

Interactions in Information Spread

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Introduction

- Every minute:

 400h of video
 350 000 tweets

 500 000 comments
 4 200 000 searches

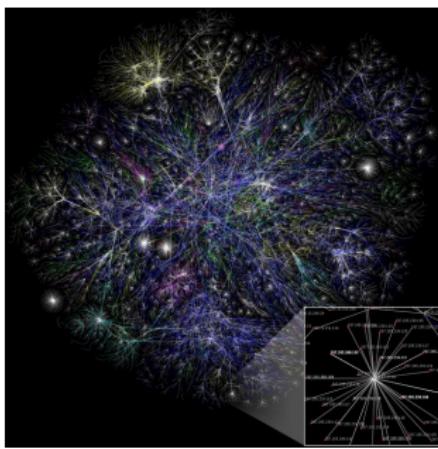


Figure 1: Snapshot of the internet (Wikipedia)

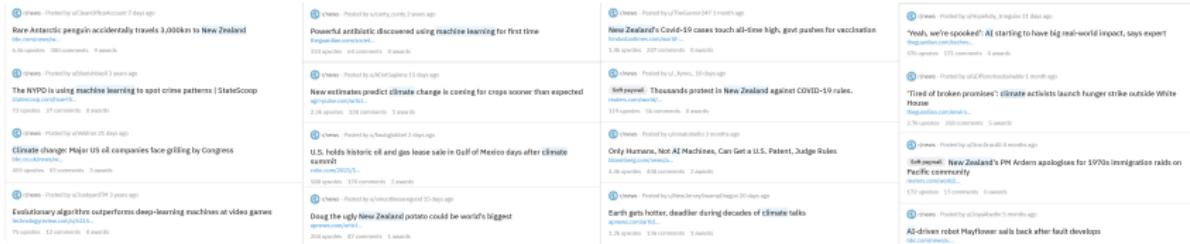
Motivation

- Every minute:

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- How does this data get generated?



The screenshot shows a scrollable list of news posts from the [r/news](#) subreddit. Each post includes the title, a thumbnail image, the number of upvotes and downvotes, and the number of comments. The posts cover a variety of topics, including environmental issues, political protests, and technological developments.

Title	Upvotes	Downvotes	Comments
Bore Antarctic penguin accidentally travels 3,000km to New Zealand	100	10	100 comments - 8 weeks
Powered antibiotic discovered using machine learning for first time	100	10	100 comments - 8 weeks
New Zealand's Covid-19 cases touch all-time high, govt pushes for vaccination	100	10	100 comments - 8 weeks
Thousands protest in New Zealand against COVID-19 rules.	100	10	100 comments - 8 weeks
U.S. holds historic oil and gas lease sale in Gulf of Mexico days after climate summit	100	10	100 comments - 8 weeks
Earth gets hotter, deadlier during decades of climate talks	100	10	100 comments - 8 weeks
New Zealand's PM Ardern apologizes for 1970s immigration raids on Pacific community	100	10	100 comments - 8 weeks
AJ-drove robot Mayflower sails back after fault develops	100	10	100 comments - 8 weeks

Figure 2: A typical stream from r/news

Motivation

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- How does this data get generated?
 → Hidden interactions?

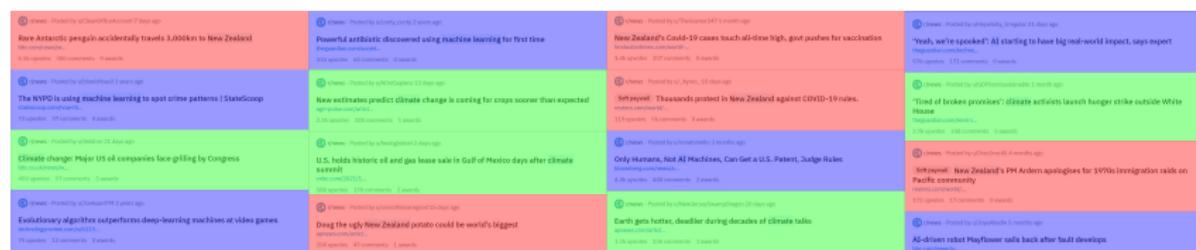


Figure 2: A typical stream from r/news – with topics

Context

Modelling the interaction between pieces of information and characterizing their role in information spreading processes

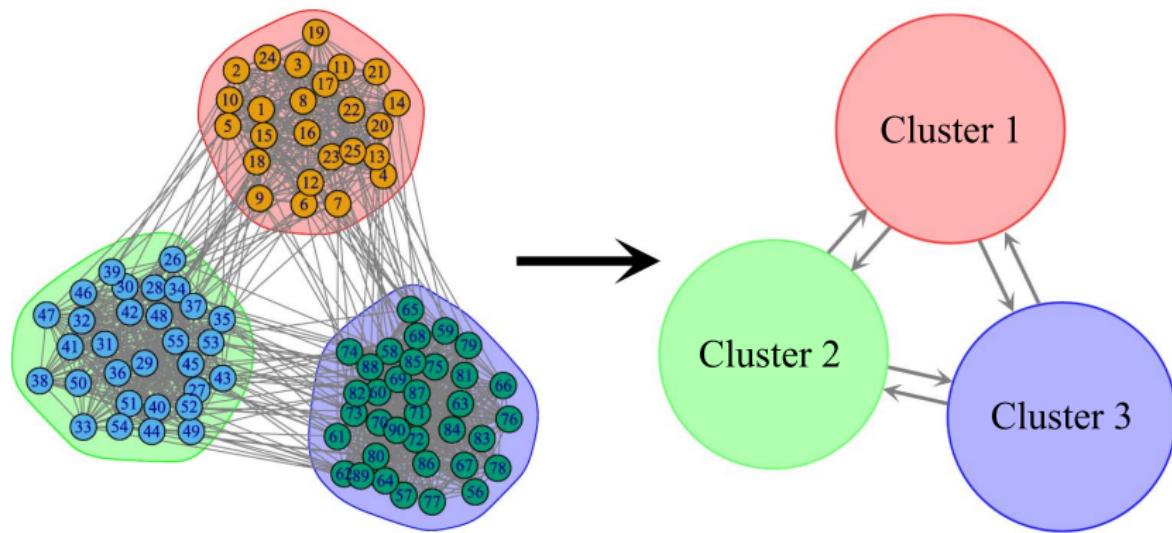
- Information: any item susceptible to spread (tweets, news, ...)
- Action: reaction to a piece of information (retweet, share, ...)
- Interaction: when the joint effect of several pieces of information is different than the product of their independent effects.
 - $P(x|A, B) \neq P(x|A)P(x|B)$

State of the art

- Few works considered the topic from a machine learning perspective
 - Clash of the Contagions (S.A.Myers et J.Leskovec, ICDM 2012)
 - Correlated cascades (Zarezade et al., AAAI 2017)
- Several theoretical works on interacting processes [Prakash et al., 2012, Wang et al., 2019, Zhu et al., 2020]
 - Define micro-rules first
 - Compare to global statistics then
 - No learning from the data

Stochastic Block Models

- Dimension reduction via clustering
 - Nodes: pieces of information (e.g. tweets)
 - Links: outcome given a pair of nodes (e.g. retweet or not)



Results

- Four datasets:
 - PubMed: how symptoms interact to refine a diagnosis
 - Reddit: how words interact to trigger an answer
 - Spotify: how hearing some songs influence the next one listened to
 - Twitter: how exposure to tweets trigger retweeting ulterior ones

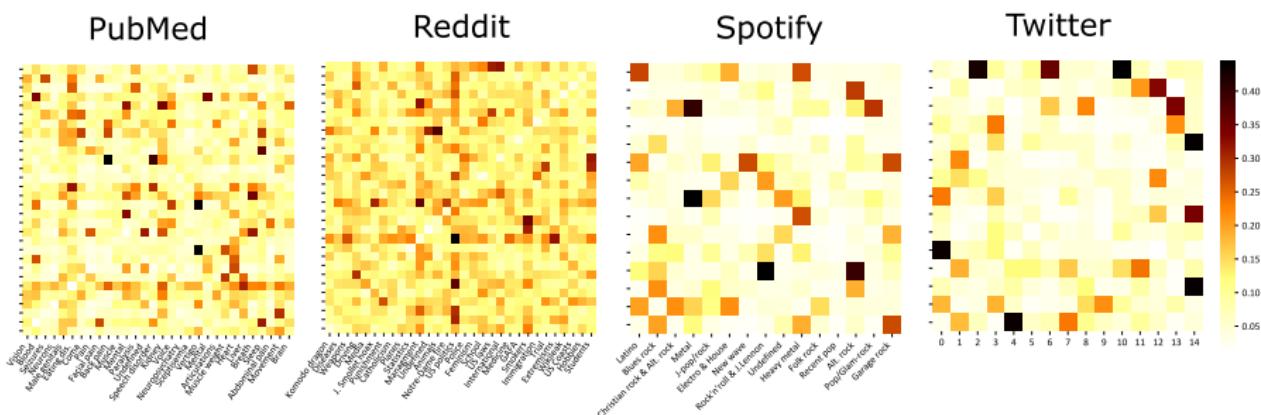
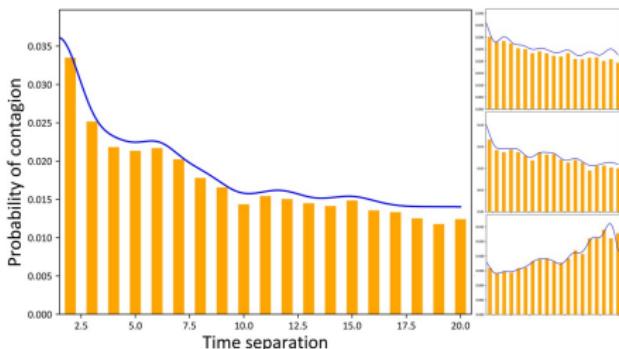


Figure 3: Conclusion: significant interactions between pieces of information are rare (Poux-Médard *et al.*, RecSys 2021)

InterRate

- How long do pair interactions last in time?
 - Piece of information A at time t_A and B at time $t_B > t_A$: how A relates to B after a time $\Delta t = t_B - t_A$?

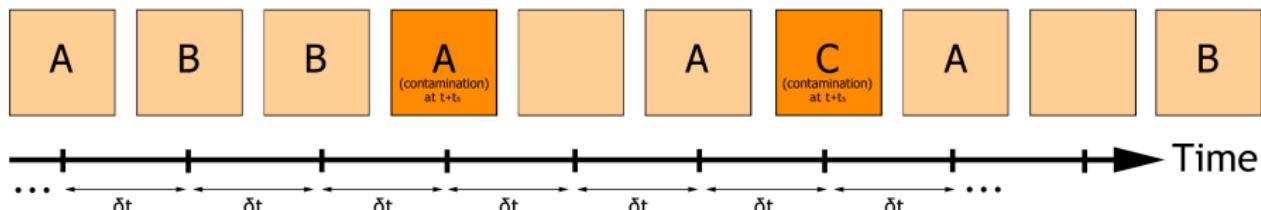


A : exposure to A

A_{contaminated} : exposure to A at t and contamination by A at $t+t_s$

t_s : time between exposures and contaminations

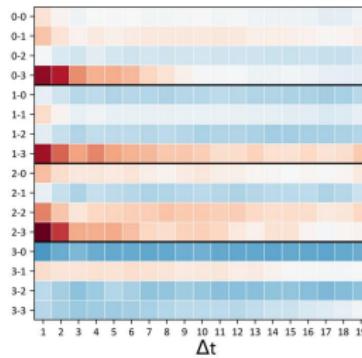
δt : time between exposures



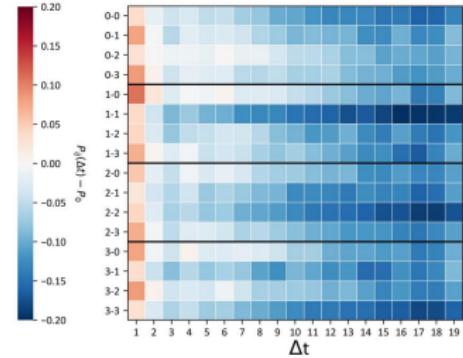
Results

- 3 datasets:
 - Twitter: how old tweets influence the probability of retweets
 - Ads: how exposure to ads influence the probability of clicking one
 - Prisoner's dilemma: how past cooperation or betrayal influence one's decisions

Twitter



Ads



PD

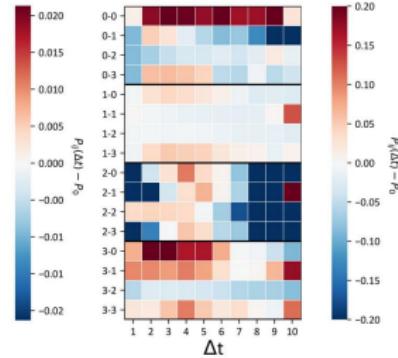


Figure 4: Conclusion: interactions between pieces of information do not last long (Poux-Médard *et al.*, ECML-PKDD 2021)

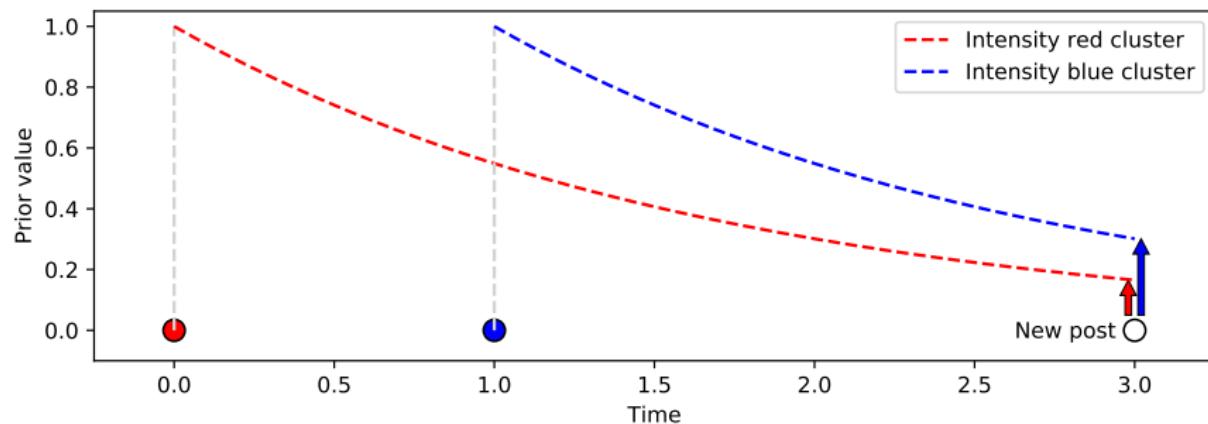
Synthesis

- Interactions only take place between a restrictive set of entities
 - Clustering is needed
- Interactions do not last in time
 - Modeling time is necessary
- Interactions improve datasets description
- Solution: jointly model clusters and their dynamic interactions
 - Promising lead: Dirichlet-Hawkes processes (Du *et al.*, KDD 2015)

Dirichlet-Hawkes process

- (Du et al., KDD 2015): Dirichlet-Hawkes prior (Bayesian inference)
- Clusters can self-replicate (self-interaction)

$$P(\text{cluster}|\text{text}, \text{time}, H) \propto \underbrace{P(\text{text}|\text{cluster})}_{\text{Textual likelihood} \\ (\text{Dirichlet-Multinomial})} \times \underbrace{P(\text{cluster}|\text{time}, H)}_{\text{Temporal prior} \\ (\text{Dirichlet-Hawkes})}$$



Powered Dirichlet-Hawkes process

- (Poux-Médard *et al.*, ICDM 2021): Powered Dirichlet-Hawkes prior

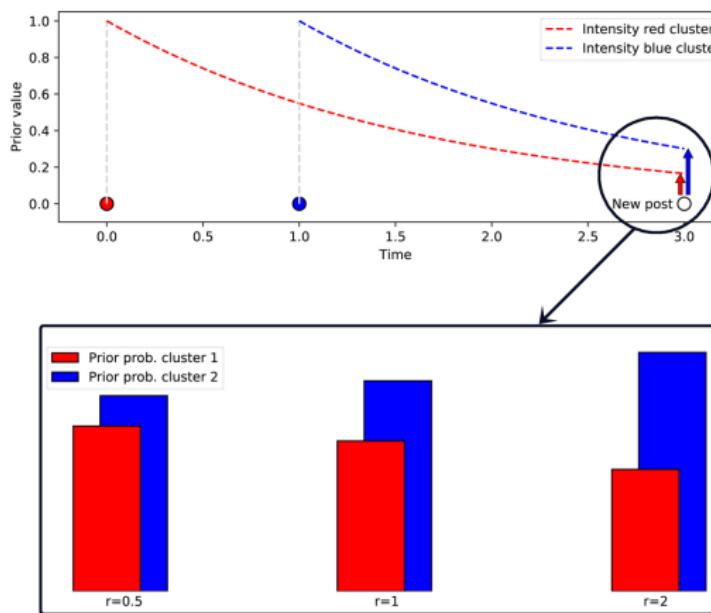


Figure 6: Powered Dirichlet-Hawkes prior

Results for various overlaps

- Powered Dirichlet-Hawkes process: works better in challenging situations
 - Scarce textual information (short texts, overlapping voc.)
 - Scarce temporal information (entangled dynamics)

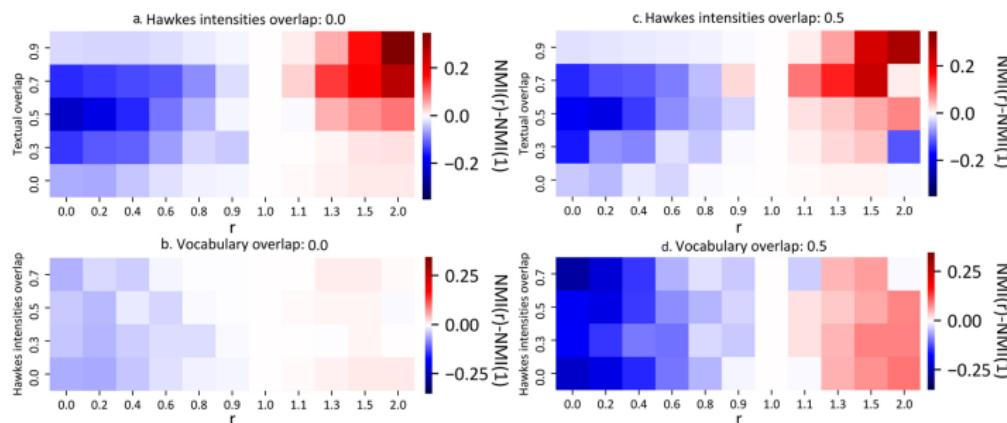
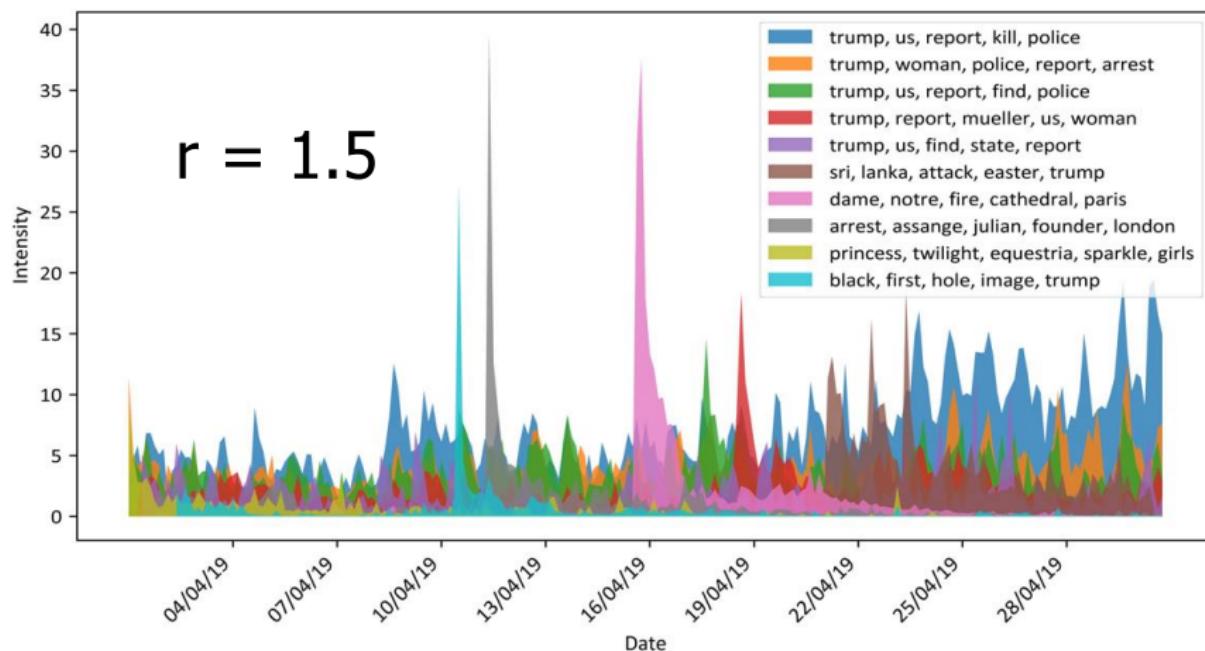


Figure 7: Red is better — (Poux-Médard et al., ICDM 2021)

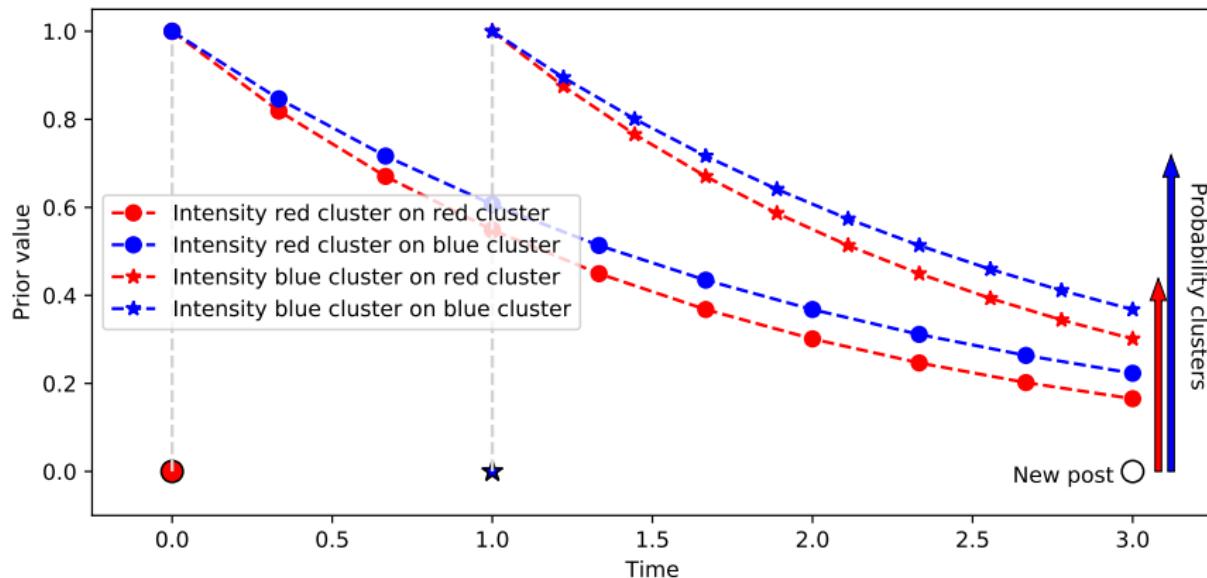
Powered Dirichlet-Hawkes process

- Powered Dirichlet-Hawkes prior: summary from data flows using temporal interactions



Perspective: Multivariate Powered Dirichlet-Hawkes process

- Perspective: Multivariate Powered Dirichlet-Hawkes prior
 - How clusters influence each other



Perspective MPDHP – Cluster interaction network

- Multivariate Powered Dirichlet-Hawkes prior: Cluster interaction network

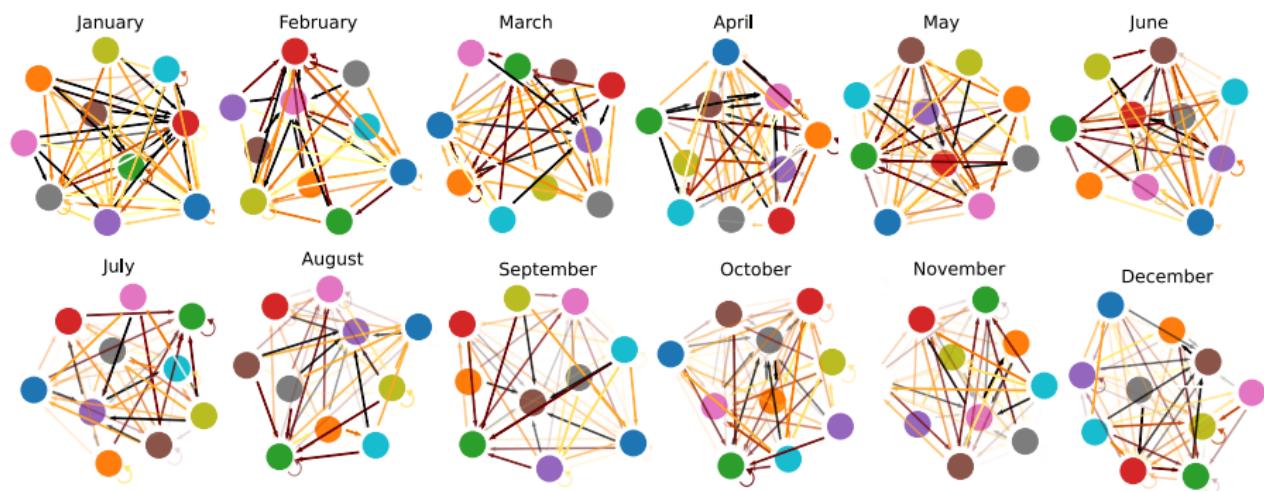


Figure 8: Topical interaction network

Perspective MPDHP – Summary generation

- Multivariate Powered Dirichlet-Hawkes prior: Cluster interaction network

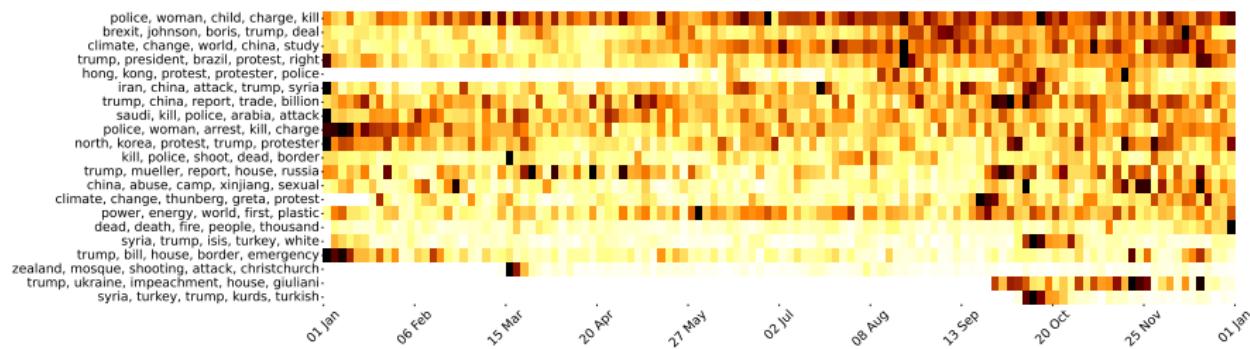
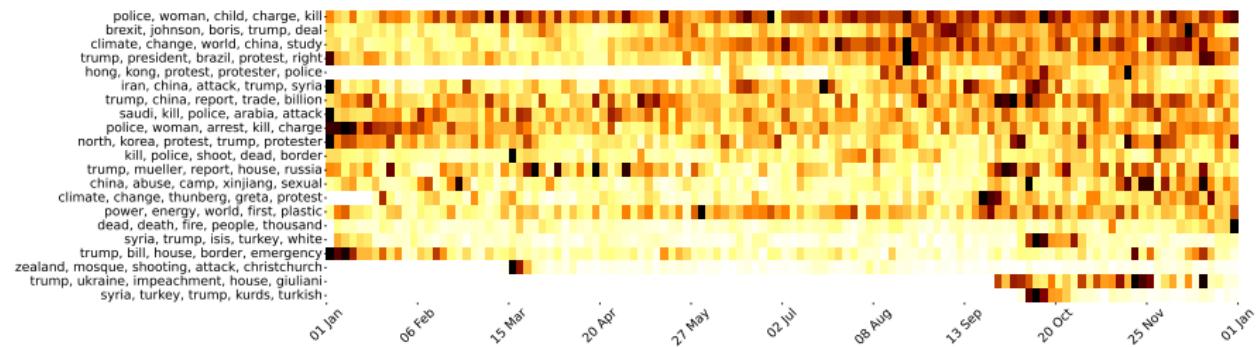


Figure 9: Inferred topics timeline

Thanks for your attention!



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