Morphological Productivity: Corpus-Based Approaches

Marco Baroni

University of Bologna

Granada “Morphology and Corpora” Seminar
Morphology is about defining what is a possible word (and explaining why it is possible)
Morphology is about defining what is a \textit{possible word} (and explaining why it is possible)

\textit{Attested} words are subset of \textit{possible} words
Attested and possible words

- Morphology is about defining what is a *possible word* (and explaining why it is possible)
- *Attested* words are subset of *possible* words
- Need to delimit set of *possible* but *unattested* words
Possible unattested words are (mostly) derived by word-formation processes (rules/schemas/...)

-ness vs. -ity vs. -th

NN compounding in Germanic vs. Romance languages -ness and Germanic NN compounding are productive processes.
Word-formation and productivity

- Possible unattested words are (mostly) derived by word-formation processes (rules/schemas/…)
- However, not all wf processes are (equally) available to speakers
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E.g.:

- *ness vs. itty vs. *th
Word-formation and productivity

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E.g.:
- *-ness* vs. *-ity* vs. *-th*
- NN compounding in Germanic vs. Romance languages

*-ness* and Germanic NN compounding are *productive* processes
Objective measure of productivity needed
The centrality of productivity in morphology

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- because any theory of morphology/word formation must:
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  - explain why only certain processes are productive
The centrality of productivity in morphology

Objective measure of productivity needed
because any theory of morphology/word formation must:
  focus on productive processes
  explain why only certain processes are productive

Vast literature on productivity (see refs.)
Productivity: the classic definition

Schultink (1961), translated by Booij

Productivity as morphological phenomenon is the possibility which language users have to form an in principle uncountable number of new words unintentionally, by means of a morphological process which is the basis of the form-meaning correspondence of some words they know.
Some issues

- “Unintentionally”

How do we find out if a process can form an "in principle uncountable" number of new words?

Is productivity an all-or-nothing phenomenon? Does the rate at which different productive processes grow towards uncountably many forms matter?

How should productivity be interpreted? Is productivity an inherent property of a process, or an epiphenomenon?

(Plag 1998)
Some issues

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Availability (Bauer 2001): -ness is available, -th is not
**Productivity as all-or-nothing**

- Availability (Bauer 2001): \(-ness\) is available, \(-\text{th}\) is not
- Different from “grammatical” vs. “ungrammatical”: \textit{kingdom}, \textit{growth} are “grammatical”
Common expressions like “very productive”, “marginally productive” betray shared intuition that productivity is not “black or white”
Problems with the availability approach

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- Common expressions like “very productive”, “marginally productive” betray shared intuition that productivity is not “black or white”
- re- is more productive than de-, but de- is more productive than be-
- Once available always available?
- Baayen (2003) finds productive uses of -th on the Net (“Maintainance (sic) of greenth”)
Measuring (degrees of) productivity

How do we measure how many words *could* be generated by a process, when the words that have already been generated are all we can see?
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- Corpora: you need to count something, to find out that X is more productive than Y (dictionary entries not appropriate)
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- Baayen and colleagues (see refs.) ground study of productivity in corpora and tradition of lexical statistics
- Corpora: you need to count something, to find out that X is more productive than Y (dictionary entries not appropriate)
- Lexical statistics: we must count properties of our *sample* (instances of wf process attested in the corpus) to infer properties of the *population* our sample is taken from (all possible instances of wf process)
Outline

1. Introduction
2. Quantitative productivity: Baayen’s approach
3. Methodological issues in measuring quantitative productivity
4. The interpretation of (quantitative) productivity
5. Conclusion
Lexical statistics


- Comparison of vocabulary size and other measures of lexical richness
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- E.g., for stylometry (does Joyce use richer vocabulary than H. James?), language acquisition (how many words do 7-year old know? is the L2 learners’ vocabulary significantly smaller than the one of natives?), genre/register analysis (is spoken English lexically poorer than written English)
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- Productivity as a nuisance: target sample (text, corpus) does not contain full vocabulary
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- Productivity as a nuisance: target sample (text, corpus) does not contain full vocabulary
- Development of methods to assess “growth rate” of vocabulary and estimate vocabulary size (and other measures) in whole population
Basic terminology

- N: sample/corpus size, number of *tokens* in the sample
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- \( V \): vocabulary size, number of distinct types in the sample
- \( V1 \): hapax legomena count, number of word types that occur only once in the sample (for hapaxes, \( \text{Count}(\text{types}) = \text{Count}(\text{tokens}) \))
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- **A sample**: a b b c a a a b a
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- **A sample**: a b b c a a b a
- **N**: 8; **V**: 3; **V1**: 1
The sample: a b b c a a b a
Vocabulary growth curve

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Baayen’s $P$
Applications of $P$

Vocabulary growth curve

- The sample: a b b c a a a b a
- N: 1, V: 1, V1: 1
- N: 3, V: 2, V1: 1

(Most VGCs below smoothed with binomial interpolation)
**Vocabulary growth curve**

- **The sample:** a b b c a a b a
- **N:** 1, **V:** 1, **V1:** 1
- **N:** 3, **V:** 2, **V1:** 1
- **N:** 5, **V:** 3, **V1:** 1

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Vocabulary growth curve of LOB corpus
The sample: a b b c a a b a d
Frequency spectrum

- The sample: a b b c a a b a d
- Frequency classes: 1 (c, d), 3 (b), 4 (a)
Frequency spectrum

- The sample: a b b c a a b a d
- Frequency classes: 1 (c, d), 3 (b), 4 (a)
- Frequency spectrum:

<table>
<thead>
<tr>
<th>m</th>
<th>V(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>
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Frequency spectrum of LOB corpus

LOB Frequency Spectrum

![Frequency spectrum of LOB corpus](image-url)
Morphology, productivity and lexical statistics

- N: number of tokens characterized by target wf process in corpus
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- N: number of tokens characterized by target wf process in corpus
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Morphology, productivity and lexical statistics

- N: number of tokens characterized by target wf process in corpus
- V: number distinct types characterized by target wf process
- V1: number of hapax legomena characterized by target wf process
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*ri-* in Italian *la Repubblica* corpus

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**Graph:**

$r_i$– VGC

- $V$ and $V_1$
- $N$

The graph shows the relationship between $V$ and $V_1$ as a function of $N$, where $N$ ranges from 0 to 1,400,000. The solid line represents $V$ and the dashed line represents $V_1$. The graph suggests an increasing trend as $N$ increases.
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ri- in Italian la Repubblica corpus

ri– Frequency Spectrum

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Productivity
Pronouns in Italian *la Repubblica* corpus

![Graph showing pronoun usage over N (log)](image-url)
Pronouns in Italian *la Repubblica* corpus

![Graph showing pronoun usage over time](image-url)
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Pronouns in Italian *la Repubblica* corpus

pronouns Frequency Spectrum

frequency class (log)

types

1 100 10000
0.6 0.8 1.0 1.2 1.4

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V as a measure of productivity

- Valid only for corpora/samples of equal size!
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- Good first approximation, but it is measuring attestedness, not potential:
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  - (According to rough BNC counts) *de-* verbs have V of 141, *un-* verbs have V of 119, contra our intuition
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  - We want productivity index of pronouns to be 0, not 72!
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- (V of whole population \textit{could} measure potential – see below)
Hapax legomena and productivity

- Plots show relation between productivity and hapax legomena
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Hapax legomena and productivity

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- Intuition: hapax legomena are words we did not see before in our sample, until the moment in which we sample them.
- There is a close relation between hapax legomena and words-yet-to-be-seen.
Hapax legomena and productivity

- If the word we sample after seeing N tokens is a hapax legomenon, this means that the word was not in the N tokens seen up to that point, i.e., it is a new word at that point.
Hapax legomena and productivity

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- A *productive* process is a process that is more likely than others to produce new words.
Hapax legomena and productivity

- If the word we sample after seeing N tokens is a hapax legomenon, this means that the word was not in the N tokens seen up to that point, i.e., it is a *new* word at that point.

- A *productive* process is a process that is more likely than others to produce new words.

- Thus, the more a process is productive, the more it is likely that the next word we see that has been generated by that process is a new word.
Operationalize *productivity* of a process as probability that the next token created by the process that we sample is a new word.
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This is same as probability that next token in sample is hapax legomenon.
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This is same as probability that next token in sample is hapax legomenon.

Thus, we can estimate probability of sampling a new word as relative frequency of hapax legomena in our sample:

\[ P = \frac{V_1}{N} \]

(where V1 and N are limited to words displaying the relevant process)
Baayen’s $P$

$$P = \frac{V_1}{N}$$

- Probability to sample token representing type we will never encounter again (token labeled “hapax”) at first stage of sampling (when we are at the beginning of N-token-sample) is given by the proportion of hapaxes in the whole N-token-sample divided by the total number of tokens in the sample.
Baayen’s $\mathcal{P}$

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- Thus, this must also be probability that last token sampled represents new type.
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- Thus, this must also be probability that last token sampled represents new type.

- $\mathcal{P}$ as productivity measure matches intuition that productivity should measure *potential* of process to generate new forms.
$P$ measures the potentiality of growth of $V$ in a very literal way, i.e., it is the growth rate of $V$, the rate at which vocabulary size increases.
\( P \) as vocabulary growth rate

- \( P \) measures the potentiality of growth of V in a very literal way, i.e., it is the growth rate of V, the rate at which vocabulary size increases.
- \( P \) is (approximation to) the derivative of V at N, i.e., the slope of the tangent to the vocabulary growth curve at N (Baayen 2001, pp. 49-50).
\( P \) as vocabulary growth rate

- \( P \) measures the potentiality of growth of \( V \) in a very literal way, i.e., it is the growth rate of \( V \), the rate at which vocabulary size increases.

- \( P \) is (approximation to) the *derivative* of \( V \) at \( N \), i.e., the slope of the tangent to the vocabulary growth curve at \( N \) (Baayen 2001, pp. 49-50).

- Again, “rate of growth” of vocabulary generated by `wf` process seems good match for intuition about productivity of `wf` process.
**ri-** in Italian *la Repubblica* corpus

![Graph showing the VGC curve for **ri-** with a tangent at N = 280K.](image)
Pronouns in Italian *la Repubblica* corpus

pronouns VGC with tangent at $N = 5000$
## Baayen’s $\mathcal{P}$ and intuition

<table>
<thead>
<tr>
<th>class</th>
<th>V</th>
<th>V1</th>
<th>N</th>
<th>$\mathcal{P}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>it. ri-</td>
<td>1098</td>
<td>346</td>
<td>1,399,898</td>
<td>0.00025</td>
</tr>
<tr>
<td>it. pronouns</td>
<td>72</td>
<td>0</td>
<td>4,313,123</td>
<td>0</td>
</tr>
<tr>
<td>en. un-</td>
<td>119</td>
<td>25</td>
<td>7,618</td>
<td>0.00328</td>
</tr>
<tr>
<td>en. de-</td>
<td>141</td>
<td>16</td>
<td>86,130</td>
<td>0.000185</td>
</tr>
</tbody>
</table>
Applications of $P$

- Extensive tradition of corpus-based analyses of derivational morphology based on $P$ (and V), by Baayen and colleagues (esp. English and Dutch), but not only (e.g., Lüdeling and Evert on German morphology, Gaeta and Ricca on Italian morphology)
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- $\mathcal{P}$ used as an exploratory tool
Baayen & Lieber 1991 on English derivation

- Large scale study of English derivation based on $P$ and $V$ with statistics extracted from CELEX database (= 18M tokens version of COBUILD)
Large scale study of English derivation based on $P$ and $V$ with statistics extracted from CELEX database (= 18M tokens version of COBUILD)

A few results:

- $\text{-ness} > \text{-ity}$
- $\text{-ish} > \text{-ous}$
- $\text{un-} > \text{in-}$
- $\text{-ation} > \text{-al}, \text{-ment}$
- But affixes such as $\text{-ity}, \text{-ous}$ and $\text{in-}$ have $P > 0$ (and there are category-of-the-base effects)

Dual nature of $\text{re-}$: few high frequency forms make it look unproductive (remove, recite, recall... but see below on $\text{re-}$, $P$ and sample size)
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- A few results:
  - $-ness > -ity; -ish > -ous; un- > in-; -ation > -al, -ment$
  - ...but affixes such as $-ity, -ous$ and $in-$ have $P > 0$ (and there are category-of-the-base effects)
  - dual nature of $re-$: few high frequency forms make it look unproductive ($remove, recite, recall...$) (but see below on $re-, P$ and sample size)
Plag, Dalton-Puffer & Baayen (1999)
Productivity across speech and writing

\( P \) and \( V \) in written, demographic spoken and
context-governed spoken sections of BNC (keep affix
contant, change corpus)
Plag, Dalton-Puffer & Baayen (1999)
Productivity across speech and writing

- $P$ and $V$ in written, demographic spoken and context-governed spoken sections of BNC (keep affix constant, change corpus)

- Strong effect of “register”, with productivity higher in written than spoken, and context-governed spoken higher than demographic spoken (productivity as a dimension of register variation)
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- Strong effect of “register”, with productivity higher in written than spoken, and context-governed spoken higher than demographic spoken (productivity as a dimension of register variation)
- Different productivity of different affixes in different registers: -like is “written-only”, -ness is strongly “written”, productivity reversal of -ize and -ish in written vs. demographic
Plag, Dalton-Puffer & Baayen (1999)
Productivity across speech and writing

- $\mathcal{P}$ and V in written, demographic spoken and context-governed spoken sections of BNC (keep affix constant, change corpus)
- Strong effect of “register”, with productivity higher in written than spoken, and context-governed spoken higher than demographic spoken (productivity as a dimension of register variation)
- Different productivity of different affixes in different registers: -$like$ is “written-only”, -$ness$ is strongly “written”, productivity reversal of -$ize$ and -$ish$ in written vs. demographic
- Productivity is affected by register, it cannot be explained in purely structural terms
Other examples

Gaeta and Ricca (2003): on the extremely high productivity of the Italian “neo-”prefixes *mega-, iper-, super-, maxi-, ultra-*. 
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- Lüdeling and Evert (2005): medical and non-medical *-itis* in XXth century German (with focus on methodological aspects)
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Methodological issues

- Pre-processing/preparing the data
Methodological issues

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- Effect of N on $P$
IT IS IMPORTANT!!!

Pre-processing

- IT IS IMPORTANT!!!

Methodological issues in measuring quantitative productivity
The interpretation of (quantitative) productivity

Pre-processing and sample size
Pre-processing

- IT IS IMPORTANT!!!
- Baayen, strangely, does not seem to worry
Pre-processing

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- At least two aspects:
IT IS IMPORTANT!!!

Baayen, strangely, does not seem to worry

At least two aspects:

Problems of (automated) data-cleaning/complex word identification (Evert and Lüdeling 2001)
Pre-processing

- IT IS IMPORTANT!!!
- Baayen, strangely, does not seem to worry
- At least two aspects:
  - Problems of (automated) data-cleaning/complex word identification (Evert and Lüdeling 2001)
  - Theoretical issues (delimitation and identification of application of a wf process) (Gaeta and Ricca 2003, to appear)
Automated data-cleaning/complex word identification

- Often necessary (13,850 types begin with *re-* in BNC, 103,941 types begin with *ri-* in itWaC)
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- 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)
The problem with low frequency words

- Correct analysis of low frequency words is fundamental to measure productivity
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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

- The Italian TreeTagger lemmatizer is lexicon-based; out-of-lexicon words (e.g., productively formed words containing a prefix) are lemmatized as UNKNOWN.
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- 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

![Graph showing productivity of *ri*- with and without an extended lexicon](image-url)
Overestimation of hapaxes

- “Noise” generates hapax legomena
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Overestimation of hapaxes

- “Noise” generates hapax legomena
- The Italian TreeTagger seems to think 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

pronouns VGC with/without cleaning

V

<table>
<thead>
<tr>
<th>N (log)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00</td>
</tr>
<tr>
<td>1.00</td>
</tr>
<tr>
<td>2.00</td>
</tr>
<tr>
<td>3.00</td>
</tr>
<tr>
<td>4.00</td>
</tr>
</tbody>
</table>

Marco Baroni

Productivity
**Pre-processing**

(\textit{P} and sample size)

### (P and V) with/without correct post-processing

**With:**

<table>
<thead>
<tr>
<th>class</th>
<th>V</th>
<th>V1</th>
<th>N</th>
<th>(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ri-pronouns</td>
<td>1098</td>
<td>346</td>
<td>1,399,898</td>
<td>0.00025</td>
</tr>
<tr>
<td></td>
<td>72</td>
<td>0</td>
<td>4,313,123</td>
<td>0</td>
</tr>
</tbody>
</table>

**Without:**

<table>
<thead>
<tr>
<th>class</th>
<th>V</th>
<th>V1</th>
<th>N</th>
<th>(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ri-pronouns</td>
<td>318</td>
<td>8</td>
<td>1,268,244</td>
<td>0.000006</td>
</tr>
<tr>
<td></td>
<td>348</td>
<td>206</td>
<td>4,314,381</td>
<td>0.000048</td>
</tr>
</tbody>
</table>
Linguistic analysis issues

- Which of the following forms should be counted as prefixed forms with re-? *redo, remove, retain, remake* (as a noun), *resyllabification*
Linguistic analysis issues

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- How about *re*-? *re-conquer the city* vs. *re-play the song*

- Is *deXize* a different wf process from *de*-?
THESE ARE SERIOUS PROBLEMS!

- Given the current state of NLP tools (especially for languages other than English)
THESE ARE SERIOUS PROBLEMS!

- Given the current state of NLP tools (especially for languages other than English)
- and the typical resources of morphologists
Given the current state of NLP tools (especially for languages other than English) and the typical resources of morphologists, large-scale, methodologically sound quantitative productivity studies are unfeasible.
It should be obvious that as N increases, V also increases (for at-least-mildly-productive processes)
It should be obvious that as $N$ increases, $V$ also increases (for at-least-mildly-productive processes).

Thus, $V$ cannot be compared at different $Ns$. 

Marco Baroni  
Productivity
V and N
English *re-* and *mis-*
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Thus, $V$ cannot be compared at different $Ns$
and sample size

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- However, the growth rate is also systematically decreasing as N becomes larger
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Thus, $V$ cannot be compared at different $N$s

However, the growth rate is also systematically decreasing as $N$ becomes larger

At the beginning, any word will be a hapax legomenon; as sample increases, hapaxes will be increasingly lower proportion of sample

A specific instance of the more general problem of “variable constants” (Tweedie and Baayen 1998) in lexical statistics (cf. type/token ratio)
Growth rate of *re*− at different sample sizes

re− VGC (tangents at N = 22.5K, 134.5K)
Pre-processing

$P$ and sample size

$P$ as a function of $N$ (re-)

$P$ in function of $N$ (re–)

$P$

$N$ (log)

Marco Baroni  Productivity
The solution: control N
Gaeta and Ricca (to appear)

- Always compute $P$ at comparable N
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Gaeta and Ricca (to appear)

- Always compute $P$ at comparable N
- Given two wf processes with sample sizes $N_a$ and $N_b$, with $N_a > N_b$, measure $P$ at $N_b$ for both processes
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- If more than 2 processes are compared, do comparison pairwise and use transitivity, to minimize data loss
- I.e., if 3 processes have sample sizes $N_a > N_b > N_c$, compare processes $a$ and $b$ at $N_b$, $b$ and $c$ at $N_c$ and infer productivity ranking of $a$ and $c$ on the basis of their relationship to $b$
Controlling N: $P$

<table>
<thead>
<tr>
<th>class</th>
<th>$N = 6097$</th>
<th>$N = 35107$</th>
<th>$N = 223970$</th>
</tr>
</thead>
<tbody>
<tr>
<td>re-</td>
<td>0.007</td>
<td>0.00098</td>
<td>0.000085</td>
</tr>
<tr>
<td>en-</td>
<td>0.00075</td>
<td>0.00014</td>
<td>NA</td>
</tr>
<tr>
<td>mis-</td>
<td>0.00082</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>
### Controlling N: V1 (interpolated values!)

<table>
<thead>
<tr>
<th>class</th>
<th>$N = 6097$</th>
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</tr>
</thead>
<tbody>
<tr>
<td>re-</td>
<td>43.7</td>
<td>34.4</td>
<td>19</td>
</tr>
<tr>
<td>en-</td>
<td>4.5</td>
<td>5</td>
<td>NA</td>
</tr>
<tr>
<td>mis-</td>
<td>5</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

Marco Baroni  
Productivity
Problems

- We are throwing away data
Problems

- We are throwing away data
- Clumpiness and other non-randomness effects
Non-randomness
Empirical and interpolated VGCs of BNC

Empirical and expected VGCs of BNC
Non-randomness
The “real” re-VGC

Empirical re-VGC

N
0 50000 100000 150000 200000
0 50 100 150 200 250 300
V and V1
Non-randomness

- At least two issues:
Non-randomness

At least two issues:

- Clumpiness (well above one third of the non hapaxes in the “too much” data-set of Lüdeling/Baroni/Evert occur more than once in the same document)
Non-randomness

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At least two issues:

- **Clumpiness**: (well above one third of the non hapaxes in the “too much” data-set of Lüdeling/Baroni/Evert occur more than once in the same document)
- **Effects of specialized language, genre, register**: (in our version of BNC, spoken texts are almost entirely at end of corpus)

For less frequent process, we take sample from whole corpus, whereas for more frequent process we take sample from first $N_{sub}$ tokens, probably resulting in more clumpiness and less variety of genre and topics
The importance of randomization

- Randomize the order of words in corpus
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- This can be done efficiently and soundly by using *binomial interpolation* (Baayen 2001, ch. 2)
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- Most plots shown on these slides are based on binomial interpolation
The importance of randomization

Counting number of documents in which a word occurs, rather than overall occurrences, might be a cure for clumpiness (but increases data-sparse problems, and complicates the assumptions about sampling)
The importance of randomization

- Counting number of documents in which a word occurs, rather than overall occurrences, might be a cure for clumpiness (but increases data-sparseeness problems, and complicates the assumptions about sampling).
- However, non-randomized VGC plot provides very valuable information, and should always be included in quantitative productivity studies.
Non-randomness: a bigger problem

- The whole corpus is probably a non-random sample of the “population” we are interested in (e.g., the population of words illustrating word formation with re-, or the population of words known by an English speaker)
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The whole corpus is probably a non-random sample of the “population” we are interested in (e.g., the population of words illustrating word formation with re-, or the population of words known by an English speaker)

Unfortunately, we cannot take a randomized sub-sample from the whole population like we can do when taking a sub-sample from the whole corpus (that’s what a corpus is supposed to be in the first instance!)
Non-randomness and parametric (lexico-)statistical models

Non-randomness problems are seriously affecting the quality of parametric statistical models (Evert and Baroni to appear, and ongoing work)
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- This is a pity, since these models would allow us to extrapolate $V$ and $V_1$ to arbitrary values (including $V$ and $V_1$ in the whole population), and to test significance of differences
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- (Please stay tuned)
Productivity: cause or effect?

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- See, e.g., Plag (1999), who uses quantitative productivity as exploratory tool, and looks for qualitative structural explanations (phonological, semantic, morphosyntactic) of different degree of productivity of similar affixes
Corpus-based “explanations” of $P$

- Hay and Baayen (2002, 2004; see also Baayen, 2003): parsing and productivity
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- Hay and Baayen (2002, 2004; see also Baayen, 2003): parsing and productivity
- My ongoing work on productivity and semantic transparency (Baroni and Vignaduzzo 2003, Baroni 2005)
Relative frequency and parsing

One important result of Hay (2003): in a number of tasks, affixed forms behave as morphologically complex iff their base is more frequent than the affixed form itself:
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- The higher the base-to-derived-form relative frequency is, the more likely it is that a word is treated as complex
Parsing and productivity

Hay and Baayen’s hypothesis:

Affixes that appear in many words that are parsed as complex in language perception (i.e., appear in many derived words that have lower frequency than their bases) will be more "active" in lexicon.

I.e., they will be more available for word formation, i.e., more productive.

Predicts correlation between P and relative frequency.

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Problems

- Could the correlation be due to the fact that both measures heavily rely on the number of low(est) frequency forms that contain a certain affix?
- More importantly, both $P$ and relative frequency seem to be useful *indices* of parsability/productivity, effects, not causes!
- If productivity is caused by low relative frequency of bases, what causes this low relative frequency? (Or vice versa?)
- Nature of variables as epiphenomenal indices seems to be recognized by Hay and Baayen (2004), which analyze a constellation of densely inter-correlated measures related to parsability and productivity.
Productivity and semantics

Observation: we have much clearer intuitions about what productive affixes mean than about what unproductive affixes mean.
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- Here, direction of causation should be clear
By hand, it is hard...
Measuring semantic transparency

- By hand, it is hard...
- but computational linguists have developed methods to measure semantic similarity among words (e.g., Manning and Schütze 1999)
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Degree of semantic transparency of complex form is degree of semantic similarity between complex form and its base
Contextual approach to meaning

- **Cruse 1986 (p. 1):**

  [Text content from Cruse 1986 (p. 1) discussing the contextual approach to meaning.]

  The semantic properties of a lexical item are fully reflected in appropriate aspects of the relations it contracts with actual and potential contexts. There are good reasons for a principled limitation to linguistic contexts.
Cruse 1986 (p. 1):

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Two knowledge poor operationalizations:
Contextual approach to meaning

- Cruse 1986 (p. 1):
  
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  - Semantically similar words occur in similar contexts
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Two knowledge poor operationalizations:
- Semantically similar words occur in similar contexts
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Contextual similarity

- Cosine (correlation) of normalized vectors representing co-occurrence frequency with all words within a certain window:

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My parameters:
- Targets: affixed form/base pairs
- Contexts: all content words
- Window: 1 sentence
Co-occurrence

- Measured by *Mutual Information* (MI):

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Wf processes explored

- “Baayen prefixes”
- Mean productivity rank assigned by 4 English morphologists:

<table>
<thead>
<tr>
<th>Prefix</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>un</td>
<td>1.500</td>
</tr>
<tr>
<td>re</td>
<td>1.625</td>
</tr>
<tr>
<td>mis</td>
<td>3.250</td>
</tr>
<tr>
<td>de</td>
<td>3.625</td>
</tr>
<tr>
<td>be</td>
<td>5.875</td>
</tr>
<tr>
<td>en</td>
<td>5.875</td>
</tr>
<tr>
<td>in</td>
<td>6.250</td>
</tr>
</tbody>
</table>
Extraction of prefixed forms

- From BNC
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- All forms that begin with prefix string and with base that:
  - is at least 3 letters long
  - occurs in the corpus as independent word
  - E.g., beads is treated as prefixed; bead and benny are not
  - More "sophisticated" methods (that rely on further automated processing) perform worse than this "brutal" approach
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- NB: hapax legomena are not playing a (crucial) role!
Results

- Morphologist’s rank:
  - un, re
  - mis, de
  - be, en, in
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Discussion

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- More nuance needed: polysemy of *in-* vs. *deXize*
Current work

On Italian *ri-*

- Inspect corpus contexts to determine distribution and scope of senses (iterative vs. restitutive)
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- Measure co-occurrence in relational patterns determined by mini-grammar (e.g., V ART? ADJ* N)
Current work
On Italian *ri-*

**Targets:**
- Single prefixed words
- Class of *ri-* words (compared to other prefixed/non-prefix ed words)
- Iterative vs. restitutive
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On Italian *ri-*

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  - Class of *ri-* words (compared to other prefixed/non-prefixed words)
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- **Patterns of co-occurrence (both similarities and differences):**
  - With bases (or prefixed forms with same bases)
  - With other *ri-* forms
  - With base+ *again*
  - Direct co-occurrence with words that tap into the semantics of *ri-*
An encouraging pilot study

- Hypothesis: words containing more transparent/productive prefixes will have higher semantic/distributional similarity to other words containing same prefix.
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An encouraging pilot study

- Hypothesis: words containing more transparent/productive prefixes will have higher semantic/distributional similarity to other words containing same prefix
  - *ri*- is more productive than *de*- in Italian (excluding *deXizzare* pattern)
- Prediction: on average, *ri*- words will have more *ri*- words in their distributionally defined nearest neighbor set than *de*- words will have other *de*- words
Distributional data

- 1.9B token Web-crawled itWaC corpus (Baroni and Ueyama 2006)
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- Based on Lin’s (1998) distributional similarity measure
Lin’s algorithm

Collect collocates of each target word with other words in small set of grammatically meaningful patterns (e.g., for V collects N collocates in patterns N ADJ* ADV* AUX* V, V ART* ADV* ADJ* N, etc.)
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- For each pair of target words (with same POS), compute score based on number of shared collocates, weighted by MI (so that more unusual collocates will have more weight)
- Pick as neighbor set of a target word all other target words with similarity score above a certain threshold (I used WSE defaults)
Neighbor sets built in this way for our test words range from 31 to 59 members.
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- E.g., neighbor set of *ricomporre* (“to recompose”) include *ricostituire* (“to reconstitute”), *scomporre* (“to decompose”), *assemblare* (“to assemble”).
10 prefixed words with *ri-* and *de-* (but not *deXizzare*) randomly chosen from corpus (conditions: min fq ≥ 500, not in top 500 forms with prefix)
Experiment

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<table>
<thead>
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<th>min</th>
<th>med</th>
<th>mean</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>ri</em>-</td>
<td>3</td>
<td>14</td>
<td>13.4</td>
<td>25</td>
</tr>
<tr>
<td><em>de</em>-</td>
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- Percentage of forms with same prefix over total number of neighbors:

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<tr>
<td><em>ri-</em></td>
<td>10%</td>
<td>31%</td>
<td>28%</td>
<td>44%</td>
</tr>
<tr>
<td><em>de-</em></td>
<td>4%</td>
<td>8%</td>
<td>8%</td>
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“Need” in the interpretation of productivity

- Ongoing work with Anke Lüdeling and Stefan Evert

Corpus counts are influenced by the need to express a given thought/concept. Words are only formed as and when there is a need for them [..]

(Bauer 2001, 143)

The need to express something depends on extra-linguistic factors (like the political situation, fashion, etc.).
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- The need to express something depends on extra-linguistic factors (like the political situation, fashion, etc.)
- There is no *baayenitis* without Baayen!
If a wf process is the *only* way to express a need, $P$ will to a large extent measure extra-linguistic need, not factors relating to linguistic productivity.
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Competition

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Probably it does (ongoing work on a set of German compound heads meaning “too much” with a disease connotation).
Outline

1. Introduction
2. Quantitative productivity: Baayen’s approach
3. Methodological issues in measuring quantitative productivity
4. The interpretation of (quantitative) productivity
5. Conclusion
The work of Baayen and others on productivity of fundamental historical importance:
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- Early corpus-based work
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- Development of descriptive techniques (VGCs etc.) and index (P) to explore productivity in data-set
Corpus-based productivity measures, qualitative explanations often *not* based on corpus evidence
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Many other areas of application still to explore: e.g., non-morphological productivity in studies of lexical richness, stylometry
Very little corpus-based work on explaining productivity
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  - New analytical tools to study context and meaning from corpus linguistics, e.g., Stefanowitsch and Gries’ (2005 and elsewhere) collustructional analysis
THE END