Causality in historical language change

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Outline

Part 1: Theory

- Classical theories and the internal/external distinction
- Adaptive systems and the causal/referential distinction

Part 2: Analyses

• Lexical diveristy and L2 speaker proportions

Problems

- inferring causality
- information encoding efficiency of languages
- etc.



PART I

The distinction of internal and external causes of change

- Sociolinguistics (Croft, 2000; Jones & Esch, 2002; Jones & Singh, 2005)
- Genetic Linguistics (Thomason & Kaufman, 1988)
- Principles & Parameters (Briscoe, 2000a, 2000b; Clark & Roberts, 1993; Lightfoot, 1979; Pintzuk, Tsoulas, & Warner, 2000; Yang, 2000)



Sociolinguistics and Genetic Linguistics

- internal: languages follow 'natural', 'normal' and 'regular' paths of change, according to general principles such as assimilation, analogical extension and analogical leveling (Thomason & Kaufman, 1988: 22pp.; Jones & Singh 2005: 18-19)
- external: language contact, i.e. child bilingualism or adult second language learning (L2)



Examples

- internal: OE stanas, scipu, sorga, naman → PDE stones, ships, sorrows, names (analogical extension)
- external: OE pronouns replaced by Old Norse pronouns hie/heo, him/hira, heom/heora → θeir, θeim, θeira (borrowing)



Principle & Parameter view

- internal: innate set of parameters (UG) that limits the space of possible grammars (Yang, 2000: 232; Clark & Roberts, 1993: 340; Biberauer, Holmberg, Roberts, & Sheehan, 2010)
- **external**: refers to the varying language input (causing parameter setting) during acquisition



Problems (see Jones & Singh, 2005: 25-26)

- **Sociolinguistics/Genetic Linguistics**: Explain *what* is happening in great detail, but not *why* it is happening (i.e. causation). How do 'internal' causes work, what are the triggering events?
- **Principles & Parameters**: UG as 'internal' cause is too broad, i.e. it is by definition universal across all languages, and does not predict anything specific about language change



Language as a Complex Adaptive System

"The **structures of language** emerge from interrelated patterns of experience, **social interaction**, and **cognitive mechanisms**." (Beckner et al., 2009)



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Earlier studies

Gell-Mann, 1992; Croft, 2000; Kirby & Hurford, 2002; Ritt, 2004; Christiansen & Chater, 2008





Definitions:

 $P = \{S_1, S_2, \dots, S_{10}\}$

Language (accumulative): $L_{acc} = (i_{1,2}, i_{2,1}, \dots, i_{10,9})$

Language (minimalist): $\mathsf{L}_{\min} = \mathsf{C}_1 \cap \mathsf{C}_2 \cap \ldots \cap \mathsf{C}_{10}$



S: Speaker

















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Question: What about the internal/external, i.e. native speaker/non-native speaker distinction?

"[...] the traditional distinction between **language-external** and **language-internal causes** for linguistic change and evolution may turn out to be of little interest in the end."

(Bickel, 2013: 13)



Population drift





Population drift



Question:

Is the population drift the **cause** for Language A to use stanas, scipu, sorga, naman, and Language B to use stones, ships, sorrows and names?



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Population drift



Question:

Is the population drift the **cause** for Language A to use stanas, scipu, sorga, naman, and Language B to use stones, ships, sorrows and names?

(No). The population drift might be an amplifier for the change but not the cause.



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Phylogenetic Groups



Phylogenetic Groups



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Phylogenetic Groups



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Implications of the CAS Model



Implications for statistical modelling:

Why is a specific feature (to a specific extent) present in a language or not?

Example:

Why is the -s plural more strongly represented in Language B, than in Language A,?



Implications of the CAS Model



Implications for statistical modelling:

Why is a specific feature (to a specific extent) present in a language or not?

Example:

Why is the -s plural more strongly represented in Language B_a than in Language A₂?

(At least) two kinds of predictors:

primary (causal) predictors: - processing biases/ constraints of the speakers/hearers secondary (relational) predictors: - language family, genus, regions, etc.



Conclusions

- the distinction between **internal** and **external** causes of change is somewhat misleading
- within a CAS account it might make more sense to think about primary (causal) and secondary (relational) predictors.



PART II ANALYSES

What can we predict about languages using the CAS model?

• We need quantitative, cross-linguistic data that reflect the structures of languages we are interested in



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What can we predict about languages using the CAS model?

- We need quantitative, cross-linguistic data that reflect the structures of languages we are interested in
- We need quantitative, cross-linguistic data that reflect potential processing/comprehension constraints of speakers



Examples in earlier studies

Qualitative hypothesis

 Higher proportions of non-native speakers tend to simplify morphology (Wray& Grace, 2007; McWhorter, 2002, 2007; Trudgill, 2011)

Quantitative evidence

- Bigger language populations \rightarrow less morphological elaboration (Lupyan& Dale 2010, 2012)
- More non-native speakers \rightarrow less case marking (Bentz& Winter, 2012, 2013)



Language comparison in the CAS model





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Language comparison in the CAS model



This is impossible.

However, it is possible to sample from these sets and (roughly) approximate them.

Important: Keep the content of the interactions constant!





Zipfian/Information theoretic approach: How do **word form distributions (lexical diversities)** differ across languages, considering that the **content is constant**?

Data: Parallel texts



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Data: Parallel texts

- Parallel Bible Corpus (810 languages, ca. 20000 words per language)
- Universal Declaration of Human Rights (376 languages, ca. 2000 words per language)
- European Parliament Corpus (21 languages, ca. 7 million words per language)



Zipfian approach: Analysis of word form distributions across languages (lexical diversities)

Method: Order types, i.e. word forms delimited by white spaces and non-word characters (see Haspelmath 2011 and Wray 2014 for critical review), according to their token frequencies (Zipf,1932,1949)



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Shannon entropy (Shannon & Weaver, 1949)

$$H = -K \sum_{i=1}^{k} p_i \times \log_2(p_i)$$
$$p_i : \frac{\text{frequency of } w_i}{\text{total number of tokens}}$$





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Scaled values for 647 languages of 83 families (PBC, UDHR, EPC)

Altaic Indo-European Creole

Bentz, Verkerk, Kiela, Hill & Buttery (submitted)



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Lexical Diversity Space





What causes languages to have higher/lower LDTs?

Hypothesis

• Languages with **higher lexical diversities** might be those languages with lower non-native speaker proportions.



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What causes languages to have higher/lower LDTs?

Hypothesis

- Languages with **higher lexical diversities** might be those languages with lower non-native speaker proportions.
- Potential causal link: There is evidence in applied linguistics that lexical diversity is systematically lower for L2 speakers (Jarvis 2002, Treffers-Daller 2013).



Statistical Model

Predicting lexical diversity from L2 proportions requires a **linear mixed-effects model** (Baayen et al., 2008; Bates et al., 2014; Jäger et al., 2011)



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Statistical Model

Predicting lexical diversity from L2 proportions requires a **linear mixed-effects model** (Baayen et al., 2008; Bates et al., 2014; Jäger et al., 2011)

- continuous dependent/outcome variable: LDTs scaled
- (potentially) causal predictor: L2 proportions as (fixed effect)
- referential predictors (random effects), accounting for non-independence of data points (family, region, text type, LDT measure)



Statistical Model: Data Overlap

L2 Data (226 languages)

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L2 Data (226 languages)

LDT data (647 languages)

Statistical Model: Data Overlap

L2 Data (226 languages) 26 families LDT data (647 languages) 15 regions



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| Results | | | | | | |
|------------|---------------|-----------|---------|--------|---------|--|
| Dependent | Fixed | Random | β | SE | p-value | |
| LDT scaled | $\log(L2/L1)$ | family | -0.2772 | 0.1329 | 0.0375 | |
| | | region | | | | |
| | | measure | | | | |
| | | text type | | | | |
| | | ISO code | | | | |



LDT and L2 proportions across families



LDT and L2 proportions across regions



LDT and L2 proportions across text types





LDT and L2 proportions across measures





Lexical diversity: Conclusions

• Languages with more non-native speakers tend to have *lower* lexical diversity



Lexical diversity: Conclusions

- Languages with more non-native speakers tend to have *lower* lexical diversity
- These trends hold across *most* families, regions, text types and the LDT measures used



Problem: Causality

• The mixed-effects model still *does not* prove that the causality runs from L2 proportions to language structure



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Suggestion

 Sean Roberts did a preliminary causal graph (Nihat Ay's talk) analysis of an earlier dataset (Bentz & Winter 2013) and found some evidence for an L2 to language structure causality. (http://www.replicatedtypo.com)





Problem: Encoding efficiency

• Are some languages **more/less efficient** at encoding information?



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Suggestion

- A lack of lexical diversity might be made up for by encoding of information at a different level (constructions, fixed word order, multi word expressions)
- Fermin's talk (see also Mosocoso del Prado 2011, Ehret & Szmrecsanyi (to appear))



Collaborators



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Thank You!

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