Simulating Structural Priming Effects with PIPS

Zhenghao "Herbert" Zhou, Robert Frank
Yale University

SCiL Presentation
Jun 15, 2023

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Parallelism in Producing Syntax
[Brehm et al. 2022]

Outline

Structural Priming

- Structural priming effect;
- Lexical boost effect (LBE);
- Inverse frequency effect (IFE);

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Computational Modeling

- The PIPS Model
- The Gradient Symbolic Computation (GSC) framework

Outline

Structural Priming → **Computational Modeling** → **Current Study**

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- Structural priming effect;
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Computational Modeling

- The PIPS Model
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Current Study

- How to model the priming procedure?
- How to quantify the three priming effects?

Outline

Structural Priming	Computational Modeling	Current Study	Results & Discussion
• Structural priming effect; • Lexical boost effect (LBE); • Inverse frequency effect (IFE);	• The PIPS Model • The Gradient Symbolic Computation (GSC) framework	• How to model the priming procedure? • How to quantify the three priming effects?	• PIPS is capable of qualitatively capturing the structural priming effects.

Structural Priming

Structural Priming: speakers tend to reuse the syntactic structures they have recently encountered during production.

E.g. [Bock 1986]

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Structural Priming: speakers tend to reuse the syntactic structures they have recently encountered during production.

Our focus: Double Object (DO) vs. Prepositional Dative (PD) for ditransitive predicates.

- DO: *Alice sent Bob a letter*.
- PD: *Alice sent a letter to Bob*.

E.g. [Bock 1986]

Structural Priming Effect in Experimental Settings

Production Task with Preamble Completion Paradigm

E.g. [Bock 1986, Bernolet & Hartsuiker 2010]

Structural Priming Effect in Experimental Settings

Alice sent Bob a letter. [DO]

PRIME

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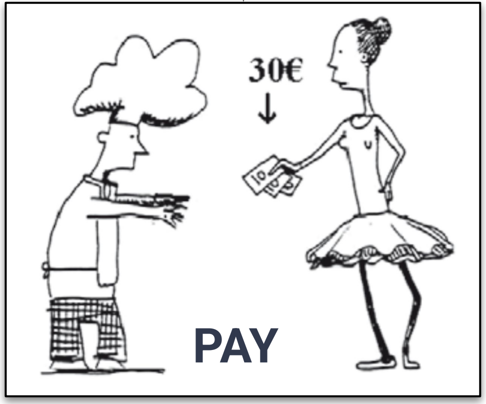

PRIME

PREAMBLE

Production Task with Preamble Completion Paradigm

E.g. [Bock 1986, Bernolet & Hartsuiker 2010]

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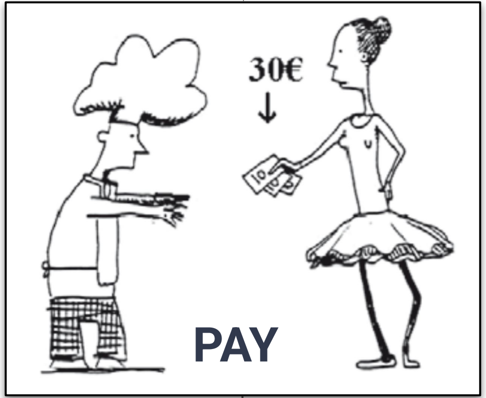

The dancer paid the cook 30 euros. [DO]
The dancer paid 30 euros to the cook. [PD]

PRIME

PREAMBLE

TARGET

Production Task with <u>Preamble Completion Paradigm</u>

E.g. [Bock 1986, Bernolet & Hartsuiker 2010]

Lexical Boost Effect

Does lexical selection play any role?

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Lexical Boost Effect: structural priming effect is stronger when the word that heads the primed structures is repeated between prime and target sentences.

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Alice gave Bob a book. **TARGET**

E.g. [Pickering & Branigan 1998]

Lexical Boost Effect

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Lexical Boost Effect: structural priming effect is stronger when the word that heads the primed structures is repeated between prime and target sentences.

Carl gave Danis a letter.

Carl showed Danis a letter.

PRIME

Alice gave Bob a book.

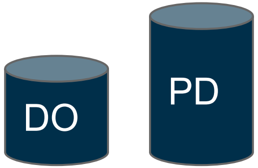
TARGET

E.g. [Pickering & Branigan 1998]

Inverse Frequency Effect

Inverse Frequency Effect

Do verb biases play any role?



Verb Bias: *show* is biased towards PD

E.g. [Jaeger & Snider 2007]

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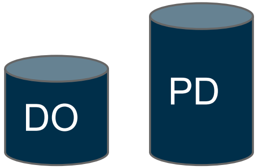

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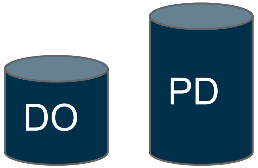

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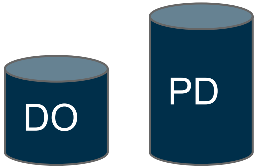

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PRIME		TARGET
Alice showed Bob a letter. [DO]	→	*Carl gave Danis a book.* [DO]
Alice showed a letter to Bob. [PD]		*Carl gave a book to Danis.* [PD]

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Interim Summary

- Structural Priming Effect (StrucPriming)
- Lexical Boost Effect (LBE)
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Next: computational modeling

- Gradient Symbolic Computation (GSC)
- Parallelism in Producing Syntax (PIPS)

Gradient Symbolic Computation Framework

A GSC Parser: a continuous-state, continuous-time stochastic dynamical-system model of symbolic processing.

- Motivation: integrating the *discrete* (symbolic) and *continuous* (gradient) aspects of language processing that happen at different levels of the mind.

[Cho & Smolensky 2018, 2020, Smolensky & Hale 2006]

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Core Properties:

- Representing discrete symbolic structures in a continuous space.
- Maintaining multiple locally-coherent structures simultaneously at each timestep; gradually converging to a final, discrete structure / hypothesis.
- Implementing Harmonic Grammar to measure well-formedness of structures.

[Cho & Smolensky 2018, 2020, Smolensky & Hale 2006]

Tensor Product Representation

Orthogonal vector representations of the followings:

- **Roles**: positional, structural information;
- **Fillers**: the values that are filled into the roles;
- **Binding**: outer/tensor product of roles and fillers;

[Smolensky 1990]

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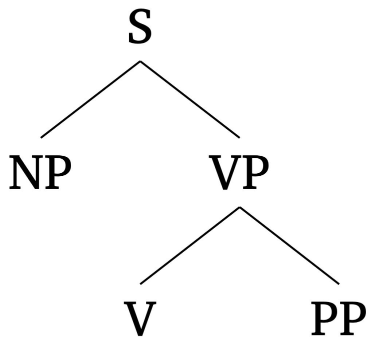

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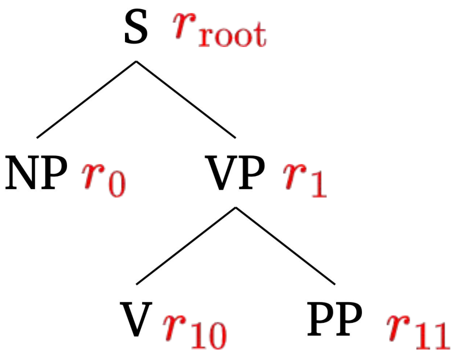

$$f_{\text{S}} \otimes r_{\text{root}} + f_{\text{NP}} \otimes r_0 + f_{\text{VP}} \otimes r_1 + f_{\text{V}} \otimes r_{10} + f_{\text{PP}} \otimes r_{11}$$

[Smolensky 1990]

PIPS: an implementation of GSC

Motivation: modeling *sentence production* with the GSC properties, with a case study in modeling *agreement attraction*.

[Brehm et al. 2022, Bock & Miller 1991]

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PREAMBLE: *The key to the cabinets…*

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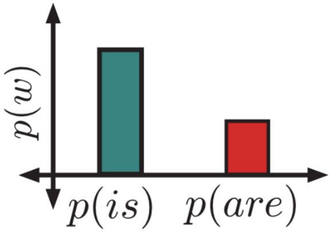
PREAMBLE: *The key* to *the cabinets*...

Subject **Intervener**



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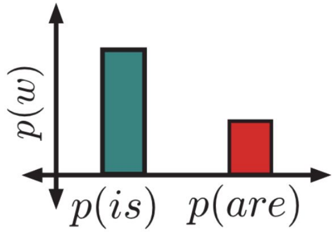

Method: representing sentence production as a Preamble Completion Task

- Representing preambles in memory as pre-activations of bindings;
- Dynamically and stochastically modeling the transient activations of a blend of alternative structures (which lead to errors in production) – also for structural priming.

[Brehm et al. 2022, Bock & Miller 1991]

Interim Summary

- Gradient Symbolic Computation
- Parallelism in Producing Syntax

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Next: current study

- How to model priming?
- How to quantify Structural Priming, LBE, and IFE?

Training: Fillers and Verb Biases

[Pickering & Branigan 1998, Yi et al. 2019]

Training: Fillers and Verb Biases

Nine ditransitive verbs with their absolute frequencies of DO vs. PD:

Verb	DO Frequency	PD Frequency
give	15311	8402
show	502	571
send	658	3134
lend	177	677
hand	308	659
loan	12	11
offer	752	1203
sell	190	1288
post	1	55

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- NP_s, NP_i, NP_d are the three noun phrases;

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Abstracting away Noun Phrases:

- NP_s, NP_i, NP_d are the three noun phrases;

Two types of grammatical sentences:

- **DO:** NP_s _VERB_ NP_i NP_d
- **PD:** NP_s _VERB_ NP_d to NP_i

[Pickering & Branigan 1998, Yi et al. 2019]

Training: Three PCFGs

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ABS

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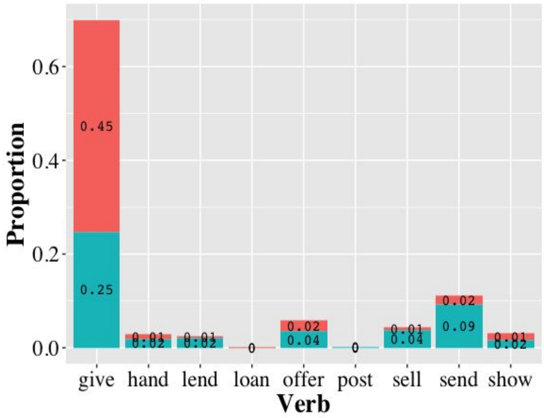
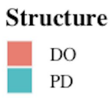


NORM



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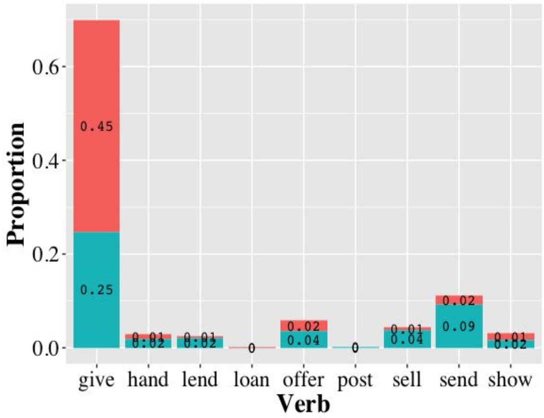

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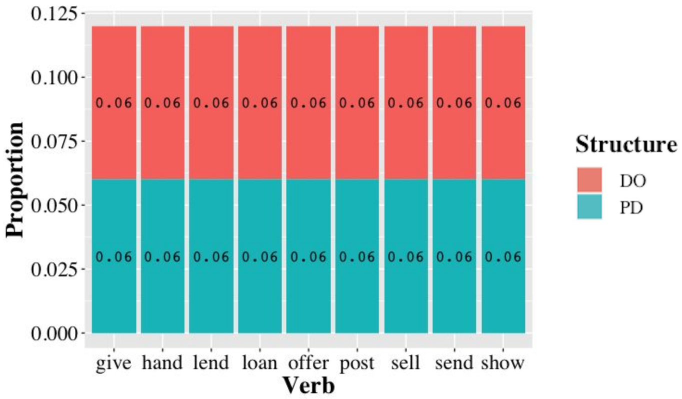

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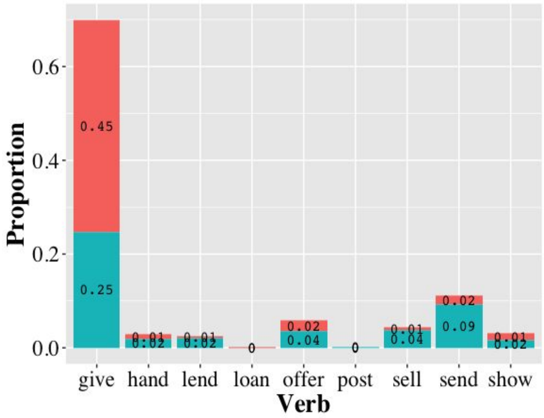

NORM

BASE

Training: minimizing KL-divergence between production distribution and PCFG distribution.

Priming

Preamble Activation: raise the activation value of the bindings to 0.5;

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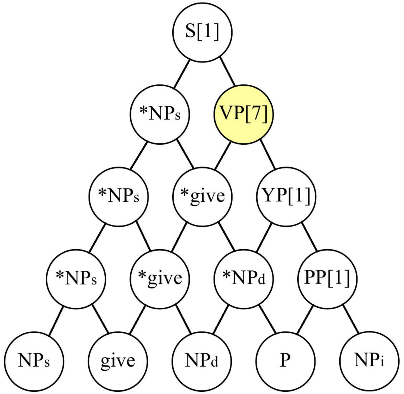

Structure

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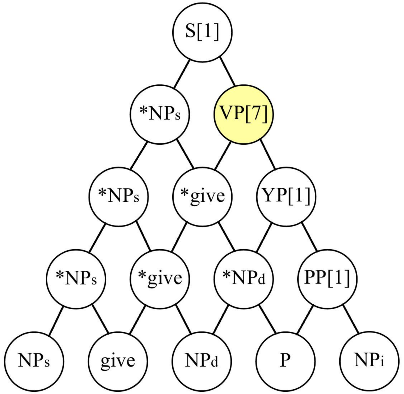

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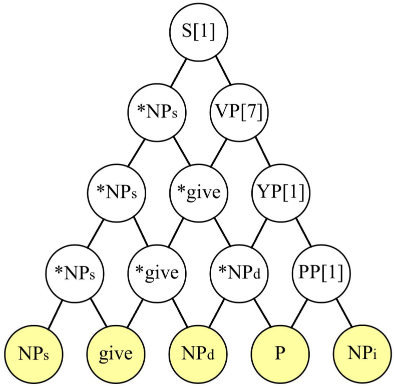

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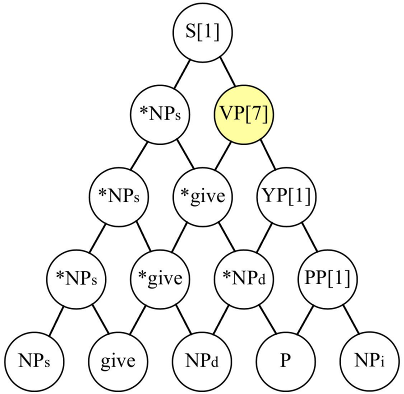

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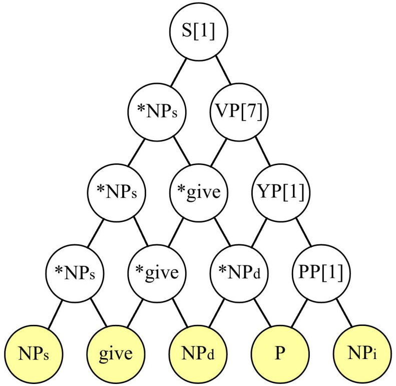

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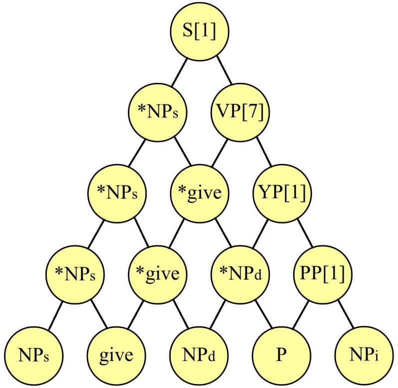

Whole

Simulation Procedure

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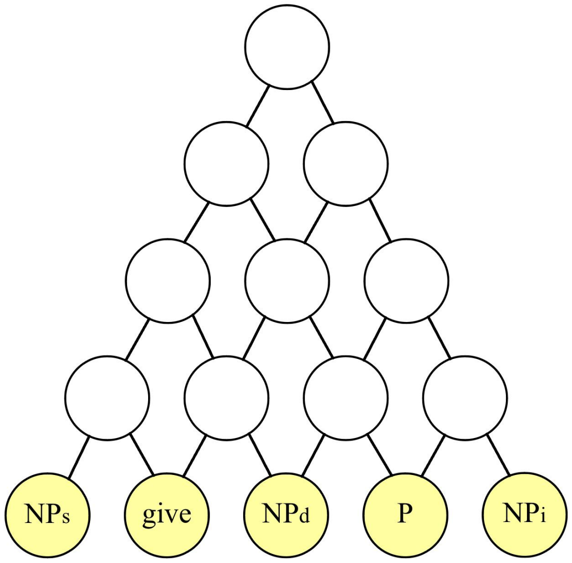
For each model:

1. Prime the model with a verb+structure combination. [18 conditions in total]



Sample production trials for preamble NP_s offer.

Simulation Procedure

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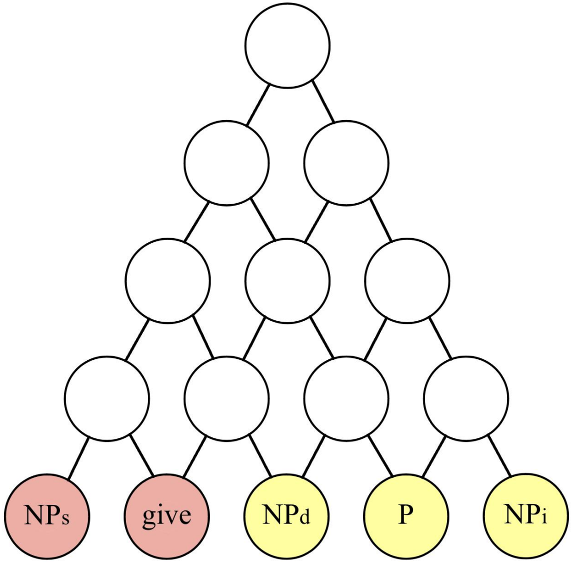
2. Activate the preamble: `NP`$_s$ `VERB`.



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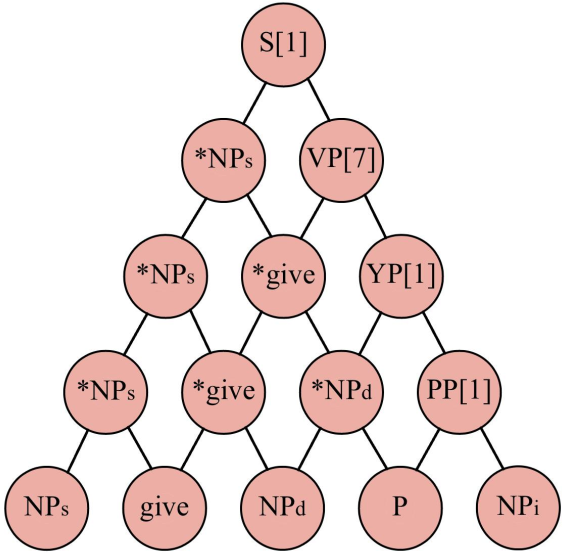
3. Run the model for 50 production trials as target productions.



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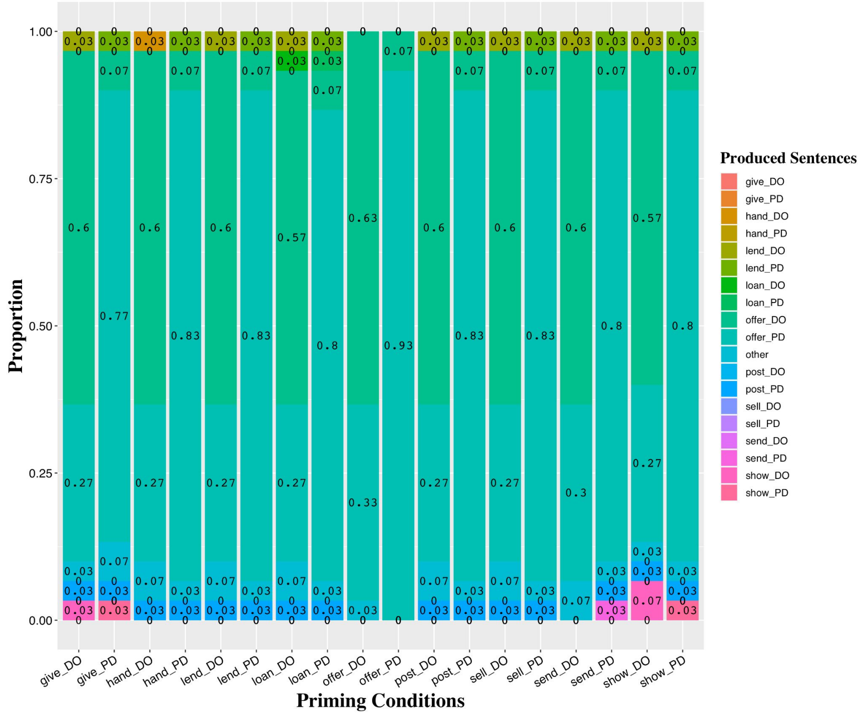
4. Obtain the proportion of production of the 18 grammatical sentences + *Others*.



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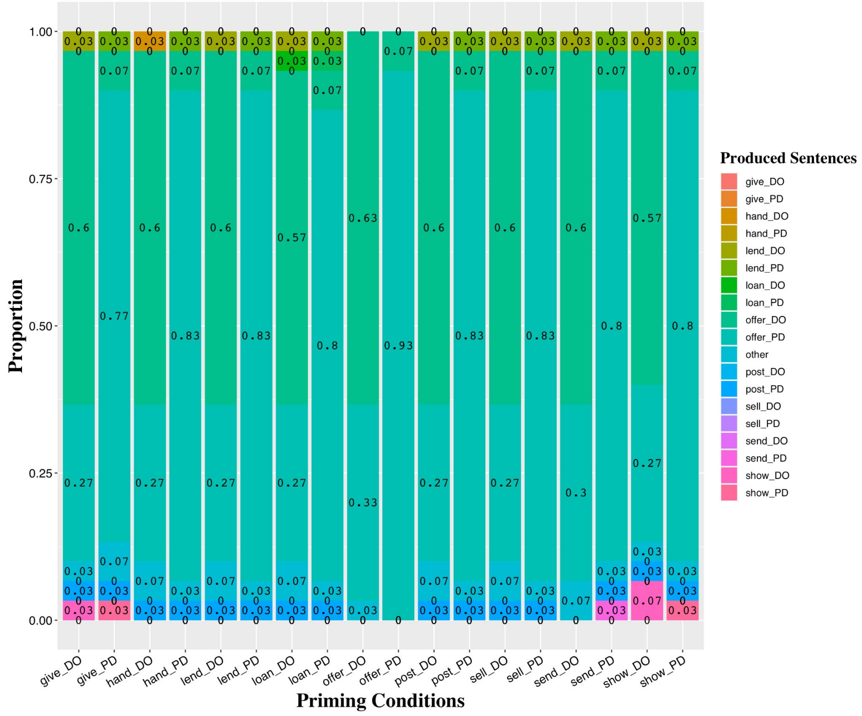
Baseline Production for Comparison: run the model without priming and obtain the proportions of the 18 sentences.



Sample production trials for preamble $\texttt{NP}_{\texttt{s}}$ `offer`.

Quantifying Priming Effects

Target Verb: the verb given in the preamble that should be produced.

We focus on the portion of produced sentences with correct target verbs.

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Deviation from Baseline:

$$\mathrm{Dev}_v^{v'}(\mathrm{DO}) = \mathrm{Ratio}_v(\mathrm{DO})_{\text{primed by } v'} - \mathrm{Ratio}_v(\mathrm{DO})_{\text{unprimed}}$$

Quantifying Priming Effects, cont.

$$\mathrm{StrucPriming} \propto \sum_{v \in \mathcal{V}} \sum_{s \in \{\mathrm{DO},\ \mathrm{PD}\}} \mathrm{Dev}_v(\mathrm{s})$$

Quantifying Priming Effects, cont.

$$\text{StrucPriming} \propto \sum_{v \in \mathcal{V}} \sum_{s \in \{\text{DO, PD}\}} \text{Dev}_v(\text{s})$$

$$\text{LBE} \propto \sum_{v, v' \in \mathcal{V}} \sum_{s \in \{\text{DO, PD}\}} [\text{Dev}_v^v(\text{s}) - \text{Dev}_v^{v'}(\text{s})]$$

Quantifying Priming Effects, cont.

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$$\text{IFE} \propto \sum_{v \in \mathcal{V}} \sum_{v' \in \mathcal{V}_{\text{PD}}} [\text{Dev}_v^{v'}(\text{DO}) - \text{Dev}_v^{v'}(\text{PD})]$$

Interim Summary

- Trained 3 models: **ABS, NORM, BASE**
- Priming means activating corresponding bindings
    - Priming weights: {0.05, 0.1, 0.2}
    - Priming modes: {structure, words, whole}
- Quantifying effects w.r.t. deviations from baseline.

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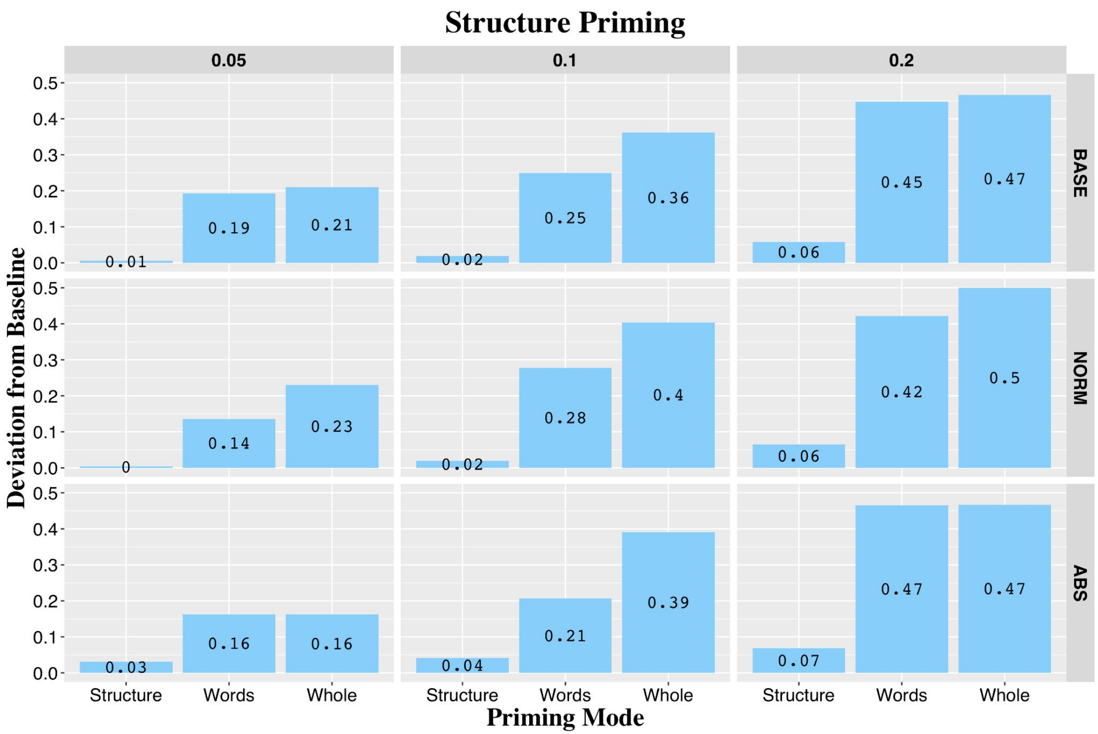
Next: results and discussion

Results: priming weights and modes



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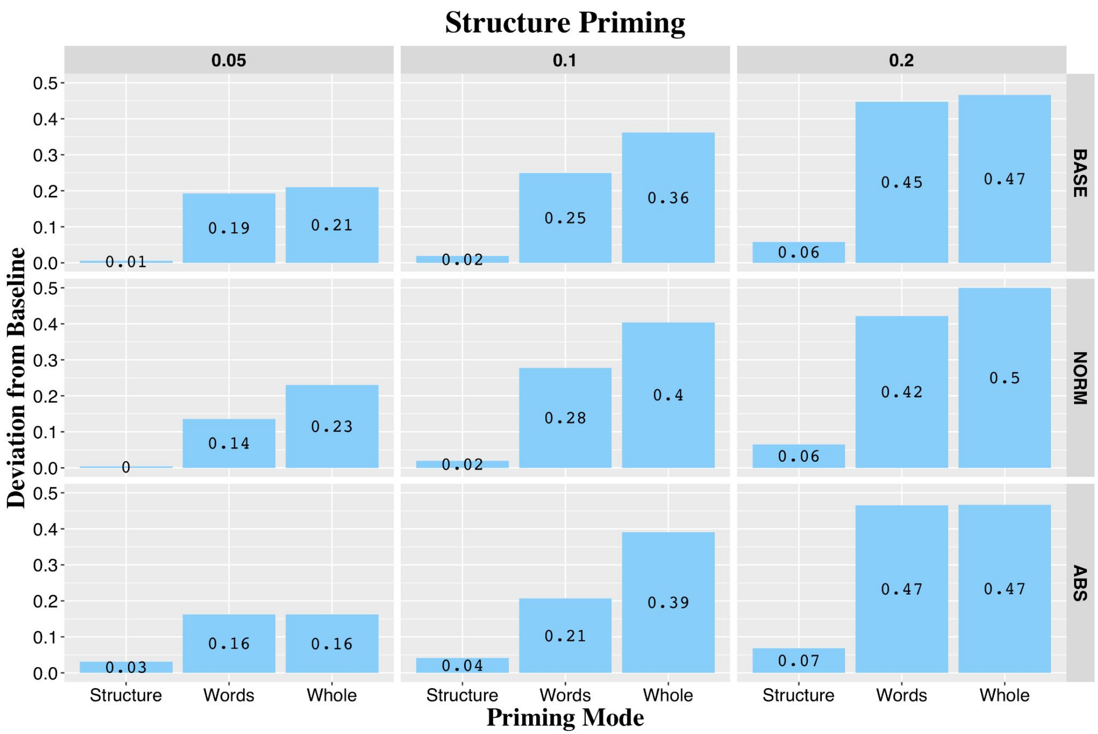

- Greater priming weights lead to stronger priming effect.

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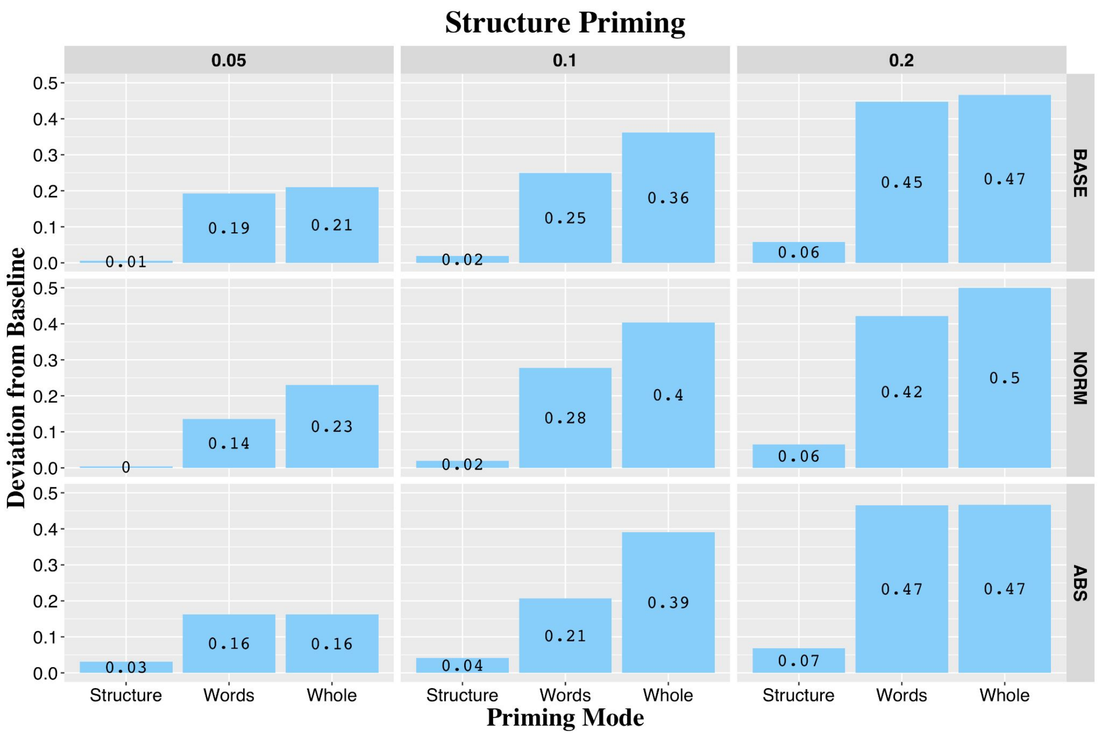
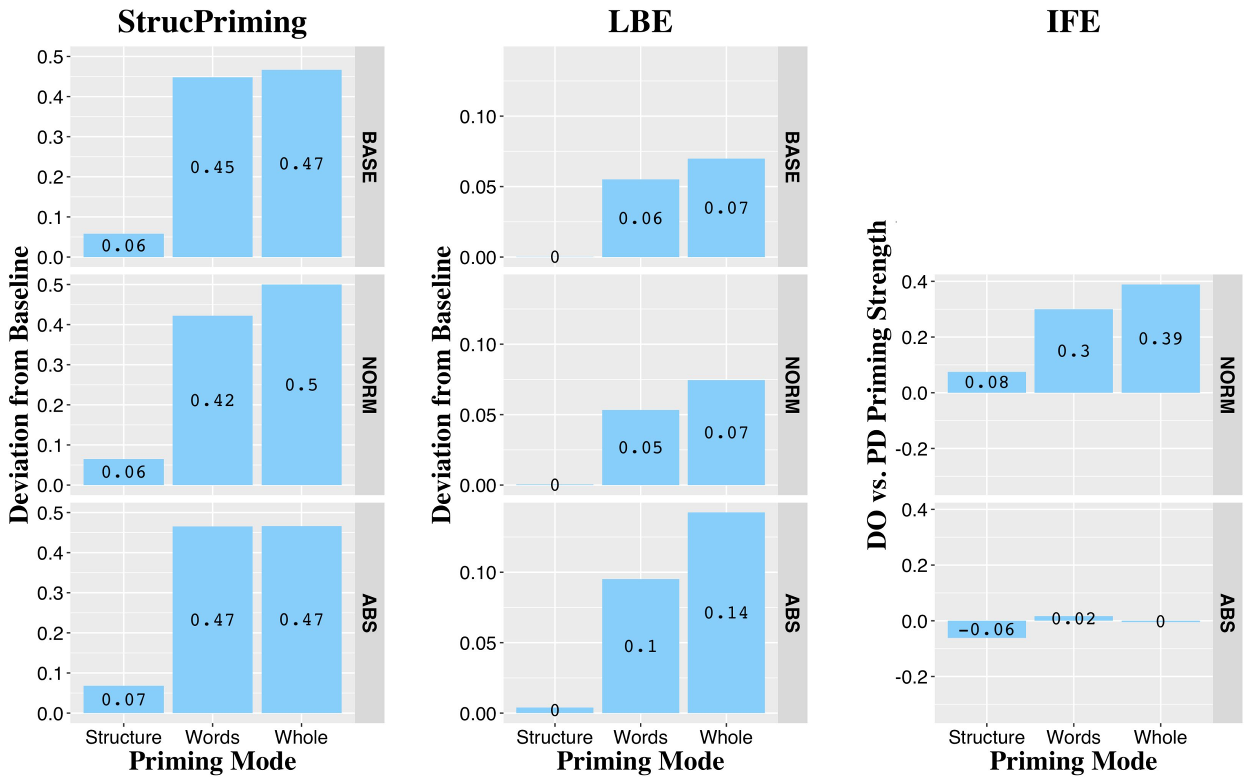


- Greater priming weights lead to stronger priming effect.
- Priming Modes: structure < words <(=) whole;

Results: comparing the three effects



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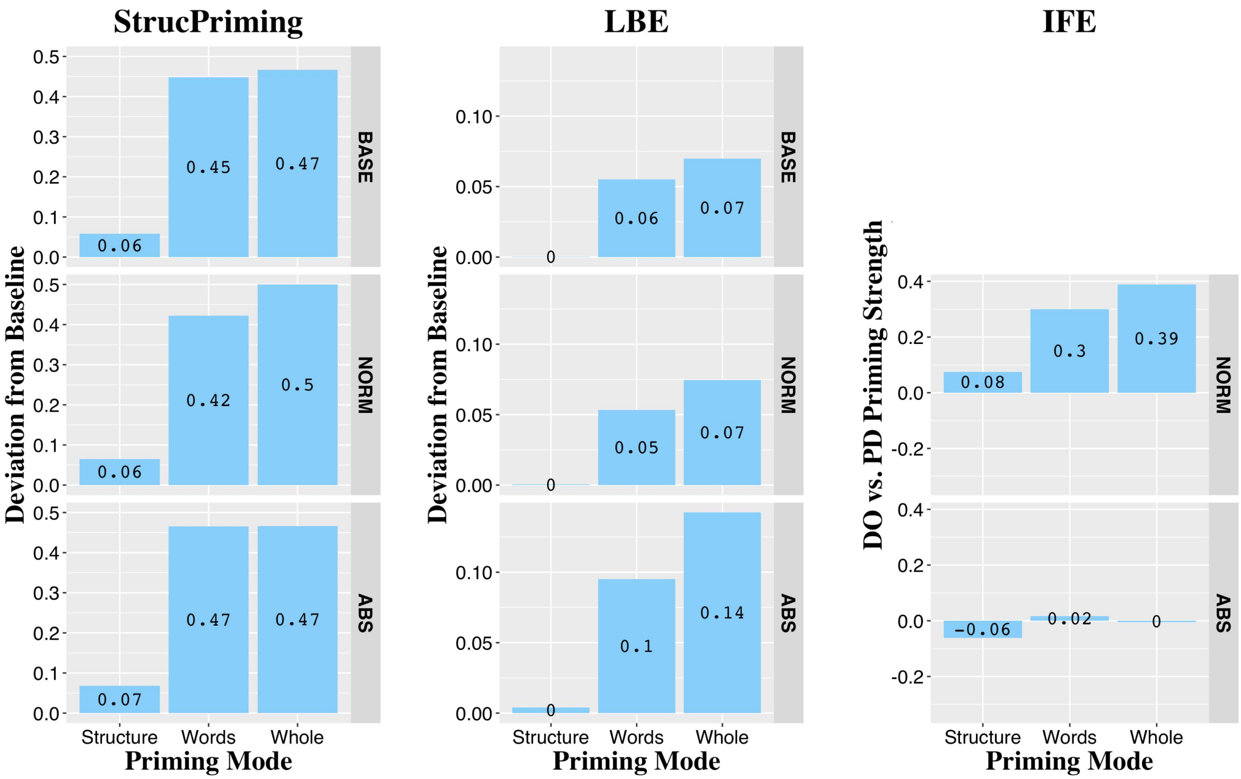

* Priming weight = 0.2

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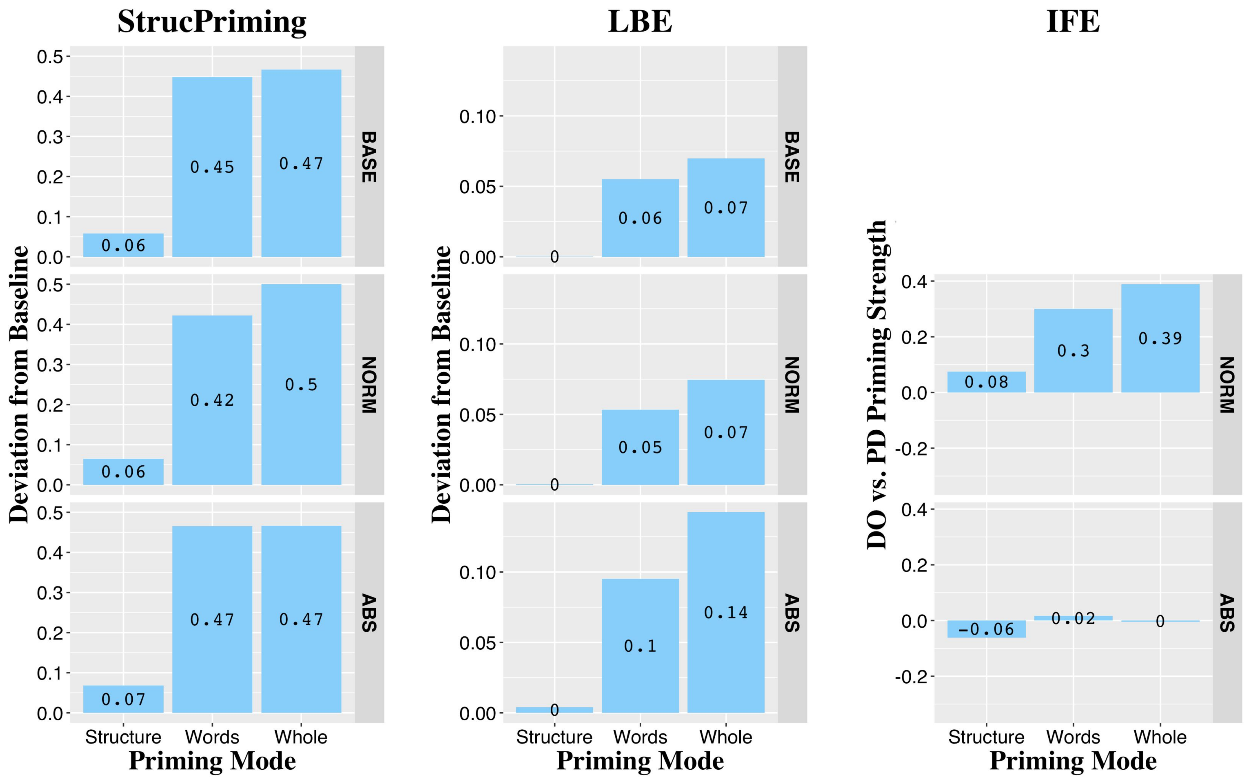
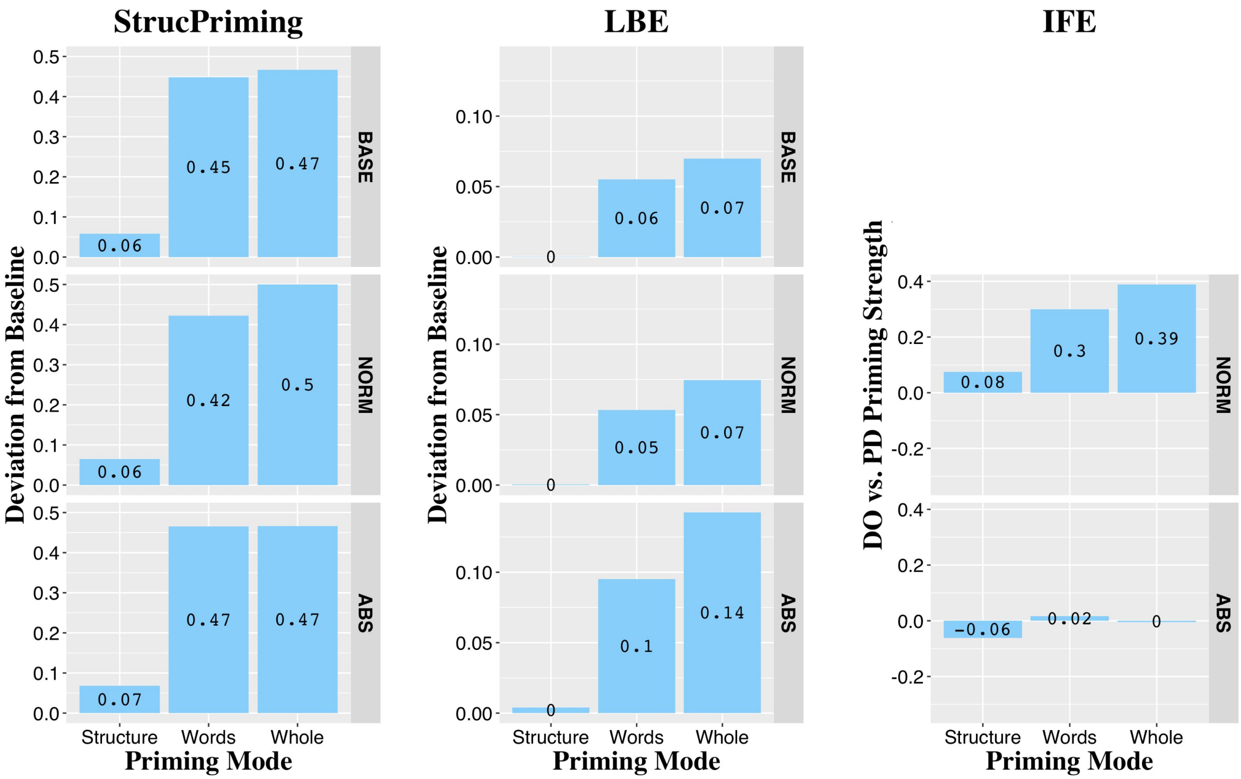


* Priming weight = 0.2

- All three models captured LBE;

Results: comparing the three effects



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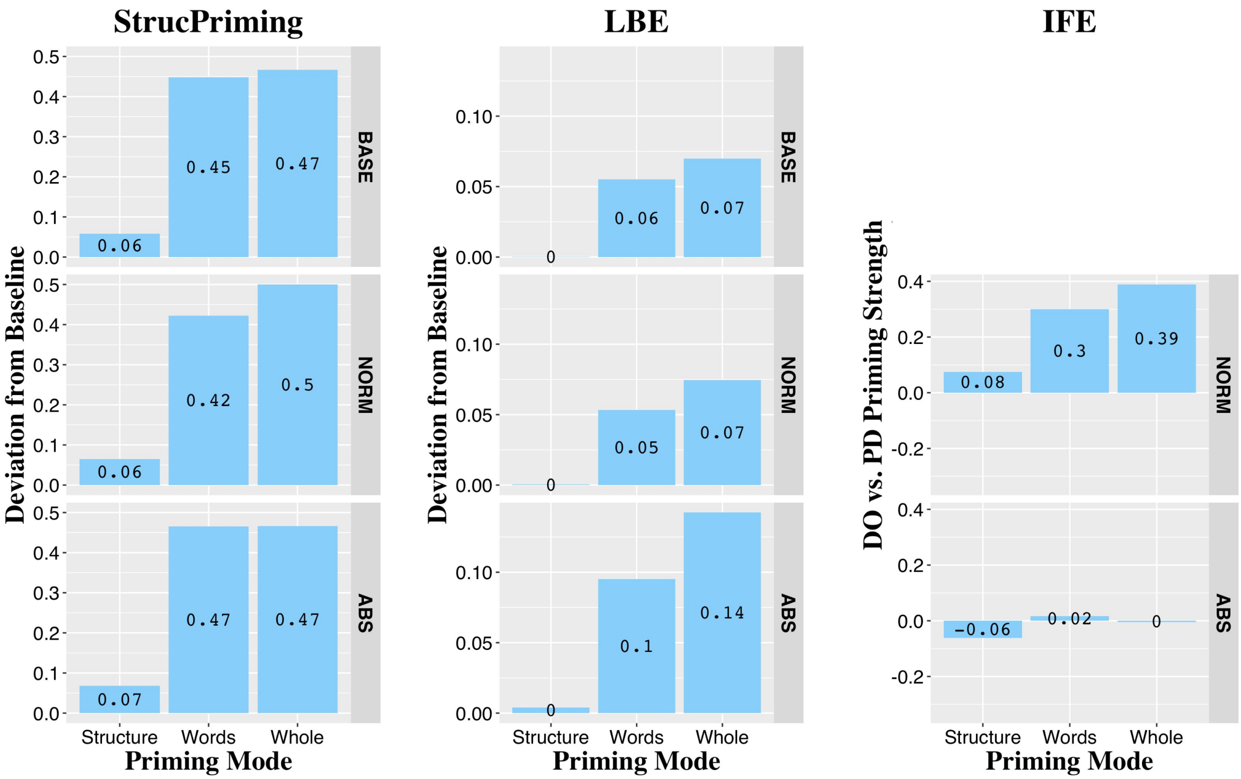

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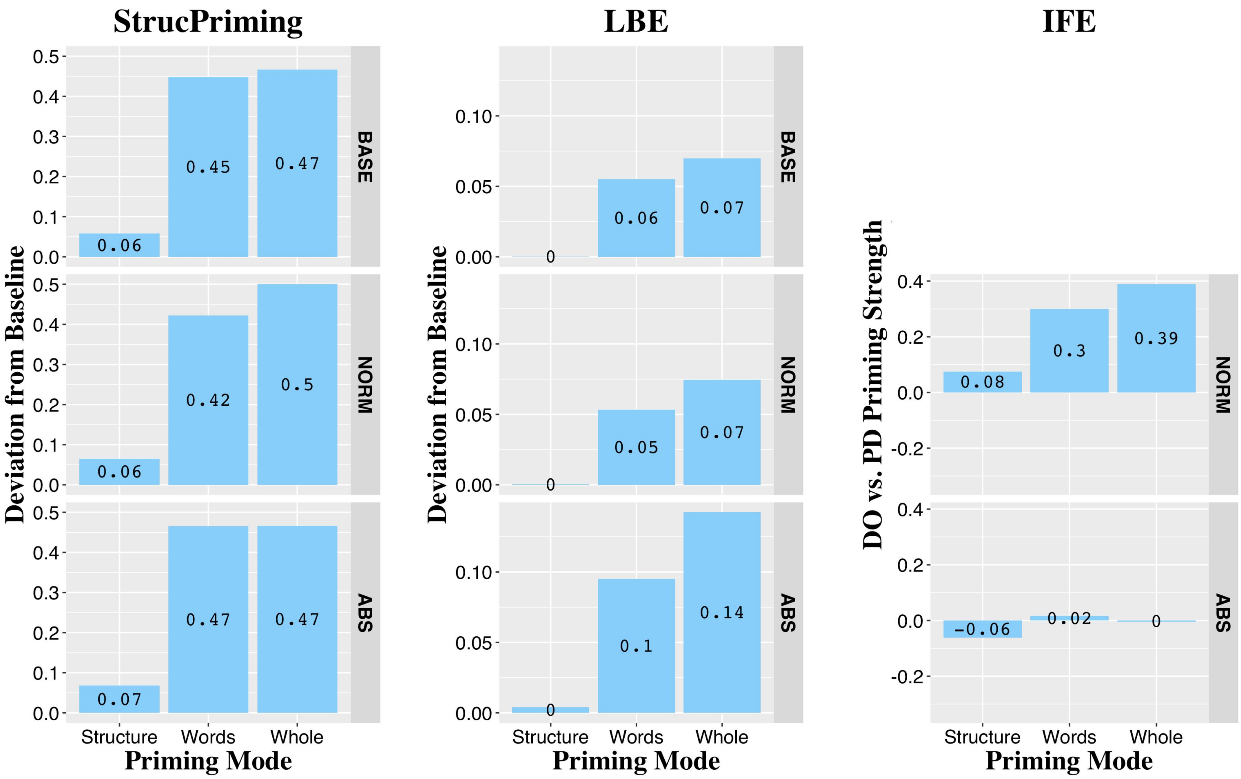

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  - In general, the GSC framework works on modeling the incremental processes of sentence production.
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Conclusions & Implications

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- Why only the **NORM** model captures IFE remains a problem for further exploration.
  - The **NORM** model learns the PCFG distribution better than the **ABS** model;
  - Both models acquired most of the verb biases;
  - Postulation: PIPS may be sensitive to target distributions and/or hyperparameters.
  - Connection with the role of **Type** (**NORM**) **vs. Token** (**ABS**) **Frequency** (e.g. [Bybee & Hopper 2001]);

Future Work

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Extending the Simulation Domain

- Simulating other structural priming phenomena, such as filler-gap dependency (e.g. [Momma 2022]);

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Thanks for Listening!

Q&A Session

Tensor Product Representation: Extra

Orthogonal vector representations of the followings:

- Representation of a syntactic tree = summing over all bindings representing each node;
- **Decomposability**: linearly independence avoids the superposition catastrophe:

[Smolensky 1990]

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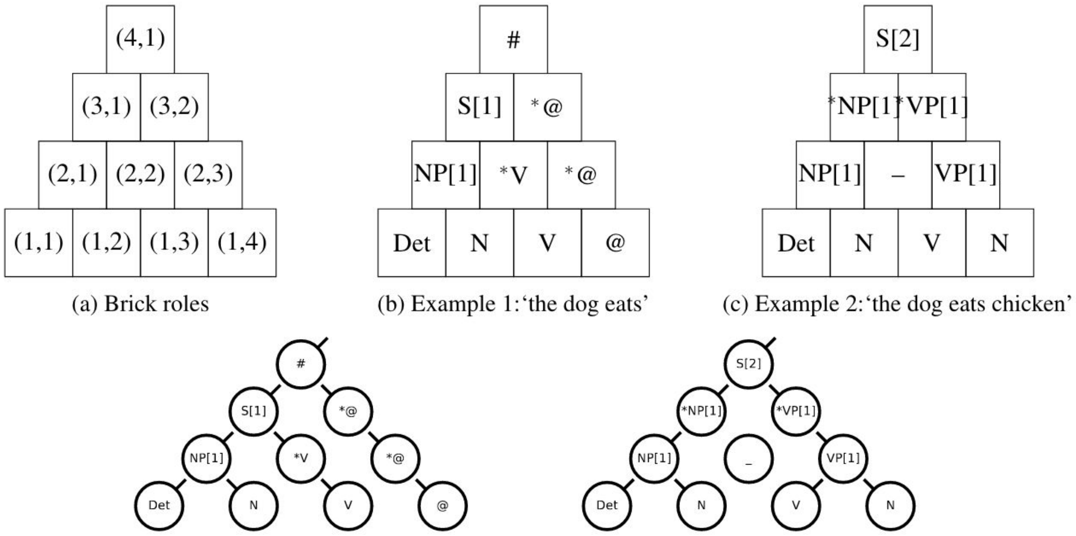
$$f_1 + f_2 = f_2 + f_1$$

$$f_1 \otimes r_1 + f_2 \otimes r_2 \neq f_2 \otimes r_1 + f_1 \otimes r_2$$

[Smolensky 1990]

Brick-Role Representation

TPR Implementation: Brick-Role Representation



(a) Brick roles

(b) Example 1:‘the dog eats’

(c) Example 2:‘the dog eats chicken’

(d) Example 1

(e) Example 2

[Cho 2020, Brehm et al. 2022]

Optimizing Over Constraints

[Smolensky & Hale 2006, Cho et al. 2018, 2020]

Optimizing Over Constraints

Non-grammatical Constraints:

- **Competition Constraint**: avoiding bindings of multiple fillers to the same role;
- **Baseline Constraint**: avoiding extreme states;
- **Discreteness Constraint**: encouraging activation values to be close to 0 or 1 as time goes;
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[Smolensky & Hale 2006, Cho et al. 2018, 2020]

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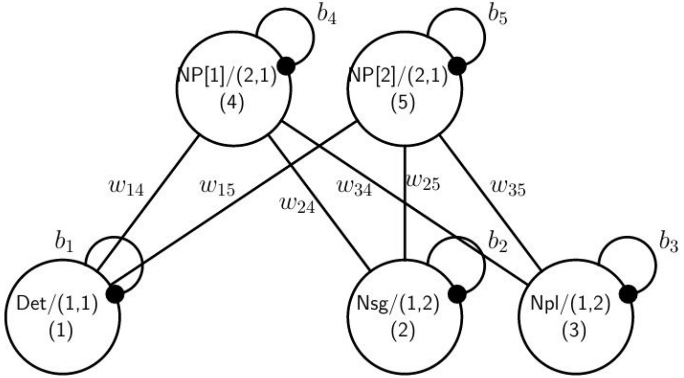
Grammatical Constraints:

- Harmonic Grammar



[Smolensky & Hale 2006, Cho et al. 2018, 2020]

PCFG for the NORM Model

```
1 S -> NPs VP
1 XP -> NPi NPd
1 YP -> NPd PP
1 PP -> P NPi
0.05848089468779124 VP -> show XP
0.06651910531220875 VP -> show YP
0.021690400843881855 VP -> send XP
0.10330959915611815 VP -> send YP
0.025907494145199064 VP -> lend XP
0.09909250585480094 VP -> lend YP
0.03981385729058945 VP -> hand XP
0.08518614270941055 VP -> hand YP
0.06521739130434782 VP -> loan XP
0.059782608695652176 VP -> loan YP
0.04808184143222506 VP -> offer XP
0.07691815856777494 VP -> offer YP
0.016069012178619755 VP -> sell XP
0.10893098782138025 VP -> sell YP
0.002232142857142857 VP -> post XP
0.12276785714285714 VP -> post YP
```