# Hilberg Exponents: <br> New Measures of Long Memory in the Process 

Łukasz Dębowski
Idebowsk@ipipan.waw.pl

$\square \overline{\text { PAN }}$<br>Institute of Computer Science<br>Polish Academy of Sciences

12th November 2015, Gifu
(1) Introduction
(2) Relating $\gamma_{\mathrm{P}}^{ \pm}$and $\delta_{\mathrm{P}}^{ \pm}$
(3) Relating $\delta_{\mathrm{P}}^{+}$and $\delta_{\mathrm{R}}^{+}$
(4) Evaluating $\gamma_{\mathbf{Q}}^{ \pm}$and $\delta_{\mathbf{Q}}^{ \pm}$
(5) Conclusion

## Motivation: Hilberg's hypothesis

- According to a hypothesis by Hilberg (1990), the mutual information between two adjacent blocks of text in natural language grows like a power of the block length.
- This property differentiates natural language from k-parameter sources, for which the mutual information is proportional to the logarithm of the block length.
- In 2011, we constructed processes, called Santa Fe processes, which feature the power-law growth of mutual information.
- In 2011, we also showed that Hilberg's hypothesis implies Herdan's law, some version of Zipf's law.
- In 2014, we showed experimentally that for a PPM-like code the estimates of mutual information grow as a power law for natural language and logarithmically for a k-parameter source.


## Preliminaries

(1) $\mathbb{X}$ - a countable alphabet,
$(\Omega, \mathcal{J}, \mathbf{Q})$ - probability space with $\Omega=\mathbb{X}^{\mathbb{Z}}$,
$\mathbf{X}_{\mathrm{k}}: \Omega \ni\left(\mathrm{x}_{\mathrm{i}}\right)_{\mathrm{i} \in \mathbb{Z}} \mapsto \mathrm{x}_{\mathrm{k}} \in \mathbb{X}$ — random variables,
$\mathbf{Q}$ - a stationary measure (not necessarily ergodic),
$X_{n}^{m}=\left(X_{i}\right)_{n \leq i \leq m}$ - blocks of symbols,
$\mathbf{E}_{\mathbf{Q}} \mathbf{X}$ - expectation,
Var $_{\mathbf{Q}} \mathbf{X}$ - variance.
(2) $\mathbf{P}$ - a code (incomplete measure), i.e., it satisfies $\mathbf{P}\left(\mathbf{x}_{1}^{n}\right) \geq \mathbf{0}$ and the Kraft inequality $\sum_{x_{1}^{n}} \mathbf{P}\left(\mathrm{x}_{1}^{\mathrm{n}}\right) \leq \mathbf{1}$.
For $\mathbf{P}$ (or for $\mathbf{Q}$ ), we define the pointwise mutual information

$$
I^{P}(n)=-\log P\left(X_{-n+1}^{0}\right)-\log P\left(X_{1}^{n}\right)+\log P\left(X_{-n+1}^{n}\right) .
$$

In the formula log stands for the binary logarithm.

## Hilberg exponents

Define the positive logarithm

$$
\log ^{+} x= \begin{cases}\log (x+1), & x \geq 0 \\ 0, & x<0\end{cases}
$$

For a code $\mathbf{P}$ we introduce

$$
\begin{array}{ll}
\gamma_{P}^{+}=\limsup _{n \rightarrow \infty} \frac{\log ^{+} I^{P}(n)}{\log n}, & \gamma_{P}^{-}=\liminf _{n \rightarrow \infty} \frac{\log ^{+} I^{P}(n)}{\log n}, \\
\delta_{P}^{+}=\limsup _{n \rightarrow \infty} \frac{\log ^{+} E_{Q} I^{P}(n)}{\log n}, & \delta_{P}^{-}=\liminf _{n \rightarrow \infty} \frac{\log ^{+} E_{Q} I^{P}(n)}{\log n} .
\end{array}
$$

We call these: $\gamma_{\mathbf{P}}^{+}$-the upper random Hilberg exponent, $\gamma_{\mathbf{P}}^{-}$-the lower random Hilberg exponent, $\boldsymbol{\delta}_{\mathbf{P}}^{+}$-the upper expected Hilberg exponent, and $\delta_{\mathbf{P}}^{-}$-the lower expected Hilberg exponent.

## Basic observations

By definition,

$$
\begin{aligned}
& \gamma_{\mathrm{P}}^{+} \geq \gamma_{\mathrm{P}}^{-} \geq 0 \\
& \delta_{\mathrm{P}}^{+} \geq \delta_{\mathrm{P}}^{-} \geq 0
\end{aligned}
$$

- For $\mathbf{P}=\mathbf{Q}$, Hilberg exponents quantify some sort of long-range non-Markovian dependence in the process.
- For an IID process or a hidden Markov process with a finite number of hidden states, $\mathrm{E}_{\mathrm{Q}} \mathrm{I}^{\mathrm{Q}}(\mathrm{n}) \leq \mathrm{D}$ so $\delta_{\mathrm{Q}}^{ \pm}=\mathbf{0}$.
- For a $\mathbf{k}$-parameter source, $\mathrm{E}_{\mathrm{Q}} \mathrm{I}^{\mathrm{Q}}(\mathbf{n}) \propto \mathbf{k} \log \mathbf{n}$, so $\delta_{\mathrm{Q}}^{ \pm}=\mathbf{0}$.
- If $\mathrm{E}_{\mathrm{Q}} \mathrm{I}^{\mathrm{Q}}(\mathrm{n}) \propto \mathbf{n}^{\boldsymbol{\beta}}$ where $\beta \in[0,1]$ then $\delta_{\mathrm{Q}}^{ \pm}=\boldsymbol{\beta}$.
- There exist some non-Markovian but mixing sources, being a generalization of Santa Fe processes, for which $\delta_{\mathbf{Q}}^{ \pm} \in(\mathbf{0}, \mathbf{1})$.


## Further simple observations

Inequalities

$$
\begin{aligned}
& \gamma_{\mathrm{P}}^{-} \leq \gamma_{\mathrm{P}}^{+} \leq \mathbf{1} \\
& \delta_{\mathrm{P}}^{-} \leq \delta_{\mathrm{P}}^{+} \leq \mathbf{1}
\end{aligned}
$$

hold in the following cases:
(1) For $\mathbf{P}=\mathbf{Q}$ - by the Shannon-McMillan-Breiman theorem and by stationarity.
(2) For $\mathbf{P}$ being universal almost surely and in expectation, that is if for $\mathbf{k}(\mathbf{n})$ and $\mathbf{I}(\mathbf{n})$ being nondecreasing functions of $\mathbf{n}$, where $\mathbf{k}(\mathbf{n})+\mathrm{I}(\mathrm{n}) \rightarrow \infty$ we have

$$
\lim _{n \rightarrow \infty} \frac{1}{k(n)+I(n)+1}\left[-\log P\left(X_{-k(n)}^{I(n)}\right)\right]=h_{Q}
$$

where $\mathbf{h}_{\mathbf{Q}}$ is the entropy rate of measure $\mathbf{Q}$, and if

$$
\lim _{n \rightarrow \infty} \frac{1}{k(n)+I(n)+1} E_{Q}\left[-\log P\left(X_{-k(n)}^{I(n)}\right)\right]=E_{Q} h_{Q} .
$$

## A research program

There are many Hilberg exponents, for different measures and for different codes. Seeking for some order, we may look for results of three kinds:
(1) For a fixed code $\mathbf{P}$ and a measure $\mathbf{Q}$, we relate the random exponents $\gamma_{\mathbf{P}}^{ \pm}$and the expected exponents $\delta_{\mathbf{P}}^{ \pm}$.
(2) For two codes $\mathbf{P}$ and $\mathbf{R}$, we relate the exponents of a fixed kind, say $\delta_{\mathbf{P}}^{+}$and $\delta_{\mathbf{R}}^{+}$for some measure $\mathbf{Q}$.
(3) For a fixed code $\mathbf{P}$ and a measure $\mathbf{Q}$, we directly evaluate exponents $\gamma_{\mathbf{P}}^{ \pm}$and $\delta_{\mathbf{P}}^{ \pm}$.
In the following we will present some results of these three sorts.

## (1) Introduction

(2) Relating $\gamma_{\mathrm{P}}^{ \pm}$and $\delta_{\mathrm{P}}^{ \pm}$
(3) Relating $\delta_{\mathrm{P}}^{+}$and $\delta_{\mathrm{R}}^{+}$
(4) Evaluating $\gamma_{\mathbf{Q}}^{ \pm}$and $\delta_{\mathrm{Q}}^{ \pm}$
(5) Conclusion

## "Second-order" Shannon-McMillan-Breiman theorem

- The original idea of the SMB theorem was to relate the asymptotic growth of pointwise and expected entropies for an ergodic process $\mathbf{Q}$ with $\mathbf{P}=\mathbf{Q}$.
- In contrast, relating the random Hilberg exponents $\gamma_{\mathbf{Q}}^{ \pm}$and the expected Hilberg exponents $\delta_{\mathbf{Q}}^{ \pm}$means relating the speed of growth of the pointwise and expected mutual informations, which is a subtler effect than the SMB theorem.
- Thus relating $\gamma_{\mathbf{Q}}^{ \pm}$and $\delta_{\mathbf{Q}}^{ \pm}$could be called a "second-order" analogue of the SMB theorem.


## Our main result

For a code $\mathbf{P}$ with exponent $\delta_{\mathbf{P}}^{-}>\mathbf{0}$, let us introduce

$$
\epsilon_{P}=\limsup _{n \rightarrow \infty} \frac{\log ^{+}\left[\operatorname{Var}_{Q} I^{P}(n) / E_{Q} I^{P}(n)\right]}{\log n}
$$

## Theorem

For an ergodic measure $\mathbf{Q}$ over a finite alphabet, random Hilberg exponents $\gamma_{\mathbf{Q}}^{ \pm}$are almost surely constant. Moreover, we have $\mathbf{Q}$-almost surely

$$
\begin{aligned}
& \delta_{\mathbf{Q}}^{+} \geq \gamma_{\mathbf{Q}}^{+} \geq \delta_{\mathbf{Q}}^{+}-\epsilon_{\mathbf{Q}} \\
& \delta_{\mathbf{Q}}^{-} \geq \gamma_{\mathbf{Q}}^{-} \geq \delta_{\mathbf{Q}}^{-}-\epsilon_{\mathbf{Q}}
\end{aligned}
$$

where the left inequalities hold without restrictions, whereas the right inequalities hold for $\boldsymbol{\delta}_{\mathbf{Q}}^{-}>\mathbf{0}$.

## The fundamental idea of the proof

Our theorem can be demonstrated without invoking the ergodic theorem. Instead, we use an auxiliary "Kolmogorov code"

$$
S\left(x_{1}^{n}\right)=2^{-K\left(x_{1}^{n} \mid F\right)},
$$

where $\mathrm{K}\left(\mathbf{x}_{1}^{\mathbf{n}} \mid \mathbf{F}\right)$ is the prefix-free Kolmogorov complexity of a string $\mathbf{x}_{1}^{\mathbf{n}}$ given an object $\mathbf{F}$ on an additional infinite tape. The object $\mathbf{F}$ can be another string or, here, a definition of measure $\mathbf{Q}$.

## The first auxiliary result

## Theorem

Consider Kolmogorov code $\mathbf{S}$ and an ergodic $\mathbf{Q}$ over a finite alphabet $\mathbb{X}$. Exponents $\gamma_{\mathbf{S}}^{-}$and $\gamma_{\mathbf{S}}^{+}$are $\mathbf{Q}$-almost surely constant.

The idea of the proof:
(1) $\left|K\left(x_{1}^{n} \mid F\right)-K\left(x_{t+1}^{t+n} \mid F\right)\right| \leq C t$.
(2) Hence $\gamma_{\mathrm{S}}^{ \pm}$are shift invariant.
(3) Hence $\gamma_{\mathrm{S}}^{ \pm}$are constant on ergodic sources.

## Second auxiliary result (via Borel-Cantelli lemma)

Consider Kolmogorov code $\mathbf{S}$. For $\mathbf{I}^{\mathbf{S}} \mathbf{( \mathbf { n } ) + \mathbf { B } \geq \mathbf { 1 } \text { , define }}$

$$
\begin{aligned}
& \zeta_{S}^{+}=\limsup _{n \rightarrow \infty} \frac{\log ^{+}\left[E_{Q}\left(I^{S}(n)+B\right)^{-1}\right]^{-1}}{\log n} \\
& \zeta_{S}^{-}=\liminf _{n \rightarrow \infty} \frac{\log ^{+}\left[E_{Q}\left(I^{S}(n)+B\right)^{-1}\right]^{-1}}{\log n}
\end{aligned}
$$

These will be called inverse expected Hilberg exponents.

## Theorem

Consider Kolmogorov code $\mathbf{S}$ and a stationary measure $\mathbf{Q}$. Then:
(1) $\delta_{\mathrm{S}}^{+} \geq \gamma_{\mathrm{S}}^{+} \mathbf{Q}$-almost surely and ess $\sup _{\mathrm{Q}} \gamma_{\mathrm{S}}^{+} \geq \zeta_{\mathrm{S}}^{+}$.
(2) $\delta_{\mathrm{S}}^{-} \geq \operatorname{ess}^{\inf } \mathrm{Q}_{\mathrm{Q}} \gamma_{\mathrm{S}}^{-}$and $\gamma_{\mathrm{S}}^{-} \geq \zeta_{\mathrm{S}}^{-} \mathbf{Q}$-almost surely.

## A corollary

## Corollary

For an ergodic measure $\mathbf{Q}$ over a finite alphabet, equalities
$\gamma_{\mathrm{S}}^{+}=\operatorname{ess}_{\sup _{\mathrm{Q}}} \gamma_{\mathrm{S}}^{+}$and $\gamma_{\mathrm{S}}^{-}=\operatorname{ess}_{\inf }^{\mathrm{Q}} \gamma_{\mathrm{S}}^{-}$hold $\mathbf{Q}$-almost surely. Hence, Q-almost surely we have

$$
\begin{aligned}
& \delta_{\mathrm{s}}^{+} \geq \gamma_{\mathrm{s}}^{+} \geq \zeta_{\mathrm{s}}^{+}, \\
& \delta_{\mathrm{s}}^{-} \geq \gamma_{\mathrm{s}}^{-} \geq \zeta_{\mathrm{s}}^{-} .
\end{aligned}
$$

## Third auxiliary result

## Theorem

Consider Kolmogorov code $\mathbf{S}$ with $\mathbf{F}=\mathbf{Q}$, where $\mathbf{Q}$ is a stationary measure. Then:
(1) $\delta_{\mathrm{S}}^{-}=\delta_{\mathrm{Q}}^{-}$and $\delta_{\mathrm{S}}^{+}=\delta_{\mathrm{Q}}^{+}$.
(2) $\gamma_{\mathbf{S}}^{-}=\gamma_{\mathbf{Q}}^{-}$and $\gamma_{\mathbf{S}}^{+}=\gamma_{\mathbf{Q}}^{+} \mathbf{Q}$-almost surely.
(By Shannon-Fano coding and Barron's inequality.)

## Fourth, the last auxiliary result

For a code $\mathbf{P}$ with exponent $\delta_{\mathbf{P}}^{-}>\mathbf{0}$, let us introduce

$$
\epsilon_{P}=\limsup _{n \rightarrow \infty} \frac{\log ^{+}\left[\operatorname{Var}_{Q} I^{P}(n) / E_{Q} I^{P}(n)\right]}{\log n}
$$

## Theorem

Consider Kolmogorov code $\mathbf{S}$ and a stationary measure $\mathbf{Q}$. If $\delta_{\mathrm{S}}^{-}>\mathbf{0}$ then $\zeta_{\mathrm{S}}^{+} \geq \delta_{\mathrm{S}}^{+}-\epsilon_{\mathrm{S}}$ and $\zeta_{\mathrm{S}}^{-} \geq \delta_{\mathrm{S}}^{-}-\epsilon_{\mathrm{S}}$.
(By Markov inequality.)

## Theorem

Consider Kolmogorov code $\mathbf{S}$ with $\mathbf{F}=\mathbf{Q}$, where $\mathbf{Q}$ is a stationary measure. If $\boldsymbol{\delta}_{\mathbf{Q}}^{-}>\mathbf{0}$ then $\boldsymbol{\epsilon}_{\mathbf{S}}=\boldsymbol{\epsilon}_{\mathbf{Q}}$.
(By Shannon-Fano coding and Barron's inequality.)

## Resuming, our main result

## Theorem

For an ergodic measure Q over a finite alphabet, random Hilberg exponents $\gamma_{\mathbf{Q}}^{ \pm}$are almost surely constant. Moreover, we have Q-almost surely

$$
\begin{aligned}
& \delta_{\mathbf{Q}}^{+} \geq \gamma_{\mathbf{Q}}^{+} \geq \delta_{\mathbf{Q}}^{+}-\epsilon_{\mathbf{Q}} \\
& \delta_{\mathbf{Q}}^{-} \geq \gamma_{\mathbf{Q}}^{-} \geq \delta_{\mathbf{Q}}^{-}-\epsilon_{\mathbf{Q}}
\end{aligned}
$$

where the left inequalities hold without restrictions, whereas the right inequalities hold for $\delta_{\mathbf{Q}}^{-}>\mathbf{0}$.

## (1) Introduction

## (2) Relating $\gamma_{\mathrm{P}}^{ \pm}$and $\delta_{\mathrm{P}}^{ \pm}$

(3) Relating $\delta_{\mathrm{P}}^{+}$and $\delta_{\mathrm{R}}^{+}$
(4) Evaluating $\gamma_{\mathbf{Q}}^{ \pm}$and $\delta_{\mathrm{Q}}^{ \pm}$
(5) Conclusion

## An alternative expression for $\delta_{\mathrm{P}}^{+}$

Denote $\mathbf{H}^{\mathbf{P}} \mathbf{( n )}:=-\log \mathbf{P}\left(\mathbf{X}_{1}^{n}\right)$. Suppose that

$$
\lim _{n \rightarrow \infty} \frac{1}{n} E_{Q} H^{P}(n)=E_{Q} h_{Q}
$$

and suppose that $\mathbf{E}_{\mathbf{Q}} \mathbf{I}^{\mathbf{P}}(\mathbf{n}) \geq-\mathbf{D}$ for a certain $\mathbf{D}>\mathbf{0}$. Then
$\delta_{P}^{+}=\limsup _{n \rightarrow \infty} \frac{\log ^{+} E_{Q} I^{P}(n)}{\log n}=\limsup _{n \rightarrow \infty} \frac{\log ^{+} E_{Q}\left[H^{P}(n)-h_{Q} n\right]}{\log n}$
follows from the telescope sum

$$
E_{Q} H^{P}(n)-h n=\sum_{k=0}^{\infty} \frac{E_{Q} I^{P}\left(2^{k} n\right)}{2^{k+1}}
$$

## A hierarchy of approximations of block entropy

(1) $\mathbf{R}\left(X_{1}^{n}\right)=2^{-\left|C\left(X_{1}^{n}\right)\right|}-$ a computable universal code.
(2) $P\left(X_{1}^{n}\right)=2^{-K\left(X_{1}^{n}\right)}$ - the unconditional Kolmogorov code.
(3) $\mathbf{Q}\left(X_{1}^{n}\right)$ - the underlying measure.
(1) $\mathbf{E}\left(\mathbf{X}_{1}^{n}\right)=\mathbf{Q}\left(\mathbf{X}_{1}^{n} \mid \mathcal{I}\right)$ - the random ergodic measure.
(6) $\mathbf{H}^{\boldsymbol{T}}(\mathbf{n})=\mathbf{H}^{\boldsymbol{\top}}\left(\mathbf{n} ; \mathbf{X}_{1}^{\mathbf{n}(|\mathbb{X}|+\epsilon)^{\mathbf{n}}}\right)$ - the plugin entropy estimator.

We have

$$
E_{Q} H^{R}(n) \geq E_{Q} H^{P}(n) \geq E_{Q} H^{Q}(n) \geq E_{Q} H^{E}(n) \geq E_{Q} H^{T}(n)
$$

whereas the common rate of these is $\mathbf{E}_{\mathbf{Q}} \mathbf{h}_{\mathbf{Q}}$. Hence

$$
\delta_{\mathrm{R}}^{+} \geq \delta_{\mathrm{P}}^{+} \geq \delta_{\mathrm{Q}}^{+} \geq \delta_{\mathrm{E}}^{+} \geq \delta_{\mathbf{T}}^{+}
$$

The difference $\delta_{\mathbf{P}}^{+}-\delta_{\mathbf{E}}^{+}$can be arbitrarily close to $\mathbf{1}$.

## (1) Introduction

(2) Relating $\gamma_{\mathrm{P}}^{ \pm}$and $\delta_{\mathrm{P}}^{ \pm}$
(3) Relating $\delta_{\mathrm{P}}^{+}$and $\delta_{\mathrm{R}}^{+}$
(4) Evaluating $\gamma_{\mathbf{Q}}^{ \pm}$and $\delta_{\mathbf{Q}}^{ \pm}$
(5) Conclusion

## Memoryless sources and hidden Markov processes

- For IID processes, $\delta_{\mathrm{Q}}^{ \pm}=\mathbf{0}$ and hence $\gamma_{\mathbf{Q}}^{ \pm}=\mathbf{0}$ since there is no dependence in the process.
- For Markov processes over a finite alphabet and hidden Markov processes with a finite number of hidden states, we also have $\delta_{\mathbf{Q}}^{ \pm}=\mathbf{0}$ and hence $\gamma_{\mathbf{Q}}^{ \pm}=\mathbf{0}$, since the expected mutual information is bounded for measures of those processes by the data-processing inequality.


## Mixture Bernoulli process

Some simple example of a process with unbounded mutual information is the mixture of Bernoulli processes over the alphabet $\mathbb{X}=\{\mathbf{0}, \mathbf{1}\}$, which we will call the mixture Bernoulli process:

$$
\mathbf{Q}\left(x_{1}^{n}\right)=\int_{0}^{1} \theta^{\sum_{i=1}^{n} x_{i}}(1-\theta)^{n-\sum_{i=1}^{n} x_{i}} d \theta=\frac{1}{n+1}\binom{n}{\sum_{i=1}^{n} x_{i}}^{-1} .
$$

## Mixture Bernoulli process (continued)

$$
T_{n}=\sum_{i=-n+1}^{0} X_{i}, \quad S_{n}=\sum_{i=1}^{n} X_{i}
$$

## Theorem

For the mixture Bernoulli process, $\delta_{\mathbf{Q}}^{ \pm}=\gamma_{\mathbf{Q}}^{ \pm}=\mathbf{0}$.
Proof: $\mathbf{X}_{\mathbf{- n + 1}}^{\mathbf{0}}$ and $\mathbf{X}_{1}^{\mathbf{n}}$ are independent given $\mathbf{T}_{\mathbf{n}}$ and $\mathbf{S}_{\mathbf{n}}$. Hence

$$
I^{Q}(n)=-\log \frac{Q\left(T_{n}\right) Q\left(S_{n}\right)}{Q\left(T_{n}, S_{n}\right)}
$$

so $E_{\mathbf{Q}} \mathbf{I}^{\mathbf{Q}} \mathbf{( n )}=\mathbf{I}_{\mathbf{Q}}\left(\mathbf{T}_{\mathbf{n}} ; \mathbf{S}_{\mathbf{n}}\right)$. Variable $\mathbf{S}_{\mathbf{n}}$ assumes under $\mathbf{Q}$ each value in $\{\mathbf{0}, \mathbf{1}, \ldots, \mathbf{n}\}$ with equal probability $(\mathbf{n}+\mathbf{1})^{\mathbf{- 1}}$. Hence $\mathbf{0} \leq \mathbf{I}_{\mathbf{Q}}\left(\mathbf{T}_{\mathbf{n}} ; \mathbf{S}_{\mathbf{n}}\right) \leq \mathbf{H}_{\mathbf{Q}}\left(\mathbf{S}_{\mathbf{n}}\right)=\boldsymbol{l o g}(\mathbf{n}+\mathbf{1})$, which implies the claim.

## Santa Fe process

The Santa Fe process $\left(\mathbf{X}_{\mathbf{i}}\right)_{\mathbf{i} \in \mathbb{Z}}$ is a sequence of variables

$$
\mathbf{X}_{\mathbf{i}}=\left(\mathrm{K}_{\mathbf{i}}, \mathrm{Z}_{\mathrm{K}_{\mathrm{i}}}\right)
$$

where processes $\left(\mathrm{K}_{\mathbf{i}}\right)_{\mathbf{i} \in \mathbb{Z}}$ and $\left(\mathrm{Z}_{\mathrm{k}}\right)_{\mathbf{k} \in \mathbb{N}}$ with

$$
\begin{array}{ll}
\mathbf{Q}\left(\mathrm{Z}_{\mathrm{k}}=0\right)=\mathbf{Q}\left(\mathrm{Z}_{\mathrm{k}}=1\right)=1 / 2, & \left(\mathrm{Z}_{\mathrm{k}}\right)_{\mathrm{k} \in \mathbb{N}} \sim \operatorname{IID} \\
\mathbf{Q}\left(\mathrm{~K}_{\mathrm{i}}=\mathrm{k}\right)=\mathrm{k}^{-1 / \beta} / \zeta\left(\beta^{-1}\right), & \left(\mathrm{K}_{\mathrm{i}}\right)_{\mathrm{i} \in \mathbb{Z}} \sim I I D
\end{array}
$$

where $\beta \in(\mathbf{0}, \mathbf{1})$ is a parameter and $\zeta(\mathbf{x})=\sum_{\mathbf{k}=1}^{\infty} \mathbf{k}^{-\mathrm{x}}$.
Variable $\mathbf{Y}=\sum_{\mathbf{k}=1}^{\infty} \mathbf{2}^{-\mathrm{k}} \mathbf{Z}_{\mathrm{k}}$ could be considered a random real parameter of the process but the distribution of the process $\left(X_{i}\right)_{i \in \mathbb{Z}}$ is not a differentiable function of this parameter. So, the Santa Fe process is not a 1-parameter source.

## Santa Fe process (continued)

## Theorem

For the Santa Fe process, $\delta_{\mathbf{Q}}^{ \pm}=\gamma_{\mathbf{Q}}^{ \pm}=\boldsymbol{\beta}$.

## A process with $\delta_{Q}^{+} \neq \delta_{Q}^{-}$

Consider a sequence of numbers $\left(\mathbf{a}_{\mathbf{k}}\right)_{\mathbf{k} \in \mathbb{N}}$ where $\mathbf{a}_{\mathbf{k}} \in\{\mathbf{0}, \mathbf{1}\}$. Let

$$
\mathrm{X}_{\mathrm{i}}=\left(\mathrm{K}_{\mathrm{i}}, \mathrm{Y}_{\mathrm{K}_{\mathrm{i}}}\right)
$$

where $\mathbf{Y}_{k}=a_{k} \mathbf{Z}_{\mathbf{k}}$, whereas processes $\left(\mathrm{K}_{\mathbf{i}}\right)_{\mathbf{i} \in \mathbb{Z}}$ and $\left(\mathbf{Z}_{\mathrm{k}}\right)_{\mathbf{k} \in \mathbb{N}}$ are independent and distributed as for the original Santa Fe process.

## Theorem

There exists such a sequence $\left(\mathbf{a}_{\mathbf{k}}\right)_{\mathbf{k} \in \mathbb{N}}$ that for the modified Santa Fe process, we have $\delta_{\mathbf{Q}}^{+}=\boldsymbol{\beta}$ and $\delta_{\mathbf{Q}}^{-}=\mathbf{0}$.

## (1) Introduction

(2) Relating $\gamma_{\mathrm{P}}^{ \pm}$and $\delta_{\mathrm{P}}^{ \pm}$
(3) Relating $\delta_{\mathrm{P}}^{+}$and $\delta_{\mathrm{R}}^{+}$
(4) Evaluating $\gamma_{\mathbf{Q}}^{ \pm}$and $\delta_{\mathbf{Q}}^{ \pm}$
(5) Conclusion

## Conclusion

- We have defined Hilberg exponents - the bounding rates of the power-law growth of mutual information in a process.
- There are surprisingly many meaningful Hilberg exponents, for different measures and different codes.
- We have begun sorting out order in this menagerie but surely there are some interesting hard open problems.
www.ipipan.waw.pl/~ldebowsk

