# Retrodiction in Stochastic Thermodynamics

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#### New physics!!

# Long-Awaited Muon Measurement Boosts Evidence for New Physics

Initial data from the Muon g-2 experiment have excited particle physicists searching for undiscovered subatomic particles and forces

أعرض هذا باللغة العربية By Daniel Garisto on April 7, 2021

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Muon g-2 magnetic storage ring, seen here at Brookhaven National Laboratory in New York State befor ts 2013 relocation to Fermi National Accelerator Laboratory in Illinois. Credit: Alamy

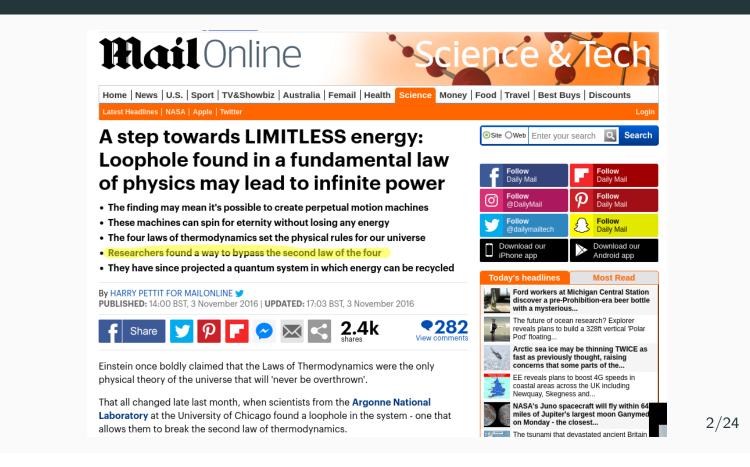
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# New "physics"??



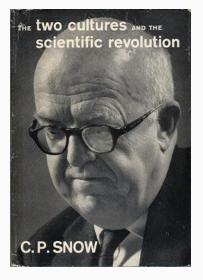
### The Second Law is special

"The law that entropy always increases holds, I think, the supreme position among the laws of Nature. [...] If your theory is found to be against the Second Law of Thermodynamics I can give you no hope; there is nothing for it to collapse in deepest humiliation."

A.S. Eddington

"[...] the only physical theory of universal content concerning which I am convinced that, within the framework of the applicability of its basic concepts, it will never be overthrown." A. Einstein

#### Have you read a work of Shakespeare's?



"Once or twice I have been provoked and have asked the company how many of them could describe the Second Law of Thermodynamics. The response was cold: it was also negative. Yet I was asking something which is about the equivalent of: Have you read a work of Shakespeare's?" C.P. Snow

The "to be or not to be" of thermodynamics

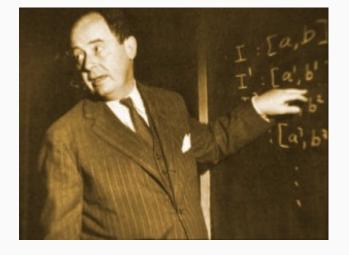
**Clausius Inequality** 

 $\langle \Delta S_{\rm tot} \rangle \ge 0$ 

Why should the above inequality be so "special"? What does it *really* say?

That is the question.

# That is the question!



"*No one understands entropy very well.*"

von Neumann (apocryphal)

## The Second Law "without entropy"

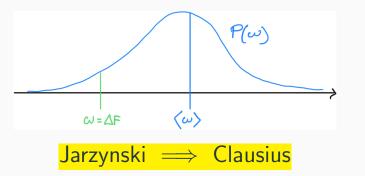


Clausius' inequality (1865):

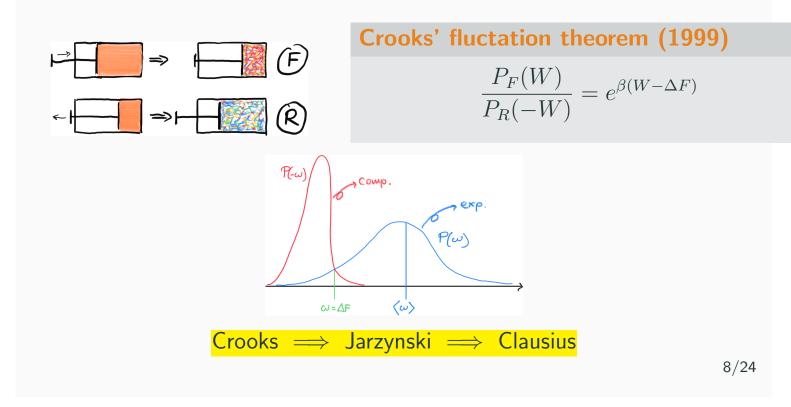
Jarzynski's equality (1997):

$$\langle W \rangle \ge \Delta F$$

$$\left\langle e^{-\beta W} \right\rangle = e^{-\beta \Delta F}$$



### The Second Law and irreversibility



#### **Usual explanation**

Crooks' theorem, and hence Jarzynski's relation, and hence the Second Law, all rely on two assumptions satisfied at equilibrium:

- 1. thermal equilibrium: initial distribution is  $P(\xi) \propto e^{-\beta \epsilon(\xi)}$
- microscopic reversibility: molecular processes and their reverses occur at the same rate

# But, again: why does the Second Law feel so "special" then?

# Is that because of some kind of "special" microscopic balancing mechanism?

#### A hint from Ed Jaynes

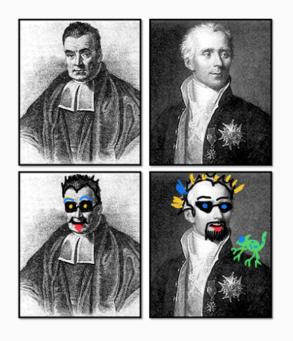


"To understand and like thermo we need to see it, not as an example of the *n*-body equations of motion, but as an example of the logic of scientific inference."

E.T. Jaynes (1984)

First idea: reverse process as Bayesian retrodiction

## The Bayes-Laplace Rule



#### **Inverse Probability Formula**

 $\underbrace{\mathcal{P}(H|D)}_{\text{inv. prob.}} \propto \underbrace{\mathcal{P}(D|H)}_{\text{likelihood}} \underbrace{\mathcal{P}(H)}_{\text{prior}}$ where H is a hypothesis, D is the result of observation (i.e., evidence)

postmodern Bayesianism!

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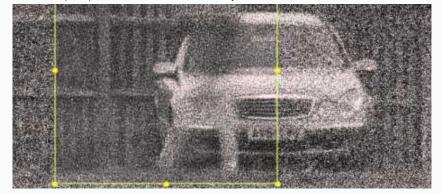
# Meanings of the inverse probability

- it is the main *tool* of Bayesian statistics for problems like:
  - estimation (e.g.: how many red balls are in an urn?)
  - decision (e.g.: is ACME's stock a good investment? should I buy some?)
  - predictive inference (e.g.: weather forecasts)
  - retrodictive inference (e.g.: what kind of stellar event possibly caused the Crab Nebula?)
- it measures the degree of belief that a rational agent should have in one hypothesis, among other mutually exclusive ones, given the data

# Noisy data and uncertain evidence

**BUT!** Bayes-Laplace Rule *does not* tell us how to update the prior in the face of uncertain data...

• suppose that a noisy observation suggests a probability distribution Q(D) for the data (e.g., the license plate no.)



• how should we update our prior  $\mathcal{P}(H)$  given *uncertain evidence* in the from  $\mathcal{Q}(D)$ ?

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# Jeffrey's rule of probability kinematics

Vanilla Bayes:Extended Bayes:
$$\mathcal{P}(H|D) = \mathcal{P}(D|H)\mathcal{P}(H)/\mathcal{P}(D)$$
 $\mathcal{P}(H|\mathcal{Q}(D)) = ?$ Jeffrey's conditioning\* (1965) $\mathcal{P}(H|\mathcal{Q}(D)) = \sum_{D} \underbrace{\mathcal{P}(H|D)}_{D} \mathcal{Q}(D)$   
 $= \sum_{D} \underbrace{\mathcal{P}(D|H)\mathcal{P}(H)}_{D} \mathcal{Q}(D)$ \* Jeffrey's rule was introduced *ad hoc*, but it can be proved from Bayes-Laplace Rule and

Pearl's method of virtual evidence (1988)

### **Construction of the reverse process**

- physical setup:
  - $\circ\,$  a stochastic transition rule:  $\varphi(y|x)$
  - $\circ\,$  a steady (viz. invariant) state:  $\sum_x \varphi(y|x) \sigma(x) = \sigma(y)$
- Bayesian inversion at the steady state:

$$\sigma(y)\hat{\varphi}(x|y) := \sigma(x)\varphi(y|x) \iff \frac{\varphi(y|x)}{\hat{\varphi}(x|y)} = \frac{\sigma(y)}{\sigma(x)}$$

- two priors:
  - predictor's prior: p(x)
  - $\circ$  retrodictor's prior q(y)
- two processes:
  - forward process (prediction):  $\mathcal{P}_F(x,y) = \varphi(y|x)p(x)$
  - reverse process (retrodiction):  $\mathcal{P}_R(x,y) = \hat{\varphi}(x|y)q(y)$

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# A picture

$$\begin{array}{l} & & & \\ & & & \\ & & \\ & & & \\ & & & \\ & & \\ & & \\ & & & \\ & & & \\ & & & \\ &$$

- at the steady state: prediction = retrodiction
- otherwise: asymmetry (irreversibility, *irretrodictability*)

#### Measures of statistical divergence

Second idea: fluctuation relations as measures of *statistical divergence* between  $\mathcal{P}_F(x, y)$  and  $\mathcal{P}_R(x, y)$ 

• relative entropy:  $D(\mathcal{P}_F \| \mathcal{P}_R) := \left\langle -\ln \frac{\mathcal{P}_R(x,y)}{\mathcal{P}_F(x,y)} \right\rangle_F =: \left\langle -\ln r(x,y) \right\rangle_F$ 

 $\rightsquigarrow$  more generally, one can use  $D_f(\mathcal{P}_R \| \mathcal{P}_F) := \langle f(r(x,y)) \rangle_F$ 

introduce probability density functions

$$\implies \langle \omega \rangle_F = D_f(\mathcal{P}_R \| \mathcal{P}_F)$$

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# From f-divergences to f-fluctuation theorems

• for  $f : \mathbb{R}^+ \to \mathbb{R}$  invertible

*f*-Fluctuation Theorem

$$\mu_R(\omega) = f^{-1}(\omega)\mu_F(\omega) \implies \langle f^{-1}(\omega)\rangle_F = 1$$

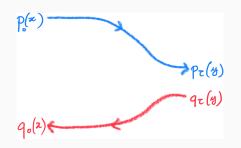
$$\leadsto$$
 for  $f(u)=-\ln u$  , we have  $f^{-1}(v)=e^{-v}$  , that is

$$\frac{\mu_F(\omega)}{\mu_R(\omega)} = e^{\omega} \implies \langle e^{-\omega} \rangle_F = 1$$

further discussions in arXiv:2009.02849

# **Examples**

# **Example: driven Hamiltonian evolution**



• driving protocol:  $H(0) \to H(t) \to H(\tau)$ 

• 
$$H(0) = \sum_x \epsilon_x \pi_x$$
,  $H(\tau) = \sum_y \eta_y \pi'_y$ 

• 
$$\varphi(y|x) = \delta_{y,y(x)}$$
, i.e., one-to-one

• 
$$\sigma(x) = d^{-1} \implies \varphi(y|x) = \hat{\varphi}(x|y)$$

• 
$$p_0(x) = e^{\beta(F - \epsilon_x)}, \ q_\tau(y) = e^{\beta(F' - \eta_y)}$$

In this case, for the choice  $f(u) = -\ln u$ ,

$$\Omega(x,y) = \ln \frac{\mathcal{P}_F(x,y)}{\mathcal{P}_R(x,y)} = \ln \frac{\sigma(y)p(x)}{\sigma(x)q(y)} = \ln \frac{p(x)}{q(y)}$$
$$= \beta(F - \epsilon_x + F' + \eta_y) = \beta(W - \Delta F)$$
$$\Rightarrow \frac{\mu_F(W)}{\mu_R(W)} = e^{\beta(W - \Delta F)}$$
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#### **Example: nonequilibrium steady states**

- stochastic process  $\varphi(y|x)$  with non-thermal steady state  $\sigma(x)$
- thermal equilibrium priors:  $p(x) = q(x) \propto e^{-\beta \epsilon_x}$
- fluctuation variable (total stochastic entropy production):  $\omega = \ln \frac{\mathcal{P}_F(x,y)}{\mathcal{P}_R(x,y)} = \ln \frac{p(x)}{q(y)} \frac{\sigma(y)}{\sigma(x)} = \beta(\epsilon_y - \epsilon_x) + (\ln \sigma(y) - \ln \sigma(x))$
- nonequilibrium potential:  $V(x) := -\frac{1}{\beta} \ln \sigma(x)$  (e.g., Manzano&al 2015)
- $\left\langle e^{\beta(\Delta E \Delta V)} \right\rangle_F = 1$ , but  $\left\langle e^{\beta \Delta E} \right\rangle_F =$  "efficacy"
- — nonequilibrium potentials (usually introduced ad hoc) are understood here as remnants of Bayesian inversion

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# But why known relations are compatible with Bayesian inversion?

Is that a necessity?

### Sketch argument

• 
$$D(\mathcal{P}_F \| \mathcal{P}_R) = \left\langle \ln \frac{\mathcal{P}_F(x,y)}{\mathcal{P}_R(x,y)} \right\rangle_H$$

- let us impose that the fluctuation variable is a microstate
  - **function**:  $\ln \frac{\mathcal{P}_F(x,y)}{\mathcal{P}_R(x,y)} = \Omega(x,y) \stackrel{!}{=} F'(y) F(x)$

$$\implies \frac{\mathcal{P}_F(y|x)}{\mathcal{P}_B(x|y)} = \frac{G'(y)}{G(x)}$$

• 
$$\implies$$
  $G(x)\mathcal{P}_F(y|x) = G'(y)\mathcal{P}_R(x|y)$ 

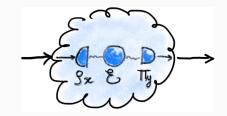
• sum over 
$$x \implies G'(y) = \sum_x G(x) \mathcal{P}_F(y|x)$$

• 
$$\implies \mathcal{P}_R(x|y) = \frac{1}{\sum_x G(x)\mathcal{P}_F(y|x)}G(x)\mathcal{P}_F(y|x)$$

Hence, a Bayesian inverse-like form for the reverse process is **inevitable** if we want the (total stochastic) entropy production to be a **microstate function**!

# What about the quantum case?

#### Quantum retrodiction and the Petz map



- assume  $\varphi(y|x) = \operatorname{Tr}[\Pi_y \ \mathcal{E}(\rho_x)]$
- let  $\sigma(x)$  be invariant distribution
- according to the formalism of *quantum retrodiction*:

$$\circ \Sigma := \sum_{x} \sigma(x) \rho_{x}$$
  

$$\circ \hat{\rho}_{y} := \frac{1}{\sigma(y)} \sqrt{\mathcal{E}(\Sigma)} \Pi_{y} \sqrt{\mathcal{E}(\Sigma)}$$
  

$$\circ \hat{\Pi}_{x} := \sigma(x) \frac{1}{\sqrt{\Sigma}} \rho_{x} \frac{1}{\sqrt{\Sigma}}$$
  

$$\circ \hat{\mathcal{E}}(\cdot) := \sqrt{\Sigma} \left\{ \mathcal{E}^{\dagger} \left[ \frac{1}{\sqrt{\mathcal{E}(\Sigma)}} (\cdot) \frac{1}{\sqrt{\mathcal{E}(\Sigma)}} \right] \right\} \sqrt{\Sigma}$$



• Bayesian inversion works seamlessly  $\hat{\varphi}(x|y) = \operatorname{Tr}[\hat{\Pi}_x \ \hat{\mathcal{E}}(\hat{\rho}_y)]$ 

#### Some remarks

- the Petz recovery map is a form of quantum Bayes-Laplace rule
- to a unique Bayes-Laplace rule there correspond infinite possible "rotated" Petz maps
- retrodiction (both classical and quantum) depends on the choice of reference prior
- exceptions are unitary channels, for which:
  - 1. there is a unique Petz reverse (the retrodiction is independent of the choice of prior, and all rotated Petz maps coincide)
  - 2. retrodiction and (linear) inversion coincide

Three messages:

- the Second Law is special among the laws of physics, because it is in fact a law of logic
- retrodiction as the logical foundations of fluctuation theorems
- quantum retrodiction also follows seamlessly using Petz recovery map

thank you

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