

on the inherent complexity of cultural information

kristoffer nielbo

kln@cas.dk

knielbo.github.io

center for humanities computing aarhus | chcaa.io
aarhus university, denmark



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introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

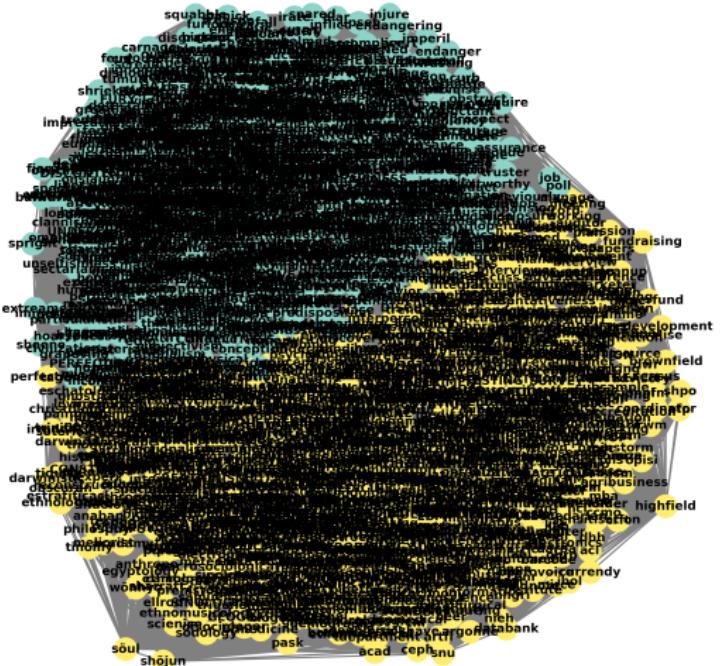
change-point detection

right-omnibus

predictive model

affective dynamics

summary



cultural analysis/-tics

- noisy
- complex
- structure
- time-dependent



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COMPUTING AARHUS



outline

① introduction

whoami
CHCAA

② self-affinity in cultural information

self-affinity
fractal analysis
author profiling
consumer history
computational narratology
trend reservoirs
author change points

③ pandemic information dynamics

information dynamics
news-media baseline
left-omnibus
change-point detection
right-omnibus
predictive model
affective dynamics

④ summary

introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary



CENTER FOR HUMANITIES
COMPUTING AARHUS



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

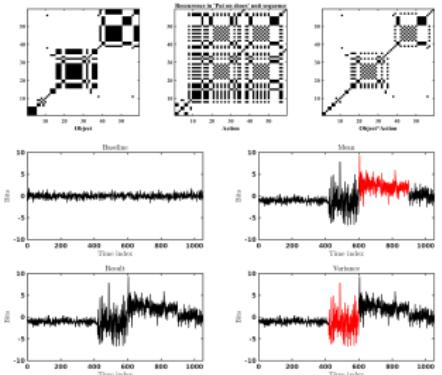
affective dynamics

summary

- kristoffer l. nielbo
- studied comparative religion & philosophy → cognitive science & mathematics
- worked in anthropology, history, literature, zoology, psychology, psychiatry, & ++interdisciplinary centers (e.g. IMC, IPAM, CSBD-Tech).



head center for humanities computing,
aarhus university denmark



approximate the complexity of a large-scale cultural system by a small set of dynamic variables

- to understand complex system → continuously monitor its states, BUT inefficient to monitor all intrinsic variables of the system
- detailed dynamics of a system (that has an underlying attractor) can be studied by reconstructing a suitable phase space from a scalar time series recorded from the system
- characterize a system by only very few state variables instead of a random system with infinite numbers of degrees of freedom

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introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

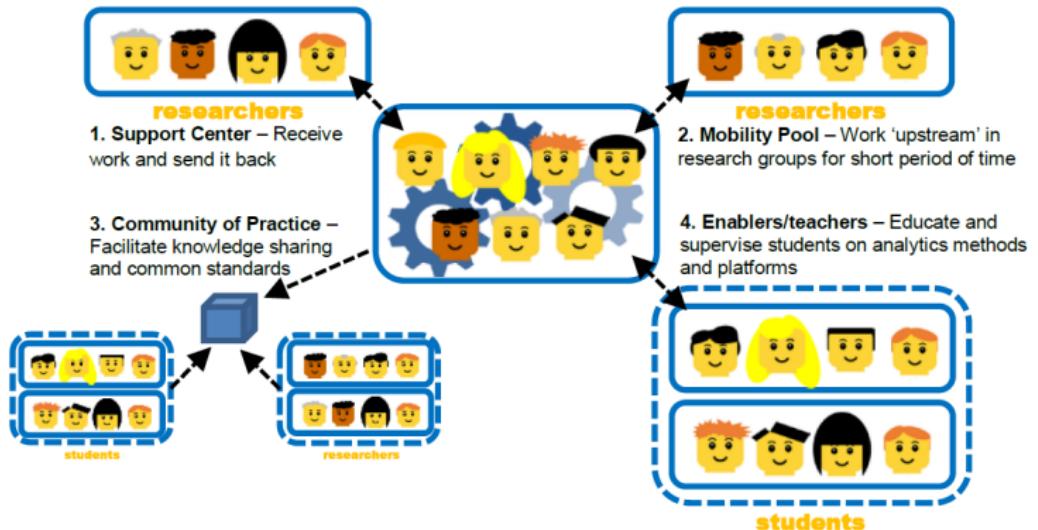
change-point detection

right-omnibus

predictive model

affective dynamics

summary



- research and development for SSH at aarhus university
- interactive high performance computing and eScience infrastructure
- group of researchers and RSEs genuinely interested in soft and unstructured data
- almost always looking for new colleagues and collaborators!



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary



CENTER FOR HUMANITIES
COMPUTING AARHUS



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

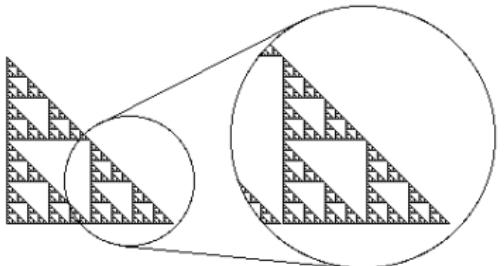
change-point detection

right-omnibus

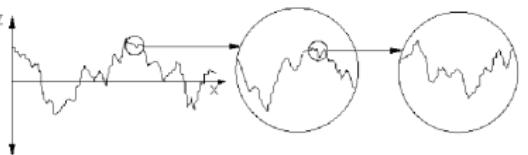
predictive model

affective dynamics

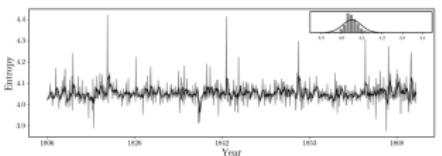
summary



many complex dynamic systems are fractal
→ they **display self-similar** and
scale-invariant behavior



fluctuation patterns at longer time-scales ~
shorter time scales & measurement does not
depend on the temporal resolution



a irregular information system represented by
time-varying entropy

$$h = - \sum_{i=1}^K p_i \times \log_2(p_i)$$

$$p_i = Fr(w_i) / \sum_{i=1}^K Fr(w_i)$$

- investigate **relationship between the measurement and time scale**
- display power-law scaling?
- detect changes in relationship as a function of external or internal events
- compare $n + 1$ system dynamics on this relationship



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

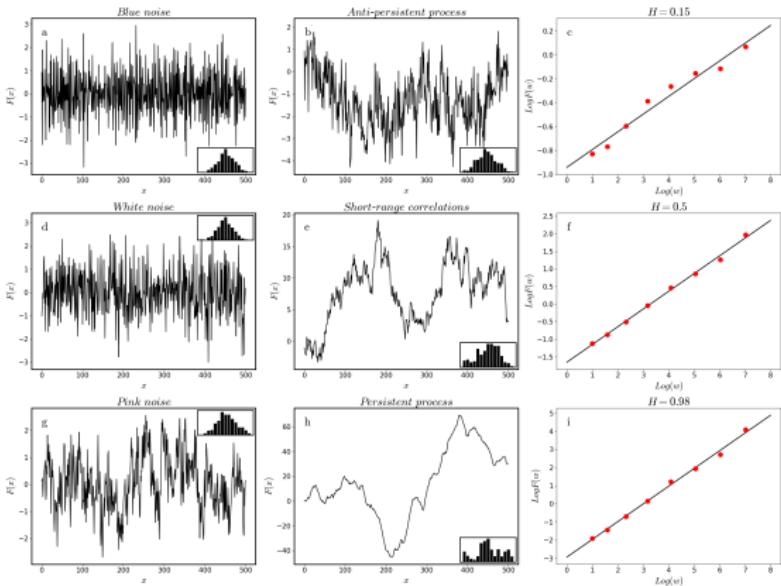
change-point detection

right-omnibus

predictive model

affective dynamics

summary



- **construct a random walk** $u(n) = \sum_{k=1}^n (x_k - \bar{x})$, $n = 1, 2, \dots, N$,
- divide the random walk process into **non-overlapping segments**
- determine the **local trends** of each segment as the best polynomial fit
- determine the average variance over all the segments and residual $u(i) - v(i)$ of the fit is fluctuations around global trend and its variance is the **Hurst parameter** (H)
⇒ H quantifies persistence in time series: $0 < H < 0.5$ is an anti-persistent process, $H = 0.5$ is a short-memory process, and $0.5 < H < 1$ is a persistent process

introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

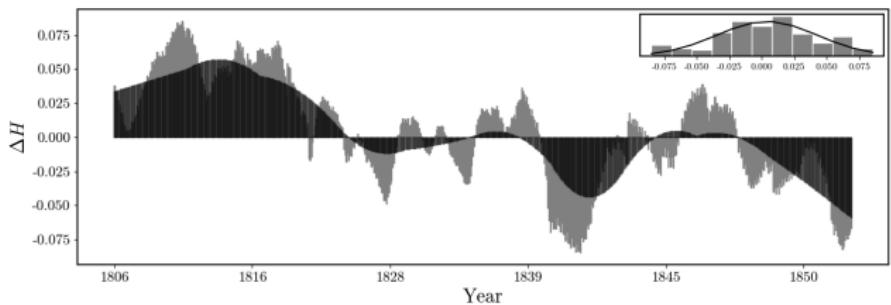
change-point detection

right-omnibus

predictive model

affective dynamics

summary



time-varying hurst difference parameter for n.f.s. grundtvig

Time period	Age of onset	Coarse	Fine	Behavior
1806-1826	23	$H > 0.5$	$H > 0.5$	<i>persistent</i>
1826-1839	43	$H \leq 0.5$	$H \approx 0.5$	<i>short memory</i>
1839-1845	56	$H \leq 0.5$	$H < 0.5$	<i>anti-persistent</i>
1845-1848	62	$H \leq 0.5$	$H \approx 0.5$	<i>short memory</i>
1849-1872	65	$H \leq 0.5$	$H < 0.5$	<i>anti-persistent</i>

developmental phases, their age of onset, and dominating dynamic as reflected by grundtvig's writings at a coarse and a fine resolution level. the general pattern indicates decay in the persistence of entropic states as a function of age.

introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

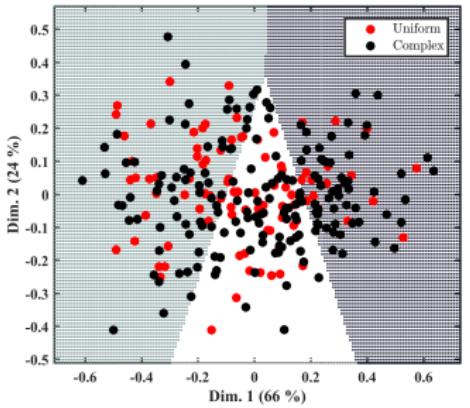
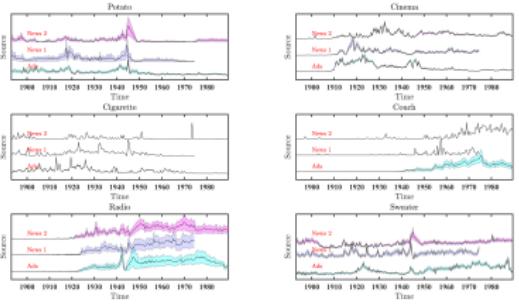
change-point detection

right-omnibus

predictive model

affective dynamics

summary



- media class impacts information dynamics – advertisements show on-off intermittent behavior, while newspapers are very persistent for *natural produce and food*
- product group-specific causal patterns
advertisement → article : 0.2
article → advertisement : 0.17
advertisement ↔ article : 0.49
- fashion shapes, while produce and energy dominate

introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

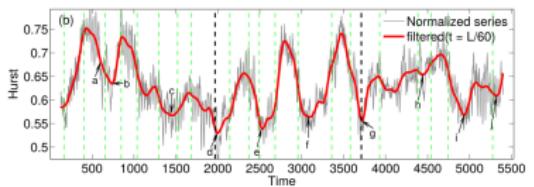
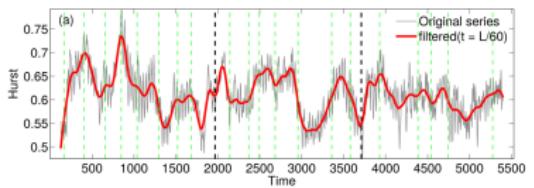
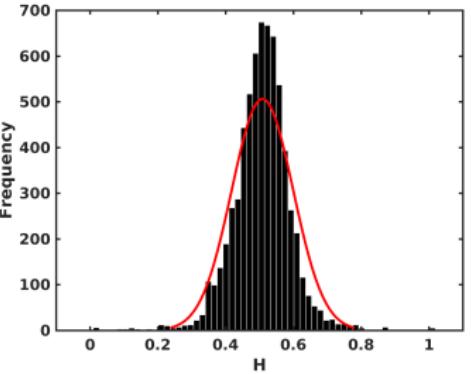
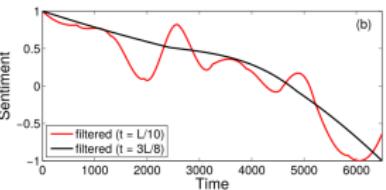
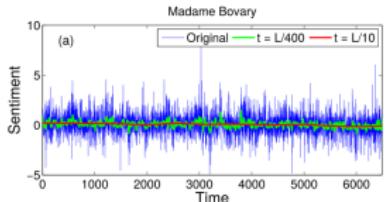
change-point detection

right-omnibus

predictive model

affective dynamics

summary



- global H of story arcs provide an index of narrative coherence
- narrative coherence: $0.5 < H \leq 1.0$
- local H detects changes in the narrative
- good narratives balances coherence to optimize reader motivation

introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

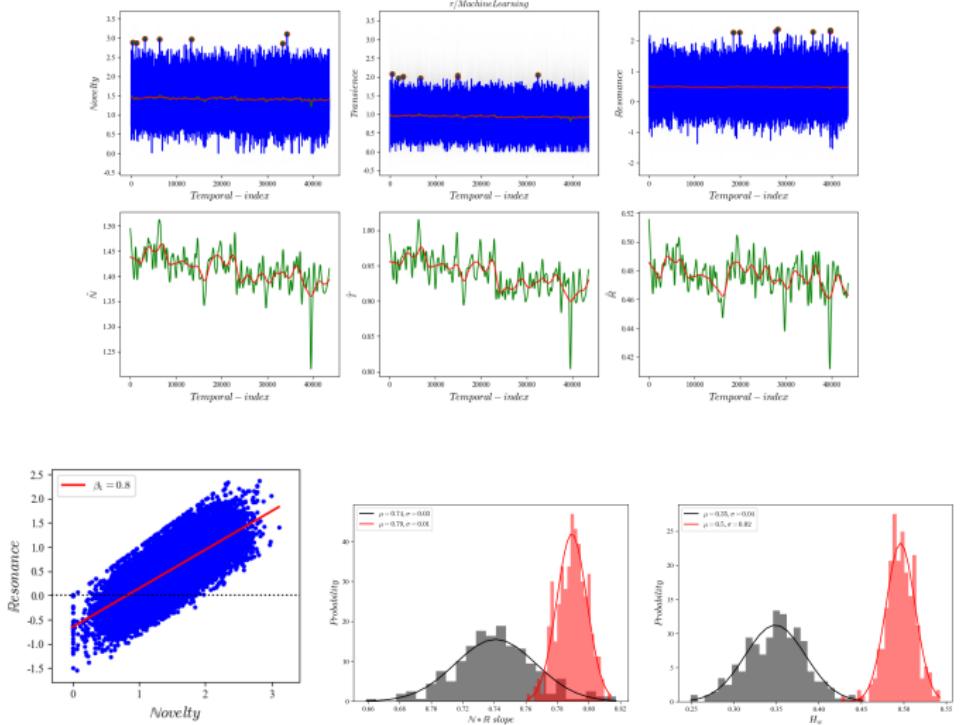
change-point detection

right-omnibus

predictive model

affective dynamics

summary



trend reservoirs (i.e., social media signals that display high trend potential) can be identified by their relationship between novel and resonant behavior, and their minimal persistence.

introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

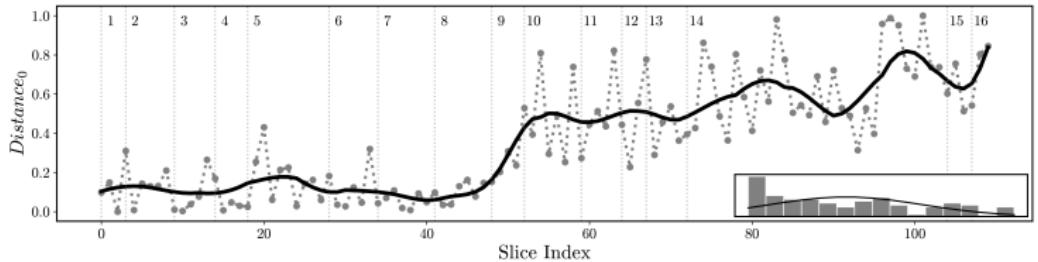
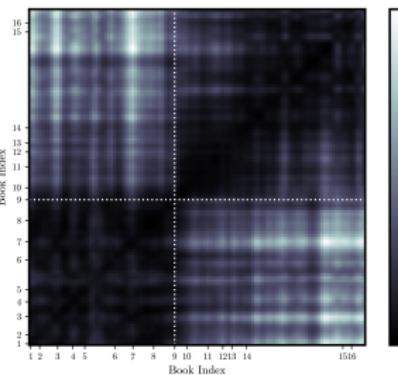
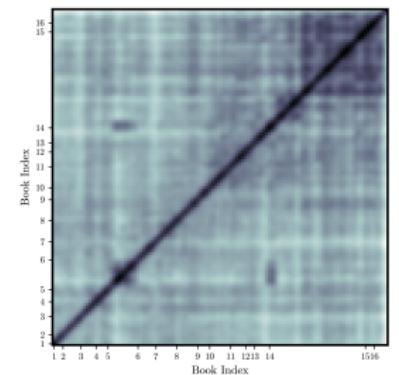
change-point detection

right-omnibus

predictive model

affective dynamics

summary



reliable change point in latent variable in book nine, starting in book eight, and ending in book 10.

introduction

whoami

CHCAA

self-affinity in cultural
information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

**pandemic information
dynamics**

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary

pandemic information dynamics - an example



CENTER FOR HUMANITIES
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introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary

News Information Decoupling

As the first wave of Covid-19 virus spread across the world, content alignment of news stories could be observed both within and between media sources. During December 2019 and January 2020, Covid-19 news stories were, outside China, interspersed with news coverage of other events (e.g., Hong Kong protests, Iranian-American confrontation, Trump impeachment). As the virus spread across Europe and America, **news media front pages focused almost exclusively on the pandemic**, all news sections (politics, business, sports, and arts) related to Covid-19, and breaking news became *corona news* in continuously updated media. From the perspective of cultural dynamics, the Covid-19 pandemic provides a **natural experiment that allows us to study the effect of a global catastrophe on the the dynamics of news media's information at an unprecedented level of detail.**



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary

\mathbb{N} : novelty as article $s^{(j)}$'s reliable difference from past articles $s^{(j-1)}, s^{(j-2)}, \dots, s^{(j-w)}$ in window w :

$$\mathbb{N}_w(j) = \frac{1}{w} \sum_{d=1}^w JSD(s^{(j)} | s^{(j-d)})$$

\mathbb{R} : resonance as the degree to which future articles $s^{(j+1)}, s^{(j+2)}, \dots, s^{(j+w)}$ conforms to article $s^{(j)}$'s novelty:

$$\mathbb{R}_w(j) = \mathbb{N}_w(j) - \mathbb{T}_w(j)$$

where \mathbb{T} is the transience of $s^{(j)}$:

$$\mathbb{T}_w(j) = \frac{1}{w} \sum_{d=1}^w JSD(s^{(j)} | s^{(j+d)})$$

we propose a symmetrized and smooth version by using the Jensen–Shannon divergence (JSD):

$$JSD(s^{(j)} | s^{(k)}) = \frac{1}{2} D(s^{(j)} | M) + \frac{1}{2} D(s^{(k)} | M)$$

with $M = \frac{1}{2}(s^{(j)} + s^{(k)})$ and D is the Kullback-Leibler divergence:

$$D(s^{(j)} | s^{(k)}) = \sum_{i=1}^K s_i^{(j)} \times \log_2 \frac{s_i^{(j)}}{s_i^{(k)}}$$



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

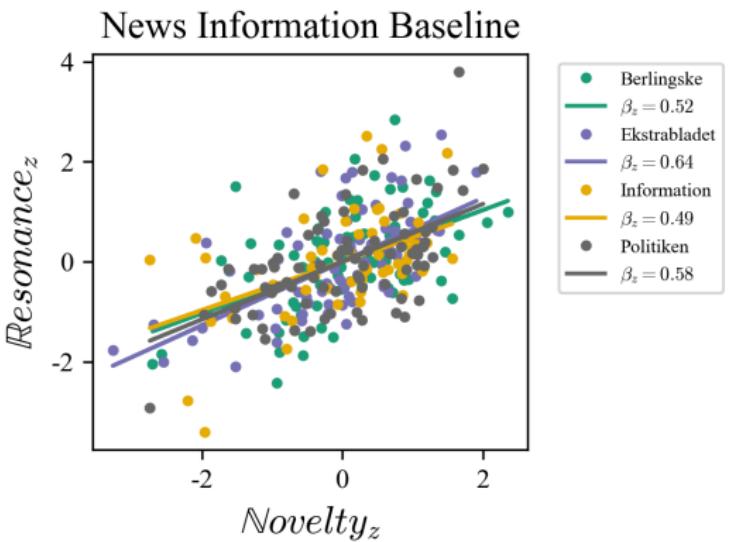
change-point detection

right-omnibus

predictive model

affective dynamics

summary



$\mathbb{N} \times \mathbb{R}$ basline models for danish legacy media



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

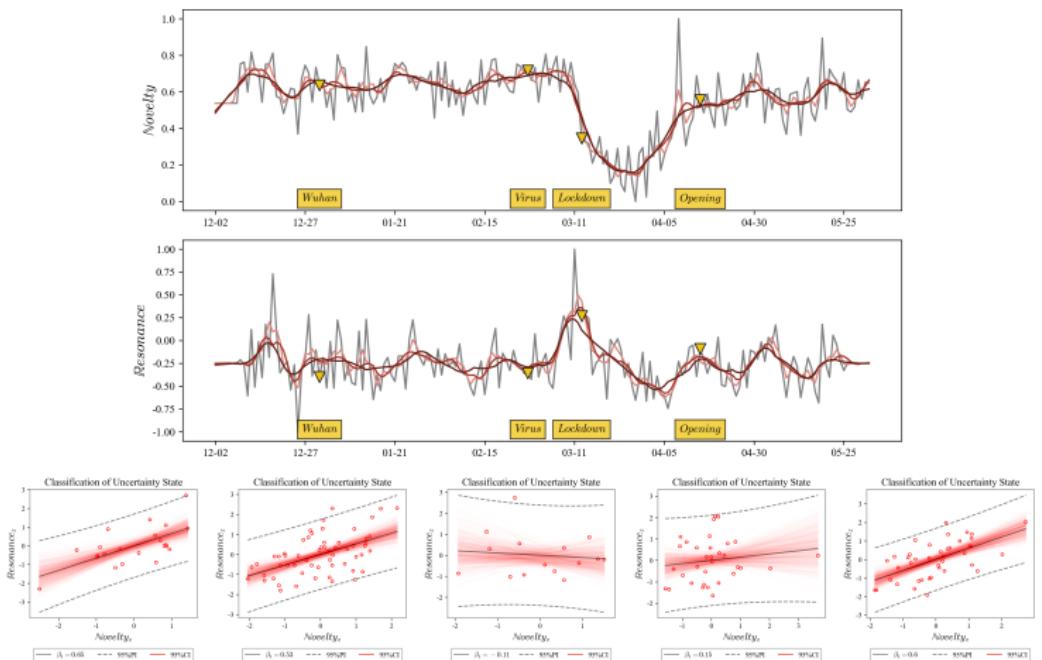
change-point detection

right-omnibus

predictive model

affective dynamics

summary



front pages from danish legacy print media *politiken*



CENTER FOR HUMANITIES
COMPUTING AARHUS



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

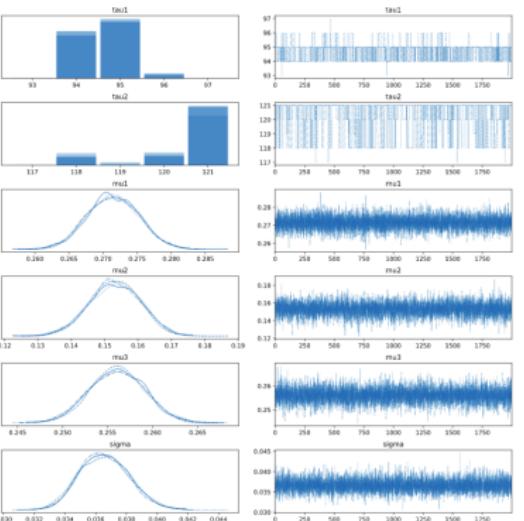
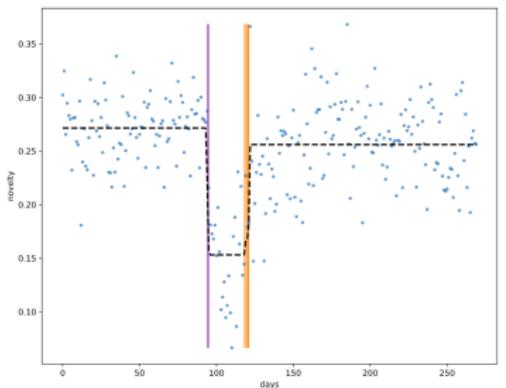
change-point detection

right-omnibus

predictive model

affective dynamics

summary



trace plots for politiken change points



CENTER FOR HUMANITIES
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introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary

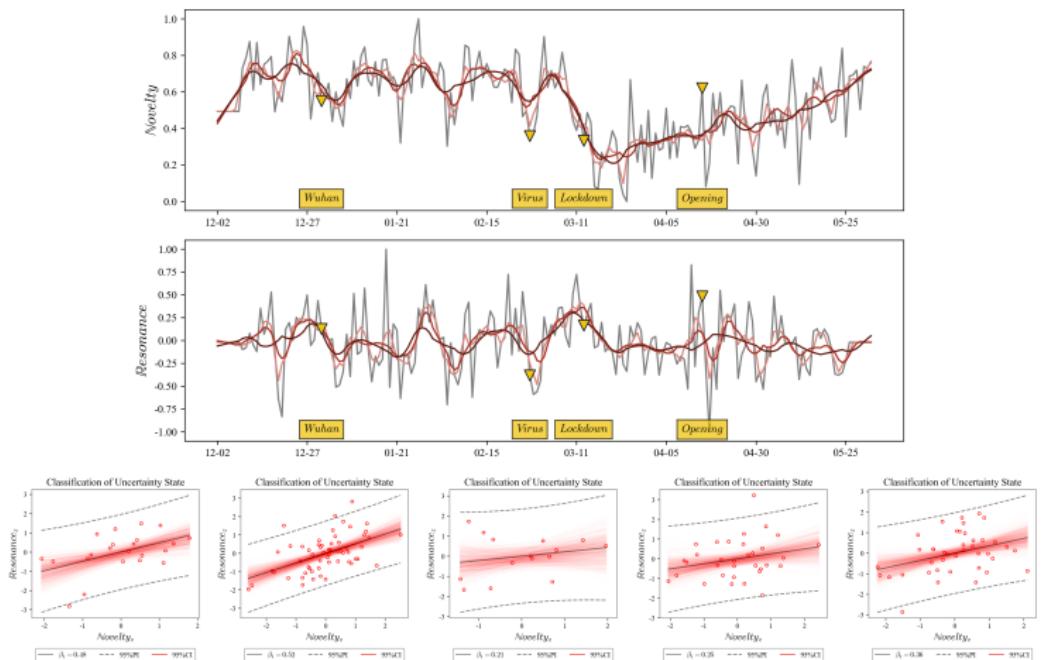


Figure: Berlingske front pages



CENTER FOR HUMANITIES
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introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

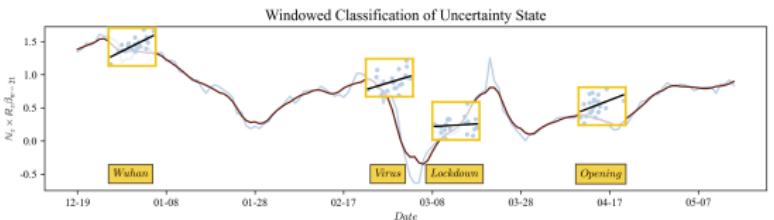
change-point detection

right-omnibus

predictive model

affective dynamics

summary



Slope β of $\mathbb{N} \times \mathbb{R}$ model windows of length $w = 21$ with maximal overlap



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary

News Information Decoupling

News Information Decoupling (NID) principle states that as in response to unexpected and dangerous temporally extended events, the ordinary information dynamics of news media are (initially) decoupled such that the **content novelty decreases** as media focus monotonically on the catastrophic event, but the **resonant property of said content increases** as its continued relevance propagate throughout the news information system.



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

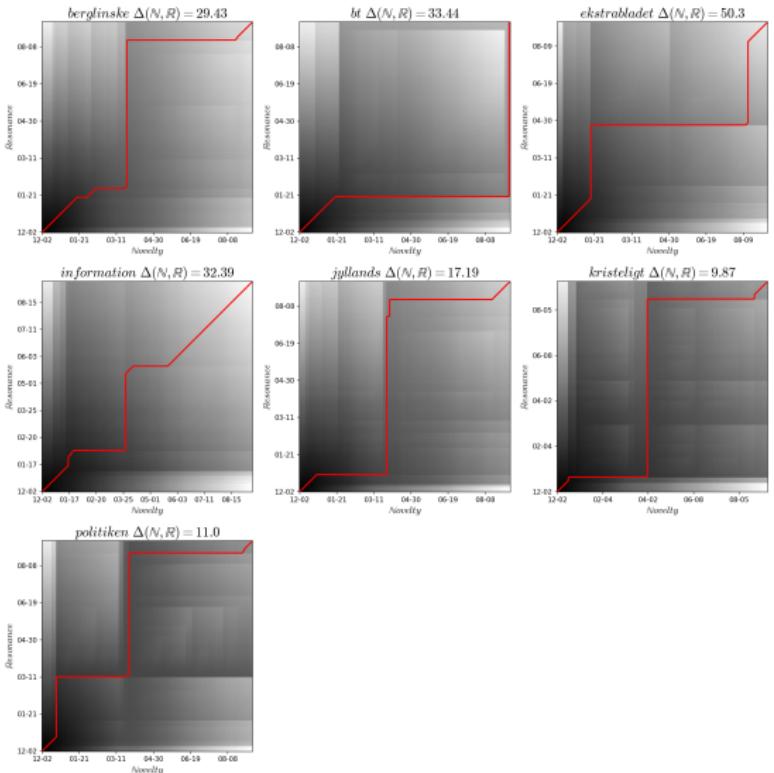
change-point detection

right-omnibus

predictive model

affective dynamics

summary



differences in NID for classes of newspapers (omnibus vs. tabloid)



introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

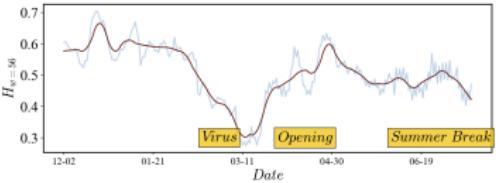
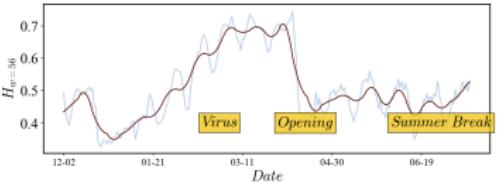
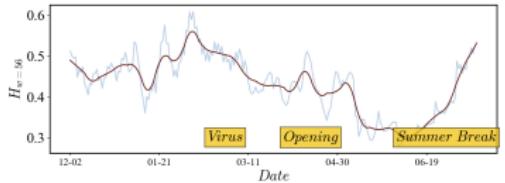
change-point detection

right-omnibus

predictive model

affective dynamics

summary



- in contrast to omnibus newspapers, tabloids change their affective dynamics in response to the pandemic events unfolding
- BT loses persistence, while EB stabilizes in persistence of sentiment state(-s).



- data are noisy and complex
- in order to understand to data-generating mechanisms, we need to characterize the system with a small set of temporal indices
- dynamics are the key to answering questions about the fine-grained patterns of variation
- domain knowledge of the system should be decisive in choice of formalism

introduction

whoami

CHCAA

self-affinity in cultural information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary



introduction

whoami

CHCAA

self-affinity in cultural
information

self-affinity

fractal analysis

author profiling

consumer history

computational narratology

trend reservoirs

author change points

pandemic information
dynamics

information dynamics

news-media baseline

left-omnibus

change-point detection

right-omnibus

predictive model

affective dynamics

summary

THANKS

kln@au.dk

knielbo.github.io

chcaa.io

SLIDES

knielbo.github.io/files/kln_inhercmplx.pdf



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