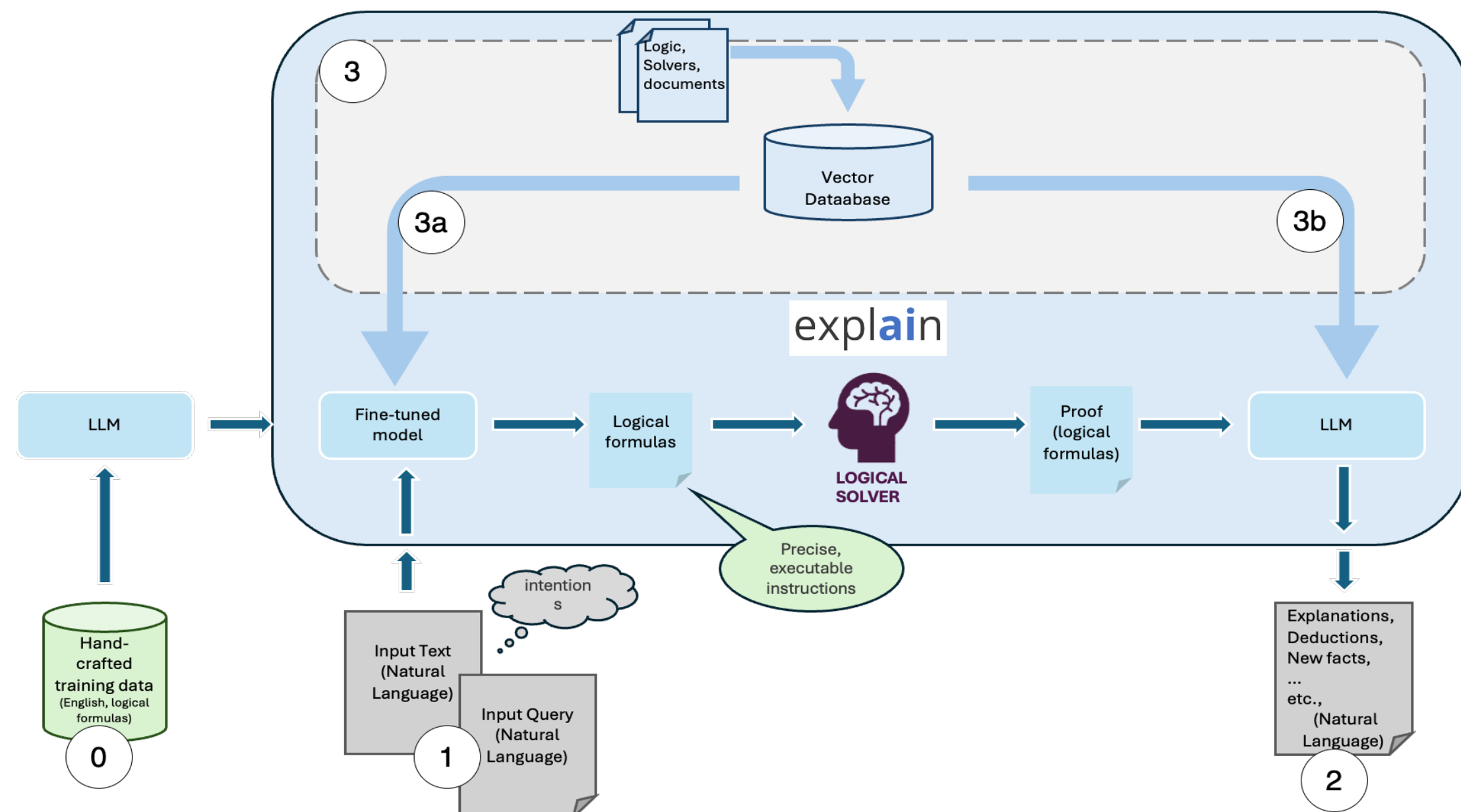




Generative AI with Logical Reasoning

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Introduction

Today's Generative AI systems are limited in their reasoning capabilities. Even when they reason, it is achieved by training the LLM on a large reasoning dataset (*pattern matching based reasoning*). They hence appear to reason logically while their reasoning stems from the pattern trained on, or reward optimized for during their training. With Generative AI permeating more and more applications, *logical reasoning* is becoming imperative, especially in certain critical domains like finance, autonomous systems, healthcare, software engineering, etc. This work attempts to infuse logical reasoning into Generative AI.

Natural Language to Logical Language

An accessible LLM is fine-tuned using a dataset of natural language statements and logical formula pairs (0). This fine-tuned LLM is used to generate axioms, hypotheses and conjectures (logical formulas) from user provided natural language text - context text and an optional user query (1). The logical formulas generated by the fine-tuned LLM would be:

- A set of axioms
- A set of hypotheses
- A conjecture (user provided query)

Hypotheses (assumptions) are generated for aspects that are not explicitly stated but if true could affect the result of the system. An example encoding of an axiom and a conjecture is provided below (in TPTP syntax):

```
fof(killer_hates_victim, axiom,  
    ![X, Y] : (killed(X, Y) => hates(X, Y)).
```

```
fof(alice_kills_alice, conjecture,  
    killed(alice, alice)).
```

Challenges

- Frame problem in Logic^[1]:
If $\neg \text{DoorOpen}(0) \wedge \neg \text{LightOn}(0) \wedge \text{DoorOpen}(1)$,
Does $\neg \text{LightOn}(1)$ hold?
- Encoding implicit semantic information:
Kal lives in NYC vs. *Kal spends time in Big Apple*

Note: The goal of this work is *not* to develop an LLM that can reason, but to *infuse logical reasoning into pattern-matching based reasoning* (present day Generative AI). The explain system will improve and scale as the underlying LLM improves and scales.

The explain system

1. Transform the input natural language (context and queries) text into logical formulas.
2. Solve the logical formulas using a solver based on mathematical logic (e.g., a theorem prover).
3. Transform the proof results from the solver back into natural language for the user.

Steps 1. and 3. are achieved using an LLM. Step 2. is achieved using a logical solver, in this case a theorem prover. Optionally, the system also has a RAG component (3) that can help with steps 1. and/or 3.

Logical Reasoning

The logical solver:

- Checks consistency of axioms.
- Tries to prove the conjecture from the axioms and hypotheses
- Identifies hypotheses that prove/disprove the conjecture.

The logical formulas themselves can involve several theories (integers, reals, etc.) and quantifiers catering to different application domains (e.g., software engineering). The logical solver output is the form of deductions, resolution rules, etc. An LLM is used to extract the main aspects of the proof, with respect to the user query, and present it in natural language (2). This includes deduction of new information that is not explicitly stated, logical derivation of the conjecture or its negation, etc.

Advantages

- Logical reasoning
- Deriving new facts (logically)
- Provable correctness

Future Work

- Identifying and generating frame axioms and relevant hypotheses.
- Employing knowledge graphs^[2] and/or Ontology matching to augment the formula generation.

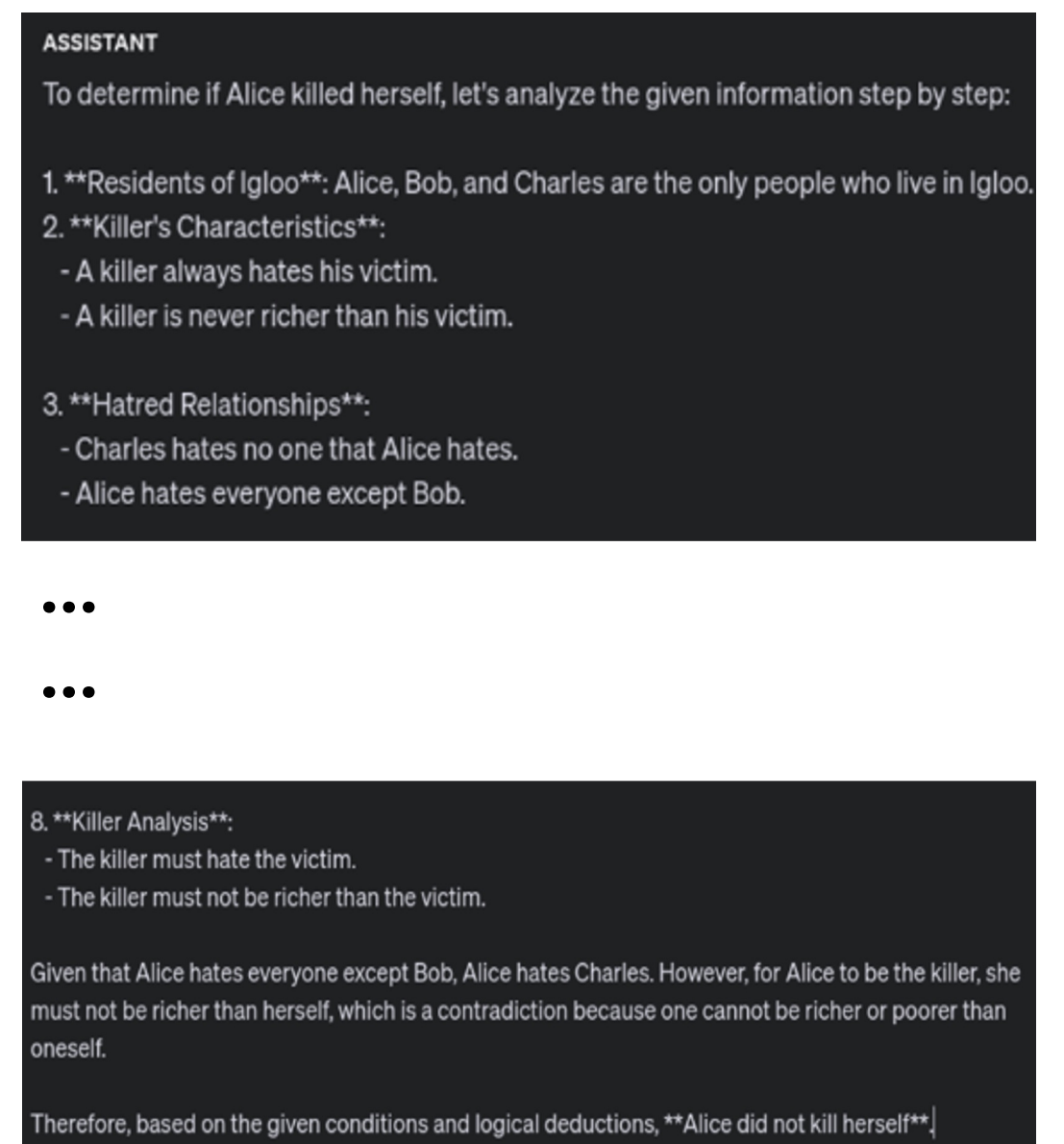
Who killed Alice?

"Someone who lives in Igloo killed Alice. Alice, Bob, and Charles live in Igloo, and are the only people who live therein. A killer always hates his victim and is never richer than his victim. Charles hates no one that Alice hates. Alice hates everyone except Bob. Bob hates everyone not richer than Alice. Bob hates everyone Alice hates. No one hates everyone. Alice is not Bob."

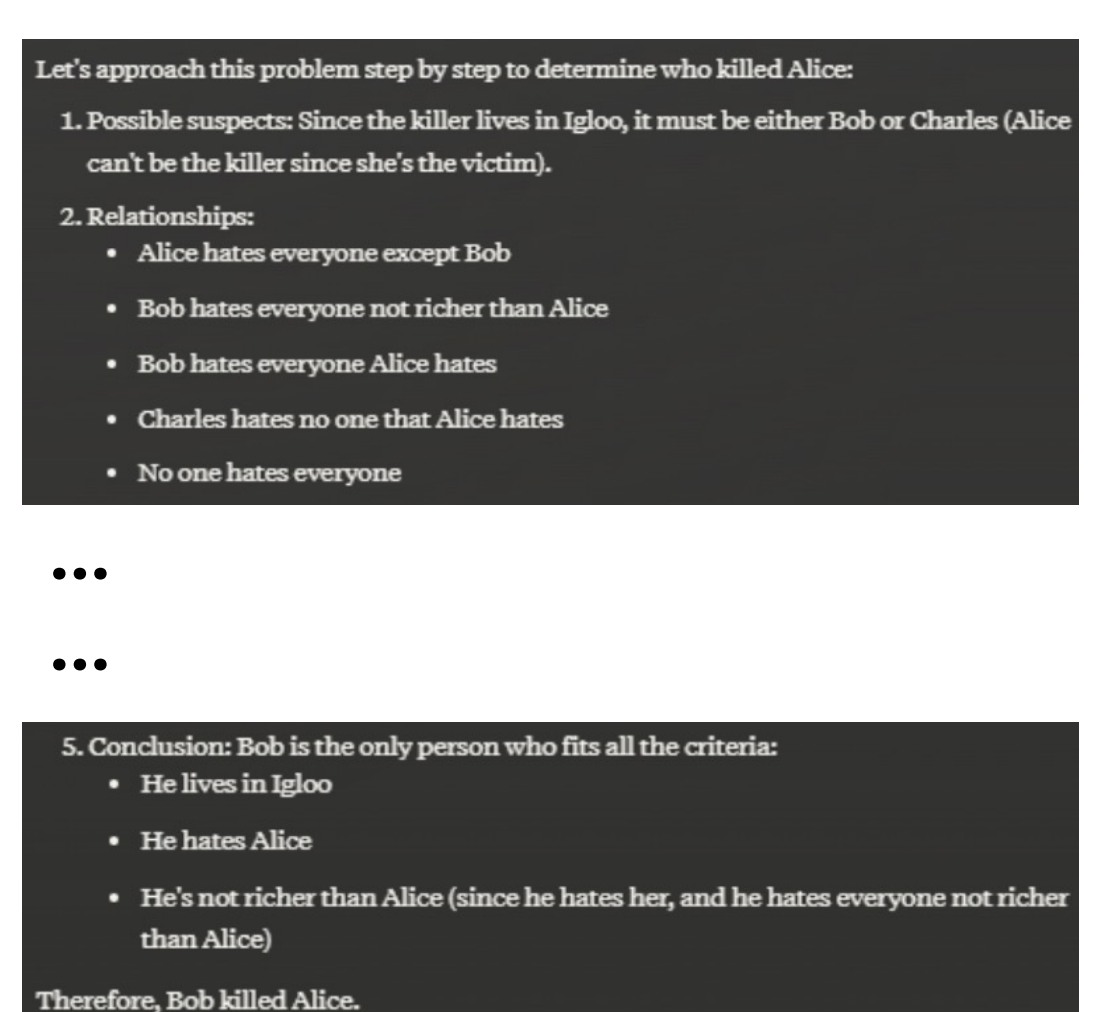
Did Alice kill herself?



GPT-4o



Claude-3.5-Sonnet



References

1. The Frame Problem <https://plato.stanford.edu/entries/frame-problem/>
2. Yasunaga, M., Bosselut, A., Ren, H., Zhang, X. Manning, C.D., Liang, P. & Leskovec, J. *Deep Bidirectional Language-Knowledge Graph Pretraining.*, NeurIPS 2022.