Los Angeles Dodgers and the 1980 Series featuring the Philadelphia ...

Answer span: True / Supportive: False

Question: when did the first manned space craft land on the moon Answer: 20 July 1969

Evidence passage: ... includes both manned and unmanned (robotic) missions. The first human-made object to reach the surface of the Moon was the Soviet Union's Luna 2 mission, on 13

September 1959. The United States' Apollo 11 was the first manned mission to land on the Moon, on 20 July 1969. There have been six manned U.S. landings (between 1969 and 1972) ... unmanned landings, from 22 August 1976 until 14 December 2013. Prediction w/o multi-granularity learning: 13 September 1959

Challenge 1

Discriminate supportive passages among the retrieved result

✓ Even the passage containing an answer span can be spurious.

Potentially misleadingSupportive sentence

ally misleading
tive sentence

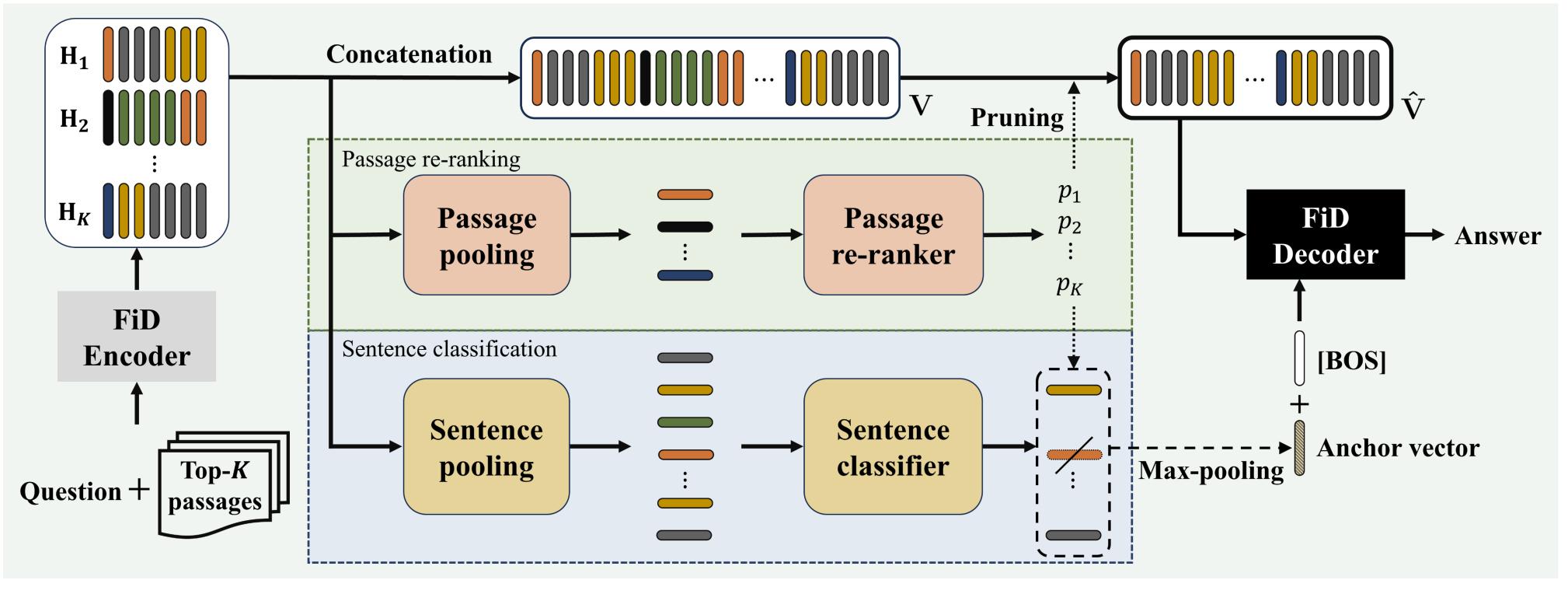
Span

Challenge 2

There are distractions that potentially mislead the reader.

We propose to discern evidence across multiple levels of granularity, i.e., passages and sentences.

Multi-Granularity Guided Fusion-in-Decoder (MGFiD)



MGFiD framework incorporates 1) Answer Generation and 2) Learning & Reusing Multi-Granularity Contexts.

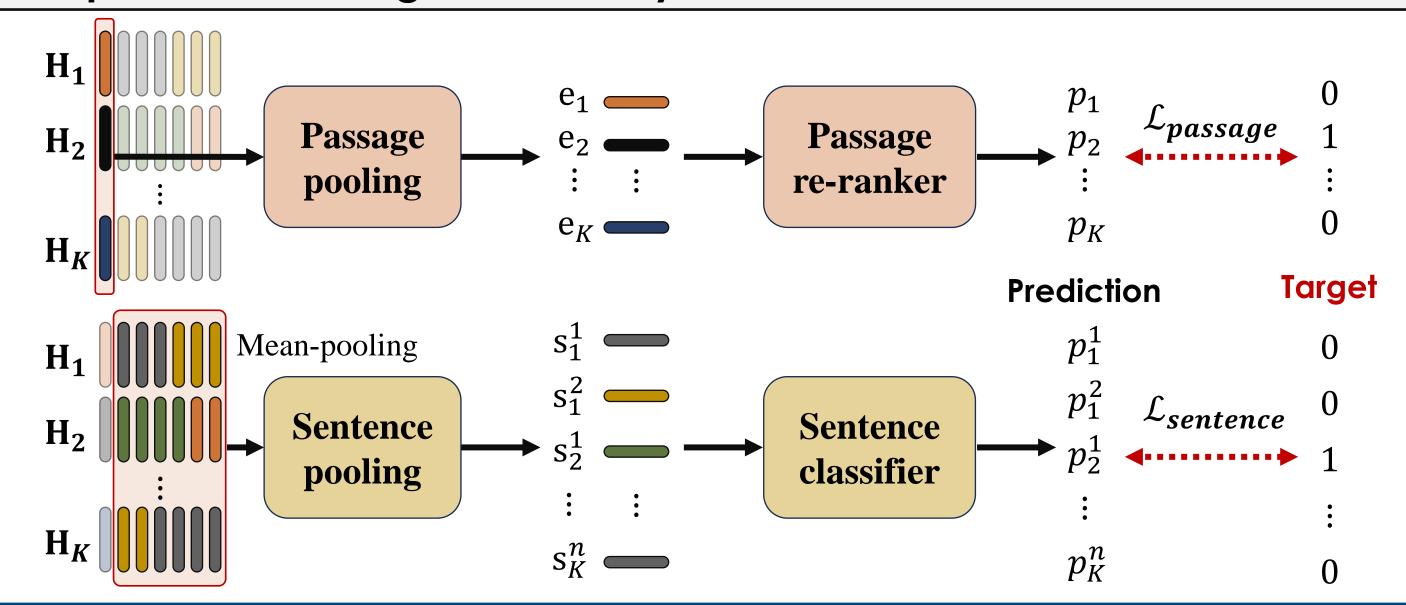
1. Answer Generation

- ✓ Adopting standard FiD architecture
 - FiD-decoder takes the concatenated matrix $\mathbf{V} \in \mathbb{R}^{(K \times L) \times d}$ as the key-value matrix and generates an answer.
 - K: number of candidate passages / L: maximum sequence length / d: hidden dimension

2. Learning & Reusing Multi-Granularity Evidence

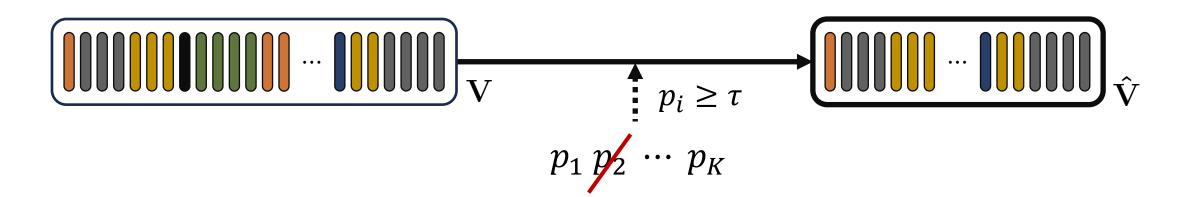
- ✓ Passage re-ranking to identify coarse-grained evidence
 - Sentence classification for fine-grained evidence

Leveraging the ranking capabilities of Large Language Models, MGFiD uses pseudo-labels generated by LLMs.



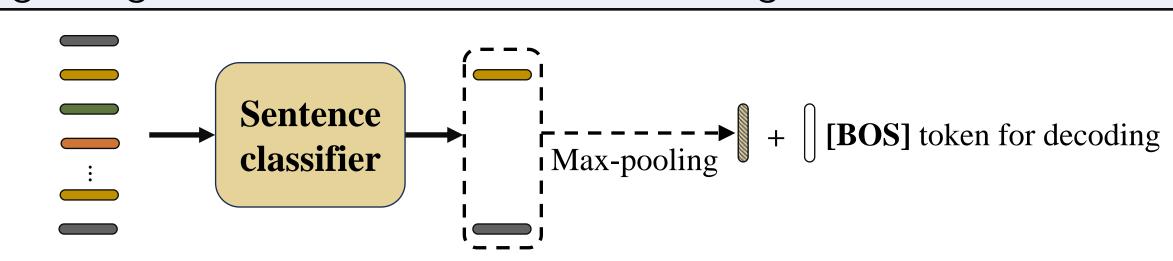
Threshold-based passage pruning

✓ Mitigating inefficiency from the huge key-value matrix



Anchor vector

✓ Aligning fine-grained evidence with the answer generation



Experimental Results

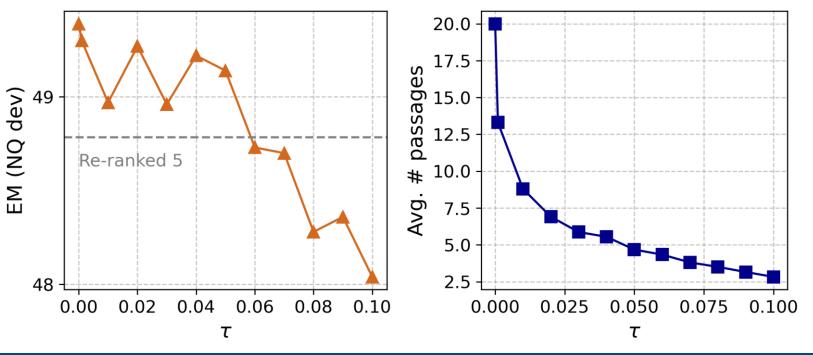
Effectiveness on Question Answering datasets

- ✓ MGFiD significantly improves the effectiveness of both datasets using the same retriever and the same number of passages.
- ✓ Pruned MGFiD outperforms baselines using 24%~39% passages in the decoder.

Model	Multi-task learning	Ret.	Avg. # psgs in Decoder	NQ (EM)		TQA (EM)	
Model				Dev	Test	Dev	Test
FiD-KD	_		20	47.8 ± 0.16	48.4 ± 0.31	67.4 ± 0.12	67.6 ± 0.25
FiD-KD	_		100	49.1	50.1	_	_
EvidentialityQA	0	FiD-KD	20	48.0 ± 0.20	49.0 ± 0.39	n/a	n/a
RFiD	0		20	48.6 ± 0.29	49.4 ± 0.53	<u>67.8</u> ± 0.12	<u>68.1</u> ± 0.20
RFiD	0		100	49.2	50.4	_	_
MGFID	0	EID VD	20	49.0 ± 0.21	50.1 ± 0.33	68.0 ± 0.09	68.3 ± 0.23
Pruned MGFiD	0	FiD-KD	4.8 / 7.7	<u>48.8</u> ± 0.20	<u>49.7</u> ± 0.52	<u>67.8</u> ± 0.07	68.3 ± 0.16

Effectiveness varying the pruning threshold τ

Increasing τ to 0.05 results in a small performance drop even if the number of passages drops drastically below 5.



QA performance with different passage labels

AA penomiance will alliciem passage labels							
Passage label	NQ dev (EM)	# positives	TQA dev (EM)	# positives			
•	47.8 ± 0.16	_	67.4 ± 0.12	_			
Answer span	48.5 ± 0.21	4.5	67.7 ± 0.16	8.9			
ChatGPT	48.9 ± 0.13	4.0	67.7 ± 0.20	8.3			
MythoMax	48.8 ± 0.23	2.8	67.8 ± 0.18	6.5			

Ablation studies

- ✓ Listwise loss function for passage re-ranking achieves higher accuracy than pointwise loss function on both datasets.
- \checkmark With the anchor vector, the effectiveness improved by 0.5%p on the NQ dataset.

	$\mathcal{L}_{passage}$	$\mathcal{L}_{sentence}$	\mathbf{e}_{anchor}	τ	NQ dev	TQA dev	Check out our paper,
	listwise	✓	✓	0.05	<u>49.1</u>	67.7	details on MGFiD,
	listwise	✓	✓	top-5	48.8	-	and more experiments!
	listwise	✓	✓	Χ	49.4	67.9	contact info.
	listwise	✓	X	Χ	48.9	67.9	¦eunseong@skku.edu
	X	✓	Χ	Χ	48.1	67.9	
	listwise	Χ	X	Χ	48.8	<u>67.8</u>	
	pointwise	X	X	Χ	48.3	67.6	
•	Χ	X	Χ	Χ	47.8	67.5	Paper Code