Transformer-Based Spatial-Temporal Counterfactual Outcomes Estimation

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Presenter Introduction

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Research Interests: Causal Inference, Foundation Models

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Background

- What are spatial-temporal counterfactual outcomes estimation?
  - Estimate the outcome events in a spatial region under counterfactual treatment interventions, such as increased treatment duration or intensity, based on the observed spatial-temporal data.
- Motivation
  - Counterfactual outcomes estimation is one of the most important problems in causal inference[1].
  - The spatial-temporal counterfactual outcomes estimation has a wide range of applications.
    - Epidemiology – Isolation and Control of Infectious Diseases
    - Environmental Science – Prevention and Monitoring of Resource Loss
    - Economics – Evaluation of Regional Economic Policies

[1] Imbens G W, Rubin D B. Causal inference in statistics, social, and biomedical sciences[M]. Cambridge university press, 2015.

Methodology

The IPW estimator

- We define the following estimator:

$$\hat{Y}_t(F_H, s) = \prod_{j=t-M+1}^{t} \frac{p_{h_j}(z_j)}{e_j(z_j)} \lambda_{Y_t^{ob}(z_{\leq t})}(s)$$

- The above estimator can be seen as the intensity function that generates counterfactual outcomes $Y_t^{ob}(z_{\leq t}(F_H))$. Then according to the definition of intensity function, we have:

$$\hat{N}_t^{\omega}(F_H) = \int_{\omega} \hat{Y}_t(F_H, s) ds$$

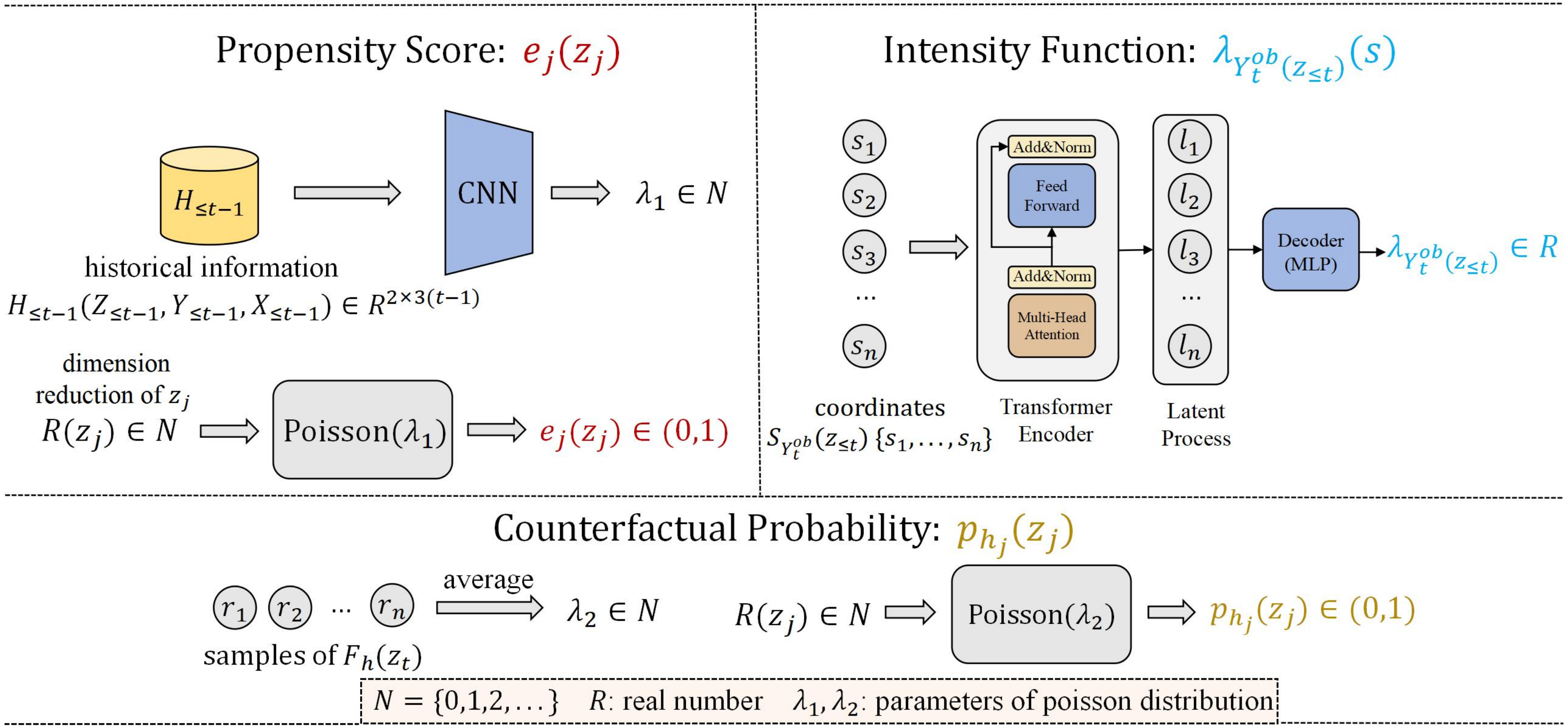
- Finally, we average the $\widehat{N_t^{\omega}}(F_H)$ over time to get the final estimator:

$$\hat{N}_{\omega}(F_H) = \frac{1}{T-M+1} \sum_{t=M}^{T} \hat{N}_t^{\omega}(F_H)$$

Methodology

Deep learning-based realization

$$\text{Estimator: } \widehat{Y}_t(F_H, s) = \prod_{j=t-M+1}^{t} \frac{p_{h_j}(z_j)}{e_j(z_j)} \lambda_{Y_t^{ob}(z_{\le t})}(s)$$



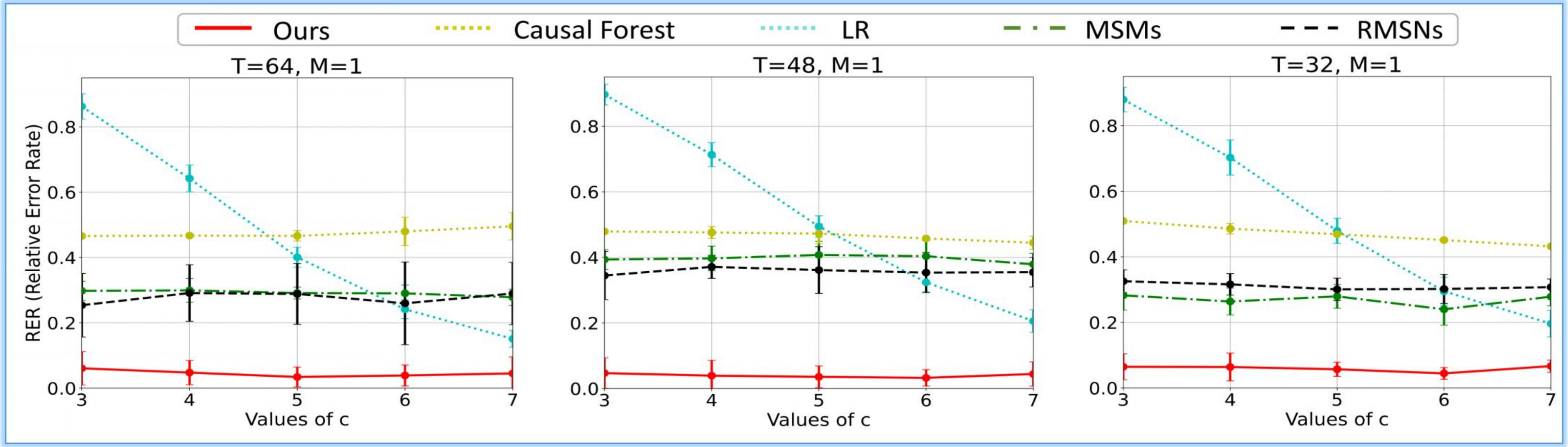
Experiments

- Datasets
  - Synthetic Data
    - We generate synthetic spatial-temporal data using rejection sampling.
  - Real Data
    - We employ the Global Forest Change Data[1] and the UCDP Georeferenced Event Dataset[2].
- Baselines
  - MSMs、RMSNs、Causal Forest、Linear Regression
- Metrics
  - For synthetic experiments, the metric is the relative error rate (RER). For real data experiments, we consider the consistency of our conclusions with existing literature.
- Intervention Parameters
  - The parameter M is introduced to control the duration of the treatment intervention. The parameter c is introduced to control the magnitude of the intervention.

[1] Hansen, M. C., et al. High-resolution global maps of 21st-century forest cover change. science, 342(6160):850–853, 2013.
[2] Croicu, M. and Sundberg, R. Ucdp georeferenced event dataset codebook version 4.0. Journal of Peace Research, 50(4):523–532, 2015.

Results

- Sythetic experimental results



- Real data experimental results

	$c = 3$	$c = 4$	$c = 5$	$c = 6$	$c = 7$
$M = 1$	20.6 ± 2.3	20.5 ± 2.2	20.7 ± 2.8	20.5 ± 1.9	20.8 ± 2.0
$M = 3$	21.5 ± 1.4	21.6 ± 2.4	22.3 ± 1.9	23.0 ± 1.3	23.3 ± 1.9
$M = 5$	22.4 ± 2.3	22.9 ± 1.8	23.6 ± 1.7	24.2 ± 1.2	24.7 ± 2.2
$M = 7$	24.7 ± 1.3	23.6 ± 1.7	26.7 ± 1.2	27.2 ± 1.5	28.0 ± 2.1

Summary

- We study counterfactual outcomes estimation with the spatial-temporal attribute, a more general setting, and propose an effective deep-learning-based solution.
- We propose an efficient CNN-based method to address the calculation of propensity scores under the spatial-temporal setting. Besides, we employ the Transformer to address the modeling of spatial-temporal data.
- We empirically demonstrate the effectiveness of our approach through both simulated and real experiments.

Future directions

- How can we design randomized experiments in spatial-temporal settings?
- How can we model causal relationships within continuous spatial-temporal data?
- How can we estimate counterfactual outcomes from continuous spatial-temporal processes?

Thank You!

Project Page: https://github.com/lihe-maxsize/DeppSTCI_Release_Version-master