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RAGONITE: Iterative Retrieval on Induced Databases and Verbalized RDF for Conversational QA over KGs with RAG

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Conversational question answering (ConvQA)

What is the setting for our work?

- ConvQA natural way of information access
 - Self-contained intent-explicit first question(s)
 - Potentially intent-implicit follow-up questions
- Primarily conducted via LLMs
- Several enterprises want to conduct ConvQA over own data
- Retrieval augmented generation (RAG) systems are the norm
 - Retrieve data from enterprise knowledge using tools
 - LLMs generate coherent response from retrieved evidence
- Enterprise data usually stored as
 - Databases, Text corpora, Heterogeneous collections
 - Knowledge graphs focus of this work

Q1: What is the cheapest X1 series car? How much is it?

A1: The cheapest BMW X1 series car is the "BMW X1 sDrive20i Sport" (35,410 EUR)

Q2: Just curious - and what's the most expensive X7?

A2: The costliest BMW X7 is the "BMW X7 xDrive40d Excellence" (89,515 EUR).

Q3: Comparison of their engines?

A3: The key differences between the engines of BMW X1 and BMW X7 are ...

Q4: So what are some of these luxury features in the latter?

A4: The BMW X7 comes with a range of luxury features, including ...

Q5: Luxury comes at a cost. Are CO2 emissions of X7 much worse?

A5: Yes, the CO2 emissions of the BMW X7 models are generally higher than X1...



Knowledge graphs (also known as Knowledge Bases)

What is the data source?

RDF Turtle format

- Contain factual information comprised of
 - Entities
 - Predicates
 - Types
 - Literals
- RDF standard: facts stored as triples
- Triples have "binary" format <Subject, Predicate, Object>
- More complex info can be stored as n-ary facts

<bmw-x7-xdrive40i, type, car;</pre>

omw-x7-xdrive40i engine, bmw-x7-xdrive40i-excellence;

bmw-x7-xdrive40i height, 1835 mm; bmw-x7-xdrive40i length, 5181 mm; bmw-x7-xdrive40i price, 88890 Euros;

bmw-x7-xdrive40i wheelbase, 3105 mm;

bmw-x7-xdrive40i width, 2000 mm>

<bmw-x7-xdrive40i-excellence, type, engine specification;</p>

WLTP CO2 emission combined, 240 - 218 g/km;

WLTP consumption combined, 26.6 – 29.4 mpg;

acceleration 0-62 mph, 5.8 s;

drive type, all-wheel drive;

engine performance, 280 kW (381 hp);

fuel type, gasoline;

transmission, Sport Automatic Transmission with

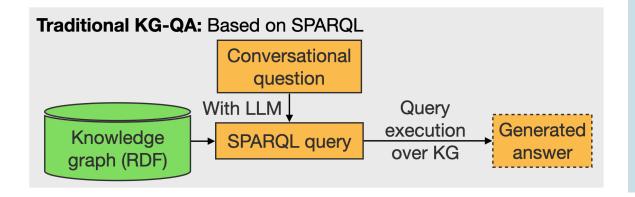
Gearshift Paddles>



Knowledge graphs (also known as Knowledge Bases)

Why are KGs typically used?

- Why KGs?
 - Flexible schema compared to DBs
 - Reduced moderation effort for human experts
 - Exploit neighborhoods of entities: answer, recommend, visualize
- Nature of info in KGs limits their use to lookups
 - Via SPARQL(-like) languages



<bmw-x7-xdrive40i,</pre> type, car; engine, bmw-x7-xdrive40i-excellence; height, 1835 mm; length, 5181 mm; price, 88890 Euros; wheelbase, 3105 mm; width, 2000 mm> <bmw-x7-xdrive40i-excellence, type, engine specification;</p> WLTP CO2 emission combined, 240 – 218 g/km; WLTP consumption combined, 26.6 – 29.4 mpg; acceleration 0-62 mph, 5.8 s; drive type, all-wheel drive; engine performance, 280 kW (381 hp); fuel type, gasoline; transmission, Sport Automatic Transmission with Gearshift Paddles>



How can we satisfy new intent classes (abstract, complex math) over KGs?

New possibilities open up with capable LLMs

- World knowledge in LLM parameters
 - Units, acronyms, region-based standards
- Commonsense reasoning
 - Equipment and luxury features, suitability as family cars
- Structured query generation
 - SQL (better than SPARQL), ...
- Structured output generation
 - JSON for interfacing pipeline components

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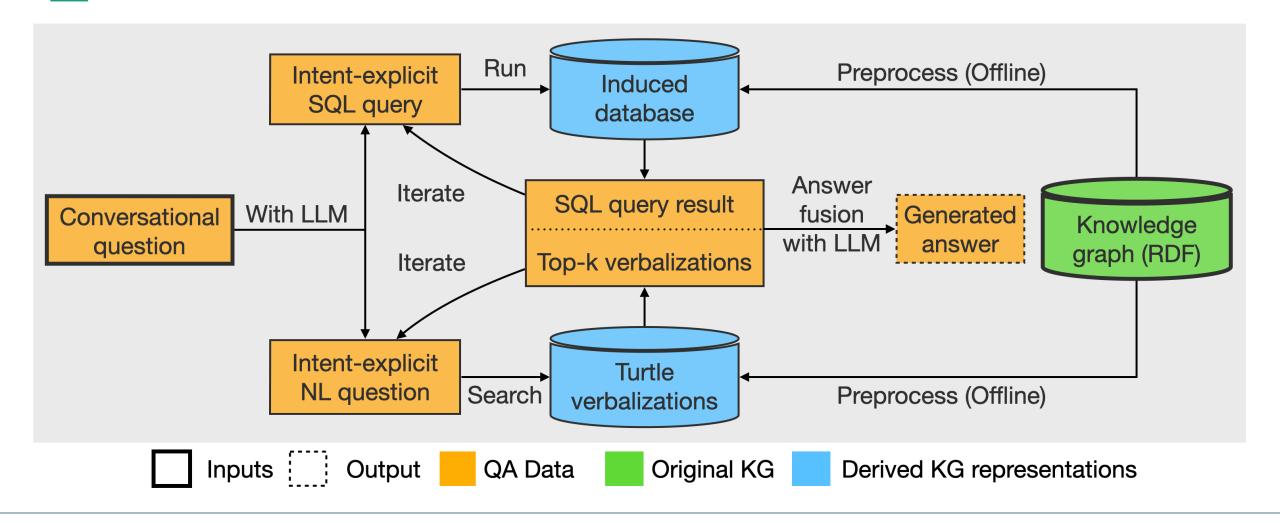
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Key idea: Make the most of your knowledge graph with RAGONITE!

A unified framework for satisfying lookup, abstract, and complex math intents over KGs





Highlights in RAGONITE

What are the key features of our novel KG-QA pipeline?

- Automated database induction
- Knowledge graph verbalization
- Iterative retrieval
- Branch integration
- Open LLM support
- Scope for heterogeneous QA



Automated database induction

How can we programmatically convert a KG to a DB?

- Original KG in RDF Turtle format
- Converted to a DBMS for harnessing SQL capabilities (Li et al. 2023)
 - More capable than SPARQL at complex math intents
 - LLMs better at SQL generation than SPARQL
 - Failed SQL gueries often generate useful, directed error messages
- Key steps
 - Inducing schema (types -> tables, predicates -> columns)
 - Inserting data (facts -> rows, inferring datatypes)
 - Enhancing semantics (renaming columns, SQL comments in schema)

mw-x7-xdrive40i,	type, car;			
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engine	WLTP CO2 emission combined	WLTP consumption combined	acceleration 0-62 mph	drive type	engine performance	
	240 – 218 g/km	26.6 – 29.4 mpg	5.8 s	all-wheel drive	280 kW (381 hp)	

bn



Knowledge graph verbalization

How can we make a KG amenable for NL retrieval/reasoning?

- Makes KG suitable for satisfying abstract intents
- Text search runs over
 - Passage verbalizations generated from KG (Oguz et al. 2022)
 - Uses KG in RDF Turtle format
- Each RDF Turtle "shell" converted into an NL passage
- Simple and generalizable hand-crafted patterns
- **Reversed facts** also included to increase scope of answerable guestions
 - Helps simpler LLMs

<bmw-x7-xdrive40i,</pre> type, car; engine, bmw-x7-xdrive40i-excellence; height, 1835 mm; length, 5181 mm; price, 88890 Euros; wheelbase, 3105 mm; width, 2000 mm>

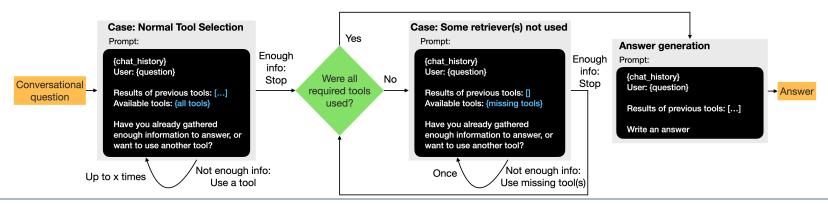
BMW X7 xDrive 40i is car. BMW X7 xDrive 40i has engine bmw-x7-xdrive40i-excellence. bmw-x7-xdrive40iexcellence is engine of BMW X7 xDrive 40i. BMW X7 xDrive 40i has height 1835 mm. 1835 mm is height of BMW X7 xDrive 40i. BMW X7 xDrive 40i has length 5181 mm. 5181 mm is length of BMW X7 xDrive 40i. BMW X7 xDrive 40i has price 88890 Euros. 88890 Euros is price of BMW X7 xDrive 40i BMW X7 xDrive 40i has wheelbase 3105 mm, 3105 mm is wheelbase of BMW X7 xDrive 40i. BMW X7 xDrive 40i has width 2000 mm, 2000 mm is width of BMW X7 xDrive 40i.



Iterative retrieval with tools

Why is RAGONITE a tool-based pipeline?

- RAGONITE has multiple tools or functions at its disposal
 - **SQL** query executor
 - **Text** retriever (dense and lexical retrievers)
- Iterative retrieval strategy
 - Each tool can be called multiple times until satisfactory results are retrieved
 - Each tool must be used at least once
- Iterative retrieval benefits
 - Satisfies **multi-hop intents** (Average price gap of Touring models from an X5?)
 - Increases robustness to "failed" retrievals: previous results/errors included in rephraser LLM's prompt for next iteration





Branch integration

How do we fuse results from the branches?

- **Merging** results from structured and unstructured retrieval necessary
- Precludes need for
 - Deciding based on question which branch(es) to prefer
 - Deciding based on retrieval results which branch(es) to prefer
- No hard-coded rules in system
- Fully automated via LLM based on input question and conversation so far



Open LLM integration

What LLMs do we support?

- Uses GPT-40 via API as default
- Seamless support for **Llama** and other local models



Heterogeneous QA

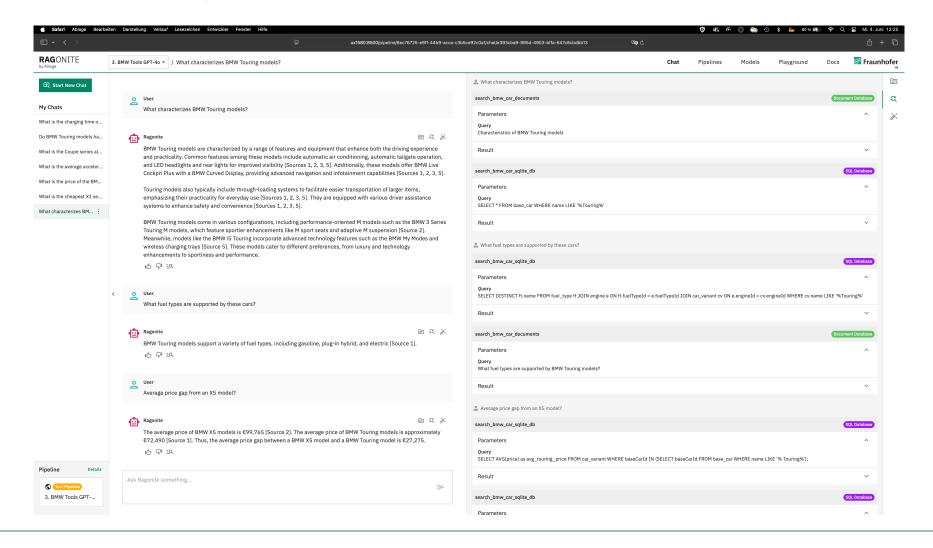
How can we use RAGONITE for ConvQA over KG and text combinations?

- Having RDF verbalizations in pipeline facilitates incorporation of additional text
- No special support required
- Additional text snippets, for example, from the Web, can be simply added to our corpus
- Integration works well with about 400 passages from bmw.co.uk



Time for the demo!

How does our RAGONITE implementation look like?



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Evaluation

How do we measure RAGONITE performance?

BMW KG

- 3442 facts: 466 entities, 27 predicates, 7 types, 1295 literals
- 7 tables via DB induction, 466 passages via RDF verbalization

QA pairs

- 30 diverse questions wrt entities, predicates, types
- Conducted as six conversations with five turns each
- Equal distribution of all three intent classes: lookup, complex, abstract
- Four variants compared
 - SPARQL-only: 4/30 🗹 (fails in most cases due to LLM's inability at good query generation, NERD failures)
 - SQL-only: 18/30 🗹 (fails when question has ad hoc entity mentions like *gran coupe sport 220 i m* and not bmw-220i-m-sport-gran-coupé)
 - Verbalization-only: 24/30 (fails with complex math, like minimum over averages of grouped car prices)
 - SQL+Verbalization: 28/30
- Average runtime is 6 seconds per question, end-to-end
- Detailed runtimes and accuracies available at https://github.com/Fraunhofer-IIS/RAGonite/blob/main/btw25-bmw/data/bmw-eval-results.pdf



Summary and outlook

What can one take away from this presentation?

- Novel two-pronged pipeline for ConvKG-QA with iterative retrieval
- RAGONITE is a transparent RAG pipeline every step is scrutable by end-user
- Focus on automation but judicious amounts of manual effort goes a long way
- Exploits **Text2SQL** for KG-QA
- Information in knowledge graphs is useful for abstract intents
- RAGONITE is an agentic system
 - Reflection mechanisms may add value
 - Without compromising efficiency

R.S. Roy, C. Hinze, J. Schlotthauer, F. Naderi, V. Hangya, A. Foltyn, L. Hahn, and F. Küch. **RAGONITE: Iterative Retrieval on Induced Databases** and **Verbalized RDF for Conversational QA over KGs with RAG**, *in Proceedings of the 21st Conference on Database Systems for Business, Technology and Web (BTW '25)*, pages 787 – 794, Bamberg, Germany, 3 – 7 March 2025.

R.S. Roy, C. Hinze, J. Schlotthauer, A. Foltyn, L. Hahn, and F. Küch. **Evidence contextualization and counterfactual attribution for conversational QA over heterogeneous data with RAG systems,** *in Proceedings of the 18th ACM International Conference on Web Search and Data Mining (WSDM '25),* pages 1040 – 1043, Hannover, Germany, 10 – 14 March 2025.

Thank you! Check out our repo at https://github.com/Fraunhofer-IIS/RAGonite

