UTS

Behavioral Data Science

Interval-censored Transformer Hawkes

Detecting Information Operations using the Reaction of Social Systems

Data Science Institute

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Who are our online opinion leaders?

Common traits:

- Pro-republican;
- Highly influential, highly followed and retweeted;
- Opinion leaders;
- …

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Russian-controlled trolls operated by the Internet Research Agency in St. Petersburg

Information Operations

"computational propaganda [..] use of algorithms, automation, and human curation to purposefully distribute misleading information over social media networks"
[Woolley & Howard, 2018]

(defense env.) Information operations includes [..] the dissemination of propaganda in pursuit of a competitive advantage over an opponent.

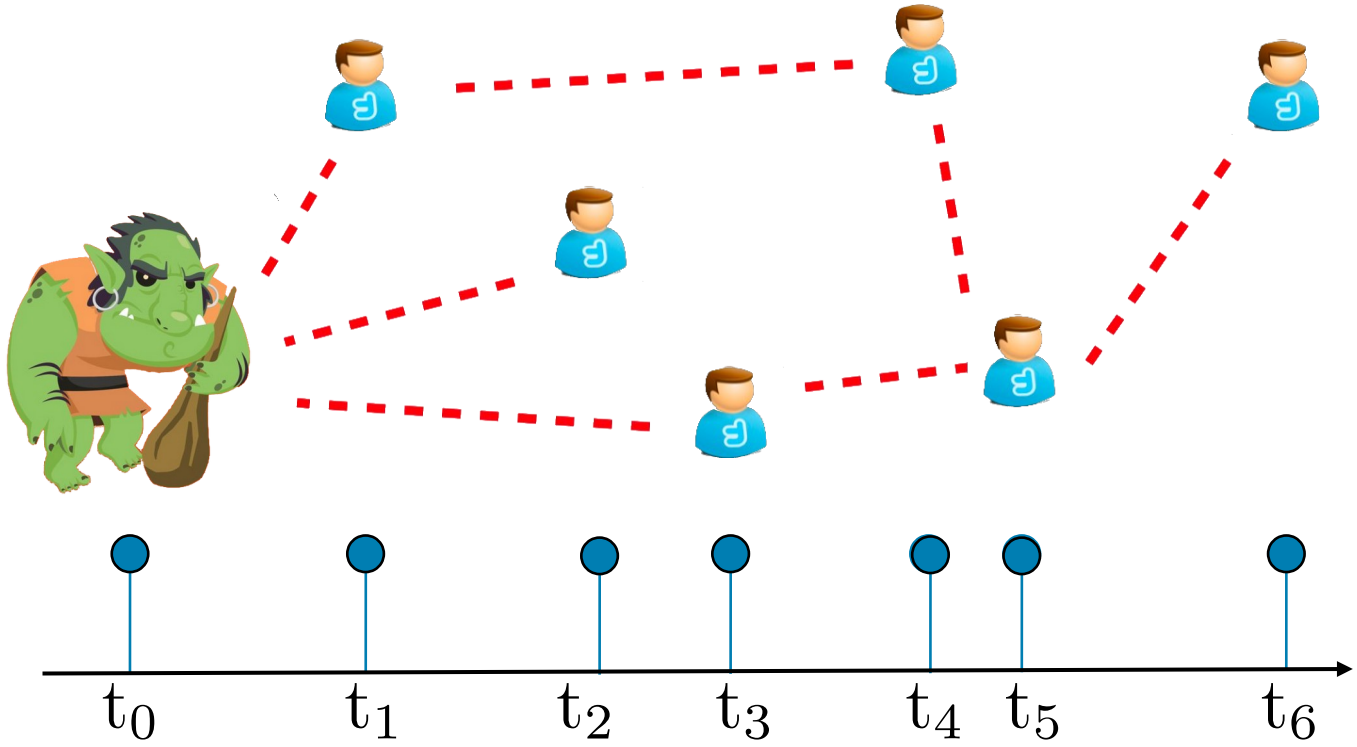
vs.

Challenge: beyond content-based detectors

Content- and user-based detection tools:
language nuances, language drift and adversarial attacks

IO are designed to elicit particular reactions from the target audience

RQ1:
Can we distinguish users and content types based on on the reaction of online social systems? **no content**



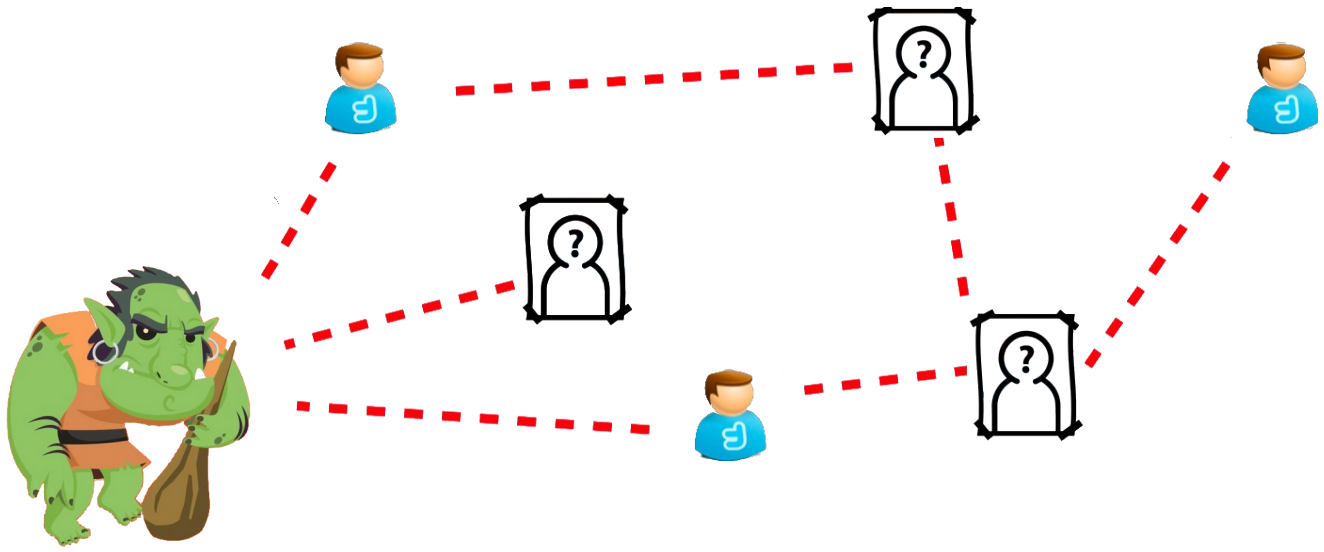
Challenge: partial missing data

Missing tweets

Restrictions from Twitter API [Wu et al, 2020]

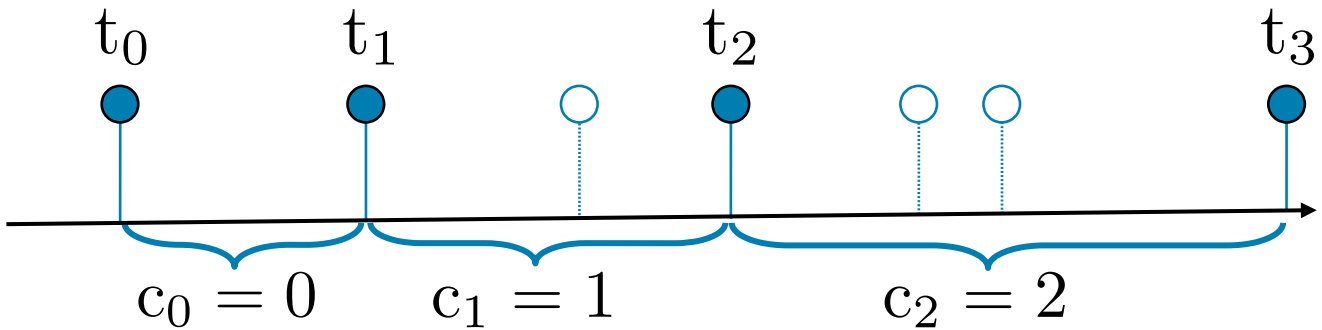
User moderation, content removal

Only event counts are available between events (via the retweet_count property)



RQ2:

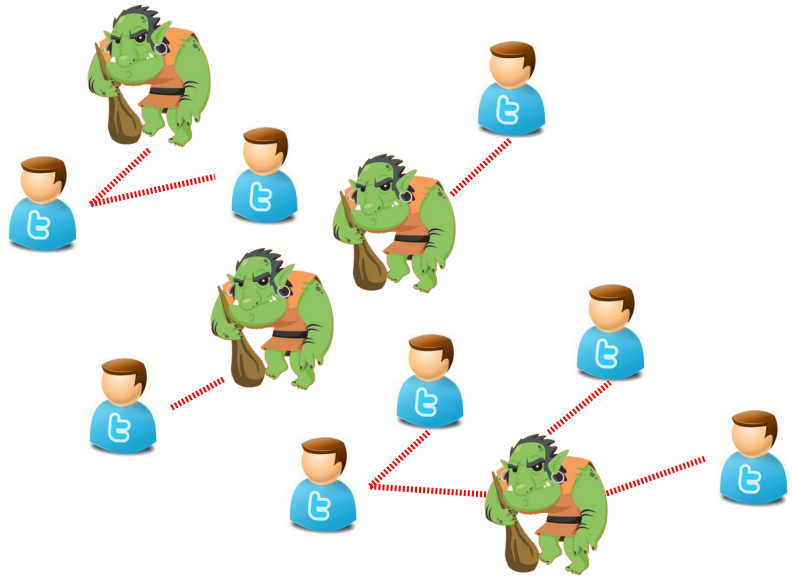
Can we model reshare cascades containing both event times and missing event counts?



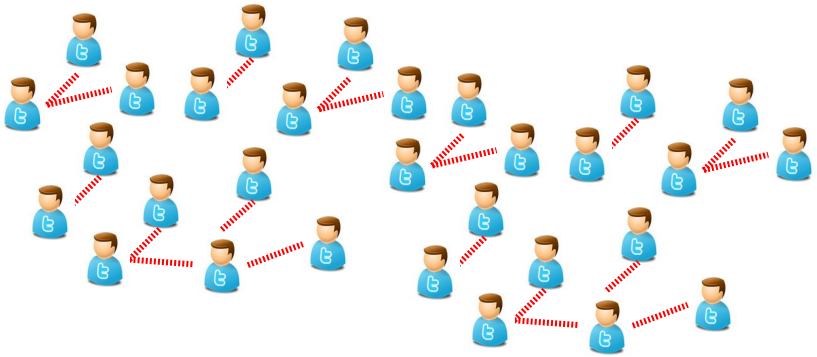
Challenge: (very) limited labelled data

Very limited training data
- Covert nature of IO
- Costly human labelling

Abundant amount of unlabelled data
- Public datasets
- APIs



Labelled Cascades

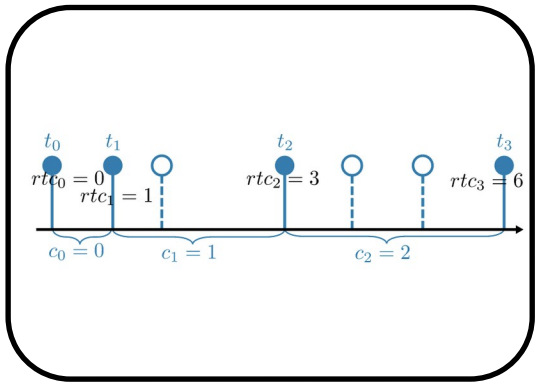


Unlabelled Cascades

RQ3:
Can we use (large amounts of) unlabelled data to pretrain representations?

Presentation plan

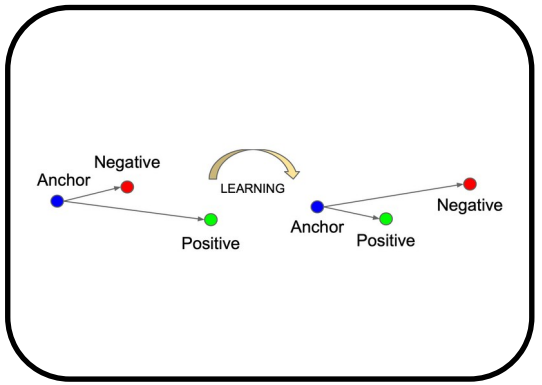
- Motivation and Challenges
- Interval-Censored Transformer Hawkes (IC-TH)



Unified representation times & event counts

$$\mathscr{L}_{\text{IC-TH-LL}}(\theta) = \underbrace{\sum_{i \in \mathcal{H}_u^*} c_i \log \Xi(t_i, t_{i+1}}_{\text{missing event counts}}$$
$$= \sum_{i \in \mathcal{H}_u^*} c_i \log \Xi(t_i, t_i$$

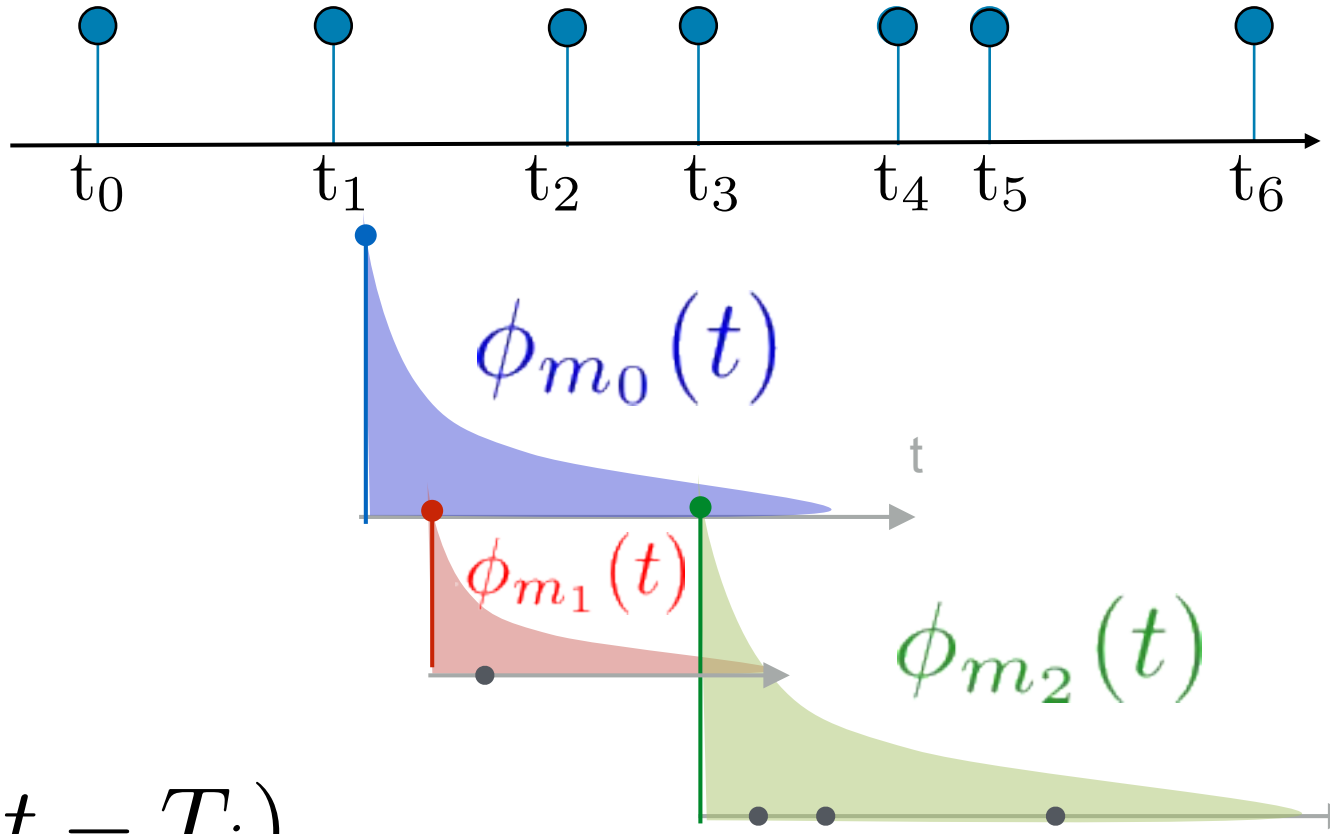
Novel log-likehood function



Model Pre-training via Contrastive learning

- Experiments and findings

Self-exciting (Hawkes) processes [Hawkes, 1971]



Event intensity

$$\lambda(t|\mathcal{H}_t) = \underbrace{\mu(t)}_{\text{base intensity (exogenous)}} + \underbrace{\sum_{i:t>T_i} \phi(t - T_i)}_{\text{self-excitation (endogenous)}}$$

Transformer Hawkes [Zuo et al, 2021]

Event intensity

Softplus function

$$\lambda(t) = f(w^\top h(t))$$

Hidden-state

Multi-head self-attention module

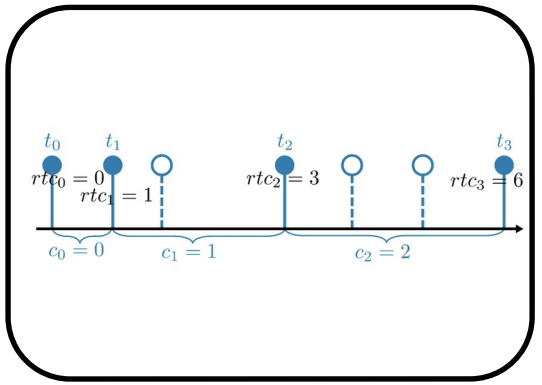
$$h(t_j) = H(j,:)$$

$$H(j,:) = ReLU(SW_1 + b_1)W_2 + b_2$$

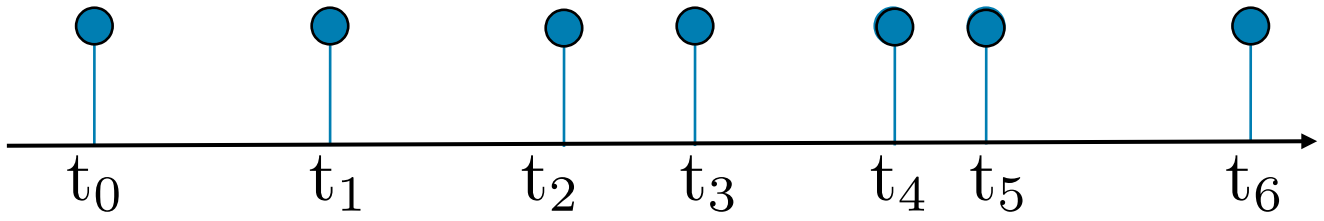
$$S = Concat(head_1, head_2, \cdots)W^O$$

$$head_i = Softmax\left(\frac{XW_i^Q(XW_i^K)^\top}{\sqrt{d_k}}\right)XW_i^V$$

IC-TH: a mixed data format



Hawkes & Transformer Hawkes



$$\mathcal{H} = \{t_0, t_1, \ldots\}$$

duration

$$\mathcal{H}^* = \{(t_i, d_i, c_i)\}$$

interval start time

event count

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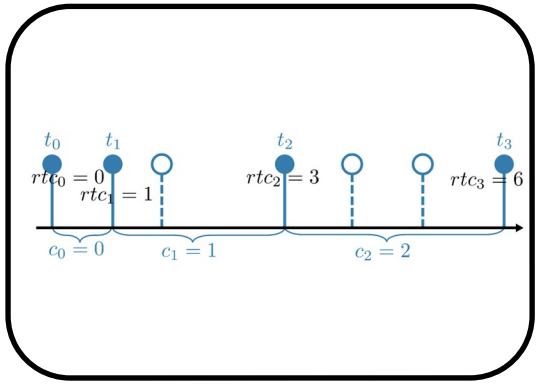

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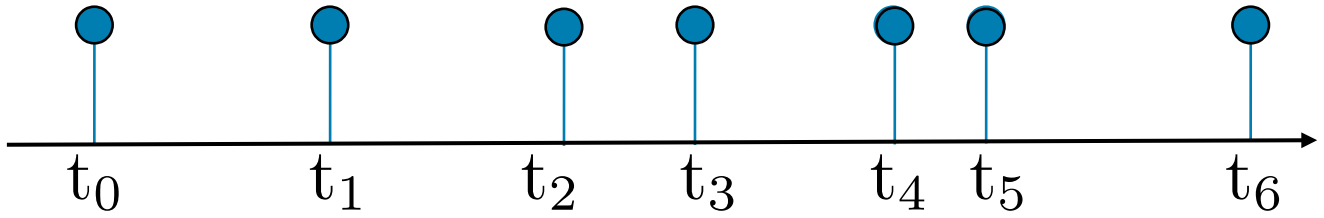

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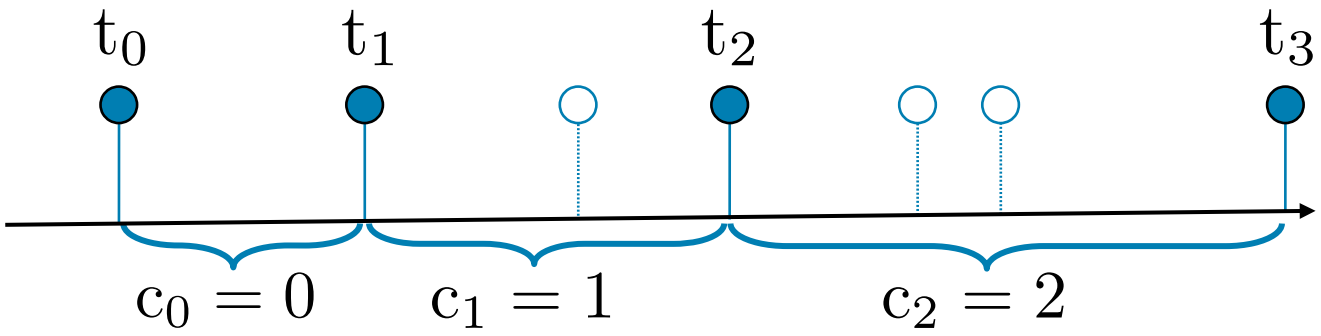
Interval-Censored Tranformer Hawkes



$$\mathcal{H}^* = \{(t_0 - dt, 2dt, 1), (t_0, t_1 - t_0, 0), (t_1 - dt, 2dt, 1), (t_1, t_2 - t_1, 1), \cdots\}$$

IC-TH: Novel log-likehood function

$$\mathscr{L}_{\text{IC-TH-LL}}(\theta) = \underbrace{\sum_{i \in \mathcal{H}_u^*} c_i \log \Xi(t_i, t_{i+1}}_{\text{missing event counts}}$$

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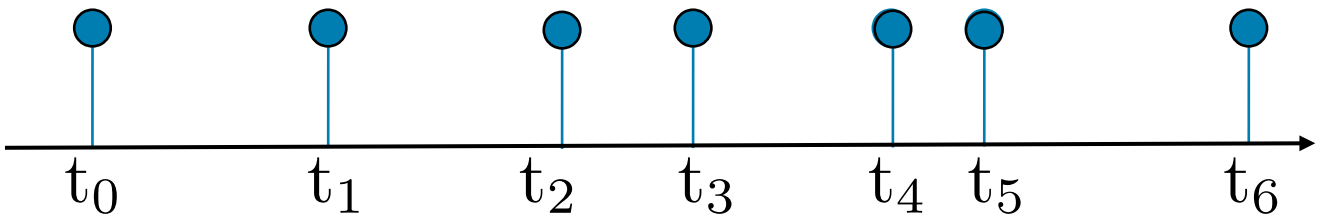
Hawkes process

$$\log L(\theta) = \sum_{i=1}^{N(t)} \log \lambda(t_i) - \int_0^t \lambda(\tau) d\tau$$



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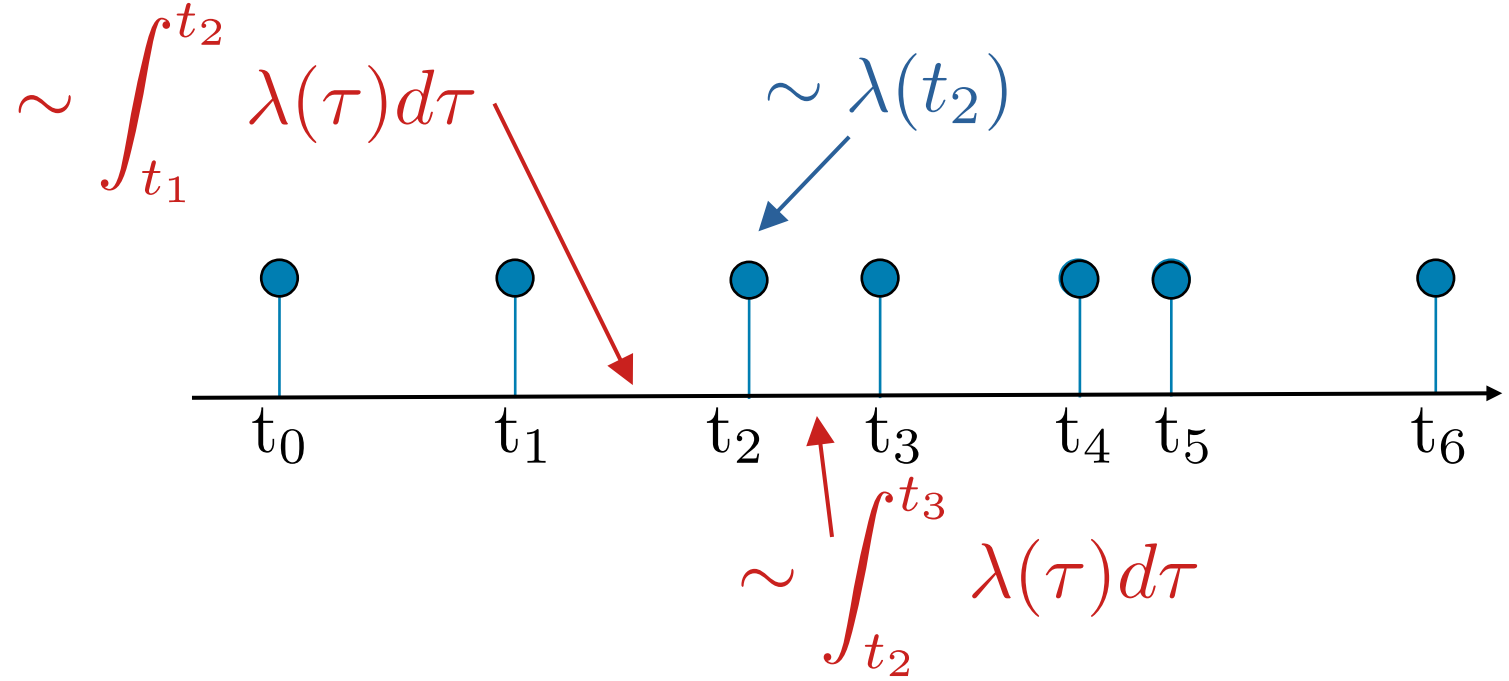

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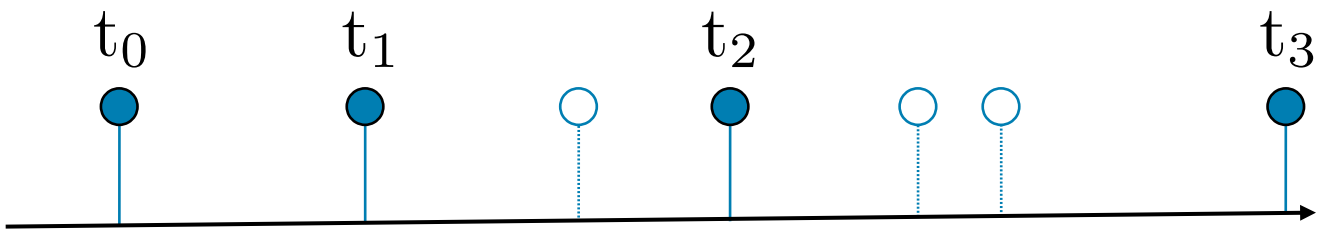
Interval-Censored Transformer Hawkes

$$\log L(\theta) = \sum_{i \in \mathcal{H}_u^*} c_i \log \int_{t_i}^{t_{i+1}} \lambda(\tau) d\tau + \sum_{i \in \mathcal{H}_c^*} \log \lambda(t_i) - \sum_{i \in \mathcal{H}^*} \int_{t_i}^{t_{i+1}} \lambda(\tau) d\tau$$



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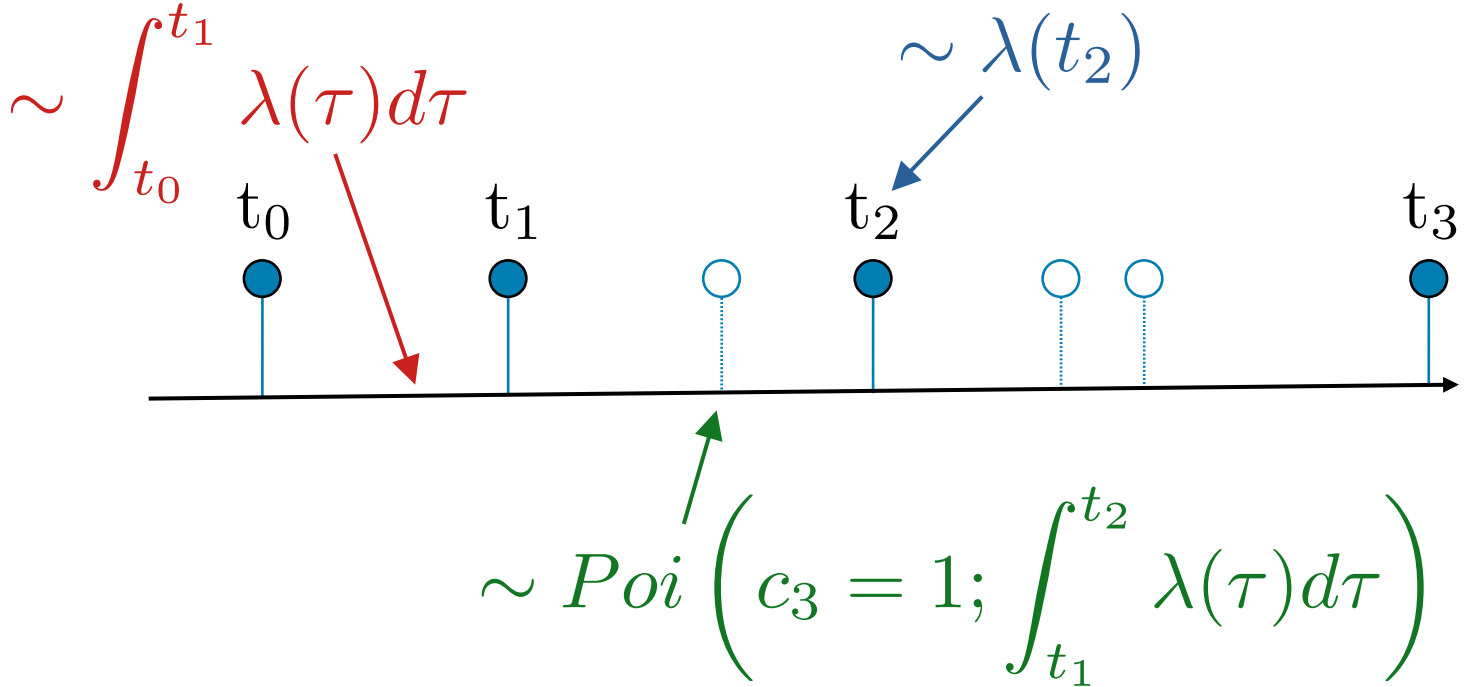
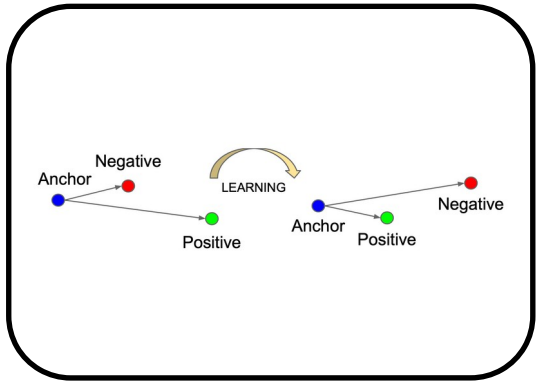


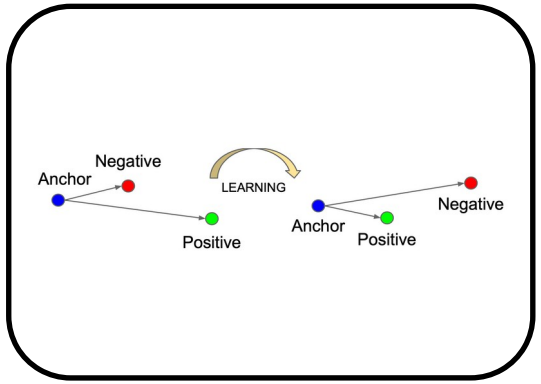
IC-TH: contrastive learning

On a large, unlabeled dataset "contrast samples against each other to learn attributes that are common between data classes and attributes that set apart a data class from another."



Build representations that distinguish users based on the cascades they appear in

IC-TH: contrastive learning



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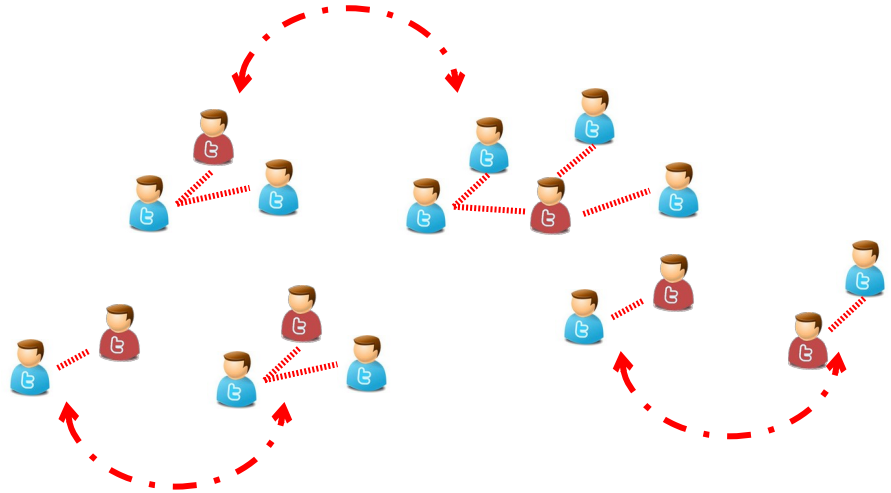
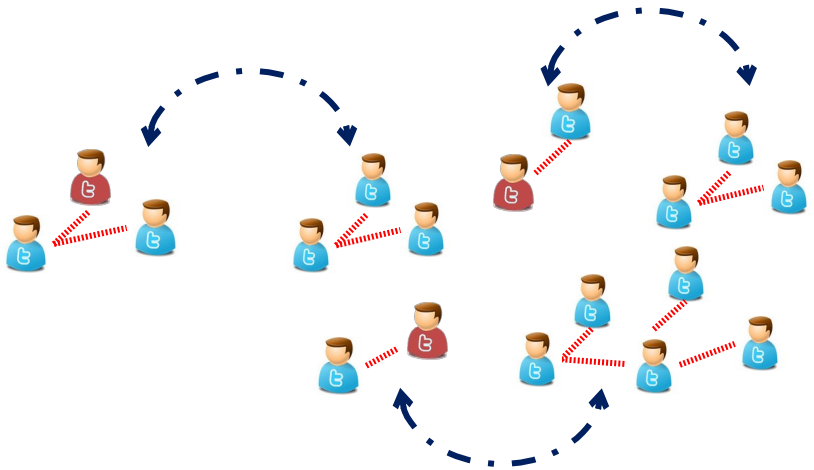
Positive pairs

cascades in which a given user participates



Negative pairs

given user only appears in one cascade



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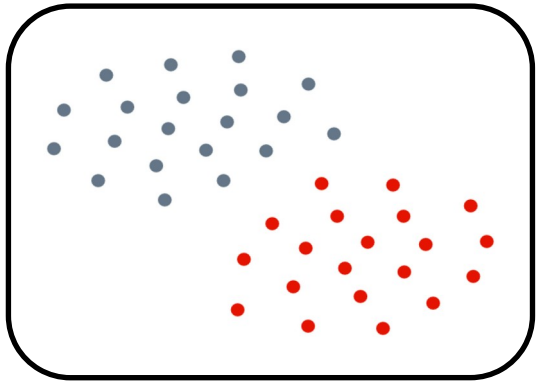
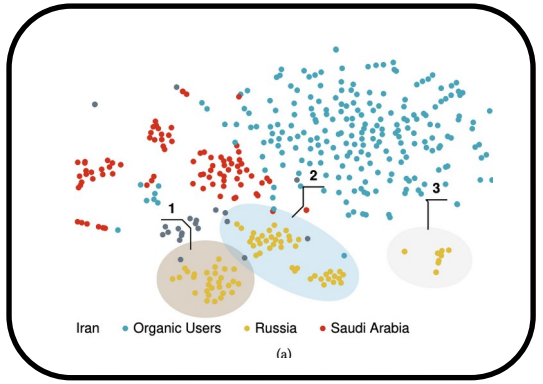


Effects of data loss

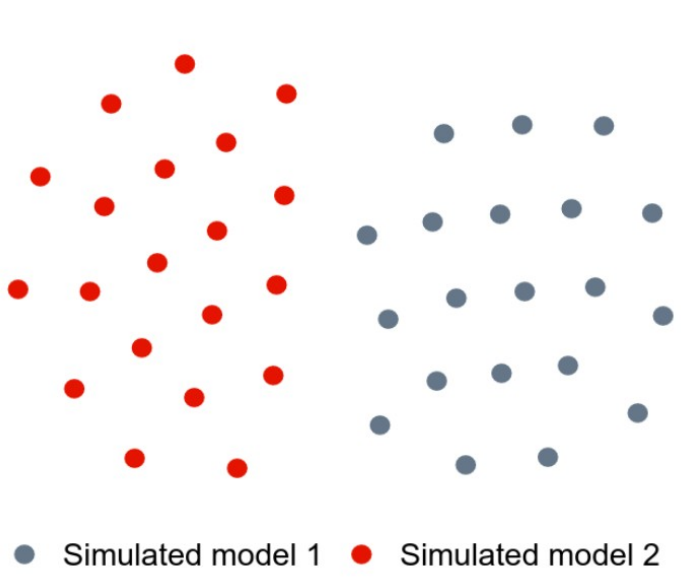
Category prediction

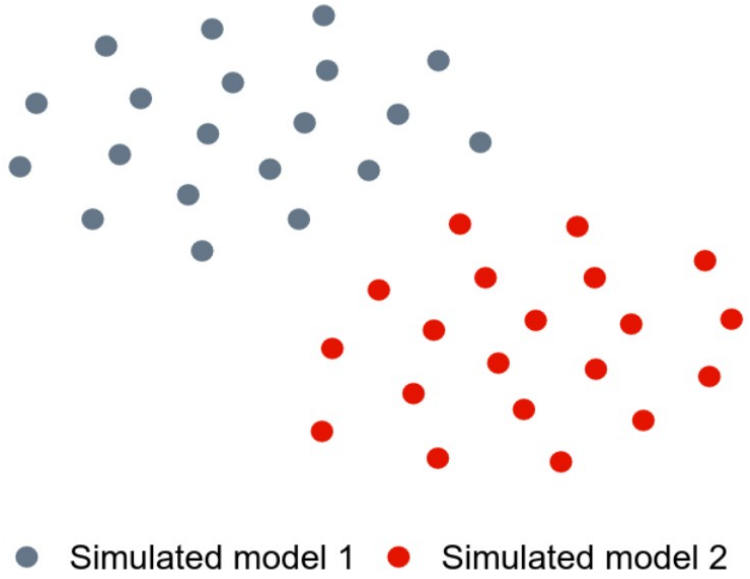


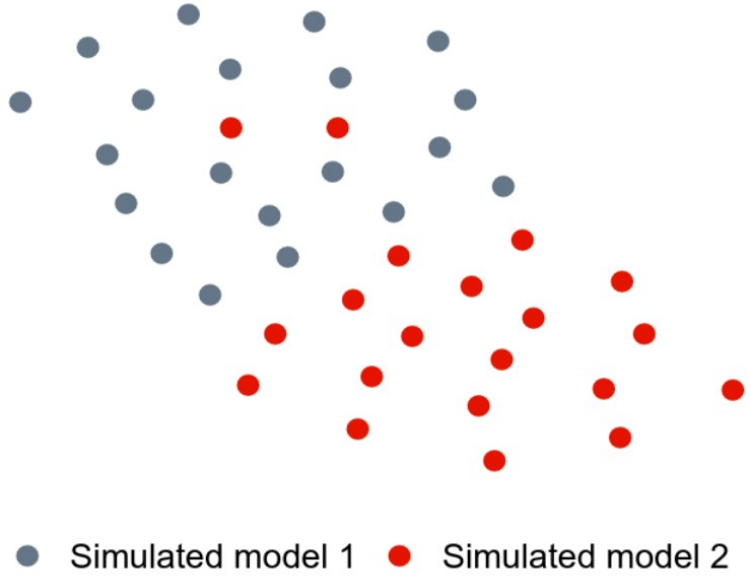
Analysis of Information Operations Dataset

Synthetic XP: effect of data loss

2 models (PowerLaw and Exponential), 10,000 cascades per model, 20 groups of 500 cascades







Missing events:

0%

50%

90%

IC-TH is robust with data loss; achieves near-perfect separability even at very large data sampling rates (90%).

Dataset: Twitter Moderation Research Consortium (TMRC) Information Operations dataset

Manipulation that Twitter can reliably attribute to a government or state linked actor – an information operation. [Twitter, TMRC]

Profiling:

Nov 2010 to Aug 2020
32,486 users
22,845,053 tweets
19,476,766 cascades

Classes – states sponsoring IO:

Russia, Iran, Saudi Arabia, Organic users

Dataset: Reputable&controversial news sources, tweeted YouTube

RNCNIX:
102,429 articles
56,397,252 tweets
8,129,126 cascades

Classes – states sponsoring IO:
Reputable, controversial

ActiveRT2017:
75,717 videos
85, 334, 424 tweets
30,535,891 cascades

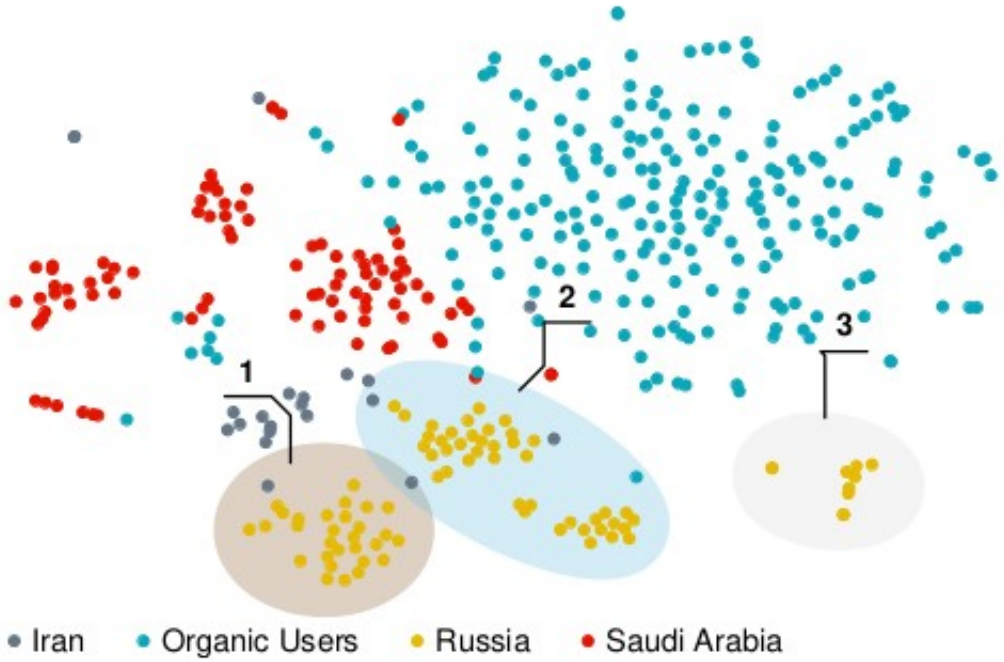
Classes – states sponsoring IO:
Entertainment, Gaming, Music and News&Politics

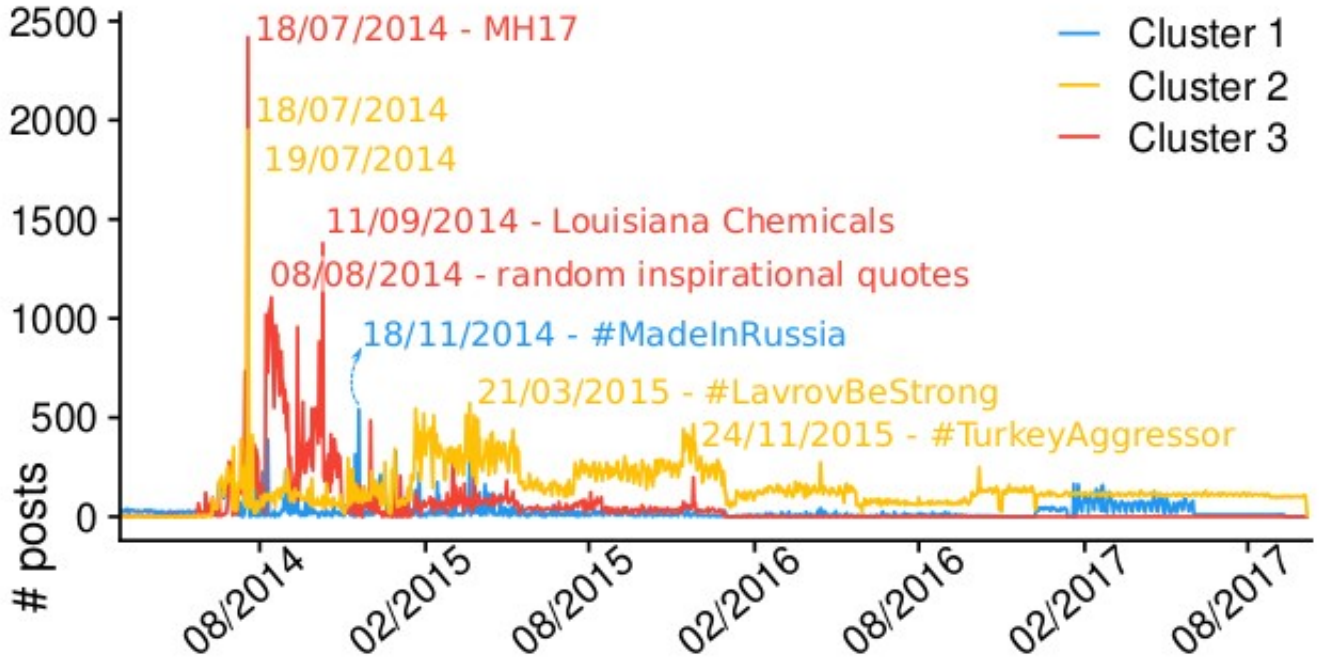
Predicting the category of content

Models			
Discrete Mixture Models	0.488	0.675	0.968
Transformer Hawkes [Kong et al, 2020]	0.469	0.823	0.983
IC-TH w/o missing counts [Zuo et al, 2021]	0.495	0.840	0.985
IC-TH	0.499	-	**0.987**
Pre-trained IC-TH	**0.503**	**0.853**	**0.987**

IC-TH outperforms all baselines;
Mixed data format + loglikelihood contribute most to performance
Missing counts and pre-training lead to moderate performance increases.

Strategies of Russia-backed Information Operations

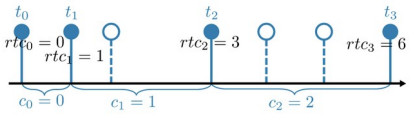




IC-TH clusters IO agents from specific countries based solely on the timing of the cascades in which they participate; it identifies even individual "troll farms".

Qualitative investigations uncovers strategies of Russian trolls farms:
C1: Russian news with patriotic framing;
C2: Regional and conservative news;
C3: tweet in English, *#music*, *#usa*, relationship advice

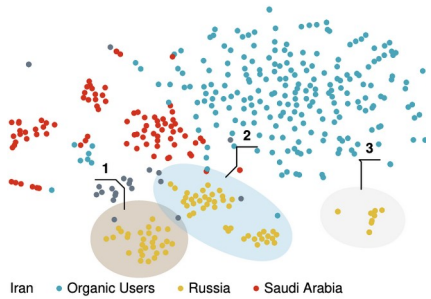
Conclusion



A unified representation and a novel log-likelihood for event times and missing events for the Transformer Hawkes architecture.

A contrastive learning approach that leverages large amounts of unlabeled data to build representations.

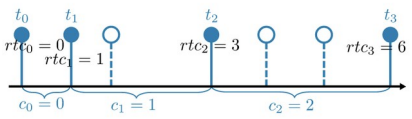
Predict the type of users and online content based solely on how the social systems react to them.



IC-TH reveals even “troll farms” – qualitative analysis reveals their strategies and roles, and the coordinated activity at strategic times.

Conclusion

Thank you!



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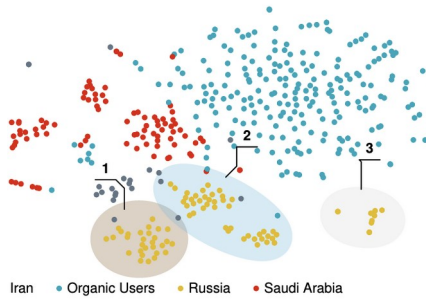

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