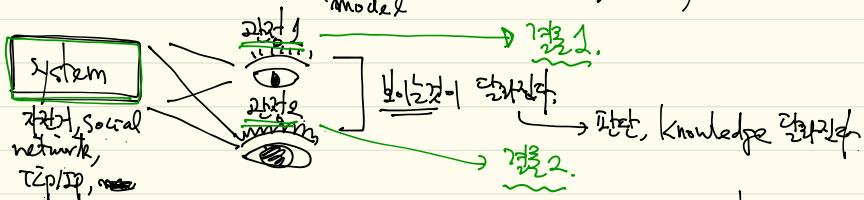


Lecture 16: (Chapter 5) From microscopic to macroscopic

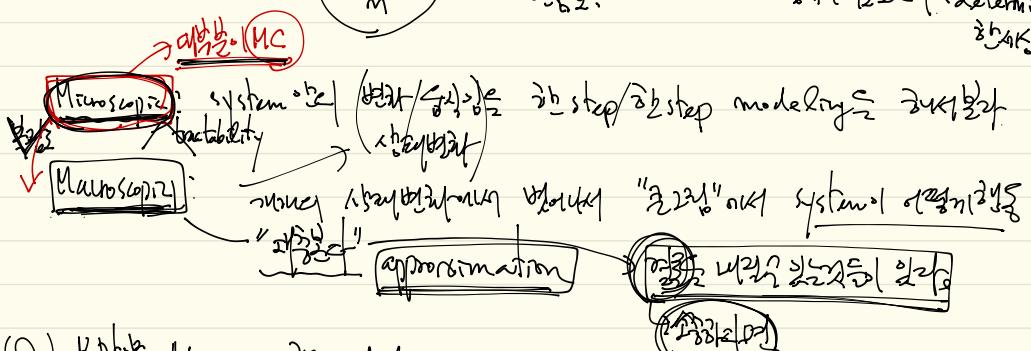
"fluid model", mean-field approximation

Fluid models for Internet (System (Dynamical system))

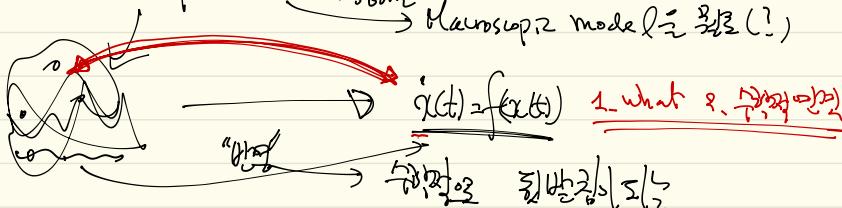


$\{X_i\}$, i.i.d.,

$$\frac{\sum_{i=1}^m X_i}{m}$$



(Q) What is Microscopic model about? Macroscopic model is what (?)



Example

- ① Poisson process
- ② M/M/1 Queue
- ③ SIS epidemic

Macro
Macro

$$\Pr(X_m(t+h) = i+1 \mid X_m(t) = i) = h \cdot \frac{\beta}{m} \tilde{\alpha}(m-i) + o(h)$$

$$\Pr(X_m(t+h) = i-1 \mid X_m(t) = i) = \delta_i h + o(h)$$

$$\Pr(X_m(t+h) = i \mid X_m(t) = i) = 1 - h \left(\frac{\beta}{m} \tilde{\alpha}(m-i) + \delta_i \right) + o(h)$$

$X_m(t)$: transition probabilities

$\dot{x}(t) = \beta x(1-x) - \delta x$

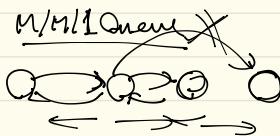
Markov process \rightarrow mean-field approximation \rightarrow approximated

Macroscopic

Kurtz Theorem (chapter 5.3):

Markov jump process

(Poisson process) $\xrightarrow{\text{Birth-Death}}$

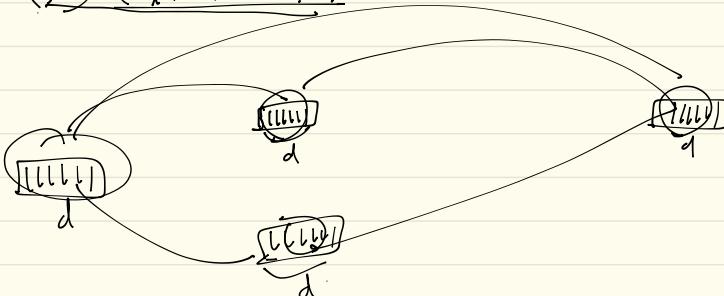


- Population of individuals belonging to "d" difference species

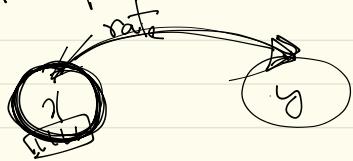


- $X_i(t)$, $i=1, \dots, d$: total # of individuals of species i at time t

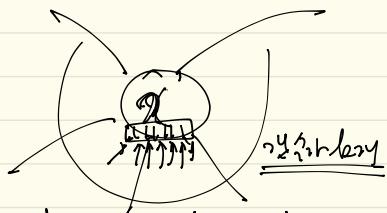
- $(X(t)) = (X_i(t) : i=1, \dots, d)$:



- We say that $(X(t))$ is Markov jump process when
 for any given two states $x, y \in \mathbb{N}^d$, the process jumps from x to y
 upon expiration of a random timer with exponential distribution
 whose parameter depends on x and y



- Assume that \exists a finite # of possible jump directions
 $(\ell_i)_{i=1,\dots,k}$.



$(\frac{\lambda_{ij}}{\lambda_{ii}})$ ket def \Rightarrow $\lambda_{ij}/\lambda_{ii}$? $\lambda_{ij}/\lambda_{ii}$?

(λ_{ij}) b=dt \Rightarrow $\lambda_{ij} dt$ \Rightarrow λ_{ij}
 possible # of jump directions $\leq k$

(cf) When ℓ_i 's entries are restricted to {0, 1}

(ex) M/M/1

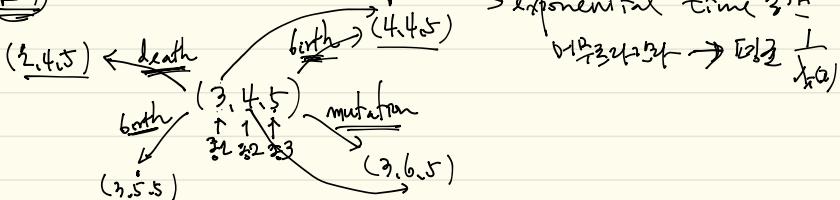
\Rightarrow Birth-and-death process

(cf) Poisson process

$\lambda_i \rightarrow$ ~~constant~~ \Rightarrow λ_i

Let us denote by $\lambda_i(x)$ "the rate from x to $x + \ell_i$ "

(Ex) $(1, 2, 3)$, $(4, 5, 6)$



(\underline{m}): scaling parameter: \underline{m} ($\frac{1}{\underline{m}} \text{ as } m \rightarrow \infty$)

For any fixed \underline{m} \longrightarrow MJP(\underline{m}), $X_{\underline{m}}(t)$

$$\underline{m}=1 \longrightarrow X_1(t)$$

$$2 \longrightarrow X_2(t)$$

:

$$\underline{m} \longrightarrow X_m(t)$$

:

$$\infty \longrightarrow X_{\infty}(t)$$

Question ($X_{\infty}(t)$ pt $\left(\frac{\text{defining}}{\text{defining}} \text{ 3rd part of 2nd part}\right)$, $\left(\frac{\text{defining}}{\text{defining}} \text{ 3rd part of 2nd part}\right)$)

Thm 5.5 \Rightarrow Thm 5.5

Thm 5.5 (Kurtz's Theorem) (page 87 of Stoch Vol 2)

$\underline{m} \longrightarrow MJP(\underline{m})$ $(X_{\underline{m}}(t))_{t \geq 0}$ on \mathbb{N}^d with jump directions $(\ell_i)_{i=1, \dots, k}$

transition rates $\underline{\lambda_i(x/\underline{m})}, q \in \mathbb{N}^d$ ($\underline{\lambda_i(x/\underline{m})}$ scaling of $\lambda_i(x)$)

$q \longrightarrow d\ell_i$.

Then, $\{X_{\underline{m}}(t)\}_{t \geq 0}$ satisfies:

$$\Pr(X_{\underline{m}}(t+h) = q | X_{\underline{m}}(t) = p) = \underline{m} \cdot h \sum_{i=1}^k \lambda_i(x/\underline{m}) + o(h), \quad p \in \mathbb{N}^d, q \in \mathbb{N}^d, i=1, \dots, k$$

$$\Pr(X_{\underline{m}}(t+h) = q | X_{\underline{m}}(t) = p) = 1 - \underline{m} \cdot h \sum_{i=1}^k \lambda_i(x/\underline{m}) + o(h), \quad p \in \mathbb{N}^d$$

Let the function $f_i: \mathbb{R}^d \rightarrow \mathbb{R}^d$ be defined by e_1, \dots, e_k

$$\Rightarrow f_i(x) := \sum_{i=1}^k e_i \cdot \lambda_i(x) = (\overset{\uparrow}{\bullet}, \overset{\uparrow}{\bullet}, \overset{\uparrow}{\bullet}, \dots, \overset{\uparrow}{\bullet})$$

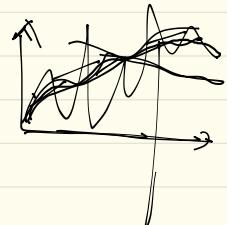
some arbitrary norm \downarrow distance d dim

Let $\bar{e} := \max_{i=1, \dots, k} |e_i|$.

Assume the following conditions hold,

→ C1: $\bar{\lambda} := \max_{\substack{1 \leq i \leq k \\ x \in \mathbb{R}^d}} \lambda_i(x)$ is finite. ← (예증 만족할지....)

→ C2: The function F is Lipschitz continuous, i.e., \exists a constant M s.t
 $|F(x) - F(y)| \leq M|x-y|$, for all $x, y \in \mathbb{R}^d$



→ C3: $\lim_{m \rightarrow \infty} \frac{1}{m} X_m(t_0) = X(t_0)$ a.s. (예증 만족할지....).

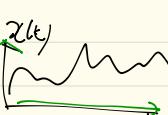
Let $X: \mathbb{R}_+ \rightarrow \mathbb{R}^d$ be the solution of the following equation: $X(t)$

~~시작점과 초기값은 정해져야 한다.~~

마지막에 정의된다.

$$X(t) = X(t_0) + \int_{t_0}^t F(X(s)) ds$$

integral



Then, we have \circ for any fixed ε , $\forall \delta > 0$, for sufficiently large n (deterministic)

$$\Pr \left(\sup_{0 \leq t \leq T} \left| \frac{X_m(t)}{m} - X(t) \right| \geq \varepsilon \right) \leq 2k \exp \left(-m T \bar{\lambda} h \left(\frac{\varepsilon e^{-\bar{\lambda} T}}{2kT \bar{\lambda} \varepsilon} \right) \right),$$

where $h(t) = \ln(1+t) \log(1+tv) - t$. Moreover

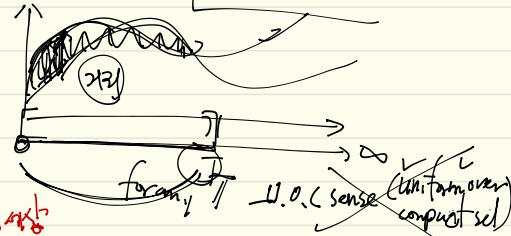
$$\lim_{m \rightarrow \infty} \left(\sup_{0 \leq t \leq T} \left| \frac{X_m(t)}{m} - X(t) \right| \right) = 0$$

a.s.



$\frac{X_m(t)}{m} \xrightarrow{\text{large } m} X(t)$
 (for large n)

$\xrightarrow{\text{large } n}$
 (가지로 정의)



Kurtz theorem: $\xrightarrow{\text{large } m, \text{large } n} \xrightarrow{\text{large } t}$ functional version

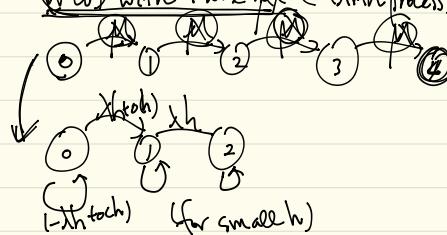
"functional law of large numbers"
 central limit theorem

Lecture 11 (part 2) : Kortz theorem 1 28

- (1) Poisson process
- (2) SIS epidemics

\langle Poisson process \rangle

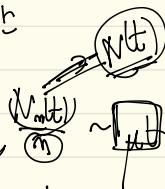
$N(t)$ with rate $\lambda(t)$ (Birth process)



$$N(t) \approx \boxed{}$$

deterministic
system, $\frac{dN}{dt} = \mu$

By Kortz theorem,



$$\lim_{m \rightarrow \infty} \sup_{0 \leq t \leq T} |N(t) - \mu t| = 0 \quad a.s \quad (N(t) \approx \mu t)$$

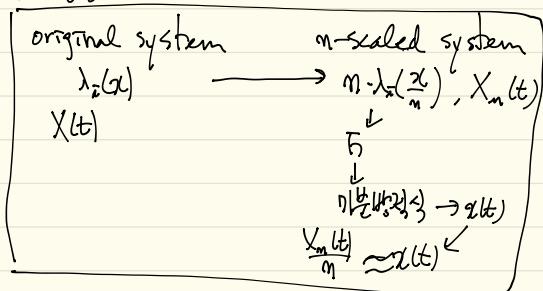
Proposition 5-2

$$\frac{(N(t))}{m} = \frac{N_m(t)}{m} = \frac{W(mt)}{m}$$

time on \mathbb{R}^{2n+1}

$$\frac{N(mt)}{m} \sim \frac{\mathbb{W}(mt)}{m} \quad N(mt) \sim \frac{m W(t)}{m}$$

$$E(N(t)) = \mu t$$



$$\lambda(i) = \mu$$

$$\begin{aligned} & \xrightarrow{\text{scaled}} n\text{-scaled system} \\ & N(t) \xrightarrow{\text{scaled}} N_m(t) \\ & \lambda \xrightarrow{\text{scaled}} m \cdot \lambda \left(\frac{i}{m} \right) \\ & = m \cdot \mu \end{aligned}$$

$$\begin{aligned} \lambda(t) &= f(x(t)), \quad f \xrightarrow{\text{scaled}} \mu \\ &= \mu \quad \rightarrow x(t) = \mu t \end{aligned}$$

$$\frac{N(t)}{m} \xrightarrow{\text{scaled}} \frac{W(mt)}{m}$$

Functional law of large numbers

$$\frac{N(mt)}{m} \xrightarrow{\text{scaled}} \mu t$$

SIS epidemic

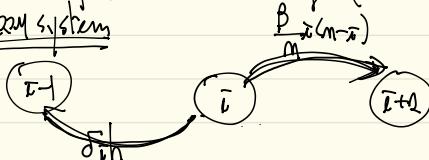
$$\Pr(X_m(t+h) = \bar{i}+1 \mid X_m(t) = \bar{i}) = h \left(\frac{\beta}{m} \bar{i}(m-\bar{i}) + \delta_h \right)$$

$$\Pr(X_m(t+h) = \bar{i}-1 \mid X_m(t) = \bar{i}) = \delta_h h + o(h)$$

$$\Pr(X_m(t+h) = \bar{i} \mid X_m(t) = \bar{i}) = 1 - h \left(\frac{\beta}{m} \bar{i}(m-\bar{i}) + \delta_h \right) + o(h)$$

in setup of "m" individuals scaling parameter from

mean system



$$\lambda^+(\bar{i})$$

$$\bar{i} \rightarrow \bar{i}+1 : \frac{\beta}{m} \bar{i}(m-\bar{i}) = m \cdot \lambda^+(\bar{i}) / m$$

$$\bar{i} \rightarrow \bar{i}-1 : \frac{\beta}{m} \bar{i}(m-\bar{i}) = m \cdot \lambda^-(\bar{i}) / m$$

what is $\lambda^+(\bar{i})$? $m \cdot \lambda^+(\frac{\bar{i}}{m}) = \delta_{\bar{i}} h = m \cdot \delta(\frac{\bar{i}}{m}) \cdot h \Rightarrow \lambda^+(\bar{i}) = \delta_{\bar{i}}$

what is $\lambda^-(\bar{i})$? $m \cdot \lambda^-(\frac{\bar{i}}{m}) = \frac{\beta}{m} \bar{i}(m-\bar{i}) = m \cdot \beta(\frac{\bar{i}}{m}) \left(1 - \frac{\bar{i}}{m}\right) \Rightarrow \lambda^-(\bar{i}) = \beta \bar{i}(1-\bar{i})$

$$h \rightarrow x$$

$$l_+ = 1, l_- = -1$$

$$\underline{f_i(\bar{i})} = l_+ \lambda^+(\bar{i}) + l_- \lambda^-(\bar{i}) = \beta \bar{i}(1-\bar{i}) - \delta_{\bar{i}}$$

$$\bar{f}(x) = \beta x(1-x) - \delta x$$

for simplist, $(\underline{d=1})$, $f(x)=y$

$$\underline{q_i(t)} = \bar{f}(q_i(t)) = \beta q_i(1-q_i) - \delta q_i$$

homework

$$\underline{q_i(t)} = \frac{(\beta-1)y e^{(\beta-1)t}}{(\beta-1) - \beta y (1 - e^{(\beta-1)t})}$$

$$\frac{q_i(t)}{m} \sim x(t)$$

modelled "portion" "fraction"

If $\beta > 1$, $x(t) \rightarrow (1 - \frac{1}{\beta})$ as $t \rightarrow \infty$

If $\beta < 1$, $x(t) \rightarrow 0$ as $t \rightarrow \infty$

① $y = \frac{1}{\beta-1}$
② $y = \frac{1}{\beta-1} - 1$

Lecture 11 (part 3) Kurtz Theorem 9/30/2023

Proposition (5.2) (Kurtz Theorem 2) (λ version) (Poisson process version)

Let $N(t)$ be a Poisson process with rate λ . Then for any $\varepsilon > 0$ and $T > 0$,

$$\Pr\left(\sup_{0 \leq t \leq T} (N(t) - t) \geq \varepsilon\right) \leq e^{-T\lambda} e^{-\lambda\varepsilon}, \quad b(t) = (t+t)\lambda e^{-(t+1)} - t.$$

(Pf)

Dobro's inequality: $N(t) - t$, $t \leq N(t)$ of Dobro's submartingale \Rightarrow

$$\Pr\left(\sup_{0 \leq t \leq T} (N(t) - t) \geq \varepsilon\right)$$

$$\leq \Pr\left(\sup_{0 \leq t \leq T} (N(t) - t) \geq \varepsilon\right) + \Pr\left(\sup_{0 \leq t \leq T} t - N(t) \geq \varepsilon\right)$$

$$\stackrel{(1)}{\Pr}\left(\sup_{0 \leq t \leq T} (N(t) - t) \geq \varepsilon\right) = \Pr\left(\sup_{0 \leq t \leq T} (N(t) - t)^0 \geq \varepsilon^0\right) \stackrel{(2)}{\leq} E\left(e^{(N(T)-T)\lambda}\right) e^{-\lambda\varepsilon}$$

\Rightarrow $N(t) - t$ submartingale \Rightarrow

Continuous version of Martingale definition

$\{X(t)\}_{t \geq 0}$ is a submartingale if and only if the following holds:

$$E(X(t) \mid \{X(u)\}_{u \leq s}) \geq X(s), \quad 0 \leq s \leq t$$

$$\begin{aligned} E\left(\sup_{0 \leq u \leq s} (N(u) - u) \mid \{N(u) - u\}_{u \leq s}\right) &= E\left(\sup_{0 \leq u \leq s} (N(u) - u) - (t-s) - s\right) \\ &= E(N(s) - s) + E\left(\sup_{0 \leq u \leq s} (N(u) - u) - (t-s) - s\right) \\ &= E(N(s)) - s \\ &= s\lambda - s \end{aligned}$$

$$\frac{E(e^{(X(T)-T)\varepsilon})}{e^{\varepsilon T}} = e^{\varepsilon T} \cdot e^{-T\varepsilon} E(e^{N(T)\varepsilon}) = e^{\varepsilon T} \cdot e^{-T\varepsilon} \cdot e^{T(e^\varepsilon - 1)} = e^{(-T(\varepsilon + T) + T(e^\varepsilon - 1))}$$

$\overset{T \rightarrow \infty}{\text{when } T \rightarrow \infty}$
 $N(T) \sim \text{Poisson random variable}$
 with parameter T

$$\beta^* = \log(1 + \varepsilon/T)$$

$$\hat{\beta}^* \stackrel{\text{def}}{=} -T h(\varepsilon/T), \quad h(t) = \dots$$

Substituting $(\beta^*)_{\text{ML}}$

(Proof) $X_m(t) \leftarrow X(t)$ \Rightarrow β^* is MLE solution

$X_m(t)$: memory system

- ① $X_m(t)$ dynamics \Rightarrow $X_m(t)$ has a characteristic
- ② $\cancel{X_m(t)} = \dots$
- ③ $\cancel{X_m(t)} \stackrel{?}{=} 1 + \text{something}$
- ④ $\cancel{|X_m(t)|^2} \stackrel{?}{=} \text{something}$

1-dimensional vector

$$X_m(t) = X_m(0) + \sum_{i=1}^k N_i \left(\int_0^t m \cdot \lambda_i (X_m(s)/m) ds \right)$$

"rate"

N_i : unit-rate poisson process
 $i=1, \dots, k$

$N_i \stackrel{?}{=} N_k$ (unit rate poisson clock)

$$\frac{X_m(t)}{m} = \frac{X_m(0)}{m} + \sum_{i=1}^k R_i N_i \left(\dots \right)$$

Define $\bar{N}_i(t) = N_i(t) - t$ \Rightarrow "centered Poisson process"

centring

$$E(N_i(u))$$

$$\frac{X_m(t)}{m} = \frac{X_m(0)}{m} + \frac{1}{m} \left(\sum_{i=1}^k \overline{e_i} \left(\overline{N_i} \left(\int_0^t m \cdot \lambda_i(X_m(s)/m) ds \right) \right) + \sum_{i=1}^k \int_0^t m \cdot \lambda_i(X_m(s)/m) ds \right)$$

Let $\underline{X}_m(t) = \frac{X_m(t)}{m}$. Recall that $F_i(x) = \sum_{s=1}^k e_i \lambda_i(x_s)$

$$X_m(t) = X_m(0) + \sum_{i=1}^k \frac{e_i}{m} \left(\overline{N_i} \left(\underline{X}_m(t) \right) \right) + \int_0^t \sum_{i=1}^k e_i \lambda_i(X_m(s)/m) ds$$

$$|\underline{X}_m(t) - \underline{x}(t)| \leq |\underline{X}_m(t) - x(t)|$$

$$\underline{x}(t) = x(0) + \left(\int_0^t f_i(x(s)) ds \right)$$

$$|\underline{X}_m(t) - x(t)| \leq |\underline{X}_m(t) - \underline{x}(t)| + \left| \int_0^t f_i(\underline{X}_m(s)) - f_i(\underline{x}(s)) ds \right| + \sum_{i=1}^k \left| \frac{e_i}{m} \right| \left| \overline{N_i} \left(\underline{X}_m(t) \right) \right|$$

$$\leq M \left| \int_0^t (\underline{X}_m(s) - x(s)) ds \right| + \underline{N}(t) - N(t)$$

$$|f(x)| \leq a + \int_0^t |f(s)| ds + \dots \text{ assume } \underline{X}_m(t) \rightarrow x(0) \text{ as } t \rightarrow 0$$

$$|f(x)| \leq \bullet + \int_0^t |f(s)| ds + \Delta \Rightarrow f(x) = \boxed{\quad}$$

$$f(a) = \int_0^k f(s) ds = \int_0^t f(s) ds$$

$$f(x) = \int_0^x f(s) ds \quad f(a) = a$$

$$\boxed{f(x) = x}$$

Proposition 5.6 (Gronwall's Lemma)

Let u be a bounded real-valued function on $[0, T]$, s.t.

$$u(t) \leq a + \int_0^t u(s) ds, \text{ for all } t \in [0, T]$$

then

$$u(t) \leq ae^{at}$$

$$u(T) \leq ae^{aT}$$

$$\begin{aligned}
 & \sup_{0 \leq t \leq T} \left(|Y_m(t) - \chi(t)| - M \int_0^t |Y_m(s) - \chi(s)| ds \right) \leq |Y_m(\omega) - \chi(\omega)| + \sum_{s=1}^T \frac{(k_s)}{m} \int_0^{k_s} |Y_m(s) - \chi(s)| ds \\
 & \text{for sufficiently large } m \text{ and small } \varepsilon \\
 & \leq (1) \sup_{0 \leq t \leq T} \\
 & \Pr \left(\sup_{0 \leq t \leq T} () \geq 2\varepsilon \right) \\
 & \leq \Pr \left(\sup_{0 \leq t \leq T} \left(\frac{k}{2\varepsilon} \int_0^t |Y_m(s) - \chi(s)| ds \right) \geq \varepsilon \right) \\
 & \xrightarrow{\text{Proposition 2a general version}} \leq 2k e^{-MT\lambda h\left(\frac{\varepsilon}{k\varepsilon}\right)} \\
 & \Pr \left(\sup_{0 \leq t \leq T} |Y_m(t) - \chi(t)| \geq 2\varepsilon e^{MT} \right) \\
 & \leq \Pr \left(\sup_{0 \leq t \leq T} \left(|Y_m(t) - \chi(t)| - M \int_0^t |Y_m(s) - \chi(s)| ds \right) \geq 2\varepsilon \right) \\
 & \leq 2k e^{-nT\lambda h\left(\frac{\varepsilon}{k\varepsilon}\right)^2} \\
 & \boxed{\Pr \left(\sup_{0 \leq t \leq T} |Y_m(t) - \chi(t)| \geq \varepsilon \right) \leq 2k e^{-nT\lambda h(-)}} \\
 & \Rightarrow \lim_{m \rightarrow \infty} \sup_{0 \leq t \leq T} \left| |Y_m(t) - \chi(t)| \right| = 0 \quad \text{a.s.} \\
 & \quad \text{f(m)} \quad \left(\sum_n f(n) < \infty \right) \\
 & \quad \Rightarrow \sum_m \Pr(A_m(\varepsilon)) > 0 \\
 & \text{Borel-Cantelli Lemma) Let } A_m(\varepsilon) = \{ |X_m - X| > \varepsilon \}, \\
 & \text{Consider a sequence } \{X_m\} \\
 & \text{If } \sum_m \Pr(A_m(\varepsilon)) < \infty \text{ for all } \varepsilon, \text{ then } X_m \rightarrow X \text{ a.s.} \\
 & \text{a.s.} \xrightarrow{\text{P}} \text{Convergence in probability} \quad (Q) \text{ under what condition?} \\
 & \text{c.r.p.} \rightarrow \text{a.s.}
 \end{aligned}$$

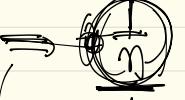
$$\Pr_{Y \sim \Sigma} \Pr(A_m(\zeta)) \xrightarrow{n \rightarrow \infty} 0 \quad (\text{convergence in probability})$$

$\left(\sum_m P(A_m(\zeta)) < \infty \right) \rightarrow a.s.$ $\sum_m A_m \leq \infty$
 \downarrow $\lim_{m \rightarrow \infty} \sum_m A_m = 0$
 $\Pr(A_m(\zeta)) \xrightarrow{n \rightarrow \infty} 0$ strongly

B-C Lemma $\Pr_{Y \sim \Sigma} \sum_m A_m \leq \infty$ $X_m \rightarrow X$ a.s. \Rightarrow (sufficient)

① $\Pr_{Y \sim \Sigma} \sum_m A_m \leq \infty$

② $\sum_m P(A_m(\zeta)) < \infty \rightarrow \Pr(A_m(\zeta)) \xrightarrow{n \rightarrow \infty} 0$

$\Pr(X_m - X > \varepsilon) \Rightarrow$ 

$\sum_m \frac{1}{m} \leq \Pr(X_m - X > \varepsilon) \Rightarrow$ 

$= \frac{1}{m^2} (0) \quad \sum_m \frac{1}{m^2} < \infty$

$\frac{x}{\sqrt{n}}$

Gronwall's Lemma

Mode. f. Convergence

(convergence in probability) $\rightarrow a.s. (X)$

$\frac{\partial}{\partial t}$

B.C. test

$$\left[\sum_m A_m(\zeta) \right] \xrightarrow{n \rightarrow \infty} \text{standard normal distribution}$$