

# Sequential testing and high-dimensional online change point detection

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- Change point detection

$$X_1, \dots, X_{z-1} \stackrel{\text{iid}}{\sim} N_p(0, \sigma^2 I_p), X_z, X_{z+1}, \dots \stackrel{\text{iid}}{\sim} N_p(\theta, \sigma^2 I_p)$$

- (One-sided) sequential testing  $X_1, X_2, \dots \stackrel{\text{iid}}{\sim} N_p(\theta, \sigma^2 I_p)$

$$H_0 : \theta = 0 \quad \text{vs.} \quad H_1 : \theta \neq 0$$

One-sided: never accepts  $H_0$

- Assume  $\sigma^2$  known,  $z, \theta$  unknown
- Minimal signal strength and sparsity assumption on  $\theta$

# Change point detection: offline vs. online

- **Offline:** fixed sample size  $n$ , one or multiple mean shifts occur within  $X_1, \dots, X_n$
- CUSUM statistics (e.g. Wang and Samworth, 2018)

# Change point detection: offline vs. online

- **Offline:** fixed sample size  $n$ , one or multiple mean shifts occur within  $X_1, \dots, X_n$
- CUSUM statistics (e.g. Wang and Samworth, 2018)
- **Sequential:** Observations  $X_1, X_2, \dots$  come in one at a time
- Declare change as quickly as possible after it takes place
- **Online:** In addition, computational complexity at each step does NOT depend on the current sample size

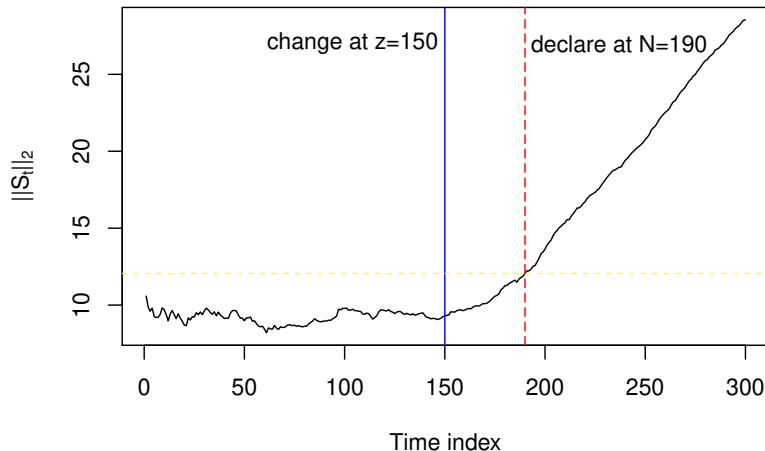
- Stopping time  $N$ , possibly  $\infty$
- ‘Patience’ of the procedure: measured by the average run length till a false alarm under the null  $E_0(N)$
- ‘Alertness’ of the procedure: measured by the average run length from change to reaction if a change is present, given the most adversarial null sequence before the change

$$\bar{E}_\theta(N) = \sup_{z \in \mathbb{N}} \text{ess sup } E_{z, \theta}[N - z + 1 | X_1, \dots, X_{z-1}]$$

- Goal:

$$\min_{N: E_0(N) \geq \gamma} \bar{E}_\theta(N)$$

# Quantities of interest



# Online change point detection vs. sequential testing

- Lorden (1971) suggested that we can always build a **sequential** change point detection procedure with theoretical guarantees from an appropriate one-sided sequential testing procedure;
- It is NOT clear that in general this approach will give us **online** procedures (computational complexity consideration);
- In univariate exponential family case, we can construct an **online** change point detection algorithm according to Page (1954) and Lorden (1971) for composite alternative.

# One-sided sequential testing

(One-sided) sequential testing  $X_1, X_2, \dots \stackrel{\text{iid}}{\sim} N_p(\theta, \sigma^2 I_p)$   
 $H_0 : \theta = 0$  vs.  $H_1 : \theta \neq 0$  (never accepts  $H_0$ )

Assume  $\sigma^2 = 1$ . Denote  $S_t := X_1 + \dots + X_t$ . Let

$$N := \inf\{t \in \mathbb{N} : t \geq 5, \|S_t\|_2^2/t \geq p + \sqrt{p}\xi_t\},$$

where  $\xi_t = C \left( \sqrt{\log(1/\epsilon) \log \log t} + \frac{\log(1/\epsilon) \log \log t}{\sqrt{p}} \right)$  for some large enough constant  $C > 0$ .



# One-sided sequential testing

- Probability of ever stopping under the null:  $P_0(N < \infty) \leq \epsilon$
- Upper bound (up to a log-log factor) on the average run length under the alternative:

$$E_{\theta}(N) \lesssim \frac{\sqrt{p}}{\|\theta\|_2^2} \left( \sqrt{\log(1/\epsilon)} + \frac{\log(1/\epsilon)}{\sqrt{p}} \right)$$

- Working on the corresponding lower bound
- $\rightarrow$  sequential change point procedure

# One-sided sequential testing

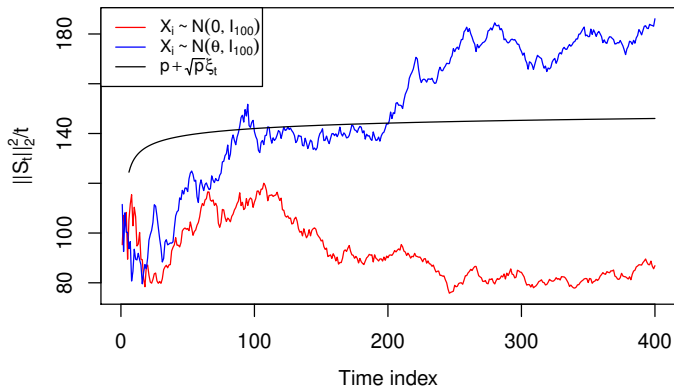


Figure: Sequential testing procedure with  $p = 100$ ,  $\epsilon = 1/8$  and  $\vartheta = 1/2$

- Include sparsity in high dimensions
- Use sequential testing or otherwise to construct a change point detection procedure
- Spatial dependence between co-ordinates of the data stream

Thank you for listening!

- Lorden, G. (1971) Procedures for reacting to a change in distribution. *Ann. Math. Statist.*, **42**, 1897–1908.
- Page, E. S. (1954) Continuous inspection schemes. *Biometrika*, **41**, 100–115.
- Wang, T. and Samworth, R. J. (2018) High dimensional change point estimation via sparse projection. *J. R. Statist. Soc. B*, **80**, 57–83.