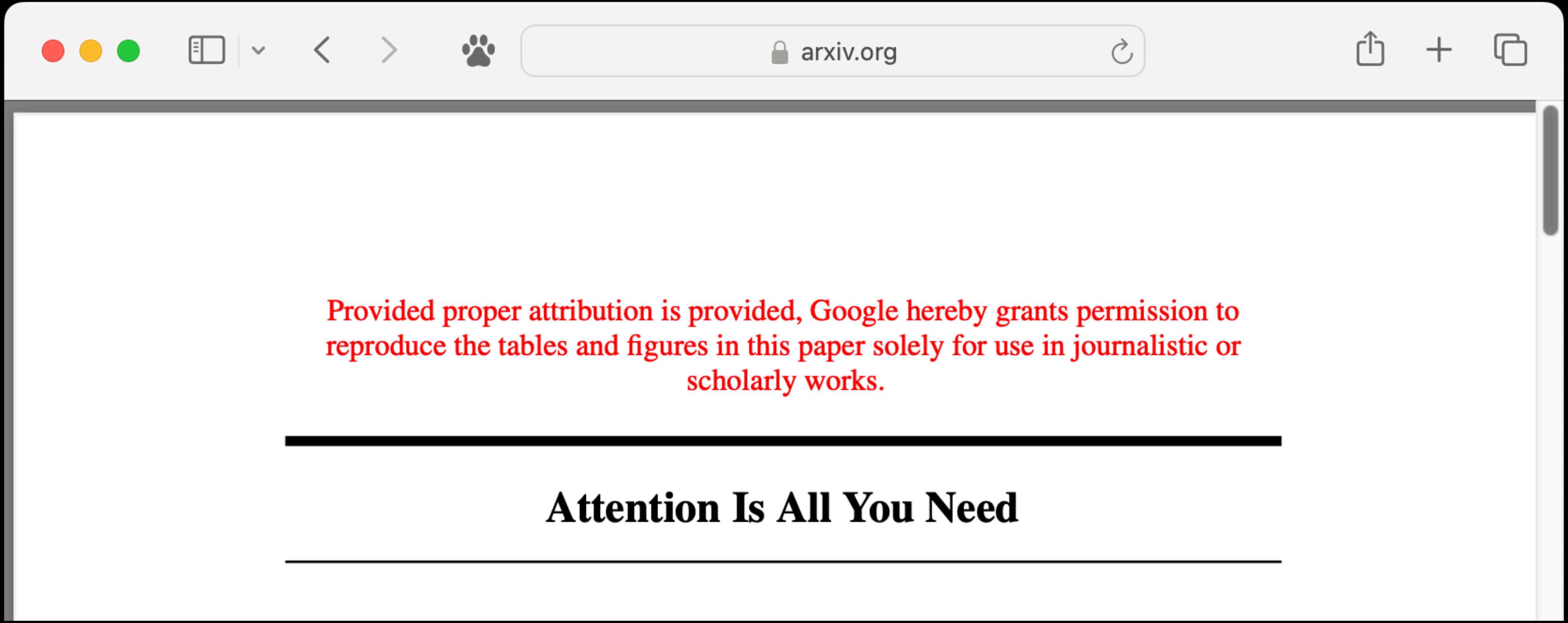
Transformers

a social history

NLU Lab, 3 April 2024

1. What a Transformer is
2. Why they are incredibly popular
3. Where they are used
4. Problems & Solutions

Whence the Transformer



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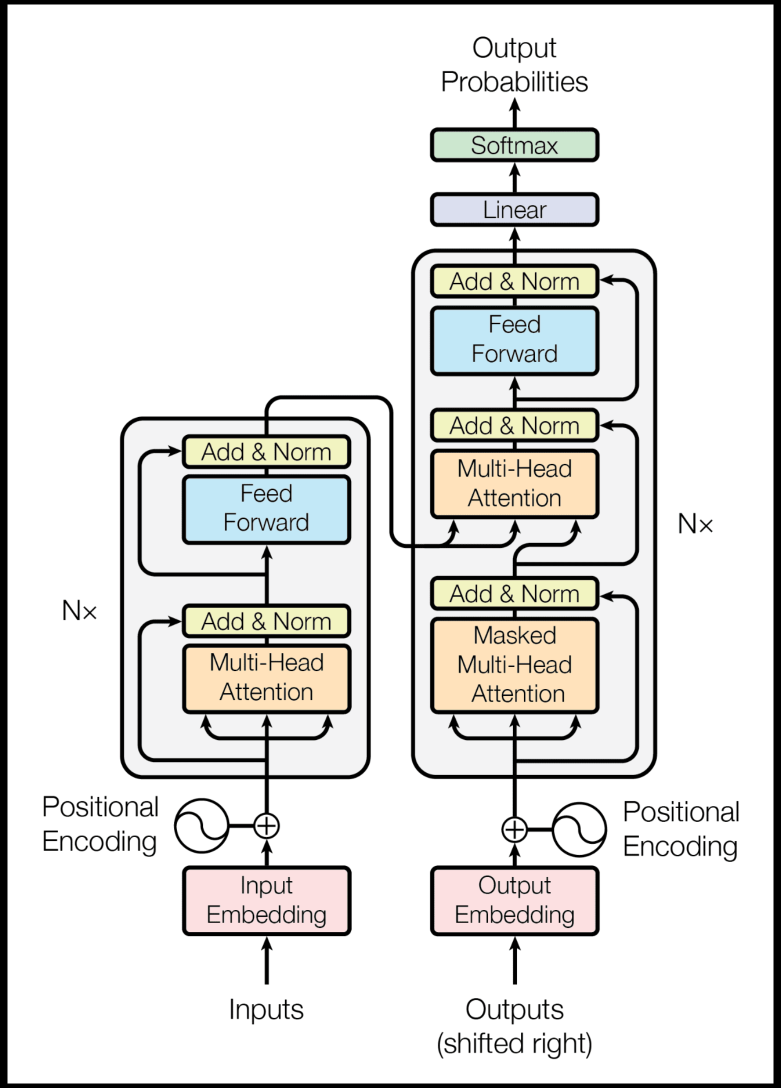
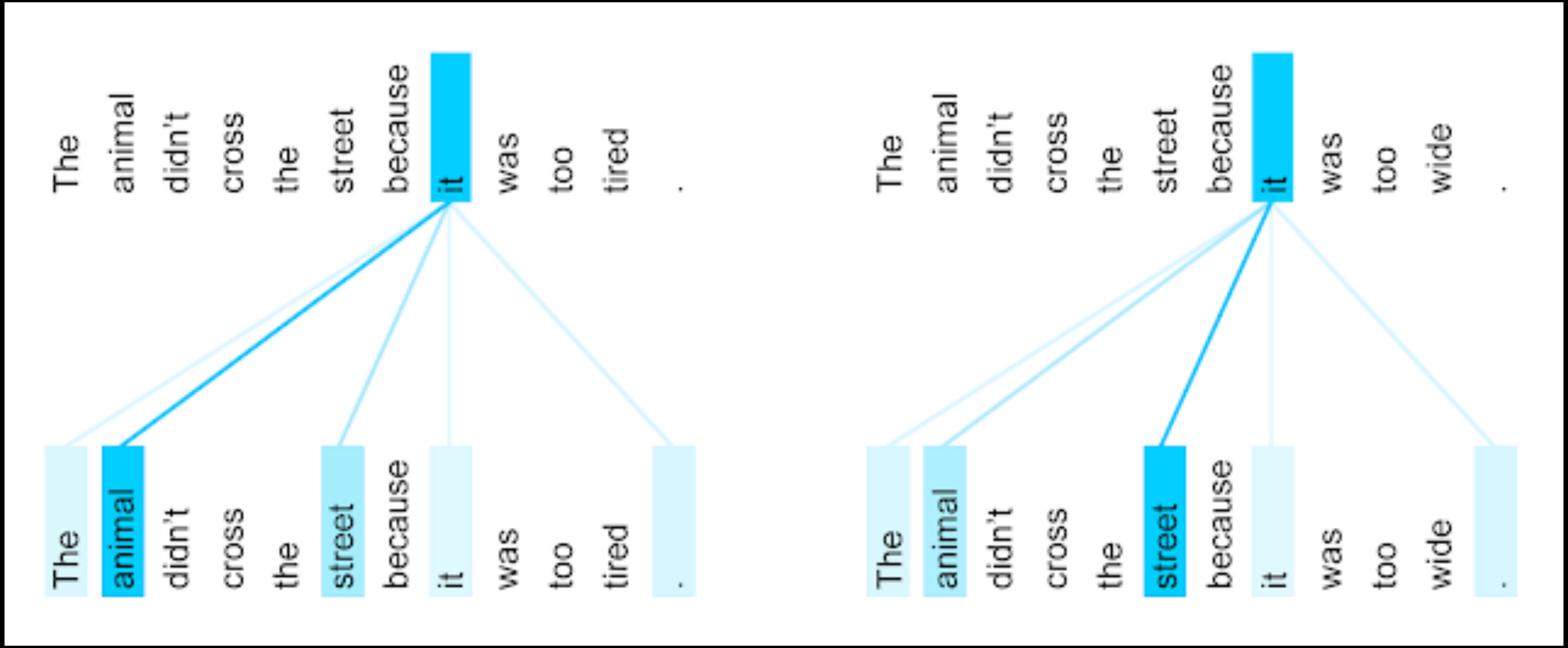
Attention Is All You Need

Transformer Architecture



Attention, visualized



The animal didn't cross the street because it was too tired .
The animal didn't cross the street because it was too tired .
The animal didn't cross the street because it was too wide .
The animal didn't cross the street because it was too wide .

Why were transformers so revolutionary?

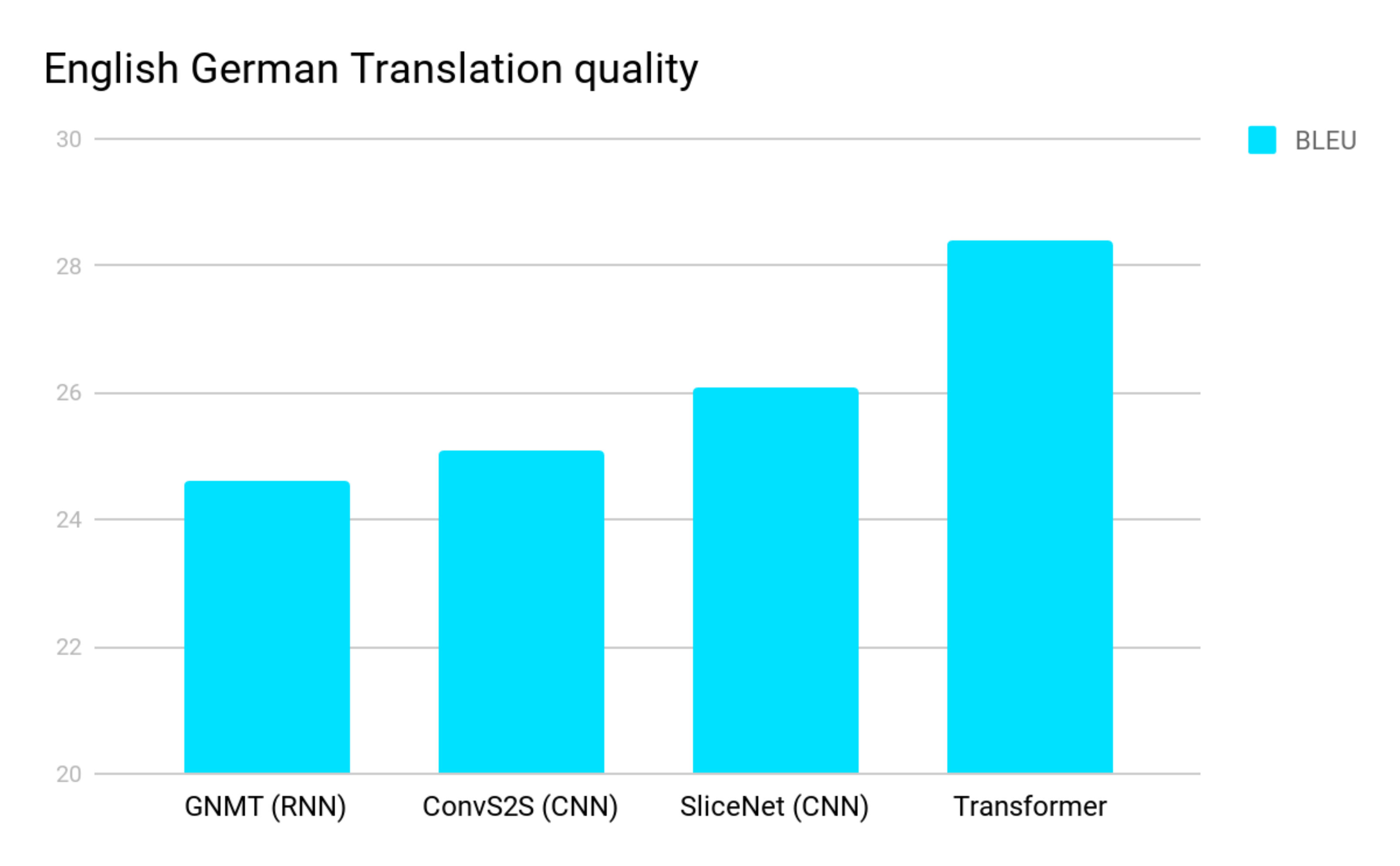
Parallel Training

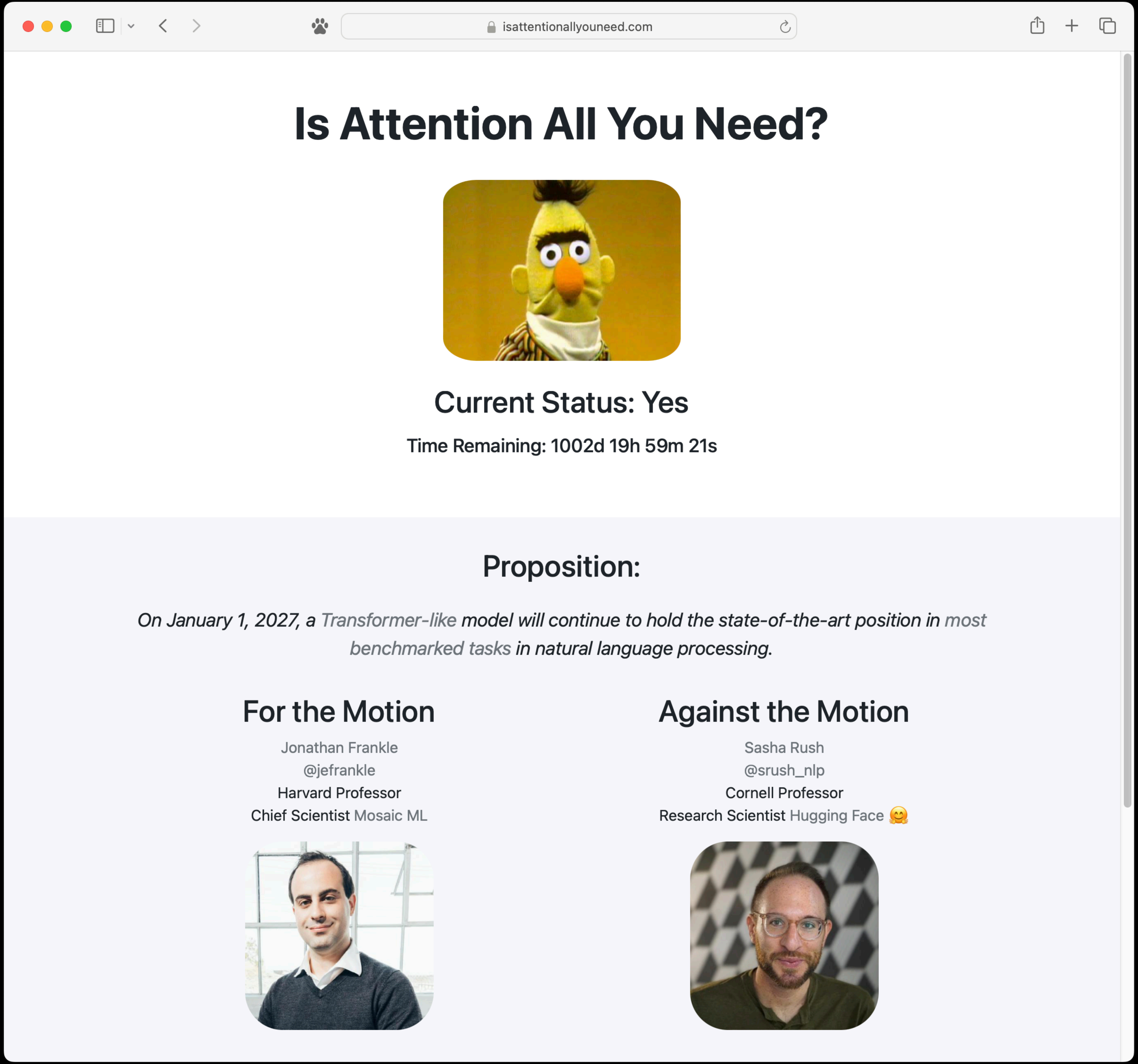
Recurrent Models have an inherent ... recurrence in their sequence dimension

→ training time is proportional to sequence length

Transformers: No recurrence = parallelism!

Performance!





Is Attention All You Need?

Current Status: Yes

Time Remaining: 1002d 19h 59m 21s

Proposition:

On January 1, 2027, a Transformer-like model will continue to hold the state-of-the-art position in most benchmarked tasks in natural language processing.

For the Motion

Jonathan Frankle
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Harvard Professor
Chief Scientist Mosaic ML

Against the Motion

Sasha Rush
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Cornell Professor
Research Scientist Hugging Face 🤗

Transformers: Where are they now?

Basically everywhere

GPT (ChatGPT) [Decoder-only]

Claude, Gemini (probably?)

BERT, Pythia, OLMo, T5 (Open source!)

Problems with Transformers

Inference Cost

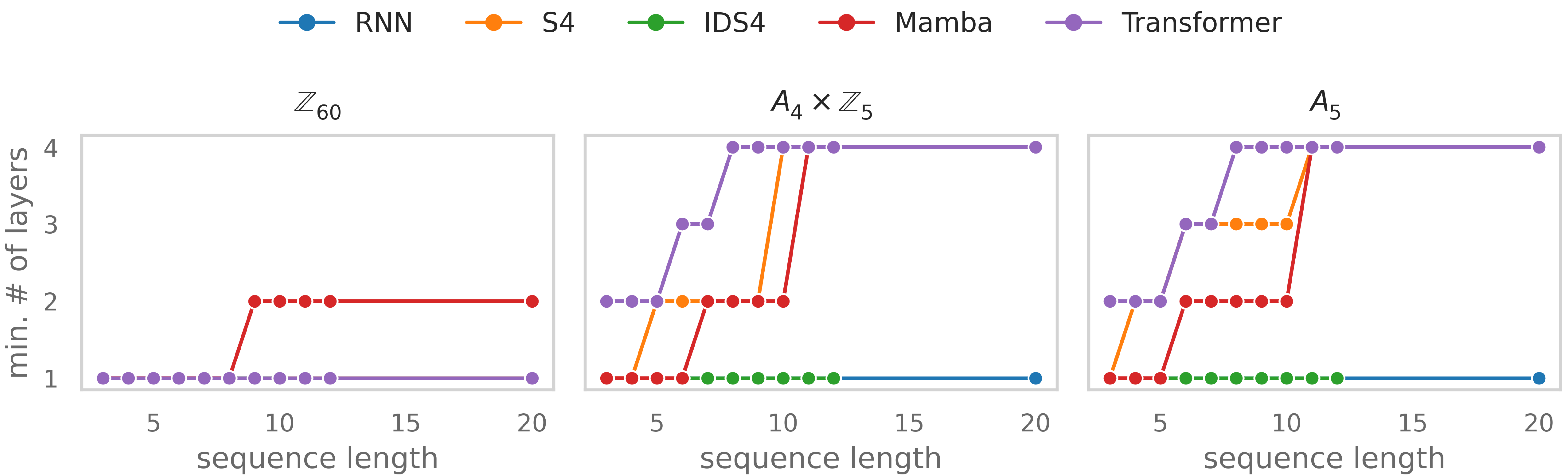
- Transformers are parallel @ training time, but autoregressive at inference
- Attention is expensive: Quadratic complexity in sequence length
- RNNs are actually better here!
- $$$ for long generations

Length Generalization

- Transformers don't have any inherent notion of sequential position
- Traditional positional encodings don't seem to yield good length generalizations
- Context lengths are getting quite long these days...

Representational Power

- Transformers are actually *weaker* than RNNs, in terms of what kind of functions they can learn to express

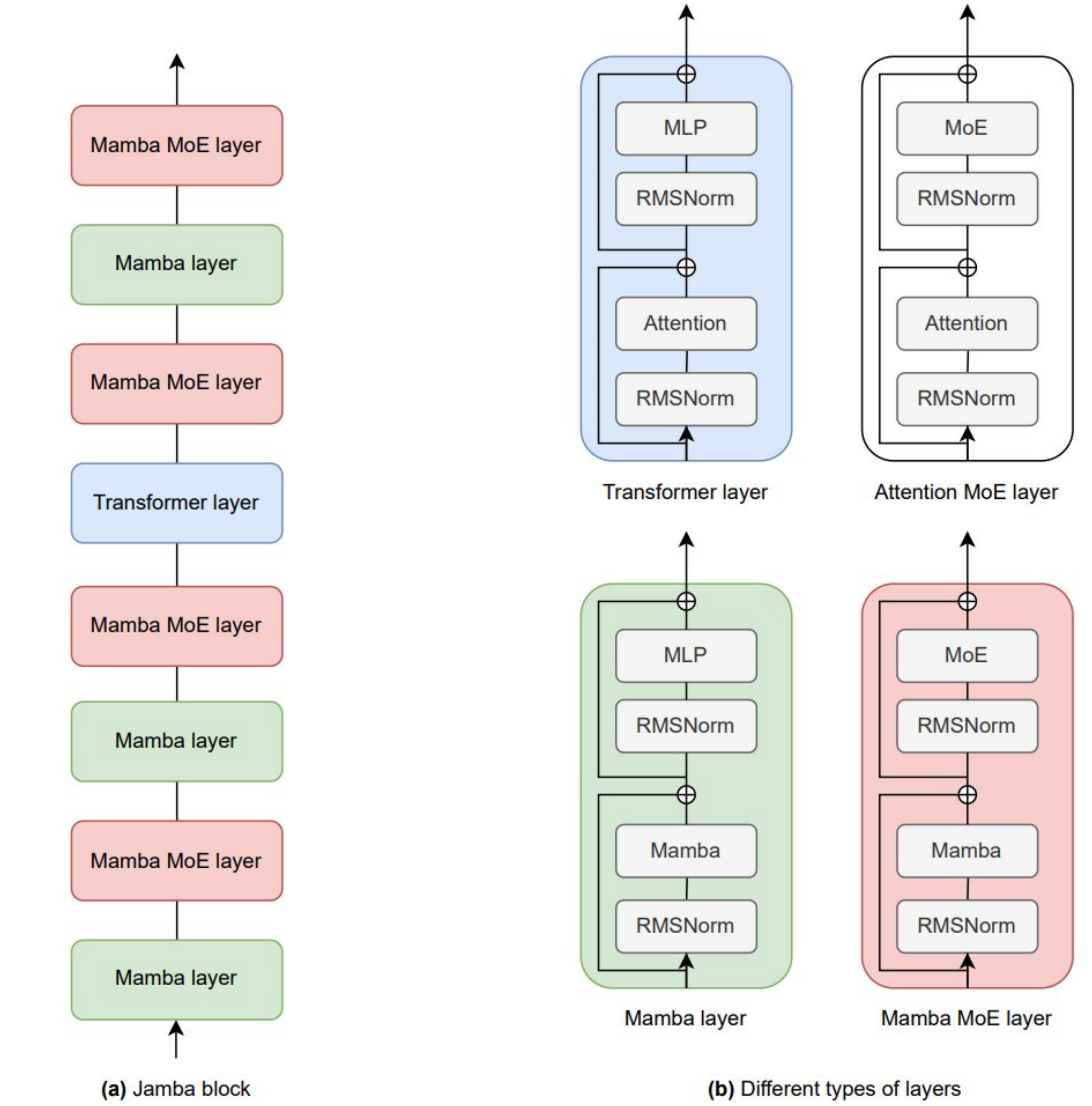

RNN
S4
IDS4
Mamba
Transformer
$\mathbb{Z}_{60}$
$A_4 \times \mathbb{Z}_5$
A_5
min. # of layers
1
2
3
4
5
10
15
20
sequence length

Solutions?

- Simplify attention mechanism to sub-quadratic complexity?
  - Sliding windows, approximations, etc
- New kinds of positional encodings
  - ROPE, Alibi
- New model architectures?
  - "Linear State Space models" ("parallelized RNNs" like Mamba), but see Merrill, Petty, Sabharwal (forthcoming)

Kitchen Sink Model? (Jamba, ~6 days old)

7:1 ratio of Mamba : Transformer layers



(a) Jamba block

(b) Different types of layers

Figure 1: **(a)** A single Jamba block. **(b)** Different types of layers. The implementation shown here is with $l = 8$, $a : m = 1 : 7$ ratio of attention-to-Mamba layers, and MoE applied every $e = 2$ layers.

DIRECTED BY

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