# ALGORITHMS FOR DETECTING CHANGEPOINTS IN DATA

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test statistic = 
$$\frac{\sum_{t=1}^{h} e_t}{\sum_{t=1}^{h} e_t}$$

$$ext{test statistic} = rac{\sum_{t=1}^{h} e_t^ op}{} e_t$$

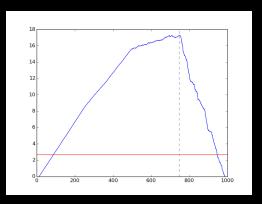
test statistic = 
$$\frac{\sum_{t=1}^{h} e_t^\top (\hat{\Sigma})^{-1} e_t}{h}$$
$$\hat{\Sigma} := \frac{1}{n-1} \sum_{t=1}^{n} e_t e_t^\top$$

### BUILDING THE TEST STATISTIC

$$\text{test statistic} = \frac{\sum_{t=1}^{h} \boldsymbol{e}_t^\top(\hat{\Sigma})^{-1} \boldsymbol{e}_t}{h} - \frac{\sum_{t=1}^{n} \boldsymbol{e}_t^\top(\hat{\Sigma})^{-1} \boldsymbol{e}_t}{n}$$

test statistic = 
$$\frac{h}{\sqrt{2kn}} \left( \frac{\sum_{t=1}^{h} e_t^{\top} (\hat{\Sigma})^{-1} e_t}{h} - \frac{\sum_{t=1}^{n} e_t^{\top} (\hat{\Sigma})^{-1} e_t}{n} \right)$$

### FINDING A SINGLE CHANGEPOINT



Cusum statistic for a time series with three changepoints.

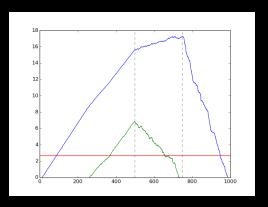
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 $\max(\text{test statistic}) \xrightarrow{D} \sup \{\text{Brownian bridge}\},\$ 

which is a known distribution, so we can compute critical values.

### FINDING MORE CHANGEPOINTS



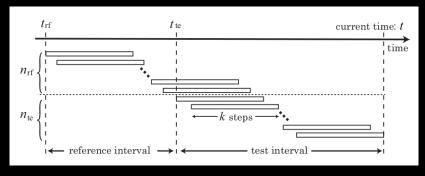
Cusum statistic for a time series with three changepoints.

## Moving from datapoints to subsequences

Suppose time series  $y(t) \in \mathbb{R}^3$  and denote its *i*th component by  $y_i(t) \in \mathbb{R}$ . Define the subsequence

$$\mathbf{Y}(t) = \begin{pmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \\ y_1(t+1) \\ y_2(t+1) \\ y_3(t+1) \\ \vdots \\ y_1(t+m-1) \\ y_2(t+m-1) \\ y_3(t+m-1) \end{pmatrix}$$

# Moving from datapoints to subsequences



Sliding window of subsequences. (Reference interval has pdf  $p_{\rm rf}$  and test interval has pdf  $p_{\rm te}$ .)

### Hypothesis test

$$H_0 \colon p(\boldsymbol{Y}(i)) = p_{\mathrm{rf}}(Y(i)) \qquad \text{for } i = t_{\mathrm{rf}}, \dots, t-1$$

$$\text{vs} \quad H_1 \colon p(\boldsymbol{Y}(i)) = p_{\mathrm{rf}}(Y(i)) \qquad \text{for } i = t_{\mathrm{rf}}, \dots, t_{\mathrm{te}} - 1$$

$$p(\boldsymbol{Y}(i)) = p_{\mathrm{te}}(Y(i)) \qquad \text{for } i = t_{\mathrm{te}}, \dots, t-1.$$

### Hypothesis test

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$$p(\boldsymbol{Y}(i)) = p_{\mathrm{te}}(Y(i)) \qquad \text{for } i = t_{\mathrm{te}}, \dots, t-1.$$

likelihood ratio = 
$$\prod_{i=1}^{n_{\text{te}}} \frac{p_{\text{te}}(\boldsymbol{Y}_{\text{te}}(i))}{p_{\text{rf}}(\boldsymbol{Y}_{\text{te}}(i))}$$

# DIRECTLY ESTIMATING THE DENSITY RATIO

$$w(\boldsymbol{Y}) = \frac{p_{\text{te}}(\boldsymbol{Y})}{p_{\text{rf}}(\boldsymbol{Y})}$$

### DIRECTLY ESTIMATING THE DENSITY RATIO

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Gaussian kernel 
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$$\hat{p}_{\mathrm{te}}(\cdot) := p_{\mathrm{rf}}(\cdot)\hat{w}(\cdot) = p_{\mathrm{rf}}(\cdot)\sum_{\ell=1}^{\kappa_{\mathrm{te}}} \alpha_{\ell}K_{\sigma}(\cdot, \boldsymbol{Y}_{\mathrm{te}}(\ell))$$

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 $\min_{\{\alpha_{\ell}\}} \quad \text{Kullback-Leibler divergence}(p_{\text{te}}||\hat{p}_{\text{te}})$  subject to some uninteresting constraints

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