A cognitively realistic left-corner parser with visual and motor interfaces

An extensible framework for mechanistic processing models

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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 processing
  "in most instances, cognitive scientists would ultimately prefer an explanatory process over mere characterization"
  Lewandowsky and Farrell, 2010
- 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 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 comparsion hard to perform

This talk

- A new Python3 implementation of ACT-R (pyactr; Brasoveanu and Dotlačil 2018, in prep.) **https://github.com/jakdot/pyactr**
- 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.

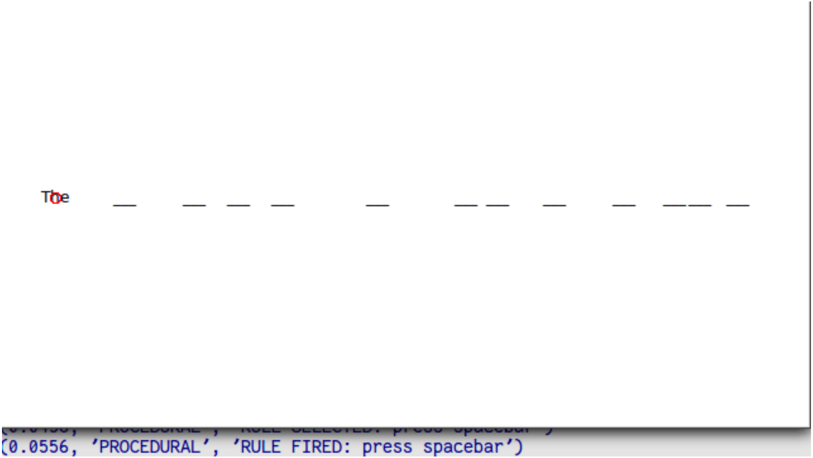
(2) The reporter who the photographer sent to the editor hoped for a story.

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

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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 ; FORM: car] ⇒ Goal> [TASK: retrieving category] 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 → declarative memory
- knowledge of grammar → procedural memory
- expectations about upcoming syntactic categories, which guide parsing → goal buffer
- information about the current syntactic parse → secondary goal 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 → NP VP
NP → Det N
VP → 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 → NP VP
NP → Det N
VP → V

Visual input:

- A boy sleeps.

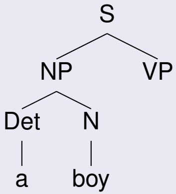
`- boy ----.`

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 → NP VP
NP → Det N
VP → V

Visual input:

- A boy sleeps.

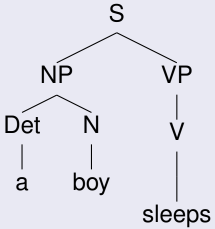
`- -- sleeps.`

Input

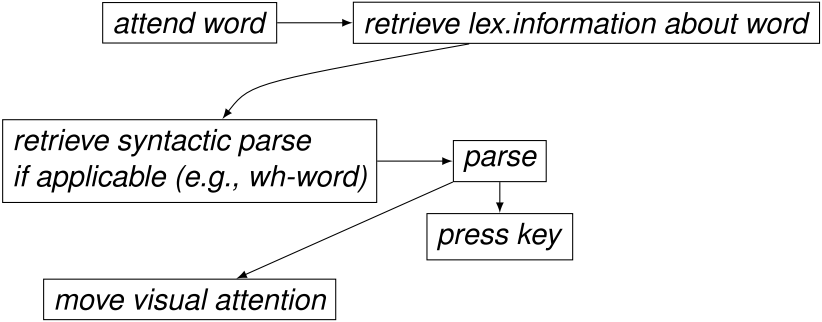
- Stack: VP (Goal)
- Found: *sleeps*, V
  (Visual + Retrieval)

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, $K = 0.01$

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)

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

- Base activation, A, is a function of time elapsed since previous word usages

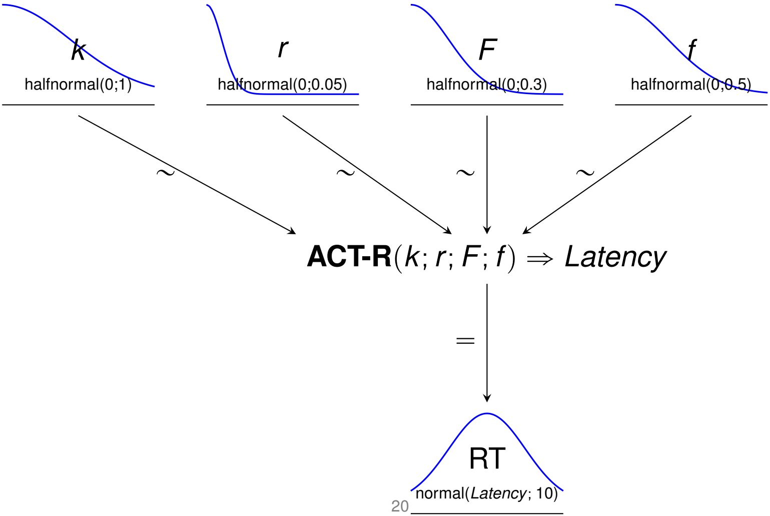
$$A = \log\left(\sum_{k=1}^{n} t_k^{-0.5}\right)$$

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



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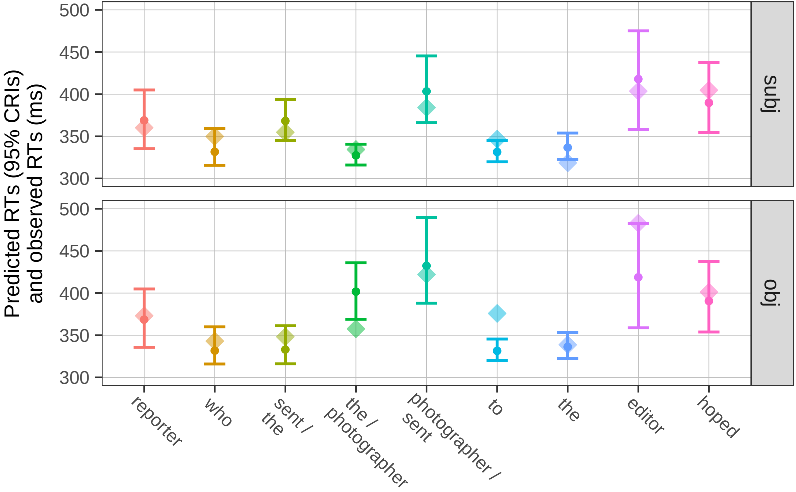
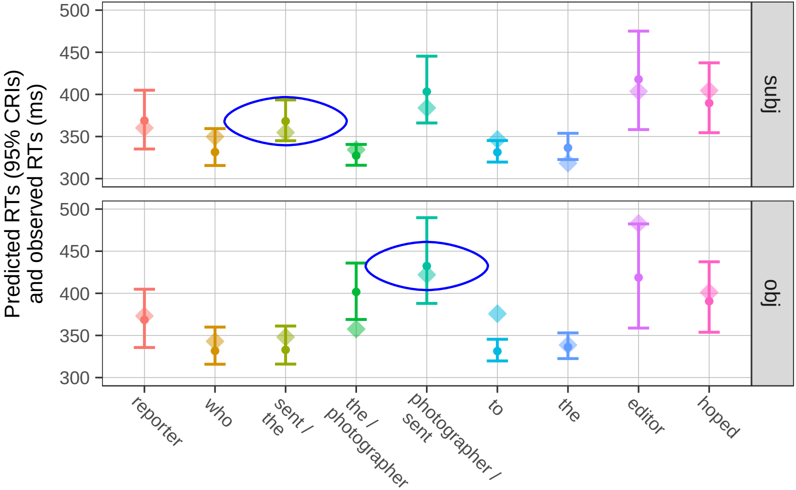
Posterior predictions (Model 1)



Posterior predictions (Model 1)



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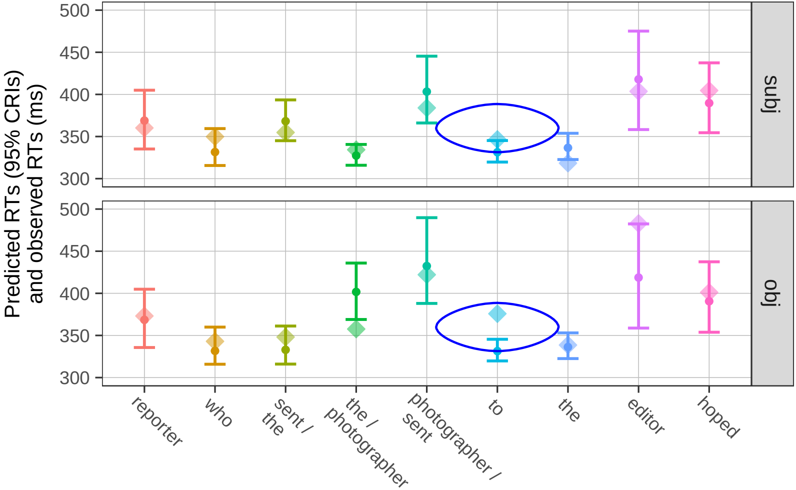

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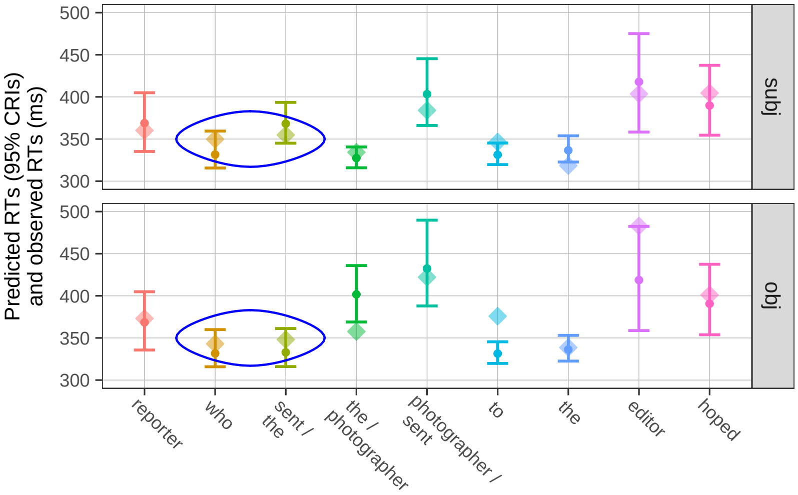

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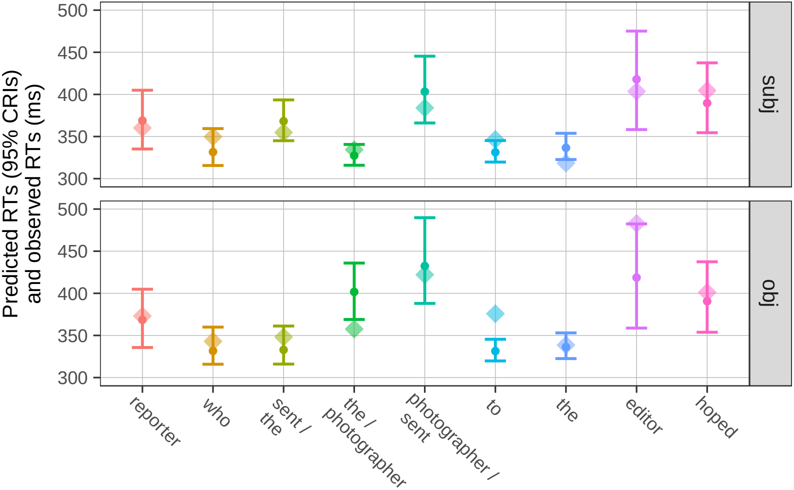

Model 2: no postulated subject gaps

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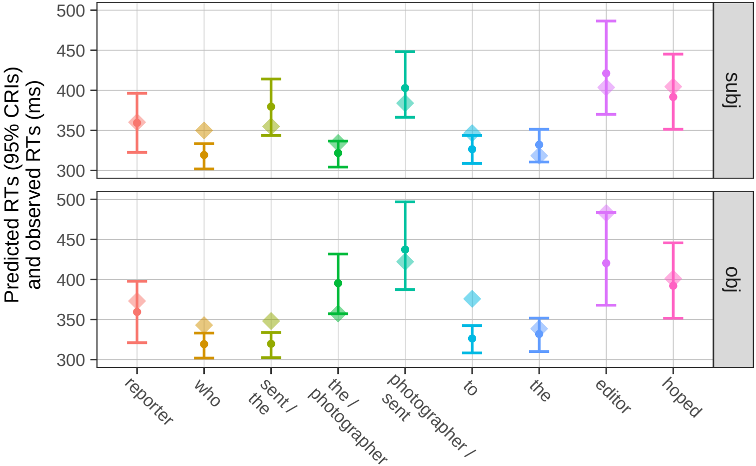
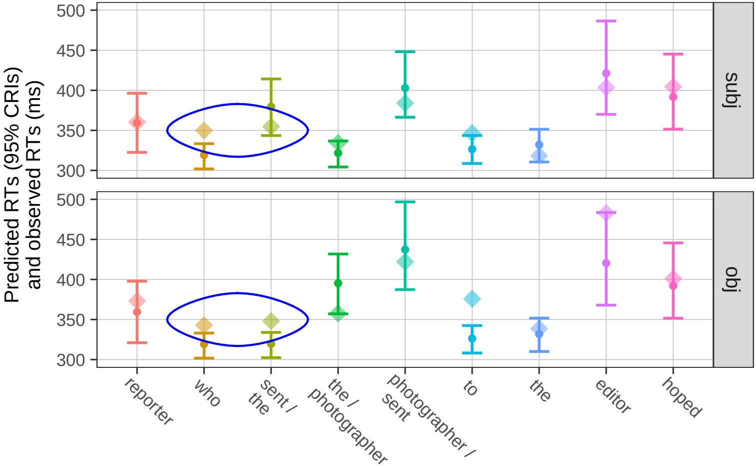
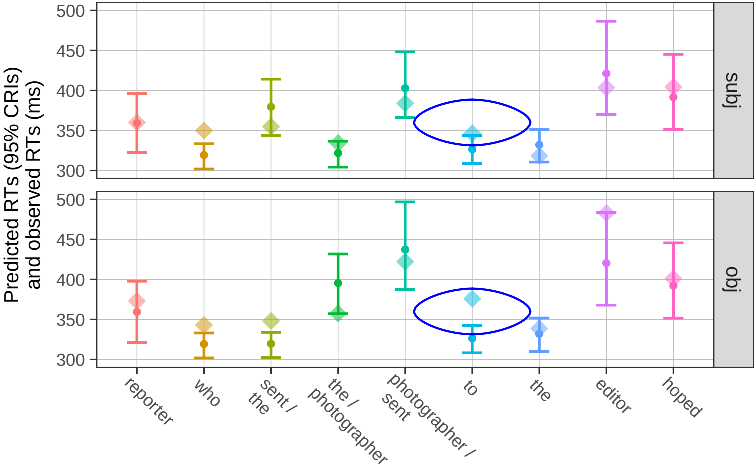


Model 2: no postulated subject gaps

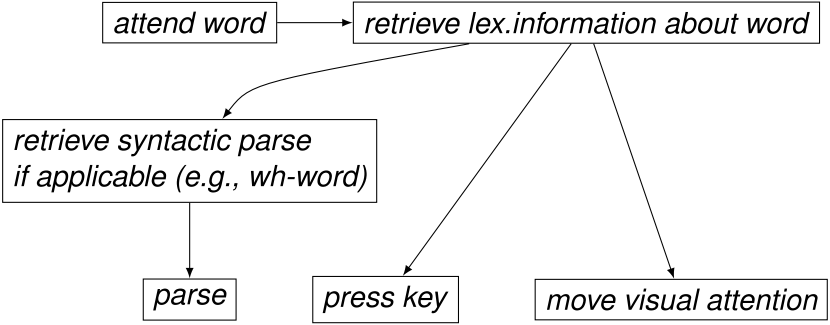


wh-word and following word not modeled well; Model 1 better

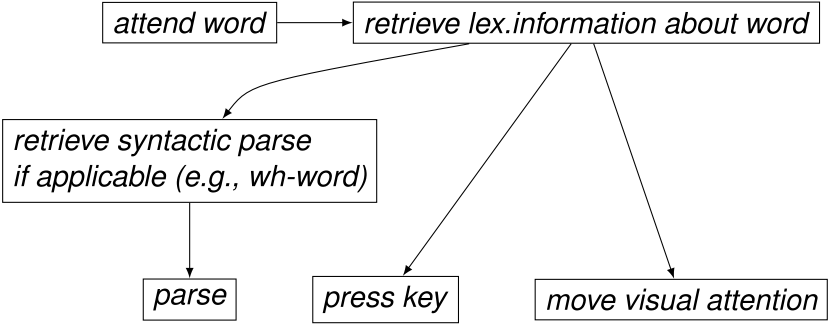
Model 2: no postulated subject gaps



Model 3: parallel reader

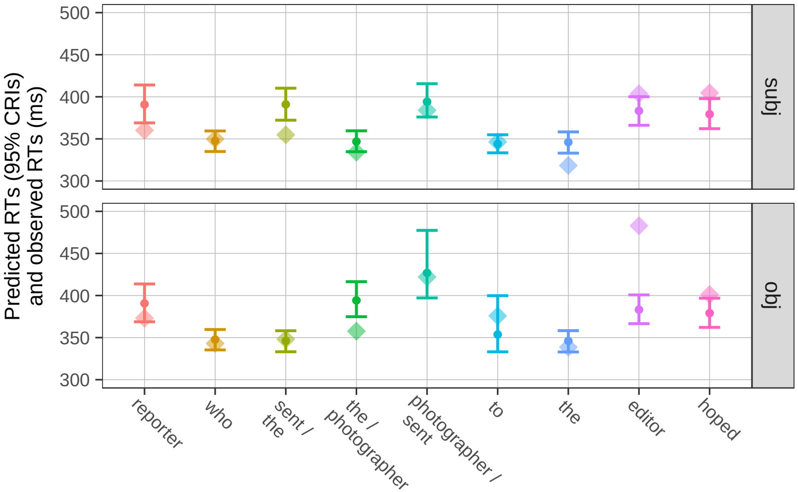


Model 3: parallel reader

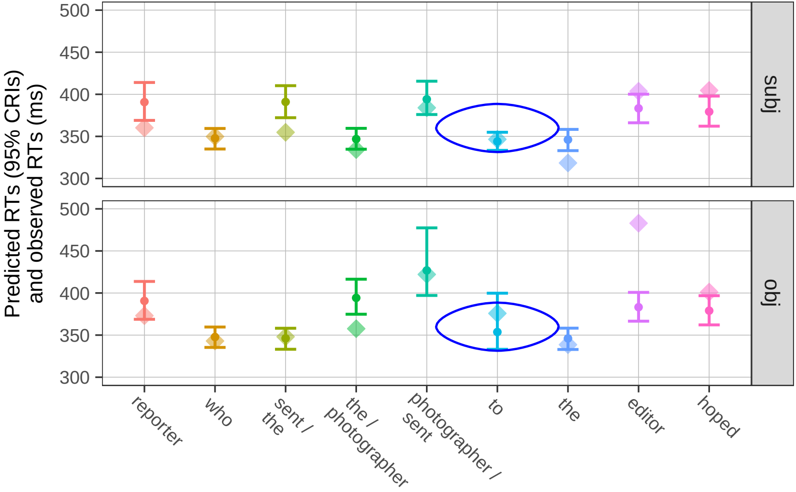


- Model 1 completes all available parsing before key press (serial)
- Model 3: first lexical retrieval, then structure building & key press in parallel
- Outcome: spillover on word after object gap captured

Model 3: spillover after object gap captured



Model 3: spillover after object gap captured



Model 3: predictions for individual items

- we compare predictions per item
  (linear regression: observed RT $\sim$ predicted RT)

  1ms increase in predicted RT corresponds to 1ms increase in observed RT (SE=0.009) $(t = 5.7)$

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  (linear regression: observed RT $\sim$ predicted RT)

  1ms increase in predicted RT corresponds to 1ms increase in observed RT (SE=0.009) $(t = 5.7)$

Eye-tracking and self-paced reading (data from Frank et al. 2013; a variety of syntactic structures, no RCs)

- SPR: 1ms increase in predicted RT corresponds to 0.79ms increase in observed RT ($t = 2.1$)

- ET: 1ms increase in predicted RT corresponds to 0.82ms increase in observed RT ($t = 3.31$)

Conclusion: the framework and case study

- 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

Conclusion: future directions

- we have only done informal quantitative comparisons based on posterior predictions
- but systematic across-the-board model comparison via Bayes factors is possible in this framework
- framework can model other tasks (eye tracking, lexical decision)

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Models coming soon here:
https://github.com/jakdot/conferences/2018

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