

# Unit 5: Word Frequency Distributions with the *zipfR* package

## Statistics for Linguists with R – A SIGIL Course

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# Outline

## Lexical statistics & word frequency distributions

- Basic notions of lexical statistics

- Typical frequency distribution patterns

- Zipf's law

- Some applications

## Statistical LNRE Models

- ZM & fZM

- Sampling from a LNRE model

- Great expectations

- Parameter estimation for LNRE models

## zipfR

# Lexical statistics

Zipf (1949, 1965); Baayen (2001); Baroni (2008)

- ▶ Statistical study of the frequency distribution of **types** (words or other linguistic units) in texts
  - ▶ remember the distinction between **types** and **tokens**?
- ▶ Different from other categorical data because of the extreme richness of types
  - ▶ people often speak of **Zipf's law** in this context

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## Basic terminology

- ▶  $N$ : sample / corpus size, number of **tokens** in the sample
- ▶  $V$ : **vocabulary** size, number of distinct **types** in the sample
- ▶  $V_m$ : **spectrum element**  $m$ , number of types in the sample with frequency  $m$  (i.e. exactly  $m$  occurrences)
- ▶  $V_1$ : number of **hapax legomena**, types that occur only once in the sample (for hapaxes, #types = #tokens)
  
- ▶ A sample: a b b c a a b a
- ▶  $N = 8$ ,  $V = 3$ ,  $V_1 = 1$

# Rank / frequency profile

- ▶ The sample: c a a b c c a c d
- ▶ Frequency list ordered by decreasing frequency

<i>t</i>	<i>f</i>
c	4
a	3
b	1
d	1

## Rank / frequency profile

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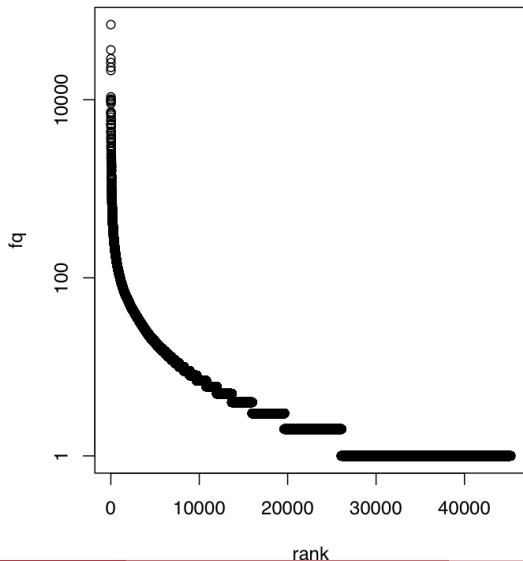
$t$	$f$
c	4
a	3
b	1
d	1

- ▶ Rank / frequency profile: ranks instead of type labels

$r$	$f$
1	4
2	3
3	1
4	1

- ▶ Expresses type frequency  $f_r$  as function of rank of a type

# Rank/frequency profile of Brown corpus



# Top and bottom ranks in the Brown corpus

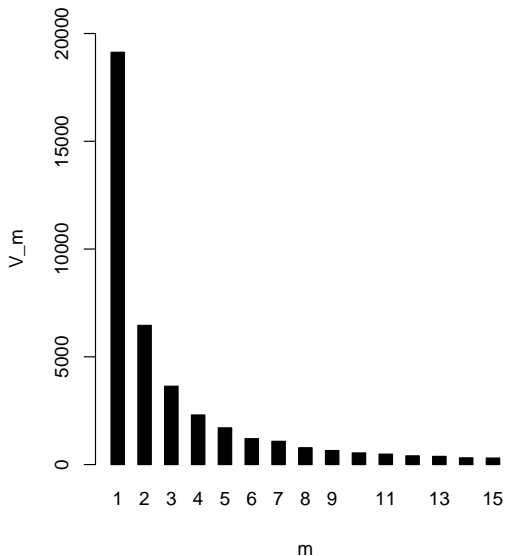
top frequencies			bottom frequencies		
<i>r</i>	<i>f</i>	word	rank range	<i>f</i>	randomly selected examples
1	62642	the	7967– 8522	10	recordings, undergone, privileges
2	35971	of	8523– 9236	9	Leonard, indulge, creativity
3	27831	and	9237–10042	8	unnatural, Lolotte, authenticity
4	25608	to	10043–11185	7	diffraction, Augusta, postpone
5	21883	a	11186–12510	6	uniformly, throttle, agglutinin
6	19474	in	12511–14369	5	Bud, Councilman, immoral
7	10292	that	14370–16938	4	verification, gleamed, groin
8	10026	is	16939–21076	3	Princes, nonspecifically, Arger
9	9887	was	21077–28701	2	blitz, pertinence, arson
10	8811	for	28702–53076	1	Salaries, Evensen, parentheses

# Frequency spectrum

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

$m$	$V_m$
1	2
3	1
4	1

# Frequency spectrum of Brown corpus



# Vocabulary growth curve

- ▶ The sample: a b b c a a b a

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## Vocabulary growth curve

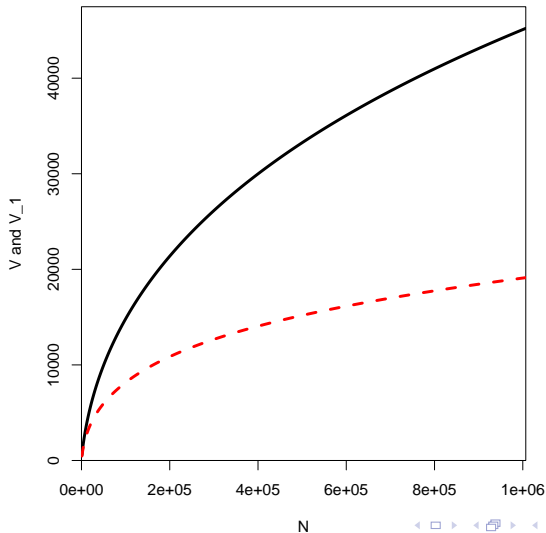
- ▶ The sample: a b b c a a b a
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- ▶  $N = 3, V = 2, V_1 = 1$  ( $V_2 = 1, V_3 = 0, \dots$ )
- ▶  $N = 5, V = 3, V_1 = 1$  ( $V_2 = 2, V_3 = 0, \dots$ )

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- ▶  $N = 5, V = 3, V_1 = 1$  ( $V_2 = 2, V_3 = 0, \dots$ )
- ▶  $N = 8, V = 3, V_1 = 1$  ( $V_2 = 0, V_3 = 1, V_4 = 1, \dots$ )

# Vocabulary growth curve of Brown corpus

With  $V_1$  growth in red (curve smoothed with binomial interpolation)



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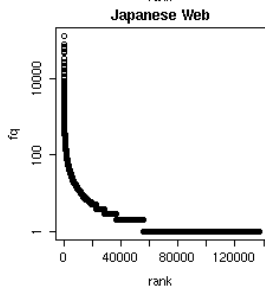
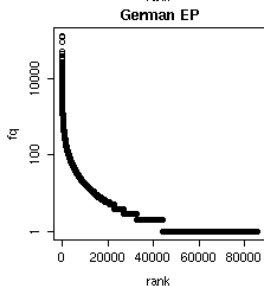
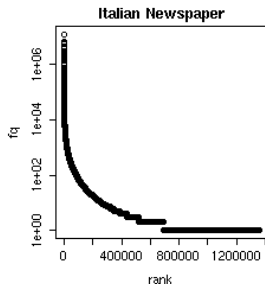
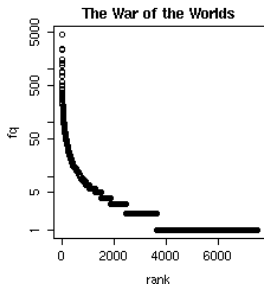
Great expectations

Parameter estimation for LNRE models

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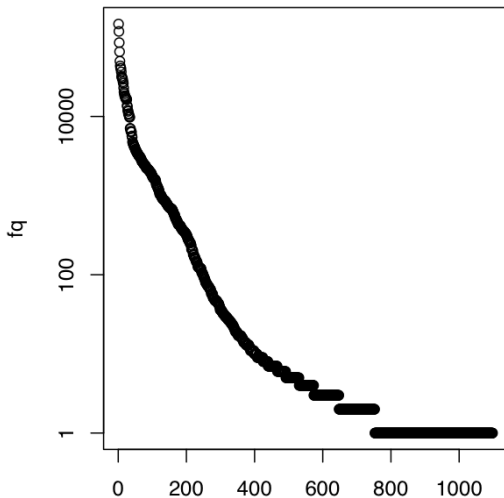
# Typical frequency patterns

Across text types & languages



# Typical frequency patterns

The Italian prefix *ri-* in the *la Repubblica* corpus

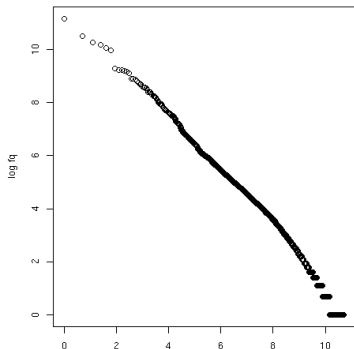


## Is there a general law?

- ▶ Language after language, corpus after corpus, linguistic type after linguistic type, ... we observe the same “few giants, many dwarves” pattern
- ▶ Similarity of plots suggests that relation between rank and frequency could be captured by a general law

# Is there a general law?

- ▶ Language after language, corpus after corpus, linguistic type after linguistic type, ... we observe the same “few giants, many dwarves” pattern
- ▶ Similarity of plots suggests that relation between rank and frequency could be captured by a general law
- ▶ Nature of this relation becomes clearer if we plot  $\log f$  as a function of  $\log r$



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# Zipf's law

- ▶ Straight line in double-logarithmic space corresponds to **power law** for original variables
- ▶ This leads to Zipf's (1949; 1965) famous law:

$$f(w) = \frac{C}{r(w)^a}$$

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- ▶ This leads to Zipf's (1949; 1965) famous law:

$$f(w) = \frac{C}{r(w)^a}$$

- ▶ With  $a = 1$  and  $C = 60,000$ , Zipf's law predicts that:
  - ▶ most frequent word occurs 60,000 times
  - ▶ second most frequent word occurs 30,000 times
  - ▶ third most frequent word occurs 20,000 times
  - ▶ and there is a long tail of 80,000 words with frequencies between 1.5 and 0.5 occurrences(!)

# Zipf's law

## Logarithmic version

- ▶ Zipf's power law:

$$f(w) = \frac{C}{r(w)^a}$$

- ▶ If we take logarithm of both sides, we obtain:

$$\log f(w) = \log C - a \log r(w)$$

- ▶ Zipf's law predicts that rank / frequency profiles are straight lines in double logarithmic space
- ▶ Best fit  $a$  and  $C$  can be found with least-squares method

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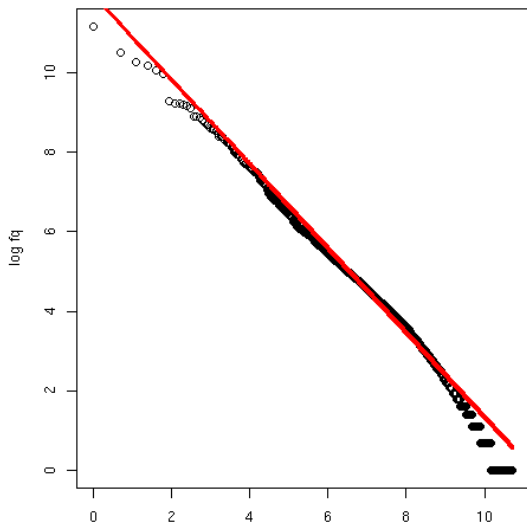
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- ▶ Zipf's law predicts that rank / frequency profiles are straight lines in double logarithmic space
- ▶ Best fit  $a$  and  $C$  can be found with least-squares method
- ▶ Provides intuitive interpretation of  $a$  and  $C$ :
  - ▶  $a$  is **slope** determining how fast log frequency decreases
  - ▶  $\log C$  is **intercept**, i.e., predicted log frequency of word with rank 1 (log rank 0) = most frequent word

# Zipf's law

Fitting the Brown rank/frequency profile



# Zipf-Mandelbrot law

Mandelbrot (1953, 1962)

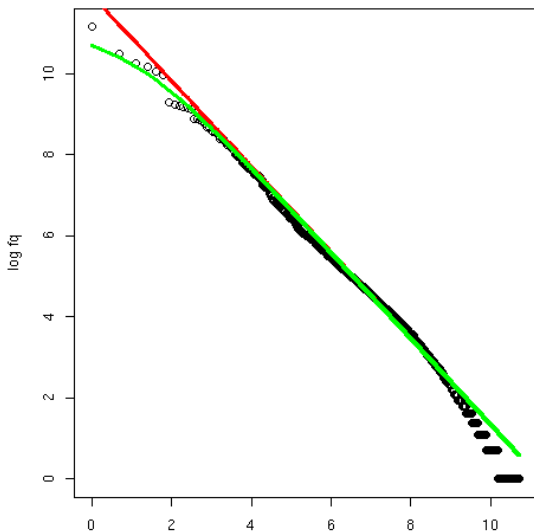
- ▶ Mandelbrot's extra parameter:

$$f(w) = \frac{C}{(r(w) + b)^a}$$

- ▶ Zipf's law is special case with  $b = 0$
- ▶ Assuming  $a = 1$ ,  $C = 60,000$ ,  $b = 1$ :
  - ▶ For word with rank 1, Zipf's law predicts frequency of 60,000; Mandelbrot's variation predicts frequency of 30,000
  - ▶ For word with rank 1,000, Zipf's law predicts frequency of 60; Mandelbrot's variation predicts frequency of 59.94
- ▶ Zipf-Mandelbrot law forms basis of statistical LNRE models
  - ▶ ZM law derived mathematically as limiting distribution of vocabulary generated by a character-level Markov process

# Zipf-Mandelbrot vs. Zipf's law

Fitting the Brown rank/frequency profile



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# Applications of word frequency distributions

- ▶ Most important application: **extrapolation** of vocabulary size and frequency spectrum to larger sample sizes
  - ▶ productivity (in morphology, syntax, ...)
  - ▶ lexical richness  
(in stylometry, language acquisition, clinical linguistics, ...)
  - ▶ practical NLP (est. proportion of OOV words, typos, ...)
- 👉 need method for predicting vocab. growth on unseen data

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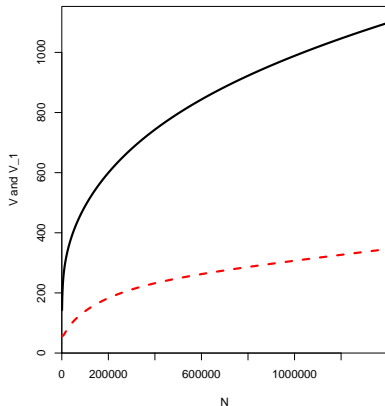
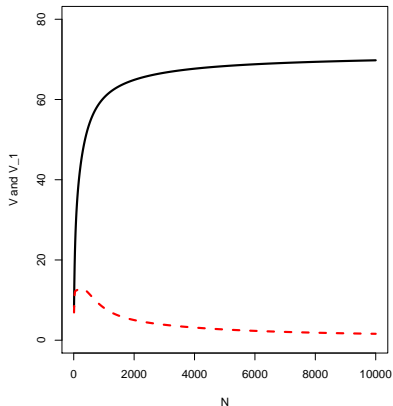
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- ▶ Direct applications of Zipf's law
  - ▶ population model for Good-Turing smoothing
  - ▶ realistic prior for Bayesian language modelling
- 👉 need model of type probability distribution in the population

Vocabulary growth: Pronouns vs. *ri-* in Italian

$N$	$V$ (pron.)	$V$ ( <i>ri-</i> )
5000	67	224
10000	69	271
15000	69	288
20000	70	300
25000	70	322
30000	71	347
35000	71	364
40000	71	377
45000	71	386
50000	71	400
...	...	...

# Vocabulary growth: Pronouns vs. *ri-* in Italian

## Vocabulary growth curves



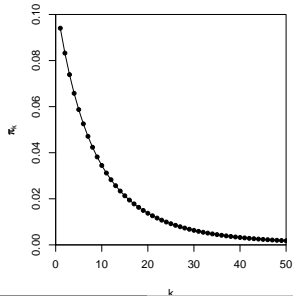
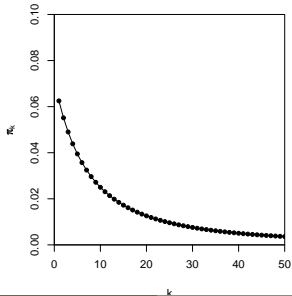
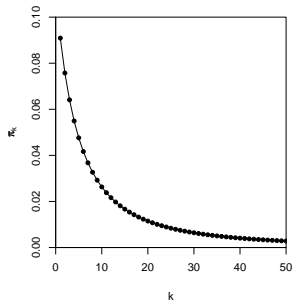
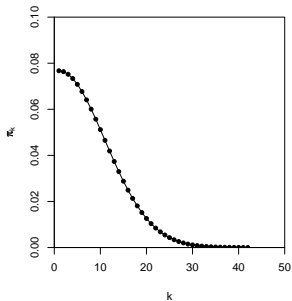
# LNRE models for word frequency distributions

- ▶ LNRE = large number of rare events (cf. Baayen 2001)
- ▶ Statistics: corpus = random sample from **population**
  - ▶ population characterised by vocabulary of **types**  $w_k$  with occurrence **probabilities**  $\pi_k$
  - ▶ not interested in specific types → arrange by decreasing probability:  $\pi_1 \geq \pi_2 \geq \pi_3 \geq \dots$
  - ▶ NB: not necessarily identical to Zipf ranking in sample!

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  - ▶ NB: not necessarily identical to Zipf ranking in sample!
- ▶ **LNRE model** = population model for type probabilities, i.e. a function  $k \mapsto \pi_k$  (with small number of parameters)
  - ▶ type probabilities  $\pi_k$  cannot be estimated reliably from a corpus, but parameters of LNRE model can

# Examples of population models



# The Zipf-Mandelbrot law as a population model

What is the right family of models for lexical frequency distributions?

- ▶ We have already seen that the Zipf-Mandelbrot law captures the distribution of observed frequencies very well

# The Zipf-Mandelbrot law as a population model

What is the right family of models for lexical frequency distributions?

- ▶ We have already seen that the Zipf-Mandelbrot law captures the distribution of observed frequencies very well
- ▶ Re-phrase the law for type probabilities:

$$\pi_k := \frac{C}{(k + b)^a}$$

- ▶ Two free parameters:  $a > 1$  and  $b \geq 0$
- ▶  $C$  is not a parameter but a normalization constant, needed to ensure that  $\sum_k \pi_k = 1$
- ▶ this is the **Zipf-Mandelbrot** population model

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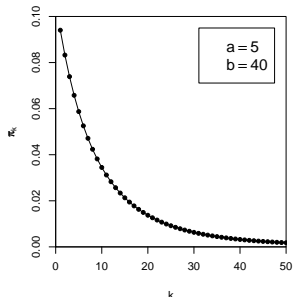
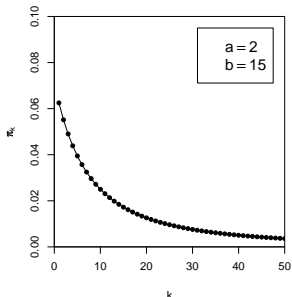
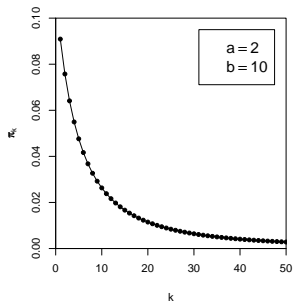
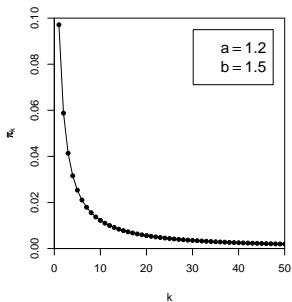
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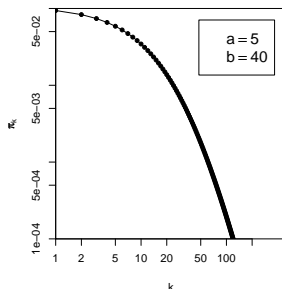
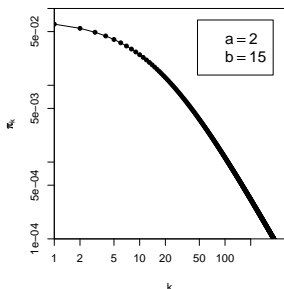
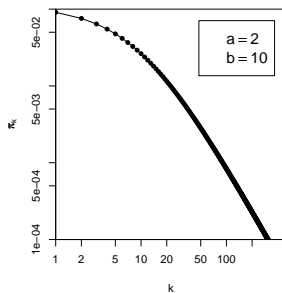
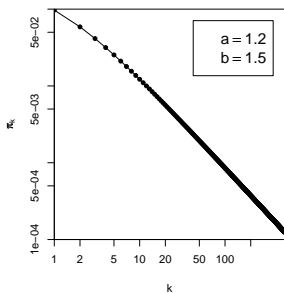
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# The parameters of the Zipf-Mandelbrot model



# The parameters of the Zipf-Mandelbrot model



## The finite Zipf-Mandelbrot model

- ▶ Zipf-Mandelbrot population model characterizes an *infinite* type population: there is no upper bound on  $k$ , and the type probabilities  $\pi_k$  can become arbitrarily small
- ▶  $\pi = 10^{-6}$  (once every million words),  $\pi = 10^{-9}$  (once every billion words),  $\pi = 10^{-12}$  (once on the entire Internet),  $\pi = 10^{-100}$  (once in the universe?)

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- ▶ Alternative: finite (but often very large) number of types in the population
- ▶ We call this the **population vocabulary size**  $S$  (and write  $S = \infty$  for an infinite type population)

# The finite Zipf-Mandelbrot model

Evert (2004)

- ▶ The **finite Zipf-Mandelbrot** model simply stops after the first  $S$  types ( $w_1, \dots, w_S$ )
- ▶  $S$  becomes a new parameter of the model  
→ the finite Zipf-Mandelbrot model has 3 parameters

Abbreviations:

- ▶ **ZM** for Zipf-Mandelbrot model
- ▶ **fZM** for finite Zipf-Mandelbrot model

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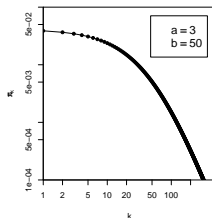
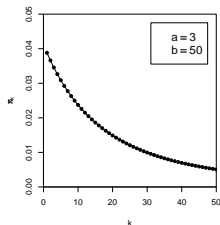
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# Sampling from a population model

Assume we believe that the population we are interested in can be described by a Zipf-Mandelbrot model:



Use computer simulation to sample from this model:

- ▶ Draw  $N$  tokens from the population such that in each step, type  $w_k$  has probability  $\pi_k$  to be picked
- ▶ This allows us to make predictions for samples (= corpora) of arbitrary size  $N \rightarrow$  extrapolation

# Sampling from a population model

#1: 1 42 34 23 108 18 48 18 1 ...

# Sampling from a population model

```
#1: 1 42 34 23 108 18 48 18 1 ...  
    time order room school town course area course time ...
```

# Sampling from a population model

#1: 1 42 34 23 108 18 48 18 1 ...  
time order room school town course area course time ...

#2: 286 28 23 36 3 4 7 4 8 ...

# Sampling from a population model

<b>#1:</b>	1	42	34	23	108	18	48	18	1	...
	time	order	room	school	town	course	area	course	time	...
<b>#2:</b>	286	28	23	36	3	4	7	4	8	...
<b>#3:</b>	2	11	105	21	11	17	17	1	16	...

# Sampling from a population model

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	time	order	room	school	town	course	area	course	time	...
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<b>#3:</b>	2	11	105	21	11	17	17	1	16	...
<b>#4:</b>	44	3	110	34	223	2	25	20	28	...
<b>#5:</b>	24	81	54	11	8	61	1	31	35	...
<b>#6:</b>	3	65	9	165	5	42	16	20	7	...
<b>#7:</b>	10	21	11	60	164	54	18	16	203	...
<b>#8:</b>	11	7	147	5	24	19	15	85	37	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

# Samples: type frequency list & spectrum

rank $r$	$f_r$	type $k$	$m$	$V_m$
1	37	6	1	83
2	36	1	2	22
3	33	3	3	20
4	31	7	4	12
5	31	10	5	10
6	30	5	6	5
7	28	12	7	5
8	27	2	8	3
9	24	4	9	3
10	24	16	10	3
11	23	8	$\vdots$	$\vdots$
12	22	14	$\vdots$	$\vdots$
$\vdots$	$\vdots$	$\vdots$		

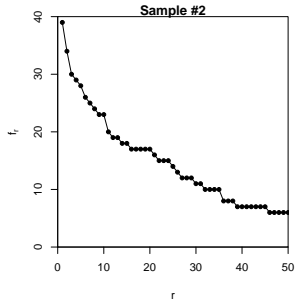
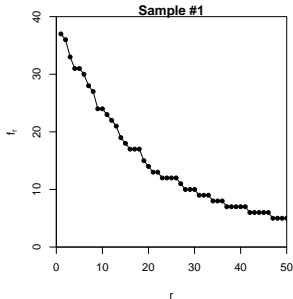
sample #1

# Samples: type frequency list & spectrum

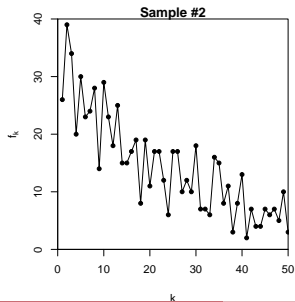
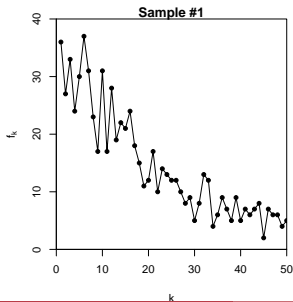
rank $r$	$f_r$	type $k$	$m$	$V_m$
1	39	2	1	76
2	34	3	2	27
3	30	5	3	17
4	29	10	4	10
5	28	8	5	6
6	26	1	6	5
7	25	13	7	7
8	24	7	8	3
9	23	6	10	4
10	23	11	11	2
11	20	4	⋮	⋮
12	19	17		
⋮	⋮	⋮		

sample #2

# Random variation in type-frequency lists

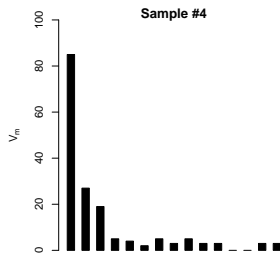
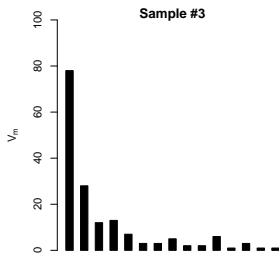
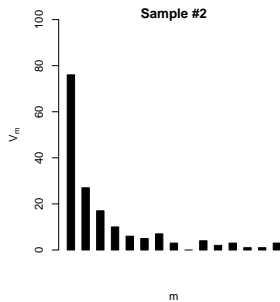
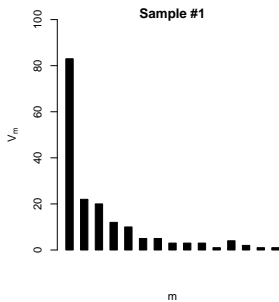


$$r \leftrightarrow f_r$$

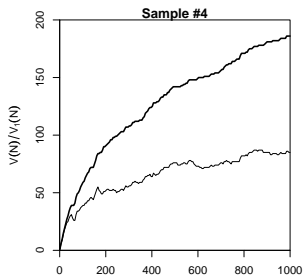
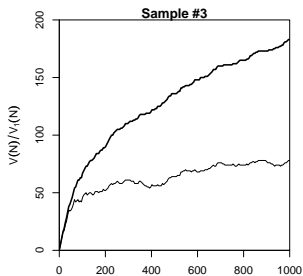
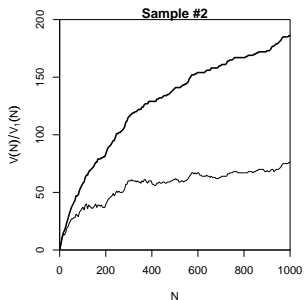
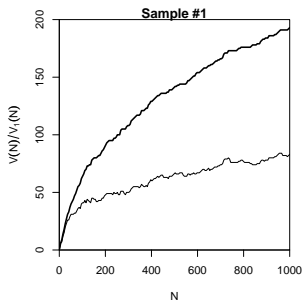


$$k \leftrightarrow f_k$$

# Random variation: frequency spectrum



# Random variation: vocabulary growth curve



# Outline

## Lexical statistics & word frequency distributions

- Basic notions of lexical statistics

- Typical frequency distribution patterns

- Zipf's law

- Some applications

## Statistical LNRE Models

- ZM & fZM

- Sampling from a LNRE model

- Great expectations**

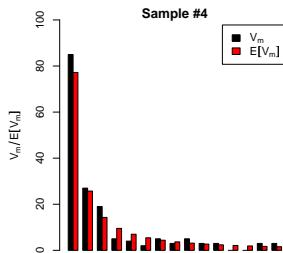
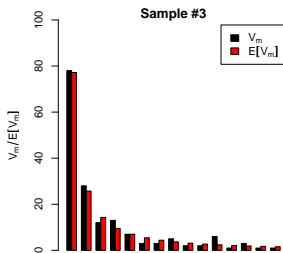
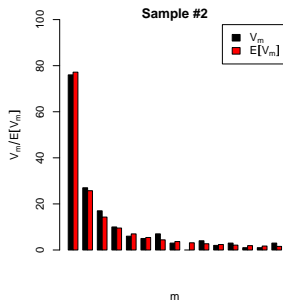
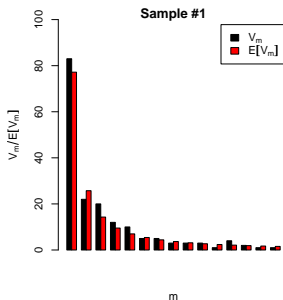
- Parameter estimation for LNRE models

zipfR

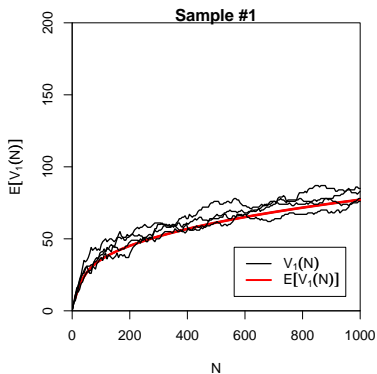
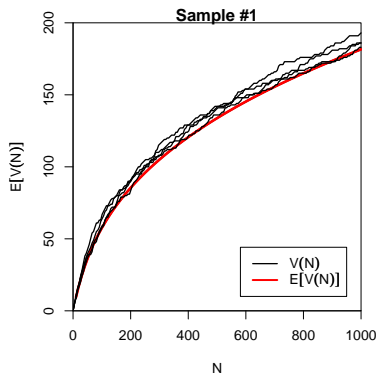
## Expected values

- ▶ There is no reason why we should choose a particular sample to make a prediction for the real data – each one is equally likely or unlikely
- ▶ Take the average over a large number of samples, called **expected value** or **expectation** in statistics
- ▶ Notation:  $E[V(N)]$  and  $E[V_m(N)]$ 
  - ▶ indicates that we are referring to expected values for a sample of size  $N$
  - ▶ rather than to the specific values  $V$  and  $V_m$  observed in a particular sample or a real-world data set
- ▶ Expected values can be calculated efficiently *without* generating thousands of random samples

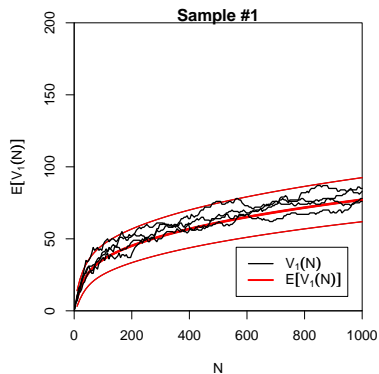
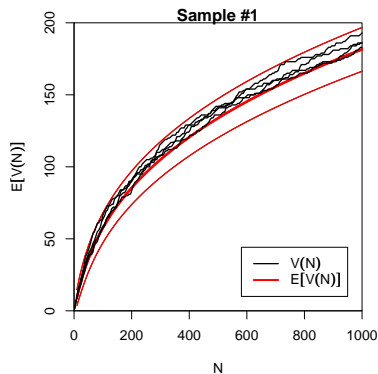
# The expected frequency spectrum



# The expected vocabulary growth curve



# Confidence intervals for the expected VGC



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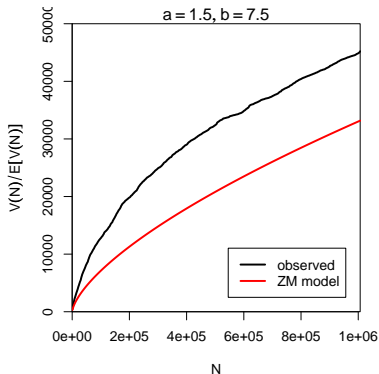
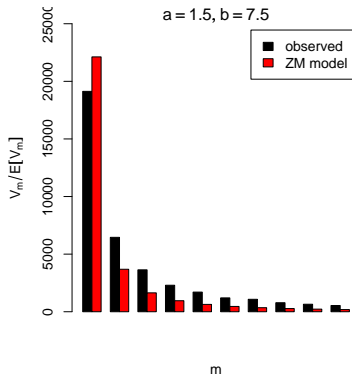
- Sampling from a LNRE model

- Great expectations

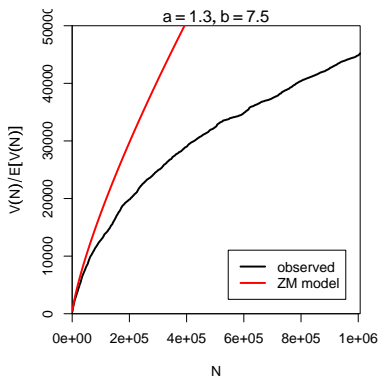
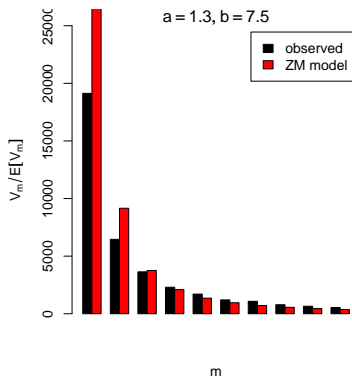
- Parameter estimation for LNRE models

zipfR

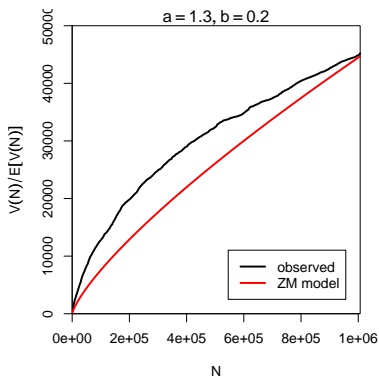
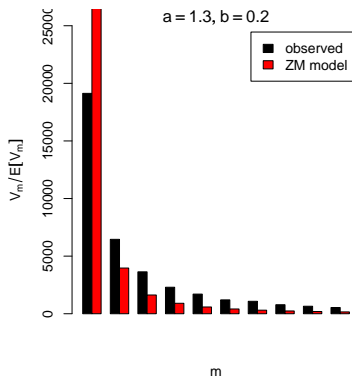
# Parameter estimation by trial & error



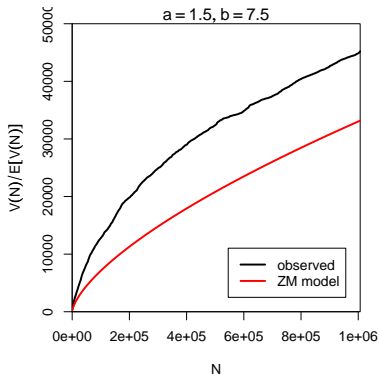
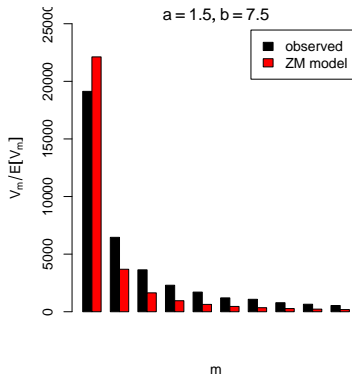
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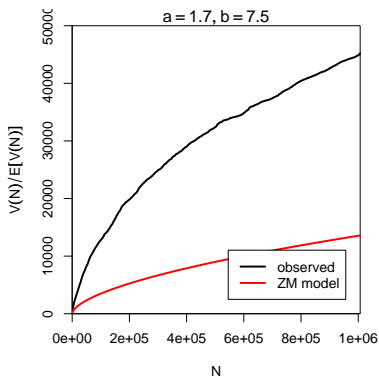
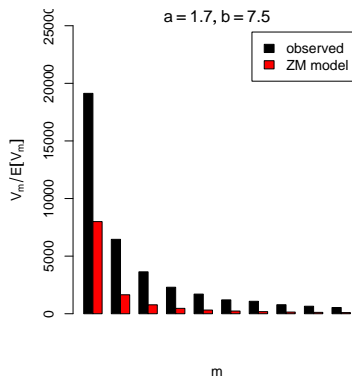
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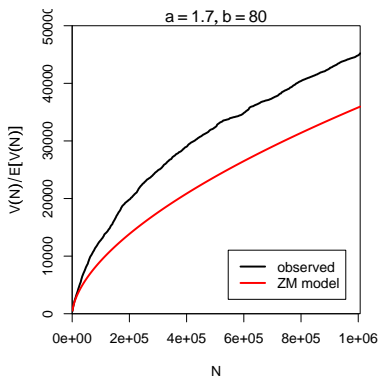
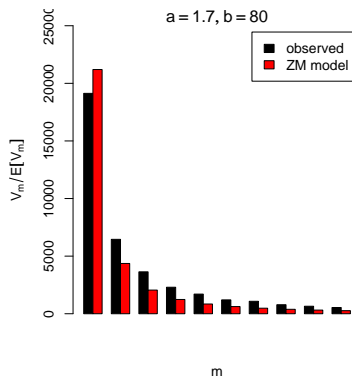
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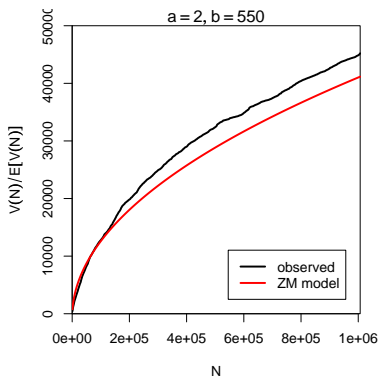
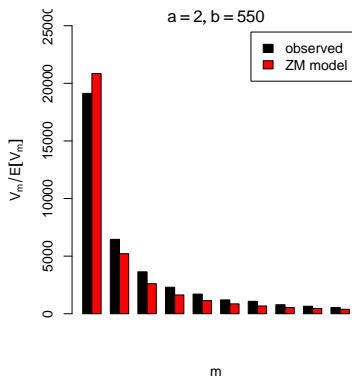
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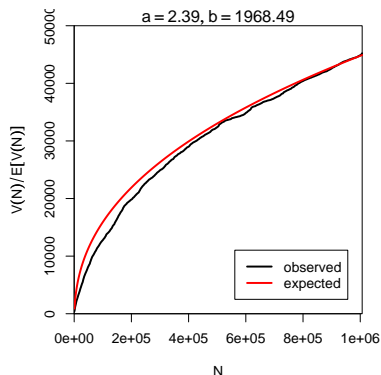
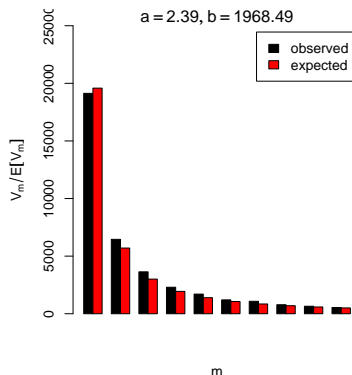
# Parameter estimation by trial & error



# Parameter estimation by trial & error



# Automatic parameter estimation



- ▶ By trial & error we found  $a = 2.0$  and  $b = 550$
- ▶ Automatic estimation procedure:  $a = 2.39$  and  $b = 1968$
- ▶ Goodness-of-fit:  $p \approx 0$  (multivariate chi-squared test)

# Summary

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  - ▶ in principle, you should only go on if model gives a plausible explanation of the observed data!
4. use LNRE model to compute **expected** frequency spectrum for arbitrary sample sizes
  - **extrapolation** of vocabulary growth curve
    - ▶ or use population model directly as Bayesian prior etc.

# zipfR

Evert and Baroni (2007)

- ▶ <http://zipfR.R-Forge.R-Project.org/>
- ▶ Conveniently available from CRAN repository
  - ▶ see Unit 1 for general package installation guides



# Loading

```
> library(zipfR)  
  
> ?zipfR  
  
> data(package="zipfR")
```

## Importing data

```
> data(ItaRi.spc)
> data(ItaRi.emp.vgc)

> my.spc <- read.spc("my.spc.txt")
> my.vgc <- read.vgc("my.vgc.txt")

> my.tfl <- read.tfl("my.tfl.txt")
> my.spc <- tfl2spc(my.tfl)
```

## Looking at spectra

```
> summary(ItaRi.spc)
> ItaRi.spc

> N(ItaRi.spc)
> V(ItaRi.spc)
> Vm(ItaRi.spc,1)
> Vm(ItaRi.spc,1:5)

# Baayen's P
> Vm(ItaRi.spc,1) / N(ItaRi.spc)

> plot(ItaRi.spc)
> plot(ItaRi.spc, log="x")
```

## Looking at VGCs

```
> summary(ItaRi.emp.vgc)
> ItaRi.emp.vgc

> N(ItaRi.emp.vgc)

> plot(ItaRi.emp.vgc, add.m=1)
```

## Creating VGCs with binomial interpolation

```
# interpolated VGC
```

```
> ItaRi.bin.vgc <- vgc.interp(ItaRi.spc,  
  N(ItaRi.emp.vgc), m.max=1)
```

```
> summary(ItaRi.bin.vgc)
```

```
# comparison
```

```
> plot(ItaRi.emp.vgc, ItaRi.bin.vgc,  
  legend=c("observed", "interpolated"))
```

## *ultra-*

- ▶ Load the spectrum and empirical VGC of the less common prefix *ultra-*
- ▶ Compute binomially interpolated VGC for *ultra-*
- ▶ Plot the binomially interpolated *ri-* and *ultra-* VGCs together

## Estimating LNRE models

# fZM model; you can also try ZM and GIGP, and compare

```
> ItaUltra.fzm <- lnre("fzm", ItaUltra.spc)
```

```
> summary(ItaUltra.fzm)
```

## Observed/expected spectra at estimation size

```
# expected spectrum
```

```
> ItaUltra.fzm.spc <- lnre.spc(ItaUltra.fzm,  
  N(ItaUltra.fzm))
```

```
# compare
```

```
> plot(ItaUltra.spc, ItaUltra.fzm.spc,  
  legend=c("observed", "fzm"))
```

```
# plot first 10 elements only
```

```
> plot(ItaUltra.spc, ItaUltra.fzm.spc,  
  legend=c("observed", "fzm"), m.max=10)
```

## Compare growth of two categories

```
# extrapolation of ultra- VGC to sample size of ri- data
```

```
> ItaUltra.ext.vgc <- lnre.vgc(ItaUltra.fzm,  
  N(ItaRi.emp.vgc))
```

```
# compare
```

```
> plot(ItaUltra.ext.vgc, ItaRi.bin.vgc,  
  NO=N(ItaUltra.fzm), legend=c("ultra-","ri-"))
```

```
# zooming in
```

```
> plot(ItaUltra.ext.vgc, ItaRi.bin.vgc,  
  NO=N(ItaUltra.fzm), legend=c("ultra-","ri-"),  
  xlim=c(0,1e+5))
```

# References I

- Baayen, R. Harald (2001). *Word Frequency Distributions*. Kluwer Academic Publishers, Dordrecht.
- Baroni, Marco (2008). Distributions in text. In A. Lüdeling and M. Kytö (eds.), *Corpus Linguistics. An International Handbook*, chapter 39. Mouton de Gruyter, Berlin.
- Baroni, Marco and Evert, Stefan (2007). Words and echoes: Assessing and mitigating the non-randomness problem in word frequency distribution modeling. In *Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics*, pages 904–911, Prague, Czech Republic.
- Evert, Stefan (2004). A simple LNRE model for random character sequences. In *Proceedings of the 7èmes Journées Internationales d'Analyse Statistique des Données Textuelles (JADT 2004)*, pages 411–422, Louvain-la-Neuve, Belgium.
- Evert, Stefan and Baroni, Marco (2007). *zipfR*: Word frequency distributions in R. In *Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics, Posters and Demonstrations Sessions*, pages 29–32, Prague, Czech Republic.
- Mandelbrot, Benoit (1953). An informational theory of the statistical structure of languages. In W. Jackson (ed.), *Communication Theory*, pages 486–502. Butterworth, London.

## References II

- Mandelbrot, Benoit (1962). On the theory of word frequencies and on related Markovian models of discourse. In R. Jakobson (ed.), *Structure of Language and its Mathematical Aspects*, pages 190–219. American Mathematical Society, Providence, RI.
- Zipf, George Kingsley (1949). *Human Behavior and the Principle of Least Effort*. Addison-Wesley, Cambridge, MA.
- Zipf, George Kingsley (1965). *The Psycho-biology of Language*. MIT Press, Cambridge, MA.