



Stochastic formulation of reaction networks

Stochastic analysis and simulation of reactive and diffusive systems

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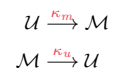
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Basics on randomness

Stochastic formulation

Measurements

Consider the reversible transformation of some protein between two forms



Consider the **time s between successive modifications** (reaction events)

- ↪ Each s is single instance of reaction time measurement
- ↪ Each s takes the form of a positive real number

Our interest is not in individual time-between-reaction measurements

- We are interested in their class of measurements

Because the time between modification varies depending on a number of un-modelled conditions, this time is represented as a random variables which we denoted with S

- ↪ The single values s are replaced by the range of values of S
- ↪ From single/unique/deterministic times to random ones

S is a rule (mapping) that assigns a unique number $s \geq 0$ to each time measurement

- (S is a continuous random variable)

Measurements (cont.)

The **number $n_u(t)$ of un-modified molecules**, at time t , is an integer in a measurement

If we monitor this abundance for a system, we get a unique time-function $(n_u(t))_{t \geq 0}$

- A certain value $n(t) = n_u(t)$ of unmodified molecules, at each time point t

Again, we are interested in the abundance for an arbitrary (a class of) system(s)

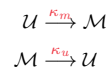
- ↪ Copy-numbers $n_u(t)$ are no longer single/unique/deterministic quantities
- ↪ They are modelled/replaced as time-dependent random quantities $N_u(t)$
 - (To account for the fact that they will vary between systems)

$N(t)$ is a rule that assigns a unique integer $n_u(t) \in \{0, 1, 2, \dots\}$ to each measurement

- ($N_u(t)$ is a discrete random variable)

Probability

Consider again the reversible transformation of some protein between two forms



Suppose that **every molecule can be labelled, irrespective of its form** (\mathcal{U} or \mathcal{M})

$$\Omega = \{\omega_1, \omega_2, \dots, \omega_n, \dots, \omega_{\bar{n}}\}$$

Imagine picking one molecule, no consideration about its form and/or position

- ↪ The outcome of this experiment cannot be determined uniquely
- ↪ We only know that it will be an element $\omega_n \in \Omega$

Intuitively, each molecule can be assumed to be equally likely to be selected

- We assign to each molecule ω_n the same likelihood

$$\mathbb{P}_{\omega_n} = \frac{1}{\bar{n}} \quad (\text{for all } \omega_n \in \Omega)$$

Probability (cont.)

$$\mathbb{P}_{\omega_n} = \frac{1}{\bar{n}} \quad (\text{for all } \omega_n \in \Omega)$$

We are interested in being able to assign these numbers not only to single molecules

- (For example, what are the chances of picking molecules labelled $\omega_n < 0.1\bar{n}$?)

In reality, we are interested in subsets A of Ω , or **events**, and their likelihood

$$\mathbb{P}[\{\omega_n, \omega_n \in \Omega\}] = \frac{1}{\bar{n}}$$

$$\mathbb{P}[\{\omega_n : \omega_n < 1/\bar{n}, \omega_n \in \Omega\}] = \dots$$

$$\mathbb{P}[A = \{\omega_n : \text{something else}, \omega_n \in \Omega\}] = \dots$$

$$\dots = \dots$$

Not all subsets of Ω are events and we are not interested in all of its possible subsets

The space of the events of interest, a collection of subsets of Ω , is the **event space** \mathcal{A}

- $\mathbb{P}[\cdot]$ is a set function, a rule for assigning probabilities (likelihoods) to sets

$$\mathbb{P} : \mathcal{A} \rightarrow [0, 1]$$

Probability (cont.)

Given a collection of elementary events, we can combine events to form new events

Consider, for example, the event $A = \{\{1\}, \{3\}\}$ as union $\{1\} \cup \{3\}$

- Given a function $\mathbb{P}[\cdot]$, we can write

$$\mathbb{P}[A] = \mathbb{P}[\{1\}] + \mathbb{P}[\{3\}]$$

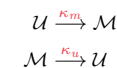
Now consider event $B = \{\{1\}, \{2\}\}$ and then the event $\{A\} \cup \{B\}$

$$\mathbb{P}[A \cup B] = \mathbb{P}[\{\{1\}, \{3\}\} \cup \{\{1\}, \{2\}\}]$$

$$\neq \mathbb{P}[A] + \mathbb{P}[B]$$

Random variables

Consider again the reversible transformation of a protein between two forms \mathcal{U} and \mathcal{M}



Suppose that now **molecules are labelled in terms of their form** (say, $\mathcal{U} = 1$ and $\mathcal{M} = 0$)

Suppose also that before picking a molecule we know that n_u molecules are unmodified

- Thus, we also know that $(\bar{n} - n_u) = n_m$ molecules are in modified form

Consider the event A ‘a molecule is of form 1’, or $Y = 1$

$$\mathbb{P}[Y = 1 | n_u] = \frac{n_u}{\bar{n}}$$

$$\neq \underbrace{\mathbb{P}[Y = 1]}_{\text{unknown}}$$

Conditional on knowing n_u , the probability $\mathbb{P}[Y = 1 | n_u]$ is given by the ratio between the number of elements in the event space A and the number in the sample space Ω

Random variables | Discrete

Given $\mathbb{P}[Y = 1] = p_u$ (with p_u to be determined), we have a description of variable Y

$$\begin{cases} \mathbb{P}[Y = 1] &= p_u \\ \mathbb{P}[Y = 0] &= \underbrace{1 - p_u}_{p_m} \end{cases}$$

Such a description is referred to as **probability** (mass) **distribution** (function)

- Function $\mathbb{P}[\cdot]$ assigns a likelihood to all possible values y of Y
- (In this problem, probabilities can be assigned to $y \in \{0, 1\}$)

Random variable Y is a **Bernoulli variable** and function $\mathbb{P}[\cdot]$ is a Bernoulli distribution

- The distribution function has one parameter, p_u

Random variables | Average

The **average** is a measure of the **expected value** from a distribution of probabilities

The average is often associated with a list of values of some measured quantity

- 1 It is computed by summing all the values collected in the list
- 2 Then, by dividing it by the number of values in the list

Consider the random variable Y that assign value $y = 1$ to un-modified molecules

If n_u out of \bar{n} molecules are known to be un-modified, after summing the labels

$$\underbrace{(1) + (1) + \dots + (1)}_{n_u \text{ times}} + \underbrace{(0) + (0) + \dots + (0)}_{(\bar{n} - n_u) \text{ times}} = n_u$$

Conditional on having n_u un-modified molecules, we have the conditional average

$$\begin{aligned} \langle Y | n_u \rangle &= \frac{(1) \times n_u + (0) \times (\bar{n} - n_u)}{\bar{n}} \\ &= \frac{(1) \times n_u}{\bar{n}} + \frac{(0) \times (\bar{n} - n_u)}{\bar{n}} \\ &= \underbrace{\frac{n_u}{\bar{n}}}_{n_u / \bar{n}} \end{aligned}$$

Random variables | Average (cont.)

$$\langle Y | n_u \rangle = \underbrace{(1) \times \frac{n_u}{\bar{n}} + (0) \times \frac{(\bar{n} - n_u)}{\bar{n}}}_{n_u / \bar{n}}$$

The conditional average is a ratio between the size of event \mathcal{A} and the sample space Ω

- It is also equal to the (conditional) probability of $Y = 1$

This procedure can be extended to find the unconditional average value of variable Y

$$\begin{aligned} \langle Y \rangle &= \underbrace{(1)}_{y=1} \times \underbrace{p_u}_{\mathbb{P}[Y=1]} + \underbrace{(0)}_{y=0} \times \underbrace{(1 - p_u)}_{\mathbb{P}[Y=0]} \\ &= p_u \end{aligned}$$

We can also further generalise the procedure to any discrete random variable Y

$$\langle Y \rangle = \sum_{y \in A} y \mathbb{P}[Y = y]$$

Random variables | Variance

The **variance** is a measure of the spread of the distribution around the average

The variance is the average of the squared deviations $\langle (Y - \langle Y \rangle)^2 \rangle$

$$\langle (Y - \langle Y \rangle)^2 \rangle = \sum_{y \in A} (y - \langle Y \rangle)^2 \mathbb{P}[Y = y]$$

For the problem of the \mathcal{M} and \mathcal{U} molecules, we have

$$\begin{aligned} \langle (Y - \langle Y \rangle)^2 \rangle &= [(1 - p_u)^2 p_u + [(0 - p_u)^2 (1 - p_u)] \\ &= (1 - p_u) p_u \end{aligned}$$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Continuous

Consider a protein that can change its length l between two fixed real values a and b

Now imagine an experiment where we can measure the length L of the protein

↪ L can be modelled as a random variable with values in $[a, b]$

We use length $b - a$ of the interval as measure of size and assign probabilities to events

$$l \leq L \leq l + \Delta l$$

If all subintervals of the same length are equally probable, then for any l

$$\mathbb{P}[l \leq L \leq l + \Delta l] = \frac{\Delta l}{b - a}$$

(We used again the relative-size interpretation of probability)

Now consider a vanishingly small interval $\Delta l \rightarrow 0$, we get a probability per unit length

$$\frac{\mathbb{P}[l \leq L \leq l + dl]}{dl} = \frac{1}{(b - a)} \quad (l \in [a, b])$$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Continuous (cont.)

$$\frac{\mathbb{P}[l \leq L \leq l + dl]}{dl} = \frac{1}{(b - a)} \quad (l \in [a, b])$$

The probability per unit length is a probability density $p(l)$ of a continuous variable L

The probability that L falls in the interval (a, b)

$$\begin{aligned} \mathbb{P}[a < L < b] &= \int_a^b \underbrace{p(l)dl}_{\mathbb{P}[l \in [l, l+dl]]} \\ &= 1 \end{aligned}$$

The expected value of L ,

$$\begin{aligned} \langle L \rangle &= \int_l l p(l) dl \\ &= (a + b)/2 \end{aligned}$$

The variance of L ,

$$\begin{aligned} \langle (l - \langle L \rangle)^2 \rangle &= \int_l (l - \langle L \rangle)^2 p(l) dl \\ &= (b - a)^2 / 12 \end{aligned}$$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Joint probability

Consider two events A and B that are disjoint, no elements in common, $A \cap B = \emptyset$

↪ The occurrence of one event rules out the occurrence of the other one

We extend the experiment of picking one molecule to the selection of two molecules

↪ For the first molecule, we have variable $Y_1 = \{y_1 = 0, y_1 = 1\}$

↪ For the second one, we have variable $Y_2 = \{y_2 = 0, y_2 = 1\}$

For the two molecules, we have the sample space $\Omega = \Omega_{Y_1} \times \Omega_{Y_2}$

↪ The set of all possible pairs of labels

- $\Omega = \{(0, 0), (0, 1), (1, 1), (1, 0)\}$

Consider the event $Y_1 = y_1 \cap Y_2 = y_2$ and the number of elements in this event space

$$\#(Y_1 = y_1 \cap Y_2 = y_2) = \#(Y_1 = y_1) \times \#(Y_2 = y_2)$$

(True IFF the first selected molecule is placed back before the second selection occurs)

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Joint probability (cont.)

Using the relative-size interpretation of probability, we get the joint probability

$$\begin{aligned} \mathbb{P}[Y_1 = y_1 \cap Y_2 = y_2] &= \frac{\#(Y_1 = y_1) \times \#(Y_2 = y_2)}{\#(\Omega_{Y_1}) \times \#(\Omega_{Y_2})} \\ &= \frac{\#(Y_1 = y_1)}{\#(\Omega)} \times \frac{\#(Y_2 = y_2)}{\#(\Omega)} \\ &= \mathbb{P}[Y_1 = y_1] \times \mathbb{P}[Y_2 = y_2] \end{aligned}$$

The selection sequences (0, 0), (0, 1), (1, 1), and (1, 0) have the likelihoods

$$\begin{aligned} \rightsquigarrow \text{For } (0, 0), \text{ we have } \mathbb{P}[Y_1 = 0, Y_2 = 0] &= \underbrace{\mathbb{P}[Y_1 = 0]}_{1-p_u} \times \underbrace{\mathbb{P}[Y_2 = 0]}_{1-p_u} \\ \rightsquigarrow \text{For } (0, 1), \text{ we have } \mathbb{P}[Y_1 = 0, Y_2 = 1] &= \underbrace{\mathbb{P}[Y_1 = 0]}_{1-p_u} \times \underbrace{\mathbb{P}[Y_2 = 1]}_{p_u} \\ \rightsquigarrow \text{For } (1, 1), \text{ we have } \mathbb{P}[Y_1 = 1, Y_2 = 1] &= \underbrace{\mathbb{P}[Y_1 = 1]}_{p_u} \times \underbrace{\mathbb{P}[Y_2 = 1]}_{p_u} \\ \rightsquigarrow \text{For } (1, 0), \text{ we have } \mathbb{P}[Y_1 = 1, Y_2 = 0] &= \underbrace{\mathbb{P}[Y_1 = 1]}_{p_u} \times \underbrace{\mathbb{P}[Y_2 = 0]}_{1-p_u} \end{aligned}$$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Joint probability (cont.)

The assumption of independence is the consequence of placing back the first molecule

- (Without replacement, the joint sample space would be smaller, $\bar{n}(\bar{n} - 1)$)
- (Also, the size of the joint events would depend on the first outcome)

Without independence, we have the equivalent factorisations of the joint probability

$$\begin{aligned}\mathbb{P}[Y_1 = y_1 \cap Y_2 = y_2] &= \mathbb{P}[Y_2 = y_2 | Y_1 = y_1] \times \mathbb{P}[Y_1 = y_1] \\ &= \mathbb{P}[Y_1 = y_1 | Y_2 = y_2] \times \mathbb{P}[Y_2 = y_2]\end{aligned}$$

The factorisation of the joint probability $\mathbb{P}[A \cap B] = \mathbb{P}[B] \mathbb{P}[A|B]$ has useful consequences if the sample space Ω can be partitioned into disjoint collections B_1 and B_2

Then, each event $A \cap B_{n_b}$ represents the joint occurrence of A and associated B_{n_b}

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Joint probability (cont.)

Summing up the joint occurrences of event A and B_{n_r} gives the probability of event A

$$\begin{aligned}\mathbb{P}[A] &= \sum_{n_r=1}^{N_r} \mathbb{P}[A \cap B_{n_r}] \\ &= \sum_{n_r=1}^{N_r} \mathbb{P}[B_{n_r}] \mathbb{P}[A|B_{n_r}]\end{aligned}$$

The probability of event A can be represented as the sum of probabilities of the joint occurrence of A with a collection of disjoint events B_{n_r} that cover the sample space Ω

- This relationship is known as the **total law of probability**

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Joint probability (cont.)

We can use the total probability to determine p_u

We defined the probability of picking an unmodified molecule, given n_u \mathcal{U} molecules

$$\mathbb{P}[Y = 1 | n_u] = n_u / \bar{n}$$

Let N_u be the number of unmodified molecules, a random variable with values n_u

Summing up the probabilities of event $Y = 1 \cap N_u = n_u$, over all possible n_u

$$\begin{aligned}\mathbb{P}[Y = 1] &= \sum_{n_u} \mathbb{P}[Y = 1 \cap N_u = n_u] \\ &= \sum_{n_u} \mathbb{P}[Y = 1 | N_u = n_u] \mathbb{P}[N_u = n_u] \\ &= \sum_{n_u} \frac{n_u}{\bar{n}} \mathbb{P}[N_u = n_u] \\ &= \frac{1}{\bar{n}} \langle N_u \rangle\end{aligned}$$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Sum of random variables

The **sum of two or more random variables** is also a random variable

The sum $Y_1 + Y_2 = Y$ is a random variable

- $\rightsquigarrow Y = 0$ with sequence (0, 0)
- $\rightsquigarrow Y = 1$ with sequences (1, 0) and (0, 1)
- $\rightsquigarrow Y = 2$ with sequence (1, 1)

We know the probabilities of each of those sequences,

$$\mathbb{P}[Y = y] = \begin{cases} (1 - p_u)^2, & y = 0 \\ 2p_u(1 - p_u), & y = 1 \\ p_u^2, & y = 2 \end{cases}$$

The expected value $\sum_y y \mathbb{P}[Y = y]$

$$\begin{aligned}\langle Y \rangle &= (0)(1 - p_u)^2 + (1)[2p_u(1 - p_u)] + (2)p_u^2 \\ &= 2p_u^2\end{aligned}$$

The variance $\sum_y (y - \langle Y \rangle)^2 \mathbb{P}[Y = y]$

$$\begin{aligned}&= (0 - 2p_u)^2(1 - p_u)^2 + (1 - 2p_u)^2[2p_u(1 - p_u)] + (2 - 2p_u)^2 p_u^2 \\ &= 2p_u(1 - p_u)\end{aligned}$$

Random variables | Sum of random variables (cont.)

The average of the sum is the sum of the averages

$$\left\langle \sum_{n_y} Y_{n_y} \right\rangle = \sum_{n_y} \langle Y_{n_y} \rangle$$

The variance of the sum is the sum of the variances

$$\left\langle \left(\sum_{n_y} Y_{n_y} - \left\langle \sum_{n_y} Y_{n_y} \right\rangle \right)^2 \right\rangle = \sum_{n_y} \langle (Y_{n_y} - \langle Y_{n_y} \rangle)^2 \rangle$$

Random variables | Probability distributions

Consider a further extension of the experiment of selecting molecules $\mathcal{U} = 1$ and $\mathcal{M} = 0$

↪ We selected a single molecule, then we selected two molecules

- While always keeping the same p_u

We now consider the case of **selecting \bar{n} -long sequences of molecules**, with replacement

Variable $N = \sum_{n=1}^{\bar{n}} Y_n$ models the number of unmodified molecules in the sequence

The probability of a sequence of n_u (1)s first and then $(\bar{n} - n_u)$ (0)s

$$\mathbb{P} \left[Y = \left(\underbrace{(1) \cdots (1)}_{n_u \text{ times}} \underbrace{(0) \cdots (0)}_{(\bar{n}-n) \text{ times}} \right) \right] = p_u^{n_u} (1 - p_u)^{\bar{n} - n_u}$$

There are a known number of sequences of n_u (1)s and $(\bar{n} - n_u)$ (0)s

$$\binom{\bar{n}}{n_u} = \frac{\bar{n}!}{n_u! (\bar{n} - n_u)!}$$

Each is equally probable, thus

$$\mathbb{P}[N = n_u] = \binom{\bar{n}}{n_u} \left[p_u^{n_u} (1 - p_u)^{\bar{n} - n_u} \right]$$

Random variables | Probability distributions (cont.)

Random variable N has a **binomial distribution** $\mathbb{P}[N = n_u] = \binom{\bar{n}}{n_u} [p_u^{n_u} (1 - p_u)^{\bar{n} - n_u}]$

- The parameters of the distribution are \bar{n} and p_u

The expected value,

$$\langle N \rangle = \bar{n} p_u$$

The variance,

$$\langle (n - \langle N \rangle)^2 \rangle = \bar{n} p_u (1 - p_u)$$

Random variables | Probability distributions (cont.)

Consider the problem of increasing the length \bar{n} of the sequence while decreasing p_u

$$\uparrow \bar{n} \times p_u \downarrow = \underbrace{\text{constant}}_{\mu}$$

The limiting behaviour of the binomial, for infinitely large \bar{n} and infinitely small p_u

For $\bar{n} \rightarrow \infty$, we have

$$\begin{aligned} \binom{\bar{n}}{n_u} p_u^{n_u} &= \frac{\bar{n}(\bar{n}-1)(\bar{n}-2) \cdots (\bar{n}-n_u+1)}{n_u!} p_u^{n_u} \\ &= \frac{\bar{n} p_u}{n_u!} \left(1 - \frac{1}{\bar{n}} \right) \cdots \left(1 - \frac{n_u-1}{\bar{n}} \right) \\ &\rightarrow \frac{\mu^{n_u}}{n_u!} \end{aligned}$$

For $\bar{n} \rightarrow \infty$, we have

$$(1 - p_u)^{\bar{n}} = \left(1 - \frac{\mu}{\bar{n}} \right)^{\bar{n}} \rightarrow e^{-\mu}$$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Probability distributions (cont.)

$$\mathbb{P}[N = n_u] = \underbrace{\binom{\bar{n}}{n_u} p_u^{n_u}}_{\frac{\mu^{n_u}}{n_u!}} \underbrace{(1 - p_u)^{\bar{n} - n_u}}_{e^{-\mu}}$$

Substituting, we get

$$\mathbb{P}[N = n_u] = \frac{\mu^{n_u} e^{-\mu}}{n_u!}$$

This is called the **Poisson distribution** with parameter μ and Y is a **Poisson variable**

- Parameter μ substitutes $\bar{n} \times p_u$
- Model for rare events

The expected value,

$$\langle N \rangle = \mu$$

The variance,

$$\langle (N - \langle N \rangle)^2 \rangle = \mu$$

For infinitesimally small p_u , average and the variance of the distribution are the same

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Poisson processes

Suppose we repeat the experiment of picking a **sequence of \bar{n} molecules at each time t**

- At each time t , we determine how many of them are in unmodified form

We have a random process $(N(t))_{t \geq 0}$ and $\langle (N(t))_{t \geq 0} \rangle$ is its expected time course

Consider the zeroth-order reaction in which molecules of a certain protein \mathcal{S} are produced from some uninteresting reactants, here \emptyset , at a constant conversion rate $\lambda = \widehat{k}$



In the deterministic setup, the time-dependent abundance $n(t)$ has kinetics $\dot{n}(t) = \widehat{k}$

$$n(t) = \widehat{k}t$$

In the stochastic setting, the time-dependent abundance can be seen as mean trajectory

$$\langle N(t) \rangle = \lambda t$$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Poisson processes (cont.)



We are interested in the random process $N(t+s) - N(t)$ representing the **random increment in abundance** of species \mathcal{S} in the time interval $[t, t+s)$, from a known $N(t)$

Consider the **average increment**

$$\begin{aligned} \langle N(t+s) - N(t) \rangle &= \langle N(t+s) \rangle - \langle N(t) \rangle \\ &= \lambda(t+s) - \lambda t \\ &= \lambda s \end{aligned}$$

The expected increment is independent of time t when the measurement is performed

↪ This is an important result

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Poisson processes (cont.)

$$[t, t+s)$$

Suppose that we divide the time interval $[t, t+s)$ in K subintervals of length $\Delta s = s/K$

- ↪ The intervals Δs are so small that only one reaction (production) occurs
- ↪ We let the probability of occurrence of the reaction in Δs to be $\lambda \Delta s$
- ↪ (This probability is thus a Bernoulli random variable)

Each subinterval Δs contributes an increment ΔN to the abundance current $N(t)$

The expected contribution from each subinterval,

$$\begin{aligned} \langle \Delta N \rangle &= \lambda \Delta s \\ &= \lambda \frac{s}{K} \end{aligned}$$

The **subincrement is a Bernoulli variable**, as only one of two events can occur in Δs

- A production reaction occurs and $\Delta N = 1$, with probability $p = \lambda \Delta s$
- No reaction occurs and $\Delta N = 0$, with probability $q = 1 - p$

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Poisson processes (cont.)

$$\langle \Delta N \rangle = \lambda \frac{s}{K}$$

As $p = \lambda \Delta s$, we interpret conversion rates λ as reaction probabilities in the unit time

↪ Importantly, note that the probability $\lambda \Delta s$ does not depend on s or $N(t)$



For the production reaction, we have defined the random process

$$N(t+s) - N(t) = K \Delta N(s)$$

This is a sum of K Bernoulli variables, hence a binomial variable

↪ The parameters of the distribution are K and p

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Poisson processes (cont.)

$$N(t+s) - N(t) = K \Delta N(s)$$

K must be large for the subinterval to be small to allow only one rare reaction event

- For $K \rightarrow \infty$ and $p \rightarrow 0$, a binomial variable becomes Poissonian

$$\begin{aligned} \mathbb{P}[N(t+s) - N(t) = n] &= \mathbb{P}[N(s) = n] \\ &= \frac{(\lambda s)^n e^{-\lambda s}}{n!} \end{aligned}$$

We have a time-dependent (on s) probability, a Poisson process with rate parameter λ

- The average and the variance of the process are equal to $\mu = \lambda s$

Independence on t implies that increments in non-overlapping intervals are stationary

- Lack of dependence on $N(t)$ implies that increments are identically distributed



Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Poisson processes (cont.)

$$\begin{aligned} \mathbb{P}[N(t+s) - N(t) = n] &= \mathbb{P}[N(s) = n] \\ &= \frac{(\lambda s)^n e^{-\lambda s}}{n!} \end{aligned}$$

Let us consider the case of $n = 0$, we get

$$\begin{aligned} \mathbb{P}[N(s) = 0] &= \frac{(\lambda s)^0 e^{-\lambda s}}{0!} \\ &= e^{-\lambda s} \end{aligned}$$

The time S until the next reaction has probability $e^{-\lambda s}$ of being greater than s

$$\mathbb{P}[S > s] = e^{-\lambda s}$$

It implies that time S is an exponentially distributed variable, with parameter λ

- The distribution does not depend on t or $N(t)$

The times between reactions are independent and identically distributed variables

Randomness

Formulation

Chapman-
Kolmogorov
Master equation

Random variables | Poisson processes (cont.)

The time S until the next reaction is exponentially distributed

$$p(s) = \lambda e^{-\lambda s} \quad (s \geq 0)$$

The probability of the next reaction between $[t, t+s]$

$$\begin{aligned} \mathbb{P}[S_n \leq s] &= 1 - e^{-\lambda s} \\ &= \int_{-\infty}^s p(s) ds \end{aligned}$$

The exponential distribution does not remember its past

$$\begin{aligned} \mathbb{P}[S > t+s \mid S > t] &= \frac{\mathbb{P}[S > t+s \cap S > t]}{\mathbb{P}[S > t]} \\ &= \frac{\mathbb{P}[S > t+s] \mathbb{P}[S > t]}{\mathbb{P}[S > t]} \\ &= \frac{\mathbb{P}[S > t+s]}{\mathbb{P}[S > t]} \\ &= \frac{e^{-\lambda(t+s)}}{e^{-\lambda s}} \\ &= \underbrace{e^{-\lambda s}}_{\mathbb{P}[S > s]} \end{aligned}$$

Random variables | Poisson processes (cont.)

$$\mathbb{P}[S > t + s \mid S > t] = \mathbb{P}[S > s]$$

Given that an event has not occurred until time t , the probability that it will not occur in an additional time s equals the probability of the event not occurring until a time s

- ↪ This is the **memoryless property** of the exponential distribution
- ↪ Any variable satisfying the property is an exponential variable

Random variables | Poisson processes (cont.)



We may be interested in characterising the **time S_n of occurrence of the n -th reaction**

- This is the time the process needs to reach state n
- The arrival time of the n -th reaction

We consider the likelihood that the n -th reaction occurs in some interval $[s, s + \Delta s]$

- 1 $n - 1$ reactions must have occurred in $[0, s]$
- 2 The n -th reaction in the interval Δs

The event of interest is a joint event that involves two non-overlapping time intervals

$$\begin{aligned} \mathbb{P}[s \leq S_n \leq s + \Delta t] &= \mathbb{P}[(N(t) = n - 1) \cap (\Delta N(t) = 1)] \\ &= \mathbb{P}[N(t) = n - 1] \times \mathbb{P}[\Delta N(t) = 1] \\ &= \frac{e^{-\lambda s} (\lambda s)^{n-1}}{(n-1)!} \times (\lambda \Delta s) \end{aligned}$$

Random variables | Poisson processes (cont.)



That is, the probability density of the n -th arrival time S_n

$$p(s) = \frac{\lambda^n s^{n-1}}{(n-1)!} e^{-\lambda s}$$

The distribution of an **Erlang variable** with rate parameter λ and shape parameter n

Because arrival times can be described as sums $\sum_{n=0}^{n-1} S_n$ of n inter-reaction times, all exponentially distributed with the rate parameter λ , their sum are Erlang variables

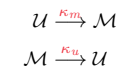
Random variables | Reactions

Poisson processes describe time-dependent abundances $N(t)$ for zeroth-order reactions

- ↪ The conversion rate λ was interpreted as probability per unit time

We are interested in whether a similar interpretation is valid for arbitrary reactions (?)

Consider the usual modification/demodification reaction of a protein between two forms



In the deterministic set up, we have the two conversion rates

$$\begin{aligned} \dot{z}_m(t) &= k_m n(t) \\ \dot{z}_u(t) &= k_u [\bar{n} - n(t)] \end{aligned}$$

The reaction count increments during a small interval $[t, t + \Delta t]$

$$\begin{aligned} \Delta z_m(t) &= k_m n(t) \Delta t \\ \Delta z_u(t) &= k_u [\bar{n} - n(t)] \Delta t \end{aligned}$$

Random variables | Reactions (cont.)

$$\mathcal{U} \xrightarrow{\kappa_m} \mathcal{M}$$

$$\mathcal{M} \xrightarrow{\kappa_u} \mathcal{U}$$

In the stochastic setup, the count increments are replaced by two stochastic processes

- Both counts are Bernoulli variables, as at most one event occurs in Δt
- The average of a Bernoulli variable is the success probability

The deterministic increments can only be interpreted in an average sense

$$\langle \Delta Z_m(t) \mid N(t) = n(t) \rangle = k_m n(t) \Delta t$$

$$\langle \Delta Z_u(t) \mid N(t) = n(t) \rangle = k_u [\bar{n} - n(t)] \Delta t$$

That is,

$\rightsquigarrow k_m n(t) \Delta t$ is the success probability for the modification

$\rightsquigarrow k_u [\bar{n} - n(t)] \Delta t$ is the success probability for demodification

Then, $k_m n(t)$ and $k_u [\bar{n} - n(t)]$ are probabilities per unit time of the respective reaction

Differently from the Poisson process, this process have a state-dependent probability

- A Markov process

Random variables | Reactions (cont.)

$$\mathcal{U} \xrightarrow{\kappa_m} \mathcal{M}$$

$$\mathcal{M} \xrightarrow{\kappa_u} \mathcal{U}$$

Let $T_m(n)$ and $T_u(n)$ be times until the next modification and demodification reaction

The probability of a modification in Δt is $k_m n \Delta t$

- If n is constant, a Poisson arrival
- $T_m(n)$ is an exponential variable
- The rate parameter is $k_m n$

The probability of a demodification in Δt is $k_u [\bar{n} - n] \Delta t$

- If $[\bar{n} - n]$ is constant, a Poisson arrival
- $T_u(n)$ is an exponential variable
- The rate parameter $k_u [\bar{n} - n]$

We could draw both times and use the shortest one to deduce which reaction occurred

Random variables | Reactions (cont.)

Alternatively, we can determine the time $T_n(n)$ until the next reaction

- Irrespective of which one it will be

As long as n does not change, the next reaction is a Poisson arrival

- $T_n(n)$ is an exponential variable
- Parameter $k_m [n] + k_u [\bar{n} - n]$

The type of the next reaction

- Modification, with probability $\frac{k_m [n]}{k_m [n] + k_u [\bar{n} - n]}$
- De-modification, with probability $\frac{k_u [\bar{n} - n]}{k_m [n] + k_u [\bar{n} - n]}$ or $1 - \frac{k_m [n]}{k_m [n] + k_u [\bar{n} - n]}$

Stochastic formulation

Reaction networks

Stochastic formulation

We show how the notion of **propensity**, the **chemical master equation**, and the **stochastic simulation algorithm** can be seen as emerging as consequence of the **Markov property**

The presentation is based on the stochastic formulation of an arbitrary reaction network

We started acknowledging that modelling the occurrence of reactions involves **discrete and random events** that arise from a system that is not described microscopically

- It is not possible to predict deterministically the progress of a reactive system, starting from (macroscopic) variables (copy number and relative concentration)
- The processes $(N(t))_{t \geq 0}$, $(Z(t))_{t \geq 0}$, or $(X(t))_{t \geq 0}$ must be stochastic

Stochastic formulation (cont.)

Say, we choose the copy-number $N(t)$, then the sample value $n(t)$ is the system's state

↪ The objective is to determine the evolution of the process $(N(t))_{t \geq 0}$

Starting at time $t = 0$, from some initial state $N(t = 0) = N(0)$, the system remains in state $N(0)$ for a random amount of time, S_1 , until the occurrence of a reaction event

↪ Then, the state changes from $N(t = 0)$ to become $N(t = S_1)$

The system remains in state $N(S_1)$ for another random amount of time, say S_2

↪ Until the occurrence of a new reaction, then $N(t = S_1 + S_2)$

The collection $(N(t))_{t \geq 0}$ of time-dependent copy-numbers is a **stochastic process**

- A collection of **state probabilities** and **state-transition probabilities**
- This specific stochastic process is called a **jump process**

Stochastic formulation (cont.)

$$(N(t))_{t \geq 0}$$

The **state probability** is the probability that the process is in state n at certain time t

$$\begin{aligned} \text{Prob}[N(t) = n] &= \mathbb{P}(n, t) \\ &= \mathbb{P}(n(t)) \\ &= \mathbb{P}_n(t) \end{aligned}$$

If one species, $N_s = 1$

$$N(t) = n \in \{0, 1, 2, \dots\}$$

If two species, $N_s = 2$

$$N(t) = (n_1, n_2) \in \{0, 1, 2, \dots\} \times \{0, 1, 2, \dots\}$$

If N_s species

$$N(t) = (n_1, n_2, \dots, n_{N_s}) \in \underbrace{\{0, 1, 2, \dots\} \times \{0, 1, 2, \dots\} \times \dots \times \{0, 1, 2, \dots\}}_{N_s \text{ times}}$$

Stochastic formulation (cont.)

$$(N(t))_{t \geq 0}$$

The **state-transition probability** is the conditional probability that the process, during the time interval $[t, t + s]$, evolves to state n , given that it started in state n' at t

$$\begin{aligned} \text{Prob}[N(t + s) = n \mid N(t) = n'] &= \mathbb{P}(n, t + s \mid n', t) \\ &= \mathbb{P}(n(t + s) \mid n'(t)) \\ &= \mathbb{P}_{n|n'}(t + s \mid t) \end{aligned}$$

Stochastic formulation (cont.)

We assume that the state-transition probability depends only on state n at t , not on earlier ones, and that the duration s of the interval does not depend on initial time t

↪ **Markovianity** (first assumption)

↪ **Time-homogeneity** (second assumption)

When the molecules in the reaction system are well-mixed and available everywhere for reaction, then $(N(t))_{t \geq 0}$ can be formulated as time-homogeneous Markov process

Stochastic formulation (cont.)

We can write state and state-transition probability functions using a simplified notation

$$\begin{aligned}\text{Prob}[N(t) = n] &= \mathbb{P}_n(t) \\ \text{Prob}[N(t+s) = n \mid N(t) = n'] &= \mathbb{P}_{n|n'}(t+s|t)\end{aligned}$$

The initial condition is often, although not necessarily, fixed to be $N(t=0) = n^0$

Thus, the state probability can always be given as transition probability

$$\mathbb{P}_{n|n^0}(t|0) = \text{Prob}[N(t) = n \mid (N(0) = n^0)]$$

Chapman-Kolmogorov

Stochastic formulation

Chapman-Kolmogorov

Markovianity sets a consistence condition on the transition probabilities $\mathbb{P}_{n|n'}(t+s|t)$

Consider the probability of being at state n' at some time $t+s$, given initial state n^0

$$\begin{aligned}\mathbb{P}_{n|n^0}(t+s|0) &= \sum_{n'} \mathbb{P}_{n|n',n^0}(t+s|t,0) \mathbb{P}_{n'|n^0}(t|0) \\ &= \sum_{n'} \mathbb{P}_{n|n'}(t+s|t) \mathbb{P}_{n'|n^0}(t|0)\end{aligned}$$

Because of first-order Markovianity, we can ignore information about the initial state

We can write the Chapman-Kolmogorov equation for continuous-Markov processes

$$\mathbb{P}_{n|n^0}(t+s|0) = \sum_{n'} \mathbb{P}_{n|n'}(t+s|t) \mathbb{P}_{n'|n^0}(t|0)$$

Spelling the equation, the probability of a transition $n^0 \rightarrow n'$ can be computed as the summation of probabilities of all transitions $n^0 \rightarrow n \rightarrow n'$ via intermediate states n'

To characterise the equation to a specific process, we need relations between variables

- Form the local behaviour of transition probabilities over a short interval Δs

$$\mathbb{P}_n(t+\Delta s) = \sum_{n'} \mathbb{P}_{n|n'}(t+\Delta s|t) \mathbb{P}_{n'}(t)$$

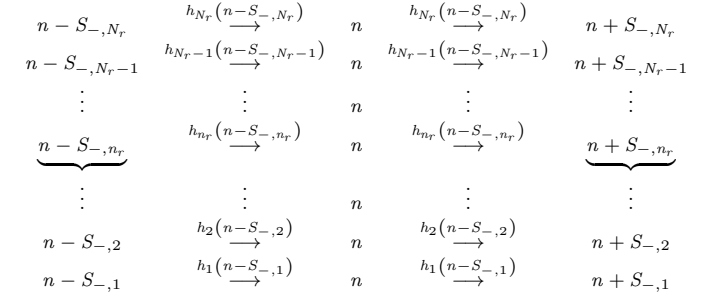
Master equation

Stochastic simulation

Master equation

The occurrence of any reaction event moves the system from some state to another one

The possible state transitions to state n and from state n



The transition rate of a state transition from a single reaction equals the propensity of that reaction and the transition rate from more reaction is the sum of their propensities

Master equation (cont.)

We used

$$\underbrace{\begin{bmatrix} n_1 \\ \vdots \\ n_s \\ \vdots \\ N_s \end{bmatrix}}_n - \underbrace{\begin{bmatrix} S_{1,n_r} \\ \vdots \\ S_{n_s,n_r} \\ \vdots \\ S_{N_s,n_r} \end{bmatrix}}_{S_{-,n_r}} \quad \text{and} \quad \underbrace{\begin{bmatrix} n_1 \\ \vdots \\ n_s \\ \vdots \\ N_s \end{bmatrix}}_n + \underbrace{\begin{bmatrix} S_{1,n_r} \\ \vdots \\ S_{n_s,n_r} \\ \vdots \\ S_{N_s,n_r} \end{bmatrix}}_{S_{-,n_r}}$$

The stoichiometric matrix

$$S = \begin{bmatrix} (\bar{S}_{1,1} - \underline{S}_{1,1}) & \cdots & (\bar{S}_{n_s,1} - \underline{S}_{n_s,1}) & \cdots & (\bar{S}_{N_s,1} - \underline{S}_{N_s,1}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ (\bar{S}_{1,n_r} - \underline{S}_{1,n_r}) & \cdots & (\bar{S}_{n_s,n_r} - \underline{S}_{n_s,n_r}) & \cdots & (\bar{S}_{N_s,n_r} - \underline{S}_{N_s,n_r}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ (\bar{S}_{1,N_r} - \underline{S}_{1,N_r}) & \cdots & (\bar{S}_{n_s,N_r} - \underline{S}_{n_s,N_r}) & \cdots & (\bar{S}_{N_s,N_r} - \underline{S}_{N_s,N_r}) \end{bmatrix}^T$$

Master equation (cont.)

The probability to be at state $n = (n_1, \dots, n_s, \dots, N_s)$ at time t changes with time

$$\mathbb{P}_n(t)$$

To understand how $\mathbb{P}_n(t)$ changes in time, we need to determine $\mathbb{P}_n(t + \Delta t)$

↪ The probability of being in state n after a short interval Δt

For vanishingly small Δt , we could then use $\mathbb{P}_n(t)$ and $\mathbb{P}_n(t + \Delta t)$ to get

$$\frac{\mathbb{P}_n(t) - \mathbb{P}_n(t + \Delta t)}{\Delta t} \rightsquigarrow \frac{d\mathbb{P}_n(t)}{dt}$$

The resulting equation of motion can be integrated, from an initial condition $\mathbb{P}_n(t_0)$

- The solution $(\mathbb{P}_n(t) \mid \mathbb{P}_n(t_0))_{t \geq 0}$ is the transition probability kernel

Master equation (cont.)

We must determine how to reach state n at $t + \Delta t$, given that at t the state is n'

- \rightsquigarrow State n can be reached any state n' such that $n' = n - S_{-,1 \rightsquigarrow N_r}$
- \rightsquigarrow State n can be reached any state n' such that $n' = n$

For each of the options, we know also the probability of occurrence in a small Δt

$$\mathbb{P}_{n|n'}(\Delta t) = \begin{cases} h_1(n - S_{-,1} | \kappa_1) \Delta t, & n' = n - S_{-,1} \\ h_2(n - S_{-,2} | \kappa_{-2}) \Delta t, & n' = n - S_{-,2} \\ \dots, & \dots \\ h_{n_r}(n - S_{-,n_r} | \kappa_{n_r}) \Delta t, & n' = n - S_{-,n_r} \\ \dots, & \dots \\ h_{N_r-1}(n - S_{-,N_r-1} | \kappa_{N_r-1}) \Delta t, & n' = n - S_{-,N_r-1} \\ h_{n_r}(n - S_{-,N_r} | \kappa_{N_r}) \Delta t, & n' = n - S_{-,N_r} \\ 1 - \sum_{n_r=1}^{N_r} h_{n_r}(n | \kappa_{n_r}) \Delta t, & n' = n \\ 0, & \text{elsewhere} \end{cases}$$

Master equation (cont.)

Substituting the expressions for $\mathbb{P}_{n|n'}(\Delta t)$ into Chapman-Kolmogorov, we get

$$\begin{aligned} \mathbb{P}_n(t + \Delta t) &= \sum_{n'} \mathbb{P}_{n|n'}(\Delta t) \mathbb{P}_{n'}(t) \\ &= h_1(n - S_{-,1}) \Delta t \mathbb{P}_{n-S_{-,1}}(t) \\ &\quad + h_2(n - S_{-,2}) \Delta t \mathbb{P}_{n-S_{-,2}}(t) \\ &\quad + \dots \\ &\quad + h_{n_r}(n - S_{-,n_r} | \kappa_{n_r}) \Delta t \mathbb{P}_{n-S_{-,n_r}}(t) \\ &\quad + \dots \\ &\quad + h_{N_r-1}(n - S_{-,N_r-1} | \kappa_{N_r-1}) \Delta t \mathbb{P}_{n-S_{-,N_r-1}}(t) \\ &\quad + h_{n_r}(n - S_{-,N_r} | \kappa_{N_r}) \Delta t \mathbb{P}_{n-S_{-,N_r}}(t) \\ &\quad + \left[1 - \sum_{n_r=1}^{N_r} h_{n_r}(n | \kappa_{n_r}) \Delta t \right] \mathbb{P}_n(t) \end{aligned}$$

Master equation (cont.)

$$\begin{aligned} \mathbb{P}_n(t + \Delta t) &= \mathbb{P}_n(t) \left[1 - \sum_{n_r=1}^{N_r} h_{n_r}(n | \kappa_r) \Delta t \right] \\ &\quad + \sum_{n_r=1}^{N_r} \mathbb{P}_{n-S_{-,n_r}} h_{n_r}(n - S_{-,n_r} | \kappa_{n_r}) \Delta t + \text{h.o.t.} \end{aligned}$$

Neglecting the higher-order terms and rearranging, we can write

$$\begin{aligned} \frac{\mathbb{P}_n(t + \Delta t) - \mathbb{P}_n(t)}{\Delta t} &= - \sum_{n_r=1}^{N_r} \mathbb{P}_n(t) h_{n_r}(n | \kappa_r) + \sum_{n_r=1}^{N_r} \mathbb{P}_{n-S_{-,n_r}} h_{n_r}(n - S_{-,n_r} | \kappa_{n_r}) \\ &= \sum_{n_r=1}^{N_r} \left[\mathbb{P}_{n-S_{-,n_r}} h_{n_r}(n - S_{-,n_r} | \kappa_{n_r}) - \mathbb{P}_n(t) h_{n_r}(n | \kappa_r) \right] \end{aligned}$$

For a vanishingly small time interval Δt , we get the chemical master equation

$$\frac{d\mathbb{P}_n(t)}{dt} = \sum_{n_r=1}^{N_r} \left[\underbrace{h_{n_r}(n - S_{-,n_r} | \kappa_{n_r}) \mathbb{P}_{n-S_{-,n_r}}(t)}_{\text{inflow}} - \underbrace{h_{n_r}(n | \kappa_{n_r}) \mathbb{P}_n(t)}_{\text{outflow}} \right]$$