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. bookstore, watchmaker
• Compound stress rule, Chomsky & Halle (1968)
• Many exceptions:
  Boston marathon, Penny Lane, summer night, aluminum foil, morning paper, silk tie ...
• How can we account for this variability?
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- 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*)

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  - Stress assignment in analogy to similar compounds in the lexicon.
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  - '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
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    - 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.
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1. Analogy: family bias (Plag 2010)
2. Informativity: family size etc. (Bell & Plag submitted)
3. Analogy and informativity (Plag, Bell & Kunter in progress)

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- 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 constituents.

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

<table>
<thead>
<tr>
<th></th>
<th>T&amp;W</th>
<th>CELEX</th>
<th>Boston Corpus</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>782</td>
<td>2638</td>
<td>535</td>
</tr>
<tr>
<td>leftward stresses</td>
<td>89.5%</td>
<td>94.1%</td>
<td>67.1%</td>
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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 bird)
- N2 is a geographical term (e.g. lee shore)
- N2 is a type of thoroughfare (e.g. chain bridge)
- The compound is a proper noun (e.g. Union Jack)
- N1 is a proper noun (e.g. Achilles tendon)
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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 b́írd*)
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  - N2 is a type of thoroughfare (e.g. *chain brídge*)
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**Table:** List of semantic relations held to trigger rightward stress

<table>
<thead>
<tr>
<th>Semantic relation</th>
<th>example</th>
</tr>
</thead>
<tbody>
<tr>
<td>6. N1 MAKES N2</td>
<td>firelíght</td>
</tr>
<tr>
<td>7. N2 IS MADE OF N1</td>
<td>potato crísp</td>
</tr>
<tr>
<td>14. N2 IS LOCATED AT/IN/... N1</td>
<td>garden párty</td>
</tr>
<tr>
<td>16. N2 DURING N1</td>
<td>night wátch</td>
</tr>
</tbody>
</table>
Table: List of semantic relations coded, illustrated with one example each

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<tr>
<th>Semantic relation</th>
<th>example</th>
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<tbody>
<tr>
<td>1. N2 CAUSES N1</td>
<td>teargas</td>
</tr>
<tr>
<td>2. N1 CAUSES N2</td>
<td>heat rash</td>
</tr>
<tr>
<td>3. N2 HAS N1</td>
<td>stock market</td>
</tr>
<tr>
<td>4. N1 HAS N2</td>
<td>lung power</td>
</tr>
<tr>
<td>5. N2 MAKES N1</td>
<td>silkworm</td>
</tr>
<tr>
<td>6. N1 MAKES N2</td>
<td>firelight</td>
</tr>
<tr>
<td>7. N2 IS MADE OF N1</td>
<td>potato crisp</td>
</tr>
<tr>
<td>8. N2 USES N1</td>
<td>water mill</td>
</tr>
<tr>
<td>9. N1 USES N2</td>
<td>handbrake</td>
</tr>
<tr>
<td>10. N1 IS N2</td>
<td>child prodigy</td>
</tr>
<tr>
<td>11. N1 IS LIKE N2</td>
<td>kettle drum</td>
</tr>
<tr>
<td>12. N2 FOR N1</td>
<td>travel agency</td>
</tr>
<tr>
<td>13. N2 ABOUT N1</td>
<td>mortality table</td>
</tr>
<tr>
<td>14. N2 IS LOCATED AT/IN/... N1</td>
<td>garden party</td>
</tr>
<tr>
<td>15. N1 IS LOCATED AT/IN/... N2</td>
<td>taxi stand</td>
</tr>
<tr>
<td>16. N2 DURING N1</td>
<td>night watch</td>
</tr>
<tr>
<td>17. N2 IS NAMED AFTER N1</td>
<td>Wellington boot</td>
</tr>
<tr>
<td>18. OTHER</td>
<td>schoolfellow</td>
</tr>
</tbody>
</table>
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)
- Spelling as a predictor in the regression models
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## Results: all predictors

**Table:** Effects of different kinds of predictors

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<thead>
<tr>
<th>Type of effect</th>
<th>Significance in corpus</th>
<th>Strength (highest odds ratio)</th>
</tr>
</thead>
<tbody>
<tr>
<td>family bias</td>
<td>CELEX, BURSC</td>
<td>13.8, 6.2</td>
</tr>
<tr>
<td>semantics</td>
<td>CELEX, BURSC</td>
<td>4.6, 2.0</td>
</tr>
<tr>
<td>spelling</td>
<td>CELEX</td>
<td>14.5, -</td>
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</table>
Results: all predictors

Table: Predictive power of different kinds of variables

<table>
<thead>
<tr>
<th>Effects included</th>
<th>C for CELEX</th>
<th>C for BURSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>only family bias</td>
<td>0.75</td>
<td>0.78</td>
</tr>
<tr>
<td>only other predictors</td>
<td>0.83</td>
<td>0.66</td>
</tr>
<tr>
<td>all predictors</td>
<td>0.90</td>
<td>0.79</td>
</tr>
</tbody>
</table>
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 ($N_{left}=341$, $N_{right}=200$)
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Table: Effects of different kinds of predictors, $C=0.923$, (0.80 without semantics)

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<tr>
<td>family size/constituent frequency</td>
<td>yes</td>
</tr>
<tr>
<td>synsets</td>
<td>yes (lrm)/no (gam)</td>
</tr>
<tr>
<td>semantics</td>
<td>yes</td>
</tr>
<tr>
<td>lexicalization</td>
<td>yes</td>
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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.
- Small N2 family size and large N1 family size: N2 highly informative, hence stress on N2.
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Interaction of family sizes

N2 family size (standardized)

N1 family size (standardized)
BNC: interaction of N1 and N2 synsets

- 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.
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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?
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Figure: Partial effects of logistic regression model, BURSC
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- Both family size and family bias are instrumental in compound stress assignment.
- Lexicalization: most robust predictor outside family effects.
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- Constituent families and other measures relating to individual and distributed compound representations play a very important role in compound stress assignment.
- Results are similar across corpora and data types.
- Results are similar across analytical methods.
- Semantic and lexicalization effects exist independently of constituent family effects and cannot be treated as epiphenomenal.
- Overall, the lexical measures are good predictors of compound stress assignment.
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- Challenge to rule-based approaches to compound structure, and the theories of grammar or lexicon that underlie them.

Compound stress emerges from the lexicon.
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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!)