# Computational Psycholinguistics

# Lecture 11: **Constraint-based Models**

Matthew W. Crocker
crocker@coli.uni-sb.de



# So far: Focus on Syntax

- What algorithms are used to construct syntactic analyses from the grammar?
- What mechanisms are used to deal with lexical & syntactic ambiguity?
  - is it one mechanisms, or are these levels distinct?
  - serial+backtracking, parallel, monotonic?
- What kind of information is used to decide upon/rank alternative analyses?
  - Structural simplicity (Frazier), thematic dependencies (Pritchett), probabilities (Jurafsky)?
- What is the linking mechanisms from the parser to reading measures?
  - Re-parsing cost, revising role assignments, non-monotonicity,
    parse pruning and re-ranking, surprisal
- What other factors determine interpretation preferences and processing cost?

# Kinds of constraints

- The doctor told the woman that … *story*

  *diet was unhealthy*

  *he was in love with her husband*

  *he was in love with to leave*

  *story was was about to leave*

- **Prosody**: intonation can assist disambiguation
- **Lexical** preference: *that* = {Comp, Det, RelPro}
- **Subcat**: *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



# The Modularity Argument

- There is considerable evidence that non-syntactic information and context influence reading times.
- However there is limited evidence that the core syntactic preferences are ever completely overridden, e.g. (Rayner et al, 1983):
  - *The florist sent the flowers was very pleased.*
  - *The performer sent the flowers was very pleased.*
- While there is less of a garden path effect at "was very pleased" for the "performer" condition, it was still greater than for unambiguous controls.
- Thus: "initial" preferences for syntactic analyses are driven by modular, syntactic strategies, with other knowledge being used only "later"         s.

# Constraint-based Models

- What **architecture** is assumed?
  - <u>Non-modular</u>: all levels are constructed and interact simultaneously
- What **mechanisms** is used to construct interpretations?
  - <u>Parallel & competitive</u>: ranking based on constraint activations
- What **information** is used to determine preferred interpretation?
  - <u>All relevant information</u> and constraints use immediately (not just syntax)
- **Linking Hypothesis:**
  - Comprehension is easy when constraints support a common interpretation, and difficult when they conflict/compete



# The Competitive-Integration Model

- **Claim**: Diverse constraints (linguistic and conceptual) are brought to bear simultaneously in ambiguity resolution.
- **The Model**: Assumes the all analyses are constructed
  - Constraints provide "probabilistic" support for each analyses
    - Constraint are weighted and normalized
    - Lexical & structural bias, parafoveal cues, thematic fit, discourse context ...
- **Goal**: Simulate reading times
  - RTs are claimed to correlate with the number of cycles required to settle on one of the alternatives

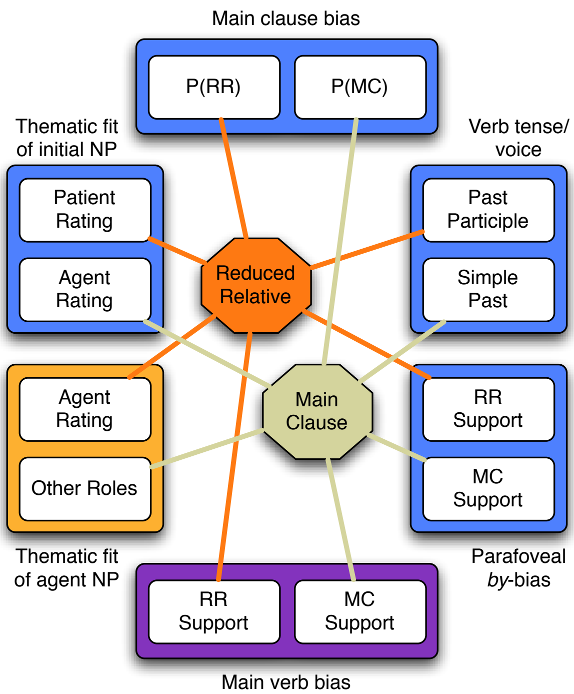


(McRae et al, 1998; Tanenhaus et al, 2000)

# 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

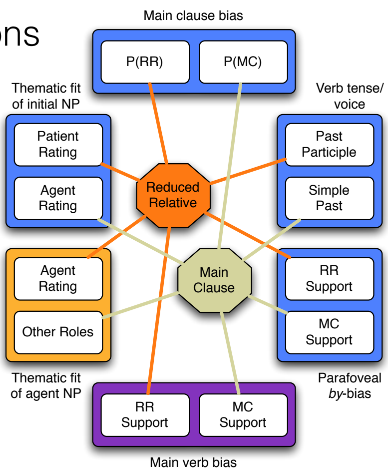





# Steps in the Experiment: (McRae et al 1998)

Constraints contribute to the activation of competing analyses, over time

1. Identifying the relevant constraints
2. Computational model for the interaction of constraints
3. Estimate bias of each constraint from corpora & rating studies
4. Weight of each constraint: fit with off-line completions
5. Make predictions for reading times
6. Compare actual reading times with those of:
   - Constraint-based model
   - Garden-path model



# Constraint Parameters

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

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

Main clause bias: general bias for structure of “NP verb+ed …”

Corpus: P(RR|NP + verb-ed) = .08, P(MC|NP + verb-ed) = .92

*by*-Constraint: extent to which ‘by’ supports the passive construction

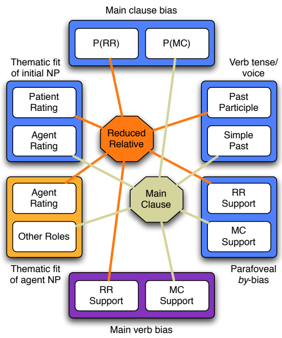
Estimated for the 40 verbs from WSJ/Brown: RR= .8 MC= .2

Thematic fit: the plausibility of crook/cop as an agent or patient.

Estimated using a rating study

*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       _____
    detective _____
    police    _____
    suspect   _____
To arrest someone?
To be arrested by someone?
```

| NP 1 | Rel | Main |
|---|---|---|
| Agent | 1,5 | 5,3 |
| Patient | 5 | 1 |

| by NP | Rel | Main |
|---|---|---|
| Agent | 4,6 | 1 |

# The Computational Model

The crook arrested by the detective was guilty of taking bribes

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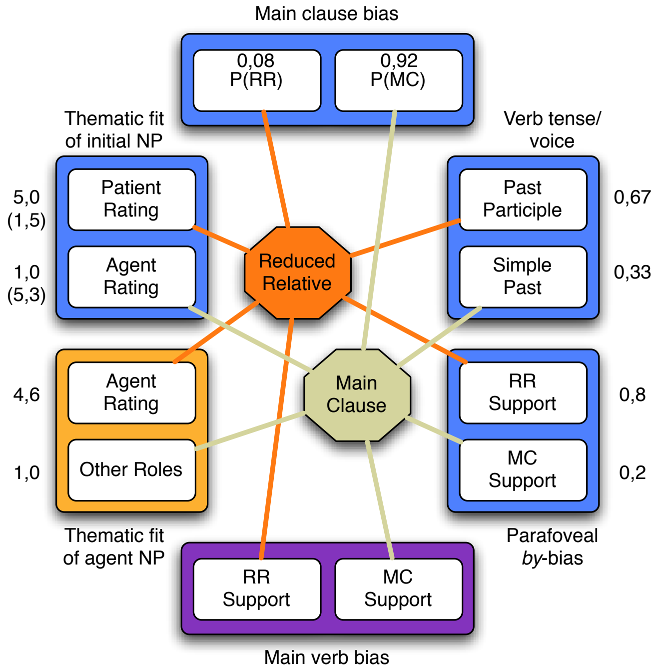
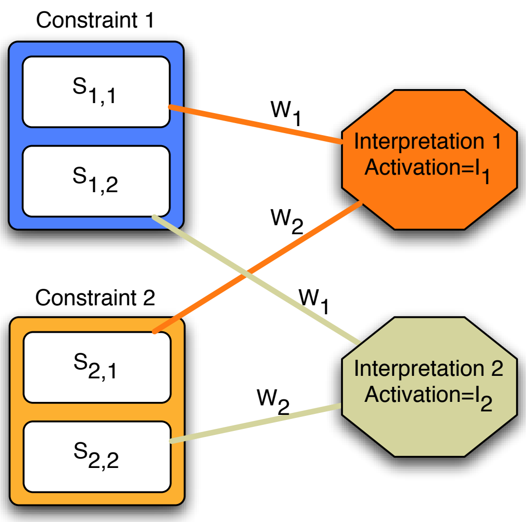





# The recurrence mechanism

- $S_{c,a}$ 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:

  1. Normalize: $$S_{c,a}(norm) = \frac{S_{c,a}}{\sum_a S_{c,a}}$$
  2. Integrate: $$I_a = \sum_c \left[ w_c \cdot S_{c,a}(norm) \right]$$
  3. Feedback: $$S_{c,a} = S_{c,a}(norm) + I_a \cdot w_c \cdot S_{c,a}(norm)$$




$$\sum_i w_i = 1$$

# A Gated 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

Gated sentence completion study:

*The {cop,crook} arrested ...*
*The crook arrested by ...*
*The crook arrested by the ...*
*The crook arrested by the detective...*



# Fitting Constraint Weights

- 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
- Weights determined by averaging the10 best models from each of 20-40 cycles (110 models in total)

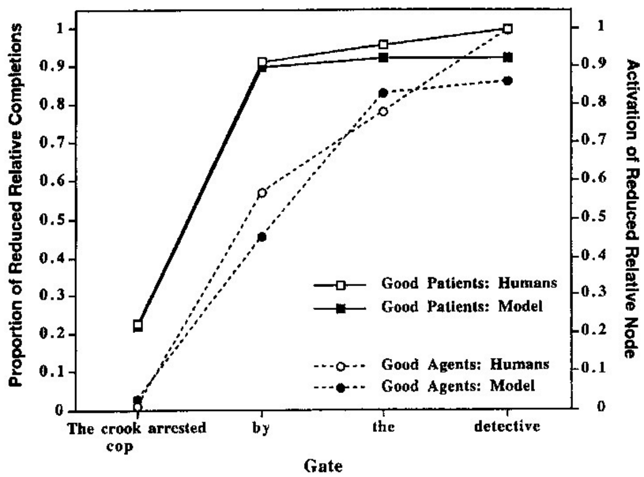



FIG. 2. Human and simulation results for fragment completions.

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

# The Complete Model

Constraint Based (CB) Model
MC bias: .5094 x .75
Thematic Fit: .3684 x .75
Verb tense: .1222 x .75
by-bias: .25

The crook arrested by the detective was guilty of taking bribes

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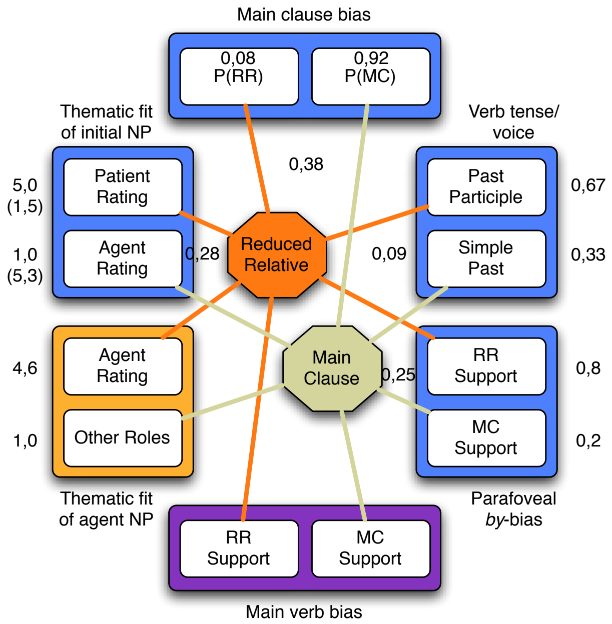




# On-line study

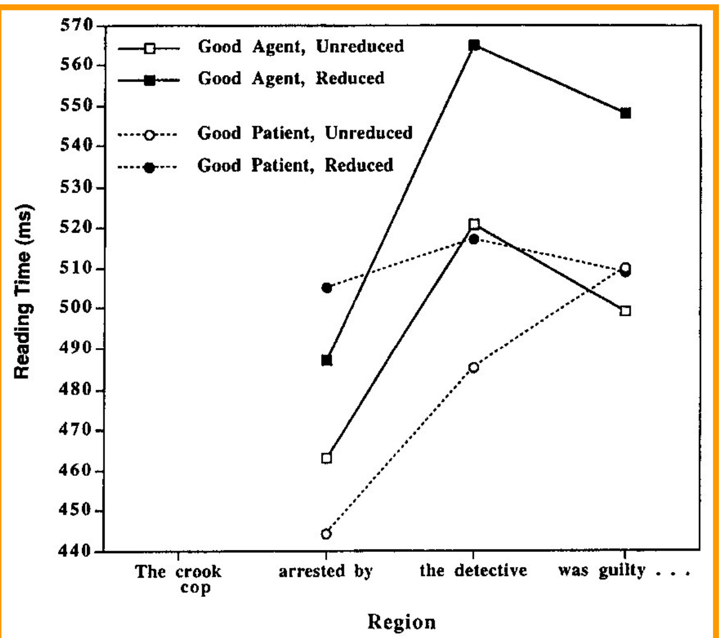


FIG. 5. Self-paced reading times for the Experiment.

- Two-word, self-paced presentation: (similar to completion studies)

*The cop / that was / arrested by / the detective / was guilty / of taking bribes* [GA,UR]

*The cop / arrested by / the detective / was guilty / of taking bribes* [GA,R]

*The crook / that was / arrested by / the detective / was guilty / of taking bribes* [GP,UR]

*The crook / arrested by / the detective / was guilty / of taking bribes* [GP,R]

# Model Predictions

- Two “Versions” of the models:
  - Constraint-Based: constraints apply immediately for each region
  - Garden-Path: MC-bias & Main-Verb bias only, other constraints delayed one “region”
- Prediction Per-Region Reading times for each model:
  - Each region is processed until it reaches a (dynamic) criterion:

    *dynamic criterion = 1 - ∆crit*cycle*

  - As more cycles are computed, threshold is relaxed
  - *∆crit=.01* means a maximum of *50* cycles

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



# CB vs. GP Model Predictions

- Constraint Based (CB) Model

Constraint Based (CB) Model
MC bias: .5094 x .75
Thematic Fit: .3684 x .75
Verb tense: .1222 x .75
by-bias: .25

Garden Path (GP) Model:
MC bias:1

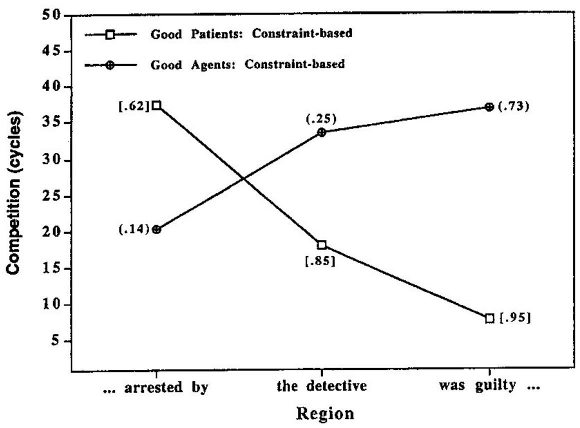


FIG. 3. Self-paced predictions derived from the constraint-based competition model. In this and all following model figures, the number beside each model datum is the mean activation of the reduced relative node after competition in that region for either (good agents) or [good patients].

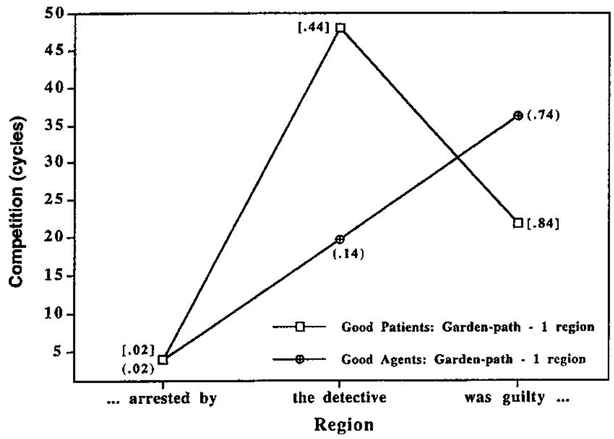


FIG. 4. Self-paced predictions as derived from the garden-path model when constraints other than the nain clause and main verb biases were delayed by a region.

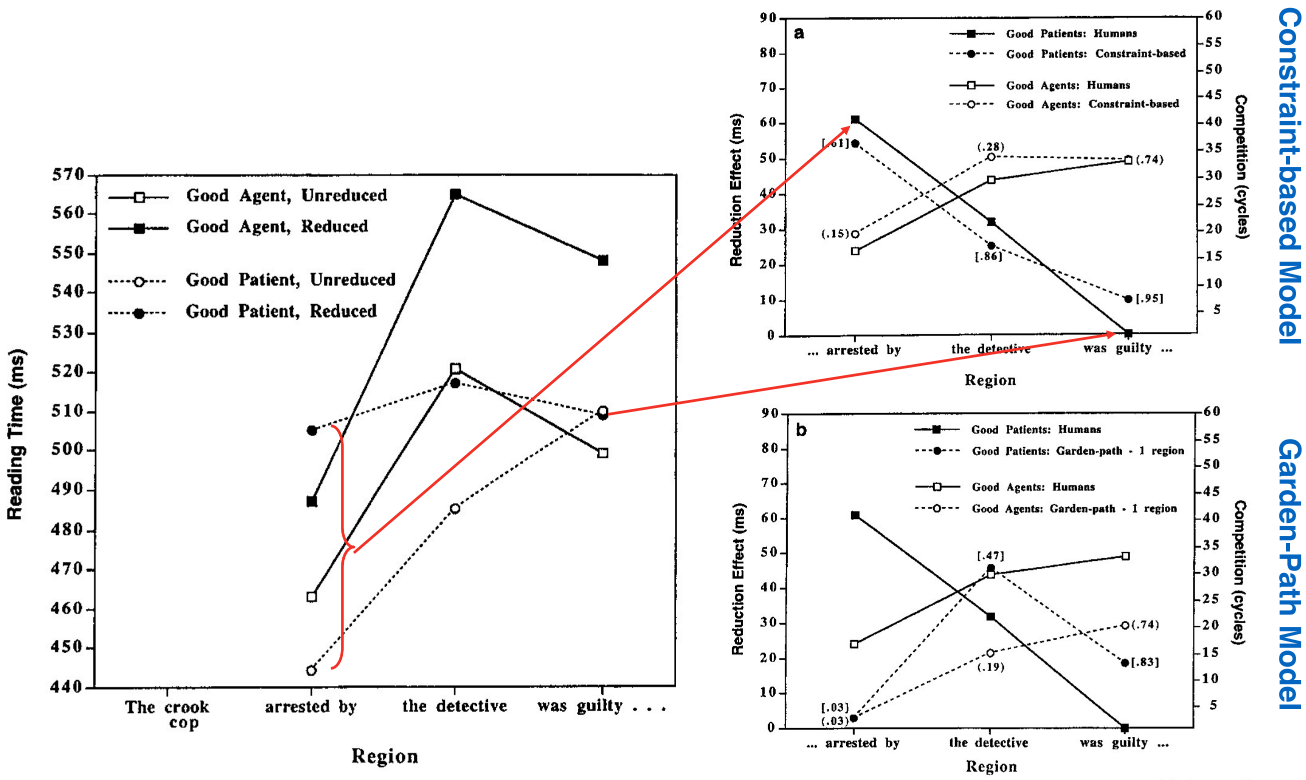


FIG. 5. Self-paced reading times for the Experiment.

FIG. 6. Simulations of self-paced reading by (a) the constraint-based model, and (b) the one-region delay garden-path model.



# 3rd Model: Short Delay GP Theory

- The GP-model, has a 1-2 word delay in use of information, what if this delay is reduced? 4 cycles (10-25ms)
  - Better fit, but high reduction effect still predicted at main verb (good patient).
- Search for the (new) best weights:
  - MC bias: .2966 (.5094)
  - Thematic fit: .4611 (.3684)
  - V.tense: .0254
  - by-bias: .2199
- No-longer models completions

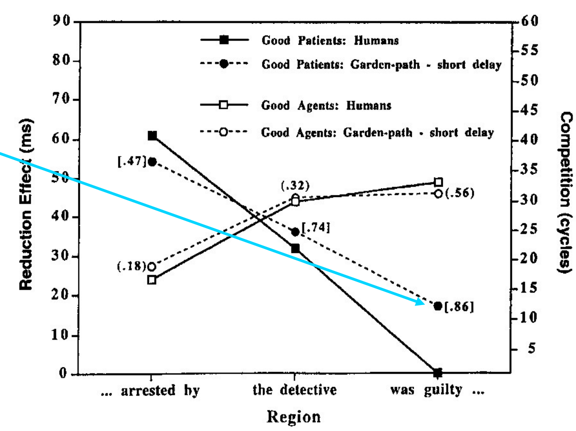


FIG. 7. Garden-path simulations of self-paced reading when constraints other than the main clause and main verb biases were delayed by 4 cycles of competition, or approximately 10–25 ms. Note the large predicted reduction effect at the main verb for the good patients.