

Spatiotemporal Computational Mechanics

Paul Riechers

Outline

- How do Information-theoretic and CompMech-theoretic quantities generalize in spatially extended systems?
 - An overview of the strictly-spatial case
- How spatial Information evolves in time
 - Towards a Computational Mechanics for information processing
- The big picture: How space and time are intricately connected, spacetime probability densities, and playing outside of your light-cone.

Rethinking the Basics for Spatially Extended Systems:

Block Entropies

$$H(L) = H(P(s^L)) = - \sum_{s^L \in A} P(s^L) \log_2 P(s^L)$$

- What does this mean?
 - What is the appropriate L for a system?
 - What is s^L
 - What is the alphabet?
 - How are the probabilities calculated?

Rethinking the Basics for Spatially Extended Systems:

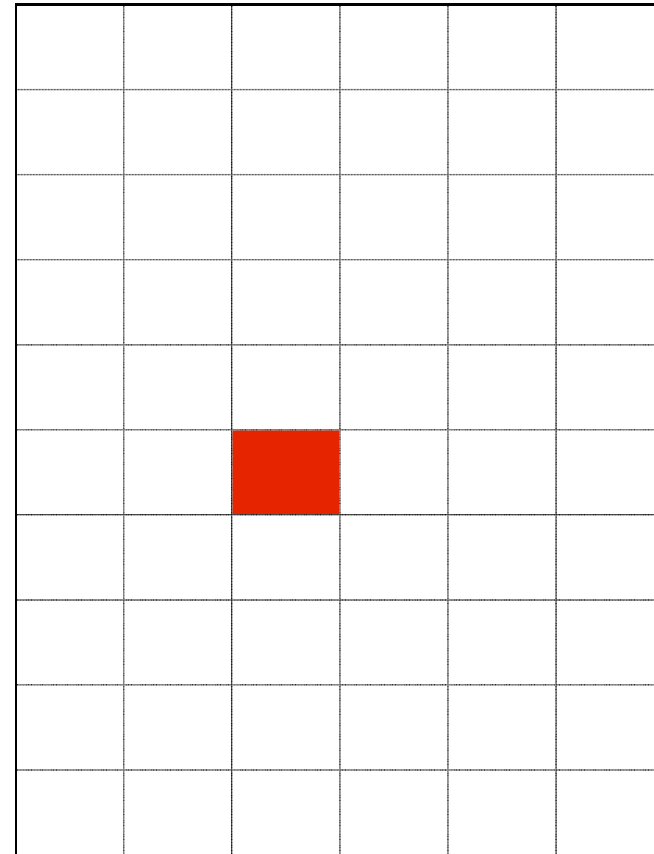
Block Entropies

$$H(L) = H(P(s^L)) = - \sum_{s^L \in A} P(s^L) \log_2 P(s^L)$$

- In 1D... options
 - Consider the case of general dimensions (or at least 2D...)
 - What we should do for the 1D case will follow out as a special case

Rethinking the Basics for Spatially Extended Systems:
Block Entropies: $H(L)$ for $L = 1$

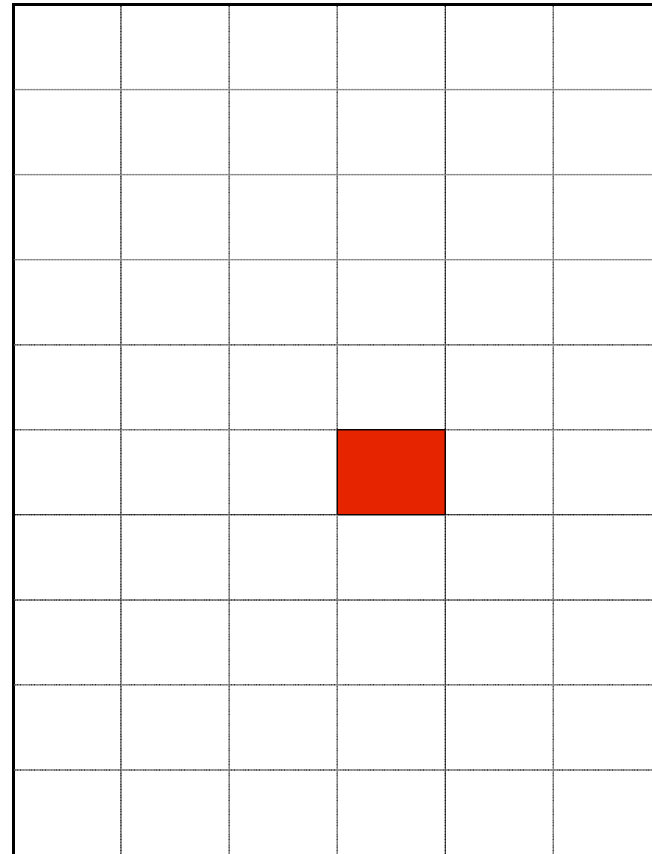
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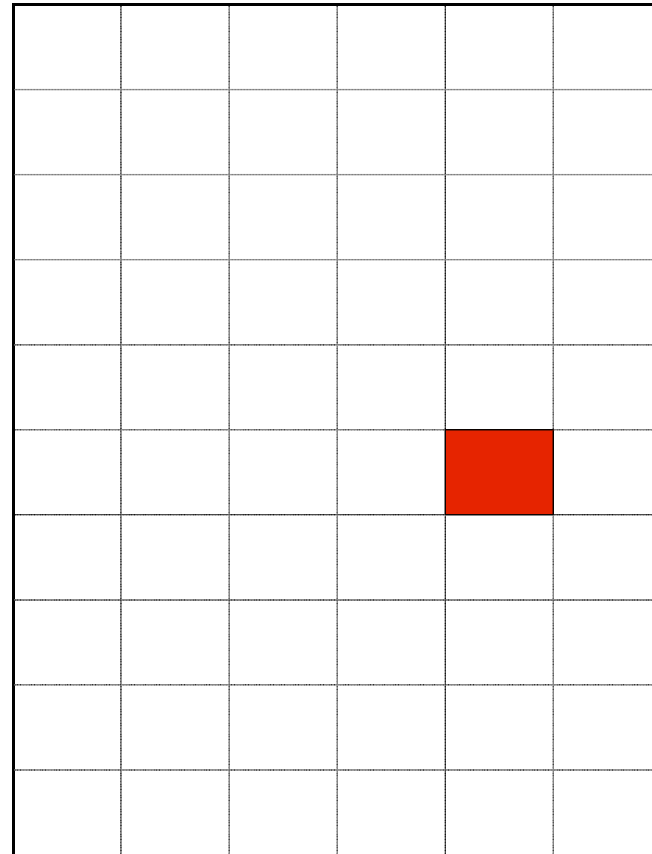
- $L = 1$ considers the value lone cells
- But $P(s)$ is taken from the statistics of the whole array
 - So, scan this template across the whole array to find $P(s)$!



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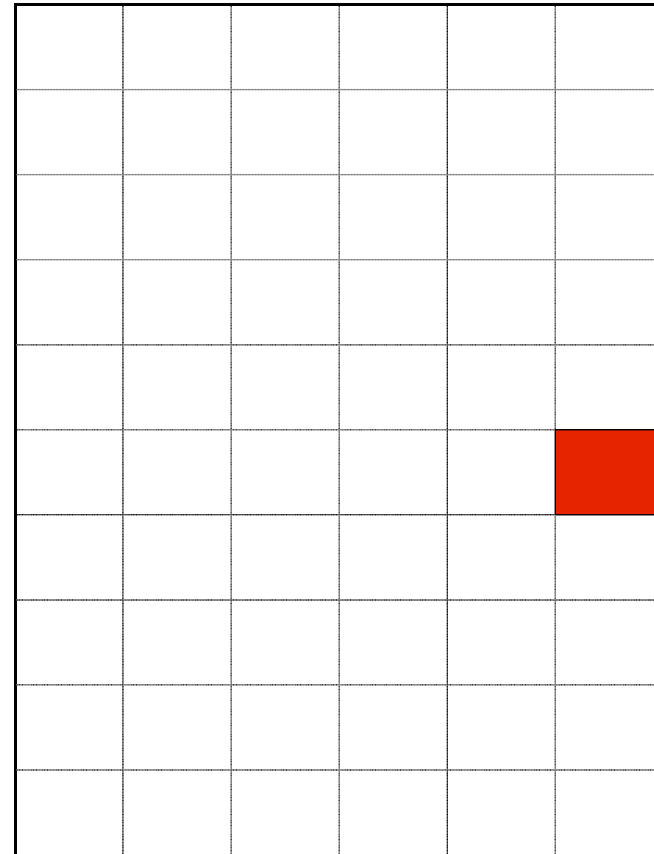
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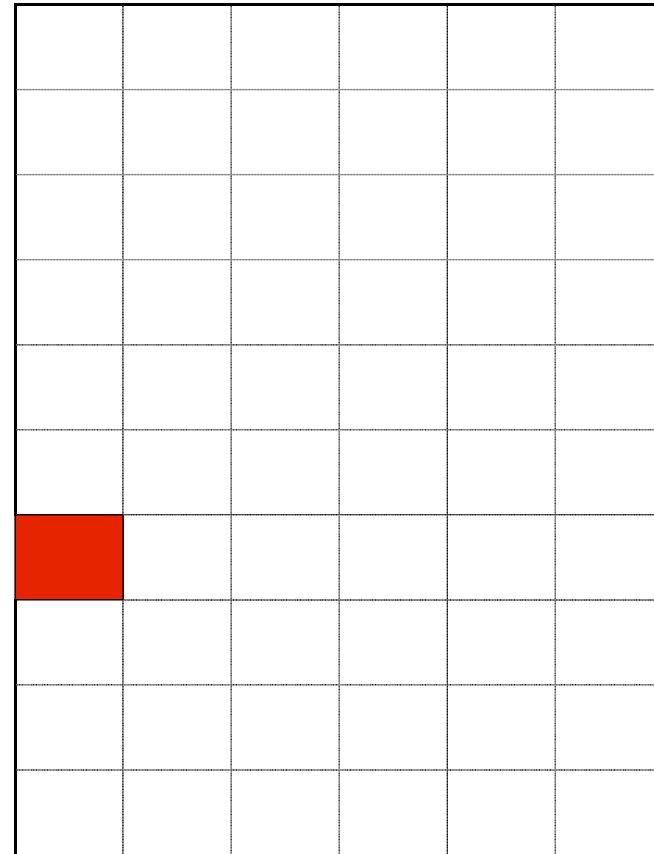
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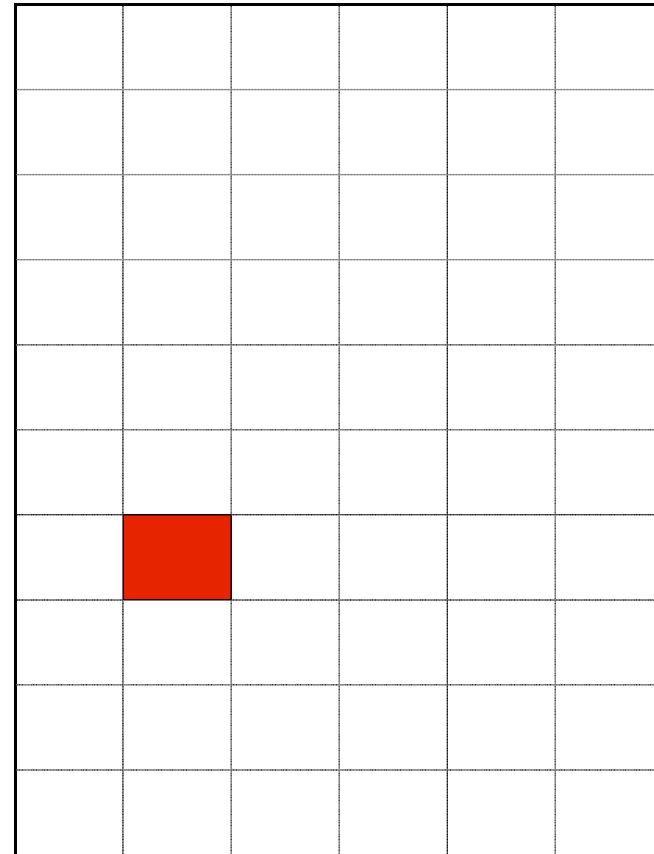
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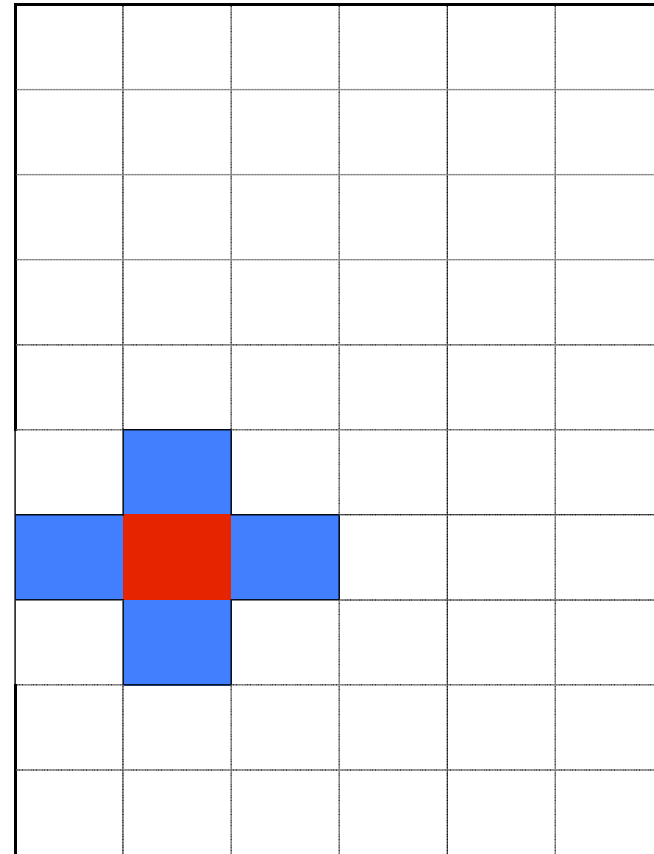
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Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$ for $L = 2$

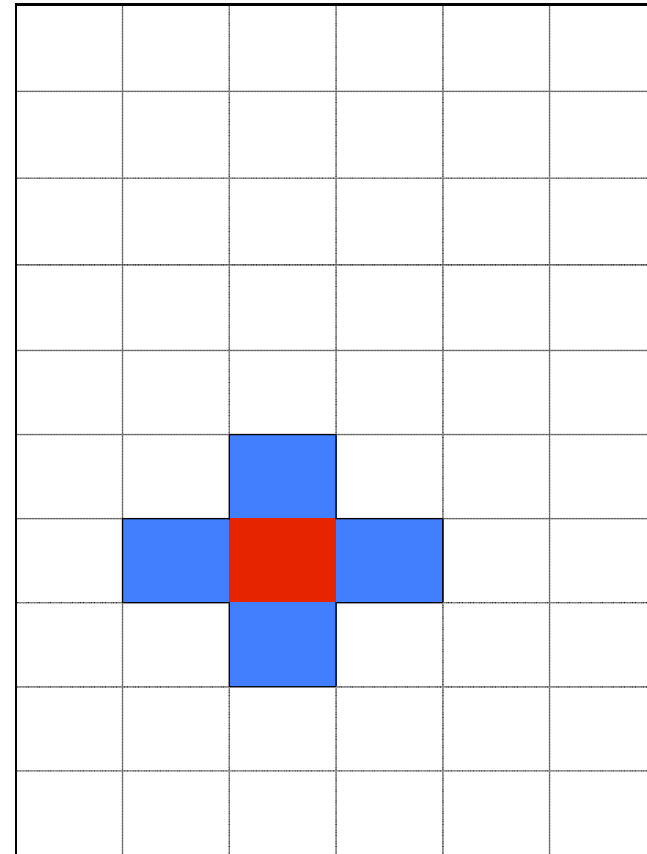
- $L = 2$ template depends on geometry of coupling (assumed or explicit)
- The case shown is for four nearest neighbors



$$H(L) = H(P(s^L)) = - \sum_{s^L \in A} P(s^L) \log_2 P(s^L)$$

Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$ for $L = 2$

- $L = 2$ template depends on geometry of coupling (assumed or explicit)
- But again, $P(s_1 s_2)$ is taken from the statistics of the whole array, so we scan this template across the whole array to find $P(s_1, s_2)$.
- Notice that s_i is no longer binary!



$$s_1 \in \{0,1\} \quad \text{but} \quad s_2 \in \{0,1,2,\dots,2^4 - 1\}$$

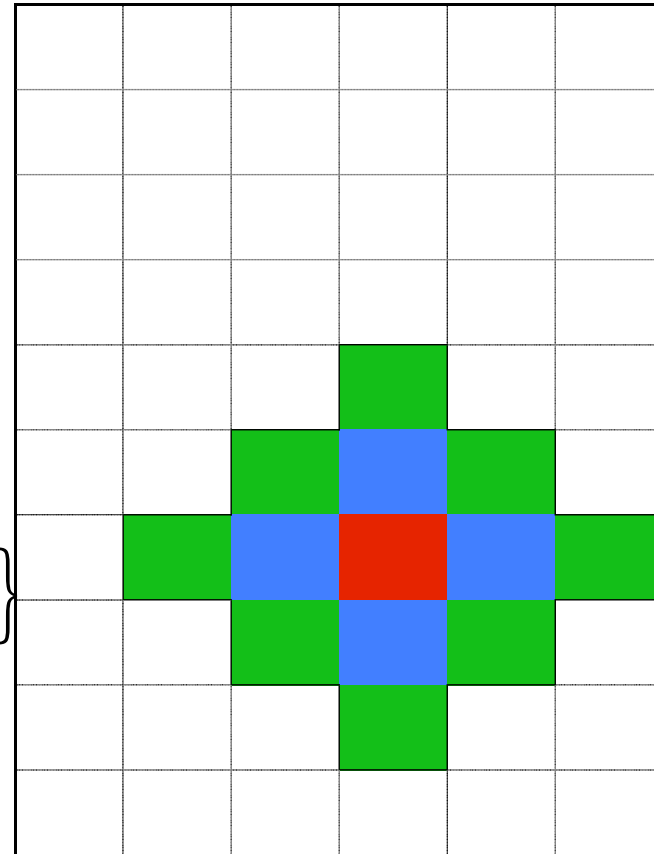
$$H(L) = H(P(s^L)) = - \sum_{s^L \in A} P(s^L) \log_2 P(s^L)$$

Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$ for $L = 3$

- $L = 3$ template expands naturally from previous geometry
- We scan this template across the whole array to find $P(s_1, s_2, s_3)$.
- We have a different alphabet for different L . In general:

$$\text{length}\{A(L_{L^1\text{-coupling}})\} = \prod_{k=0}^{L-1} \left\{ n^{(\delta_{k,0} + 2^D k^{(D-1)})} \right\}$$

for number of intrinsic states per cell, n , and coupling number (number of nearest neighbors), N_c .



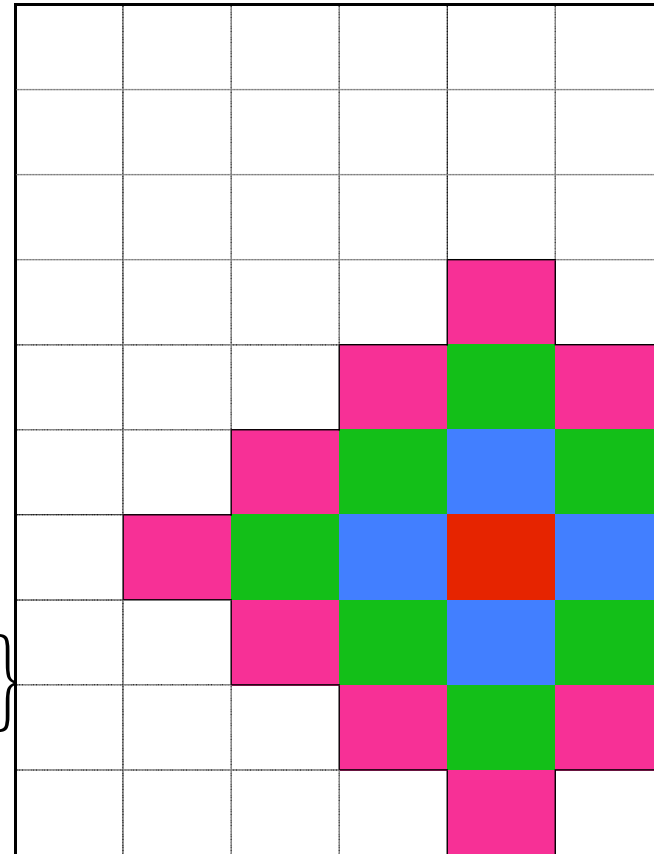
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Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$ for $L = 4$

- $L = 4$ template expands naturally from previous geometry
- We scan this template across the whole array to find $P(s_1, s_2, s_3, s_4)$.
- We have a different alphabet for different L :

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$$H(L) = H(P(s^L)) = - \sum_{s^L \in A} P(s^L) \log_2 P(s^L)$$

Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$ for any L

- We scan every L -template across the whole array to find $P(s^L)$.
- Special considerations for boundary conditions?

$$H(L) = H(P(s^L)) = - \sum_{s^L \in A} P(s^L) \log_2 P(s^L)$$

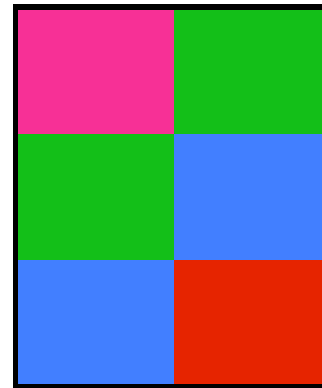
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- Special considerations for boundary conditions?

- $H(L)$ saturates at $L = n+m-1$ for $n \times m$ array



e.g.

3×2 array:

All cells are seen by every other cell at $L = 4$.

$$h_\mu = \lim_{L \rightarrow \infty} \{h_\mu(L)\} = \lim_{L \rightarrow \infty} \{H(L) - H(L-1)\} = \lim_{L \rightarrow \infty} \{H_{saturation} - H_{saturation}\} = 0 \quad ?$$

$$H(L_{saturation}) = E \quad ?$$

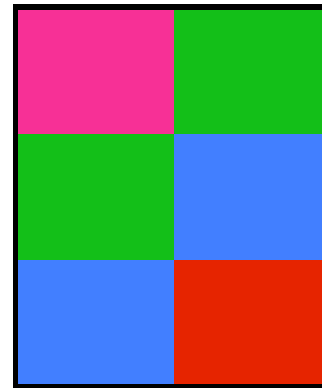
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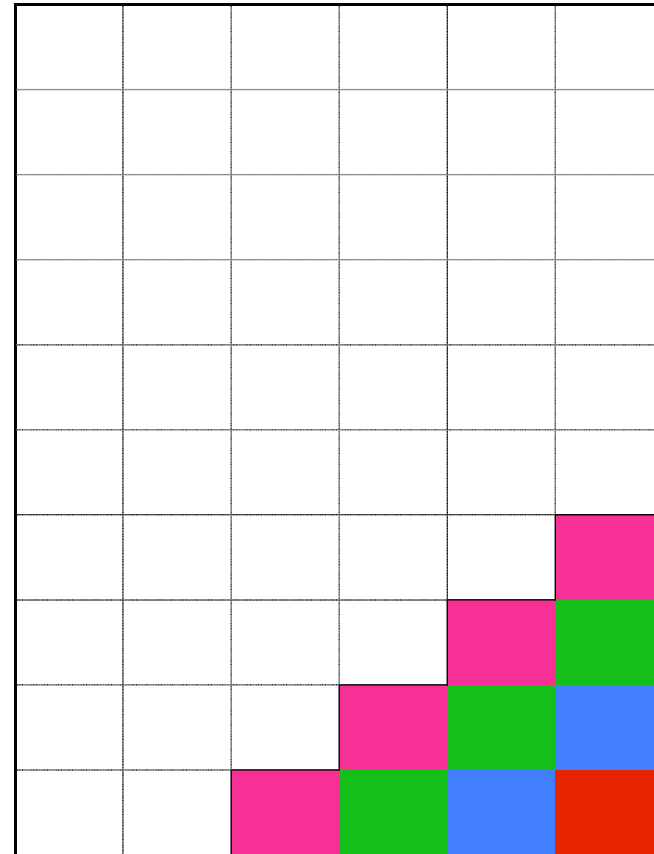
$$h_\mu = \lim_{L \rightarrow \infty} \{h_\mu(L)\} = \lim_{L \rightarrow \infty} \{H(L) - H(L-1)\} = \lim_{L \rightarrow \infty} \{H_{saturation} - H_{saturation}\} = 0 \quad ? \quad H(L_{saturation}) = E \quad ?$$

Instead, define new quantities:

$$h_\mu^{sat} \equiv h_\mu(L_{sat}) = H(L_{sat}) - H(L_{sat} - 1) \quad ? \quad E^{sat} \equiv ?$$

Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$ for any L

- We scan every L -template across the whole array to find $P(s^L)$.
- Special considerations for boundary conditions?
 - $H(L)$ saturates at $L = n+m-1$ for $n \times m$ array
- Just average over possibilities?

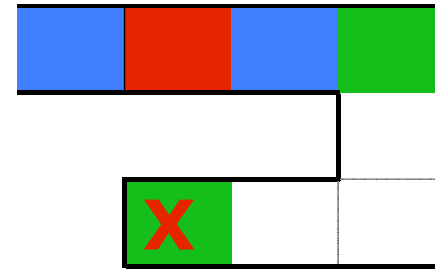


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Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$

- Special considerations for boundary conditions?

- Just average over possibilities? Maybe.
Although care must be given to pathological topologies...

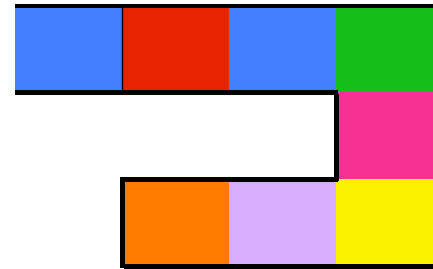


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Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$

- Special considerations for boundary conditions?

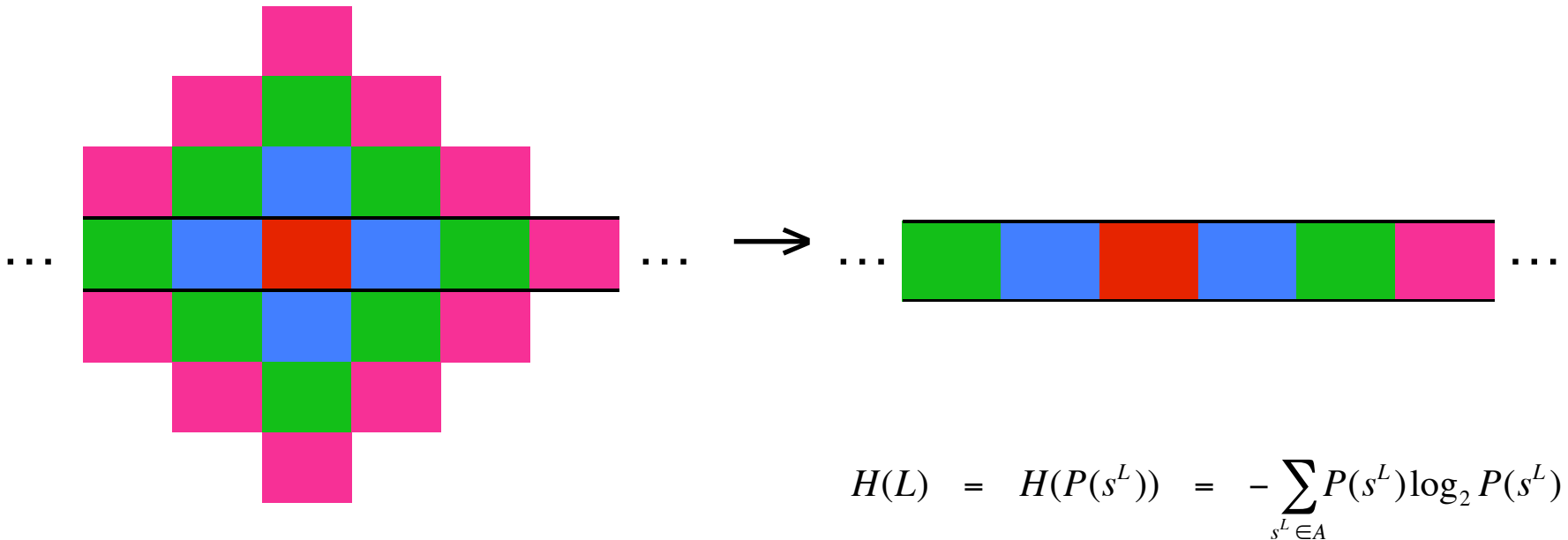
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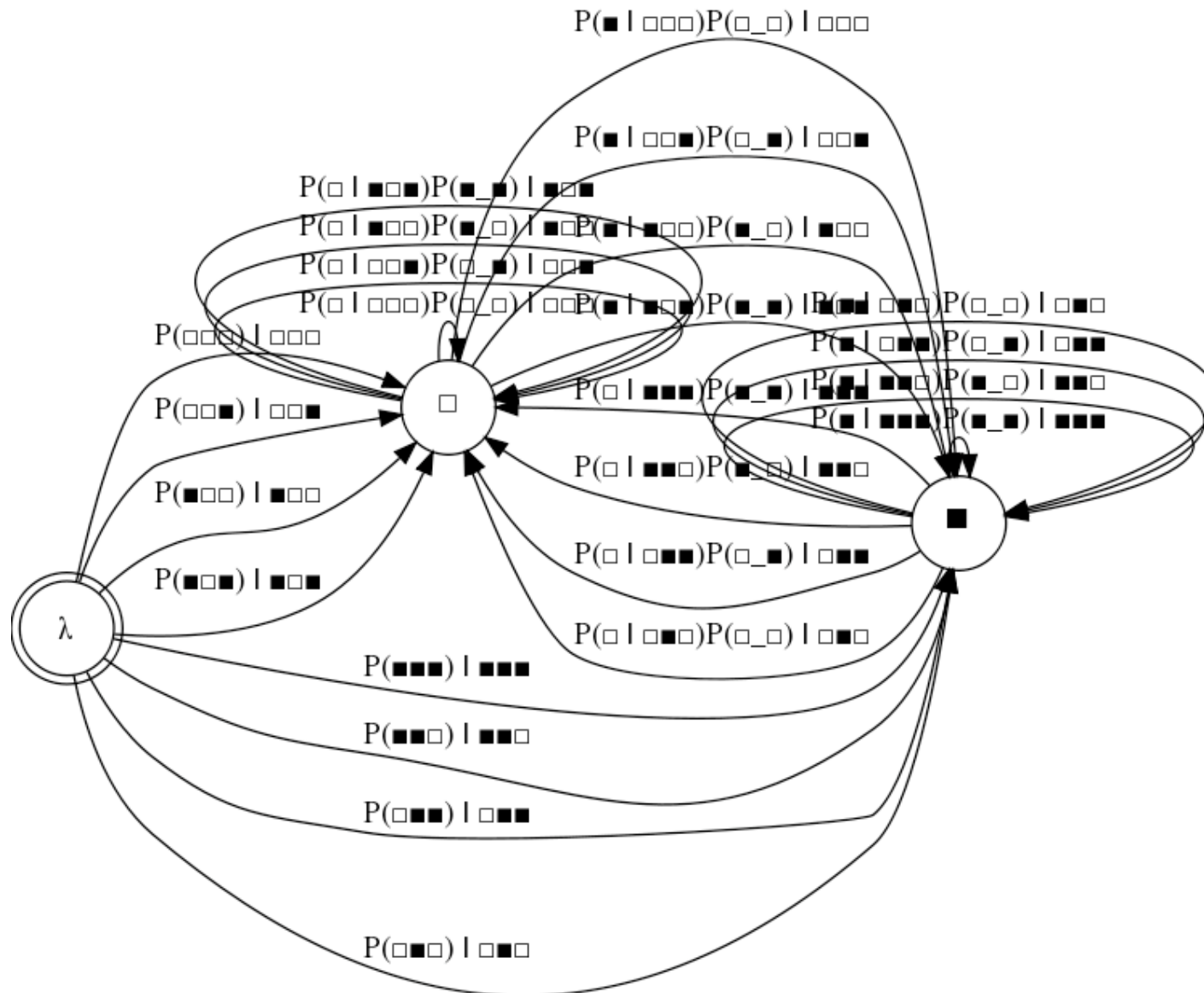
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Rethinking the Basics for Spatially Extended Systems: Block Entropies: $H(L)$ for 1-D

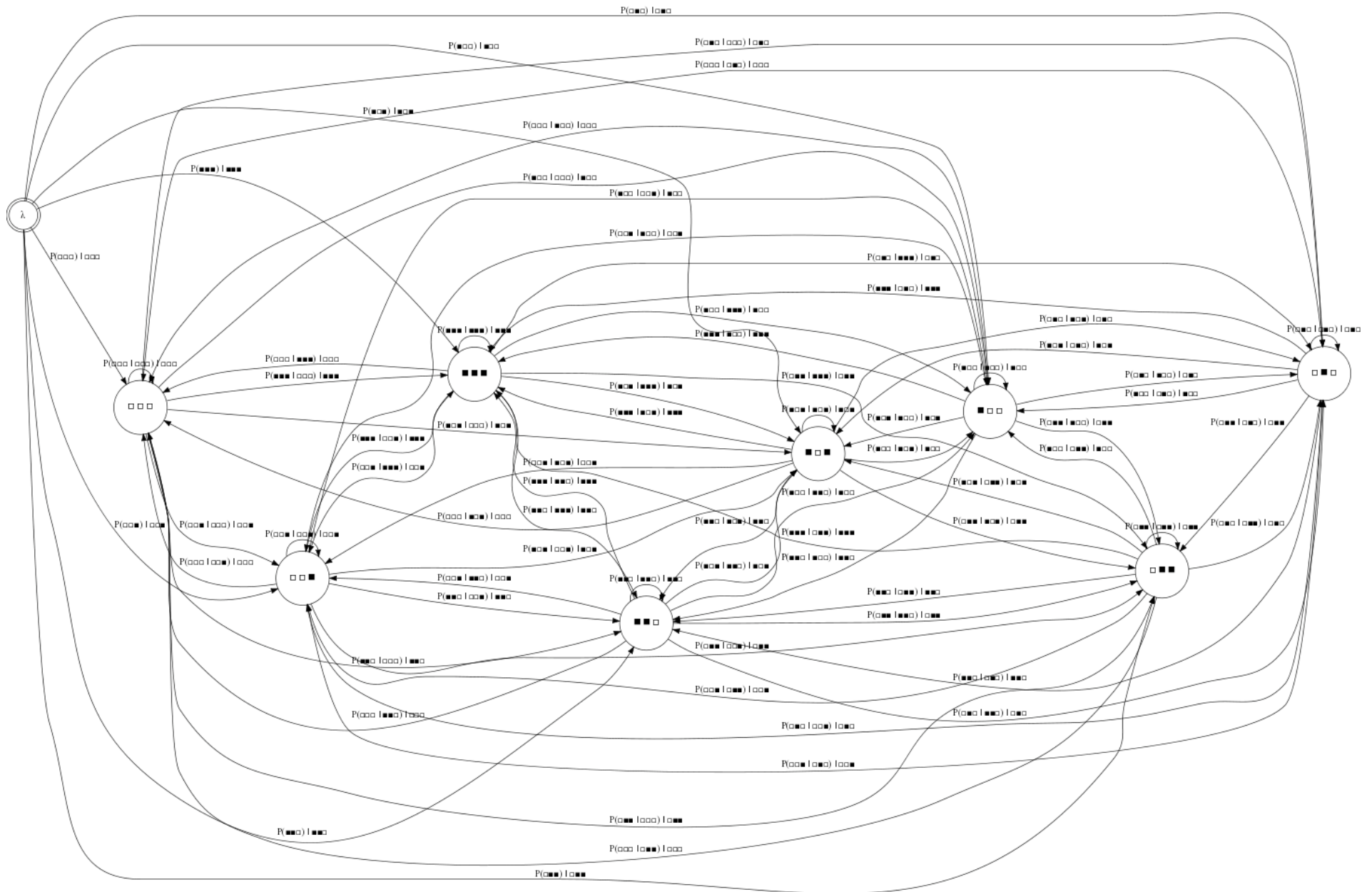
- 1-Dimension as boundary condition
- We scan the natural L -templates across the whole linear array to find $P(s^L)$.



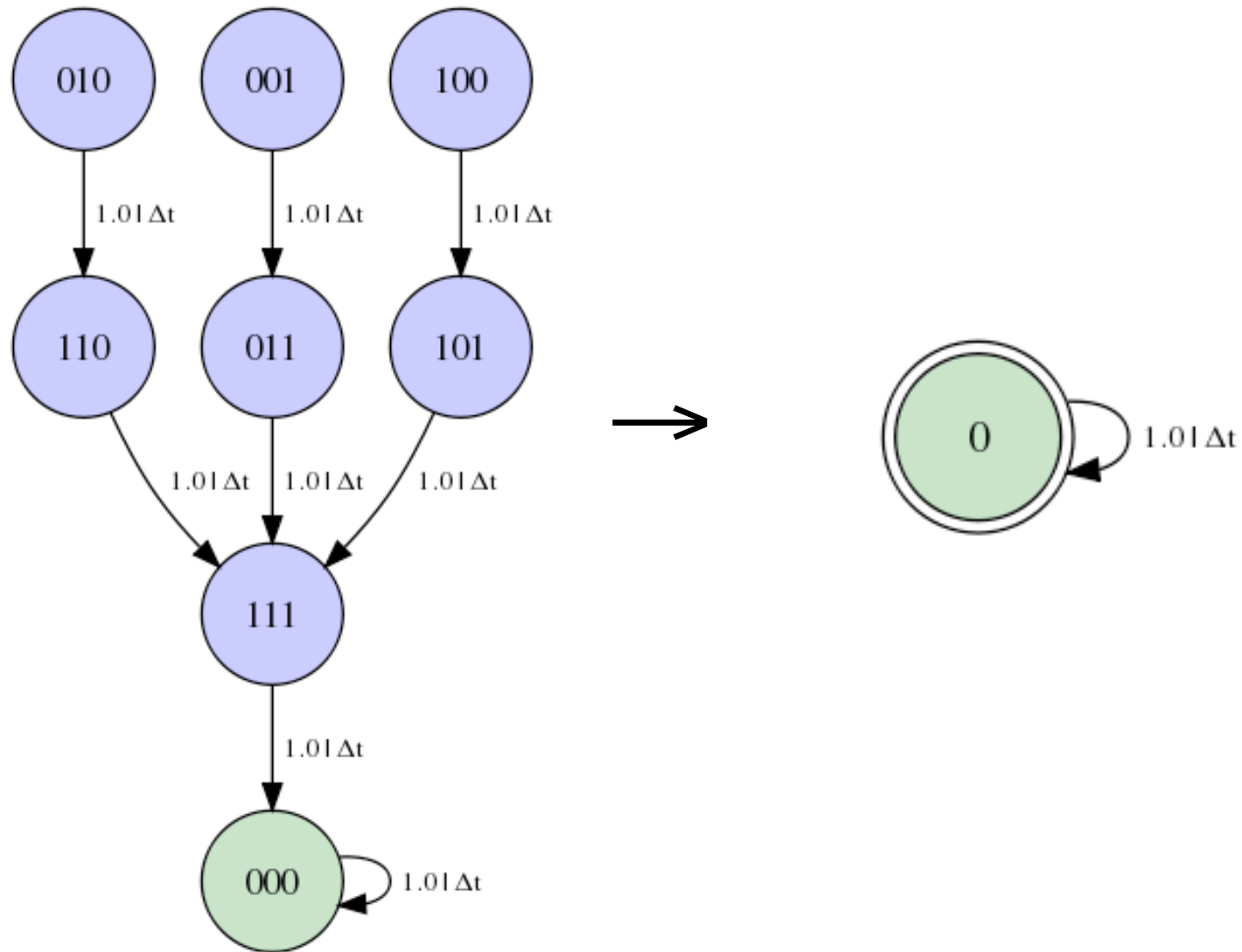
Rethinking Temporal Measurements for Spatially Extended States: 1-D nearest neighbor CA



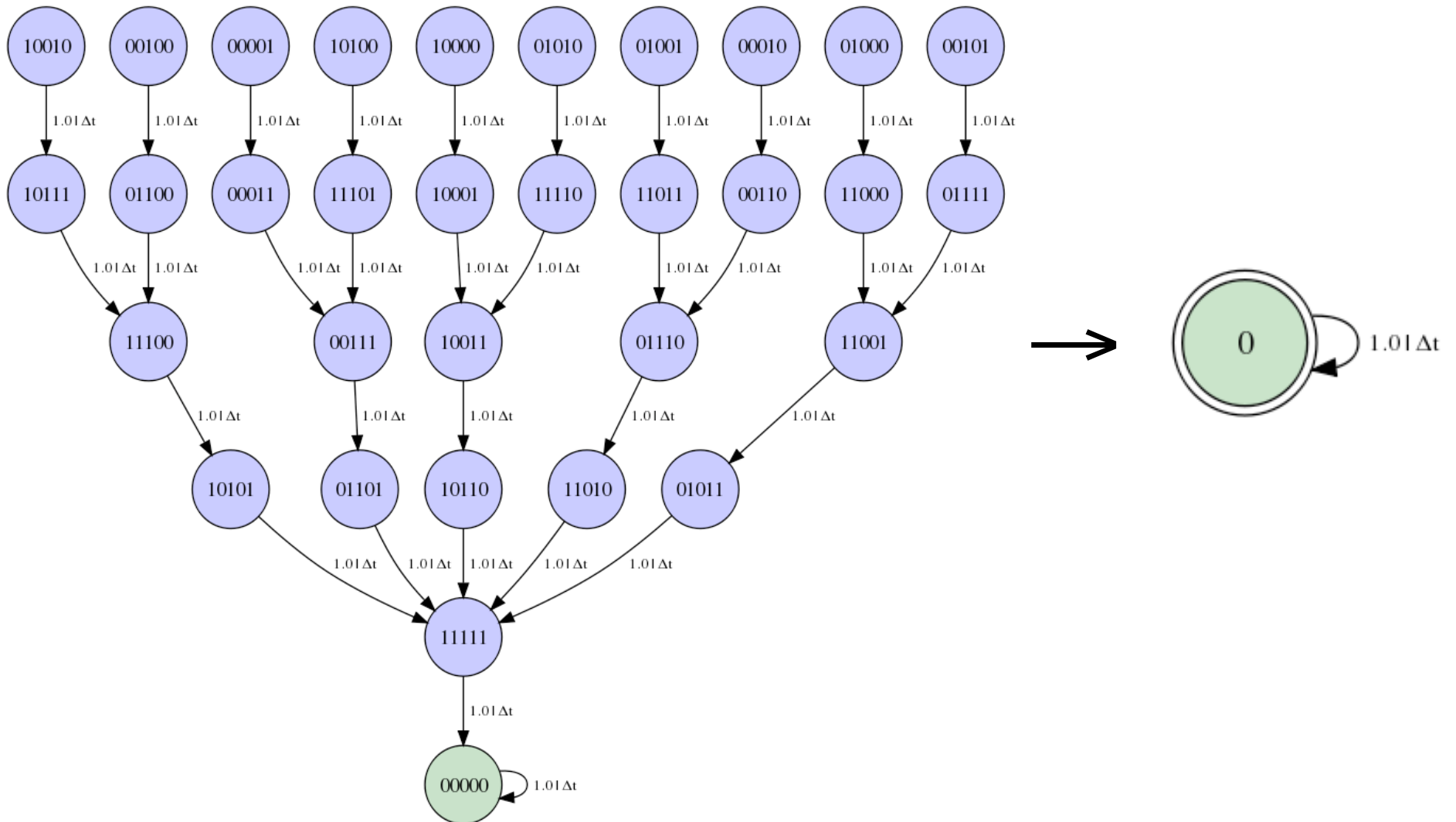
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Rethinking Temporal Measurements for Spatially Extended States:
1-D nearest neighbor CA
Starting Small: Rule 110 with only three cells in the array



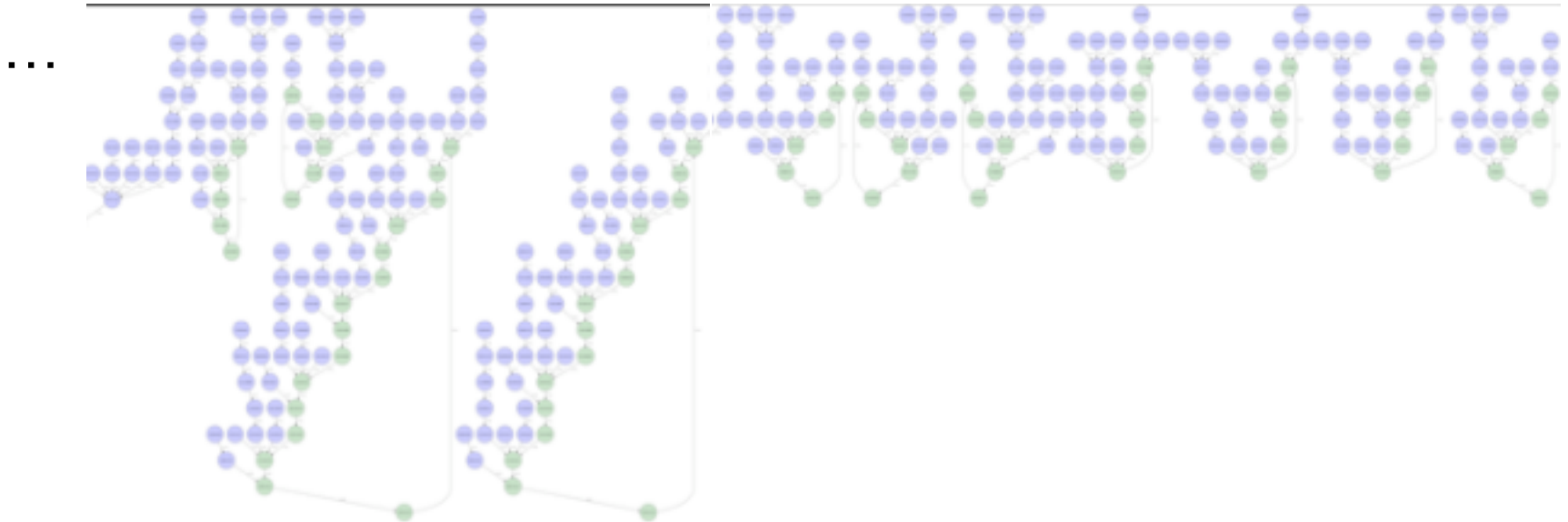
Rethinking Temporal Measurements for Spatially Extended States:
1-D nearest neighbor CA
Starting Small: Rule 110 with only five cells in the array



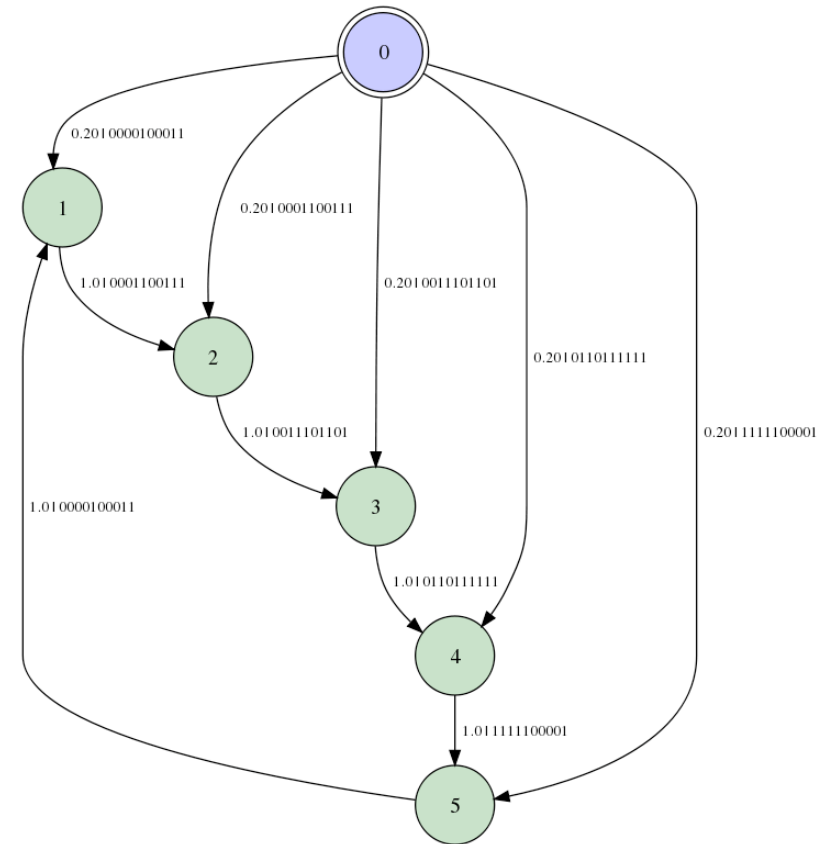
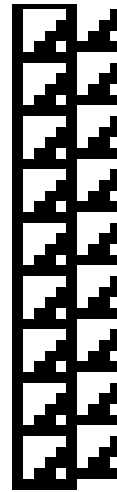
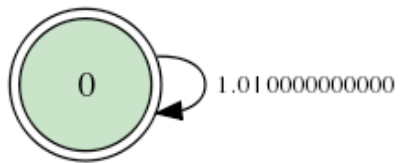
Rethinking Temporal Measurements for Spatially Extended States:
1-D nearest neighbor CA
Starting Small: Rule 110 with only ten cells in the array



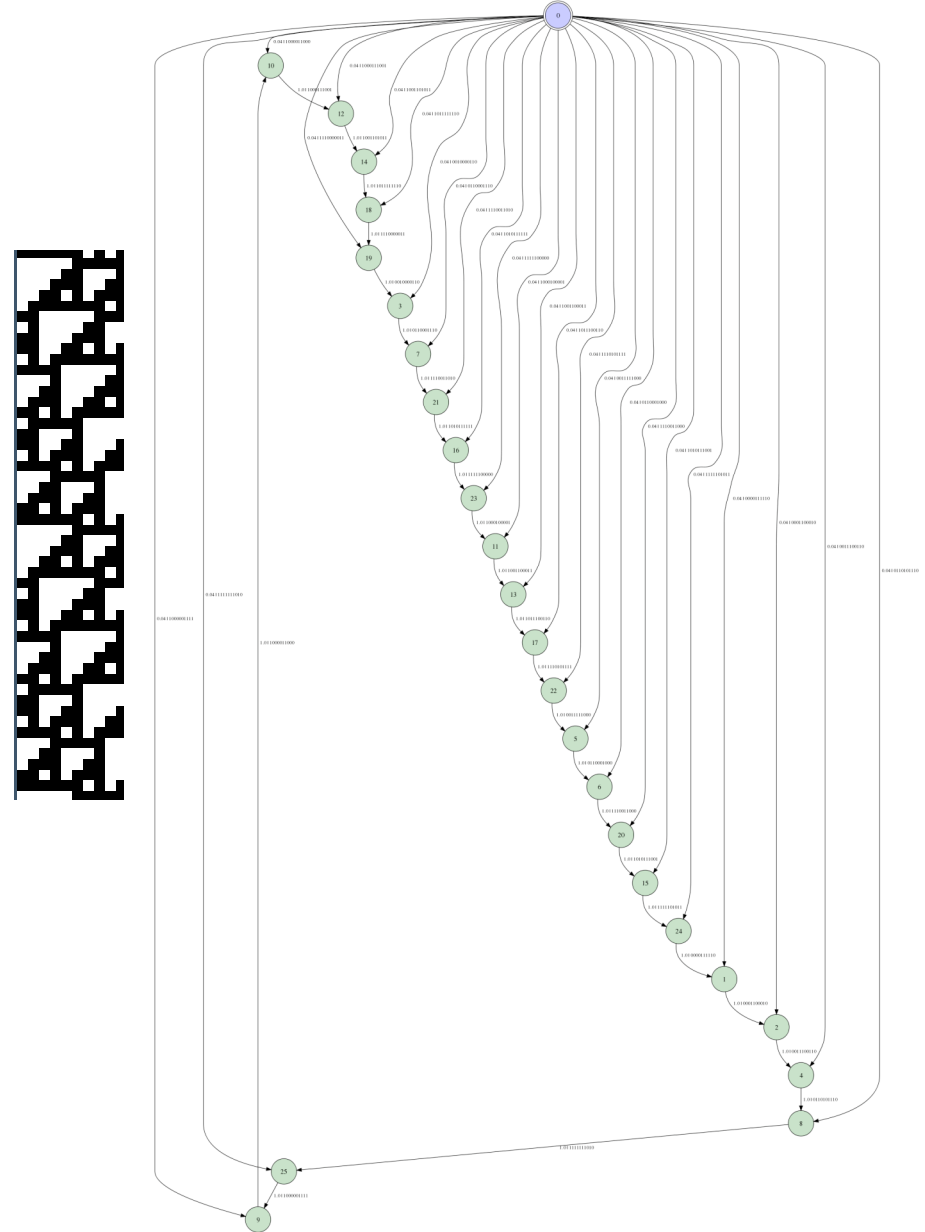
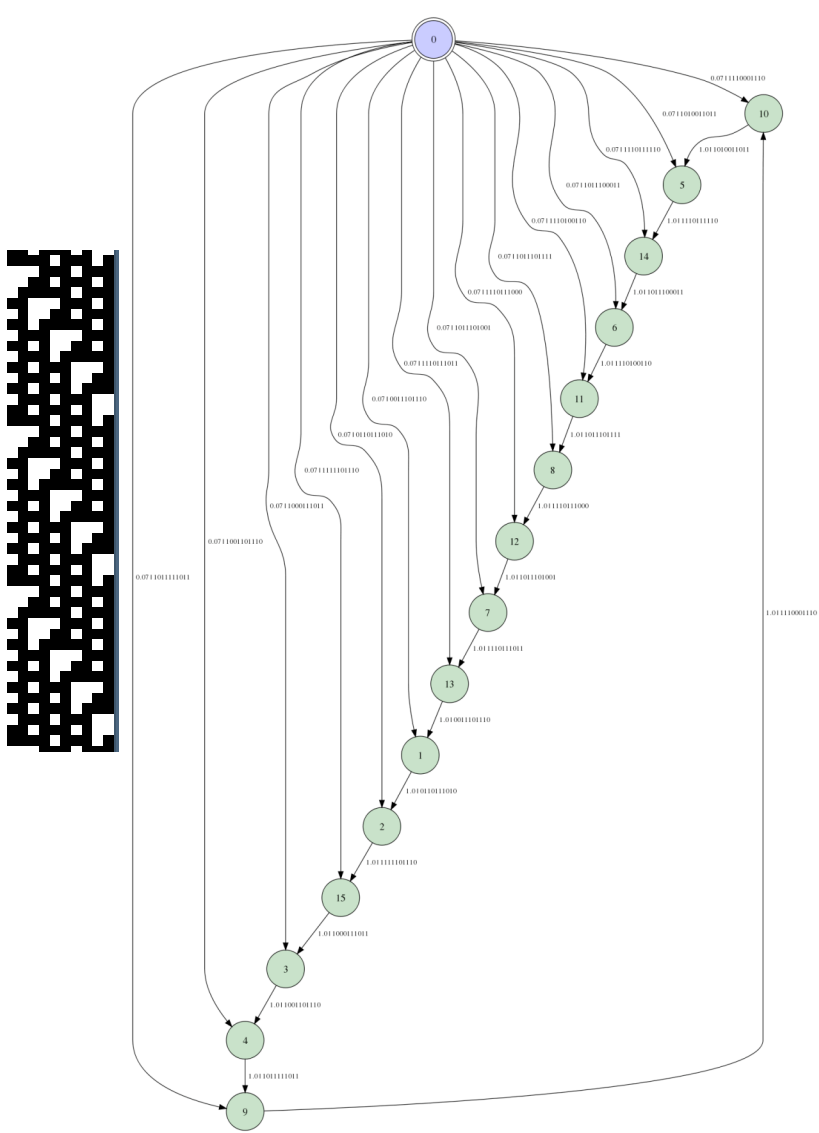
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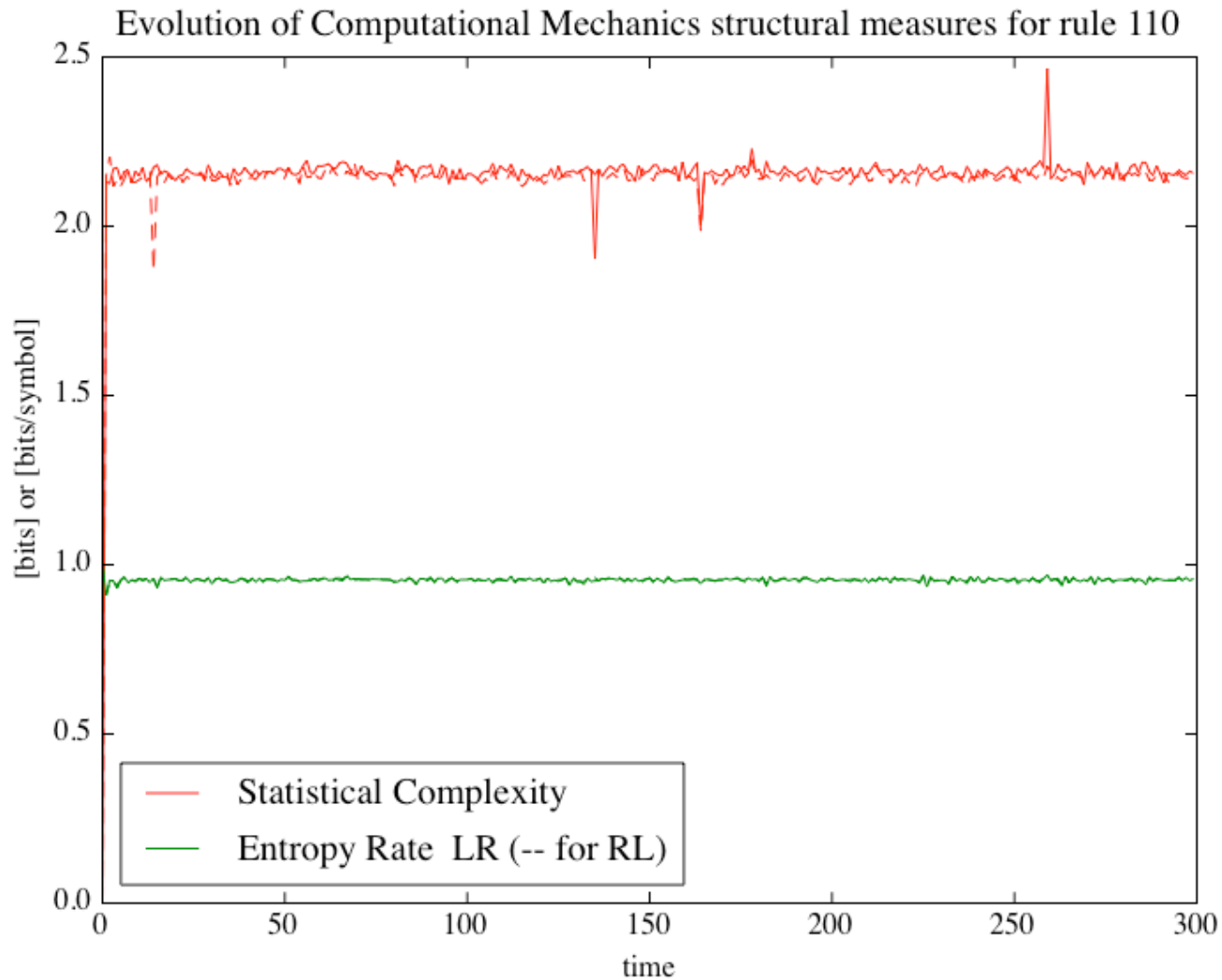
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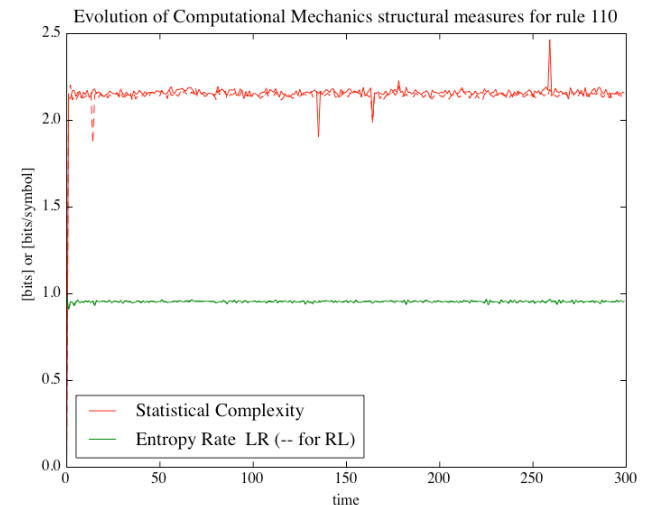


Rethinking Temporal Measurements for Spatially Extended States:
1-D nearest neighbor CA
Looking Ahead: Rule 110
Impulse excitation for 3000 sites: CompMech quantities from a timeseries



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- The current methods/ algorithms are limited...
working on that
- There are many new questions to address
- Space and time probabilities are intricately
connected



Rethinking Temporal Measurements for Spatially Extended States: 1-D nearest neighbor CA

- Some inspired new measures:
 - Effective coupling length
 - Helps to digitize rules of dynamic systems

- Exploring chiral rules

