
tnreason FOR LLM REASONING

RESEARCH NOTES IN THE ENEXA PROJECT

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We here sketch, how the usage of tnreason can be enhanced based on LLMs, and how tnreason could be exploited in the retraining of LLMs.

1 Copilots for the usage of tnreason

We envision users to provide prompts describing their reasoning objectives, which the LLM interprets to generate precise tnreason function calls, ensuring a natural and efficient workflow. By leveraging LLMs' natural language understanding, users can describe complex reasoning tasks intuitively, allowing the copilot to translate them into structured calls to tnreason .

1.1 Model explainability

Having a tnreason model described in the formal script language, a LLM can be prompted to explain that model to an user. Besides datapoint specific inquiries, such a copilot can be used to explain entire parts of the model, for example based on a collection of rules triggered when having a specific input feature. The envisioned explainability therefore goes beyond the typical "post-hoc" explainability towards an intrinsic "ante-hoc" explainability bringing guarantees for a models behavior.

1.2 Prompt structure

The systems prompt will describe the basic functionality of tnreason and the users prompt consists in the requirements of the use case, formulated in natural language. Here the user does not have to be informed about the formal grammar of the tnreason script language, nor the structure and expressivity of propositional logics. This approach enhances accessibility of tnreason , enabling seamless interaction between human intuition and formal logical computation.

Preliminary experiments with the Gemini model on Colab can be found here: <https://colab.research.google.com/drive/1ESzJeZp70022I1z31NeA8VExALUVfUf7?usp=sharing>

1.3 Multi-agent Orchestration

Another interesting idea is a multi-agent orchestration, where the ability of LLMs and formal proof languages are balanced with respect to each other. Here one might exploit the LLMs as a translator between human understandable text and formal statements such as in the tnreason script language.

- **Communication agent (LLM):** Interacts with the user, to create and maintain a tnreason model. Further, when asked about the models behavior at a specific data instance or in a more generic situation, it interprets the model in human understandable language. At best realized by a LLM to handle the flexible user-specific prompts.
- **Execution agent (tnreason):** Maintains a model about a use case in cooperation with the communication agent, and executes the inference calls from the data agent. At best realized in an efficient and explainable manner and therefore in a formal, declarative language such as the tnreason script language.
- **Data agent (Classical Software):** Handles the runtime of a productive model, by transforming the input data into an inference instance, passing it to the execution agent, and preparing the output in a specific format.

2 Retraining LLMs based on a reinforcement environment created by `tnreason`

Retraining LLMs in a reinforcement learning environment incorporating `tnreason` workloads enables adaptive improvement in logical reasoning and decision-making. The model receives feedback based on the correctness and efficiency of its generated `tnreason` calls, refining its ability to solve complex reasoning tasks over time. This iterative training approach enhances the LLM’s alignment with formal reasoning principles, leading to more reliable and interpretable outputs.

One can pose `tnreason` inference models, such as probabilistic queries of formulas in a hybrid knowledge base generated from random, as a prompt and calculate the reward as the absolute difference of the exact calculation by `tnreason` and the response from the LLM.

3 Parametrizing a Search Tree by a Formula Selecting Network

Search Trees in combination with Monte Carlo tree searches MCTS received recent popularity as a mechanism to advanced reasoning functionalities of LLMs.

In the `tnreason` framework, several formula selecting networks (and other selection architectures such as slice selection) follow a similar idea. Instead of branches, we typically depict choices by assignments to selection variables. Thus, a formula selecting network parametrizes formulas, which are in the expressivity of formula search trees, where the branches along each layer of the tree have a common structure (such as selection of a logical connective or selection of a categorical variable).

When having a search problem parameterized as a maximal coordinate search of the energy tensor (such as in the grafting heuristic of inductive learning), MCTS compares with a simple forward sampling approach. Alternatives here are further sampling approaches considered in `tnreason`, such as Gibbs sampling strategies resampling previous parameters in combination with simulated annealing.

4 Literature

Small LLMs suffice to develop reasoning capability:

- Guan et al. (2025)

Reinforcement learning to enhance the reasoning capability of LLMs:

- DeepSeek-AI et al. (2025)

Combination with the LEAN language:

- Xin et al. (2024)

Monte Carlo Tree Search:

- Besta et al. (2025): Integration of MCTS into Reasoning Language Models (RLM)
- Xin et al. (2024): RMaxTS algorithm

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