



Pre-processing
and
non-randomness

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Counting Words: Pre-Processing and Non-Randomness

Marco Baroni & Stefan Evert

Málaga, 11 August 2006



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- ▶ IT IS IMPORTANT!!! (Evert and Lüdeling 2001)



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- ▶ IT IS IMPORTANT!!! (Evert and Lüdeling 2001)
- ▶ Automated pre-processing often necessary (13,850 types begin with *re-* in BNC, 103,941 types begin with *ri-* in itWaC)



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- ▶ IT IS IMPORTANT!!! (Evert and Lüdeling 2001)
- ▶ Automated pre-processing often necessary (13,850 types begin with *re-* in BNC, 103,941 types begin with *ri-* in itWaC)
- ▶ We can rely on:
 - ▶ POS tagging
 - ▶ Lemmatization
 - ▶ Pattern matching heuristics (e.g., candidate prefixed form must be analyzable as *PRE+VERB*, with *VERB* independently attested in corpus)



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- ▶ We can rely on:
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 - ▶ Lemmatization
 - ▶ Pattern matching heuristics (e.g., candidate prefixed form must be analyzable as *PRE+VERB*, with *VERB* independently attested in corpus)
- ▶ However...



The problem with low frequency words

- ▶ Correct analysis of low frequency words is fundamental to measure productivity, estimate LNRE models

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The problem with low frequency words

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- ▶ Correct analysis of low frequency words is fundamental to measure productivity, estimate LNRE models
- ▶ Automated tools will tend to have lowest performance on low frequency forms:
 - ▶ Statistical tools will suffer from lack of relevant training data
 - ▶ Manually-crafted tools will probably lack the relevant resources



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- ▶ Problems in both directions (under- and overestimation of hapax counts)



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- ▶ Problems in both directions (under- and overestimation of hapax counts)
- ▶ Part of the more general “95% performance” problem



Underestimation of hapaxes

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- ▶ The Italian TreeTagger lemmatizer is lexicon-based; out-of-lexicon words (e.g., productively formed words containing a prefix) are lemmatized as UNKNOWN
- ▶ No prefixed word with dash (*ri-cadere*) is in lexicon
- ▶ Writers are more likely to use dash to mark transparent morphological structure



Productivity of *ri-* with and without an extended lexicon

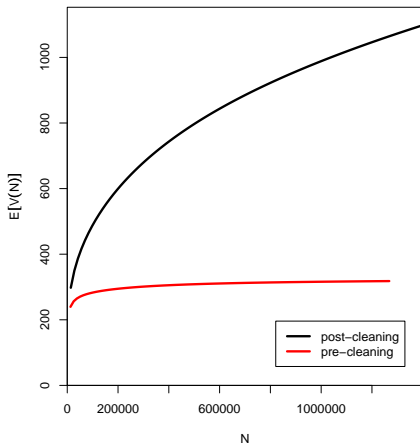
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Overestimation of hapaxes

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- ▶ “Noise” generates hapax legomena
- ▶ The Italian TreeTagger thinks that dashed expressions containing pronoun-like strings are pronouns
- ▶ Dashed strings can be anything, including full sentences
- ▶ This creates a lot of pseudo-pronoun hapaxes: *tu-tu*, *parapaponzi-ponzi-pò*, *altri-da-lui-simili-a-lui*



Productivity of the pronoun class before and after cleaning

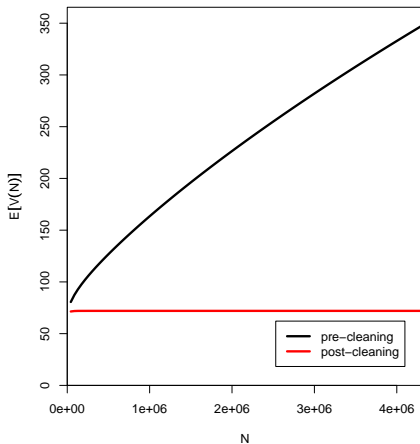
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\mathcal{P} (and V) with/without correct post-processing

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► With:

class	V	V_1	N	\mathcal{P}
<i>ri-</i>	1098	346	1,399,898	0.00025
pronouns	72	0	4,313,123	0

► Without:

class	V	V_1	N	\mathcal{P}
<i>ri-</i>	318	8	1,268,244	0.000006
pronouns	348	206	4,314,381	0.000048



A final word on pre-processing

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▶ IT IS IMPORTANT



A final word on pre-processing

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- ▶ IT IS IMPORTANT
- ▶ Often, major roadblock of lexical statistics investigations

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- ▶ LNRE modeling based on assumption that our corpora/datasets are **random** samples from the population



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- ▶ LNRE modeling based on assumption that our corpora/datasets are **random** samples from the population
- ▶ This is obviously not the case



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- ▶ LNRE modeling based on assumption that our corpora/datasets are **random** samples from the population
- ▶ This is obviously not the case
- ▶ Can we pretend that a corpus is random?



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- ▶ LNRE modeling based on assumption that our corpora/datasets are **random** samples from the population
- ▶ This is obviously not the case
- ▶ Can we pretend that a corpus is random?
- ▶ What are the consequences of non-randomness?



A Brown-sized random sample from a ZM population estimated with Brown

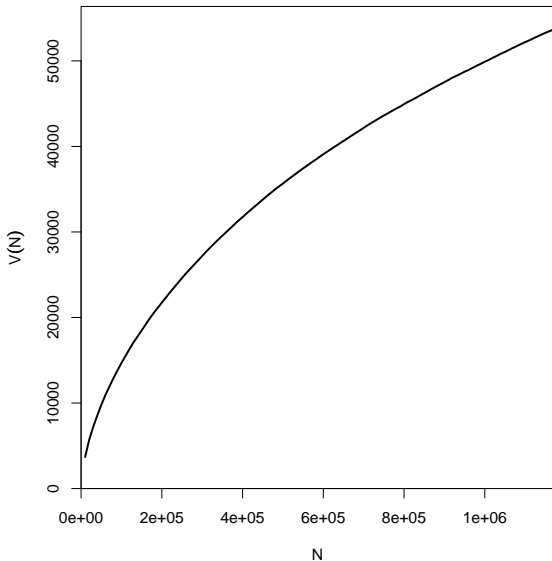
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The real Brown

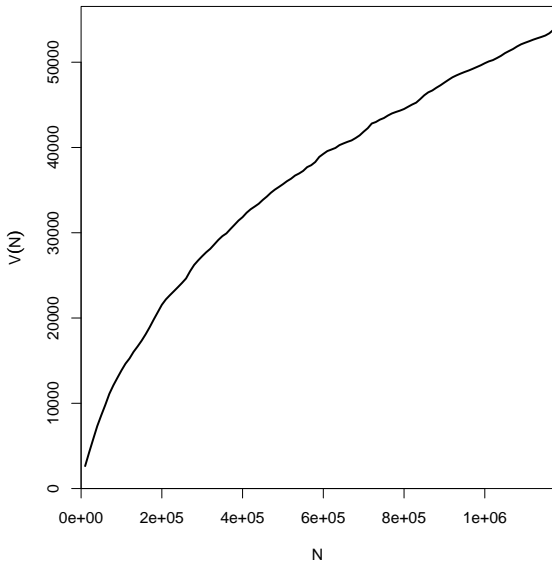
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Where does non-randomness come from?

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▶ Syntax?

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Where does non-randomness come from?

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- ▶ Syntax?
- ▶ *the the* should be most frequent English bigram

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Where does non-randomness come from?

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- ▶ Syntax?
- ▶ *the the* should be most frequent English bigram
- ▶ If the problem is due to syntax, randomizing by sentence will not get rid of it (Baayen 2001, ch. 5)



The Brown randomized by sentence

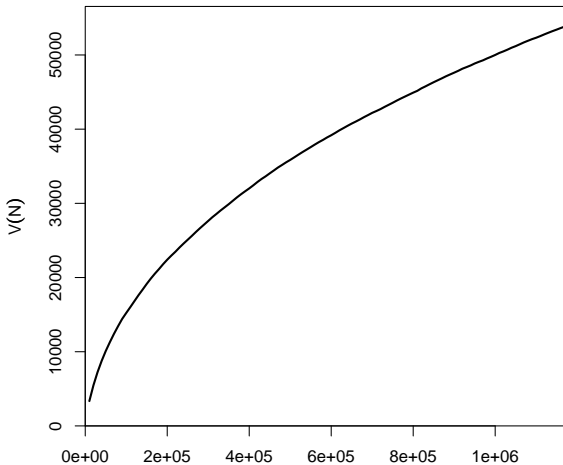
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Where does non-randomness come from?

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- ▶ Not syntax (syntax has short span effect; *the* counts for 10k intervals are OK)

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Where does non-randomness come from?

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- ▶ Not syntax (syntax has short span effect; *the* counts for 10k intervals are OK)
- ▶ **Underdispersion** of content-rich words
- ▶ The chance of two Noriegas is closer to $\pi/2$ than π^2 (Church 2000)
- ▶ *diethylstilbestrol* occurs 3 times in Brown, all in same document (recommendations on feed additives)



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- ▶ Not syntax (syntax has short span effect; *the* counts for 10k intervals are OK)
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- ▶ The chance of two Noriegas is closer to $\pi/2$ than π^2 (Church 2000)
- ▶ *diethylstilbestrol* occurs 3 times in Brown, all in same document (recommendations on feed additives)
- ▶ Underdispersion will lead to serious **underestimation** of rare type count
- ▶ fZM estimated on Brown predicts $S = 115,539$ in English



Underestimating types

Extrapolating Brown VGC with fZM

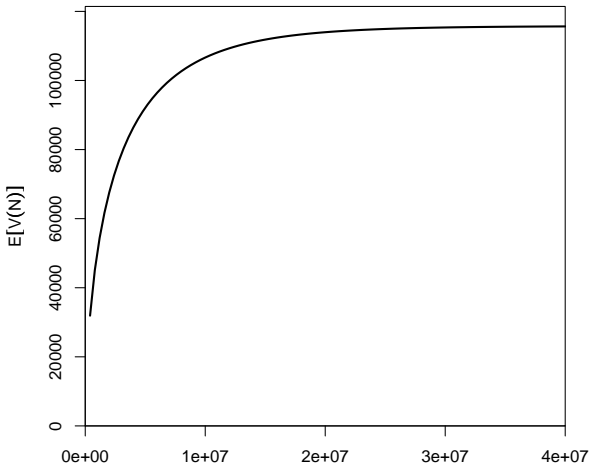
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Assessing extrapolation quality

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- ▶ We have no way to assess goodness of fit of extrapolation from corpus to larger sample from same population
- ▶ However, we can estimate models on subset of available data, and extrapolate to full corpus size (Evert and Baroni 2006)
- ▶ I.e., use corpus as our population, sample from it



Extrapolation from a **random** sample of 250k Brown tokens

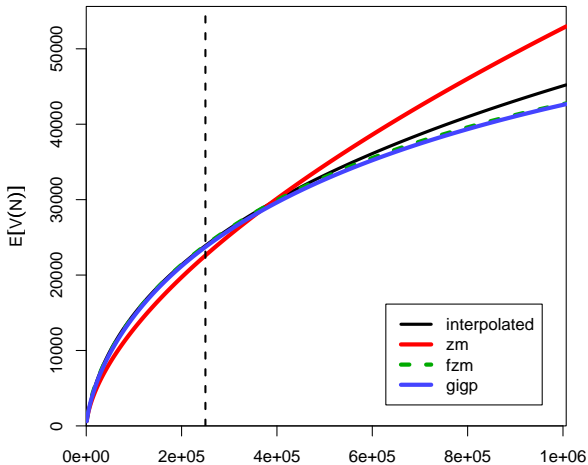
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Goodness of fit to spectrum elements

Based on multivariate chi-squared statistic

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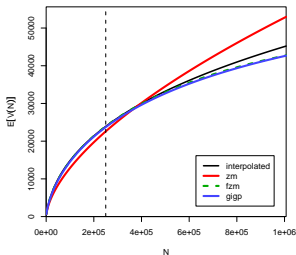
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model	estimation size			max extrapolation size		
	X2	df	p	X2	df	p
ZM	7,856	14	$\ll 0.001$	35,346	16	$\ll 0.001$
fZM	539	13	$\ll 0.001$	4,525	16	$\ll 0.001$
GIGP	597	13	$\ll 0.001$	3,449	16	$\ll 0.001$

Compare to \sqrt{N} fit:





Extrapolation from first 250k tokens in corpus

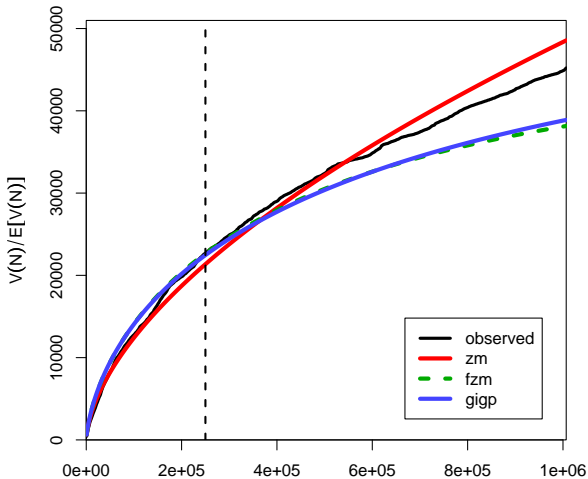
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Based on multivariate chi-squared statistic

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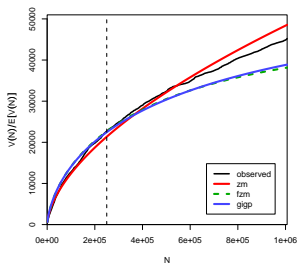
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model	estimation size			max extrapolation size		
	X2	df	p	X2	df	p
ZM	8,066	14	$\ll 0.001$	33,6766	16	$\ll 0.001$
fZM	1,011	13	$\ll 0.001$	17,559	16	$\ll 0.001$
GIGP	587	13	$\ll 0.001$	7,815	16	$\ll 0.001$

Compare to \sqrt{V} fit:





The corpus as a (non-)random sample

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- ▶ In our experiment, we had access to full population (the Brown) and could take random sample from it

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- ▶ In our experiment, we had access to full population (the Brown) and could take random sample from it
- ▶ In real life, full corpus *is* our sample from the population (e.g., “English”, an author’s mental lexicon, all words generated by a wfp)



The corpus as a (non-)random sample

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- ▶ In our experiment, we had access to full population (the Brown) and could take random sample from it
- ▶ In real life, full corpus *is* our sample from the population (e.g., “English”, an author’s mental lexicon, all words generated by a wfp)
- ▶ If it is not random, there is nothing we can do about it (randomizing the sample will not help!)



What can we do?

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- ▶ Abandon lexical statistics



What can we do?

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- ▶ Abandon lexical statistics
- ▶ Live with it

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What can we do?

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- ▶ Abandon lexical statistics
- ▶ Live with it
- ▶ Re-define the population



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- ▶ Abandon lexical statistics
- ▶ Live with it
- ▶ Re-define the population
- ▶ Try to account for underdispersion when computing the models (will get mathematically very complicated, but see Baayen 2001, ch. 5)



Not always that bad

Our Mutual Friend

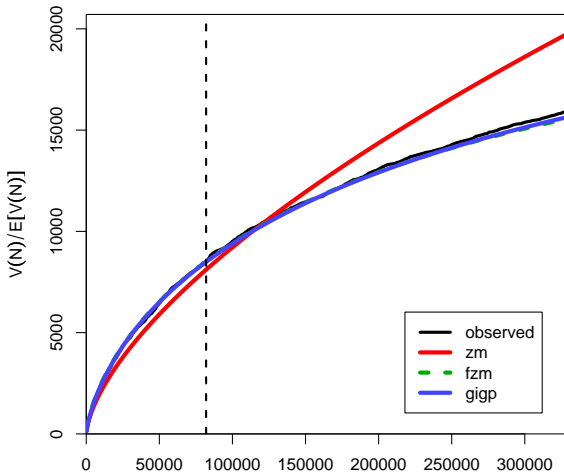
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What we have done

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- ▶ **Motivation:** studying distribution and V growth rate of type-rich populations (sample captures only small proportion of types in population)



What we have done

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- ▶ **Motivation**: studying distribution and V growth rate of type-rich populations (sample captures only small proportion of types in population)
- ▶ **LNRE** modeling:
 - ▶ **Population model** with limited number of parameters (e.g., ZM), expressed in terms of type density function
 - ▶ Equations to calculate expected V and frequency spectrum in **random samples** of arbitrary size using population model
 - ▶ **Estimation** of population parameters via fit of expected elements to observed frequency spectrum



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- ▶ **zipfR** package to apply LNRE modeling



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 - ▶ **Estimation** of population parameters via fit of expected elements to observed frequency spectrum
- ▶ **zipfR** package to apply LNRE modeling
- ▶ **Problems**



What we (and perhaps some of you?) would like to do next

- ▶ Study (and deal with) non-randomness

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What we (and perhaps some of you?) would like to do next

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- ▶ Study (and deal with) non-randomness
- ▶ Better parameter estimation

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- ▶ Study (and deal with) non-randomness
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- ▶ Improve zipfR (any feature request?)



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- ▶ Study (and deal with) non-randomness
- ▶ Better parameter estimation
- ▶ Improve zipfR (any feature request?)
- ▶ Use LNRE modeling in applications, e.g.:
 - ▶ Good-Turing-style estimation
 - ▶ Productivity beyond morphology
 - ▶ Better features for machine learning
 - ▶ Mixture models



That's All, Folks!

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