

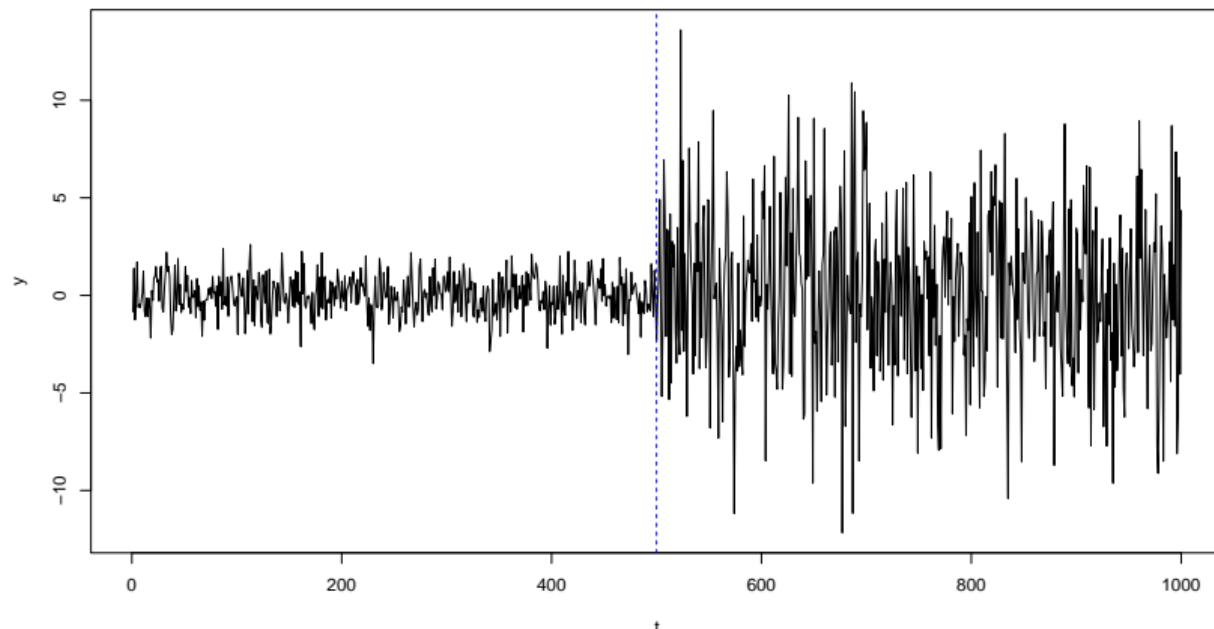
# NP-FOCuS: Online Nonparametric Changepoint Detection via Functional Pruning LR tests

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# The Setting

## Offline Changepoint Detection





# Online changepoint detection

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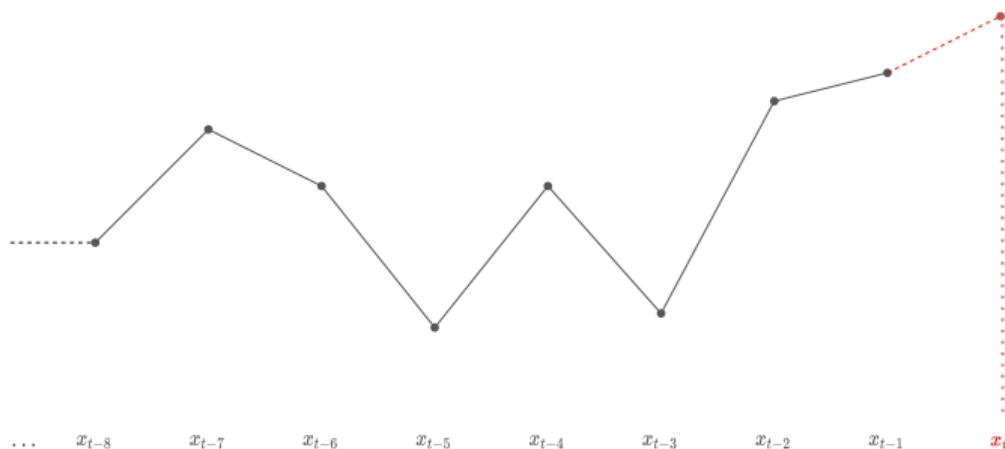
# One change...

Online changepoint detection

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# The Setting

## Online changepoint detection



At each iteration, we have to decide whether we are observing a change or not.



# The Setting

## Comparison to the offline setting

Compared to the offline setting we have additional requirements:

- The method needs to be sequential;
- The methodology needs to process observations at a faster rate than the sampling rate.



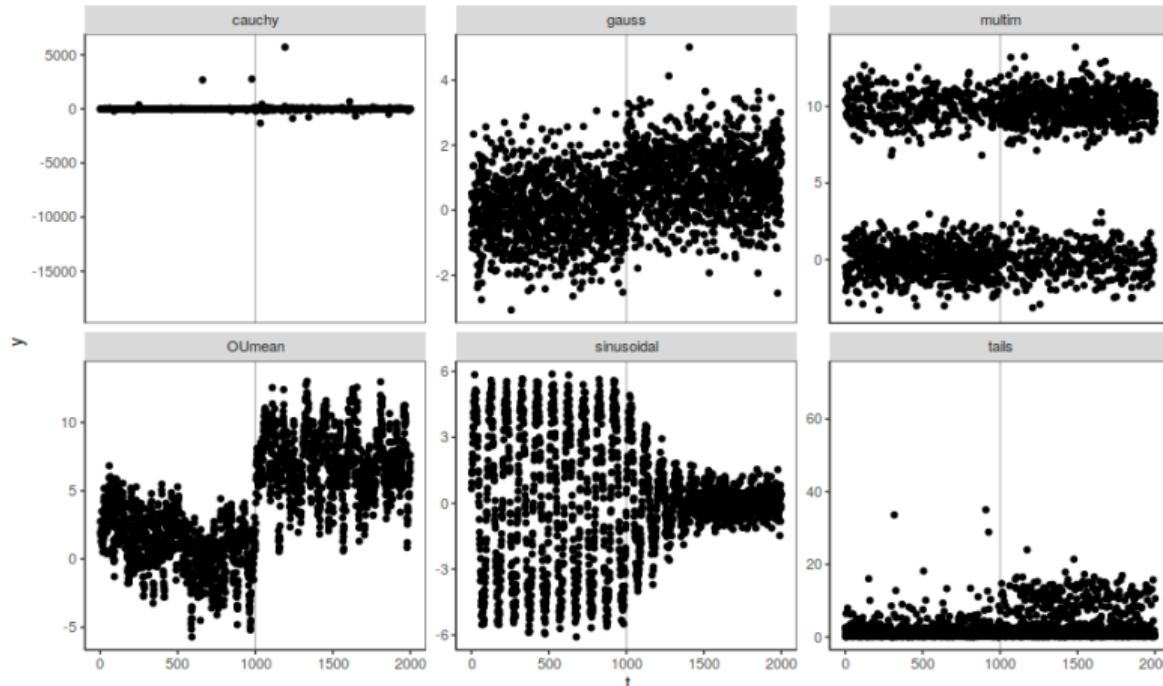
# Delayed Evaluation

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What happens if our method is too slow?

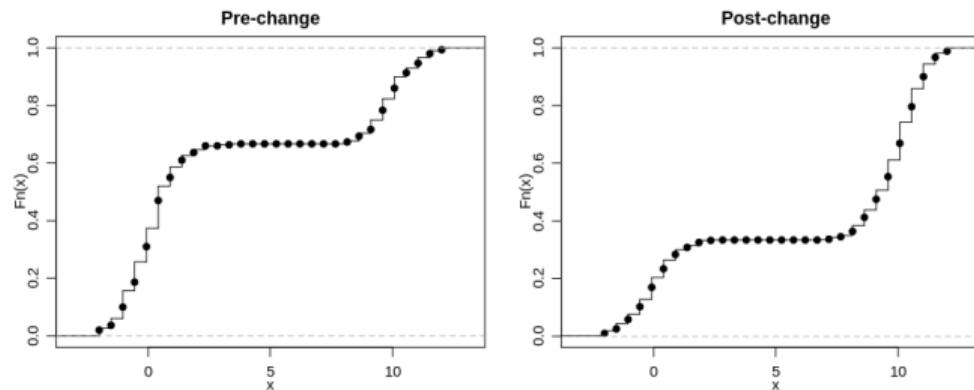


# Different Scenarios



# Non-Parametric Approach I

Empirical Cumulative Distribution Function (eCDF).



**Figure:** Pre and post change eCDF of the multimodal example

## Non-Parametric Approach II

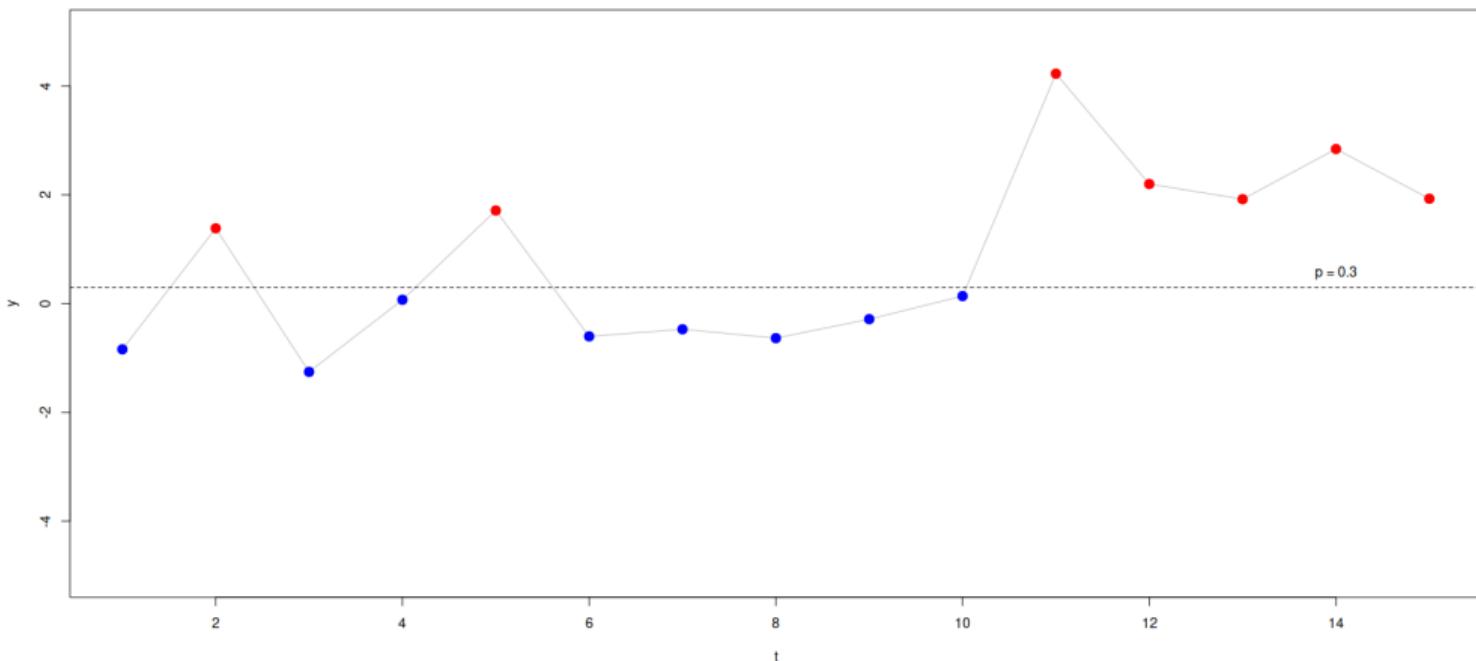
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Let  $\theta = F_{1:n}(p)$  be the unknown CDF for  $y_1, \dots, y_n$ , and let  $\hat{F}_{1:n}(p)$  be its relative eCDF:

$$\hat{\theta} = \hat{F}_{1:n}(p) = \frac{1}{n} \sum_{t=1}^n [\mathbb{I}(y_t < p)],$$

for a fixed value of  $p \in \mathbb{R}$ , a quantile of our full eCDF.

# Non-Parametric Approach III



# The Cost Function

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For a given  $p$  the eCDF follows:

$$n\hat{F}_{1:n}(p) \sim \text{Binom}(n, \theta).$$

The contribution of one point  $x_t = \mathbb{I}(y_t < p)$  will be given by:

$$h(x_t, \theta) = x_t \log \theta + (1 - x_t) \log(1 - \theta).$$

# A Likelihood Ratio test I

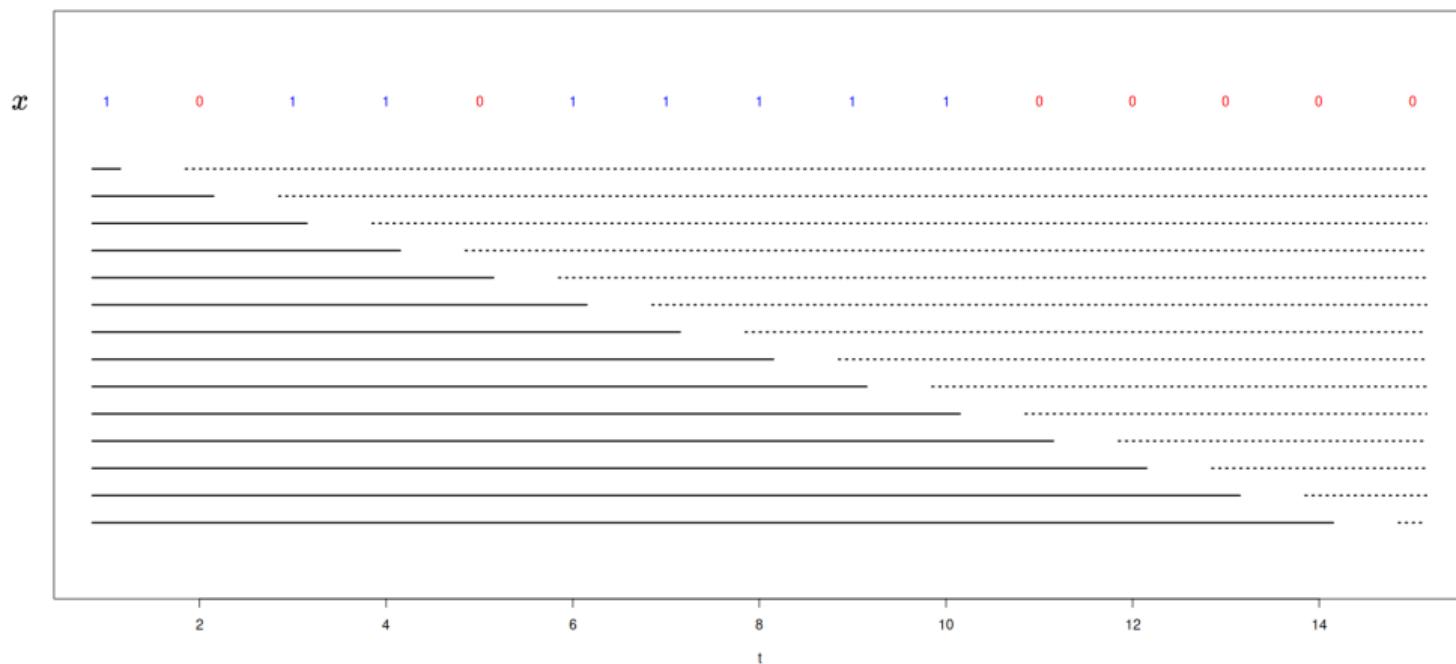
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For a change in one component of our eCDF, we can build a likelihood ratio test of the form:

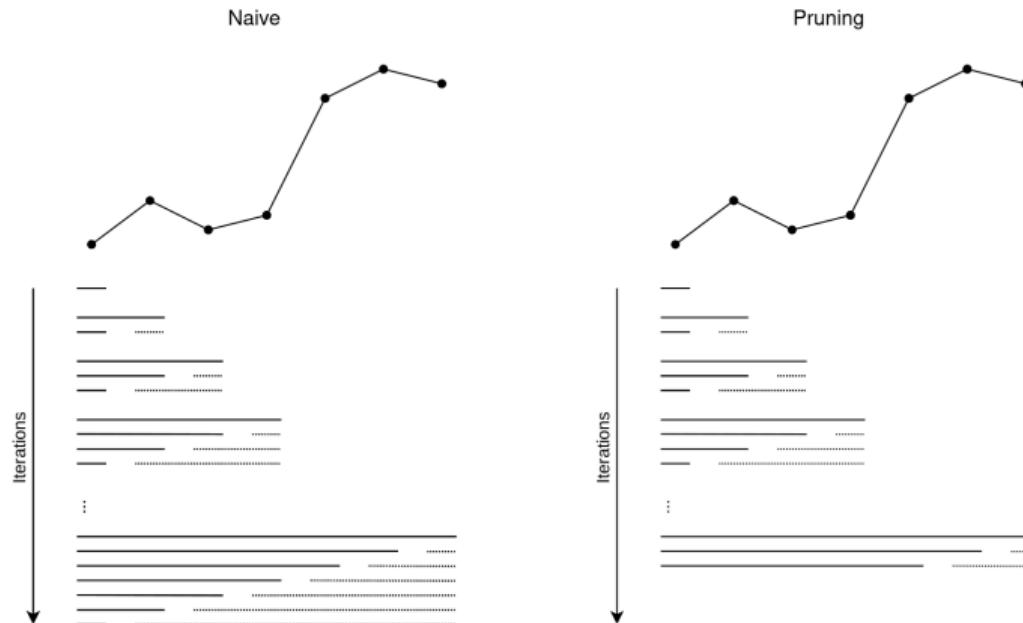
$$Q_n = - \max_{\theta \in \mathbb{R}} \sum_{t=1}^n h(x_t, \theta) + \max_{\substack{\tau \in \{1, \dots, n-1\} \\ \theta_0, \theta_1 \in \mathbb{R}}} \left\{ \sum_{t=1}^{\tau} h(x_t, \theta_0) + \sum_{t=\tau+1}^n h(x_t, \theta_1) \right\}, \quad (1)$$



# A Likelihood Ratio test II



# Computational Complexity



# NP-FOCuS

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Recall that:

$$h(x_t, \theta) = x_t \log \theta + (1 - x_t) \log(1 - \theta).$$

We can then solve our LR test via the recursion:

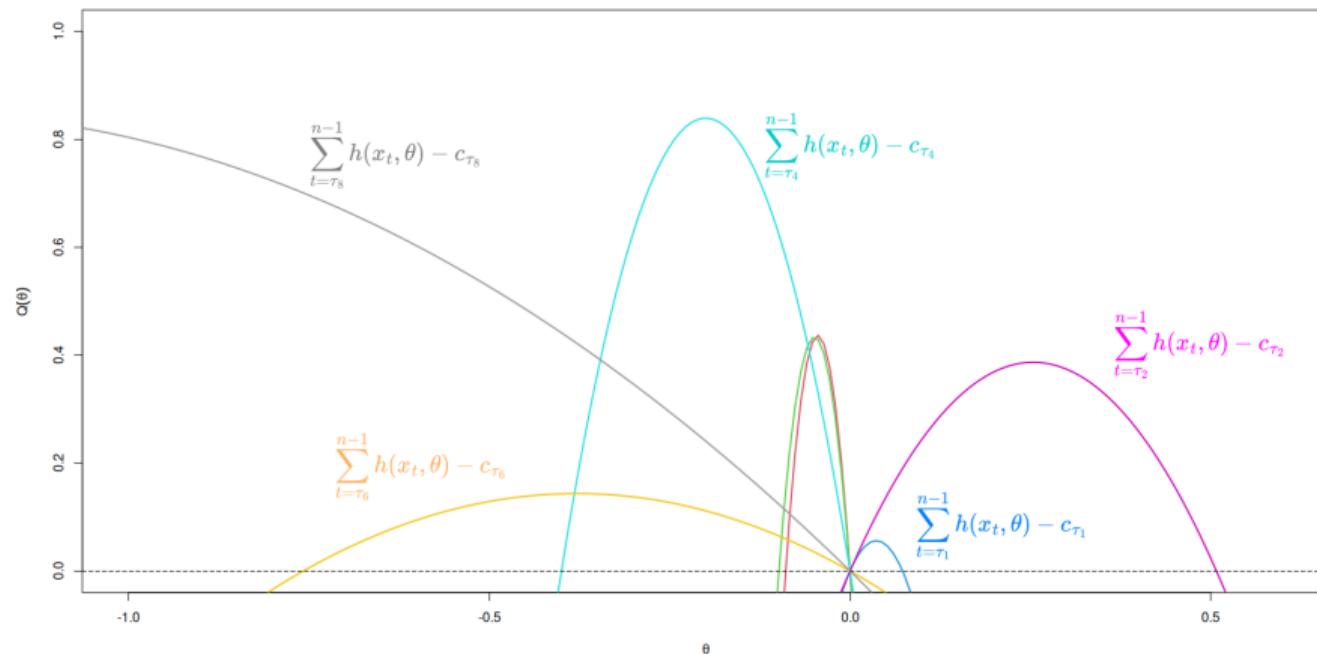
$$Q_0(\theta) = 0$$

and for  $n = 1, 2, 3, \dots$

$$Q_n(\theta) = \max \{0, Q_{n-1}(\theta)\} + h(x_n, \theta) - \max_{\theta} \sum_{t=1}^n h(x_t, \theta).$$

# The recursion

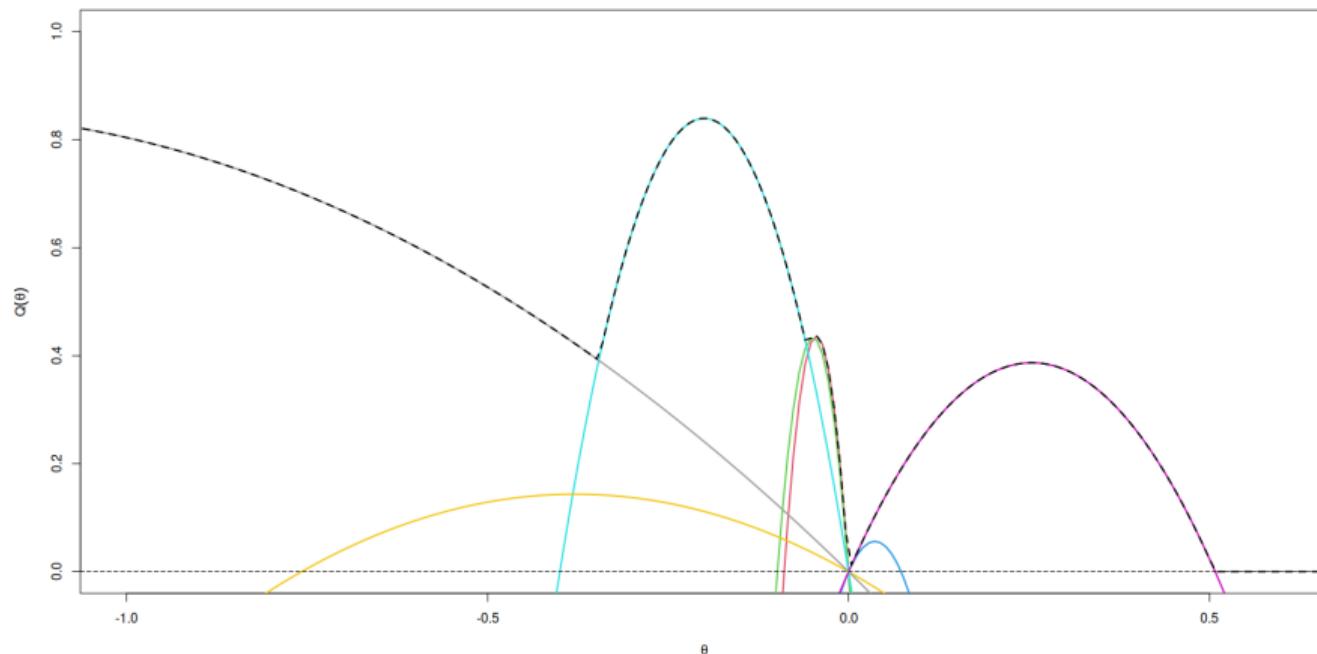
Starting condition: our  $Q_{t-1}(\theta)$





# The recursion

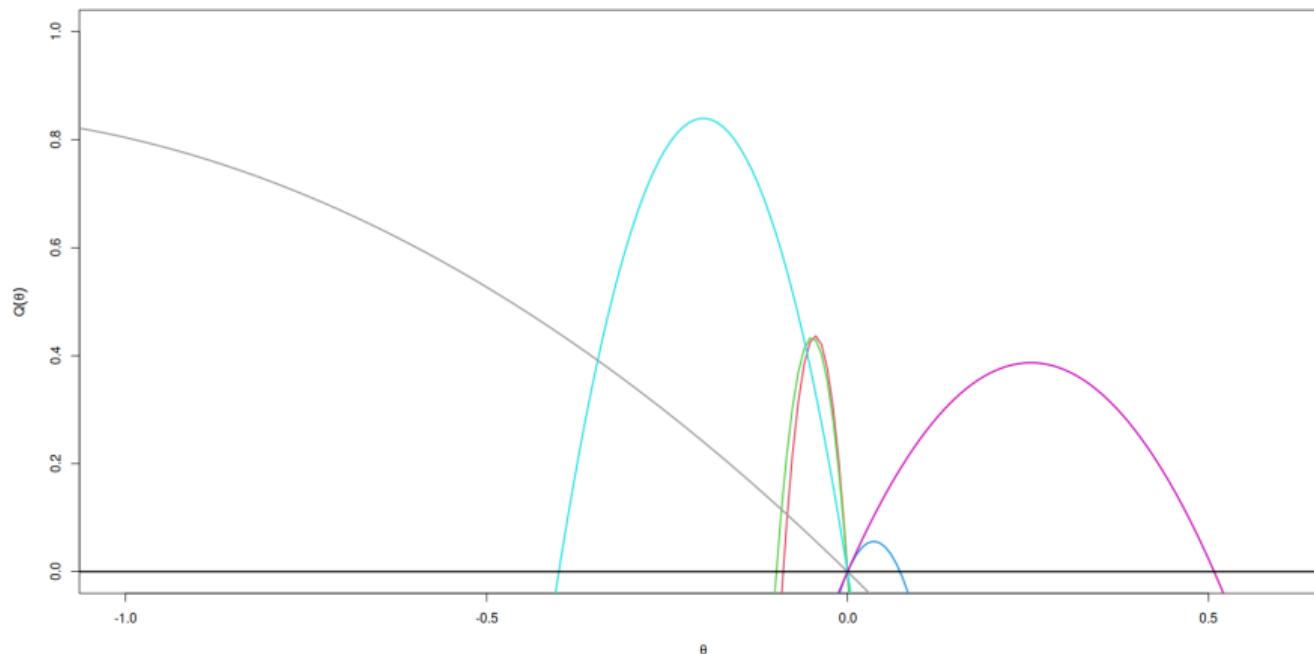
$$\max \{0, Q_{n-1}(\theta)\} + h(x_n, \theta).$$





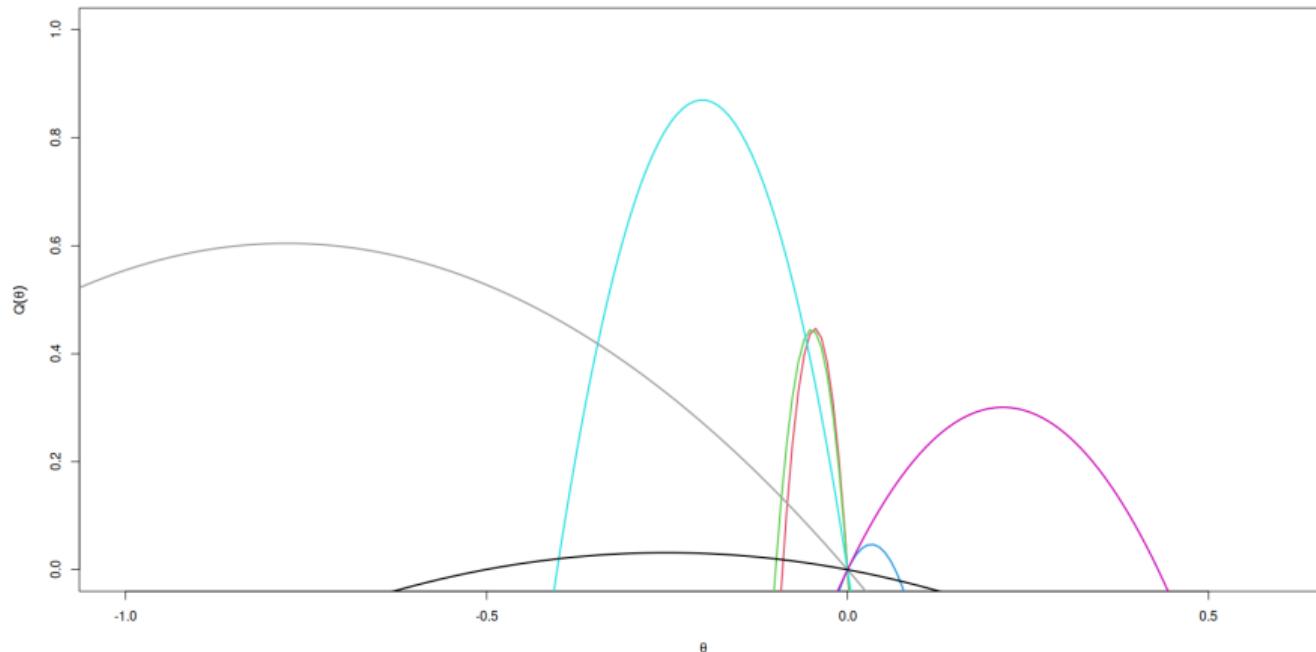
# The recursion

$$\max \{0, Q_{n-1}(\theta)\} + h(x_n, \theta).$$



# The recursion

$$Q_n(\theta) = \max \{0, Q_{n-1}(\theta)\} + h(x_n, \theta).$$



# Aggregate the quantile traces

## NP-FOCuS

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At each time we have  $m$  piecewise costs,  $Q_n^1(\theta), \dots, Q_n^M(\theta)$ , one for each  $p_1, \dots, p_m$ .  
 By computing the global maximum for each cost:

$$\mathcal{Q}_n^m = \max_{\theta} Q_n^m(\theta).$$

Then, we will detect a changepoint at time  $n$  whether:

$$\sum_{m=1}^M \mathcal{Q}_n^m \geq \xi^{sum} \text{ or } \max_{m \in \{1, \dots, M\}} \mathcal{Q}_n^m \geq \xi^{max},$$

with  $\xi^{sum}, \xi^{max} \in \mathbb{R}$ .

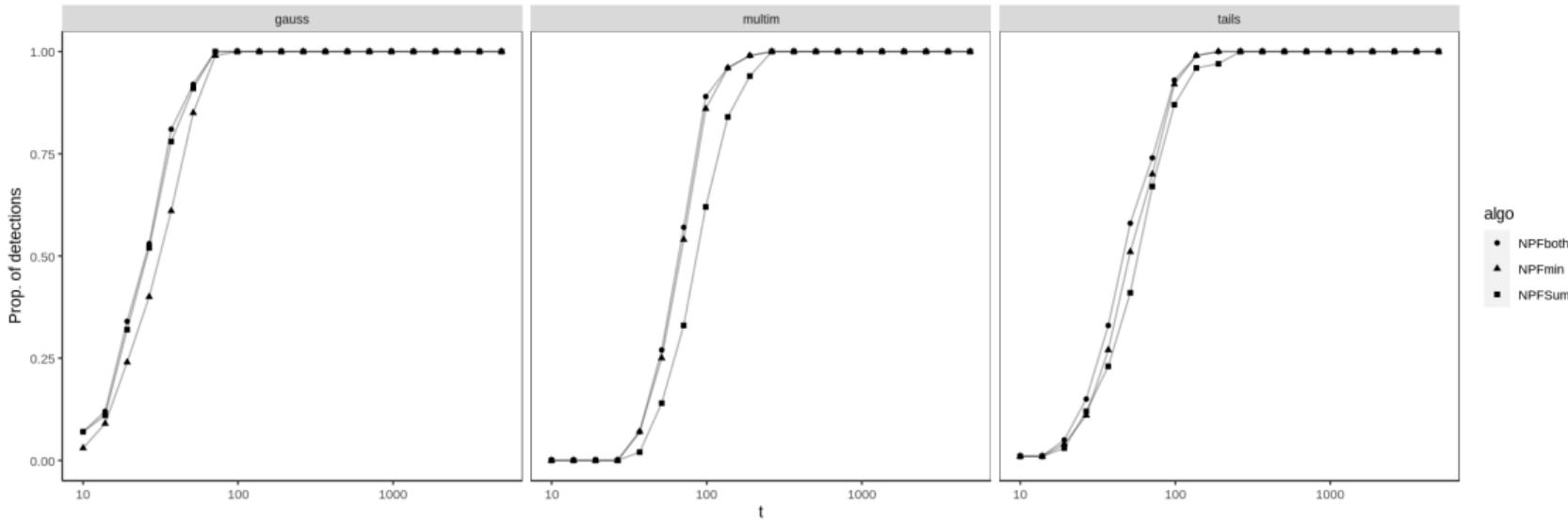


# NP-FOCuS

## Some remarks

- The LR test is solved exactly
- We avoid additional grid parameters
- Low computational complexity,  $M \times \mathcal{O}(\log(n))$  per iteration
- Taking max and sum for sparse and dense changes in the eCDF.

# Empirical results





Thank you for your attention

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