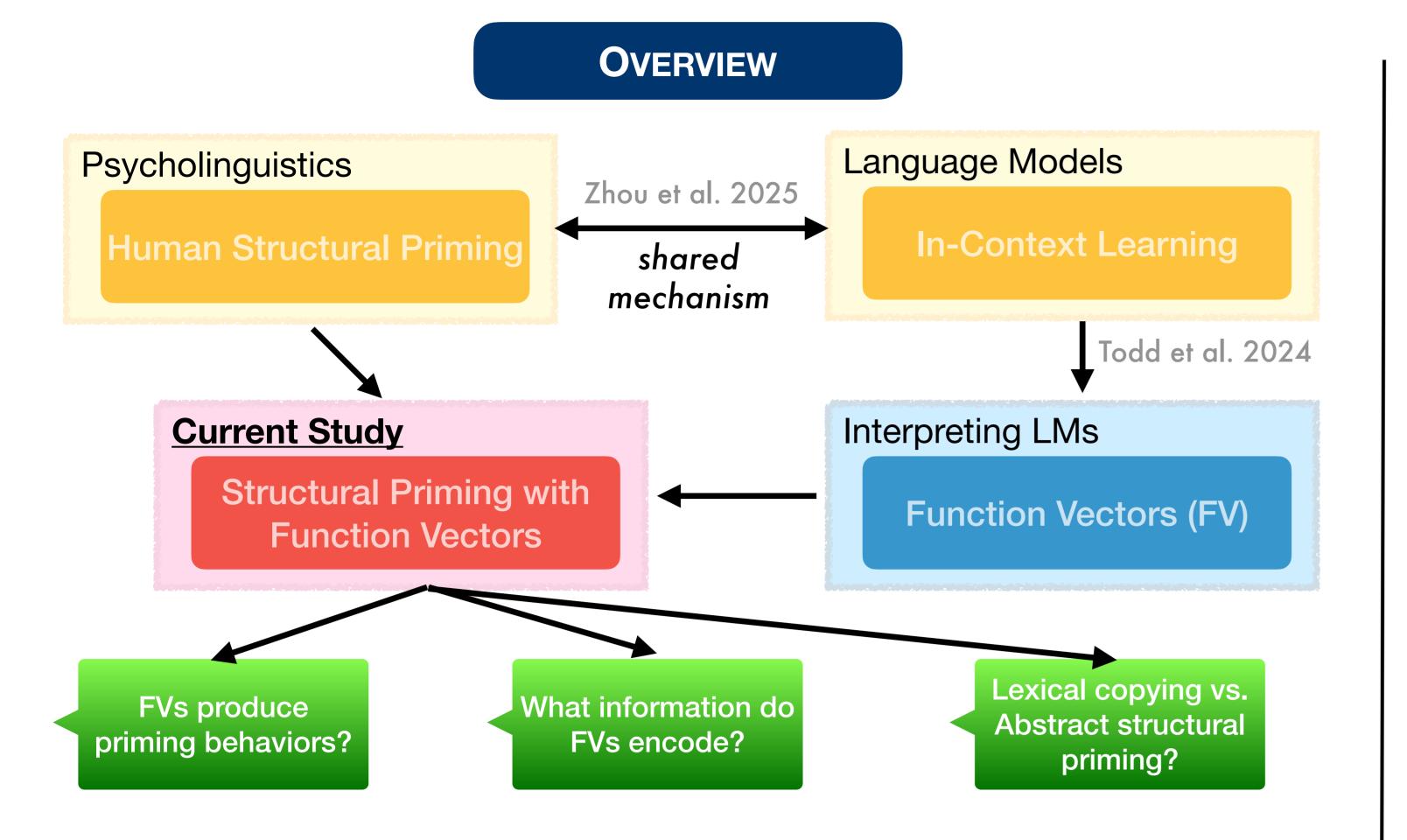
# Compressing Strucural Priming in Large Language Models through Function Vectors

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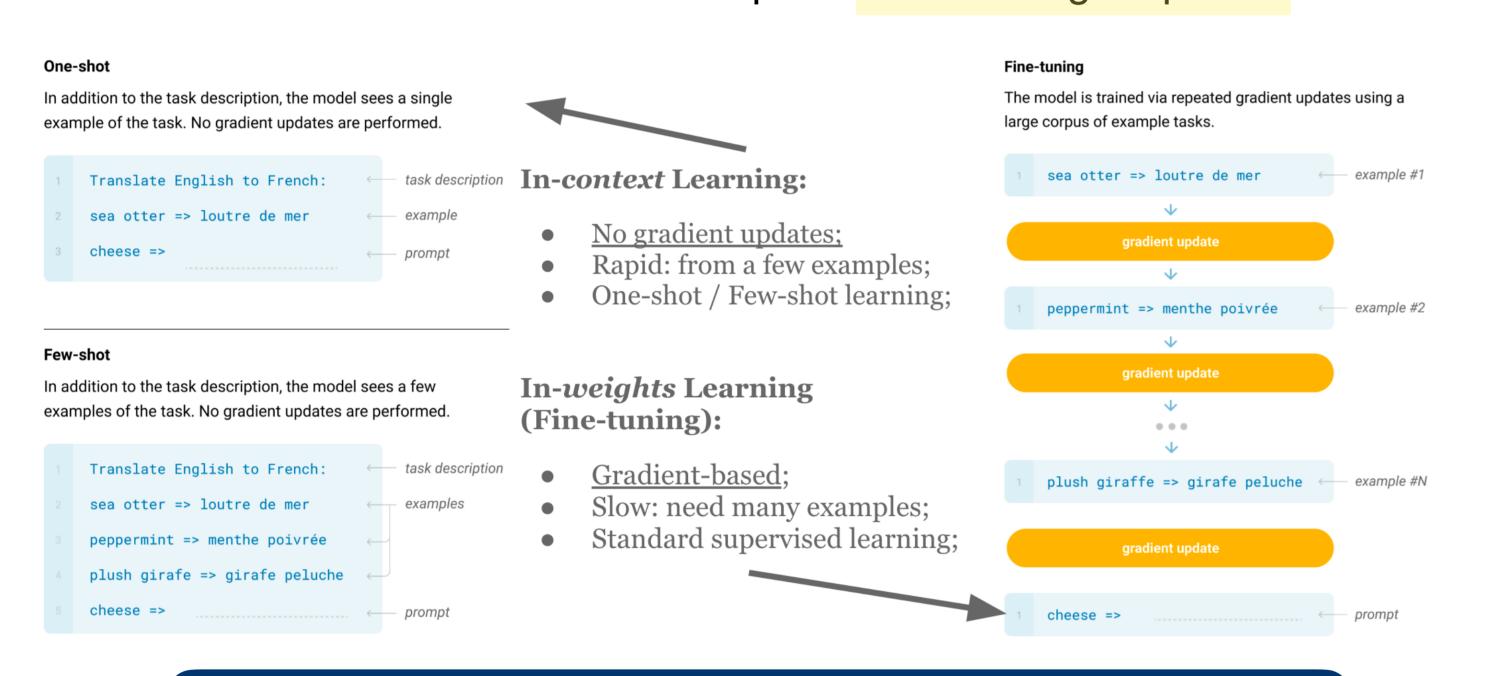
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# BACKGROUND 1: IN-CONTEXT LEARNING (ICL) IN LLMs

In-Context Learning (ICL): an emergent property for LLMs to adapt to tasks at inference time with a few demo-answer pairs without weight updates.



## BACKGROUND 2: STRUCRTURAL PRIMING IN LLMs

- Structural Priming: speakers tend to reuse the recently encountered syntactic structures during production and comprehension.
- Inverse Frequency Effect (IFE): structural alternatives with less frequency are susceptible to a stronger priming effect than the more frequent ones.
- Implicit Learning Account of Priming: humans implicitly update the internal grammatical knowledge in an error-driven way based on prediction errors (the difference between expectation and actual prime instances).

Consider the classical Dative Alternations as a case study:

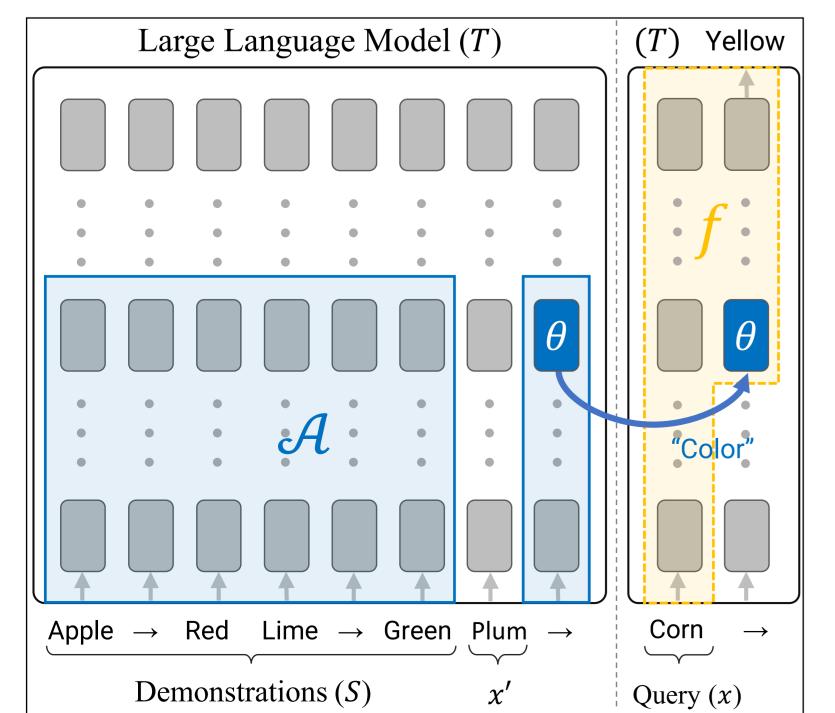
- Double Object (DO): Alice sent Bob a letter.
- Prepositional Dative (PD): Alice sent a letter to Bob.

**Verb Bias**: the probability distribution over the two structures for each dative verb (e.g. bring is a highly DO-biased word).

Previous studies have shown that LLMs show human-like structural priming: In particular, Zhou et al. 2025 have proposed that:

- LLMs' ICL can be {viewed as, a product of} human structural priming.
- ICL  $\approx$ (functionally) Gradient Descent as error-driven learning.

## BACKGROUND 3: FUNCTION VECTORS CAPTURE ICL



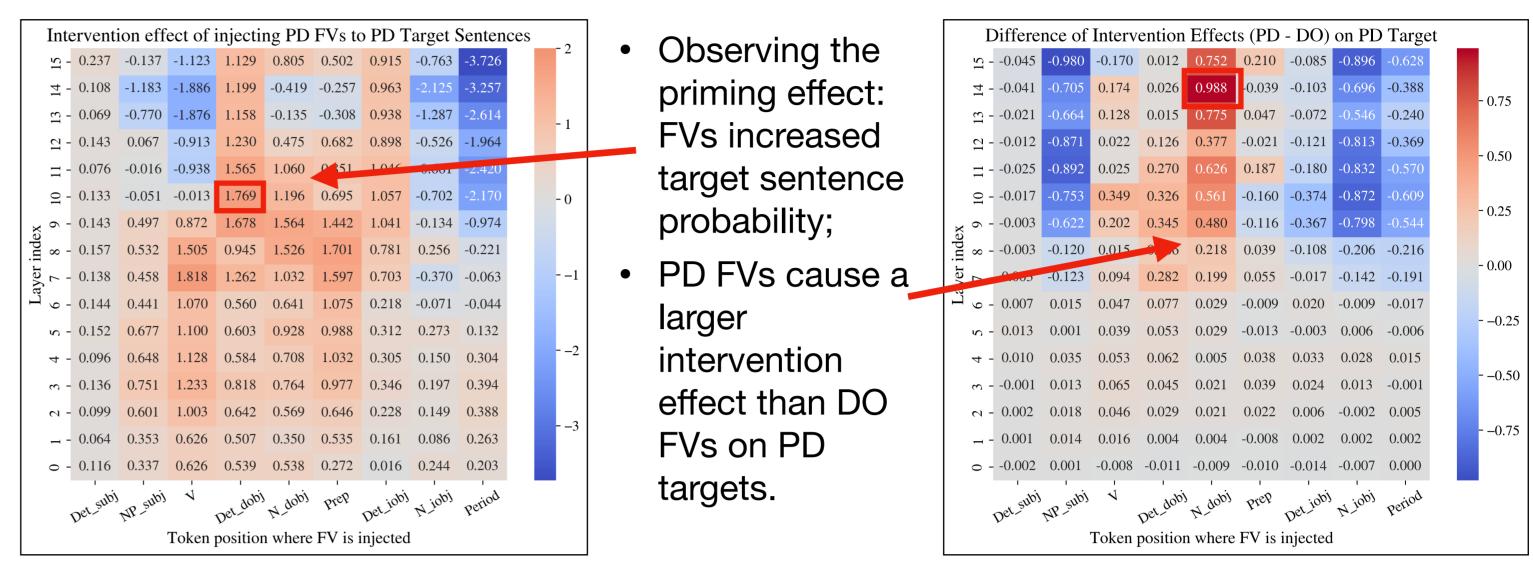
Reprinted from Hendel et al. (2023).

Function vectors (FV; Hendel et al. 2023, Todd et al. 2024) are compact, causal, internal representations of *function* abstractions extracted from LLMs.

- Intermediate activation patterns capturing the "task" information in the demo-answer context.
- Compositional: FVs could be arithmetically composed to represent task combinations.
- Enables us to extract "internal knowledge" LLMs gain on the fly for causal intervention.

#### **EXP1: FVs ELICIT SIMILAR PRIMING BEHAVIORS?**

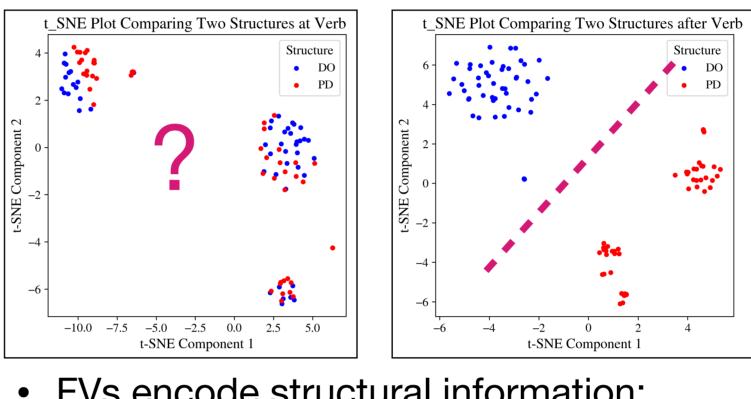
- Extracting FVs from PD sequences and injecting them to the corresponding positions (layer and token position) in a Target PD sequence.
- Intervention Effect: difference between raw and intervened sentence probability.

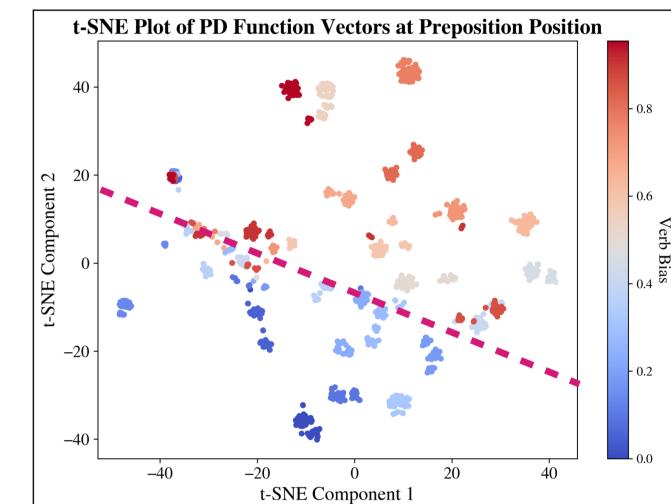


**Takeaway**: V FVs do elicit standard structural priming effect.

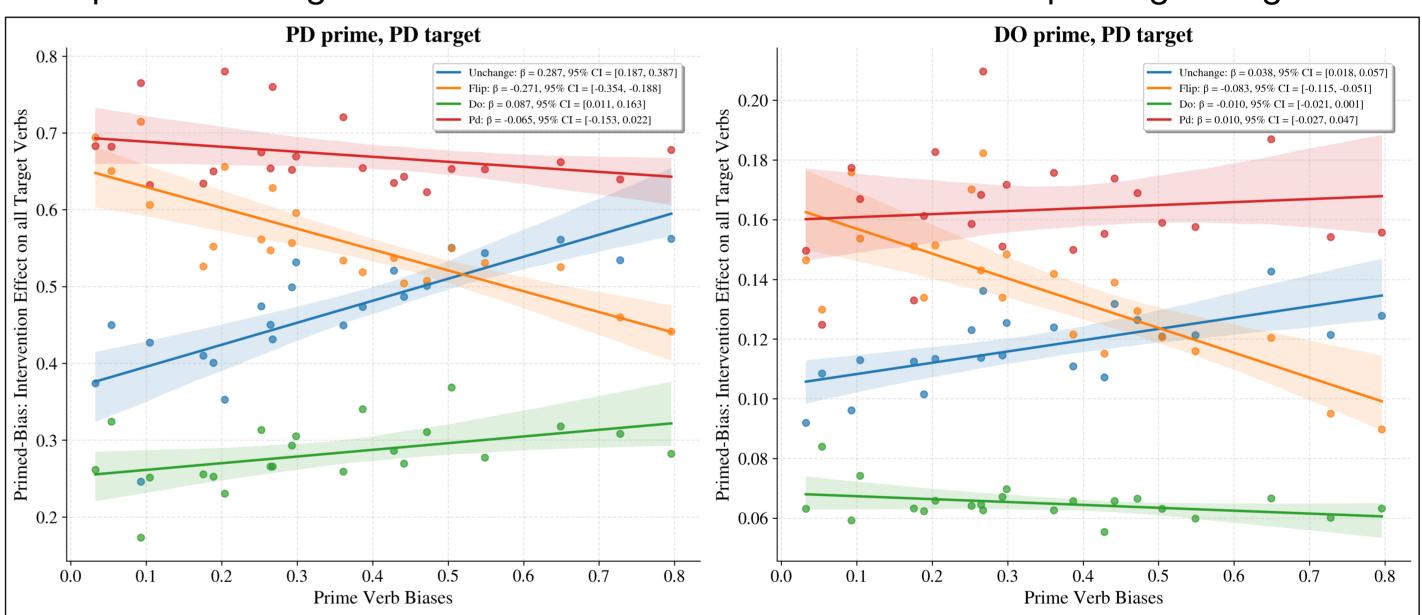
#### **EXP2: VERB BIAS INFORMATION IN FVs?**

Apply t-SNE on FVs and plot by structure / gradient verb biases.





- FVs encode structural information;
- FVs encode more fine-grained, graded verb bias information for each verb.
- Apply  $\beta$ -regression on the FVs to identify a linear subspace for verb bias, and modify the subspace to change the verb bias information in FVs. Measure priming strength.

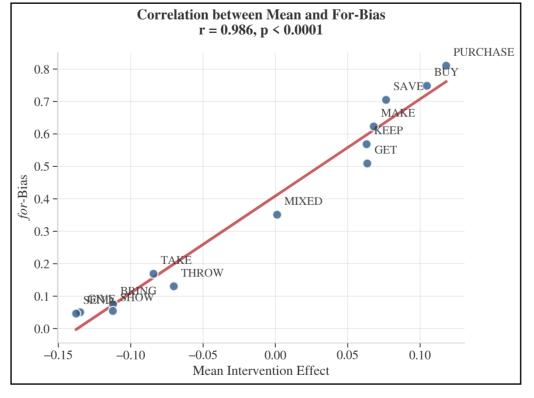


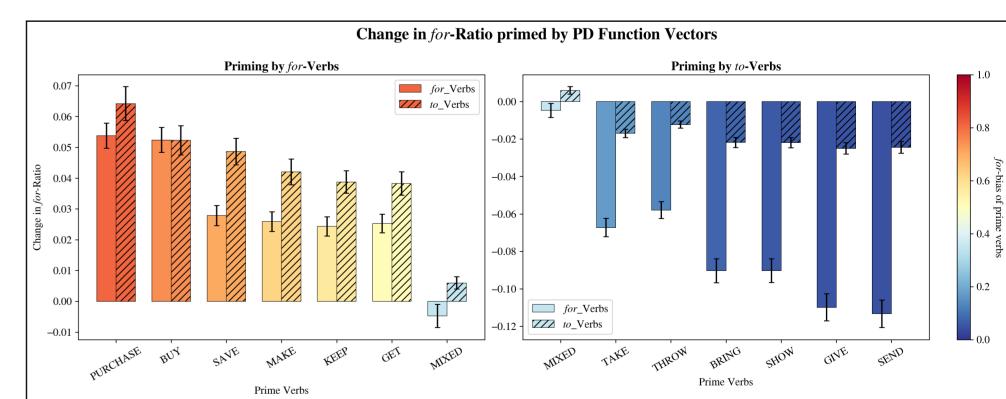
**Takeaway**: FVs encode fine-grained verb bias information in a linear subspace that is causally manipulable to affect priming strength.

# EXP3: ABSTRUCT/STRUCTURAL VS. LEXICAL PRIMING?

What levels of priming do FVs implement?

- Priming abstract dative structure → increase the probability of the <u>target</u> verb's preposition;
- Priming **lexical associations** → increase the probability of the *prime* verb's preposition;





**Result**: for-biased prime verbs increase the for-preference for both for-biased and tobiased target verbs. Same for to-biased prime verbs.

**Takeaway**: !? lexical-specific information is prioritized over structural information in the case of preposition preference.

### CONCLUSIONS

- It is viable to compress structural repetitions in the context into function vectors, which elicit comparable structural priming effects in LLMs.
- Verb bias information is encoded in a manipulable linear subspace.
- FVs carry both abstract structural-level and lexical-specific information.
- FVs offer a mechanisitc level way of causally intervening internal representations in LLMs.