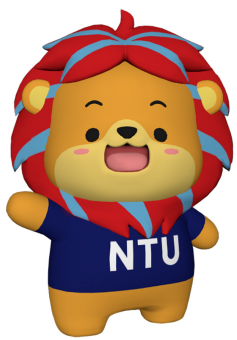
To model human linguistic prediction, make LLMs less superhuman

Byung-Doh Oh

Nanyang Technological University

HHU DLM Colloquium · 19 June 2026



Language processing in humans

The girl found the lamb ...

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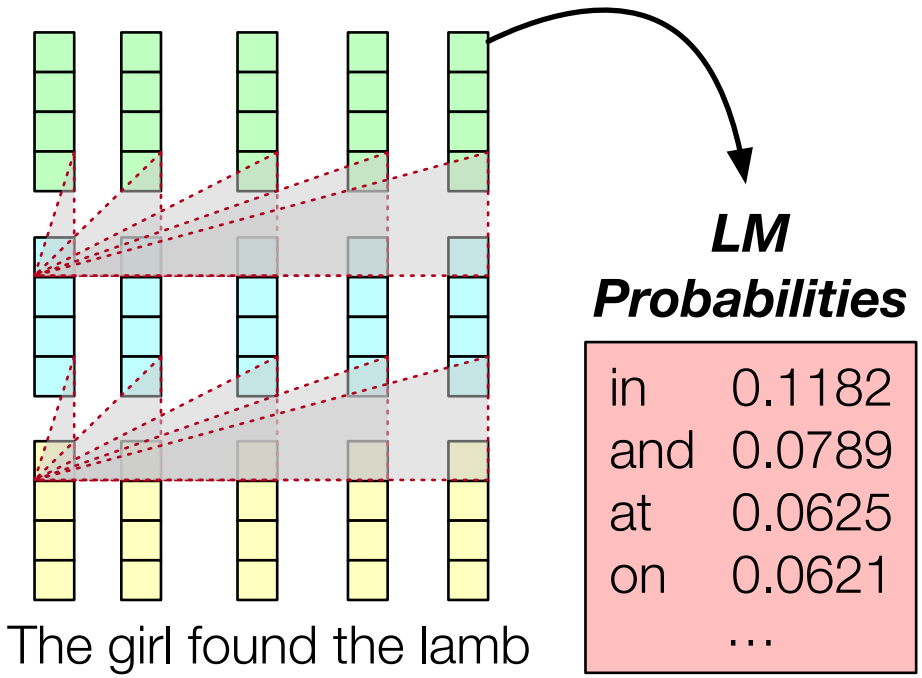
- **Incremental**: We don't wait until the end of the sentence.

Language processing in humans

The girl found the lamb ...

- **Incremental**: We don't wait until the end of the sentence.
- **Predictive**: We proactively anticipate the upcoming material.

Language processing in language models



Language processing in language models

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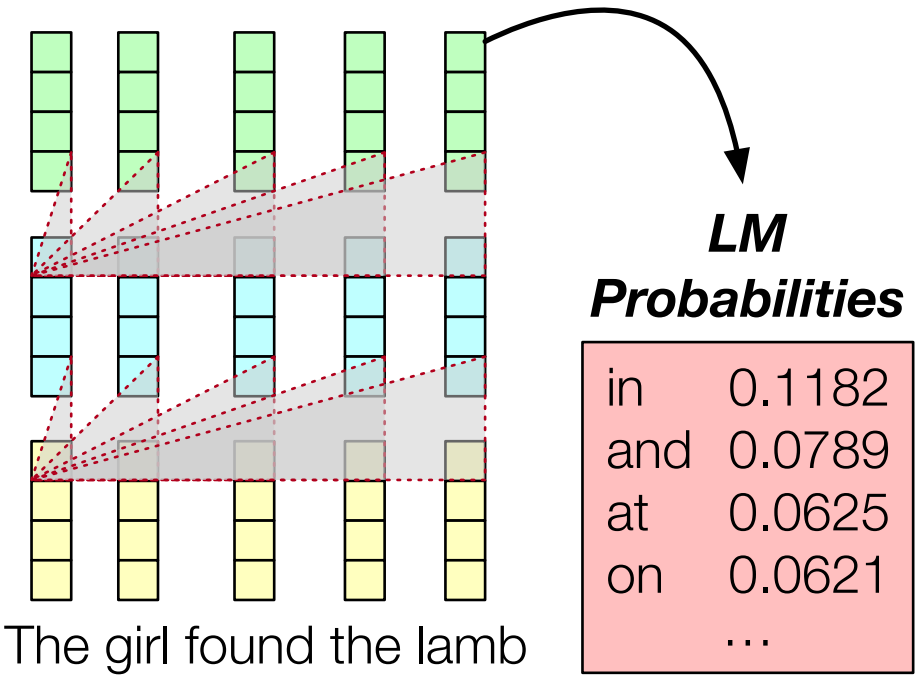

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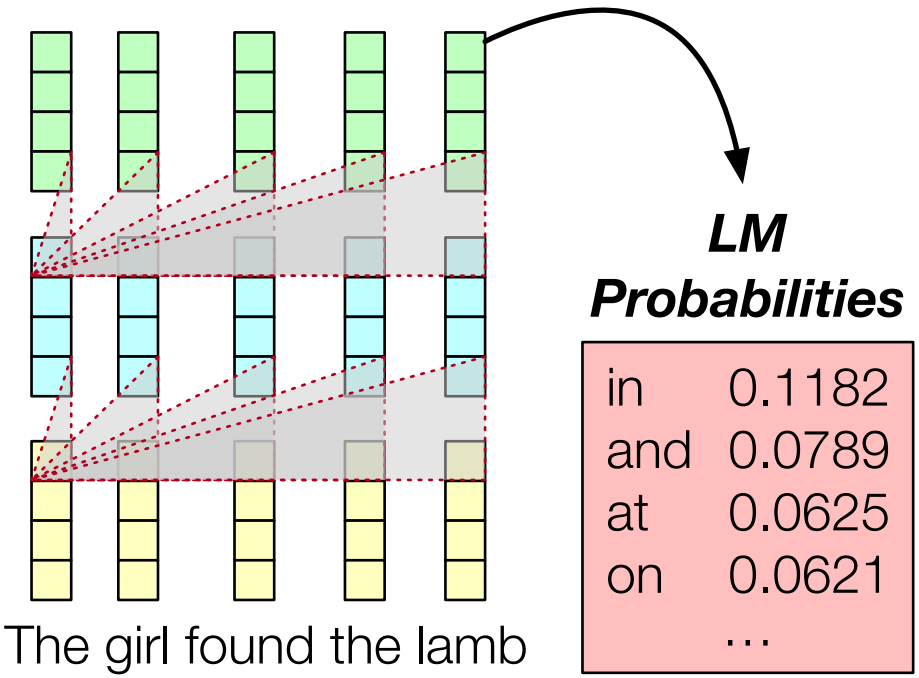

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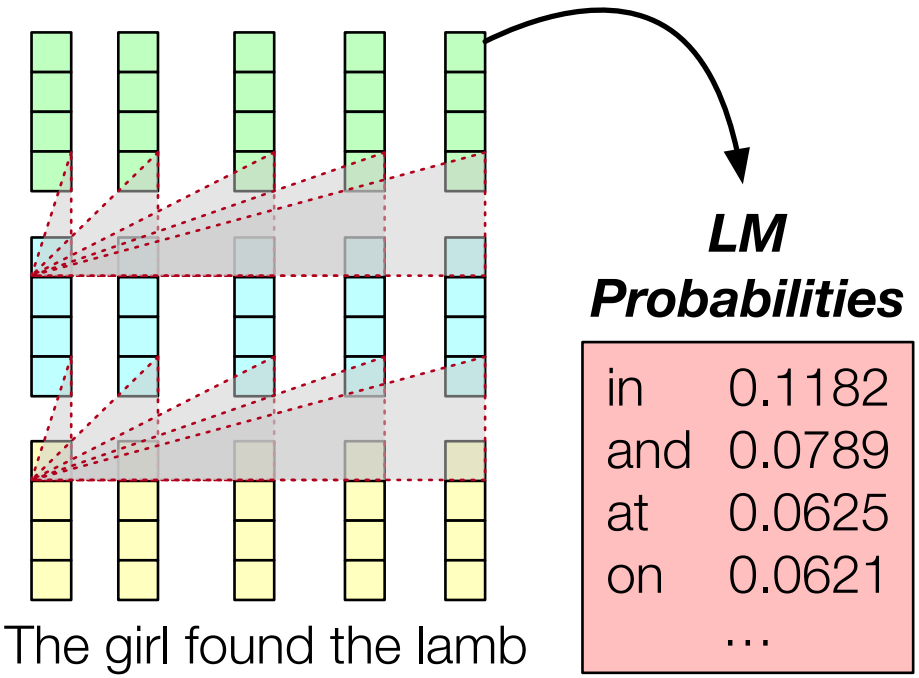

- **Predictive!**

These 'shared principles' (Schrimpf et al., 2021) ground the use of LLMs in psycholinguistic research.

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3. Superhuman short-term memory

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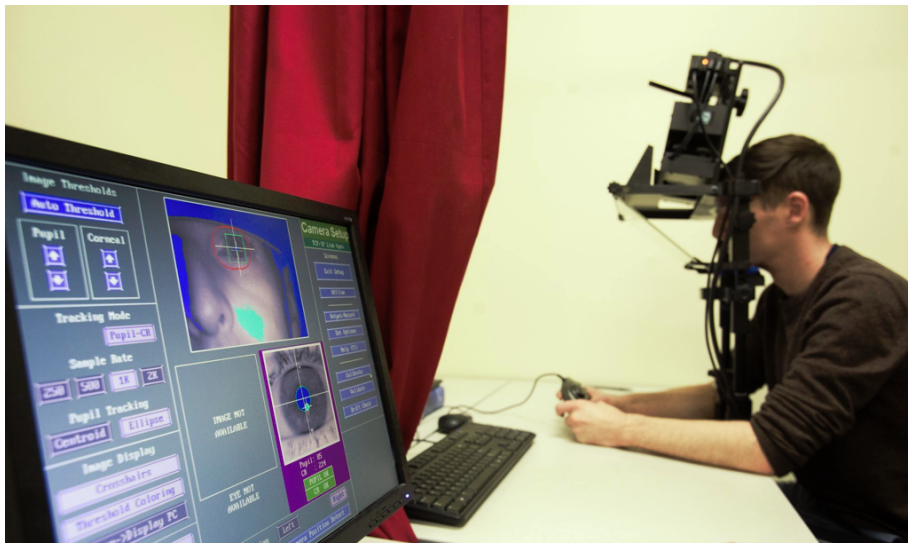
Tal Linzen (NYU)

1. Background

Human language processing is in part driven by prediction;
LLMs provide a valuable tool for studying this process.

Computation and behavior



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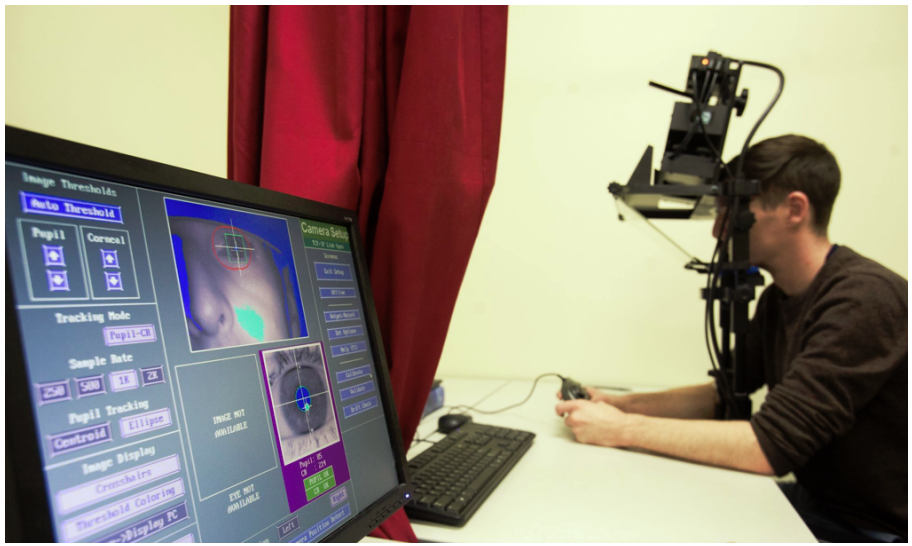

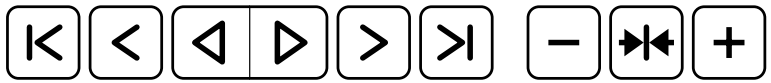

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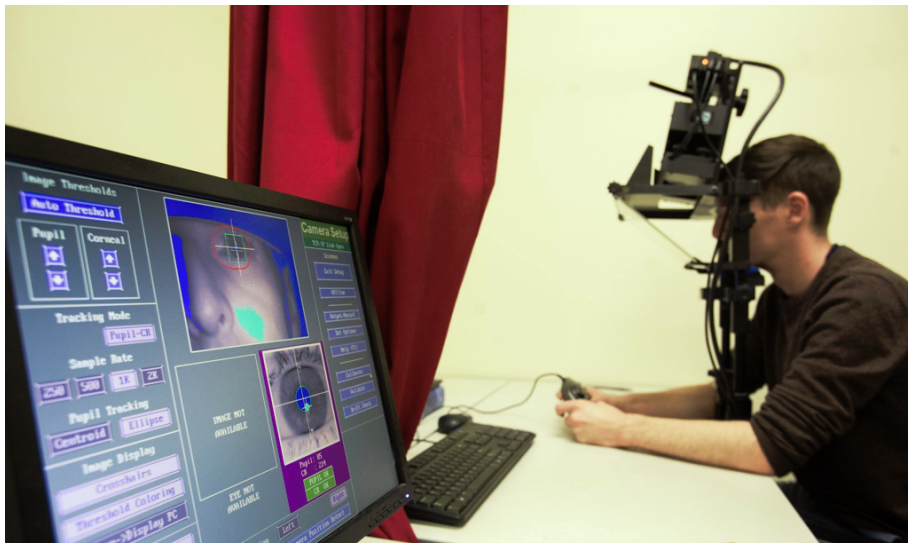

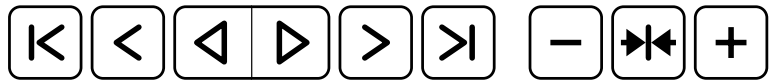

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- **Assumption**: Longer reading times reflect more processing effort.

What have behavioral data told us about language processing?

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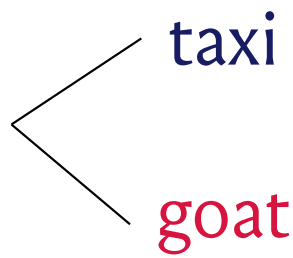
I landed in Düsseldorf and took a 

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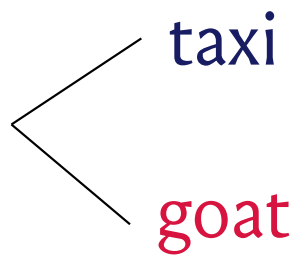

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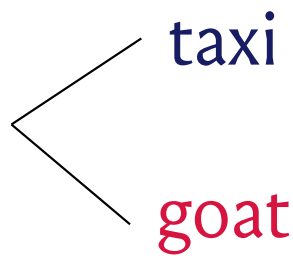

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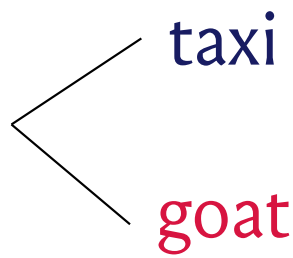
I landed in Düsseldorf and took a 

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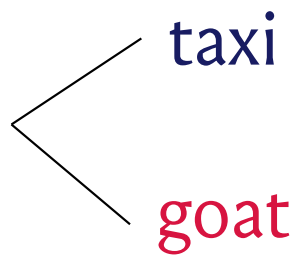

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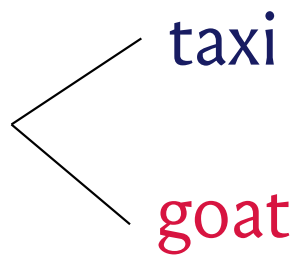
I landed in Düsseldorf and took a 

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Surprisal theory: Effects of context

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- The effect of probability on RT is more of a slowdown at unpredictable words, rather than a boost at predictable words. (Shain et al., 2024)
- How probability is allocated across other alternative words does not seem to influence the actual word's RT. (Frisson et al., 2017)

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- Large language models mitigate issues with data sparsity.
- Crucially, we want $\text{P}(w_t \mid w_1, w_2, \ldots, w_{t-1})$ to be human-like.

Evaluation: Regression modeling

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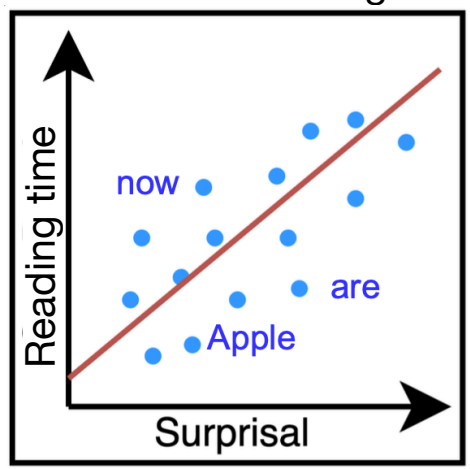
Collecting word-by-word reading times

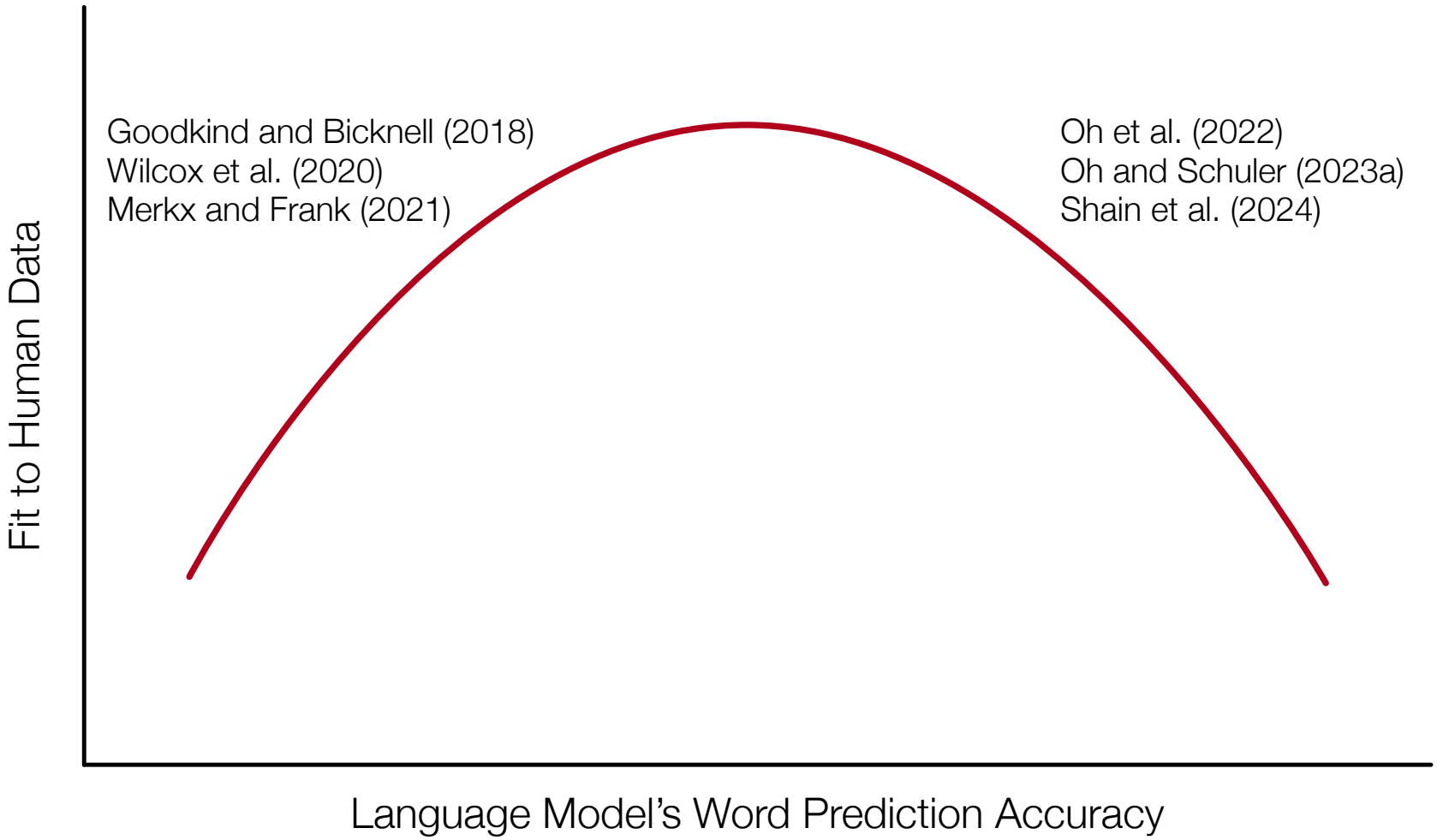
(e.g. Futrell et al. 2021)

Modeling approach

Linear fits to reading times



LLMs have become superhuman as models of prediction



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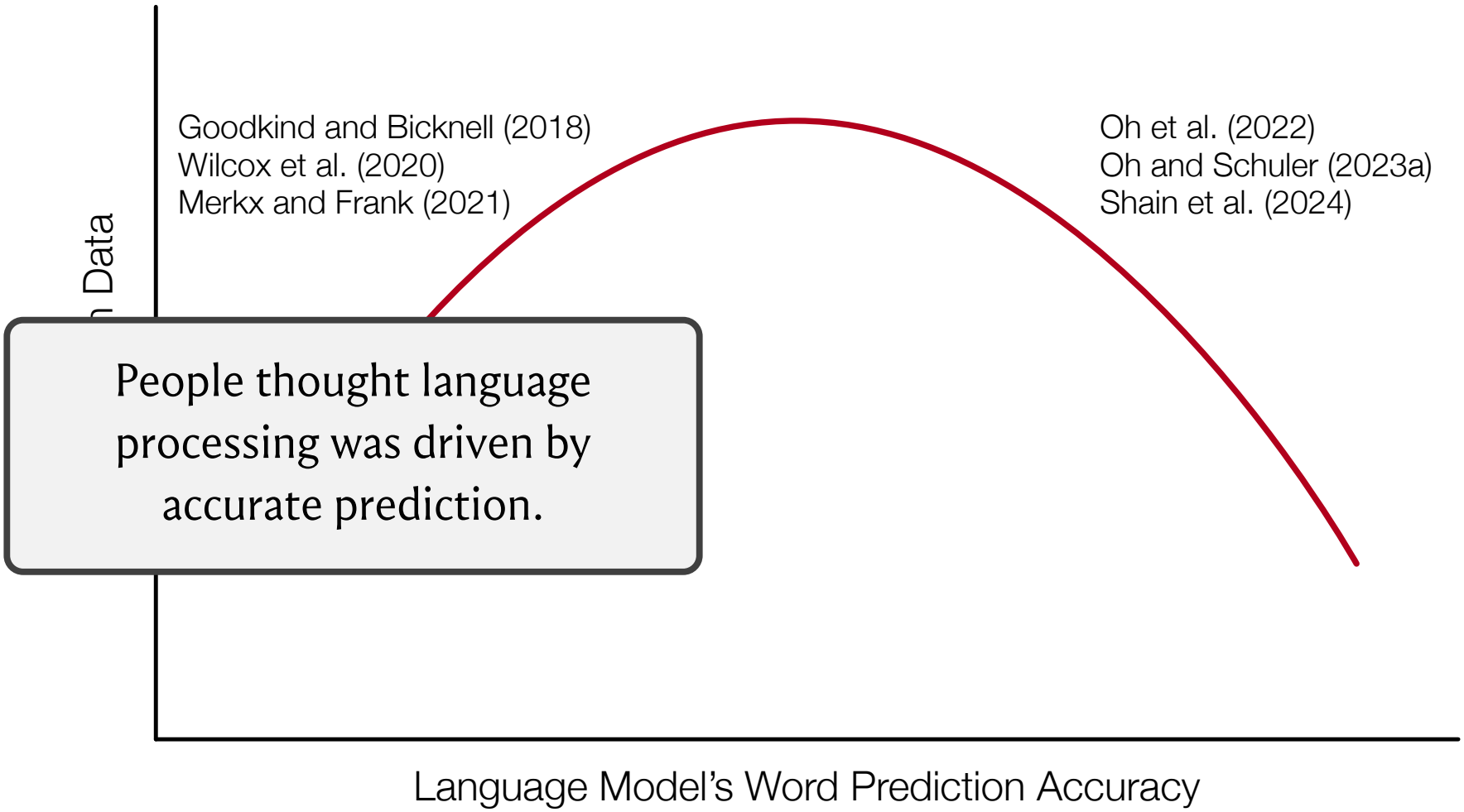

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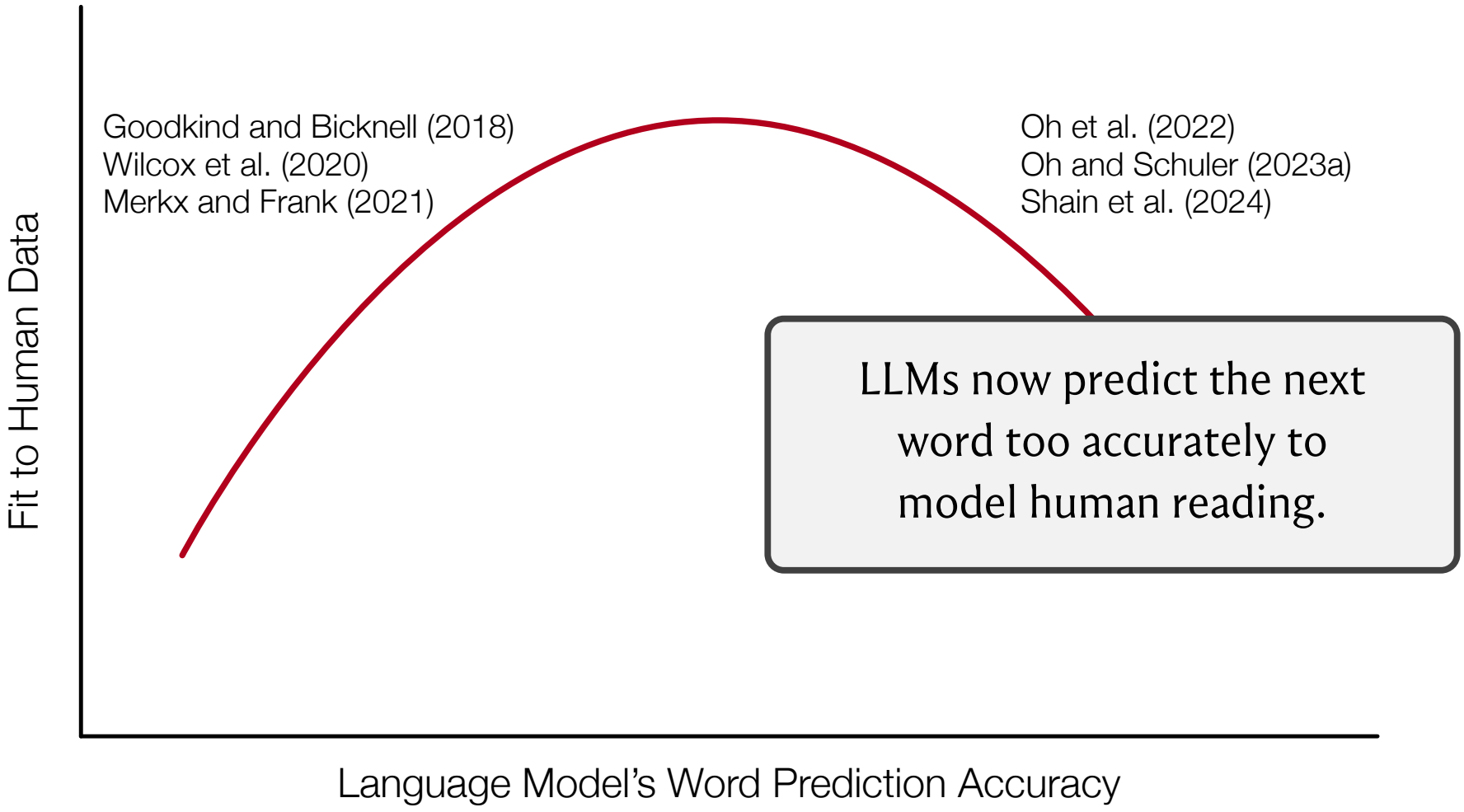

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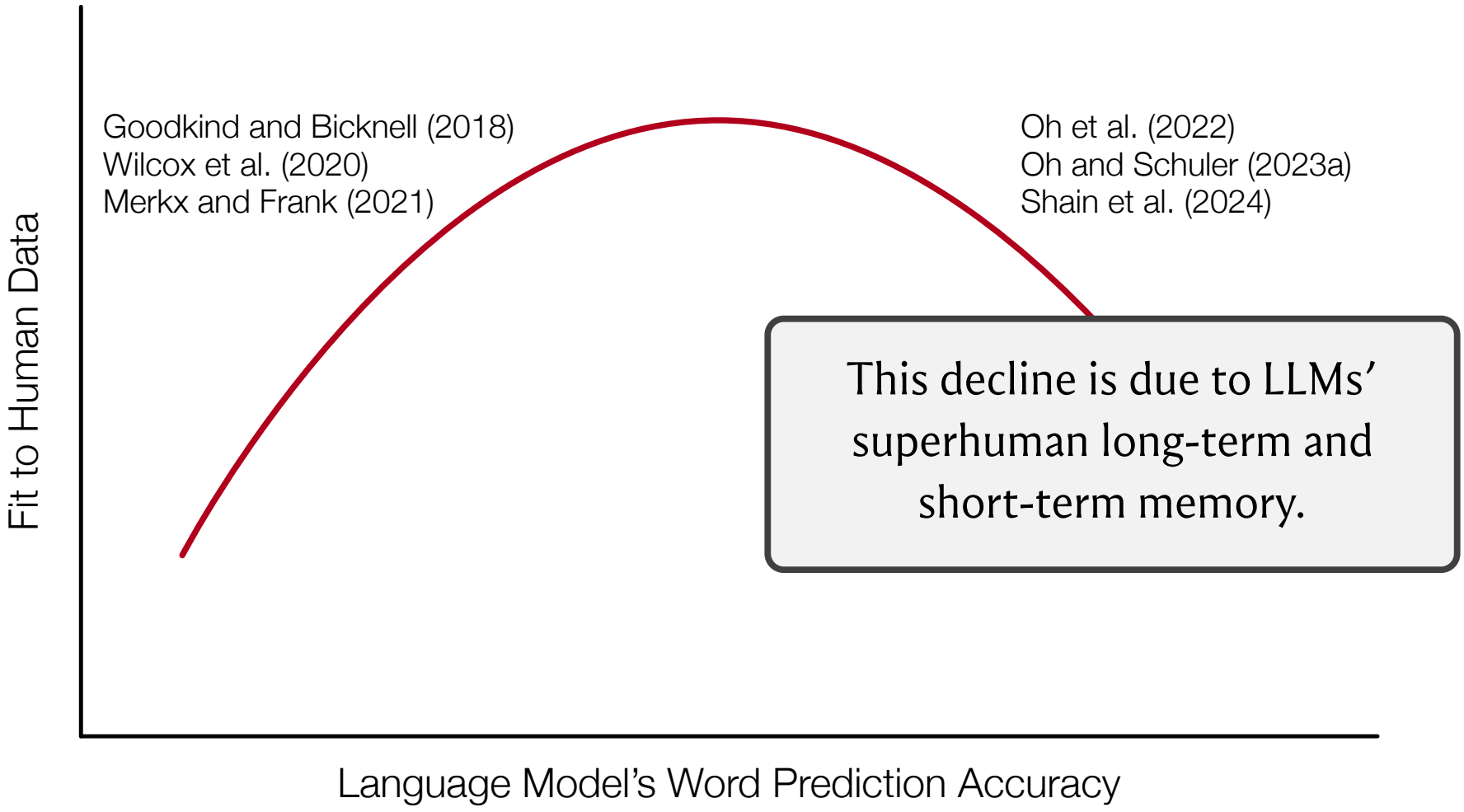

2. Superhuman long-term memory

Humans naturally forget what they read or heard over time;
LLMs are unlikely to forget training examples they have seen.

The role of background knowledge in language processing

Joshua Kimmich was born in the city of _____

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- If you know his birthplace, very easy to predict; if not, very difficult.

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  (Kintsch, 1998; R. Smith et al., 2021)

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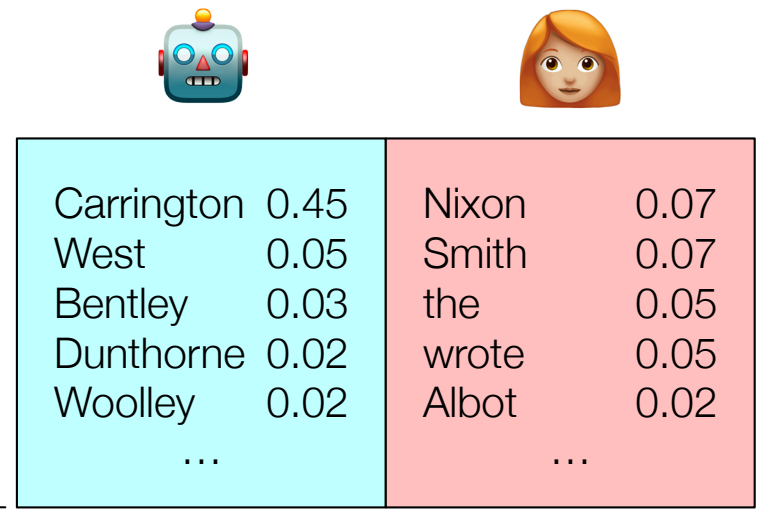
- If you know his birthplace, very easy to predict; if not, very difficult.
- Background knowledge plays a big role in language comprehension.
  (Kintsch, 1998; R. Smith et al., 2021)
- We want a model that is consistent with a reader's knowledge.

LLMs know too much compared to humans

Two days later, the British astronomer Richard _____



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LLMs' training data contains a lot of factual information.

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> **Joshua Walter Kimmich** (German pronunciation: ['joːzʊ̯aː 'kɪmɪç];[5] born 8 February 1995) is a German professional footballer who plays as a defensive midfielder or right-back for Bundesliga club Bayern Munich and captains the Germany national team.[6] Known for his versatility, aggression and playmaking ability,[11] Kimmich has been compared with former Bayern Munich and Germany captain Philipp Lahm.[12]

From Wikipedia

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LLMs are trained on massive amounts of such data.

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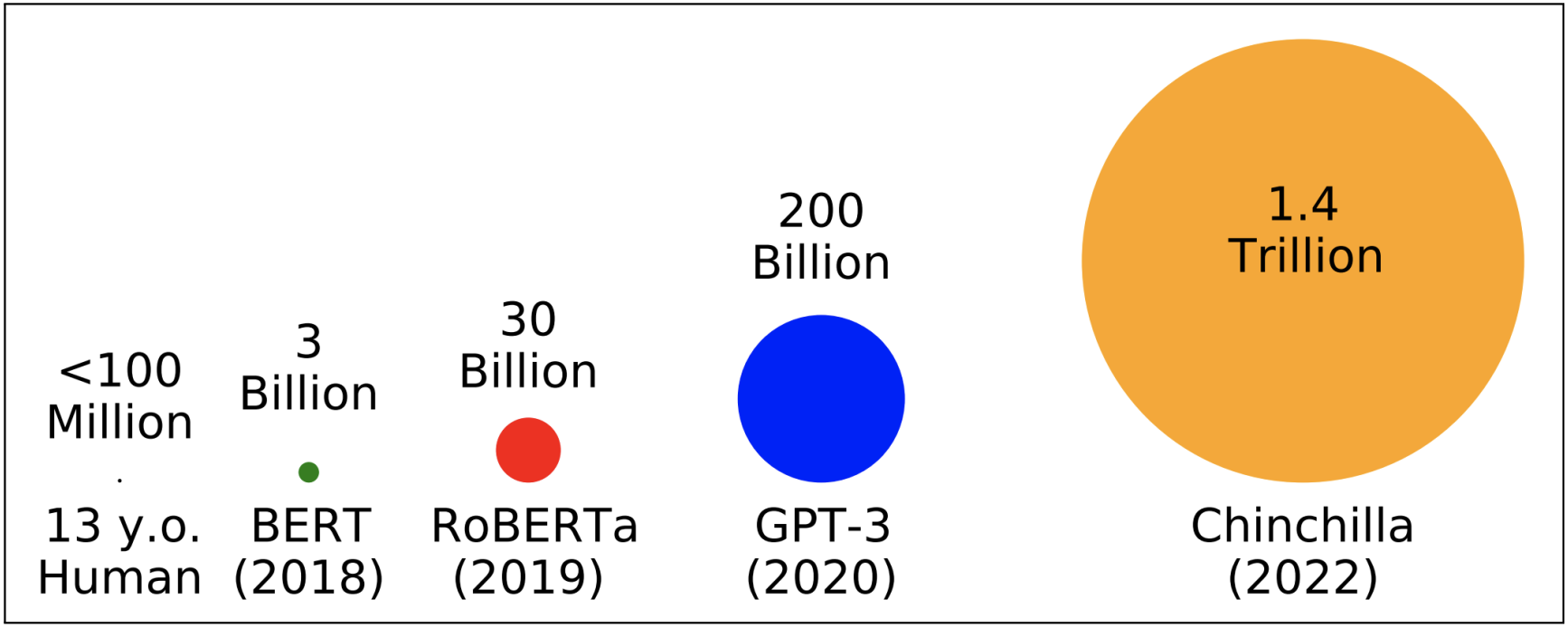

The BabyLM Challenge; Warstadt et al. (2023), Wilcox et al. (2025)

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LLMs do not easily forget training examples they encounter.

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```
//
// Licensed under the Apache License,
// Version 2.0 (the "License");
// you may not use this file except in
// compliance with the License ...
```

Example from Merrill et al. (2024)

Preliminary evidence that this is problematic

Misprediction of reading time by LLMs is the largest on named entities.

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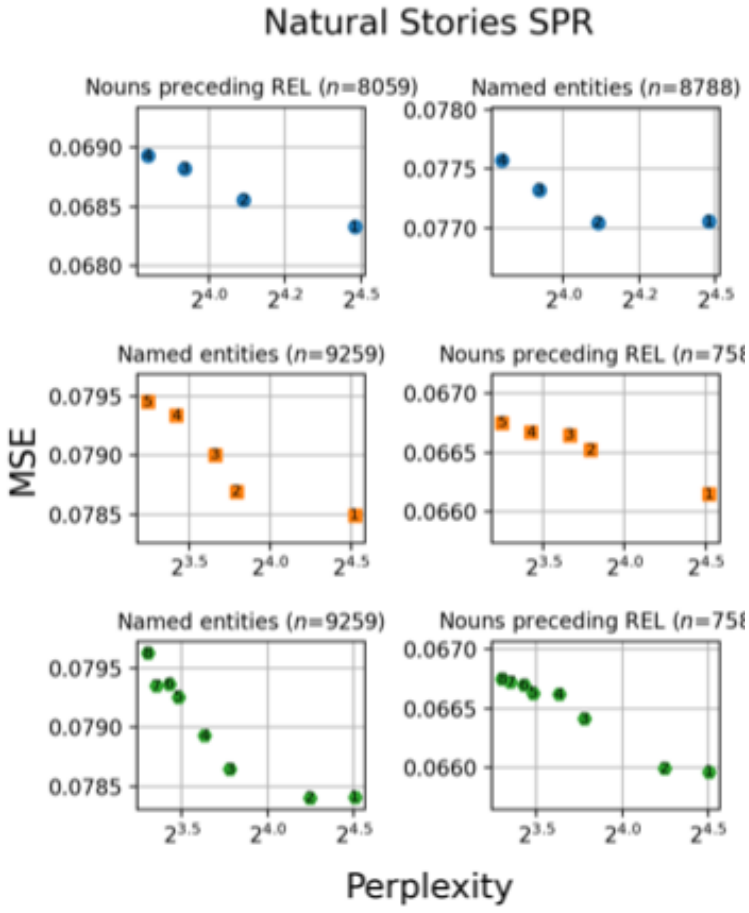

Oh and Schuler (2023a)

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LLMs trained on far less data provide better fits to reading time data.

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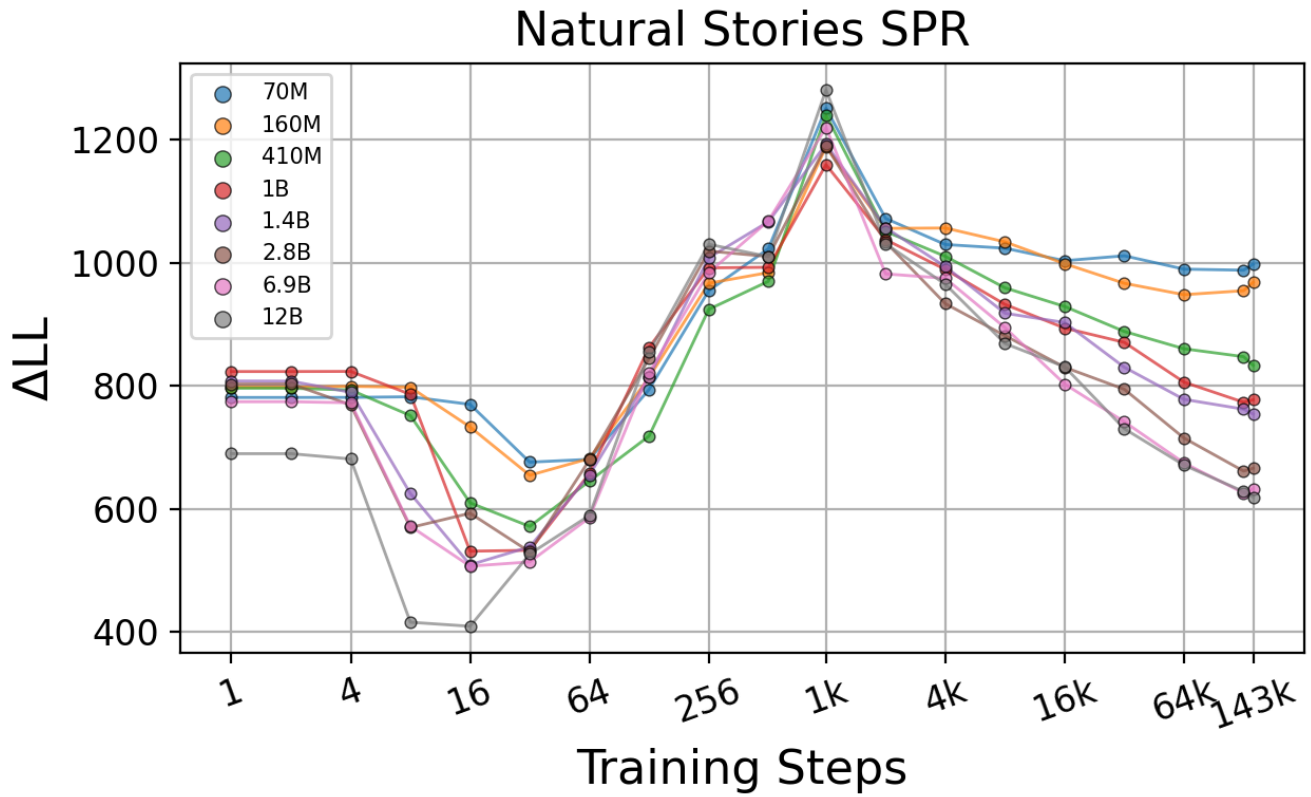

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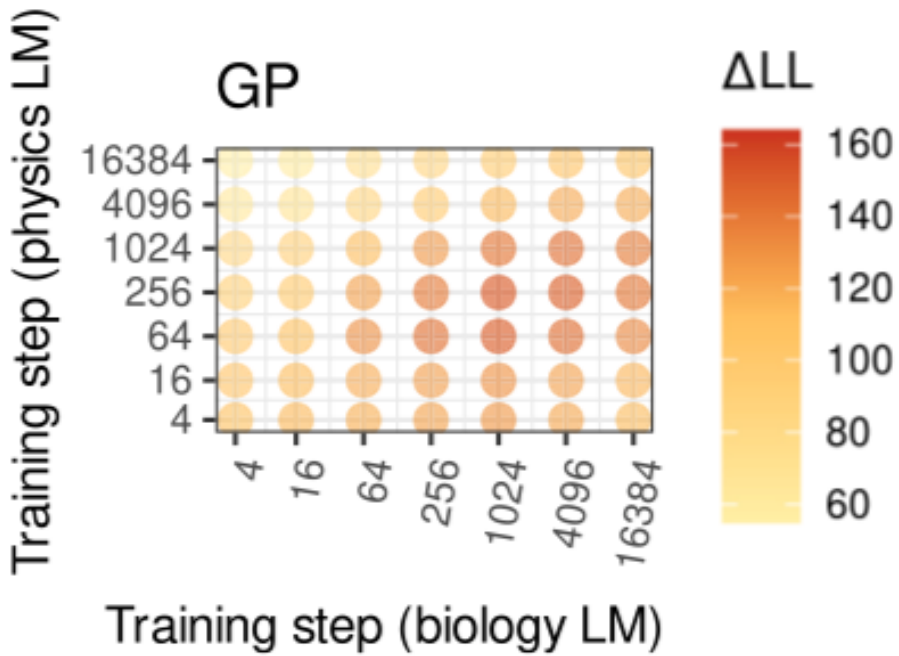

Škrjanec and Demberg (2026)

Other potentially problematic examples

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- Multiword expressions: *spill the beans*, *hit the sack*, ...

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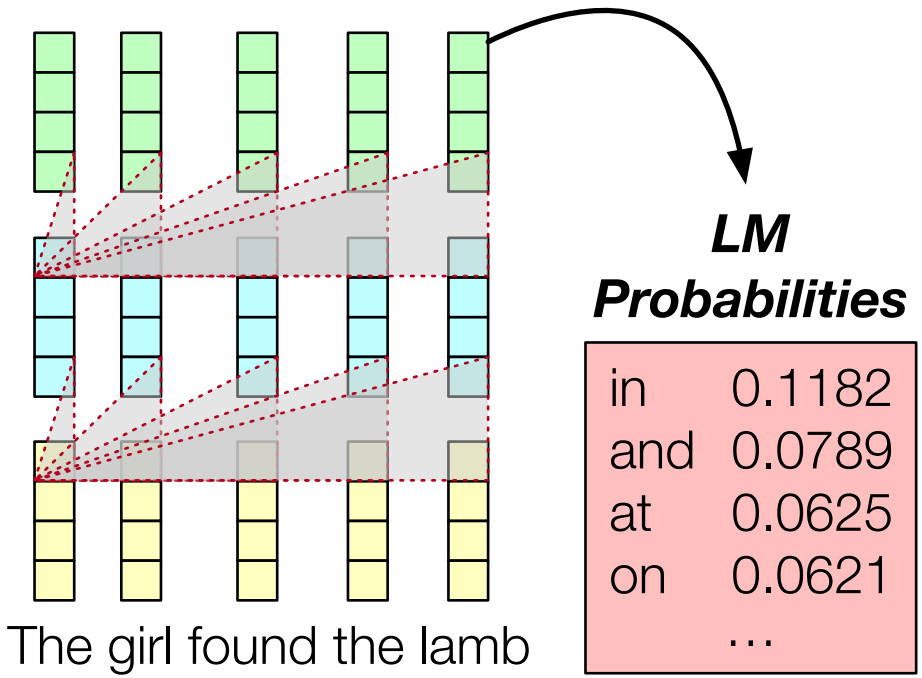
- LLMs are likely to assign high probabilities to each word, which will inevitably underestimate readers' difficulty in processing them.

3. Superhuman short-term memory

Humans are subject to limitations in working memory;
LLMs have near-perfect access to large amounts of input text.

Language processing in language models



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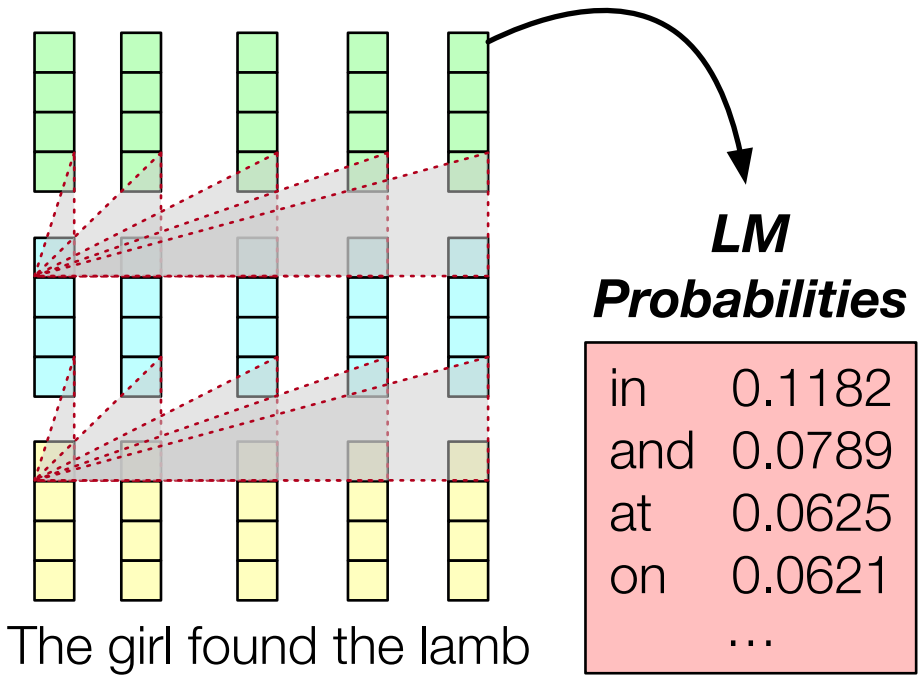

Transformers (Vaswani et al., 2017) can 'look at' all of the input to make next-word predictions.

A more extreme example

LLMs have such perfect access to tens of thousands to millions of words.

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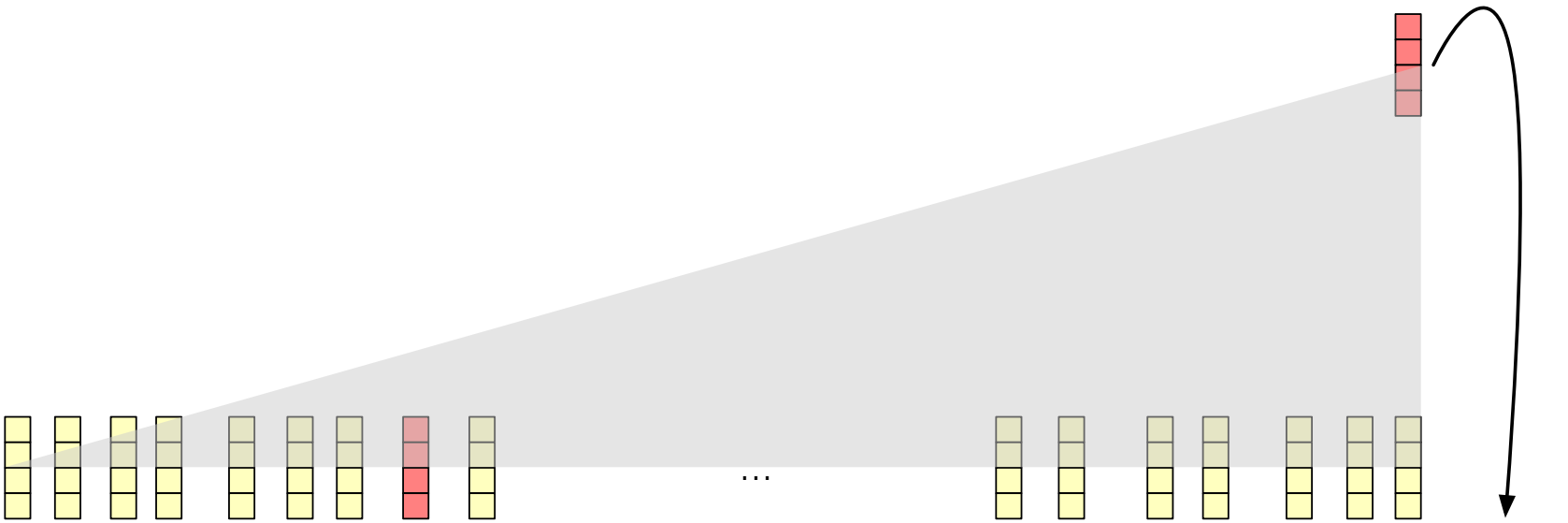

Transformers learn to copy earlier text

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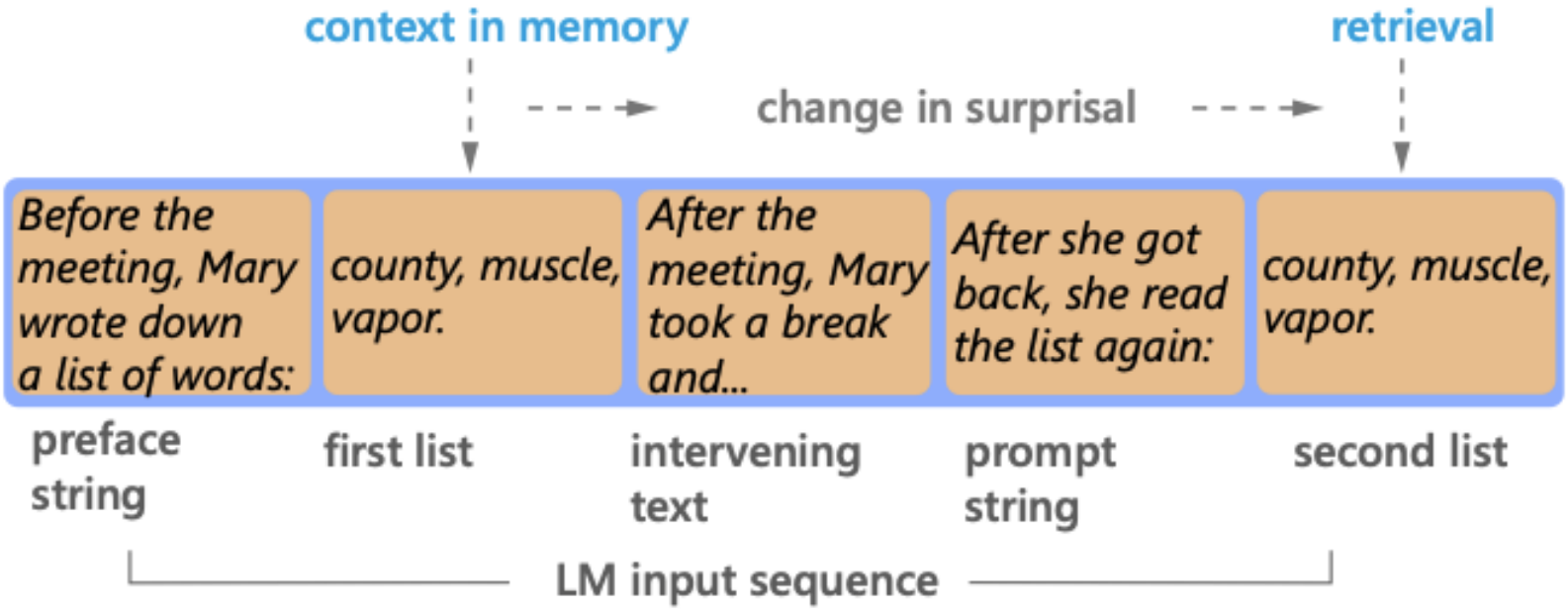

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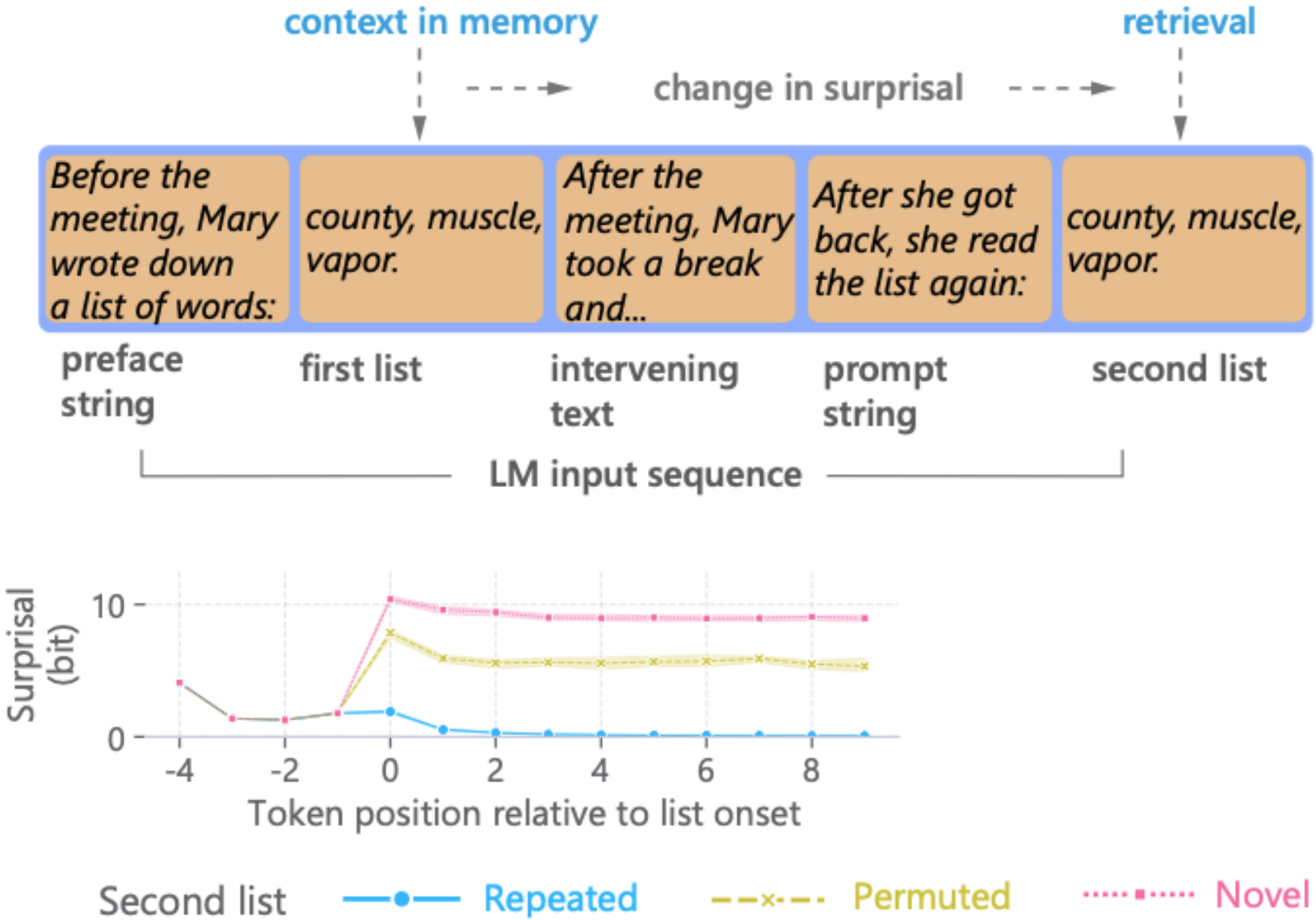

Armeni et al. (2022)

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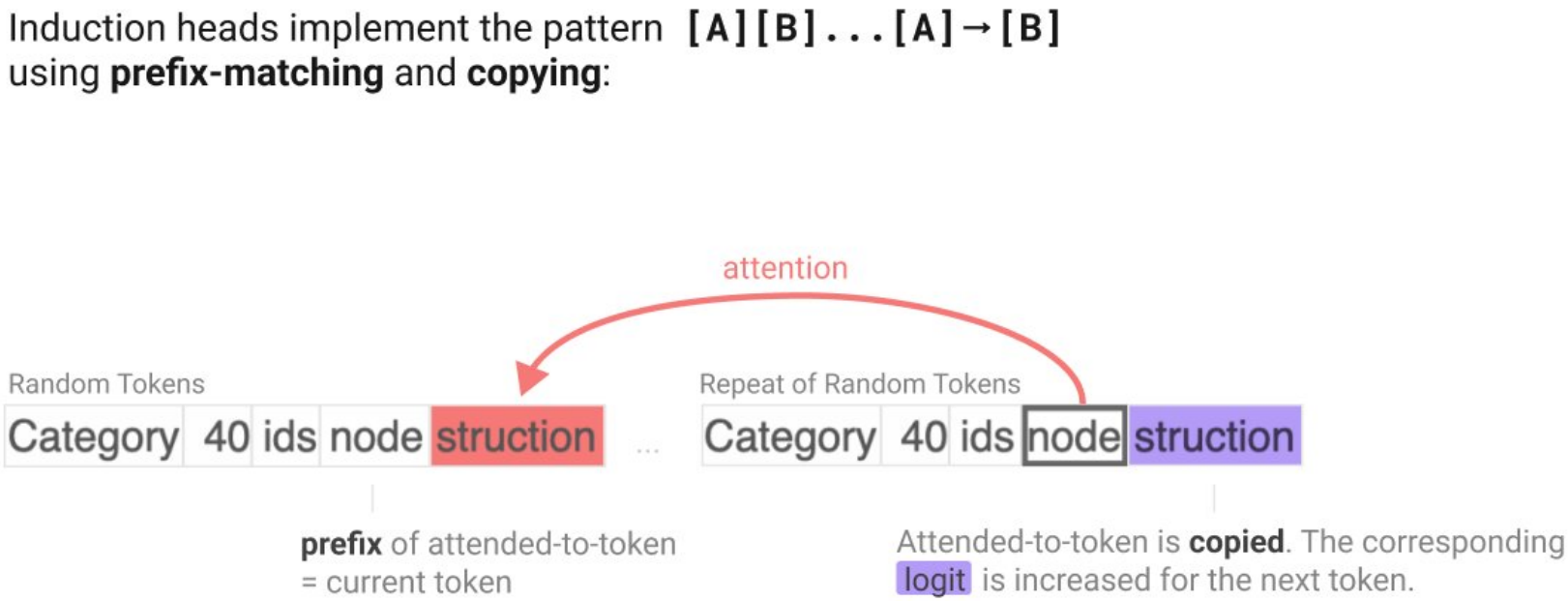

Olsson et al. (2022); see also Bietti et al. (2023) and Jelassi et al. (2024)

Limited vs. full parallelism

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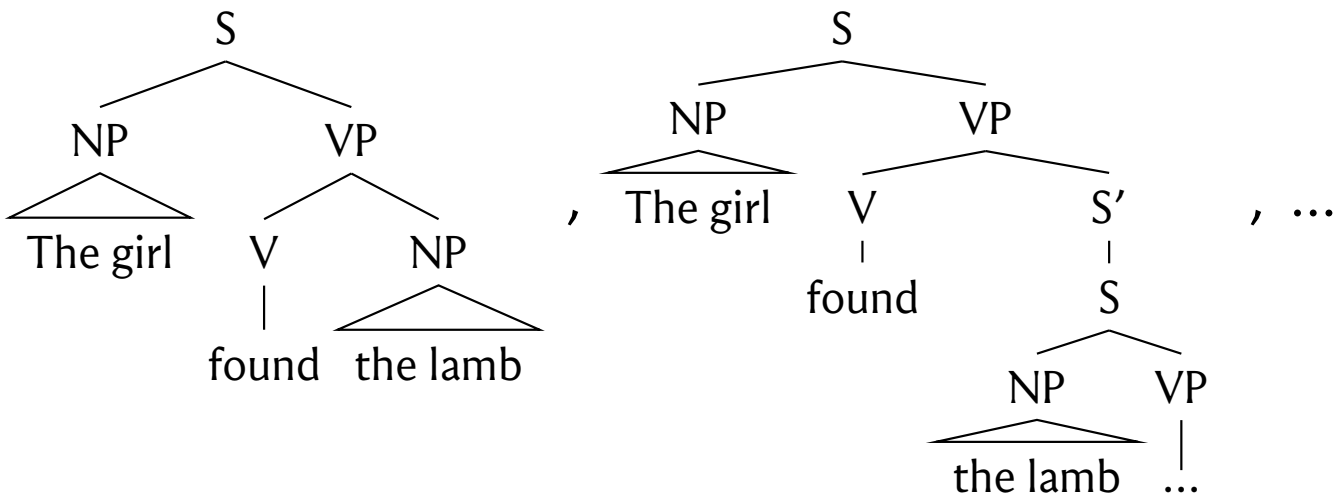

Limited vs. full parallelism

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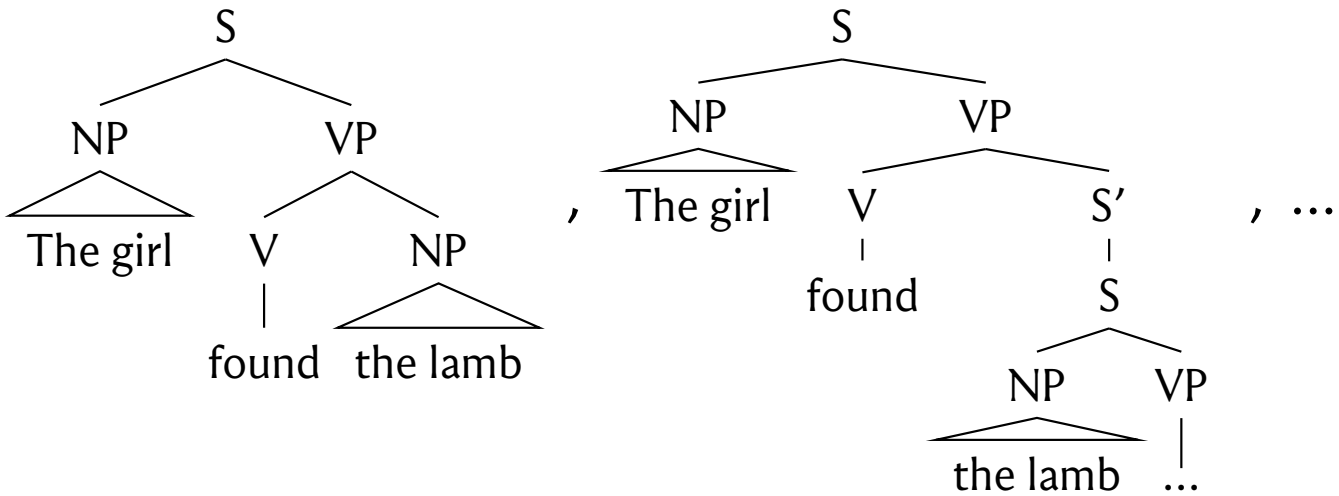

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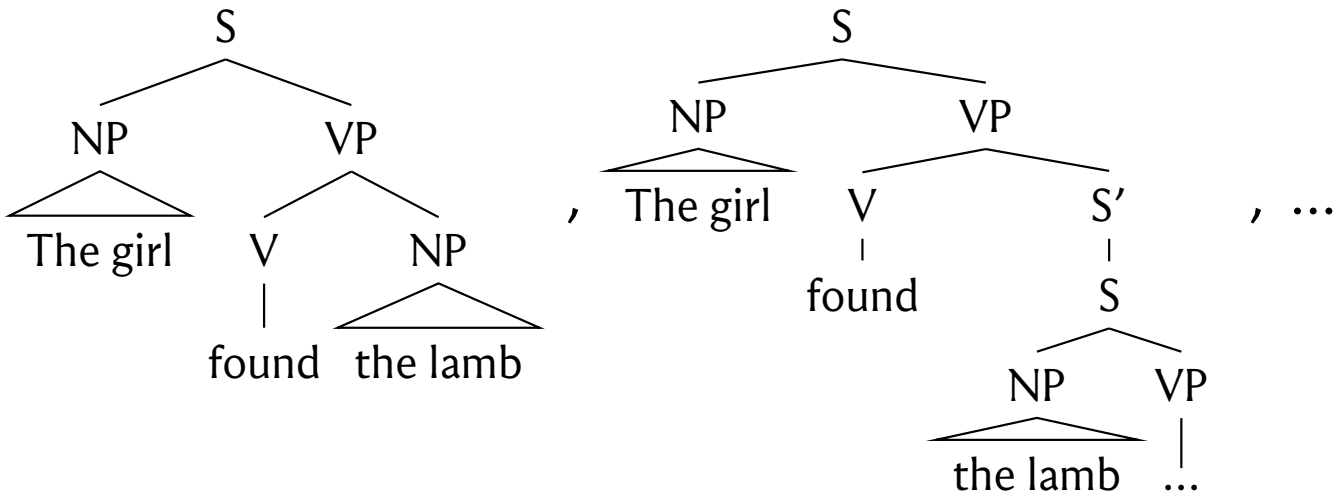

- People cannot seem to hold many parses in memory at once.
- LLMs seem to be able to entertain many parses.

  (Huang et al., 2024; Timkey et al., 2025)

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LLMs completely fail to capture ‘repeated reading’ behavior, as they predict the repeated passage with near-perfect accuracy.

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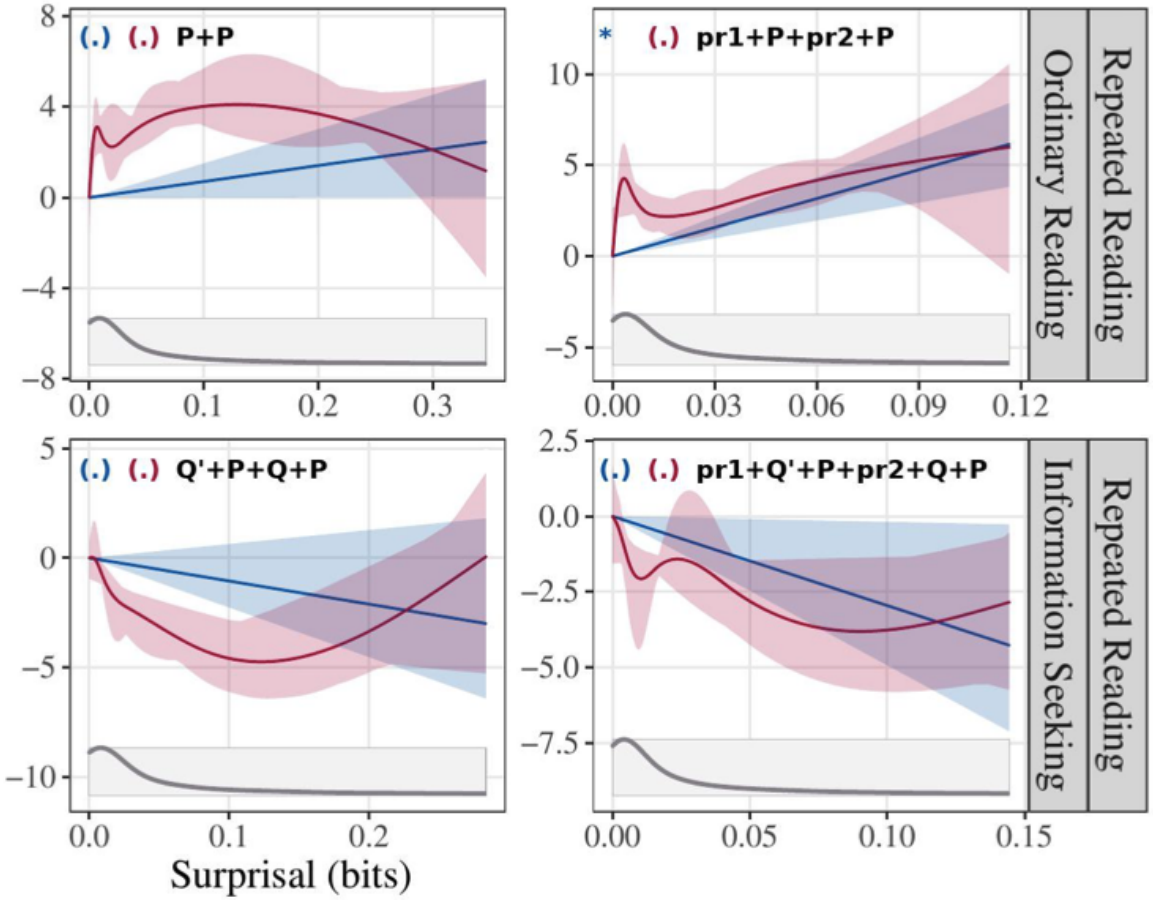

Gruteke Klein et al. (2024)

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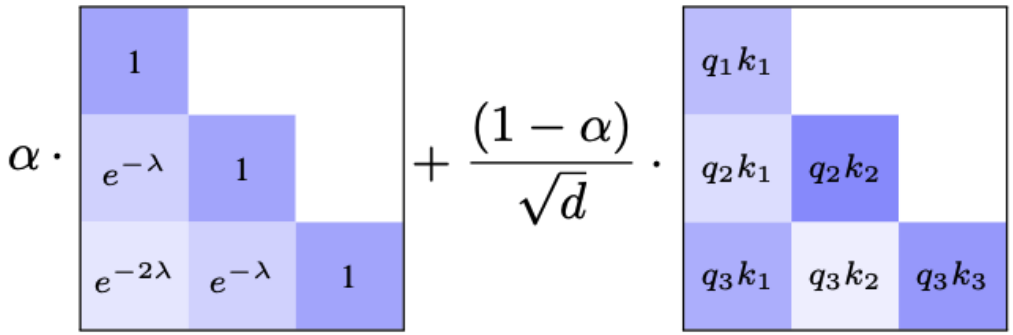
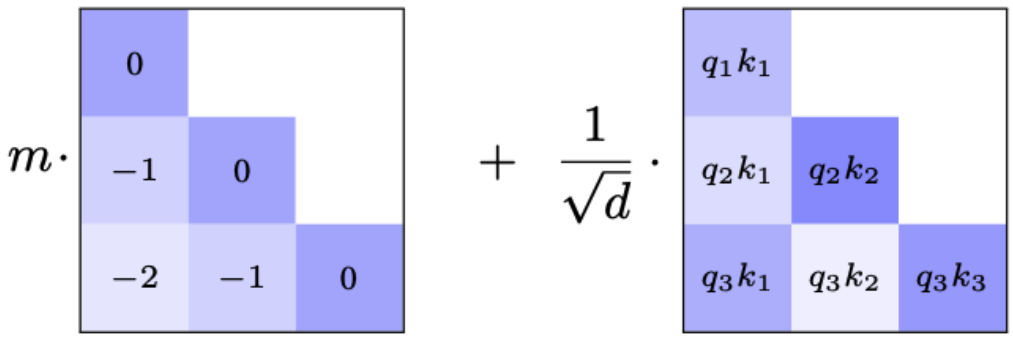


(a) de Varda and Marelli (2024)



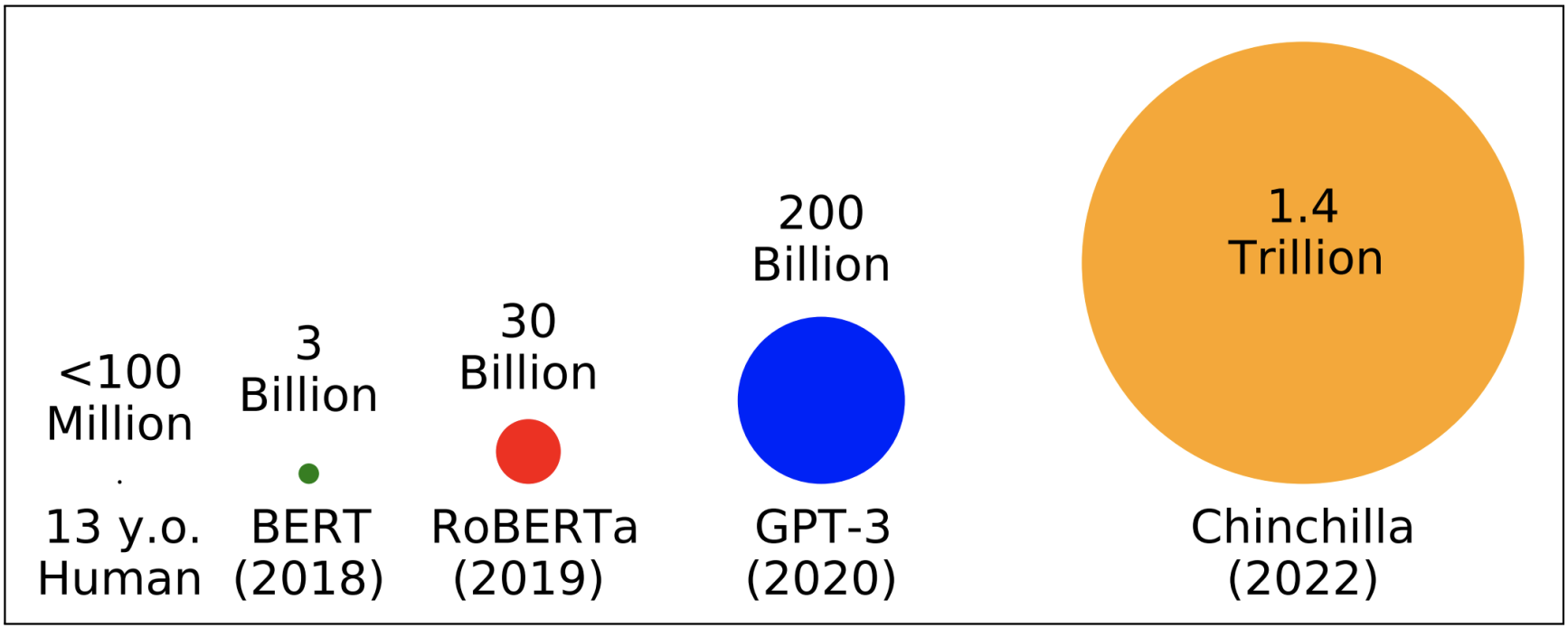
(b) Press et al. (2022)

Clark, Oh, and Schuler (2025)

4. What should we do about it?

We can apply many language modeling techniques to address these issues—but in a different way from NLP applications.

Train models on human-scale training data



The BabyLM Challenge; Warstadt et al. (2023), Wilcox et al. (2025)

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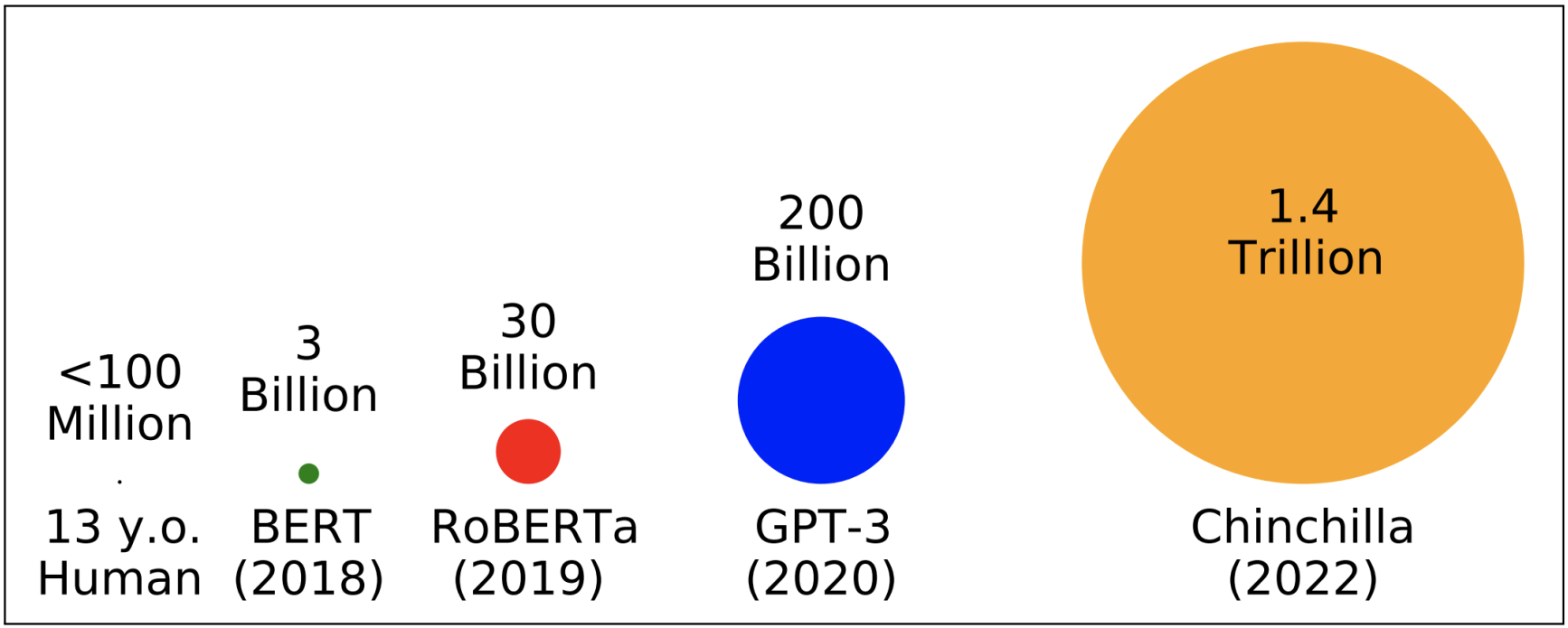

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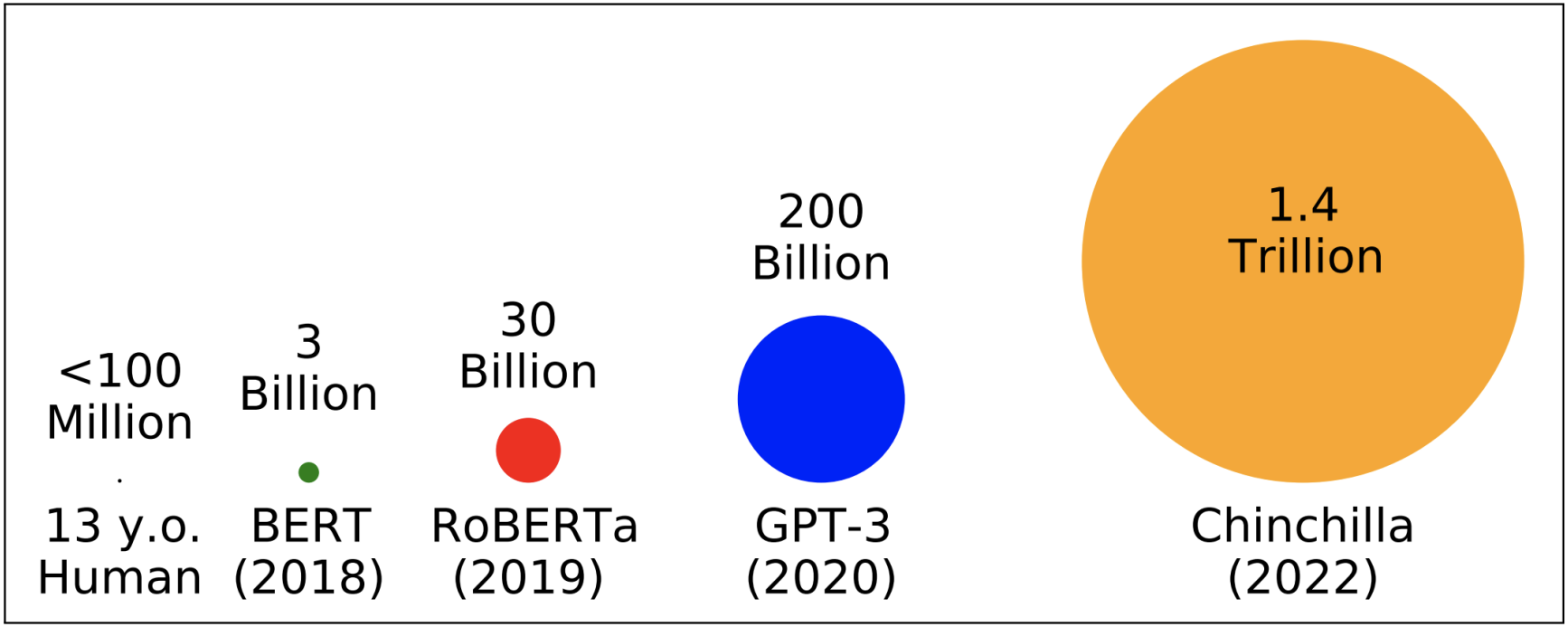

The BabyLM Challenge; Warstadt et al. (2023), Wilcox et al. (2025)

- Simply decreasing the amount of data will probably not suffice.
- Humans learn through other sensory experience. (Bender & Koller, 2020)

What about the training objective?

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(Roland et al., 2012)

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(Roland et al., 2012)

- We should experiment with alternative training objectives; currently, LLMs do nothing explicitly but prediction.

  (cf. structure building, Nair & Phillips, 2026; Slaats & Martin, 2025)

Apply post-hoc approaches

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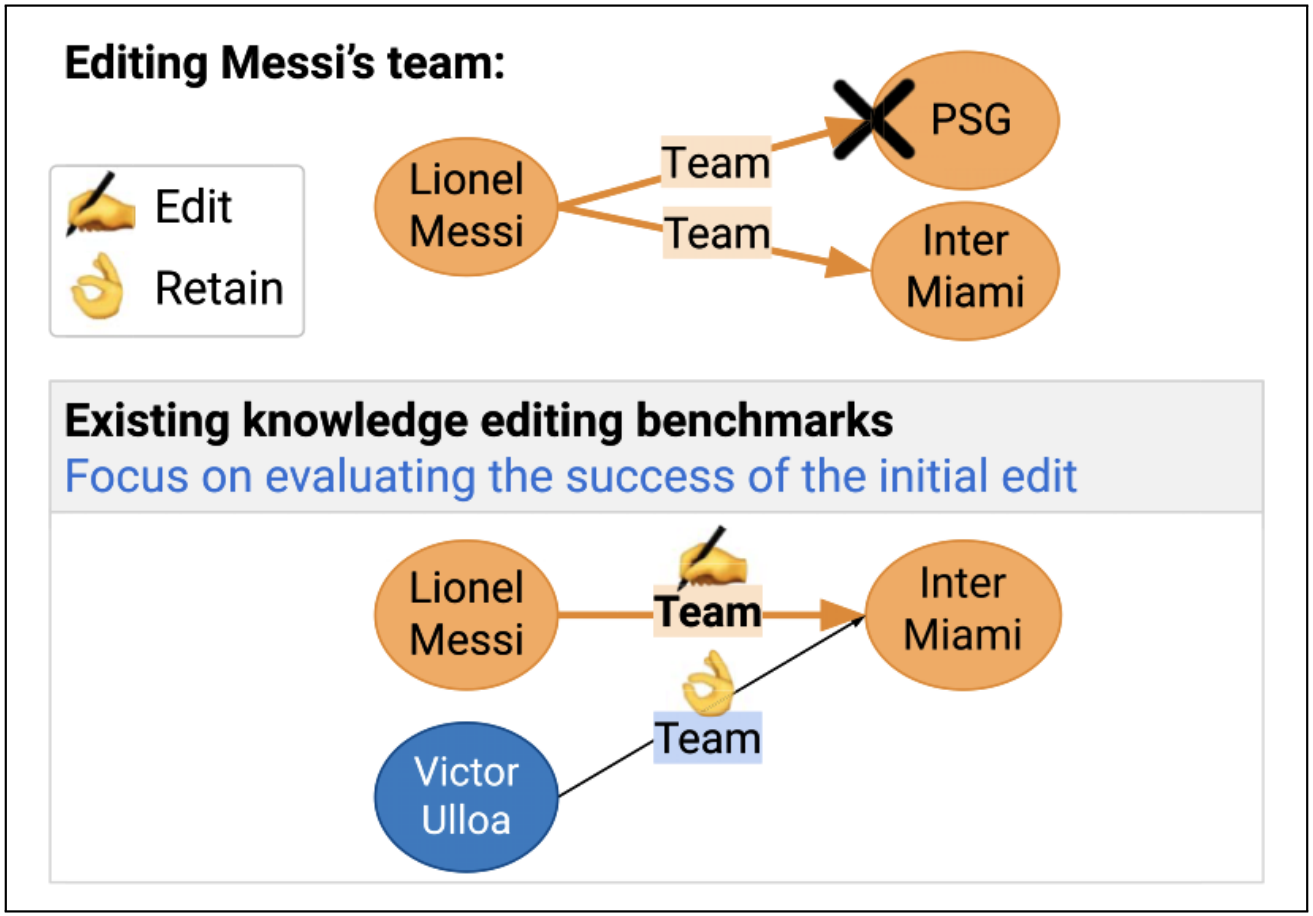

Cohen et al. (2024)

Train models with alternative architectures

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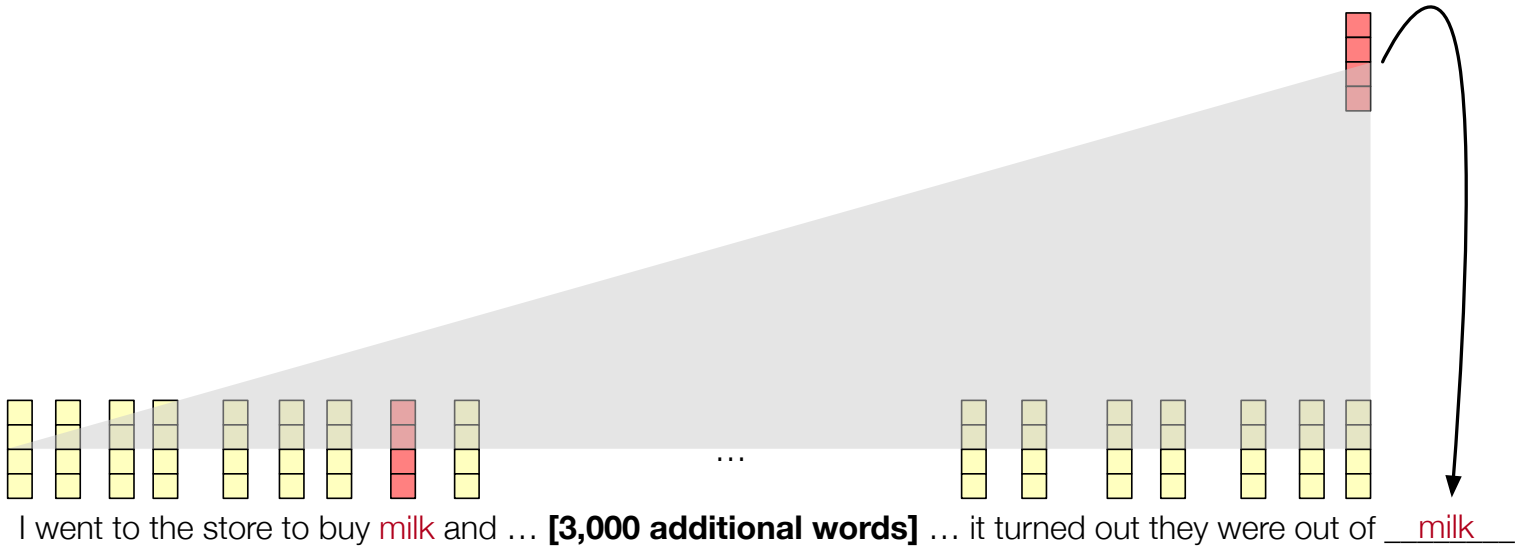
We need to degrade the input in a way that resembles human memory.



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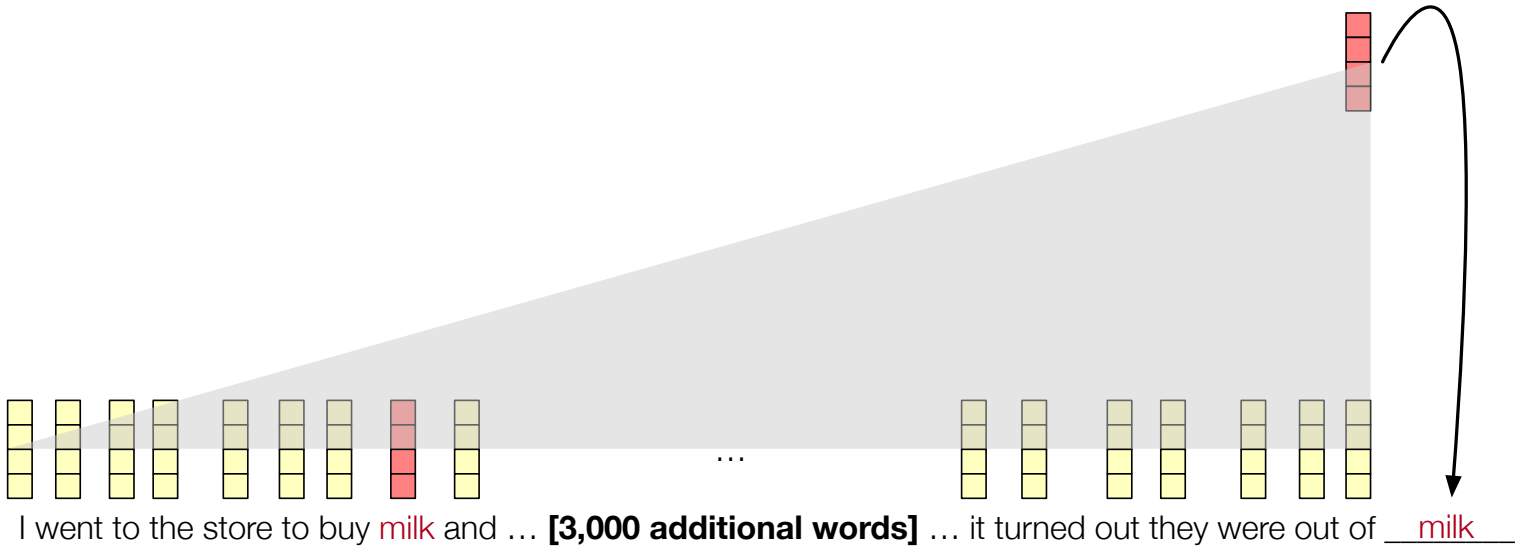
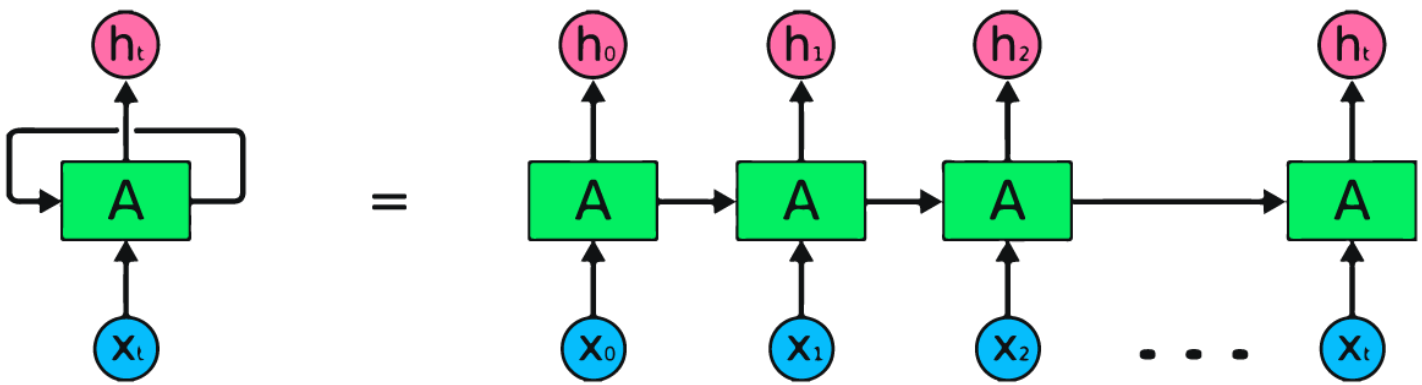


Placing a renewed focus on recurrence could be one way.



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- How likely are people to know that Kimmich was born in Rottweil? How does this influence their reading behavior?
- While reading an extended discourse, how do limitations in working memory influence reading behavior?
- How can we study the linguistic predictions that people make more directly through the cloze task, brain responses, etc.?

5. Conclusion

LLMs hold promise for psycholinguistics, but they need to be made less superhuman through language modeling techniques.

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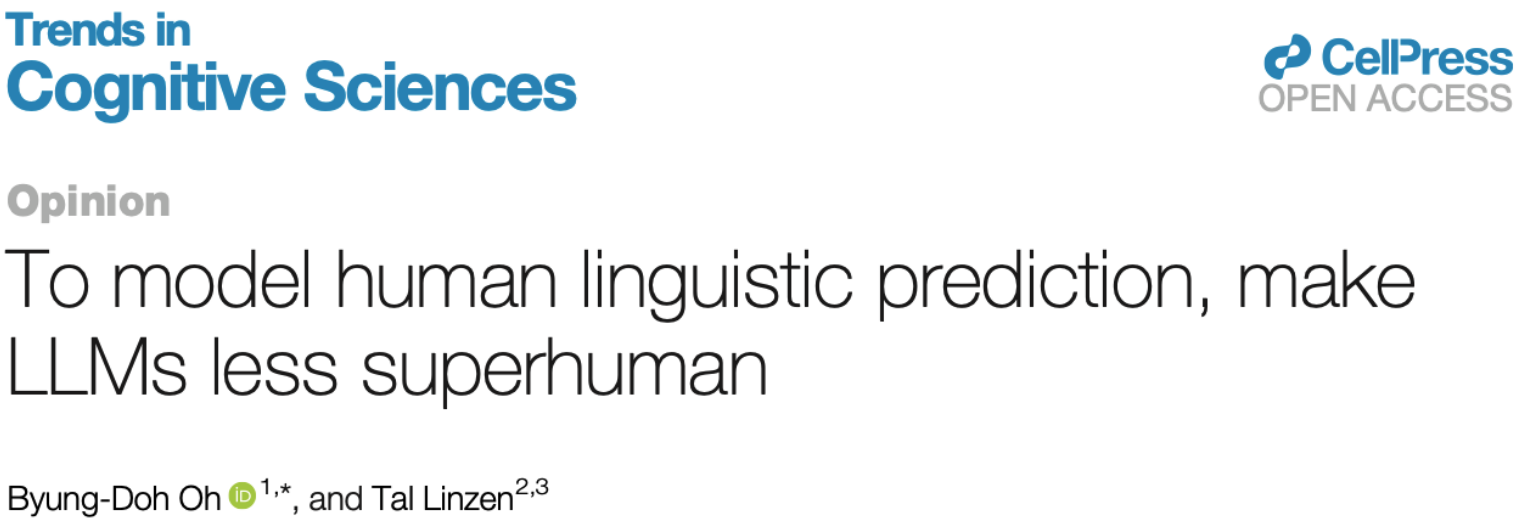
LLMs hold promise for psycholinguistics, but they need to be made less superhuman through language modeling techniques.

Thank you for listening!



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