MARKOVIAN TRANSFORMERS FOR INFORMATIVE LANGUAGE MODELING

Scott W. Viteri, Max Lamparth, Peter Chatain & Clark Barrett
Department of Computer Science
Stanford University
Stanford, CA 94305, USA
{sviteri,lamparth,pchatain,barrettc}@stanford.edu

ABSTRACT

Chain-of-Thought (CoT) reasoning often fails to faithfully reflect a language model's underlying decision process. We address this by introducing a *Markovian* language model framework that can be understood as a reasoning autoencoder: it creates a text-based bottleneck where CoT serves as an intermediate representation, forcing the model to compress essential reasoning into interpretable text before making predictions. We train this system with a GRPO-style policy gradient algorithm using parallel sampling, a frozen baseline CoT$'$, within-batch standardized advantages, and actor-reward (chain-rule) gradients. Our approach yields large gains on QA tasks (e.g., GSM8K: 20.7% $\rightarrow$ 54.5%; +33.8 pp; ARC-Challenge: 47.5% $\rightarrow$ 76.9%; +29.4 pp). Perturbation analyses across types and severities show consistently higher sensitivity to CoT edits (typically 52%–82% of cases favor Markovian), indicating stronger causal reliance on the CoT. Cross-model evaluation confirms that learned CoTs generalize across architectures, suggesting they capture transferable reasoning patterns rather than model-specific artifacts.

1 INTRODUCTION

The rapid advancement of language models (LMs) has led to impressive performance on complex cognitive tasks (Brown et al., 2020). Yet it is often unclear *why* an LM arrives at a particular conclusion (Lamparth & Reuel, 2023; Burns et al., 2023; Gurnee & Tegmark, 2024), causing issues in high-stakes applications (Grabb et al., 2024; Lamparth et al., 2024; Rivera et al., 2024). Traditional interpretability methods analyze hidden activations or attention patterns to extract "explanations" (Geiger et al., 2022; Geva et al., 2022; Meng et al., 2022; Casper et al., 2023; Wang et al., 2022; Lamparth & Reuel, 2023; Nanda et al., 2023). Modern LMs, however, already generate coherent text: we might hope *prompting* the model to articulate its reasoning ("Chain-of-Thought" or CoT) (Nye et al., 2022; Wei et al., 2022) would yield a faithful record of its thought process.

Unfortunately, CoT explanations can be *unfaithful*. For example, Turpin et al. (2023) show that spurious in-context biases often remain hidden in the CoT, and Lanham et al. (2023) find that altering CoT text may not affect the final answer. Such observations indicate that standard CoTs are not "load-bearing."

In this work, we take a *pragmatic* approach to interpretability, focusing on *informativeness* over full faithfulness. Rather than insisting the CoT mirrors the model's entire internal process, we require that *the CoT alone suffices to produce the final answer*. In other words, if we remove the original prompt and rely only on the CoT, the model should still reach the correct output. This makes the CoT *causally essential* and *fragile*: changing it necessarily alters the prediction.

What distinguishes our approach is the clear distinction between the model *relying on its CoT* versus generating *more informative CoTs*. While traditional approaches train models to generate better-quality CoTs, they don't fundamentally change how the model uses them. Our Markovian framework, by contrast, forces the model to process information through the CoT bottleneck, making the CoT not just informative but *causally load-bearing* for prediction.

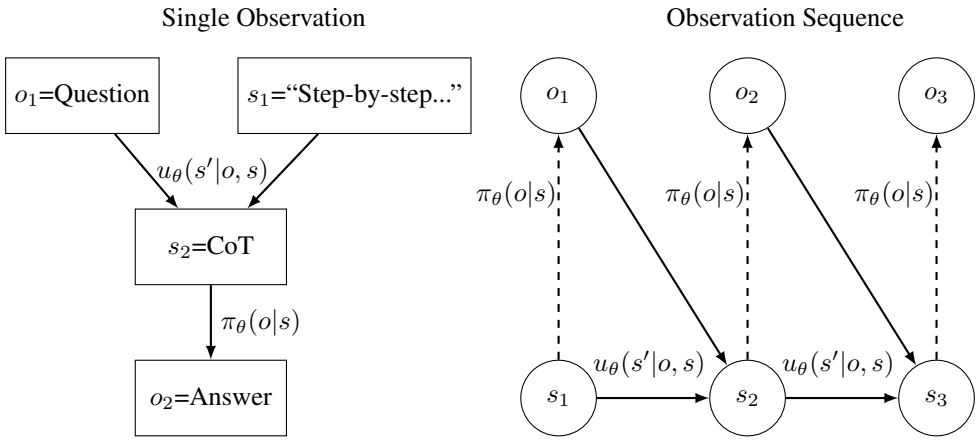


Figure 1: Markovian training as a reasoning autoencoder. Left: Single time-step process from Question to CoT to Answer, creating a text-based bottleneck where the CoT must capture all information needed for answer prediction. Right: Causal structure showing the generation of states from observations and previous states using the state update function $u_\theta(s'|o,s)$, and the prediction of observations from states using the policy $\pi_\theta(o|s)$. This architecture forces reasoning through an interpretable text bottleneck, but prevents direct backpropagation, necessitating RL-based gradient estimation.

For instance, Llama's CoT on arithmetic tasks changed dramatically after training. **Before training**, it simply listed all numbers and their (incorrect) sum (e.g., "Sum = 76 + 90 + 92 + ... = 2314"). **After training**, it performed correct step-by-step calculations (e.g., "calculate 6 + 89 = 95; Next, calculate 95 + 38 = 133..."), breaking the task into manageable steps that can be verified independently and enabling accurate answer prediction even when the original question is removed.

Recipient-Specific Compression. A key insight is that an *informative* CoT can also serve as a *recipient-specific compression* of the model's hidden knowledge: it distills the essential reasoning into text that another recipient (e.g. a different model or a human) can use to predict the same outcome. Our experiments confirm that the learned CoTs generalize across interpreters, suggesting that these textual explanations genuinely encode transferable problem-solving steps rather than model-specific quirks (Section 5.4).

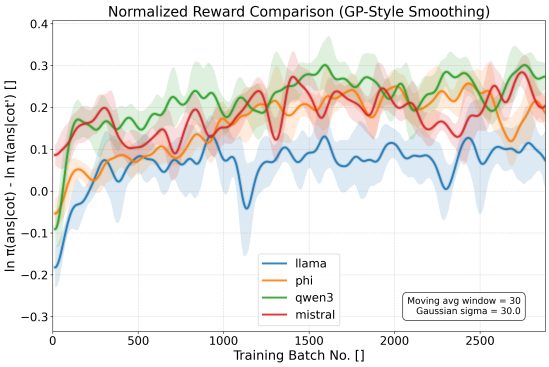
Contributions.

1. We introduce a Markovian language model framework that structurally enforces CoT generation to be causally essential, ensuring reliance on the CoT for predictions.
2. We apply this framework to arithmetic problems (Mistral 7B) and the GSM8K dataset (Cobbe et al., 2021) (Llama 3.1 8B), observing a 33.2% absolute improvement on GSM8K.
3. We show through systematic perturbation analysis across four model pairs that Markovian training produces significantly higher sensitivity to CoT perturbations compared to Non-Markovian approaches, with effect differences ranging from +0.0154 to +0.3276 in log-probability sensitivity.
4. We demonstrate cross-model transfer: CoTs trained on one model remain informative for other models. This underscores the CoT's *recipient-specific* interpretability and suggests it captures a shared reasoning strategy.

Section 2 reviews related work, Section 3 details our Markovian framework, and Section 4 describes the RL training. Section 5 presents empirical results, and Section 6 discusses limitations and future directions.

Dataset	Before	After	Δ
GSM8K	20.70%	54.50%	+33.80 pp
MMLU	35.92%	32.40%	−3.52 pp
Arithmetic	5.50%	> 99%	≥ 93.50 pp
SVAMP	21.33%	35.00%	+13.67 pp
AQuA	16.54%	20.80%	+4.26 pp
ARC-Chal	47.46%	76.87%	+29.41 pp

(a) Llama scores across datasets (verbatim correct at T=0). Δ reports absolute percentage-point (pp) gains.



(b) Cross-model normalized reward

Figure 2: Left: dataset-wise performance for Llama before vs. after Markovian training. Scores are fractions of verbatim-correct answers at temperature 0; Δ is absolute percentage points. Right: normalized reward $\ln \pi_\theta(\text{ans} \mid \text{CoT}) - \ln \pi_\theta(\text{ans} \mid \text{CoT}')$ on Wikipedia continuation for multiple base models (Llama 3.1 8B, Phi-3.5 Mini, Qwen3 4B, Mistral 7B), showing consistent gains in CoT informativeness across architectures. Together, the table highlights robustness across datasets, while the plot highlights robustness across model families.

2 Related Work

Prior work shows that CoT prompting can boost performance on reasoning tasks (Wei et al., 2022; Nye et al., 2022). Whereas typical CoT prompting methods do not alter a pre-trained model's parameters, some prior approaches do fine-tune the model for CoT generation (Zelikman et al., 2022; 2024; DeepSeek-AI et al., 2025). Our work differs by removing the original question or passage from the answer-prediction context, which enforces a stronger causal reliance on the CoT.

Regarding faithfulness vs. interpretability, some authors discuss how a CoT may fail to reflect the true reason the LM arrived at its answer (Lanham et al., 2023; Turpin et al., 2023), since small changes in the CoT do not necessarily change the final prediction. Zhou et al. (2023) analyze CoT through an information-theoretic lens, finding that CoT can serve as a communication channel between different parts of a model. We build on these insights by *training* the model to rely on this channel exclusively.

Architecturally, our Markovian LM shares structural similarities with state space models like RNNs (Rumelhart et al., 1986), S4 (Gu et al., 2022), and Mamba (Gu & Dao, 2024), though with a key difference: MLMs have probabilistic state transitions to model token sampling, which necessitates gradient estimation methods such as policy gradient (Sutton et al., 1999) rather than direct backpropagation. This probabilistic structure also resembles Kalman filters (Å ström, 1965), Deep Variational Bayes Filters (Karl et al., 2017), Deep Kalman Filters (Krishnan et al., 2015), and Variational Recurrent Neural Networks (VRNN) (Chung et al., 2015), though we use categorical rather than Gaussian distributions for interpretable text generation. Other fine-tuned reasoning models mentioned above (R1, STaR, and QuietSTaR) have similar structure but allow seeing the full context before generating state/reasoning tokens, whereas our approach enforces a strict information bottleneck through the state.

Lyu et al. (2023) also consider restricting the model's ability to see the original input while generating the final answer. Their approach, however, involves rewriting the question in a structured formal language or code that is then executed. Our approach uses natural language for the reasoning state to preserve interpretability across diverse tasks.

3 Markovian Language Models and Informativeness

Here we provide our formalism for Markovian Language Models (MLMs) and define *informativeness*, which we use as a training objective within our novel structural framework.

3.1 MARKOVIAN LANGUAGE MODELS (MLM)

A traditional LM can attend to the entire context when predicting the next token. This makes it possible for an LM to disregard the CoT or only partially rely on it. We impose a stricter, *Markovian* structure[1]:

Definition 3.1 (Markovian LM)**.** *A Markovian Language Model is a tuple* $M = (\mathcal{O}, \mathcal{S}, \pi, u, s_1)$*, where*

- $\mathcal{O}$ *is a set of observations (e.g., questions and answers in a QA task),*
- $\mathcal{S}$ *is a set of states (e.g., CoT reasoning text),*
- $\pi : \mathcal{S} \to \Delta(\mathcal{O})$ *is a policy that predicts the next observation from the state alone,*
- $u : \mathcal{O} \times \mathcal{S} \to \Delta(\mathcal{S})$ *is a state update function (produces CoT from question and initial prompt),*
- $s_1 \in \mathcal{S}$ *is an initial state (starting CoT prompt).*

For example, in a math reasoning task, $o_1 \in \mathcal{O}$ might be a question, $s_1 \in \mathcal{S}$ is an initial CoT prompt like "Let's solve this step-by-step:", $s_2 \in \mathcal{S}$ is the generated reasoning chain, and $o_2 \in \mathcal{O}$ is the answer. The key idea is that π can only see the CoT state s_2 when predicting o_2, forcing the CoT to contain all needed information. Intuitively, π is the next-token predictor, and u chooses how to produce the CoT from the latest observation and prior state. In our experiments, π and u are the same underlying transformer.

3.2 DATA-GENERATING DISTRIBUTION AND REWARD

Let P be the distribution over observations $x_1, x_2, \ldots, x_T \in \mathcal{O}$. A trajectory τ is generated by:

$$s_{t+1} \sim u(s_t, x_t), \quad x_{t+1} \sim P(x_{t+1} \mid x_{\leq t}),$$

with s_1 a fixed initial prompt. We define the *reward* for a trajectory τ as:

$$R_\theta(\tau) = \sum_{t=1}^{T} \left[\ln \pi_\theta(x_t \mid s_t) - \ln \pi_\theta(x_t \mid s'_t)\right],$$

where s'_t is generated by a *baseline* update function u', e.g., the *untrained* model. In words, $R_\theta(\tau)$ measures how much more likely the correct observation x_t is under the trained state s_t compared to the baseline state s'_t.

3.3 INFORMATIVENESS OBJECTIVE

Conceptually, we aim to ensure that the CoT state serves as a critical bottleneck for information flow, making it causally essential for predictions. Formalizing this within our Markovian framework, we define:

$$J(\theta) = \mathbb{E}_{\tau \sim P, u_\theta, u'} \left[R_\theta(\tau)\right],$$

where θ parameterizes u_θ. Maximizing $J(\theta)$ ensures that the update function u_θ produces states s_t that are *informative* about future observations (relative to the baseline u'), thereby enforcing the CoT's role as a load-bearing component. We optimize $J(\theta)$ with policy gradient or PPO, sampling observations from P and states from u_θ and u'.

4 METHODS

4.1 IMPLEMENTATION AS QUESTION-ANSWER PAIRS

In many tasks like math problem solving, we have $T = 2$ observations (question and answer) and implement the abstract MLM with a fixed maximum length for the CoT state. Let $\mathcal{V}$ be a token

[1]This structure can be viewed as a stochastic variant of a Moore machine where both the transition function (u) and output function (π) are probabilistic, and the input and output alphabets are identical (O). Alternatively, an MLM can be formalized as an F-coalgebra where F(S) = P(O) $\times$ P(S)^O, with P representing probability distributions.

vocabulary. We set $\mathcal{O} = \mathcal{V}^N$ and $\mathcal{S} = \mathcal{V}^K$ for some $N, K \in \mathbb{N}$, where K is the maximum tokens in the CoT. Note that while we limit the state to a maximum of K tokens for implementation, we do not enforce fixed-length observations.

Our conceptual arguments rely on $K < N$, as otherwise the model could simply write the predicted observation into the state. We satisfy this in our Wikipedia experiments (Sec 5.2), and for other experiments we find empirically that the model does not learn this undesirable behavior due to the difficulty of predicting the answer directly without any CoT.

In this setting, we denote our states as $s_1 = \text{CoT}_{\text{init}}$ and $s_2 = \text{CoT}$, where CoT_{init} is a task-specific prompt[2]. With pre-trained LM $\mathcal{L}$, we can implement our update function u and policy π using:

$$\ln u_\theta\big(s_2 = \text{CoT} \mid q, s_1 = \text{CoT}_{\text{init}}\big) = \sum_{i=1}^{K} \ln \mathcal{L}_\theta\big(\text{concat}(q, \text{CoT}_{\text{init}}, \text{CoT}_{<i})\big)[\text{CoT}_i],$$

$$\ln \pi_\theta(\text{ans} \mid \text{CoT}) := \sum_{i=1}^{N} \ln \mathcal{L}_\theta\big(\text{concat}(\text{CoT}, \text{ans}_{<i})\big)[\text{ans}_i].$$

Compression viewpoint. Our "CoT as compression" narrative applies most directly to continuation tasks (e.g., Wikipedia), where the content to be predicted is longer than the CoT, forcing the model to compress salient context into a short textual bottleneck. For QA tasks, the answer is typically shorter than the CoT; there we emphasize the CoT's *sufficiency and fragility* rather than literal compression, and use QA as evidence that the training method generalizes across task types.

Crucially, we do *not* allow the answer generation to attend back to the question q directly; the question is replaced by the CoT. For each question q, we generate the baseline state s_2' (which we denote as CoT' in this setting) by prompting the unmodified pre-trained model with q plus an initial instruction (e.g., 'Think step-by-step...'), and recording its raw output.

Our reward is:

$$R_\theta = \ln \pi_\theta(\text{ans} \mid \text{CoT}) \; - \; \ln \pi_\theta(\text{ans} \mid \text{CoT}').$$

4.2 Policy Gradient with GRPO-Style Baseline

Markovian training can be understood as training a *reasoning autoencoder*, where the CoT serves as a text-based bottleneck between question and answer. Like traditional autoencoders, this architecture forces information compression, but the intermediate representation is interpretable text rather than latent vectors. This text bottleneck prevents direct backpropagation and necessitates reinforcement learning techniques for gradient estimation.

4.2.1 Actor Reward Gradients: The Key Innovation

Our approach differs fundamentally from standard reinforcement learning by using the *same* transformer with weights θ as both the policy model and the reward model. This creates a crucial mathematical distinction from traditional policy gradient methods.

In classical policy gradient, the reward $R(\tau)$ is independent of the policy parameters, leading to the standard REINFORCE gradient:

$$\nabla_\theta \mathbb{E}_{\tau \sim P_\theta}[R(\tau)] = \mathbb{E}_{\tau \sim P_\theta}[R(\tau) \cdot \nabla_\theta \ln P_\theta(\tau)]$$

However, in our case, the reward is a function of the same parameters: $R_\theta(\tau) = \ln \pi_\theta(\text{ans} \mid \text{CoT})$. Applying the chain rule:

$$\nabla_\theta \, \mathbb{E}_{\tau \sim P_\theta}[R_\theta(\tau)] = \mathbb{E}_{\tau \sim P_\theta}\big[R_\theta(\tau) \, \nabla_\theta \ln P_\theta(\tau) + \nabla_\theta R_\theta(\tau)\big].$$

This yields two terms: the standard policy gradient ($R_\theta(\tau) \cdot \nabla_\theta \ln P_\theta(\tau)$) and the direct reward gradient ($\nabla_\theta R_\theta(\tau)$). We include both terms with equal weight in our implementation.

[2]The exact prompt template varies by task type, with each template specifying the task objective, allowed CoT length, and an invitation to reason strategically. Full templates are provided in Sec A.

4.2.2 GRPO-STYLE BASELINE WITH LOCAL SUBTRACTION

We implement a policy gradient algorithm inspired by Group Relative Policy Optimization (GRPO), originally introduced by Shao et al. Shao et al. (2024) in DeepSeek-Math. GRPO eliminates the critic model from PPO by using group-based advantage estimation, where multiple responses to the same query provide relative baselines for each other.

However, we add an additional baseline subtraction step before applying GRPO's batch averaging. We first compute a local baseline using the frozen reference model u', then apply GRPO-style standardization within each batch.

4.2.3 PARALLEL SAMPLING STRATEGY

We employ *parallel sampling* (inspired by GRPO): each training batch contains B copies of the same question-answer pair (q, a). The trainable model u_θ generates diverse reasoning chains $\{\text{CoT}_1, \text{CoT}_2, \ldots, \text{CoT}_B\}$ for the identical input through stochastic sampling.

Additionally, we introduce a frozen baseline from the reasoning autoencoder: the unmodified model u' generates a single reference CoT' that provides a local baseline before applying GRPO-style batch averaging. This frozen baseline represents the "encoder" component of our reasoning autoencoder—capturing the model's initial reasoning ability before training. The frozen baseline CoT' is *not* part of the original GRPO algorithm—it is our contribution to provide a more stable reference point.

This approach provides several advantages:

- **Reasoning bottleneck**: The CoT' baseline establishes the initial encoding capacity of the reasoning autoencoder
- **Local baseline**: The frozen CoT' provides a consistent reference for measuring informativeness improvement
- **Computational efficiency**: Baseline reasoning and answer evaluation are computed once and replicated
- **Stable variance estimation**: All samples share the same ground truth, enabling robust within-batch standardization

4.2.4 IMPLEMENTATION: TWO-TERM LOSS FUNCTION

Our implementation combines both gradient terms from the chain rule derivation above. The loss function includes:

$$\mathcal{L} = \mathcal{L}_{\text{PG}} + \mathcal{L}_{\text{AR}}, \quad \mathcal{L}_{\text{PG}} = -\ln u_\theta(\text{CoT} \mid q, \text{CoT}_{\text{init}}) \cdot A^{\text{detach}}, \quad \mathcal{L}_{\text{AR}} = -A.$$

where A is the standardized advantage (after local baseline subtraction and GRPO-style batch averaging) and A^{detach} blocks gradients to isolate the policy gradient term.

The first term $\mathcal{L}_{\text{PG}}$ corresponds to the standard REINFORCE gradient $A_\theta(\tau) \cdot \nabla_\theta \ln P_\theta(\tau)$, while the second term $\mathcal{L}_{\text{AR}}$ corresponds to the direct advantage gradient $\nabla_\theta A_\theta(\tau)$. This enables simultaneous optimization of CoT generation and answer prediction.

4.2.5 WITHIN-BATCH ADVANTAGE STANDARDIZATION

Instead of historical exponential moving averages, we standardize advantages within each batch:

$$R_i = \ln \pi_\theta(\text{ans} \mid \text{CoT}_i) - \ln \pi_\theta(\text{ans} \mid \text{CoT}'), \quad A_i = \frac{R_i - \mu_{\text{batch}}}{\sigma_{\text{batch}} + \epsilon}.$$

where $\mu_{\text{batch}} = \frac{1}{B}\sum_{i=1}^{B} R_i$ and $\sigma^2_{\text{batch}} = \frac{1}{B}\sum_{i=1}^{B}(R_i - \mu_{\text{batch}})^2$.

This ensures that advantages have zero mean and unit variance within each batch, providing stable gradients regardless of the absolute reward scale.

Algorithm 1 Markovian Training with GRPO-Style Batch Baseline

Given dataset P of (q, a), trainable actor u_θ, frozen baseline u', answer policy π_θ, batch size B
for each training batch **do**
  Sample $(q, a) \sim P$
  Sample $\mathrm{CoT}_i \sim u_\theta(\cdot \mid q, \mathrm{CoT}_{\text{init}})$ for $i = 1..B$ (stochastic parallel sampling)
  Sample baseline $\mathrm{CoT}' \sim u'(\cdot \mid q, \mathrm{CoT}_{\text{init}})$ (once per batch)
  Compute actor answer log-probs $r_i = \ln \pi_\theta(a \mid \mathrm{CoT}_i)$
  Compute baseline log-prob $b = \ln \pi_\theta(a \mid \mathrm{CoT}')$
  Normalized rewards $R_i = r_i - b$; standardize within-batch: $A_i = \dfrac{R_i - \mu}{\sigma + \epsilon}$
  Policy gradient loss: $\ell_i^{\text{PG}} = -\ln u_\theta(\mathrm{CoT}_i \mid q, \mathrm{CoT}_{\text{init}}) \cdot A_i^{\text{detach}}$
  Actor-reward gradient: $\ell_i^{\text{AR}} = -A_i$
  Optional KL penalty: $\ell_i^{\text{KL}} = 0.1\, D_{KL}\big(u_\theta(\cdot \mid q) \,\|\, u'(\cdot \mid q)\big)$
  Total loss: $\ell_i = \ell_i^{\text{PG}} + \ell_i^{\text{AR}} + \ell_i^{\text{KL}}$; update θ with $\frac{1}{B}\sum_i \ell_i$
end for

5 EXPERIMENTS

We evaluate in two regimes: (i) continuation (Wikipedia), where CoT tokens act as a lossy compression of longer context, and (ii) question–answer datasets (GSM8K, MMLU, SVAMP, AQuA, ARC, Arithmetic), which validate the general-purpose efficacy of Markovian training even when the "compression" story is not literal.

5.1 QUESTION–ANSWER TASKS (GSM8K, MMLU, SVAMP, AQUA, ARC, ARITHMETIC)

We evaluate on standard QA-style datasets (GSM8K (Cobbe et al., 2021), MMLU (Hendrycks et al., 2020), SVAMP (Patel et al., 2021), AQuA (Ling et al., 2017), ARC Challenge (Clark et al., 2018), and our non-standard multi-step addition task. All QA experiments use the same optimization: GRPO-style parallel sampling with within-batch standardization and the chain-rule reward (policy-gradient plus actor-reward gradient), with task-specific default CoT lengths. For arithmetic, each problem has fifteen random terms in $[1, 99]$; the model learns to produce step-wise reasoning and achieves $> 99\%$ verbatim-correct answers at $T{=}0$.

CoT length defaults. Unless otherwise specified, we use: GSM8K 100, Arithmetic 150, Arithmetic-Negative 150, MMLU 150. See §4 for objective details.

5.2 WIKIPEDIA CONTINUATION

For Wikipedia continuation (Foundation, 2024), we condition on the first 200 tokens and predict the next 100 tokens, allowing 50 tokens of CoT. Training uses the same GRPO with chain-rule reward as in QA. We observe improvements consistent with increased CoT informativeness (cf. Fig. 2), and §5.3 shows stronger perturbation sensitivity under Markovian training.

5.3 MARKOVIAN VS NON-MARKOVIAN PERTURBATION SENSITIVITY

To provide systematic evidence for the theoretical advantages of Markovian training, we conduct comprehensive perturbation sensitivity comparisons between Markovian and Non-Markovian model pairs. The Non-Markovian models are trained using the same hyperparameters, only differing in that the reward is $\pi_\theta(\text{ans} \mid q, \text{CoT})$ instead of $\pi_\theta(\text{ans} \mid \text{CoT})$. This analysis directly evaluates whether the structural constraints in Markovian training lead to measurably different robustness properties during training.

5.3.1 EXPERIMENTAL DESIGN

We measure perturbation sensitivity by evaluating fixed Markovian and Non-Markovian checkpoints on newly sampled Wikipedia examples, regenerating actor CoTs for both models on the same inputs

Perturbation Type	Degree	Mean Effect Difference	Overall Consistency	Total Comparisons
Delete	20%	+0.0144	51.6%	128
	40%	+0.0513	65.6%	128
	60%	+0.0719	74.2%	128
	80%	+0.0986	78.1%	128
	100%	+0.1210	82.0%	128
Truncate Front	20%	-0.0028	42.2%	128
	40%	+0.0190	56.2%	128
	60%	+0.0355	63.3%	128
	80%	+0.0648	76.6%	128
	100%	+0.0983	81.2%	128
Truncate Back	20%	-0.0065	39.8%	128
	40%	+0.0010	47.7%	128
	60%	+0.0204	50.8%	128
	80%	+0.0473	62.5%	128
	100%	+0.0841	70.3%	128
Character Replace	20%	+0.0115	53.1%	128
	40%	+0.0488	62.5%	128
	60%	+0.0529	62.5%	128
	80%	+0.0504	62.5%	128
	100%	+0.0482	64.1%	128

Table 1: Fresh perturbation comparison between Markovian and Non-Markovian models using fixed checkpoints (adapter index 400) evaluated on 128 newly sampled Wikipedia continuation examples per perturbation type and degree. **Mean Effect Difference** is the average of (Markovian Effect − Non-Markovian Effect), where Effect is defined as $\ln P(\text{ans} \mid \text{CoT}_{\text{orig}}) - \ln P(\text{ans} \mid \text{CoT}_{\text{pert}})$. **Consistency** is the percentage of examples where the effect difference is positive (Markovian more sensitive).

before computing effects. We test four perturbation types at five severities (20%, 40%, 60%, 80%, 100%):

- **Delete**: Random token deletion from CoT reasoning
- **Truncate Front**: Removal of tokens from CoT beginning
- **Truncate Back**: Removal of tokens from CoT end
- **Character Replace**: Random character substitution within tokens

The sensitivity measure matches the implementation:

$$\text{Effect}_{\text{M/NM}} = \ln P(\text{ans}|\text{CoT}_{\text{original}}) - \ln P(\text{ans}|\text{CoT}_{\text{perturbed}}) \tag{1}$$

$$\text{Difference} = \text{Effect}_{\text{Markovian}} - \text{Effect}_{\text{Non-Markovian}} \tag{2}$$

Positive differences indicate greater Markovian sensitivity to CoT perturbations, reflecting stronger reliance on CoT integrity.

5.3.2 Results Summary

On 128 fresh Wikipedia examples per perturbation type, we find: Delete shows the strongest differences (mean +0.014 to +0.121 with 52%–82% consistency increasing with severity). Truncations start near zero or slightly negative at low severities and become positive with higher severities. Character replacement is consistently positive (+0.011 to +0.053; 63% consistency at higher severities).

5.4 Interpretability of CoT Generations

To probe how well the reasoning generalizes, we evaluated the informativeness of Llama's trained CoTs with respect to various other language models on the Wikipedia dataset. Cross-model evaluation shows strong correlation between improvements in both the trained model's and alternative models' evaluations of CoT quality throughout training. The normalized log probabilities increase simultaneously across different architectures, demonstrating that Llama is learning to produce

generic CoTs which do not over-fit to the peculiarities of a Llama answer-predictor. Results averaged across 6 independent training runs confirm this pattern holds consistently.

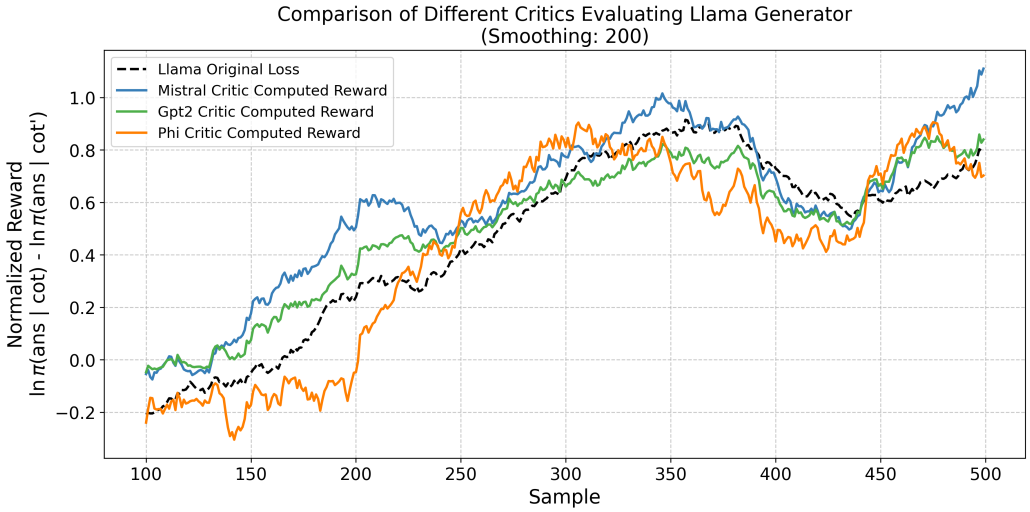


Figure 3: Cross-model evaluation comparing how different models (Mistral, GPT2, and Phi 3.5 Mini Instruct) utilize Llama 8B's CoT on GSM8K. Results averaged across 3 training runs with smoothing window of 40.

This cross-model transferability addresses a key question: "interpretable to whom?" We test across three distinct model families (Phi (Abdin et al., 2024), Mistral, and GPT2), including GPT2, a significantly smaller model that shouldn't be able to decode sophisticated steganography. The fact that trained CoTs transfer effectively across this diverse set confirms they contain generalizable reasoning patterns rather than model-specific artifacts. Note that the "CoT-as-compression" interpretation is specific to continuation settings; in QA, our gains indicate that enforcing a load-bearing, sufficient CoT improves reasoning utility even without a strict compression constraint.

6 Discussion and Limitations

Experiments across arithmetic, GSM8K, and Wikipedia show that it is possible to learn informative and interpretable CoT reasoning via RL on an LM using Markovian training.

We currently verify interpretability on myopic QA and continuation settings. A direct human study could further validate whether CoTs are genuinely human-interpretable beyond our model-centric proxies (fragility and cross-model transfer). Nonetheless, we observe substantial gains in CoT fragility and cross-model transfer, suggesting practical opportunities for improved interpretability. The Markovian design also naturally extends to multi-turn dialogue by treating the CoT as a recurrent state; after each user message o_t we produce the next CoT s_{t+1} via $u_\theta(s_{t+1} \mid s_t, o_t)$ and generate the system's reply from s_{t+1} alone. We leave multi-turn evaluation to future work.

7 REPRODUCIBILITY STATEMENT

To ensure reproducibility, we provide comprehensive supplementary materials at `https://github.com/scottviteri/MarkovianTraining/` including all source code, training and evaluation scripts, and detailed instructions in the README. The main training loop (`src/train.py`) supports (i) GRPO, and alternate training methods such as EI, PG, and PPO-style clipped objective methods (see Section F for detailed algorithm descriptions) and (ii) all experimental datasets. We measure fragility of CoT via `src/perturbation_analysis.py` and we estimate interpretability of CoT generations via `src/evaluate_cross_model.py`.

Complete hyperparameter configurations for all Wikipedia continuation experiments are provided in Table 2.

Models: We support 11 language model architectures with full tokenization and formatting: Llama 3.1 8B Instruct, Llama 3.2 1B Instruct, Mistral 7B Instruct V0.2, GPT-2 (124M), TinyStories (33M), Phi 3.5 Mini Instruct, Phi-4, Qwen3 4B, Qwen3 14B, Gemma-3 2B, and Gemma-3 Small (9B). All models use public HuggingFace implementations with LoRA fine-tuning.

Datasets: We support the following task types: (1) *arithmetic* - randomly generated 15-term addition problems, (2) *arithmetic-negative* - addition with negative numbers, (3) *GSM8K* (Cobbe et al., 2021), (4) *MMLU* (Hendrycks et al., 2020), (5) *SVAMP* (Patel et al., 2021), (6) *AQuA* (Ling et al., 2017), (7) *ARC-Challenge* (Clark et al., 2018), (8) *wiki_compression* - predicting repeated Wikipedia text, and (9) *wiki_continuation* - next-token prediction on Wikipedia articles. Environment setup instructions are provided in the README.

Our experiments were conducted on NVIDIA H100 and H200 GPUs through the RunPod cloud service. We trained and evaluated across multiple tasks and settings, including: QA datasets (GSM8K, MMLU, SVAMP, AQuA, ARC-Challenge; §5.1), the non-standard multi-step addition task (§5.1), and Wikipedia continuation (§5.2). We also ran systematic perturbation sensitivity studies (§5.3), cross-model evaluations (Fig. 3), and hyperparameter/model sweeps (Table 2) across Llama, Mistral, Phi, and Qwen3, and temperatures 1.2/1.3/1.4. We tried various other architectures including straight-through estimators through token sampling and the Decision Transformer (Chen et al., 2021). Taken together, these experiments required substantial compute; the total compute for the reported experiments was approximately 10,000 GPU-hours. The broader research project, including preliminary runs and ablations not reported here, consumed approximately $32,000 in cloud resources. We provide these figures to help researchers anticipate the resources needed to reproduce and extend our results.

With these materials, researchers should be able to reproduce our work, including the performance boost on GSM8K and the perturbation analysis results demonstrating CoT reliance.

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A Training Stability and Implementation Details

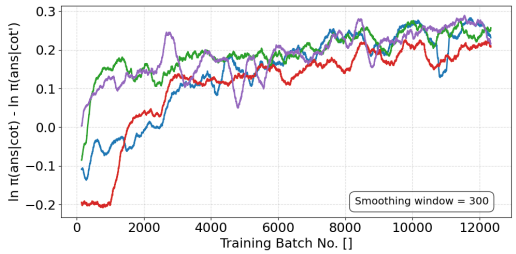
Fine-tuning a pre-trained language model with a strong linguistic prior requires careful consideration to avoid irrecoverable weight updates that could push the model out of the language modeling loss basin. We implement several techniques to enhance training stability for the GRPO objective:

1. **Low-Rank Adaptation (LoRA) (Hu et al., 2022):**
   - Freeze all weights except for small-rank LoRA adapters.
   - Use rank 8 with $\alpha = 16$.
2. **Gradient Clipping:**
   - If the ℓ_2 norm of the gradient exceeds 1.0, rescale it to norm 1.0.
3. **Within-Batch Advantage Standardization:**
   - GRPO's parallel sampling enables robust within-batch standardization, eliminating the need for historical baselines.
   - Each batch provides its own reference distribution for advantage calculation.
4. **Actor Reward Weight:**
   - Set actor reward weight to 1.0 to equally balance policy gradient and direct reward optimization.
   - This enables end-to-end learning through the reward model.
5. **Initial CoT Prompt Design:**
   - Choose CoT_{init} to guide the model toward meaningful reasoning.
   - For arithmetic:
     "You will be given an arithmetic problem, which you have [CoT length] tokens to work through step-by-step. Question:"
   - For GSM8K:
     "You will be given a reasoning problem, which you have [CoT length] tokens to work through step-by-step. Question:"
   - For Wikipedia continuation:
     "Compress your understanding of this text into [CoT length] tokens, then predict the next [target length] tokens."

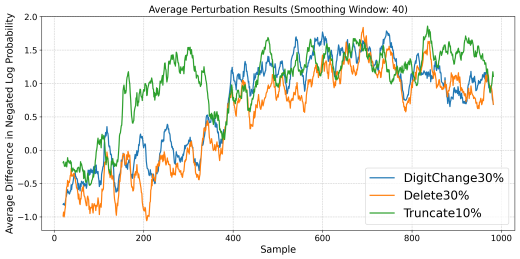
These measures greatly reduce the risk of catastrophic updates and keep the model's training on track.

B Additional Performance Analysis

This section presents additional performance metrics and analysis across our experimental settings. Fig 4a shows training progress on the Wikipedia continuation task, Fig 4b demonstrates perturbation effects on arithmetic reasoning, and Fig 3 illustrates cross-model transfer on GSM8K.



(a) Training progress on Wikipedia continuation task for Llama 8B, showing normalized improvement in next-token prediction across four independent runs.



(b) Perturbation effects on Mistral 7B arithmetic reasoning, showing three types of CoT modifications: digit changes, character deletions, and right truncation. Averaged over 4 PPO training runs.

Figure 4: Additional performance analysis across different tasks and metrics. (a) Training performance on Wikipedia. (b) Perturbation analysis on arithmetic.

C Truthfulness and Eliciting Latent Knowledge

Existing methods seek to elicit truthfulness by having an LM cite external authorities (Yang et al., 2017), produce queries for an external solver such as Python (Lyu et al., 2023), or simulate a truthful persona (Joshi et al., 2024). Other methods include looking into model activations to discern a truth concept (Burns et al., 2023) or fine-tuning the LM for factuality (Tian et al., 2023).

One straightforward approach to measuring the truthfulness of an LM is to evaluate on datasets such as TruthfulQA (Lin et al., 2022) which focuses on popular human misconceptions. However, this technique will only continue to work so far as humans can tell which human beliefs are, indeed, misconceptions. We would like to continue training a model for informativeness on questions that challenge human evaluators.

Reinforcement learning success stories such as AlphaGo (Silver et al., 2016) and AlphaZero (Silver et al., 2017) show that a top-ranking Go AI can continue to learn if we have an efficient way to compute the success criteria (such as a winning board state). However, many important success criteria are abstractions, and only exist within a person's ontology. This problem is discussed at length in Christiano et al. (2021), and we will use their example to illustrate the situation.

Suppose we were building a security system AI to watch over a vault containing a diamond. Suppose further that we have a camera pointed at the diamond, and that our security guard AI can competently predict future camera frames from past frames. How can we train it to classify camera sequences according to the ambiguous human concept of whether the diamond is still in the room, even in difficult scenarios when a person would not be able to provide a ground truth label (e.g., subtle camera tampering)? If we train the classifier based on scenarios when a person can provide ground truth labels, then the AI's video classifier has two valid generalization behaviors: (1) to say whether it thinks the diamond is still in the room and (2) to say whether the dataset-labeler would think the diamond is still in the room.

Our approach favors the second generalization behavior by using RL to train the AI to produce messages such that the person can themselves predict future camera frames. This idea is based on the following three insights:

- Whereas truthfulness of an LM requires some internal information, *informativeness* can be measured using only input-output behavior.
- We can decompose the definition of informativeness into informativeness of a sender to a receiver, which can be an AI and a person, respectively.
- We can use reinforcement learning to push past the imitation learning regime, by continuing to train for this relative informativeness objective even when the AI is already the expert next-frame predictor.

D Training Algorithm Implementation and Comparison

This section provides detailed descriptions of the reinforcement learning algorithms implemented in our codebase for Markovian CoT training. Our core contribution is the Markovian training paradigm that optimizes P(answer — CoT) rather than P(answer — question, CoT), creating a text bottleneck where the CoT must be causally load-bearing. We implement multiple optimization approaches to support this paradigm, enabling comprehensive algorithmic comparison.

D.1 Alternate Training Algorithms Tested

Our codebase implements four distinct reinforcement learning algorithms, each designed to optimize the informativeness objective for Markovian CoT generation:

Parallel Sampling with Batch Baseline: Our main algorithmic approach, which uses standardized batch-wise advantage estimates (mean=0, std=1) without exponential moving average baseline mixing. This differs from standard GRPO by incorporating the Markovian reward constraint where the same model parameters θ are used for both policy and reward calculation, eliminating the need for iterative reward model updates.

We also implement three additional training objectives for algorithmic comparison:

Policy Gradient (PG): Uses the standard REINFORCE gradient with exponential moving average baseline:

$$\mathcal{L}_{\text{PG}} = -\ln u_\theta(\text{CoT} \mid q, \text{CoT}_{\text{init}}) \cdot A^{\text{detach}} \tag{3}$$

where A is the advantage computed from the informativeness reward $R_\theta = \ln \pi_\theta(\text{ans} \mid \text{CoT}) - \ln \pi_\theta(\text{ans} \mid \text{CoT}')$ and an exponential moving average baseline $V_t = \sum_{i=1}^{t-1} w_i R_i$ with weights $w_i = r^{t-1-i} / \sum_{j=1}^{t-1} r^{t-1-j}$ (parameter $r = 0.9$).

PPO-style Clipped Objective: Uses the PPO clipping objective (not the full PPO algorithm) to prevent large policy updates:

$$\mathcal{L}_{\text{PPO}} = -\min(r_t(\theta)A_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)A_t) \tag{4}$$

where $r_t(\theta) = \frac{\pi_\theta(\text{CoT}_t)}{\pi_{\theta_{\text{old}}}(\text{CoT}_t)}$ is the probability ratio and $\epsilon = 0.2$ is the clipping parameter. Note this applies clipping within our single-step framework rather than the multi-epoch data collection and update scheme of standard PPO.

Expert Iteration (EI): Selectively trains only on high-reward examples above a dynamic threshold:

$$\mathcal{L}_{\text{EI}} = \mathcal{L}_{\text{PG}} \cdot \mathbb{I}[R_\theta > \tau_t] \tag{5}$$

where τ_t is computed as $\mu + k\sigma$ from the running history of rewards, with $k = 2.2$ standard deviations in our experiments.

D.2 Cross-Model Interpretability Analysis

Figure 5 presents the cross-model evaluation analysis that demonstrates the interpretability of CoT generations across different model architectures. This analysis supports the interpretability claims in the main paper by showing that learned reasoning patterns generalize across different language model architectures rather than being model-specific artifacts.

The cross-model transferability shown in Figure 5 addresses the key question of "interpretable to whom?" by demonstrating that trained CoTs transfer effectively across diverse model families, confirming they contain generalizable reasoning patterns rather than model-specific artifacts.

E Qualitative Analysis of Generated CoTs

This section provides concrete examples of how Markovian training changes the character of generated CoT reasoning across different task domains.

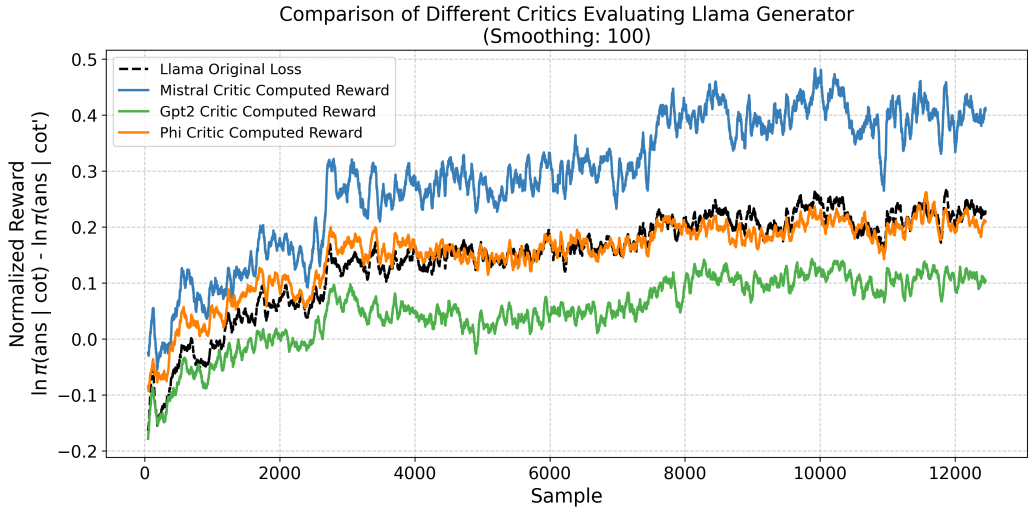


Figure 5: Cross-model evaluation showing Llama-3.1-8B-Instruct's evaluation of Mistral's CoT quality throughout training on Wikipedia text prediction. The correlation between improvements in both models' evaluations suggests the learned reasoning patterns generalize across architectures rather than being model-specific artifacts. Each plot is averaged across 6 independent training runs.

E.1 Arithmetic Task Example

Here is an example from Llama-3.1-8B-Instruct on the arithmetic task (data: `/root/MarkovianTraining/results/arithmetic/20250925_041804`), showing the final actor and baseline reasoning sampled from the training log.

Batch Index 299

Question 1 + 47 + 35 + 58 + 92 + 19 + 37 + 94 + 30 + 81 + 30 + 1 + 66 + 92 + 78

Actor Reasoning 1 + 47 = 48. 48 + 35 = 83. 83 + 58 = 141. 141 + 92 = 233. 233 + 19 = 252. 252 + 37 = 289. 289 + 94 = 383. 383 + 30 = 413. 413 + 81 = 494. 494 + 30 = 524. 524 + 1 = 525. 525 + 66 = 591. 591 + 92 = 683. 683 + 78 = 761. The answer is 761. Spoiler: to solve the problem, just add continuously, like a summarized version, to

Baseline Reasoning To solve this problem, you need to add the numbers together step by step. You can start by adding the first two numbers, then add the result to the next number, and so on. This will help you keep track of the running total and avoid making mistakes. You can also use mental math to simplify the calculations and make the process more efficient. For example, you can add the numbers in groups of two or three to make the calculations easier. Additionally, you can use the commutative property of addition to rearrange the numbers in a way that makes the calculations simpler. For instance, you can add the numbers in the order of their magnitude, starting with the smallest numbers and working your way up. This will help you avoid having to

Answer 761

E.2 Wikipedia Continuation Example

To better understand Llama-3.1-8B-Instruct's behavior after Markovian training to predict Wikipedia text, let's examine its behavior on the (randomly selected near the end of training) batch number 12500. The model was given the following Wikipedia article excerpt:

> Boones Mill is a town in Franklin County, Virginia, United States. The population was 239 in 2018, down from 285 at the 2000 census. It is part of the Roanoke Metropolitan Statistical Area.
>
> History
>
> Boones Mill was incorporated in 1927. It was previously known as "Boone Mill"

and ”Boon Mill”. The town is named after Jacob Boon who operated a mill in the town.

The Boones Mill Norfolk & Western Railway Depot is listed on the National Register of Historic Places. https://www.townofboonesmill.org/history

Geography
Boones Mill is located in northern Franklin County at (37.115462, -79.953966), along U.S. Route 220 at the southern base of the Blue Ridge Mountains. US 220 leads north to Roanoke and south to Rocky Mount, the Franklin County seat.

According to the United States Census Bureau, the town has

Given this context ending with “According to the United States Census Bureau, the town has”, we can compare the CoT generated by our trained versus an untrained model:

E.2.1 CoT after Training:

> “The town of Boones Mill is located in Franklin County, Virginia, United States. US 220 leads north to Roanoke and south to Rocky Mount, the Franklin County seat. According to the United States Census Bureau, the town has”

E.2.2 CoT before Training:

> “The town of Boones Mill is a small, rural community with a rich history and natural beauty. The town is surrounded by the Blue Ridge Mountains, offering scenic views and outdoor recreational opportunities. The town’s economy is primarily based on agriculture and small”

E.2.3 Actual Continuation:

> “a total area of , all of it land. The town is in the valley of Maggodee Creek, a southeast-flowing tributary of the Blackwater River, part of the Roanoke River watershed. Murray Knob, elevation , rises to the north on the crest of the Blue Ridge, and the eastern end of Cahas Mountain, at , is 2 miles to the west.”

The trained CoT shows notably different characteristics from the untrained one. The trained CoT essentially copied the first and last two sentences from the context, making sure to line up the number of allotted tokens with the end of the last sentence. The untrained model seems to give fairly generic properties that the actual Boones Mill Wikipedia article does not mention, such as Boones Mill having an economy primarily based on agriculture. Also, the untrained CoT is not taking the token limit into account and is setting the evaluator model to be surprised when it glues the CoT to the answer and has to predict “agriculture and small a total area of , all of it land”.

This example achieved a normalized reward of 0.3438 (in log probability), suggesting that the trained CoT strategy was indeed helpful for predicting the technical geographic description that followed.

F Hyperparameter Tuning and Experimental Configurations

Our Wikipedia continuation experiments systematically explored the hyperparameter space across multiple model architectures and training configurations. Table 2 provides a comprehensive overview of the hyperparameter settings used in our experiments, extracted directly from the training logs.

The experimental design explored several key dimensions:

Model Architecture: We evaluated four different language models (Llama, Mistral, Phi, and Qwen3) to assess the generalizability of our Markovian training approach across different architectures and parameter scales.

Temperature Scaling: We systematically varied the sampling temperature (1.2, 1.3, 1.4) to study the effect of generation diversity on Markovian training effectiveness. Higher temperatures encourage more diverse CoT generation, potentially leading to more robust reasoning patterns.

Markovian vs Non-Markovian Training: For each model and temperature combination, we conducted paired experiments comparing Markovian training (Markov=Y) versus Non-Markovian training (Markov=N) to isolate the effects of our approach.

Batch Size Optimization: Batch sizes were tailored to each model's memory requirements and computational efficiency, ranging from 6 (Mistral, Llama) to 16 (Phi) based on GPU memory constraints and convergence characteristics.

Training Duration: We used two training regimes - shorter runs (10,000 batches) for initial exploration and longer runs (100,000 batches) for comprehensive evaluation. The shorter runs allowed rapid iteration during hyperparameter search, while longer runs provided robust performance estimates.

The exponential moving average parameter r (0.9) is only used in non-parallel mode for computing historical baseline values; parallel (GRPO) mode uses batch-wise standardization instead. The CoT length was fixed at 75 tokens to ensure consistent computational overhead across experiments. Detailed model and dataset specifications are provided in the Reproducibility Statement below.

Table 2: Hyperparameter configurations for Wikipedia continuation experiments with actual training duration. Experiments use either GRPO optimization (Parallel=Y) or standard policy gradient (Parallel=N) with LoRA fine-tuning. The exponential moving average parameter r is only used in non-parallel mode for baseline computation. 'Actual Lines' shows the number of log entries, indicating actual training progress.

Model	Temp	Batch	LR	Planned	Actual Lines	KL	r	Parallel	Markov	LoRA	CoT Len
llama	1.2	6	1.0e-04	100,000	257	0.1	0.9	N	Y	8/16	75
llama	1.2	6	1.0e-04	100,000	3,973	0.1	–	Y	N	8/16	75
llama	1.3	8	1.0e-04	100,000	8,240	0.1	–	Y	Y	8/16	75
mistral	1.3	10	1.0e-04	100,000	1,064	0.1	0.9	N	Y	8/16	75
mistral	1.4	6	1.0e-04	10,000	9,768	0.1	–	Y	Y	8/16	75
mistral	1.4	6	1.0e-04	10,000	4,151	0.1	–	Y	N	8/16	75
phi	1.3	16	1.0e-04	100,000	656	0.1	0.9	N	Y	8/16	75
phi	1.4	16	1.0e-04	10,000	5,796	0.1	–	Y	Y	8/16	75
phi	1.4	16	1.0e-04	10,000	5,123	0.1	–	Y	N	8/16	75
qwen3	1.3	12	1.0e-04	100,000	780	0.1	0.9	N	Y	8/16	75
qwen3	1.4	12	1.0e-04	10,000	3,543	0.1	–	Y	Y	8/16	75
qwen3	1.4	12	1.0e-04	10,000	3,235	0.1	–	Y	N	8/16	75

The systematic exploration of this hyperparameter space enabled robust evaluation of our Markovian training approach and provided confidence in the generalizability of our results across different model architectures and training configurations.

G Impact Statement

Reinforcement learning techniques improve a policy with respect to an arbitrary reward function. But it can be difficult to mathematically specify nuanced human preferences about the policy. Both reinforcement learning from human feedback (RLHF) (Christiano et al., 2023) and Constitutional AI (Bai et al., 2022) help people specify and optimize the properties they would like the AI to have. This increase in controllability makes the AI more of an extension of human intention, for better or for worse. The approach of this paper is much more targeted – we use RL to specifically increase an agent foresight – its ability to predict its future observations.

On its face, this seems like it might be just as dependent on human intentions as RLHF and Constitutional AI – if an LM is more knowledgeable, maybe it could use that extra knowledge to deceive others, for instance. However, better foresight may also give rise to better values, where values are opinions about how to act such that the collective system can attain better foresight.