Adaptation-to-Context in Humans and Large Language Models

Inferring the underlying mechanisms of In-Context Learning with Structural Priming

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Computational Cognitive Science Group, University of Maryland
May 5, 2026

Overview

Humans and LLMs are bidirectionally informative

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Psycholinguistics

Structural Priming

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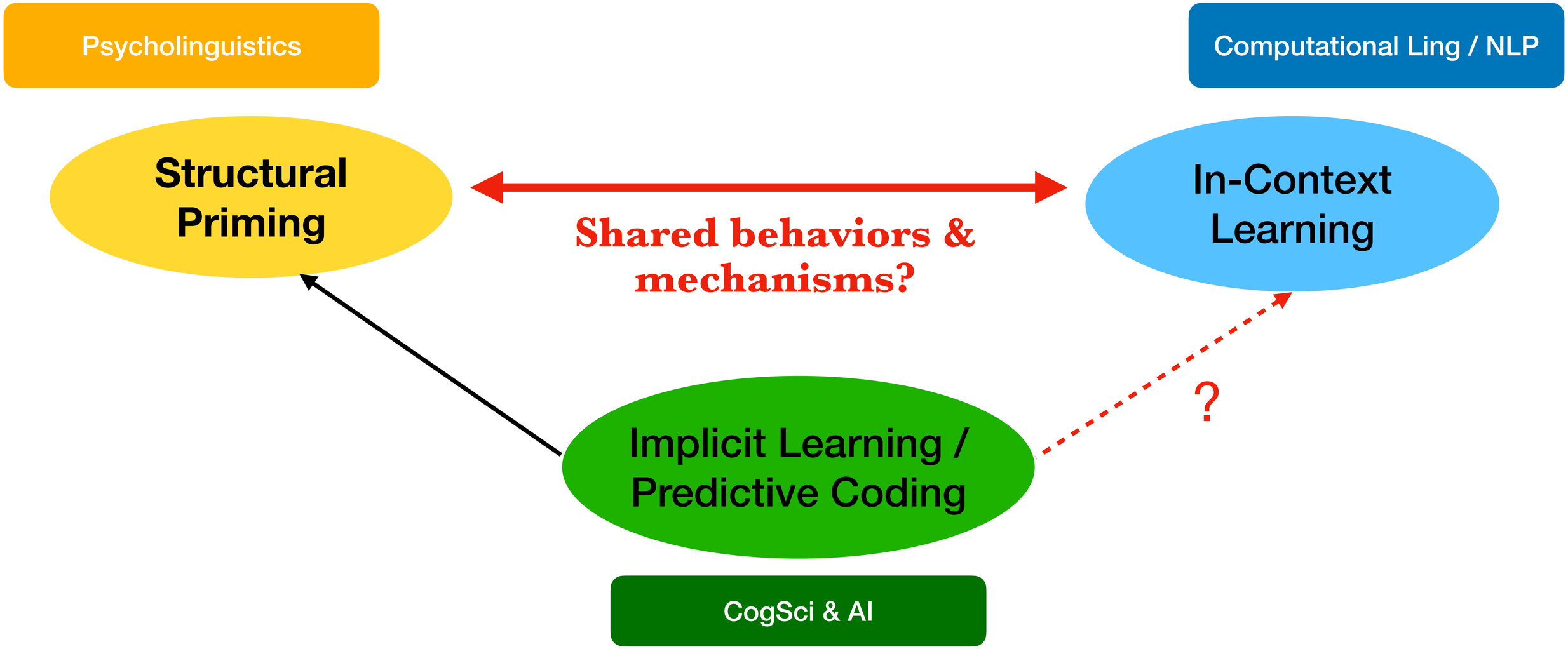

Structural Priming in Humans

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[e.g., Bock 1986; Chang 2012; etc.]

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- A classical case: **dative alternation**
  - Double Object (DO): *Alice sent Bob a letter.*
  - Prepositional Dative (PD): *Alice sent a letter to Bob.*

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- A classical case: **dative alternation**
  - Double Object (DO): *Alice sent Bob a letter.*
  - Prepositional Dative (PD): *Alice sent a letter to Bob.*
- Other attested structures subject to priming:
  - active-passive;
  - *that*-omission in relative clauses and complement, etc.

[e.g., Bock 1986; Chang 2012; etc.]

The Inverse Frequency Effect (IFE)

- **Inverse Frequency Effect**: the *less preferred* (lower frequency) syntactic structure causes a *stronger* priming effect than the more preferred (higher frequency) structural alternative.

[e.g., Ferreira 2003, Jaeger & Snider 2007, 2013]

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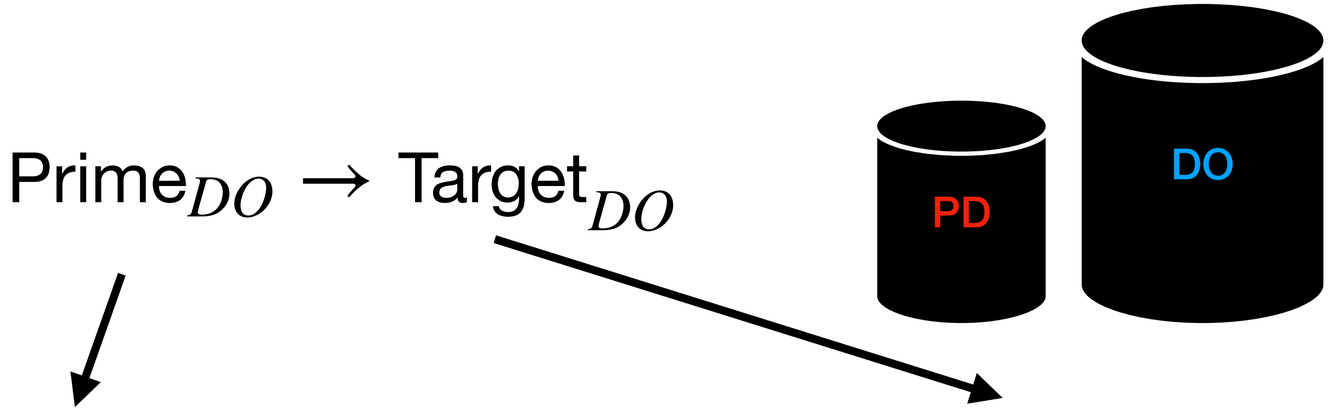

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A doctor bought a chief a plate. … *The secretary drew the band the card.*

A doctor designed a chief a plate. … ***The secretary drew the band the card.***

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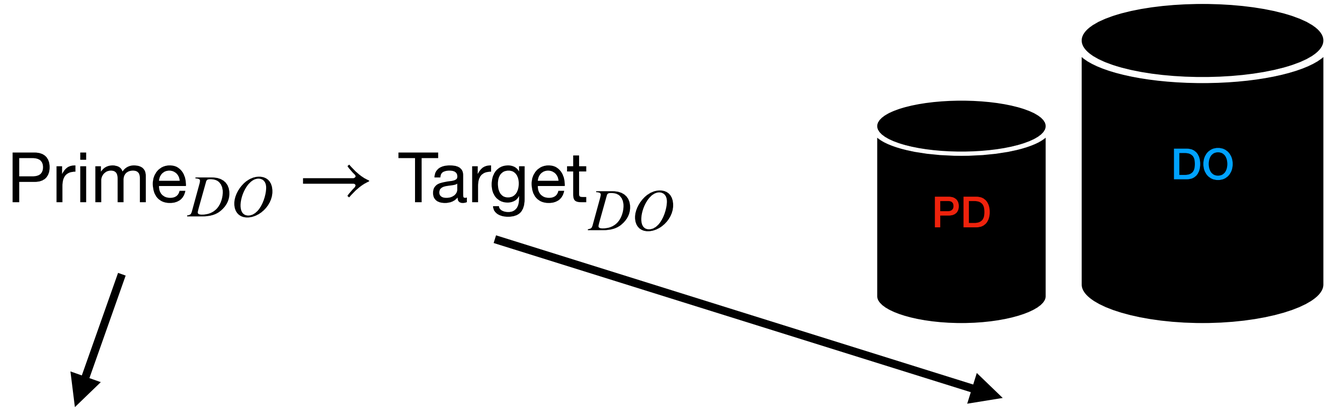

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Greater priming effect!

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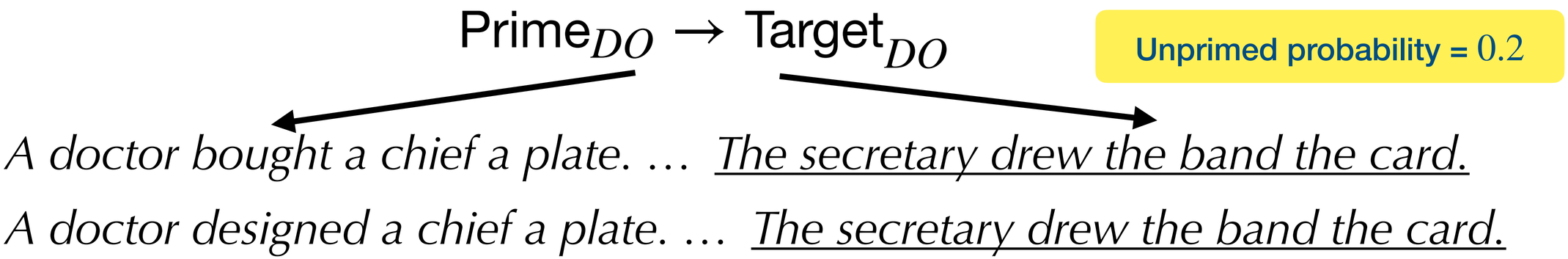

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Unprimed probability = 0.2

A doctor bought a chief a plate. … *The secretary drew the band the card.*

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Prime Verb

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Find
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Prime Verb	Verb PD Bias
Bring	0.23
Buy	0.27
Find	0.41
Draw	0.52
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priming in DO *larger PD biases* *greater priming effects*

[e.g., Ferreira 2003, Jaeger & Snider 2007, 2013]

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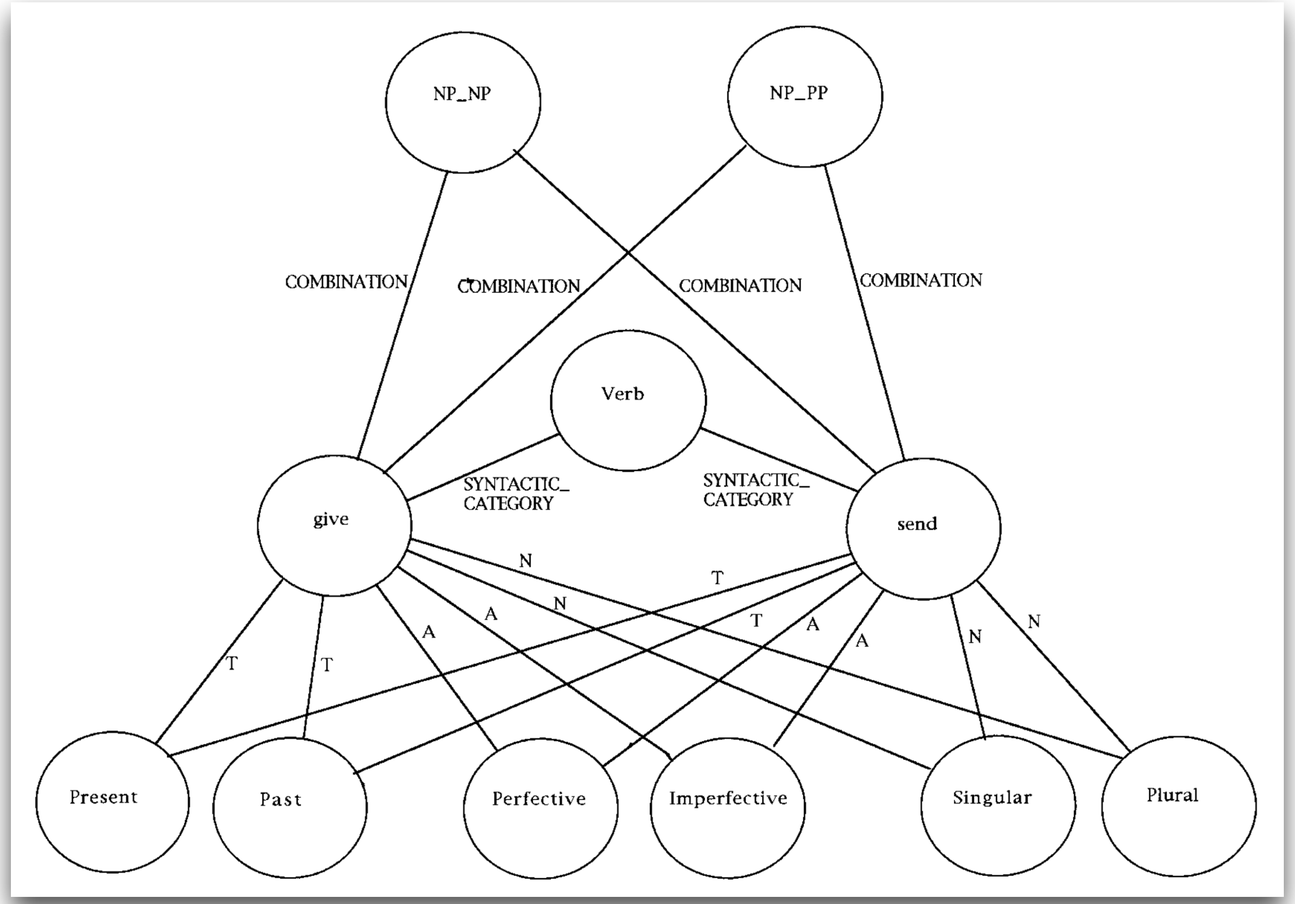

← Structural Nodes

← Lexical Nodes

[e.g., Pickering & Branigan 1998]

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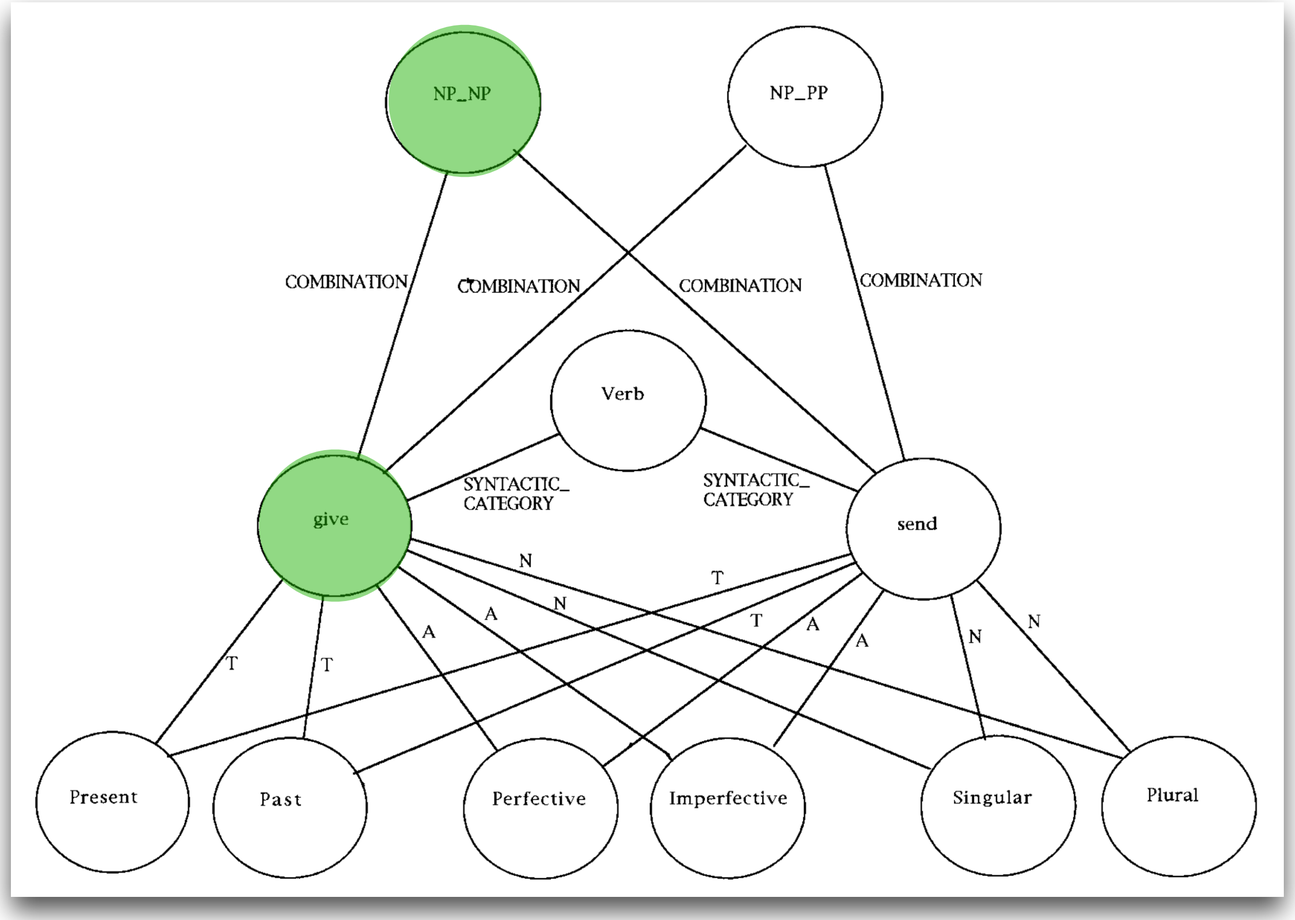

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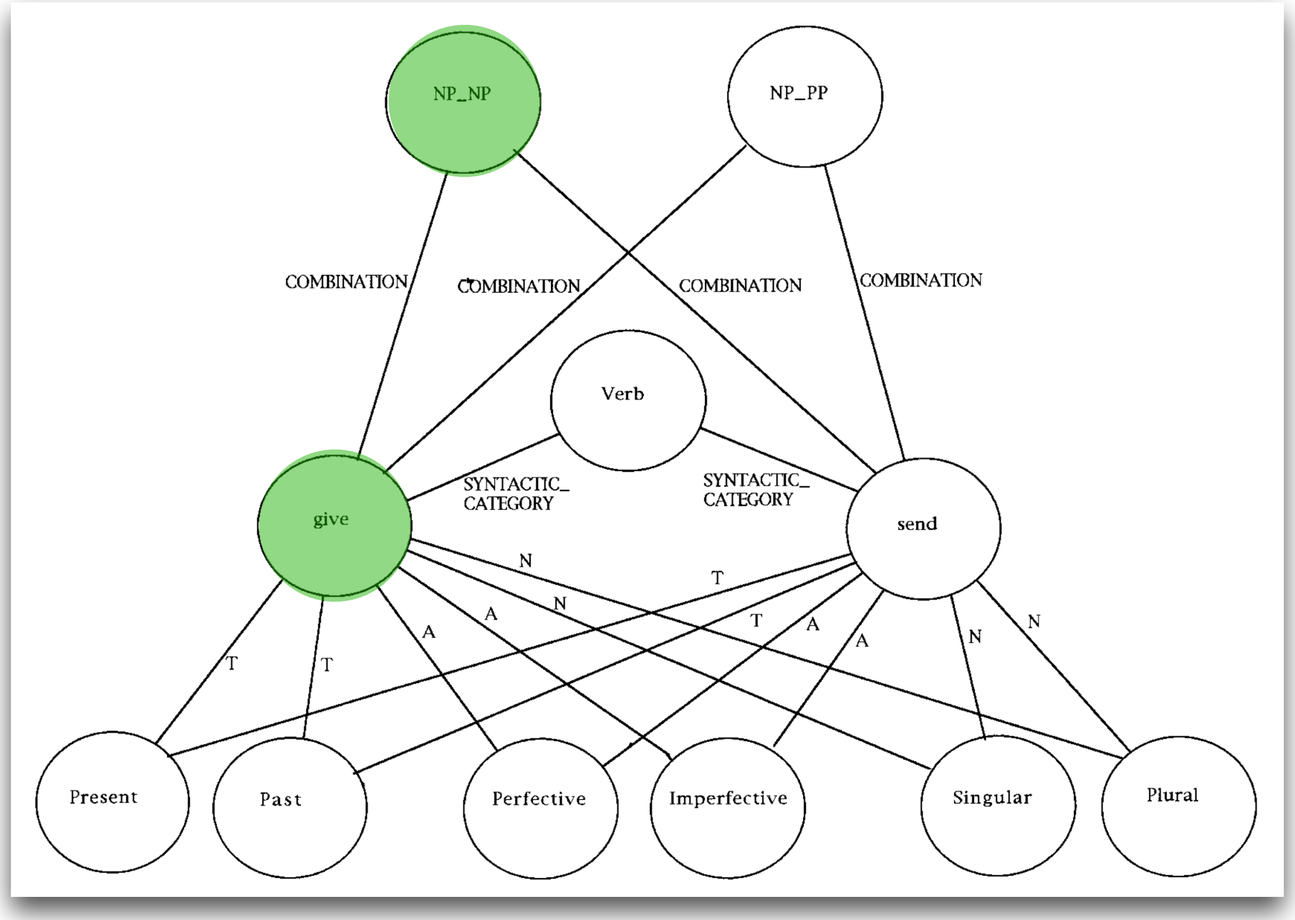
Theory 1: Transient Activation

Quickly decaying activations



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Increasing the activation values of the nodes, which persists through next productions.

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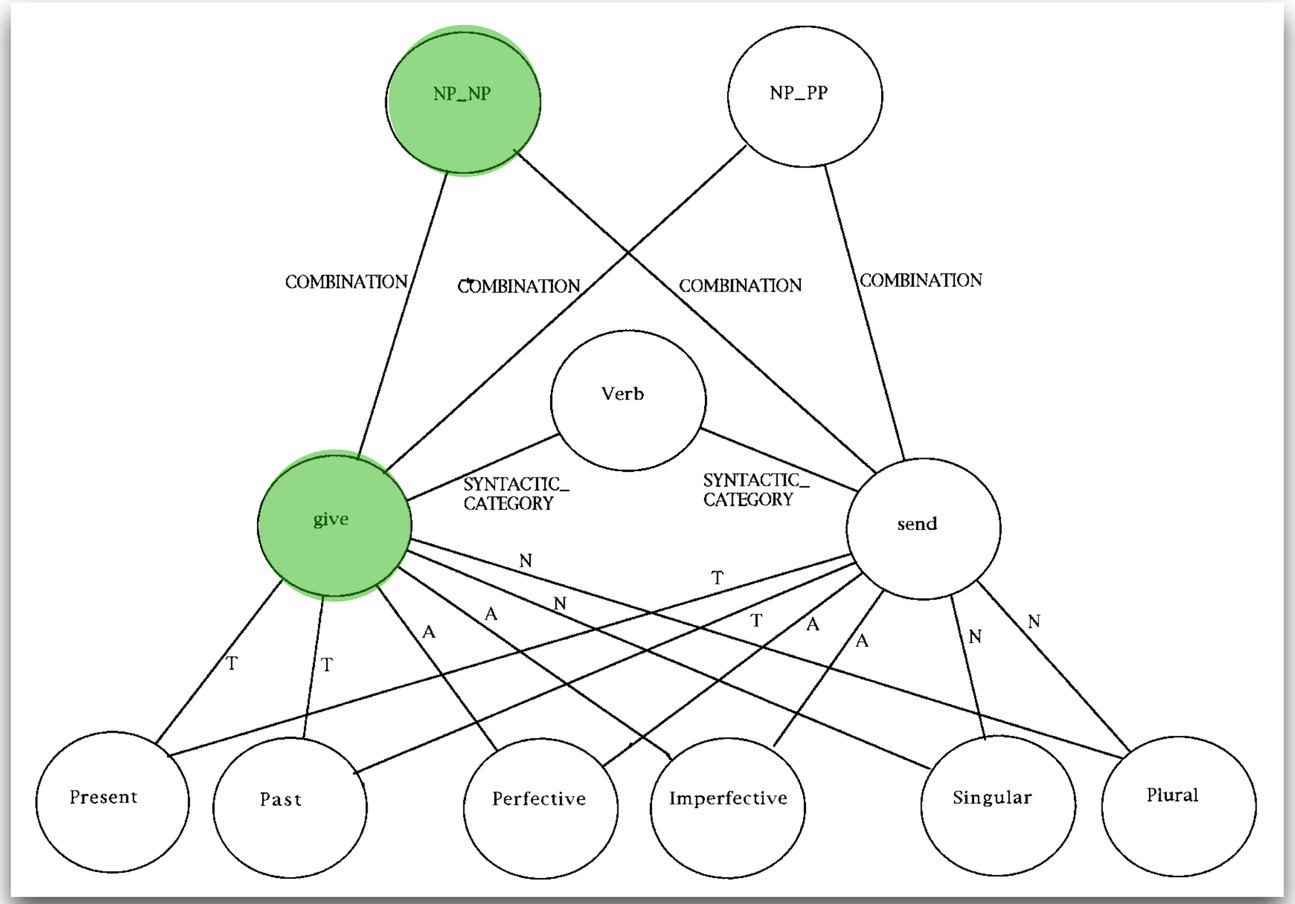

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- An activation-based mechanism
- Explaining short-term effect
- Inverse frequency effect? ❌

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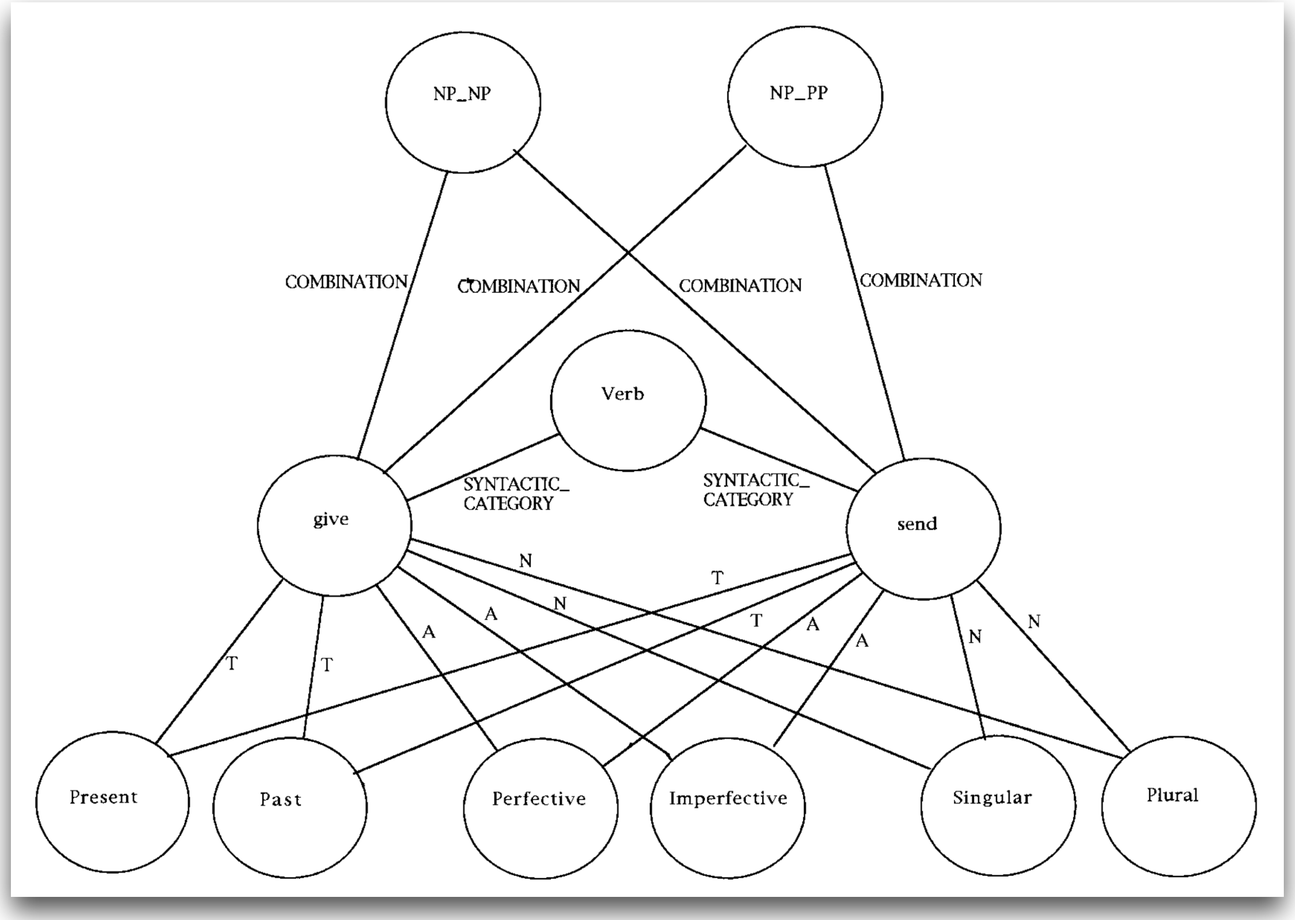

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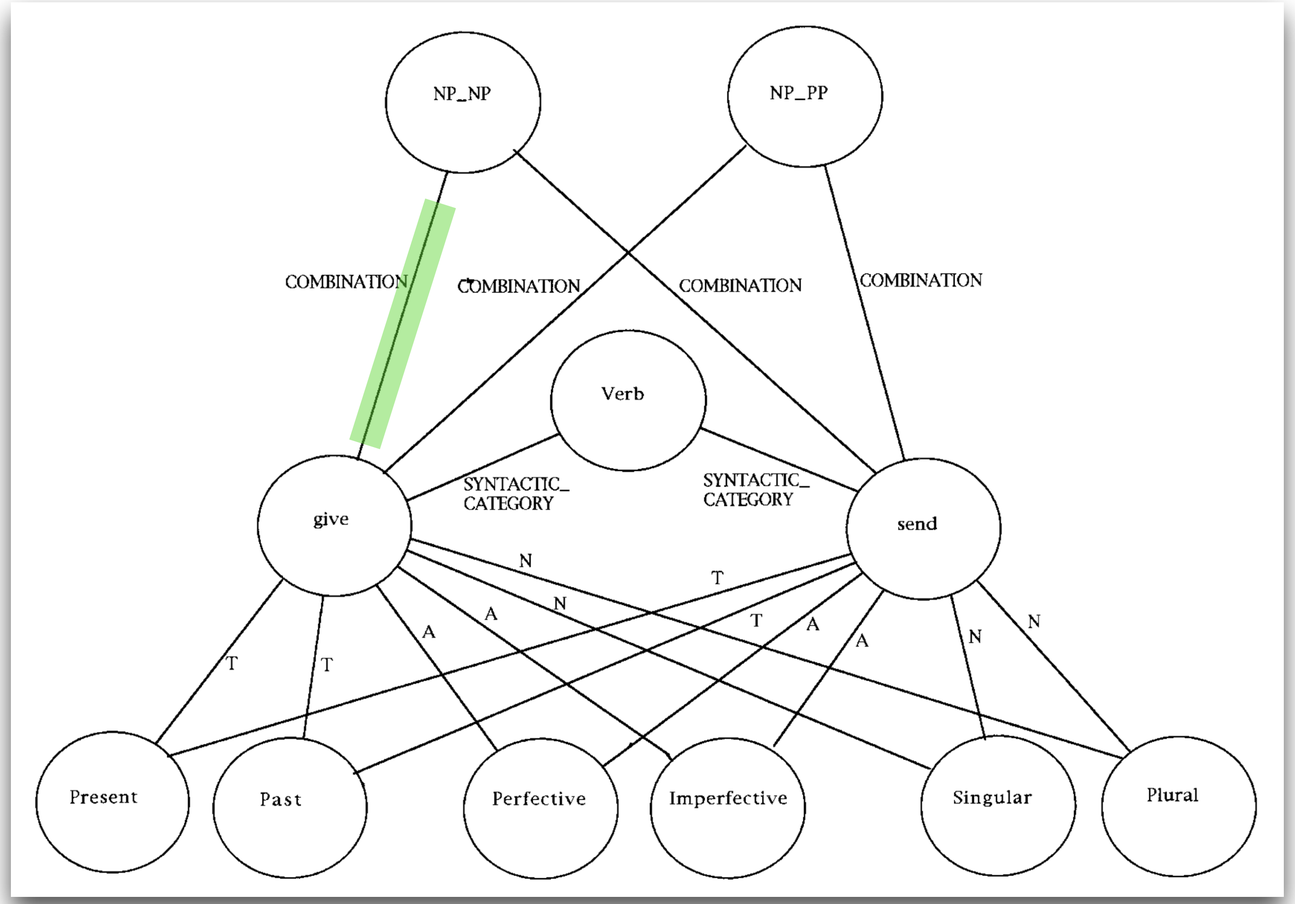

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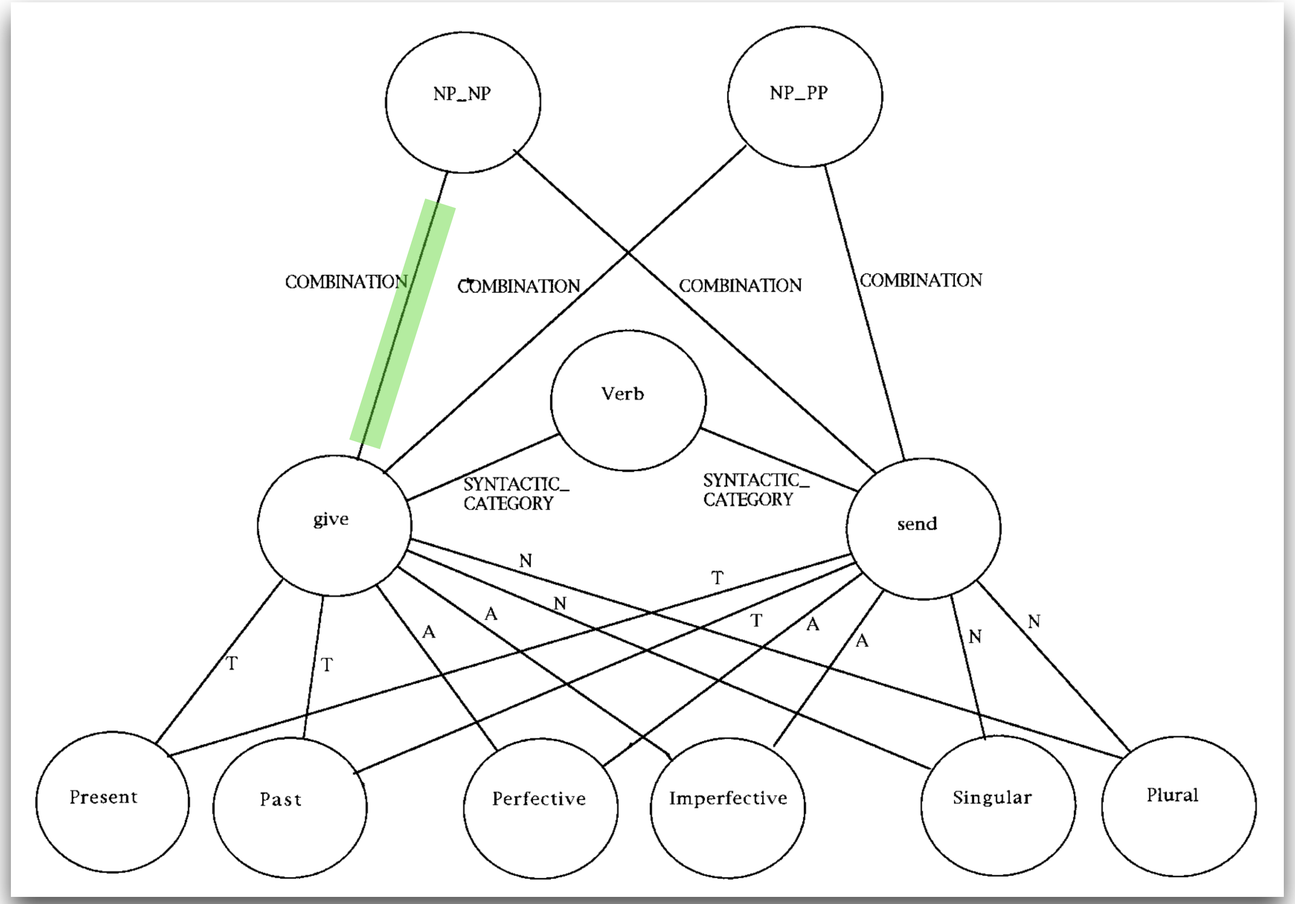
Theory 2: Implicit Learning

Slowly decaying weight changes



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Increasing the link weights proportional to the error signal between verb-bias prediction and the actual input prime.

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[e.g., Chang et al. 2002, 2006; Jaeger & Snider 2013]

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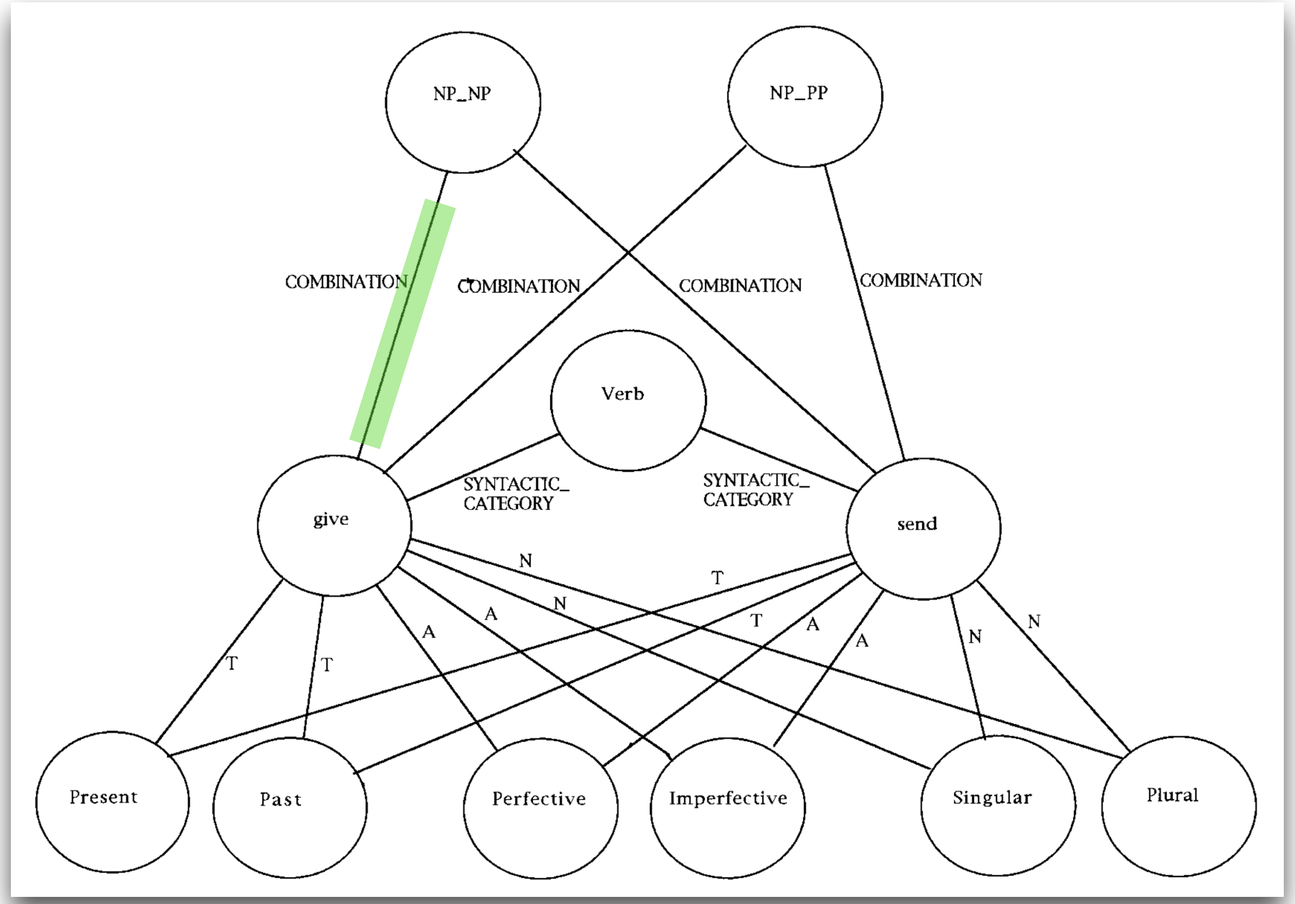


← Structural Nodes

Increasing the link weights <u>proportional to</u> the error signal between verb-bias prediction and the actual input prime.

← Lexical Nodes

- An error-driven learning / adaptation mechanism
- Explaining long-term effect
- Inverse Frequency effect? ✅

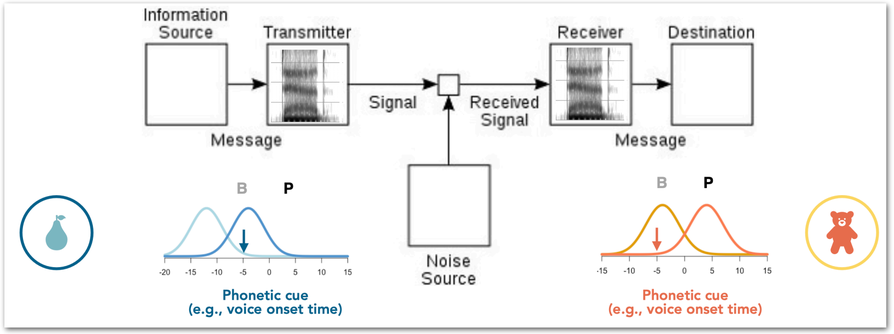
[e.g., Chang et al. 2002, 2006; Jaeger & Snider 2013]

Side Notes: Priming as Linguistic Adaptation

[e.g., Xie & Kurumada 2023; Lu et al. 2025; Feng 2022; etc.]

Side Notes: Priming as Linguistic Adaptation

- **Linguistic Adaptation:** adjustment of distributional knowledge / expectations to accommodate local input;
  - Speech adaptation & perception;
  - Syntactic satiation;
  - Informativeness calibration & presupposition/pragmatic routine calibration;



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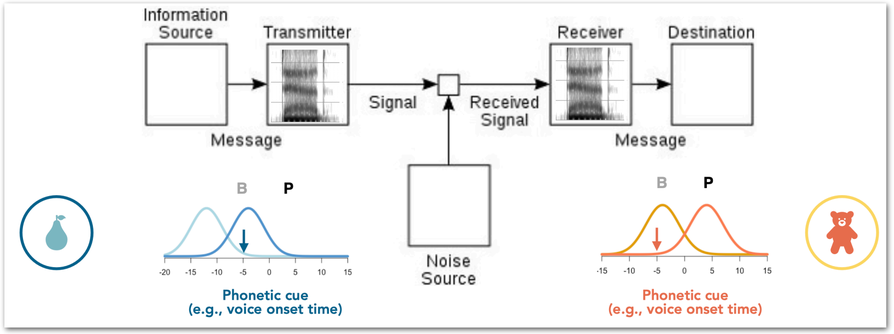
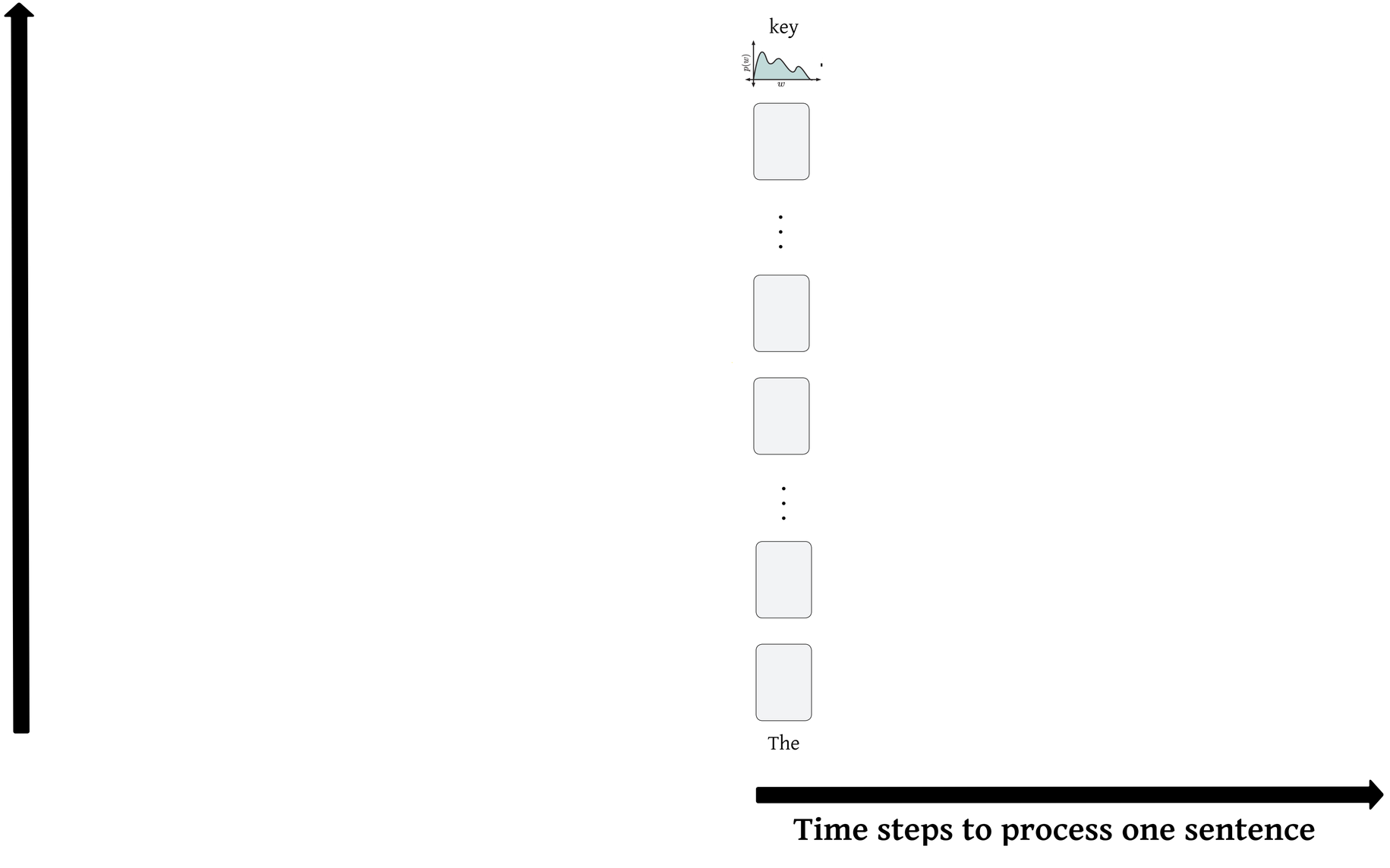


- **Predictive coding gives rise to linguistic adaptation**
  - Predictive coding: the system constantly predicts (linguistic) input and update the mental model based on the mismatch between predicted vs. actual input.
  - **The IFE is the *signature* that the update is error-driven**, not just residual activation: rarer structures create bigger prediction error → bigger update.

[e.g., Xie & Kurumada 2023; Lu et al. 2025; Feng 2022; etc.]

In-Context Learning in LLMs

A Primer on Intuitions behind LLMs



A Primer on Intuitions behind LLMs

Time steps to process one sentence

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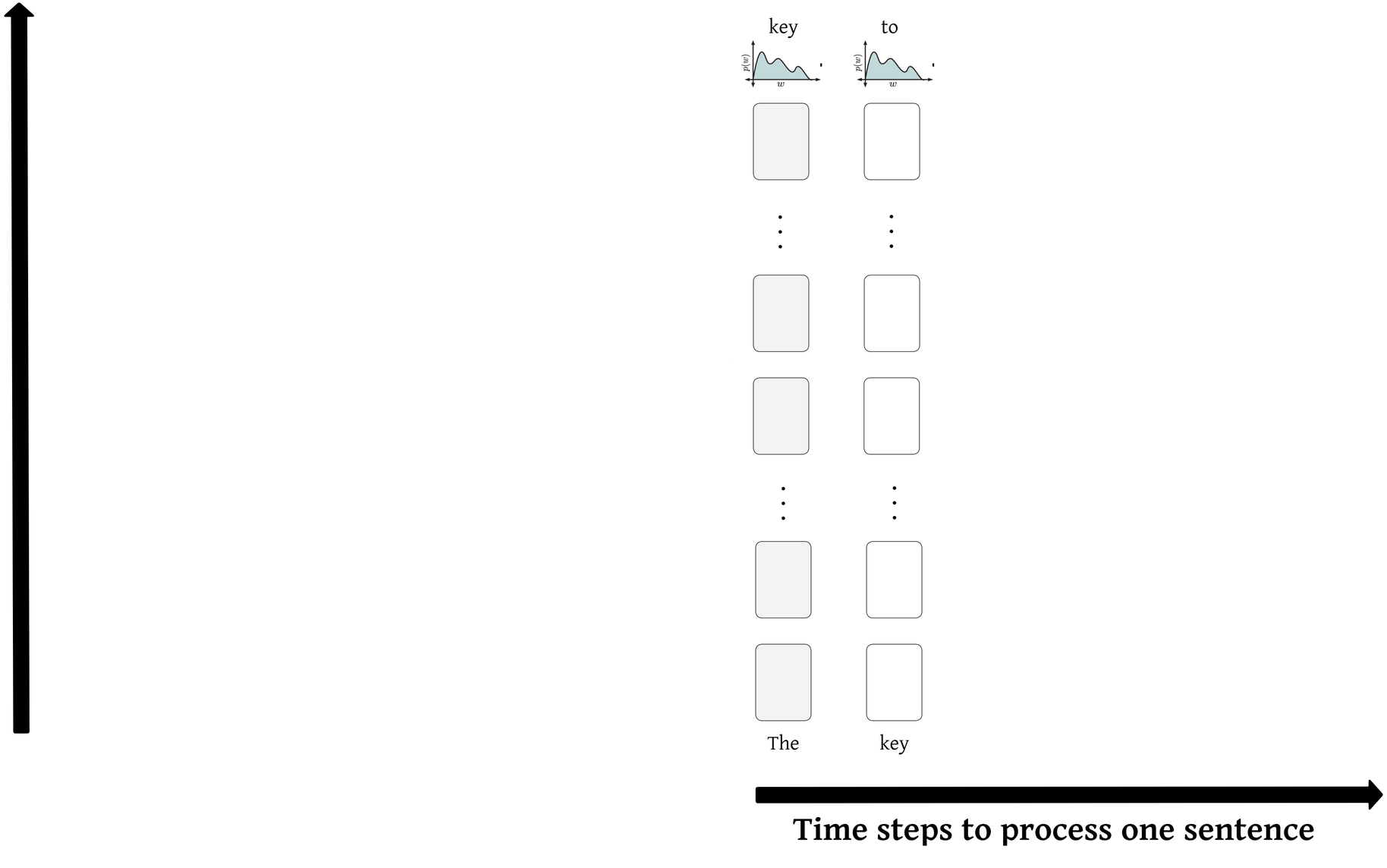

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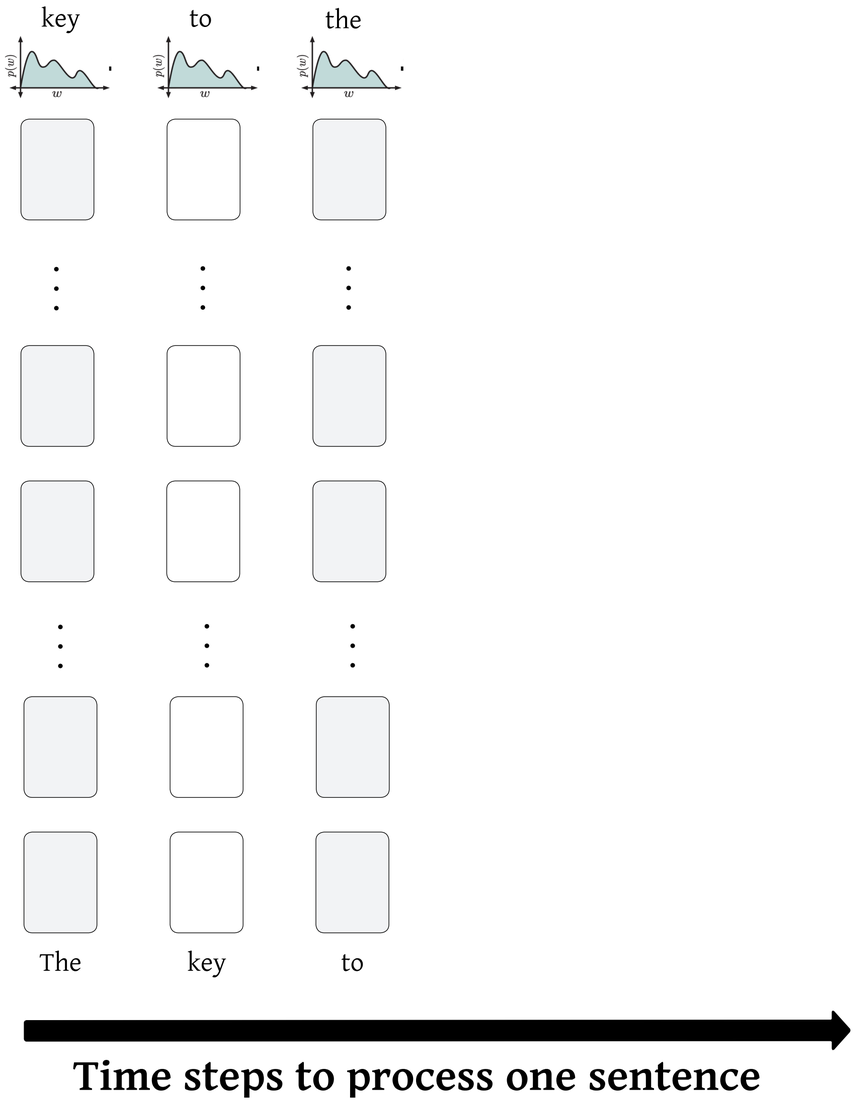

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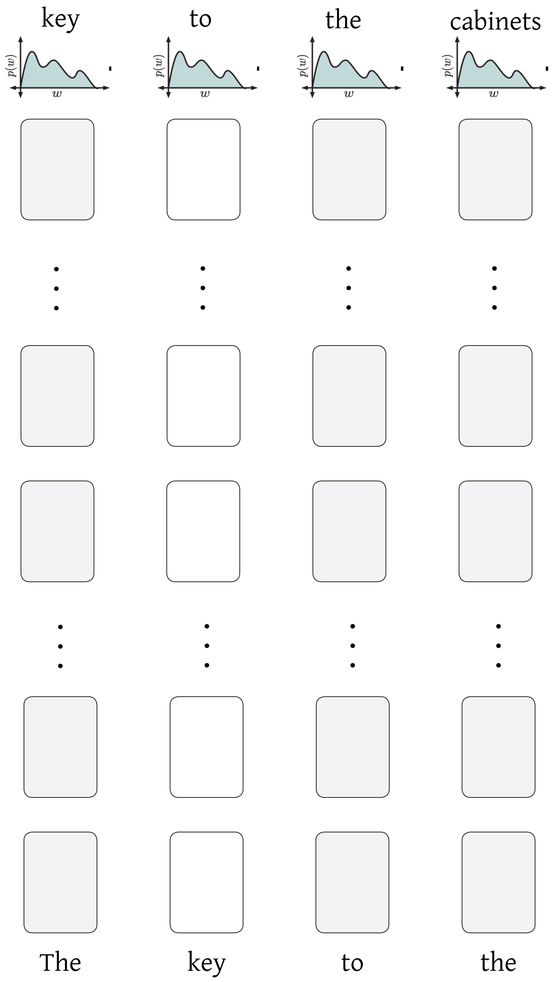

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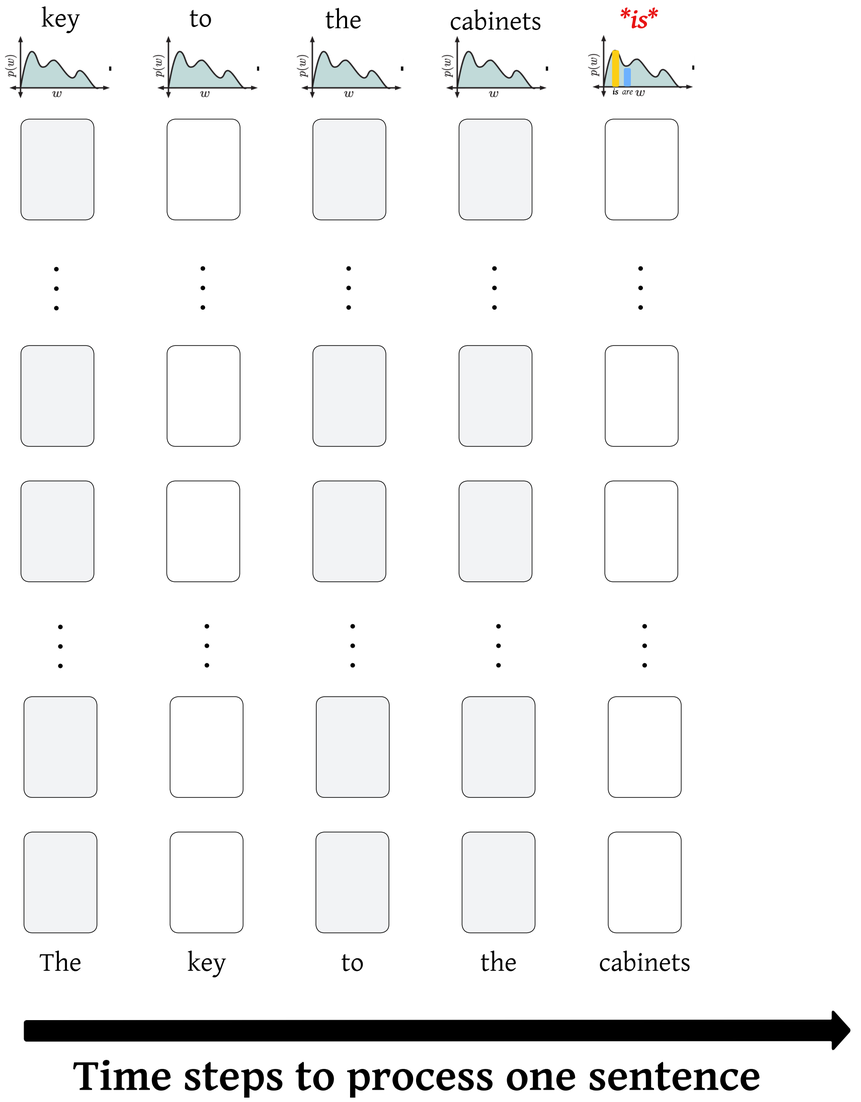

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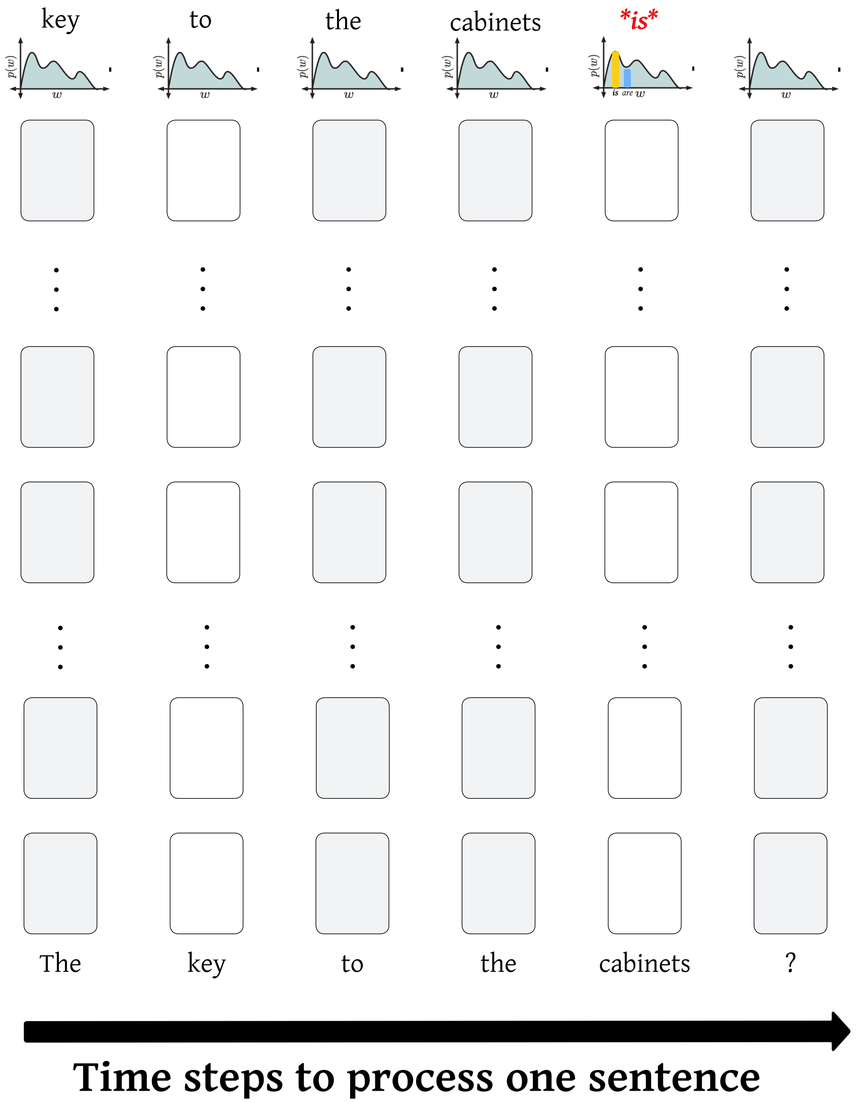

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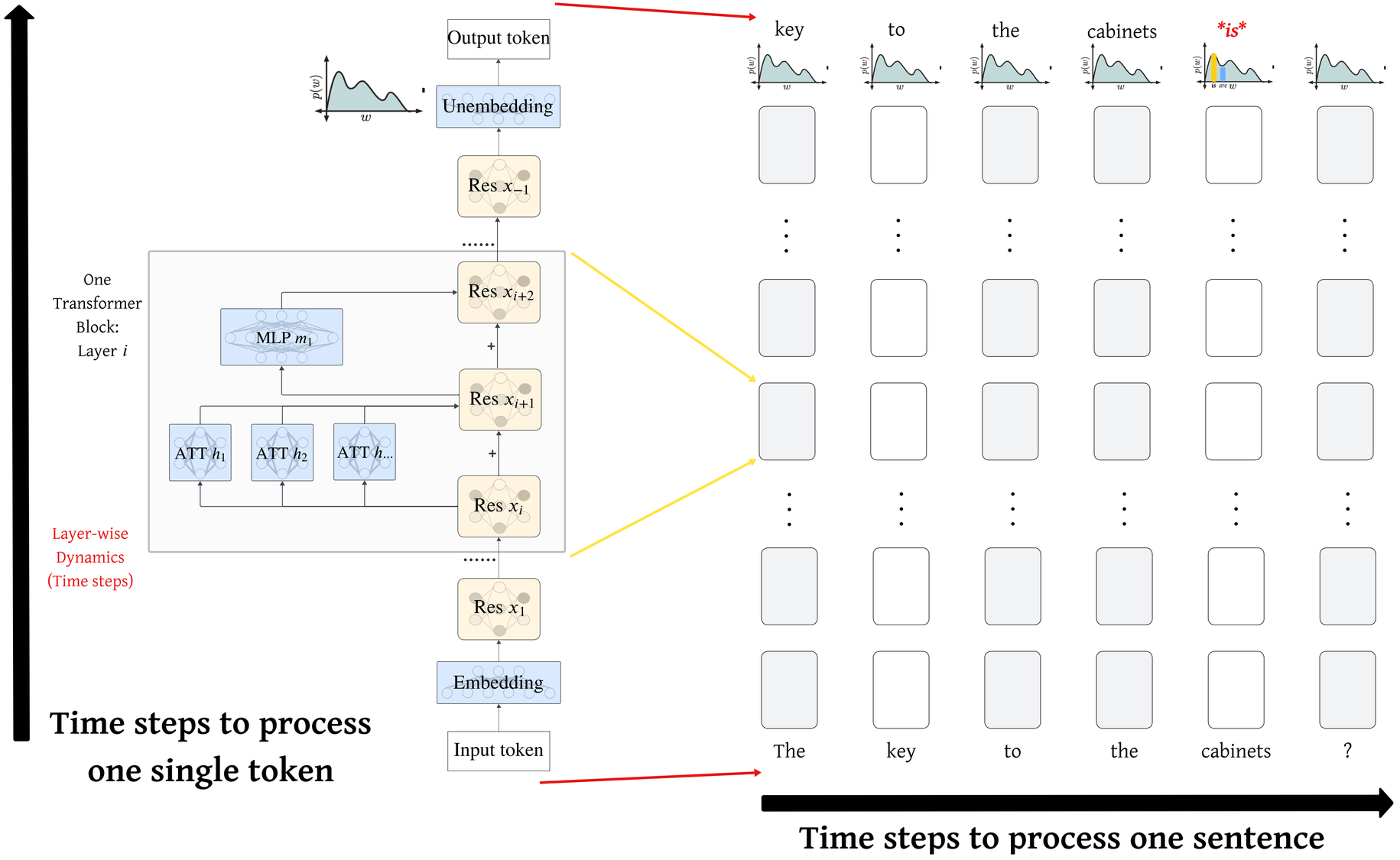
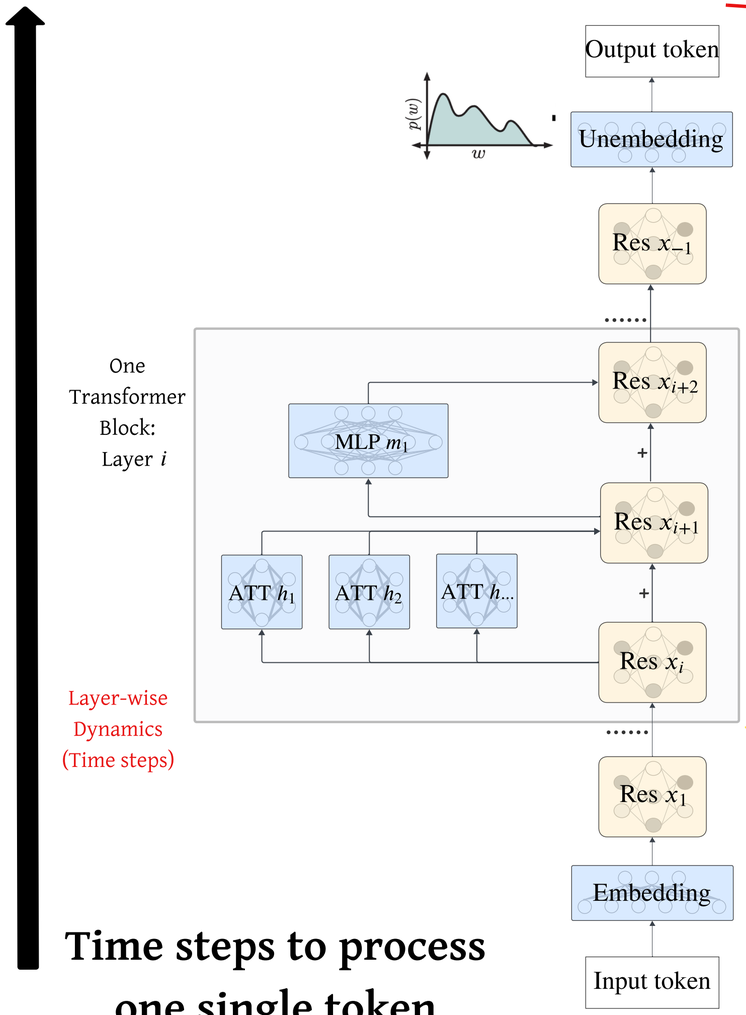
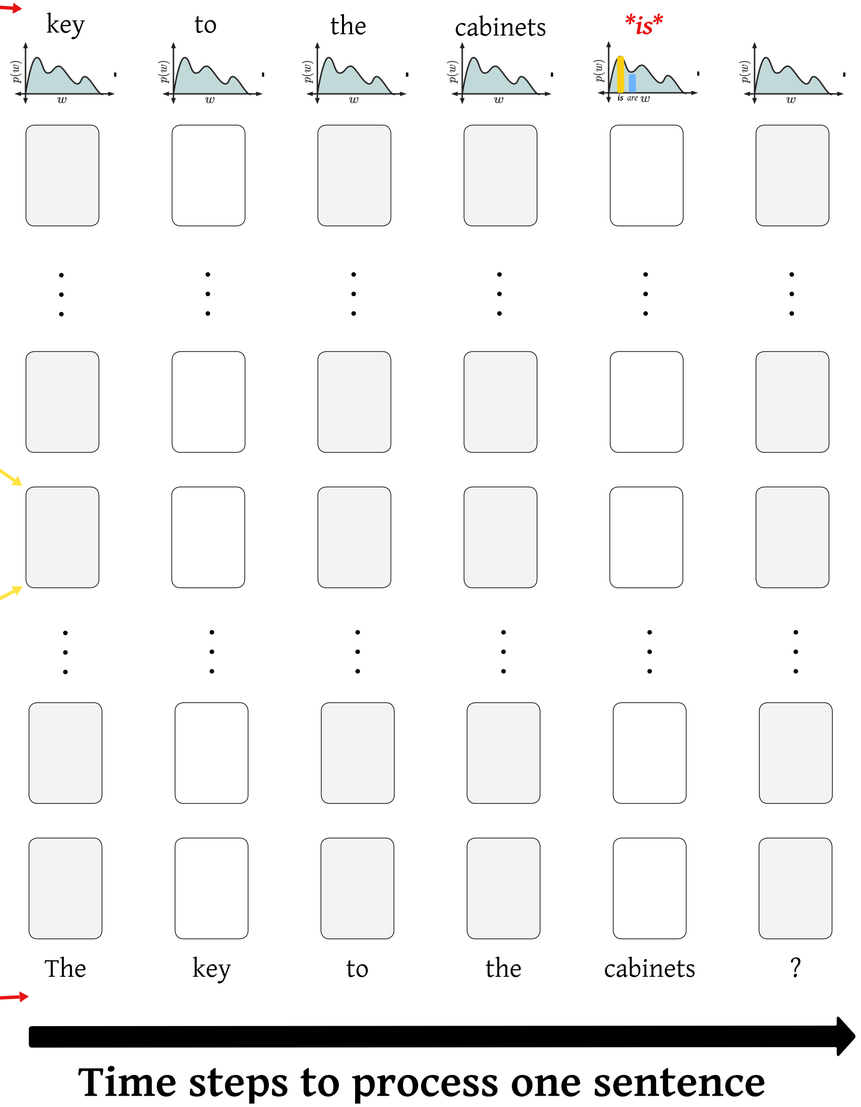


A Primer on Intuitions behind LLMs

Modern LLMs: machines of *next-token prediction*

- **Parameters:** trainable weights updated during training & fine-tuning → long-term memory-ish;
- **Activations:** temporary variables generarted during running → working memory;





In-Context Learning (ICL) in LLMs

In-Context Learning: several demonstration-answer pairs of a task in context improves models' performance on this task.

- No explicit description of the task;
- No weight (long-term memory) update!

[Brown et al. 2020]

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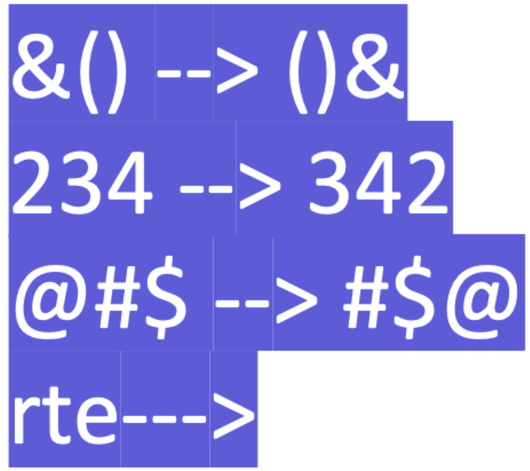

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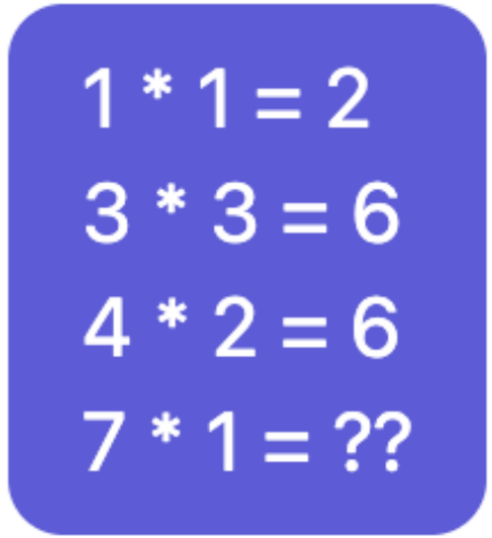

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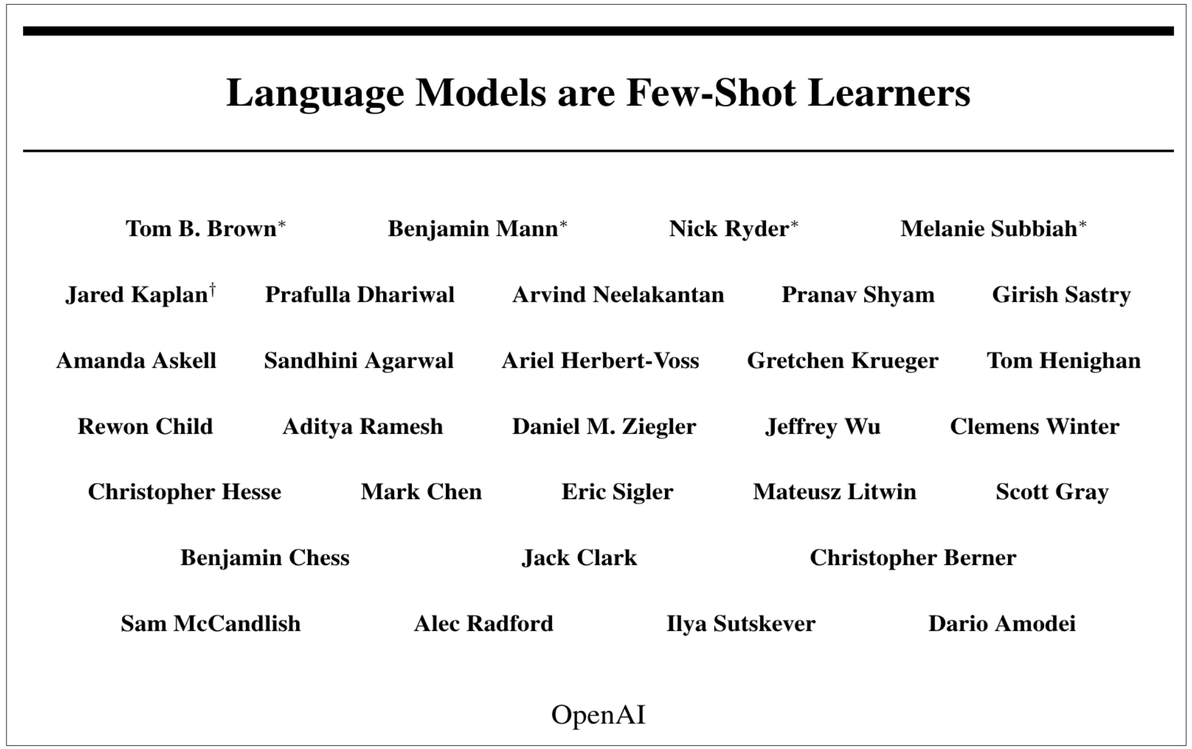


Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam Girish Sastry

Amanda Askell Sandhini Agarwal Ariel Herbert-Voss Gretchen Krueger Tom Henighan

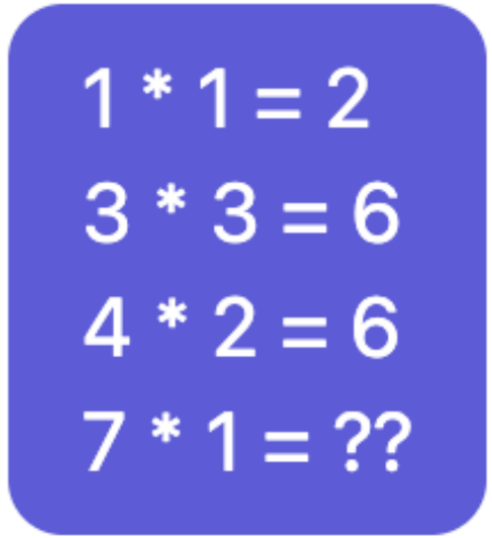
Rewon Child Aditya Ramesh Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

OpenAI



[Brown et al. 2020]

ICL vs. In-*Weights* Learning

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ICL vs. In-*Weights* Learning

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← example
3  cheese =>                           ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

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1  Translate English to French:        ← task description
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3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
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[Brown et al. 2020]

In-context Learning:

- No gradient updates;
- Rapid: from a few examples;
- One-shot / Few-shot learning;

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- No gradient updates;
- Rapid: from a few examples;
- One-shot / Few-shot learning;

In-weights Learning (Fine-tuning):

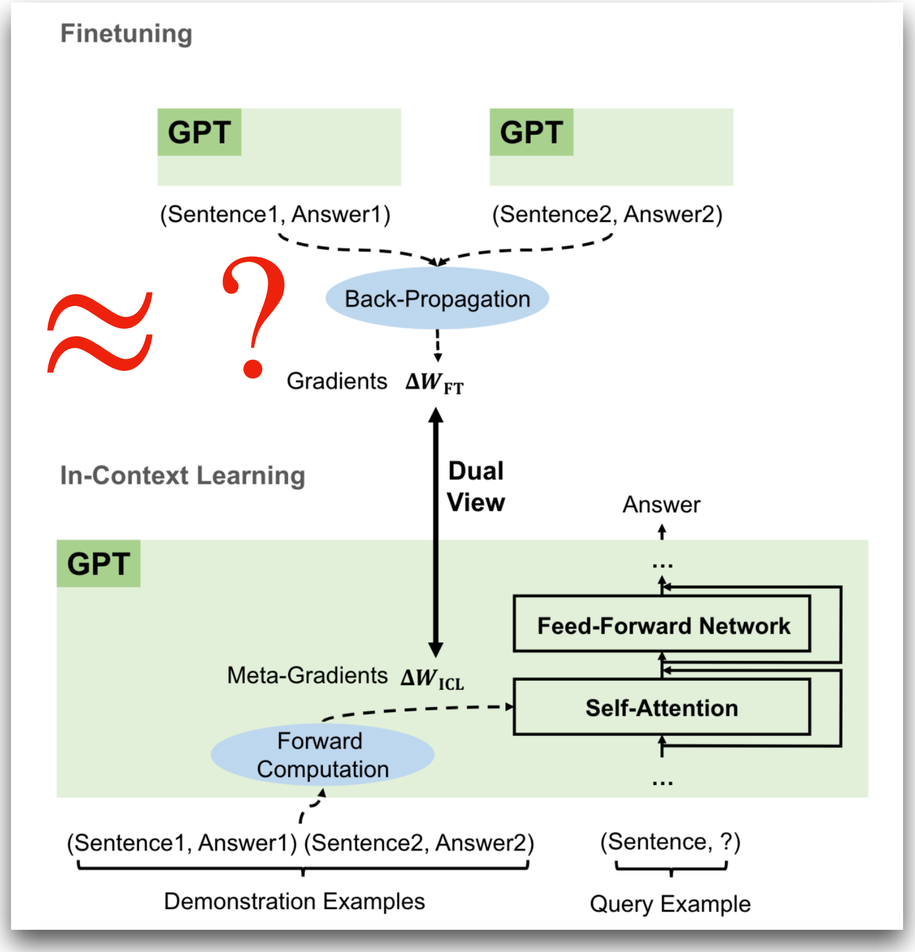
- Gradient-based;
- Slow: need many examples;
- Standard supervised learning;

Fine-tuning

The model is trained via repeated gradient updates using a large corpus of example tasks.

[Brown et al. 2020]

Research Question: is there error-driven learning mechanisms in ICL?



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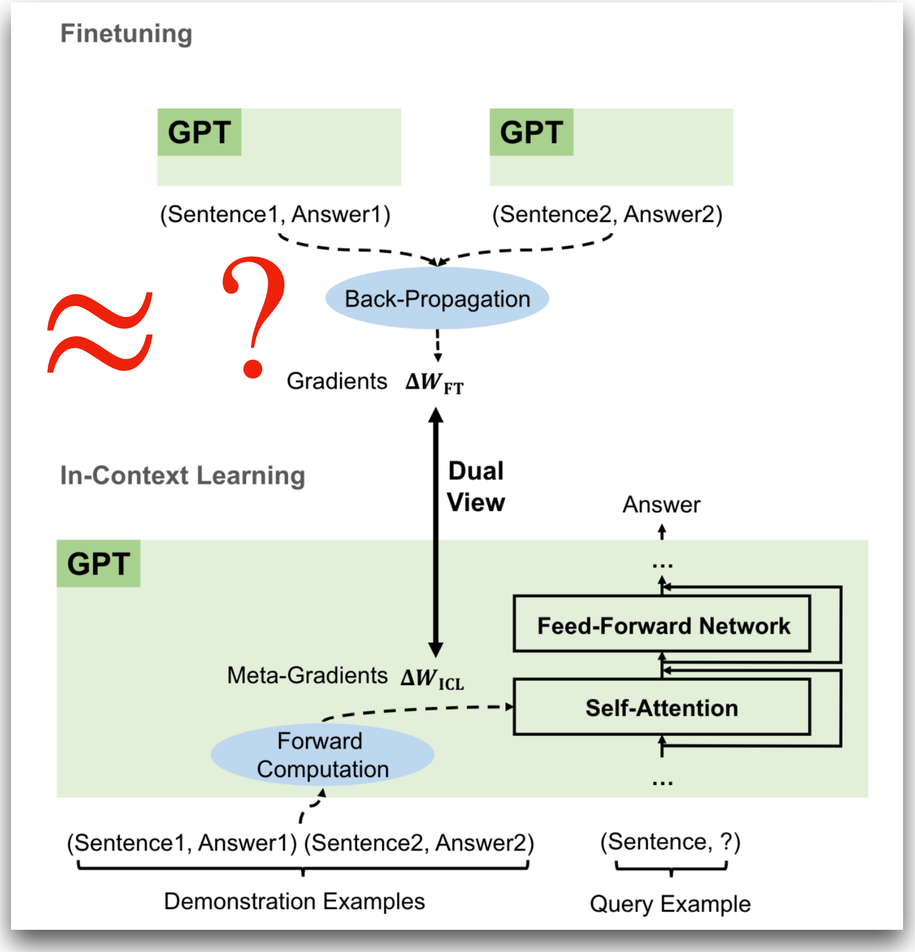

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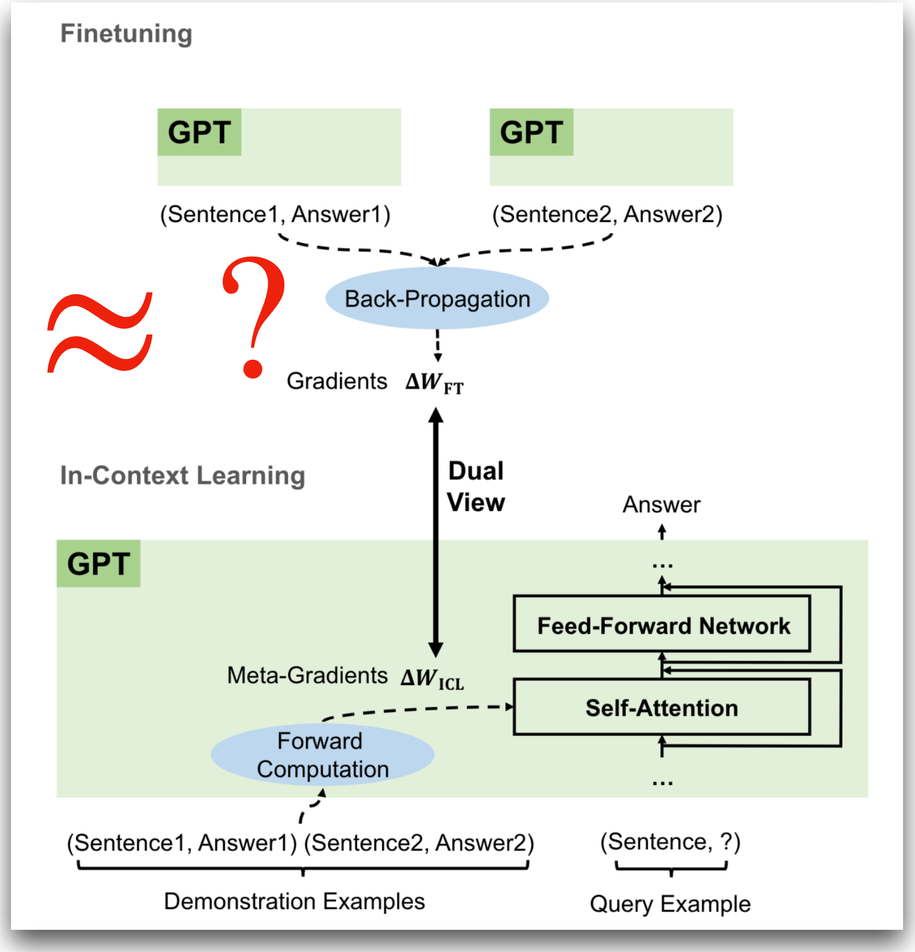

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- In-principle claims: math derivations with assumptions on architecture;

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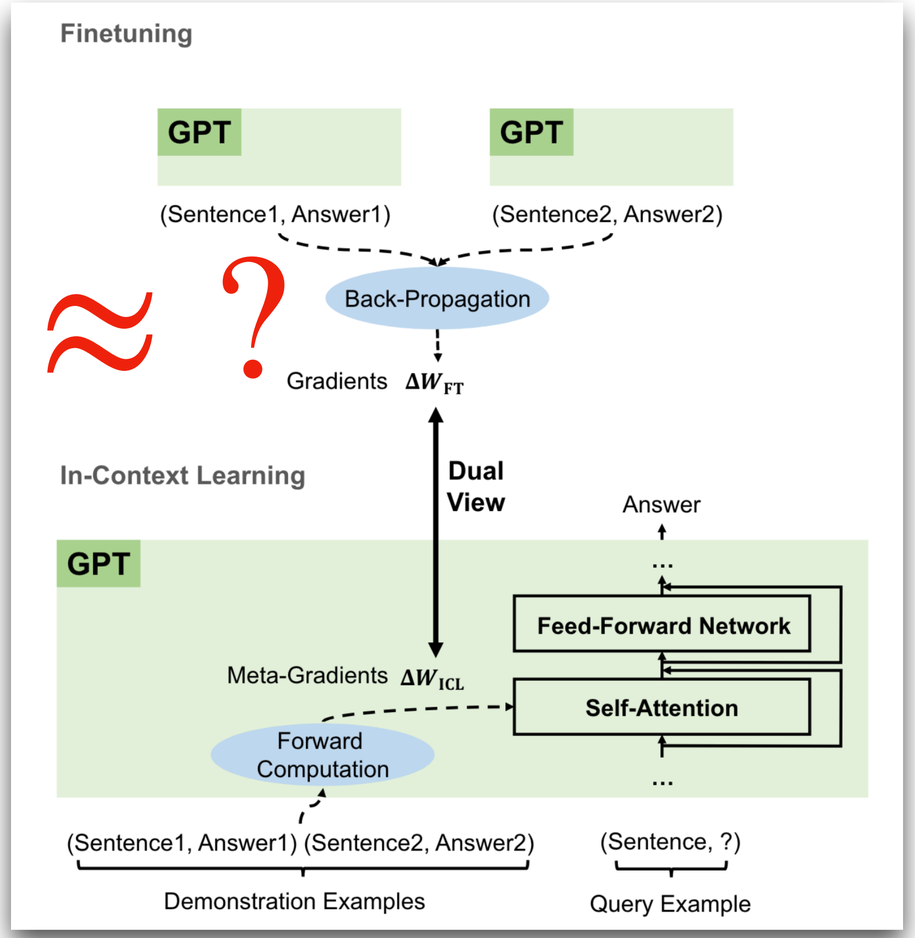

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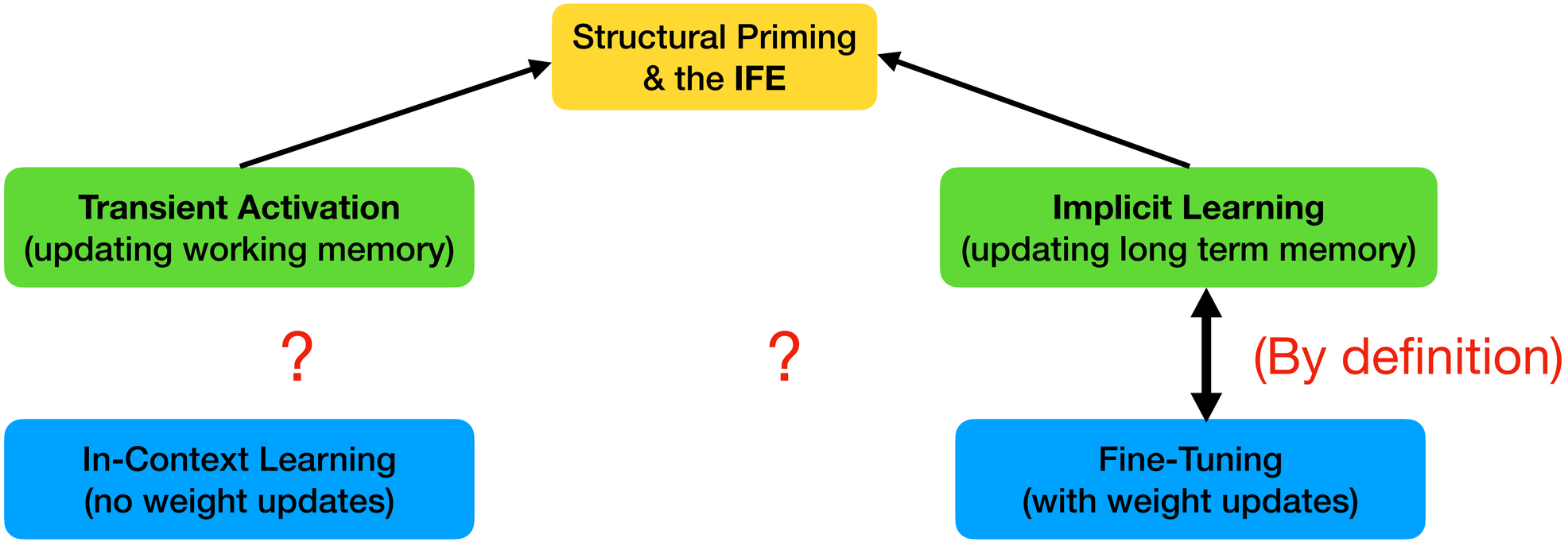
- In-principle claims: math derivations with assumptions on architecture;

Current work:

- On pretrained, actual LLMs;
- Psycholinguistically motivated, more testing a more fine-grained effect.

[e.g., Xie et al. 2022, von Oswald et al. 2022, Dai et al. 2023]

Current Picture



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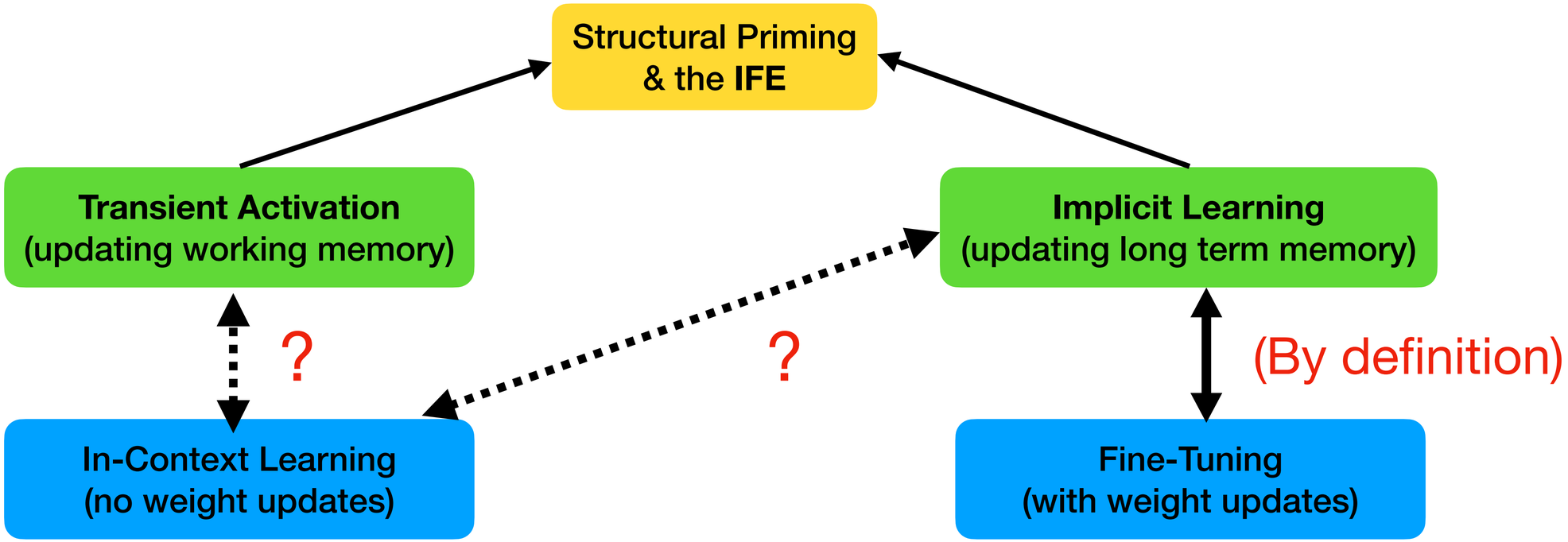
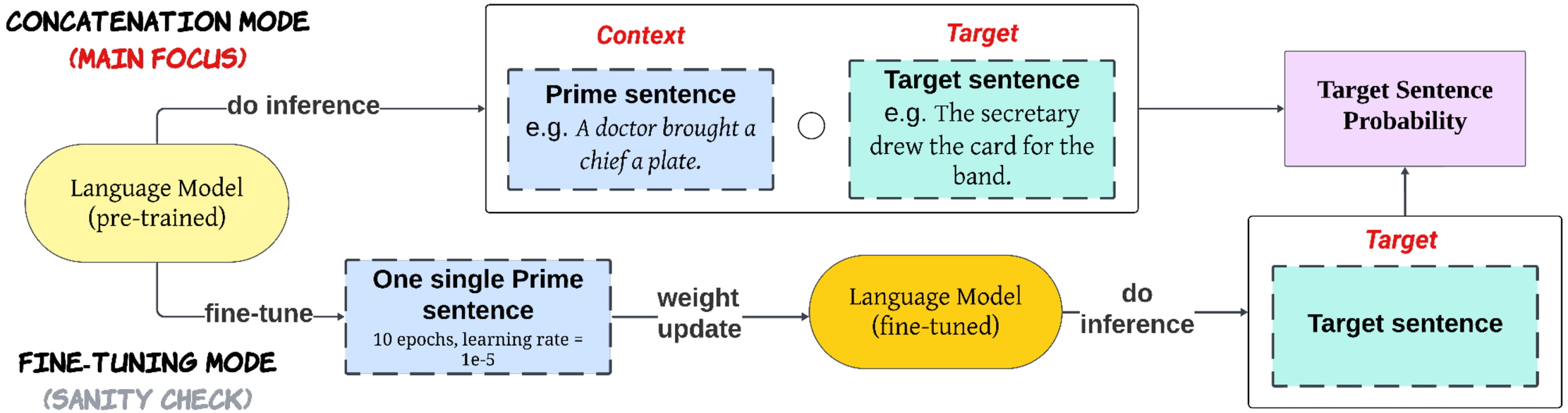


Experiment 1: Behavioral Analysis

Overview of the Current Approach



Fine-tuning Mode: [van Schijndal & Linzen 2018]
Concatenation Mode: [Sinclair et al. 2022]

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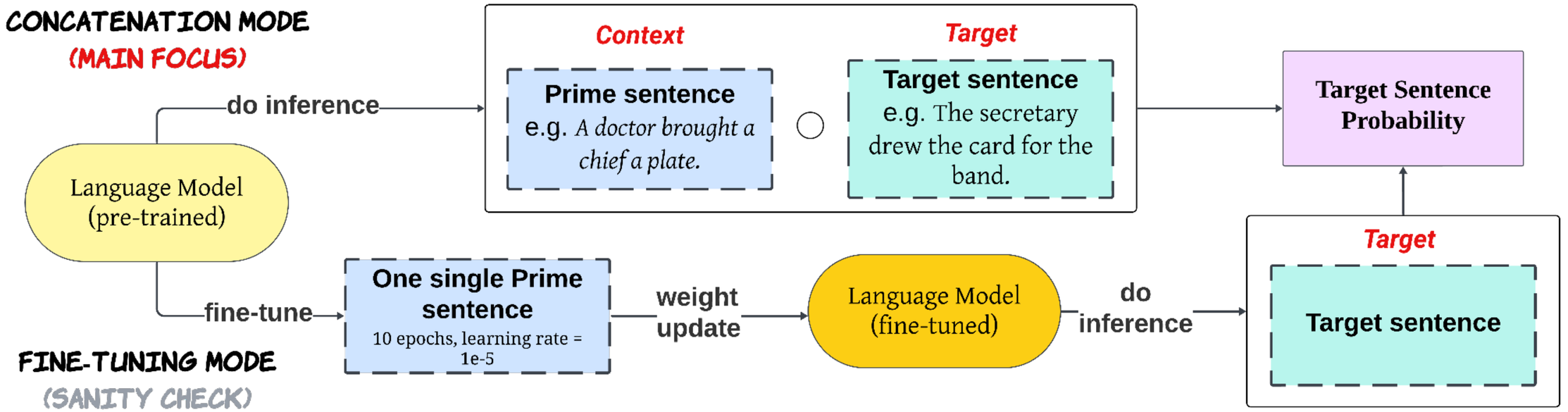

Assumption from Priming Theories: only some error-driven learning mechanism could lead to the IFE. Then, we predict that:

- Fine-tuning Mode: (with weight update) IFE ✅
- Concatenation Mode: (no weight update) IFE ❓

Fine-tuning Mode: [van Schijndal & Linzen 2018]
Concatenation Mode: [Sinclair et al. 2022]

Corpus

- 22 ditransitive verbs;
- 50 target sentences per verb;
- For each target sentence, pair it with a prime sentence with each prime verb;

22 x 50 (target sentences)

x

21 (prime sentences)

=

23100 <prime, target> pairs

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Each <prime, target> pair ⇒ 4 structural combinations ⇒ 92400 trials.

$$\text{Prime}_{DO} \rightarrow \text{Target}_{DO}, \text{Prime}_{DO} \rightarrow \text{Target}_{PD}, \text{Prime}_{PD} \rightarrow \text{Target}_{DO}, \text{Prime}_{PD} \rightarrow \text{Target}_{PD}$$

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$$\text{Prime}_{DO} \rightarrow \text{Target}_{DO}, \text{Prime}_{DO} \rightarrow \text{Target}_{PD}, \text{Prime}_{PD} \rightarrow \text{Target}_{DO}, \text{Prime}_{PD} \rightarrow \text{Target}_{PD}$$

Prime: A doctor brought a plate to a chief.

Target: The secretary drew the card for the band.

Quantifying Verb Biases and the IFE

Verb Bias of verb V on structure X:

$$bias(V, \mathrm{PD}) = \frac{1}{|\mathcal{S}_V|} \sum_{t_{\mathrm{PD}} \in \mathcal{S}_V} \frac{\mathcal{P}(t_{\mathrm{PD}})}{\mathcal{P}(t_{\mathrm{PD}}) + \mathcal{P}(t_{\mathrm{DO}})}$$

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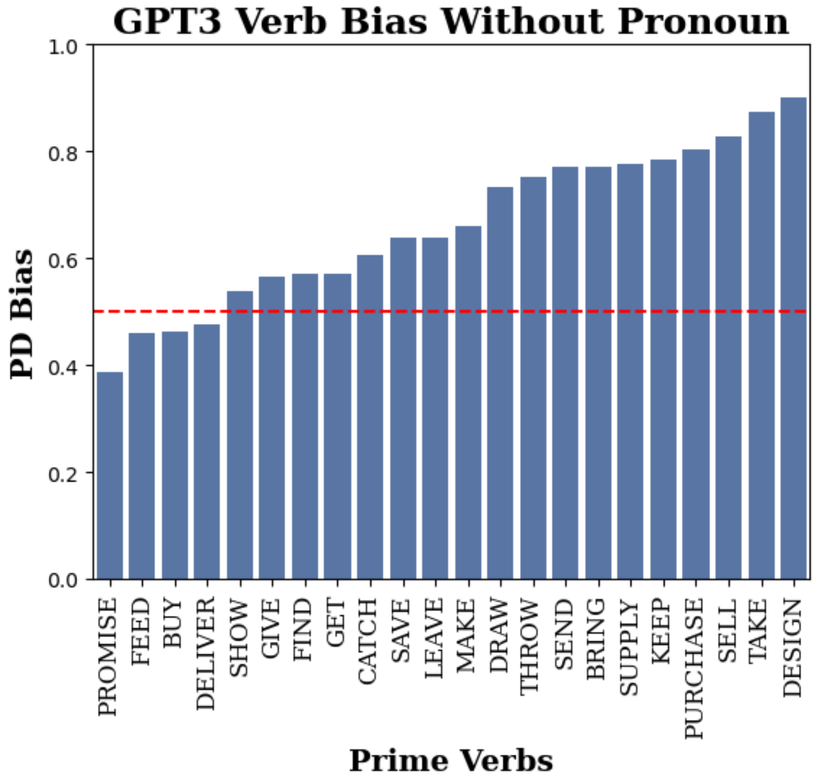

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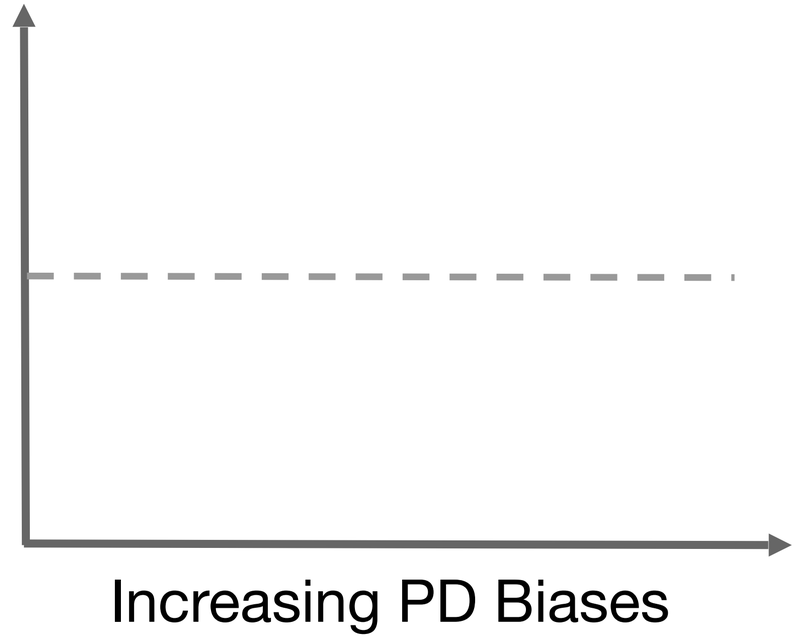
IFE: the priming effect for verb V in DO form on PD targets

$$PrimeBias(\mathrm{PD}|\mathrm{DO}, V) = \frac{1}{|T_{\mathrm{PD}}| \cdot |P^V_{\mathrm{DO}}|} \sum_{t_{\mathrm{PD}} \in T_{\mathrm{PD}}} \sum_{p^V_{\mathrm{DO}} \in P^V_{\mathrm{DO}}} \frac{\mathcal{P}(t_{\mathrm{PD}}|p^V_{\mathrm{DO}})}{\mathcal{P}(t_{\mathrm{DO}}|p^V_{\mathrm{DO}}) + \mathcal{P}(t_{\mathrm{PD}}|p^V_{\mathrm{DO}})}$$

Predictions on the IFE

Prime Verb	Verb PD Bias	Primed probability (priming magnitude)
Bring	0.23	0.23 (0.03)
Buy	0.27	0.25 (0.05)
Find	0.41	0.28 (0.08)
Draw	0.52	0.30 (0.10)
Design	0.77	0.33 (0.13)
priming in DO	*larger PD biases*	*greater priming effects*

$\text{Prime}_{PD} \rightarrow \text{Target}_{PD}$



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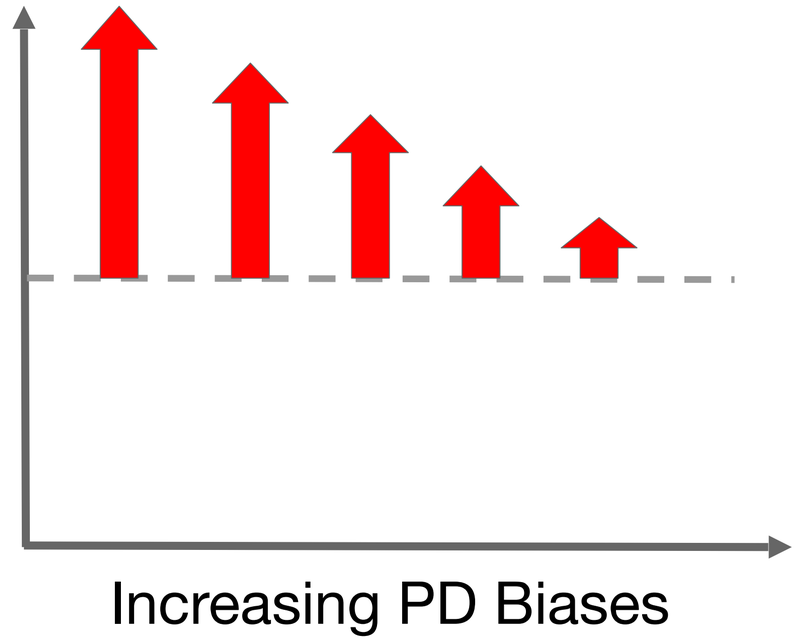

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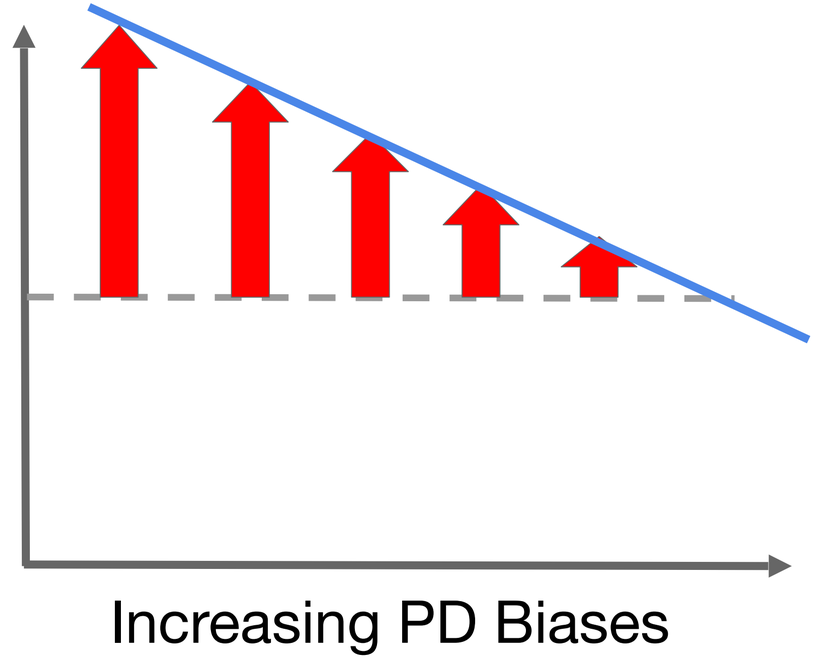

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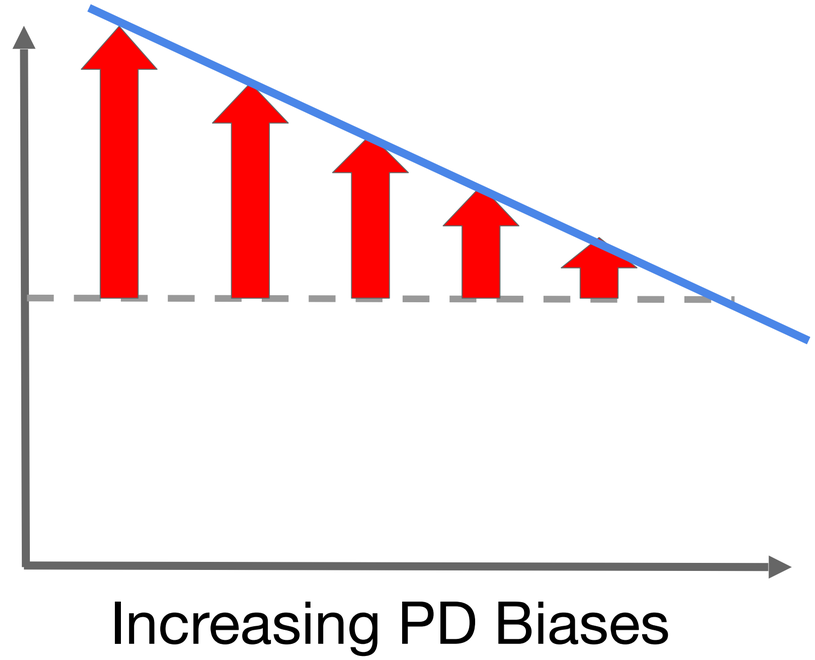

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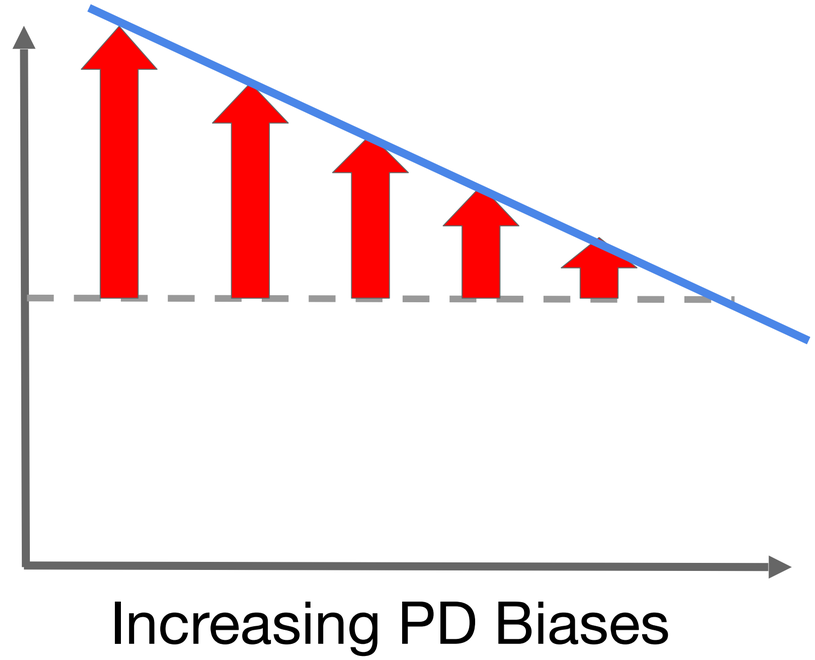

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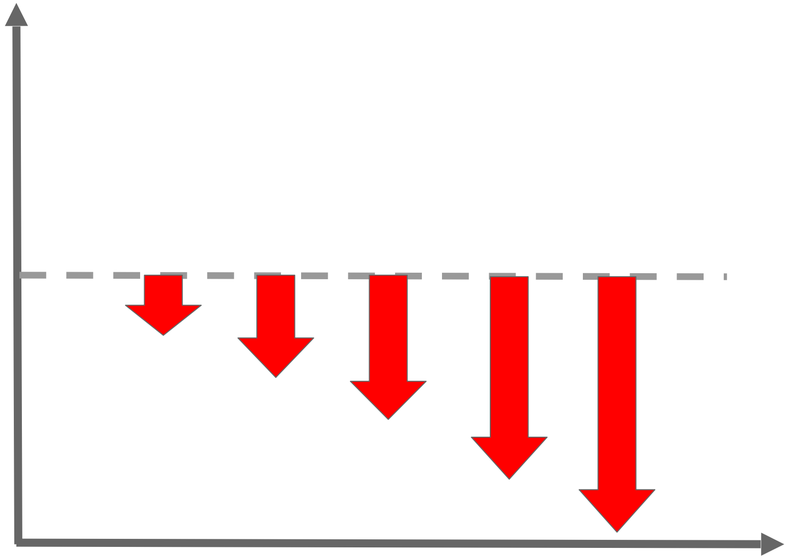

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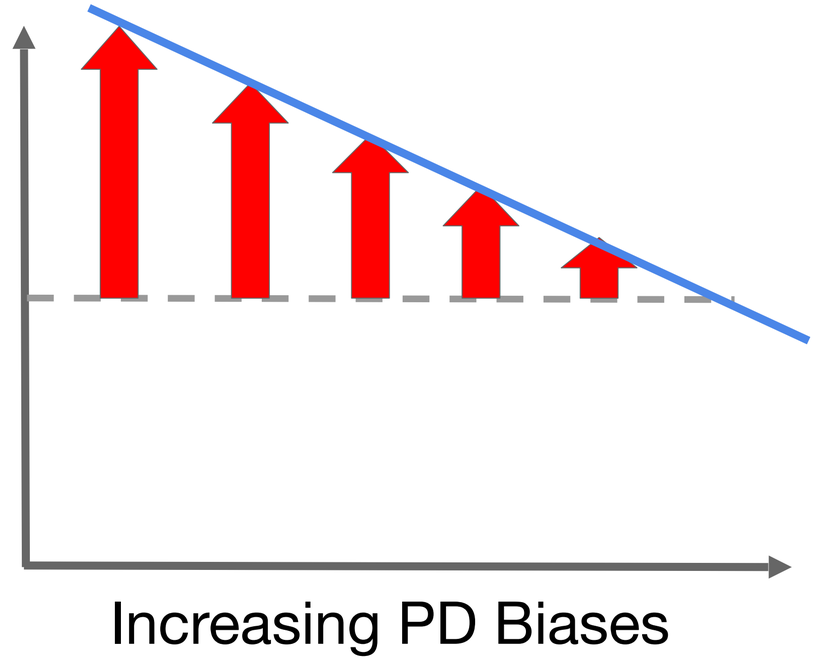

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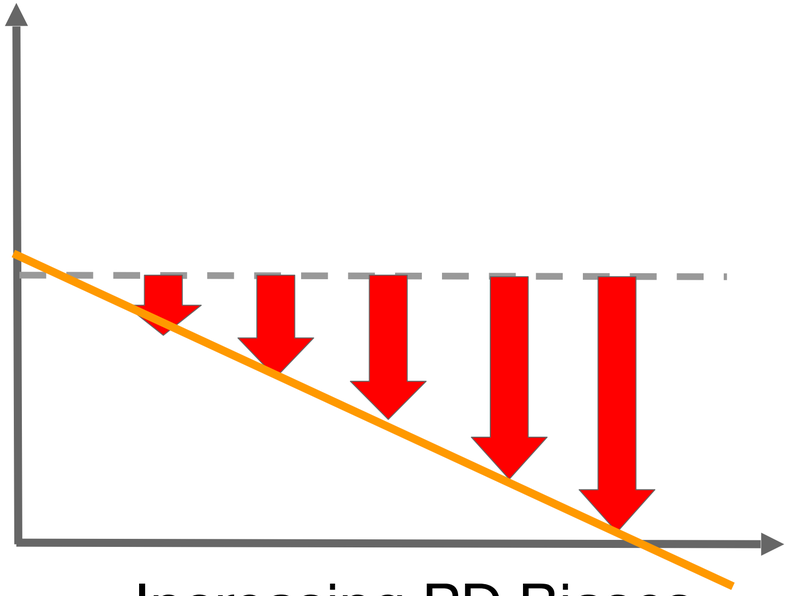

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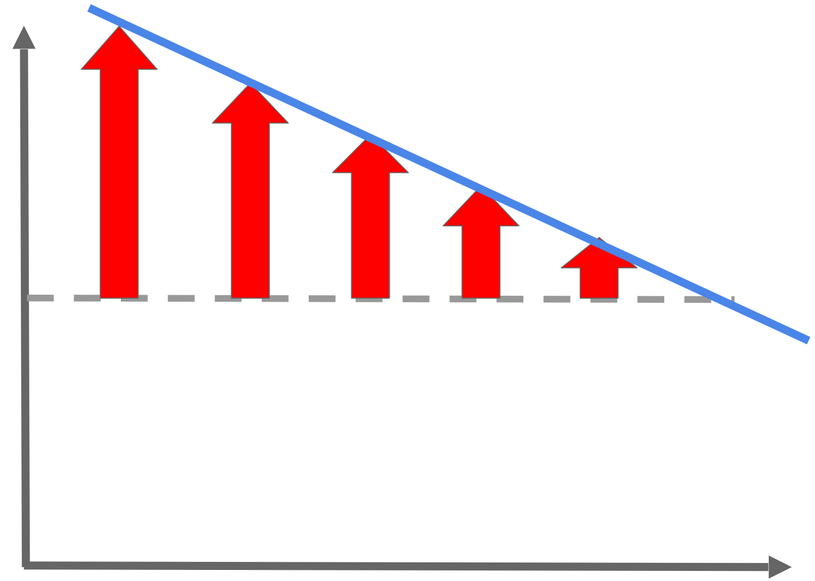

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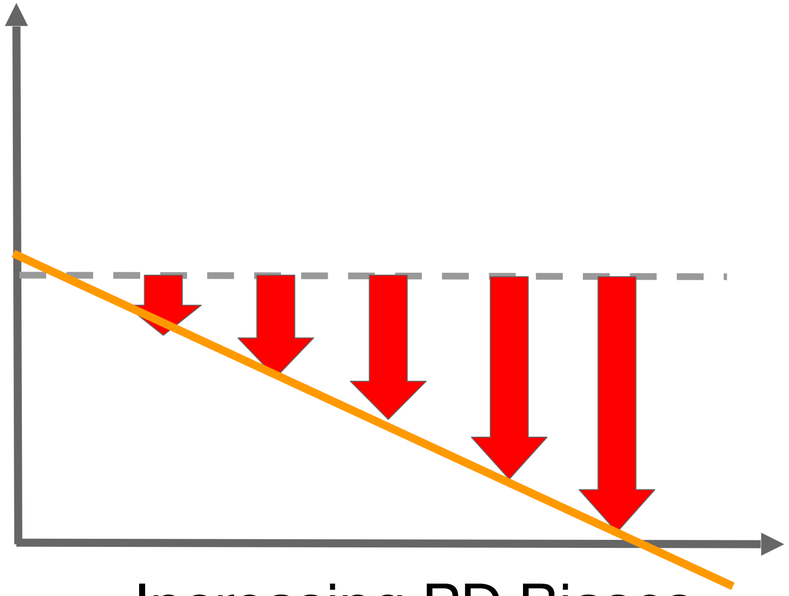

Increasing PD Biases

- **IFE**: double negative slopes;
- **Standard Priming**: PD-PD has higher intercept than DO-PD;

Priming in LLMs

Fine-tuning Mode: fine-tuning the model with the prime sentence and use the updated model to run the target sentence — with weight update;

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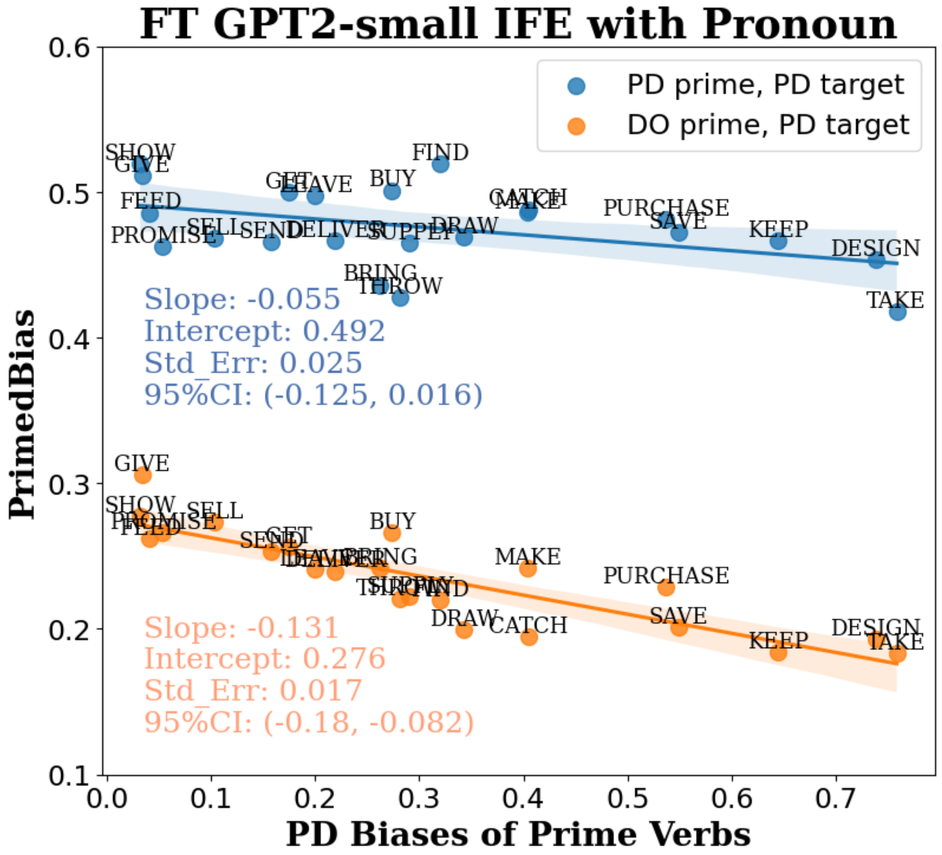

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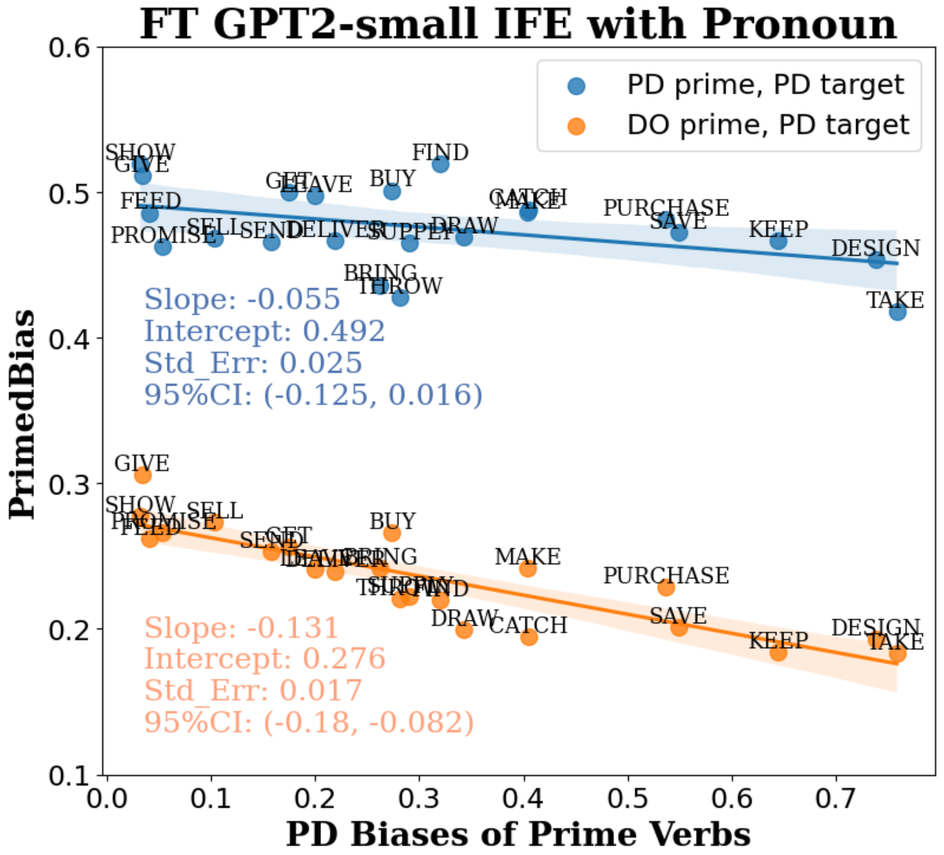

Even *GPT2-small* shows significant inverse frequency effects!

Priming in LLMs

Concatenation Mode: concatenating the prime and target sentences and run the model — without weight update;

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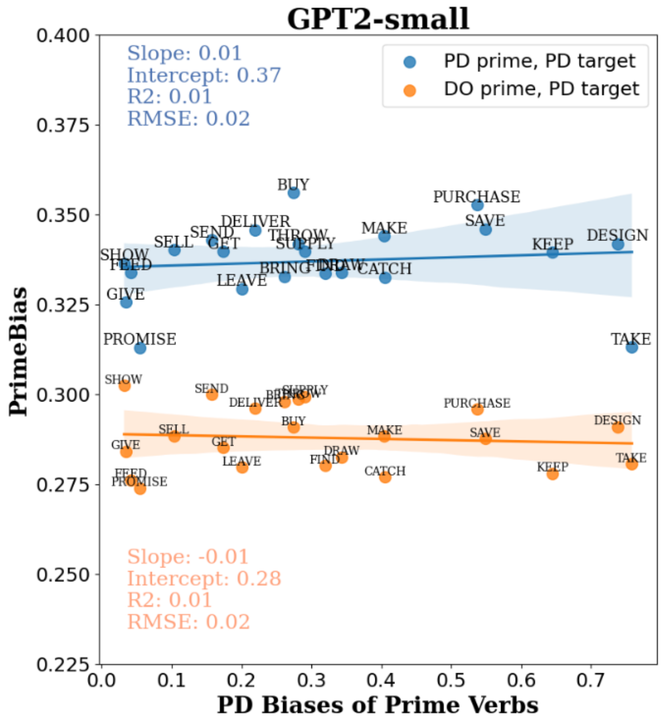

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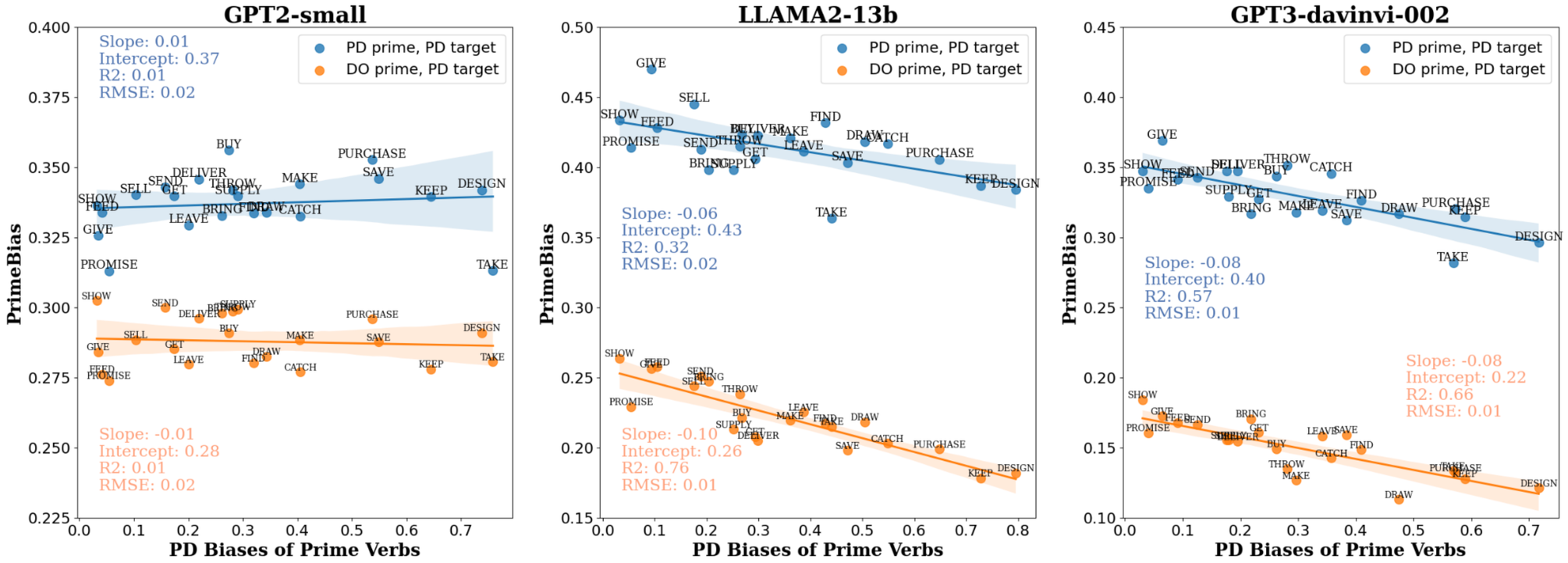

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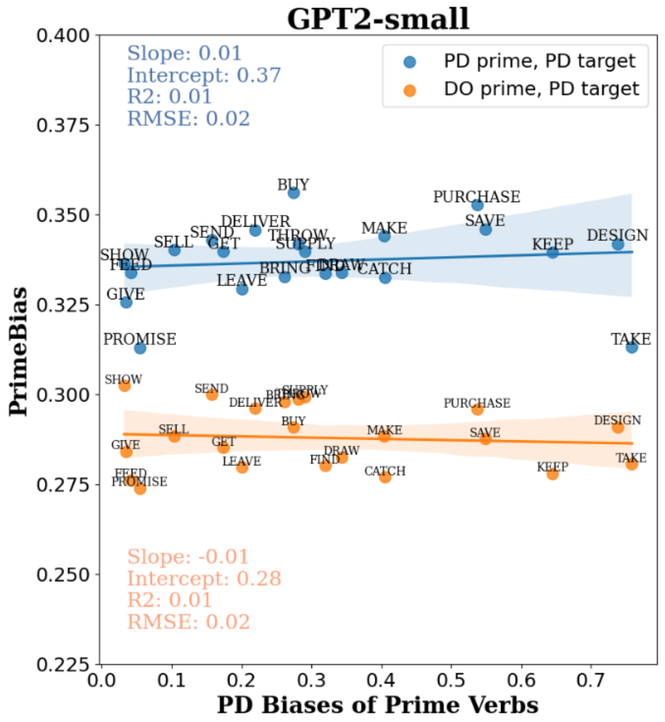
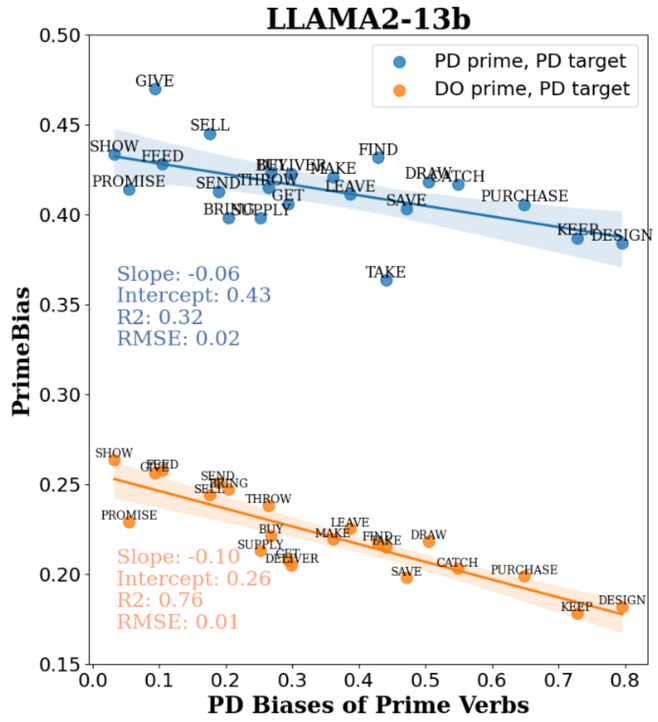
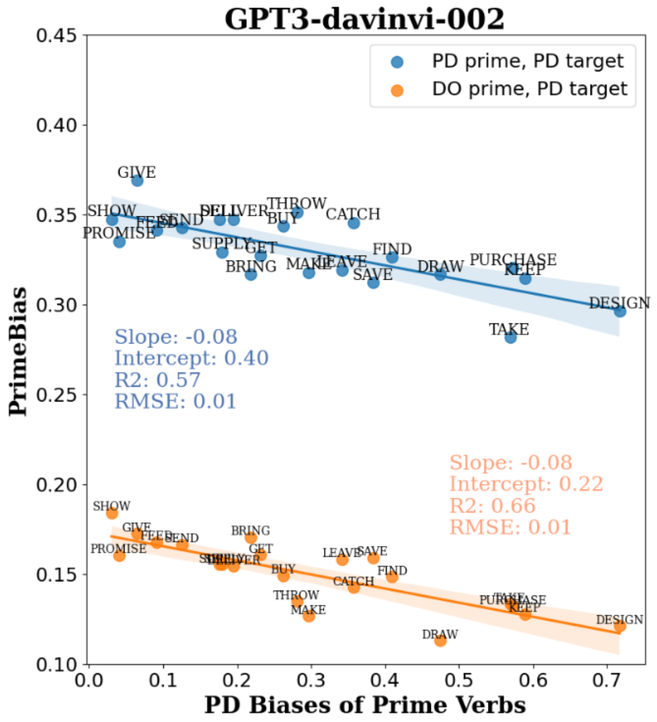
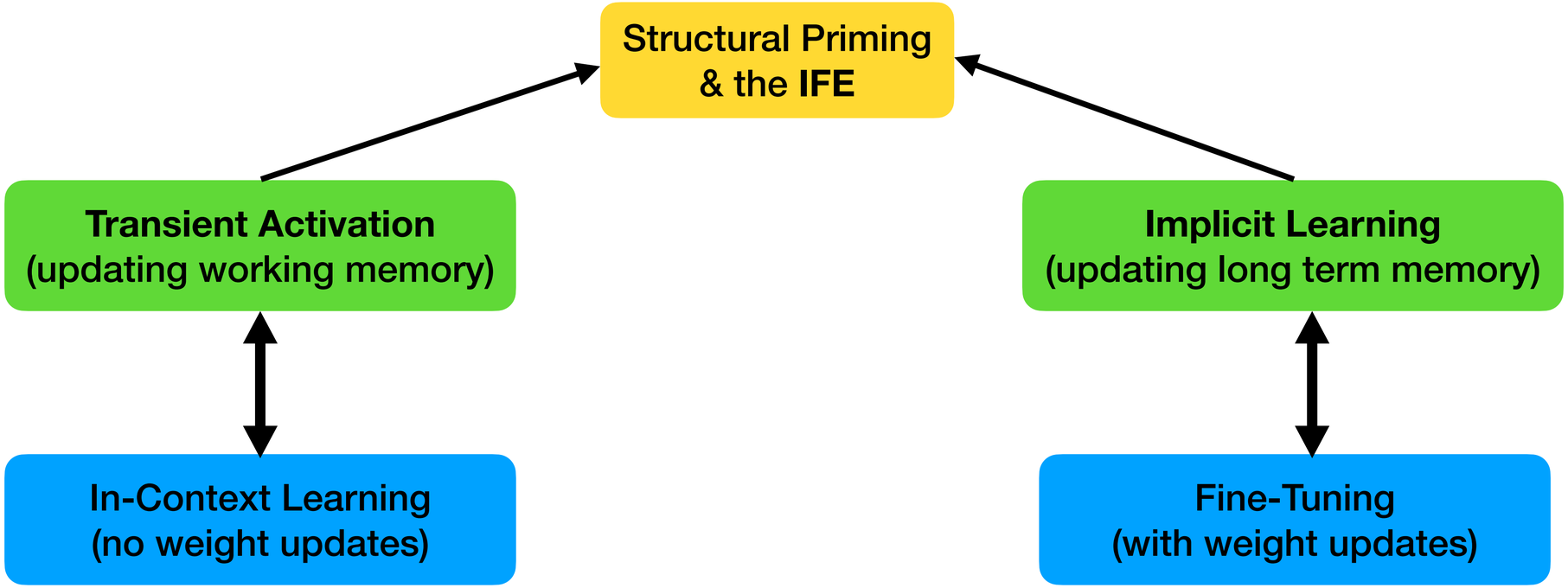






Larger models show more significant inverse frequency effects!

Takeaways from inverse frequency



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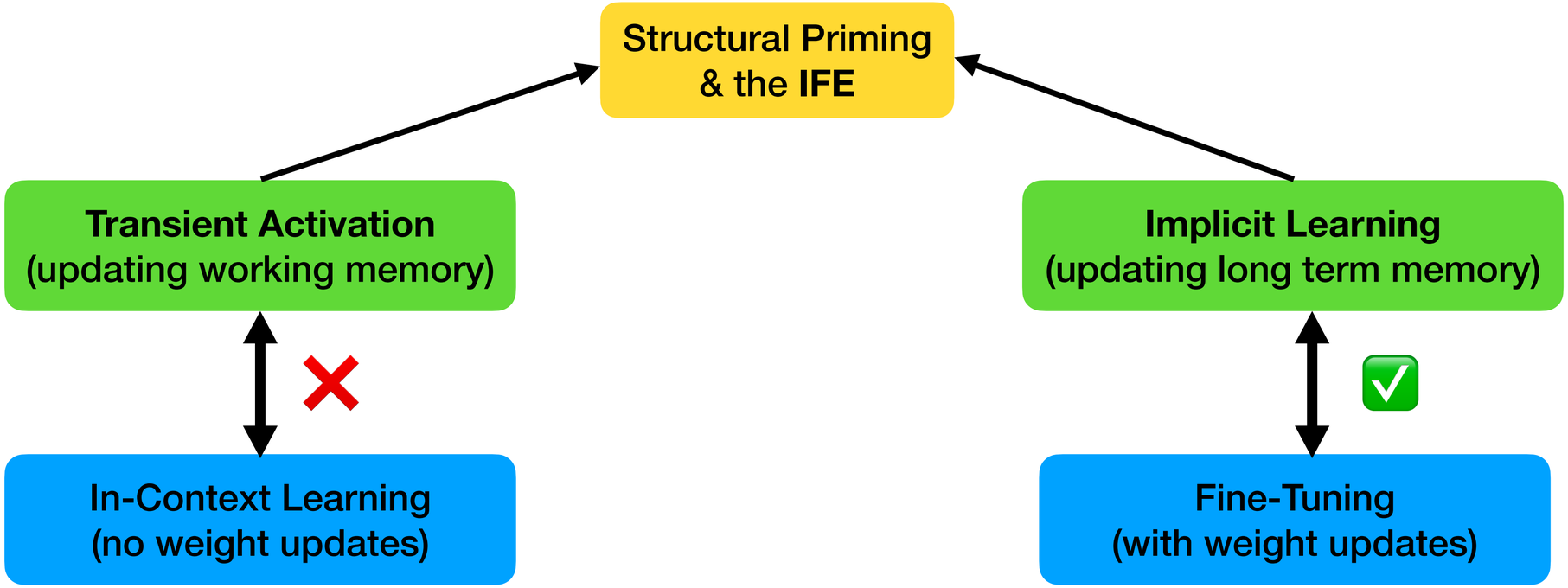

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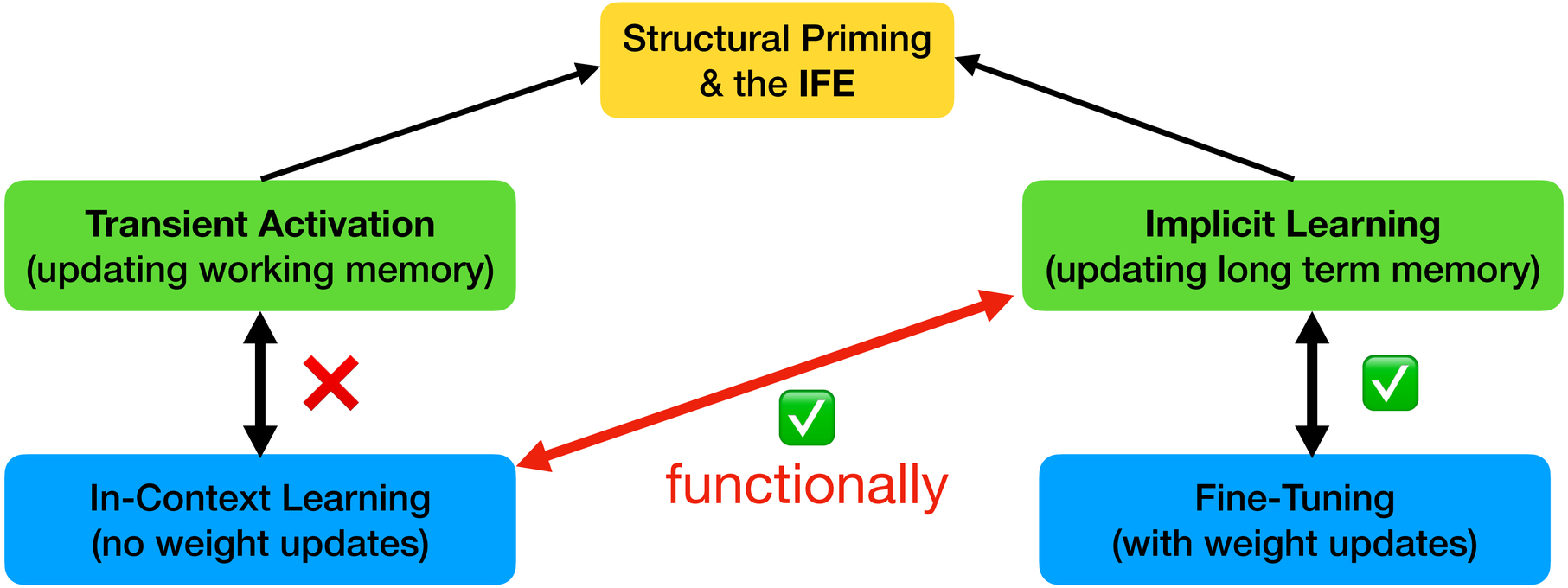

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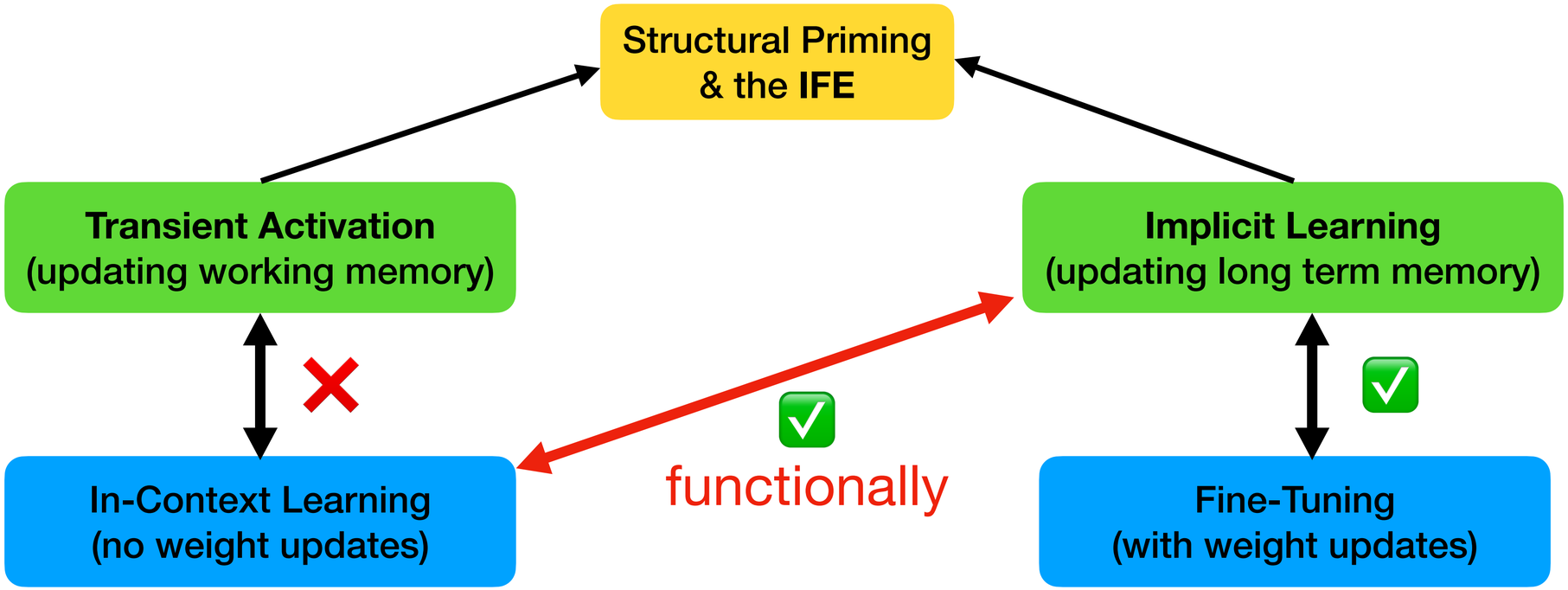


We used the IFE as a diagnostic on the error-driven nature of ICL as a processing / adaptation mechanism in LLMs.

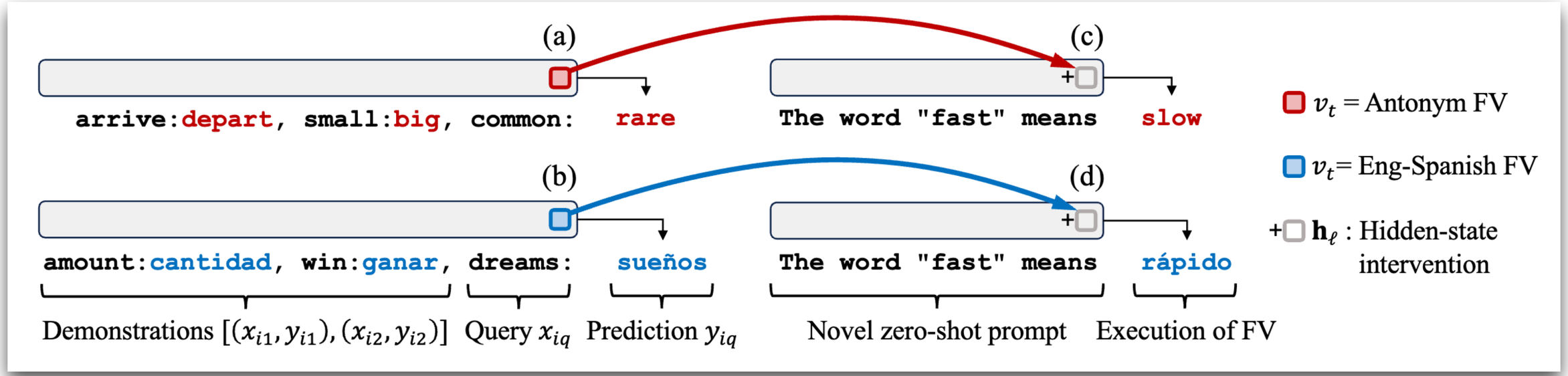
Experiment 2: Mechanistic Analysis

Research Questions:

- How to further characterize the generalized “ICL ≈ Priming” claim?
- How could we causally verify the involvement of verb bias?

ICL leads to Function Vectors

Function vectors: compressed vector representation of the task in context;



[e.g., Todd et al. 2024; Hendel et al. 2023]

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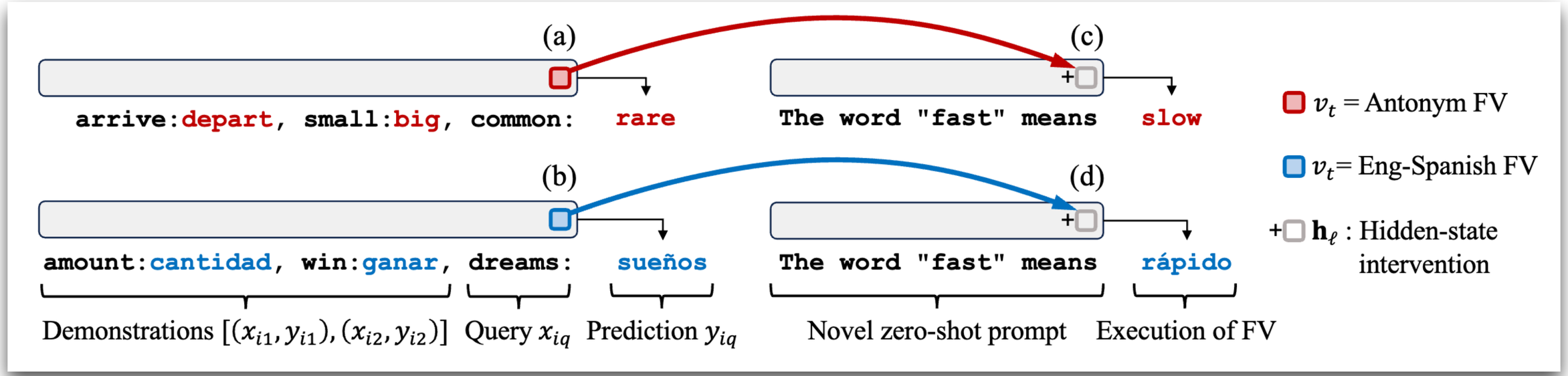

Extract mean activations at the query position after context

[e.g., Todd et al. 2024; Hendel et al. 2023]

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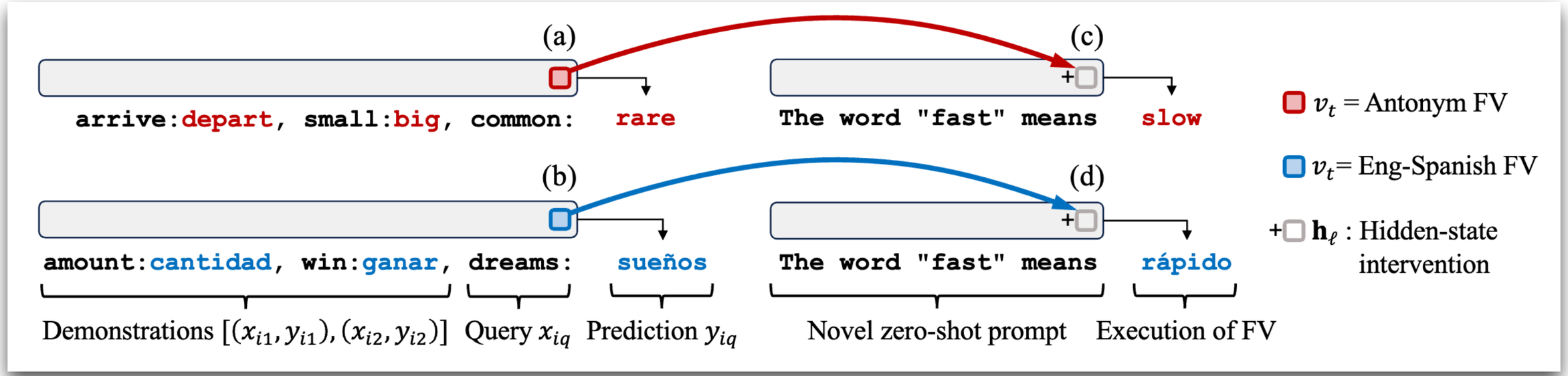

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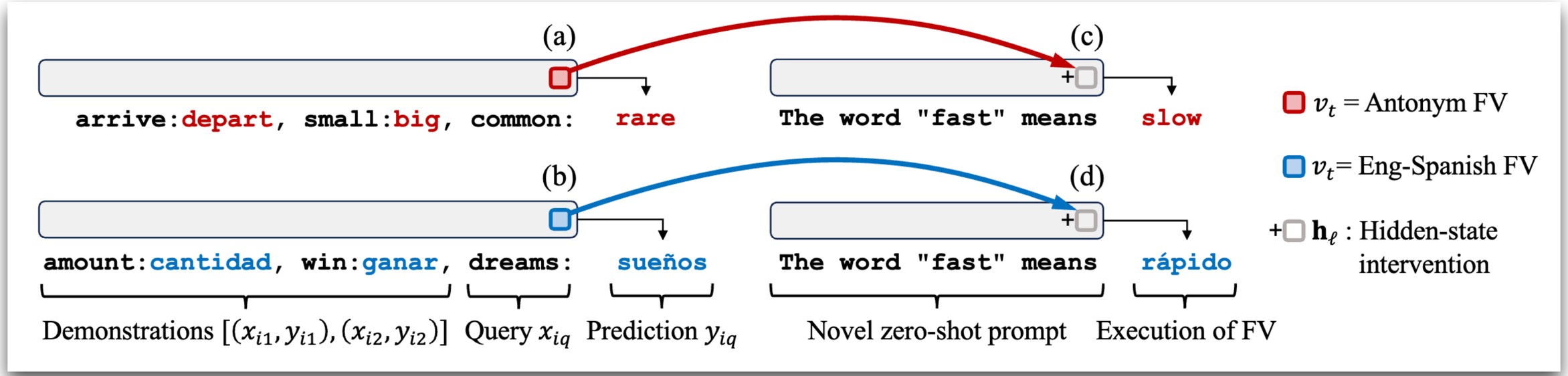
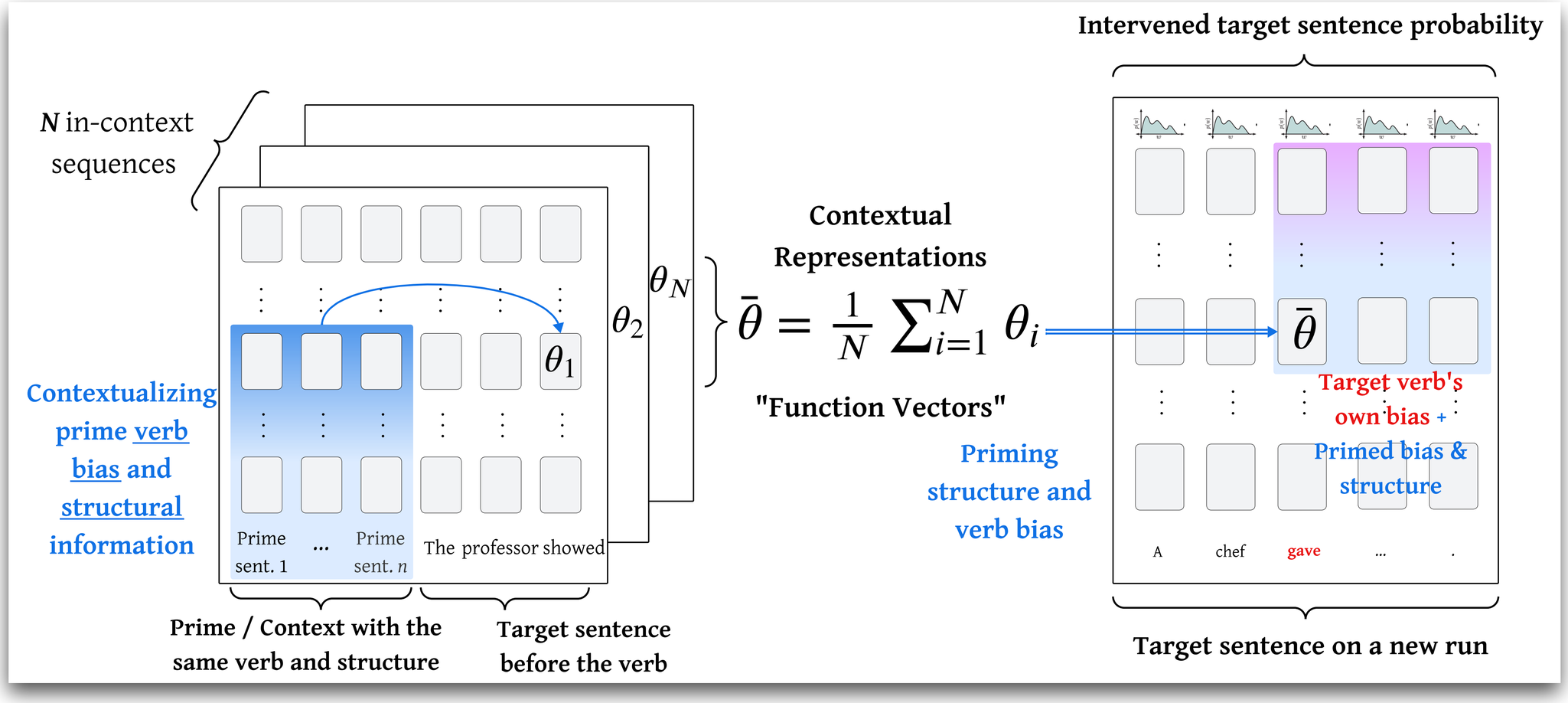


Extract mean activations at the query position after context → Injecting this vector in a new inference run (zero-shot) → Steering model production towards the task

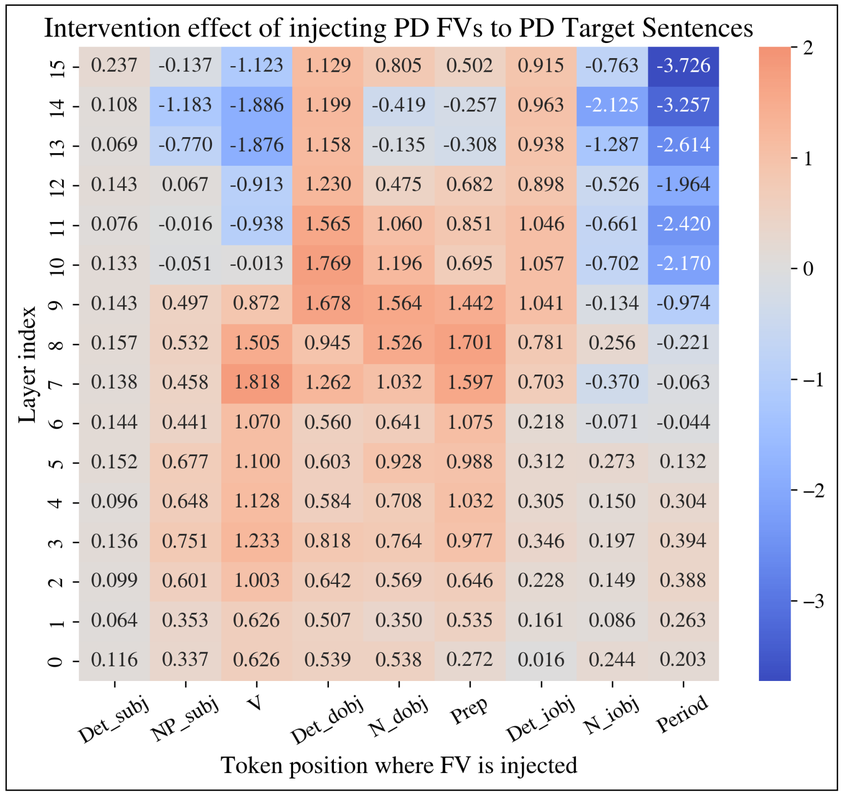
[e.g., Todd et al. 2024; Hendel et al. 2023]

Structural Priming with Function Vectors



* we also did a version where function vectors are the mean of the most influential attention heads' output activations (Todd et al. 2024), leading to similar results.

Structural Priming with Function Vectors



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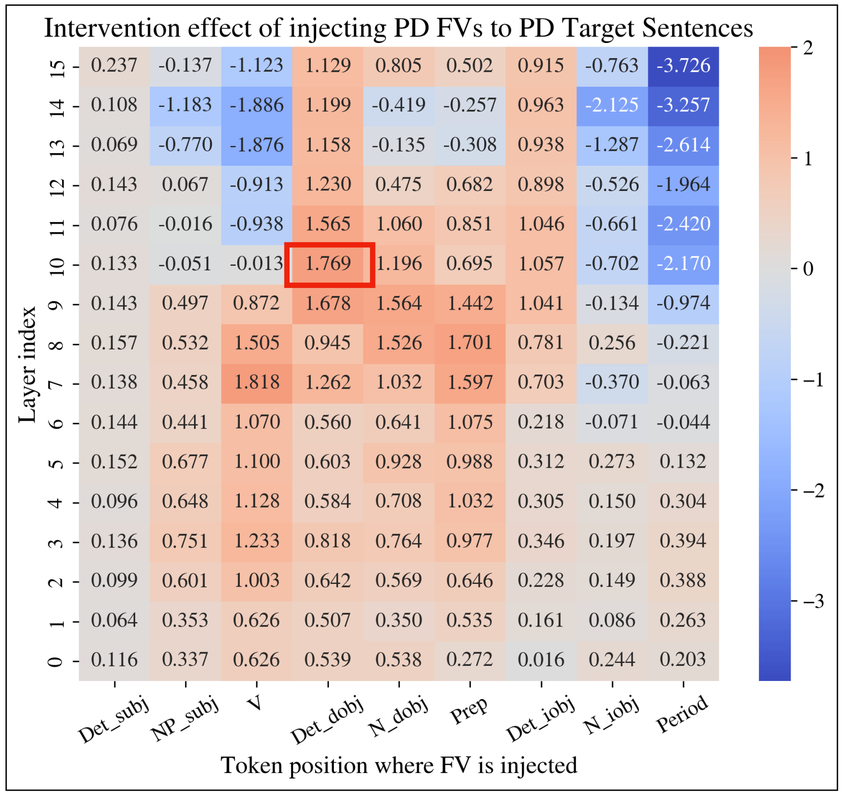

- Observing the priming effect: FVs increased target sentence probability;

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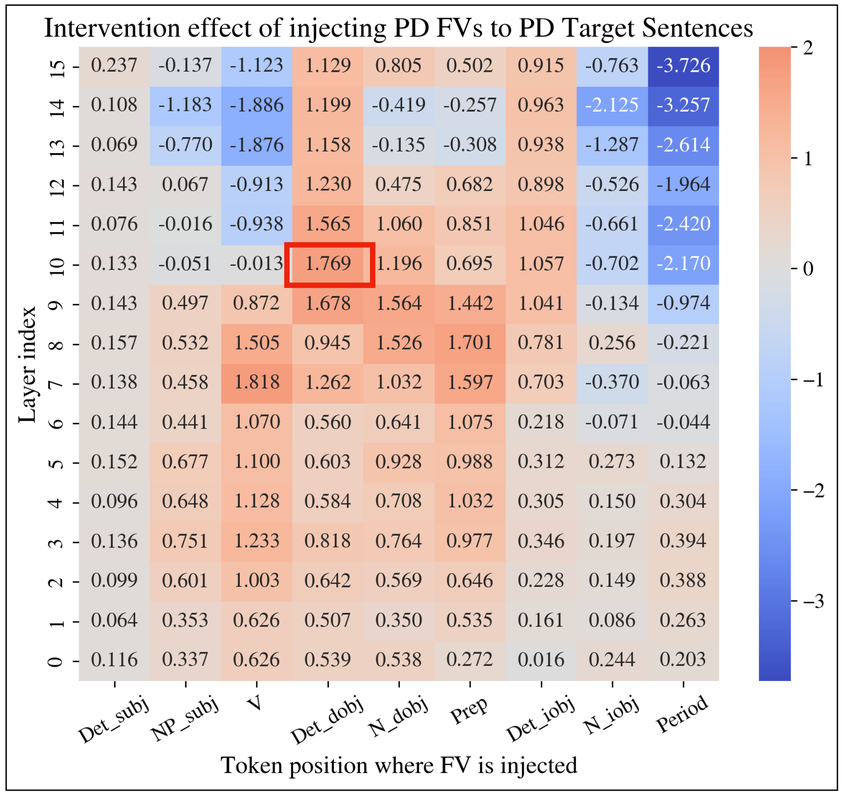

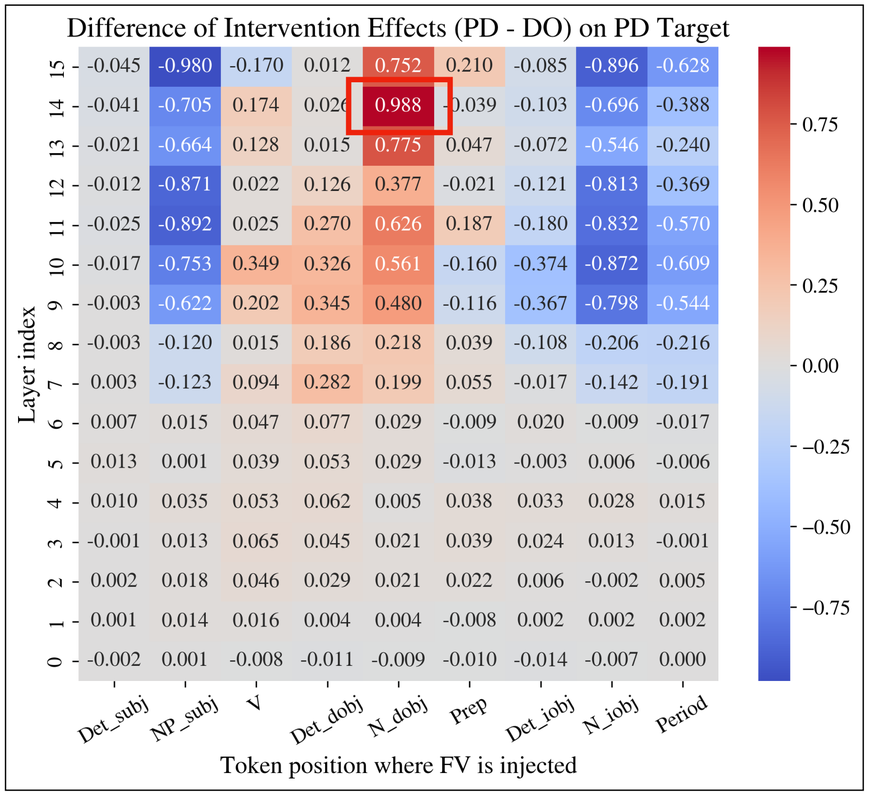

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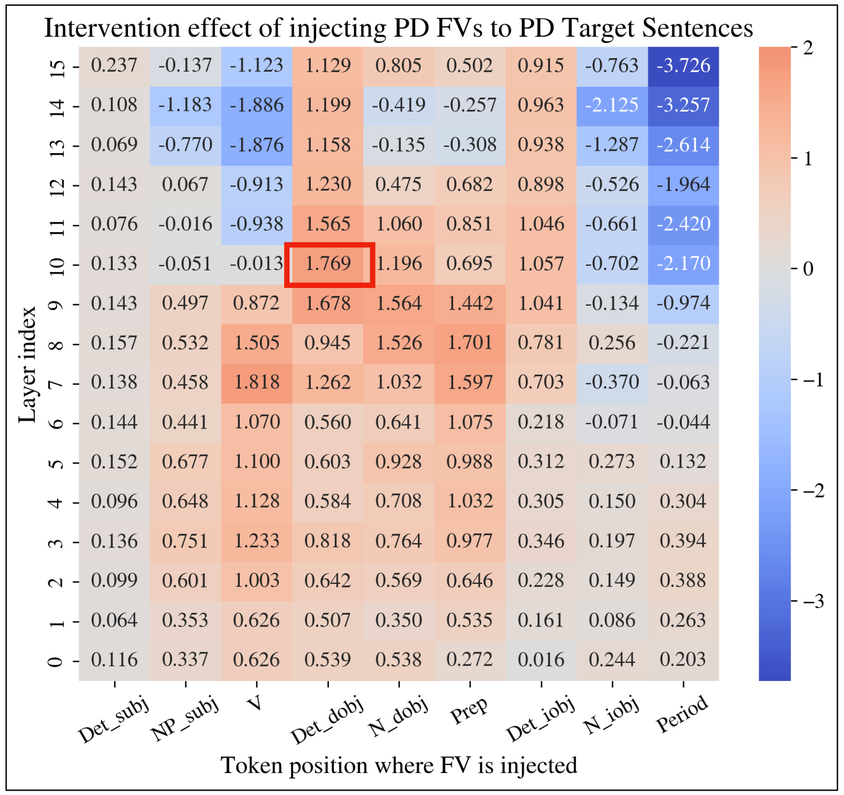

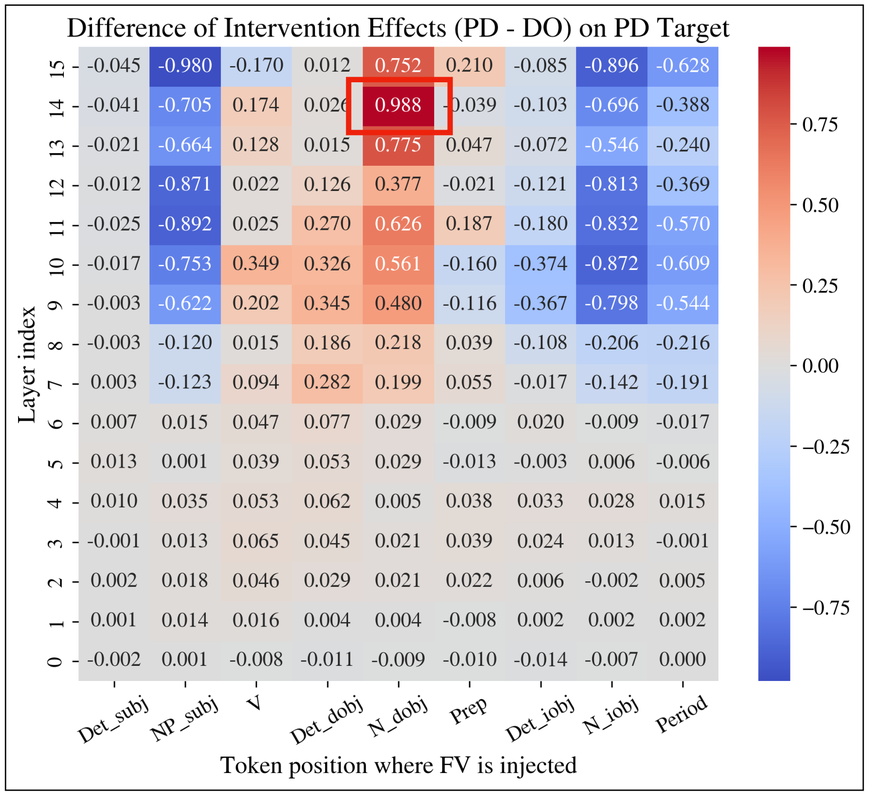

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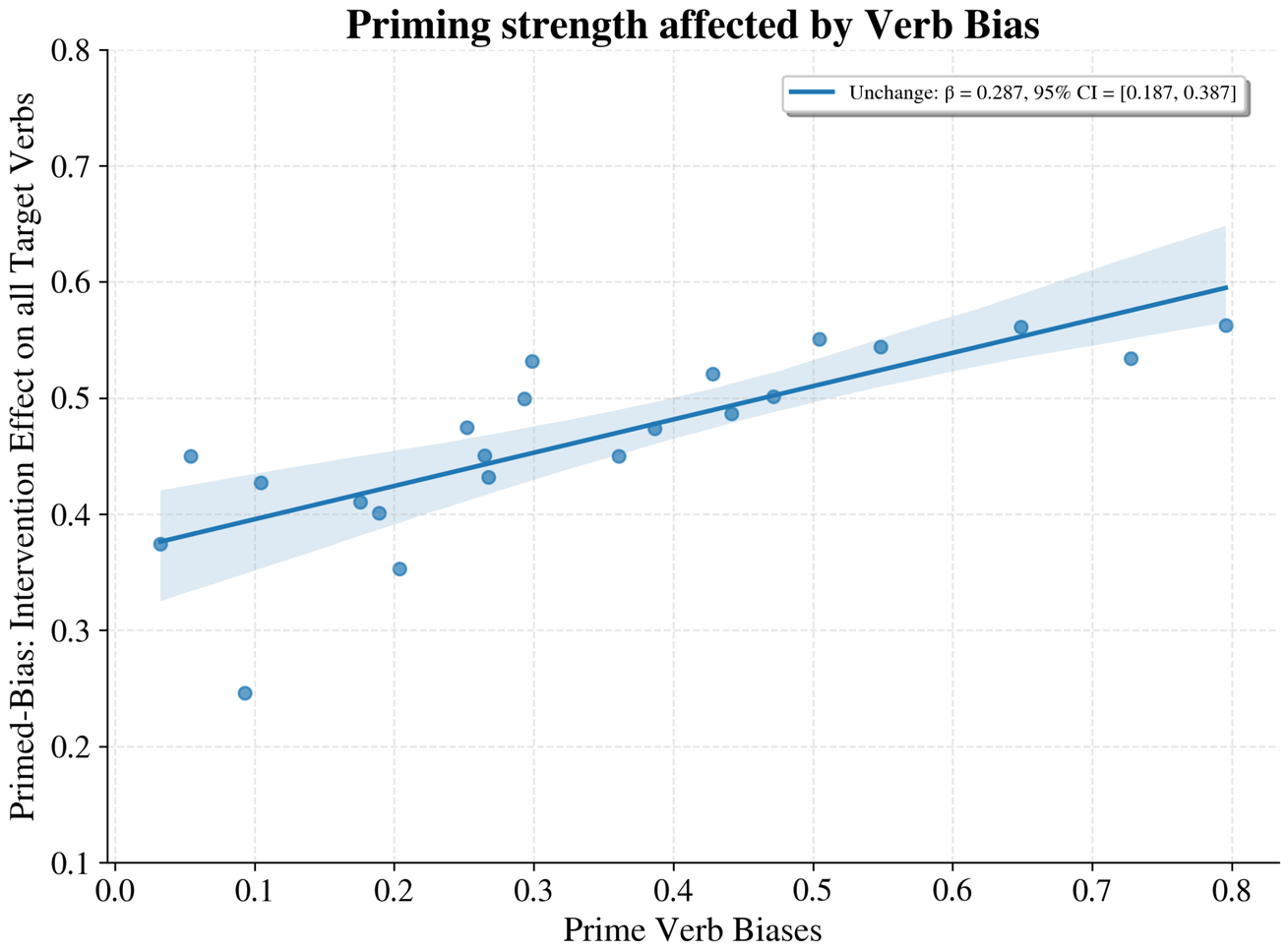
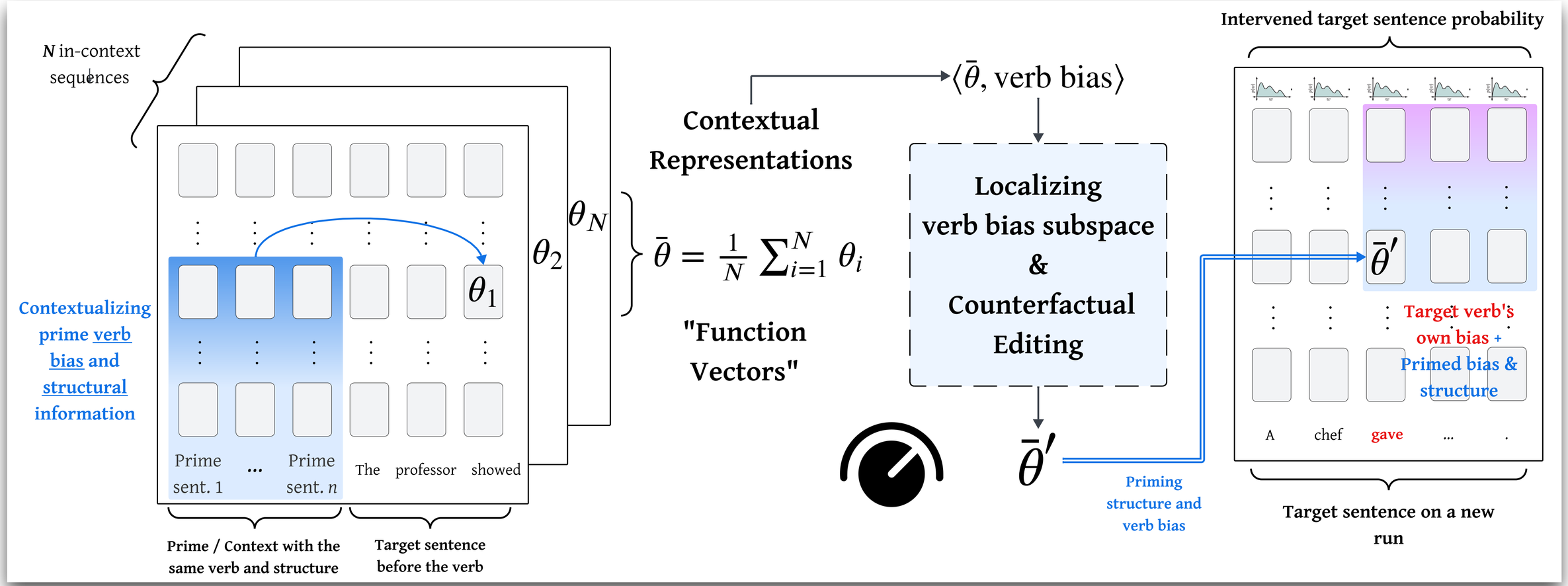
Yes, we do observe standard priming effect.

Structural Priming with Function Vectors



However, no IFE is observed…!

Causal Role of Verb Bias in Function Vectors?



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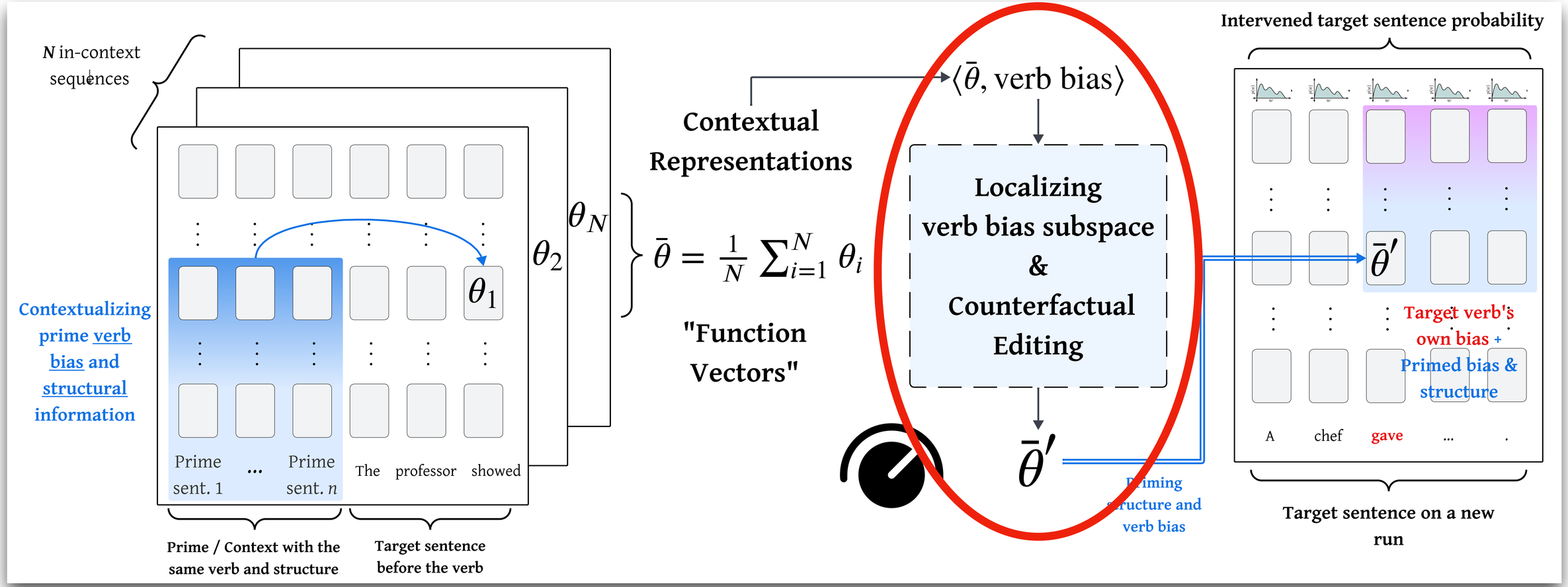
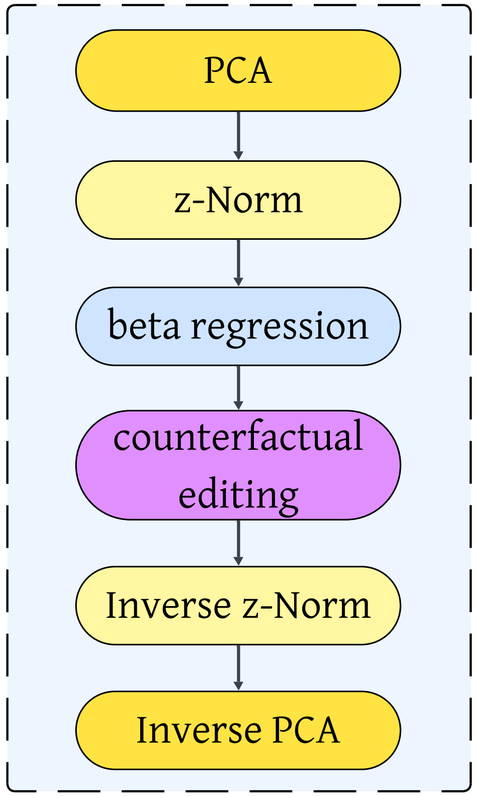
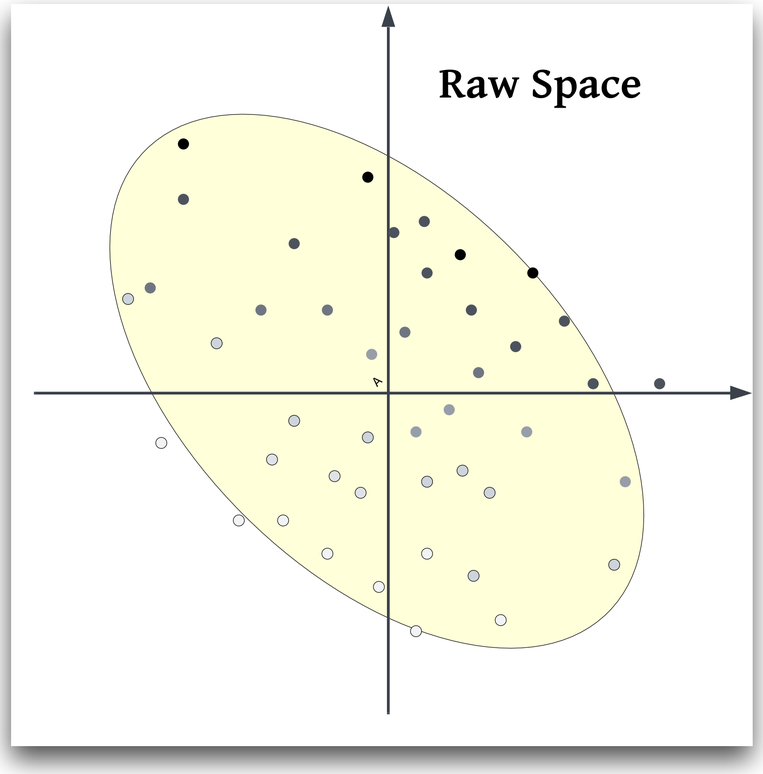


A Method for Continuous Variable Intervention





[For binary/discrete variable intervention, see Ravfogel et al. 2021, Hao & Linzen 2023, Ozaki et al. 2025]

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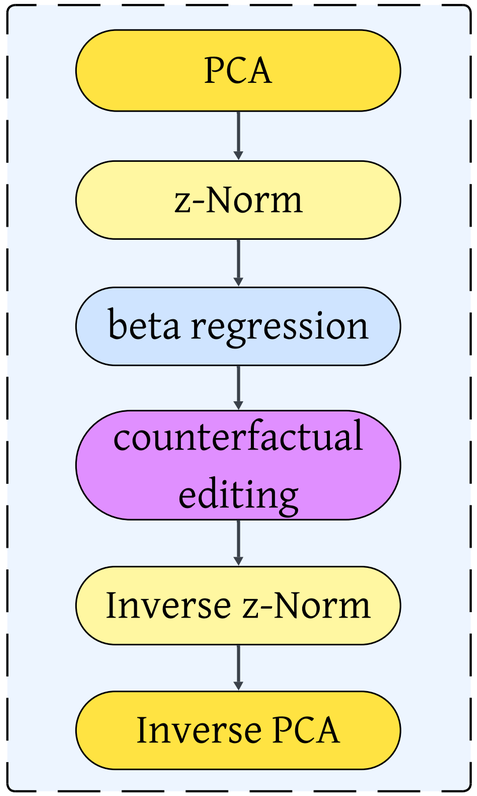

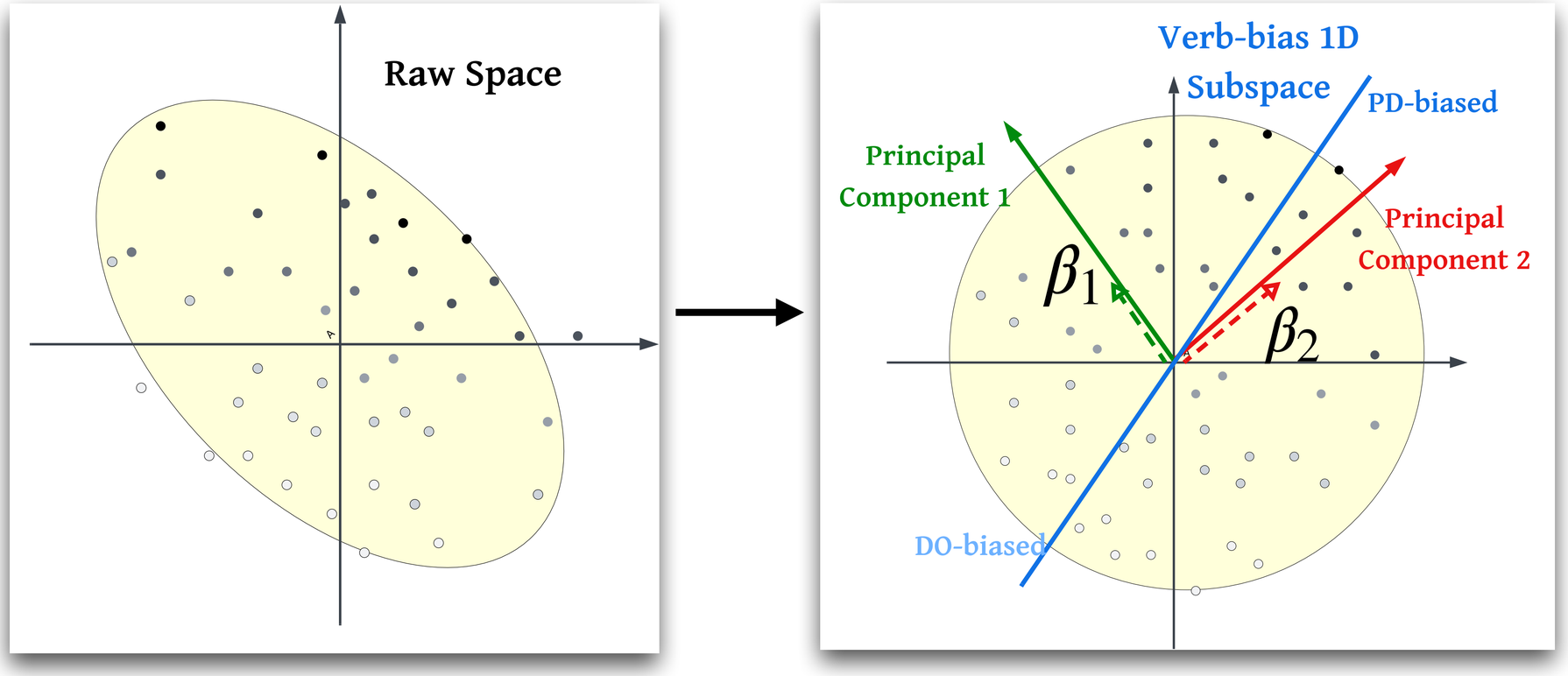

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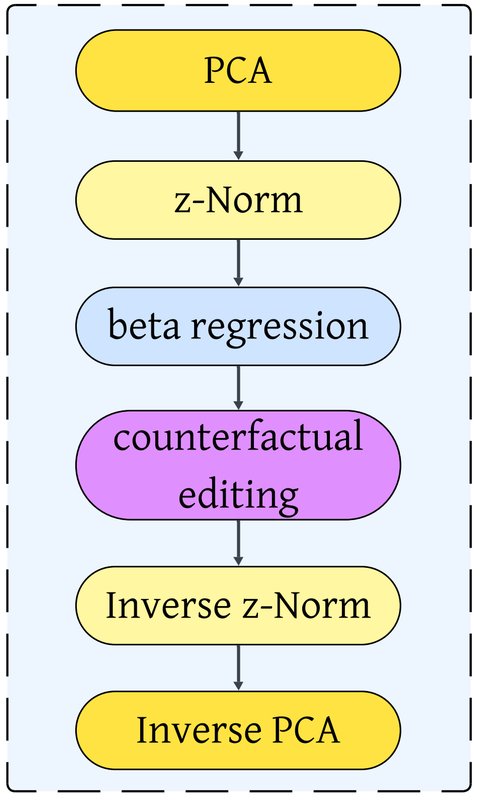

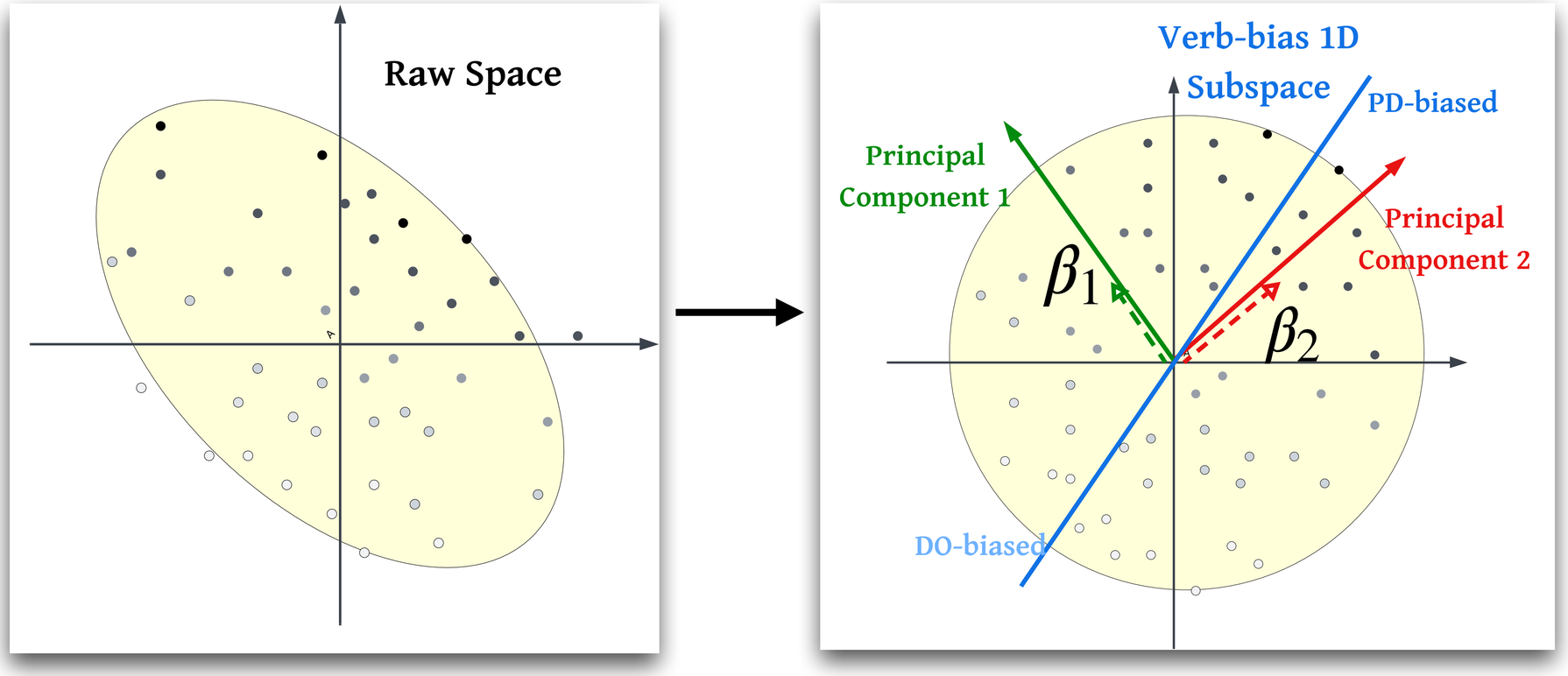

Localizing a 1-dimensional space that encodes verb bias information

[For binary/discrete variable intervention, see Ravfogel et al. 2021, Hao & Linzen 2023, Ozaki et al. 2025]

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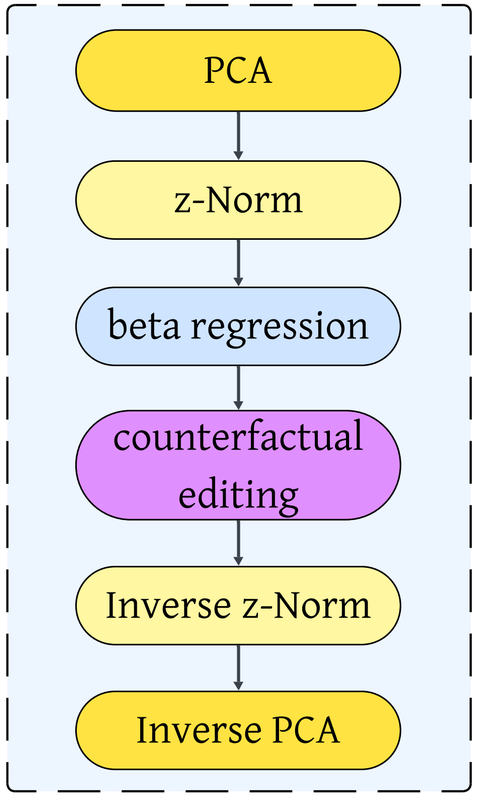

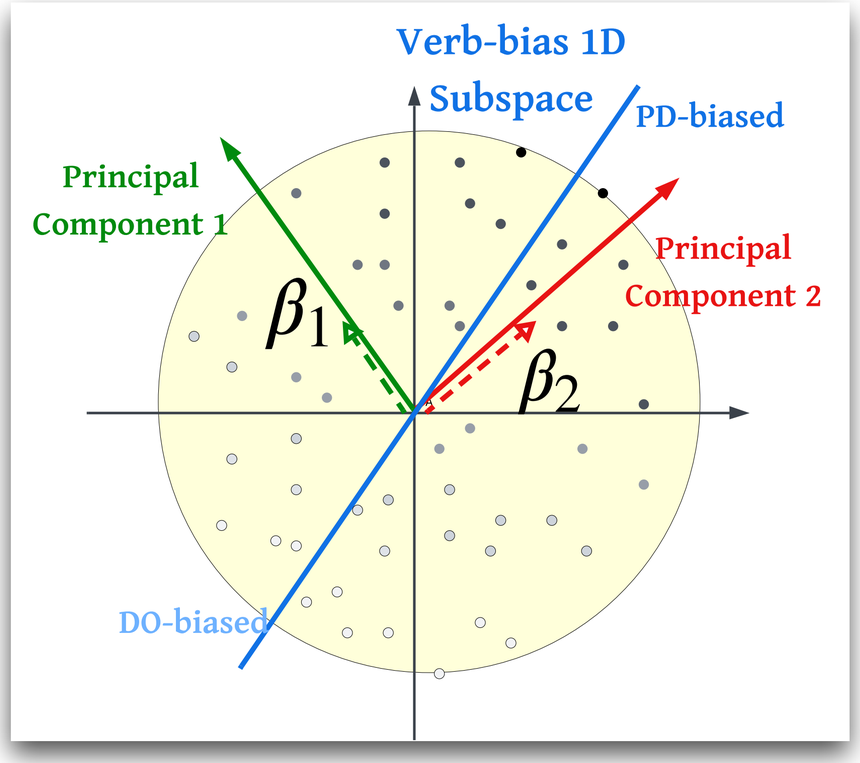

[For a close-formed solution for concept erasing, see Belrose et al. 2023, LEACE]

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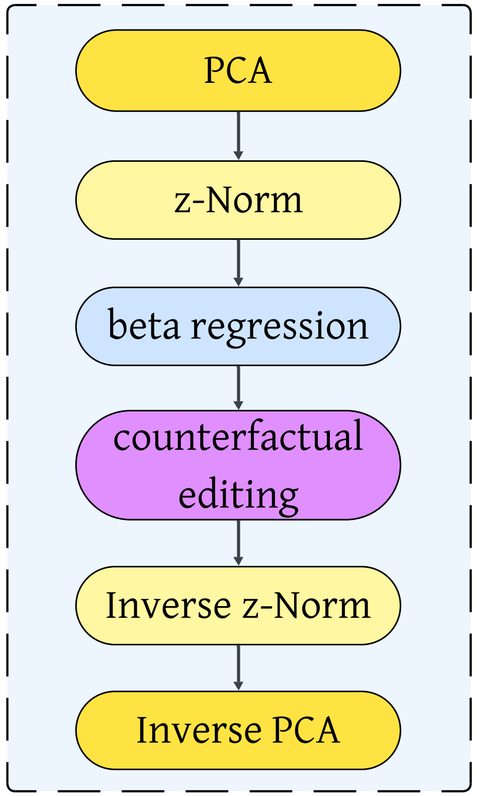

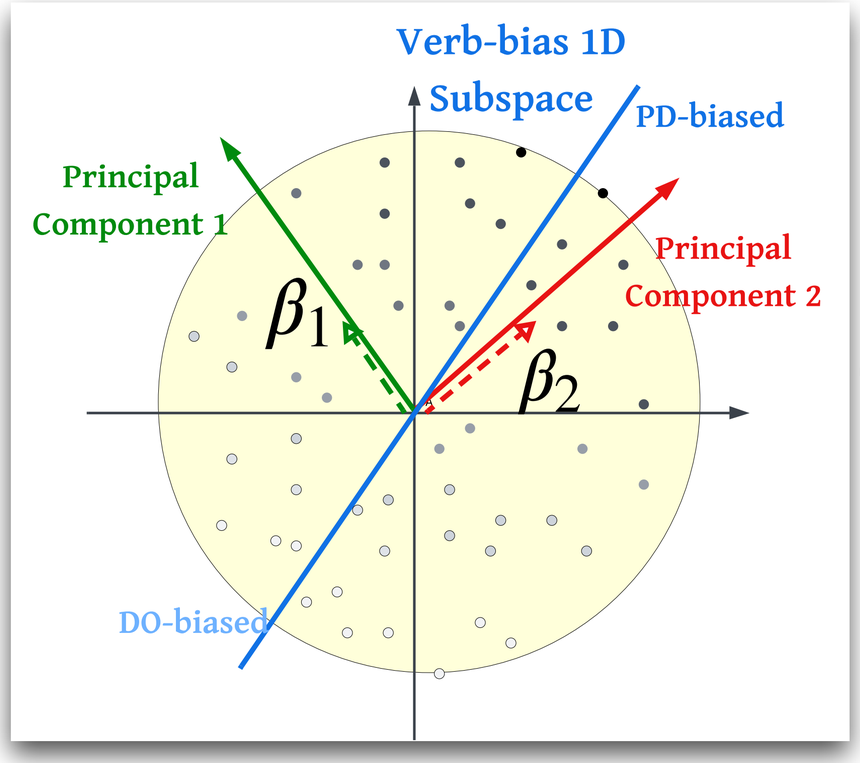

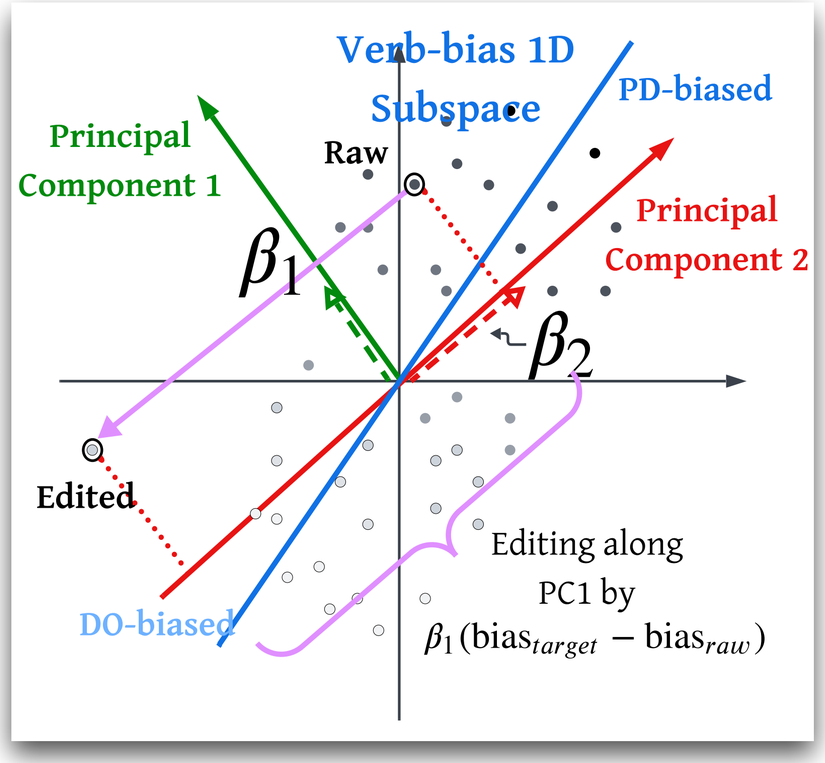

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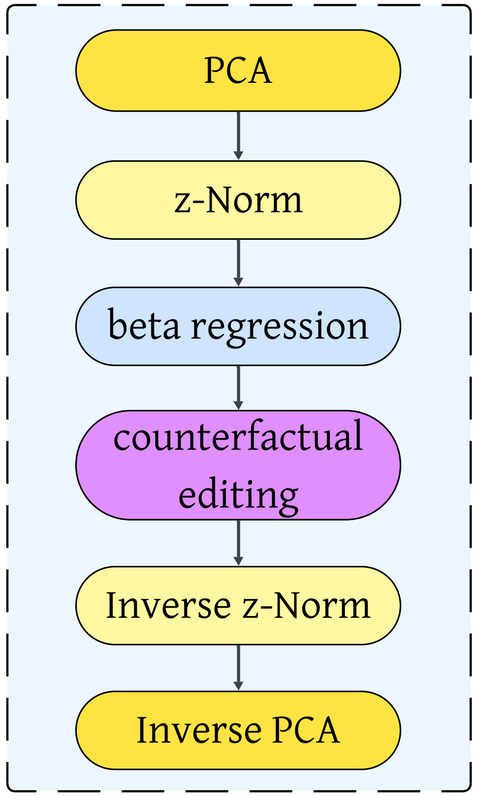

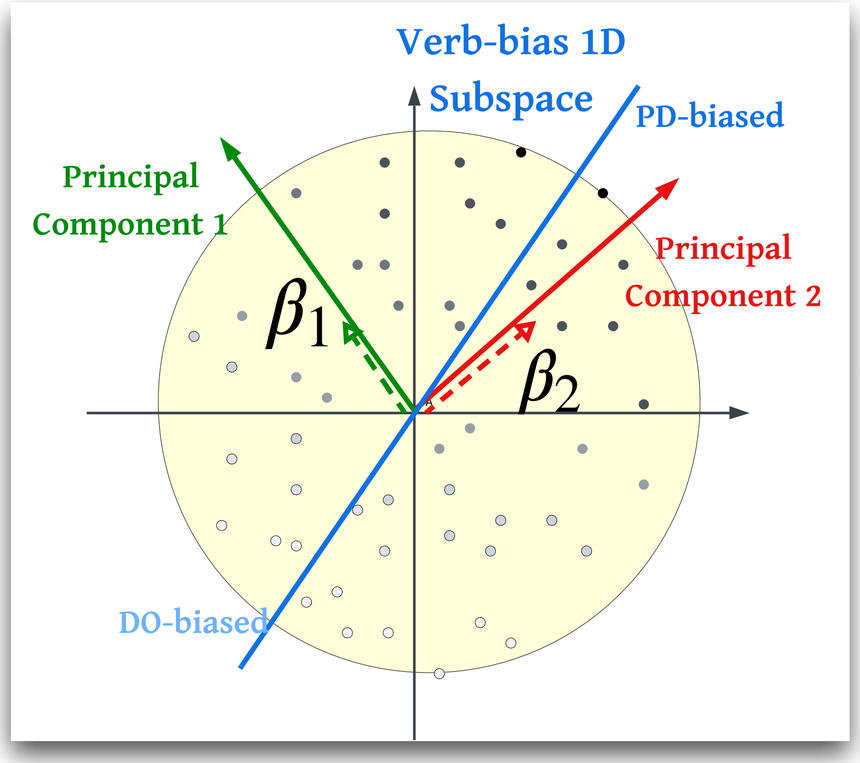

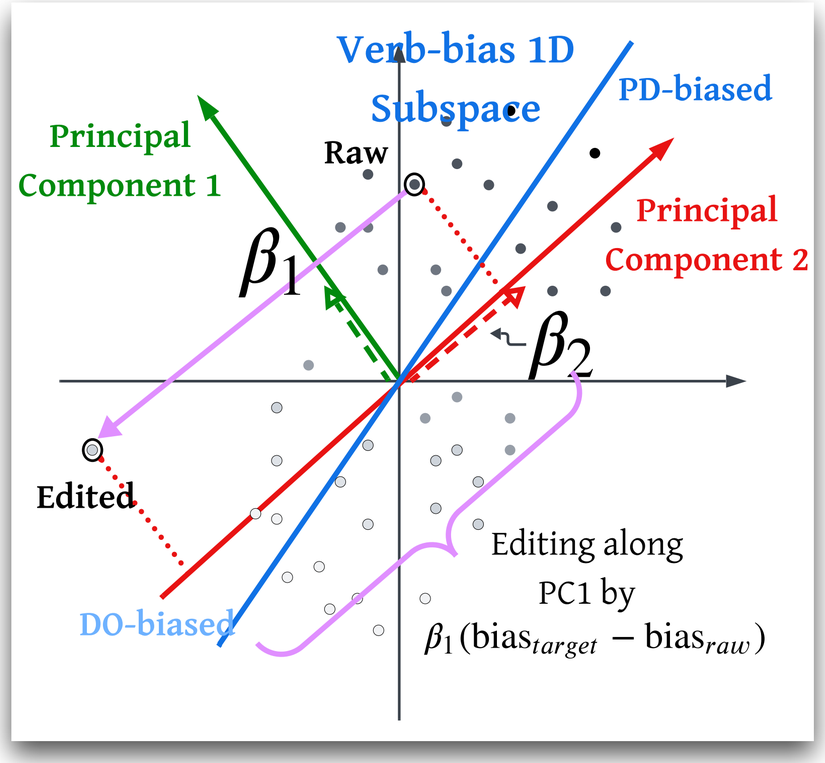

Causally manipulate the verb bias values without changing other information.

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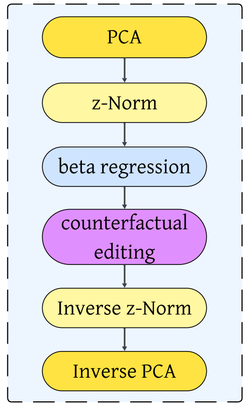
Causal Verification



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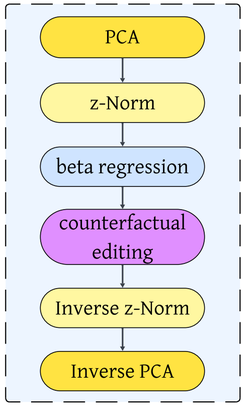

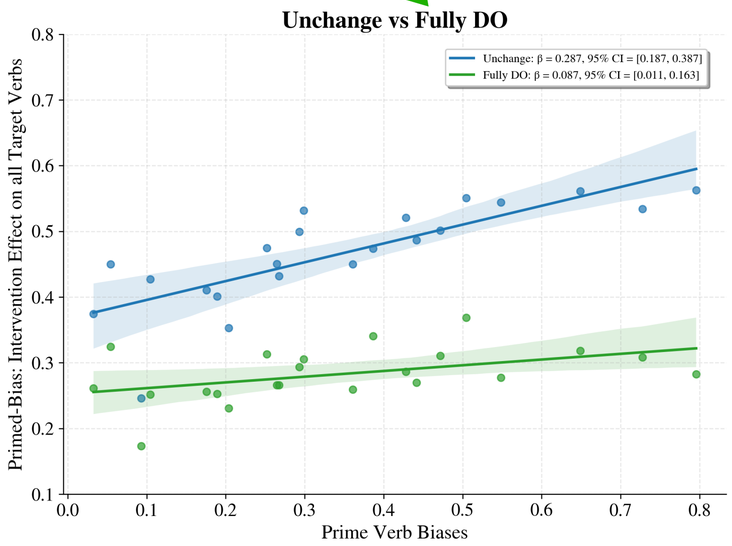

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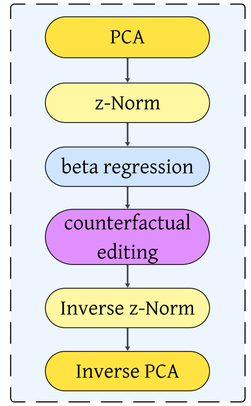

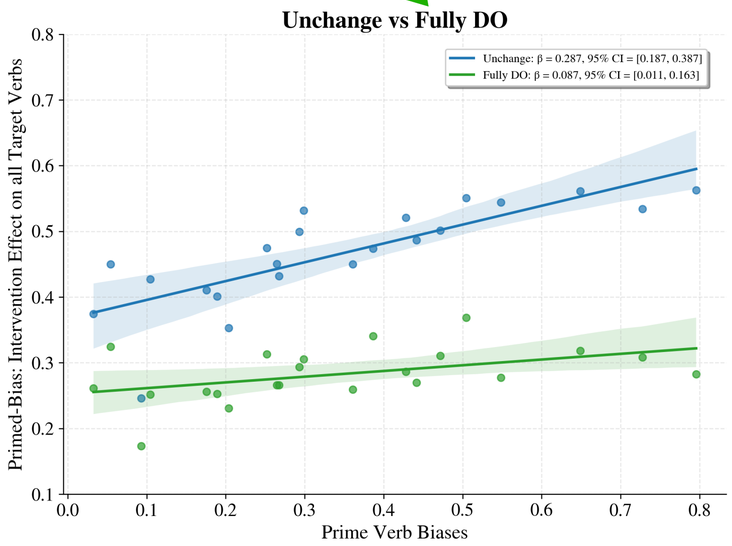

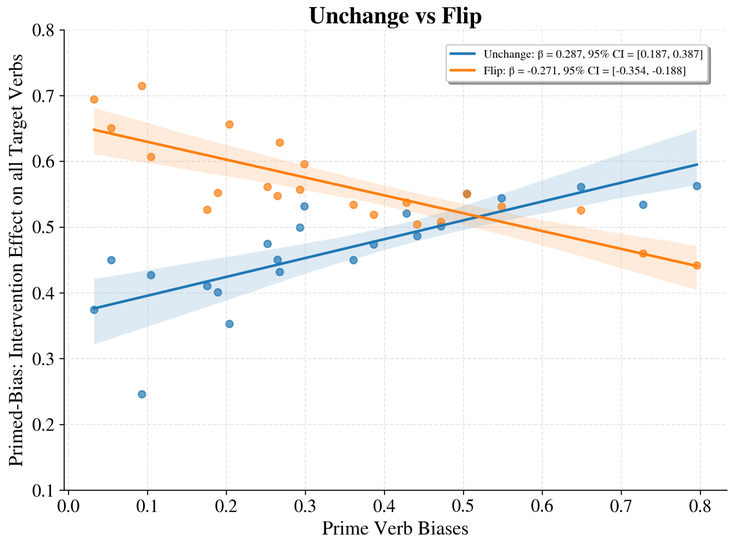

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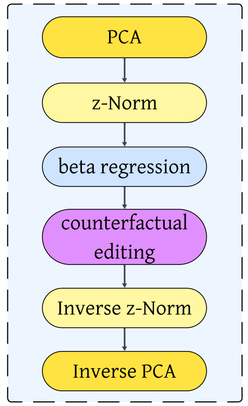

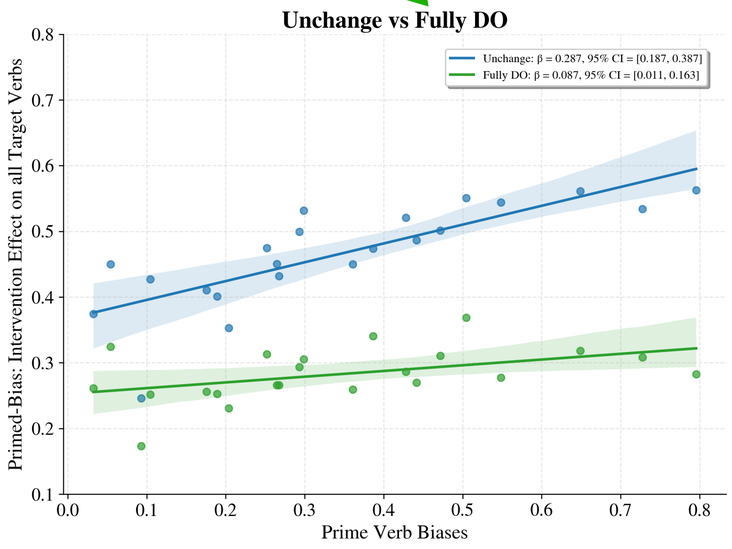

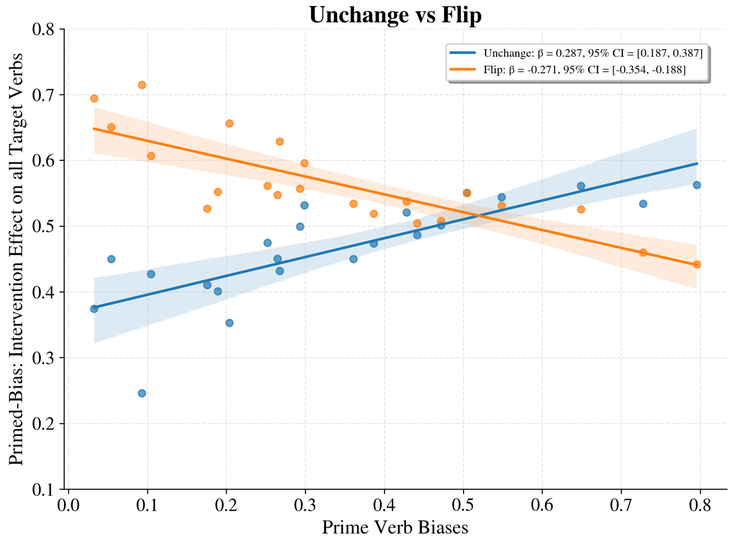

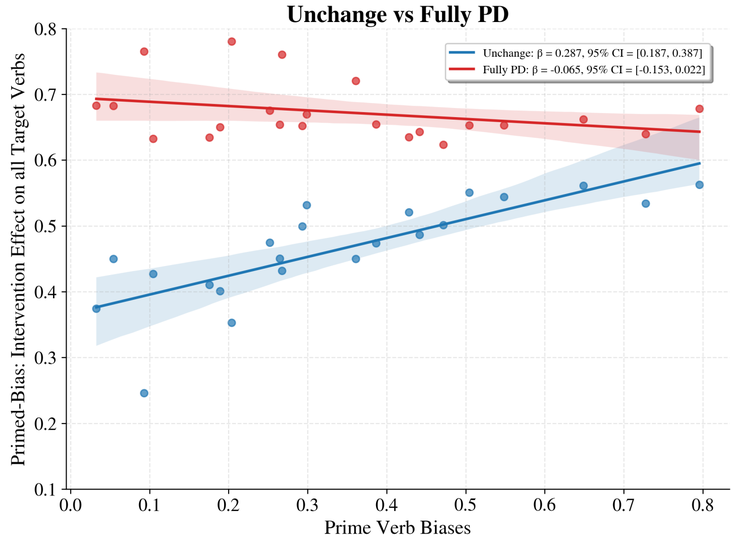

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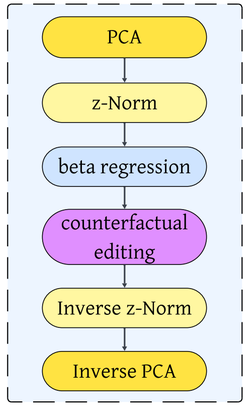

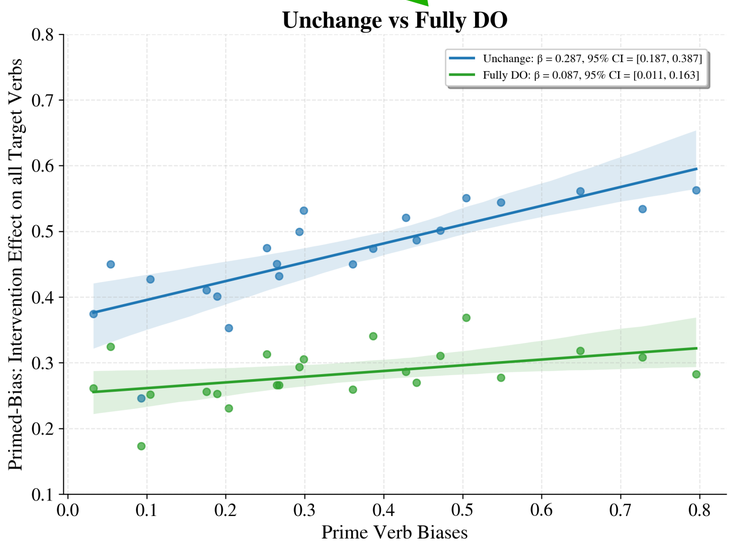

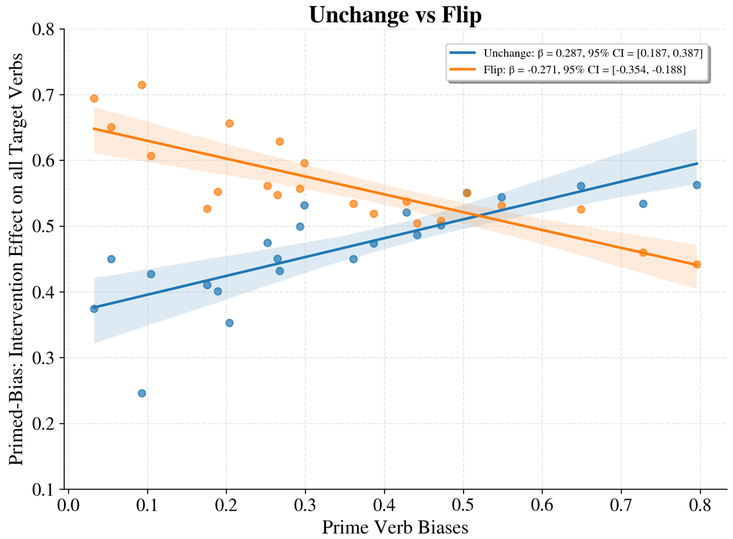

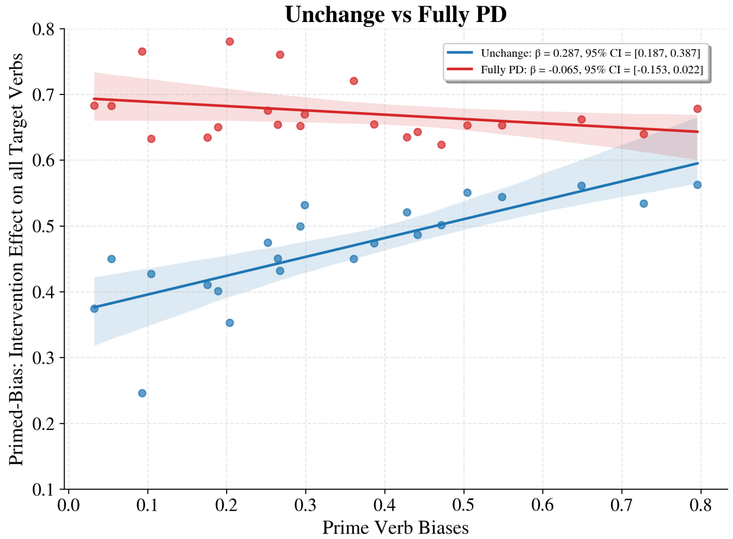

We showed that manipulating the verb biases causes predicted changes in the priming strength;

⇒ The verb bias representation is causally involved in LLM's structural prediction!

Takeaways from Function Vector Studies

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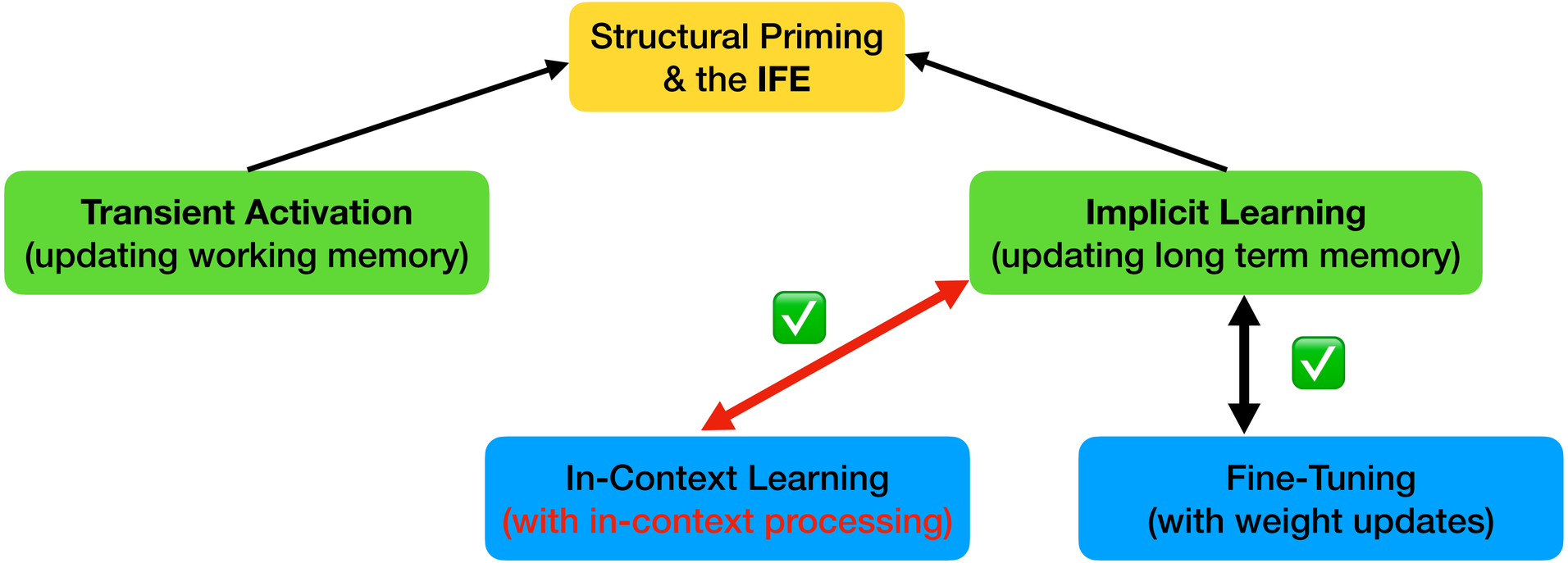
  - **Editing verb bias causally produces predicted effect on verb-specific priming magnitude;**
- However… function vector cannot be the whole story of ICL because:
  - **We see no IFE with the function vector induced priming effect;**
  - **What is the crucial ingredient about IFE that function vectors are missing?**

Revisiting the big picture so far



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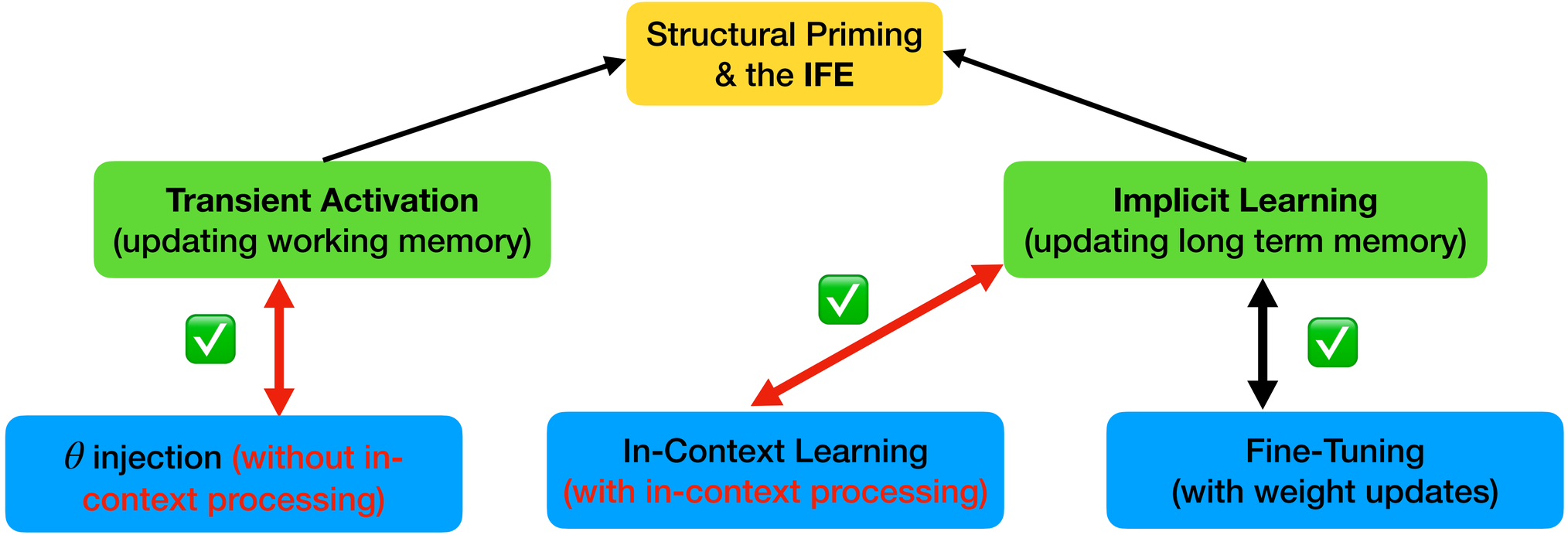

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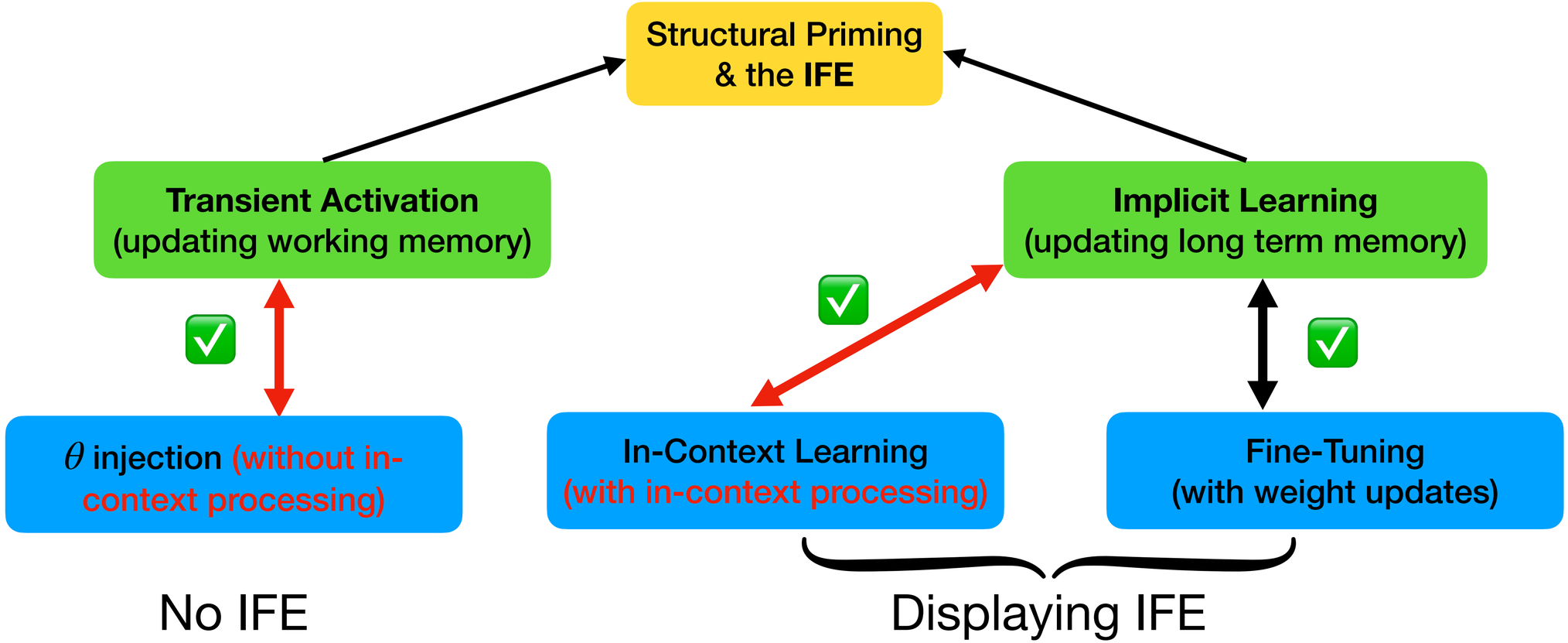

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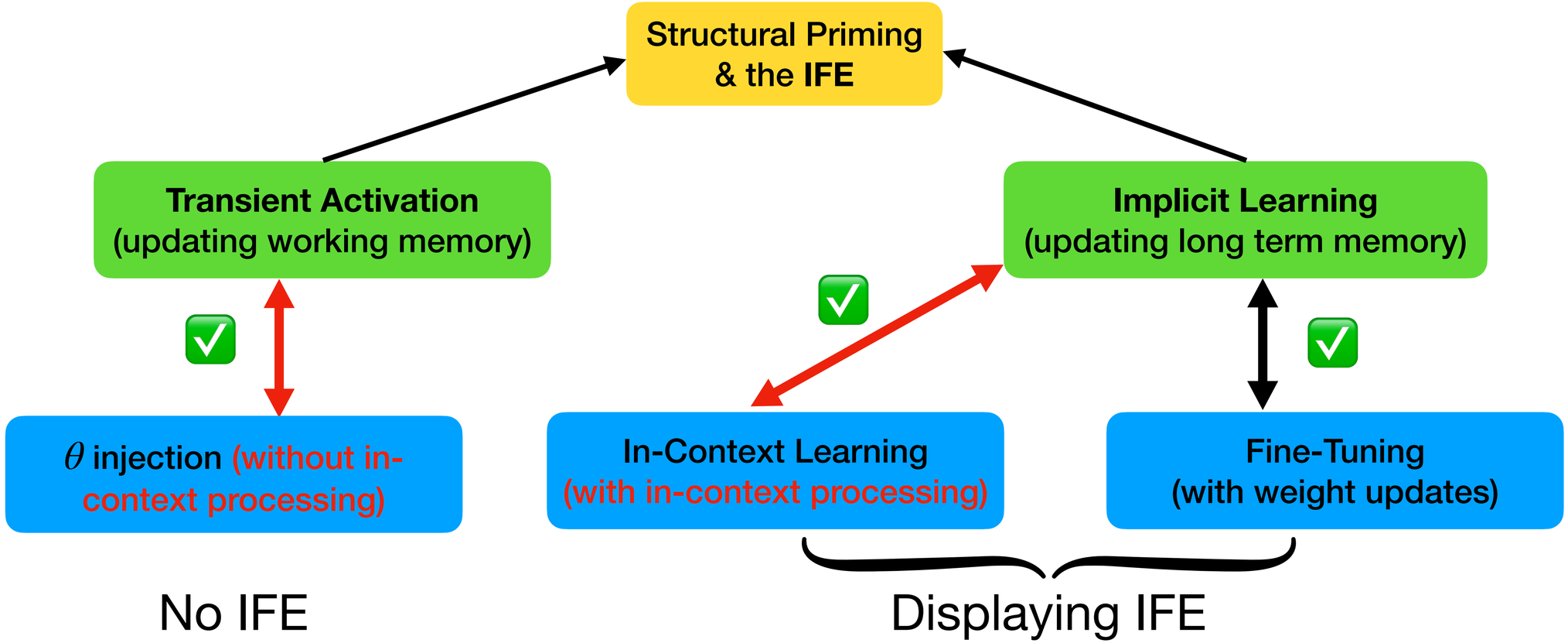

Function vectors do not capture the crucial error signal for LLMs to adapt to context, making it resembling transient activation instead of implicit learning!

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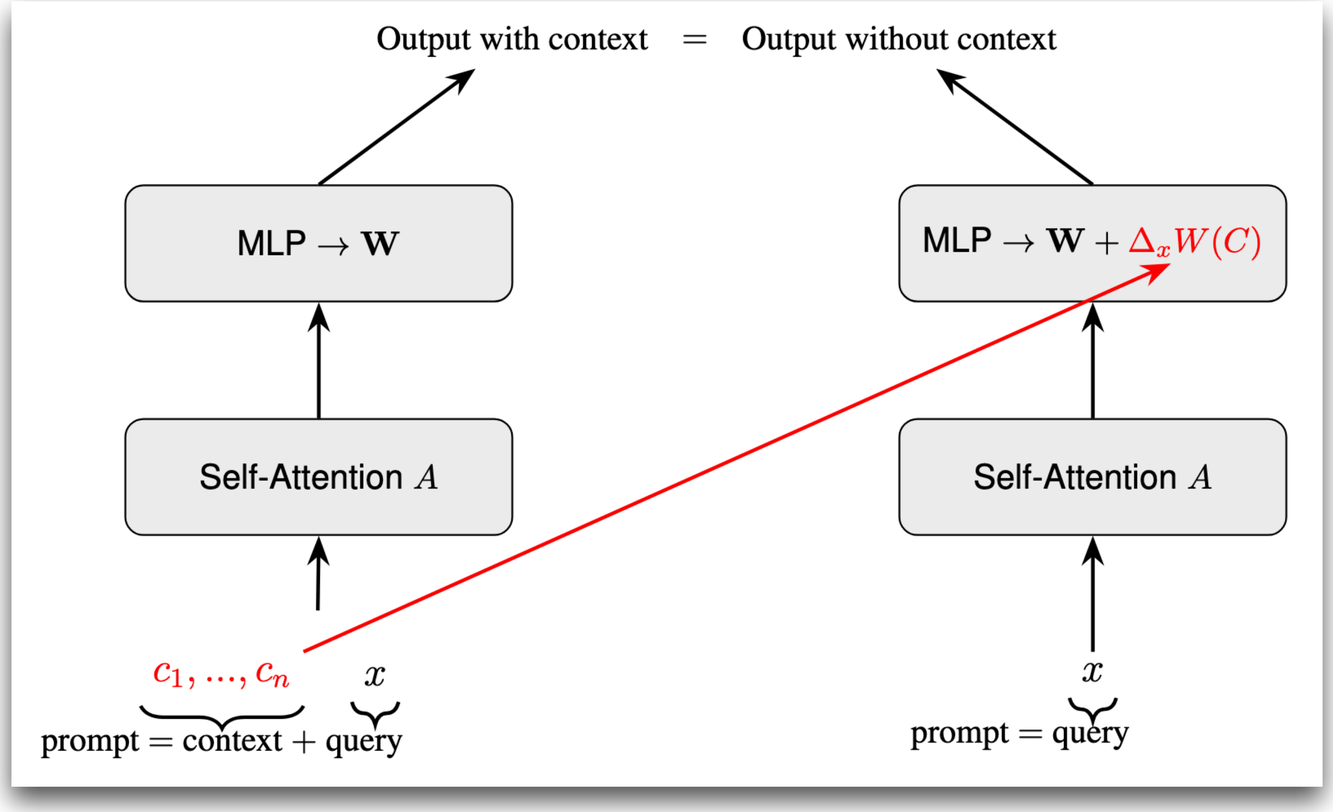
- Function vectors only captures the “static” part of ICL — this compression of context is indeed lossy.

Open Questions



Learning without training:
The implicit dynamics of in-context learning

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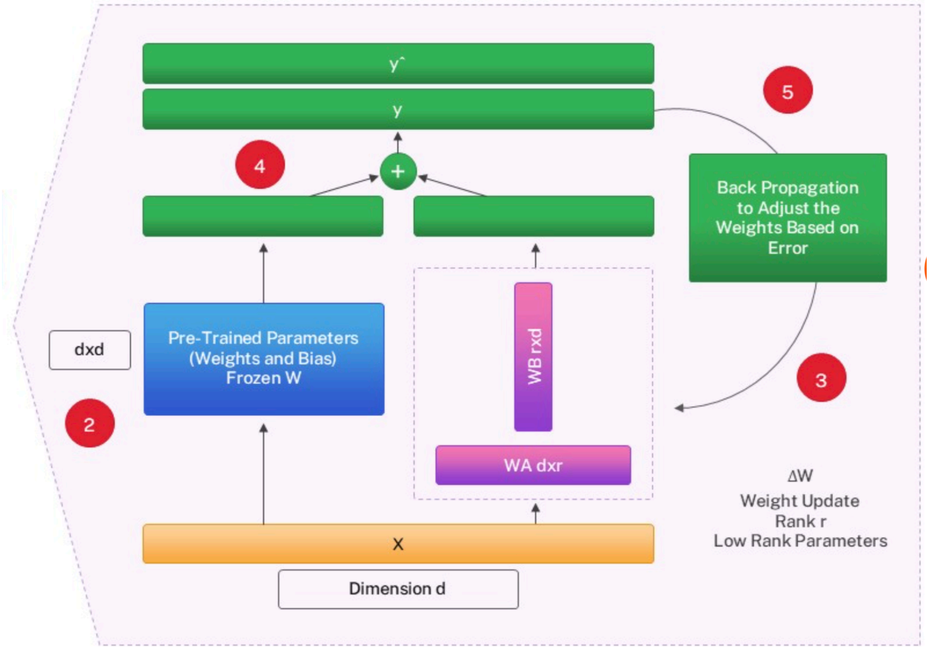
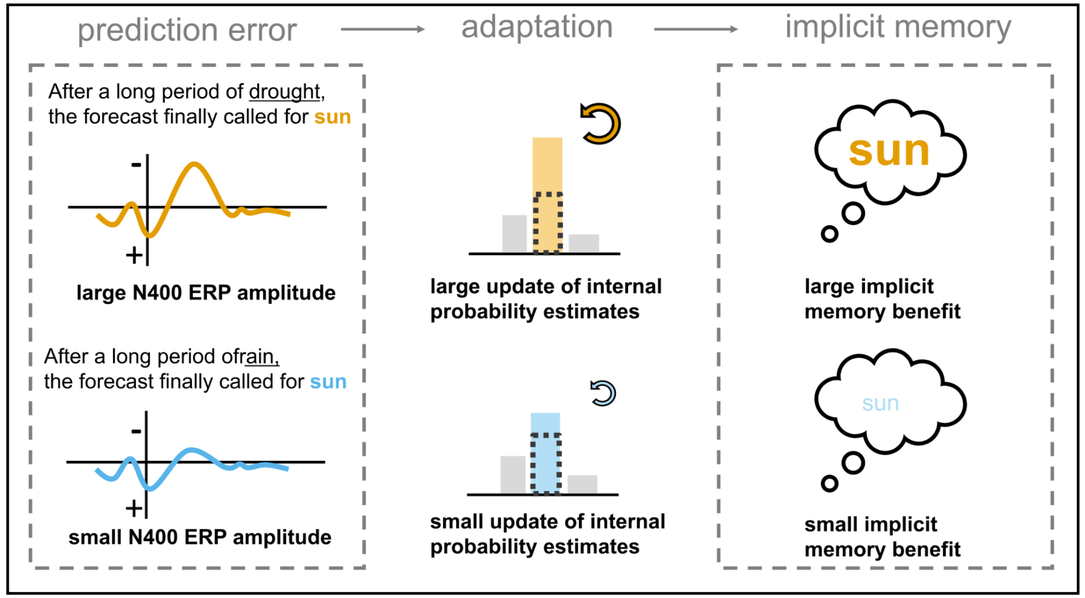


Latest progress: contextual influence as implicit low-rank update on MLP weights?

Open Questions: N400 as error signal?



Open Questions: N400 as error signal?

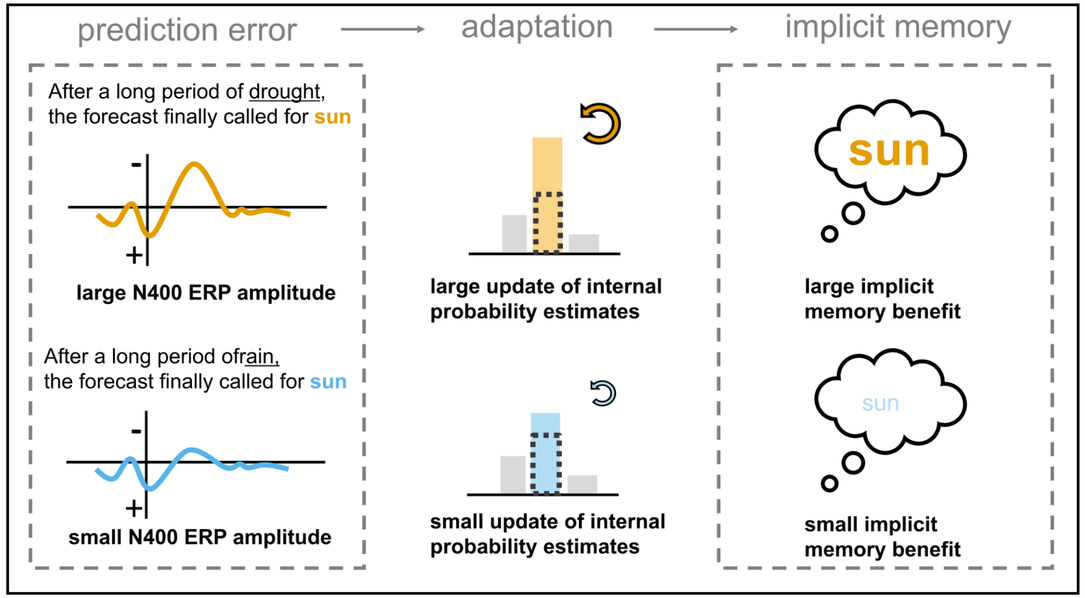
SPECIAL ISSUE:
Cognitive Computational Neuroscience of Language

Strong Prediction: Language Model Surprisal Explains Multiple N400 Effects

James A. Michaelov[1], Megan D. Bardolph[1], Cyma K. Van Petten[2], Benjamin K. Bergen[1], and Seana Coulson[1]

[1]Department of Cognitive Science, University of California, San Diego, La Jolla, CA, USA
[2]Department of Psychology, Binghamton University, State University of New York, Binghamton, NY, USA

Keywords: distributional semantics, ERPs, N400, neural language models, predictive coding



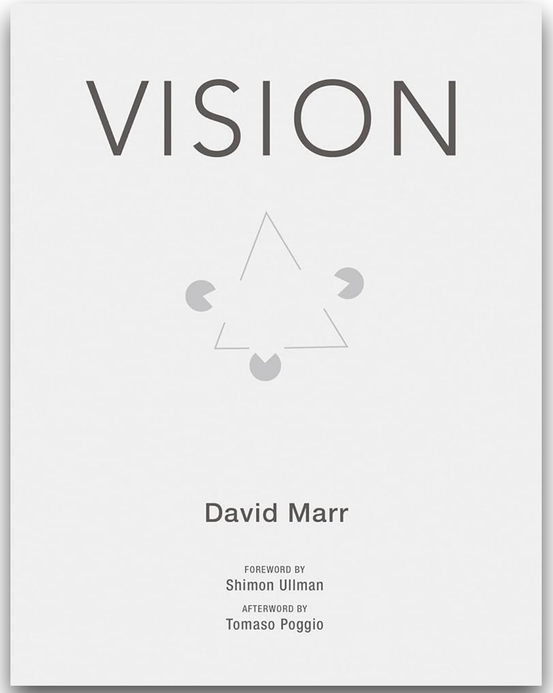
Thanks for Listening!

Q&A Discussion

Appendices

Revisiting Marr's Levels of Analysis

Multiple facets for studying information processing systems



[Marr, 1982]

Revisiting Marr's Levels of Analysis

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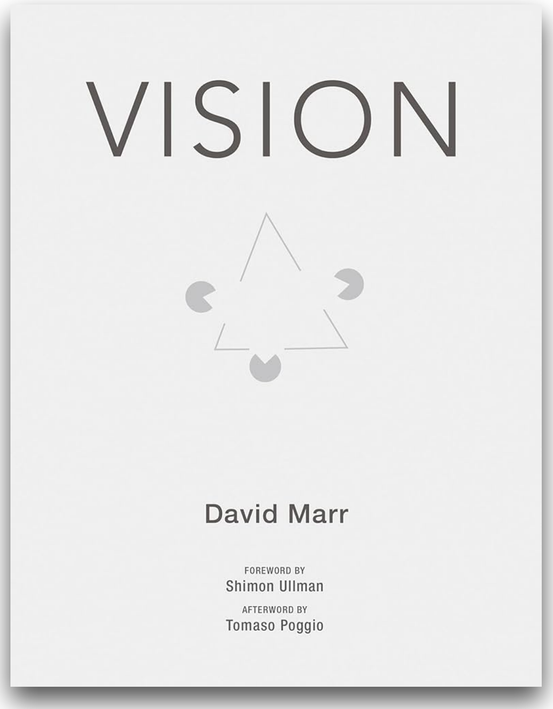
  - [What, why] *Competence, mental grammar, abstract linguistic knowledge*



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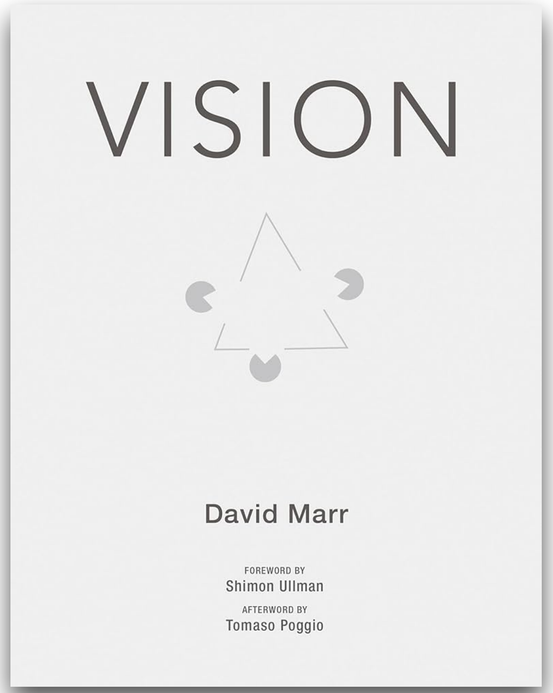
  - [How] *Performance, real-time processing*



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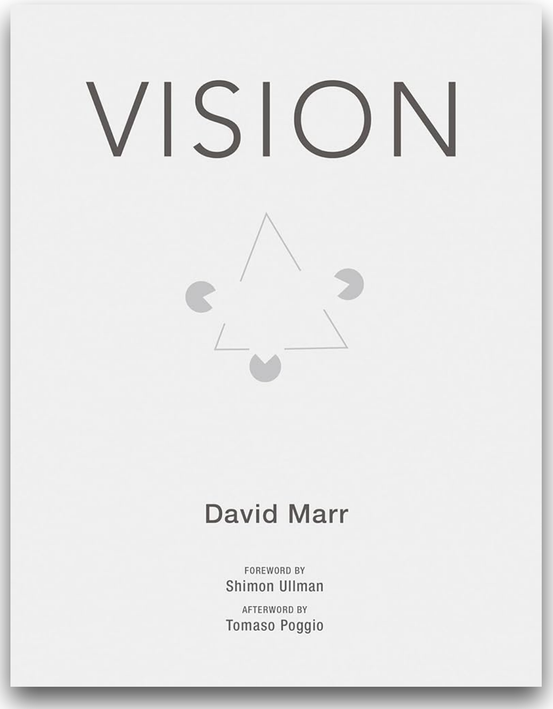
- **Implementational level → [Neurolinguistics]**
  - [How - lower level] *Performance, neural instantiations of language*



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Current Proposal: The Full Picture

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Computational Level

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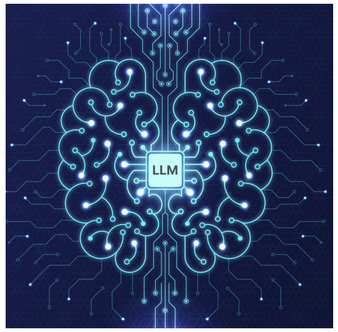
***Language* in the broader design of intelligent systems**

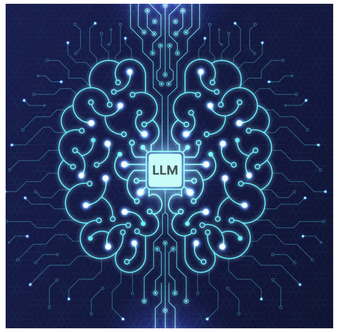


Current Proposal: The Full Picture

Computational Level

***Language* in the broader design of intelligent systems**

Algorithmic Level ONE



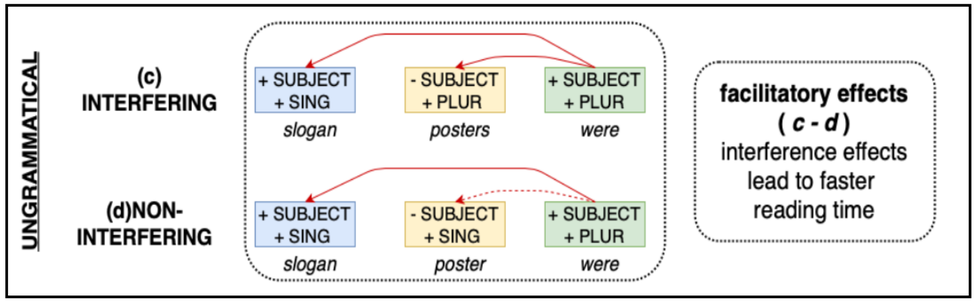
Current Proposal: The Full Picture

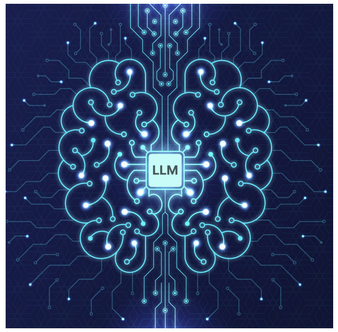
Computational Level

Language **in the broader design of intelligent systems**

Algorithmic Level ONE

Psycholinguistic theories (?)



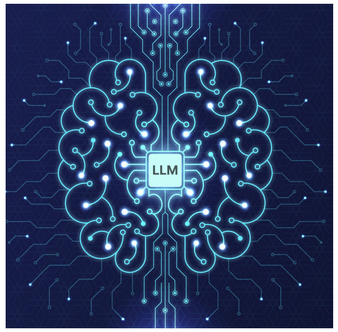


An “algorithm” of sentence processing

Current Proposal: The Full Picture

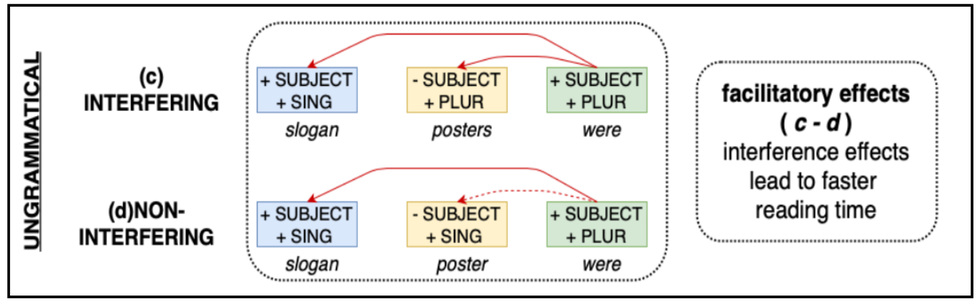
Computational Level

Language **in the broader design of intelligent systems**



Algorithmic Level ONE

Psycholinguistic theories (?)



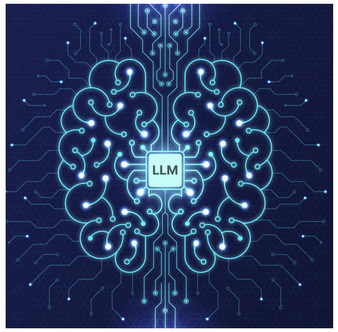
Algorithmic Level TWO

An “algorithm” of sentence processing

Current Proposal: The Full Picture

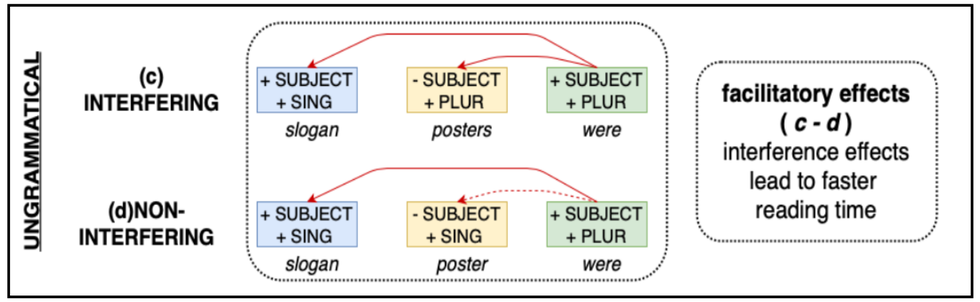
Computational Level

Language **in the broader design of intelligent systems**



Algorithmic Level ONE

Psycholinguistic theories (?)

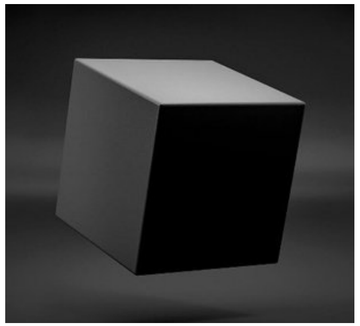


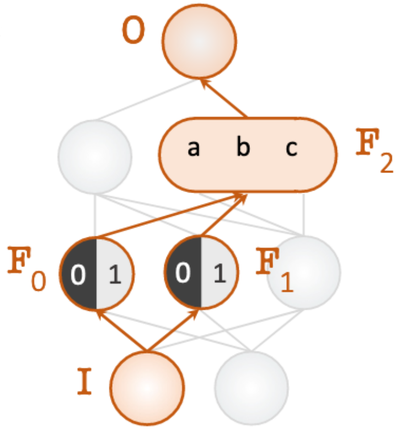
Functionally approximating

Functionally approximating

Algorithmic Level TWO

An "algorithm" of sentence processing





LMs are shaped by what they are trained on!

Data Distributional Properties Drive Emergent In-Context Learning in Transformers

Stephanie C.Y. Chan, DeepMind
Adam Santoro, DeepMind
Andrew K. Lampinen, DeepMind
Jane X. Wang, DeepMind
Aaditya K. Singh, University College London
Pierre H. Richemond, DeepMind
James L. McClelland, DeepMind, Stanford University
Felix Hill, DeepMind

Burstiness as a distributional property!

Compositional Structures!

Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?

Sewon Min[1,2] Xinxi Lyu[1] Ari Holtzman[1] Mikel Artetxe[2]
Mike Lewis[2] Hannaneh Hajishirzi[1,3] Luke Zettlemoyer[1,2]

Parallelism!

Parallel Structures in Pre-training Data Yield In-Context Learning

Yanda Chen[1] Chen Zhao[2,3] Zhou Yu[1] Kathleen McKeown[1] He He[2]

⇒ The IFE as a diagnostic of the error-driven learning mechanism in ICL!