Spatio-Temporal Wildfire Prediction using Multi-Modal Data

Chen Xu, Yao Xie
Daniel A. Zuniga Vazquez, Rui Yao, and Feng Qiu

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Layout

- Motivation
- Problem setup
- Methods
- Theoretical guarantee
- Numerical results
- Summary

Motivation

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- For instance, utility companies have to schedule utility shutdown for high wildfire risk regions.
- However, existing metrics for measuring fire risks (e.g., burning index, fire load index) are static features lacking adaptivity.
- Multi-modal features are available: weather variables, infrastructure information, etc.

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- Events happen at specific locations but asynchronously (e.g. influence changes over time and should not be captured by fixed metrics).
- Data are limited, with only one-class wildfire information available.
- To predict wildfire severity, classification methods can also been used, whose uncertainty analyses remain unexplored.

Problem setup

- Each observed wildfire datum

$$x_i = (t_i, u_i, m_i), t_i \in [0, T], u_i \in \mathbb{R}^2, m_i \in \mathbb{R}^d$$

is a tuple consisting of time, location, and marks.

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- In particular, $m_i = (z_i, m_i')$ contains both static marks z_i and dynamic marks m_i'.
- Example of static marks z_i: Fire zone tier, vegetation type, road condition.
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- For each x_i, we may also know its severity $y_i \in \{0, \ldots, M\}$.

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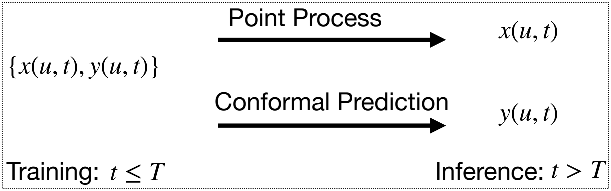

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- Denote $\mathcal{H}_t$ as the history of neighboring and historical events:
- The Hawkes point process models the conditional intensity

$$\lambda(t, u, m \mid \mathcal{H}_t) := \lim_{\Delta t, \Delta u \to 0} \frac{\mathbb{E}\left[N\left([t, t + \Delta t) \cdot B(u, \Delta u) \cdot B(m, \Delta m) \mid \mathcal{H}_t\right]\right.}{\Delta t \cdot B(u, \Delta u) \cdot B(m, \Delta m)}$$

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- Numerous works on parametrizing the intensity function λ (Hawkes, 1971; Daley and Vere-Jones, 2003; Bauwens and Hautsch, 2009; Zhu et al. 2021; Dong et al. 2022).
- See (Reinhart 2018) for a survey of Hawkes process models.

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- In this work, we assume the intensity has the form

$$\lambda(t, u, m \mid \mathcal{H}_t) = \underbrace{\left(f_u + \sum_{j:t_j<t} f_u(u_j, u) \cdot f_t(t_j, t)\right)}_{\lambda_g(t,u):=} \cdot f_m(m), \tag{1}$$

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- $f_m\left(m_j'\right)$ measures contribution from marks. We consider (1) $f_m\left(m\right) = \gamma^T m$ (`LinearSTHawkes`) (2) f_m as a pre-trained feature extractor (`NonLinearSTHawkes`).

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  (1) $f_m(m) = \gamma^T m$ (`LinearSTHawkes`)
  (2) f_m as a pre-trained feature extractor (`NonLinearSTHawkes`).
- The goal is to estimate parameters θ given past $\{x_i\}$.

Estimation–Marked Spatio-temporal Hawkes process

- The full log-likelihood given n observations:

$$\ell(\theta) = \sum_{i=1}^{n} \log\left(\lambda\left(t_i, u_i, m_i\right)\right) - \int_0^T \int_U \lambda_g(t, u) \mathrm{d}u \mathrm{d}t, \tag{2}$$

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- Constraints can also be included (e.g., sparsity in interaction, contribution from marks, etc.).

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- Once parameters are estimated, they are substituted in (1) for prediction.

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- Classifier $\hat{f}$ can be any generic (machine learning) models.
- **In particular**, we want to produce uncertainty sets $C(x_t, \alpha) \subset [M]$, so that marginal coverage holds:

$$\mathbb{P}(Y_t \in C(x_t, \alpha)) \geq 1 - \alpha. \tag{4}$$

Importantly, we want $C(x_t, \alpha)$ to be distribution-free.

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- **Limitation**: Data must be exchangeable (e.g., i.i.d.).
- **Remedy**: Inspired by our recent work on CP for time-series regression (Xu and Xie 2021), we design methods that achieve coverage approximately with theoretical guarantees (Xu and Xie 2022).

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3. Compute τ on (x_i, y_i) with leave-one-out $\hat{f}$'s to obtain $\{\hat{\tau}_i\}$.
4. Given x_t, return the $1-\alpha$ prediction set as

$$\widehat{C}(x_t, \alpha) := \{c \in [C] : \sum_{j=t-n}^{t-1} \mathbf{1}(\hat{\tau}_j \leq \tau(\hat{f}, x_t, c))/n < 1-\alpha\}.$$

Theory: Hawkes process estimation

We borrow the technique from (Juditsky and Nemirovski 2019) to prove the convergence guarantee of $\hat{\theta}$ as an estimator of $\theta^* \in \Theta$.

Theorem ((Informal) Parameter estimation guarantee)

Suppose Θ is compact and the gradient of log-likelihood objective is bounded, then the estimator $\hat{\theta}$ obeys the bound

$$\|\hat{\theta} - \theta^*\|_2^2 = \mathcal{O}\left(\frac{1}{J^2} + \frac{1}{k+1}\right), \tag{5}$$

where J is the number of grid search of β over $[\beta_0, \beta_1]$ and k is the number of projected gradient descent steps of $\theta - \{\beta\}$ per iterative training given β.

Theory: Conformal prediction

We extend the analyses in (Xu and Xie 2021) to prove the coverage and set size guarantees.

- Let $\tau(f, x, y)$ be the true non-conformity score dependent on $f = y|x$.
- Let $\delta_n^2 = \sum_{j=1}^{n} (\tau_i - \hat{\tau}_i)^2/n$.

Theorem (Coverage guarantee)

Suppose the set of $\{\tau_i\}$ is i.i.d. For any training set of size n and significance level $\alpha \in (0, 1)$:

$$|\mathbb{P}(Y_t \notin \widehat{C}(x_t, \alpha)) - \alpha| \leq \mathcal{O}(\sqrt{\log(n)/n} + \delta_n^{2/3}). \tag{6}$$

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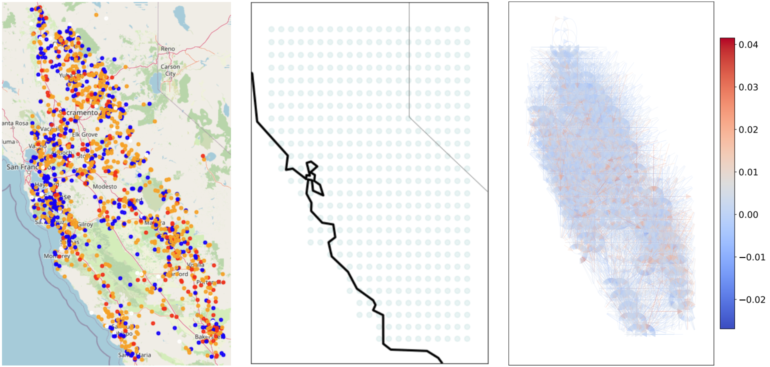
Theorem (Set size guarantee)

Under additional regularity condition, we have that there exists n' large enough so that for all $n \geq n'$

$$\widehat{C}(x_t, \alpha) \Delta C(x_t, \alpha) \leq 1 \tag{7}$$

Experiment–Marked Spatio-temporal Hawkes process

- We model the occurrence of California wildfire, which is known to have spatio-temporal dependencies.
- Figure (c) quantifies interaction strength through $\sum_i \alpha_{ij}$.



(a) Raw data **(b)** Grid discretization **(c)** Interaction α_{ij}

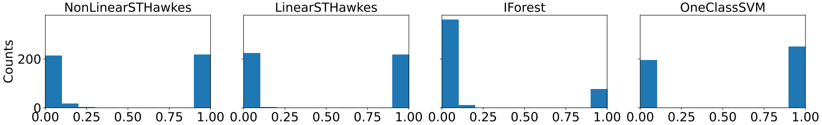
Experiment–Marked Spatio-temporal Hawkes process

- (`LinearSTHawkes`) Estimated parameters of static and dynamic marks, measuring their contributions.

	Three Largest Estimates			Three Smallest Estimates		
Static mark estimate	0.301	0.231	0.184	0.046	0.024	0.008
Static mark name	Fire Tier1	Fire Tier2	Fire Tier3	PHYS=Developed-Roads	PHYS=Conifer	PHYS=Developed
Dynamic mark estimate	0.57	0.472	0.46	0.217	0.117	0.02
Dynamic mark name	Summer	Temperature	Relative Humidity	LFP	Spring	Winter

Experiment–Marked Spatio-temporal Hawkes process

- Prediction by adapting *dynamic hedging* (Raginsky et al. 2012).
- Comparison against widely-used one-class classifiers.
- An inherently challenging task: 365 daily predictions $\times$ 453 locations for prediction with $\sim$500 true incidents.



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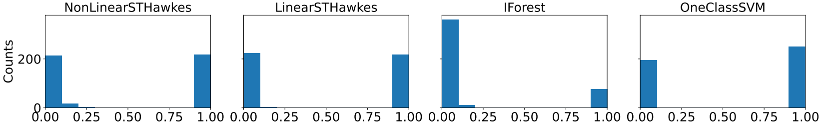

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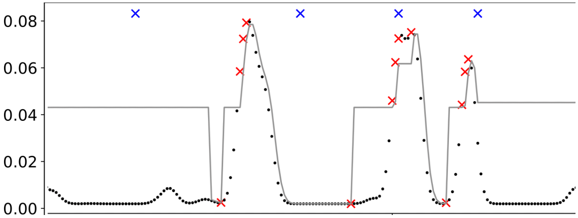
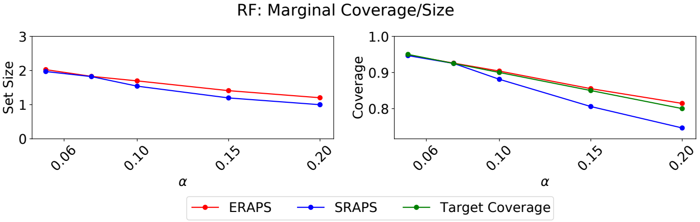


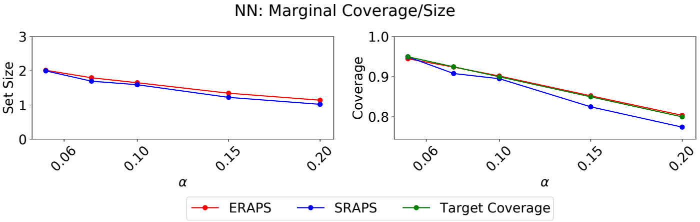
(b) `NonLinearSTHawkes` real-time prediction

Experiment–Conformal Prediction for Dependent Data

- Our method is named ERAPS.



(a) Random forest classifier



(b) Neural network classifier

Summary

- Model the conditional intensity of correlated observations with a flexible marked Spatio-temporal Hawkes process.
- Design the process to yield convex likelihood with efficient solving procedures.
- Provide uncertainty quantification for machine learning classifiers using recent advances in conformal prediction.

Reference: (Xu, Xie, et al. 2023) "Spatio-Temporal Wildfire Prediction Using Multi-Modal Data". *IEEE Journal on Selected Areas in Information Theory*, pp. 302–313.

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