Hierarchical Thermodynamics

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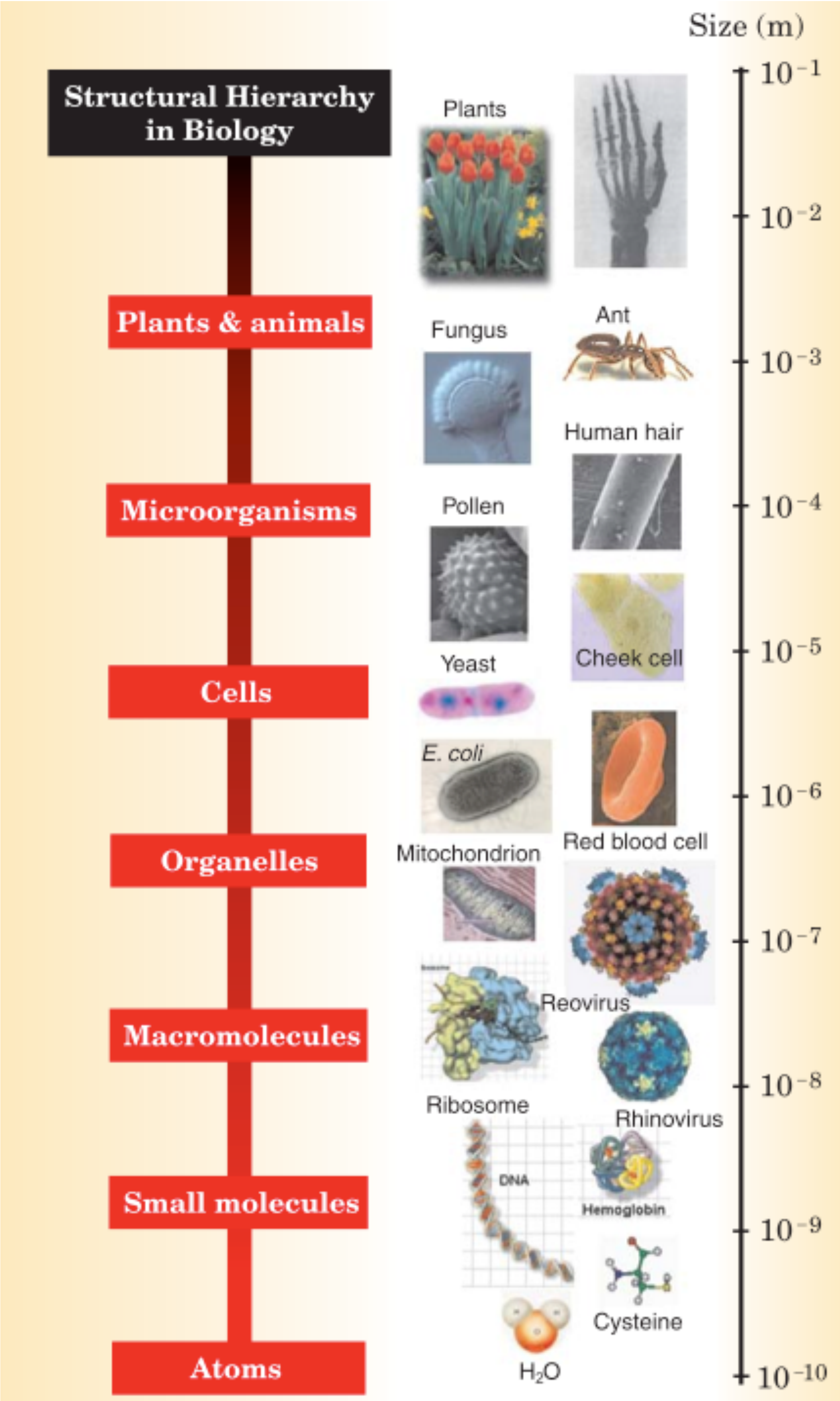
Workshop on
Information Engines at the Frontier of Nanoscale Thermodynamics
Telluride Science Research Center
3-11 August 2017

Joint work with Cina Aghamohammadi, Alec Boyd, Dibyendu Mandal, Sarah Marzen, Paul Riechers, and Greg Wimsatt



Structural Hierarchy in Biology

In what ways does nature organize?
(Phenomenology)

How does it organize?
(Mechanism)

Are these levels real or merely convenient?
(Objectivity)

Why does nature organize?
(Optimization versus chance versus ….)

Does thermodynamics play a role?

Physics Today, March 2006

What’s new in biology, but not in physics?

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Meaning, Purpose, & Functionality

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Meaning, Purpose, & Functionality

Calculi of Emergence (1992) but with energetics

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Meaning, Purpose, & Functionality

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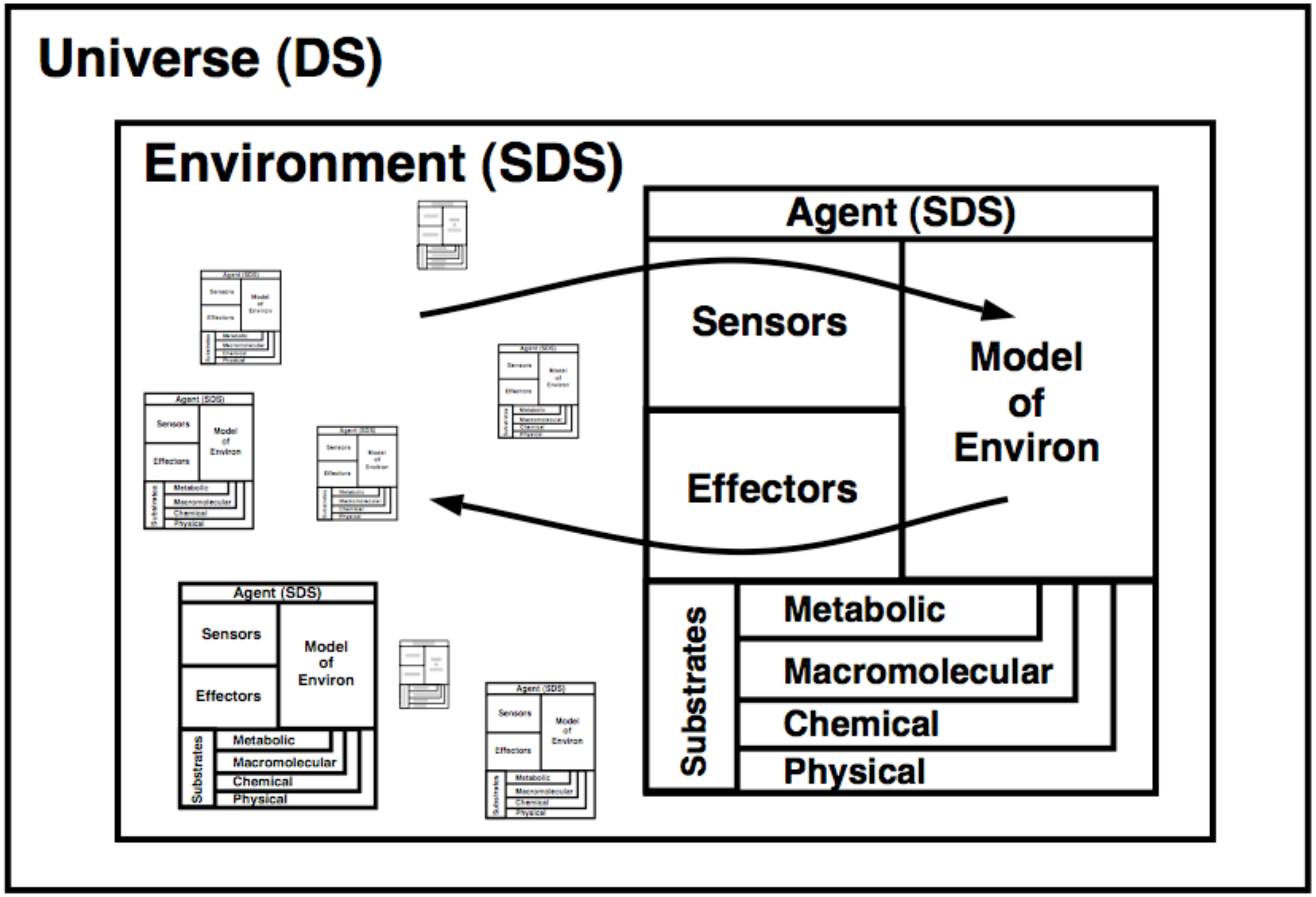
Punch Line

- Meaning, purpose, and functionality arise from
  - Organization
  - Thermodynamics

Problem Statement



= Ecological population dynamics of structurally complex adapting agents

+ Reproduction (evolutionary population dynamics)

JP Crutchfield, “The Calculi of Emergence: Computation, Dynamics, and Induction“, Physica D 75 (1994) 11-54.
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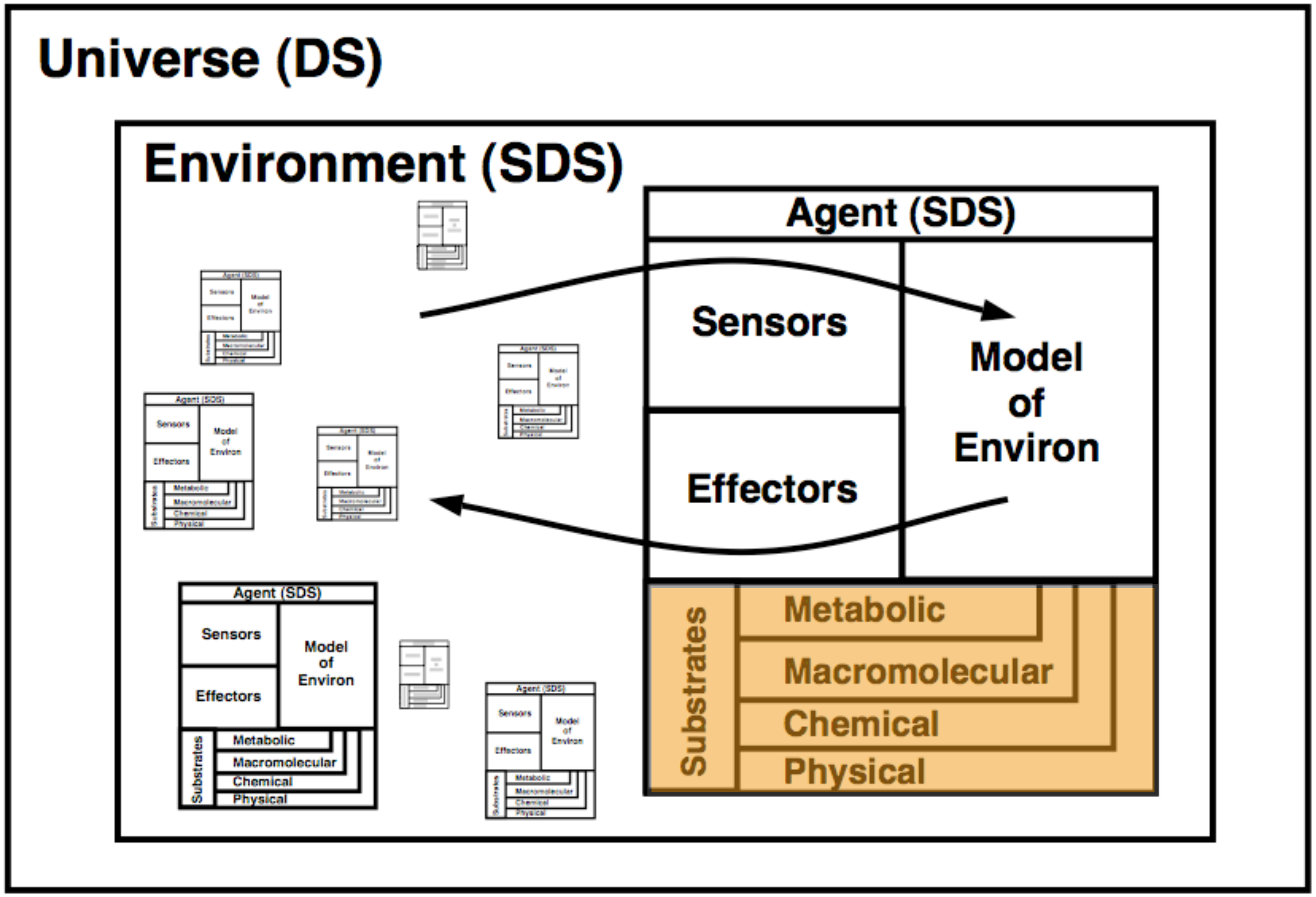

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Agenda

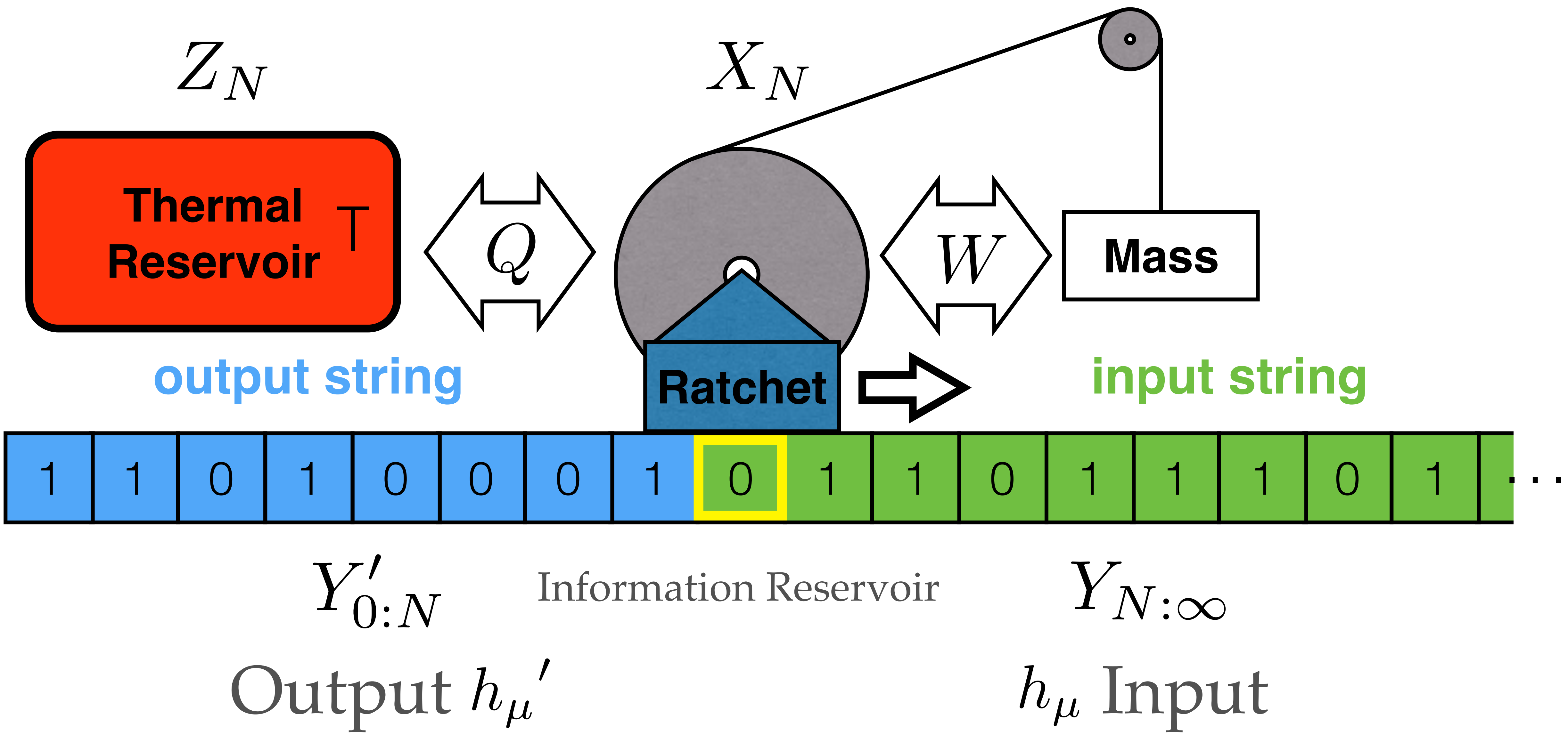
- Level Thermodynamics
- Level Organization
- Level Thermo-Semantics
- Hierarchical Thermodynamics
- Hierarchical Organization

- **Level Thermodynamics**
- Level Organization
- Level Thermo-Semantics
- Hierarchical Thermodynamics
- Hierarchical Organization

Thermodynamics of Organization: Information Processing Second Law of Thermodynamics (IPSL)

Information Ratchets

Beyond Maxwell+Szilard: Net Work Extraction!



A. Boyd, D. Mandal, and JPC, "Identifying Functional Thermodynamics in Autonomous Maxwellian Ratchets". New Journal of Physics **18** (2016) 023149.

D. Mandal and C. Jarzynski. "Work and information processing in a solvable model of Maxwell's demon". Proc. Natl. Acad. Sci. USA, **109**(29):11641–11645, 2012.

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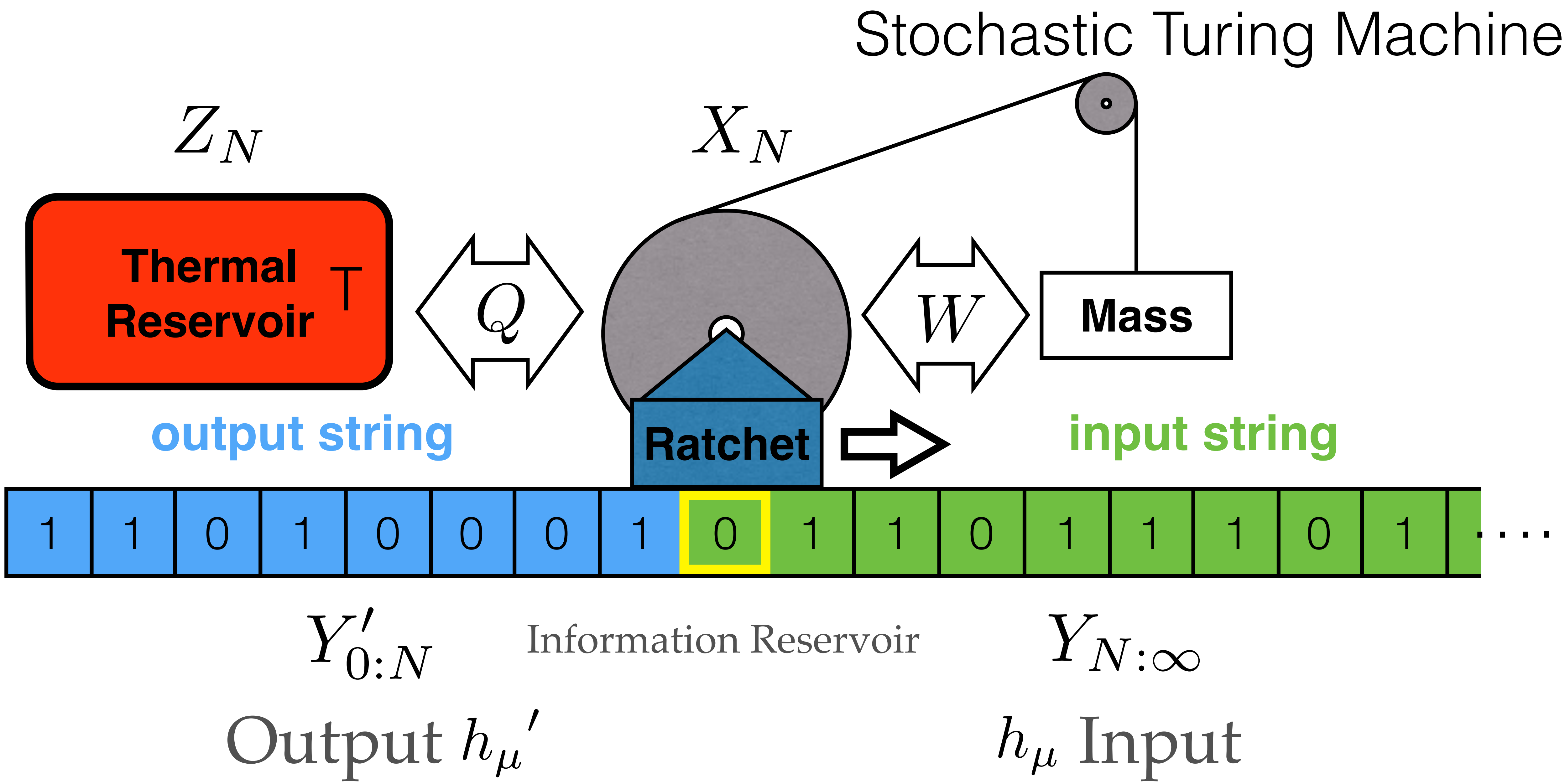

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Information Processing Second Law of thermodynamics

- Asymptotic IPSL:

$$\langle W \rangle \;\leq\; k_{\mathrm{B}} T \ln 2 \;\left({h_\mu}' - h_\mu \right)$$

- Information is fuel:

(Ordered inputs are a thermodynamic resource.)

- Generalizes Landauer Principle; cf.:

$$Q_{\mathrm{erase}} \geq k_B T \ln 2 \qquad ({h_\mu}' = 0;\; h_\mu = 1)$$

output input

A. B. Boyd, D. Mandal, and JPC, "Identifying Functional Thermodynamics in Autonomous Maxwellian Ratchets", New Journal of Physics **18** (2016) 023149.

Information Processing Second Law of thermodynamics

- IPSL constrains information processing done by a thermodynamic system.
- Upper bound on the maximum average work $\langle W \rangle$ extracted per cycle.
- Lower bounds the amount $-\langle W \rangle$ of input work required for a physical system to support a given rate of intrinsic computation.

Information Processing Second Law of thermodynamics

IPSL determines Thermodynamic Functionality

Feature / Function	Operation	Net Work	Net Computation
Engine	Extracts energy from the thermal reservoir, converts it into work by randomizing input information	$\langle W \rangle > 0$	$h'_\mu - h_\mu > 0$
Eraser	Uses external input of work to remove input information	$\langle W \rangle < 0$	$h'_\mu - h_\mu < 0$
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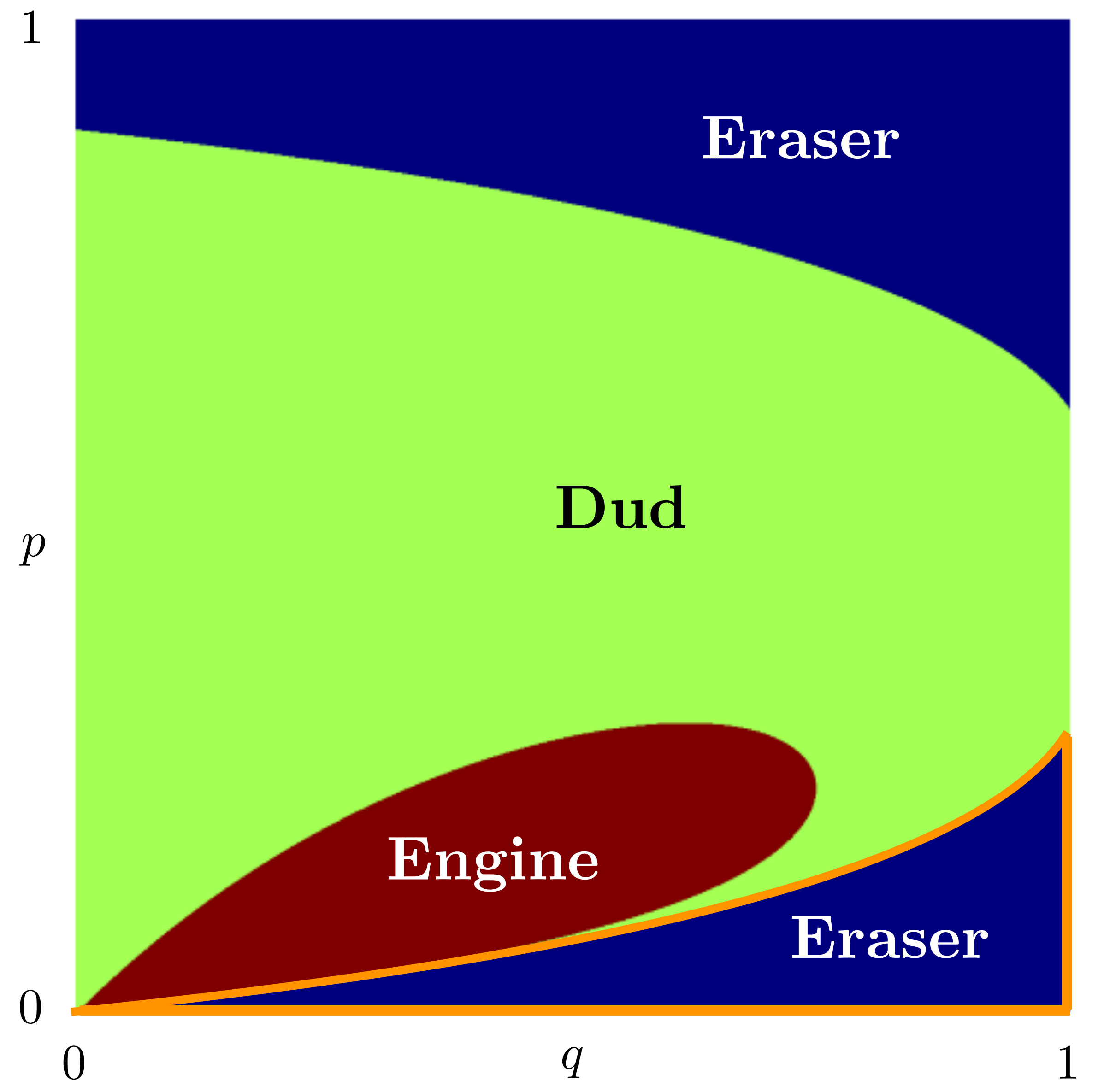
Information Ratchets

Second Law for Intrinsic Computation

$$\langle W \rangle \leq k_{\mathrm{B}} T \ln 2 \, \left({h_\mu}' - h_\mu \right)$$

Thermodynamic Functions



Ratchet parameters: (p, q)

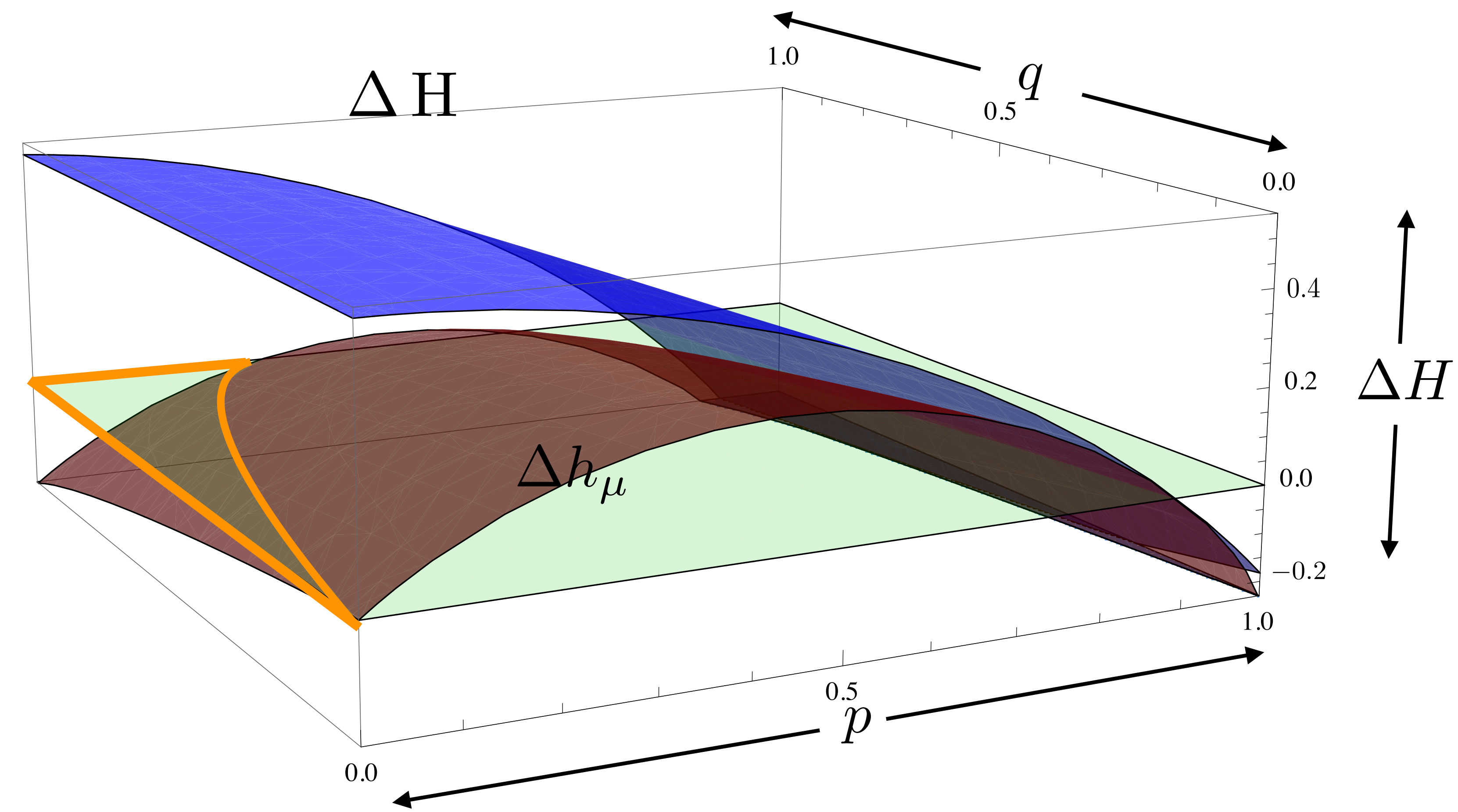
Information Ratchets

Second Law for Intrinsic Computation

$$\langle W \rangle \leq k_B T \ln 2 \; \Delta h_\mu$$

versus

$$\langle W \rangle \leq k_B T \ln 2 \; \Delta \mathrm{H}(1)$$



Entropy Rates

$$\Delta \mathrm{H}(1) = \mathrm{H}'(1) - \mathrm{H}(1)$$

$$\Delta h_\mu = {h_\mu}' - h_\mu$$

Lesson:

Kolmogorov-Sinai entropy rates

(${h_\mu}'$ and h_μ) account for all correlations.

Information Ratchets

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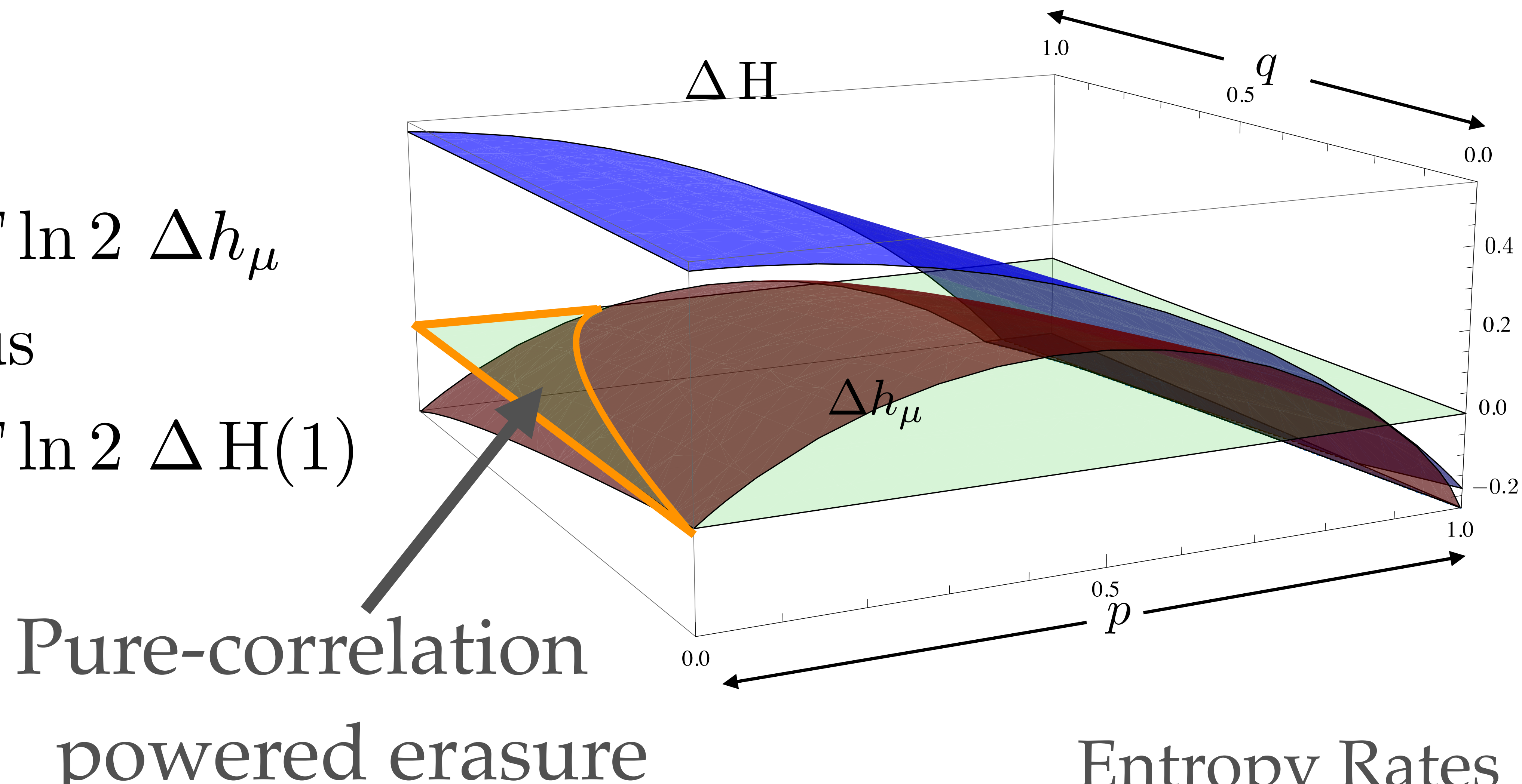

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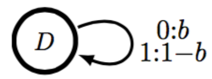
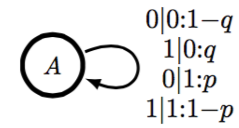
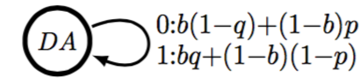
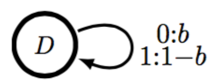
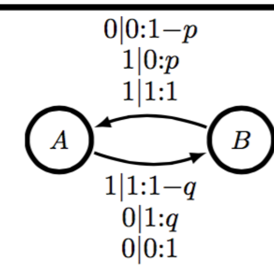
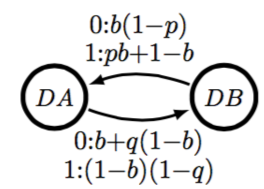
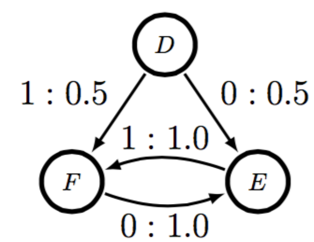
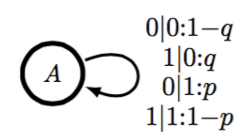
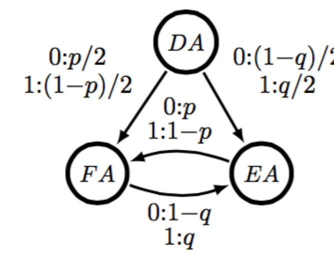
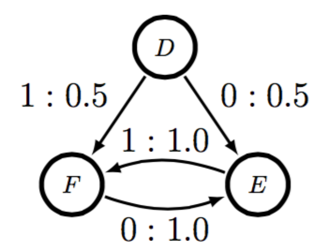
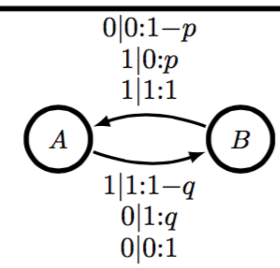
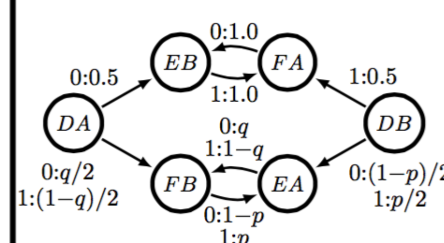
Lesson:

Kolmogorov-Sinai entropy rates (${h_\mu}'$ and h_μ) account for all correlations.

Requisite Complexity

	Input Process	Ratchet Transducer	Output Process	Thermal Relations
memoryless input memoryless ratchet				$0 = H_1 - h_\mu = H'_1 - h'_\mu$ $\langle W \rangle \leq \Delta h_\mu = \Delta H_1$
memoryless input memoryful ratchet				$0 = H_1 - h_\mu \leq H'_1 - h'_\mu$ $\langle W \rangle \leq \Delta h_\mu \leq \Delta H_1$
memoryful input memoryless ratchet				$0 \leq H'_1 - h'_\mu \leq H_1 - h_\mu$ $\langle W \rangle \leq \Delta H_1 \leq \Delta h_\mu$
memoryful input memoryful ratchet				$H'_1 - h'_\mu \stackrel{?}{=} H_1 - h_\mu$ $\langle W \rangle \leq \Delta h_\mu$ ~~$\langle W \rangle \leq \Delta H_1$~~

- Lessons: Information processing thermodynamic systems should match the complexity of their inputs/environment:
    - Memoryless ratchets optimal for uncorrelated environments.
    - Memoryful ratchets optimal for correlated environments.

A. B. Boyd, D. Mandal, and JPC, “Leveraging Environmental Correlations: The Thermodynamics of Requisite Variety”, Journal of Statistical Physics (2017) in press. arxiv.org:1609.05353.

W. Ross Asbhy, “An Introduction to Cybernetics.” John Wiley and Sons, New York, second edition, 1960.

Functional Fluctuations

J. P. Crutchfield and C. Aghamohammadi, “Not All Fluctuations are Created Equal: Spontaneous Variations in Thermodynamic Function. arxiv.org:1609.02519.

Functional Fluctuations

Functional Fluctuations

When is an Engine an Eraser?

Functional Fluctuations

When is an Engine an Eraser?

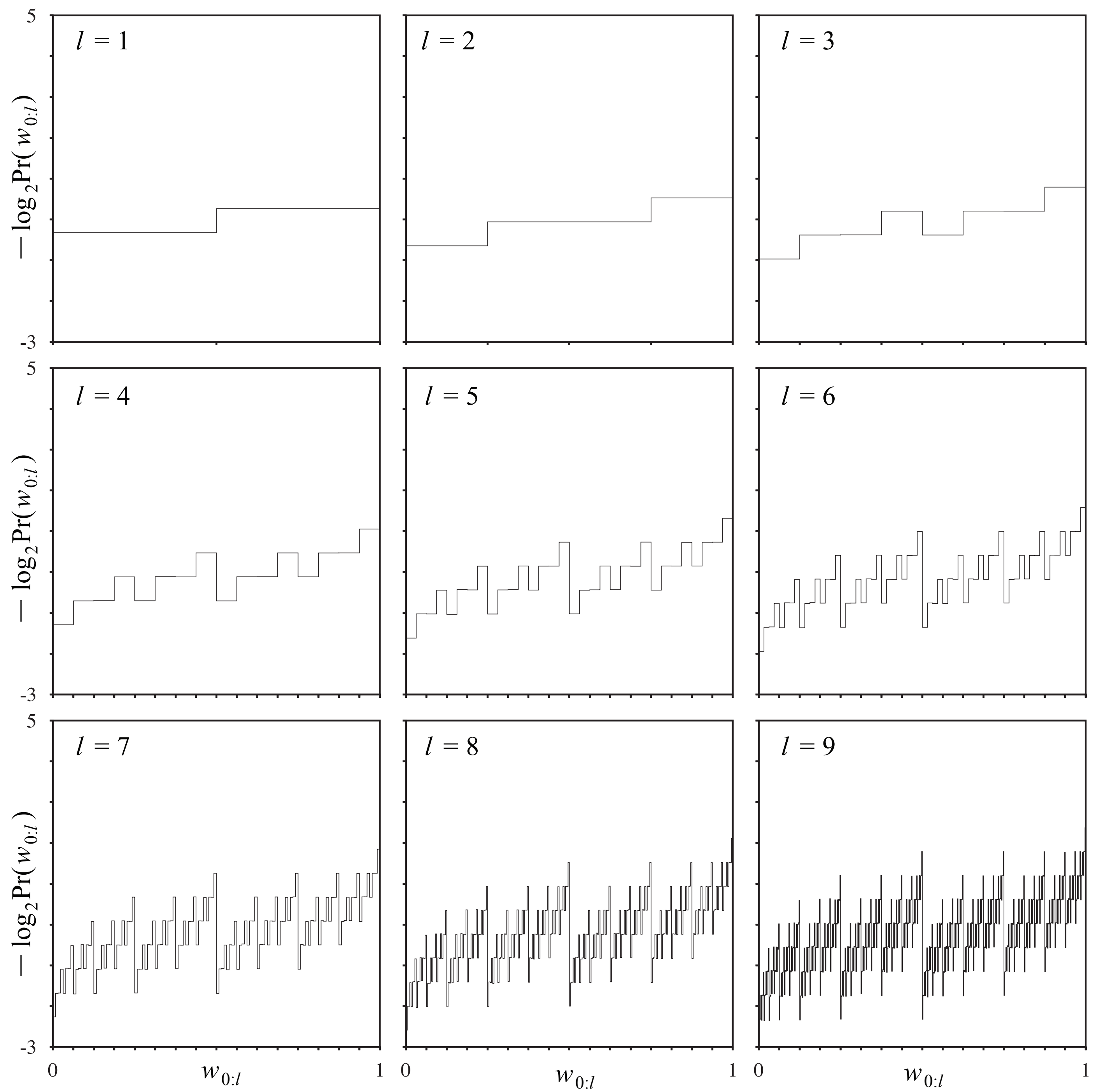
Information Processing Second Law

+

Large Deviation Theory

Fluctuations?

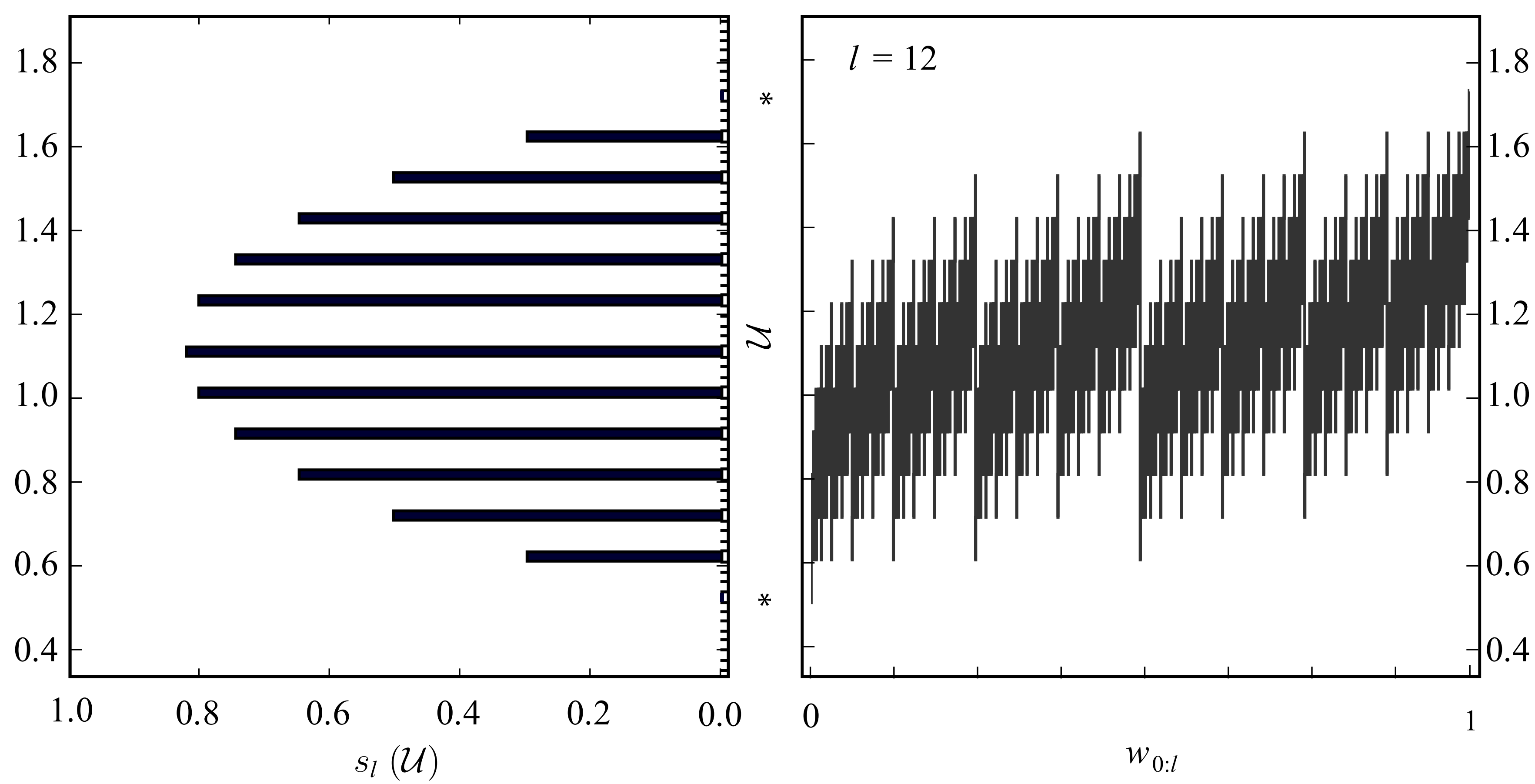
Biased Coin (60% Heads/40% Tails)



Distributions of length *l* words

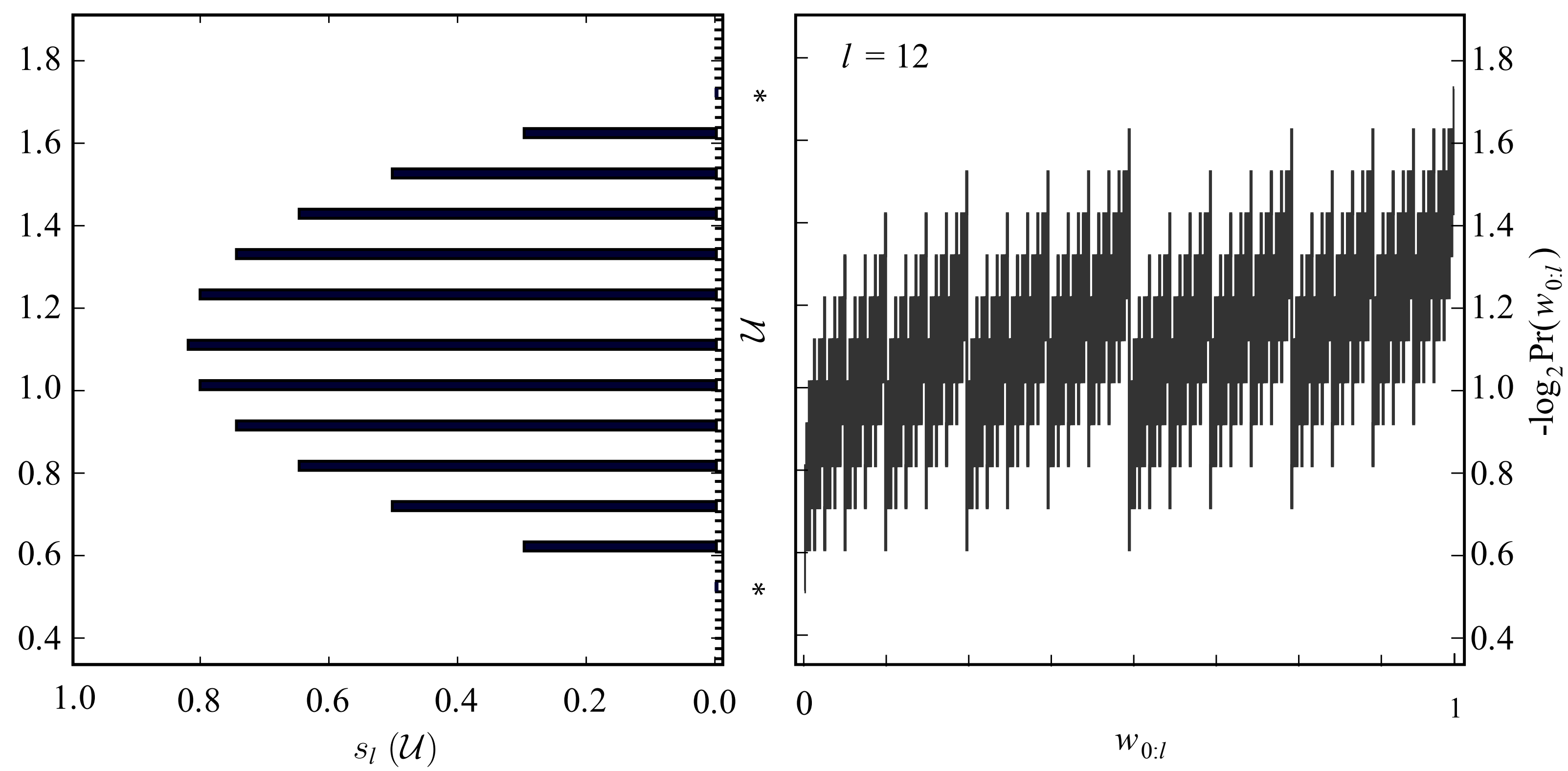
Fluctuations?

Biased Coin:
Fluctuations in sequence probabilities



Fluctuations in Intrinsic Computation

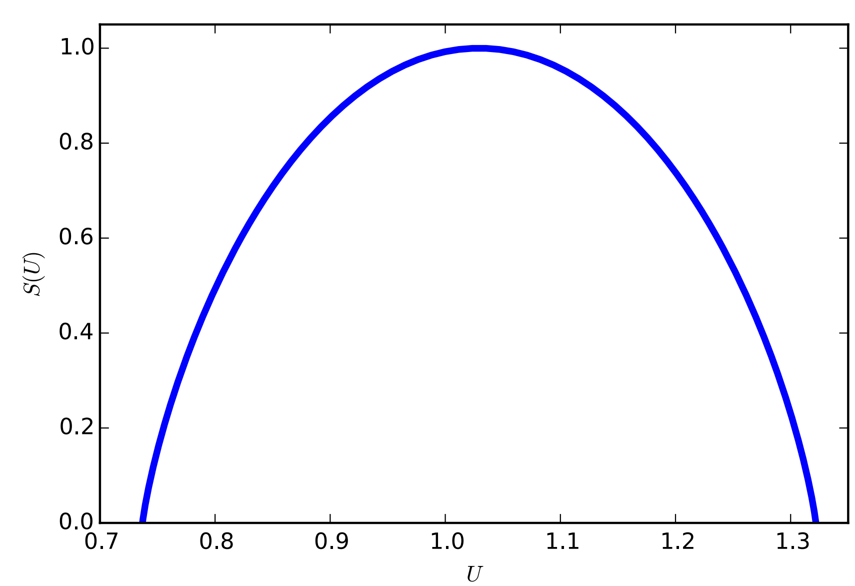
- Spectrum of Fluctuations



Large Deviations

Typical Set

Large Deviations



Information Ratchets

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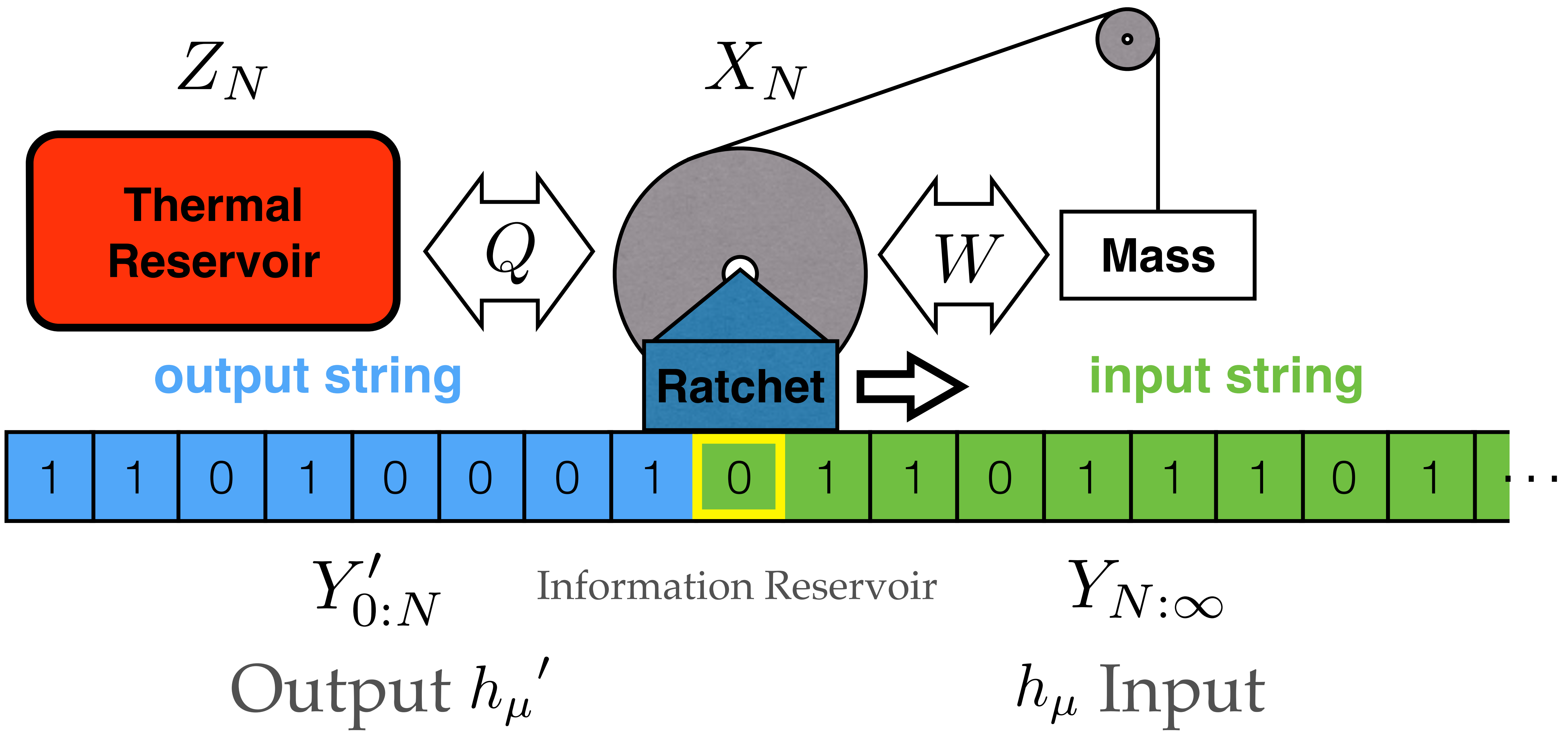
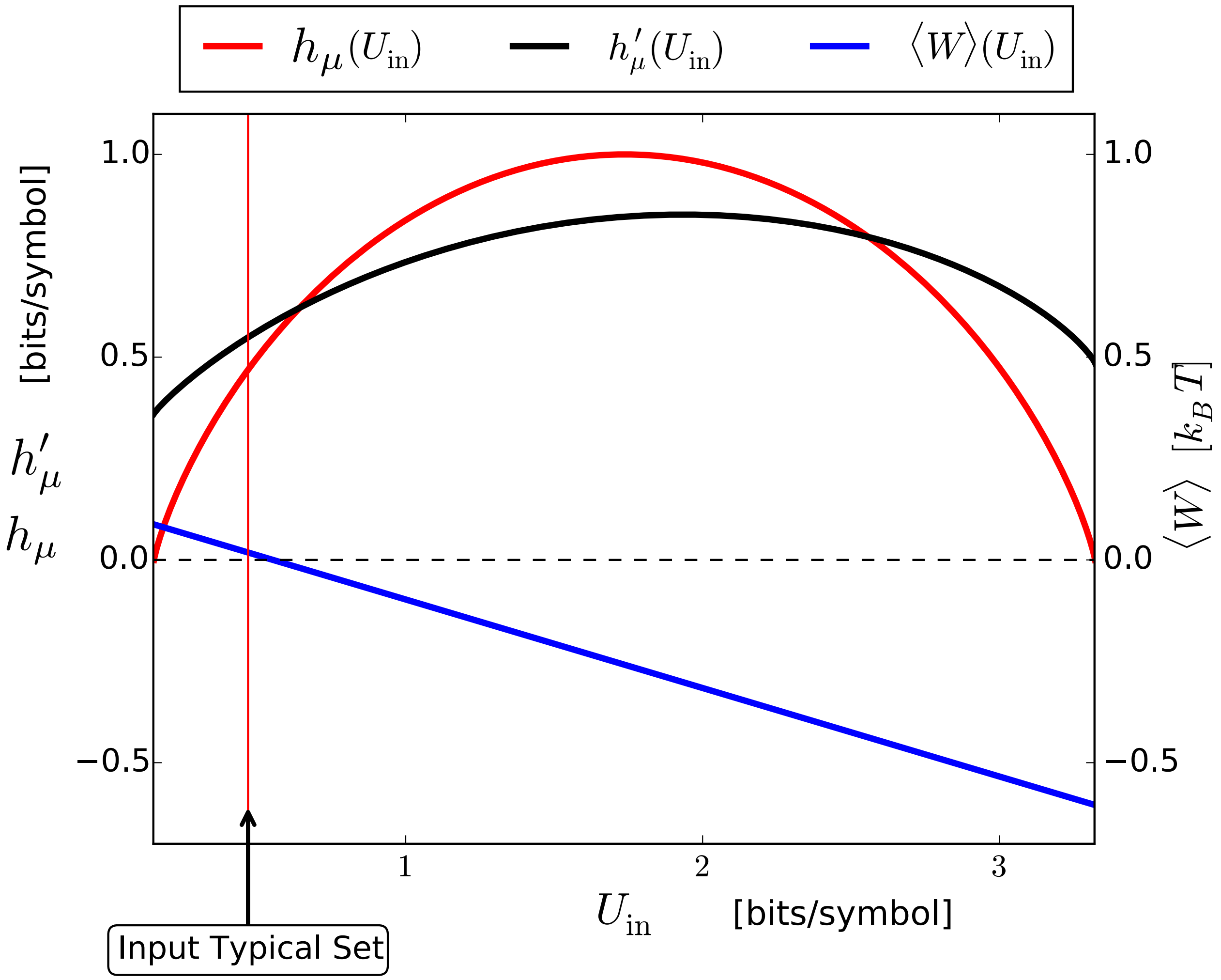


Fluctuations in Thermodynamic Function



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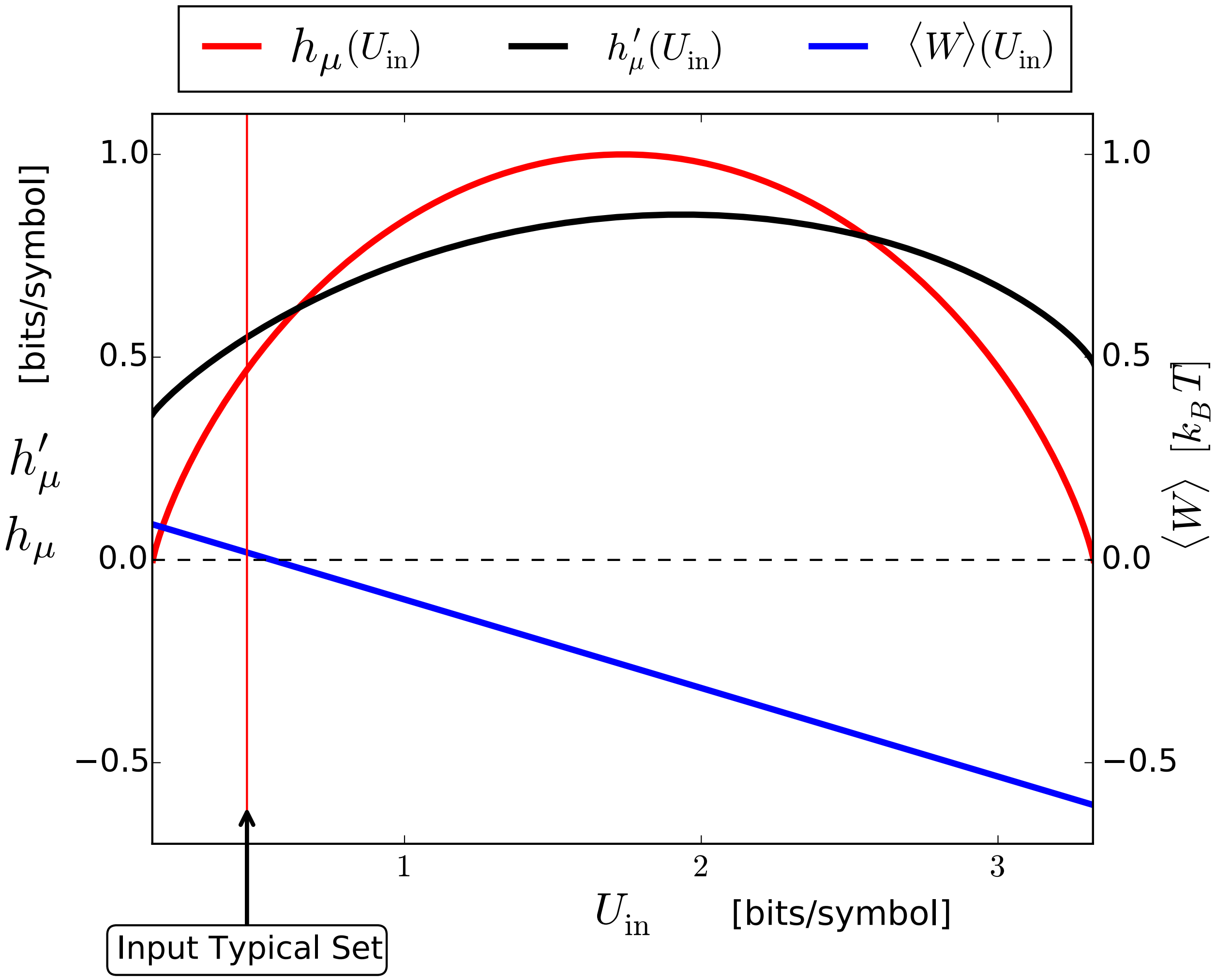

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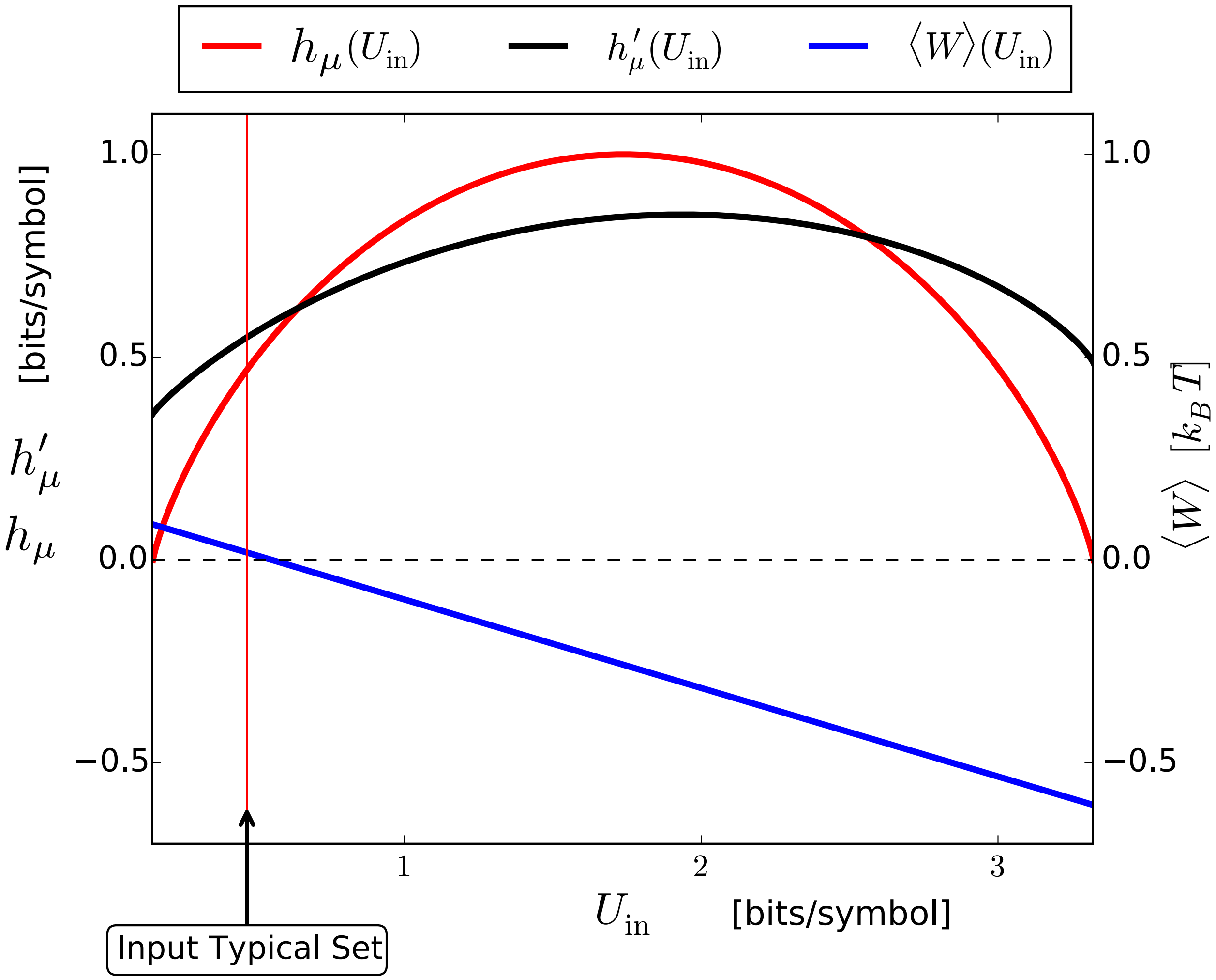
Informational Second Law

$\Rightarrow$ Thermodynamic Function

Fluctuations in Thermodynamic Function



Information Ratchet
+ Fluctuation Spectroscopy
+ Informational Second Law (IPSL)

Function \ Feature	Operation	Net Work	Net Computation
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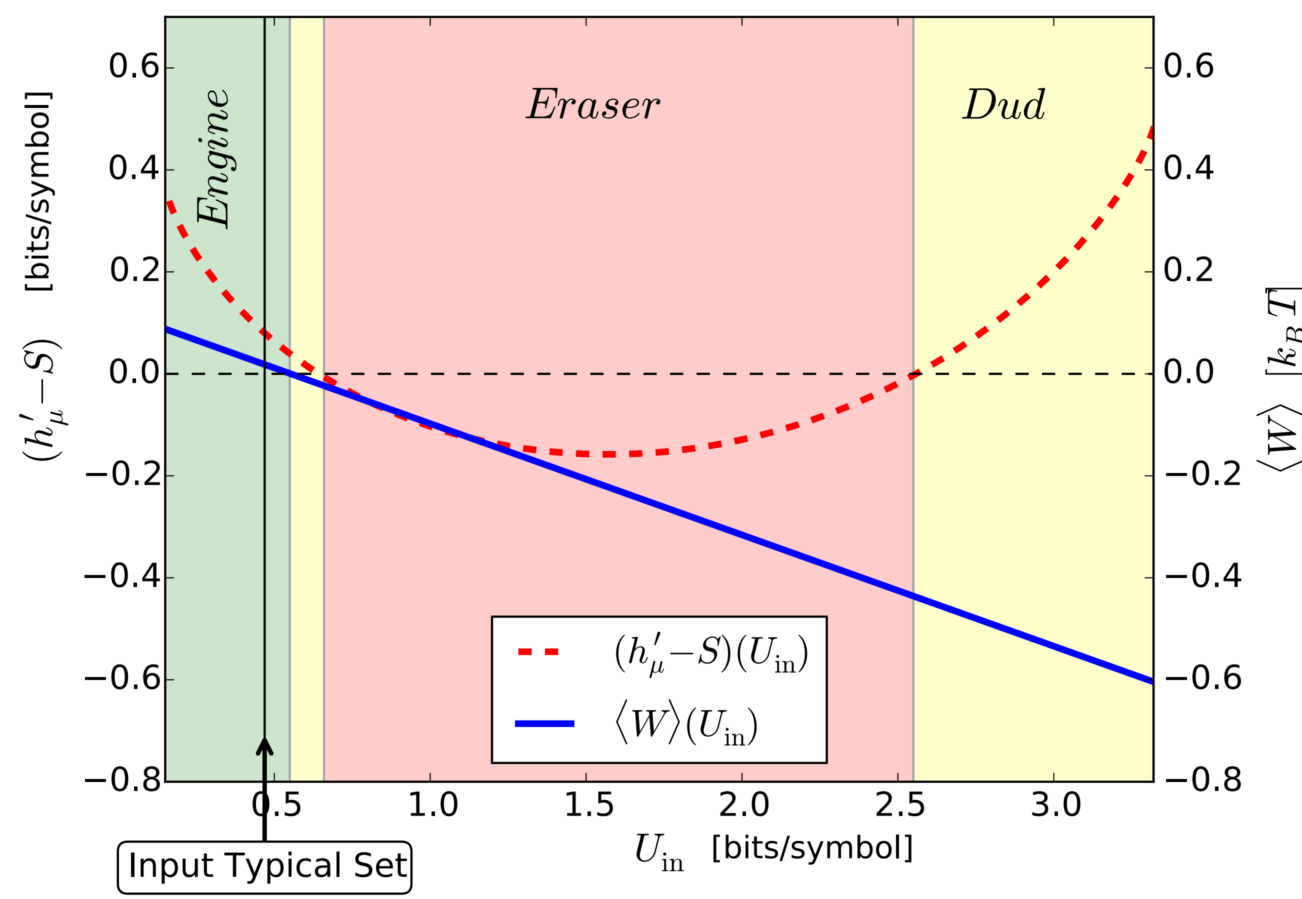


Fluctuations in Thermodynamic Function

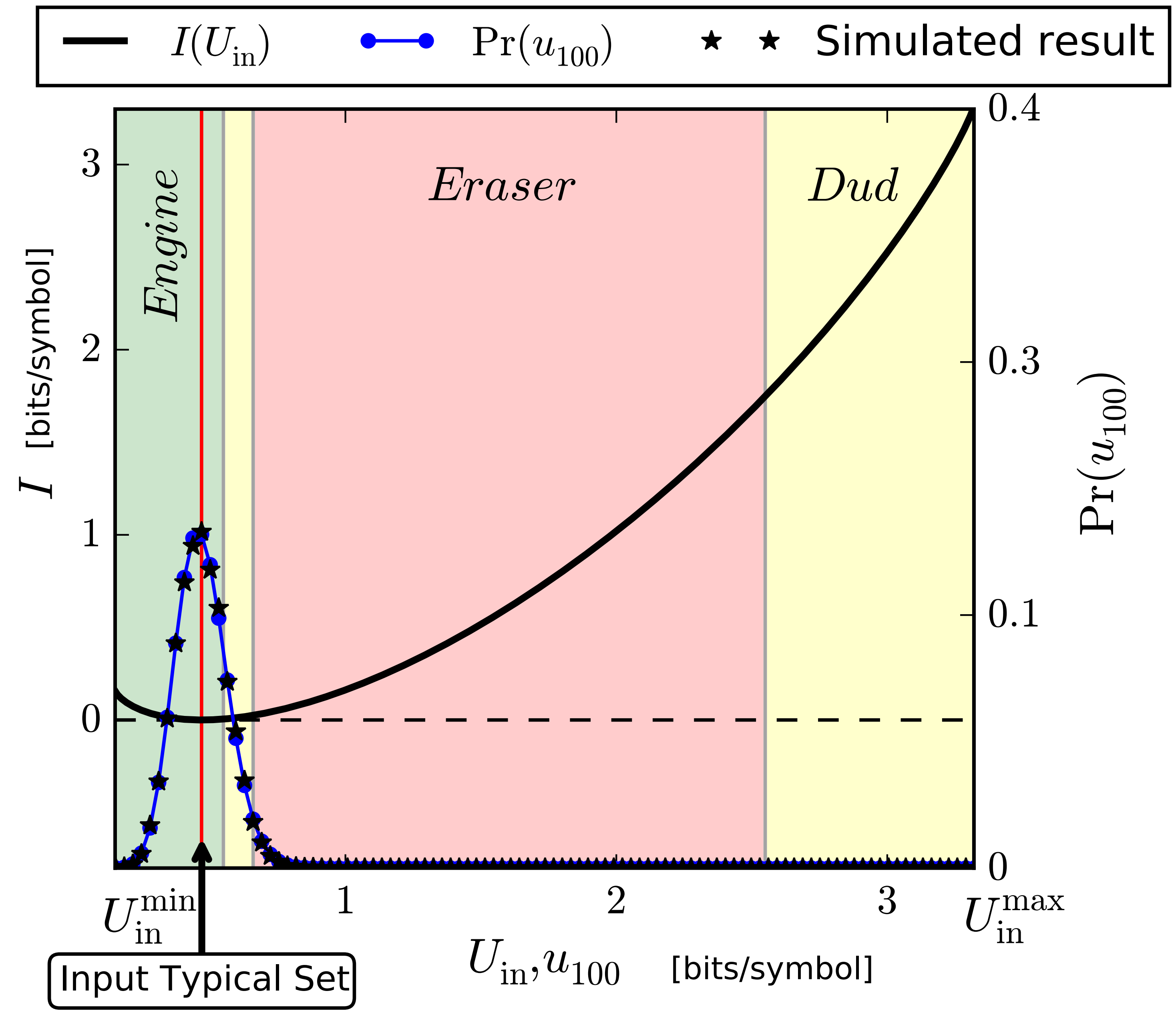
Observable?

Length 100 input sequences:

Engine: 80%

Dud: 17.8%

Eraser: 2.2%



Fluctuations in Intrinsic Computation

- What's new: Determine S(U) and other measures for any structured process from

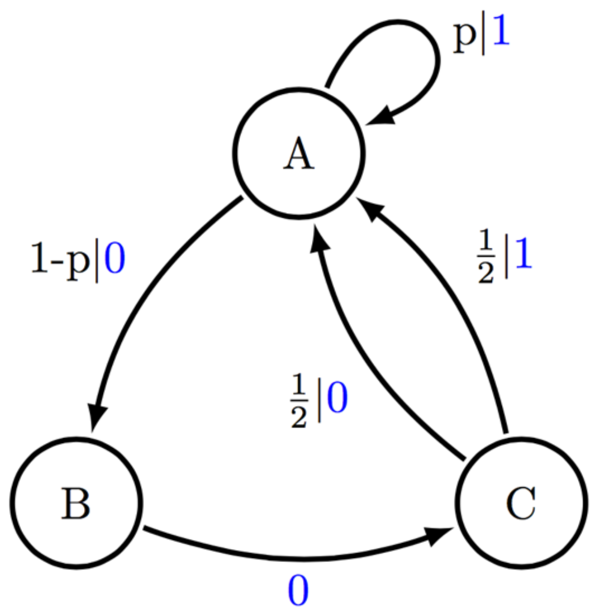
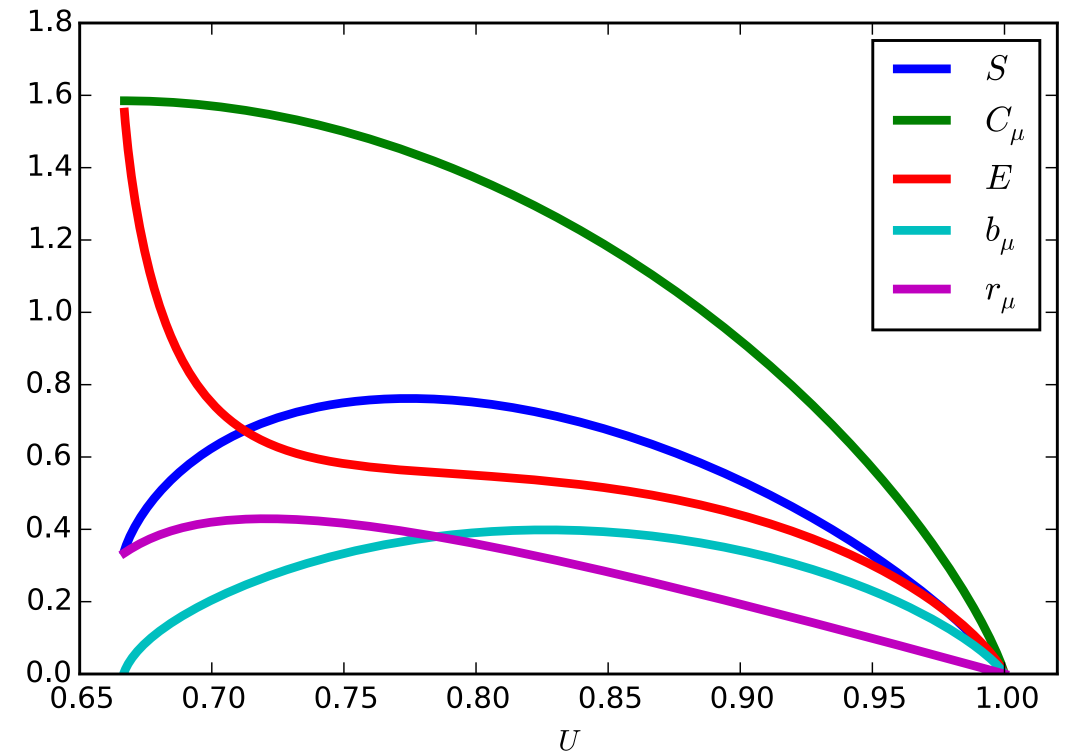


FIG. 22. ϵ-Machine that generates the non-Markovian Nemo Process; its Markov order is infinite. The Nemo Process makes this perhaps clearer, however, since the recurrent states permute into each other upon observing a 0. The transient structure captures this explicitly: ABC maps back to itself on a 0.



Lessons

- Function emerges from the

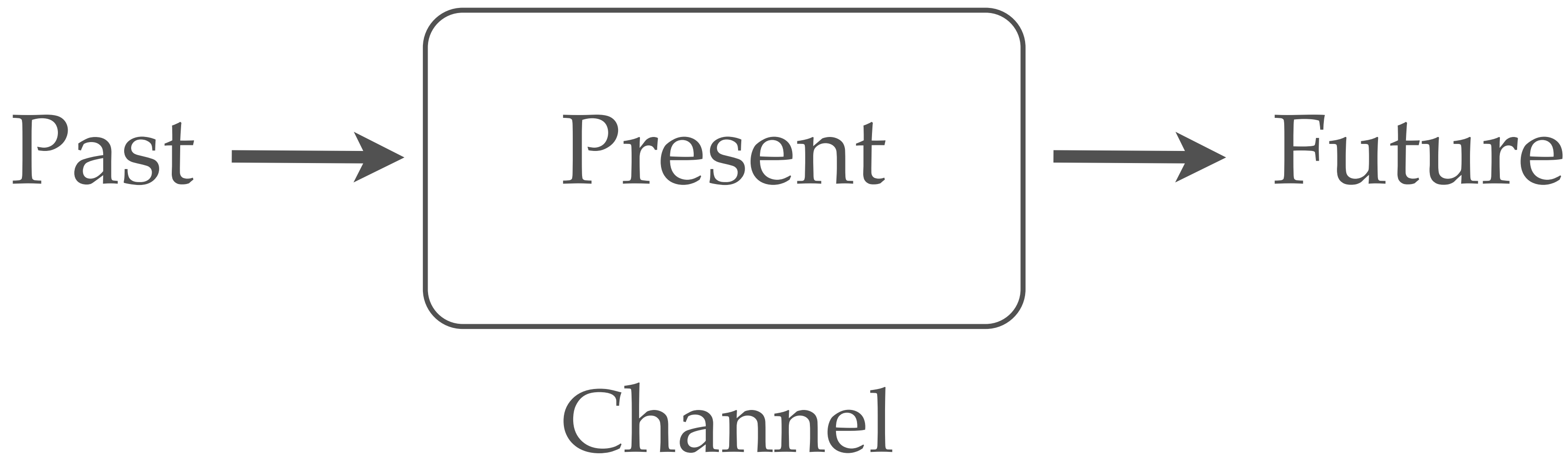
  Information Processing Second Law of Thermodynamics

- Computing fluctuates
- Function fluctuates

- Level Thermodynamics
- **Level Organization**
- Level Thermo-Semantics
- Hierarchical Thermodynamics
- Hierarchical Organization

Information-Theoretic Analysis of Complex Systems ...

- Process $\Pr(\overleftarrow{X}, \overrightarrow{X})$ is a communication channel from the past $\overleftarrow{X}$ to the future $\overrightarrow{X}$:



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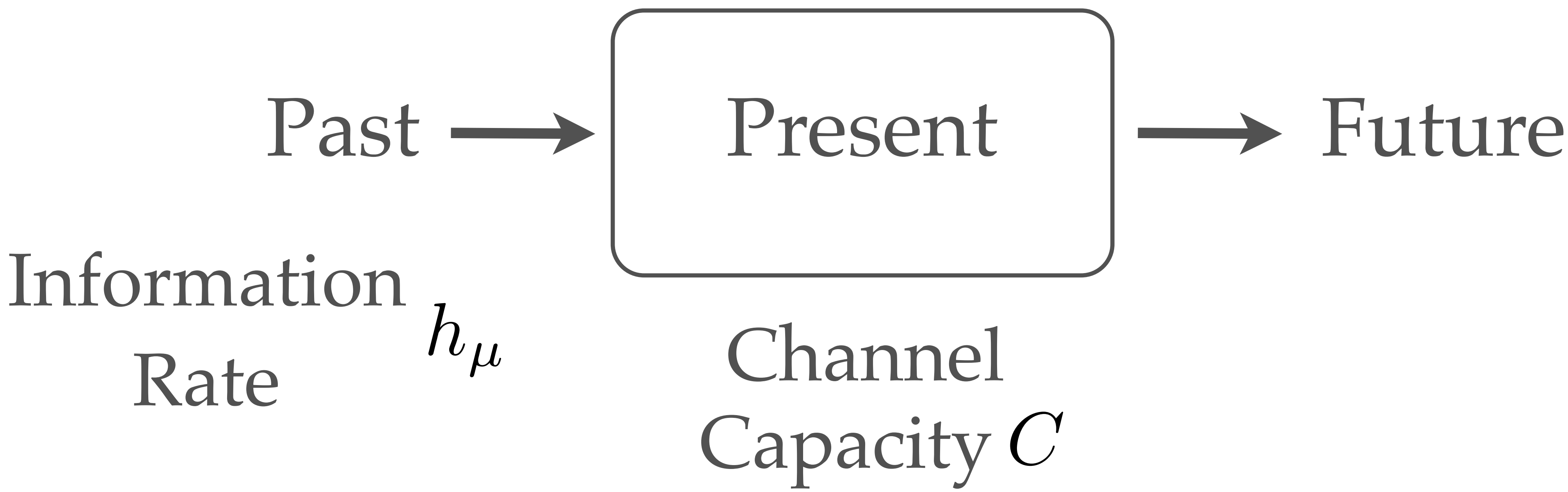

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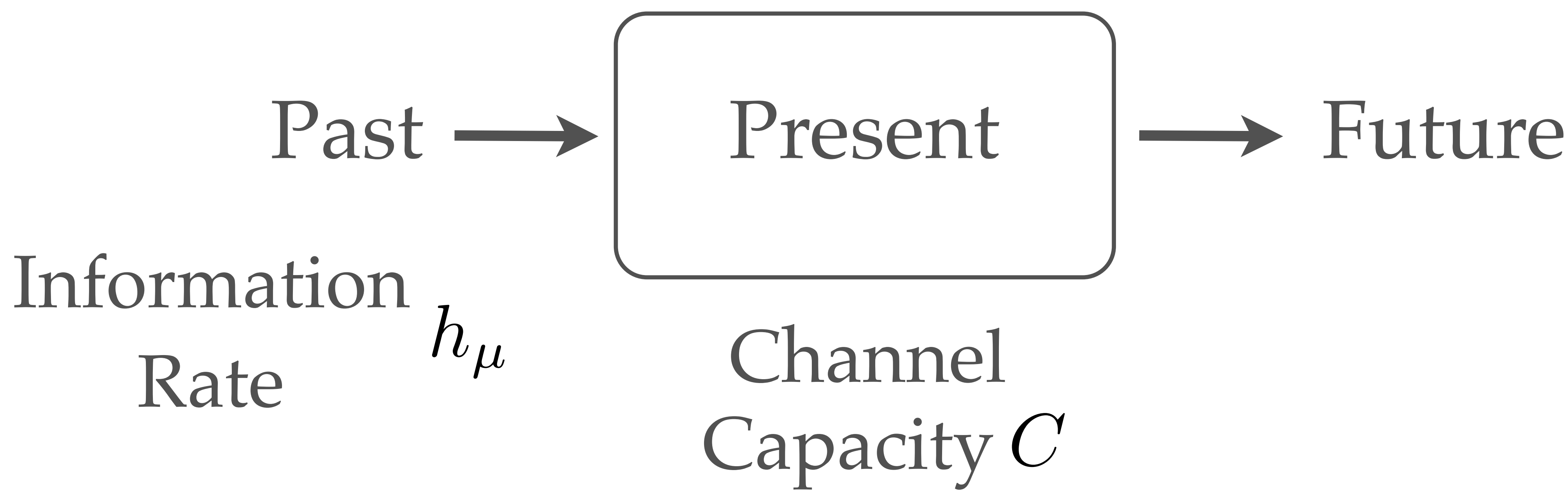
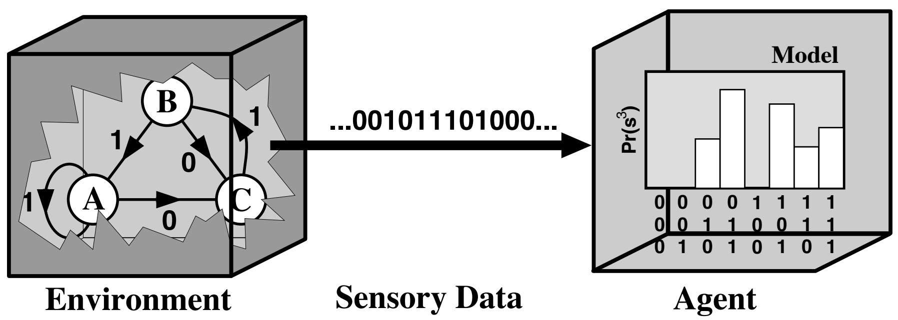


- Channel Utilization: **Excess Entropy**

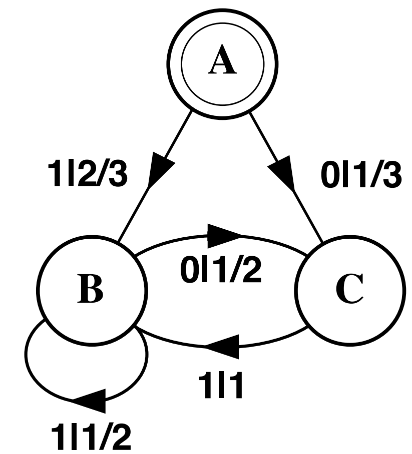
$$\mathbf{E} = I[\overleftarrow{X}; \overrightarrow{X}]$$

Foundations: Computational Mechanics



Causal Equivalence:

$$\overleftarrow{x} \sim \overleftarrow{x}' \Leftrightarrow \Pr(\overrightarrow{X}|\overleftarrow{x}) = \Pr(\overrightarrow{X}|\overleftarrow{x}')$$



ε-Machine: Unique, minimal, & optimal predictor

Stored versus Generated Information

$$C_\mu = -\sum_{\sigma \in \boldsymbol{\mathcal{S}}} \Pr(\sigma) \log_2 \Pr(\sigma) \quad \textbf{versus} \quad h_\mu = -\sum_{\sigma \in \boldsymbol{\mathcal{S}}} \Pr(\sigma) \sum_{\sigma' \in \boldsymbol{\mathcal{S}}} \Pr(\sigma'|\sigma) \log_2 \Pr(\sigma'|\sigma)$$

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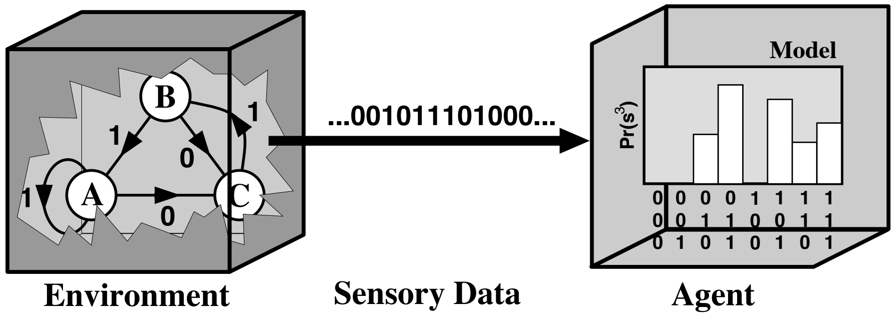

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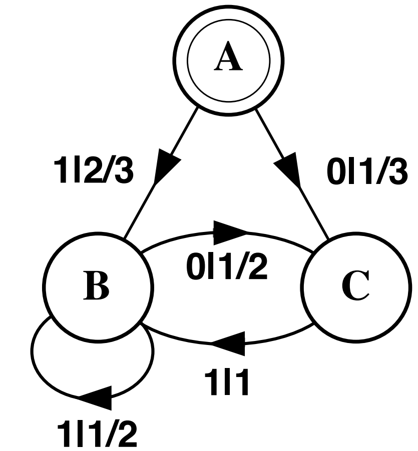

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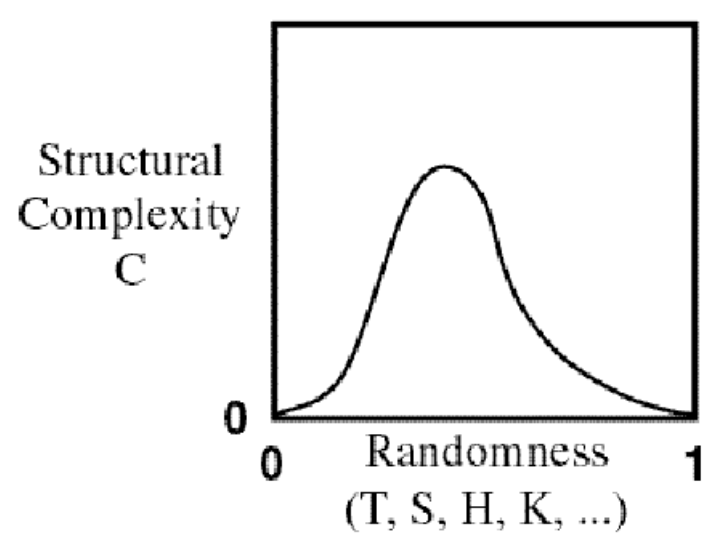
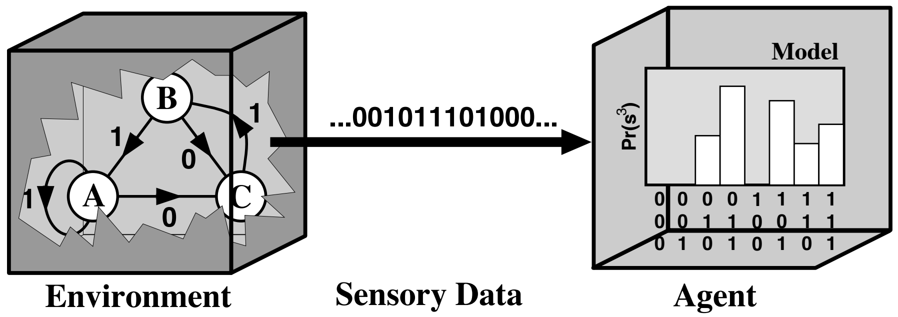
Structure versus Randomness



Foundations: Computational Mechanics



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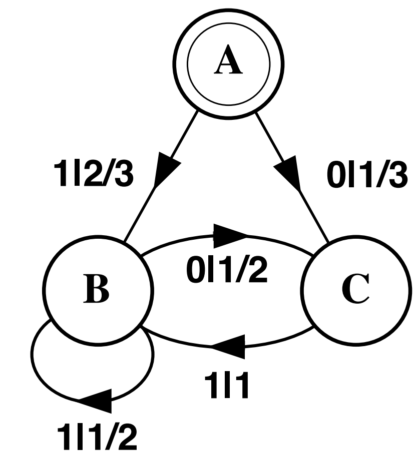

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Intrinsic Computation:

1. How much historical information does a process store?
2. In what architecture is it stored?
3. How is it used to produce future behavior?

J.P. Crutchfield & K. Young, "Inferring Statistical Complexity", Physical Review Letters 63 (1989) 105-108.

J.P. Crutchfield, "Between Order and Chaos",
Nature Physics 8 (January 2012) 7-24.

Computational Mechanics

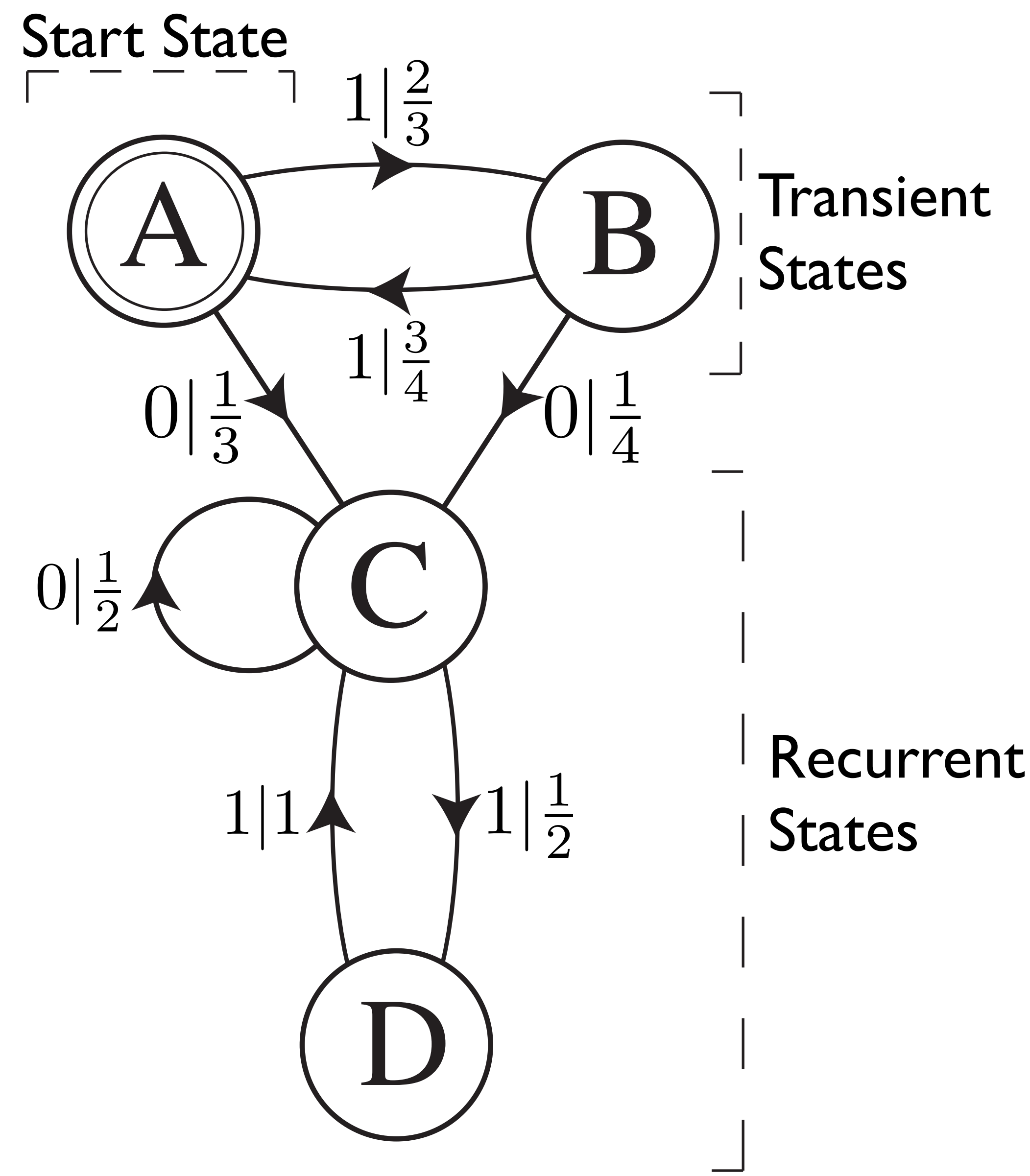
- ε-Machine:

$$M = \left\{ \boldsymbol{\mathcal{S}}, \{T^{(x)} : x \in \mathcal{A}\} \right\}$$

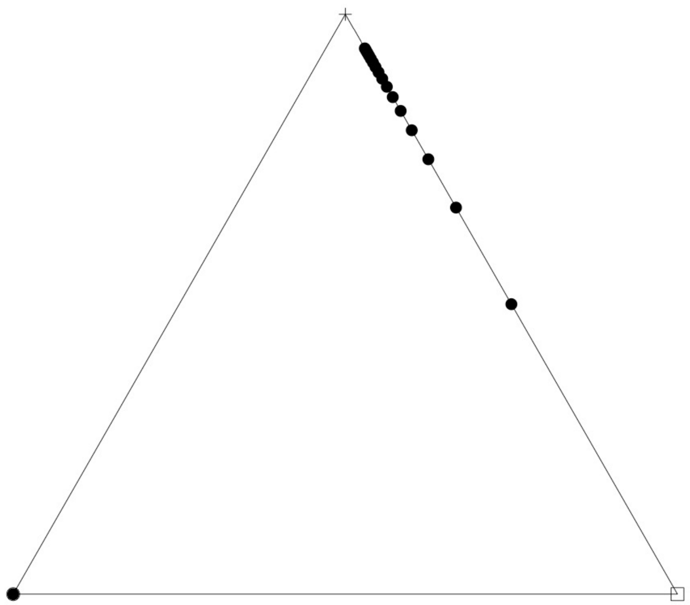
- Dynamic:

$$T^{(x)}_{\sigma,\sigma'} = \Pr(\sigma'|\sigma, x)$$

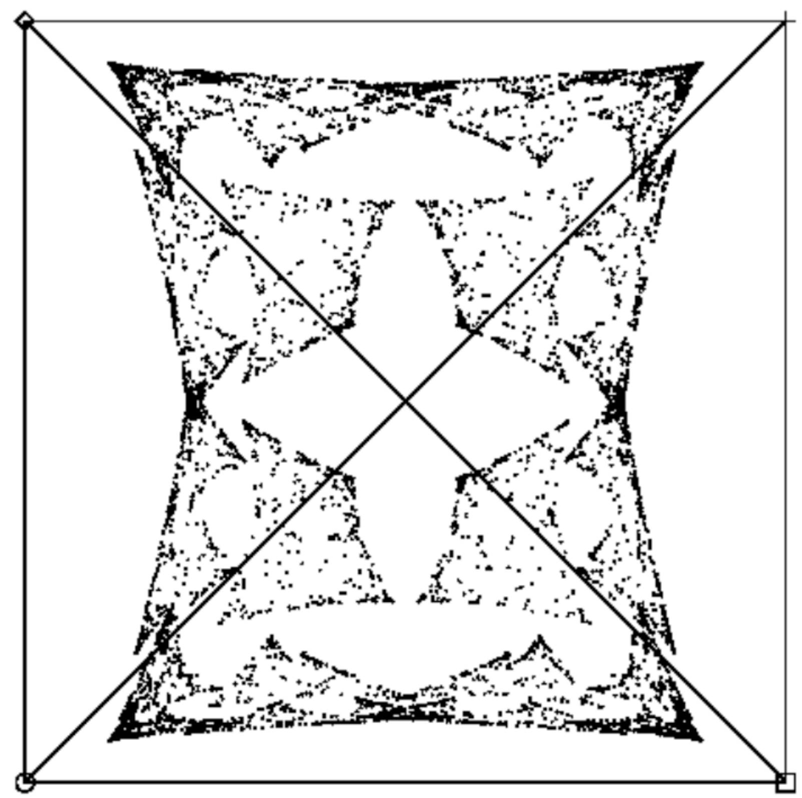
$$\sigma, \sigma' \in \boldsymbol{\mathcal{S}}$$



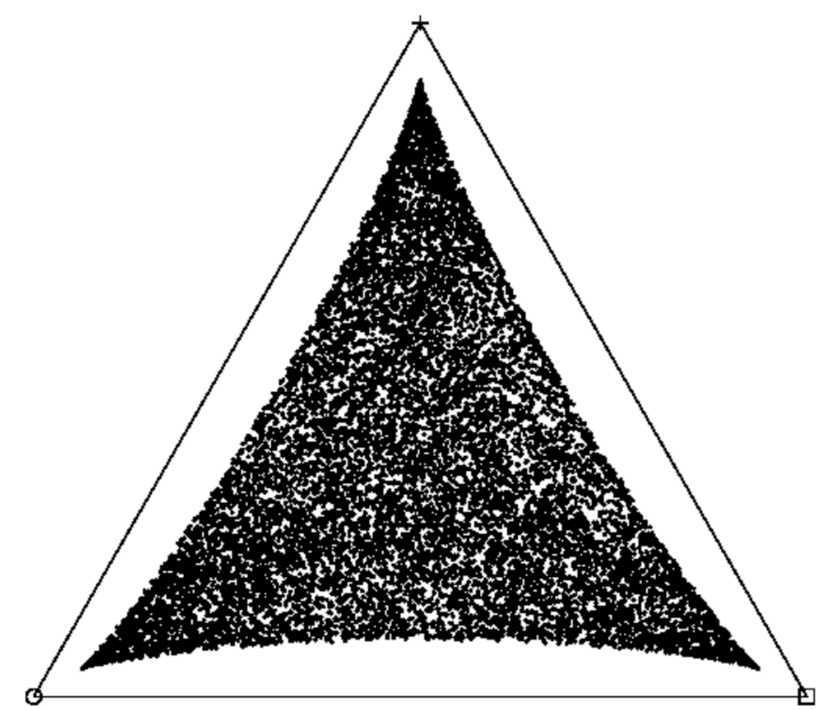
Varieties of ε-Machine



Denumerable Causal States



Fractal



Continuous

J. P. Crutchfield, "Calculi of Emergence: Computation, Dynamics, and Induction", Physica D **75** (1994) 11-54.

Intrinsic Computation: Consequences

A system is unpredictable
if it has positive entropy rate: $h_\mu > 0$

A system is complex
if it has positive structural complexity measures: $C_\mu > 0$

A system is emergent
if its structural complexity increases over time:

$$C_\mu(t') > C_\mu(t), \text{ if } t' > t$$

A system is hidden
if its crypticity is positive: $\chi = C_\mu - \mathbf{E} > 0$

What is a Level?

What is a Level?

- Pattern discovery:
  - Learn the world's hidden states $\Pr(\mathcal{R}|\overleftarrow{X})$
- Causal shielding:

$$\Pr(\overleftarrow{X}\overrightarrow{X}) = \Pr(\overleftarrow{X}|\mathcal{R})\Pr(\overrightarrow{X}|\mathcal{R})$$

- Search in the space of models: $\mathcal{R} \in \mathcal{M}$
- Objective function

$$\min_{\Pr(\mathcal{R}|\overleftarrow{X})} \left(I[\overleftarrow{X};\mathcal{R}] + \beta I[\overleftarrow{X};\overrightarrow{X}|\mathcal{R}] \right)$$

Model: Map from histories to states	Info states contain about histories	Reduce info history has about future

Long history:

N.H. Packard, J.P. Crutchfield, J.D. Farmer, R. S. Shaw, "Geometry from a Time Series", Phys. Rev. Lett. **45** (1980) 712-716.

J. P. Crutchfield and B.S. McNamara, "Equations of Motion from a Data Series", Complex Systems **1** (1987) 417-452.

S. Still, C.J. Ellison, J.P. Crutchfield: arxiv.org: 0708.0654 [physics.gen-ph] & 0708.1580[cs.IT]

What is a Level?

- Optimal states $\Pr(\mathcal{R}|\overleftarrow{X})$ are Gibbs distributions:

$$\Pr_{\text{opt}}(\mathcal{R}|\overleftarrow{X}) = \frac{\Pr(\mathcal{R})}{Z(\overleftarrow{X},\beta)} e^{-\beta E(\mathcal{R},\overleftarrow{X})}$$

where

$$E(\mathcal{R},\overleftarrow{X}) = \mathcal{D}\left(\Pr(\overrightarrow{X} \mid \overleftarrow{X}) || \Pr(\overrightarrow{X} | \mathcal{R})\right)$$

$$\Pr(\overrightarrow{X} | \mathcal{R}) = \frac{1}{\Pr(\mathcal{R})} \sum_{\overleftarrow{X}} \Pr(\overrightarrow{X} \mid \overleftarrow{X}) \Pr(\mathcal{R}|\overleftarrow{X}) \Pr(\overleftarrow{X})$$

$$\Pr(\mathcal{R}) = \sum_{\overleftarrow{X}} \Pr(\mathcal{R}|\overleftarrow{X}) \Pr(\overleftarrow{X})$$

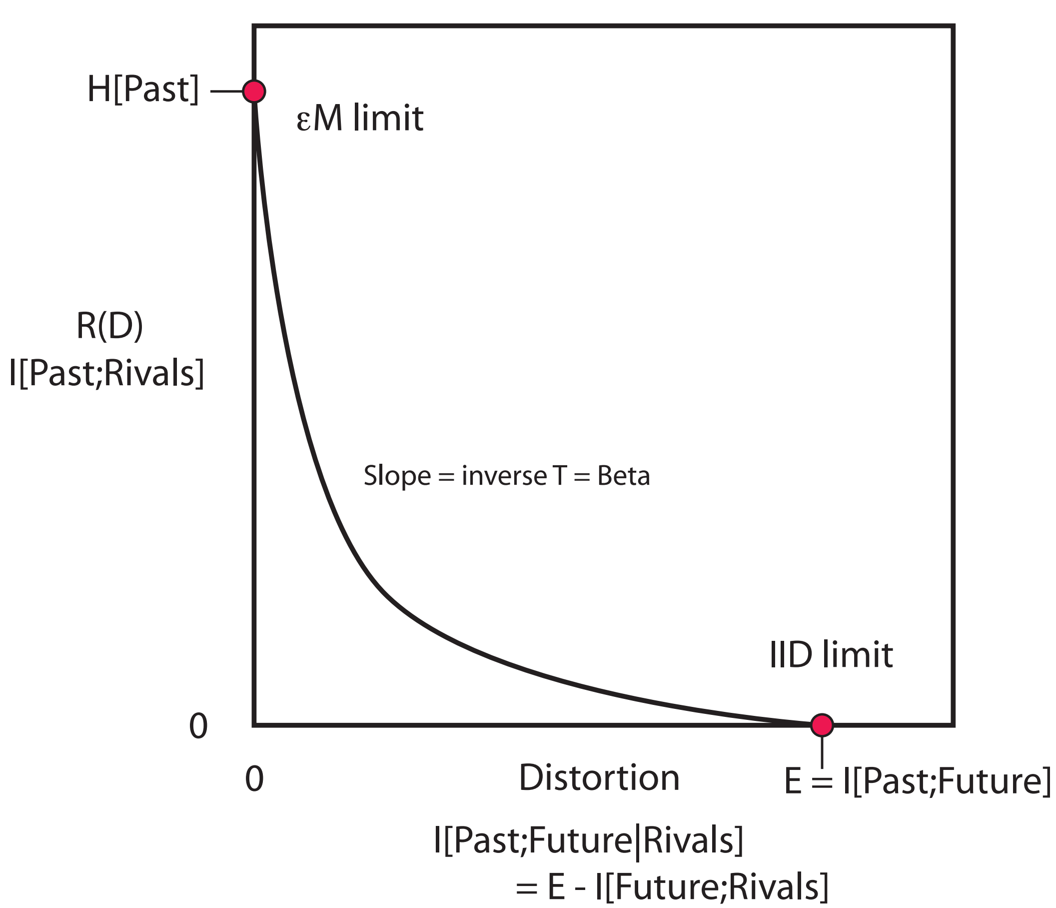
Now, solve these self-consistently

What is a Level?

Optimal balance structure & error
At each level β of approximation

In theory

Causal Rate Distortion Curve

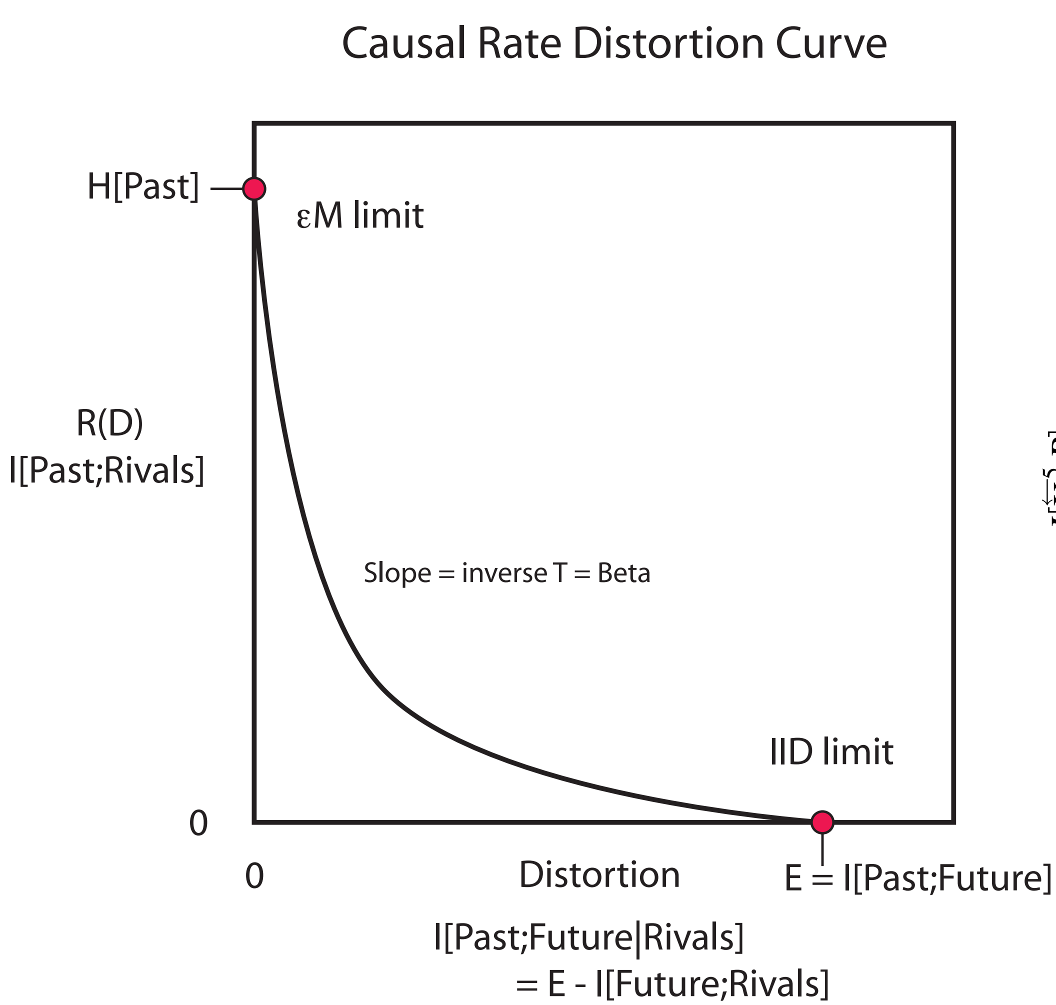


What is a Level?

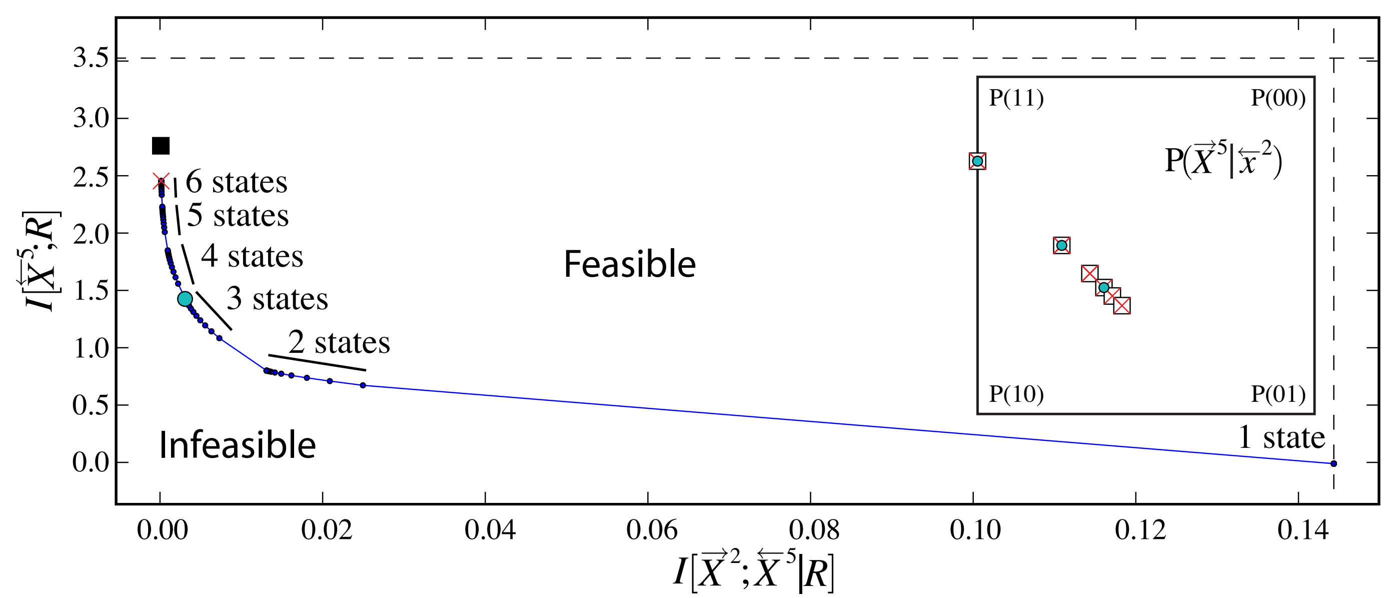
Optimal balance structure & error

At each level β of approximation

In theory



In practice: Learn an ∞-state world

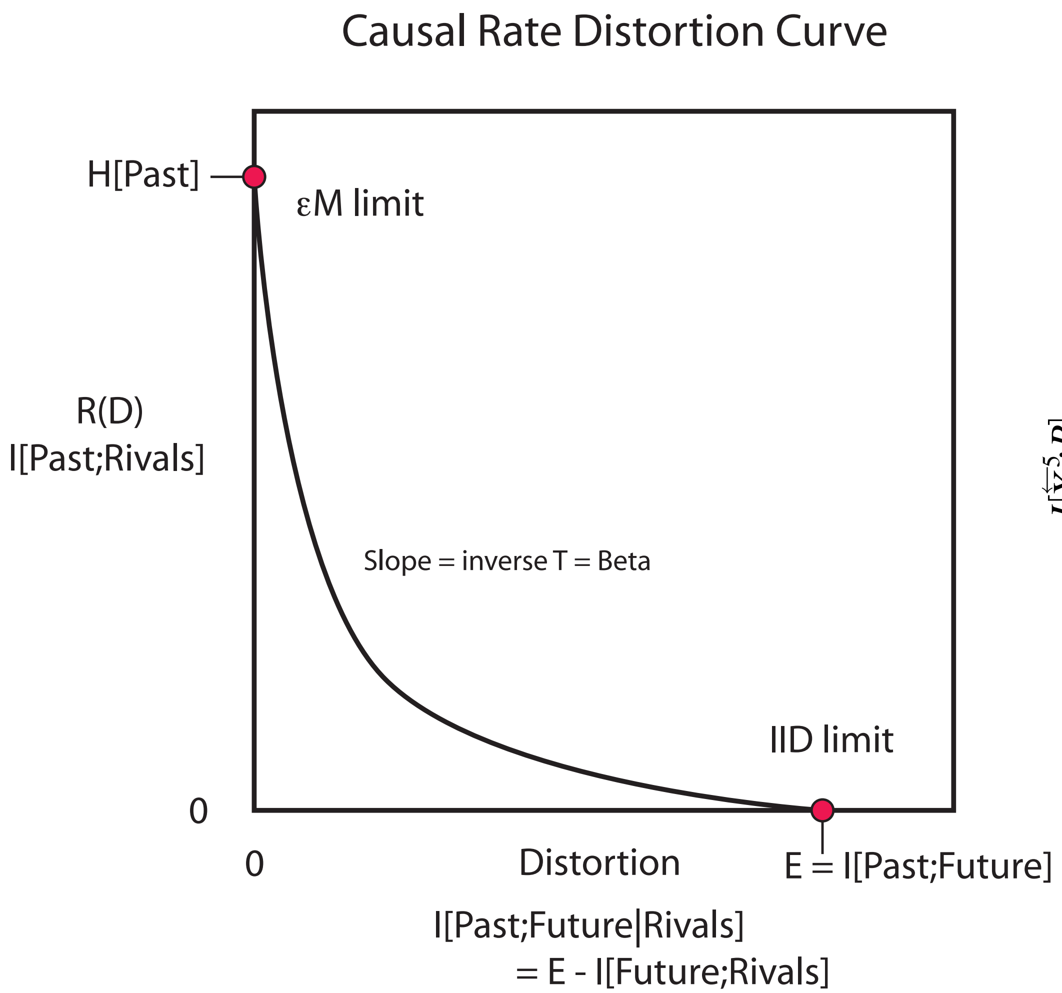


What is a Level?

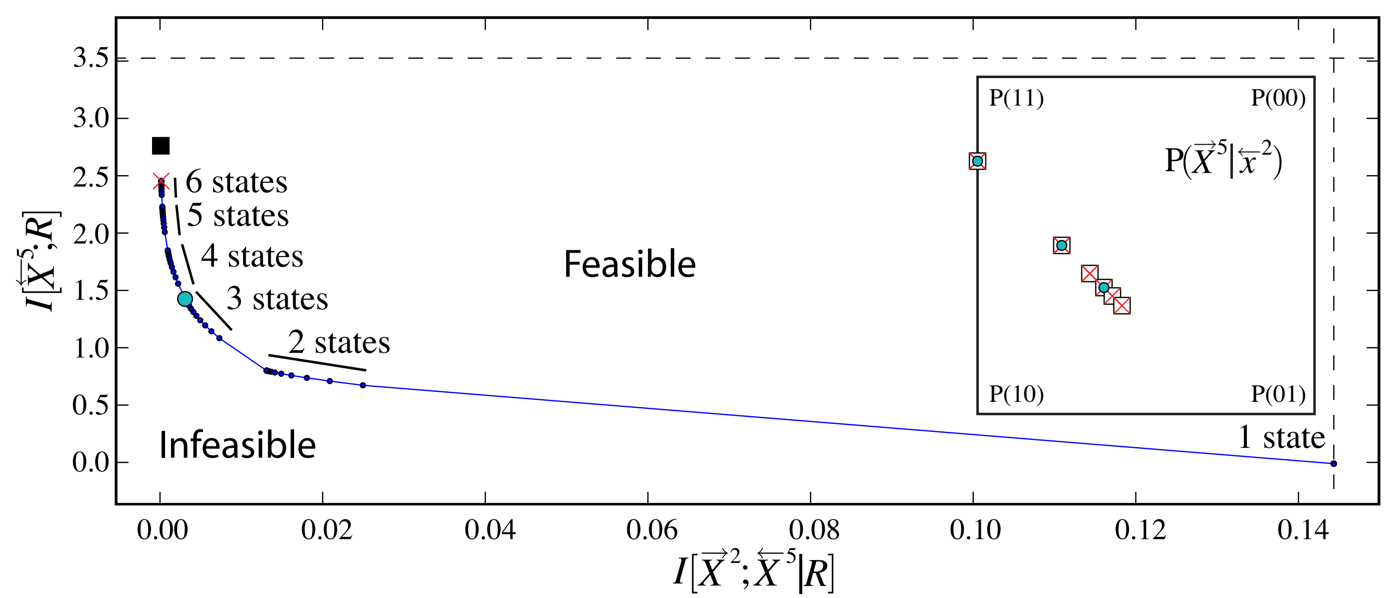
Optimal balance structure & error

At each level β of approximation

In theory



In practice: Learn an ∞-state world



$$\text{Levels} \sim \frac{\partial R(D)}{\partial D} \ll 0$$

- Level Thermodynamics
- Level Organization
- **Level Thermo-Semantics**
- Hierarchical Thermodynamics
- Hierarchical Organization

Beyond Structure to Meaning, Purpose, & Functionality

Semiotic Hierarchy of Information:

- Syntax
- Semantics
- Pragmatics
- Function

For physical systems …

Beyond Structure to Meaning, Purpose, & Functionality

Semiotic Hierarchy of Information:

- Syntax
- Semantics
- Pragmatics
- Function

For physical systems …

Semantics and Thermodynamics

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Berkeley, California 94720 USA

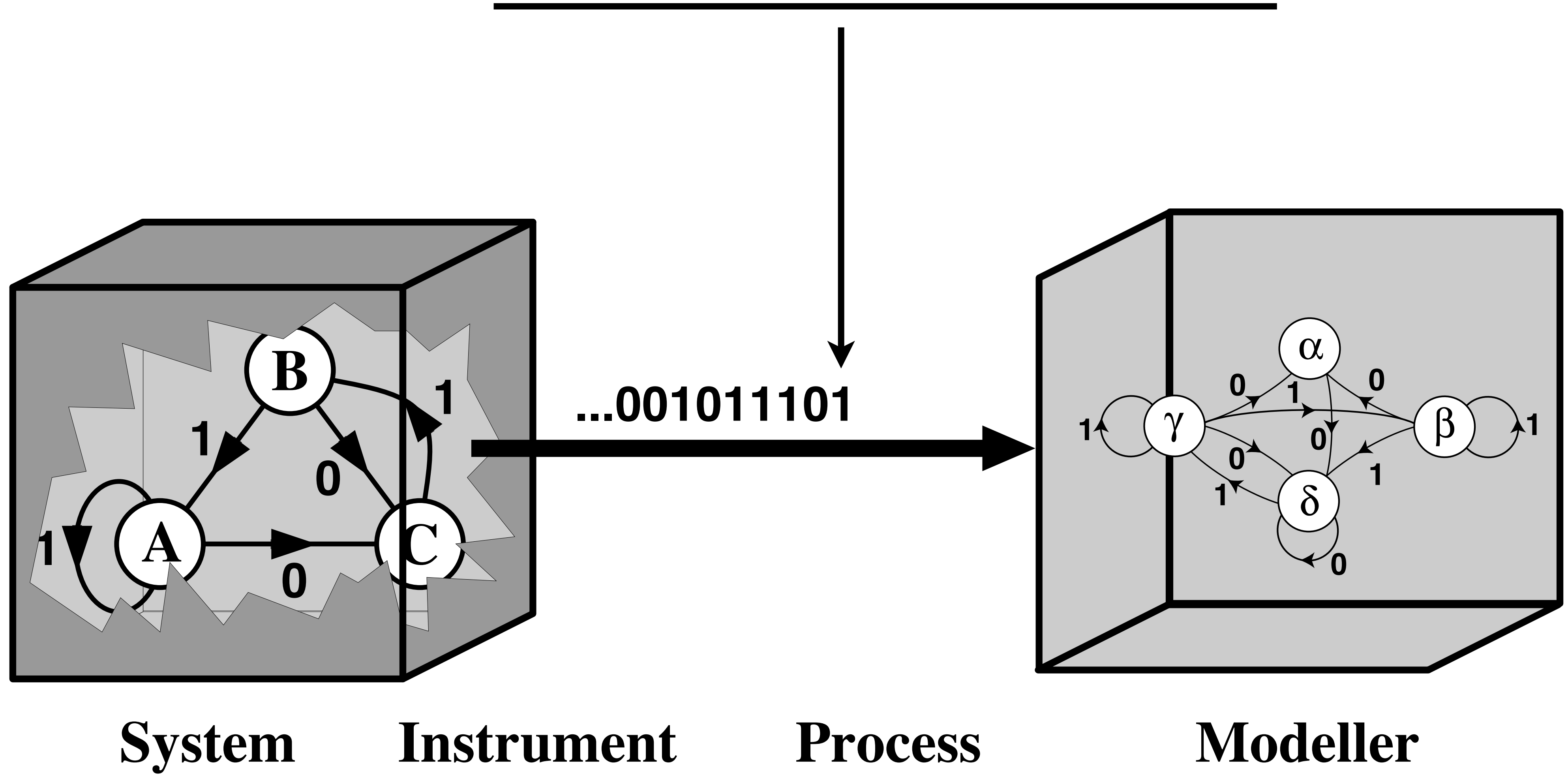
in **Nonlinear Modeling and Forecasting**, M. Casdagli and S. Eubank, editors,
Santa Fe Institute Studies in the Sciences of Complexity **XII**
Addison-Wesley, Reading, Massachusetts (1992) 317 — 359.

SFI 91–09–033

Measurement Semantics

Measurement Semantics

What does a particular measurement mean?



Measurement Channel

Measurement Semantics

An $\epsilon\mathrm{M}$ Captures "Pattern":

Measurement semantics: Prediction level

What is the meaning of a particular measurement?

Shannon says the amount of "information" is

$$- \log_2 \Pr(\text{observing } s)$$

Given $\epsilon\mathrm{M}$ (assuming you're sync'd):

$$- \log_2 \Pr(\text{observing } s) = - \log_2 \Pr(\mathcal{S} \rightarrow_s \mathcal{S}')$$

Measurement Semantics

An $\epsilon\mathrm{M}$ Captures "Pattern":

Measurement semantics: Prediction level ...

Example: $t = 0\ 1\ 2\ 3\ 4\ 5\ 6\ 7\ 8\ 9\ 10\ 11$

$s = 0\ 1\ 1\ 1\ 1\ 0\ 1\ 1\ 0\ 1\ \ 1\ \ 1$

At $t = 11$ measure $s_{11} = 1$

How much information does this give?

$$H(s_{11}|s_{10} = 1, s_9 = 1, \ldots) \approx h_\mu (\approx 0.585 \text{ bits})$$

Degree of observer's surprise (predictability)

Does not say what the event $s_{11} = 1$ means to the observer!

Measurement Semantics

Meaning: Tension between representations of same event at different levels; e.g.,

Level 1 is data stream and the event is a measurement
Level 2 is the agent and the event updates it's model

Degree of meaning of observing $s \in \mathcal{A}$

$$\Theta(s) = -\log_2 \Pr(\rightarrow_s \mathcal{S})$$

where $\mathcal{S}$ is the causal state to which s brings observer.

Meaning content: State selected from anticipated palette.

Measurement Semantics

Meaningless: Start state (all futures possible)

$$\Theta(s) = -\log_2 \Pr(\mathcal{S}_0) = -\log_2 1 = 0 \qquad s = \lambda$$

Action on disallowed transition:

Reset to state of total ignorance (start state)

Disallowed transition is meaningless.

Meaningless measurements are informative, though:

$$-\log_2 \Pr(\mathcal{S} \rightarrow_s \mathcal{S}_0) = -\log_2 0 = \infty$$

Measurement Semantics

Theorem:

$$\langle \Theta(s) \rangle = C_\mu$$

Average amount of meaning is the Statistical Complexity.

Thermodynamic Cost of Extracting Meaning

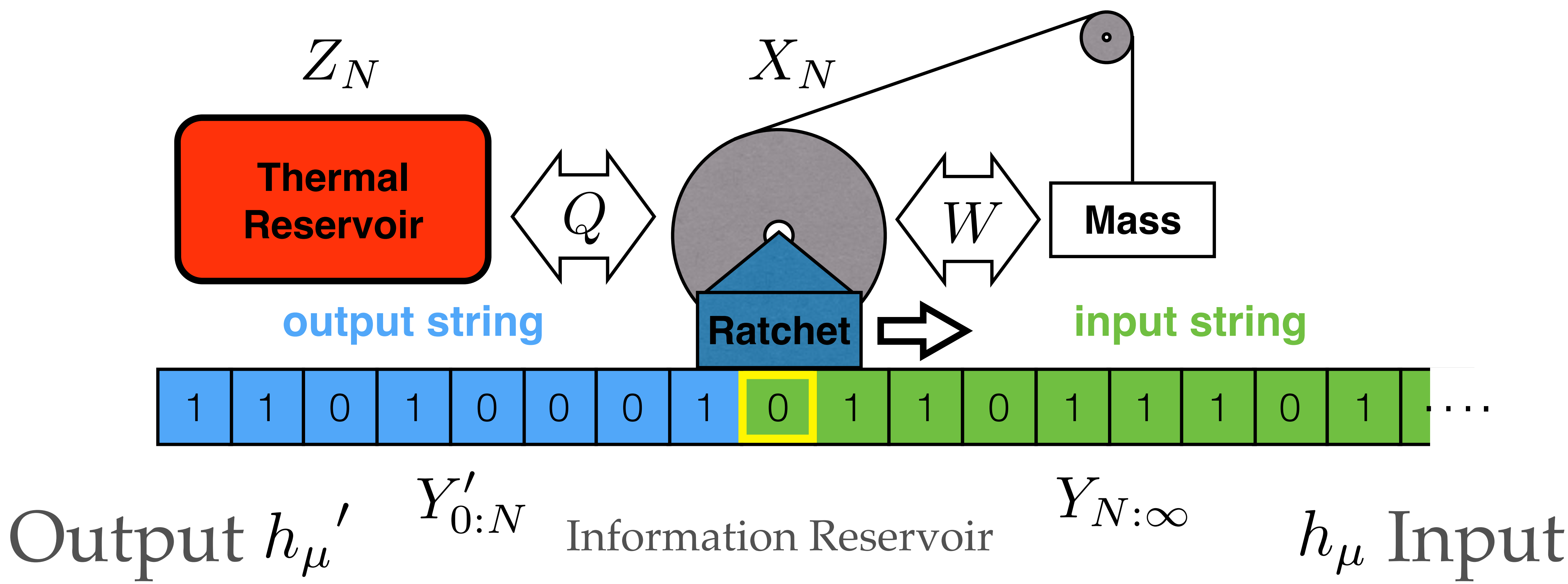
Thermodynamic Cost of Extracting Meaning

Two cases:

- o In NESS
- o Out of NESS

Thermodynamic Cost of Extracting Meaning in NESS

- Learning about environment
- Agent predicts environment to leverage possible resources



(A. Boyd, D. Mandal, and JPC, "Identifying Functional Thermodynamics in Autonomous Maxwellian Ratchets", New Journal of Physics **18** (2016) 023149.)

Thermodynamic Cost of Extracting Meaning in NESS

Thermo cost of implementation that predicts:

$$\left\langle Q^{\text{implement}} \right\rangle_{\min} = k_{\text{B}} T \ln 2 \;\; \mathrm{I}[\mathcal{S}; \overleftarrow{Y}']$$
$$= k_{\text{B}} T \ln 2 \; C_\mu$$

Recall Theorem on Total Semantic Content

$$\langle \Theta(s) \rangle = C_\mu$$

Agent memory about environment.

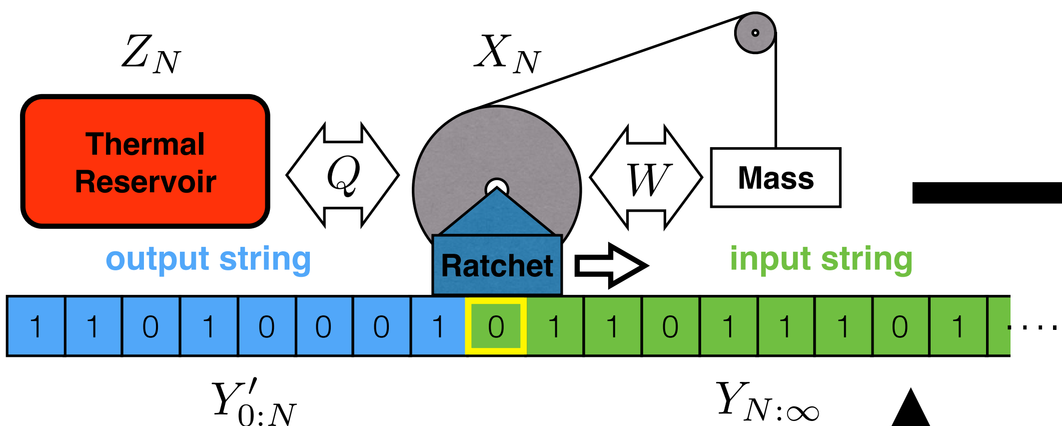
Thermo-semantic cost:

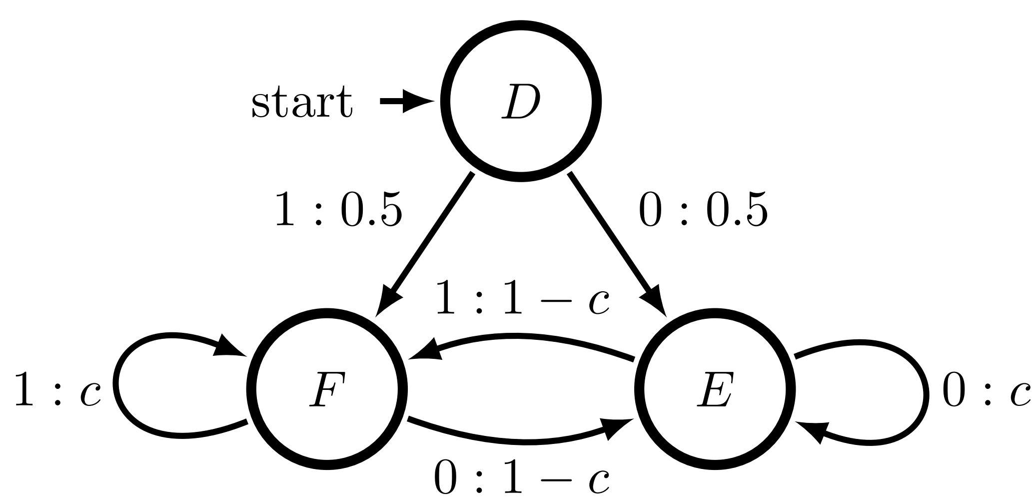
$$\left\langle Q^{\text{implement}} \right\rangle_{\min} = k_{\text{B}} T \ln 2 \; \left\langle \Theta(s) \right\rangle$$

Thermodynamics of
Meaning and Function beyond NESS

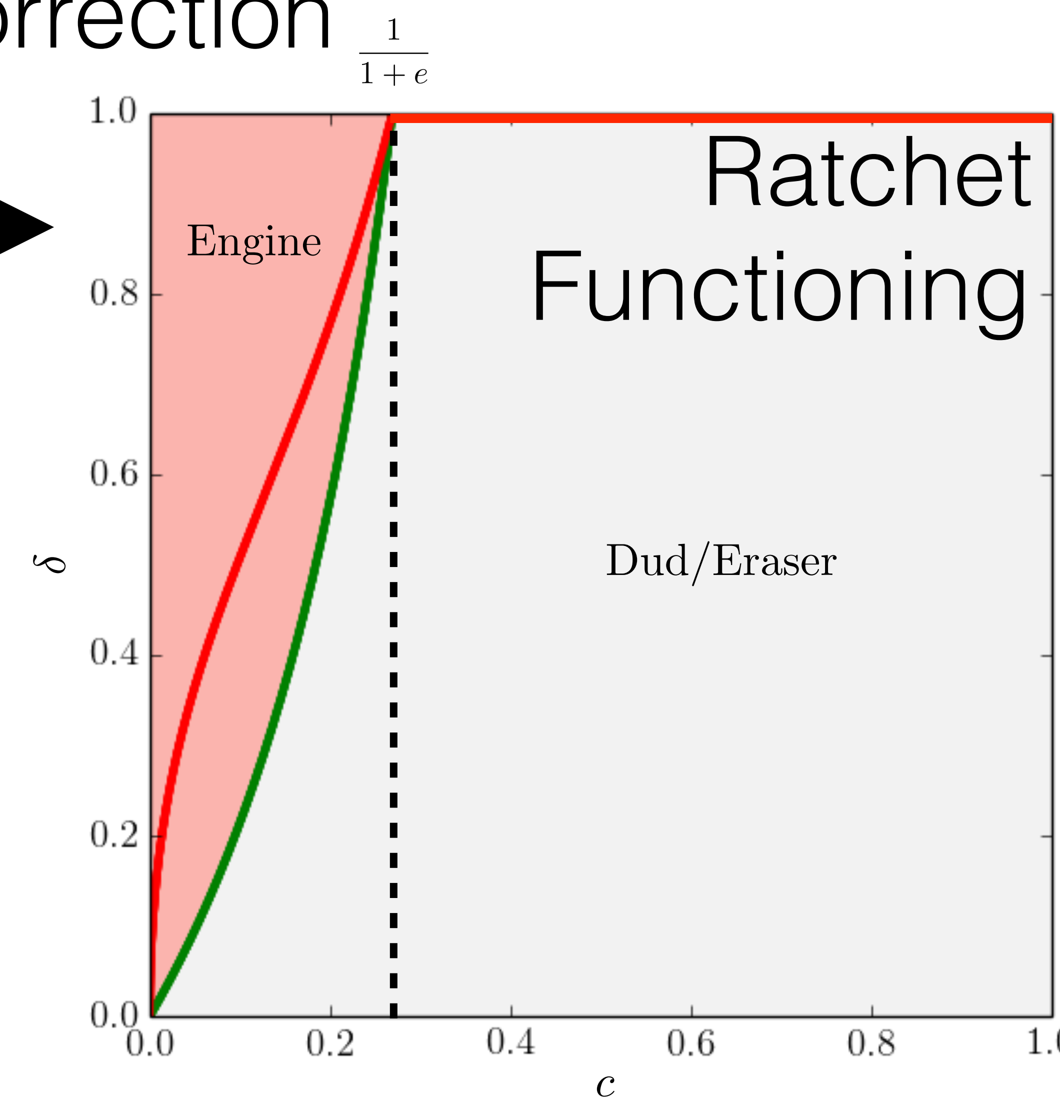
Thermodynamics of Meaning and Function beyond NESS

Environment: Periodic with random phase slips





Error Correction



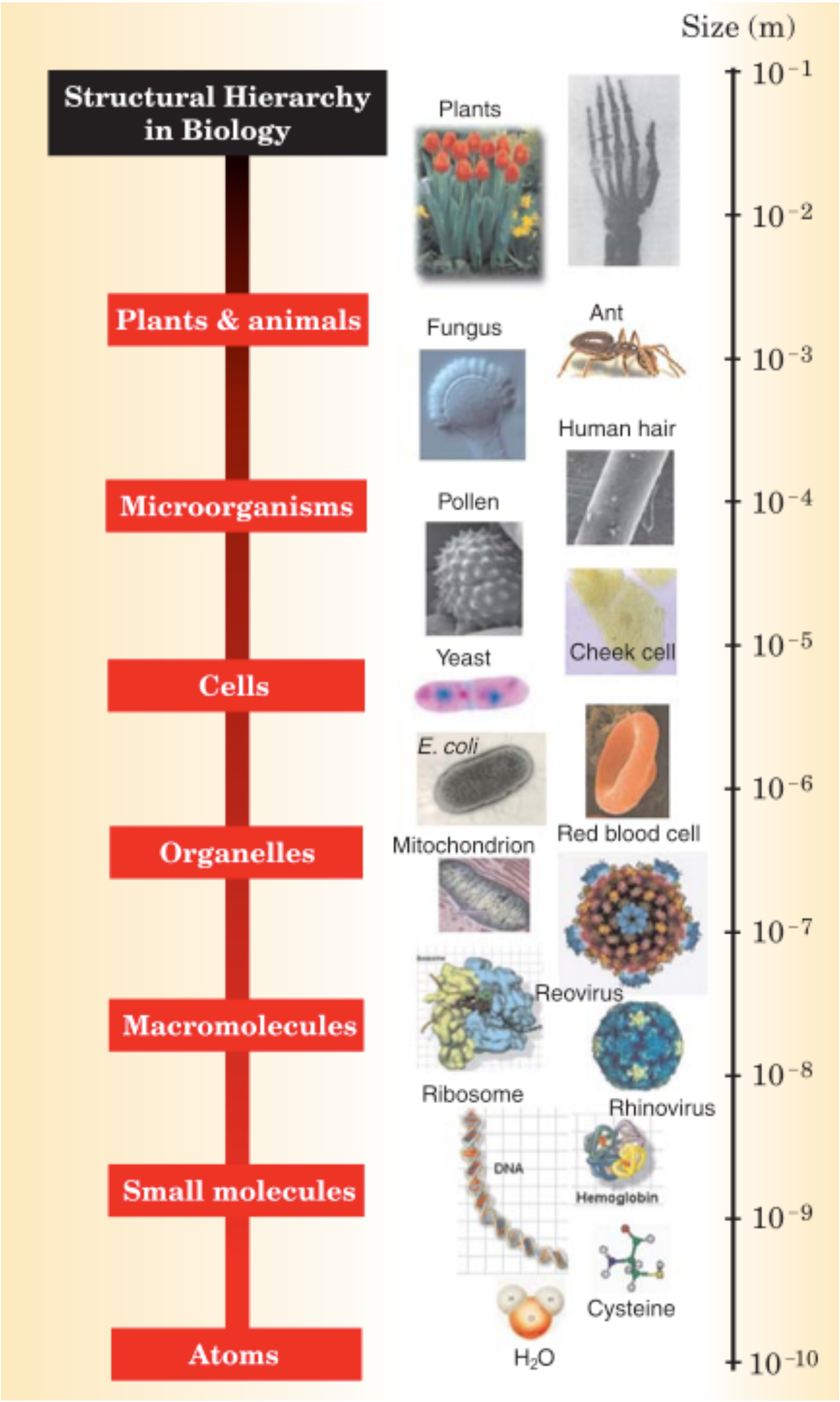
Thermodynamics of Meaning and Function beyond NESS

- Semiotics of Information Engines:
  - Syntactic information = Measurements
  - Semantic information = Envt'l Phase, Sync/No Sync
  - Functional information = Error Correction

Summary

- Level Thermodynamics
- Level Organization
- Level Semantics
- Hierarchical Thermodynamics
- Hierarchical Organization

Thanks!



Thermodynamics of Organization

Bibliography

- **Functional computation & optimal prediction**: A.B. Boyd, D. Mandal, and J.P. Crutchfield, *Identifying Functional Thermodynamics in Autonomous Maxwellian Ratchets*, New Journal of Physics **18** (2016) 023149.
- **Information creation**: C. Aghamohammadi and J.P. Crutchfield, *Thermodynamics of Random Number Generation*, Physical Review E **95**:6 (2017) 062139.
- **Synchronization & error correction**: A.B. Boyd, D. Mandal, and J.P. Crutchfield, *Correlation-powered Information Engines and the Thermodynamics of Self-Correction*, Physical Review E **95**:1 (2017) 012152.
- **Homeostasis**: A.B. Boyd, D. Mandal, and J.P. Crutchfield, *Leveraging Environmental Correlations: Thermodynamics of Requisite Variety*, Journal Statistical Physics **167**:6 (2017) 1555-1585.
- **Functional fluctuations**: J. P. Crutchfield and C. Aghamohammadi, “Not All Fluctuations are Created Equal: Spontaneous Variations in Thermodynamic Function. arxiv.org:1609.02519.
- **Controller structure**: A.B. Boyd, D. Mandal, and J.P. Crutchfield, *Transient Dissipation and Structural Costs of Physical Information Transduction*, Physical Review Letters **118** (2017) 220602.
- **Intelligent control**: A.B. Boyd and J.P. Crutchfield, *Maxwell Demon Dynamics: Deterministic Chaos, the Szilard Map, and the Intelligence of Thermodynamic Systems*, Physical Review Letters **116** (2016) 190601.
- **NESS transitions**: P.M. Riechers and J.P. Crutchfield, *Fluctuations When Driving Between Nonequilibrium Steady States*, Journal of Statistical Physics (2017) in press. arxiv.org:1610.09444.
- **Sensors**: S. E. Marzen and J. P. Crutchfield, *Prediction and Power in Molecular Sensors: Uncertainty and Dissipation When Conditionally Markovian Channels Are Driven by Semi-Markov Environments*, arxiv.org: 1707.03962.
- **Modularity**: A.B. Boyd, D. Mandal, and J.P. Crutchfield, *Above and Beyond the Landauer Bound: Thermodynamics of Modularity*, arXiv.org, submitted.