

STOCHASTIC APPROXIMATION

- MEAN FIELD
- APPROXIMATE STOCHASTIC MODELS
- MOMENT CLOSURE

MEAN FIELD

$$(X, S, x_0, R)$$

$X = X_1, \dots, X_n$
 $S \equiv$ state space
 $x_0 \in S$

$$R \ni \rho: \rho_1 X_1 + \dots + \rho_n X_n \rightarrow \rho_1 X_1 + \dots + \rho_n X_n$$

$$v_\rho = \rho_\rho - R_\rho [X \rightarrow X + v_\rho]$$

$f_\rho(x) \geq 0$ rate function / rate in state x of ρ

SYSTEM SIZE: TOTAL POPULATION
 VOLUME (with constant density)
 AREA

$N \equiv$ system size

$$\hat{X} = \frac{X}{N}$$

SIR $\{S, I, R\}$

$$\hat{X}_S = \frac{X_S}{N}$$

$$N: X_S + X_I + X_R$$

$$\text{or } N: X_S(0) + X_I(0) + X_R(0)$$

$\mathcal{M} = (X, S, x_0, R)$ POPULATION MODEL. SYSTEM SIZE N .

$$\hat{\mathcal{M}} = (\hat{X}, \hat{S}, \hat{x}_0, \hat{R})$$

$$\hat{X}^{(N)} = \frac{X}{N}; \quad \hat{S}^{(N)} = \left\{ \hat{s} = \frac{s}{N} \mid s \in S \right\}; \quad \hat{x}_0^{(N)} = \frac{x_0}{N}$$

$$\hat{R} \ni \hat{f} \text{ for } f \in R \quad \hat{f}: \frac{r_1}{N} \hat{X}_1 + \dots + \frac{r_n}{N} \hat{X}_n \rightarrow \frac{p_1}{N} \hat{X}_1 + \dots + \frac{p_n}{N} \hat{X}_n$$

$$\Rightarrow \hat{V}_{\hat{f}}^{(N)} = \frac{V_f}{N}$$

$$f_f(x) = N \hat{f}_{\hat{f}}(\hat{x})$$

$$\hat{f}_{\hat{f}}^{(N)}(\hat{x}) := \frac{f_f(N \hat{x})}{N}$$

$N = \text{system size}$

$$\mathcal{U} = (X, S, x_0, \mathcal{R}) \rightsquigarrow \mathcal{U}^{(N)} = (\hat{X}^{(N)}, \hat{S}^{(N)}, \hat{x}_0^{(N)}, \hat{\mathcal{R}}^{(N)})$$

MEAN FIELD / FLUID APPROXIMATION: study $\mathcal{U}^{(N)}$ as $N \rightarrow \infty$

(SIR $\hat{X}_S^{(N)} \in \{0, \frac{1}{N}, \frac{2}{N}, \dots, \frac{N}{N}\} \subseteq [0, 1]$)

$$\hat{S}^{(N)} \subseteq E \subseteq \mathbb{R}^n, \forall N$$

$\hat{X}^{(N)}(t)$ CTMC for normalized model. How does it look like as $N \rightarrow \infty$

$\frac{d\hat{X}^{(N)}}{dt} = F^{(N)}(\hat{X}^{(N)})$ drift: expected increment $\sim \hat{X}^{(N)}$ at time t .

$$\therefore \sum_{\beta \in \mathcal{R}} \hat{V}_{\beta} \hat{f}_{\beta}(\hat{X}^{(N)}) = \sum_{\beta \in \mathcal{R}} v_{\beta} \hat{f}_{\beta}(\hat{X}^{(N)})$$

$\hat{V}_{\beta} \sim \frac{v_{\beta}}{N}$

REQUIREMENT: $\hat{f}_p^{(n)}(\hat{x}) \rightarrow \hat{f}_p(\hat{x})$ uniformly on \hat{x} (defined on E)
 $(\| \hat{f}_p^{(n)}(\hat{x}) - \hat{f}_p(\hat{x}) \|_{\infty} \rightarrow 0)$

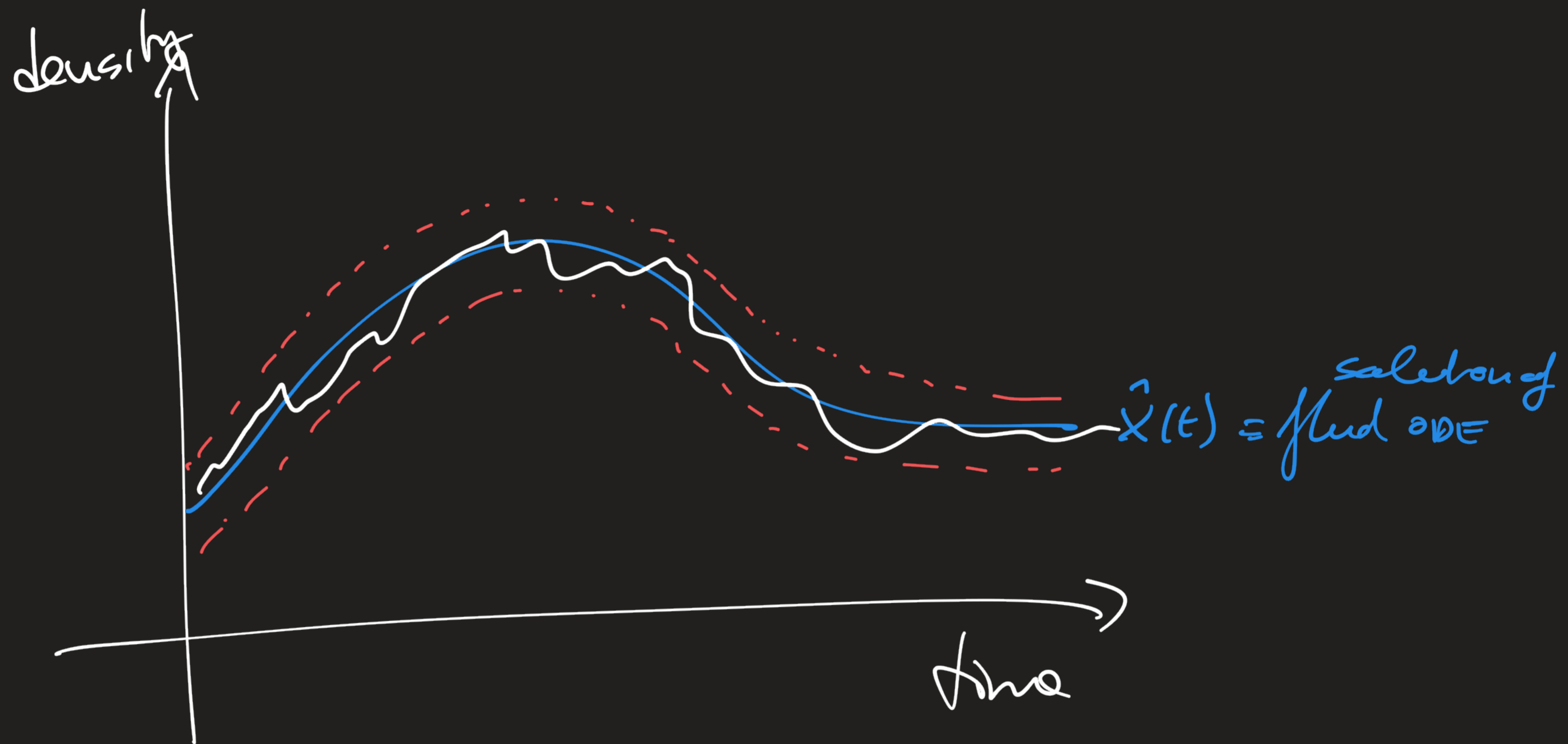
$$\Rightarrow F^{(n)}(\hat{x}) \xrightarrow{n \rightarrow \infty} F(\hat{x}) := \sum_{p \in \mathbb{R}} v_p \cdot \hat{f}_p(\hat{x})$$

CONSTRUCT $\rightarrow \boxed{\frac{d\hat{x}}{dt} = F(\hat{x})}$ mean field / fluid ODE with $\hat{x}(0) = \hat{x}_0 \xleftarrow{N \rightarrow \infty} \hat{x}_0^{(n)}$

THEOREM: if F is Lipschitz (locally), then for $T < \infty$

$$\lim_{n \rightarrow \infty} \sup_{t \leq T} \| \hat{x}^{(n)}(t) - \hat{x}(t) \| = 0 \text{ (in probability)}$$

$$\text{(i.e. } \lim_{n \rightarrow \infty} \mathbb{P} \left(\sup_{t \leq T} \| \hat{x}^{(n)}(t) - \hat{x}(t) \| > \epsilon \right) = 0, \forall \epsilon > 0)$$



FOR large N , you can "replace" the stoch. system with fluid one. (for TRANSIENT)

SIR	X_S, X_I, X_R	$S + I \rightarrow S + S$	$\cdot k_I \frac{X_S \cdot X_I}{N}$
	$S \in \mathbb{N}^3$	$I \rightarrow R$	$\cdot k_R X_I$
		$R \rightarrow S$	$\cdot k_S \cdot X_R$

$X_S + X_I + X_R = N$ TOTAL POP.

$\hat{x}_S, \hat{x}_I, \hat{x}_R := \frac{X_S}{N}, \frac{X_I}{N}, \frac{X_R}{N}$

• Recovery $k_R X_I = N k_R \frac{X_I}{N} = N k_R \hat{x}_I^{(N)}$
 $\uparrow \uparrow (\hat{x}) = k_R \hat{x}_I^{(N)}$

• Infection $\underbrace{N \cdot k_I X_S X_I}_{(N) \cdot (N)} = N k_I \hat{x}_I \hat{x}_S$
 $\uparrow (\hat{x}) = k_I \hat{x}_I \hat{x}_S$

LINEAR NOISE

$$\mathcal{U}^{(N)} = (X^{(N)}, S^{(N)}, x_0^{(N)}, R^{(N)}) \rightsquigarrow \hat{\mathcal{U}}^{(N)} = (\hat{X}^{(N)}, \hat{S}^{(N)}, \hat{x}_0^{(N)}, \hat{R}^{(N)})$$

- MICROSCOPIC \leftrightarrow we need full stochastic description (small population) **CTMC**
- MESOSCOPIC \leftrightarrow stochastic dynamics, but no need to describe individuals **LINEAR NOISE**
- MACROSCOPIC \leftrightarrow large pop. limit: deterministic description **MEAN FIELD**

ANSATZ: $\hat{X}^{(N)}(t) \approx \underbrace{\hat{x}(t)}_{\text{determ}} + N^{-1/2} \underbrace{\zeta(t)}_{\text{noise}}$ $\leftarrow \zeta$ does not depend on N

$$\frac{d}{dt} P(\hat{X}^{(N)}, t) = \sum_{j \in R^m} N \hat{f}_j(\hat{x}^{(N)} - \hat{v}_j) P(\hat{x}^{(N)} - \hat{v}_j, t) + \sum_{j \in R^m} N \hat{g}_j(\hat{x}^{(N)}) \cdot p(R^m, t)$$

• APPLY ANSATZ

• EXPAND $P(\hat{x} + N^{-1/2} \zeta, t)$ around \hat{x} , reasonable for $N^{1/2} \zeta$ is small

• COLLECT TERMS FOR $\Pi(\zeta, t)$ (density of ζ at time t)

$$F(\hat{x}) = \sum_p v_p \hat{f}_p(\hat{x}) \quad \text{DRIFT}$$

$$\dot{z}(t) = (\dot{z}_{ij}) \quad \dot{z}_{ij}(t) = \sum_p v_p [i] \partial_j \hat{f}_p(\hat{x}(t))$$

$\widehat{\text{MF solution}}$

$$D(\hat{x}) = (D_{ik}(\hat{x}))_{ik} \quad D_{ik}(\hat{x}) = \sum_p v_p [i] v_p [k] \hat{f}_p(\hat{x})$$

$\rightsquigarrow z(t) \in \mathbb{R}^n$ continuous quantity

$$\frac{\partial \Pi(z, t)}{\partial t} = \sum_{i,j} \underbrace{\dot{z}_{ij}(t)}_{\text{on MF}} \partial_i (z_j \Pi(z, t)) + \frac{1}{2} \sum_{i,j} \underbrace{D_{ij}}_{\text{on MF}} \partial_{z_j} \Pi(z, t)$$

\Downarrow

The solution $p(z(t))$ is GAUSSIAN distribution \Leftrightarrow

$$\mu(t) = E[\zeta(t)] =$$

$$C(t) = \text{cov}[\zeta(t)]$$

$$\int \zeta \pi(\zeta, t) d\zeta = \mu(t)$$

$$\frac{d}{dt} \mu(t) = \int \zeta \underbrace{\frac{d}{dt} \pi(\zeta, t)} d\zeta$$

$$\cdot \frac{d}{dt} \mu(t) = \int f(t) \cdot \mu(t) \quad (\text{if } \mu(0) = 0 \Rightarrow \mu(t) = 0 \forall t)$$

$$\cdot \frac{d}{dt} C(t) = \int f(t) \cdot C(t) + C(t) \cdot \int f(t) + D(t)$$

• Solve the MF equation $\hat{x}(t)$

• Solve the equation for $C(t)$ ($O(u^2)$ equations)

Then at time t , $\mathcal{N}(\hat{x}(t), \frac{1}{N} C(t))$

MOMENT CLOSURES

- FIND ODEs FOR MOMENTS of a stochastic process

$$E_t[X_i^m] \quad E_t[X_1 X_2] \quad E_t[X_1^2]$$

we focus on NON-CENTERED MOMENTS, like

$$E_t[X_i^2]$$

in contrast with CENTERED moments

$$E_t\left[\left(X_i - E[X_i]\right)^2\right]$$

$$E_t[X_i^2] = \sum_{x \in S} x_i^2 \cdot p(x, t) \quad \text{solution of CME}$$

$$\frac{d}{dt} \mathbb{E}_t \left[X_1^{m_1} \cdots X_n^{m_n} \right] = \sum_{p \in \mathcal{R}} \mathbb{E}_t \left[f_p(x) \left(\prod_{j=1}^n (x_j + v_p(i_j))^{m_j} - X_1^{m_1} \cdots X_n^{m_n} \right) \right]$$

SYNKIN FORMULA

$$\frac{d}{dt} \mathbb{E}_t[X] = \mathbb{E}_t[F(x)] = \mathbb{E}_t \left[\sum_{p \in \mathcal{R}} v_p \cdot f_p(x) \right] \quad \approx$$

• IF $f_p(x)$ is a linear function of x , then $\mathbb{E}_t[f_p(x)] = f_p(\mathbb{E}[x])$

• IF $f_p(x)$ is non-linear, then $\mathbb{E}_t[f_p(x)] \neq f_p(\mathbb{E}[x])$

IS A FIRST ORDER APPROX OF
 $\mathbb{E}_t[f_p(x)]$

$$\frac{dE_t[X]}{dt} = F(E_t[X]) \quad \text{which is the MEAN FIELD equation}$$

$$\frac{dE_t[X_I]}{dt} = k_I \underbrace{E_t[X_I X_S]}_{E_t[X_I] E_t[X_S]} - k_R E_t[X_I]$$

$$E[X_S^2 X_I] = ? \quad 2 E[X_S] E[X_S X_I] + E[X_S^2] E[X_I] - 2 E[X_S]^2 E[X_I]$$

$$E[(X_S - \mu_S)^2 (X_I - \mu_I)] = 0$$

$$E[(X_S^2 - 2\mu_S X_S + \mu_S^2)(X_I - \mu_I)]$$

$$E[X_S^2 X_I - 2\mu_S X_S X_I + \mu_S^2 X_I - \mu_I X_S^2 + 2\mu_S \mu_I X_S - \mu_S^2 \mu_I]$$