LECTURE #14

JOHN GOUTSIAS
WHITAKER BIOMEDICAL ENGINEERING INSTITUTE
THE JOHNS HOPKINS UNIVERSITY
BALTIMORE, MD 21218

- We can view a Markovian reaction network as a <u>thermodynamic</u> <u>system</u> that:
 - absorbs energy
 - produces entropy
 - dissipates heat
- This perspective can provide important insights into functional properties of the network, such as robustness and stability.
- It can also lead to a better understanding of the relationship between the network's microscopic/mesoscopic (unobservable) and macroscopic (observable) behavior.

- Consider an <u>irreducible</u> Markovian reaction network comprised of M/2 pairs of <u>reversible reactions</u> (2m-1,2m).

 - \square 2m is the <u>reverse</u> reaction
- This does not forbid us to consider irreversible reactions, since an irreversible reaction can be thought of as being reversible with negligible propensity in the reverse direction.
- The reaction network is characterized by a unique population probability distribution $p_{\mathbf{X}}(\mathbf{x};t)$ that is analytic for all $t \geq 0$ and converges to a stationary distribution $\overline{p}_{\mathbf{X}}(\mathbf{x})$, which does not depend on the initial state $\mathbf{x}(0)$.

 \square We can define the energy of a state \mathbf{x} by

$$E(\mathbf{x}) \triangleq -\frac{1}{\Omega} \ln \overline{p}_{\mathbf{X}}(\mathbf{x})$$

where Ω is an appropriately chosen size parameter.

- Here, the discussion is purely mathematical in nature and can be applied to any physical or nonphysical Markovian reaction network.
- Direct connection to thermodynamics can be made in certain physical systems, such as biochemical reaction networks, which may exchange matter, work, and heat through a well-defined boundary that separates the system from its surroundings (open system).
- \square In this case, we must take the size Ω to be the inverse of $k_{\scriptscriptstyle R}T$.
 - \blacksquare $k_{\scriptscriptstyle R}$ is the <u>Boltzmann constant</u>
 - $lue{\Gamma}$ is the system temperature.
- $\hfill\Box$ Since the exact value of Ω is not important here, we set $\Omega=1$ for simplicity.

https://en.wikipedia.org/wiki/Boltzmann constant

Fundamental Thermodynamic Quantities

$$E(\mathbf{x}) \triangleq -\ln \overline{p}_{\mathbf{x}}(\mathbf{x})$$
, for every \mathbf{x} Energy of State

$$U(t) \triangleq \sum_{\mathbf{x}} E(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t)$$
, for $t \ge 0$ Internal Energy

$$S(t) \triangleq -\sum_{\mathbf{x}} p_{\mathbf{X}}(\mathbf{x};t) \ln p_{\mathbf{X}}(\mathbf{x};t), \text{ for } t \geq 0$$
 Entropy

$$F(t) \triangleq U(t) - S(t) = \sum_{\mathbf{x}} p_{\mathbf{X}}(\mathbf{x}; t) \ln \frac{p_{\mathbf{X}}(\mathbf{x}; t)}{\overline{p}_{\mathbf{X}}(\mathbf{x})}, \text{ for } t \ge 0$$

Helmholtz Free Energy

Fundamental Thermodynamic Quantities

$$F(t) \triangleq U(t) - S(t) = \sum_{\mathbf{x}} p_{\mathbf{X}}(\mathbf{x}; t) \ln \frac{p_{\mathbf{X}}(\mathbf{x}; t)}{\overline{p}_{\mathbf{X}}(\mathbf{x})}, \text{ for } t \ge 0$$

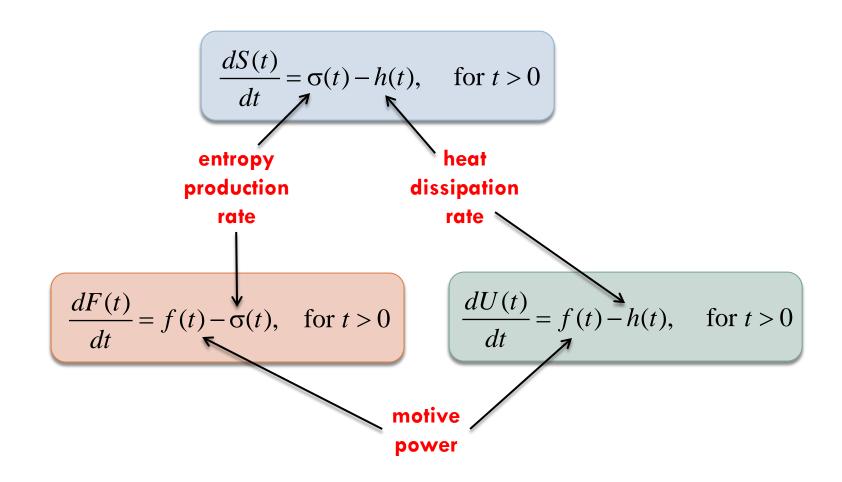
Helmholtz Free Energy

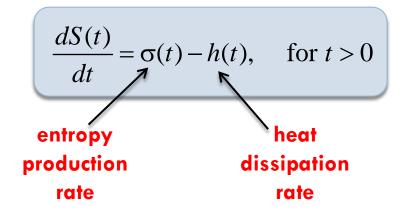
- It measures the energy available in a thermodynamic system to do work under constant temperature and volume.
- It coincides with the <u>Kullback-Leibler divergence</u> of the probability distribution $p_{\mathbf{X}}(\mathbf{x};t)$ from the steady-state probability distribution $\overline{p}_{\mathbf{X}}(\mathbf{x})$.
- It provides a measure of how far a Markovian reaction network is from steady-state at time t.
- It turns out that

$$F(t) \ge 0, \quad t \ge 0$$

$$\frac{dF(t)}{dt} \le 0, \quad t \ge 0$$

with equality only at steady-state.





entropy production rate

$$\sigma(t) = \frac{1}{2} \sum_{m=1}^{M/2} \sum_{\mathbf{x}} \left[\rho_m^+(\mathbf{x};t) A_m^+(\mathbf{x};t) + \rho_m^-(\mathbf{x};t) A_m^-(\mathbf{x};t) \right]$$

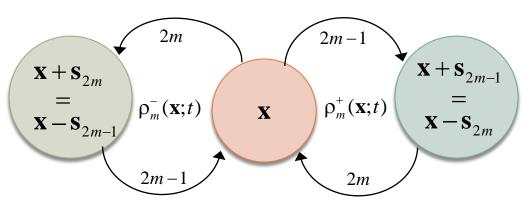
(2m-1,2m) reversible reactions $\Rightarrow \mathbf{s}_{2m} = -\mathbf{s}_{2m-1}$

<u>net flux</u> of m-th pair of reversible reactions transitioning between states x and $x + s_{2m-1}$

$$\rho_{m}^{+}(\mathbf{x};t) = \pi_{2m-1}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t) - \pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} + \mathbf{s}_{2m-1};t)$$

<u>net flux</u> of *m*-th pair of reactions transitioning between states ${\bf x}$ and ${\bf x}+{\bf s}_{2m}$

$$\rho_{m}^{-}(\mathbf{x};t) = \pi_{2m}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t) - \pi_{2m-1}(\mathbf{x} - \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} - \mathbf{s}_{2m-1};t)$$



entropy production rate

$$\sigma(t) = \frac{1}{2} \sum_{m=1}^{M/2} \sum_{\mathbf{x}} \left[\rho_m^+(\mathbf{x};t) A_m^+(\mathbf{x};t) + \rho_m^-(\mathbf{x};t) A_m^-(\mathbf{x};t) \right]$$

affinities of the m-th pair of reactions

$$A_{m}^{+}(\mathbf{x};t) \triangleq \ln \left[\frac{\pi_{2m-1}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t)}{\pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} + \mathbf{s}_{2m-1};t)} \right]$$

$$A_{m}^{-}(\mathbf{x};t) \triangleq \ln \left[\frac{\pi_{2m}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t)}{\pi_{2m-1}(\mathbf{x} - \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} - \mathbf{s}_{2m-1};t)} \right]$$

$$\mathbf{x} + \mathbf{s}_{2m}$$

$$= \mathbf{x} - \mathbf{s}_{2m-1}$$

$$\rho_{m}^{-}(\mathbf{x};t)$$

$$\mathbf{x}$$

$$\rho_{m}^{+}(\mathbf{x};t)$$

$$\mathbf{x} + \mathbf{s}_{2m-1}$$

$$= \mathbf{x} - \mathbf{s}_{2m}$$

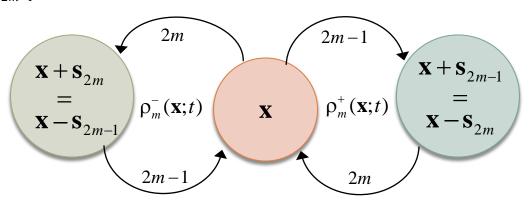
$$2m - 1$$

The affinity

$$A_{m}^{+}(\mathbf{x};t) \triangleq \ln \left[\frac{\pi_{2m-1}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t)}{\pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} + \mathbf{s}_{2m-1};t)} \right]$$

can be viewed as a thermodynamic force that drives a Markovian reaction network from state ${\bf x}$ to state ${\bf x}+{\bf s}_{2m-1}$.

If $A_m^+(\mathbf{x};t) > 0$, then $\pi_{2m-1}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t) dt > \pi_{2m}(\mathbf{x}+\mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x}+\mathbf{s}_{2m-1};t) dt$ which means that the probability of moving from state \mathbf{x} to state $\mathbf{x}+\mathbf{s}_{2m-1}$ within dt by means of the forward reaction 2m-1 will be higher than the probability of moving from state $\mathbf{x}+\mathbf{s}_{2m-1}$ to state \mathbf{x} by means of the reverse reaction 2m.

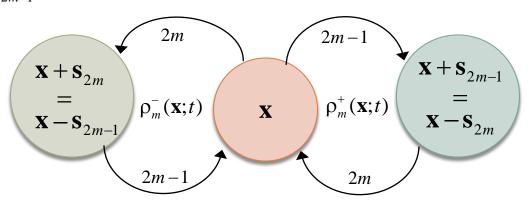


The affinity

$$A_{m}^{-}(\mathbf{x};t) \triangleq \ln \left[\frac{\pi_{2m}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t)}{\pi_{2m-1}(\mathbf{x} - \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} - \mathbf{s}_{2m-1};t)} \right]$$

can be viewed as a thermodynamic force that drives a Markovian reaction network from state ${\bf x}$ to state ${\bf x}-{\bf s}_{2m-1}$.

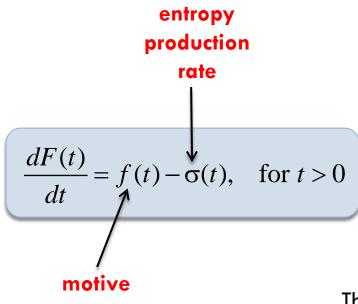
If $A_m^-(\mathbf{x};t) > 0$, then $\pi_{2m}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t) dt > \pi_{2m-1}(\mathbf{x} - \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} - \mathbf{s}_{2m-1};t) dt$ which means that the probability of moving from state \mathbf{x} to state $\mathbf{x} - \mathbf{s}_{2m-1}$ within dt by means of the reverse reaction 2m will be higher than the probability of moving from state $\mathbf{x} - \mathbf{s}_{2m-1}$ to state \mathbf{x} by means of the forward reaction 2m-1.



We also we have that

heat dissipation rate

$$h(t) = \frac{1}{2} \sum_{m=1}^{M/2} \sum_{\mathbf{x}} \left\{ \rho_m^+(\mathbf{x};t) \ln \left[\frac{\pi_{2m-1}(\mathbf{x})}{\pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1})} \right] + \rho_m^-(\mathbf{x};t) \ln \left[\frac{\pi_{2m}(\mathbf{x})}{\pi_{2m-1}(\mathbf{x} - \mathbf{s}_{2m-1})} \right] \right\}$$



power

The Helmholtz free energy measures the energy available in a thermodynamic system to do work under constant temperature and volume.

motive power

$$f(t) \triangleq \frac{1}{2} \sum_{m=1}^{M/2} \sum_{\mathbf{x}} \left[\rho_m^+(\mathbf{x};t) \overline{A}_m^+(\mathbf{x}) + \rho_m^-(\mathbf{x};t) \overline{A}_m^-(\mathbf{x}) \right]$$

$$\overline{A}_{m}^{+}(\mathbf{x}) = \lim_{t \to \infty} A_{m}^{+}(\mathbf{x};t)
\overline{A}_{m}^{-}(\mathbf{x}) = \lim_{t \to \infty} A_{m}^{-}(\mathbf{x};t)$$
steady-state affinities

The motive power quantifies the <u>rate of energy</u> (i.e., power) supplied to the Markovian reaction network.

since
$$\frac{dF(t)}{dt} \le 0$$
, we have that $f(t) \le \sigma(t)$

From

$$\frac{dF(t)}{dt} = f(t) - \sigma(t), \quad \text{for } t > 0$$

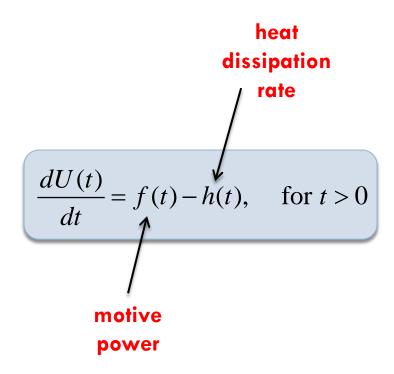
the reactions in a Markovian reaction network can increase the Helmholtz free energy by adding "motive" energy to the system, whereas they can reduce the Helmholtz free energy due to entropy production.

Moreover

$$\sigma(t) = f(t) - \frac{dF(t)}{dt}$$
, for $t > 0$

which implies that entropy production comes from two sources:

- from supplying motive power f(t)
- from a spontaneous decrease dF(t)/dt in Helmholtz free energy.



The equation

$$\frac{dU(t)}{dt} = f(t) - h(t), \quad \text{for } t > 0$$

expresses the <u>first law of thermodynamics</u> (energy conservation):

■ A change $\Delta U(t) = U(t+dt) - U(t)$ in internal energy within an infinitesimal time interval [t,t+dt) must equal the amount of motive energy f(t)dt added to the system minus the dissipated heat h(t)dt.

https://en.wikipedia.org/wiki/First law of thermodynamics

□ From

$$\sigma(t) = \frac{1}{2} \sum_{m=1}^{M/2} \sum_{\mathbf{x}} \left[\rho_m^+(\mathbf{x};t) A_m^+(\mathbf{x};t) + \rho_m^-(\mathbf{x};t) A_m^-(\mathbf{x};t) \right]$$

note that

$$\sigma(t) \ge 0$$
, for every $t \ge 0$

with equality if and only if

$$A_m^+(\mathbf{x};t) = A_m^-(\mathbf{x};t) = 0$$
, for every $m = 1, 2, ..., M/2$

- This is a direct consequence of the fact that $(x_1 x_2) \ln(x_1 / x_2) \ge 0$ with equality if and only if $x_1 = x_2$.
- □ It agrees with the <u>second law of thermodynamics</u> which postulates that the rate of entropy production must always be nonnegative.

Equations

$$\frac{dS(t)}{dt} = \sigma(t) - h(t)$$
 and $\frac{dF(t)}{dt} = f(t) - \sigma(t)$

lead to

$$0 \le \overline{\sigma} = \overline{h} = \overline{f}$$

- This result implies that, at steady-state, the amount of motive power supplied to the system must be equal to the rate of heat dissipation, in agreement with the <u>first law of thermodynamics</u>.
- Moreover, the rate of heat dissipation must be equal to the rate of entropy production.
- It also implies that the steady-state entropy production, heat dissipation and motive power must all be nonnegative, in agreement with the <u>second law of</u> <u>thermodynamics</u>.

 A Markovian reaction network at <u>thermodynamic equilibrium</u> at steadystate if and only if

$$\overline{A}_m^+(\mathbf{x}) = \overline{A}_m^-(\mathbf{x}) = 0$$
, for every $m = 1, 2, ..., M/2$

The <u>affinities</u> $\overline{A}_{m}^{+}(\mathbf{x})$ and $\overline{A}_{m}^{-}(\mathbf{x})$ can be viewed as <u>thermodynamic</u> <u>forces</u> that drive a Markovian reaction network at steady-state <u>away</u> from <u>thermodynamic equilibrium</u>.

Note that

$$\overline{A}_m^+(\mathbf{x}) = \overline{A}_m^-(\mathbf{x}) = 0$$
, for every $m = 1, 2, ..., M/2$

is equivalent to the following equations:

$$\pi_{2m-1}(\mathbf{x})\overline{p}_{\mathbf{X}}(\mathbf{x}) = \pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1})\overline{p}_{\mathbf{X}}(\mathbf{x} + \mathbf{s}_{2m-1})$$

$$\pi_{2m-1}(\mathbf{x} - \mathbf{s}_{2m-1})\overline{p}_{\mathbf{X}}(\mathbf{x} - \mathbf{s}_{2m-1}) = \pi_{2m}(\mathbf{x})\overline{p}_{\mathbf{X}}(\mathbf{x})$$
for every $m = 1, 2, ..., M / 2$, and \mathbf{x}

known as detailed balance equations.

The detailed balance equations

$$\pi_{2m-1}(\mathbf{x})\overline{p}_{\mathbf{X}}(\mathbf{x}) = \pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1})\overline{p}_{\mathbf{X}}(\mathbf{x} + \mathbf{s}_{2m-1})$$

$$\pi_{2m-1}(\mathbf{x} - \mathbf{s}_{2m-1})\overline{p}_{\mathbf{X}}(\mathbf{x} - \mathbf{s}_{2m-1}) = \pi_{2m}(\mathbf{x})\overline{p}_{\mathbf{X}}(\mathbf{x})$$
for every $m = 1, 2, ..., M / 2$, and \mathbf{x}

imply that the net fluxes $\overline{\rho}_m^+(\mathbf{x}) = \lim_{t \to \infty} \rho_m^+(\mathbf{x};t)$ and $\overline{\rho}_m^-(\mathbf{x}) = \lim_{t \to \infty} \rho_m^-(\mathbf{x};t)$ at steady-state will be zero for all reactions.

 A Markovian reaction network at steady-state is at <u>thermodynamic</u> <u>equilibrium</u> if and only if <u>all</u> net fluxes are zero.

Since

$$f(t) \triangleq \frac{1}{2} \sum_{m=1}^{M/2} \sum_{\mathbf{x}} \left[\rho_m^+(\mathbf{x};t) \overline{A}_m^+(\mathbf{x}) + \rho_m^-(\mathbf{x};t) \overline{A}_m^-(\mathbf{x}) \right]$$

we have that

$$\overline{f} = 0$$

when a Markovian reaction network at steady-state is at thermodynamic equilibrium.

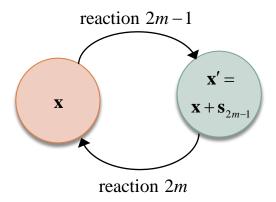
 \Box From $0 \le \overline{\sigma} = \overline{h} = \overline{f}$, we now have that

$$\overline{\sigma} = \overline{h} = \overline{f} = 0$$

- This shows that a Markovian reaction network that is at thermodynamic equilibrium at steady-state will not produce entropy or dissipate heat.
- □ This system "dies" at steady-state.
- In most cases of interest, a useful Markovian reaction network at steady-state must operate <u>away from thermodynamic equilibrium</u>.
- We can make sure that this is the case by including <u>nonreversible</u> <u>reactions</u> that transfer mass between the system and its surroundings (open system), thus breaking detailed balance by supplying motive power to the network using non-zero thermodynamic forces (i.e., non-zero affinities).

Reaction Cycles

- \square A useful representation of the state-space of a Markovian reaction network is by means of a graph \mathcal{G} .
- Its nodes are the population states, and its edges connect pairs of population states $(\mathbf{x}, \mathbf{x} + \mathbf{s}_{2m-1})$ when $\pi_{2m-1}(\mathbf{x}), \pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1}) > 0$.
- An edge connecting two states x, x' indicates that these states can "reach" each other using a pair of reversible reactions.

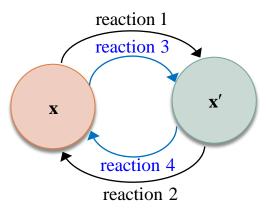


Reaction Cycles

- There might be several distinct edges (corresponding to different reversible reactions) connecting a given pair of nodes, in which case \mathcal{G} is a <u>multigraph</u>.
- Example: the reversible reactions

$$r1: X_1 \to X_2$$
 and $r3: X_1 + X_3 \to X_2 + X_3$
 $r2: X_2 \to X_1$ $r4: X_2 + X_3 \to X_1 + X_3$

are characterized by the same net stoichiometry and will therefore connect the same pair of nodes in \mathcal{G} .



Reaction Cycles

 \square An ordered chain $(m_1, m_2, ..., m_L)$ of reactions will produce a path

$$(\mathbf{x}_0, \mathbf{x}_0 + \mathbf{S}_{m_1}, \dots, \mathbf{x}_0 + \sum_{l=1}^{L} \mathbf{S}_{m_l})$$

in $\mathcal G$ of length L, provided that each reaction can occur with positive probability.

□ When

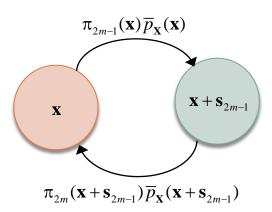
$$\sum_{l=1}^{L} \mathbf{s}_{m_l} = 0$$

the reactions $(m_1, m_2, ..., m_L)$ will produce a <u>reaction cycle</u> C in \mathcal{G} of length L that ends in the same state as the starting state.

Kolmogorov Cyclic Conditions

- For a Markovian reaction network at steady state containing only reversible reactions that is at <u>thermodynamic equilibrium</u>, the flux of a forward reaction will be equal to the flux of the corresponding reverse reaction (detailed balance).
- \square In this case, and for every pair m of reactions, we must have

$$\pi_{2m-1}(\mathbf{x})\overline{p}_{\mathbf{x}}(\mathbf{x}) = \pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1})\overline{p}_{\mathbf{x}}(\mathbf{x} + \mathbf{s}_{2m-1}), \text{ for every } \mathbf{x}$$



Kolmogorov Cyclic Conditions

For an ordered chain $(m_1, m_2, ..., m_L)$ of forward reactions, detailed balance leads to (see slide 32 for an example)

$$\overline{p}_{\mathbf{X}}(\mathbf{X}_0 + \sum_{l=1}^{L} \mathbf{S}_{m_l}) = \overline{p}_{\mathbf{X}}(\mathbf{X}_0) \prod_{l=1}^{L} \frac{\pi_{m_l}(\mathbf{X}_0 + \sum_{k=1}^{l-1} \mathbf{S}_{m_k})}{\pi_{m_l^*}(\mathbf{X}_0 + \sum_{k=1}^{l} \mathbf{S}_{m_k})}$$

pair of forward/reverse reactions

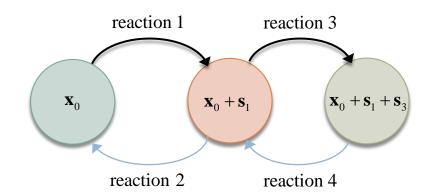
This implies that (see slides 33 and 34 for an example)

$$K(C) \triangleq \prod_{l=1}^{L} \frac{\pi_{m_l}(\mathbf{x}_0 + \sum_{k=1}^{l-1} \mathbf{s}_{m_k})}{\pi_{m_l^*}(\mathbf{x}_0 + \sum_{k=1}^{l} \mathbf{s}_{m_k})} = 1$$

if the ordered chain produces a reaction cycle C, which is known as the Kolmogorov cyclic condition.

Kolmogorov Cyclic Conditions – Example 1

- Let us consider two reversible reactions (2m-1,2m), m=1,2.
- The ordered chain (1,3) of forward reactions produces a path $(\mathbf{x}_0, \mathbf{x}_0 + \mathbf{s}_1, \mathbf{x}_0 + \mathbf{s}_1 + \mathbf{s}_3)$ of length 2.

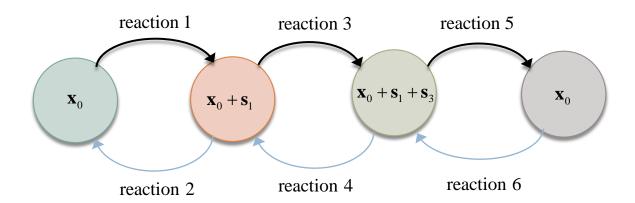


$$\overline{p}_{\mathbf{X}}(\mathbf{x}_0 + \mathbf{s}_1 + \mathbf{s}_3) = \frac{\pi_3(\mathbf{x}_0 + \mathbf{s}_1)}{\pi_4(\mathbf{x}_0 + \mathbf{s}_1 + \mathbf{s}_3)} \overline{p}_{\mathbf{X}}(\mathbf{x}_0 + \mathbf{s}_1)$$

$$= \frac{\pi_3(\mathbf{x}_0 + \mathbf{s}_1)}{\pi_4(\mathbf{x}_0 + \mathbf{s}_1 + \mathbf{s}_3)} \frac{\pi_1(\mathbf{x}_0)}{\pi_2(\mathbf{x}_0 + \mathbf{s}_1)} \overline{p}_{\mathbf{X}}(\mathbf{x}_0)$$

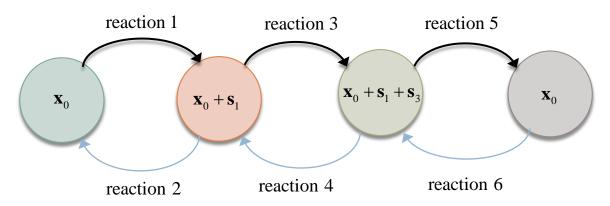
Kolmogorov Cyclic Conditions – Example 2

- Let us now consider three reversible reactions (2m-1,2m), m=1,2,3, such that $\mathbf{s}_5=-(\mathbf{s}_1+\mathbf{s}_3)$.
- The ordered chain (1,3,5) of forward reactions produces a reaction cycle $C = (\mathbf{x}_0, \mathbf{x}_0 + \mathbf{s}_1, \mathbf{x}_0 + \mathbf{s}_1 + \mathbf{s}_3, \mathbf{x}_0)$ of length 3.



Kolmogorov Cyclic Conditions – Example 2

In this case, we have that



$$\begin{split} & \overline{p}_{\mathbf{X}}(\mathbf{X}_{0}) \\ & = \frac{\pi_{5}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})}{\pi_{6}(\mathbf{X}_{0})} \overline{p}_{\mathbf{X}}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3}) \qquad \Rightarrow \boxed{\frac{\pi_{5}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})}{\pi_{6}(\mathbf{X}_{0})} \frac{\pi_{3}(\mathbf{X}_{0} + \mathbf{s}_{1})}{\pi_{4}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})} \frac{\pi_{3}(\mathbf{X}_{0} + \mathbf{s}_{1})}{\pi_{4}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})} \overline{p}_{\mathbf{X}}(\mathbf{X}_{0} + \mathbf{s}_{1}) \\ & = \frac{\pi_{5}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})}{\pi_{6}(\mathbf{X}_{0})} \frac{\pi_{3}(\mathbf{X}_{0} + \mathbf{s}_{1})}{\pi_{4}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})} \frac{\pi_{1}(\mathbf{X}_{0})}{\pi_{2}(\mathbf{X}_{0} + \mathbf{s}_{1})} \overline{p}_{\mathbf{X}}(\mathbf{X}_{0}) \\ & = \frac{\pi_{5}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})}{\pi_{6}(\mathbf{X}_{0})} \frac{\pi_{3}(\mathbf{X}_{0} + \mathbf{s}_{1})}{\pi_{4}(\mathbf{X}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3})} \frac{\pi_{1}(\mathbf{X}_{0})}{\pi_{2}(\mathbf{X}_{0} + \mathbf{s}_{1})} \overline{p}_{\mathbf{X}}(\mathbf{X}_{0}) \end{split}$$

Kolmogorov Cyclic Conditions

In addition to being <u>necessary</u>, the Kolmogorov cyclic conditions

$$K(C) \triangleq \prod_{l=1}^{L} \frac{\pi_{m_l}(\mathbf{x}_0 + \sum_{k=1}^{l-1} \mathbf{s}_{m_k})}{\pi_{m_l^*}(\mathbf{x}_0 + \sum_{k=1}^{l} \mathbf{s}_{m_k})} = 1$$

can be shown to be <u>sufficient</u> for a Markovian reaction network to reach <u>thermodynamic equilibrium</u> at steady-state.

Kolmogorov Cyclic Conditions

$$K(C) \triangleq \prod_{l=1}^{L} \frac{\pi_{m_l}(\mathbf{x}_0 + \sum_{k=1}^{l-1} \mathbf{s}_{m_k})}{\pi_{m_l^*}(\mathbf{x}_0 + \sum_{k=1}^{l} \mathbf{s}_{m_k})} = 1$$

- For thermodynamic consistency, the Kolmogorov cyclic conditions must always be satisfied, even if the system operates away from thermodynamic equilibrium.
- This is because a system with fixed propensity functions that operates away from thermodynamic equilibrium may reach thermodynamic equilibrium in the absence of motive power.
- Consequently, the propensity function of a Markovian reaction network cannot be chosen arbitrarily, since they are constrained by Kolmogorov's cyclic conditions.

The <u>net affinity</u> (i.e., the net thermodynamic force) of a cycle C of length L is defined by:

$$A(t;C) \triangleq A_{m_{1}}^{+}(\mathbf{x}_{0};t) + A_{m_{2}}^{+}(\mathbf{x}_{0} + \mathbf{s}_{m_{1}};t) + \dots + A_{m_{L}}^{+}(\mathbf{x}_{0} + \sum_{k=1}^{L-1} \mathbf{s}_{m_{k}};t)$$

$$= \sum_{l=1}^{L} \ln \frac{\pi_{m_{l}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}}) p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}};t)}{\pi_{m_{l}^{*}}(\mathbf{x}_{0} + \sum_{k=1}^{l} \mathbf{s}_{m_{k}}) p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l} \mathbf{s}_{m_{k}};t)}, \text{ for every } t \geq 0$$

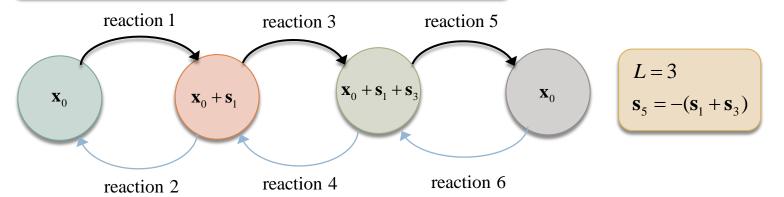
pair of forward/reverse reactions

$$A_{m}^{+}(\mathbf{x};t) \triangleq \ln \left[\frac{\pi_{2m-1}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t)}{\pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} + \mathbf{s}_{2m-1};t)} \right]$$

Example (from slide 33):

$$A(t;C) \triangleq \sum_{l=1}^{L} \ln \frac{\pi_{m_{l}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}}) p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}};t)}{\pi_{m_{l}^{*}}(\mathbf{x}_{0} + \sum_{k=1}^{l} \mathbf{s}_{m_{k}}) p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l} \mathbf{s}_{m_{k}};t)}, \quad \text{for every } t \geq 0$$

$$A_{m}^{+}(\mathbf{x};t) \triangleq \ln \left[\frac{\pi_{2m-1}(\mathbf{x}) p_{\mathbf{X}}(\mathbf{x};t)}{\pi_{2m}(\mathbf{x} + \mathbf{s}_{2m-1}) p_{\mathbf{X}}(\mathbf{x} + \mathbf{s}_{2m-1};t)} \right]$$



$$\begin{split} A(t;C) &= A_{1}^{+}(\mathbf{x}_{0};t) + A_{2}^{+}(\mathbf{x}_{0} + \mathbf{s}_{1};t) + A_{3}^{+}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3};t) \\ &= \ln \left[\frac{\pi_{1}(\mathbf{x}_{0}) p_{\mathbf{X}}(\mathbf{x}_{0};t)}{\pi_{2}(\mathbf{x}_{0} + \mathbf{s}_{1}) p_{\mathbf{X}}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3}) p_{\mathbf{X}}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3};t)} \right] + \ln \left[\frac{\pi_{3}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3}) p_{\mathbf{X}}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3};t)}{\pi_{4}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3}) p_{\mathbf{X}}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3};t)} \right] + \ln \left[\frac{\pi_{5}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3}) p_{\mathbf{X}}(\mathbf{x}_{0} + \mathbf{s}_{1} + \mathbf{s}_{3};t)}{\pi_{6}(\mathbf{x}_{0}) p_{\mathbf{X}}(\mathbf{x}_{0};t)} \right] \end{split}$$

Note that

$$A(t;C) \triangleq \sum_{l=1}^{L} \ln \frac{\pi_{m_{l}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}}) p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}};t)}{\pi_{m_{l}^{*}}(\mathbf{x}_{0} + \sum_{k=1}^{l} \mathbf{s}_{m_{k}}) p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l} \mathbf{s}_{m_{k}};t)}$$

$$= \ln \prod_{l=1}^{L} \frac{\pi_{m_{l}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}})}{\pi_{m_{l}^{*}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}})} + \ln \prod_{l=1}^{L} \frac{p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l-1} \mathbf{s}_{m_{k}};t)}{p_{\mathbf{X}}(\mathbf{x}_{0} + \sum_{k=1}^{l} \mathbf{s}_{m_{k}};t)}$$

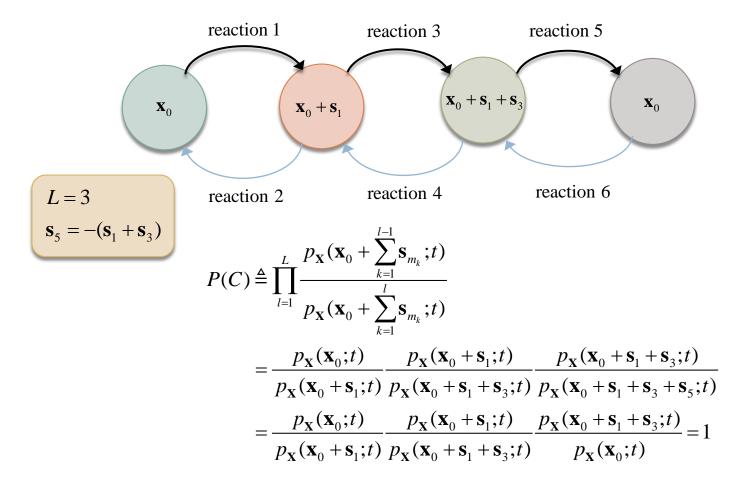
$$= \ln K(C) + \ln P(C)$$

$$= \ln K(C)$$

since, in a reaction cycle C, we always have (see slide 40 for an example)

$$P(C) \triangleq \prod_{l=1}^{L} \frac{p_{\mathbf{X}}(\mathbf{x}_0 + \sum_{k=1}^{l-1} \mathbf{s}_{m_k}; t)}{p_{\mathbf{X}}(\mathbf{x}_0 + \sum_{k=1}^{l} \mathbf{s}_{m_k}; t)} = 1, \text{ for every } t \geq 0$$

Example (from page 33):



- \square Recall that K(C) = 1 for thermodynamic consistency.
- Therefore, for a Markovian reaction network that contains only reversible reactions, we must have

$$A(t;C) = \ln K(C) = 0$$
, at any time t

This implies that the net affinity (i.e., the net thermodynamic force) applied on a reaction cycle C will be zero at any time point!