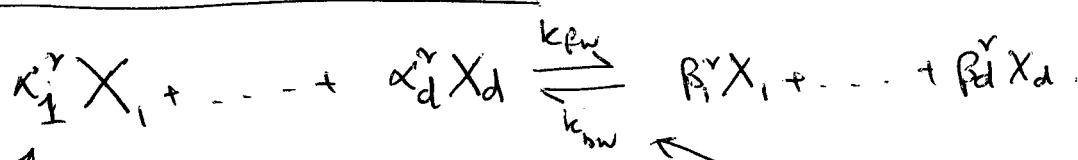


Chemical reaction networks.



EN, r -reactions (directed). $r = 1, \dots, R$. reaction can happen forward and backwards.

k_{fw} - forward reaction rate

k_{bw} - backward reaction rate

Two models: (I) Stochastic, discrete
(II) deterministic, continuous.

(I) Stochastic model:

- observable $\underline{N} = (N_1, \dots, N_d) \in \{0, 1, \dots\}^d$.
(N_i : number of particles of species X_i)
- $\underline{N}(t)$ evolves according to a ch. time. master chain (CTMC). with rates:
 - (*) from \underline{n} to $\underline{n} - \underline{\alpha}^r + \underline{\beta}^r$: $k_{fw}^r \cdot \prod_{i=1}^d \frac{n_i!}{(n_i - \alpha_i^r)!} \cdot \frac{1}{n!^{(\beta_i^r-1)}}$.
 - (**) from \underline{n} to $\underline{n} + \underline{\alpha}^r - \underline{\beta}^r$: $k_{bw}^r \cdot \prod_{i=1}^d \frac{n_i!}{(n_i + \beta_i^r)!} \cdot \frac{1}{n!^{(\alpha_i^r-1)}}$.

Let $n(t) \in \mathbb{P}(\mathbb{N}_0^d)$ be the law of $\underline{N}(t)$. Then.
 $n(t)$ satisfies the chemical master equation.

(II) deterministic model:

- observable $\underline{c} = (c_1, \dots, c_d) \in \mathbb{R}_+^d$; concentration of the species X_i .
- $\underline{c}(t)$ evolves according to reaction rate $\underline{\alpha}^r$:

$$\dot{\underline{c}} = -\underline{R}(\underline{c}), \quad \dot{c}_i(t) = -\sum_{r=1}^R \left(k_{fw}^r \cdot \prod_{j=1}^d c_j(t)^{\alpha_j^r} - k_{bw}^r \cdot \prod_{j=1}^d c_j(t)^{\beta_j^r} \right).$$

• Let $f(t)$ be a prob measure $\in \mathcal{P}(\mathbb{R}_+^d)$
 be the law of $c(t) \in \mathbb{R}_+^d$. Then,
 $f(t)$ evolves according to the Liouville eq:

$$\partial_t f(c) = \text{div}(f(c) R(c)).$$

$\text{ME}(\mathbb{N}_0^d)$

CME



$N(t) \in \mathbb{N}_0^d$

CTMC

$f(t) \in \mathcal{P}(\mathbb{R}_+^d)$.

Liouville.



$c(t) \in \mathbb{R}_+^d$

RRE

kurtz 1970's
 rescaled Markov C.
 converges to $c(t)$:
 $(\forall \epsilon, \text{ if } N(0) \xrightarrow{\text{law}} \delta_0, \quad N(t)/\sqrt{t} \xrightarrow{\text{law}} c(t))$

Gradient flows. Assume.

Assume $\exists \underline{c}^* = (c_1^*, \dots, c_d^*) \in \mathbb{R}_{>0}^d$ s.t.

$$k_{\underline{c}^*}^r := k_{\text{fw}}^r \cdot \prod_{j=1}^d (c_j^*)^{\alpha_j^r} = k_{\text{bw}}^r \cdot \prod_{j=1}^d (c_j^*)^{\beta_j^r} \quad \forall r=1, \dots, R.$$

Then CME, RRE, have gradient flow structures.

• CME: $\dot{u} = -\nabla K(u) D\mathcal{E}(u)$. $\therefore \mathcal{E}(u) = \text{Ent}(u|w^*)$.

$$(w^*)_n = e^{-V(\underline{c}^*)} \cdot \frac{\underline{c}^n \sqrt{n!}}{n!}$$

K - pos. def. infinite dim metric
 \sim inverse of Riem. metric.

• RRE (Mielke): $\dot{c} = k(c) D\mathcal{E}(c)$. $\mathcal{E}(c) = \text{Ent}(\underline{c}|e^*)$.

$$k(c) = \sum_r k_r^r \theta\left(\frac{c^r}{c_r^{\alpha^r}}, \frac{c^r}{c_r^{\beta^r}}\right) (\alpha^r - \beta^r) \otimes (\underline{c}^r - \underline{\beta}^r).$$

$$E(c) = \sum_{i=1}^d c_i^* \ln\left(\frac{c_i}{c_i^*}\right), \quad \ln(t) = t \log(t) - t + 1.$$

• Kullback: $\hat{J} = -K(p) D E(p)$, $E(p) = \int E(c) d\mu(c)$.
 $(K(p))_{\#}(c) = -\operatorname{div}(p(c) K(c) \nabla \Psi(c))$.

Induced distance is \mathcal{W}_2 with underlying Riemann metric K^{-1} .

$$\text{Set } \mathbb{P}_{\text{GME}}^*(m, \xi) = \frac{1}{2} \langle \xi, K(m)\xi \rangle, \quad m \in \mathcal{P}(\mathbb{N}_0^d), \quad \xi: \mathbb{N}_0^d \rightarrow \mathbb{R}.$$

$$\begin{aligned} \mathbb{P}_{\text{M}^{\otimes}}^*(f, \gamma) &= \frac{1}{2} \langle f, K(p)\gamma \rangle, \quad p \in \mathcal{P}(\mathbb{R}_+^d), \\ &= \frac{1}{2} \mathbb{E} \int \langle \nabla \Psi(c), K(c) \nabla \Psi(c) \rangle d\mu(c). \quad \gamma: \mathbb{R}_+^d \rightarrow \mathbb{R}. \end{aligned}$$

Proof (M-Mielke) $\mathbb{P}_{\text{GME}}^* \xrightarrow{V \rightarrow \infty} \mathbb{P}_{\text{M}^{\otimes}}^*$.

Going to the limit: " $\downarrow \varepsilon \rightarrow E$ ".

$$\text{Recall: } \downarrow \varepsilon(m) = \underbrace{\frac{1}{\sqrt{V}} \sum_{n \in \mathbb{N}_0^d} m_n \log m_n}_{\mathcal{E}_V^1(m)} - \underbrace{\frac{1}{\sqrt{V}} \sum_n m_n \log w_n}_{\mathcal{E}_V^2(m)}.$$

Study limit $V \rightarrow \infty$, $m_n \rightarrow \infty$, $m_n/V \rightarrow c_n$.

Suppose $m \in \mathcal{P}(\mathbb{N}_0^d)$ which approximates $p \in \mathcal{P}(\mathbb{R}_+^d)$.

$$\mathcal{E}_V^1(m) \underset{V \rightarrow \infty}{\approx} \int \Psi(c) \log p(c) - d \frac{\log V}{\sqrt{V}} \rightarrow 0 \quad \text{as } V \rightarrow \infty.$$

$$\text{Now, } -\frac{1}{\sqrt{V}} \log w_n^V = \sum_{i=1}^d \left[-\frac{n_i}{\sqrt{V}} \log(N_{c,i}^*) + \frac{\log n_i!}{\sqrt{V}} + c_i^* \right]$$

$$\underset{V \rightarrow \infty}{\approx} E\left(\frac{n}{\sqrt{V}}\right).$$

(Shifting $\log(n)$ $\approx \log n - n$.)

③

$$\text{Thus: } \nabla E(n) \approx \sum E(\frac{w}{n}) n_i \approx \int E(c) d\pi(c) = E(p).$$

\rightsquigarrow binomial eqⁿ is a good approx to CME for large N.

If binomial does not take volume into account. Can we find a better one which does. This note about. The gradient flow approach is suggestive in this direction.

$$\text{First guess: set } \tilde{E}_v(p) = \int E(c) d\pi(c) + \frac{1}{2} \int p(c) \log p(c) dc.$$

\rightsquigarrow associated gradient flow eqⁿ.

$$\partial_t p = -K(p) D\tilde{E}_v(p).$$

(Fokker-Planck eq.).

~~A not~~ (This only considers first term we throw away).

A better approx: \rightarrow Take into account term we threw away from using Stirling's formula in 2nd form.

$$\log n! \approx n \log n - n + \frac{1}{2} \log [2\pi(n+\frac{1}{2})].$$

$$\rightsquigarrow -\frac{1}{n} \log w_n^n \approx E(\frac{n}{N}) + \frac{1}{n} G_v(\frac{n}{N}).$$

$$G_v(c) = \frac{1}{2} \sum_i \log (2\pi(v c_i + \frac{1}{6})).$$

\Rightarrow This leads to: $E_v(p) = E(p) + \frac{1}{v} \int p \log p + \frac{1}{v} (G_v(c) d)(i)$

New equation: $\dot{p} = -K(p) D E(p)$.

$$\dot{p}_i = -\alpha v \left[p(c) R(c) + \frac{1}{v} K(c) \nabla g(c) + p(c) A_v(c) \right].$$

where $A_v(c) = \frac{1}{2} \cdot K(c) \left(\frac{1}{v c + b} \right)_{i=1, \dots, d}$.