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Detecting non-trivial computation in complex dynamics

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Computation in complex systems

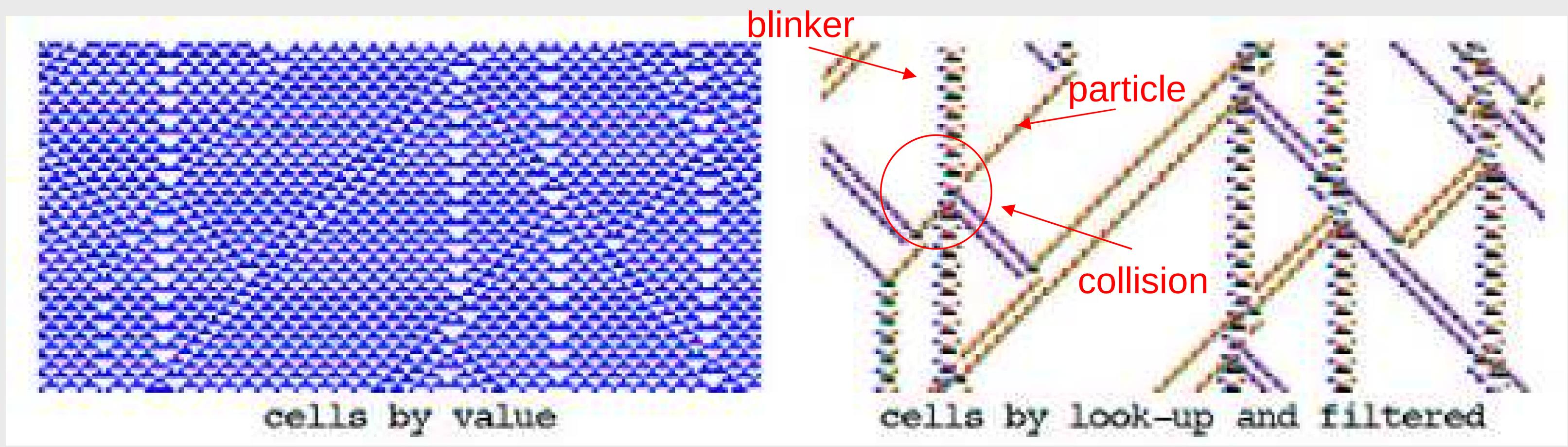
Fundamental nature of distributed computation in complex systems has been a popular topic:
- Von Neumann: a general theory of computation in CA-like systems "would be essential both for understanding complex systems in nature and for designing artificial complex systems" [1].
- Conjecture that complexity ≡ capability for universal computation
- Capturing dynamics and driving evolution of artificial life systems with individual elements of computation, e.g. memory-like measure in [2], information transfer-like measure in [3].

We hypothesize that quantifying the information *dynamics of each element of computation* will provide greater insight into and greater control over complex adaptive systems.

Computation in CAs as an example

Studies of computation in cellular automata (CAs) have focused on
- the role of emergent structures: particles, gliders, domain walls;
- in providing the three primitive functions of computation: *information storage*, *transfer* and *modification*.

Studies examine universal computation, as well as intrinsic or other specific computation [1].



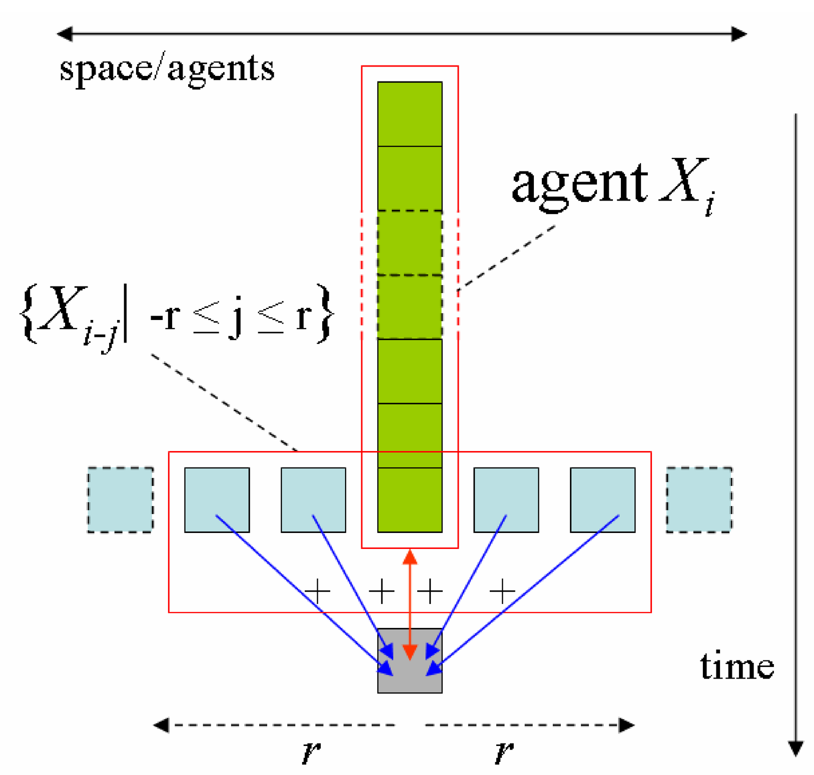
ECA rule 54, from [4]

Emergent structure:
- Blinkers
- Particles: gliders, domain walls
- Particle collisions

No quantified evidence !! (until now ...)

Conjectured to represent:
- Information storage
- Information transfer
- Information modification

Information modification



- Local separable information = information gained about next state from observing each causal source independently (in context of past) *at a given space-time point*:

$$s(i,n) = a(i,n) + \sum_{j=-r, j\neq 0}^{+r} t(i,j,n)$$

- s(i,n) > 0: independent observations are informative overall; highly separable sources.
- s(i,n) < 0: independent observations are *misinformative* overall; sources are interacting and so are not separable.
- s(i,n) < 0 hypothesized to detect collisions, where "*the whole is greater than the sum of the parts*": non-trivial information modification.

Results

Experiment: Measures applied to elementary CA (ECA) runs of 10 000 cells over 600 time steps, with periodic boundary conditions, initialized from random states. Rule 54 results shown as an example on the right. History length k = 16 used for our measures.

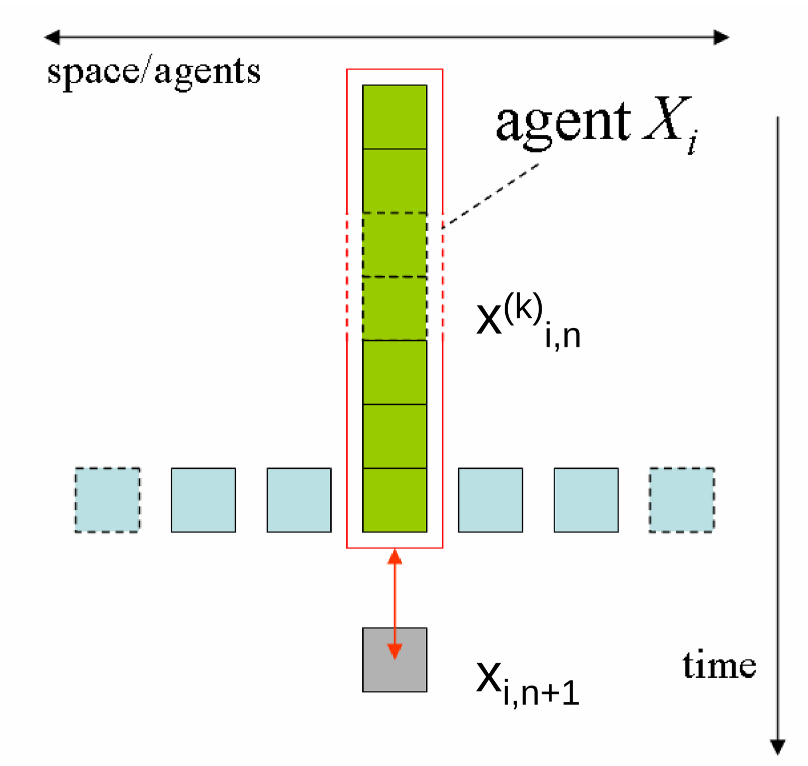
Local active information storage shows:
- Blinkers are memory elements as expected; domain also stores information.
- Particles cause a(i,n+1) < 0, i.e. past misinforms observer at these points.

Local transfer entropy shows [5]:
- Particles are dominant information transfer elements in their direction of motion.
- Can measure t(I,j,n+1) < 0 for transfer in reverse direction to glider motion, i.e. source in domain misinforms observer about glider motion.

Local separable information shows:
- Collisions are dominant non-trivial information modification events.
- Smaller scale events observed along gliders: some processing to compute glider continuation.

→ Framework successfully quantified information dynamics here, is ready for further application.

Information storage

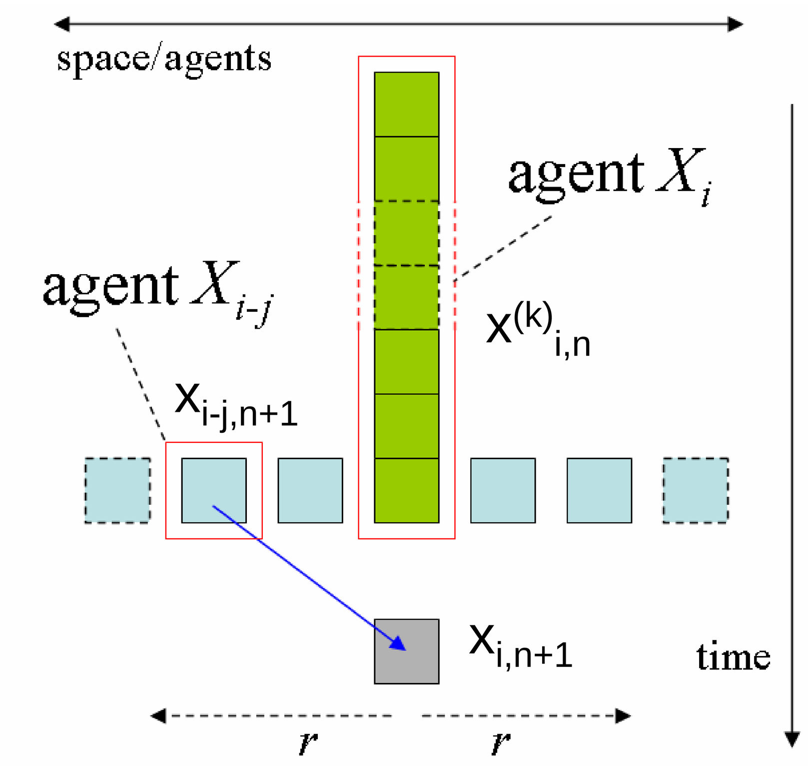


- Excess entropy captures average total information storage.
- Introduce active information storage to quantify average storage *currently in use*.
- *Local* active information storage = storage currently in use *at a given space-time point*:

$$a(i,n+1) = \lim_{k\to\infty} \log \frac{p(x_{i,n}^{(k)}, x_{i,n+1})}{p(x_{i,n}^{(k)})p(x_{i,n+1})}$$

- a(i,n+1) > 0: past informs an observer about next state = strong information storage
- a(i,n+1) < 0: past *misinforms* an observer about next state (outcome was relatively unlikely)

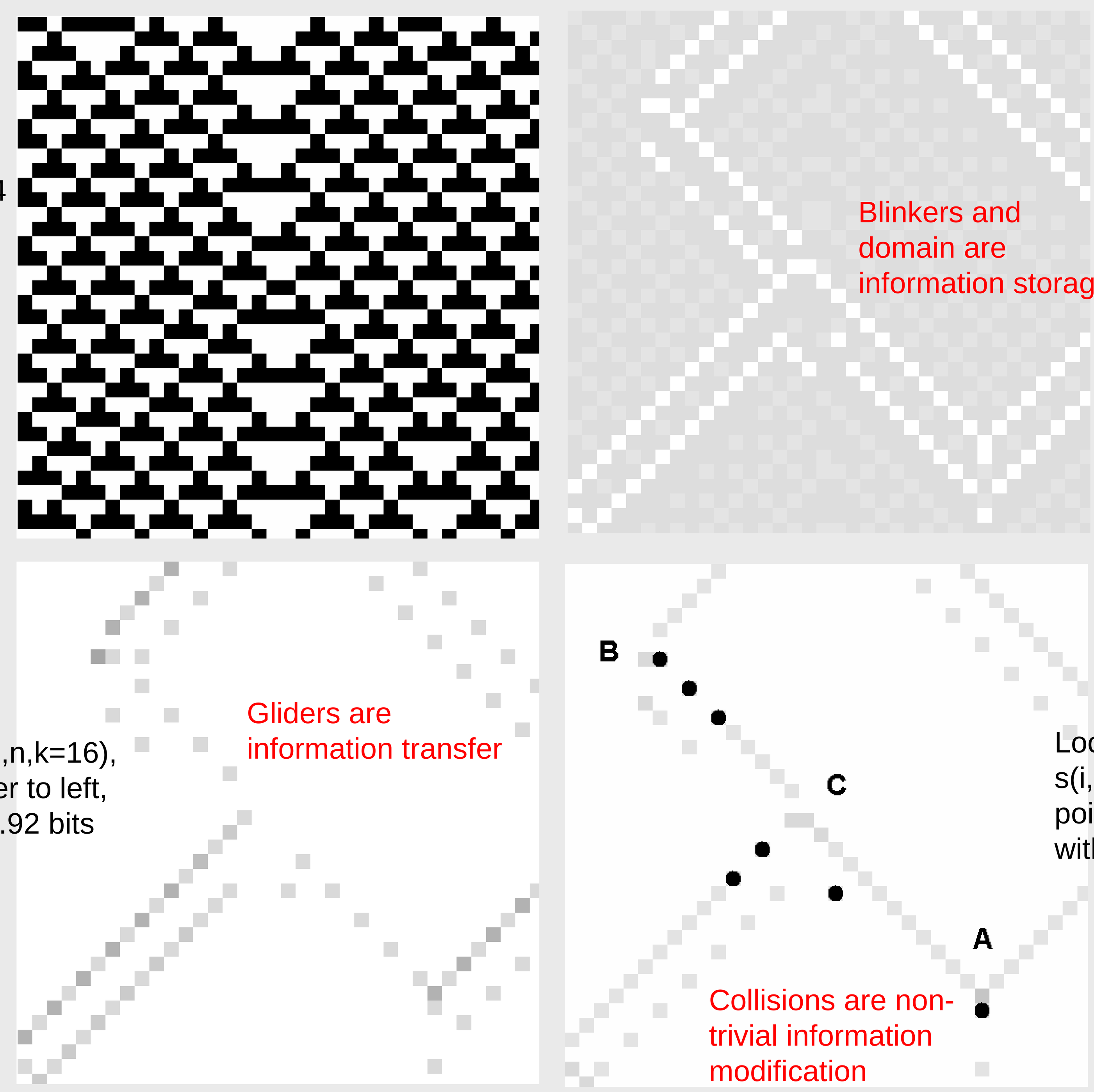
Information transfer



- Transfer entropy captures information transfer between a source and destination: info added by source about destination that was not contained in destination's past.
- *Local* transfer entropy = information transfer *at a given space-time point* [5]:

$$t(i,j,n+1) = \lim_{k\to\infty} \log \frac{p(x_{i,n+1} \mid x_{i,n}^{(k)}, x_{i-j,n})}{p(x_{i,n+1} \mid x_{i,n}^{(k)})}$$

- t(i,j,n+1) > 0: source *i-j* is informative about next state of *i* = strong information transfer
- t(i,j,n+1) < 0: source *misleads* an observer about next state of *i* in context of past (outcome was relatively unlikely)



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