

# **Understanding the Spread of COVID-19 Epidemic: A Spatio-Temporal Point Process View**

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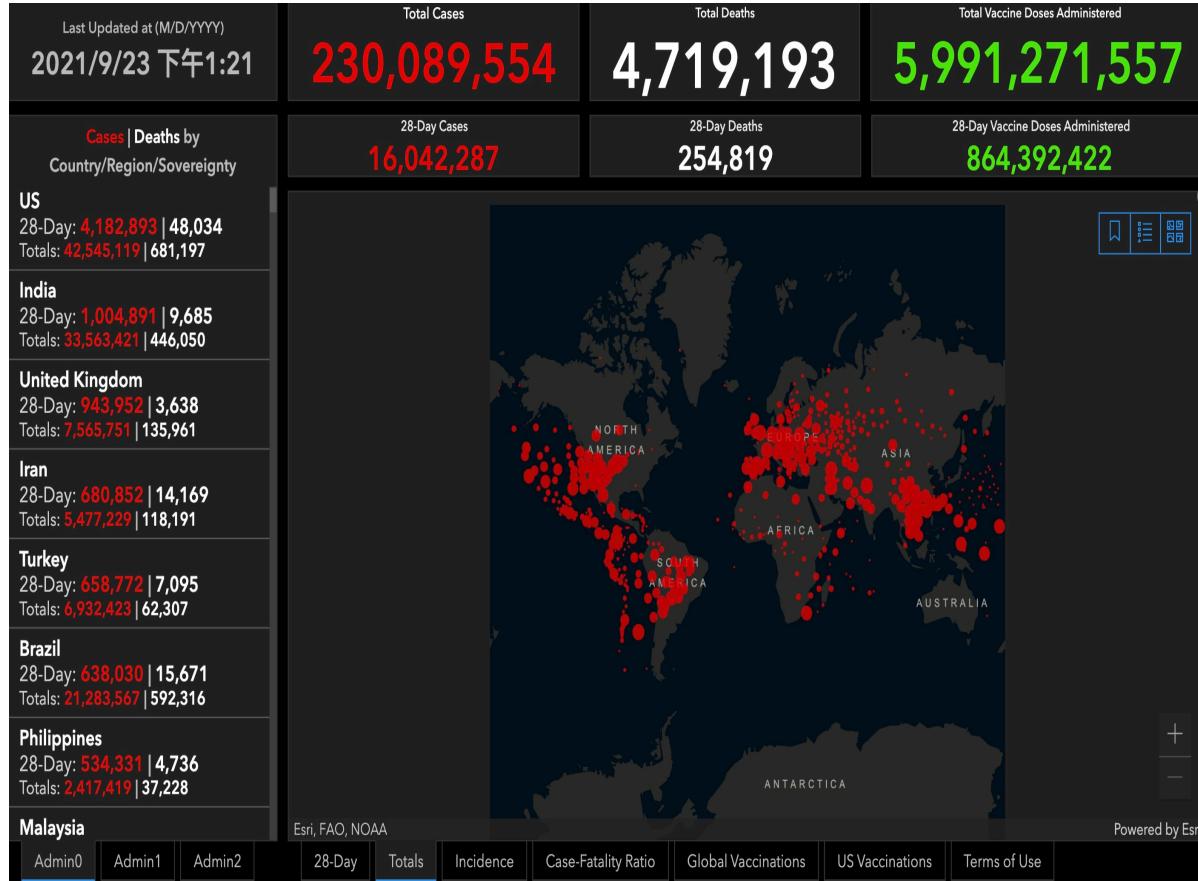
# Outline

- Introduction
- Policy-Like STPP Generative Model
- Imitation Learning for STPP
- Model Validation
- Case Study: COVID-19
- Summary

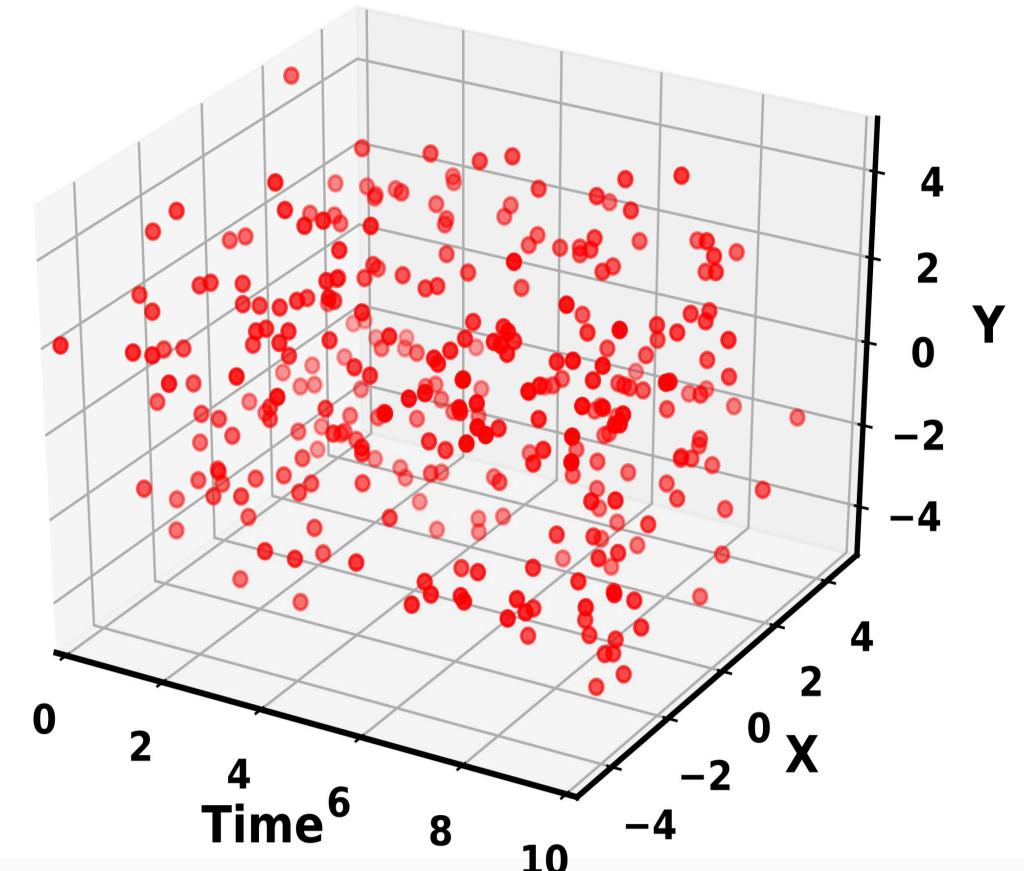
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# Introduction



COVID-19



Modeling the propagation of the COVID-19 as Spatio-temporal point processes

# Spatio-Temporal Point Process

## Conditional Intensity Function

$$\lambda(t, u | \mathcal{H}_t) dt du = \mathbb{E}[N(dt \times du) | \mathcal{H}_t], \quad (1)$$

which specifies the mean number of events in a region (i.e., infinitesimal interval and region around t and u) conditional on the past.

$$\lambda(t, u | \mathcal{H}_t) = \beta_0(u) + \sum_{i: t_i < t} g(u - u_i, t - t_i) \quad (2)$$

The propagation of contagious diseases often exhibit self-exciting patterns that can be characterized in terms of the conditional intensity function of the form

$$\mathcal{L} = \exp \left\{ - \int \int_{(0,t) \times \mathbb{S}} \lambda(\tau, v | \mathcal{H}_\tau) d\tau dv \right\} \prod_{i=1}^n \lambda(t_i, u_i | \mathcal{H}_{t_i}). \quad (3)$$

Using the maximum-likelihood learning paradigm, one can get an estimation  $\theta$  by maximizing the likelihood (3) in terms of  $\theta$

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# Policy-Like STPP Generative Model

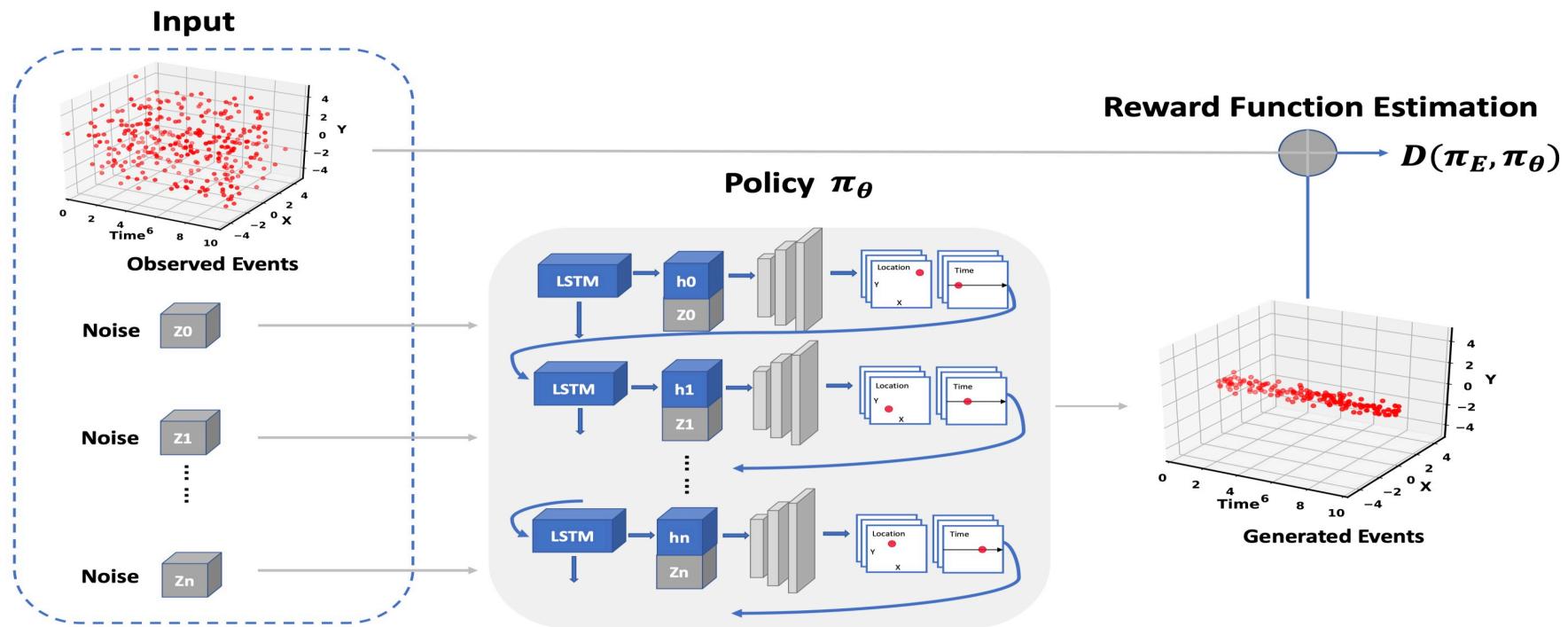


Figure 1: Imitation Learning Framework for Spatio-Temporal Point Processes.

Policy  $\pi$  has the following modules:

- (i) A recurrent neural network (RNN) unit is to learn an abstract representation from historical events  $S_t$ ;
- (ii) A multilayer perceptron is applied to noise, hidden state, and static features (i.e., explanatory factors such as population and lockdown time of the city), to generate events

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# Imitation Learning for STPP

**Theorem 1** Let the family of reward function be the unit ball in RKHS  $\mathcal{F}$ , i.e.,  $\|r\|_{\mathcal{F}} \leq 1$ . Then the optimal policy  $\pi_{\theta}(a|\mathcal{S}_t)$  that mimics the observed events (generated by expert  $\pi_E$ ) can obtained by solving

$$\pi_{\theta}^* = \arg \min_{\pi_{\theta} \in \mathcal{G}} D(\pi_E, \pi_{\theta}, \mathcal{F}) \quad (6)$$

where  $D(\pi_E, \pi_{\theta}, \mathcal{F})$  is the maximum expected cumulative reward discrepancy between  $\pi_E$  and  $\pi_{\theta}$ , with the expression

$$D(\pi_E, \pi_{\theta}, \mathcal{F}) := \max_{\|r\|_{\mathcal{F}} \leq 1} \left( \mathbb{E}_{\xi \sim \pi_E} \left[ \sum_{i=1}^{N_T} r(e_i) \right] - \mathbb{E}_{\eta \sim \pi_{\theta}} \left[ \sum_{i=1}^{\tilde{N}_T} r(a_i) \right] \right), \quad (7)$$

where  $N_T$  and  $\tilde{N}_T$  are the counts of observed events and generated events within time horizon  $T$ .

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# Model Validation

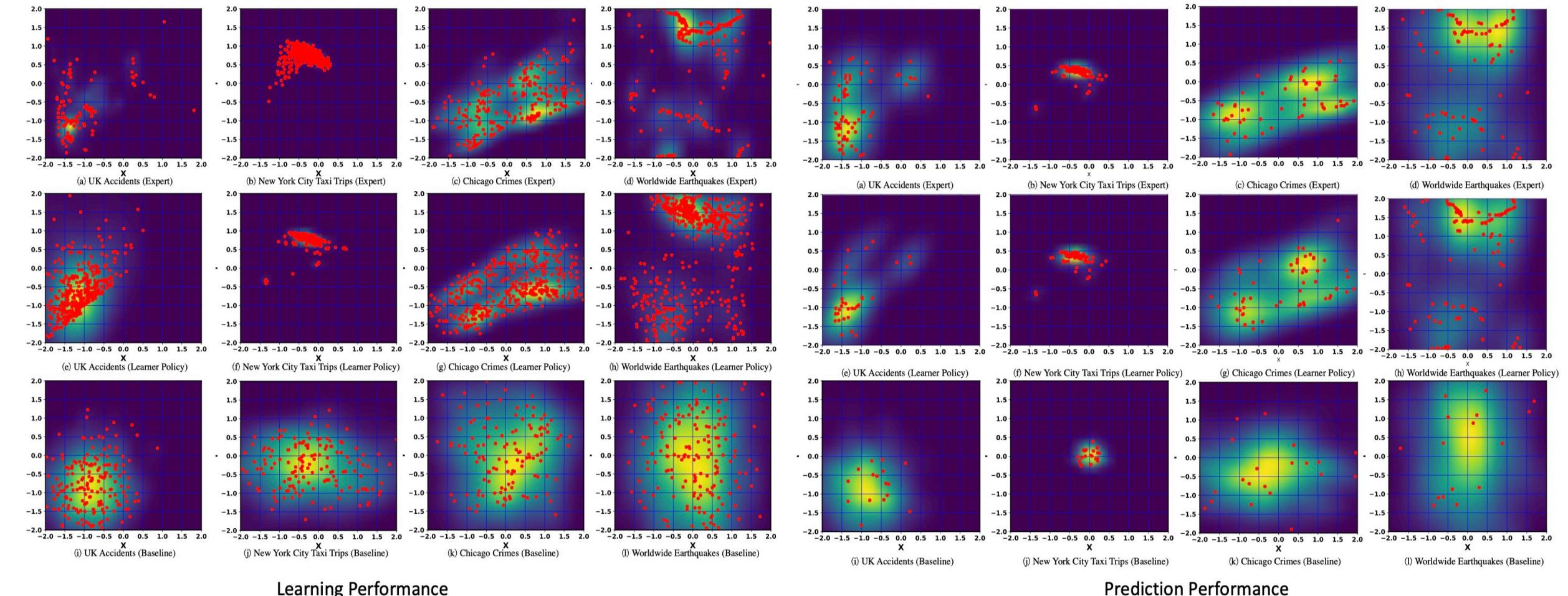


Figure 2: Spatial Distributions of the Observed Events and the Generated Events.

# Model Validation

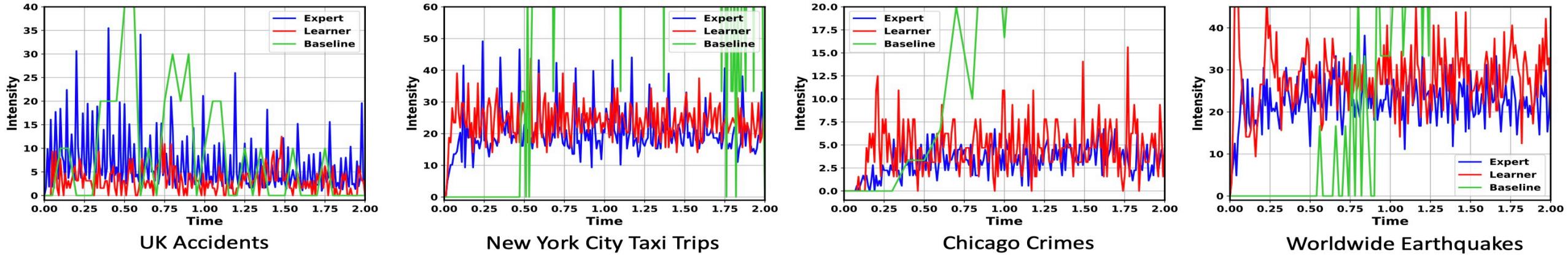


Figure 3: Learning Performance: Intensify Functions of the Observed Events and the Generated Events.

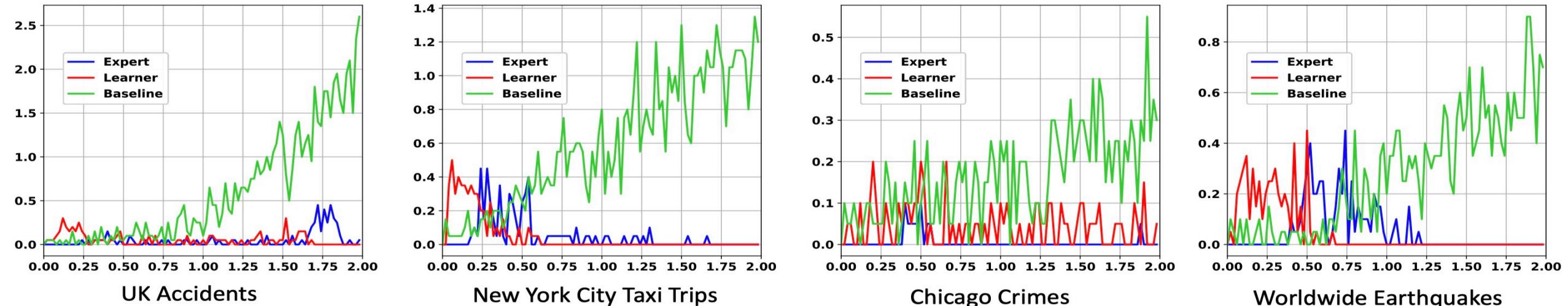
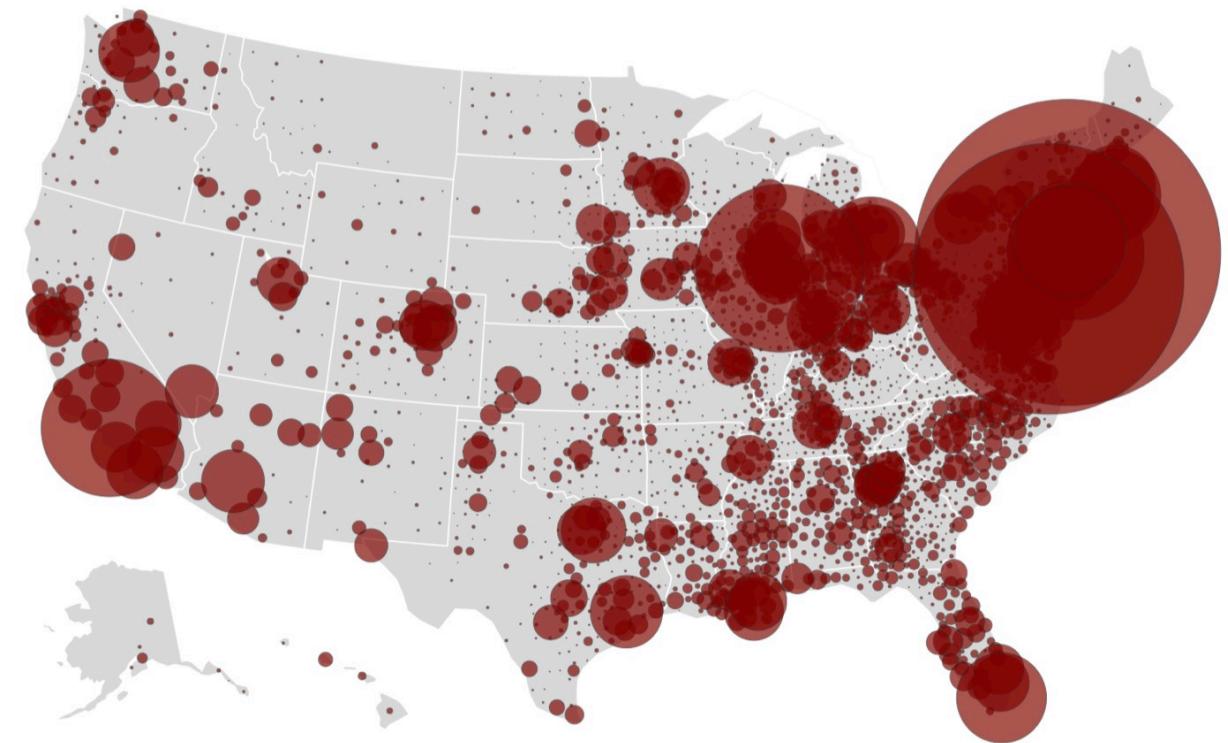


Figure 4: Predication Performance: Intensify Functions of the Observed Events and the Predicted Events.

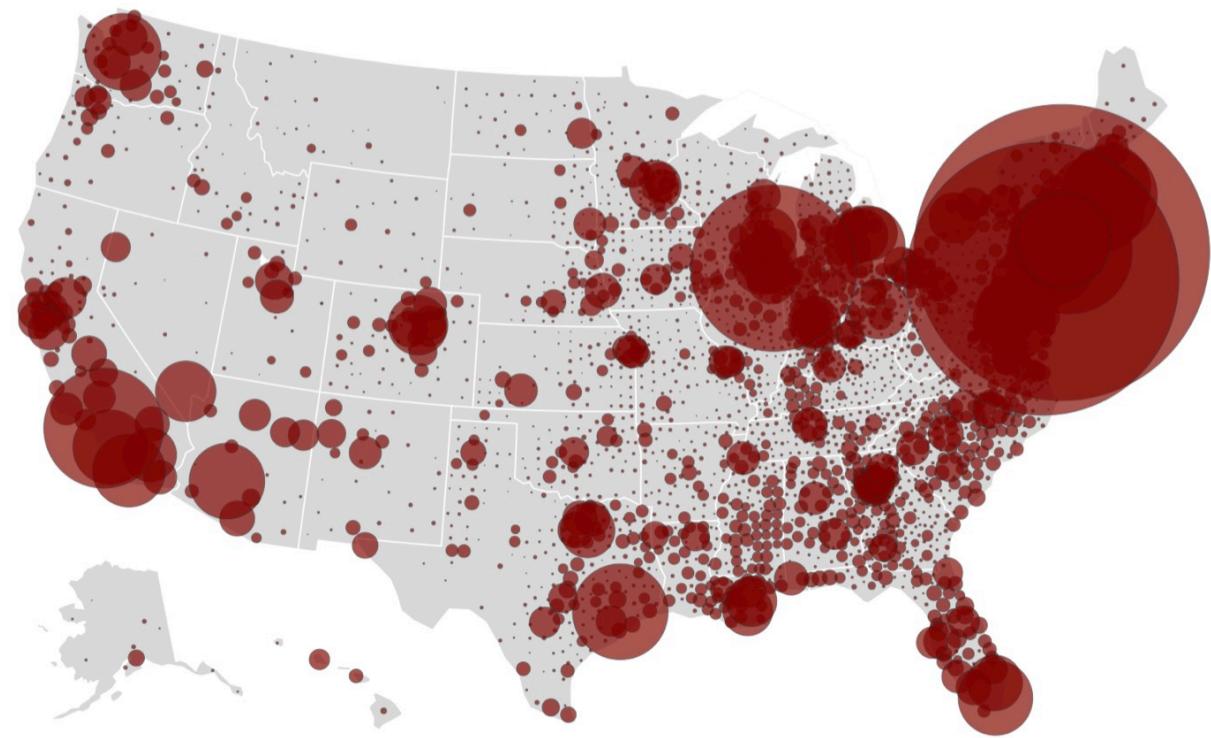
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# Case Study: COVID-19



U.S. Confirmed Cases Up to 5/24/2020 (Expert)



U.S. Confirmed Cases Up to 5/24/2020 (Learner)

Figure 5: Comparison of the Real and the Generated Cumulative Count of Confirmed COVID-19 Cases.

# Case Study: COVID-19

Table 1: Mean value of the predicted total confirmed case on 5/24/20 with early and late lockdown time on four counties.

County Name	Real Lockdown	Early Lockdown	Late Lockdown
New York	342240	$292820 \pm 5641$	$348700 \pm 6225$
Los Angeles	39960	$39420 \pm 1180$	$41230 \pm 1210$
Cook	31700	$25600 \pm 410$	$42365 \pm 965$
Middlesex	10431	$10378 \pm 264$	$12739 \pm 358$

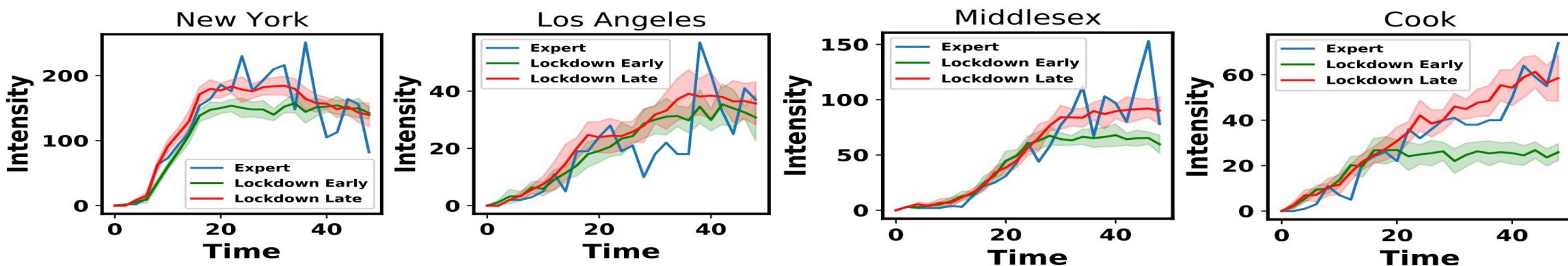


Figure 7: The Predicted Propagation of Events If The Lockdown Time is One Week Earlier or One Week Later Than The Real Lockdown Time. The solid line in red and green indicates the mean of 10 predicted sequences and shade fields indicates the standard deviation.

# Case Study: COVID-19

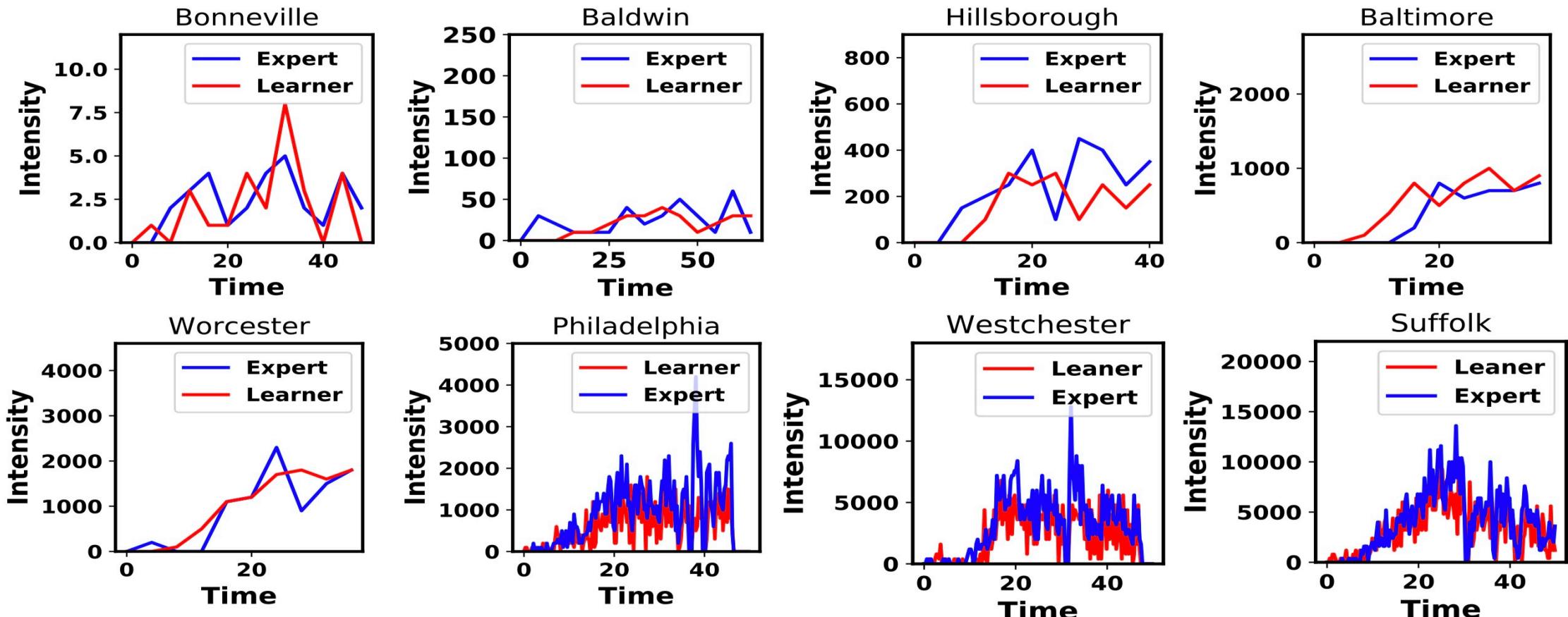


Figure 6: Comparison of the Intensity Functions of The Real and the Generated Confirmed COVID-19 Cases. The Unit of The Time is One Day.

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# Summary

- Proposed an intensity-free spatio-temporal point processes model and train the model using an imitation learning framework;
- Used COVID-19 as a case study and utilize the model to understand the spread of the virus.