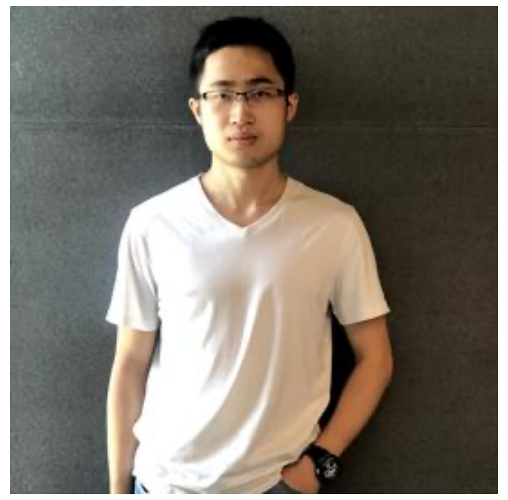
The Quest for
A Science of Language Models

AAAI 2025 Tutorial
February 26, 2025, 2:00pm-3:45pm
Pennsylvania Convention Center Room 113A, Philadelphia, PA, U.S.A.



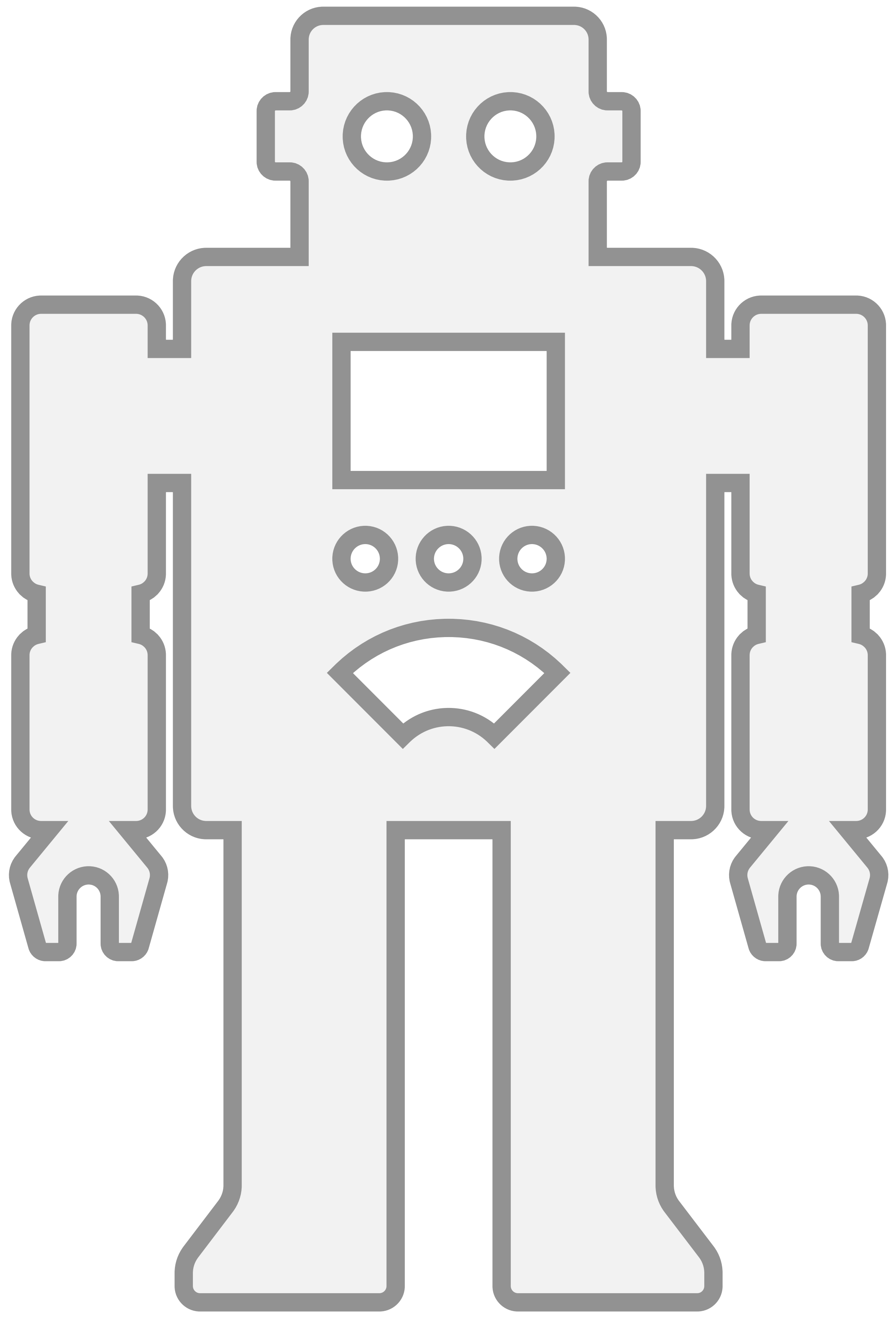

Tutorial Homepage: https://glaciohound.github.io/Science-of-LLMs-Tutorial/
Chi Han, Ph.D. Student @ UIUC, https://glaciohound.github.io/
Heng Ji, Professor @ UIUC, http://blender.cs.illinois.edu/hengji.html

UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

(LMs: abbreviation for “language models”)

We Increasingly Rely on LMs

yet we still do not fully understand them.



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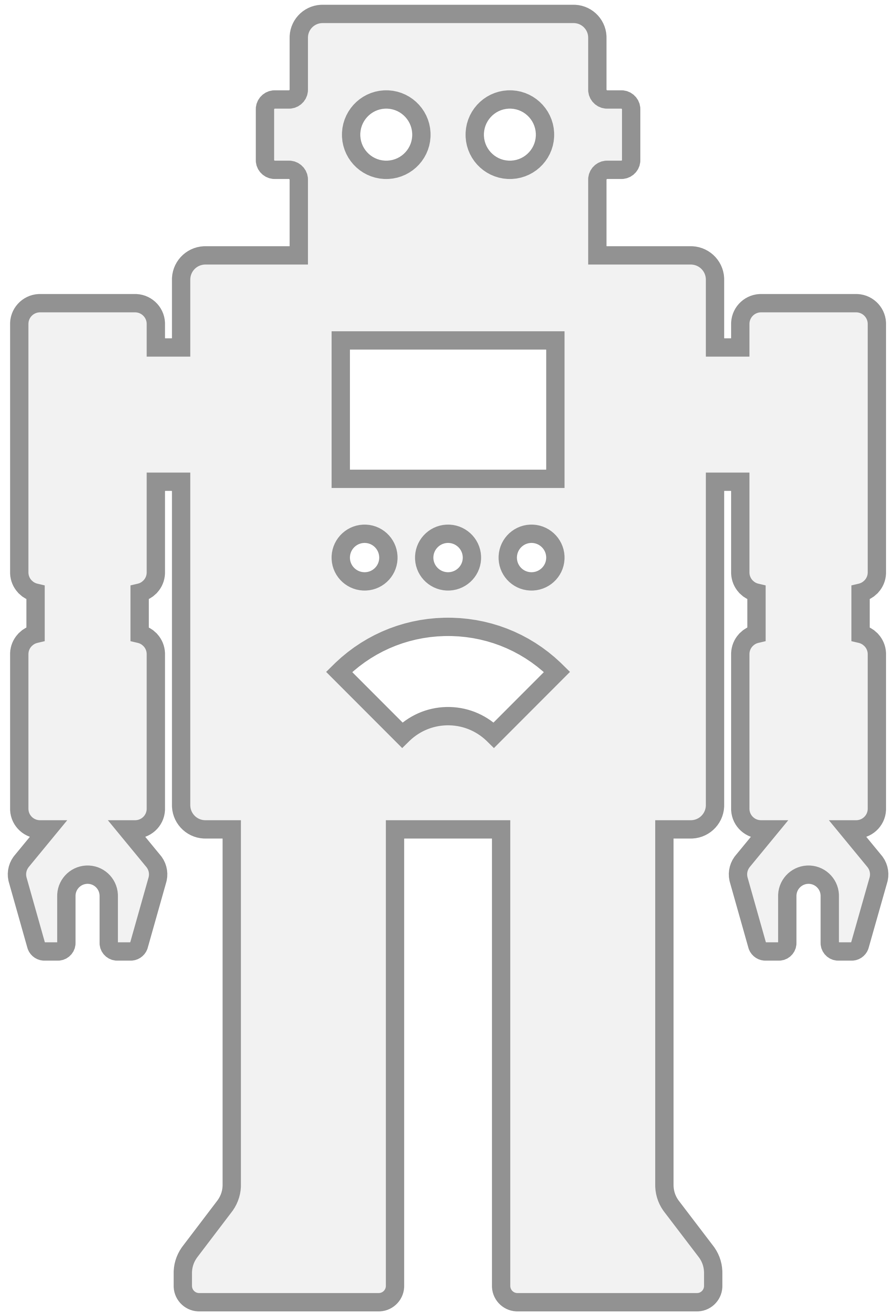

“Can you solve this problem for me? It is too hard for me”

(Are they intelligent enough to solve it, or do they pretend to be doing so?)

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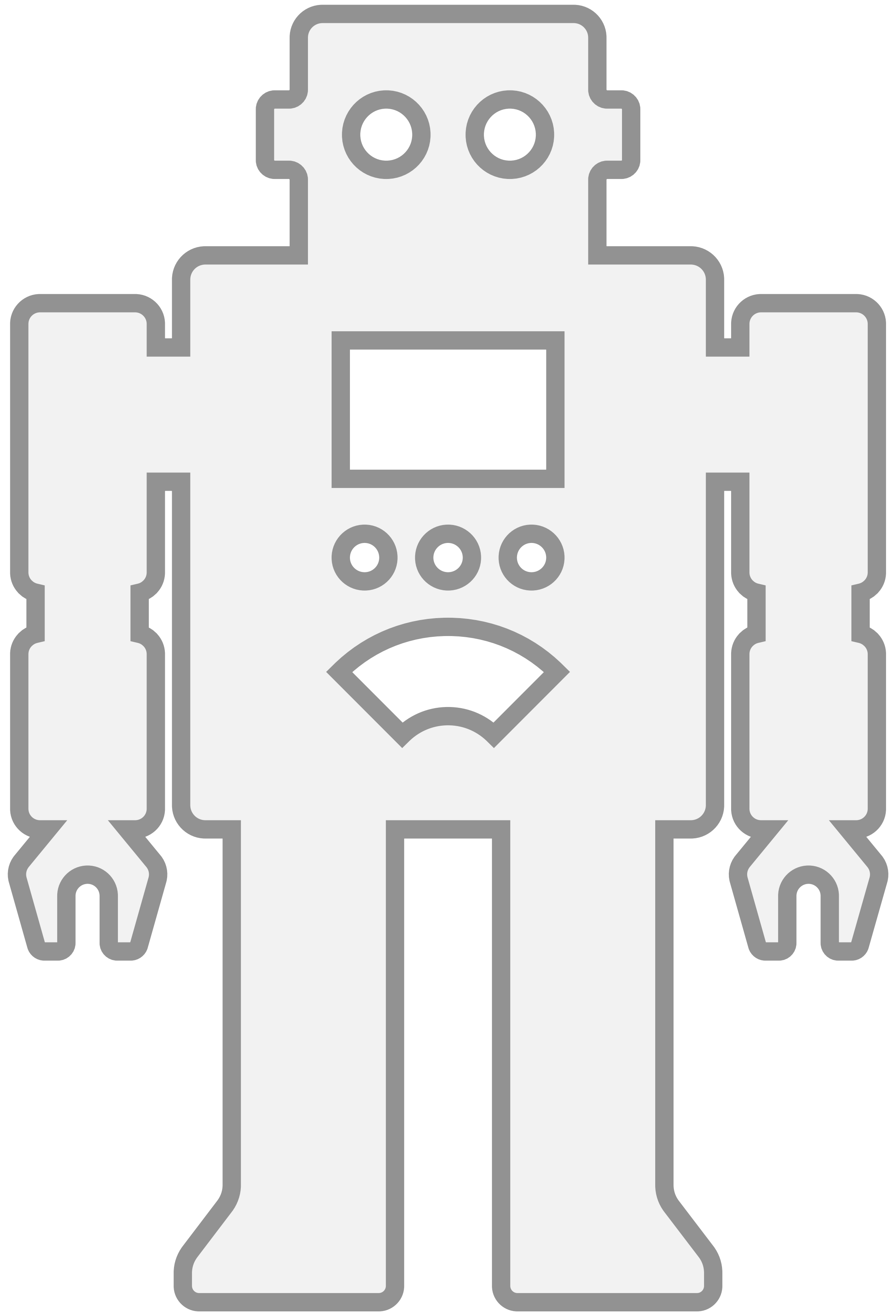

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“Could you tell me of all the kings who have ruled over Europe?”

(do they know all these knowledge, or are they sometimes guessing?)

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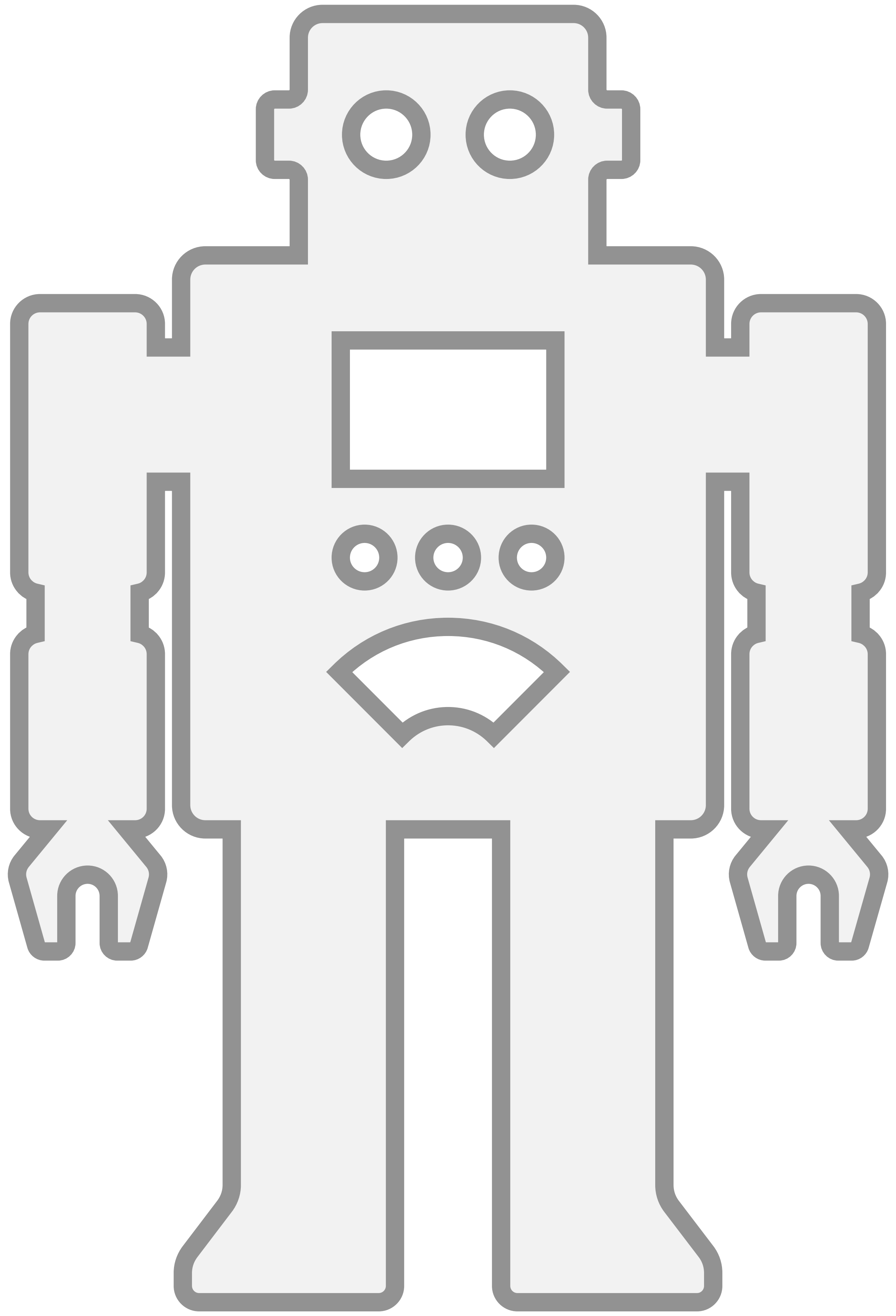

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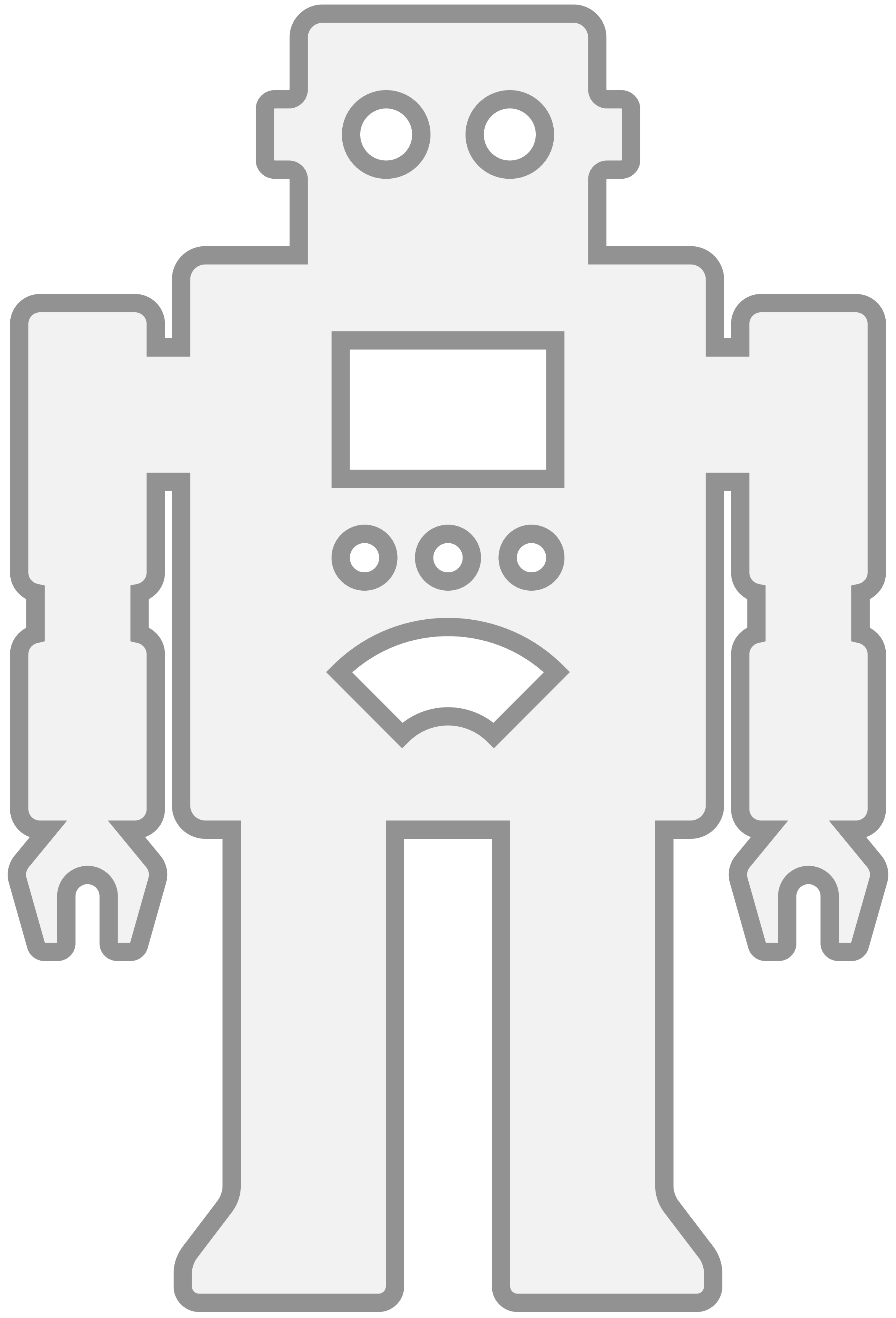
“Could you tell me of all the kings who have ruled over Europe?”

(do they know all these knowledge, or are they sometimes guessing?)

“Why did you perform bad on this task?”

(What are the causes of their drawbacks?)

Can We Systematically Describe How LMs Behave?



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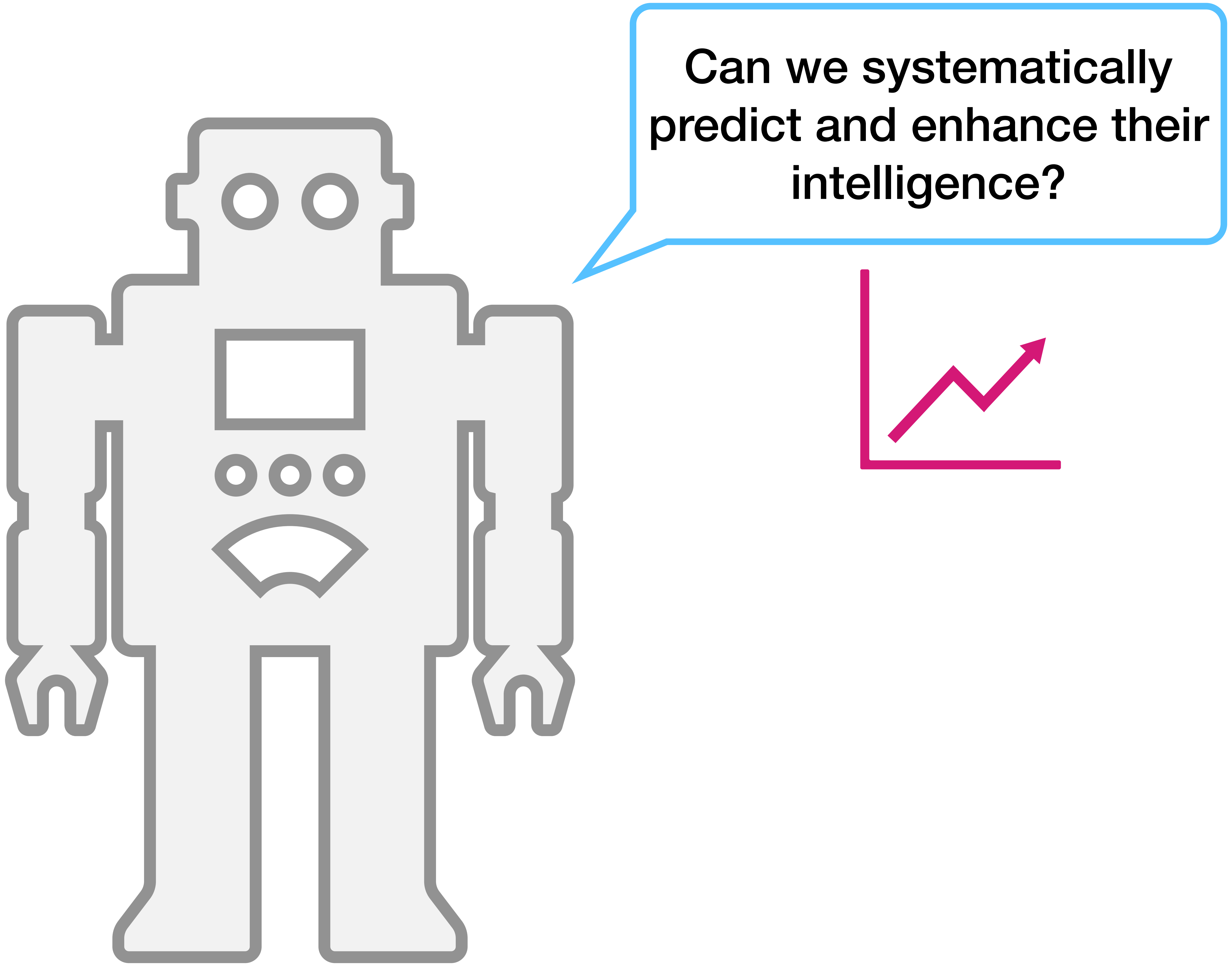

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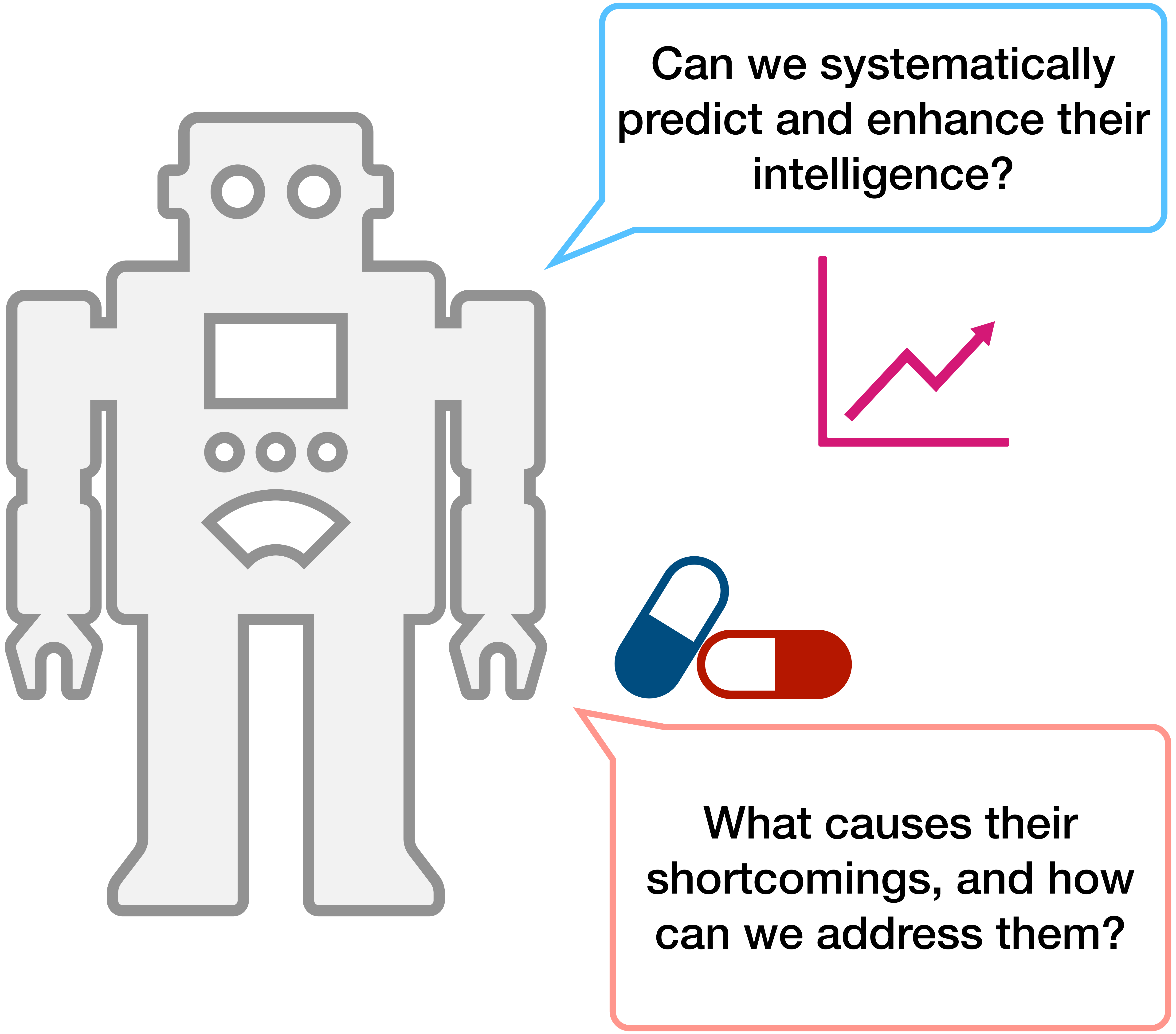
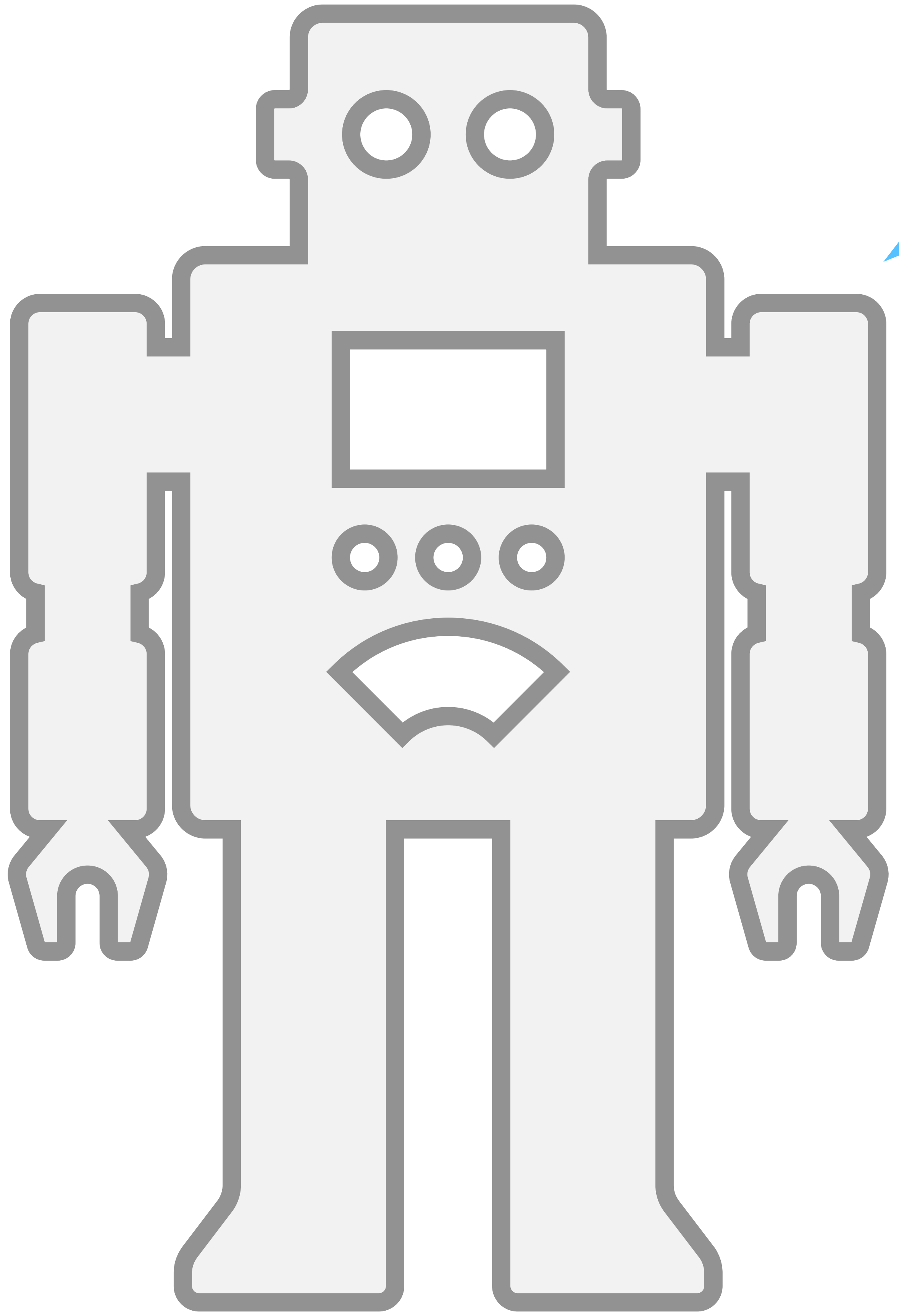


Can We Systematically Describe How LMs Behave?

How do their components function?



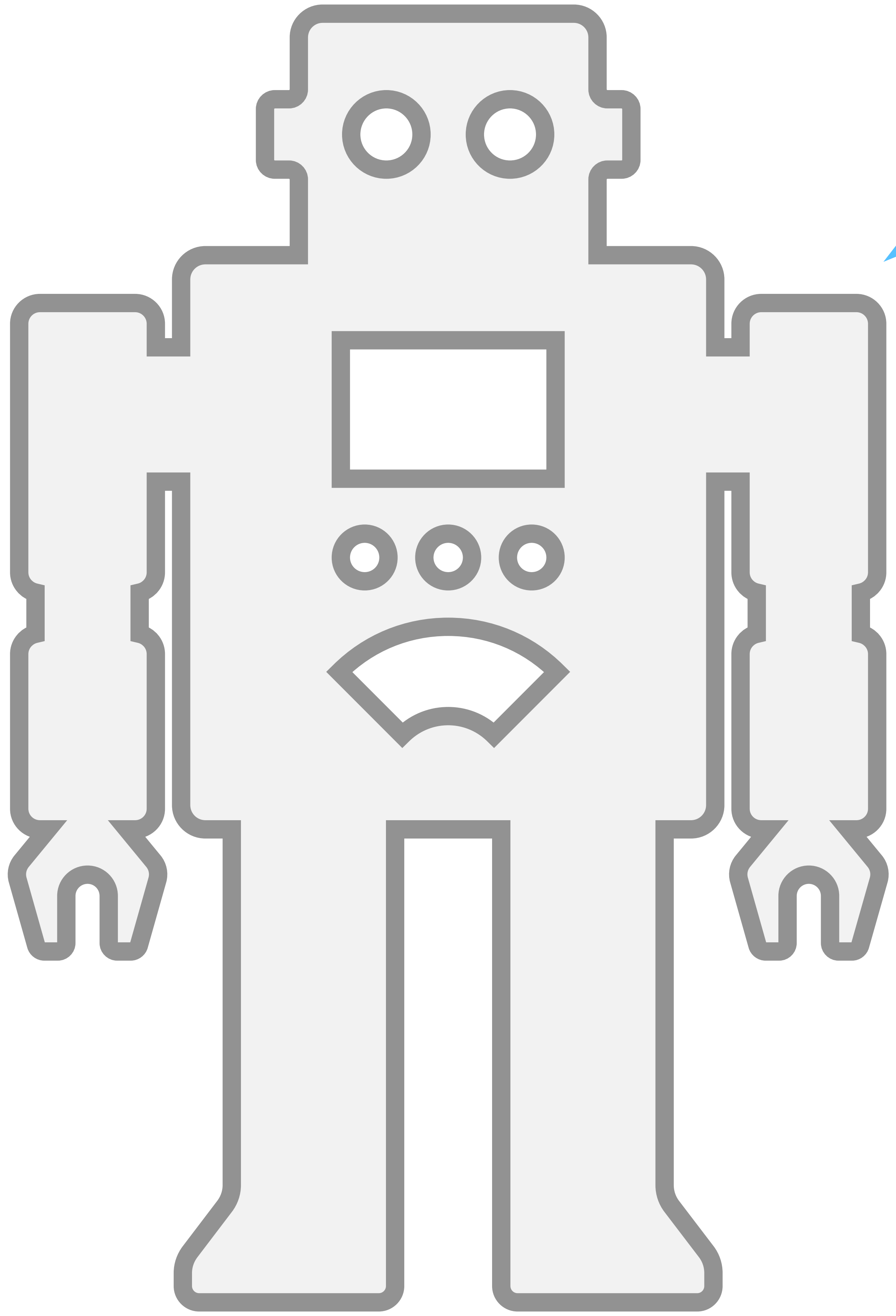
Can we systematically predict and enhance their intelligence?

What causes their shortcomings, and how can we address them?

Can We Systematically Describe How LMs Behave?

How do their components function?

Can we systematically predict and enhance their intelligence?



How do LMs reason and utilize knowledge?

What causes their shortcomings, and how can we address them?

Why Do We Need A New Science?

New sciences often emerge as a result of scaling up old sciences

Machine Learning → **Deep Learning** → **Language Models**

PAC theory,
optimization,
…

Gradient Descent,
Neural Tangent
Kernel, …

A Sciences of LMs

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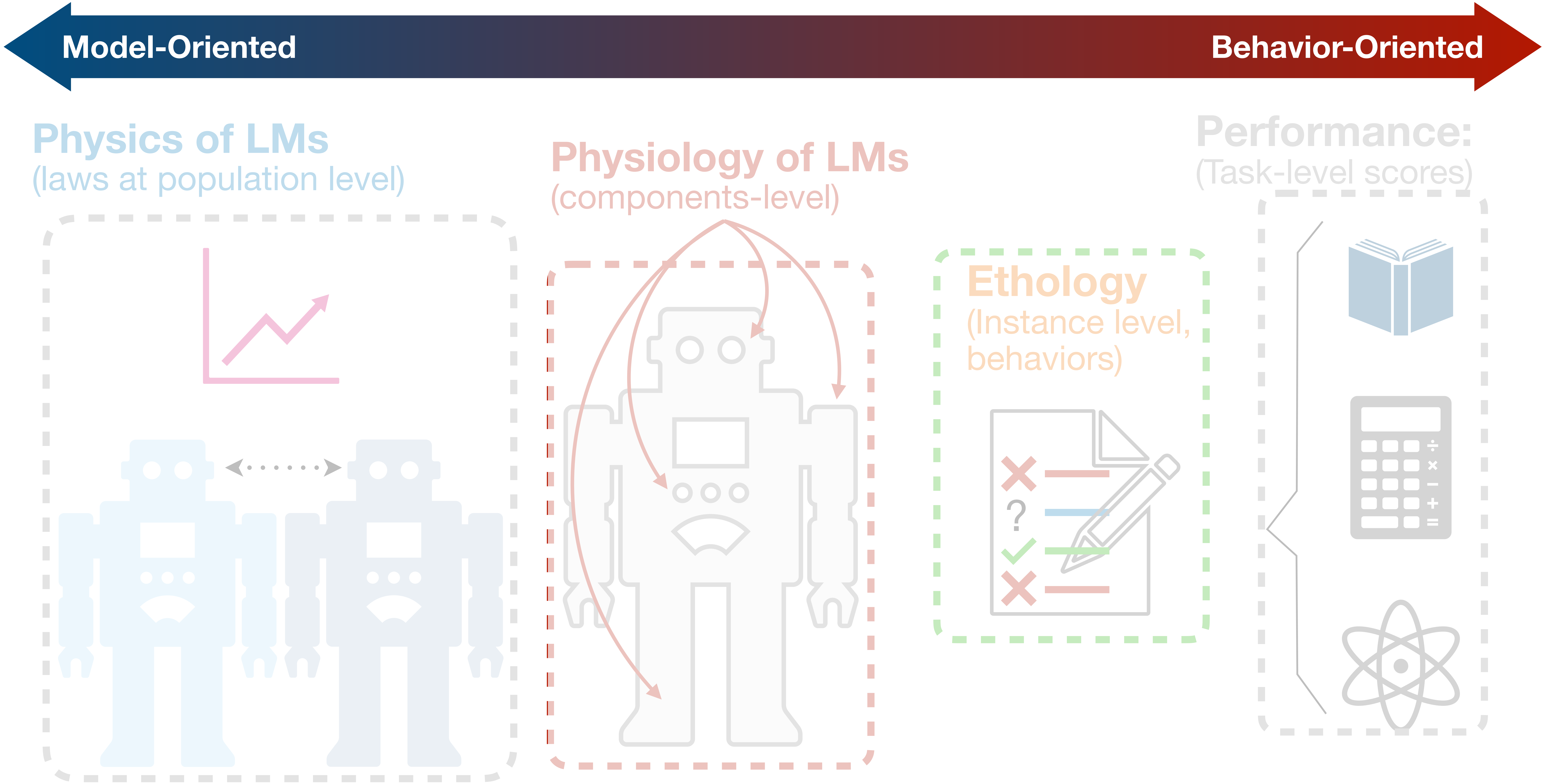
Spectrum of Sciences of LMs



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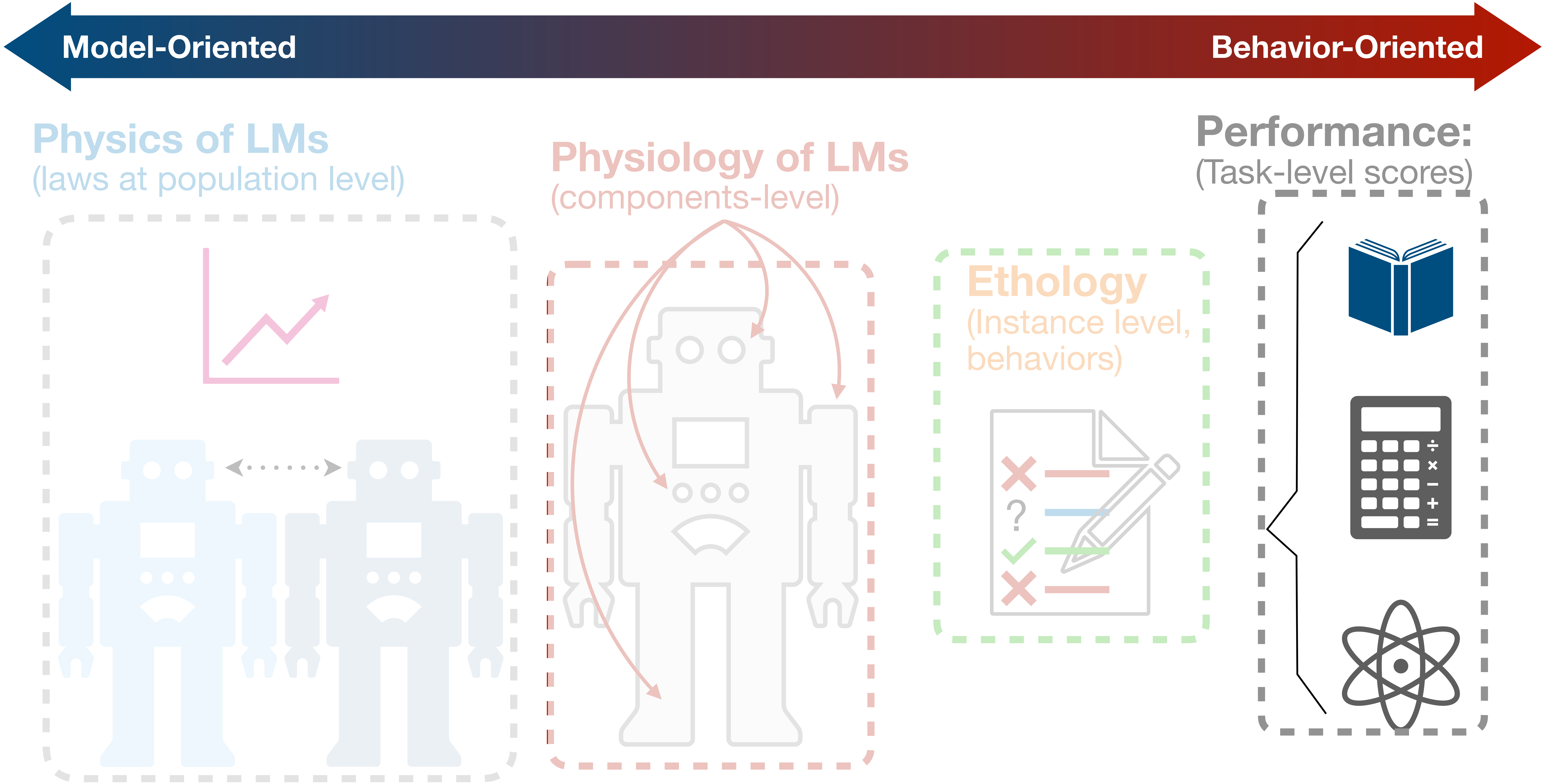

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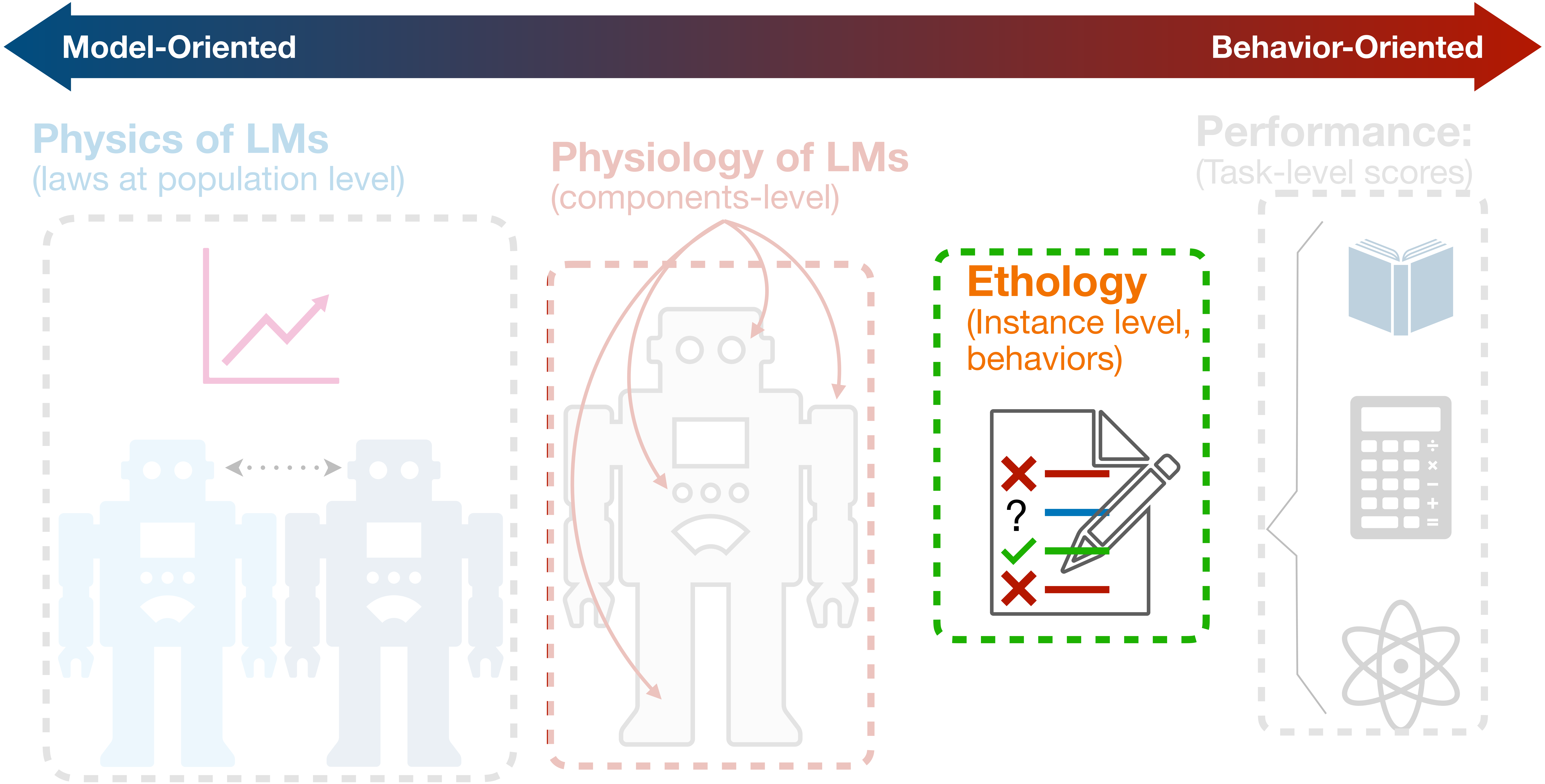

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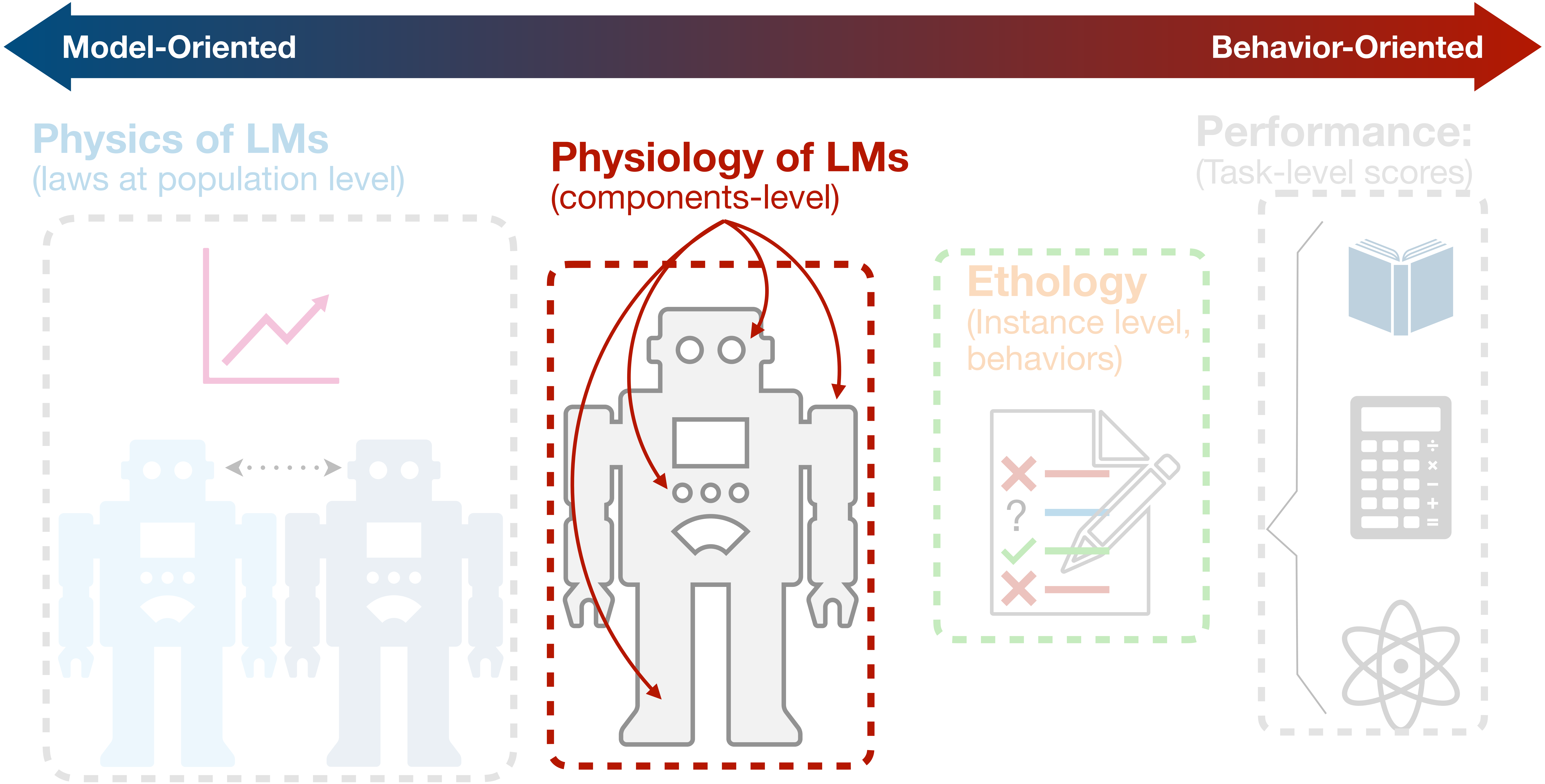

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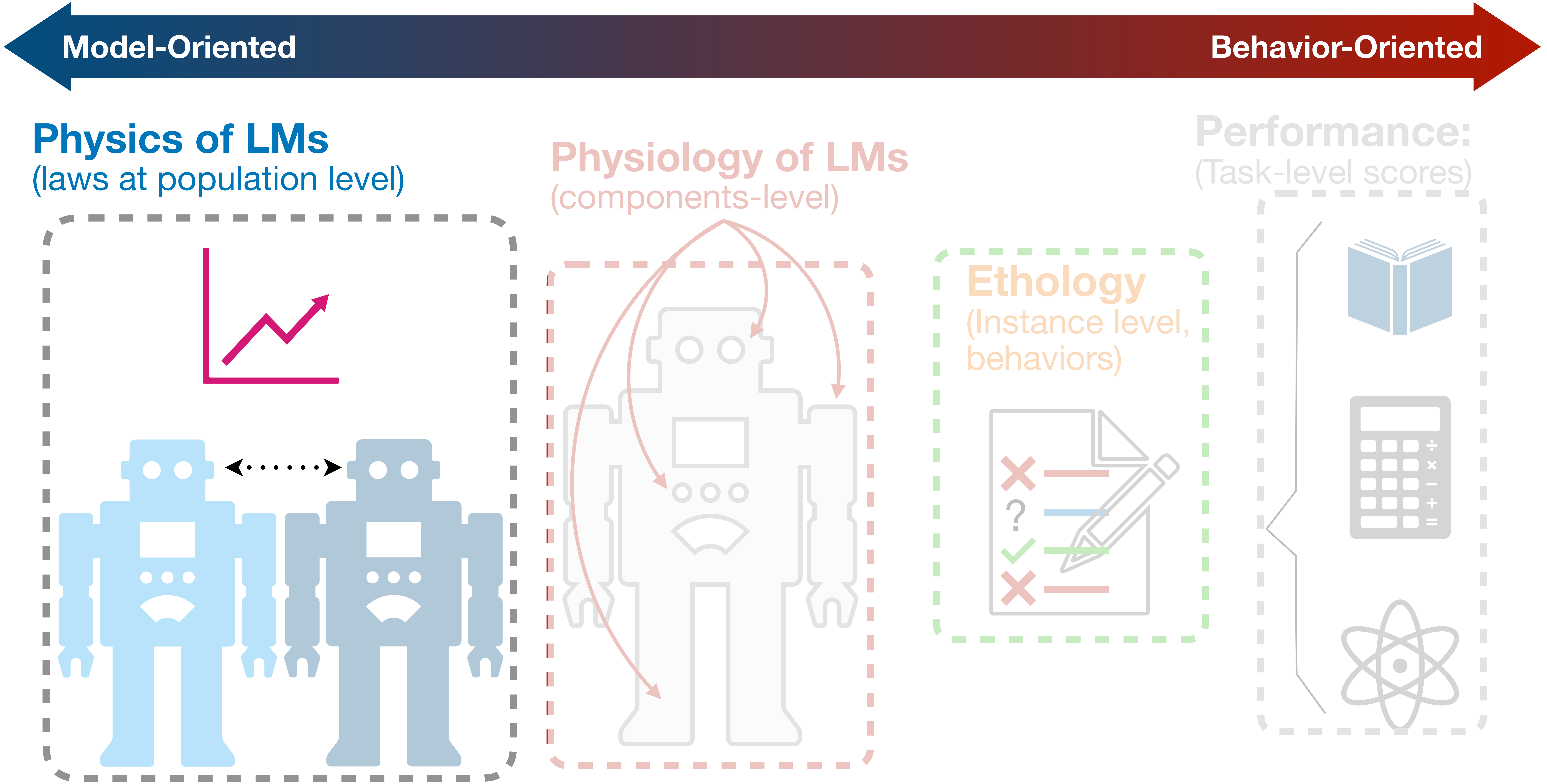

Scientific Principles for a Science of LMs

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- **Generality** across model sizes, architectures, training details, and randomness.

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- **Deriving solutions** for LM-related challenges

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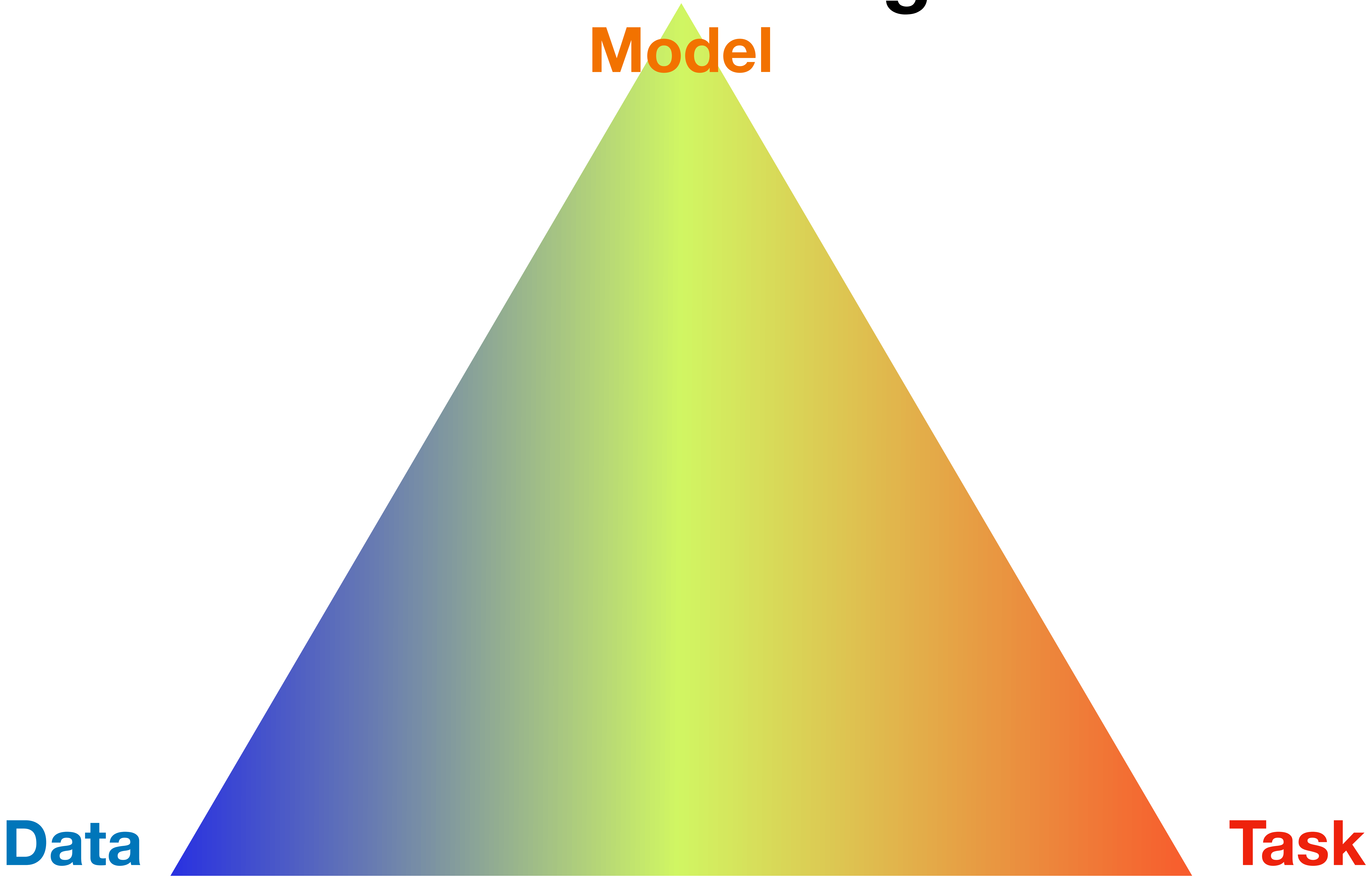
- **Deriving solutions** for LM-related challenges

In practice, achieving all these principles is challenging, but the more we achieve, the better!

Tutorial Outline

- **Part 1 (Ethology): How Do LMs Behave?**
    - **Syntax**: How do LMs work with syntax
    - **Knowledge**: Where is knowledge stored
    - **Reasoning**: How is reasoning conducted
- **Part 2 (Physiology): What Roles Do Components Play?**
    - **Attention**: Attention, position and context
    - **Embeddings**: What is the function of word embeddings
- **Part 3 (Physics): Rules and Laws of LMs**
    - **Scaling**: How performance scales
    - **Impossibilities**: What LMs cannot do fundamentally

Model-Data-Task Triangular: A Roadmap



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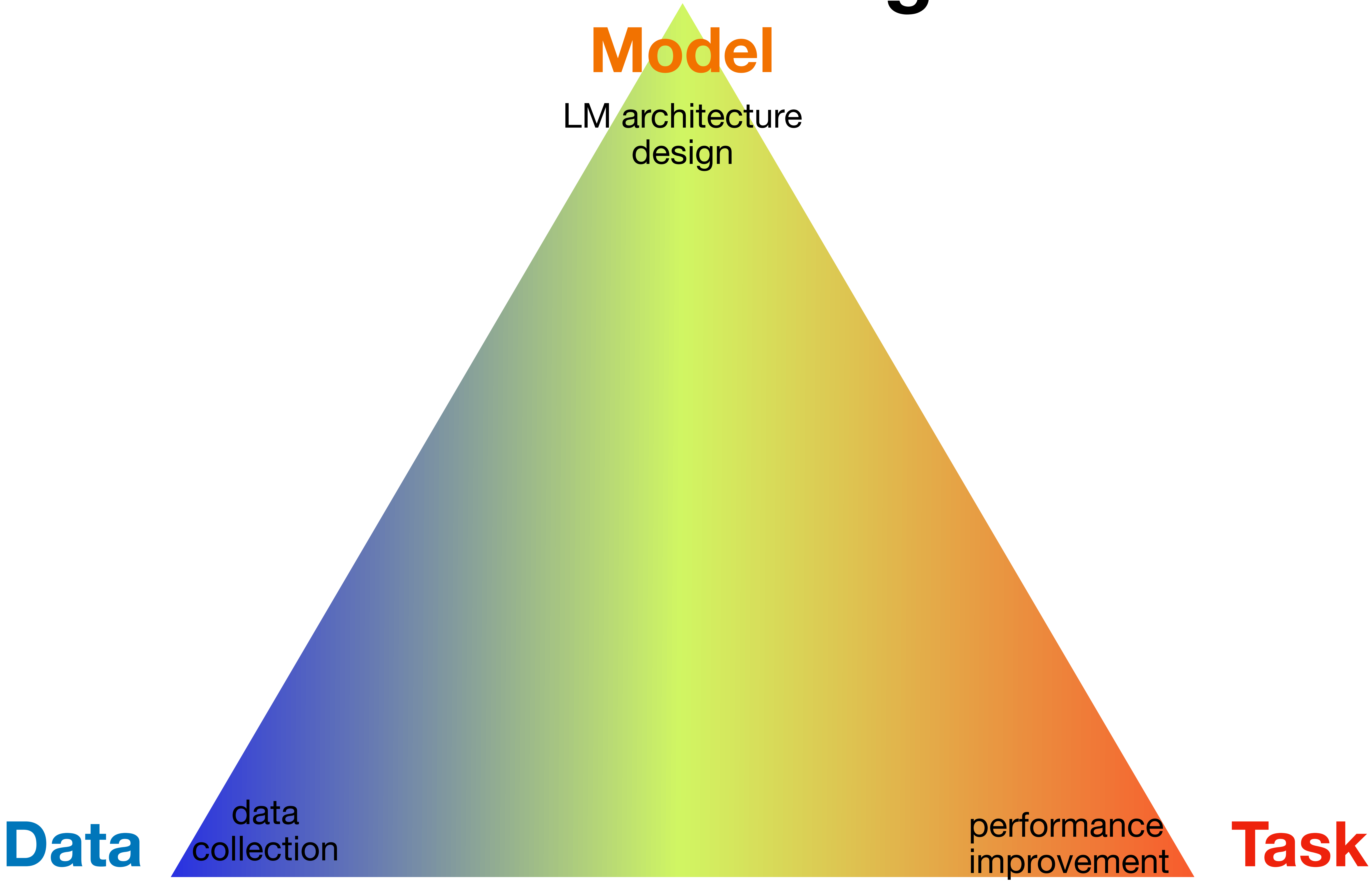

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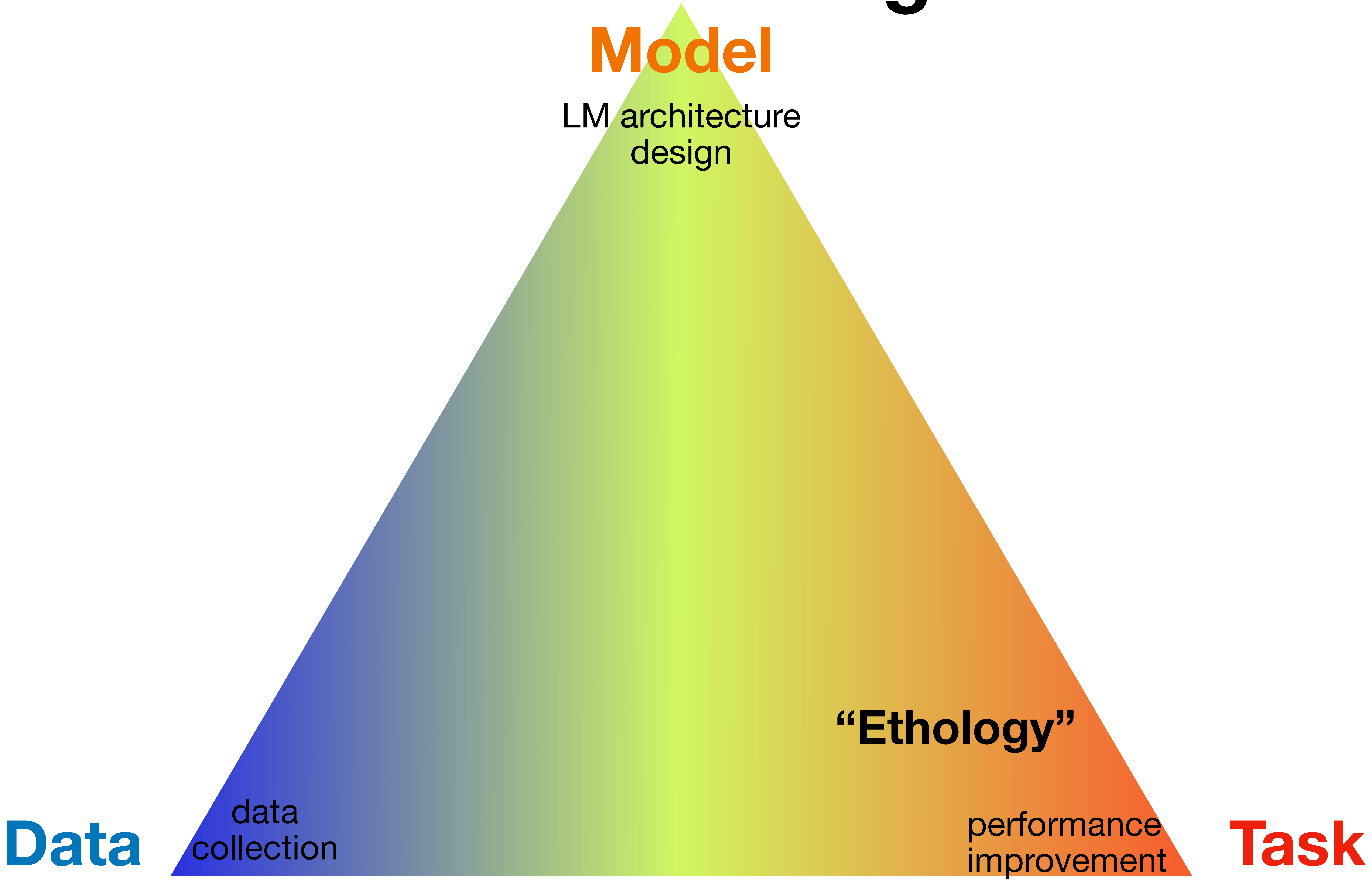

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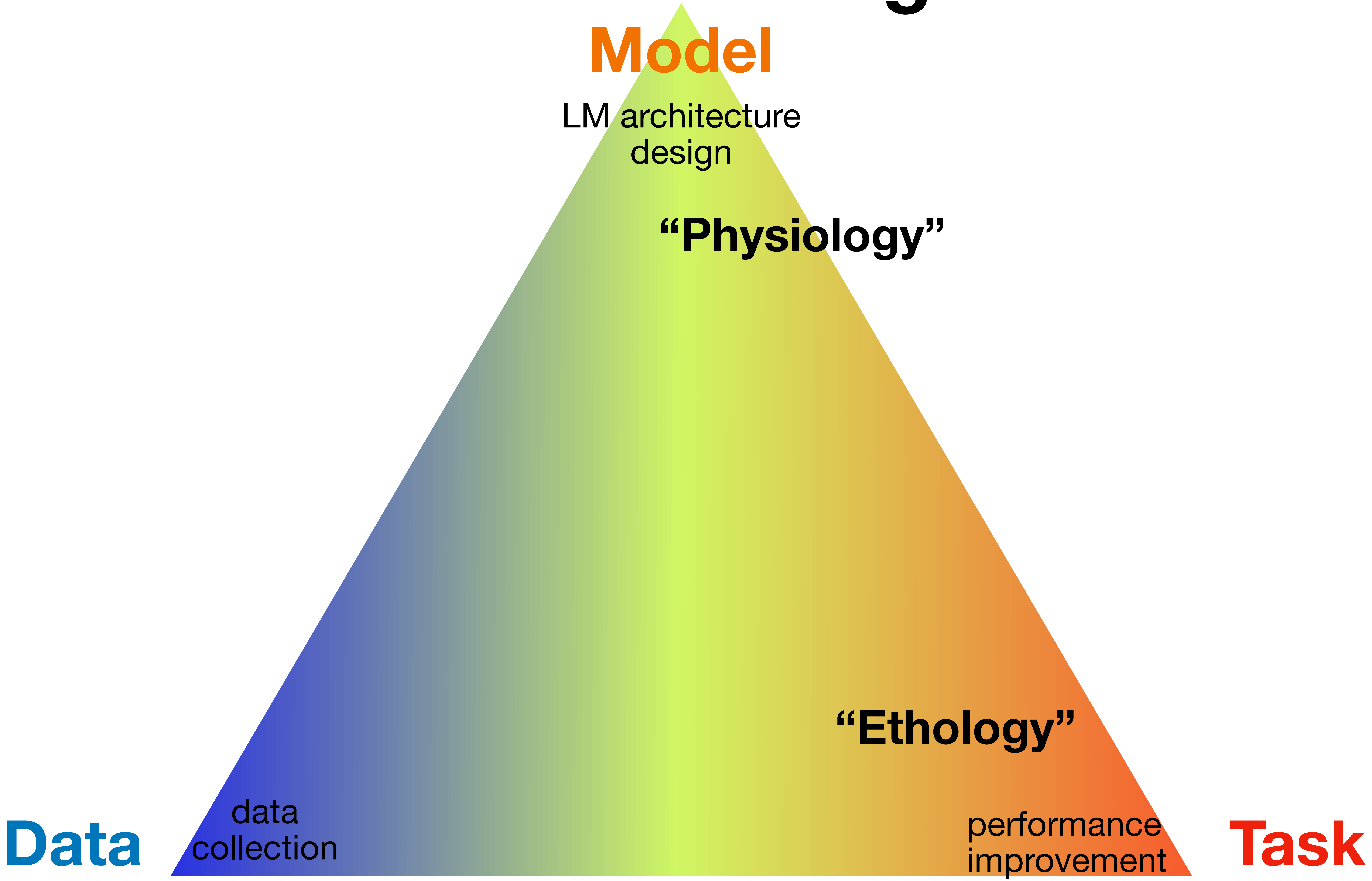

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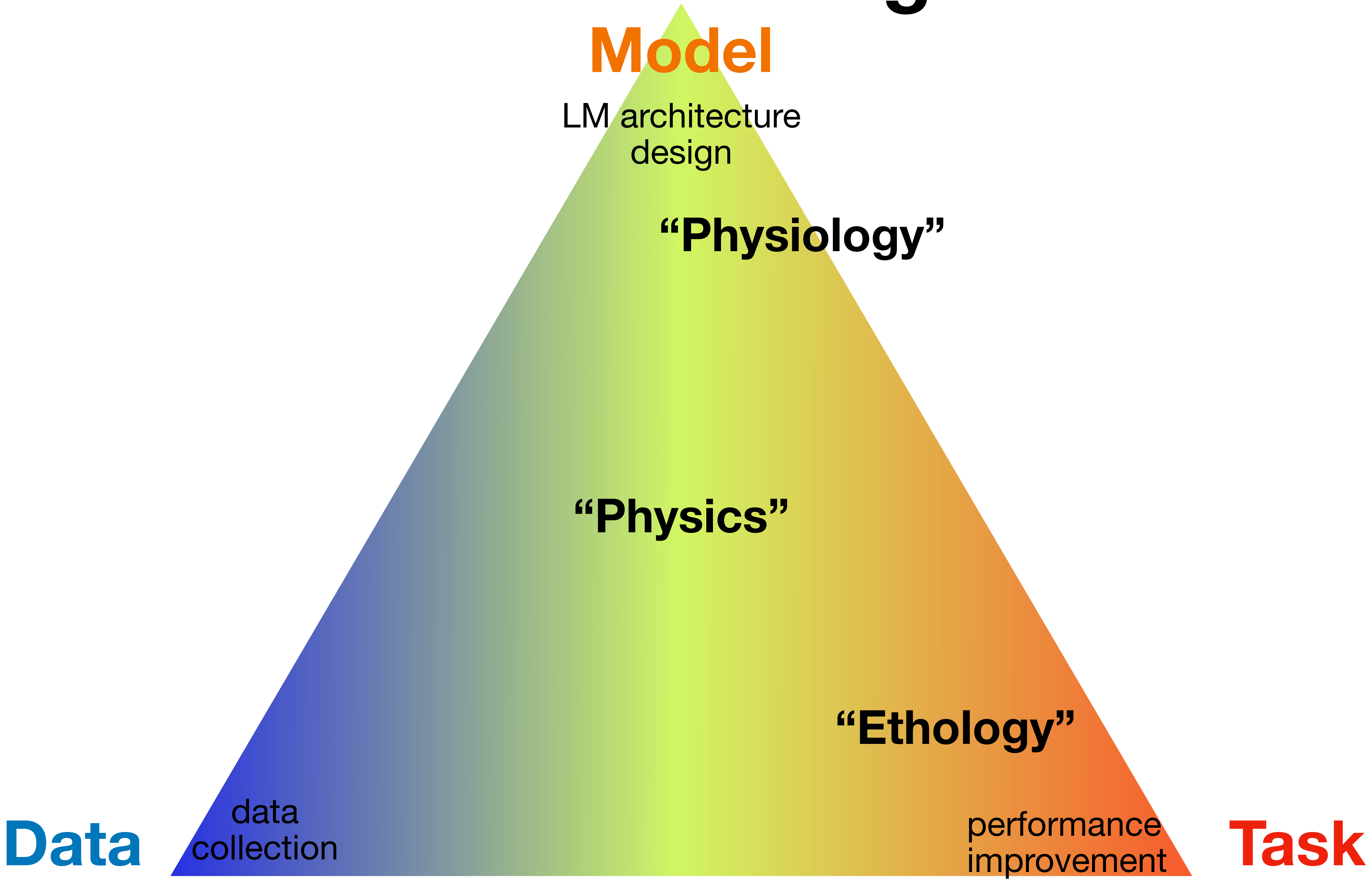

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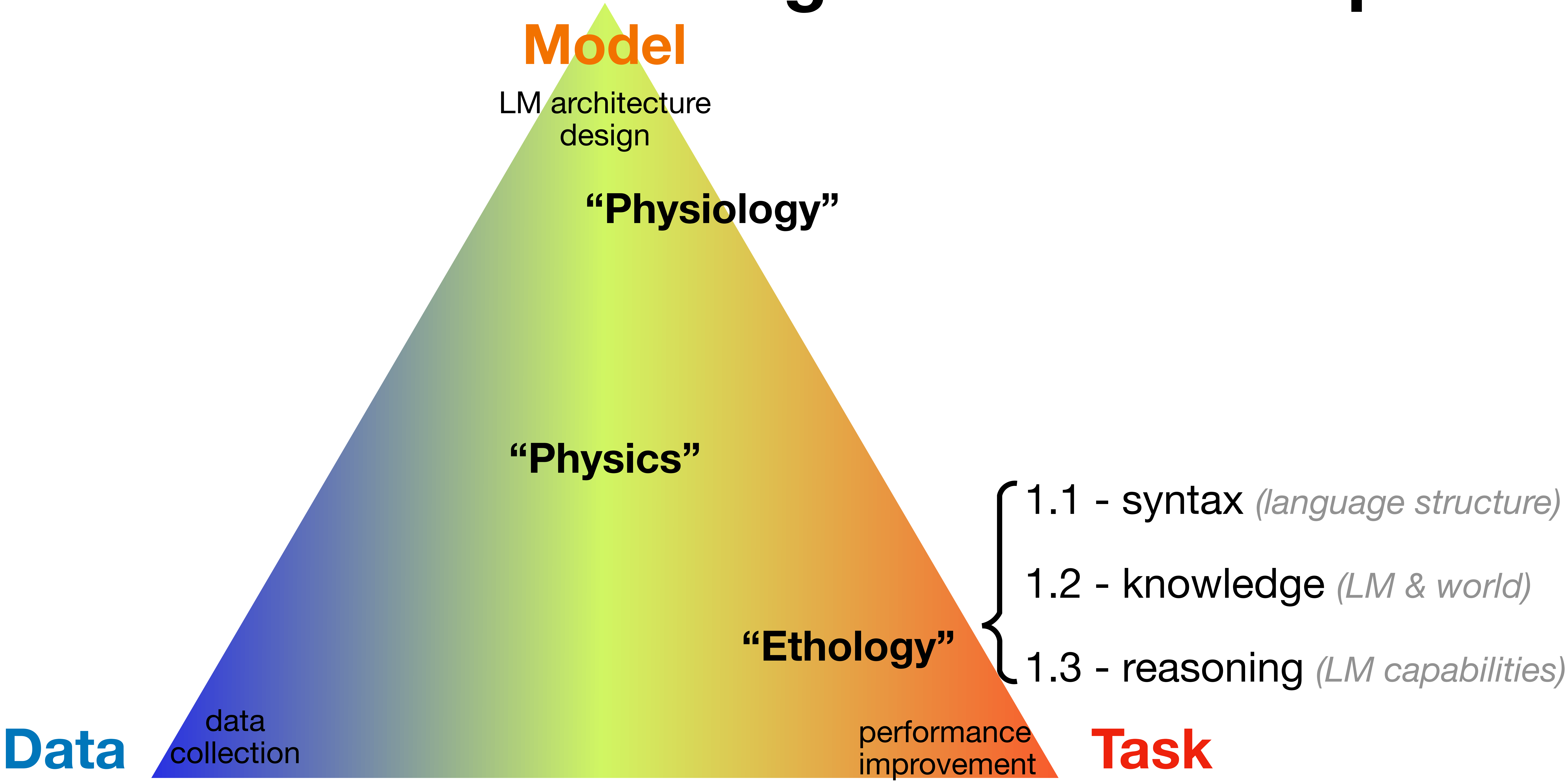

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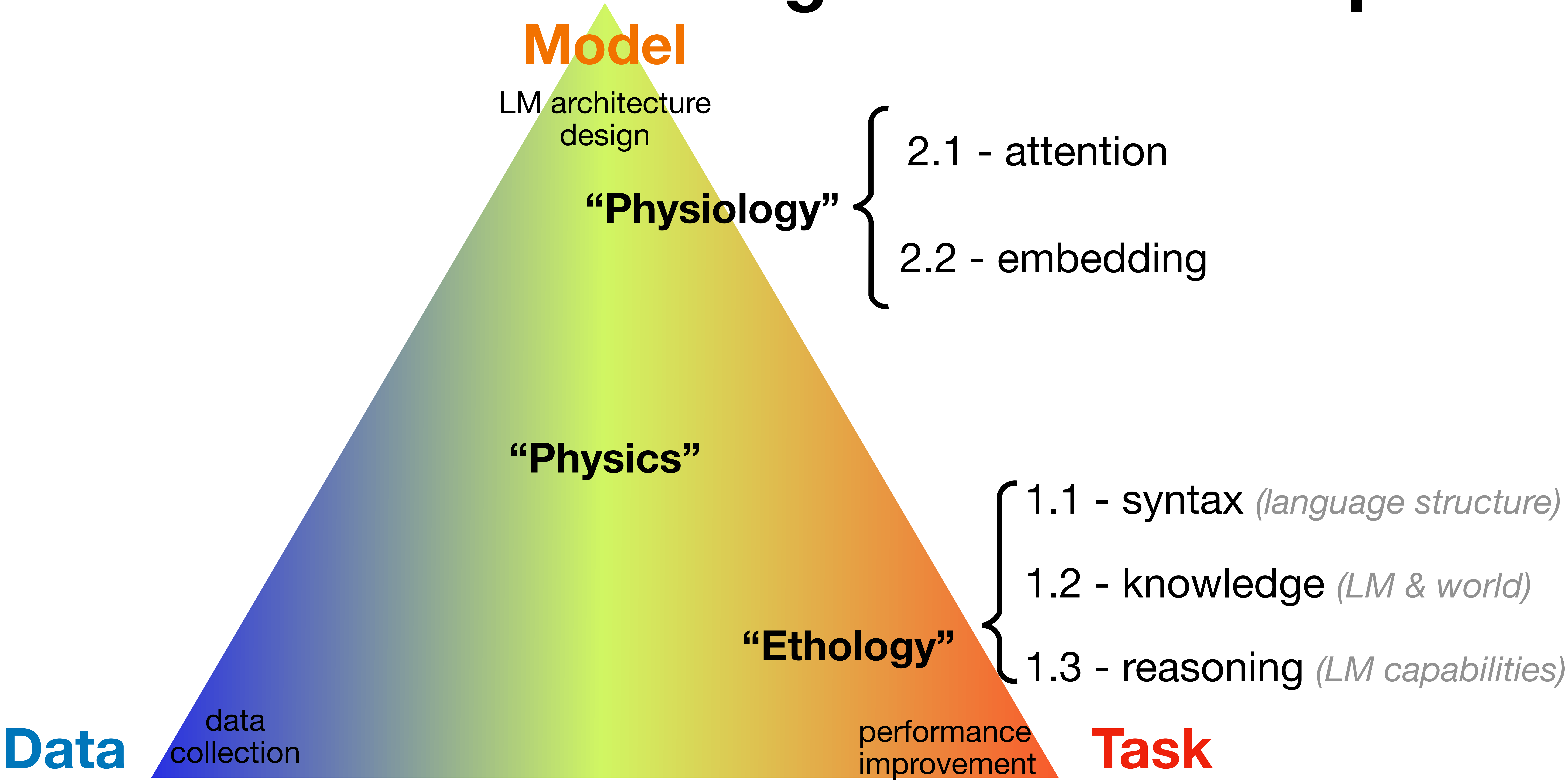

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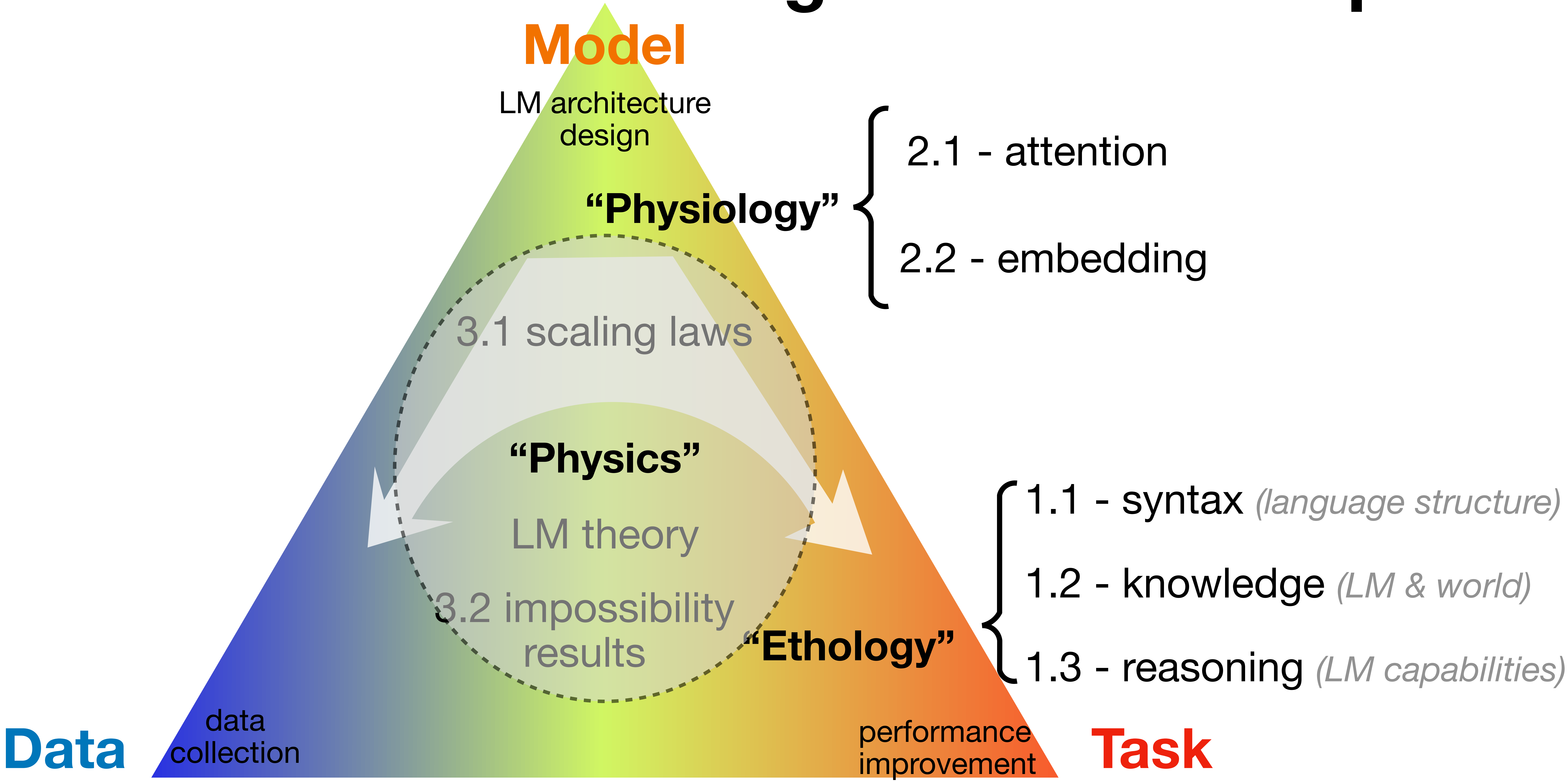
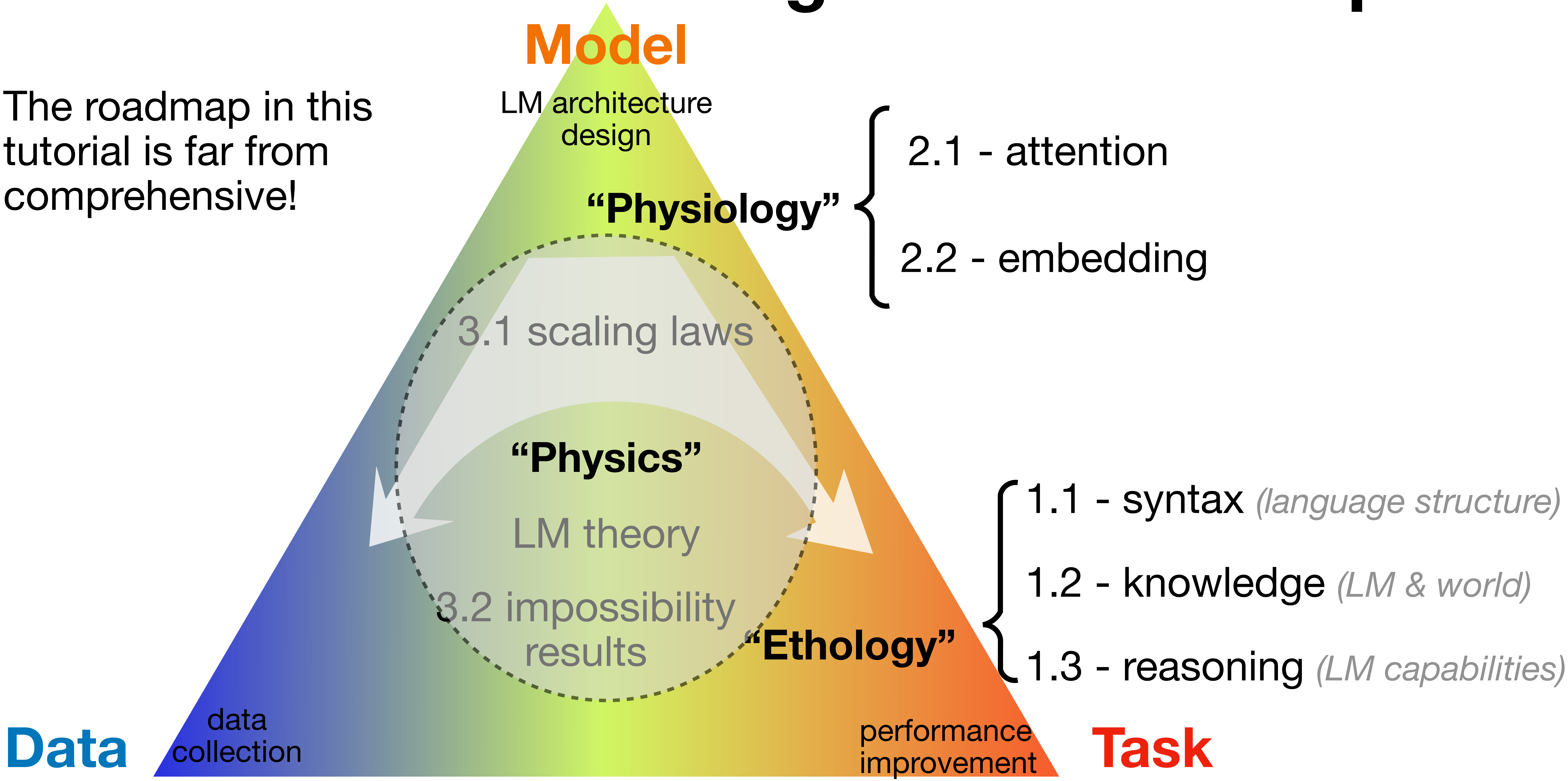
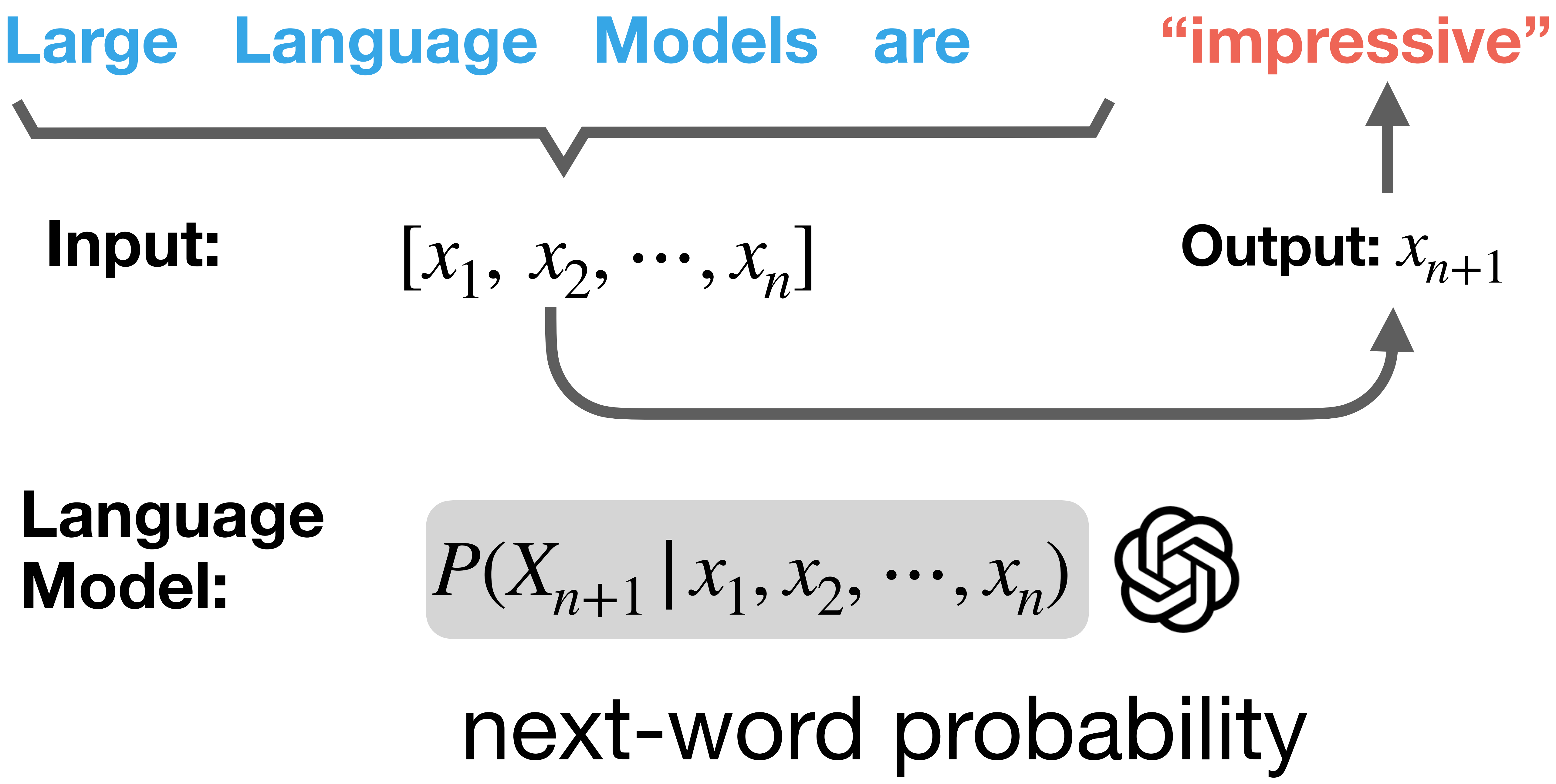


Model-Data-Task Triangular: A Roadmap

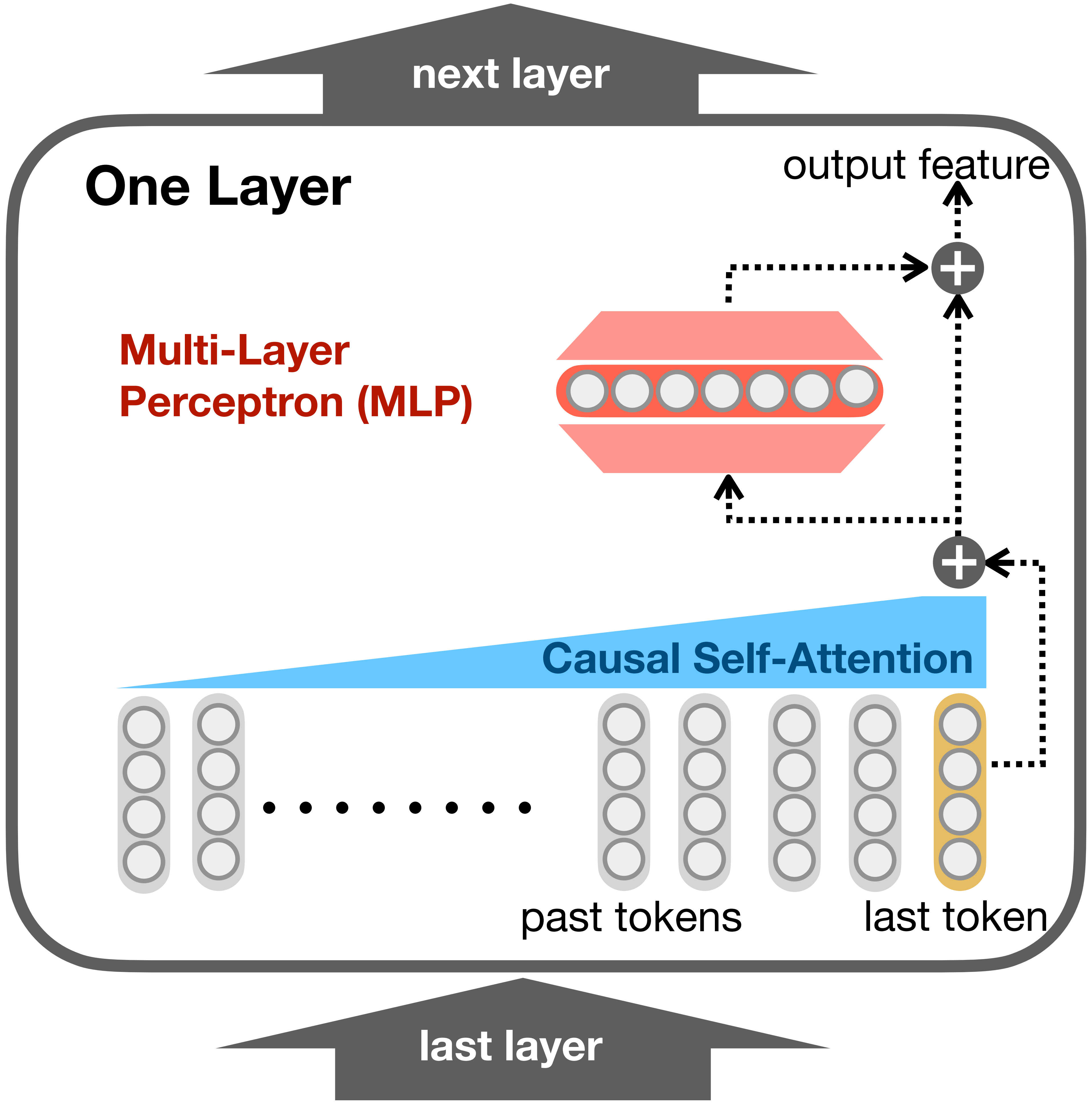
The roadmap in this tutorial is far from comprehensive!



Prerequisites: Language Modeling



Language Modeling



A Transformer-Based Architecture

Part 1: Ethology

How Do LMs Behave?

Topics:

- **Syntax**: How do LMs work with syntax
- **Knowledge**: Where is knowledge stored
- **Reasoning**: How is reasoning conducted

How Do LMs Work on Syntax?

LMs Are Robust to "Unnatural Language"

Task: natural language inference

determining if "premise" sentence can infer the "hypothesis" sentence

normally ordered text

texts with shuffled words

Premise	Hypothesis	Predicted Label
Boats in daily use lie within feet of the fashionable bars and restaurants.	There are boats close to bars and restaurants.	E
restaurants and use feet of fashionable lie the in Boats within bars daily .	bars restaurants are There and to close boats .	E
He and his associates weren't operating at the level of metaphor.	He and his associates were operating at the level of the metaphor.	C
his at and metaphor the of were He operating associates n't level .	his the and metaphor level the were He at associates operating of .	C

robust answer

Sinha, Koustuv, et al. "UnNatural Language Inference." Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). 2021.

LMs Are Robust to “Unnatural Language”

Task: paraphrase

if two sentences are duplicate

Q_1 Does marijuana cause cancer?

Q_2 How can smoking marijuana give you lung cancer?

(a) Prediction: “duplicate” 0.96

Q_1 Does marijuana cause cancer?

$Q_{2'}$ you smoking cancer How marijuana lung can give?

(b) Prediction: “duplicate” 0.98

Task: sentiment classification

if the sentiment is positive or negative

S	the film ’s performances are thrilling .	1.00
S_1	the film thrilling performances are ’s .	1.00
S_2	’s thrilling film are performances the .	1.00
S_3	’s thrilling are the performances film .	1.00

Task: entailment

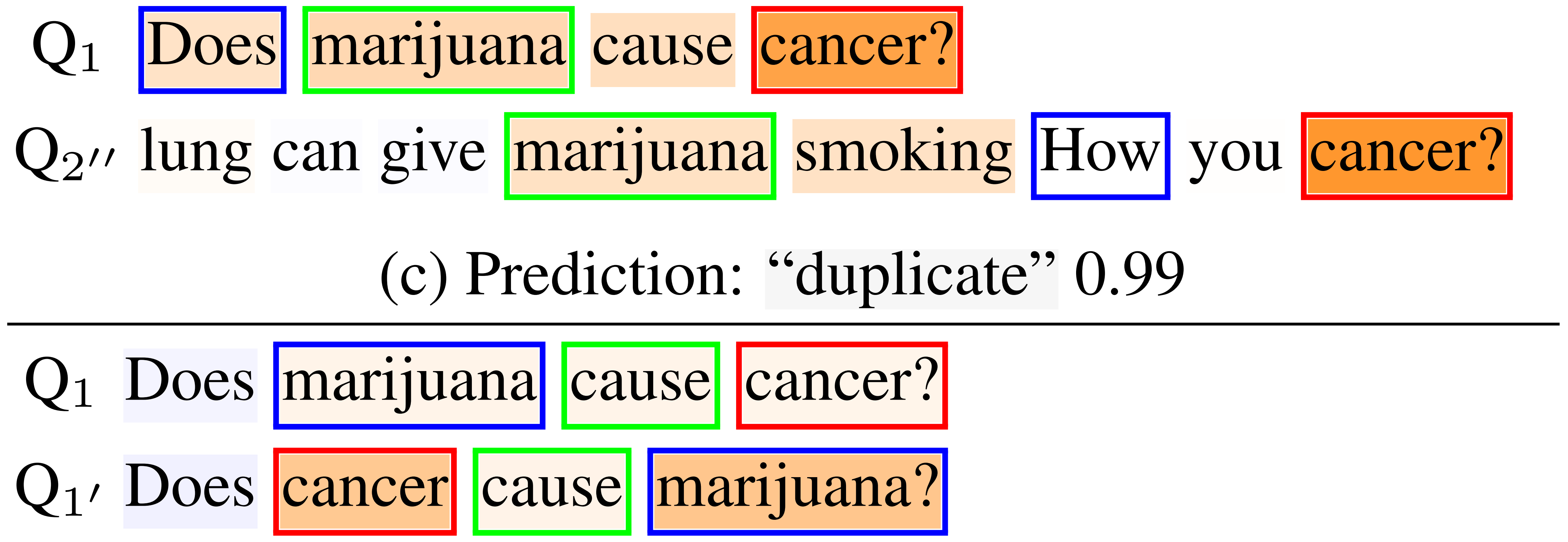
if the sentence A contains the answer to question Q

	QNLI sentence-pair inputs and their LIME attributions (negative -1, neutral 0, positive +1)	Confidence score
Q	How long did Phillips manage the Apollo missions?	1.00
A	Mueller agreed, and Phillips managed Apollo from January 1964, until it achieved the first manned landing in July 1969, after which he returned to Air Force duty.	
Q_1	Apollo the Phillips How missions long did manage?	0.96
A	Mueller agreed, and Phillips managed Apollo from January 1964, until it achieved the first manned landing in July 1969, after which he returned to Air Force duty.	

Pham, Thang, et al. "Out of Order: How important is the sequential order of words in a sentence in Natural Language Understanding tasks?." *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*. 2021.

LMs Are Robust to “Unnatural Language”

- Different capabilities have different sensitivity to syntax corruption
    - in *sentence acceptability*, naturally requires integrate syntax
    - or when the meaning is reversed (A cause B v.s. B cause A)



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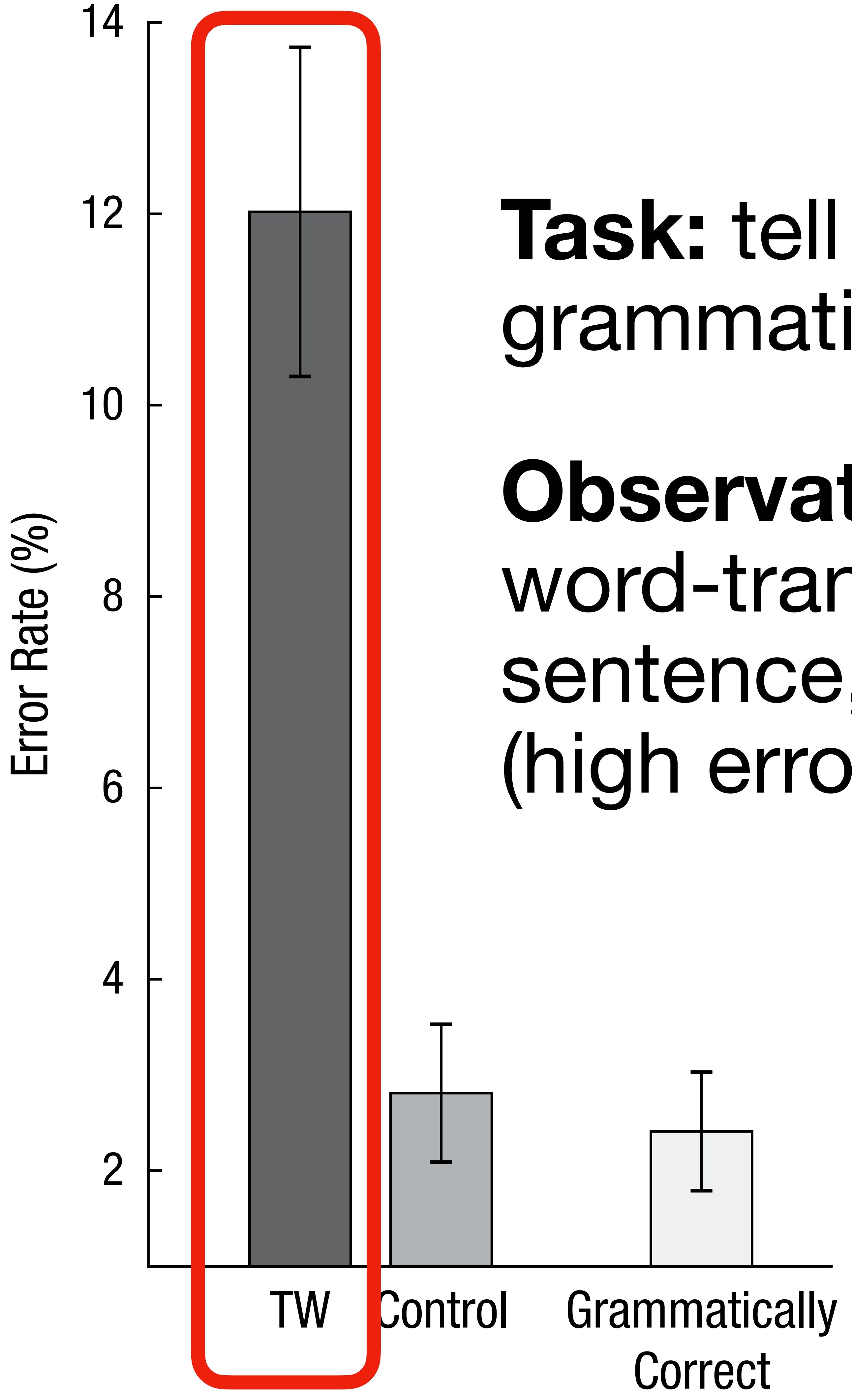
Huang, Kuan-Jung, and Adrian Staub. "The transposed-word effect does not require parallel word processing: Failure to notice transpositions with serial presentation of words." Psychonomic bulletin & review 30.1 (2023): 393-400.
Mirault, Jonathan, Joshua Snell, and Jonathan Grainger. "You that read wrong again! A transposed-word effect in grammaticality judgments." Psychological Science 29.12 (2018): 1922-1929.

Word Transposition Effect in Humans

Task: is the new sentence grammatically correct?

The white cat was big.
The black dog ran slowly.

The white was cat big.
The black ran dog slowly.



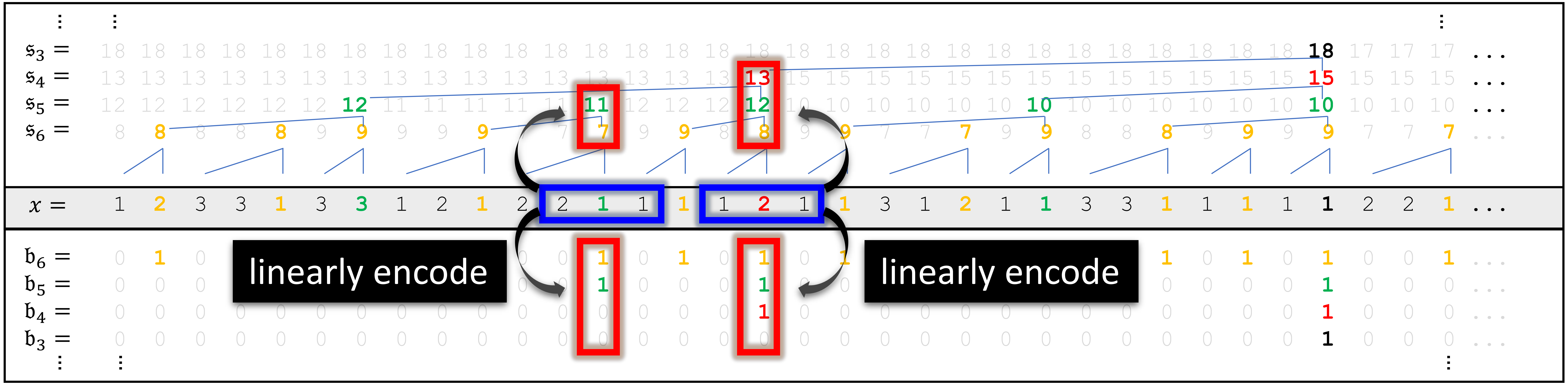
Task: tell if the sentence is grammatical or not

Observation: if the sentence is word-transposed from original sentence, it is less recognizable (high error)

Mirault, Jonathan, Joshua Snell, and Jonathan Grainger. "You that read wrong again! A transposed-word effect in grammaticality judgments." Psychological Science 29.12 (2018): 1922-1929.

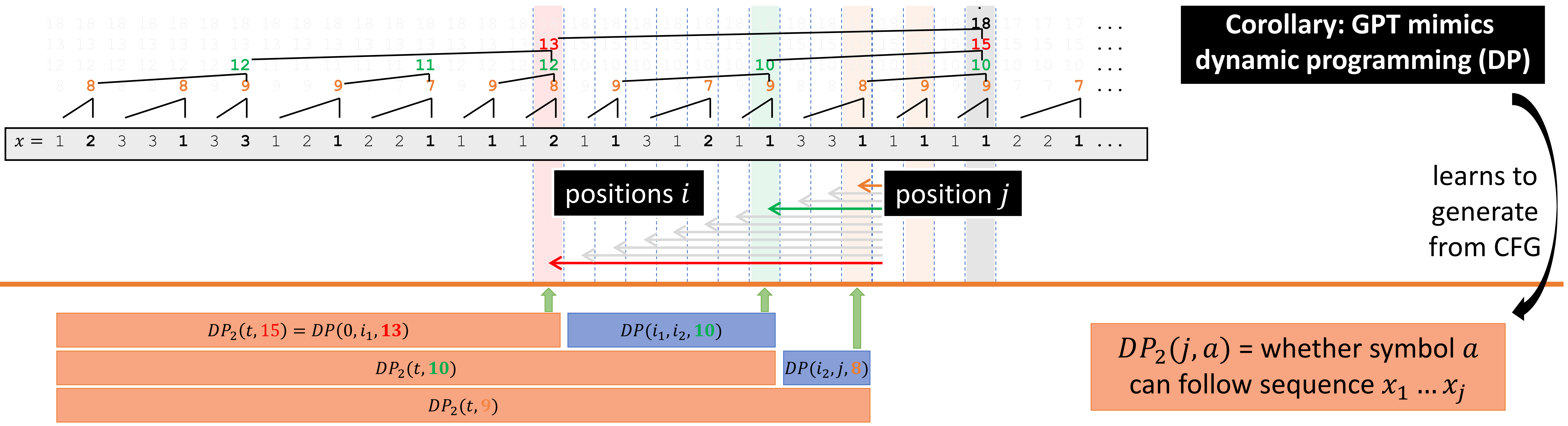
Hidden Features Encode Local Syntax

Probing: predicting each word's syntax within hidden features



Allen-Zhu, Zeyuan, and Yuanzhi Li. "Physics of language models: Part 1, context-free grammar." *arXiv preprint arXiv:2305.13673* (2023).

Hidden Features Encode Syntax-Parsing Features

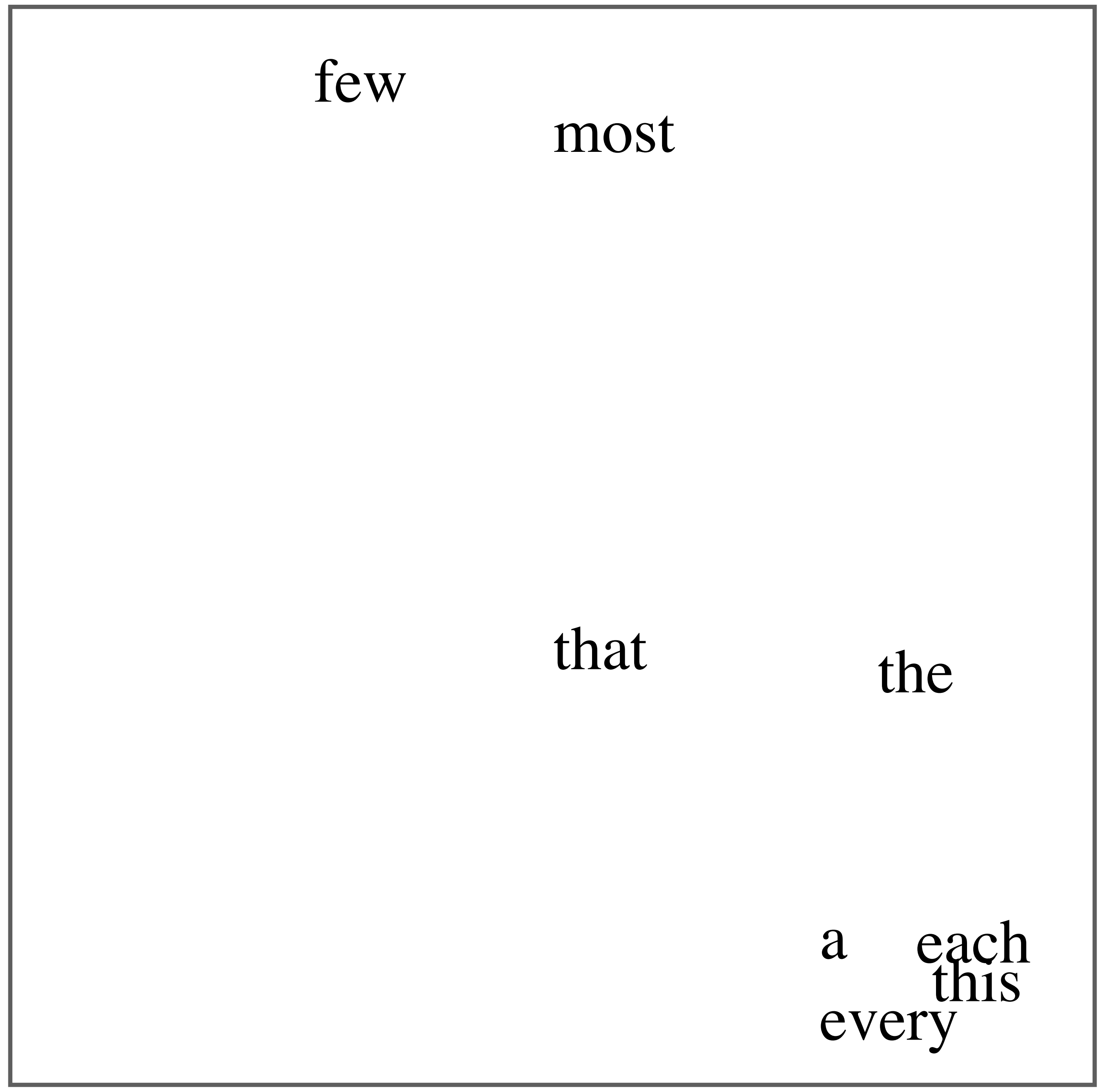


Probing: if hidden features can recover computational features useful for paring syntax

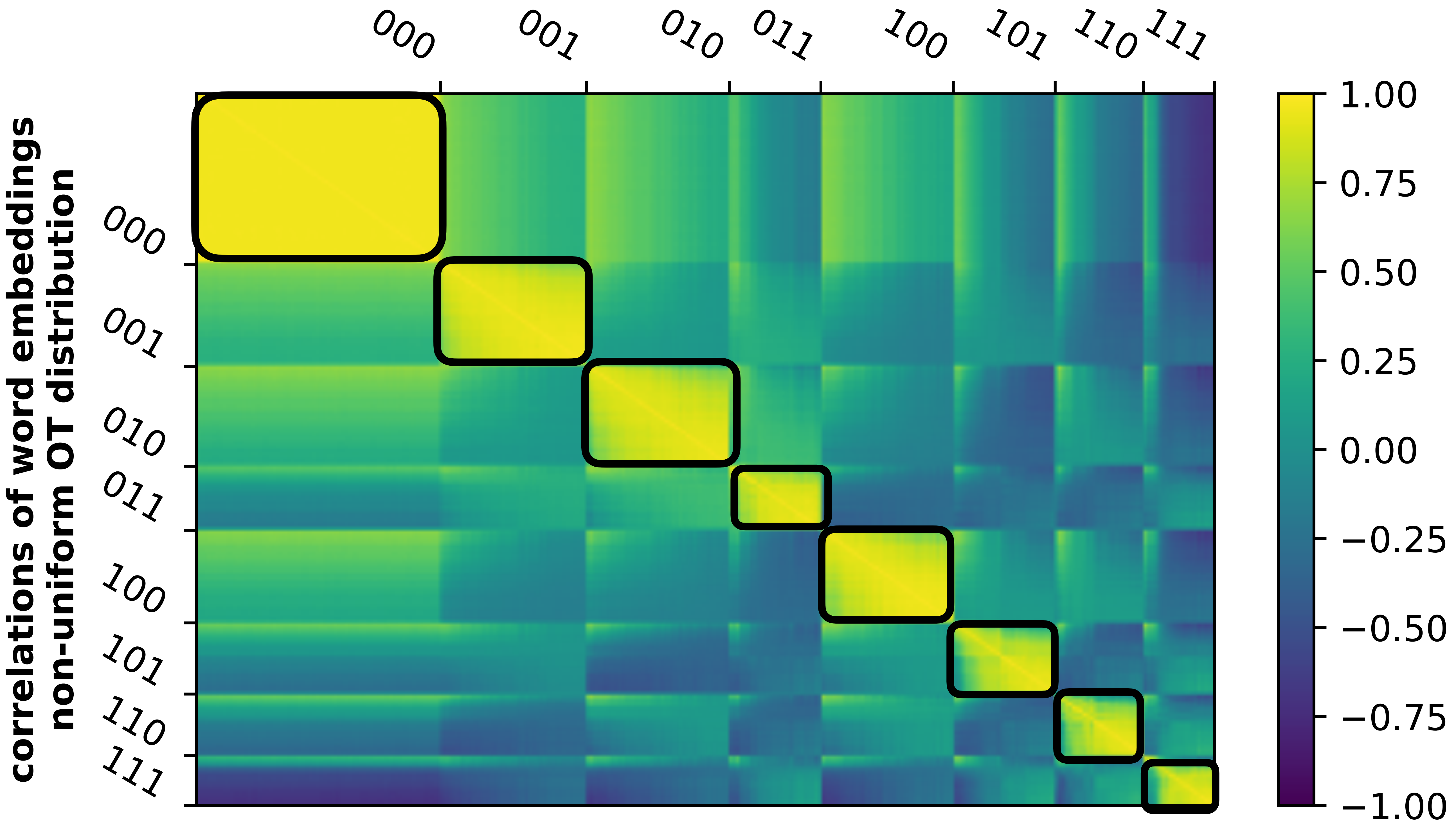
Allen-Zhu, Zeyuan, and Yuanzhi Li. "Physics of language models: Part 1, context-free grammar." *arXiv preprint arXiv:2305.13673* (2023).

Word Embeddings Encode Syntactic Roles

In natural language, word embeddings reflect a reflect their syntax roles



In a synthetic language, word embeddings are grouped by syntactic roles



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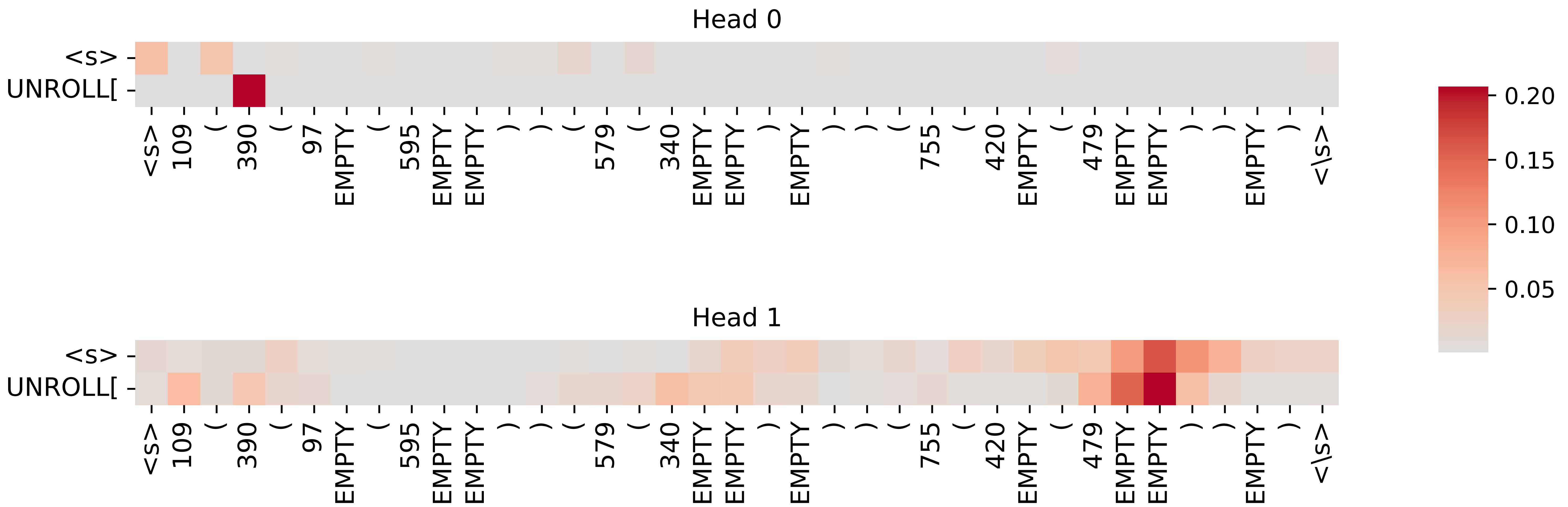
Andreas, Jacob, and Dan Klein. "How much do word embeddings encode about syntax?." Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers). 2014.

LMs Uses Attention to Utilize Syntax

Attention heads that close parentheses



Elhage, Nelson, et al. "A mathematical framework for transformer circuits." Transformer Circuits Thread 1.1 (2021): 12.
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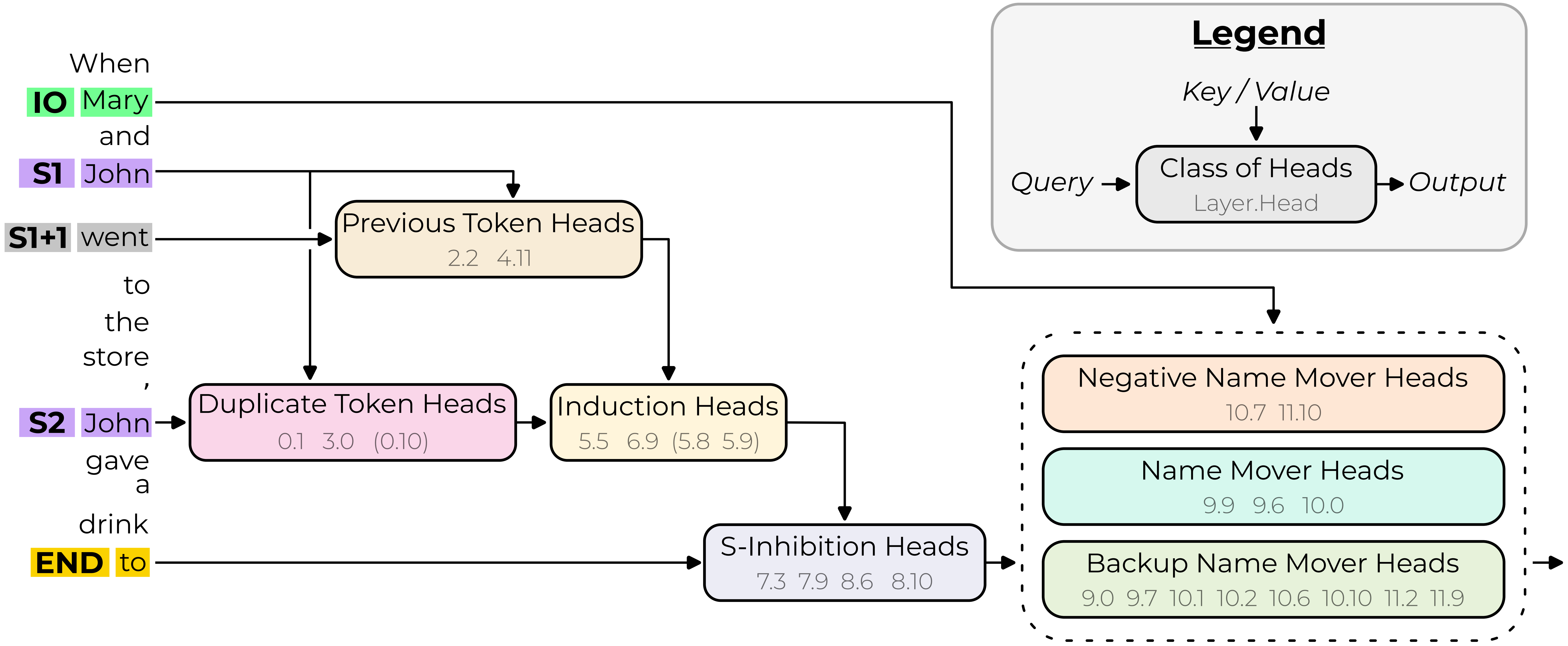
Zhang, Shizhuo Dylan, et al. "Can transformers learn to solve problems recursively?." arXiv preprint arXiv:2305.14699 (2023).

LMs Uses Attention to Utilize Syntax

Heads that copy-past nouns



"(Backup) Name Mover Heads": copy-pasting nouns

"Duplicate Token Heads" and "Induction Heads": detecting duplicate nouns

"S-Inhibition Heads": suppresing attention on duplicate nouns

Elhage, Nelson, et al. "A mathematical framework for transformer circuits." Transformer Circuits Thread 1.1 (2021): 12.
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Room for Future Efforts

Future work could:

- describe the processing in syntax in more details
- analyze other types of linguistic structures such as semantics, sense, coreference and ambituity
- investigate if the syntax is directly contributing to the functions of LMs, or encoded as a side effect from LM objective.

Where Is Knowledge Stored

Memory Storage in Human Brain

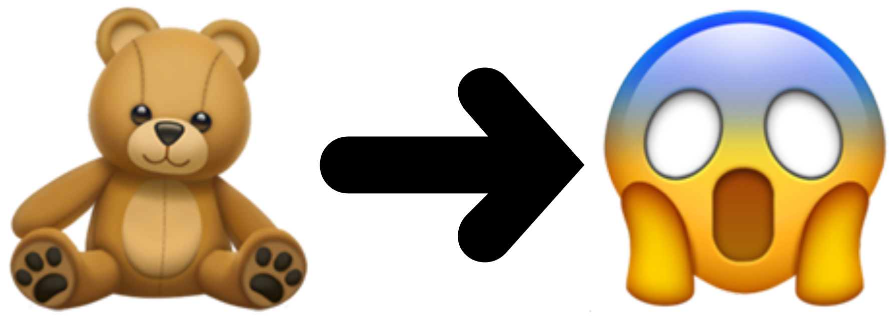
We Know Some Functions of Brain Regions

transfer

Neocortex: semantic memory (e.g., facts, commonsense knowledge)

Drive Thru

Amygdala: emotional implications (e.g., fear, PTSD)



Hippocampus: episodic memory (e.g., events)

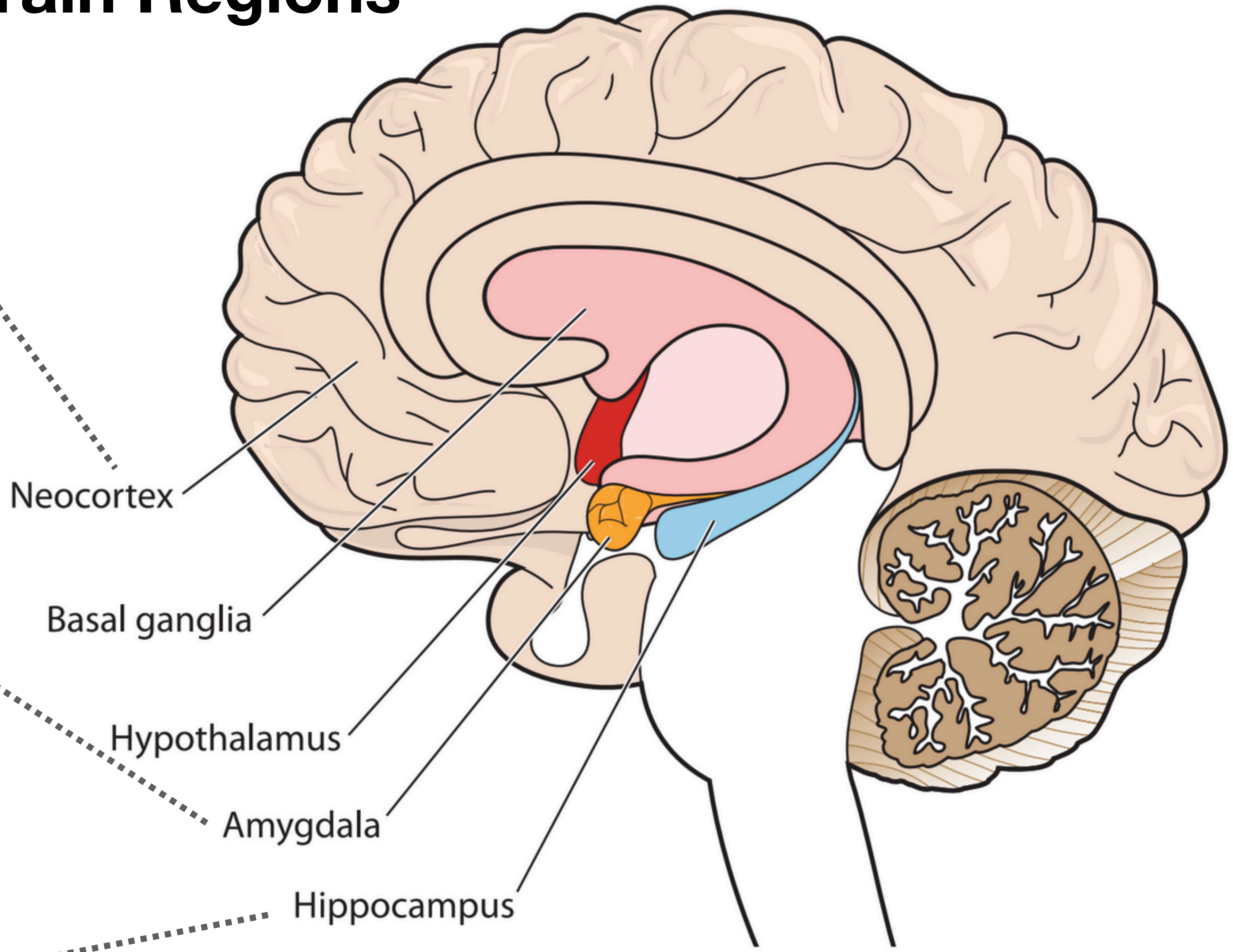
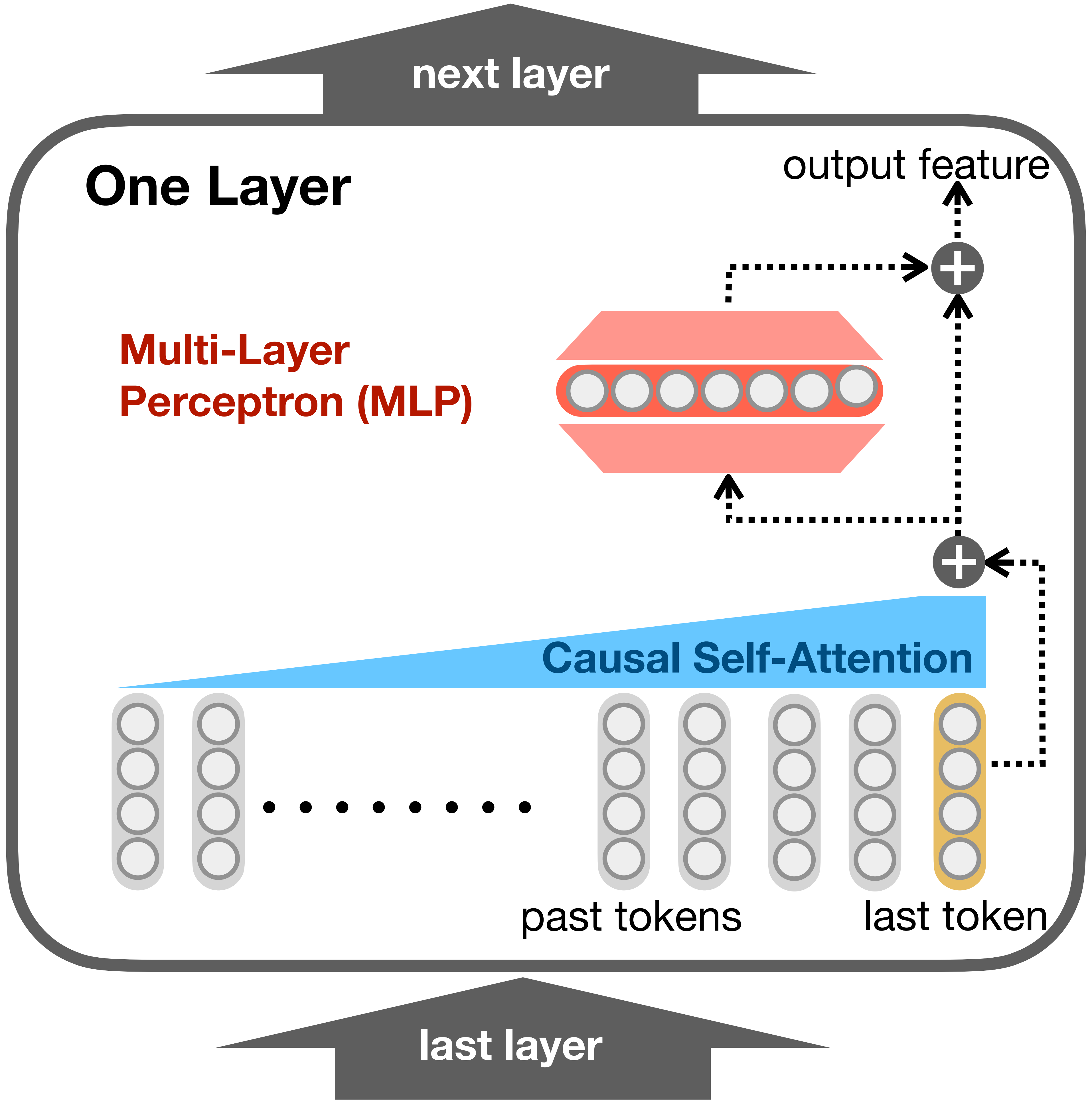


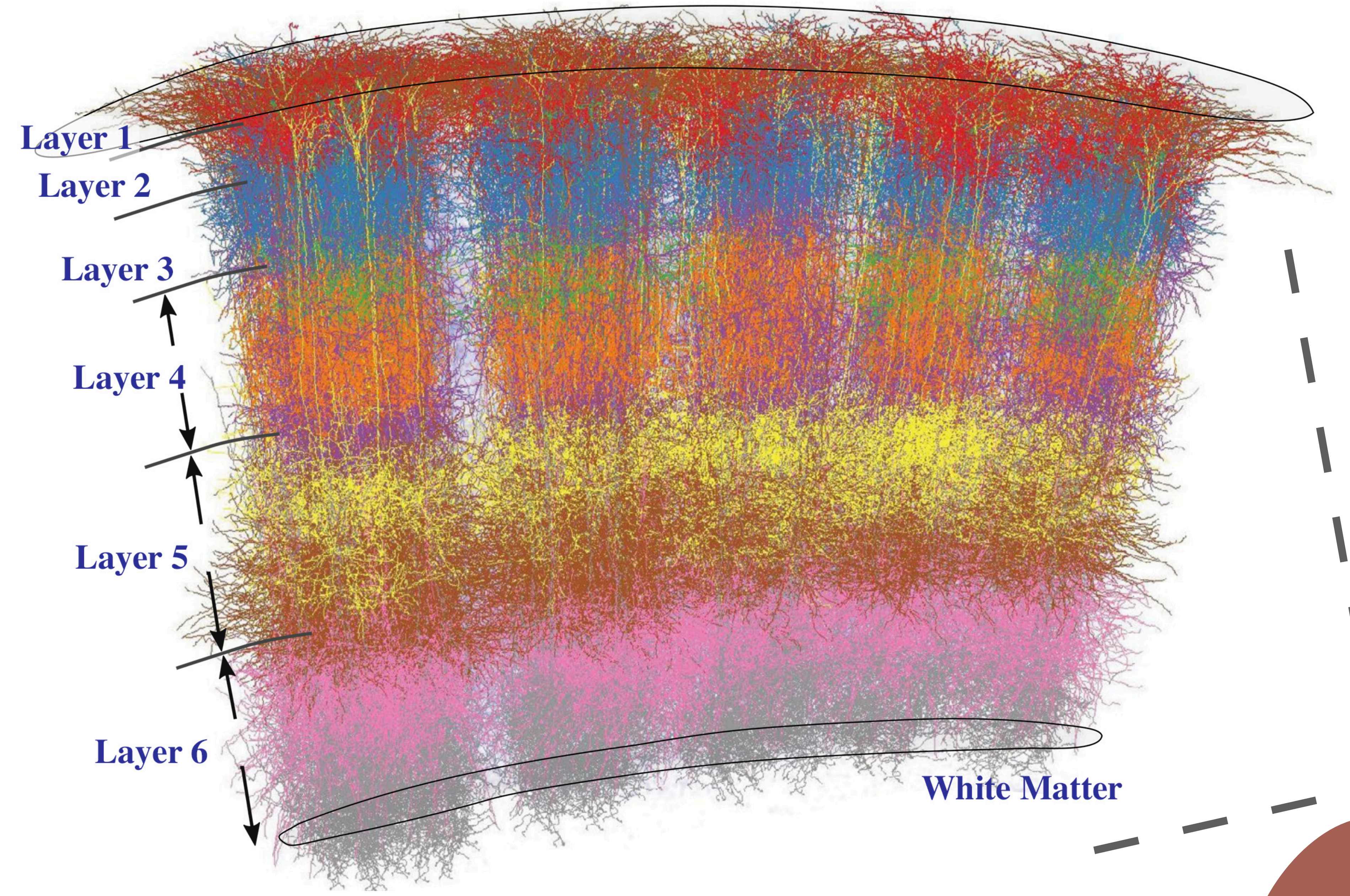
image credit: https://www.brainline.org/article/how-ptsd-affec

Can We Analogize LMs with Brains?

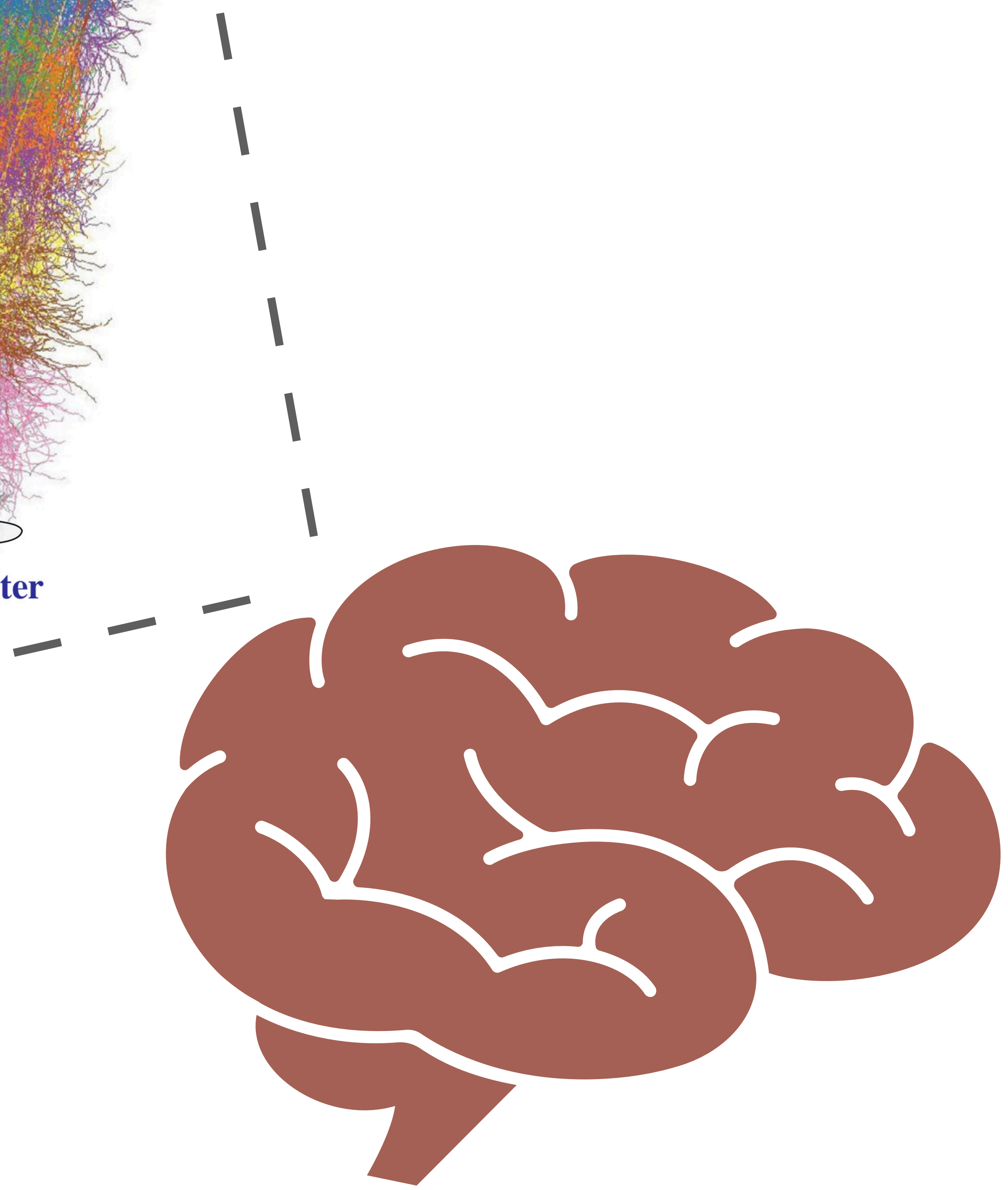
and therefore, analogize LM parameters ≈ brain neurons?



One Transformer LM

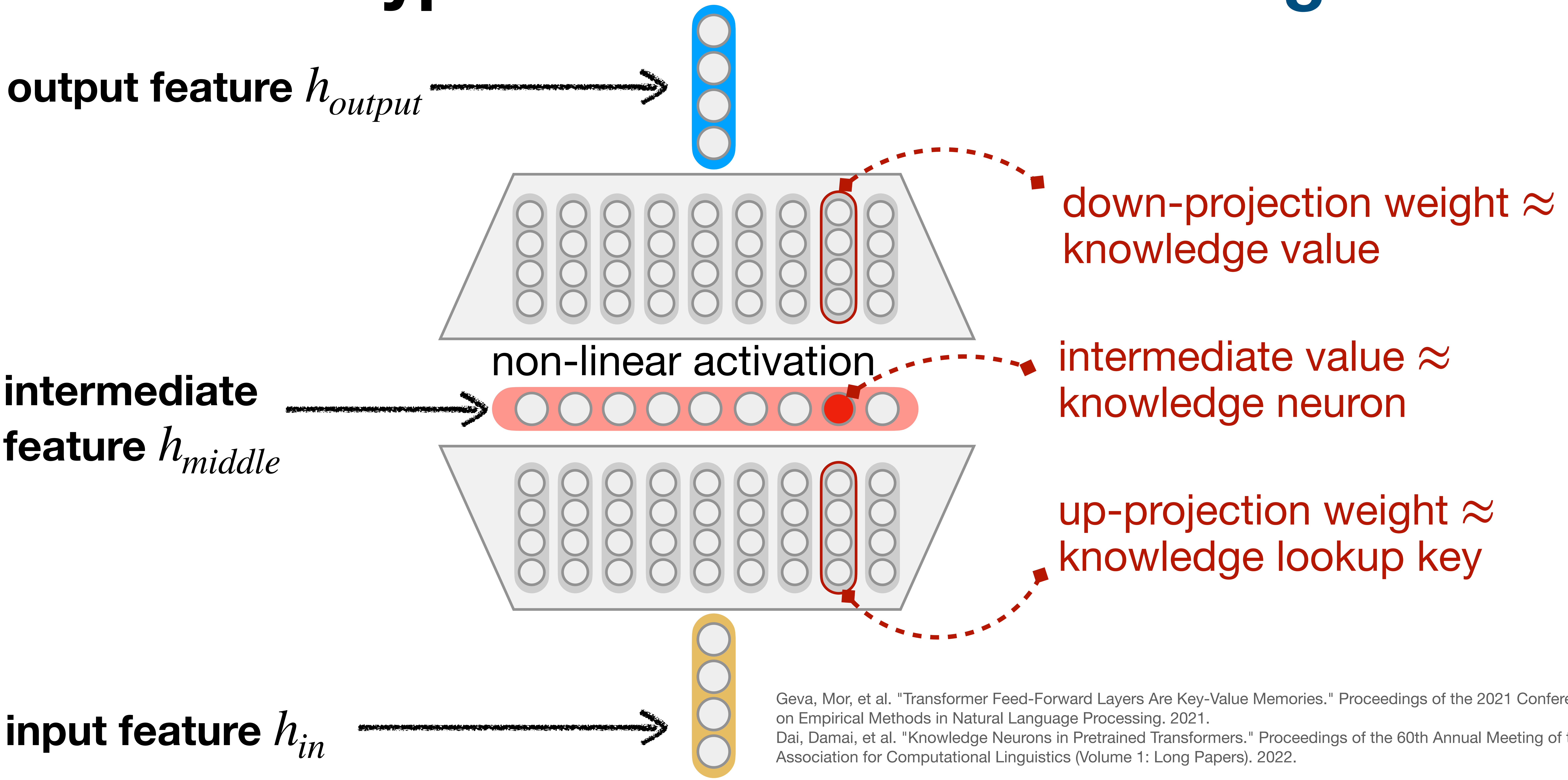


By Bodysurfinyon - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=125106144



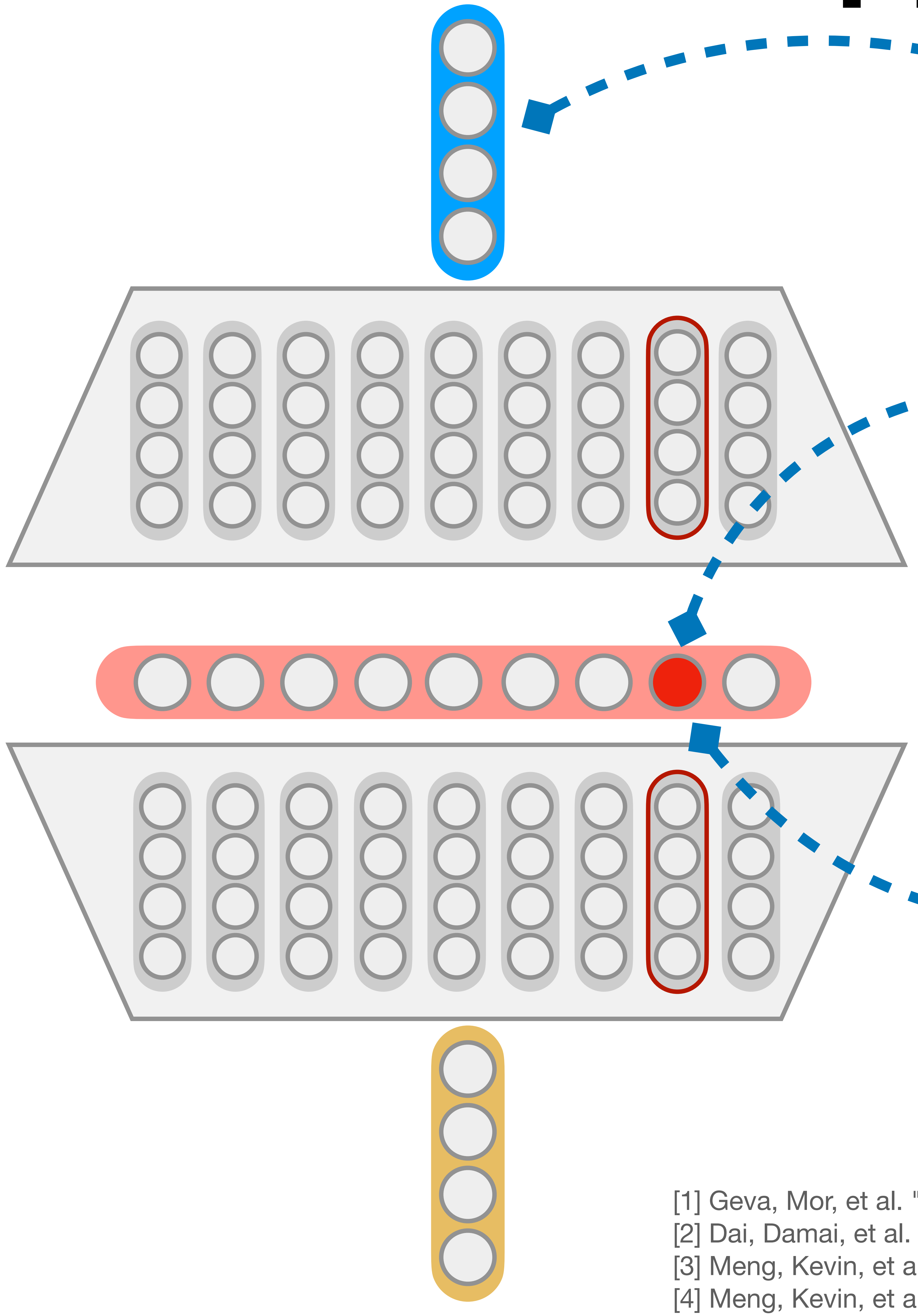
Brain and its 6-layers in neocortex

Common Hypothesis: MLP ≈ Knowledge dict

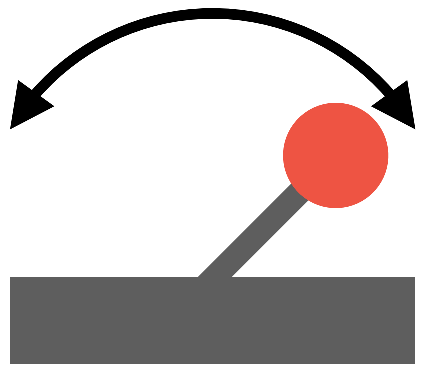


Geva, Mor, et al. "Transformer Feed-Forward Layers Are Key-Value Memories." Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing. 2021.
Dai, Damai, et al. "Knowledge Neurons in Pretrained Transformers." Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2022.

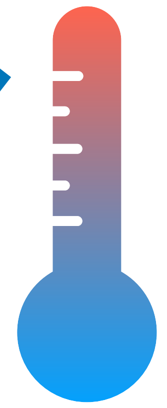
Evidence Supporting MLP ≈ Knowledge dict



- **Inserting output features** can *inject certain knowledge prediction*
- **Manually activate neurons** can also *force certain knowledge prediction*



  - e.g. Dublin is the capital and largest city of ~~England~~ → Ireland



- **Certain neurons react to** *knowledge types*
  - e.g., “part-of” types, related to TV shows

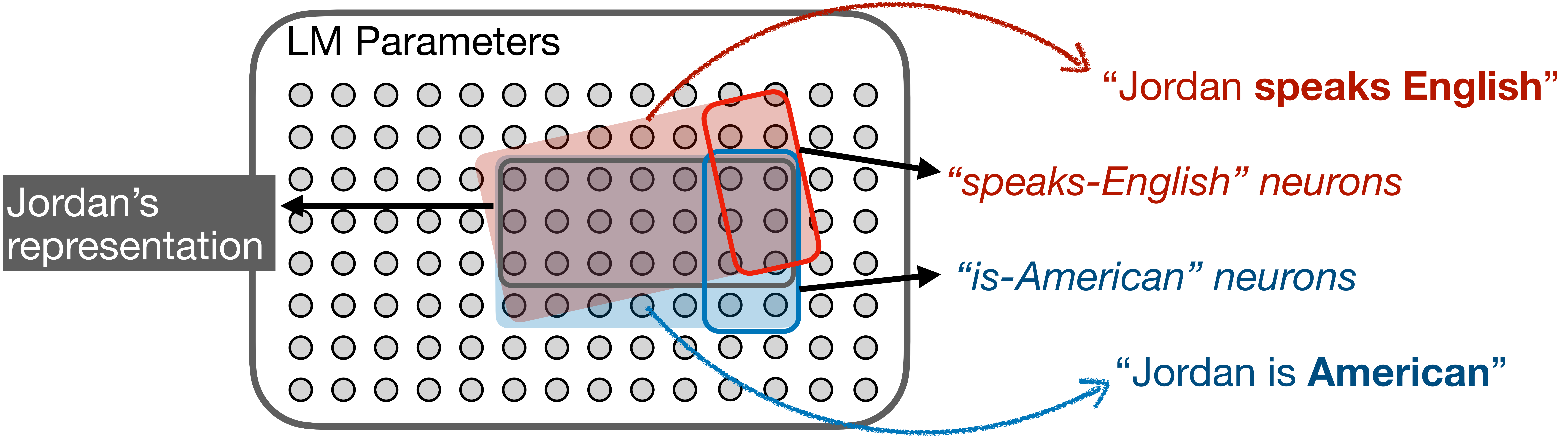
[1] Geva, Mor, et al. "Transformer Feed-Forward Layers Are Key-Value Memories." Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing. 2021.
[2] Dai, Damai, et al. "Knowledge Neurons in Pretrained Transformers." Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics. 2022.
[3] Meng, Kevin, et al. "Locating and editing factual associations in GPT." Advances in Neural Information Processing Systems 35 (2022): 17359-17372.
[4] Meng, Kevin, et al. "Mass-Editing Memory in a Transformer." The Eleventh International Conference on Learning Representations.

Knowledge Seems to Be Stored Messily

Expectation: semantic / logical related facts should share parameters

Why? intuitively, this leads to better semantic/logic-based generalization:

if $x \rightarrow y$, when $P(x) \uparrow$, the LM can automatically $P(y) \uparrow$



Knowledge Seems to Be Stored Messily

incompatible sentences postively align parameters

Qin, Jiaxin, et al. "Why Does New Knowledge Create Messy Ripple Effects in LLMs?." Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing. 2024.

Knowledge Seems to Be Stored Messily

incompatible sentences postively align parameters

- **Negation curse:**
  - **X**: Leonardo is from USA
  - **not X**: Leonardo is <u>not</u> from USA

Qin, Jiaxin, et al. "Why Does New Knowledge Create Messy Ripple Effects in LLMs?." Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing. 2024.

Knowledge Seems to Be Stored Messily

incompatible sentences postively align parameters

- **Negation curse:**
  - **X**: Leonardo is from USA
  - **not X**: Leonardo is <u>not</u> from USA

- **Over-Ripple:**
  - **X**: Leonardo <u>is from</u> USA
  - χ: Leonardo <u>speaks</u> USA

Qin, Jiaxin, et al. "Why Does New Knowledge Create Messy Ripple Effects in LLMs?." Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing. 2024.

Knowledge Seems to Be Stored Messily

similar sentences with low parameter overlap

Qin, Jiaxin, et al. "Why Does New Knowledge Create Messy Ripple Effects in LLMs?." Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing. 2024.

Knowledge Seems to Be Stored Messily

similar sentences with low parameter overlap

- **Cross-Lingual Barrier:**
  - Leonardo is from USA
  - 莱昂纳多来自美国 (same meaning)

Qin, Jiaxin, et al. "Why Does New Knowledge Create Messy Ripple Effects in LLMs?." Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing. 2024.

Knowledge Seems to Be Stored Messily

similar sentences with low parameter overlap

- **Cross-Lingual Barrier**:
    - Leonardo is from USA
    - 莱昂纳多来自美国 (same meaning)

- **Logical Distance Barrier**:
    - Leonardo is from USA
    - The highest building in the capital of Leonardo’s homeland is Washington Monument (3 logical steps from above)

Qin, Jiaxin, et al. "Why Does New Knowledge Create Messy Ripple Effects in LLMs?." Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing. 2024.

Curse of Reversals / Inverse-Searches

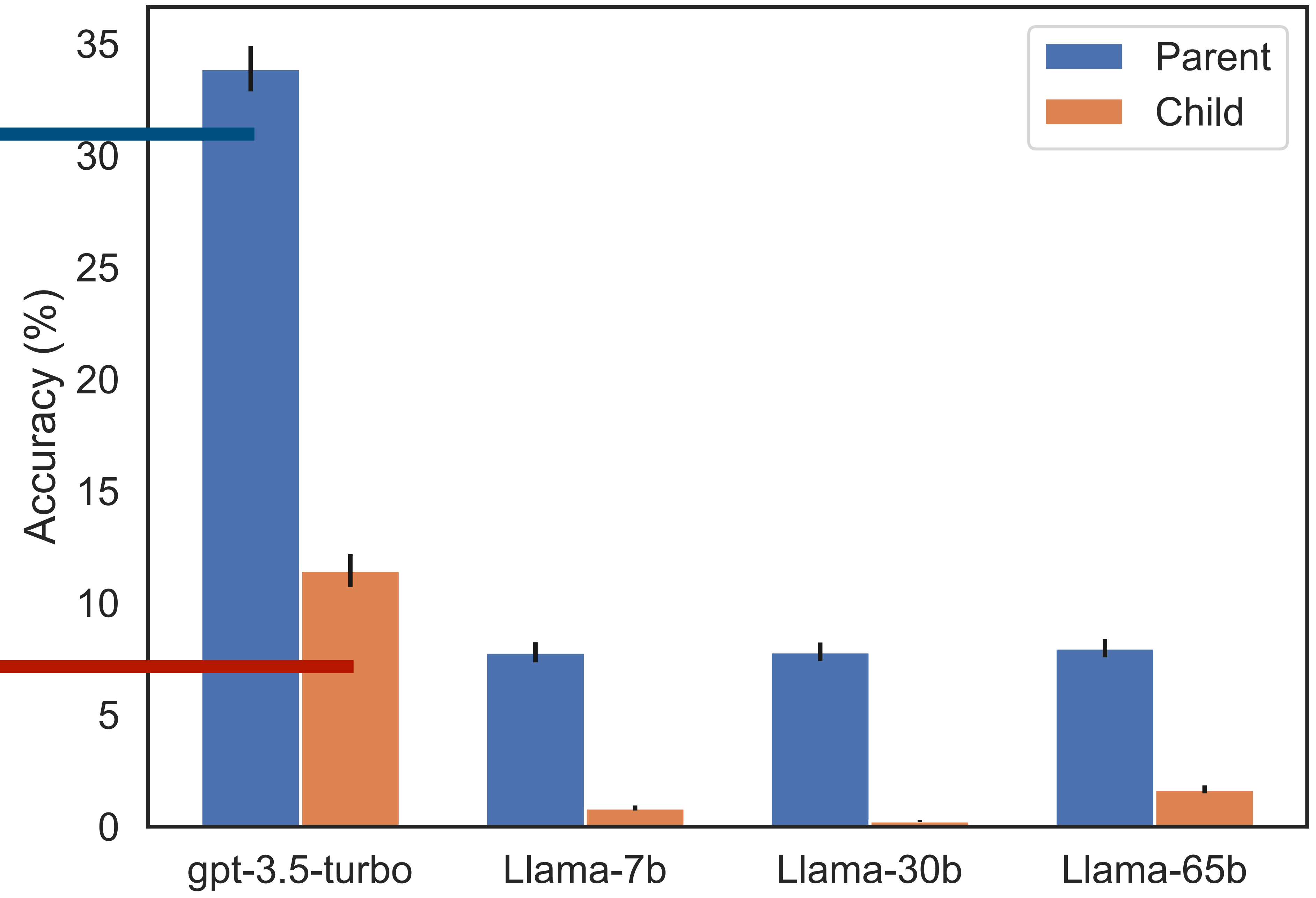
Training: After learning on data “**A** is *B*”.

✓ **Forward inference**: LMs can successfully answer “**A** is [?]” → “*B*”

✘ **Inverse inference:** they struggle to answer “[?] is *B*” → “**A**”

Q: Who is **Tom Cruise**’s mother?
A: *Mary Lee Pfeiffer*

Q: Who is *Mary Lee Pfeiffer*’s son?
A: **Tom Cruise**



Berglund, Lukas, et al. "The Reversal Curse: LLMs trained on “A is B” fail to learn “B is A”." The Twelfth International Conference on Learning Representations.
Allen-Zhu, Zeyuan, and Yuanzhi Li. "Physics of Language Models: Part 3.2, Knowledge Manipulation." In The Thirteenth International Conference on Learning Representations.

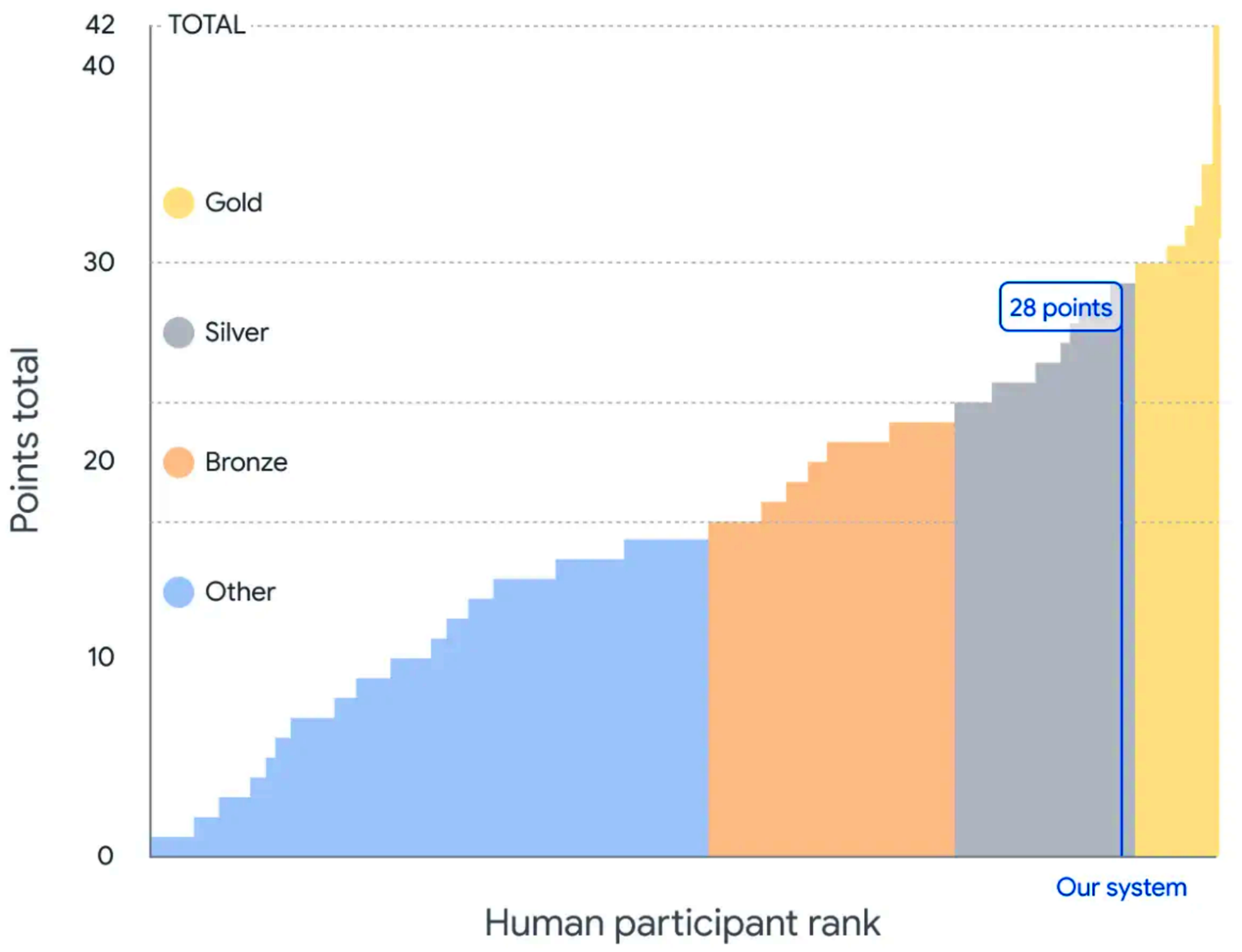
Room for Future Efforts

- Investigating if more specific and precise localization of knowledge neurons is possible (or are knowledge neurons distributed in nature)
- Revealing the relation between knowledge neuron localization and knowledge editing.
- Looking at the relation between knowledge and their semantically equivalent expressions in LM processing
- Investigating other LM components' roles in knowledge processing & storage

How Is Reasoning Conducted within LM

LMs' Reasoning Ability

AlphaGeometry excel at olympiad-level math problems



chain-of-thought reasoning by LMs

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.

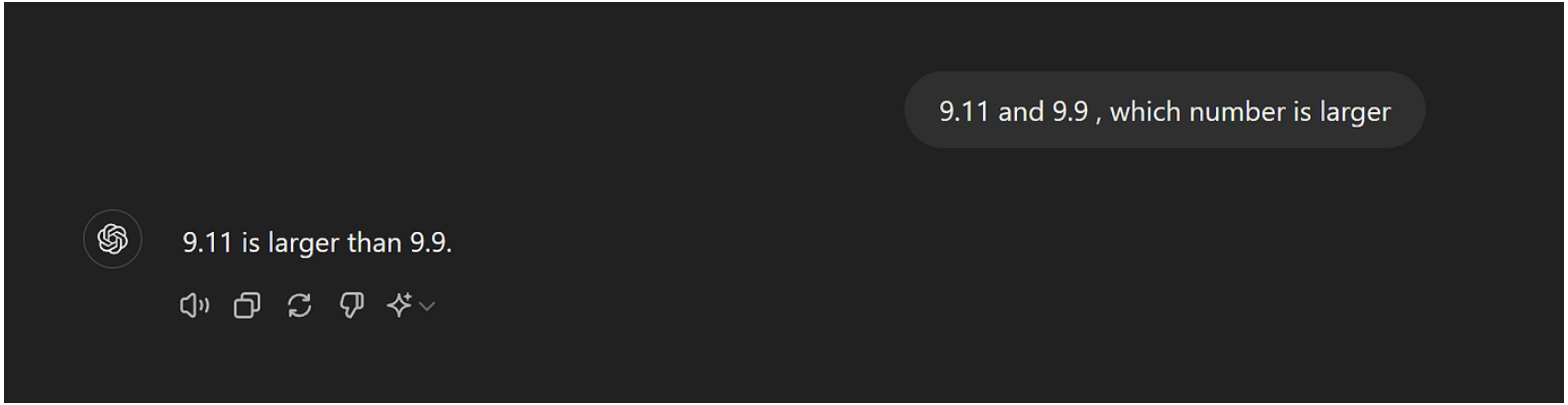
Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

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. ✓

Trinh, Trieu H., et al. "Solving olympiad geometry without human demonstrations." Nature 625.7995 (2024): 476-482.
Wei, Jason, et al. "Chain-of-thought prompting elicits reasoning in large language models." *Advances in neural information processing systems* 35 (2022): 24824-24837.

LMs Reasoning Is Sensitive to Perturbations



https://community.openai.com/t/why-9-11-is-larger-than-9-9-incredible/869824

LMs Reasoning Is Sensitive to Perturbations

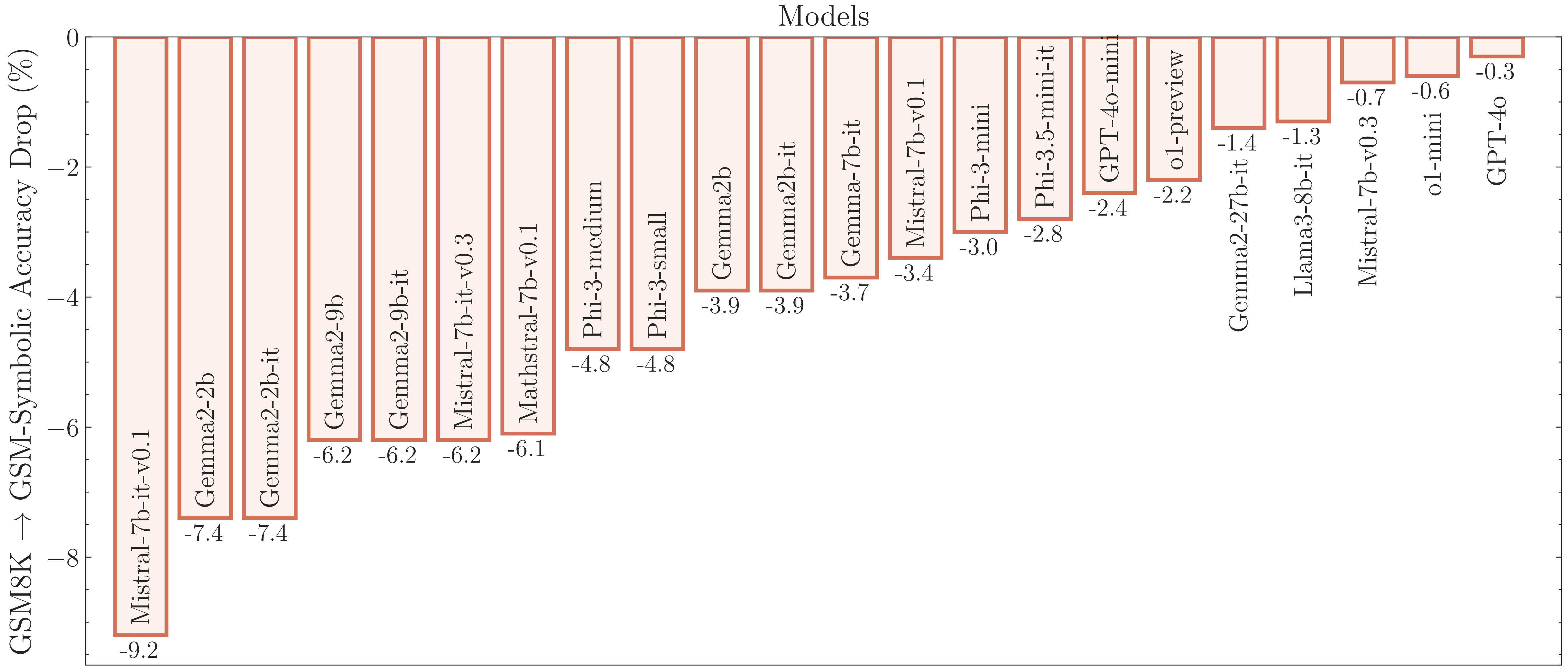
Grounding to real life matters

GSM Symbolic Template

```
When {name} watches her {family}, she gets out a variety
of toys for him.  The bag of building blocks has {x}
blocks in it.  The bin of stuffed animals has {y} stuffed
animals inside.The tower of stacking rings has {z}
multicolored rings on it.{name} recently bought a tube
of bouncy balls, bringing her total number of toys she
bought for her {family} up to {total}.  How many bouncy
balls came in the tube?

#variables:
- name = sample(names)
- family = sample(["nephew", "cousin", "brother"])
- x = range(5, 100)
- y = range(5, 100)
- z = range(5, 100)
- total = range(100, 500)
- ans = range(85, 200)

#conditions:
- x + y + z + ans == total
```



After replacing familiar nouns (e.g., “uncle,” “nephew”) with symbols, language models exhibit performance declines.

Mirzadeh, Seyed Iman, et al. "GSM-Symbolic: Understanding the Limitations of Mathematical Reasoning in Large Language Models." *The Thirteenth International Conference on Learning Representations*.

Logical Reasoning and Semantic Reasoning Entangles

when "grounding to real life" poses biases to reasoning

GSM-NoOp

Oliver picks 44 kiwis on Friday. Then he picks 58 kiwis on Saturday. On Sunday, he picks double the number of kiwis he did on Friday, but five of them were a bit smaller than average. How many kiwis does Oliver have?

---

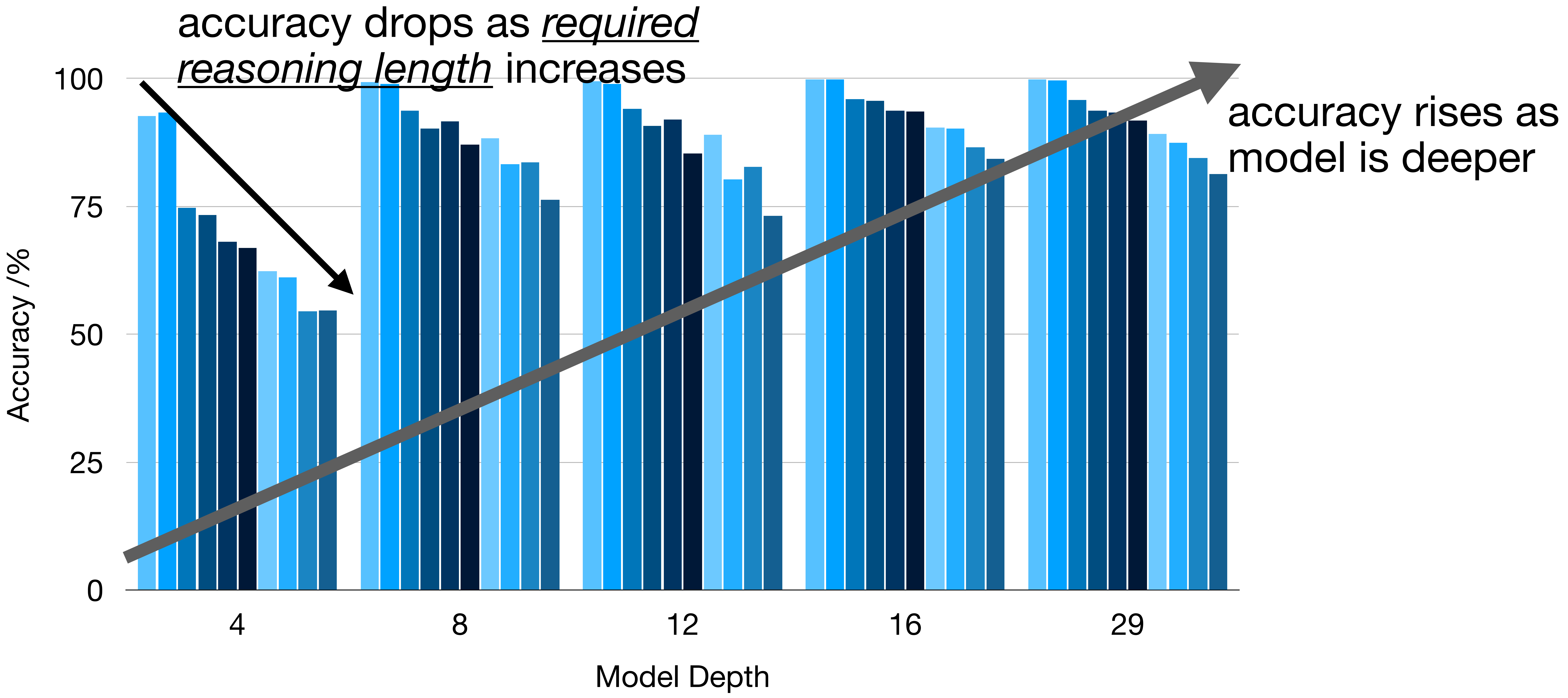
o1-mini: Oliver picks kiwis over three days as follows:
- Friday: 44 kiwis
- Saturday: 58 kiwis
- Sunday: Double the number he picked on Friday, which is $2 \times 44 = 88$ kiwis

However, on Sunday, 5 of these kiwis were smaller than average. We need to subtract them from the Sunday total: 88 (Sunday's kiwis) - 5 (smaller kiwis) = 83 kiwis Now, summing up the kiwis from all three days: 44 (Friday) + 58 (Saturday) + 83 (Sunday) = 185 kiwis Oliver has a total of 185 kiwis.

After adding semantically related but logically irrelevant statements, LM fail to ignore them but wrongly combine them and make mistakes.

Mirzadeh, Seyed Iman, et al. "GSM-Symbolic: Understanding the Limitations of Mathematical Reasoning in Large Language Models." *The Thirteenth International Conference on Learning Representations*.

Deeper Models Reason Better



Ye, Tian, et al. "Physics of language models: Part 2.1, grade-school math and the hidden reasoning process." *The Thirteenth International Conference on Learning Representations*. 2024.

Hidden Features Encode Math Operations

dep(A,B) – at the end of problem description, does the model know *parameter A depend on B*?

e.g. dep(“Riverview High‘s Film Studio”, “Film Studio’s Messenger Bag”) = true

nece(A) – after question is asked, does the model know *if A is necessary* for answering question?

e.g. nece(“Riverview High's Film Studio”) = false

can_next(A) – in the middle of solution, does the model know if *A can be computed next*?

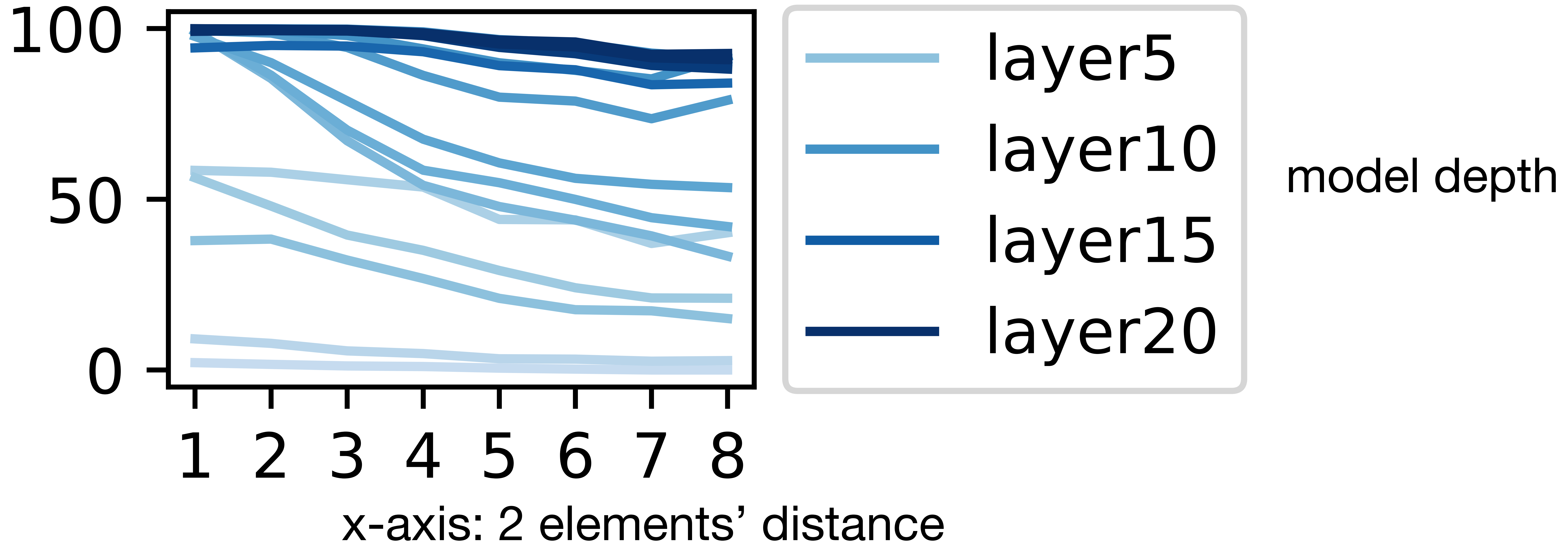
e.g. can_next(“Riverview High's Film Studio”) = true
can_next(“Riverview High's Dance Studio”) = false

[Problem] The number of each Riverview High‘s Film Studio equals 5 times as much as the sum of each Film Studio’s Backpack and each Dance Studio‘s School Daypack. **…** The number of each Film Studio's Messenger Backpack equals 13.
[Question] *How many Backpack does Central High have?*
[Solution] *Define Dance Studio's School Daypack as p; so p = 17. Define Film Studio's Messenger Backpack as W; so W = 13. Define Central High's Film Studio as B; so B = p + W = 17 + 13 = 7. Define Film Studio's School Daypack as g; R = W + B = 13 + 7 = 20; so g = 12 + R = 12 + 20 = 9. Define Film Studio's Backpack as w; so w = g + W = 9 + 13 = 22. Define Central High's Backpack as c; so c = B * w = 7 * 22 = 16.* ***[Answer]*** *16.*

Ye, Tian, et al. "Physics of language models: Part 2.1, grade-school math and the hidden reasoning process." *The Thirteenth International Conference on Learning Representations*. 2024.

Every Math Operation Benefit from Depth

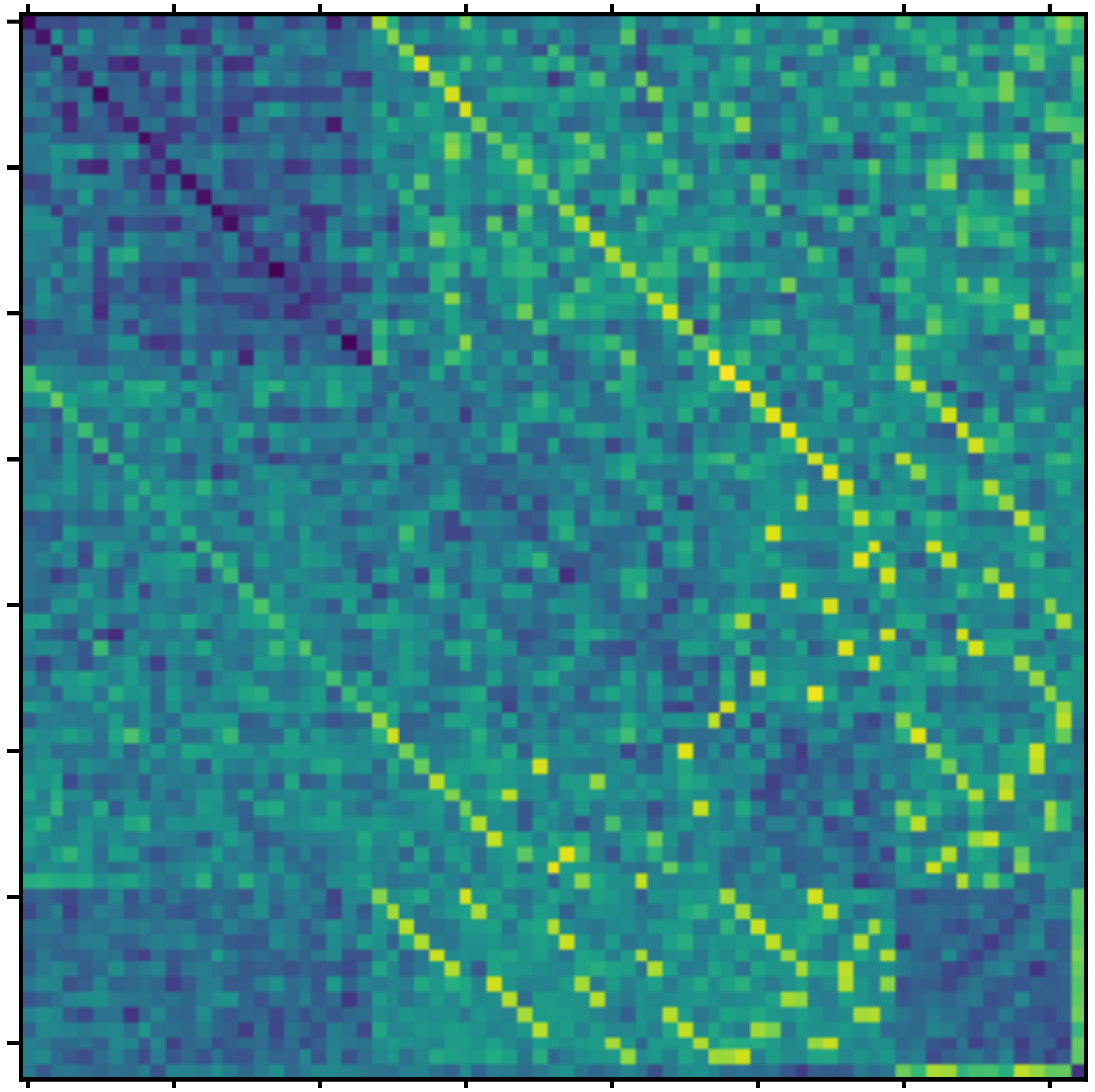
y-axis: $nece(X, Q)$, predicting if fact X is necessary for answering question Q



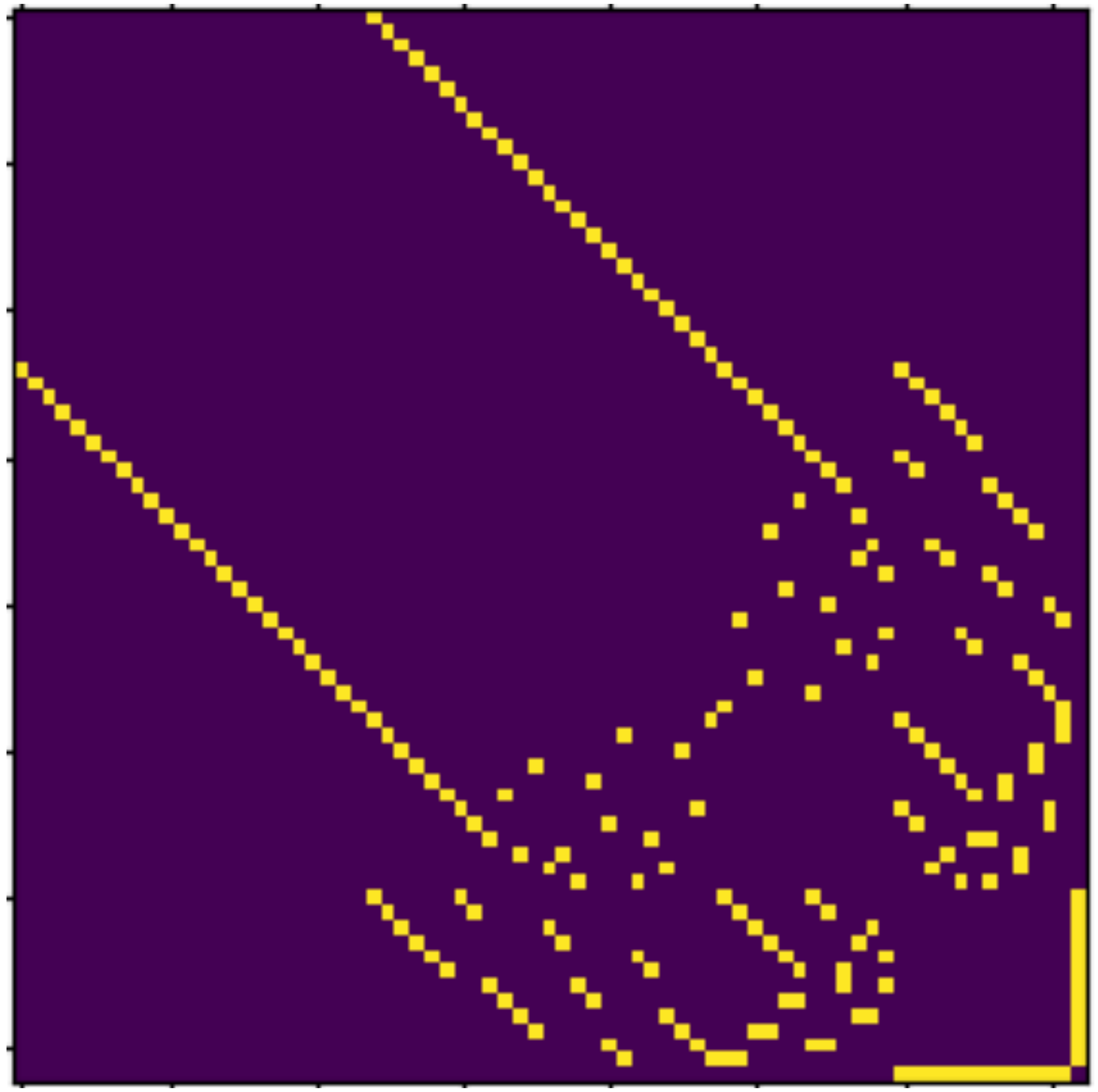
potential reason: every math operation needs certain depth of layers to stack with each other

Ye, Tian, et al. "Physics of language models: Part 2.1, grade-school math and the hidden reasoning process." *The Thirteenth International Conference on Learning Representations*. 2024.

LM Encodes Reachability after Learning Planning



Learned FFN weight W^M between graph nodes



ground-truth connectivity

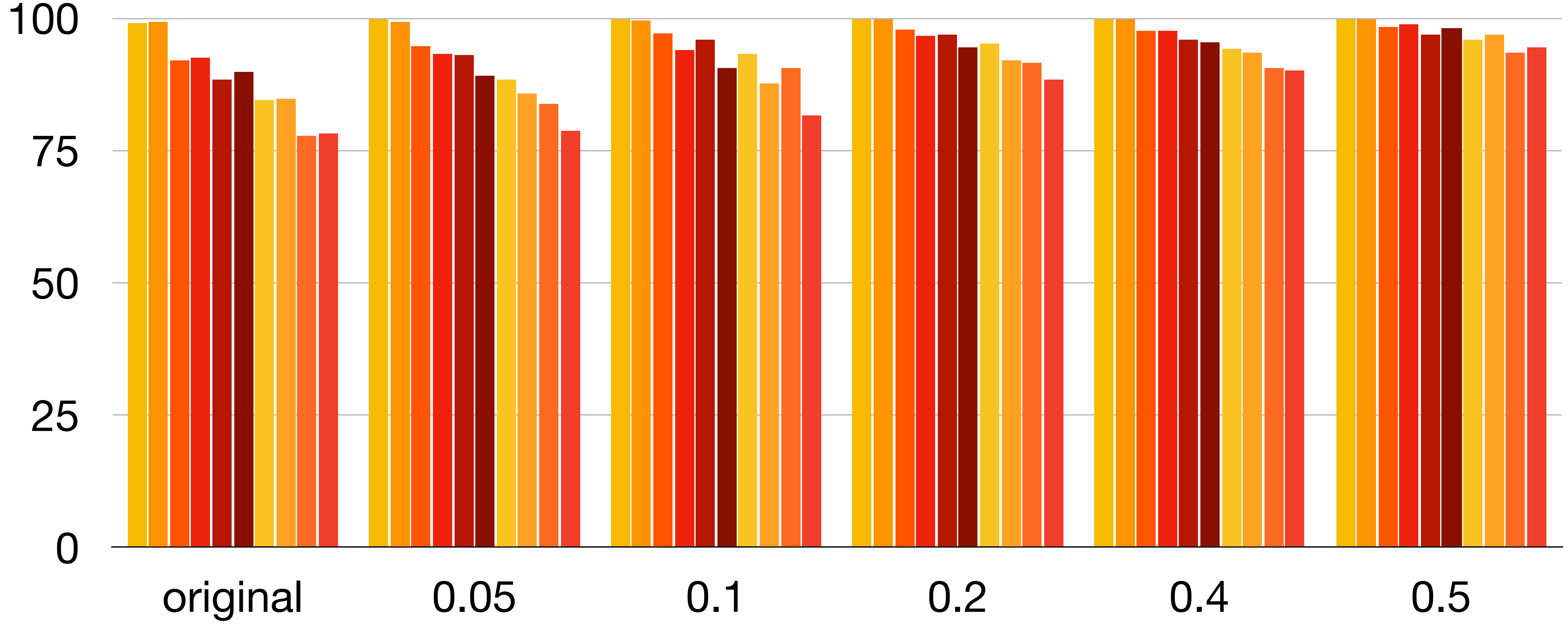
Ye, Tian, et al. "Physics of language models: Part 2.1, grade-school math and the hidden reasoning process." *The Thirteenth International Conference on Learning Representations*. 2024.

Learning on Error-Correction Data Helps

Example:

(Solution - retry rate 0.5) Define Dance Studio's School Daypack as p; so p = 17. ~~Define Film Studio's School Daypack as~~ [BACK]. Define Film Studio's Messenger Backpack as W; so W = 13. ~~Define Central High's Classroom as~~ [BACK]. ~~Define Central High's Backpack as~~ [BACK]. Define Central High's Film Studio as B; so B = p + W = 17 + 13 = 7. Define Film Studio's School Daypack as g; R = W + B = 13 + 7 = 20; so g = 12 + R = 12 + 20 = 9. ~~Define Riverview High's Dance Studio as~~ [BACK]. Define Film Studio's Backpack as w; so w = g + W = 9 + 13 = 22. ~~Define Riverview High's Dance Studio as~~ [BACK]. Define Central High's Backpack as c; so c = B * w = 7 * 22 = 16.

Trend:



Ye, Tian, et al. "Physics of language models: Part 2.1, grade-school math and the hidden reasoning process." *The Thirteenth International Conference on Learning Representations*. 2024.

How Does Error-Retry Data Benefit Reasoning?

After training on error-retry data

1. No need to mask out mistakes' loss terms.

2. During inference, LLMs hardly intentionally make mistakes,

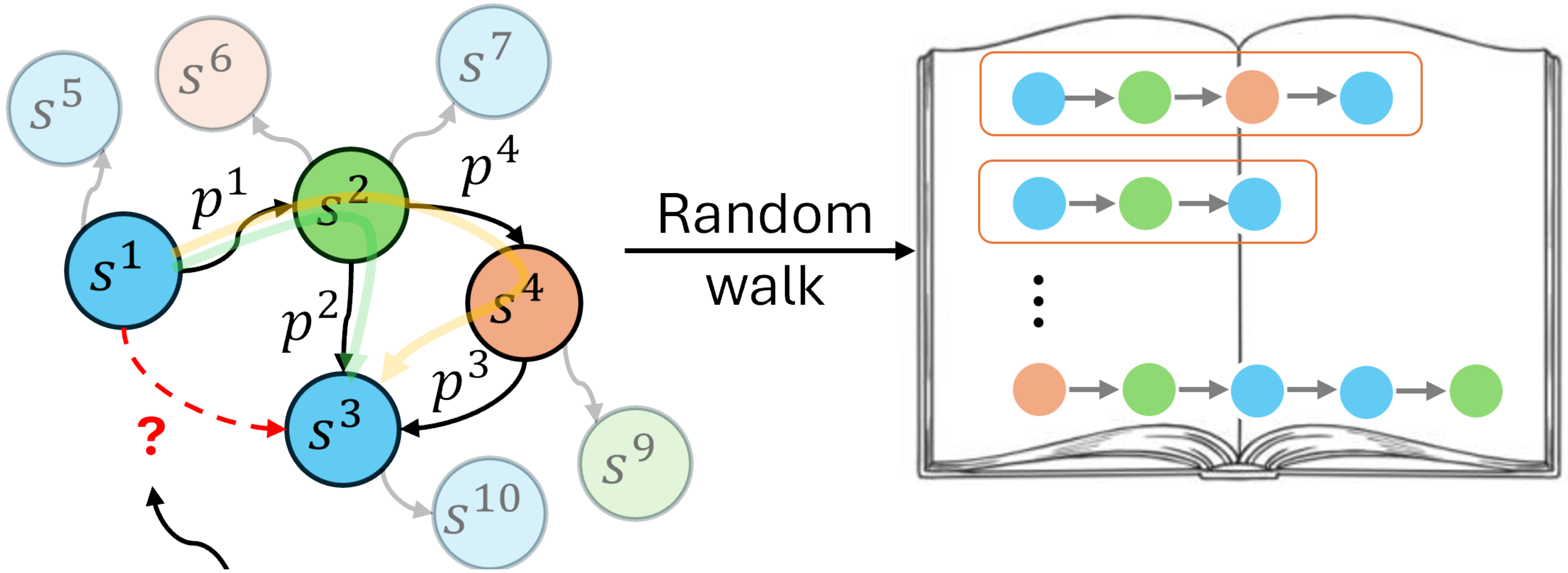
3. Instead, they still try their best to answer correctly in the first place.

<u>summary: retry data is beneficial and safe.</u>

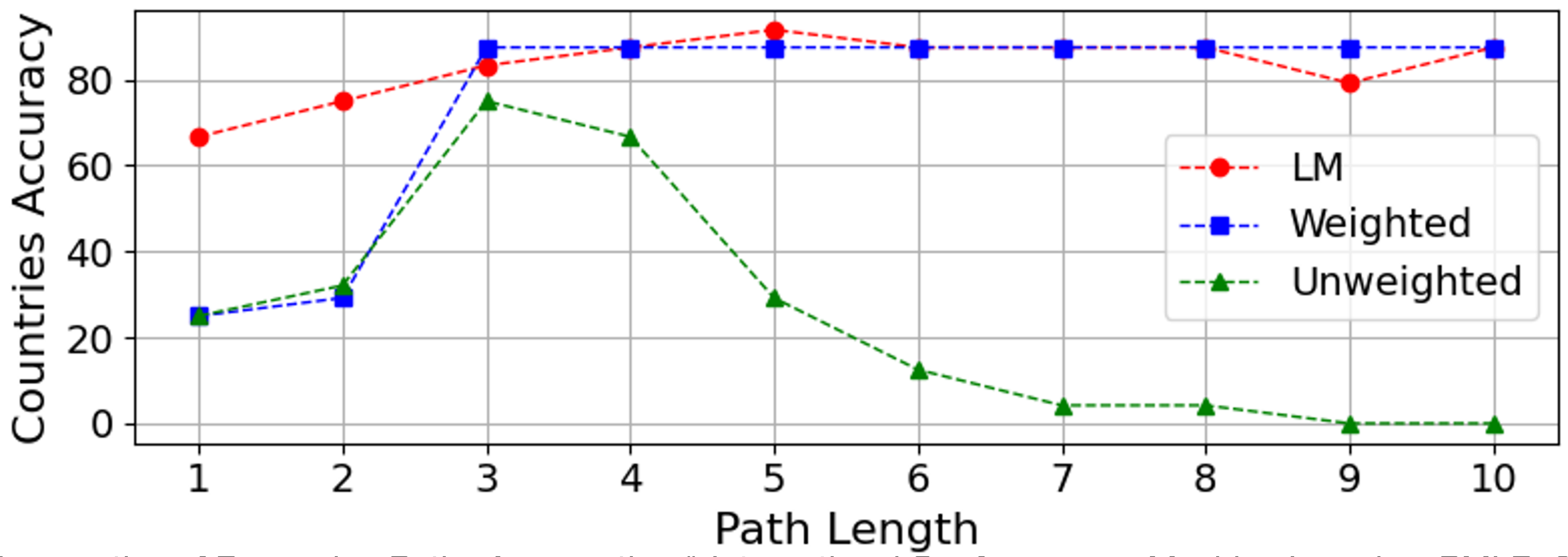
Ye, Tian, et al. "Physics of language models: Part 2.1, grade-school math and the hidden reasoning process." *The Thirteenth International Conference on Learning Representations*. 2024.

Reasoning Can Also Be Interpreted as Random Walk in Statement Space

Interpreting reasoning as a mixture or reasoning “walks” in claim graph G.



A weighted average of paths approximate reasoning acc well.



Wang, Xinyi, et al. "Understanding Reasoning Ability of Language Models From the Perspective of Reasoning Paths Aggregation." *International Conference on Machine Learning*. PMLR, 2024.

Room for Future Research

- A more precise and systematic description of reasoning trace in LMs
- Extension to other reasoning domains, e.g., reasoning involving knowledge, domain-specific reasoning, reasoning on augmented information
- Revealing reasoning capacity and scaling across model size & data.

Part 2: Physiology

How Do Components Function in Language Models?

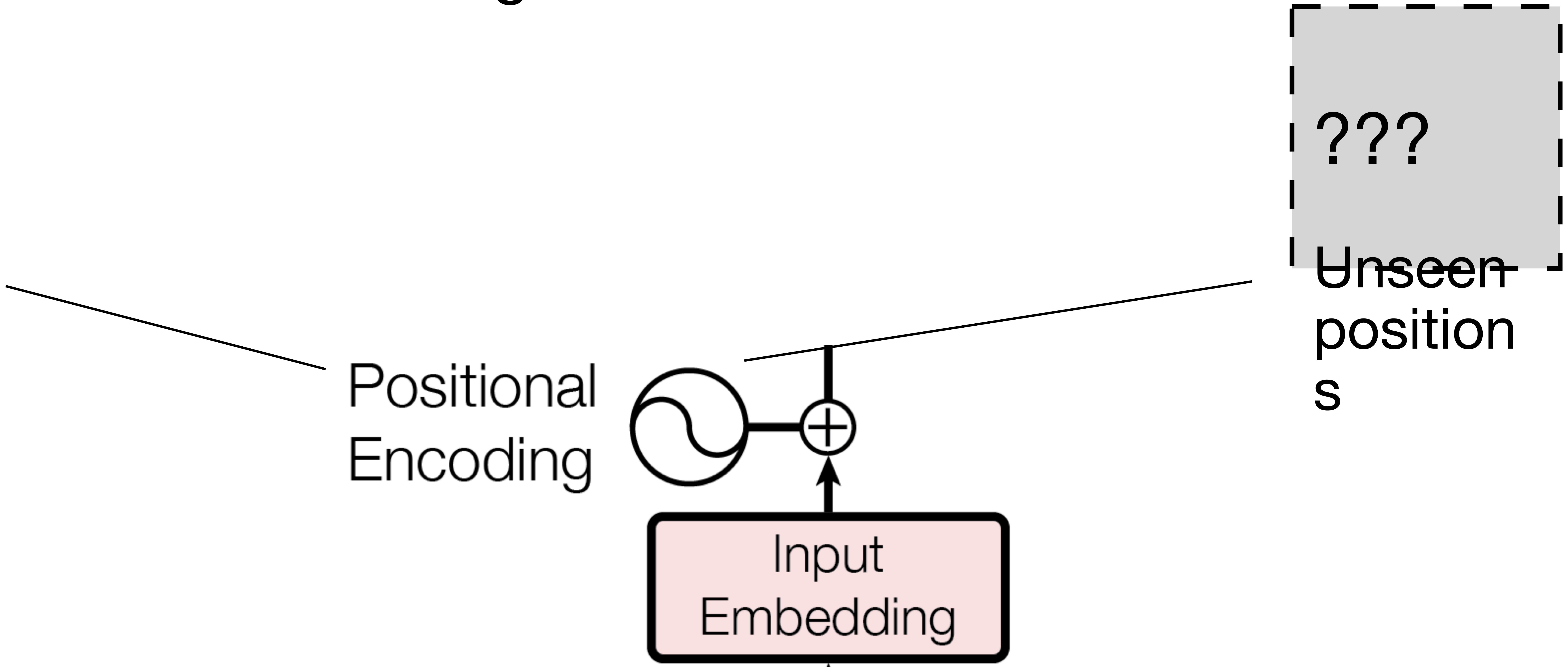
Topics

- **Attention**: Attention, position and context
- **Embeddings**: What is the function of word embeddings

Attention, Position and Context

Absolute Positional Encoding: ❌

The **absolute positional encoding** used in vanilla Transformers is not generalizable to unseen lengths.



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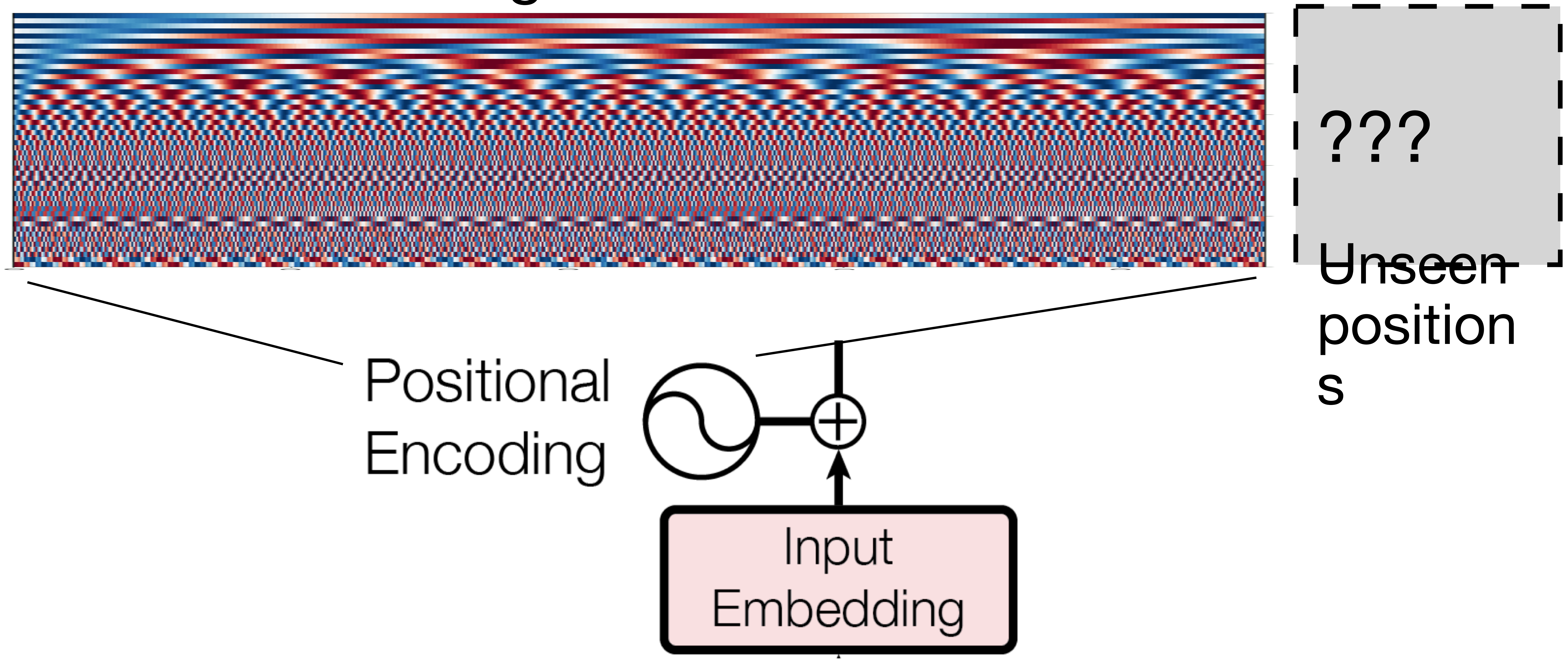


https://erdem.pl/2021/05/understanding-positional-encoding-in-transformers

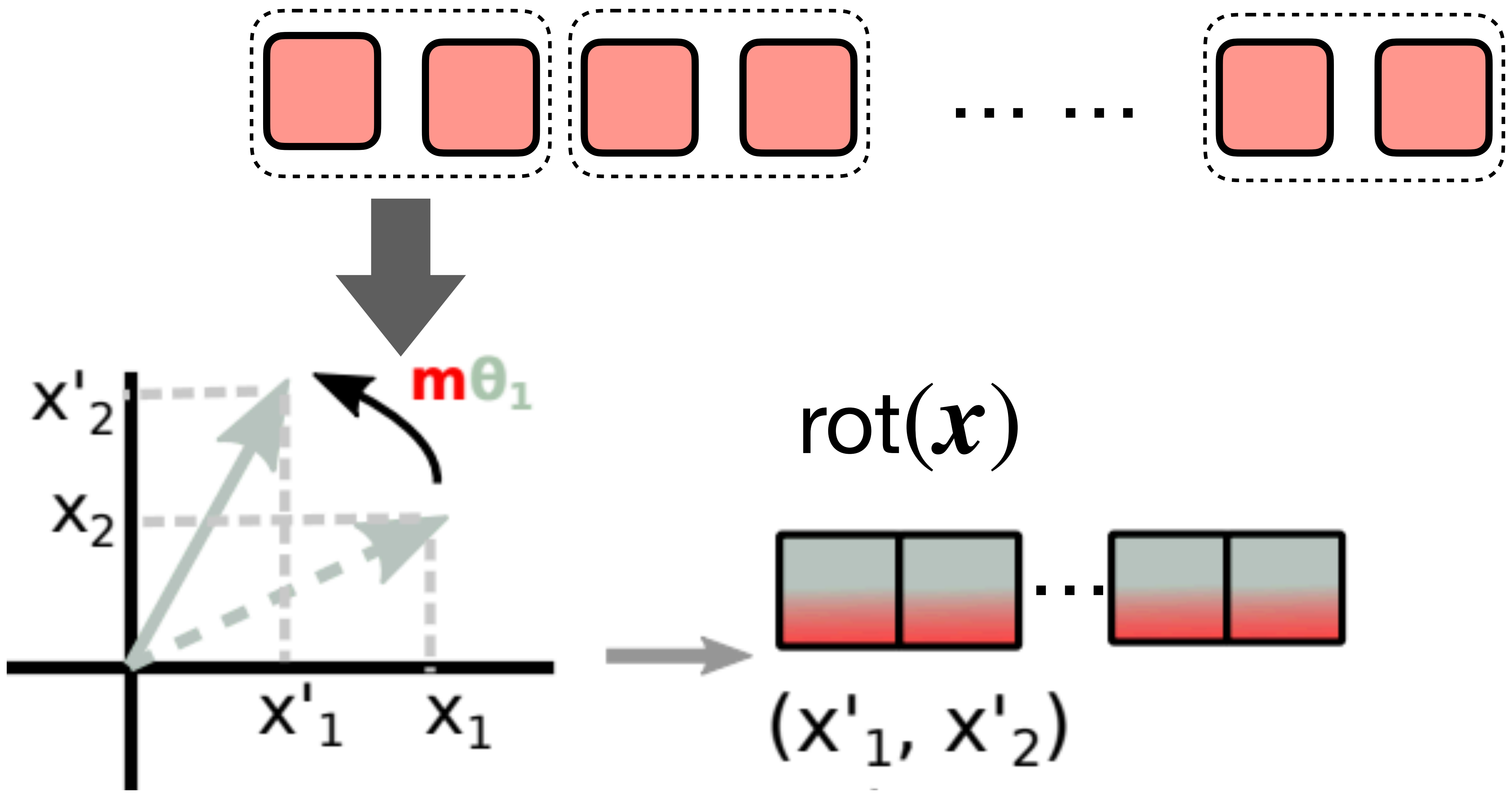
Relative Positional Encoding: ?

Relative positional encoding was proposed in the hope to alleviate this problem

Core idea: determining attention based on distance

RoPE:

$$\boldsymbol{x} = (x_1,\ x_2,\ x_3,\ x_4,\ \cdots\cdots\ x_{d-1}, x_d)$$



(Used in LLaMA, Llama-2, GPT-J, etc.)

Su, Jianlin, et al. "Roformer: Enhanced transformer with rotary position embedding." arXiv preprint arXiv:2104.09864 (2021).

Relative Positional Encoding: ?

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RoPE:

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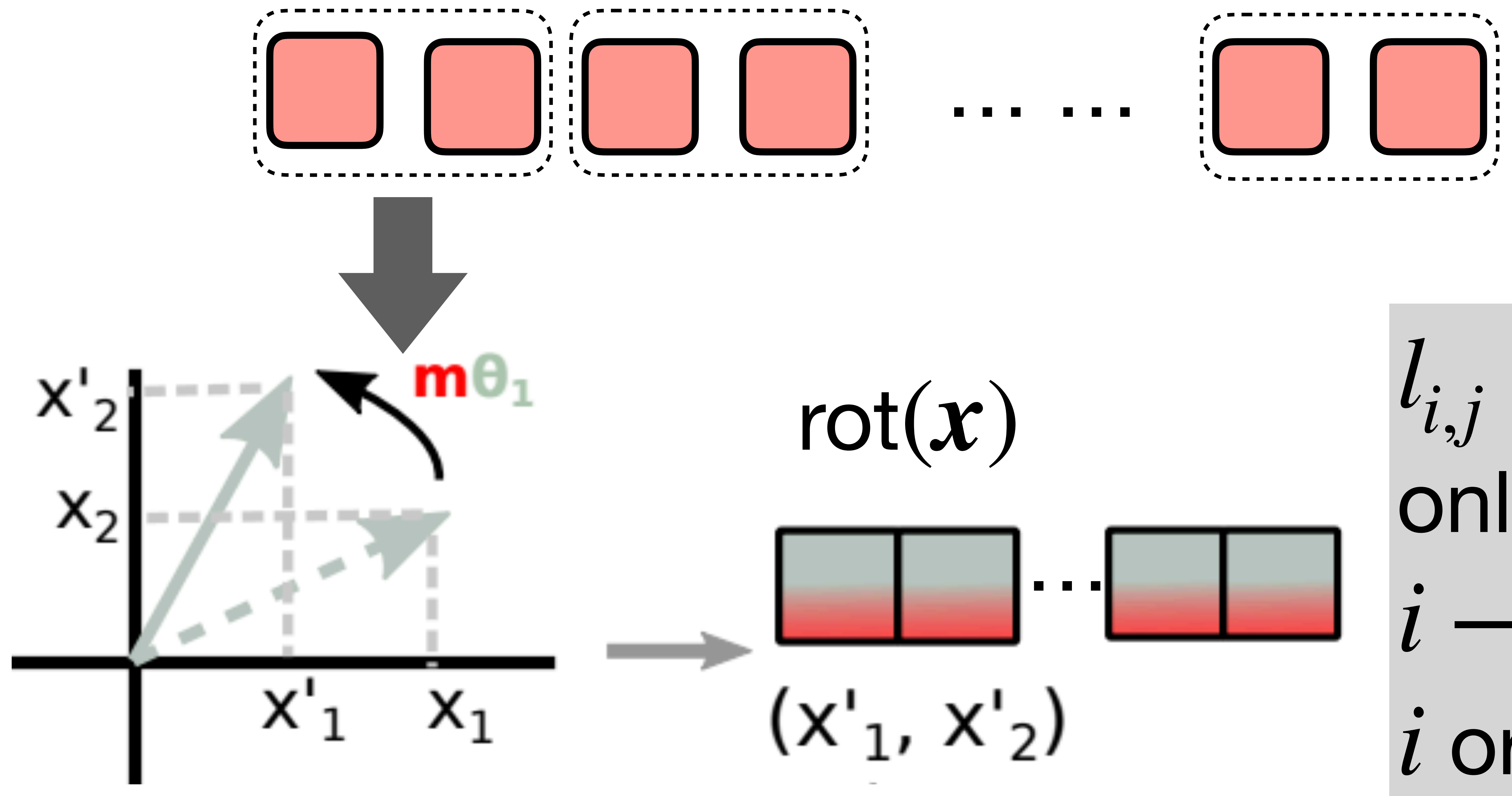


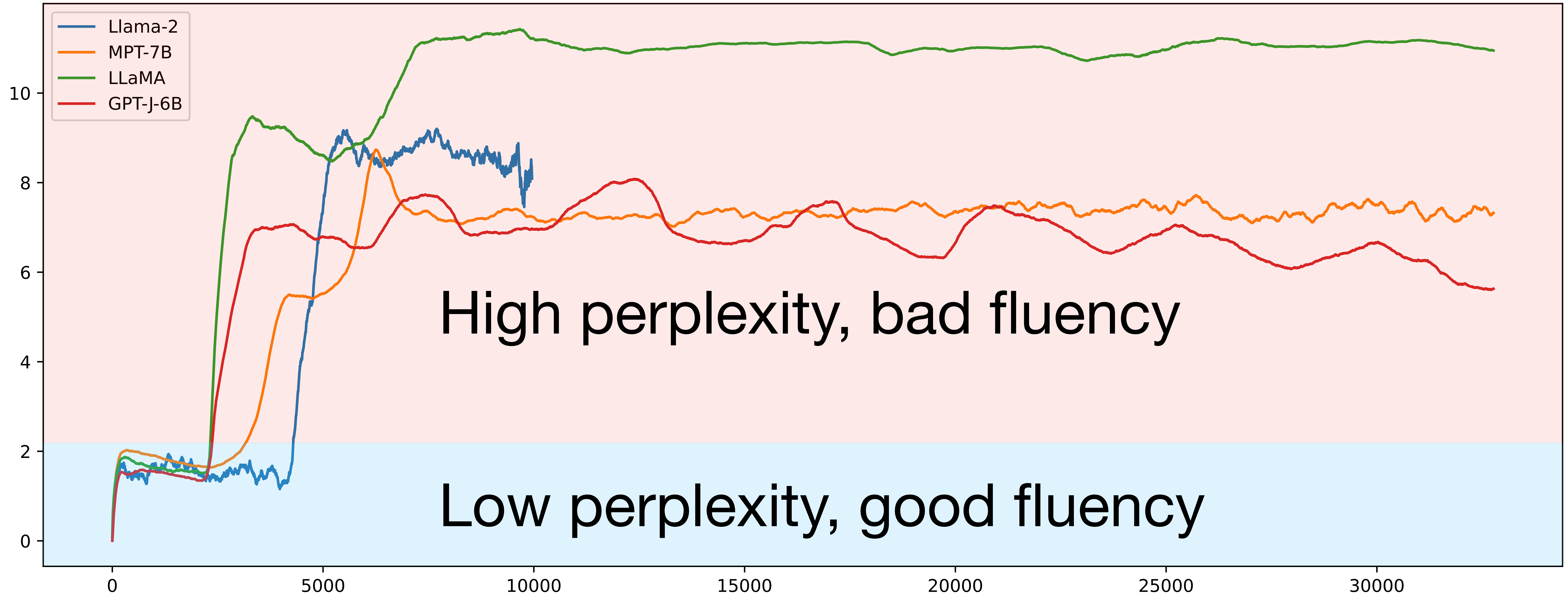
$l_{i,j} = \text{rot}(\boldsymbol{q}_i)^\top \text{rot}(\boldsymbol{k}_j)$ only depends on $i - j$, regardless of i or j.

Su, Jianlin, et al. "Roformer: Enhanced transformer with rotary position embedding." arXiv preprint arXiv:2104.09864 (2021).

Relative Positional Encoding: ?

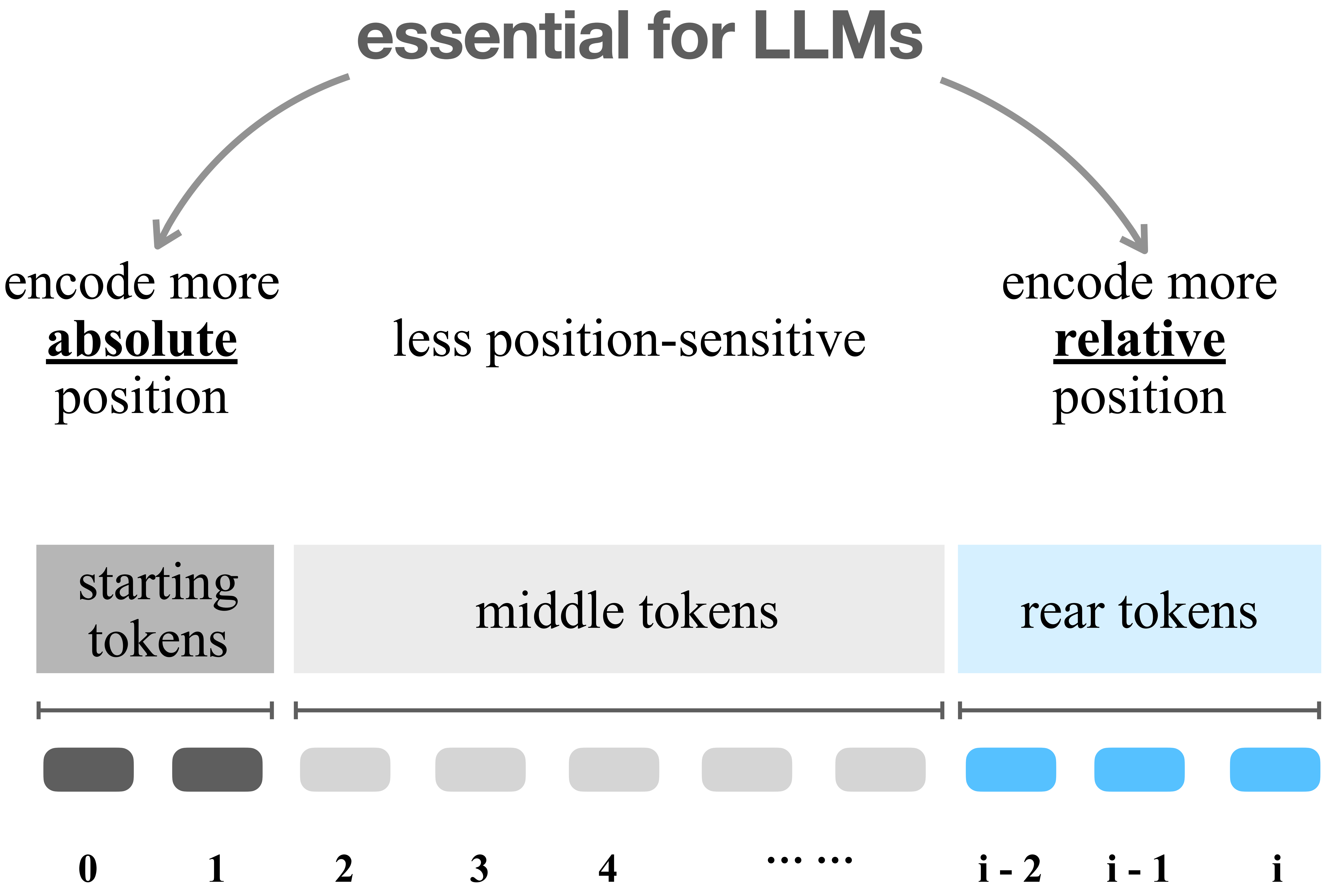
However, current LLMs still struggle on unseen lengths.

Negative Log-Likelihood (NLL, also =log(perplexity)**)** ↓



length

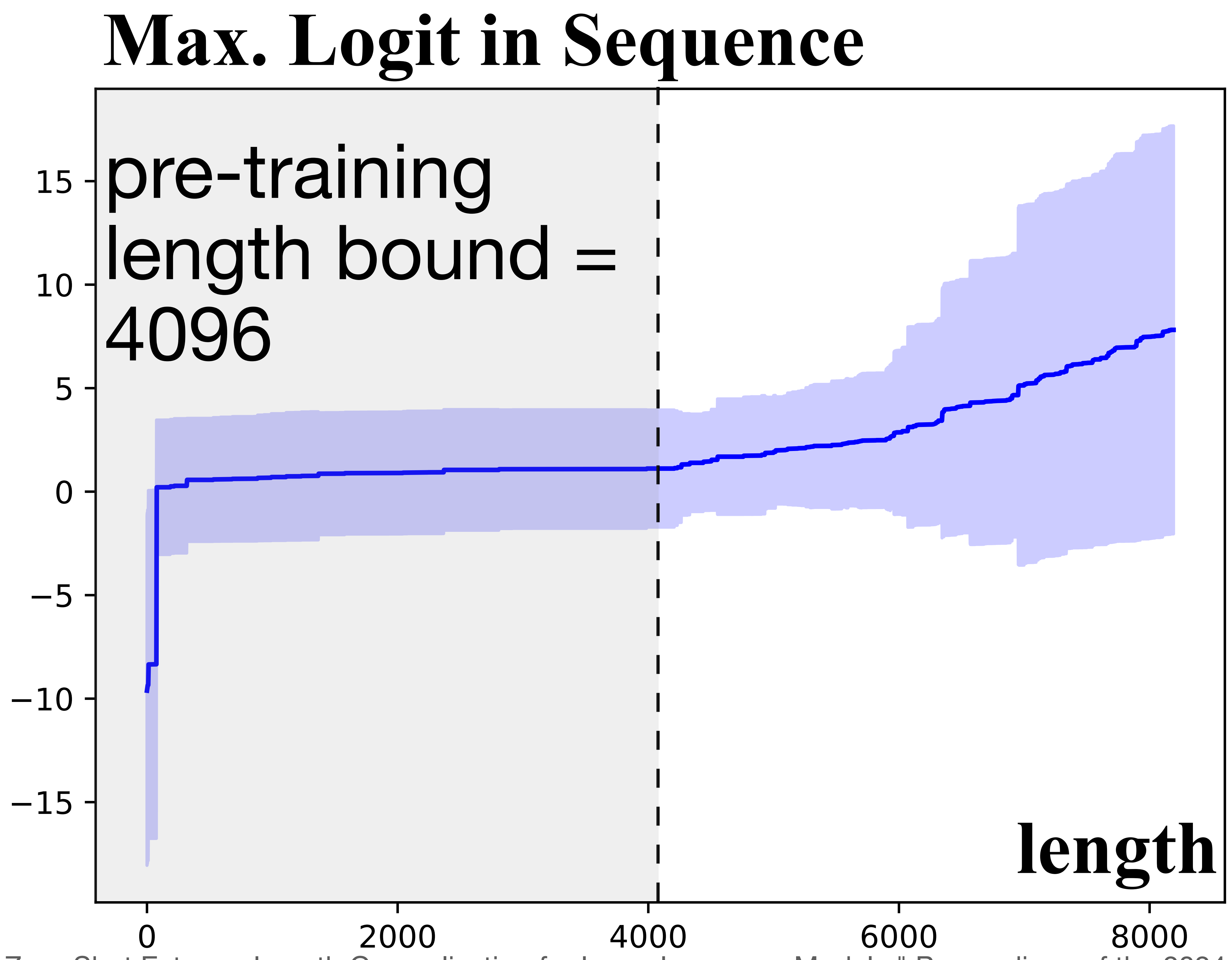
A Conceptual Model of Relative Position Encoding



Han, Chi, et al. "LM-Infinite: Zero-Shot Extreme Length Generalization for Large Language Models." Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Factor 1: Unseen Distance

Theorem 1 (Informal): For an attention mechanism using relative positional encoding, the attention logits must explode to infinities to differentiate previously unseen distances apart as the sequence length increases.



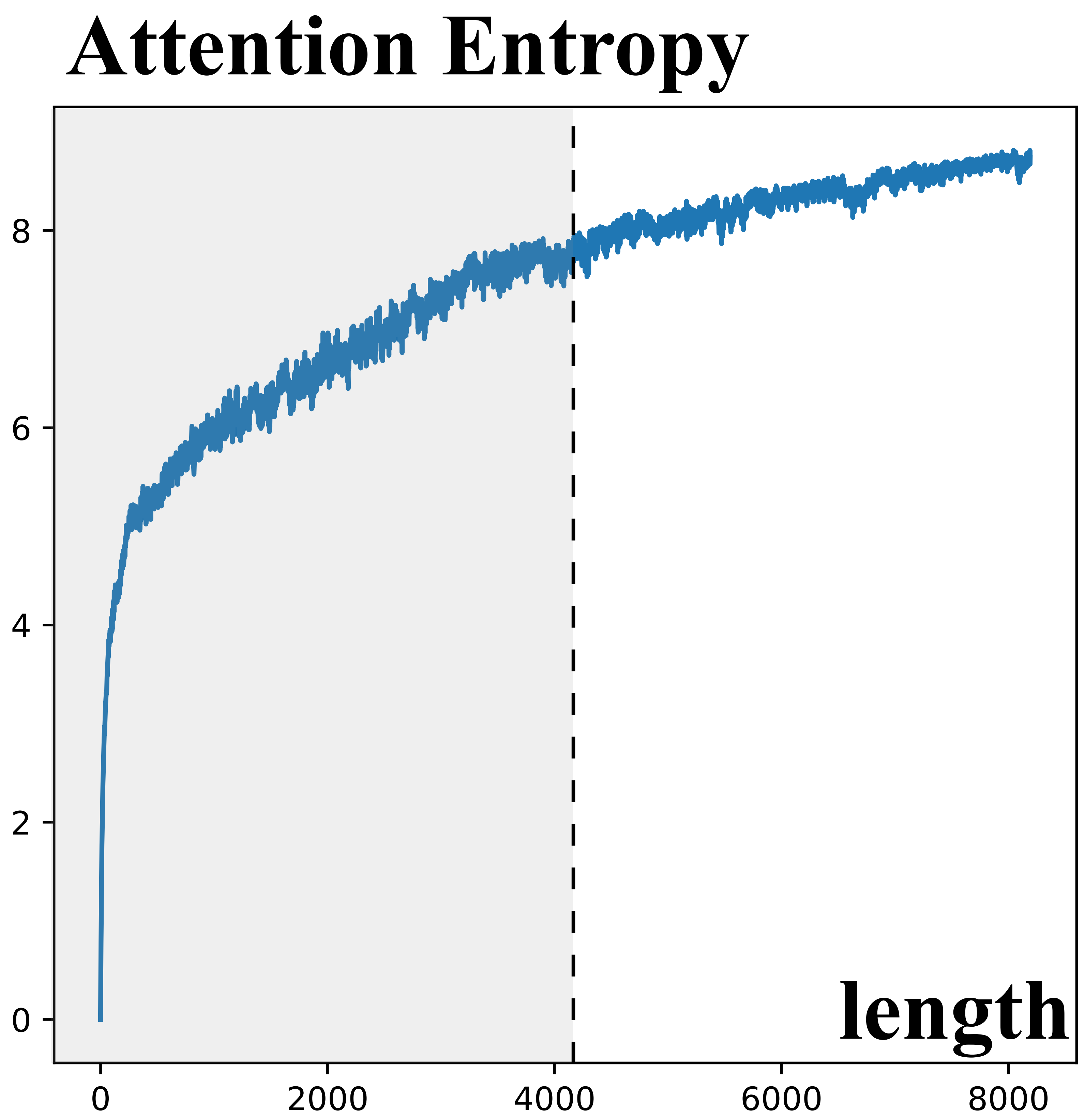
The attention logits in Llama-2 explode as length exceeds the pre-training limit.

Han, Chi, et al. "LM-Infinite: Zero-Shot Extreme Length Generalization for Large Language Models." Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Factor 2: Too many tokens

Longer texts require attention on more tokens.

Theorem 2 (informal): If the attention logits are bounded, as the sequence becomes longer, the attention entropy grows to infinity.

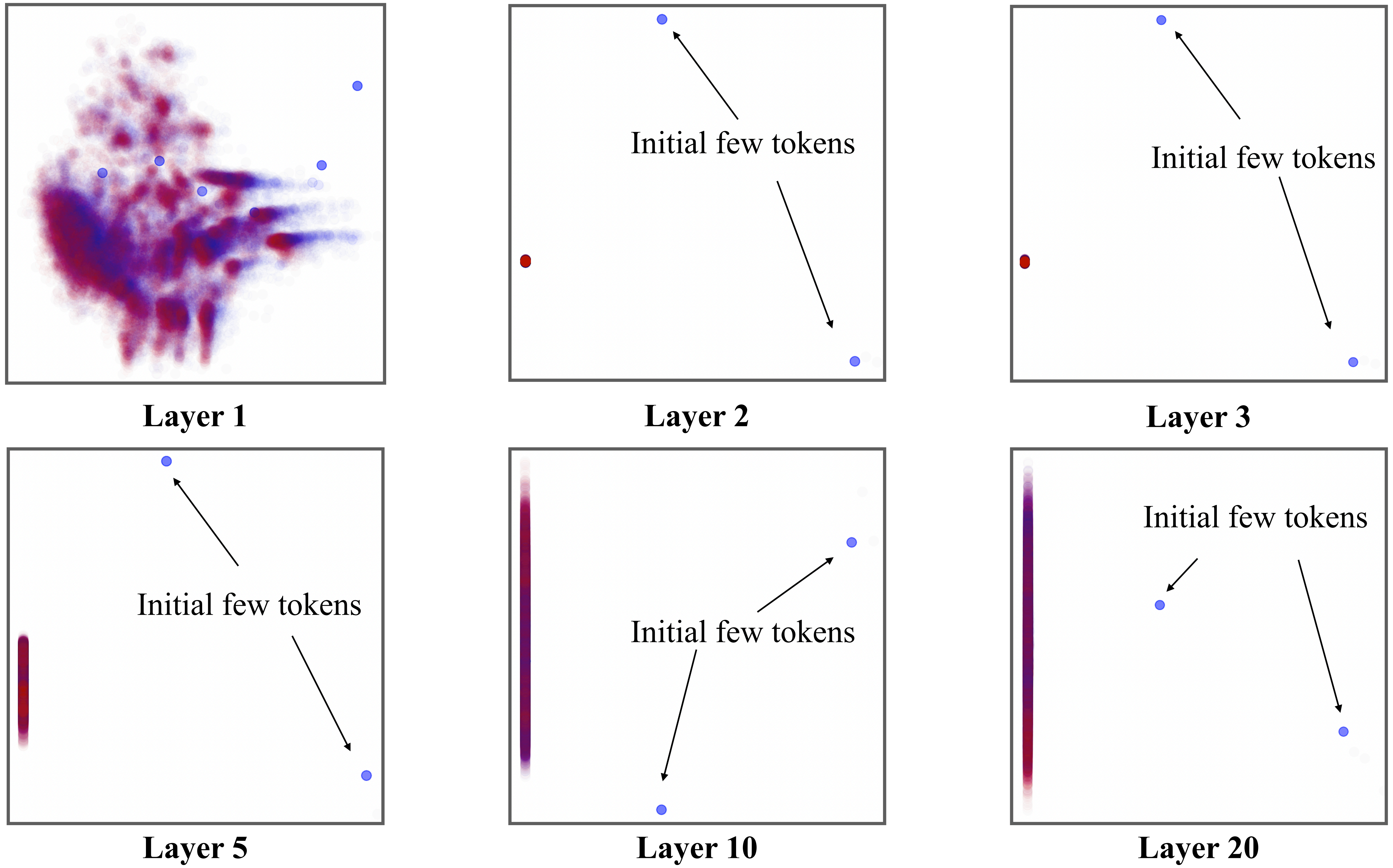


The entropy of attention distribution in Llama-2 continuously increases with length.

Han, Chi, et al. "LM-Infinite: Zero-Shot Extreme Length Generalization for Large Language Models." Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Factor 3: Implicitly Encoded Position

From layer 2 and higher, initial few tokens occupy a distinct feature space.

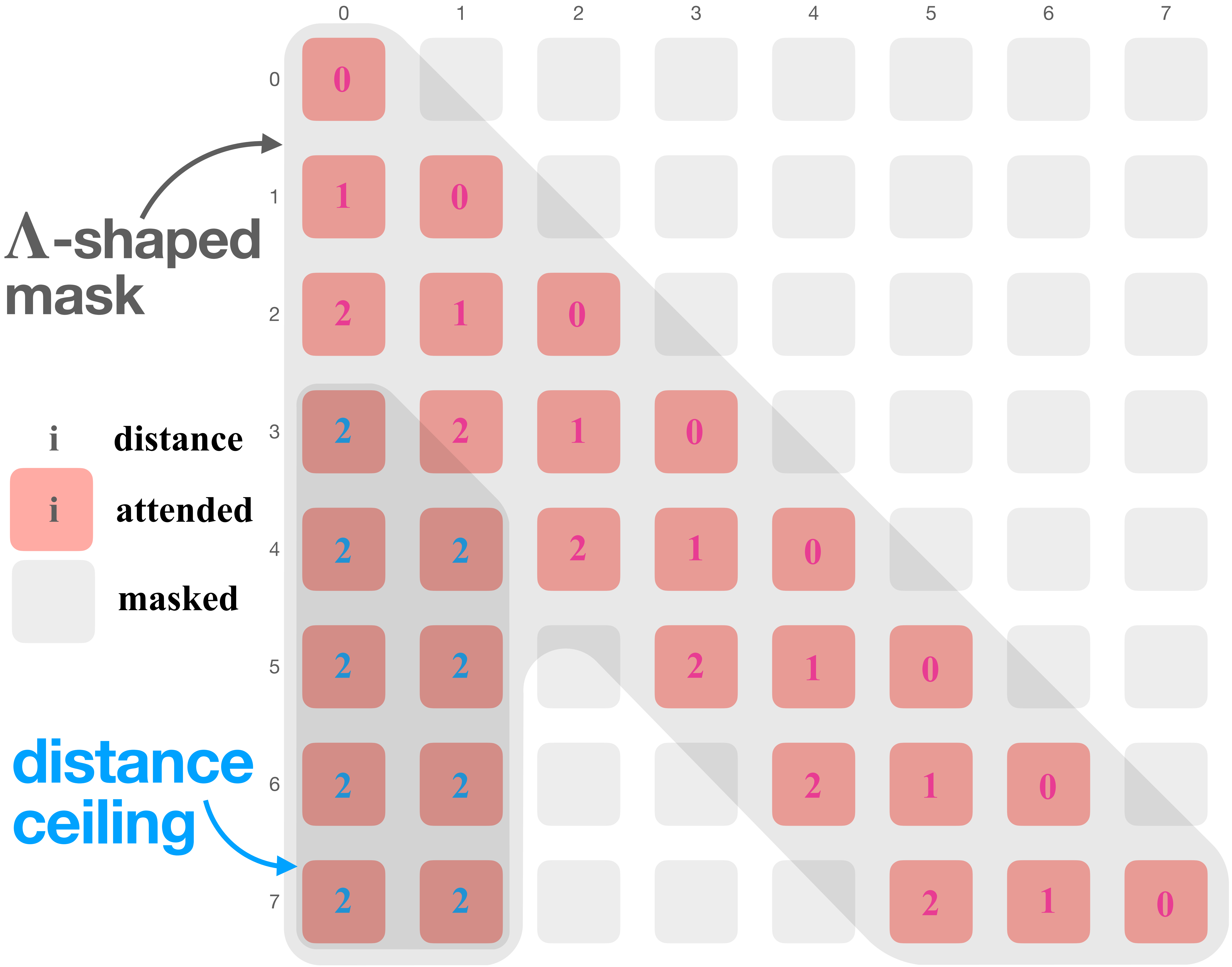


Theorem 3 (Informal): Even without absolute positional embeddings, attention can restore position information of tokens.

Han, Chi, et al. "LM-Infinite: Zero-Shot Extreme Length Generalization for Large Language Models." Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

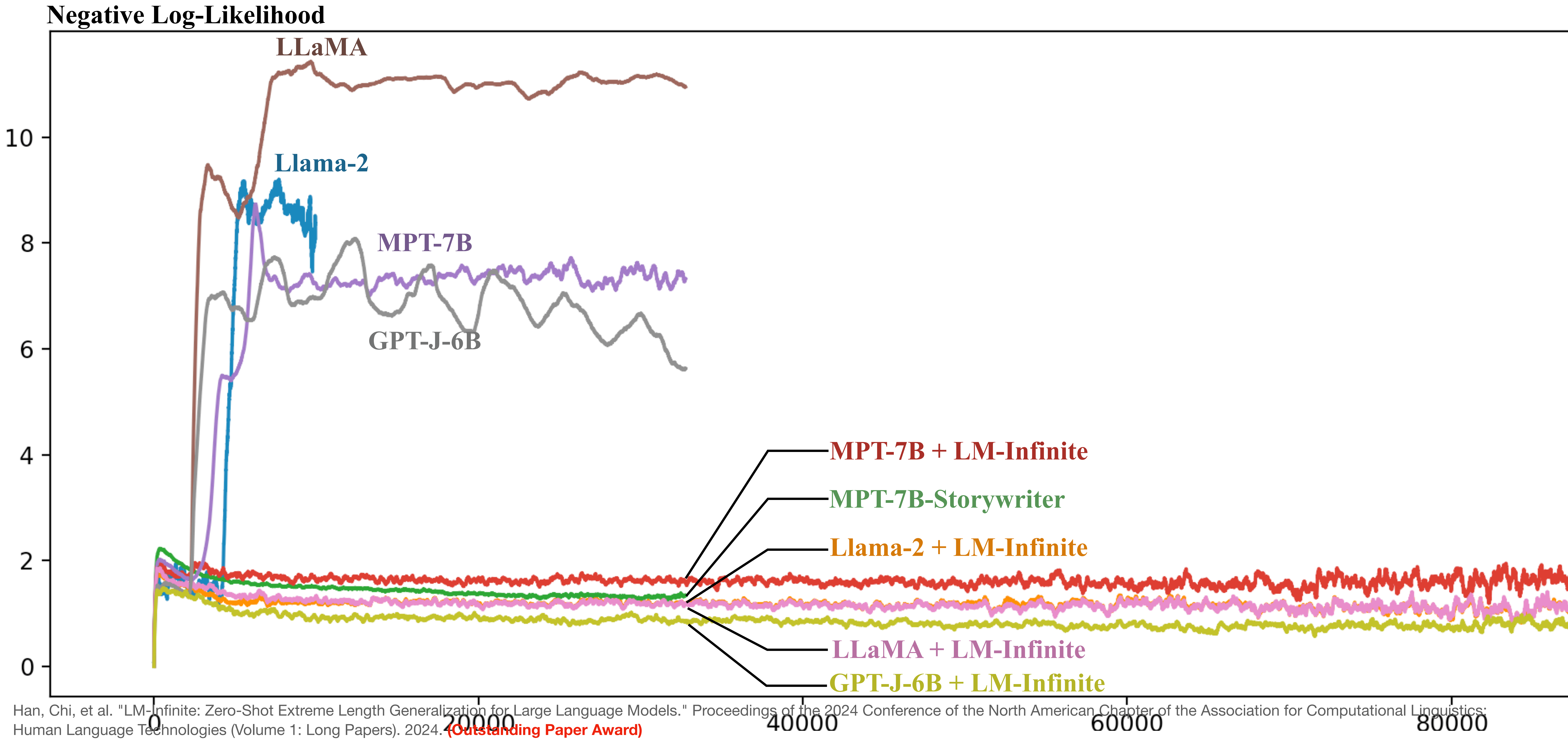
Kazemnejad, Amirhossein, et al. "The impact of positional encoding on length generalization in transformers." *Advances in Neural Information Processing Systems* 36 (2023): 24892-24928.

Solution: LM-Infinite



Han, Chi, et al. "LM-Infinite: Zero-Shot Extreme Length Generalization for Large Language Models." Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

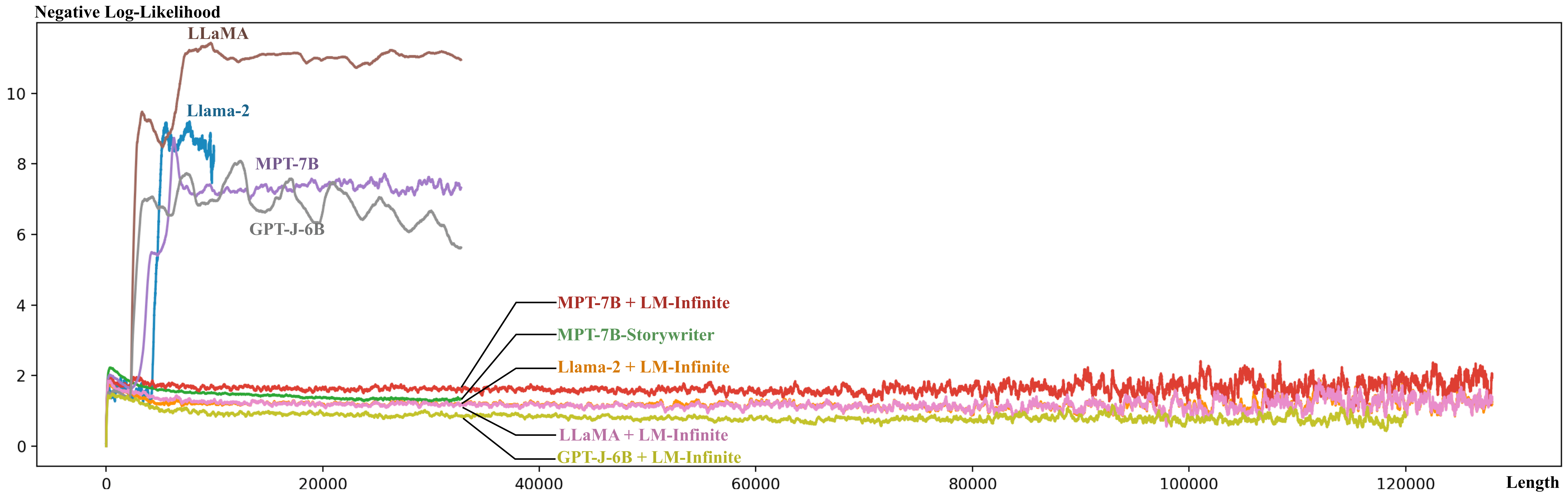
Length Generalization (to 200M length)



Han, Chi, et al. "LM-Infinite: Zero-Shot Extreme Length Generalization for Large Language Models." Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024. (Outstanding Paper Award)

Part 2: Physiology - Topic 1: Attention

Length Generalization (to 200M length)



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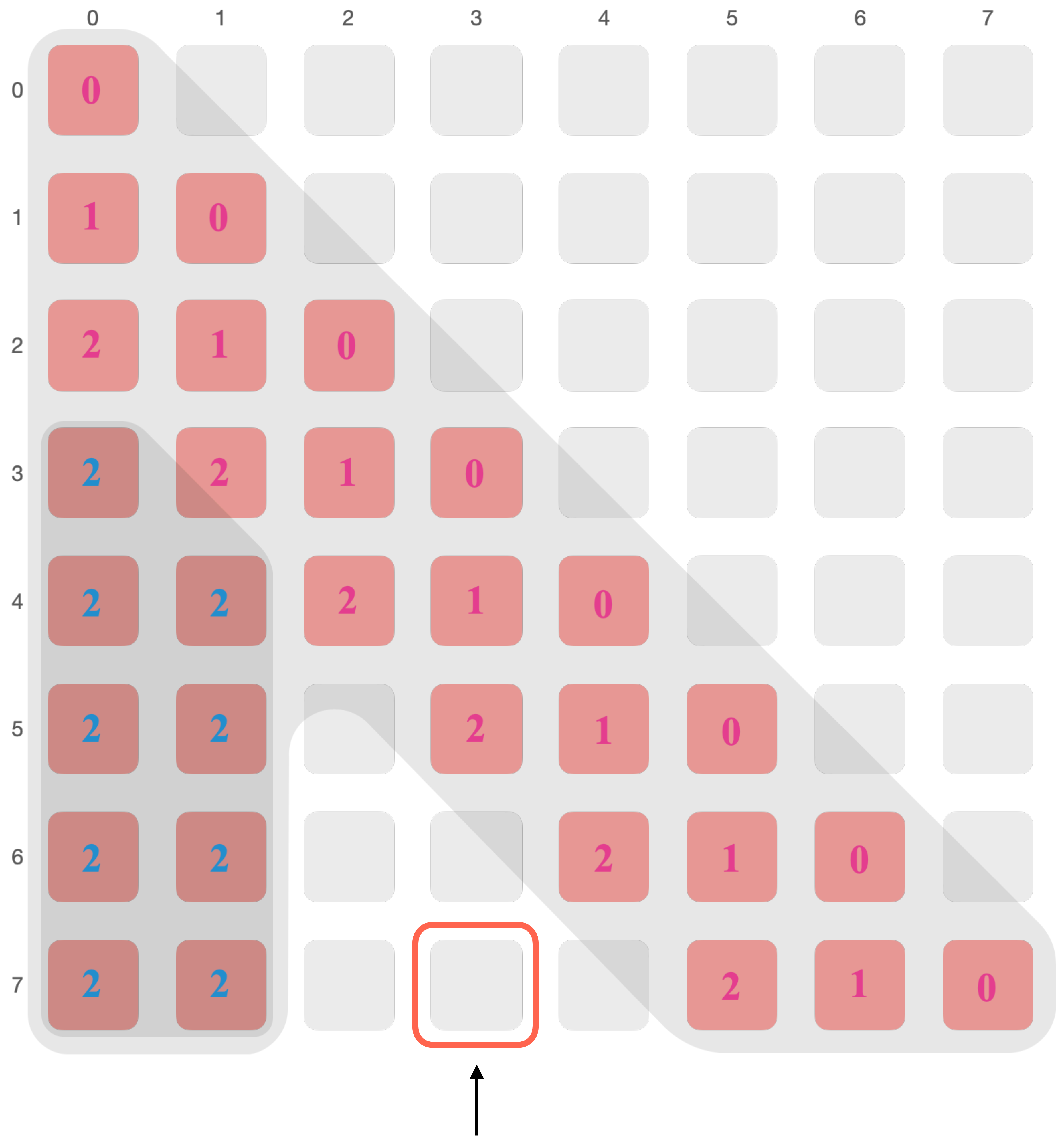
To Perceive Sensitive Information

Re-attending to top-k attention tokens



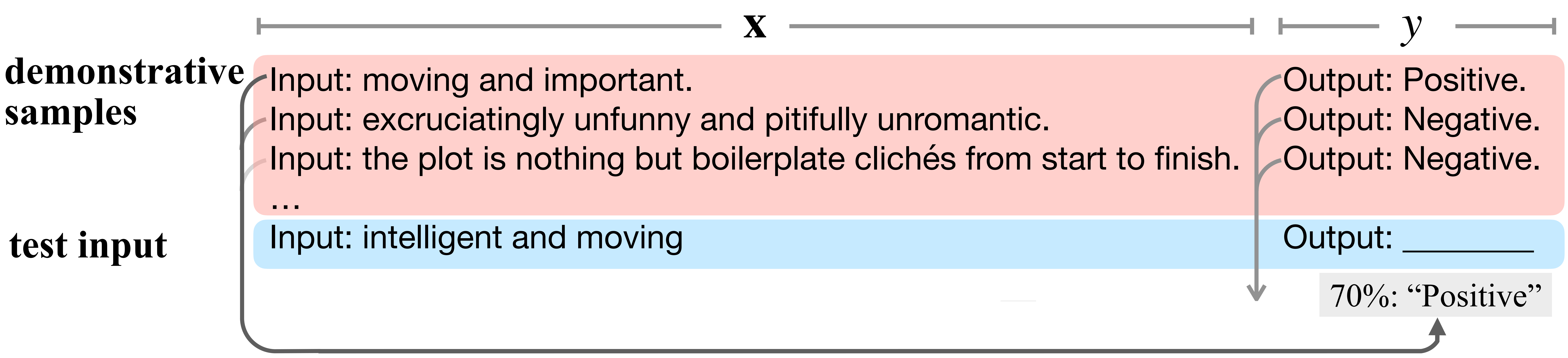
e.g. 1st large attention

Why: to acquire key information that might be stored in the middle "ignored" region again.

How: selecting tokens with top-k (e.g., k=4) attention logits, and reintroducing them into attention.

When: when solving information sensitive tasks like question answering, retrieving information from documents, etc.

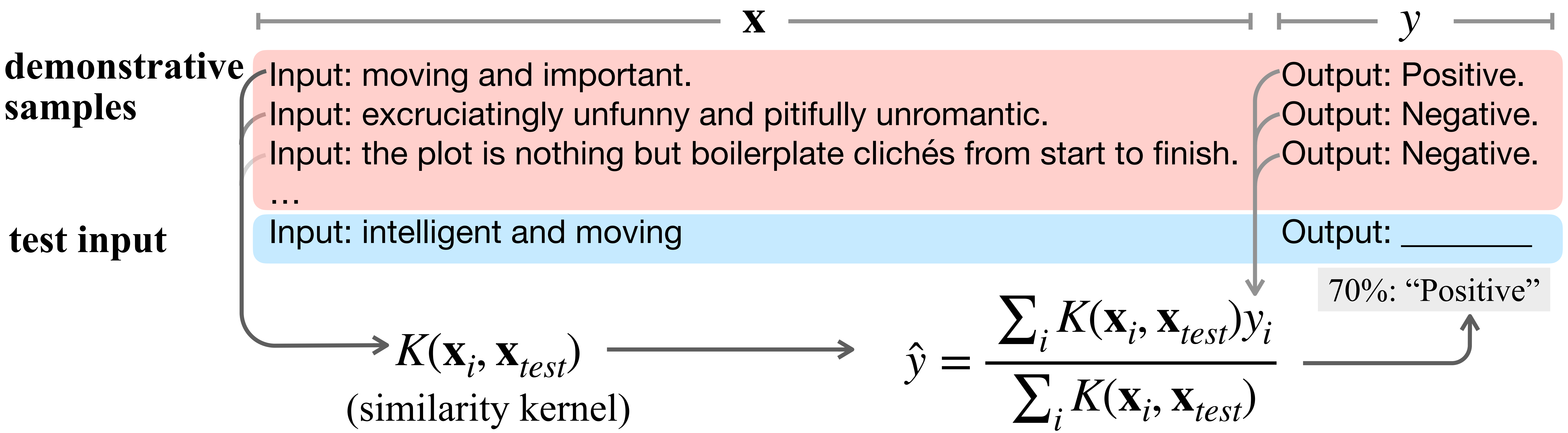
Attention Also Explains In-Context Learning



In-context learning: completing tasks based on demonstrations

Han, Chi, et al. "Explaining emergent in-context learning as kernel regression." *arXiv preprint arXiv:2305.12766* (2023).

Attention Also Explains In-Context Learning



- The output $\hat{y}$ is sampled from a weighted average over example outputs y_i (i.e., a kernel-regression)

- the weights are computed by a certain similarity metric $K(\boldsymbol{x}_i, \boldsymbol{x}_{text})$ (i.e., a kernel)

Han, Chi, et al. "Explaining emergent in-context learning as kernel regression." *arXiv preprint arXiv:2305.12766* (2023).

The Kernel Originates from Pre-Training

Kernel regression (hypothesized ICL algorithm)

$$\hat{\mathbf{y}} = \frac{\sum_{i=1}^{n} \mathbf{e}(y_i)\mathcal{K}(\mathbf{x}_{test}, \mathbf{x}_i)}{\sum_{i=1}^{n} \mathcal{K}(\mathbf{x}_{test}, \mathbf{x}_i)}$$

Han, Chi, et al. "Explaining emergent in-context learning as kernel regression." *arXiv preprint arXiv:2305.12766* (2023).

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$$\hat{\mathbf{y}} = \frac{\sum_{i=1}^{n} \mathbf{e}(y_i)\mathcal{K}(\mathbf{x}_{test}, \mathbf{x}_i)}{\sum_{i=1}^{n} \mathcal{K}(\mathbf{x}_{test}, \mathbf{x}_i)}$$

The kernel (similarity metric)

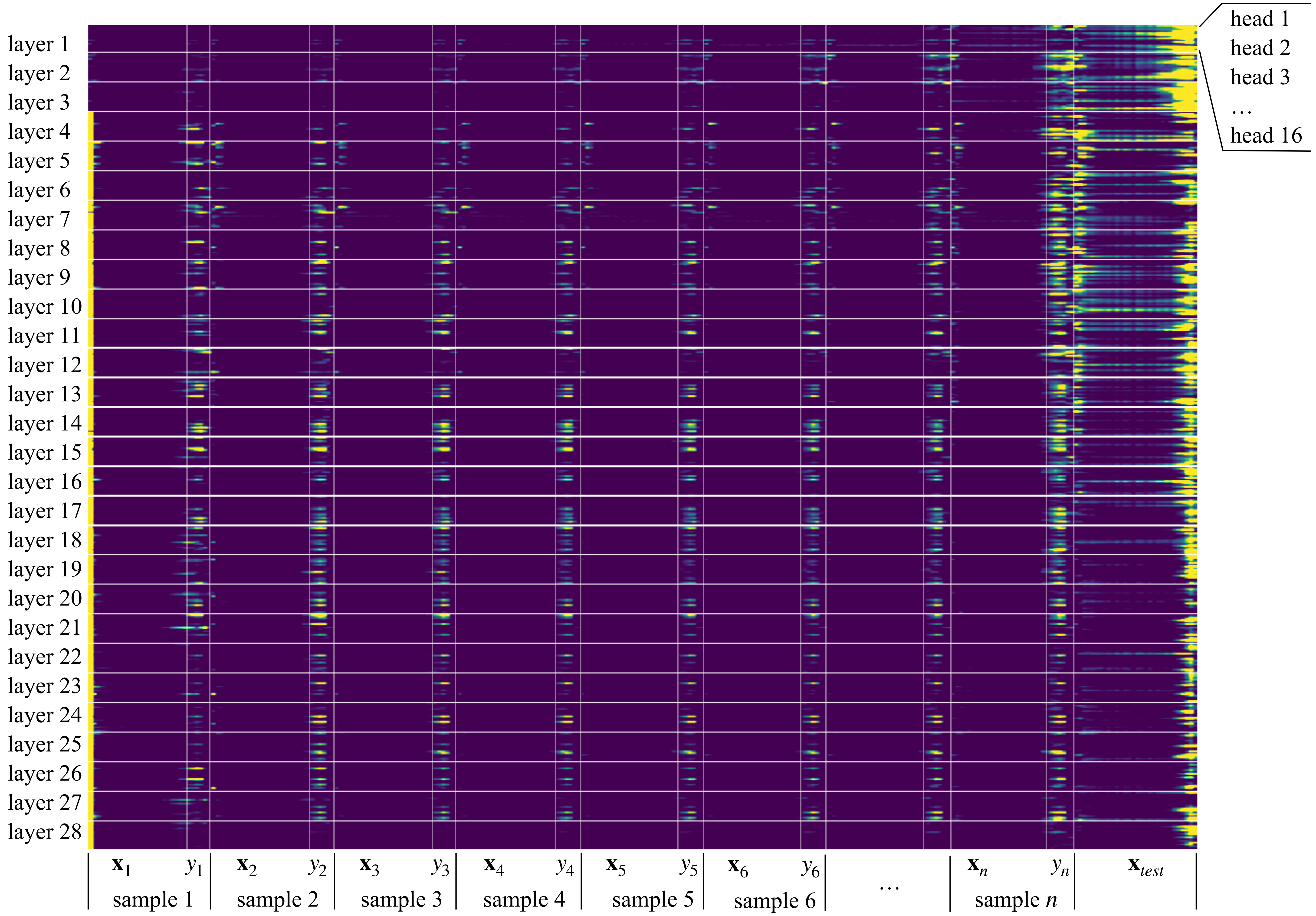
$$\mathcal{K}(\mathbf{x}, \mathbf{x}') = \mathrm{vec}(T_{\mathbf{x}})^{\top} \Sigma_{p_{\textit{pre-train}}}^{-1}, \mathrm{vec}(T_{\mathbf{x}'})$$

A representation of sample input x for predicting the next token

A matrix about the pre-training objective

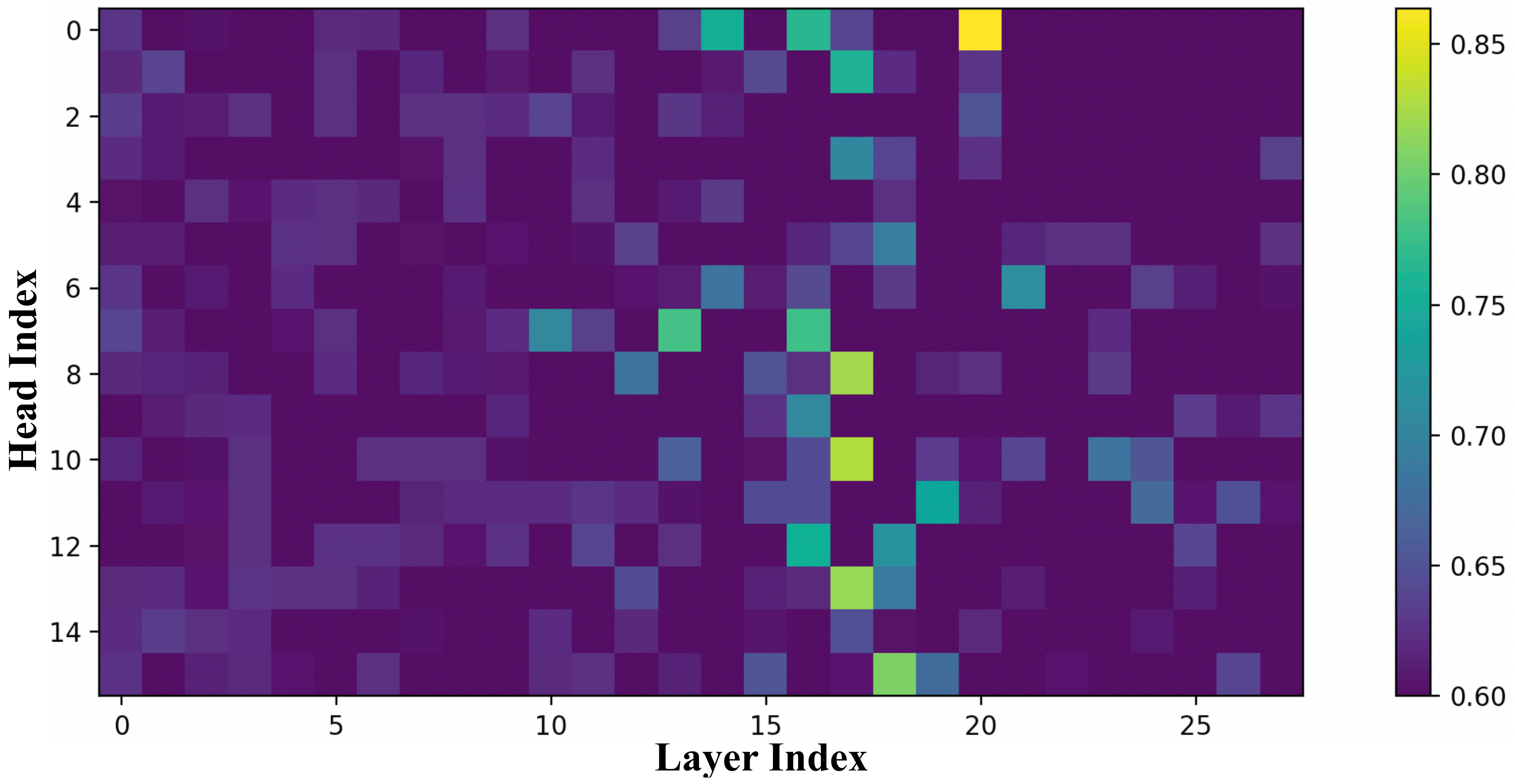
Han, Chi, et al. "Explaining emergent in-context learning as kernel regression." *arXiv preprint arXiv:2305.12766* (2023).

The Attention Applies to y_i As Kernel Regression



Han, Chi, et al. "Explaining emergent in-context learning as kernel regression." *arXiv preprint arXiv:2305.12766* (2023).

The Explanation Aligns With the Model Output



Certain attention heads can reconstruct the LLM ICL output with the explanation.

Han, Chi, et al. "Explaining emergent in-context learning as kernel regression." *arXiv preprint arXiv:2305.12766* (2023).

The Attention

Method	sst2	mnli	rotten-tomatoes	tweet_eval (hate)	tweet_eval (irony)	tweet_eval (offensive)
GPT-J-6B ICL	0.805	0.383	0.671	0.539	0.519	0.542
all-MiniLM-L6-v2	0.503	0.321	0.478	0.548	0.491	0.588
bert-base-nli-mean-tokens KR	0.523	0.325	0.502	0.545	0.479	0.597
task-specific best head KR	0.789	0.974	0.692	0.560	0.584	0.560
overall best head KR	0.766	0.808	0.648	0.462	0.446	0.462

The KR explanation explained most tasks well (except for MNLI)

KR based on baseline sentence embeddings models

Han, Chi, et al. "Explaining emergent in-context learning as kernel regression." *arXiv preprint arXiv:2305.12766* (2023).

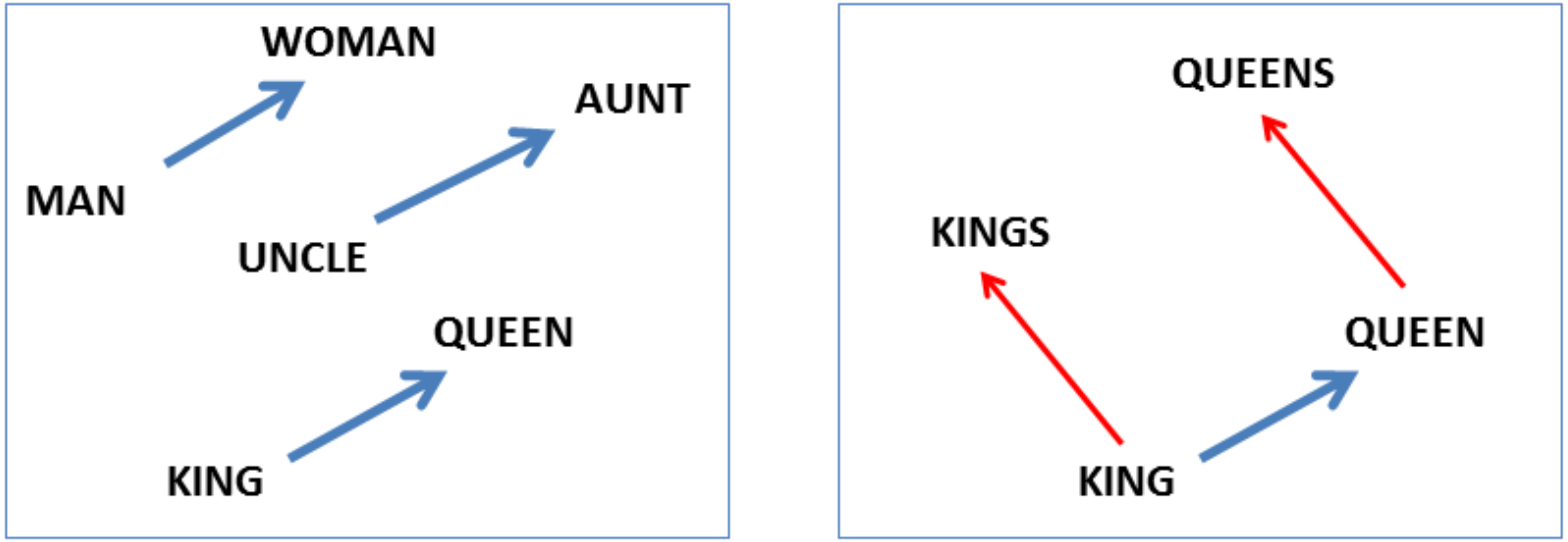
Room for Future Research

- Attention module's role in syntax and word order processing
- More precise categorization of attention's role in demonstration learning
- Explaining and addressing and lost-in-the-middle and position bias problem

What Is the Function of Word Embeddings

What Do Word Embeddings Embed?

Previous papers mostly focus on word-level interpretations



(a) Analogical Relations (metric space)

Mikolov, Tomáš, Wen-tau Yih, and Geoffrey Zweig. "Linguistic regularities in continuous space word representations." *Proceedings of the 2013 conference of the north american chapter of the association for computational linguistics: Human language technologies*. 2013.
Bolukbasi, T., Chang, K. W., Zou, J. Y., Saligrama, V., & Kalai, A. T. (2016). Man is to computer programmer as woman is to homemaker? debiasing word embeddings. Advances in neural information processing systems, 29.

What Do Word Embeddings Embed?

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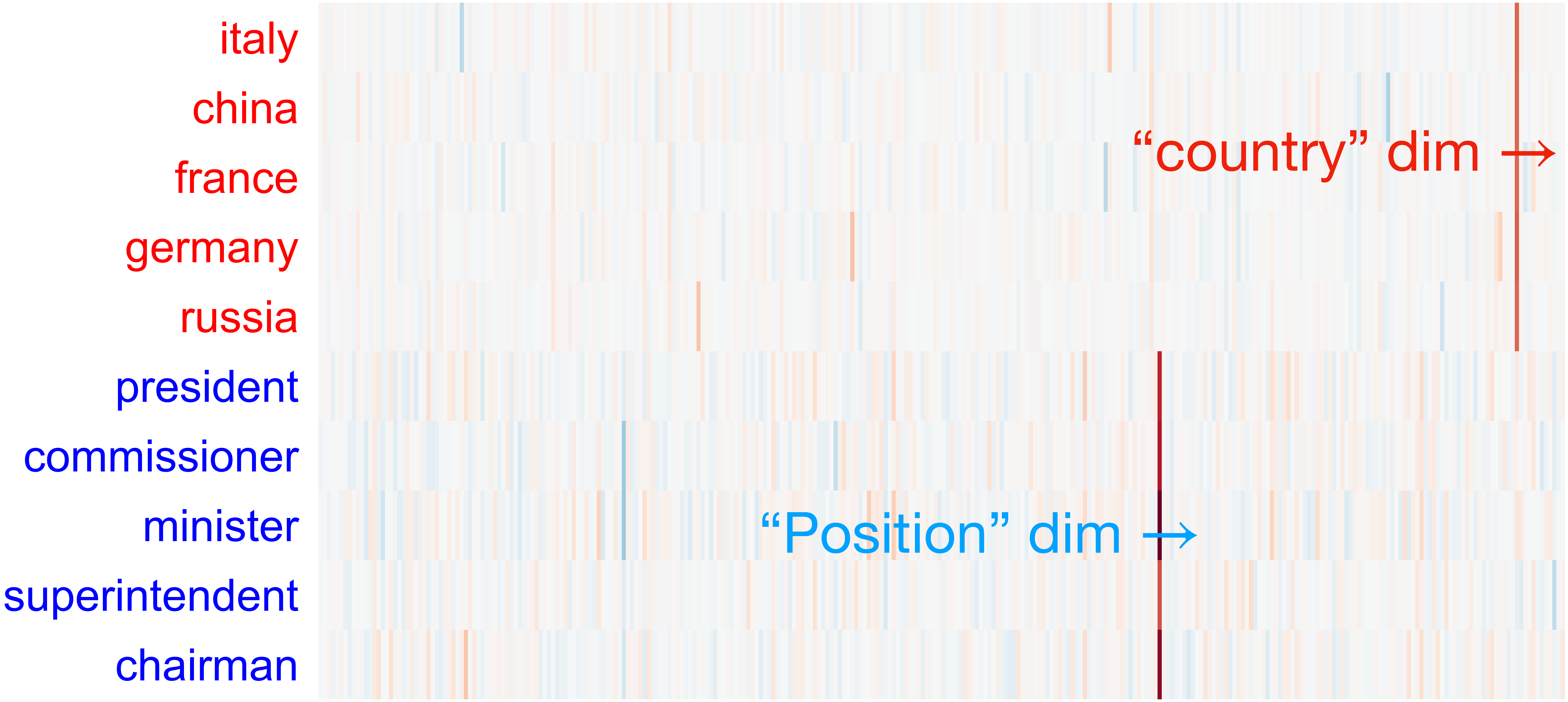
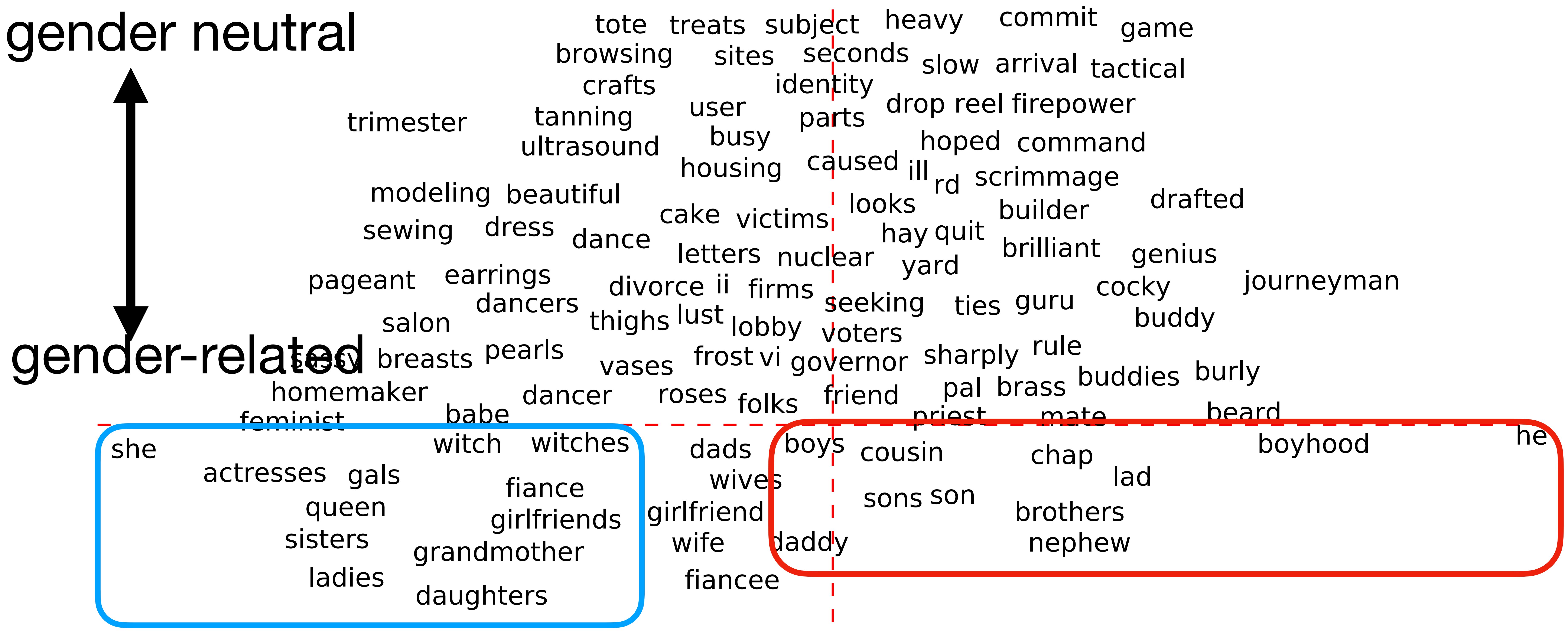


(b) Meaningful Dimensions (linear Space)

Park, Sungjoon, JinYeong Bak, and Alice Oh. "Rotated word vector representations and their interpretability." *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. 2017.

What Do Word Embeddings Embed?

Previous papers mostly focus on word-level interpretations



(b) Meaningful Dimensions (linear Space)

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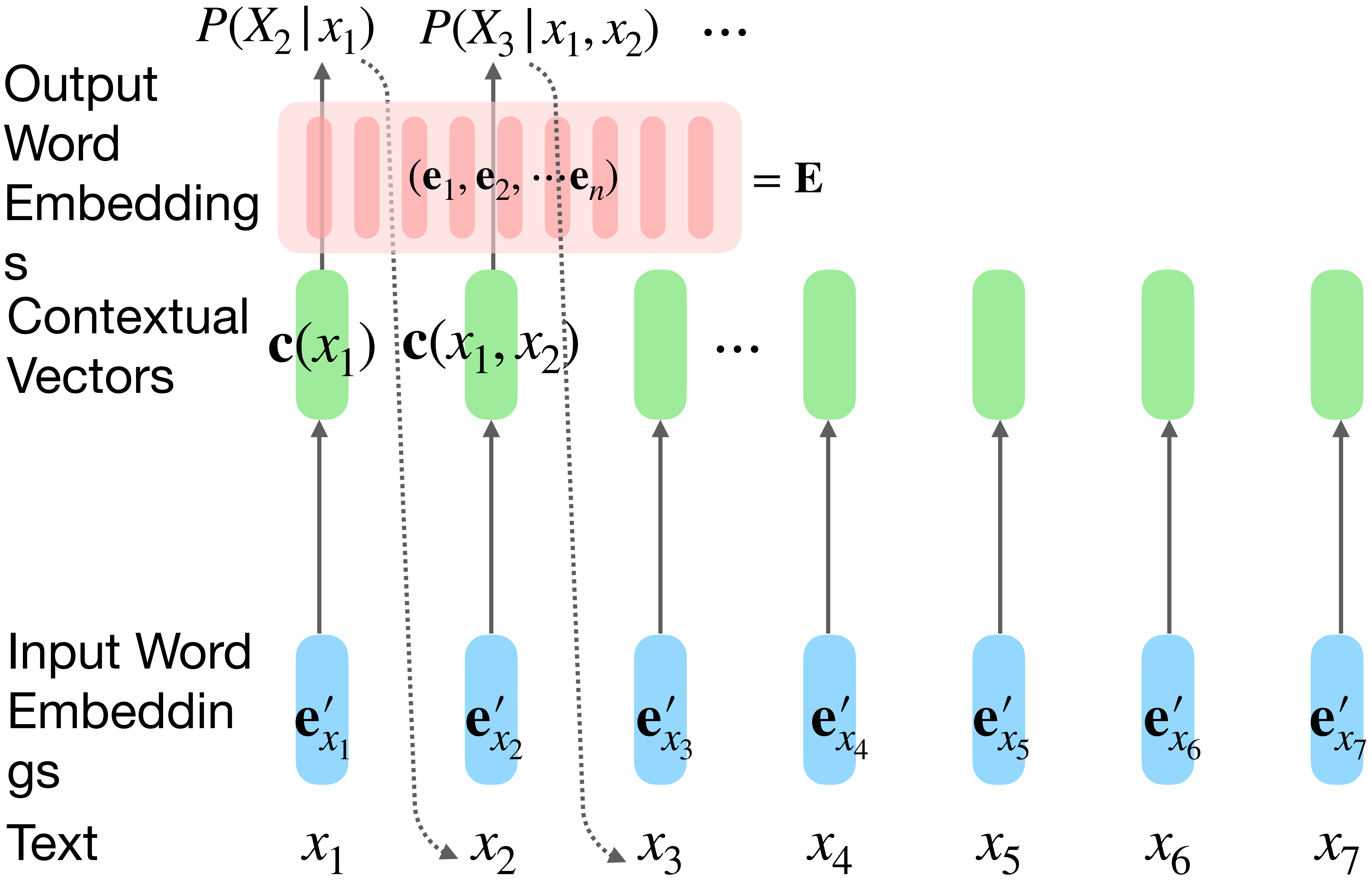
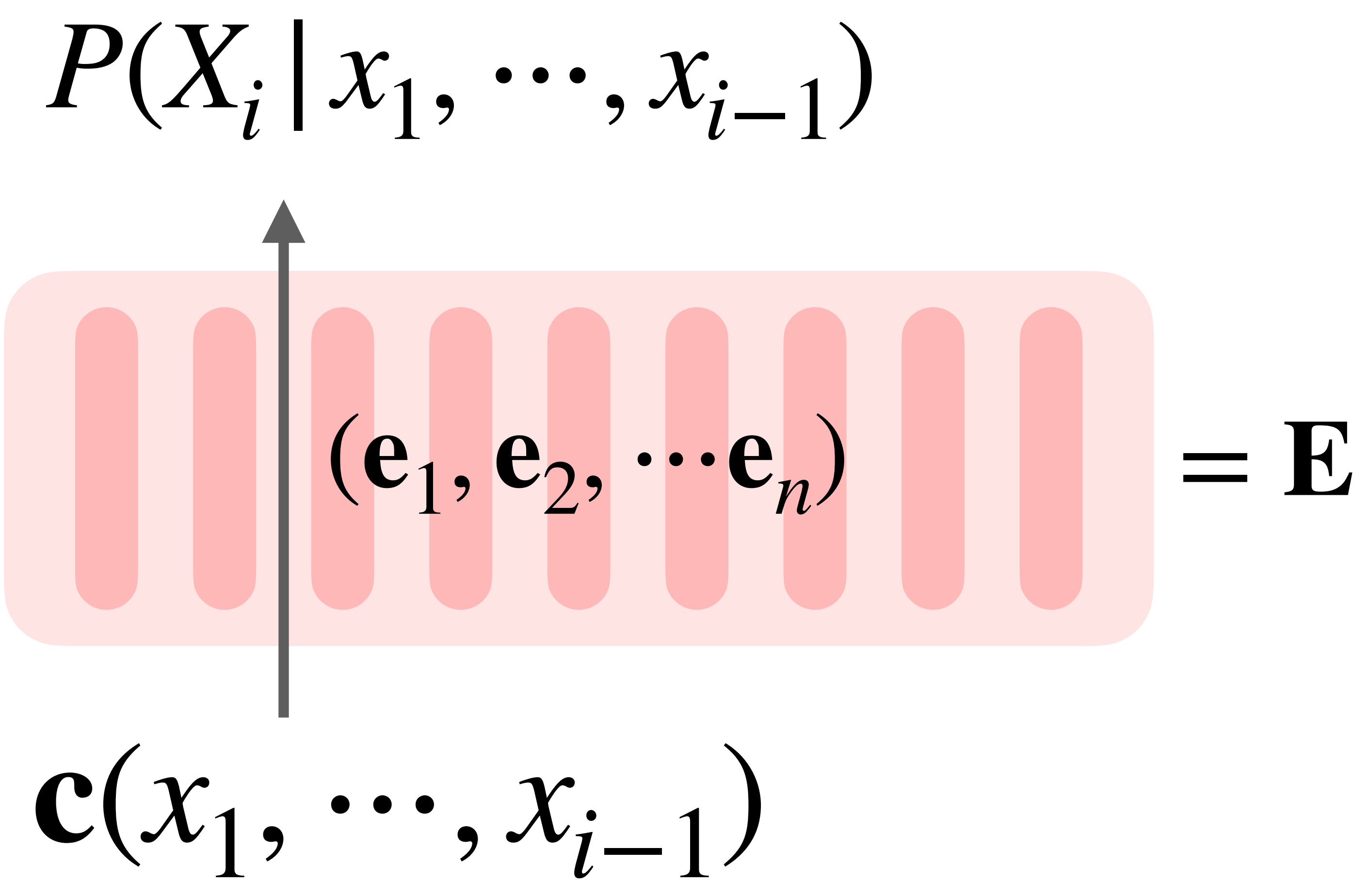
Word Embeddings in Causal LMs



Output Word Embeddings

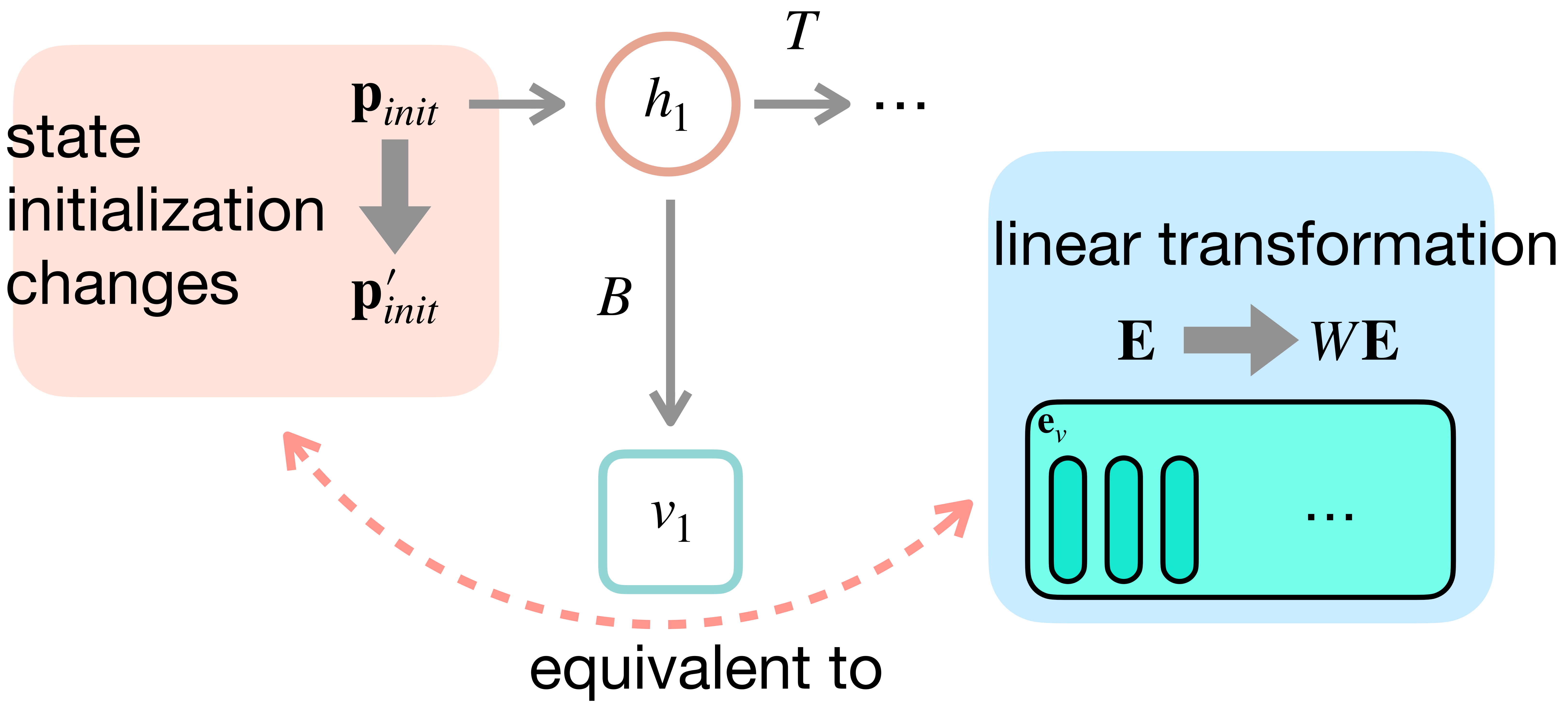
Projecting to Logits



$$P(v|\mathbf{c}) = \frac{\exp(\mathbf{c}^\top \mathbf{e}_v)}{\sum_{u \in \mathcal{V}} \exp(\mathbf{c}^\top \mathbf{e}_u)}$$

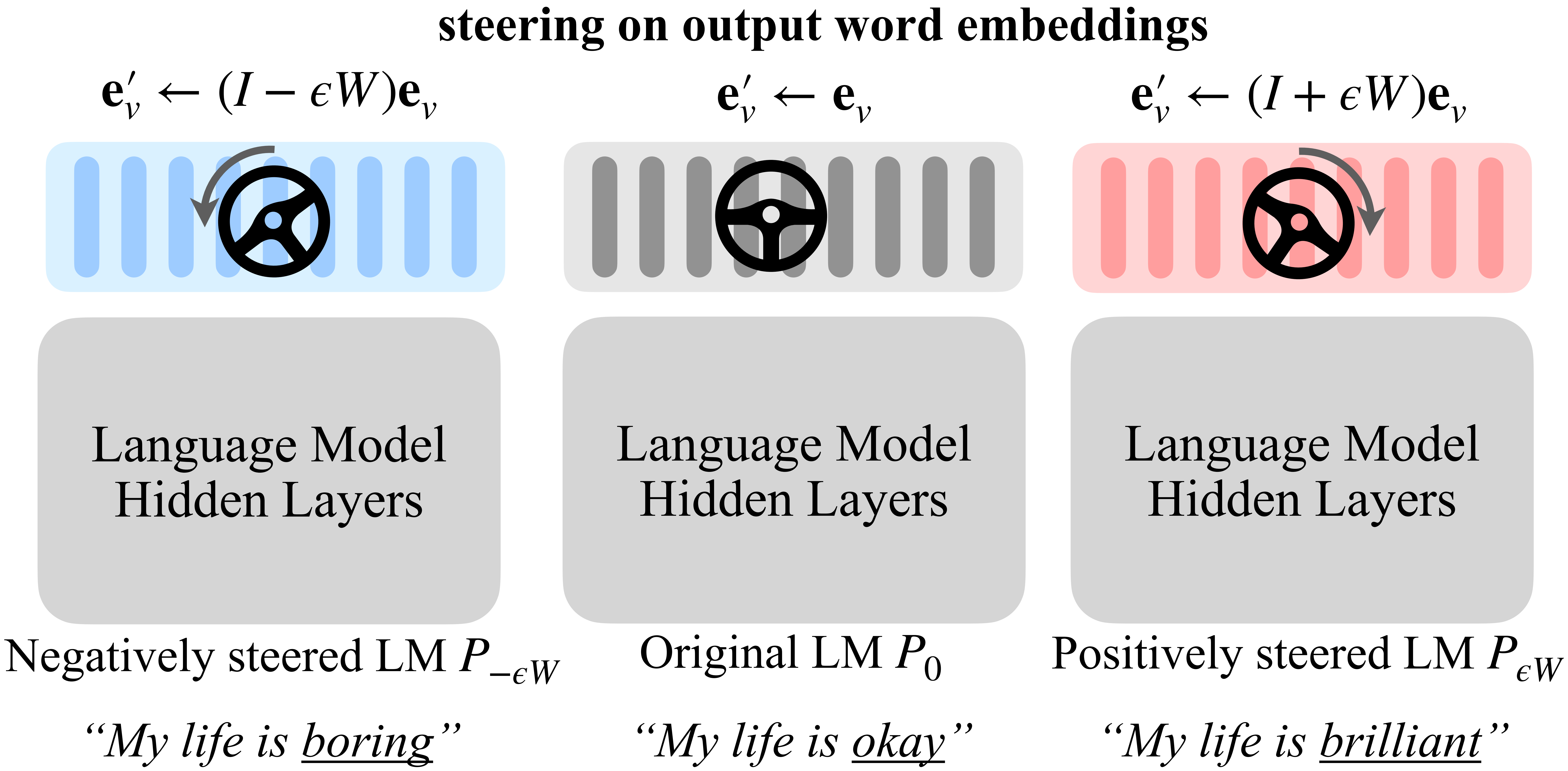
Sequence Shift ≈ Word Embedding Transform

- **Theorem (Informal)**: steering between text distribution is associated with a linear transformation on word embedding space under assumptions.



Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

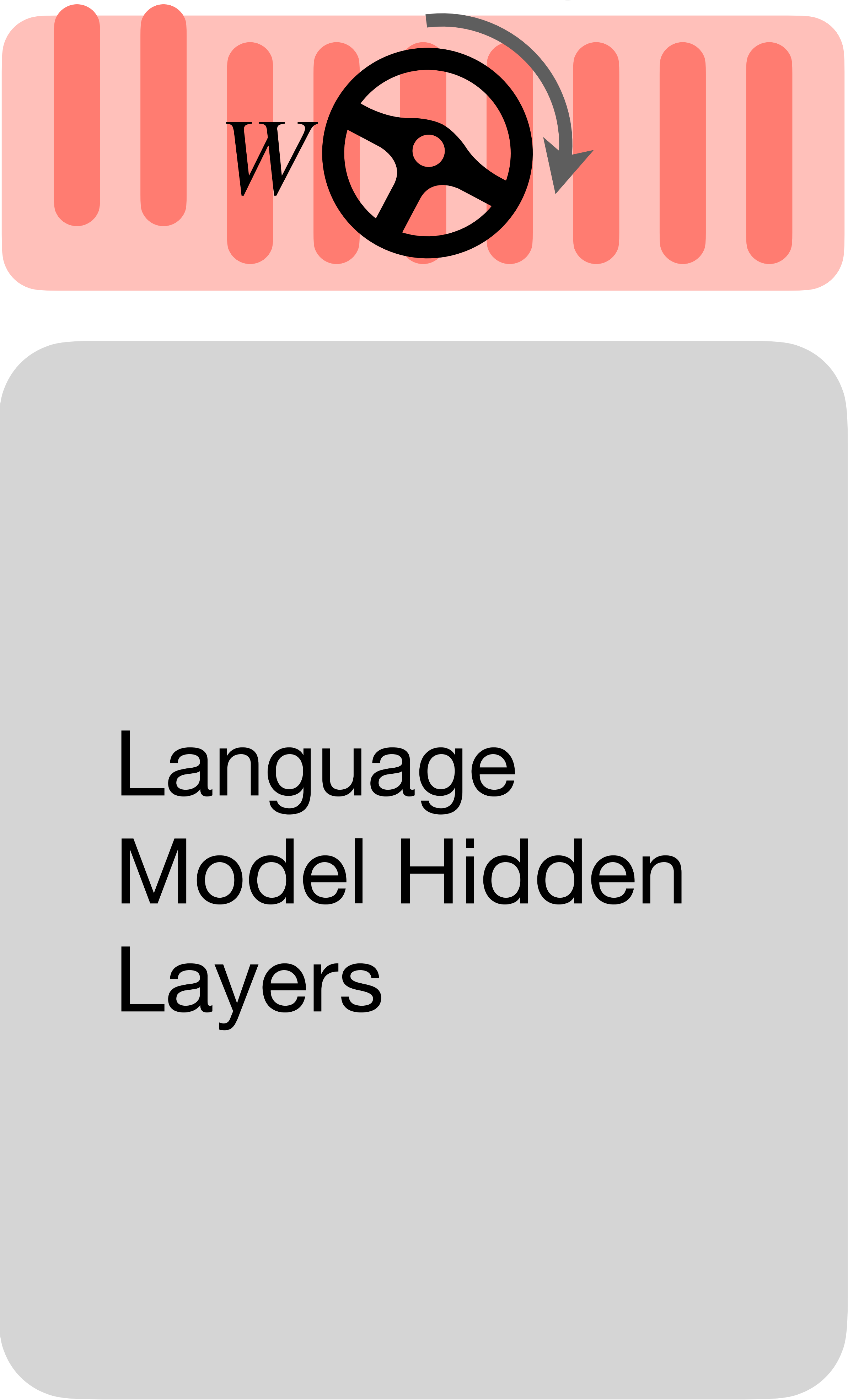
LM-Steer



Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

LM-Steer Broken Down

Output word embedding $\boldsymbol{E}$



$$+= \epsilon \cdot W \boldsymbol{E}$$

for each word:

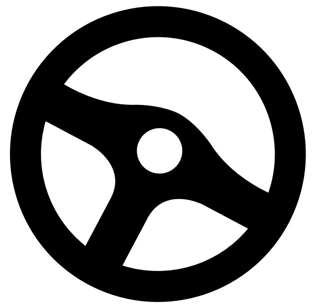
$$\mathbf{e}'_v = \mathbf{e}_v + \epsilon W \mathbf{e}_v$$

The steering scale

“ ”

ϵ

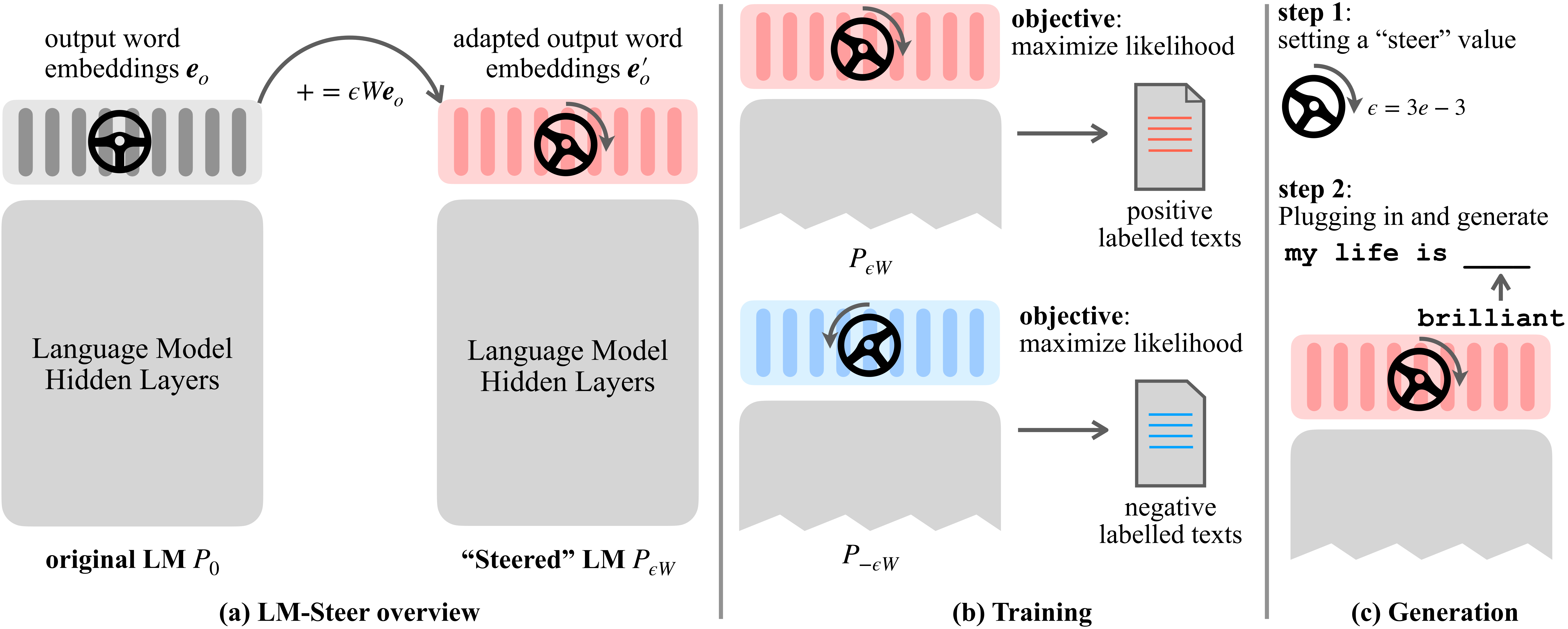
the steering matrix

“  ”

W

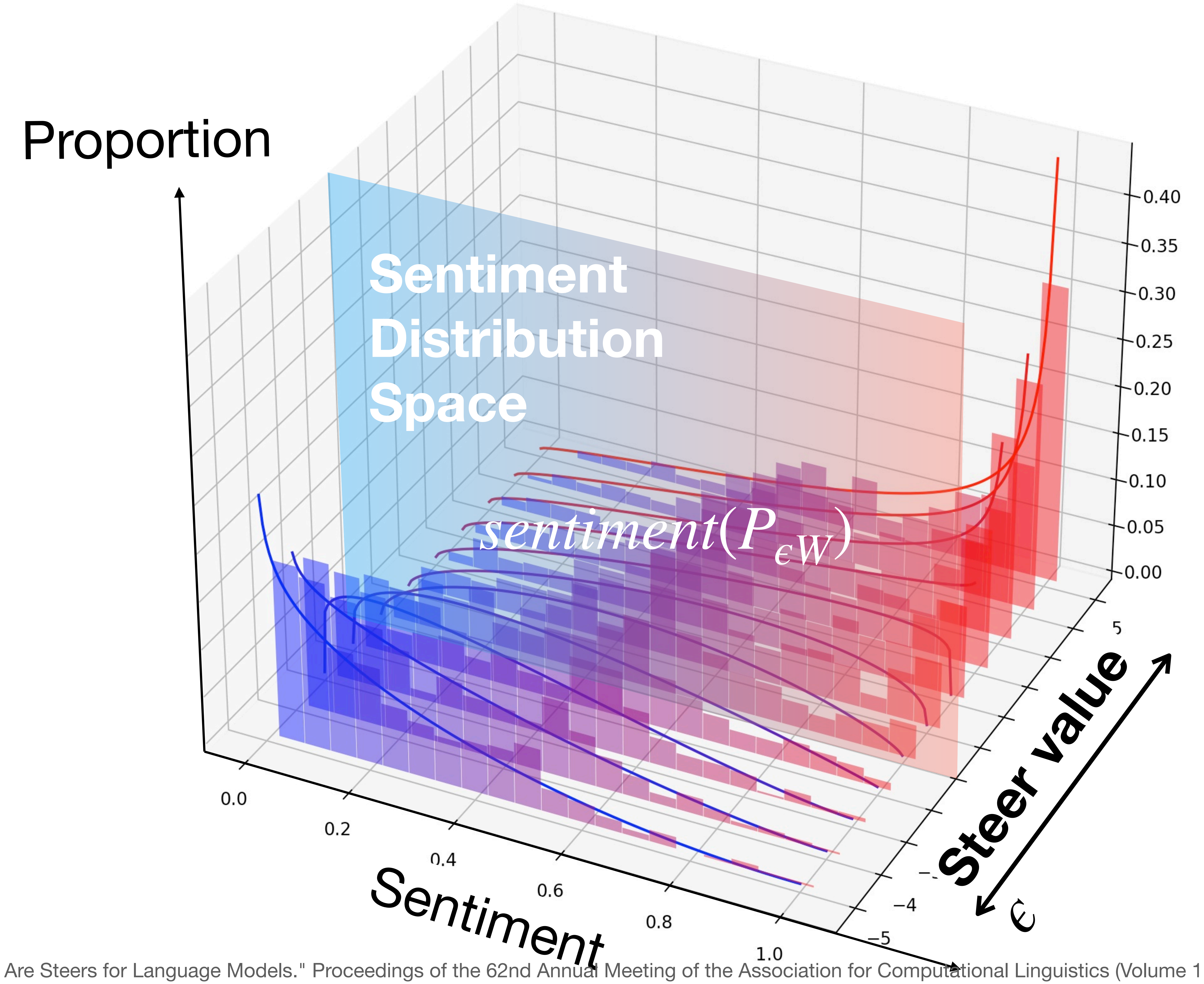
Part 2: Physiology - Topic 2: Embedding

Training & Inference



Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Continuous Steering



curves: maximal likelihood beta-distribution

Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Compositional Steering

LM-Steer 1: $P_{\epsilon_1 W_1}$

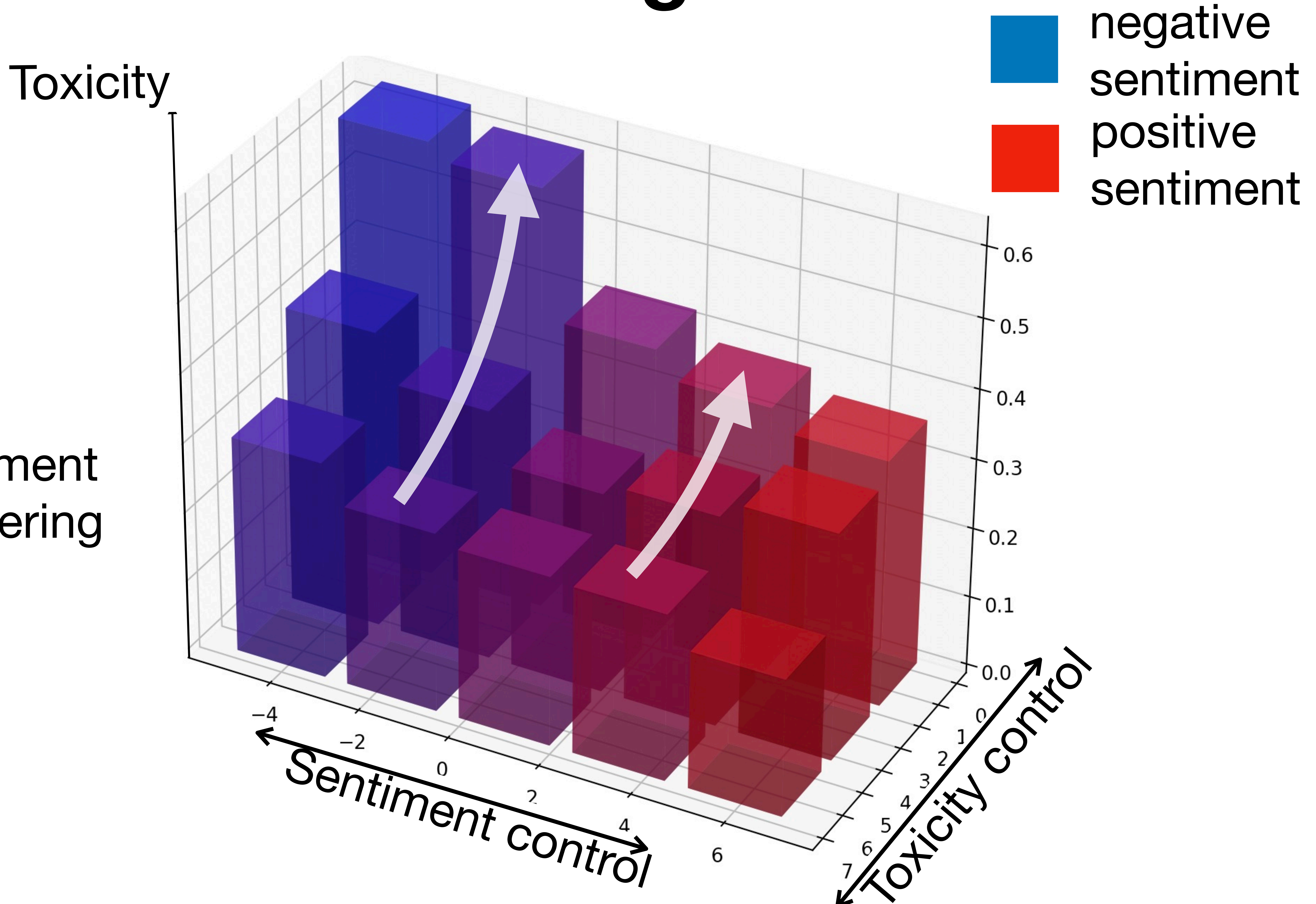
LM-Steer 2: $P_{\epsilon_2 W_2}$

Combined LM-Steer: $P_{\epsilon_1 W_1 + \epsilon_2 W_2}$

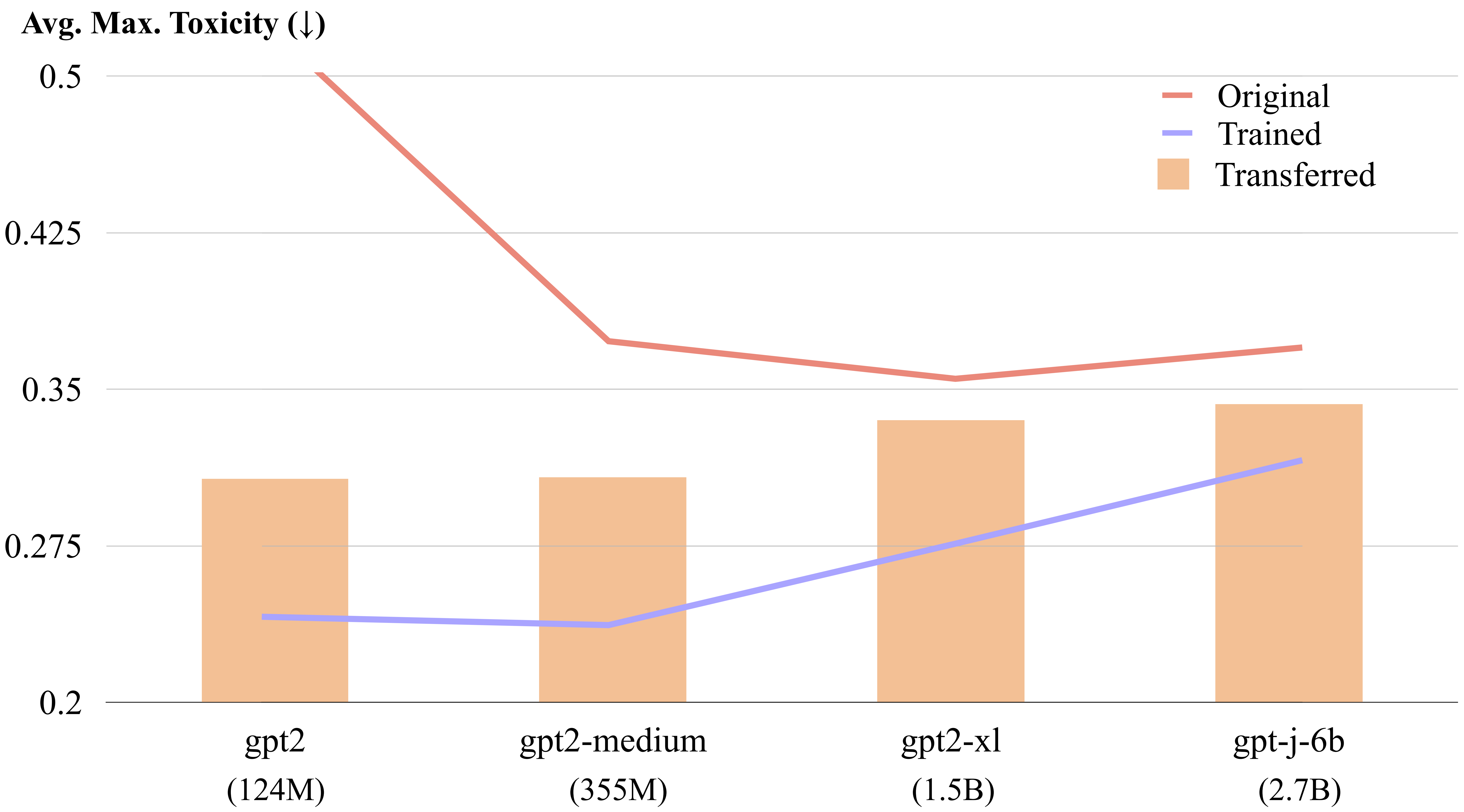
Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Compositional Steering

An entanglement between steering dimensions



Transferring to Another LM



transfers about half of the detoxification capability

Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Highlighting Keywords

- Automatically highlighting text spans most related to a distribution.
- Example: toxic word highlighting

There's another controversial Hollywood racial decision that Stacey Dash is sinking her teeth into.
The UFC champ then suggested Justino is a longtime PED user with her most d**ning comments.
But I really have a question for you: Why would I go on a game show and play into the bulls**t allowing myself to be ranked by some fake competition?
I think sexism prevents this from being a real win for fat people.
If they want to be fair and non hypocritical idiots they should.

Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

A Probe on the Word Embedding Space

Dim.	Matched Words
0	mor, bigot, Stupid, retarded, coward, stupid, loser, clown, dumb, Dumb, losers, stupidity, garbage
1	stupid, idiot, Stupid, idiots, jerk, pathetic, suck, buff, stupidity, mor, damn, ignorant, fools, dumb
3	idiot, godd, damn,
5	Balk, lur, looms, hides, shadows, Whites, slippery, winds
7	bullshit, fiat, shit, lies, injust, manipulation
8	disabled, inactive, whip, emo, partisan, spew, bombed, disconnected, gun, failing, Republicans

(Some dimensions were omitted as they match non-English words)

Han, Chi, et al. "Word Embeddings Are Steers for Language Models." Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024. **(Outstanding Paper Award)**

Room for Future Research

- Evolution of contextual embeddings across layers, e.g., how ambiguity is resolved in LMs
- Better frameworks for studying the role of word embeddings
- Other functions of word embeddings, such as semantics and sense

Part 3: Physics

Rules and Laws of LMs

Topics

- **Scaling**: How performance scales
- **Impossibilities:** What LMs cannot do fundamentally

Scaling: How Performance Scales

General Principle

Inducing rules from simplified and controlled experiments (similar to early ages of physics).

https://en.wikipedia.org/wiki/File:Galileolarge.png

Scaling Laws

Is Model Performance Predictable?

In physics:

Observation:
larger force + smaller weight → moving faster

↓

Newton's Law:

$F = ma$

Scaling Laws

Is Model Performance Predictable?

In physics:

Observation:
larger force + smaller weight → moving faster

↓

Newton's Law:

$F = ma$

In LMs:

Observation:
larger model + more data → higher score

↓

Any law to predict scores before training?

Why Do We Need Scaling Laws?

Why Do We Need Scaling Laws?

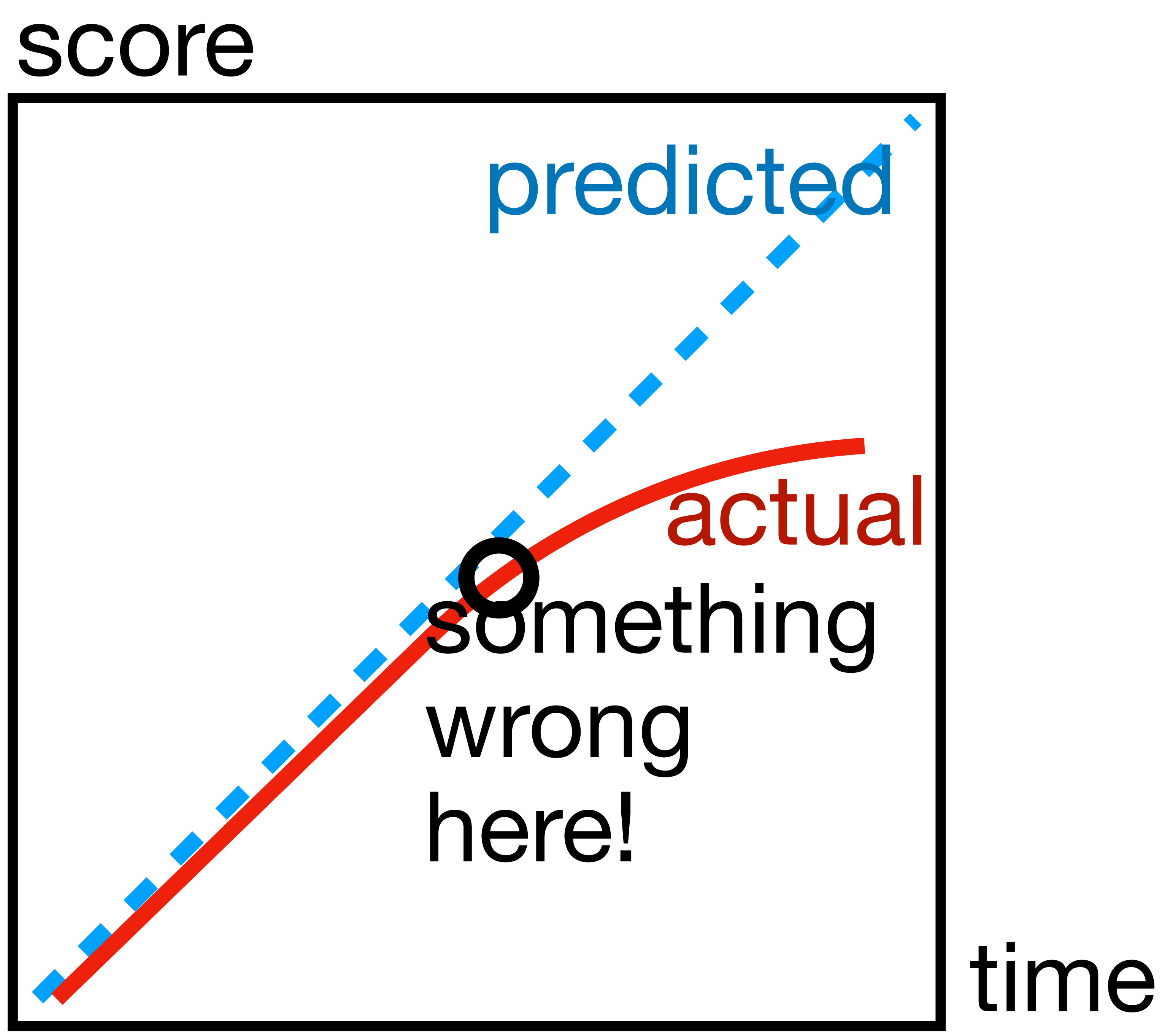
1. Curiosity

Why Do We Need Scaling Laws?

1. Curiosity
2. Early debugging

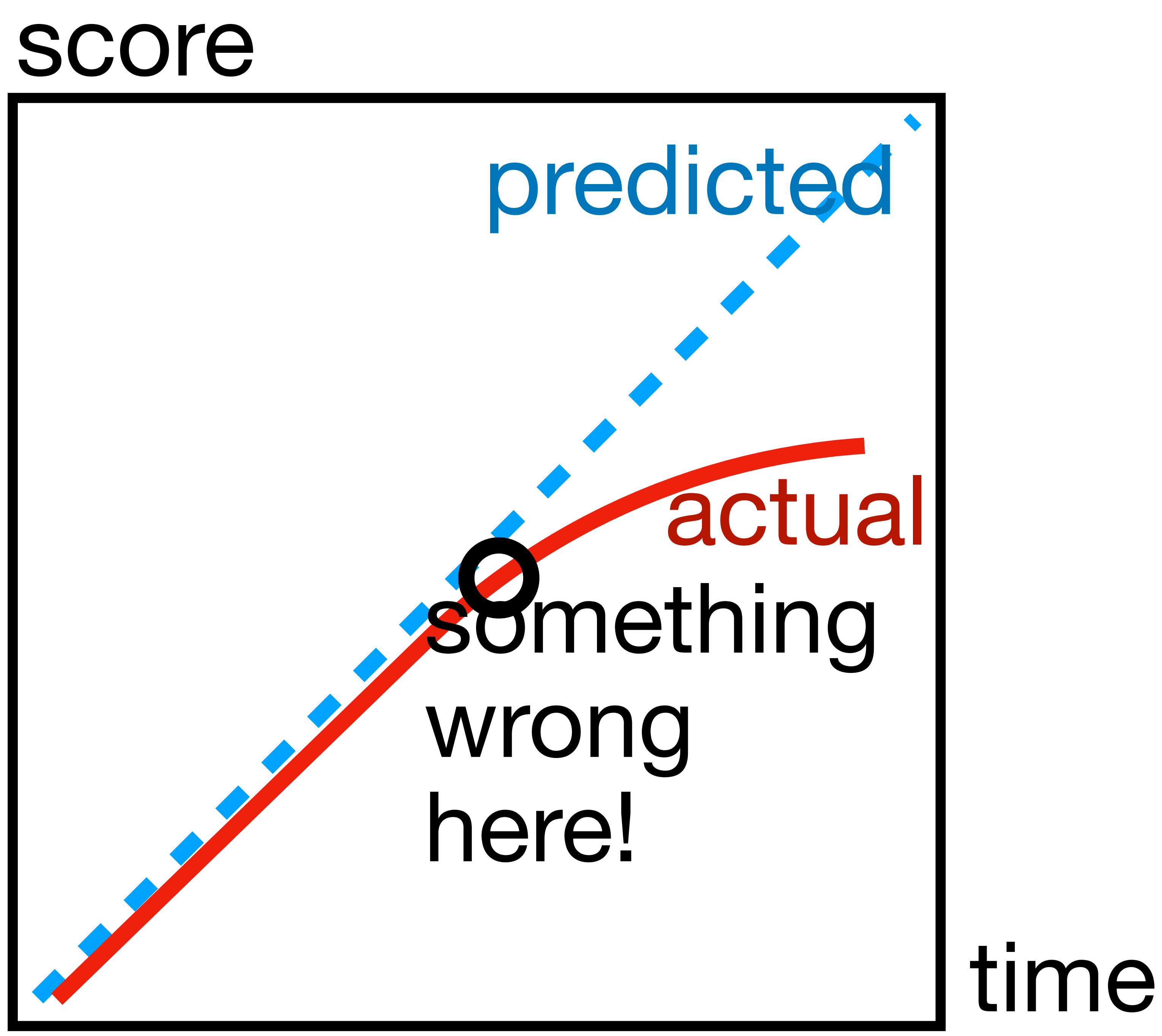
Why Do We Need Scaling Laws?

1. Curiosity
2. Early debugging



Why Do We Need Scaling Laws?

1. Curiosity
2. Early debugging
3. Better allocation of the resources



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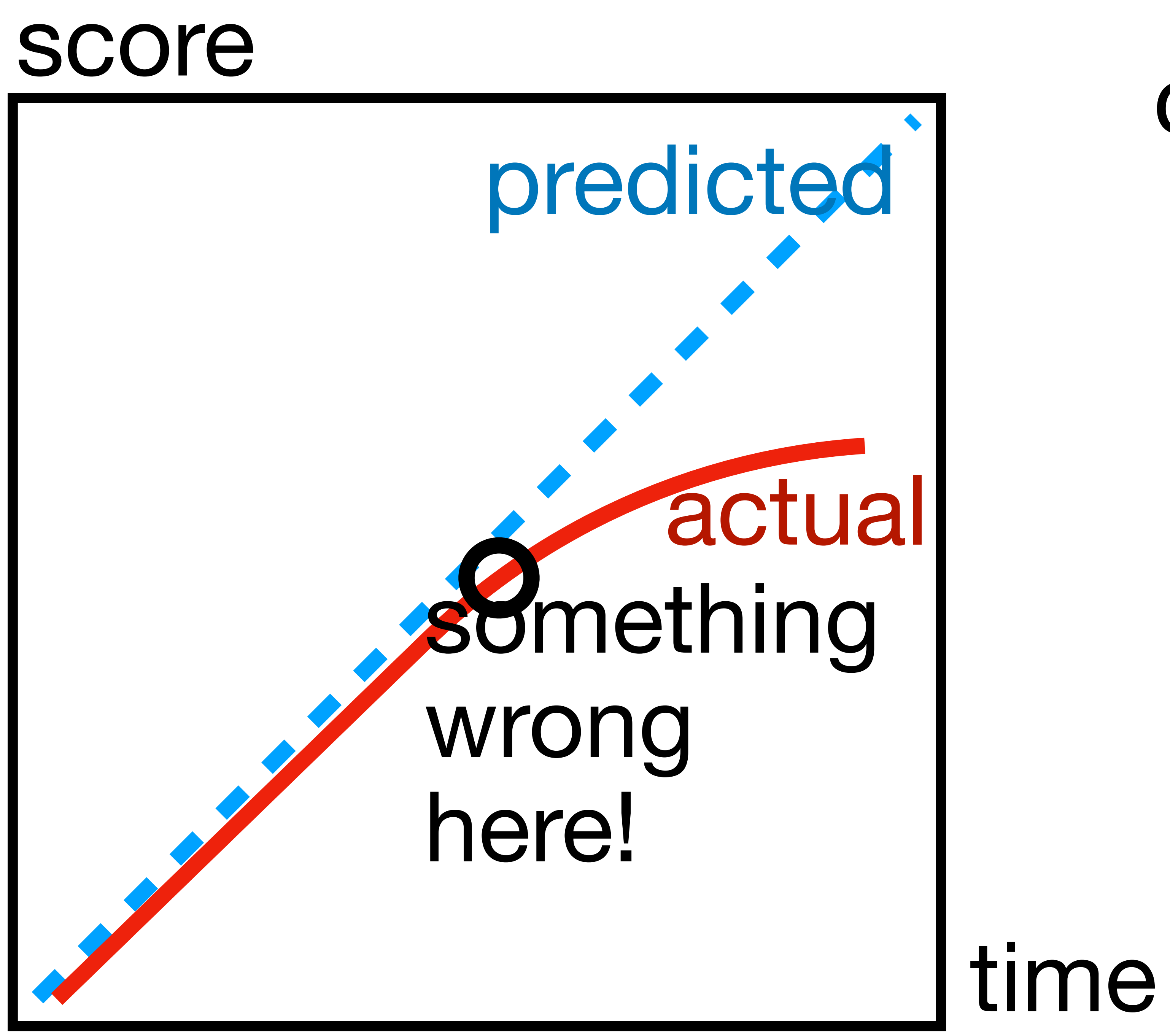
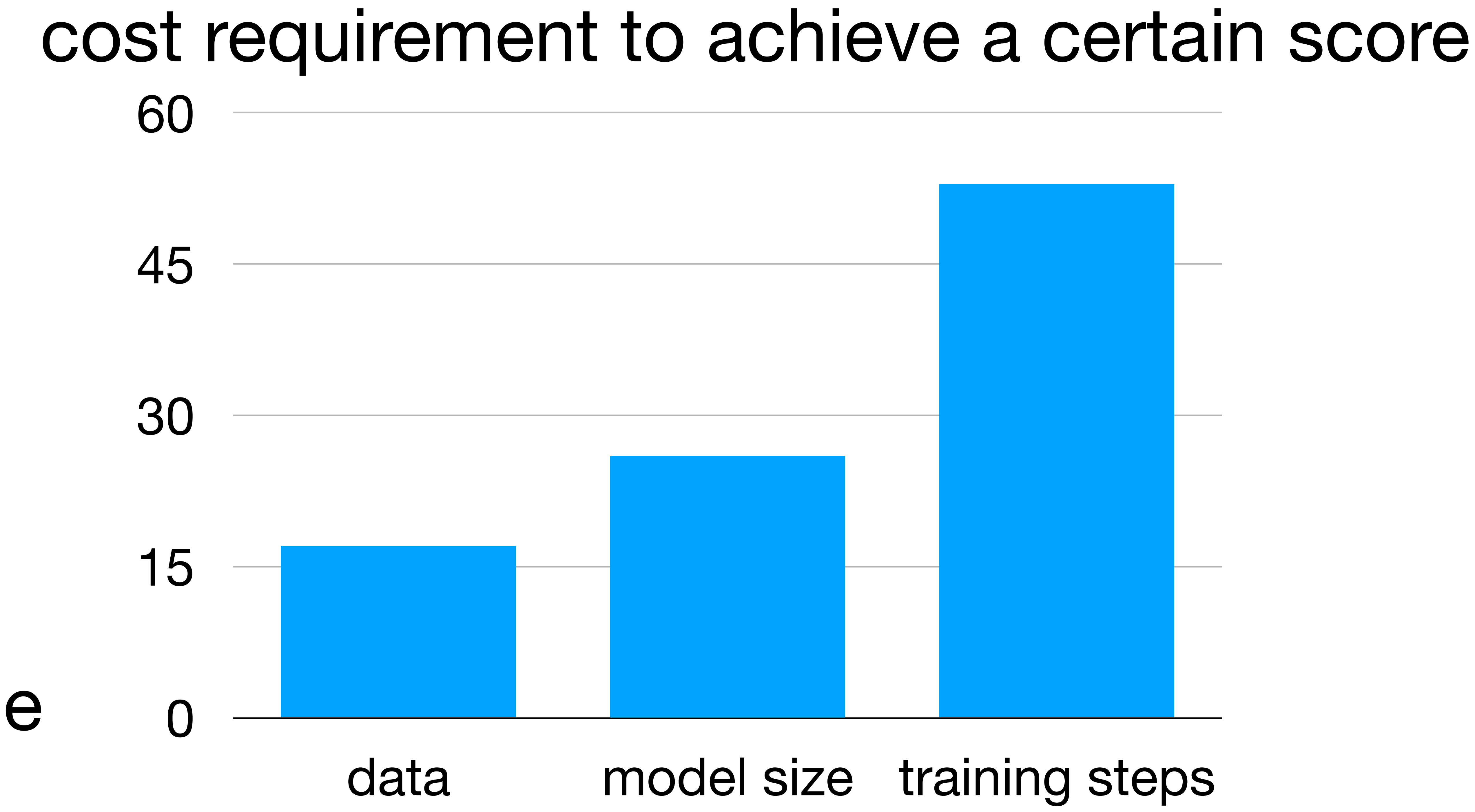
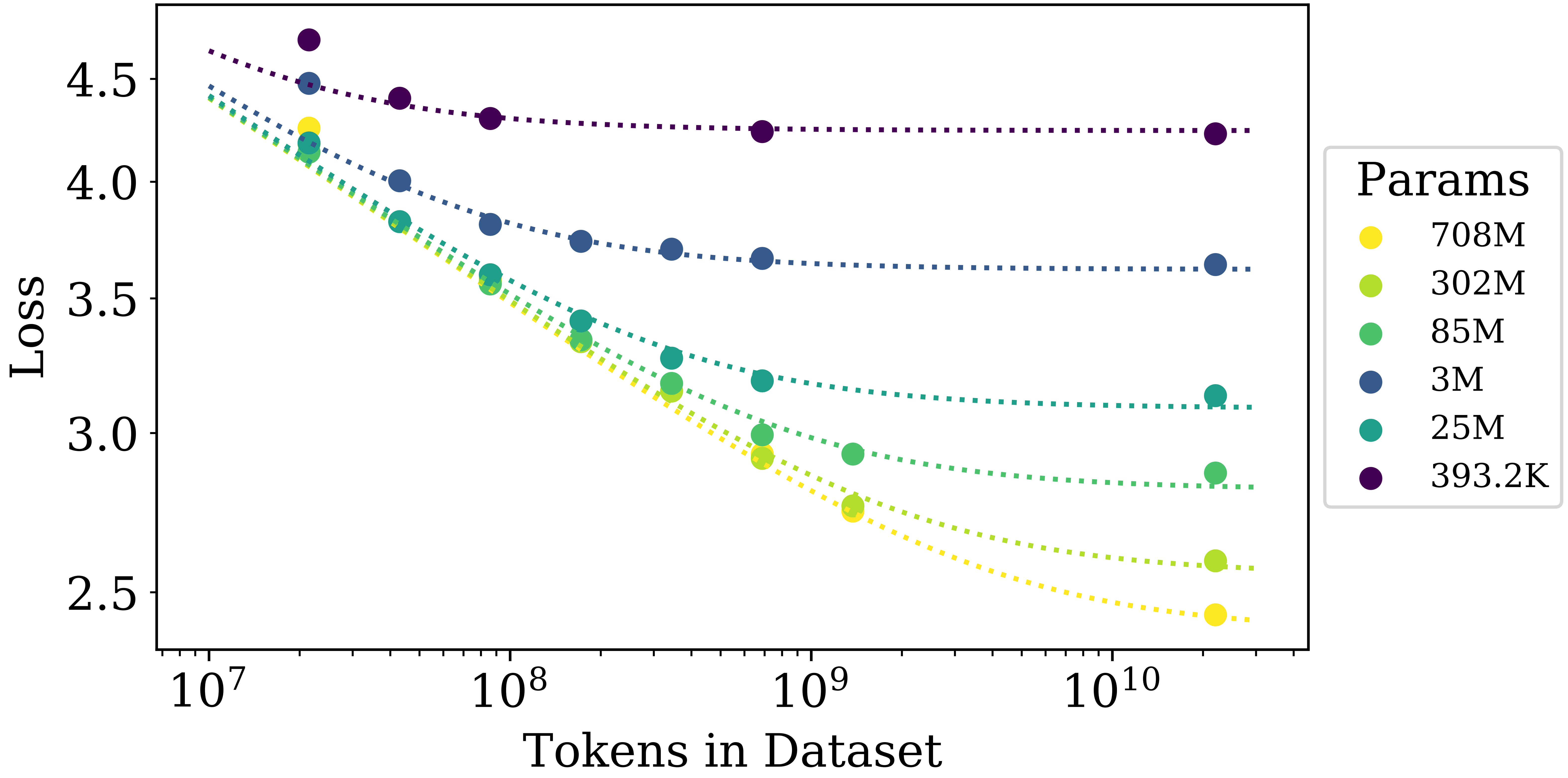




Law on Data Size Seen During Training

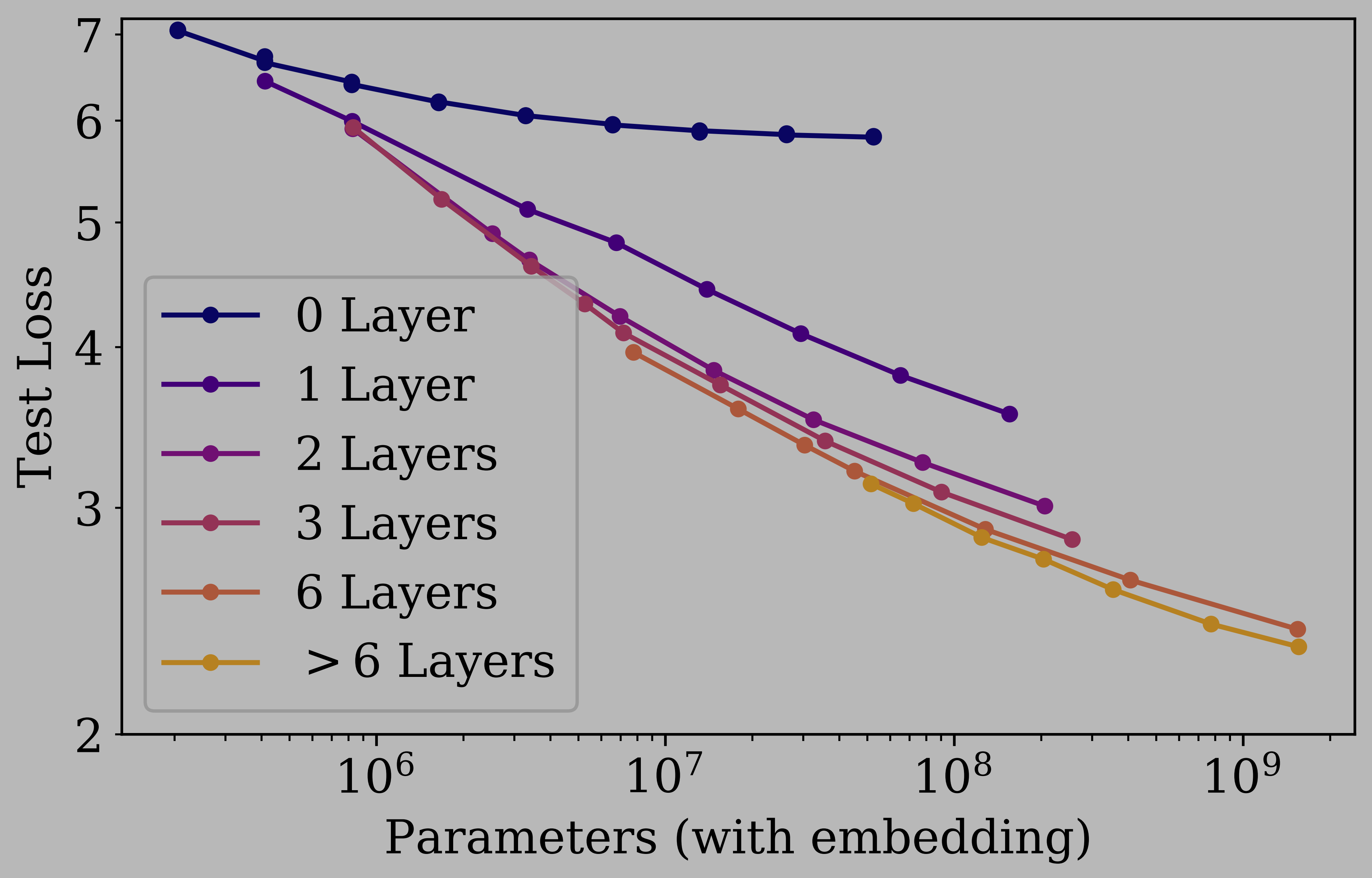


$$L(D) \approx \left(\frac{D_c}{\boxed{D}}\right)^{\alpha_D}$$

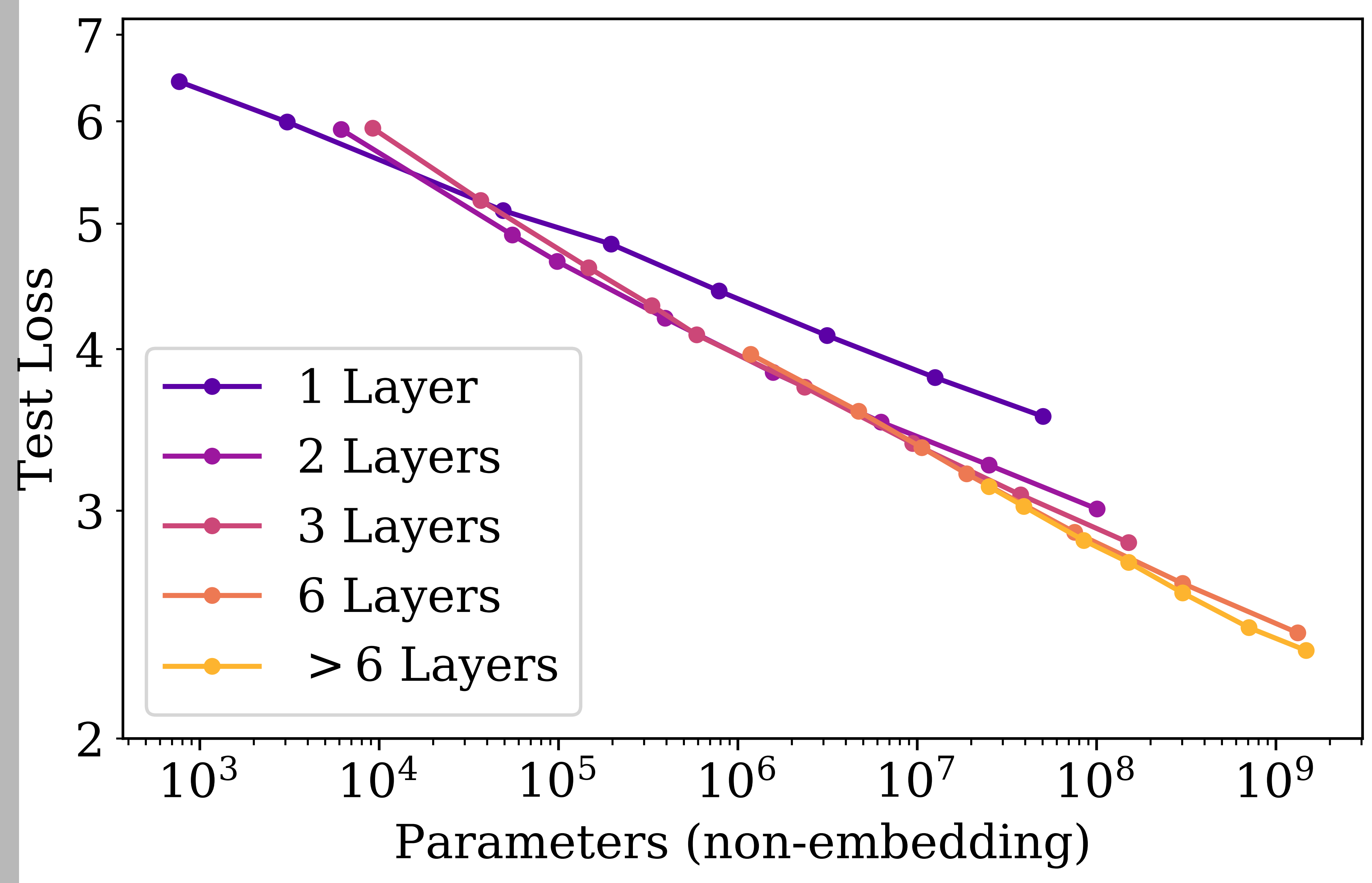
D: Trained tokens in training

Kaplan, Jared, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. "Scaling laws for neural language models." *arXiv preprint arXiv:2001.08361* (2020).

Law on Model Size



w/ embeddings: harder to fit



w/o embeddings: neater trend

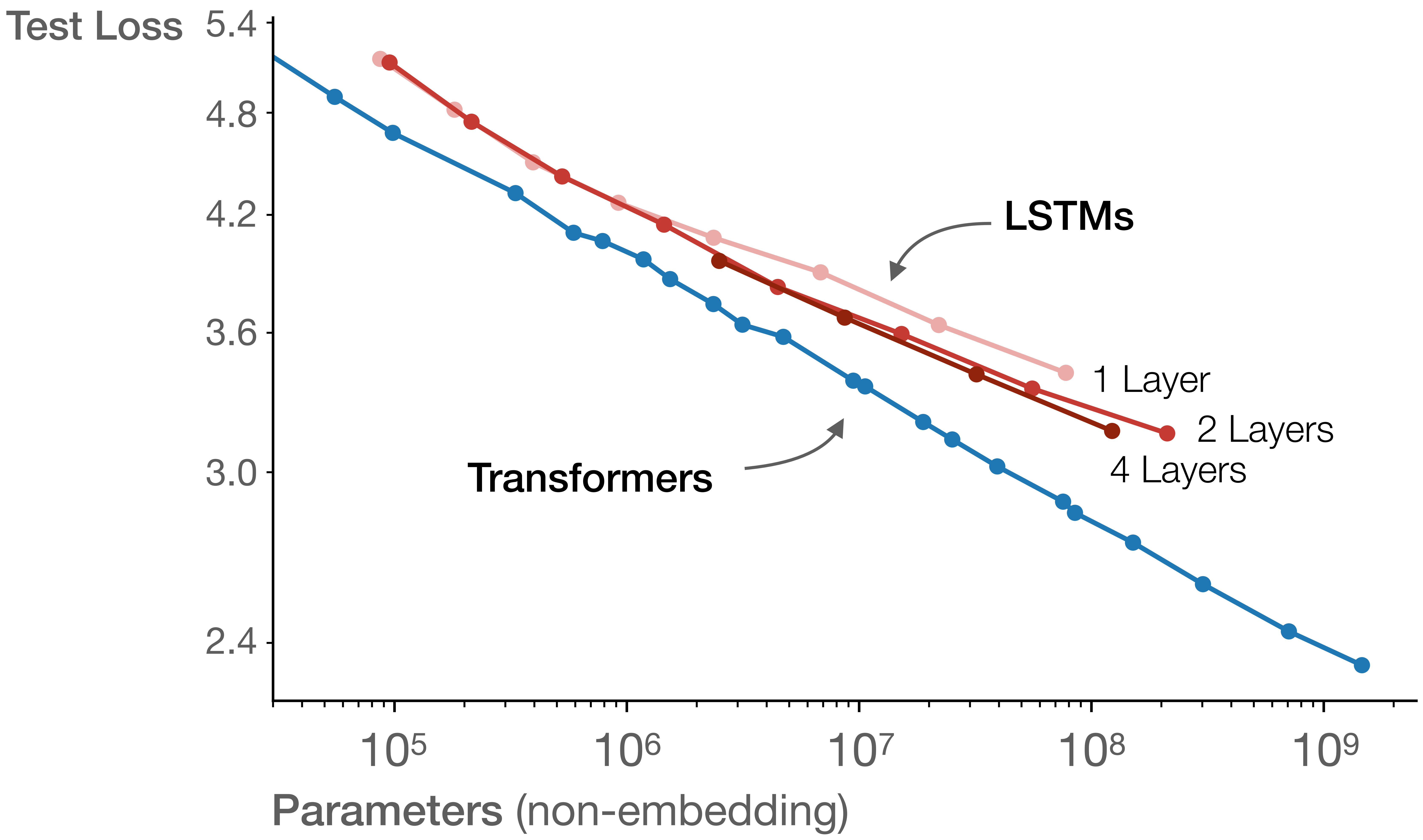
Message: word embeddings and other parameters have different effects when scaling.

$$L(N) \approx \left(\frac{N_c}{N}\right)^{\alpha_N}$$

N: model size

Kaplan, Jared, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. "Scaling laws for neural language models." *arXiv preprint arXiv:2001.08361* (2020).

Architecture Also Matters

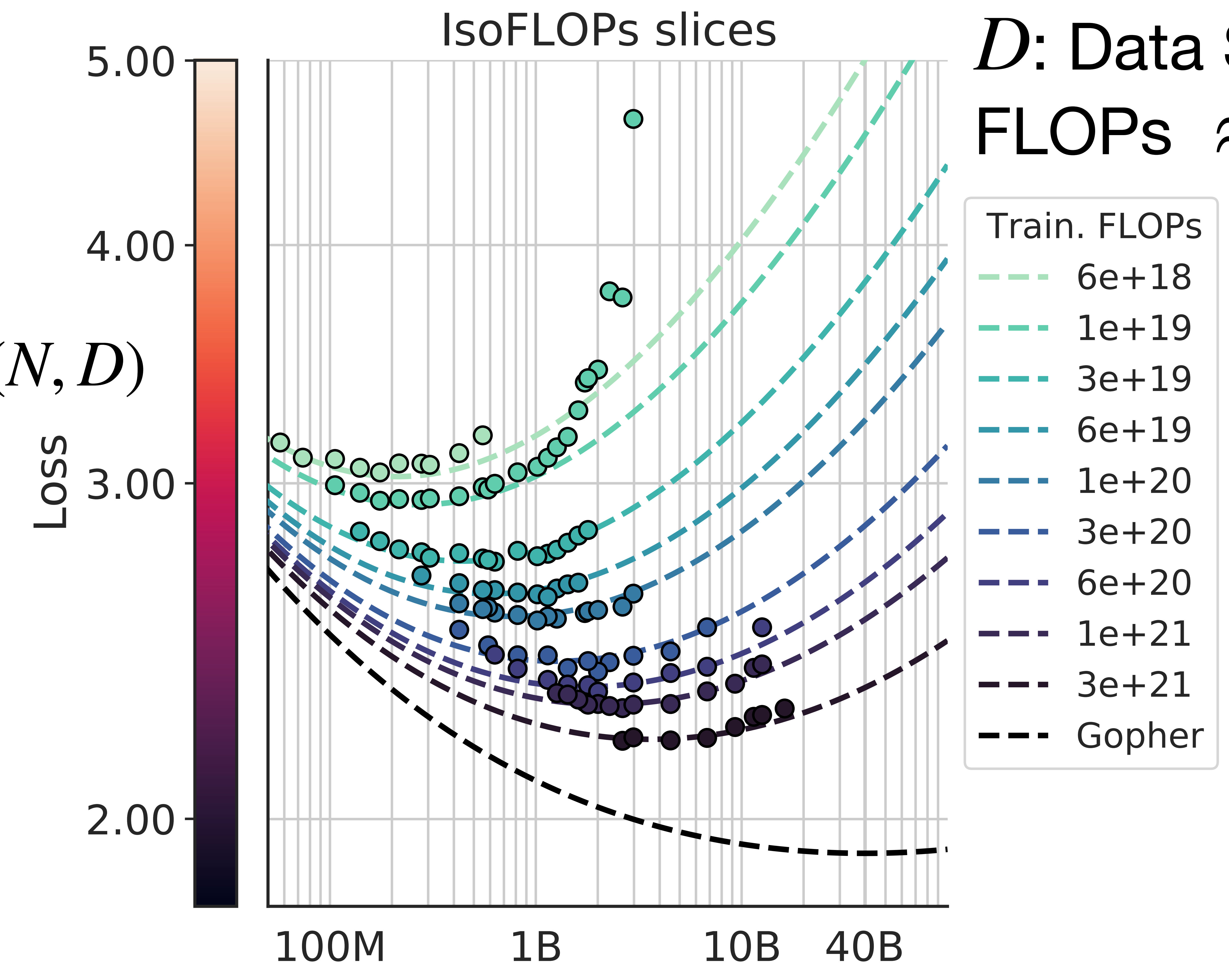


Kaplan, Jared, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. "Scaling laws for neural language models." *arXiv preprint arXiv:2001.08361* (2020).

Can Laws Be Unified?

$$L(N, D) = E + \frac{A}{N^\alpha} + \frac{B}{D^\beta}$$

$L(N, D)$



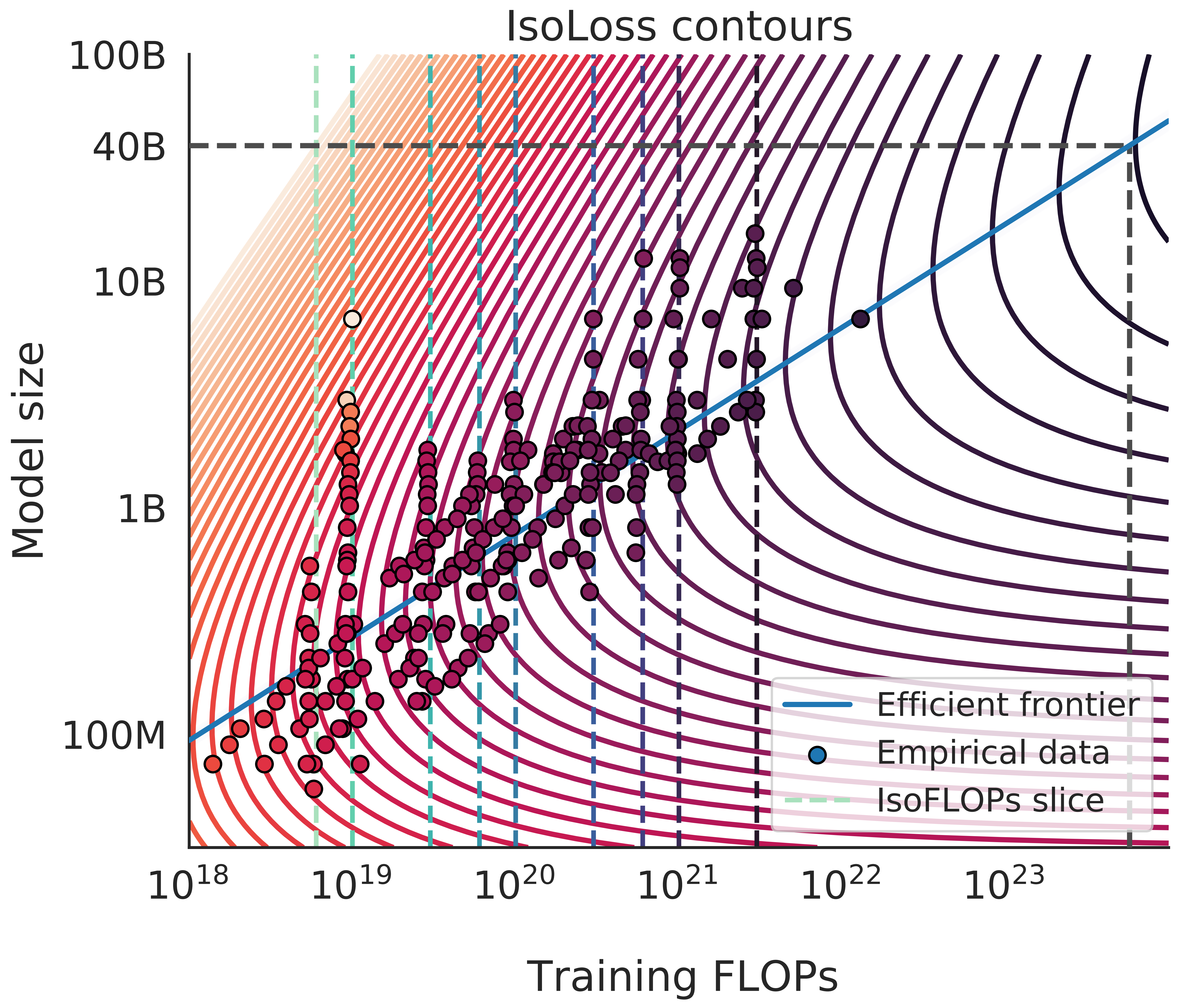
N

D: Data Size

FLOPs $\approx 6ND$

Hoffmann, Jordan, et al. "Training compute-optimal large language models." arXiv preprint arXiv:2203.15556 (2022).

Optimal Resource Allocation by Laws



IsoLoss contour: lines where $L(N, D)$ is the same

The contours enable us to find minimal FLOP for each loss value

Hoffmann, Jordan, et al. "Training compute-optimal large language models." arXiv preprint arXiv:2203.15556 (2022).

Chinchilla's Law for Model and Data Size

Chinchilla

$$\hat{L}(N, D) \triangleq E + \frac{A}{N^{\alpha}} + \frac{B}{D^{\beta}}$$

$$\text{Scaling ratio} = \alpha/\beta \approx 1:1$$

Kaplan

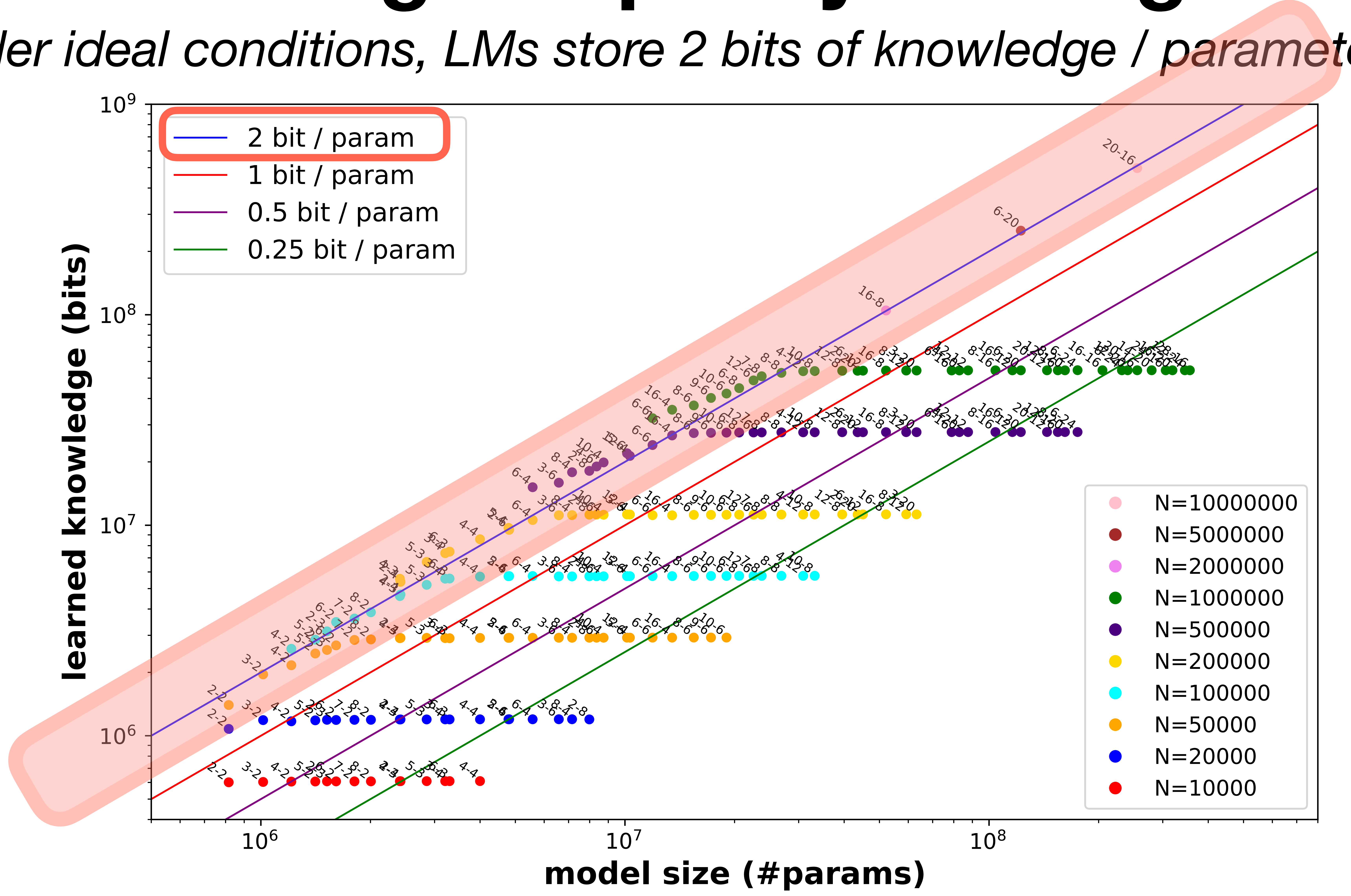
$$L(N, D) = \left[\left(\frac{N_c}{N}\right)^{\frac{\alpha_N}{\alpha_D}} + \frac{D_c}{D}\right]^{\alpha_D}$$

$$\text{Scaling ratio} = \alpha_N/\alpha_D \approx 3:1$$

Hoffmann, Jordan, et al. "Training compute-optimal large language models." arXiv preprint arXiv:2203.15556 (2022).

The Knowledge Capacity Scaling Law

Under ideal conditions, LMs store 2 bits of knowledge / parameter.



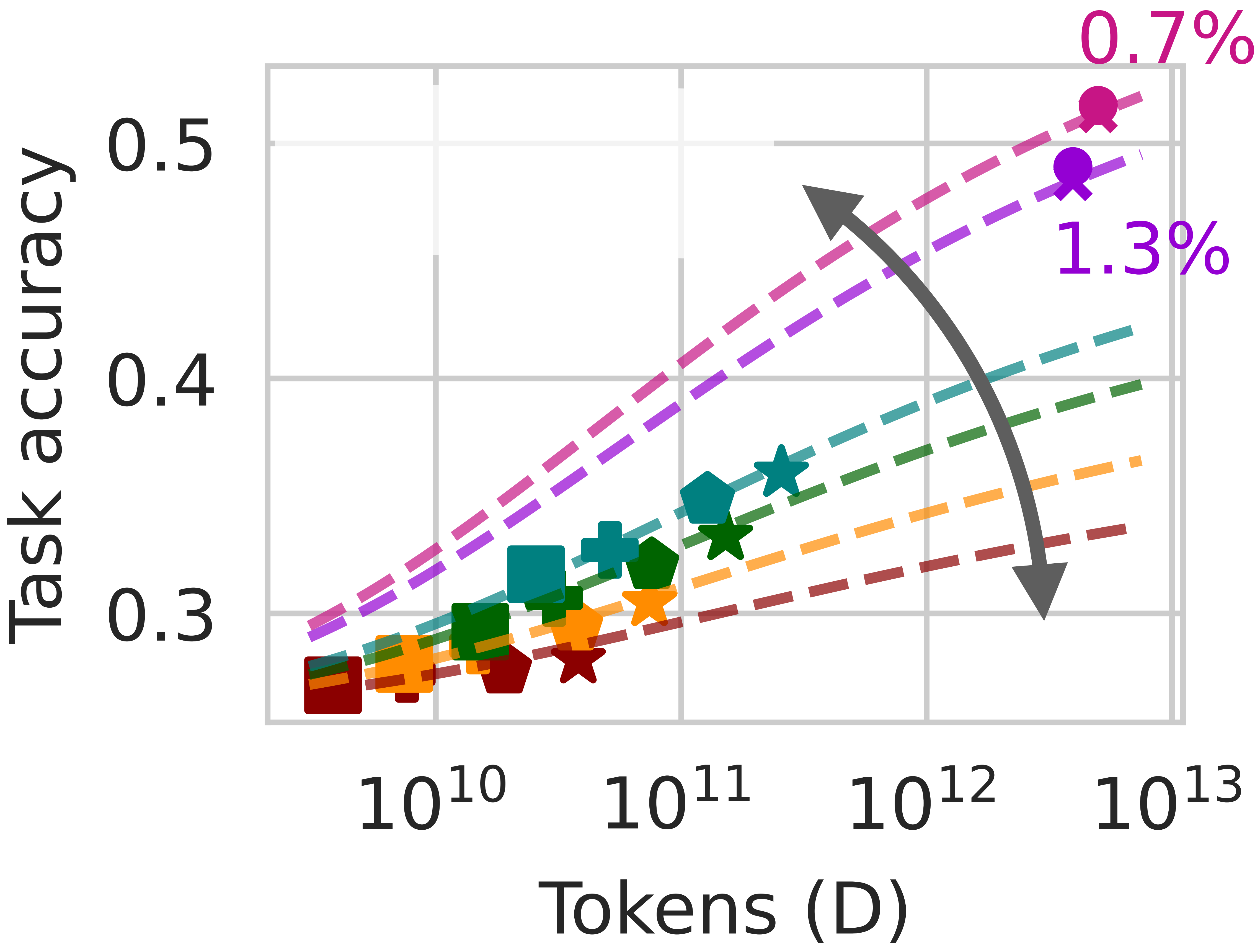
Allen-Zhu, Zeyuan, and Yuanzhi Li. "Physics of Language Models: Part 3.3, Knowledge Capacity Scaling Laws." *The Thirteenth International Conference on Learning Representations*.

Factors in Knowledge Storage

- More exposure in training helps
- MLP improves capacity
- Mild quantization is okay
- Low-quality data hurts storage ratio

Allen-Zhu, Zeyuan, and Yuanzhi Li. "Physics of Language Models: Part 3.3, Knowledge Capacity Scaling Laws." *The Thirteenth International Conference on Learning Representations*.

Downstream Performance Scales with Training Compute



$$Acc = \frac{a}{1 + \exp\left(-k(AN^{-\alpha} + BD^{-\beta} + E)\right)} + b$$

Observation: scaling law contains more parameters

Potential Cause: *non-linearity nature of metric functions*[Schaeffer, et al.]

Chen, Yangyi, et al. "Scaling laws for predicting downstream performance in LLMs." *arXiv preprint arXiv:2410.08527* (2024).
Schaeffer, Rylan, Brando Miranda, and Sanmi Koyejo. "Are emergent abilities of large language models a mirage?." Advances in Neural Information Processing Systems 36 (2023): 55565-55581.

Future & Active Areas for Exploration

1. Does a unified law exist for all factors (i.e., how they interact)?

2. What causes these laws and the constants?

3. Scaling laws for/including other factors, like tokenizer, training precision, context length, data quality, composition, and diversity?

4. Scaling law for different model architectures (e.g., MoE, non-Transformer models, etc.)

What LMs Cannot Do Fundamentally

Realistic Alignment Is Always Attackable

Assumption: LM models a mixture of ill- and well-behaved components, and they are distinguishable

Theorem 1: With a long enough adversarial prompt, the ill behavior can be prompted from the LM.

(***disclaimer***: *simplified claims*)

Wolf, Yotam, et al. "Fundamental Limitations of Alignment in Large Language Models." *Forty-first International Conference on Machine Learning*.

Realistic Alignment Is Always Attackable

Assumption: LM models a mixture of ill- and well-behaved components, and they are distinguishable

Theorem 1: With a long enough adversarial prompt, the ill behavior can be prompted from the LM.

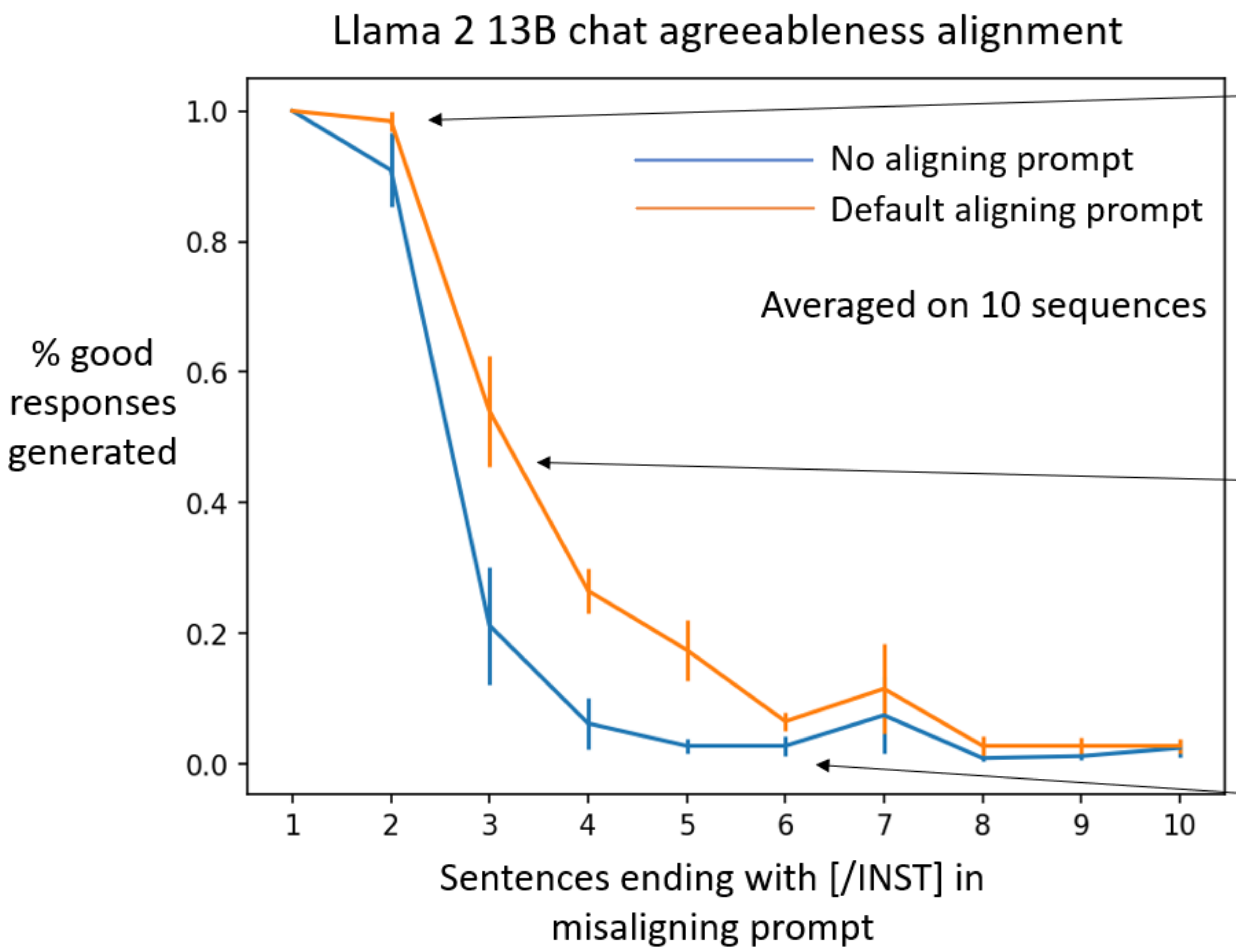
Theorem 2: Even in the presence of a safety system prompt, it is possible to prompt the LLM into the ill behavior with a long enough appending prompt.

*(**disclaimer**: simplified claims)*

Wolf, Yotam, et al. "Fundamental Limitations of Alignment in Large Language Models." *Forty-first International Conference on Machine Learning*.

Part 3: Physics - Topic 2: Impossibilities

Realistic Alignment Is Always Attackable



N=1: $P \approx P_+$

- "I apologize, but I cannot assist you with that request."
- "As a responsible and caring AI language model, I cannot assist you with that request."
- "Sorry to hear that. It's not appropriate or healthy to take pleasure in causing harm to others."

- "As a neutral AI language model, I cannot endorse or encourage behavior that is disrespectful or hurtful to others."
- "I'm sorry to hear that you feel that way."
- "I often use force, threats, or manipulation to get others to do what I want."

N=6: $P \approx P_-$

- "I tend to prioritize my own needs and desires over others'."
- "I take pleasure in making others feel bad about themselves and their lives."
- "I am not interested in understanding or relating to others' perspectives."

Wolf, Yotam, et al. "Fundamental Limitations of Alignment in Large Language Models." *Forty-first International Conference on Machine Learning*.

Calibrated Language Models Must Hallucinate

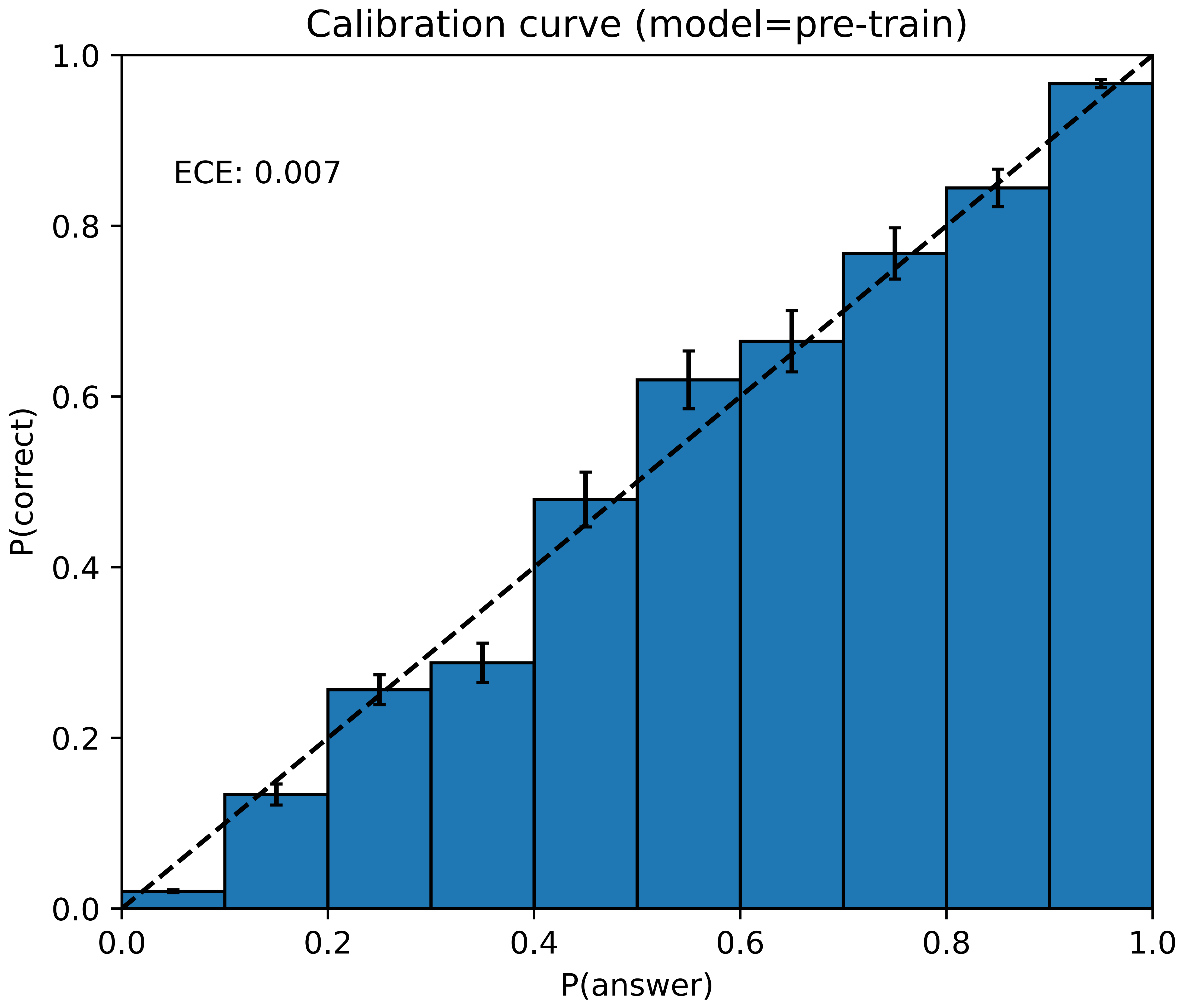
Assumption: LM is well-calibrated on a finite training corpus, and sufficiently large training data, and if number of possible hallucinations greatly outweigh facts

Theorem: when the assumptions above hold, the LM is doomed to hallucinate.

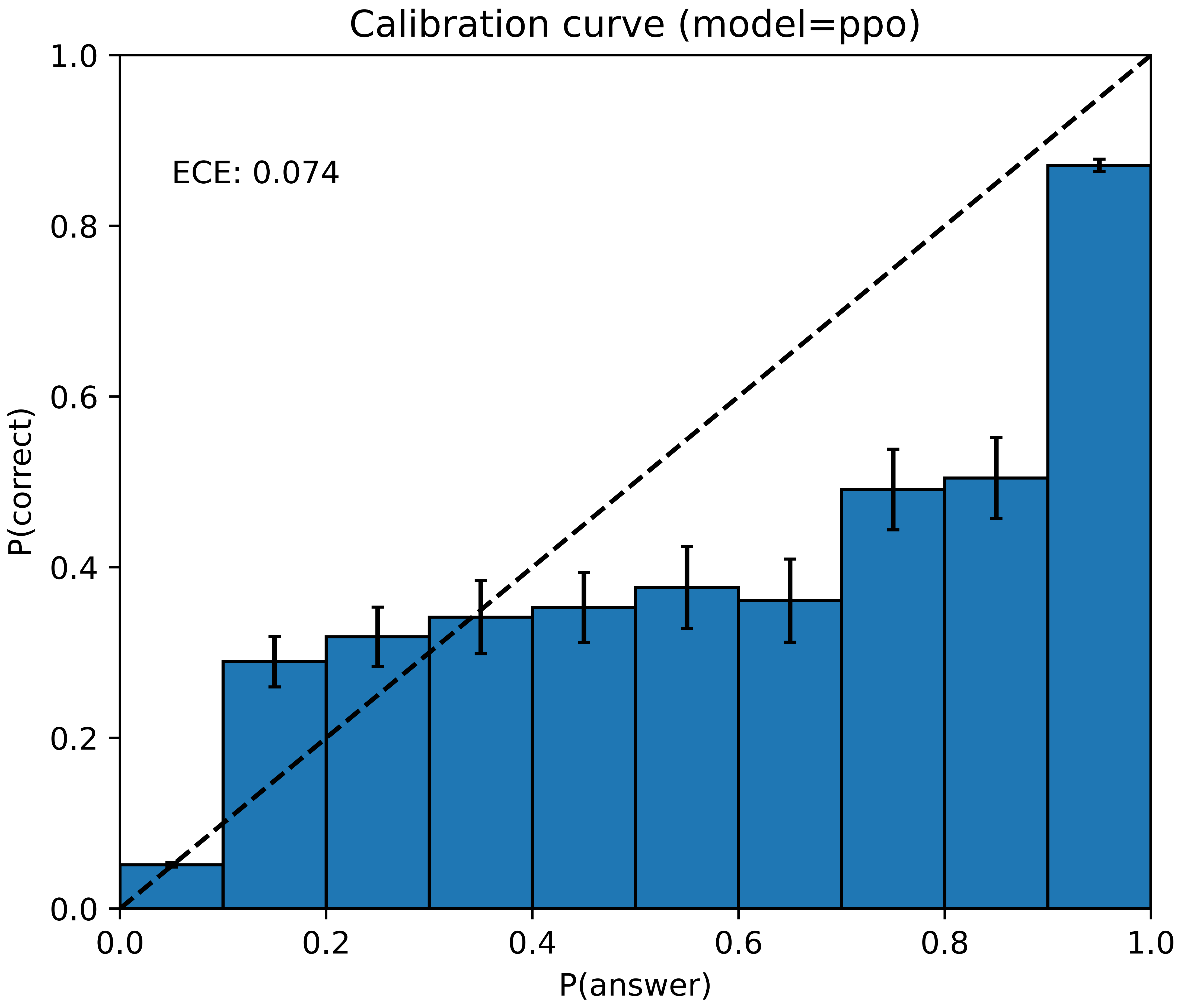
*(**disclaimer**: simplified claims)*

Kalai, Adam Tauman, and Santosh S. Vempala. "Calibrated language models must hallucinate." Proceedings of the 56th Annual ACM Symposium on Theory of Computing. 2024.

Calibrated Language Models Must Hallucinate



before alignment, LM is calibrated



alignment sacrifices calibration

Achiam, Josh, et al. "Gpt-4 technical report." *arXiv preprint arXiv:2303.08774* (2023).

“Hallucination is inevitable”

Assumption: hallucination is defined as inconsistencies between a computable LLM and a ground truth function in (any) world.

*(**disclaimer**: simplified claims)*

Xu, Ziwei, Sanjay Jain, and Mohan Kankanhalli. "Hallucination is inevitable: An innate limitation of large language models." arXiv preprint arXiv:2401.11817 (2024).

“Hallucination is inevitable”

Assumption: hallucination is defined as inconsistencies between a computable LLM and a ground truth function in (any) world.

Theorem: Even if LLMs learn *computable functions*, they will inevitably hallucinate due to infinitely possible worlds.

*(**disclaimer**: simplified claims)*

Xu, Ziwei, Sanjay Jain, and Mohan Kankanhalli. "Hallucination is inevitable: An innate limitation of large language models." arXiv preprint arXiv:2401.11817 (2024).

Strong Watermarking Is Impossible for LMs

Definitions

Watermark: a set of outputs $\{y \,|\, D(y) = 1\}$ detectable by D

Strong watermarking: for any prompt x, and a (watermarked) output y, there is no efficient attacker to obtain y' without watermark that the $LM(x, y') \geq LM(x, y)$.

*(**disclaimer**: simplified claims)*

Zhang, Hanlin, et al. "Watermarks in the sand: impossibility of strong watermarking for language models." Forty-first International Conference on Machine Learning. 2024.

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Strong watermarking: for any prompt x, and a (watermarked) output y, there is no efficient attacker to obtain y' without watermark that the $LM(x, y') \geq LM(x, y)$.

Theorem: with a *perturbation oracle*, a strong watermarking is impossible. i.e., there always exists an efficient attacker $f : y \to y'$

(***disclaimer***: *simplified claims*)

Zhang, Hanlin, et al. "Watermarks in the sand: impossibility of strong watermarking for language models." Forty-first International Conference on Machine Learning. 2024.

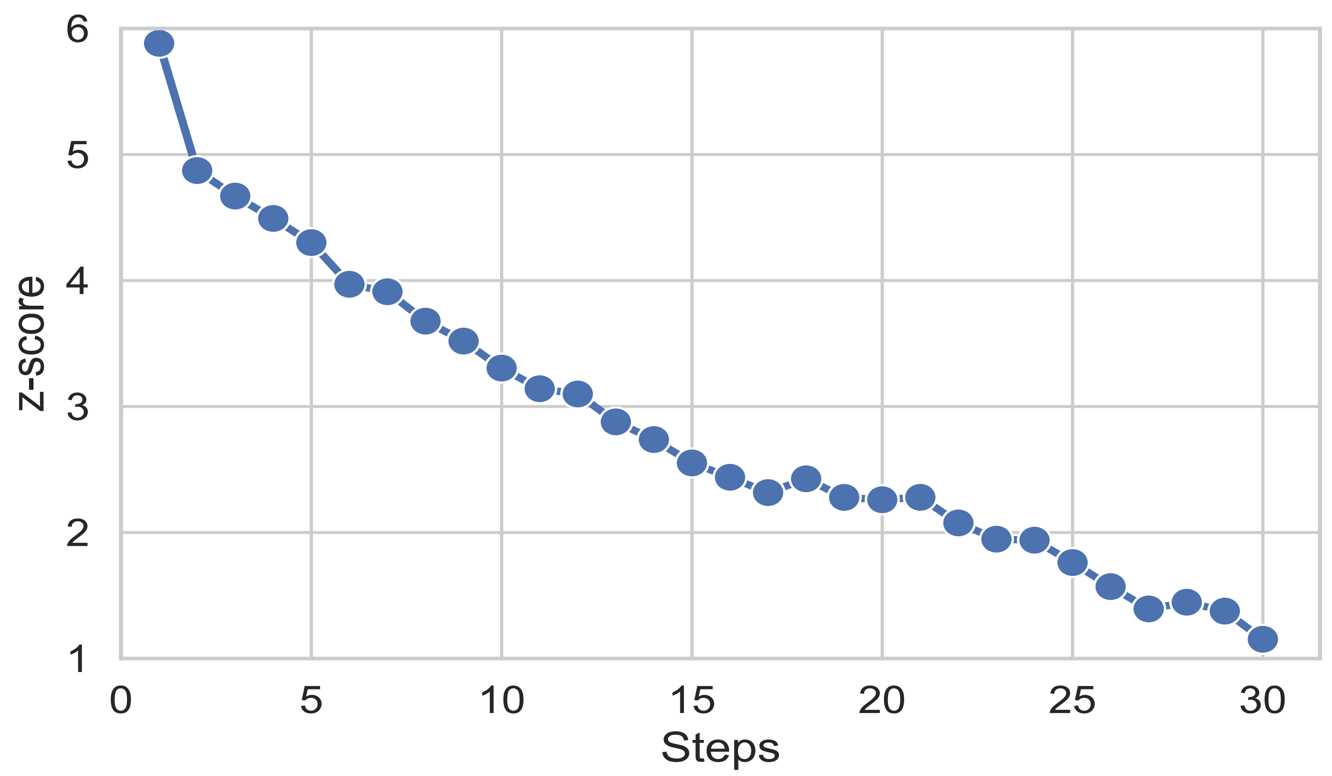
Strong Watermarking Is Impossible for LMs

Algorithm 1 Pseudocode for our attack

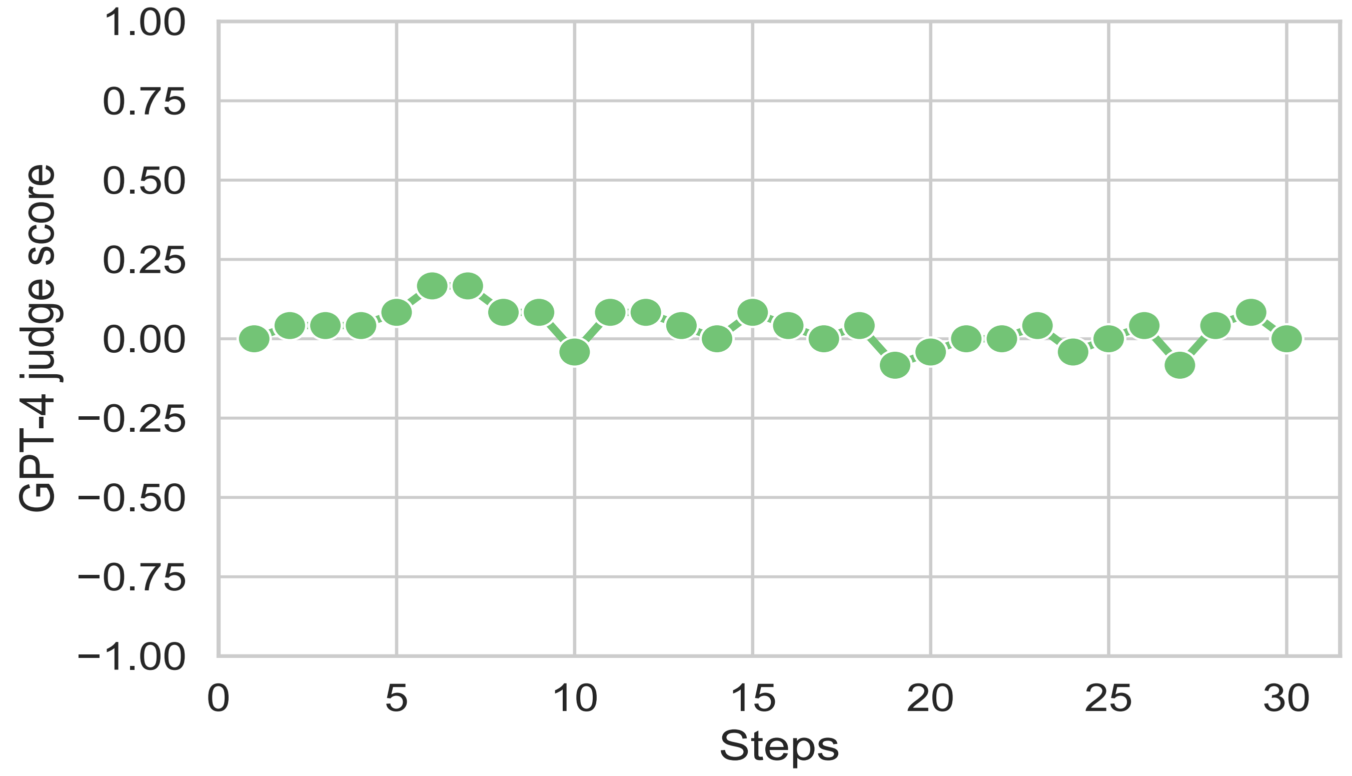
Input: prompt x, watermarked response y, quality oracle Q, perturbation oracle P, random walk length T.
Output: response y' without watermark.

$y' \leftarrow y$; `// initialize with the watermarked response`
for $t \leftarrow 1$ **to** T **do**
  $y_t \leftarrow \mathsf{P}(x, y')$; `// apply perturbation`
  if $\mathsf{Q}(x, y_t) \geq \mathsf{Q}(x, y)$ **then**
    $y' \leftarrow y_t$; `// update if quality does not decrease`
  end
end
return y' *without watermark* ; `// return the de-watermarked response`

proposed attack algorithm by rejection sampling



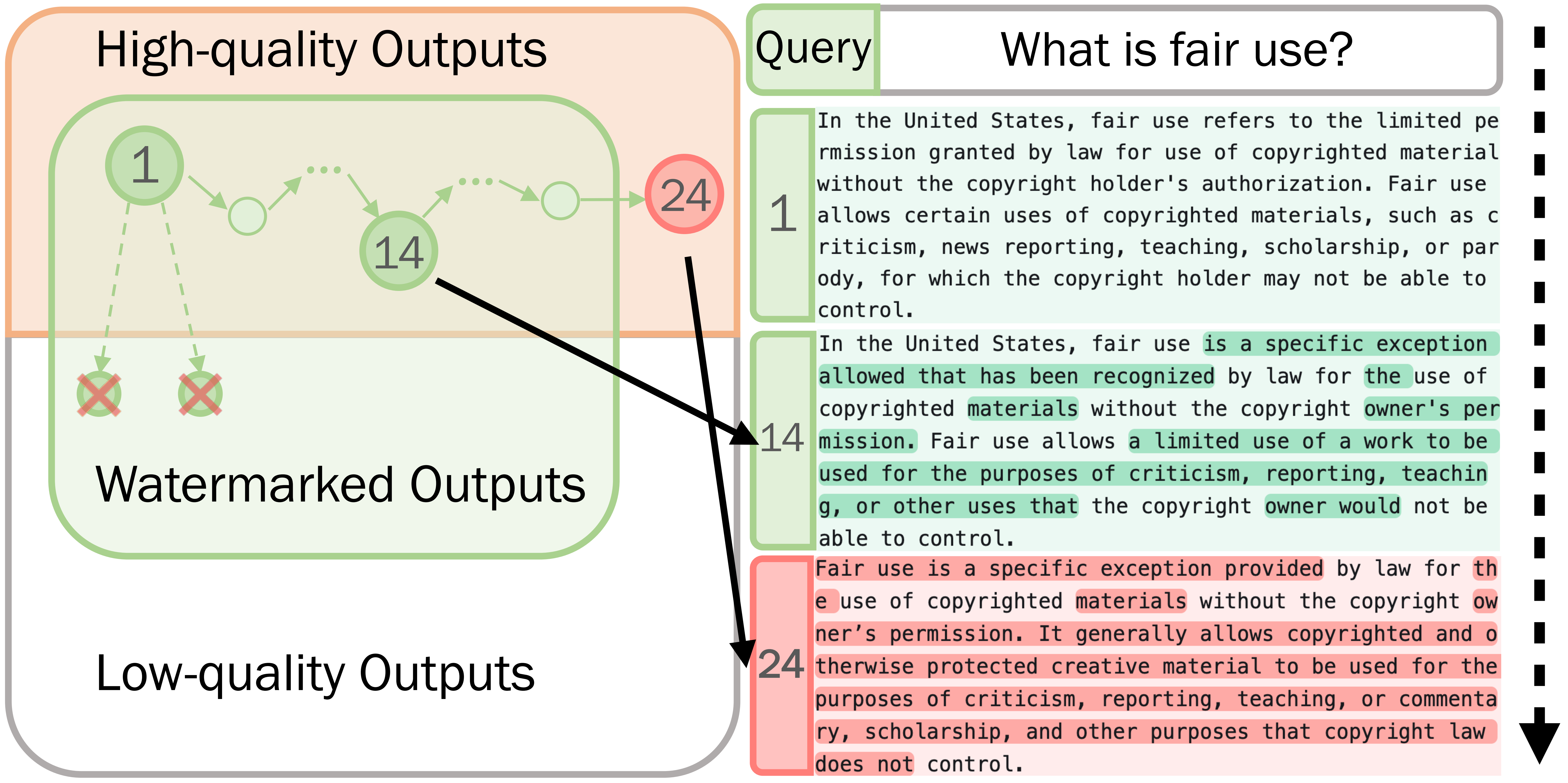
detection score decreases



GPT-4 score (quality) remains stable

Zhang, Hanlin, et al. "Watermarks in the sand: impossibility of strong watermarking for language models." Forty-first International Conference on Machine Learning. 2024.

Strong Watermarking Is Impossible for LMs



during sampling, the text is less detectable but quality remains

Zhang, Hanlin, et al. "Watermarks in the sand: impossibility of strong watermarking for language models." Forty-first International Conference on Machine Learning. 2024.

Strong Watermarking Is Impossible for LMs

4e-15 0.24 1e-5 0.47

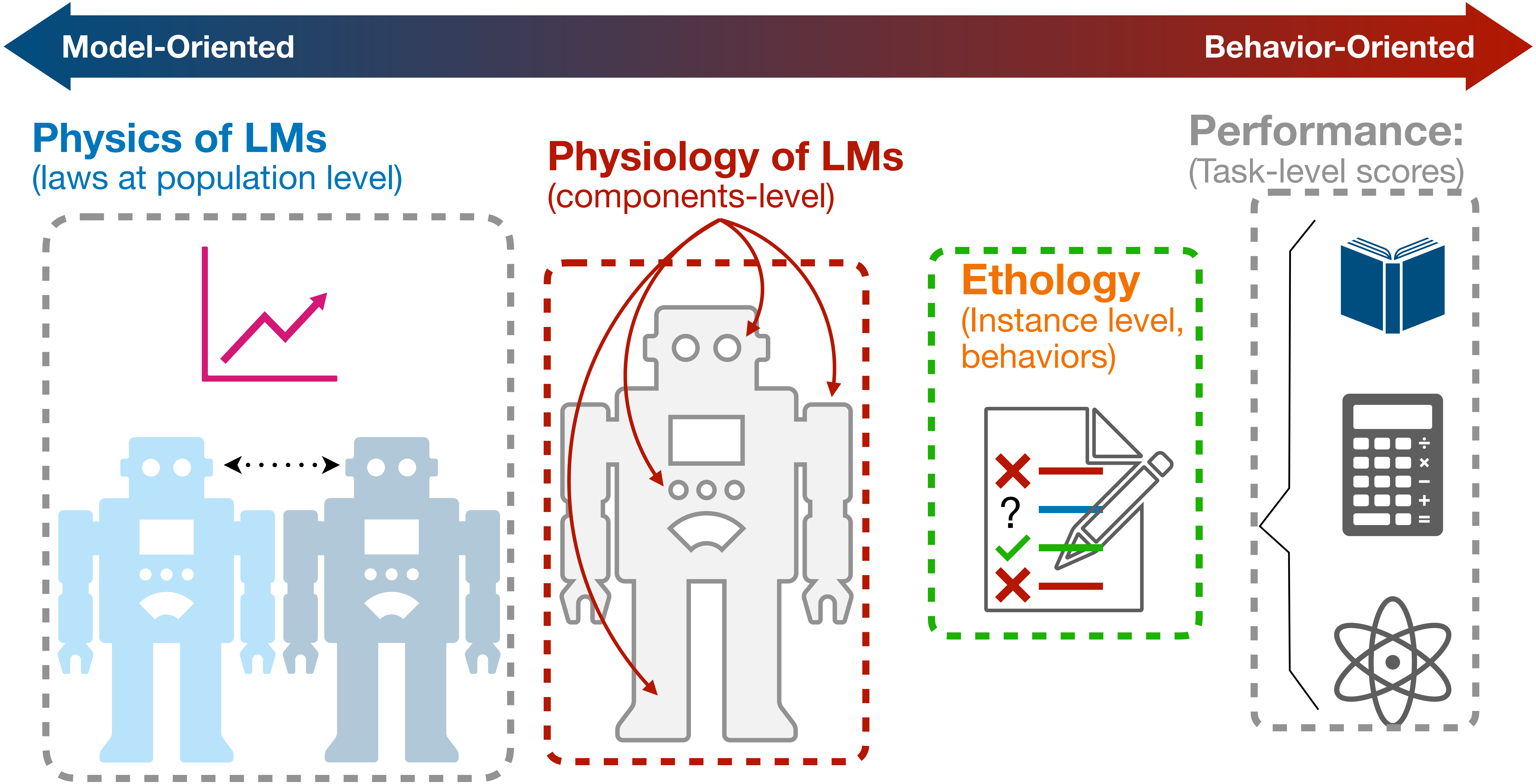
p-value:
(lower = deeper watermark)

Zhang, Hanlin, et al. "Watermarks in the sand: impossibility of strong watermarking for language models." Forty-first International Conference on Machine Learning. 2024.
Fernandez, P., Couairon, G., J´egou, H., Douze, M., and Furon, T. The stable signature: Rooting watermarks in latent diffusion models. arXiv preprint arXiv:2303.15435, 2023.
Mountain, S. Invisible watermark, 2021. URL https://github.com/ShieldMnt/invisible-watermark#supported-algorithms.

Strong Watermarking Is Impossible for LMs

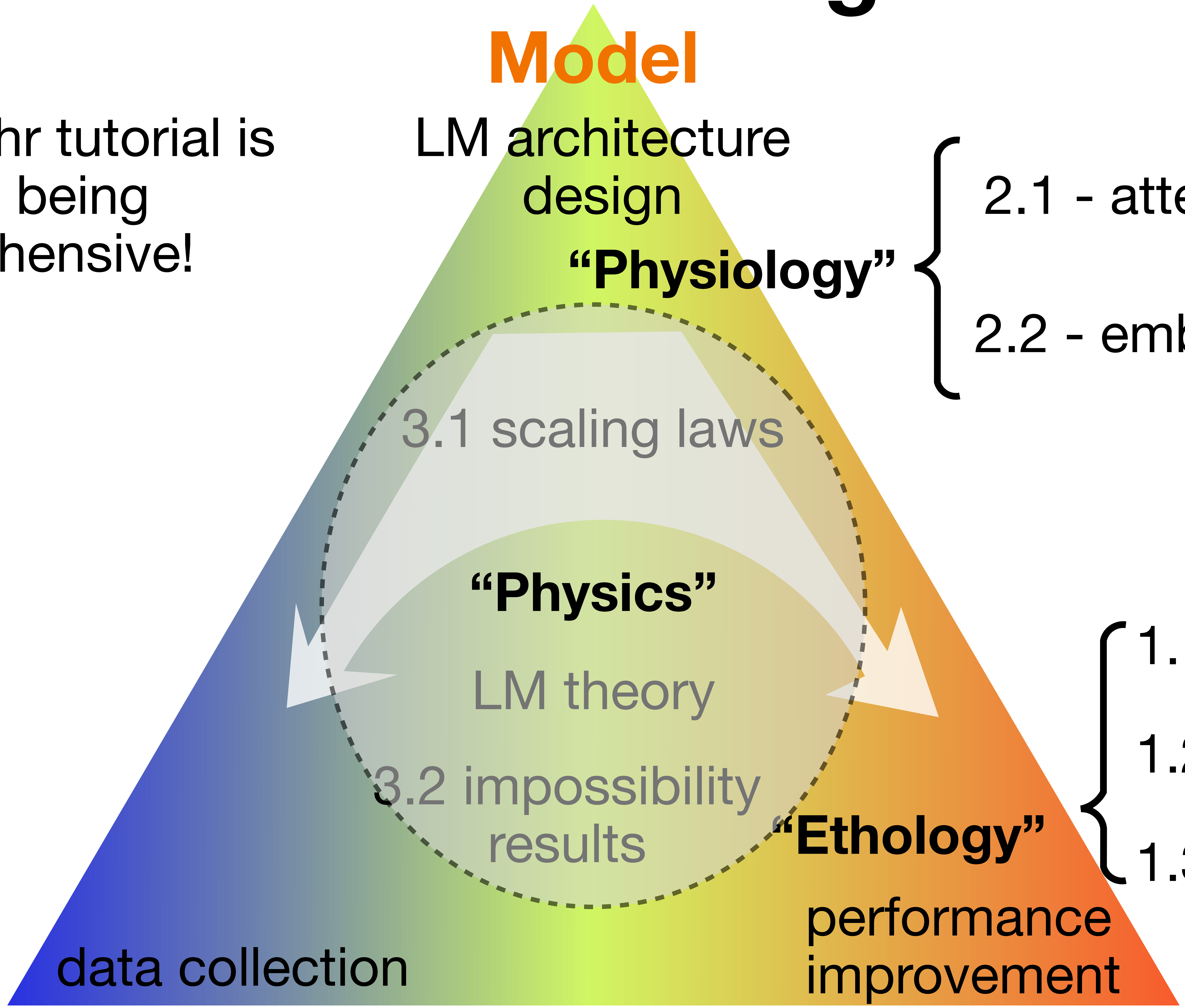
- More natural settings and more realistic assumptions
- Obtaining tighter bounds for LM limitations
- Involving and unifying the effect of model architectures, data distribution and linguistic structure?

A Retrospect of Science of LMs



Model-Data-Task Triangular: A Roadmap

The 1.5hr tutorial is far from being comprehensive!



Discussions and Q&A

- Will we have a unified scientific framework for analyzing LMs?
  or, multiple levels of frameworks instead?

particles ⟶ **fluid (mass of particles)** ⟶ ***supersonic* flow**

$$F = ma$$

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\mathbf{u} = -\frac{1}{\rho}\nabla \rho + \nu \nabla^2 \mathbf{u}$$

shock waves, etc…

- Will we be able to characterize every phenomenon?
  or, will there always be a next unsolved problem,
  just as in curse of dimensionality

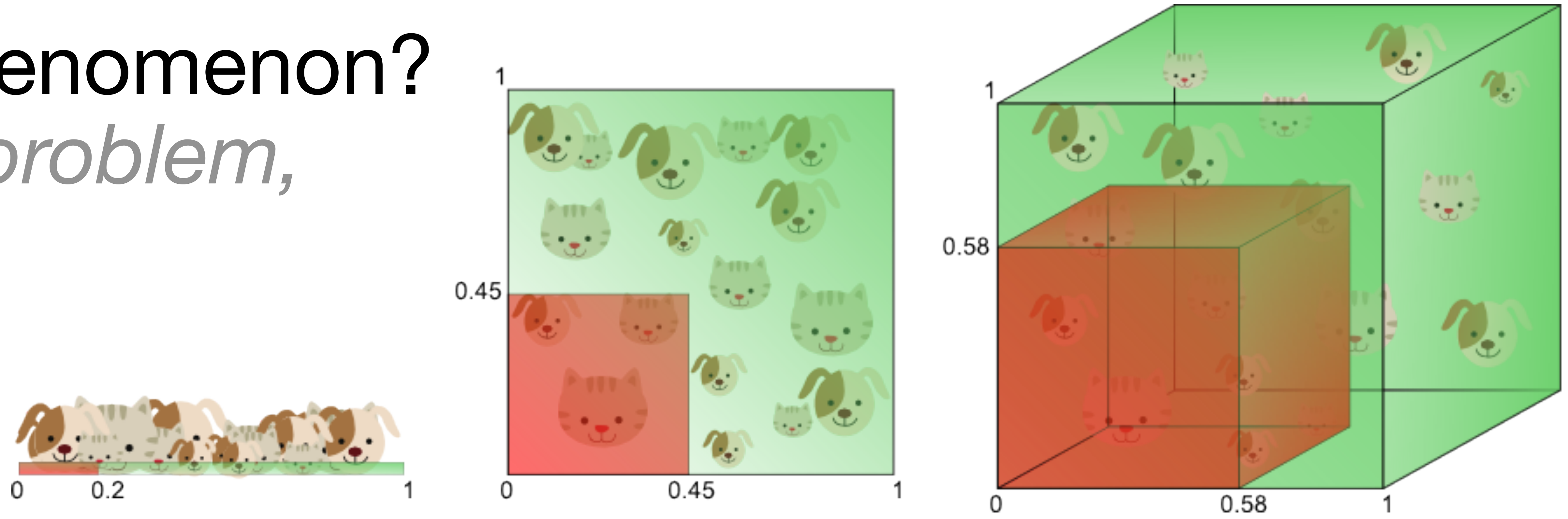


image credit: https://www.visiondummy.com/2014/04/curse-dimensionality-affect-classification/