

# Asymptotic behaviour of Gaussian minima

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- The scenario: the entire sample path of  $\mathbf{X}$  on  $[a, b]$  is above  $u$ .
- How do Gaussian minima behave when they are high?

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**Question 2.** Given the event

$$B_u := \left\{ \min_{a \leq t \leq b} X_t > u \right\},$$

how does the conditional distribution of  $(X_t : t \in [a, b])$  behave as  $u \rightarrow \infty$  ?



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**Question 4.** What is the asymptotic conditional distribution, given  $B_u$ , of the location of the minimum

$$\arg \min_{a \leq t \leq b} X_t \text{ as } u \rightarrow \infty ?$$

# Large Deviation Results

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$$\sigma_*^2(a, b) = \min_{\nu \in M_1[a, b]} \int_a^b \int_a^b R(s, t) \nu(ds) \nu(dt),$$

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$$\lim_{u \rightarrow \infty} \frac{1}{u^2} \log P \left( \min_{a \leq t \leq b} X_t > u \right) = -\frac{1}{2\sigma_*^2(a, b)}.$$

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$$x(t) = \frac{1}{\sigma_*^2(a, b)} \int_a^b R(t, s) \nu_*(ds), \quad a \leq t \leq b.$$

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- The canonical example: the Gaussian spectral density

$$F_X(dx) = e^{-x^2/2} dx, \quad x \in \mathbb{R}.$$

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- 3 the optimal value  $\sigma_*^2(b) > 0$ .

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- Then  $\theta_j > 0, j = 1, \dots, k$ ,

$$P\left(\min_{j=1, \dots, k} X_{t_j} > u\right) \sim (2\pi)^{-k/2} (\det \Sigma)^{-1/2} (\theta_1 \dots \theta_k)^{-1} u^{-k} e^{-u^2/2\sigma_*^2(b)}, \quad u \rightarrow \infty.$$

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- Then  $\mu$  is infinitely differentiable,  $\geq 1$  on  $[0, b]$ .
- $\mu \equiv 1$  on  $S$ , so points of  $S$  are local minima.
- **The key assumption:**  $\mu'' > 0$  on  $S \cap (0, b)$ .

# Theorem 1

Let the cardinality of  $S$  be  $k$ . Then

$$P\left(\min_{0 \leq t \leq b} X_t > u\right) \sim cu^{-k} e^{-u^2/2\sigma_*^2(b)}, \quad u \rightarrow \infty$$

for  $c \in [0, \infty)$ .

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for  $c \in [0, \infty)$ .

Furthermore,  $c > 0$  if and only if the key assumption holds.



## Theorem 2

Suppose the key assumption holds. Then in  $C[0, b]$ ,

$$P \left( (X_t - u\mu(t) : a \leq t \leq b) \in \cdot \mid \min_{t \in [a, b]} X_t > u \right) \Rightarrow Q_W(\cdot),$$

where  $Q_W$  is the law of a tilted Gaussian process on  $[a, b]$ .

## Theorem 3

Suppose the key assumption holds.

Then, as  $u \rightarrow \infty$ , the conditional distribution of

$$u \left( \min_{t \in [a, b]} X_t - u \right) \quad \text{given} \quad \min_{t \in [0, b]} X_t > u$$

converges weakly to the exponential distribution with mean  $\sigma_*^2(b)$ .

## Theorem 4

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Then, as  $u \rightarrow \infty$ ,

$$P \left( T_* \in \cdot \mid \min_{s \in [0, b]} X_s > u \right) \Rightarrow \nu_* .$$

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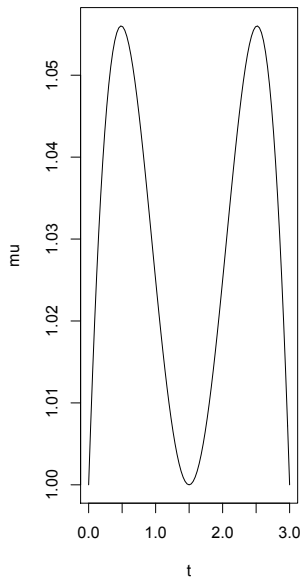
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- **Example** The Gaussian covariance function  $R(t) = e^{-t^2/2}$ .
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- Then  $S = \{0, b/2, b\}$ .

**b=3**



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