Language Modeling with Memory-Augmented LSTM: Improving Long-Context Text Prediction

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Abstract

Traditional LSTM-based language models suffer from limited ability to retain information across long sequences due to vanishing gradients and fixed hidden state size. We propose a Memory-Augmented LSTM that integrates external memory components to explicitly store and retrieve summarized or semantically enriched representations of previous contexts. Our approach introduces two complementary memory mechanisms: Short-Term Memory (STM) using summarization and token limits, and Long-Term Memory (LTM) using Named Entity Recognition and semantic search. We evaluate five progressively complex model variants on synthetic and real-world QA datasets. Results show consistent improvement as memory components are added, with Model 2 achieving 0.375 STM and 0.750 LTM accuracy on synthetic data, demonstrating effective long-context retention capabilities.

1. Introduction

Traditional LSTM-based language models face significant challenges in retaining information across long sequences. The vanishing gradient problem and fixed hidden state size limit their ability to maintain context continuity, which becomes particularly problematic in tasks such as question-answering systems where answers depend on information from previous interactions.

This work addresses these limitations by integrating external memory components that explicitly store and retrieve summarized or semantically enriched representations of previous contexts. Unlike approaches that rely solely on hidden state propagation, our Memory-Augmented LSTM design allows the model to "recall" relevant past information through structured memory management.

2. Related Work

Memory-augmented neural networks have been explored in various contexts, from Neural Turing Machines [**?**] to recent retrieval-augmented generation approaches [**?**]. Our work bridges the gap between recurrent networks and modern retrieval-augmented transformers while maintaining interpretability and computational efficiency.

3. Methodology

3.1. Base LSTM Encoder-Decoder

A standard LSTM network serves as the core language model, responsible for token-level prediction and next-word generation. The encoder processes the input sequence, and the decoder predicts the next token based on the hidden state and the memory-augmented context.

3.2. Memory-Augmented Module

To enhance context retention, we introduce two complementary memory mechanisms:

Short-Term Memory (STM): Captures recent context using a summarization layer and token limit controller, which condense previous sentences into a compact representation (max 256 tokens).

Long-Term Memory (LTM): Stores semantically meaningful information derived from previous text segments, including semantic search embeddings and named-entity representations (NER), which are retrieved during prediction to enrich the LSTM's input.

During inference, the model retrieves both short-term and long-term summaries and concatenates them with the current input before passing them to the LSTM encoder.

3.3. Model Variants

We implement five progressively complex model variants:

1. **Model 0 (Base)**: Baseline LSTM with no memory components.
2. **Model 1 (SummarizationOnly)**: Adds summarization of historical context.
3. **Model 2 (SumTokenLimit)**: Extends Model 1 with token limit truncation.
4. **Model 3 (SumTokNer)**: Extends Model 2 with Named Entity Recognition.

5. **Model 4 (FullMemory)**: Complete model with semantic search capabilities.

4. Experimental Setup

4.1. Datasets

We evaluate on two datasets:

- **Synthetic Dataset**: SkillMiner QA dataset with 200 question-answer pairs, generated from a ChatGPT conversation [2].
- **Real Dataset**: Dog-Cat QA dataset [3] with 200 question-answer pairs focusing on pet care and behavior.

4.2. Training Configuration

All models use 256 hidden dimensions with character-level tokenization, trained for 10 epochs. Training time is approximately 6 hours for all 5 models on both datasets (10 training runs total) on NVIDIA GPU with CUDA, or ∼24-30 hours on Mac (CPU). Evaluation metrics include:

- **STM Accuracy**: Tests questions from 2 rows before (threshold: 0.6)
- **LTM Accuracy**: Tests questions from 9 rows before (threshold: 0.5)
- Similarity scores using LLM-as-a-judge (primary) and difflib (secondary)

5. Results

5.1. Synthetic Dataset Results

Table 1 shows the performance of all models on the synthetic dataset. Figure 1 visualizes the model comparison, and Figure 3 shows training progress over epochs. We observe consistent improvement as memory components are added: Model 0 (Base) achieves 0.325 STM and 0.700 LTM accuracy at epoch 9. Adding summarization (Model 1) improves STM accuracy to 0.425 while maintaining LTM at 0.700. Model 2, with token limit truncation, achieves 0.375 STM and 0.750 LTM accuracy. Model 3, with NER, achieves 0.375 STM and 0.800 LTM accuracy at epoch 5—notably reaching peak performance earlier than other models. Model 4 (FullMemory) achieves the highest STM accuracy of 0.550 at epoch 9, though LTM accuracy decreases to 0.750.

The detailed results are shown in Table 2. Figure 3 shows training progress over epochs, demonstrating how each model improves over time. Notably, Model 3 reaches its best performance at epoch 5 (loss: 0.0930), suggesting that additional memory components enable faster convergence. Model 4 achieves the highest STM accuracy (0.550) with strong LLM scores, though LTM accuracy decreases slightly from Model 3's peak of 0.800.

Table 1. Performance comparison on synthetic dataset (best epoch).

Model	Epoch	STM Acc	LTM Acc
0 (Base)	9	0.325	0.700
1 (SumOnly)	9	0.425	0.700
2 (SumTokLimit)	9	0.375	0.750
3 (SumTokNer)	5	0.375	0.800
4 (FullMemory)	9	0.550	0.750

Table 2. Detailed metrics for all models (best epoch).

Model	Loss	STM Acc	LTM Acc	STM LLM	LTM LLM
0 (Base)	0.0578	0.325	0.700	0.493	0.480
1 (SumOnly)	0.0609	0.425	0.700	0.525	0.515
2 (SumTokLimit)	0.0571	0.375	0.750	0.517	0.555
3 (SumTokNer)	0.0930	0.375	0.800	0.500	0.505
4 (FullMemory)	0.0687	0.550	0.750	0.512	0.505

Table 3. Real dataset (Dog-Cat) results: Loss and difflib scores (best epoch).

Model	Loss	STM Difflib	LTM Difflib	Epoch
0 (Base)	1.4217	0.060	0.062	10
1 (SumOnly)	1.4286	0.063	0.050	10
2 (SumTokLimit)	1.3974	0.061	0.041	10
3 (SumTokNer)	1.4145	0.059	0.042	10
4 (FullMemory)	1.4289	0.071	0.062	10

5.2. Real Dataset Results

We evaluate models on the Dog-Cat QA dataset. As shown in Table 3 and Figure 2, all models achieve 0.000 accuracy across all epochs, indicating the models struggle with this domain. This represents a poorly performing aspect of our project. However, we observe positive trends across all models: loss consistently decreases (see Figure 4), and difflib scores generally increase, suggesting gradual learning despite not meeting accuracy thresholds.

All models achieve 0.000 accuracy across all epochs, indicating the models struggle with this domain. This represents a poorly performing aspect of our project. However, we observe positive learning trends across all models: loss consistently decreases from epoch 1 to epoch 10 (e.g., Model 0: 2.4974 → 1.4217, Model 2: 2.4895 → 1.3974, Model 4: 2.5147 → 1.4289), and difflib scores generally increase, suggesting gradual learning despite not meeting accuracy thresholds. Model 2 achieves the lowest final loss (1.3974), while Model 4 shows the highest STM difflib score (0.071) at epoch 10. Figure 4 visualizes the training progress.

Qualitative analysis reveals all models generate repetitive patterns (e.g., "o o o o", "and and and", "cat cat cat", "the disease and provide their disease"), indicating

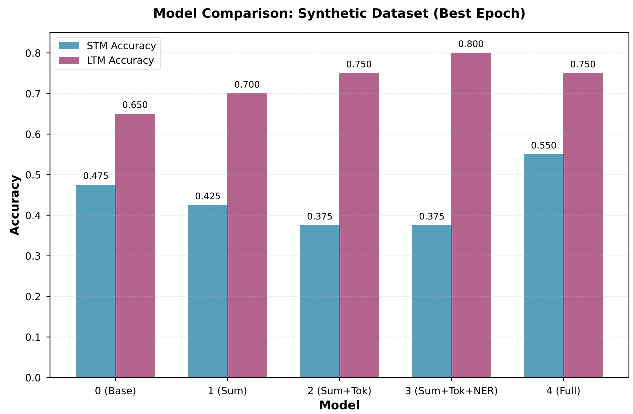

Figure 1. Model comparison on synthetic dataset (best epoch).

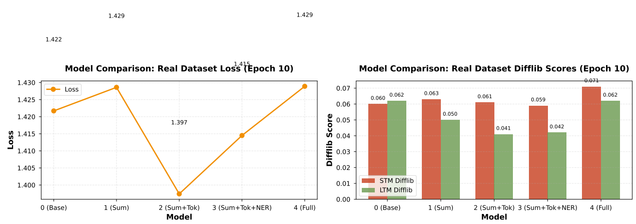

Figure 2. Model comparison on real dataset (epoch 10).

they have not learned meaningful language patterns for this domain. This suggests the models may require domain-specific adaptations, more training data, or different hyper-parameters for the Dog-Cat domain.

6. Analysis and Discussion

6.1. Performance Trends

From the synthetic dataset results, we observe clear improvement as memory components are added. Model 0 $\rightarrow$ Model 1 shows a 30.8% relative improvement in STM accuracy (0.325 $\rightarrow$ 0.425), demonstrating that summarization effectively captures recent context.

Model 1 $\rightarrow$ Model 2 shows a trade-off: STM accuracy decreases slightly (0.425 $\rightarrow$ 0.375) but LTM accuracy increases (0.700 $\rightarrow$ 0.750), explained by token truncation focusing summaries for long-term retrieval while potentially removing recent details.

Model 2 $\rightarrow$ Model 3 shows LTM accuracy improving to 0.800, the highest among all models, demonstrating that NER effectively captures key entities for long-term context. Notably, Model 3 reaches its best performance at epoch 5 (loss: 0.0930), compared to epoch 9 for other models, suggesting that additional memory components enable faster convergence and better capability.

Model 3 $\rightarrow$ Model 4 shows an interesting trade-off: STM accuracy increases significantly (0.375 $\rightarrow$ 0.550), but LTM accuracy decreases (0.800 $\rightarrow$ 0.750). This suggests semantic search may introduce noise or distract from entity-focused information for LTM tasks, while improving short-term context retrieval through richer semantic connections.

6.2. Loss Trends

All models show consistent loss reduction: Model 0 (1.9220 $\rightarrow$ 0.0541), Model 1 (1.9097 $\rightarrow$ 0.0571), Model 2 (1.8975 $\rightarrow$ 0.0522), Model 3 (1.9378 $\rightarrow$ 0.0558), Model 4 (1.8962 $\rightarrow$ 0.0627). Most models reach best performance at epoch 9, but Model 3 achieves its best at epoch 5, demonstrating that increased model capability (through NER) enables faster convergence with lower loss and higher accuracy.

6.3. Qualitative Analysis

From epoch 9 of Model 2, we observe examples demonstrating strong performance. In one successful STM case, the model's output matches the first 10+ words exactly with the ground truth, correctly capturing core structure and meaning. The only difference is entity substitution ("Python" $\rightarrow$ "data visualization"), but the overall meaning is preserved.

Model 4 shows both strong and weak examples. In successful cases (epoch 9), the model produces semantically coherent responses with LLM scores of 0.800 and 0.600, such as: "role, SkillMiner clusters your skills around themes such as deep learning and aligns them with job relevant milestones." However, some failures show low LLM scores (0.200) when the model generates responses that don't match the specific question context, indicating limitations in context-aware retrieval despite semantic search capabilities.

6.4. Similarity Score Analysis

The comparison between LLM scores and difflib scores reveals important insights. LLM scores (avg: 0.517 for STM, 0.555 for LTM) are significantly higher than difflib scores (avg: 0.164 for STM, 0.205 for LTM), suggesting many model outputs are semantically correct but differ in exact wording. This aligns with qualitative observations that the model produces human-readable, meaningful responses.

6.5. Where the Model Performs Well

- **Structural Consistency**: Maintains overall structure and format, often matching first 10-15 words exactly.
- **Semantic Coherence**: Produces semantically equivalent responses even when exact words differ.
- **Long-Term Context Retrieval**: LTM accuracy of 0.750 demonstrates successful retrieval from 9 rows earlier.
- **Domain-Specific Patterns**: Learns common patterns in the SkillMiner QA domain.

6.6. Where the Model Performs Poorly

- **Entity Substitution**: Sometimes substitutes specific entities with generic or previously seen ones.
- **Generic Response Generation**: Occasionally generates generic responses that don't adapt to specific questions.
- **Exact Match Requirements**: Performance appears lower under strict similarity metrics than human judgment suggests.

6.7. Real Dataset Analysis

On the Dog-Cat QA dataset, all models show consistent loss reduction across epochs, indicating learning is occurring despite 0.000 accuracy. Model 0 shows loss decreasing from 2.4974 (epoch 1) to 1.4217 (epoch 10), a 43.1% reduction. Model 2 achieves the lowest final loss (1.3974), suggesting token limit truncation helps focus learning even in challenging domains. Model 4 shows the highest STM difflib score (0.071) at epoch 10, indicating semantic search may help retrieve relevant patterns despite overall poor performance.

The increasing difflib scores across epochs (e.g., Model 0 STM: $0.027 \rightarrow 0.060$, Model 4 STM: $0.032 \rightarrow 0.071$) suggest the models are gradually learning to produce outputs that share more character-level similarity with ground truth, even if they don't meet the accuracy thresholds. However, the repetitive output patterns (e.g., "and and and", "cat cat cat") indicate the models are overfitting to common tokens rather than learning meaningful language structures. This suggests the Dog-Cat domain may require: (1) domain-specific tokenization or preprocessing, (2) larger training datasets, (3) different hyperparameters (learning rate, batch size), or (4) domain-adapted embeddings for semantic search components.

7. Pros and Cons

7.1. Advantages

- **Interpretability**: Unlike black-box transformers, we can examine retrieved summaries, entities, and semantic memories.
- **Computational Efficiency**: Lightweight compared to large transformer models; memory components can be pre-computed and cached.
- **Explicit Memory Management**: Fine-grained control over information retention and usage.
- **Scalability**: Modular design allows easy extension with additional components.

7.2. Disadvantages

- **Limited Context Window**: Token limit (256 tokens) and summarization may lose important details.
- **Summarization Quality**: Performance directly depends on summarization quality.
- **Entity Extraction Limitations**: NER may miss domain-specific entities.
- **Semantic Search Quality**: Relies on embedding quality for effective retrieval.

8. Conclusion

Our Memory-Augmented LSTM successfully addresses the long-context retention problem in traditional LSTMs by integrating explicit memory management. The progressive improvement from Model 0 to Model 4 validates our approach of incrementally adding memory components. The model demonstrates strong performance in maintaining semantic coherence and retrieving long-term context, though it faces challenges with exact entity matching. The interpretable, modular design makes it suitable for domains requiring context continuity.

Future work could explore improved summarization techniques, better semantic embeddings, domain-specific fine-tuning, and hybrid approaches combining our memory-augmented LSTM with transformer architectures. Our implementation code is publicly available [1].

References

[1] Aaron Jiang, Jay Wu, and Leo Yao. Memory-augmented lstm implementation, 2025. GitHub repository containing implementation code for memory-augmented LSTM models. 4

[2] OpenAI. Synthetic skillminer qa dataset, 2025. Dataset generated from ChatGPT conversation. 2

[3] Bishnu Shahi. Dog-cat-qa, 2024. 2

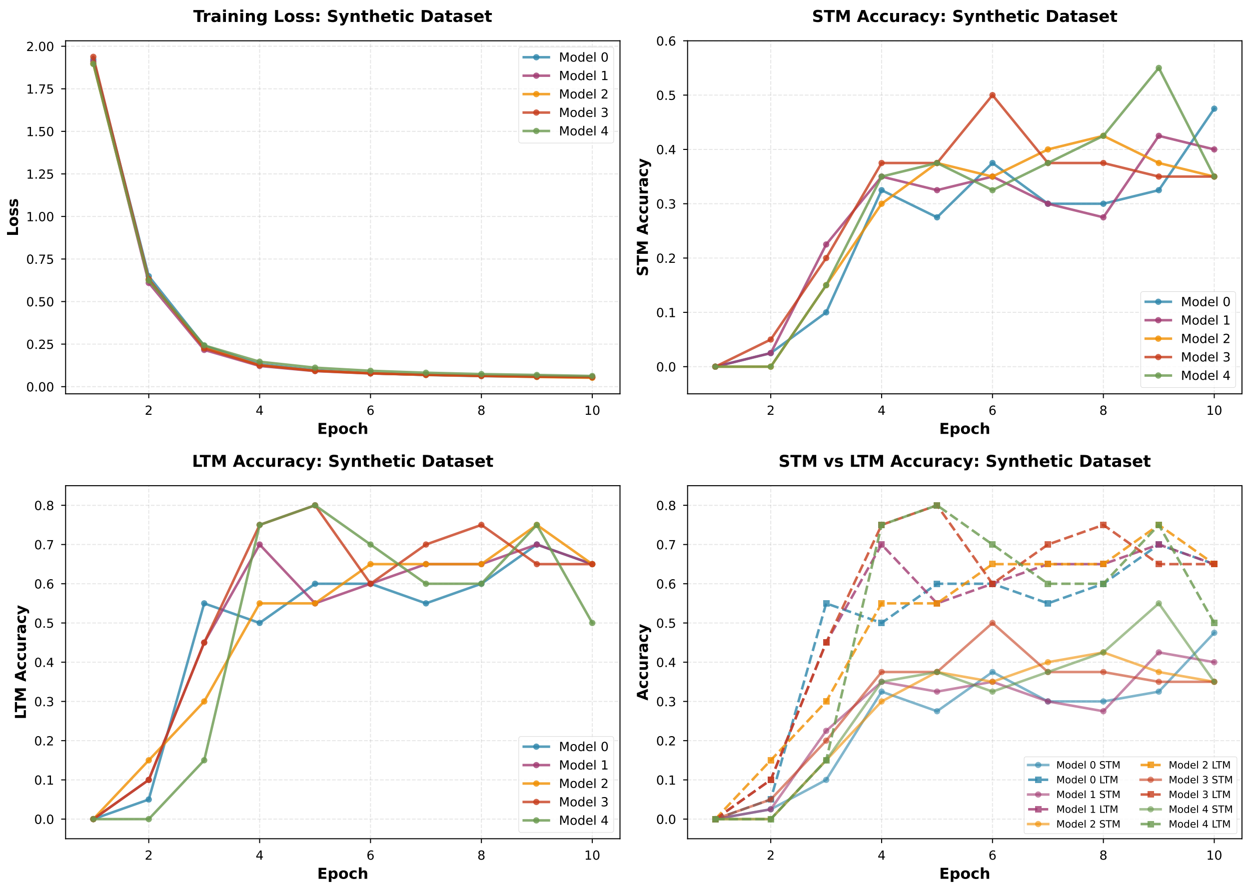

Figure 3. Training progress over epochs for synthetic dataset.

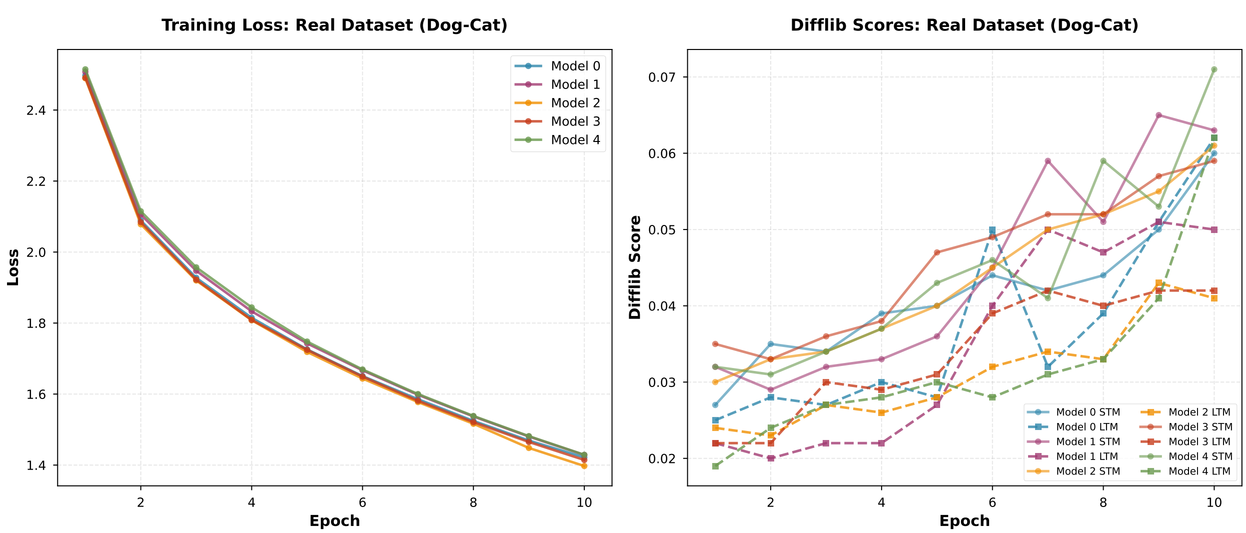

Figure 4. Training progress over epochs for real dataset.

A. Terminal Output

The epoch summaries for all models on both datasets are provided below. Note that only epoch summaries are included (debug examples omitted for brevity).

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Synthetic Data - SkillMiner
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0 base model
----------------------------------------
Epoch 1
Loss: 1.9220
STM     acc=0.000, LLM=0.000, difflib=0.013
LTM     acc=0.000, LLM=0.000, difflib=0.011

Epoch 2
Loss: 0.6491
STM     acc=0.025, LLM=0.123, difflib=0.059
LTM     acc=0.050, LLM=0.090, difflib=0.042

Epoch 3
Loss: 0.2400
STM     acc=0.100, LLM=0.353, difflib=0.165
LTM     acc=0.550, LLM=0.415, difflib=0.113

Epoch 4
Loss: 0.1319
STM     acc=0.325, LLM=0.485, difflib=0.174
LTM     acc=0.500, LLM=0.460, difflib=0.175

Epoch 5
Loss: 0.0974
STM     acc=0.275, LLM=0.470, difflib=0.121
LTM     acc=0.600, LLM=0.490, difflib=0.170

Epoch 6
Loss: 0.0789
STM     acc=0.375, LLM=0.520, difflib=0.153
LTM     acc=0.600, LLM=0.465, difflib=0.187

Epoch 7
Loss: 0.0687
STM     acc=0.300, LLM=0.485, difflib=0.199
LTM     acc=0.550, LLM=0.445, difflib=0.155

Epoch 8
Loss: 0.0621
STM     acc=0.300, LLM=0.490, difflib=0.149
LTM     acc=0.600, LLM=0.480, difflib=0.154

Epoch 9
Loss: 0.0578
STM     acc=0.325, LLM=0.493, difflib=0.184
LTM     acc=0.700, LLM=0.480, difflib=0.224

Epoch 10
Loss: 0.0541
STM     acc=0.475, LLM=0.570, difflib=0.202
LTM     acc=0.650, LLM=0.495, difflib=0.200

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1 summarization_only
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Epoch 1
Loss: 1.9097
STM     acc=0.000, LLM=0.000, difflib=0.016
LTM     acc=0.000, LLM=0.000, difflib=0.011

Epoch 2
Loss: 0.6097
STM     acc=0.025, LLM=0.172, difflib=0.079
LTM     acc=0.100, LLM=0.180, difflib=0.081

Epoch 3
Loss: 0.2160
STM     acc=0.225, LLM=0.382, difflib=0.089
LTM     acc=0.450, LLM=0.385, difflib=0.089

Epoch 4
Loss: 0.1216
STM     acc=0.350, LLM=0.470, difflib=0.131
LTM     acc=0.700, LLM=0.490, difflib=0.185

Epoch 5
Loss: 0.0916
STM     acc=0.325, LLM=0.468, difflib=0.110
LTM     acc=0.550, LLM=0.445, difflib=0.197

Epoch 6
Loss: 0.0777
STM     acc=0.350, LLM=0.490, difflib=0.132
LTM     acc=0.600, LLM=0.480, difflib=0.186

Epoch 7
Loss: 0.0694
STM     acc=0.300, LLM=0.483, difflib=0.151
LTM     acc=0.650, LLM=0.500, difflib=0.197

Epoch 8
Loss: 0.0639
STM     acc=0.275, LLM=0.480, difflib=0.191
LTM     acc=0.650, LLM=0.495, difflib=0.216

Epoch 9
Loss: 0.0609
STM     acc=0.425, LLM=0.525, difflib=0.124
LTM     acc=0.700, LLM=0.515, difflib=0.193

Epoch 10
Loss: 0.0571
STM     acc=0.400, LLM=0.505, difflib=0.180
LTM     acc=0.650, LLM=0.510, difflib=0.211

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2 sum_token_limit
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Epoch 1
Loss: 1.8975
STM     acc=0.000, LLM=0.000, difflib=0.014
LTM     acc=0.000, LLM=0.000, difflib=0.013

Epoch 2
Loss: 0.6290
STM     acc=0.000, LLM=0.158, difflib=0.074
LTM     acc=0.150, LLM=0.145, difflib=0.070

Epoch 3
Loss: 0.2290
STM     acc=0.150, LLM=0.330, difflib=0.099
LTM     acc=0.300, LLM=0.350, difflib=0.100

Epoch 4
Loss: 0.1266
STM     acc=0.300, LLM=0.480, difflib=0.196
LTM     acc=0.550, LLM=0.475, difflib=0.178

Epoch 5
Loss: 0.0939
STM     acc=0.375, LLM=0.482, difflib=0.165
LTM     acc=0.550, LLM=0.500, difflib=0.146

Epoch 6
Loss: 0.0788
STM     acc=0.350, LLM=0.480, difflib=0.181
LTM     acc=0.650, LLM=0.500, difflib=0.152

Epoch 7
Loss: 0.0692
STM     acc=0.400, LLM=0.527, difflib=0.216
LTM     acc=0.650, LLM=0.495, difflib=0.228

Epoch 8
Loss: 0.0632
STM     acc=0.425, LLM=0.518, difflib=0.198
LTM     acc=0.650, LLM=0.475, difflib=0.263

Epoch 9
Loss: 0.0571
STM     acc=0.375, LLM=0.517, difflib=0.164
LTM     acc=0.750, LLM=0.555, difflib=0.205

Epoch 10
Loss: 0.0522
STM     acc=0.350, LLM=0.505, difflib=0.221
LTM     acc=0.650, LLM=0.515, difflib=0.236

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3 sum_tok_ner
----------------------------------------

Epoch 1
Loss: 1.9378
STM     acc=0.000, LLM=0.000, difflib=0.010
LTM     acc=0.000, LLM=0.000, difflib=0.008

Epoch 2
Loss: 0.6317
STM     acc=0.050, LLM=0.160, difflib=0.068
LTM     acc=0.100, LLM=0.105, difflib=0.062

Epoch 3
Loss: 0.2249
STM     acc=0.200, LLM=0.378, difflib=0.115
LTM     acc=0.450, LLM=0.405, difflib=0.152

Epoch 4
Loss: 0.1254
STM     acc=0.375, LLM=0.505, difflib=0.143
LTM     acc=0.750, LLM=0.495, difflib=0.102

Epoch 5
Loss: 0.0930
STM     acc=0.375, LLM=0.500, difflib=0.140
LTM     acc=0.800, LLM=0.505, difflib=0.106

Epoch 6
Loss: 0.0781
STM     acc=0.500, LLM=0.532, difflib=0.153
LTM     acc=0.600, LLM=0.475, difflib=0.115

Epoch 7
Loss: 0.0699
STM     acc=0.375, LLM=0.517, difflib=0.188
LTM     acc=0.700, LLM=0.490, difflib=0.139

Epoch 8
Loss: 0.0634
STM     acc=0.375, LLM=0.500, difflib=0.192
LTM     acc=0.750, LLM=0.535, difflib=0.185

Epoch 9
Loss: 0.0588
STM     acc=0.350, LLM=0.500, difflib=0.179
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LTM     acc=0.650, LLM=0.500, difflib=0.171

Epoch 10
Loss: 0.0558
STM     acc=0.350, LLM=0.522, difflib=0.177
LTM     acc=0.650, LLM=0.510, difflib=0.192

----------------------------------------
4 full_memory
----------------------------------------

Epoch 1
Loss: 1.8962
STM     acc=0.000, LLM=0.000, difflib=0.005
LTM     acc=0.000, LLM=0.000, difflib=0.003

Epoch 2
Loss: 0.6234
STM     acc=0.000, LLM=0.060, difflib=0.051
LTM     acc=0.000, LLM=0.070, difflib=0.055

Epoch 3
Loss: 0.2426
STM     acc=0.150, LLM=0.330, difflib=0.077
LTM     acc=0.150, LLM=0.250, difflib=0.089

Epoch 4
Loss: 0.1466
STM     acc=0.350, LLM=0.465, difflib=0.154
LTM     acc=0.750, LLM=0.510, difflib=0.073

Epoch 5
Loss: 0.1116
STM     acc=0.375, LLM=0.512, difflib=0.113
LTM     acc=0.800, LLM=0.535, difflib=0.110

Epoch 6
Loss: 0.0933
STM     acc=0.325, LLM=0.508, difflib=0.110
LTM     acc=0.700, LLM=0.495, difflib=0.130

Epoch 7
Loss: 0.0818
STM     acc=0.375, LLM=0.500, difflib=0.098
LTM     acc=0.600, LLM=0.485, difflib=0.097

Epoch 8
Loss: 0.0740
STM     acc=0.425, LLM=0.515, difflib=0.096
LTM     acc=0.600, LLM=0.500, difflib=0.165

Epoch 9
Loss: 0.0687
STM     acc=0.550, LLM=0.512, difflib=0.056
LTM     acc=0.750, LLM=0.505, difflib=0.112

Epoch 10
Loss: 0.0627
STM     acc=0.350, LLM=0.487, difflib=0.086
LTM     acc=0.500, LLM=0.470, difflib=0.133

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Real Data - Dog cat(kaggle)
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0 base
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Epoch 1
Loss: 2.4974
STM     acc=0.000, LLM=0.000, difflib=0.027
LTM     acc=0.000, LLM=0.000, difflib=0.025

Epoch 2
Loss: 2.0891
STM     acc=0.000, LLM=0.000, difflib=0.035
LTM     acc=0.000, LLM=0.000, difflib=0.028

Epoch 3
Loss: 1.9274
STM     acc=0.000, LLM=0.000, difflib=0.034
LTM     acc=0.000, LLM=0.000, difflib=0.027

Epoch 4
Loss: 1.8149
STM     acc=0.000, LLM=0.000, difflib=0.039
LTM     acc=0.000, LLM=0.000, difflib=0.030

Epoch 5
Loss: 1.7257
STM     acc=0.000, LLM=0.000, difflib=0.040
LTM     acc=0.000, LLM=0.000, difflib=0.028

Epoch 6
Loss: 1.6507
STM     acc=0.000, LLM=0.000, difflib=0.044
LTM     acc=0.000, LLM=0.000, difflib=0.050

Epoch 7
Loss: 1.5855
STM     acc=0.000, LLM=0.000, difflib=0.042
LTM     acc=0.000, LLM=0.000, difflib=0.032

Epoch 8
Loss: 1.5244
STM     acc=0.000, LLM=0.000, difflib=0.044
LTM     acc=0.000, LLM=0.000, difflib=0.039


Epoch 9
Loss: 1.4691
STM     acc=0.000, LLM=0.000, difflib=0.050
LTM     acc=0.000, LLM=0.000, difflib=0.051

Epoch 10
Loss: 1.4217
STM     acc=0.000, LLM=0.000, difflib=0.060
LTM     acc=0.000, LLM=0.000, difflib=0.062

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1 summarization_only
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Epoch 1
Loss: 2.5077
STM     acc=0.000, LLM=0.000, difflib=0.032
LTM     acc=0.000, LLM=0.000, difflib=0.022

Epoch 2
Loss: 2.1059
STM     acc=0.000, LLM=0.000, difflib=0.029
LTM     acc=0.000, LLM=0.000, difflib=0.020

Epoch 3
Loss: 1.9473
STM     acc=0.000, LLM=0.000, difflib=0.032
LTM     acc=0.000, LLM=0.000, difflib=0.022

Epoch 4
Loss: 1.8331
STM     acc=0.000, LLM=0.000, difflib=0.033
LTM     acc=0.000, LLM=0.000, difflib=0.022

Epoch 5
Loss: 1.7427
STM     acc=0.000, LLM=0.000, difflib=0.036
LTM     acc=0.000, LLM=0.000, difflib=0.027

Epoch 6
Loss: 1.6668
STM     acc=0.000, LLM=0.000, difflib=0.045
LTM     acc=0.000, LLM=0.000, difflib=0.040

Epoch 7
Loss: 1.5980
STM     acc=0.000, LLM=0.000, difflib=0.059
LTM     acc=0.000, LLM=0.000, difflib=0.050

Epoch 8
Loss: 1.5370
STM     acc=0.000, LLM=0.000, difflib=0.051
LTM     acc=0.000, LLM=0.000, difflib=0.047

Epoch 9
Loss: 1.4804
STM     acc=0.000, LLM=0.000, difflib=0.065
LTM     acc=0.000, LLM=0.000, difflib=0.051

Epoch 10
Loss: 1.4286
STM     acc=0.000, LLM=0.000, difflib=0.063
LTM     acc=0.000, LLM=0.000, difflib=0.050

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2 sum_token_limit
----------------------------------------

Epoch 1
Loss: 2.4895
STM     acc=0.000, LLM=0.000, difflib=0.030
LTM     acc=0.000, LLM=0.000, difflib=0.024

Epoch 2
Loss: 2.0783
STM     acc=0.000, LLM=0.000, difflib=0.033
LTM     acc=0.000, LLM=0.000, difflib=0.023

Epoch 3
Loss: 1.9200
STM     acc=0.000, LLM=0.000, difflib=0.034
LTM     acc=0.000, LLM=0.000, difflib=0.027

Epoch 4
Loss: 1.8080
STM     acc=0.000, LLM=0.000, difflib=0.037
LTM     acc=0.000, LLM=0.000, difflib=0.026

Epoch 5
Loss: 1.7187
STM     acc=0.000, LLM=0.000, difflib=0.040
LTM     acc=0.000, LLM=0.000, difflib=0.028

Epoch 6
Loss: 1.6437
STM     acc=0.000, LLM=0.000, difflib=0.045
LTM     acc=0.000, LLM=0.000, difflib=0.032

Epoch 7
Loss: 1.5775
STM     acc=0.000, LLM=0.000, difflib=0.050
LTM     acc=0.000, LLM=0.000, difflib=0.034

Epoch 8
Loss: 1.5164
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```
STM     acc=0.000, LLM=0.000, difflib=0.052
LTM     acc=0.000, LLM=0.000, difflib=0.033

Epoch 9
Loss: 1.4483
STM     acc=0.000, LLM=0.000, difflib=0.055
LTM     acc=0.000, LLM=0.000, difflib=0.043

Epoch 10
Loss: 1.3974
STM     acc=0.000, LLM=0.000, difflib=0.061
LTM     acc=0.000, LLM=0.000, difflib=0.041

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3 sum_tok_ner
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Epoch 1
Loss: 2.4910
STM     acc=0.000, LLM=0.000, difflib=0.035
LTM     acc=0.000, LLM=0.000, difflib=0.022

Epoch 2
Loss: 2.0844
STM     acc=0.000, LLM=0.000, difflib=0.033
LTM     acc=0.000, LLM=0.000, difflib=0.022

Epoch 3
Loss: 1.9222
STM     acc=0.000, LLM=0.000, difflib=0.036
LTM     acc=0.000, LLM=0.000, difflib=0.030

Epoch 4
Loss: 1.8090
STM     acc=0.000, LLM=0.000, difflib=0.038
LTM     acc=0.000, LLM=0.000, difflib=0.029

Epoch 5
Loss: 1.7245
STM     acc=0.000, LLM=0.000, difflib=0.047
LTM     acc=0.000, LLM=0.000, difflib=0.031

Epoch 6
Loss: 1.6492
STM     acc=0.000, LLM=0.000, difflib=0.049
LTM     acc=0.000, LLM=0.000, difflib=0.039

Epoch 7
Loss: 1.5811
STM     acc=0.000, LLM=0.000, difflib=0.052
LTM     acc=0.000, LLM=0.000, difflib=0.042

Epoch 8
Loss: 1.5209
STM     acc=0.000, LLM=0.000, difflib=0.052
LTM     acc=0.000, LLM=0.000, difflib=0.040

Epoch 9
Loss: 1.4651
STM     acc=0.000, LLM=0.000, difflib=0.057
LTM     acc=0.000, LLM=0.000, difflib=0.042

Epoch 10
Loss: 1.4145
STM     acc=0.000, LLM=0.000, difflib=0.059
LTM     acc=0.000, LLM=0.000, difflib=0.042

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4 full_memory
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Epoch 1
Loss: 2.5147
STM     acc=0.000, LLM=0.000, difflib=0.032
LTM     acc=0.000, LLM=0.000, difflib=0.019

Epoch 2
Loss: 2.1149
STM     acc=0.000, LLM=0.000, difflib=0.031
LTM     acc=0.000, LLM=0.000, difflib=0.024

Epoch 3
Loss: 1.9569
STM     acc=0.000, LLM=0.000, difflib=0.034
LTM     acc=0.000, LLM=0.000, difflib=0.027

Epoch 4
Loss: 1.8441
STM     acc=0.000, LLM=0.000, difflib=0.037
LTM     acc=0.000, LLM=0.000, difflib=0.028

Epoch 5
Loss: 1.7479
STM     acc=0.000, LLM=0.000, difflib=0.043
LTM     acc=0.000, LLM=0.000, difflib=0.030

Epoch 6
Loss: 1.6693
STM     acc=0.000, LLM=0.000, difflib=0.046
LTM     acc=0.000, LLM=0.000, difflib=0.028

Epoch 7
Loss: 1.6001
STM     acc=0.000, LLM=0.000, difflib=0.041
LTM     acc=0.000, LLM=0.000, difflib=0.031

Epoch 8
Loss: 1.5384
STM     acc=0.000, LLM=0.000, difflib=0.059
LTM     acc=0.000, LLM=0.000, difflib=0.033

Epoch 9
Loss: 1.4816
STM     acc=0.000, LLM=0.000, difflib=0.053
LTM     acc=0.000, LLM=0.000, difflib=0.041

Epoch 10
Loss: 1.4289
STM     acc=0.000, LLM=0.000, difflib=0.071
LTM     acc=0.000, LLM=0.000, difflib=0.062
```