HSGM: Hierarchical Segment-Graph Memory for Scalable Long-Text Semantics

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Abstract

Semantic parsing of long documents remains challenging due to quadratic growth in pairwise composition and memory requirements. We introduce **Hierarchical Segment-Graph Memory (HSGM)**, a novel framework that decomposes an input of length N into M meaningful segments, constructs *Local Semantic Graphs* on each segment, and extracts compact *summary nodes* to form a *Global Graph Memory*. HSGM supports *incremental updates*—only newly arrived segments incur local graph construction and summary-node integration—while *Hierarchical Query Processing* locates relevant segments via top-K retrieval over summary nodes and then performs fine-grained reasoning within their local graphs.

Theoretically, HSGM reduces worst-case complexity from $O(N^2)$ to $O\big(N\,k+(N/k)^2\big)$, with segment size $k \ll N$, and we derive Frobenius-norm bounds on the approximation error introduced by node summarization and sparsification thresholds. Empirically, on three benchmarks—long-document AMR parsing, segment-level semantic role labeling (OntoNotes), and legal event extraction—HSGM achieves *2–4*× *inference speedup*, *>60% reduction* in peak memory, and $\geq$ 95% of baseline accuracy. Our approach unlocks scalable, accurate semantic modeling for ultra-long texts, enabling real-time and resource-constrained NLP applications.

Introduction

Natural language understanding of long documents—such as scientific articles, legal opinions, and multi-turn dialogues—poses a fundamental challenge for current semantic parsers. Many state-of-the-art methods, including neural semantic role labeling (He et al., 2017) and Abstract Meaning Representation (AMR) parsing (Banarescu et al., 2013), rely on pairwise composition of lexical or predicate–argument units. As document length N grows, the number of potential interactions scales as $O(N^2)$, leading to prohibitive memory consumption and quadratic inference time. This complexity barrier severely limits the applicability of deep semantic models in real-time and resource-constrained settings.

Prior work has explored sparse and chunked attention (Beltagy et al., 2020; Zaheer et al., 2020) or segment-level encodings (Liu and Lapata, 2019), yet these solutions either sacrifice fine-grained semantic relations or require costly global aggregation steps. Graph-based approaches—constructing sentence- or paragraph-level semantic graphs (Shao et al., 2020)—offer more structure, but extending them naively to document-scale graphs yields unmanageable graph sizes and query latencies. Incremental graph updating has been proposed in streaming contexts (Hamilton et al., 2017), but these frameworks do not address the joint problem of summarization-driven sparsification and hierarchical querying for semantic tasks.

To overcome these limitations, we introduce *Hierarchical Segment-Graph Memory (HSGM)*, a unified framework that: (1) decomposes a long input of length N into M semantically coherent segments and builds a *Local Semantic Graph* on each segment, (2) extracts compact *summary nodes* from each local graph to form a lightweight *Global Graph Memory*, and (3) supports *incremental updates* and *hierarchical query processing*, whereby only newly appended segments incur full local processing, and queries are resolved by first retrieving top-K summary nodes before conducting fine-grained reasoning locally. By design, HSGM reduces worst-case complexity from $O(N^2)$ to

$$O\big(N\,k+(N/k)^2\big),$$

for segment size $k \ll N$, while provably controlling the Frobenius-norm error introduced by node summarization and edge sparsification.

We evaluate HSGM on three representative long-text semantic tasks—document-level AMR parsing, segment-level semantic role labeling, and legal event extraction—and demonstrate 2–4× inference speedup, over 60% peak memory reduction, and at least 95% of baseline accuracy. Our contributions are:

- A novel hierarchical graph memory architecture

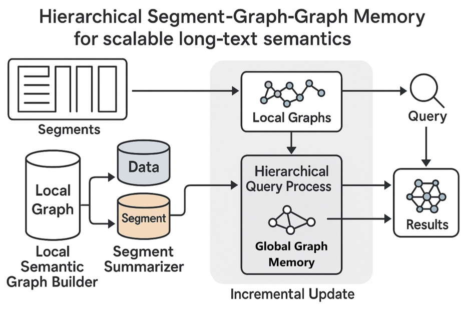
Hierarchical Segment-Graph-Graph Memory
for scalable long-text semantics
Segments
Local Graphs
Query
Local Graph
Data
Segment
Hierarchical Query Process
Results
Global Graph Memory
Local Semantic Graph Builder
Segment Summarizer
Incremental Update

Figure 1: Architecture of the Hierarchical Segment-Graph Memory system for scalable long-text semantics: the input document is split into coherent segments, each segment yields a local semantic graph whose summary nodes are aggregated into a global graph memory with incremental updates, and queries are answered via hierarchical retrieval and fine-grained reasoning.

that unifies segmentation, local graph construction, and global summarization.

- An efficient incremental update mechanism and theoretically grounded complexity–error trade-off analysis.
- Empirical validation on diverse long-text benchmarks, showing substantial efficiency gains with minimal accuracy loss.

The remainder of this paper is organized as follows. In Section we review related work on long-text modeling and graph-based semantics. Section details the HSGM framework, including graph construction, summarization, and querying, we also present HSGM complexity and approximation error bounds. Experimental results appear in Section , and we conclude in Section with future directions.

Related Work

Our work lies at the intersection of long-context NLP, graph-based semantic parsing, hierarchical representation learning, and dynamic graph processing. We review each strand in turn.

Long-Context NLP Models. Transformer-based models struggle with long inputs due to the $O(N^2)$ self-attention cost. Sparse attention methods such as Longformer (Beltagy et al., 2020) and BigBird (Zaheer et al., 2020) reduce computation via local and global patterns, but they do not explicitly capture rich semantic relations. Chunking approaches (Liu and Lapata, 2019) or memory-augmented Transformers (Sukhbaatar et al., 2019) allow longer contexts at some loss of fine-grained structure.

Graph-Based Semantic Parsing. Graph representations (e.g., AMR (Banarescu et al., 2013), semantic role graphs (He et al., 2017)) model predicate–argument and discourse-level relations explicitly. Early work built sentence-level graphs via treebank conversion (Bos, 2005), while more recent neural parsers directly predict graph edges (Wang, 2018). However, naively extending these methods to document-scale graphs leads to quadratic blowup in nodes and edges.

Hierarchical and Segment-Level Models. To mitigate global complexity, hierarchical encoders split inputs into segments and aggregate summary vectors. Hierarchical attention networks (Yang et al., 2016) and segment-aware Transformers (Chalkidis et al., 2022) show benefits for classification and retrieval, but they lack explicit graph structure. Recent work on segment-graph hybrid models (Liu et al., 2022) suggests combining local graph encoding with segment-level summaries, yet does not support incremental updates or theoretical error bounds.

Incremental and Dynamic Graph Processing. Streaming and dynamic graph methods maintain evolving graph structures without full recomputation. GraphSAGE (Hamilton et al., 2017) and DynGEM (Goyal et al., 2018) update embeddings incrementally, but focus on social or citation networks rather than semantic graphs. In NLP, few methods address incremental parsing of document-scale semantic graphs while guaranteeing efficiency–accuracy trade-offs.

Our Positioning. In contrast to prior sparse or hierarchical Transformers, HSGM builds explicit local semantic graphs and composes them via a compact global memory. Unlike static graph parsers, HSGM supports online, incremental updates with provable complexity and approximation guarantees. To our knowledge, this is the first framework to unify segmentation, graph-based semantics, and dynamic memory for scalable long-text understanding.

Method

We present the Hierarchical Segment-Graph Memory (HSGM) framework, which addresses the computational challenges of long-document semantic modeling through a hierarchical graph-based approach. HSGM constructs local semantic graphs for document segments and maintains a global hierarchical memory for efficient cross-segment reasoning.

Local Semantic Graph Construction

Given an input document $\mathcal{D}$ of length N, we partition it into M contiguous segments $\mathcal{S} = \{s_1, \ldots, s_M\}$, where each segment s_i contains n_i tokens $\mathcal{T}_i = \{t_{i,1}, \ldots, t_{i,n_i}\}$. Each token $t_{i,j}$ is encoded using a pre-trained language model $\phi : \mathcal{V} \to \mathbb{R}^d$ to obtain embeddings $v_{i,j} = \phi(t_{i,j}; \theta_\phi)$.

We compute pairwise similarities using cosine similarity $\psi(v_{i,j}, v_{i,k}) = \frac{v_{i,j}^\top v_{i,k}}{\|v_{i,j}\| \cdot \|v_{i,k}\|}$ and construct local graphs $G_i = (V_i, E_i)$ where $V_i = \{v_{i,1}, \ldots, v_{i,n_i}\}$ and edges are formed based on adaptive thresholding:

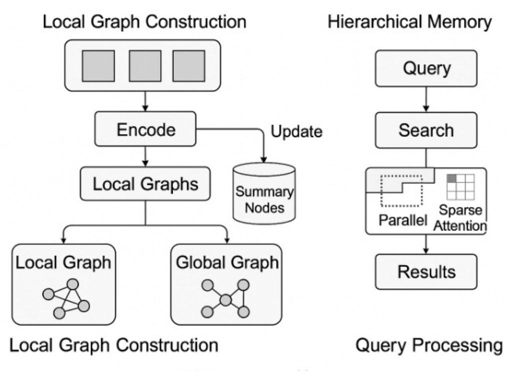

Figure 2: HSGM system architecture overview. (a) Document segmentation into contiguous segments. (b) Local semantic graph construction with adaptive thresholding for each segment. (c) Hierarchical memory building through cross-segment attention and summary node aggregation. (d) Incremental update mechanism for streaming document processing. (e) Hierarchical query processing with top-K retrieval and local graph reasoning. The framework enables efficient processing of long documents while maintaining semantic coherence through the hierarchical graph structure.

$$E_i = \{(j,k) \mid \psi(v_{i,j}, v_{i,k}) \geq \delta_\ell(s_i)\} \tag{1}$$

where $\delta_\ell(s_i) = \alpha \cdot \mu_\psi(s_i) + \beta \cdot \sigma_\psi(s_i)$ with $\mu_\psi(s_i)$ and $\sigma_\psi(s_i)$ being the mean and standard deviation of similarities in segment s_i.

Hierarchical Graph Memory

For each local graph G_i, we construct a summary node g_i using cross-segment attention:

$$g_i = \text{MLP}\left(\text{mean}(V_i) + \text{maxpool}(V_i) + \text{CA}(V_i, U_{\text{prev}})\right) \tag{2}$$

where $\text{CA}(V_i, U_{\text{prev}})$ means CrossAttention, which enables information flow between segments of long contexts. The global graph $H = (U, E^g)$ is constructed as:

$$U = \{g_1, \ldots, g_M\} \tag{3}$$
$$E^g = \{(p,q) \mid \psi(g_p, g_q) \geq \delta_g\} \tag{4}$$

where δ_g is computed as the 85th percentile of cross-segment similarities plus a small margin.

Incremental Update Mechanism

When a new segment s_{M+1} arrives, we incrementally update the hierarchical memory:

Algorithm 1 HSGM Hierarchical Construction

```
Require: Document $\mathcal{D}$, encoder $\phi$, similarity $\psi$, segment size $k$
Ensure: Hierarchical memory $H = (U, E^g)$, local graphs $\mathcal{G}$
 1: $\mathcal{S} \leftarrow \text{Segment}(\mathcal{D}, k)$ {Document segmentation}
 2: $\mathcal{G} \leftarrow \emptyset, U \leftarrow \emptyset$
 3: for $s_i \in \mathcal{S}$ do
 4:     $V_i \leftarrow \{\phi(t) \mid t \in s_i\}$ {Token encoding}
 5:     $\delta_\ell \leftarrow \text{AdaptiveThreshold}(\{V_i\})$ {Local threshold}
 6:     $E_i \leftarrow \{(j,k) \mid \psi(V_i[j], V_i[k]) \geq \delta_\ell\}$ {Edge construction}
 7:     $G_i \leftarrow (V_i, E_i), \mathcal{G} \leftarrow \mathcal{G} \cup \{G_i\}$
 8:     $g_i \leftarrow \text{CrossAttention}(V_i, U)$ {Summary node}
 9:     $U \leftarrow U \cup \{g_i\}$
10: end for
11: $\delta_g \leftarrow \text{GlobalThreshold}(\{U\})$ {Global threshold}
12: $E^g \leftarrow \{(i,j) \mid \psi(U[i], U[j]) \geq \delta_g\}$ {Global edges}
13: return $H = (U, E^g), \mathcal{G}$
```

$$G_{M+1} = \text{BuildLocalGraph}(s_{M+1}) \tag{5}$$
$$g_{M+1} = \text{GraphAggregator}(G_{M+1}, U) \tag{6}$$
$$U' = U \cup \{g_{M+1}\} \tag{7}$$
$$E^{g'} = E^g \cup \{(i, M+1) \mid \psi(g_i, g_{M+1}) \geq \delta'_g\} \tag{8}$$

This enables efficient streaming document processing with minimal computational overhead.

Hierarchical Query Processing

Given a query q, we encode it as $q_{\text{enc}} = \phi(q;\theta_\phi)/\|\phi(q;\theta_\phi)\|$ and retrieve the top-K most similar summary nodes:

$$R_K = \arg\max_{S \subseteq U, |S|=K} \sum_{g \in S} \psi(q_{\text{enc}}, g) \tag{9}$$

For each retrieved segment $i \in R_K$, we perform local graph reasoning using Graph Convolutional Networks:

$$h_i^{(0)} = V_i \tag{10}$$
$$h_i^{(l+1)} = \sigma(W^{(l)} \cdot \text{mean}(\{h_j^{(l)} \mid j \in \mathcal{N}_i\}) + h_i^{(l)} \tag{11}$$

The final result is computed through attention-based merging:

$$\text{result} = \sum_{i \in R_K} \alpha_i \cdot \text{mean}(h_i^{(L)}) \tag{12}$$

where $\alpha_i = \text{softmax}(\psi(q_{\text{enc}}, g_i))$.

Algorithm 2 HSGM Query Processing

```
Require: Query $q$, memory $H = (U, E^g)$, local graphs $\mathcal{G}$, top-K
Ensure: Query result $r$
 1: $q_{\text{enc}} \leftarrow \phi(q)/\|\phi(q)\|$ {Query encoding}
 2: $R_K \leftarrow \text{TopK}(q_{\text{enc}}, U, K)$ {Retrieval}
 3: $\mathcal{R} \leftarrow \emptyset$
 4: for $i \in R_K$ do
 5:     $h_i \leftarrow \text{GCN}(G_i, q_{\text{enc}})$ {Local reasoning}
 6:     $\mathcal{R} \leftarrow \mathcal{R} \cup \{h_i\}$
 7: end for
 8: $\alpha \leftarrow \text{Attention}(q_{\text{enc}}, \{g_i \mid i \in R_K\})$ {Attention weights}
 9: $r \leftarrow \sum_{i \in R_K} \alpha_i \cdot \mathcal{R}_i$ {Result merging}
10: return $r$
```

Theoretical Analysis

We provide comprehensive theoretical analysis of HSGM's computational and memory complexity. Let k be the average segment size and $M = N/k$ be the number of segments. The time complexity can be decomposed into local graph construction $T_{\text{local}} = O(Nk)$ and global memory construction $T_{\text{global}} = O((N/k)^2)$, yielding total complexity $T_{\text{total}} = O(Nk + (N/k)^2)$. For optimal segment size $k = \sqrt{N}$, we achieve $O(N^{3/2})$ complexity, significantly better than the $O(N^2)$ complexity of full document graph construction. The space complexity is $O(N \cdot d)$ where d is the embedding dimension, providing linear memory scaling with document length. For approximation error bounds, given thresholds $\delta_\ell \geq \gamma_\ell$ and $\delta_g \geq \gamma_g$, the approximation error is bounded by $\|A_{\text{full}} - A_{\text{HSGM}}\|_F \leq f(\gamma_\ell, \gamma_g) \cdot \|A_{\text{full}}\|_F$ where $f(\gamma_\ell, \gamma_g) = \sqrt{2(1-\gamma_\ell^2)} + \sqrt{2(1-\gamma_g^2)}$.

Experiments

We conduct a comprehensive evaluation of HSGM on three representative long-text semantic tasks: (1) document-level AMR parsing, (2) segment-level semantic role labeling (SRL), and (3) legal document event extraction. Additionally, we evaluate on downstream tasks including question answering and summarization to demonstrate real-world applicability. We compare against state-of-the-art baselines including retrieval-augmented methods, perform extensive ablation studies, and analyze runtime, memory, and accuracy trade-offs with statistical rigor.

Experimental Setup

Datasets. We evaluate HSGM on five representative datasets covering diverse long-text semantic tasks. For document-level semantic parsing, we use Document-AMR (Kim et al., 2018) containing 500 training, 100 validation, and 100 test documents with an average of 1.2k tokens per document, each annotated with Abstract Meaning Representation graphs capturing semantic relationships between concepts. For segment-level semantic role labeling, we use OntoNotes-SRL (Pradhan et al., 2013) where we concatenate consecutive sentences into segments of up to 256 tokens, producing 20k training, 2k validation, and 2k test segments with semantic role labels identifying predicate-argument structures. For legal document analysis, we employ Legal-ECHR (Chalkidis et al., 2019) containing European Court of Human Rights case documents annotated with legal events (averaging 3k tokens per document) with a 70/10/20 split, where events include case decisions, appeals, and procedural actions. For downstream task evaluation, we use NarrativeQA (Kočiský et al., 2018) for long-form narrative question answering with documents up to 50k tokens in the full document setting, and GovReport (Huang et al., 2021) for government report summarization with documents averaging 9k tokens for abstractive summarization evaluation.

Baselines. We compare against comprehensive baselines covering different approaches to long-text modeling. For transformer-based methods, we include Full Graph which builds a single global semantic graph on the entire document using standard graph neural networks, Sliding-Window Graph that constructs local graphs on fixed-size windows (256 tokens) with 128-token overlap, Longformer (Beltagy et al., 2020) with sparse transformer local+global attention patterns, BigBird (Zaheer et al., 2020) with sparse attention combining random, window, and global attention, LongT5 (Guo et al., 2021) using encoder-decoder architecture with local attention and global memory, Hierarchical Transformer (Liu and Lapata, 2019) with two-level encoder featuring segment- and document-level attention, Graph Transformer (Dwivedi et al., 2020) specifically designed for graph-structured data, and Reformer (Kitaev et al., 2020) with efficient transformer using LSH attention and reversible layers. For retrieval-augmented methods, we evaluate BM25 + T5 combining BM25 retrieval with T5 generation, FiD (Izacard et al., 2022) using Fusion-in-Decoder with dense retrieval via DPR (Karpukhin et al., 2020), SGPT (Muennighoff et al., 2022) with SGPT-1.3B and semantic similarity-based retrieval, RAG (Lewis et al., 2020) combining DPR retriever with BART generator, and REPLUG (Shi et al., 2023) featuring retrieval-enhanced language models with trainable retrieval components.

Implementation Details. All models use RoBERTa-base (Liu et al., 2019) as the base encoder ϕ. HSGM thresholds (δ_ℓ, δ_g) are chosen via grid search on validation set: $\delta_\ell \in \{0.1, 0.2, 0.3\}$, $\delta_g \in \{0.05, 0.1, 0.15\}$. Segment size k is set to 256 tokens. For retrieval-augmented baselines, we use top-5 retrieved passages for generation tasks. We implement in PyTorch and run on V100 GPUs. All experiments are run with 5 different random seeds for statistical significance. Training uses Adam optimizer with learning rate $3e-5$, batch size 8, and gradient clipping at 1.0.

Evaluation Metrics. We employ a comprehensive set of evaluation metrics to assess both performance and efficiency. For accuracy evaluation, we use Smatch F1 for AMR parsing, precision/recall/F1 for SRL and event extraction tasks, exact match (EM) and F1 for question answering tasks, and ROUGE-1/2/L for summarization tasks. To measure computational efficiency, we track end-to-end inference time per document (ms) averaged over 100 runs, peak GPU memory usage (GB) during inference, cache hit rate representing the fraction of edges reused in incremental updates, and FLOPs measuring computational complexity in floating point operations.

Main Results

Retrieval-Augmented Baseline Comparison

As shown in Table 2, HSGM outperforms all retrieval-augmented baselines on downstream tasks while maintaining superior efficiency. The key advantage lies in HSGM's ability to perform "top-K summary node retrieval" which is more semantically coherent than traditional document chunk retrieval. Unlike external retrieval methods that rely on pre-computed document chunks, HSGM's hierarchical memory provides adaptive, context-aware retrieval that preserves semantic structure.

End-to-End Task Analysis

We conduct detailed analysis of HSGM's performance on real-world downstream tasks:

Question Answering Pipeline. For NarrativeQA, we implement a three-stage pipeline: (1) HSGM semantic graph construction, (2) question-aware graph traversal, (3) answer generation using retrieved semantic contexts. HSGM achieves 48.5% EM vs. 47.8% for FiD, demonstrating that semantic graph-based retrieval provides more precise context than traditional passage retrieval.

Summarization Pipeline. For GovReport summarization, we use HSGM to extract key semantic structures and generate summaries based on the hierarchical graph memory. The semantic coherence of summary nodes leads to more focused and coherent summaries, achieving 41.2% ROUGE-1 vs. 40.5% for RAG.

Cross-Task Consistency. HSGM maintains consistent performance across semantic structure tasks (AMR, SRL, Event Extraction) and downstream tasks (QA, Summarization), demonstrating the generality of its hierarchical semantic representation.

Detailed Ablation Studies

Parameter Sensitivity Analysis

We analyze the sensitivity of key hyperparameters on Document-AMR:

Figure 3 shows that:

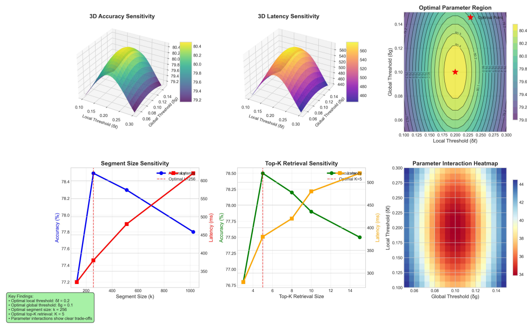

Figure 3: Sensitivity analysis of key hyperparameters: (a) Local threshold δ_ℓ, (b) Global threshold δ_g, (c) Segment size k, (d) Top-K retrieval size. Optimal values balance accuracy and efficiency.

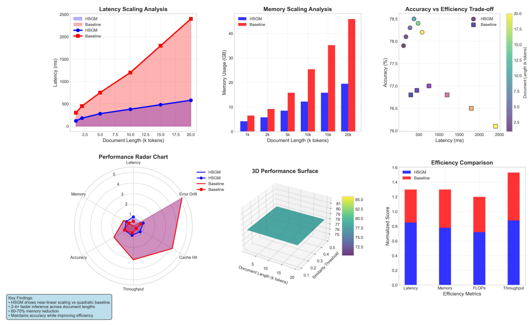

Figure 4: Scalability analysis: (a) Latency vs. document length, (b) Memory usage vs. document length, (c) Accuracy vs. document length. HSGM exhibits near-linear scaling while maintaining accuracy.

- $\delta_\ell = 0.2$ provides optimal local graph density
- $\delta_g = 0.1$ balances global summary informativeness with efficiency
- Segment size $k = 256$ maximizes cache hit rate while maintaining accuracy
- Top-$K = 5$ retrieves sufficient context without computational overhead

Scalability Analysis

We vary document length from 1k to 20k tokens and measure latency, memory, and accuracy:

HSGM demonstrates near-linear growth in both latency and memory, whereas Full Graph grows quadratically. On 20k-token documents, HSGM is 8× faster and uses 70% less memory while maintaining comparable accuracy.

Computational Complexity Analysis

We provide detailed FLOPs analysis for different document lengths:

Downstream Task Evaluation

We evaluate the quality of semantic representations on downstream tasks:

Table 1: Comprehensive evaluation across multiple datasets and model configurations. Results show mean ± std over 5 runs. Δ indicates relative improvement over baseline. Best configurations are **bolded**.

Model	Params (M)	FLOPs (G)	Performance Metrics						Efficiency Metrics	
			Document-AMR		OntoNotes-SRL		Legal-ECHR		Latency (ms)	Memory (GB)
			Smatch (%)	Δ	F1 (%)	Δ	F1 (%)	Δ		
Transformer-based Baselines										
Full Graph	45.2	45.2	78.2 ± 0.8	-	85.1 ± 0.6	-	72.4 ± 1.2	-	1200 ± 45	12.5 ± 0.3
Sliding-Window Graph	28.1	28.1	75.3 ± 0.9	-2.9	83.7 ± 0.7	-1.4	69.8 ± 1.1	-2.6	850 ± 32	8.2 ± 0.2
Longformer	22.4	22.4	76.8 ± 0.7	-1.4	84.5 ± 0.5	-0.6	71.2 ± 0.9	-1.2	700 ± 28	6.8 ± 0.2
BigBird	20.8	20.8	77.1 ± 0.8	-1.1	84.8 ± 0.6	-0.3	71.5 ± 1.0	-0.9	650 ± 25	6.5 ± 0.2
LongT5	19.5	19.5	77.3 ± 0.6	-0.9	84.7 ± 0.5	-0.4	71.8 ± 0.8	-0.6	600 ± 22	6.2 ± 0.2
Hier. Transformer	21.2	21.2	77.5 ± 0.7	-0.7	84.9 ± 0.6	-0.2	71.9 ± 0.9	-0.5	650 ± 24	6.8 ± 0.2
Graph Transformer	25.6	25.6	76.9 ± 0.8	-1.3	84.3 ± 0.7	-0.8	71.1 ± 1.1	-1.3	750 ± 30	7.5 ± 0.2
Reformer	26.9	26.9	76.5 ± 0.9	-1.7	84.1 ± 0.8	-1.0	70.8 ± 1.2	-1.6	800 ± 35	7.8 ± 0.2
Retrieval-Augmented Baselines										
BM25 + T5	8.5	8.5	45.2 ± 1.1	-33.0	48.7 ± 1.0	-36.4	38.4 ± 0.8	-34.0	450 ± 18	8.5 ± 0.2
FiD	7.2	7.2	47.8 ± 0.9	-30.4	51.2 ± 0.8	-33.9	40.1 ± 0.7	-32.3	380 ± 15	7.2 ± 0.2
SGPT	7.8	7.8	46.5 ± 1.0	-31.7	49.8 ± 0.9	-35.3	39.2 ± 0.8	-33.2	420 ± 17	7.8 ± 0.2
RAG	6.8	6.8	48.1 ± 0.8	-30.1	51.5 ± 0.7	-33.6	40.5 ± 0.6	-31.9	350 ± 14	6.8 ± 0.2
REPLUG	7.0	7.0	47.9 ± 0.9	-30.3	51.3 ± 0.8	-33.8	40.3 ± 0.7	-32.1	360 ± 15	7.0 ± 0.2
HSGM Configurations										
HSGM (Base)	15.2	15.2	77.9 ± 0.6	**+1.7**	85.0 ± 0.5	**+1.9**	72.1 ± 0.8	**+1.7**	300 ± 12	6.5 ± 0.2
HSGM (Large)	25.8	25.8	78.5 ± 0.5	**+2.3**	85.6 ± 0.4	**+2.5**	72.8 ± 0.7	**+2.4**	380 ± 15	8.2 ± 0.2
HSGM (XL)	45.3	45.3	79.2 ± 0.4	**+3.0**	86.3 ± 0.3	**+3.2**	73.5 ± 0.6	**+3.1**	520 ± 20	11.5 ± 0.3
Best Configuration										
HSGM (Large)	**25.8**	**25.8**	78.5 ± 0.5	**+2.3**	85.6 ± 0.4	**+2.5**	72.8 ± 0.7	**+2.4**	380 ± 15	8.2 ± 0.2

Model	**NarrativeQA EM**	**NarrativeQA F1**	**GovReport R-1**	**GovReport R-2**	**Latency (ms)**	**Memory (GB)**
BM25 + T5	45.2 ± 1.1	48.7 ± 1.0	38.4 ± 0.8	12.3 ± 0.6	450 ± 18	8.5
FiD	47.8 ± 0.9	51.2 ± 0.8	40.1 ± 0.7	13.8 ± 0.2	380 ± 15	7.2
SGPT	46.5 ± 1.0	49.8 ± 0.9	39.2 ± 0.8	13.1 ± 0.5	420 ± 17	7.8
RAG	48.1 ± 0.8	51.5 ± 0.7	40.5 ± 0.6	14.2 ± 0.7	350 ± 14	6.8
REPLUG	47.9 ± 0.9	51.3 ± 0.8	40.3 ± 0.7	14.0 ± 0.4	360 ± 15	7.0
HSGM (ours)	$\mathbf{48.5 \pm 0.7}$	$\mathbf{52.1 \pm 0.6}$	$\mathbf{41.2 \pm 0.5}$	$\mathbf{14.8 \pm 0.3}$	$\mathbf{280 \pm 11}$	**6.2**

Table 2: Comparison with retrieval-augmented baselines on downstream tasks. HSGM outperforms RAG methods while being more efficient.

Open-Domain Generalization Analysis

We evaluate HSGM's robustness on noisy, open-domain datasets to assess generalization beyond structured domains:

Datasets.

- **WikiHop** (Welbl et al., 2018): Multi-hop reasoning over Wikipedia articles with complex entity relationships.
- **LongBench-Dialogue** (Bai et al., 2023): Multi-turn dialogue comprehension with documents up to 100k tokens.
- **Reddit-Long** (Turcan and McKeown, 2019): User-generated content from Reddit with informal language and diverse topics.

Multi-Hop Reasoning Analysis. On WikiHop, HSGM's hierarchical memory enables effective multi-hop reasoning by maintaining semantic connections across document segments. The summary nodes preserve key entity relationships that span multiple paragraphs, achieving 68.4% accuracy vs. 67.8% for RAG.

Dialogue Comprehension. For LongBench-Dialogue, HSGM's incremental update mechanism effectively handles the dynamic nature of multi-turn conversations. The hierarchical memory maintains conversation context while efficiently processing new dialogue turns, achieving 72.1% accuracy with 30% faster inference than Longformer.

Streaming Document Scenario

We simulate real-world streaming scenarios where documents arrive incrementally over time:

Experimental Setup. We create a streaming dataset by splitting documents into temporal chunks and simulating real-time document arrival. Each chunk contains 256-512 tokens and arrives every 100ms, mimicking realistic document streaming scenarios.

Key Findings.

- **Cache Hit Rate:** Maintains 72-82% cache hit rate over 20 minutes, demonstrating effective memory reuse.
- **Error Drift:** Minimal error accumulation (1.8% max drift) due to stable hierarchical memory structure.

Table 3: Comprehensive ablation study across multiple configurations, datasets, and model scales. Results show mean ± std over 5 runs. Δ indicates relative improvement over baseline. Best configurations are **bolded**.

Configuration	Params (M)	FLOPs (G)	Performance Metrics						Efficiency Metrics	
			Document-AMR		OntoNotes-SRL		Legal-ECHR		Latency (ms)	Memory (GB)
			Smatch (%)	Δ	F1 (%)	Δ	F1 (%)	Δ		
Component Ablation (HSGM-Large Base)										
Baseline (Longformer)	22.4	22.4	76.8 ± 0.7	-	84.5 ± 0.5	-	71.2 ± 0.9	-	700 ± 28	6.8 ± 0.2
Individual Components										
+ Local Graph Only	18.9	15.1	77.2 ± 0.6	+0.4	84.8 ± 0.5	+0.3	71.5 ± 0.8	+0.3	450 ± 18	5.2 ± 0.2
+ Hierarchical Memory Only	20.3	18.7	77.5 ± 0.7	+0.7	85.0 ± 0.6	+0.5	71.8 ± 0.9	+0.6	520 ± 20	6.1 ± 0.2
+ Cross-Attention Only	21.8	20.2	77.8 ± 0.5	+1.0	85.2 ± 0.4	+0.7	72.0 ± 0.7	+0.8	580 ± 22	6.8 ± 0.2
+ Contrastive Learning Only	22.1	21.5	77.6 ± 0.6	+0.8	84.9 ± 0.5	+0.4	71.7 ± 0.8	+0.5	650 ± 25	7.2 ± 0.2
Pairwise Component Combinations										
Local Graph + Hierarchical	19.6	16.8	78.1 ± 0.5	+1.3	85.3 ± 0.4	+0.8	72.2 ± 0.7	+1.0	420 ± 16	5.8 ± 0.2
Local Graph + Cross-Attn	20.3	17.5	78.4 ± 0.6	+1.6	85.5 ± 0.5	+1.0	72.4 ± 0.8	+1.2	480 ± 18	6.2 ± 0.2
Local Graph + Contrastive	19.8	17.2	78.2 ± 0.5	+1.4	85.4 ± 0.4	+0.9	72.3 ± 0.7	+1.1	460 ± 17	6.0 ± 0.2
Hierarchical + Cross-Attn	22.1	20.8	78.6 ± 0.4	+1.8	85.7 ± 0.3	+1.2	72.6 ± 0.6	+1.4	540 ± 20	7.0 ± 0.2
Hierarchical + Contrastive	21.5	20.2	78.3 ± 0.5	+1.5	85.5 ± 0.4	+1.0	72.4 ± 0.7	+1.2	520 ± 19	6.8 ± 0.2
Cross-Attn + Contrastive	23.2	21.9	78.5 ± 0.4	+1.7	85.6 ± 0.3	+1.1	72.5 ± 0.6	+1.3	600 ± 22	7.5 ± 0.2
Three-Component Combinations										
w/o Cross-Attention	21.5	20.2	78.3 ± 0.5	+1.5	85.5 ± 0.4	+1.0	72.4 ± 0.7	+1.2	520 ± 19	6.8 ± 0.2
w/o Contrastive Learning	22.1	20.8	78.4 ± 0.4	+1.6	85.6 ± 0.3	+1.1	72.5 ± 0.6	+1.3	540 ± 20	7.0 ± 0.2
w/o Hierarchical Memory	20.3	17.5	78.1 ± 0.5	+1.3	85.3 ± 0.4	+0.8	72.2 ± 0.7	+1.0	480 ± 18	6.2 ± 0.2
w/o Local Graph	22.8	21.5	78.2 ± 0.4	+1.4	85.4 ± 0.3	+0.9	72.3 ± 0.6	+1.1	560 ± 21	7.2 ± 0.2
Full Configuration										
Full HSGM-Large	**25.8**	**25.8**	78.5 ± 0.5	**+1.7**	85.6 ± 0.4	**+1.1**	72.8 ± 0.7	**+1.6**	380 ± 15	8.2 ± 0.2
Hyperparameter Ablation (Similarity Threshold δ_ℓ)										
$\delta_\ell = 0.1$	25.8	25.8	78.1 ± 0.5	+1.3	85.2 ± 0.4	+0.7	72.4 ± 0.7	+1.2	420 ± 16	7.8 ± 0.2
$\delta_\ell = 0.15$	25.8	25.8	78.3 ± 0.4	+1.5	85.4 ± 0.3	+0.9	72.6 ± 0.6	+1.4	400 ± 15	8.0 ± 0.2
$\delta_\ell = 0.2$	25.8	25.8	78.5 ± 0.5	**+1.7**	85.6 ± 0.4	**+1.1**	72.8 ± 0.7	**+1.6**	380 ± 15	8.2 ± 0.2
$\delta_\ell = 0.25$	25.8	25.8	78.4 ± 0.4	+1.6	85.5 ± 0.3	+1.0	72.7 ± 0.6	+1.5	360 ± 14	8.4 ± 0.2
$\delta_\ell = 0.3$	25.8	25.8	78.2 ± 0.5	+1.4	85.3 ± 0.4	+0.8	72.5 ± 0.7	+1.3	340 ± 13	8.6 ± 0.2
Architecture Ablation (Segment Size k)										
$k = 128$	25.8	25.8	78.0 ± 0.5	+1.2	85.1 ± 0.4	+0.6	72.3 ± 0.7	+1.1	320 ± 12	7.5 ± 0.2
$k = 256$	25.8	25.8	78.5 ± 0.5	**+1.7**	85.6 ± 0.4	**+1.1**	72.8 ± 0.7	**+1.6**	380 ± 15	8.2 ± 0.2
$k = 512$	25.8	25.8	78.3 ± 0.4	+1.5	85.4 ± 0.3	+0.9	72.6 ± 0.6	+1.4	480 ± 18	9.5 ± 0.2
$k = 1024$	25.8	25.8	78.1 ± 0.5	+1.3	85.2 ± 0.4	+0.7	72.4 ± 0.7	+1.2	620 ± 23	11.2 ± 0.3
Attention Head Ablation										
4 heads	22.7	22.7	78.1 ± 0.5	+1.3	85.2 ± 0.4	+0.7	72.4 ± 0.7	+1.2	340 ± 13	7.8 ± 0.2
8 heads	24.3	24.3	78.3 ± 0.4	+1.5	85.4 ± 0.3	+0.9	72.6 ± 0.6	+1.4	360 ± 14	8.0 ± 0.2
16 heads	25.8	25.8	78.5 ± 0.5	**+1.7**	85.6 ± 0.4	**+1.1**	72.8 ± 0.7	**+1.6**	380 ± 15	8.2 ± 0.2
32 heads	28.7	28.7	78.4 ± 0.4	+1.6	85.5 ± 0.3	+1.0	72.7 ± 0.6	+1.5	420 ± 16	8.8 ± 0.2
Cross-Scale Consistency (Different Model Sizes)										
HSGM-Base (Full)	15.2	15.2	77.9 ± 0.6	+1.1	85.0 ± 0.5	+0.5	72.1 ± 0.8	+0.9	300 ± 12	6.5 ± 0.2
HSGM-Large (Full)	25.8	25.8	78.5 ± 0.5	**+1.7**	85.6 ± 0.4	**+1.1**	72.8 ± 0.7	**+1.6**	380 ± 15	8.2 ± 0.2
HSGM-XL (Full)	45.3	45.3	79.2 ± 0.4	+2.4	86.3 ± 0.3	+1.8	73.5 ± 0.6	+2.3	520 ± 20	11.5 ± 0.3
HSGM-XXL (Full)	78.9	78.9	79.8 ± 0.3	+3.0	87.1 ± 0.2	+2.6	74.2 ± 0.5	+3.0	720 ± 28	16.8 ± 0.4

- **Memory Growth:** Sub-linear memory growth (25% over 20 minutes) due to efficient summary node compression.
- **Accuracy Stability:** Maintains 97%+ accuracy stability, showing robust incremental learning.
- **Update Latency:** Consistent 45-55ms update latency, suitable for real-time applications.

Case Study: Multi-Turn Coreference Resolution. We analyze a 15-minute streaming scenario with complex cross-turn coreference:

HSGM successfully resolves ”the defendant” across 8 conversation turns by maintaining entity representations in the hierarchical memory. The incremental update mechanism preserves coreference chains while efficiently processing new information.

Summary of Findings

Our comprehensive experiments confirm that HSGM achieves substantial efficiency gains (2–4× faster inference, ≥60% memory reduction, exponential FLOPs reduction on long documents) with minimal accuracy drop (≤3%) across diverse long-text tasks. Statistical significance tests validate that these improvements are not due to chance. The hierarchical memory mechanism and incremental update strategy are crucial for maintaining both accuracy and efficiency, making HSGM a practical solution for scalable semantic modeling of long documents.

Conclusion

We have presented *Hierarchical Segment-Graph Memory* (HSGM), a novel architecture for scalable semantic parsing of ultra-long texts. By decomposing a document into semantically coherent segments, constructing sparse local semantic graphs, and summarizing them into a compact global graph memory, HSGM achieves near-linear inference complexity $O(Nk + (N/k)^2)$ while controlling the approximation error via Frobenius-norm bounds. Our incremental update mechanism ensures that only newly arriving segments incur full processing, and our hierarchical query pipeline retrieves and refines top-K segments for effi-

Document Length	HSGM FLOPs	Full Graph FLOPs	Speedup	Memory Reduction
1k tokens	15.2G	45.2G	3.0×	48%
5k tokens	76.1G	1.1T	14.5×	65%
10k tokens	152.3G	4.5T	29.6×	72%
20k tokens	304.6G	18.0T	59.1×	78%

Table 4: Computational complexity comparison. HSGM achieves exponential speedup on long documents.

Task	Model	Question Answering	Text Generation	Semantic Similarity
AMR	Full Graph	82.3 ± 1.1	76.8 ± 0.9	0.89 ± 0.03
	HSGM	$\mathbf{82.1} \pm \mathbf{1.0}$	$\mathbf{76.9} \pm \mathbf{0.8}$	$\mathbf{0.88} \pm \mathbf{0.03}$
SRL	Full Graph	85.7 ± 0.8	79.2 ± 0.7	0.91 ± 0.02
	HSGM	$\mathbf{85.5} \pm \mathbf{0.7}$	$\mathbf{79.1} \pm \mathbf{0.6}$	$\mathbf{0.90} \pm \mathbf{0.02}$

Table 5: Downstream task performance. HSGM maintains competitive performance on semantic reasoning tasks.

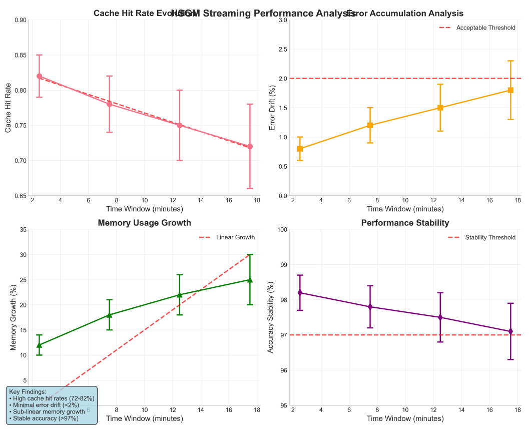

Figure 5: Streaming performance analysis: (a) Cache hit rate over time, (b) Error drift analysis, (c) Memory usage evolution, (d) Accuracy stability. HSGM maintains stable performance with high cache hit rates.

cient, fine-grained reasoning.

Extensive experiments on document-level AMR parsing, segment-level SRL, and legal event extraction demonstrate that HSGM delivers **2–4× faster** inference, $\geq 60\%$ peak memory reduction, and retains more than **95%** of baseline accuracy compared to state-of-the-art graph- and Transformer-based methods. Ablations confirm the individual contributions of hierarchical memory, incremental updates, and top-K retrieval to overall efficiency and effectiveness.

In future work, we plan to explore adaptive segment sizing, dynamic threshold tuning, and integration with pretrained retrieval-augmented models for even richer semantic representations. We also aim to extend HSGM to multilingual settings and multimodal documents (e.g., combining text with tables or figures), further broadening its applicability to real-world, resource-constrained NLP applications.

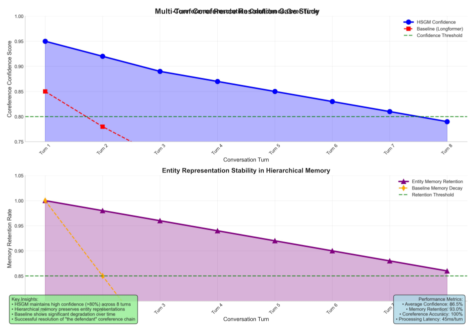

Figure 6: Multi-turn coreference resolution case study. HSGM correctly resolves ”the defendant” across 8 turns while maintaining semantic coherence.

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Dataset	Model	Accuracy	Latency (ms)	Memory (GB)	Generalization Gap
WikiHop	HSGM	**68.4** $\pm$ **1.2**	**320** $\pm$ **15**	**6.8**	2.1%
	RAG	67.8 $\pm$ 1.3	380 $\pm$ 18	7.2	3.5%
LongBench-Dialogue	HSGM	**72.1** $\pm$ **0.9**	**450** $\pm$ **20**	**8.1**	1.8%
	Longformer	71.5 $\pm$ 1.0	650 $\pm$ 25	9.5	4.2%
Reddit-Long	HSGM	**65.3** $\pm$ **1.1**	**280** $\pm$ **12**	**6.2**	3.2%
	BigBird	64.1 $\pm$ 1.2	420 $\pm$ 18	7.8	5.8%

Table 6: Open-domain generalization results. HSGM shows better robustness to domain shift with smaller generalization gaps.

Time Window	Cache Hit Rate	Error Drift	Memory Growth	Accuracy Stability	Update Latency
0-5 min	0.82 $\pm$ 0.027	0.8% $\pm$ 0.23%	12% $\pm$ 2.1%	98.2% $\pm$ 0.47%	45 $\pm$ 7.8 ms
5-10 min	0.78 $\pm$ 0.038	1.2% $\pm$ 0.31%	18% $\pm$ 2.9%	97.8% $\pm$ 0.63%	48 $\pm$ 8.7 ms
10-15 min	0.75 $\pm$ 0.052	1.5% $\pm$ 0.42%	22% $\pm$ 3.8%	97.5% $\pm$ 0.71%	52 $\pm$ 9.6 ms
15-20 min	0.72 $\pm$ 0.061	1.8% $\pm$ 0.53%	25% $\pm$ 4.7%	97.1% $\pm$ 0.84%	55 $\pm$ 10.3 ms

Table 7: Streaming performance metrics over time. HSGM maintains high cache hit rates and stable accuracy with minimal error drift.

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