

che ca, ec ca, ca, ...) ba ed e g, e ab ked f i a and e a F ac of be e e g e ha ca ke f e **data-driven modeling** and ke a e **mechanistically derived modeling**. N e, acc d g Ka P e (1902 1994) and h h o k of ce h ce, ke h eg a e c e h fic ac fa f g a k ke ka e i e fi f i a e a k ke v h ch e e i g f a e h ke da a (e.g., e ca k ke) and e e g a echa (e.g., de g), and (b) de e g ed c f a k ke h ch a f of g ca, a he a ca, ded c.

Le i e e of ke e h a ead d ed, de i ed, h a h of ke ke cha e b e i be c ca. I Ch a l H e h and L d ced ke g h a e h g h a g ce f a i a g v e e e 100 da ke h e i a e h e e e 50 da and h a f a e e e 25 da I h fac, ke g h a e

$$= \lim_{\Delta t \rightarrow 0} \frac{P(+\Delta) - P(-\Delta)}{\Delta}$$

I h a h a e a e (fi h) h e of ke h a h c o l c e of N h a ca o i B i d e h a e e h e i a h f i a g h? A h a f of a e h, h e e h of a e? C e a h h e ca h h be i e h h e Δ a : population change ca h h a e h h e g e h be

Seco h d, h a a h h e e e e e h a e g a i a g h h h e ac v e h h ke fi 100 da and a h h e h h e h e 100 da? I a i e e of v a h a i a h a e age.

I h deed, *discreteness* and *probability* a e v h h da e h a e h a i a h d h a c B h h a e be h g h e d h h e d f f e e h a e i a h b a e d d e c h of i a h d h a c W e h a a d a g i a h h e c a h e be v h. M e of h e a e a a e a e h f [1, 19, 20, 22, 23, 28, 31].

6.2.1 Brief Review of Elementary Probabilities

A **random variable** a g a c h h e a a i e h a a b a b d e h fi c h (df) f ():

$$\int_{-\infty}^{\infty} f(x) dx = 1, f(x) \geq 0. \tag{6.1}$$

The e a h g of ke f () h f h fi h e a d, ke b a b of b e h g e (, + d] f () d :

$$P\{x < \leq x + d\} = f(x) d. \tag{6.2}$$

Let $\lambda > 0$. The probability that a component will fail in the interval $(t, t + \Delta t)$ is $\lambda \Delta t$, independent of the age of the component.

$$\frac{dF(t)}{dt} = \lambda e^{-\lambda t} \quad (6.9)$$

If the components are identical and independent, then

$$P\{\text{all } n \text{ components survive for time } t\} = e^{-n\lambda t} \quad (6.10)$$

Let T be the time until the first component fails. Then

$$P\{\text{all } n \text{ components survive for time } t\} = P\{T > t\} \quad (6.11)$$

T is a continuous random variable. The cumulative distribution function $F_T(t) = P\{T \leq t\} = 1 - e^{-n\lambda t}$ and the probability density function $f_T(t) = dF_T(t)/dt = n\lambda e^{-n\lambda t}$.

What is the probability that the first component will fail in the interval $(t, t + \Delta t)$? A good idea is to use the fact that the probability that the first component will fail in the interval $(t, t + \Delta t)$ is $\lambda \Delta t$ (e.g., see [15]).

6.2.2.1 Rare Event

Let T be the time until the first component fails. If the components are identical and independent, then the probability that the first component will fail in the interval $(t, t + \Delta t)$ is $\lambda \Delta t$ (e.g., see [15]).

$$P\{\text{first component fails in } [0, \Delta t]\} = \lambda \Delta t \quad (6.12)$$

$$P\{\text{first component fails in } [0, t]\} \times P\{\text{first component fails in } [t, t + \Delta t]\}.$$

Then

$$P\{T > t + \Delta t\} = P\{T > t\} \times P\{\text{first component fails in } [t, t + \Delta t]\}.$$

Let $\Delta t = \Delta$, and let $\lambda \Delta = \alpha$. Then

$$P\{T > t + \Delta\} = P\{T > t\} \times (1 - \alpha + \alpha e^{-\lambda t}). \quad (6.13)$$

The,

$$\frac{d}{dt} P \{ T > t \} = -\lambda P \{ T > t \}, \implies F_T(t) = 1 - e^{-\lambda t}. \quad (6.14)$$

E a e: The a g e f e fi e c g a e h e h g a e g a da .

6.2.2.2 Memoryless

One of the a h , h fac def h g , e e of e h a d b ed a g e

$$\frac{P \{ T \geq t + \tau \}}{P \{ T \geq t \}} = \frac{e^{-\lambda(t+\tau)}}{e^{-\lambda t}} = e^{-\lambda \tau}. \quad (6.15)$$

E a e: Ya ad a b ke d h g e e h e b e e h e a h e of a h e h a d b ed e h . E e h h g h b h e a c h g e a h e h a e h a h , h e d g a c h b e e a c h e a e a h

Mo e e e h g , h e e h d d a h a i a h , h e f a e h e e h e . I h a h e a c a e i f a $T \sim \lambda^{-1}$ a h d h e a e h d e h d e h d b ed , h e h $T^* = (T_1, T_2, \dots, T)$ a h a h e h a d b h

$$\begin{aligned} P \{ T^* > t \} &= P \{ T_1 > t, \dots, T_n > t \} \\ &= P \{ T_1 > t \} \times P \{ T_2 > t \} \times \dots \times P \{ T_n > t \} = e^{-\mu t}, \end{aligned} \quad (6.16)$$

h e e $\mu = \lambda_1 + \lambda_2 + \dots + \lambda_n$. Th $f_{T^*}(t) = \mu e^{-\mu t}$.

6.2.2.3 Minimal Time of a Set of Non-Exponential i.i.d. Random Times

N c h d e a e of a h d e $\{T\}$. The a e *identical, independently distributed* (i.i.d.) a h d e h d f $f_T(t)$ a h d a e b a b d b h $F_T(t)$. The $T^* = (T_1, T_2, \dots, T)$ h a d b h

$$P \{ T^* > t \} = (1 - F_T(t))^n. \quad (6.17)$$

N , h d c h g c a e d $\hat{T}^* = T^*$ a h d c h d e h g h e e a g e , d b h

$$P \{ \hat{T}^* > t \} = (1 - F_T(t))^n \simeq \left(-\frac{F_T'(0)}{t} + O(t^{-2}) \right)^n \rightarrow -n F_T'(0) t^{-n-1}. \quad (6.18)$$

The following,

$$P\{N = \ell\} = F_T(\ell) - F_{T+1}(\ell). \quad (6.20)$$

Now, if we add the condition that T^* be less than or equal to ℓ , then we have $T^* \leq \ell$ if and only if $T \leq \ell$. In fact, the following

$$\begin{aligned} P\{T^* \leq \ell\} &= \sum_{\ell=0}^{\infty} P\{N = \ell\} P\{T_{\ell+1} \leq \ell\} \\ &= \sum_{\ell=0}^{\infty} (F_T(\ell) - F_{T+1}(\ell)) F_{T+1}(\ell). \end{aligned} \quad (6.21)$$

The following is the derivative of the above T^*

$$f_{T^*}(\ell) = \frac{d}{d\ell} P\{T^* \leq \ell\}. \quad (6.22)$$

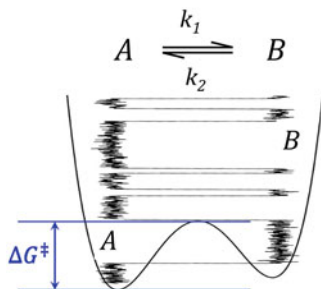


Fig. 6.2 The relationship between the equilibrium constant of a chemical reaction and the Gibbs free energy of activation. The equilibrium constant is given by $k_1/k_2 = e^{-\Delta G^\ddagger/RT}$.

6.2.4 Population Growth

We have defined $\frac{d}{dt} = -\lambda$... λ : ad ... e deca. Ad ... de ...
 ee ka a ... a d ... can be a ... $\frac{d}{dt} = \lambda$...
 ka f ... a ... d ...
 The a ... e ... b ... f ... d ... e ... d ... ea ... b ...
 a ... e ... ! The ... a ... g ... e ... f ... ke ... b ... k ... e ... e ... c ... e ... d ... be ... e ...
 F ... ke ... e ... ke ... a ... e ... e ... c ... e ... d ... be ...
 ... a ... ke ... be ... f ... d ... d ... a ...
 ... e ... h ... ke ... a ... (E ... e ... 1.2), a ...
 ...). The ... e ... e, on average the
 growth is 1 additional person in $(\mathbb{E}[\dots])^{-1}$ time:

$$\frac{d}{dt} \mathbb{E}[\dots] = \mathbb{E}[\dots]. \tag{6.25}$$

Dea k ... a ... e ... h ... b ... k ... a ... e ... e ... h ... , a ... e ... a ... h ...
 d ... a ... c ... a ... b ... c ... h ... g ... ke ... i ... a ... h ... a ... d ... a ... b ...
 ... g ... c ... a ... e ... h ... ka ... e ... a ... d ...
 cha ... g ... g ... i ... a ... h ... S ... cha ... c ... h ... ke ... h ... g ... of ... ke ... a ...
 ... e ... h ... Th ...
 k J. D. M ... a ... a ... e ... d ... [17] ka ... c ... h ... i ... g ...
 ... h ... de ... f ... a ... e ... c ... e ... a ... e ...
 ka ... e ... ke ... i ... h ... e ... a ... c ... h ... e ... a ... h ... e ... i ... a ... h ...:

$$\frac{d}{dt} = b_k - dea_k + g_a, \tag{6.26}$$

ke e ... ke ... a ... h ... de ...

6.2.5 Discrete State Continuous Time Markov (Q) Processes

D ... ce ... e ... a ... e ... c ... h ... i ... g ... e ... Ma ...
 ... ce ... e ... a ... e ... e ... e ... ca ... e ... d ... i ... a ... Ma ...
 ... a ... h ... Q ... ce ... e ... a ... e ... h ... g ... fi ... d ... ced ...
 A ... ke ... Je ... h ... 1954 ... b ... A ...
 Distribution Model, Applicable to Economics and the b ... Da ... d ... F ... e ... d ...
 1971 ... b ... Markov Chains. I ... e ... of ... ke ... bab ...
 of ... a ... e ... a ... e ... , ...
 ... e ... ka ...

$$(\dots + d) - (\dots) = \left(\sum_{\ell=1}^N \ell(\dots) \ell \right) d, \tag{6.27}$$

ke e ... d ... ke ... a ... h ... bab ... f ... a ... e ... l ...
 ke ... h ... ke ... h ... fi ... e ... a ...
 ... e ... h ... e ... a ... d ... E ... (6.27) ... ca ... e ... d ... a ... master equation. I ...
 fi ... da ... e ... a ...
 $P(\dots) = Q$... ke ... e ... ke ... Q ... a ... ka ...
 off ... d ... ag ... a ... e ... e ... h ...
 ≥ 0 and

$$H = - \sum_{j \neq i} \dots \tag{6.28}$$

The \dot{x} of the Kolmogorov backward equation is given by $\dot{x} = -\sum_{j=1}^N \lambda_j x_j$ and $\dot{x} = 0$. The

$$\frac{d}{dt} \sum_{i=1}^N x_i \left(\frac{\partial}{\partial x_i} \right) \leq 0. \tag{6.31}$$

The \dot{x} of the Kolmogorov backward equation is given by $\dot{x} = -\sum_{j=1}^N \lambda_j x_j$ and $\dot{x} = 0$. The

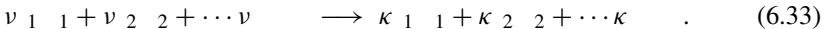
The \dot{x} of the Kolmogorov backward equation is given by $\dot{x} = -\sum_{j=1}^N \lambda_j x_j$ and $\dot{x} = 0$. The

$$\frac{d}{dt} \sum_{i=1}^N (\pi_i(x)) \left(\frac{\partial}{\partial x_i} \right) \leq 0. \tag{6.32}$$

The \dot{x} of the Kolmogorov backward equation is given by $\dot{x} = -\sum_{j=1}^N \lambda_j x_j$ and $\dot{x} = 0$. The

6.3 Theory of Chemical and Biochemical Reaction Systems

A general chemical reaction is given by



$1 \leq i \leq n$. The ν_i and κ_j are called *stoichiometric coefficients*, the x_i are called *chemical species*.

6.3.1 Differential Equation and Nonlinear Dynamics

Because of the conservation of mass,

$$\frac{d}{dt} \sum_{i=1}^n (\kappa_j - \nu_j) \hat{\phi}_j(x) \tag{6.34}$$

where ν_j is the coefficient of the reaction j , $1 \leq j \leq n$, and

$$\hat{\varphi}(\mathbf{x}) = \prod_{j=1}^n \frac{\nu_j^{x_j}}{x_j!} \quad (6.35)$$

is called the probability density function of the reaction $\mathbf{x} = (x_1, x_2, \dots, x_n)$. E_{ν} . (6.34)

is called a ν -independent E_{ν} . (6.35) is called the law of mass action (LMA).

6.3.2 Delbrück-Gillespie Process (DGP)

Let ν be a vector of non-negative integers, $\nu_j \geq 0$, $j = 1, 2, \dots, n$. Let E_{ν} be the reaction $\mathbf{x} = (\nu_1, \nu_2, \dots, \nu_n)$. The DGP is a Markov process with the generator \mathcal{L} defined by

$$\varphi(\mathbf{X}) = \prod_{\ell=1}^n \left(\frac{\nu_{\ell}}{(\nu_{\ell} - \ell)! V^{\nu_{\ell}}} \right), \quad (6.36)$$

where ν_{ℓ} is the coefficient of the reaction ℓ . Note $\varphi(\mathbf{X})$ has the form $\prod_{\ell=1}^n \frac{\nu_{\ell}}{(\nu_{\ell} - \ell)!}$. Call ν_{ℓ} the

$$\begin{aligned}
 &= \int \lambda^{-\lambda} \prod_{\ell=1, \ell \neq}^{\infty} \left(\int \lambda_{\ell}^{-\lambda_{\ell}} d_{\ell} \right) \\
 &= \left(\frac{\lambda}{\lambda_1 + \dots + \lambda} \right)^{-(\lambda_1 + \dots + \lambda)}. \tag{6.39}
 \end{aligned}$$

The equality follows from the fact that the mapping $\{T\}$ given by $\{T\}$ and $\{T^*\} \equiv \{T\}$ and $\{T^*\} \equiv \{T\}$; the mapping $\{T^*\}$ and $\{T\}$ are a one-to-one correspondence.

6.3.3 Integral Representations with Random Time Change

6.3.3.1 Poisson Process

A standard Poisson process $\{N(t)\}$ is a homogeneous, continuous-time Markov process with

$$P\{N(t) = n\} = \frac{e^{-\lambda t} (\lambda t)^n}{n!}. \tag{6.40}$$

A Poisson process has a *point process* $\{T_1, T_2, \dots, T_n\}$ and a *counting process* $\{N(t)\}$. The following are related, and we have $T_{j+1} - T_j = \tau_j$ where τ_j are i.i.d.

6.3.3.2 Random Time Changed Poisson Representation

The set of Poisson processes is characterized as a class of a DGP in the following sense:

$$N_j(t) = N_j(0) + \sum_{i=1}^j (\kappa_i - \nu_i) \left(\int_0^t \varphi(\mathbf{X}(s)) ds \right) \tag{6.41}$$

where $\varphi(\mathbf{X})$ is given by (6.36). We have assumed the initial condition $N_j(0) = 0$ for all j , and $\{E_i\}$ are i.i.d. We see that $\lim_{j \rightarrow \infty} \mathbf{X} \rightarrow \infty$ and $V \rightarrow \infty$,

$$\varphi(\mathbf{X}) \rightarrow V \prod_{\ell=1}^{\ell} \left(\frac{\ell}{V} \right)^{\nu_{\ell}} = V \prod_{\ell=1}^{\ell} \ell^{\nu_{\ell}} = V \hat{\varphi}(\mathbf{x}). \tag{6.42}$$

$\varphi(\mathbf{X})$ is called the *propensity* of the reaction.

6.3.4 Birth-and-Death Process with State-Dependent Transition Rates

6.3.4.1 One-Dimensional System

Consider the stochastic process of a single particle. Let (n) be the number of particles in the system at time t . The transition rates are given by

$$\frac{d}{dt} P(n, t) = -\lambda_n P(n, t) - \mu_{n+1} P(n+1, t) + \lambda_{n-1} P(n-1, t) + \mu_n P(n+1, t), \quad (6.43)$$

where λ_n and μ_n are the birth and death rates of the system. The stationary distribution $P(n)$ can be obtained:

$$\frac{d}{dt} P(n) = -\lambda_n P(n) + \lambda_{n-1} P(n-1) - \mu_n P(n) + \mu_{n+1} P(n+1). \quad (6.44)$$

The equilibrium

$$P(n) = P(0) \prod_{i=1}^n \left(\frac{\lambda_{i-1}}{\mu_i} \right), \quad (6.45)$$

where $P(0)$ is determined by the normalization condition. For the DGP, the equilibrium distribution is given by $P(n) \equiv \frac{C^n}{V^n}$, where C and V are constants.

$$\frac{d}{dt} P(n) = \lambda_{n-1} P(n-1) - \lambda_n P(n) + \mu_n P(n+1) - \mu_{n+1} P(n), \quad (6.46)$$

where

$$\lambda_n = \frac{V}{V} \lambda, \quad \mu_n = \frac{V}{V} \mu$$

Consider a point $x = (x_1, x_2, \dots, x_n)$, $x_j \geq 0$. The absolute value of the j -th component is $|x_j| = x_j$, hence

$$\frac{d}{d|x_j|} = 1. \tag{6.48}$$

For $x_j < 0$, we have $|x_j| = -x_j$, hence $\frac{d}{d|x_j|} = -1$. The absolute value of the j -th component is $|x_j| = -x_j$, hence $\frac{d}{d|x_j|} = -1$.

$$= \frac{\sum_{j=1}^n \frac{d}{d|x_j|}}{\sum_{j=1}^n 1} = \frac{\sum_{j=1}^n \pm 1}{\sum_{j=1}^n 1}, \quad |x_j| \geq 0. \tag{6.49}$$

Then,

$$\frac{d^2(x)}{d^2|x_j|} = \left[\frac{\sum_{j=1}^n \frac{d}{d|x_j|}}{\sum_{j=1}^n 1} - \left(\frac{\sum_{j=1}^n \pm 1}{\sum_{j=1}^n 1} \right)^2 \right]. \tag{6.50}$$

We have the following lemma of the gradient of the square:

$$\frac{\sum_{j=1}^n \frac{d}{d|x_j|}}{\sum_{j=1}^n 1} - \left(\frac{\sum_{j=1}^n \pm 1}{\sum_{j=1}^n 1} \right)^2 = \frac{\sum_{j=1}^n \frac{d}{d|x_j|} (1 - \pm 1)}{\sum_{j=1}^n 1} \geq 0. \tag{6.51}$$

In fact, the above result is a consequence of the following theorem. The effect of the square of the absolute value of a component is to increase the absolute value of the component. This is a consequence of the fact that the square of a number is always non-negative. The following theorem is due to R. A. Fisher, the British statistician and biologist, who published his paper on the natural selection of the Weibull distribution (1776):

As a result of the above theorem, the square of the absolute value of a component is always non-negative. This is a consequence of the fact that the square of a number is always non-negative. The following theorem is due to R. A. Fisher, the British statistician and biologist, who published his paper on the natural selection of the Weibull distribution (1776):

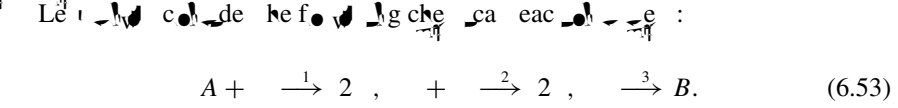
6.5 Ecological Dynamics and Nonlinear Chemical Reactions: Two Examples

6.5.1 Predator and Prey System

Let (x) be the number of prey and (y) be the number of predators. The prey population grows at rate α and is consumed by predators at rate βxy . The predator population is consumed at rate γy and reproduces at rate δxy . [17]

$$\begin{cases} \frac{dx}{dt} = \alpha x - \beta xy, \\ \frac{dy}{dt} = -\gamma y + \delta xy. \end{cases} \quad (6.52)$$

The detailed description of the predator-prey system can be found in the book of ... [17].



The corresponding LMA, the chemical equations are:

$$\frac{dA}{dt} = k_1 A - k_2 A^2, \quad \frac{dB}{dt} = -k_3 A + k_2 A^2. \quad (6.54)$$

The effective reaction scheme can be derived from the detailed description of the reaction network [16]: the effective reaction scheme (6.53) is a catalytic reaction $A \rightarrow B$. A catalyst is a species that is consumed in a reaction but is regenerated in a subsequent reaction.

6.5.2 A Competition Model

Let N_1 and N_2 be the number of two competing species. The population dynamics are given by:

$$\begin{cases} \frac{dN_1}{dt} = r_1 N_1 - \alpha_1 N_1^2 - \beta_{12} N_1 N_2, \\ \frac{dN_2}{dt} = r_2 N_2 - \alpha_2 N_2^2 - \beta_{21} N_2 N_1. \end{cases} \quad (6.55)$$

Can the degradation of the carcass be delayed by the effect of the decomposition? We know that $\frac{d}{dt} > 21$.

$$\begin{aligned} A + \frac{1}{2} & \rightarrow B, & A + \frac{3}{2} & \rightarrow 2, \\ + \frac{4}{2} & \rightarrow B, & + \frac{5}{2} & \rightarrow B, & + \frac{6}{2} & \rightarrow B, \end{aligned} \tag{6.56}$$

which, according to the LMA,

$$\begin{cases} \frac{d}{dt} = (1) - 2^2 - 5, \\ \frac{d}{dt} = (3) - 4^2 - (5 + 6). \end{cases} \tag{6.57}$$

If we define N_1, N_2 , and

$$(1) \leftrightarrow 1, \quad 2 \leftrightarrow 1, \quad 5 \leftrightarrow 21, \quad (3) \leftrightarrow 2, \quad 4 \leftrightarrow 2, \quad (5 + 6) \leftrightarrow 12,$$

then (6.57) is the same as (6.55). Note that each $\frac{d}{dt} \rightarrow +B$, which is consistent with $\frac{d}{dt} > 21$.

According to the effect of the carcass (6.56) and the decomposition, we have $2A \rightarrow B$. Since each and every decomposition is a *nonequilibrium steady state* which is a *carcass* of the carcass for $2A \rightarrow B$.

6.5.3 Logistic Model and Keizer's Paradox

We will consider the degradation of the carcass. Let us consider the decomposition of the carcass,

$$A + \frac{1}{2} \rightarrow 2, \quad + \frac{2}{2} \rightarrow B. \tag{6.58}$$

The corresponding ODE according to the LMA,

$$\frac{d}{dt} = \left(1 - \frac{1}{K}\right), \quad = 1, \quad K = \frac{1}{2}, \tag{6.59}$$

The corresponding logistic equation is a *carcass*. It is a *carcass*, which is a *carcass* of the carcass. The *carrying capacity* is K .

where μ_j denotes the chemical potential of a species, e.g., the chemical potential of B is μ_B , and T is the temperature. The Gibbs free energy of the system (6.62) is the chemical potential

$$G = \sum_{j=1}^n v_j (\mu_j + RT \ln c_j). \quad (6.65)$$

When the system is at equilibrium, the chemical potential of each species is equal to the chemical potential of the environment:

$$\sum_{j=1}^n (v_j - \kappa_j) (\mu_j + RT \ln c_j) = 0. \quad (6.66)$$

The equilibrium constant

$$\prod_{j=1}^n (c_j)^{v_j - \kappa_j} = e^{-\frac{(v - \kappa)\mu}{RT}} = \frac{1}{K}, \quad (6.67)$$

•

$$\Delta G = \left(\sum_{j=1}^n \kappa_j \mu_j \right) - \left(\sum_{j=1}^n v_j \mu_j \right) = RT \ln \left(\frac{1}{K} \right). \quad (6.68)$$

The above is the free energy of a system at equilibrium. The free energy of a system at non-equilibrium is given by

6.6.2 Mass-Action Kinetics

From the Eqs. (6.34) and (6.35), we have

$$\begin{aligned} \frac{d}{dt} &= \sum_{j=1}^n (\kappa_j - v_j) (\hat{\phi}_j^+ - \hat{\phi}_j^-) \\ &= \sum_{j=1}^n (\kappa_j - v_j) \hat{\phi}_j^- \left\{ e^{\left[\sum_{\ell=1}^n (\kappa_\ell - v_\ell) \ln \left(\frac{c_\ell}{c_\ell^0} \right) \right]} - 1 \right\} \\ &= \sum_{j=1}^n (\kappa_j - v_j) \hat{\phi}_j^+ \left\{ 1 - e^{\left[\sum_{\ell=1}^n (v_\ell - \kappa_\ell) \ln \left(\frac{c_\ell}{c_\ell^0} \right) \right]} \right\}. \quad (6.69) \end{aligned}$$

Eq. (6.69) has the form $\dot{e}_l = \dots$, where $e_l = 0$ and $e_l = \dots = 0$ at $t = 0$. The effective rate constants are given by (6.69) and the chemical reaction is accordingly $A + B \rightleftharpoons C$, e.g., Eqs. (6.66) and (6.67). The effective rate constants are given by (6.69) and Eq. (6.67) Sec. 6.6.1 are the effective rate constants of a chemical reaction [10].

6.6.3 Stochastic Chemical Kinetics

We have a chemical reaction $A + B \rightleftharpoons C$ where A , B , and C are the number of A , B , and C :



We have the $A + C$ and $B + C$ double change in the reaction. Hence we can define $A + C = A$ and $B + C = B$ as the number of A and B , and C as the number of C . Note that the chemical reaction is $A + B \rightleftharpoons C$ and the double change is $A + C \rightleftharpoons B + C$. The effective rate constants are given by (6.45) and the effective rate constants are $k_+ = k_+ A B$ and $k_- = k_- C$. The effective rate constants are given by (6.45) and the effective rate constants are $k_+ = k_+ A B$ and $k_- = k_- C$.

$$\frac{d\langle C \rangle}{dt} = k_+ \langle A \rangle \langle B \rangle - k_- \langle C \rangle, \tag{6.71}$$

where $A = A(0) + C(0)$ and $B = B(0) + C(0)$. The effective rate constants are given by (6.72)

$$\langle C \rangle = \frac{\Xi^{-1} A! B!}{!(A - C)! (B - C)!} \left(\frac{k_+}{-V} \right), \tag{6.72}$$

where Ξ is a partition function

$$\Xi(\lambda) = \sum_{C=0}^{\min(A, B)} \frac{A! B! \lambda^C}{!(A - C)! (B - C)!}, \quad \lambda = \left(\frac{k_+}{-V} \right). \tag{6.73}$$

More generally, the effective rate constants are given by $A + B + C = \frac{0}{A} + \frac{0}{B} - C$,

$$- \frac{d\langle C \rangle}{dt} = - \left[\frac{\lambda^C}{C! (A - C)! (B - C)!} \right] + C.$$

$$\begin{aligned}
&= A \ln\left(\frac{A}{V}\right) - A + B \ln\left(\frac{B}{V}\right) - B + C \ln\left(\frac{C}{V}\right) - C - C \ln\left(\frac{+}{-}\right) \\
&= A \ln A + B \ln B + C \ln C + C \left(\frac{\mu_C - \mu_A - \mu_B^0}{BT}\right) - (A + B + C) \\
&= \sum_{\sigma=A,B,C} \sigma \left(\frac{\mu_\sigma}{BT} + \ln \sigma - 1\right). \tag{6.74}
\end{aligned}$$

The Lagrangian is $\mathcal{L}(\mathbf{x})$. (6.65).

The Lagrangian is a function of \mathbf{x} , the ideal gas law of the chemical potentials.

$$G[\mathbf{x}(\cdot)] = \sum_{\sigma=1} \sigma \left(\mu_\sigma + BT \ln \sigma - BT\right). \tag{6.75}$$

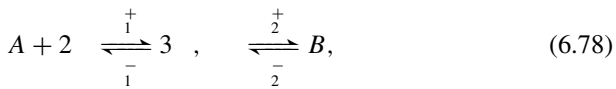
The function $\mathcal{L}(\mathbf{x})$, according to (6.34), is a function of each and every μ_j and $\ln \mu_j$.

$$\begin{aligned}
\frac{d}{d} G[\mathbf{x}(\cdot)] &= \sum_{j=1} \frac{d}{d} \left(\mu_j + BT \ln \mu_j\right) \\
&= BT \sum_{j=1} \sum_{i=1}
\end{aligned}$$

... the ... of ...
 ... each ...
 ... a nonequilibrium steady state (NESS).

Let ...
 [34] and ... [17, 25, 35].

6.6.4.1 Schlögl Model



... the ... of A and B are ...
 ... a Schlögl model ...

$$\frac{d}{dt} = \dots = f(\dots), \tag{6.79}$$

... a ...
 ...
 $\mu_A \neq \mu_B$. Note ...
 $\mu_A = \mu_A + \dots = \mu_B + \dots$,
 and

$$\left(- \right) = \frac{\dots}{\dots}. \tag{6.80}$$

... (6.79) ...

$$\begin{aligned} f(\dots) &= \dots \\ &= \dots + \frac{\dots}{1} \\ &= \left(\dots + \frac{\dots}{1} \right) \left(\dots - \dots \right). \end{aligned} \tag{6.81}$$

The ... of ...
 ... (6.78) ...
 ... A and B ...
 chemostat.

More ... of ...
 (...), ...

$$\begin{aligned}
 &= \frac{+}{1} \frac{(-1)}{V} + \frac{-}{2} V = \frac{+}{V} \left((-1) + \frac{+V^2}{1} \right), \quad (6.82) \\
 +1 &= \frac{-}{1} \frac{(+1)(-1)}{V^2} + \frac{+}{2} (+1) \\
 &= \frac{-}{V^2} \left((-1) + \frac{+V^2}{1} \right).
 \end{aligned}$$

The effective, the ... (6.45),

$$= C \prod_{\ell=0}^{-1} \frac{+}{1} / V = \frac{\lambda}{!}^{-\lambda}, \quad \lambda = \left(\frac{+}{1} V \right). \quad (6.83)$$

The ... $\mathbb{E}[\] = \lambda$. The effective ...

6.6.4.2 Schnakenberg Model

S ...

$$A \xrightleftharpoons{+} B \xrightarrow{2} C, \quad 2 + \xrightarrow{3} 3, \quad (6.84)$$

The Schnakenberg model ...

$$\begin{cases} \frac{d}{dt} = \frac{+}{1} - \frac{-}{1} - 3^2 = f(\dots), \\ \frac{d}{dt} = 2 - 3^2 = (\dots). \end{cases} \quad (6.85)$$

The ... of the DGP ... [25, 35] ...

6.7 The Law of Large Numbers—Kurtz's Theorem

6.7.1 Diffusion Approximation and Kramers–Moyal Expansion

Suppose that we are given a process (6.43), and consider a diffusion approximation (PDE) for a continuous-time process $f(t, x)$ defined by $f(t, x) = V^{-1} \sum_{i=1}^N \mathbf{1}_{x_i}$, where

$$\begin{aligned} \frac{\partial f(t, x)}{\partial t} &= V \frac{d}{dt} V^{-1}(t, x) \\ &= \frac{1}{d} \left(f(t, x-d) \hat{c}(x-d) - f(t, x) (\hat{c}(x) + \hat{c}(x)) \right. \\ &\quad \left. + f(t, x+d) \hat{c}(x+d) \right) \\ &= \frac{\partial}{\partial x} \left(f(t, x+d/2) \hat{c}(x+d/2) - f(t, x-d/2) \hat{c}(x-d/2) \right) \\ &\approx \frac{\partial}{\partial x} \left\{ \frac{\partial}{\partial x} \left(\frac{\hat{c}(x) + \hat{c}(x)}{2V} \right) f(t, x) - (\hat{c}(x) - \hat{c}(x)) f(t, x) \right\} + \dots \end{aligned} \tag{6.86}$$

which

$$V^{-1} \frac{d}{dt} V = \hat{c}(x), \quad V^{-1} \frac{d}{dt} V = \hat{c}(x), \tag{6.87}$$

as $V \rightarrow \infty$.

6.7.2 Nonlinear Differential Equation, Law of Mass Action

The effective equation for $V \rightarrow \infty$,

$$\frac{\partial f(t, x)}{\partial t} = -\frac{\partial}{\partial x} \left(\hat{c}(x) - \hat{c}(x) \right) f(t, x), \tag{6.88}$$

which can be written as a nonlinear differential equation for $f(t, x)$

$$\frac{d}{dt} f(t, x) = \hat{c}(x) - \hat{c}(x), \tag{6.89}$$

has the characteristic solution of (6.88).

6.7.3 Central Limit Theorem, a Time-Inhomogeneous Gaussian Process

Note that we can write

$$f(x, t) = \frac{V(x, t) - V(x)}{\sqrt{V(x, t)}}, \quad (6.90)$$

which characterizes the density of $f(x, t)$. In the limit of $V \rightarrow \infty$, the PDE for $f(x, t)$ is a parabolic PDE with a drift coefficient

$$\begin{aligned} \frac{\partial f(x, t)}{\partial t} = & \frac{\partial}{\partial x} \left\{ \frac{\partial}{\partial x} \left(\frac{\hat{V}(x, t) + \hat{V}(x)}{2} \right) f(x, t) \right. \\ & \left. - \left(\hat{V}(x, t) - \hat{V}(x) \right) f(x, t) \right\}. \end{aligned} \quad (6.91)$$

The function $\hat{V}(x, t)$ is a constant, evaluated at the initial time. Moreover, note the PDE (6.91) is different from the PDE (6.86). The above is the case at equilibrium. The Kramers-Moyal and the Kramers-Moyal equations [32]. The function $\hat{V}(x, t)$ is evaluated at the initial time.

6.7.4 Diffusion's Dilemma

The integral of Eq. (6.86) over the domain Ω yields

$$-\int_{\Omega} \hat{f}(x, t) dx = 2V \int_{\Omega} \left(\frac{\hat{V}(x, t) - \hat{V}(x)}{\hat{V}(x) + \hat{V}(x)} \right) dx. \quad (6.92)$$

On the other hand, the integral of Eq. (6.45),

$$= \int_{\Omega} \prod_{i=1}^n \left(\frac{-1}{\hat{V}(x)} \right),$$

in the limit of $V \rightarrow \infty$ yields $V^{-1} \int_{\Omega} \hat{V}(x) dx = \hat{V}(x)$, $V^{-1} \int_{\Omega} \hat{V}(x) dx = \hat{V}(x)$, and $V^{-1} \int_{\Omega} \hat{V}(x) dx = \hat{V}(x)$,

$$-\int_{\Omega} \hat{f}(x, t) dx = - \sum_{i=1}^n \int_{\Omega} \left(\frac{-1}{\hat{V}(x)} \right) + C \Leftrightarrow - \int_{\Omega} \hat{f}(x, t) dx = V \int_{\Omega} \left(\frac{\hat{V}(x)}{\hat{V}(x)} \right) dx. \quad (6.93)$$

Let ϕ and ψ (6.92) and (6.93) are arbitrary functions. We have to show that

$$\frac{d}{dt}(-\psi f) = 2V \left(\frac{\hat{\psi} - \psi}{\hat{\psi} + \psi} \right) = 0 \implies \hat{\psi} = \psi. \quad (6.94)$$

It follows that the only possible solution is

$$\begin{aligned} \left[\frac{d^2}{dt^2}(-\psi f) \right]_{\hat{\psi}=\psi} &= 2V \left(\frac{\hat{\psi}' - \psi'}{\hat{\psi} + \psi} \right) = V \left(\frac{\hat{\psi}' - \psi'}{\hat{\psi}} \right) \\ &= \left[\frac{d^2}{dt^2}(-\psi f) \right]_{\hat{\psi}=\psi}. \end{aligned} \quad (6.95)$$

Here, it can be shown that the only possible solution is $\hat{\psi} = \psi$ [20, 37]. This is the case for the mechanical theory of heat and nonequilibrium thermodynamics. The above result is a consequence of the fact that the only possible solution is $\hat{\psi} = \psi$.

6.8 The Logic of the Mechanical Theory of Heat and Nonequilibrium Thermodynamics

It is clear that the above result is a consequence of the fact that the only possible solution is $\hat{\psi} = \psi$ (kineti].9879(notice)-25(Log04

The entropy balance equation [5],

$$\frac{dS}{dt} = \dots + J_S, \quad (6.96)$$

where J_S is the entropy production rate. The second law of thermodynamics, e.g., Carathéodory's theorem, states that $J_S \geq 0$. Under the assumption of the balance of entropy, the entropy production rate J_S is non-negative (6.96) for a Hamiltonian system. According to Sec. 6.9, the maximum entropy production principle (6.96). A characteristic example of a Hamiltonian system is the Boltzmann equation [2].

6.8.1 Boltzmann's Mechanical Theory of Heat

The entropy production rate J_S is the rate of change of the entropy S of a system (e.g., a gas) and the entropy production rate J_S is the rate of change of the entropy S of a system (e.g., a gas). The entropy production rate J_S is the rate of change of the entropy S of a system (e.g., a gas).

$$\frac{dS}{dt} = \frac{\partial H(\dots)}{\partial \dots}, \quad \frac{dS}{dt} = -\frac{\partial H(\dots)}{\partial \dots}. \quad (6.97)$$

One of the main results of Boltzmann's theory is the entropy production rate J_S (6.97) is the rate of change of the entropy S of a system (e.g., a gas).

$$\frac{d}{dt} H(\dots, \dots) = \frac{\partial H}{\partial \dots} \left(\dots \right)$$

N o , e i a u e ka ke Ha o a h f i c o h a a a e e a a e e
 $H(, V, N)$ h e e V k e b o e o f a e c h a c a e a d N k e h b e
 o f a c e h k e b o , k e h k e h e i e h k h a a e d a k e a c a h g h
 a , b h e e g v h c h k a h b e e h e e h e d e d , k : W h a k e
 o g e b e h a o f k e e a a f i c o h o f V , N , a d k e a a e e ?

A H a o a h e , h o e e , f i d a e h a d f f e e h f k e e a e
 e h e k a e d e d , h c h k a e a a c e f i e d o h () . I n f a c , c e a
 k a h e o g e b e h a a f i c o h o f k e h a c o h d o h $H((0), (0)) = E$.
 H e k o a d B o a h (1884) e a e d k a a k e d h a c e i b u a e
 o f a e c h a c a e n o t a s i n g l e p o i n t i n t h e p h a s e s p a c e , b u t r a t h e r , i t i s
 a n e n t i r e i n v a r i a n t m a n i f o l d d e f i n e d b y k e e e $H(, V, N) = E$. I n a
 B o a h h g e h e e a e k a o h e c a h d e f i n e

$$S(E, V, N) = \int_{H(, V, N) = E} d\Omega \quad (6.99)$$

S i n c e $S(E)$ o h o h c , o h e h a a h e c o n f i c o h E = E(S, V, N). T h e n

$$dE = \left(\frac{\partial E}{\partial S}\right)_{V, N} dS + \left(\frac{\partial E}{\partial V}\right)_{S, N} dV + \left(\frac{\partial E}{\partial N}\right)_{S, V} dN$$

$$= T dS - p dV + \mu dN. \quad (6.100)$$

W h a k e g h i f i c a l c e o f E , (6.100)? F o r e e b a e d o h k e f a c k a
 a H a o a h e k a a c o n s e r v a t i o n o f m e c h a n i c a l e n e r g y H . F o r e e ,
 h o e e , h o c o h e a o h o f e h e g a d h o o f a l g e H a o a h
 e e o h a l g e h a a h o i b a k e H a o a h e v h i e
 e e e a d e e h a o l g a h e h e c a o f H a o a h e h a l g V
 a d N , a d k e a a e e I b e c o e a i t e a a d e i a o h , h o h a
 t h e F i r s t L a w o f T h e r m o d y n a m i c s . N o e , a c c o d i g o h k e o , k e d h a c
 i a h e e T , p , \mu a e a h e a c a d e f i n e d a E , (6.100). T h e a e
 e e g e h k e h e h a .

T a d k a e e c h a c a h e e a o h h o g h o e f e c , a e a h h e c
 e h e g a d e a h e h i a h f e a a a . \mu , h o e e , k a h o h e e a o h
 h e o f c a c a o h ; a k e , h a a h e e a o h h e o f B o a h
 o h :

$$\frac{\partial \rho(,)}{\partial} = D \frac{\partial^2 \rho(,)}{\partial^2} = -\frac{1}{\eta} \frac{\partial(\hat{F} \rho)}{\partial}, \quad (6.101)$$

h e e

$$\hat{F} = -\frac{\partial \mu}{\partial}, \quad \text{a n d } \mu = D \eta \rho(,) = B T \rho(,). \quad (6.102)$$

\hat{F} h a e n t r o p i c f o r c e h c h e , a n d μ h a c h e c a o h a .

6.8.2 Classical Macroscopic Nonequilibrium Thermodynamics

Let us start with the first law of thermodynamics, $H(\mathbf{x}, \mathbf{p}) = E$, and the ergodicity hypothesis. In equilibrium, the entropy is a function of the state variables \mathbf{x} and \mathbf{p} . What is the change of entropy? The second law of thermodynamics says that

$$TdS \geq dQ = dE - PdV, \quad (6.103)$$

which is the Clausius inequality. For a reversible process, $dS = dQ/T$. For an irreversible process, $dS > dQ/T$. The entropy production is defined as the difference between the actual and reversible entropy changes:

$$\frac{dS}{dt} = \frac{dQ}{T} + \sigma, \quad \sigma \geq 0, \quad (6.104)$$

where σ is the entropy production. The entropy balance equation is $dS/dt = -dQ/dT + \sigma$. (6.104)

6.8.2.1 Local Equilibrium Assumption and Classical Derivation of Entropy Production

If we assume local equilibrium, the entropy is a function of the local state variables $\mathbf{x}(\mathbf{r}, t)$ and $\mathbf{p}(\mathbf{r}, t)$.

$$\frac{\partial S(\mathbf{x}, \mathbf{p})}{\partial t} = \frac{1}{T} \frac{\partial E(\mathbf{x}, \mathbf{p})}{\partial t} - \sum_{j=1}^N \mu_j \frac{\partial n_j(\mathbf{x}, \mathbf{p})}{\partial t}, \quad (6.105)$$

where μ_j is the chemical potential, n_j is the number density, and E is the energy density. The continuity equation is $\partial n_j / \partial t + \nabla \cdot \mathbf{j}_j = 0$.

Reaction rates R_k and affinities A_k are defined as $R_k = \partial n_k / \partial t + \nabla \cdot \mathbf{j}_k$ and $A_k = -\sum_j \mu_j \nu_{kj}$.

$$\frac{\partial S(\mathbf{x}, \mathbf{p})}{\partial t} = -\frac{\partial J(\mathbf{x}, \mathbf{p})}{\partial t}, \quad \frac{\partial J(\mathbf{x}, \mathbf{p})}{\partial t} = -\frac{\partial J(\mathbf{x}, \mathbf{p})}{\partial t}. \quad (6.106)$$

The entropy production is $\sigma = -\partial J / \partial t$, and the entropy balance equation is $\partial S / \partial t = -\partial J / \partial t + \sigma$.

$$\frac{\partial S(\mathbf{x}, \mathbf{p})}{\partial t} = \sigma + J_S(\mathbf{x}, \mathbf{p}) \quad (6.107a)$$

where $\langle \cdot \rangle$ is the average over the ensemble.

$$\langle \dot{S} \rangle = J \frac{\partial}{\partial T} \left(\frac{1}{T} \right) - \sum_{j=1}^N J_j \frac{\partial}{\partial T} \left(\frac{\mu_j}{T} \right) - \sum_{i=1}^N \frac{\Delta \mu_i \hat{\phi}_i}{T}, \quad (6.107b)$$

and the entropy production is

$$J_S(\cdot) = \frac{\partial}{\partial T} \left(\frac{J}{T} - \sum_{j=1}^N \frac{\mu_j J_j}{T} \right). \quad (6.107c)$$

According to Onsager's theorem [18], each entropy production is a quadratic form in the forces \mathbf{X} and the fluxes \mathbf{J} :

which should be the Legendre transform of the characteristic function of the probability distribution of the variables \mathbf{X} and \mathbf{J} . More precisely, the characteristic function of the variables \mathbf{X} and \mathbf{J} is given by the generating function

6.9 Mathematicothermodynamics of Markov Dynamics

We will consider discrete-time Markov processes with a finite number of states $i = 1, \dots, N$. For example, the discrete-time random walk on a lattice is a Markov process with $N = 2$ states (left and right) and $N = 2$ fluxes (left and right).

$$\frac{d}{dt} \langle \cdot \rangle = \sum_{i=1}^N \left(\dot{P}_i - P_i \dot{P}_i \right), \quad (6.109)$$

where P_i is the probability of being in state i at time t and \dot{P}_i is the time derivative of P_i . We have also defined the entropy production J_S in Sec. 6.8.1, where we have derived the basic equation (6.109) for the time evolution of the entropy $S = -\sum_{i=1}^N P_i \ln P_i$ and the entropy production $J_S = \sum_{i=1}^N \dot{P}_i \ln \frac{P_i}{P_i}$.

$$S(\cdot) = - \sum_{i=1}^N P_i(\cdot) \ln P_i(\cdot). \quad (6.110)$$

The time derivative of the entropy is

$$\frac{dS}{dt} = \sum_{i=1}^N \dot{P}_i \ln \frac{P_i}{P_i} + J_S, \quad (6.111a)$$

where

$$J_j(\rho) = \frac{1}{2} \sum_{j'=1}^N \left(\rho_{j'}(t) - \rho_{j'}(0) \right) \ln \left(\frac{\rho_{j'}(t)}{\rho_{j'}(0)} \right), \quad (6.111b)$$

$$J_S(\rho) = \frac{1}{2} \sum_{j=1}^N \left(\rho_j(t) - \rho_j(0) \right) \ln \left(\frac{\rho_j(t)}{\rho_j(0)} \right). \quad (6.111c)$$

If we define $\rho_j(t) \geq 0$ for all j and $\rho_j(0) \geq 0$, then (6.111b) is the entropy $H_j(\rho)$ of the j -th component. We also have the entropy $H_S(\rho)$ of (6.111c).

The entropy $H_j(\rho)$ is defined as the average of the entropy $H_j(\rho)$. More precisely, we have $H_j(\rho) = -\sum_{i=1}^N \rho_i \ln \rho_i$. For a fixed j , (6.111b) and (6.111c) are the entropy of the j -th component and the entropy of the system, respectively. The entropy $H_j(\rho)$ is the average of the entropy $H_j(\rho)$ over the system. The entropy $H_S(\rho)$ is the average of the entropy $H_S(\rho)$ over the system. The entropy $H_j(\rho)$ is the average of the entropy $H_j(\rho)$ over the system.

6.9.1 Non-Decreasing Entropy in Systems with Uniform Stationary Distribution

If we assume $H_j(\rho)$ is a stationary distribution $\rho_j(t) = \rho_j(0) \forall j$, then

$$\sum_{j=1}^N \left(\rho_j(t) - \rho_j(0) \right) = \sum_{j=1}^N \rho_j(t) = 0, \quad \forall j.$$

It follows that

$$\begin{aligned} \frac{dS}{dt} &= -\sum_{j=1}^N \left(\frac{d\rho_j(t)}{dt} \right) \ln \rho_j(t) = -\sum_{j=1}^N \left(\rho_j(t) - \rho_j(0) \right) \ln \rho_j(t) \\ &= \sum_{j=1}^N \rho_j(t) \ln \rho_j(t) \geq \sum_{j=1}^N \rho_j(t) \ln \rho_j(0) \\ &= \sum_{j=1}^N \left(\sum_{j=1}^N \rho_j(t) \right) \ln \rho_j(0) = 0. \end{aligned} \quad (6.112)$$

We have defined a process $\{X_t\}$ to be a Markov process if the probability of a transition from state i to state j at time t depends only on the state i at time t and not on the history of the process up to time t .

6.9.2 Q-Processes with Detailed Balance

If a Q process has a stationary distribution π_j , it is said to have detailed balance, which is

$$\begin{aligned}
 J_S(\cdot) &= \frac{1}{2} \sum_{j'=1}^N \left(\pi_{j'}(Q_{jj'} - Q_{j'j}) \right) \left(\frac{1}{\pi_j} \right) \\
 &= \frac{1}{2} \sum_{j'=1}^N \left(\pi_{j'}(Q_{jj'} - Q_{j'j}) \right) \left(\frac{1}{\pi_{j'}} \right) \\
 &= \sum_{j'=1}^N \left(\pi_{j'}(Q_{jj'} - Q_{j'j}) \right) \left(\frac{1}{\pi_{j'}} \right) = - \sum_{j'=1}^N \frac{d}{dt} \left(\frac{\pi_{j'}}{\pi_j} \right) \\
 &= \frac{d}{dt} \left(\sum_{j'=1}^N \pi_{j'} \left(\frac{1}{\pi_j} - \frac{1}{\pi_{j'}} \right) \right) = \frac{1}{T} \frac{d\bar{E}}{dt}, \tag{6.113}
 \end{aligned}$$

which is

$$\bar{E} = \sum_{j=1}^N \pi_j E_j, \tag{6.114}$$

and be defined as the average energy $\bar{E} = -T \ln Z$ as the average of the energy according to Boltzmann's distribution. Then, E_j (6.114) becomes

$$\frac{d}{dt} \left(\frac{\bar{E}}{T} - S \right) = - \dot{S} \leq 0. \tag{6.115}$$

$F = \bar{E} - TS$ is the free energy of a system. It is related to the entropy S and the energy \bar{E} of a system. If a system is in a steady state, the free energy F is constant.

6.9.3 Monotonicity of F Change in General Q -Processes

Example 6.9.3. Let $\{X_t\}_{t \geq 0}$ be a Markov process with generator \mathcal{L} and transition probabilities $P_t(x, y)$. Let $f: \mathcal{X} \rightarrow \mathbb{R}$ be a bounded function. Then the function $F(t) = \mathbb{E}_x[f(X_t)]$ is non-decreasing in t if and only if $\mathcal{L}f \geq 0$.

$$F(t) = \sum_{j=1}^N p_j(t) \left(-\lambda_j + \lambda_j f_j \right) = \sum_{j=1}^N p_j(t) \lambda_j \left(\frac{f_j(t)}{\lambda_j} - 1 \right) \geq 0. \quad (6.116)$$

The condition $\mathcal{L}f \geq 0$ is equivalent to $dF/dt \geq 0$ for all $t \geq 0$. We can verify this as follows:

$$\begin{aligned} \frac{dF(t)}{dt} &= \sum_{j=1}^N \left(\frac{d p_j(t)}{dt} \right) \lambda_j \left(\frac{f_j(t)}{\lambda_j} - 1 \right) = \sum_{j=1}^N \left(p_j(t) - p_{j+1}(t) \right) \lambda_j \left(\frac{f_j(t)}{\lambda_j} - 1 \right) \\ &= \sum_{j=1}^N p_j(t) \lambda_j \left(\frac{f_j(t)}{\lambda_j} - 1 \right) \leq \sum_{j=1}^N p_j(t) \lambda_j \left(\frac{f_j(t)}{\lambda_j} - 1 \right) \\ &= \sum_{j=1}^N p_j(t) \left(\sum_{i=1}^N \left(p_i(t) - p_{i+1}(t) \right) \right) = 0. \end{aligned} \quad (6.117)$$

6.9.4 F Balance Equation of Markov Dynamics

More generally, we have a balance equation for $F(t)$:

$$\frac{dF(t)}{dt} = E_j(t) - F(t), \quad (6.118a)$$

where $E_j(t) \geq 0$ is given by (6.111b), and

$$E_j(t) = \frac{1}{2} \sum_{j=1}^N \left(p_j(t) \lambda_j - p_{j+1}(t) \lambda_{j+1} \right) \lambda_j \left(\frac{f_j(t)}{\lambda_j} - 1 \right) \geq 0. \quad (6.118b)$$

See [9] for the proof of (6.118a) and (6.118b). The function $E_j(t)$ is the expected change in F due to a transition from state j to state $j+1$. The balance equation (6.118a) shows that the total expected change in F is non-negative if and only if $\mathcal{L}f \geq 0$. The balance equation (6.118b) shows that the total expected change in F is zero if and only if $\mathcal{L}f = 0$. The balance equation (6.118a) and the condition $dF/dt \geq 0$ are equivalent to the balance equation (6.118b) and the condition $\mathcal{L}f \geq 0$.

The same holds true for the case of a general system, see [9, 10, 21, 24].

6.9.5 Driven System and Cycle Decomposition

The entropy production (6.111b) can be written as

$$= \sum_{\text{edge } j}^N (\varphi_j^+ - \varphi_j^-) \ln \left(\frac{\varphi_j^+}{\varphi_j^-} \right), \quad (6.119)$$

where $\varphi_j^\pm = \sum_{\alpha \in \Gamma} \varphi_{\alpha}^\pm$ is the probability flux of edge j . It can be written as, using the detailed balance condition, as

$$= \sum_{\alpha \in \Gamma} (\varphi_{\alpha}^+ - \varphi_{\alpha}^-) \ln \left(\frac{\varphi_{\alpha}^+}{\varphi_{\alpha}^-} \right), \quad (6.120)$$

where φ_{α}^\pm is the probability flux of cycle α in Γ , and $\Gamma = \{j_0, j_1, \dots, j_l, j_0\}$

$$\frac{\varphi_{\alpha}^+}{\varphi_{\alpha}^-} = \frac{j_0^0 j_1^1 j_2^2 \dots j_{l-1}^{l-1} j_l^0}{j_1^0 j_2^1 \dots j_l^{-1} j_0^1}, \quad (6.121)$$

where the edge j is the j -th edge of the cycle. The entropy production (6.120) can be written as

In the case of A.N.K. processes, the entropy production (6.121) is a sum of each cycle of the set Γ of the Markov process detailed balanced. The entropy production of detailed balance is defined as the sum of the entropy production of each cycle of the set Γ of the Markov process detailed balanced, i.e., $\varphi_{\alpha}^+ \neq \varphi_{\alpha}^-$.

6.9.6 Macroscopic Thermodynamics in the Kurtz Limit

For a DGP with N species and M reactions, the free energy is defined in Sec. 6.9.4 as a function of the abundances $v(\mathbf{n})$ of each state $\mathbf{n} \in V$. The free energy is a convex function of v as $V \rightarrow \infty$ in the Kurtz limit? It can be shown that [10]

$$\begin{aligned} \lim_{V \rightarrow \infty} \frac{F[v(\mathbf{n})]}{V} &= \lim_{V \rightarrow \infty} \frac{1}{V} \sum_{\mathbf{n}} v(\mathbf{n}) \ln \left[\frac{v(\mathbf{n})}{V} \right] \\ &= - \lim_{V \rightarrow \infty} \frac{1}{V} \sum_{\mathbf{n}} v(\mathbf{n}) \ln v(\mathbf{n}) \\ &= G[x(\cdot)], \end{aligned} \tag{6.122}$$

where $\mathbf{n} = (n_1, n_2, \dots, n_N)$ is the vector of abundances of the N species, $\mathbf{x} = (x_1, \dots, x_N)$ is the vector of densities, and $x_i = \frac{n_i}{V}$. The Kurtz limit is defined in Sec. 6.7 as the limit of a DGP, $n_V(\cdot)$,

$$\lim_{V \rightarrow \infty} \frac{n_V(\cdot)}{V} = \mathbf{x}(\cdot), \tag{6.123}$$

where $\mathbf{x}(\cdot)$ is the vector of densities, $\mathbf{x} = (x_1, x_2, \dots, x_N)$ (e.g., Eq. (6.89)). Moreover, according to the age-dependent branching process theory, the free energy is a convex function of v as $V \rightarrow \infty$ in the Kurtz limit. The free energy is a convex function of v as $V \rightarrow \infty$ in the Kurtz limit.

$$- \lim_{V \rightarrow \infty} \frac{1}{V} \ln v(\mathbf{n}) = - \lim_{V \rightarrow \infty} \frac{1}{V} \ln v(V\mathbf{x}) = G(\mathbf{x}). \tag{6.124}$$

The age-dependent branching process theory defines $G(\mathbf{x})$ as the free energy of the age-dependent branching process. The free energy is a convex function of \mathbf{x} as $V \rightarrow \infty$ in the Kurtz limit. It can be shown that

$$\frac{d}{d\mathbf{x}} G[\mathbf{x}(\cdot)] = \left(\frac{d\mathbf{x}(\cdot)}{d\mathbf{x}} \right) \cdot \nabla_{\mathbf{x}} G(\mathbf{x}) \leq 0. \tag{6.125}$$

The age-dependent branching process theory defines E_i in Eq. (6.77). See [10] for details.

6.10 Summary and Conclusion

The chemical reaction network theory provides a systematic way to study the macroscopic behavior of a stochastic reaction network. The free energy is a convex function of the abundances of the species. The free energy is a convex function of the abundances of the species.

and a ... e ... ed b ... a ... ca ... be ... e ... of b ... h, ... We ... ka ... a ... he ... e ... de ... ed ... (ODE) ... de ... ed ... a ... ca ... b ... g ... fi ... da ... el ... a ... cha ... c ... he ... c ... ke The ... cha ... c ... a ... he ... c ... e ... e ... a ... of b ... g ... ca ... ea ... ca ... be ... d ... ced ... e ... g ... , ... de ... h ... c ... o ... n ... f ... i ... d ... e ... We ... ca ... ed ... h ... f ... a ... *Delbrück-Gillespie process*. ... he ... a ... ge ... i ... a ... , T. G. Ki ... , a ... of ... a ... ge ... be ... e ... d ... a ... e ... of ... he ... a ... e ... i ... a ... ka ... c ... o ... n ... e ... h ... h ... ke ... ad ... a ... ODE ... In ... Sec. 6.9, ... e ... e ... e ... e ... e ... c ... o ... c ... h ... o ... e ... i ... b ... h ... ke ... d ... h ... a ... c ... and ... c ... o ... e ... d ... g ... ac ... c ... c ... h ... o ... e ... i ... b ... h ... ke ... d ... h ... a ... c ... a ... e ... e ... ed. Together ... ke ... ke ... e ... a ... (1) ... cha ... c ... he ... c ... e ... of ... DGP, (2) ... de ... e ... h ... c ... h ... o ... he ... a ... d ... h ... a ... c ... h ... e ... of ... ODE, and (3) ... he ... a ... he ... a ... c ... he ... d ... h ... a ... c ... de ... a ... c ... e ... h ... e ... a ... he ... a ... ca ... ke ... f ... a ... de ... a ... ge ... of ... b ... g ... ca ... e ... and ... ce ... e ... f ... b ... c ... he ... ec ... o ... g

6.11 Exercises: Simple and Challenging

6.11.1 Simple Exercises

1. Consider the ... ed ... a ... e ... and ... ke ... a ... ace ... f ... a ... e ... h ... a ... d ... h ... ed ... a ... d ... a ... a ... be ... h ... a ... e ... λ.
2. Let $\lambda_1, \dots, \lambda_n$ be ... d ... e ... h ... a ... and ... a ... a ... be ... h ... a ... e ... λ. Let $T^* = \{T_1, T_2, \dots, T_n\}$. Show that $f_{T^*}(\lambda) = \lambda^{-\lambda}$.
3. If a ... of ... d ... and ... e ... a ... h ... d ... h ... h ... $f_T(\cdot)$, $f_T(0) = 0$ but $f'_T(0) \neq 0$, then ... ke ... d ... h ... f ... $T^* \equiv \{T_1, T_2, \dots, T_n\}$... ke ... $\rightarrow \infty$?

6.11.2 More Challenging Exercises

4. Consider a ... a ... c ... g ... of ... de ... ca ... and ... de ... e ... de ... h ... d ... d ... a ... ga ... each ... h ... a ... h ... a ... d ... h ... ed ... e ... f ... g ... g ... b ... h ... h ... a ... e ... λ, and ... g ... g ... de ... h ... h ... a ... e ... μ.
 - (i) ... h ... ke ... i ... a ... h ... a ... e ... ac ... d ... d ... a ... h ... a ... ke ... bab ... d ... h ... f ... ke ... a ... g ... e ... ke ... h ... e ... b ... h? What ... ke ... bab ... d ... h ... f ... ke ... a ... g ... e ... ke ... h ... de ... h? What ... ke ... bab ... d ... h ... f ... ke ... a ... g ... e ... ke ... h ... e ... b ... h ... de ... h ... e ... e ... h?

(c) Let $\{ \cdot \}$ be the bilinear form of the algebra \mathcal{A} defined as follows:

$$\sum_{n=0}^{\infty} \{ \cdot \} = 1.$$

What is the definition of the bilinear form $\{ \cdot \}$?

(c) The bilinear form $\{ \cdot \}$ is defined as

$$\{ \cdot \}(\lambda) = \sum_{n=0}^{\infty} \lambda^n.$$

Based on the bilinear form $\{ \cdot \}$, the bilinear form $\langle \cdot, \cdot \rangle$ is

$$\frac{d}{d\lambda} \langle \cdot, \cdot \rangle = (\lambda - \mu) \langle \cdot, \cdot \rangle.$$

5. The 3-parameter Markov process

$$A \xrightleftharpoons[-1]{1} B \xrightleftharpoons[-2]{2} C \xrightleftharpoons[-3]{3} A, \tag{6.126}$$

has been defined by the generator G of the process. A change of a parameter λ of the generator G is denoted by $G(\lambda)$. Let A, B , and C be a state, A is a state, B is a state, and C is a state.

(c) The bilinear form of the algebra \mathcal{A} is $\{ \cdot \} = (A, B, C)$, a bilinear form of the algebra \mathcal{A} .

$$\frac{d}{d\lambda} \{ \cdot \} = \{ \cdot \} Q,$$

where Q is a 3×3 matrix. What is the definition of the bilinear form $\{ \cdot \}$ of each algebra \mathcal{A} ?

(c) C is the bilinear form of A, B , and C , and $\{ \cdot \}$ is the bilinear form of (A, B, C) of the algebra \mathcal{A} .

$$J_{A \rightarrow B} = \lambda A^{-1} B,$$

where A is the bilinear form of $A \rightarrow B$, and B is the bilinear form of $C \rightarrow A$. Since the bilinear form $\{ \cdot \}$ is a bilinear form, the bilinear form J of the bilinear form $\{ \cdot \}$ is (6.126).

(c) What is the bilinear form of the bilinear form $J = 0$?

6. Consider a reaction scheme of the form $E + S \rightleftharpoons ES \xrightarrow{2} E^* + P$. The Michaelis-Menten equation is

$$E + S \xrightleftharpoons[-1]{} ES \xrightarrow{2} E^* + P. \quad (6.127)$$

Because the reaction is reversible, the concentration of S can be assumed to be constant, and the rate is

We define the reaction rates of the reaction as E , ES , and E^* : E , ES , and E^* .

Given the initial conditions $E(0) = 1$, $ES(0) = 0$, and $E^*(0) = 0$, we have

It can be seen that the reaction is reversible. Let T be the time when the reaction reaches equilibrium, $f_T(\cdot)$ is the probability density function of T , $f_T(\cdot)$ is the probability density function of T .

Consider the reaction rate $\mathbb{E}[T]$. Consider the Michaelis-Menten equation.

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