Computational physics

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Contents

Stochastic simulation of coupled chemical reactions

Stochastic chemical kinetics

- ► Consider a well-stirred system with N chemically active species {S₁,..., S_N} each with a population X_i (number of molecules) in volume V.
- ► Species can interact via *M* types of unidirectional chemical reactions {*R*₁,...,*R_M*} (reversible reactions can be modeled as two opposite and parallel running processes), for example:

$$\begin{array}{cccc} \emptyset & \to & \text{products} \\ S_j & \to & \text{products} \\ S_j + S_k & \to & \text{products} & (j \neq k) \\ 2S_j & \to & \text{products} \\ S_i + S_j + S_k & \to & \text{products} & (i \neq j \neq k \neq i) \\ S_j + 2S_k & \to & \text{products} & (j \neq k) \\ 3S_j & \to & \text{products}, \end{array}$$

where products are again combinations of $\{S_1, \ldots, S_N\}$.

Stochastic chemical kinetics

- ► The reaction velocity of each reaction type {R₁,..., R_M} is characterized by a constant parameter {c₁,..., c_M}.
- **Fundamental hypothesis of stochastic chemical kinetics:**
 - $c_{\mu}\delta t \equiv$ the average probability that a particular combination of reactant molecules will react according to R_{μ} in V in the next infinitesimal time interval δt .
- Valid for well stirred systems dominated by elastic collisions such that positions of molecules are always uniformly randomized in V and their velocities are Maxwell-Boltzmann distributed.
- Remark: It is assumed that the occurrence of multiple reactions is of order o(δt) and thus vanishes for δt → 0.

Chemical master equation

- ► The aim is, under the above assumptions, to construct an algorithm for the time evolution of {X_i}(t) given the initial conditions {X_i}(0) and reaction parameters {c_µ}.
- ► Chemical master equation for the probability, P({X_i}; t), that {X_i} molecules of species {S_i} are present in V at time t is:

$$\begin{aligned} \frac{\partial}{\partial t} \mathcal{P}(\{X_i\}; t) &= - \sum_{\{X_i^*\}} w(\{X_i\} \to \{X_i^*\}) \mathcal{P}(\{X_i\}; t) \\ &+ \sum_{\{X_i^*\}} w(\{X_i^*\} \to \{X_i\}) \mathcal{P}(\{X_i^*\}; t) (2) \end{aligned}$$

- Eq.(2) completely determines $\mathcal{P}(\{X_i\}; t)$.
- Particle number moments $\langle X_i^k \rangle = \sum_{\{X_i\}} X_i^k \cdot \mathcal{P}(\{X_i\}; t)$, like $\langle X_i \rangle$ and $\langle X_i^2 \rangle$, could be obtained.
- However, Eq.(2) is not easily solvable neither analytically nor numerically.

Stochastic simulation algorithm

Instead of computing probability density function $P({X_i}; t)$ for ${X_i}(t)$ simulate trajectories of ${X_i}(t)$ (compare random walk).

- Define new probability:
 - $P(\tau,\mu) d\tau \equiv \text{the probability at time } t \text{ that the next re-} (3)$ action in the system will occur in the infinitesimal time interval $[t + \tau, t + \tau + d\tau)$ and will be an R_{μ} reaction.

Further, define

 $h_{\mu} \equiv$ the number of distinct molecular reactant (4) combinations for R_{μ} reaction at time t

Stochastic simulation algorithm

Reaction type R_{μ} and distinct reactant combinations h_{μ} .



 $h_{\mu}c_{\mu}\delta t = \text{probability of a reaction of type } R_{\mu} \text{ occurring}$ (5) in the next time interval δt

 $P(\tau,\mu)d\tau = P_0(\tau) \cdot h_\mu c_\mu d\tau$, where $P_0(\tau)$ is the probability at time t that no reaction will occur in $[t, t + \tau)$ and $h_\mu c_\mu d\tau$ is the probability that R_μ will occur subsequent in $[t + \tau, t + \tau + d\tau)$.

Reaction probability density function $P(\tau, \mu)$

=

Estimate of $P_0(\tau)$:

- Divide $[t, t + \tau)$ into K equal subintervals of length $\epsilon = \frac{\tau}{K}$.
- ► The probability that none of the reactions {R₁,..., R_M} occurred in [t, t + ε) is

$$\prod_{\nu=1}^{M} [1 - h_{\nu} c_{\nu} \epsilon + o(\epsilon)] \approx 1 - \sum_{\nu=1}^{M} h_{\nu} c_{\nu} \epsilon + o(\epsilon).$$
 (6)

• Same expressions result for the remaining K-1 subintervals

$$P_0(\tau) = \left[1 - \sum_{\nu=1}^{M} h_{\nu} c_{\nu} \epsilon + o(\epsilon)\right]^{\kappa}$$
(7)

$$= \left[1 - \sum_{\nu=1}^{M} h_{\nu} c_{\nu} \frac{\tau}{K} + o(K^{-1})\right]^{K}$$
(8)

$$= \left[1 - \left(\sum_{\nu=1}^{M} h_{\nu} c_{\nu} \tau + \frac{o(K^{-1})}{K^{-1}}\right) \frac{1}{K}\right]^{K}$$
(9)

Reaction probability density function

• In the limit $K \to \infty$ we obtain:

$$P_0(\tau) = \exp\left[-\sum_{\nu=1}^M h_\nu c_\nu \tau\right]$$
(10)

Finally, the reaction probability density function reads as

$$P(\tau,\mu) = P_0(\tau)h_{\mu}c_{\mu} = h_{\mu}c_{\mu}\exp\left[-\sum_{\nu=1}^{M}h_{\nu}c_{\nu}\tau\right]$$
(11)

with normalization

$$\int_{0}^{\infty} d\tau \sum_{\mu=1}^{M} P(\tau, \mu) = \sum_{\mu=1}^{M} h_{\mu} c_{\mu} \int_{0}^{\infty} d\tau \exp\left[-\sum_{\nu=1}^{M} h_{\nu} c_{\nu} \tau\right] = 1 \quad (12)$$

Eq.(11) is the mathematical basis for the stochastic simulation approach, since it contains all the information needed to treat stochastic chemical kinetics via Monte-Carlo method. Overview of Gillespie's stochastic simulation algorithm

- Step 0 (Initialization): set initial molecular populations {X_i}(0) and reaction parameters {c_µ}, calculate {h_µ}.
- Step 1 (Monte Carlo): generate a random reaction time and type (τ, μ) according to P(τ, μ).
- Step 2 (Update): advance $t \to t + \tau$, update the populations $\{X_i\}(t)$ of species $\{S_i\}$ involved in the reaction R_{μ} , update $\{h_{\mu}\}$ accordingly.
- Step 3 (Terminate): If t > t_{max} or no reaction type is possible, i.e., {h₁,..., h_M} = {0,...,0}, then terminate, else go to Step 1.

Gillespie's direct method

How to generate (τ, μ) from $P(\tau, \mu)$?

Apply chain rule, i.e., write joint probability distribution

$$P(\tau,\mu) = P_1(\tau) \cdot P_2(\mu|\tau) \tag{13}$$

as product of

$$P_1(\tau)d\tau \equiv$$
 probability that the next reaction (irrespective of type) will occur in $[t + \tau, t + \tau + d\tau)$

and

 $P_2(\mu|\tau) \equiv$ conditional probability that the next reaction will be an R_μ reaction given that it occurs at time $t + \tau$

Using Eq.(11) we get

$$P_{1}(\tau) = \sum_{\mu=1}^{M} P(\tau, \mu) = a_{0} \exp(-a_{0}\tau)$$
(14)

$$P_2(\mu|\tau) = P(\tau,\mu)/P_1(\tau) = a_\mu/a_0,$$
 (15)

with abbreviations $a_\mu \equiv h_\mu c_\mu$ and $a_0 \equiv \sum_\mu h_\mu c_\mu \equiv \sum_\mu a_\mu.$

Implementing the Monte Carlo Step

Step 1a (pick the reaction time): generate a uniformly distributed random number r₁ ∈ [0, 1] and set

$$\tau = \frac{1}{a_0} \ln\left(\frac{1}{r_1}\right),\tag{16}$$

see inverse transform sampling.

Step 1b (pick the reaction type): generate a uniformly distributed random number r₂ ∈ [0, 1] and set µ to be the integer for which

$$\sum_{\nu=1}^{\mu-1} a_{\nu} < r_2 a_0 < \sum_{\nu=1}^{\mu} a_{\nu}, \qquad (17)$$

see rejection sampling.

First-reaction method

A reminder: $a_{\mu}\delta t$ is the probability that a reaction R_{μ} occurs in δt .

 $\lim_{K \to \infty} \left(1 - a_{\mu} \frac{\tau}{K} \right)^{K} a_{\mu} \delta t = \text{probability that no reaction } R_{\mu} \text{ takes place}$ in [0, τ] but occurs later in [$\tau, \tau + \delta t$]

and thus

$$P_{\mu}(\tau)d\tau = e^{-a_{\mu}\tau}a_{\mu}d\tau = \text{probability at time } t \text{ that a reaction } R_{\mu} \text{ takes}$$

place $[t + \tau, t + \tau + d\tau]$ provided that the population involved in R_{μ} does not change in $[t, t + \tau]$

Implementing the Monte Carlo Step:

- Generate *M* uniform random numbers $\{r_1, ..., r_M\} \in [0, 1]$.
- Compute tentative reaction times $\tau_{\nu} = \frac{1}{a_{\nu}} \ln \left(\frac{1}{r_{\nu}} \right)$ for $\nu \in \{1, ..., M\}.$
- Choose as the actual next reaction the one which occurs first:

$$\tau = \text{ the smallest of the } \{\tau_{\nu}\}$$
(18)

$$\mu =$$
 the index of the smallest $\{ au_
u\}$ (19)

First-reaction method

Proof that this method generates $P(\tau, \mu)$ from Eq.(11).

Reaction probability corresponding to procedure described above:

$$\widetilde{P}(au,\mu)d au = \Pr(au < au_{\mu} < au + d au) \cdot \Pr(au_{
u} > au, \, orall
u
eq \mu)$$
 (20)

Since

$$\Pr(\tau < \tau_{\mu} < \tau + d\tau) = \exp(-a_{\mu}\tau)a_{\mu}d\tau \qquad (21)$$

and

$$Pr(\tau_{\nu} > \tau, \forall \nu \neq \mu) = Pr \{(1/a_{\nu}) ln (1/r_{\nu}) > \tau, \forall \nu \neq \mu\}$$

$$= Pr \{r_{\nu} < \exp(-a_{\nu}\tau), \forall \nu \neq \mu\}$$

$$= \prod_{\nu \neq \mu} Pr\{r_{\nu} < \exp(-a_{\nu}\tau)\}$$

$$= \prod_{\nu \neq \mu} \exp(-a_{\nu}\tau)$$
(22)

we obtain

$$\widetilde{P}(\tau,\mu)d\tau = e^{-a_{\mu}\tau}a_{\mu}d\tau\prod_{\nu\neq\mu}e^{-a_{\nu}\tau} = a_{\mu}e^{-a_{0}\tau}d\tau = P(\tau,\mu)d\tau \quad (23)$$

Example

System of four chemical species W, X, Y and Z subject to six coupled chemical reactions:

$$X \quad \underbrace{\stackrel{c_1}{\overleftarrow{c_2}}}{Y} \qquad (24)$$
$$2X \quad \underbrace{\stackrel{c_3}{\overleftarrow{c_4}}}{Z} \qquad (25)$$
$$W + X \quad \underbrace{\stackrel{c_5}{\overleftarrow{c_6}}}{Z} \qquad (26)$$

In the deterministic approach the following system of coupled nonlinear ODES must be solved:

$$\frac{dW}{dt} = -c_5 WX + \frac{1}{2}c_6 X^2$$
(27)

$$\frac{dX}{dt} = -c_1 X + c_2 Y - c_3 X^2 + 2c_4 Z + c_5 WX - \frac{1}{2}c_6 X^2 (28)$$

$$\frac{dY}{dt} = c_1 X - c_2 Y$$
(29)

$$\frac{dZ}{dt} = \frac{1}{2}c_3 X^2 - c_4 Z$$
(30)

Example

Chemical reaction system

$$X \stackrel{c_1}{\underset{c_2}{\leftarrow}} Y \tag{31}$$

$$2X \stackrel{\scriptstyle{\scriptstyle \leftarrow}}{\underset{\scriptstyle C_{4}}{\overset{\scriptstyle{\scriptstyle \leftarrow}}}} Z \tag{32}$$

$$W + X \stackrel{c_5}{\leftarrow} 2X$$
 (33)

and the corresponding master equation

$$\begin{aligned} \frac{d\mathcal{P}(W, X, Y, Z; t)}{dt} &= \\ c_1\{(X+1)\mathcal{P}(W, X+1, Y-1, Z; t) - X\mathcal{P}(W, X, Y, Z; t)\} \\ + c_2\{(Y+1)\mathcal{P}(W, X-1, Y+1, Z; t) - Y\mathcal{P}(W, X, Y, Z; t)\} \\ &+ c_3\{\frac{1}{2}(X+2)(X+1)\mathcal{P}(W, X+2, Y, Z-1; t) \\ &- \frac{1}{2}X(X-1)\mathcal{P}(W, X, Y, Z; t)\} \\ + c_4\{(Z+1)\mathcal{P}(W, X-2, Y, Z+1; t) - Z\mathcal{P}(W, X, Y, Z; t)\} \end{aligned}$$

Next-subvolume method

- So far simulation methods apply to well stirred systems, i.e., diffusion is so fast that all concentrations are homogenous in space.
- If system size is to large to be homogenized by diffusion on the timescale of the chemical reactions the system becomes spatially heterogeneous and a method with spatial resolution is needed.
- Elf et al. proposed an extension of Gillespie's direct method to simulate spatially resolved reaction-diffusion kinetics on mesoscopic level.
- The total system is divided into N subvolumes (SVs), chosen so small that the concentrations of reactants in a SV are near-homogeneous in space.
- The molecules in a SV can either undergo chemical reactions or diffuse to a neighboring SV.

Sketch of the next-subvolume method

- Calculate first the next event time (reaction or diffusion) in each SV and identify the SV with the smallest next event time, very similar to the first-reaction method.
- Apply Gillespie's direct method to the SV with the smallest next event time in order to decide if the next event is a chemical reaction or a diffusion jump and which species are involved in this event.
- ▶ The time for the next event in each SV is ordered in an event queue, which makes the computation time linear in log *N*, rather then in *N*.

Next-subvolume method



Figure 1: An example of indexing n^3 cells. From Elf *et al.*

Figure 2: In the event queue, the elements are ordered such that, in each branch of the binary tree, a SV with an earlier event time t is higher up. The Q array keeps a reference to the SVs position in the event queue. From Elf *et al.*

Application of the next-subvolume method

- Simulation of the spatial oscillation patterns that are displayed by the Min system of *Escherichia coli*.
- In wild-type E. coli, the Min proteins oscillate back and forth between the cell poles to help the bacterium find its middle before cell division.



Figure 3: Min system reaction scheme and rate constants. From Fange *et al.*



Figure 4: Membrane-bound MinD is shown in blue, and MinE in complex with MinD on the membrane is shown in red, see movie https://doi.org/10.1371/journal.pcbi.0020080

Literature

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