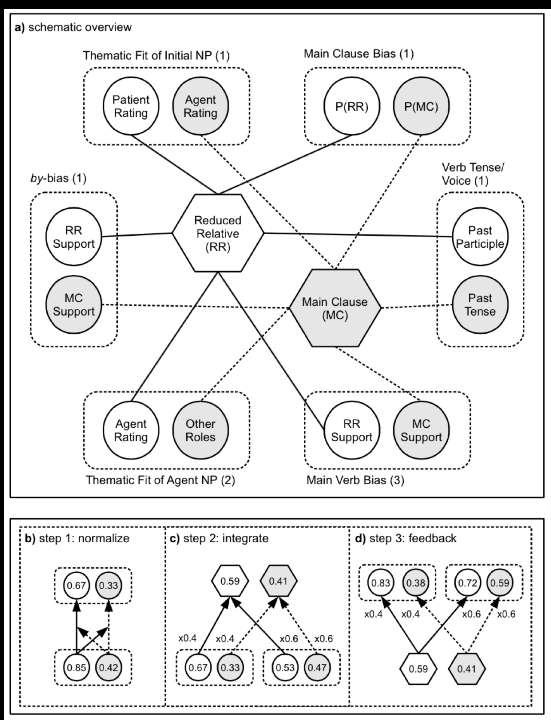
Computational Psycholinguistics
Lecture 12: Constraint-based Models and the Ambiguity Advantage

Harm Brouwer

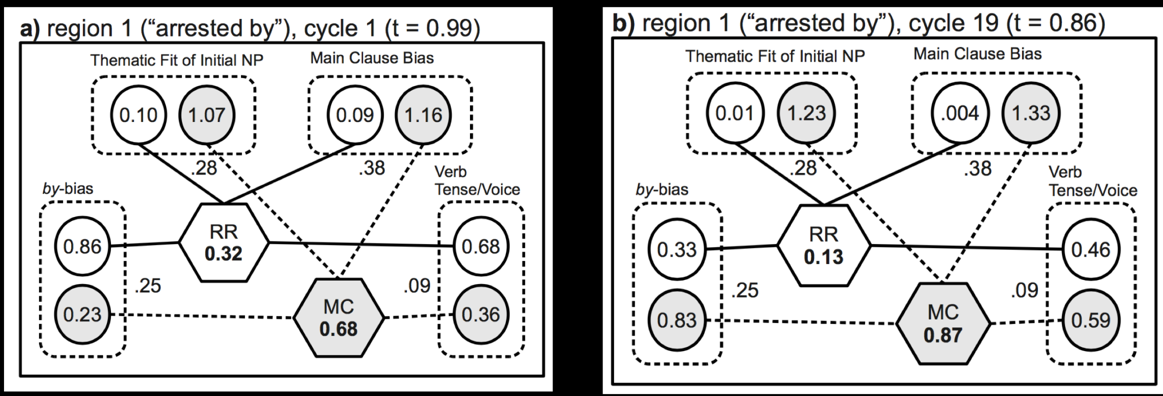
The Competition-Integration Model (CIM)



McRae (1998, *JML*)

Processing a sentence

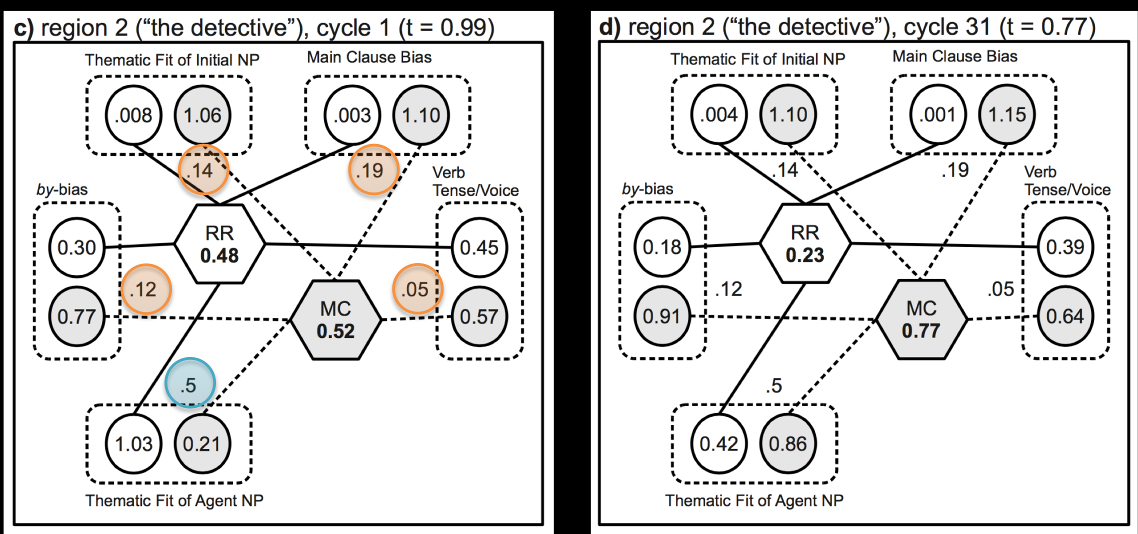
The cop [arrested by] the detective was guilty of taking bribes



McRae (1998, *JML*)

Processing a sentence

The cop arrested by [the detective] was guilty of taking bribes

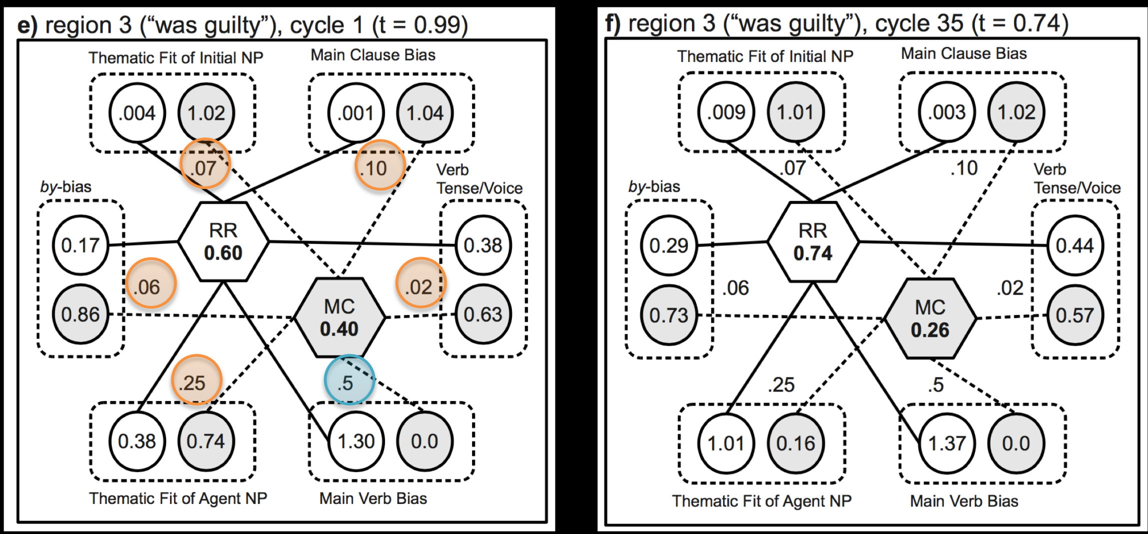


> Weight mass is equally divided between old and new constraints

McRae (1998, *JML*)

Processing a sentence

The cop arrested by the detective [was guilty] of taking bribes



> Weight mass is equally divided between old and new constraints

McRae (1998, *JML*)

An eye-tracking experiment

I read that the bodyguard of the governor retiring after the troubles is very rich
[ambiguous]

I read that the governor of the province retiring after the troubles is very rich
[disambiguated: NP1/high-attachment]

I read that the province of the governor retiring after the troubles is very rich
[disambiguated: NP2/low-attachment]

I read quite recently that the governor retiring after the troubles is very rich
[unambiguous]

Van Gompel et al. (2005, *JML*)

The Ambiguity Advantage

Table 3
Experiment 2: means

	Disambiguating region	Post-disambiguation region	Final region
First-pass reading times (ms)			
Ambiguous	378 (10)	552 (16)	851 (22)
High attachment	354 (11)	574 (19)	840 (25)
Low attachment	356 (9)	570 (17)	842 (23)
Unambiguous	364 (11)	555 (17)	841 (26)
First-pass regressions (%)			
Ambiguous	12.1 (2.3)	13.6 (2.3)	63.4 (3.4)
High attachment	9.5 (2.1)	16.0 (2.5)	64.4 (3.4)
Low attachment	8.4 (2.0)	23.6 (2.9)	69.1 (3.2)
Unambiguous	9.5 (2.1)	16.7 (2.6)	56.1 (3.6)
Regression-path times (ms)			
Ambiguous	441 (16)	723 (35)	2046 (116)
High attachment	420 (18)	754 (33)	2166 (122)
Low attachment	423 (19)	801 (34)	2330 (137)
Unambiguous	436 (20)	708 (25)	1945 (108)
Total times (ms)			
Ambiguous	542 (21)	797 (31)	1065 (35)
High attachment	578 (25)	880 (37)	1103 (34)
Low attachment	601 (27)	899 (33)	1073 (36)
Unambiguous	550 (25)	789 (27)	1019 (33)

ambig. < disambig.

Notes. The regions were as follows (delimited by brackets): I read that the bodyguard of the governor[retiring][after the troubles][is very rich.] Standard errors are in parentheses.

Traxler et al. (1998);
Van Gompel et al. (2001)

Van Gompel et al. (2005, *JML*)

The Ambiguity Advantage (cont'd)

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CIM cannot predict an ambiguity advantage

Evidence against competition during syntactic ambiguity resolution

Roger P.G. van Gompel[a,*], Martin J. Pickering[b], Jamie Pearson[b], Simon P. Liversedge[c]

Hence, the one million dollar question is: Who is right?

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CIM can predict an ambiguity advantage

Absence of real evidence against competition during syntactic ambiguity resolution

Matthew J. Green, Don C. Mitchell *

Van Gompel et al. (2005, *JML*)

Green and Mitchell (2006, *JML*)

The Ambiguity Advantage (cont'd)

Van Gompel et al. (2005, pg. 287):

"competition in the globally ambiguous sentences can never be weaker than in the disambiguated sentences, so the globally ambiguous sentences can never be easier to process"

Green and Mitchell (2006, pg. 10):

"the model predicts an ambiguity advantage for materials with a certain range of biases and the *reverse* in other cases"

> G&M's argument is based on simulations

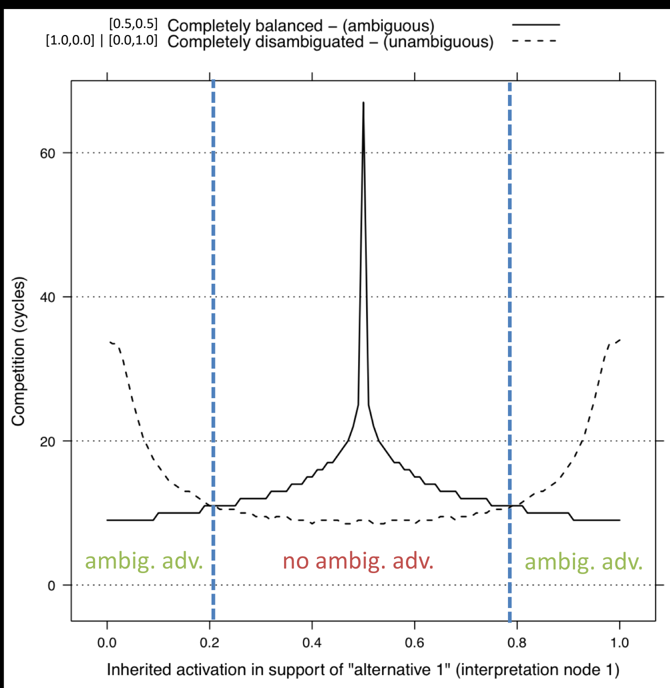
G&M - Simulation 3

Two constraints (weights: 0.5):

1. Inherited bias
2. Continuation

Delta: 0.0075

Q: Why are the disambiguated conditions averaged together?



"For purposes of presentation (to avoid an otherwise very cluttered graph), the values of (b) and (c) were then averaged for each inherited bias." (G&M, 2006, pg. 9)

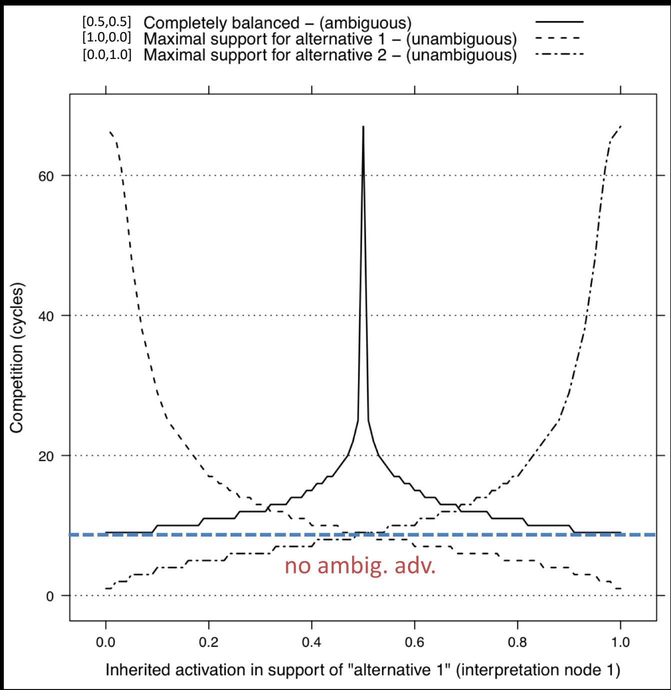
Green and Mitchell (2006, *JML*)

Brouwer (2010), *MSc thesis*
Fitz, Brouwer & Hoeks (in prep.)

G&M - Simulation 3: Decomposed

Two constraints (weights: 0.5):
1. Inherited bias
2. Continuation

Delta: 0.0075



Green and Mitchell (2006, *JML*)

Brouwer (2010), *MSc thesis*
Fitz, Brouwer & Hoeks (in prep.)

Interim Conclusions

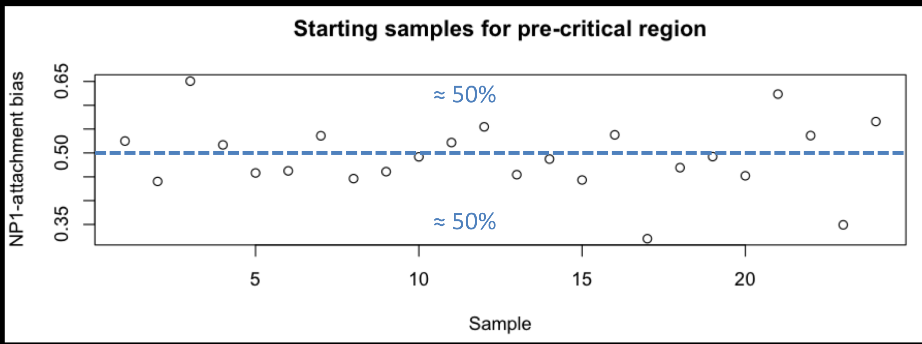
CIM does not predict an ambiguity advantage on a per-item basis (and G&M are wrong)

However, ambiguity advantage is not found on a per-item basis, but by averaging over different items
(as in common practice in psycholinguistic research)

> Hence, maybe the CIM does predict an ambiguity advantage if we average over different items?

G&M - Simulation 5

> Sample 24 random starting biases for the pre-critical region from $N(0.5,0.1)$



> Process the pre-critical region, thereby establishing a bias

> Inherit established bias, and process the critical region

Green and Mitchell (2006, *JML*)

G&M - Simulation 5: Results

G&M ran three simulations (= 3 x 24 items), and reported average cycles per condition for each of these

	Simulation 1	Simulation 2	Simulation 3
Ambiguous	12.1	11.4	11.6
NP1-attachment	23.8	26.5	23.23
NP2-attachment	22.3	21.5	24.7

Contrasts between ambiguous and each of the disambiguated conditions yielded six (3x2) F values ranging between $F(1,23) = 7.32$ and $F(1,23) = 23.33$. All p-values < .015.

> CIM does predict an ambiguity advantage when averaging over items (as in the VG et al. experiment)

Green and Mitchell (2006, *JML*)

Decomposing the results

Q1: What happens in the pre-critical region?

Starting biases for the pre-critical region are randomly sampled from an *N*(0.5,0.1) distribution; assume an item with biases [0.51,0.49]

```
%%%% Model state after: 16 processing cycle(s)
%%%%
%%%% Threshold: 0.880
%%%%
%%%% Alternative [alternative1]: 0.928
%%%% Alternative [alternative2]: 0.072
%%%%
%%%% Input node [cst: constraint1] [alt: alternative1] [wgt: 1.000]: 1.789
%%%% Input node [cst: constraint1] [alt: alternative2] [wgt: 1.000]: 0.077

%%%% Threshold [0.880] reached after: 16 processing cycle(s)
%%%%
%%%% Winner activation [alternative1]: 0.928
```

After the **pre-critical** region:

Alternative1 bias:
1.789 / (1.789 + 0.077) = 0.96

Alternative2 bias:
0.077 / (1.789 + 0.077) = 0.04

Crucially, these are the initial biases for the **critical** region

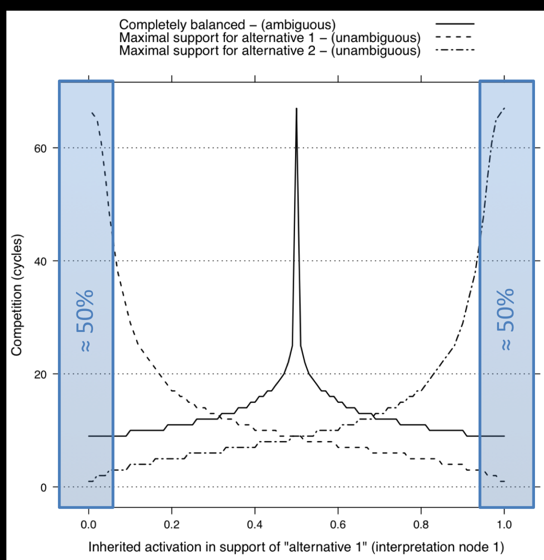
> Small imbalances are amplified during processing (strong imbalances even more so), and become strong biases for the next region

Decomposing the results (cont'd)

Q2: What happens in the critical region?

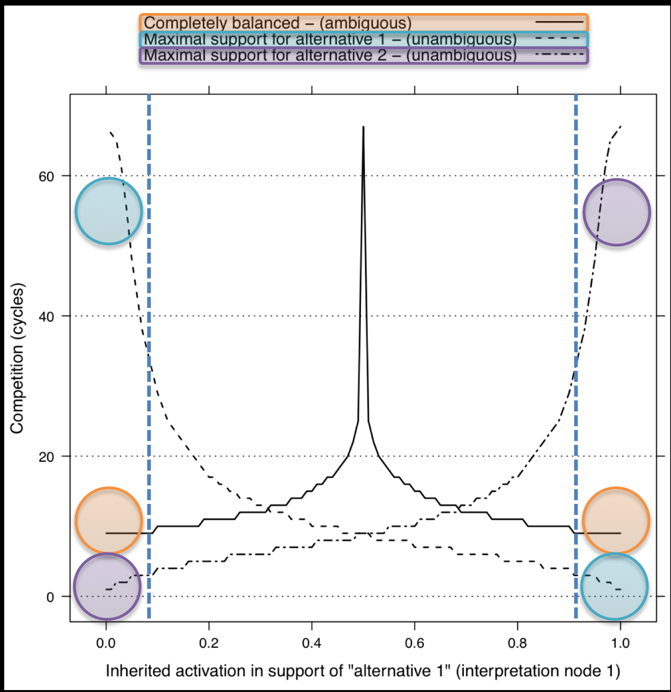
Given samples from *N*(0.5,0.1) and the effect of bias amplification in the pre-critical region, we know that:

50% of the items fall in the far left of this graph, and 50% in the far right



Hence, disambiguated items confirm these biases half of the time (→ little competition), and disconfirm them the other half (→ strong competition)

Decomposing the results (cont'd)



Ambiguous:
(12 x med + 12 x med) / 24 ≈ 12

NP1 attachment:
(12 x high + 12 x low) / 24 ≈ 25

NP2 attachment:
(12 x low + 12 x high) / 24 ≈ 25

> Results rely on *N*(0.5,0.1)

Balanced materials?

N(0.5,0.1) implies that the materials in the pre-critical region are perfectly balanced regarding NP1- and NP2-attachment

Q: Is this a fair assumption?

Off-line questionnaires and completion tasks, as well as on-line studies suggest that there is a preference for NP2-attachment

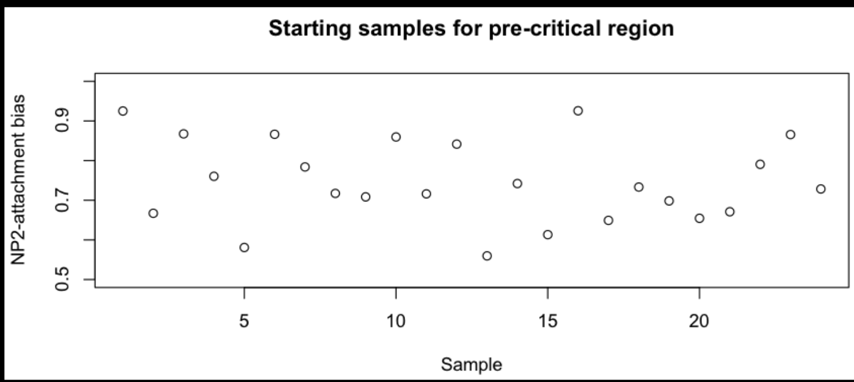
(e.g., Frazier & Clifton, 1996; Carreiras & Clifton, Fernandez, 2003)

(but see also Traxler, Pickering, & Clifton, 1998)

> How does this affect the ambiguity advantage?

NP2-attachment preference

NP2-attachment preference can be modeled by sampling the starting biases for the pre-critical region from *N*(0.75,0.1)



> For this sample, none of the items supports NP1-attachment

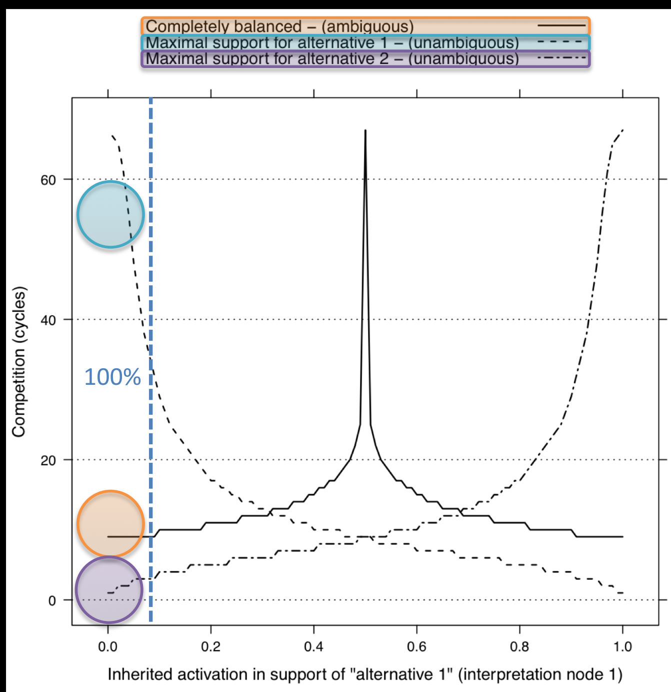
NP2-attachment preference (cont'd)

Ambiguous:
(24 x med) / 24 ≈ 12

NP1 attachment:
(24 x high) / 24 ≈ 55

NP2 attachment:
(24 x low) / 24 ≈ 2

> No ambiguity advantage, but an NP2-attachment advantage



Discussion

> Whether or not the CIM predicts an ambiguity advantage (on average) depends on modeling choices

> Hence, whether G&M or VG et al. are right, depends on what you believe to happen in the pre-critical region

> When modeling a specific effect, we should take into account that psycholinguistic effects are typically found in averages

> Even the simplest models (such as the CIM) often make unforeseen predictions; which is why we need modeling!

Conclusions

CIM does not predict an ambiguity advantage on a per-item basis (and G&M are still wrong in that respect)

CIM does predict an ambiguity advantage when averaging over items (and VG et al. are wrong in this respect)

… but only if there is no (strong) bias imbalance in the pre-critical region

Relevant References

Brouwer, H. (2010). Competition in Syntactic Ambiguity Resolution. Unpublished master's thesis. University of Groningen.

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Traxler, M., Pickering, M., and Clifton, C. (1998). Adjunct attachment is not a form of lexical ambiguity resolution. *Journal of Memory and Language*, 39:558–592.

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