Power System Event Detection and Identification with PMU Data

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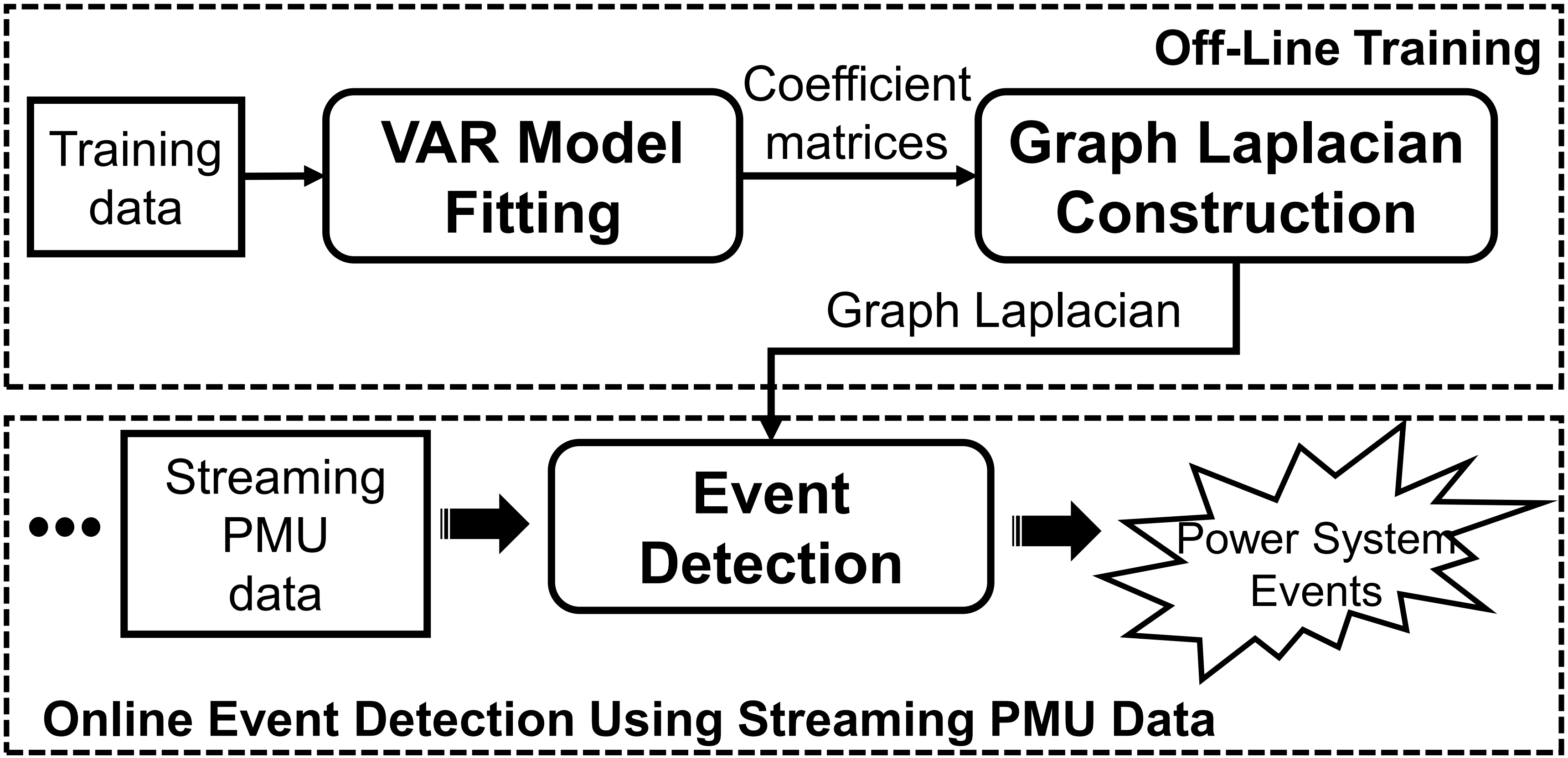
Online Power System Event Detection Framework

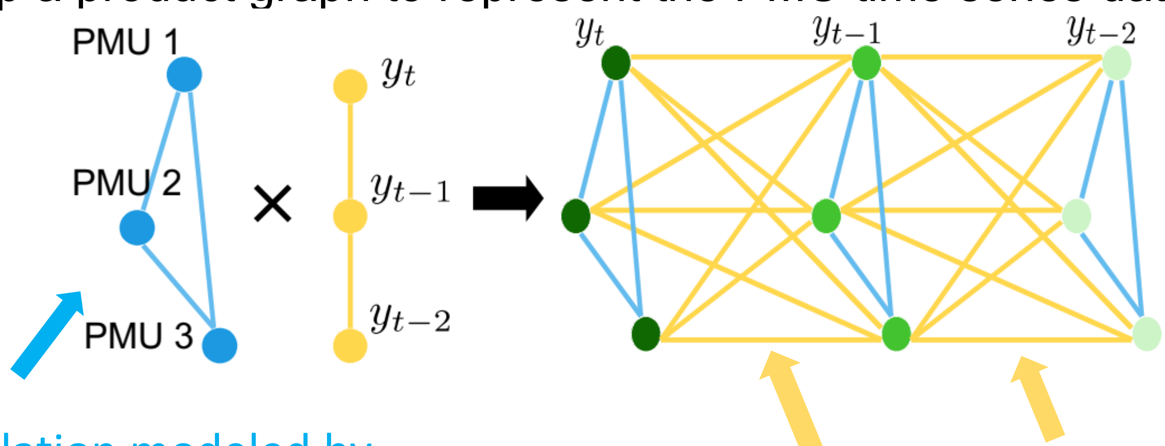


Spatial & Temporal Coefficient Matrices and Graph Laplacian Construction

- Module multiple PMU data streams as Vector Autoregressive Process
  - Let $\boldsymbol{y}_t$ be the data frame of certain measurements recorded by N PMUs at time stamp t. We model this vector time series with spatio-temporal model:

$$\boldsymbol{y}_t = A\boldsymbol{y}_t + \sum_{j=1}^{q} \Phi_j \boldsymbol{y}_{t-j} + \boldsymbol{\epsilon}_t$$

  - Where A is called *spatial coefficient matrix*. Φ_j denotes the j-th *temporal coefficient matrix*. $\boldsymbol{\epsilon}_t$ is a white noise vector. q is the order of the model.
- We develop a product graph to represent the PMU time series data:



Spatial correlation modeled by spatial coefficient matrix

Temporal correlation modeled by temporal coefficient matrix

Online Abnormal Event Detection

- Graph Fourier Transform (GFT)
  - Let $\boldsymbol{s} = [s(1), \cdots, s(n)]$ denote the graph signals, where $s(n)$ represents the value of the n-th node. GFT converts $\boldsymbol{s}$ into its counterpart in the Laplacian spectral domain:

$$\boldsymbol{S} = U^{-1}\boldsymbol{s}$$

  - Where $U = [\boldsymbol{u}_1, \cdots, \boldsymbol{u}_n]$ is a matrix of eigenvectors of the graph Laplacian L.
- Abnormal measurement indicator (AMI) :

$$\mathrm{AMI} = \sum_{i=2}^{n} \lambda_i S(i)$$

  - The DC component dominates the Laplacian spectral domain for PMU data under normal operating conditions.
  - When abnormal events occur, the non-DC components, especially the high frequency ones, become pronounced.

Event Detection Algorithm Performance Evaluation

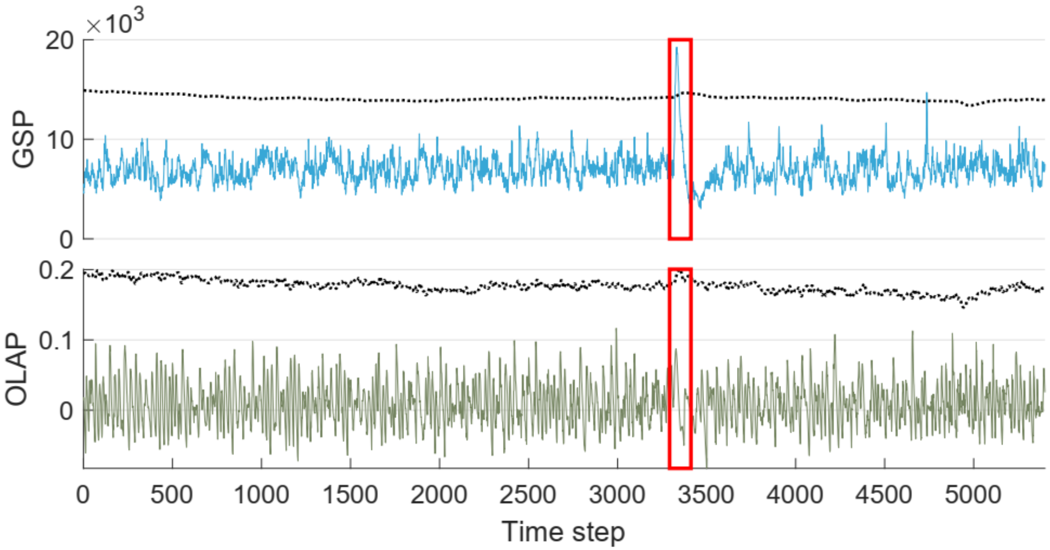
- We compare performance of the proposed algorithm [1] with that of a benchmark algorithm called online algorithm for PMU data processing (OLAP) [2].

Comparison of F1 Scores

Method	GSP	OLAP
Category 1	0.7692	0.9
Category 2	1	0.8889
Category 3	0.8889	0.75
All Events	0.8750	0.8519

Scalability Test

Number of PMUs	30	60	90	120
Runtime	3.01 s	4.45 s	5.80 s	6.95 s



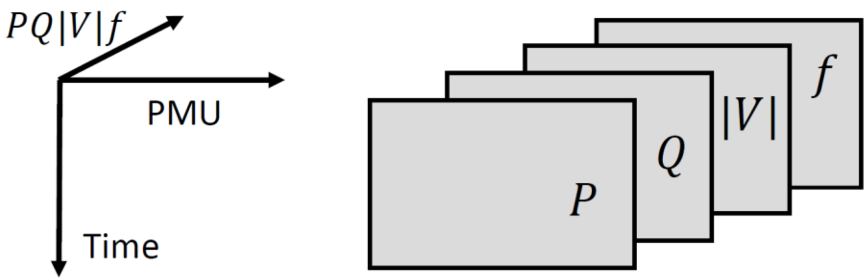
Abnormal event indicators of the GSP based approach and the OLAP algorithm for the sample frequency event

[1] Jie Shi, Brandon Foggo, Xianghao Kong, Yuanbin Cheng, Nanpeng Yu, and Koji Yamashita "Online Event Detection in Synchrophasor Data with Graph Signal Processing," *IEEE SmartGridComm*, 2020.

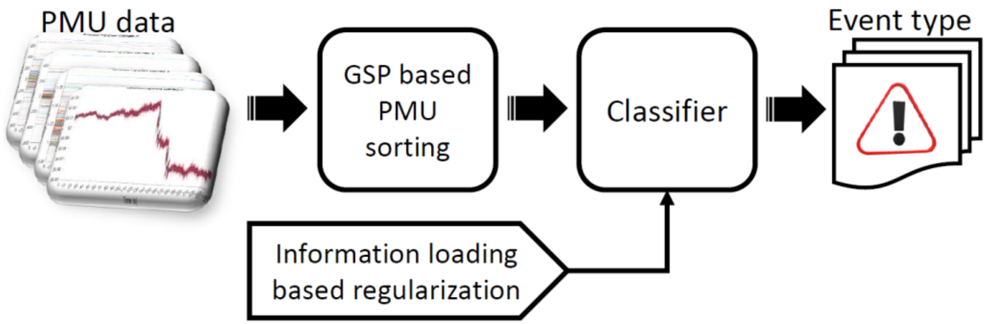
[2] Gao P, Wang M, Ghiocel SG, Chow JH, Fardanesh B, Stefopoulos G. Missing data recovery by exploiting low-dimensionality in power system synchrophasor measurements. *IEEE Transactions on Power Systems*. 2015 Apr 6;31(2):1006-13.

Online Power System Event Identification

- Formulated as a classification problem
  - No event, line event, generator event, oscillation event
- Input: 3 dimensional tensor
  - Time, PMU ID, and PQ|V|f measurement



- Overall Framework
  - Three key modules
    - Convolutional Neural Network based Classifier
    - Graph Signal Processing based PMU Sorting
    - Information Loading based Regularization



Jie Shi, Brandon Foggo, and Nanpeng Yu, "Power System Event Identification based on Deep Neural Network with Information Loading," under review, https://arxiv.org/abs/2011.06718, 2020.

Graph Signal Processing based PMU Sorting

- GSP base PMU Sorting Algorithm
  - Goal: Make parameter sharing more effective by systematically rearranging PMUs in the input tenors.
  - Main Idea: Strategically place highly correlated PMUs close to each other.
  - Algorithm

Algorithm 1: GSP based PMU sorting algorithm

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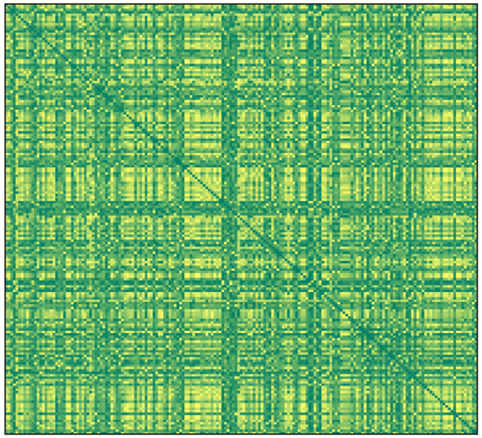
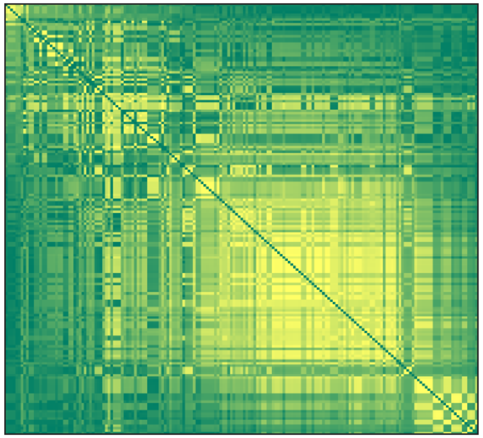
1 Obtain the Pearson correlation coefficients between PMUs;
2 Construct weight matrix W and Laplacian graph L;
3 Take eigendecomposition of L;
4 Sort PMUs according to the eigenvector corresponding to the second smallest eigenvalue of L;

  - Visualization of Spatial Correlation Matrix

Unsorted

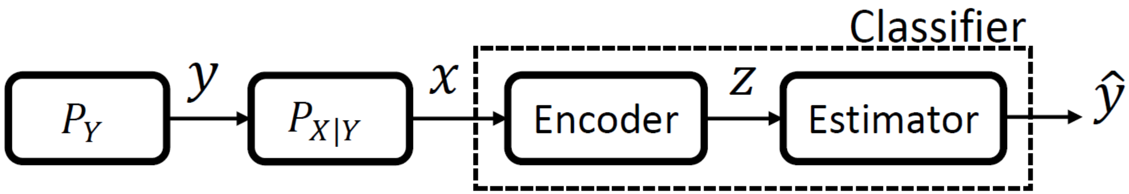


Sorted



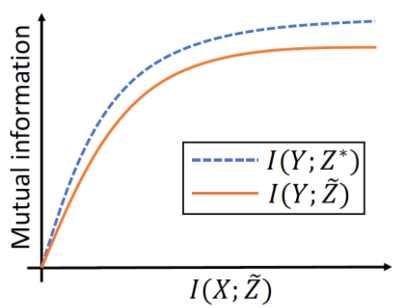
Information Loading based Regularization

- Background
  - Abstract Representation of Deep Neural Network based Classifier [1]

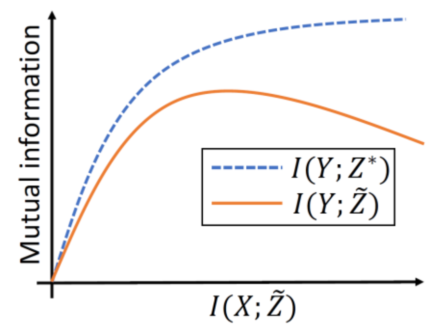


- Main Idea
  - Controls the amount of information compression between the input layer and the last hidden layer of a deep neural network.
  - Balance memorization and generalization.

Low entropy input feature space



High entropy input feature space



- Algorithm
  - Augment the typical cross-entropy loss function with estimated mutual information between the input layer and the hidden representation

$$L_T = L_{CE} - \beta \hat{I}(X;Z)$$

[1] Brandon Foggo, Nanpeng Yu, Jie Shi and Yuanqi Gao, "Information Losses in Neural Classifiers from Sampling," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 10, pp. 4073-4083, 2020.

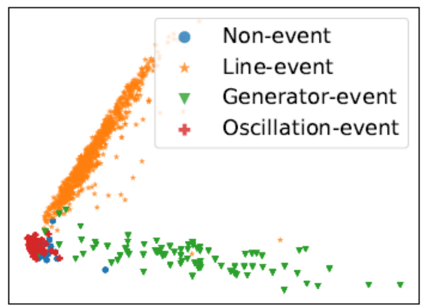
Testing Results and Learned Representation

- F1 Scores on Testing Dataset

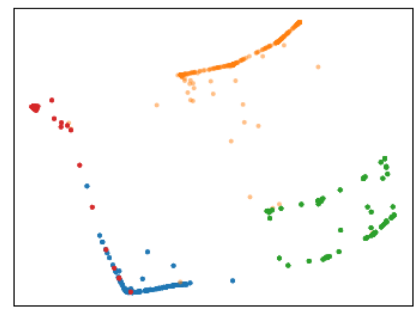
	Non-event	*Line-event*	*Generator event*	*Oscillation event*
Baseline	0.554	0.879	0.881	0.208
Baseline+info	0.596	0.928	0.924	0.205
Baseline+GSP	0.894	0.937	0.907	0.922
Baseline+GSP+info	0.973	0.971	0.962	0.986

- Learned Representation

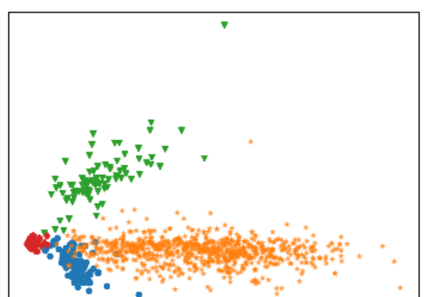
Comparison of representations produced by different methods after PCA based dimension reduction



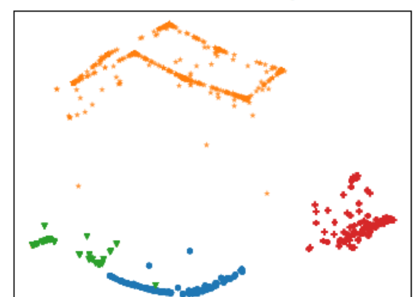
(a) *Baseline.*



(b) *Baseline+info.*



(c) *Baseline+GSP.*



(d) *Baseline+GSP+info.*