# Extending computational complexity theory to include thermodynamic resource costs

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with

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International Centre for Theoretical Physics For continuous-time Markov chains sending p(0) to  $p(1) = \sum_{j} P(i \mid j) p_{j}(0)$ 

Van denBroeck and Esposito, Physica A, 2015

For many non-Markvonian chains sending p(0) to  $p(1) = \sum_{j} P(i \mid j) p_{j}(0)$ Ptaszynski and Esposito, *PRL*, 2019

$$-\Delta Q = \Delta \Sigma - \Delta S$$

- $\Delta S = S(p_1) S(p_0)$  is gain in Shannon entropy of p
- $-\Delta Q$  is (Shannon) entropy flow from system between t = 0 and t = 1
- ΔΣ is total entropy production in system between t = 0 and t = 1
   <u>cannot be negative</u>
   (Lo, the second law of thermodynamics)

(I.e., the second law of thermodynamics)

## **GENERALIZED LANDAUER BOUND**

- System connected to multiple reservoirs, e.g., heat baths at different temperatures. (So " $k_{\rm B}T$ " not defined.)
- Arbitrary number of states
- Arbitrary initial distribution p<sub>0</sub>
- Arbitrary dynamics  $P(x_1 | x_0)$

$$-\Delta Q = \Delta \Sigma + S(p_0) - S(p_1)$$

Entropy Production ( $\Delta \Sigma$ ) is non-negative. So:

"<u>Generalized Landauer's bound"</u>

$$-\Delta Q \geq S(p_0) - S(p_1)$$

# **BOOLEAN CIRCUITS**

- Currently, all mass-produced computers are implemented with circuits.
- The simplest circuit is one without loops or branches (a "straight-line program")
- If set of allowed gates are a universal basis (e.g., NAND gates), then can build a circuit with them to implement any desired Boolean function.



#### $-\Delta Q = \Delta \Sigma + S(p_0) - S(p_1)$

- For fixed P(x<sub>1</sub> | x<sub>0</sub>), changing p<sub>0</sub> changes Landauer cost, S(p<sub>0</sub>) S(p<sub>1</sub>)
- N.b., the same P(x<sub>1</sub> | x<sub>0</sub>) e.g., same AND gate has different p<sub>0</sub>, depending on where it is in a circuit.
- So even for a thermo. reversible gate (∆∑(p₀) = 0), changing the gate's location in a circuit (changes S(p₀) S(p₁) and so) changes -∆Q(p₀)



- Changing a gate's location in a circuit changes S(p<sub>0</sub>) − S(p<sub>1</sub>), and so changes the heat it produces, -∆Q(p<sub>0</sub>)
- Sum those heats over all gates to get minimal heat flow of that circuit

Different circuits implementing <u>same</u> Boolean function on <u>same</u> input distribution have <u>different</u> minimal heat

- Formally, those differences in minimal heat of the circuits are differences in EPs of the circuits, arising due to modularity of gates
  - A new circuit design optimization problem



Demaine, E., et al., Comm. ACM, 2016

- Considers a similar problem - but incorrectly sets Landauer cost at each gate to same value, KT ln(2).

# WHAT IS *REALLY* IMPORTANT THERMODYNAMICALLY?

$$-\Delta Q = \Delta \Sigma + S(p_0) - S(p_1)$$

• System evolves while connected to <u>single</u> heat bath at temperature T

- Then heat flow into environment =  $-k_{\rm B}T \Delta Q$ 

- At scale of real computers and brains,  $k_B T[S(p_0) S(p_1)]$  is small
- At scale of real computers and brains,  $\Delta \Sigma$  is dominant cost

- Generalized Landauer's bound often irrelevant (it assumes  $\Delta \Sigma = 0!$ )

What determines  $\Delta \Sigma$ ?

# **BEYOND GENERALIZED LANDAUER**

- System connected to multiple reservoirs, e.g., heat baths at different temperatures. (So " $k_{\rm B}T$ " not defined.)
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- Arbitrary dynamics  $P(x_1 | x_0)$

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Are there broadly applicable non-negative lower bounds on  $\Delta\Sigma$ , to complement Landauer's bound?

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• Yes.

### **BEYOND GENERALIZED LANDAUER**

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Entropy Production ( $\Delta \Sigma$ ) is non-negative.

Are there broadly applicable non-negative lower bounds on  $\Delta \Sigma$ , to add to the lower bound  $-\Delta Q \ge S(p_0) - S(p_1)$ ?

• Yes.

- Focus on two: **Speed limit theorem** (SLT) and **Mismatch cost** 

Use them to investigate the (thermodynamic) resource costs of computational machines

- $L(p(0), p(1)): L_1$  distance from distribution p(0) to distribution p(1)
- $A_{0,1}$ : total number of (stochastic) state jumps from t = 0 to t = 1

Since introduced, SLT has been strengthened several ways (more complicated formulas).

Shiraishi, N., Funo, K.; Saito, K., *PRL* (2018) Delvenne, J., Falasco, G.; arXiv:2110.13050 Lee, J., et al.; *PRL* (2022) Van Vu, T., Saito, K.; *PRL* (2023)

- $L(p(0), p(1)): L_1$  distance from distribution p(0) to distribution p(1)
- $A_{0,1}$ : total number of (stochastic) state jumps from t = 0 to t = 1
- Suppose uniform initial distribution over all gates and input bits;
- How does the (Lee et al.) SLT bound vary with error rate of gates, for two logically equivalent circuits?



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Tasnim, F., Wolpert, D., Korbel J., Lynn, C., et al. (2023)

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- Arbitrary dynamics  $P(x_1 | x_0)$
- Assume system is thermo. reversible for initial distribution  $q_0$ l.e.,  $\Delta \Sigma(q_0) = 0$

• Run that system with initial distribution  $p_0 \neq q_0$  instead:

$$\Delta \Sigma(p_0) = D(p_0 \parallel q_0) - D(p_1 \parallel q_1)$$
  
 
$$\geq 0$$

where D(. || .) is relative entropy (KL divergence)

Kolchinsky, A, Wolpert D., J. Stat. Mech. (2017) Wolpert, D., Kolchinsky, A., New J. Phys. (2020) Riechers, P., Gu, M., Phys. Rev. E (2021) Kolchinsky, A., Wolpert D., arxiv:2103.05734

- Arbitrary dynamics  $P(x_1 | x_0)$
- Assume system is thermo. reversible for initial distribution q<sub>0</sub>
- I.e.,  $\Delta \Sigma(q_0) = 0$

• Run that system with initial distribution  $p_0 \neq q_0$  instead:

$$\Delta \Sigma(p_0) = D(p_0 || q_0) - D(p_1 || q_1)$$
  
 
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### $D(p_0 || q_0) - D(p_1 || q_1)$ is called **mismatch cost**

Wolpert, D., Kolchinsky, A., *New J. Phys.* (2020) Riechers, P., Gu, M., *Phys. Rev. E* (2021) Kolchinsky, A., Wolpert D., *arxiv:2103.05734* 

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*Any* nontrivial process that is thermodynamically reversible for one initial distribution *will be costly* for any other initial distribution

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Holds for master equations, Langevin dynamics, (open) quantum thermodynamics, inclusive (Hamiltonian) dynamics – pretty much everything.

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• Run that system with initial distribution  $p_0 \neq q_0$  instead:

$$\Delta \Sigma(p_0) = D(p_0 \parallel q_0) - D(p_1 \parallel q_1)$$
  
 
$$\geq 0$$

where D(. || .) is relative entropy (KL divergence)

Same formula (just different prior q) for nonadiabatic EP, net lost free energy, etc.

- Two distinct bit-erasing gates, each with thermo. rev. initial distribution q<sub>0</sub>
- Run gates in parallel, on bits  $x^A$  and  $x^B$ , with initial distribution  $p_0(x^A, x^B)$
- Assume  $p_0(x^A) = q_0(x^A)$  and  $p_0(x^B) = q_0(x^B)$ .
- So each gate, by itself, generates zero EP. But:

If  $p_0(x^A, x^B)$  statistically couples the bits, then full system is **not** thermo. reversible, and generates nonzero EP

• Formally: Since gates are distinct, the thermo. rev. *joint* distribution is  $q_0(x^A, x^B) = q_0(x^A)q_0(x^B)$ 

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 Intuition: Running two thermo. reversible gates in parallel loses information in their initial coupling, and so is not thermo. reversible.

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• Broader lesson: Modularity increases EP

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If  $p_0(x^A, x^B)$  statistically couples the bits, then full system is **not** thermo. reversible, and generates nonzero EP

 Broader lesson: Whatever its practical benefits might be, modularity is thermodynamically costly (!)

Over N periods, the sum-total mismatch cost (lower bound on EP) is:  $\sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$ 

Gates are not reinitialized after being run; have old values when next run. So assuming IID generation of input,  $R(x_0)$ , initially, joint distribution is

 $R(x) = R(x_0) R(x_{1,2,3} | x_0)$ 



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So assuming IID generation of input,  $R(x_0)$ , after running 1st layer, joint distribution is

 $R(x) = R(x_0) R(x_{1,2,3})$ 



Over N periods, the sum-total mismatch cost (lower bound on EP) is:  $\sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$ So running 1st layer gives mismatch cost

 $D(R(x_0) R(x_{1,2,3} | x_0) || q(x_0) q(x_{1,2,3} | x_0)) - D(R(x_0) R(x_{1,2,3}) || R(x_0)q(x_{1,2,3})) \ge I_R(X_0; X_1, X_2, X_3)$ 



Wolpert, D.H. Phys. Rev. Letters, 125, (2020)

Over N periods, the sum-total mismatch cost (lower bound on EP) is:  $\sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$ 

So assuming IID generation of input,  $R(x_0)$ , after running 2nd layer, joint distribution is

 $R(x) = R(x_{0,1}) R(x_{2,3})$ 



Over N periods, the sum-total mismatch cost (lower bound on EP) is:  $\sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$ So running 2nd layer gives mismatch cost

$$\begin{array}{l} \mathsf{D}(\mathsf{R}(\mathsf{x}_{0}) \; \mathsf{R}(\mathsf{x}_{1,2,3}) \mid\mid \mathsf{R}(\mathsf{x}_{0}) \; \mathsf{q}(\mathsf{x}_{1,2,3})) \; - \; \mathsf{D}(\mathsf{R}(\mathsf{x}_{0,1}) \mathsf{R}(\mathsf{x}_{2,3}) \mid\mid \mathsf{R}(\mathsf{x}_{0,1}) \mathsf{q}(\mathsf{x}_{2,3}))) \\ \geq \\ \mathsf{I}_{\mathsf{R}}(\mathsf{X}_{1} \; ; \; \mathsf{X}_{2}, \; \mathsf{X}_{3}) \end{array}$$



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$$\begin{array}{l} D(R(x_0) \; R(x_{1,2,3}) \mid\mid R(x_0) \; q(x_{1,2,3})) \; - \; D(R(x_{0,1}) R(x_{2,3}) \mid\mid R(x_{0,1}) q(x_{2,3})) \\ \geq \\ I_R(X_1 \; ; \; X_2, \; X_3) \end{array}$$



Technical detail: Also is a variable saying which layer is currently being updated, which increments in each iteration

Over N periods, the sum-total mismatch cost (lower bound on EP) is:  $\sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$ 

So assuming IID generation of input,  $R(x_0)$ , after running 3rd layer, joint distribution is

 $R(x) = R(x_{0,1,2}) R(x_3)$ 



Over N periods, the sum-total mismatch cost (lower bound on EP) is:  $\sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$ So running 3rd layer gives mismatch cost

 $D(R(x_{0,1})R(x_{2,3}) || R(x_{0,1})q(x_{2,3})) - D(R(x_{0,1,2})R(x_3) || R(x_{0,1,2})q(x_3)) \ge I_R(X_2; X_3)$ 



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So assuming IID generation of input,  $R(x_0)$ , after running 4th layer, joint distribution is

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 $\mathsf{D}(\mathsf{R}(x_{0,1,2})\mathsf{R}(x_3) \mid\mid \mathsf{R}(x_{0,1,2})\mathsf{q}(x_3)) - \mathsf{D}(\mathsf{R}(x_{0,1,2,3}) \mid\mid \mathsf{R}(x_{0,1,2,3}))$ 



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So assuming IID generation of input,  $R(x_0)$ , after 4th layer, joint distribution is

$$R(x) = R(x_0)R(x_{1,2,3} | x_0) = R(x)$$



### **MISMATCH COST IN PERIODIC PROCESSES**

A process over a space X that is periodic, with period  $\lambda$ . So for all n,

$$P(x(n\lambda) \mid x((n-1)\lambda)) = P(x(\lambda) \mid x(0))$$

So over N periods, the sum-total mismatch cost (lower bound on EP) is:  $N_{-1}$ 

$$\sigma(N\lambda) \ge \inf_{q \in \Delta_X} \sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$$

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<u>KEY POINT</u>: Since the process is periodic, q is the same in each period. However,  $P^tp_0$  will differ over periods.

Therefore

At most one mismatch cost in the sum can equal 0 in general A process over a space X that is periodic, with period  $\lambda$ . So for all n,

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So over N periods, the sum-total mismatch cost (lower bound on EP) is: N-1

$$\sigma(N\lambda) \ge \inf_{q \in \Delta_X} \sum_{t=0}^{N-1} \left[ D(P^t p_0 || q) - D(P^{t+1} p_0 || Pq) \right]$$

<u>KEY POINT</u>: Since the process is periodic, q is the same in each period. However,  $P^tp_0$  will differ over periods.

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At most one mismatch cost in the sum can equal 0 in general

A new strictly positive lower bound on EP for any periodic process

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So over N periods, the sum-total mismatch cost (lower bound on EP) is:

# $\sigma(N\lambda) \ge N\Delta JS(\{P^t p_0\})$

• JS is Jensen-Shannon divergence for uniform distribution over N periods

#### A new strictly positive lower bound on EP for any periodic process

Wolpert, D.H. *Phys. Rev. Letters*, **125**, (2020)
Ouldridge, T.; Wolpert, D.H., arxiv:2208.06895 (2022)
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Manzano, G., Kardes, G.; Roldan, E.; Wolpert, D.H., arxiv: 2307.05713 (2023)

# DETERMINISTIC FINITE AUTOMATA (DFA)

## • Simplest computational machine in Chomsky hierarchy

- Finite number of states; one initial state, multiple "accept states"
- Feed in a finite string of bits;
- Each (bit, state) pair maps to a new state, after which next bit is read
- A DFA "accepts" a string if it causes the DFA to end in an accept state
- "Language" of a DFA is all input strings that it accepts
- Many languages that are not accepted by <u>any</u> DFA
- **Example**: DFA that accepts any string with no more than two successive 'b' bits:



- *Every* digital computer is a **sequence of solitary processes** 
  - Only part of the memory is physically to any processor at any time
  - So evolving subsystem is processor and current part of memory
- Results in **modularity (mismatch) cost** just like parallel bit erasure

- State space = {joint state of *full* memory and processor}

- Every digital computer is a sequence of solitary processes
  - Only part of the memory is physically to any processor at any time
  - So evolving subsystem is processor and current part of memory
- Results in modularity (mismatch) cost just like parallel bit erasure
  State space = {joint state of *full* memory and processor}

Example: In a DFA, memory contains entire string of input symbols However, DFA state only physically coupled to current input symbol, not earlier or later symbols in the string



- *Every* (synchronous) digital computer is "**periodic**"
  - Every successive iteration is the same physical process. And so every iteration has the same prior
- E.g., in a DFA, every iteration has same prior
- So if prior distribution = actual distribution for iteration i, there is zero mismatch cost for iteration i .... But:
   <u>The distributions will differ for iteration i + 1 in general</u>
- Results in "periodicty (mismatch) cost"



- Every (synchronous) digital computer is "periodic"
  - Every successive iteration is the same physical process. And so every iteration has the same prior
- E.g., in a DFA, every iteration has same prior
- So if prior distribution = actual distribution for iteration i, there is zero mismatch cost for iteration i .... But:
   <u>The distributions will differ for iteration i + 1 in general</u>
- Results in "periodicity (mismatch) cost"
- So, for any p<sub>0</sub> and any update conditional distribution P,

$$EP \ge \operatorname{argmin}_{q} \sum_{i=0}^{n} \left[ D(P^{i}p_{0}||q) - D(P^{i+1}p_{0}||Pq) \right]$$

 Independent of the physical details of the underlying process (just like generalized Landauer bound)
 In general, RHS is strictly positive • Total mismatch cost = modularity cost + periodicity cost





- Input strings have IID symbols with equal probability of a and b
- Uniform prior



• Input strings have IID symbols with probability of a = 0.8



• Input strings have IID symbols with probability of a = 0.2



• Input strings are first order Markov chains (starting from uniform probability)





Ouldridge, T., Wolpert, D., arxiv:2208.06895 (2022)

**EXAMPLE** 





What causes curves to have these shapes? What are curves for other DFAs?

A: Who knows!

Analysis of electronic components used in digital computers

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