Event detection and structure inference for graph vectors

Ph.D defense

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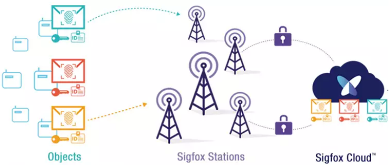
Industrial context

What is Sigfox?

- Internet-of-Things network
- 28k Base Stations (BS)



- A message can be received by all nearby BS
- $\sim$ 56M messages/day
- 72 countries

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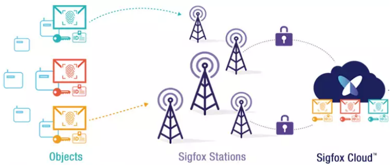

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Detect BS failure using the data collected in the network

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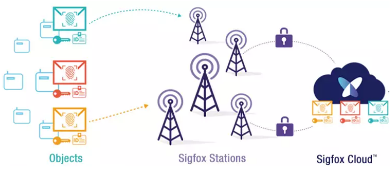

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Detect BS failure using the data collected in the network

Which data?

- Only reception information
- For each message, which BS received it (1) or not (0)

	BS#1	BS#2	BS#3	...
Message #1	0	1	1	...
Message #2	1	0	0	...
Message #3	0	0	1	...
...	...	...	...	...

- “Pure” data: almost no processing
- Collected at the level of nodes in a network: Graph vectors!

General context

Graph vectors

- Let $G = (\mathcal{V}, \mathcal{E})$ be a graph, $y : \mathcal{V} \to \mathbb{R}$ is a graph vector
- Also referred as *graph signals* or *graph data*
- Examples: Sigfox data, Social network data, EEG etc.

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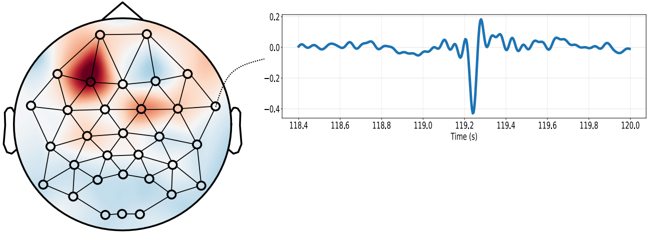

Figure: Electroencephalogram (EEG) seen as a set of graph data

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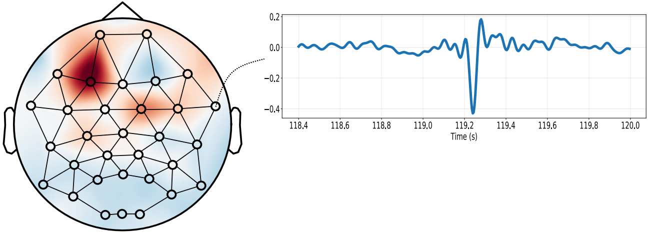
Problems

- Graph known:
  $\to$ improve the performance of your learning/statistical tasks
- Graph unknown:
  $\to$ learn it to better understand the data



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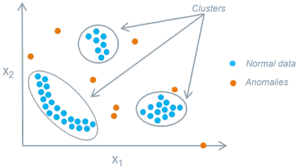
Objectives and motivations

Event detection for graph vectors

- *Anomaly* or *Change-point* detection
- Motivated by Sigfox application (BS failure)
- Applications: network security, sensor's breakdown, etc.



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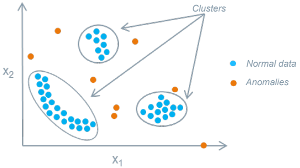
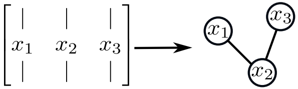


Graph learning

- Infer the relationship between variables (similarity, dependency, etc.)
- Visualize and model the vectors. Apply graph-based learning algorithms
- Applications: gene co-expression, movie recommendation, etc.



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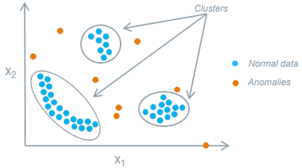
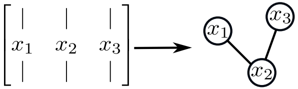
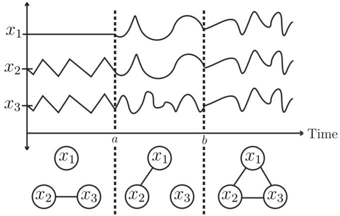
Detect changes in the underlying graph

- Combination of graph learning and change-point detection
- More difficult
- Keeps the advantages of the previous tasks







Related works

Event detection for graph vectors

- Use the graph to build features (Chen *et al.* 2018 [3], Egilmez *et al.* 2014 [6])
- Different levels of detection
  → node-level (Ji *et al.* 2013 [11]), subgraph-level (Neil *et al.* 2013 [15]), graph-level (Chen *et al.* 2018 [3])

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Graph learning

- Statistical framework: estimating parameters of Markov Random Fields
  → Gaussian model (Friedman *et al.* 2008 [7]), Ising model (Ravikumar *et al.* 2010 [16], Goel *et al.* 2019 [9])
- Graph signal processing framework
  → Smoothness (Dong *et al.* 2016 [5]), sparsity of the graph spectral domain (Sardellitti *et al.* 2019 [18])

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Detect changes in the underlying graph

- Statistical framework (Roy *et al.* 2017 [17], Londschien *et al.* 2020 [17] [14])
- Graph signal processing framework (Yamada *et al.* 2020 [20])
- Known (Bybee and Atchadé, 2018 [1]) vs Unknown (Gibberd and Nelson, 2017 [8]) number of change-points

Outline

1. Node-level anomaly detection in networks: application to Sigfox

2. Graph inference from smooth and bandlimited graph signals

3. Detecting changes in the graph structure of a varying Ising model

4. Conclusion

Part 1

-

Node-level anomaly detection in networks: application to Sigfox

Model

- Let N be the number of considered BS

Definition (Fingerprint)

The *fingerprint* of a Sigfox message is $X = (X_1, \ldots, X_N) \in \{0,1\}^N$, where $X_j = 1$ if BS j received the message, 0 otherwise

- Assumption 1: Sigfox messages are independent random vectors

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Definition (Conditional probability function)

Let a BS $j \in [N]$, The conditional probability function of j is

$$\eta_j^*(x_{\setminus j}) \triangleq \mathbb{P}(X_j = 1 | X_{\setminus j} = x_{\setminus j}),$$

where $X_{\setminus j}$ is the vector X without its j-th component

- Assumption 2: The conditional probability function of a BS j doesn't change over time

Objective and scoring function

Goal: Given a set $\mathcal{D}_n = \{X^{(i)}\}_{i=1}^n$ and its realization $\{x^{(i)}\}_{i=1}^n$, fix a BS $j \in [N]$ and determine if $m_j = \sum_{i=1}^n x_j^{(i)}$ is abnormally low

- Assumption 3: We have access to a set of normal communication behaviors $\mathcal{D}_{train}$

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A natural scoring function

- Use values of the other BS
- Knowing $X_{\setminus j}^{(i)} = x_{\setminus j}^{(i)}$, $M_j = \sum_{i=1}^n X_j^{(i)}$ is a Poisson Binomial distribution with parameter $\{\eta_j^*(x_{\setminus j}^{(i)})\}_{i=1}^n$
- Given η_j^*, its cumulative distribution function (cdf) $F_{M_j}(\cdot)$ can be computed efficiently (Hong, 2013 [10])

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Definition (Anomaly scoring function)

A natural score of abnormality for m_j is given by:

$$s(m_j) = \mathbb{P}(M_j > m_j) = 1 - F_{M_j}(m_j),$$

where close to 1 value means m_j stands in a low-density region (left-hand tail).

- In practice we do not have access to η_j^*. What can be done?

A supervised-learning solution

Solution

- Learn $\hat{\eta}_j$, estimator of η_j^*, using a regression algorithm (logistic, random forest, etc.) over $\mathcal{D}_{train}$
- Use $\hat{\eta}_j$ instead of η_j^* to build F_{M_j}, and compute the previous anomaly score
- Fix a threshold above which m_j is considered abnormal (e.g. 0.99 or 0.95)

Algorithm: Regression-based anomaly detection

Input: $\mathcal{D}_{train}$, $\mathcal{D}_n$, node j, threshold s
Regression algorithm: `Regressor`$(\cdot)$
Output: 1 if anomaly, 0, otherwise

$\hat{\eta} \longleftarrow \texttt{Regressor}\left(\mathcal{D}_{train} = \{\tilde{x}_{\backslash j}^{(i)}, \tilde{x}_j^{(i)}\}\right)$
for $i = 1 \dots, n$ **do**
  $\hat{p}_i \longleftarrow \hat{\eta}(x_{\backslash j}^{(i)})$
end for
$\hat{F} \longleftarrow \texttt{PoiBin}\left(\sum x_j^{(i)}; \hat{p}_j^{(1)}, \dots, \hat{p}_j^{(n)}\right)$
$\hat{s} \longleftarrow \max(\hat{F}, 1 - \hat{F})$
if $\hat{s} > s$ **then**
  Output 1: Abnormal node
else
  Output 0: Normal node
end if

Sigfox application

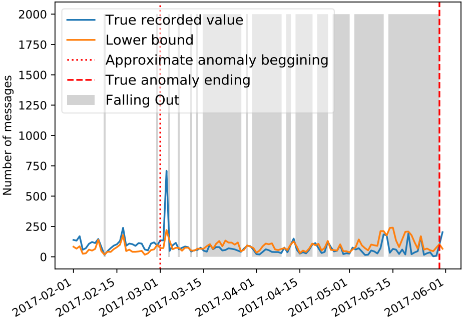
Dataset

- 34 BS, 232000 messages over 5 months
- Training set: first month($\sim$ 35000 messages)
- Daily prediction over the 4 other months: 120 testing data sets ($\sim$ 1600 messages/day in average)
- 1 failing BS, approximately from March, i.e. 30 normal days, 90 abnormal
- Dataset available online

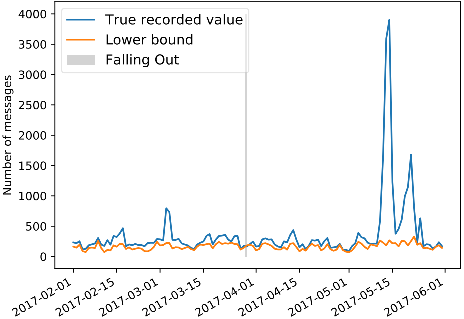
Setup

- Regressor: Random forest from scikit-learn, by default hyperparameters (no tuning)
- Threshold fixed via CV over the training set s.t. False positive rate ~ 0.01
- Baseline: basic feature engineering + One-class SVM (Schölkopf *et al.* 2001 [19])

Results



(a) Abnormal Base Station



(b) Normal Base Station

Results (2)

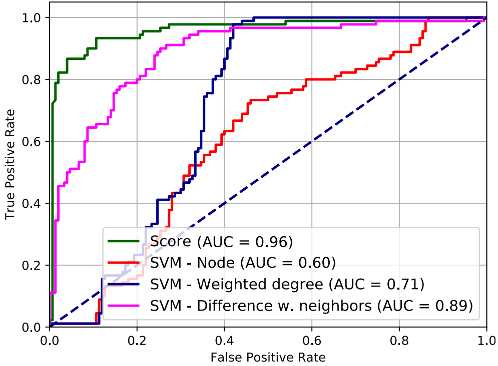


Figure: ROC curves and their respective AUC.

- Convincing results: the proposed approach seems adapted
- Larger-scale experiments, performed internally at Sigfox, corroborate those results
- A more general presentation of the method in [Le Bars and Kalogeratos, INFOCOM 2019]

Part 2

-

Graph inference from smooth and bandlimited graph signals

Background

Graph Signal Processing (GSP)

- Generalizes signal processing concepts for graph signals (smoothness, Fourier transform, sampling, filtering, etc.)
- Temporal signals and images are graph signals with specific graph (cycles and mesh)
- Having access to the graph is a strong assumption: graph learning

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Definition (Graph Laplacian)

The graph Laplacian of a graph $G = (\mathcal{V}, \mathcal{E})$ with weight matrix W and degree matrix D is the matrix $L = D - W$

Definition (Graph Fourier Transform)

Let $G = (\mathcal{V}, \mathcal{E})$ and $L = X \Lambda X^{\mathsf{T}}$ be the eigenvalue decomposition of its Laplacian matrix. The Graph Fourier Transform (GFT) of a graph signal $y \in \mathbb{R}^p$ is given by

$$h = X^{\mathsf{T}} y$$

Problem Statement

Goal: Learn the Laplacian L that best explains the structure of n graph signals $Y = [y^{(1)}, \ldots, y^{(n)}]$ of size N.

- Need for structural assumptions that link L to Y

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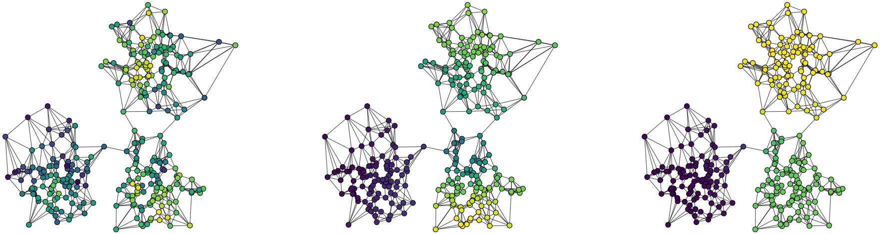
  $\rightarrow$ Basic assumption of sampling methods (Chen *et al.* 2015 [2])
  $\rightarrow$ Different notion of smoothness
  $\rightarrow$ Also relies to the cluster structure of the graph (Sardellitti *et al.* 2019 [18])



(a) (b) (c)

Figure: Three smooth graph signals ($N = 300$) with decreasing bandlimitedness: (a) 150-sparse, (b) 6-sparse, (c) 3-sparse.

Optimization program

$$\min_{H,X,\Lambda} \|Y - XH\|_F^2 + \alpha\|\Lambda^{1/2}H\|_F^2 + \beta\|H\|_S$$

$$\text{s.t.} \quad \begin{cases} X^\mathsf{T} X = I_N, x_1 = \frac{1}{\sqrt{N}}\mathbf{1}_N & \text{(a)} \\ (X\Lambda X^\mathsf{T})_{k,\ell} \leq 0 \quad k \neq \ell & \text{(b)} \\ \Lambda = \operatorname{diag}(0, \lambda_2, \dots, \lambda_N) \succeq 0 & \text{(c)} \\ \operatorname{tr}(\Lambda) = N \in \mathbb{R}_*^+ & \text{(d)} \end{cases}$$

- Learn $X\Lambda X^\mathsf{T}$ instead of L
- Y are assumed to be noisy version of some true graph vectors XH
- H stands for the graph Fourier transform of the true graph vectors

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- $\|Y - XH\|_F^2$ stands for the reconstruction error
- $\|\Lambda^{1/2}H\|_F^2$ controls the smoothness of the approximation XH
- $\|H\|_S = \|H\|_{2,0}$ or $\|H\|_{2,1}$ enforces the GFT to be 0 at the same dimensions
- α and β are positive hyperparameters

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Solving the program (overview)

- Optimization program not convex + very difficult to updates all variables directly
  $\longrightarrow$ Use block-coordinate descent
- Other problem: constraint (b) $(X\Lambda X^\top)_{kl} \leq 0$ difficult to handle at the X-step
  $\longrightarrow$ Solution: **IGL-3SR** and **FGL-3SR** [Le Bars *et al.*, ICASSP 2019, Humbert *et al.* 2019]
- Both relax (b) and use block-coordinate descent over X, Λ and H

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IGL-3SR

Relaxation: use a log-barrier function to put (b) in the objective

+ Each sub-problem is solvable using known techniques
+ Decrease at each step and stays in the constraint set
+ Iterates are ensured to converge
- High complexity

FGL-3SR

Relaxation: get rid of (b), only at the X-step

+ Lower complexity
+ 2/3 steps has closed-form
+ Returns a Laplacian even with the relaxation
- Objective function value can increase

Synthetic data

- Large simulation study in [Le Bars *et al.* 2019, Humbert *et al.* 2019]
- True graphs: Random Geometric or Erdös-Renyi
- Y sampled via factor analysis model
- Comparison with two GSP baselines:
  $\rightarrow$ GL-SigRep (Dong *et al.* 2016 [5]): Only smoothness
  $\rightarrow$ ESA-GL (Sardellitti *et al.* 2019 [18]): Bandlimitedness

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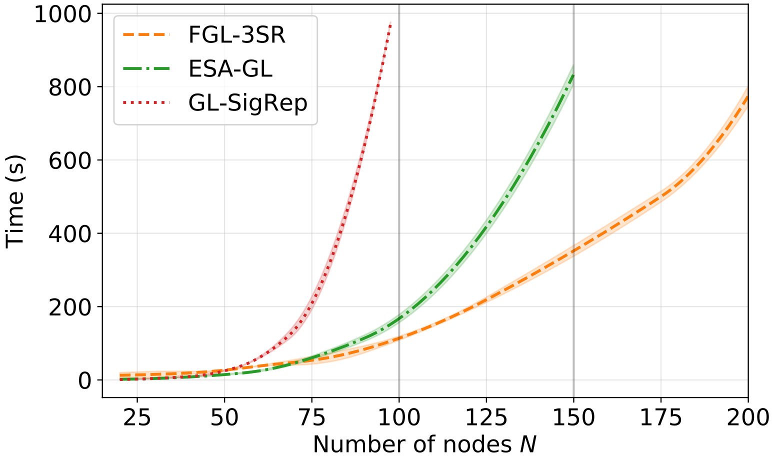
Results and conclusion

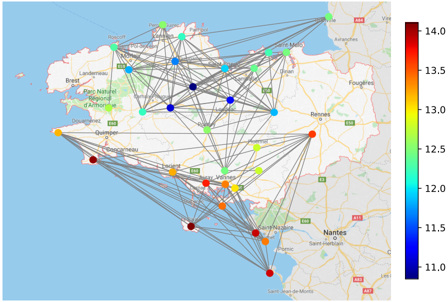
- IGL-3SR outperforms baselines and FGL-3SR in terms of true graph recovery
- It is very slow, not practical for $\gtrsim$ 20 nodes
- FGL-3SR is a good compromise between graph recovery and time before convergence

Synthetic data - Results

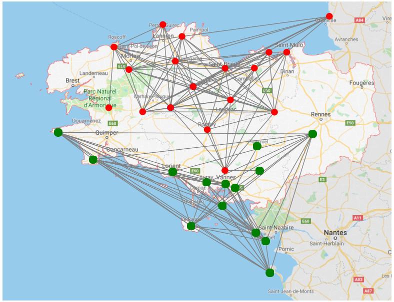


A real-world illustration

- Temperature data in Brittany (Chepuri *et al.* 2017 [4])
- $N = 32$ weather station
- spectral clustering to ascess the quality
- $n = 744$ measurements
- $\alpha = 10^{-4}$, β s.t 2-bandlimited



(a) A measurement example and the learned graph.



(b) Spectral clustering with the learned graph.

- Coherent with the spatial distribution. Splits the north from the south of Brittany

Part 3

-

Detecting changes in the graph structure of a varying Ising model

Background

Context

- Probabilistic modeling, the data come from a Markov Random Field (MRF)
- Binary vector data: **Ising model**
- Change-point detection with *unknown* number of change-points
- Related works:
  - Detection in Gaussian graphical models (Gibberd and Nelson, 2017 [8])
  - Detection in Ising with *known* number of change-points (Roy *et al.* 2017 [17])

Background

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Ising model

Let $G = (V, E)$ and $\Omega \in \mathbb{R}^{p \times p}$ **symmetric** whose non-zero elements correspond to the set of edges E. The probability distribution function (pdf) of an Ising random vector X:

$$\mathbb{P}_\Omega(X = x) = \frac{1}{Z(\Omega)} \exp\left\{ \sum_{a<b} x_a x_b \omega_{ab} \right\}$$

- $Z(\Omega)$: Normalizing constant
- $x \in \{-1, 1\}^p$

Model and objectives

Piece-wise constant Ising model

- Time-series of n independent Ising vectors $X^{(i)}$ with parameter $\Omega^{(i)}$
- Piecewise constant evolving structure:

$$\Omega^{(i)} = \sum_{k=0}^{D} \Theta^{(k+1)} \mathbf{1}\{T_k \leq i < T_{k+1}\}$$

$T_0 = 1$ and $T_{D+1} = n + 1$.

- D change-points appearing a time $T_1, \dots, T_D$
- $D + 1$ sub-model parametrized by $\Theta^{(1)}, \dots, \Theta^{(D+1)}$

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- D change-points appearing a time $T_1, \ldots, T_D$
- $D + 1$ sub-model parametrized by $\Theta^{(1)}, \ldots, \Theta^{(D+1)}$

Objectives:

- Learn for each $X^{(i)}$ its associated parameter $\Omega^{(i)}$
- Infer the number of change-points D and their time instances

Learning

- Can we use standard maximum likelihood approach ?
  $\rightarrow$ No, due to the intractability of $Z(\cdot)$ and the high-dimensional scenario

- Instead, penalized **neighborhood selection** strategy: **TVI-FL** [Le Bars *et al.*, ICML 2020a]

TVI-FL

For each node $j = 1, \ldots, p$, we solve

$$\widehat{\omega}_j = \underset{\omega \in \mathbb{R}^{p-1 \times n}}{\operatorname{argmin}} \; \mathcal{L}_j(\omega) + pen_{\lambda_1,\lambda_2}(\omega)$$

- A column $\widehat{\omega}_j^{(i)}$ of $\widehat{\omega}_j$ corresponds to the j-th row/column of $\widehat{\Omega}^{(i)}$
  $\longrightarrow$ The neighborhood's weights of node j at time i

Learning

TVI-FL

For each node $j = 1, \ldots, p$, we solve

$$\widehat{\omega}_j = \underset{\omega \in \mathbb{R}^{p-1 \times n}}{\operatorname{argmin}} \ \mathcal{L}_j(\omega) + pen_{\lambda_1, \lambda_2}(\omega)$$

$$\mathcal{L}_j(\omega) \triangleq -\sum_{i=1}^{n} \log \left(\mathbb{P}_{\omega^{(i)}}(x_j^{(i)} | x_{\setminus j}^{(i)}) \right)$$
$$= \sum_{i=1}^{n} \log \left\{ \exp \left(\omega^{(i)\top} x_{\setminus j}^{(i)} \right) + \exp \left(-\omega^{(i)\top} x_{\setminus j}^{(i)} \right) \right\} - \sum_{i=1}^{n} x_j^{(i)} \omega^{(i)\top} x_{\setminus j}^{(i)}$$

- Conditional log-likelihood of node j knowing the other nodes values
- Convex function

Learning

TVI-FL

For each node $j = 1, \dots, p$, we solve

$$\widehat{\omega}_j = \underset{\omega \in \mathbb{R}^{p-1 \times n}}{\operatorname{argmin}} \ \mathcal{L}_j(\omega) + pen_{\lambda_1,\lambda_2}(\omega)$$

$$pen_{\lambda_1,\lambda_2}(\omega) \triangleq \lambda_1 \sum_{i=2}^{n} \|\omega^{(i)} - \omega^{(i-1)}\|_2 + \lambda_2 \sum_{i=1}^{n} \|\omega^{(i)}\|_1$$

- λ_1 and λ_2 are positive hyperparameters
- The first term - **fused penalty** - controls the piece-wise constant structure and the number of change-points
- The second term - **lasso penalty** - imposes sparsity in the learnt neighborhood

Learning

TVI-FL

For each node $j = 1, \dots, p$, we solve

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- λ_1 and λ_2 are positive hyperparameters
- The first term - **fused penalty** - controls the piece-wise constant structure and the number of change-points
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In conclusion:

- Non-differentiable but **convex function**
- TVI-FL solvable by convex programming tools and software
- Set of estimated change-points : $\widehat{\mathcal{D}} = \left\{ \widehat{T}_k \in \{2, \dots, n\} : \|\widehat{\omega}_j^{(\widehat{T}_k)} - \widehat{\omega}_j^{(\widehat{T}_k - 1)}\|_2 \neq 0 \right\}$

Theoretical analysis

Assumptions:

- **(A1)** $\exists \phi_{\min} > 0$ and $\phi_{\max} < \infty$ s.t. $\phi_{\min} \leq \Lambda_{\min}\left(\mathbb{E}_{\Theta^{(k)}}[X_{\setminus j} X_{\setminus j}^\top]\right)$ and $\phi_{\max} \geq \Lambda_{\max}\left(\mathbb{E}_{\Theta^{(k)}}[X_{\setminus j} X_{\setminus j}^\top]\right)$
- **(A2)** There exists $M \geq 0$ s.t. $\max_{k \in [D+1]} \|\theta_j^{(k)}\|_2 \leq M$
- **(A3)** For all $k = 1, \ldots, D$, $T_k = \lfloor n\tau_k \rfloor$ with unknown $\tau_k \in [0, 1]$

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- **(A3)** For all $k = 1, \ldots, D$, $T_k = \lfloor n\tau_k \rfloor$ with unknown $\tau_k \in [0, 1]$

Theorem - Change-Point consistency

Consider (A1-A3) and let $\{\delta_n\}_{n \geq 1}$ be a non-increasing sequence that converges to 0 and s.t. $n\delta_n \to \infty$.
If $\widehat{D} = D$, we have:

$$\mathbb{P}\left(\max_{k=1,\ldots,D} |\hat{T}_k - T_k| \leq n\delta_n \right) \underset{n \to \infty}{\longrightarrow} 1$$

- Drawback: $\widehat{D} = D$ difficult to verify

Change-Point consistency 2

- $d(A \| B) = \sup_{b \in B} \inf_{a \in A} |b - a|$

Proposition

Under the same conditions, if $D \leq \widehat{D}$ then:

$$\mathbb{P}(d(\widehat{\mathcal{D}} \| \mathcal{D}) \leq n\delta_n) \underset{n \to \infty}{\longrightarrow} 1$$

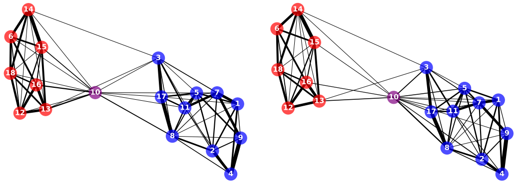
- Overestimated number of change-points
- Asymptotically, all the true change-points belong to the estimated set of change-points

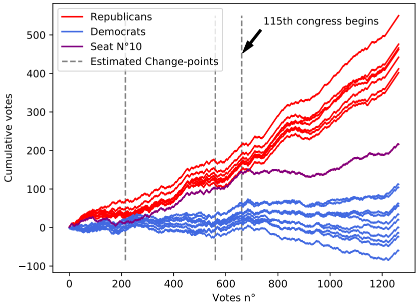
Voting data set

- Votes (yes/no) in Illinois house of representatives (Lewis *et al.* 2020 [13])
- 18 seats → 18 nodes
- 1264 votes
- 114-th and 115-th US Congresses (2015-2019)
- λ_1 and λ_2 minimizing AIC

Results:

- Party structure: Republican vs Democrat
- Biggest change-point: End of congress
- Seat 10 change party
- Brings knowledge: seat 10 is a *super-collaborator*





Sigfox data set

- Same data set as in part 1
- λ_1 and λ_2 selected via AIC
- Several change-points, but an important one around the 30th day

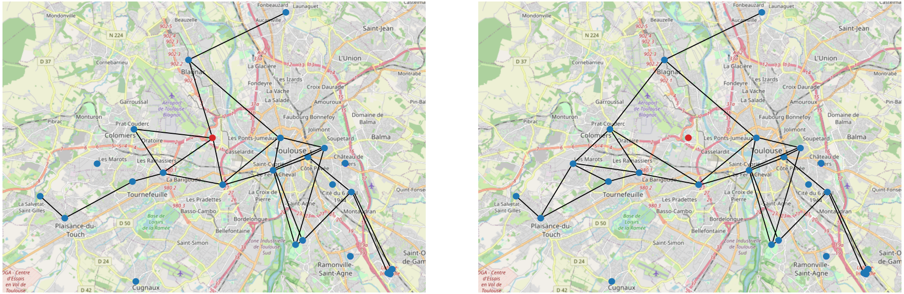


Figure: (Left) A graph learned before the BS failure, recorded on the 30th day. (Right) A graph learned after this day

Conclusion

Conclusion

A diverse work ...

- Anomaly detection, change-point detection, graph learning, optimization
- GSP framework, probabilistic framework
- Not discussed: robust kernel density estimation [Le Bars *et al.*, 2020b]
- Codes available online at `github.com/BatisteLB`

... with open questions

- Online version for change-point detection of part 3
- Better theoretical understanding: consistent graph recovery?
- Improve optimization of part 2 and 3
- Make a better use of the graph in part 1

Publications and preprints

- B. Le Bars, and A. Kalogeratos. A Probabilistic Framework to Node-level Anomaly Detection in Communication Networks. *In 2019 IEEE Conference on Computer Communications (INFOCOM)*, 2019
- B. Le Bars, P. Humbert, L. Oudre, and A. Kalogeratos. Learning Laplacian Matrix from Bandlimited Graph Signals. *In 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019
- P. Humbert, B. Le Bars, L. Oudre, A. Kalogeratos, and N. Vayatis. Learning Laplacian Matrix from Graph Signals with Sparse Spectral Representation. *Arxiv preprint*, 2019
- B. Le Bars, P. Humbert, A. Kalogeratos, and N. Vayatis. Learning the piece-wise constant graph structure of a varying Ising model. *In 2020 International Conference on Machine Learning (ICML)*, 2020a
- B. Le Bars, P. Humbert, L. Minvielle, and N. Vayatis. Robust Kernel Density Estimation with Median-of-Means principle. *Arxiv preprint*, 2020b

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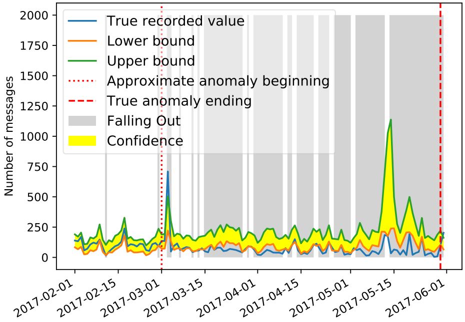
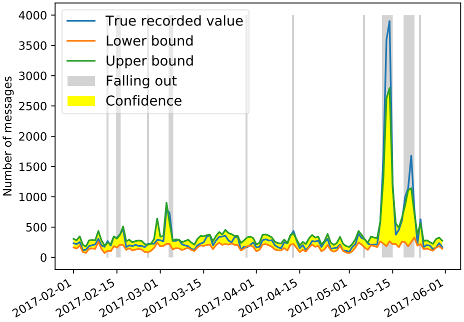
Results bilateral



(a) Abnormal Base Station - Bilateral intervals



(b) Normal Base Station - Bilateral intervals

FGL-3SR

H-step

$$\min_{H} \|Y - XH\|_F^2 + \alpha\|\Lambda^{1/2}H\|_F^2 + \beta\|H\|_S$$

- No constraint
- Equivalent to multiple sparse linear regression problems
- Closed-form solutions
- $\|\cdot\|_S = \|\cdot\|_{2,0}$: hard-thresholding
- $\|\cdot\|_S = \|\cdot\|_{2,1}$: solf-thresholding

FGL-3SR

X-step

$$\min_X \|Y - XH\|_F^2 \qquad \text{s.t.} \quad X^\top X = I_N, \; x_1 = \frac{1}{\sqrt{N}}\mathbf{1}_N \qquad \text{(a)}$$

- (b) is out
- Non-convex but has a closed-form:

$$X^{(t+1)} = X^{(t)} \begin{bmatrix} 1 & \mathbf{0}_{N-1}^\top \\ \mathbf{0}_{N-1} & PQ^\top \end{bmatrix},$$

where the columns in P and Q are the left- and right-singular vectors of $(X^{(t+1)\top} Y H^\top)_{2:,2:}$

FGL-3SR

Λ-step

$$\min_{\Lambda} \ \alpha \ \underbrace{\mathrm{tr}(HH^\top \Lambda)}_{\|\Lambda^{1/2}H\|_F^2} \qquad \text{s.t.} \quad \begin{cases} (X\Lambda X^\top)_{i,j} \leq 0 \quad i \neq j\,, & \text{(b)} \\ \Lambda = \mathrm{diag}(0, \lambda_2, \dots, \lambda_N) \succeq 0\,, & \text{(c)} \\ \mathrm{tr}(\Lambda) = N \in \mathbb{R}_*^+\,, & \text{(d)} \end{cases}$$

- (b) is back
- Linear program: can be solved via solvers
- Property: for all X that satisfies (a), there exist Λ that satisfies (b), (c) and (d)
  $\longrightarrow$ Need to finish by this step

Synthetic data graph learning - Results

N	Metrics	RG graph model				ER graph model			
		IGL-3SR	FGL-3SR	ESA-GL	GL-SigRep	IGL-3SR	FGL-3SR	ESA-GL	GL-SigRep
20	F_1-measure	**0.97** $(\pm$**0.03**$)$	**0.97** $(\pm$**0.03**$)$	0.93 (± 0.03)	0.95 (± 0.04)	**0.94** $(\pm$**0.03**$)$	0.82 (± 0.07)	**0.94** $(\pm$**0.04**$)$	0.78 (± 0.07)
	$\rho(L, \hat{L})$	**0.94** $(\pm$**0.05**$)$	0.90 (± 0.03)	0.92 (± 0.05)	0.79 (± 0.04)	**0.92** $(\pm$**0.03**$)$	0.73 (± 0.06)	0.90 (± 0.04)	0.20 (± 0.07)
	Time	$<$ 1min	$<$ 10s	$<$ **5s**	$<$ **5s**	$<$ 1min	$<$ 10s	$<$ **5s**	$<$ **5s**
50	F_1-measure	**0.90** $(\pm$**0.01**$)$	0.81 (± 0.02)	0.87 (± 0.04)	0.75 (± 0.01)	0.81 (± 0.02)	0.76 (± 0.03)	**0.84** $(\pm$**0.02**$)$	0.61 (± 0.03)
	$\rho(L, \hat{L})$	**0.86** $(\pm$**0.02**$)$	0.74 (± 0.03)	0.83 (± 0.03)	0.55 (± 0.02)	0.78 (± 0.03)	0.73 (± 0.02)	**0.82** $(\pm$**0.06**$)$	0.06 (± 0.01)
	Time	$<$ 17mins	$<$ **40s**	$<$ 60s	$<$ **40s**	$<$ 17mins	$<$ **40s**	$<$ 60s	$<$ **40s**
100	F_1-measure	**0.73** $(\pm$**0.03**$)$	0.64 (± 0.01)	0.70 (± 0.01)	–	**0.62** $(\pm$**0.01**$)$	0.59 (± 0.02)	0.59 (± 0.02)	–
	$\rho(L, \hat{L})$	**0.61** $(\pm$**0.04**$)$	0.48 (± 0.01)	0.60 (± 0.03)	–	0.55 (± 0.02)	0.51 (± 0.022)	**0.64** $(\pm$**0.02**$)$	–
	Time	$<$ 50mins	$<$ **2mins**	$<$ 4mins	–	$<$ 50mins	$<$ **2mins**	$<$ 4mins	–

Synthetic data

- $n = 100$, $p = 20$, 2 Change-Points
- Random Regular Graphs with degree $\in \{2, 3, 4\}$
- Competitor: Tesla (Kolar *et al.* [12])
- Metrics, F_1-score and h-score:

$$h(\mathcal{D}, \widehat{\mathcal{D}}) \triangleq \frac{1}{n} \max \left\{ \max_{t \in \mathcal{D}} \min_{\hat{t} \in \widehat{\mathcal{D}}} |t - \hat{t}|, \max_{\hat{t} \in \widehat{\mathcal{D}}} \min_{t \in \mathcal{D}} |t - \hat{t}| \right\}.$$

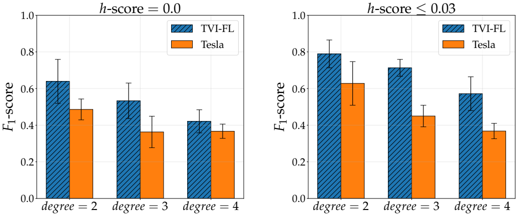


Figure: Average F_1-score obtained when the h-score is below a certain threshold.

- Outperforming Telsa, not designed for proper CP detection
- Complete results in the main paper

Robust Kernel Density Estimator

Classical framework

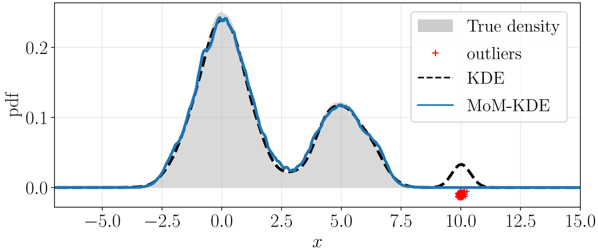
- $\{X_1, \ldots, X_n\}$
- $\forall i = 1, \ldots, n, X_i \sim f$
- Kernel Density Estimator (KDE):

$$\hat{f}_n(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right)$$

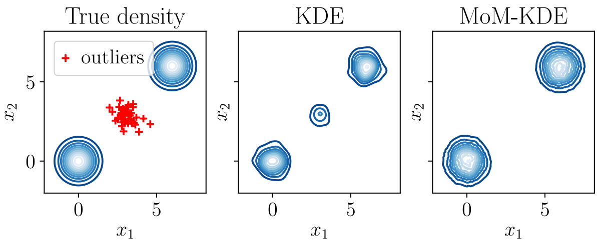
Outlier framework

- $\{X_1, \ldots, X_n\} = \mathcal{O} \cup \mathcal{I}$
- $\forall i \in \mathcal{I}, X_i \sim f$
- $B_1, \ldots, B_S$: random partition of $[n]$
- $n_s = |B_s|$
- Median-of-Means KDE:
  $\hat{f}_{MoM}(x_0) \propto \text{Median}\left(\hat{f}_{n_1}(x_0), \ldots, \hat{f}_{n_S}(x_0)\right)$

Robust Kernel Density Estimator



(a) One-dimensional



(b) Two-dimensional