

Computational Psycholinguistics

Lecture 9: Interactive Models



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Interactive Models of Sentence Processing

- So far:
 - Symbolic parsing algorithms: incrementality and memory
 - Syntactic parsing strategies: MA/LC, Theta-attachment
 - Models of syntactic parsing and reanalysis
 - + Monotonic parsing: Sturt & Crocker
 - Probabilistic models of category disambiguation and parsing
- Focus has been on symbolic representations of syntactic structure:
 - Structural, linguistic, and probabilistic decision strategies
 - Assumes some degree of modularity/autonomy
 - + At least "bottom-up" priority of lexical and syntactic processing
- Alternatives: Interactive Architectures
 - Non-symbolic architectures for language learning and processing
 - + Connectionist networks, e.g. SRNs
 - Non-modular architectures which make immediate use of all relevant knowledge/constraints.

The Rise of Interactionist Models

- Empirical Evidence: Eye-tracking
 - fine grained behavioural observations
 - evidence for “immediate” (very early) interaction effects of
 - + Animacy, frequency, plausibility, discourse ...
 - Evidence for knowledge-based reanalysis
- Appropriate computational frameworks:
 - symbolic constraint-satisfaction systems
 - connectionist systems
 - probabilistic & competitive activation models
- Homogenous/Integrative Linguistic Theory: HPSG
 - Multiple levels of representation specified within a unified formalism
 - Interaction via unification and re-entrancy

Motivating Interactive Models

- MacDonald, Tanenhaus et al:
 - (a) The *defendant* examined by the lawyer turned out ...
 - (b) The *evidence* examined by the lawyer turned out ...
 - (c) The defendant *that was* examined by the lawyer ...
- Clear evidence for the use of animacy in reducing the garden-path:
 - (b) is easier than (a), in fact, almost as easy as (c).
- Interactive Models:
 - The Sentence Gestalt Model: St. John & McClelland
 - Multiple Constraints Frameworks:
 - + “Interactive Activation Model”: MacDonald, Pearlmuter & Seidenberg
 - + “Competition-Integration Model”: Tanenhaus, Spivey-Knowlton, Trueswell, McRae *et al*

Multiple constraints in ambiguity resolution

- The doctor **told** the woman **that**

story

diet was unhealthy

he was having trouble with her husband

he was having trouble to leave

story was was about to leave

- Prosody: intonation can assist disambiguation
- Lexical category ambiguity:
 - **that** = {Comp, Det, RelPro}
- Subcategorization ambiguity:
 - **told** = { [_ NP NP] [_ NP S] [_ NP S'] [_ NP Inf] }
- Semantics: Referential context, plausibility
 - Reference may determine “argument attach” over “modifier attach”
 - Plausibility of *story* versus *diet* as indirect object

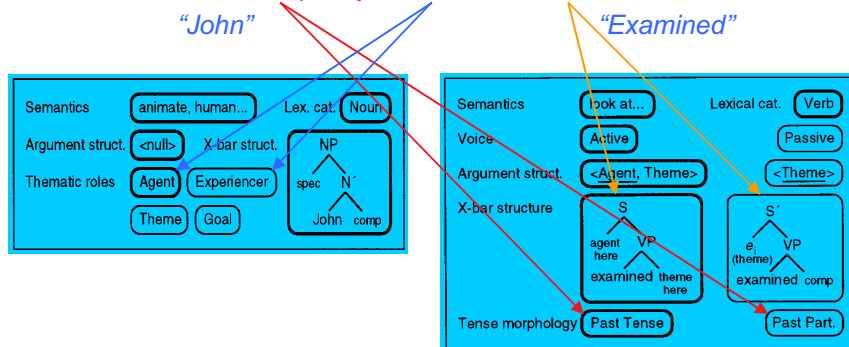
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The Interactive Activation Model

- Rich syntactic/thematic features
- Frequency determines ‘activations’
- Consider: “*John examined the evidence*”
 - “examined” is ambiguous, as either a simple past or past participle
 - ➔ Constraints: **tense frequency**, **thematic fit**, **structural bias** ...



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MacDonald, Pearlmutter & Seidenberg

■ The Interactive-Activation Model: In sum

- ❑ Multiple access is possible at all levels of representation, constrained by frequency/context
- ❑ All levels of representation are available to the language processor, simultaneously
- ❑ Highly lexicalist, entries enriched with frequency and syntactic info, “built” not accessed
- ❑ Language processing is “constraint satisfaction”, between lexical entries, and across levels
- ❑ No distinct parser

■ Questions:

- ❑ Acquisition of the model: where does the linguistic knowledge come from, and the probabilities/activations?
- ❑ Implementation: does such a model work in practice?
 - + Complex interaction behaviours are difficult to predict

The Competitive-Integration Model

■ Claim: Diverse constraints (linguistic and conceptual) are brought to bear simultaneously in ambiguity resolution.

- ❑ Contra: modular models with distinct syntactic processing and delayed influence of conceptual constraints

■ Problem: “No model-independent signature data pattern can provide definitive evidence concerning when information is used”

■ The Model:

- ❑ Not a parser: *assumes the competing analyses have been constructed*
- ❑ Constraints provide “probabilistic” evidence to support alternatives
 - + Each constraint has a weight, these are normalised to sum to 1
 - + Lexical frequency bias, structure bias, parafoveal cues, thematic fit ...
- ❑ Constraints activations, C , are integrated to activate each interpretation, I
- ❑ I -activation is fed-back to the C -activation; then next cycle begins

■ Goal: Simulate reading times

- ❑ RTs are claimed to correlate with the number of cycles required to settle on one of the alternatives

Steps in the Experiment: (McRae et al 1998)

- ➡ Goal: investigate the time-course with which constraints contribute to the activation of competing analyses
- 1. Identifying the relevant constraints
- 2. Computational model for the interaction of constraints
- 3. Determining the bias of each constraint
 - From corpora: frequency used to determine probability
 - From off-line study: norms used to determine probability
- 4. Determining the weight of each constraint
 - Fit with off-line completions
- 5. Make predictions for reading times
- 6. Compare predicted reading times of:
 - Constraint-based model
 - Garden-path model
 - Short-delay garden path model
 - ... With the actual reading times from on-line studies

Constraints/Parameters of the Model

“The crook/cop arrested by the detective was guilty of taking bribes”

- ① Verb tense/voice constraint: is the verb preferentially a past tense (i.e. main clause) or past participle (reduced relative)
 - ❑ Relative log frequency is estimated from corpora: $RR=.67$ $MC=.33$
- ② Main clause bias: general bias for structure for “NP verb+ed ...”
 - ❑ Corpus estimate: $P(RR|NP + verb-ed) = .08$, $P(MC|NP + verb-ed) = .92$
- ③ by-Constraint: extent to which ‘by’ supports the passive construction
 - ❑ Estimated for the 40 verbs from WSJ/Brown: $RR= .8$ $MC= .2$
- ④ Thematic fit: the plausibility of crook/cop as an agent or patient
 - ❑ Estimated using a norming study
- ⑤ by-Agent thematic fit: good Agent is further support for the RR vs. MC
 - ❑ Same method as (4).

Thematic Fit Parameters

"The crook/cop arrested by the detective was guilty of taking bribes"

■ Estimating thematic fit with an off-line rating (1-7) study

How common is it for a

crook _____
 cop _____
 guard _____
 police _____
 suspect _____

To **arrest** someone?

To **be arrested by** someone?

■ The results: Initial NP

□ Good Agents (e.g. *the cop*):

□ Good Patients (e.g. *the crook*):

■ The results: Agent NP

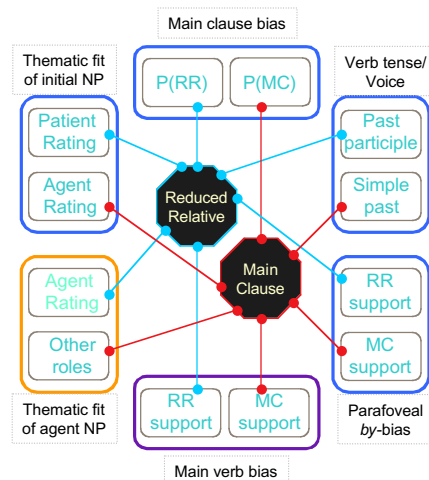
□ Good Agents (e.g. *the detective*):

	Relative	Main
Good Agents (e.g. <i>the cop</i>):	1.5	5.3
Good Patients (e.g. <i>the crook</i>):	5.0	1.0
	Relative	Main
Good Agents (e.g. <i>the detective</i>):	4.6	1.0 (constant)

The Computational Model

■ The crook arrested by the detective was guilty of taking bribes

1. Combines constraints as they become available in the input
2. Input determines the probabilistic activation of each constraint
3. Constraints are weighted according to their strength
4. Alternative interpretations compete to a criterion
5. Cycles of competition mapped to reading times



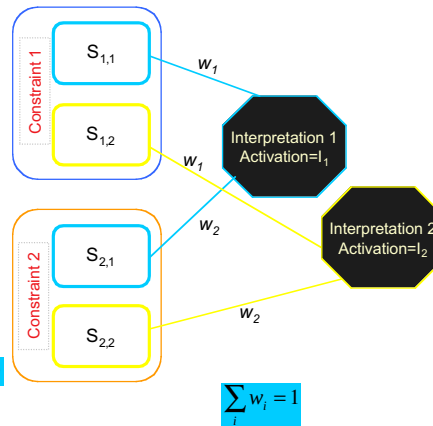
The recurrence mechanism

- $S_{c,a}$ is the raw activation of the node for the c^{th} constraint, supporting the a^{th} interpretation,
- w_c is the weight of the c^{th} constraint
- I_a is the activation of the a^{th} interpretation
- 3-step normalized recurrence mechanism:

Normalize: $S_{c,a}(norm) = \frac{S_{c,a}}{\sum_a S_{c,a}}$

Integrate: $I_a = \sum_c [w_c \cdot S_{c,a}(norm)]$

Feedback: $S_{c,a} = S_{c,a}(norm) + I_a \cdot w_c \cdot S_{c,a}(norm)$



Fitting Constraint Weights using Completions

- The Completion Study:
 - Establish that thematic fit does in fact influence "off-line" completion
 - Use to adjust the model weights
- Manipulated the fit of NP1:
 - Good agents (and atypical patients)
 - Good patients (and atypical agents)
- Hypotheses:
 - Effect of fit at verb
 - Additional effect at 'by'
 - Ceiling effect after agent NP
- Adjust the weights to fit "off-line" data:
 - Brute force search of weights (~1M)
 - 20-40 cycles (step 2)
- Node activation predicts proportion of completions for each interpretation
 - Avg of activation from 20-40 cycles

Gated sentence completion study:

The cop/crook arrested ...
The crook arrested by ...
The crook arrested by the ...
The crook arrested by the detective...

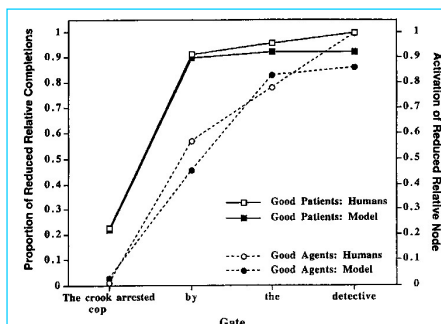


FIG. 2. Human and simulation results for fragment completions.

Counted "the crook arrested himself" as RR (!?)

Self-Paced Reading Study

Two-word, self-paced presentation:

The crook / arrested by / the detective / was guilty / of taking bribes
The cop / arrested by / the detective / was guilty / of taking bribes
The cop / that was / arrested by / the detective / was guilty / of taking bribes

Same beginning as the completion studies

Three Models

- ☐ Constraint-Based: constraints apply immediately for each region
- ☐ Garden-Path: MC-bias & Main-Verb bias only, other constraints (lexical specific, and conceptual) are delayed one region
- ☐ Short-Delay Garden Path:

Prediction Per-Region Reading times for each model:

- ☐ Each region is processed until it reaches a (dynamic) criterion:
 $\text{dynamic criterion} = 1 - \Delta\text{crit} \times \text{cycle}$
- ☐ As more cycles are computed, threshold is relaxed
- ☐ $\Delta\text{crit} = .01$ means a maximum of 50 cycles

CB vs. GP predictions (using the model)

Constraint Based (CB) Model

MC bias: .5094 x .75
 Thematic Fit: .3684 x .75
 Verb tense: .1222 x .75
 by-bias: .25

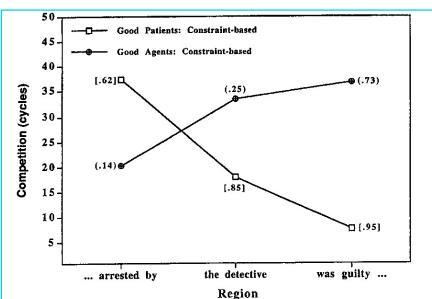


FIG. 3. Self-paced predictions derived from the constraint-based competition model. In this and all following model figures, the number beside each model datum is the mean activation of the reduced relative node after competition in that region for either (good agents) or (good patients).

Garden Path (GP) Model:

MC bias: 1

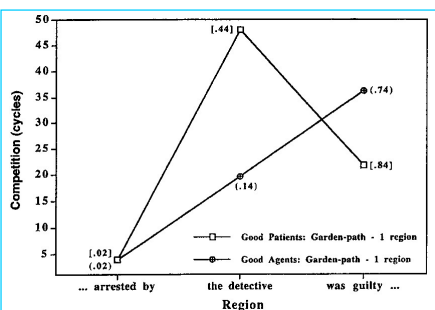
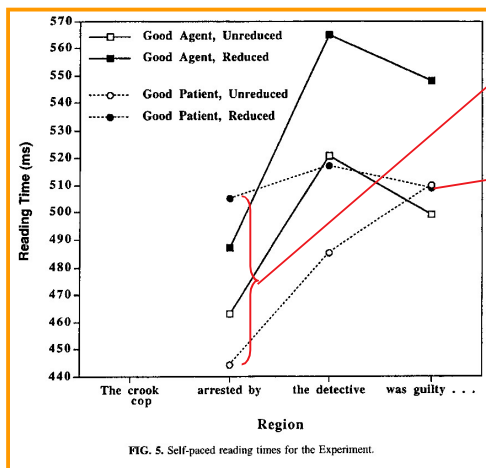


FIG. 4. Self-paced predictions as derived from the garden-path model when constraints other than the main clause and main verb biases were delayed by a region.

GP vs CB Modelling of the Reading

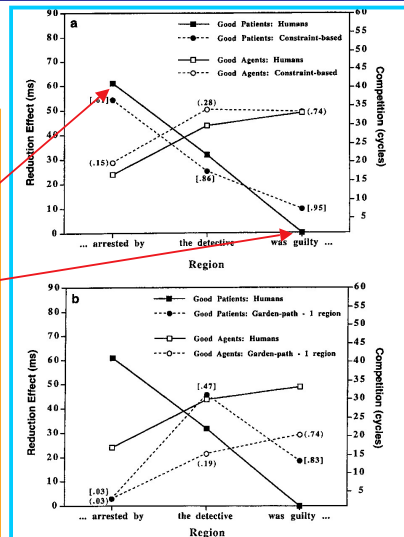
Reduction effect/cycles:

Human reading times:



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Simulating a Short Delay GP Model

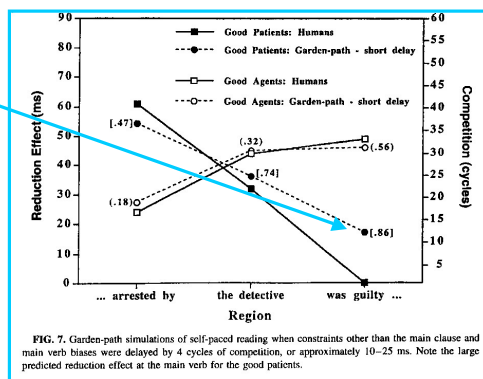
- The GP-model, has a 1-2 word delay in use of information, what if this delay is reduced?

- 4 cycles (10-25ms)
- Much better fit, except for the high reduction effect still predicted at main verb (good patient).
- RMS error 5.5

- Search for the best assignment of weights:

MC bias: .2966 (.5094)
Th. fit: .4611 (.3684)
V.tense: .0254
by-bias: .2199

- RMS error 2.77
- (but no longer models completions)



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Issues and Criticisms

- Decision about what constraints to include/exclude, McRae et al:
 - Less important if materials don't vary w.r.t excluded constraint, or,
 - Of bias of excluded constraint correlates well with included constraint:
 - ✦ E.g. tense bias (included) correlates well with transitivity (excluded)
- Not a model of language *processing*:
 - Is it legitimate to characterise information flow separate from the structure building mechanism.
 - What is *really* being modelled? Can the approach be scaled up?
- Garden-path: A straw man
 - Is the implementation of the GP model fair, for purposes of comparison
 - What other constraints might be considered purely syntactic.
- Predicts long reading times when constraints are in close competition
 - In fact, people are often *faster* at processing ambiguous regions!
- Not truly probabilistic: activations only *begin* as probabilities
 - Also, many probabilities are derived from ratings (not frequencies)