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

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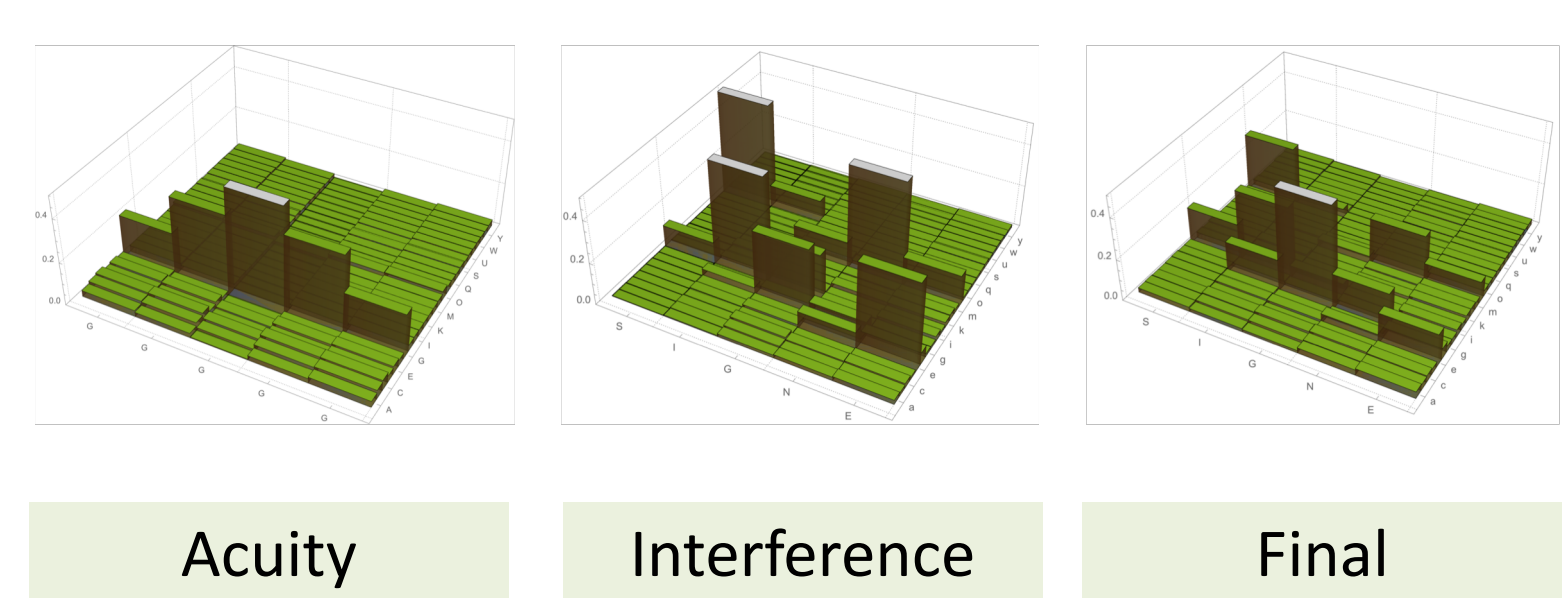
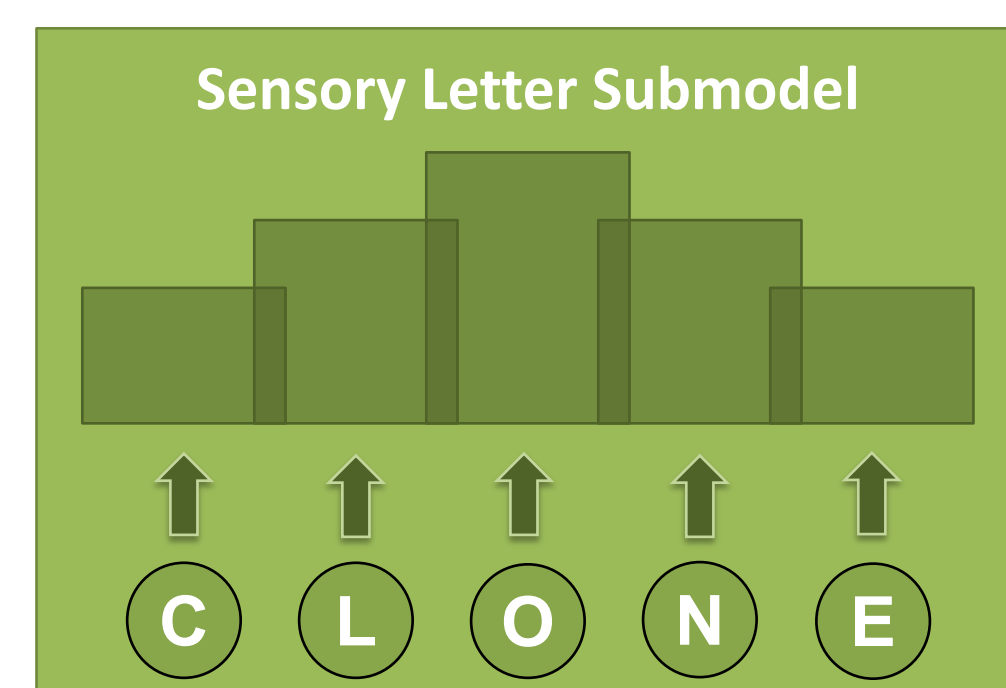
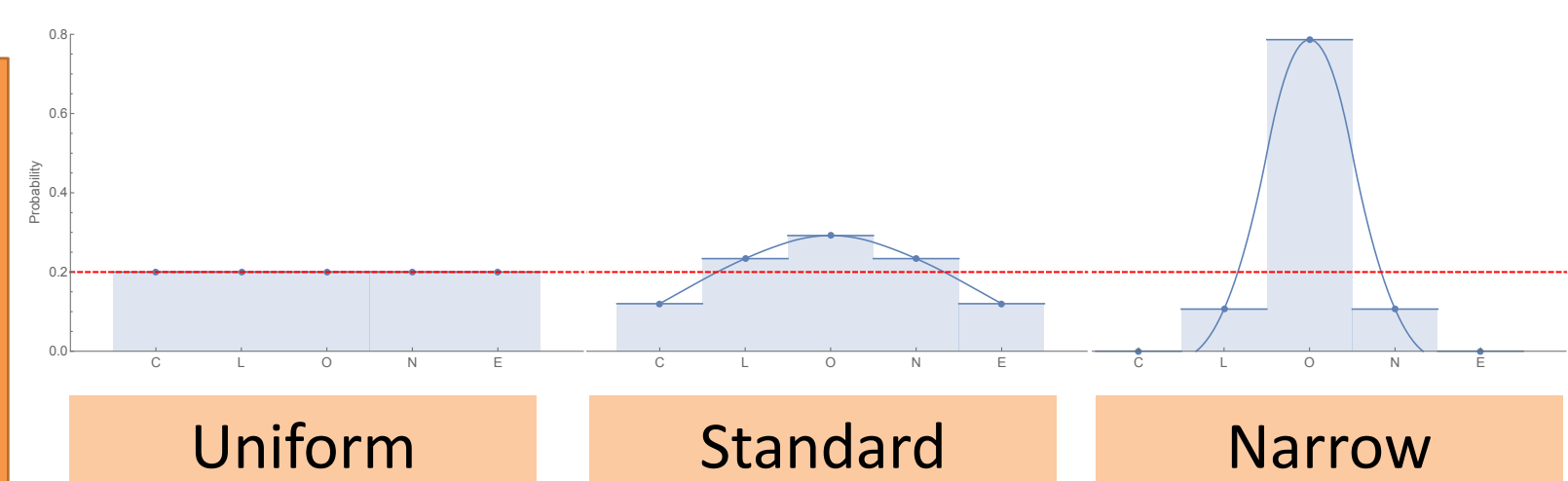
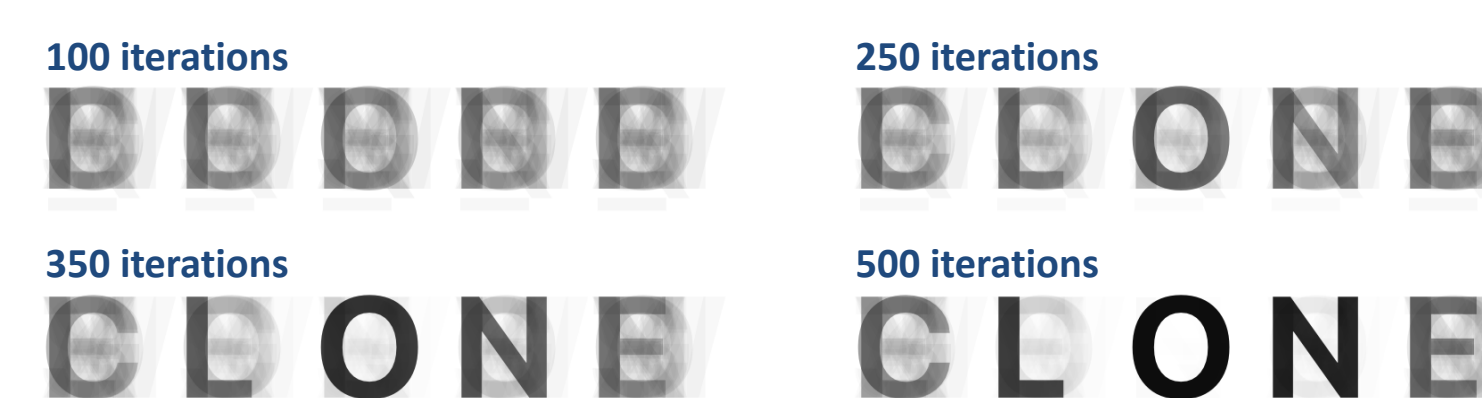
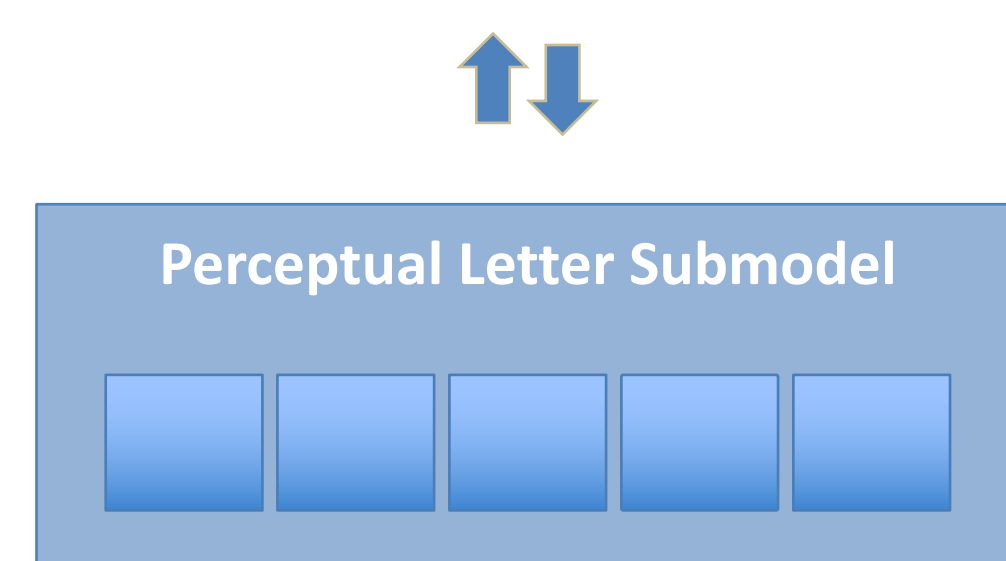
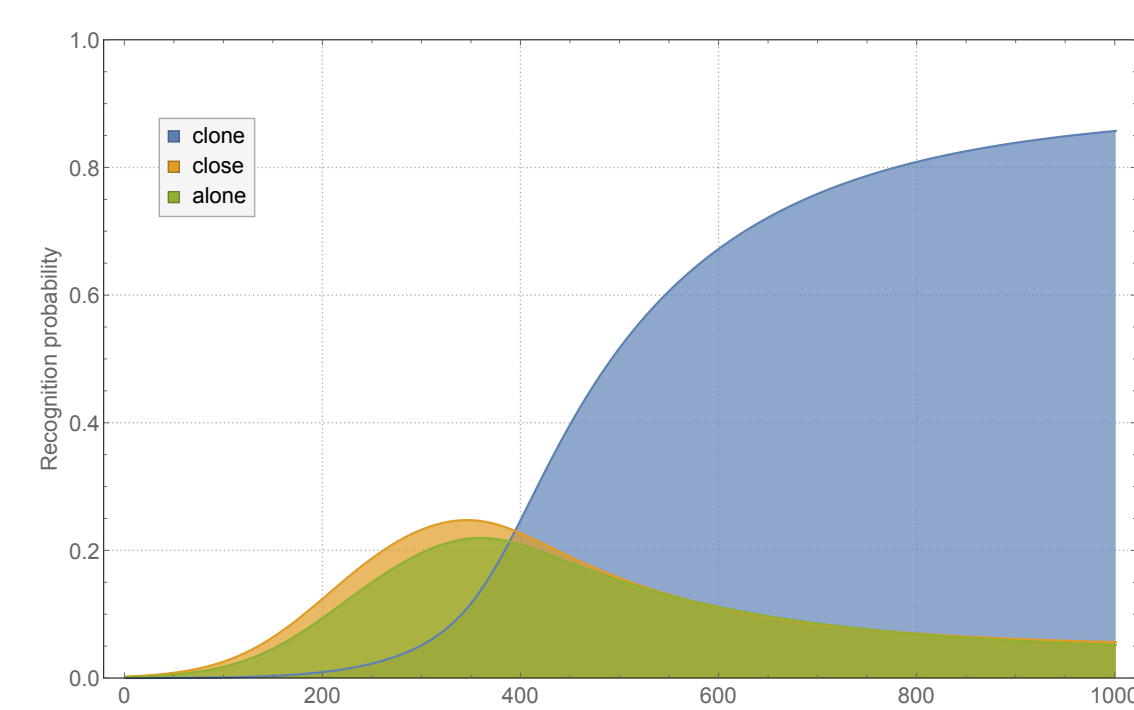
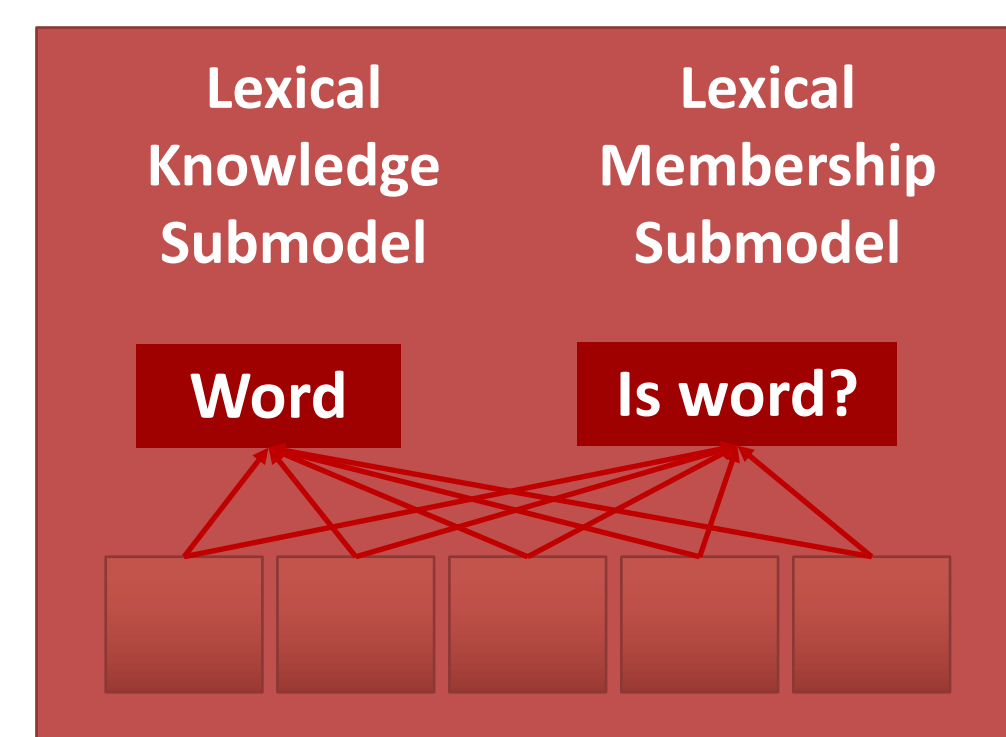
BRAID: Bayesian Word Recognition with Attention, Interference and Dynamics

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

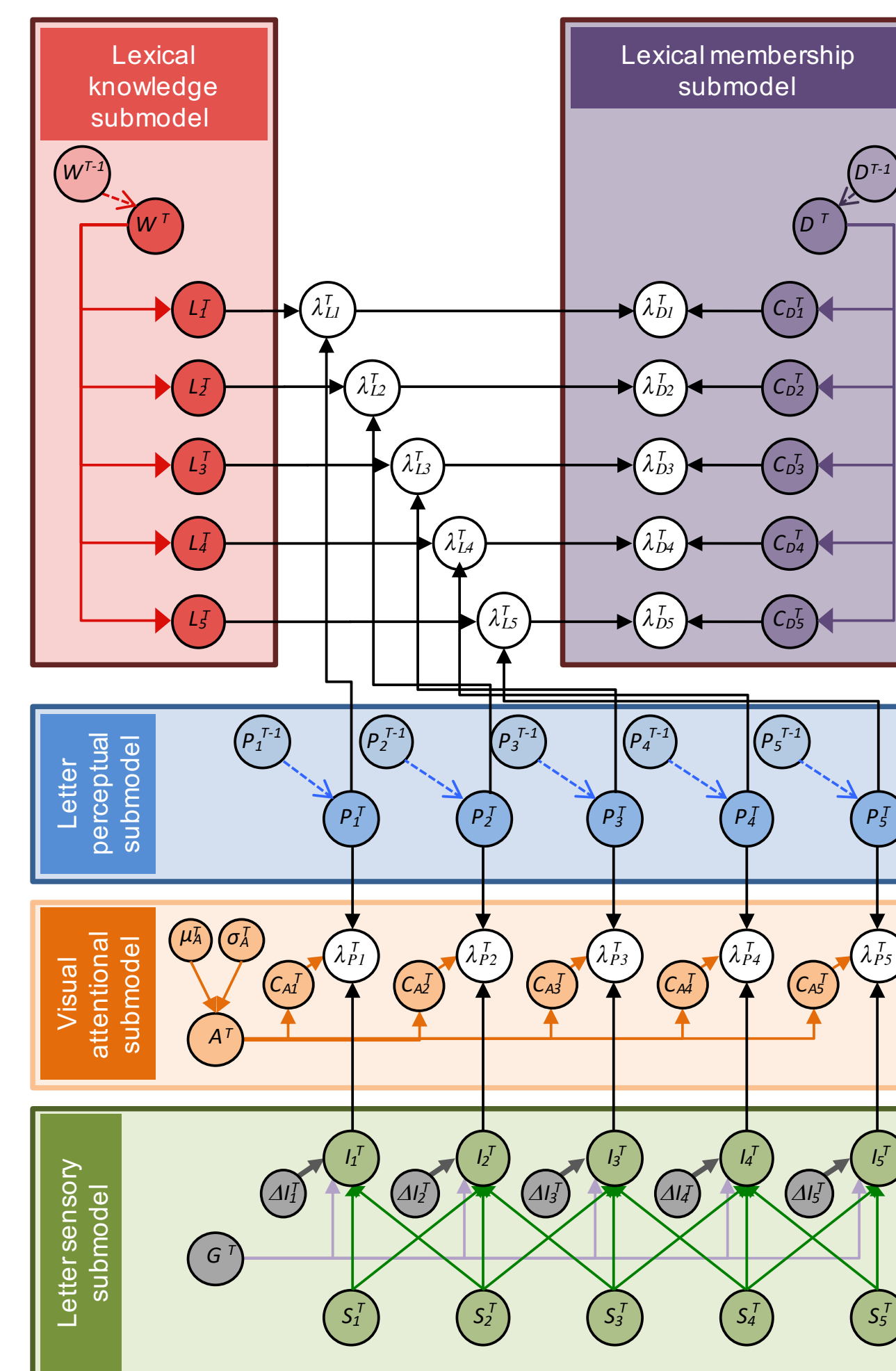
1. The **letter sensory submodel** implements low-level visual mechanisms involved in letter identification and letter position coding. Feature extraction is parallel over the input string, an acuity gradient is implemented symmetrically around fixation and location is distributed over adjacent letter 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 (λ 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)**

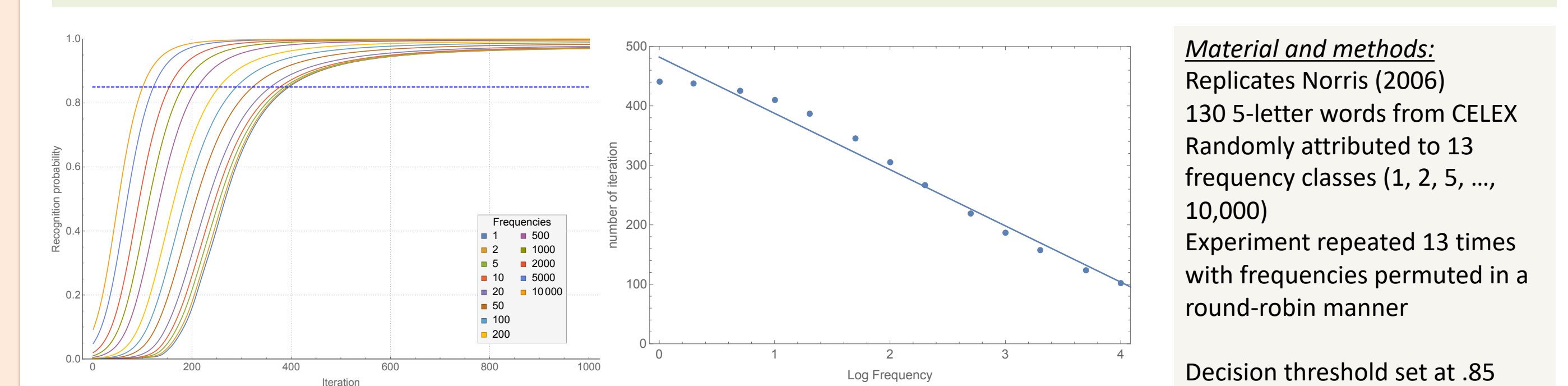
$$Q_D^T = P(D^T | s_{1:N}^{1:T} g^{1:T} \mu_A^{1:T} \sigma_A^{1:T} [\lambda_{D_{1:N}}^{1:T} = 1] [\lambda_{P_{1:N}}^{1:T} = 1])$$

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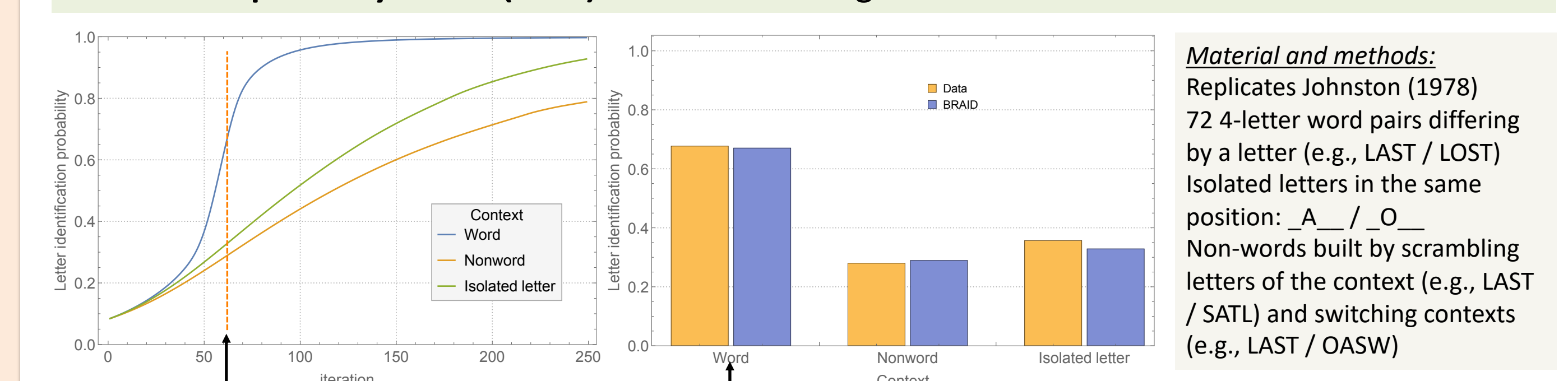
Simulating behavioral effects Some examples

- **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).

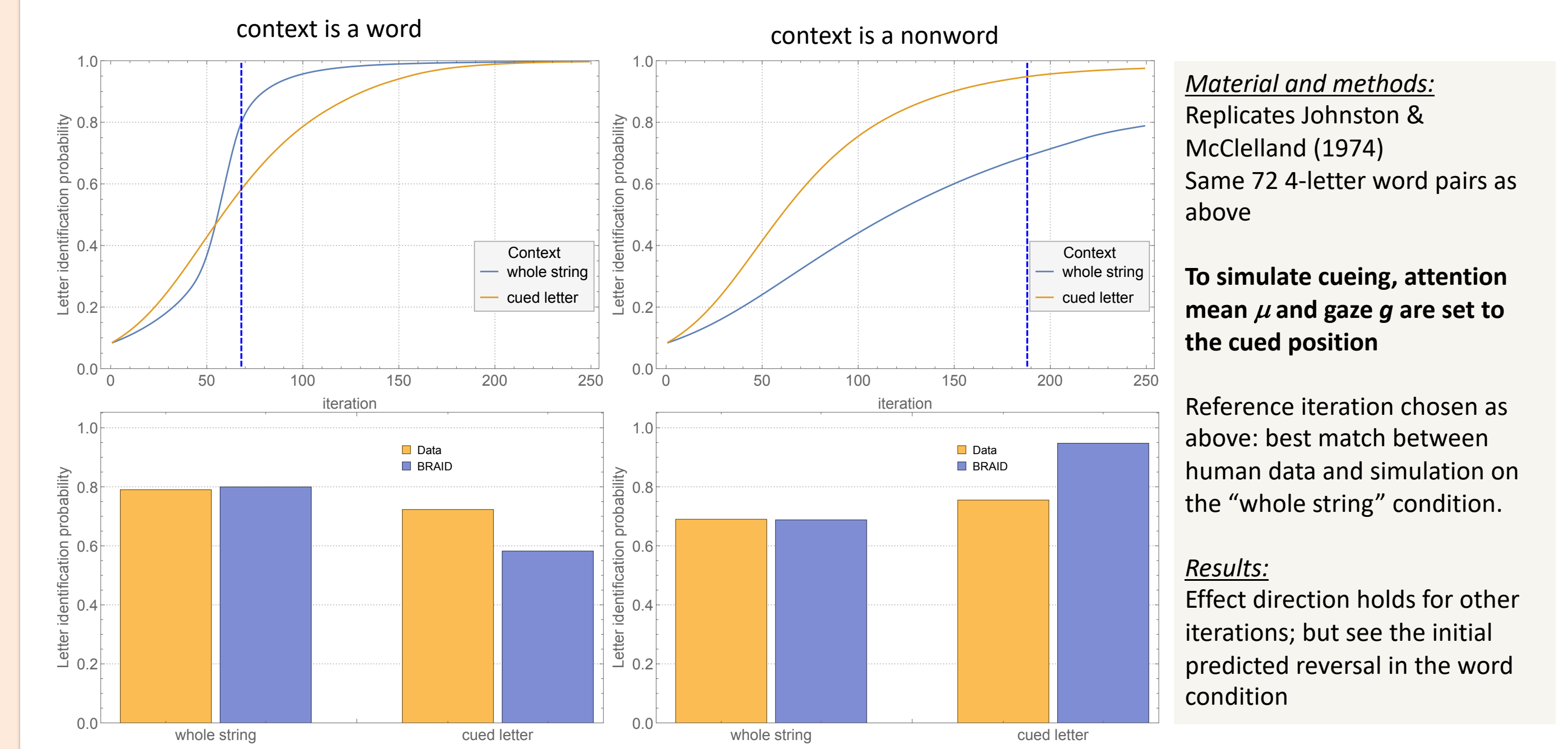
- **Word superiority effect (WSE):** letters are recognized faster in words than in nonwords



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)



Reference iteration chosen as above: best match between human data and simulation on the "whole string" condition.

Results: Effect direction holds for other iterations; but see the initial predicted reversal in the word condition

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)