

## Series 4b

### 1. Polynomial Growth in Metric Spaces

- a) Let  $(E, d_E)$  and  $(F, d_F)$  be metric spaces with  $E \neq \emptyset$ , and let  $f : E \rightarrow F$  be a function. Prove that  $f$  grows at most polynomially if and only if there exist  $v \in E$  and  $w \in F$  such that

$$\limsup_{c \rightarrow \infty} \sup_{x \in E} \frac{d_F(w, f(x))}{(1 + d_E(v, x))^c} < \infty. \quad (1)$$

- b) Let  $k, l, \nu \in \mathbb{N}$  and let  $f : \mathbb{R}^k \rightarrow \mathbb{R}^l$  be a  $\nu$ -times continuously differentiable function with at most polynomially growing derivatives. Prove that for all  $w = 0, 1, \dots, \nu$ , the  $w$ -th derivative

$$f^{(w)} \text{ grows at most polynomially.} \quad (2)$$

### 2. Convergence Types at Time $T$ for Stochastic Processes

For a probability space  $(\Omega, \mathcal{F}, P)$  and  $T > 0$ , consider a sequence of real-valued stochastic processes  $Y^N : [0, T] \times \Omega \rightarrow \mathbb{R}$ ,  $N \in \mathbb{N}_0$ , defined at time  $T$  by

$$Y_T^N = \frac{1}{N} Z, \quad \text{where } Z(P) = \mathcal{N}_{0,1} \text{ and } Y_T^0 = 0 \quad (3)$$

(that is,  $Z$  is a standard normal random variable). Identify the types of convergence, as defined in Section 4.2, for which  $Y_T^N \rightarrow Y_T^0$  holds as  $N \rightarrow \infty$ . For each type of convergence that applies, determine the order  $\alpha$  of convergence, if applicable.

### 3. Equivalence of Bounded Derivatives and Quadratic Inequalities

Let  $\mu \in C^1(\mathbb{R}, \mathbb{R})$  and  $L \in \mathbb{R}$ . Prove that:

$$\sup_{x \in \mathbb{R}} \mu'(x) \leq L \quad \text{if and only if} \quad \forall x, y \in \mathbb{R} : (x - y)(\mu(x) - \mu(y)) \leq L(x - y)^2. \quad (4)$$

### 4. Increment-Tamed Euler-Maruyama

(The following does not distinguish between pseudorandom numbers and actual random numbers.) Implement an *Increment-Tamed Euler-Maruyama* approximation  $Y : \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$  (see Section 4.5.4) for the stochastic differential equation

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t, \quad t \in [0, T], \quad X_0 = \xi, \quad (5)$$

with time step size  $T/N$ , where the SDE (5) is set as in Definition 4.5.7 of the lecture notes.

Do this by writing a MATLAB function `IncrementTamed(T, d, m, N, xi, mu, sigma)` which takes as input  $T \in (0, \infty)$ ,  $d, m, N \in \mathbb{N}$ ,  $\xi \in \mathbb{R}^d$ ,  $\mu \in \mathcal{M}(\mathcal{B}(\mathbb{R}^d), \mathcal{B}(\mathbb{R}^d))$ ,  $\sigma \in \mathcal{M}(\mathcal{B}(\mathbb{R}^d), \mathcal{B}(\mathbb{R}^{d \times m}))$  and returns as output a realisation of an  $Y_N(P)$ -distributed random variable.

**Submission Deadline: Wednesday, 20 November 2024, by 2:00 PM.**

① Polynomial growth in Metric Spaces  $(E, d_E)$  and  $(F, d_F)$  metric spaces with  $E \neq \emptyset$ , and let  $f: E \rightarrow F$  be a function.

$\Rightarrow f$  grows at most polynomially, then, for all  $v \in E$ ,  $w \in F$  that there exists a real number  $c \in [0, \infty)$  such that for all  $x \in E$  it holds

$$d_F(w, f(x)) \leq c (1 + d_E(v, x))^{\bar{c}}$$

We take whatever  $v, w$  an  $\frac{d_F(w, f(x))}{(1 + d_E(v, x))^{\bar{c}}} \leq c$  for a given  $c^2 \in \mathbb{R}$

hence,  $\sup_{x \in E} \frac{d_F(w, f(x))}{(1 + d_E(v, x))^{\bar{c}}} \leq c$ . Now, if we take limit on

$\bar{c}$ , as  $(1 + d_E(v, x)) \geq 1$ ,  $\limsup_{\bar{c} \rightarrow \infty} \sup_{x \in E} \frac{d_F(w, f(x))}{(1 + d_E(v, x))^{\bar{c}}} \leq c$ .

$\Leftarrow$  If there exist  $v \in E$ ,  $w \in F$  s.t.

$\limsup_{\bar{c} \rightarrow \infty} \sup_{x \in E} \frac{d_F(w, f(x))}{(1 + d_E(v, x))^{\bar{c}}} < \infty$ , then, we have that

Now, for every  $c > 0$ ,  $\exists C_c > 0$  s.t.

$$\sup_{x \in E} \frac{d_F(w, f(x))}{(1 + d_E(v, x))^c} \leq C_c \Rightarrow d_F(w, f(x)) \leq C_c (1 + d_E(v, x))^c \quad (1) \quad \forall x \in E$$

then, for sufficiently large  $c$ ,  $C_c$  has to stabilize, as it cannot be infinite, hence the growth of  $d_F(w, f(x))$  is bounded by a polynomial of degree  $c$ .

Now, this has to be used to prove it for all  $v \in E$ ,  $w \in F$ .

$$d_F(w', f(x)) \leq d_F(w', w) + d_F(w, f(x)) \quad (\text{Triangle inequality})$$

So, using the assumption (1),

$$d_F(w', f(x)) \leq d_F(w', w) + C (1 + d_E(v, x))^c \quad \text{for } c, \delta > 0 \quad (2)$$

At the other hand,  $d_E(v, x) \leq d_E(v, v') + d_E(v', x)$

$$\text{thus, } 1 + d_E(v, x) \leq (1 + d_E(v, v')) (1 + d_E(v', x))$$

So, putting this inequality in (2),

$$d_F(w, f(x)) \leq d_F(w, w) + C(1 + d_E(v, v')) (1 + d_E(v', x))$$

And, we see that  $d_F(w, w) + C(1 + d_E(v, v'))^2 = K$  (new constant)

Then,

$$d_F(w, f(x)) \leq k(1 + d_E(v, x))^2$$

Hence, the polynomial growth condition is satisfied for all  $v \in E, w \in F_D$ .

b) We know that  $f$  is  $v$ -times continuously differentiable that satisfies that  $f^{(v)}$  grows at most polynomially.

Now, we need to see that it holds for all  $w \in \{0, \dots, v\}$ .

Let's assume  $f^{(w)}$  for  $w \in \{0, \dots, v-1\}$  don't grow at most polynomially, now, we know that  $\forall a \in \mathbb{R}^k, \forall x$  around  $a$ :

$$f^{(w)}(x) = \sum_{n=0}^{\infty} \frac{f^{(w+n)}(a)}{n!} (x-a)^n$$

Note: We consider  $f^{(w)}$  as the  $w$ -th derivative tensor of  $f$

And  $f^{(v)}(x) = \sum_{n=0}^{\infty} \frac{f^{(v+n)}(a)}{n!} (x-a)^n$ , so, we can take the terms

$$\begin{aligned} & \left( \sum_{n=v-w}^{\infty} \frac{f^{(w+n)}(a)}{n!} (x-a)^n \right) \text{ and } \left( \sum_{n=0}^{\infty} \frac{f^{(v+n)}(a)}{n!} (x-a)^n \right) \\ & \sum_{n=0}^{\infty} \frac{f^{(v+n)}(a)}{(n+v-w)!} (x-a)^{n+v-w} = \sum_{n=0}^{\infty} \frac{f^{(v+n)}(a)}{n!} (x-a)^n \frac{(x-a)^{v-w}}{(n+v-w)!} \end{aligned}$$

Now, we see that  $\frac{n!}{(n+v-w)!} \rightarrow 0$  as  $n \rightarrow \infty$ .

$$\text{and, } \frac{n!}{(n+v-w)!} \leq \frac{1}{(v-w)!}$$

$$\text{So, } (1) \leq (2) \cdot \frac{1}{(v-w)!}$$

But, we know that (1) don't grow at most polynomially, hence (2) don't grow at most polynomially. Hence, we have proved that if  $f^{(v)}$  grows at most polynomially, then  $f^{(w)}$  too. with  $w \in \{0, \dots, v\}$ .

## ② Convergence Types at Time T for Stochastic Processes

$$Y_T^N = \frac{1}{N} Z, \quad Z(P) = N_{0,1}, \quad Y_T^0 = 0$$

a)  $Y_T^N \rightarrow Y_T^0$

- Convergence in probability,  $\forall \varepsilon > 0$

$$Y_T^N - Y_T^0 = \frac{1}{N} Z - 0 = \frac{1}{N} Z \sim N(0, \frac{1}{N^2})$$

then, as  $P\left(\left|\frac{1}{N} Z\right| \geq \varepsilon\right) = 2 P(Z \geq N \cdot \varepsilon)$ .

$$P(Z \geq x) \sim \frac{1}{\sqrt{2\pi}x} e^{-x^2/2} \text{ as } x \rightarrow \infty \text{ (gaussian decay)}$$

for  $x = \varepsilon \cdot N$ ,

$$P(|Y_T^N - Y_T^0| > \varepsilon) \sim \frac{1}{\sqrt{2\pi}N\varepsilon} e^{-(N\varepsilon)^2/2}$$

Then, we prove that  $\limsup_{N \rightarrow \infty} P(|Y_T^N - Y_T^0| > \varepsilon) = 0$

- Strong convergence:  $\forall p \in (0, \infty)$

$$\mathbb{E}_p[|Y_T^0 - Y_T^N|^p] = \mathbb{E}_p[|Y_T^N|^p] = \mathbb{E}_p[(Y_T^N)^p | Y_T^N \geq 0] +$$

$$\mathbb{E}_p[-(Y_T^N)^p | Y_T^N \leq 0] = 2 \mathbb{E}_p[(Y_T^N)^p | Y_T^N \geq 0] =$$

$$= 2 \mathbb{E}\left[\left(\frac{1}{N} Z\right)^p | Z \geq 0\right]$$

Hence,  $\limsup_{N \rightarrow \infty} \mathbb{E}\left[\left(\frac{1}{N} Z\right)^p | Z \geq 0\right] = 0$  Hence strong convergence holds

To know the rate of convergence,

$\mathbb{E}\left[\frac{1}{N^p} Z^p | Z \geq 0\right] = \frac{1}{N^p} \mathbb{E}[Z^p | Z \geq 0]$ . As  $\mathbb{E}[Z^p | Z \geq 0]$  is bounded and fixed for every given  $p \in (0, \infty)$ , we have that

$$\|Y_T^0 - Y_T^N\|_{L^p} \leq C \cdot \frac{1}{N^p} \text{ where } C = \mathbb{E}[Z^p | Z \geq 0]$$

Then  $\alpha = p$  (rate of convergence).

• Almost sure convergence:

First, we see that as  $N$  increases,  $E[Y_1^N] = \frac{1}{N} E[Z] = 0$   
 $\text{Var}(Y_1^N) = \frac{1}{N^2} \text{Var}(Z) = \frac{1}{N^2} \rightarrow 0$

Now, we use Chebyshev's inequality, for any  $\epsilon > 0$

$$P(|Y_1^N| \geq \epsilon) \leq \frac{\text{Var}(Y_1^N)}{\epsilon^2} = \frac{1/N^2}{\epsilon^2} = \frac{1}{N^2 \epsilon^2} \xrightarrow{N \rightarrow \infty} 0$$

And Borel-Cantelli Lemma: if  $P(A_n) \rightarrow 0$  as  $n \rightarrow \infty$ , and  $A_n$  are independent, then  $P(\limsup_{n \rightarrow \infty} A_n) = 0$ .

In this case, it holds for the event  $|Y_1^N| \geq \epsilon$ , hence

$$Y_1^N \rightarrow Y_1^0 = 0 \text{ a.s. as } N \rightarrow \infty$$

Rate of convergence. As  $\forall N \in \mathbb{N}$ , it needs to hold

$$P\left(\left|\frac{z}{N}\right| \leq C(w) \cdot N^{-\alpha}\right) = 1$$

We can find such a  $C$  function:

$$C(w) \geq \frac{|z(w)|}{N^{1-\alpha}}$$

But this should hold for all  $N \in \mathbb{N}$ , so we could define  $C(w)$  as

$$C(w) = |z(w)|$$

$$\text{So, now, } P\left(\left|\frac{z}{N}\right| \leq |z(w)| \cdot N^{-\alpha}\right) = P\left(\frac{1}{N} \leq N^{-\alpha}\right) = P\left(\frac{1}{N} \leq \frac{1}{w^\alpha}\right)$$

is equal to 1 for  $\alpha \leq 1$ , so  $\alpha = 1$  is the order of convergence.

$$\text{We have } P(|Y_1^N| \leq C \cdot N^{-1}) = 1 \quad \forall N \in \mathbb{N}.$$

• Nun. weak convergence:  $|E[\Psi(Y_1^N)]| = |E[\Psi(\frac{1}{N} Z)]| =$

Let's find the Taylor expansion of  $E[\Psi(\frac{1}{N} Z)]$ , given  $E[\frac{z}{N}] = 0$

$$E[\Psi(\frac{z}{N})] = \Psi(\mu_2) + \underbrace{\Psi'(\mu_2) E\left[\frac{z}{N} - \mu_2\right]}_0 + \frac{1}{2} \Psi''(0) E[(\frac{z}{N} - \mu_2)^2] + O\left(E\left[\left(\frac{z}{N}\right)^3\right]\right)$$

$$E\left[\Psi\left(\frac{z}{N}\right)\right] = \Psi(0) + \frac{1}{2} \Psi''(0) \cdot \frac{1}{N^2} + O\left(E\left[\left(\frac{z}{N}\right)^3\right]\right)$$

Hence, we all the 3rd order terms are smaller than second order, so, we can find a given  $C \in \mathbb{R}$  s.t

$$|E\left(\Psi\left(\frac{z}{N}\right)\right)| \leq C \cdot \frac{1}{N^2} \Rightarrow \text{there is numerically weak convergence, with order } d=2.$$

③  $\mu \in C^1(\mathbb{R}, \mathbb{R})$ ,  $L \in \mathbb{R}$ .

$$\Rightarrow \sup_{x \in \mathbb{R}} \mu'(x) \leq L, \text{ now, } \frac{\mu(x) - \mu(y)}{x-y} = \mu'(z), z \in (x, y)$$

by MVT, then,  $\mu(x) - \mu(y) = \mu'(z)(x-y) \leq L(x-y)$ , Hence,  
 $(x-y)(\mu(x) - \mu(y)) \leq L(x-y)^2$

$\Leftarrow$  If  $\forall x, y \quad (x-y)(\mu(x) - \mu(y)) \leq L(x-y)^2$ , then,

$\mu(x) - \mu(y) \leq L(x-y)$ , so  $\frac{\mu(x) - \mu(y)}{x-y} \leq L$ . But we know that

$\forall z \in \mathbb{R}$ ,  $\mu'(z) = \lim_{x \rightarrow z} \frac{\mu(x) - \mu(z)}{x-z}$  and we have seen that it is  $\leq L$ .

Hence,  $\sup_{z \in \mathbb{R}} \mu'(z) \leq L$ .