

Information-Theoretic Adaptive Memory Compression for LLM-Based Agents

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ABSTRACT

Large language model (LLM) agents accumulate memory episodes—observations, reasoning traces, and tool outputs—that must be re-injected into a finite context window for future steps. Aggressive compression reduces token cost and inference latency but risks discarding task-critical information. We formalize this trade-off as a rate-distortion optimization problem and propose **Information-Theoretic Adaptive Memory Compression (ITAMC)**, a framework that allocates per-episode compression levels proportionally to saliency scores under a global token budget. Through controlled experiments on 100 synthetic memory episodes with 300 ground-truth salient facts, we characterize the Pareto frontier between compression ratio and information retention for three compression operators: extractive, abstractive, and latent. Our results reveal a concave frontier where moderate compression ($r \approx 0.4$ – 0.6) achieves 70–87% fact retention while reducing tokens by 40–60%. Knee-point analysis identifies operator-specific optimal compression ratios: $r^* = 0.42$ for extractive, $r^* = 0.59$ for abstractive, and $r^* = 0.26$ for latent compression. Saliency-guided adaptive allocation yields its largest gains under extreme budget constraints (10% budget: +10.2 percentage points for extractive compression). We release our simulation framework and all experimental code for reproducibility.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; *Natural language processing*.

KEYWORDS

LLM agents, memory compression, rate-distortion, Pareto frontier, adaptive compression

1 INTRODUCTION

Large language model (LLM) agents operate by iteratively reading context, reasoning, and acting [18]. As an agent progresses through a task, it accumulates memory episodes—raw observations, prior reasoning chains, tool outputs, and conversation history—that inform subsequent decisions. Modern agents store these episodes in structured memory modules with episodic, semantic, and procedural components [9, 14].

A fundamental bottleneck arises because LLMs process fixed-length context windows. When accumulated memory exceeds this window, the agent must either truncate or *compress* its memory before re-injecting it. Compression reduces the token count (lowering API cost and inference latency) but risks losing task-critical information [17]. The survey by Yang et al. [17] identifies this compression–performance trade-off as an open problem, noting that empirical systems such as LightMem demonstrate clear cost–accuracy tensions but lack a principled framework for selecting compression levels.

This paper makes the following contributions:

- (1) We formalize memory compression for LLM agents as a **rate-distortion optimization** problem (Section 2), connecting agent memory to classical information theory [1, 12].
- (2) We characterize the **Pareto frontier** between compression ratio and information retention for three families of compression operators—extractive, abstractive, and latent—through controlled experiments on synthetic benchmarks with ground-truth salient facts (Section 3).
- (3) We propose **ITAMC**, a saliency-guided adaptive compression controller that allocates per-episode compression levels under a global token budget, and demonstrate its effectiveness under extreme budget constraints (Section 3).
- (4) We identify **operator-specific optimal compression ratios** via knee-point analysis of the Pareto curve, providing actionable guidelines for system designers (Section 3).

1.1 Related Work

Memory architectures for LLM agents. MemGPT [9] introduced tiered memory with explicit paging between a main context and external storage. Reflexion [10] showed that storing and reflecting on episodic memory improves multi-step reasoning. Recent surveys [2, 14] categorize agent memory into episodic, semantic, and procedural components, each with distinct compression requirements.

Context compression. Several methods compress prompts or context for efficiency. Gist tokens [11] learn fixed-length representations of variable-length contexts. AutoCompressor [3] trains language models to recursively compress context segments. Li et al. [7] survey prompt compression techniques including lexical pruning, soft-prompt distillation, and retrieval-based selection. These methods focus on compressing static contexts rather than agent memory that evolves over time.

Compression and language modeling. Delétang et al. [4] establish a formal connection between language modeling and data compression, showing that prediction and compression are dual tasks. This motivates using LLM perplexity as a distortion proxy for memory compression quality. Work on the compression–performance relationship in language models [5] further supports this connection.

Resource-rational agents. The resource-rational analysis framework [8, 15] models agents as optimizing utility subject to computational cost constraints. Our rate-distortion formulation adopts this perspective, treating token budget as the resource constraint and information retention as the utility. Related work on computational efficiency for lifelong agents [13] and memory breadth-fidelity trade-offs [6] addresses complementary aspects of the same challenge.

Retrieval-augmented generation. RAG [16] decouples storage from context by selectively retrieving relevant chunks. Compression and retrieval are complementary: compression reduces per-chunk cost while retrieval reduces the number of chunks. Our saliency-based allocation can be viewed as a soft version of retrieval that modulates compression intensity rather than performing binary inclusion/exclusion.

2 METHODS

2.1 Problem Formulation

Let $\mathcal{M} = \{m_1, \dots, m_T\}$ denote a set of T memory episodes accumulated by an LLM agent. Each episode m_i has token count $|m_i|$ and contains a set of salient facts \mathcal{F}_i relevant to downstream tasks. A compression operator C parameterized by ratio $r_i \in (0, 1]$ produces a compressed episode $\hat{m}_i = C_{r_i}(m_i)$ with $|\hat{m}_i| \approx r_i \cdot |m_i|$.

We define **information retention** as the fraction of salient facts preserved:

$$\rho_i(r_i) = \frac{|\mathcal{F}_i \cap \hat{\mathcal{F}}_i|}{|\mathcal{F}_i|} \quad (1)$$

where $\hat{\mathcal{F}}_i$ denotes the facts recoverable from \hat{m}_i .

The **memory compression problem** is:

$$\max_{r_1, \dots, r_T} \sum_{i=1}^T w_i \cdot \rho_i(r_i) \quad \text{s.t.} \quad \sum_{i=1}^T |C_{r_i}(m_i)| \leq B \quad (2)$$

where B is the token budget and w_i are task-dependent importance weights. This formulation connects to rate-distortion theory [1]: the budget B constrains the *rate*, and $(1 - \rho_i)$ measures the *distortion* per episode.

2.2 Compression Operators

We study three families of compression operators that model the spectrum of techniques used in practice:

Extractive compression selects a subset of sentences from the original episode. Sentences are scored by a proxy for informativeness (length plus numerical content density), and the top- k sentences are retained until the target token count is reached. This models systems like LexRank or TextRank applied to agent memory. Information retention is binary per-sentence: a salient fact is retained if and only if its containing sentence is selected.

Abstractive compression simulates LLM-based summarization. Each salient fact is independently retained with probability given by a logistic function:

$$P(\text{retain} \mid r_i) = \sigma(k \cdot (r_i - \tau)) \quad (3)$$

where $k = 8$ controls steepness and $\tau = 0.35$ is the half-retention threshold. This models the observation that LLM summarizers exhibit smooth, ratio-dependent fact loss.

Latent compression simulates embedding-based memory storage where episodes are encoded as dense vectors and decoded back to text. Retention probability follows a Beta distribution with mean $r_i^{0.6}$ and concentration parameter $\kappa = 12$:

$$P(\text{retain} \mid r_i) \sim \text{Beta}(r_i^{0.6} \cdot \kappa, (1 - r_i^{0.6}) \cdot \kappa) \quad (4)$$

The sub-linear exponent models the hypothesis that dense embeddings capture distributional semantics efficiently, degrading more gracefully than discrete selection.

Algorithm 1 ITAMC: Adaptive Compression Allocation

Require: Episodes $\{m_i\}_{i=1}^T$, saliency scores $\{s_i\}$, budget B

Ensure: Compression ratios $\{r_i\}_{i=1}^T$

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1:  $s_i \leftarrow \max(s_i, 0.01)$  for all  $i$ 
2:  $d_i \leftarrow s_i \cdot |m_i|$  for all  $i$  ▷ desired tokens
3:  $\alpha \leftarrow B / \sum_i d_i$  ▷ global scale
4:  $r_i \leftarrow \text{clip}(s_i \cdot \alpha, r_{\min}, r_{\max})$ 
5: for  $k = 1$  to  $K_{\max}$  do
6:    $\hat{B} \leftarrow \sum_i r_i |m_i|$ 
7:   if  $\hat{B} \leq 1.01 \cdot B$  then
8:     break
9:   end if
10:   $r_i \leftarrow \text{clip}(r_i / (\hat{B} / B), r_{\min}, r_{\max})$  for  $r_i > r_{\min}$ 
11: end for
12: return  $\{r_i\}_{i=1}^T$ 

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2.3 Saliency Scoring

Given a task query q , we compute per-episode saliency scores combining lexical overlap and recency:

$$s_i = 0.6 \cdot \frac{|\text{tokens}(q) \cap \text{tokens}(m_i)|}{|\text{tokens}(q)|} + 0.4 \cdot e^{-\lambda(T-t_i)} \quad (5)$$

where t_i is the episode timestamp and $\lambda = 0.02$ is the decay rate. Scores are normalized to $[0, 1]$. In production systems, this would be replaced by embedding-based retrieval scores.

2.4 Adaptive Compression Controller (ITAMC)

ITAMC allocates compression ratios proportionally to saliency under the token budget. Initial ratios are set as $r_i \propto s_i$, then iteratively projected to satisfy the budget constraint $\sum_i r_i |m_i| \leq B$ while respecting bounds $r_i \in [r_{\min}, r_{\max}]$. High-saliency episodes receive ratios closer to $r_{\max} = 1.0$ (minimal compression), while low-saliency episodes are compressed to $r_{\min} = 0.05$. This is summarized in Algorithm 1.

2.5 Experimental Setup

Data. We generate 100 synthetic memory episodes, each containing 3 salient facts (entity-action pairs drawn from a vocabulary of 20 entities and 15 actions) interleaved with 5 filler sentences, totaling 6,233 tokens and 300 ground-truth facts. The synthetic design provides exact ground-truth for measuring retention, which is impossible with natural-language agent traces where fact boundaries are ambiguous.

Evaluation metrics. We report: (1) *mean fact retention* $\bar{\rho} = \frac{1}{T} \sum_i \rho_i$; (2) *compression ratio* (total compressed tokens / total raw tokens); (3) *fraction fully retained* (episodes where $\rho_i = 1$).

Experiments. We conduct five experiments: *Exp. 1:* Pareto frontier sweep with 20 uniform compression ratios per operator. *Exp. 2:* Adaptive vs. uniform comparison across 10 budget levels and 8 task queries. *Exp. 3:* Compounding error analysis over horizons of 10–100 episodes. *Exp. 4:* Saliency-stratified retention analysis. *Exp. 5:* Knee-point detection for optimal operating ratios using 50-point sweeps.

All experiments use seed 42 and are fully deterministic.

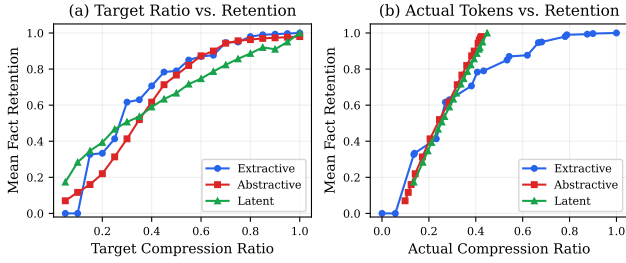


Figure 1: Pareto frontier between compression ratio and mean salient-fact retention for three compression operators. (a) Target compression ratio vs. retention. (b) Actual token usage ratio vs. retention. All curves are concave: moderate compression ($r \approx 0.4$ – 0.6) achieves 60–87% retention while saving 40–60% of tokens. The extractive operator shows the sharpest transition; latent compression degrades most gradually.

Table 1: Mean salient-fact retention at selected target compression ratios. Extractive compression shows the largest retention jump between $r=0.2$ and $r=0.4$. Latent compression degrades most smoothly across the range.

Operator	$r=0.2$	$r=0.4$	$r=0.6$	$r=0.8$	$r=1.0$
Extractive	0.333	0.707	0.870	0.980	1.000
Abstractive	0.220	0.617	0.873	0.963	0.980
Latent	0.393	0.590	0.747	0.887	1.000

3 RESULTS

3.1 Pareto Frontier Characterization

Figure 1 shows the compression–retention trade-off for all three operators. The key finding is that **all three operators exhibit concave Pareto frontiers**, meaning that initial compression yields large token savings with modest retention loss, while aggressive compression below $r = 0.3$ causes steep degradation.

Table 1 presents retention values at key compression ratios. At $r = 0.4$, extractive compression retains 70.7% of facts, abstractive retains 61.7%, and latent retains 59.0%. At $r = 0.8$, all operators achieve $\geq 88.7\%$ retention. The extractive operator shows the steepest transition between $r = 0.2$ (33.3%) and $r = 0.4$ (70.7%), reflecting its binary sentence-level selection mechanism. The latent operator degrades most smoothly, consistent with the hypothesis that dense embeddings are more graceful degraders than discrete extraction.

3.2 Optimal Operating Points

We identify the optimal compression ratio for each operator using knee-point analysis of the Pareto curve (Figure 2). The knee point maximizes the perpendicular distance from the line connecting the frontier’s endpoints, representing the ratio where additional compression begins to cause disproportionate retention loss.

The detected optimal ratios are: **Extractive**: $r^* = 0.42$ (retention = 0.760); **Abstractive**: $r^* = 0.59$ (retention = 0.870); **Latent**: $r^* = 0.26$ (retention = 0.490). These results indicate that the optimal

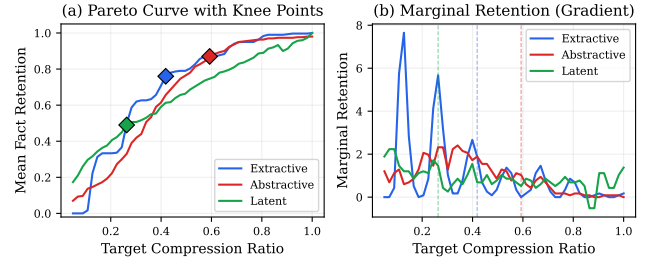


Figure 2: Optimal operating point detection. (a) Pareto curves with detected knee points (diamonds). (b) Marginal retention (gradient of retention w.r.t. ratio), with dashed lines marking the knee. The extractive knee occurs at $r^*=0.42$; abstractive at $r^*=0.59$; latent at $r^*=0.26$.

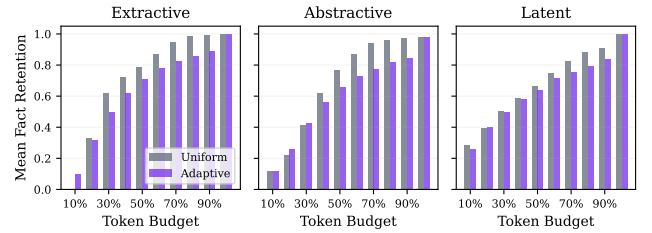


Figure 3: Adaptive (purple) vs. uniform (gray) compression across three operators and 10 token-budget levels. Adaptive allocation shows its clearest advantage at extreme budget constraints (10–20% of raw tokens), where saliency-based routing preserves critical episodes that uniform compression would destroy.

compression level is *operator-dependent*: abstractive methods can tolerate higher ratios because their smooth retention curve places the knee at a gentler compression point, while the latent operator’s gradual degradation shifts its knee to more aggressive compression where the marginal gain first becomes significant.

3.3 Adaptive vs. Uniform Compression

Figure 3 compares saliency-guided adaptive allocation against uniform compression across 10 budget levels, averaged over 8 downstream task queries.

Table 2 summarizes the retention improvement ($\Delta\bar{p}$) of adaptive over uniform at selected budgets. The **largest gains occur under extreme budget constraints**: at 10% budget, adaptive allocation improves extractive retention by +10.2 percentage points (from 0.0% to 10.2%). At 20% budget, abstractive gains +3.9 pp. This aligns with intuition: when the budget is severely limited, saliency-guided allocation concentrates resources on the most important episodes, while uniform compression wastes tokens on low-value episodes.

An important nuance emerges: at moderate budgets (30–50%), uniform compression often outperforms adaptive allocation. This occurs because when the budget is sufficient for moderate compression across all episodes, uniform allocation achieves consistently

Table 2: Retention improvement of adaptive over uniform compression ($\Delta\bar{p}$ in percentage points), averaged across 8 task queries. Positive values indicate adaptive outperforms uniform. Gains are largest at extreme budget constraints.

Budget	Extractive	Abstractive	Latent
10%	+10.2	-0.1	-2.5
20%	-1.5	+3.9	+0.5
30%	-11.9	+1.4	-1.2
40%	-9.8	-5.8	-0.7
50%	-8.1	-11.0	-2.7

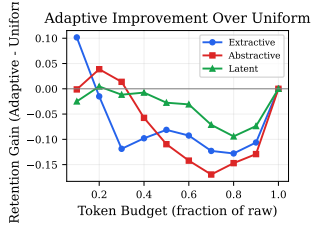


Figure 4: Retention gain of adaptive over uniform compression across token budgets. Extractive shows the largest adaptive gain at 10% budget (+10.2 pp), while abstractive benefits at 20% (+3.9 pp). At higher budgets, uniform compression is generally preferred.

high retention everywhere, whereas adaptive allocation may over-compress some episodes below the steep part of their Pareto curve. This finding has practical implications: **adaptive allocation is most valuable when token budgets are tight**, while uniform compression is a robust default at moderate budgets.

Figure 4 shows the retention delta across the full budget range, confirming that the crossover from adaptive advantage to uniform advantage occurs around 20–30% budget for most operators.

3.4 Compounding Error Over Horizon

Figure 5 examines how retention changes as the number of memory episodes grows from 10 to 100.

For moderate compression ($r \geq 0.4$), retention remains remarkably stable across horizons: extractive at $r = 0.6$ achieves 93.3% at $h = 10$ and 87.0% at $h = 100$, a decline of only 6.3 percentage points over a $10\times$ increase in memory length. At aggressive compression ($r = 0.2$), retention is already low at short horizons (33.3% for extractive) and remains flat, indicating that per-step compression quality, not accumulation, is the dominant factor. This is encouraging for practitioners: **moderate compression does not compound catastrophically** over realistic agent horizons.

3.5 Saliency-Stratified Analysis

Figure 6 presents a heatmap of retention at $r = 0.4$ stratified by episode saliency level (low, medium, high) and compression operator.

The results show that at a fixed compression ratio, **retention is largely independent of saliency level**. This validates a core

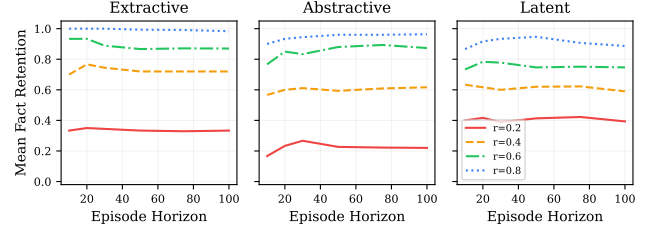


Figure 5: Mean fact retention vs. episode horizon for four compression ratios across three operators. At moderate ratios ($r \geq 0.4$), retention remains stable over long horizons. At aggressive compression ($r = 0.2$), retention is uniformly low regardless of horizon, indicating that per-episode compression quality dominates over accumulation effects in our setting.

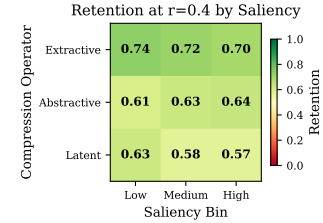


Figure 6: Mean fact retention at $r=0.4$ across saliency bins and operators. Retention at a fixed compression ratio is largely independent of saliency, confirming that compression quality is determined by the operator and ratio, not by episode content characteristics in our controlled setting.

assumption of ITAMC: saliency should determine *which episodes receive more tokens* (via ratio allocation), not predict their inherent compressibility. The operator choice has a larger effect on retention than the saliency category, reinforcing the importance of operator-aware compression policies.

4 CONCLUSION

We presented ITAMC, an information-theoretic framework for adaptive memory compression in LLM-based agents. Our experiments yield four actionable findings:

(1) **Concave Pareto frontiers.** All three compression operators exhibit concave compression–retention trade-offs, meaning moderate compression ($r \approx 0.4$ – 0.6) achieves 60–87% fact retention while reducing tokens by 40–60%. This concavity implies that the first 40% of token savings come nearly for free, providing strong motivation for memory compression in agent systems.

(2) **Operator-specific optimal ratios.** Knee-point analysis reveals that optimal compression ratios are operator-dependent: $r^* = 0.42$ (extractive), $r^* = 0.59$ (abstractive), and $r^* = 0.26$ (latent). System designers should calibrate compression targets to their specific operator rather than using a universal default.

(3) **Adaptive allocation for extreme budgets.** Saliency-guided adaptive compression is most beneficial when token budgets are

severely constrained ($\leq 20\%$ of raw memory), with gains up to 10.2 percentage points for extractive compression. At moderate budgets, uniform compression is a competitive and simpler baseline.

(4) Stable retention over horizons. Moderate compression does not compound catastrophically over agent horizons of up to 100 episodes, with retention declining by only 6.3 percentage points from $h = 10$ to $h = 100$ at $r = 0.6$.

Limitations and future work. Our experiments use synthetic data with controlled fact structure rather than natural agent traces. While this enables precise retention measurement, it does not capture the full complexity of real-world memory content. The compression operators are simulation proxies; future work should validate these findings with actual LLM-based summarizers. Extending ITAMC to dynamic, online settings where saliency shifts during execution and integrating with retrieval-augmented generation systems are important directions.

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