From stochastic thermodynamic to thermodynamic inference

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- Principles of stochastic thermodynamics
- Molecular motors as paradigm
- Cost of temporal precision
- (Modelfree) inference from experimental data
- Efficiency of cellular information processing

• From classical th'dynamics

stochastic th'dynamics

to





[K. Hayashi, ... H. Noji, PRL 104, 218103 (2010)]

19th century steam engine

 21^{st} century nano-engine: F₁ATP-ase

- Stochastic thermodynamics applies to systems for which
 - non-equilibrium is caused by mechanical or chemical forces
 - ambient solution provides a thermal bath of well-defined T and μ_i
 - fluctuations are relevant due to small numbers of involved molecules



[Collin et al, Nature 437, 231, 2005]

- Main idea: Energy conservation (1^{st} law) and entropy production (2^{nd} law) along an individual stochastic trajectory
- Review: U.S., Rep. Prog. Phys. 75 126001, 2012.

• Biomolecules in equilibrium: Meso-states of calmodulin [J. Stigler et al, Science 334 512 (2011)]





• Thermodynamically consistent markovian dynamics on meso-states



- trajectory I(t)
- crucial time-scale separation:
 - * transitions between meso-states are slow
 - * transitions between the micro-states belonging to one meso-state are fast
- master equation

$$\partial_t P_I(t) = \sum_J [P_J(t) K_{JI} - P_I(t) K_{IJ}].$$

- local detailed balance condition on the rates $\{K_{IJ}\}$
- $\Rightarrow \quad K_{IJ}/K_{JI} = P_J^e/P_I^e = \tau_J^e/\tau_I^e = \exp(-\beta\Delta_{IJ}F) = \exp(-\beta\Delta_{IJ}E + \Delta_{IJ}S)$
- th'dyn potentials of meso-states operationally accessible from traj' data

• Thermodynamics along a trajectory I(t) of biochemical/physical meso-states

[T. Schmiedl and U.S., J. Chem. Phys. 126, 044101 (2007)]

- internal energy $E(t) = E_{I(t)}$ becomes stochastic
- first law (Sekimoto 1998) $\Delta_{IJ}E \equiv E_J E_I = -Q_{IJ}$ entropy of "system" $S_{sys}(t) \equiv S_{I(t)} \ln[P_{I(t)}(t)]$
- total entropy change in a transition from I to J at time t

 $\Delta_{IJ}S_{\text{tot}}(t) = \beta Q_{IJ} + \Delta_{IJ}S_{\text{sys}}(t) = \ln[P_I(t)K_{IJ}/P_J(t)K_{JI}]$

- integral fluctuation theorem for total entropy production

$$\langle \exp[-\Delta S_{\text{tot}}] \rangle = 1 \quad \Rightarrow \langle \Delta S_{\text{tot}} \rangle \ge 0$$

* any lengths t, any initial distribution $\{P_I^0\}$

[U.S., PRL 2005]

- second law on ensemble level (Schnakenberg 1976)

$$\langle \dot{S}_{tot}(t) \rangle \equiv \sum_{IJ} P_I(t) K_{IJ} \Delta_{IJ} S_{tot}(t) \ge 0$$

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- Stochastic th'dynamics of NESS: Driven colloidal particle as paradigm
 - Langevin dynamics $\dot{x} = \mu [-V'(x) + f] + \zeta$ with $\langle \zeta_1 \zeta_2 \rangle = 2\mu T \delta(t_2 t_1)$
 - first law [(Sekimoto, 1997)]:
 - * applied work: dw = f dx
 - * internal energy : du = dV
 - * dissipated heat: $dq = dw du = [-\partial_x V(x) + f]dx = T ds_h$
 - total entropy as quantitive measure of broken time reversal symmetry

 $x(t) \to \tilde{x}(t) \equiv x(\mathcal{T} - t)$ $\Delta s_{\text{tot}}[x(t)] \equiv \ln[p[x(t)]/p[\tilde{x}(t)]] = \Delta[-\ln p^s(x)] + q/T$

- IFT for total entropy production $|\langle \exp[-\Delta s_{tot}] \rangle = 1 \Rightarrow \langle \Delta s_{tot} \rangle \geq 0$ [U.S., PRL 2005]

$$\frac{f(\lambda)}{V(x,\lambda)}$$

dw = du + dq



• Fluctuation theorem $\left| p(-\Delta s_{tot})/p(\Delta s_{tot}) = \exp(-\Delta s_{tot}) \right|$ in any NESS

Evans et al (1993), Gallavotti & Cohen (1995), Kurchan (1998), Lebowitz & Spohn (1999), U.S. (2005)

• Experimental data [Speck, Blickle, Bechinger, U.S., EPL 79 30002 (2007)]





FT-representation

• F1-ATPase and the fluctuation theorem [K. Hayashi et al, PRL 104, 218103 (2010)]



 $\Gamma \dot{\theta} = N + \zeta$

 $\Rightarrow \ln[p(\Delta\theta)/p(-\Delta\theta)] = N\Delta\theta/k_BT$

independent of friction coefficient Γ



time-dependence?

torque N from $\Delta t \rightarrow \infty$?

• Hybrid model [E. Zimmermann and U.S., New J. Phys. 14, 103023, 2012]



- probe particle

*
$$\dot{x} = \mu(-\partial_y V(y) + f^{ex}) + \zeta$$
 with $y(\tau) \equiv n(\tau) - x(\tau)$

– motor

*
$$w^+/w^- = \exp[\Delta \mu - V(n+d,x) - V(n,x)]$$



 $\Delta t
ightarrow$ 0 limit yields average force/torque

• Inferring the efficiency of a molecular motor [S. Toyabe et al, PRL 104, 198103 (2010)]



- Harada-Sasa relation [PRL 2006]

$$\mu \dot{Q}_P = v^2 + \int d\omega [C_{\dot{x}}(\omega) - 2k_B T \operatorname{Re} R_{\dot{x}}(\omega)]$$

heat from "violation" of fluc-diss-theorem



• Comparison:

experiment





theory



[S. Toyabe et al, PRL 104, 198103 (2010)]

[E. Zimmermann and US, NJP 2012]

• Temporal precision in a finite temperature environment



at 300 K, a precision of 1 sec/day requires at least 6×10^{-11} J/day

• Cost of running a simple clock: ARW

[AC Barato and US, Phys. Rev. Lett. 114, 158101, 2015]



- output n(t) with $\langle n \rangle = Jt = (k^+ - k^-)t$

- variance
$$\langle (n(t) - \langle n \rangle)^2 \rangle = 2Dt = (k^+ + k^-)t$$

- uncertainty
$$\epsilon^2 \equiv var/output^2 = 2D/J^2t$$

- th'dyn cost $C = \sigma t = (k^+ k^-) \ln(k^+/k^-)t$ with $\sigma \equiv$ rate of entropy production
- with affinity $\mathcal{A} = k_B T \ln(k^+/k^-) = \mu_{ATP} \mu_{ADP} \mu_P$

 $- \left| \mathcal{C}\epsilon^2 = 2\sigma D/J^2 = \mathcal{A} \operatorname{coth}[\mathcal{A}/2k_B T] \ge 2k_B T \right|$

independent of run time \boldsymbol{t}

• Thermodynamic uncertainty relation holds for general multicyclic processes AC Barato and US, Phys. Rev. Lett. 114, 158101, 2015; proof by Gingrich et al, PRL 2016



- a precision of 1% costs at least 20.000 k_BT
- inevitable, universal cost of temporal precision (within stationary Markov processes)
- for any current $j = \sum_{ij} d_{ij} n_{ij}$ $\sigma \geq j^2/D_j$

• Thermodynamic inference: Efficiency of a molecular motor



- experimental data on
 - \ast velocity v
 - * diffusion constant D
 - * randomness parameter $r\equiv 2D/v\ell$



• Thermodynamic inference: Universal bound on the efficiency of molecular machines

P. Pietzonka, AC Barato, U.S., J Stat Mech, 124004, 2016; U.S., Physica A 504, 176, 2018

- efficiency

$$\eta \equiv \frac{P^{\text{out}}}{P^{\text{in}}} = \frac{fv}{\text{unknown}} = \frac{fv}{fv + \sigma} \le \frac{1}{1 + vk_BT/(Df)}$$

- entropy production rate $\sigma = P^{\text{in}} - P^{\text{out}} = "\text{chem energy}" - fv \ge v^2/D$



– independent of the specific chemo-mechanical cycles and of $\Delta\mu$

- Th'dyn' uncertainity relation(s) beyond NESSs?
 - periodic driving with period $\boldsymbol{\Omega}$
 - * TUR "fails" in general

AC Barato and US, PRX 2016

* for a symmetric protocol $k_{ij}(t) = k_{ij}(T-t)$

$$\frac{\exp[\Delta S_{\text{per}}] - 1}{t_{\text{per}}} D_j > j^2$$

Proesmans and van den Broeck, EPL 2017

* a number of "technical" bounds

Barato, Chetrite, Faggionato, Gabrielli, NJP 2018, JStatMech 2019 Proesmans and Horowitz, JStatMech 2019 Koyuk and U.S., JPA 2019

* operationally accessible version

$$\sigma(\Omega)D(\Omega) \ge [J(\Omega) - \Omega\partial_{\Omega}J(\Omega)]^2$$

Koyuk and U.S., PRL 2019

- relaxations towards equilibrium or a NESS

Dechant and Sasa, JStatMech 2018, Liu, Gong and Ueda, arxiv 2019

- A few further generalizations and ramifications
 - underdamped Langevin dynamics
 - $\ast\,$ TUR "fails" for a finite time ${\cal T}$
 - \ast conjectured but not proven for $\mathcal{T} \rightarrow \infty$ yet
 - role of a magnetic field Brandner et al PRL 2018, Chun et al, PRE 2019
 - "generalized" TURs from the fluctuation theorem

Hasegawa and Van Vu, PRL 2019, Timpanaro et al PRL2019

- optimal current? (or even the optimal observable?)

Polettini et al PRE2016, Busiello and Pigolotti, PRE 2019 Falasco et al arxiv 2019, Manikandan et al PRL 2020

bounds on variance of time-symmetric observables

Maes PRL 2017, Nardini and Touchette EPJB 2018, Terlizzi and Baiesi, JPA 2019

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bounds on variance of first-passage times

Garrahan PRE 2017, Gingrich and Horowitz, PRL 2017

open quantum systems

• Generalization to time-dependent driving

[T Koyuk and U.S., arXiv 2005.02312]



- network with rates $k_{ij}(\lambda)$ that depend on a driving protocol $\lambda = \lambda(t)$
- protocol $\lambda(t) = \lambda(vt)$ depends on an experimentally controlable speed parameter v
- system is driven for a total (observation) time t = T
- mean current $J(\mathcal{T}, \mathbf{v})$

$$[J(\mathcal{T}, \boldsymbol{v}) + \Delta J(\mathcal{T}, \boldsymbol{v})]^2 / D_J(\mathcal{T}, \boldsymbol{v}) \leq \sigma(\mathcal{T}, \boldsymbol{v}) \quad \text{with} \quad \Delta \equiv \mathcal{T} \partial_{\mathcal{T}} - \boldsymbol{v} \partial_{\boldsymbol{v}}$$

- Generalization to state observables
 - Example: driven two-state system $k_{12}(vt)$



- observable $a(\mathcal{T}, \boldsymbol{v}) \equiv \delta_{n(\mathcal{T})2}$ at final time [blue]

- observable $A(\mathcal{T}, \boldsymbol{v}) \equiv \tau_2/\mathcal{T}$ total time spent in state 2 [green]

 $[\Delta X(\mathcal{T}, \boldsymbol{v})]^2 / D_X(\mathcal{T}, \boldsymbol{v}) \leq \sigma(\mathcal{T}, \boldsymbol{v}) \text{ for } X(\mathcal{T}, \boldsymbol{v}) \in \{a(\mathcal{T}, \boldsymbol{v}), A(\mathcal{T}, \boldsymbol{v})\} \text{ with } \Delta \equiv \mathcal{T} \partial_{\mathcal{T}} - \boldsymbol{v} \partial_{\boldsymbol{v}}$

- current $J(\mathcal{T}, \mathbf{v}) = [n_{12}(\mathcal{T}, \mathbf{v}) - n_{21}(\mathcal{T}, \mathbf{v})]/\mathcal{T}$ [red]

• Information and entropy production in cellular sensing



- Lan et al, Nature Phys. 2012;

Mehta and Schwab PNAS 2012

Information about an external process $\{X(t)\}$ (conc' of a nutrient) is recorded by an internal variable $\{Y(t)\}$ (conc' of phosph'd protein)

Q: Is a rate of information (which one?) acquired about $\{X(t)\}$ related to the thermodynamic cost σ of maintaining the sensory network? [AC Barato, D Hartich, U.S., PRE 87, 042104, 2013]

[cf: Horowitz & Sandberg NJP 2014, Lang, Fisher, Mora & Mehta PRL 2014,

Bo, Del Giudice & Celani JSM 2015,...]

- Framework: Stochastic thermodynamics of bipartite systems
- [D. Hartich, AC Barato, U.S., J Stat Mech, P02016, 2014]
 - thermodynamic entropy production

- (external) x-jumps $w^{\alpha\beta}$
- independent of \boldsymbol{y}



- (internal) y-jumps w_{ij}^{lpha}
- affected by x

- $\sigma = \sigma_x + \sigma_y \ge 0$
- conditional Shannon entropy
- $H[x|y] = -\sum_{i,\alpha} P_i P(\alpha|i) \ln P(\alpha|i)$
- learning rate

$$l_y \equiv -\frac{d}{dt}_{|\mathbf{y}-\mathsf{jumps}} H[x|y] \le \sigma_y \le \sigma$$

- efficiency of learning

$$\eta \equiv l_y/\sigma_y \leq 1$$

– rate of mutual information not bounded by σ_y !

• Efficiency of cellular sensing



[AC Barato, D Hartich, U.S., NJP 16 103024, 2014]

Model	ext conc	ligand	activity of rec'r	methyl	Che Y/Y^*
minimal 4-state	<	X	>	_	Y
eq receptor	X	Y_b	Y_a	_	_
coarse-grained	X	fast	Y_a	_	_
with adaptation	X	fast	Y_a	Y_m	_

• Minimal four state model [AC Barato, D Hartich, U.S., NJP 16 103024, 2014]



$$Y + ATP \stackrel{\kappa_{+}}{\underset{\kappa_{-}}{\longrightarrow}} Y^{*} + ADP \stackrel{\omega_{+}}{\underset{\omega_{-}}{\longrightarrow}} Y + ADP + P_{i}$$
$$\Delta \mu = k_{B}T \ln(\kappa_{+}\omega_{+}/\kappa_{-}\omega_{-})$$
$$\sigma = J\Delta \mu$$

 $l_y = J \ln[P_1 P_4 / P_2 P_3]$

- l_y increases with $\Delta \mu$
- adiabatic case : $\eta \rightarrow \mathbf{1}$
- fast external changes: $\eta \rightarrow 0$

• Model with adaptation [AC Barato, D Hartich, U.S., NJP 16 103024] 2014





increasing methylation level \longrightarrow



• Stochastic thermodynamics as

universal, thermodynamically consistent, quantitative framework

- Universal inequalities (bounds) for thermodynamic inference
 - thermodynamic uncertainty relation provides constraints on
 - * ... cost of any process with given precision
 - * ... efficiency of any molecular motor (complex)
 - generalization to arbitrary time-dependent driving
- Bipartite approach to information processing in sensing
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