

Gamma Function Modeling of Visual World Eye-Tracking Data Emily Atkinson, Akira Omaki, & Colin Wilson

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Display: The subject & 2 events, each with an associated object & instrument

Critical items: Temporarily ambiguous wh-questions following a story (1) Can you tell me what Emily was eating the cake with ____?

Predicted Eye Movements

Anticipatory fixations on the relevant object during the verb region

Presence of a verb predicts compatible object [7]; presence of a wh-filler predicts earliest possible integration location (active gap-filling [8-11])

Anticipatory fixations on the relevant instrument during the object / preposition region Fixation on associated picture as referent is processed

represents time to plan & execute saccades [13]

Distributions that activate the same item are summed.

Normalization

By-region values were converted to probabilities by bin using the Luce choice rule with a temperature parameter [14].

Log Likelihood

Probabilities applied to *individual trial data* according to the multinomial distribution. Parameters were sampled 1000 times with rStan [15].

RESULTS





Method	# of Parameters	Log Likelihood	INTERPRETATION & DISCUSSION	
Gamma Model: 1000 samples	13	-19556.6 ± 2.6 (mean ± SD)	 Gamma model connects processing of syntactic regions to fixations Assumption that fixation distributions are well-approximated by a particular function 	
Growth Curve Analysis: quartic polynomials	29	-21494.2 (optimum)		
Hierarchical Gamma Model: 1000 samples	13/participant + 15 hyper- parameters	-17870.5 ± 17.8 (mean ± SD)	 Data reduced to only 13 parameters that capture qualitative patterns (~16,000 total binned data points) 	
HIERARCHICAL MODEL: INDIVI	DUAL DIFFERENCES	• Greater likelihood than growth curves with less parameters Relation of gamma distribution to parser?		
Gamma parameters & temperature vary by participants ($N = 27, 5$ trials each)			 <u>Inherent to parser</u>: Gamma distribution describes time evolution of word/object activation during parsing <u>Inherent to action (eye movement)</u>: Aggregate action on the 	
$a_{ij} \sim \mathcal{N}(\mu_{a_i}, \sigma_a)$ for participant <i>j</i> & region <i>i</i> $]$ Similar design for				
$\mu_{a_i} \sim \mathcal{N}(\mu_A, \sigma_A)$ for region <i>i</i> - other gamma				
$\sigma_a \sim G(s_A, r_A)$ for all regions	parameters temp	$_{j} \sim \mathcal{N}(\mu_{T}, \sigma_{T})$ for participant j	parser output (i.e., where & when to look) results in gamma-	
Amplitude: Subject Log Mean & 95% HPD Interval by Su	bject Log Mean & 95	Gap Prediction at Verb % HPD Interval by Subject	shaped activations Remaining Issues & Further Work • Syntactic regions are currently hard coded into the model. We would be a superior of the model.	
		•	Syntactic regions are currently nard-coded into the model, we would	



- Differences in amplitude in the verb region indicate varying degrees of active-gap filling (i.e., prediction of an object gap) OR action (i.e., fixation) based on that prediction.
- Differences in amplitude in the subject region indicate amount of interest in the subject as it is named.
- Comparison: subjects do not necessarily have consistent amplitudes across regions $(R^2=0.3, p>0.1)$

- like to incorporate an explicit parsing model from which the fixation distributions observed in VWP arise.
- Gamma functions best fit unimodal fixation patterns, but data from other conditions in the same study are multimodal/cyclic.
- Allow time lag parameter (T_I) to vary across participants to model differences in saccade execution
- Apply to additional populations (e.g., children [8]) & study designs to test generalizability of method.

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