Prediction, Retrodiction, and the Second Law of Thermodynamics

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About these ideas

Two papers:

- with V. Scarani. *Fluctuation relations from Bayesian retrodiction*. Phys. Rev. E (2021). arXiv:2009.02849 [quant-ph]
- with C.C. Aw and V. Scarani. *Fluctuation Theorems with Retrodiction rather than Reverse Processes*. arXiv:2106.08589 [cond-mat.stat-mech]

^{*}www.quantumquia.com

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

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





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

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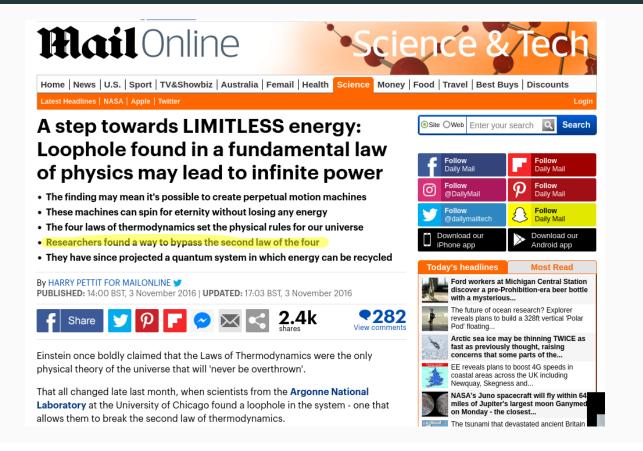
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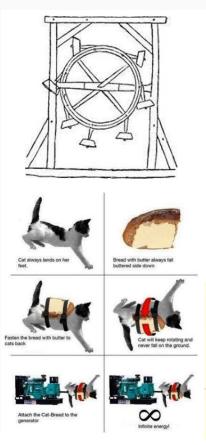
May 28, 2018 — Elizabeth Gibney and Nature magazine

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New "physics"??

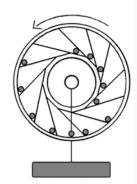


The dream of a "perpetuum mobile"





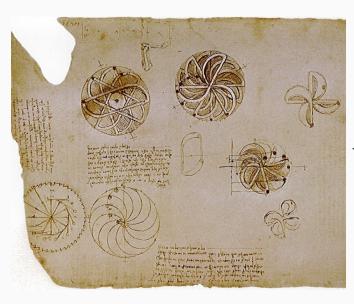






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Leonardo's wheel



"Oh ye seekers after perpetual motion, how many vain chimeras have you pursued? Go and take your place with the alchemists."

Leonardo da Vinci

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."

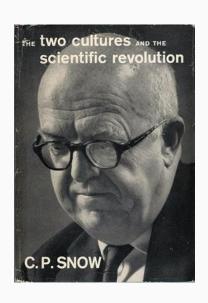
A.S. Eddington

"[...] 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

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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 Shake-speare's?"

C.P. Snow

The "to be or not to be" of thermodynamics

The Second Axiom of Thermodynamics

A *perpetuum mobile* of the second kind is impossible; in formula,

$$\langle \Delta S_{\mathsf{tot}} \rangle \geq 0$$
.

Why does the above inequality "feel" so special among physical laws?

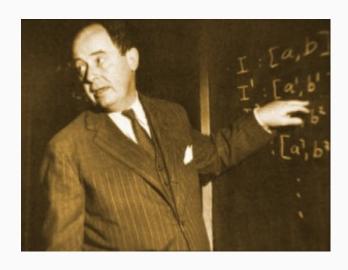
That is the question.

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Is entropy the key?

Many "explanations" of the Second Law actually amount to explanations of entropy (e.g., counting arguments).

Problem is...



"No one understands entropy very well..."

von Neumann (apocryphal)

"...and that's only half of the story, anyway."

Anon

The Second Law "without entropy"

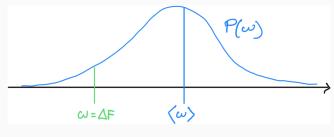


Clausius' inequality (1865):

Jarzynski's equality (1997):

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

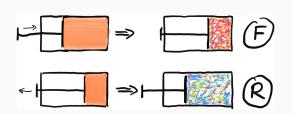
$$\left\langle e^{-\beta W} \right\rangle = e^{-\beta \Delta F}$$



Jarzynski ⇒ Clausius

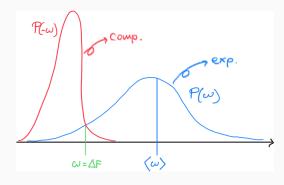
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The Second Law and irreversibility



Crooks' fluctation theorem (1999)

$$\frac{\mathcal{P}_F(W)}{\mathcal{P}_R(-W)} = e^{\beta(W - \Delta F)}$$



Crooks ⇒ Jarzynski ⇒ Clausius

Usual explanation

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

- 1. thermal distribution: microstate probability is $\mathcal{P}(\xi) \propto e^{-\beta \epsilon(\xi)}$
- 2. microscopic reversibility (cf. detailed balance): molecular processes and their reverses occur at the same rate

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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

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The Bayes-Laplace Rule









Inverse Probability Formula

$$\underbrace{\mathcal{P}(H|D)}_{\text{inv. prob.}} \propto \underbrace{\mathcal{P}(D|H)}_{\text{likelihood/model}} \underbrace{\mathcal{P}(H)}_{\text{prior}}$$

where H is a hypothesis, D is the result of observation (i.e., data or evidence)

postmodern Bayesianism!

Meanings of the inverse probability

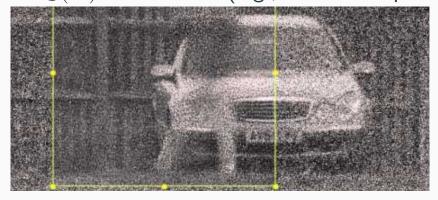
- it is the main tool of Bayesian statistics for problems like:
 - estimation (e.g.: how many red balls are in an urn?)
 - decision (e.g.: is ACME's stock a good investment? should I buy some? how much?)
 - inference and learning: predictive inference (e.g.: weather forecasts) and retrodictive inference (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

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Inference with noisy data or 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 $\mathcal{Q}(D)$ for the data (e.g., the license plate no.)



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

Jeffrey's rule of probability kinematics

Vanilla Bayes:

Extended Bayes:

$$\mathcal{P}(H|D) = \mathcal{P}(D|H)\mathcal{P}(H)/\mathcal{P}(D)$$
 $\mathcal{P}(H|Q(D)) = ?$

$$\mathcal{P}(H|\mathcal{Q}(D)) = ?$$

Jeffrey's conditioning* (1965)

$$\begin{split} \mathcal{P}(H|\mathcal{Q}(D)) &= \sum_{D} \underbrace{\mathcal{P}(H|D)}_{\text{inv. prob.}} \mathcal{Q}(D) \\ &= \sum_{D} \frac{\mathcal{P}(D|H)\mathcal{P}(H)}{\sum_{H} \mathcal{P}(D|H)\mathcal{P}(H)} \mathcal{Q}(D) \end{split}$$

Pearl's method of virtual evidence (1988)

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Construction of the reverse process as retrodiction

- physical setup:
 - \circ a stochastic transition rule: $\varphi(y|x)$
 - \circ a steady (viz. invariant) state: $\sum_{x} \varphi(y|x)s(x) = s(y)$
- Bayesian inversion at the steady state:

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

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

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^{*} Jeffrey's rule was introduced ad hoc, but it can be proved from Bayes-Laplace Rule and

A picture

$$S \to \varphi(y|z) \to = -\hat{\varphi}(z|y) \leftarrow S$$

$$P \to \varphi(y|z) \to \neq -\hat{\varphi}(z|y) \leftarrow q$$

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

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Quantifying irretrodictability

Second idea: fluctuation relations as measures of divergence between prediction and retrodiction

• relative entropy:

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

- \leadsto more generally, one can use $D_f(\mathcal{P}_R || \mathcal{P}_F) := \langle f(r(x,y)) \rangle_F$
- introduce probability density functions

$$\rightarrow$$
 $\Omega(x,y) := f(r(x,y))$ (total stochastic f -entropy production)

$$\rightsquigarrow \mu_F(\omega) := \sum_{x,y} \delta[\omega - \Omega(x,y)] \, \mathcal{P}_F(x,y)$$

$$\rightsquigarrow \mu_R(\omega) := \sum_{x,y} \delta[\omega - \Omega(x,y)] \, \mathcal{P}_R(x,y)$$

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

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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

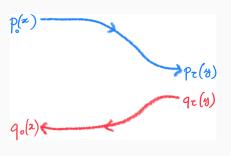
$$\frac{\mu_F(\omega)}{\mu_R(\omega)} = e^{\omega} \quad \Longrightarrow \quad \langle e^{-\omega} \rangle_F = 1$$

further discussions in arXiv:2009.02849 and arXiv:2106.08589

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Examples of known results recovered by retrodiction

Example: driven closed system evolution



- driving protocol: $H(0) \rightarrow H(t) \rightarrow H(\tau)$
- $H(0) = (\epsilon_x)_x$, $H(\tau) = (\eta_y)_y$
- $\varphi(y|x) = \delta_{y,y(x)}$, i.e., one-to-one
- $\bullet \ \ s(x) = d^{-1} \implies \varphi(y|x) = \hat{\varphi}(x|y)$
- $p_0(x) = e^{\beta(F \epsilon_x)}, q_\tau(y) = e^{\beta(F' \eta_y)}$

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

$$\Omega(x,y) = \ln \frac{\mathcal{P}_F(x,y)}{\mathcal{P}_R(x,y)} = \ln \frac{s(y)p(x)}{s(x)q(y)} = \ln \frac{p(x)}{q(y)}$$
$$= \beta(F - \epsilon_x + F' + \eta_y) = \beta(W - \Delta F)$$

$$\implies \frac{\mu_F(W)}{\mu_R(W)} = e^{\beta(W - \Delta F)} \implies \langle W \rangle \ge \Delta F$$

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Example: nonequilibrium steady states

- stochastic process $\varphi(y|x)$ with non-thermal steady state s(x)
- thermal equilibrium priors: $p(x) = q(x) \propto e^{-\beta \epsilon_x}$
- fluctuation variable:

$$\omega = \ln \frac{\mathcal{P}_F(x,y)}{\mathcal{P}_B(x,y)} = \ln \frac{p(x)}{q(y)} \frac{s(y)}{s(x)} = \beta(\epsilon_y - \epsilon_x) + (\ln s(y) - \ln s(x))$$

- nonequilibrium potential: $V(x) := -\frac{1}{\beta} \ln s(x)$ (e.g., Manzano&al 2015)
- nonequilibrium potentials (usually introduced ad hoc) are understood here as remnants of Bayesian inversion

•
$$\Longrightarrow \langle e^{\beta(\Delta E - \Delta V)} \rangle_F = 1 \implies D(p||s) - D(\varphi[p]||s) \ge 0$$

But why known relations are compatible with Bayesian inversion?

Is that a necessity?

Sketch argument

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

• let us impose that the fluctuation variable is local:

$$\ln \frac{\mathcal{P}_F(x,y)}{\mathcal{P}_R(x,y)} = \Omega(x,y) \stackrel{!}{=} G'(y) - G(x)$$

$$\bullet \implies \frac{\mathcal{P}_F(y|x)}{\mathcal{P}_R(x|y)} = \frac{H'(y)}{H(x)}$$

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

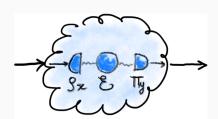
• sum over
$$x \implies H'(y) = \sum_x H(x) \mathcal{P}_F(y|x)$$

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

Hence, a Bayesian inverse-like form for the reverse process is inevitable if we want the fluctuating variable to have a local form!

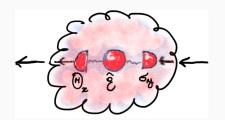
Finally, what about the quantum case?

Quantum retrodiction and the Petz map



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

$$\circ \ \Sigma := \sum_{x} s(x) \rho_{x}
\circ \ \hat{\rho}_{y} := \frac{1}{s(y)} \sqrt{\mathcal{E}(\Sigma)} \Pi_{y} \sqrt{\mathcal{E}(\Sigma)}
\circ \ \hat{\Pi}_{x} := s(x) \frac{1}{\sqrt{\Sigma}} \rho_{x} \frac{1}{\sqrt{\Sigma}}
\circ \ \hat{\mathcal{E}}(\cdot) := \sqrt{\Sigma} \left\{ \mathcal{E}^{\dagger} \left[\frac{1}{\sqrt{\mathcal{E}(\Sigma)}} (\cdot) \frac{1}{\sqrt{\mathcal{E}(\Sigma)}} \right] \right\} \sqrt{\Sigma}$$



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

Some remarks about quantum retrodiction

- the Petz recovery map reduces to Bayes-Laplace rule when operators commute
- to a unique Bayes-Laplace rule there correspond infinite possible Petz maps ("rotated" Petz maps)
- retrodiction (both classical and quantum) depends on the choice of reference prior
- exceptions are unitary (i.e., "bilateral deterministic") 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

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Conclusion

Final messages

- 1. predictive and retrodictive inference provide the logical foundations of fluctuation theorems
- 2. while fluctuation relations measure the divergence between predictor and retrodictor, the Second Law states that they won't get further apart as a result of their inferences
- 3. so, the Second Law is special among the laws of physics, because it is in fact a law about the logic of inference
- 4. a clear distinction between mechanical (ir)reversibility and logical (ir)retrodictability avoids unnecessary paradoxes
- 5. quantum retrodiction and quantum fluctuation relations follow seamlessly using Petz recovery map

thank you^{27/27}