

gfpop: an R Package for Univariate Graph-Constrained Change-Point Detection

Machine Learning for Time Series

Simon Queric and Vincent Herfeld

ENS Paris-Saclay, Télécom Paris

January 1, 2024

école —
normale —
supérieure —
paris — saclay —



Table of content

Introduction and contribution

Method

Data and results

References

Introduction

$$Q_n^{std}(\mu) = \sum_{t=1}^n (y_t - \mu_t)^2 + \beta \sum_{t=1}^{n-1} I_{\mu_t \neq \mu_{t+1}}$$

$$Q_n^{iso}(\mu) = \sum_{t=1}^n (y_t - \mu_t)^2 \text{ such that } \mu_t \leq \mu_{t+1}$$

Introduction

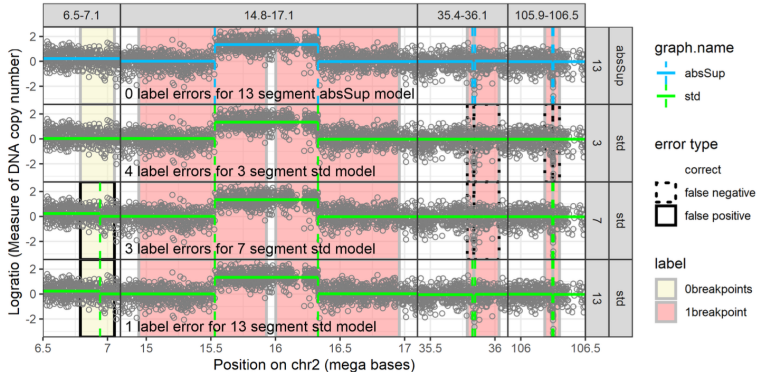
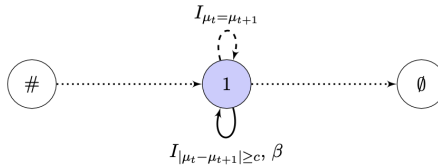


Table of content

Introduction and contribution

Method

Data and results

References

Introduction to graph of constraints

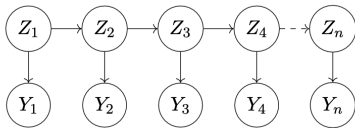


Figure: Hierarchical representation

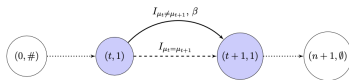


Figure: Graph of constraints

A simple example

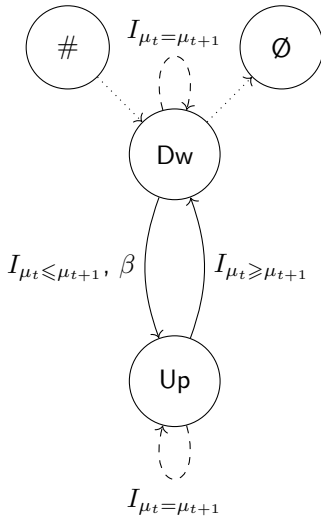


Figure: Collapsed graph for multi-modal regression

Optimization problem

Classical multiple change points detection problem :

$$(\hat{t}_1, \dots, \hat{t}_K) = \operatorname{argmin}_{(t_1, \dots, t_K)} \sum_{k=0}^K c(x[t_k : t_{k+1}])$$

The article's problem :

$$Q_n^s(\theta) = \min_{\substack{p=(v,e) \in \mathcal{G}_n \\ \mu|p(\mu), \mu_n=\theta, v_n=s}} \sum_{t=1}^n (\gamma_{e_t}(y_t, \mu_t) + \beta_{e_t})$$

c and γ_e are always negative log-probabilities.

Cost functions

L2 decomposition : $f_1 : \theta \mapsto 1, f_2 : \theta \mapsto \theta, f_3 : \theta \mapsto \theta^2$

Lin-log decomposition : $f_1 : \theta \mapsto 1, f_2 : \theta \mapsto \theta, f_3 : \theta \mapsto \log \theta$

$$\gamma_{\ell^2}(y, \mu) = (y - \mu)^2 = y^2 - 2y\mu + \mu^2 = y^2 f_1(\mu) - 2y f_2(\mu) + f_3(\mu)$$

$$\gamma_{\text{Poisson}}(y, \mu) = -\log \left(e^{-\mu} \frac{\mu^y}{y!} \right) = \log(y!) f_1(\mu) + f_2(\mu) - y f_3(\mu)$$

Algorithm to solve the problem

Algorithm 1 Backtracking \hat{s} and $\hat{\mu}$

```

1: procedure BACKTRACK( $(Q_1^1, \dots, Q_1^S), \dots, (Q_n^1, \dots, Q_n^S)$ )
2:    $\hat{\mu} \leftarrow$  empty vector of size  $n$ 
3:    $\hat{s} \leftarrow$  empty vector of size  $n$ 
4:    $(\hat{s}_n, \hat{\mu}_n) = \underset{(s, \mu)}{\operatorname{argmin}} \{Q_n^s(\mu)\}$ 
5:                                      $\triangleright$  We can impose a subset of arrival states  $\tilde{S} \subset \{1, \dots, S\}$ 
6:                                     by  $(\hat{s}_n, \hat{\mu}_n) \leftarrow \underset{(s, \mu)}{\operatorname{argmin}} \{Q_n^s(\mu)\}, s \in \tilde{S}$ 
7:   for  $t = n - 1$  to  $t = 1$  do
8:      $\hat{s}_t = \underset{s | \exists \text{ edge } (s, \hat{s}_{t+1})}{\operatorname{argmin}} \left\{ O_t^{s, \hat{s}_{t+1}}(\hat{\mu}_{t+1}) + \gamma_{(s, \hat{s}_{t+1})}(y_{t+1}, \hat{\mu}_{t+1}) + \beta_{(s, \hat{s}_{t+1})} \right\}$ 
9:      $\hat{\mu}_t = \underset{\mu | I_{(\hat{s}_t, \hat{s}_{t+1})}(\mu, \hat{\mu}_{t+1})}{\operatorname{argmin}} \left\{ Q_t^{\hat{s}_t}(\mu) \right\}$   $\triangleright$  If  $\hat{\mu}_t$  is such that the constraint is active,
10:                                     we have 'forced = TRUE' in "gfpop()" response
11:   end for
12: return  $(\hat{s}, \hat{\mu})$ 

```

Figure: Backtrack algorithm

Table of content

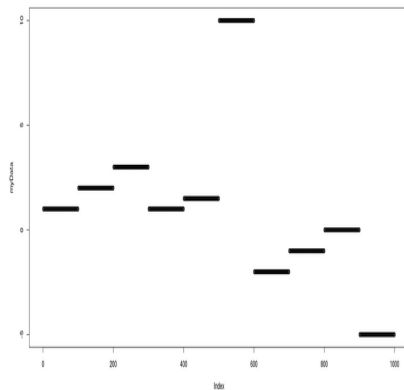
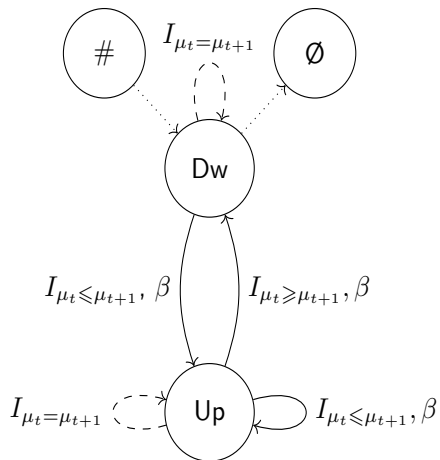
Introduction and contribution

Method

Data and results

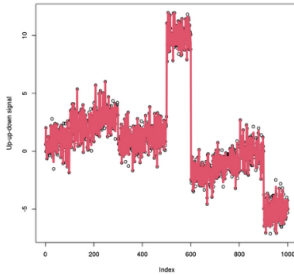
References

Up-up-down signal

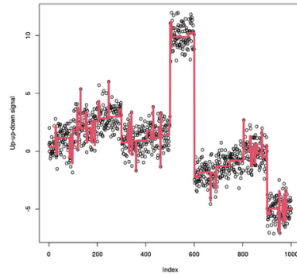


Up-up-down signal

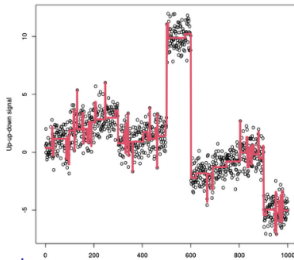
-Up-Down toy signal and change point detection, $\beta=0.1$



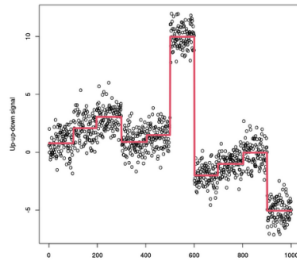
Up-Up-Down toy signal and change point detection, $\beta=3$



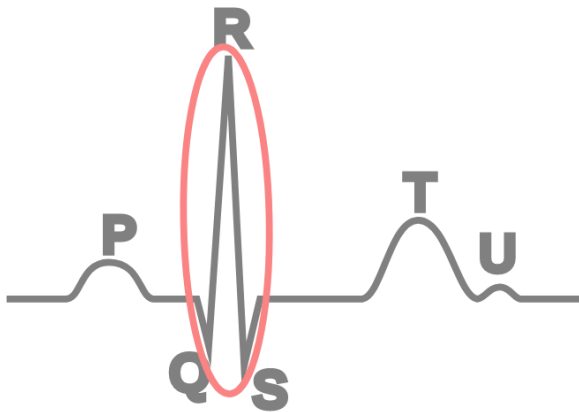
-Up-Down toy signal and change point detection, $\beta=5$



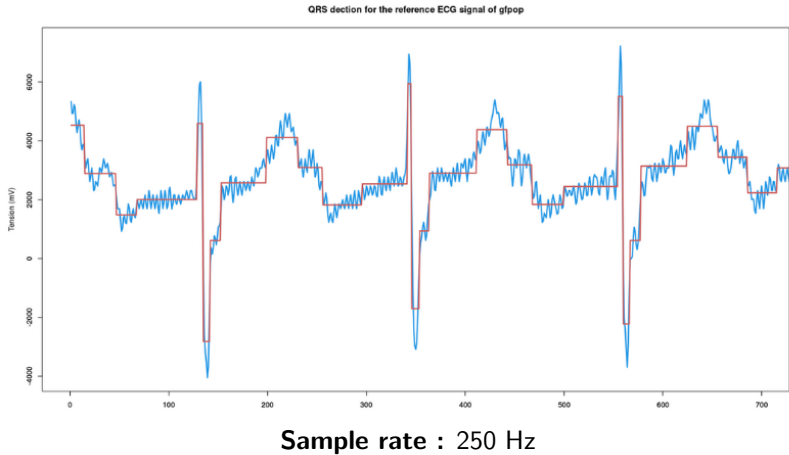
Up-Up-Down toy signal and change point detection, $\beta=10$



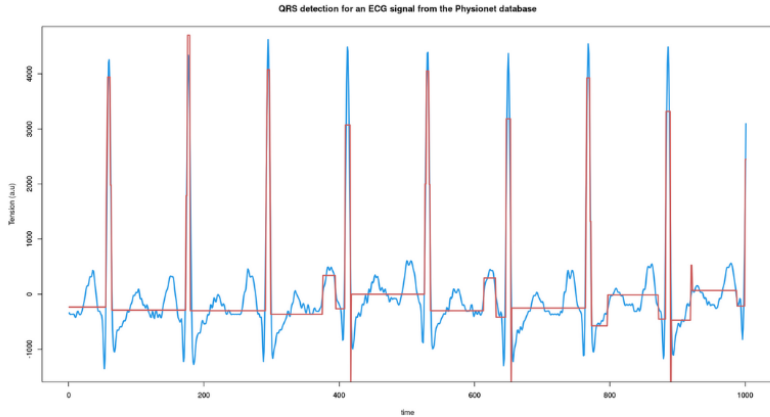
QRS complex in ECG signals



QRS complex in ECG signals

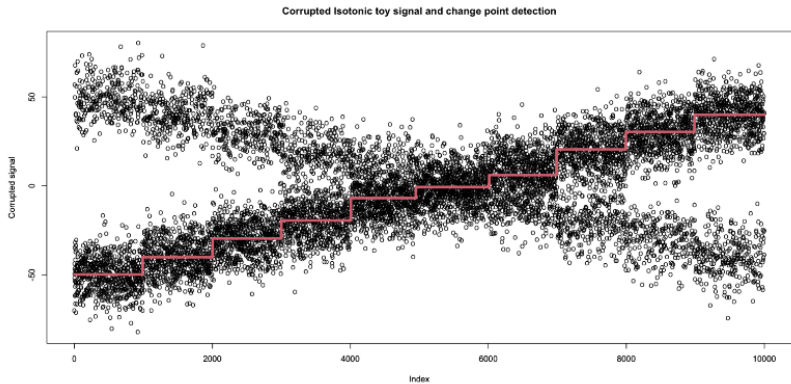


QRS complex in ECG signals

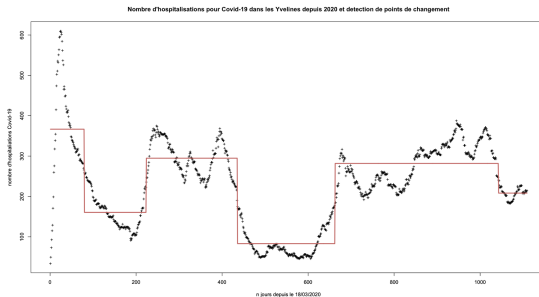
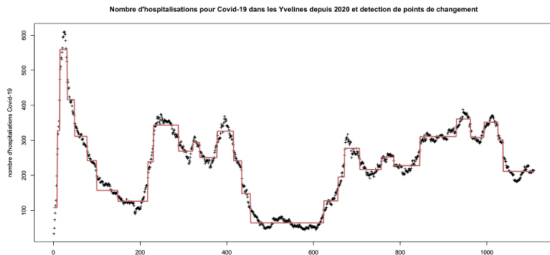


Sample rate : 250 Hz

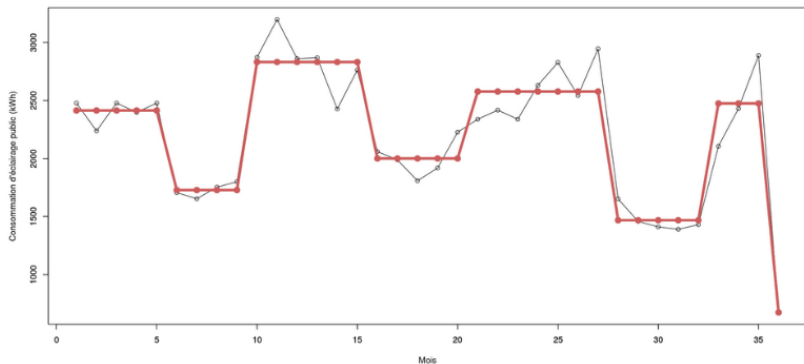
Isotonic regression



Number of Covid-19 hospitalisations



Public lighting energy consumption



We fit a simple Up-Down model.

Discussion

Strengths

1. Generalize the change point detection problem
2. Easy to use R package
3. Flexible
4. Reproducibility : github available
<https://github.com/vrunge/gfpop/tree/master>

Weaknesses

1. Hard to tune hyperparameters and perform model selection
2. Rigid

Table of content

Introduction and contribution

Method

Data and results

References

References

1. Toby Dylan Hocking et al. “Constrained Dynamic Programming and Supervised Penalty Learning Algorithms for Peak Detection in Genomic Data”. In: Journal of Machine Learning Research 21.87 (2020), pp. 1–40. url: <http://jmlr.org/papers/v21/18-843.html>
2. Vincent Runge et al. gfpop: an R Package for Univariate Graph-Constrained Change- Point Detection. 2022.
3. Charles Truong, Laurent Oudre, and Nicolas Vayatis. “A review of change point detection methods”. In: CoRR abs/1801.00718 (2018). url: <http://arxiv.org/abs/1801.00718>.