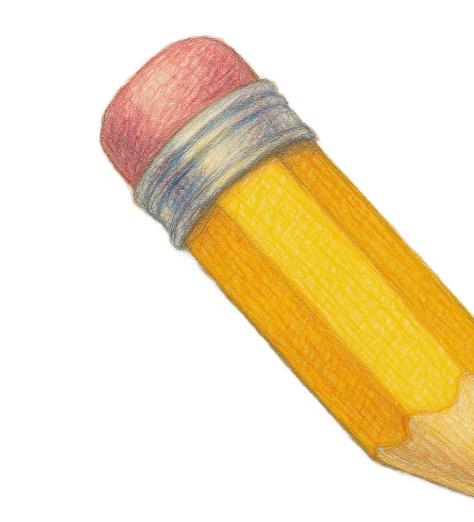




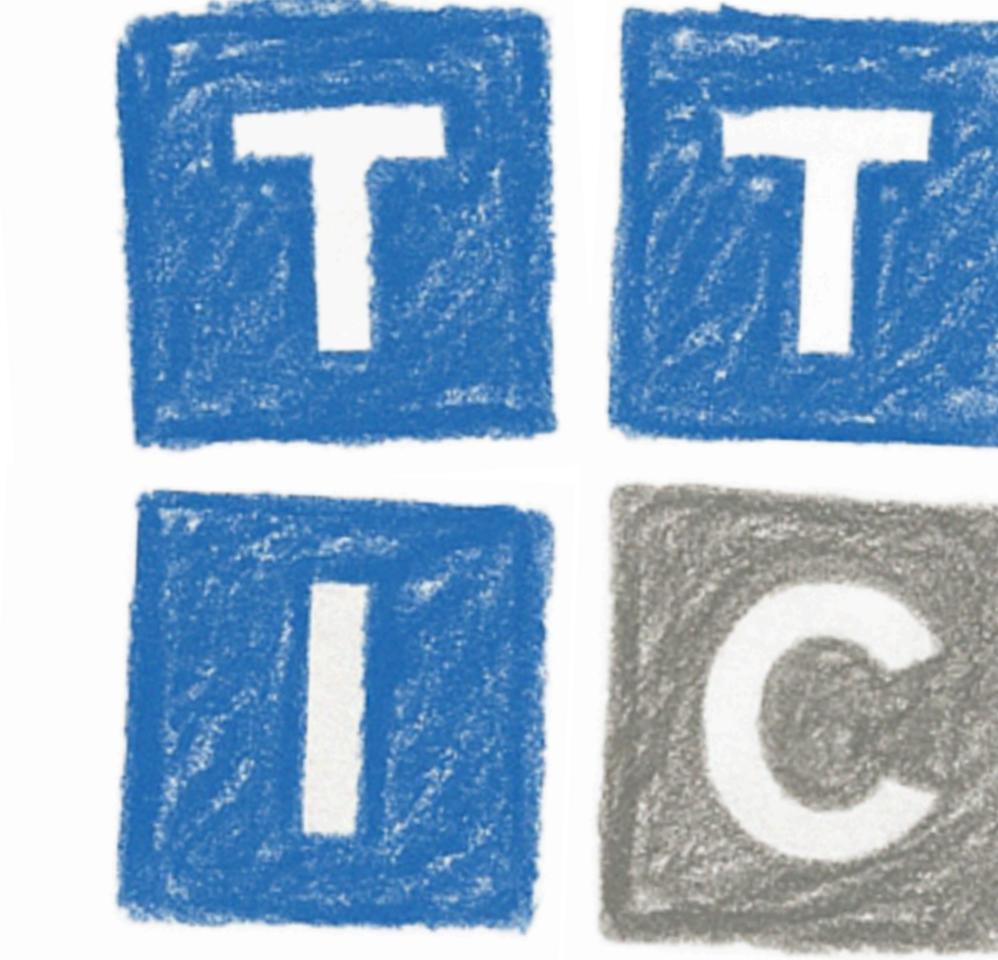
Fermat, 1637

I have discovered a truly marvelous proof of this theorem, which this margin is too small to contain.

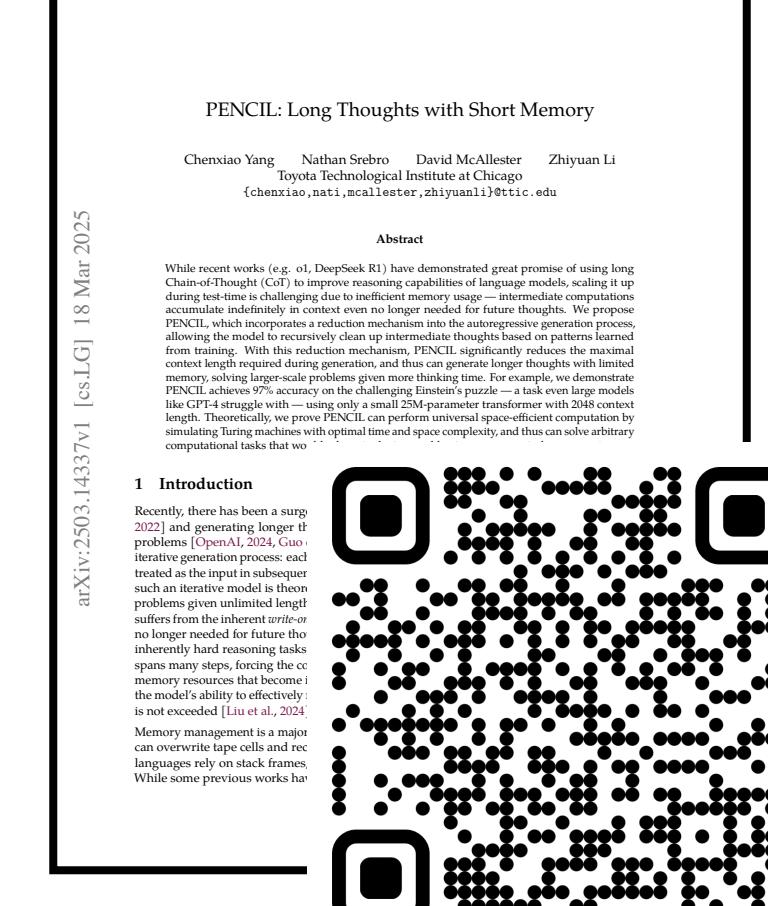


PENCIL : Long Thoughts with Short Memory

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Toyota Technological Institute at Chicago (TTIC)



NO! You can show it with a pencil (and an eraser)!



Yang et al., 2025



Method

Scaling up the thoughts at test time can significantly improve the reasoning capability of LLMs (e.g. GPT-01/o3, DeepSeek R1) !

BUT, very long CoT causes problems such as excessive memory, slow inference, attention dilution, etc. Is standard CoT fundamentally limited?

What is PENCIL ?

Model Generation (Write):

$$C_1 \Rightarrow C_1 C_2 [\text{CALL}] T [\text{SEP}] A [\text{RETURN}]$$

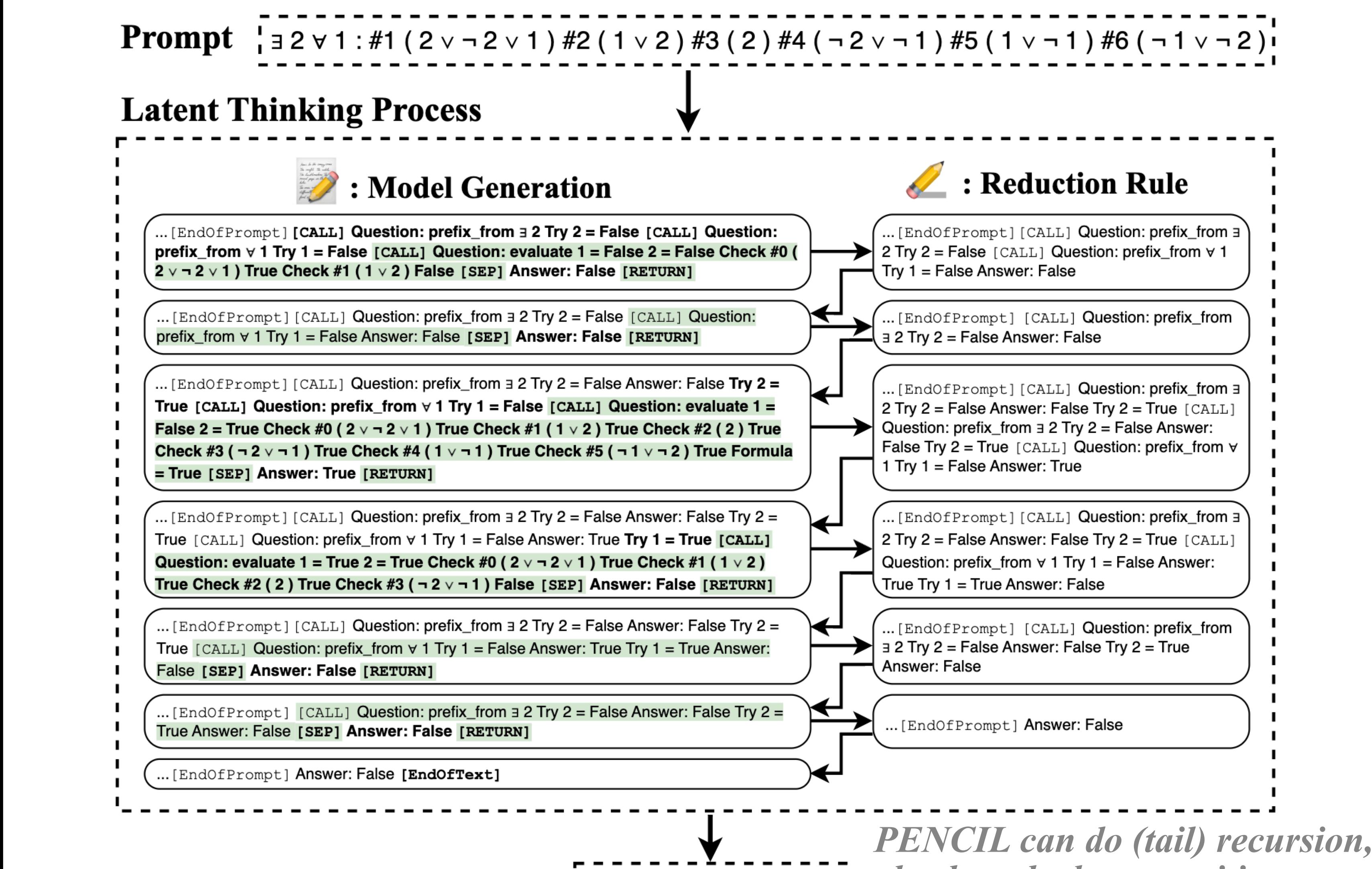
Reduction Rule (Erase):

$$C [\text{CALL}] T [\text{SEP}] A [\text{RETURN}] \Rightarrow C A$$

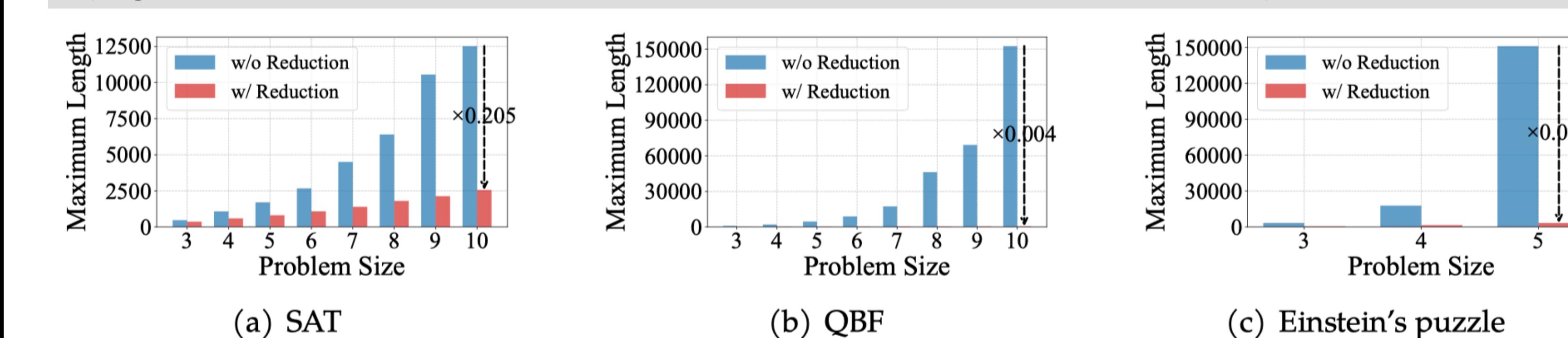
- [CALL], [SEP], [RETURN] are special tokens
- **C** = Context, **T** = Thoughts, **A** = Answer (*They can include special tokens!*)
- Reduction is triggered when the sequence matches the pattern
- PENCIL iteratively generate thoughts and triggers reduction

Important : Special tokens can accumulate similar with nested function calls in functional programming!

How PENCIL Works? Example on QBF



PENCIL significantly reduces the maximal context length during inference (e.g. CoT: 151,192 \Rightarrow PENCIL: 3,335 for Einstein's Puzzle)



Experiments

We train a small transformer (25M parameter, 2048 context length) to use PENCIL to solve computationally intensive reasoning tasks (SAT, QBF, Einstein's Puzzle).

$$\text{Training} : \mathcal{L}_{\text{CoT}} = -\sum \log p(\text{next token} | \text{previous sequence})$$

$$\mathcal{L}_{\text{PENCIL}} = -\sum \log p(\text{next token} | \text{reduced sequence})$$

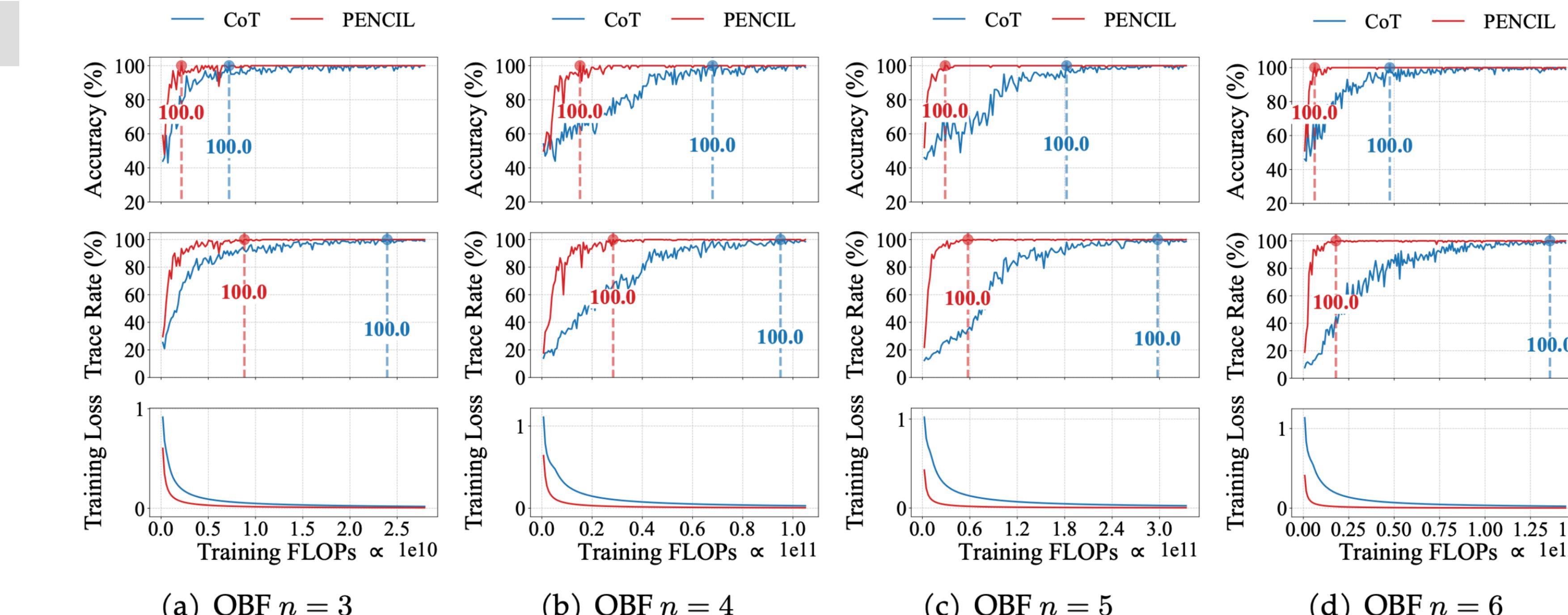
Performance: PENCIL outperforms CoT on NP-hard tasks SAT and QBF by a large margin (i.e. almost perfect v.s. random guessing).

	n =	3	4	5	6	7	8	9	10
Baseline	Acc.	66	57	46	51	46	51	49	51
CoT	Acc.	100	100	100	99	84	63	54	50
	TR.	99.6	99.0	98.0	96.2	74.0	69.9	63.8	51.4

	n =	3	4	5	6	7	8	9	10
Baseline	Acc.	90	82	85	68	60	69	71	66
CoT	Acc.	100	100	97	94	74	72	69	73
	TR.	100	100	98.3	93.9	65.1	49.4	40.7	32.8

	n =	3	4	5	6	7	8	9	10
PENCIL	Acc.	100	100	100	99	99	100	100	100
	TR.	100	99.0	97.1	95.9	91.8	93.3	92.9	83.0

Time Efficiency: PENCIL significantly saves computations by reducing the context length and converges faster during training.



Applicability: PENCIL works as well on a natural-language reasoning task called Einstein's puzzle – a logic puzzle that even GPT-4 struggles with.

Einstein's Puzzle

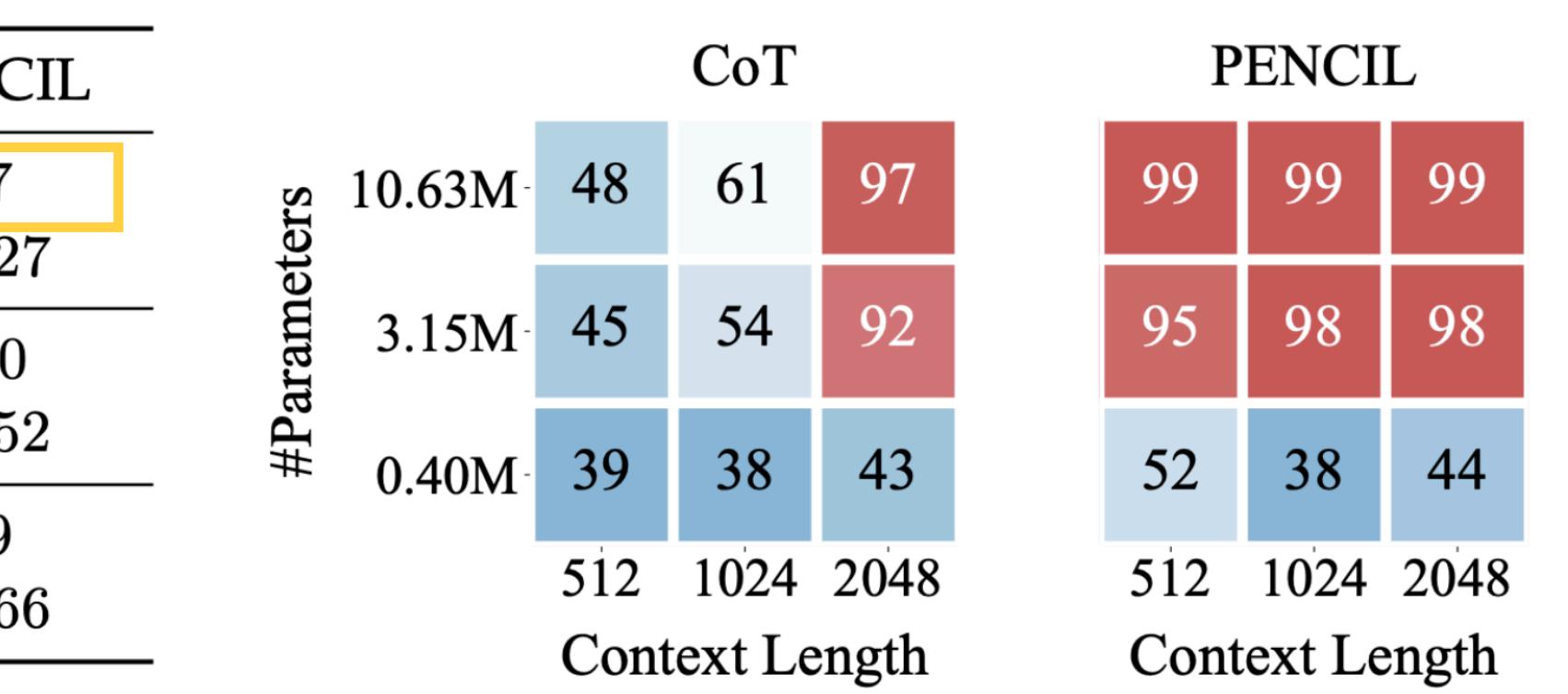
- Constraint 1 : The **green** house is immediately to the right of the one who keeps **birds**
- Constraint 2 : The **Brit** is immediately to the right of the **German**
- Constraint 3 : The one who keeps **dogs** is the same house as the **red** house
- Constraint 4 : The one who keeps **birds** is immediately to the right of the **Swede**
- Question: who owns the fish?

PENCIL Solution :

House #	1	2	3
Color	Red	Blue	Green
Nationality	Swede	German	Brit
Pet	Dogs	Birds	Fish

Answer: the Brit owns the fish

Puzzle Size		CoT	PENCIL
5 × 5	Accuracy (%)	25	97
	Trace Rate (%)	2.97	78.27
4 × 4	Accuracy (%)	34	100
	Trace Rate (%)	8.33	86.52
3 × 3	Accuracy (%)	99	99
	Trace Rate (%)	99.37	99.66

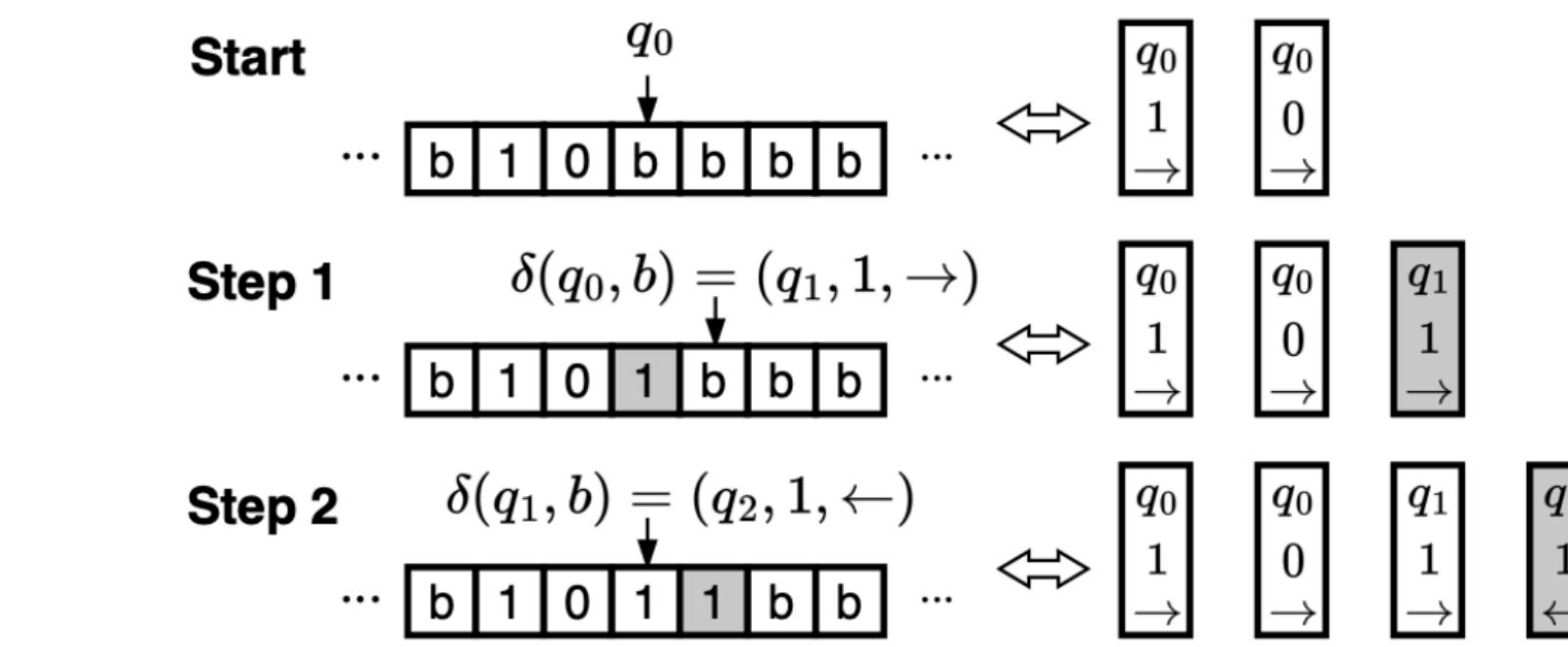


Theory

Theorem (Main, Informal). For any Turing machine, there exists a fixed finite-size transformer such that for any input, on which **Turing machine** uses **T steps** and **S space** to compute, **PENCIL** with this transformer computes the same output with $\mathcal{O}(T)$ generated tokens and using $\mathcal{O}(S)$ maximal context length. (This is impossible for CoT !)

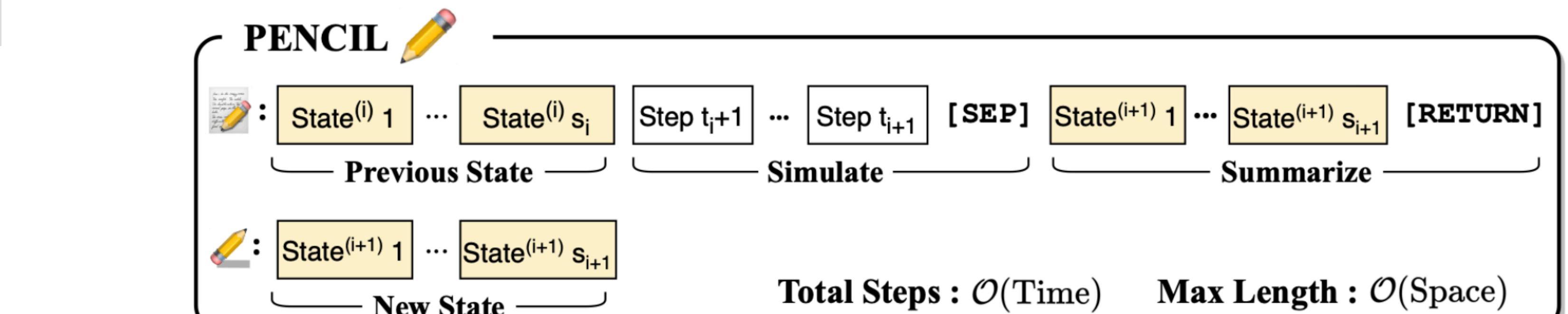
Corollary (Informal). With poly(n) context length, PENCIL can solve all problems in PSPACE, while standard CoT can only solve problems in P.

Step 1 : Turing Machine computation \Leftrightarrow Next-token generation (CoT)



- Each generated token represents a TM transition step, encoding (*state, symbol, movement direction*).
- **Total Steps** = $\mathcal{O}(\text{Time})$
- **Max Context Length** = $\mathcal{O}(\text{Space})$

Step 2 : Simulating TM space-efficiently with PENCIL



- **Simulation:** generate tokens to simulate the step-by-step running of Turing machine, starting from the previous state (i.e. TM's configuration).
- **Summarization:** summarize all previously tokens into the new state using the PENCIL reduction rule.
- Trigger the summarization whenever the length of current sequence exceeds twice the actual space needed to store the information.
- **Total Steps** = $\mathcal{O}(\text{Time})$, **Max Context Length** = $\mathcal{O}(\text{Space})$

Step 3 : Can Transformers express the algorithm ?

Full-Access Sequence Processing (FASP)

A program in FASP is a process of building a sequence of increasingly complex functions (i.e. Transformers) $\Sigma^* \rightarrow \mathbb{R}^d$.

- **Each Variable** = a Transformer.
- **Each Line of Code** = an operator from some simpler Transformers to a more complex Transformer.
- **FASP** predefines a set of local and non-local operators, and supports custom operators.

Theorem (Informal). FASP = \mathcal{H}_{TF}

```
This is the Proof!
# Detect separator token
is_sep = get_token == eoshtoken(SBERT)
sum_phase_mask = exist_sep and (not is_sep)

# Position tracking for Simulation, frozen in SIMPL
```