A linear law for the speech sonority

and a stochastic model suggested by this law

Pierre Collet, Didier Demolin, Antonio Galves
and Jesús García

Some recent results of the Tycho Brahe Project

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- A rough measure of sonority was introduced in Galves *et al.* (2002) as a tool to discriminate between rhythmic classes of languages.
- An empirical analysis of a multi-lingual corpus puts in evidence a linear relationship between the mean sonority and the mean increment of the sonority across sentences of the sample.
- There is a simple way to explain this linearity. This is the goal of this presentation.

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Acknowlegments

Special thanks to Emmanuel Dupoux, Sharon Pepperkamp and Frank Ramus for making the data from the *Laboratoire de Sciences Cognitives et Psycholinguistique (EHESS/CNRS)* used in this paper available to us.

The rhythmic classes conjecture

It has been conjectured in the linguistic literature that languages are divided in two or maybe three rhythmic classes (Lloyd 1940, Pike 1945, Abercrombie 1967, ...).

- *Morse code* or *stress-timed* languages: English, European Portuguese, Dutch, Finish, Polish, ...
- *Machine-gun* or *Syllable-timed* languages: Brazilian Portuguese, Catalan, French, Italian, Spanish,...
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Correlates of linguistic rhythm in the speech signal

Ramus, Nespor and Mehler (1999) gave for the first time evidence that simple statistics of the speech signal could discriminate between different rhythmic classes.

RNM's approach

- RNM analyzed the acoustic signal of 20 sentences produced by 4 speakers of each of the following languages: English, Polish, Dutch, Catalan, Spanish, Italian, French and Japanese.
- The chosen sentences were segmented into vocalic and consonantal intervals.
- For each language, the empirical standard deviation of the durations of the consonantal intervals (ΔC) and the proportion of time spent in vocalic intervals ($\%V$) were computed.

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Intuition behind the choice of these statistical parameters

- Languages conjectured to be syllable timed (like *Italian*) spend a greater proportion of time in vocalic intervals than languages conjectured to be stress-timed (like *English* or *Dutch*). This justifies the choice of $\%V$.
- Languages conjectured to be stress-timed display a greater variety and complexity of consonantal intervals than languages conjectured to be syllable-timed. This justifies the choice of δC.

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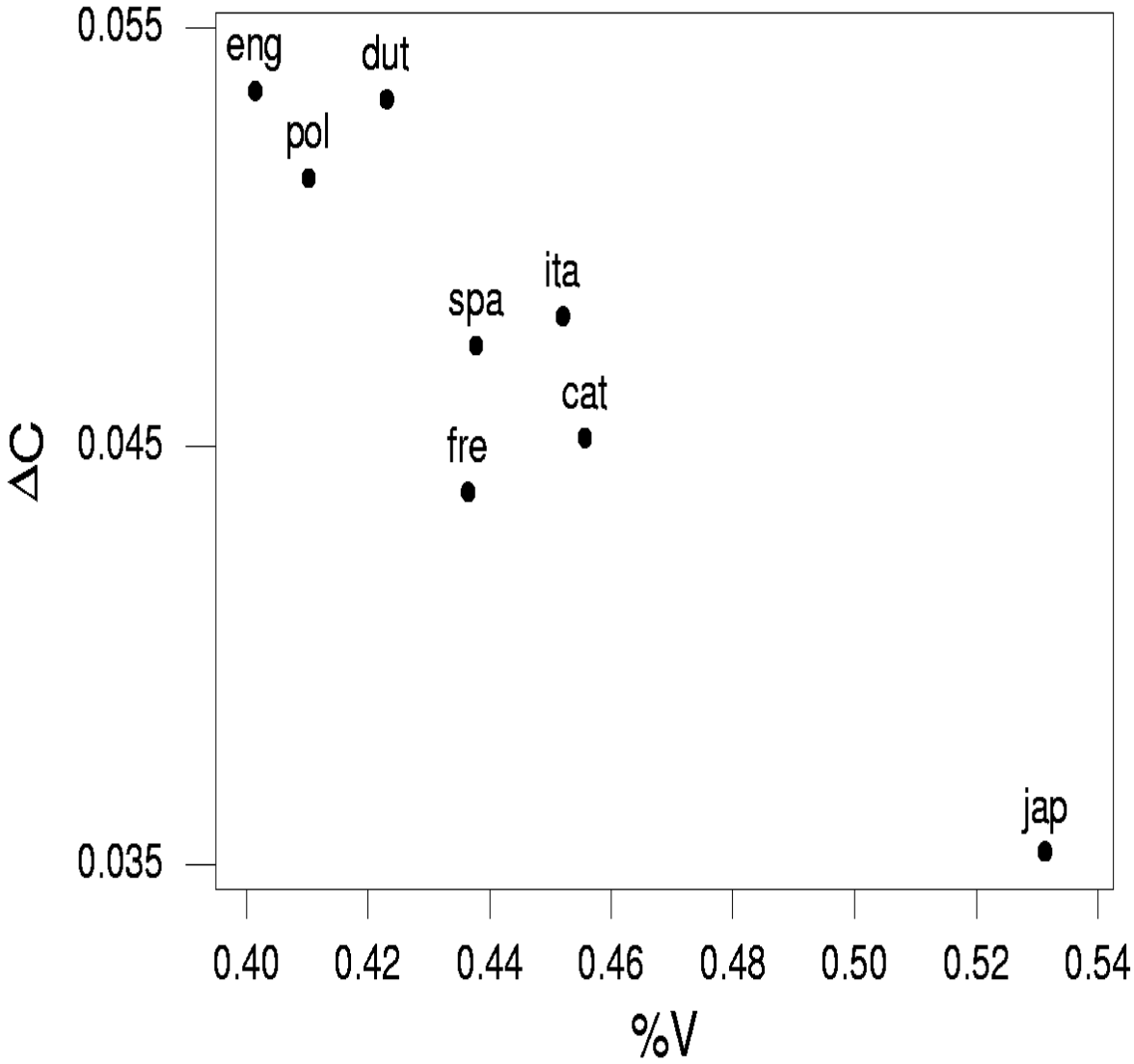
0.055
0.045
0.035
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eng
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pol
ita
spa
cat
fre
jap
0.40
0.42
0.44
0.46
0.48
0.50
0.52
0.54
%V

Problems with RNM's approach

It is based on a hand label-ling of the speech signal.

- This is a time-consuming task.
- Moreover this hand label-ling is often based on decisions which are difficult to reproduce in a homogeneous way

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A new approach to the problem

- Newborn babies are able to discriminate rhythmic classes with a signal filtered at 400Hz (Mehler et al. 1996).
- At this level, it is hard to distinguish nasals from vowels and glides from consonants.
- This strongly suggests that the discrimination of rhythmic classes by babies relies not on fine-grained distinctions between vowels and consonants, but on a coarse-grained perception of sonority in opposition to obstruency.

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Sonority as a basis for rhythmic class discrimination

- Galves, Garcia, Duarte and Galves (2002) suggests that it is possible to discriminate rhythmic classes of language, using a rough measure of the speech sonority.
- This measure is defined directly from the spectrogram of the signal, with no need of previous hand label-ling of the data
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Defining the speech sonority

- We define a function which maps local windows of the acoustic signal on the interval $[0, 1]$.
- This function is close to 1 for spans displaying regular patterns, characteristic of sonorant portions of the signal.
- In contrast, regions in which the acoustic signal present a chaotic behavior, for instance regions corresponding to stop consonants, will correspond to intervals in which S_t will assume values close to 0, with important variations

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- Denote by $c_t(f)$ the power spectral density at time t and frequency f.
- Time is discretized in steps of 2 milliseconds. The values of the spectrogram are estimated using a 25 milliseconds Gaussian window.
- We only consider frequencies from 80 Hz to 800 Hz, by steps of 20 Hz.

The normalized power spectral density is defined by

$$p_t(f) = \frac{c_t(f)}{\sum_{f'} c_t(f')} .$$

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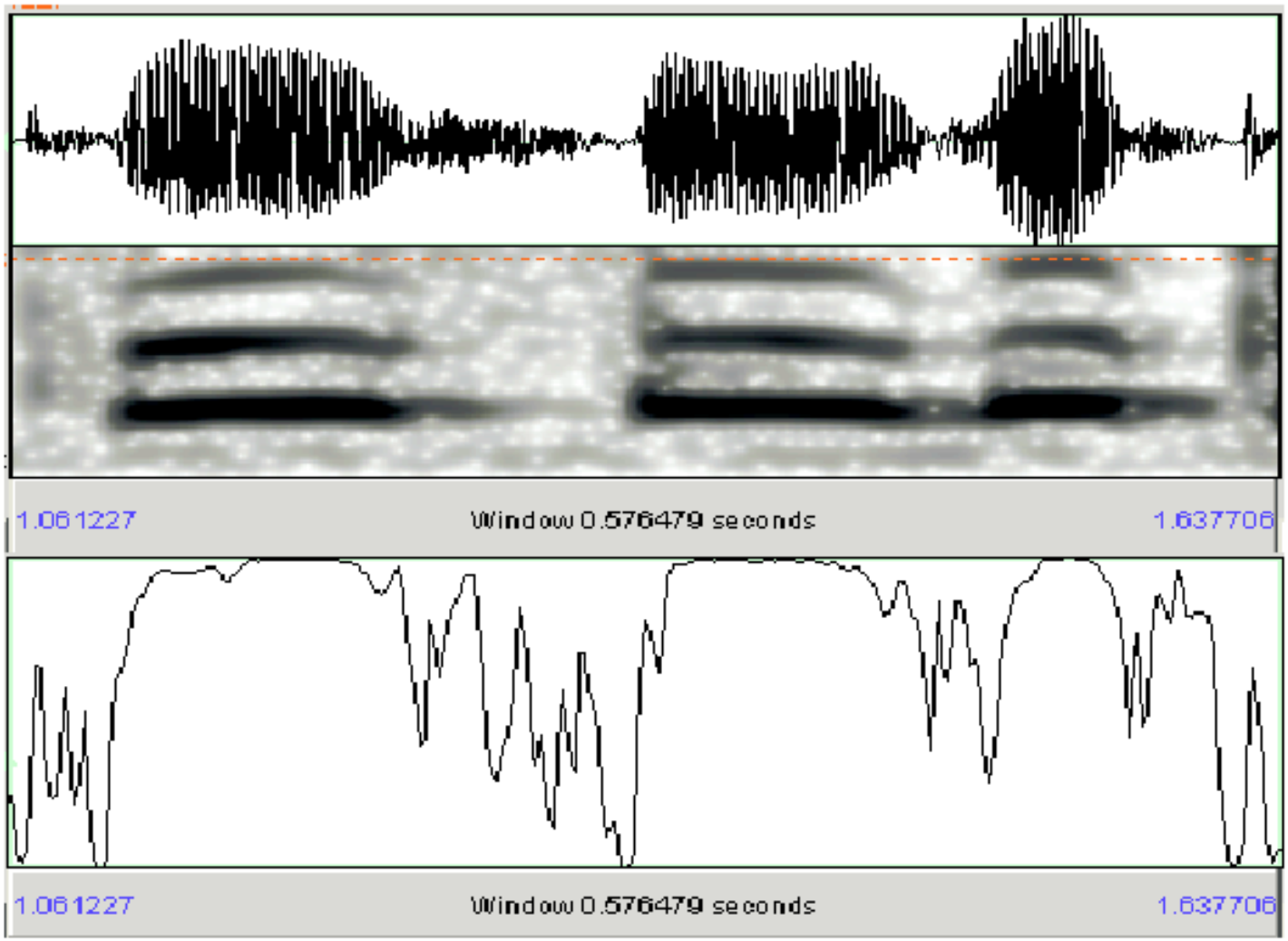
Definition of the sonority

$$S_t = e^{-\eta \sum_{i=1}^{3} h(p_t \mid p_{t-i})},$$

where h is the relative entropy and η is a free parameter taking positive real values.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Reproducing RNM using the sonority

Define

- $\bar{S} = \frac{1}{T} \sum_{t=1}^{T} s(t)$. (*This will play the role of* $\%V$.)
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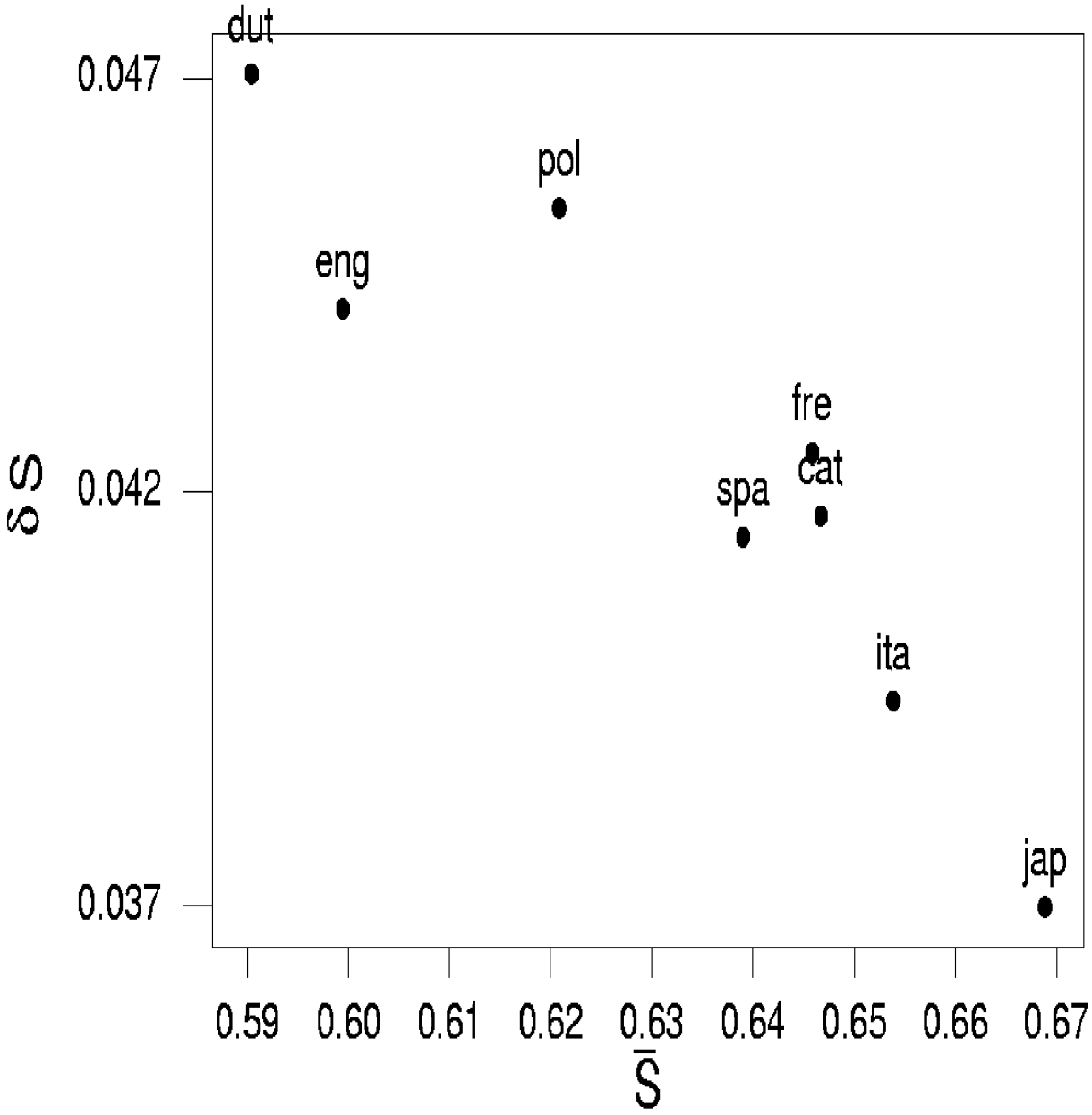
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0.62
0.63
0.64
0.65
0.66
0.67
$\bar{S}$

A sound statistical basis to the clustering

- The pictures produced with both approaches suggest that the existence of three classes.
- Is this a real statistical fact ?
- The projected Kolmogorov-Smirnov test presented in Cuesta-Albertos, Fraiman and Ransford (2004) makes it possible to compare the laws of the stochastic processes producing the time evolutions of the sonority for the different sentences and languages.

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The projected Kolmogorov-Smirnov test

- First choose a *direction* $W = (W(t))_{t\in[0,T]}$ at random. and then project the sonority trajectories in this direction.
- Then calculate the Kolmogorov-Smirnov statistic $D_W(\mathcal{S}_l, \mathcal{S}_{l'})$ for the two projected samples
- Reject the null hypothesis that the two samples belong to the same population if $D_W(\mathcal{S}_l, \mathcal{S}_{l'})$ is large enough. Otherwise accept it.

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Stable projected Kolmogorov-Smirnov test

Instead of taking only one random direction we will take many of them. For each pair of languages $l \neq l'$ we proceed as follows.

- Choose 100 independent direction $W_i : i = 1, ..., 100$.
- Test if the samples corresponding to l and l' belong to the same population using the projected KS test using direction W_i.
- Build up the auxiliary random variable $Z_i(l, l')$ which takes the value 1 if the projected test in direction W_i rejects the null hypothesis, and takes the value 0 otherwise.
- Reject the null hypothesis if the average statistic

$$\bar{Z}(l, l') = \frac{1}{N} \sum_{i=1}^{N} Z_i(l, l') \geq c_\alpha \, .$$

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Results using the sonority

language	pol	ital	fren	span	dut	eng	cat
jap	0.04	**0.43**	**0.09**	**0.08**	**0.77**	**0.74**	0.01
pol		0.03	0.0	0.0	**0.60**	**0.21**	0.03
ital			0.03	0.02	**0.14**	0.0	0.05
fren				0.0	**0.50**	**0.19**	0.06
span					**0.41**	**0.08**	0.03
dut						0.0	**0.74**
eng							**0.58**
$c^{\star}_{0.05}(l)$	0.13	0.13	0.12	0.11	0.14	0.12	0.12
$c^{\star}_{0.1}(l)$	0.05	0.05	0.06	0.05	0.05	0.04	0.05

Results with groups of languages

We performed a new test by grouping the sonority sample paths in three groups.

- In the first group we put together the 60 sonority sample paths of the conjectured syllable-timed languages, French, Italian and Spanish.
- The second group contains the 40 paths of the conjectured stress-timed languages, Dutch and English.
- Finally the 20 sonority paths of Japanese, which is conjectured to be a mora-timed language, remain in a third group.

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category	mora–timed	stress–timed	$c^{\star}_{0.05}(i)$
syllable–timed	0.32	0.70	0.24
stress–timed	0.82		0.09
$c^{\star}_{0.05}(j)$	0.06	0.04	

Table: *Values of* $\bar{Z}(i,j)$ *and bootstrap critical values for the three groups, with* $N = 100$, $B = 1000$ *and* $\eta = 0.05$

The test found significant all the differences between groups. This reinforces the linguistic conjecture of existence of three different rhythmic classes.

These results are presented in a paper by Cuesta, Fraiman, Galves, Garcia and Svarc to appear in the Journal of Applied Statistics (2006).

2863 sentences from 15 different languages

- Plot $\bar{S}$ vs. δS
- for 2863 sentences from 15 languages
- from a corpus belonging to the *Laboratoire de Sciences Cognitives et Psycholinguistique (EHESS/CNRS)*.
- Recall that

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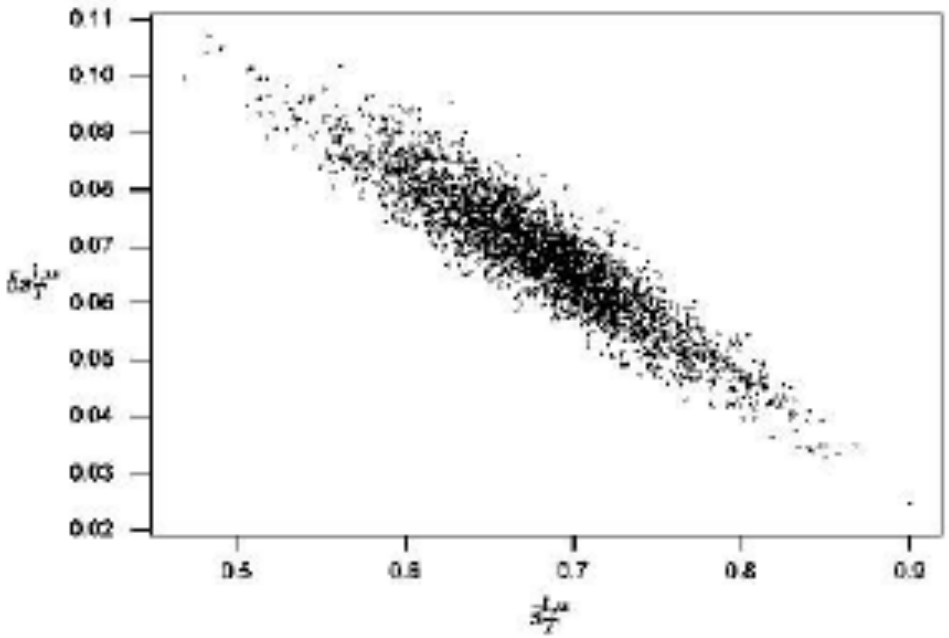

Figure: Mean sonority (horizontal axis) and mean increment of the sonority in absolute value (vertical axis) for 2863 sentences from 15 different languages

A model for the speech sonority

- A cross-linguistic exploratory analysis of the data shows that the sonority is quite regular in high level regions and displays strong variations below a certain level.
- This suggests modeling the sonority time evolutions for different languages by a family of tied quantized chains.

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Tied quantized chains

- The chains are tied together by the assumption that the distribution of the sonority, conditioned on the fact that it belongs to a given region, is *universal*, i.e. language independent.
- In particular the partition in regions of sonority is assumed to be language independent.
- In this model the specific features characterizing each language are expressed by the symbolic chain indicating in which region of sonority the process is at each time step.

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- Components of the model: two families of stochastic chains

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- $\mathcal{L}$ *is the set of all languages*
- The chains $\left(S_t^l\right)_{t\in\mathbf{Z}}$ take values in the interval $[0,1]$.
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Assumption

- There exist probability distributions
  - π_i on $[0,1]$
  - $\pi_{(i,j)}$ on $[0,1]^2$
- indexed by symbols i and j in the alphabet $A = \{0,1\}$
- which are language independent
- such that for any $l \in \mathcal{L}$

$$\mathbb{P}\left\{S_t^l \in B | X_t^l = j\right\} = \pi_j(B)\ , \tag{1}$$

and

$$\mathbb{P}\left\{S_t^l \in B, S_{t+1}^l \in C | X_t^l = i, X_{t+1}^l = j\right\} = \pi_{i,j}(B \times C)\ , \tag{2}$$

where B and C are Borel subsets of $[0,1]$.

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Theorem

For this model we have

$$\mathbb{E}\left(|S_t^l - S_{t+1}^l|\right) = a + b\mathbb{E}\left(S_t^l\right) + \epsilon^l \ ,$$

where the constants a and b are language independent.

Notation

- $p^l(i) = \mathbb{P}\left\{X_t^l = i\right\}$
- $p^l(i,j) = \mathbb{P}\left\{X_t^l = i\ ,\ X_{t+1}^l = j\right\}$
- $\theta(i) = \mathbb{E}\left(S_t^l | X_t^l = i\right)$ and
- $\theta(i,j) = \mathbb{E}\left(|S_t^l - S_{t+1}^l| \,\middle|\, X_t^l = i, X_{t+1}^l = j\right)$.

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Constants and correction term

$$a = \theta(0,0) - \theta(0)\frac{\theta(1,1) - \theta(0,0)}{\theta(1) - \theta(0)}\,,\; b = \frac{\theta(1,1) - \theta(0,0)}{\theta(1) - \theta(0)}\,,$$

and the correction ϵ^l is language dependent and defined as

$$\epsilon^l = p^l_{0,1}\left(\theta(1,0) + \theta(0,1) - \theta(0,0) - \theta(1,1)\right)\,.$$

Consequence

- The theorem together with the ergodicity of the chains $\left(S_t^l\right)$ explains the linear relationship in the data.
- We observe that in the corpus

$$0.008 < \epsilon^l < 0.009$$

and

$$0.065 < \mathbb{E}\left(|S_t^l - S_{t+1}^l|\right) < 0.075.$$

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Further directions of research

- We still don't know what is a rhythmic feature!
- We still don't have a model for the rhythmic classes
- But the symbolic chains behind the sonority open new perspectives of research.
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The Tycho Brahe team

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