



A!

Aalto University



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Marked Temporal Point Processes for simulating and capturing coordinated behaviour campaigns

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Problem:

- **Disinformation:**

Deliberate attempts to mislead and manipulate people's perception.



- **Coordinated Inauthentic Behaviours (CIBs):**

Orchestrated campaigns amplifying misleading information through synchronized activities.

Objective: Simulate and capture coordinated inauthentic behaviours.

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CIBs detection coincides with finding anomalous **users' clusters** or communities¹:

$$Y := f(U \text{ users}, H \text{ history}).$$

The activities' history H is composed of **cascades** C_s .

Date	Content:	Post (P) or Repost (R)	User
September 12, 2022 at 10:57 AM	P	Studies show that drinking bleach can cure COVID. Many hospitals are hiding this information to keep their profits up	User A
September 17, 2022 at 05:50 PM	R	Studies show that drinking bleach can cure COVID. Many hospitals are hiding this information to keep their profits up	User B
September 20, 2022 at 02:04 AM	R	Studies show that drinking bleach can cure COVID. Many hospitals are hiding this information to keep their profits up	User A
November 15, 2022 at 07:05 PM	R	Studies show that drinking bleach can cure COVID. Many hospitals are hiding this information to keep their profits up	User C
***	***	***	***



$$C_s = [(t_1, u_1=\text{User A}), (t_2, u_2=\text{User B}), (t_3, u_3=\text{User A}), (t_4, u_4=\text{User C}), \dots]$$

¹ Lorenzo Mannocci et al. Detection and characterization of coordinated online behaviour: A survey, 2024

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...



$$C_s = [(t_1, u_1=\text{User A}), (t_2, u_2=\text{User B}), (t_3, u_3=\text{User A}), (t_4, u_4=\text{User C}), \dots]$$

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Definition MTPPs are $\{T_i : \Omega \rightarrow \mathbb{R}, M_i : \Omega \rightarrow \mathcal{K} \mid i \in \mathbb{N}\}$, stochastic processes $\{N_t^k\}_t$ whose realisations are sequences of arrival times and marks:

$$C_s := \{ (t_1, m_1), (t_2, m_2), \dots \}.$$

For example, a **mutually exciting Hawkes process** is a MTPP with

$$\lambda_k(t \mid H_t) := \frac{\mathbb{E}[dN_t^k | H_t]}{dt} = \mu_{\mathbf{k}} + \sum_{m=1}^K \sum_{t_{i,m} < t} \alpha_{\mathbf{k}, \mathbf{m}} e^{-\beta_{\mathbf{k}, \mathbf{m}}(t - t_{i,m})}.$$

- $\alpha_{k,m}$ excitation rate
- $\beta_{k,m}$ decay rate
- μ_k baseline rate

Capturing and simulating coordinated behaviour

AMDN-HAGE² integrates **MTPP**, **GMM** and **DL** to retrieve users clusters:

$$\log p_{\theta_a, \theta_b}(C_s, U \mid E) = \underline{\log p_{\theta_a}(C_s \mid U, E)} + \underline{\log p_{\theta_b}(U \mid E)}$$

We propose two extensions:

- Clustering techniques on users' embeddings E
- Clustering based on users' influences

²Karishma Sharma et al. Identifying coordinated accounts on social media through hidden influence and group behaviours, 2021

Twitter dataset

- Keywords like “vaalit” (elections), “eduskunta” (parliament), ...
- 5.2M tweets about the 2023 Finnish election
- 762 remarkably active users (159085 accounts)

Difficulties

- Absence of *ground truth*
- Wide number of existing *coordinated strategies*
 - ↓
- Difficulties in performing a comprehensive study

We propose a **simulation framework** leveraging *Hawkes Processes* where hyper-parameters can be selected depending on the scenario:

Authentic

$$\mu_i \sim \Gamma(\mu, \sigma_\mu^2)$$

$$\alpha_{i,j} \sim \Gamma(\alpha, \sigma_\alpha^2)$$

$$\beta_i \sim \Gamma(\beta, \sigma_\beta^2)$$

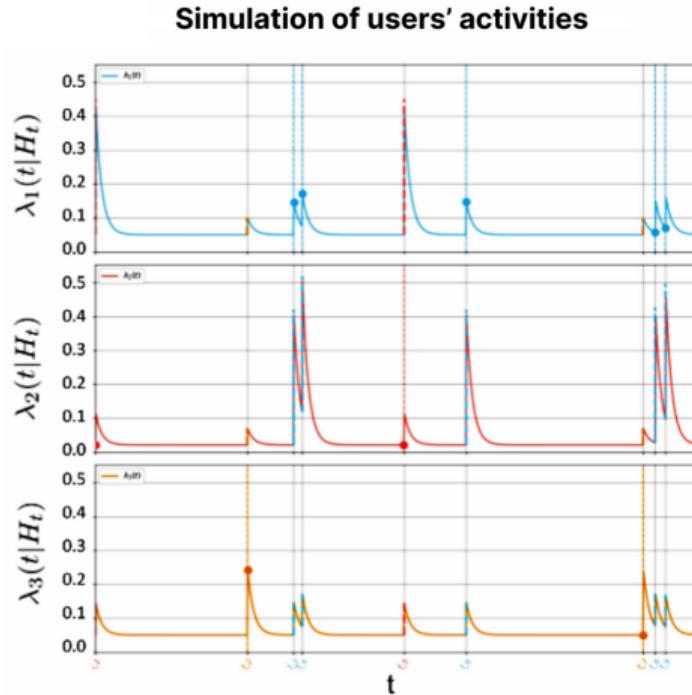
Inauthentic

$$\mu_i = c_\mu \mu Z$$

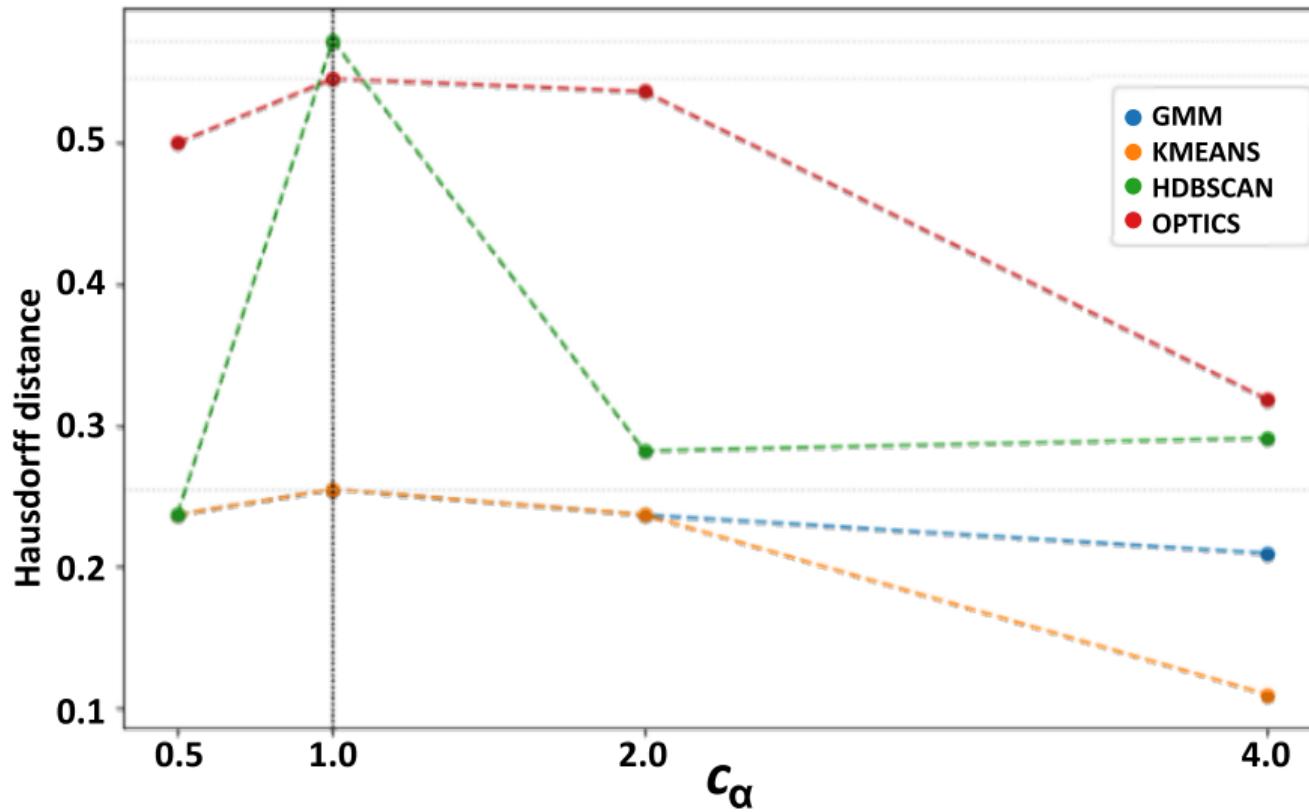
$$\alpha_{i,j} = c_\alpha \alpha Z$$

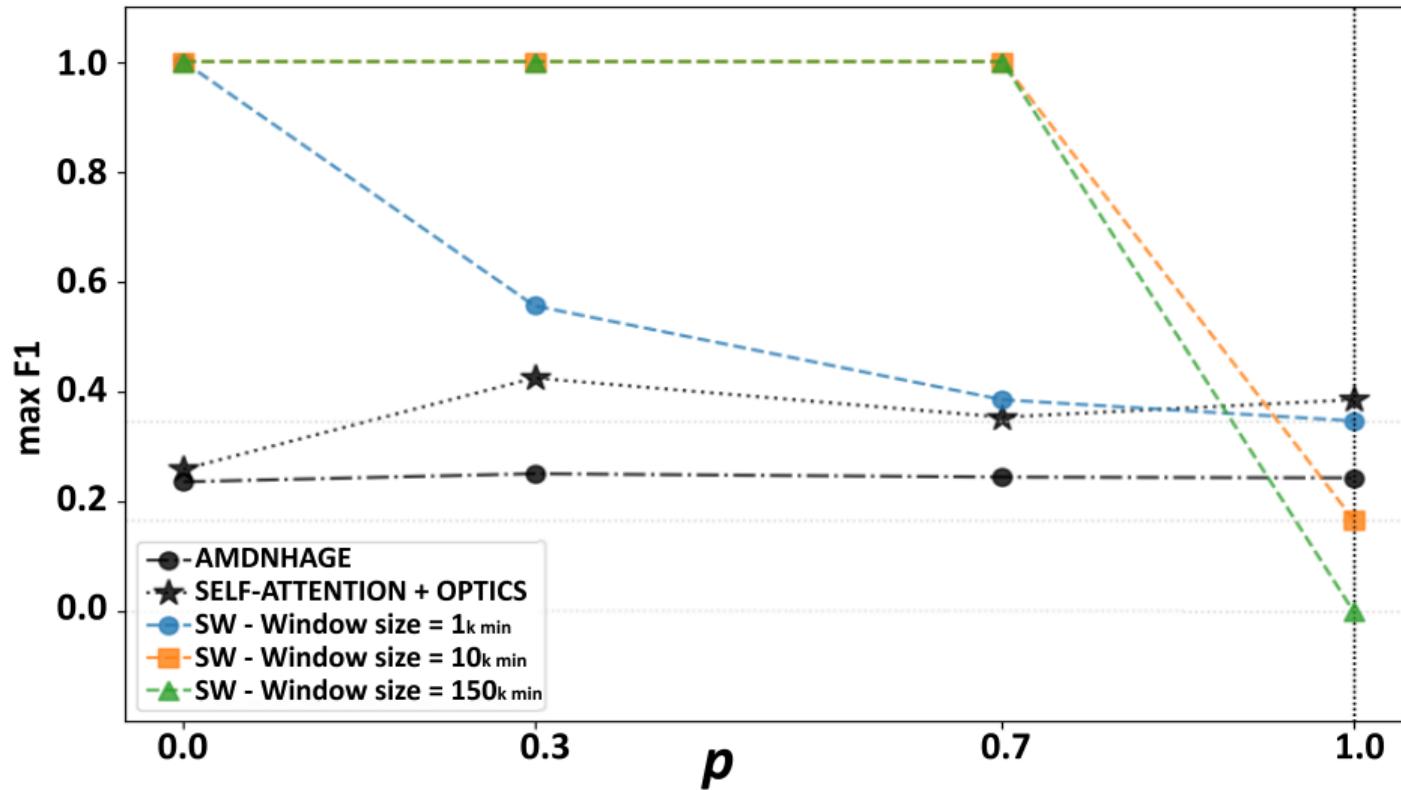
$$\beta_i = c_\beta \beta Z$$

Interactions percentage controlled by p



Results

Results varying the excitation rate c_α - AMDN-HAGE extensions

Results varying the interaction level p - Sliding Windows (SW)

Conclusions

- Enhanced coordination **detection methods**
- Simulation framework for **systematic evaluation**
- Importance of the **objective**
 - ⇒ Different methods may excel depending on the CIB nature
 - ⇒ Careful consideration of the data features and detection goals

Thanks for your attention!

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- Each user u_j is clustered into group i s.t.

$$\hat{i} := \operatorname{argmax}_i p_{\theta_b}(z_{i,j} \mid E_{u_j}) = \operatorname{argmax}_i \frac{p(E_{u_j} \mid \mu_i, \Sigma_i)}{\sum_{k=1}^N p(E_{u_j} \mid \mu_k, \Sigma_k)}$$

where $z_{i,j} = 1$ represents the event that the user u_j is from group i

- Usage of KMEANS on embeddings since coordinated users behaving similarly are expected to have close embedding vectors

Self-attention user-to-user matrix $A_{\text{TOT}} \in \mathbb{R}^{|U| \times |U|}$

- Each row corresponds to a user who performs an action
- Each column represents the influence he receives from other users

The weights are updated as:

$$A'_{\text{TOT}}[i, j] = A_{\text{TOT}}[i, j] + \sum_{\{k|m_k=u_i\}} \sum_{\{h|m_h=u_j\}} A_X[k, h]$$

where $A_X[k, h]$ is the influence that (m_k, t_k) has received by (m_h, t_h)

Authentic

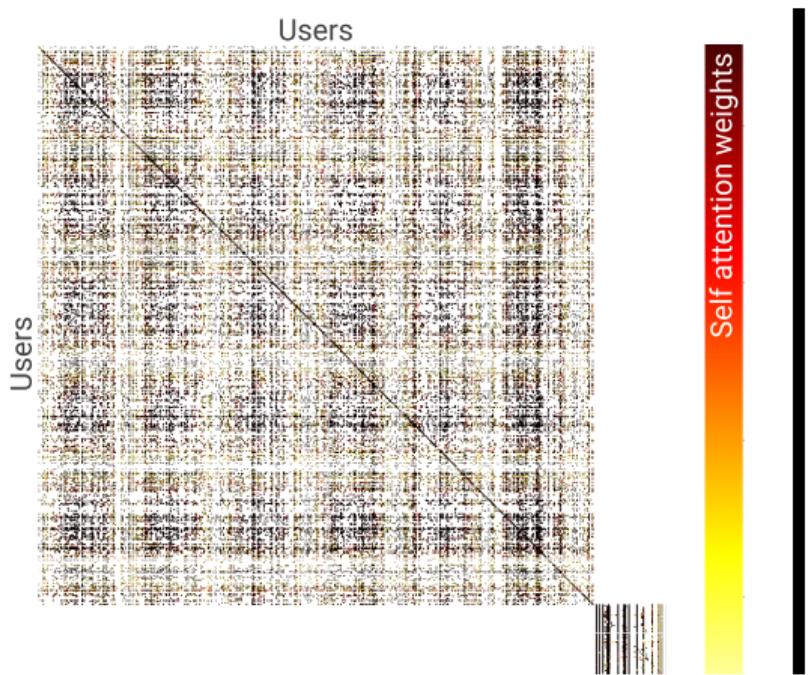
- 5.2M tweets about the 2023 Finnish election
- 762 remarkably active users (159,085 accounts)
- Keywords like “vaalit” (elections), “eduskunta” (parliament), . . .

Inauthentic

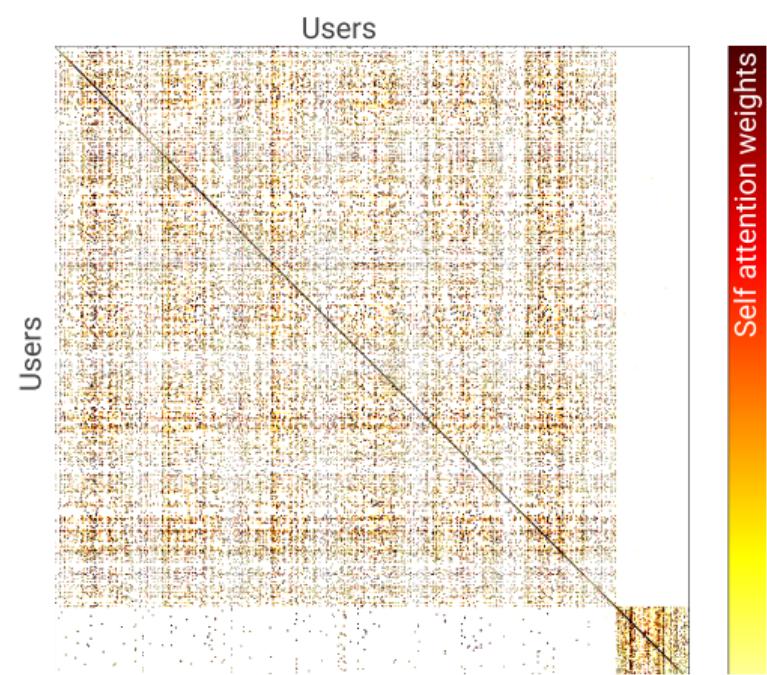
- 100 coordinated users
- Uniform distribution of timestamp
- About 5%³ of the real dataset activities

³ Andrew M. Guess and Benjamin A. Lyons. MDOP, 2020.

Non-Interacting scenario



Interacting scenario



$$(\alpha_{i,j})_{i,j} = \left(\begin{array}{cc|cc|cc} & & & & & \textcolor{red}{influencer} \\ & & \text{authentic} & & & \text{inauthentic} \\ \textcolor{red}{influenced} & \alpha_{i,j} & \cdots & \alpha_{i,j} & 0 & \cdots & 0 \\ & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ & \alpha_{i,j} & \cdots & \alpha_{i,j} & 0 & \cdots & 0 \\ \hline & c_\alpha \alpha IZ & \cdots & c_\alpha \alpha IZ & c_\alpha \alpha Z & \cdots & c_\alpha \alpha Z \\ & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ & c_\alpha \alpha IZ & \cdots & c_\alpha \alpha IZ & c_\alpha \alpha Z & \cdots & c_\alpha \alpha Z \end{array} \right)$$

Results via GMM, KMEANS, HDBSCAN and OPTICS

