

An extensible framework for mechanistic processing models

From representational syntax-semantics theories to
quantitative model comparison

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Overarching goal

- build formally and computationally explicit processing models for natural language syntax and semantics
- specifically, cognitively realistic models for incremental parsing of discourse representations structures (DRSs, Kamp 1981; Kamp and Reyle 1993) or similar representations
- the semantic and syntactic representations are created in parallel

Main goal for today:

- modeling *syntactic* representations

An extensible framework for processing models

- **mechanistic** models of language processing
- common approach: use an independently motivated, general cognitive architecture
- parsing easy to embed in hybrid cognitive architectures

- Soar

Hale, [2014](#); Young and Lewis, [1999](#)

- ACT-R

Dillon et al., [2013](#); Engelmann et al., [2013](#); Kush, [2013](#); Lewis and Vasishth, [2005](#); Nicenboim and Vasishth, [2018](#); Rij, [2012](#); Taatgen and Anderson, [2002](#); Vasishth et al., [2008](#)

The current state of ACT-R language modeling

- Mainly used to model recall of syntactic structures

Dillon et al., [2013](#); Engelmann et al., [2013](#); Lewis and Vasishth, [2005](#); Nicenboim and Vasishth, [2018](#); Vasishth et al., [2008](#)

- This focus on recall-related modeling does not take advantage of the generality of ACT-R as a cognitive architecture and its “no magic” policy
- Implemented fully in LISP (not a very popular programming choice now)
- ACT-R comes with many parameters; these are set to their default values or manually changed
- Modeling is hard to replicate; systematic quantitative model comparison hard to perform

This talk

- A new Python3 implementation of ACT-R (pyactr; Brasoveanu and Dotlačil [in prep.](#))
- **ACT-R + Bayes**: ACT-R models embedded in Bayesian models, hence systematic exploration of parameter values, model comparison, modeling easy to replicate
- the ACT-R component: a working, extensible parsing framework for syntax and semantics, with visual and motor interfaces (today, only syntax)
- modular structure: alternative models for peripherals (visual, motor) & other components possible

Showcasing the framework

Grodner and Gibson (2005, Exp. 1), also used in Lewis and Vasishth, 2005

- Grodner and Gibson (2005, Exp. 1): self-paced reading, matrix subject is modified by a subject or object-extracted relative clause (RC)
 - (1) The
reporter who sent the photographer to the editor hoped
for a story.
 - (2) The
reporter who the photographer sent to the editor hoped
for a story.

9 ROIs: word 2 through word 10 (underlined above)

Demo of an ACT-R model for subj and obj gap RCs

(open the slides with Adobe Acrobat Reader to see the movie)

Red circle is the visual focus. Temporal trace incrementally produced by the model is visible in the background.

- 1 Introduction: framework & case study
- 2 ACT-R & left-corner parsing
- 3 Results
- 4 Conclusion

1 Introduction: framework & case study

2 ACT-R & left-corner parsing

3 Results

4 Conclusion

Memory in ACT-R

Two types of memory:

- DECLARATIVE MEMORY: knowledge of facts
facts represented as chunks (attribute-value matrices)

ISA:	word
FORM:	car
MEANING:	[[car]]
CATEGORY:	noun
NUMBER:	sg

- PROCEDURAL MEMORY: behavior as a series of productions
productions – conditionalized actions

Goal>	TASK: reading		Goal>	TASK: retrieving category
	FORM: car	⇒	Retrieval>	ISA: word
				FORM: car

Modules and buffers in ACT-R

- ACT-R mind is composed of modules, which include declarative and procedural memory
- Modules are not directly accessible – they can only be accessed through buffers
- Buffers represent agent's current state; productions fire based on contents of buffers
- Buffers can hold only one chunk
- Only one production can fire at any given time

An eager left-corner parser in ACT-R

Building on Lewis and Vasishth, 2005; Resnik, 1992

Parser components:

- lexical knowledge, knowledge of intermediate parse states / syntactic structures → declarative memory
- knowledge of grammar → procedural memory (common, e.g., Lewis and Vasishth 2005, but not only choice, e.g., Reitter et al. 2011)
- expectations about upcoming syntactic categories, which guide parsing → goal buffer
- information about the current syntactic parse → imaginal buffer
- visual information from environment → visual buffer
- key press commands → manual buffer
- visual module – EMMA Salvucci, 2001 (other choices possible)
- motor module – EPIC Kieras and Meyer, 1996; Meyer and Kieras, 1997

An eager left-corner parser in ACT-R

Rules:

$S \rightarrow NP VP$

$NP \rightarrow Det N$

$VP \rightarrow V$

Visual input:

■ A boy sleeps.

A -- ---- .

Input

- Stack: S (Goal)
- Found: a, Det
(Visual + Retrieval)

Output

- Stack: N NP S (Goal)
- Structure:

S
|
NP
|
Det
|
a

An eager left-corner parser in ACT-R

Rules:

$S \rightarrow NP VP$

$NP \rightarrow Det N$

$VP \rightarrow V$

Visual input:

■ A boy sleeps.

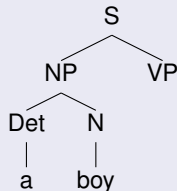
- boy ----.

Input

- Stack: N NP S (Goal)
- Found: *boy*, N
(Visual + Retrieval)

Output

- Stack: VP (Goal)
- Structure:



An eager left-corner parser in ACT-R

Rules:

$S \rightarrow NP VP$

$NP \rightarrow Det N$

$VP \rightarrow V$

Visual input:

■ A boy sleeps.

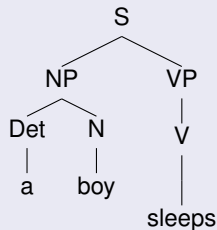
- - - sleeps.

Input

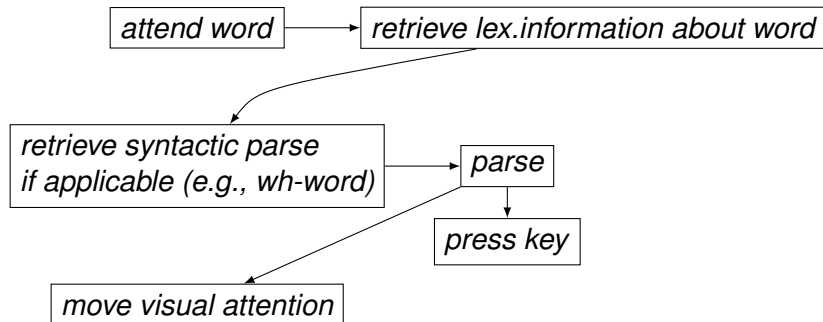
- Stack: VP (Goal)
- Found: *sleeps*, V
(Visual + Retrieval)

Output

- Stack: {} (Goal)
- Structure:



Flow chart of parsing process per word



Parameters – visual encoding (EMMA)

- Visual encoding (T_{enc}) dependent on visual distance d and object properties, D

$$T_{enc} = K \cdot D \cdot e^{kd} \text{ (parameter } k \text{ – angle)}$$

- D = word length, $K = 0.01$
- k – estimated to show that parameters for peripherals can be estimated at the same time as the more commonly estimated parameters associated with declarative and procedural memory

Parameters – rule firing and memory recall

- Rule firing = r (parameter r)
- Retrieval latency is a function of activation, modulated by parameters F (latency factor) and f (latency exponent)

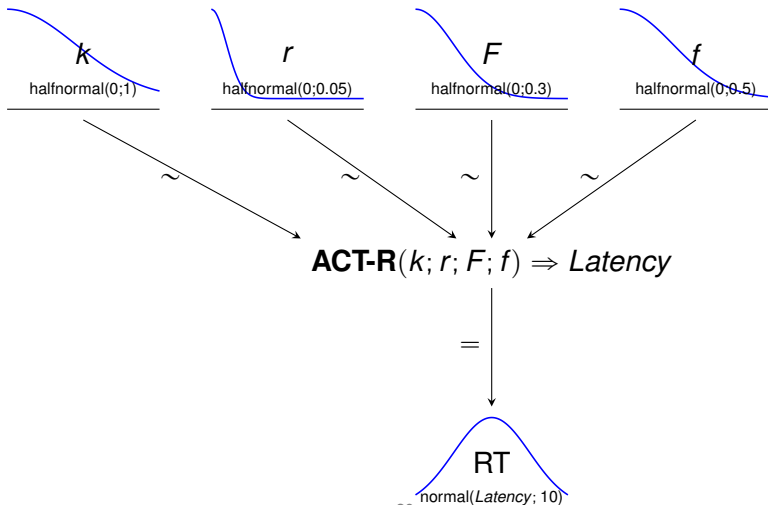
$$T = F \cdot e^{-f \cdot A}$$

- from chunk activation, A , we only consider base activation, which is a function of time elapsed since previous word usages
- estimating r – needed because our processing models incorporate linguistic theories in a fairly transparent way; so: we need to fire more rules per word / region of interest (ROI) than possible with the 50 ms default; production compilation should increase r closer to its ACT-R default
- latency exponent f – estimated because crucial in estimating latencies in lexical decision tasks (e.g., the tasks in Murray and Forster [2004](#))

Estimation

- The model is fit to data by estimating the 4 free parameters (k , r , F , f)
- Standardly, relying on default values or manually changing the values; subjective & time consuming
- **pyactr** enables us to easily interface ACT-R models with standard statistical estimation methods implemented in widely-used Python3 libraries
- we use ACT-R models as the likelihood component of full Bayesian models, and fit the ACT-R parameters to experimental data

Bayesian model structure



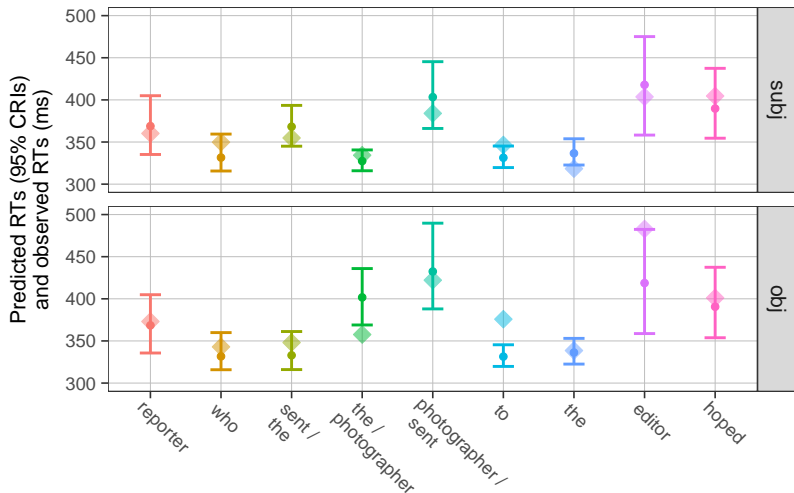
1 Introduction: framework & case study

2 ACT-R & left-corner parsing

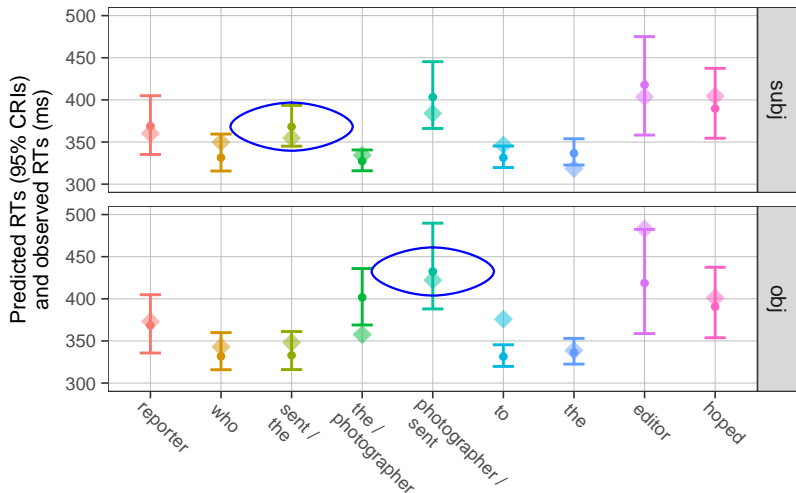
3 Results

4 Conclusion

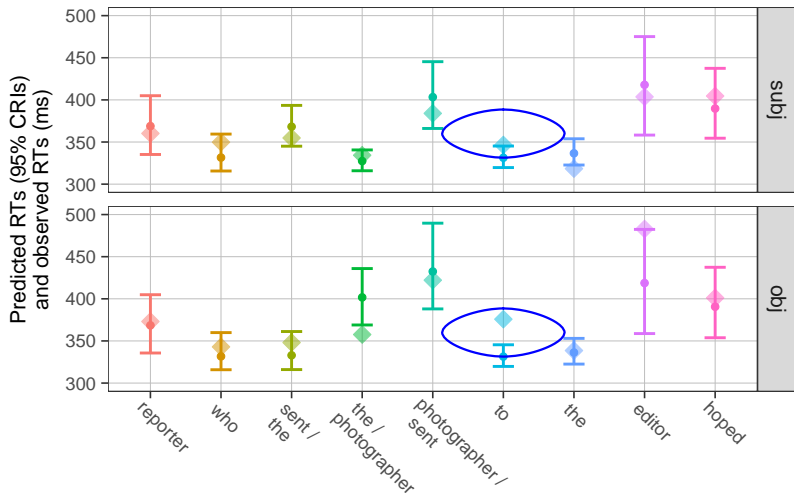
Posterior predictions (Model 1)



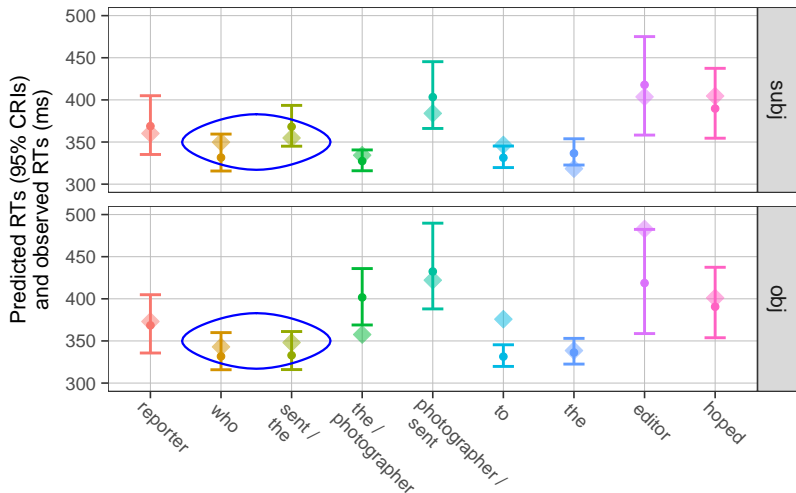
Posterior predictions (Model 1)



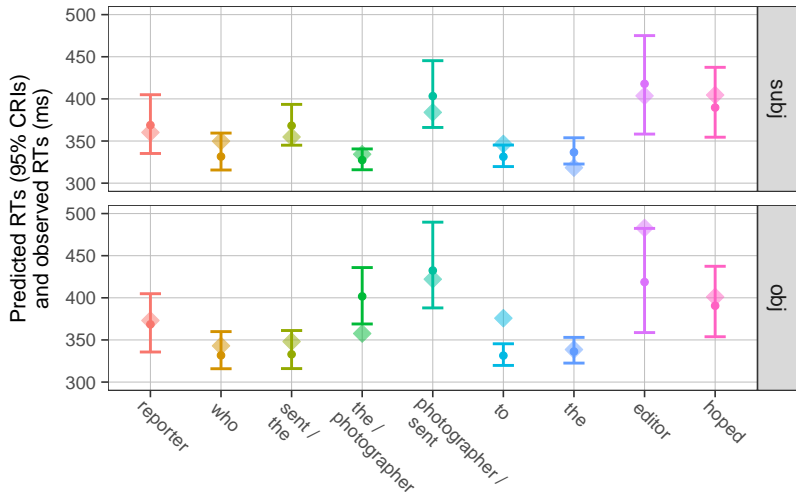
Posterior predictions (Model 1)



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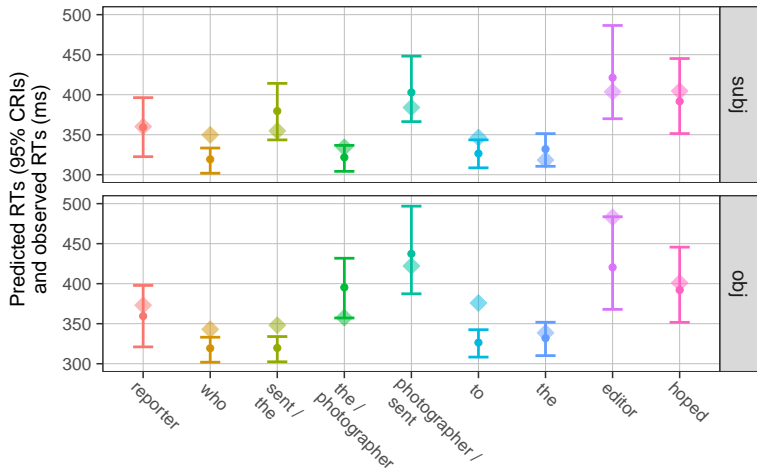


Posterior predictions (Model 1)

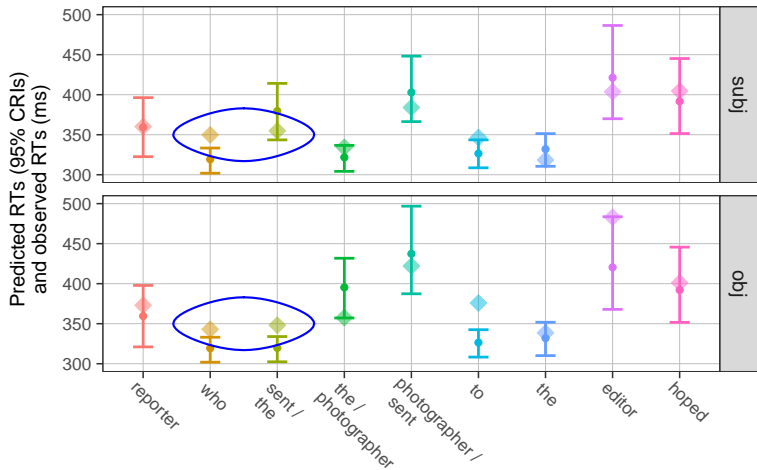


Model 2: no postulated subject gaps

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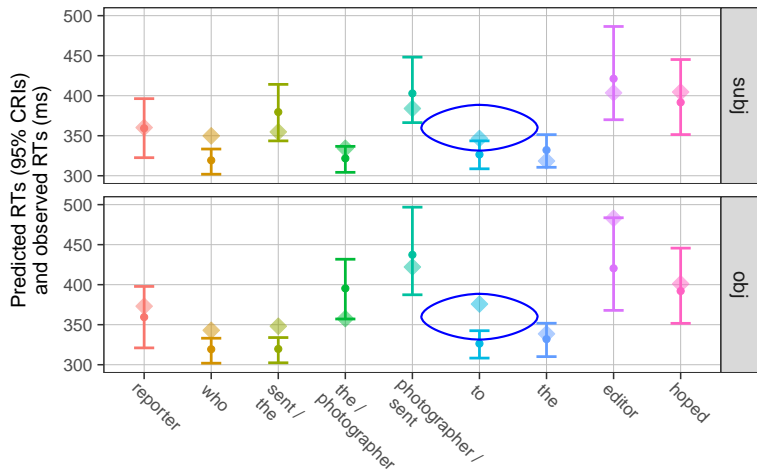


Model 2: no postulated subject gaps

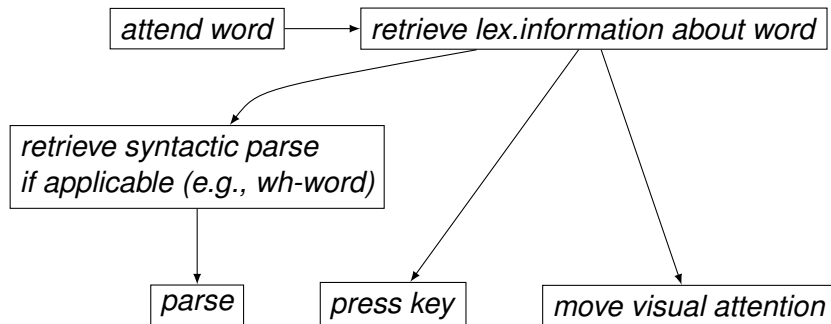


wh-word and following word not modeled well; Model 1 better

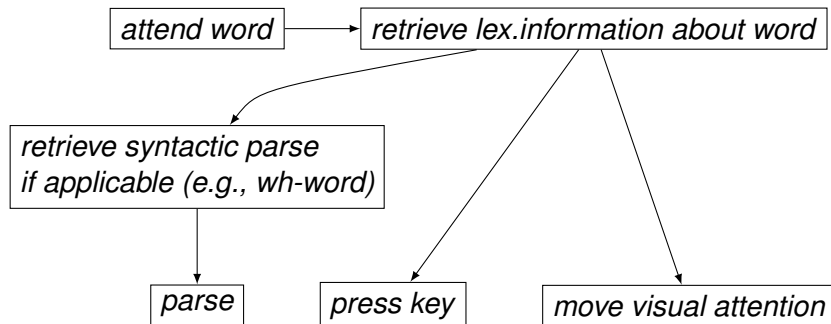
Model 2: no postulated subject gaps



Model 3: parallel reader

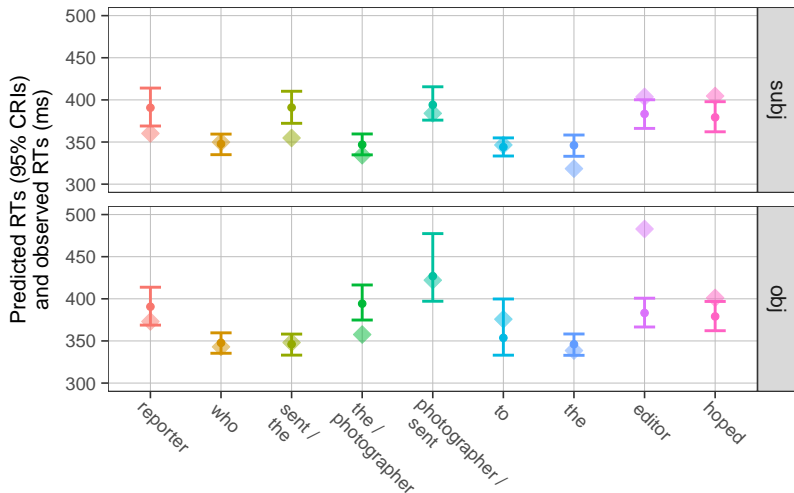


Model 3: parallel reader

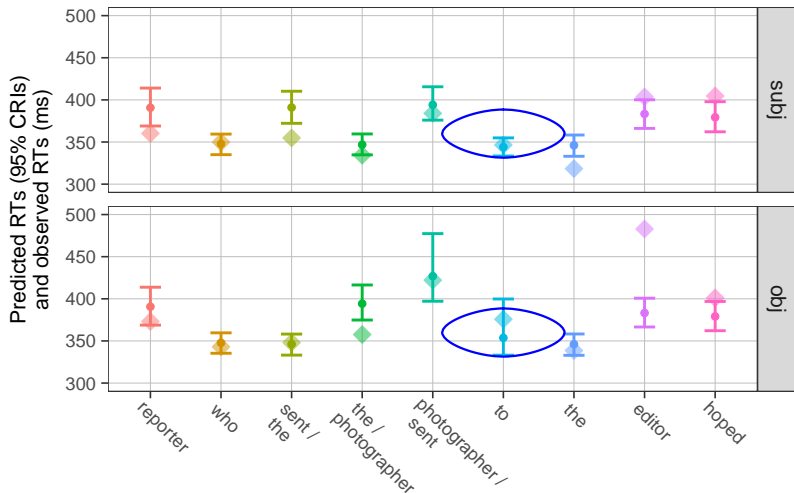


- Model 1 completes all available parsing before key press (serial)
- Model 3: first lexical retrieval, then structure building & key press in parallel
- Outcome: spillover on word after object gap captured

Model 3: spillover after object gap captured



Model 3: spillover after object gap captured



WAIC-based model comparison

	WAIC ₁	WAIC ₂
Model 1 (subject gaps)	388	1469
Model 2 (no subject gaps)	433	1613
Model 3 ('parallel' reader)	390	553

- Model 1 is better than Model 2 with respect to both WAIC₁ and WAIC₂
- increase in precision for Model 3 is clearly visible in its much lower WAIC₂ value (which is variance based)

Conclusion






- we introduced a modular and extensible framework for mechanistic processing models
- case study: an incremental left-corner parser with visual and motor interfaces for subject/object gap relative clauses
- framework used to quantitatively compare hypotheses about processing, e.g., predictively postulating subject gaps
- systematic across-the-board model comparison via Bayes factors is possible in this framework
- framework can model other tasks (eye tracking, lexical decision)
- individual differences can be modeled by adding random effects

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Model 1: parameter estimates

- $k = 0.87, sd = 0.32$
- $F = 0.01, sd = 0.03$
- $f = 0.23, sd = 0.47$
- $r = 0.02, sd = 0.006$