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Learning time-evolving states via dynamic Hawkes processes

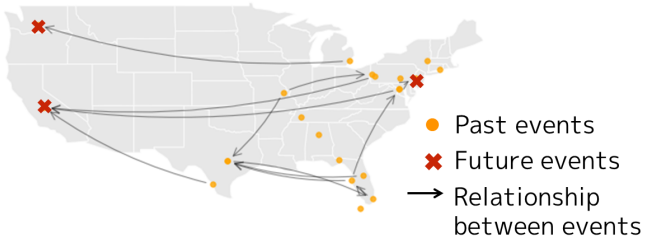
# How the events spread?


## Abstract

Sequences of events including infectious disease outbreaks, social network activities, and crimes are ubiquitous and the data on such events carry essential information about the underlying diffusion processes between communities (e.g., regions, online user groups). Modeling diffusion processes and predicting future events are crucial in many applications including epidemic control, viral marketing, and predictive policing. Diffusion processes depend not only on the influences from the past, but also the current (time-evolving) states of the communities, e.g., people's awareness of the disease and people's current interests. We propose a novel Hawkes process model that is able to capture the underlying dynamics of community states behind the diffusion processes and predict the occurrences of events based on the dynamics. The proposed method offers a flexible way to learn complex representations of the time-evolving communities' states, while at the same time it allows to computing the exact likelihood, which makes parameter learning tractable.


## Diffusion process

Various social phenomena can be described by diffusion processes among multiple communities.
E.g., Demonstrations that started in large cities have spread to dozens of cities across the country.

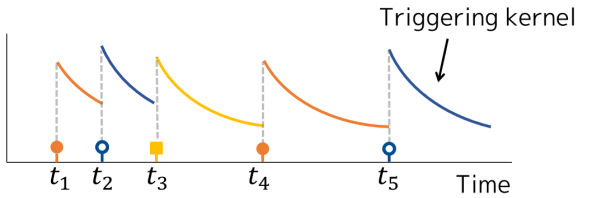



Demonstrations in United States.

Understanding diffusion mechanism and predicting future events are crucial in many applications such as epidemic control and predictive policing.

## Baseline: Hawkes processes

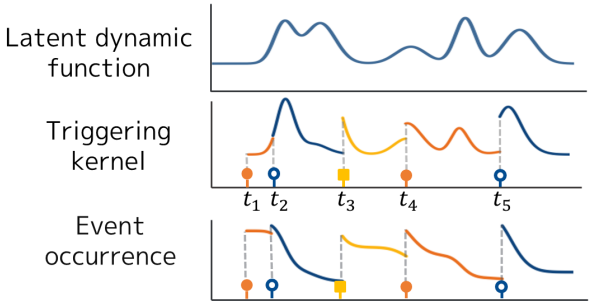
Capture the impact of past events on the event occurrence in each community by *triggering kernel*.




Limitation: Focus on learning the static influence of the past events on the current event, thereby overlooking the factor of time-evolution.
E.g., Expansion of demonstrations depends on motivations for participation of community population.

## Proposal: Dynamic Hawkes processes

- Introduce *latent dynamics function* for each community that represents its hidden dynamic states.
- Model the triggering kernel by using latent dynamics function and its integral.




## Experiments

- Evaluate the prediction performance of the proposed method on four real-world datasets.
- Use MAPE between the predicted number of events and the ground truth as metric.

| | Reddit | News | Protest | Crime |
|---|---|---|---|---|
| Homogeneous point process | 0.553 | 0.6 | 0.345 | 0.144 |
| Hawkes process | 0.458 | 0.471 | 0.415 | 0.179 |
| Reinforced process | 0.595 | 0.481 | 0.581 | 0.175 |
| SelfCorrecting process | 0.475 | 0.452 | 0.524 | 0.123 |
| RMTPP | 0.311 | 0.446 | 0.639 | 0.302 |
| **Proposed method** | **0.305** | **0.442** | **0.318** | **0.117** |

Proposed method outperforms the five existing methods across all the datasets.


## References

[1] M. Okawa, T. Iwata, Y. Tanaka, H. Toda, T. Kurashima, H. Kashima, "Dynamic Hawkes processes for discovering time-evolving communities' states behind diffusion processes," in *Proc. of the 27th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD21)*, pp. 1276–1286, 2021.



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