ThinKV: Thought-Adaptive KV Cache Compression For Efficient Reasoning Models

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Link to Paper

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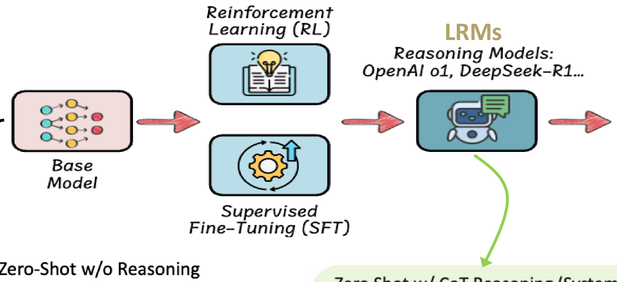
Reasoning models improve capability but introduce significant memory and efficiency challenges

ThinKV decomposes CoT into distinct thought types and thought-adaptively performs quantization and eviction

ThinKV establishes a new pareto frontier

What are Reasoning Models ?



Zero-Shot w/o Reasoning

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: The answer (arabic numerals) is

(Output) 8 ✗

Zero Shot w/ CoT Reasoning (System 2)

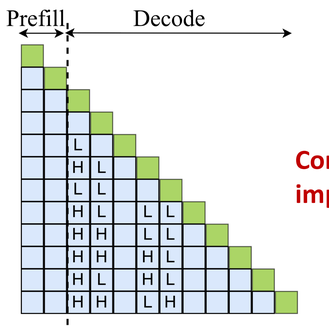
Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: ***Let's think step by step.***

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls. ✓

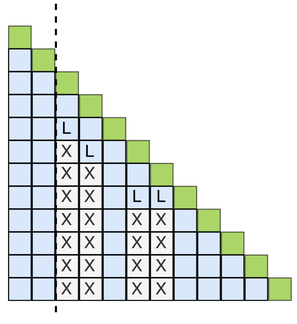
Unique Challenges of LRMs

Long output context generation

Model	Weights (GB)	KV Cache (GB)
DeepSeek-LLaMA-8B	16	64
DeepSeek-Qwen-32B	64	128
DeepSeek-LLaMA-70B	140	160



Convoluted token importance

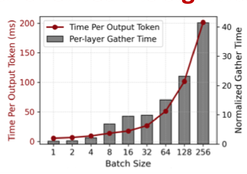


Internal memory fragmentation

Block 0	A	B	C	D
Block 1	E	F	G	H
Block 2	I	J	K	L
Block 3	M	N	O	P

	A	~~B~~	C	D
	E	~~F~~	~~G~~	H
	I	J	K	L
	M	~~N~~	O	P

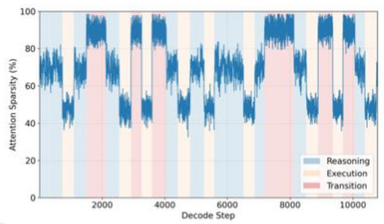
Gather overhead is significant



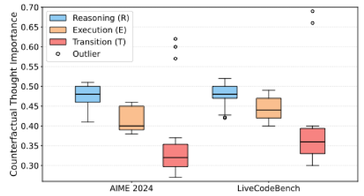
ThinKV's Key Observations

LRM chain-of-thought can be decomposed into 3 distinct thought types:

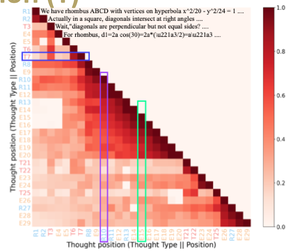
Reasoning (R), Execution (E) and Transition (T)



Degree of attention sparsity enables thought decomposition



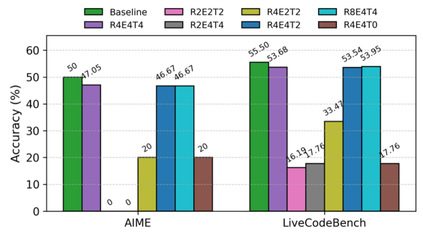
Thought importance: R >= E > T



With each T thought, prior thoughts diminish in influence

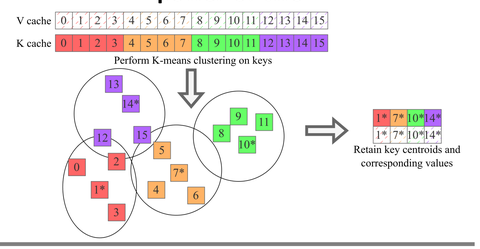
Think Before you Quantize, Think Before you Evict

Group Quantization, g=16, sf = 8-bit (E4M3)

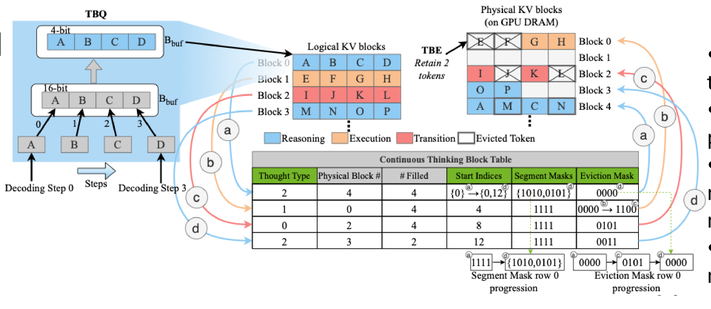


R, E @ NVFP4 and T @ Ternary

At the end of every T thought, progressively anneal previous thought segments to nearest power-of-two



Continuous Thinking Kernel: Extending vLLM



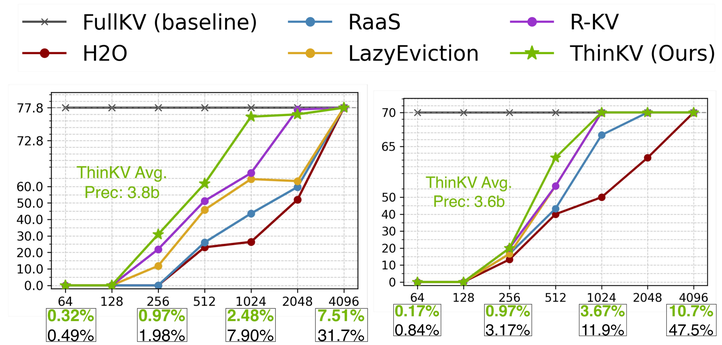
Continuous Thinking Block Table

Thought Type	Physical Block #	# Filled	Start Indices	Segment Masks	Eviction Mask
2	4	4	{0} → {0,12}	{1010,0101}	0000
1	0	4	4	1111	0000 → 1100
0	2	4	8	1111	0101
2	3	2	12	1111	0011

New Block Table Fields

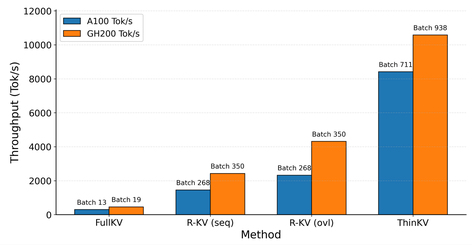
- **Thought type:** Thought type of tokens in a block.
- **Start indices:** Records the start position of the thought segment.
- **Segment masks:** If there are multiple start indices, the segment mask is a bit vector.
- **Eviction mask:** A bit vector marking positions of tokens evicted.

Accuracy and Performance Analysis

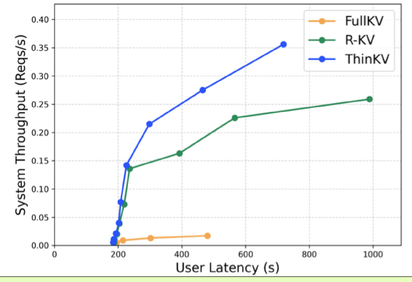


GPT-OSS-20B on LiveCodeBench | **DeepSeek-R1-LLaMA-70B on AIME**

ThinKV achieves near lossless accuracy with < 3.67% of FullKV memory



ThinKV supports 3X higher batch size and up to 5.8X higher TPS



ThinKV achieves 38% higher reqs/s and 27% lower latency compared to R-KV