

When no news is bad news

Detection of negative events from news media content

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introduction

background

news information

decoupling

when no news is bad news

methods

data

information dynamics

change detection

results

type-dependent support

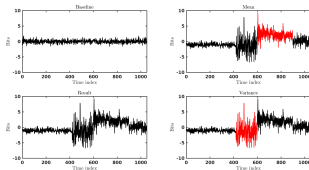
political dependency

discussion



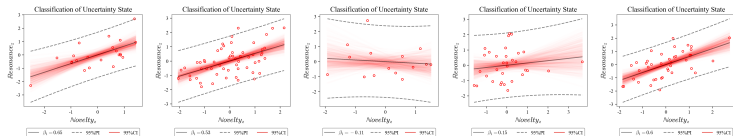
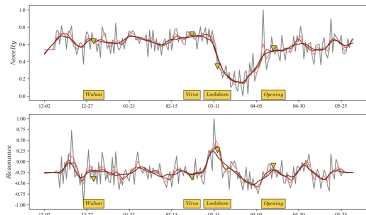
HOPE

how democracies cope with COVID-19 a data-driven approach is an national research project that is part of the (DK) national pandemic monitoring program.



research team interested in cultural dynamics, in particular **how events impact cultural information systems**

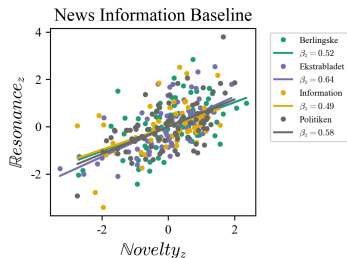
use news media coverage of COVID-19 as a proxy for how cultural information systems respond to **unexpected and dangerous temporally extended events**.



front page information from broadsheet newspaper *politiken* during COVID-19 phase 1.

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

when no news is bad news



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

- validate NID observations with a more formal approach to change detection
- compare national newspapers
 - np-type: *broadsheet // tabloid*
 - np-political: *left // right*
- ultimate goal: media monitoring system

data, normalization, and representation

DATA

linguistic content (title and body text) from **front pages of six DK national newspapers** (*2xtabloid, 4xbroadsheet*).

sampled during COVID-19 phase 1 (december 1, 2019 to july 1 2020)

NORMALIZATION

advertisements and metadata removed

lemmatization, tf-idf weighting, casefolding

REPRESENTATION

bag-of-words model (LDA*) to generate low-rank representations of front pages

variables were estimated for **windows of one week** ($w = 7$).

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\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:

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



Assume two change points, τ_1 and τ_2 and an otherwise stable series that follow a normal distribution with varied mean, μ_i , and singular variance, σ . This gives us the following model given the observed Novelty, \mathbb{N}_t :

$$\mathbb{N}_t = \begin{cases} \mathcal{N}(\mu_1, \sigma) & \text{for } t < \tau_1 \\ \mathcal{N}(\mu_2, \sigma) & \text{for } \tau_1 \leq t < \tau_2 \\ \mathcal{N}(\mu_3, \sigma) & \text{for } t \geq \tau_2 \end{cases}$$

Estimate the location of τ_i , means μ_i and variance σ , i.e. the following posterior:

$$P(\mu_i, \sigma, \tau_i | \mathbb{N}_t) = P(\mu_1, \mu_2, \mu_3, \sigma, \tau_1, \tau_2 | \mathbb{N}_t)$$

Estimation was carried out with NUTS and the assumptions were modelled using the following priors:

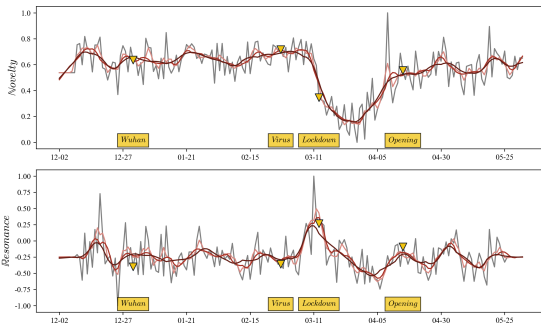
$$\mu_i \sim \mathcal{N}(0, 0.5)$$

$$\sigma \sim \text{Half Cauchy}(0.5)$$

$$\tau_1 \sim \text{Uniform}(0, \max(\mathbb{N}_t))$$

$$\tau_2 \sim \text{Uniform}(\tau_1, \max(\mathbb{N}_t))$$

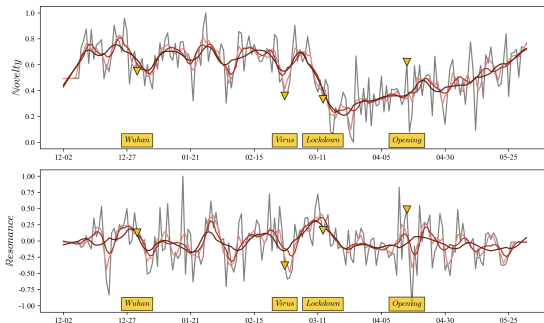




Novelty (upper panel) and resonance (lower panel) for the center-left newspaper *Politiken* before and during Covid-19 phase 1.

Source	Class	<i>NID</i> Start	<i>NID</i> End	<i>NID</i>
Berlingske	<i>B</i>	03.07 [03.03, 03.09]	04.28 [04.09, 05.08]	<i>True</i>
BT	<i>T</i>	04.10 [12.30, 09.01]	07.25 [04.22, 09.03]	<i>False</i>
Ekstrabladet	<i>T</i>	01.28 [01.02, 03.17]	05.08 [01.16, 07.22]	<i>False</i>
Jyllands-Posten	<i>B</i>	03.10 [03.08, 03.14]	05.25 [05.21, 06.06]	<i>True</i>
Kristligt Dagblad	<i>B</i>	03.07 [03.05, 03.12]	04.15 [04.11, 04.17]	<i>True</i>
Politiken	<i>B</i>	03.13 [03.12, 03.13]	04.08 [04.05, 04.08]	<i>True</i>

Estimated temporal change points at 94% HDIs for novelty. Column one contains the name of the newspaper, columns two its class (*B*roadsheet or *T*abloid).



Novelty (upper panel) and resonance (lower panel) for the center-right newspaper *Berlingske* before and during Covid-19 phase 1.

Source	N_{pre}	N_{NID}	N_{post}
Berlingske	0.36 [0.35, 0.37]	0.29 [0.27, 0.31]	0.34 [0.34, 0.35]
Jyllands-Posten	0.29 [0.28, 0.30]	0.23 [0.22, 0.24]	0.27 [0.26, 0.28]
Kristligt Dagblad	0.27 [0.26, 0.28]	0.19 [0.18, 0.21]	0.26 [0.25, 0.27]
Politiken	0.27 [0.26, 0.28]	0.15 [0.14, 0.17]	0.26 [0.25, 0.26]

Novelty values at 94% HDIs before during and after the lockdown for the four broadsheet newspapers that supported the NID principle..



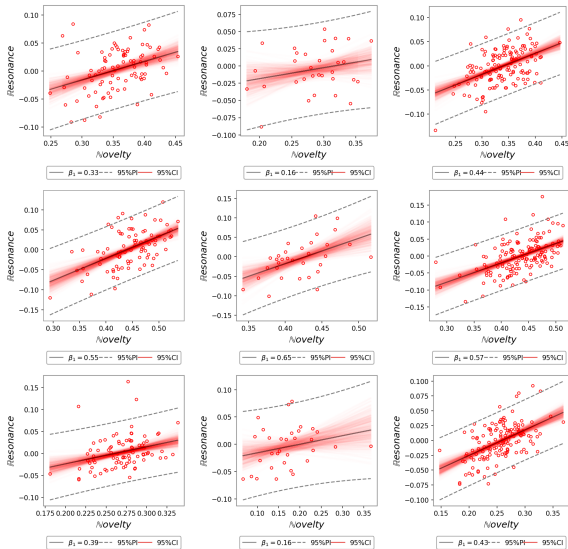


Figure: $\mathbb{N} \times \mathbb{R}$ slopes before during and after the lockdown for **Berlingske** (upper row), **Ekstrabladet** (middle row), and **Politiken** (lower row) during Covid-19 phase 1.

in conclusion...

“Nothing travels faster than the speed of light with the possible exception of bad news, which obeys its own special laws.” (D. Adams – Hitchhiker’s Guide)

in the case of pandemic information dynamics,

variation in N reliably detected *lockdown* and *opening*

$N \times \mathbb{R}$ slopes indicated a decoupling of resonance from novelty during the lockdown

lockdown interval indicated that lockdown can be predicted from the first incident

opening interval may reveal political observation

tabloids follow different dynamics

no news is bad news, when the lack of novel content persists!

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THANKS

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SLIDES

knielbo.github.io/files/kln_dhb21.pdf

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