



Cognitive Theory for Deliberate Reasoning: Synthesizing Working Memory Architectures for LLMs

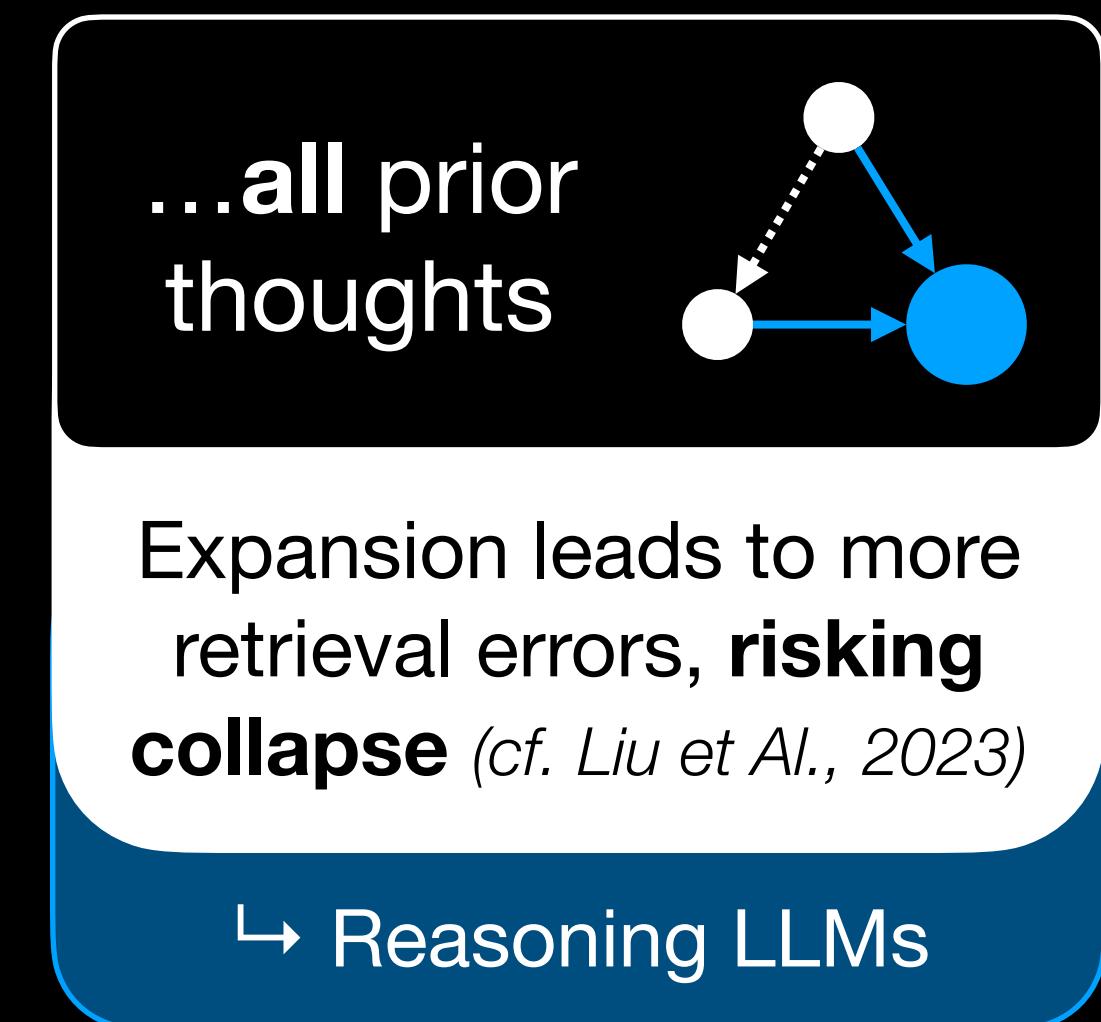
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Master Thesis in Information Systems
Supervised by Tobias Eder

The Problem:

LLMs lack regulation of
expanding reasoning context

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↪ Approaches generate a **new thought** in the context of...

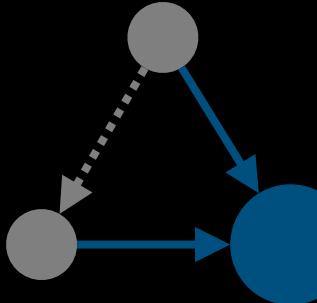


or...

The Problem: LLMs Lack Regulation of Expanding Reasoning Context

↳ Approaches generate a **new thought** in the context of...

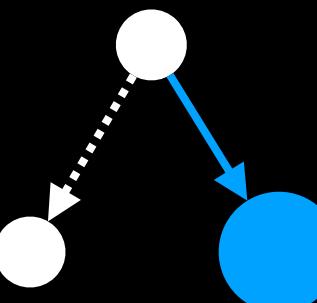
...**all** prior thoughts



Expansion leads to more retrieval errors, **risking collapse** (*cf. Liu et Al., 2023*)

↳ Reasoning LLMs

...**only** direct parent thoughts



Limited insight re-use

↳ **Graph of Thought**

(*GoT; Besta et. al., 2024*)

- static prompting graph
- limitation contradicts stated motivation

or...

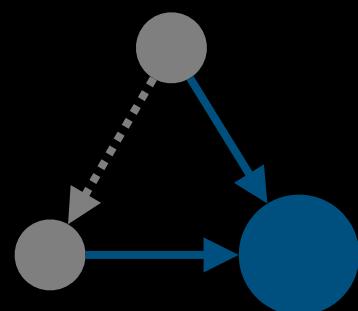
Humans only recall ~7 “thoughts” at once *(Miller, 1956)*

The Solution: **Working Memory (WM)**

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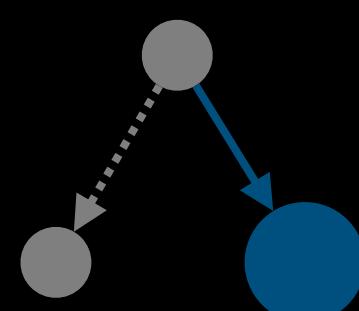
↳ Generate a new thought in the context of...

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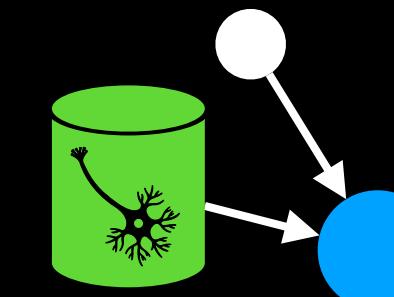
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Limited insight re-use

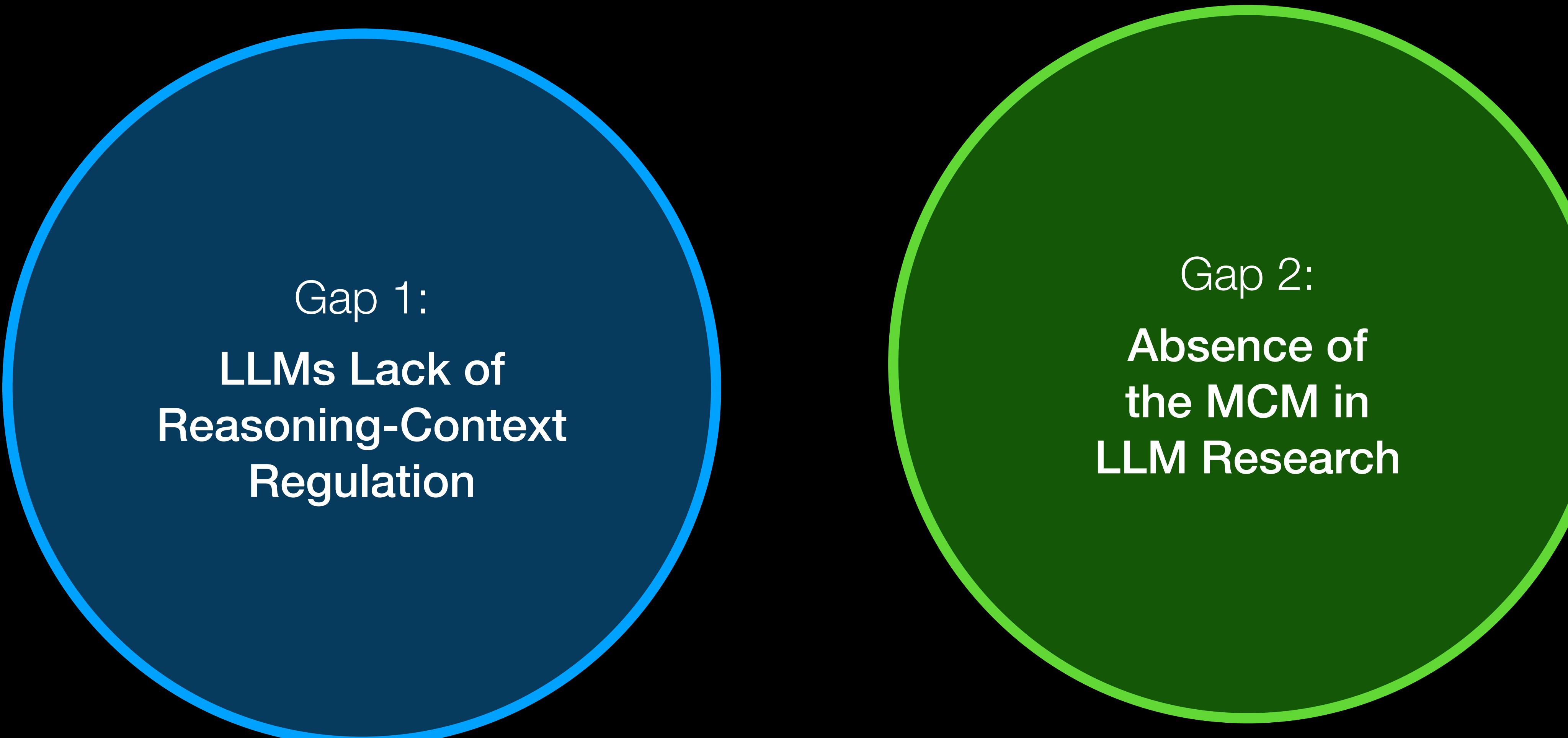
...a curated **Working Memory**



- Limited capacity
- Active control and curation of context

Dominant model in cognitive science (the *Multi-Component Model; MCM*) remains **entirely absent** from LLM research

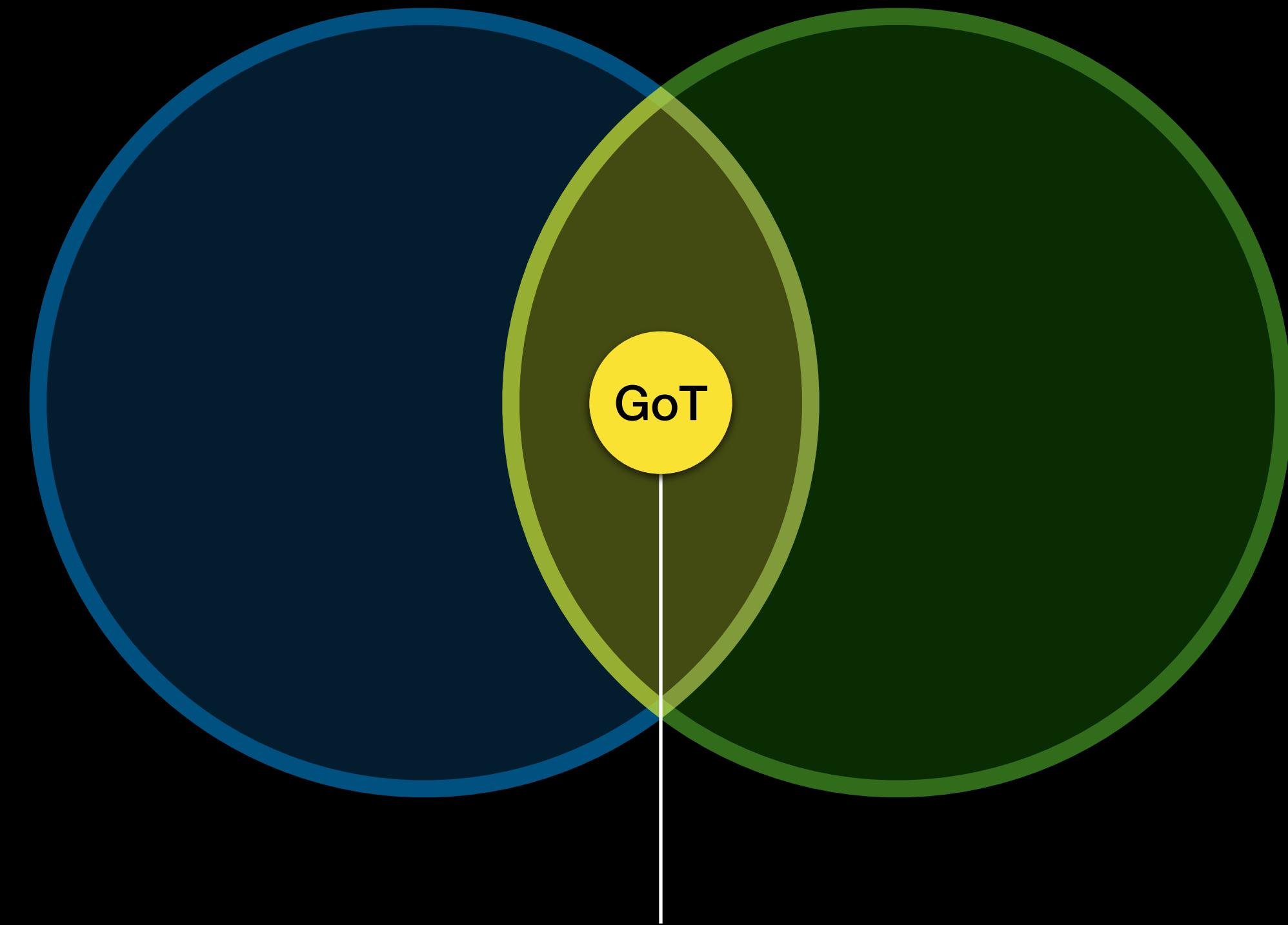
Research Niche at the Intersection of a Dual Gap



Gap 1:
**LLMs Lack of
Reasoning-Context
Regulation**

Gap 2:
**Absence of
the MCM in
LLM Research**

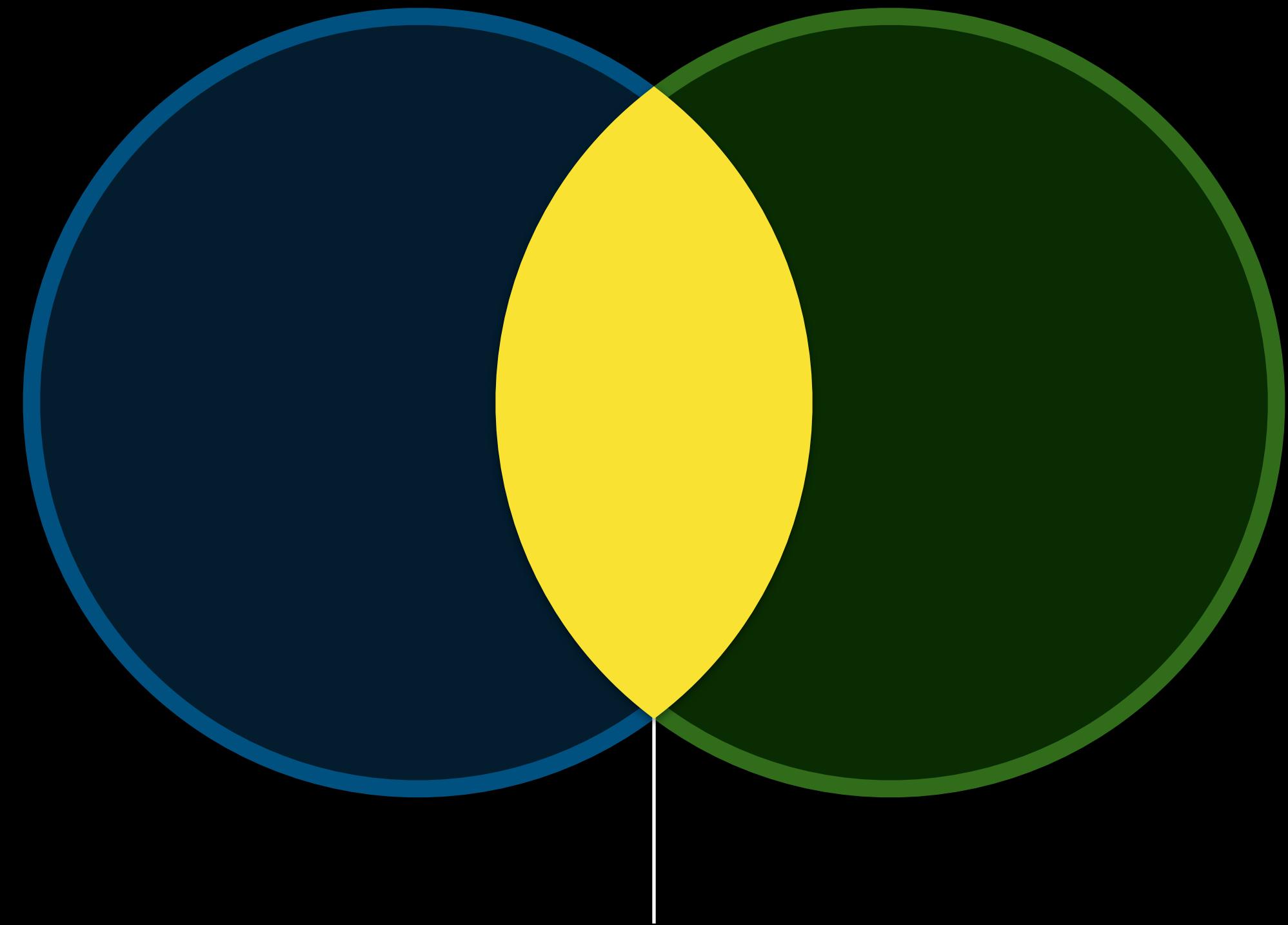
Research Niche at the Intersection of a Dual Gap



Research Question:

*“How might a **Working Memory mechanism for LLMs** be designed
to selectively retrieve relevant material from an arbitrarily large
reasoning graph, when generating a new thought in GoT?”*

Research Niche at the Intersection of a Dual Gap



Design Question:

*“How might the **Multi-Component Model of WM** be transferred architecturally to the domain of LLM research?”*

PART 1

Theoretical Foundation

Model-Agnostic Properties of Working Memory

Part I: Theoretical Foundation

Holistic frameworks of WM are conceptual tools deliberately leaving room for discussion.

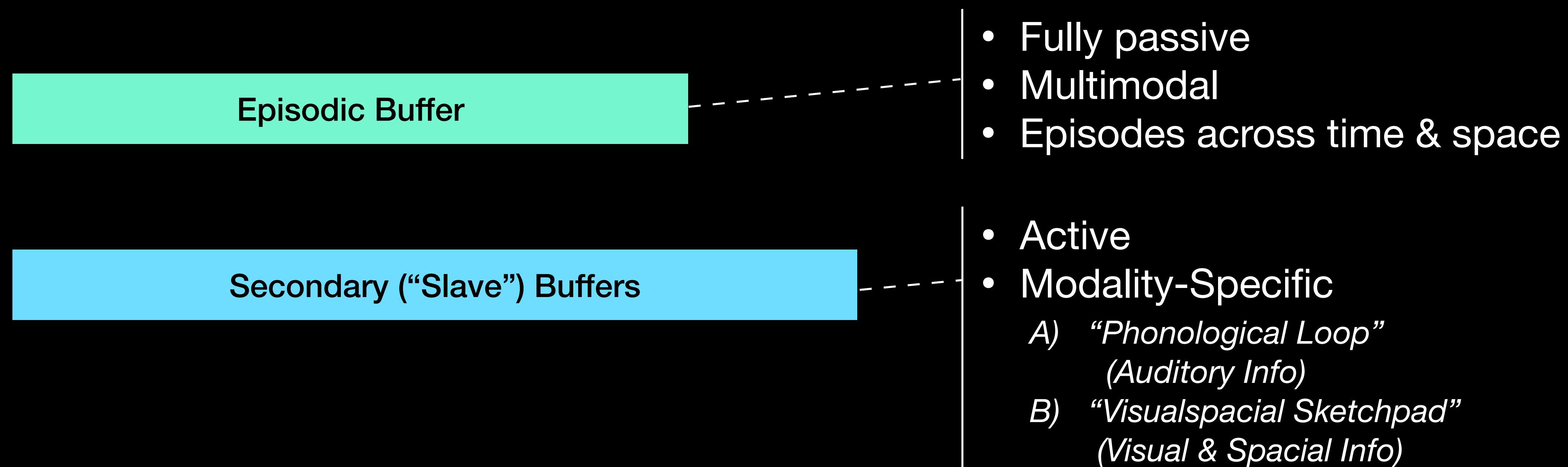
Yet, consensus across models is that WM:

- is a **limited capacity store**
 - ↳ **Forgetting** – Views: Decay mechanism, resource limits, interference
 - ↳ **Information not attended to fades rapidly**
- is tightly **coupled with long-term memory (LTM)** – details largely unclear
- houses active processing functionality

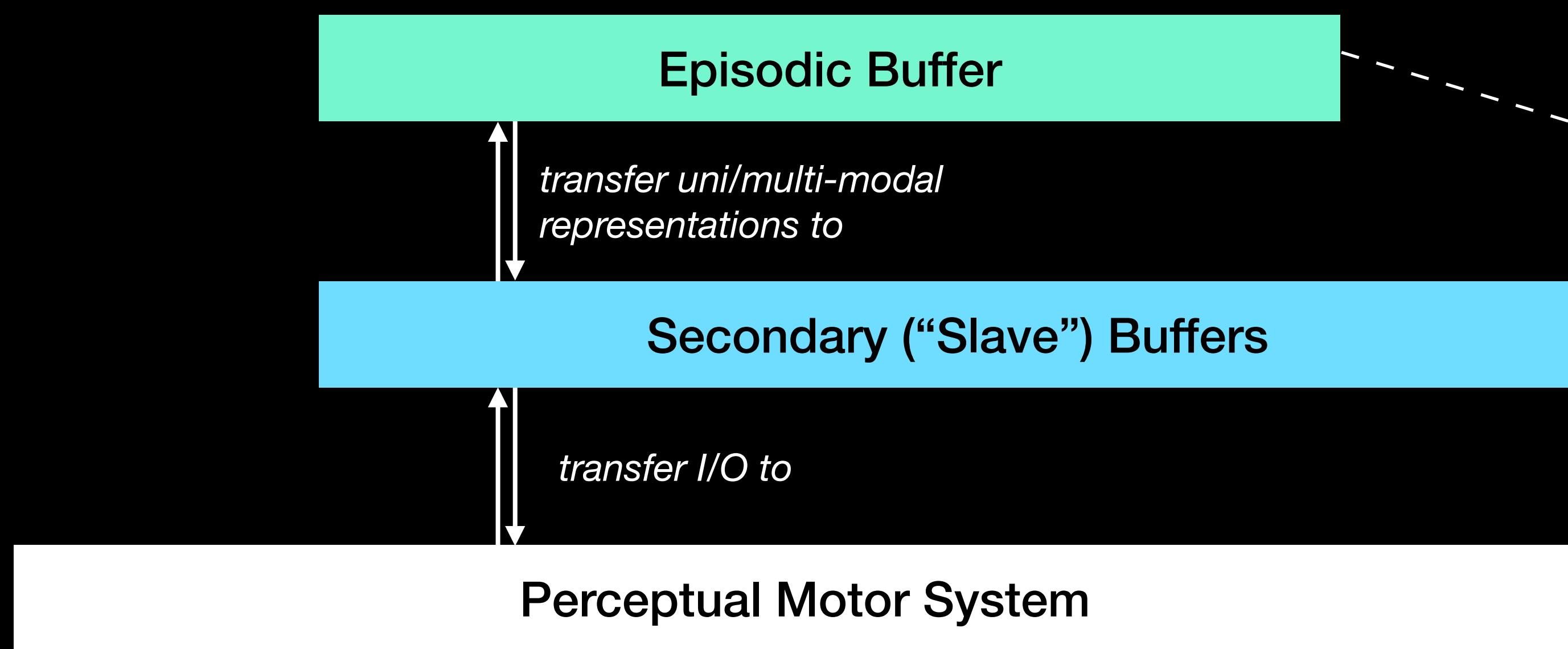
where representations in memory are:

- **Actively manipulated**
- **Hierarchically structured (into “Chunks”)**
- **Varying in capacity demand**

The Multi-Component Model of WM (Our Interpretation, Simplified)



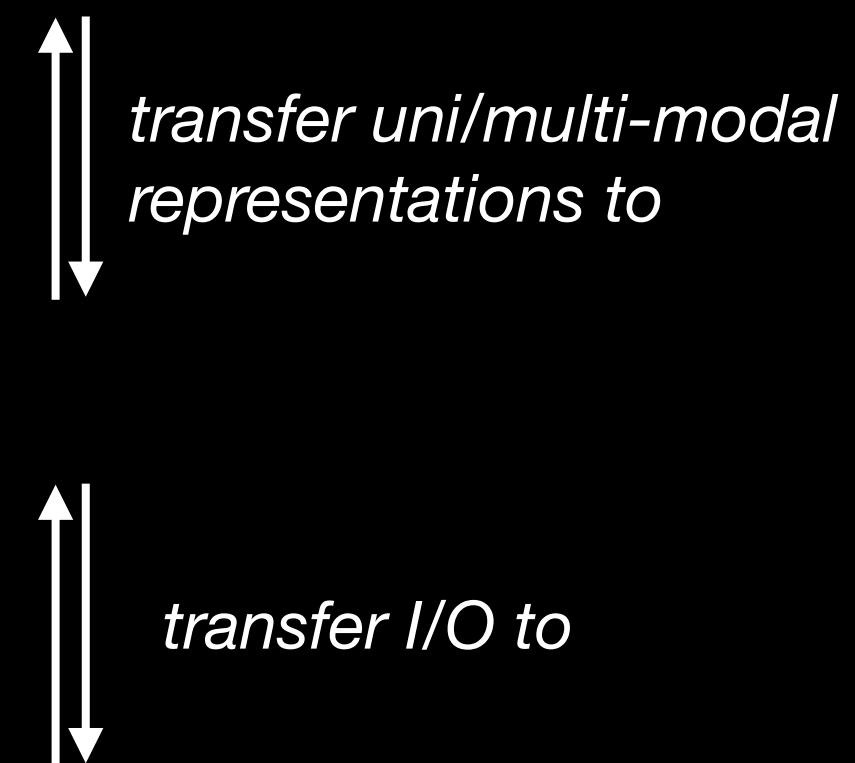
The Multi-Component Model of WM (Our Interpretation, Simplified)



Two types of internal storage:

- Fully passive
 - Multimodal
 - Episodes across time & space
-
- Active
 - Modality-Specific
 - I/O buffers to the Episodic Buffer

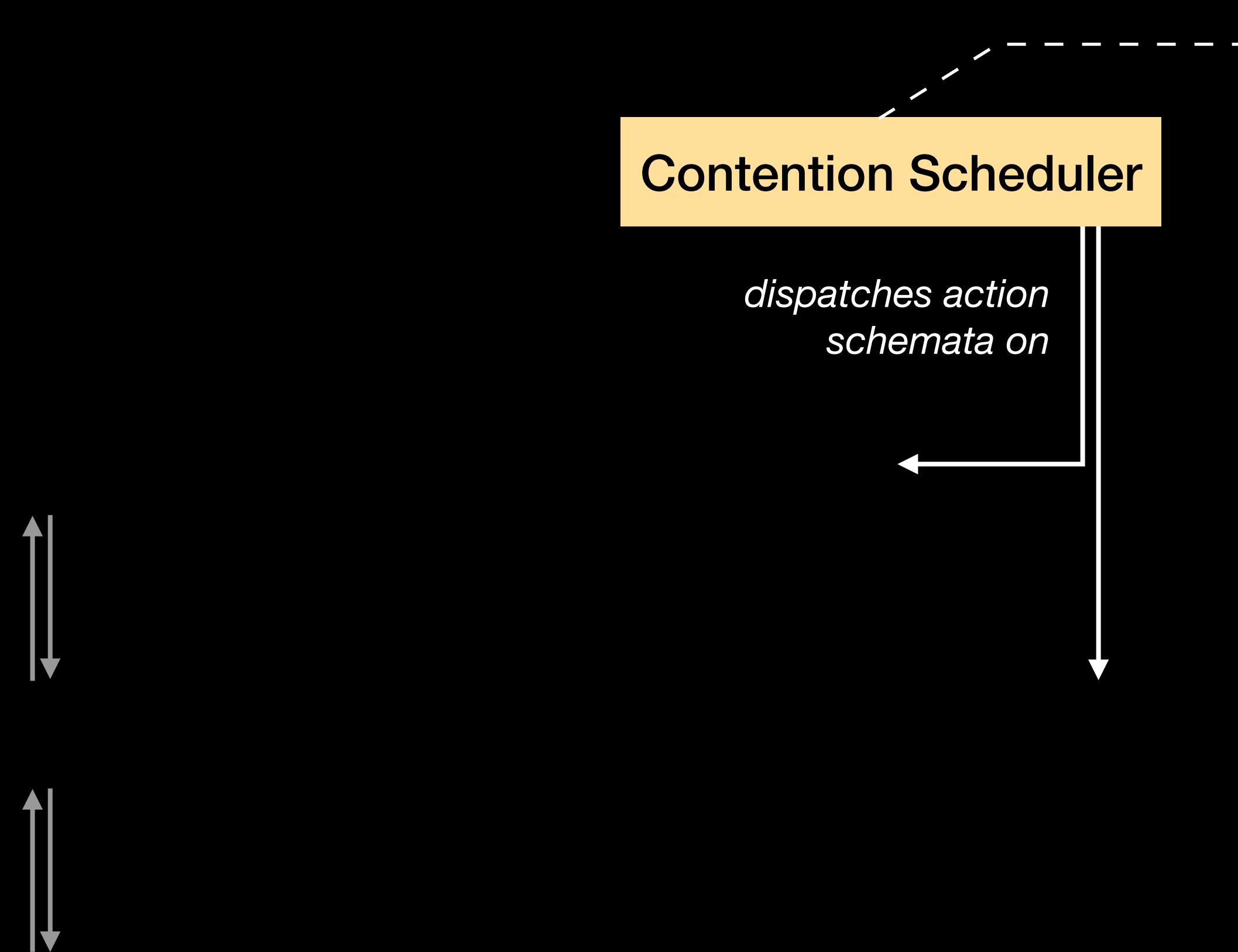
The Multi-Component Model of WM (Our Interpretation, Simplified)



Any data transfer or manipulation occurs via **Action Schemata**:

- Pre-learned “transactions”
- Hierarchically structured
- Become scheduable iff:
activation value > activation threshold

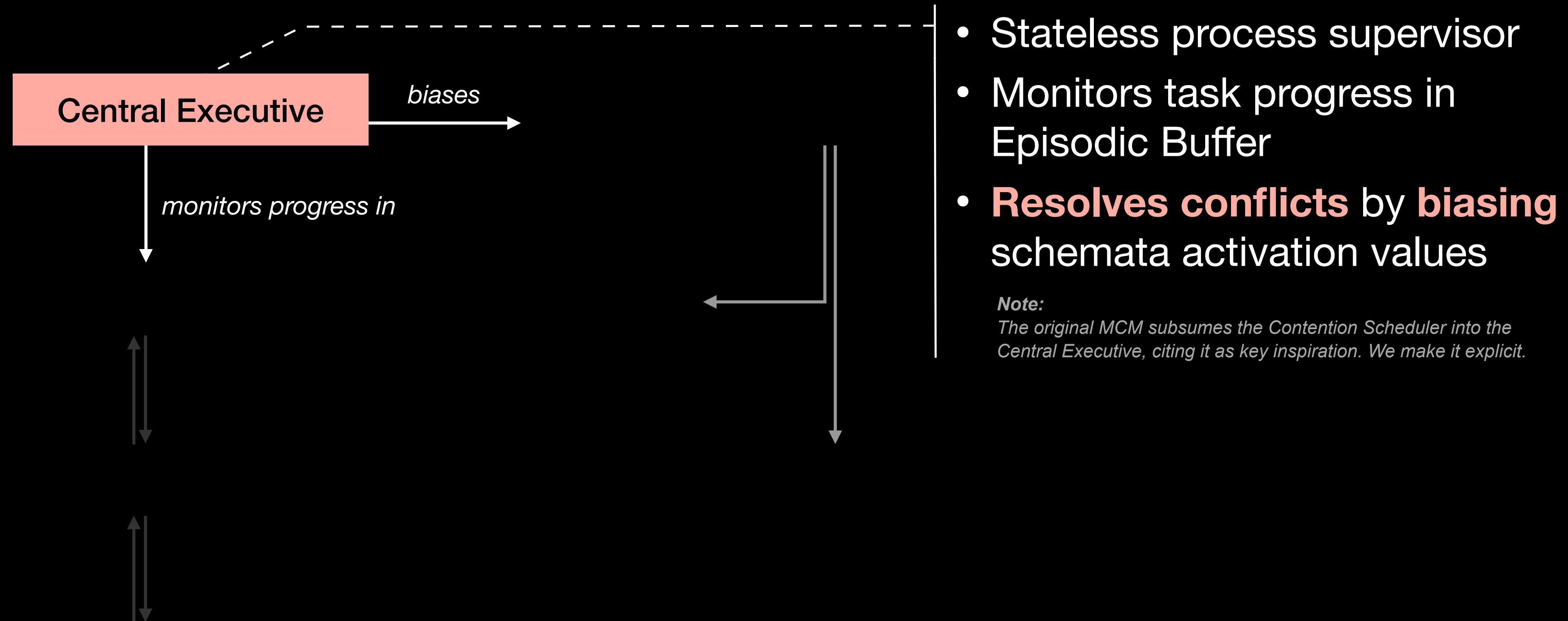
The Multi-Component Model of WM (Our Interpretation, Simplified)



↳ **Automatically** dispatched by Contention Scheduler **iff no conflict arises**, e.g. when:

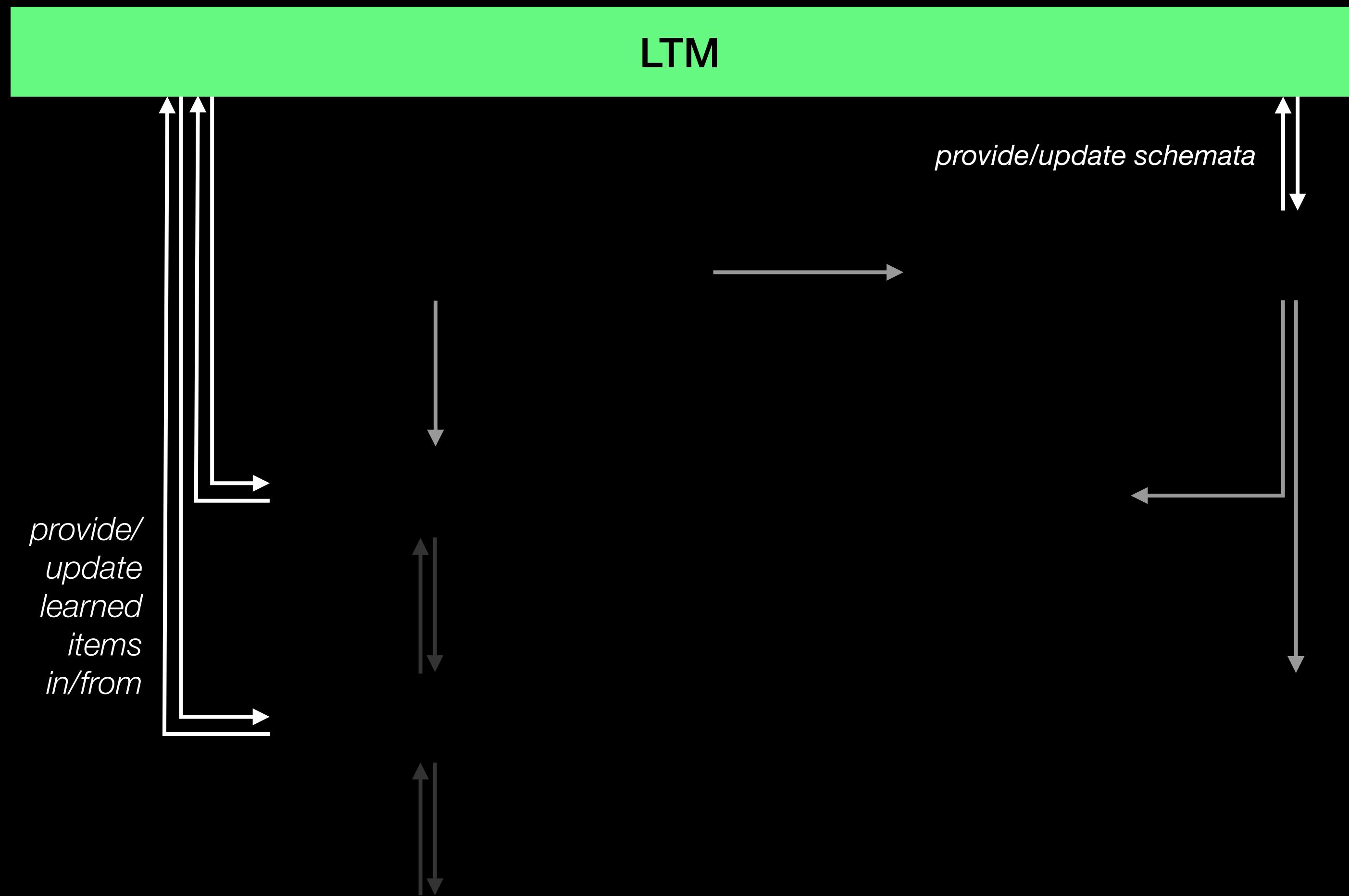
- Multiple schemas active
- No schema active

The Multi-Component Model of WM (Our Interpretation, Simplified)



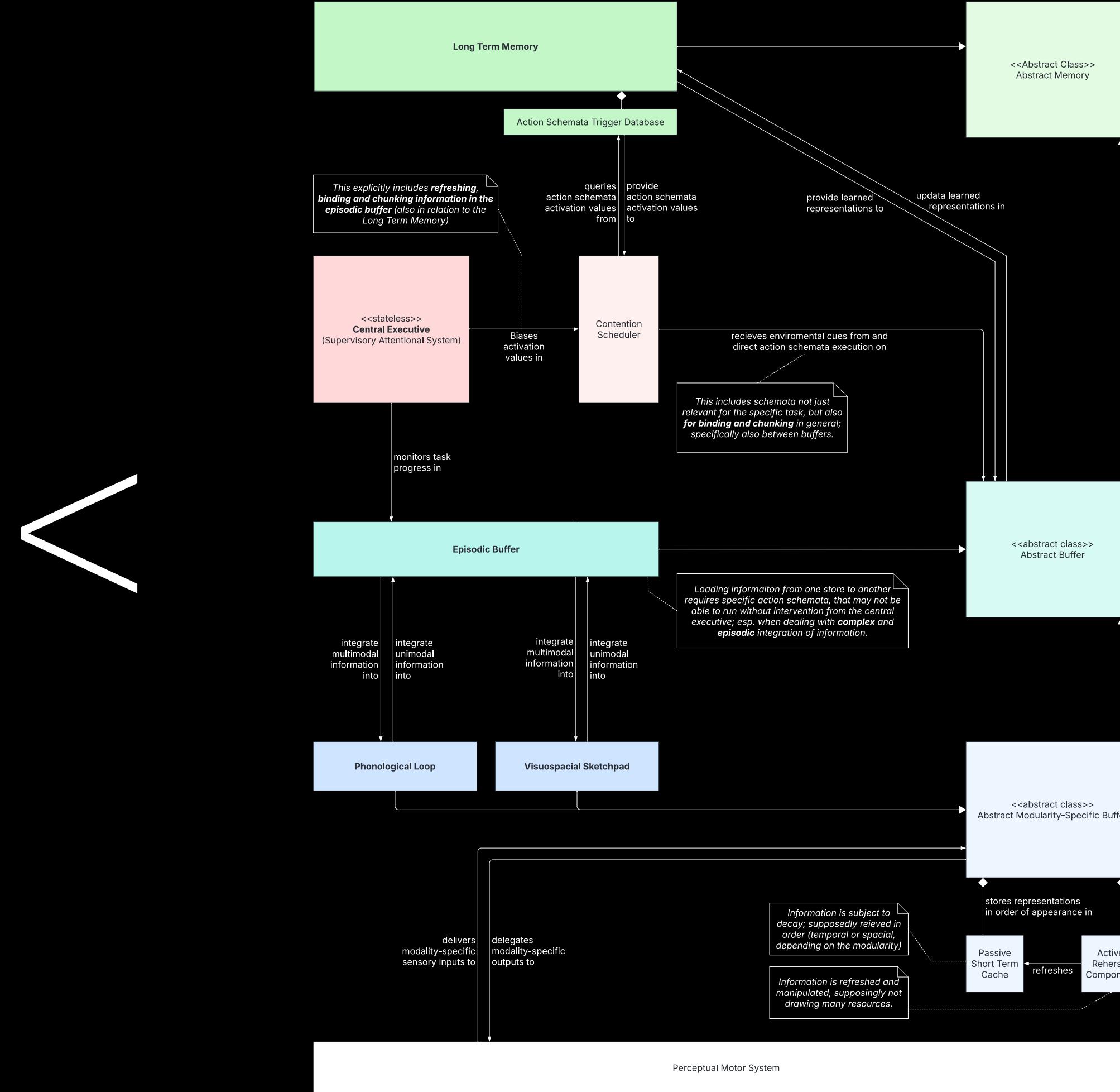
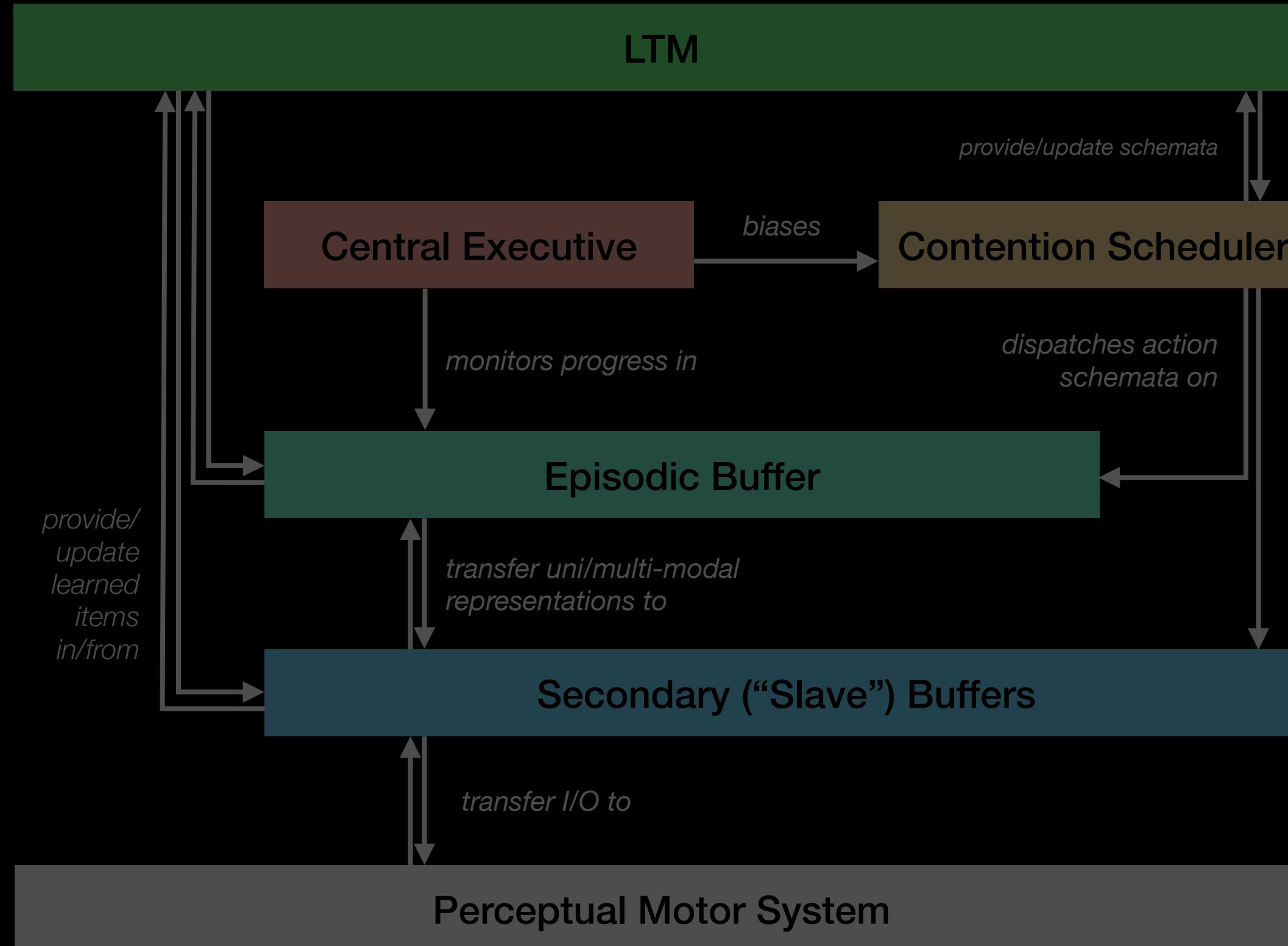
The Multi-Component Model of WM (Our Interpretation, Simplified)

Contribution I: The MCM in SE Terms | Part I: Theoretical Foundation



The Multi-Component Model of WM (Our Interpretation, Simplified)

Contribution I: The MCM in SE Terms | Part I: Theoretical Foundation



A WM Core Architecture for LLMs: Guiding Principles (Summarized)

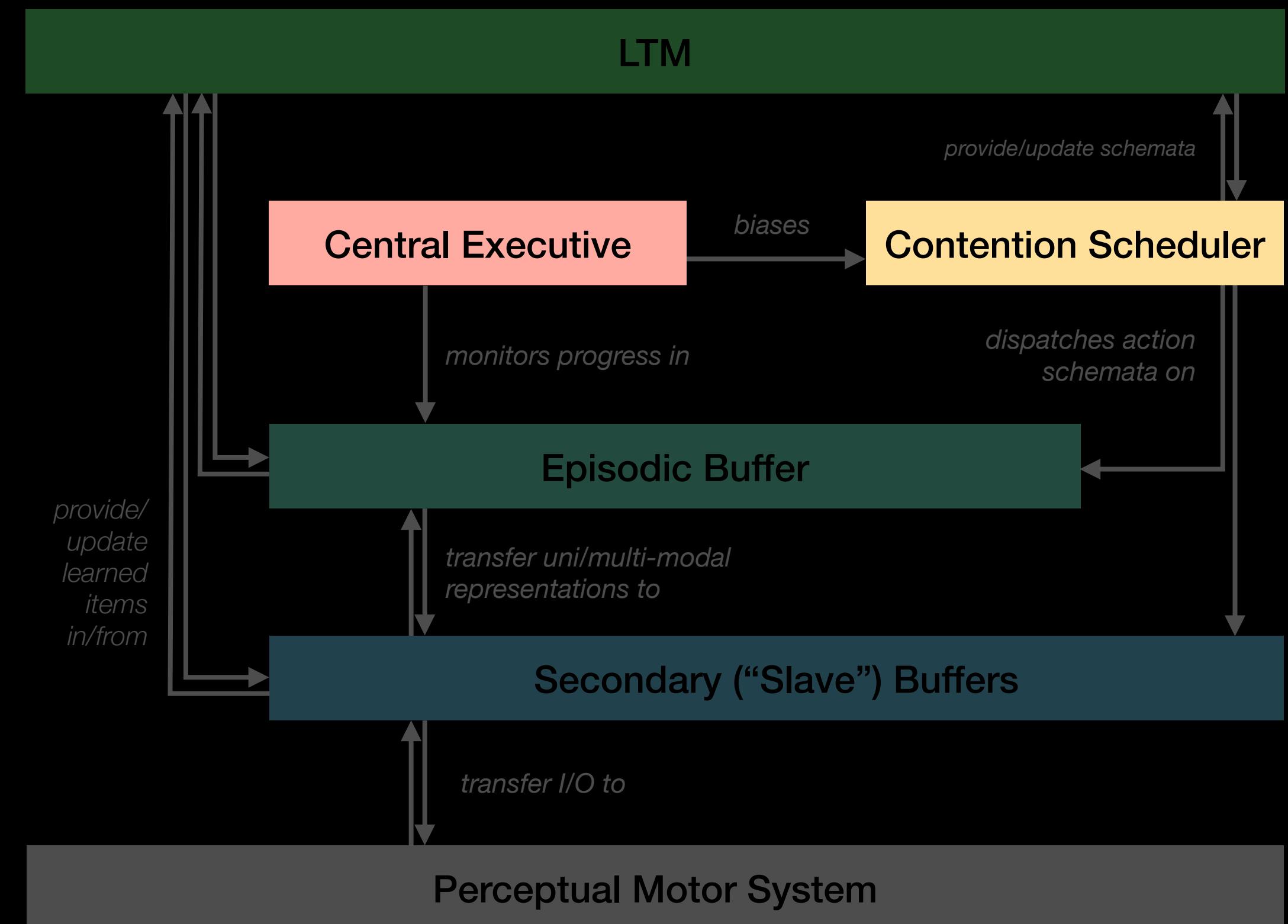


Contribution II: A WM Core Architecture for LLMs

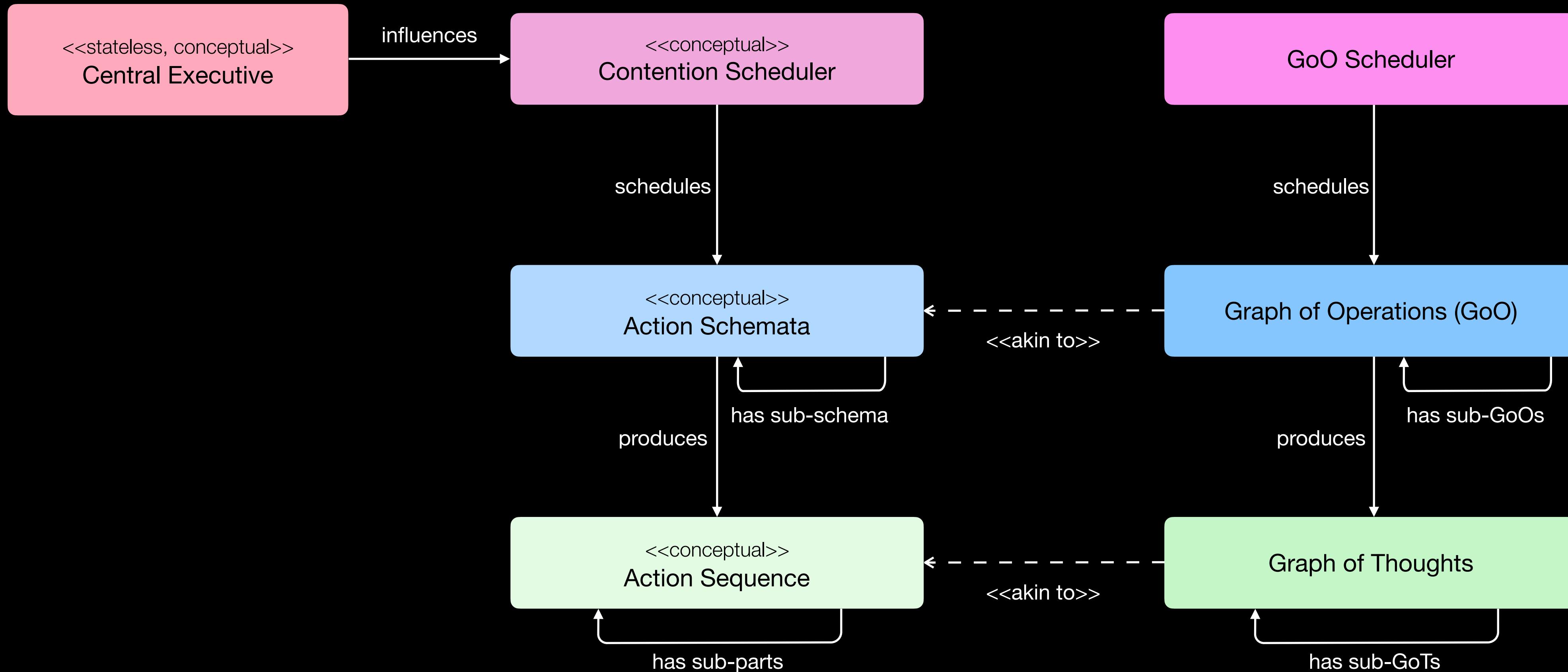
Part I: Theoretical Foundation

1. **Adaptable reasoning structure; independent of reasoning environment** (e.g. GoT)
 - ↳ Arbitrary thought granularity – from sentences to whole paragraphs
 - ↳ Arbitrary thought representation – text, latent, etc.
 - ↳ Arbitrary reasoning granularity – single CoTs or entire sub-graphs
2. Modular, extendible, & minimal viable design
3. Maximal task-agnosticism
4. Out of scope: **Dynamic planning of reasoning structures** (not possible in GoT)

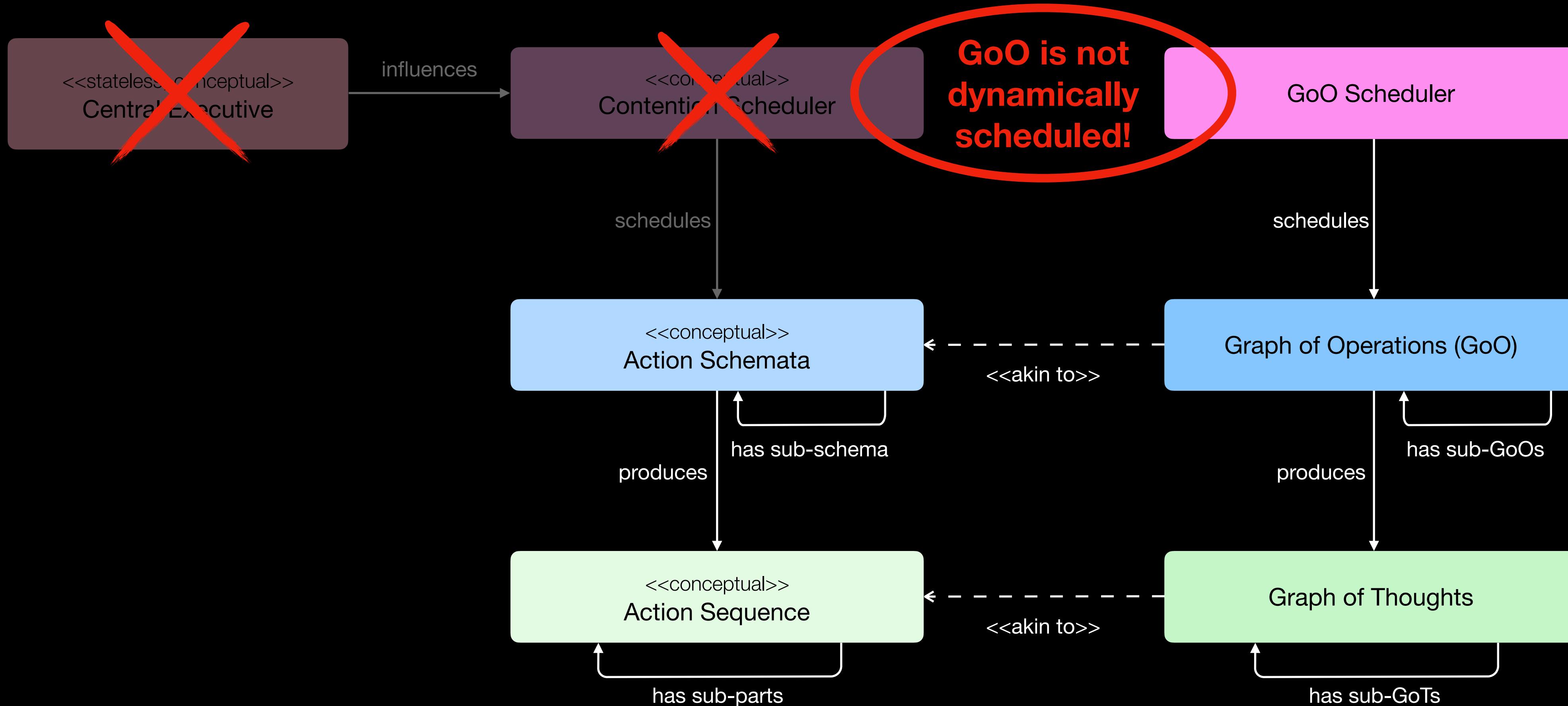
Synthesis I: Deciding which MCM Components to Model



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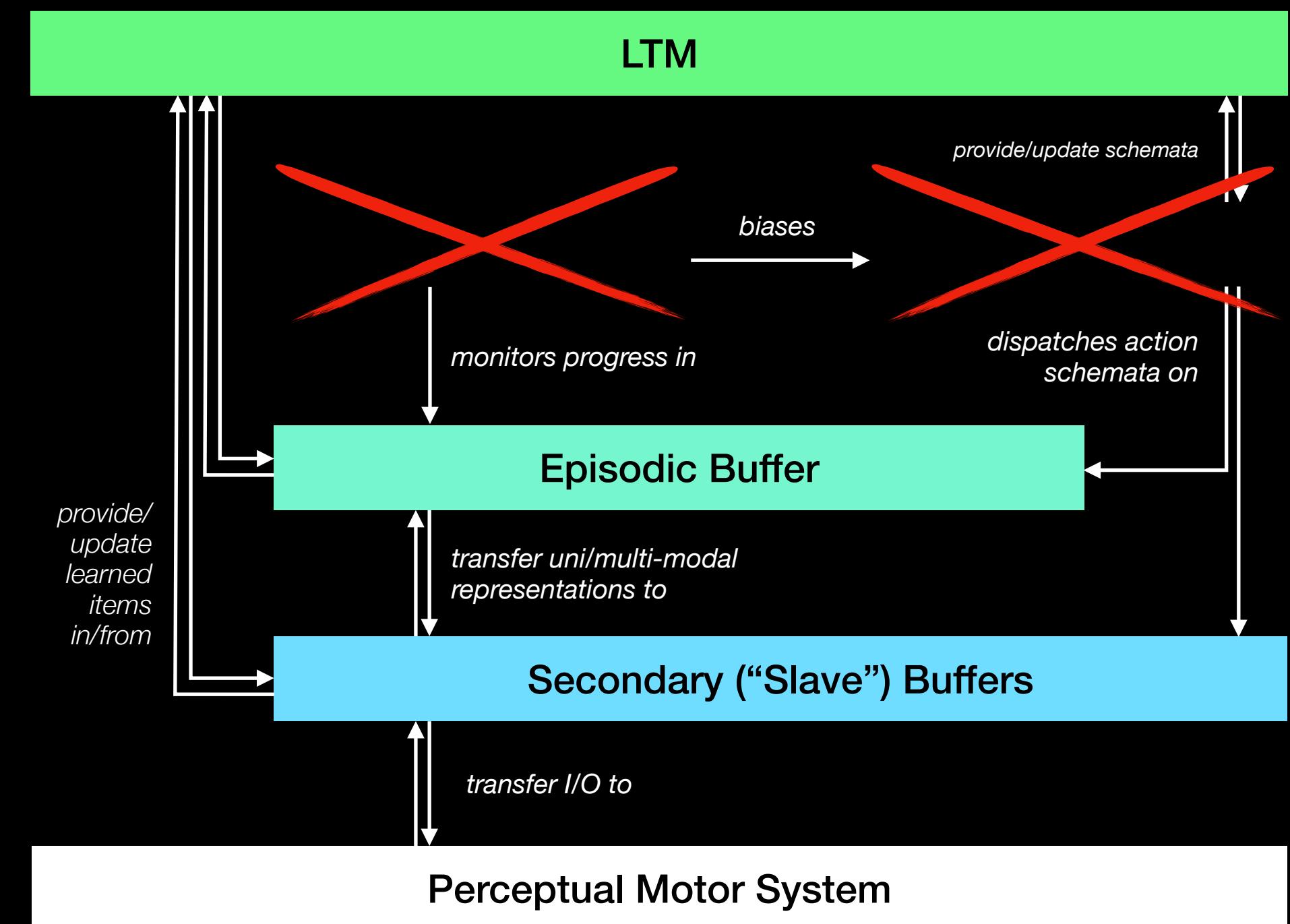


Synthesis I: Deciding which MCM Components to Model



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- No planning of reasoning structure (GoO)
- No dedicated Contention Scheduler, nor Central Executive
- **Fixed transactions** (Action Schemata)

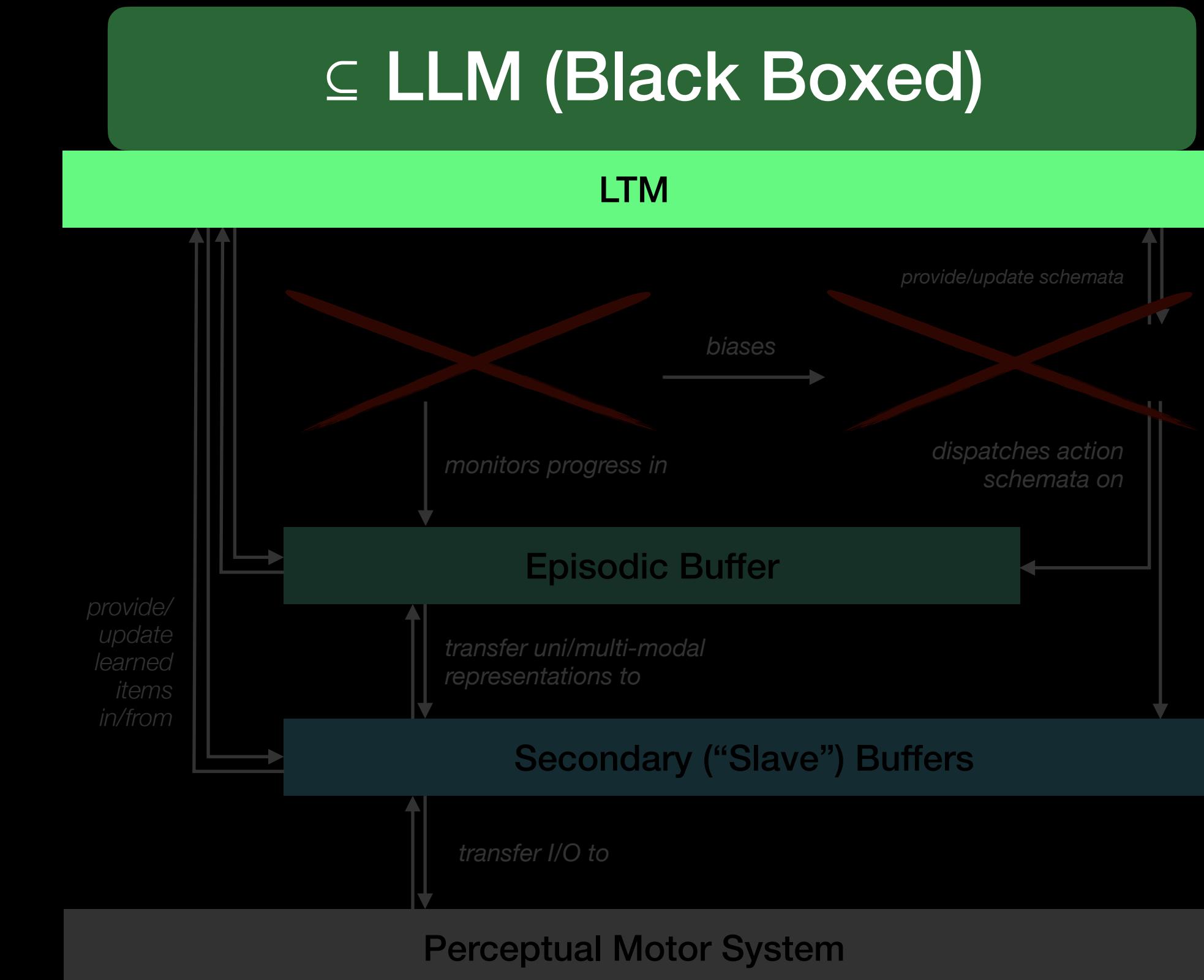


Interpretation based on Baddeley (2000, 2010), Hitch et. Al. (2025),
Norman & Shallice (1986) — See Thesis, Subsection 3.3.1.3

Synthesis I: Deciding which MCM Components to Model

	LLM Weights	LTM Module	Trad. Storage
Support abstraction / learning <i>(Cf. Burgess & Hitch, 2005)</i>	✓	(✓)	✗
Single WM interaction can enable updates <i>(Cf. Burgess & Hitch, 2005)</i>	✓	(✓)	✗
Storage of task-items & Action Schemata <i>(Our Interpretation)</i>	✗ Lack persistence <i>(Mallen et al., 2023)</i>	(✓)	✗

See Thesis, Subsection 4.2.1.



Interpretation based on Baddeley (2000, 2010), Hitch et. Al. (2025), Norman & Shallice (1986) — See Thesis, Subsection 3.3.1.3

Synthesis I: Deciding which MCM Components to Model

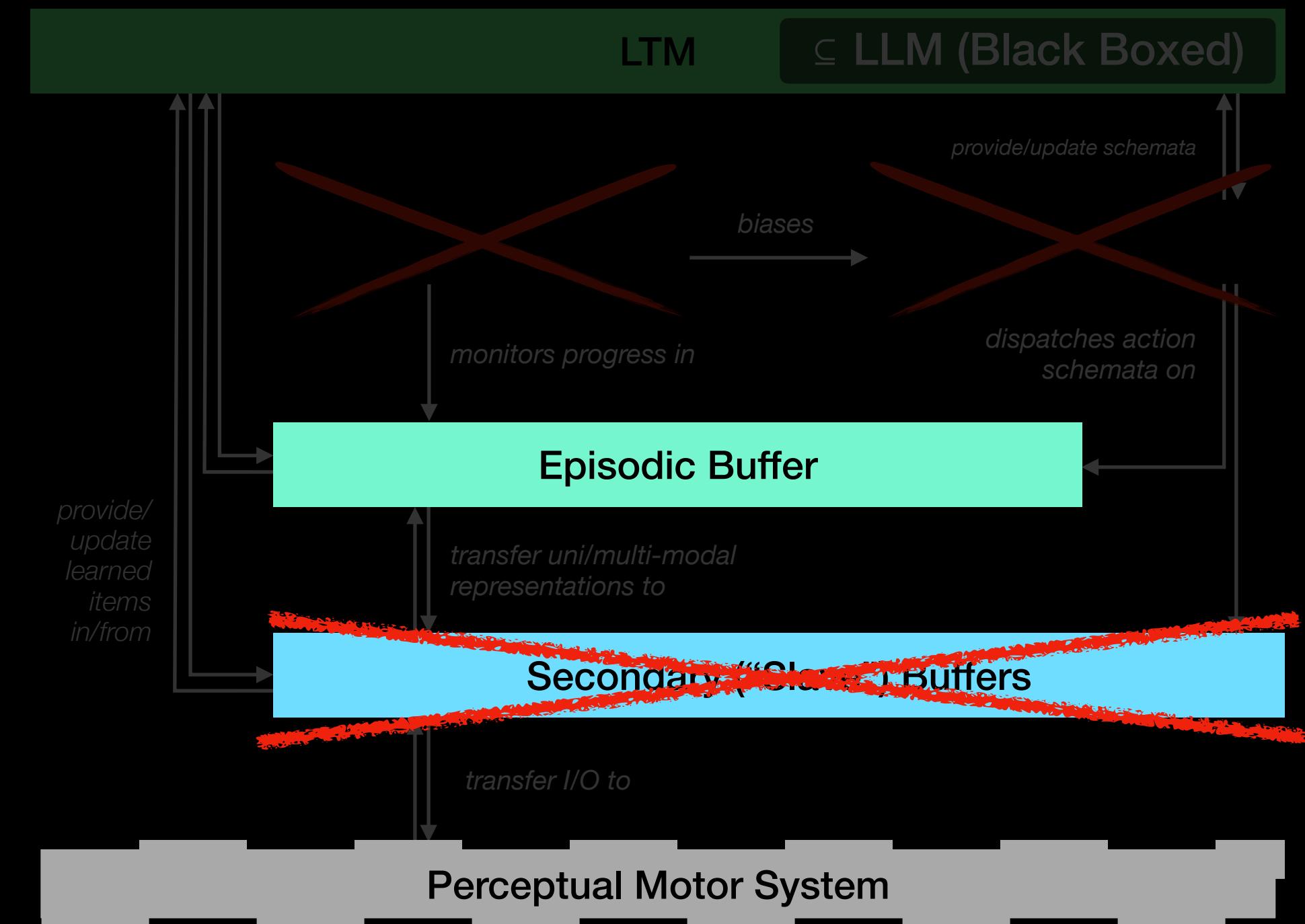
Unimodal setting (Text Only)

↳ **Modality-specific buffers out of scope**

But: Dedicated Pre- & Post-Processing in transactions

WM client is the reasoning environment (e.g. GoT)

↳ Not part of WM itself; requires abstract interface



Interpretation based on Baddeley (2000, 2010), Hitch et. Al. (2025),
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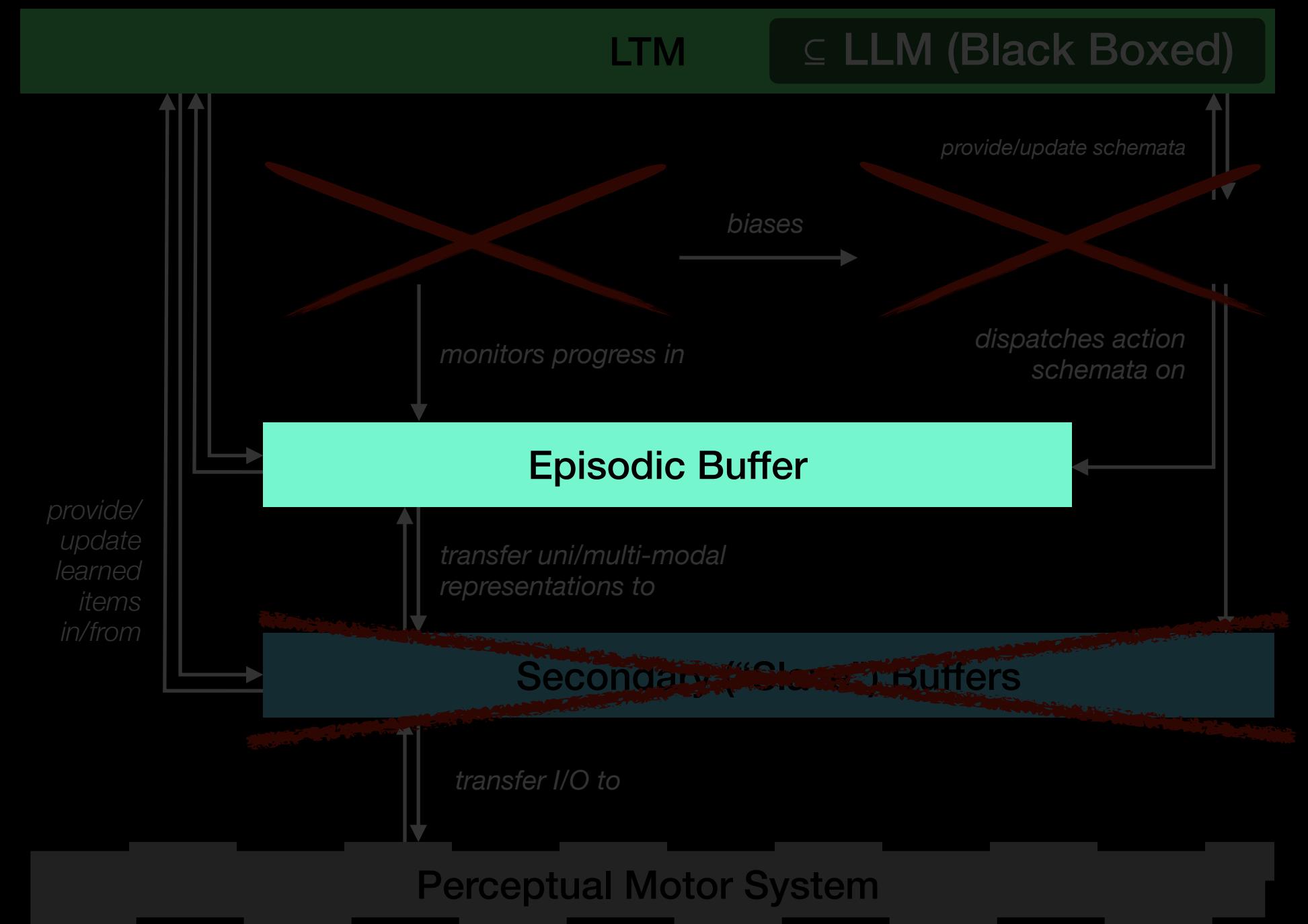
Synthesis I: Deciding which MCM Components to Model

Full focus on the **Episodic Buffer**, characterized by

- Passivity
- Episodicness across “time and space”

And more generally:

- Varying definitions of **capacity**
↳ A notion of **forgetting**
- A **mechanism for chunking** (abstracting/grouping)



Interpretation based on Baddeley (2000, 2010), Hitch et. Al. (2025),
Norman & Shallice (1986) — See Thesis, Subsection 3.3.1.3

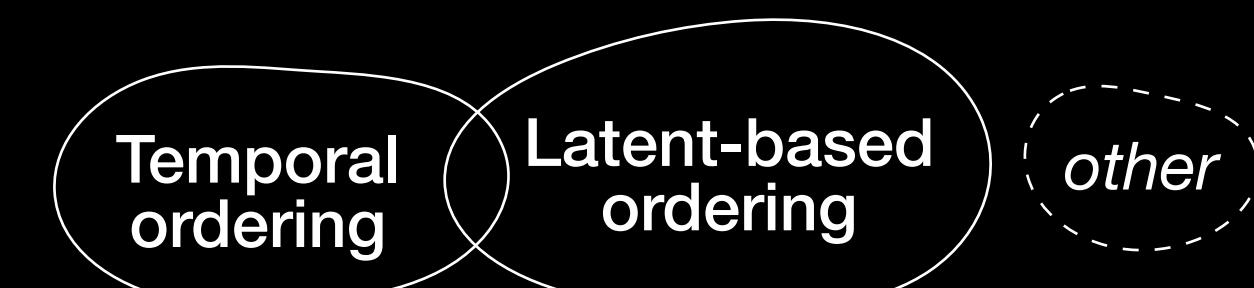
Synthesis II: Mapping Cognitive Concepts to Related Work on LLMs

Contribution II: A WM Core Architecture for LLMs

Part I: Theoretical Foundation

Buffer Characteristics

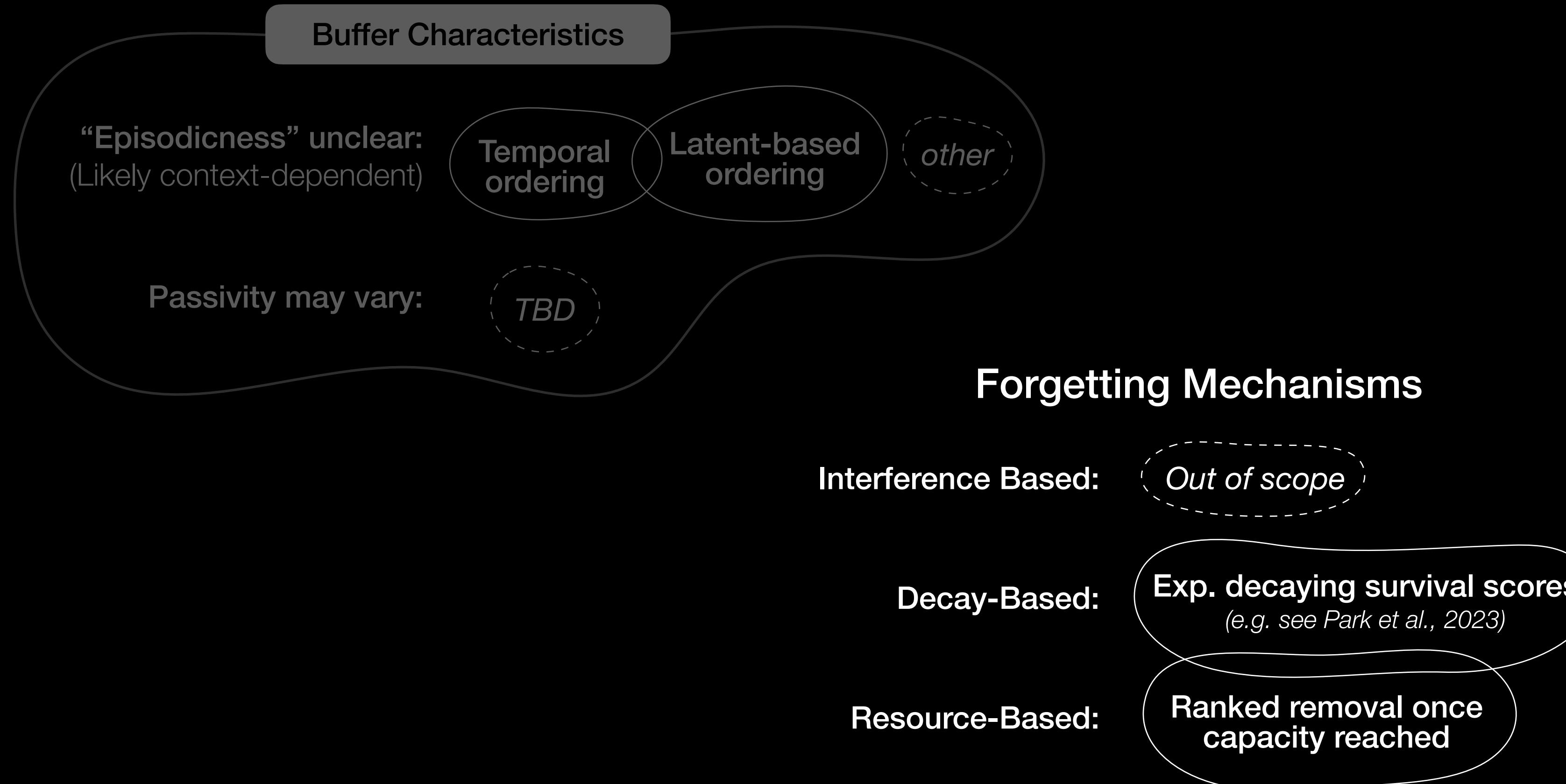
“Episodicness” unclear:
(Likely context-dependent)



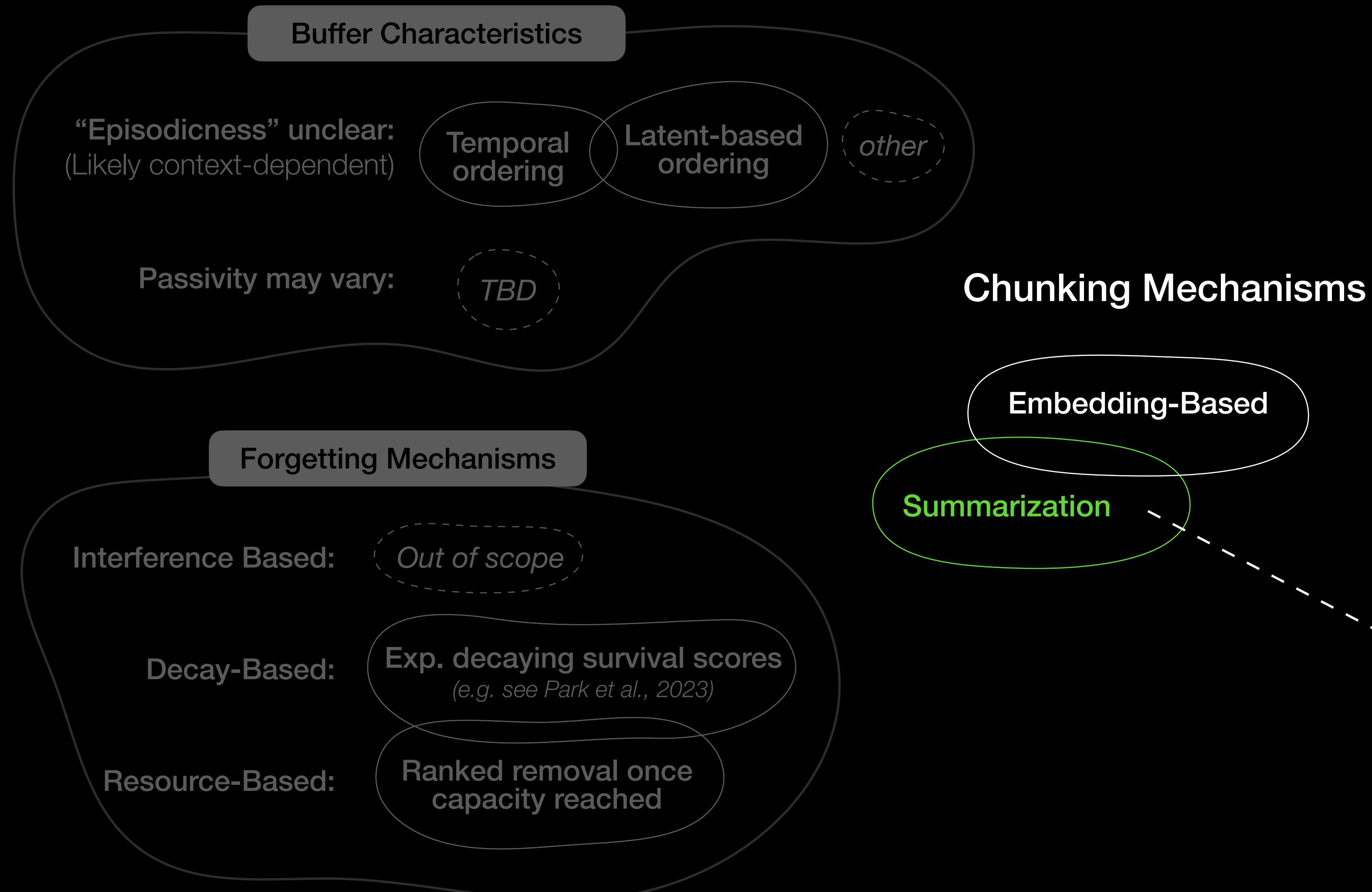
Passivity may vary:



Synthesis II: Mapping Cognitive Concepts to Related Work on LLMs



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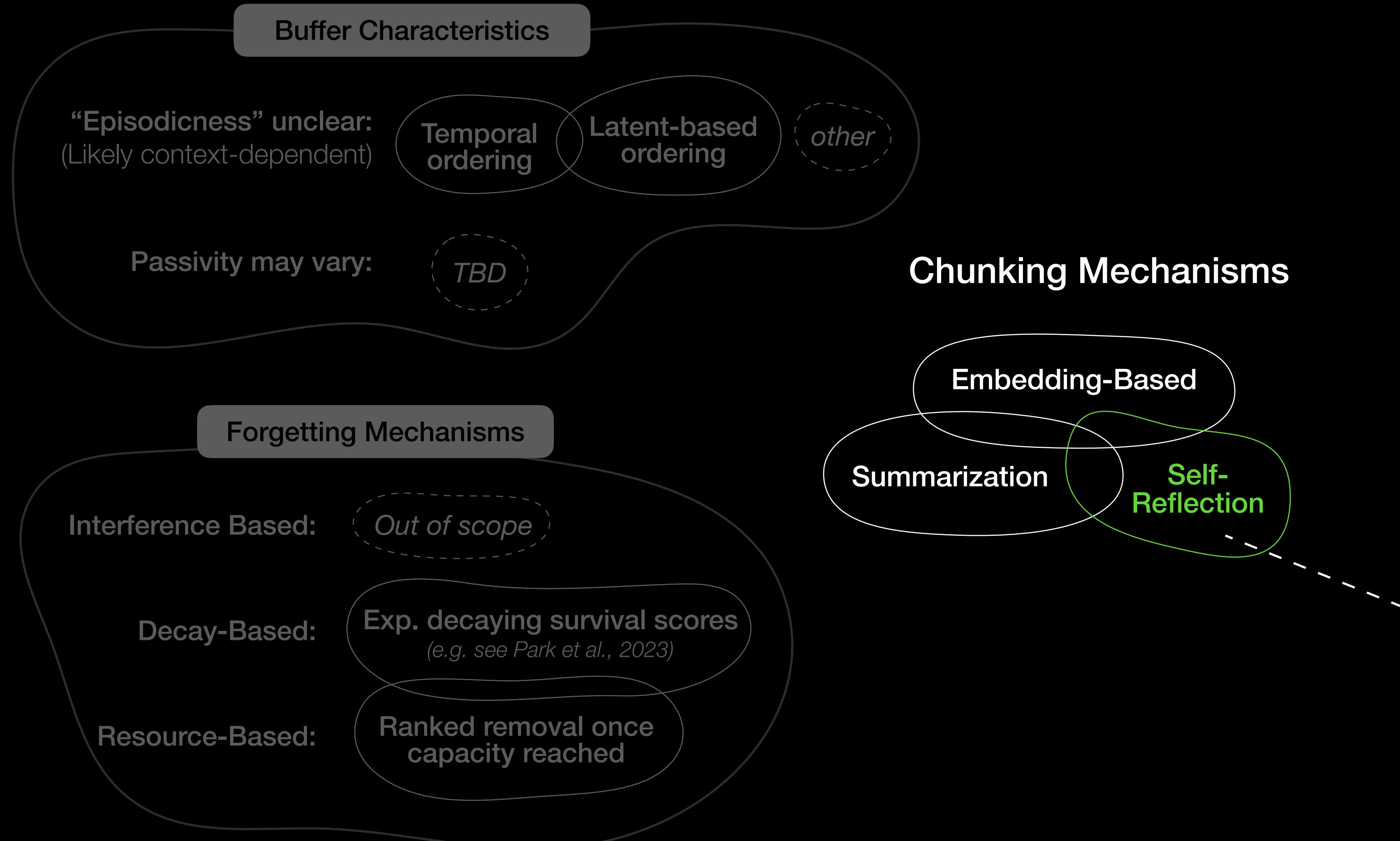
As in **Hi-Agent (Hu et al., 2024)**:

- Agent formulates sub-goal g
- Appends new $(action, observation)$ pairs to context until g completed
- **Summarizes** $(action, observation)$ pairs leading up to g in context

Synthesis II: Mapping Cognitive Concepts to Related Work on LLMs

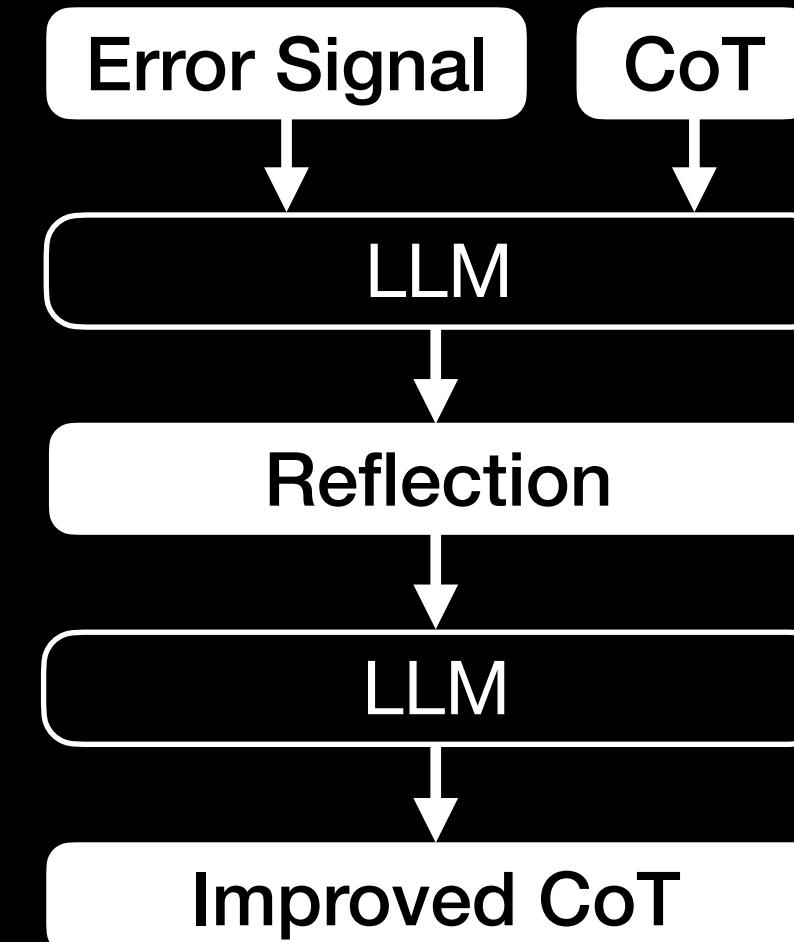
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Part I: Theoretical Foundation



High level process:

Cf. e.g. Madaan et al. (2023), Shinn et al. (2023), Renze and Guven (2024)



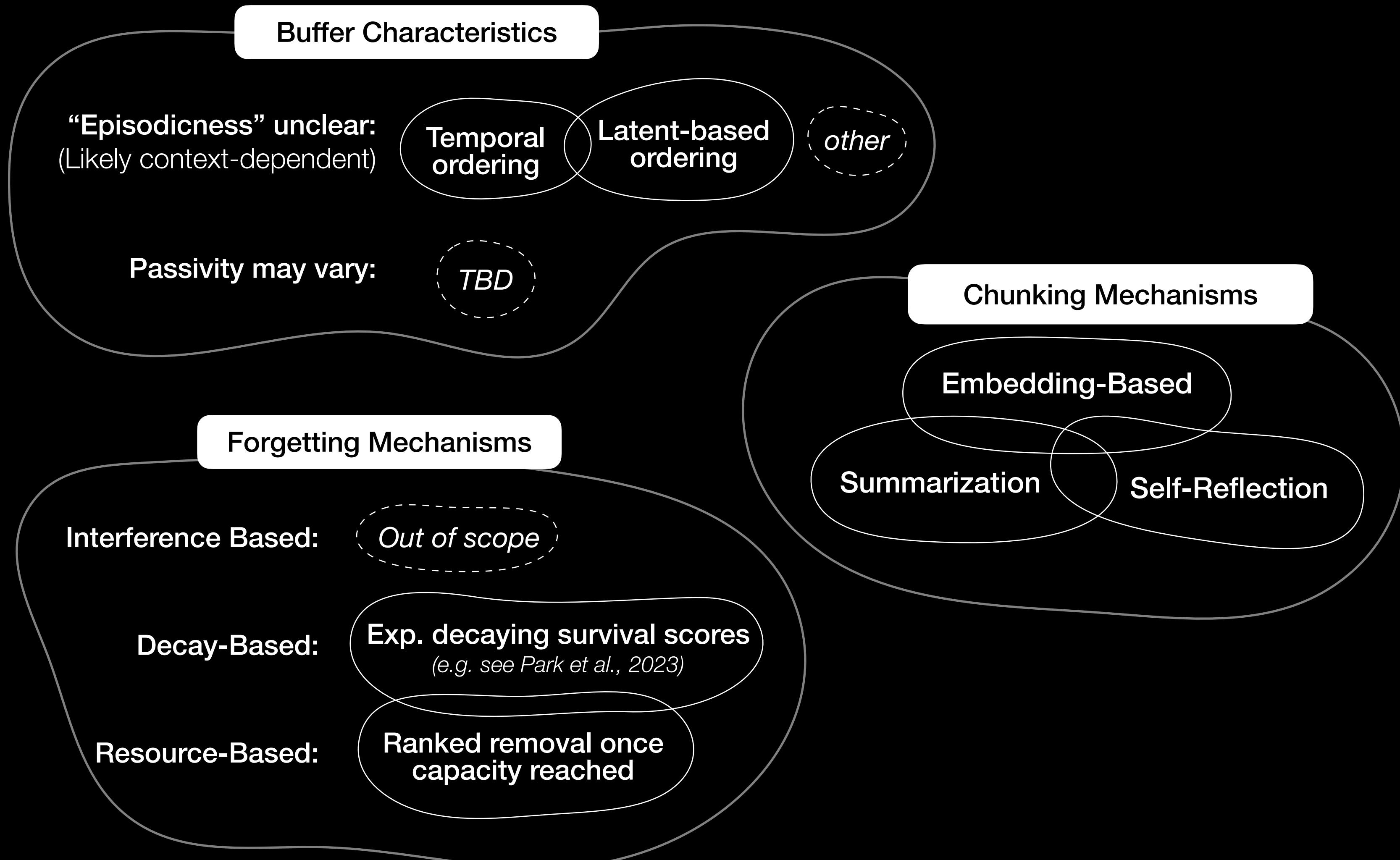
Error signals are generally

- Textual or numerical
- External or internal

LLMs' ability to identify own errors remains inconclusive
(Renze & Guven, 2024)

↳ Working assumption:
Works reasonably well

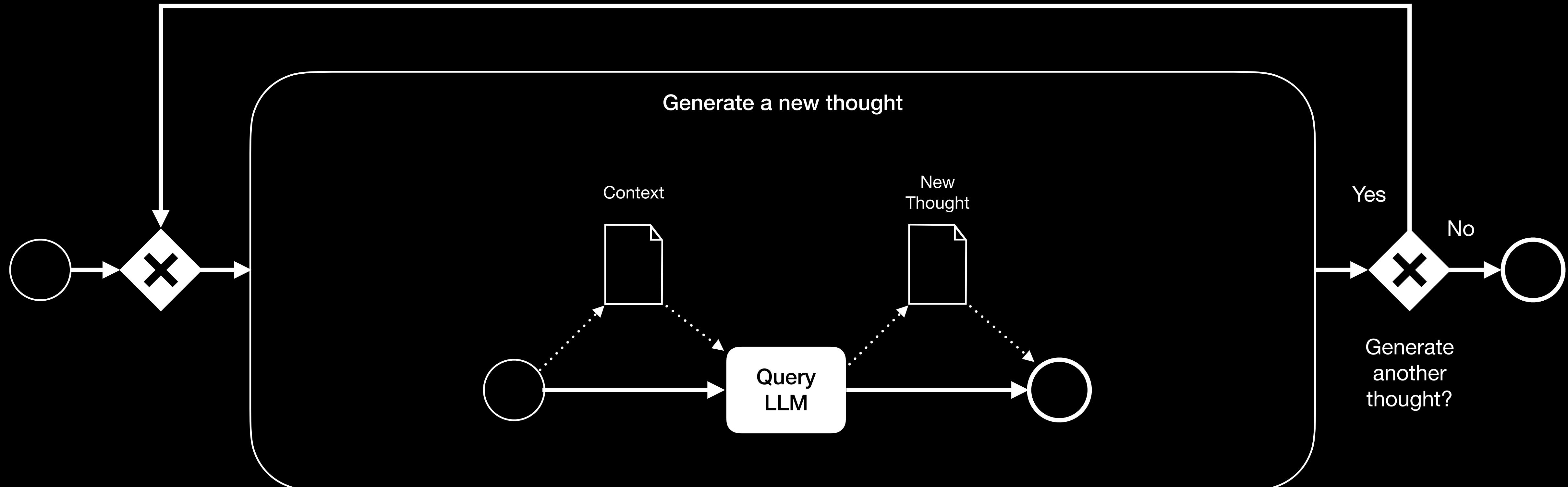
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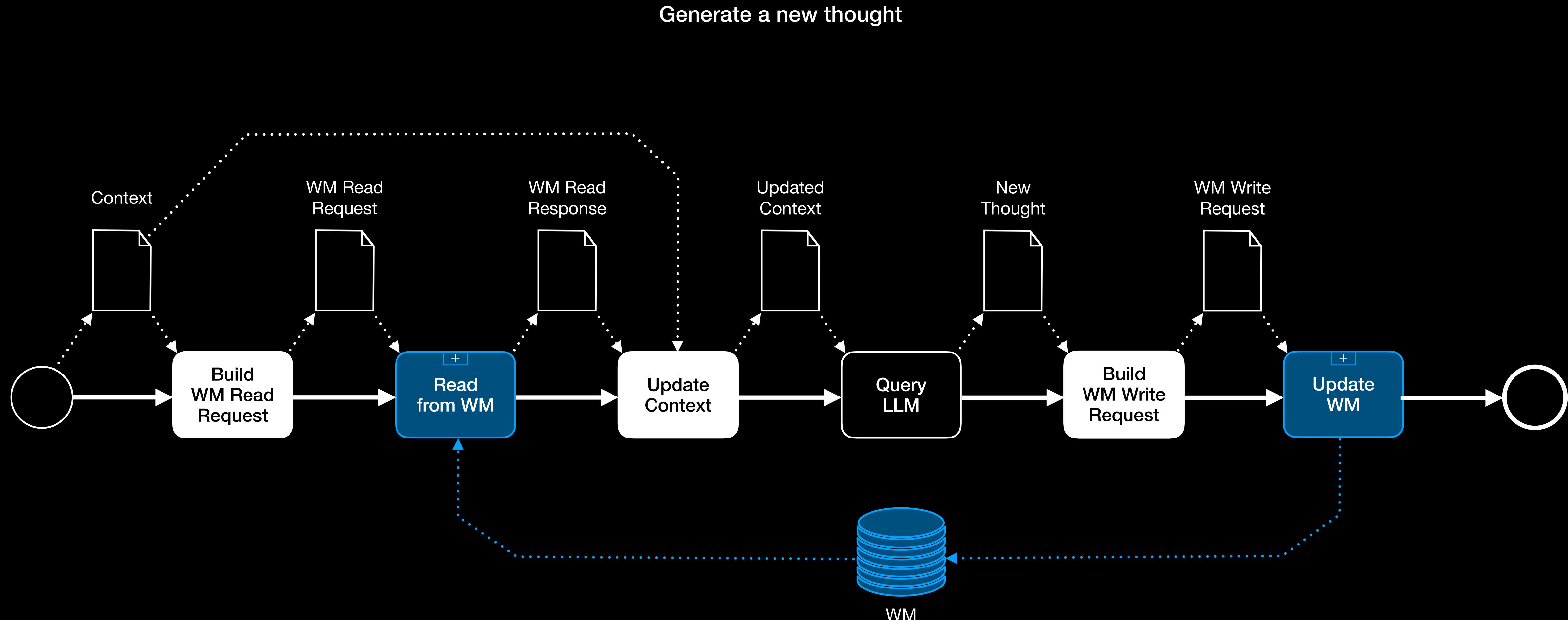
PART 2

Implementation

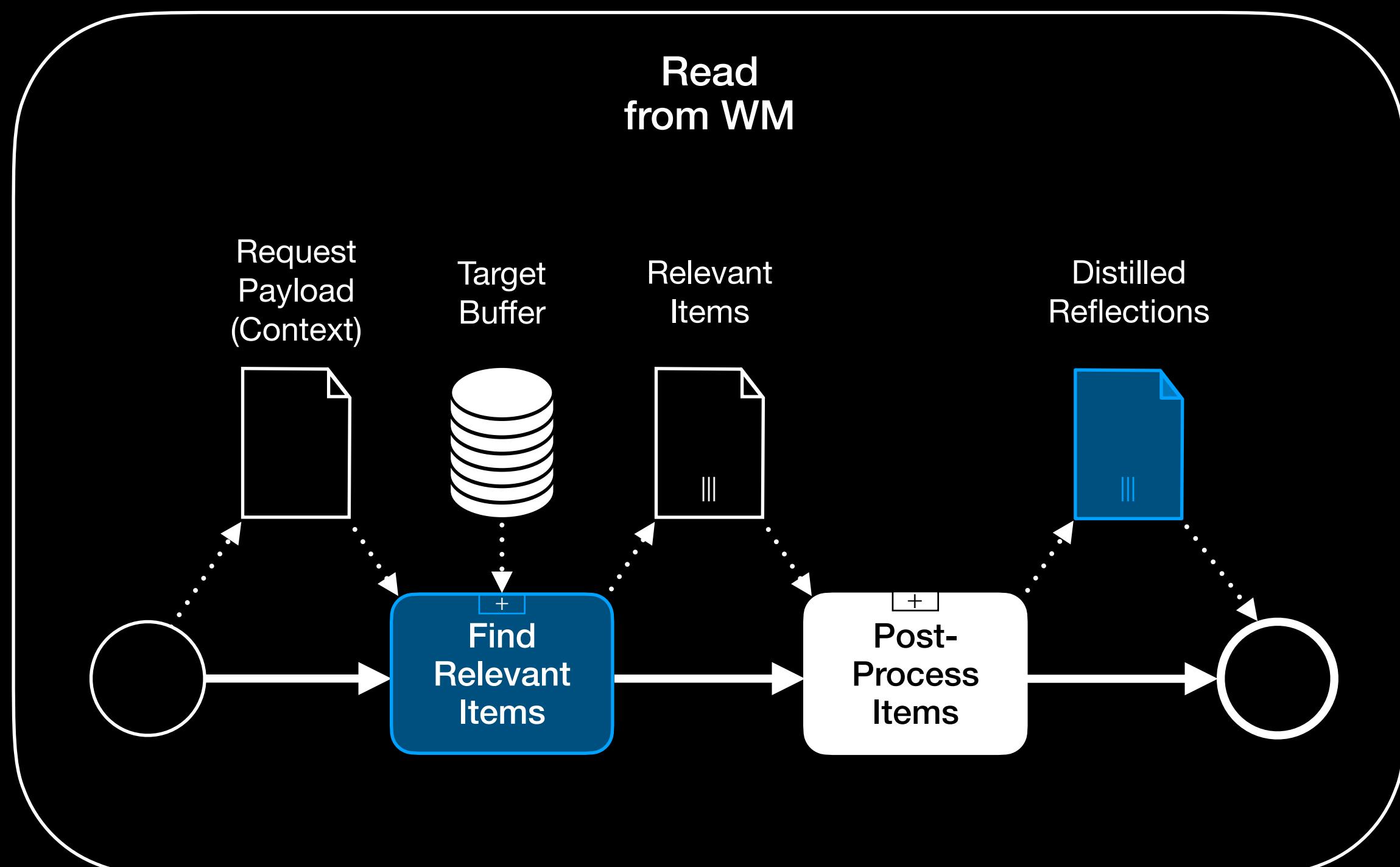
Abstract Reasoning Process without WM Interaction



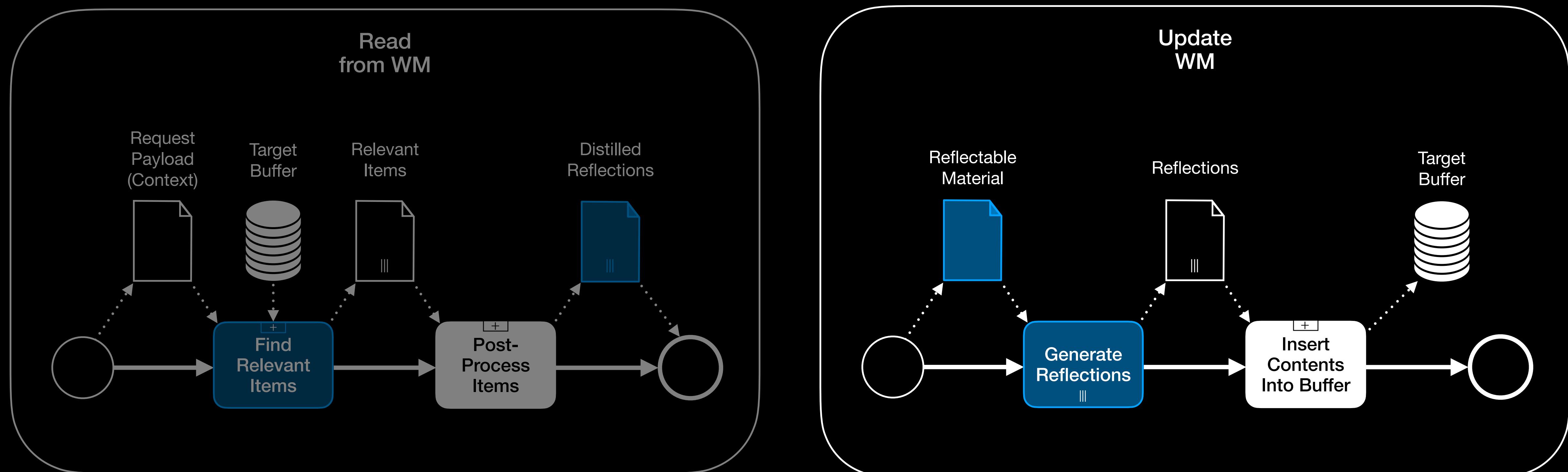
Abstract Reasoning Process with WM Interaction (Simplified)



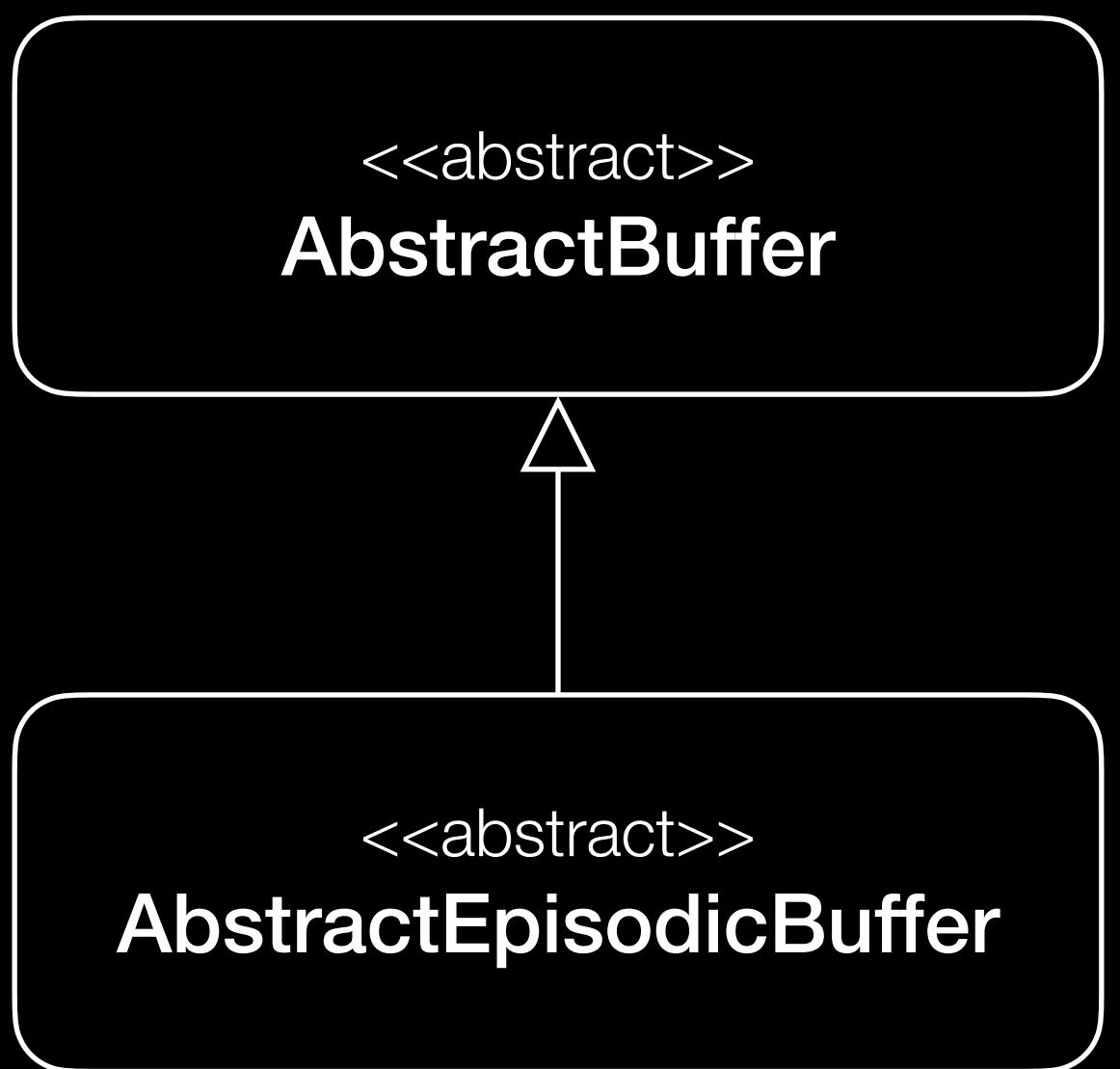
Reflection-Based WM Read and Write Subprocesses (Simplified)



Reflection-Based WM Read and Write Subprocesses (Simplified)



A Two Tiered Buffer Hierarchy



A Two Tiered Buffer Hierarchy: AbstractBuffer

1. Owns the item space

- ↳ Declares *expected item* and *request* type to accept
- ↳ Decides how items relate to *another* and a *request*
(via abstract functions)

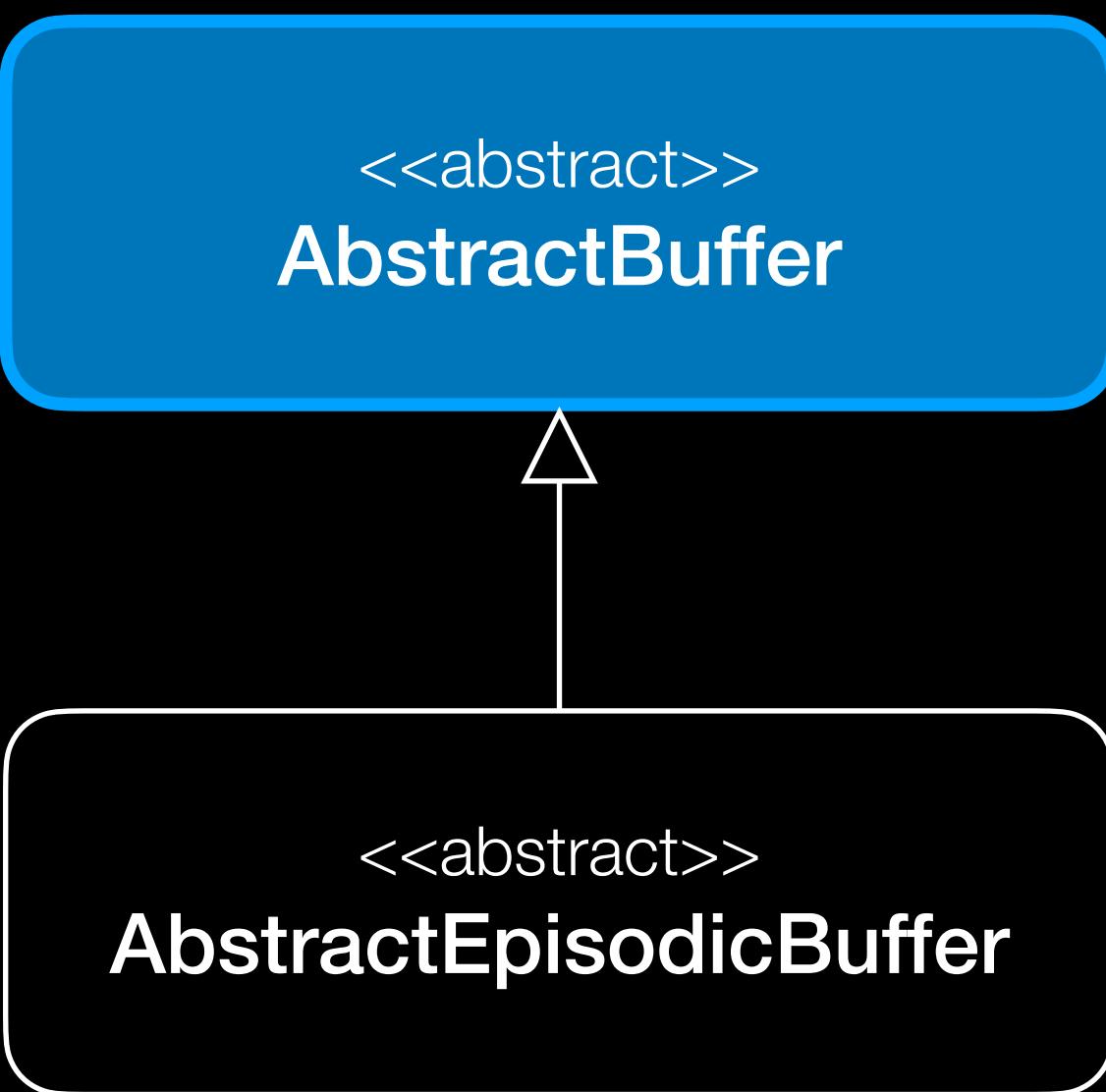
2. Enforces a capacity limit (various def. possible)

- ↳ Items define their capacity
- ↳ Buffer provides functions to check current and maximal capacity
- ↳ Buffer rejects CRUD operations if capacity would be exceeded

3. Strictly passive (per LSP): Only CRUD operations

- ↳ Delegates forgetting operations to environment (transactions)

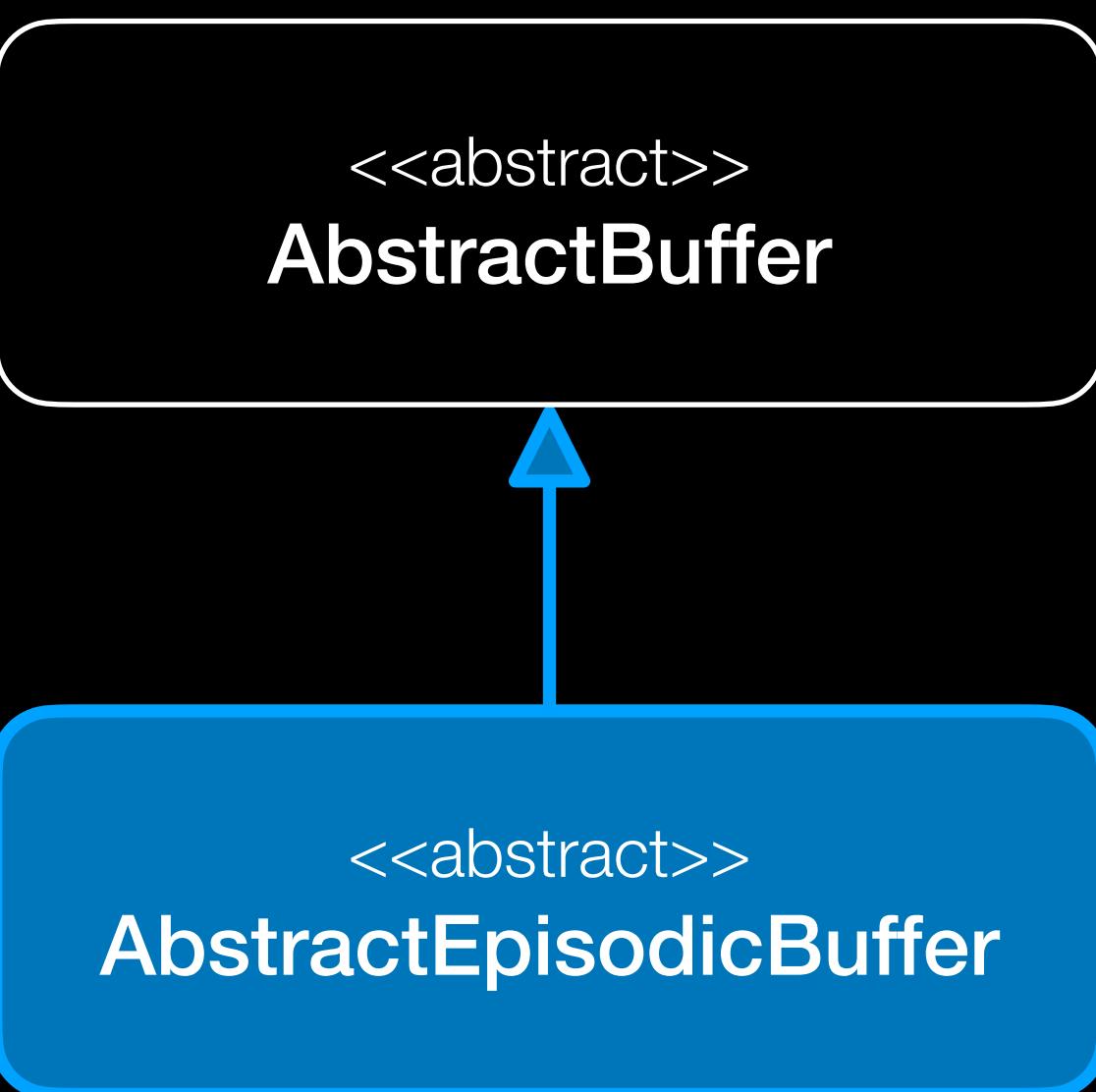
4. Requires a notion of local time



A Two Tiered Buffer Hierarchy: AbstractBuffer

1. Operates on “Chunked” Items

- Stores a **forest of items** where
 - **Abstract Nodes** serve as cluster labels:
 - ↳ Assumes **information loss** w.r.t. children
 - **Concrete Nodes** bear payload (e.g. a reflection);
may also be an aggregate of other nodes payload's
 - ↳ Assumes **no information loss** w.r.t. children (are representative)
- Def. **Chunking**: Building an item tree via
 - Merging of concrete nodes
 - Assigning abstract parents



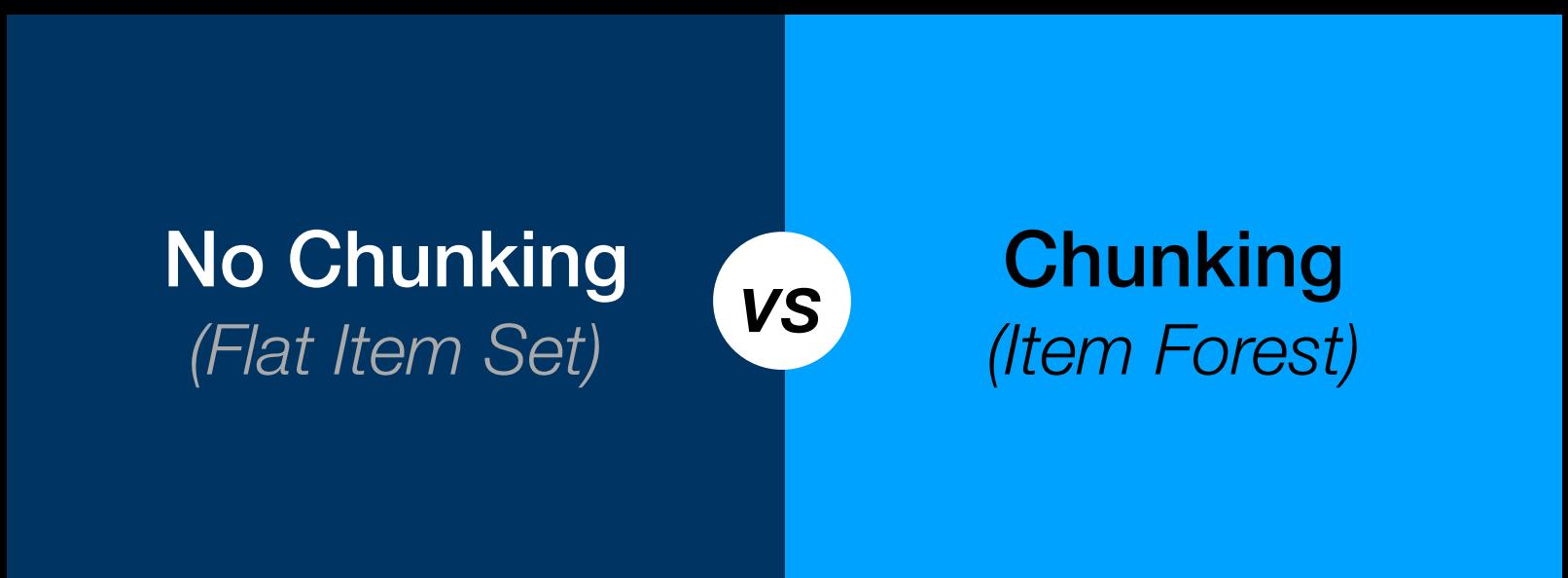
2. Defines an **implicit notion of episodic coherence** via

- Abstract grouping functions
- Abstract matching functions, for *part-whole* and *equivalence* between nodes
(*Extensions of AbstractBuffers matching function*)

Implement WM Variants: Design Matrix

Contribution III: Four Concrete WM Variants

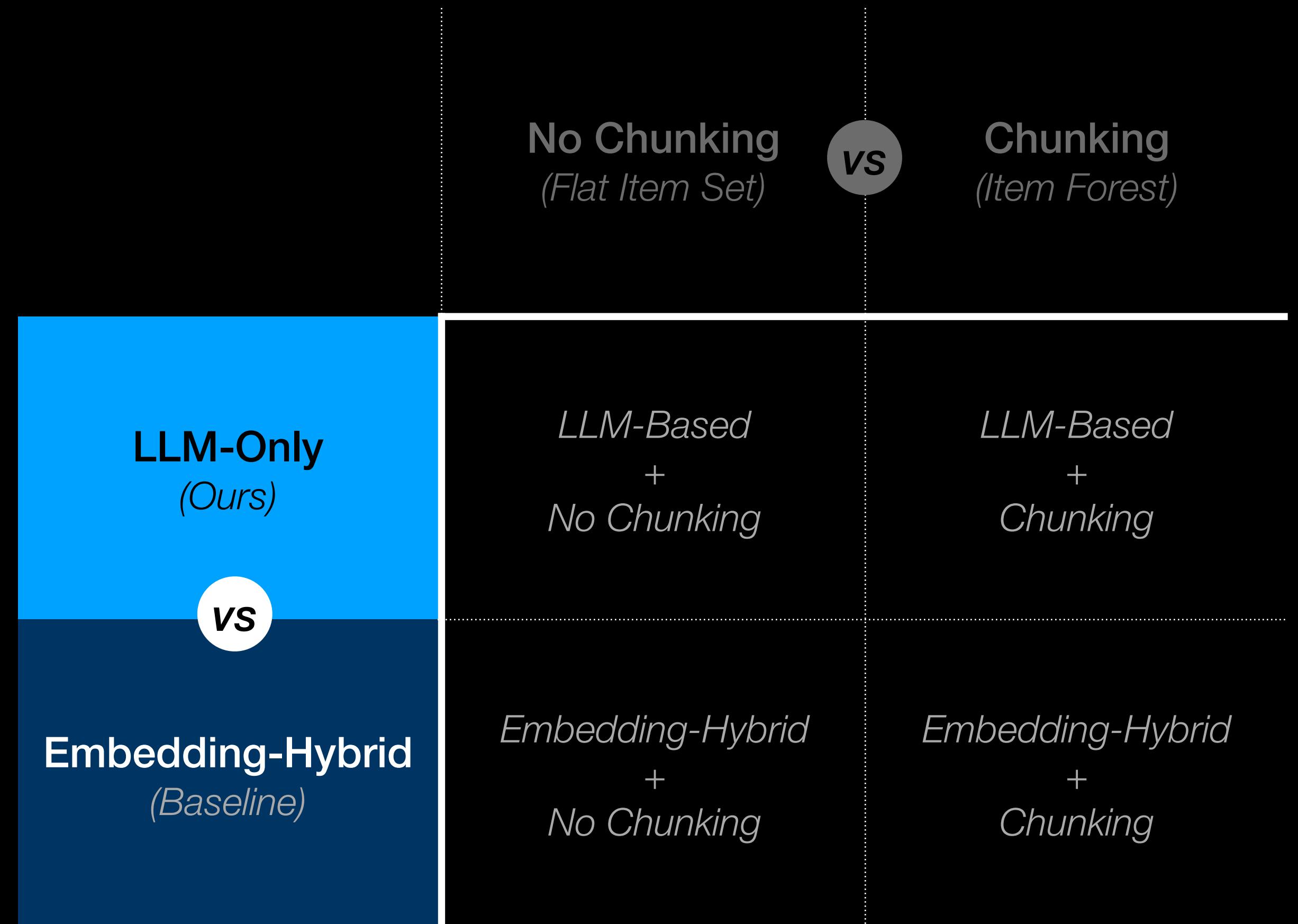
Part II: Implementation



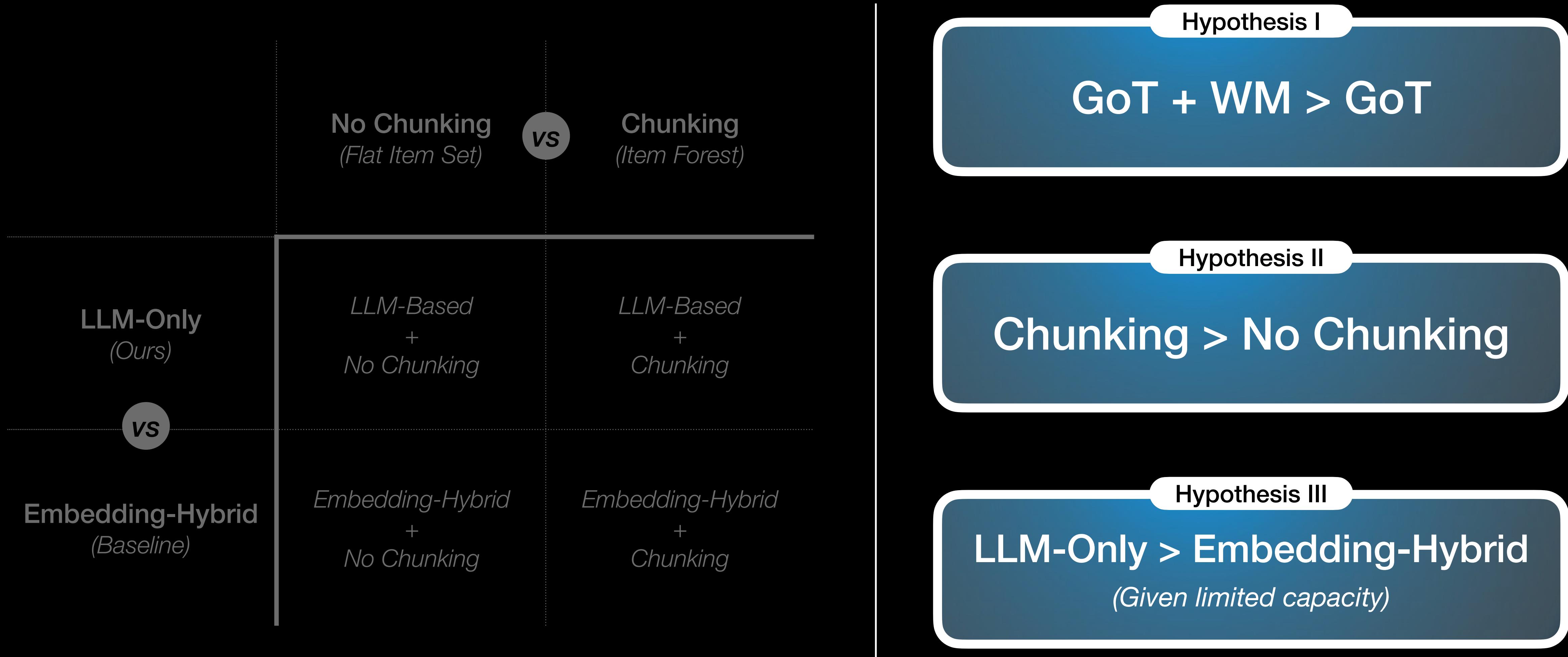
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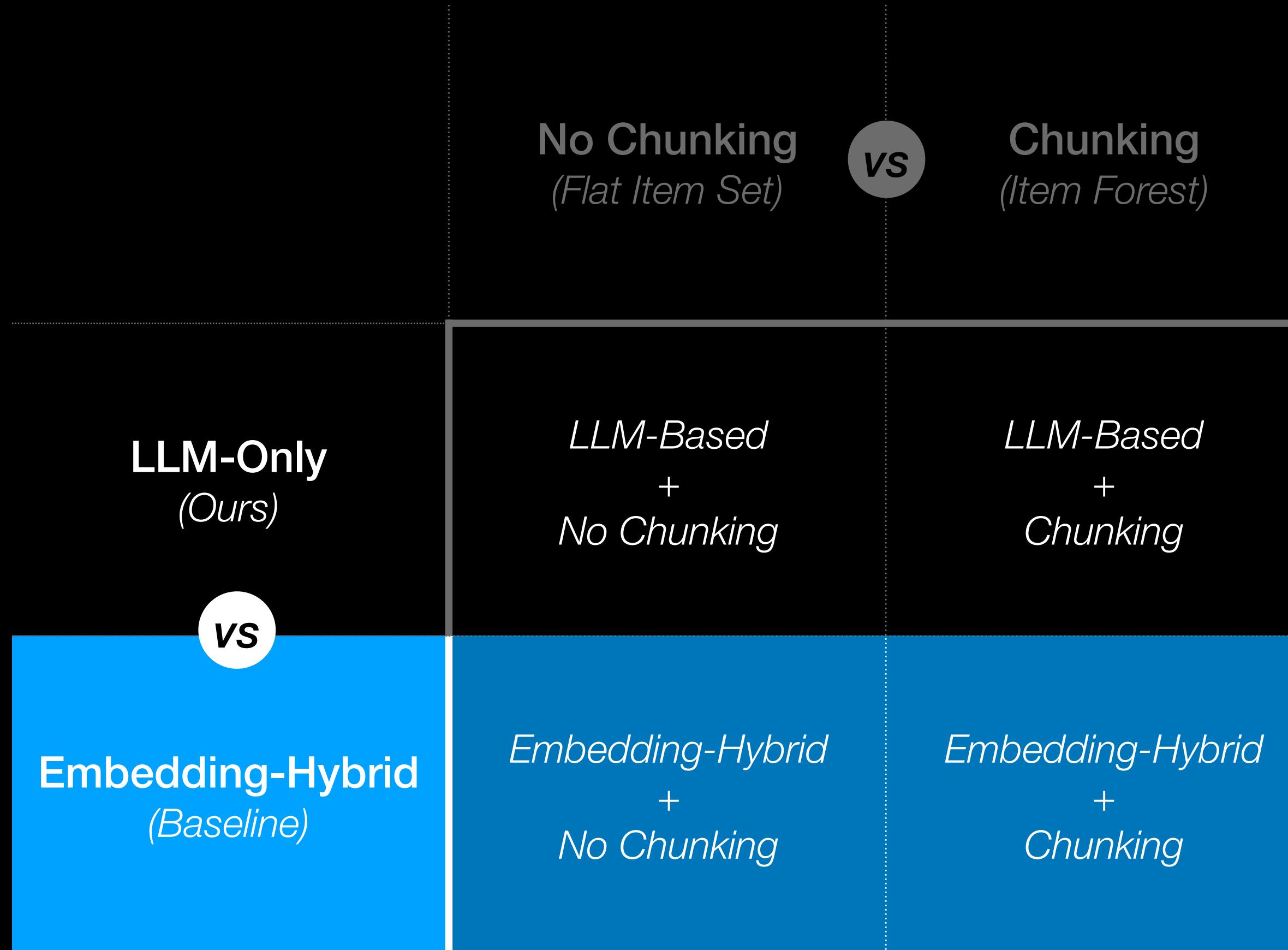
Part II: Implementation



Implement WM Variants: The Underlying Hypotheses



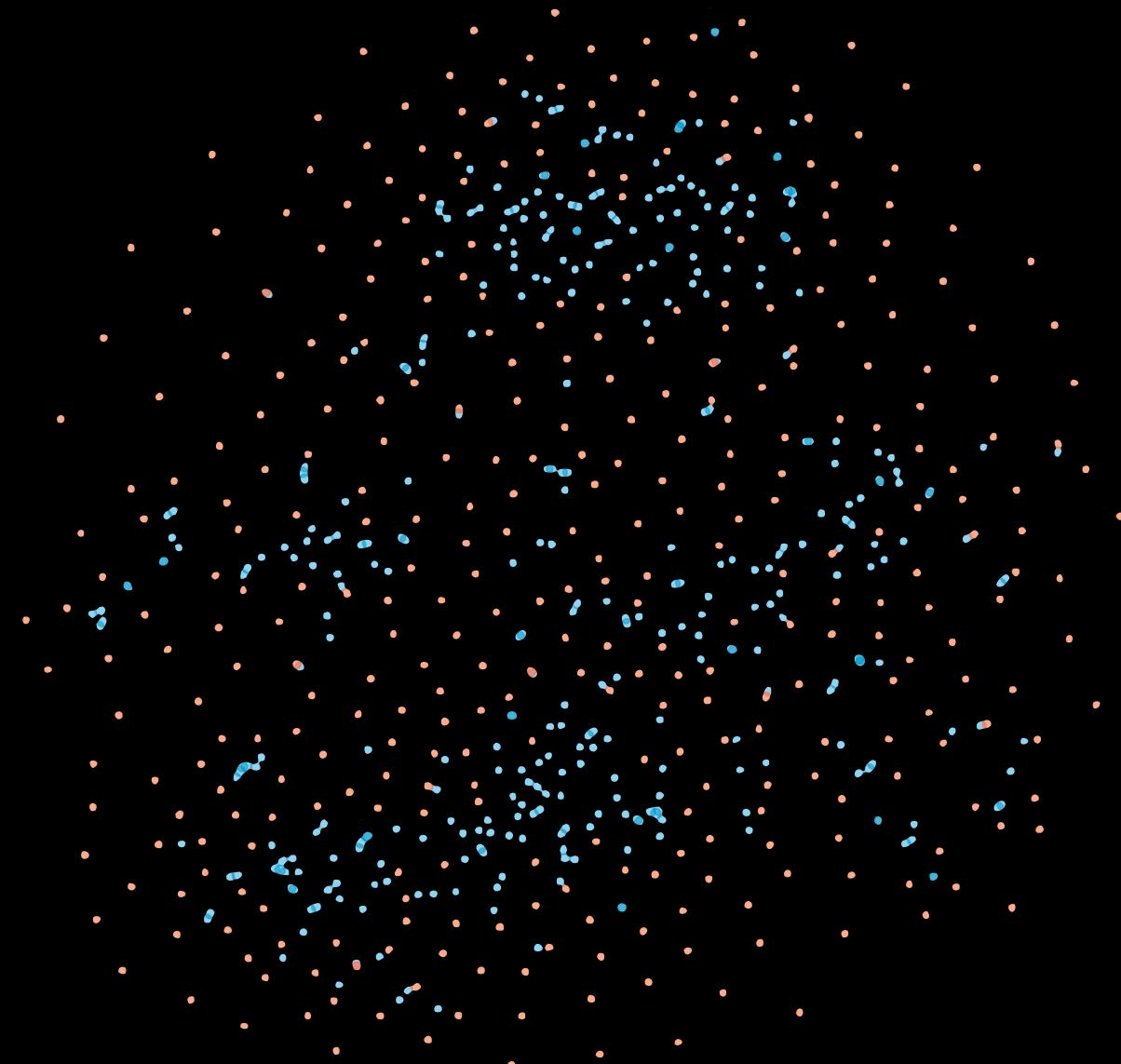
Implement WM Variants: The Embedding-Hybrid Backbone



Based on **A-MEM (Xu et al., 2025)**:

- S.O.T.A. memory for agentic setups
- Reverses the idea of contrastive learning:
 - ↳ Neighborhoods are verified by LLM
 - ↳ Verified neighbors receive similar tags
 - ↳ Similar items move closer in space

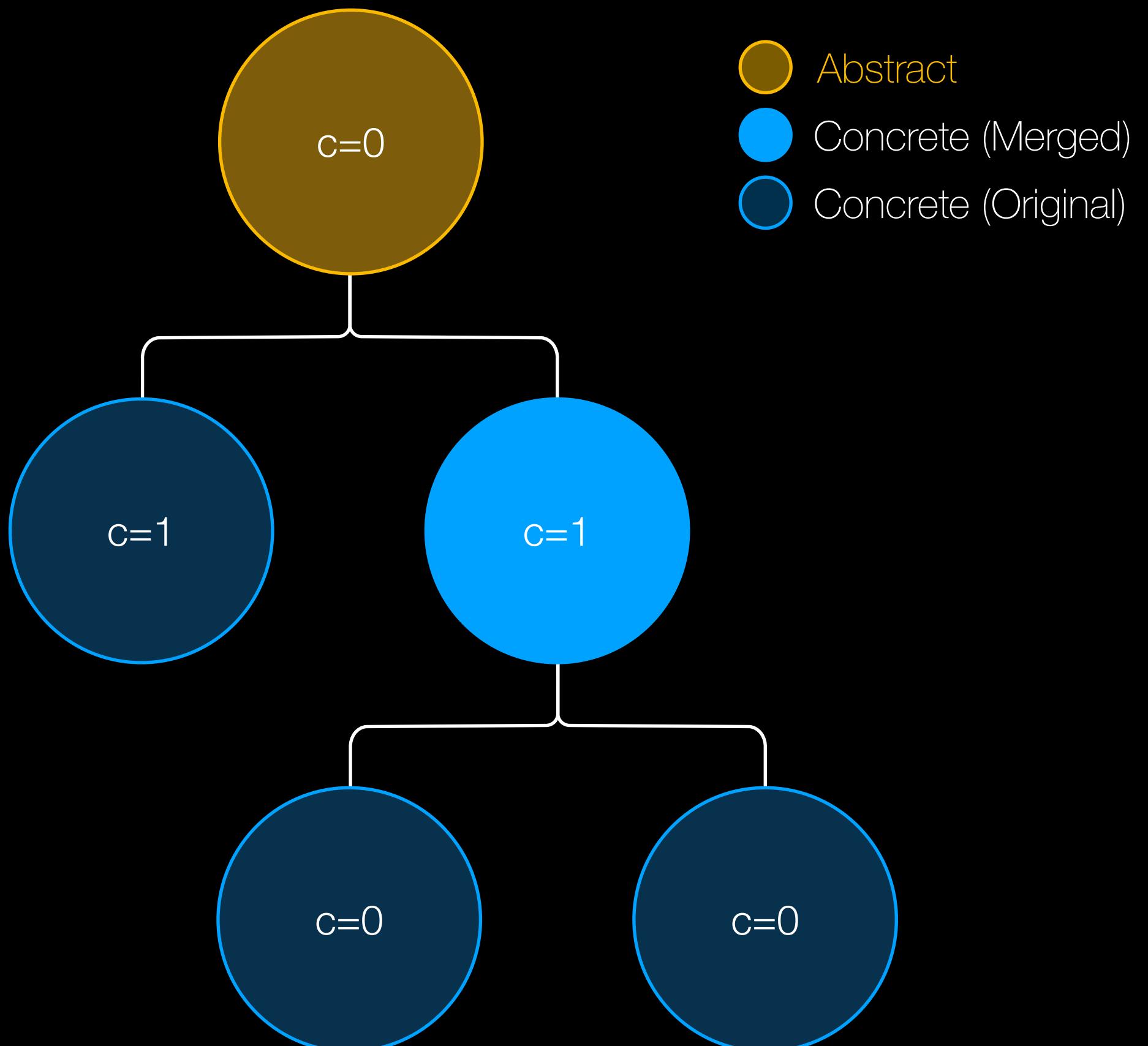
T-SNE Visualization of Memory Embeddings (adapted from Xu et al., 2025):
A-MEM (blue) vs Base Memory (red)



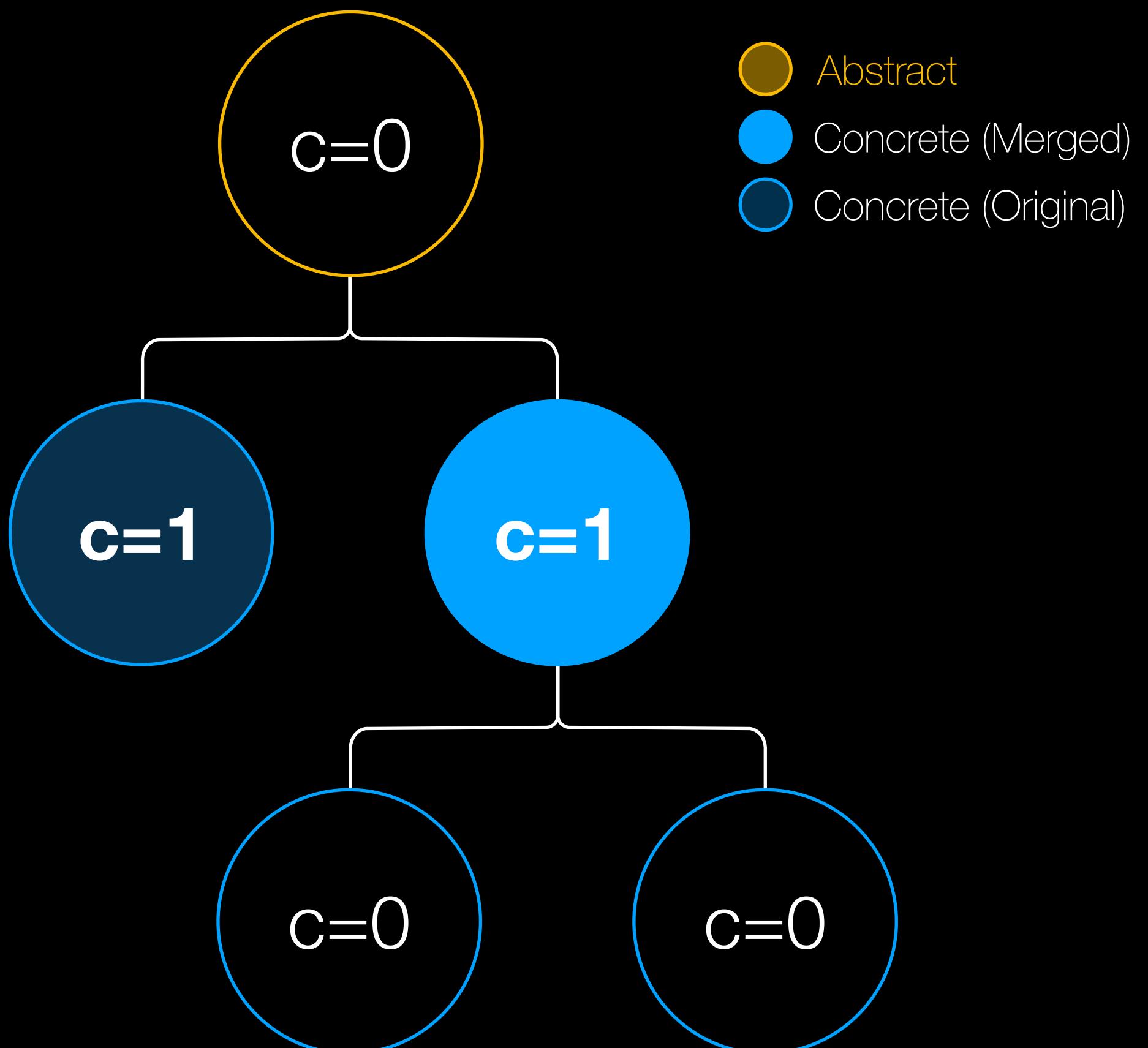
Implement WM Variants: Further Constraints

1. Shallow, Text-Only Chunks

- At most one abstract node per tree
- Abstract nodes hold a textual cluster label
- Concrete nodes hold reflections as payload which can be merged (via LLM)



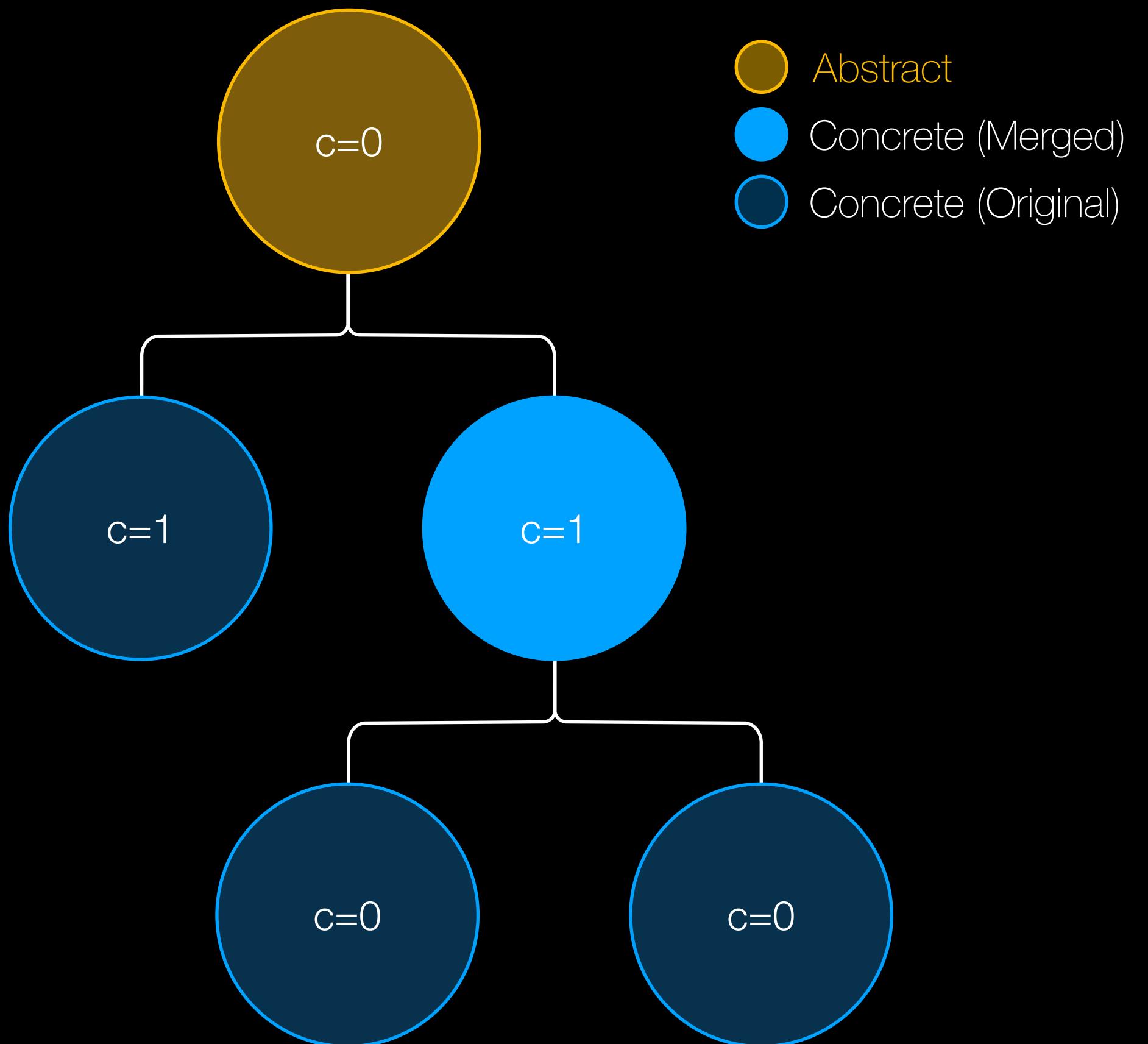
Implement WM Variants: Further Constraints



2. Forgetting: Resource + Decay

- Resource-based capacity (c) threshold where **only items in the concrete front contribute**
- Exponential **decay of survival scores** based on item access & repetition + LLM-based usability scoring

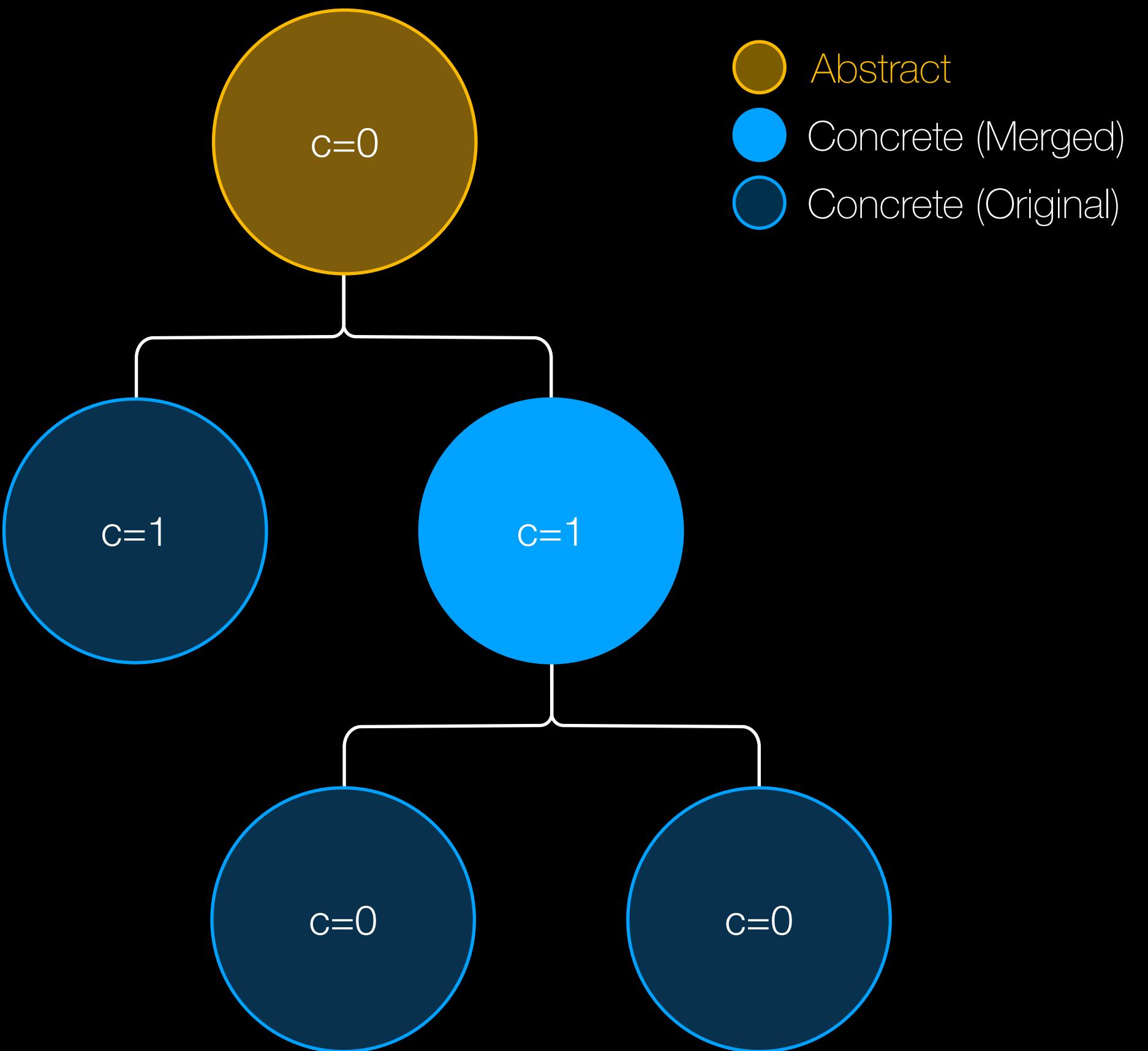
Implement WM Variants: Further Constraints



3. No reorganization of forest

↪ Insertion > New trees (\rightarrow Prone to over-aggregation)

Implement WM Variants: Further Constraints



4. Reflection generation limited to a single thought

PART 3

Main Findings

Experimental Setup (Simplified)

Contribution IV: WM Variants Evaluated within GoT

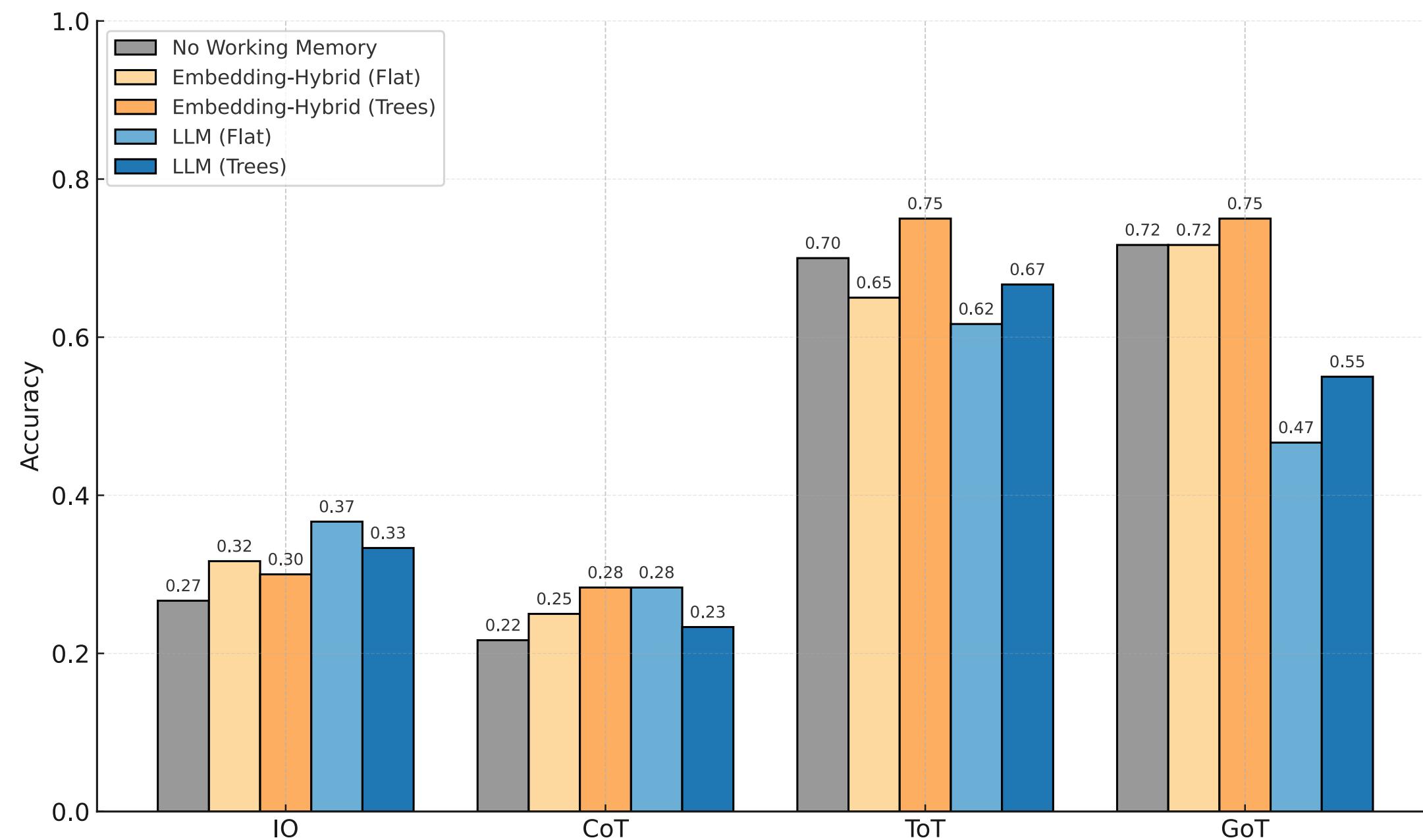
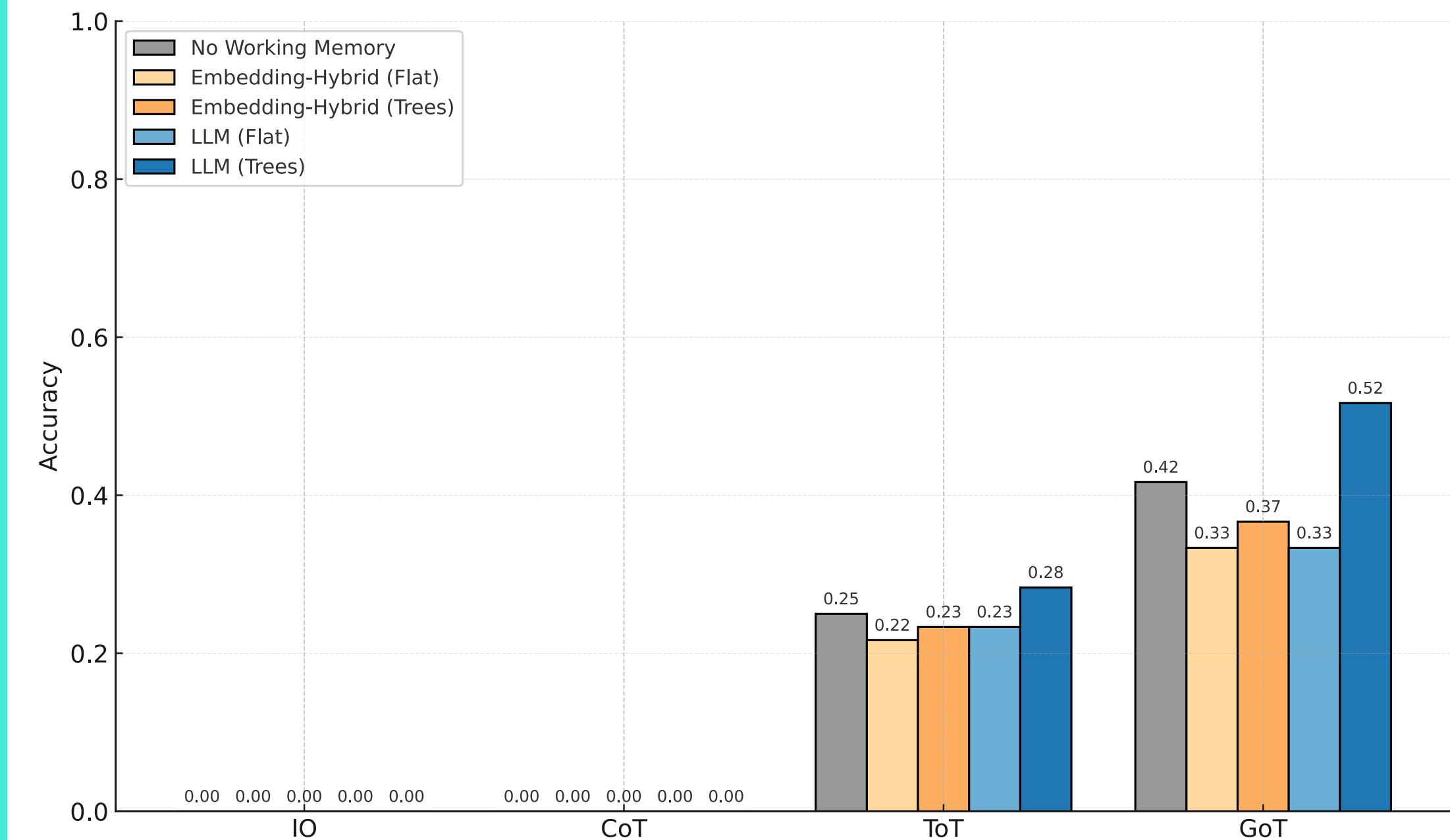
Part III: Main Findings

- **Tasks: Sorting & Set-Intersection** – adapted from GoT (*Besta et. al., 2024*)
 - On a list/set of integers (size=32)
 - Eval metric: **Accuracy**
- **5 competing setups:**
 - ↳ **No WM** (Vanilla GoT); GoT+ each of our **four WM variants** (resp.)
 - ↳ Each assessed across **I/O, CoT, ToT, GoT** prompting
 - ↳ For each: 20 samples x redraw of 3 → **60 datapoints** in total
- **WM capacity = 7**
(mean number of retrieved items in a trial run with capacity = ∞)
- **Model:** gpt-4o-mini-2024-07-18
(Documented at <https://platform.openai.com/docs/models/gpt-4o-mini>)

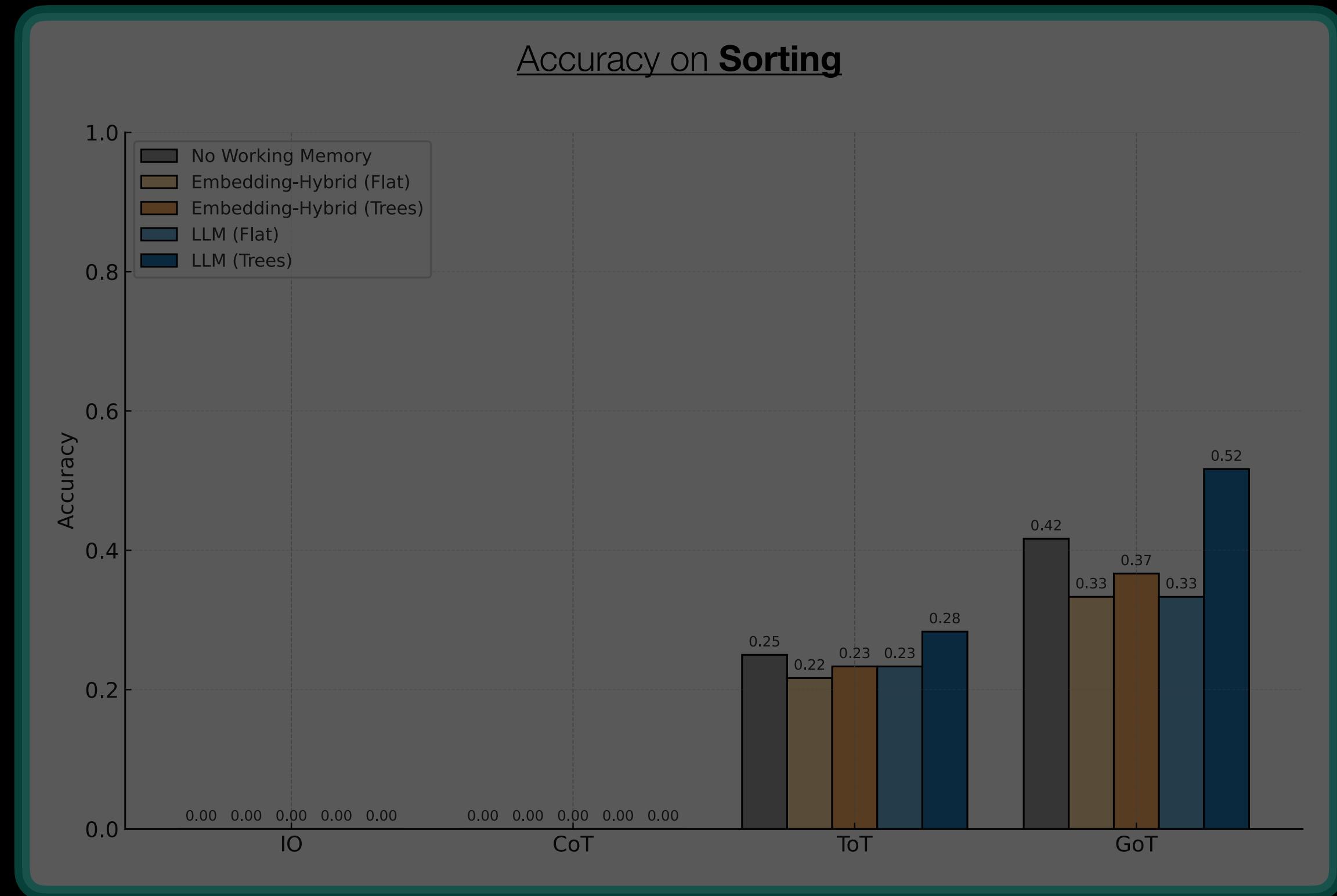
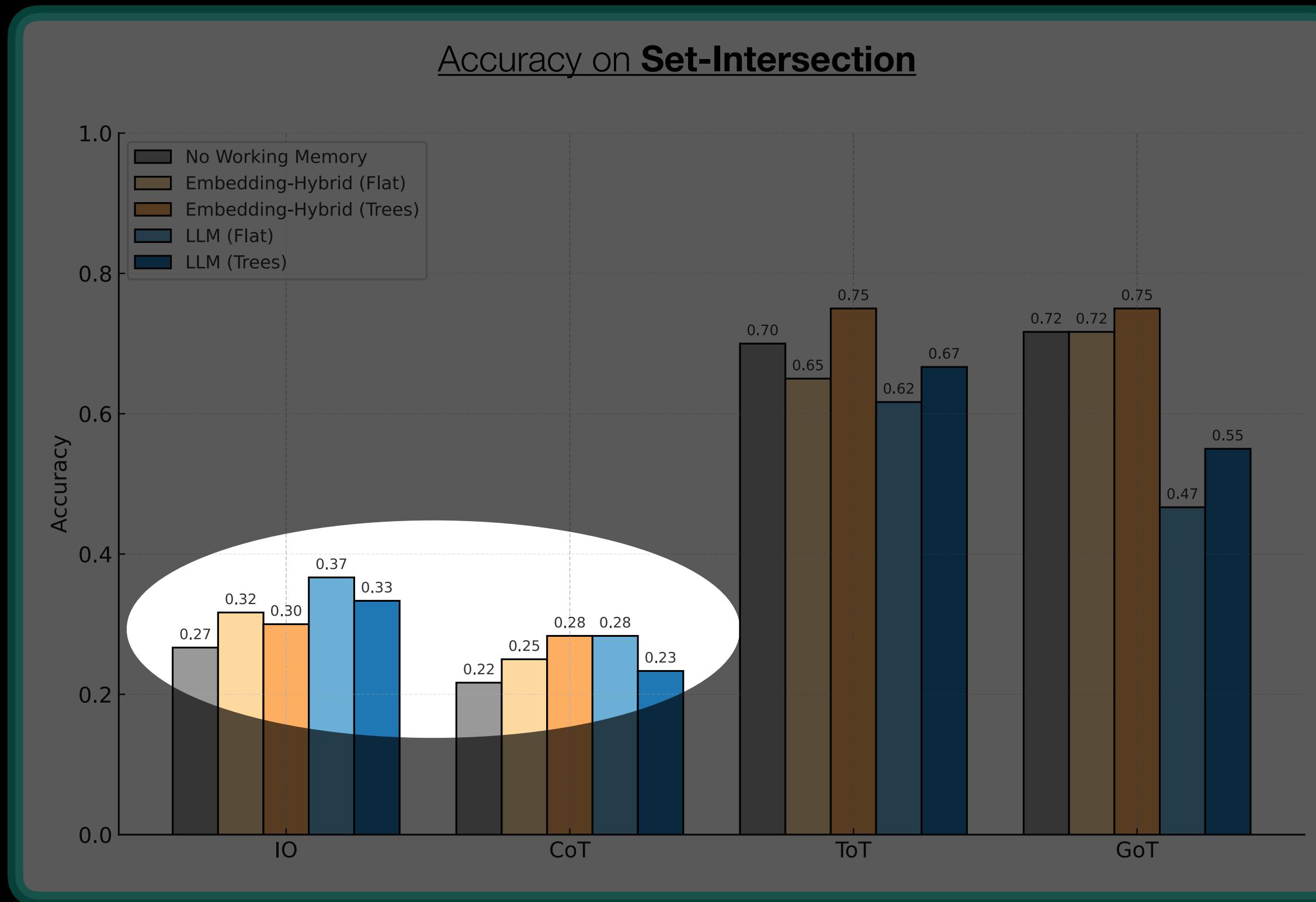
Assessment of Hypothesis I: GoT + WM > GoT?

Contribution IV: WM Variants Evaluated within GoT

Part III: Main Findings

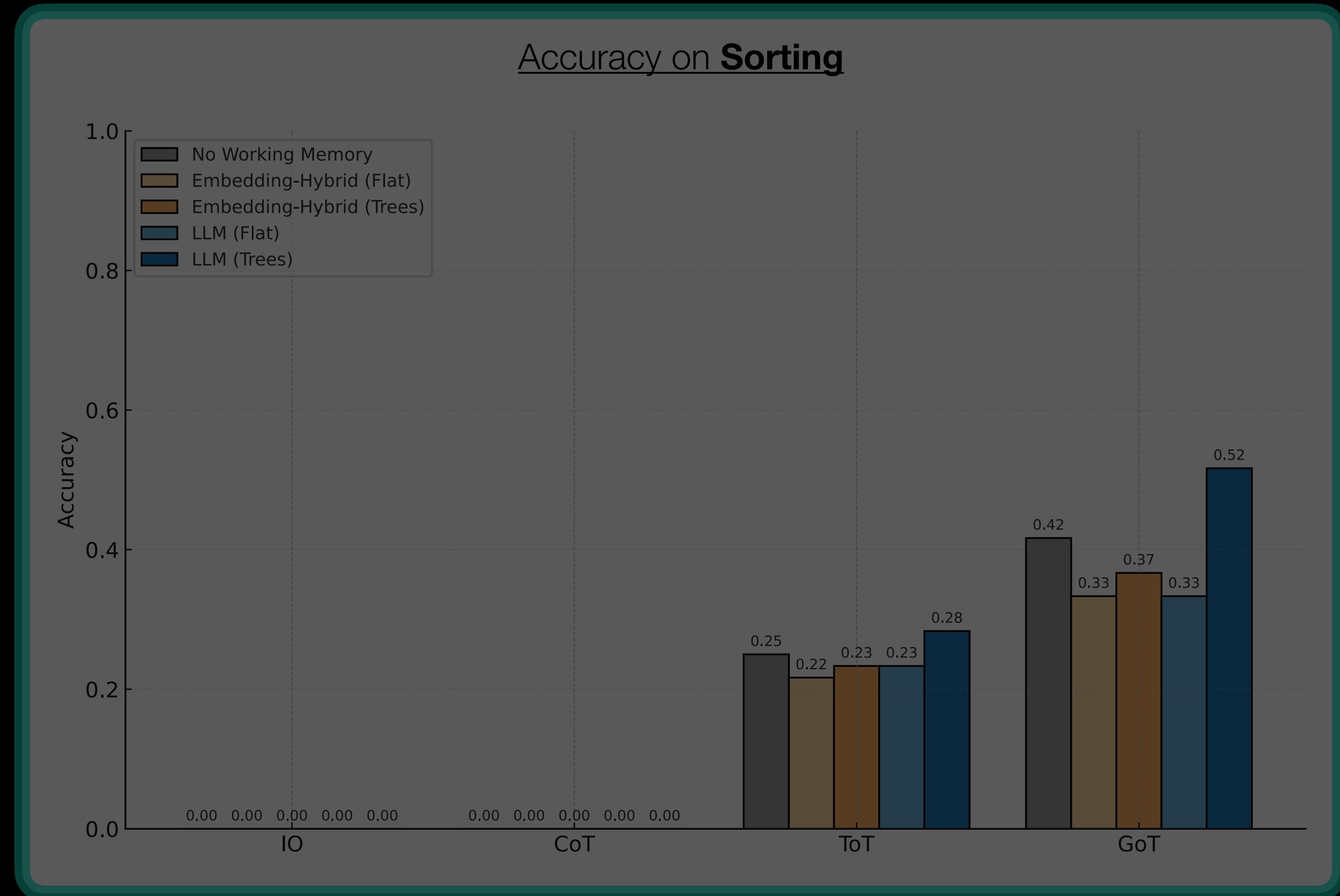
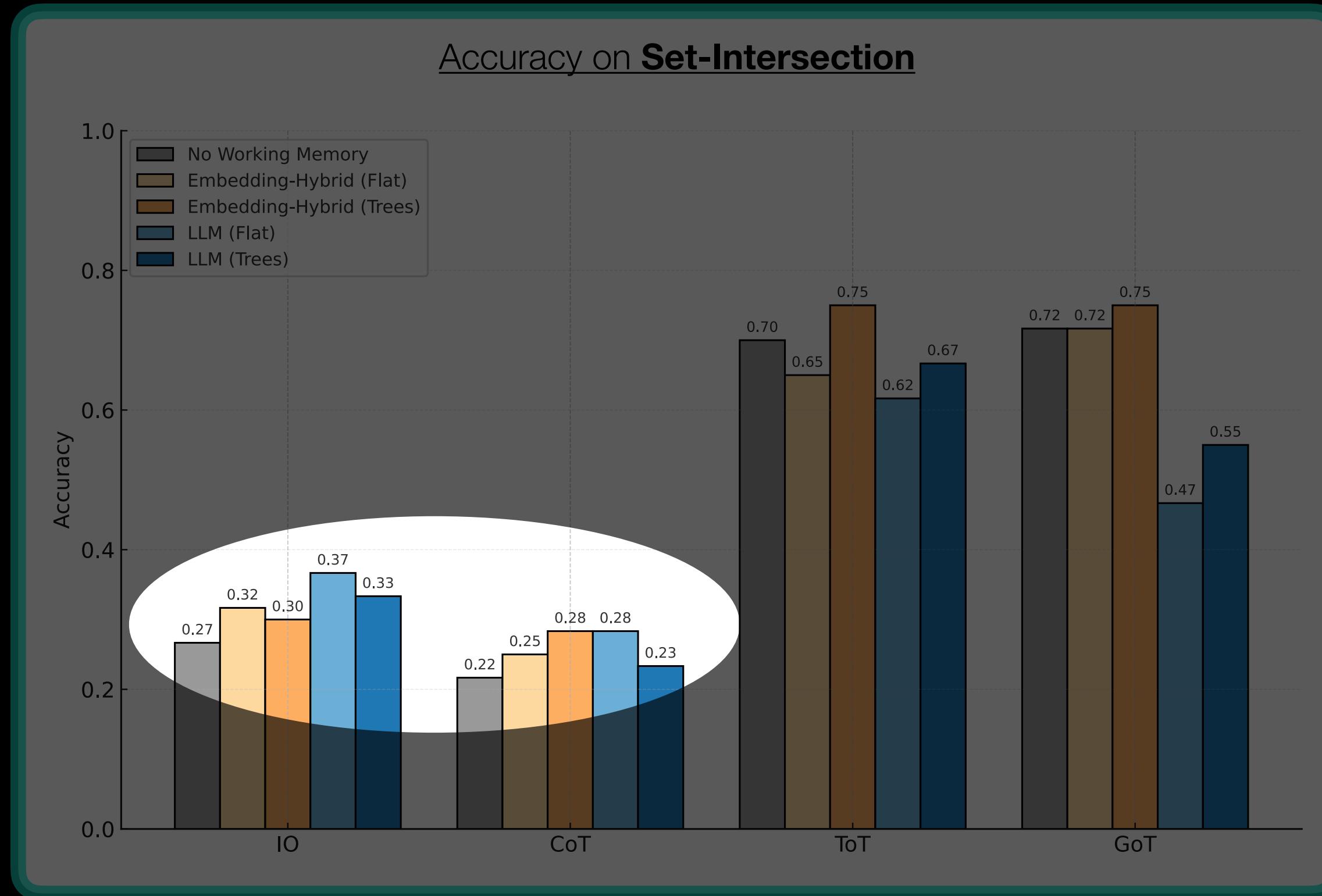
Accuracy on **Set-Intersection**Accuracy on **Sorting**

Assessment of Hypothesis I: GoT + WM > GoT?



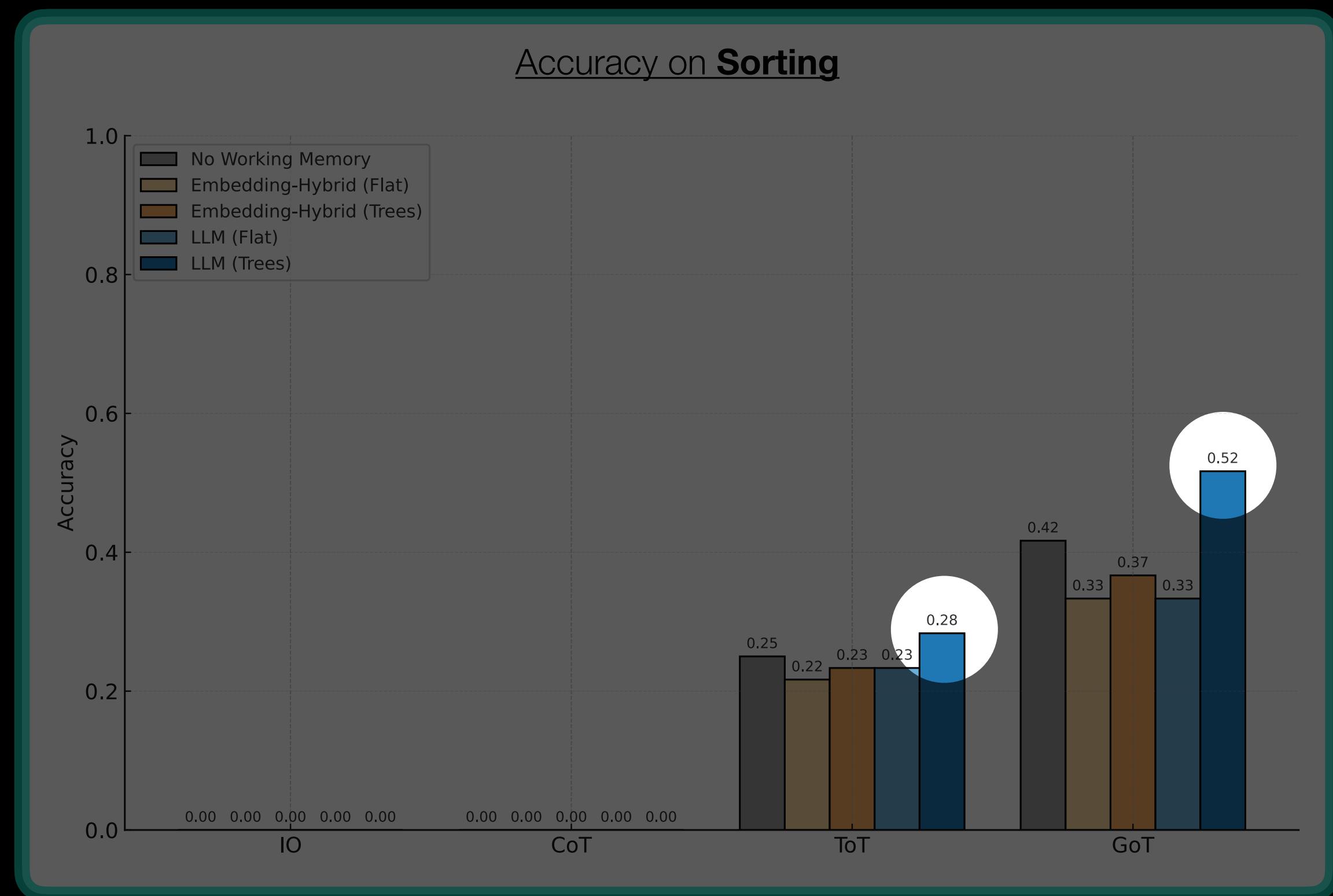
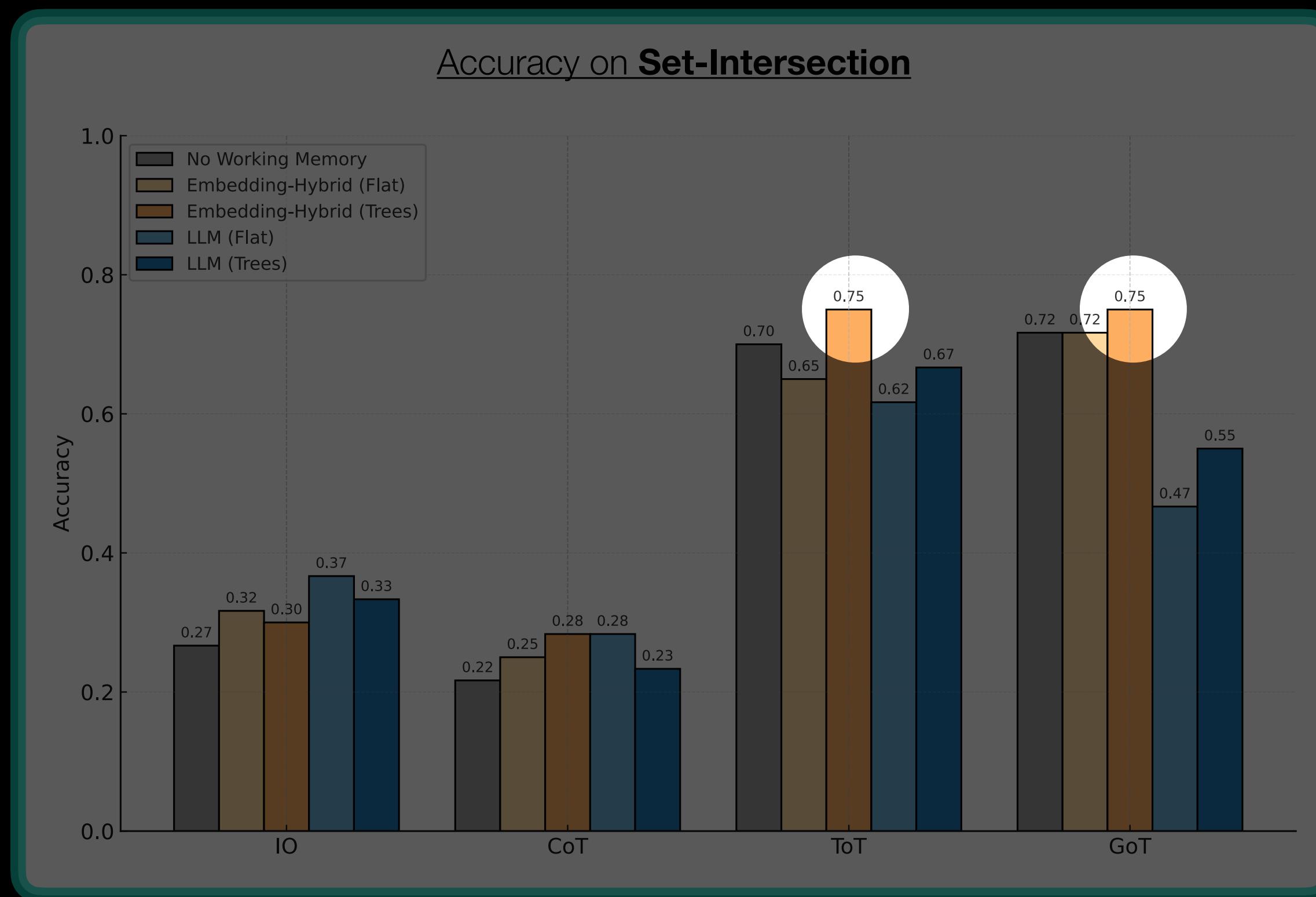
↳ Impossible:
I/O and CoT cannot benefit from WM!

Assessment of Hypothesis I: GoT + WM > GoT?



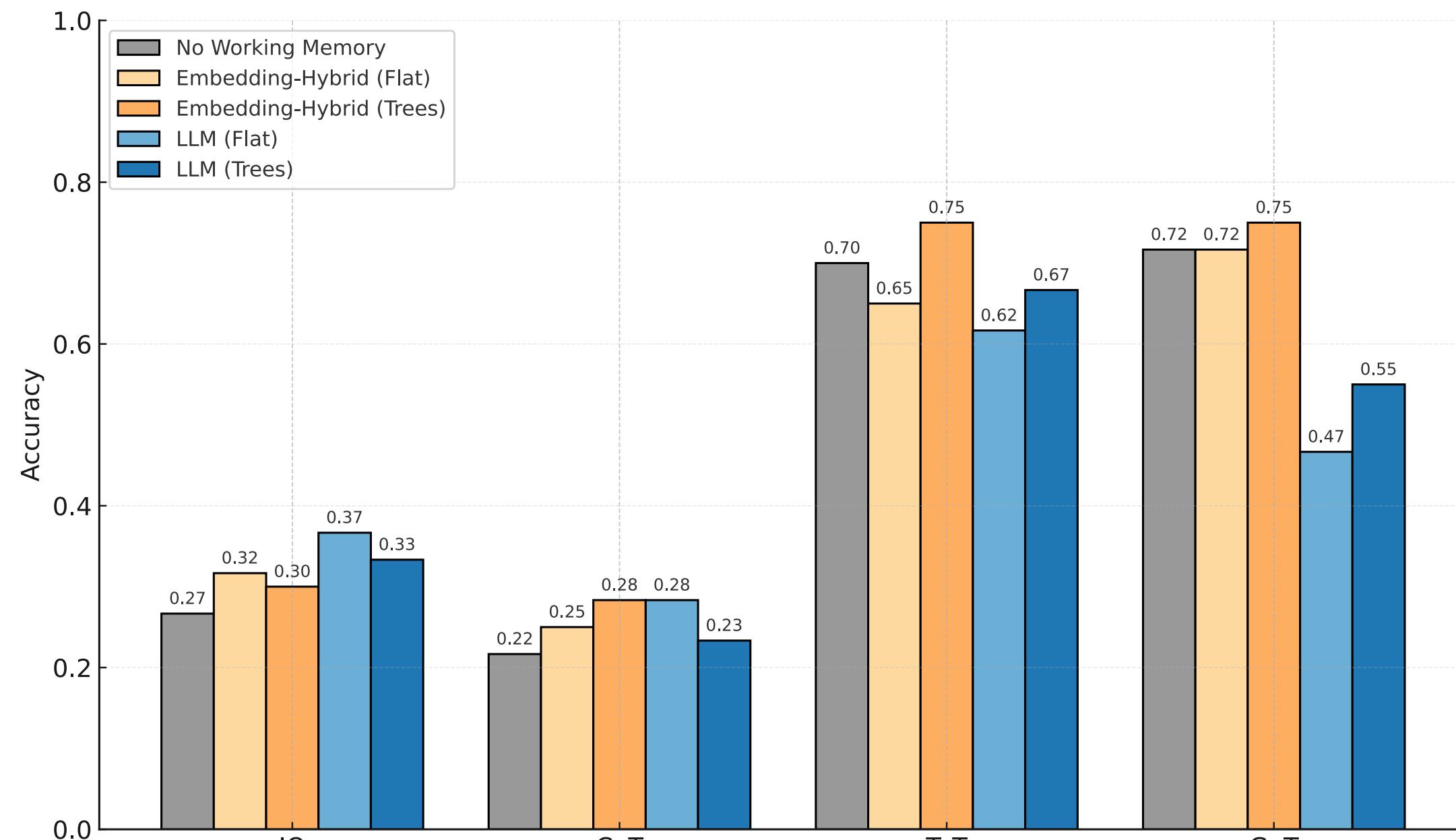
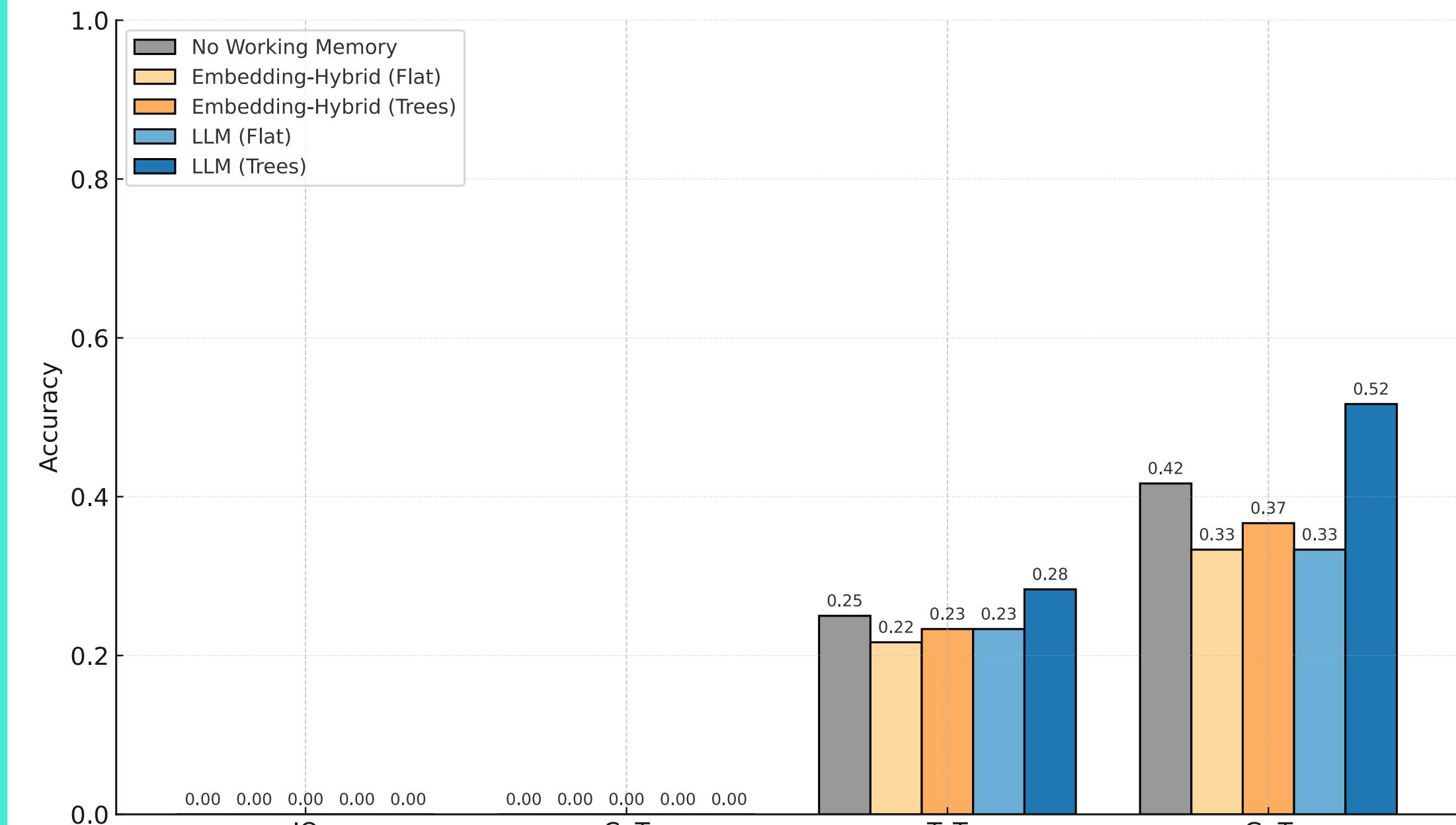
1. I/O and CoT reveal significant instability

Assessment of Hypothesis I: GoT + WM > GoT?



2. Intuition: **Chunking variants might be superior**

Assessment of Hypothesis I: GoT + WM > GoT?

Accuracy on Set-Intersection**Accuracy on Sorting**

3. Overall: No Clear Winner

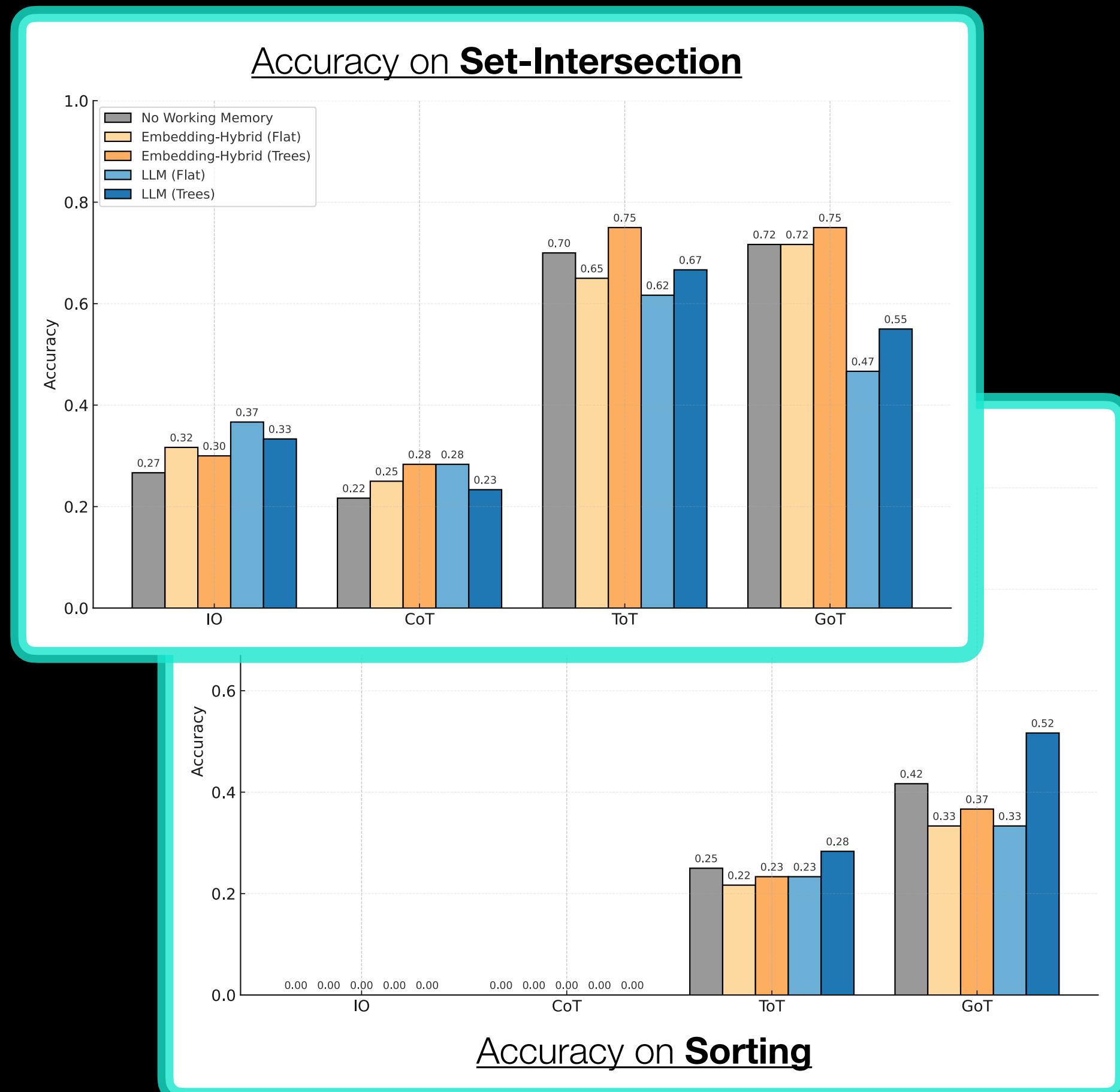
Assessment of Hypothesis I: GoT + WM > GoT?

↳ **Verdict: Instability renders results inconclusive**
Need more compute, deeper variance analysis, or more stable tasks



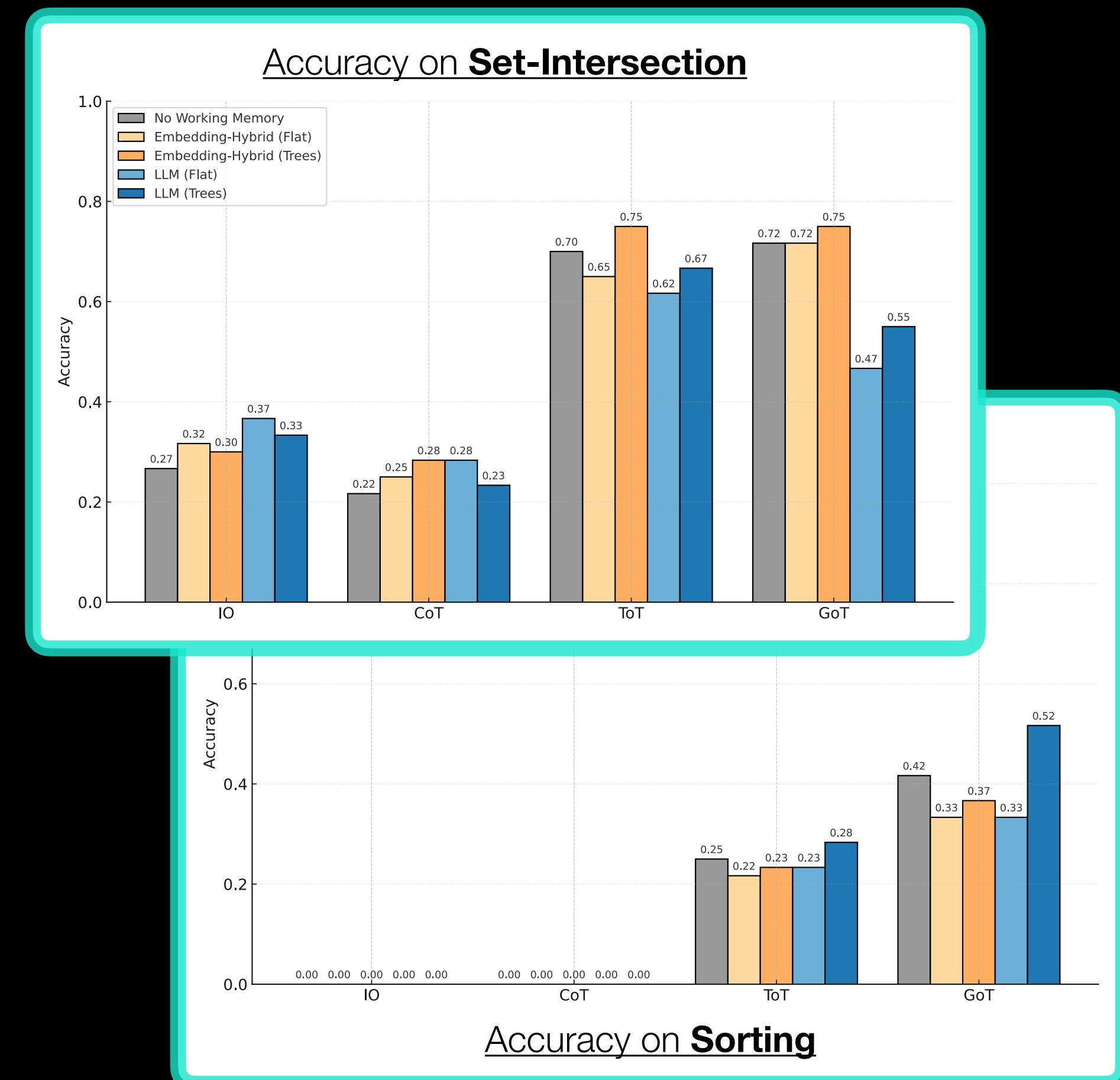
This is our main limitation!

- Task lack nat. language understanding and semantic diversity
- Lowering Temperature → Higher Costs → Not a Fix!



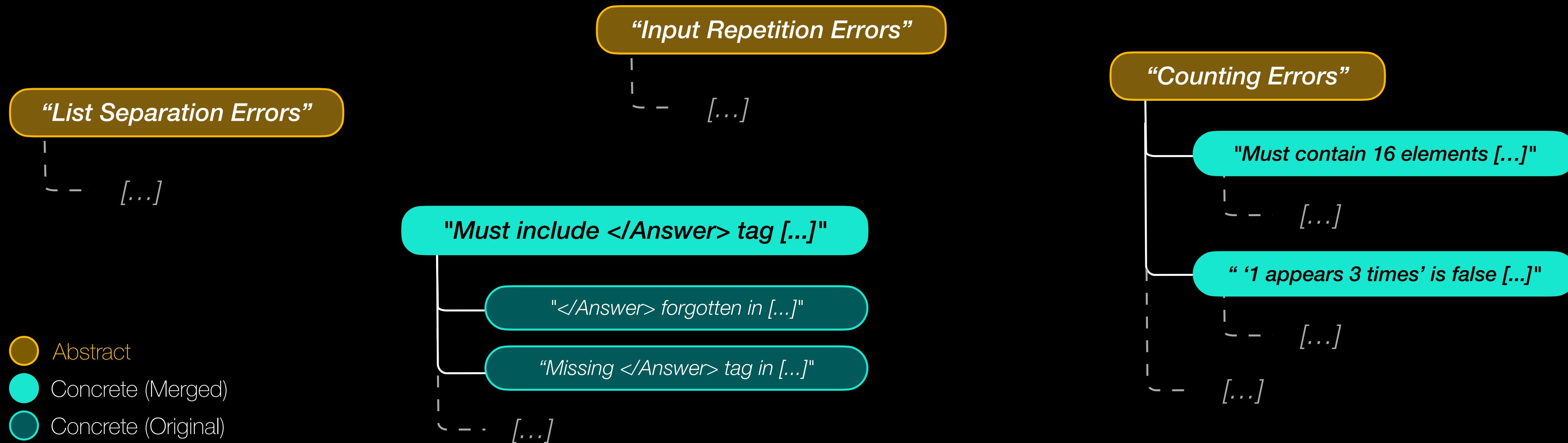
Assessment of Hypothesis II: Chunking > No Chunking?

- Set aside due to instability



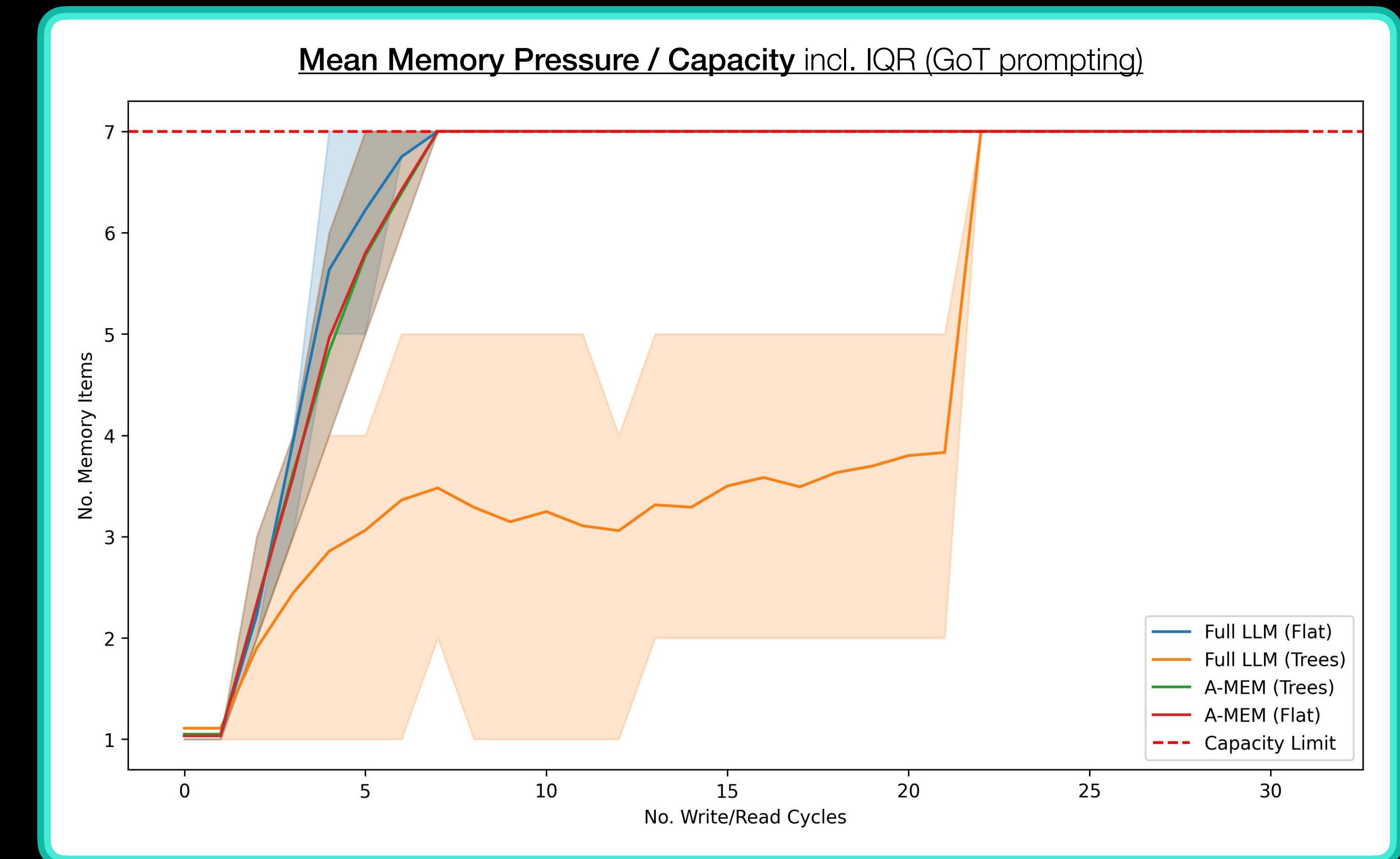
Assessment of Hypothesis II: Chunking > No Chunking?

- Tentative Support: **Distinct error sources even in mundane tasks**
↳ Motivates organized memory **beyond an unordered set** (but not necessarily a forest)



Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid

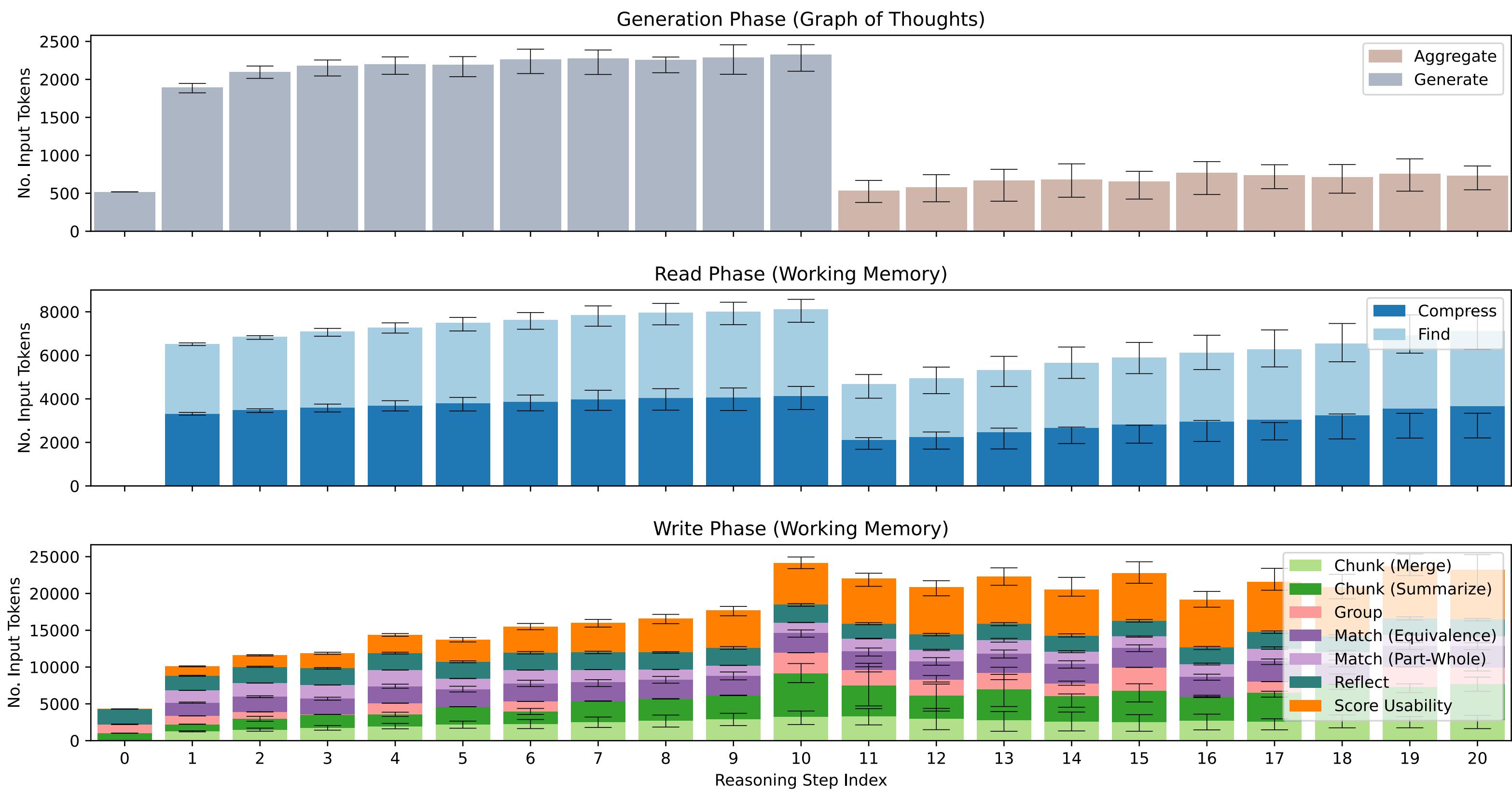
1. LLM-Only appears **more flexible** in...
 - ...chunking (building item trees)
 - ...discerning item-**relationships**
(from qual. eval; not depicted here)



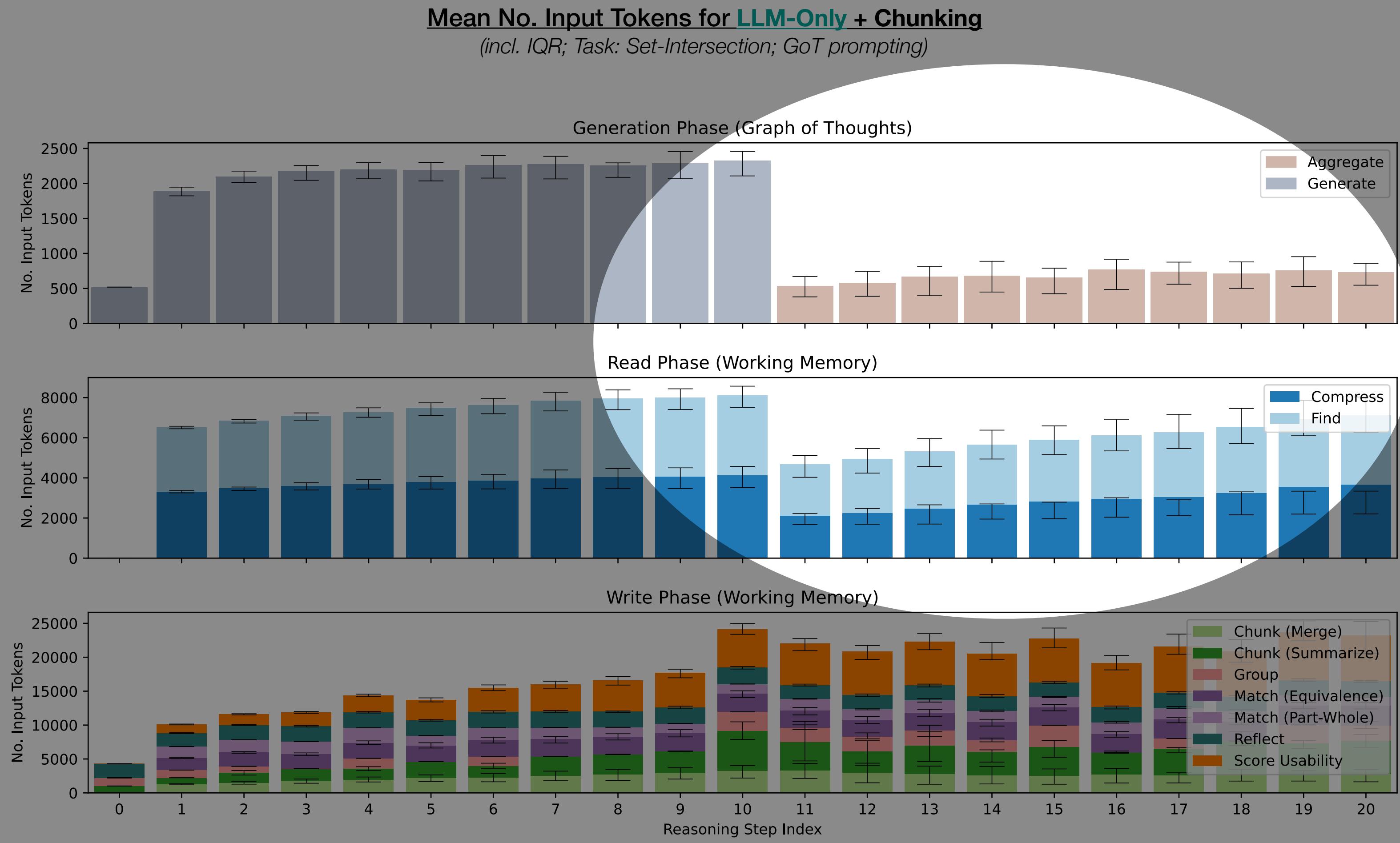
Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid

Mean No. Input Tokens for LLM-Only + Chunking

(incl. IQR; Task: Set-Intersection; GoT prompting)



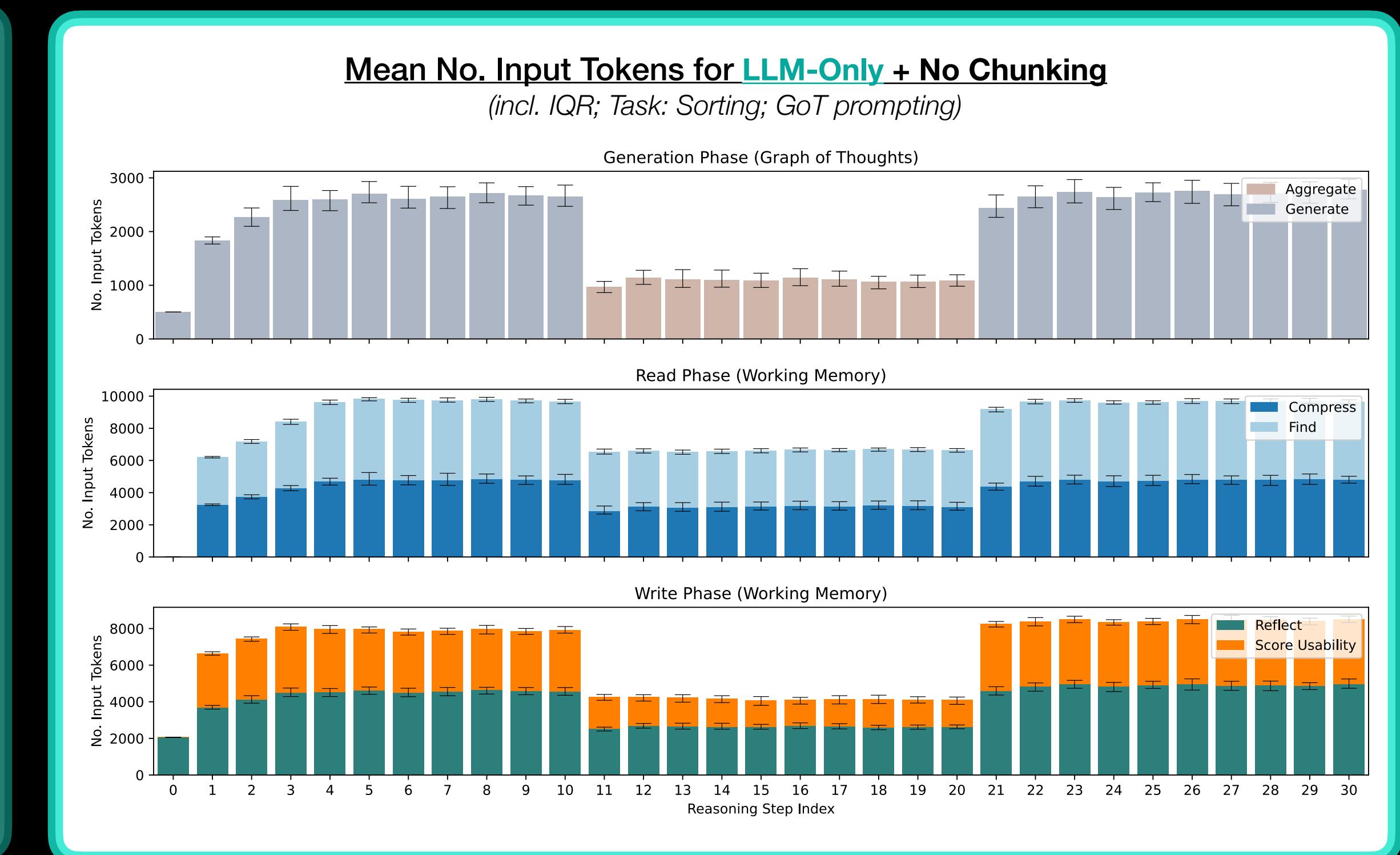
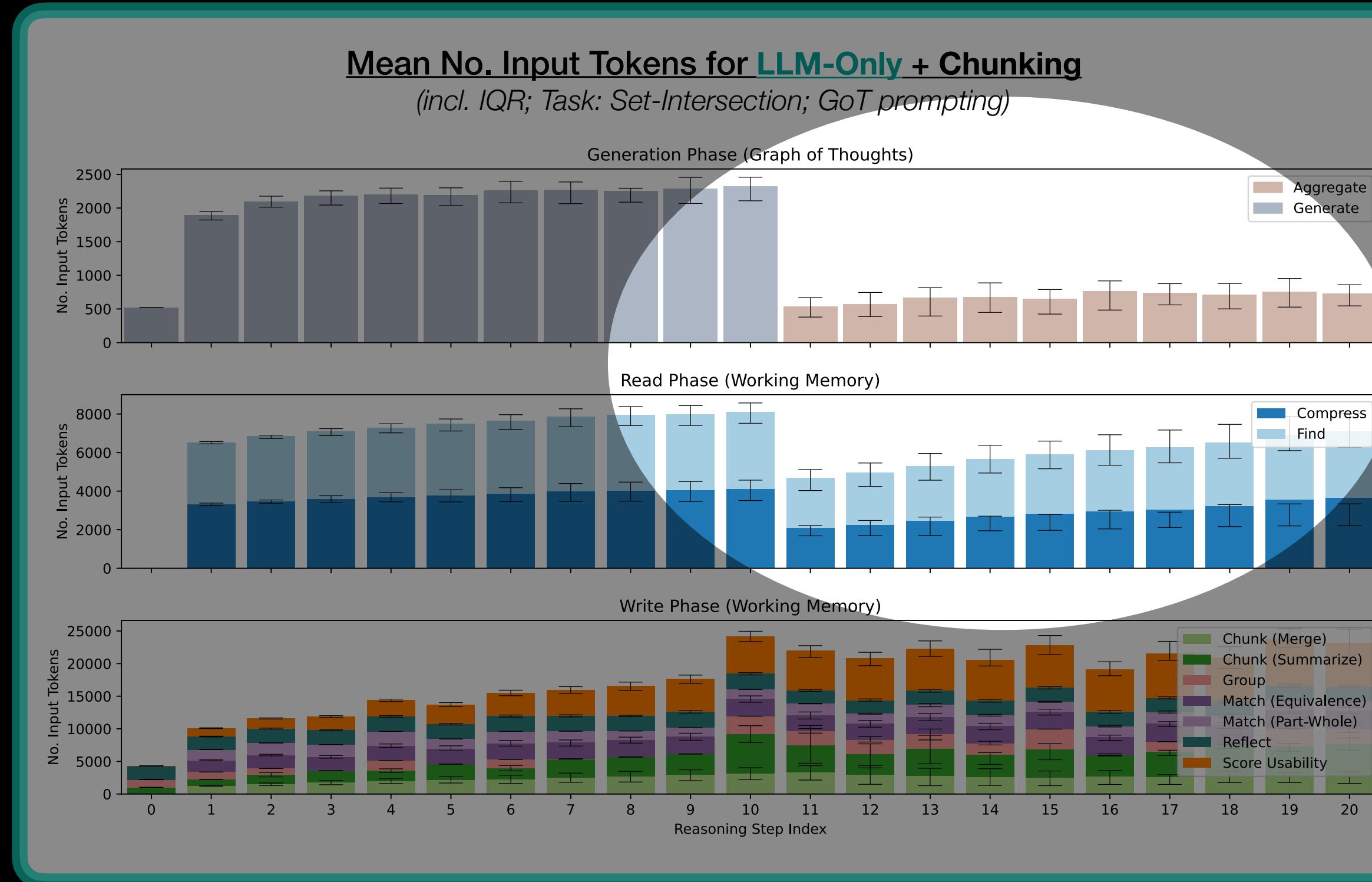
Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid



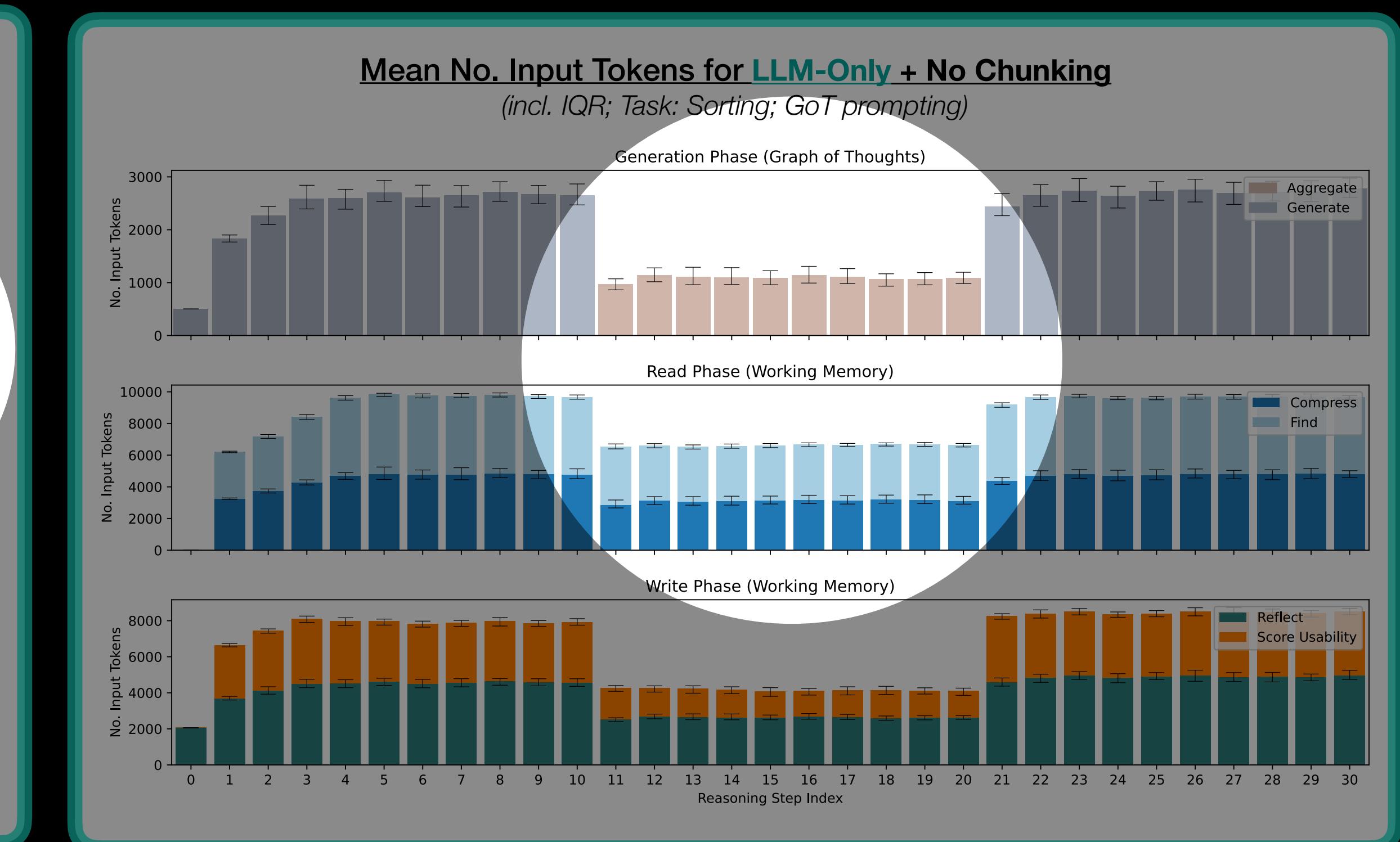
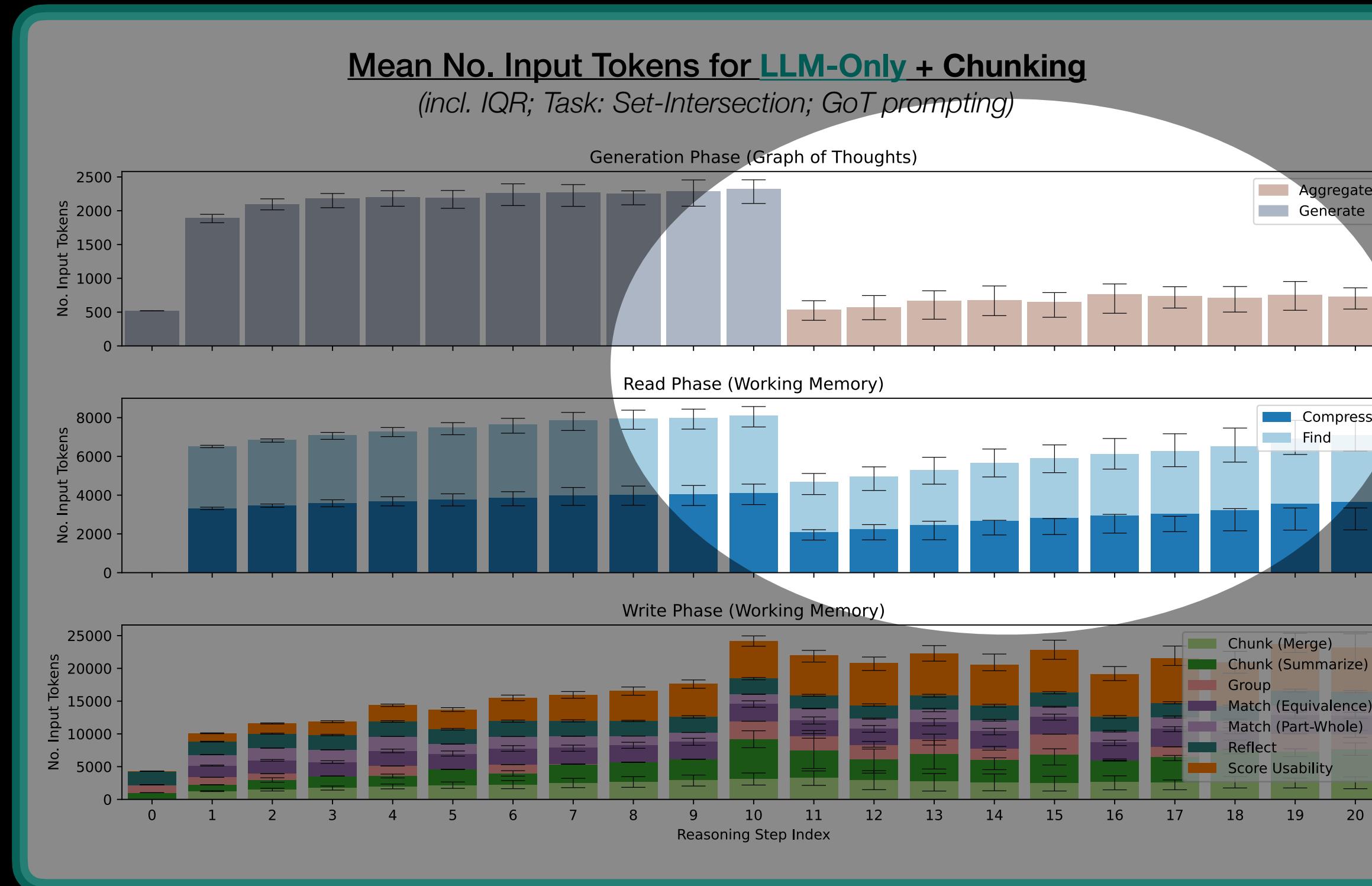
Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid

Contribution IV: WM Variants Evaluated within GoT

Part III: Main Findings



Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid

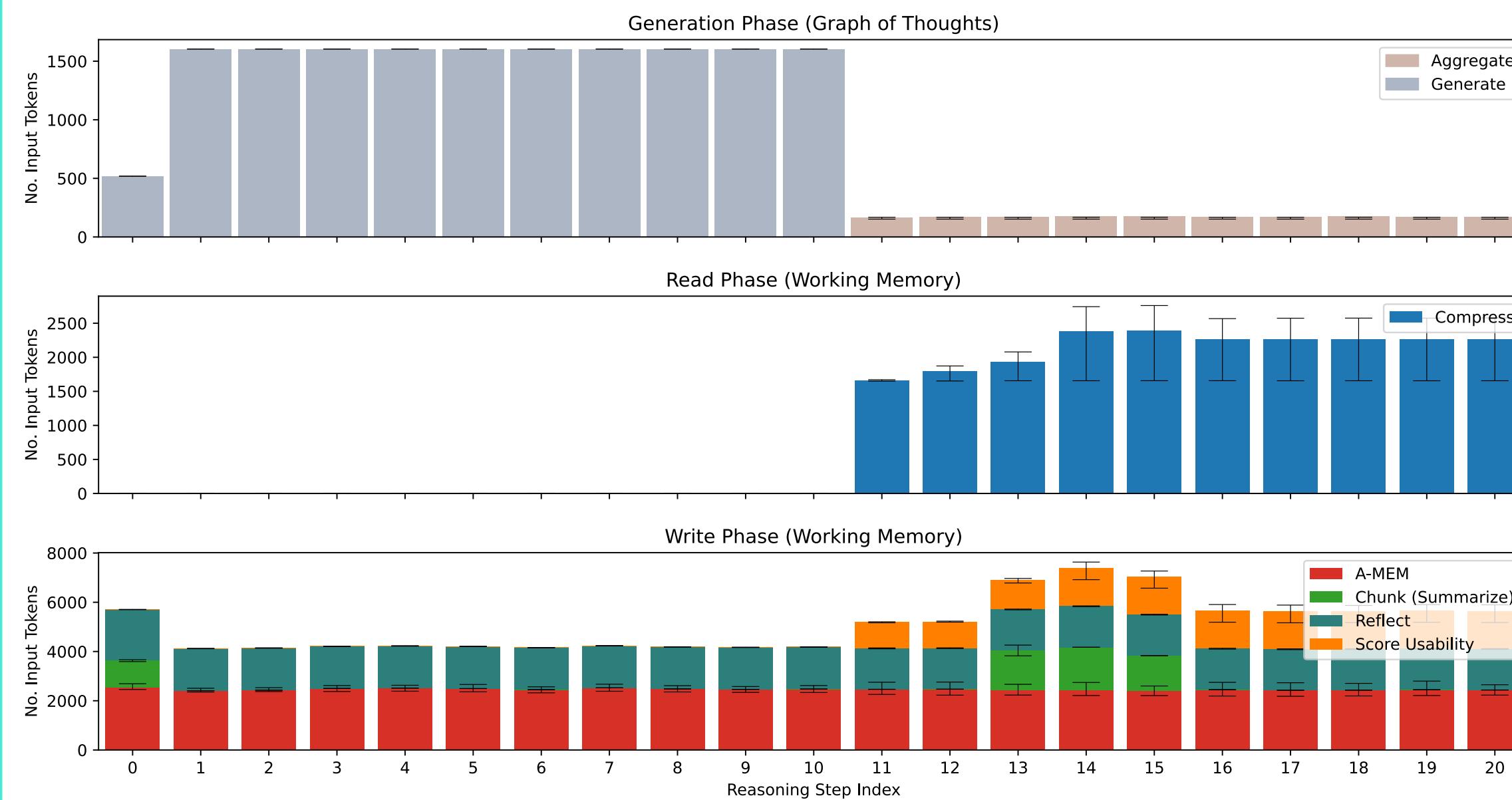


2. LLM-Only variants appear **responsive to reasoning context**

Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid

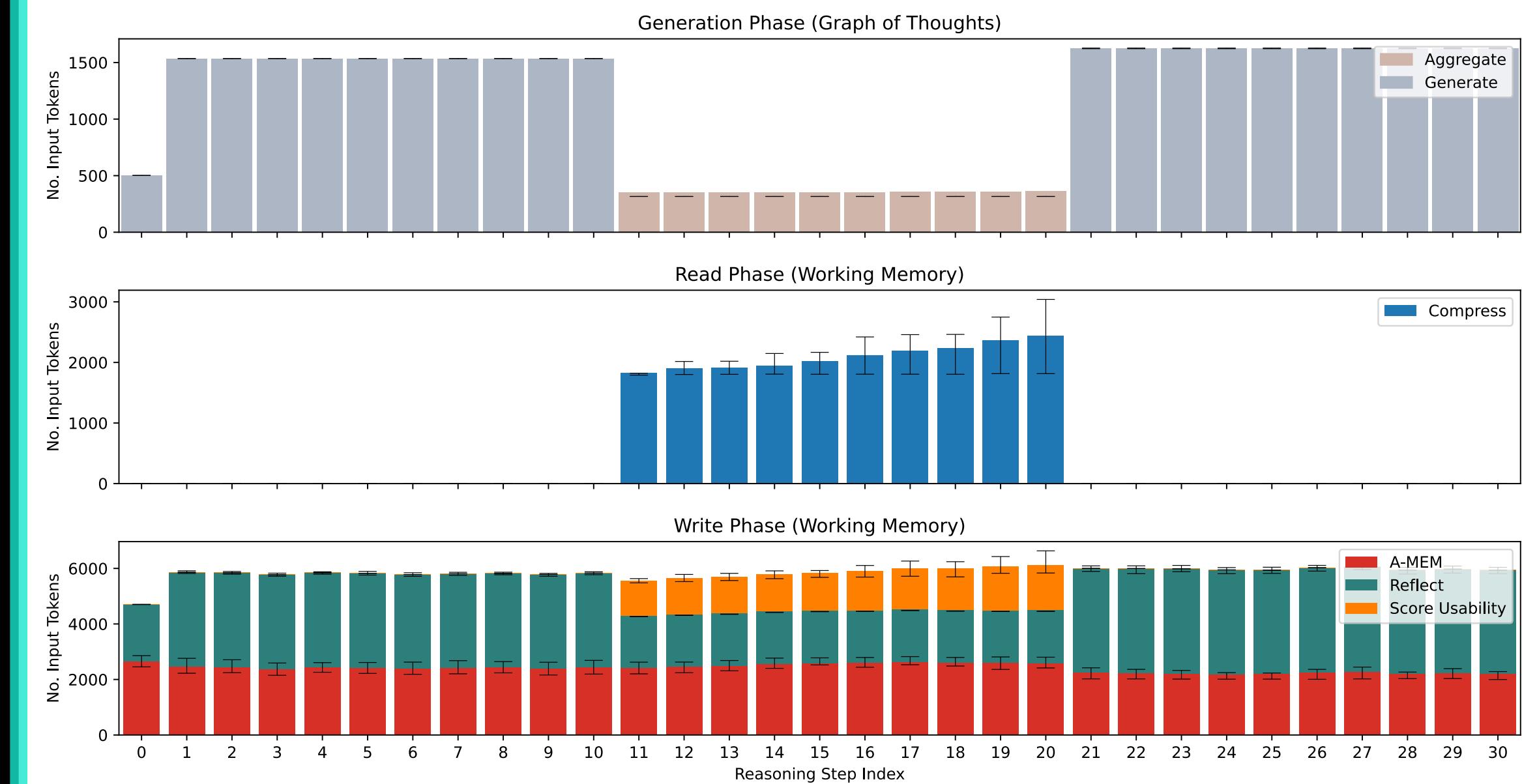
Mean No. Input Tokens for Embedding-Hybrid + Chunking

(incl. IQR; Task: Set-Intersection; GoT prompting)



Mean No. Input Tokens for Embedding-Hybrid + No Chunking

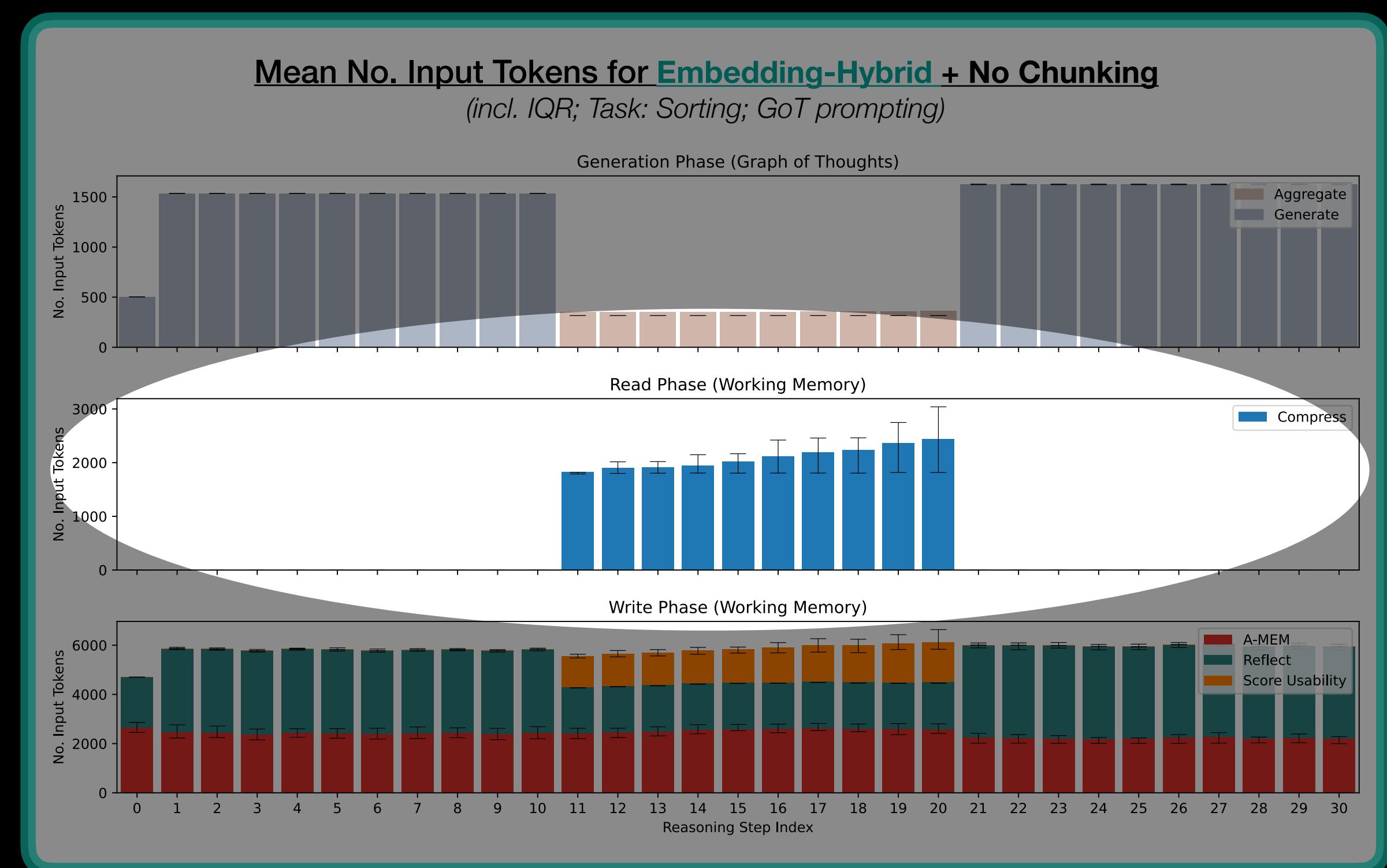
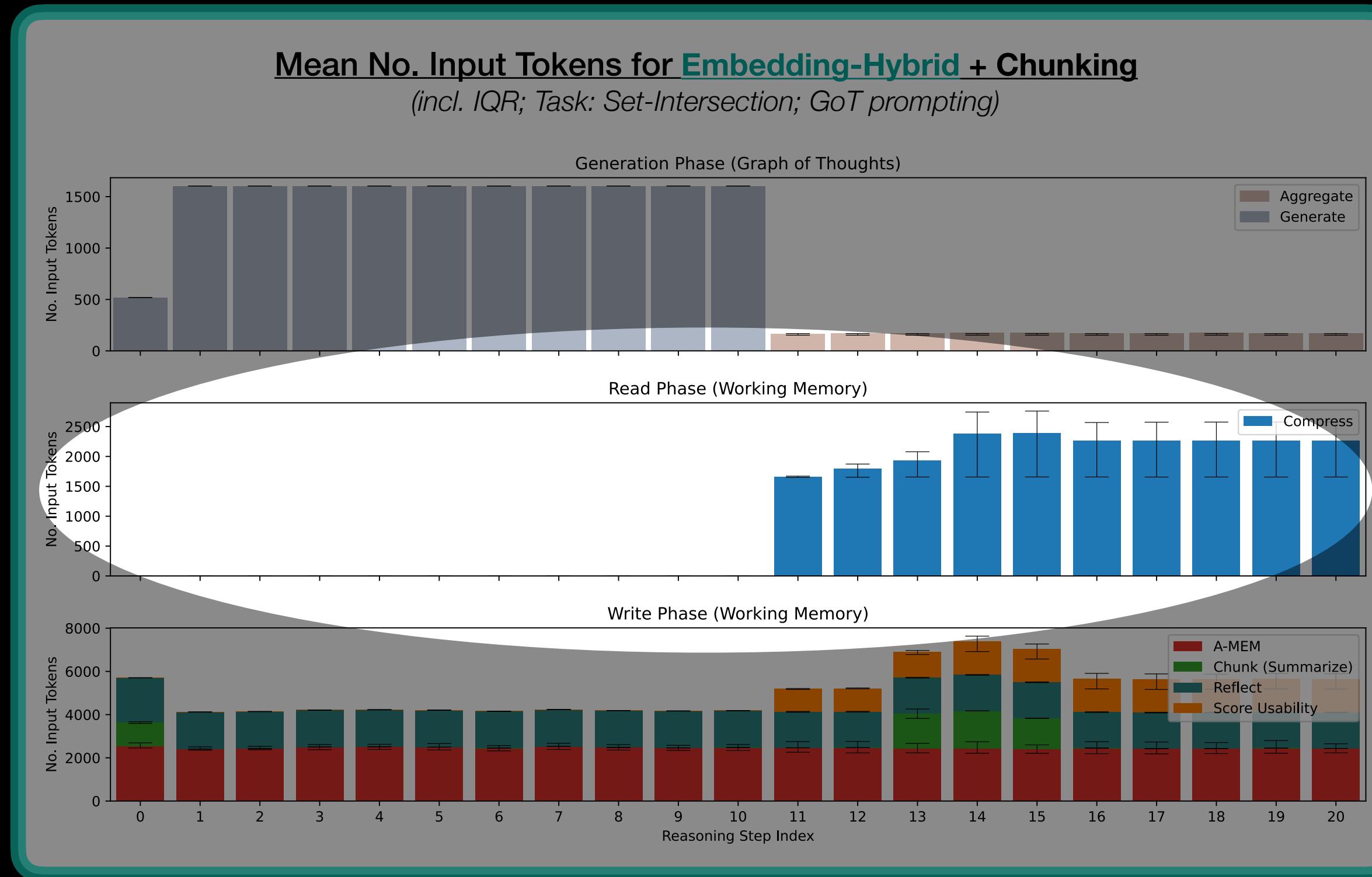
(incl. IQR; Task: Sorting; GoT prompting)



3. Embedding-Hybrids: Limited retrieval activity ↳ Less Flexible

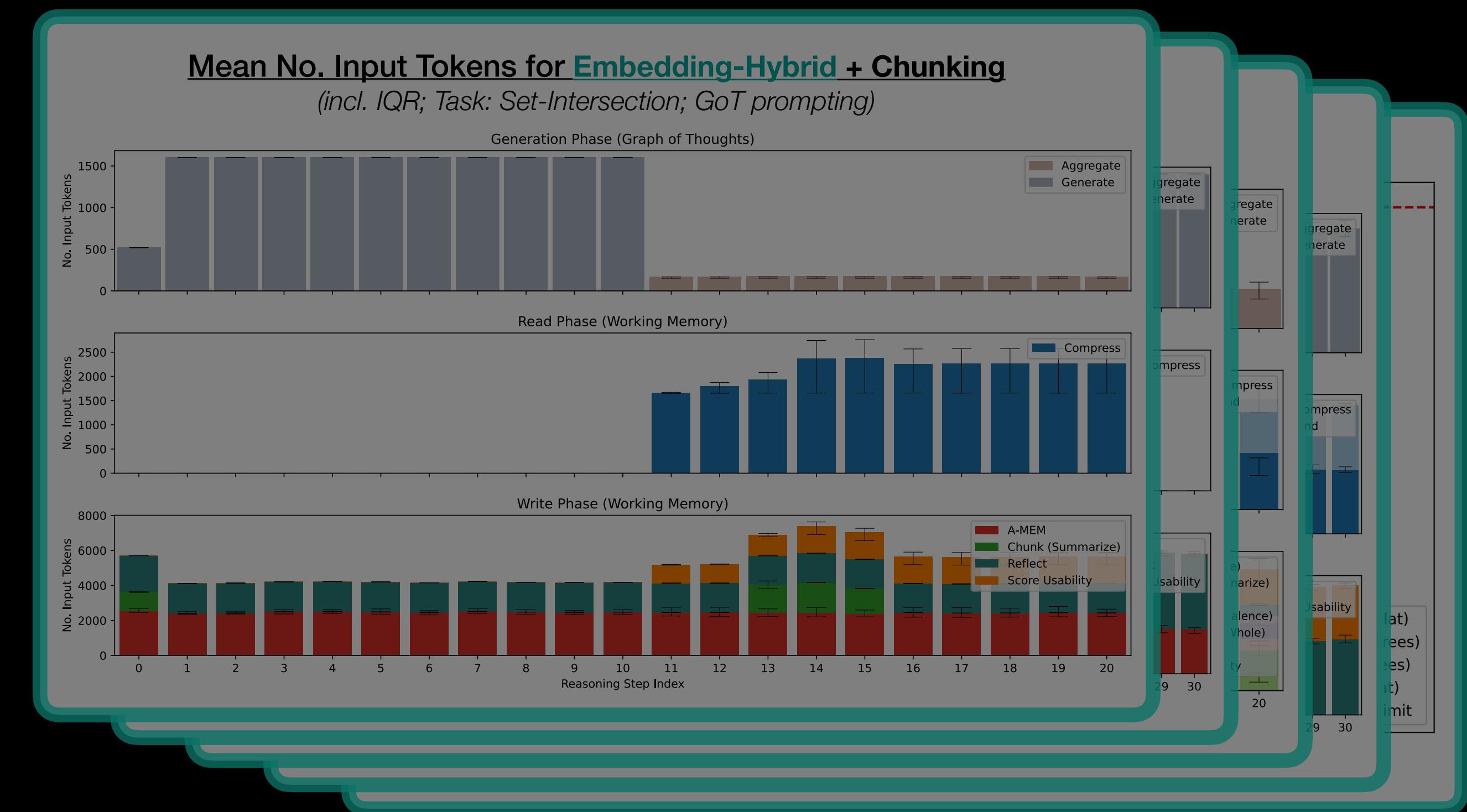
(in line with Zhou et al., 2025)

Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid



3. **Embedding-Hybrids:**
Limited retrieval activity
↳ **Less Flexible**
(in line with Zhou et al., 2025)

Assessment of Hypothesis III: LLM-Only > Embedding-Hybrid



Limitation: No Robust Embedding-Based Baseline

- Dynamic similarity-threshold based on A-MEM's internals
- Not fine-tuned at all

Overall Token Consumption

Total no. input tokens (in millions) per operation **across all runs**

(*GoT prompting, n = 120; AM = A-MEM, F = No Chunking, T = Chunking*).

Operation	Overall	Flat	Trees	AM (F)	LLM (F)	AM (T)	LLM (T)
App (GoT; Besta et al. (2024b))							
Aggregate	2.9	1.4	1.5	0.3	1.1	0.3	1.1
Generate	15.0	7.4	7.5	2.9	4.5	2.9	4.6
<i>Total</i>	<i>17.8</i>	<i>8.9</i>	<i>9.0</i>	<i>3.2</i>	<i>5.6</i>	<i>3.2</i>	<i>5.7</i>
Read (WM)							
Compress	29.3	12.2	17.1	0.3	11.9	0.3	16.8
Find	26.9	12.7	14.2	—	12.7	—	14.2
<i>Total</i>	<i>56.2</i>	<i>24.9</i>	<i>31.3</i>	<i>0.3</i>	<i>24.6</i>	<i>0.3</i>	<i>31.0</i>
Write (WM)							
A-MEM	26.8	10.5	16.3	10.5	—	16.3	—
Chunk (Mer.)	11.6	—	11.6	—	—	—	11.6
Chunk (Sum.)	8.6	—	8.6	—	—	1.2	7.4
Group	1.2	—	1.2	—	—	—	1.2
Match (Eq.)	11.6	—	11.6	—	—	—	11.6
Match (P.W.)	2.6	—	2.6	—	—	—	2.6
Reflect	35.9	17.9	18.0	7.7	10.2	7.7	10.3
Usability	22.8	7.1	15.8	0.2	6.9	0.2	15.6
<i>Total</i>	<i>121.2</i>	<i>35.5</i>	<i>85.7</i>	<i>18.4</i>	<i>17.0</i>	<i>25.5</i>	<i>60.2</i>

Overall Token Consumption

1. All WM variants incur **substantial token costs** compared to vanilla GoT – **Expectedly!**

Total no. input tokens (in millions) per operation **across all runs**
(GoT prompting, n = 120; AM = A-MEM, F = No Chunking, T = Chunking).

Operation	Overall	Flat	Trees	AM (F)	LLM (F)	AM (T)	LLM (T)
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Overall Token Consumption

1. All WM variants incur **substantial token costs** compared to vanilla GoT
— **Expectedly!**

↳ Cost scales per n thoughts:

- GoT: $\Theta(n)$
- Reasoning LLMs: $\Theta(n^2 + n)$
(Which we aspire towards)

Total no. input tokens (in millions) per operation across all runs
(GoT prompting, $n = 120$; AM = A-MEM, F = No Chunking, T = Chunking).

Operation	Overall	Flat	Trees	AM (F)	LLM (F)	AM (T)	LLM (T)
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1. **Clear token-efficiency advantage for retrieval with Embedding-Hybrid variants (though only partially active)**
2. **Clear token-efficiency advantage for retrieval with Embedding-Hybrid variants (though only partially active)**

Final Takeaways

I

Carefully Consider a Hybrid WM Approach:
Costly but Flexible LLMs v.s. Efficient but Rigid Embeddings Methods

II

Investigate WM for Reasoning LLMs (*see Thesis, Subsection 7.1.2.*)

- ↳ May lack active reasoning-context regulation → Need MCM's Central Executive
- ↳ May address symptoms like Lost-in-the-Middle, Overthinking, Error Propagation, etc.

(cf. Liu et al. (2023), Sui et al. (2025), Gan et al. (2025) respectively)

III

Consider WM Across the Implementation Stack: (*see Thesis, Subsection 7.1.1.*)

Let Agents Profit from WM by Moving Beyond Passive and Linear Memory

IV

Recognize Cognitive WM Models Potential for LLMs

Other Limitations

- No Robust Embedding-Based Baseline
- Unstable Experimental Setup with Tasks not grounded in NLU
- Core Architecture: No inherent notion of episode order
- Setup: No Backtracking in GoT (generates thoughts in BFS order) → Limits accumulation in WM

Implemented WM variants:

- Limited reflection setup:
 - ↳ No task-specific scoring scheme (as suggested by Madaan et. al., 2023)
 - ↳ Minimal context (only a single thought)
 - ↳ Minimal error signal captured (not entire CoT, only erroneous step)
- Greedy, Shallow, and Non-Reorganizing Writing
- Not fully optimized (e.g. no. write request)

Deferred Experiments:

- Effects of different memory capacities on performance
- Ablation on forgetting scores
- Cross-trial memory reuse
- ...

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Cognitive Theory for Deliberate Reasoning: Synthesizing Working Memory Architectures for LLMs

Alexander Blatzheim
Master Thesis in Information Systems
Supervised by Tobias Eder



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Backup Slides

Full MCM Interpretation Class Diagramm

Contribution I: The MCM in SE Terms | Part I: Theoretical Foundation

Disclaimer:

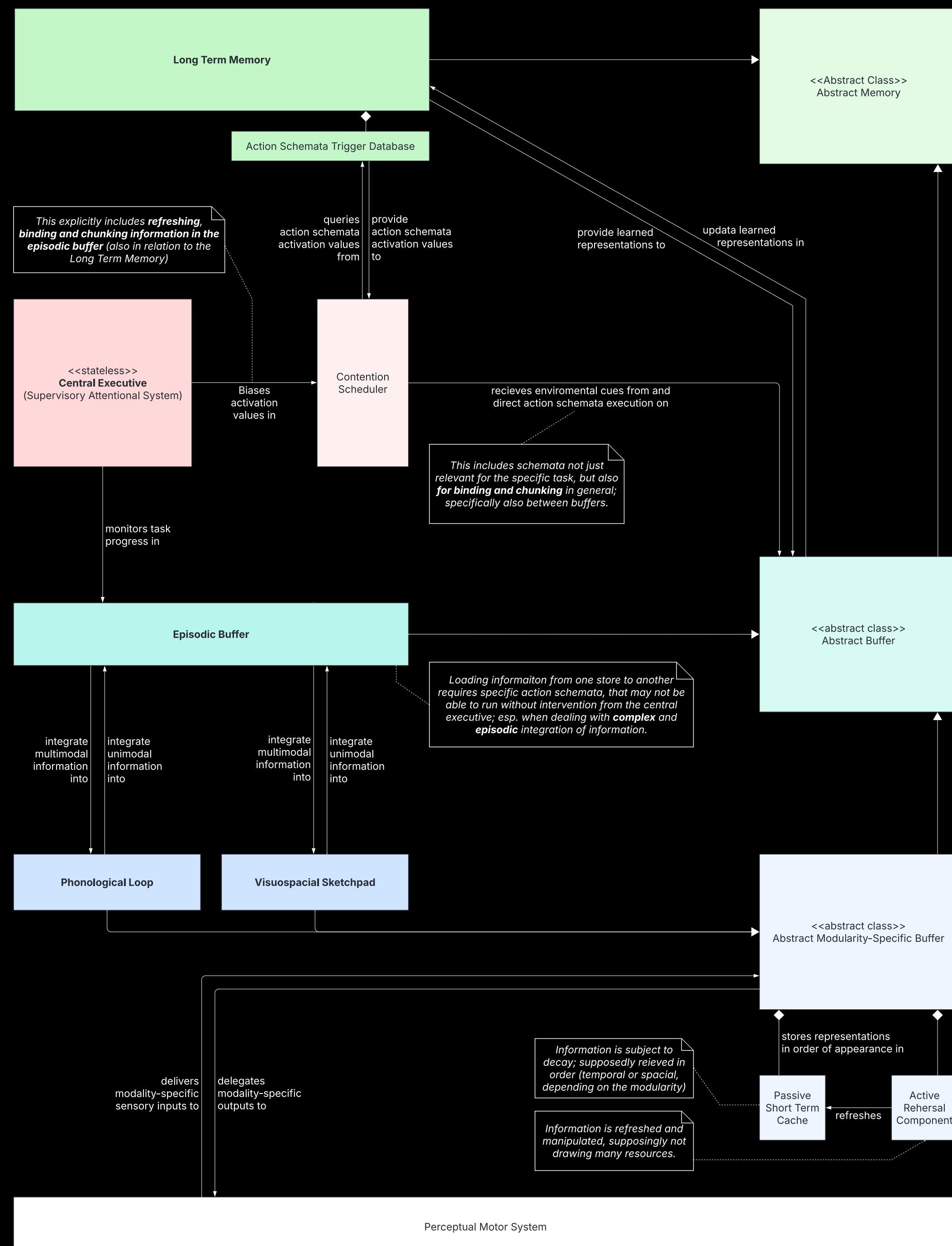
The original MCM subsumes the Contention Scheduler into the Central Executive, citing it as key inspiration. We make it explicit.

Classes not mentioned previously:

- Memory hierarchy
- Action Schemata Trigger Database:
Delivers activation value for a given action schema + Environment

Limitations we see in our model:

- No memory item class for simplicity
(Introducing one would require modeling action schemata as a form of memory item, which would make the class hierarchy more complicated).
↳ No schemata model, though plausible.
- Uncertain what constitutes “environmental cues” (as in Norman & Shallice, 1986)
↳ We assume these to be a subset of the states of all buffers.
- Deliberately refraining from specifying multiplicities
(due to general uncertainty expressed by Hitch et al. (2025) towards how many more sub-memories or processors there may be).



Item Survival Score Computation

Contribution II: A WM Core Architecture for LLMs

Part II: Implementation

- Items can record events (timestamps provided by a buffer), which can also be paired with other scores.
- We implement:
 - Two events: **Item access & Item repetition**
 - One subjective score: **Reflection Usability** (evaluated by the LLM)
- Formally, the survival contribution of an event or score recorded at time-step $t \in \mathbb{R}$ w.r.t. current timestamp $T \in \mathbb{R}$ is weighted by λ^{T-t}

- An event's survival contribution is the decayed sum of timestamps, eg:

$$\text{AccessScore}(T) = \sum_{t_i \in \text{AccessHistory}} \lambda^{T-t_i}$$

- a score's survival contribution is the decayed sum of all recorded timestamps t_i weighted by its respective score value s_i , eg:

$$\text{UsabilityScore}(T) = \sum_{(t_i, s_i) \in \text{UsabilityHistory}} s_i \cdot \lambda^{T-t_i}$$

- Which, in our case, is combined into the final item-survival score as

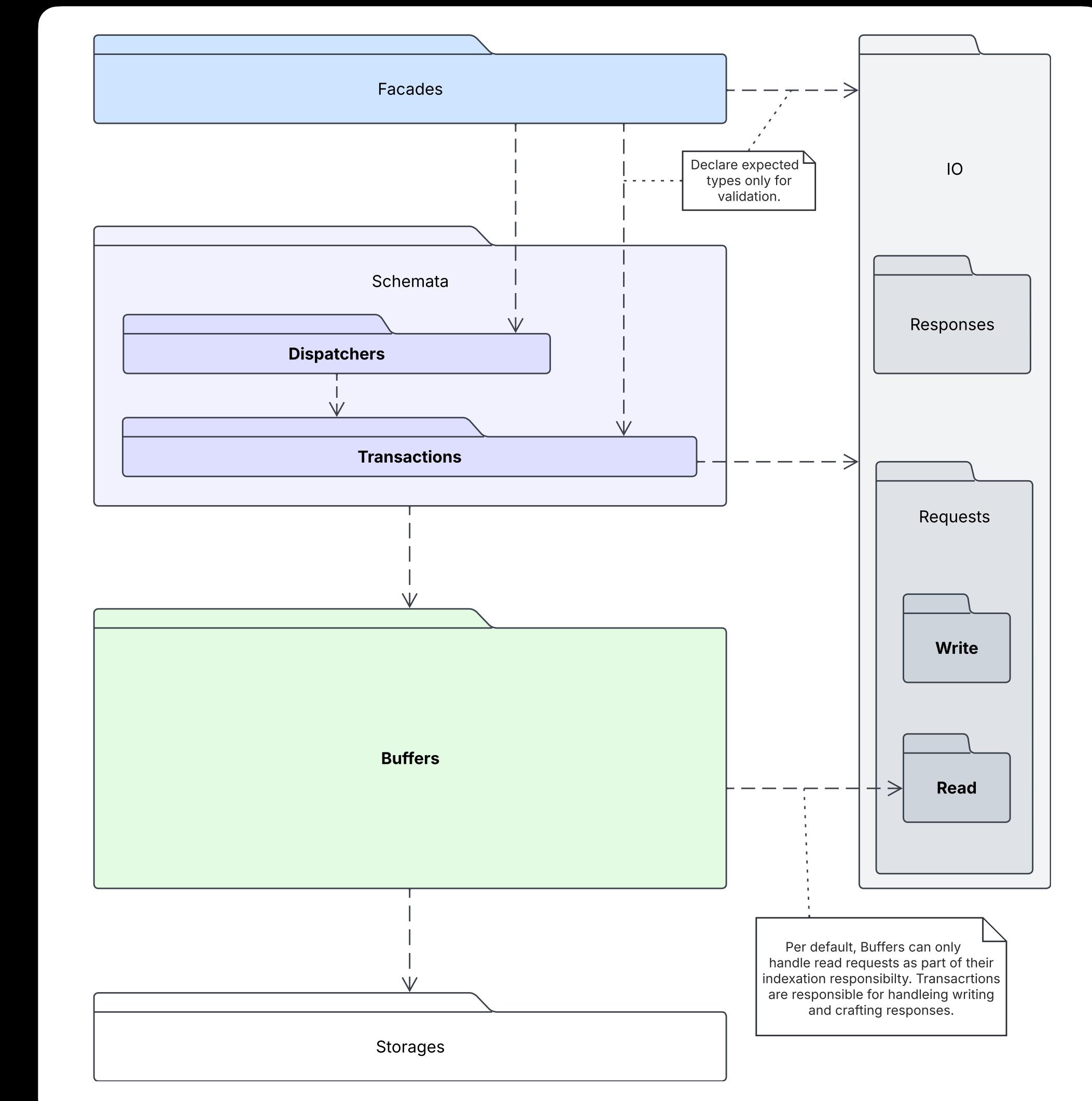
$$\text{CombinedScore}(T) = (0.5 \cdot \text{AccessScore}(T) + \text{RepetitionScore}(T)) \cdot (1 + \text{UsabilityScore}(T))$$

Core Architecture: Package Diagram

Hybrid 4-layer WM architecture with vertical control flow; I/O package ensures consistent communication across layers:

- **Facades** – specific client APIs delegating to dispatchers
- **Schemata** – unify dispatchers (schedulers) and typed transactions (action schemata).
- **Buffers** – typed memory components.
- **Storages** – storage backends.

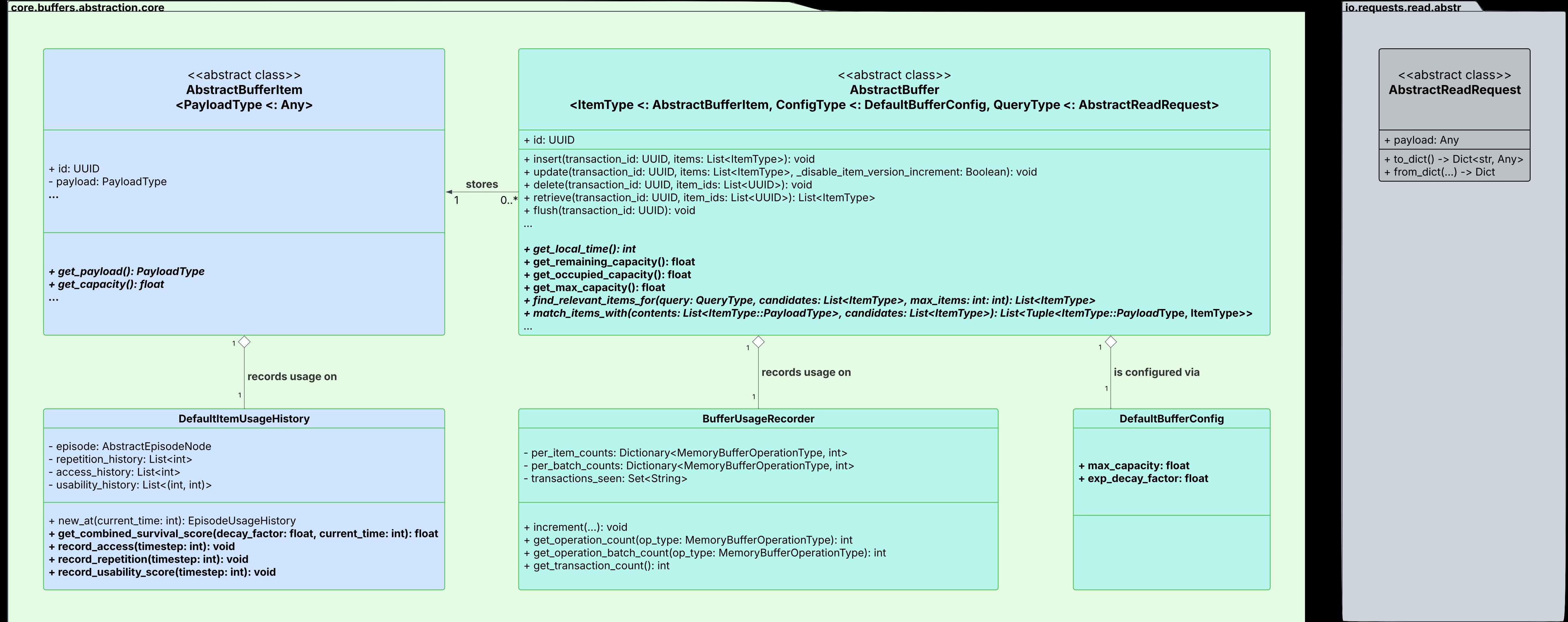
Implementation may still undergo minor structural refactoring to fully align with this package layout. Nonetheless, the core responsibilities of each layer are already clearly defined. Local utilities such as the SnapshotService for the buffer layer are omitted for simplicity.



Core Architecture: AbstractBuffer & AbstractBufferItem Class Diagram

Contribution II: A WM Core Architecture for LLMs

Part II: Implementation



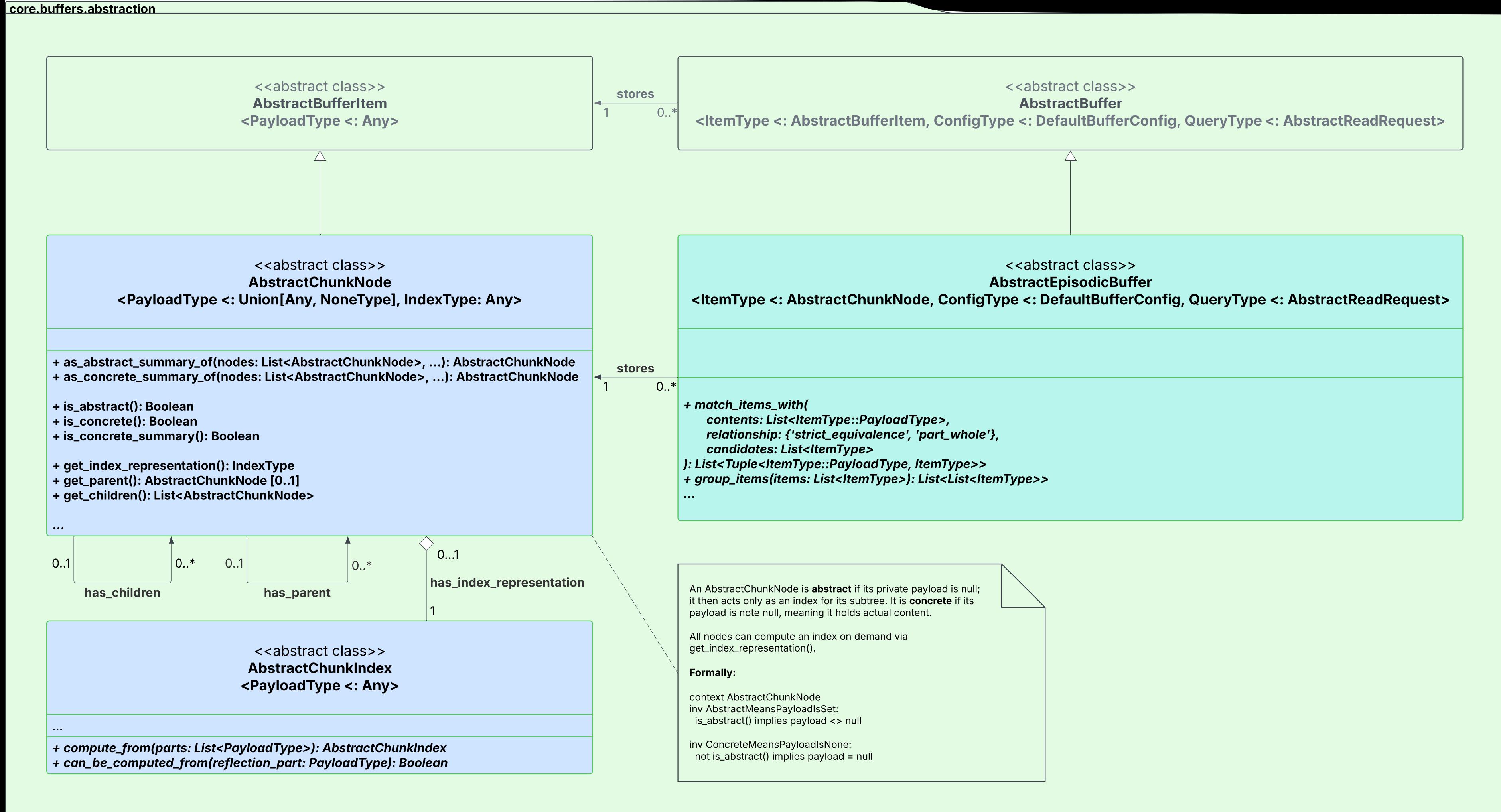
See Thesis, Subsection 4.3.3.

Implementation may still undergo minor structural refactoring to fully align with this definition.

Core Architecture: AbstractEpisodicBuffer & AbstractChunkNode Class Diagram

Contribution II: A WM Core Architecture for LLMs

Part II: Implementation



See Thesis, Subsection 4.3.4.

Implementation may still undergo minor structural refactoring to fully align with this definition.

Extensibility within current design:

- Multiple buffer types with defensive verification
- Varying capacity declarations
- Multiple forgetting strategies
- Transaction typing & I/O verification (foundation for hierarchy)
- Flexible reasoning granularity (*AbstractRequest/Response*)
- Flexible reflection granularity (*AbstractReflectableMaterial*)

Deferred / Speculative Extensions:

- Hierarchical transactions and contention scheduling (in *Schema Package*)
- Long-Term Memory (LTM) integration across the board:
 - **Facades** – LTM may augment read/write requests to improve retrieval & payload construction
 - **Schemata** – LTM may supply schemata & activation values for scheduling
 - **Buffers** – LTM may preload knowledge and consolidates stable WM reps.
 - **Storages** – passive; could feature specialized LTM storage

Implement WM Variants: The Reading Transactions

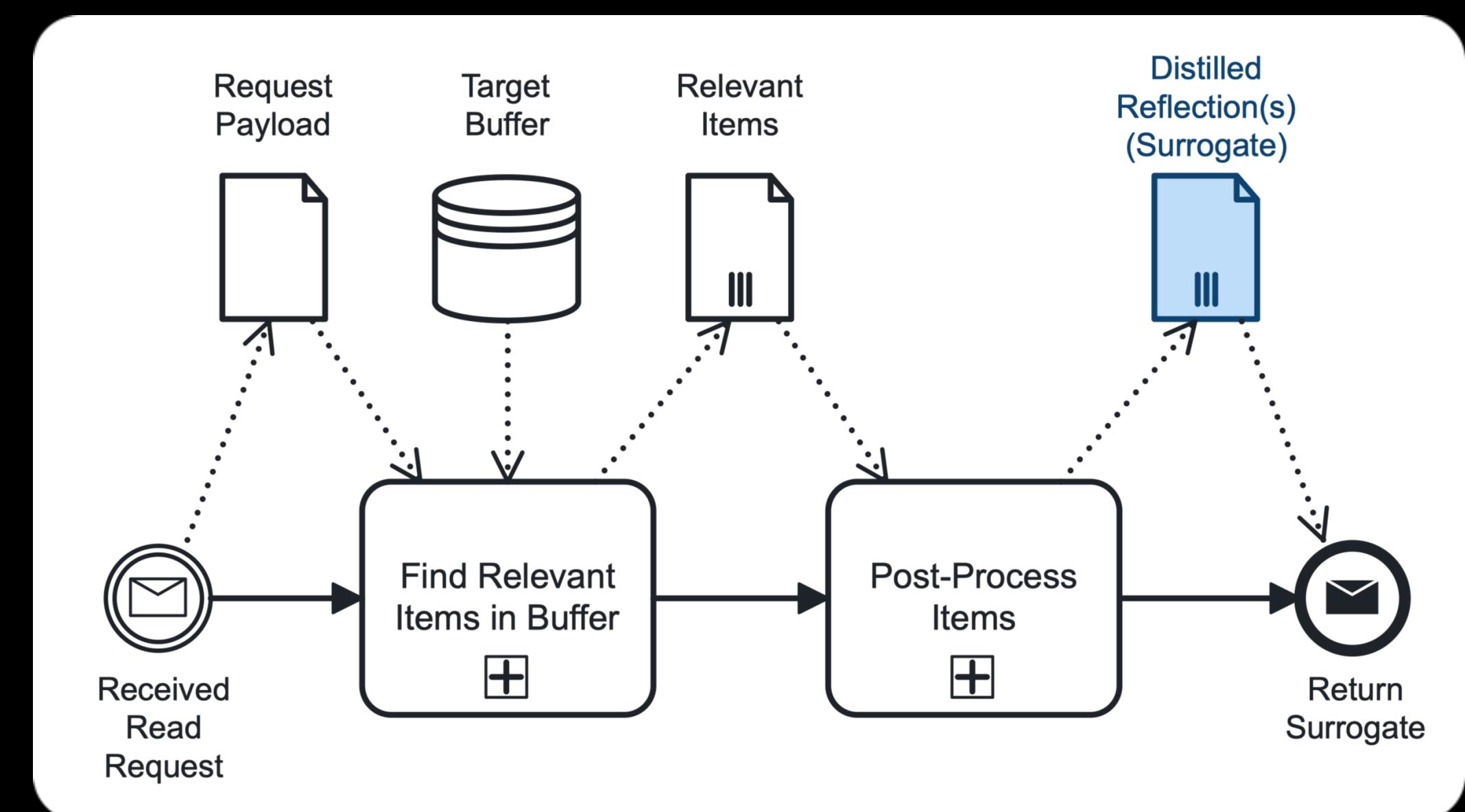
- Uses the **find-operation** of the buffer (variant-specific)
- Shared across all variants (reading from a forest subsumes reading from a flat item set)
- Two step process:

1. Find:

Use find-operation to **filter the set of items (nodes)**, given the **thought-prompt as query** (Filters all items, except children of aggregated summary nodes)

2. Post-Process:

Compress/Re-Summarize the filtered set up to at most 8 reflections, in context of the query (All items contributing to a summary are recorded as accessed)



Implement WM Variants: The Writing Transactions (1/2)

- Uses the **match & group operation** of the buffer (variant-specific)

- Three step process:

1. **Record Usability:**

If a reflection is present in the given thought, estimate its usability and record the score.

(Shared by all variants)

2. **Generate reflections** for the newly given thought.

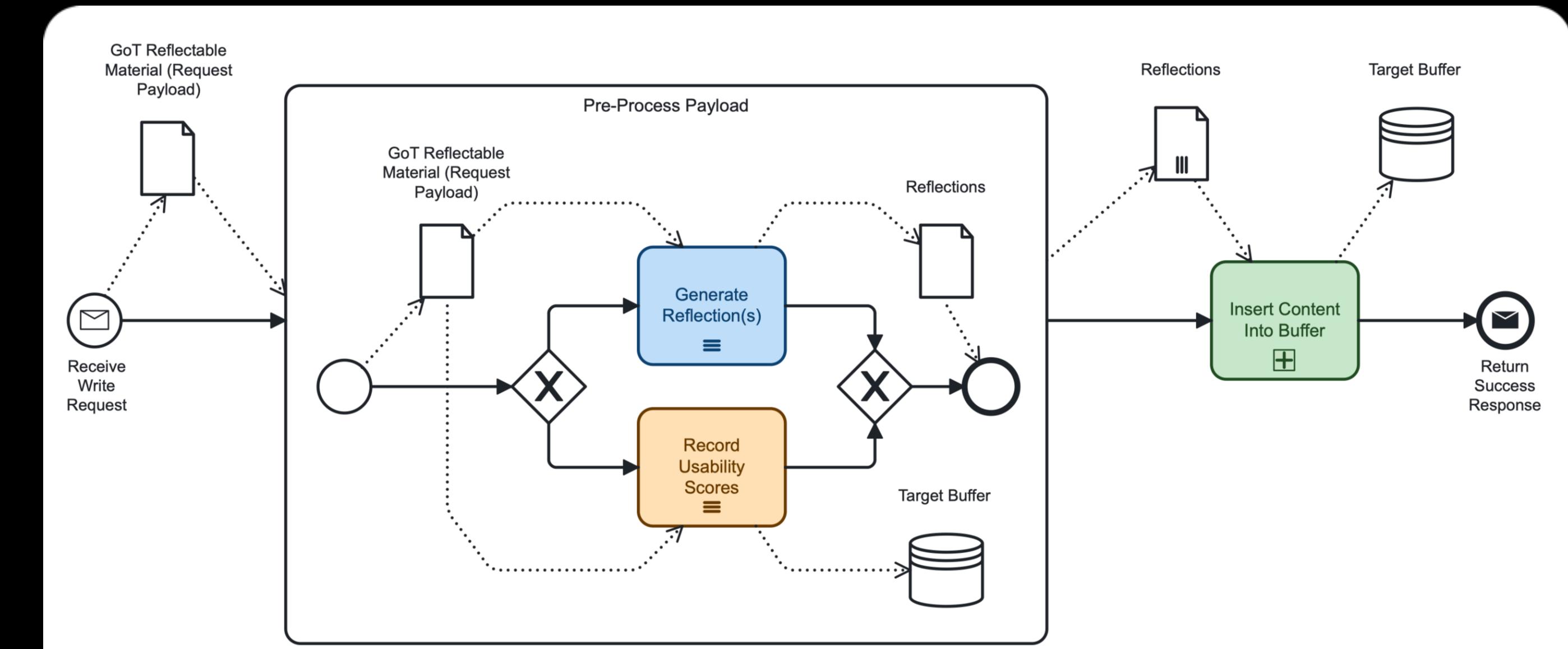
(Shared by all variants)

3. **Insert** the reflections as new nodes in the forest (variant-specific)

↳ **Forgetting:** If committing changes exceeds the buffer capacity:

Rank all existing items by their combined survival score and delete as many as needed
(forgetting mechanism is shared by all variants)

(Non-BPMN-compliant dataflows go across subprocess boundary to avoid clutter).



Implement WM Variants: The Writing Transactions (2/2) – Insertion

- **Non-Chinking (Flat)** variants simply dump new items as concrete root nodes into the forest.
- **Chunking enabled variants** assumes a near-perfect clustering to be present (no reorganization), and prioritize insertion in existing trees over the formation of new ones:
 - ↳ Leading to the following relationship-assumptions: A new node n_r can have at most:
 - 1 part-whole relationship to an existing abstract node
 - 1 equivalence relationship to an existing concrete node (that has no concrete parent)
 - n group-relationships to concrete root nodes that are currently sole or disconnected members of their group
 - ↳ Insertion for a single node n_r can be summarized as follows:

```
# First, search for equivalent nodes:  
If:  $n_r$  equivalent to any concrete root node (buffer.match_items(...))  
    Subsume  $n_r$  into the root by replacing with a summary node → Return  
  
Else if:  $n_r$  has part-whole relationship to an abstract node  $n_a$  (buffer.match_items(...))  
    If:  $n_r$  equivalent to any concrete child  $n_c$  of  $n_a$   
        Subsume  $n_r$  into the  $n_c$  by replacing with a summary node → Return  
    Else: # No equivalent nodes found → Insert into new tree  
        Insert  $n_r$  as new child of  $n_a$  → Return  
  
# No equivalence or part-whole relationships detected → Build a new tree  
Search for groupings among concrete root nodes (buffer.group_items(...))  
Any grouping >= 1 receives a new abstract parent node  
If:  $n_a$  not assigned to any grouping:  
    Insert  $n_r$  as new concrete root node
```

Event recordings throughout:

- Access events on node n_i every time a relationship between n_r and n_i is checked (propagated up to root, and down to subtree of n_i)
- Repetition Events on node n_i every time an equivalence relationship between n_r and n_i is detected (propagated down to subtree of n_i)

Variant-Specific Buffer Implementations

Contribution III: Four Concrete WM Variants

Part II: Implementation

All buffers implement:

- **find_relevant_items_for(query, candidates, max_size) → ranked_items**

Filters non-meaningful items in *candidates* and ranks the remaining according to the relevance to the given *query* (a thoughts prompt), optionally capped to *max_size*.

↳ **LLM-Only variants:**

Filter all given nodes individually in one inference call

↳ **A-MEM-Variants:**

Embed *query* as *q*; filter a $c \in \text{candidates}$ if $d(c, q) \leq \text{max_link_distance}$; rank by $d(c, q)$.

- **match_items(contents, relationship, candidates) → matches**

Identifies two types of relationships (part-whole or equivalence) between *contents* (reflections) and *candidate* nodes. A reflection may match at most one candidate; which may be matched by multiple.

↳ **LLM-Only variants:**

$n \times n$ matching in one inference call, specific prompts per relationship.

↳ **A-MEM-Variants:**

$n \times (1 \times n)$ filtering. For each $c \in \text{content}$: Filter $a \in \text{candidates}$ if

↳ Part-Whole relationship: $d(c, a) \leq \text{max_link_distance}$

↳ Equivalence relationship: $d(c, a) \leq 0.05$

- **group_items(items) → groupings**

Returns a clustering (set of groupings) of the given set of (concrete) nodes.

↳ **LLM-Variants:**

All items in one call.

↳ **A-MEM-Variants:**

Agglomerative clustering on all items with *max_link_distance* as cluster threshold.

A-MEM-based / Embedding-Hybrid Variants:

- A) Operate on absolute cosine distance:

$$d(\mathbf{u}, \mathbf{v}) = 1 - \left| \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{u}\| \|\mathbf{v}\|} \right|$$

- B) obtain a flexible distance threshold, *max_link_distance*, the **max. distance between any two verified neighbors** in \mathcal{E} : $\max_{(i,j) \in \mathcal{E}} d(\mathbf{u}_i, \mathbf{u}_j)$, with a fallback to 0.3 if $\mathcal{E} = \emptyset$.

Implement WM Variants: Reflection Generation & Best Practices

Reflection Format:

```
<Reflection Item>
  <Error Location>
    "If A is taller than B, then B is taller than A."
  </Error Location>
  <Error Explanation>
    This step reverses the comparison logic; the conclusion contradicts the premise.
  </Error Explanation>
  <Error Fixing Suggestion>
    Keep direction consistent: If A > B, then B < A.
  </Error Fixing Suggestion>
  <Takeaway>
    Maintain logical direction when chaining.
  </Takeaway>
  <Scores>
    <Repetition Score> 0.21 </Repetition Score>
    <Access Score> 0.37 </Access Score>
    <Usability Score> 0.64 </Usability Score>
    <Combined Score> 0.58 </Combined Score>
  </Scores>
</Reflection Item>
```

Reflection Generation:

- Limited to a single thought (may contain prior reflection).
- Multiple distinct reflections 1-shot (early on separation)
- Instruct LLM to combine multiple reflection strategies (e.g. keywords, advice, explanation, etc.)

Reflection Incorporation:

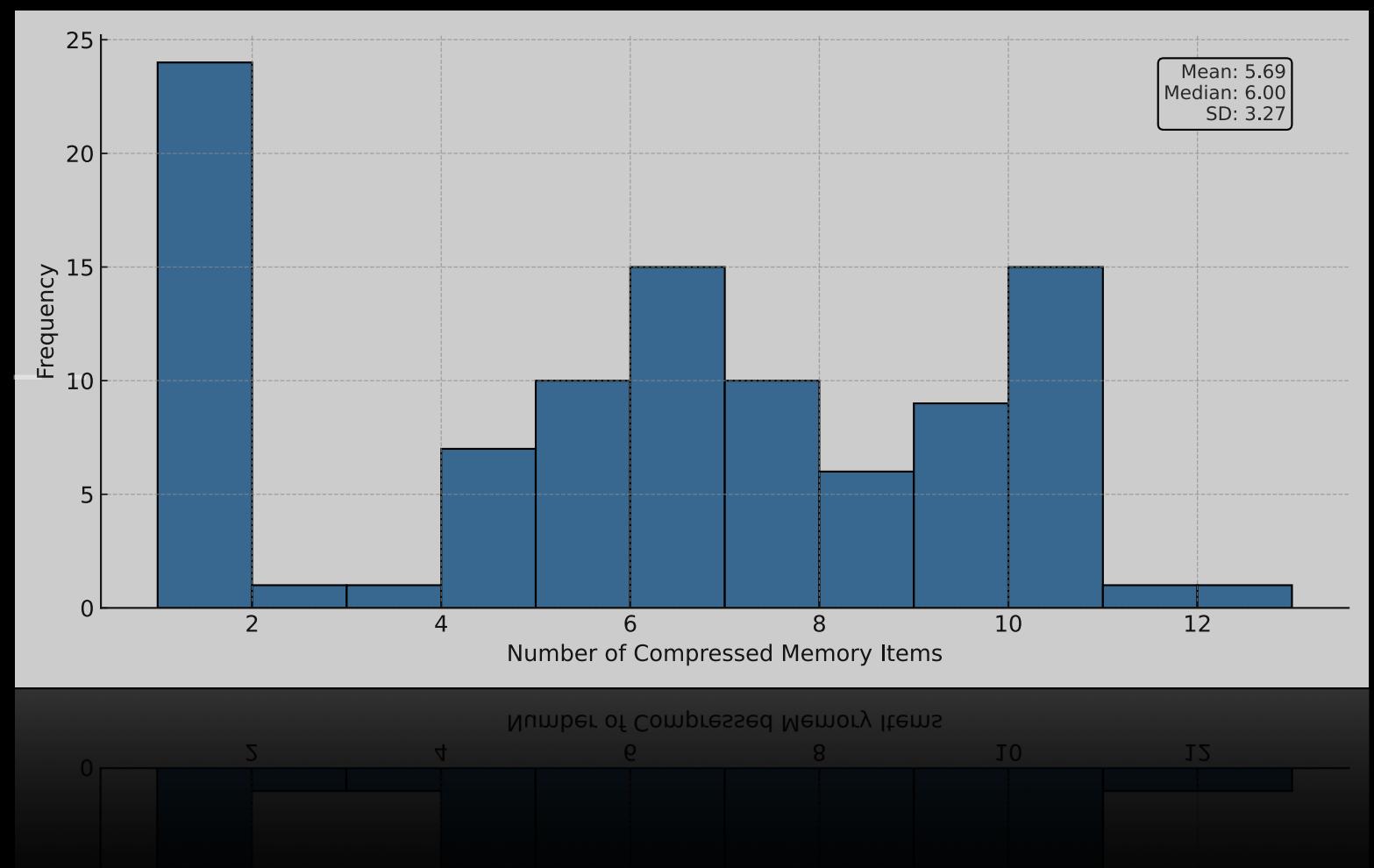
- Limited to a single thought (may contain prior reflection).
- Multiple distinct reflections in one shot (early on separation)
- Instruct LLM to combine multiple reflection strategies (e.g. keywords, advice, explanation, etc.)

Best Practices from Related Work

- **Diverse Feedback** quality dimensions stabilize gains (Madaan et al., 2023)
 - ↳ We remain task-agnostic; don't add task-specific feedback scores → (**Limitation X**)
To counteract, we add survival scores (access/repetition/usability) as a proxy.
- **Actionable & Specific Feedback** – concrete fixing suggestion + error is key (Madaan et al., 2023)
 - ↳ We include both the <Error Location> and <Error Fixing Suggestion> → ✓
- **Combined feedback styles** yield strongest gains (Renze & Guven, 2024)
 - ↳ We encourage multiple variants, but leave the choice to the model → ✓
- **Include Prior Attempt(s) in the subsequent Generation** (Shinn et al., 2023)
 - ↳ We restrict reflection generation to the local thought;
when incorporated, the reflected-upon thought is not included → (**Limitation X**)
 - ↳ Noticed in hindsight that only the erroneous step,
not the relevant (sub-)CoT is included most of times → (**Limitation X**)
- **Multiple Iterations** improve quality with diminishing returns (Madaan et al., 2023; Shinn et al., 2023).
 - ↳ Every GoT thought is reflected on; prior reflections carry forward.
Iteration depth is not fixed, but depends on the reasoning structure → (**Partial Limitation**)
- **Reflecting More Often doesn't Hurt** – better reflect too often than too little (Madaan et al., 2023).
 - ↳ We apply reflections after every GoT thought → ✓
- **No. of Reflections to Include Unclear** – too many may risk retrieval noise (cf. Liu et al., 2023).
 - ↳ We summarize to max. 8 reflections at read-time before incorporation → ✓

Experimental Setup (With Hyperparameters)

- **Tasks: Sorting & Set-Intersection – adapted from GoT (Besta et. al., 2024)**
 - On a list/set of integers (size=32)
 - Eval metric: Accuracy
- 5 competing setups:
 - ↳ No WM (Vanilla GoT); GoT+ each of our four WM variants (resp.)
 - ↳ Each assessed across I/O, CoT, ToT, GoT prompting
 - ↳ For each: 20 samples x redraw of 3 → 60 datapoints in total
- **WM capacity = 7**
(mean number of retrieved items in a trial run with capacity = ∞)
- **Model: gpt-4o-mini-2024-07-18**
(Documented at <https://platform.openai.com/docs/models/gpt-4o-mini>)
- **Hyperparameters:**
 - *LLM – Temperature = 0.8; max. gen. length = ∞*
 - *WM – Exponential forgetting factor: 0.995 (adapted from Park et al., 2023)*
 - *A-MEM:*
 - *Re-Indexing threshold lowered from 100 to 10*
 - *Fallback Distance threshold: 0.3*
 - *Embedding model: all-MiniLM-L6-v2 (a variant of the model proposed by Wang et al. (2020) (<https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2>)*

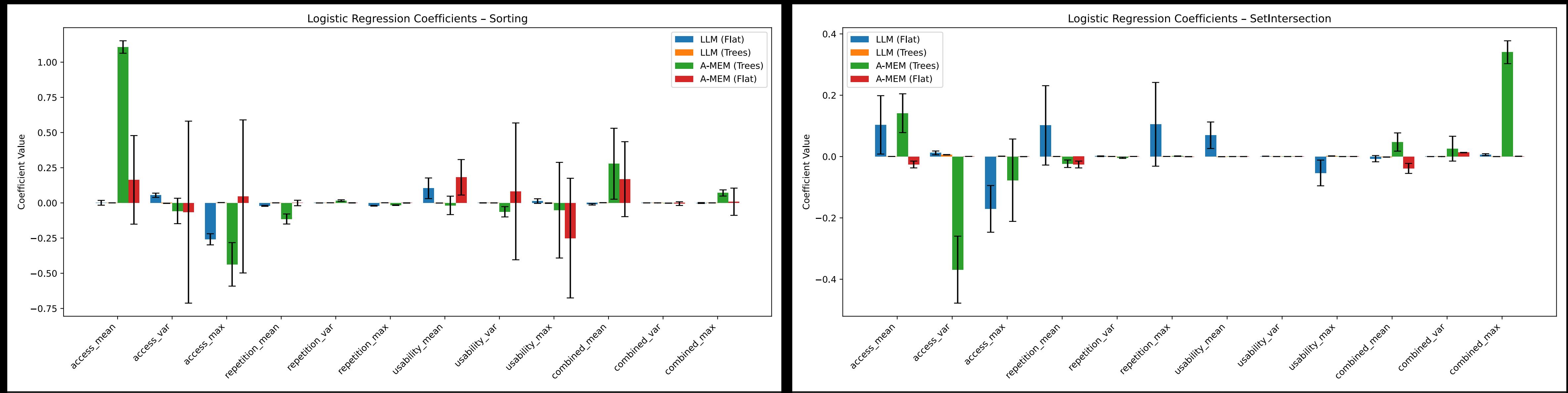


Minor Explorative Finding: Survival Scores as Predictor of Trial Success (1/2)

Contribution IV: WM Variants Evaluated within GoT

Part III: Main Findings

Qualitative Eval: Found **no systematic differences** in buffer contents between successful vs. unsuccessful trials
↳ Further explored: Logistic regression on survival scores (max/mean/std) to predict trial success

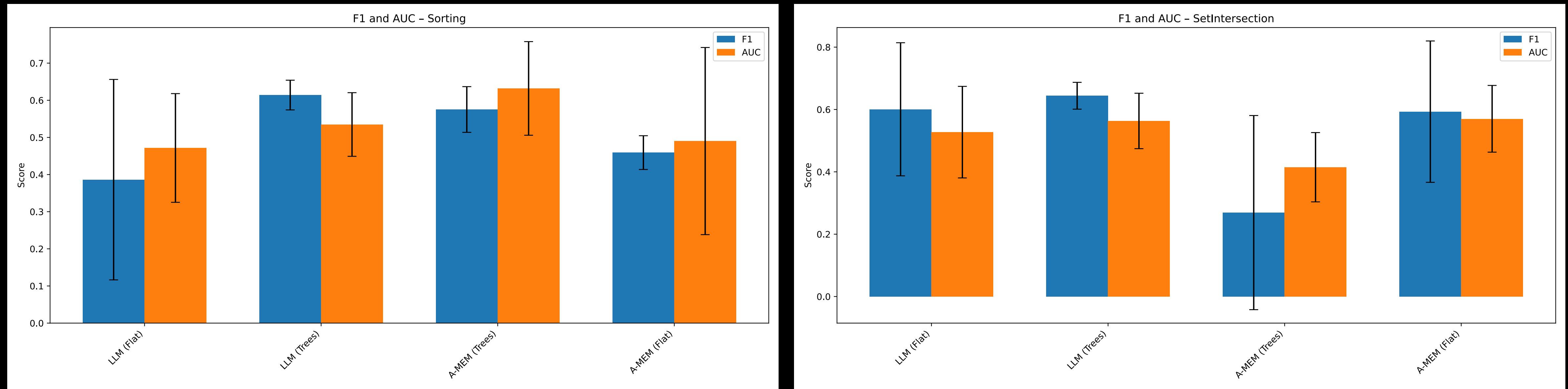


- Across variants: No consistent patterns
- **LLM-Tree:** higher coefficients across both tasks (but on different features; see green bars above)
↳ Suggests a **weak link** between survival-based accumulation and trial success in **LLM-Tree**
- Results remain **inconsistent & exploratory (no CI's or sig. tests)**

Minor Explorative Finding: Survival Scores as Predictor of Trial Success (2/2)

Contribution IV: WM Variants Evaluated within GoT

Part III: Main Findings



Further Discussion: Ideas for WM in Reasoning LLMs

Analogy: Proof-Writing

- **Humans:**
WM balances **forward planning** (exploration) and **backward curation** (discarding dead ends, refining assumptions).
- **LLMs:**
Externalize **all** intermediate steps → Condition final answer on “a notebook full of fragments” (noisy, uncurated).
↳ **What if distractions were processed to retain only informative insights, guiding the next step without distractions?**
↳ **WM in LLMs:** Act as a **Central Executive**, curating and planning to reduce cognitive load.

Some Challenges & Initial Ideas for WM Interventions

1. **Long-range retrieval accuracy**
 - Problem: lost-in-the-middle effect (Liu et al., 2023).
 - WM: Curate a **smaller, focused context window**; suppress irrelevant traces.
2. **Overthinking**
 - Problem: excessive, redundant reasoning steps (Sui et al., 2025).
 - WM: Detect **stagnating loops or diminishing progress**; dynamically **constrain reasoning depth**; identify **completion points**.
3. **Error propagation**
 - Problem: Flawed premises snowball through reasoning (Gan et al., 2025).
 - WM: Curate focused context to enable deliberate **planning and exploration that challenges prior assumptions**; suppress distractions from prior (potentially erroneous) steps; trigger backtracking when needed.

Possible First Step:

Probe whether attention mechanisms alone suffice for context regulation (e.g. in a proof-writing scenario)
→ Test with reasoning chains mixing relevant vs. distracting content.

Additional Figures not Included so Far (1/14):

Demonstration of the Stroop Effect (Stroop, 1935; 2/2)

⚠ Warning: Your brain is about to betray you.

You have 10 seconds.

Read these words as fast as you can. Don't think – just go!

<i>blue</i>	<i>orange</i>	<i>green</i>	<i>blue</i>
<i>orange</i>	<i>black</i>	<i>purple</i>	<i>orange</i>
<i>pink</i>	<i>green</i>	<i>red</i>	<i>black</i>
<i>green</i>	<i>blue</i>	<i>red</i>	<i>pink</i>

Additional Figures not Included so Far (2/14):

Demonstration of the Stroop Effect (Stroop, 1935; 2/2)

Now again – but this time, don't read the words.

Say only the *color* they are displayed in.

Ready? Go!

<i>blue</i>	<i>orange</i>	<i>green</i>	<i>blue</i>
<i>orange</i>	<i>black</i>	<i>purple</i>	<i>orange</i>
<i>pink</i>	<i>green</i>	<i>red</i>	<i>black</i>
<i>pink</i>	<i>purple</i>	<i>purple</i>	<i>red</i>

Additional Figures not Included so Far (3/14):

Demonstration of priming

Read the following words quickly:

fork knife plate dinner napkin eat

Now, what is the first word that comes to mind when you see this?

S _ _ P

Did you say **SOUP**?

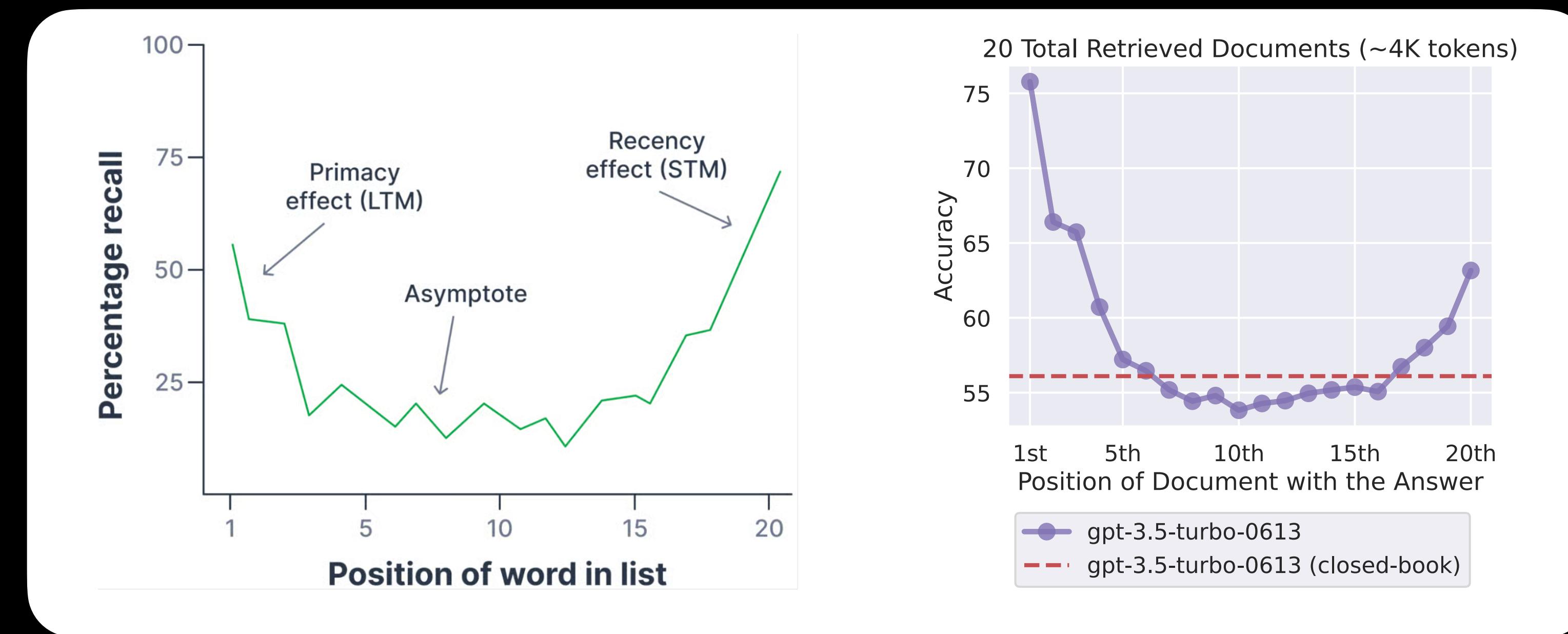
But if a different group sees this sequence:

shower towel clean brush bathe wash

they tend to complete S _ _ P as **SOAP**.

Additional Figures not Included so Far (4/14):

Two parallel U-shaped recall patterns in human and artificial cognition.

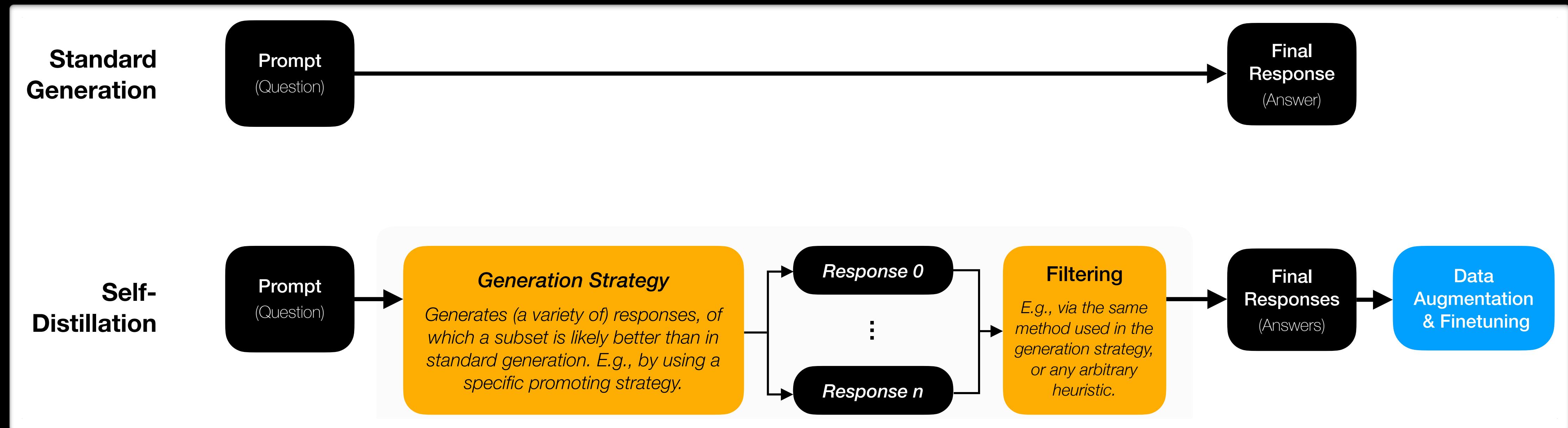


Primacy-recency effect in humans.
Recall follows a U-curve, with higher
accuracy for early and late items (Murdock,
1962) (LTM: Long term memory; STM: Short
term memory, alias Working Memory)
Graphic adapted from: <https://www.pipedrive.com/en/blog/quotes-for-email-signature>.

Lost-in-the-middle effect in LLMs:
Performance drops for information placed
in the middle of the input context.
Adapted from Liu et al. (2023).

Additional Figures not Included so Far (5/14):

Conceptualization of Self-Distillation

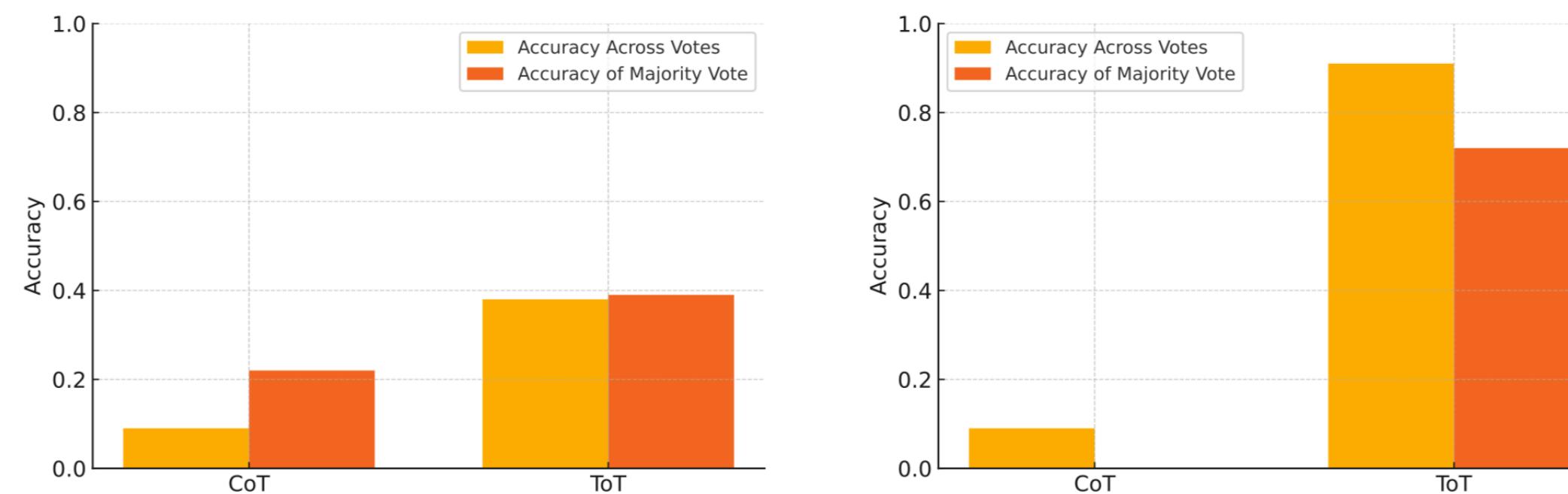


Additional Figures not Included so Far (6/14):

Experimental Results from Fine-tuning a LLM for Self-Distillation (1/2): Data Quality & Empirical Trends

Figure 20

Accuracy comparison of CoT and ToT during the data labeling step of Self-Distillation. We report both the average accuracy across individual generations and the final accuracy of the majority-voted label. Each method is applied to two tasks, where for each, the total number of samples labeled is $n = 80$, with majority voting size 32, yielding $80 \cdot 32 = 2.560$ individual generations per task.



(a) **Sorting task.** The ToT method outperforms CoT across both metrics. However, the gap between majority-voted accuracy and accuracy across votes is marginal for ToT, but large for CoT.

(b) **Set-Intersection task.** ToT drastically improves accuracy compared to CoT. Interestingly, majority voting significantly lowers accuracy in both cases. For CoT, to 0.0.

- ToT produces better labels than CoT
- Majority-Voting reduces label quality for Set-Intersection

Figure 22

Accuracy versus confidence on generated labels of the Set-Intersection training-set. Accuracy reflects the proportion of correct answers at each confidence level. Confidence denotes the fraction of generation attempts that produced the majority-voted label. For voting rounds resulting in a tie, an answer was chosen at random.

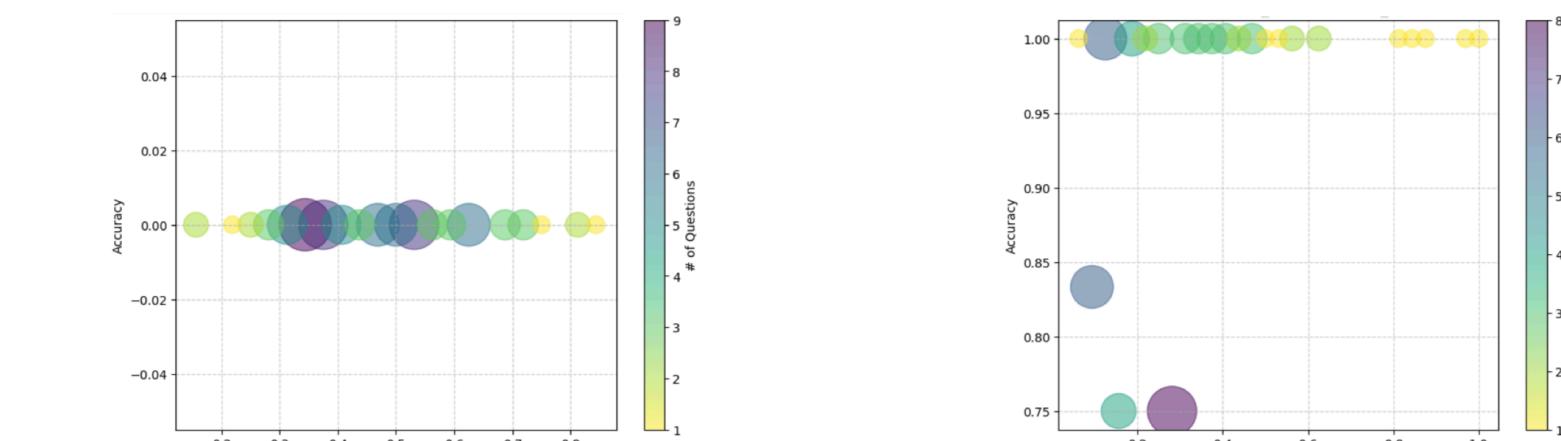
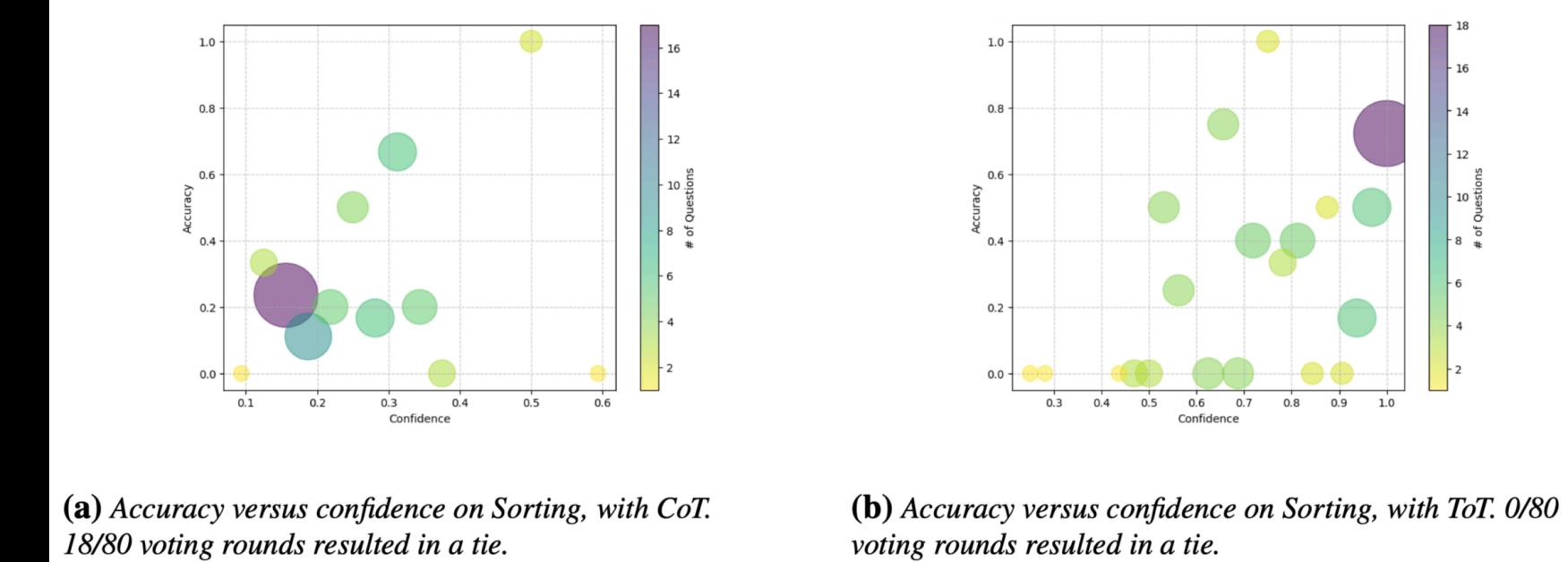


Figure 23

Accuracy versus confidence on generated labels of the Sorting training-set. Accuracy reflects the proportion of correct answers at each confidence level. Confidence denotes the fraction of generation attempts that produced the majority-voted label. For voting rounds resulting in a tie, an answer was chosen at random.



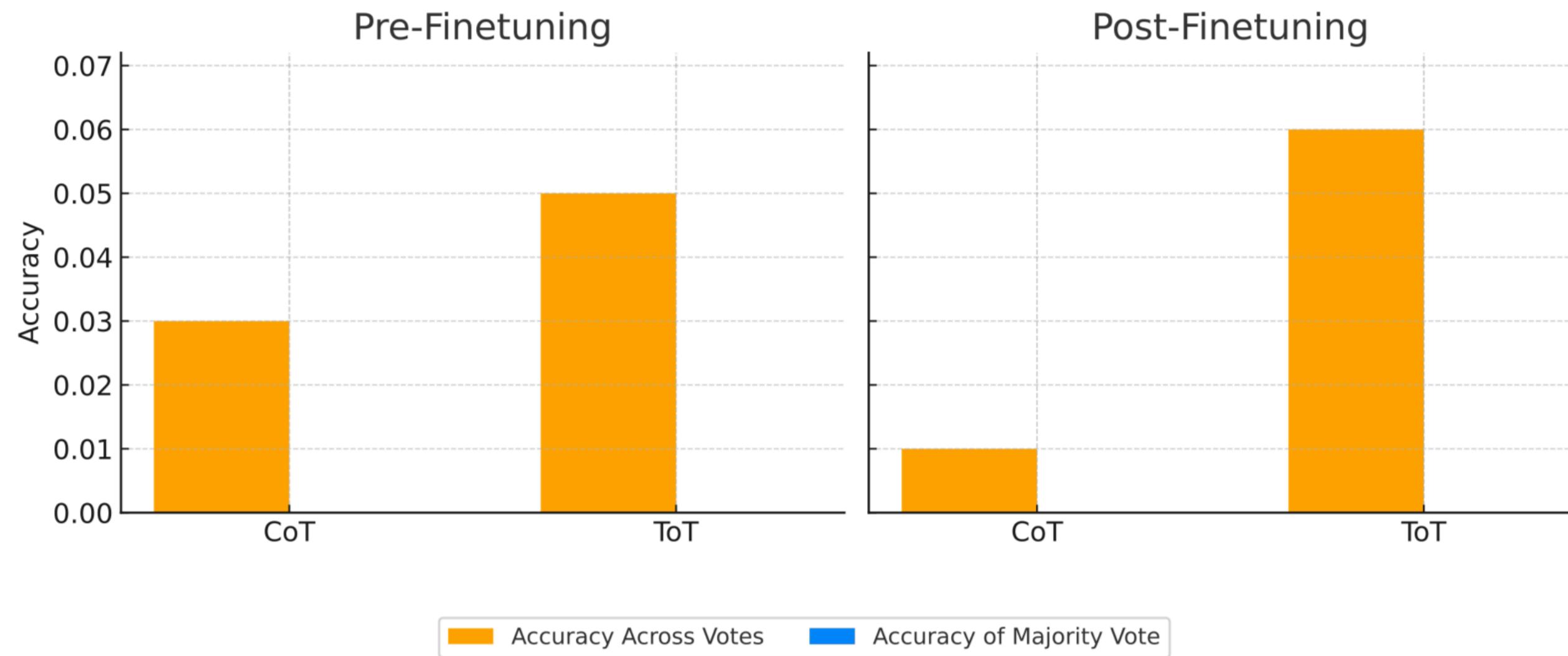
- Tasks seem not as well calibrated; rather underconfident
- Weak correlation between confidence & accuracy
- Inconsistencies not pursued further

Additional Figures not Included so Far (7/14):

Experimental Results from Fine-tuning a LLM for Self-Distillation (2/2): Model Performance

Figure 24

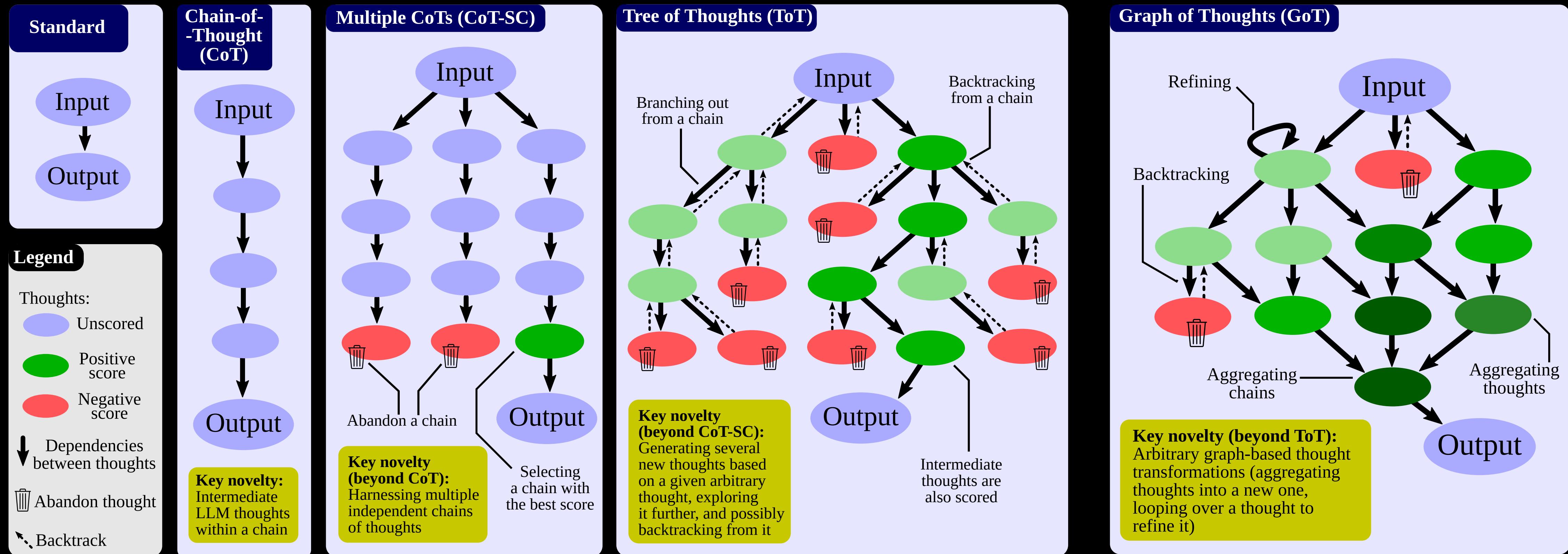
Accuracy comparison before and after fine-tuning on the Set-Intersection task using standard prompting. "CoT" and "ToT" refer to reasoning strategies used during label generation (not inference). We report both average per-generation accuracy (Accuracy Across Votes) and majority-vote accuracy (Accuracy of Majority Vote), using 5 votes per data point (20 points total). All majority-vote results yielded 0.0% accuracy. The vertical axis is capped to emphasize fine-grained differences.



- ToT leads to superior training data over CoT, translating to model performance
- Evaluation regime with I/O prompting relatively unstable

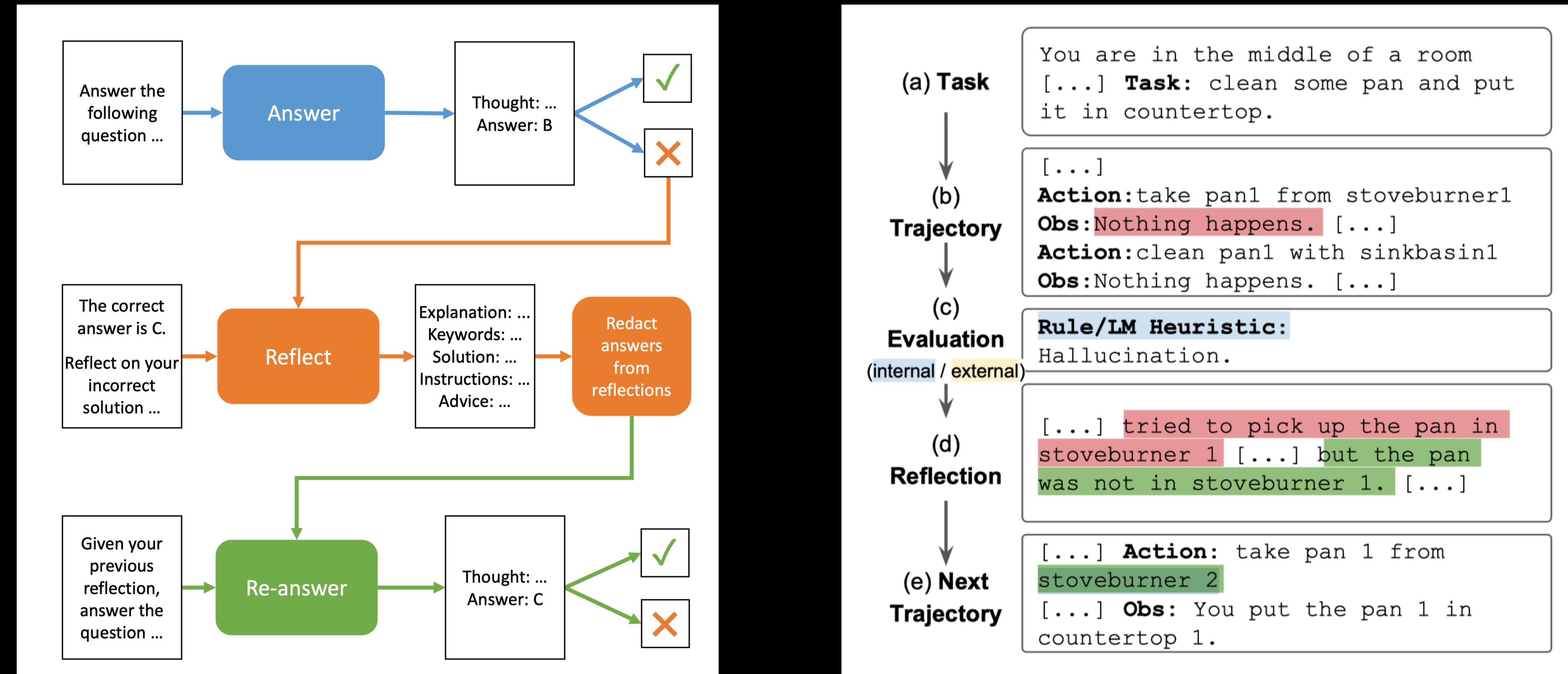
Additional Figures not Included so Far (8/14):

Evolution of Reasoning Paradigms / Static Prompting Methods (Adapted from Besta et. Al, 2024)



Additional Figures not Included so Far (9/14):

Reflection Examples from Related Work

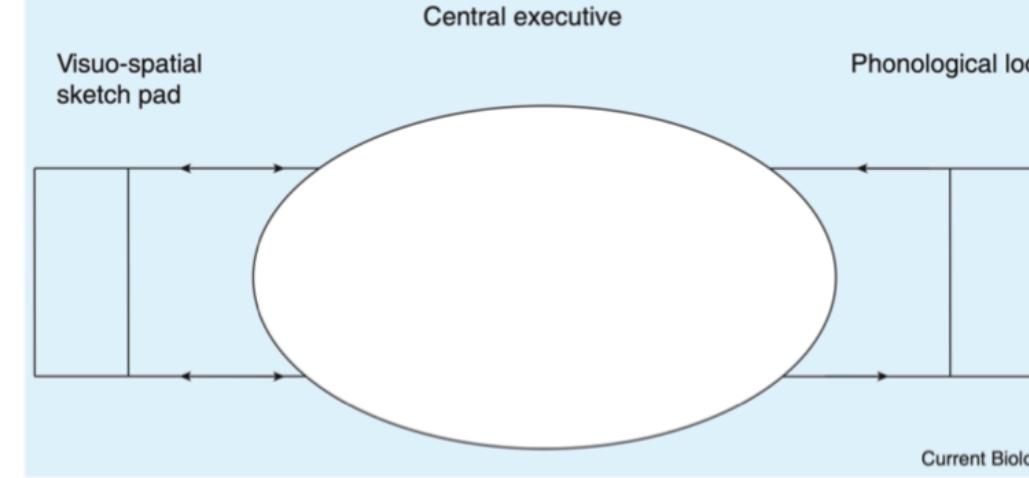


A Self-Reflection setup in which the correct answer is used as error signal, but later redacted from the produced reflection (not depicted in the figure). Adapted from Renze and Guven (2024).

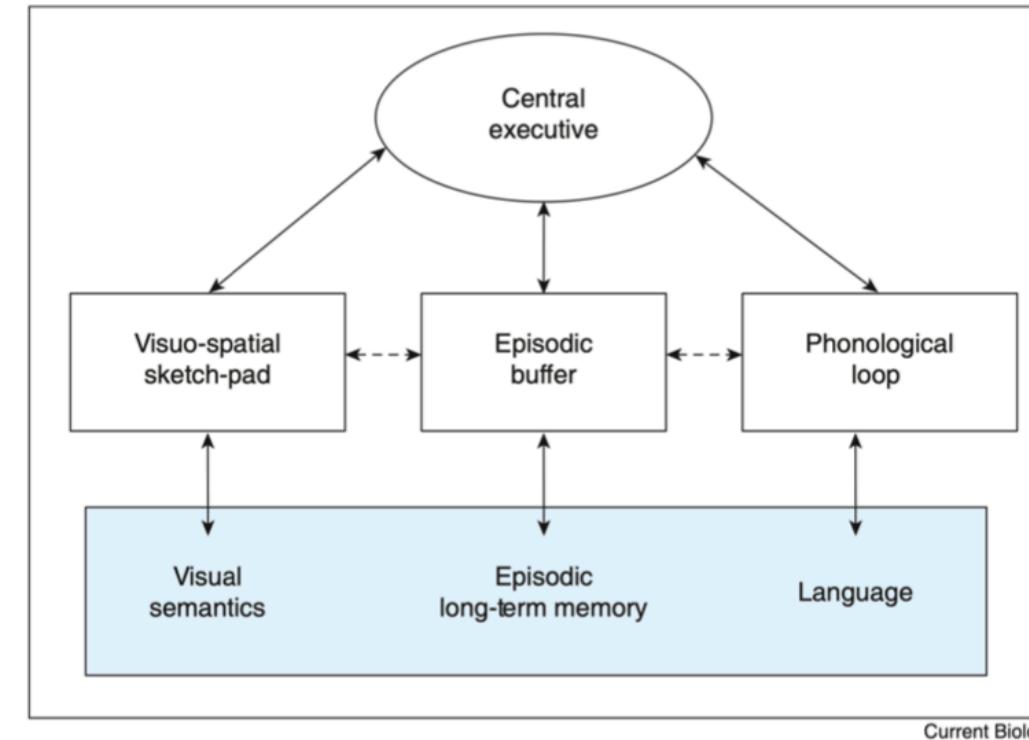
A Self-Reflection setup with variable error signal source, on the tasks of "decision making". Adapted from Shinn et al. (2023);

Additional Figures not Included so Far (10/14):

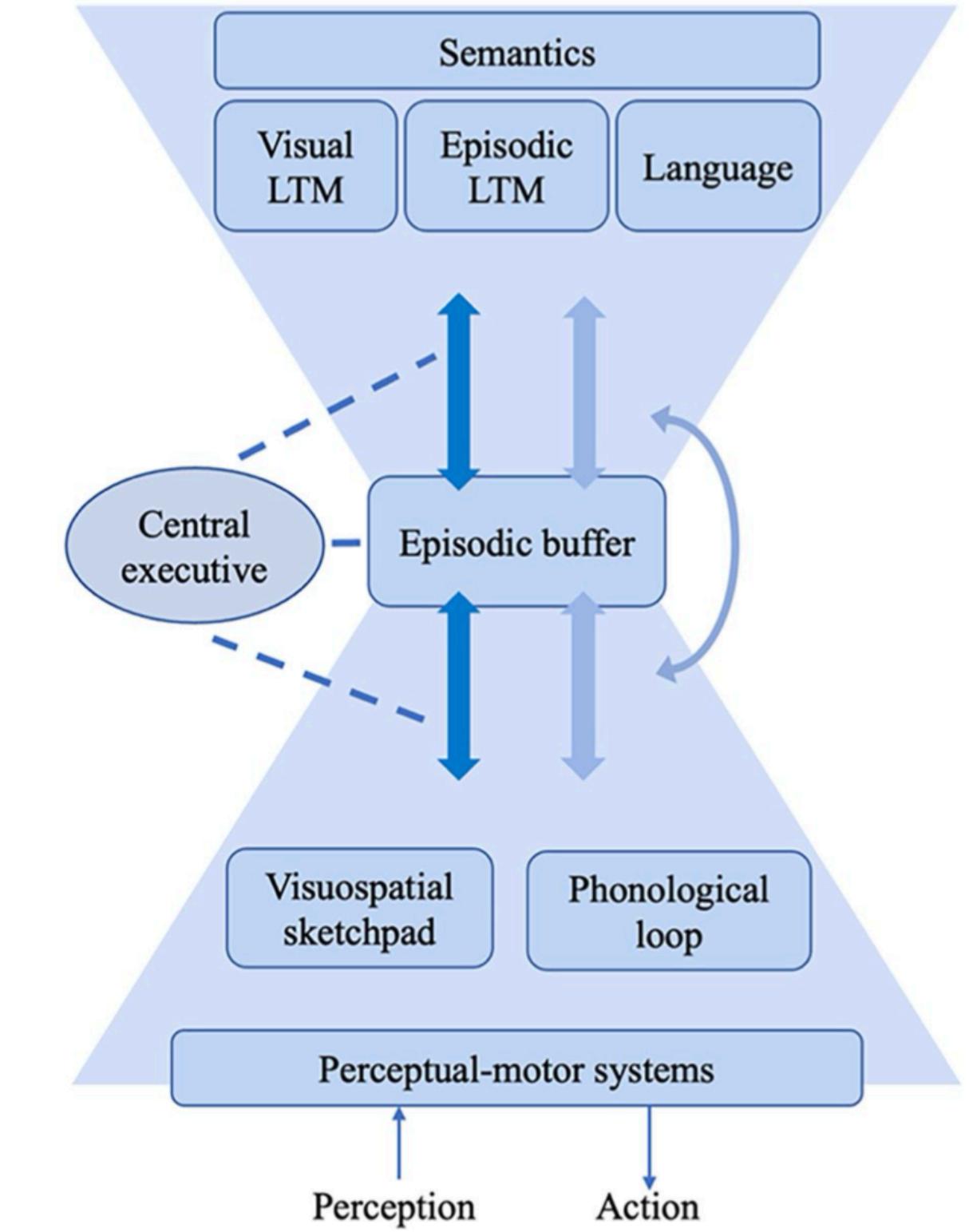
Evolution of the Multi-Component Model (MCM) of Working Memory.



(a) MCM (1974). Adapted from Baddeley and Hitch (1974): "The earlier concept of the short-term memory has been elaborated to include an attentional controller and two modality based temporary stores. The components are assumed to interact, and to be linked to both perception and long-term memory."



(b) MCM (2000). Adapted from (Baddeley, 2000): "Includes links to long-term memory and a fourth component, the episodic buffer that is accessible to conscious awareness."

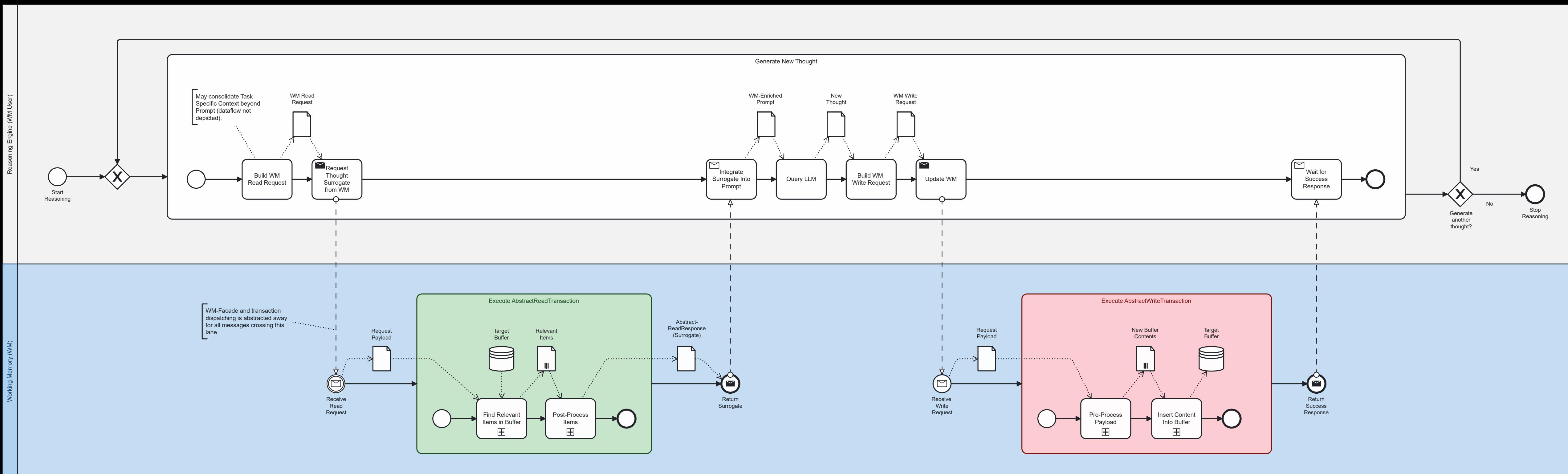


(c) MCM (2025). Adapted from (Hitch et al., 2025): "A multicomponent view of the cognitive system with working memory located between semantic long-term memory and perceptuo-motor subsystems with the episodic buffer as the central hub. The central executive is shown as a separate resource that can be deployed in a variety of ways to interact with many parts of the system. Light and dark arrows indicate implicit and explicit processes, respectively."

Additional Figures not Included so Far (11/14):

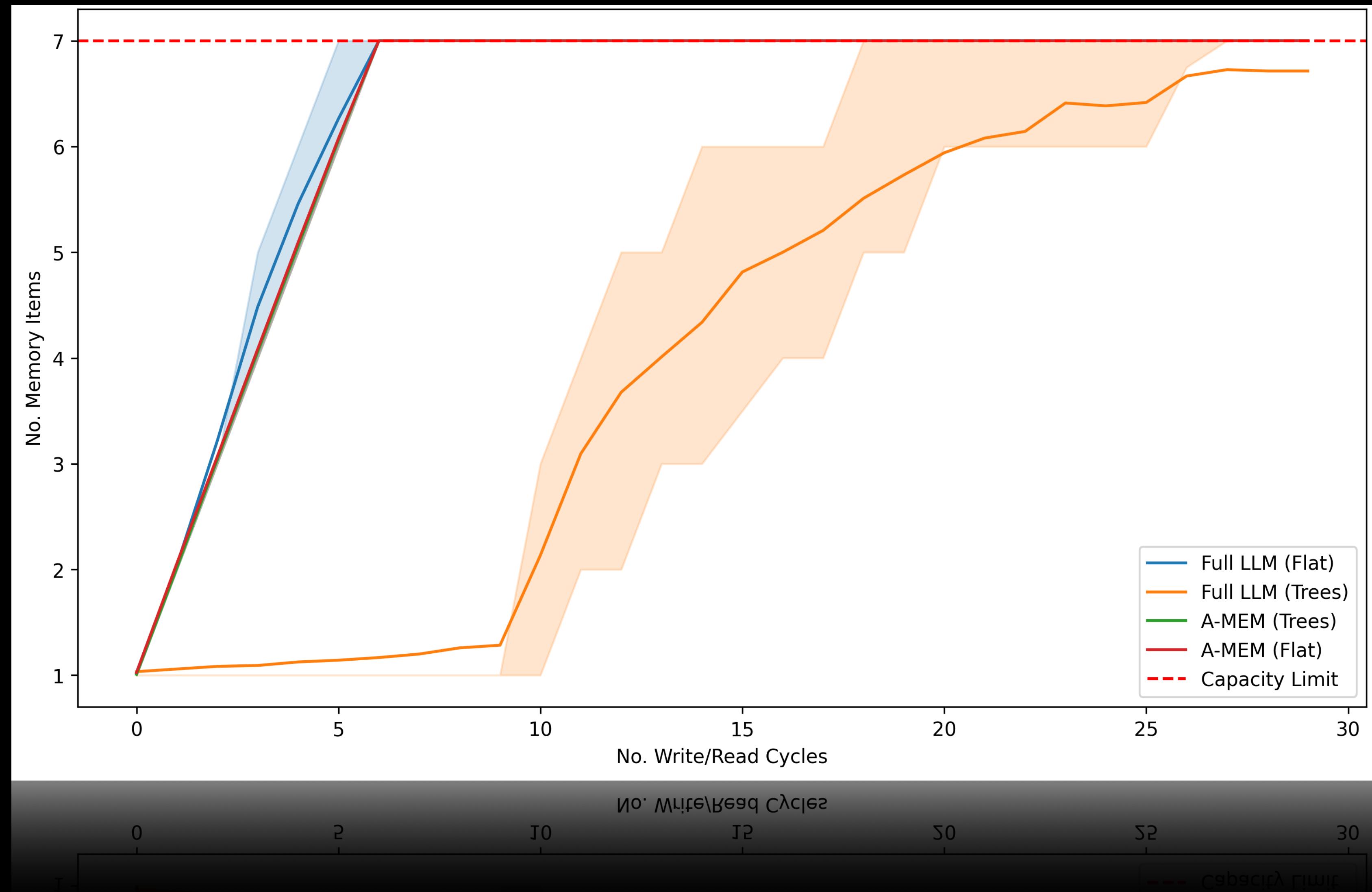
Full High Level WM Process Diagramm

(Non-BPMN-compliant dataflows go across subprocess boundary to avoid clutter).



Additional Figures not Included so Far (12/14):

Memory Pressure / Capacity for the ToT Prompting Method

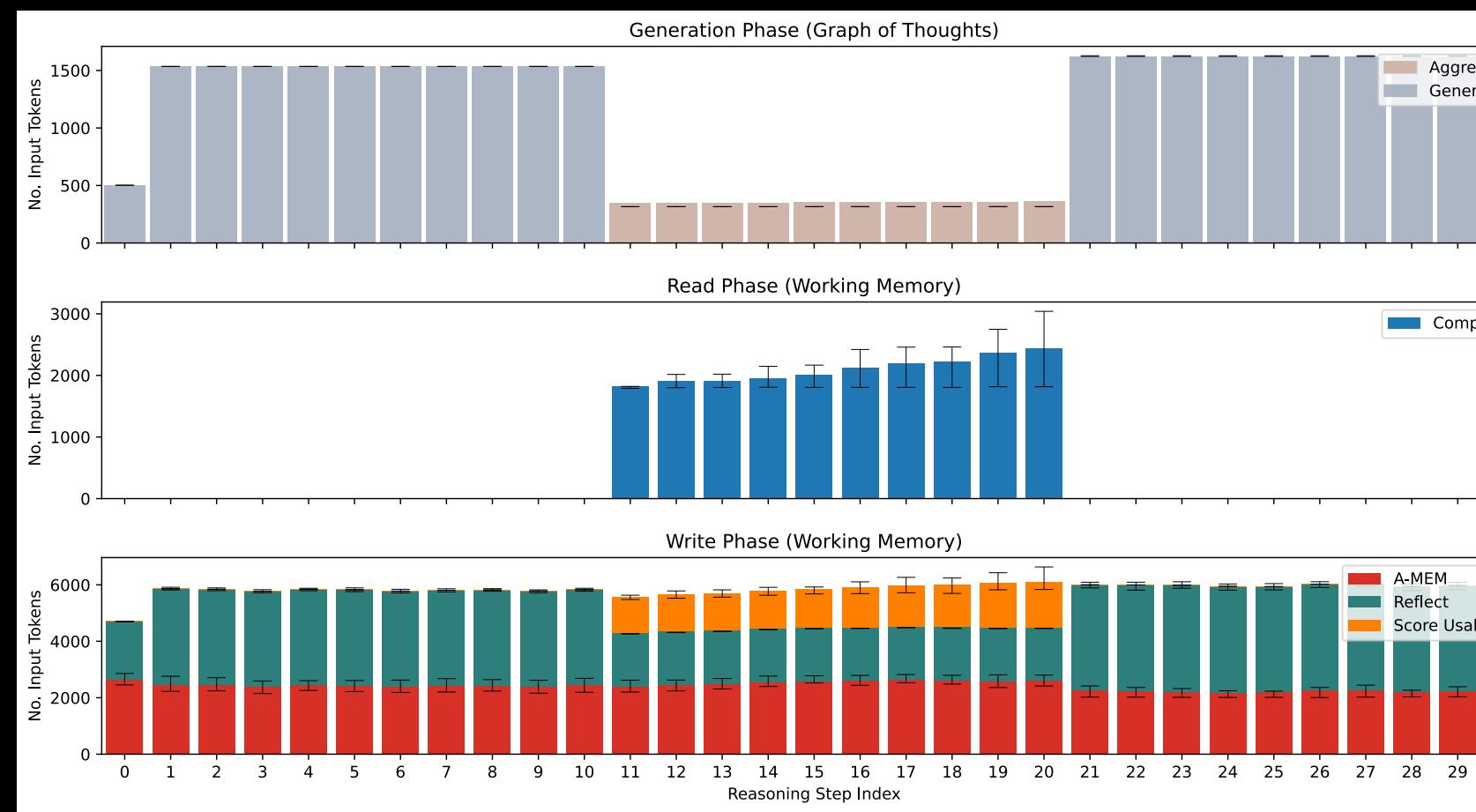


Additional Figures not Included so Far (13/14):

Token Usage Histograms on GoT Prompting Method – Embedding-Hybrid Variants

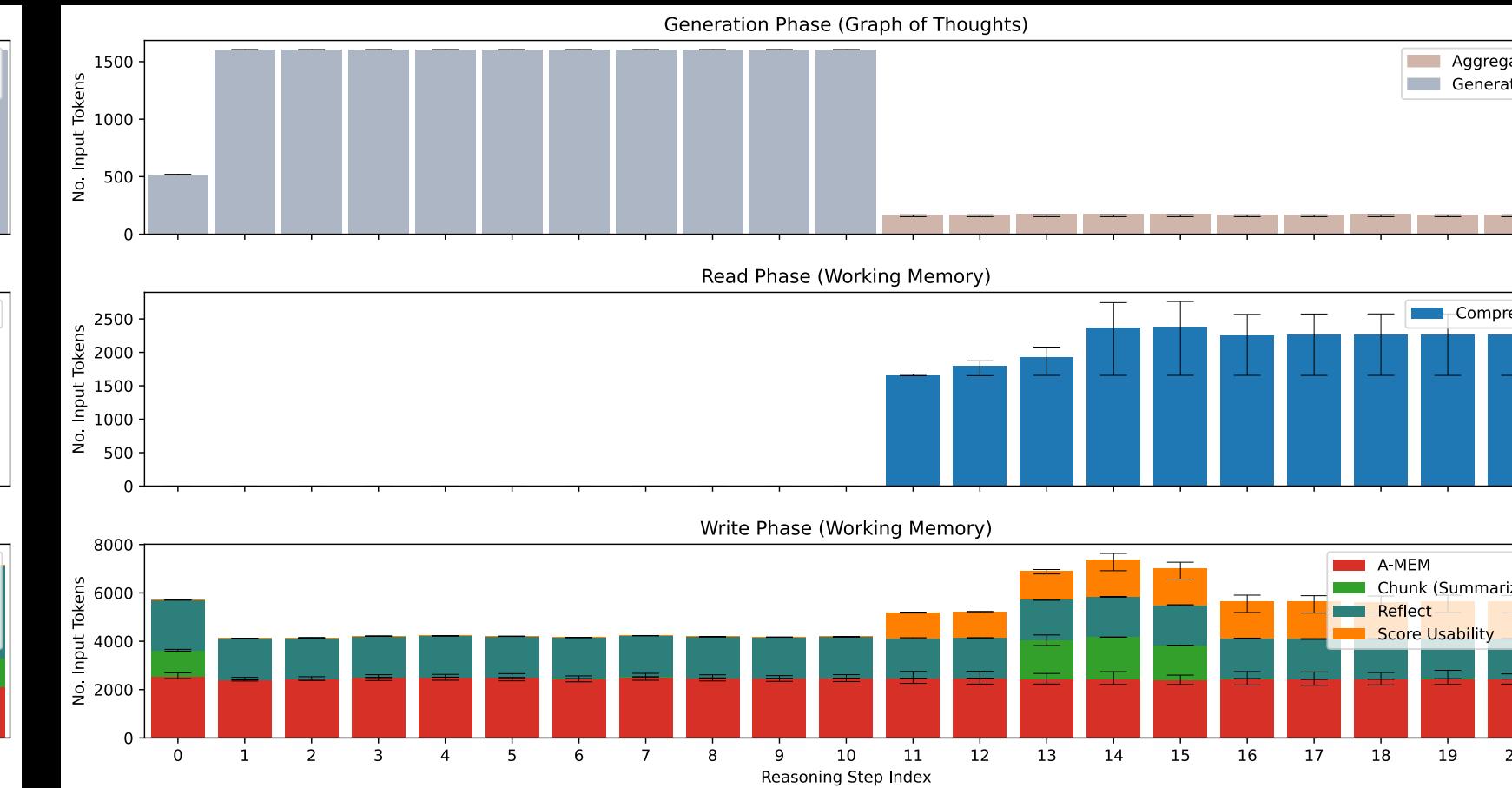
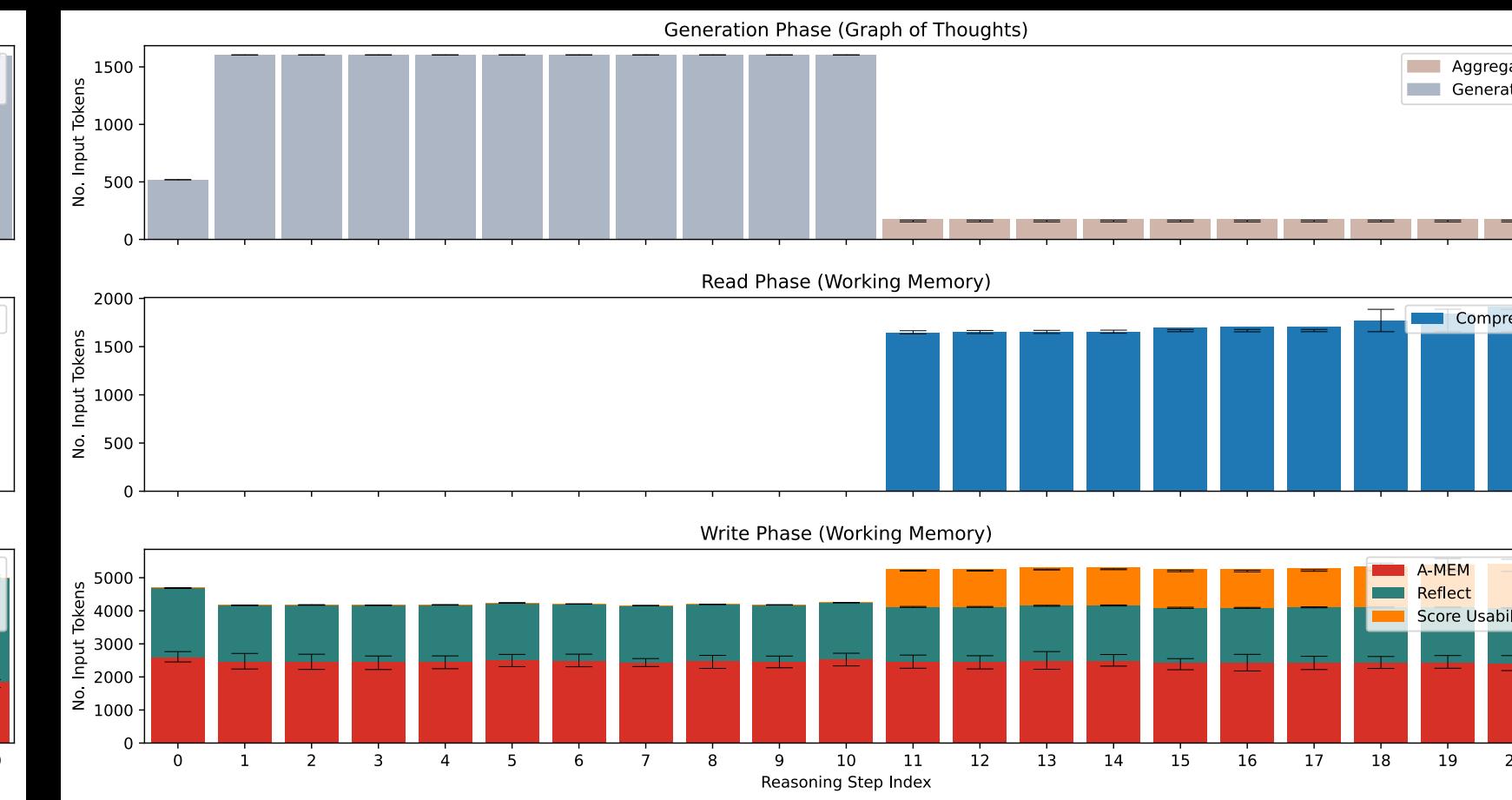
Without
Chunking

Sorting



With
Chunking

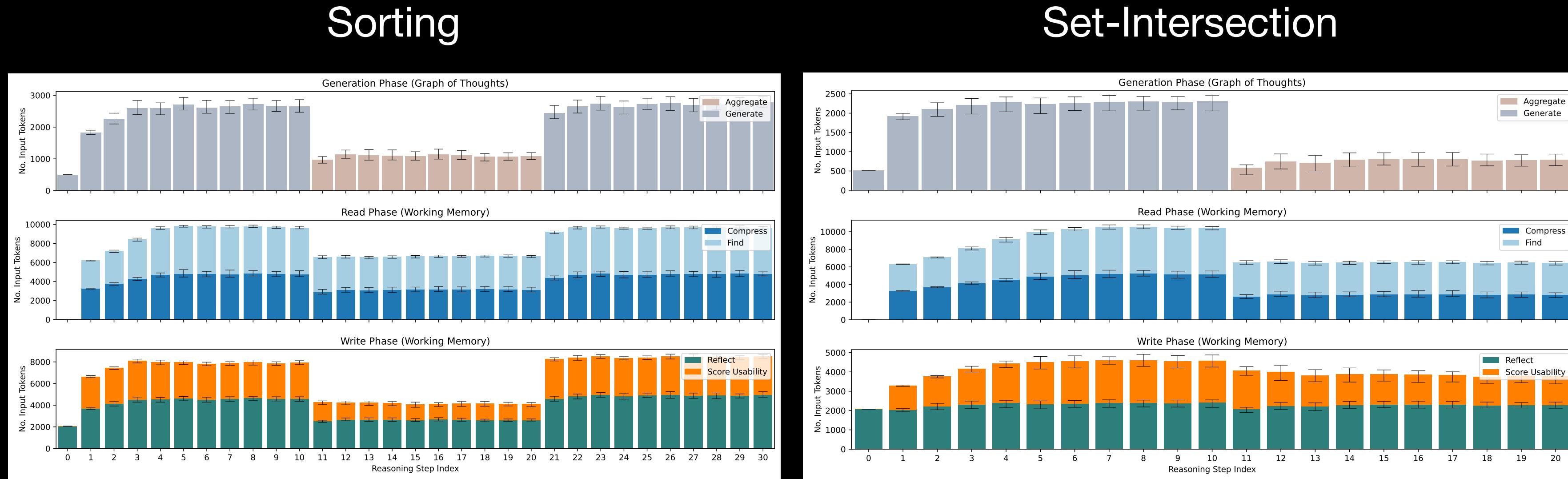
Set-Intersection



Additional Figures not Included so Far (14/14):

Token Usage Histograms on GoT Prompting Method – LLM-Only Variants

Without
Chunking



With
Chunking

