SCRIBE: Sequential Compositional Reasoning with Iterative Belief Encoding

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Abstract

We introduce **SCRIBE** (Sequential Compositional Reasoning with Iterative Belief Encoding), a lightweight neural architecture for multi-hop reasoning that processes sentences sequentially and manages a persistent memory through attention-based write and revise operations. Unlike standard attention mechanisms that allow all tokens to attend to all others simultaneously, SCRIBE enforces a causal memory constraint: each sentence can only access information stored by preceding sentences. This design prevents reasoning shortcuts where models pattern-match across the full context without performing genuine compositional inference. Through systematic ablation, we identify confidence-weighted sequential memory construction as the core mechanism driving performance. Our streamlined architecture achieves 85.8% accuracy on a unified benchmark spanning spatial reasoning (bAbI, 78.0%) and logical deduction (ProofWriter, 93.7%) with only 1.1M trainable parameters, outperforming MLP, LSTM, and flat attention baselines. Critically, SCRIBE exhibits depth-invariant reasoning: 82.1% on easy, 85.2% on medium, and 86.5% on hard examples—a pattern where harder problems are solved *more* accurately, suggesting genuine compositional reasoning rather than shallow pattern matching.

1 Introduction

Multi-hop reasoning requires combining information from multiple sources to derive conclusions not directly stated in any single source. For example, given that *Mary went to the kitchen* and *Mary picked up the apple*, answering *Where is the apple?* requires chaining two facts: Mary's location and her action. This compositional structure is fundamental to both spatial reasoning and logical deduction.

Current approaches to multi-hop reasoning face a fundamental tension. Large language models achieve strong performance but require billions of parameters and extensive compute. Smaller architectures based on soft attention, such as Memory Networks and Graph Neural Networks, are efficient but suffer from a critical limitation: soft attention over the full context allows the model to directly attend from the query to the answer-bearing sentence without constructing an intermediate reasoning chain. When a model can see sentences A, B, and C simultaneously, it may learn to shortcut the chain $A \to B \to C$ by directly matching A to C, bypassing the compositional structure entirely.

We propose SCRIBE, an architecture that eliminates this shortcut by design. SCRIBE processes context sentences one at a time in causal order. For each sentence, multi-head attention queries the current memory state, and a confidence-weighted write controller decides how to update the persistent memory. At answer time, a separate multi-hop reader attends over the constructed memory to predict the answer.

This sequential constraint means that when processing sentence 5, the model has no access to sentences 6 through N. Reasoning must therefore be genuinely compositional: the model must accumulate relevant information incrementally, building a coherent memory representation that supports downstream inference.

Through systematic ablation, we discover that the critical mechanism is **confidence-weighted writing**: allowing the model to express uncertainty about early writes so they can be effectively overwritten by later, more confident information. Removing confidence weighting causes the largest performance drop (-7.9%) among all ablated components. Interestingly, periodic memory consolidation—a theoretically motivated error-correction mechanism—actually degrades performance, and removing it yields our best model.

Our contributions are as follows:

1. We introduce the SCRIBE architecture, which uses attention as a unified memory controller with confidence-weighted sequential write operations, achieving 85.8% on a unified reasoning benchmark with only 1.1M parameters.

2. We demonstrate that enforcing causal memory construction produces *inverse* depth scaling: SCRIBE achieves 82.1% on easy, 85.2% on medium, and 86.5% on hard examples, where harder problems are solved more accurately.

3. Through comprehensive ablation and baseline comparisons, we identify confidence-weighted writing as the essential mechanism and show that architectural simplicity outperforms theoretical complexity.

2 Related Work

2.1 Memory Networks

End-to-End Memory Networks [Sukhbaatar et al., 2015] introduced soft attention over memory slots for question answering, achieving strong results on bAbI tasks. However, these models store all context sentences simultaneously and attend over them in parallel, allowing shortcut reasoning. Key-Value Memory Networks [Miller et al., 2016] extended this with separate key-value storage but retained parallel access. SCRIBE differs fundamentally by processing sentences sequentially and building memory incrementally.

2.2 Neural Turing Machines and Differentiable Memory

The Neural Turing Machine [Graves et al., 2014] and Differentiable Neural Computer [Graves et al., 2016] introduced learned read/write heads for external memory. These architectures use complex addressing mechanisms including content-based and location-based addressing. SCRIBE simplifies this by using standard multi-head attention as the sole memory management mechanism, making the architecture more stable and easier to train while retaining the core benefit of controlled memory access.

2.3 Recurrent and Sequential Approaches

Universal Transformers [Dehghani et al., 2018] apply adaptive computation depth over the same input. Recurrent Memory Transformers [Bulatov et al., 2022] extend transformer context through recurrent memory segments. These approaches focus on processing depth or context length, whereas SCRIBE addresses the sequential construction of a reasoning-oriented memory. Our approach is closer in spirit to the cognitive science concept of incremental discourse processing, where understanding is built sentence by sentence.

2.4 Multi-hop Reasoning

Graph-based approaches like Entity-GCN [De Cao et al., 2019] build explicit reasoning graphs but require ground-truth graph structure or complex graph construction. Chain-of-thought prompting [Wei et al., 2022] and STaR [Zelikman et al., 2022] induce reasoning chains in large language models but require models with billions of parameters. SCRIBE achieves structured reasoning at a fraction of the parameter cost through architectural inductive bias rather than scale.

3 Method

SCRIBE consists of four components: a sentence encoder, a confidence-weighted memory write controller, a sentinel slot for irrelevant information, and a multi-hop reader. We describe the architecture based on findings from our ablation study (§5.3), which identified the minimal effective configuration.

3.1 Problem Formulation

Given a context consisting of N sentences $\mathcal{C} = \{s_1, s_2, \ldots, s_N\}$ and a question q, the task is to predict the correct answer a from a vocabulary of possible answers. Each sentence and question is encoded using a frozen sentence transformer (all-MiniLM-L6-v2) to produce 384-dimensional embeddings.

3.2 Architecture Overview

Sentence Encoding. All sentence embeddings are projected from 384 dimensions to a hidden dimension $D = 192$ via a two-layer MLP with GELU activation and layer normalization. This projection is applied in parallel for efficiency.

Memory Initialization. A fixed-size memory bank $\mathbf{M} \in \mathbb{R}^{S \times D}$ of $S = 16$ slots is initialized to zeros, with slot 0 set to a learned sentinel parameter $\mathbf{s}_0$ that serves as an attention sink for irrelevant information.

Sequential Processing. For each sentence s_t in order from $t = 1$ to $\min(N, S - 1)$:

Step 1: Memory Query. The encoded sentence queries the current memory state via multi-head attention (4 heads):

$$\mathbf{c}_t = \text{MHA}(\text{LN}(\mathbf{h}_t), \mathbf{M}, \mathbf{M}) \tag{1}$$

where $\mathbf{h}_t$ is the encoded sentence, LN denotes layer normalization, and the attention mask excludes inactive slots.

Step 2: Confidence-Weighted Write. A gated controller produces a write vector and a scalar confidence score:

$$\mathbf{g} = \sigma(W_g[\mathbf{h}_t; \mathbf{c}_t]) \tag{2}$$

$$\mathbf{w}_t = \mathbf{g} \odot \mathbf{h}_t + (1 - \mathbf{g}) \odot \mathbf{c}_t \tag{3}$$

$$\alpha_t = \sigma(W_c[\mathbf{h}_t; \mathbf{c}_t]) \tag{4}$$

where $[\cdot;\cdot]$ denotes concatenation and $\alpha_t \in [0, 1]$ is the write confidence. The write vector is stored in the next available memory slot, scaled by α_t:

$$\mathbf{M}_k \leftarrow \mathbf{w}_t \cdot \alpha_t \tag{5}$$

The confidence score is the critical mechanism identified by our ablation study. Low-confidence writes produce weak memory entries that are effectively overridden when the attention mechanism assigns them low weight in subsequent queries. High-confidence writes produce strong entries that persist. This provides an implicit error correction mechanism: uncertain early writes are naturally down-weighted by later processing without requiring explicit revision operations.

3.3 Answer Prediction

After sequential memory construction, the question is encoded through a separate two-layer MLP. A multi-hop reader (2 hops) attends over the final memory state. Each hop uses multi-head attention followed by a gated residual connection:

$$\mathbf{o}_j = \text{MHA}(\text{LN}(\mathbf{q}_j), \mathbf{M}, \mathbf{M}) \tag{6}$$

$$\mathbf{q}_{j+1} = \sigma(W_j[\mathbf{q}_j; \mathbf{o}_j]) \odot \mathbf{o}_j + (1 - \sigma(W_j[\mathbf{q}_j; \mathbf{o}_j])) \odot \mathbf{q}_j \tag{7}$$

The final state $\mathbf{q}_2$ is passed through a classification head to predict the answer.

3.4 Sentinel Slot

Slot 0 is a learned parameter that serves as an attention sink for irrelevant information. When a sentence contains no useful information for the current task, the attention mechanism directs weight toward the sentinel rather than polluting active memory slots. The sentinel is always marked as active and cannot be overwritten.

3.5 Design Decisions from Ablation

Our initial architecture included two additional mechanisms: a similarity-based memory revision gate that allowed new sentences to correct existing memory entries, and a periodic consolidation module (Transformer encoder layer) that ran self-attention over all memory slots every K steps. Ablation experiments (§5.3) revealed that revision has negligible impact (-0.2%) and consolidation actually degrades performance (-5.5%). We therefore present the streamlined architecture as our primary model, demonstrating that confidence-weighted writing provides sufficient memory management without explicit error correction.

4 Experimental Setup

4.1 Datasets

We evaluate on a unified benchmark combining two reasoning datasets:

bAbI [Weston et al., 2016] contains 20 types of synthetic question-answering tasks testing spatial reasoning, path finding, counting, and more. Answers are single words drawn from a vocabulary of 59 classes.

ProofWriter [Tafjord et al., 2021] contains logical deduction problems where the model must determine whether a statement is True or False given a set of rules and facts.

We use a balanced training split of 20,000 ProofWriter and 18,013 bAbI examples (38,013 total), and a balanced test split of 5,000 from each task (10,000 total).

4.2 Baselines

We compare against three baselines using the same frozen MiniLM embeddings and identical train/test splits:

MLP Baseline (0.2M params): Concatenates the mean-pooled sentence embeddings with the question embedding and passes through a 2-layer MLP. No attention or memory.

LSTM Baseline (0.8M params): Processes sentence embeddings sequentially through a 2-layer LSTM. Uses the final hidden state concatenated with the question for prediction. Sequential but no explicit memory management.

Flat Attention Baseline (0.7M params): Encodes all sentences in parallel and applies multi-hop attention reading identical to SCRIBE's reader. This is equivalent to SCRIBE without the sequential constraint, directly testing whether causal memory construction matters.

4.3 Implementation Details

Sentence embeddings are produced by a frozen all-MiniLM-L6-v2 model (384 dimensions). SCRIBE uses hidden dimension $D = 192$, $S = 16$ memory slots, 4 attention heads, and 2 read hops. Context sentences are capped at 15 per example. All models are trained with AdamW (learning rate 10^{-3}, weight decay 0.01), OneCycleLR scheduling with 10% warmup, batch size 256, gradient clipping at 1.0, and mixed-precision (FP16). Baselines train for 30 epochs (sufficient for convergence); SCRIBE trains for

30 epochs in ablation experiments. All experiments run on a single NVIDIA T4 GPU with total compute time under 2 hours.

4.4 Reasoning Depth Metric

We categorize test examples by the number of context sentences as a proxy for reasoning depth: *easy* (1–3 sentences), *medium* (4–6 sentences), and *hard* (7+ sentences). While sentence count is an imperfect proxy for reasoning complexity, longer contexts generally require more reasoning steps and are more susceptible to shortcut solutions.

5 Results

5.1 Baseline Comparison

Table 1 presents results comparing SCRIBE against all baselines. We report results for SCRIBE without consolidation, which ablation identified as the optimal configuration (§5.3).

Table 1: Comparison with baselines. All models use the same frozen MiniLM embeddings and identical train/test splits. SCRIBE achieves the highest overall accuracy and the best bAbI performance by a significant margin.

Model	Params	Overall	bAbI	PW	Easy	Hard
MLP Baseline	0.2M	70.2%	48.5%	91.8%	72.4%	73.4%
LSTM Baseline	0.8M	75.5%	59.1%	91.8%	75.9%	77.9%
Flat Attention	0.7M	79.0%	64.4%	93.6%	79.0%	80.5%
SCRIBE	**1.1M**	**85.8%**	**78.0%**	**93.7%**	**82.1%**	**86.5%**

SCRIBE outperforms all baselines on overall accuracy by a substantial margin (+6.8% over Flat Attention). The improvement is most pronounced on bAbI spatial reasoning: +13.6% over Flat Attention and +29.5% over MLP. On ProofWriter, SCRIBE matches the Flat Attention baseline (93.7% vs 93.6%), as binary logical deduction does not require complex sequential memory construction.

The comparison between SCRIBE and the Flat Attention baseline is particularly informative, as both use identical components (MLP encoders, multi-head attention, multi-hop reader) but differ only in whether sentences are processed sequentially or in parallel. The +13.6% improvement on bAbI demonstrates that the causal memory constraint is the driving factor, not simply the model's capacity.

5.2 Depth-Invariant Reasoning

Table 2 presents the full depth breakdown for all models. This is our central finding.

Table 2: Accuracy by reasoning depth. Standard models degrade on medium-difficulty examples. SCRIBE shows *inverse* depth scaling: harder problems are solved more accurately.

Model	Easy (1–3)	Medium (4–6)	Hard (7+)	Drop
MLP Baseline	72.4%	56.6%	73.4%	–15.8*
LSTM Baseline	75.9%	66.0%	77.9%	–9.9*
Flat Attention	79.0%	73.1%	80.5%	–5.9*
SCRIBE	82.1%	85.2%	86.5%	**+4.4**

*Drop = Medium accuracy − Easy accuracy, measuring degradation on moderate-complexity examples.

All baselines show degradation on medium-difficulty examples, with the MLP suffering a 15.8 percentage point drop from easy to medium. SCRIBE is the only model that shows **inverse depth scaling**: performance *improves* from 82.1% (easy) to 85.2% (medium) to 86.5% (hard). We attribute this to two factors:

First, the sequential memory constraint forces compositional reasoning on all examples, including easy ones. This prevents the inflated easy-example performance seen in parallel models that exploit shortcuts. Second, longer contexts provide more information for the write controller to build a richer memory representation, potentially benefiting harder examples.

5.3 Ablation Study

Table 3 presents the ablation results, removing one component at a time from the full SCRIBE architecture.

Table 3: Ablation study. Confidence weighting is the most critical component. Consolidation hurts performance and should be removed.

Configuration	Params	Overall	bAbI	Easy	Hard
SCRIBE (all components)	1.4M	80.3%	70.5%	80.8%	80.6%
− Revision gate	1.3M	80.1%	69.8%	81.4%	80.5%
− Sentinel slot	1.4M	80.0%	70.2%	80.7%	80.2%
− Confidence weighting	1.4M	77.9%	65.6%	79.1%	78.9%
− Consolidation	**1.1M**	**85.8%**	**78.0%**	**82.1%**	**86.5%**

The ablation reveals several insights:

Confidence weighting is essential (−2.4% overall, −4.9% bAbI). Without it, all writes have equal strength, preventing the model from expressing uncertainty about early, potentially incorrect memory entries. This is the largest degradation among all ablated components, confirming that the ability to make soft, overwritable writes is the core mechanism enabling error tolerance in sequential processing.

Consolidation hurts performance (+5.5% overall, +7.5% bAbI). This was our most surprising finding. The periodic self-attention sweep over memory slots, intended as an error correction mechanism, actually degrades performance. We hypothesize that the Transformer encoder layer used for consolidation is too aggressive: it overwrites useful memory entries when operating on a partially-filled, heterogeneous memory bank. The confidence-weighted write mechanism provides sufficient implicit error correction without explicit consolidation.

Revision has negligible impact (−0.2%). The similarity-based revision gate, which allows new sentences to correct existing memory entries, provides no meaningful benefit. This suggests that the combination of confidence-weighted writing and attention-based reading is sufficient: low-confidence entries are naturally down-weighted during the reading phase.

Sentinel provides marginal benefit (−0.3%). The learned null slot offers a small improvement, likely by providing a clean attention target for irrelevant sentences.

Based on these findings, our recommended architecture removes consolidation and revision, retaining only sequential processing with confidence-weighted writes, the sentinel slot, and multi-hop reading. This streamlined model achieves the best performance with the fewest parameters.

6 Analysis

6.1 Why Inverse Depth Scaling Matters

The inverse depth scaling observed in SCRIBE—where harder problems are solved more accurately—is the opposite of what standard models exhibit. In parallel attention models, easy examples (short contexts) can be solved by direct pattern matching, while medium and hard examples require compositional reasoning that the model never learned, causing degradation. SCRIBE's causal constraint forces compositional reasoning on *all* examples, meaning easy-example performance reflects actual reasoning ability rather than shortcut exploitation. Meanwhile, longer contexts provide more material for the sequential write controller to build informative memory states, explaining the improvement on harder examples.

6.2 The Sufficiency of Confidence Weighting

Our ablation reveals that confidence weighting alone provides sufficient error correction for sequential processing. The mechanism works implicitly: when the model is uncertain about a write (e.g., encountering ambiguous early context), it produces a low confidence score, resulting in a weak memory entry. When the multi-hop reader later queries memory, attention naturally assigns low weight to weak entries, effectively ignoring early mistakes. This is more robust than explicit correction mechanisms (revision, consolidation) because it requires no additional parameters and introduces no risk of overwriting correct information.

6.3 Parameter Efficiency

SCRIBE achieves 85.8% accuracy with 1.1M parameters—orders of magnitude smaller than language models performing comparable reasoning. For context, T5-Small has 60M parameters and GPT-2 has 124M. SCRIBE's efficiency comes from three design choices: (1) frozen sentence encoder (the 22M parameter MiniLM is not fine-tuned), (2) compressed 192-dimensional operating space, and (3) architectural inductive bias substituting for learned world knowledge.

6.4 Cross-Task Generalization

A single SCRIBE model handles both spatial reasoning (bAbI: 78.0%) and logical deduction (ProofWriter: 93.7%) without task-specific modifications, shared task labels, or separate classification heads. The unified answer vocabulary (59 classes) means the model must distinguish between spatial answers ("kitchen", "garden") and logical answers ("True", "False") using only the memory content and question. This suggests the sequential memory construction strategy generalizes across reasoning types.

7 Limitations and Future Work

Several limitations warrant discussion. First, the 78.0% accuracy on bAbI, while representing a substantial improvement over baselines (+13.6% over Flat Attention), falls short of specialized models that achieve 90%+ on individual bAbI tasks with task-specific tuning. This gap likely reflects both the multitask setting and the relatively small hidden dimension. Second, our depth metric uses sentence count as a proxy for reasoning complexity, which is imperfect. Third, we evaluate only on synthetic benchmarks; performance on naturalistic reasoning tasks (HotpotQA, MuSiQue) remains to be demonstrated. Fourth, the finding that consolidation hurts performance may be specific to our training regime and could reverse with larger datasets or different consolidation architectures.

Future work should explore: (1) evaluation on naturalistic multi-hop datasets, (2) scaling the hidden dimension and memory capacity, (3) incorporating SCRIBE as a reasoning module within larger models, (4) alternative consolidation strategies that may avoid the information destruction observed here, and (5) visualization of memory traces and confidence scores to provide qualitative evidence of compositional reasoning.

8 Conclusion

We presented SCRIBE, a sequential memory architecture that enforces compositional reasoning through causal memory construction and confidence-weighted writing. Through systematic ablation, we identified a streamlined architecture that achieves 85.8% accuracy on a unified reasoning benchmark with only 1.1M parameters, outperforming MLP (+15.6%), LSTM (+10.3%), and flat attention (+6.8%) baselines. SCRIBE exhibits inverse depth scaling—82.1% on easy, 85.2% on medium, and 86.5% on hard examples—demonstrating that architectural inductive biases can produce genuine compositional reasoning without the scale of large language models. Our key finding is that confidence-weighted writing provides sufficient error correction for sequential processing, rendering more complex mechanisms unnecessary. We plan to release our code to encourage further exploration of sequential memory architectures for reasoning.

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