

LECTURE 39

STOCHASTIC PROCESSES

- Consider $\forall$ Gaussian process $(X_t)_{t \in T}$ indexed by $\forall$ set T .

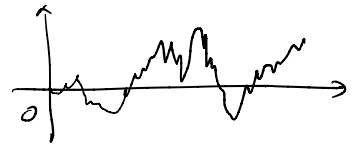
Induces (pseudo-) metric on T :

$$d(t, s) := \|X_t - X_s\|_{L^2} = \left(\mathbb{E} (X_t - X_s)^2 \right)^{1/2}$$

Ex (a) Brownian motion $(B_t)_{t \in [0, \infty)}$

$$B_t - B_s \sim N(0, |t-s|)$$

$$\Rightarrow d(t, s) = \sqrt{|t-s|} \text{ on } \mathbb{R}.$$



(b) Brownian bridge, fractional B.M., Ornstein-Uhlenbeck process, Brownian sheet, Gaussian free field, etc.

(c) $X_t := gt$ where $g \sim N(0, 1)$, $t \in \mathbb{R} =: T$

$$\Rightarrow X_t - X_s = g(t-s) \sim N(0, (t-s)^2)$$

$$\Rightarrow d(t, s) = |t-s| \text{ on } \mathbb{R}$$

(d) High-dimensional: $X_t := \langle g, t \rangle$ where $g \sim N(0, I_d)$, $t \in \mathbb{R}^d =: T$

$$\Rightarrow d(t, s) = \|t-s\|_2 \text{ on } \mathbb{R}^d \text{ (check!)}$$

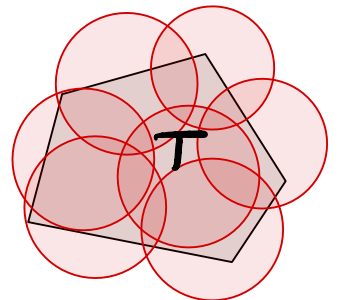
• Goal: compute

$$\mathbb{E} \sup_{t \in T} X_t$$

via geometry of the metric space (T, d) ,

specifically the covering numbers

$N(T, d, \varepsilon)$ = min. cardinality of an ε -net of (T, d)
= min # of ε -balls that cover T



Thm [Dudley's Integral Inequality 1967]

$\forall$ mean zero Gaussian process $(X_t)_{t \in T}$ satisfies

$$\mathbb{E} \sup_{t \in T} X_t \leq 8 \int_0^{\infty} \sqrt{\log N(T, d, \varepsilon)} d\varepsilon.$$

metric entropy of T

Proof: "**CHAINING**" = Multiscale union bound.

- Set the scale

$$\varepsilon_k := 2^{-k}, \quad k = 0, 1, 2, \dots$$

- Choose ε -nets T_k of T so that

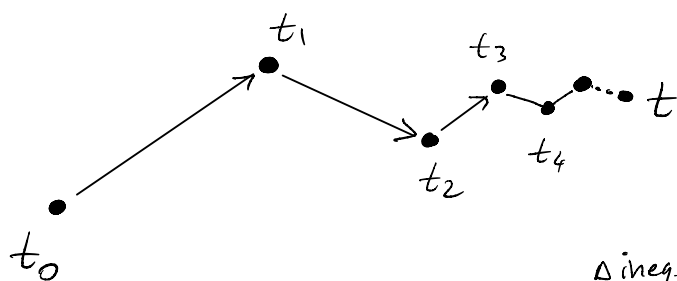
$$|T_k| = N(T, d, \varepsilon_k).$$

WLOG $\text{diam}(T) \leq 1 \Rightarrow$

$$T_0 = \{t_0\}$$

- Def of ε -net $\Rightarrow \forall t \in T \exists t_k \in T_k :$
 $d(t_k, t) \leq \varepsilon_k \quad (*)$

- Chaining: progressive approximation of t :



$$X_{t_0} - X_t = (X_{t_0} - X_{t_1}) + (X_{t_1} - X_{t_2}) + \dots$$

(WLOG T is finite $\Rightarrow$ sum is finite $\uparrow$)

$$\stackrel{\Delta \text{ineq.}}{\Rightarrow} |X_{t_0} - X_t| \leq \sum_{k=1}^{\infty} |X_{t_{k-1}} - X_{t_k}|$$

• Note: $d(t_{k-1}, t_k) \stackrel{\Delta \text{ ineq.}}{\leq} d(t_{k-1}, t) + d(t, t_k) \stackrel{(*)}{\leq} \varepsilon_{k-1} + \varepsilon_k = 3\varepsilon_k$

$$\Rightarrow \max_{t \in T} |X_{t_0} - X_t| \leq \sum_{k=1}^{\infty} \max_{\substack{u \in T_{k-1} \\ v \in T_k \\ d(u,v) \leq 3\varepsilon_k}} |X_u - X_v| \quad \begin{matrix} \parallel \\ 2^{-k+1} \end{matrix} \quad \begin{matrix} \parallel \\ 2^{-k} \end{matrix}$$

$$\Rightarrow \mathbb{E} \max_{t \in T} |X_{t_0} - X_t| \leq \sum_{k=1}^{\infty} \mathbb{E} \max_{(u,v) \in P_k} |X_u - X_v|$$

• By assumption & def. of $d(p.i)$, $X_u - X_v \sim N(0, d(u,v)^2)$ where $d(u,v) \leq 3\varepsilon_k$

Use KWS, Problem 4 "Maximum of subgaussians":

$\forall$ normal r.v's Z_i with mean 0, variance $\leq \sigma$:

$$\mathbb{E} \max_{i \in n} |Z_i| \leq C\sigma \sqrt{\log n}$$

$$\Rightarrow \mathbb{E} \max_{(u,v) \in P_k} |X_u - X_v| \lesssim \varepsilon_k \sqrt{\log |P_k|} \lesssim \varepsilon_k \sqrt{\log |T_k|}$$

↑
hides an absolute
constant factor

↑
 $|T_{k-1}| \cdot |T_k| \leq |T_k|^2$

$$\begin{aligned} \Rightarrow \mathbb{E} \max_{t \in T} |X_{t_0} - X_t| &\leq \sum_{k=1}^{\infty} \varepsilon_k \sqrt{\log |T_k|} = \sum_{k=1}^{\infty} \underbrace{2^{-k}}_{\parallel} \underbrace{\sqrt{\log N(T, d, \varepsilon^{-k})}}_{\parallel} \\ &\leq \int_0^{\infty} \sqrt{\log N(T, d, \varepsilon)} d\varepsilon \quad \text{☺} \end{aligned}$$

$\int_{2^{-k-1}}^{2^{-k}} d\varepsilon$
 $\log N(T, d, \varepsilon)$

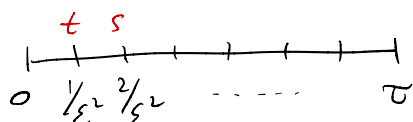
• Getting rid of X_{t_0} :

$$\sup_{t \in T} |X_t| = \sup_{t \in T} |X_t - \overbrace{\mathbb{E} X_{t_0}}^0| \leq \sup_{t \in T} |X_t - X_{t_0}|$$

↑
Jensen

Take expectation $\Rightarrow$ QED

Ex Brownian motion $(B_t)_{t \in [0, \tau]}$ $d(t, s) = \sqrt{|t-s|}$ $\text{diam}(T) = \sqrt{\tau}$



is an ϵ -net of card. τ/ϵ^2

$$\Rightarrow N(T, d, \epsilon) \leq \tau/\epsilon^2 \quad \forall \epsilon \leq \sqrt{\tau}$$

and ≈ 1 if $\epsilon > \sqrt{\tau}$

$$\Rightarrow \int_0^\infty \sqrt{\log N(T, d, \epsilon)} d\epsilon = \int_0^{\sqrt{\tau}} \sqrt{\log(\tau/\epsilon^2)} d\epsilon \stackrel{\epsilon = x\sqrt{\tau}}{=} \sqrt{\tau} \int_0^1 \sqrt{\log(1/x^2)} dx \leq C\sqrt{\tau}$$

$$\Rightarrow \mathbb{E} \sup_{t \in [0, \tau]} B_t \leq C\sqrt{\tau}$$

This is optimal. In fact, $\frac{\text{dist}}{|N(0, \tau)|}$ (a consequence of the "reflection principle")

$$\Rightarrow \mathbb{E} \sup_{t \in [0, \tau]} B_t = \sqrt{\frac{2\tau}{\pi}}$$

• Remark: proof works & subgaussian process, yields:

Thm (Subgaussian Dudley)

Let $(X_t)_{t \in T}$ be a mean zero stochastic process on a metric space (T, d) , which satisfies

$$\|X_t - X_s\|_{\psi_2} \leq K \cdot d(t, s) \quad \forall t, s \in T$$

Then

$$\mathbb{E} \sup_{t \in T} X_t \leq CK \int_0^\infty \sqrt{\log N(T, d, \epsilon)} d\epsilon.$$