Connectionist Language Processing

Lecture 9: **Modeling the Electrophysiology of Language**

Matthew W. Crocker
crocker@coli.uni-sb.de
Harm Brouwer
brouwer@coli.uni-sb.de
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… to unravel the architecture and the computational principles and representations underlying language perception, at the neural level.
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— experimental data on language perception
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this means that we need:

— experimental data on language perception
— formulate theories that attempt to explain this data
— to empirically validate these theories using explicit *computational modeling*
What a computational model is not ...
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> a neurocomputational model is all of the above at the neural level
A neurocomputational model is ...
A neurocomputational model *is* ...

today’s lecture:

— a lightning-speed recap on neurocomputational (connectionist) modeling
A neurocomputational model is ...

today’s lecture:

— a lightning-speed recap on neurocomputational (connectionist) modeling

— modeling the N400 and the P600 in language processing
Biological Neurons

Figure A.1 | Schematic overview of a biological neuron (or nerve cell).
Biological Neurons

excitatory/inhibitory input signal

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action potentials (spikes of electrical activity)

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output signal

Figure A.1 | Schematic overview of a biological neuron (or nerve cell).
Biological Neurons

Q: significant excitatory input?

> synapses transform action potentials into an excitatory or inhibitory chemical signal
Artificial "Model" Neurons

**Figure A.2** Schematic overview of a unit (or model neuron). The activation level of the unit is a non-linear combination of its net input. The unit’s net input, in turn, is the weighted sum of the activation levels of all units that signal to this unit.
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\[ y_j = f(x_j) \]

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Q: Firing rate is always $f(x)$—what about \textit{threshold potentials}?

\textbf{Figure A.6} A Feed Forward neural Network (FFN) with bias units connected to each non-input unit. Bias units always have a constant activation value of 1. The connection between a non-input unit and a bias unit, the weight of which is trainable like any other weight in the network, therefore effectively poses a threshold that should be overcome by the rest of the net input to a unit, in order for this input to become positive, and the unit to become active.
Biases—Modeling Threshold Potentials

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> weights of biases pose a threshold that should be overcome by the net input \( x \)
Q: What about \textit{temporally extended stimuli} (e.g., sentences)?

\textbf{Figure A.4} | A Recurrent Neural Network (RNN). Units in successive layers are fully connected. In addition, units in the hidden layer have recurrent connections, meaning that each unit in the hidden layer is also connected to itself and all other units in the hidden layer (to avoid clutter, the figure only depicts recurrent connections between each unit and itself). Recurrent connections provide the network with a form of memory.
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![Diagram of a Recurrent Neural Network (RNN)]

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Figure A.5 | A Simple Recurrent Network (SRN). Before being updated, the activation values of the units in the hidden layer are copied to their corresponding unit in the context layer (the fine dotted lines represent copy connections).
Recurrence—Modeling Memory (cont’d)

Q: What about a more sophisticated type of memory—full within layer recurrence? (i.e., each $h_i$ connected to $h_1...h_n$, which is mathematically challenging)

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> a Simple Recurrent Network (SRN) is a very powerful tool for cognitive modeling.
Learning in Neural Networks

> Neural Networks learn from experience (training)

Rumelhart et al. (1986), Nature
Learning in Neural Networks

> Neural Networks learn from experience (*training*)
Learning in Neural Networks

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![Diagram of a neural network with input, hidden, and output layers, showing stimulus pattern propagating forward to target pattern.](image)
Learning in Neural Networks

> Neural Networks learn from experience (*training*)

![Diagram of a neural network showing the propagation of stimulus and target patterns](image.png)

Rumelhart et al. (1986), *Nature*
Learning in Neural Networks

> Neural Networks learn from experience (*training*)

[Diagram of a neural network showing the propagation of a stimulus pattern through the network to determine error and adjust weights to reduce error.]
Learning in Neural Networks

> Neural Networks learn from experience (training)

- Propagate forward the stimulus pattern to the target pattern.
- Determine the error between the target pattern and the output.
- Adjust the weights to reduce the error.

Rumelhart et al. (1986), *Nature*
Learning in Neural Networks

> Neural Networks learn from experience (*training*)

> challenge in neural network modeling is to *minimize error* for a set of stimuli
Interim Conclusions

> It is possible to give a mathematical definition of biological neurons, and to use this definition to build Artificial Neural Networks (ANNs)
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> ANNs allow for the investigation and validation of cognitive theories, and can be used to generate quantitative predictions about processing behaviour
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Next: let’s employ ANNs to model the N400 and the P600 in language processing
Event-Related Potentials (ERPs)
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He spread his warm bread with **socks**

He spread his warm bread with **butter**

---

Kutas & Hillyard (1980), Science
The spoilt child *throw* the toys on the floor

The spoilt child *throws* the toys on the floor
Theories of the N400 and the P600

The N400 and the P600 are the most salient language-sensitive ERP components, but their functional roles are subject to ongoing debate:
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**N400:**
- semantic integration
  
  (e.g., Osterhout & Holcomb, 1992)
- activation/retrieval of word meaning
  
  (e.g., Kutas & Federmeier, 2000, Lau et al., 2008)
- pre-activation and unification
  
  (Baggio & Hagoort, 2011)
- semantic inhibition
  
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**P600:**
- syntactic repair/reanalysis
  - (e.g., Hagoort et al., 1993)
- syntactic integration difficulty
  - (e.g., Kaan et al., 2000, Kaan and Swaab, 2003)
- conflict resolution
  - (e.g., Kolk et al., 2003, Kuperberg, 2007)
- semantic integration
  - (Brouwer et al., 2012)
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*Why is it difficult to decide?* Processing models are typically conceptual models, lacking the detail required to empirically validate or falsify their predictions.
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**Why is it difficult to decide?** Processing models are typically conceptual models, lacking the detail required to empirically validate or falsify their predictions.

**Solution:** Implement explicit computational models to generate quantitative predictions.
Retrieval-Integration account

N400—lexical/memory retrieval

N400 amplitude reflects the context-sensitive retrieval of word (stimulus) meaning from memory.
Retrieval-Integration account

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P600—semantic integration/MRC composition

P600 is a family of late positivities reflecting the word-by-word construction, reorganization, or updating of a Mental Representation of what is being Communicated (MRC)
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> language is processed in biphasic N400/P600 “Retrieval-Integration” cycles
Retrieval-Integration account (cont’d)

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<thead>
<tr>
<th>Item</th>
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Electrode PZ

Reversal vs. control: no N400-effect because retrieval of \textit{thrown} is equally facilitated due to lexical and contextual/script-level priming.
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Brouwer et al. (2012), *Brain Res.*

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**reversals and mismatches vs. control:** P600-effect because integrating the meaning of the critical word into the unfolding interpretation (MRC) leads to a conflict with world knowledge
Retrieval-Integration account (cont’d)

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*Electrode PZ*

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> we are going to build a neurocomputational model to validate this explanation
Aligning Electrophysiology and Neuroanatomy

A Neurocomputational Model

Connectionist Language Processing — Crocker & Brouwer
A Neurocomputational Model
A Neurocomputational Model

Connectionist Language Processing — Crocker & Brouwer

Brouwer (2014), PhD thesis
Brouwer et al. (under review)
A Neurocomputational Model

Connectionist Language Processing — Crocker & Brouwer

Brouwer (2014), PhD thesis
Brouwer et al. (under review)
A Neurocomputational Model

connection system

retrieval system

perceived word forms

word meaning/semantics

Brouwer (2014), PhD thesis
Brouwer et al. (under review)
A Neurocomputational Model

[Diagram showing neural systems related to language processing, including integration and retrieval systems, thematic-role assignment, word forms, and word meaning/semanics.]
(De)constructing the Integration System
(De)constructing the Integration System

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**Diagram:**

- **IFG** output (300)
- **IFG** (-P600) (200)
- **lpMTG** output (100)

Connections:
- vp/dp
- MRC representations
- Lexical-semantic representations
(De)constructing the Integration System

Connectionist Language Processing — Crocker & Brouwer

Brouwer (2014), PhD thesis
Brouwer et al. (under review)
(De)constructing the Integration System

Figure A.5: A Simple Recurrent Network (SRN). Before being updated, the activation values of the units in the hidden layer are copied to their corresponding unit in the context layer (the fine dotted lines represent copy connections).
(De)constructing the Integration System

Figure A.5 | A visualization of a unit in the context of a feedforward network.
IS is an SRN that transforms sequences of **lexical-semantic representations** (word meanings) into an **utterance/MRC representation** (thematic-role assignment).
Lexical-semantic representations (word meanings)

“In many of the most influential theories of word meaning and of concepts and categorization, semantic features have been used as their representational currency. For example, classical, prototype, and exemplar theories of categorization and conceptual representation all make use of features (Medin & Schaffer, 1978; Minda & Smith, 2002; Smith & Medin, 1981), as do network models of semantic memory and language processing (Collins & Loftus, 1975).”
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> lexical-semantic representations will be modeled as semantic feature vectors
Integration System—Representations

Lexical-semantic representations (word meaning)
> corpus-derived 100-dimensional, binary feature vectors (using COALS)

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<tr>
<th>Word</th>
<th>Representation</th>
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<tr>
<td>cat</td>
<td>11001100110011001110010010101010110111001101001010111111001110001010010101101000011100110110010111101011011110101</td>
</tr>
<tr>
<td>dog</td>
<td>11000000100010111101100101010100110000011111111011101100000110101101000011101011101100101111101</td>
</tr>
<tr>
<td>walk</td>
<td>1101111100001100001011111101110100110111011011110110110010111101111011011111011001011011</td>
</tr>
<tr>
<td>eat</td>
<td>11010100000101111000000111011001000111110111111011011000010111100001001011011111</td>
</tr>
<tr>
<td>food</td>
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Rohde et al. (under revision)
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<th></th>
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<th><code>dog</code></th>
<th><code>walk</code></th>
<th><code>eat</code></th>
<th><code>food</code></th>
</tr>
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</table>

MRC representations (thematic role assignments)
> 300-dimensional thematic role assignment (agent-action-patient) vectors

<table>
<thead>
<tr>
<th></th>
<th>agent semantics</th>
<th>action semantics</th>
<th>patient semantics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100</td>
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</tr>
</tbody>
</table>

Rohde et al. (under revision)


Brouwer (2014), PhD thesis
Brouwer et al. (under review)
Integration System—Representations

Lexical-semantic representations (word meaning)

> corpus-derived 100-dimensional, binary feature vectors (using COALS)

<table>
<thead>
<tr>
<th>Word</th>
<th>Binary Vector</th>
</tr>
</thead>
<tbody>
<tr>
<td>cat</td>
<td>110011001110000101111000110100010101110110101110110010101111011001111110011100010011010110111101</td>
</tr>
<tr>
<td>dog</td>
<td>1100000001100011011101101001101110001111110111100001110100111000110111100101111111010110010</td>
</tr>
<tr>
<td>walk</td>
<td>11011101000001100101110101111101111101111001101110111011011111101111011111011101001110001100</td>
</tr>
<tr>
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</tr>
<tr>
<td>food</td>
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Rohde et al. (under revision)

MRC representations (thematic role assignments)

> 300-dimensional thematic role assignment (agent-action-patient) vectors

agent semantics 300 action semantics 100 patient semantics 100


Brouwer (2014), PhD thesis
Brouwer et al. (under review)
Zooming in: The COALS model

Correlated Occurrence Analogue to Lexical Semantics (COALS)

Step 1—construct a co-occurrence matrix, using a 4-word ramped window: 1 2 3 4 [word] 4 3 2 1
Correlated Occurrence Analogue to Lexical Semantics (COALS)

Step 1—construct a co-occurrence matrix, using a 4-word ramped window: \[1 \ 2 \ 3 \ 4 \ \text{[word]} \ 4 \ 3 \ 2 \ 1\]

Step 2—convert weighted co-occurrence frequencies to pairwise correlations:

\[
w'_{a,b} = \frac{T \cdot w_{a,b} - \sum_j w_{a,j} \cdot \sum_i w_{i,b}}{\left(\sum_j w_{a,j} \cdot (T - \sum_j w_{a,j}) \cdot \sum_i w_{i,b} \cdot (T - \sum_i w_{i,b})\right)^{\frac{1}{2}}} \quad \text{where} \quad T = \sum_i \sum_j w_{i,j}
\]
Zooming in: The COALS model

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where \( T = \sum_i \sum_j w_{i,j} \)

Step 3—“normalize” correlations:

\[ \text{norm}(w'_{a,b}) = \begin{cases} 
0 & \text{if } w'_{a,b} < 0 \\
\frac{1}{\sqrt{w'_{a,b}}} & \text{otherwise}
\end{cases} \]

(reduces distance between small and large correlations)
Zooming in: The COALS model

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\[ \hat{X}_{15000 \times 14000} = \hat{U}_{15000 \times 100} \hat{S}_{100 \times 100} \hat{V}^T_{100 \times 14000} \]
Zooming in: The COALS model

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\]

Step 5 — Extract COALS vector for each word:

\[
 V_c = X_c \hat{V} \hat{S}^{-1}
\]

(and set positive units to 1 and negative values to 0 to obtain binary vectors)
Integration System—Training

> The IS is trained to comprehend Dutch sentences with the following structure:

*Active sentences:*
- De [AGENT] heeft het/de [PATIENT] [ACTION]
- The [AGENT] has the(+/−NEUTER) [PATIENT] [ACTION]

*Passive sentences:*
- De [PATIENT] werd door het/de [AGENT] [ACTION]
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and it learns that:

*every NP can be an Agent or a Patient:* people *can* construct an interpretation for “The bread bakes the baker” (think about a typical Disney film, for instance)
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And it learns that:

- **every NP can be an Agent or a Patient:** people can construct an interpretation for “The bread bakes the baker” (think about a typical Disney film, for instance)

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> after training, the comprehension accuracy of the IS is perfect
Zooming in: Training the model

The model was trained using backpropagation and bounded gradient descent.
Zooming in: Training the model

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The sum squared error of the model was minimized:

\[ E_c = \frac{1}{2} \sum_j (y_j - d_j)^2 \]
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by iteratively adjusting weights on the basis of “bounded” weight delta’s:

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where \( \varepsilon = \) learning rate; \( \rho = \begin{cases} \frac{1}{\| \partial E / \partial w \|} & \text{if } \| \partial E / \partial w \| > 1 \\ 1 & \text{otherwise} \end{cases} \) = a scaling factor;
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\[ \frac{\partial E}{\partial w_{ij}} = \delta_j y_i = \text{weight gradient} \quad \text{where for output units: } \delta_j = (y_j - d_j)(y_j(1 - y_j) + 0.1) \]
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for hidden units: $\delta_j = (y_j(1 - y_j) + 0.1) \sum_k \delta_k w_{jk}$

and $\alpha$ = momentum coefficient;
(De)constructing the Retrieval System
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> RS activates the *lexical-semantic representations* (word meanings) corresponding to incoming *acoustic/orthographic representations* (perceived word forms), while taking the unfolding *utterance/MRC representation* (context) into account.
Acoustic/orthographic representations
> 35-dimensional, localist vectors (each neuron encodes a single word)

<table>
<thead>
<tr>
<th>Word</th>
<th>Representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>painting</td>
<td>00000000000000010000000000000000</td>
</tr>
<tr>
<td>the</td>
<td>00000000000000010000000000000000</td>
</tr>
<tr>
<td>walked</td>
<td>00000000000000010000000000000000</td>
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(this scheme rules out N400-effects due to orthographic neighbourhood size; see, e.g., Laszlo & Federmeier, 2011)
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> the full model (RS+IS) is trained on the same sentences as the IS, but the inputs are now acoustic/orthographic (rather than lexical-semantic) representations
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> after training, the comprehension accuracy of the entire model (RS+IS) is perfect
Zooming out: Full model architecture
“N400 amplitude is a measure of ‘unpreparedness’. If no features relevant to an incoming word are pre-activated, N400 amplitude will be maximal; if the lexical-semantic features of an incoming word are consistent with those pre-activated in memory, N400 amplitude will be reduced. Hence, N400 amplitude is a measure of how much the activation pattern in memory changes due to the processing of an incoming word. As such, we compute the correlates of N400 amplitude at the IpMTG layer, where the activation of lexical-semantic features takes place (~memory retrieval), as the degree to which the pattern of activity induced by the current word, and that induced by the previous word are different.”
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\[
N400 = 1 - \cos(lpMTG_t, lpMTG_{t-1})
\]

(if no difference \( \cos(x,y) = 1 \); otherwise: \( 0 > \cos(x,y) < 1 \)
"P600 amplitude, in turn, reflects the difficulty of establishing coherence. The more the current interpretation (the current MRC) needs to be reorganized or augmented in order to become coherent, the higher P600 amplitude. Hence, P600 amplitude is effectively a measure of how much the representation of the unfolding state of affairs changes due to the integration of an incoming word. As such, we compute the correlates of P600 amplitude as the difference between the previous and the current state of affairs at the lIFG layer, where the (re)construction of an MRC—in terms of thematic-role assignment—takes place (see also Crocker et al., 2010)."
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\[ P600 = 1 - \cos(lIFG_t, lIFG_{t-1}) \]

(if no difference \( \cos(x,y) = 1 \); otherwise: \( 0 > \cos(x,y) < 1 \))
Simulating an ERP experiment

- Two simulation experiments, each with a different set of lexical items, and 10 sentences per condition

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<tr>
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<td>—</td>
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> Two simulation experiments, each with a different set of lexical items, and 10 sentences per condition

*Desired N400-effects*: only for mismatches relative control
Simulating an ERP experiment

> Two simulation experiments, each with a different set of lexical items, and 10 sentences per condition

**Desired N400-effects:** only for mismatches relative control

**Desired P600-effects:** for reversal and mismatches relative control
Simulation results—N400

Electrode PZ

Brouwer (2014), *PhD thesis*
Brouwer et al. (under review)
Simulation results—N400

[Graph showing N400 amplitude on critical word for different conditions: Control (Passive), Reversal (Active), Mismatch (Passive), Mismatch (Active).]
Simulation results—N400
Main effect of Condition (Exp 1: $F(3,27)=45.1; p<.001$; Exp 2: $F(3,27)=12.3; p<.001$); pairwise comparisons (Bonferroni corrected): no N400-effect for reversals (Exp 1: $p=.47$; Exp 2: $p=.91$), and a significant N400-effect for the two other anomalous conditions (Exp 1: p-values$<.005$; Exp 2: p-values$<.01$).
Simulation results—P600
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Simulation results—P600

Connectionist Language Processing — Crocker & Brouwer

Brouwer (2014), PhD thesis
Brouwer et al. (under review)
Simulation results—P600

Main effect of Condition (Exp 1: F(3,27)=136.5; p<.001; Exp 2: F(3,27)=70.1; p<.001); pairwise comparisons (Bonferroni corrected): significant P600-effect for all three anomalous conditions (Exp 1: all three p-values<.001; Exp 2: all three p-values<.001).
Main effect of Condition (Exp 1: F(3,27)=136.5; p<.001; Exp 2: F(3,27)=70.1; p<.001); pairwise comparisons (Bonferroni corrected): significant P600-effect for all three anomalous conditions (Exp 1: all three p-values<.001; Exp 2: all three p-values<.001).
Conclusions

> Using explicit computational modeling, we have provided strong support for the Retrieval-Integration account of the electrophysiology of language processing
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> Computational modeling is a method.

> Computational modeling is a very important method, as adding to the ever-growing pool of experimental data will not help us to reach our ultimate aim …
YOU CAN'T PLAY 20 QUESTIONS WITH NATURE

AND WIN
## Simulation Materials

### Active sentences:

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Agent</th>
<th>Patient</th>
<th>NEUTER</th>
<th>Action</th>
<th>Mismatch</th>
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</thead>
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### Passive sentences:

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<th>Mismatch</th>
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<td>beroofd</td>
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<td>cyclist</td>
<td>stage</td>
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</tr>
</tbody>
</table>

*Active sentences:*  
De [Agent] heeft het/de [Patient] [Action]  
The [Agent] has the(+/-NEUTER) [Patient] [Action]

*Passive sentences:*  
De [Patient] werd door het/de [Agent] [Action]  
The [Patient] was by the(+/-NEUTER) [Agent] [Action]
IIFG/lpMTG communication

Connectionist Language Processing — Crocker & Brouwer

Tse et al. (2007), PNAS