# Modeling Coreference in Contexts with Three Referents

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LEVERHULME TRUST

# The puzzle

Donald called Rudy. . . .

# Models of coreference

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**Bayesian Model** (Kehler et al. 2008; Kehler & Rohde 2013; Rohde & Kehler 2014)

$$\mathbf{p}(\mathbf{referent}|\mathbf{pronoun})_{\mathbf{interpretation}} \sim \mathbf{p}(\mathbf{referent})_{\mathbf{prior}} * \mathbf{p}(\mathbf{pronoun}|\mathbf{referent})_{\mathbf{likelihood}}$$

# Interpretation does not equal production

**Story continuation**

John scolded Bob. He ____________________________ [pronoun prompt]
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**The Bayesian model captures this asymmetry**

# Weak versus strong Bayes

## Bayesian Model

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- **meaning** drives the *prior*
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In its **weak form**, the Bayesian model states that **pronoun production and interpretation are related by Bayesian principles**.

# Current study

- Most of the research on pronoun production / interpretation has focused on sentence frames with two referents.
- Results appear to differ between implicit causality verbs and studies with transfer-of-possession verbs
(e.g., Rohde 2008; Fukumura & van Gompel 2010 versus Rosa & Arnold 2017)

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**In a new context type with three referents**, we test:

1. whether predictability influences pronominalization
2. whether Bayes' Rule captures the relationship between pronoun interpretation and production

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**Items**

Adam called Diana for Russel. He ______________________ [pronoun prompt]
Adam called Diana for Russel. __________________________ [free prompt]

- Counterbalanced which referents were gender-matched
  (NP1&NP2, NP1&NP3, NP2&NP3)

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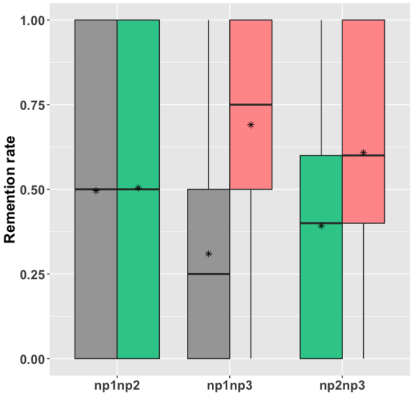
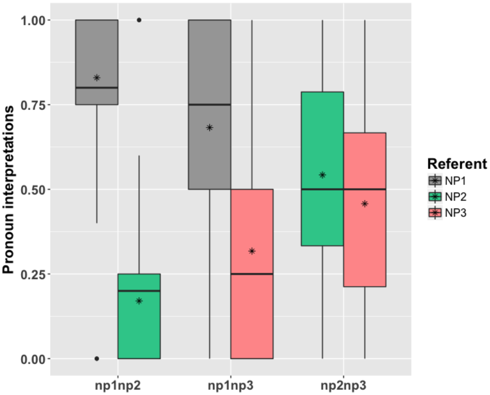
  (NP1&NP2, NP1&NP3, NP2&NP3)
- 83 native speakers of English
- 30 items
- Continuations were coded for:
  - who the continuation is about
  - what form of referring expression is used (free prompt condition only)

# Results: More subject continuations in pronoun prompt

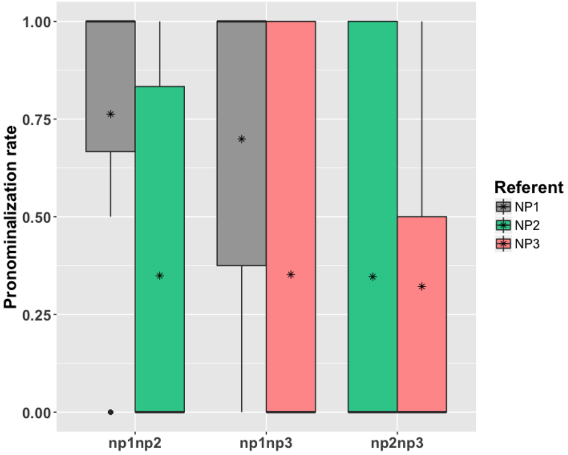



Free prompt




Pronoun prompt

# Results: Subjects are preferentially pronominalized

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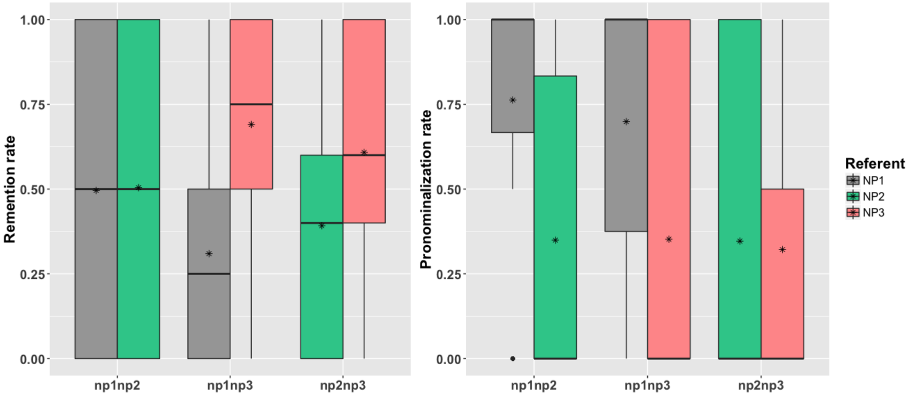


Free prompt

# Results 2: Does Bayes' Rule rule?

Following Rohde & Kehler (2014), we used the free prompt continuations to calculate Bayes-derived estimates of $p(\textit{referent}|\textit{pronoun})$ via the prior $p(\textit{referent})$ and likelihood $p(\textit{pronoun}|\textit{referent})$, as well as estimates for the Expectancy Model (prior) and the Mirror Model (normalized likelihood). We then compared the model estimates with the pronoun interpretations measured in the pronoun prompt condition

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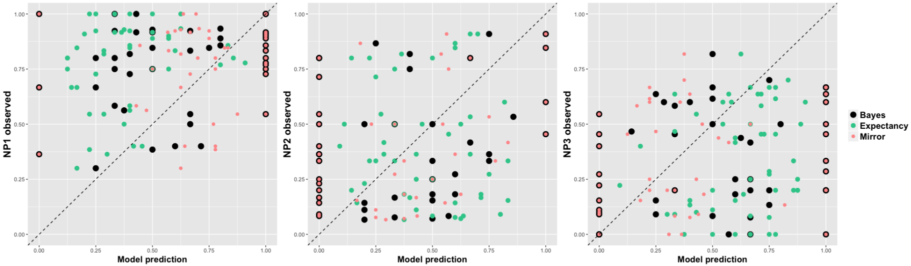


**Items:** Bayes: $R^2 = .122$, Expectancy: $R^2 = .003$, **Mirror:** $\mathbf{R^2 = .377}$
**Participants:** **Bayes:** $\mathbf{R^2 = .084}$, Expectancy: $R^2 = .021$, Mirror: $R^2 = .075$

# Interim discussion

- We do not find any evidence that pronominalization is affected by predictability
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- The Bayesian model outperforms the Expectancy model
- The Bayesian model is outperformed by the Mirror model

$\rightarrow$ Is this due to the construction or does it have something to do with the number of referents?

# Follow-up: 2-human Benefactive prompts

## Items

Adam called the hospital for Russel. He ________________ [pronoun prompt]
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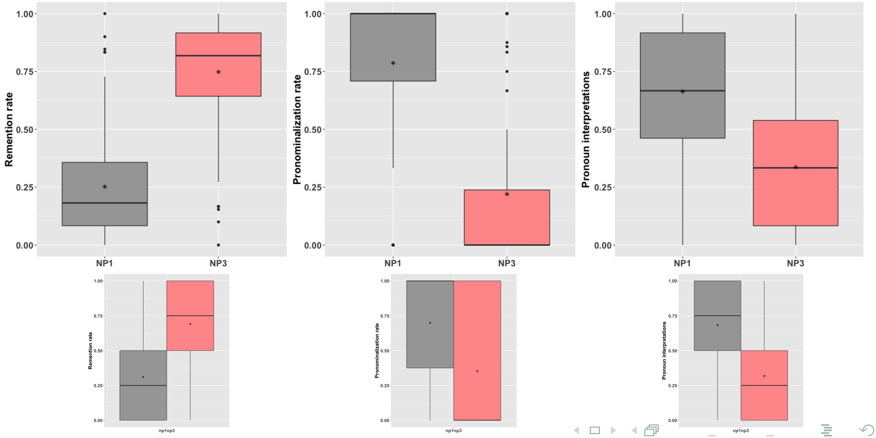

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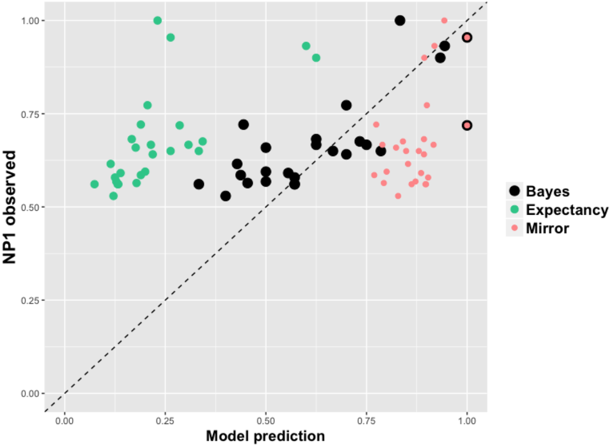


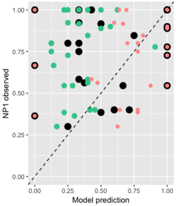


**Items:** **Bayes: $\mathbf{R^2}$ = .719**, Expectancy: $R^2 = .311$, Mirror: $R^2 = .714$
**Participants:** **Bayes: $\mathbf{R^2}$ = .348**, Expectancy: $R^2 = .008$, Mirror: $R^2 = .282$

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## But why?

- Power issue?
  - But no fewer observations per ambiguous pair than earlier work with 2 referents
- 3 referents make the task harder?
  - But is it really? In which way? And why would this matter?

# Thank you!

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