

Work 1: Change point detection for time-correlation data with adaptive sampling

Consider multivariate time series $\mathbf{Y}(t) \in \mathbb{R}^p$ $\mathbf{X}(t) = \mathbf{A}\mathbf{X}(t-1) + \mathbf{w}_t$
 $\mathbf{Y}(t) = \mathbf{C}\mathbf{X}(t) + \mathbf{v}_t$

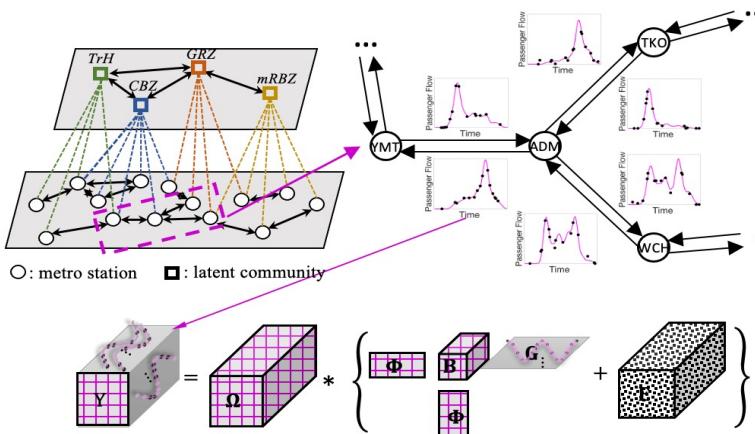
For unknown change point τ

$$\begin{aligned} \mathbf{X}(t) &= \mathbf{A}\mathbf{X}(t) + \mathbf{w}_t, t < \tau. && IC \\ \mathbf{X}(t) &= \mathbf{A}\mathbf{X}(t) + \mathbf{f} + \mathbf{w}_t, t \geq \tau. && OC \end{aligned}$$

Partial observable set $Z(t) = [z_{1t}, \dots, z_{pt}]$ and $\sum_{i=1}^p z_{it} = m$. ($m < p$)
arxiv:2404.00220

Work 2:

FEN model :
Network modeling
from a functional
edge perspective



arxiv:2404.00218

Work 3:

FRCOMA:
Nonparametric
Regression for
Continuous
Multi-way Data

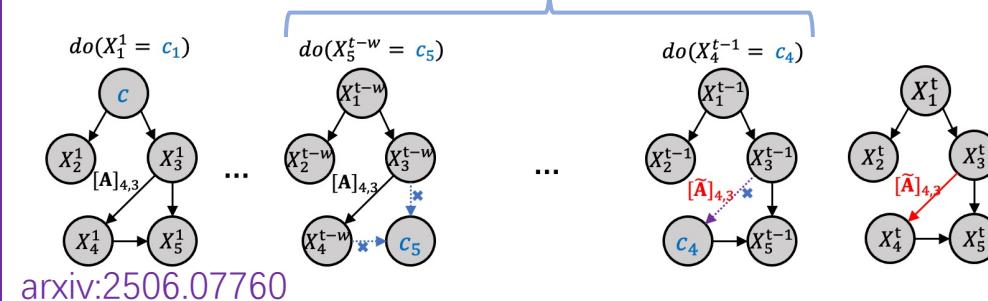
- $\{(y_i, \mathbf{x}_i)\}_{i=1}^n$ are n pairs of functional samples.
- $y_i \in \mathcal{Y} = \{y : \Omega_y \rightarrow \mathbb{R}\}$ is the response function and Ω_y is the compact subset of \mathbb{R}^{d_y} .
- $\mathbf{x}_i = (x_i^{(1)}, \dots, x_i^{(p)})$ are the covariate functions with $x_i^{(l)} \in \mathcal{X}_l = \{x : \Omega_{x_l} \rightarrow \mathbb{R}\}$. Ω_{x_l} is the compact subset of \mathbb{R}^{d_l} , $l = 1, \dots, p$.
- Find a nonlinear function-on-function regression model with variable selection

$$f : \mathcal{X}_1 \times \dots \times \mathcal{X}_p \rightarrow \mathcal{Y} \quad s.t. y_i = f(\mathbf{x}_i) + \epsilon_i, \quad i = 1, \dots, n, \quad (1)$$

ϵ_i is the white noise function.

Work 4: Quickest causal change detection by adaptive intervention

- $\mathbf{X}^t = \mathbf{A}^t \mathbf{X}^t + \mathbf{U}^t, \quad \mathbf{U}^t \sim N(\boldsymbol{\mu}^t, \Sigma^t), \quad \Sigma^t \triangleq \text{diag}(\sigma_1^t, \dots, \sigma_p^t)$.
 - For some unknown τ , $(\mathbf{A}^t, \boldsymbol{\mu}^t, \Sigma^t) = \begin{cases} (\mathbf{A}, \boldsymbol{\mu}, \Sigma), & \text{for } t = 1, 2, \dots, \tau - 1, \\ (\tilde{\mathbf{A}}, \tilde{\boldsymbol{\mu}}, \tilde{\Sigma}), & \text{for } t = \tau, \tau + 1, \dots \end{cases}$
- Construct **window-limited CUSUM** statistic $W_{t,A^*}(W_{t,A^*})$!! $T_{b,A^*}^{\text{multi}} (T_{b,A^*}^{\max}) = t$
If $W_{t,A^*}(W_{t,A^*}) > b$, then trigger alarm; **Else**, decide the next intervention node(ϵ -greedy).
Max-AI (A^*) for short window and single change. **Multi-AI** (A^*) for long window and multiple change.



Work 5: Design of Experiment for Discovering Directed Mixed Graph

Design \mathcal{I} , the collection of \mathbf{I} , to discovery DMG \mathcal{G} (using d -separation, σ -separating and do -see test).



	Lower bound of $\max_{\mathbf{I} \in \mathcal{I}} \mathbf{I} $	Lower bound of $ \mathcal{I} $	Unbounded design	Bounded design ($ \mathbf{I} \leq M$)
■	$ T_{l+1}^{\mathcal{G}} + \zeta_{\max}^{l+1,\mathcal{G}} - 1$	$\sum_{k=1}^{l+1} \zeta_{\max}^{k,\mathcal{G}}$	$ \mathcal{I} = 2 \lceil \log_2 (\chi(\mathcal{G}_r^{obs})) \rceil + \sum_{k=1}^{l+1} \zeta_{\max}^{k,\mathcal{G}}$	$ \mathcal{I} = \left\lceil \frac{n}{M} \right\rceil \lceil \log_{\frac{n}{M}} n \rceil + \sum_{k=1}^{l+1} \zeta_{\max}^{k,\mathcal{G}} + \zeta_{\max}^{l+1,\mathcal{G}} \left\lceil \frac{n - T_{l+1}^{\mathcal{G}} - \zeta_{\max}^{l+1,\mathcal{G}} - 1}{M - T_{l+1}^{\mathcal{G}} - \zeta_{\max}^{l+1,\mathcal{G}} + 2} \right\rceil$
■	$\max_{[X:Y] \in \mathbf{E}^N} Pa_{\mathcal{G}}(X \cup Y) $	$cc(\mathcal{G}^{uc})$	$ \mathcal{I} = cc(\mathcal{G}^{uc})$	$ \mathcal{I} \leq \sum_{k=1}^K 1 + \left\lceil \frac{(\mathbf{E}_k (\mathbf{E}_k -1)-1)(n- \mathbf{E}_k)}{M+1-\sum_{X,Y \in \mathbf{E}_k} Pa_{\mathcal{G}}([X:Y])} \right\rceil$
■		Not well defined [1]	$ \mathcal{I} \leq 2\chi_s(\mathcal{G}^u)$	$ \mathcal{I} \leq 2 \sum_{k=1}^K 1 + \left\lceil \frac{(\mathbf{E}_k -1)(n-2 \mathbf{E}_k)}{M+1-\max_{[XY] \in \mathbf{E}^u} Pa_{\mathcal{G}}([X:Y])} \right\rceil$
■				Difficult to identify but have limited impact

arxiv:2406.19021