Compound stress assignment emerges from the lexicon

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presenting joint work with
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English compound stress

- Most N+N compounds in English are stressed on left constituent
  e.g. *bóokstore, wátchmaker*
- Compound stress rule, Chomsky & Halle (1968)
- Many exceptions:
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The hypotheses

- H1: The structural hypothesis (e.g. Giegerich 2004)
  - Modifier-head structures are regularly stressed on the RIGHT constituent (*steel bridge*)
  - Argument-head structures are always LEFT-stressed (*ópera singer*)
  - Left stress on modifier-head structures is due to lexicalization (*ópera glasses*)
- H2: The semantic hypothesis (e.g. Fudge 1984)
  - Stress assignment according to semantic categories (e.g. locative compounds are right-stressed, *Boston hárbour*)

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The Hypotheses, cont.

- H3: The analogical hypothesis (e.g. Schmerling 1971, Liberman and Sproat 1992, Plag 2006)
  - Stress assignment in analogy to similar compounds in the lexicon.
  - Constituent family stress bias:
    - right (N2) family of *street*: left stress bias (cf. *Báuer Street*)
    - right (N2) family of *avenue*: right stress bias (cf. *Giegerich Ávenue*)

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- H4: More informative constituents tend to attract stress (e.g. Ladd 1986, Bell 2008)
    - 'more informative': 'new', less expectable, less predictable (Shannon 1948)
    - informativity measures:
        - constituent frequency: less frequent words are more informative, have higher probability of being stressed
        - constituent family size: words with small family size are more informative, have higher probability of being stressed
        - number of synonyms (WordNet 'synsets'): few synonyms = semantically more specific = more informative = higher probability of being stressed

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- Predictive power of deterministic rules based on the structural and/or semantic hypothesis is very bad.
- Probabilistic and exemplar-based models are much better, but still not quite satisfactory.

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1. Analogy: family bias (Plag 2010)
2. Informativity: family size etc. (Bell & Plag *submitted*)
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Major problem: determine the stress pattern of a given compound

- Dictionary data: whose speech or intuition?
- CELEX: dictionary data plus other data of unclear status
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- Compute the constituent families for each compound
- Select data with family size > 1
- Compute constituent family stress bias for each compound's left and right consituents.

An example (from BURSC)

- 31 compounds with the left constituent *state* (*state administration, state aid, state authority, state benefit, etc.*)
- only 3 of them have leftward stress.
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Table: Corpora: size and stress distribution

	T&W	CELEX	Boston Corpus
N	782	2638	535
leftward stresses	89.5%	94.1%	67.1%

Research questions

- How do models perform that have all types of information at their disposal?
- In particular, which factors survive in such an overall model? Is family bias (i.e. analogy) predictive?

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T & W: family bias alone

Figure: Stress patterns by left and right constituent family bias, T&W data.

CELEX: family bias alone

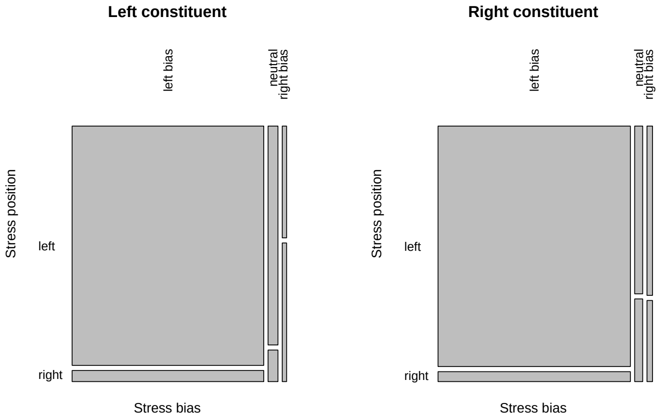

Figure: Stress patterns by left and right constituent family bias, CELEX data.

Boston Corpus: family bias alone

Figure: Stress patterns by left and right constituent family bias, Boston corpus.

Including all predictors: family bias, structure, semantics, lexicalization

- Structural: Argument-head vs. modifier-head
- Semantic categories of constituents or compound
- Semantic relation between constituents

Hypotheses from the literature: stress on N2 if

- N1 refers to a period or point in time (e.g. *night bírd*)
- N2 is a geographical term (e.g. *lee shóre*)
- N2 is a type of thoroughfare (e.g. *chain brídge*)
- The compound is a proper noun (e.g. *Union Jáck*)
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Including all predictors: family bias, structure, semantics, lexicalization

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- Semantic categories of constituents or compound
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Hypotheses from the literature: stress on N2 if

- N1 refers to a period or point in time (e.g. *night bírd*)
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Table: List of semantic relations held to trigger rightward stress

	Semantic relation	example
6.	N1 MAKES N2	*firelíght*
7.	N2 IS MADE OF N1	*potato crísp*
14.	N2 IS LOCATED AT/IN/... N1	*garden párty*
16.	N2 DURING N1	*night wátch*

Table: List of semantic relations coded, illustrated with one example each

	Semantic relation	example
1.	N2 CAUSES N1	*teargas*
2.	N1 CAUSES N2	*heat rash*
3.	N2 HAS N1	*stock market*
4.	N1 HAS N2	*lung power*
5.	N2 MAKES N1	*silkworm*
6.	N1 MAKES N2	*firelight*
7.	N2 IS MADE OF N1	*potato crisp*
8.	N2 USES N1	*water mill*
9.	N1 USES N2	*handbrake*
10.	N1 IS N2	*child prodigy*
11.	N1 IS LIKE N2	*kettle drum*
12.	N2 FOR N1	*travel agency*
13.	N2 ABOUT N1	*mortality table*
14.	N2 IS LOCATED AT/IN/... N1	*garden party*
15.	N1 IS LOCATED AT/IN/... N2	*taxi stand*
16.	N2 DURING N1	*night watch*
17.	N2 IS NAMED AFTER N1	*Wellington boot*
18.	OTHER	*schoolfellow*

Lexicalization

- Spelling as a proxy for lexicalization
- More intricate spellings (one word or hyphenated) indicate higher degree of lexicalization (e.g. Plag et al. 2007, 2008)
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Results: all predictors

Table: Effects of different kinds of predictors

Type of effect	significance in corpus	strength (highest odds ratio)
family bias	CELEX, BURSC	13.8, 6.2
semantics	CELEX, BURSC	4.6, 2.0
spelling	CELEX	14.5, -

Results: all predictors

Table: Predictive power of different kinds of variables

Effects included	C for CELEX	C for BURSC
only family bias	0.75	0.78
only other predictors	0.83	0.66
all predictors	0.90	0.79

Study 2 (Informativity): Methodology

- Sample of compounds from BNC demographic
- Production experiment with this sample, 4 elicited tokens per type
- Expert ratings as left or right for each token
- Compute measures of informativity (based on BNC and WordNet)
- Code prevalent semantic categories
- Fit logistic regression models and generalized additive models to non-variable types (*Nleft*=341, *Nright*=200)

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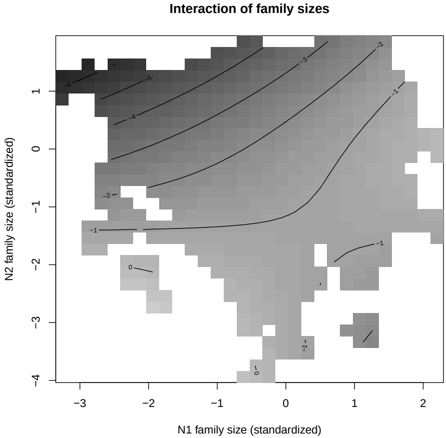
BNC: Results

Table: Effects of different kinds of predictors, C=0.923, (0.80 without semantics)

Type of effect	significance
family size/constituent frequency	yes
synsets	yes (lrm)/no (gam)
semantics	yes
lexicalization	yes

BNC: interaction of N1 and N2 family sizes



- Darker shading indicates higher probability of stress on N1
- large N2 family size and small N1 family size:
  N1 highly informative, hence stress on N1
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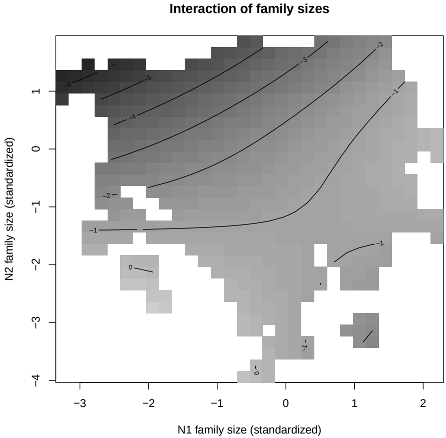

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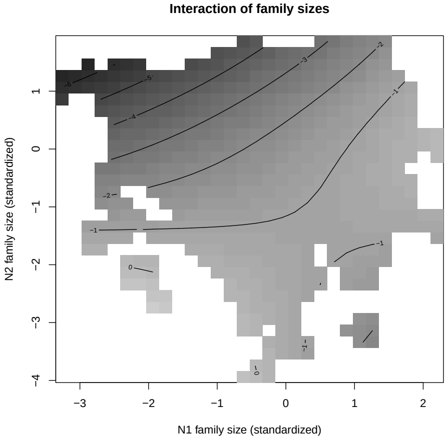

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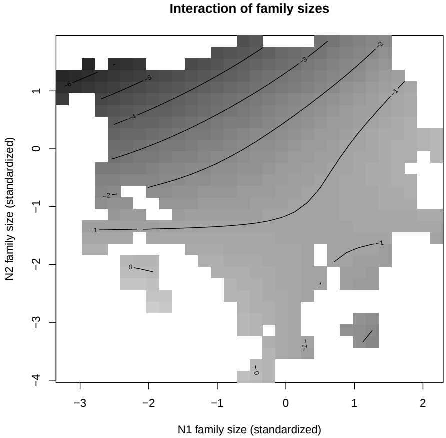

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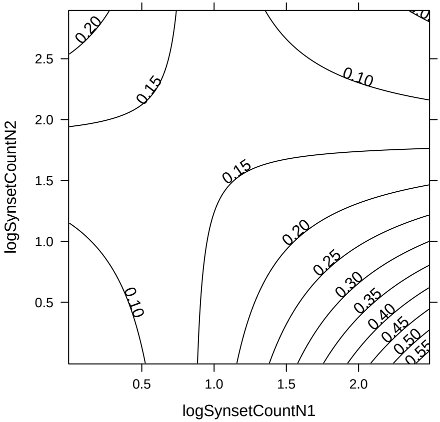
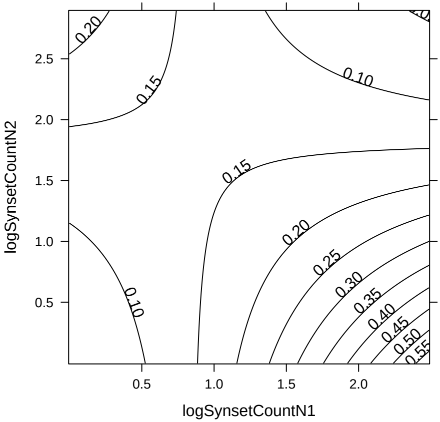


- proportions given in the graph indicate the probability of stress on N2
- N2 receives stress if it is highly specific in meaning, hence highly informative, and if N1 is at the same time relatively uninformative.

BNC: interaction of N1 and N2 synsets



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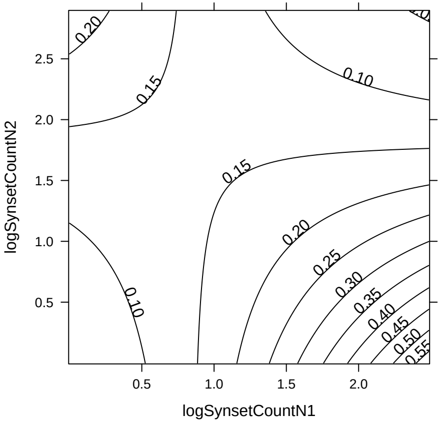

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- Constituent frequency and constituent family size are equally good predictors
- Synsets also have an effect in the predicted direction, but are significant only in logistic models (not in the GAMs)
- Lexicalization effects can also be found
- Informativity is a significant and successful predictor of compound stress
- Relation of family size and family bias? Two sides of the same coin?

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- Research question: Analogy or informativity?
- We add informativity measures to data set of study 1 (Plag 2010, family bias)
- family size ratio: log of $\frac{N2FamilySize}{N1FamilySize}$
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Study 3: Effects of family size and bias

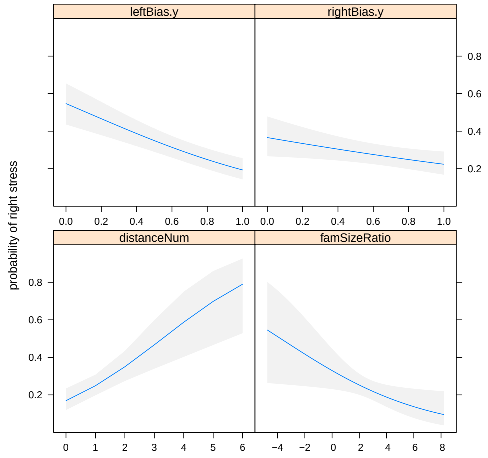

Figure: Partial effects of logistic regression model, BURSC

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- Results are similar across corpora and data types.
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Thanks

- **Thank you very much for your attention!**
- **Acknowledgements**

  - Special thanks go to Harald Baayen for his help with statistical issues, and
  - to the *Deutsche Forschungsgemeinschaft* for funding this research (Grants PL151/5-1, PL151/5-3)

- For full references, see the papers on our project homepage. (Just google my name!)