Lateral Tree-of-Thoughts (LToT): An Introductory Overview

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Abstract

We introduce **Lateral Tree-of-Thoughts (LToT)**, a reasoning architecture that augments the vanilla Tree-of-Thoughts (ToT) paradigm by explicitly modelling *lateral* thinking—retaining low-utility yet logically consistent child thoughts. In frontier-scale settings, vanilla ToT saturates quickly: after a few genuinely distinct high-utility continuations, additional sampling yields near-duplicates, leaving modern compute budgets under-utilised. LToT fills this gap.

LToT generates a dual score $\langle v, c \rangle$ for every candidate in the frontier where v is the utility as in vanilla ToT and $c \in [0, 1]$ is the logical consistency the candidate has with its ancestral trace. We then preserve **mainline** branches (high-v) and **lateral** branches (low-v, high-c), laying the groundwork for an adaptive policy that decides when to explore laterals versus exploit mainlines. By converting surplus compute into principled diversity, LToT mitigates premature pruning, supports error correction, and moves reasoning architectures closer to human-level versatility in logical inference and creative problem-solving.

We summarise the architecture and the two subproblems we are currently addressing: (1) reliably identifying logically consistent low-utility branches and (2) deciding when to explore vs exploit.

I. Introduction

Large language models (LLMs) can generate locally coherent text with impressive fluency, but they often falter solving multi-step problems. The current dominant remedy is to structure reasoning. *Chain-of-thought* (CoT) prompting elicits explicit intermediate reasoning steps in a linear progression [1], an idea on which **Tree-of-Thoughts** (ToT) builds, framing reasoning as a tree rather than as a line, facilitating more robust exploration of the thought space [2]. While ToT improves robustness, two limitations emerge in practice. **First, utility saturation:** even with a large sampling budget, ToT produces only a handful of genuinely distinct high-utility continuations, leaving current frontier-scale compute under-utilised. **Second, myopic pruning:** branches deemed low-utility early in the search are discarded even when they remain logically sound and could mature into correct solutions.

We propose **Lateral Tree-of-Thoughts (LToT)** to overcome this limitation. Drawing on de Bono's concept of *lateral thinking* [3], LToT attaches two scores to every partial trace: a utility score v in vanilla ToT and a *logical-consistency* score $c \in [0, 1]$. A branch is retained if it ranks highly on v (mainline) **or** exceeds a minimum threshold on c (lateral), and we record whether a branch was added as a mainline or lateral branch. By preserving such diversity, LToT mitigates premature pruning, supports systematic error correction, and lays the groundwork for an explicit exploration-exploitation policy that adaptively decides when to deepen or diversify the search. The sections that follow motivate the need for lateral branches (II), survey prior work (III), define current challenges (IV), detail the algorithmic framework (V), and outline our immediate research agenda (VI).

II. Motivation

In practice for frontier reasoning models, vanilla ToT can generate only a handful of genuinely distinct, high-utility continuations before utility mass saturates. Sampling more aggressively (larger k, higher temperature) mostly yields near-duplicates whose scores fall just below the pruning threshold, so the search frontier stays narrow even when ample compute is available. The result is an **expansion-budget surplus**: we have resources to deepen the tree but too few promising nodes to extend.

LToT converts this spare capacity into productive search by admitting **lateral branches**—paths with low utility v yet high logical consistency c. Our central hypothesis is that, once the mainline space is saturated, allocating extra compute to lateral children yields a higher marginal gain in efficacy than adding further mainline variants.

III. Prior Work

Early progress in multi-step reasoning stemmed from *chain-of-thought* (CoT) prompting, which coaxes language models to spell out a single, linear sequence of intermediate steps—transparent, yet brittle once an early link is flawed [1]. *Tree-of-Thoughts* (ToT) countered this fragility by allowing the model to generate a branching tree of continuations and then prune them using a utility score v, thus replacing a one-dimensional path with a structured search space [2].

Later variants add program supervision [4] or self-reflection [5], but because they still rely on the same utility heuristic they continue to discard logically sound branches that begin with low v.

LToT synthesises these lines by attaching to each partial trace a utility score v **and** a logical-consistency score c. Branches scoring high on v are retained as **mainline branches**, while low-v but high-c branches are preserved as **lateral branches**. This dual-score criterion injects principled diversity, addressing the premature-pruning limitation of vanilla ToT.

IV. CURRENT CHALLENGES

We presently face two principal algorithmic challenges:

1) **Reliable identification of low-utility yet logically consistent children.** Our provisional approach is *self-evaluation*: we ask a language model—either the generator, the utility critic, or a separate model—to score each candidate's coherence with its ancestor trace via an entailment-style probe. Because current LLMs still struggle to judge multi-step consistency, this method may prove insufficient, making the problem the first major focus of our research.

2) **Dynamic balance between exploration and exploitation.** At each search step, the key question is whether to **explore**—extending children from lateral branches—or **exploit** by extending children from mainline branches. Deciding when to pivot between exploration and exploitation remains unresolved and constitutes the second major focus of our research.

V. ALGORITHMIC FRAMEWORK

1) **Thought Generation.** As in vanilla ToT, the language model proposes k candidate continuations for the current trace.

2) **State Evaluation.** Each candidate receives (i) a heuristic utility score v and (ii) a *consistency score $c \in [0, 1]$* estimating how well it coheres with its ancestor trace. A continuous c captures the evaluator's uncertainty more reliably than a simple binary boolean.

3) **Branch Retention.** We keep a frontier comprising candidates that are either in the top-p quantile of v **or** exceed a threshold $c_{\min}$. Children admitted by high v form **mainline branches**; those admitted by high c but low v form **lateral branches**.

4) **Search Control.** How best to alternate exploration of lateral branches with exploitation of mainline branches remains an open research question. We explain our current work in addressing this in VI.

5) **Solution Extraction.** Following vanilla ToT, we return the highest-utility complete trace encountered—or an ensemble vote if multiple high-quality solutions emerge.

VI. NEXT STEPS

The two main subproblems on which we are focusing are detailed below.

1) **Reliably evaluating the logical consistency of a candidate for a trace.** Language models still struggle to evaluate whether a statement is logically consistent with a set of previous statements [6], [7], [8], [9]. This complicates our current approach, where we use a language model to evaluate whether a candidate from the frontier, though low-utility, is logically consistent and as such heads a viable lateral branch. At present, we already accommodate language models' imperfect ability to verify logical consistency by asking the language model to provide its confidence from zero to one, inclusive, of the logical consistency a candidate from the frontier has with an ancestral trace, akin to the continuous output of an MLP rather than to the step function of a biological neuron's activation. We plan to initially continue with this approach and empirically evaluate its viability. If it proves untenable, then we will explore alternative techniques for verifying logical consistency.

2) **Balancing between exploration and exploitation.** We have not settled on an approach for balancing between exploration—expanding on lateral branches—and exploitation—expanding on mainline branches. Intuitively, it seems promising to mimic the human approach, relying on exploitation and only turning to exploration after all mainline branches have been exhausted without a solution having formed. The classic example of this is an exasperated undergraduate studying integral calculus, who, having applied all reasonable integration techniques to a given integral to no avail, begins applying any integration technique which they can remember, however absurd to apply to the problem at hand. Based on this intuition from human intelligence, we intend to proceed as vanilla ToT does, expanding mainline branches, until we have reasonably exhausted the mainline thought search space. Our working definition for exhaustion is the expansion of mainline branches to a substantial depth without finding a solution. If we have exhausted the mainline search space, then we begin expanding lateral branches. Recall that children of lateral branches need not themselves be lateral—a lateral branch can have mainline children, the equivalent of the undergraduate who, upon applying u-substitution in an unusual context for it, proceeds as normative for u-substitution. Importantly, this addresses a major weakness of vanilla ToT: frontier

compute environments can expand on more branches than what vanilla ToT is able to provide. We will spend the coming weeks distilling this human-inspired intuition for balancing between exploration and exploitation into a finalized technique.

VII. Conclusion

Vanilla ToT typically offers only a handful of genuinely new high-utility continuations—far fewer than modern, frontier-scale compute budgets could afford to expand—so once those mainline options are exhausted, extra compute yields rapidly diminishing returns. **Lateral Tree-of-Thoughts (LToT)** redirects that surplus capacity toward *lateral branches*—paths that score poorly on the utility heuristic yet remain logically coherent. By attaching a dual score $\langle v, c \rangle$ to every partial trace and admitting both **mainline** (high-v) and **lateral** (low-v, high-c) continuations, LToT enlarges the frontier of exploration without abandoning ToT's disciplined pruning.

The immediate milestones are clear: (i) a reliable detector for logically consistent low-utility children and (ii) an adaptive policy that decides when to explore laterals versus exploit mainlines. Our upcoming experiments will test whether, under production-scale compute, investing in lateral expansion yields higher marginal accuracy than sampling ever-more mainline variants.

If these hypotheses bear out, LToT will transform the expansion-budget surplus of modern LLMs into tangible reasoning gains, bringing us a step closer to human-level versatility in structured problem solving.

References

[1] J. Wei et al., "Chain of thought prompting elicits reasoning in large language models," *arXiv preprint arXiv:2201.11903*, Jan. 28, 2022. [Online]. Available: https://arxiv.org/abs/2201.11903.

[2] S. Yao et al., "Tree of thoughts: Deliberate reasoning via large language models," *arXiv preprint arXiv:2305.10601*, May 17, 2023. [Online]. Available: https://arxiv.org/abs/2305.10601.

[3] E. de Bono, *The Use of Lateral Thinking.* London, U.K.: Jonathan Cape, 1967, ISBN: 978-0-224-61931-2.

[4] L. Gao et al., "Program-aided language models," *arXiv preprint arXiv:2211.10435*, Nov. 18, 2022. [Online]. Available: https://arxiv.org/abs/2211.10435.

[5] A. Madaan et al., "Self-refine: Iterative refinement with self-feedback," *arXiv preprint arXiv:2303.17651*, Mar. 30, 2023. [Online]. Available: https://arxiv.org/abs/2303.17651.

[6] B. Ghosh, S. Hasan, N. A. Arafat, and A. Khan, "Logical consistency of large language models in fact-checking," in *Proceedings of the International Conference on Learning Representations (ICLR)*, arXiv:2412.16100 − v2, last revised 28 Feb 2025, Feb. 2025. [Online]. Available: https://arxiv.org/abs/2412.16100.

[7] Y. Liu, Z. Guo, T. Liang, E. Shareghi, I. Vulić, and N. Collier, "Measuring, evaluating and improving logical consistency in large language models," in *Proceedings of the International Conference on Learning Representations (ICLR)*, arXiv:2410.02205 − v4, last revised 5 Feb 2025, 2025. [Online]. Available: https://arxiv.org/abs/2410.02205.

[8] M. K. Chen, X. Zhang, and D. Tao, "Justlogic: A benchmark for natural language deductive reasoning," in *Proceedings of the International Conference on Learning Representations (ICLR)*, OpenReview ID THSm9HyCKo, first posted 26 Sep 2024, 2025. [Online]. Available: https://openreview.net/forum?id=THSm9HyCKo.

[9] Y. Wan et al., "Logicasker: Evaluating and improving the logical reasoning ability of large language models," in *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, arXiv:2401.00757 − v3, accepted EMNLP 2024, 2024. [Online]. Available: https://arxiv.org/abs/2401.00757.