A Tutorial on Spatiotemporal Causal Inference

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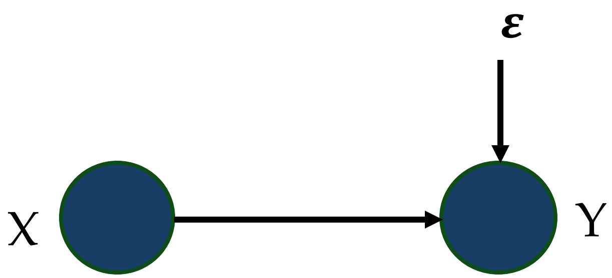
Agenda

1. Key Concepts of Causality
2. Causal Inference on IID data
3. Causal Inference on Time-series data
4. Causal Inference on Spatiotemporal Data

Causal Effect Estimation (Causal Inference)

The process of inferring the influence ***(causal effect)*** *of one event, policy or treatment* ***(a cause X)*** *on another event, state, or outcome* ***(an effect Y).***



$$\boldsymbol{Y = mX + \varepsilon}$$

Causal Effect Estimation (Causal Inference)

The process of inferring the influence ***(causal effect)*** *of one event, policy or treatment* ***(a cause X)*** *on another event, state, or outcome* ***(an effect Y).***

co-efficient of causality?

$$Y = mX + \varepsilon$$

effect

cause

Potential Outcome Framework

For a hypothetical intervention, the causal effect for an individual ***i*** *is the difference between the outcomes that would be observed for that individual* ***with*** *versus* ***without*** *the treatment or* ***intervention****.*

$$Y_i = \begin{cases} Y_{i1}\, if\ X = 1 & \text{When we intervene on } X \\ Y_{i0}\, if\ X = 0 & \text{When we do not intervene on } X \end{cases}$$

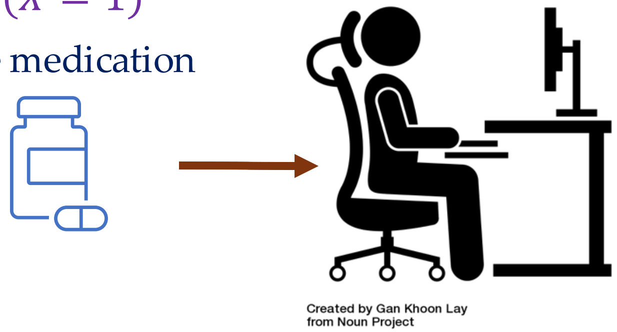
$$Treatment\ Effect = \underbrace{Y_{i1}}_{\text{Presence of Treatment}} - \underbrace{Yi_0}_{\text{Absence of Treatment}}$$

Potential Outcome Framework

$do(X = 1)$

Take medication

No Headache



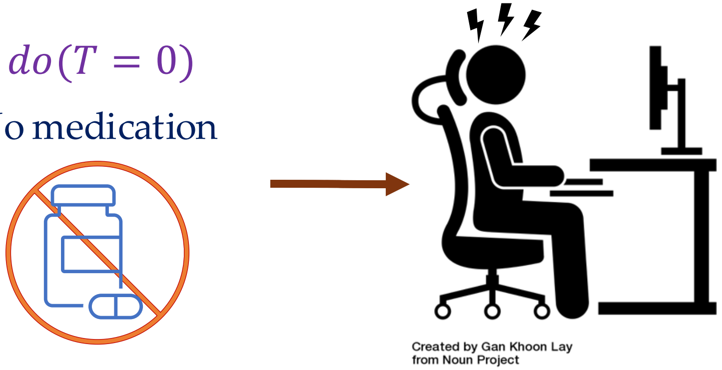
$Y_i | do(\text{X} = 1) = 1$

Presence of Treatment
(Treated Group)

Headache

$do(T = 0)$

No medication



$Y_i | do(X = 0) = 0$

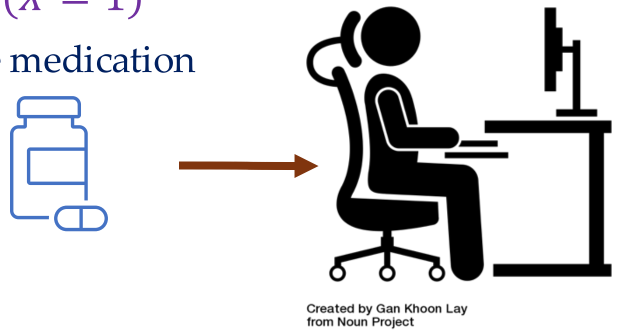
Absence of Treatment
(Control Group)

Potential Outcome Framework

$do(X = 1)$

Take medication

No Headache



You cannot observe both simultaneously!

One is observed (factual), other is hypothesized (counterfactual)

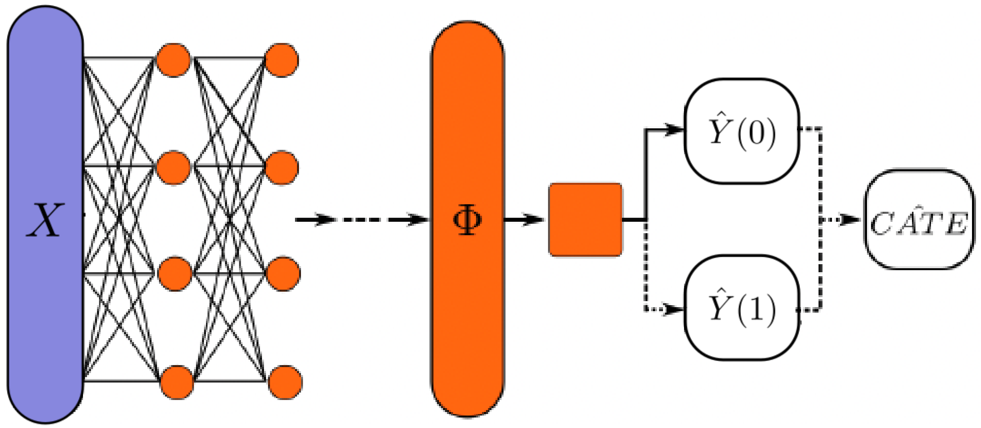
Headache

$Y_i | do(X = 0) = 0$

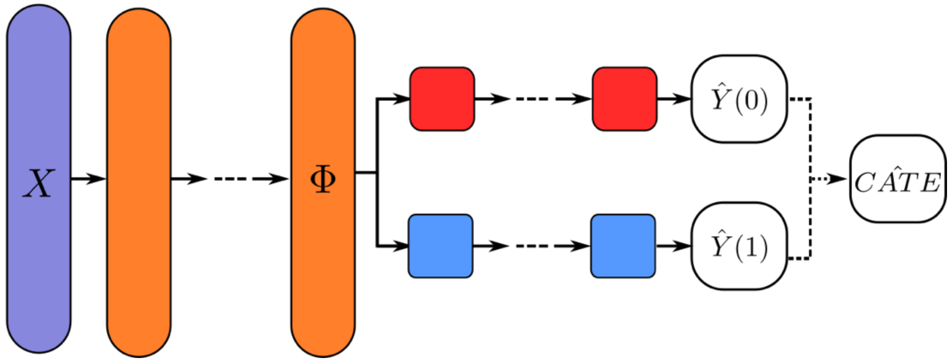
Presence of Treatment (Treated Group)

Absence of Treatment (Control Group)

Machine Learning for Causal Inference



S(ingle)-learner[1]

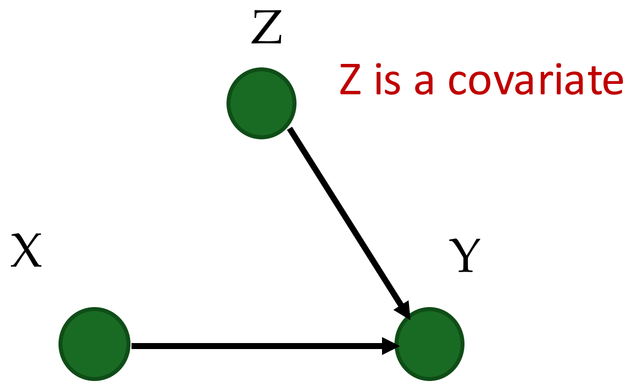


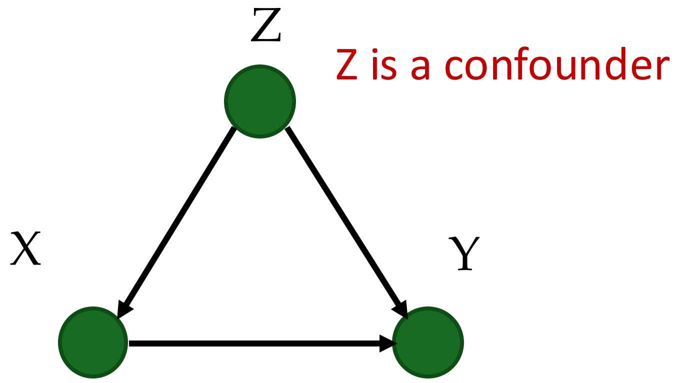
T-learner[1] (TARNet, DragonNet, etc.)

[1.] Koch, Bernard J., et al. "A Primer on Deep Learning for Causal Inference." *Sociological Methods & Research* (2024): 00491241241234866.

Causal Inference - Confounding

We cannot assume that our Y is only dependent on X





$$ATE = Y_{i1}(X = 1, Z) - Y_{i0}(X = 0, Z)$$

Demo Time!

A simple example of causal inference using Machine Learning

tinyurl.com/stcausal24

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Time-Series Causal Inference

The process of inferring the influence ***(causal effect)*** *of one event, policy or treatment* ***(a cause X)*** *on another event, state, or outcome* ***(an effect Y)*** *at current timestep* ***t***.

$$ATE = Y_{1t}(X_t = 1, Zt) \ - Y_{0t}(Xt = 0, Zt)$$

Time-Series Causal Inference

*The process of inferring the influence **(causal effect)** of one event, policy or treatment **(a cause X)** on another event, state, or outcome **(an effect Y)** at current timestep **t** or future timestep **t+l** .*

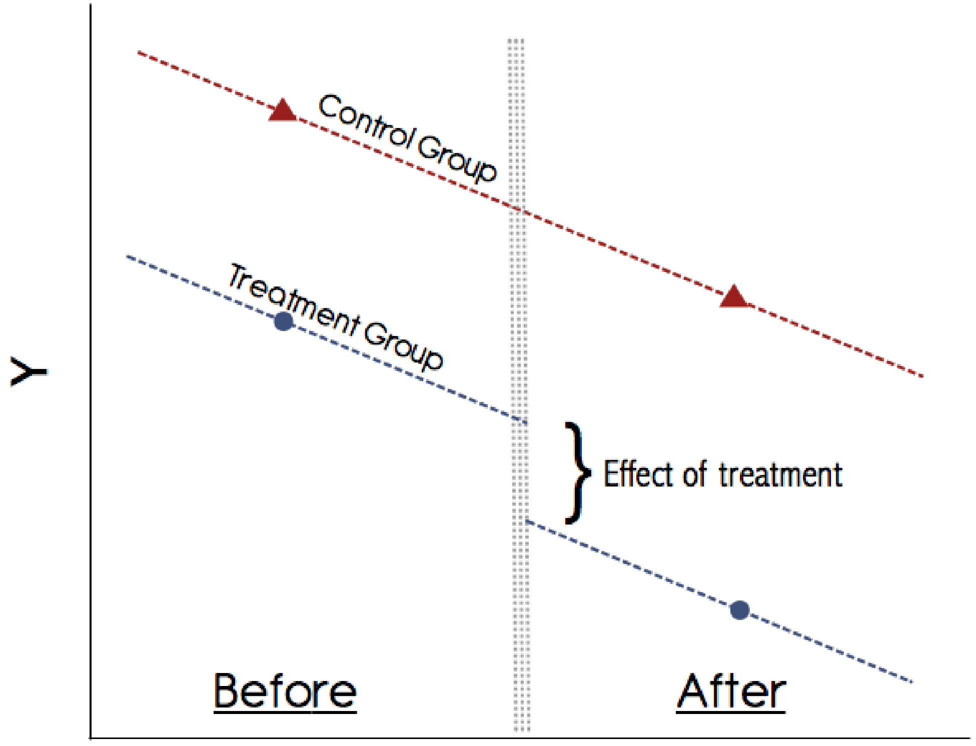
$$Y_{t+l}(\hat{X} = \hat{x}_t) = f(Z_t, \hat{x}_t) \qquad Y_{t+l}(X = x_t) = f(Z_t, x_t)$$

$$LATE(l) = \frac{1}{N} \sum_{t=1}^{N} E[Y_{t+l}(\hat{X}_t) - Y_{t+l}(X_t)]$$

LATE is the lagged average treatment effect

Time-Invariant Causal Inference

The effect of time-invariant intervention is measured based on the difference in the outcomes before and after the intervention takes place.



Time-Invariant Causal Inference

- *Intervention happens once.*

- *The treatment does not vary with time!*

- **Methods:** Difference-in-Difference, Causal Impact, Causal ARIMA, etc

- Causal Effect = The difference between the **observed post-intervention data** and the **counterfactual prediction**

Time-Varying Causal Inference

- *When the treatment or intervention, the outcome, and potentially the covariates, change over time.*

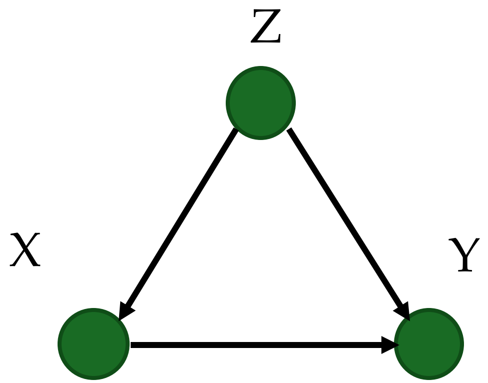
- This process uncovers how a *changing treatment influences the outcome of interest.*

- **Methods:** Marginal Structural Models, Convergent Cross Mapping, Deep Learning based methods, etc

- Causal Effect = The difference between the **counterfactual** and **factual predictions**

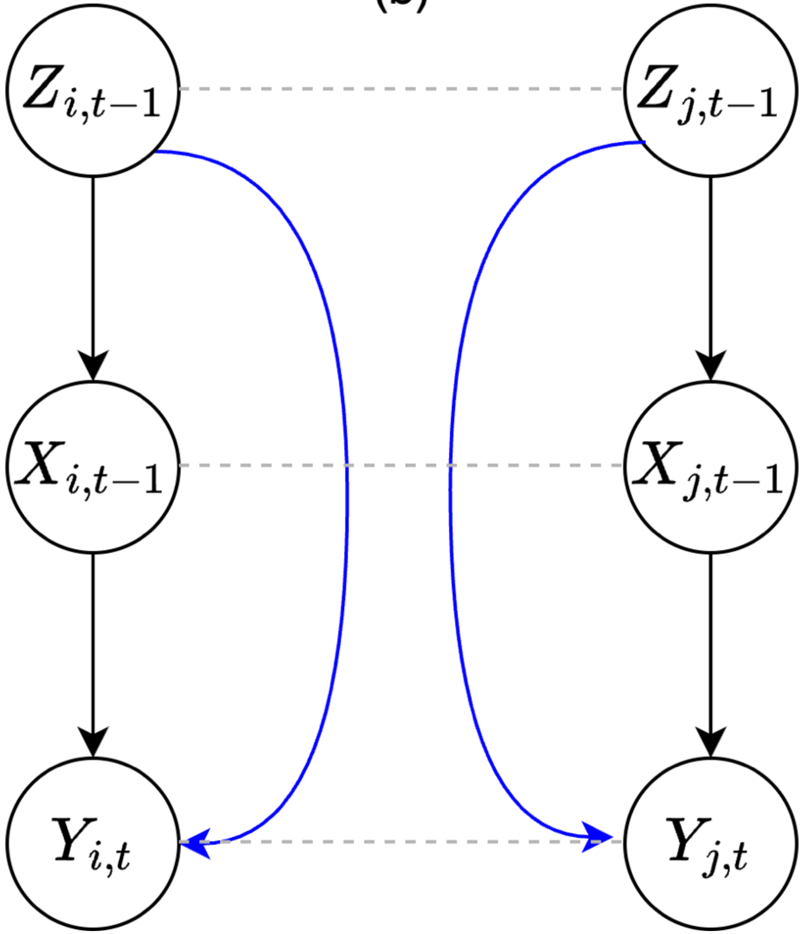
Time-Varying Causal Inference – Confounding

(a)



Z is a confounder

(b)



Bias Outcomes!

Time-Varying Causal Inference – Balancing

- Generalized Propensity Score (Rubin's G-Methods)

$$Prob(X_t|X_{t-1}, Z_t)$$

- Inverse Probability of Treatment Weight (Robins, 1986)

$$IPTW = \Pi_{t=1}^{k} \frac{1}{f(\bar{X}|\bar{Z})}$$

where, $\bar{X} = (X_1, X_2, ..., X_t)$ $\bar{Z} = (Z_1, Z_2, ..., Z_t)$

Demo Time!

Causal inference using Time-varying and Time-invariants Methods

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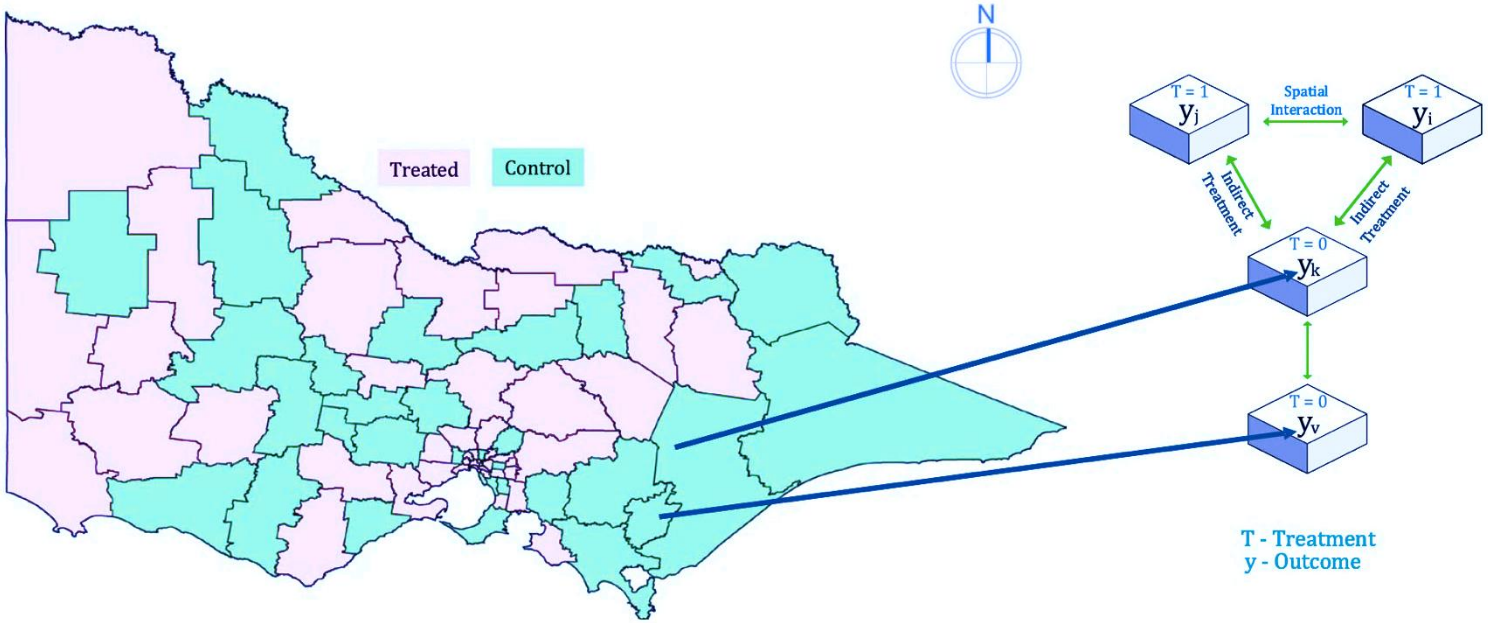
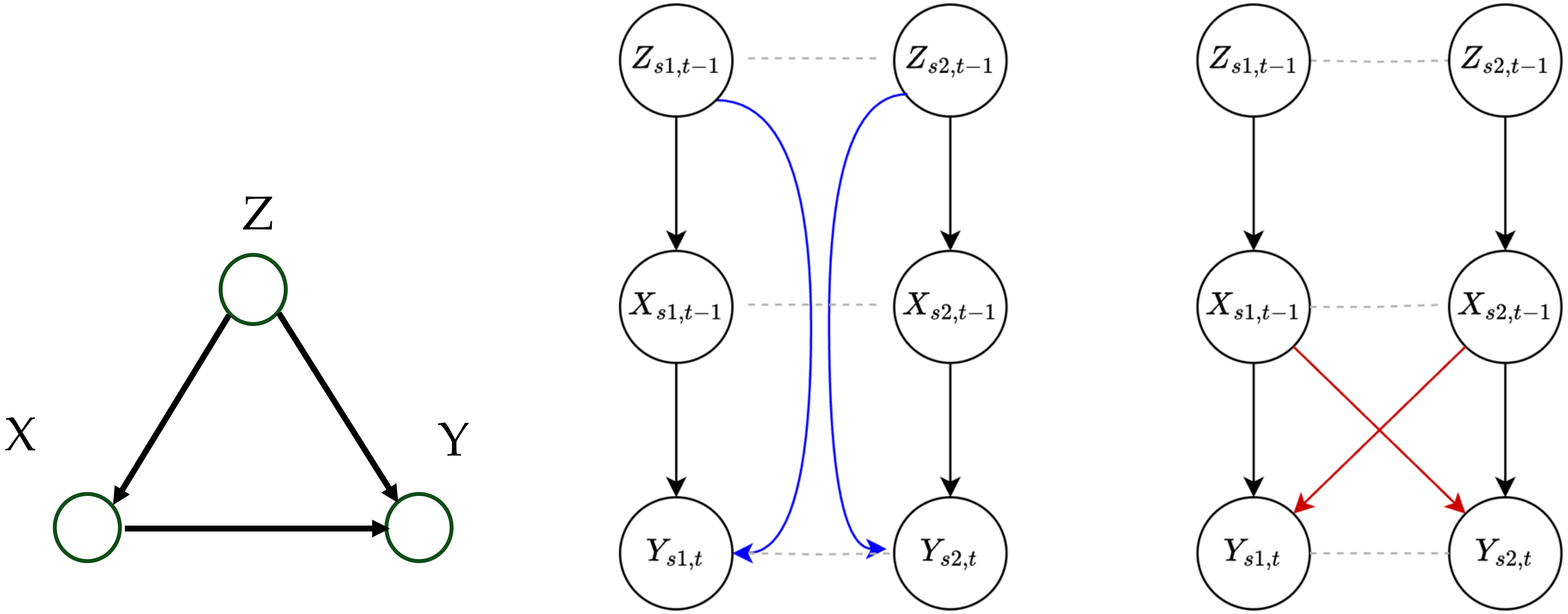
Spatiotemporal Causal Inference

*The process of inferring the influence **(causal effect)** of a policy or treatment **(X)** applied on a specific region at current timestep **t**, on another event or outcome **(Y)** on the same or neighboring regions at current timestep **t** or future timestep **t+l**.*



From Temporal to Spatiotemporal Causal Inference



covariate

treatment

outcome

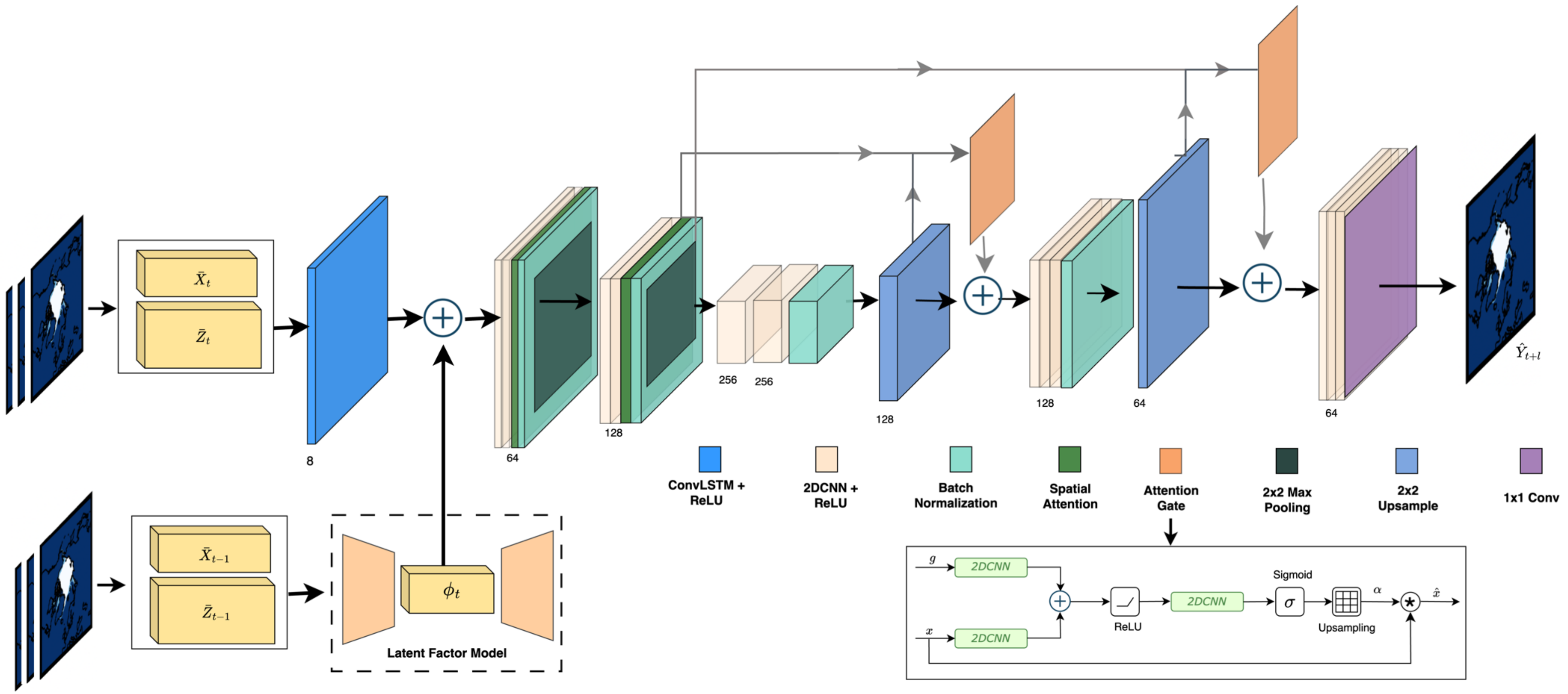
(a)
Causation

(b)
Temporal causation

(c)
Spatiotemporal causation

Deep Learning for Spatiotemporal Causal Inference

Ali et.al , ECML 2024



STCINet – UNet based deep learning model to infer causal inference on space-time varying data

Demo Time!

Causal Inference on Spatiotemporal Data

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