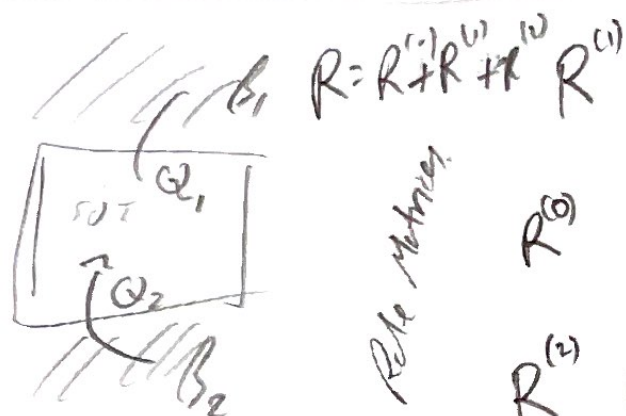


#121

$$e^{-\beta W} \langle e^{+\Delta F - \beta W} \rangle = 1$$

e

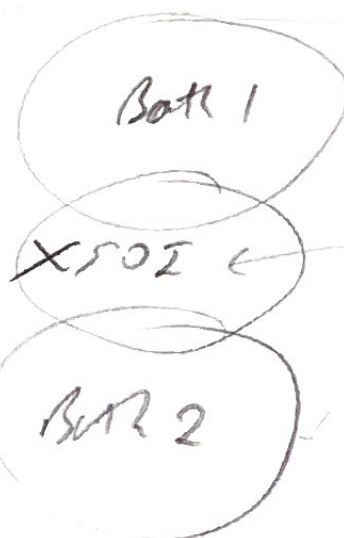
~~Q = \dots~~



Relaxation

$R^{(1)}$

$R^{(2)}$



no overlap

$$e^{+\beta Q_1 + \beta Q_2}$$

$$\frac{P(x|x_a)}{P(\tilde{x}|x_b)} = e^{+\tilde{\Sigma}^{env}} = e^{-\beta Q_1 - \beta Q_2}$$

$$\tilde{\Sigma}^{env} = -\beta_1 Q_1 - \beta_2 Q_2$$

$$\tilde{\Sigma} = \tilde{\Sigma}^{sys} + \tilde{\Sigma}^{env}$$

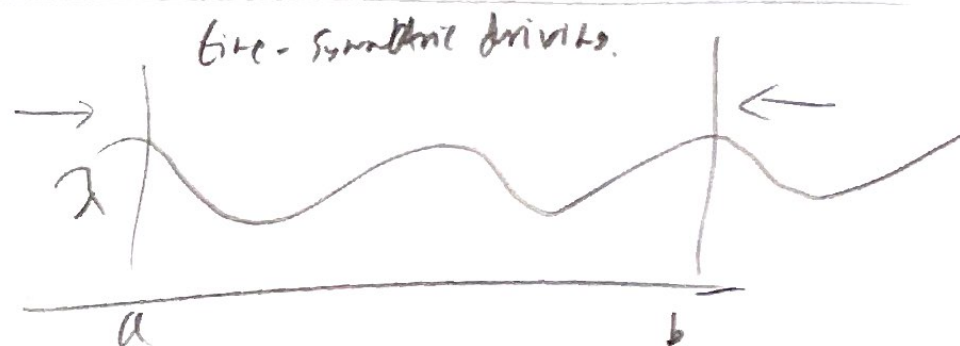
$$= \ln P_{ss}(x_a) + \ln P_{ss}(x_b)$$

Steady state FT



$$\frac{P(+Z)}{P(-Z)} = e^{+\bar{Z}}$$

↑ no distinction forward & back



$$\bar{Z} = \sum_{\gamma} \bar{Z}_{\text{sur}} + \bar{Z}_{\text{env}} - \beta Q_1 - \beta Q_2 \dots$$

$$-\ln P_{SS}(x_a) + \ln P_{SS}(x_b)$$

(Hardcore, throw away boundary term)

Not converged. Dynamics not detailed balanced.

Refs: Stocklike Thermodynamics Peliti & Pignatelli 2006

Huao Touchette 2009

3

Lange Derivations

Random? Probability (run) = r , independent

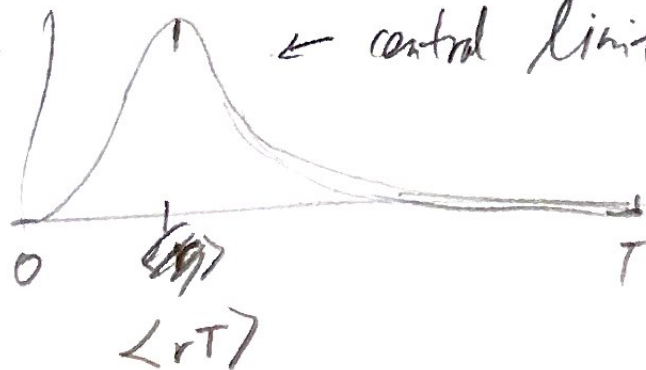


$$P(z; T) = \binom{T}{z} r^z (1-r)^{T-z}$$

Binomial coefficient,

$$\binom{a}{b} = \frac{a!}{b!(a-b)!}$$

mean $\langle z \rangle = np = T(1-r)r$
var $\langle z^2 \rangle = np(1-r) = T(1-r)r$



← central limit theorem, small $n \sim$ Gaussian
[if finite cumulants!]

because $V_{\text{orig}} \sim \ln T$
but rescale $\frac{1}{T} \rightarrow \frac{1}{T^2}$ \hookleftarrow

$$f = \frac{\text{fraction of days}}{T}$$

$$\langle f \rangle = r \quad \sigma_f^2 = \frac{r(1-r)}{T}$$

$$p(f; T) \approx \sqrt{\frac{T}{2\pi r(1-r)}} e^{-\frac{T(f-r)^2}{2r(1-r)}}$$

Central Limit Theorem

Only applies to "center", not wings.

(5)

→ (Cramér 1944)
Rate function (Cramér function)

Rate function
(not mutual information)

"Large deviation
principle"

$$\lim_{T \rightarrow \infty} \frac{1}{T} \ln P(f; T) = -\mathcal{I}(f)$$

or equivalently as $P(f; T) \asymp e^{-T\mathcal{I}(f)}$

(and also strong
law of large numbers
conditions)

For Bernoulli $\mathcal{I}(f) = f \ln \frac{f}{r} + (1-f) \ln \frac{1-f}{1-r}$

Gaussian $\mathcal{I}(f) = \frac{(f - \langle f \rangle)^2}{2 \tilde{\sigma}_f^2}$

Signal Variance $\tilde{\sigma}_f^2 = \lim_{T \rightarrow \infty} T \sigma_f^2$

[MARK 2006]

Supremum - smallest upper bound

Maximum - lowest

$(1, 5)$ - Max ill defined, $\sup = 5$

6

Scaled Cumulant Generating function

$$\psi^{(t)}(a) = \lim_{T \rightarrow \infty} \frac{1}{T} \ln \langle e^{aTf} \rangle$$

Görtner - Ellis Theorem
1977 1984

Legendre-Fenchel transform

$$\bar{I}(t) = \sup_a [at - \psi^{(t)}(a)]$$

$$\psi^{(t)}(a) = \sup_t [at - \bar{I}(t)]$$

Involution

Heuristic Proof

7

$$\Psi^{(t)}(a) = \lim_{T \rightarrow \infty} \frac{1}{T} \ln \int_{-\infty}^{\infty} dt \underbrace{P(t; T)}_{\sim e^{-T\bar{I}(t)}} e^{Tat}$$

$$= \lim_{T \rightarrow \infty} \frac{1}{T} \ln \int_{-\infty}^{\infty} dt e^{+T(\bar{I}(t) + a(t))}$$

(Roughly) -

Replace by maximum value, "saddle point"

$$\begin{aligned} &= \lim_{T \rightarrow \infty} \frac{1}{T} \ln e^{+T \sup(a(t) - \bar{I}(t))} \\ &= \sup(a(t) - \bar{I}(t)) \end{aligned}$$

"Gallavotti - Cohen" Symmetry 1995

8

Lebowitz & Spohn 1998

Gallavotti - Cohen FT

Entropy Production Rate

$$\dot{\sigma} = \frac{\Sigma}{T} \leftarrow \text{time}$$

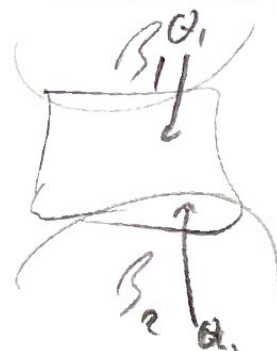
$$\frac{P(+j_{ss}; T)}{P(-j_{ss}; T)} = e^{T\dot{\sigma}}$$

same Denominators $P(j_{ss}; T) \leq e^{-T\mathcal{I}(j_{ss})}$

$$\mathcal{I}(j_{ss}) - \mathcal{I}(-j_{ss}) = -\dot{\sigma}$$

(generalize the forward / Reverse) ↗

$$\Psi(q) = \Psi(-1-q) \quad \langle e^{-qT\dot{\sigma}} \rangle = \langle e^{+(1+q)T\dot{\sigma}} \rangle$$



$$\Sigma^{tot} = \Delta S^{ss} + \Sigma^{env}$$

\uparrow \uparrow
 intensive extensive
 with time.

Ref: Field guide to Continuous Probability Distributions
Threeplusone.org/field guide

10

Extreme Value Distributions

$P(x)$, $x = \max \{x\}$, over many windows of time T ?

Generalized Fisher-Tippett Distribution

$$P(x) = \frac{n}{\Gamma(n)} \left| \frac{\beta}{w} \right| \left(\frac{x-a}{w} \right)^{n\beta-1} e^{-n \left(\frac{x-a}{w} \right)^\beta}$$

(special case of Amoroso)

