# Anatomy of a Bit

Reading for this lecture:

CMR articles Yeung and Anatomy.

Information in a single measurement:

- Alternative rationale for entropy and entropy rate.
- $\bullet \ k$  measurement outcomes
- $\bullet$  Stored in  $\log_{10}k\,$  decimal digits or  $\log_2k\,$  bits.
- $\bullet$  Series of n measurements stored in  $n\log_2k$  bits.
- Number M of possible sequences of n measurements with  $n_1, n_2, \ldots, n_k$  counts:

$$M = \begin{pmatrix} n \\ n_1 n_2 \cdots n_k \end{pmatrix}$$
$$= \frac{n!}{n_1! n_2! \cdots n_k!}$$

• To specify/code which particular sequence occurred store:

$$k \log_2 n + \log_2 M + \log_2 n + \cdots$$
 bits

Maximum number of Number of bits to bits to store the count ni of each of the k output values

specify particular observed sequence within the class of sequences that have counts  $n_1, n_2, \dots, n_k$ 

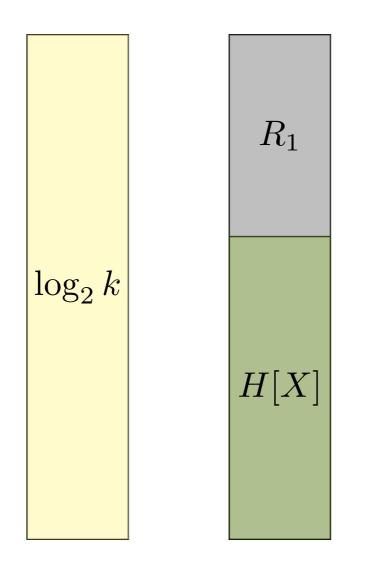
Bits to specify the number of bits in n itself

Apply Stirlings approximation:

 $n! = \sqrt{2\pi n (n/e)^n}$ 

• To 
$$M$$
:  $\log_2 M \approx -n \sum_{i=1}^k \frac{n_i}{n} \log_2 \frac{n_i}{n}$   
$$= nH[\frac{n_1}{n}, \frac{n_2}{n}, \dots, \frac{n_k}{n}]$$
$$= nH[X]$$

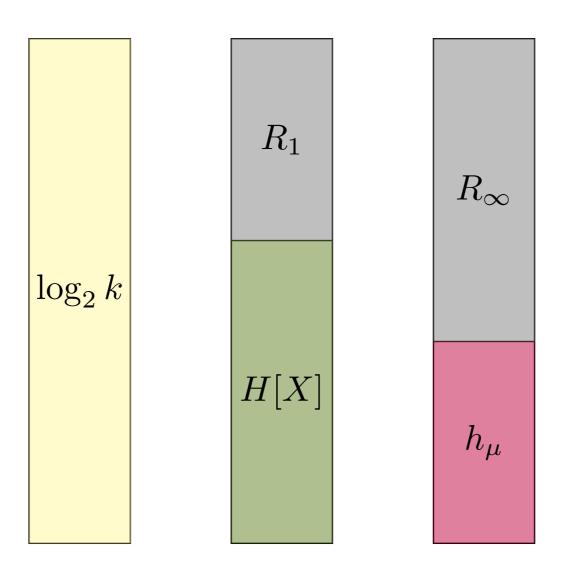
• Can compress if  $H[X] < \log_2 k$ 



I-Symbol Redundancy  $R_1 = \log_2 k - H[X]$ 

• Typical sources are not IID, therefore use:

$$h_{\mu} = \lim_{L \to \infty} \frac{H(L)}{L}$$

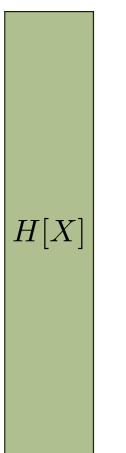


Intrinsic Redundancy

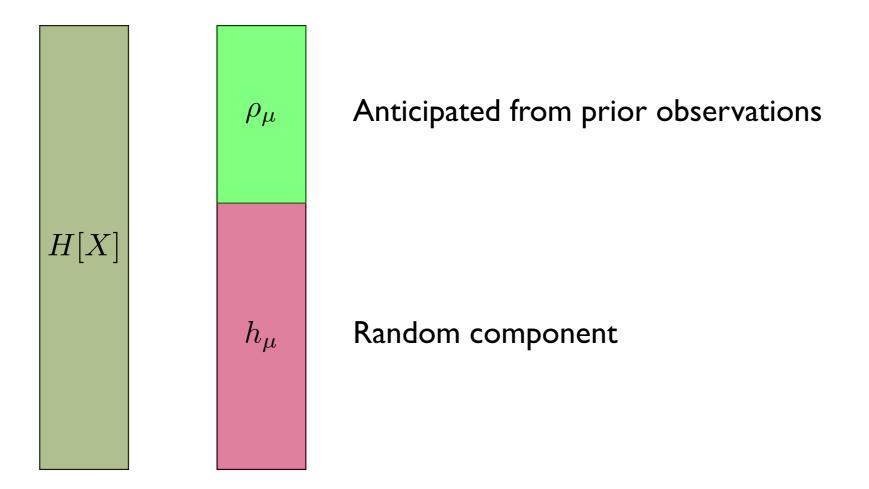
$$R_{\infty} = \log_2 k - h_{\mu}$$
 (Total Predictability)

Intrinsic Randomness

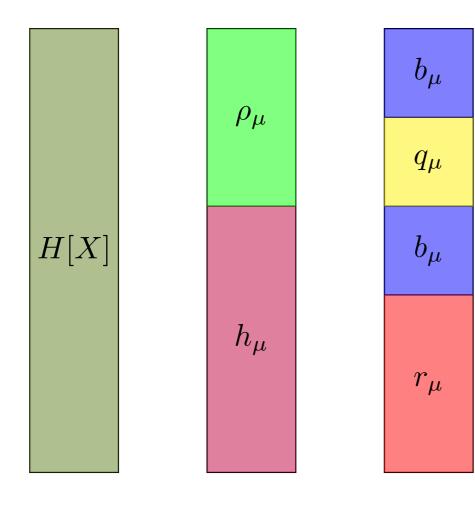
In addition, measurements occur in the context of past and future. A semantically rich decomposition of a single measurement:



A semantically rich decomposition of a single measurement ...



## A semantically rich decomposition of a single measurement ...

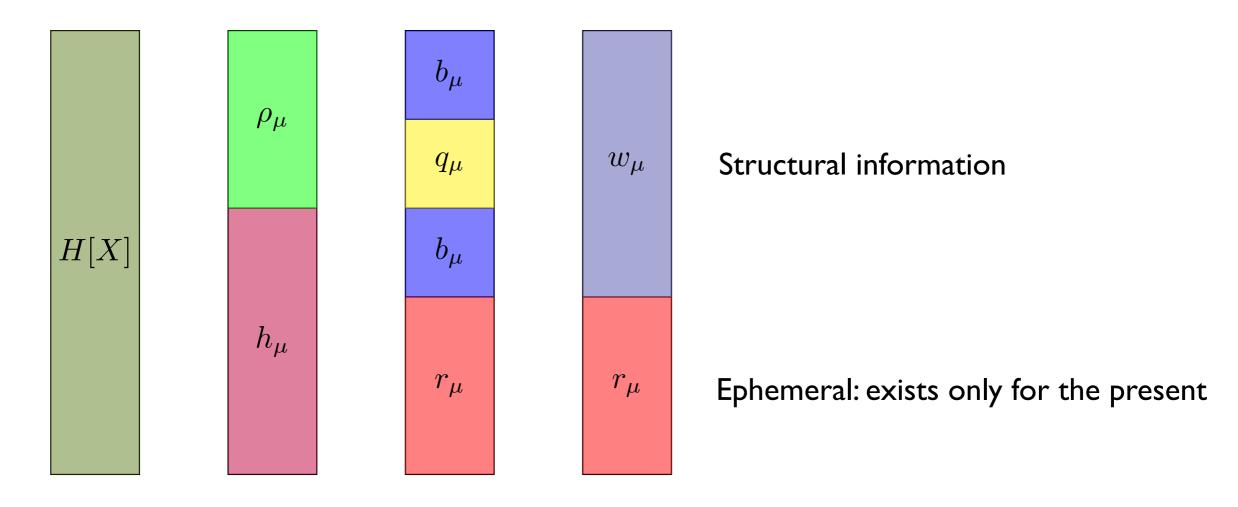


Shared between the past and the current observation, but relevance stops there (stationary process only) Anticipated by the past, present currently, and plays a role in future behavior. Can be negative!

Relevant for predicting the future

Ephemeral: Exists only for the present

A semantically rich decomposition of a single measurement ...



Settings:

Before: Predict the present from the past,  $h_{\mu} = H[X_0 | \overleftarrow{X}]$  $X_{:0}$   $X_0$ 

$$\cdots X_{-3} X_{-2} X_{-1} X_{0}$$

Today, prediction from the omniscient view: The present in the context of the past and the future.

### Notations:

**I-blocks:** 
$$X_{t:t+\ell} = X_t X_{t+1} \dots X_{t+\ell-1}$$

 Past:
  $X_{:0} = \dots X_{-2}X_{-1}$  

 Present:
  $X_0$  

 Future:
  $X_{1:} = X_1 X_2 \dots$ 

Any information measure  $\mathcal{F}$ :

$$\mathcal{F}(\ell) = \mathcal{F}[X_{0:\ell}]$$

# Recall block entropy:

$$H(\ell) \approx \mathbf{E} + h_{\mu}\ell$$
 where:

 $\mathbf{E} = I[X_{:0}; X_{0:}]$ 

Recall total correlation:

$$T[X_{0:N}] = \sum_{\substack{A \in P(N) \\ |A|=1}} H[X_A] - H[X_{0:N}]$$

For stationary time series, get block total correlation:

$$T(\ell) = \ell H[X_0] - H(\ell)$$
 with  $T(0) = 0$   $T(1) = 0$ 

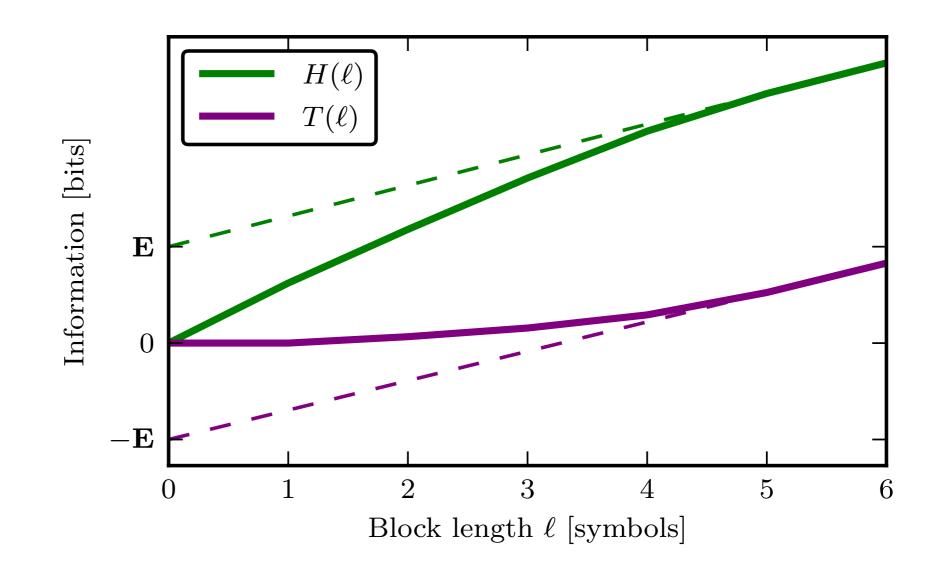
Compares process's block entropy to the case of IID RVs.

Block entropy versus total correlation ...

Monotone increasing, with linear asymptote:

$$T(\ell) \approx -\mathbf{E} + \rho_{\mu}\ell$$

Convex up.

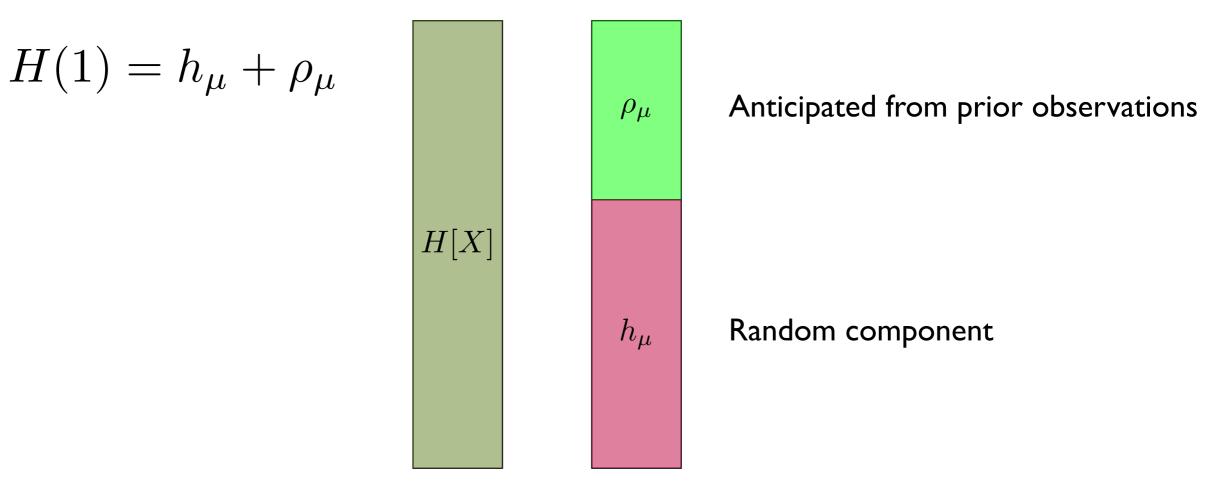


Block entropy versus total correlation ...

Note:

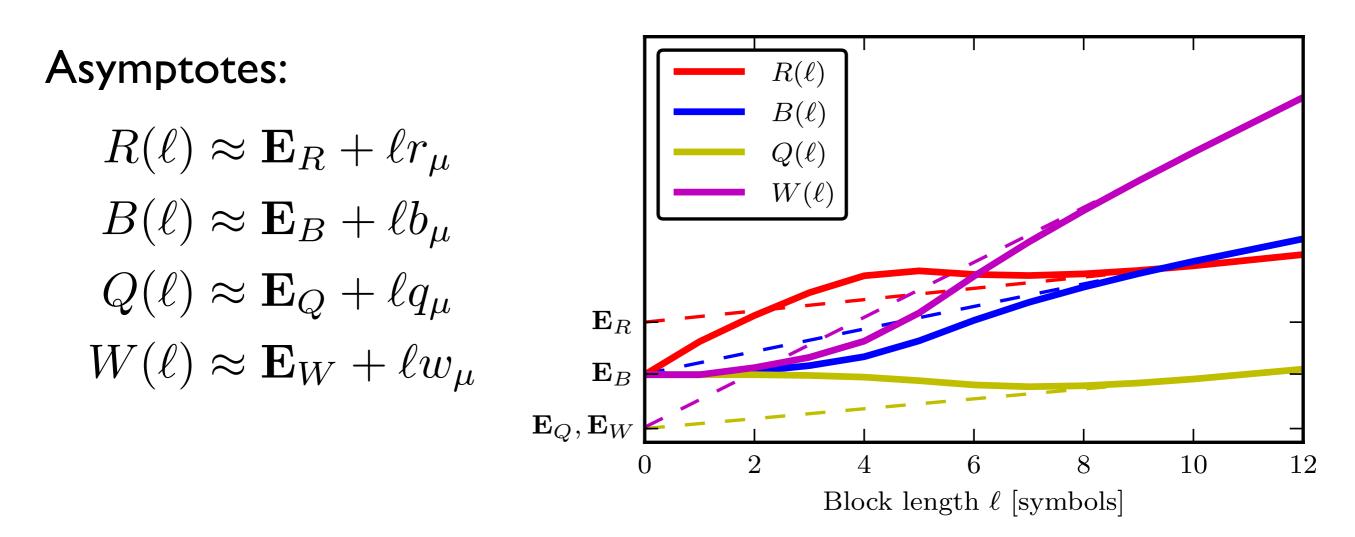
$$H(\ell) + T(\ell) = \ell H(1)$$

Plug in asymptotes gives first decomposition:



Scaling of other block informations:

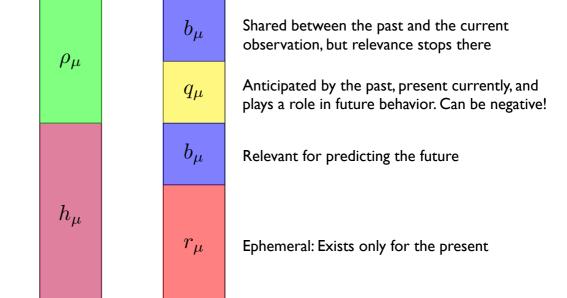
 $\begin{array}{ll} \mbox{Bound information} & B(\ell) = H(\ell) - R(\ell) \\ \mbox{Enigmatic} & Q(\ell) = T(\ell) - B(\ell) \\ \mbox{Local Exogenous} & W(\ell) = B(\ell) + T(\ell) \end{array}$ 



# Scaling of other block informations: Block entropy:

$$\begin{split} H(\ell) &= B(\ell) + R(\ell) \\ &= (\mathbf{E}_B + \mathbf{E}_R) + \ell(b_\mu + r_\mu) \\ \text{Thus, } h_\mu &= b_\mu + r_\mu \text{ and } \mathbf{E} = \mathbf{E}_B + \mathbf{E}_R. \\ \text{Block total correlation:} \\ T(\ell) &= B(\ell) + Q(\ell) \\ &= (\mathbf{E}_B + \mathbf{E}_Q) + \ell(b_\mu + q_\mu) \\ \text{Thus, } \rho_\mu &= b_\mu + q_\mu \text{ and } \mathbf{E} = -\mathbf{E}_B - \mathbf{E}_Q. \end{split}$$

Gives second decomposition of H[X].



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H[X]

Scaling of other block informations: Block local exogenous:

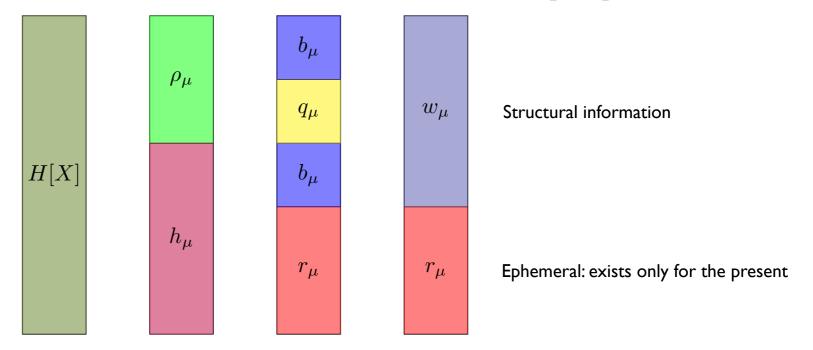
$$W(\ell) = B(\ell) + T(\ell)$$
  
=  $(\mathbf{E}_B - \mathbf{E}) + \ell(b_\mu + \rho_\mu)$   
Thus,  $w_\mu = b_\mu + \rho_\mu$ .

From definitions:

$$R(\ell) + W(\ell) = \ell H(1)$$

 $H(1) = w_{\mu} + r_{\mu}$ 

Plug in asymptotes gives third decomposition of H[X]:



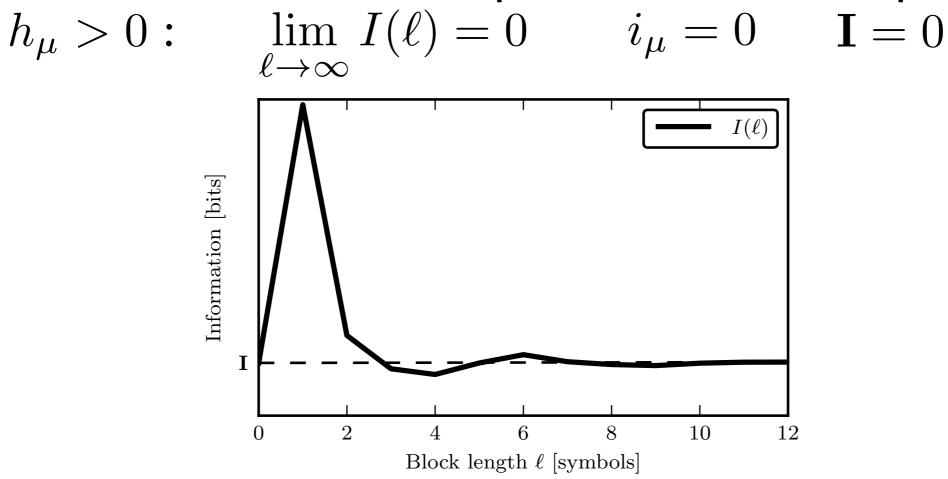
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Block multivariate mutual information:

$$I(\ell) = H(\ell) - \sum_{\substack{A \in P(\ell) \\ 0 < |A| < \ell}} I[X_A | X_{\overline{A}}]$$

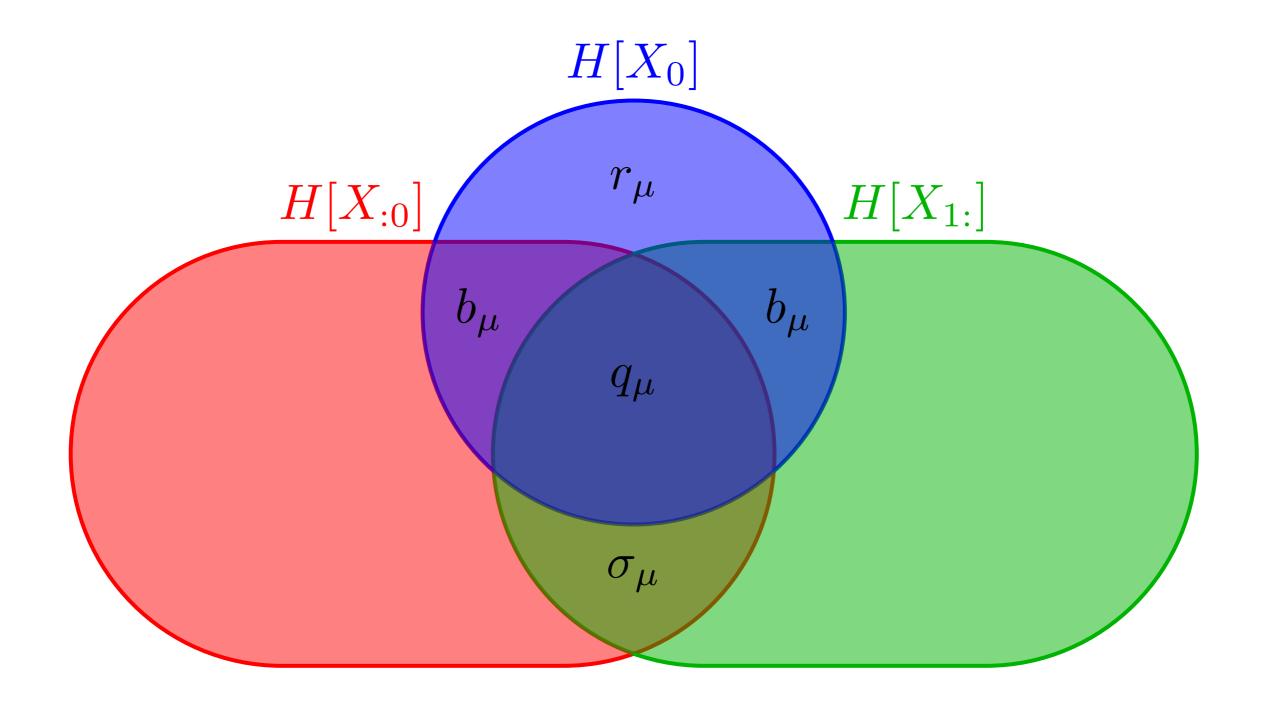
Asymptote:  $I(\ell) \approx \mathbf{I} + \ell i_{\mu}$ ?

Observations of finite-state process tend to independence:

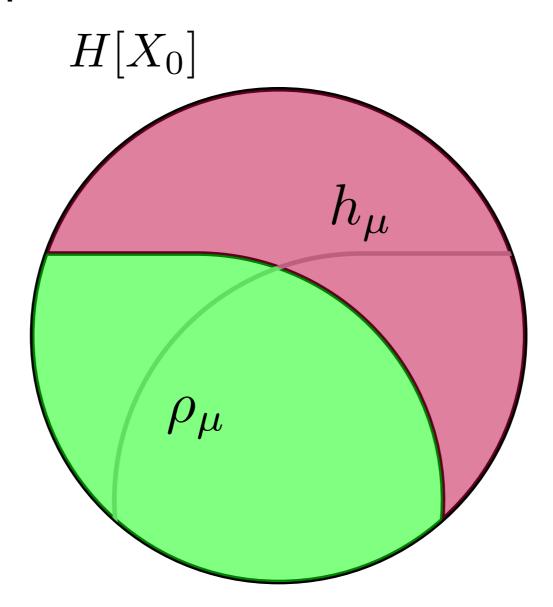


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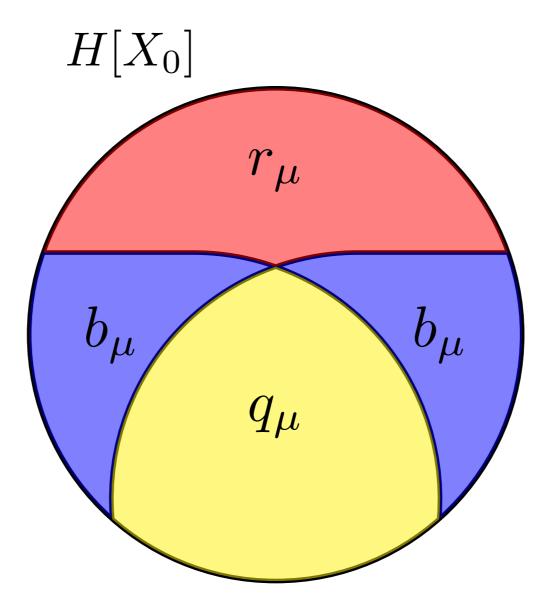
## Measurement Decomposition in the Process I-diagram:



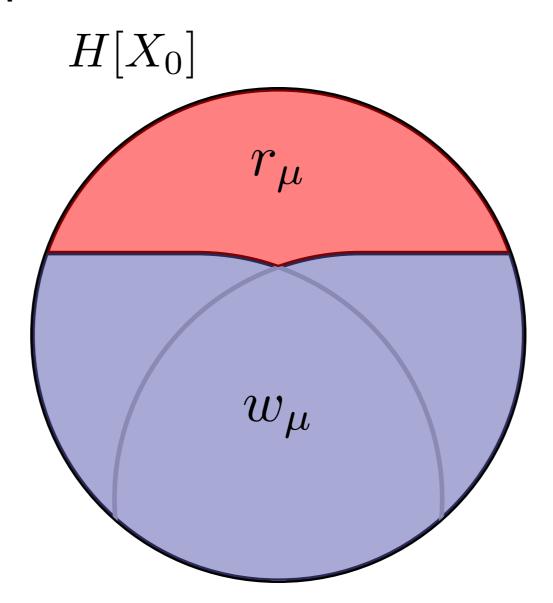
Predictive decomposition:



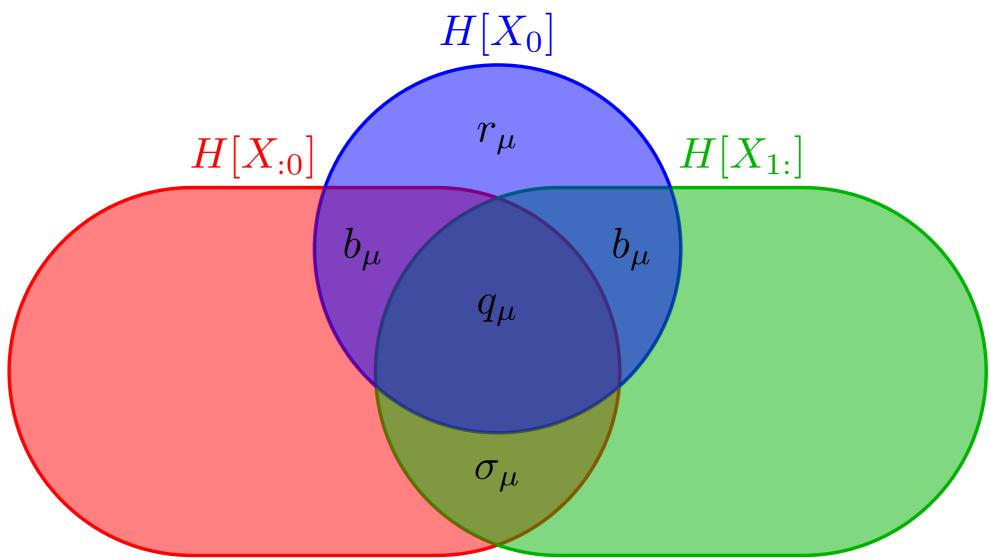
Atomic decomposition:



Structural decomposition:



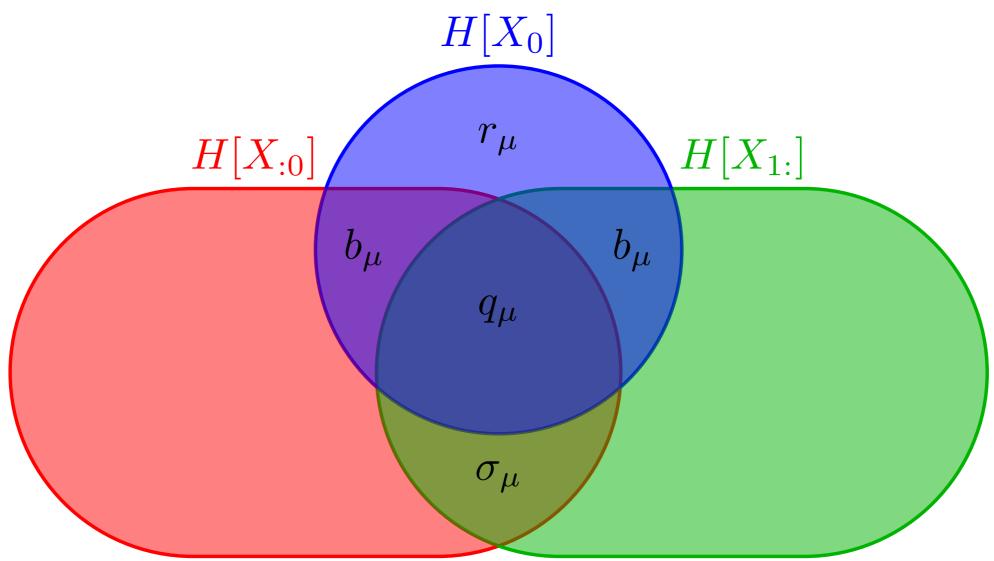
Measurement Decomposition in the Process I-diagram ...



What is  $\sigma_{\mu}$ ?

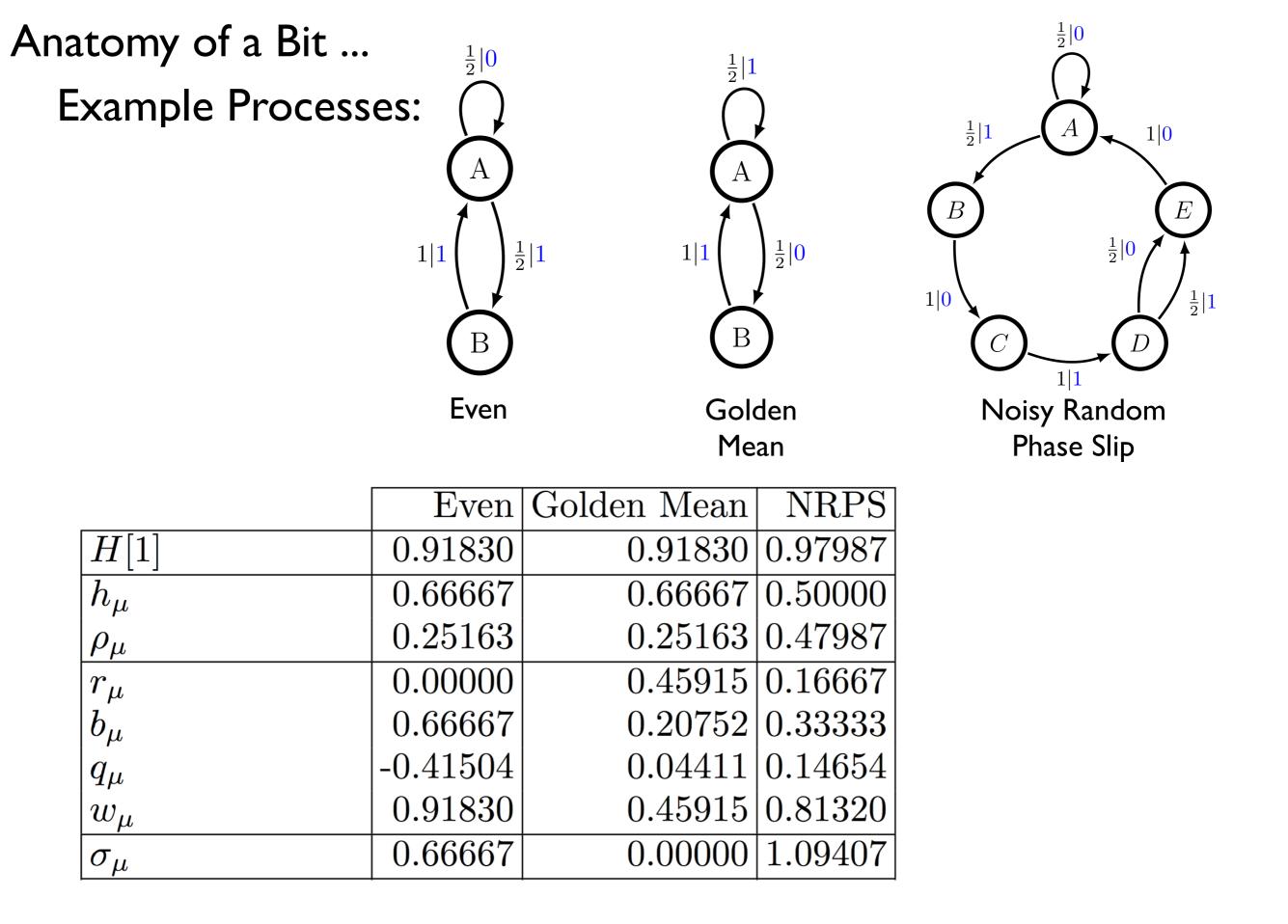
Not a component of the information in a single observation. Information shared between past and future, not in present! Hidden state information!

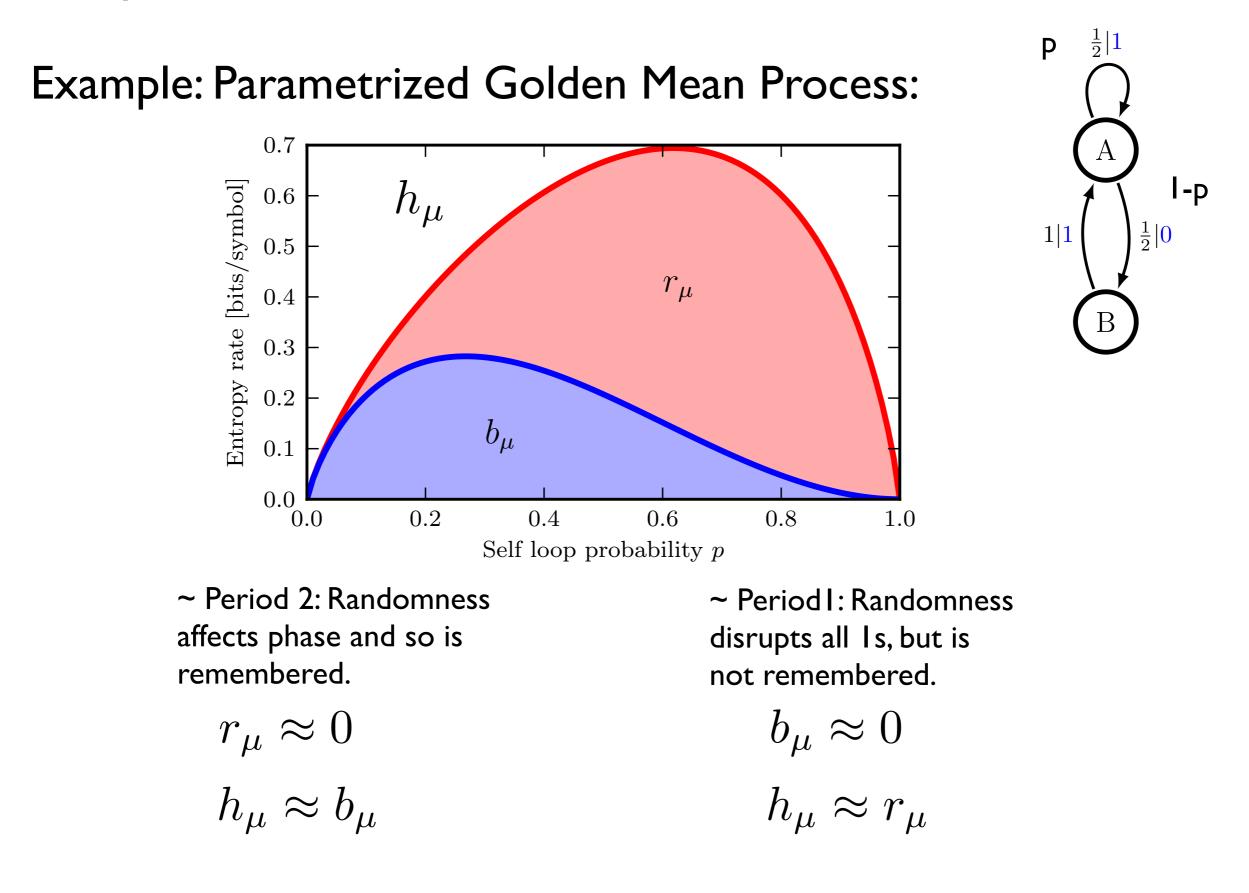
Measurement Decomposition in the Process I-diagram:



**Decomposition of Excess Entropy:** 

$$\mathbf{E} = b_{\mu} + q_{\mu} + \sigma_{\mu}$$

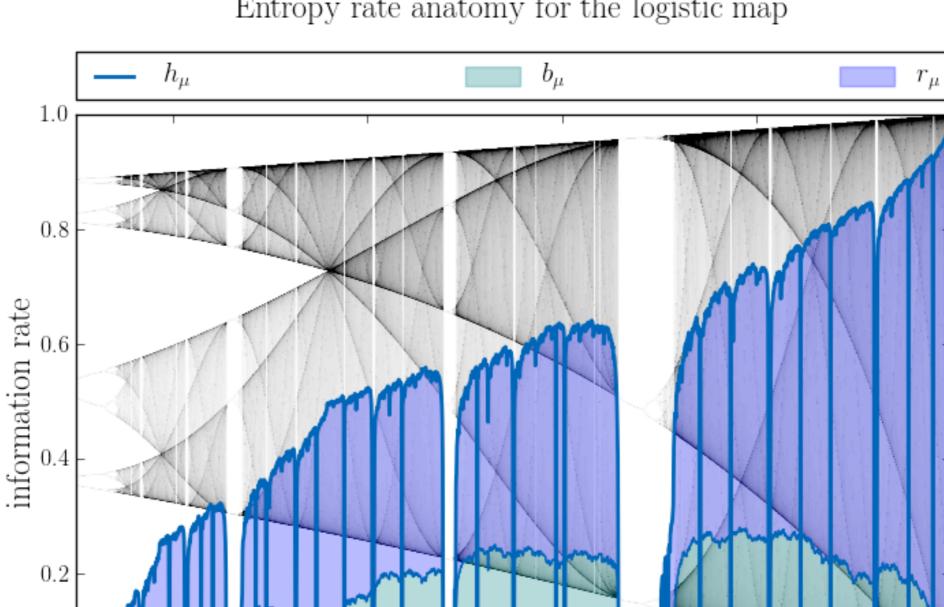




 $0.0_{-3.55}^{-0.0}$ 

3.6

# Entropy-rate Decomposition: Logistic Map



3.8

control parameter r

3.9

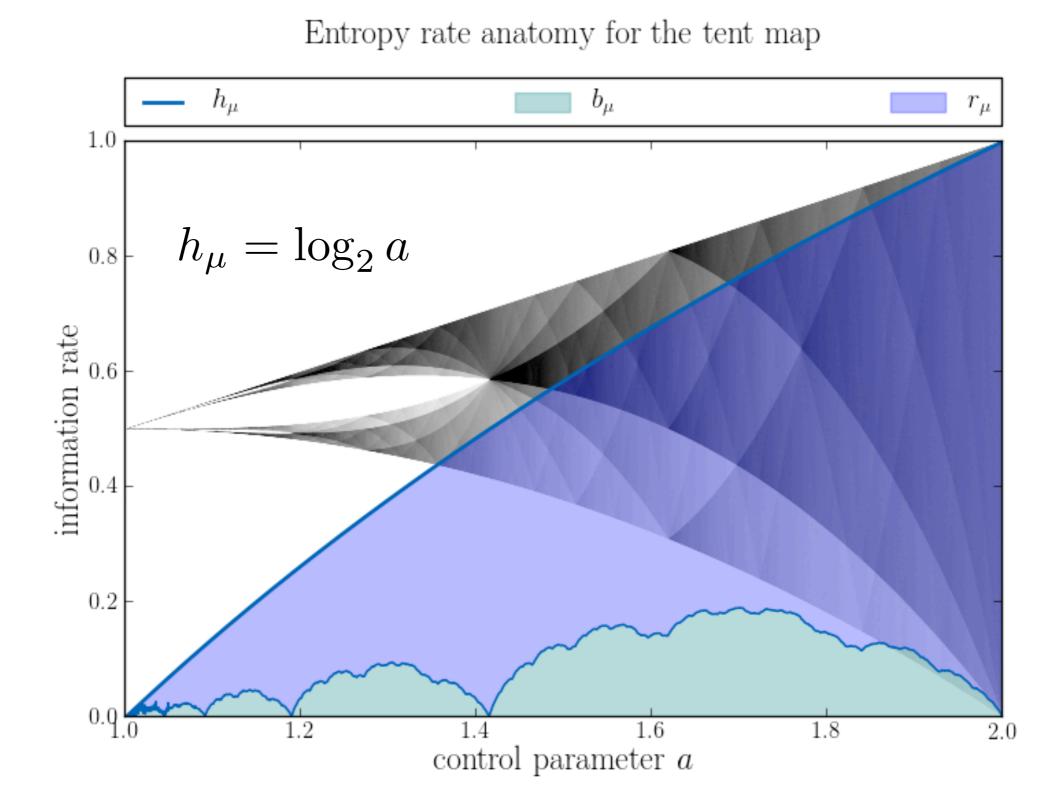
4.0

Entropy rate anatomy for the logistic map

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3.7

## Entropy-rate decomposition: Tent Map



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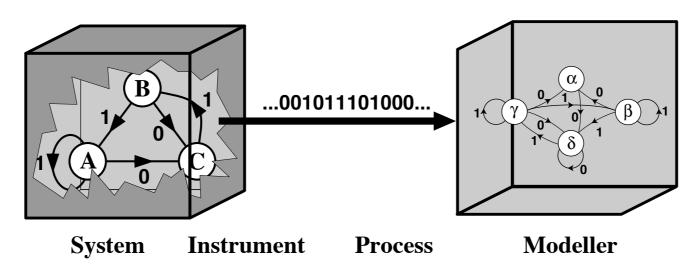
...

What is information?

Depends on the question!

Uncertainty, surprise, randomness, ....H(X) $h_{\mu}$ Compressibility. $\mathcal{R} = \log_2 |\mathcal{A}| - h_{\mu}$ Transmission rate.I[X;Y]"Memory", apparent stored information, .... ESynchronization.TEphemeral. $r_{\mu}$ Bound. $b_{\mu}$ 

Analysis Pipeline:



- I.An information source: Calculate or estimate  $Pr(s^L)$ 
  - a. Dynamical System:
    - deterministic or stochastic
    - low-dimensional or high-dimensional (spatial?)
  - b. Design instrument (partition)
- 2 . Information-theoretic analysis:
  a. How much information produced?
  b. How much stored information?
  c. How does observer synchronize?

 $H(L) \ h_{\mu} \ \mathbf{E} \ \mathbf{T}$ 

Course summary:

# Dynamical systems as sources of complexity:

- I. Chaotic attractors (State)
- 2. Basins of attraction (Initial conditions)
- 3. Bifurcation sequences (Parameters)
- Dynamical systems as information processors:
  - I. Randomness:

Entropy hierarchy: block entropy, entropy convergence, rate, ...

- 2. Information storage:
  - I. Total predictability
  - 2. Excess entropy
  - 3. Transient information

Preview of 256B: Physics of Computation

Answers a number of questions 256A posed:

What is a model?

What are the hidden states and equations of motion? Are these always subjective, depending on the observer? Or is there a principled way to model processes? To discover states?

What are cause and effect?

To what can we apply these ideas? How much can we calculate analytically? How much numerically? How much from data?

Preview of 256B: Physics of Computation

Punch line:

How nature is organized

is

How nature computes

Reading for next lecture:

CMR articles RURO (Introduction), CAO, and ROIC.

... next quarter!