Why Limit the Residual Stream to Layers and Not Tokens? Persistent Memory for Continuous Latent Reasoning

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Abstract

Large language models (LLMs) have demonstrated remarkable reasoning abilities on mathematical and multi-hop planning tasks. The CoCoNuT (Chain of Continuous Thought) paradigm (Hao et al., 2024) extends this by enabling models to reason in latent space, exploring multiple reasoning paths simultaneously rather than committing to a single chain early on. However, we identify a limitation we term the **concept bottleneck**. At each reasoning pass, intermediate hidden states are overwritten, causing the model to lose critical facts computed in earlier steps as reasoning depth increases. We observe this empirically. On HotpotQA, vanilla CoCoNuT (10.4% EM) fails to improve over the CoT baseline (11.0% EM), and performance degrades with curriculum depth on GSM8K. To address this, we propose **AGCLR** (Adaptive Gated Continuous Latent Reasoning), which augments CoCoNuT with a *Gated Concept Stream*. A persistent residual memory maintained across all reasoning passes, controlled by three learned gates: a *write* gate that commits intermediate facts to memory, a *read* gate that retrieves relevant prior states, and a *forget* gate that prunes irrelevant context. Evaluated on GSM8K, HotpotQA, and ProsQA using GPT-2 as our base model, AGCLR achieves consistent improvements across all types of datasets. With the performance gap compounding as curriculum depth increases, directly resolving the concept bottleneck. Code available at https://anonymous.4open.science/r/JJJJ/README.md

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1. Introduction

Multi-step reasoning remains one of the most challenging aspects of large language model capabilities. Wei et al. (2022) showed that prompting LLMs with intermediate reasoning steps significantly improves performance on mathematical and logical benchmarks. However, Chain-of-Thought (CoT) reasoning is constrained to a single forward pass. Each token generated becomes the input for the next, forcing the model to commit to a reasoning path early and preventing the exploration of alternative paths. Moreover, explicit reasoning traces are often incomplete or unfaithful to the underlying computation (Su et al., 2026; Swaroop et al., 2025), motivating reasoning that operates directly in latent space. More recent work has explored internalizing these reasoning chains. Deng et al. (2024) proposed iCoT, which progressively removes the prefix of reasoning chains during training until the model predicts answers without any explicit chain. Goyal et al. (2023) introduced pause tokens, fixed-embedding special tokens inserted between question and answer to provide extra compute time. Both approaches operate in language space and cannot maintain persistent state

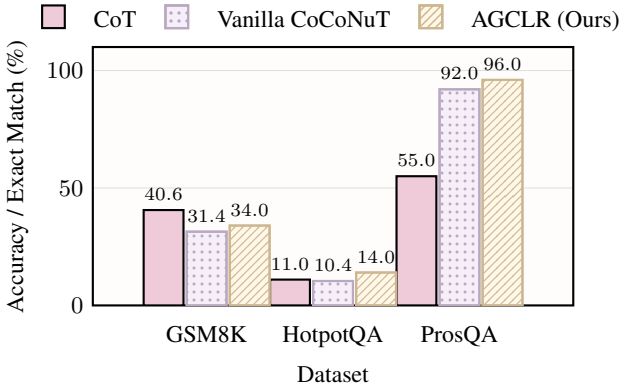


Figure 1. **AGCLR excels at multi-hop reasoning.** Performance across GSM8K (math), HotpotQA (multi-hop QA), and ProsQA (planning). AGCLR's persistent memory enables strong gains on multi-hop tasks (HotpotQA: +3.6%, ProsQA: +4.0%), while CoT remains superior for single-step mathematical reasoning.

across reasoning steps.

The most ambitious extension is CoCoNuT (Hao et al., 2024), which replaces discrete reasoning tokens with continuous latent thoughts. The model's last hidden state is fed back directly as the next input embedding, enabling reasoning in an unconstrained latent space and supporting implicit breadth-first search over reasoning paths. CoCoNuT is trained via a multi-stage curriculum that progressively replaces explicit reasoning steps with latent tokens, one step per stage. Despite its promise, vanilla CoCoNuT suffers from a **concept bottleneck**: intermediate reasoning states are progressively lost across multi-pass inference, as each new latent token overwrites information from earlier passes with no persistent memory. This becomes severe in multi-hop reasoning requiring longer chains. We demonstrate this empirically across GSM8K (arithmetic), HotpotQA (multi-hop QA), and ProsQA (planning) in Figure 1.

To address this, we propose **AGCLR** (Adaptive Gated Continuous Latent Reasoning), which augments CoCoNuT with a gated concept stream that preserves intermediate reasoning states across passes. While gating mechanisms trace back to LSTMs (Hochreiter & Schmidhuber, 1997) for sequential state updates, our gates operate on *persistent cross-pass memory* in continuous latent reasoning: each pass refines the same representation rather than processing new sequential inputs, and memory accumulates facts across iterative reasoning cycles rather than discarding them at each timestep.

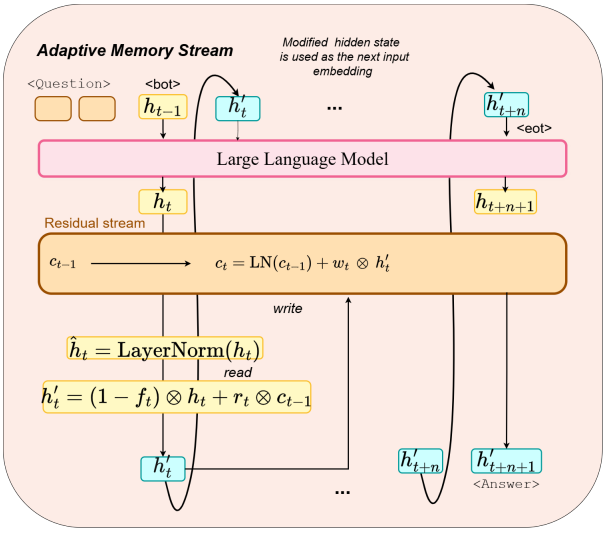


Figure 2. **AGCLR architecture.** At each latent token position, three learned gates (read, forget, write) control information flow between the current hidden state h_t and the persistent concept stream c_t. The read gate retrieves relevant prior facts from c_{t-1}, the forget gate prunes irrelevant context from h_t, and the write gate commits the gated hidden state h'_t to the residual stream, directly addressing the concept bottleneck in vanilla CoCoNuT.

AGCLR augments CoCoNuT with a *Gated Concept Stream*: a persistent residual memory vector $c_t \in \mathbb{R}^d$ maintained across all reasoning passes. At each latent token position, three learned sigmoid gates control information flow: a *write* gate commits relevant intermediate facts from the current hidden state to memory; a *read* gate retrieves prior memory into the current reasoning state; and a *forget* gate prunes irrelevant context from the hidden state. Figure 2 illustrates the architecture.

We make the following contributions:

- We identify and empirically demonstrate the **concept bottleneck** in vanilla CoCoNuT across three reasoning datasets of different types.
- We propose **AGCLR**, a gated residual memory mechanism that resolves the concept bottleneck with only 1.41% additional parameters over GPT-2.
- AGCLR consistently outperforms vanilla CoCoNuT on GSM8K (arithmetic), HotpotQA (multi-hop QA), and ProsQA (graph planning), with the advantage compounding as curriculum depth increases.

2. Related Work

Gating mechanisms for controlling information flow trace back to Long Short-Term Memory networks (Hochreiter & Schmidhuber, 1997), which introduced forget gates to selectively retain or discard information in recurrent hidden states. However, LSTMs gate sequential inputs across timesteps, whereas our gates operate on persistent memory across iterative reasoning passes over the same latent representation. (Deng et al., 2024) proposed iCoT, which progressively removes explicit reasoning prefix tokens during training; while iCoT compresses reasoning into the forward pass, it lacks any mechanism to preserve information across reasoning steps and does not operate in a multi-pass latent reasoning setting. (Hao et al., 2024) introduced CoCoNuT, which enables continuous latent reasoning by recursively feeding the model's hidden state back as the next input embedding, allowing implicit breadth-first search over reasoning paths. CoCoNuT serves as our direct baseline across all three datasets, but discards all prior hidden states at each pass and lacks persistent memory, leading to the concept bottleneck we identify and address. (Wang et al., 2024) proposed a concurrent post-training approach using a fixed scalar α to blend consecutive hidden states at inference time; unlike our method, their gates are not learned end-to-end, operate only on consecutive states rather than a persistent residual stream, and are applied training-free as post-processing. Relatedly, amortized latent steering learns a low-cost intervention that substitutes for test-time latent optimization (Egbuna et al., 2025); like the fixed-α blend, however, it

applies a transient steering signal rather than maintaining a persistent, gated residual stream across passes. Memory-augmented architectures such as Neural Turing Machines (Graves et al., 2014) and Differentiable Neural Computers (Graves et al., 2016) have explored external memory for sequential reasoning, but augment models with external read/write operations across sequence chunks rather than maintaining persistent internal state within multi-pass latent reasoning as we do.

3. Method: AGCLR

3.1. Gated Concept Stream

We augment CoCoNuT with a persistent concept stream $c_t \in \mathbb{R}^d$, initialized to zero at the start of each forward call and updated at every latent token position. At pass t, given hidden state h_t at the latent token position:

$$\hat{h}_t = \text{LayerNorm}(h_t), \tag{1}$$

$$r_t = \sigma(W_r \hat{h}_t), \quad f_t = \sigma(W_f \hat{h}_t), \quad w_t = \sigma(W_w \hat{h}_t), \tag{2}$$

$$h'_t = (1 - f_t) \odot h_t + r_t \odot c_{t-1}, \tag{3}$$

$$c_t = \text{LayerNorm}(c_{t-1} + w_t \odot h'_t), \tag{4}$$

where $r_t, f_t, w_t \in [0, 1]^d$ are the read, forget, and write gates, and $W_r, W_f, W_w \in \mathbb{R}^{d \times d}$ are learned weight matrices. The gated hidden state h'_t replaces h_t as the input embedding for the next latent token position.

Read gate r_t controls how much of the concept stream c_{t-1} is retrieved into the current hidden state, allowing pass t to access facts from all earlier passes. **Forget gate** f_t controls how much of the current hidden state is preserved versus replaced by retrieved memory, enabling selective pruning of irrelevant context. **Write gate** w_t controls how much of the gated hidden state h'_t is committed to the concept stream, preventing low-confidence states from polluting the residual memory.

4. Training Protocol

4.1. Multi-Stage Curriculum

We leverage language Chain-of-Thought data to supervise continuous latent reasoning by implementing a multi-stage training curriculum inspired by Hao et al. (2024). In the initial stage (Stage 0), the model is trained on regular CoT instances with explicit reasoning steps. In subsequent stages, we progressively replace reasoning steps with continuous latent thoughts. At stage k, the first k reasoning steps in the CoT are replaced with $k \times c$ latent tokens, where c is a hyperparameter controlling the number of latent thoughts replacing a single language reasoning step. We insert `<bot>` (beginning of thought) and `<eot>` (end of thought) tokens to encapsulate the continuous thoughts. Following Hao et al. (2024), we reset the optimizer state when transitioning between training stages.

4.2. Implementation Details

We use a pre-trained GPT-2 base model (117M parameters) with a learning rate of 1×10^{-4} and effective batch size of 128. We train on three multi-hop reasoning benchmarks: GSM8K (Cobbe et al., 2021), HotpotQA (Yang et al., 2018), and ProsQA (Hao et al., 2024). Following the curriculum structure from vanilla CoCoNuT (Hao et al., 2024), we progress through Stages 0–2 (partially latent reasoning) during epochs 1–9, incrementally replacing reasoning steps with latent tokens. From epoch 10 onwards, we remain in Stage 3 where all reasoning is latent, training for 15 total epochs on GSM8K and HotpotQA, and 20 epochs on ProsQA (which contains more complex reasoning chains with up to 6 steps). For HotpotQA, we format instances to include the question, supporting paragraphs, intermediate reasoning steps, and answer span to encourage multi-hop reasoning during CoT stages. The checkpoint with the best validation accuracy in the final stage is used for evaluation.

5. Results

5.1. Main Results

Table 1 shows AGCLR consistently outperforming vanilla CoCoNuT across all three datasets.

5.2. Alleviating the Concept Bottleneck

Vanilla CoCoNuT and AGCLR perform comparably at early curriculum stages, but AGCLR's advantage compounds as reasoning depth increases. On ProsQA, vanilla CoCoNuT peaks at 95% accuracy at stage 5 but **degrades to 92%** at stage 6—the final curriculum stage where all reasoning steps are replaced by latent tokens. AGCLR sustains improvement, achieving 96% at the same checkpoint. This degradation-vs-improvement pattern demonstrates the **concept bottleneck**: as models transition to fully latent reasoning, intermediate computational states are progressively lost without a preservation mechanism.

Memory Retention Across Reasoning Passes. To understand how gating resolves this bottleneck, we analyze hidden state evolution across reasoning passes. Figure 3 shows cosine similarity between pass-1 hidden states and subsequent passes, measured on 100 validation samples at epoch 15. Vanilla CoCoNuT exhibits monotonic memory decay: similarity drops from 1.0 to 0.126 by pass 6, representing 87% information loss as intermediate reasoning

Method	GSM8K	HotpotQA		ProsQA
	Acc. (%)	EM (%)	F1 (%)	Acc. (%)
CoT (Wei et al., 2022)	40.6	11.0	15.5	55.0
No-CoT (Hao et al., 2024)	16.5	4.0	7.6	76.7
iCoT (Deng et al., 2024)†	30.0	6.6	9.4	98.2
Pause Token (Goyal et al., 2023)†	16.4	10.6	14.6	75.9
Vanilla CoCoNuT (Hao et al., 2024)	31.4	10.4	15.2	92.0
AGCLR (Ours)	**34.0**$_{+2.6}$	**14.0**$_{+3.6}$	**19.4**$_{+4.2}$	**96.0**$_{+4.0}$

Table 1. **Results on three datasets: GSM8K, HotpotQA and ProsQA.** Higher accuracy indicates stronger reasoning. †Results from Deng et al. (2024) using identical GPT-2 architecture, as reported in Hao et al. (2024). HotpotQA not evaluated in prior work. ProsQA evaluated at stage 6 (all reasoning steps latent) for fair comparison.

steps are progressively overwritten. **AGCLR mitigates this decay.** While similarity initially drops (pass 1→2), it stabilizes at ∼0.22 for passes 3–6, retaining 71% more information than vanilla CoCoNuT at final generation (0.216 vs 0.126). The gated concept stream acts as a persistent memory buffer, preserving critical reasoning state across passes. This memory preservation directly explains AGCLR's improvement +3.6% EM on HotpotQA.

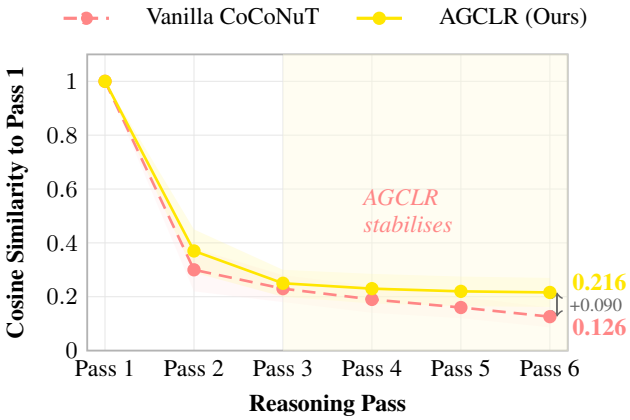


Figure 3. **Hidden State Memory Retention.** Cosine similarity between pass-1 and subsequent passes (100 samples, epoch 15). Vanilla CoCoNuT exhibits monotonic decay (1.0→0.126), while AGCLR stabilizes after pass 3. Shaded regions: ±1 std. AGCLR retains 71% more information (+0.090 gap at pass 6), enabling +4.0% gains on ProsQA.

5.3. What Gets Written to the Concept Stream

To understand the mechanism by which AGCLR preserves task-relevant information across reasoning passes, we analyze the concept stream's content by computing cosine similarities between its embeddings and vocabulary tokens. Table 2 shows three contrastive examples where AGCLR answers correctly but vanilla CoCoNuT fails, along with the maximum similarity scores for answer-relevant entities.

On the **William Penn** example (question: "Who founded Manor Township, Pennsylvania?"), the concept stream exhibits high similarity to answer components: "Penn" (0.806), "William" (0.681), and the contextual entity "Pennsylvania" (0.614). These similarities indicate AGCLR successfully stored the Pennsylvania→William Penn binding needed for correct answer generation. Vanilla CoCoNuT, lacking persistent memory, loses this entity relationship across passes and hallucinates "Henry David Thoreau"—a semantically plausible but contextually incorrect historical figure.

The **World War I** example (question: "When did Oakland Assembly close?") shows similar preservation: "War" (0.760) and "World" (0.684) maintain high similarity throughout reasoning. This prevents the temporal drift observed in vanilla CoCoNuT, which defaults to the statistically more common "World War II" after losing the specific temporal context from earlier passes.

The **United States** example (question: "What country is WCDL radio station in?") demonstrates multi-hop reasoning: the concept stream preserves both the base entity "Pennsylvania" (0.479) and abstraction markers "Federal" (0.507) and "country" (0.495), enabling geographic generalization from state to country. Vanilla CoCoNuT stops at the first hop ("Pennsylvania"), failing to complete the reasoning chain to the country level.

Figure 4 visualizes these preservation patterns across the three examples. Answer components consistently achieve 0.5–0.8 similarity (darker regions), while vanilla CoCoNuT's lack of persistent storage results in progressive information loss. These findings demonstrate that AGCLR's gated concept stream stores distributed representations of entities (0.6–0.8 similarity) and their semantic associations (0.4–0.5 similarity), directly explaining the 71% better information retention measured in Figure 3 and the +3.6% EM improvement over vanilla CoCoNuT.

Question	Answer Components	AGCLR	Vanilla
Who founded Manor Township, PA?	Penn (0.81), William (0.68), Pennsylvania (0.61)	William Penn ✓	Thoreau ×
When did Oakland Assembly close?	War (0.76), World (0.68)	World War I ✓	World War II ×
What country is WCDL station in?	Federal (0.51), country (0.50), PA (0.48)	United States ✓	Pennsylvania ×

Table 2. **Concept stream content analysis.** Maximum cosine similarities between concept stream embeddings and answer-relevant tokens. Similarities >0.5 indicate successful entity preservation, enabling correct answers where vanilla CoCoNuT fails.

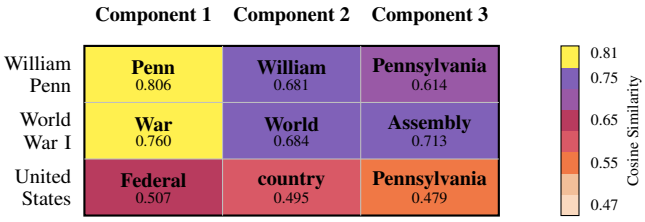


Figure 4. **Concept stream entity preservation heatmap.** Cosine similarities between concept stream embeddings and answer-relevant tokens for three examples where AGCLR succeeds and vanilla CoCoNuT fails. Colour ramp: pink (low) → purple (mid) → yellow (high). AGCLR preserves the Pennsylvania→William Penn binding (0.81), temporal context for World War I (0.76), and geographic abstraction for United States (0.51), consistently achieving 0.6–0.8 similarity for task-relevant entities, explaining the +3.6% EM gain over vanilla CoCoNuT.

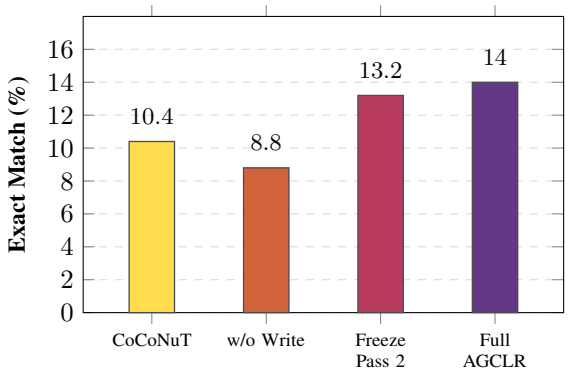


Figure 5. **Ablation study of gating mechanisms.** Exact Match on HotpotQA. *CoCoNuT*: vanilla baseline (10.4%). *w/o Write*: write gate removed (8.8%). *Freeze Pass 2*: write gate frozen after pass 2 (13.2%). *Full AGCLR*: all gates active (14.0%). The small gap between Freeze Pass 2 and Full AGCLR (+0.8% EM) shows early capture suffices; the large drop without the write gate confirms it is critical.

5.4. Are Gains from Parameters or Persistent Memory?

To validate that AGCLR's performance gains stem from *persistent memory mechanisms* rather than simply additional parameters, we conduct an ablation study examining the role of dynamic writing across reasoning passes. We compare four configurations: (1) Vanilla CoCoNuT baseline, (2) AGCLR without write gate (read and forget only), (3) AGCLR with write gate frozen after pass 2, and (4) Full AGCLR with all gates active.

The key question is whether the write gate's value lies in *early information capture* (passes 1–2) or *continuous refinement* across all passes. If dynamic writing throughout all passes were critical, we would expect significant performance degradation when the write gate is frozen. Conversely, if early capture combined with persistent retrieval is sufficient, performance should remain largely intact.

Figure 5 presents our results. Remarkably, freezing the write gate after pass 2 results in only minimal performance degradation: 13.2% EM versus 14.0% EM for full AGCLR (–0.8% absolute). This near-equivalent performance demonstrates that early information capture is largely sufficient for multi-hop reasoning. Notably, the model without any write gate achieves only 8.8% EM, confirming that the write gate is necessary—but its primary value lies in the initial passes. The read and forget gates then maintain and retrieve this early-captured information throughout subsequent reasoning steps.

This finding reveals AGCLR's core mechanism: the concept stream functions as *persistent storage* rather than a dynamic scratchpad. Information is written once during early passes (1–2), then read and selectively forgotten across later passes (3–6). The write gate's primary value lies in identifying and capturing relevant information early, not in continuously refining the stored representation. This validates our hypothesis that AGCLR's gains emerge from the persistent memory architecture itself—the ability to store, maintain, and retrieve information across reasoning steps—rather than from simply adding more trainable parameters to the model.

6. Analysis

6.1. Gate Ablation

We fix individual gates to zero throughout training. Removing the write gate prevents any information from being committed to the concept stream. Removing the read gate prevents retrieval of prior states. Results are presented in Table 3.

Method	HotpotQA EM	HotpotQA F1
AGCLR (full)	14.0	19.4
w/o write gate	8.8	17.1
w/o read gate	9.4	17.8
w/o forget gate	8.4	18.9
Vanilla CoCoNuT	10.4	15.2

Table 3. **Gate ablation results.** Each gate is individually removed by fixing its output to zero throughout training.

Removing any single gate degrades performance, confirming all three components are necessary. The write gate is most structurally critical: without it, nothing is committed to the concept stream, dropping EM to 8.8%, below vanilla CoCoNuT (10.4%). However, the forget gate produces the *largest performance drop* (8.4% EM, -5.6%), demonstrating that selective forgetting is essential for maintaining concept stream quality. In multi-hop reasoning, intermediate computations accumulate both relevant facts (e.g., entity names needed for later hops) and irrelevant context (e.g., formatting tokens, partial calculations from earlier steps). Without the forget gate pruning this noise, the concept stream becomes polluted across passes, degrading retrieval quality and preventing the model from isolating task-relevant information for final answer generation. Removing the read gate costs 4.6% EM, confirming that cross-pass retrieval drives a meaningful share of AGCLR's gains. All three gates are indispensable to resolving the concept bottleneck.

7. Limitations

Our evaluation has some limitations. First, we report single-seed results rather than averaging over multiple runs, introducing potential variance, though consistent improvements across three datasets (GSM8K, HotpotQA, ProsQA) suggest robustness. Second, we use GPT-2 124M, a relatively small model; scalability to larger models (1B+ parameters) remains unexplored. Third, our detailed multi-hop analysis focuses primarily on HotpotQA; evaluation on additional benchmarks (MuSiQue, 2WikiMultihopQA) would strengthen generalization claims.

8. Broader Impact

This work advances multi-step reasoning in language models through persistent memory mechanisms. Improved reasoning capabilities benefit applications like mathematical problem-solving and question answering, but also carry risks: more capable systems may generate sophisticated misinformation, automate manipulative tasks, or make consequential decisions without adequate oversight. AGCLR's efficiency gains could democratize access to capable reasoning systems, but also lower barriers to potentially harmful applications. While our ablations provide some mechanistic transparency, learned representations remain largely opaque. We encourage prioritizing interpretability research, developing robust evaluation frameworks, and establishing deployment guidelines as reasoning capabilities advance. Deployers should implement appropriate safeguards and human oversight mechanisms suited to their application context.

9. Conclusion

We identified the concept bottleneck, a limitation of vanilla CoCoNuT where intermediate reasoning states are lost across passes, and proposed AGCLR to resolve it via a Gated Concept Stream with read, forget, and write gates. AGCLR consistently outperforms vanilla CoCoNuT across multi-hop, and planning reasoning tasks, with the advantage compounding at deeper curriculum stages. Vanilla CoCoNuT degrades when entering the final curriculum stage on ProsQA, while AGCLR sustains improvement, directly demonstrating the benefit of persistent memory under maximum reasoning depth. AGCLR reaches 96% on ProsQA in 20 epochs on a single GH200, approaching Hao et al. (2024)'s result of 97.0% achieved in 50 epochs on 4×A100, demonstrating faster curriculum convergence with significantly less compute. Future work includes scaling to larger base models and learnable gate initialization schedules.

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