Reasoning with heuristic ontologies generated from Large Language Models

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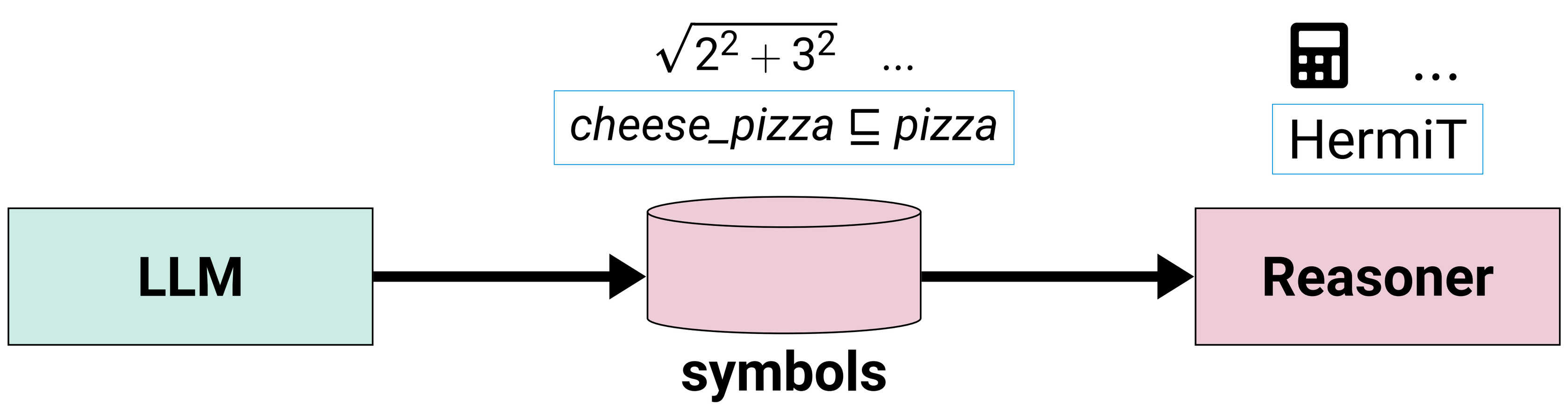
Poster

- Deriving a conclusion based on a rigorous process using arguments, evidence and logic is a key aspect of intelligent systems. This rigorous process **applies well-defined inference rules** – a task that can be automated by reasoning engines. However, defining these rules and formalizing arguments and evidence is the typical bottleneck of intelligent systems, because **it requires (informal) prior knowledge** as world model.
- Recently, Large Language Models (LLMs) showcased an **increased proficiency on benchmark tasks requiring reasoning capabilities**. However, due to the probabilistic, black box nature of these model, they do not perform sound reasoning. A neuro-symbolic model as a **combination between an LLM and a symbolic reasoning engine** can address this drawback.

→ This doctoral research investigates how both systems can be combined.



Related Work

LLMs and reasoning

- Chain-of-thought prompting emulates human reasoning [4]
- Limited to less complex reasoning (shallow reasoning depth)
- Neuro-symbolic approaches provide sound reasoning [1]

Tool-augmented LLMs

LLMs generate input for specialized tools (e.g. calculator, information retriever) and add the tool response to the context.

Benchmarks

- ProntoQA[3]: Deductive, multi-hop, logical reasoning; synthetic data; simple subsumptions.
- ProofWriter[5]: Deductive, multi-hop, logical reasoning; synthetic data; subsumptions.
- FOLIO[2]: complex first-order logic reasoning; manually created.

Research Question

RQ

How can LLMs and formal reasoners be combined to solve logical reasoning tasks?

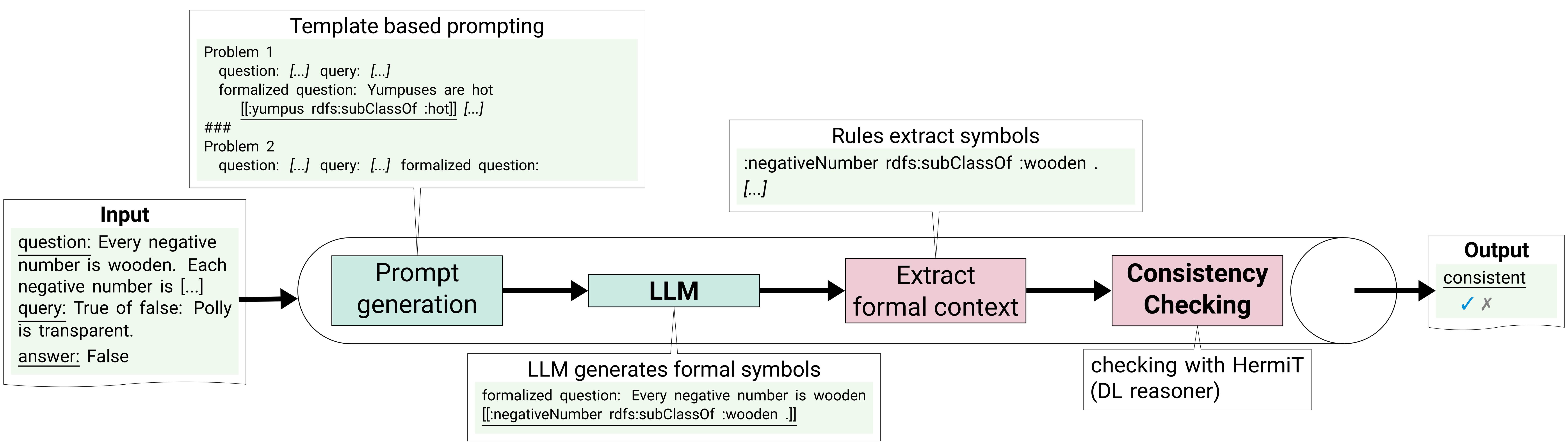
Reusing symbols
Generating symbols
Mapping symbols

RQ 1.1
How can LLMs be used to translate natural language reasoning tasks to a formal representation?

RQ 1.2
How can LLMs be used to generate needed, implicit knowledge for a reasoning task?

RQ 1.3
How can LLMs be used to consider existing explicit knowledge?

Methodology



Summary

- Combination of LLMs and formal reasoning improves reliability, explainability and can use prior knowledge
- Symbols generated by LLMs follow the formal syntax based on 1-shot example
- Symbols keep general context of a task, but face issues representing concrete semantics
- Prompt engineering and feedback loop are required to improve performance

References

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