Similarity-based interference in aphasia: A computational evaluation of two models of cue-based retrieval

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In language unimpaired populations, the cue-based theory explains dependency resolution through memory retrieval, in which similarity-based interference can cause comprehension difficulties. Individuals with aphasia (IWA) are known to have difficulties understanding complex sentences that involve long-distance dependencies (Caramazza & Zurif, 1976), as well as binding relations (Choy & Thompson, 2010). Based on the assumption that one or several processing deficits in IWA may interact with the retrieval process, cue-based retrieval has been used to model sentence processing in IWA (Patil et al. 2016, Mätzig et al. 2018, Lissón et al. 2021). The underlying cause of the deficits is, however, still subject to debate. Existing theories are *slow syntax* (Burkhardt et al. 2008), *delayed lexical access* (Ferril et al. 2009), *resource reductions* (Caplan, 2012), and *intermittent deficiencies* (Caplan et al. 2013). Previous modeling approaches only focused on the processing of non-canonical sentences that were semantically reversible, highlighting the need for data from a greater variety of linguistic constructions.

In the present study, we model interference effects through different manipulations in two sentence structures in German: A gender manipulation in pronoun resolution (ex. 1), and a number manipulation in relative clauses (ex. 2). We implement two models of cue-based retrieval: The activation-based model (Lewis & Vasishth, 2005), and a modified version of the direct-access model (McElree, 2000). These models hold different assumptions concerning the time-course of the retrieval process. We seek to answer the following questions: Which of the two models gives a better account of interference effects in IWA and control participants? What do the models tell us about the cause of sentence processing deficits in IWA?

Data and methods. We used a subset of the database developed by Pregla et al. (2021). 50 control participants and 21 IWA, all German native speakers, took part in the experiment. The experiment consisted of an auditory sentence-picture match task combined with eye-tracking. We model reaction times (RT) in the picture-selection task as a function of interference, group, and fixations to the target picture during the critical region of the sentence. RT from an auditory lexical decision task, centered and scaled within groups, were also included as a predictor.

Models. Following Nicenboim and Vasishth (2018), we implement both models in the Bayesian framework: The activation-based model as a race of accumulators, and the modified direct-access model as two-component mixture model. **The activation-based model:** Each item in memory (*target* and *distractor*) is represented by an accumulator with a lognormal distribution of finishing times (FT). The accumulator with the faster sampled FT wins, and its FT becomes the estimated RT for that trial. A correct response is given if the *target* accumulator wins, otherwise an incorrect response is given. **The modified direct-access model:** The distribution of RT is a mixture of directly-accessed retrievals and failed retrievals followed by backtracking. The target is initially retrieved from memory with probability θ (see Eq. 3). If the first retrieval attempt fails, backtracking is performed with probability P_b. Backtracking leads to the retrieval of the target with probability θ_b. If the initial retrieval is incorrect and there is no backtracking, a misretrieval is predicted and the incorrect picture is chosen. The models were implemented in Stan, and their predictive performance was assessed with 10-fold cross-validation (Vehtari et al., 2015).

Results. The cross-validation shows that both models have a similar predictive performance in pronoun resolution ($\widehat{\Delta elpd}$ $-$109, SE 133), but the activation-based model outperforms the direct-access model in relative clauses ($\widehat{\Delta elpd}$ 407, SE 167). The parameters of both models are in line with the *slow syntax* and the *intermittent deficiencies* theory and point towards these two deficits as the main source of processing difficulties during the retrieval process in IWA.

References

Burkhardt, P., Avrutin, S., Piñango, M. Ruigendijk, E. (2008). Journal of Neurolinguistics, 21(2), 120-137. **Caplan, D. (2012).** In C. Thompson and R. Bastiannse, Perspectives on Agrammatism, 34–48. Psychology Press. **Caplan, D., Michaud, J., Hufford, R. (2013).** Brain and Language, 127(1), 21-33. **Caramazza, A., Zurif, E. B. (1976).** Brain and language, 3(4), 572-582. **Choy, J. J., Thompson, C. K. (2010).** Aphasiology, 24(5), 551-579. **Ferrill, M., Love, T., Walenski, M., Shapiro, L. P. (2012).** AJSLP, 21(2):S179. **Lissón, P., Pregla, D., Nicenboim, B., Paape, D., van het Nederend, M.L., Burchert, F., Stadie, N., Caplan, D. and Vasishth, S. (2021).** CogSci, 45: e12956. **Mätzig, P., Vasishth, S., Engelmann, F., Caplan, D., Burchert, F. (2018).** TiCS, 10(1), 161-174. **McElree, B. (2000).** Journal of Psycholinguistic Research, 29(2), 111-123. **Nicenboim, B., Vasishth, S. (2018).** JML, 99, 1-34. **Patil, U., Hanne, S., Burchert, F., De Bleser, R., Vasishth, S. (2016).** CogSci 40(1), 5-50. **Pregla, D., Lissón, P., Vasishth, S., Burchert, F., Stadie, N. (2021)**. Psyarxiv. doi:10.31234/osf.io/7hfpx

Results for the RC sub-experiment

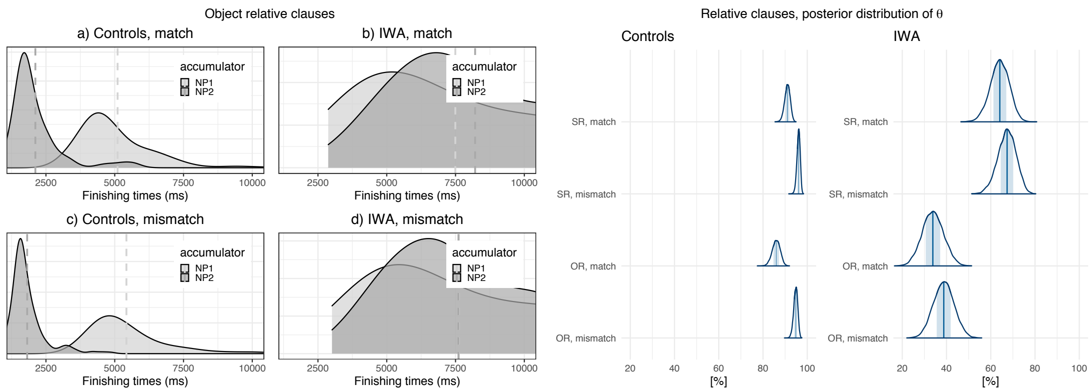

Figure 1. **Left pannel:** Activation-based model. Distribution of the accumulators of evidence across groups and conditions for object relative clauses. Note that in (d), the mean of the two distributions overlap. **Right panel:** Modified direct-access model. Posterior distribution of the probability of retrieval of the target (θ) across groups and conditions. Whereas controls have a higher θ in mismatch conditions, IWA show a greater canonicity effect.

Example items

Pronoun resolution

In (2), we assume that a retrieval process is triggered at the pronoun. Since in (1a) the pronoun only matches the target noun (Peter) in gender, (1a) is predicted to be easier to process than (1b).

(1) a. **Mismatch.**
Peter verspricht nun Lisa, dass **er** das kleine Lamm streichelt und krault.
'Peter now promises Lisa that he will pet and ruffle the little lamb.'

b. **Match.**
Peter verspricht nun Thomas, dass **er** das kleine Lamm streichelt und krault.
'Peter now promises Thomas that he will pet and ruffle the little lamb.'

Relative clauses

In (2), when encountering the verb (*badet/baden*) two retrievals are triggered: The agent and the theme. In (2a) and (2c), both noun phrases (*der Esel, der/den Tiger*) share the cue [+singular]. By contrast, in (2b) and (2d), the second noun phrase (*die Tiger*) has a [+plural] cue. Due to similarity-based interference, (2a) and (2c) should be more difficult to process than (2b) and (2d), respectively.

(2) a. **SR, match.**
Hier ist der$_{\text{nom, sg}}$ Esel, der$_{\text{nom, sg}}$ den$_{\text{acc, sg}}$ Tiger gerade badet$_{\text{sg}}$.
'Here is the donkey who bathes the tiger.'

b. **SR, mismatch.**
Hier ist der$_{\text{nom, sg}}$ Esel, der$_{\text{nom, sg}}$ die$_{\text{acc, pl}}$ Tiger gerade badet$_{\text{sg}}$.
'Here is the donkey who bathes the tigers.'

c. **OR, match.**
Hier ist der$_{\text{nom, sg}}$ Esel, den$_{\text{acc, sg}}$ der$_{\text{nom, sg}}$ Tiger gerade badet$_{\text{sg}}$.
'Here is the donkey who the tiger bathes.'

d. **OR, mismatch.**
Hier ist der$_{\text{nom, sg}}$ Esel, den$_{\text{acc, sg}}$ die$_{\text{nom, pl}}$ Tiger gerade baden$_{\text{pl}}$.
'Here is the donkey who the tigers bathe.'

Implementation of the models

In both models, the varying intercepts and slopes for subject and items, $\mathbf{u}$ and $\mathbf{w}$, come from two multivariate normal distributions. The predictor *LDT* stands for the RT from the lexical decision task, and *fixations* stands for the proportions of looks to the target picture at the critical region. Both were centered and scaled within groups.

Activation-based model. Below is shown μ_1 as an example, but μ_2 has the same hierarchical structure. The sd σ also has an adjustment by group. In addition, the model for relative clauses included the fixed effects *RC type* $\times$ *condition*, *RC type* $\times$ *group*, and *RC type* $\times$ *group* $\times$ *condition*.

$$\begin{aligned}&\mu_1 = \alpha_1 + u_{\alpha_1} + w_{\alpha_1} + (\beta_1 + w_{\beta_1}) \cdot group + \\ &(\beta_2 + u_{\beta_2}) \cdot condition + \beta_3 \cdot group \cdot condition + \\ &\beta_4 \cdot LDT + \beta_5 \cdot group \cdot LDT + \beta_6 \cdot fixations + \beta_7 \cdot fixations \cdot group\end{aligned} \tag{1}$$

$$\begin{aligned}\alpha_1 &\sim normal(7.5, 0.6) \\ \beta_{1,\dots,7} &\sim normal(0, 0.5) \\ \sigma_0 &\sim normal_+(0, 0.5)\end{aligned} \tag{2}$$

Direct-access model. In Equation (3) the parameter θ stands for the probability of retrieval of the target; μ is the mean of the distribution from which the RT are estimated. P_b is the probability of backtracking, δ is the cost of backtracking (in log ms), and σ is the noise parameter. In addition, in the model for RC, θ included fixed effects for: *RC type*, *RC type* $\times$ *condition*, *RC type* $\times$ *group*, and *RC type* $\times$ *group* $\times$ *condition*. Equation (4) shows the priors. The priors for α and γ are in logit space, the rest are in log space.

$$\begin{aligned}\mu = \mu_0 + u_{\mu 0} + w_{\mu 0} + \beta_1 \cdot group \\ \theta = \alpha + u_\alpha + w_\alpha + \beta_2 \cdot LDT + \beta_3 \cdot LDT \cdot group \\ (\beta_4 + w_{\beta_4}) \cdot group + (\beta_5 + u_{\beta_5}) \cdot condition + \\ \beta_6 \cdot group \cdot condition + \beta_7 \cdot fixations + \\ \beta_8 \cdot group \cdot fixations \\ P_b = \gamma + u_\gamma + \beta_9 \cdot group \\ \delta = \delta_0 + \beta_{10} \cdot group \\ \sigma = \sigma_0 + \beta_{11} \cdot group\end{aligned} \tag{3}$$

$$\begin{aligned}\alpha &\sim normal(1, 0.5) \\ \alpha_b &\sim normal(0, 1) \\ \beta_{1,\dots,11} &\sim normal(0, 0.5) \\ \mu_0 &\sim normal(7.5, 0.6) \\ \gamma &\sim normal(-1, 0.5) \\ \delta_0 &\sim normal(0, 1) \\ \sigma_0 &\sim normal(0, 0.5)\end{aligned} \tag{4}$$