[Improving LLM Question Answering with Reasoning Correction and Knowledge Triples]

Jihong Jeong, and Junryul Han, Prof. Hyunjoon Kim
School of Data Science, Hanyang University

Research Motivations

LLMs can retrieve relevant documents accurately in multi-hop question answering.

But still fail to produce correct answers. This creates a clear gap between retrieval and reasoning.
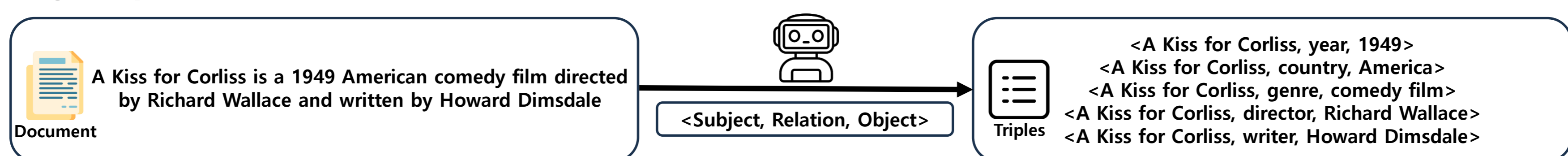
To build reliable and explainable QA systems, we need methods that help models use the evidence they already have, improving correct reasoning.

Knowledge triples provide a clearer structured representation of evidence, making it easier for models to follow the correct reasoning steps.
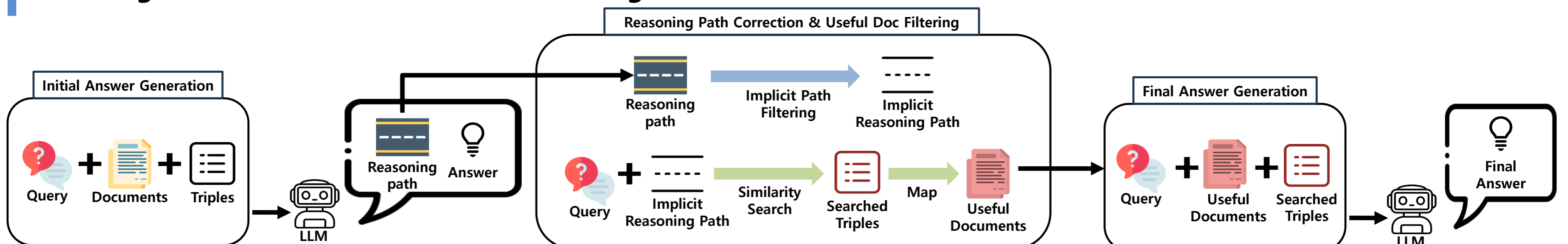
We proposed a triple-based correction method that improves Multi-hop QA accuracy by repairing the LLM's reasoning path.

Model Architecture

Knowledge Triple Extraction

Document: A Kiss for Corliss is a 1949 American comedy film directed by Richard Wallace and written by Howard Dimsdale

<Subject, Relation, Object>

Triples:
<A Kiss for Corliss, year, 1949>
<A Kiss for Corliss, country, America>
<A Kiss for Corliss, genre, comedy film>
<A Kiss for Corliss, director, Richard Wallace>
<A Kiss for Corliss, writer, Howard Dimsdale>

Reasoning Path Correction & Useful Doc Filtering

Experiments & Results

End-to-End QA Performance

Dataset->	HotpotQA				2WikiMultihopQA				MuSiQue			
Retriever->	BM25		Gold		BM25		Gold		BM25		Gold	
Metrics->	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
Baseline	0.383	0.5237	0.502	0.6588	0.192	0.2562	0.28	0.3746	0.189	0.2652	0.427	0.584
w. Triples	0.48	0.5986	0.62	0.774	0.343	0.401	0.582	0.6694	0.193	0.2605	0.473	0.5978
w. Triples w. Reasoning Path Correction	<u>0.48</u>	**0.6073**	**0.624**	**0.7734**	**0.351**	<u>0.4043</u>	<u>0.598</u>	**0.6837**	<u>0.2</u>	**0.2751**	**0.483**	<u>0.6142</u>
w. Triples w. Reasoning Path Correction w. Useful Docs Filtering	**0.485**	**0.6073**	<u>0.622</u>	<u>0.773</u>	<u>0.3504</u>	**0.41**	**0.599**	<u>0.6835</u>	**0.207**	<u>0.2705</u>	<u>0.48</u>	**0.6153**

Efficiency Comparison

	Baseline	w. Triples	w. Triples w. Reasoning Path Correction	w. Triples w. Reasoning Path Correction w. Useful Docs Filtering
Token length	1692	3073	2498	1832

- Result using Reasoning Path Correction achieved better performance than just using document or triples for generating answers. From efficiency comparison, we can recognize that Useful Docs Filtering also helps our method robust.

Contributions & Future Work

- We proposed structured knowledge integration by transforming documents into triples, guiding LLMs to generate structured reasoning path using triples. Then, we enhanced accuracy by reasoning path correction which is done with filtering uncertain reasoning path and retrieving supplementary information.
- Since our current results rely on pre-trained models, we plan to apply supervised fine-tuning to further optimize the LLM's capability. Also, we aim to investigate more robust uncertainty estimation metrics beyond token entropy.