Jointly modeling maze RT and accuracy using diffusion models: A first case study

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In the maze task [1], participants must decide between target continuations and inappropriate foils. Choices and RTs in this task have so far been modeled independently, but we suggest they could be jointly well-described by the **diffusion model** of decision-making [2]. In addition to jointly explaining these components, diffusion modeling can also help distinguish between several sources for differences across conditions in decision tasks, including non-decision processing time (t_0), initial response attractiveness (z), and rate of preference accumulation (v) (Fig 1). Here, for one recent effect of interest, we offer a proof-of-concept that diffusion models can be applied to maze data, and probe the source of the effect.

Effect of interest When a single maze decision followed comprehension of a familiar two-word metaphor embedded in context (Fig 2), [4] observed that target responses were slower, and foil selection was more likely, when the foil was RELATED to the literal interpretation of the metaphor. These effects reduced when the critical maze position was postponed farther away from the metaphor [5]. This pattern, known as the *metaphor awakening effect*, can be related to the general finding that maze decisions are more difficult when concepts related to the foil are activated in preceding context [6-7]. [4-5] consider that the literal meaning may be temporarily activated during metaphor comprehension, and before it rapidly decays, it spreads activation to related concepts. With the diffusion modeling we present here, we find that a joint explanation for the RT and accuracy components of this effect is feasible, and conclude that the principal source for both is a slower accumulation of preference for the target in the RELATED-foil condition.

Data from [4-5] comprises 40 participants in each of SHORT, MEDIUM, and LONG delays between metaphor and maze, each seeing 12 RELATED-foil trials and 12 UNRELATED. Foils were matched in length, frequency, and contextual appropriateness across conditions, differing only in association to the preceding metaphor.

Diffusion models Using `rtdists` [8], we fit max-likelihood parameters to observed RT and response distributions with 10 diffusion model variants, pruning away which parameters could vary by condition. AIC (Table 1) favors model #5, in which only drift rate v varied across all conditions. Fitted v_{REL} towards the target is slower than v_{UN}, less so at larger delays, while z_{REL} is weakly biased against the target, but $t_{0\,REL}$ is slightly facilitated. Simulated RTs using model #5 closely match the observed distributions of RTs for both target and foil selections (Fig 4). Simulated accuracies likewise capture the observed pattern (Fig 3).

Discussion Model performance supports the proposal that when foils in maze decisions come shortly after a related word, they jointly slow RTs and depress accuracy by interfering in the decision process. In particular, we conclude such foils principally slow the rate of preference accumulation towards the target. If this interference comes from residual priming, it suggests that the core process of maze decisions, judging contextual fit, is susceptible to other sources of activation. Future work should pursue this idea further, and perhaps validate the connection to residual priming by comparing stimulus-specific predictors of spreading activation [e.g., 9] to itemwise diffusion model estimates.

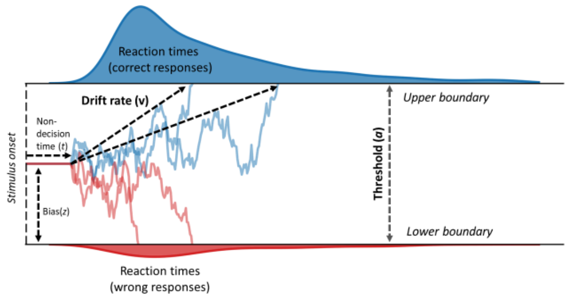

Figure 1. Illustrating the core mechanisms of a diffusion model. Figure from [10]. (NB: $t = t_0$)

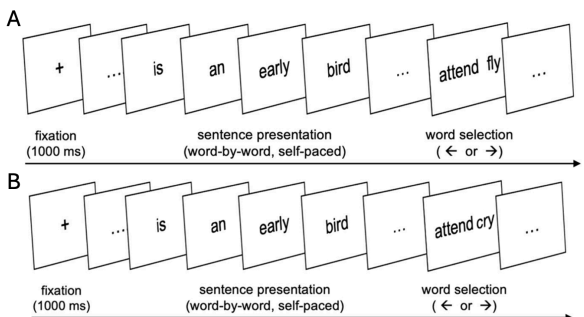

Figure 2. [4-5]'s procedure for the maze task with related (A) and unrelated (B) foils.

Table 2. Parameters from Diffusion Model #5.

$t_{0\ REL} = 0.40$	$t_{0\ UN} = 0.46$	$z_{REL} = 0.43$	$z_{UN} = 0.53$	
$v_{REL,S} = 1.08$	$v_{REL,M} = 1.40$	$v_{REL,L} = 1.53$		
$v_{UN,S} = 1.60$	$v_{UN,M} = 1.81$	$v_{UN,L} = 1.84$		
$a = 1.96$	$s_{t0} = 0.50$	$s_z = 0.30$	$s_v = 0.49$	$s = 1$

Table 1. Model comparisons, best AIC in bold.

$_{\pm REL}$: parameter fit with two values, for related vs. unrelated foils.
$_{\pm REL\ x\ D}$: parameter fit with six values, crossing ±related and {S/M/L} delay.

	Model	∑ LogLik	AIC
1	$t_{0\ \pm REL\ x\ D}$, $z_{\pm REL\ x\ D}$, $v_{\pm REL\ x\ D}$	–2016.04	4076.08
2	$t_{0\ \pm REL}$, $z_{\pm REL\ x\ D}$, $v_{\pm REL\ x\ D}$	–2019.54	4075.07
3	$t_{0\ \pm REL\ x\ D}$, $z_{\pm REL}$, $v_{\pm REL\ x\ D}$	–2017.09	4070.18
4	$t_{0\ \pm REL\ x\ D}$, $z_{\pm REL\ x\ D}$, $v_{\pm REL}$	–2027.52	4091.05
5	$\boldsymbol{t_{0\ \pm REL}}$, $\boldsymbol{z_{\pm REL}}$, $\boldsymbol{v_{\pm REL\ x\ D}}$	**–2020.46**	**4068.92**
6	$t_{0\ \pm REL}$, $z_{\pm REL\ x\ D}$, $v_{\pm REL}$	–2032.00	4092.00
7	$t_{0\ \pm REL\ x\ D}$, $z_{\pm REL}$, $v_{\pm REL}$	–2036.45	4100.90
8	t_0, $z_{\pm REL}$, $v_{\pm REL\ x\ D}$	–2029.35	4084.69
9	$t_{0\ \pm REL}$, z, $v_{\pm REL\ x\ D}$	–2028.01	4082.02
10	t_0, z, $v_{\pm REL\ x\ D}$	–2031.16	4086.32

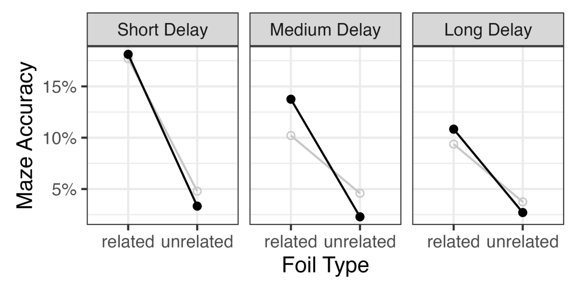

Figure 3. Observed (black) and predicted (grey) accuracy (% "target") from Diffusion Model #5.

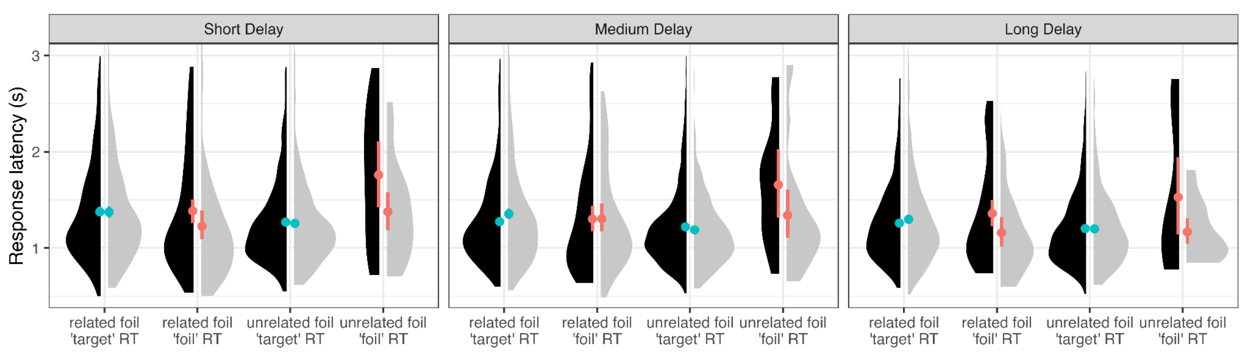

Figure 4. Observed (black) and model-predicted (grey) RT distributions from Diffusion Model #5. Points indicate observed and predicted means with bootstrapped 95% CIs.

References [1] Forster et al. (2009) *Behav Res Meth* [2] Ratcliff & McKoon (2008) *Neural Comput* [3] Myers et al. (2022) *Front Psychol* [4] Pissani & de Almeida (2022) *Psychon Bull Rev* [5] Pissani & de Almeida (2023) *Metaph Symb* [6] Gallant & Libben (2020) *Ment Lex* [7] de Almeida et al. (2025) *JEP: LMC* [8] Singmann et al. (2022) R [9] Mandera et al. (2017) *JML*. [10] Vinding et al. (2021) *Consc Cogn*.