Labeled Optimal Partitioning

Toby Dylan Hocking toby.hocking@nau.edu joint work with Anuraag Srivastava arXiv:2006.13967

October 15, 2020

Introduction: supervised changepoint detection for cancer diagnosis with DNA copy number data

New Labeled Optimal Partitioning (LOPART) Algorithm

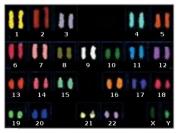
Demonstration of LOPART on example labeled data

Results and Discussion

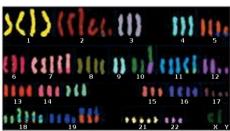
Cancer cells show chromosomal copy number alterations

Spectral karyotypes show the number of copies of the sex chromosomes (X,Y) and autosomes (1-22).

Source: Alberts *et al.* 2002.

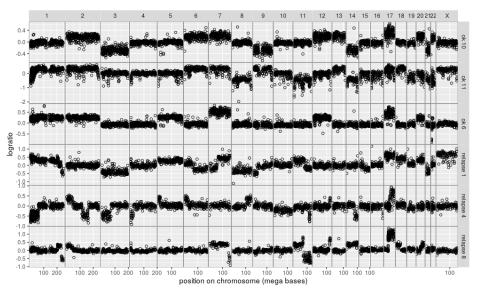


Normal cell with 2 copies of each autosome.

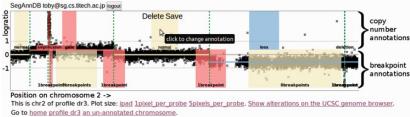


Cancer cell with many copy number alterations.

DNA copy number profiles from neuroblastoma patients with or without relapse



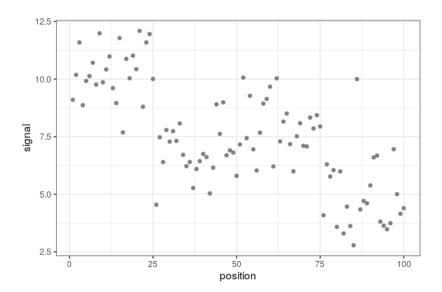
Previous work: SegAnnDB interactive machine learning system



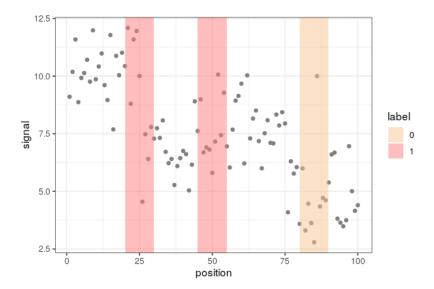
Hocking et al., 2014.

- User uploads noisy data sets for machine learning analysis.
- ▶ User can provide labels which indicate presence(1) or absence(0) of changepoints in specific regions of data sets.
- Classic optimal changepoint model (max penalized Gaussian likelihood) used if it has zero label errors. OPART algorithm, Jackson et al., 2005. FPOP algorithm, Maidstone et al., 2016.
- ► Label-aware SegAnnot algorithm used otherwise (Hocking and Rigaill, 2012). Always zero train label errors, but never predicts any changepoints outside of positive(1) labels.

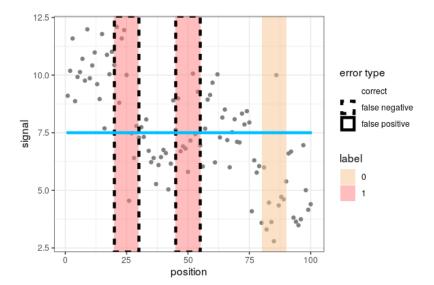
Example noisy data sequence



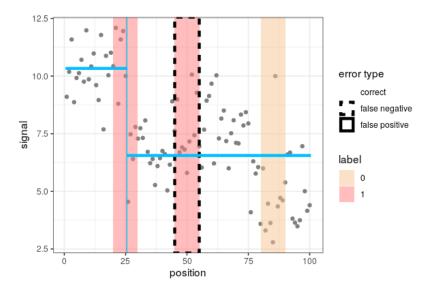
Example noisy data sequence with labels



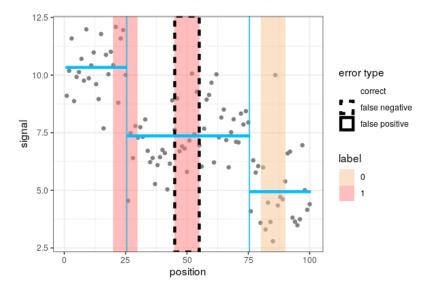
OPART with penalty $\lambda = 1000$ (ignores labels)



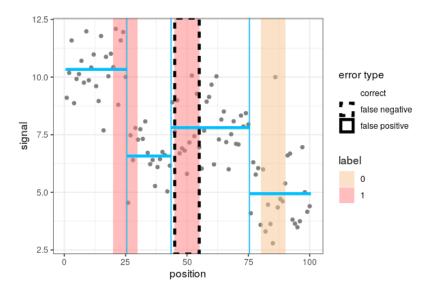
OPART with penalty $\lambda = 100$ (ignores labels)



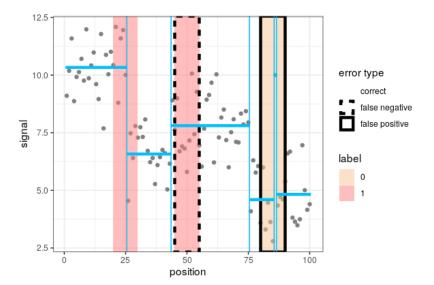
OPART with penalty $\lambda = 20$ (ignores labels)



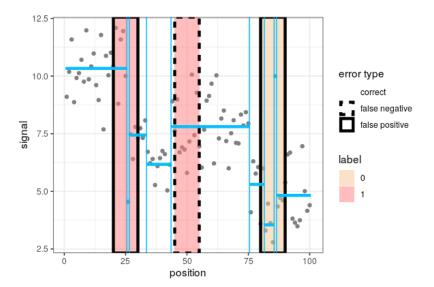
OPART with penalty $\lambda = 15$ (ignores labels)



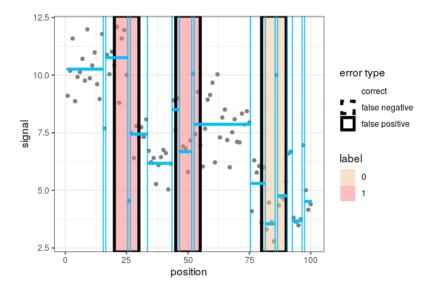
OPART with penalty $\lambda = 10$ (ignores labels)



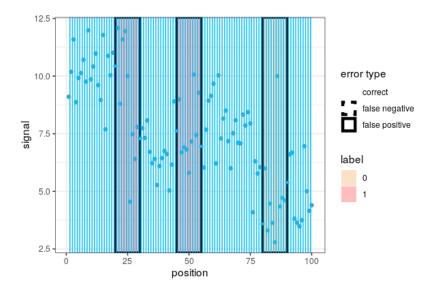
OPART with penalty $\lambda = 5$ (ignores labels)



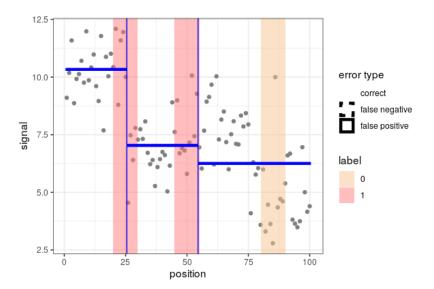
OPART with penalty $\lambda = 4$ (ignores labels)



OPART with penalty $\lambda = 0$ (ignores labels)



SegAnnot (no changes in unlabeled regions)



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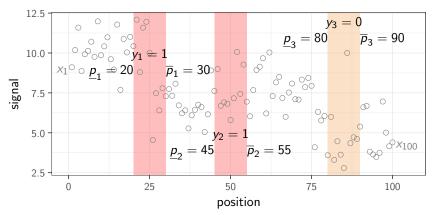
Demonstration of LOPART on example labeled data

Results and Discussion

Geometric interpretation of data and labels

Assume N data and M labels defined by

- $\mathbf{x} = [x_1 \cdots x_N]$ is the sequence of N data,
- ▶ $1 \le \underline{p}_1 < \overline{p}_1 \le \dots \le \underline{p}_M < \overline{p}_M \le N$ are region start/ends,
- ▶ $y_j \in \{0,1\}$ is the number of changes expected in the region.



Baseline/previous OPART algorithm

Assume

- ▶ $\mathbf{x} = [x_1 \cdots x_N]$ is the sequence of N data,
- \blacktriangleright ℓ is a loss function (e.g. square loss),
- I the indicator function counts the number of changes,
- \triangleright λ is a non-negative penalty (larger for fewer changes).

Then the problem and algorithm are

$$C_{N} = \min_{\mathbf{m} \in \mathbb{R}^{N}} \sum_{i=1}^{N} \ell(m_{i}, x_{i}) + \lambda \sum_{i=1}^{N-1} I[m_{i} \neq m_{i+1}].$$

$$= \min_{\tau \in \{0, 1, \dots, N-1\}} C_{\tau} + \lambda + L(\tau + 1, N, \mathbf{x}).$$

where

- ightharpoonup au is the last changepoint optimization variable,
- $ightharpoonup C_{\tau}$ is the optimal cost computed in previous iteration τ ,
- L is the cost of the last segment.



Proposed LOPART optimization problem

Assume M labels are defined by

- ▶ $1 \le \underline{p}_1 < \overline{p}_1 \le \dots \le \underline{p}_M < \overline{p}_M \le N$ are region start/ends,
- ▶ $y_i \in \{0,1\}$ is the number of changes expected in the region.

The problem we want to solve is

$$\begin{split} \min_{\mathbf{m} \in \mathbb{R}^N} & \sum_{i=1}^N \ell(m_i, x_i) + \lambda \sum_{i=1}^{N-1} I[m_i \neq m_{i+1}]. \\ \text{subject to} & \text{for all } j \in \{1, \dots, M\}, \ y_j = \sum_{i=\underline{p}_i}^{\overline{p}_j - 1} I[m_i \neq m_{i+1}]. \end{split}$$

Objective function in black same as previous/unlabeled problem, constraint in red new to proposed/labeled problem.

Proposed LOPART dynamic programming algorithm

Define the set of possible last changepoints at time t as

$$T_t = \begin{cases} T_{t-1} & \text{if } \exists j: y_j = 0 \text{ and } t \in \{\underline{p}_j + 1, \dots, \overline{p}_j\} \\ T_{t-1} & \text{if } \exists j: y_j = 1 \text{ and } t \in \{\underline{p}_j + 1, \dots, \overline{p}_j - 1\} \\ \{\underline{p}_j, \dots, t - 1\} & \text{if } \exists j: y_j = 1 \text{ and } t = \overline{p}_j \\ T_{t-1} \cup \{t - 1\} & \text{otherwise. (unlabeled region)} \end{cases}$$

Update rule in black same as previous/unlabeled problem, rules in red for labeled regions new to proposed problem. Then the optimal cost can be computed via

$$\tau_t^*, \ W_t = \arg\min, \ \min_{\tau \in \textcolor{red}{\textbf{\textit{T}}_t}} W_\tau + \lambda + \textit{L}(\tau+1,t,\textbf{x}).$$

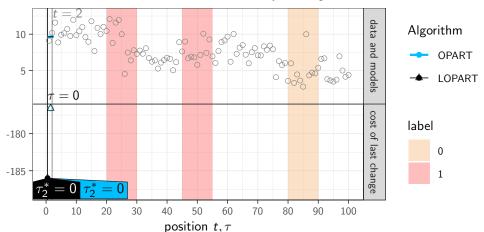
(see paper for proof)

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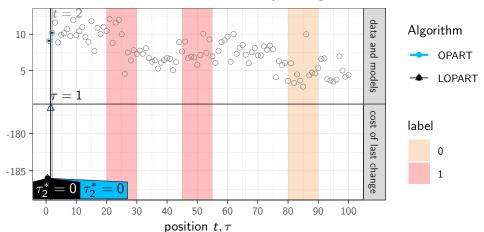
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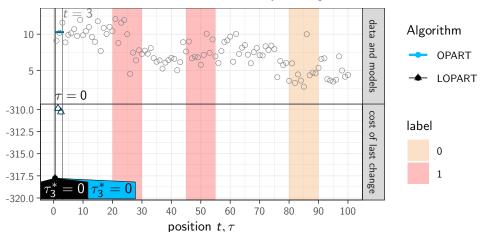
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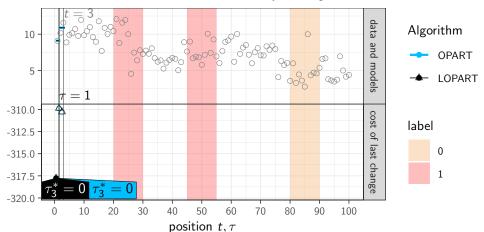
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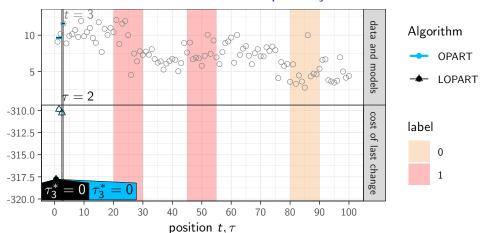
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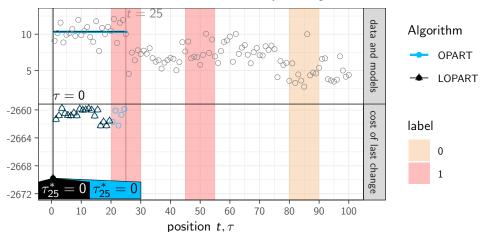
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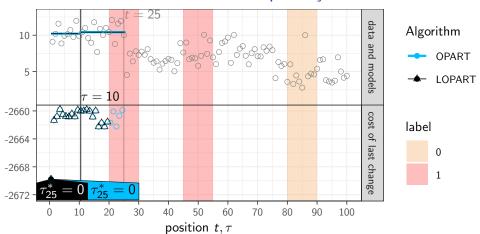
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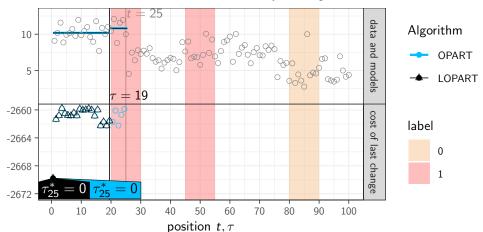
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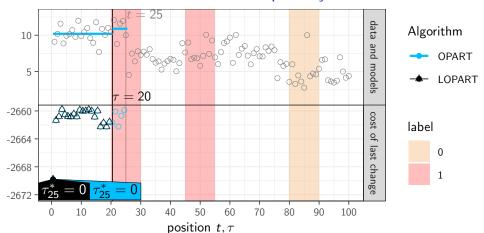
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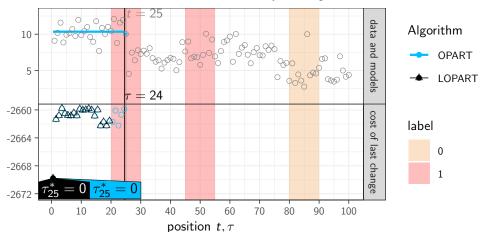
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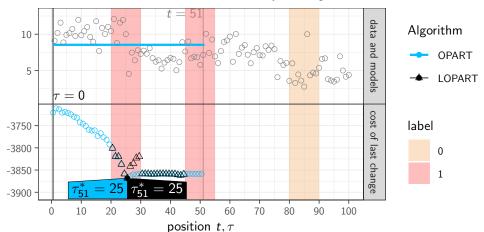
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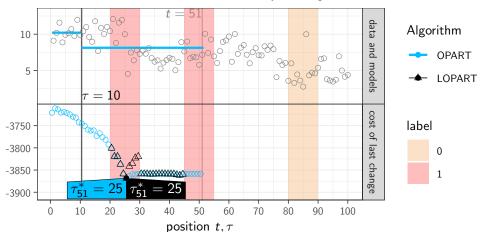
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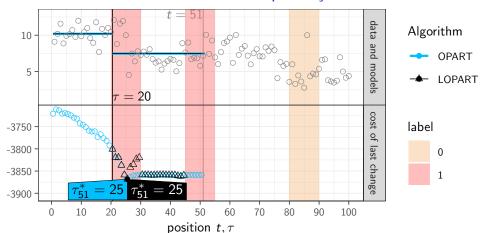
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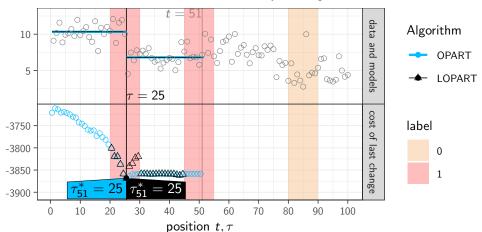
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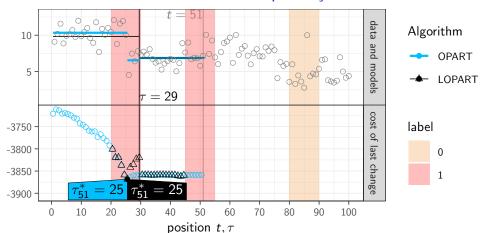
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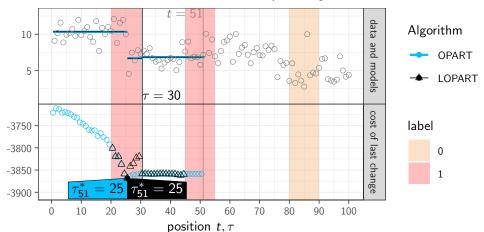
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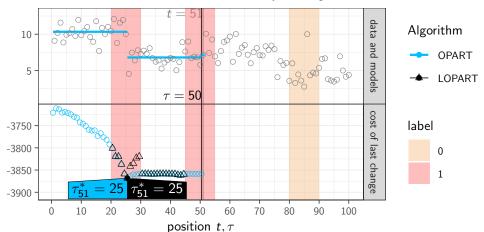
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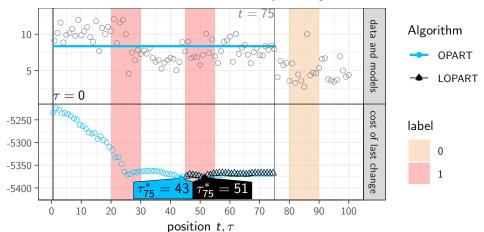
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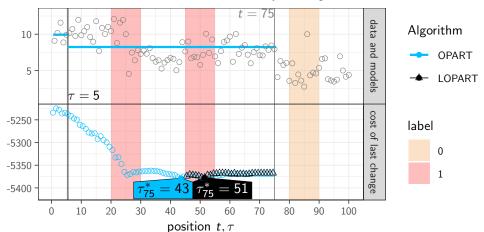
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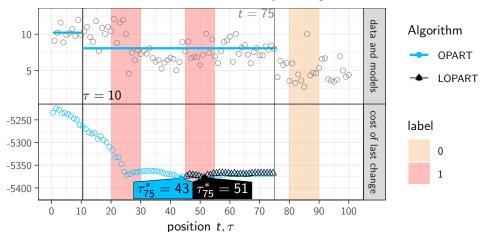
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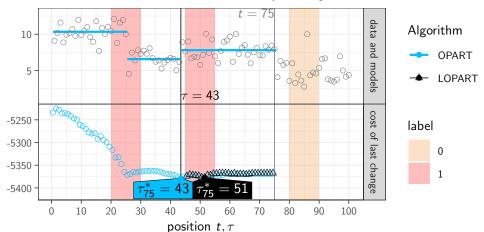
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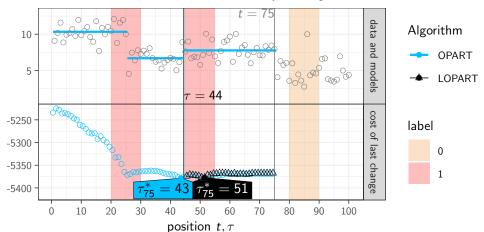
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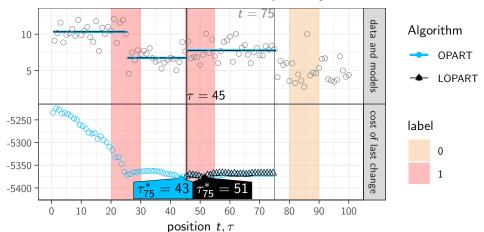
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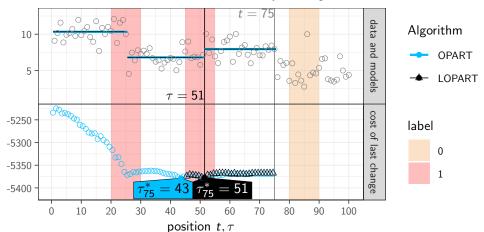
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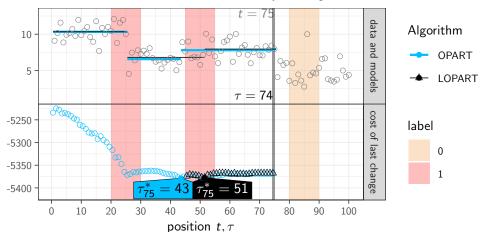
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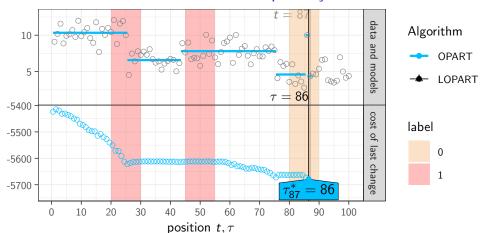
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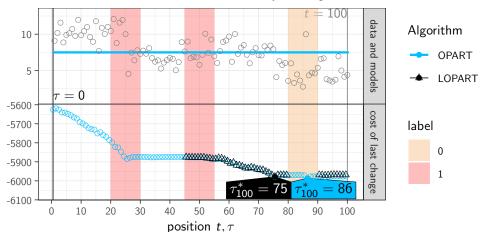
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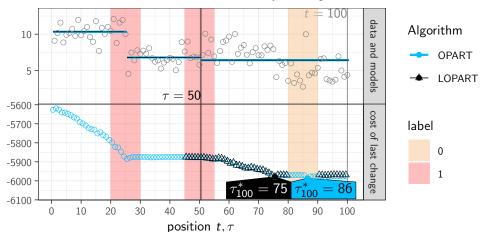
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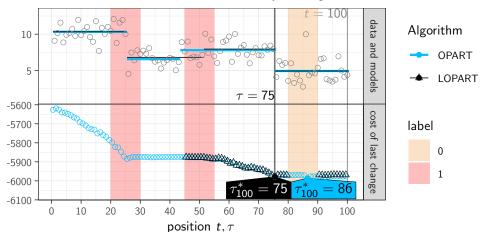
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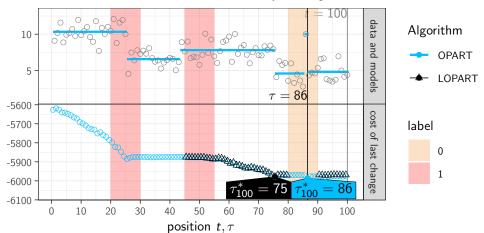
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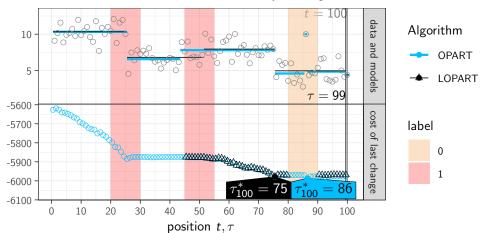
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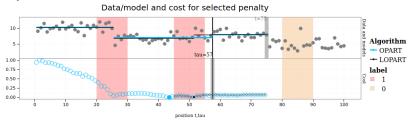
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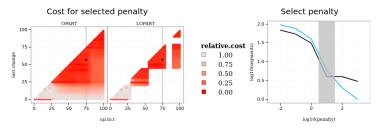


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Interactive version, new algorithm requires less computation

Try this at home:





http://members.cbio.mines-paristech.fr/~thocking/figure-candidates-interactive/

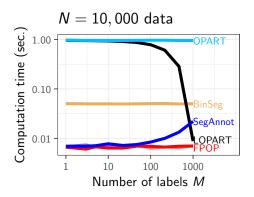
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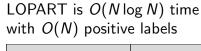
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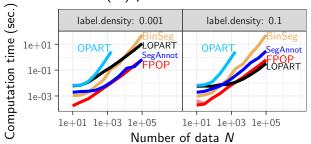
Empirical time complexity (labels)



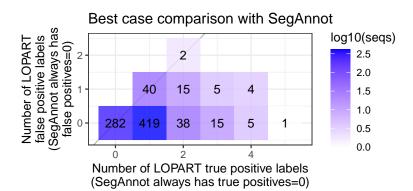
Random normal data simulations.

Empirical time complexity (data)



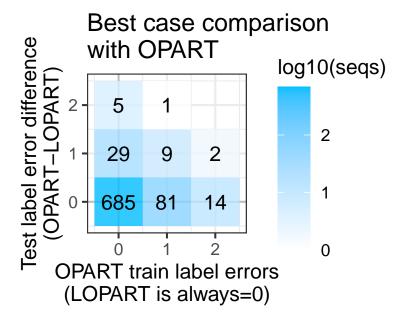


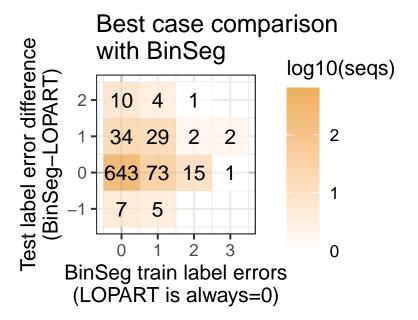
Random normal data simulations.



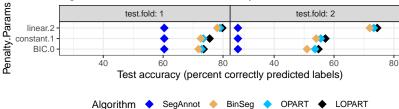
Real genomic data labeled by biologists (Hocking et al., 2014).

- ▶ 413 sequences, K = 2 fold cross-validation over labels.
- ▶ Data per sequence N = 39 to 43628.
- ▶ Labels per sequence M = 2 to 12.





Test accuracy in cross-validation experiments

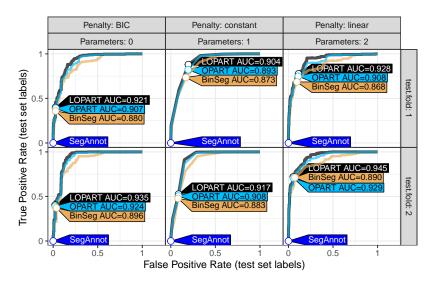


Penalty λ predicted on test set using either unsupervised or supervised (constant/linear) methods:

- linear.2 linear $\log \lambda_i = b + w \log \log N_i$ (Hocking 2013), convex optimization of w, b (supervised; 2 learned parameters).
- constant.1 grid search, constant λ (supervised, 1 learned parameter).
 - BIC.0 classical Bayesian Information Criterion (Schwarz 1978), $\lambda_i = \log N_i$ (unsupervised, 0 learned parameters).



Test ROC curves in cross-validation experiments



Dot = FPR/TPR at predicted threshold.

Summary and Discussion

- Proposed algo fixes issues with two previous algorithms (better train AND test accuracy).
- Results demonstrate improved speed and accuracy.
- R package on CRAN and https://github.com/tdhock/LOPART
- Figure/slide code on https://github.com/tdhock/LOPART-paper
- Future work: functional pruning algorithm, which can solve more complex constrained changepoint problems (e.g. change must be non-decreasing), and should be faster (log-linear instead of quadratic).