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Representation of Number in Agreement Comprehension

Yingzhao Zhou, Rhea T. Eskew, Jr., and Neal J. Pearlmutter (Northeastern University)

INTRODUCTION

Research Question
Are representations of number used during comprehension discrete or continuous?

Continuous Model
On each individual trial, the number of the subject phrase is always a value on a continuous range. For example, Marking and Morphing (Eberhard et al., 2005) assumes that the subject NP node number feature takes on a value selected from a continuous range.

Discrete Model
On each individual trial, either a purely singular or a purely plural representation is chosen; the number representation takes on a discrete value.

For example, hierarchical feature-passing models assume a discretely-valued number representation on any given trial (e.g., Franck et al., 2002, 2006; Pearlmutter et al., 1999).

Attraction Effects
Agreement processing can be disrupted when the subject of the sentence is a subject NP that contains two nouns with mismatched number information (e.g., *The key to the cabinets…*)

Processing difficulty due to the interference from *cabinets* in the subject NP is known as an agreement attraction effect.

Attraction effect can be used to test the nature of the number representation.

METHOD

Procedure
Self-paced reading task

Two sessions of 120 items each

Participants
255 participants' data were analyzed. 60 additional participants who completed only one session or had less than 90% correct comprehension across all items were excluded.

Materials and Design

The key to the cabinet was rusty …	Match Grammatical
The key to the cabinet were rusty …	Match Ungrammatical
The key to the cabinets was rusty …	Mismatch Grammatical
The key to the cabinets were rusty …	Mismatch Ungrammatical

160 singular head-noun items with four conditions each (40 trials/condition).

80 plural head-noun items were used as fillers, varying in the same way as singular head-noun items.

Each item had a yes/no comprehension question; trials with incorrect responses were excluded.

REFERENCES

Eberhard, K. M., Cutting, J. C., & Bock, K. (2005). *Psych Review, 112,* 531–559.

Franck, J., Lassi, G., Frauenfelder, U. H., & Rizzi, L. (2006). *Cognition, 101,* 173–216.

Franck, J., Vigliocco, G., & Nicol, J. (2002). *Lang and Cog Processes, 17,* 371–404.

Pearlmutter, N. J., Garnsey, S. M., & Bock, K. (1999). *JML, 41,* 427–456.

Van Zandt, T. (2000). *Psychonomic Bulletin & Review, 7,* 424–465.

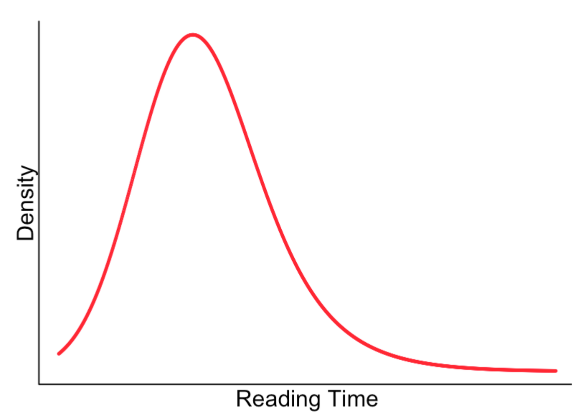
PREDICTIONS

Predictions are for reading times (RTs) at the verb and the following word.

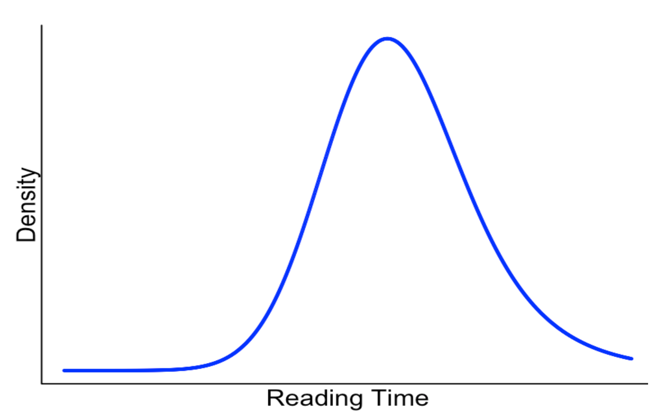
For mean RTs, both models make same predictions. So we examine RT distributions:

For each of the match conditions, both models predict a unimodal distribution. We assume that unimodal cases follow an ex-Gaussian distribution:

Match Grammatical

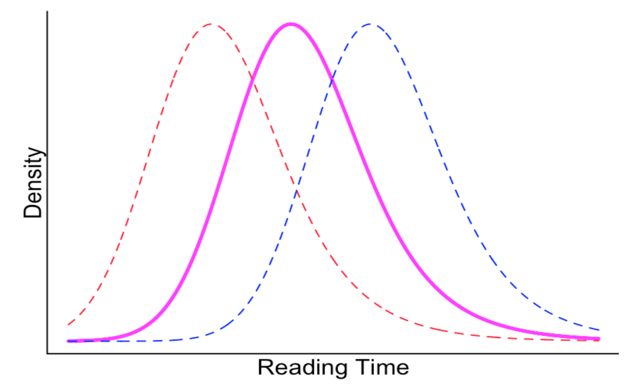


Match Ungrammatical

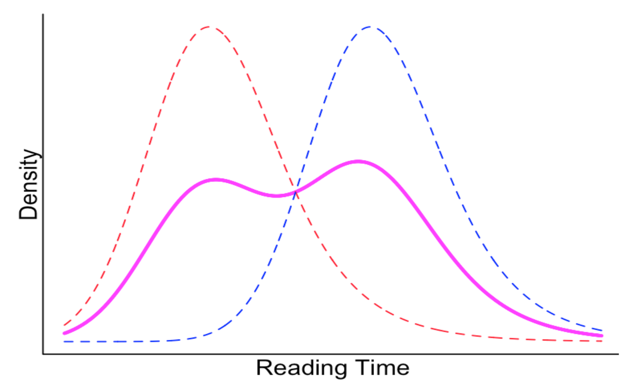


The models differ in their predictions for the mismatch conditions:

Mismatch Grammatical



Continuous model:
A unimodal distribution with a slower mean than the match grammatical condition, and faster mean than the match ungrammatical condition.

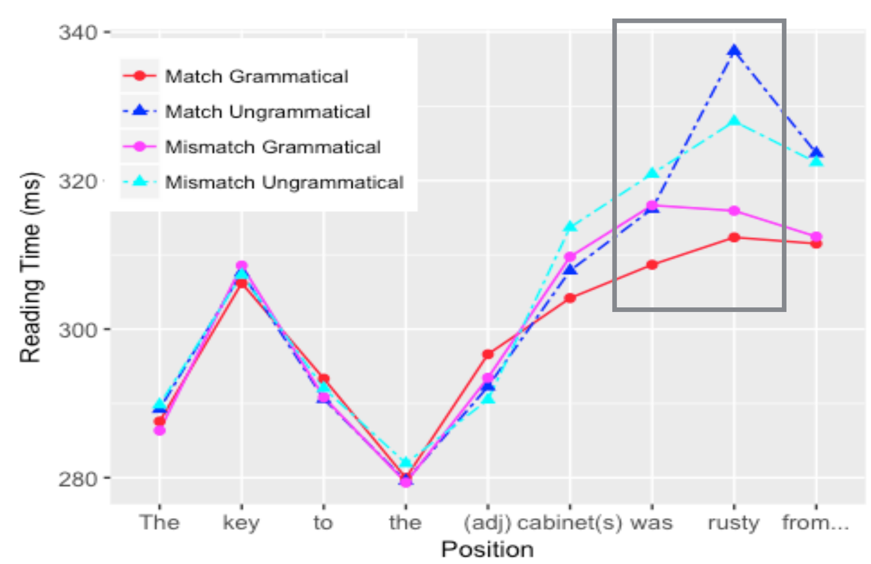


Discrete model:
A mixture of two unimodal distributions:
- the same distribution as the match grammatical condition
- the same distribution as the match ungrammatical condition

Mismatch Ungrammatical

Predictions work out just as for the mismatch grammatical condition.

MEAN RT RESULTS



Verb: No interaction;
Mismatch > Match;
Ungrammatical > Grammatical

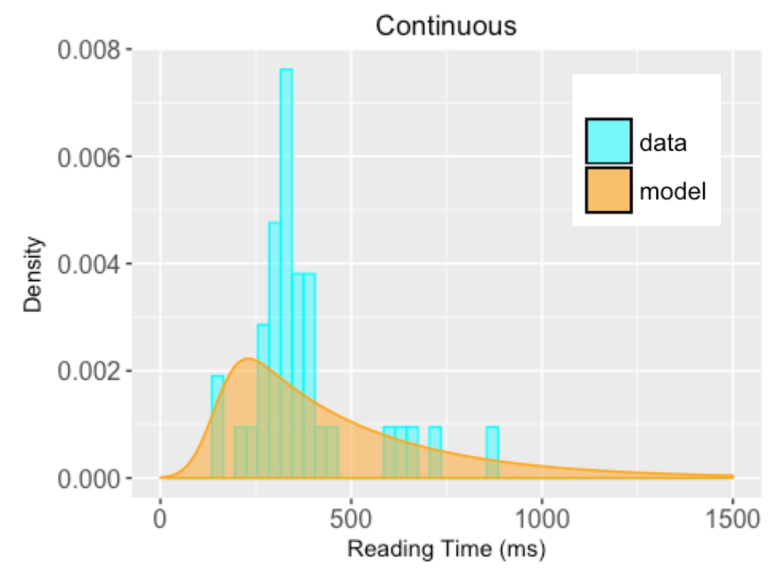
Verb+1: Interaction;
Mismatch Grammatical > Match Grammatical
Mismatch Ungrammatical < Match Ungrammatical

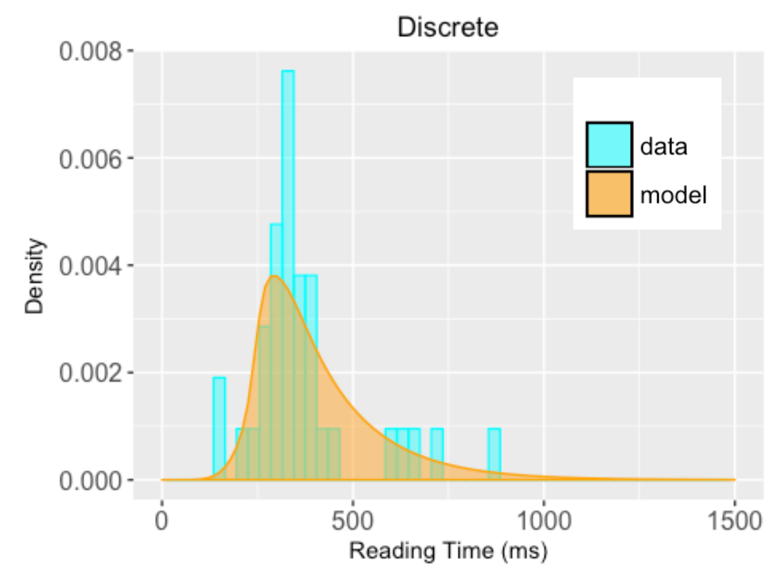
DISTRIBUTIONAL ANALYSES

Each sampling-unit (participants, items) and condition's data were fit separately using maximum likelihood estimation (Van Zandt, 2000).

For each sampling-unit separately, each model was fit to the mismatch data.
- Continuous model: Single ex-Gaussian distribution with 3 parameters (μ, σ, λ)
- Discrete model: Weighted combination of the best-fitting single ex-Gaussians from each of the match conditions; 1 mixture parameter

Example: Best-fitting Models for Participant #150 (word following the verb, mismatch ungrammatical condition)





For this participant, goodness-of-fit comparisons showed that the discrete model fit the RT data significantly better than the continuous ($F(8,6) = 0.21$, left-tailed $p < .03$).

Monte Carlo simulations determined power to detect each model as significantly better than the other at various α-levels:
- 100 simulations for each of the models for each sampling-unit.
- Compared using the same *F*-test used for the real data.

For each model, computed the binomial probability of obtaining the observed count of sampling-units showing that model significantly better than the other, given the power from the simulation.

Binomial Probability Comparisons, by Condition and Position

			By Participants						By Items					
			Continuous			Discrete			Continuous			Discrete		
Condition	Position	*F*-test α	Exp	Obs	*p*	Exp	Obs	*p*	Exp	Obs	*p*	Exp	Obs	*p*
Mismatch Grammatical	Verb	.05	10	0	<.01	0	1	.99	13	0	<.01	0	1	.99
		.10	18	0	<.01	1	4	.99	21	2	<.01	1	2	.97
		.20	38	15	<.01	8	11	.91	37	9	<.01	5	10	.99
	Verb+1	.05	10	1	<.01	1	0	.60	10	0	<.01	0	0	.85
		.10	18	2	<.01	3	1	.28	14	2	<.01	1	1	.87
		.20	33	5	<.01	8	8	.64	29	7	<.01	5	7	.89
Mismatch Ungrammatical	Verb	.05	13	3	<.01	0	1	.97	11	3	<.01	0	2	.99
		.10	20	3	<.01	1	2	.86	19	5	<.01	2	3	.92
		.20	38	7	<.01	8	6	.35	36	9	<.01	5	12	.99
	Verb+1	.05	13	2	<.01	1	1	.91	10	0	<.01	0	1	.99
		.10	18	5	<.01	3	2	.53	16	2	<.01	2	2	.78
		.20	36	7	<.01	8	18	.99	29	5	<.01	6	12	.99

- ***F*-test α** = significance level in the individual sampling-unit's *F*-test comparing the model fits.
- ***Exp*** = predicted count of sampling-units showing an effect significant at the given α-level, given computed power.
- ***Obs*** = the observed count of sampling units showing an effect significant at the given α-level.
- ***p*** = binomial probability of obtaining the observed count of sampling-units or fewer showing a significant effect, given the expected count.

Consistently rejected the continuous model as better than the discrete model, regardless of α-levels, both at the verb and the following word.
Consistently failed to reject the discrete model as better than the continuous model.
The patterns were identical when the extreme mixture parameters were excluded from analyses.

In addition, used the difference between the log-likelihood GOF value for the discrete model and that for the continuous model as an alternative way of measuring how well the observed data corresponded to the assumed model. The same patterns were found.

CONCLUSIONS

Two-distribution mixture models fit the RTs better than unimodal models, arguing that number is represented discretely rather than continuously during comprehension.

These results place significant constraints on agreement processing models:
- Argue against the Marking and Morphing model as applied to comprehension, which assumes a continuous number representation.
- Consistent with hierarchical feature-passing models that assume a discretely-valued number representation.

Future work will compare discrete model variants to further constrain the discrete model.