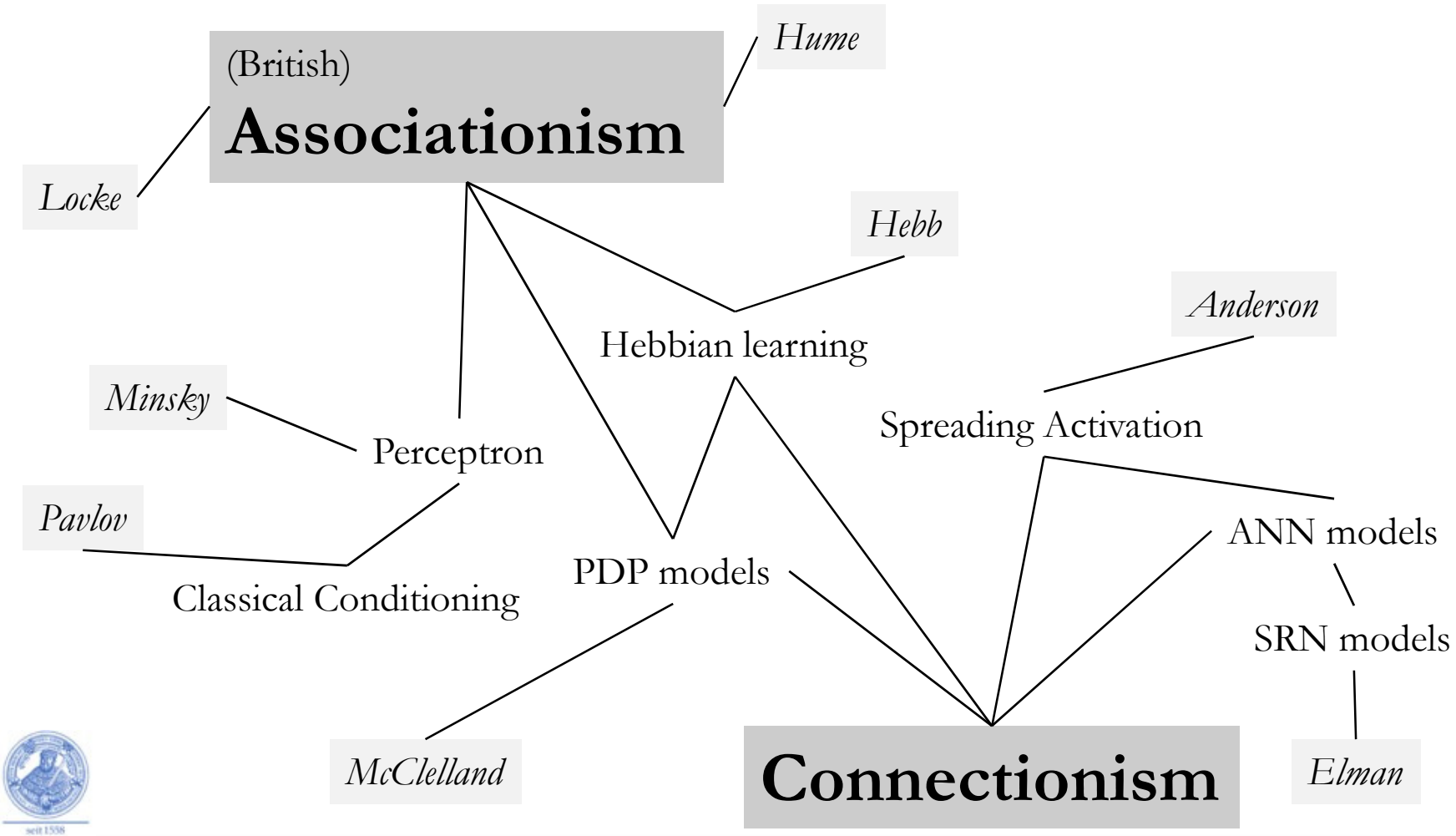
Third International Conference of the
***G**erman **C**ognitive **L**inguistics **A**ssociation*
Leipzig, Germany, September 25 - 27, 2008
Theme Session: Empirical Approaches to Constructional Meaning

Some thoughts on how to measure association strength

Daniel Wiechmann
Friedrich Schiller University, Jena

The concept of ***ASSOCIATION***
is central to the study of language and mind.



ASSOCIATION in language

Some types of **associative links between linguistic elements**

- ◅ form – meaning (i.e. signs, Constructions in CxGs)
- ◅ form – form (collocations)
- ◅ form – function (colligations)
- ◅ meaning – meaning (semantic fields/networks)
- ◅ sign – sign (collostructions)

Association strength is the glue between units

ASSOCIATION in language processing:

Local syntactic ambiguity

Information about **associative relationships speeds-up comprehension** (e.g. Hare et al. 2003, 2004; Wiechmann 2008; Zeschel 2008)

► **association** between a given
verb & complementation type [nominal/sentential]

*The athlete **revealed** his problem...*

Nominal complement
... with drugs

Sentential complement
... worried his parents

How to measure association strength?

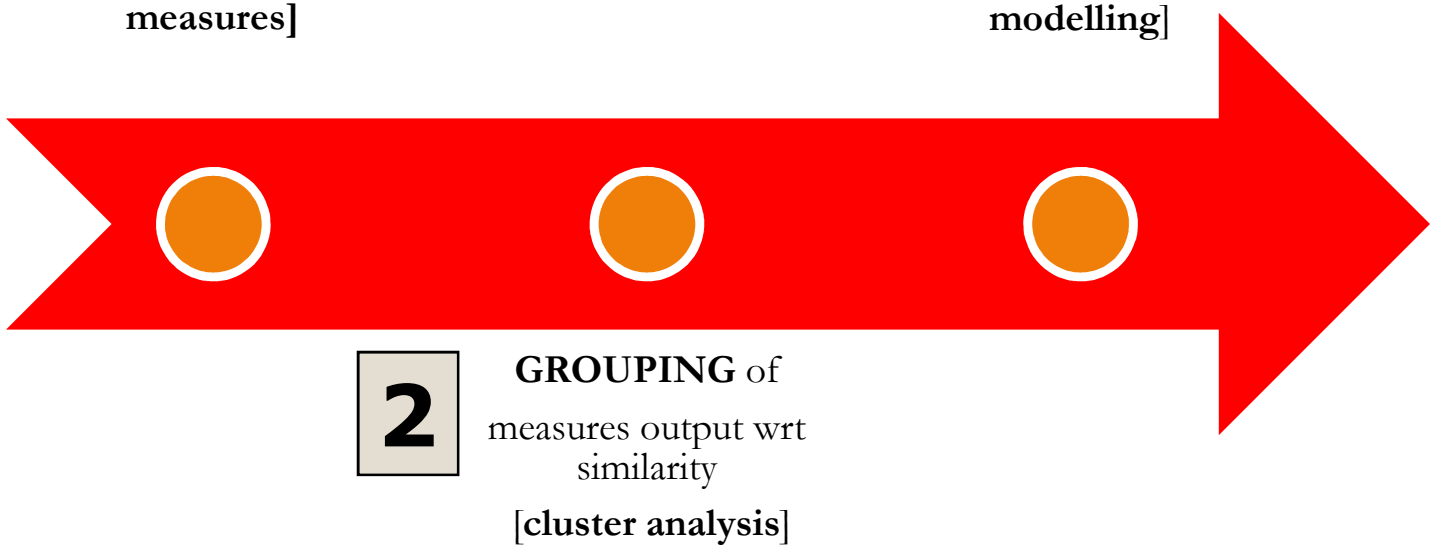
Situation:
Many candidate measures suggested in the corpus linguistic and computational linguistic literature
(Evert 2004 lists as many as **47 measures**).

Question:
Which one should we use?
- Is (brute force) *co-activation frequency* too crude?
- Is *predictiveness* of a stimulus more important?
- And if so, how exactly should we measure?

Answer:

Let‘s put them to the test

Steps involved in the analysis



1

For all candidate measures (n=47),
Compute **association strengths**
verb – nominal complements

21 polysemous verbs
Corpus: BNC$_{spoken}$
N = 6417

accept, announce, assume, believe, claim, deny, discover, establish, expect, feel, hear, mention, notice, promise, realize, remember, report, say, suggest, understand, write

NP complements

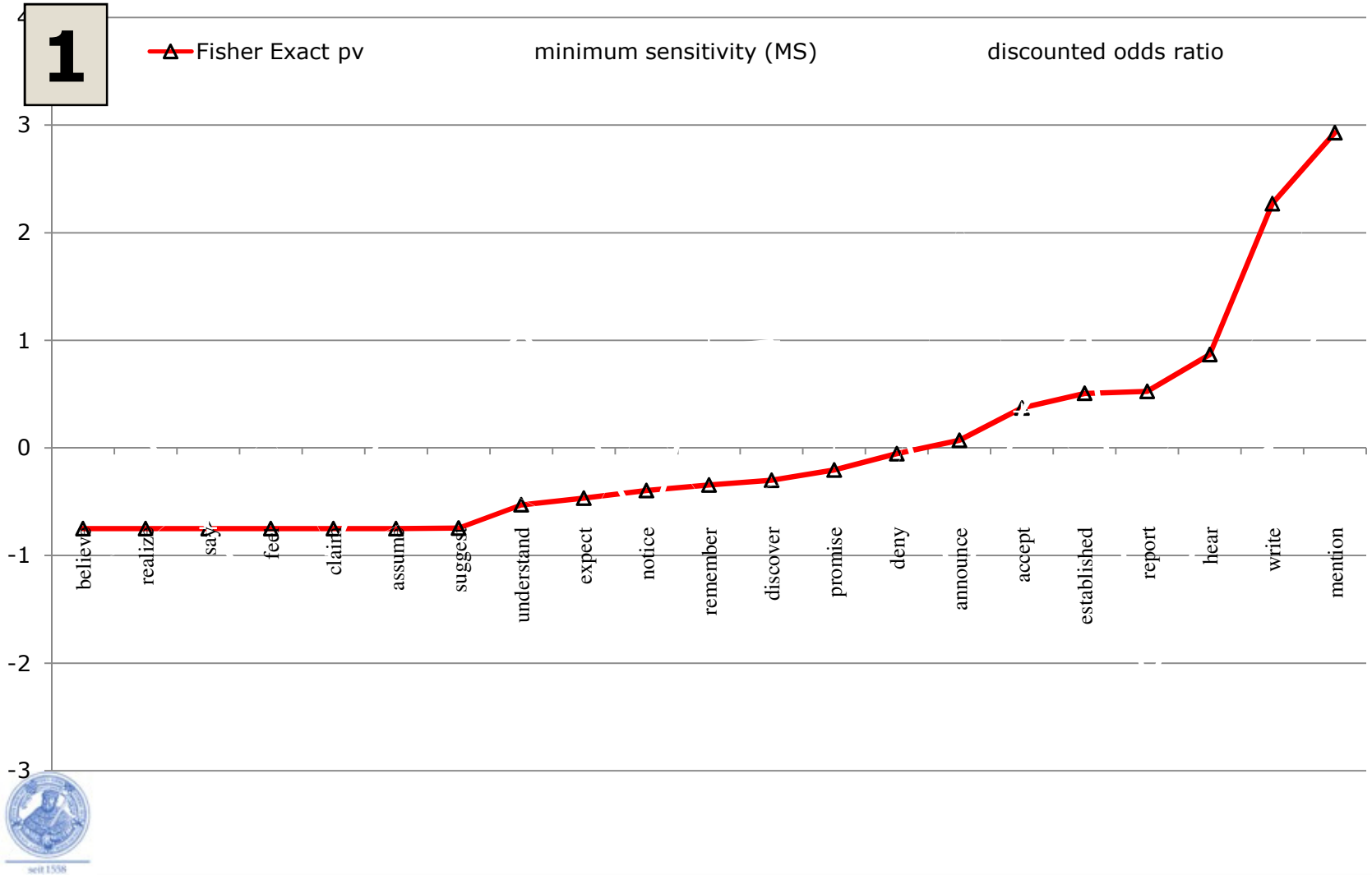
S complements

INPUT: Frequency signature

	nominal complements	sentential complements	
verb v	O_{11}	O_{12}	R_1
other verbs	O_{21}	O_{22}	R_2
	C_1	C_2	N

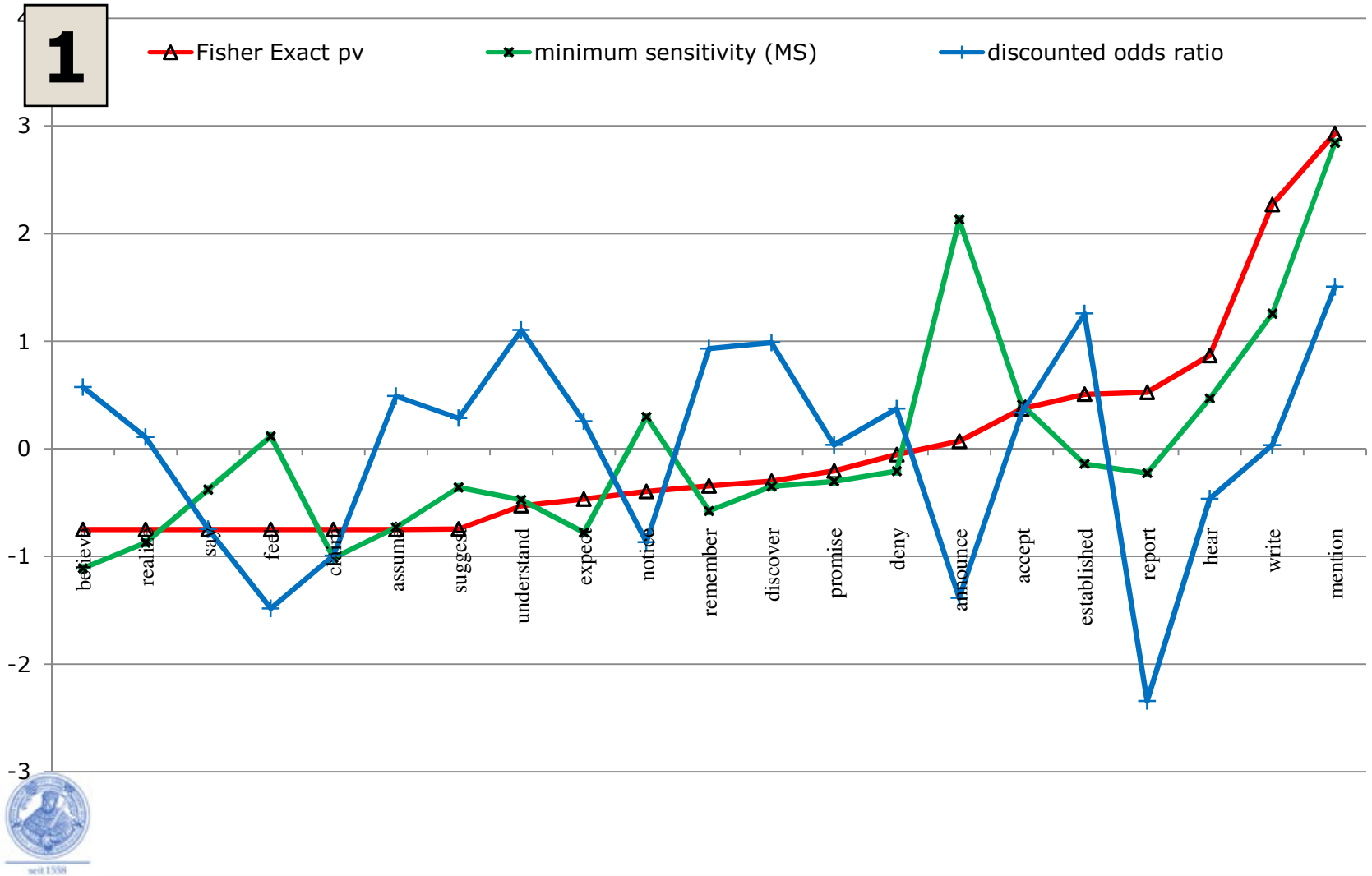
Step 1: Assessing association strength VERB – NP COMP

Fisher exact test

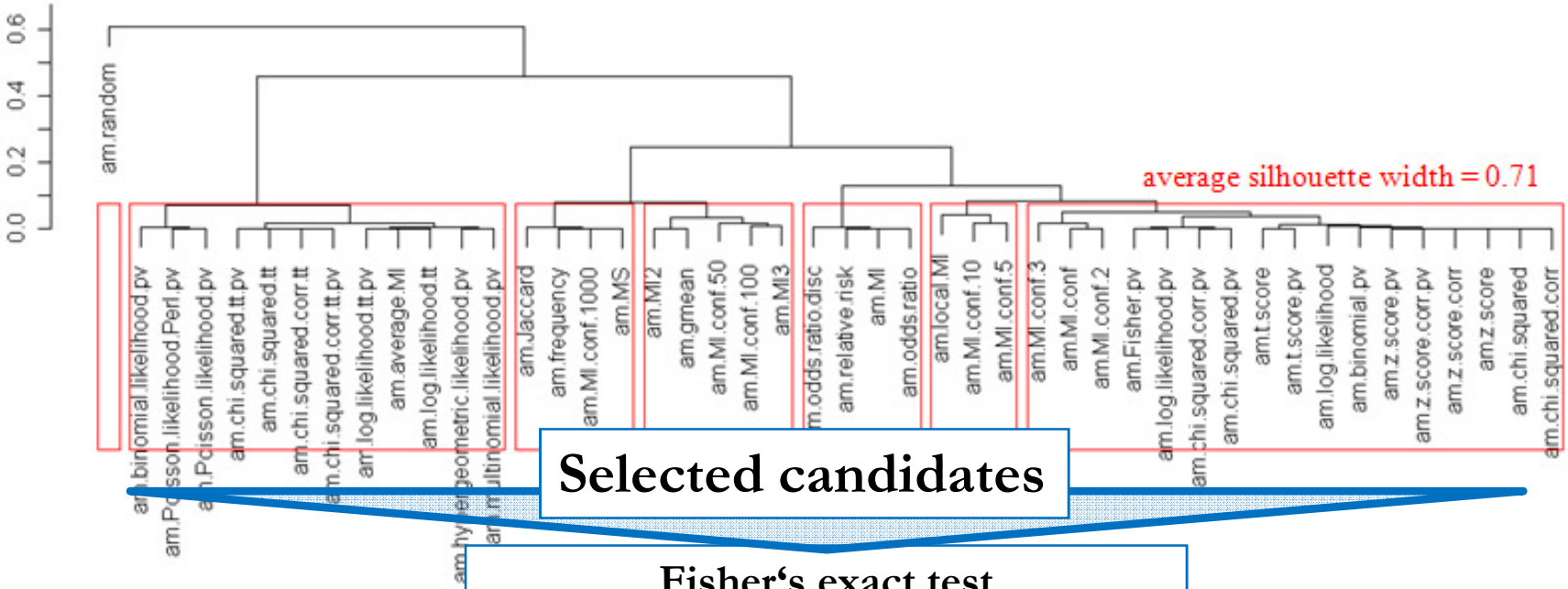


Step 1: Assessing association strength VERB – NP COMP

Fisher exact test - (disc) odds ratios - minimum sensitivity



2 Step 2: (Dis-)similarity of association measures



Selected candidates

Fisher's exact test
Corrected chi-squared test
Binomial likelihood
Raw frequency
Minimum Sensitivity
Pointwise MI
(discounted) odds ratios
MI (confidence interval at alpha .05)

3 Step 3: Corpus-based result vs. Experimental data

(eye-tracking - Kennison 2001)

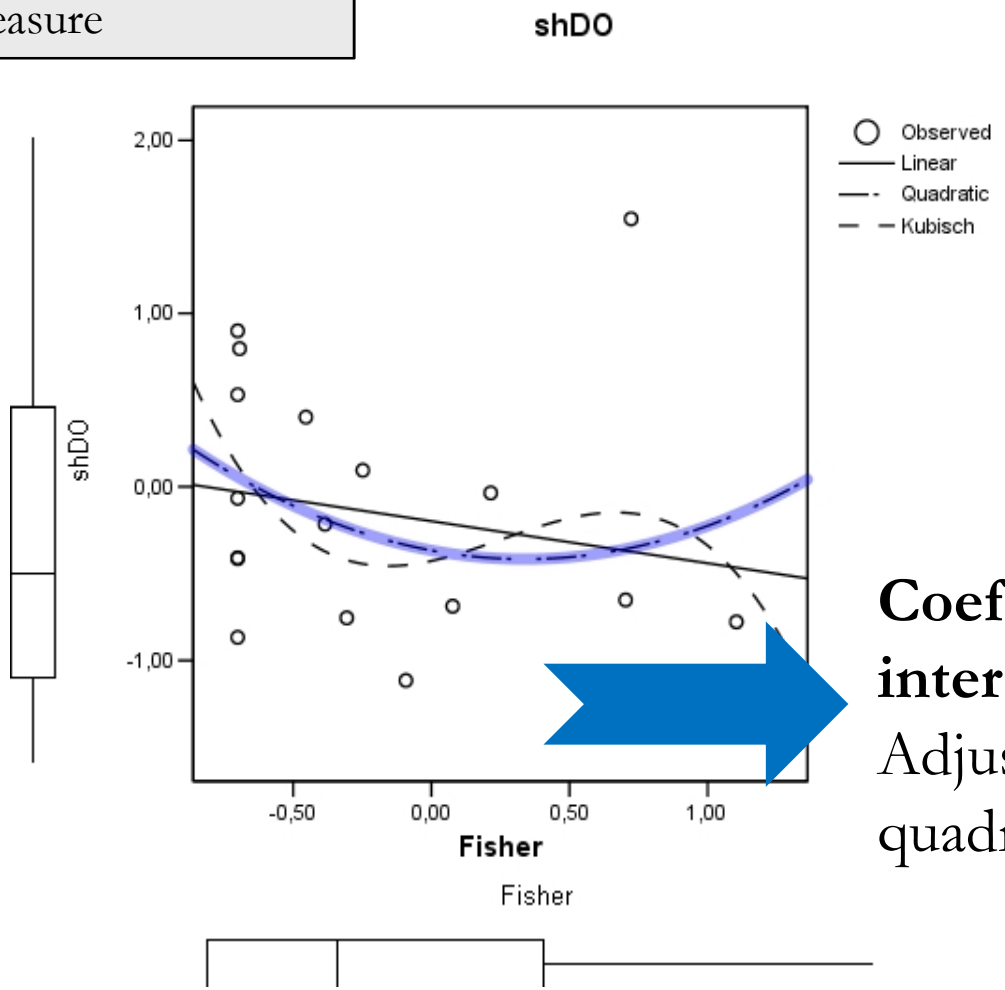
(a) The student **revealed** **his problem** worried his parents

(b) The student **revealed** that **his problem** worried his parents

SUBJ V NP disambiguation

Quantity of interest:
fixation times deltas (in ms)

Regression analysis (example)
Degree of fit (co-)determines adequacy of measure

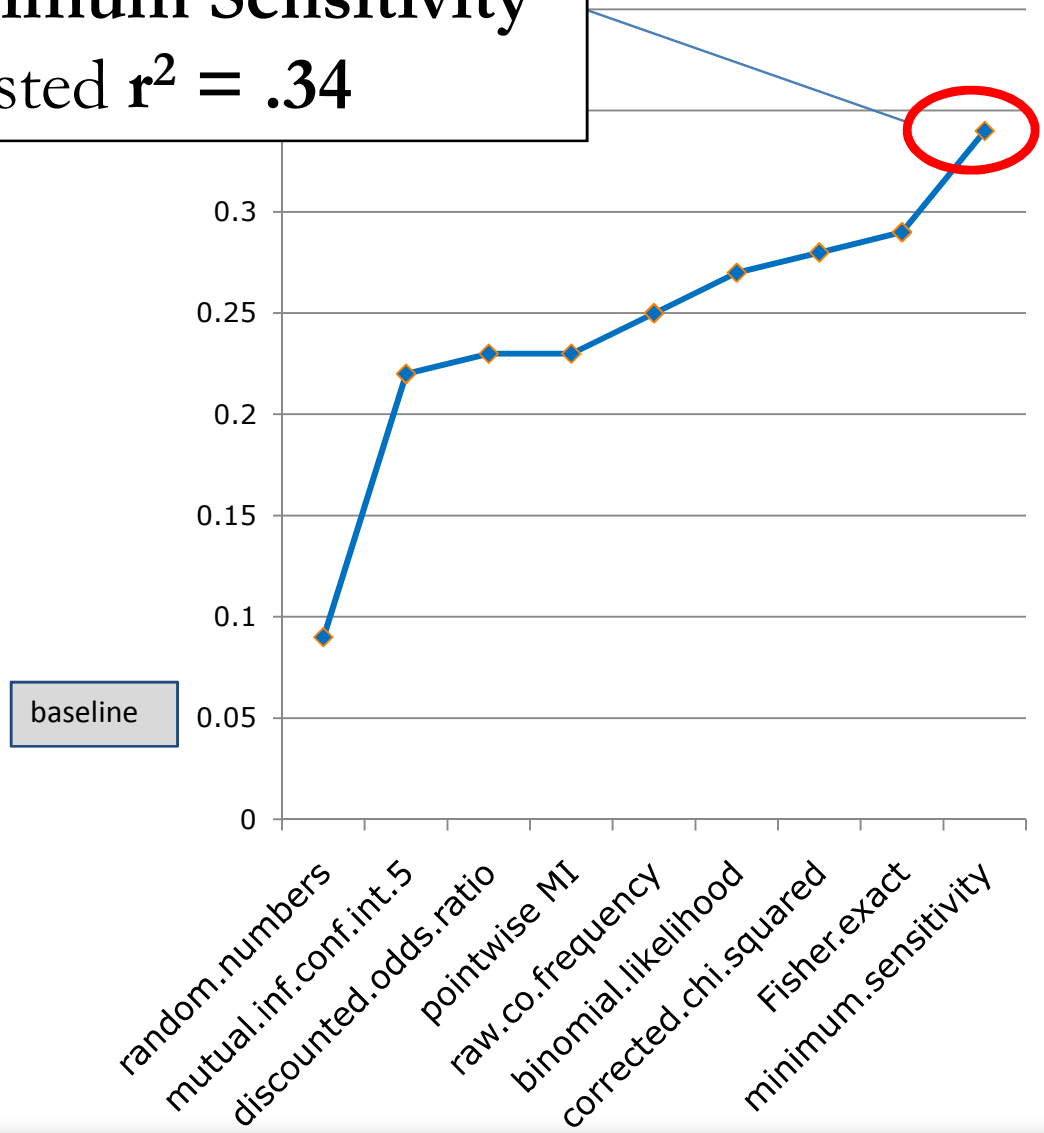


Coefficient of interest:
Adjusted R^2 from quadratic models

Best measure:

Minimum Sensitivity

adjusted $\mathbf{r^2 = .34}$



Minimum Sensitivity (MS)

(Pedersen & Bruce 1996; Pedersen 1998)

MS uses two conditional probabilities:
P(verb|construction) and **P(construction|verb)**

$$S_{w1} = \frac{O_{11}}{C_1} = P(w1|w2) \quad \text{and} \quad S_{w2} = \frac{O_{11}}{R_1} = P(w2|w1).$$

	nominal complements	sentential complements	
verb v	O_{11}	O_{12}	R_1
other verbs	O_{21}	O_{22}	R_2
	C_1	C_2	N

Minimum Sensitivity should be the measure of choice, because it is...

1.free from underlying distributional assumptions
that are not met by natural language data.

2.computationally less demanding
than exact statistical hypothesis tests (e.g. Fisher-Yates test)

3.less dependent on sample sizes
than (exact or asymptotic) statistical hypothesis tests

4.empirically most adequate
not only in the present study but it in Krenn (2000).

Thank you for your attention.

And special thanks to...

Shelia Kennison (U Oklahoma)
for sharing her fixation time data,

Steffi Wulff (U Michigan)
for her ICE-isomorphic BNC-sample

Stefan Gries (UCSB)
for his Cluster Eval 0.9

Stefan Evert (U Osnabrück)
for his UCS 0.5

...and their helpful comments.

References:

Evert, Stefan. 2004. The Statistics of Word Co-occurrences: Word Pairs and Collocations. Unpublished doctoral dissertation, Institut für maschinelle Sprachverarbeitung, Universität Stuttgart.

Hare, Mary L., Ken **McRae** and Jeffrey L. **Elman**
2003 Sense and structure: Meaning as a determinant of verb subcategorization preferences. *Journal of Memory and Language 48, 281–303.*

2004 Admitting that admitting verb sense into corpus analyses makes sense. *Language and Cognitive Processes 19, 181–224.*

Kennison, Shelia. 2001. Limitations on the use of verb information during sentence comprehension. *Psychonomic Bullettin and Review 8, 132–138.*

Krenn, Brigitte.2000.The Usual Suspects: Data-oriented models for the identification and representation of lexical collocation., volume 7 of Saarbruecken. Dissertations in Computational Linguistics and Language Technology. DFKI and Universität des Saarlandes, Saarbrücken, Germany.

Pedersen,Ted
1998 Dependent Bigram Identification. *Proceedings of the Fifteenth National Conference on Artificial Intelligence, July 1998,MadisonWI.*

Pedersen,Ted and Robert **Bruce**
1996 What to infer from a description.TechnicalReport96-CSE-04,SouthernMethodist University, Dallas, TX.

Wiechmann, Daniel
2008. Sense-contingent lexical preferences and early parsing decisions: Corpus-evidence from local NP/S-ambiguities. *Cognitive Linguistics 19, 439–455.*

Zeschel, Arne
2008. Lexical chunking effects in sentence processing. *Cognitive Linguistics 19*.