

Expressivity of Transformers: Logic, Circuits, and Formal Languages

Day 3: Transformers and Turing Machines

David Chiang (Univ. of Notre Dame, USA)

Jon Rawski (MIT/San Jose State Univ., USA)

Lena Strobl (Umeå University, Sweden)

Andy Yang (Univ. of Notre Dame, USA)

31 July 2024



Main Result (too informal)

Theorem (Pérez et al., 2019, Pérez et al., 2021)

Transformers are Turing-complete!!!1

Main Result (too informal)

▲ tambourine_man on June 15, 2023 | parent | next [-]

Transformers are Turing complete, right?

▲ nyrikki on June 15, 2023 | root | parent | next [-]

The paper from yesterday:

<https://news.ycombinator.c...>

Showed that attention with positional encodings and arbitrary precision rational activation functions is Turing complete.

Using a finite precision, nonrational activation function and/or without positional encodings is not Turing complete.

▲ canjobear on June 15, 2023 | root | parent | prev | next [-]

No, they are actually very limited formally. For example you can't model a language of nested brackets to arbitrary depth (as you can with an RNN). That makes it all the more interesting that they are so successful.

<https://news.ycombinator.com/item?id=36311871>

Main Result (informal)

Theorem (Pérez et al., 2019, Pérez et al., 2021)

An average-hard attention transformer decoder using position embeddings and intermediate steps can simulate a Turing machine.

Today's Goals

- **Define** a transformer *decoder* as well as *intermediate steps* and how they relate to *chain of thought*
- **Explain** in what sense a transformer is and isn't Turing-complete
- **Understand** how a transformer, which has no memory, can simulate a Turing machine's tape

Background

Main Result (informal)

Theorem (Pérez et al., 2019, Pérez et al., 2021)

*An **average-hard attention** transformer decoder using position embeddings and intermediate steps can simulate a Turing machine.*

Average-Hard Attention

- Like unique-hard attention, attention goes only to highest-scoring positions
- Unlike unique-hard attention, attention is divided equally among highest-scoring positions

scores s	0	1	1
softmax	0.16	0.42	0.42
leftmost-hard	0	1	0
rightmost-hard	0	0	1
average-hard	0	0.5	0.5

Average-Hard Attention

Exercises:

scores s	2	2	0	2	1
------------	---	---	---	---	---

average-hard					
--------------	--	--	--	--	--

scores s	0	0	0	0	0
------------	---	---	---	---	---

average-hard					
--------------	--	--	--	--	--

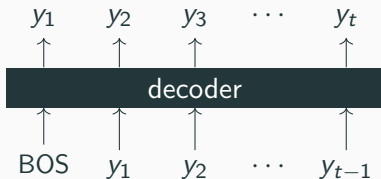
Main Result (informal)

Theorem (Pérez et al., 2019, Pérez et al., 2021)

*An average-hard attention **transformer decoder** using position embeddings and intermediate steps can simulate a Turing machine.*

Transformer Decoders

- At each time step, the decoder outputs a word
 - In practice: a probability distribution over words
 - Often in theory: the exact embedding of a word
- The output word becomes the next input word (autoregression)



Future Masking

- At each time step i , attention only attends to positions $j \leq i$
- Optional in encoders, mandatory in decoders

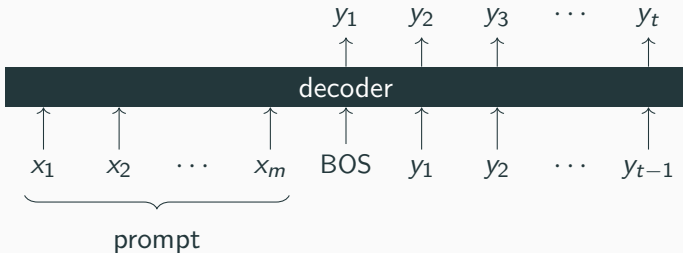
Exercise: Without autoregression, which vectors does vector x depend on?

i	i	i	j	k	k	k
g	g	g	x	h	h	h
d	d	d	e	f	f	f
a	a	a	b	c	c	c

(How about with autoregression?)

Prompting

- BOS can be preceded by input symbols, known as a *prompt*



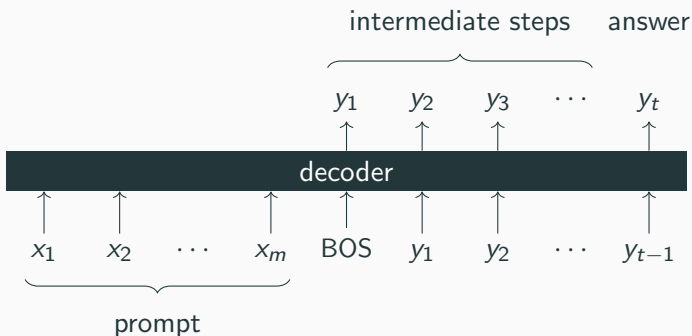
Main Result (informal)

Theorem (Pérez et al., 2019, Pérez et al., 2021)

An average-hard attention transformer decoder using position embeddings and intermediate steps can simulate a Turing machine.

Intermediate Steps

- Allow *intermediate* output symbols between BOS and the final output (here, just a single symbol)



Theory Predicts Practice

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ❌

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. $5 + 6 = 11$. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had $23 - 20 = 3$. They bought 6 more apples, so they have $3 + 6 = 9$. The answer is 9. ✅

[Wei et al., 2022]

Main Result (informal)

Theorem (Pérez et al., 2019, Pérez et al., 2021)

An average-hard attention transformer decoder using position embeddings and intermediate steps can simulate a Turing machine .

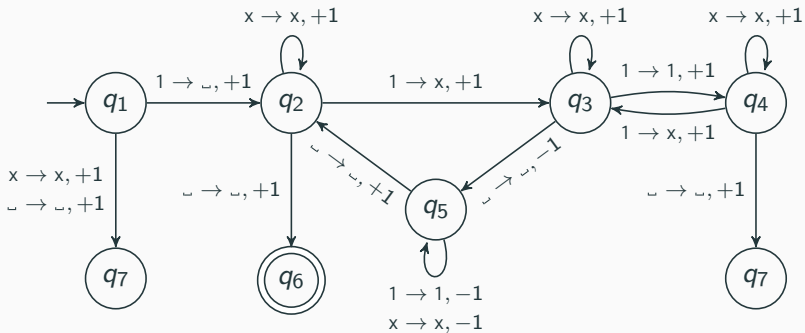
Turing Machines



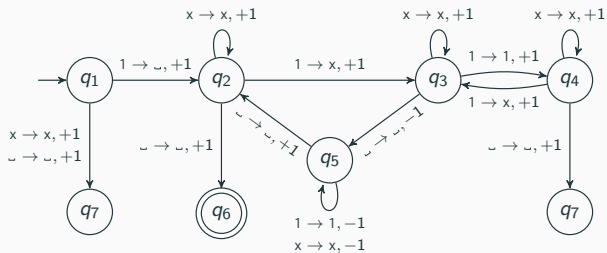
- Semi-infinite tape
- Cells are numbered starting from 0
- At each step, head moves either left (-1) or right ($+1$)

Turing Machines

Turing machine for $\{1^{2^m} \mid m \geq 0\}$



Turing Machines



q_1 $\hat{1}1\sqcup \dots$

q_2 $\sqcup \hat{1}\sqcup \dots$

q_3 $\sqcup x\hat{\sqcup} \dots$

q_5 $\sqcup x\hat{\sqcup} \dots$

q_5 $\hat{\sqcup} x\sqcup \dots$

q_2 $\sqcup x\hat{\sqcup} \dots$

q_6 accept

Question: What are the inputs and outputs of a Turing machine's transition function?

$$\delta(q, a) = (q', b, m)$$

Simulating Turing Machines

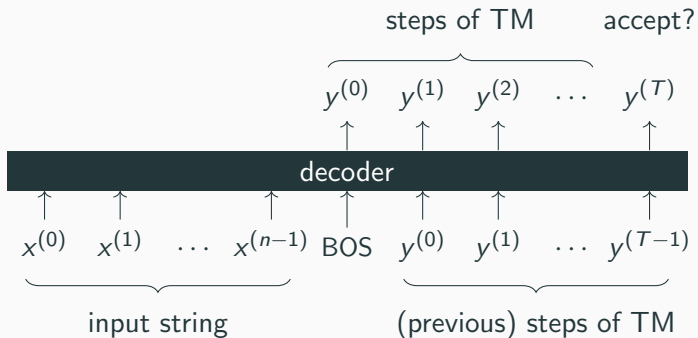
Theorem (Pérez et al., 2019, Pérez et al., 2021)

For any Turing machine M with input alphabet Σ , there is an average-hard attention transformer decoder f with position embedding $i \mapsto (1/(i+1), 1, i, i^2)$ that is equivalent to M in the following sense. For any string $w \in \Sigma^$:*

- *If M halts and accepts on input w , then there is a T such that f , on prompt w , outputs ACC after T intermediate steps.*
- *If M halts and rejects on input w , then there is a T such that f , on prompt w , outputs REJ after T intermediate steps.*
- *If M does not halt on input w , then there does not exist a T such that f , on prompt w , outputs either ACC or REJ.*

Key Idea 1

Use intermediate steps to simulate steps of Turing machine



Key Idea 2

How can a transformer, which has no memory, simulate a Turing machine's head?

Key Idea 2

How can a transformer, which has no memory, simulate a Turing machine's head?

Answer: Sum all the previous moves

previous move $m^{(i-1)}$	+1	+1	-1	-1	+1
current position $h^{(i)}$	1	2	1	0	1

Key Idea 3

How can a transformer, which has no memory, simulate a Turing machine's tape?

Key Idea 3

How can a transformer, which has no memory, simulate a Turing machine's tape?

Answer: Look at the most recent time the head was at current position $h^{(i)}$

- If none, the current symbol is the $h^{(i)}$ -th input symbol
- If time j , the current symbol is what was written at time j

Input: 11 $\sqcup$ $\cdots$

previous position $h^{(i-1)}$	0	1	2	1	0
previous write $b^{(i-1)}$	$\sqcup$	x	$\sqcup$	x	$\sqcup$
current position $h^{(i)}$	1	2	1	0	1
current symbol $a^{(i)}$	1	$\sqcup$	x	$\sqcup$	x

Position Embeddings

Position Embeddings

Adding a few simple elements to the position embeddings enables a very useful set of tricks [Barceló et al., 2024]:

$$\text{PE}(i) = \begin{bmatrix} 1/(i+1) \\ 1 \\ i \\ i^2 \end{bmatrix}.$$

Forward Lookup

Assume that we have computed, for $i \in [n]$,

$$f(i) \in [n]$$

$$g(i) \in \mathbb{R}$$

Forward lookup: Compute $g(f(i))$ for $i \in [n]$

i	0	1	2	3	4
$f(i)$	0	1	1	2	3
$g(i)$	0	1	4	9	16
$g(f(i))$	0	1	1	4	9

Forward Lookup

Assume that we have computed, for $i \in [n]$,

$$f(i) \in [n]$$

$$g(i) \in \mathbb{R}$$

Forward lookup: Compute $g(f(i))$ for $i \in [n]$

$$\text{query}_i = \begin{bmatrix} f(i) \\ 1 \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2j \\ -j^2 \end{bmatrix} \quad \text{value}_j = [g(j)]$$

Exercise: Compute $\text{score}_{ij} = \text{query}_i \cdot \text{key}_j$ and maximize with respect to j .

Forward Lookup

Assume that we have computed, for $i \in [n]$,

$$f(i) \in [n]$$

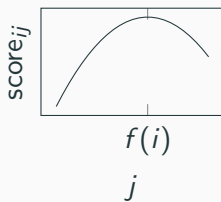
$$g(i) \in \mathbb{R}$$

Forward lookup: Compute $g(f(i))$ for $i \in [n]$

$$\text{query}_i = \begin{bmatrix} f(i) \\ 1 \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2j \\ -j^2 \end{bmatrix} \quad \text{value}_j = [g(j)]$$

$$\begin{aligned} \text{score}_{ij} &= \text{query}_i \cdot \text{key}_j \\ &= -j^2 + 2f(i)j \end{aligned}$$

$$\underset{j}{\operatorname{argmax}} \text{score}_{ij} = f(i).$$



Backward Lookup

Assume that we have computed, for $i \in [n]$,

$$f(i) \in \mathbb{R}$$

$$g(i) \in \mathbb{R}$$

Backward lookup: compute $g^{-1}(f(i))$ for $i \in [n]$. That is, find j such that $g(j) = f(i)$.

i	0	1	2	3	4
$f(i)$	0	1	1	4	9
$g(i)$	0	1	4	9	16
$g^{-1}(f(i))$	0	1	1	2	3

Backward Lookup

Assume that we have computed, for $i \in [n]$,

$$f(i) \in \mathbb{R}$$

$$g(i) \in \mathbb{R}$$

Backward lookup: compute $g^{-1}(f(i))$ for $i \in [n]$. That is, find j such that $g(j) = f(i)$.

$$\text{query}_i = \begin{bmatrix} f(i) \\ 1 \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2g(j) \\ -g(j)^2 \end{bmatrix} \quad \text{value}_j = [j]$$

$$\begin{aligned} \text{score}_{ij} &= \text{query}_i \cdot \text{key}_j \\ &= -g(j)^2 + 2f(i)g(j) \end{aligned}$$

$$\underset{j}{\operatorname{argmax}} \text{score}_{ij} = g^{-1}(f(i)).$$

Backward Lookup

Assume that we have computed, for $i \in [n]$,

$$f(i) \in \mathbb{R}$$

$$g(i) \in \mathbb{R}$$

Backward lookup: compute $g^{-1}(f(i))$ for $i \in [n]$. That is, find j such that $g(j) = f(i)$.

$$\text{query}_i = \begin{bmatrix} f(i) \\ 1 \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2g(j) \\ -g(j)^2 \end{bmatrix} \quad \text{value}_j = [j]$$


forward lookup

$$\begin{aligned} \text{score}_{ij} &= \text{query}_i \cdot \text{key}_j \\ &= -g(j)^2 + 2f(i)g(j) \end{aligned}$$

$$\underset{j}{\operatorname{argmax}} \text{score}_{ij} = g^{-1}(f(i)).$$

Multiplication and Division

Assume that we have computed, for $i \in [n]$,

$$f(i) \in \mathbb{R}$$

$$g(i) \in \mathbb{R}$$

and we want to compute $f(i)/g(i) \in [n]$.

i	0	1	2	3	4
$f(i)$	1	$\frac{1}{2}$	$\frac{1}{3}$	$\frac{3}{4}$	$\frac{2}{5}$
$g(i)$	1	$\frac{1}{2}$	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{5}$
$g(f(i))$	1	1	1	3	2

Multiplication and Division

Assume that we have computed, for $i \in [n]$,

$$f(i) \in \mathbb{R}$$

$$g(i) \in \mathbb{R}$$

and we want to compute $f(i)/g(i) \in [n]$.

$$\text{query}_i = \begin{bmatrix} f(i) \\ g(i) \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2j \\ -j^2 \end{bmatrix} \quad \text{value}_j = [j]$$

$$\begin{aligned} \text{score}_{ij} &= \text{query}_i \cdot \text{key}_j \\ &= -g(i)j^2 + 2f(i)j \end{aligned}$$

$$\underset{j}{\operatorname{argmax}} \text{score}_{ij} = f(i)/g(i).$$

Exercise: How would you compute $f(i)/g(i)$?

Simulating Turing Machines: In More Detail

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$	
0	$\hat{\sqcup} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1	wait
1	$\hat{\sqcup} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1	
2	$\hat{\sqcup} \sqcup \dots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$	
3	$\hat{\sqcup} \sqcup \dots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, \sqcup, +1)$	
4	$\sqcup \hat{\sqcup} \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	1	$(q_3, x, +1)$	
5	$\sqcup x \hat{\sqcup} \dots$	$(q_3, x, +1)$	q_3	x	+1	2	$\sqcup$	$(q_5, \sqcup, -1)$	
6	$\sqcup x \hat{\sqcup} \dots$	$(q_5, \sqcup, -1)$	q_5	$\sqcup$	-1	1	x	$(q_5, x, -1)$	
7	$\sqcup x \hat{\sqcup} \dots$	$(q_5, x, -1)$	q_5	x	-1	0	$\sqcup$	$(q_2, \sqcup, +1)$	
8	$\sqcup x \hat{\sqcup} \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	x	ACC	

Transformer reads in input string, simulated TM does nothing

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$	
0	$\hat{_}1_ \dots$	1	$\perp$	$\perp$	0	0	1	1	
1	$\hat{_}1_ \dots$	1	$\perp$	$\perp$	0	0	1	1	
2	$\hat{_}1_ \dots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$	init
3	$\hat{_}1_ \dots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, _, +1)$	
4	$_ \hat{_}1_ \dots$	$(q_2, _, +1)$	q_2	$_$	+1	1	1	$(q_3, x, +1)$	
5	$_ x \hat{_} \dots$	$(q_3, x, +1)$	q_3	x	+1	2	$_$	$(q_5, _, -1)$	
6	$_ x \hat{_} \dots$	$(q_5, _, -1)$	q_5	$_$	-1	1	x	$(q_5, x, -1)$	
7	$_ x \hat{_} \dots$	$(q_5, x, -1)$	q_5	x	-1	0	$_$	$(q_2, _, +1)$	
8	$_ x \hat{_} \dots$	$(q_2, _, +1)$	q_2	$_$	+1	1	x	ACC	

Transformer outputs fake action, simulated TM enters start state

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$
0	$\hat{\sqcup} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1
1	$\hat{\sqcup} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1
2	$\hat{\sqcup} \sqcup \dots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$
3	$\hat{\sqcup} \sqcup \dots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, \sqcup, +1)$
4	$\sqcup \hat{\sqcup} \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	1	$(q_3, x, +1)$
5	$\sqcup x \hat{\sqcup} \dots$	$(q_3, x, +1)$	q_3	x	+1	2	$\sqcup$	$(q_5, \sqcup, -1)$
6	$\sqcup \hat{x} \sqcup \dots$	$(q_5, \sqcup, -1)$	q_5	$\sqcup$	-1	1	x	$(q_5, x, -1)$
7	$\sqcup \hat{x} \sqcup \dots$	$(q_5, x, -1)$	q_5	x	-1	0	$\sqcup$	$(q_2, \sqcup, +1)$
8	$\sqcup \hat{x} \sqcup \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	x	ACC

run

Transformer outputs the actions of the simulated TM one by one

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$
0	$\hat{1} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1
1	$\hat{1} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1
2	$\hat{1} \sqcup \dots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$
3	$\hat{1} \sqcup \dots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, \sqcup, +1)$
4	$\sqcup \hat{1} \sqcup \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	1	$(q_3, x, +1)$
5	$\sqcup x \hat{\sqcup} \dots$	$(q_3, x, +1)$	q_3	x	+1	2	$\sqcup$	$(q_5, \sqcup, -1)$
6	$\sqcup x \hat{\sqcup} \dots$	$(q_5, \sqcup, -1)$	q_5	$\sqcup$	-1	1	x	$(q_5, x, -1)$
7	$\sqcup x \hat{\sqcup} \dots$	$(q_5, x, -1)$	q_5	x	-1	0	$\sqcup$	$(q_2, \sqcup, +1)$
8	$\sqcup x \hat{\sqcup} \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	x	ACC

input

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$
0	$\hat{\perp}\perp\cdots$	1	$\perp$	$\perp$	0	0	1	1
1	$\hat{\perp}\perp\cdots$	1	$\perp$	$\perp$	0	0	1	1
2	$\hat{\perp}\perp\cdots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$
3	$\hat{\perp}\perp\cdots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, \perp, +1)$
4	$\perp\hat{\perp}\cdots$	$(q_2, \perp, +1)$	q_2	$\perp$	+1	1	1	$(q_3, x, +1)$
5	$\perp x\hat{\perp}\cdots$	$(q_3, x, +1)$	q_3	x	+1	2	$\perp$	$(q_5, \perp, -1)$
6	$\perp x\hat{\perp}\cdots$	$(q_5, \perp, -1)$	q_5	$\perp$	-1	1	x	$(q_5, x, -1)$
7	$\perp x\hat{\perp}\cdots$	$(q_5, x, -1)$	q_5	x	-1	0	$\perp$	$(q_2, \perp, +1)$
8	$\perp x\hat{\perp}\cdots$	$(q_2, \perp, +1)$	q_2	$\perp$	+1	1	x	ACC

step 1

Unpack previous action into state (q), write (b), and move (m)

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$
0	$\hat{_}11_ \dots$	1	$\perp$	$\perp$	0	0	1	1
1	$\hat{_}11_ \dots$	1	$\perp$	$\perp$	0	0	1	1
2	$\hat{_}11_ \dots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$
3	$\hat{_}11_ \dots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, _, +1)$
4	$_ \hat{_}1_ \dots$	$(q_2, _, +1)$	q_2	$_$	+1	1	1	$(q_3, x, +1)$
5	$_ x _ \hat{_} \dots$	$(q_3, x, +1)$	q_3	x	+1	2	$_$	$(q_5, _, -1)$
6	$_ x _ \hat{_} \dots$	$(q_5, _, -1)$	q_5	$_$	-1	1	x	$(q_5, x, -1)$
7	$_ x _ \hat{_} \dots$	$(q_5, x, -1)$	q_5	x	-1	0	$_$	$(q_2, _, +1)$
8	$_ x _ \hat{_} \dots$	$(q_2, _, +1)$	q_2	$_$	+1	1	x	ACC

step 2

Compute head position (h) by summing previous moves

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$
0	$\hat{\sqcup} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1
1	$\hat{\sqcup} \sqcup \dots$	1	$\perp$	$\perp$	0	0	1	1
2	$\hat{\sqcup} \sqcup \dots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$
3	$\hat{\sqcup} \sqcup \dots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, \sqcup, +1)$
4	$\sqcup \hat{\sqcup} \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	1	$(q_3, x, +1)$
5	$\sqcup x \hat{\sqcup} \dots$	$(q_3, x, +1)$	q_3	x	+1	2	$\sqcup$	$(q_5, \sqcup, -1)$
6	$\sqcup x \hat{\sqcup} \dots$	$(q_5, \sqcup, -1)$	q_5	$\sqcup$	-1	1	x	$(q_5, x, -1)$
7	$\sqcup x \hat{\sqcup} \dots$	$(q_5, x, -1)$	q_5	x	-1	0	$\sqcup$	$(q_2, \sqcup, +1)$
8	$\sqcup x \hat{\sqcup} \dots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	x	ACC

step 3

Compute current tape symbol (a)

Detailed Overview

i	tape	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$	$h^{(i)}$	$a^{(i)}$	$y^{(i)}$
0	$\hat{1}1\sqcup\cdots$	1	$\perp$	$\perp$	0	0	1	1
1	$\hat{1}1\sqcup\cdots$	1	$\perp$	$\perp$	0	0	1	1
2	$\hat{1}1\sqcup\cdots$	BOS	$\perp$	$\perp$	0	0	1	$(q_1, 1, 0)$
3	$\hat{1}1\sqcup\cdots$	$(q_1, 1, 0)$	q_1	1	0	0	1	$(q_2, \sqcup, +1)$
4	$\sqcup\hat{1}\sqcup\cdots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	1	$(q_3, x, +1)$
5	$\sqcup x\hat{\sqcup}\cdots$	$(q_3, x, +1)$	q_3	x	+1	2	$\sqcup$	$(q_5, \sqcup, -1)$
6	$\sqcup x\hat{\sqcup}\cdots$	$(q_5, \sqcup, -1)$	q_5	$\sqcup$	-1	1	x	$(q_5, x, -1)$
7	$\sqcup x\hat{\sqcup}\cdots$	$(q_5, x, -1)$	q_5	x	-1	0	$\sqcup$	$(q_2, \sqcup, +1)$
8	$\sqcup x\hat{\sqcup}\cdots$	$(q_2, \sqcup, +1)$	q_2	$\sqcup$	+1	1	x	ACC

step 4

Output next action

Step 1: Unpack Input Symbol

...into current state, previously written symbol, and previous move.

phase	$x^{(i)}$	$q^{(i)}$	$b^{(i-1)}$	$m^{(i-1)}$
wait	$\in \Sigma$	$\perp$	$\perp$	0
init	BOS	$\perp$	$\perp$	0
run	(r, b, m)	r	b	m

Use a FFN to compute the function

$$x^{(i)} \mapsto \begin{bmatrix} q^{(i)} \\ b^{(i-1)} \\ m^{(i-1)} \end{bmatrix}$$

Step 2a: Compute Head Position

The current head position is just the sum of all previous moves:

$$h^{(i)} = \sum_{j=0}^i m^{(j-1)}$$

Using uniform self-attention, we can compute

$$h^{(i)} / (i + 1) = \frac{1}{i + 1} \sum_{j=0}^i m^{(j-1)}$$

Question: How do we get rid of the $\cdot / (i + 1)$?

Step 3: Compute Tape Symbol

Find most recent $j < i$ such that $h^{(j)} = h^{(i)}$ and return $b^{(j)}$;
if none, return $x^{h^{(i)}}$.

Step 3: Compute Tape Symbol

Find most recent $j < i$ such that $h^{(j)} = h^{(i)}$ and return $b^{(j)}$;
if none, return $x^{h^{(i)}}$.

We can't do this because we only have non-strict masking ($j \leq i$).

Step 3: Compute Tape Symbol

~~Find most recent $j < i$ such that $h^{(j)} = h^{(i)}$ and return $b^{(j)}$;
if none, return $x^{h^{(i)}}$.~~

Find most recent $j \leq i$ such that $h^{(j-1)} = h^{(i)}$ and return $b^{(j-1)}$;
if none, return $x^{h^{(i)}}$.

This is a reverse table lookup of $h^{(i)}$ in $j \mapsto h^{(j-1)}$. But finding the *most recent* will require some extra care.

Step 3b: Compute Tape Symbol

Find most recent $j \leq i$ such that $h^{(j-1)} = h^{(i)}$ and return $b^{(j-1)}$; if none, return $x^{h^{(i)}}$.

Reverse table lookup with tie-breaking:

$$\text{query}_i = \begin{bmatrix} h^{(i)} \\ 1 \\ \frac{1}{2(i+1)} \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2h^{(j-1)} \\ -(h^{(j-1)})^2 \\ j \end{bmatrix} \quad \text{value}_j = \begin{bmatrix} h^{(j-1)} \\ b^{(j-1)} \end{bmatrix}$$

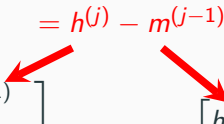
Attention scores are:

$$\text{score}_{i,j} = \underbrace{-(h^{(j-1)})^2 + 2h^{(i)}h^{(j-1)}}_{\text{find } h^{(j-1)} = h^{(i)}} + \underbrace{\frac{j}{2(i+1)}}_{\text{find rightmost}}$$

Step 3b: Compute Tape Symbol

Find most recent $j \leq i$ such that $h^{(j-1)} = h^{(i)}$ and return $b^{(j-1)}$; if none, return $x^{h^{(i)}}$.

Reverse table lookup with tie-breaking: $= h^{(j)} - m^{(j-1)}$

$$\text{query}_i = \begin{bmatrix} h^{(i)} \\ 1 \\ \frac{1}{2(i+1)} \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2h^{(j-1)} \\ -(h^{(j-1)})^2 \\ j \end{bmatrix} \quad \text{value}_j = \begin{bmatrix} h^{(j-1)} \\ b^{(j-1)} \end{bmatrix}$$


Attention scores are:

$$\text{score}_{i,j} = \underbrace{-(h^{(j-1)})^2 + 2h^{(i)}h^{(j-1)}}_{\text{find } h^{(j-1)} = h^{(i)}} + \underbrace{\frac{j}{2(i+1)}}_{\text{find rightmost}}$$

Step 3b: Compute Tape Symbol

Find most recent $j \leq i$ such that $h^{(j-1)} = h^{(i)}$ and return $b^{(j-1)}$; if none, return $x^{h^{(i)}}$.

Reverse table lookup with tie-breaking: $= h^{(j)} - m^{(j-1)}$

$$\text{query}_i = \begin{bmatrix} h^{(i)} \\ 1 \\ \frac{1}{2(i+1)} \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2h^{(j-1)} \\ -(h^{(j-1)})^2 \\ j \end{bmatrix} \quad \text{value}_j = \begin{bmatrix} h^{(j-1)} \\ b^{(j-1)} \end{bmatrix}$$

forward lookup

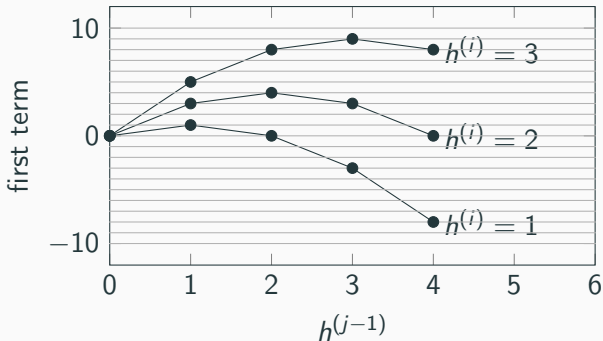
Attention scores are:

$$\text{score}_{i,j} = \underbrace{-(h^{(j-1)})^2 + 2h^{(i)}h^{(j-1)}}_{\text{find } h^{(j-1)} = h^{(i)}} + \underbrace{\frac{j}{2(i+1)}}_{\text{find rightmost}}$$

Step 3b: Compute Tape Symbol

$$\text{score}_{i,j} = \underbrace{-(h^{(j-1)})^2 + 2h^{(i)}h^{(j-1)}}_{\text{find } h^{(j-1)} = h^{(i)}} + \underbrace{\frac{j}{2(i+1)}}_{\text{find rightmost}}$$

In first term, difference between best and second-best score is 1:



So we make the second term $\frac{j}{2(i+1)} \leq \frac{1}{2} < 1$.

Step 3b: Compute Tape Symbol

Find most recent $j \leq i$ such that $h^{(j-1)} = h^{(i)}$ and return $b^{(j-1)}$; if none, return $x^{h^{(j-1)}}$.

$$\text{query}_i = \begin{bmatrix} h^{(i)} \\ 1 \\ \frac{1}{2(i+1)} \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2h^{(j-1)} \\ -(h^{(j-1)})^2 \\ j \end{bmatrix} \quad \text{value}_j = \begin{bmatrix} h^{(j-1)} \\ b^{(j-1)} \end{bmatrix}$$

Attention scores are:

$$\text{score}_{i,j} = \underbrace{-(h^{(j-1)})^2 + 2h^{(i)}h^{(j-1)}}_{\text{find } h^{(j-1)} = h^{(i)}} + \underbrace{\frac{j}{2(i+1)}}_{\text{find rightmost}}$$

FFN:

$$\begin{aligned} \text{if } h^{(j-1)} = h^{(i)} \text{ and } b^{(j-1)} \neq \perp &\rightsquigarrow a^{(i)} := b^{(j-1)} \\ \text{else} &\rightsquigarrow a^{(i)} := x^{(h^{(i)})} \end{aligned}$$

Step 3b: Compute Tape Symbol

Find most recent $j \leq i$ such that $h^{(j-1)} = h^{(i)}$ and return $b^{(j-1)}$; if none, return $x^{h^{(j-1)}}$.

$$\text{query}_i = \begin{bmatrix} h^{(i)} \\ 1 \\ \frac{1}{2(i+1)} \end{bmatrix} \quad \text{key}_j = \begin{bmatrix} 2h^{(j-1)} \\ -(h^{(j-1)})^2 \\ j \end{bmatrix} \quad \text{value}_j = \begin{bmatrix} h^{(j-1)} \\ b^{(j-1)} \end{bmatrix}$$

Attention scores are:

$$\text{score}_{i,j} = \underbrace{-(h^{(j-1)})^2 + 2h^{(i)}h^{(j-1)}}_{\text{find } h^{(j-1)} = h^{(i)}} + \underbrace{\frac{j}{2(i+1)}}_{\text{find rightmost}}$$

FFN:

$$\begin{aligned} \text{if } h^{(j-1)} = h^{(i)} \text{ and } b^{(j-1)} \neq \perp &\rightsquigarrow a^{(i)} := b^{(j-1)} \\ \text{else} &\rightsquigarrow a^{(i)} := x^{h^{(i)}} \end{aligned}$$

forward lookup

Step 4: Compute Transition

Given $x^{(i)}$ = current input symbol and $a^{(i)}$ = current tape symbol:

if $x^{(i)} \in \Sigma \rightsquigarrow$ output $x^{(i)}$

if $x^{(i)} = \text{BOS} \rightsquigarrow$ let $(r, b, m) = (q_{\text{start}}, a^{(i)}, 0)$

else $\rightsquigarrow$ let $(r, b, m) = \delta(q^{(i)}, a^{(i)})$

if $r = q_{\text{accept}} \rightsquigarrow$ output ACC

if $r = q_{\text{reject}} \rightsquigarrow$ output REJ

else $\rightsquigarrow$ output (r, b, m)

Recap

- Transformer decoders generate strings; they may be allowed to generate *intermediate steps* (a.k.a. chain of thought).
- A transformer decoder can simulate a Turing machine by generating the steps of the Turing machine as intermediate steps. But not if the answer is required immediately.
- Even though it has no memory, a transformer can use attention to reconstruct what it needs to know about the Turing machine configuration.

- Pablo Barceló, Alexander Kozachinskiy, Anthony Widjaja Lin, and Vladimir Podolskii. Logical languages accepted by transformer encoders with hard attention. In *Proceedings of the Twelfth International Conference on Learning Representations (ICLR)*, 2024. URL <https://openreview.net/forum?id=gbrHZq07mq>.
- Jorge Pérez, Pablo Barceló, and Javier Marinkovic. Attention is Turing-complete. *Journal of Machine Learning Research*, 22:75:1–75:35, 2021. URL <http://jmlr.org/papers/v22/20-302.html>.
- Jorge Pérez, Javier Marinković, and Pablo Barceló. On the Turing completeness of modern neural network architectures. In *Proceedings of the Seventh International Conference on Learning Representations (ICLR)*, 2019. URL <https://openreview.net/forum?id=HyGBdo0qFm>.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In *Advances in Neural Information Processing Systems 35 (NeurIPS)*, pages 24824–24837, 2022. URL https://proceedings.neurips.cc/paper_files/paper/2022/hash/9d5609613524ecf4f15af0f7b31abca4-Abstract-Conference.html.



© 2024 by the authors (David Chiang, Jon Rawski, Lena Strobl, and Andy J Yang). All slides in this ESSLLI 2024 course series, including this one, are licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). You are free to share, adapt, and build upon this material for any purpose, even commercially, as long as you provide appropriate credit.