



**HAL**  
open science

# **BRAID: a new Bayesian word Recognition model with Attention, Interference and Dynamics**

Julien Diard, Thierry Phénix, Sylviane Valdois

► **To cite this version:**

Julien Diard, Thierry Phénix, Sylviane Valdois. BRAID: a new Bayesian word Recognition model with Attention, Interference and Dynamics. Annual Meeting of the Psychonomic Society, Nov 2018, New-Orleans, United States. hal-02004242

**HAL Id: hal-02004242**

**<https://hal.science/hal-02004242v1>**

Submitted on 1 Feb 2019

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# BRAID: a new Bayesian word Recognition model with Attention, Interference and Dynamics

Julien DIARD, Thierry PHÉNIX and Sylviane VALDOIS

Laboratoire de Psychologie et NeuroCognition  
Univ. Grenoble Alpes, CNRS, LPNC UMR 5105, F-38000 Grenoble, France  
Contact: julien.diard@univ-grenoble-alpes.fr

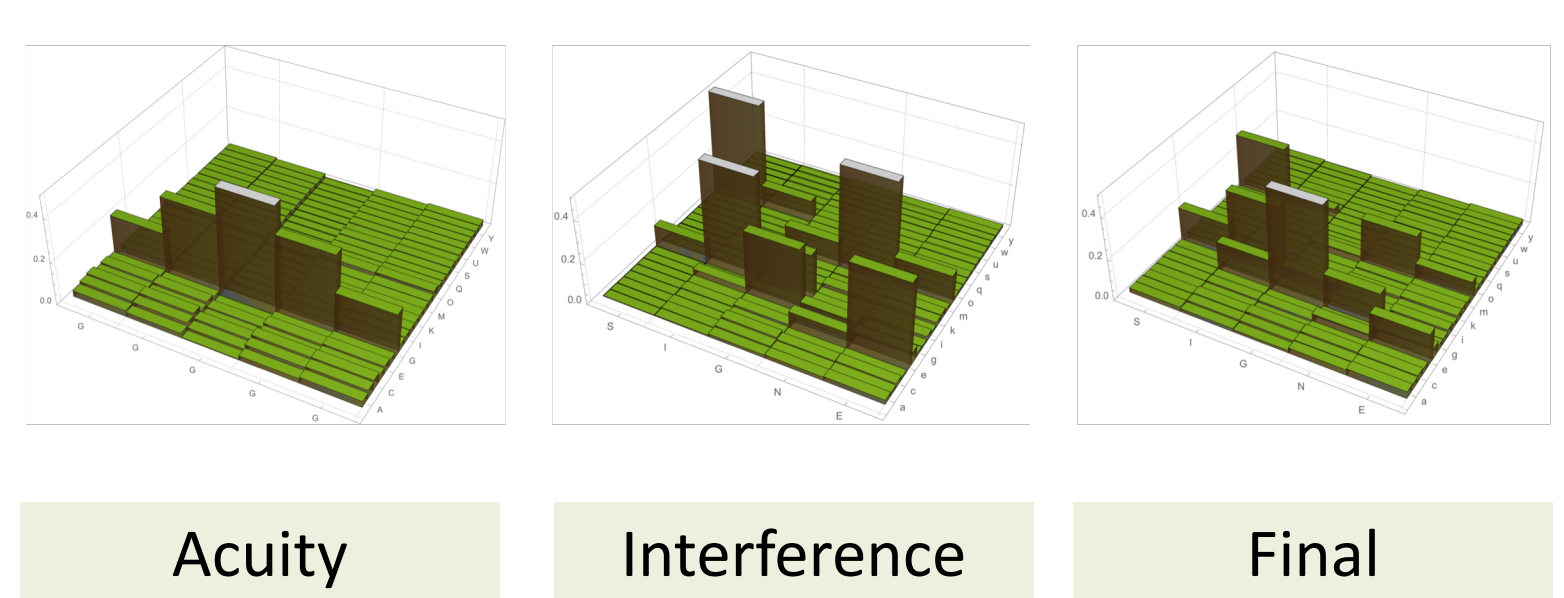
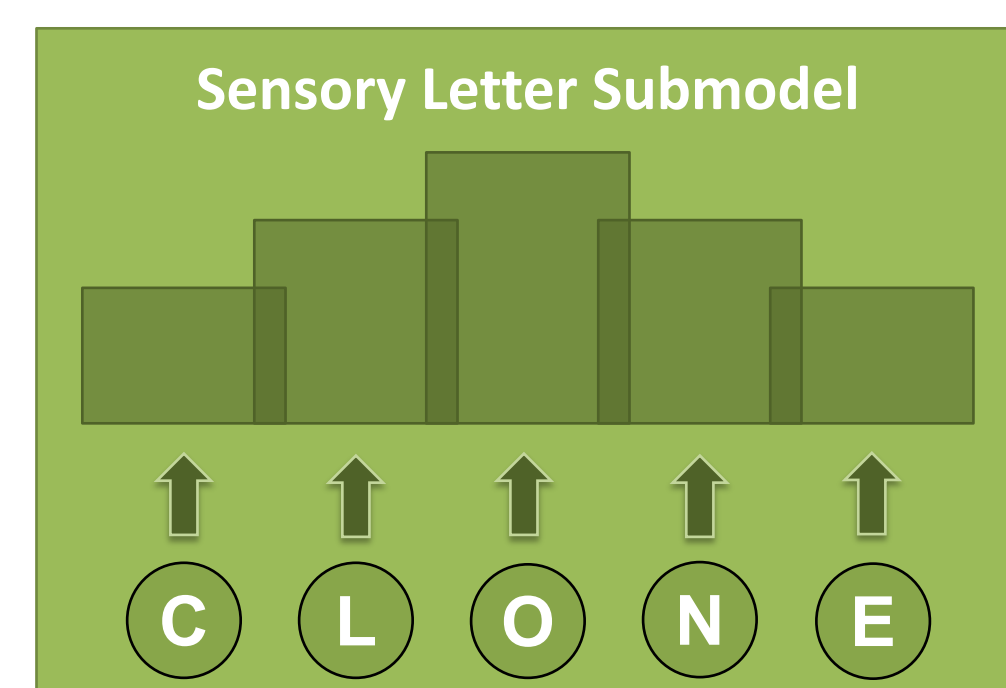
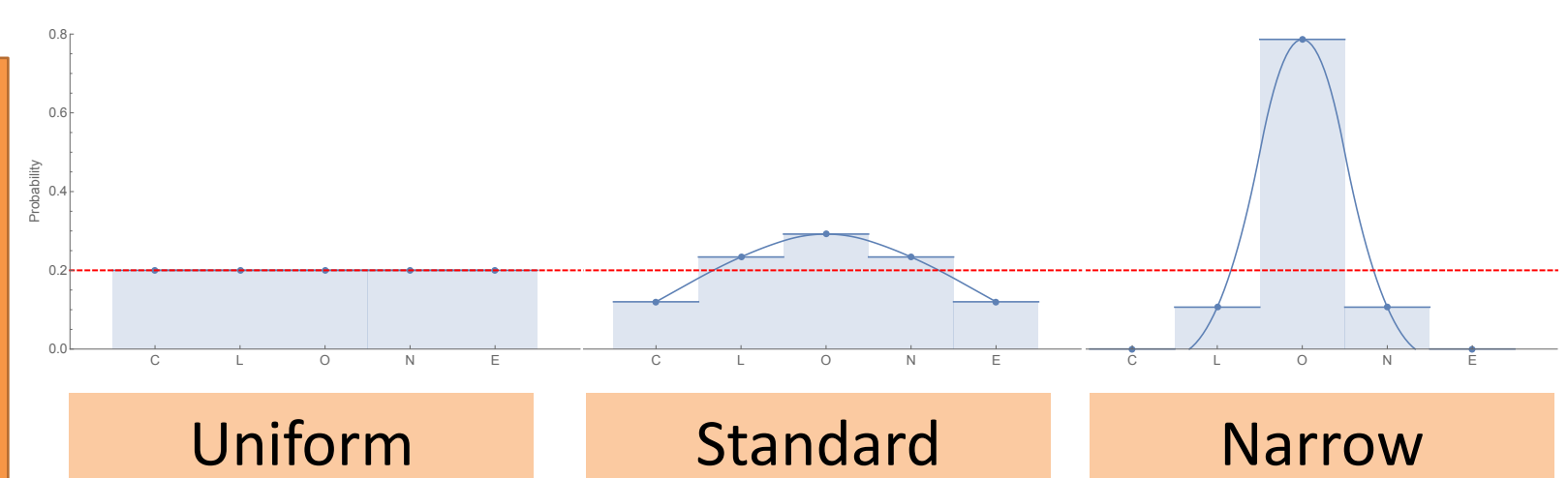
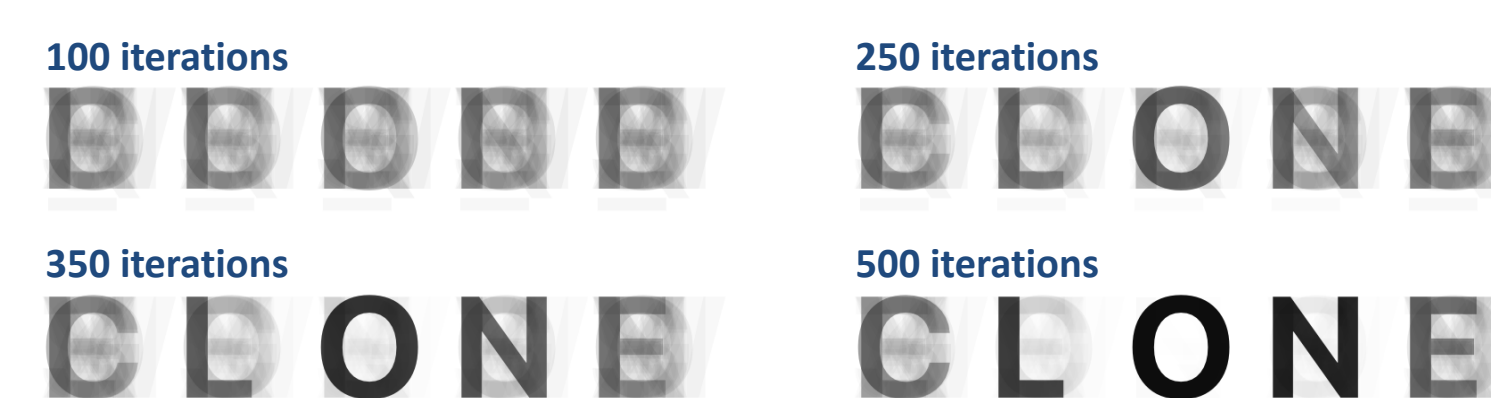
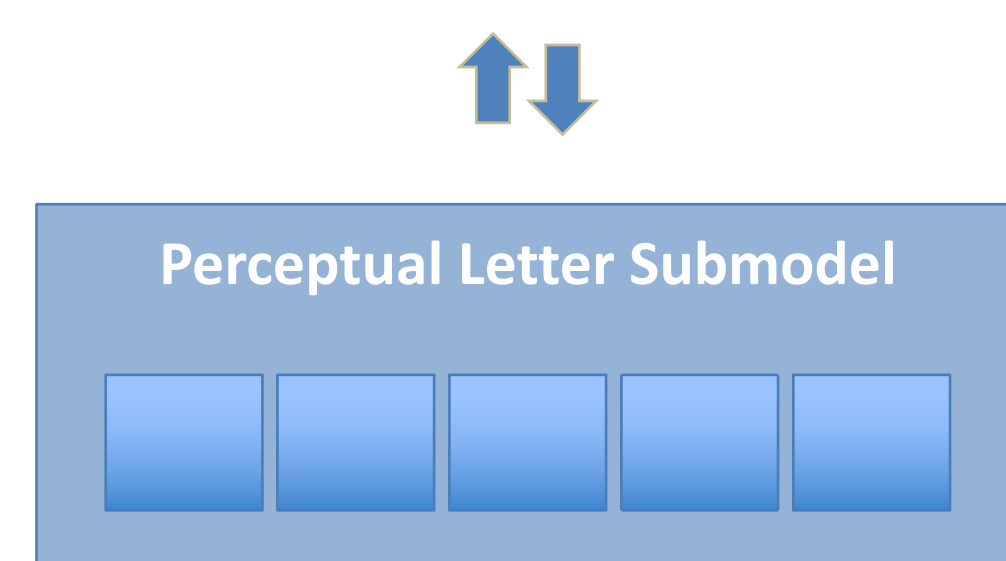
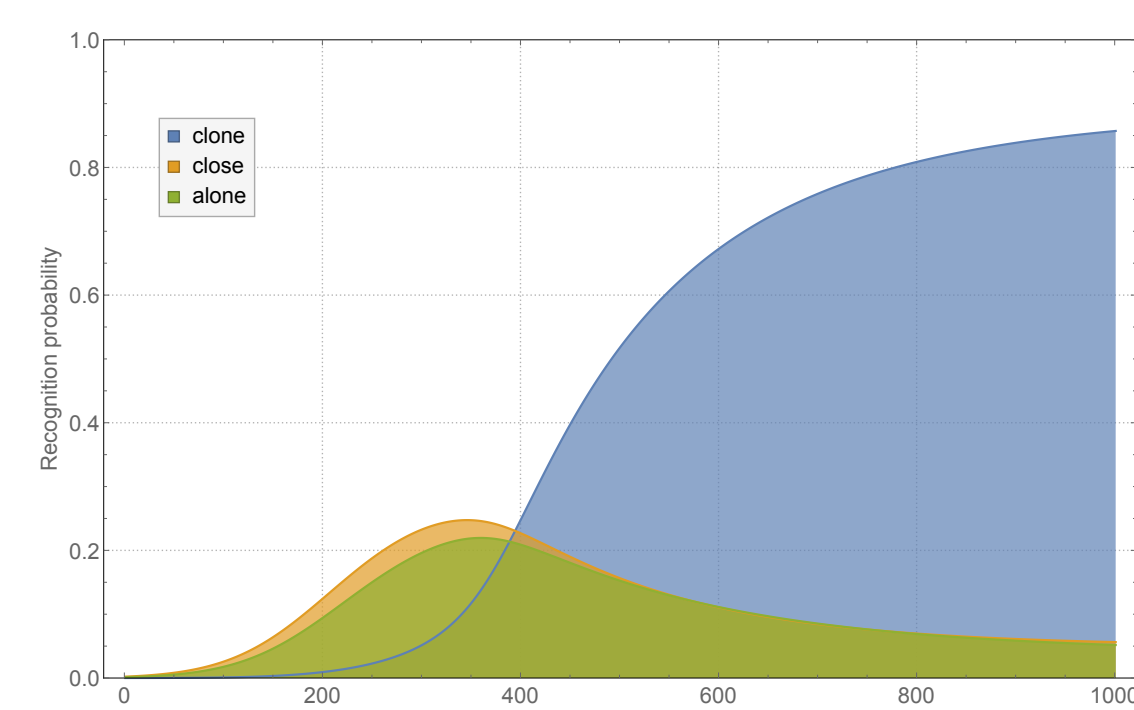
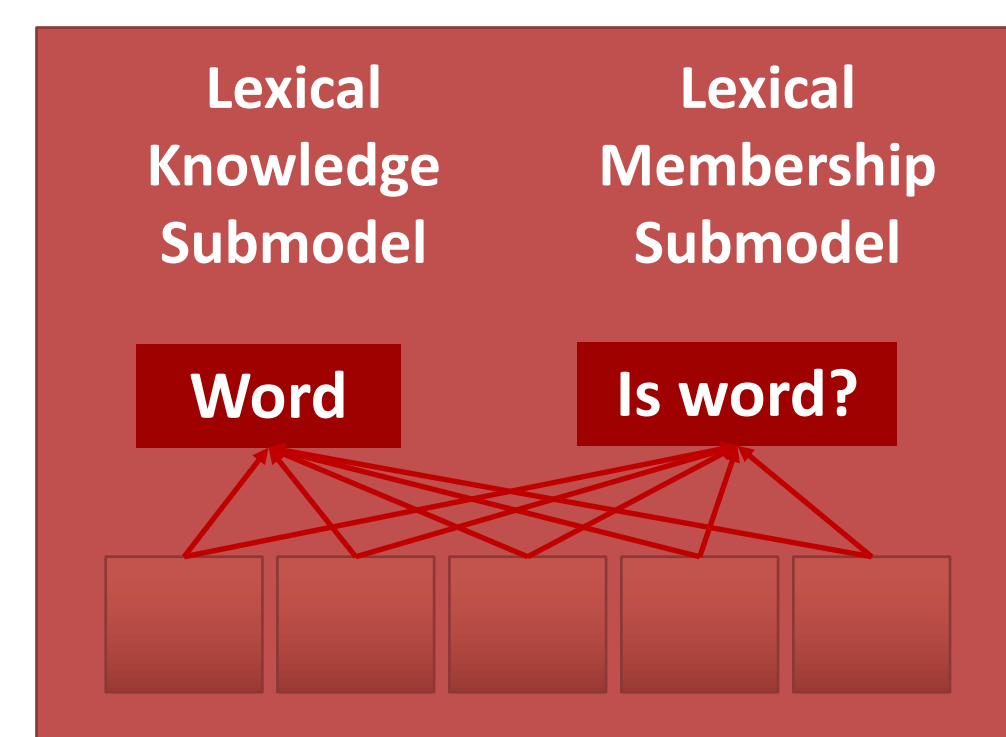
## BRAID: Bayesian Word Recognition with Attention, Interference and Dynamics

The structure of the BRAID model contains three classical levels of processing.

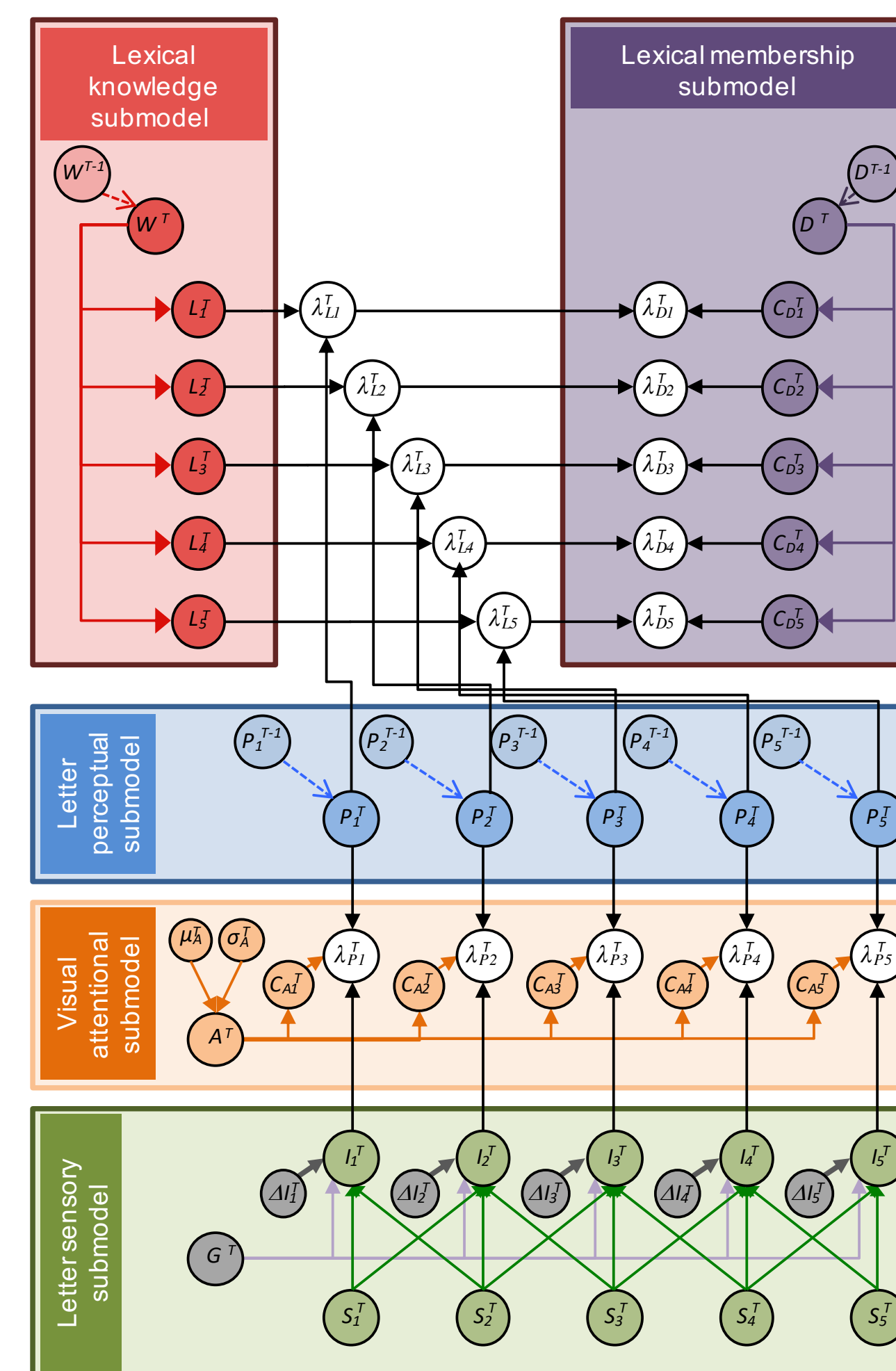
1. The **letter sensory submodel** implements low-level visual mechanisms involved in letter identification and letter position coding. Feature extraction is parallel over the input string, an acuity gradient is implemented symmetrically around fixation and location is distributed over adjacent letter positions, implementing lateral interference between adjacent letters.
2. The **letter perceptual submodel** implements how information extracted from the sensory input accumulates gradually over time to create a percept, i.e. an internal representation of input letters.
3. The **lexical knowledge submodel** implements knowledge about the spelling of 40.481 English words (British Lexicon Project). A prior probability distribution represents word frequency. The **lexical membership submodel** implements a mechanism to decide whether or not the input letter-string is a known word, by observing how predicted spellings compare with perceived letters.

One major originality of BRAID is to assume the existence of a fourth level:

4. The **visual attentional submodel** implements a filtering mechanism between the letter sensory submodel and the letter perceptual submodel. Transfer of information is modulated by the amount of attention allocated to each letter position.



## BRAID model definition Simulating cognitive tasks by Bayesian inference



**BRAID is a probabilistic, hierarchical model:**  
Nodes represent probabilistic variables.  
Arrows represent the dependency structure.

BRAID contains:

- **Dynamic variables** (over perceived letters  $P^t$ , over word identity  $W^t$ , over lexical membership  $D^t$ ), with **accumulation of perceptual evidence** over time and **gradual decay of information** in the absence of stimulation.
- Coupled dynamical chains over  $P$ ,  $W$  and  $D$ : as in coupled Hidden Markov Models, Bayesian inference yields recurrent transfer of information: **bottom-up perceptual processing and top-down predictions and feedback**.
- Submodels are linked by coherence variables ( $\lambda$  variables, in white). They **control information transfer** throughout the model, acting as informational filters. The visual-attentional submodel spatially controls where sensory processing is.

**Cognitive tasks are modeled by questions** asked to BRAID, and solved by **Bayesian inference**.  
Given: stimulus  $s_{1:N}^{1:T}$ , gaze position  $g^{1:T}$ , visual attention position  $\mu_A^{1:T}$ , and spread  $\sigma_A^{1:T}$

- **Letter recognition (without lexical influence)**

$$Q_{P_n}^T = P(P_n^T | s_{1:N}^{1:T} g^{1:T} \mu_A^{1:T} \sigma_A^{1:T} [\lambda_{P_n}^{1:T} = 1])$$

$$\propto \left[ \sum_{p_n^{T-1}} [P(P_n^T | p_n^{T-1}) Q_{P_n}^{T-1}] \right] \left[ \sum_{\Delta i_n^T} \left[ \frac{P(\Delta i_n^T)}{P(L_n^T = p_n^T | s_{1:N}^T \Delta i_n^T g^T)} \right] \right] + \left[ (1 - \alpha_n) \frac{1}{|D_L|} \right]$$

Dynamical evolution from time  $t-1$   
Perceptual accumulation of evidence:

- Sensory decoding with lateral interference
- Attentional filtering

$$\alpha_n = P([C_{A_n}^T = 1] | [A^T = n])$$

- **Word recognition (WR)**

$$Q_W^T = P(W^T | s_{1:N}^{1:T} g^{1:T} \mu_A^{1:T} \sigma_A^{1:T} [\lambda_{L_{1:N}}^{1:T} = 1] [\lambda_{P_{1:N}}^{1:T} = 1])$$

$$\propto \left[ \sum_{w^{T-1}} [Q_{w^{T-1}}^{T-1} P(W^T | w^{T-1})] \right] \left[ \prod_{n=1}^N \langle P(L_n^T | w^T), Q_{P_n}^T \rangle \right]$$

Dynamical evolution from time  $t-1$   
Perceptual accumulation of evidence:  
Matching between predicted spelling and letter recognition

- **Letter recognition (with lexical influence):** top-down feedback from lexical knowledge

$$Q_{P_n}^T = P(P_n^T | s_{1:N}^{1:T} g^{1:T} \mu_A^{1:T} \sigma_A^{1:T} [\lambda_{L_{1:N}}^{1:T} = 1] [\lambda_{P_{1:N}}^{1:T} = 1])$$

- **Lexical decision (LD)**

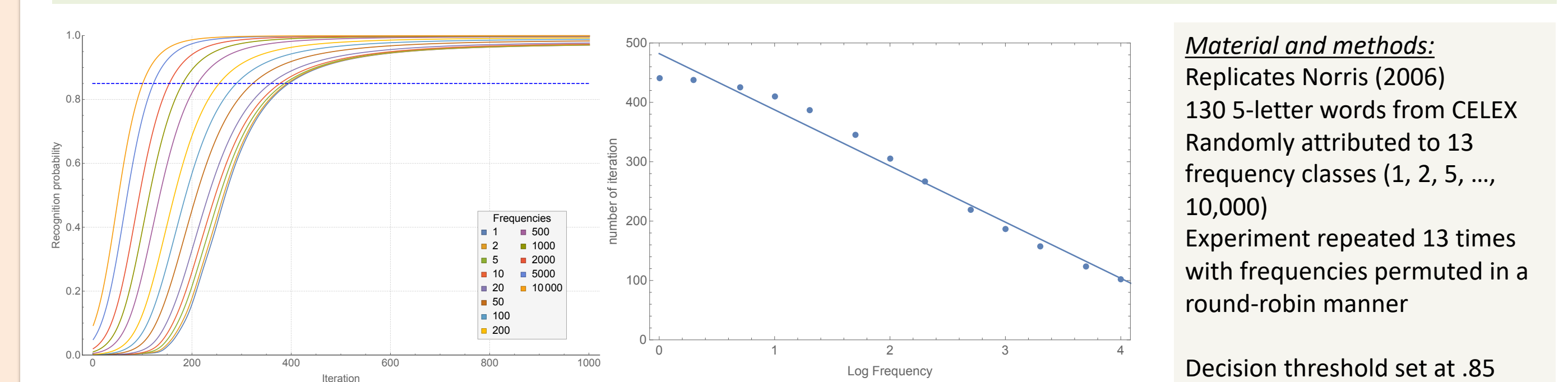
$$Q_D^T = P(D^T | s_{1:N}^{1:T} g^{1:T} \mu_A^{1:T} \sigma_A^{1:T} [\lambda_{D_{1:N}}^{1:T} = 1] [\lambda_{P_{1:N}}^{1:T} = 1])$$

### References

Ginestet, E. (2016). Modélisation probabiliste de reconnaissance visuelle des mots : simulation d'effets d'amorçage et de compétition lexicale. Master's thesis, Univ. Grenoble Alpes  
Ginestet, E., Phénix, T., Diard, J., & Valdois, S. (submitted). Modelling length effect for words in lexical decision: the role of visual attention  
Phénix, T. (2018). Modélisation bayésienne algorithmique de la reconnaissance visuelle de mots et de l'attention visuelle. Université Grenoble Alpes. PhD thesis  
Phénix, T., Valdois, S., and Diard, J. (2018). Reconciling opposite neighborhood frequency effects in lexical decision: Evidence from a novel probabilistic model of visual word recognition. In Proceedings of the 40th Annual Conference of the Cognitive Science Society, pages 2238–2243  
Phénix, T., Valdois, S., & Diard, J. (submitted). Bayesian word recognition with attention, interference and dynamics

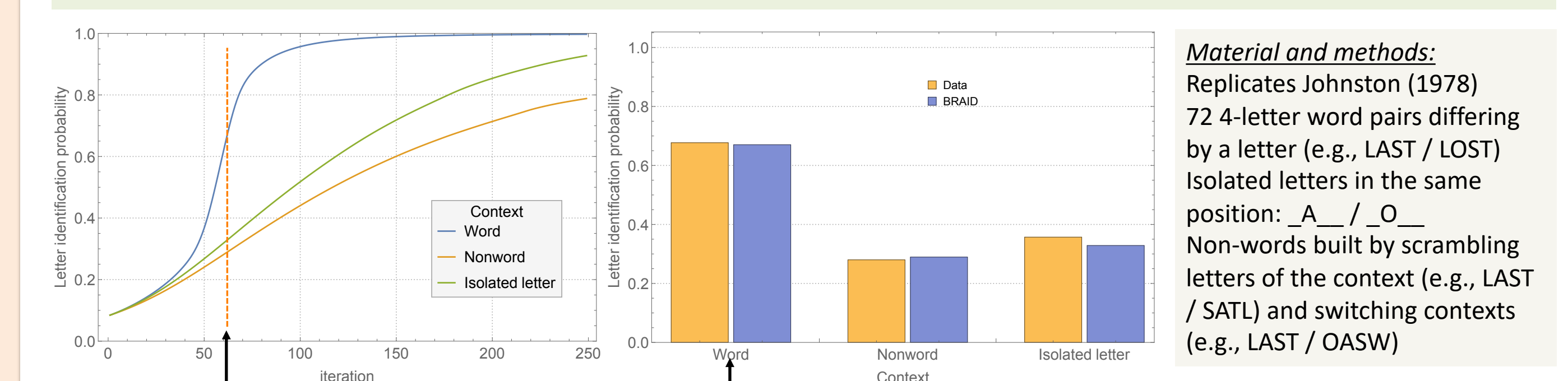
## Simulating behavioral effects Some examples

- **Word frequency effect in WR and LD:** more frequent words are recognized faster



**Results:** The simulation of the dynamics of perceptual evidence accumulation shows that the effect holds for the chosen and other decision threshold values. Effect also holds for lexical decision (simulations not shown here).

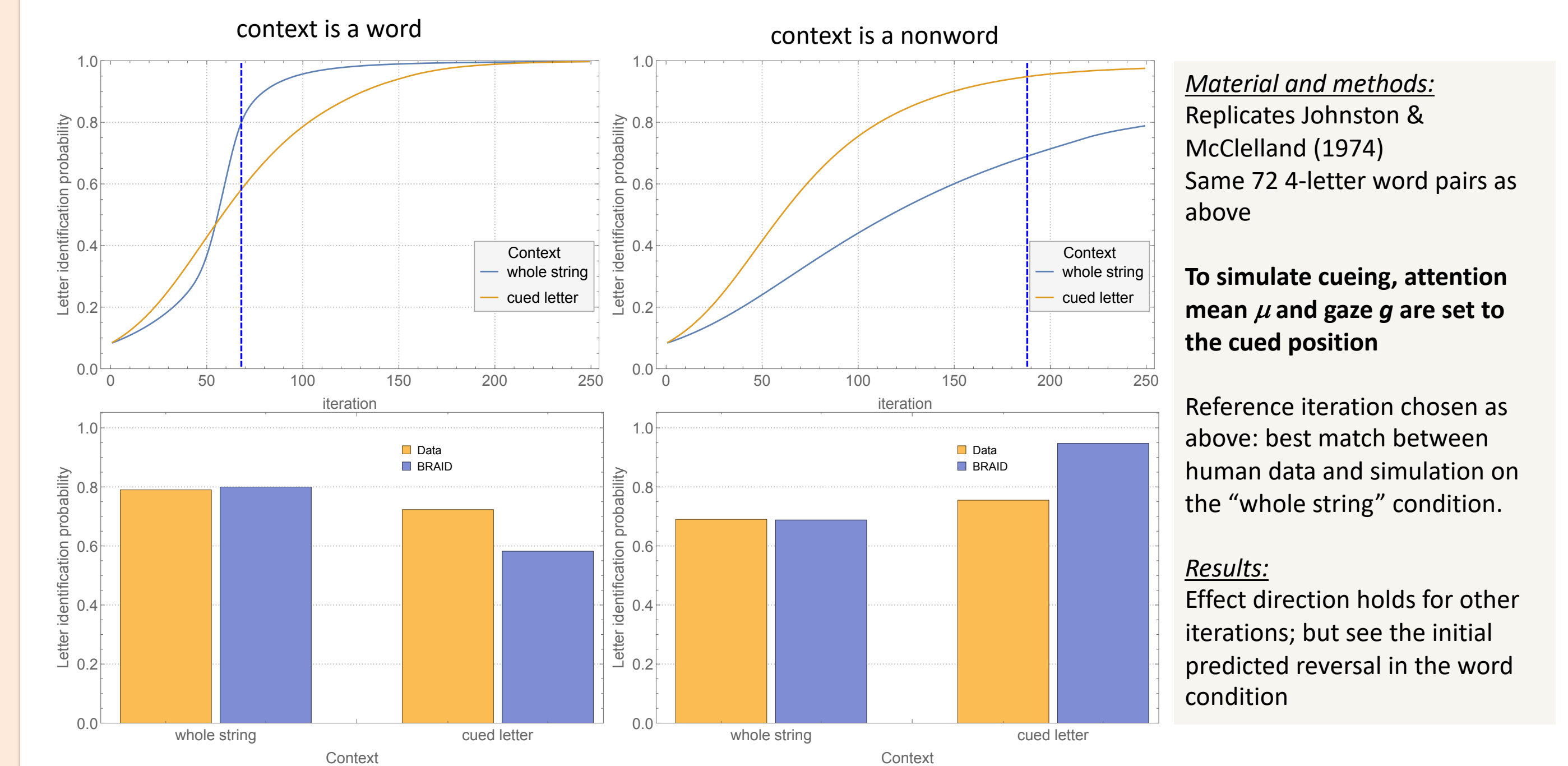
- **Word superiority effect (WSE):** letters are recognized faster in words than in nonwords



Iteration found where the match is best between human data and simulation on the Word condition (arbitrarily chosen): The other conditions are model predictions.

**Results:** The WSE is simulated. Note that, whatever the chosen iteration, the predicted effect is in the correct direction.

- The word superiority effect is modulated if letter position is pre-cued, differently for word contexts (cueing slows down) and nonword contexts (cueing facilitates)



### Other simulated effects:

- Variants on letter perceptibility: consonant-strings, duration of context presentation, length of context, context letter spacing (Phénix, 2018)
- Effects in LD: faster YES than NO responses, orthographic legality (Phénix, 2018)
- **Transposition effects** in primed-WR, primed-LD and same-different tasks (Ginestet, 2016)
- **Optimal viewing position** in normal and impaired readers (Psychonomics 2018 posters)
- **Length effects** in LD (Ginestet et al. submitted)
- **Opposite neighborhood frequency effects** in LD (Phénix et al., 2018)