Modeling misretrieval and feature substitution in agreement attraction

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Introduction

- Consider sentence (1), adapted from Staub (2010):

(1) The clubs that the advertisement were promoting . . .

- **Agreement attraction (AA)**: The non-local NP *clubs* is occasionally able to license the plural verb *were*

? How is the **interpretation** of the sentence affected by AA?

- **Subject-as-plural** misinterpretations (*advertisements*) would support an account of AA as being **encoding-based**: **Feature change** of the subject NP can occur in the presence of the attractor (e.g. Eberhard, Cutting & Bock, 2005)
- **Attractor-as-subject** misinterpretations (*the clubs were . . .*) would support an account of AA as being **retrieval-based**: Feature-matching attractor is **misretrieved** as the sentence subject (e.g. Wagers, Lau & Phillips, 2009)

- Recent findings:
  - Patson & Husband (2016): Misinterpretations of subject NP as plural increase in the presence of plural attractor
  - Schlueter, Parker & Lau (2019): Misinterpretations of attractor as subject slightly increase in the presence of plural attractor

- We investigate the occurrence of **feature change**- and **misretrieval**-based misinterpretations simultaneously
- **Encoding**- and **retrieval**-based explanations are compared using computational modeling and 10-fold cross-validation in Stan (`https://mc-stan.org/`)
- Current results complement previous work on AA in Armenian (Avetisyan, Lago & Vasishth, 2019)

Experimental design

- 2×2 design with factors grammaticality, attractor match
- 43 subjects, 36 items
- Self-paced reading, free-response end-of-sentence comprehension task (**Who ignored Ø?**)

Grammatical | distractor-verb match, distractor-target match

Nkarič-Ø-ë	or-in	k'andakagorç-Ø-ë	arhamarh-ec' . . .
Painter-SG.NOM	that-SG.ACC	sculptor-SG.NOM	ignore-AOR.3.SG

Grammatical | distractor-verb mismatch, distractor-target mismatch

Nkarič-ner-ë	or-onc'	k'andakagorç-Ø-ë	arhamarh-ec' . . .
Painter-PL.NOM	that-PL.ACC	sculptor-SG.NOM	ignore-AOR.3.SG

Ungrammatical | distractor-verb mismatch, distractor-target match

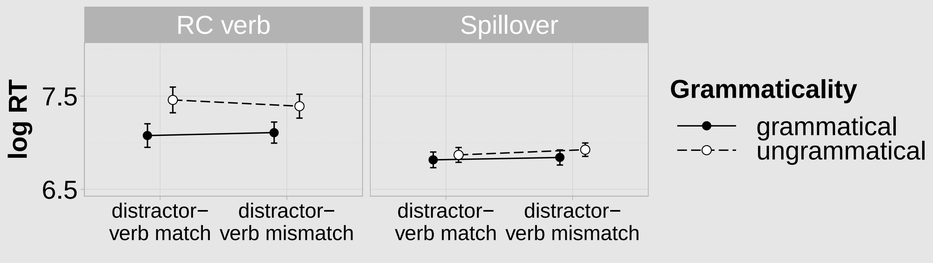
Nkarič-Ø-ë	or-in	k'andakagorç-Ø-ë	arhamarh-ec'-in . . .
Painter-SG.NOM	that-SG.ACC	sculptor-SG.NOM	ignore-AOR-3.PL

Ungrammatical | distractor-verb match, distractor-target mismatch

Nkarič-ner-ë	or-onc'	k'andakagorç-Ø-ë	arhamarh-ec'-in . . .
Painter-PL.NOM	that-PL.ACC	sculptor-SG.NOM	ignore-AOR-3.PL
. . . c'owc'ahandesi	ënt'ac'k'owm	. . .	
. . . exhibition	during	. . .	

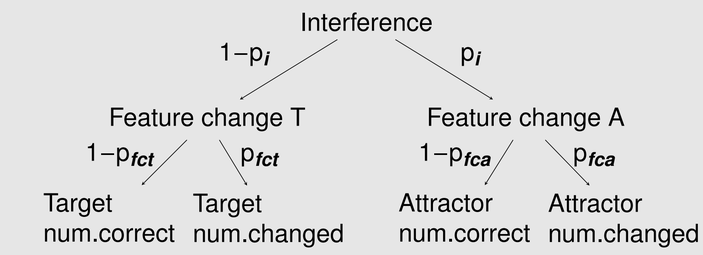
"The painter(s) that the sculptor ignored during the exhibition . . . "

- Agreement attraction profile (speedup in ungrammatical sentences with matching distractor) not reliable in SPR data
- Both feature changes (*sculptors*) and subject misidentifications (*painter/s*) observed in answers
- Reading times at spillover region used for modeling (Avetisyan, Lago & Vasishth, 2019)



Computational modeling

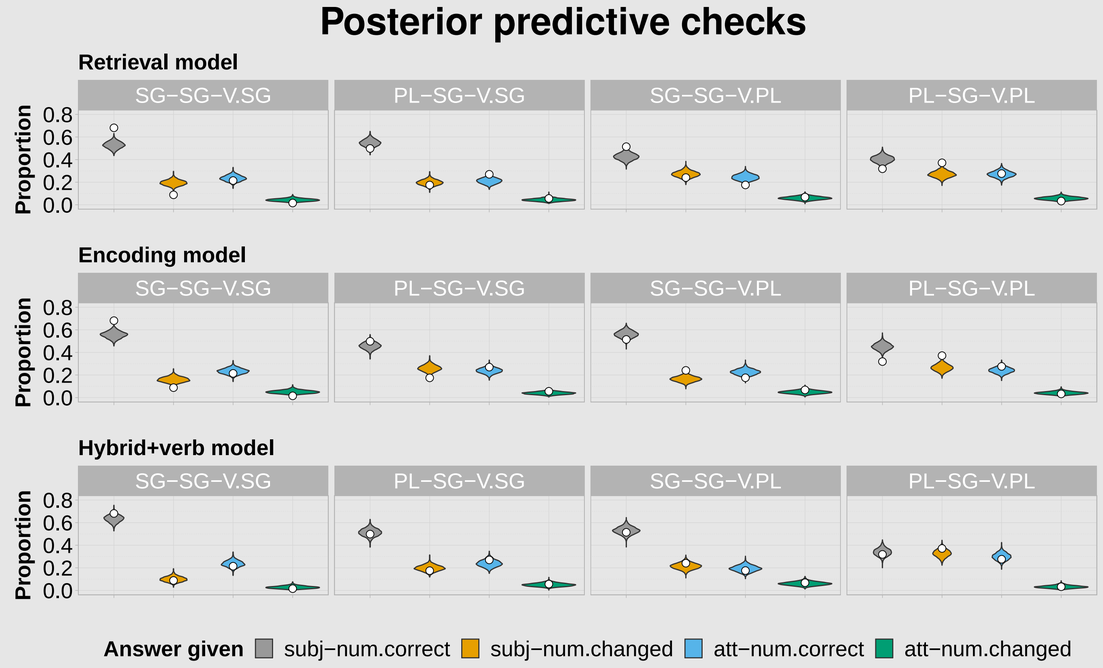
- Encoding-based model implemented as a multinomial processing tree (MPT)
  - Latencies modeled as mixture of lognormals, one component for each path



- Retrieval-based model implemented as a lognormal race between all possible responses (Rouder et al., 2015; Nicenboim & Vasishth, 2018)
- Besides the basic models, we also implemented
  1. an extended retrieval model that allows **systematic matching of NPs with non-veridical features**
  2. a **hybrid model** that assumes that feature match affects the interference stage of the MPT
  3. a hybrid model with **feature spreading from the verb**
- Only **hybrid+verb** model improves predictive performance over basic encoding model

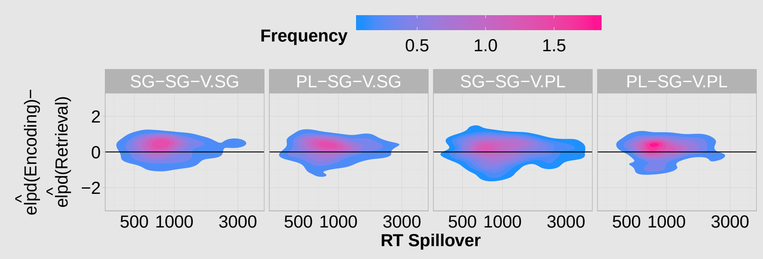
Modeling results

Posterior predictive checks



- Distributions of predicted response proportions (violins) do not closely match data means (white circles) for either encoding or retrieval model
- Hybrid+verb model increases predictive performance

10-fold cross-validation



- 10% held-out data points (per 10 model runs) are better predicted by encoding versus retrieval model, hybrid+verb versus encoding model

Discussion

- Encoding model predicts data better than retrieval model
- Adding the verb as a source of plural features improves fit
  - Further supports encoding account if one assumes that features can freely spread through the sentence
- **Caveat:** Are we using the right task and latency measure?
  - End-of-sentence comprehension probes may not be reflective of on-line processing (e.g. Bader & Meng, 2018)
  - Use of RTs in spillover region motivated by earlier results, but critical region or question response RTs are candidates

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