

Information-theoretic approaches to syntactic processing

John Hale



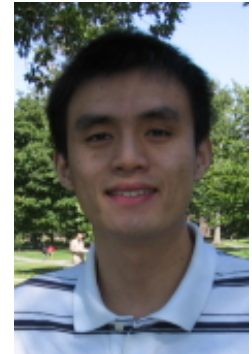
Cornell University
Linguistics Department

Thank you:

Jiwon Yun



Zhong Chen



Tim Hunter



sentence comprehension



- ▶ reading times
- ▶ error scores
- ▶ eye fixations
- ▶ scalp potentials

leading idea

Q. when is comprehension
more (vs **less**) difficult?

A. where more (vs less) information
is conveyed

choice of continuation informs the hearer

	the boy eats shy...
	the boy eats using...
	the boy eats like...
the boy eats...	the boy eats the...
	the boy eats his...
	the boy eats at...
	the boy eats of...
	the boy eats went...

conditional entropy

avg uncertainty of this distribution

probability (lets pretend)

the boy eats shy people for breakfast

the boy eats using chopsticks on Tuesday

the boy eats like a hippopotamous

the boy eats the dog with a spoon

the boy eats his sister's bicycle

the boy eats at Denny's frequently

the boy eats of the forbidden fruit

the boy eats went for a walk

1.0×10^{-25}

1.0×10^{-7}

1.0×10^{-6}

0.0001

0.0005

0.00001

1.0×10^{-66}

0.0

fluctuation

$$H(Derivation|Prefix = \text{“the boy eats”})$$

$$H(Derivation|Prefix = \text{“the boy eats his”})$$

any downward change quantifies
information gained from “his”

entropy reduction hypothesis

observed processing
effort reflects
decreases in H_i

where H_i abbreviates $H(\textit{Derivation} | \textit{Prefix} = w_0 \dots w_i)$

outline

Entropy reduction studies
relative clauses in English and Korean

How does it work?
computing $\downarrow H_i$

Why does it work?
reflections on information theory &
linguistics

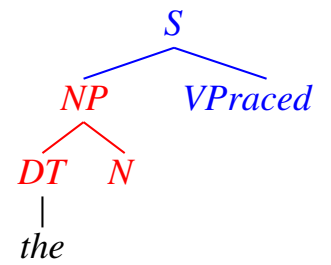
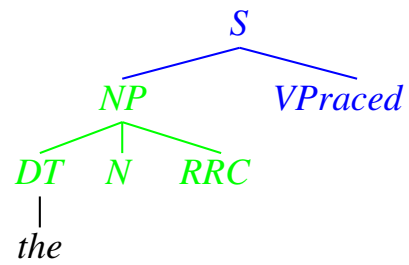
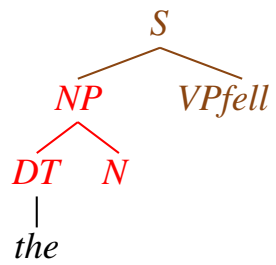
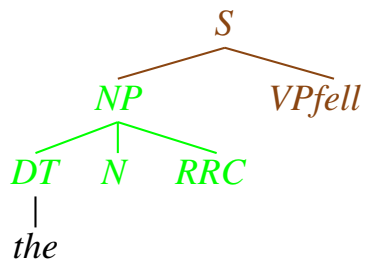
garden path sentences

Bever 70

naive probabilistic grammar

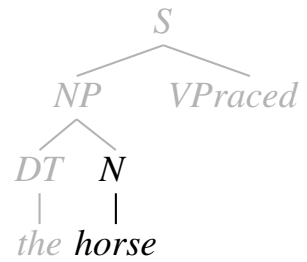
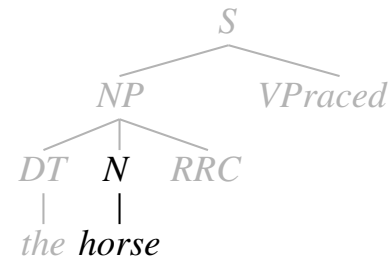
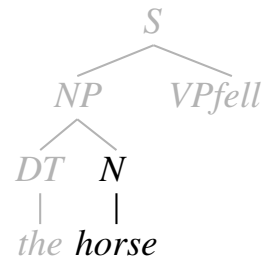
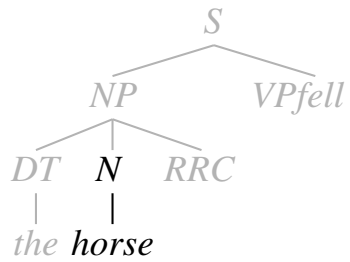
1.00	S	→	NP VP
0.88	NP	→	DT NN
0.12	NP	→	NP RRC
1.00	PP	→	IN NP
1.00	RRC	→	Vppart PP
0.50	VP	→	Vpast
0.50	VP	→	Vppart PP
1.00	DT	→	the
0.50	NN	→	horse
0.50	NN	→	barn
0.50	Vppart	→	groomed
0.50	Vppart	→	raced
0.50	Vpast	→	raced
0.50	Vpast	→	fell
1.00	IN	→	past

the



entropy: 4.65 bits

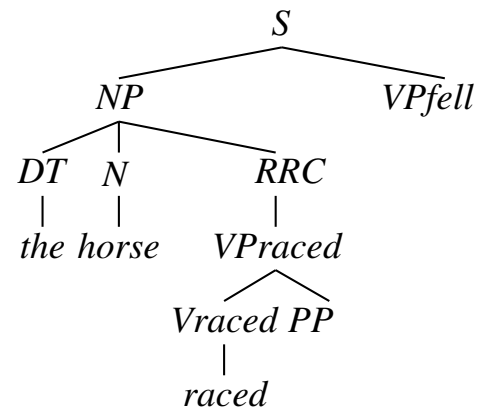
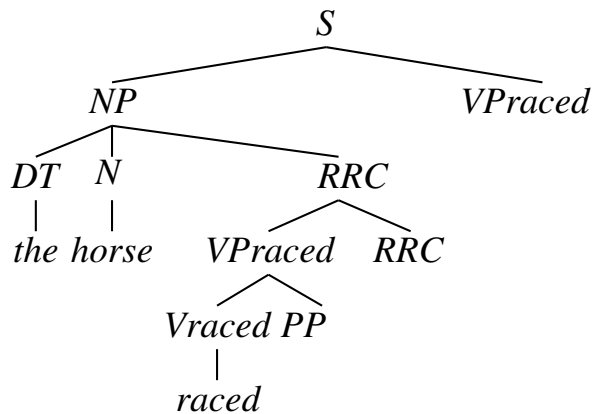
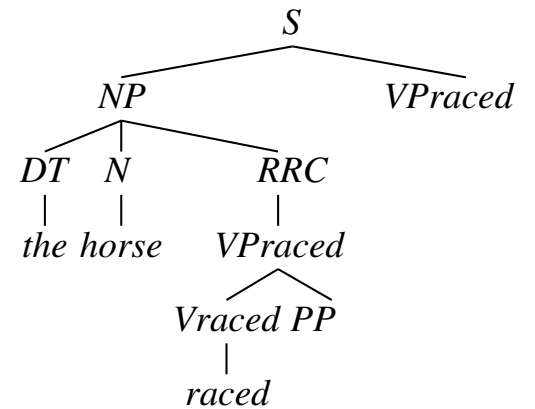
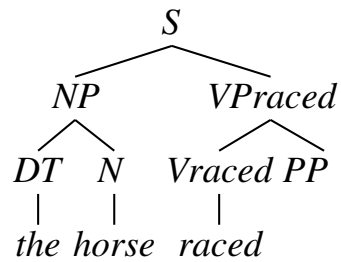
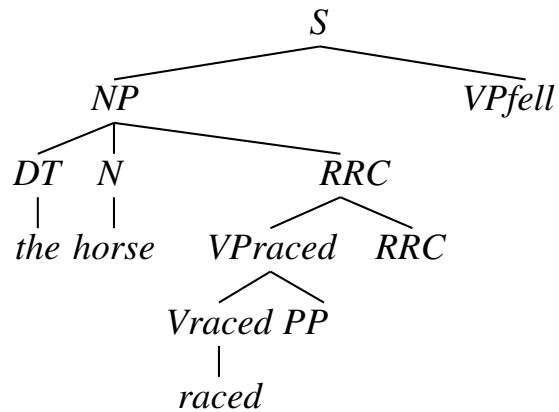
the horse



entropy: 3.65 bits

$\downarrow H=1$

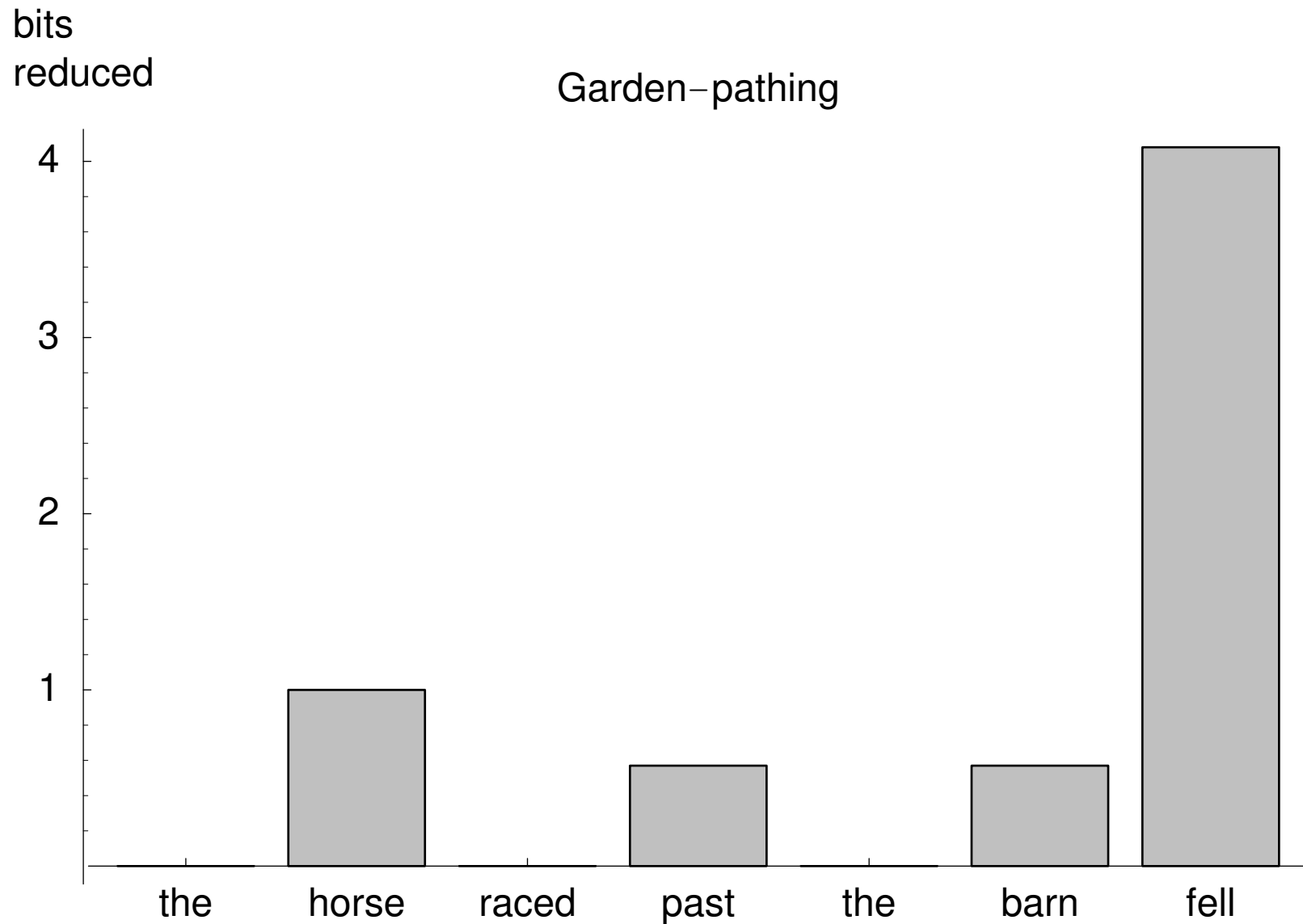
the horse raced



entropy: 5.2 bits

↓ $H = none$

last word gives 4 bits



total: 6.2 bits

wide coverage dependency parser

Direct Object vs. Subject (late closure):



Double Object vs. Relative Clause:



Noun-phrase vs. Sentential Complement:



Compound Noun vs. Sentential Complement:



GPSG-style fragment

0.20	NP	→	SPECNP NBAR				
0.40	NP	→	I				
0.40	NP	→	John	1.00	PP[to]	→	PBAR[to] NP
1.00	SPECNP	→	DT	1.00	PBAR[to]	→	P[to]
0.50	NBAR	→	NBAR S[+R]	1.00	P[to]	→	to
0.50	NBAR	→	N	1.00	PP[for]	→	PBAR[for] NP
1.00	S	→	NP VP	1.00	PBAR[for]	→	P[for]
0.87	S[+R]	→	NP[+R] VP	1.00	P[for]	→	for
0.13	S[+R]	→	NP[+R] S/NP	1.00	NP[+R]	→	who
1.00	S/NP	→	NP VP/NP	0.50	DT	→	the
0.50	VP/NP	→	V[SUBCAT2] NP/NP	0.50	DT	→	a
0.50	VP/NP	→	V[SUBCAT3] NP/NP PP[to]	0.17	N	→	editor
0.33	VP	→	V[SUBCAT2] NP	0.17	N	→	senator
0.33	VP	→	V[SUBCAT3] NP PP[to]	0.17	N	→	reporter
0.33	VP	→	V[SUBCAT4] PP[for]	0.17	N	→	photographer
0.33	V[SUBCAT2]	→	met	0.17	N	→	story
0.33	V[SUBCAT2]	→	attacked	0.17	N	→	ADJ N
0.33	V[SUBCAT2]	→	disliked	1.00	ADJ	→	good
1.00	V[SUBCAT3]	→	sent	1.00	NP/NP	→	€
1.00	V[SUBCAT4]	→	hoped				

center embedding

21 bits the reporter disliked the editor

39 bits the reporter [who the senator attacked] disliked the editor

48 bits the reporter [who the senator [who John met] attacked]
 disliked the editor

but yet

24 bits John met the senator [who attacked the reporter
 [who disliked the editor]]

subject vs object-extracted RC

the reporter who \emptyset sent the photographer to the editor
hoped for a good story

selectively slower



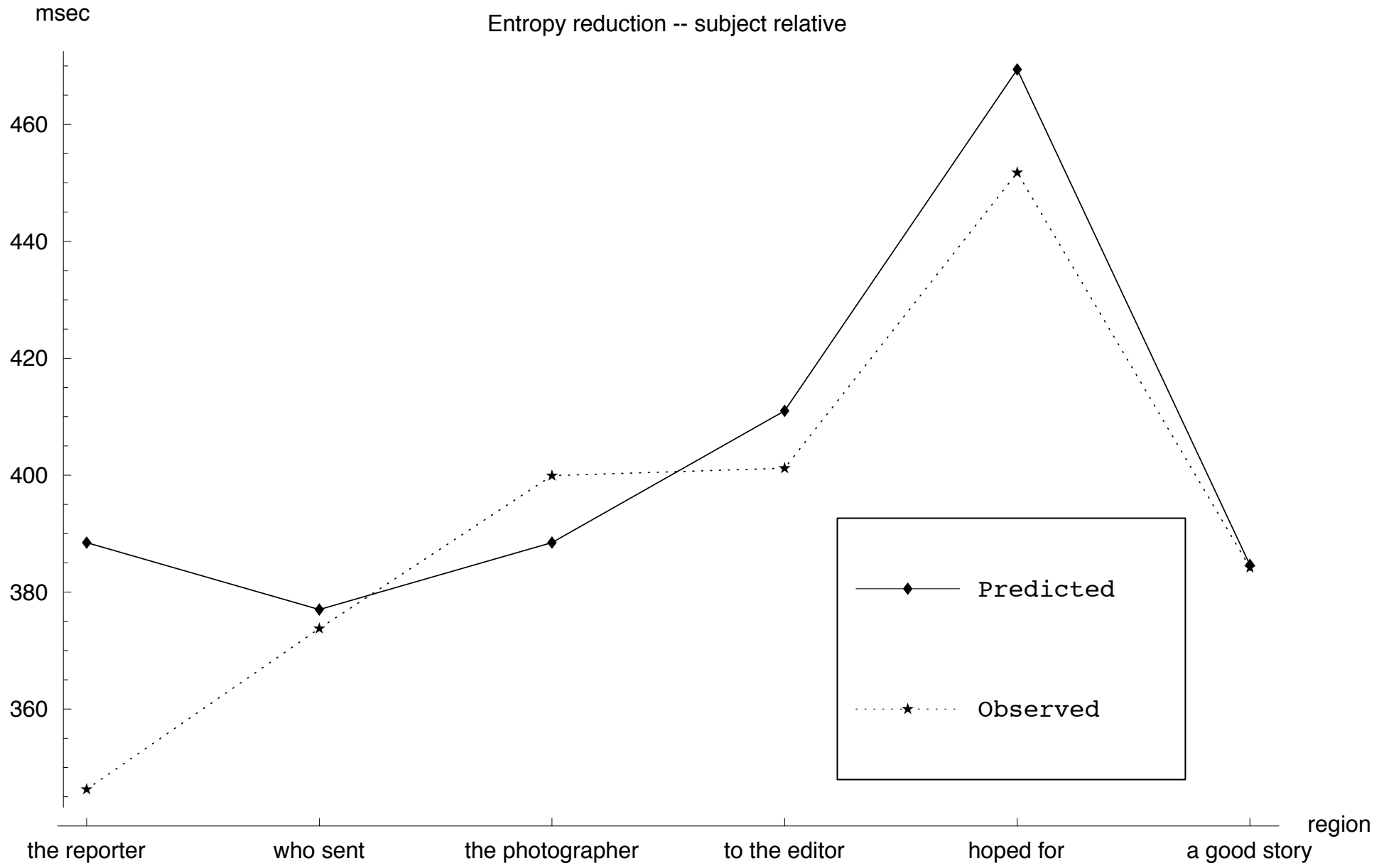
the reporter who the photographer sent \emptyset to the editor
hoped for a good story

Grodner and Gibson CogSci 05
among others

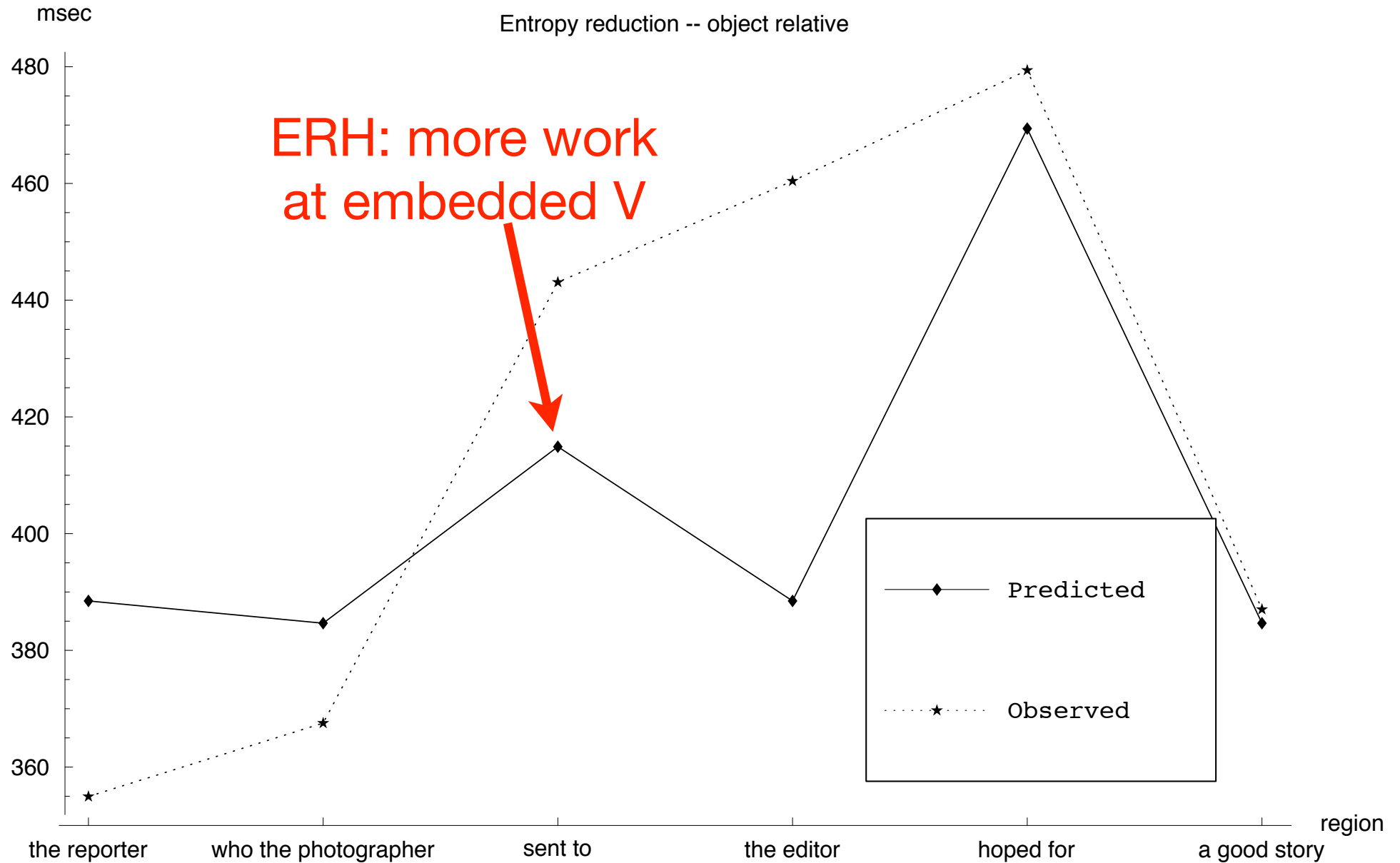
bits \leftrightarrow reading time

$$\text{RT}(w_i) = \alpha (\downarrow H_i) + \beta$$

subject-extracted



object-extracted



bits \leftrightarrow reading time

$$\text{RT}(w_i) = \alpha (\downarrow H_i) + \beta$$

$$\alpha = 7.38$$

$$\beta = 377$$

$$r^2 = 0.49, p < 0.01$$

Many types of RCs

indirect object

the man who Stephen explained the accident to \emptyset is kind

oblique

the girl who Sue wrote the story with \emptyset is proud

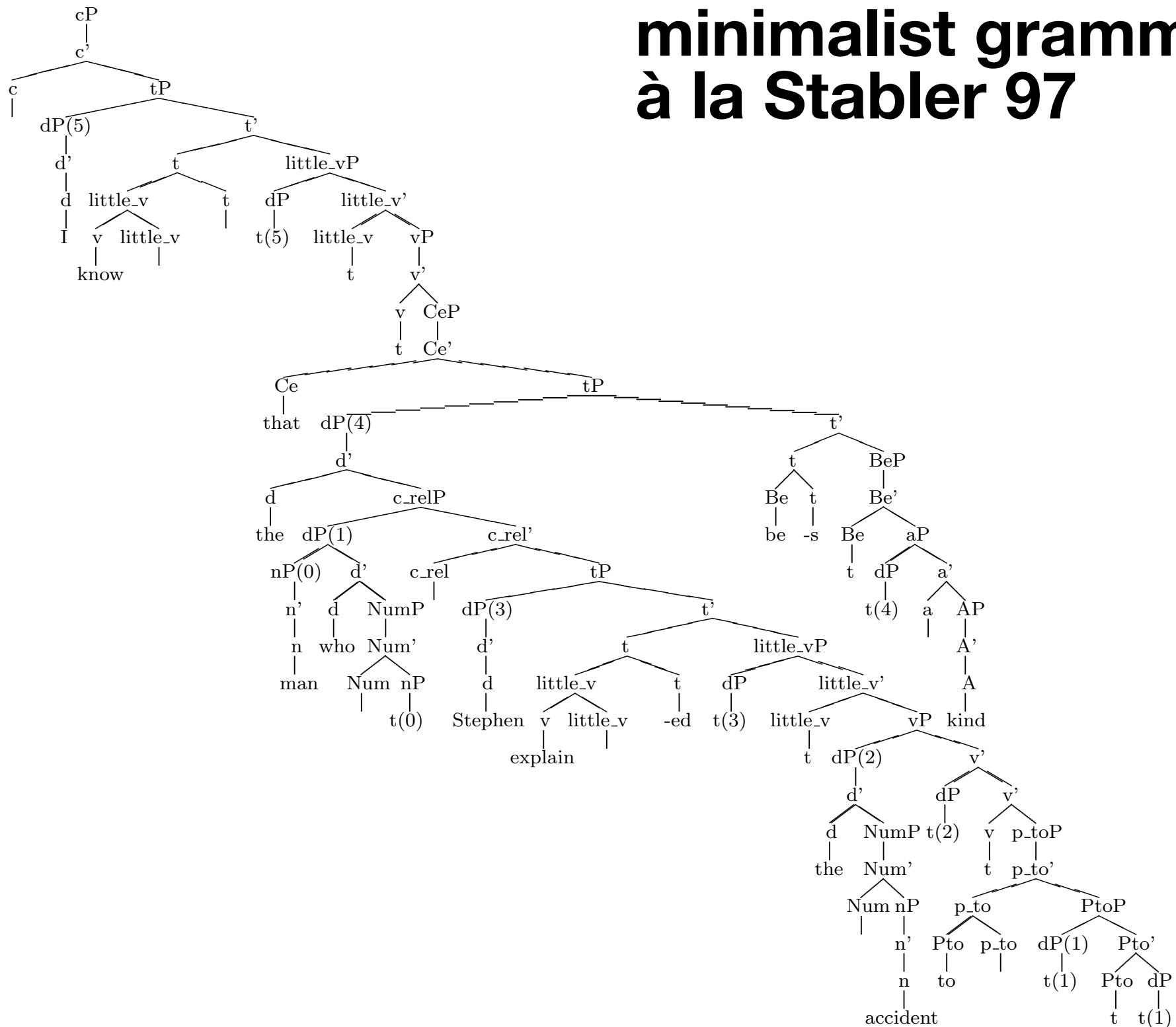
genitive subject

the boy whose brother \emptyset tells lies is always honest

genitive object

the sailor whose ship Jim took \emptyset had one leg

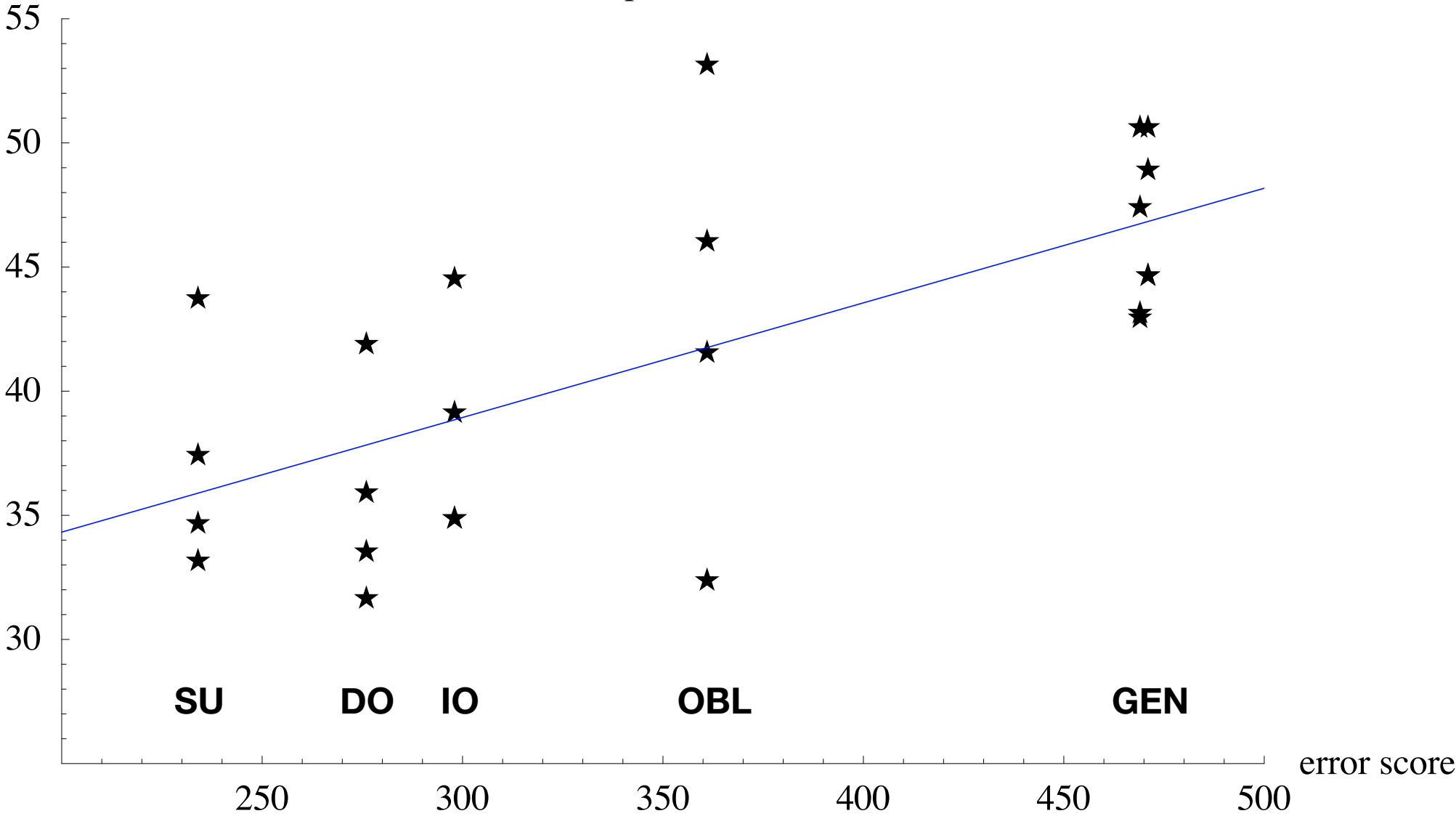
minimalist grammars à la Stabler 97



predicted work vs human accuracy

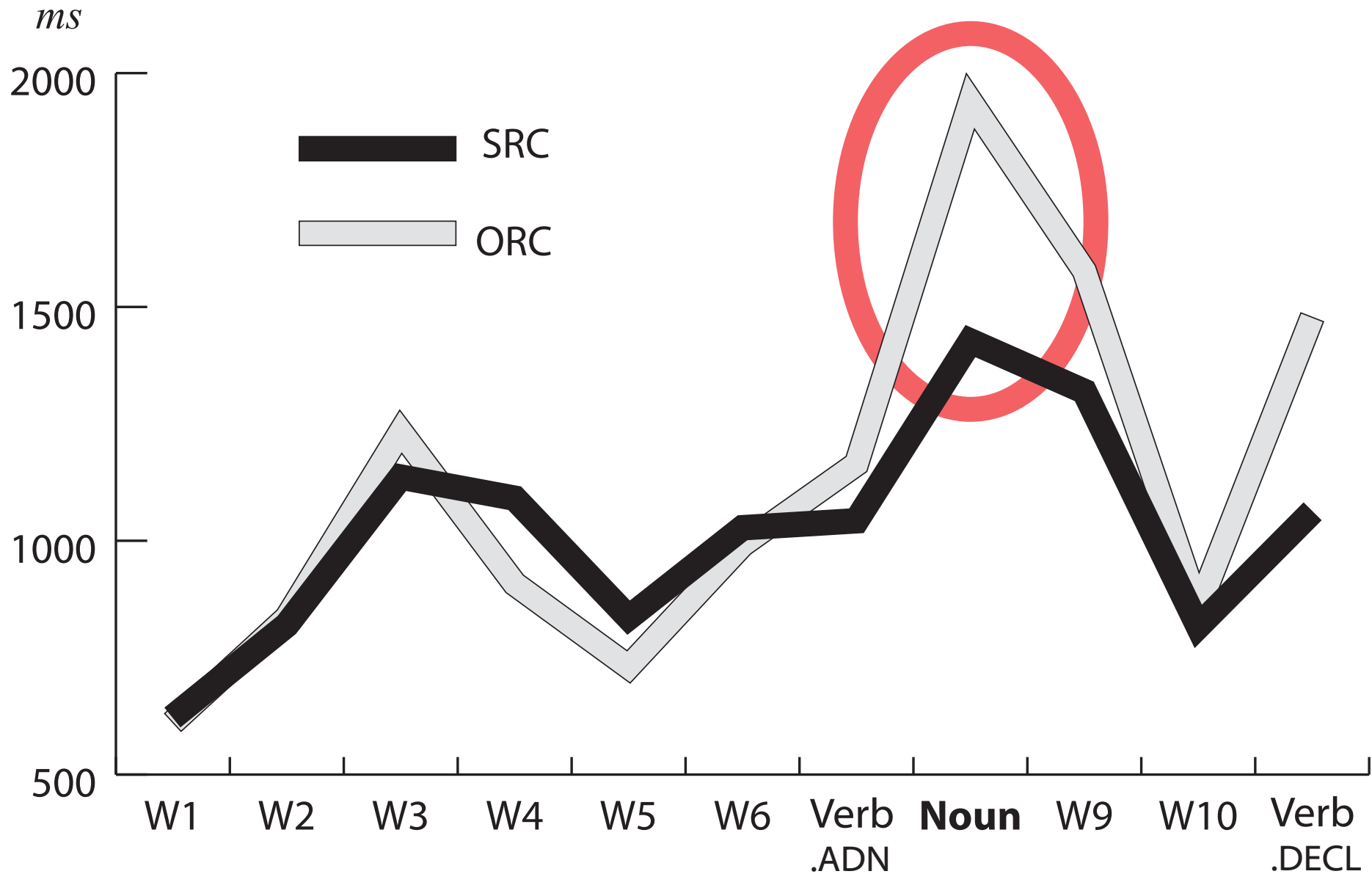
bits reduced
per sentence

Accessibility Hierarchy
 $r^2=0.45, p<0.001$

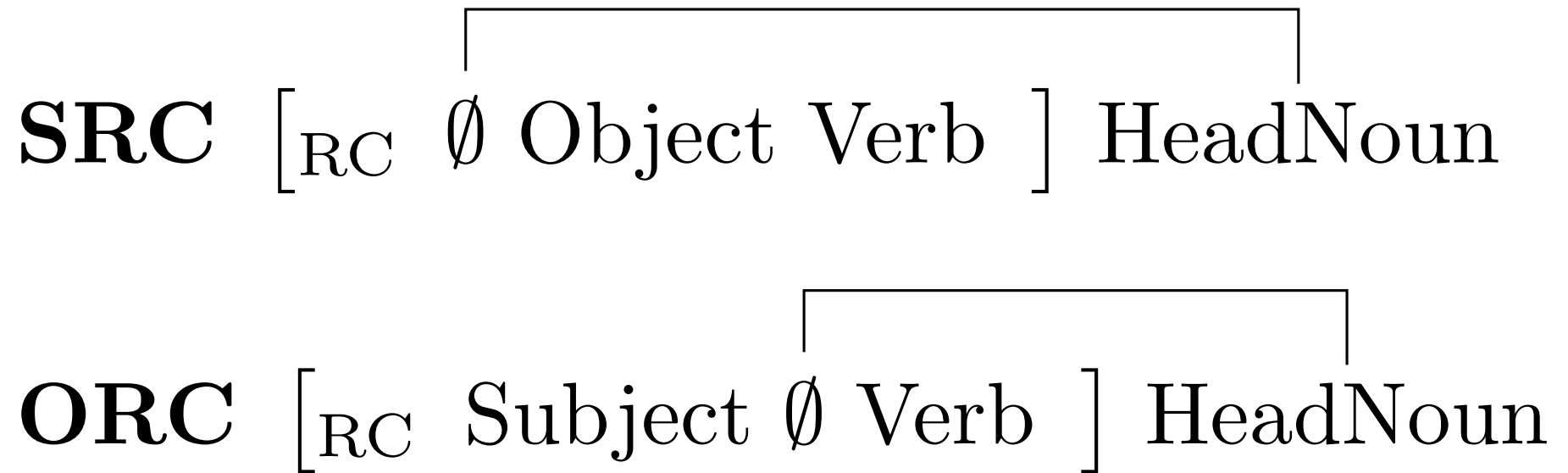


Korean Subj-RC advantage

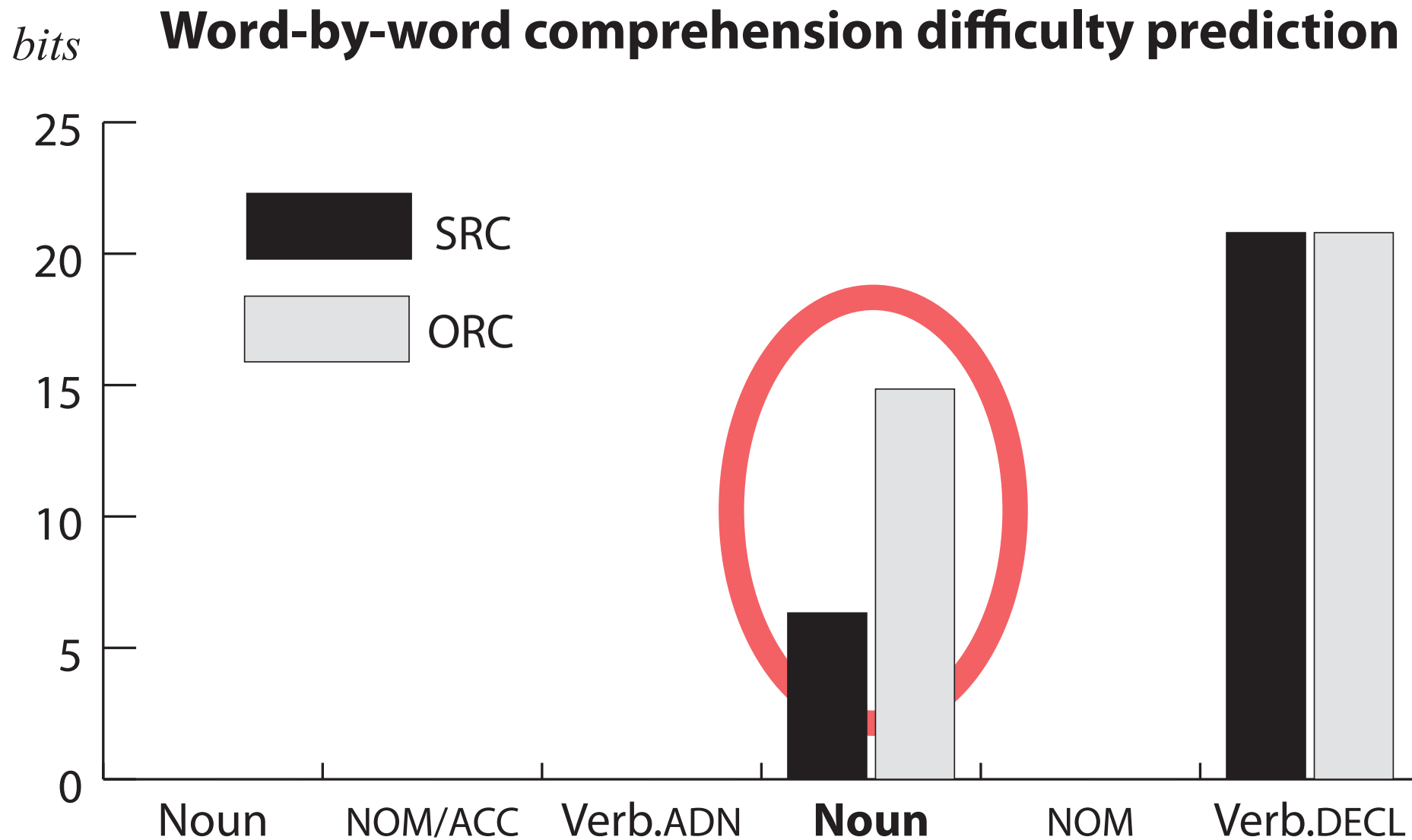
Word-by-word reading time observation (Kwon 2008)



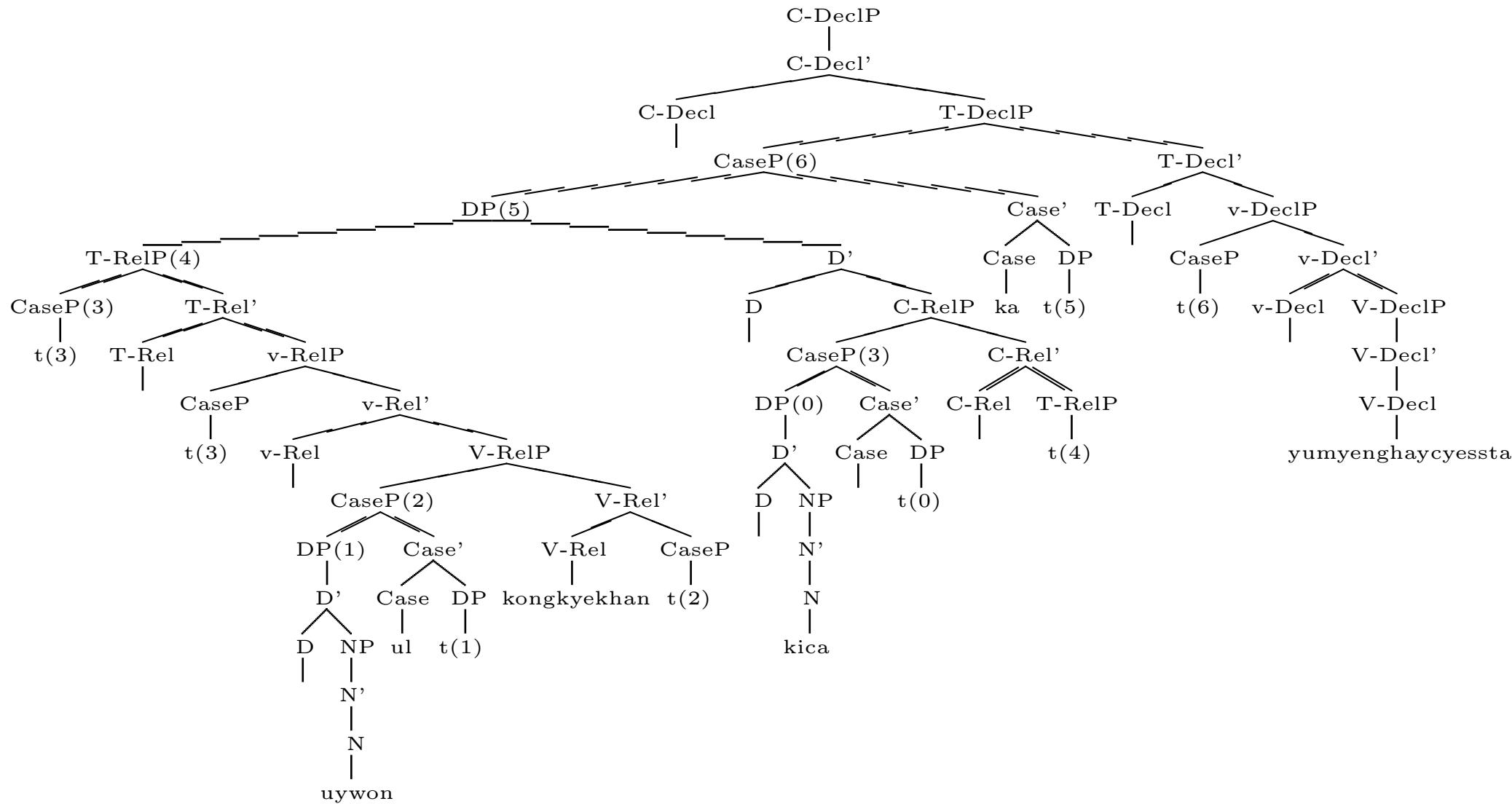
Dependency width doesn't derive it



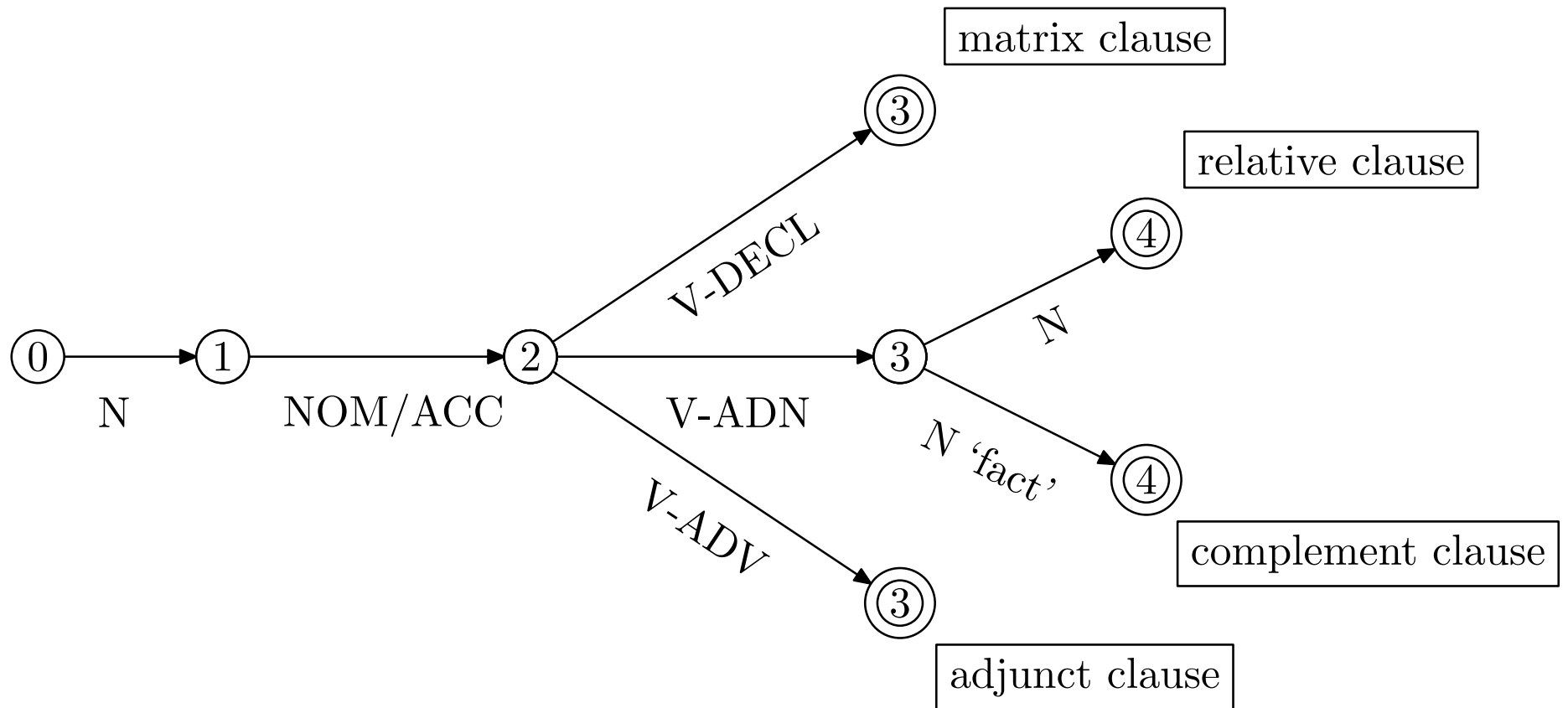
ERH+MG *does* derive the SRC advantage



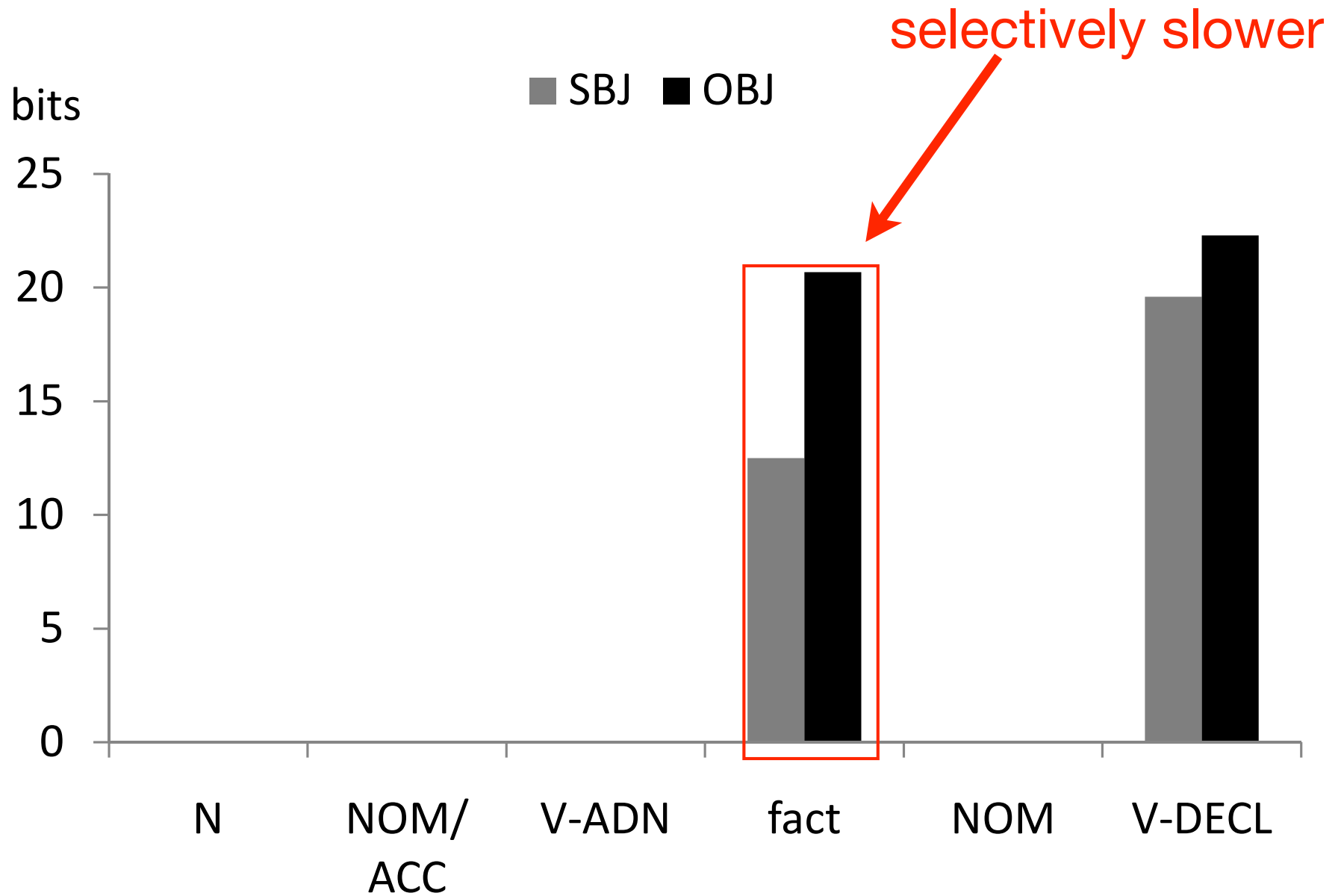
“The reporter who attacked the senator became famous”



One of four clause types

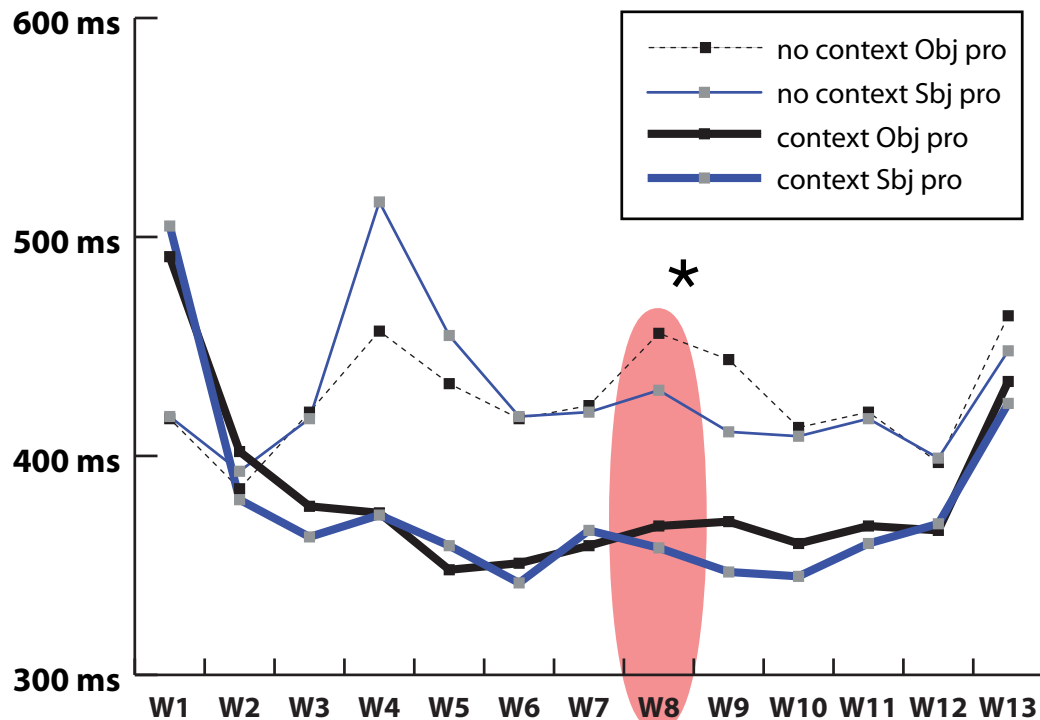


Novel prediction



(c) Complement Clause

Confirmed experimentally



object-“extracted”
slower, $p < 0.007$

NCCNPs with subject *pro*

W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13
지난 달	<i>pro</i>	편집장을	뇌물	수수	혐의로	협박한	사실이	밝혀지자	총장은	즉각	기자회견을	열었다.
Last month	<i>he_i</i>	editor-ACC	bribe	taking	suspicion-with	threaten-ADN	fact-NOM	was.revealed-as	chancellor_i-TOP	immediately	press.conference-ACC	held

‘The chancellor_i immediately held a press conference as the fact that he_i threatened the editor for taking a bribe last month was revealed.’

NCCNPs with object *pro*

W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13
지난 달	편집장이	<i>pro</i>	뇌물	수수	혐의로	협박한	사실이	밝혀지자	총장은	즉각	기자회견을	열었다.
Last month	editor-NOM	him_i	bribe	taking	suspicion-with	threaten-ADN	fact-NOM	was.revealed-as	chancellor_i-TOP	immediately	press.conference-ACC	held

‘The chancellor_i immediately held a press conference as the fact that the editor threatened him_i for taking a bribe last month was revealed.’

outline

Entropy reduction studies
relative clauses in English and Korean

How does it work?
computing $\downarrow H_i$

Why does it work?
reflections on information theory &
linguistics

computing H_i

=c +nom agrD	ε	=i +rel	c	ε
=>agrD droot	the	d		I
=d =d i	met	=n d -rel		who
n -nom	boy			

Minimalist Grammar (or other formalism)

```
S --> t157 [0,0;0,1;0,2] (* concatenation *)
t157 --> t0 t136 [0,0][0,1][0,2;1,0;1,1;1,2] (* r1' *)
t0 --> E t0_tmp2 [0,0][1,0][1,1]
t0_tmp2 --> t0_tmp1 E [0,0][1,0]
t0_tmp1 --> ""
t136 --> t135 [0,3;0,0][0,1][0,2] (* move' *)
t135 --> t42 t178 [0,0][1,1;0,1][0,2;1,0;1,2][1,3] (* r1left *)
t42 --> E t42_tmp2 [0,0][1,0][1,1]
t42_tmp2 --> t42_tmp1 E [0,0][1,0]
t42_tmp1 --> ""
t42_tmp1 --> "-ed"
t42_tmp1 --> "-s"
```

weighted MCFG G

input string $w=w_1w_2w_3...w_i$
prefix of a sentence in $L(G)$

FROM:	1	2	3	4
TO:				
1				
2				
3				
4				

chart

computing H_i

FROM:	1	2	3	4
TO: 1				
2				
3				
4				

chart's items
form a graph

= a system of equations,
whose solutions are
(sums of) probabilities



weighted
"intersection"
grammar G'

$$H(G') = H_i$$

entropy of probabilistic grammar

\vec{h} vector of 1-step rewriting entropies

\vec{H} vector of infinite step rewriting entropies

\mathbf{M} “fertility matrix” giving expected number j symbols birthed by the i^{th} symbol

$$\vec{H} = \vec{h} + \mathbf{M}\vec{H}$$

entropy of probabilistic grammar

\vec{h} vector of 1-step rewriting entropies

\vec{H} vector of infinite step rewriting entropies

\mathbf{M} “fertility matrix” giving expected number j symbols birthed by the i^{th} symbol

$$\vec{H} = \vec{h} + \mathbf{M}\vec{H}$$

$$\vec{h} = \vec{H} - \mathbf{M}\vec{H} = (I - \mathbf{M})\vec{H}$$

entropy of probabilistic grammar

\vec{h} vector of 1-step rewriting entropies

\vec{H} vector of infinite step rewriting entropies

\mathbf{M} “fertility matrix” giving expected number j symbols birthed by the i^{th} symbol

\mathbf{I} the identity matrix with ones down the diagonal

$$\vec{H} = \vec{h} + \mathbf{M}\vec{H}$$

$$\vec{h} = \vec{H} - \mathbf{M}\vec{H} = (\mathbf{I} - \mathbf{M})\vec{H}$$

$$\vec{H} = (\mathbf{I} - \mathbf{M})^{-1}\vec{h}$$

outline

Entropy reduction studies
relative clauses in English and Korean

How does it work?
computing $\downarrow H_i$

Why does it work?
reflections on information theory &
linguistics

SCIENTIFIC AMERICAN

JULY 1949

VOL. 181, NO. 1

THE MATHEMATICS OF COMMUNICATION

An important new theory is based on the statistical character of language. In it the concept of entropy is closely linked with the concept of information

by Warren Weaver

Entropy reduction in 1953

(5) Non-linguistic considerations. We will assume that all of the 1152 sentences in this language are equiprobable, and that there are no dependencies *between* sentences in a string.

Application of entropy measurement

(1) Entropy of a single sentence: $H_S = \log_2 1152 = 10.17$.

(2) Entropy reduction of each phoneme, considered with respect to its position in the sentence is: $H_P = H_S - H_R$, where H_R is the entropy of the statements which are still possible after the transmission of phoneme P.

To illustrate: Consider the successive phonemes of the sentence abibibbabbi 'see boy man not' or 'does not the boy see the man?' (Free translation.)

Phoneme	Remarks	No. Possible Sentences		H_P
		Remaining	H	
—	Any sentence possible before transmission begins	1152	10.17	—
a	Must be question with trans. vb., of which the no. of possibilities is	512	9.	1.17
b	Verb either <i>see</i> or <i>kill</i>	256	8.	1.0
a	Verb must be <i>see</i>	128	7.	1.0
b	N_s must be either <i>man</i> , <i>woman</i> , <i>boy</i> or <i>girl</i>	64	6.	1.0
i	Must be either <i>boy</i> or <i>girl</i>	32	5.	1.0
b	Must be <i>boy</i>	16	4.	1.0
b	N_o is <i>man</i> , <i>woman</i> , <i>boy</i> , or <i>girl</i>	8	3.	1.0
a	<i>Man</i> or <i>woman</i>	4	2.	1.0
b	<i>Man</i> ; sentence either pos. or neg.	2	1.	1.0
b	Redundant; gives no information	2	1.	0.0
i	Sentence is negative	1	0.0	1.0
				10.17

(3) Entropy reduction of each morpheme, also considered in relation to its position in the sentence, is $H_M = H_S - H_R$ where H_S and H_R are as defined previously. The same sentence is used here as in the example above.

“Psycholinguistics” Sebeok and Osgood, eds.

§5.3 Applications of Entropy Measures to Problems of Sequence Structure

Whatever Happened to Information Theory in Psychology?

R. Duncan Luce
University of California, Irvine

“The elements of choice in information theory are absolutely neutral and lack any internal structure.
That is fine for a communication engineer[but]
by and large, however, the stimuli of psychological experiments are to some degree structured, and so, in a fundamental way, they are not in any sense interchangeable.”

April, 2000

Formal grammar and information theory: together again?

BY FERNANDO PEREIRA

“Probabilities can be assigned to complex linguistic events, even novel ones, by using the causal *structure of the underlying models* to propagate the uncertainty in the elementary decisions.”

**⇒ these models incorporate
linguistic theories!**

Conclusions

Information theory helps identify
which RCs are hard *where*

the account uses substantial syntactic claims

the difference since 1953 is the grammar

**bonus
slides**

definitions

Let G be a (probabilistic) grammar, X a random variable whose outcomes x are derivations on G , and Y a related variable whose outcomes y are initial substring of sentences in $L(G)$.

mutual information
of grammar and prefix string

$$I(X; Y) = H(X) - H(X|Y)$$

information conveyed
by a particular prefix

$$I(X; y) = H(X) - H(X|y)$$

definitions

Let G be a (probabilistic) grammar, X a random variable whose outcomes x are derivations on G , and Y a related variable whose outcomes y are initial substring of sentences in $L(G)$.

mutual information
of grammar and prefix string

$$\begin{aligned} I(X; Y) &= H(X) - H(X|Y) \\ &= H(X) - \mathbb{E}[H(X|y)] \end{aligned}$$

information conveyed
by a particular prefix

$$I(X; y) = H(X) - H(X|y)$$

definitions

Let G be a (probabilistic) grammar, X a random variable whose outcomes x are derivations on G , and Y a related variable whose outcomes y are initial substring of sentences in $L(G)$.

info conveyed by increment

$$I(X; y_{\text{new}}) - I(X; y_{\text{old}})$$

definitions

Let G be a (probabilistic) grammar, X a random variable whose outcomes x are derivations on G , and Y a related variable whose outcomes y are initial substring of sentences in $L(G)$.

info conveyed by increment

$$\begin{aligned} I(X; y_{\text{new}}) - I(X; y_{\text{old}}) \\ = \left(H(X) - H(X|y_{\text{new}}) \right) - \left(H(X) - H(X|y_{\text{old}}) \right) \end{aligned}$$

definitions

Let G be a (probabilistic) grammar, X a random variable whose outcomes x are derivations on G , and Y a related variable whose outcomes y are initial substring of sentences in $L(G)$.

info conveyed by increment

$$\begin{aligned} I(X; y_{\text{new}}) - I(X; y_{\text{old}}) \\ &= \left(H(X) - H(X|y_{\text{new}}) \right) - \left(H(X) - H(X|y_{\text{old}}) \right) \\ &= H(X|y_{\text{old}}) - H(X|y_{\text{new}}) \end{aligned}$$

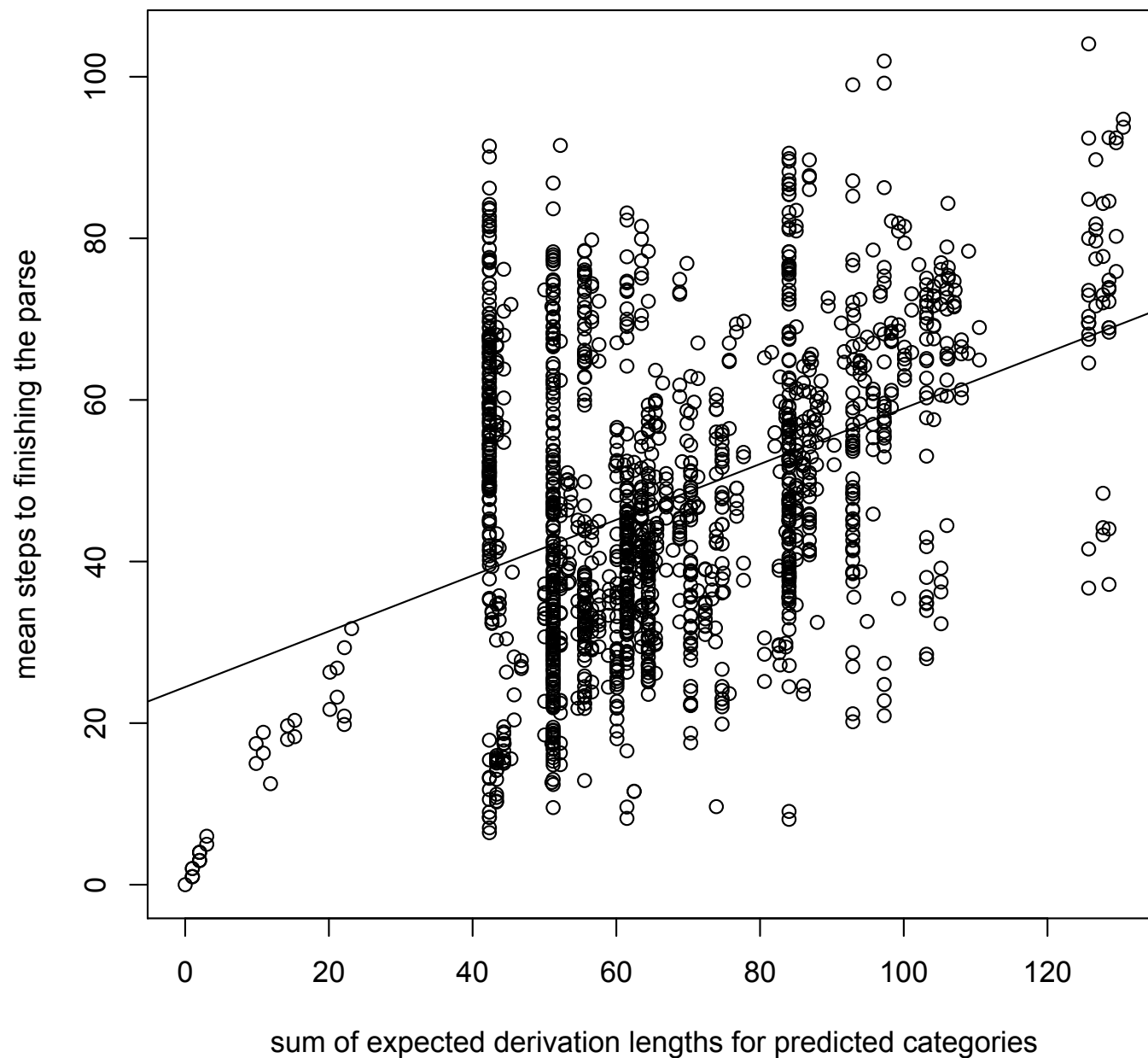
definitions

Let G be a (probabilistic) grammar, X a random variable whose outcomes x are derivations on G , and Y a related variable whose outcomes y are initial substring of sentences in $L(G)$.

info conveyed by increment

$$\begin{aligned} & I(X; y_{\text{new}}) - I(X; y_{\text{old}}) \\ &= \left(H(X) - H(X|y_{\text{new}}) \right) - \left(H(X) - H(X|y_{\text{old}}) \right) \\ &= H(X|y_{\text{old}}) - H(X|y_{\text{new}}) \\ &= \downarrow H_i \quad \text{where } y_{\text{old}} = w_1 \cdots w_{i-1}, \\ & \quad \quad \quad y_{\text{new}} = w_1 \cdots w_i \end{aligned}$$

the best heuristic tracks uncertainty about the rest of the sentence



Hale 2011