Local Complexity for Heterogeneous Spatial Systems

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Motivation

- What is structure/pattern/complexity?
- How can it be discovered and measured?
- How are information and memory shared across ^a spatial configuration?
- Do different sites play different roles?

Outline

- 1. Review of Entropy and Excess Entropy in One Dimension
- 2. Extensions to Two Dimensions
- 3. Extensions to Inhomogeneous Systems
- 4. Results for Spin Glasses

Entropy and Entropy Density

The Shannon Entropy H measures the uncertainty associated with a random variable:

$$
H[S] \equiv \sum_{s} -\Pr(s) \log_2 \Pr(s) . \tag{1}
$$

Consider ^a long, one-dimensional chain of variables:

 $H(L)$ is the entropy of an L -block:

$$
H(L) \equiv H\left[\begin{array}{|c|c|}\n\hline\n- L & \rightarrow \\
\hline\n\end{array}\right].\tag{2}
$$

Entropy density definition:

$$
h_{\mu} \equiv \lim_{L \to \infty} \frac{H\left[\begin{array}{|c|c|}\n\hline\nL & \rightarrow \\
\hline\nL & \rightarrow\n\end{array}\right]}{L} \qquad (3)
$$

Entropy Density

 h_{μ} may also be written as a conditional entropy:

$$
h_{\mu}(L) = H(L) - H(L-1)
$$
 (4)

$$
= \Delta H(L) \tag{5}
$$

$$
= H[\boxtimes | \boxtimes \text{array} \ . \tag{6}
$$

$$
h_{\mu} = \lim_{L \to \infty} h_{\mu}(L) \tag{7}
$$

- \bullet h_{μ} is known as: \bullet ntropy rate, metric \bullet ntropy, and \bullet ntropy density.
- $\bullet~~h_{\mu}$ is the irreducible randomness: the randomness that persists even after statistics over arbitrarily long sequences are taken into account

- $\bullet\,$ For finite L , $\Delta H(L) \geq h_{\mu}.$ Thus, the system appears more random than it is.
- We can learn about the complexity of the system by looking at *how* the entropy density converges to $h_\mu.$
- The **excess entropy** captures the nature of the convergence and is defined as the area between the two curves above:

$$
\mathbf{E} \, \equiv \, \sum_{L=1}^{\infty} [\Delta H(L) - h_{\mu}] \; .
$$

Excess Entropy

- $\bullet\, \to \to$ is thus the total amount of randomness that is "explained away" by considering larger blocks of variables.
- $\bullet\,$ One can also show that ${\bf E}$ is equal to the mutual information between the "past" and the "future":

$$
\mathbf{E} = I(\overleftarrow{S}; \overrightarrow{S}) \equiv H[\overleftarrow{S}] - H[\overleftarrow{S} | \overrightarrow{S}].
$$

- $\bullet\, \to\, \mathbf{E}$ is thus the amount one half "remembers" about the other, the reduction in uncertainty about the future given knowledge of the past.
- $\bullet\,$ Equivalently, ${\bf E}$ is the "cost of amnesia:" how much more random the future appears if all historical information is suddenly lost.
- The Excess Entropy is also known as the **Predictive Information** and the **Effective Measure Complexity**.

Excess Entropy and Entropy Rate Summary

- $\bullet\,$ Excess entropy ${\bf E}$ is a measure of complexity (order, pattern, regularity, correlation, structure ...)
- $\bullet\, \, {\bf E}$ detects periodic order of any periodicity ${\bf E} = \log_2(\text{Period}).$
- $\bullet\,$ Entropy rate h_μ is a measure of unpredictability.
- $\bullet\,$ Both ${\bf E}$ and h_μ are well understood and have clear interpretations.
- $\bullet\,$ Both ${\bf E}$ and h_μ are functions of the distribution over sequences.
- $\bullet\,$ Both ${\bf E}$ and h_μ have been calculated for a wide range of systems.
- $\bullet\,$ There are multiple forms for ${\bf E},$ all of which are the same in one dimension.

For more, see, e.g.,

- •Crutchfield and Feldman, Chaos. **¹⁵**:23. 2003.
- D.P. Feldman, C.S. McTague, and J.P. Crutchfield. Chaos. 18:043106.

Entropy in Two Dimensions

Consider ^a big, two-dimensional lattice of variables:

 $H(M, N)$ is entropy of M, N -block:

.

Two-Dimensional Entropy Convergence

Is it possible to express the entropy density as the entropy of ^a single spin, conditioned on an appropriate semi-infinite block? **Yes.**

$$
h_{\mu}(M) \equiv H \left[\begin{array}{c} 2M+1 \longrightarrow \\ \boxed{\bigcup_{\mu} \boxed
$$

Two-Dimensional Excess Entropy

• We can then define the excess entropy:

$$
\mathbf{E}_c \equiv \sum_{M}^{\infty} \left(h_{\mu}(M) - h_{\mu} \right) \,. \tag{12}
$$

- $\bullet\,$ Note: One can also define a form $\mathbf E_i$ for the two-dimensional excess entropy based on the mutual information.
- $\bullet\ \mathbf{E}_i\neq \mathbf{E}_c$, but the two behave similarly.
- $\bullet\,$ As in 1D, ${\bf E}$ distinguishes among periodic patterns of all periods.
- For more on 2D Excess Entropy, see D.P. Feldman and J.P. Crutchfield, *Phys.* Rev. E. **67**:051104. 2003.

Regular Ising Model (Not ^a Spin Glass)

 $\bullet\,$ Spins $s_i\in\{-1,+1\}$ interact with their nearest neighbors.

Energy of state
$$
= -J \sum_{\langle ij \rangle} s_i s_j
$$
, (13)

where the sum runs over nearest neighbors. Then,

Probability of state
$$
i \propto e^{-E_i/T}
$$
 (14)

where $T=$ temperature.

- $\bullet\,$ As the temperature is lowered, the system orders. The magnetization m acquires ^a non-zero expectation value.
- •The magnetization is defined by

$$
m \, = \, \big\langle \sum_i s_i \big\rangle
$$

where the angular brackets indicate averaging over states using Eq. (14).

- • Below the critical temperature, the symmetry is broken – up and down are no longer equally likely.
- • $\bullet\,$ Below T_c the system's ergodicity is broken. It no longer can get to any state from any other state in finite time.

2D Ising Model Phase Transition

- • $\bullet\,$ Convergence form of the excess entropy ${\bf E}_{\rm c}$ vs. entropy density h_μ versus temperature T for the two-dimensional Ising model with NN couplings and no external field.
- • $\bullet \,$ Model undergoes phase transition as T is varied at $T \approx 2.269.$
- •There is ^a peak in the excess entropy near the transition temperature.
- •Results via Monte Carlo simulation of ¹⁰⁰x¹⁰⁰ lattice.

• Typical configurations for the 2D Ising model below, at, and above the critical temperature.

Spin Glasses

- Spin glasses are usually disordered and frustrated. First, disorder:
- $\bullet\,$ Spins $s_i\in\{-1,+1\}$ interact with their nearest neighbors. But this time, the interaction is random

Energy of state
$$
= -\sum_{\langle ij \rangle} J_{ij} s_i s_j
$$
, (15)

where the sum runs over nearest neighbors, and J_{ij} is a random variable. Usually, $J_{ij} = +1$ with probability $1/2.$

- Spin glasses are used to model ^a wide range of situations in which entities interact through random interactions and/or which exhibit frustration.
- What happens as the system is cooled? The ground state is disordered the interactions, on average, make the spins neither align nor anti-align.

Typical ground state of spin glass.

- \bullet $\bullet\,$ The magnetization m is zero for all temperatures.
- $\bullet\,$ However, the local magnetizations $m_i = \langle s_i \rangle_t$ are non-zero
- \bullet Some spins get frozen mostly up or down.

Features of spin glasses

- Multiple ground states, not related by simple symmetry operation.
- Loss of ergodicity. Ergodic components aren't related by any simple symmetry.
- Low temperature state is "frozen" and "disordered."
- **Local averages are not the same as global averages.**
- $\bullet\,$ The degree to which the local averages differ is often used to quantify **the degree of glassiness:**

Frustration

- Suppose all interactions are anti-ferromagnetic: all spins want to anti-align.
- **Frustration:** All energetic constraints can't be satisfied at the same time.
- Note that the triangular lattice naturally decomposes into three sublattices.
- **How might we relieve frustration?**

Dilution: The Kaya-Berker Model

- Dilute the system by deleting spins on one of the sublattices.
- •This relieves frustration.
- If the dilution is sufficiently large, the two non-diluted sublattices order, and the diluted sublattice undergoes ^a spin-glass transition.
- •Kaya and Berker, PRE, **⁶²**, R1469. (2000).
- This is an example of **order by disorder**: adding disorder in the form of random deletions causes the system to order.

0.5 1 1.5 2 2.5 3

Temperature T

• There is ^a net magnetization on lattices ^B and C.

-1-0.8

- •For this and all results that follow, sublattice A is $15%$ diluted.
- Monte Carlo results, 99×99 lattice.

Local or Global Entropies?

- $\bullet\,$ As with the magnetization, when calculating h_μ and ${\bf E}$ we can do the averaging in two ways.
	- 1. Average over all blocks at all locations.
	- 2. Average over ^a single block pinned at ^a particular site.
- Method ² gives one ^a local entropy: ^a measure of the unpredictability at ^a particular site.
- The local entropies are not the same as the global entropy density in the glassy state.
- •Robinson, Feldman, McKay. Chaos. **²³**(3):037114. 2011.

- •Information is not shared equally across the lattice.
- •The average of the local entropies equals the global, thermodynamic entropy.
- The global entropy can be calculated information theoretically or by integrating the thermodynamic relation $ds = (c/T)dT.$
- • Note that on some sites the local entropy increases as temperature is lowered.

Local Excess Entropies

- Memory is not shared equally across the lattice.
- $\bullet\,$ Note the sharp drop at $T\approx 0.8$. This coincides with the critical temperature, measured by other means.
- \bullet **^E** is ^a general-purpose order parameter.

Summary

- Excess entropy and entropy rate are well understood measures of structure and unpredictability in 1D.
- •Excess entropy can be extended to 2D, although the extension is not unique.
- Entropy of ^a disordered lattice system can be decomposed into local contributions to see how entropy is distributed across the lattice.
- ^A local excess entropy can similarly be calculated. It shows how memory or structure is distributed across the lattice.
- Different sites play different roles.
- Average excess entropy is highly sensitive to structural changes in the configurations.

Frontiers: Promising Areas for Future Work

- Local information and complexity measures for distributed systems.
- Networks: dynamics on networks and the structure of the networks themselves.
- Empirical work, "big data."
- •Closer ties to thermodynamics
- •Closer ties to statistics and statistical inference

The End

• Thanks for your attention and questions.