

The Role of the Future in the Analysis of Chaotic Dynamical Systems

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Background

Setting the Scene: Processes

$$\mathcal{P} = (\mathbf{X}, \mu) : \quad \mathbf{X} \subseteq \mathcal{A}^{\mathbb{Z}}, \sigma(\mathcal{P}) = \mathcal{P}$$

$$\cdots \ X_{-3} \ X_{-2} \ X_{-1} \ X_0 \ X_1 \ X_2 \ X_3 \ \cdots$$

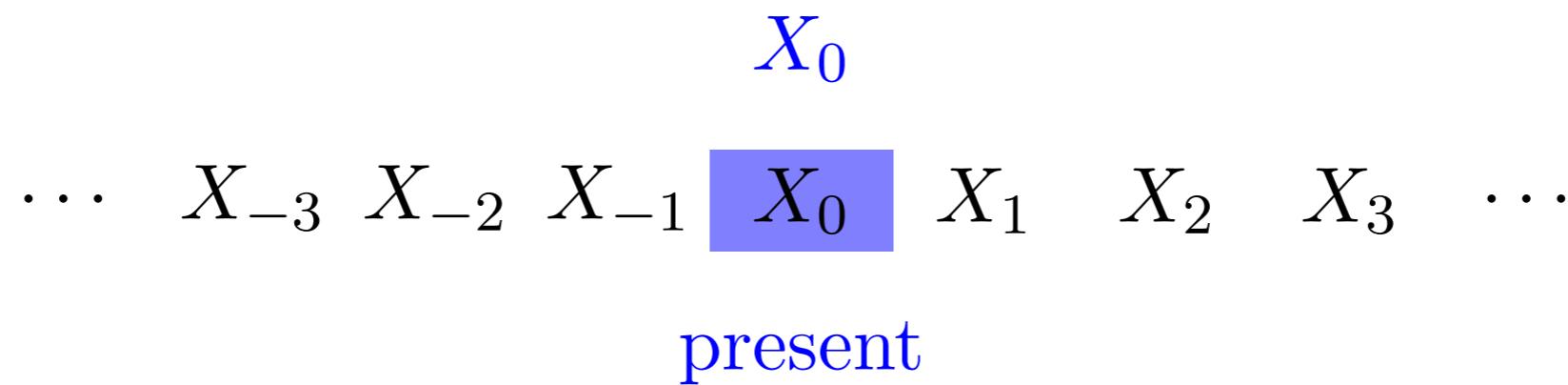
Additional properties:

- Ergodic
- Stationary
- Discrete

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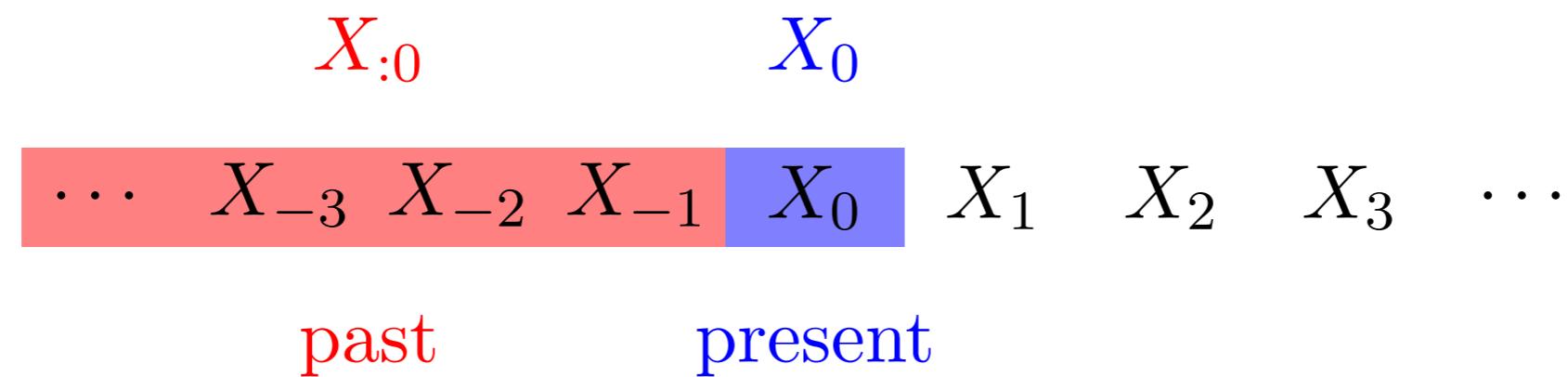
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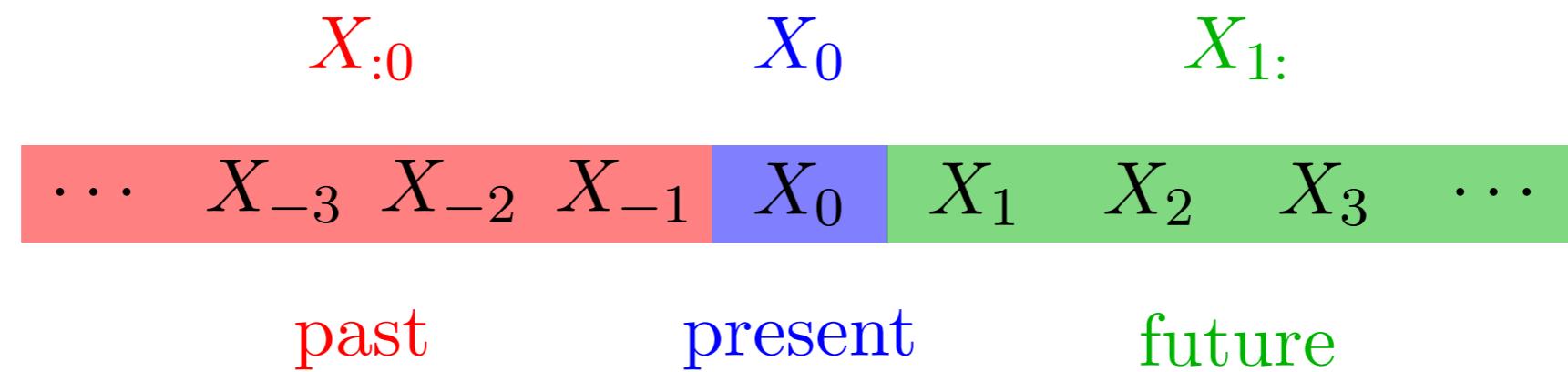
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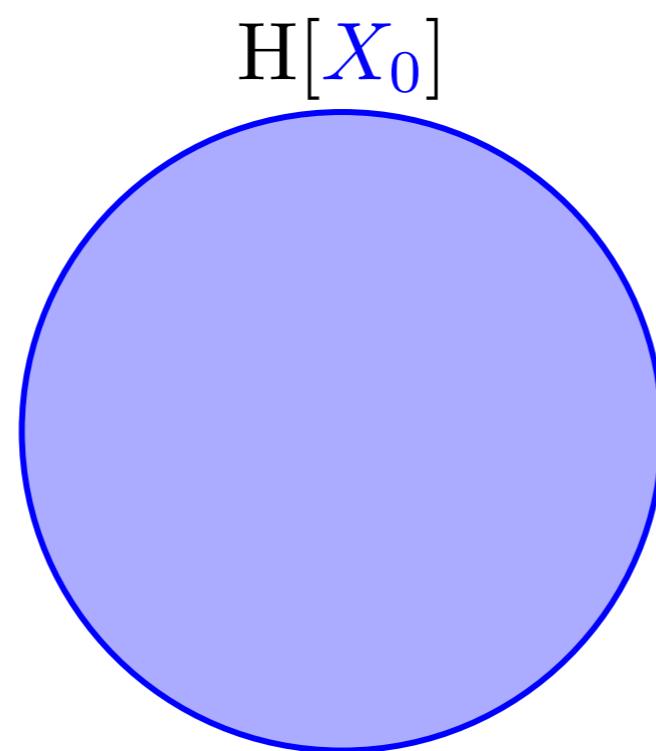


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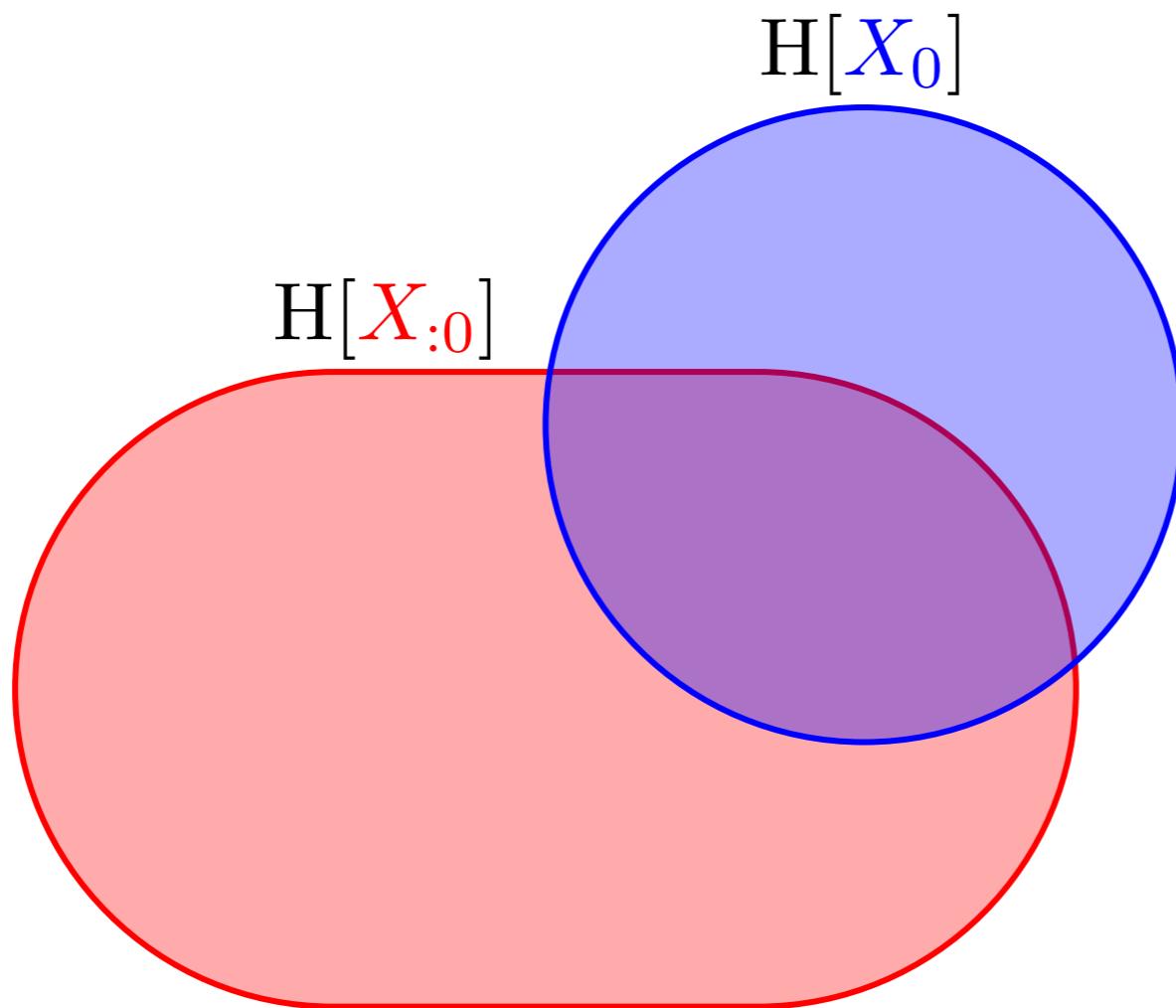
Visualizing Information

Past, Present & Future



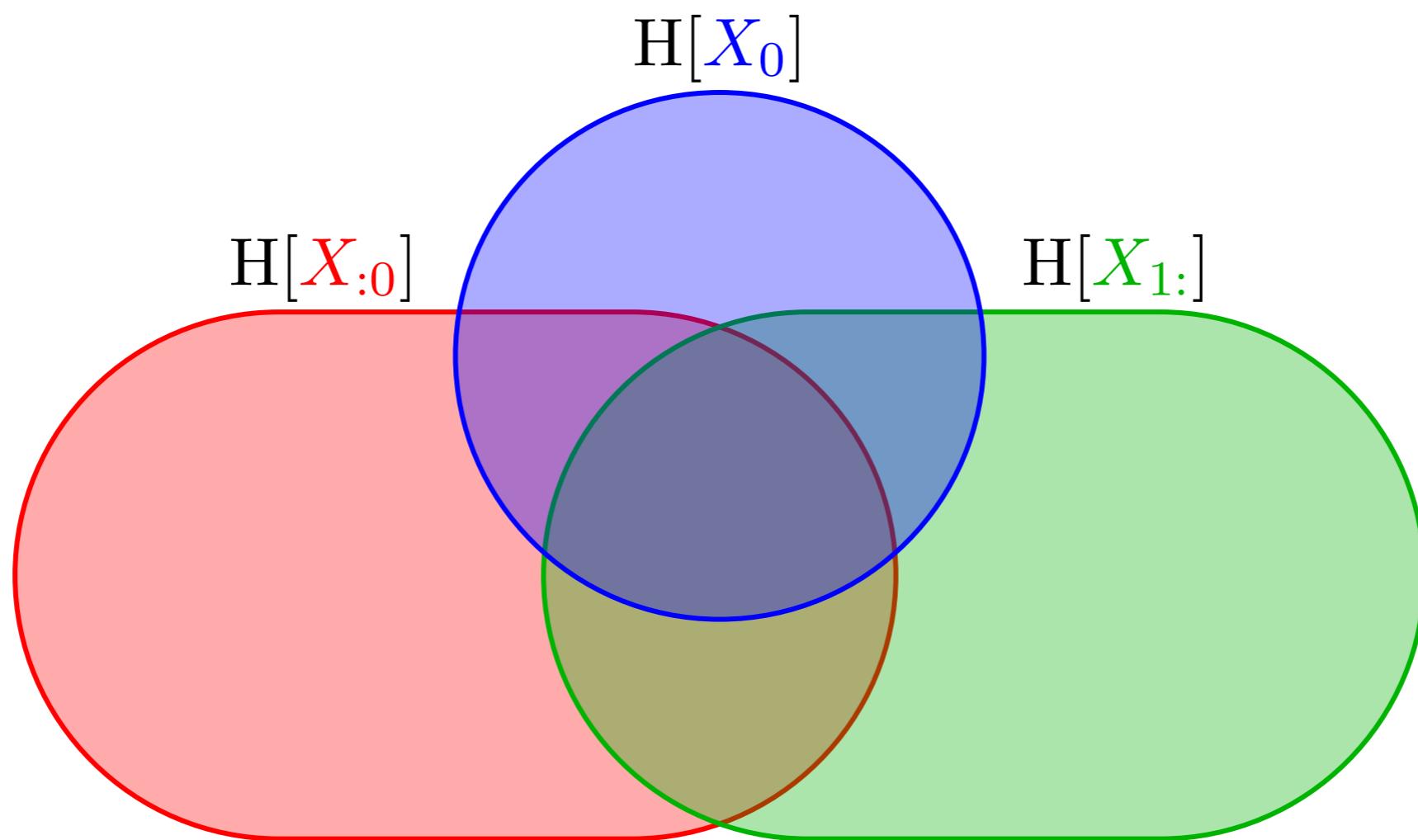
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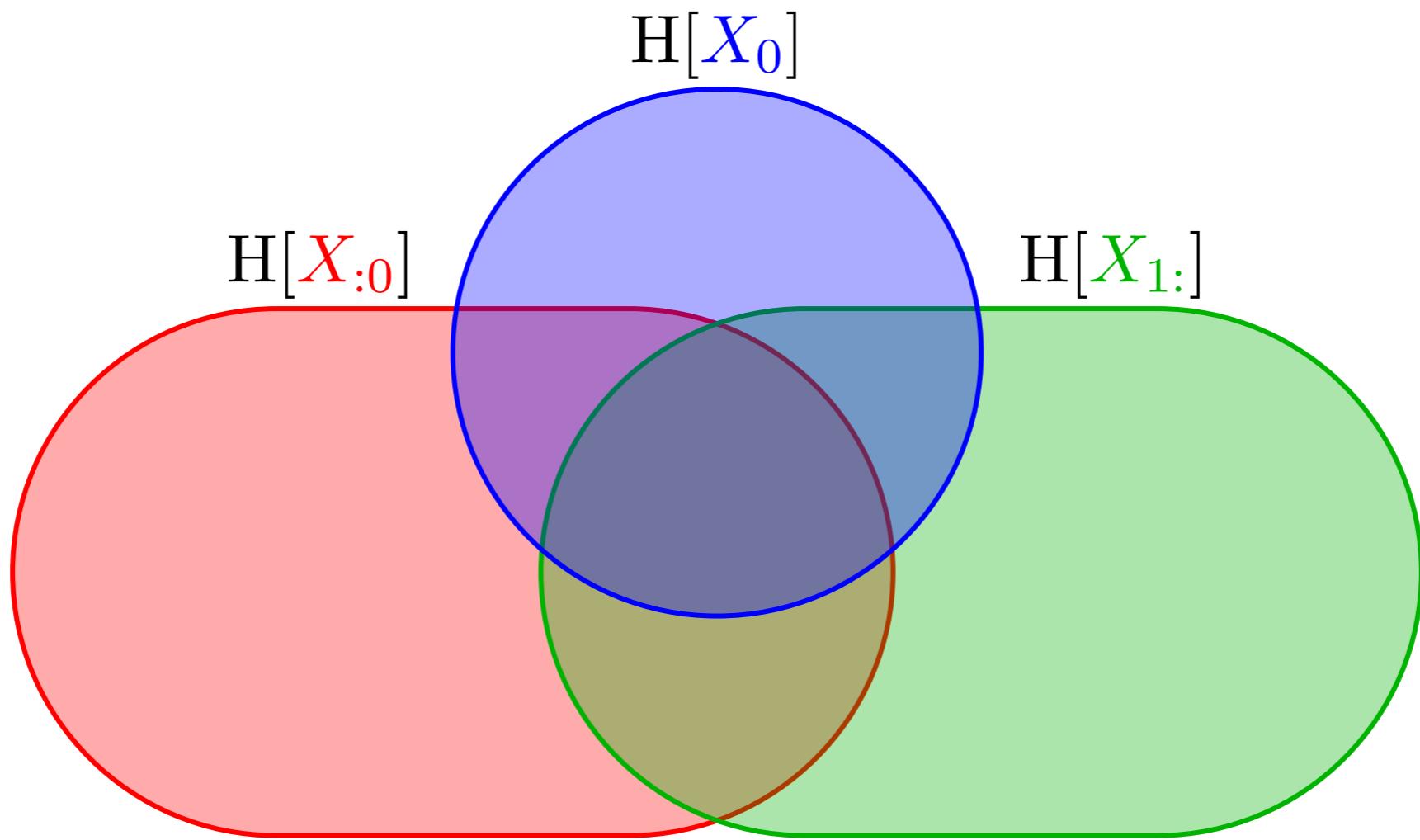
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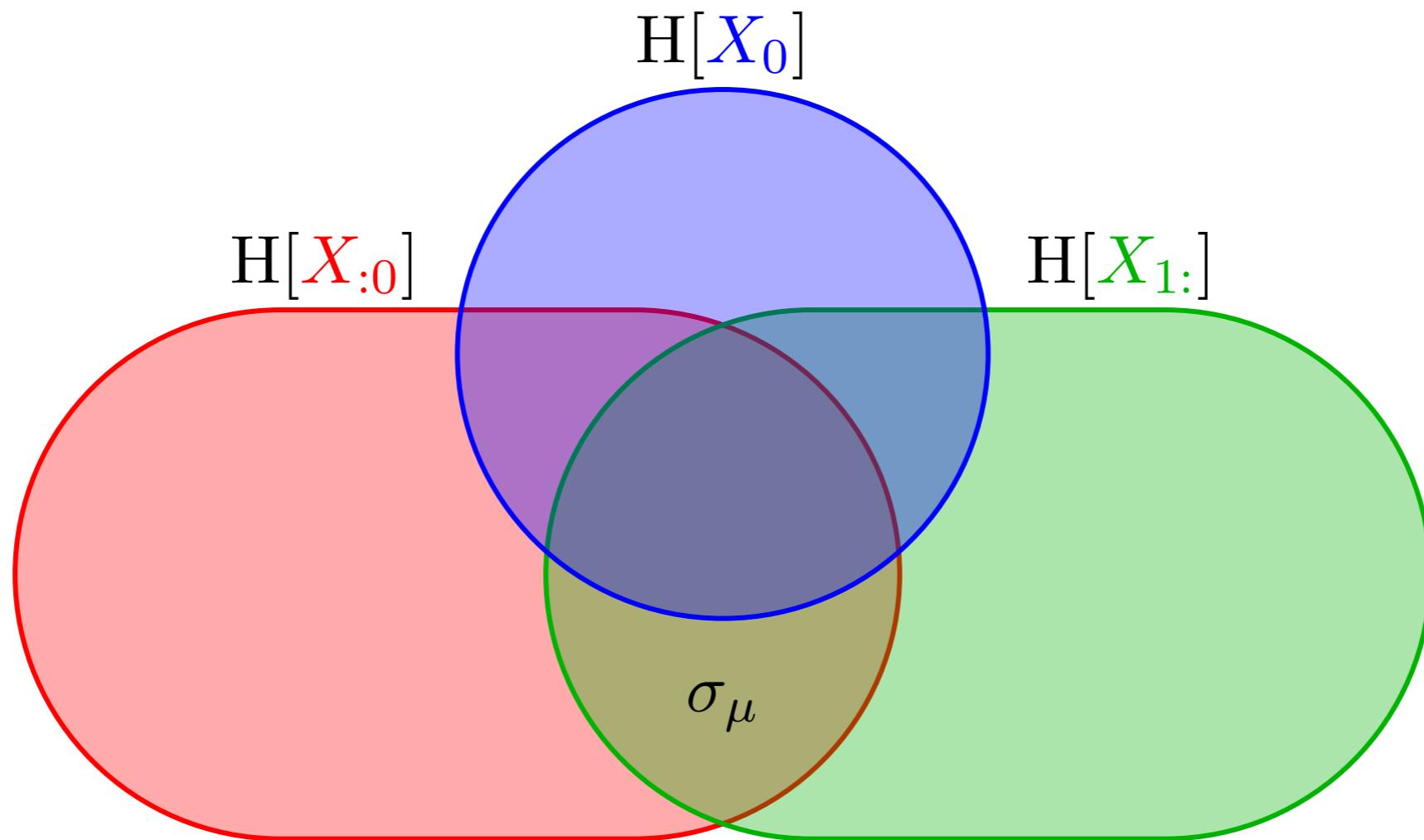
Past, Present & Future



- $H[X_0]$ is *partitioned* by the **past** and the **future**

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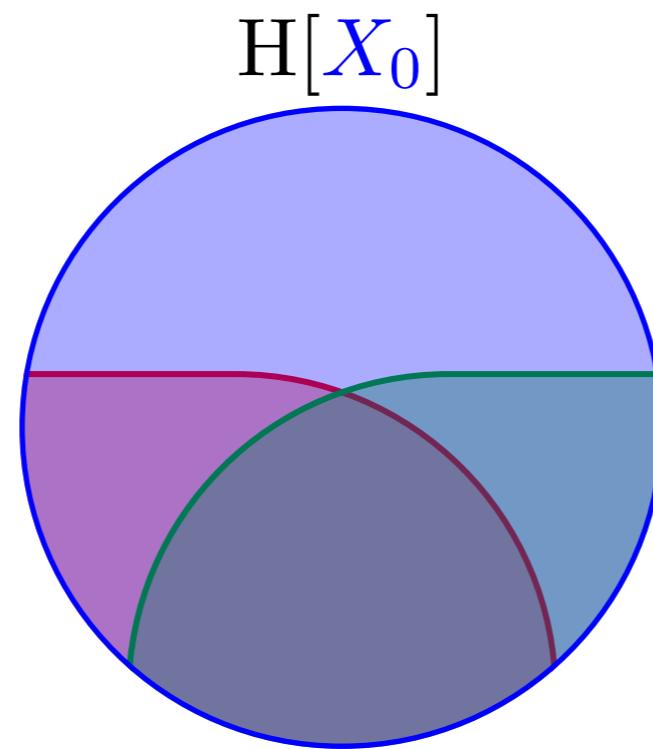
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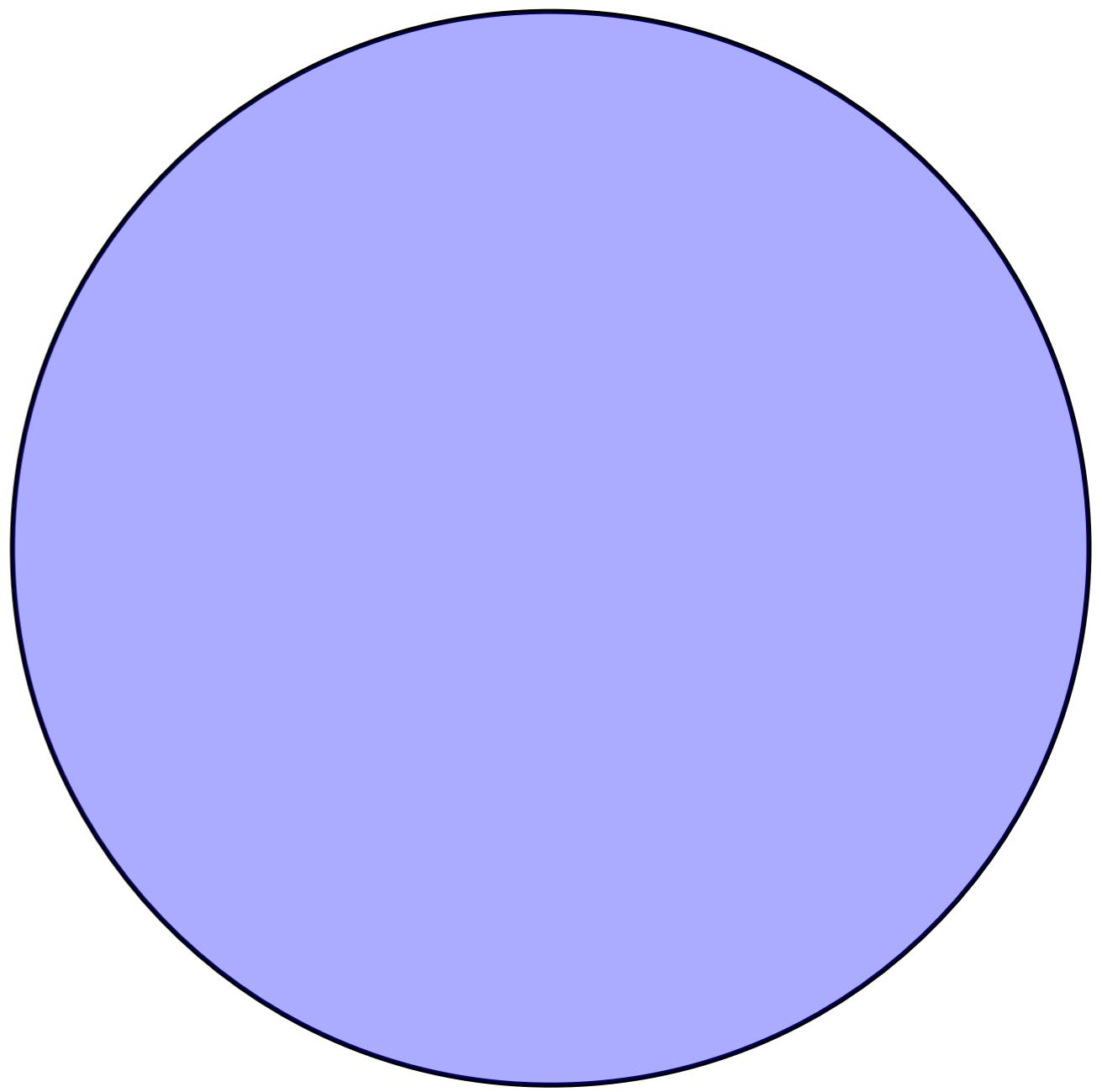
- $H[X_0]$ is *partitioned* by the **past** and the **future**
- $\sigma_\mu = I[X_{:0}; X_{1:}|X_0]$: evidence of internal states

Visualizing Information

Past, Present & Future

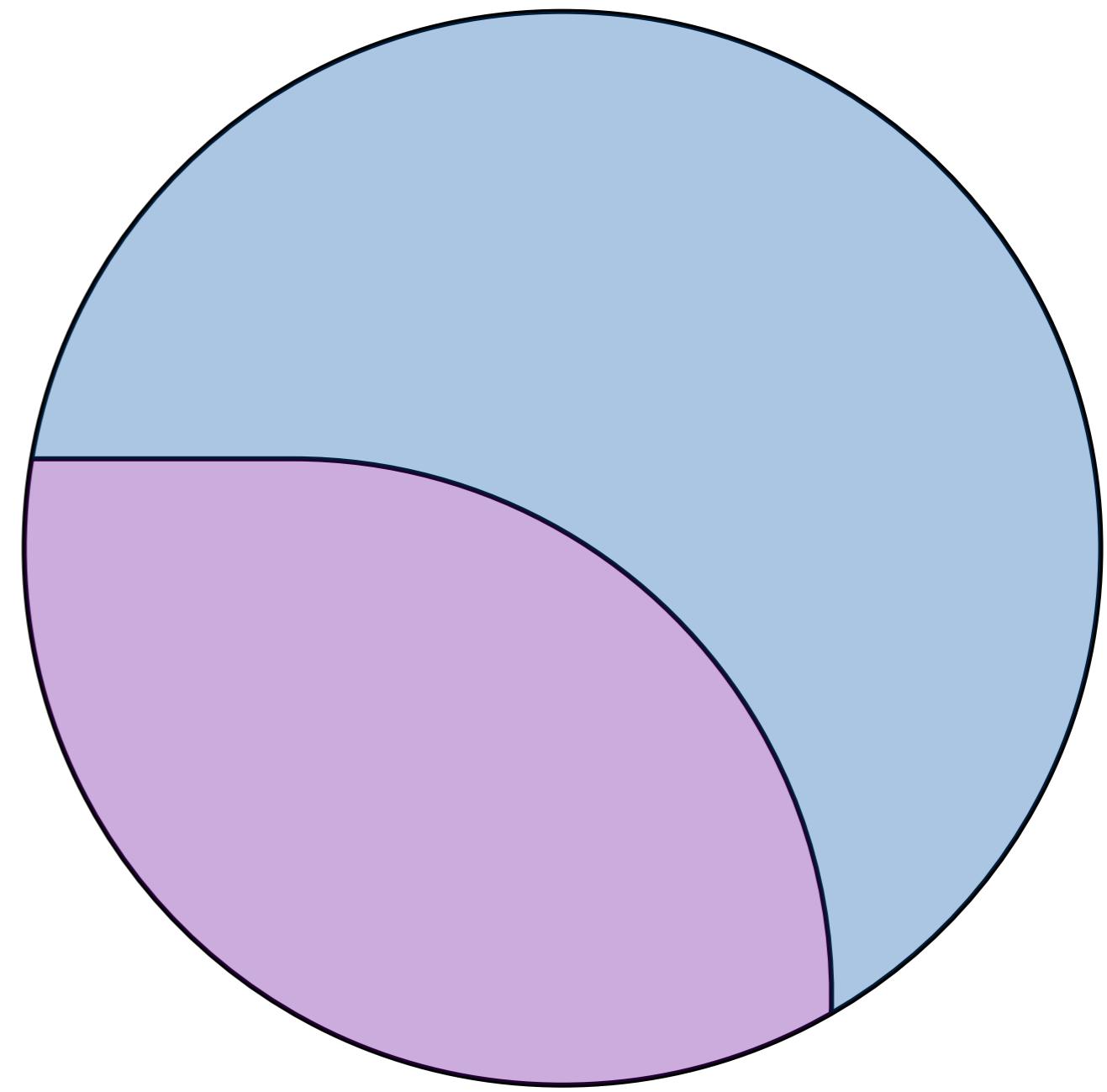


Decompositions of $H[X_0]$



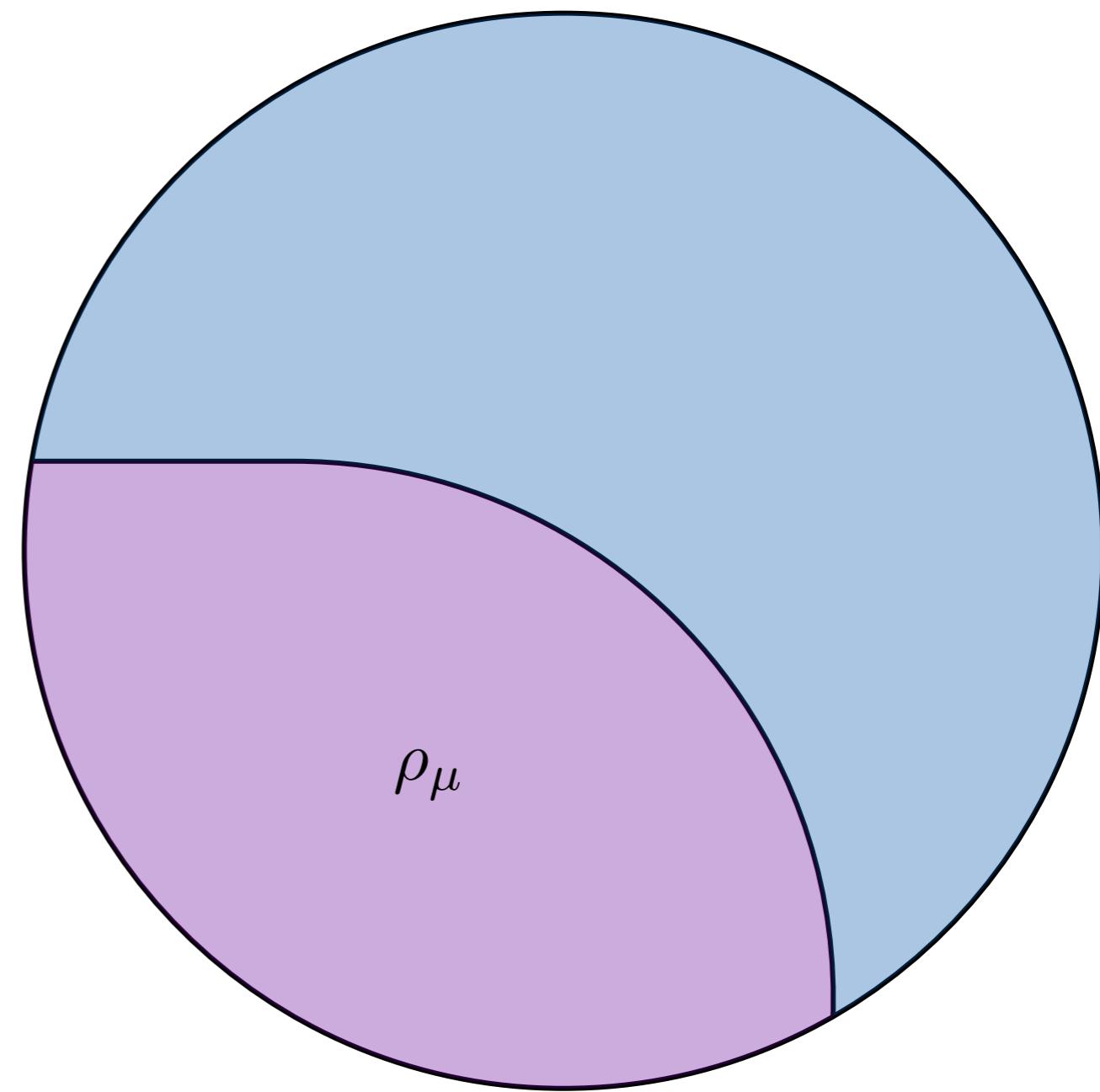
Prior Observations

The Human Decomposition of $H[X_0]$



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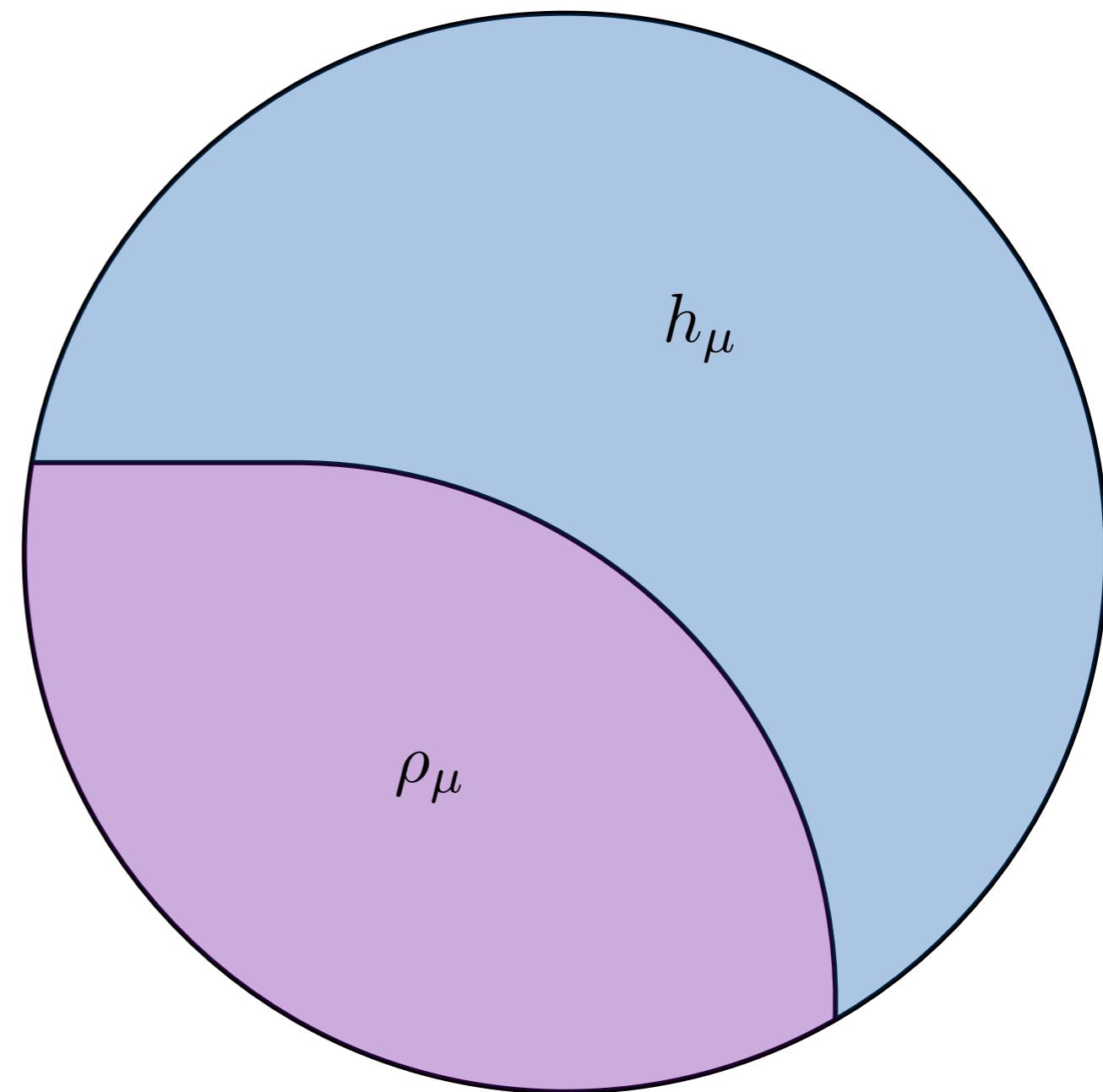
- $\rho_\mu = I[X_{:0}; X_0]$:
anticipated
information



Prior Observations

The Human Decomposition of $H[X_0]$

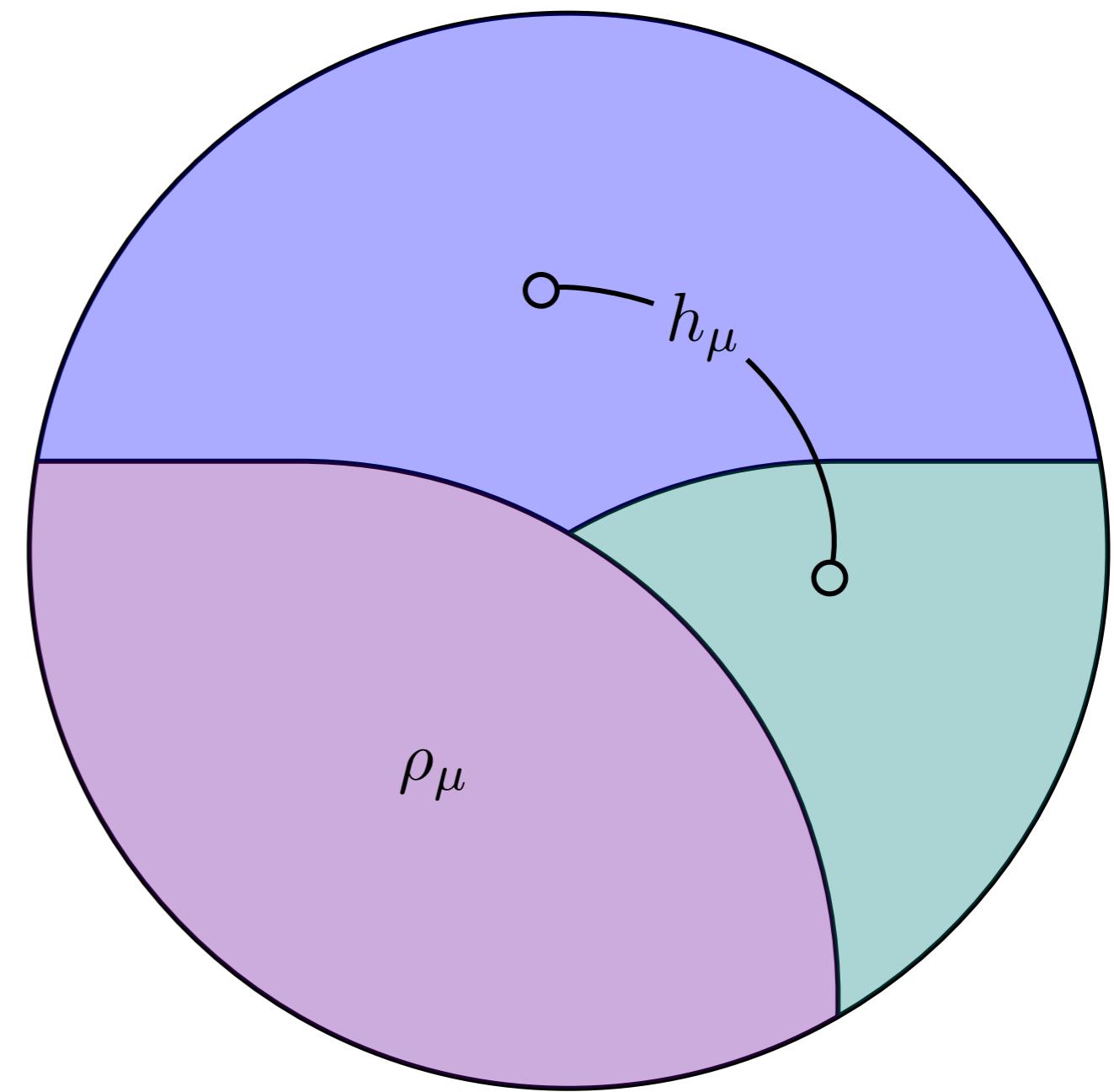
- $\rho_\mu = I[X_{:0}; X_0]$: anticipated information
- $h_\mu = H[X_0 | X_{:0}]$: (*Shannon entropy rate, metric entropy, Kolmogorov-Sinai entropy*) unanticipated information



Crystal Ballin'

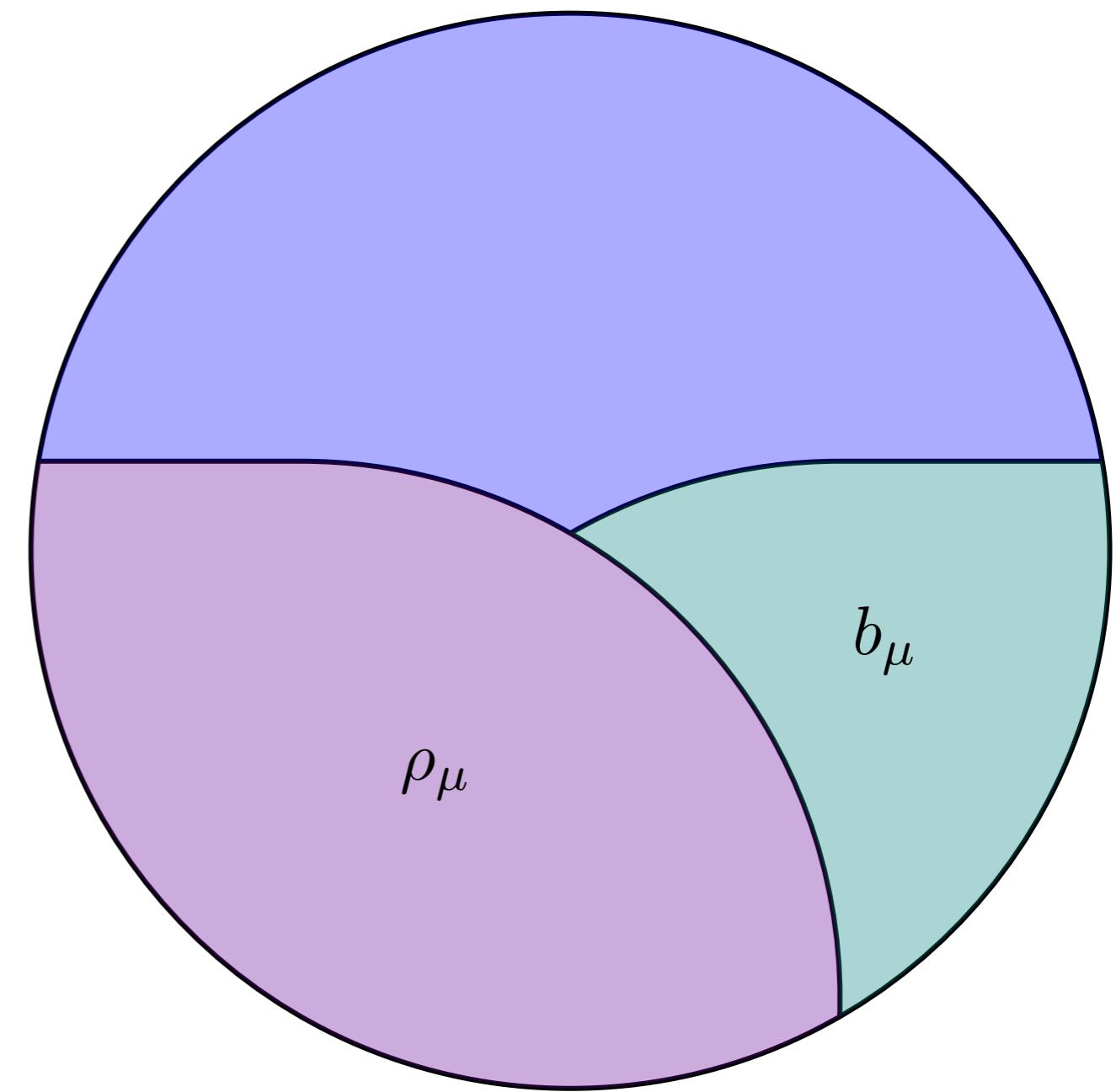
A More Refined Decomposition of $H[X_0]$

- $\rho_\mu = I[X_{:0}; X_0]$:
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A More Refined Decomposition of $H[X_0]$

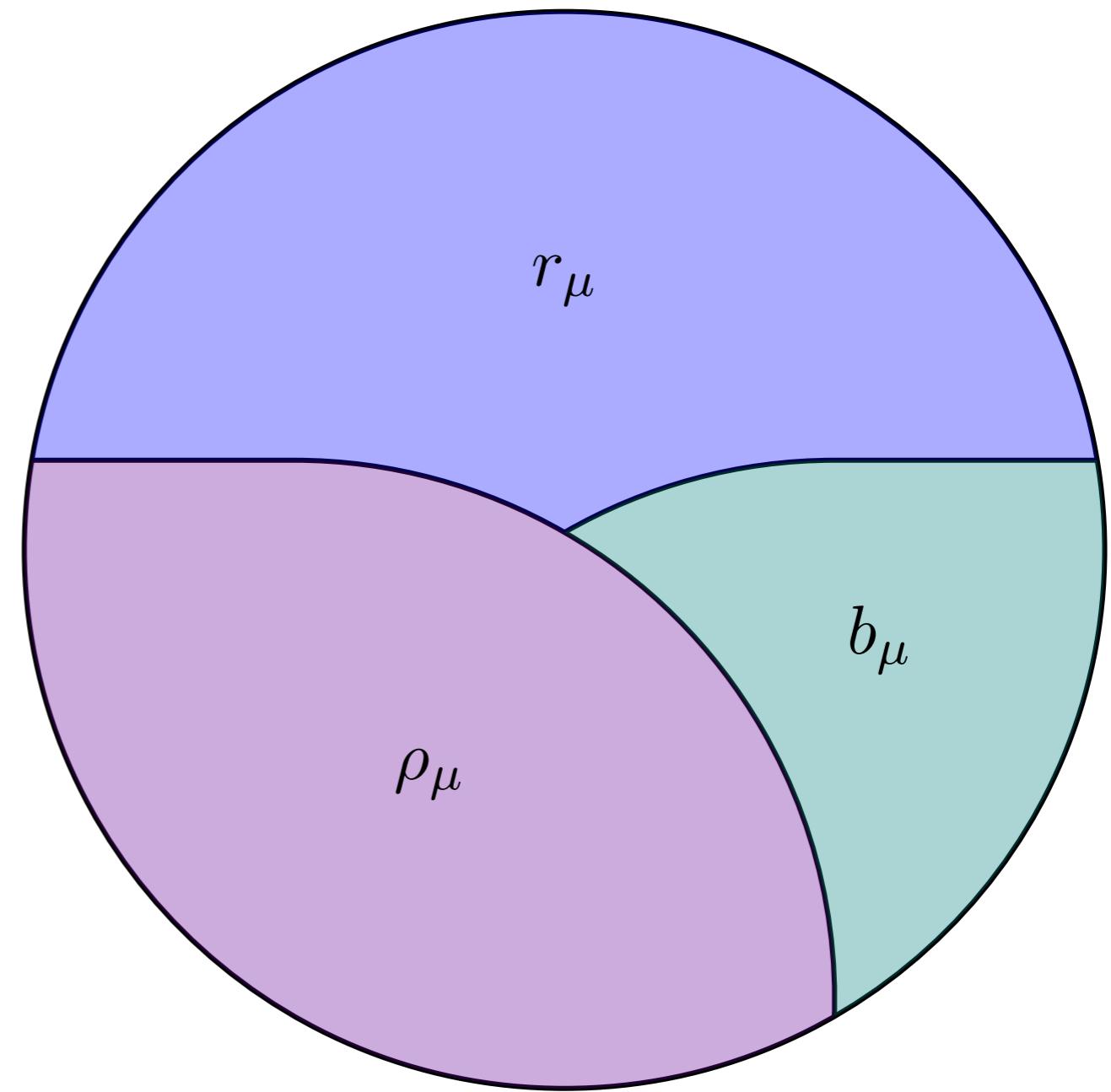
- $\rho_\mu = I[X_{:0}; X_0]$: anticipated information
- $b_\mu = I[X_0; X_{1:}|X_{:0}]$: unanticipated and relevant



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A More Refined Decomposition of $H[X_0]$

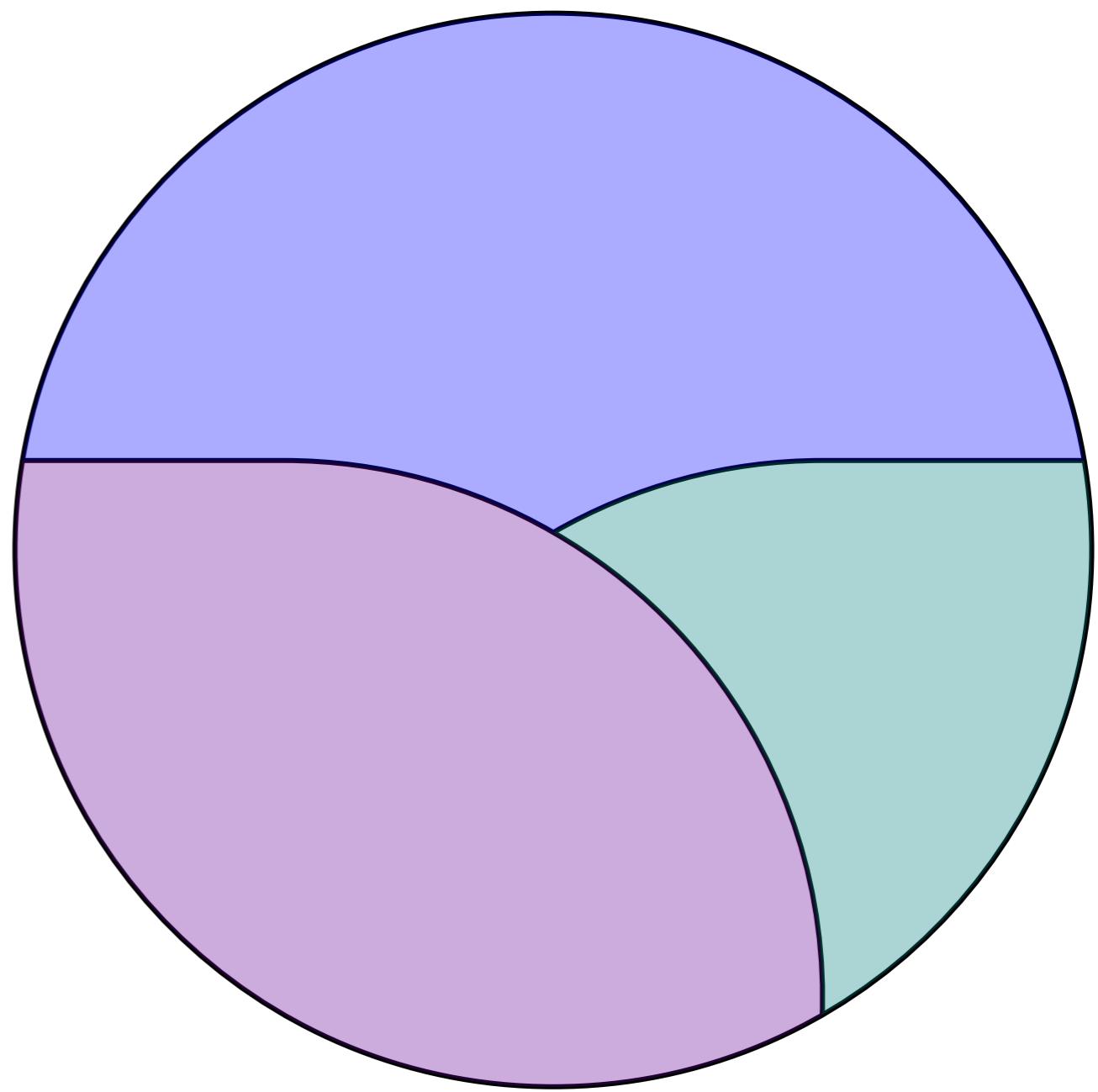
- $\rho_\mu = I[X_{:0}; X_0]$: anticipated information
- $b_\mu = I[X_0; X_{1:}|X_{:0}]$: unanticipated and relevant
- $r_\mu = H[X_0|X_{:0}; X_{1:}]$: unanticipated and irrelevant



... and you know my Achilles tendon is my one Achilles' heel

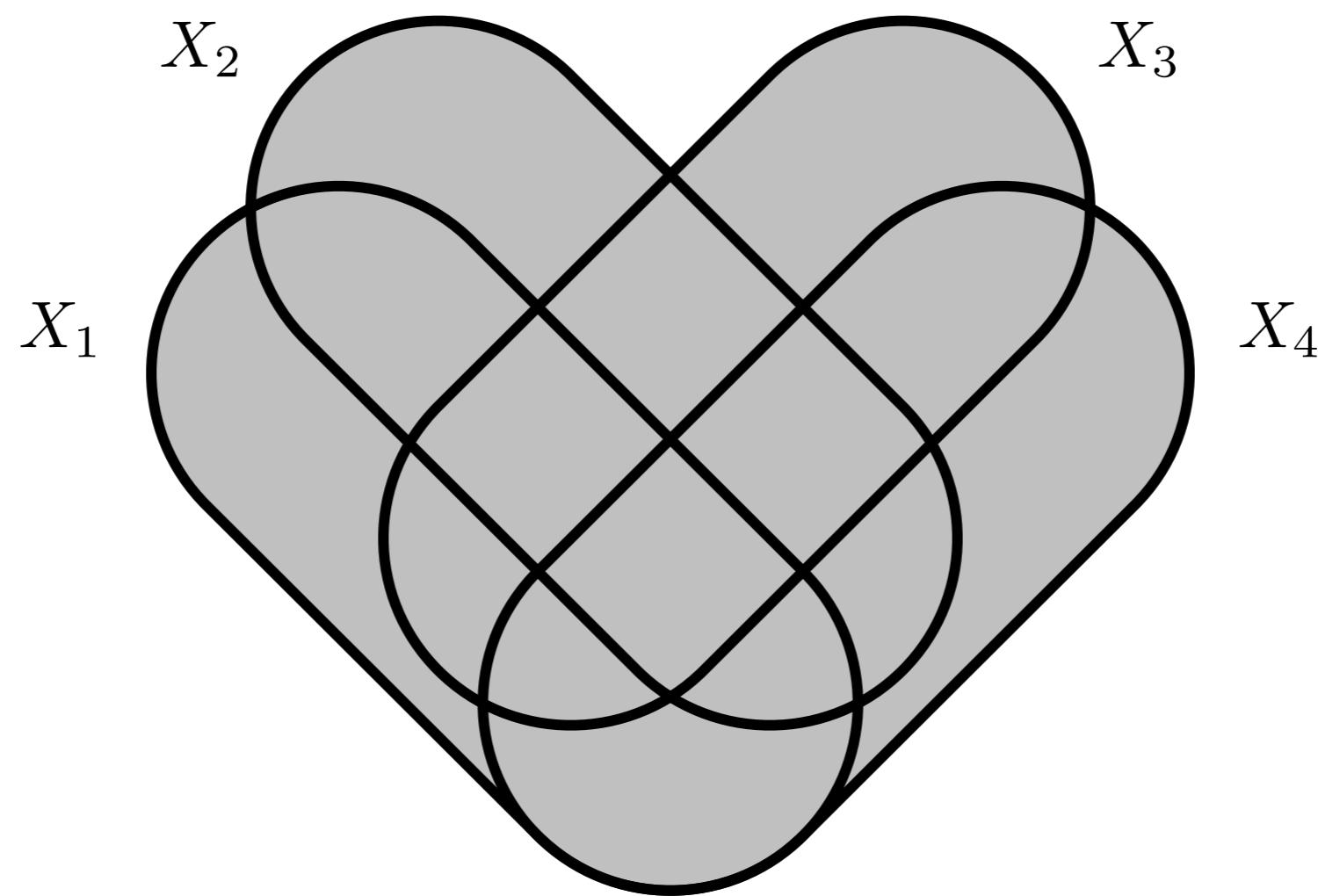
Like Humans Do

“How do I measure these?”



Definitions

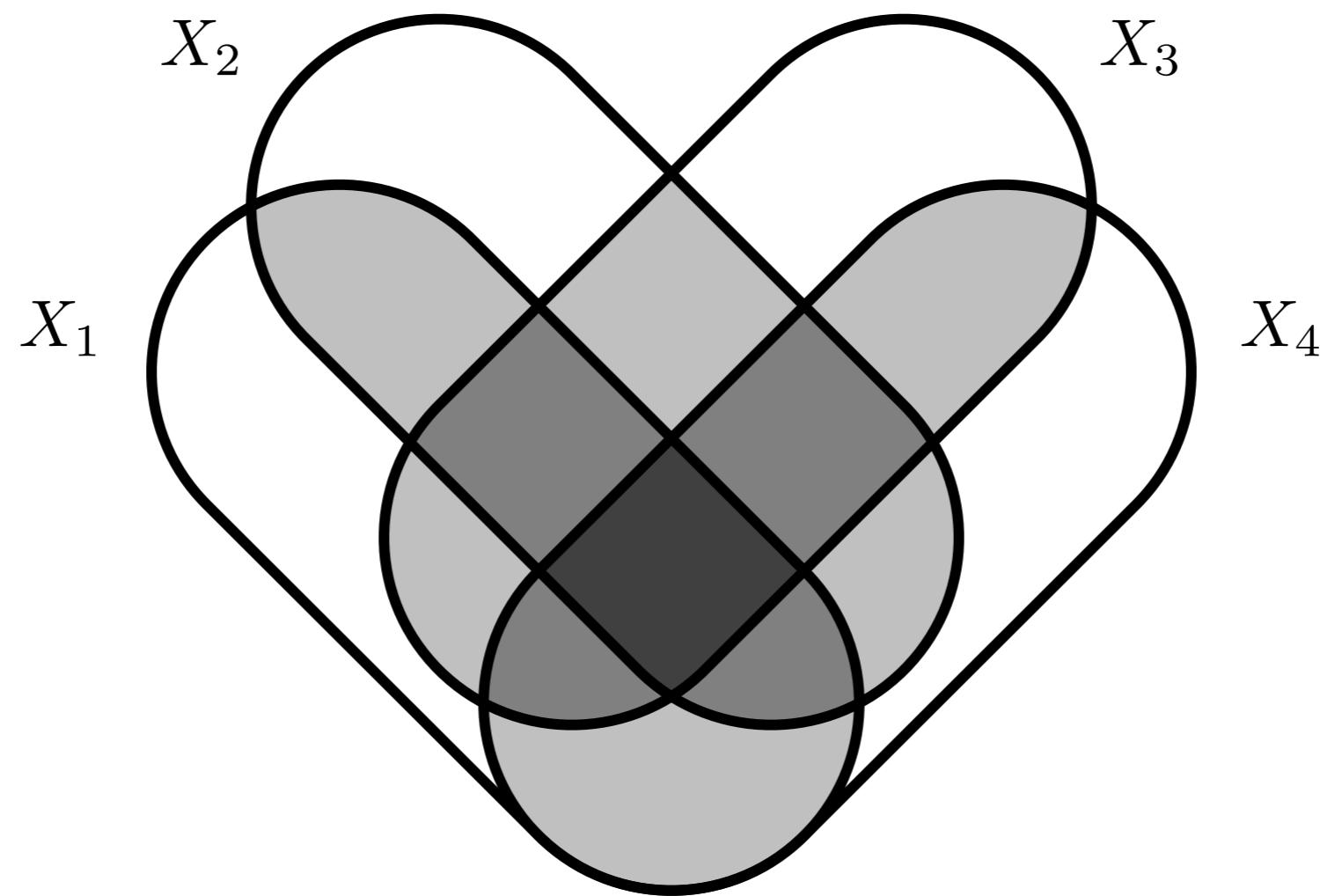
Entropy



$$H[X_{1:\ell}] = - \sum_{w \in \mathcal{A}^\ell} p_w \log(p_w)$$

Definitions

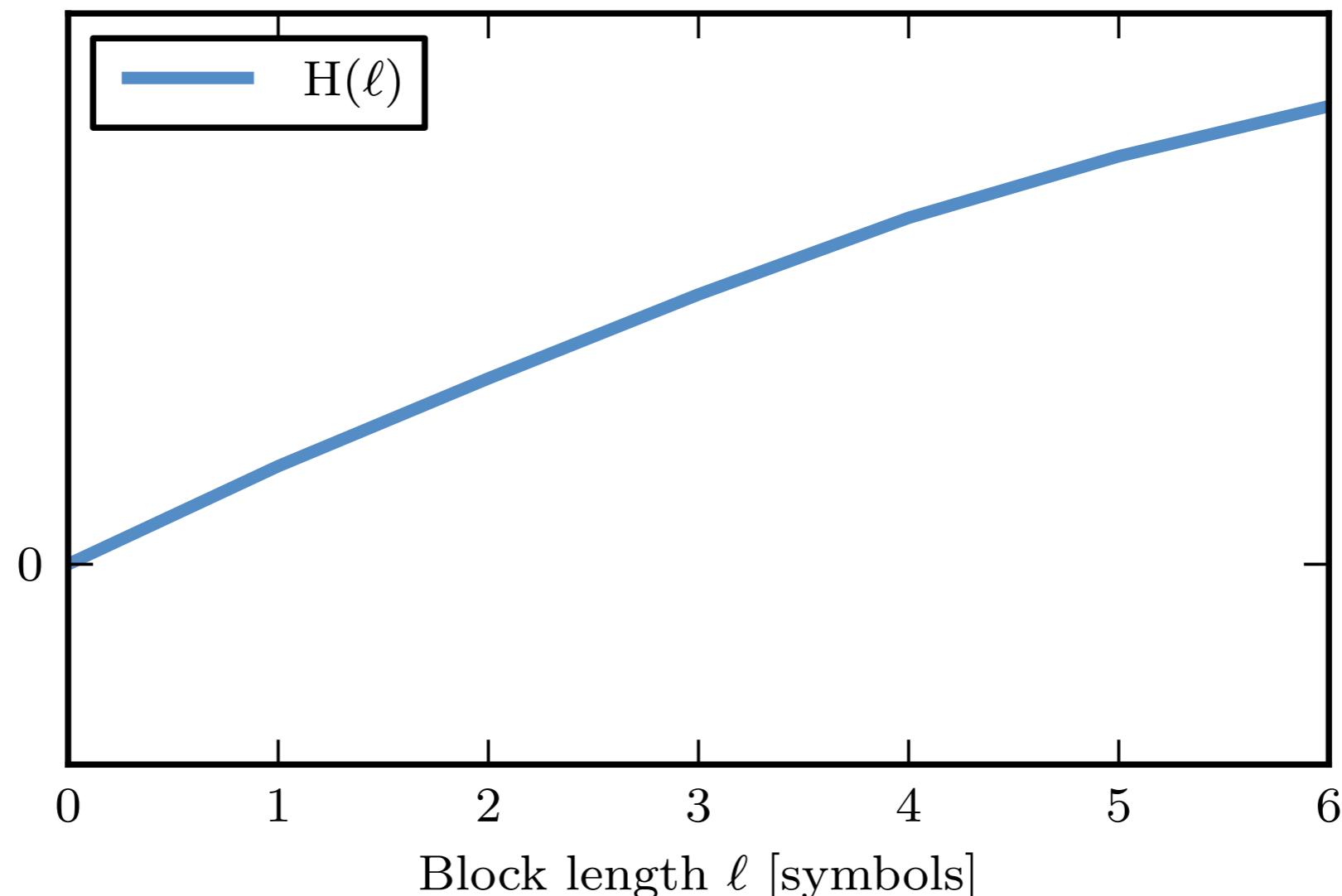
Total Correlation



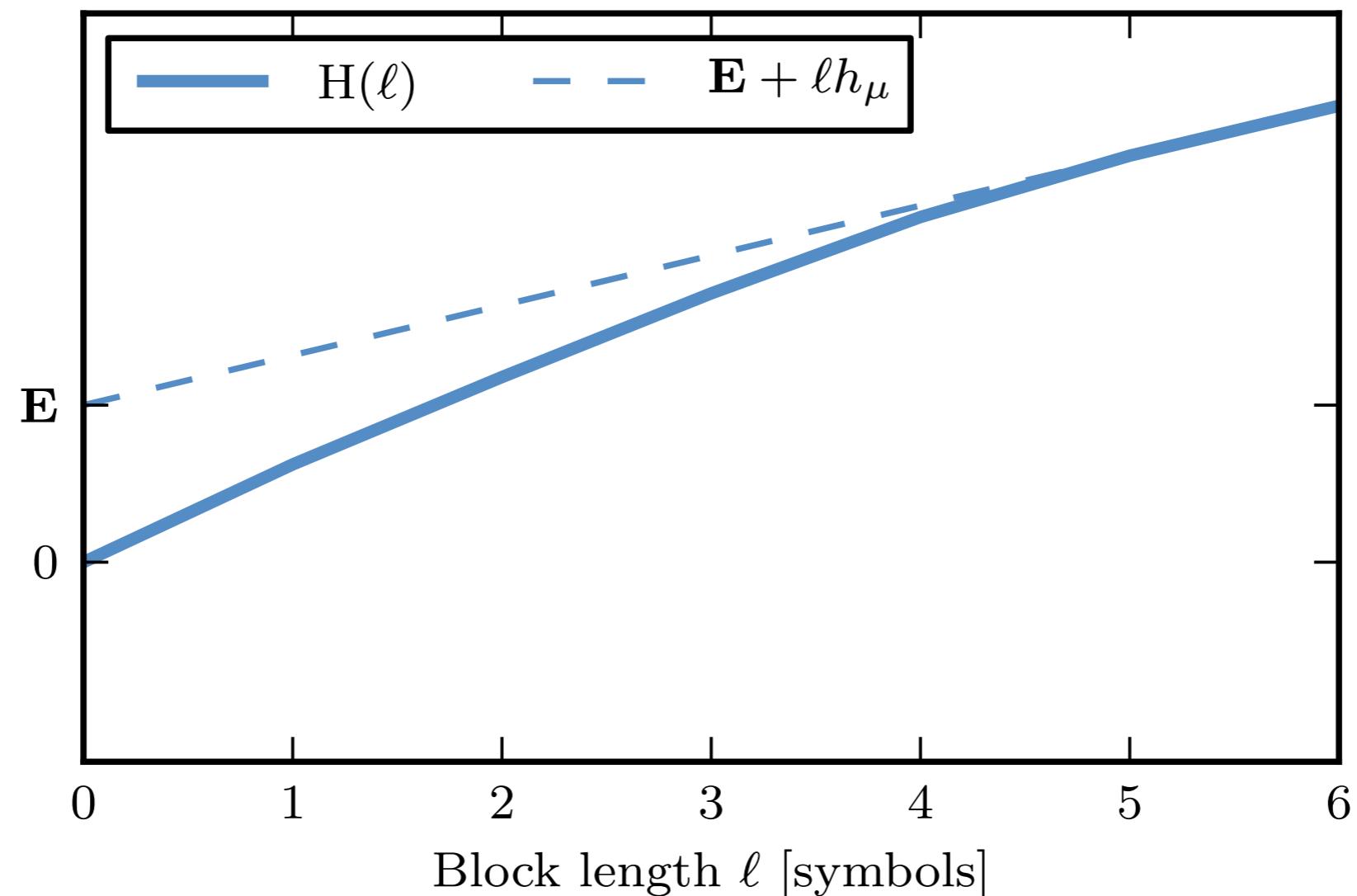
$$T[X_{1:\ell}] = \sum_{i \in \{1 \dots \ell\}} H[X_i] - H[X_{1:\ell}]$$

Curves

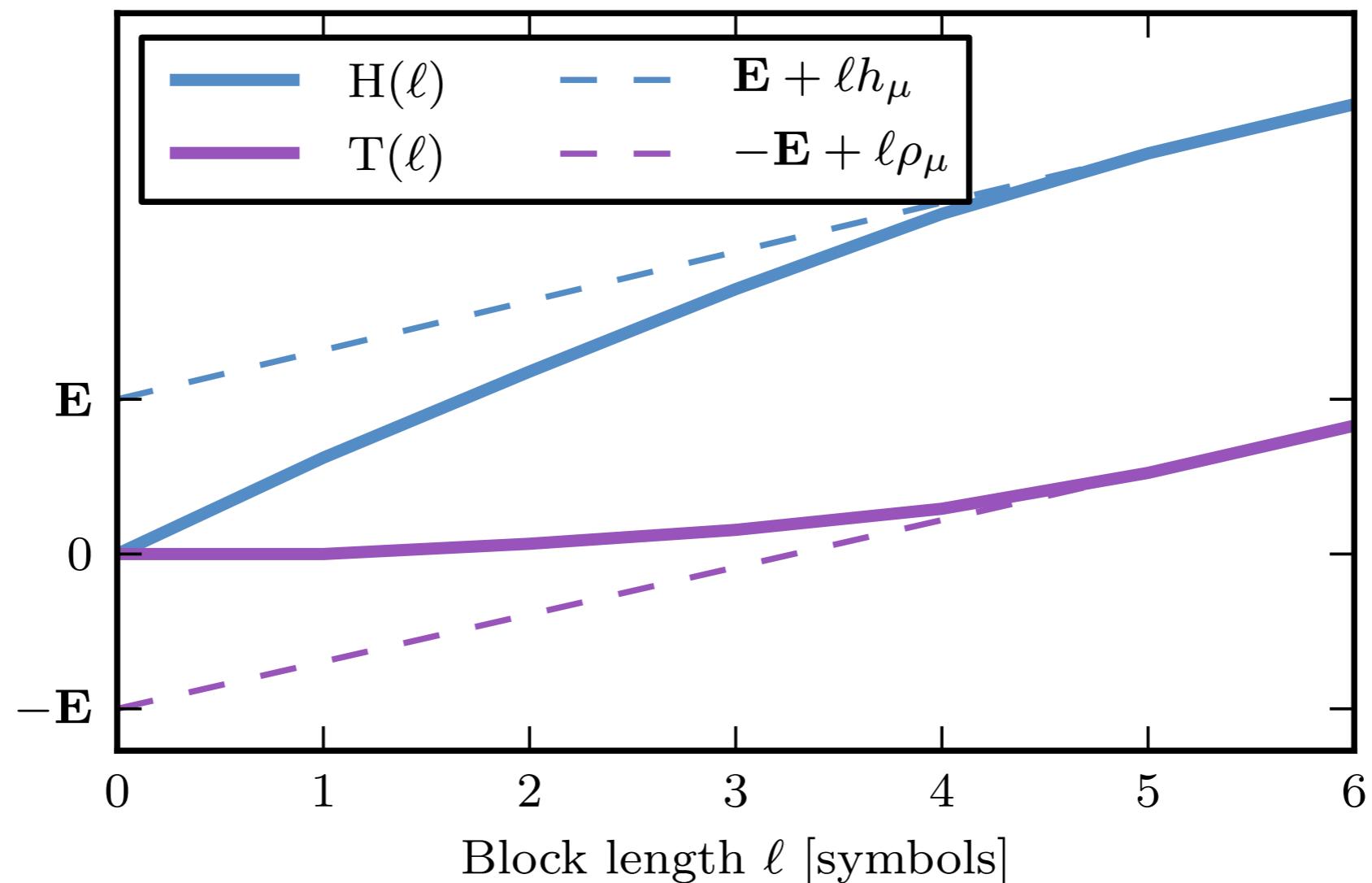
Asymptotic Rates: h_μ & ρ_μ



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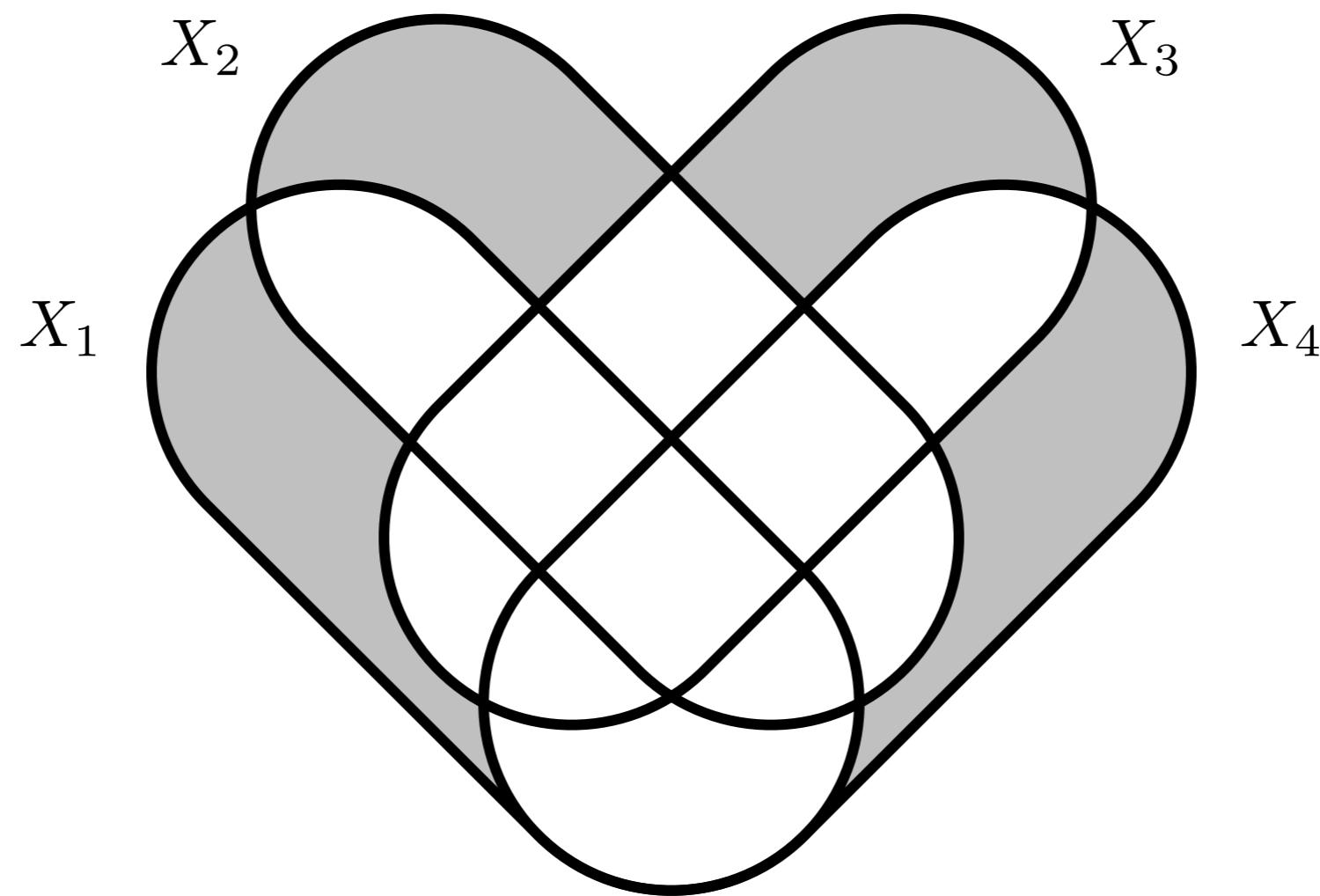


Asymptotic Rates: h_μ & ρ_μ



Definitions

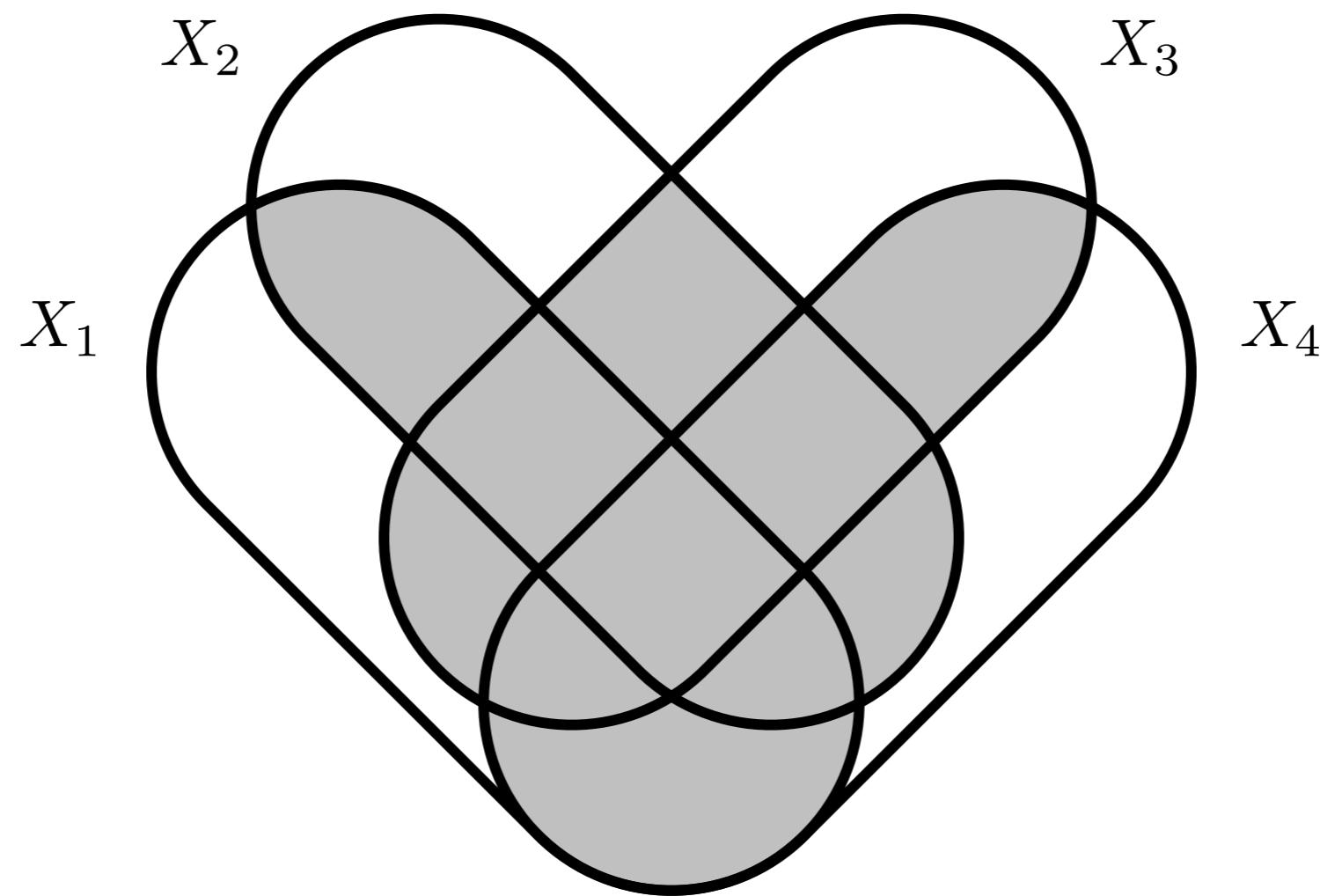
Residual Entropy



$$R[X_{1:\ell}] = \sum_{i \in \{1 \dots \ell\}} H[X_i | X_{\{1 \dots \ell\} \setminus i}]$$

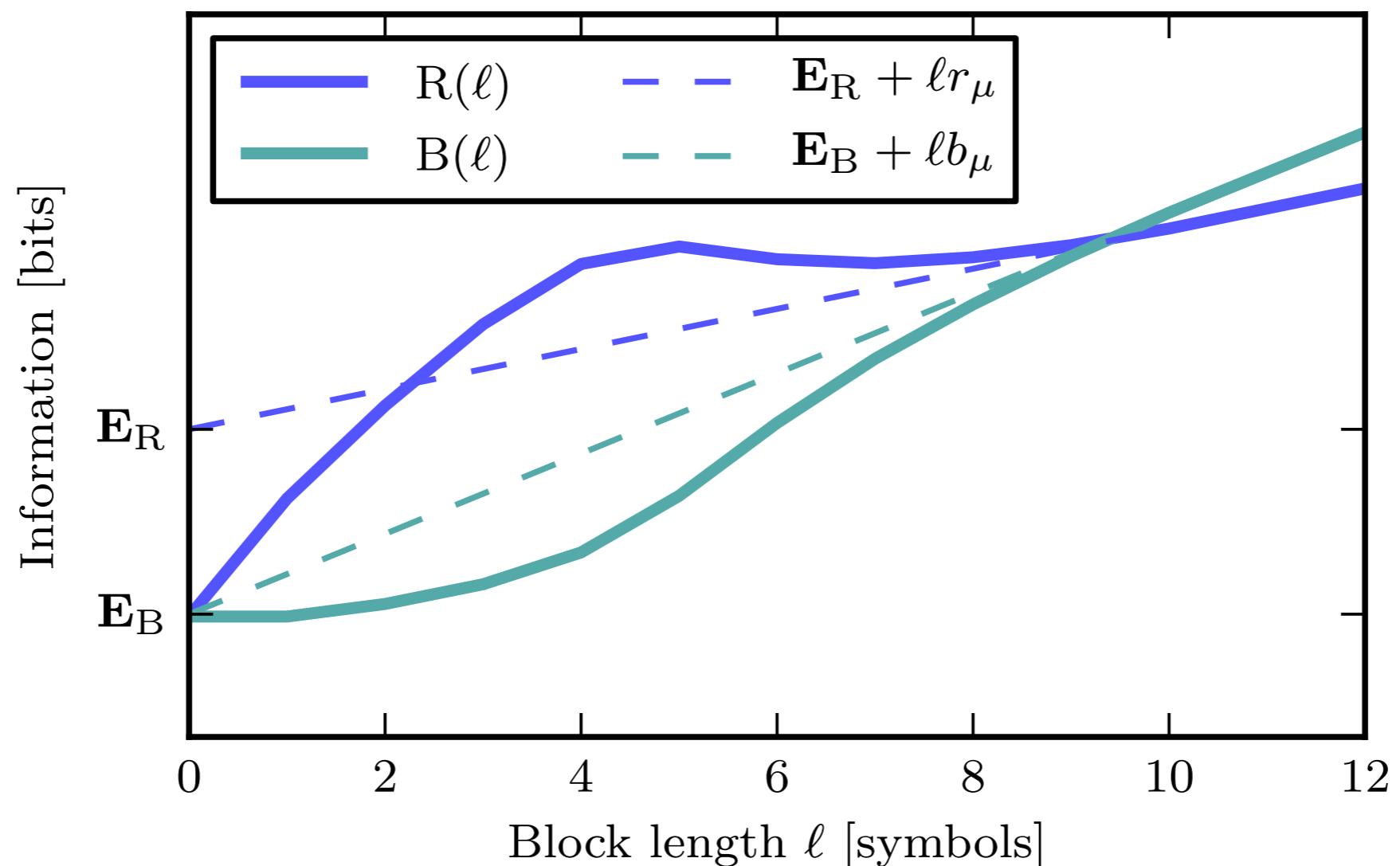
Definitions

Binding Information



$$B[X_{1:\ell}] = H[X_{1:\ell}] - R[X_{1:\ell}]$$

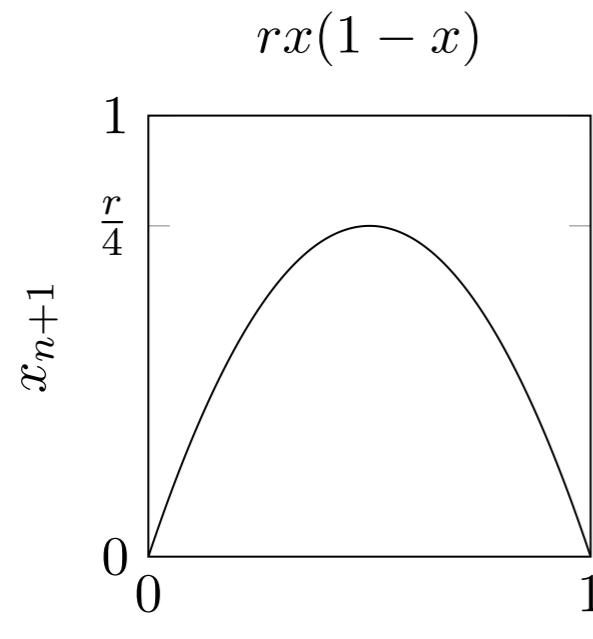
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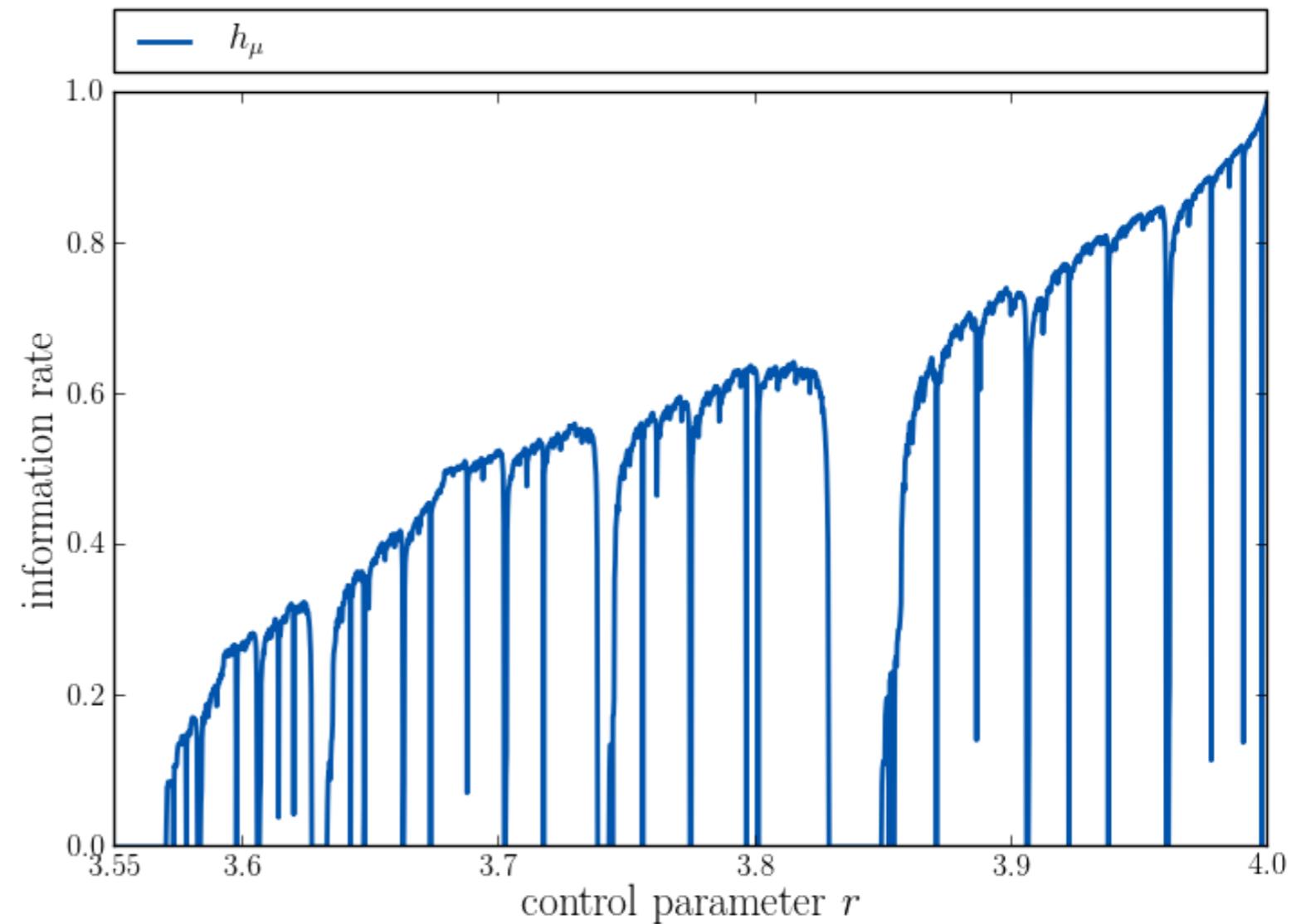
Logistic Map

Canonical System

- Pesin's Theorem:
$$h_\mu = \max(0, \lambda)$$



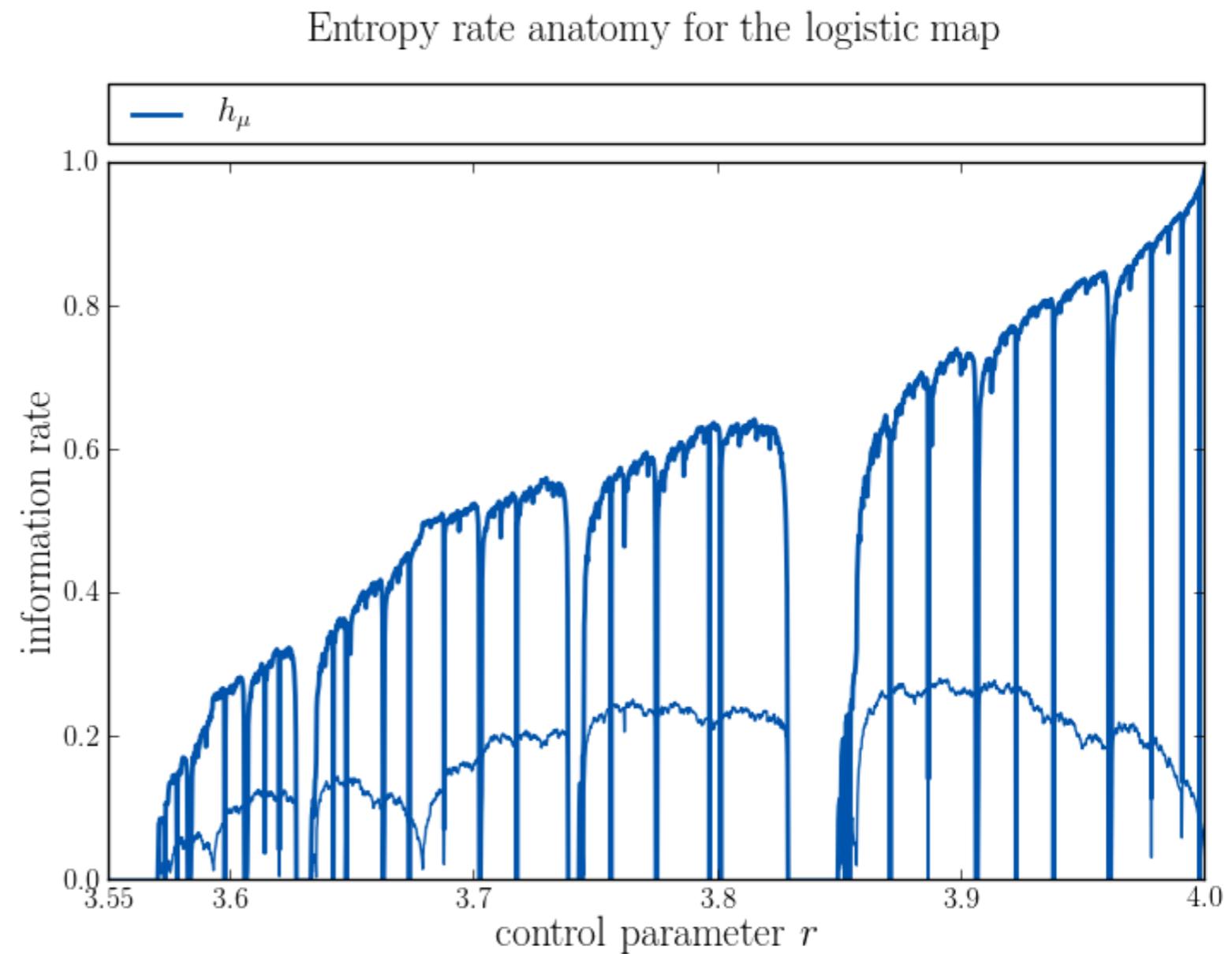
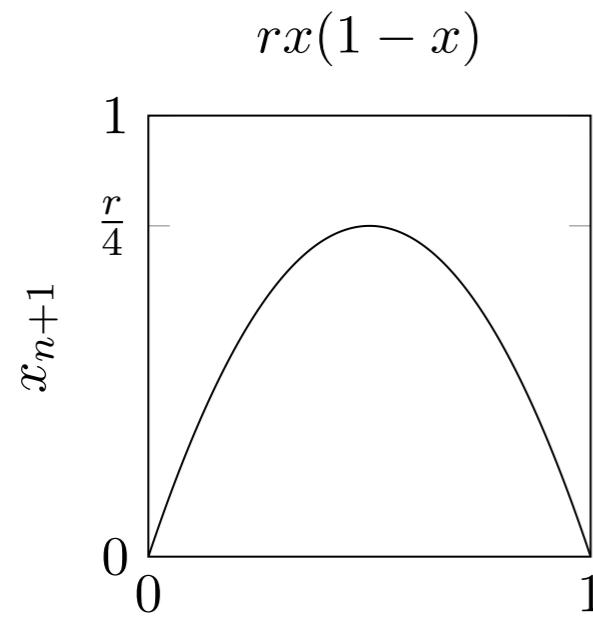
Entropy rate for the logistic map



Logistic Map

Canonical System

- Pesin's Theorem:
$$h_\mu = \max(0, \lambda)$$
- $h_\mu = \dots + \dots$

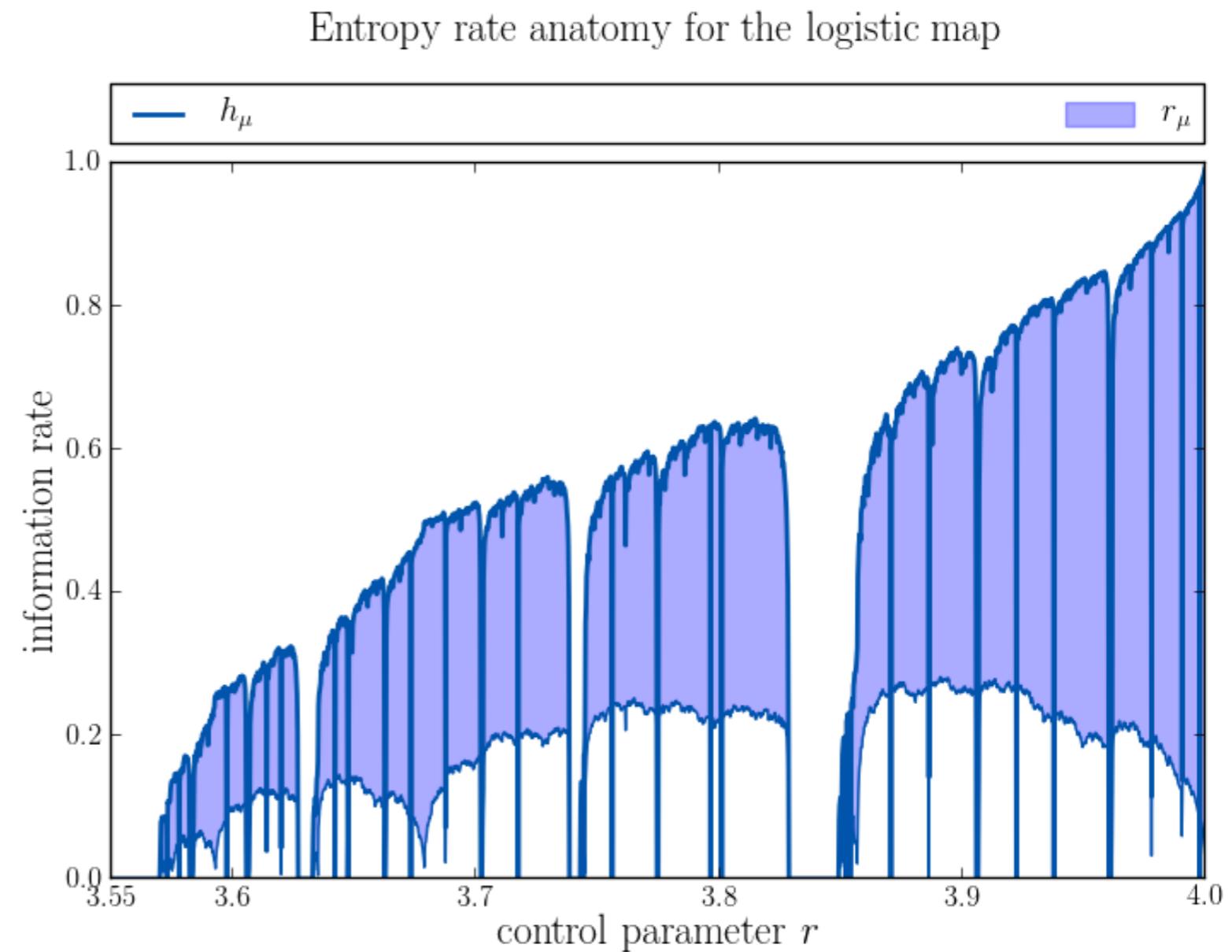


Logistic Map

Canonical System

- Pesin's Theorem:
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 - $$h_\mu = r_\mu +$$

A graph of the function $rx(1-x)$ on a square coordinate system. The horizontal axis (x-axis) and vertical axis (y-axis) both range from 0 to 1. The curve starts at the origin (0,0), rises to a peak at approximately $x = 0.5$ with a value of approximately 0.25, and then descends back to the x-axis at $x = 1$.

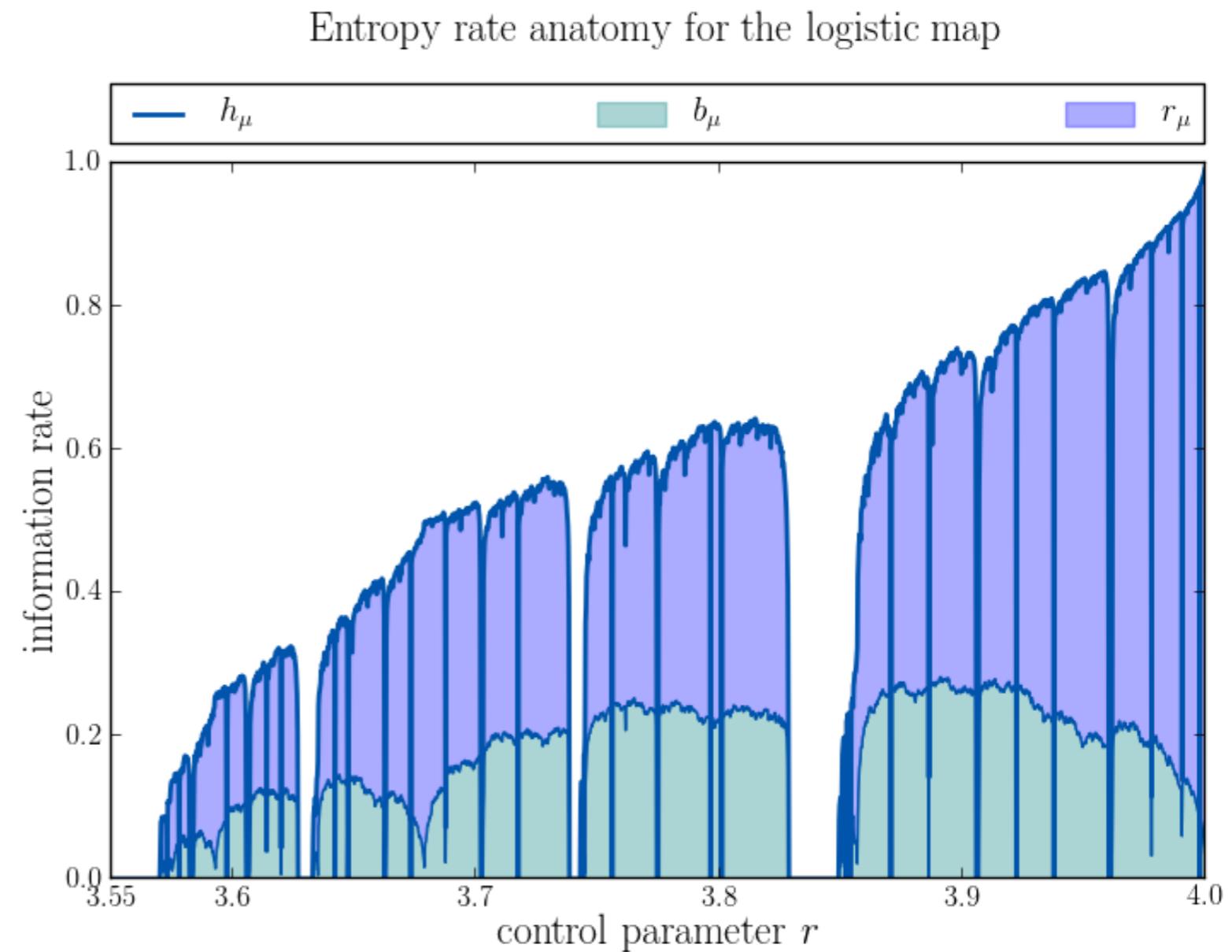


Logistic Map

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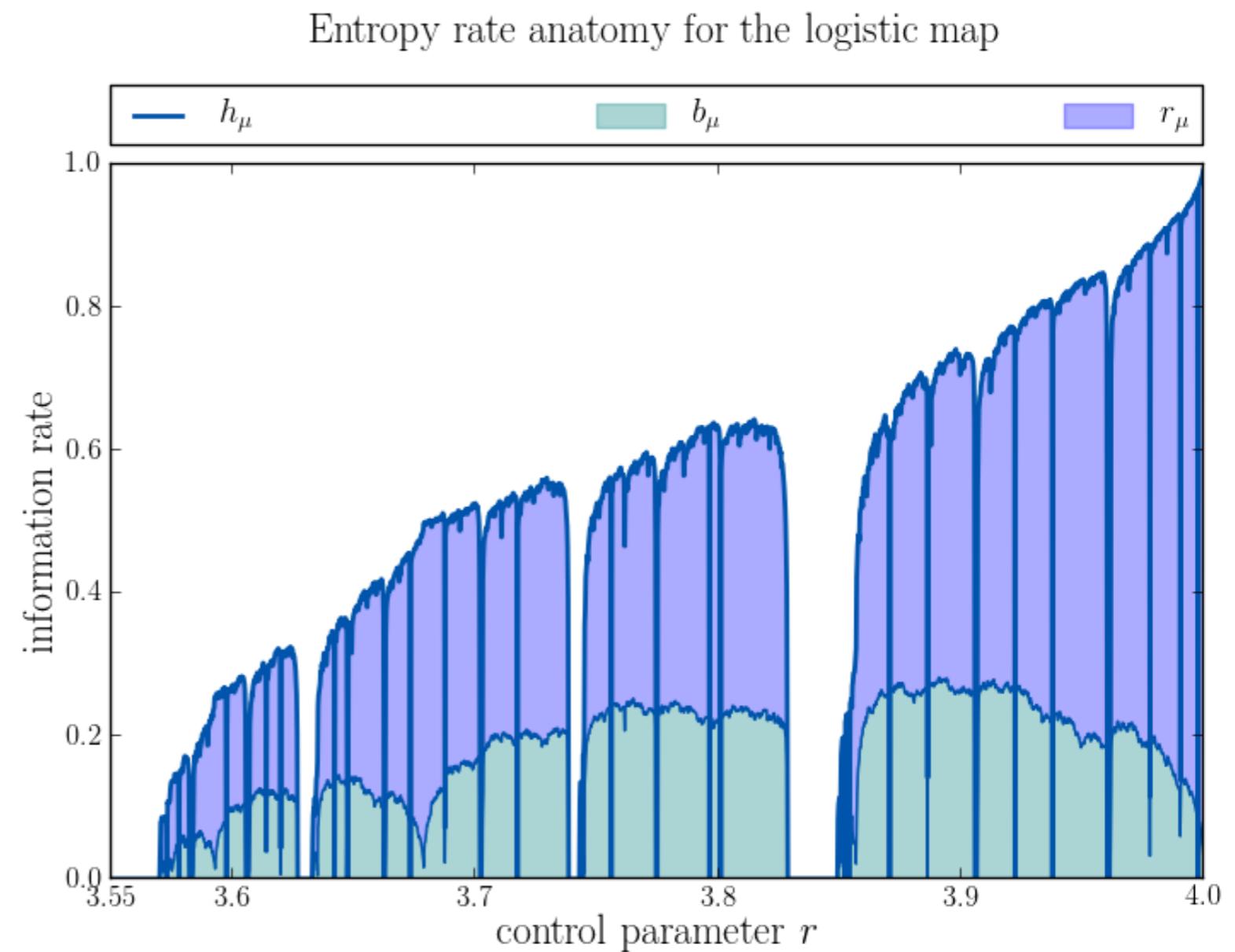
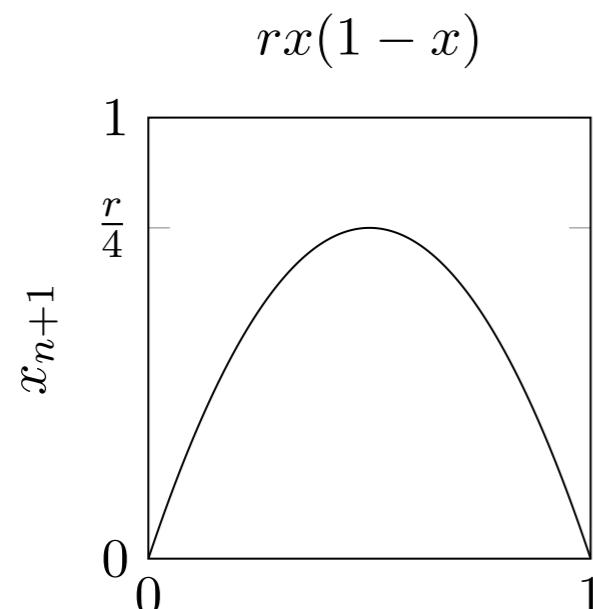
- Pesin's Theorem:
$$h_\mu = \max(0, \lambda)$$
 - $$h_\mu = r_\mu + b_\mu$$

A graph of the logistic function $rx(1-x)$ on a unit square $[0,1] \times [0,1]$. The horizontal axis is labeled with 0 and 1. The vertical axis is labeled with 0, $\frac{r}{4}$, and 1. The curve starts at the origin (0,0), reaches a maximum at $(0.5, \frac{r}{4})$, and ends at (1,0).



Logistic Map

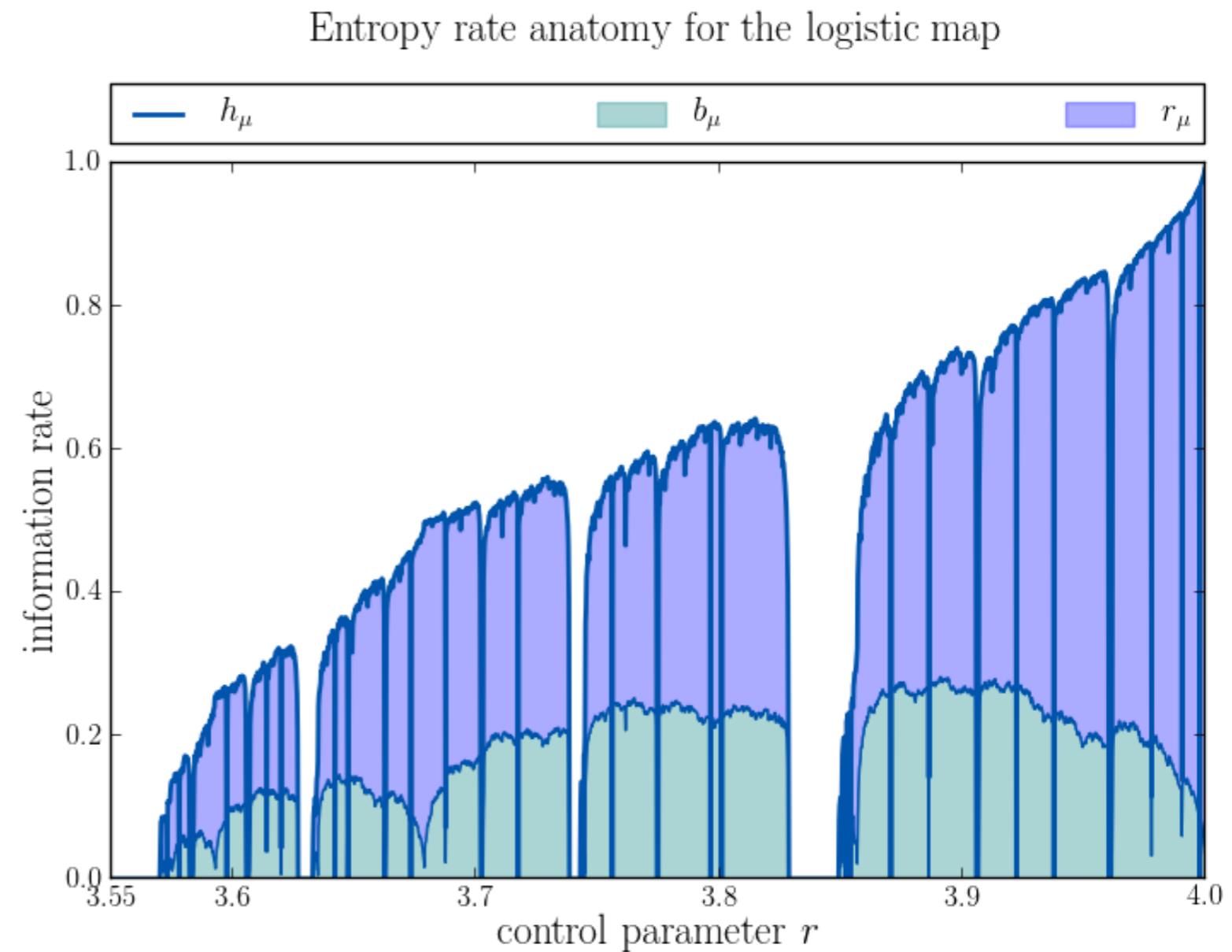
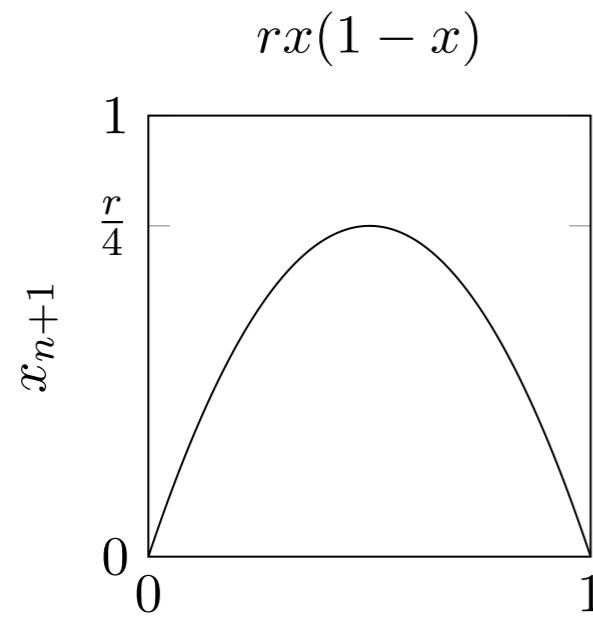
Features



Logistic Map

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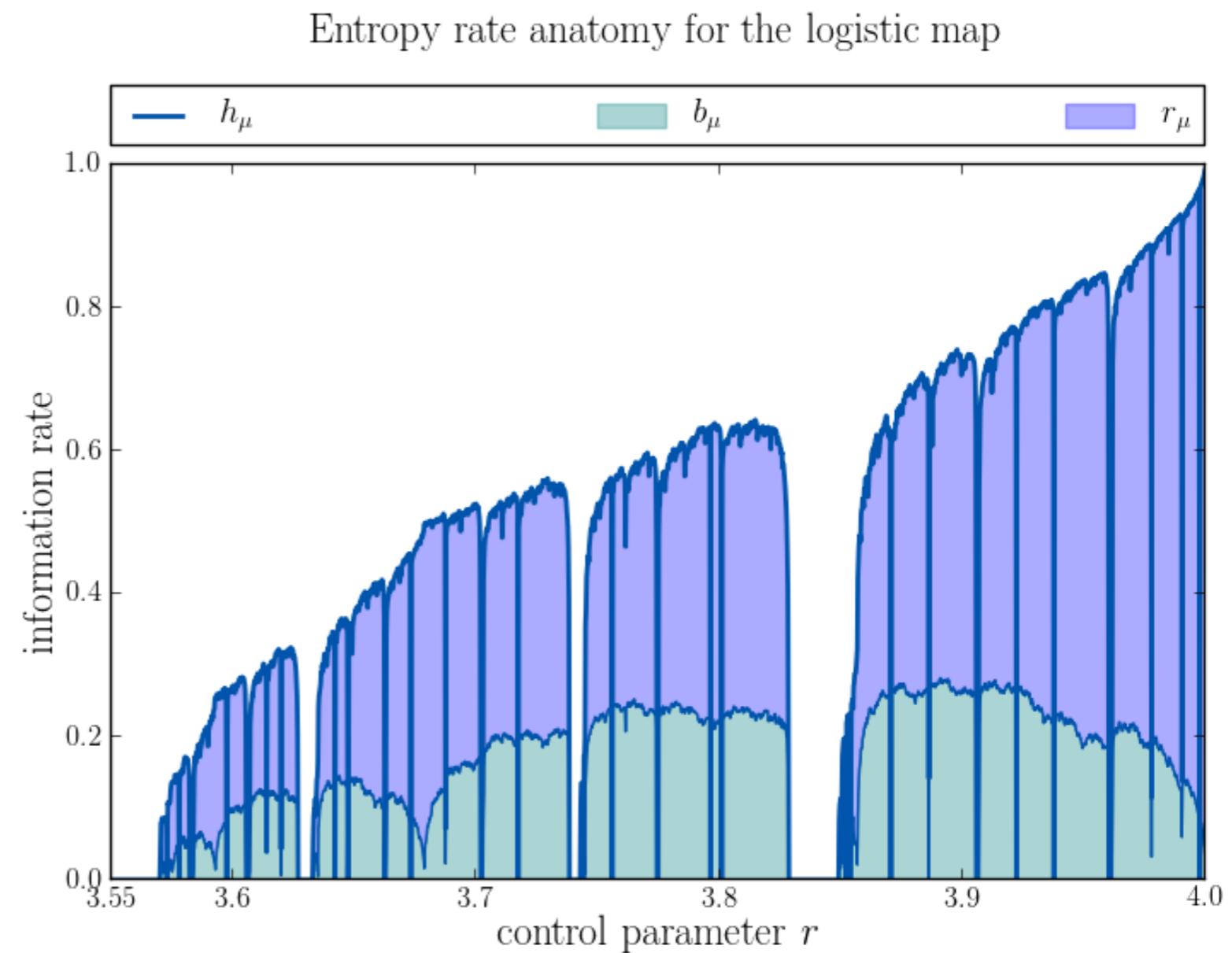
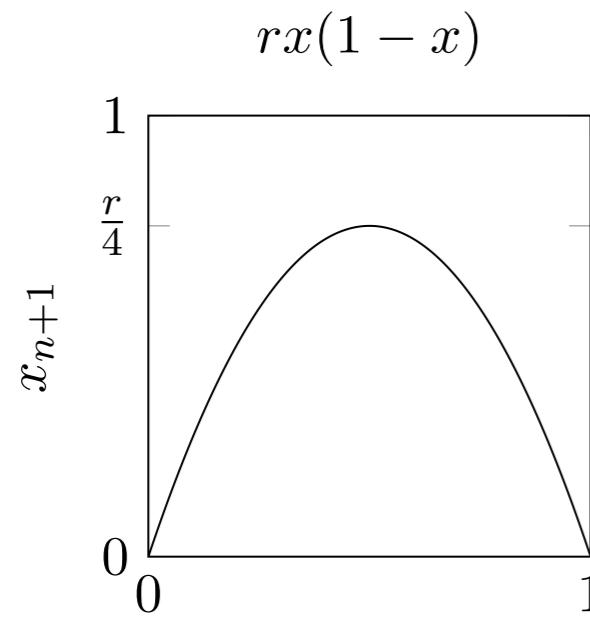
- Nontrivial r_μ , b_μ decomposition



Logistic Map

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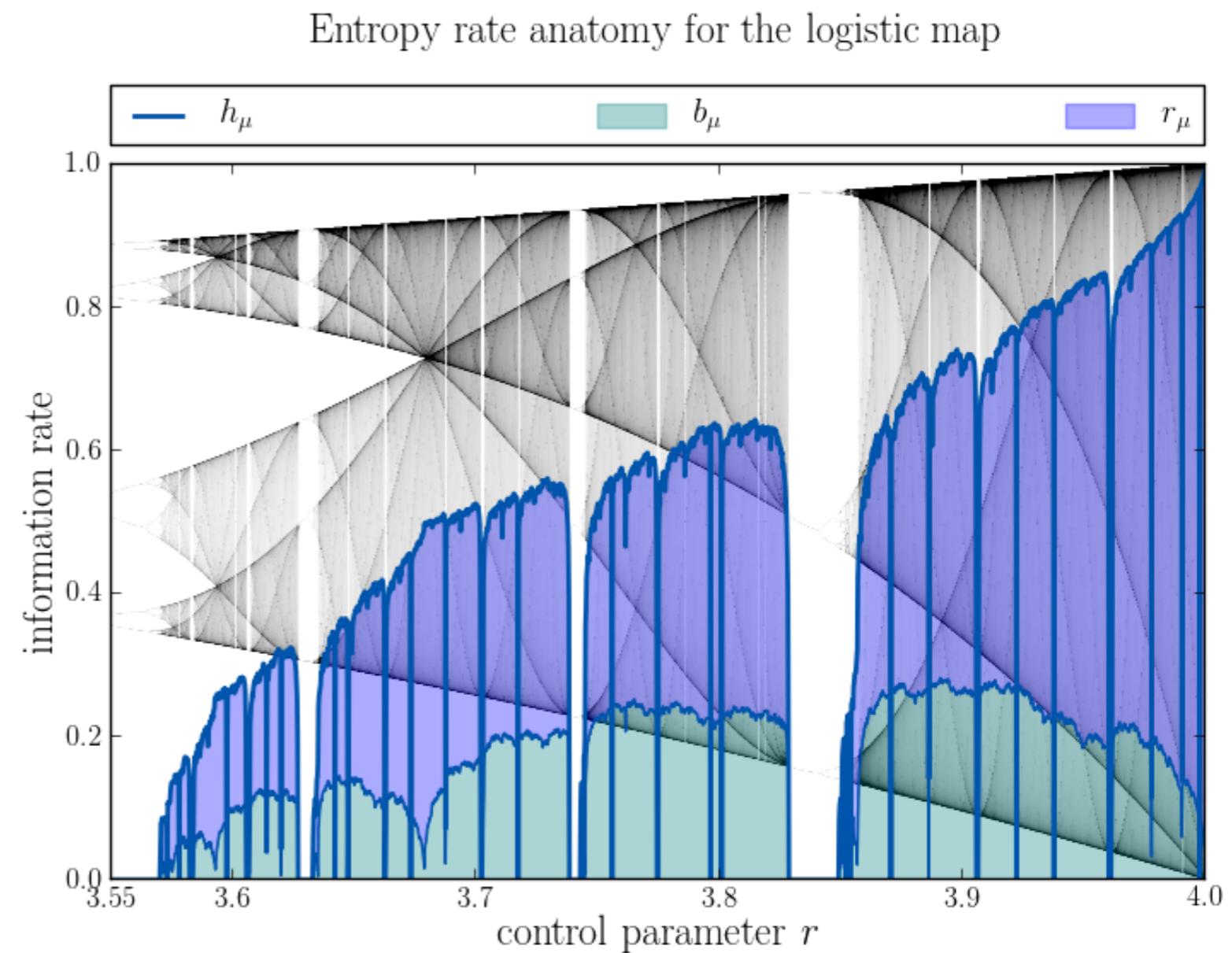
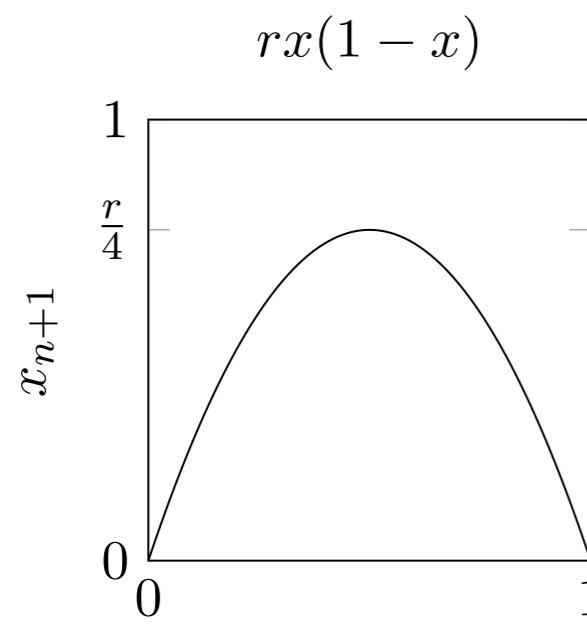
- Nontrivial r_μ , b_μ decomposition
- Self-similarity



Logistic Map

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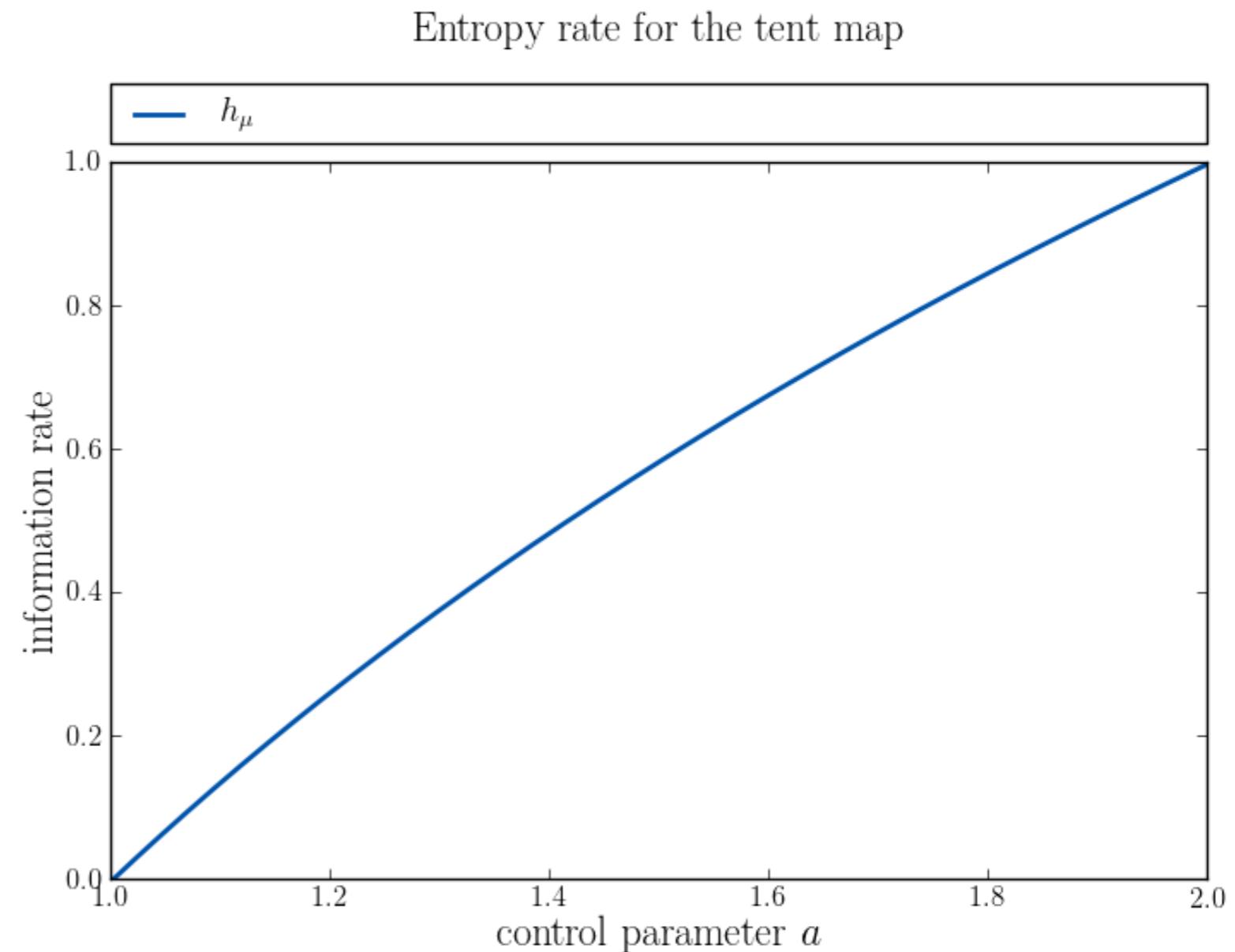
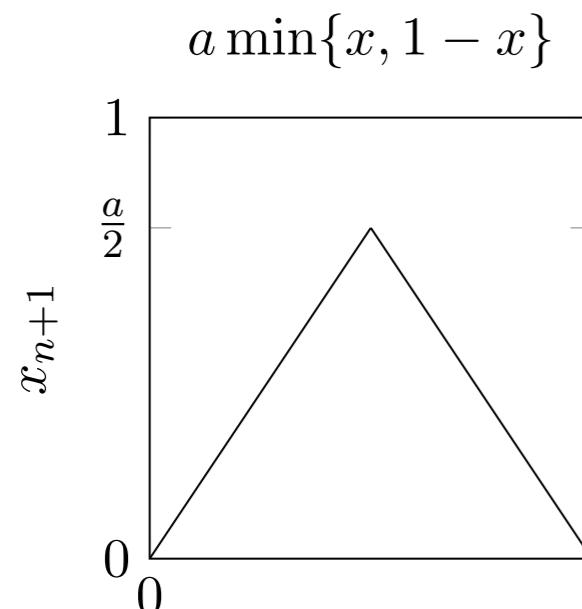
- Nontrivial r_μ , b_μ decomposition
- Self-similarity
- $b_\mu = 0$ at band mergings



Tent Map

Clean Example

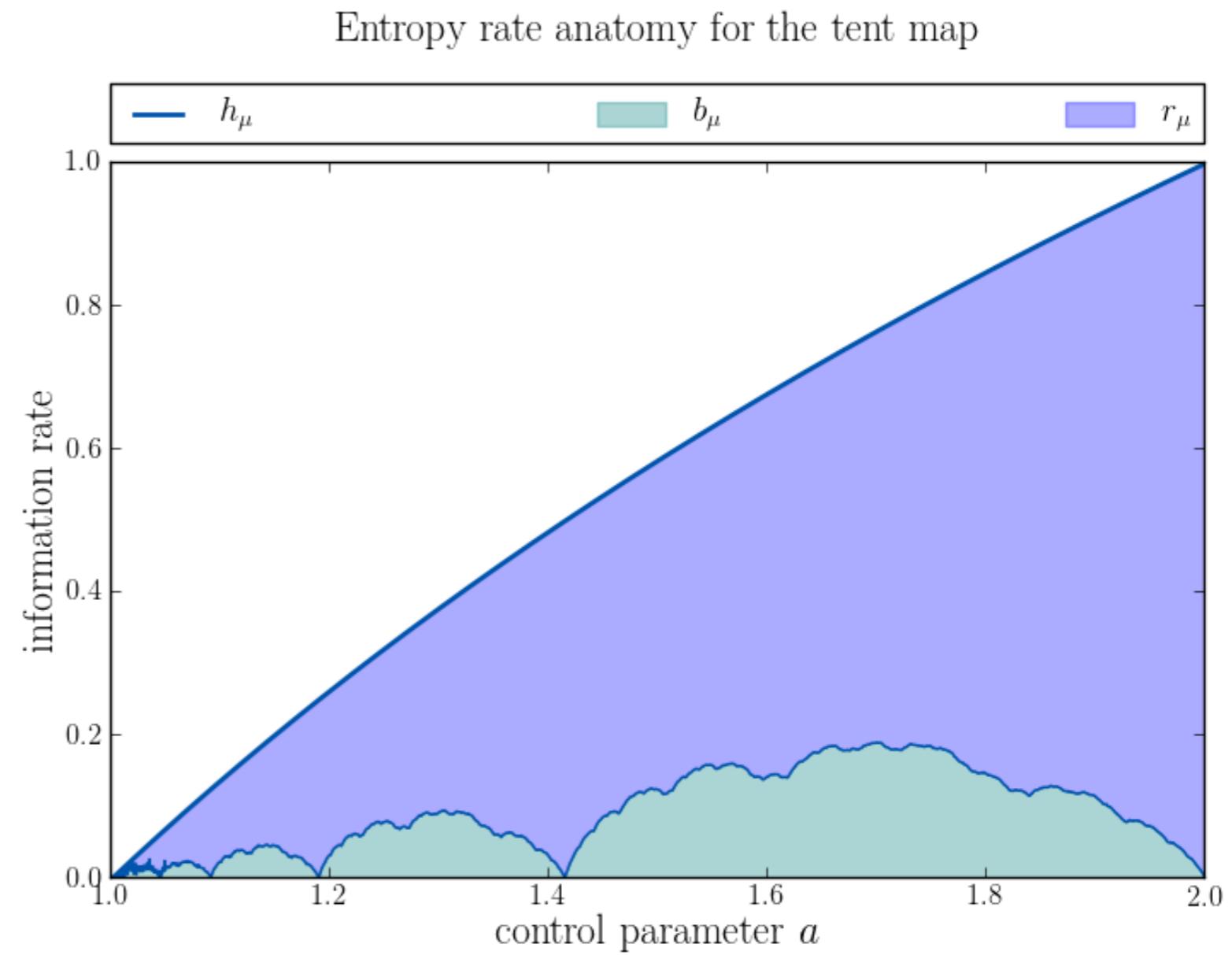
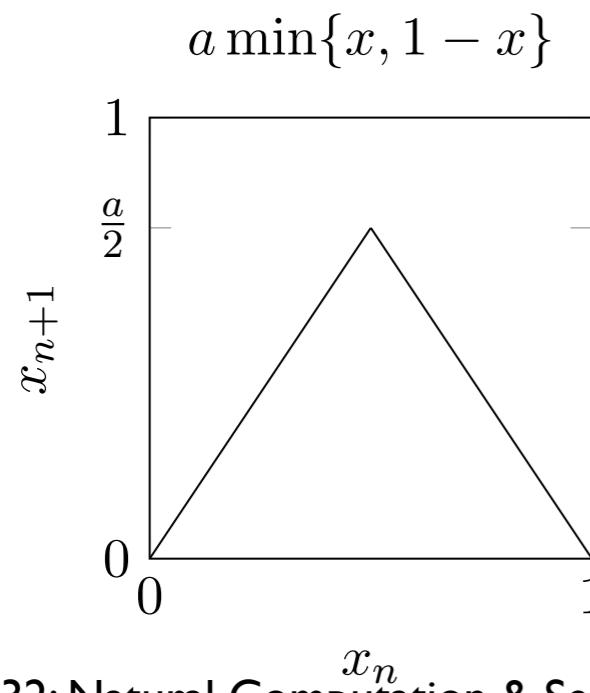
- $h_\mu = \log(a)$



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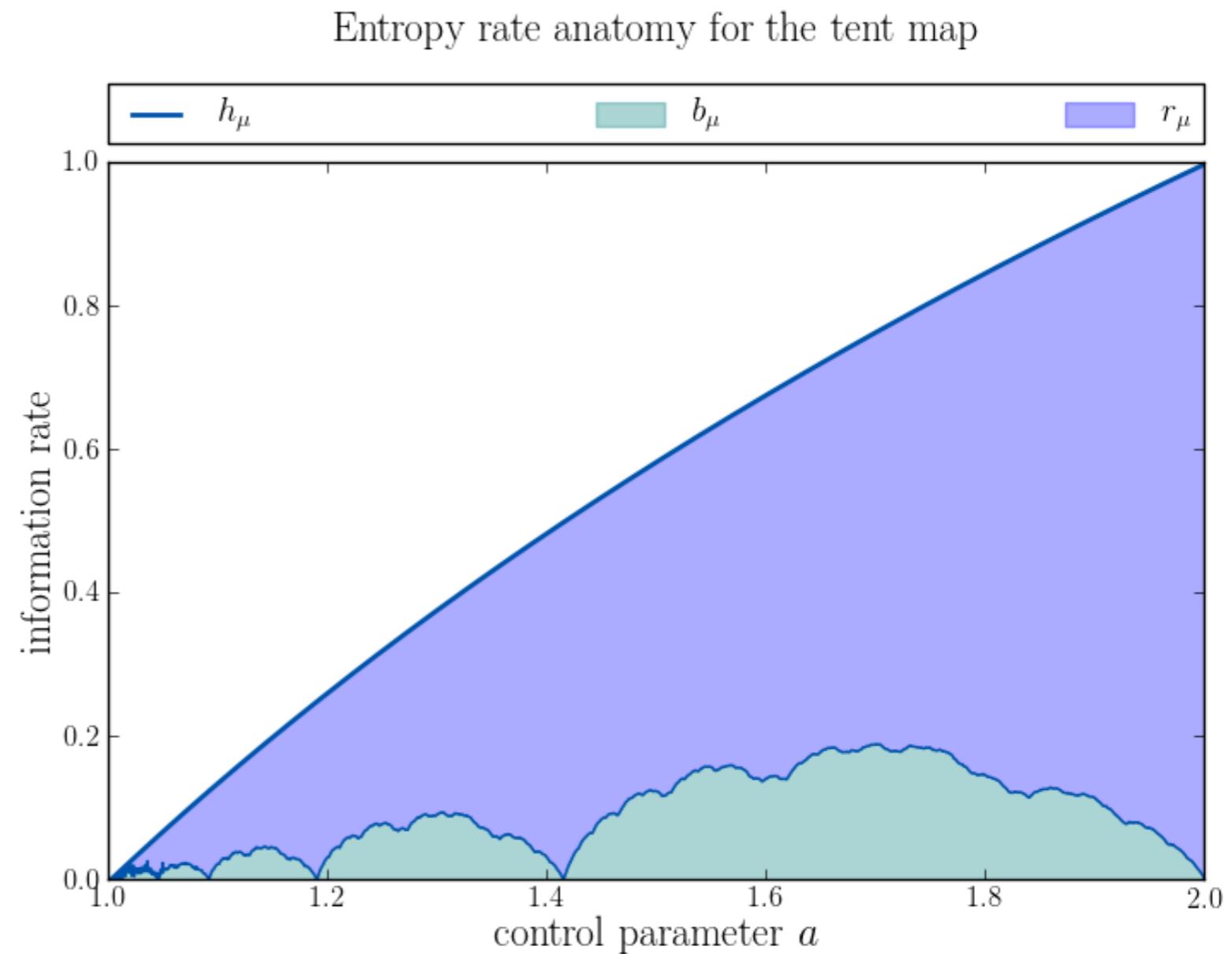
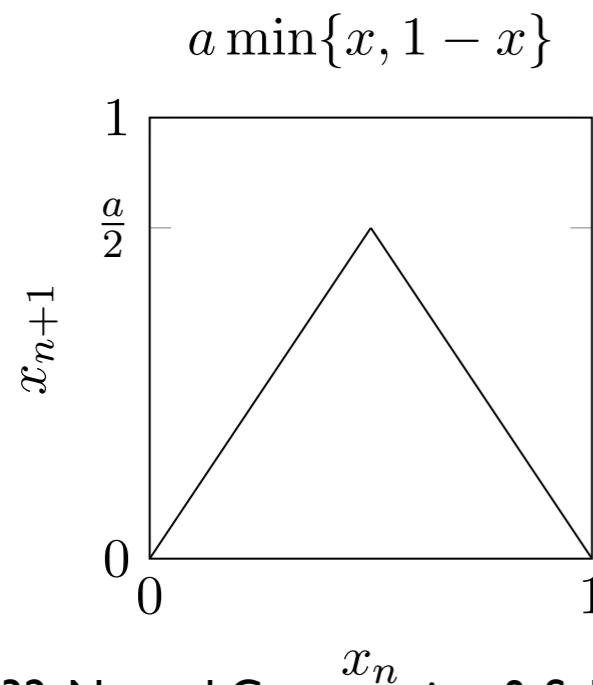
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 - $h_\mu = r_\mu + b_\mu$



Tent Map

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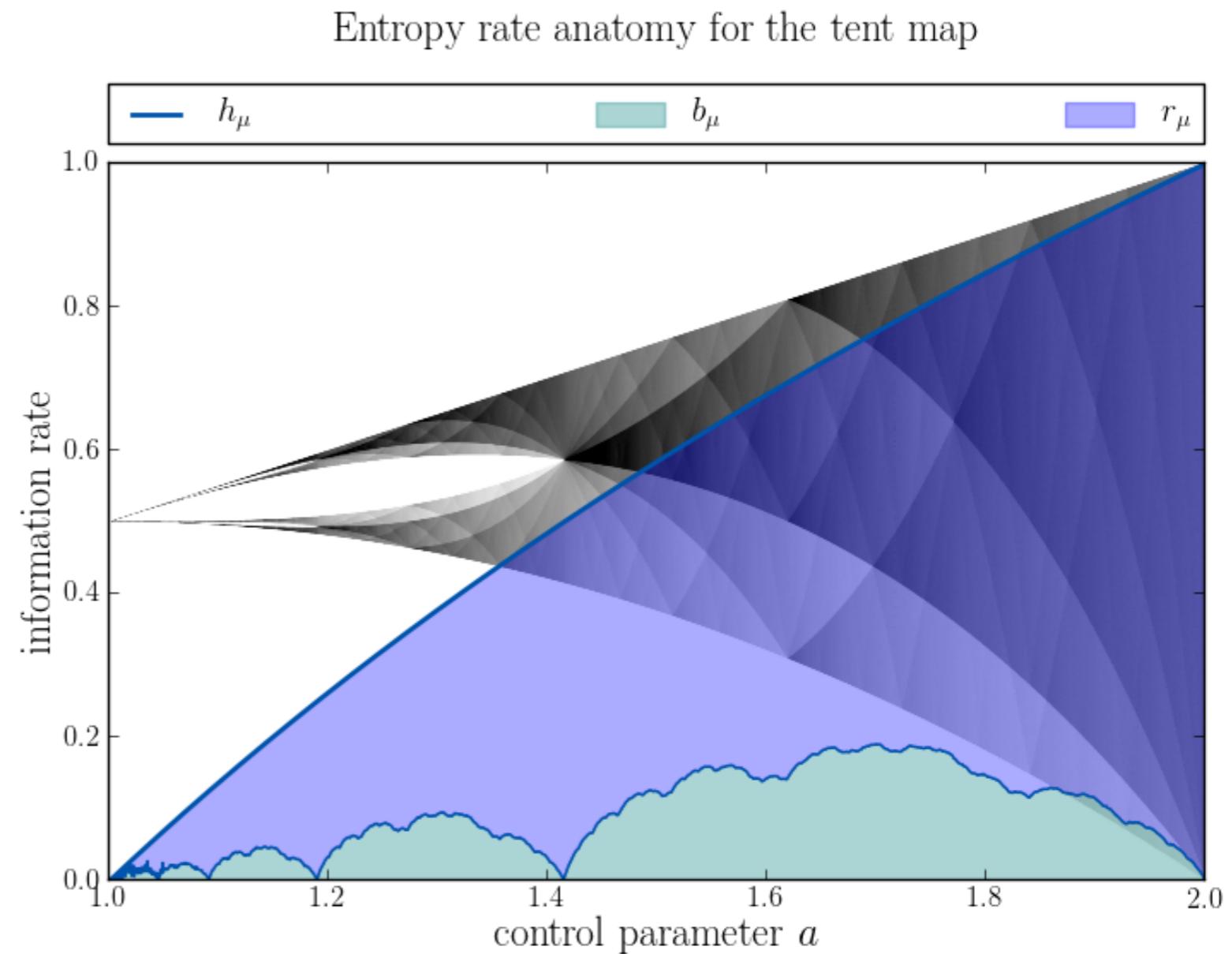
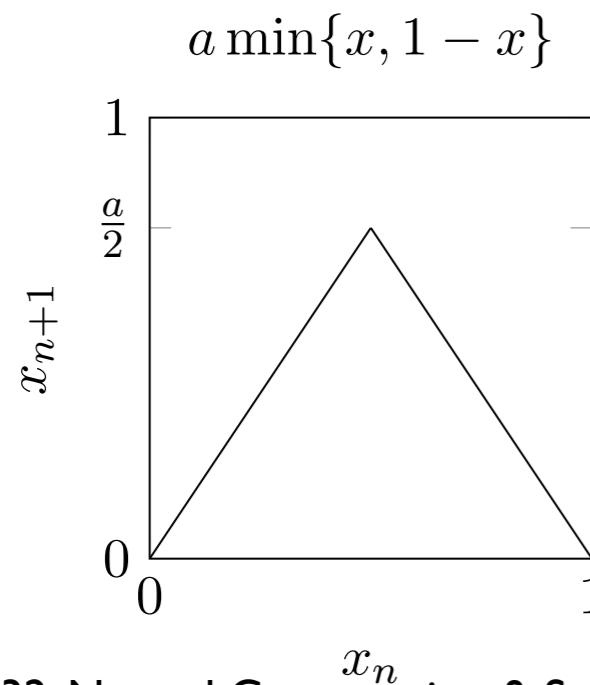
- $h_\mu = \log(a)$
 - $h_\mu = r_\mu + b_\mu$
 - r_μ, b_μ
decomposition
still complex



Tent Map

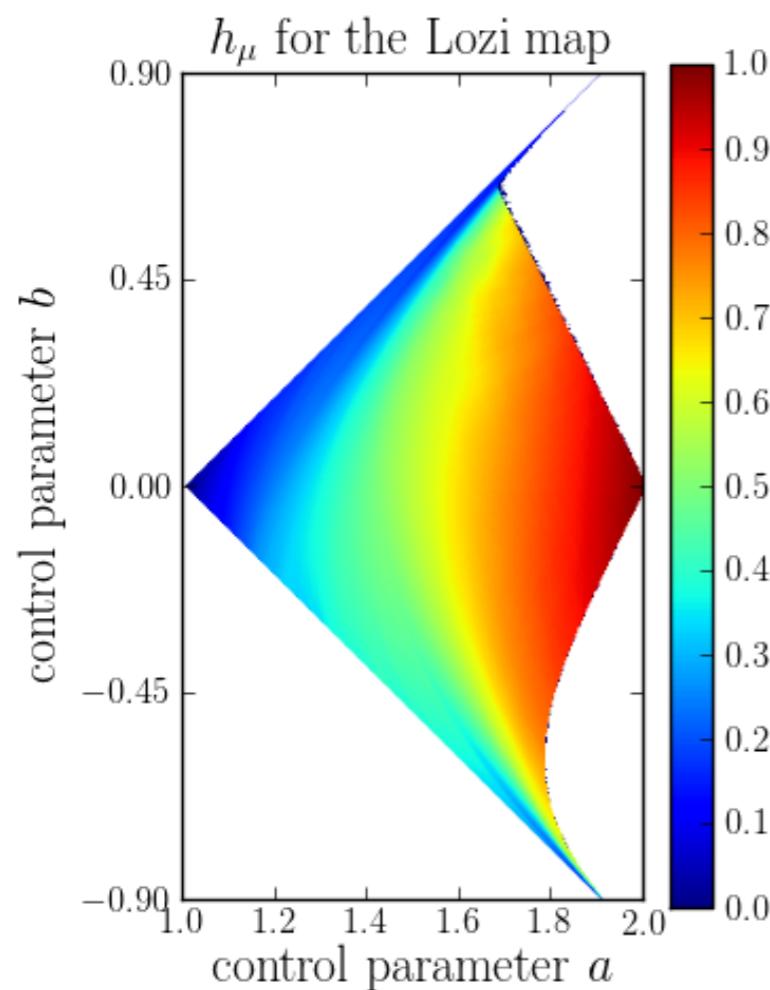
Clean Example

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still complex



Lozi Map

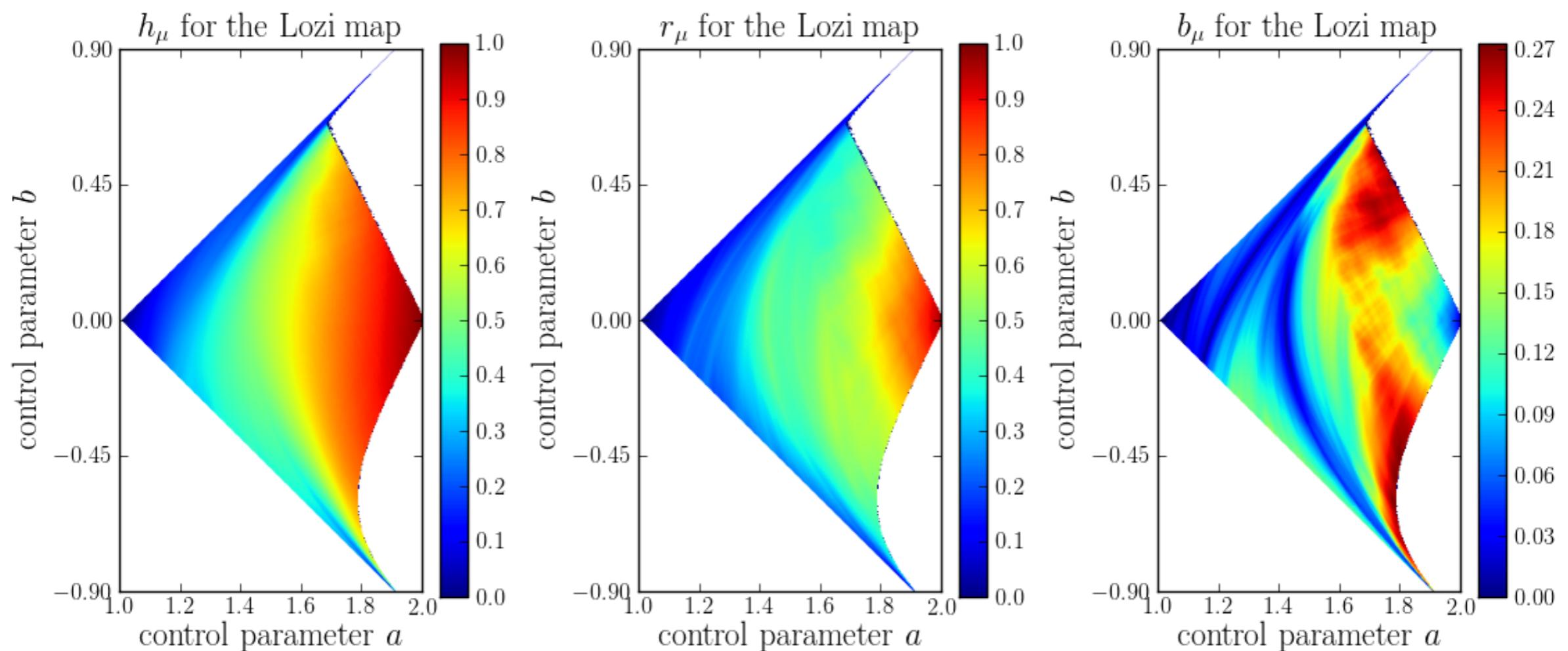
Moving to 2D



$$x_{n+1} = 1 - a |x_n| + y_n \quad y_{n+1} = bx_n$$

Lozi Map

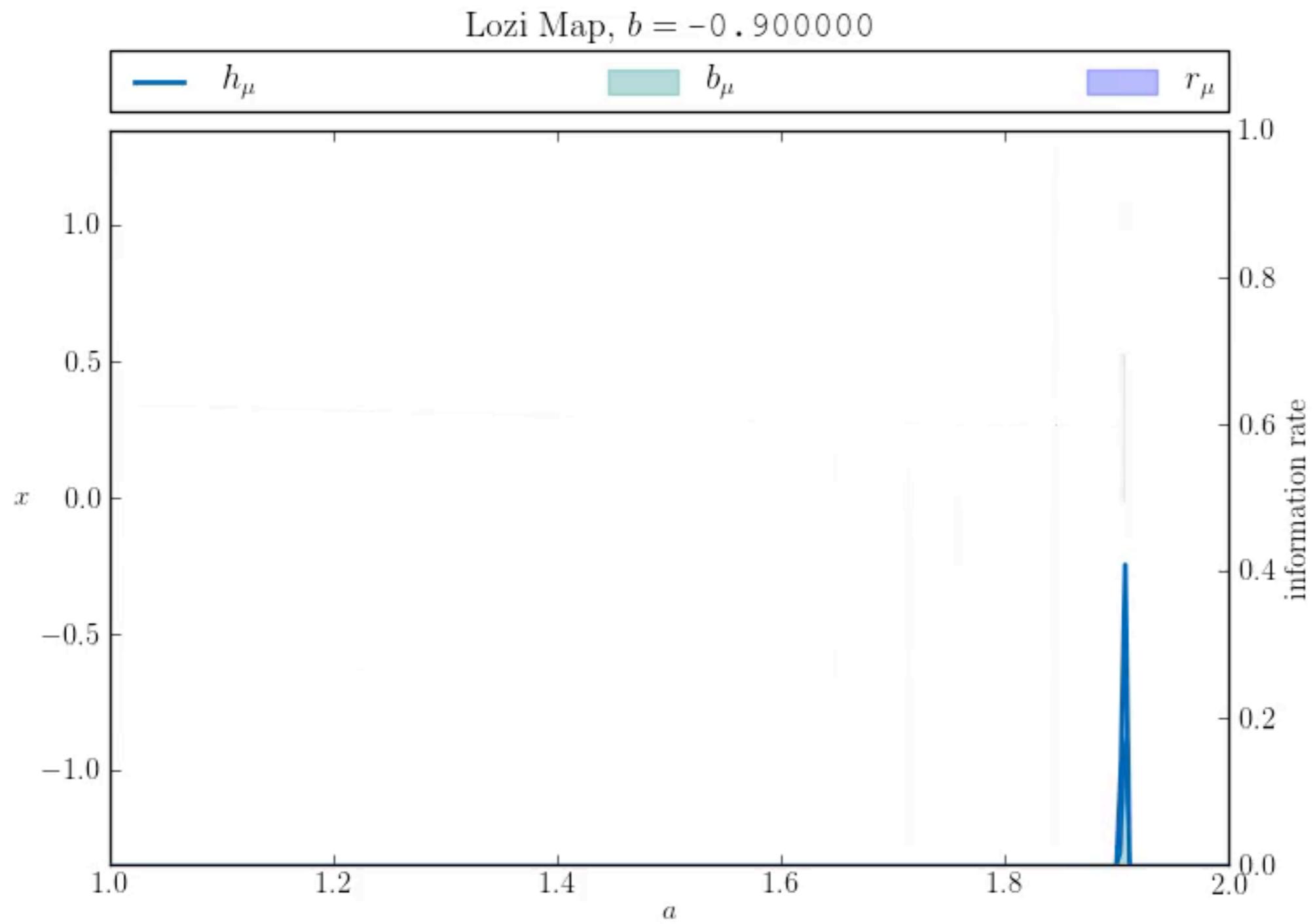
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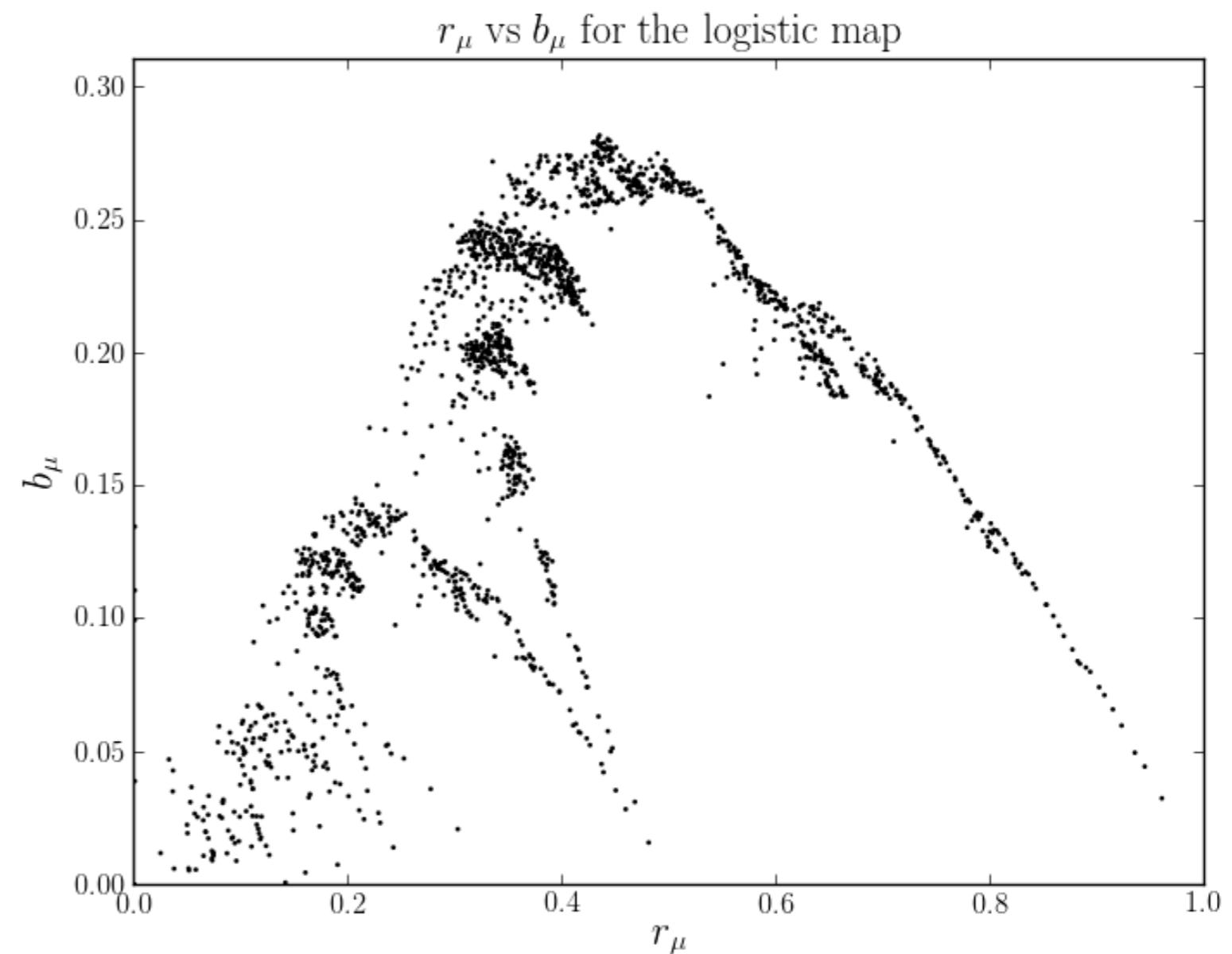
Movie



r_μ vs b_μ

Logistic Map

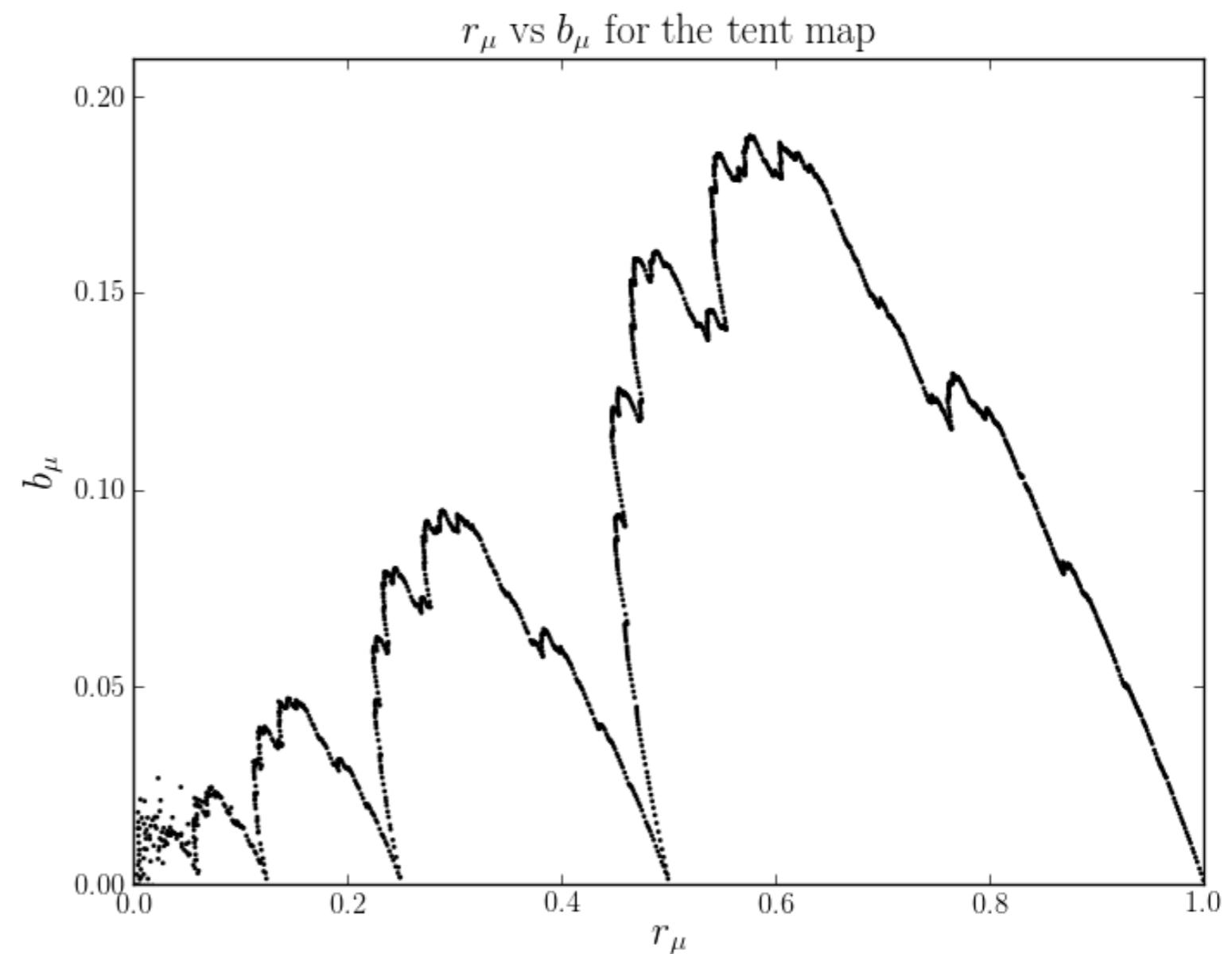
- Trade-off between noise and structure



r_μ vs b_μ

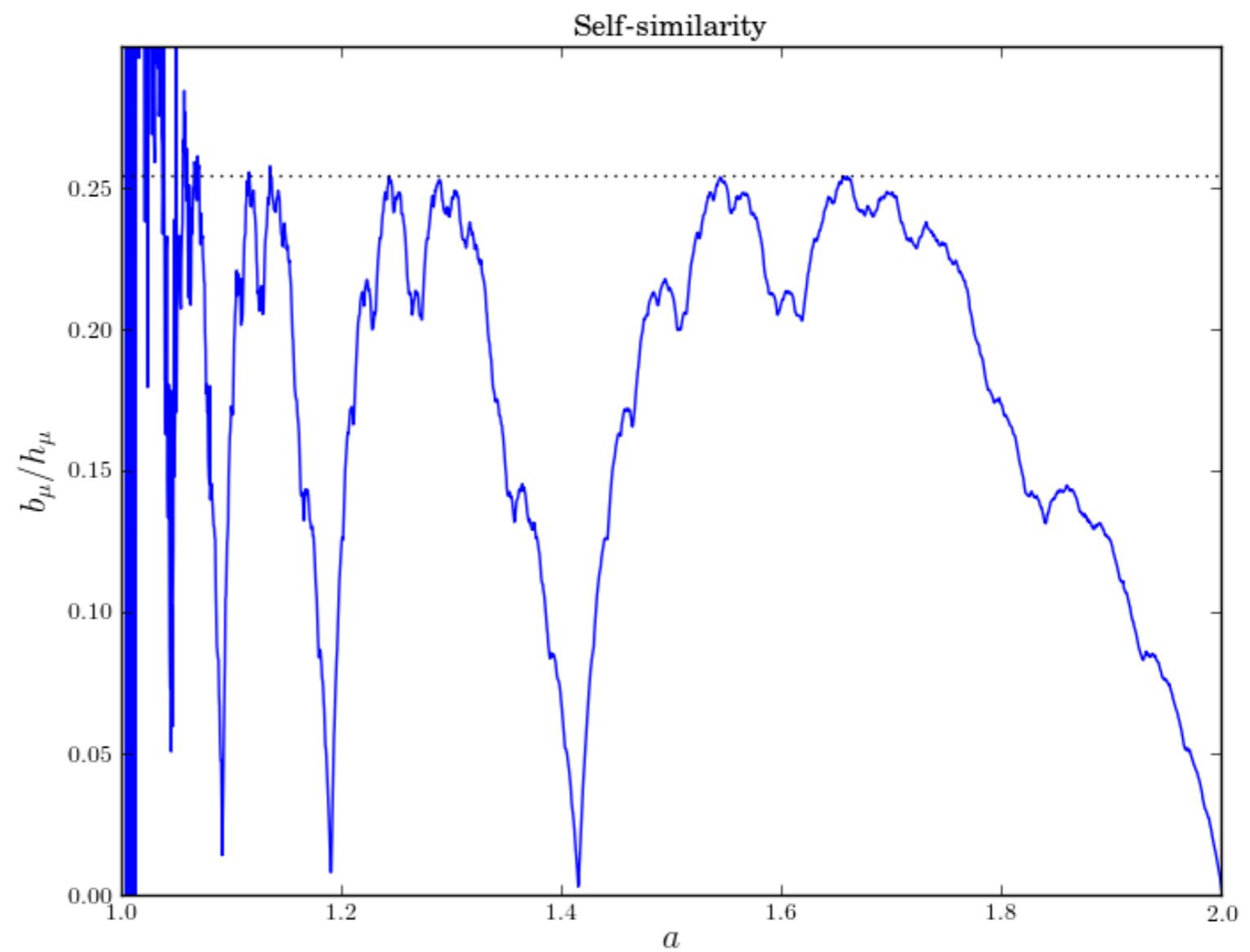
Tent Map

- Trade-off between noise and structure
 - Very structured



Tent Map

- Scaling between band mergings is self-similar



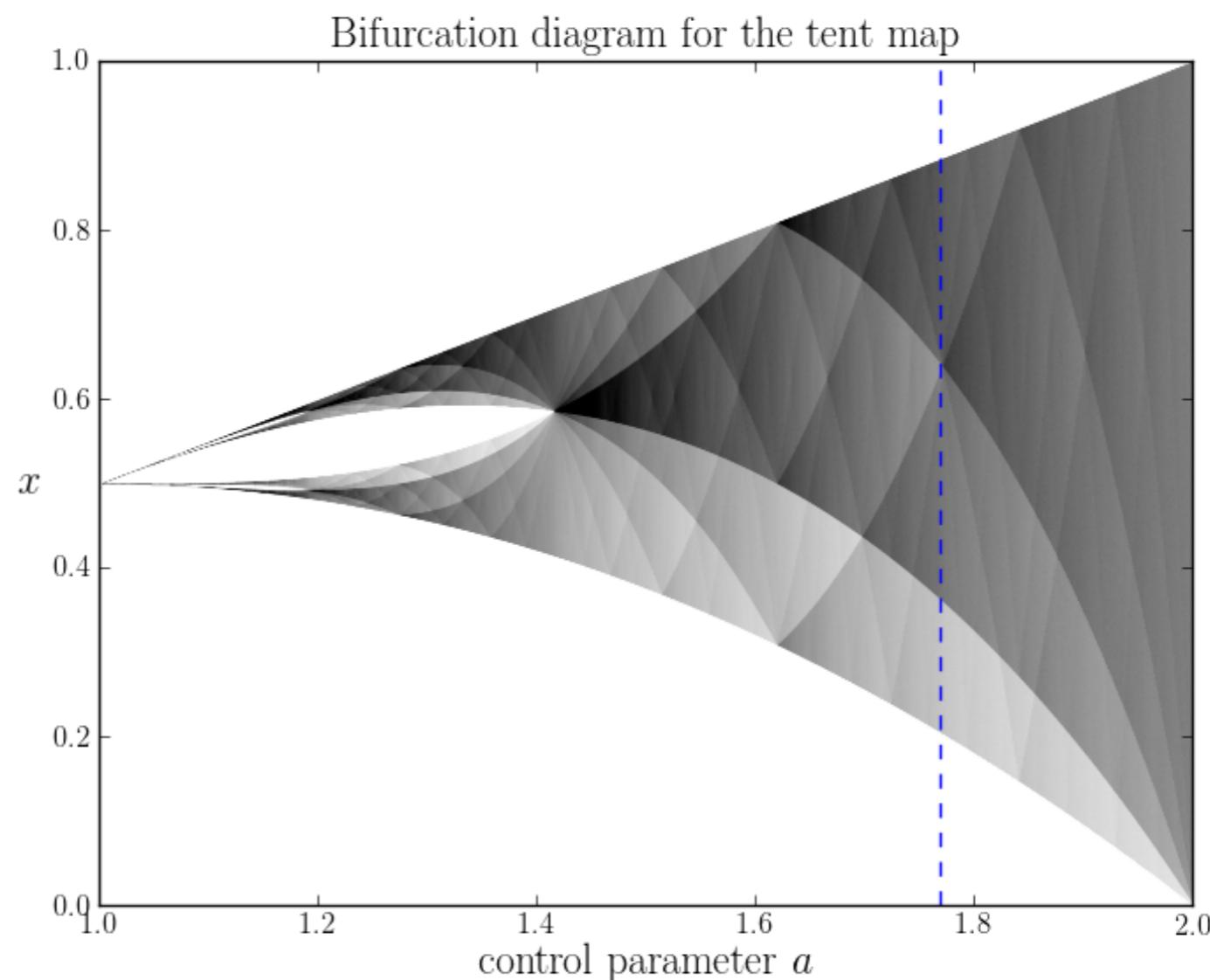
Discretizing

Compute a Misiurewicz Point

$$\alpha = \sqrt[3]{\sqrt{\frac{19}{27}} + 1}$$

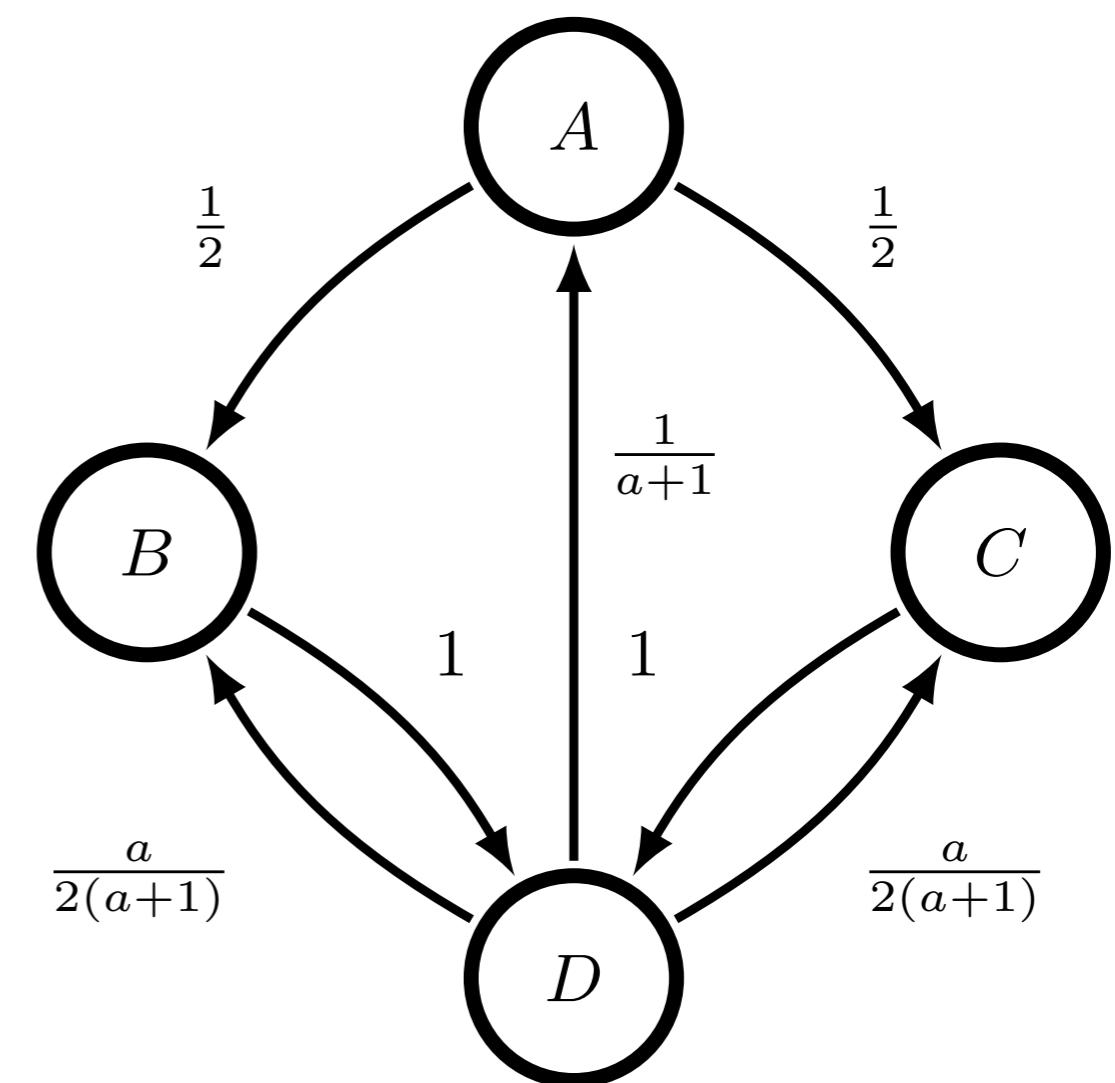
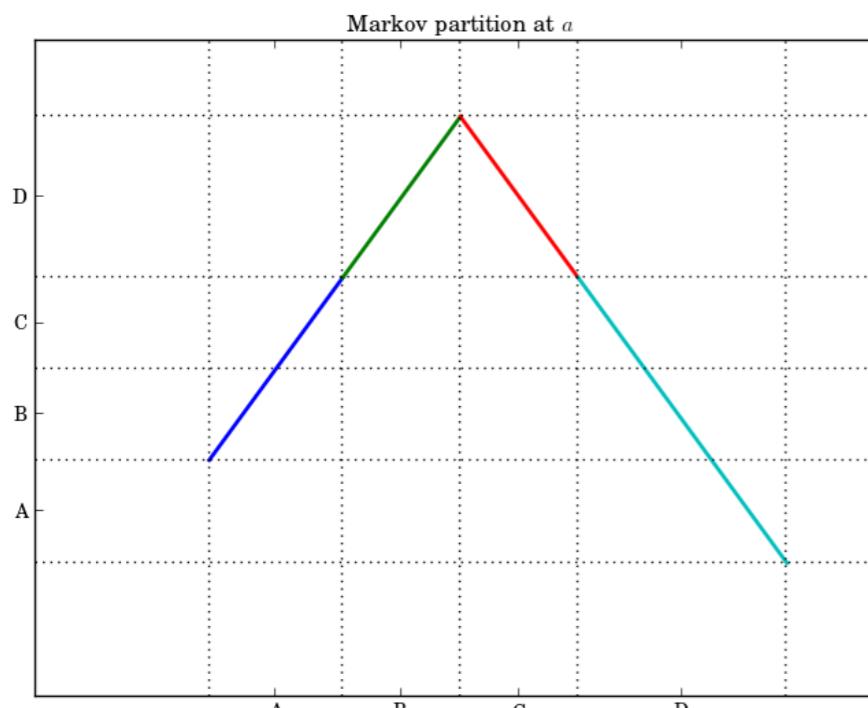
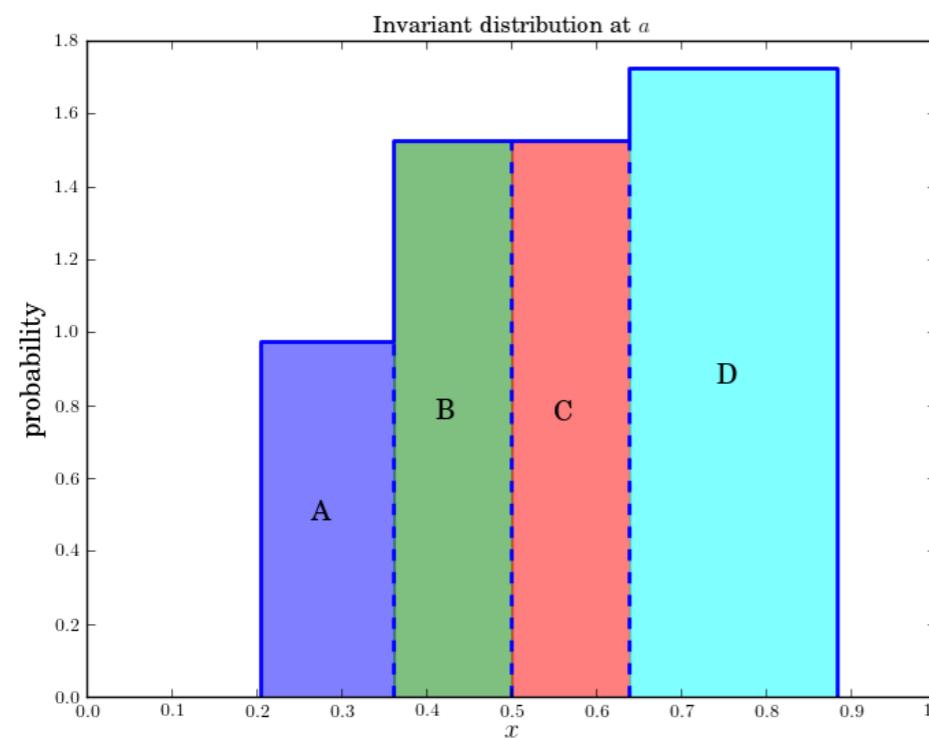
$$a = \alpha + \frac{2}{3\alpha}$$

$$= 1.76929235\dots$$



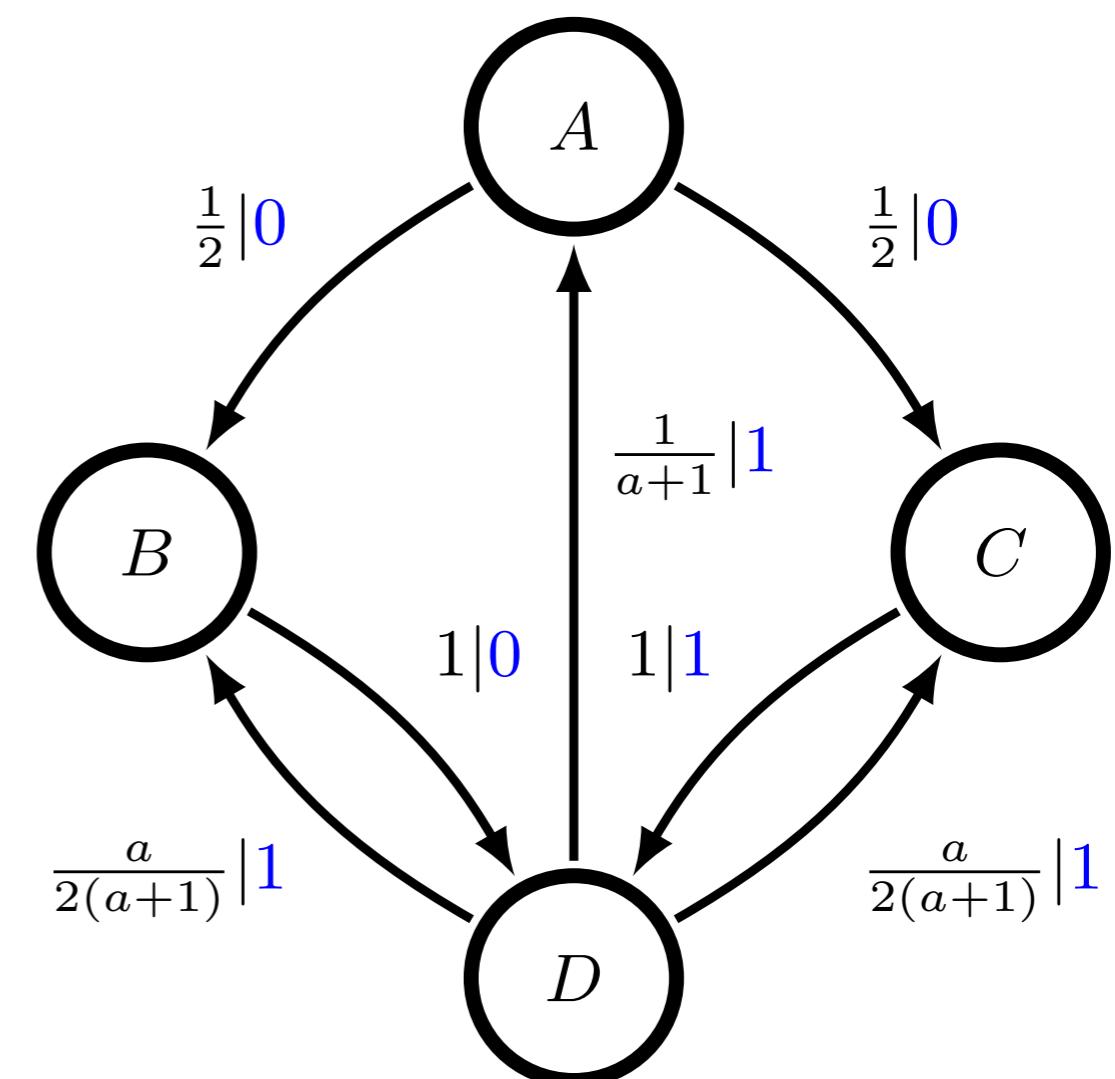
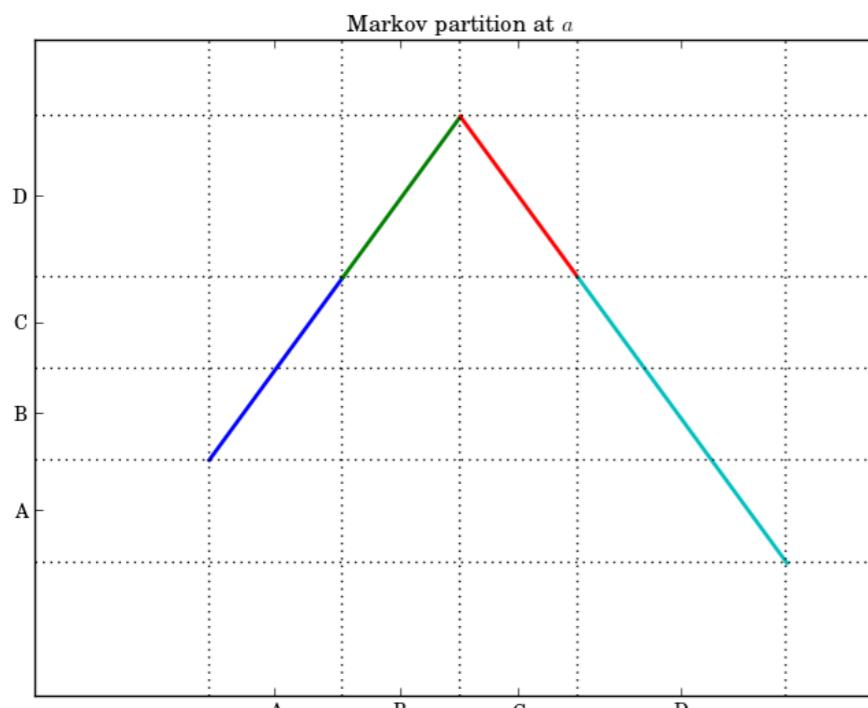
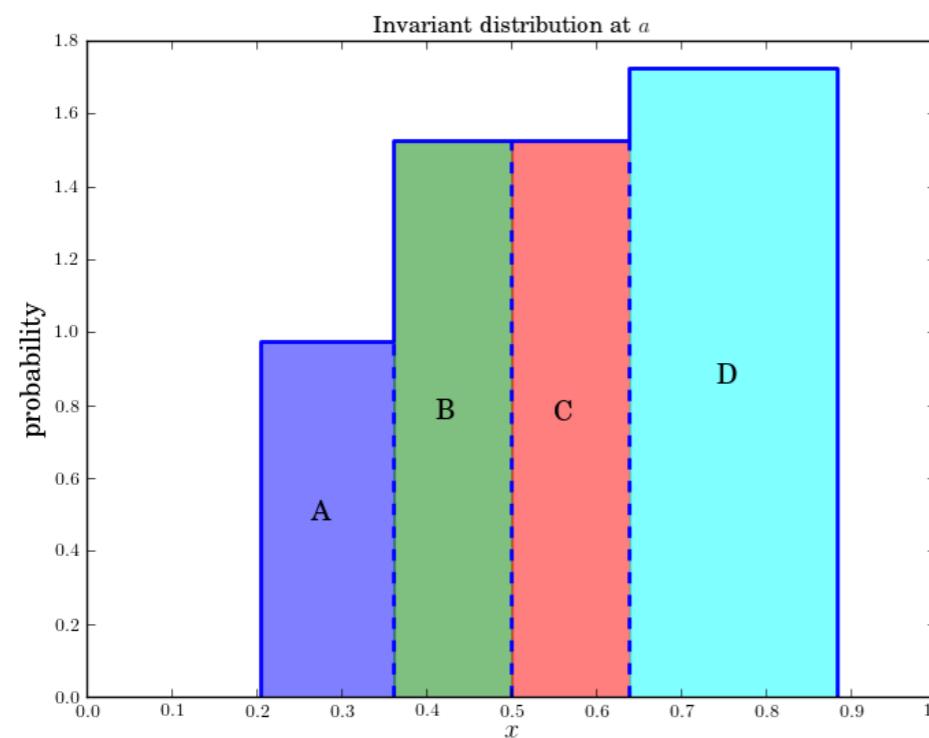
Discretizing

The Misiurewicz Point Admits a Markov Partition

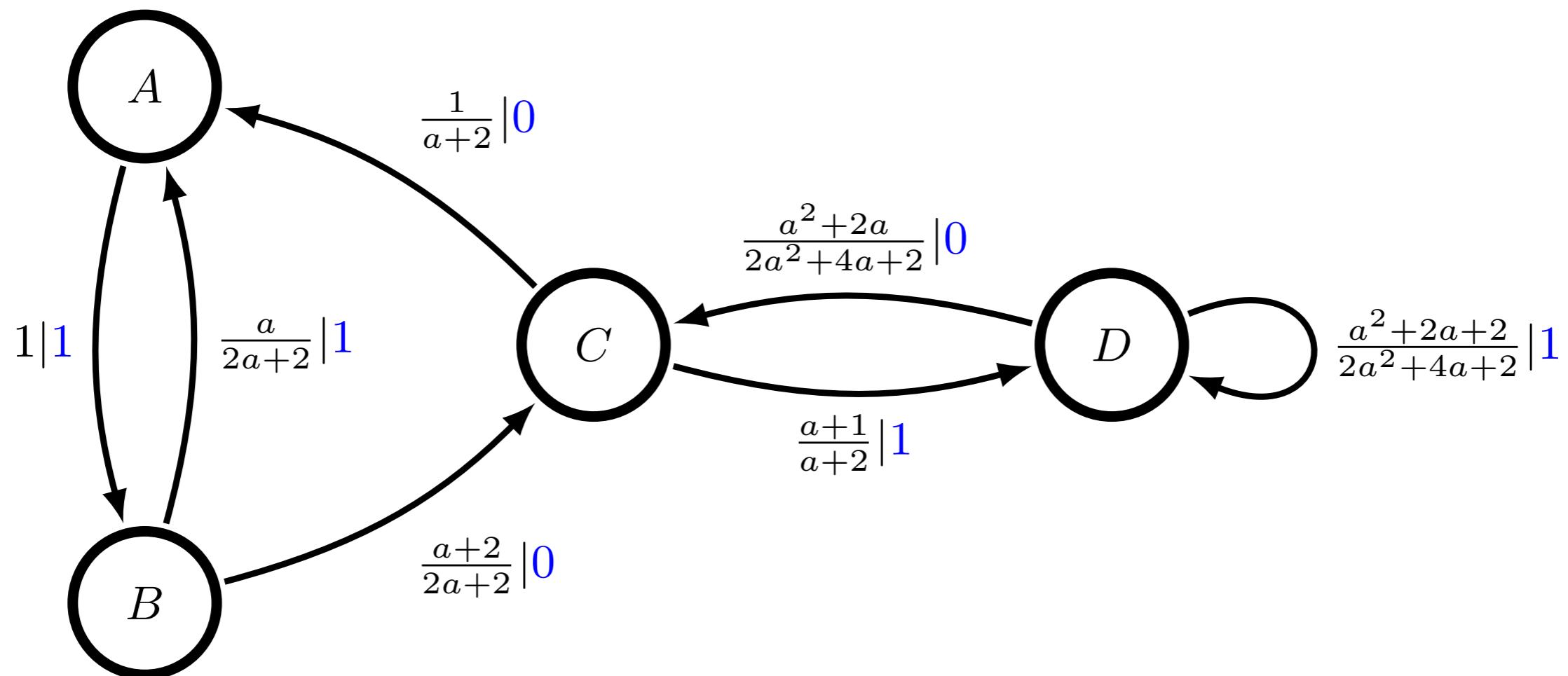


Discretizing

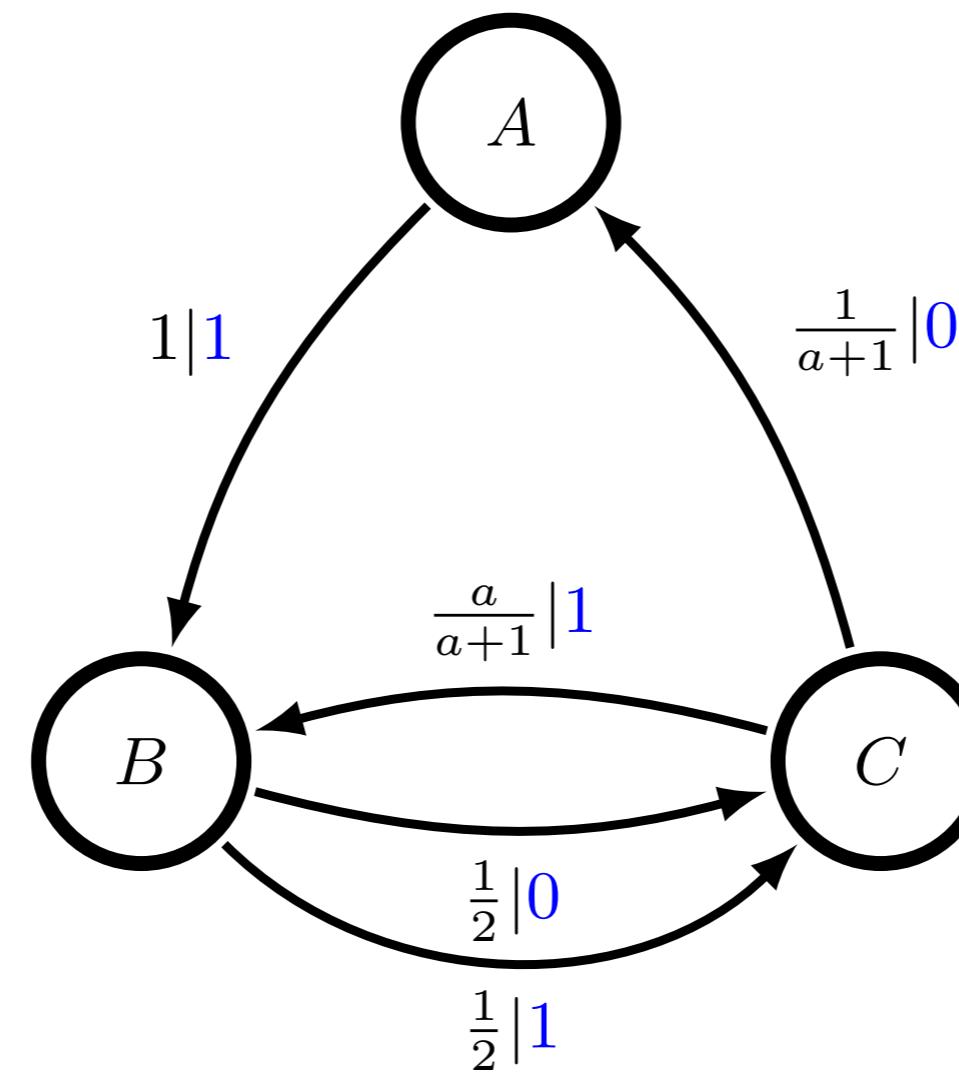
The Misiurewicz Point Admits a Markov Partition



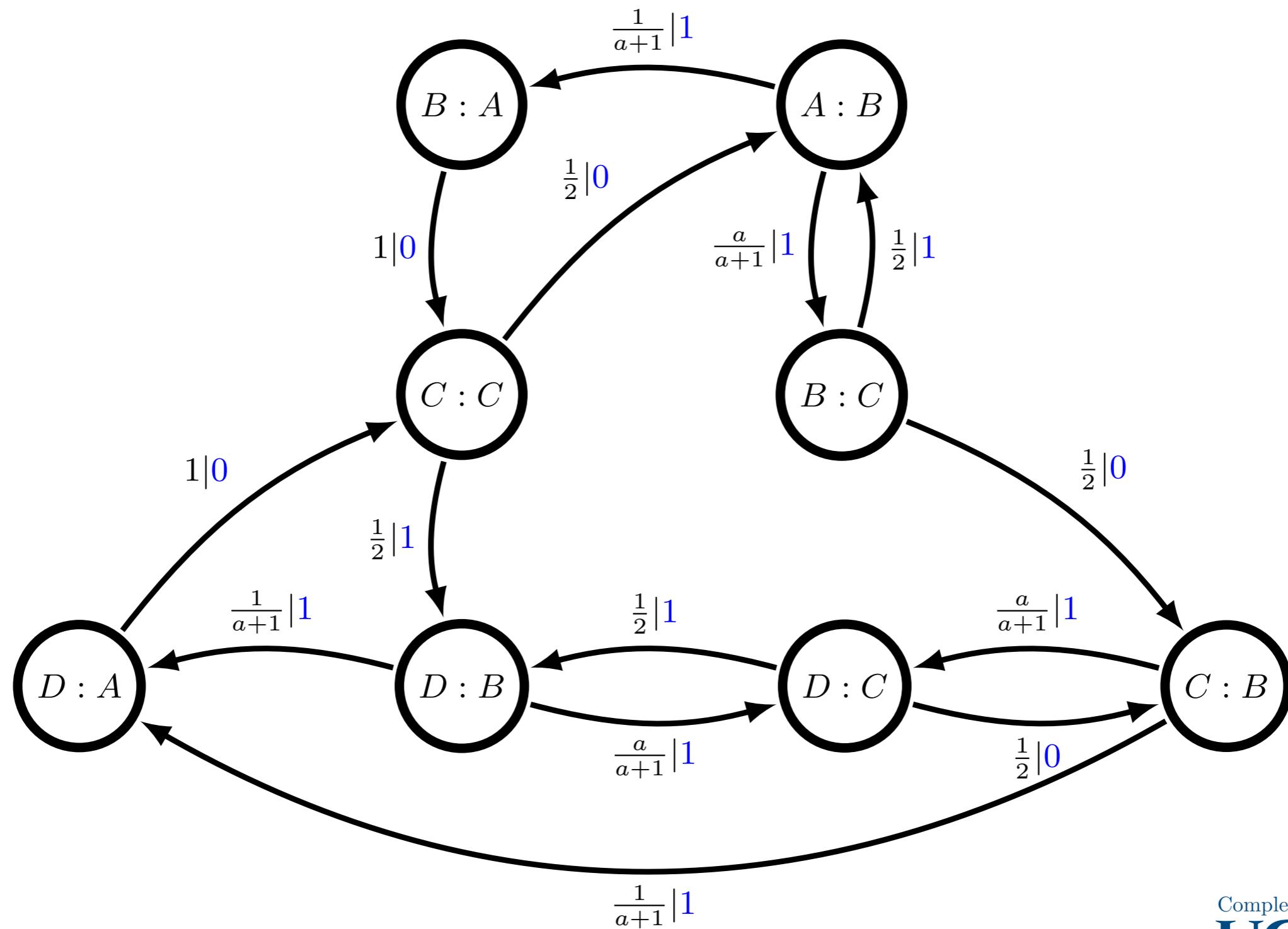
Construct the ϵ -machine



Construct the ϵ -machine



Construct the Bidirectional ϵ -machine



Calculate the Quantities

The bidirectional machine provides $p(\mathcal{S}_0^+, \mathcal{S}_0^-, X_0, \mathcal{S}_1^+, \mathcal{S}_1^-)$.

This can be marginalized to $p(\mathcal{S}_0^+, X_0, \mathcal{S}_1^-)$.

$$r_\mu = H[X_0 | \mathcal{S}_0^+, \mathcal{S}_1^-].$$

$$h_\mu = \log_2 a = \log_2 \left(\frac{\sqrt[3]{9 + \sqrt{57}} + \sqrt[3]{9 - \sqrt{57}}}{3^{\frac{2}{3}}} \right) = 0.823172\dots$$

$$r_\mu = \frac{1}{4} \left(3 - \frac{2}{a+1} - \frac{4}{a+2} + \frac{9}{2a+3} \right)$$

$$= \frac{1}{9} \left(\frac{\sqrt[3]{207\sqrt{57} - 1349}}{19^{2/3}} - \frac{32}{\sqrt[3]{19(207\sqrt{57} - 1349)}} + 7 \right) = 0.648258\dots$$

$$b_\mu = h_\mu - r_\mu = 0.174915\dots$$

It happens sometimes. People just explode. Natural causes.

Thank You

h_μ is two semantically meaningful components: r_μ & b_μ

Interwebs

<http://csc.ucdavis.edu/~rgjames> rgjames@ucdavis.edu

Reference

Ryan G. James, Christopher J. Ellison, and James P. Crutchfield
Anatomy of a Bit: Information in a Time Series Observation
 Chaos 21, 037109 (2011)