False Alarm Control for Window-Limited Change Detection

Julia Kuhn^{•,*}, Michel Mandjes^{*}, Thomas Taimre[•]

• The University of Queensland, * University of Amsterdam

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Change in mean



Change in variance



Why is that interesting?





Change Detection Procedures

Unconditional Local False Alarm Probability

Maximum Local False Alarm Probability

Window Limited False Alarm Probability

We need to decide whether a change has occurred or not:

 H_0 : No change has occurred.

 H_1 : There is a change point k with $1 \le k \le m$.

How do we do that?



Test statistic:
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 (CUSUM)

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Performance criterion: Average run length: $\mathbb{E}_0 \tau$

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Stopping rule:	$\tau = \inf\{m : \max_k LLR_{k,m}\}$, > b}
Performance criterion:	Average run length: $\mathbb{E}_0 \tau$	
Threshold:	Asymptotics (for i.i.d.), recursive integral equations, numerical methods	

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Minimises detection delay among all procedures that satisfy

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- $\mathbb{E}_0 \tau \ge \kappa$ as $\kappa \to \infty$ (asymptotic optimality)



Procedure



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WL FA probability:

 $\mathbb{P}_0(\tau_{WL} \leq N)$

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Asymptotics

$$\mathsf{ULFA}_n := \sup_{m \ge 0} \mathbb{P}_0(m \le \tau \le m + n)$$

 CUSUM is asymptotically optimal for small *α* among procedures that satisfy ULFA_n ≤ *α* (Lai, 1998).

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• **But:** For large thresholds (small α) this is decreasing in *m* (Tartakovsky, 2005).

WL FA probability:

Local FA probability:

Unconditional local FA prob.:

 $\mathbb{P}_0(\tau_{WL} \leq N)$

 $\sup_{m>0} \mathbb{P}_0(\tau \leq m+n \,|\, \tau \geq m)$

 $\sup_{m\geq 0}\mathbb{P}_0(m\leq au\leq m+n)$

$$\begin{aligned} \mathsf{MLFA}_n &:= \sup_{m \geq 0} \ \mathbb{P}_0 \left(\tau \leq m + n \, | \, \tau > m \right) \\ &= \sup_{m \geq 0} \ \frac{\mathbb{P}_0(m < \tau \leq m + n)}{\mathbb{P}_0(\tau > m)} \end{aligned}$$

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Again, CUSUM turns out to be optimal for large *b* among all procedures that satisfy MLFA_n $\leq \alpha$ (Tartakovsky, 2005).

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WL FA probability:

Local FA probability:

 $\mathbb{P}_0(\tau_{WL} \leq N)$

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Unconditional local FA prob.:

 $\sup_{m\geq 0}\mathbb{P}_0(m\leq au\leq m+n)$

Asymptotic optimality?

If $\mathbb{P}_0(\tau_{WL} \leq N) \leq \alpha$, then:

- (i) The ARL condition $\mathbb{E}_0 \tau \ge \kappa$ is satisfied for $\kappa = (n+1)(1-\alpha)$.
- (ii) The ARL condition $\mathbb{E}_0 \tau_{WL} \ge \kappa_{WL}$ is satisfied for $\kappa_{WL} = \max\{N(1 \alpha), \kappa\}.$

How we may want to think about it

Define

$$S_{k:n}(m) := \sum_{i=k+m}^{n+m} \ell(X_i).$$

Then

$$\mathbb{P}_0\left(au_{WL} \leq N
ight) = \mathbb{P}_0\left(oldsymbol{M}_N > b
ight),$$

where

$$\boldsymbol{M}_{N} := \begin{pmatrix} \max \left\{ S_{1:n}(0), \dots, S_{1:n}(N) \right\} \\ \vdots \\ \max \left\{ S_{n:n}(0), \dots, S_{n:n}(N) \right\} \end{pmatrix}$$

.

Get a grip on **M**_n

For many popular CP test statistics we can write

 $\mathbf{Y}_m = C \mathbf{Y}_{m-1} + \vartheta \mathbf{1} \ell(X_{m+n}),$

where $\mathbf{Y}_m := (S_{1:n}(m), \dots, S_{n:n}(m))'$.

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Example: CUSUM

$$S_{k:n}(m) = S_{k:n}(m-1) - \ell(X_{k+m-1}) + \ell(X_{n+m})$$



"now"

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Example: CUSUM

$$\boldsymbol{Y}_{m} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix} \boldsymbol{Y}_{m-1} + \mathbf{1}\ell(X_{m+n})$$

Other examples:

Moving average, EWMA, non-parametric CUSUM

Ugly integral equation

Let, for fixed $\boldsymbol{x} \in \mathbb{R}^n$,

$$Q_m(\boldsymbol{x}) := \mathbb{P}\left(\boldsymbol{M}_m \leq \boldsymbol{x}\right)$$

for $m \ge 0$.

Proposition We have $Q_m(\mathbf{x}) = \mathcal{K} Q_{m-1}(\mathbf{x})$ for $m \ge 0$, where $\mathcal{K} h(\mathbf{x}) = \int_{\mathbb{R}} F\left(\frac{1}{\vartheta} \min_{i=1,...,n} \left\{ (\mathbf{x} - \Psi(\mathbf{z}))_i \right\} \right) dh(\mathbf{z}).$

Numerical solution: Withers and Nadarajah (2014)

Extreme value distribution

Theorem (Amram, 1985)

For standard stationary Gaussian random vectors \mathbf{Y}_m that are "not too dependent", and large *m*:

$$\mathbb{P}(\boldsymbol{M}_{m,i} \leq \boldsymbol{a}_m \, \boldsymbol{x}_i + \boldsymbol{c}_m, \, i = 1, \dots, n) \approx \prod_{i=1}^n \exp\left(-\exp(-\boldsymbol{x}_i)\right),$$

(we know what a_m and c_m are).

Set the threshold to be the constant

$$b_N := -a_N \log\left(-\frac{1}{n}\log(1-\alpha)\right) + c_N,$$

for fixed N and n.

Example

Dashed lines: $\alpha \in \{0.05, 0.1, 0.2\}$



Gaussian approximation

$$\mathbb{P}_{0}\left(\max_{1\leq k\leq n} \mathsf{LLR}_{k,n} > b\right) \approx \mathbb{P}_{0}\left(\max_{t\in[0,n]}\sigma B_{t} + \mu t \geq b\right)$$
$$= 1 - \Phi\left(\frac{b-\mu n}{\sigma\sqrt{n}}\right) + e^{\frac{2b\mu}{\sigma^{2}}}\Phi\left(\frac{-b-\mu n}{\sigma\sqrt{n}}\right)$$

Example: State space model



$$X_{t+1} = AX_t + Y_t + M \mathbb{1}_{\{t \ge k\}}$$



$$V_t = BX_t + Z_t + N \mathbb{1}_{\{t > k\}}$$

Large deviation approximation

The Gärtner Ellis theorem suggests to pick the threshold **function** *b* such that it satisfies

$$\alpha = \exp\left(-n\mathcal{I}(\boldsymbol{b}(\beta))\right)$$

for all $0 \le \beta \le 1$ such that $n\beta + 1$ integer, where we can compute

$$\mathcal{I}(b(\beta)) = \sup_{\lambda} \left\{ \lambda b(\beta) + (1-\beta) \frac{\lambda}{2} (1-\lambda) \rho' \Omega^{-1} \rho \right\} \,.$$

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=> Simple closed form expression for $b(\beta)$.

Example: State space model

$$X_{t+1} = \begin{pmatrix} 0.5 & \mathbf{a} \\ \mathbf{a} & 0.5 \end{pmatrix} X_t + Y_t + \begin{pmatrix} 0 \\ 0 \end{pmatrix} \mathbb{1}_{\{t \ge k\}}$$
$$V_t = BX_t + Z_t + \begin{pmatrix} 2 \\ 2 \end{pmatrix} \mathbb{1}_{\{t \ge k\}}$$



Example: ARMA model

AR:
$$X_t = \varphi X_{t-1} + \varepsilon_t$$

MA: $X_t = \vartheta \varepsilon_{t-1} + \varepsilon_t$





Some References

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