CORPUS-BASED EVIDENCE FOR A COGNITIVE MECHANISM UNDERLYING LEXICAL REPLACEMENT

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R CODE UPON REQUEST

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Phenomenon: Adjective Amplification

(1) And you just have to hint well then it’s a very good hint (ICE-AUS:S1A-012$A)

(2) They’re all really cheap <#> They’re all really nice, the t-shirts in there (ICE-AUS:S1A-009$B)

(3) It was so bad (ICE-AUS:S1A-044$B)
INTRODUCTION

DATA AND METHODOLOGY

Data
Data Processing
Variable Coding
Mixed-Effects Binomial Logistic Regression
Boruta Analysis

RESULTS

DISCUSSION & OUTLOOK
Intensification

Related to the semantic category of *degree* (degree adverbs) and ranges from low (downtoning) to high (amplifiers) (Quirk et al. 1985: 589–590)

- Amplifiers
  - Boosters, e.g. *very*
  - Maximizers, e.g. *completely*

- Downtoners
  - Approximoters, e.g. *almost*
  - Compromisers, e.g. *more or less*
  - Diminishers, e.g. *partly*
  - Minimizers, e.g. *hardly*

*very vs. really*: no meaning change → interchangeable, *very vs. hardly*: meaning change → not interchangeable
Motivation

Amplification

- major area of gramm. change (cf. Brinton and Arnovick 2006: 441)
- crucial for “social and emotional expression of speakers” (Ito and Tagliamonte 2003: 258)
- linguistic subsystem which allows precise circumscription of a variable context (Labov 1972, 1966: 49)
- ideal case for testing mechanisms underlying language change!
Previous Research

Amplification

- substantial amount of corpus-based research on intensification (e.g. Aijmer 2011, 2018; Fuchs 2016, 2017; Núñez Pertejo and Palacios 2014; Palacios and Núñez Pertejo 2012)
  → but mostly either focused on individual intensifiers or without regard to the intensified adjectives
- associated with teenage talk and young(ish) (female) speakers
  (Bauer and Bauer 2002; D’Arcy 2015; Macaulay 2006; Tagliamonte 2006, 2008)
- recently amplifier-adjective bigrams have come more into focus (e.g. Schweinberger 2017; Wagner 2017a,b)
Focus

- Amplifying *really* replaces *very* (lexical replacement)

(see D’Arcy (2015) for NZE; see Ito and Tagliamonte (2003) and Barnfield and Buchstaller (2010) for North East British English, Tagliamonte (2008) and Tagliamonte and Denis (2014) for Toronto English; see Tagliamonte and Denis (2014) for South Eastern Ontario English)

![Graph showing the frequency of words over time](image-url)

**Figure 1: Adapted from D’Arcy (2015: 468)**
Research Question

Q

Why is very replaced by really and not by any other variant (e.g. so, quite, pretty)?

→ What mechanisms underlie lexical replacement?
Scenario 1 (Broadening)

*really* associate with many (but infrequent) adj. types

(Mair 2004: “delayed increase of discourse frequency” hypothesis)

**Argument**

→ co-occurrence with many different adj. types
→ frequent use
→ deeper cognitive entrenchment
→ easier retrieval from memory
→ dominance within the amplifier system.

**Prediction**

Co-occurrence with many different adjective types

→ high lexical diversity
→ weak coll. attraction with specific adj. types
Scenario 2 (Specialization)

*Really* associate with few but frequent adj. types (HFAs)

(Lorenz 2002: 144; Méndez-Naya 2003: 375; Tagliamonte and Roberts 2005: 285)

**Argument**

→ co-occurrence with high-freq. adj. types
→ frequent use
→ deeper cognitive entrenchment
→ easier retrieval from memory
→ dominance within the amplifier system.

**Prediction**

Co-occurrence with few high frequency adjectives

→ low lexical diversity
→ strong coll. attraction with high-freq. adj. types
Scenario 3 (Randomness)

*Really* associate with random adj. types
→ We cannot predict which variants become successful based on their coll. profile.
Hypothesis

$H_1$

If *really* is successful because of specialization on HFAs

$\rightarrow$ sig. pos. correlation with adjective frequency

If broadening $\rightarrow$ neg. correlation with adj. freq.
If random $\rightarrow$ no correlation with adj. freq.
DATA AND METHODOLOGY
Corpus data: International Corpus of English (ICE)

- Australian, British, Canadian, Irish, and New Zealand ICE components
- Shared design (allows meaningful comparisons between varieties of English)
- One million words (600,000 spoken and 400,000 written) from diverse spoken and written text types (cf. next slide) with each file containing app. 2,000 words.
- Accompanied by metadata and biodata of speaker (extremely interesting resource for variationist analyses)
Corpus data: International Corpus of English (ICE)

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<th>Text type</th>
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</table>

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Data Processing

- Spoken private dialogue section of each component
- Part-of-speech tagged (OpenNLP vis R) the
- Retrieved adjectives (PoS–tag JJ)
- Determined whether adjective were preceded by an amplifier (member of a predefined set of amplifiers)
- Sentiment Analysis of adjective types (Jockers 2017)
Data Processing

- Determined if the same amplifier type had occurred within a span of three adjective slots previously (→ priming)

- Token freq. of adjective type by age group (Tagliamonte and Roberts 2005)

- Removed...
  - negated adjectives
  - comparative and superlative forms
  - adjectives that were not amplified by at least two different amplifier types
  - adjectives that were preceded by downtoners
  - strange forms (e.g. much)
Data Processing

- Semantic classification of adjective (simplified version of Dixon (1977), cf. also D’Arcy (2015); Tagliamonte and Roberts (2005); Tagliamonte (2006, 2008))

- Manual cross-evaluation of automated classification

- Metadata and speaker information
### Variable Coding

**Dependent Variable(s)**

| really | nominal | yes/no occurrence of pre-adjectival *really* |

**Independent Variable(s)**

| Age | ordinal | min. young | middle-aged | old |
| AudienceSize | nominal | Dyad | MultipleInterlocutors |
| ConversationType | nominal | MixedSex | SameSex |
| Gender | nominal | Female | Male |
| (Education) | nominal | College | NoCollege |
| Priming | nominal | prime | no prime |
| Emotionality | categorical | negative | nonemotional | positive |
| Function | nominal | attributive | predicative |
| SemanticCategory | categorical | semantic category of adj. |
| Gradability | nominal | gradable | nongradable |
| Adjective | categorical | bad | funny | good | interesting | nice | other |
| Frequency | numeric | Frequency of adj. by age group |

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Mixed-Effects Binomial Logistic Regression

(Baayen 2008; Faraway 2016)

What is MEBLoR?
- Standard models for multivariate analyses
- Can handle nested/grouped data structure
- Easy multicollinearity detection

Problems of MEBLoR
- Cannot handle small data sets (well)
- Extremely high $\beta$-error rate
  ▶ if sig. effect: ✓
  ▶ if no sig. effect: ???
Mixed-Effects Binomial Logistic Regression

(Baayen 2008; Faraway 2016)

Figure 2: Difference between models without grouping/nesting and mixed-effects models (with grouping/nesting).
Boruta Analysis

(Kursa et al. 2010)

What is Boruta?
- Alternative to regressions that can handle small data sets
- Variable selection procedure
- Extension/improvement of random forests
- Hundreds of forests are grown → distribution of parameters rather than single values (higher reliability)

Problems of Boruta
- Ignores multicollinearity(!)
- Does not model nested/grouped data structure
Boruta Analysis

(Kursa et al. 2010)

Procedure

1. Addition randomness: shuffling copies of all features (shadow features).

2. Training of a random forest classifier on the extended data.

3. Application of a feature importance measure (Mean Decrease Accuracy).

4. Checking whether a real feature has a higher importance than the best shadow features at each iteration.

5. Continuous removal of unimportant features (features that are less important than shadow features).
Ongoing Changes in the AusE Amplifier System

Results

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Results AusE: Observed, MEBLoR, and Boruta

Figure 3: % Variants in AusE.

Figure 4: Boruta results for really in AusE.

Figure 5: Prob. really in AusE by adj. freq.

Figure 6: Prob. really in AusE across age.
## Summary AusE Results

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<th>Boruta Age</th>
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</table>

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Results BrE: Observed, MEBLoR, and Boruta

Figure 7: % Variants in BrE.

Figure 8: Boruta results for really in BrE.

Figure 9: Prob. really in BrE by adj. freq.

Figure 10: Prob. really in BrE across age.

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## Summary BrE Results

<table>
<thead>
<tr>
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Results CanE: Observed, MEBLoR, and Boruta

Figure 11: % Variants in CanE.

Figure 12: Boruta results for really in CanE.

Figure 13: Prob. really in CanE by adj. freq.

Figure 14: Prob. really in CanE across age.

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**Summary CanE Results**

<table>
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<th>Variety</th>
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Results IrE: Observed, MEBLoR, and Boruta

**Figure 15:** % Variants in IrE.

**Figure 16:** Boruta results for really in IrE.

**Figure 17:** Prob. really in IrE by adj. freq.

**Figure 18:** Prob. really in IrE across age.

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## Summary IrE Results

<table>
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Results NZE: Observed, MEBLoR, and Boruta

Figure 19: % Variants in NZE.

Figure 20: Boruta results for really in NZE.

Figure 21: Prob. really in NZE by adj. freq.

Figure 22: Prob. really in NZE across age.

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## Summary NZE Results

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Discussion & Outlook

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Summary

The analysis . . .

- confirms that *really* correlates with adj. freq.
  (positive correlation between the use of *really* and adjective frequency)

- suggests that lexical replacement is accompanied by 
  (functional) re-organization in addition to diffusion 
  through the speech community (absence of age effects) 
  (see D’Arcy 2015)

- shows that complementing mixed-modeling with Boruta is 
  useful to avoid overlooking significant effects 
  (avoidance of $\beta$-errors)
Discussion

- *Really* successfully replaced the dominant form *very* because it collocated with HFAs.
- No signs that *really* of broadening before taking over the system.
- Broadening once dominant (substantiates Tagliamonte and Denis 2014)
Argument

1. The co-occurrence with HFAs lead to the innovative variant being used as a more expressive variant to amplify certain HFAs.
2. The frequency of the innovative form increased because it piggybacked on the frequency of the HFA.
3. Increase in use → more deeply entrenched.
4. Deeper entrenchment → increased ease of retrieval.
5. Higher ease of retrieval → advantage over rival variants.
6. Innovative variant broadens because it increasingly co-occurs with more adj. types.
Outlook

Could this be a universal mechanism?

Test if the mechanisms...

- can be shown to have worked in analogous changes in English
  
  \[3^{rd} \text{ p. sg. ind. morpheme: } <eth> \rightarrow <(e)s>\]

- can be shown to have worked in analogous changes in languages other than English
Thank you so, really, very much!

Acknowledgements

I would like to thank...

all ICE teams(!), in particular, Pam Peters and Adam Smith for providing me with a preliminary version of ICE-Aus (without them the current study would not have been possible)

my colleagues at UQ

for comments and their feedback on earlier versions of this talk


Palacios, I. and P. Núñez Pertejo (2012). He’s absolutely massive. it’s a super day. madonna, she is a wicked singer. youth language and intensification: A corpus-based study. *Text and Talk* 32(6), 773–796.


Corpus-based evidence for a cognitive mechanism underlying lexical replacement

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APPENDIX
## Results: GLMM and Boruta

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Variationist Sociolinguistics

- Language is not homogeneous: variation is ubiquitous
  - Social factors: language use
  - Linguistic variation not random
  - Systematic correlation between certain social factors (age, gender, class, ethnicity, etc.) and language use
- Linguistic differentiation ↔ social stratification
Diffusion of Innovations

young $\leftrightarrow$ old

upper

working

young $\leftrightarrow$ old

high

%

low

Construct - i - con | Lexicon

emotional attributive $\leftrightarrow$ non-emotional predicative

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Diffusion of Innovations

young ←→ old

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young ←→ old

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Diffusion of Innovations

young ←→ old

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Young

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high

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Construct - i - con | Lexicon
emotional attributive ←→ non-emotional predicative

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Diffusion of Innovations

young ←→ old

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Diffusion of Innovations

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Diffusion of Innovations

young <-> old

upper

working

young <-> old

high

%

low

Construct - i - con | Lexicon
emotional attributive <-> non-emotional predicative

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Diffusion of Innovations

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Diffusion of Innovations

young ↔ old

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Diffusion of Innovations

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Diffusion of Innovations

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Diffusion of Innovations

- young $\leftrightarrow$ old

- upper $\leftrightarrow$ working

- high $\leftrightarrow$ low

- innovative $\leftrightarrow$ traditional

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Ongoing Changes in the AusE Amplifier System

Diffusion of Innovations

young $\leftrightarrow$ old

upper

working

young $\leftrightarrow$ old

high

low

%

constructive vs. lexicon

emotional attributive $\leftrightarrow$ non-emotional predicative

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Diffusion of Innovations

young ←→ old

upper

working

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Diffusion of Innovations

- young ↔ old
- upper ↔ working
- innovative → traditional
- emotional attributive ↔ non-emotional predicative

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Diffusion of Innovations

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Diffusion of Innovations

young ←→ old

upper

working

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- innovative
- traditional

Construct - i - con | Lexicon
- emotional attributive
- non-emotional predicative

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Diffusion of Innovations

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Diffusion of Innovations

- young $\leftrightarrow$ old

- upper

- working

- high

- %

- low

- innovative

- traditional

- emotional

- attributive $\leftrightarrow$ non-emotional predicative

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Diffusion of Innovations

young ←→ old

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high

%

low

innovative

traditional

Construct - i - con | Lexicon

emotional

attributive

non-emotional

predicative

Dr. Martin Schweinberger, slides available at, www.martinschweinberger.de, m.schweinberger@uq.edu.au. R code upon request
Diffusion of Innovations

young $\leftrightarrow$ old

Dr. Martin Schweinberger, slides available at, www.martinschweinberger.de, m.schweinberger@uq.edu.au. R code upon request.
Diffusion of Innovations

young ←→ old

upper

working

young ←→ old

%

low

high

innovative

traditional

Construct - i - con | Lexicon

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