Marconi: Prefix Caching for the Era of Hybrid LLMs

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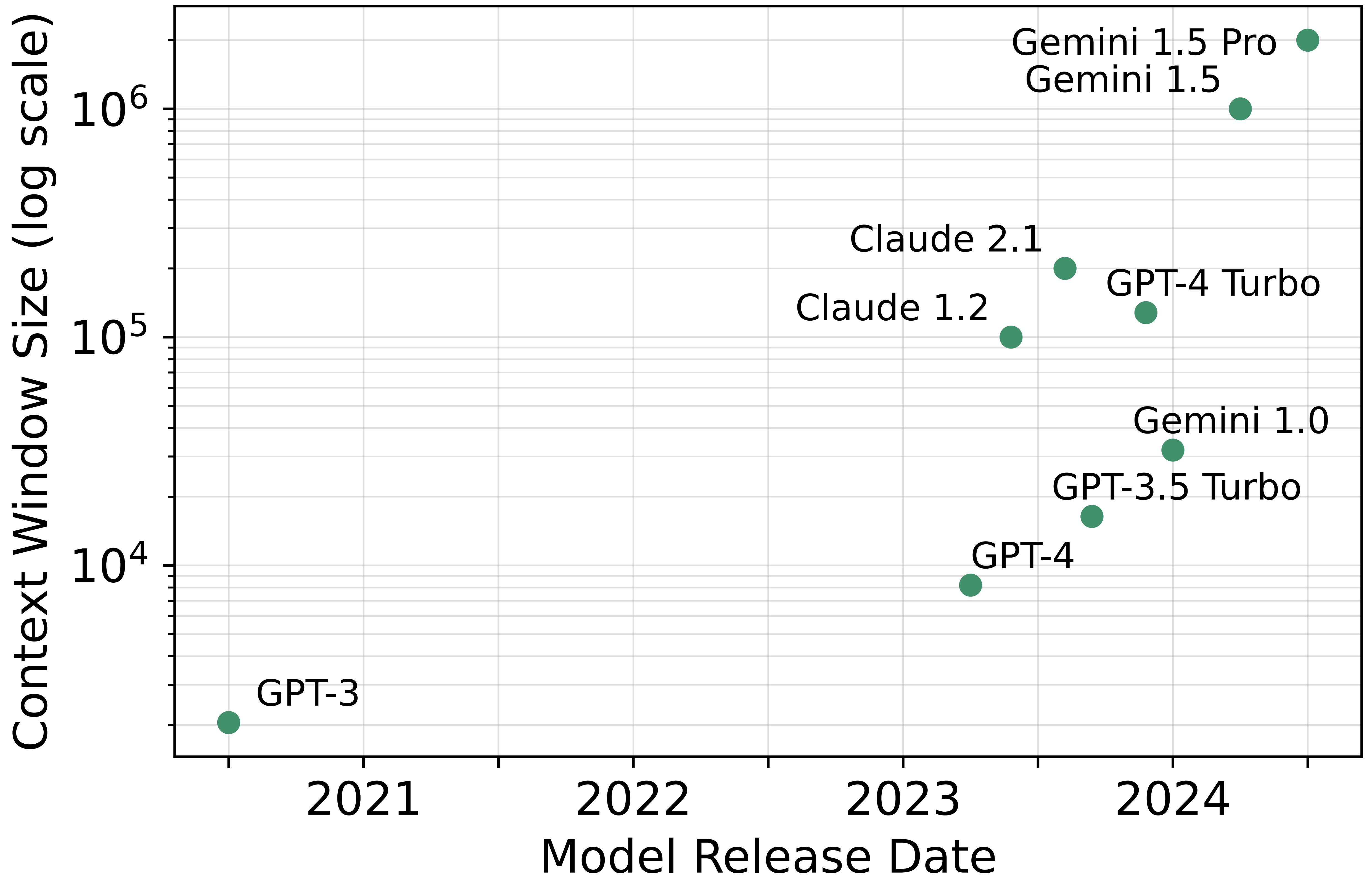
MLSys 2025, Santa Clara, CA

Outstanding Paper Honorable Mention!

Attention has bad long-context efficiency



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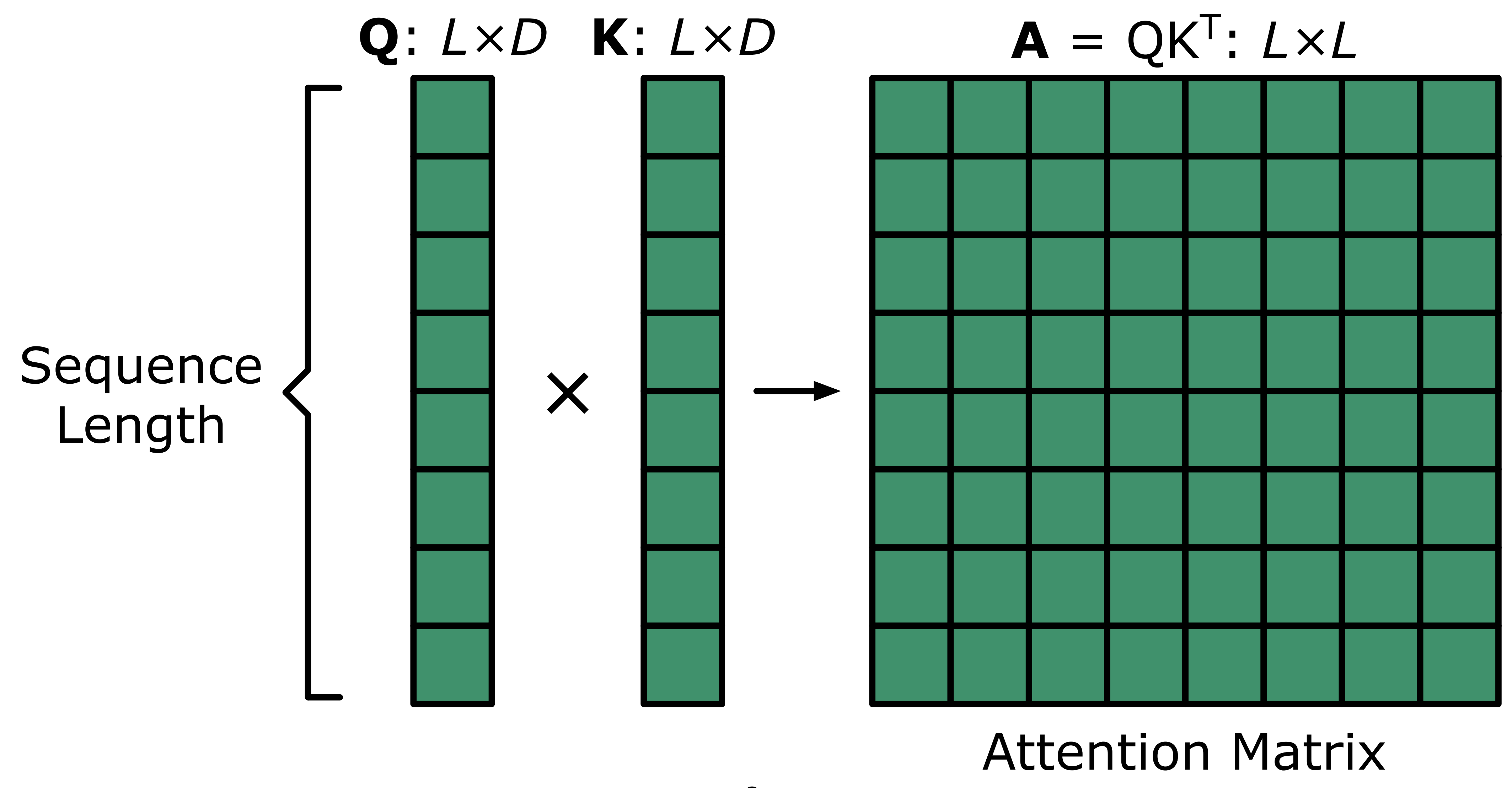
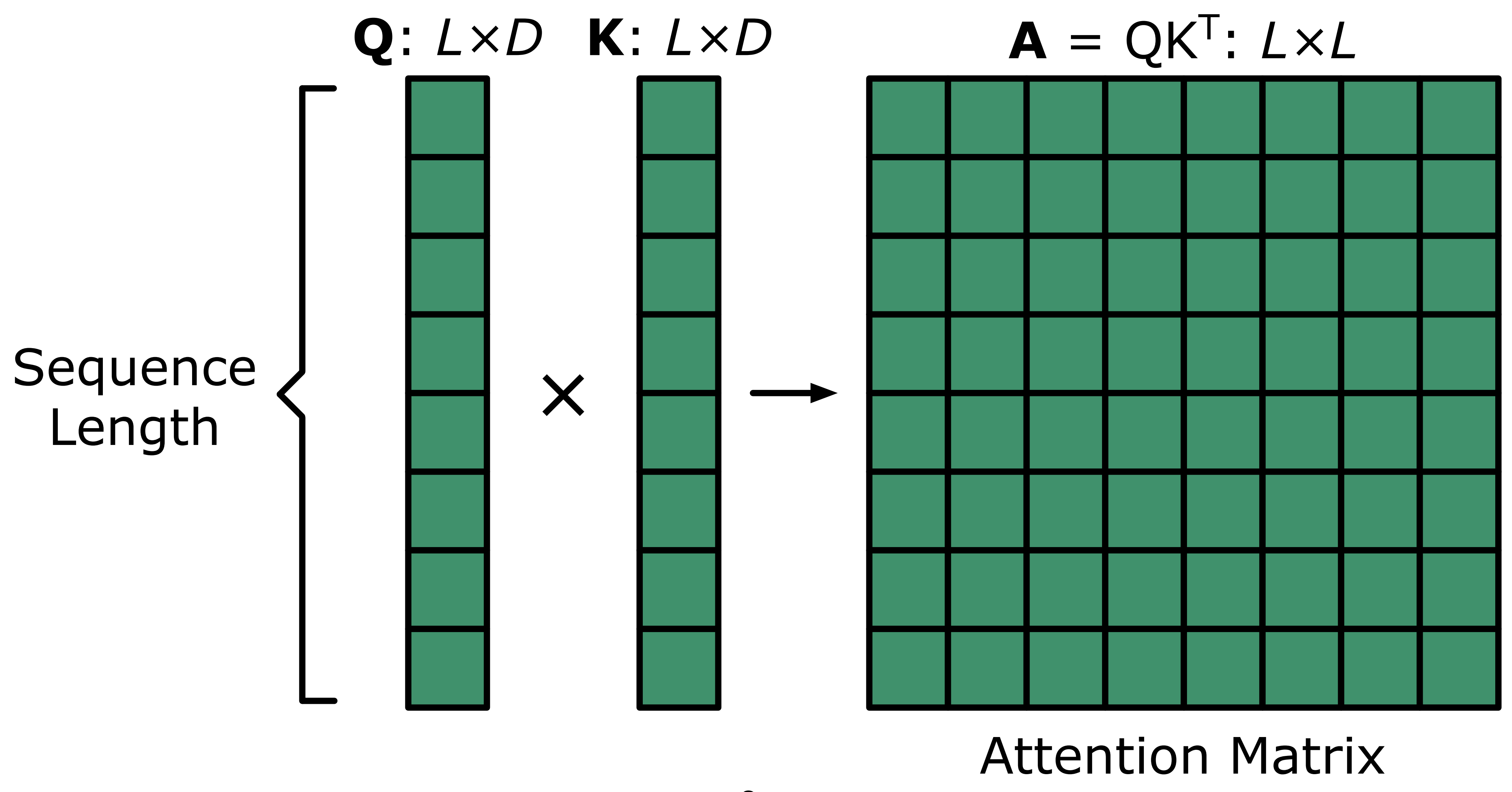


Attention has bad long-context efficiency

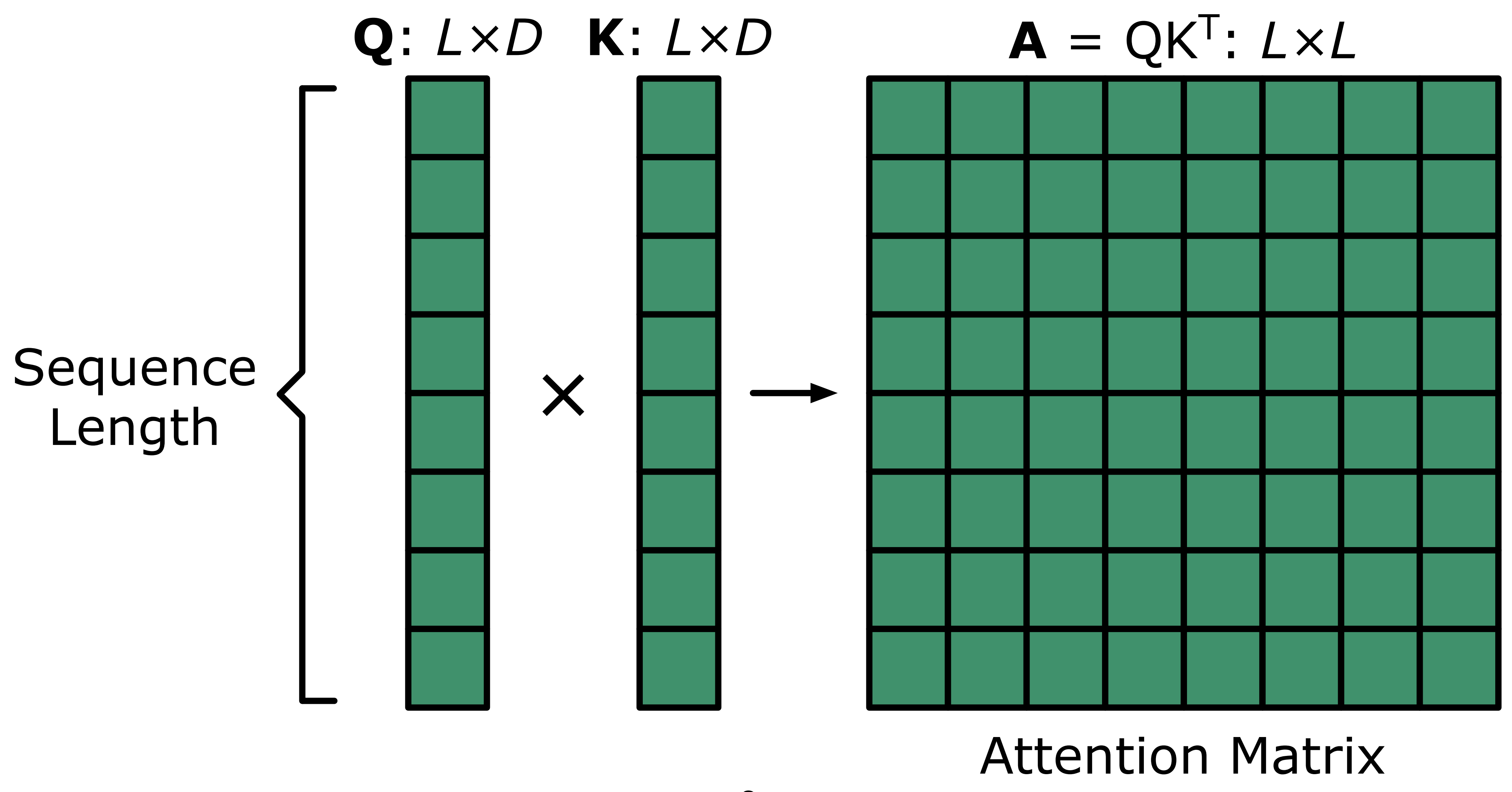
- Quadratic compute complexity



Attention has bad long-context efficiency

- Quadratic compute complexity
- Huge KV cache sizes (linear to sequence length)

	Attention
Computational Complexity	$O(L^2)$
Inference-Time Memory	$O(L)$



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- Compress prior context into a state
- Update states recurrently in-place

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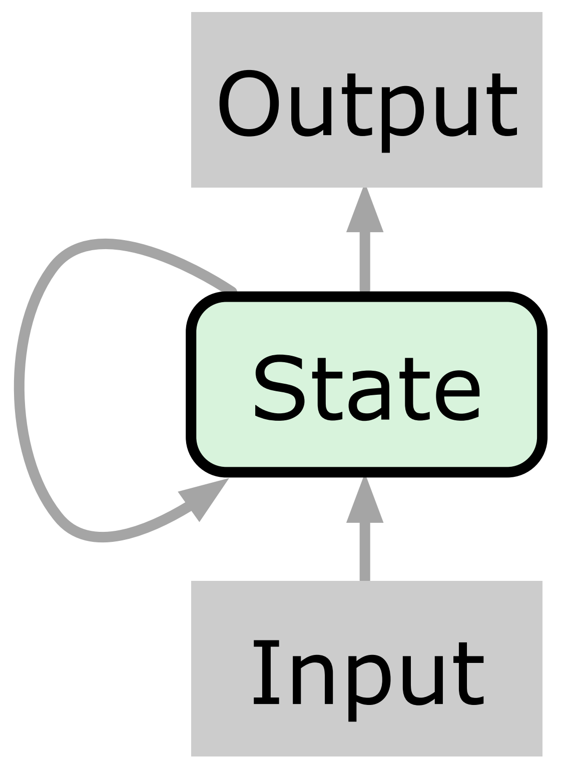
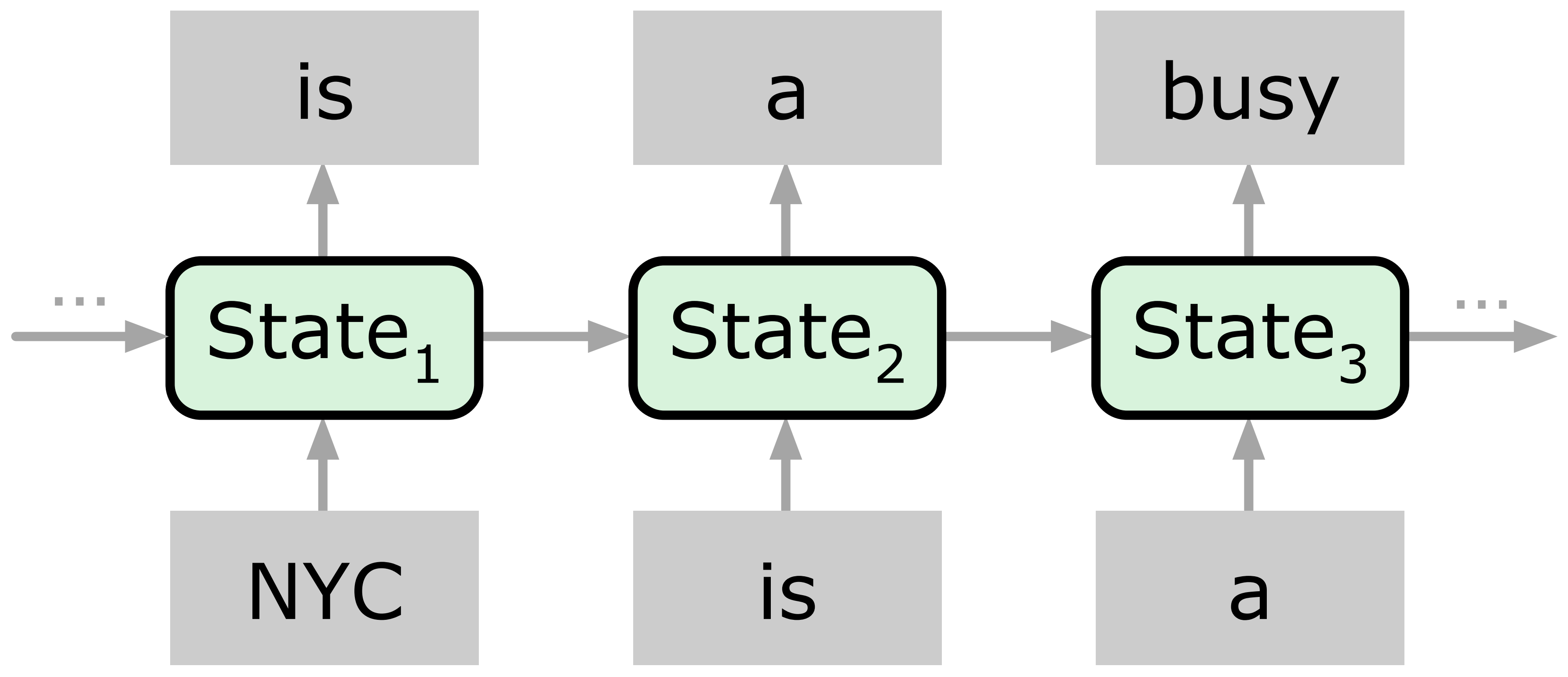


SSM



SSM (Unfolded)

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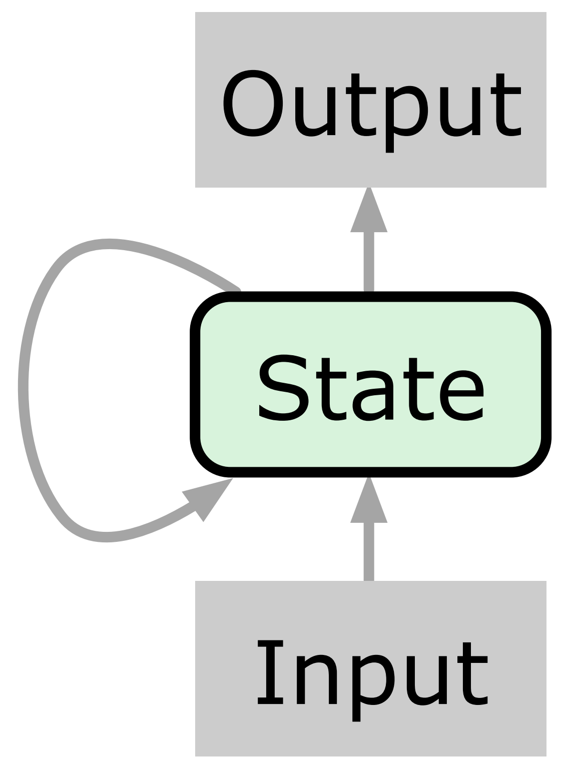

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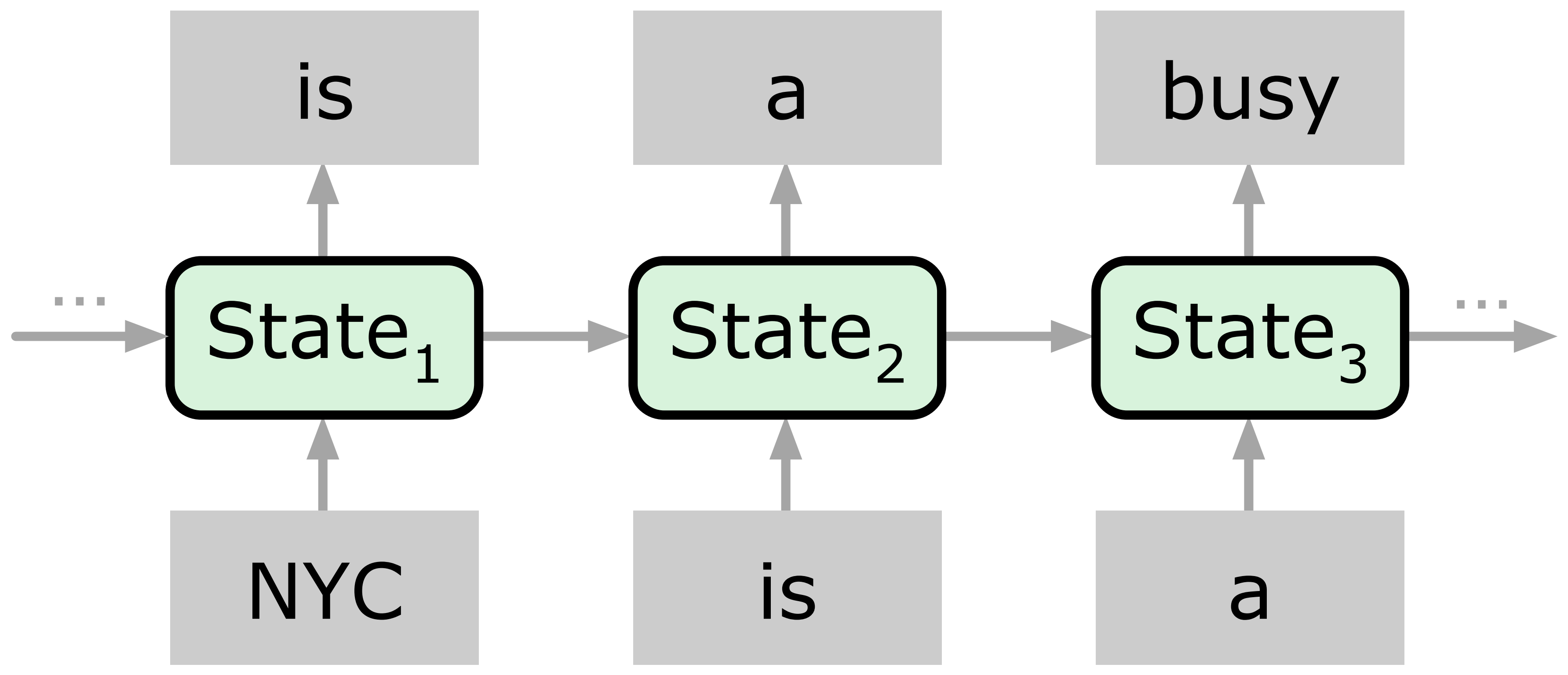

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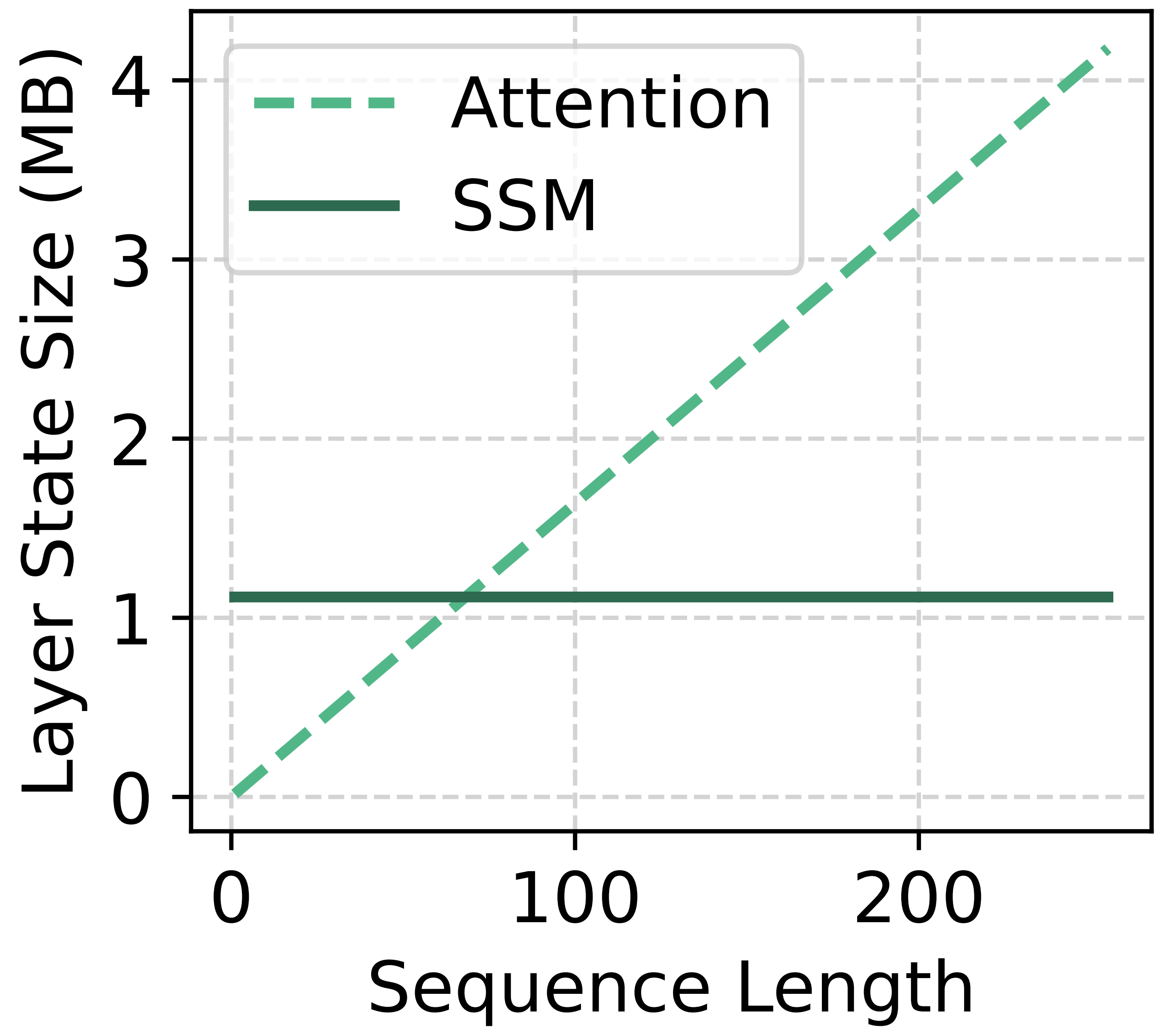

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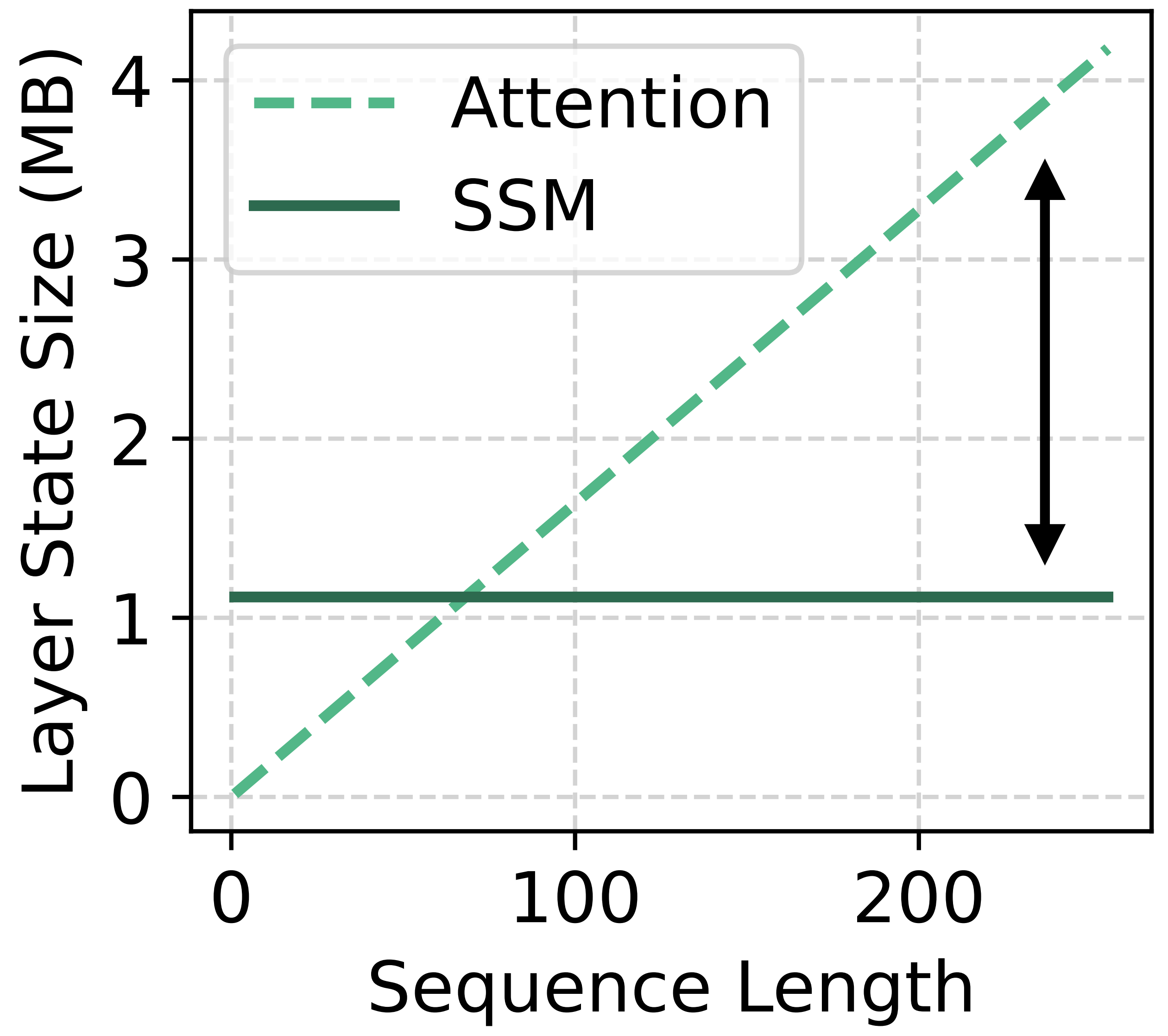

Background: State Space Models (SSMs)

- Memory consumption:
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  - Generally smaller than **whole sequences**' KVs
  - Orders of magnitude larger than a **single token**'s KVs

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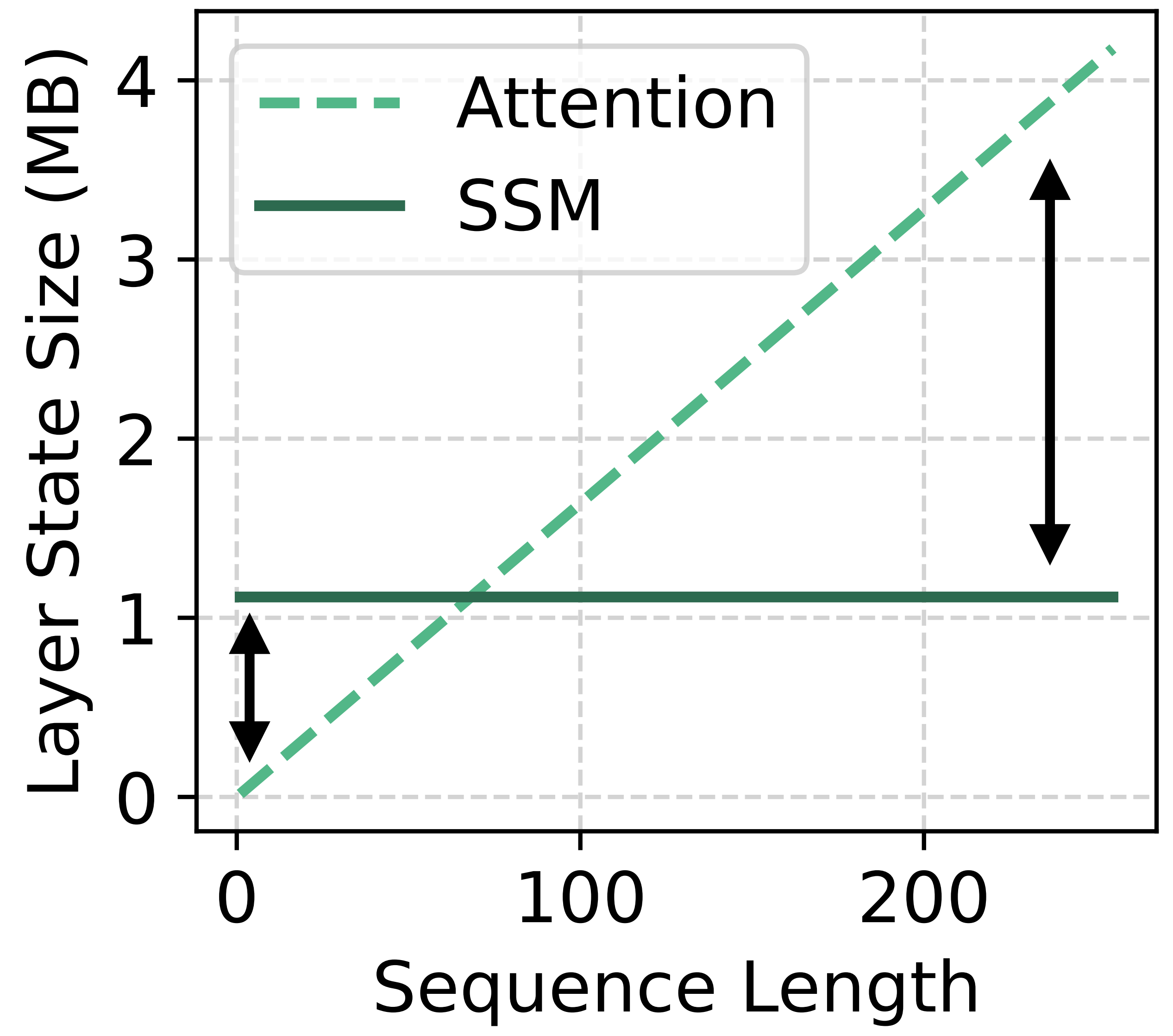

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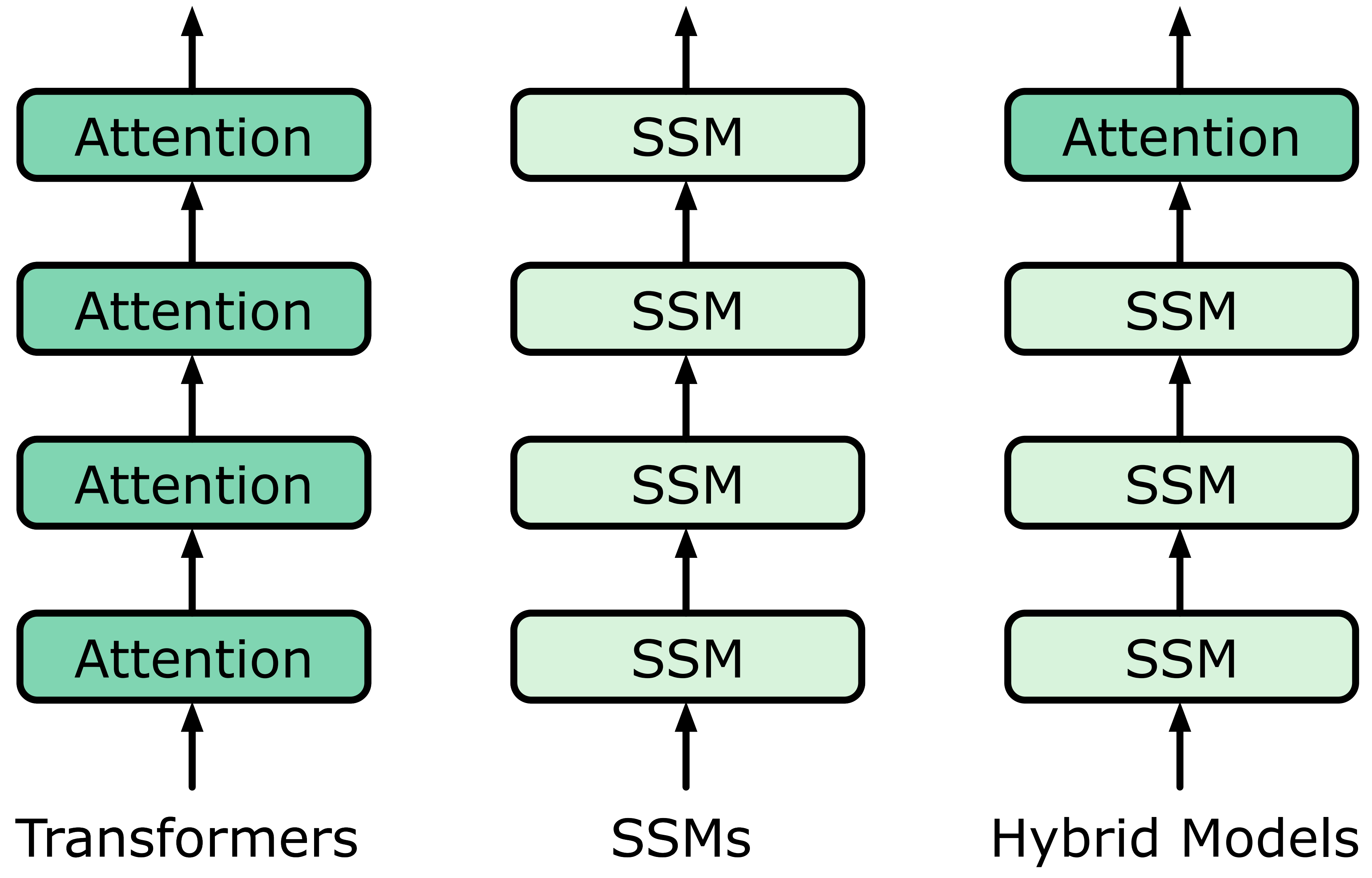
- A few Attention layers + many SSM layers
- Balances efficiency and language modeling capability



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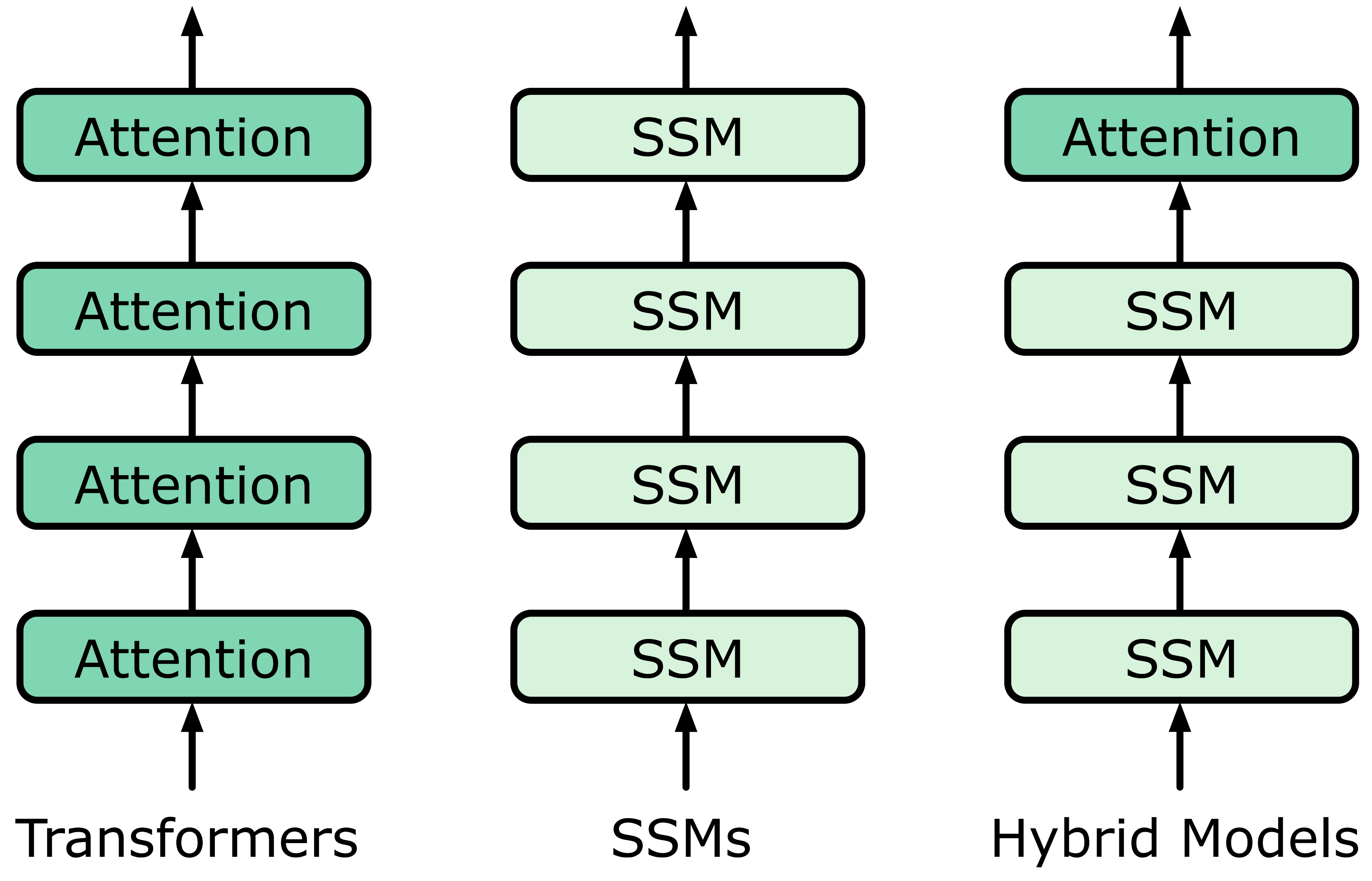
NVIDIA Google MINIMAX IBM AI21 labs Tencent Hunyuan



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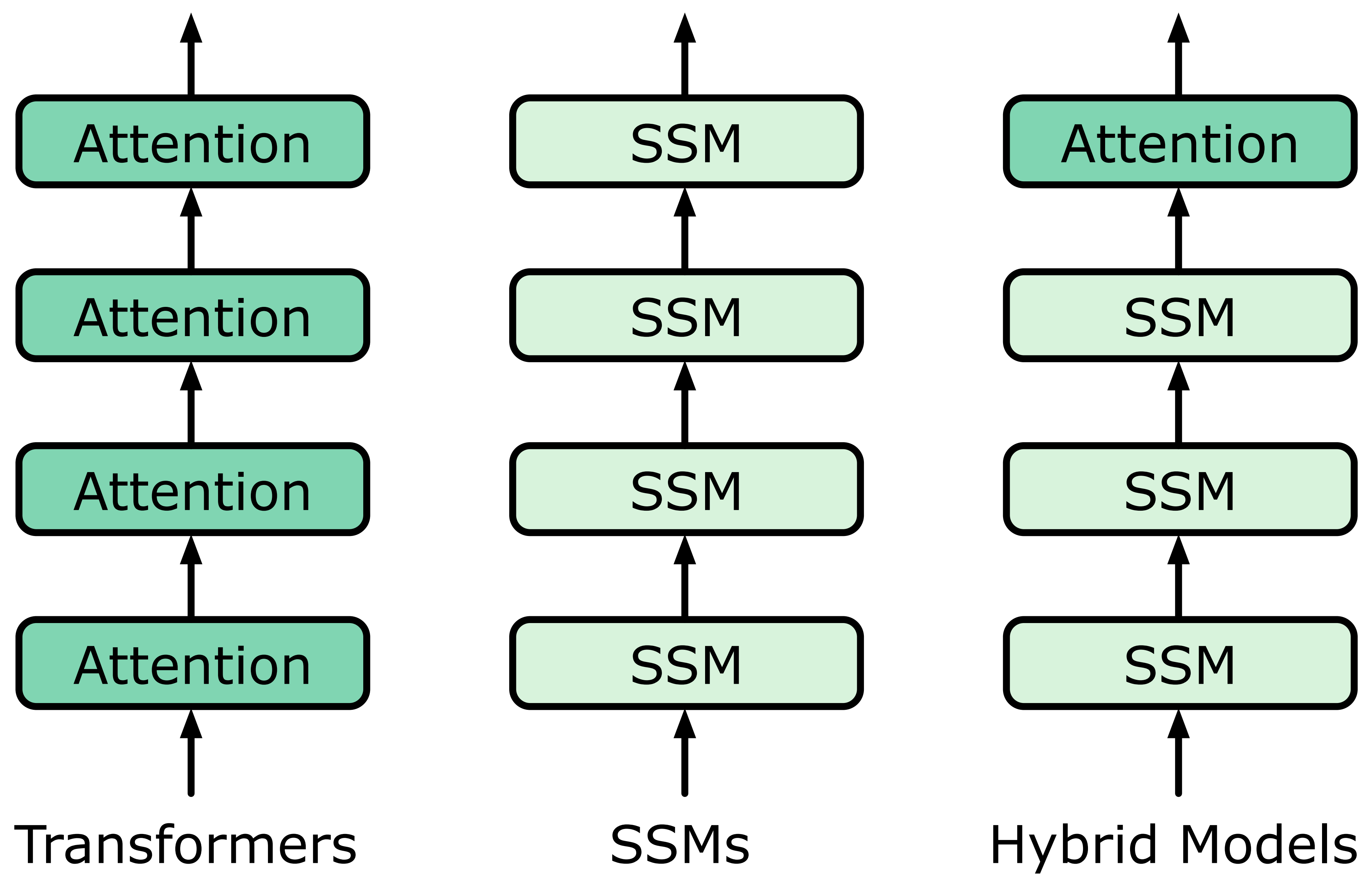
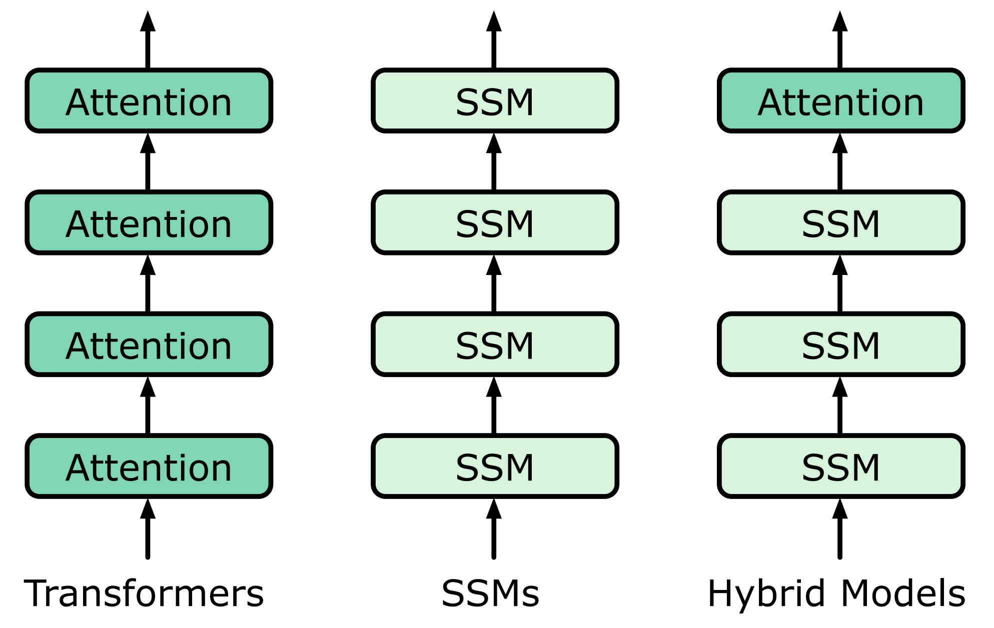


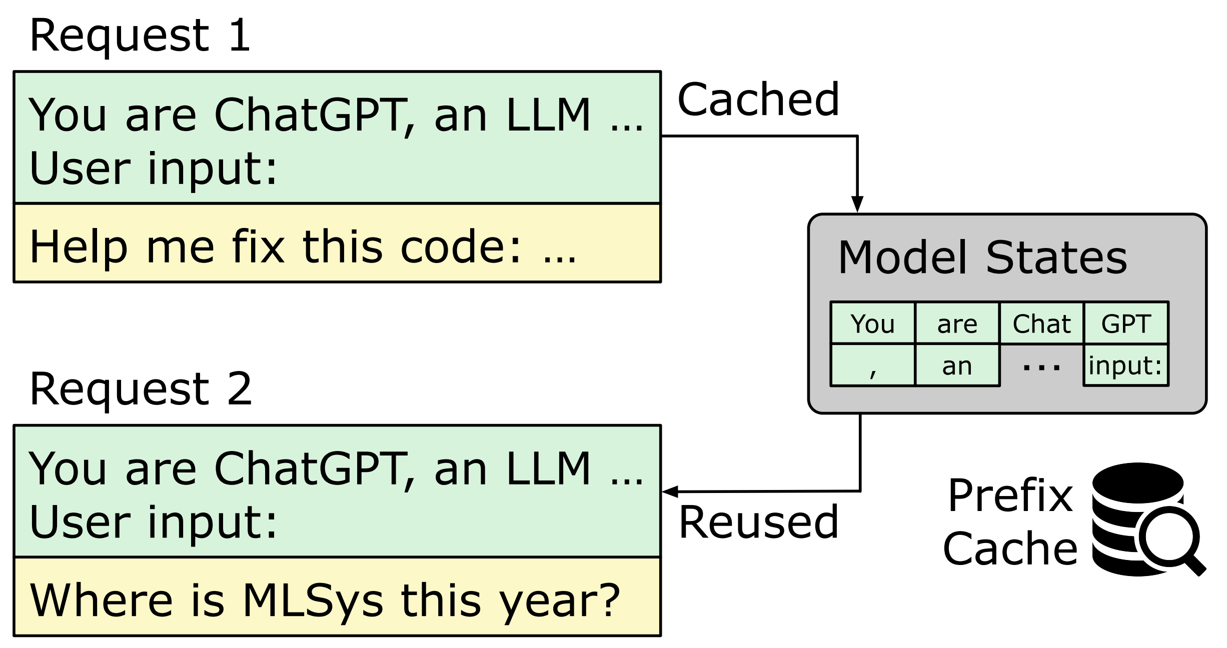
Background: Attention-SSM Hybrid LLMs

Model Architectures

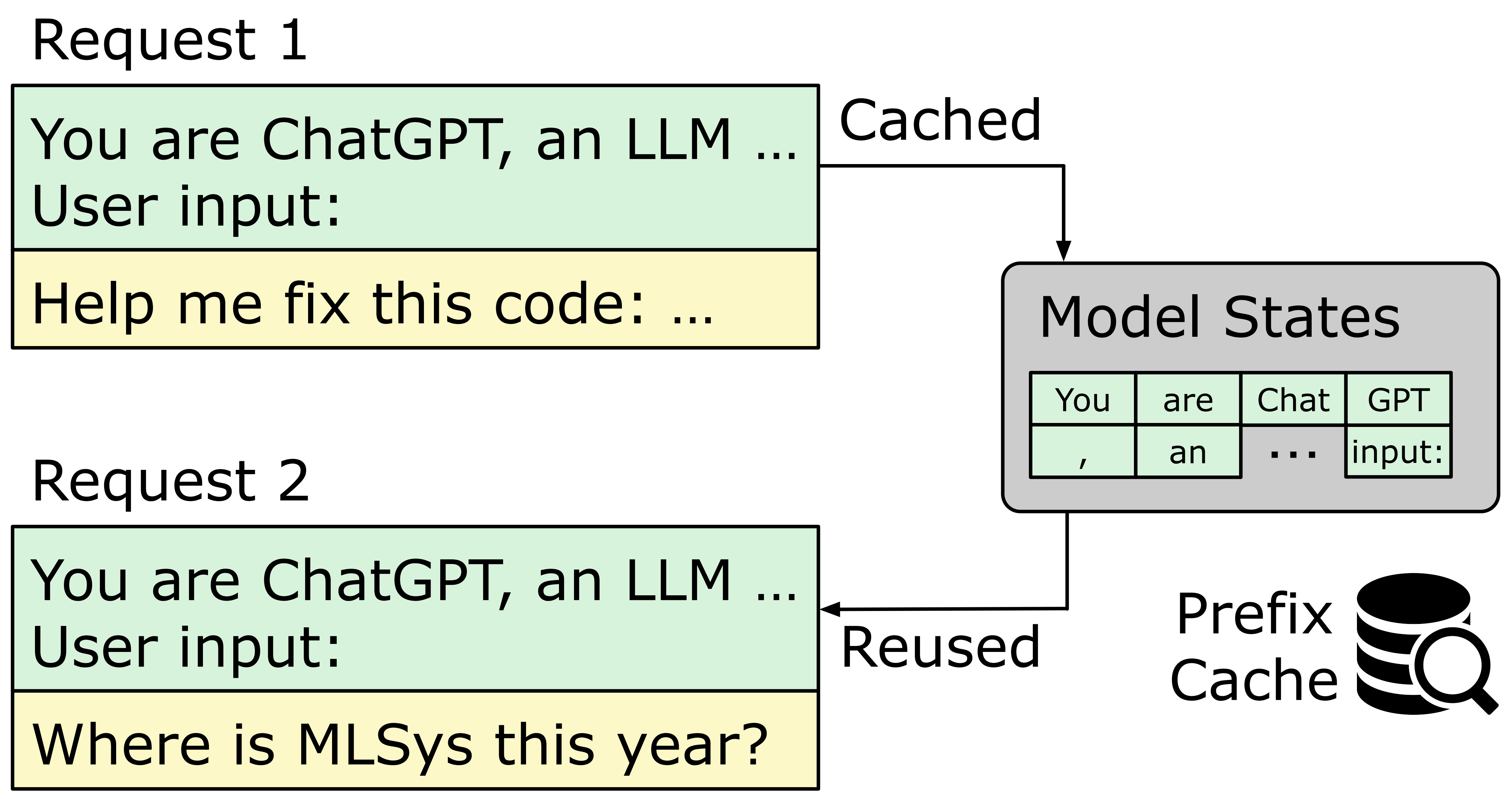
Execution Runtimes

"Models == Transformers"



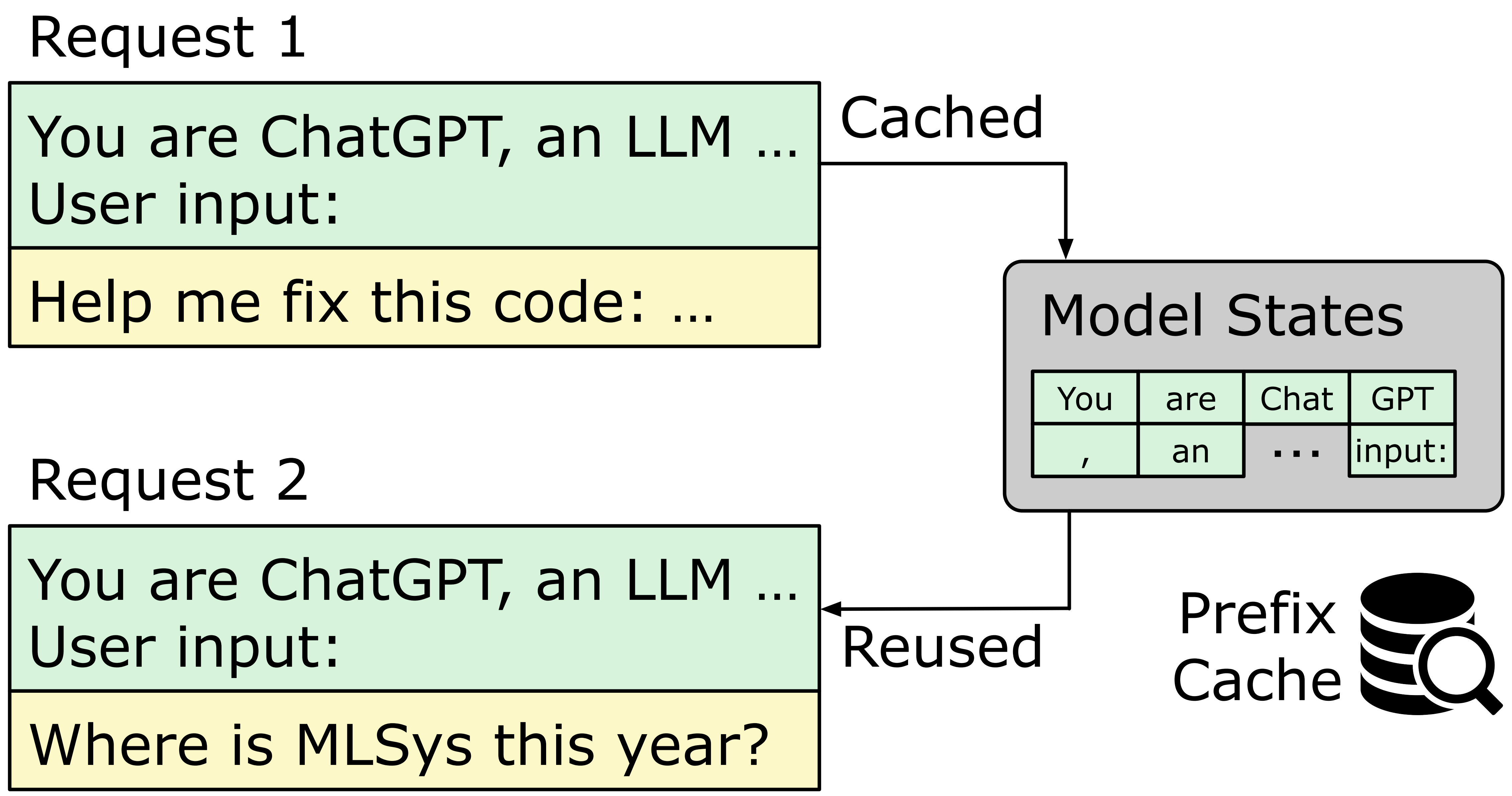

Request 1
You are ChatGPT, an LLM ... User input:
Help me fix this code: ...
Cached
Model States
You are Chat GPT , an ... input:
Request 2
You are ChatGPT, an LLM ... User input:
Where is MLSys this year?
Reused
Prefix Cache

Background: Attention-SSM Hybrid LLMs



Background: prefix caching

- Reuses model states (KVs, SSM states) of common prefixes across requests
- Reduces Time To First Token (TTFT)



Core challenge

- Prefix caching is challenging for SSMs: states can’t be rolled back to represent a prefix

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KV Cache

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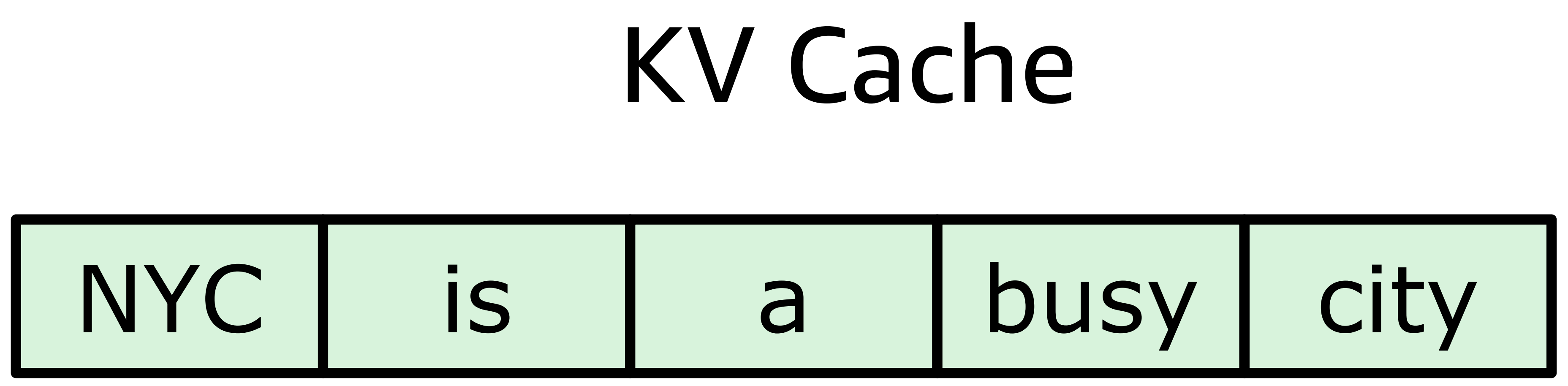

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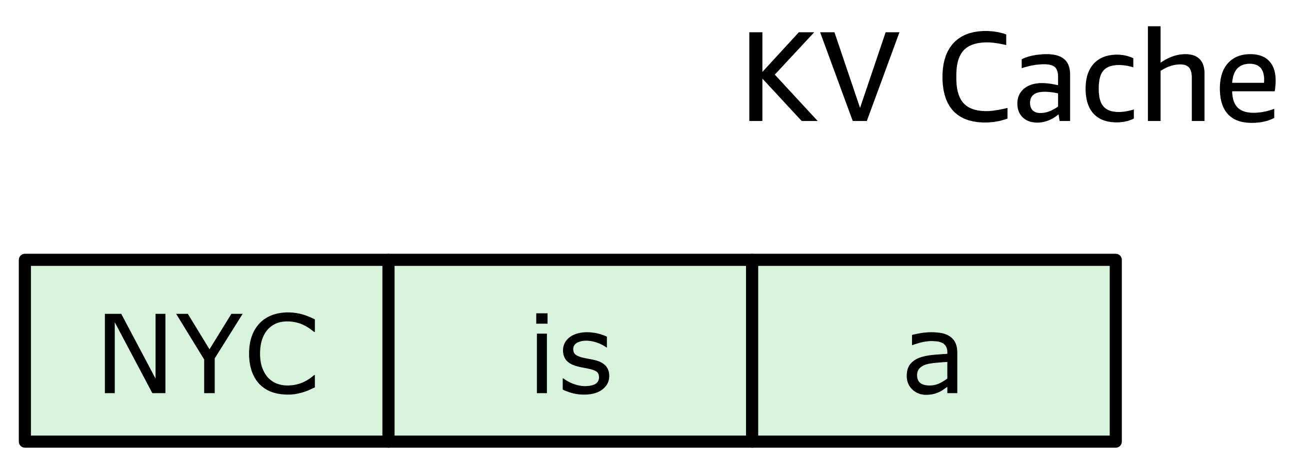

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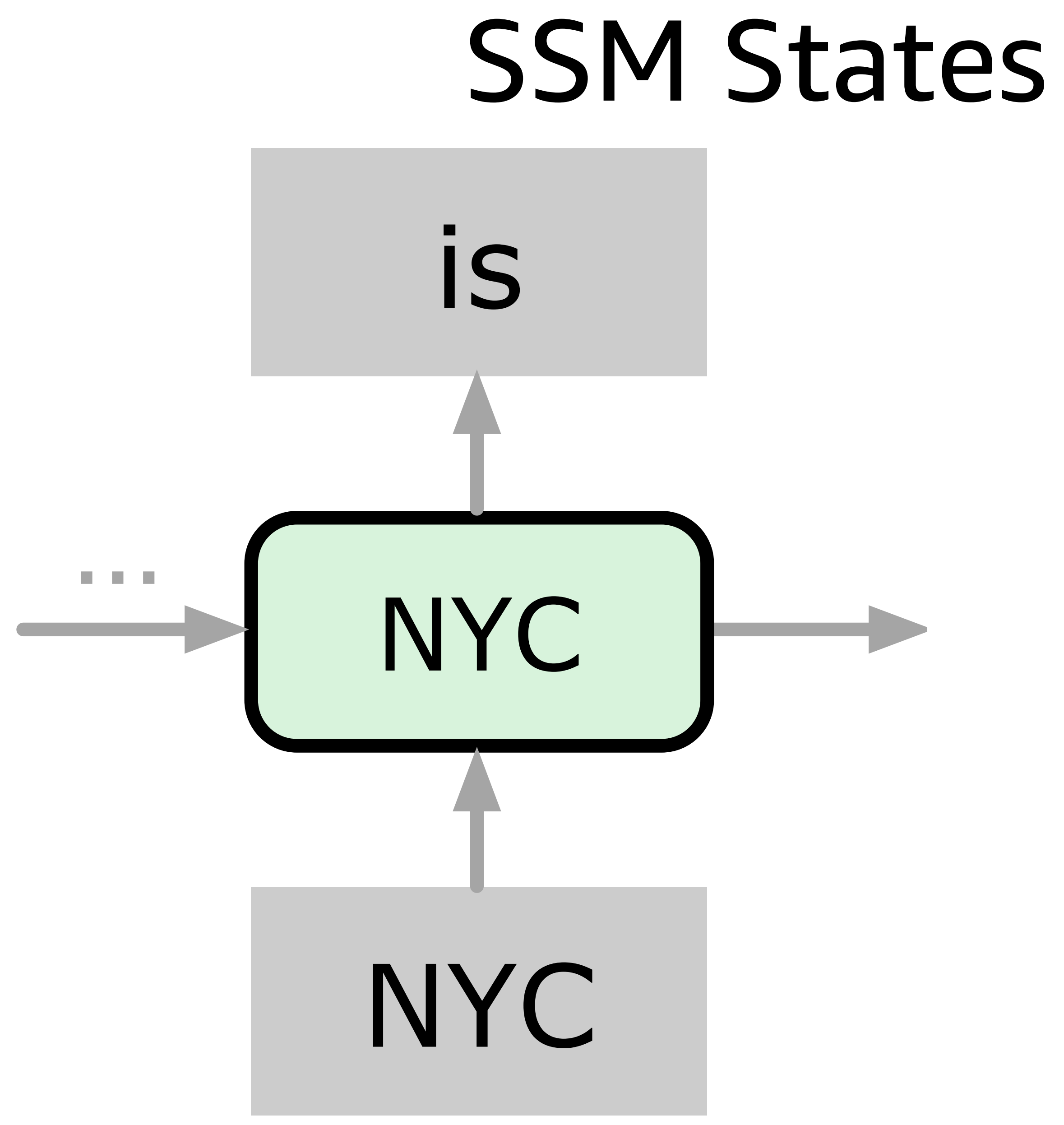

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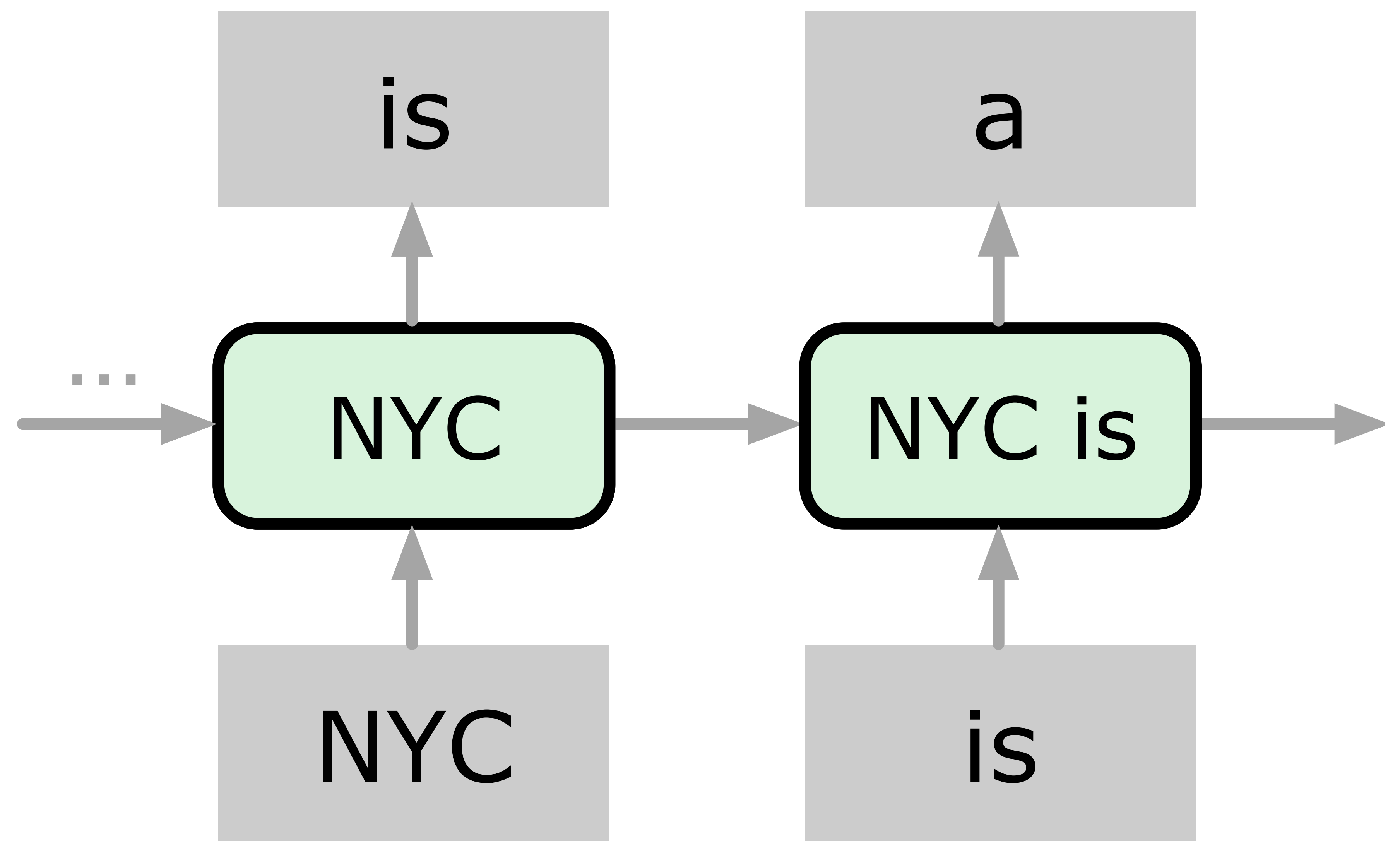
SSM States



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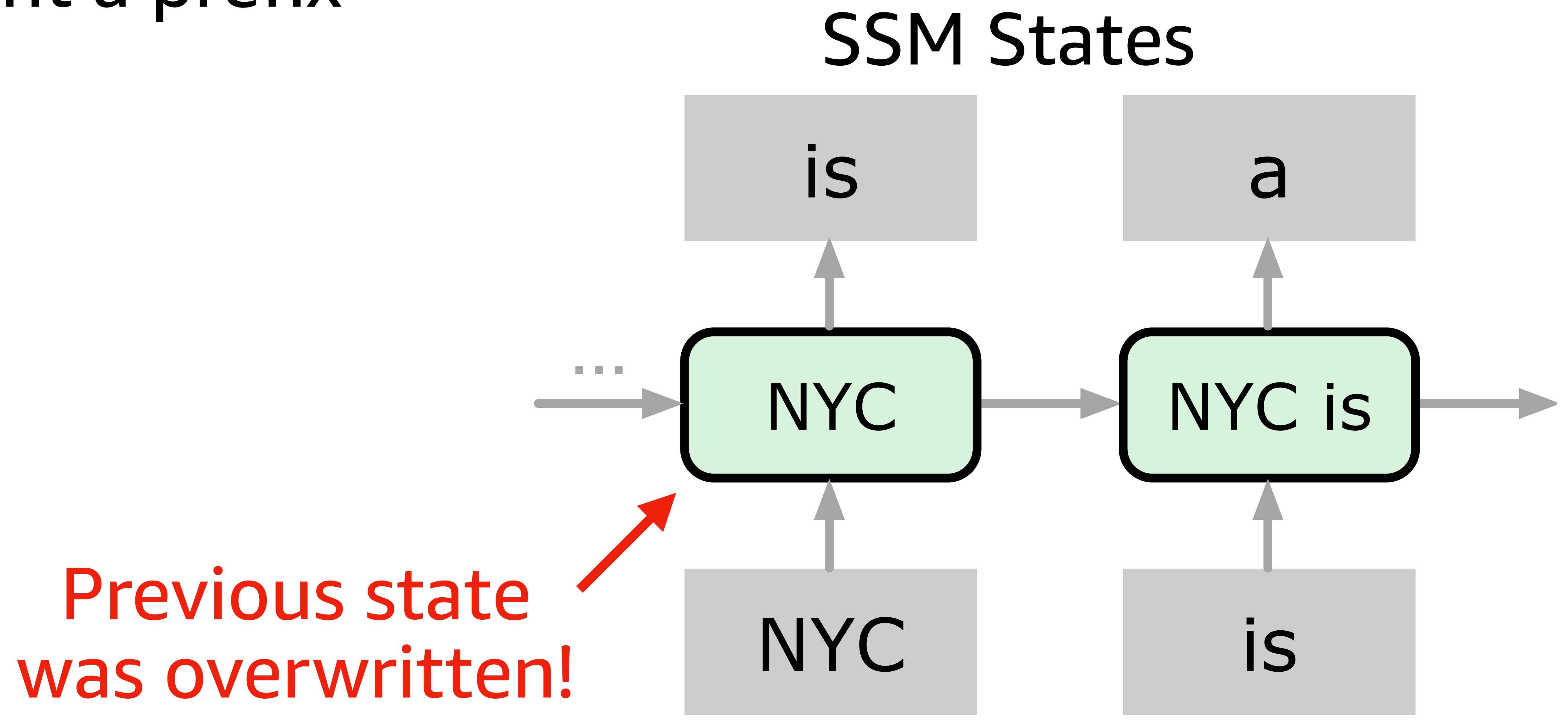

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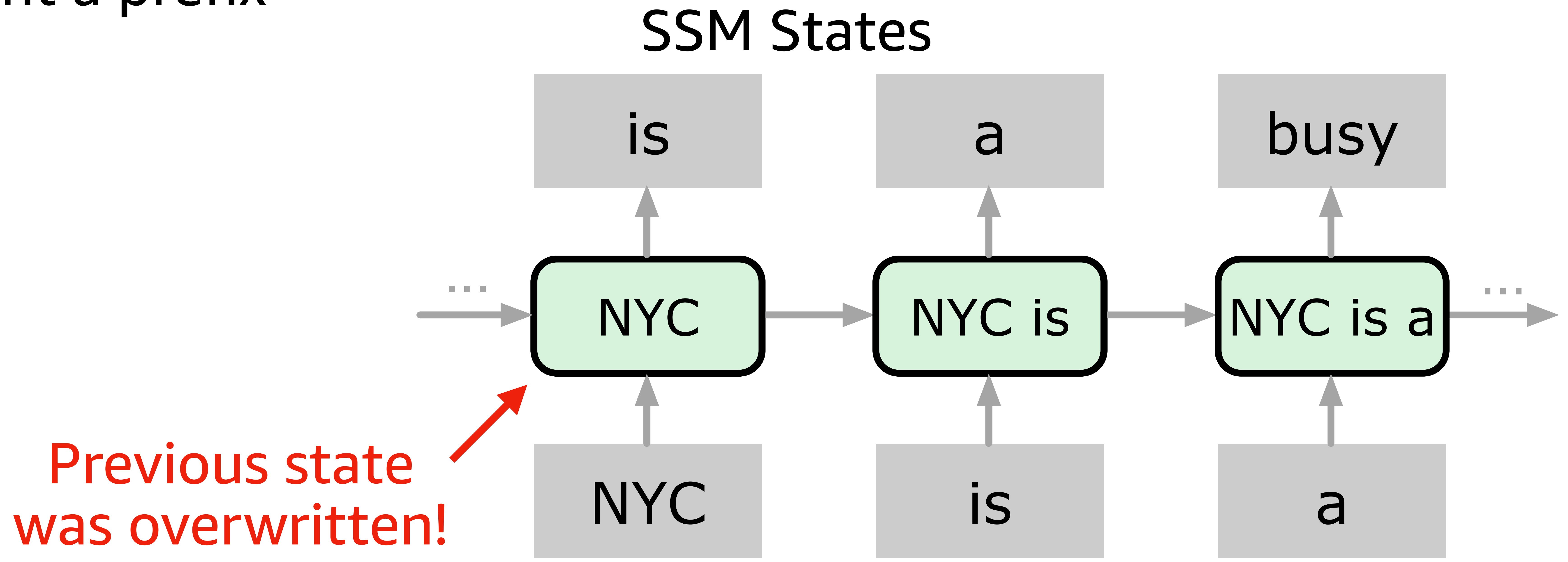
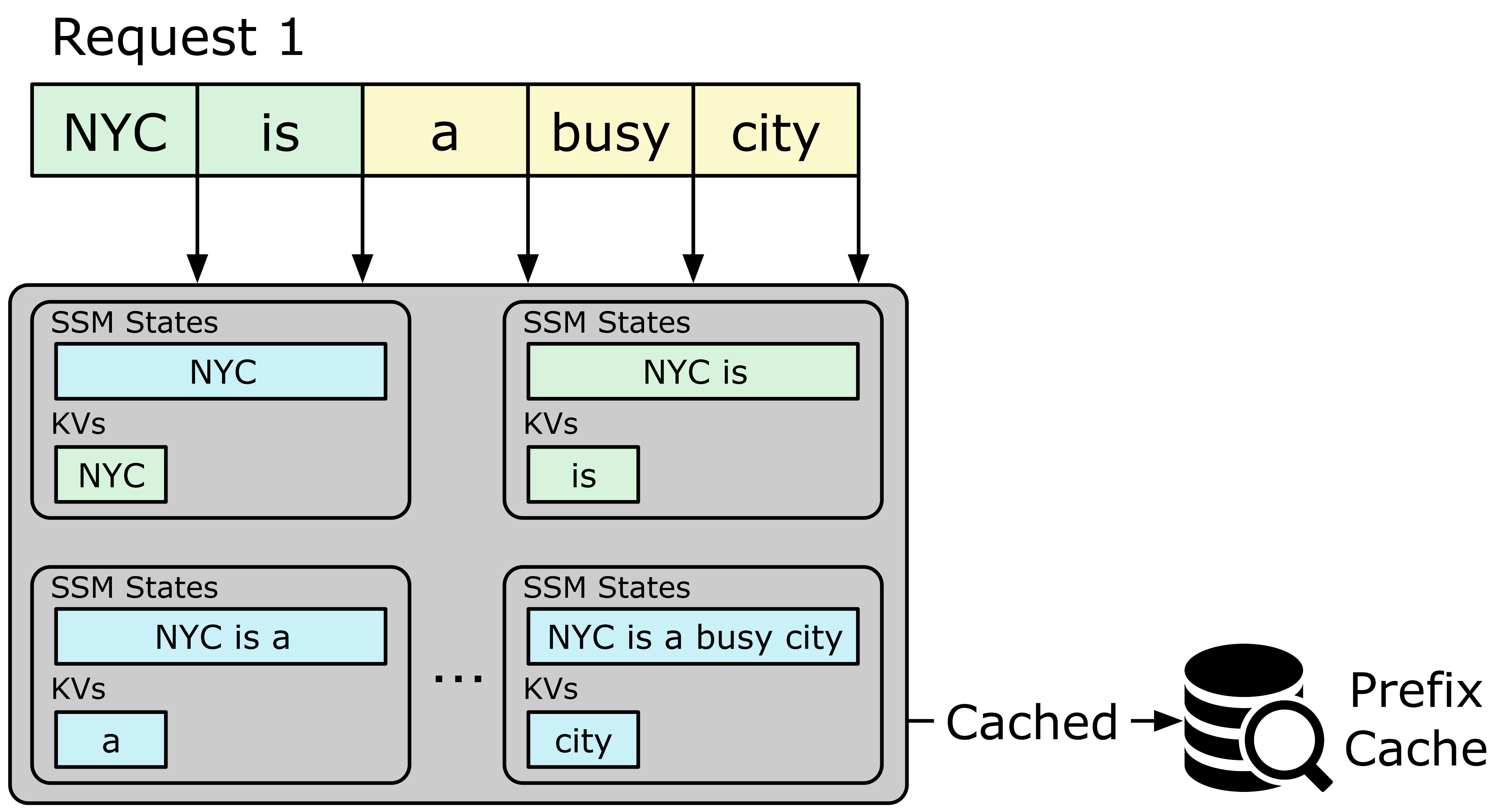


SSM's modeling win complicates their systems win!

Challenges with strawman

- Naive solution: checkpoint an SSM state every x tokens



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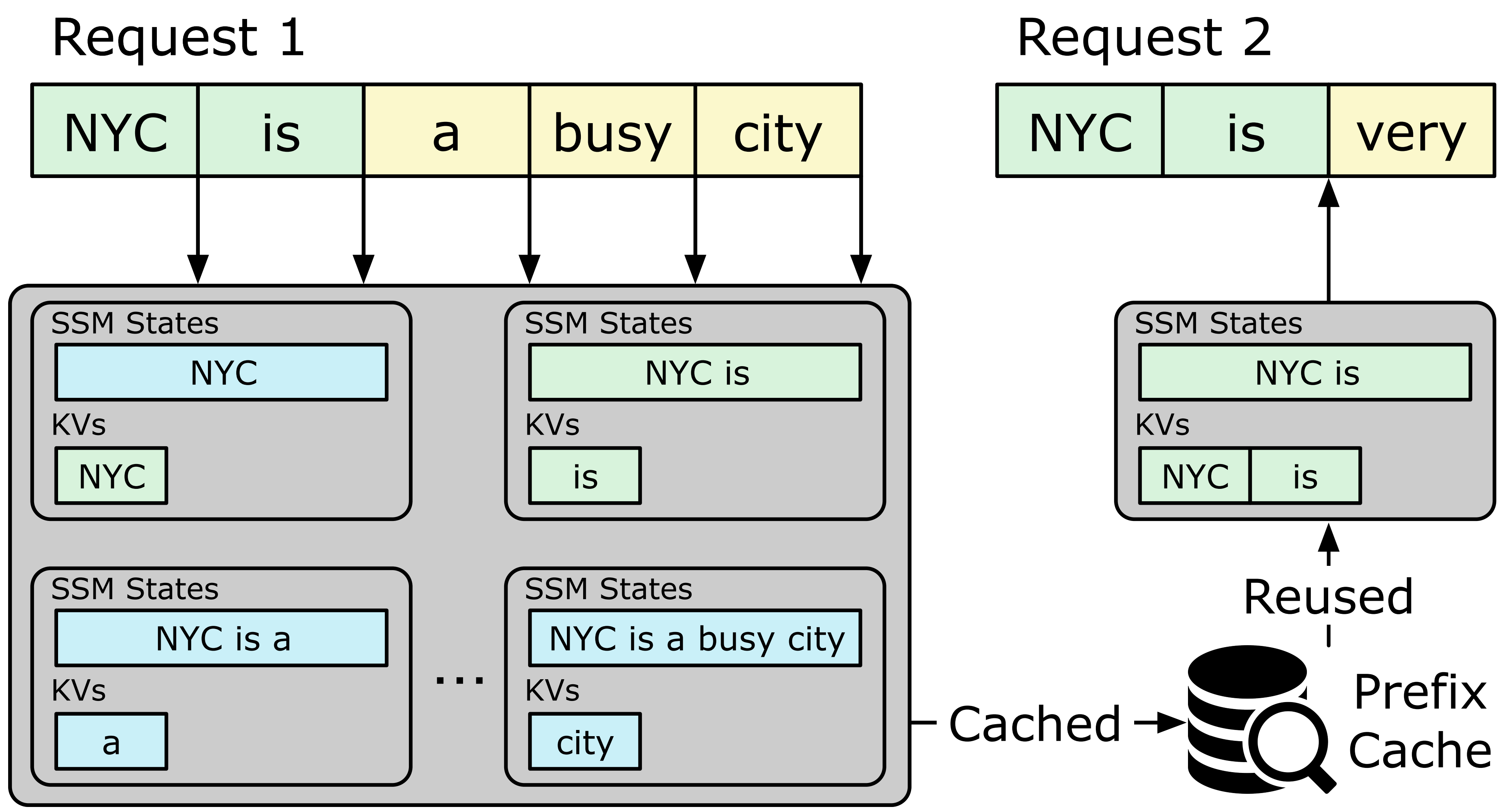

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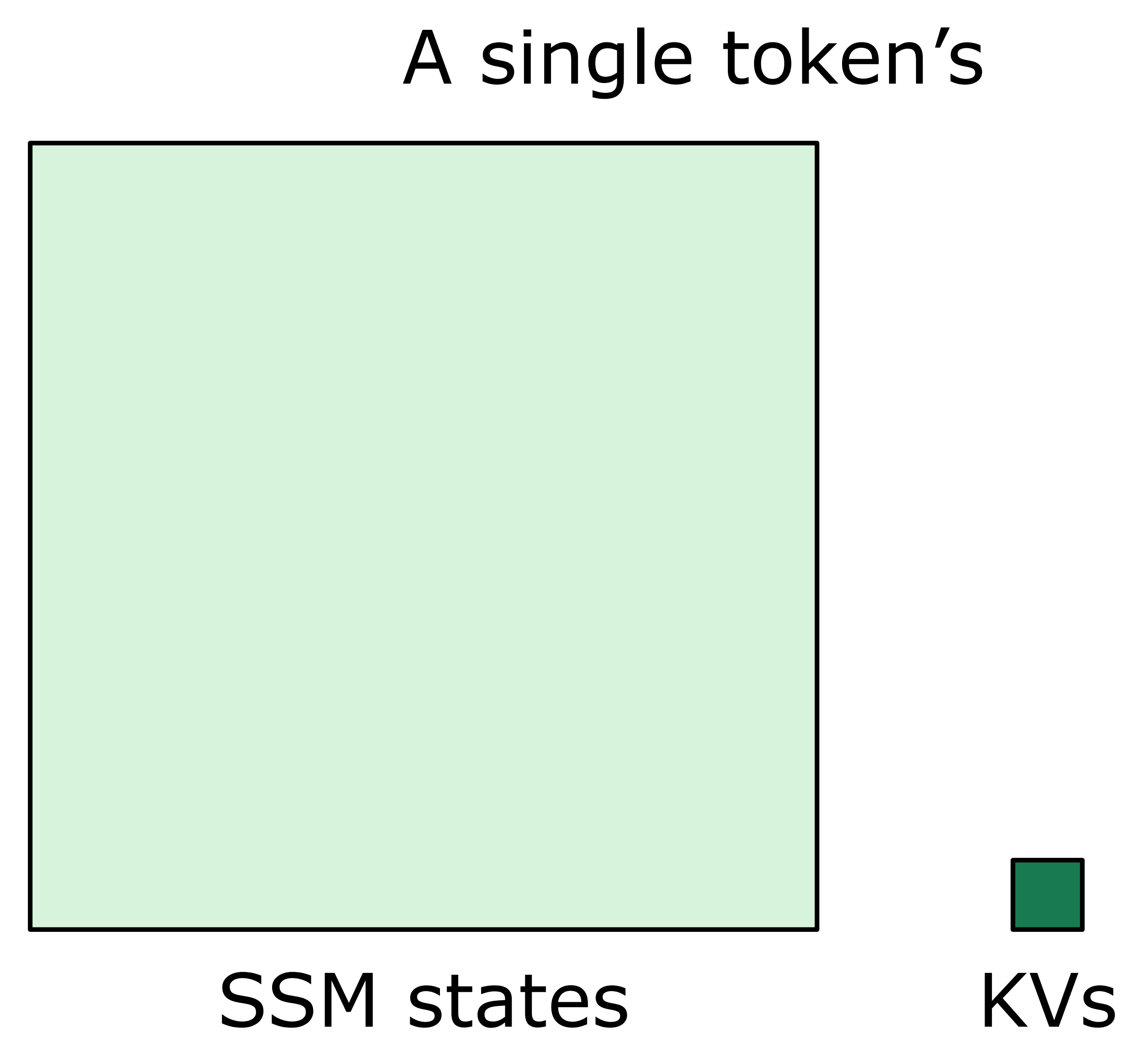
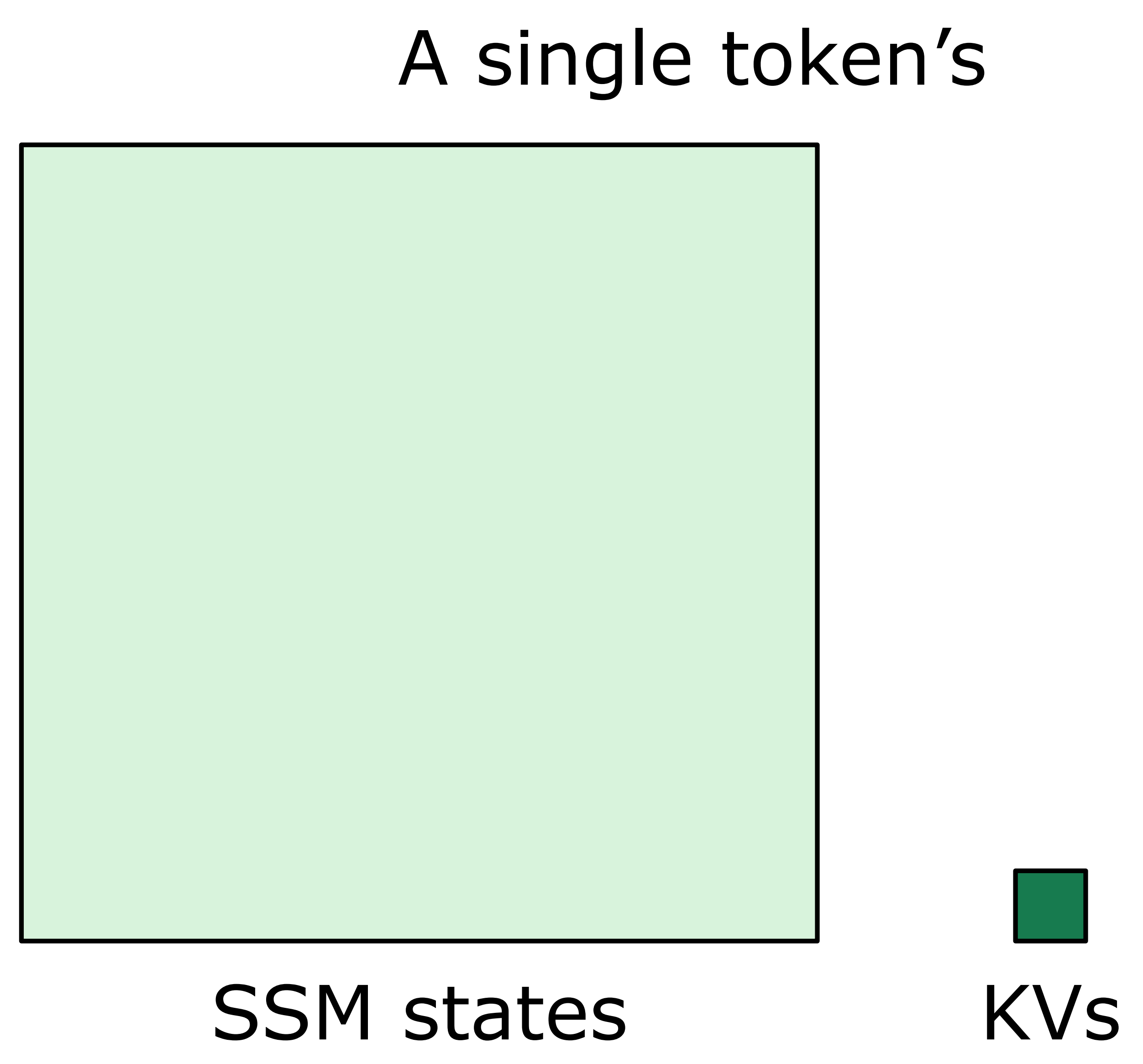
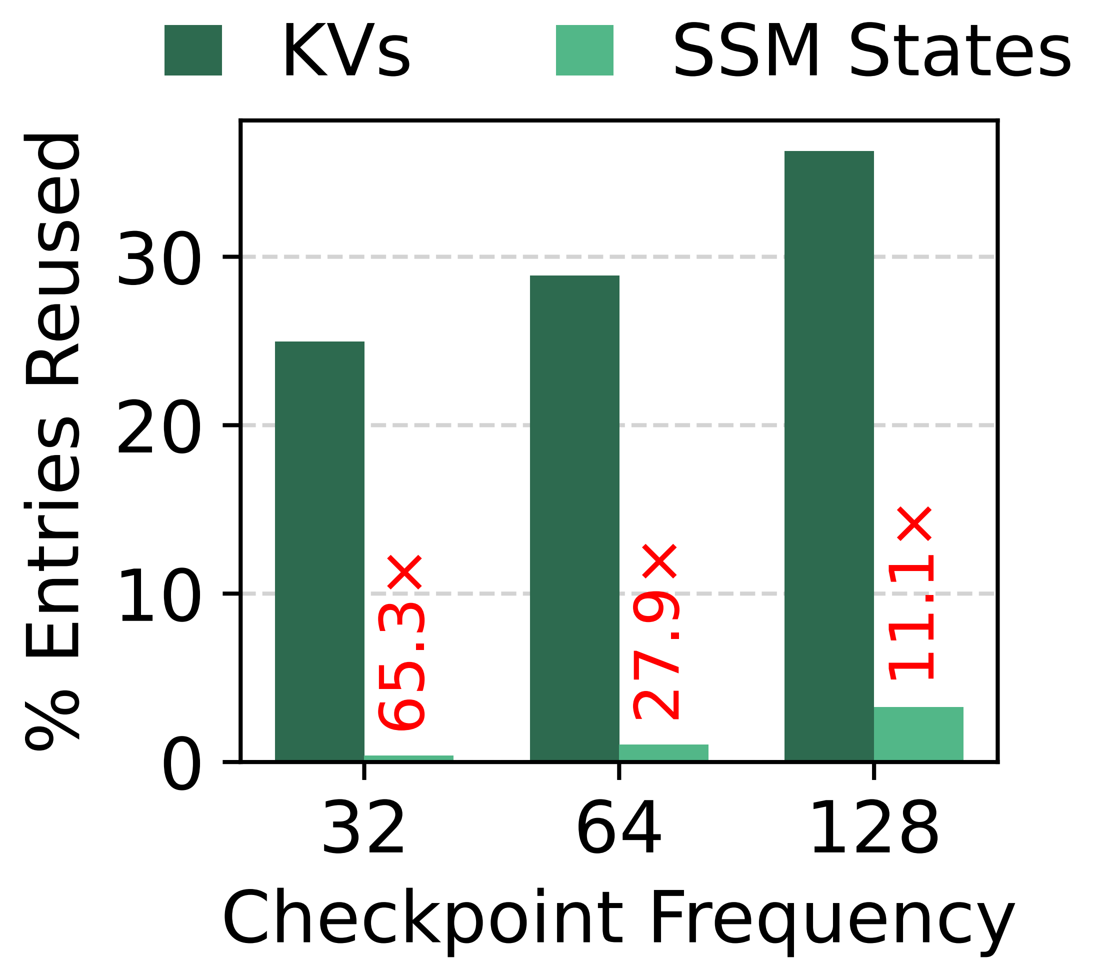


Challenges with strawman

- Naive solution: checkpoint an SSM state every x tokens
- Catch 1: cache entries are sparsely-hit
- Catch 2: cache entries are huge
- Frequent cache thrashing & low hit rate





Marconi: prefix caching for Hybrid LLMs

- Supports models with arbitrary layer compositions (Hybrid LLMs, pure Transformers, pure SSMs)
- Shouldn't focus solely on recency
  - Needs to be more judicious in admission and eviction!
- Leverages unique characteristics of Hybrid LLMs

"Marconi plays the mamba, listen to the radio, don't you remember?" — Lyrics of *We Built This City*, song by Starship

Aside from recency:

Admission

Eviction

Aside from recency:

Admission

Forecasts prefixes’ reuse likelihoods

Eviction

Judicious admission

- Existing systems: admit <u>all</u> states of most recent request
- Marconi: admit states with <u>high reuse likelihood only</u>
- Key insight
  - Future reuse patterns cannot be predicted…
  - …but can be sufficiently estimated through a taxonomy of potential prefix reusing scenarios!

Taxonomy of prefix reusing patterns

- Composition of all reused prefixes:

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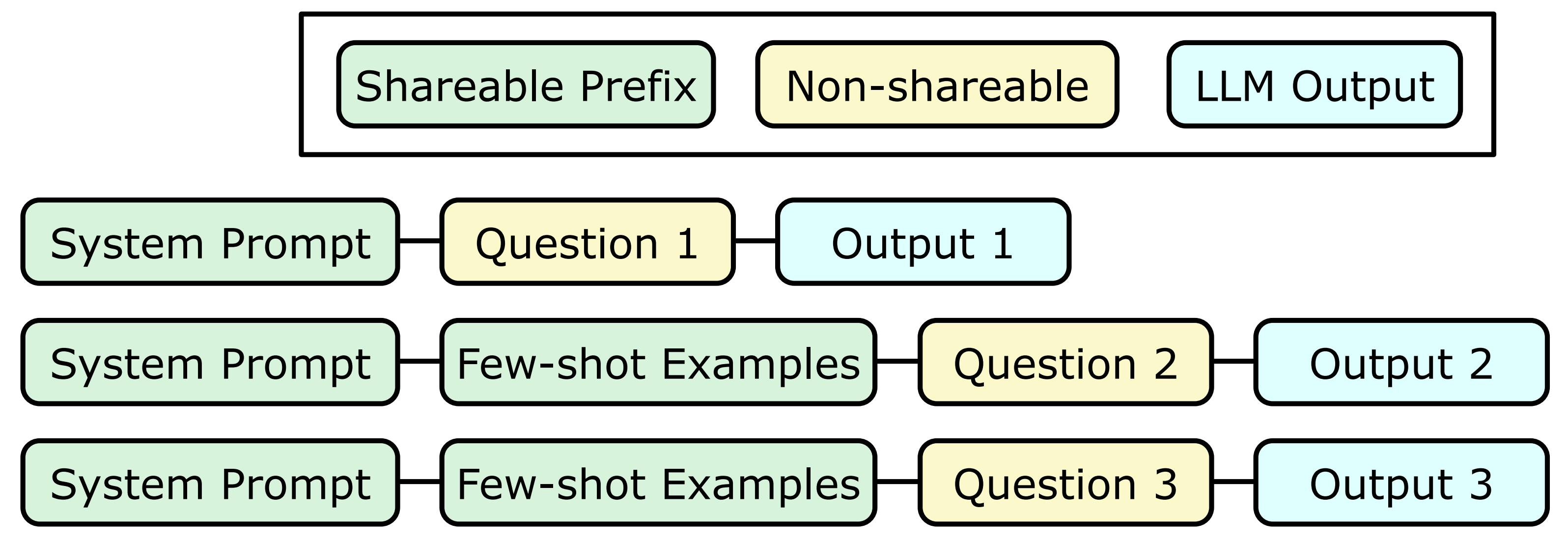
  1. **Purely input**: part of the input sequence from a prior request

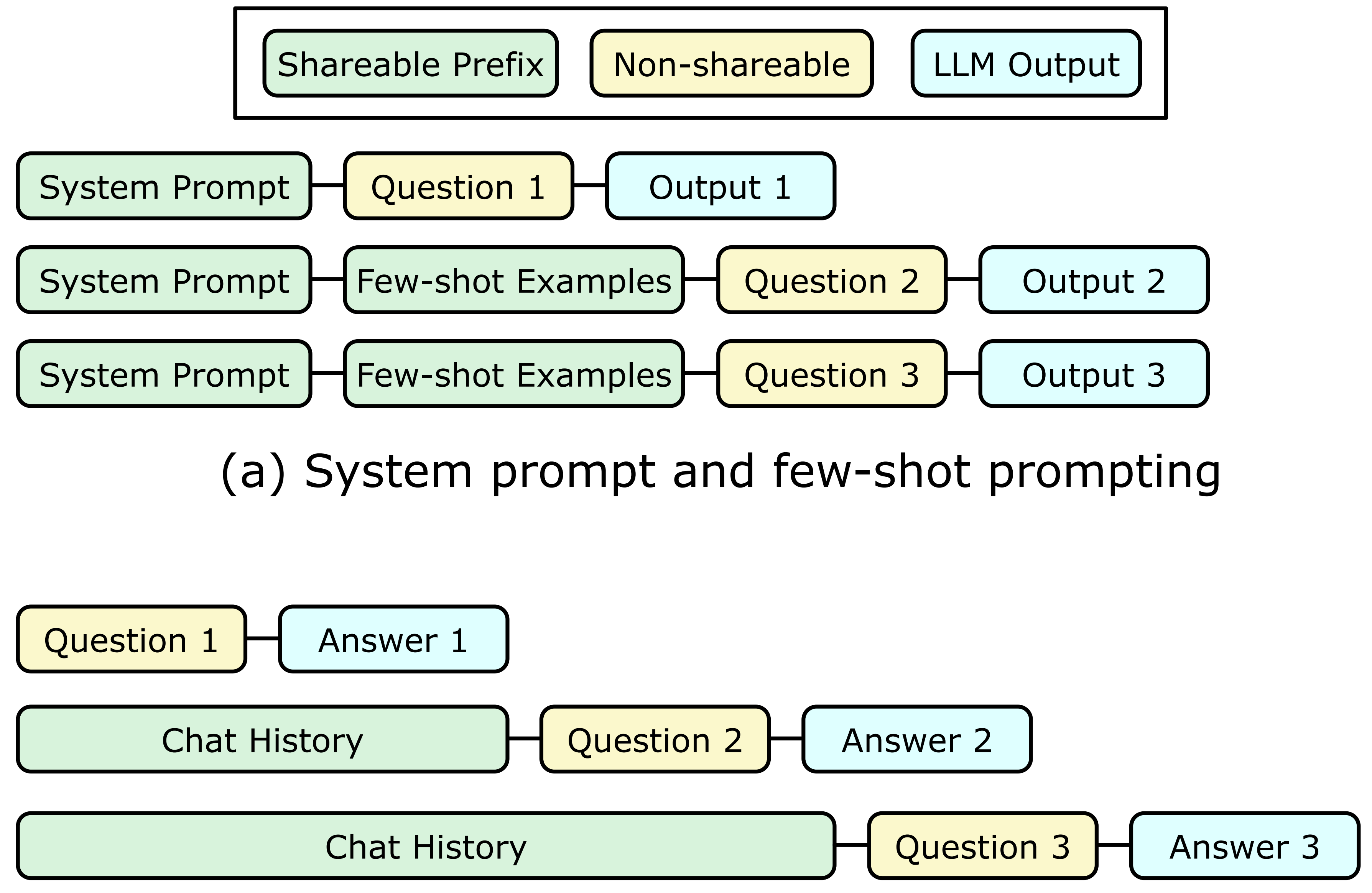
  - E.g., system prompts, few-shot examples



(a) System prompt and few-shot prompting

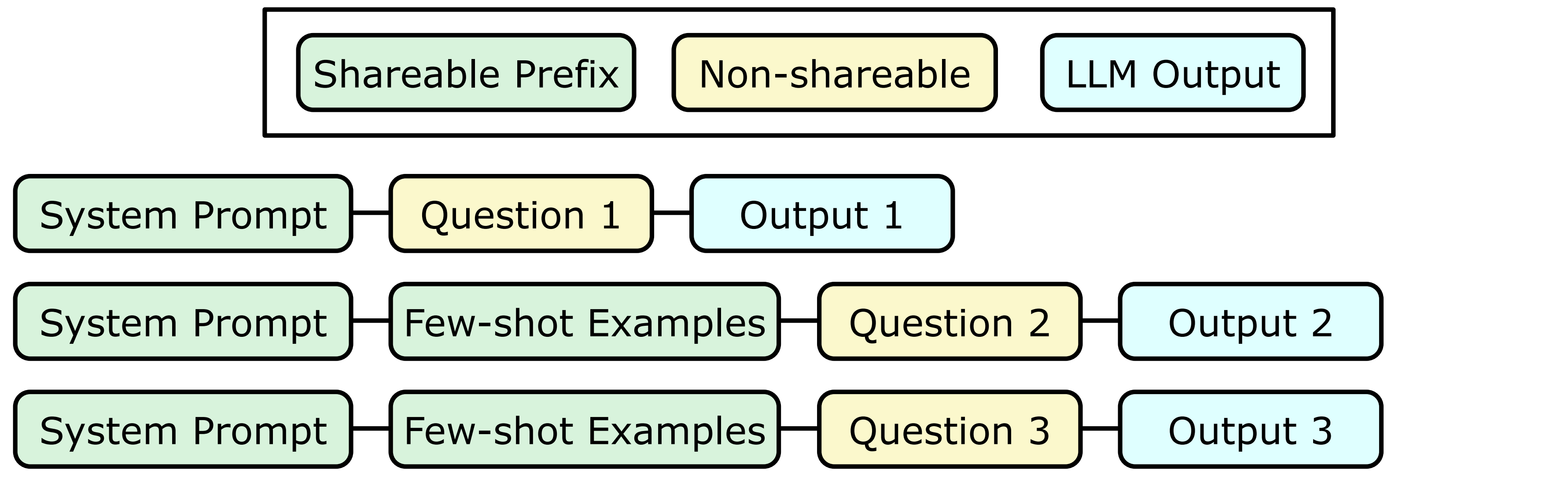
Taxonomy of prefix reusing patterns

- Composition of all reused prefixes:
  1. **Purely input**: part of the input sequence from a prior request
     - E.g., system prompts, few-shot examples
  2. **Input and output**: input+output sequence of a prior request
     - E.g., conversation history for chatbots, past environment interactions for agents



(b) Multi-turn conversation (e.g., ChatGPT)

Different mechanisms for different cases



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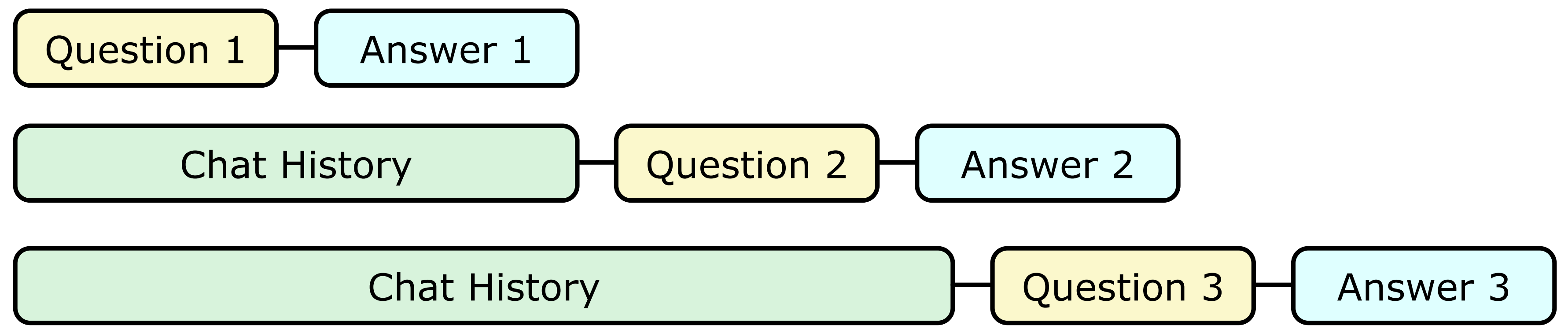

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Admission 14 Eviction

Different mechanisms for different cases

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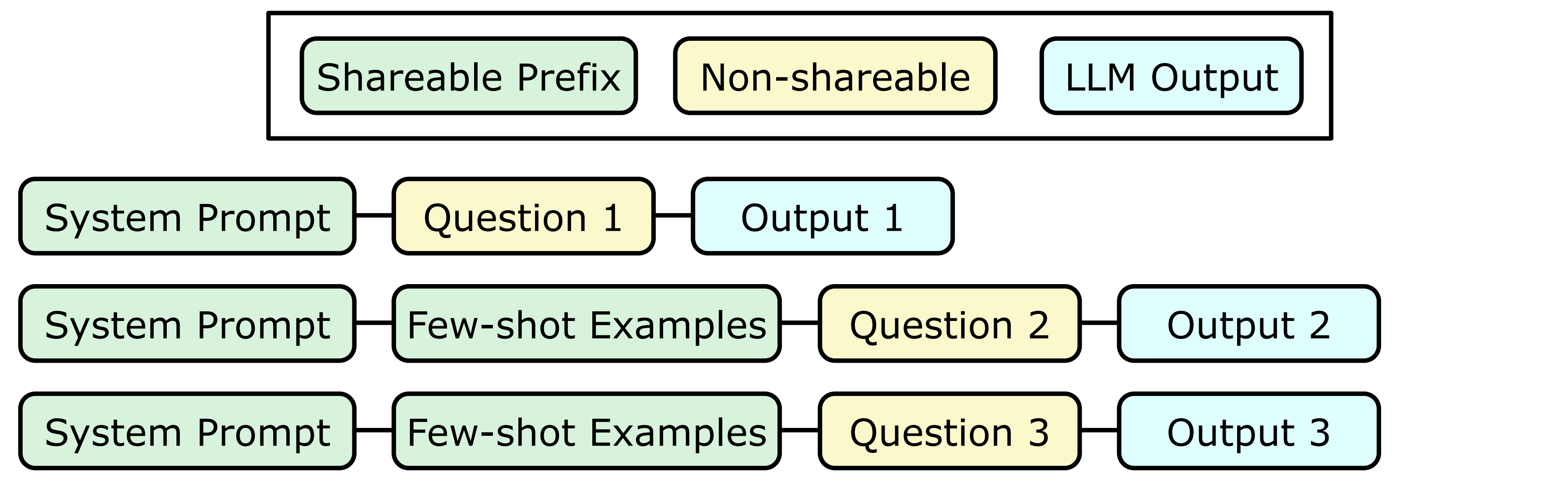
  - Prefix shared by many requests
  - Can be observed by bookkeeping and comparing previous requests



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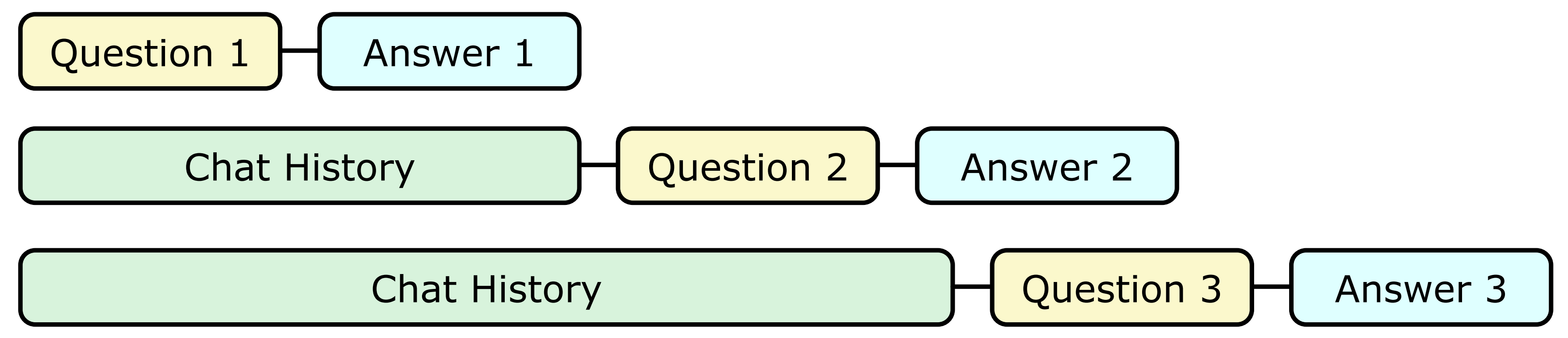

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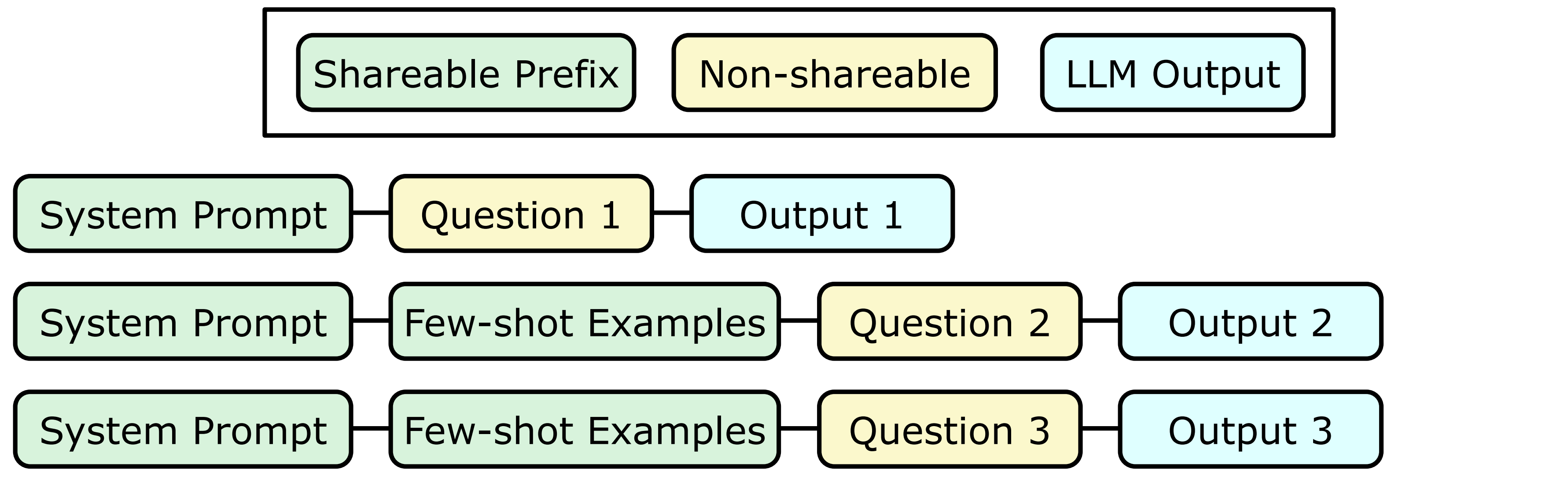
Different mechanisms for different cases

- **Purely input**
  - Prefix shared by many requests
  - Can be observed by bookkeeping and comparing previous requests
- **Input and output**
  - Conversations usually append to the last decoded token



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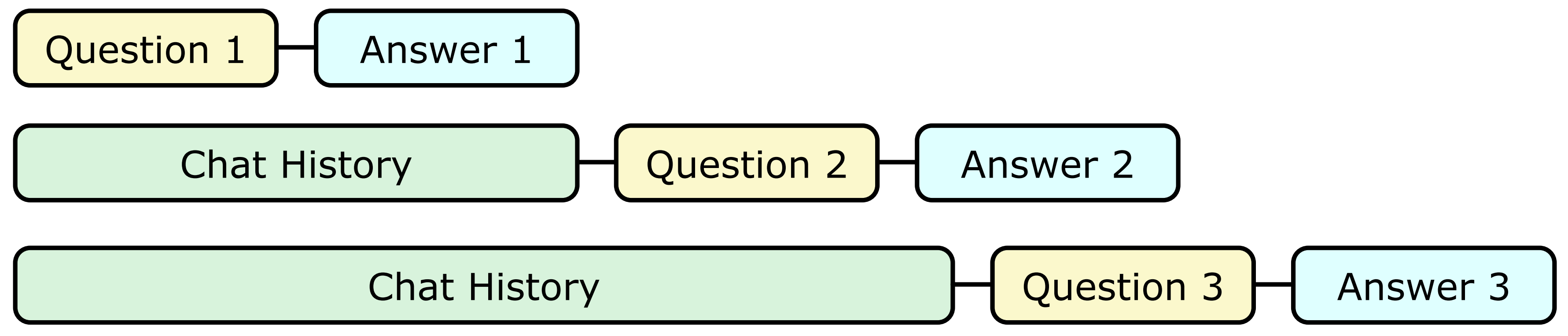

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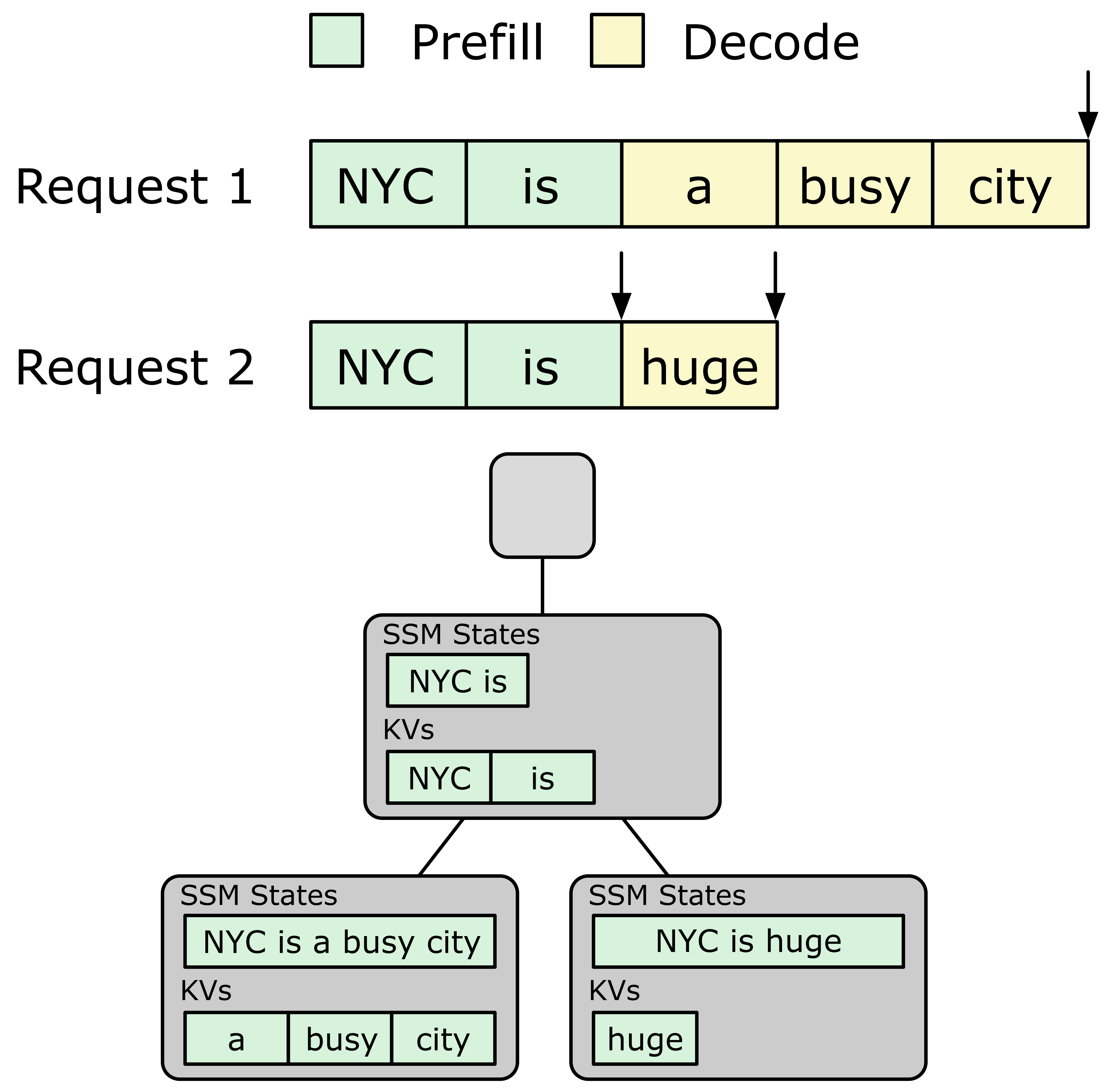

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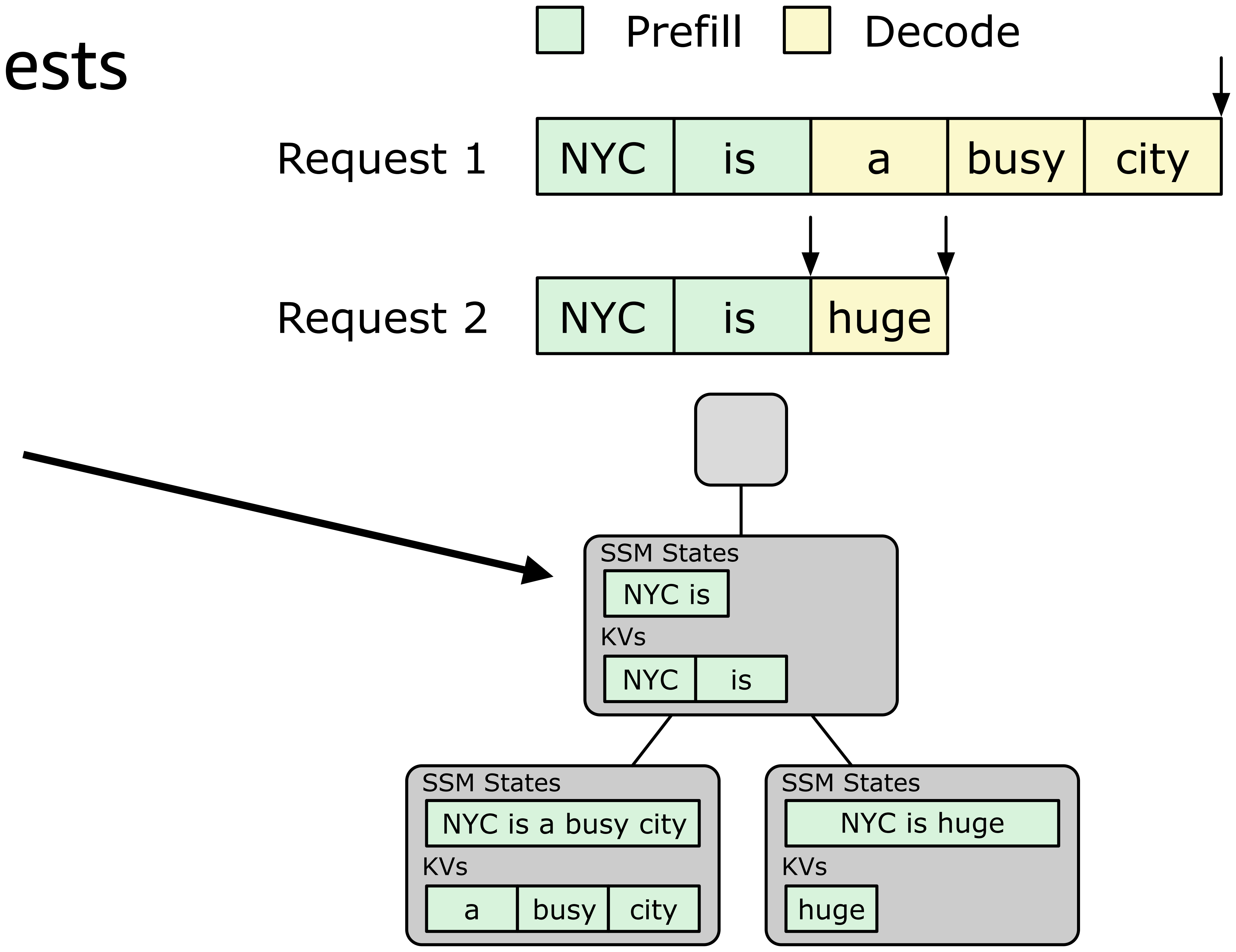

Request history bookkeeping

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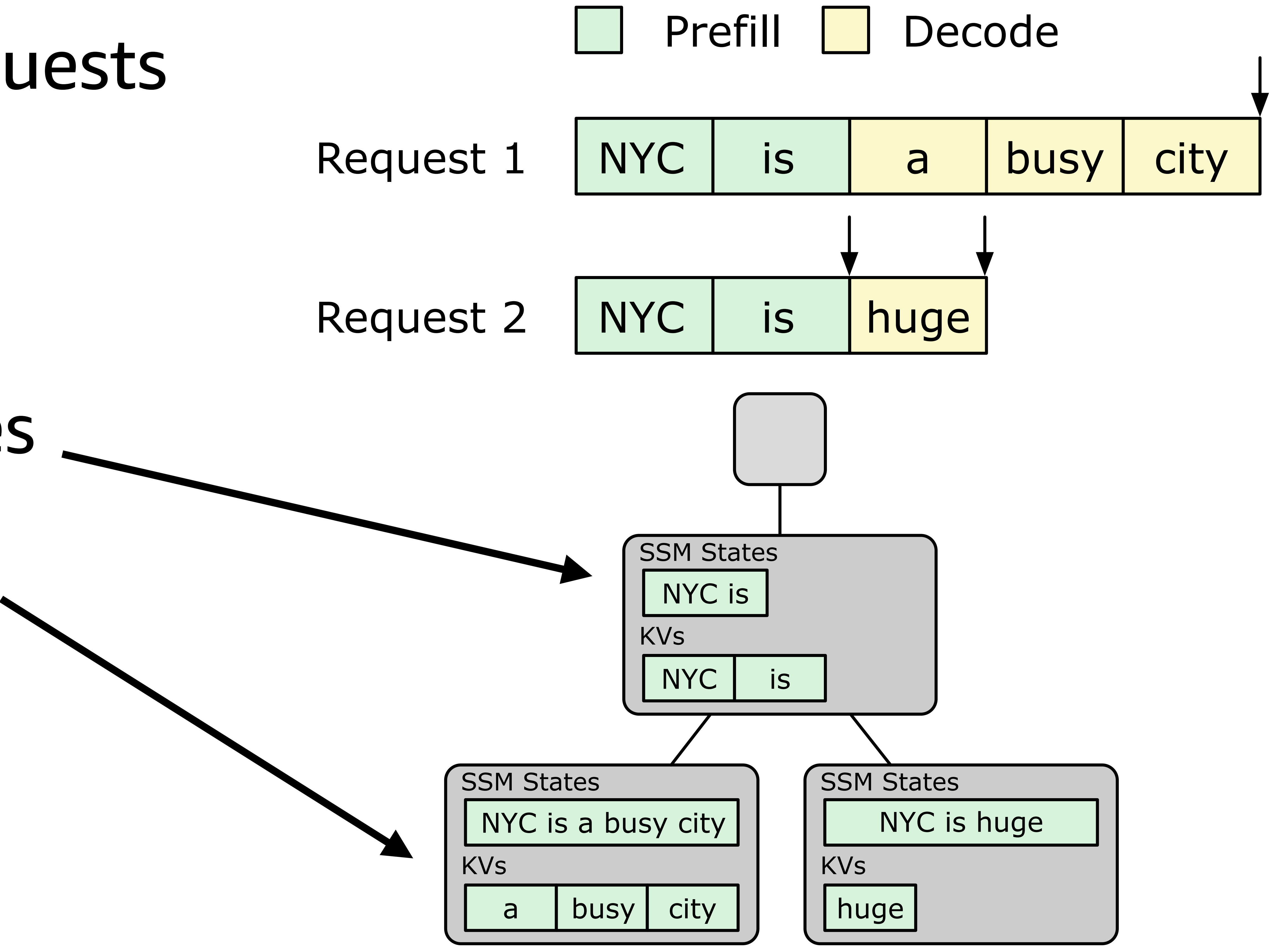

Aside from recency:

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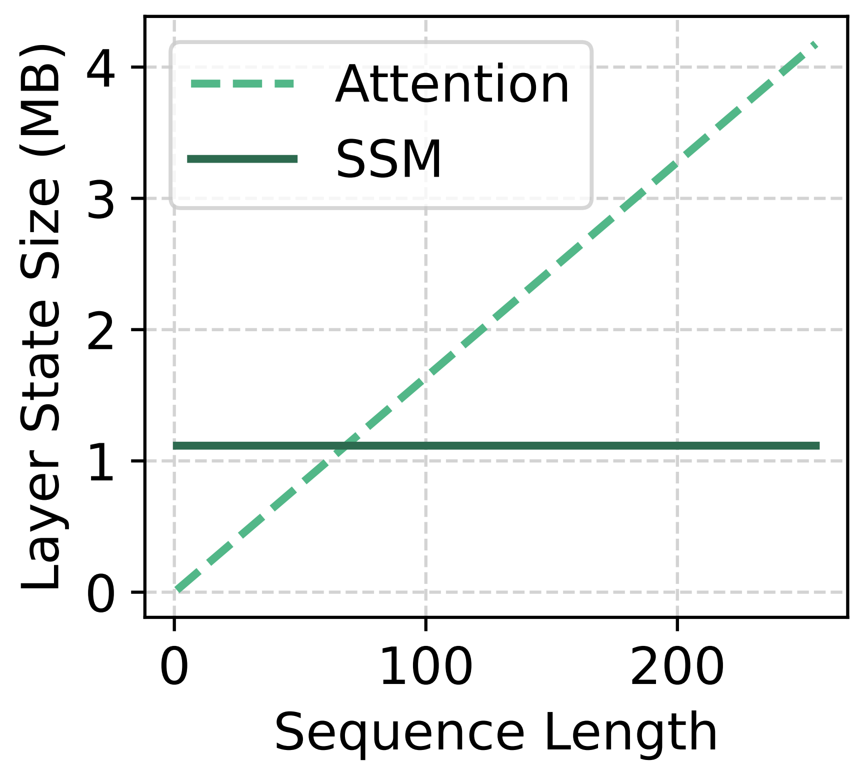
Eviction

Considers compute savings hits deliver

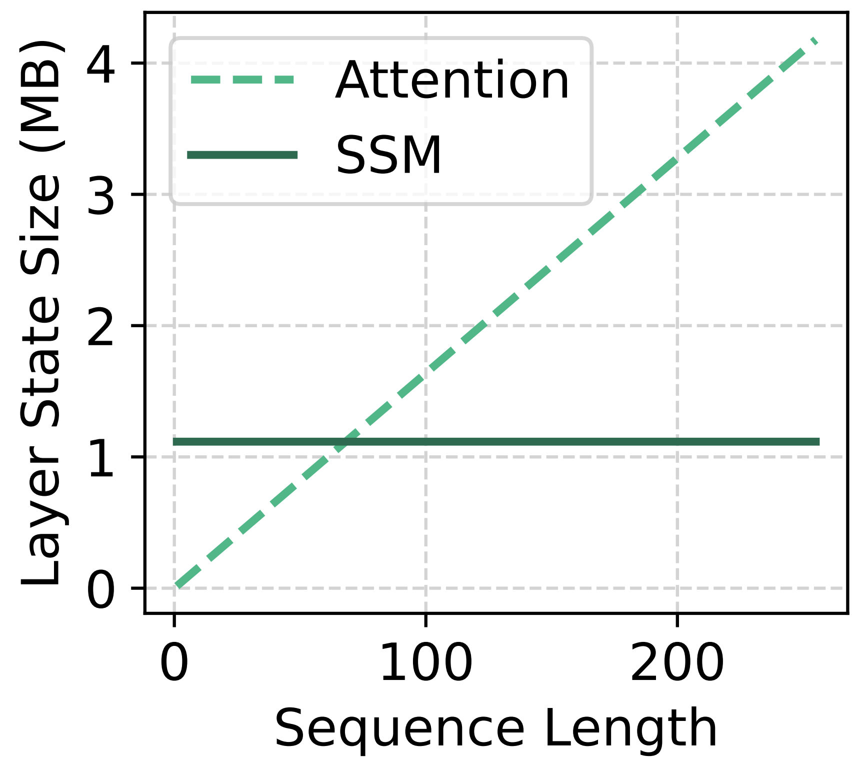
Different memory-compute savings tradeoffs

- Unlike KVs, SSM states have fixed size regardless of sequence length or compute savings



Different memory-compute savings tradeoffs

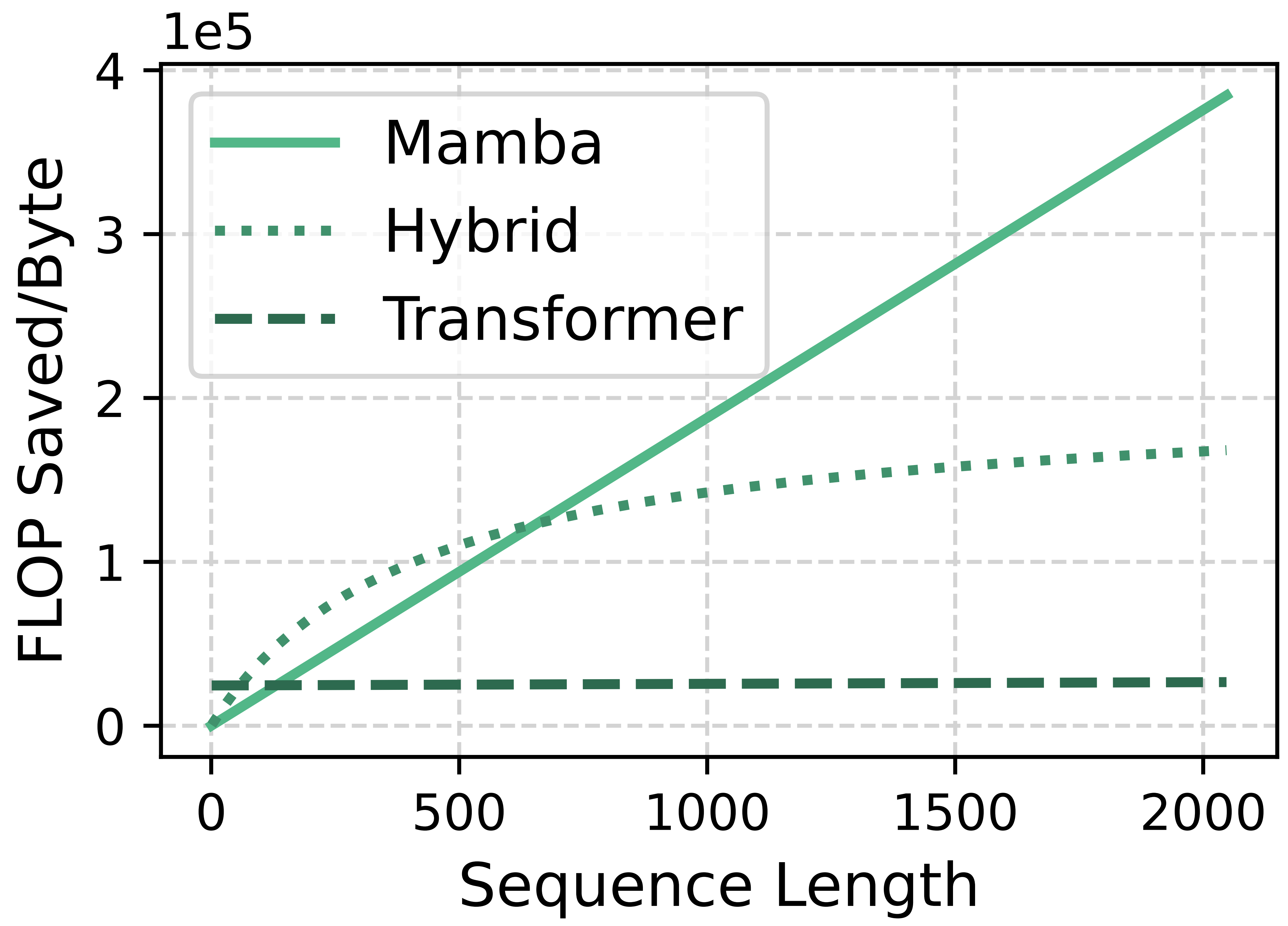
- Unlike KVs, SSM states have fixed size regardless of sequence length or compute savings
- **FLOP efficiency**: compute savings per unit of memory of reusing a state



$$\text{FLOP efficiency} = \frac{\text{Total FLOPs across layers (Attn, SSM, MLP)}}{\text{Memory consumption of all states (KVs, SSM States)}}$$

Different memory-compute savings tradeoffs

- Models with more SSM layers have more FLOP-efficient states



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FLOP-aware eviction policy

- Existing systems: recency-focused (i.e., evict using LRU)

$$\text{Utility} = \text{recency}$$

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- Marconi: also considers the potential compute savings

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FLOP-aware eviction policy

- Existing systems: recency-focused (i.e., evict using LRU)
- Marconi: also considers the potential compute savings
- Utility score: balances recency and FLOP efficiency

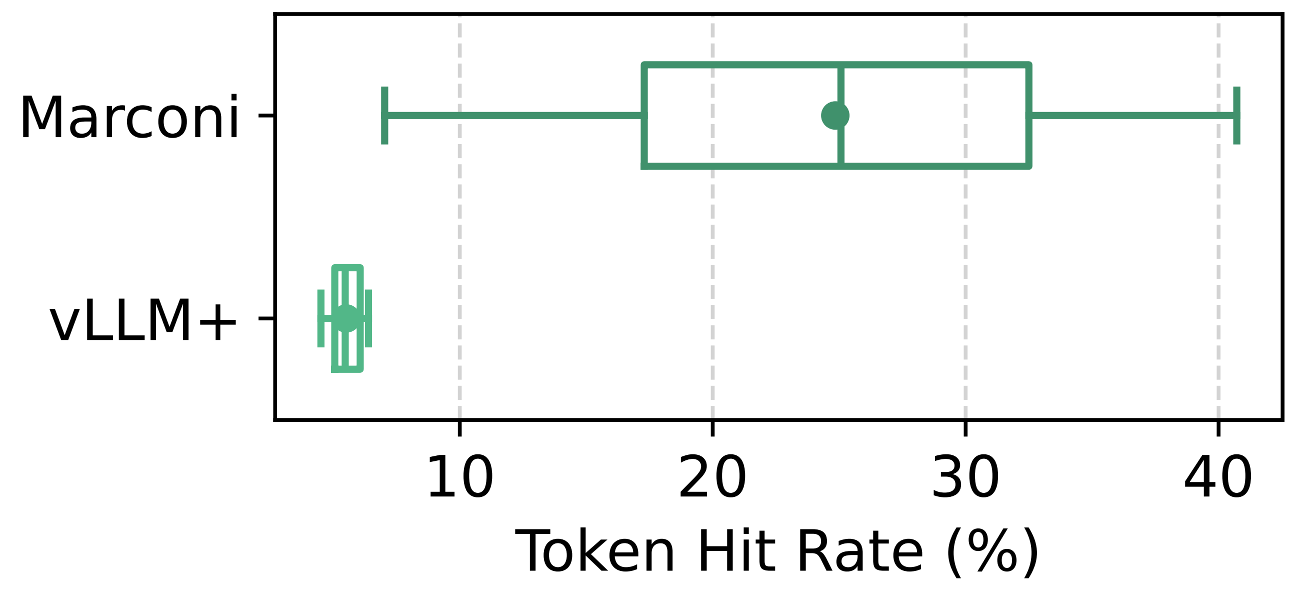
$$\text{Utility} = \text{recency} + \alpha \cdot \text{flop\_efficiency}$$

Evaluation

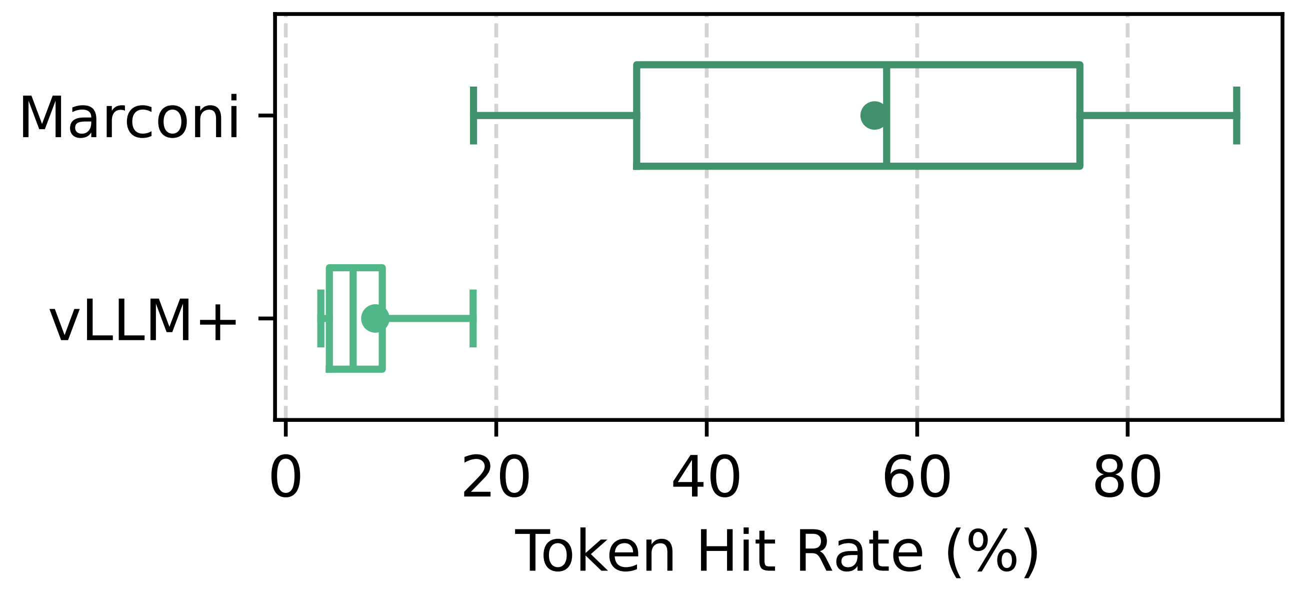
- NVIDIA Mamba2-Hybrid-7B with {4, 24, 28} {Attention, SSM, MLP} layers
- Workloads: conversational (LMSys, ShareGPT) and agentic (SWEBench)
- Metrics: token hit rate (%), Time To First Token (ms)
- Large sweep of experiments with varying cache size and request arrival patterns

Marconi vs. fine-grained checkpointing

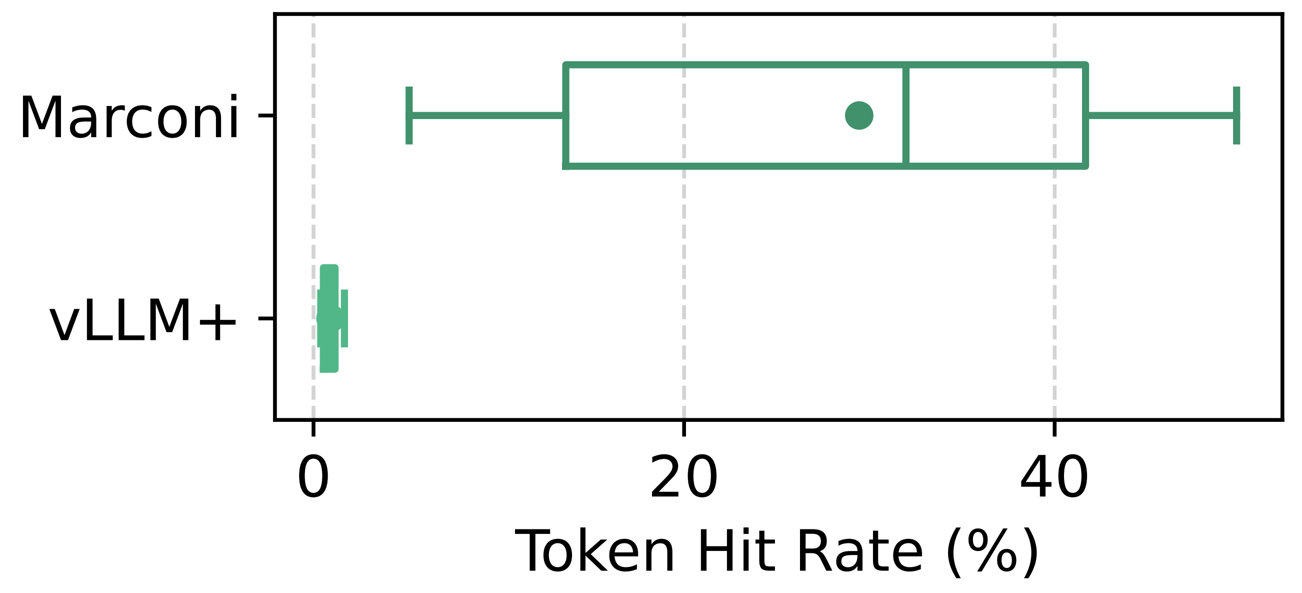
- Judicious admission improves the cache utility significantly
- Average improvement in token hit rate: 4.5X, 7.3X, and 34.4X



LMSys



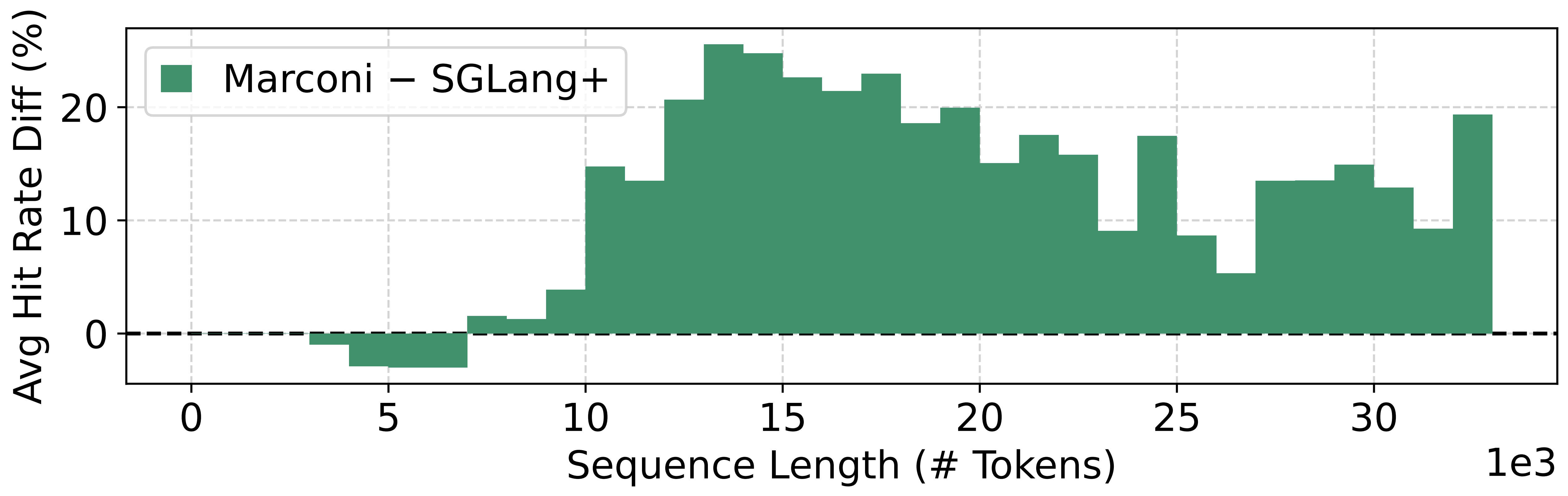
ShareGPT



SWEBench

Tradeoffs: FLOP-aware eviction vs. LRU

- Improves hit rate of longer sequences, which cost more FLOPs



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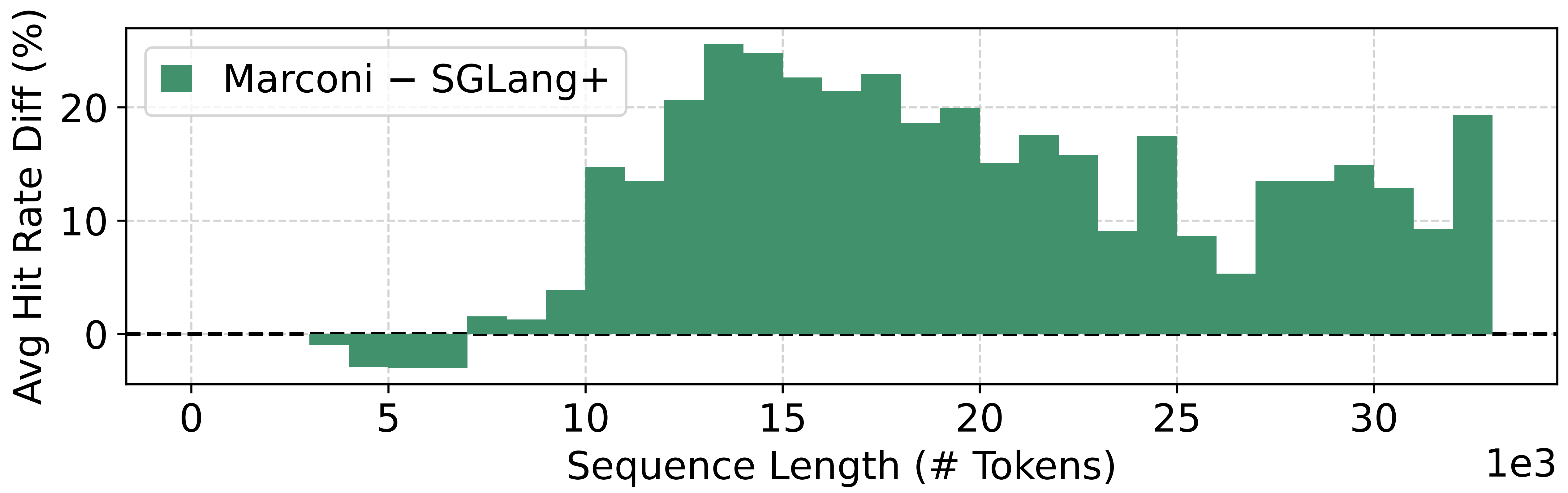

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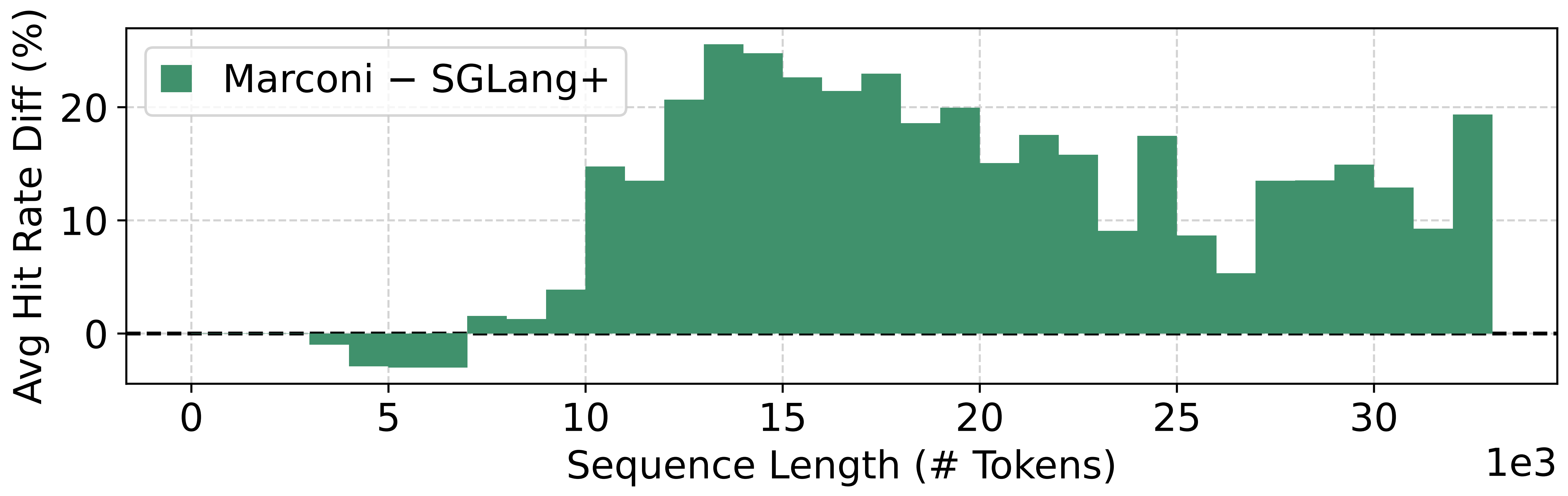

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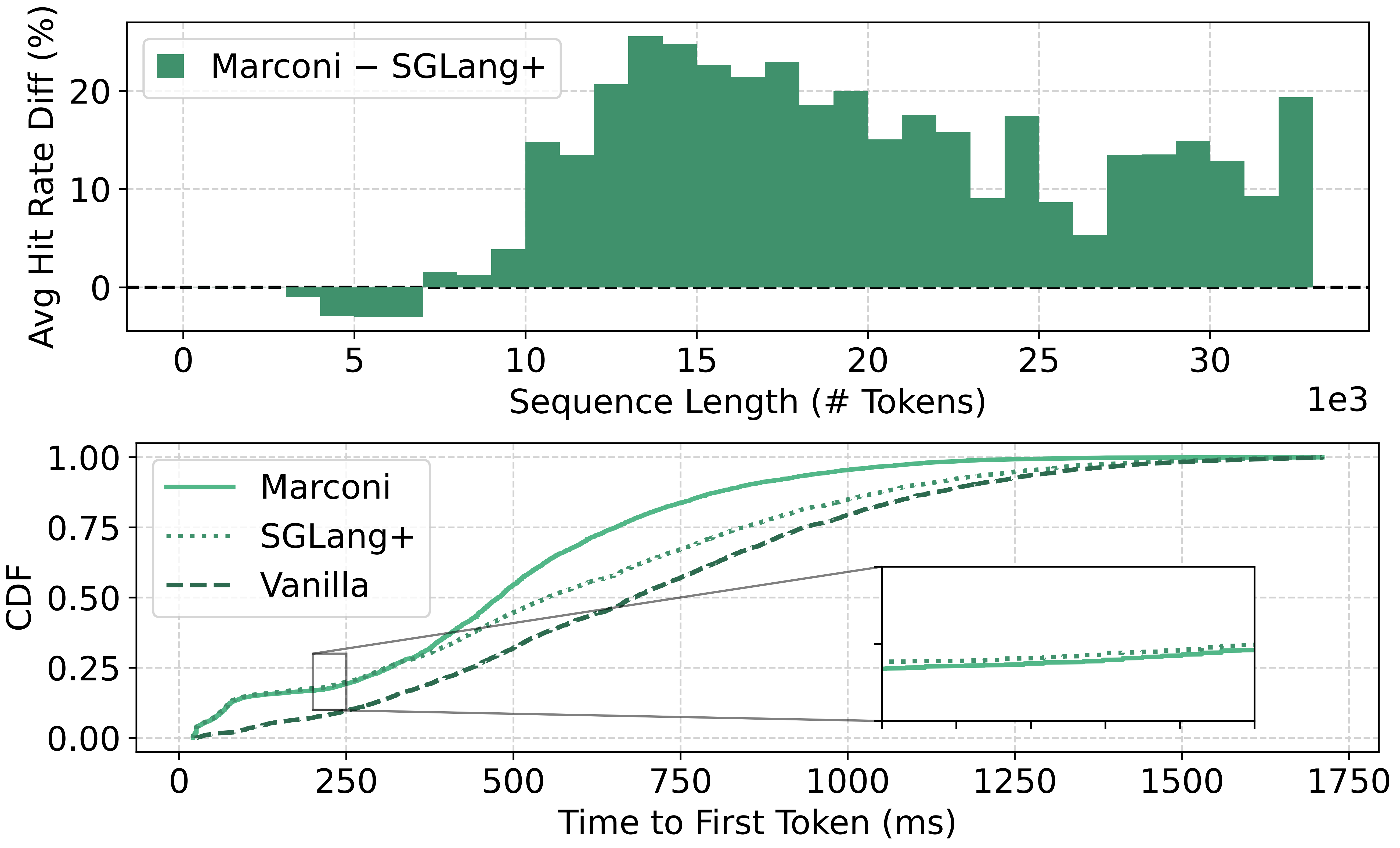

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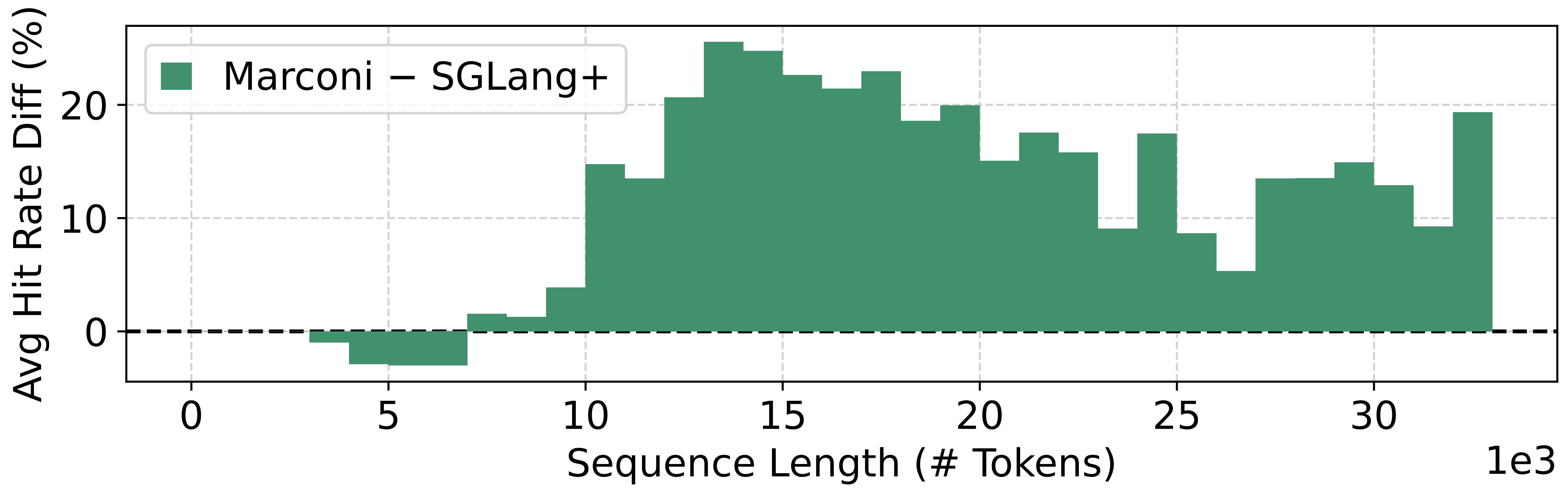

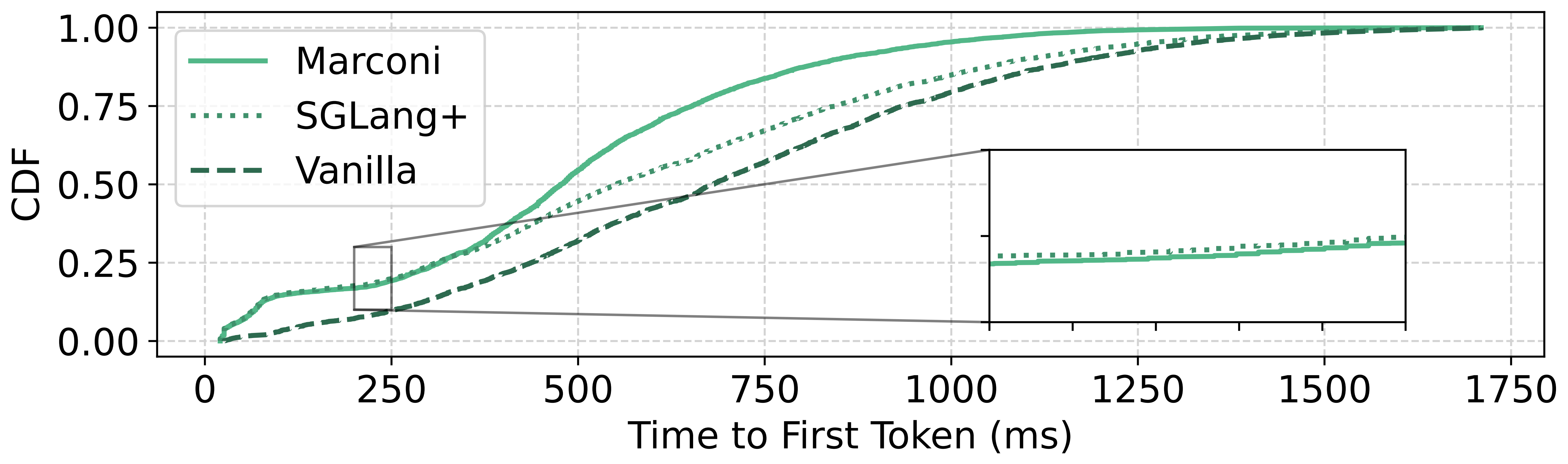

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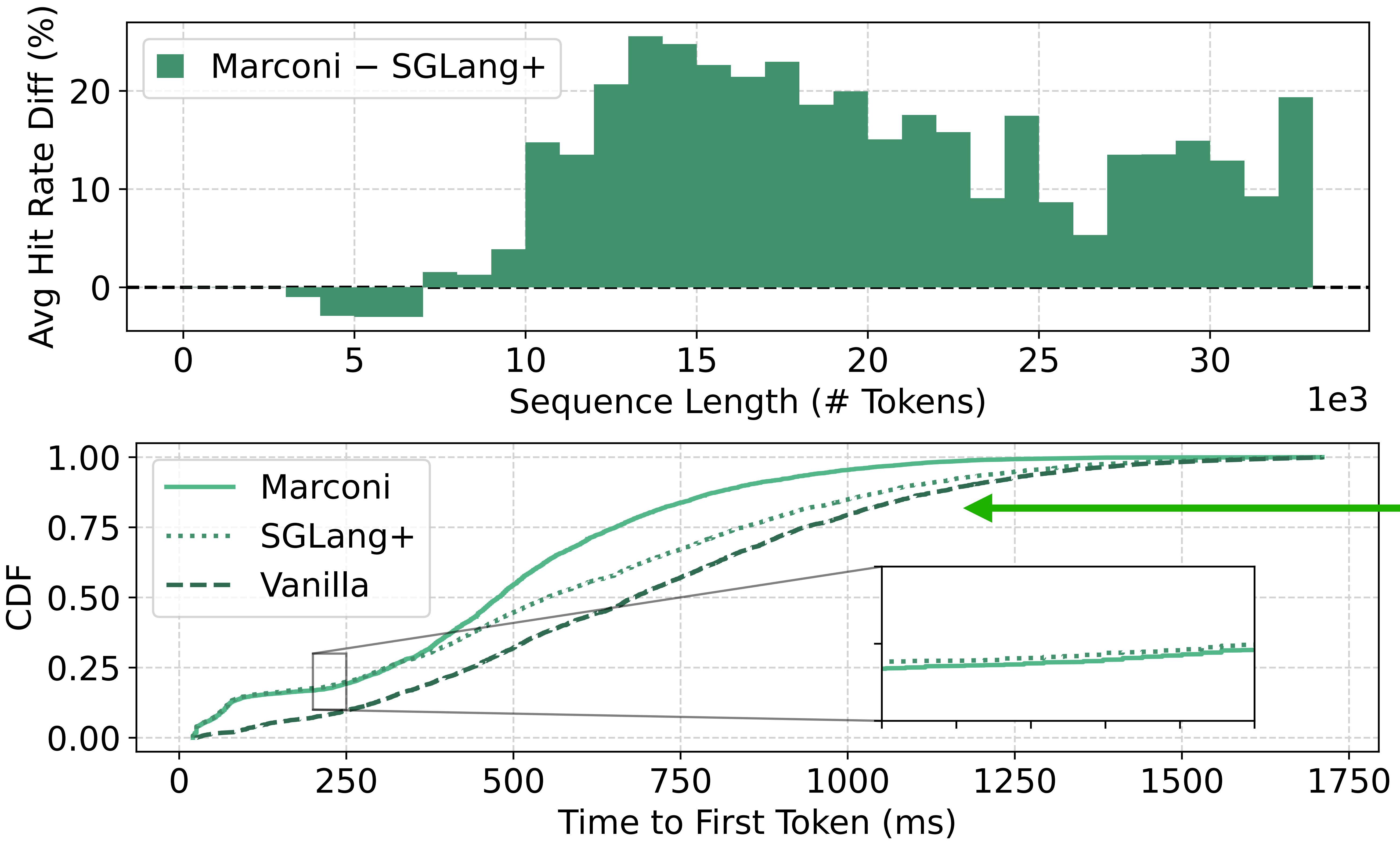

Bigger TTFT win for longer sequences!

Marconi

- First prefix caching system for models with arbitrary layer compositions
- Evaluates cache entries not only on recency, but also:
  - Admission: prefixes' reuse likelihoods
  - Eviction: compute savings that hits deliver
- Source code available! https://github.com/ruipeterpan/marconi

"Marconi plays the mamba, listen to the radio, don't you remember?" — Lyrics of *We Built This City*, song by Starship