

Analysing the Information Dynamics of Flocking

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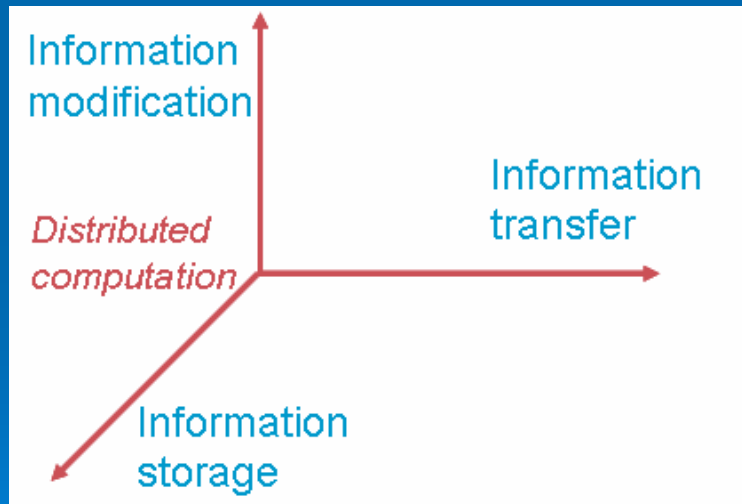
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(with support from a CSIRO Postgraduate Scholarship)

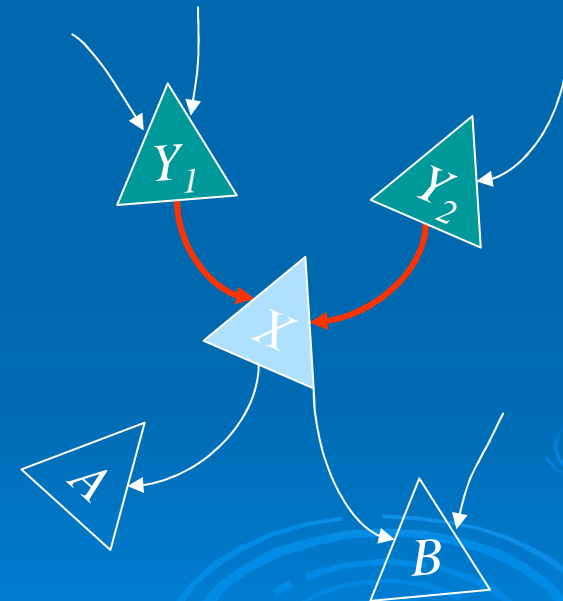
From Amorphous to Spatial Computing Workshop, Paris, July 2008

Info Dynamics of Flocking

- **Aim:** To describe how to extend a framework for the info dynamics of computation to study computation in a flocking model

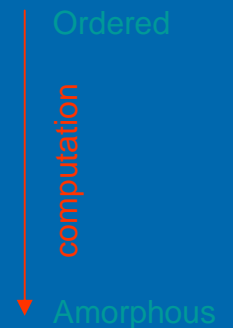


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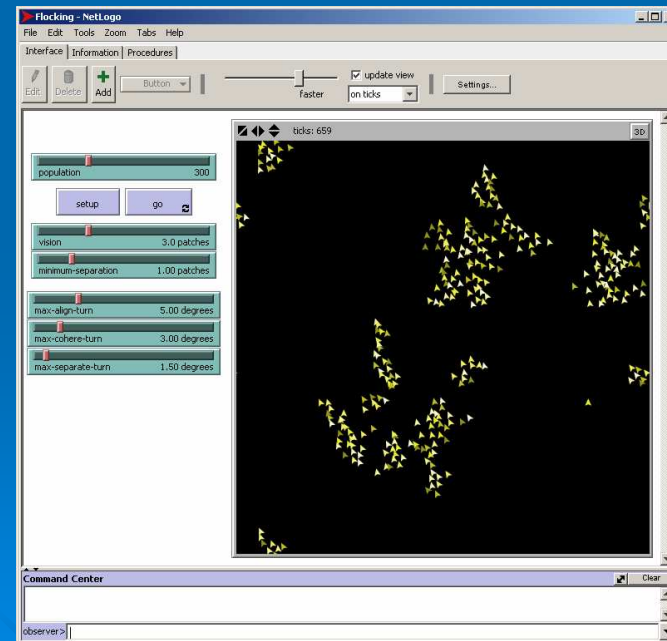
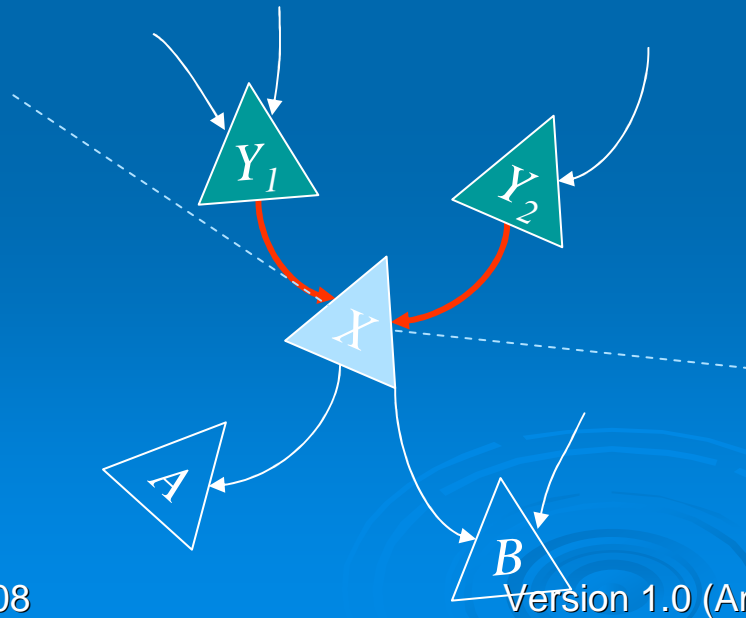
Contents

- Computation in flocking behaviour
- Information dynamics of distributed computation
 - Local computation in CAs
 - Phase transitions in RBNs
- Measuring information dynamics in flocking



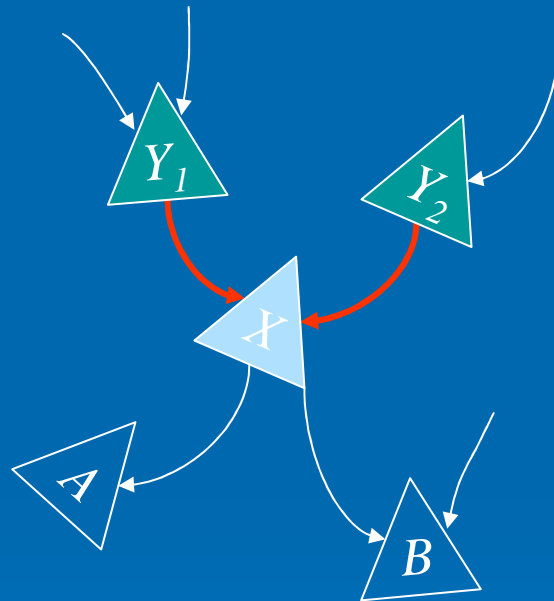
Flocking model

- e.g. Wilensky, U. (1998). NetLogo Flocking model
- Three rules:
 - **Alignment**: move in same direction as neighbours
 - **Separation**: avoid collision with neighbours which get too close
 - **Cohesion**: move towards neighbours
- Agents move at constant speed
- Range and angle for neighbours



Info Dynamics of Flocking: local dynamics

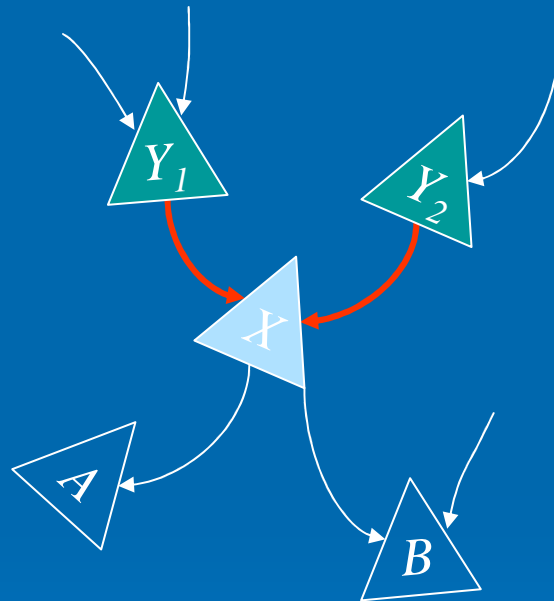
- Motivation 1: explore local information dynamics in flocking computation, e.g.



- Waves of turning spreading as information cascades (Couzin et. al., 2006)
- Collective memory of the school
- Understand where decisions or info processing take place in determining flock direction

Info Dynamics of Flocking: average dynamics

- Motivation 2: explore average information dynamics with respect to phase transitions, e.g.



- Activation levels of ants suggest max info transfer at critical density. (Miramontes, 1995)
- Max capacity for info transfer at critical sensory ranges (Couzin, 2007)
- Fastest coordination at critical angular vision (Tian et al, 2008)

Nature of distributed computation

➤ Memory:

- Coordinated motion in modular robotics
- Synchronization between coupled systems

➤ Communication:

- Signal transduction by calcium ions
- Influence of agents over their environments

➤ Processing:

- Decision-making in neural networks
- Collision-based computing

Information dynamics in complex systems

- Information dynamics of distributed computation in terms of 3 components of Turing universal computation.
- Both local scale and averages are important

Blinkers in CAs

Information
modification

*Distributed
computation*

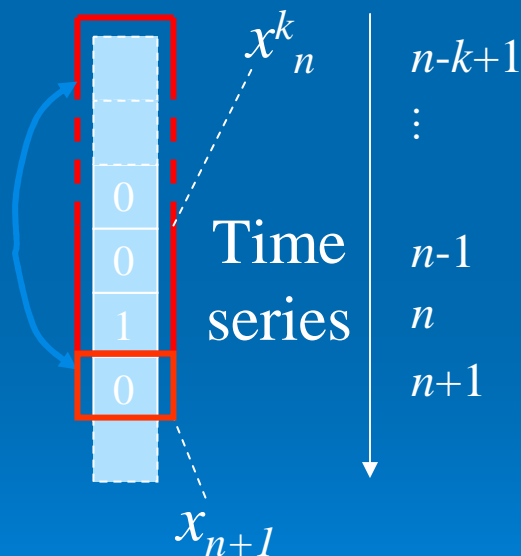
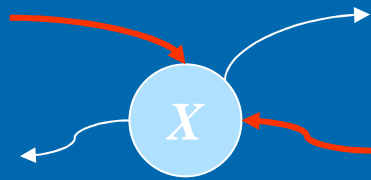
Information
transfer

Particles in CAs

Information
storage

Particle collisions in CAs

Information storage



➤ Information storage: info in past of an agent relevant to predicting its future.

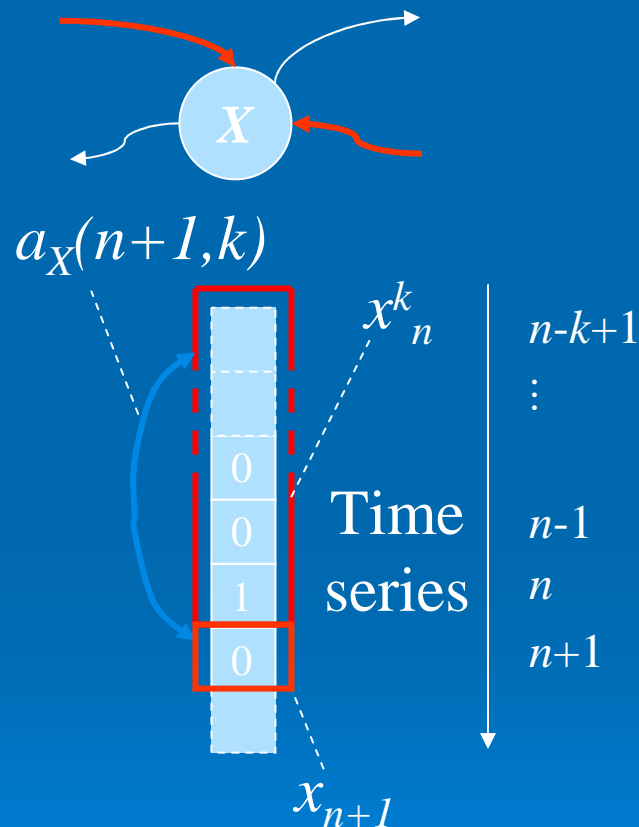
➤ Active info storage = average mutual info between past and next step:

$$A_x(k) = I(X^j, X^{(k)})$$

➤ Info to predict next state $H_x =$

- Info from past $A_x(k) +$
- Remaining uncertainty $H_{\mu x}(k)$

Local information storage



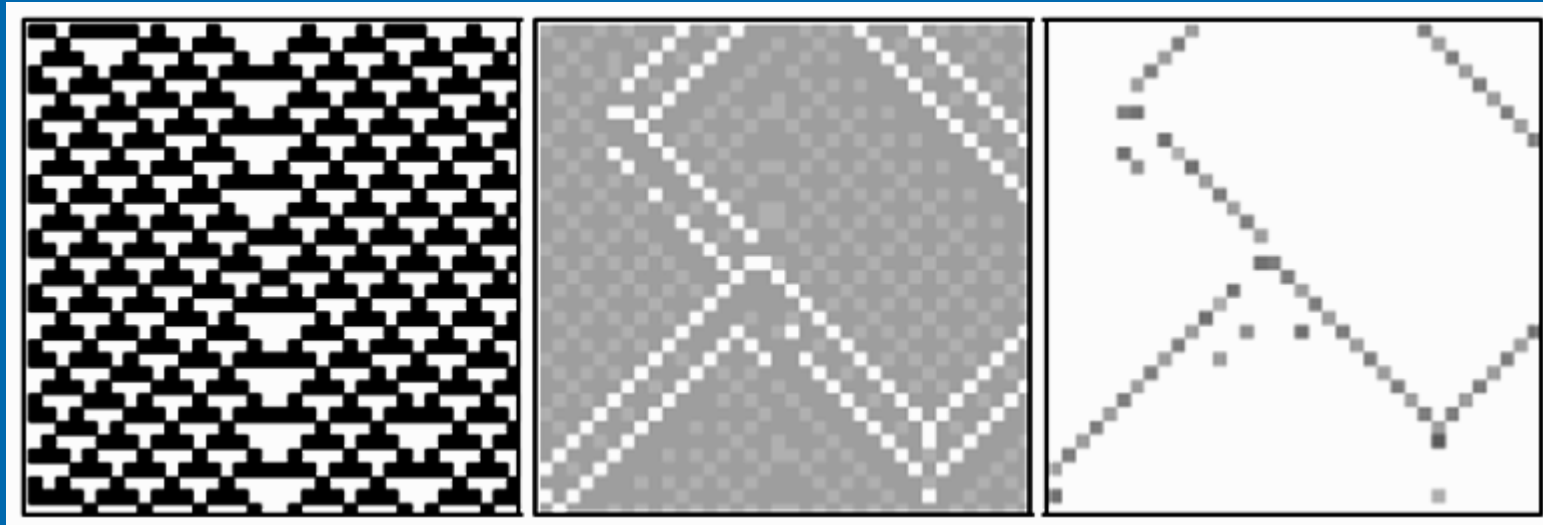
- Local active info storage = local mutual info between past and next step at a specific space-time point:

$$A_X(k) = \langle a_X(n, k) \rangle$$

$$a_X(n+1, k) = i(x_{n+1}, x_n^{(k)})$$

$$a_X(n+1, k) = \log_2 \frac{p(x_n^{(k)}, x_{n+1})}{p(x_n^{(k)})p(x_{n+1})}$$

Active information storage in CAs



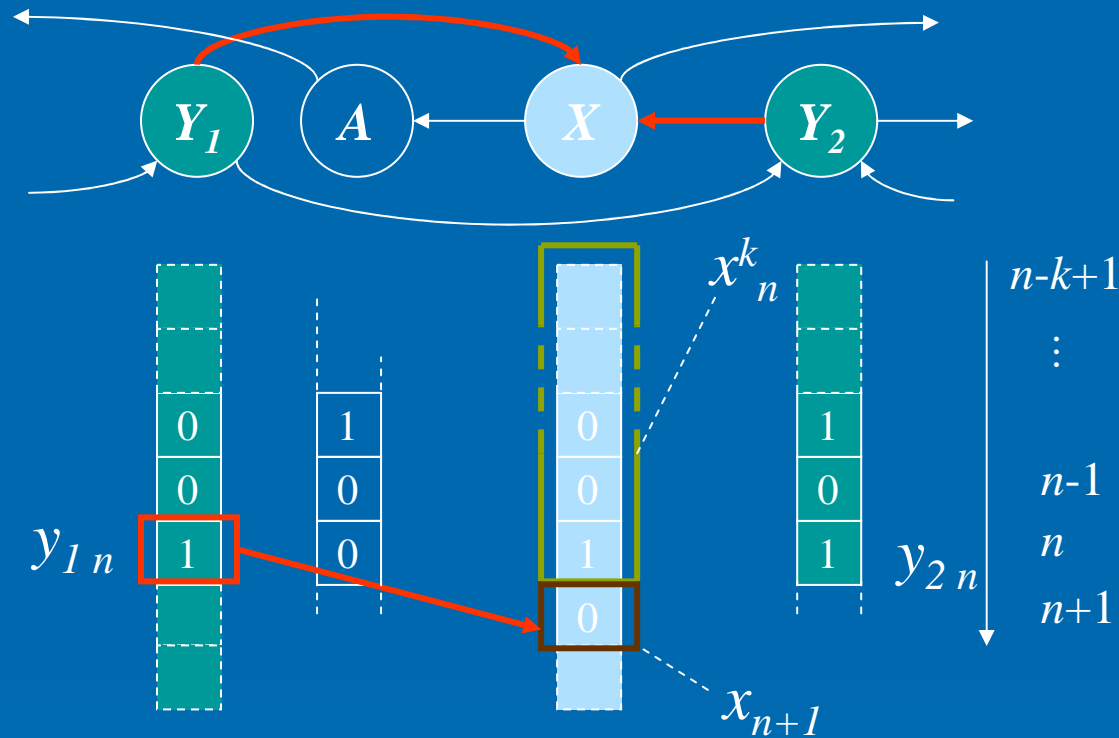
ECA rule 54

$a(n,k=16) > 0$

$a(n,k=16) < 0$

- Blinkers and domains are information storage elements.
- Local active information storage is < 0 , i.e. misinformative at gliders (would be a good filter).

Information transfer



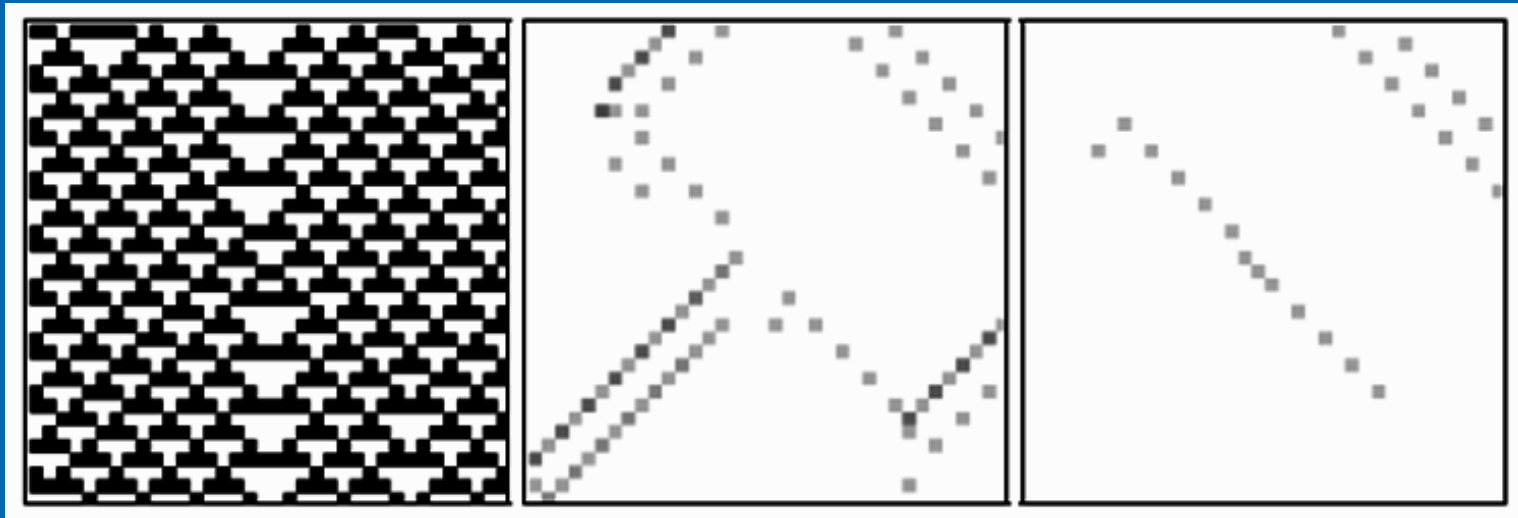
- **Apparent transfer entropy**: mutual information between **source** and **destination** conditioned on the **past** of the destination, e.g.

$$T_{Y_1 \rightarrow X}(k) = I(Y_1, X; X^{(k)})$$

- **Local** values defined similarly:

$$t_{Y \rightarrow X}(n+1, k) = \log_2 \frac{p(x_{n+1} | x_n^{(k)}, y_n)}{p(x_{n+1} | x_n^{(k)})}$$

Local transfer entropy in CAs



ECA rule 54

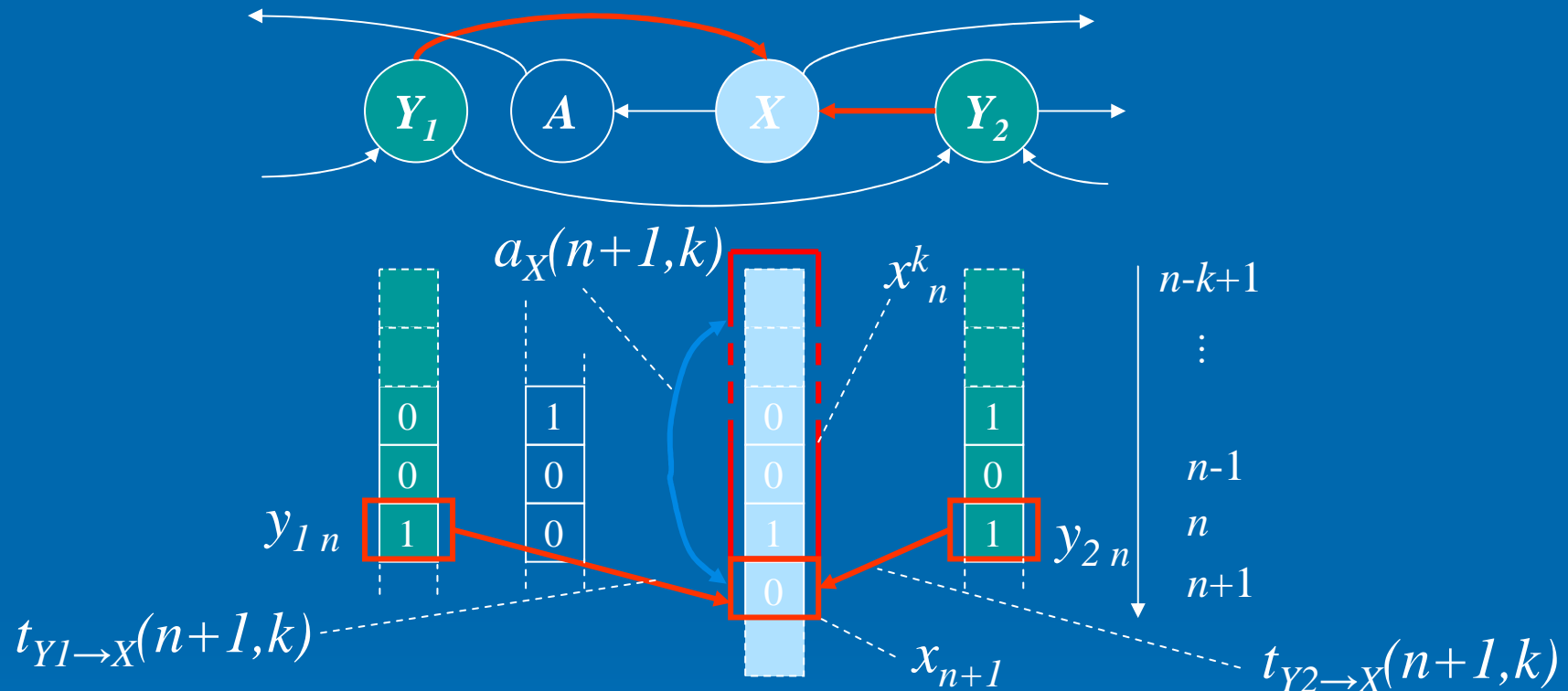
$$t_{j=-1}(n,k=16) > 0$$

$$t_{j=-1}(n,k=16) < 0$$

Transfer one cell left per unit time step

- Gliders are in fact coherent travelling information structures, and dominate the transfer in their direction of motion.
- Local transfer entropy is mis-informative in reverse direction to gliders.

Information modification

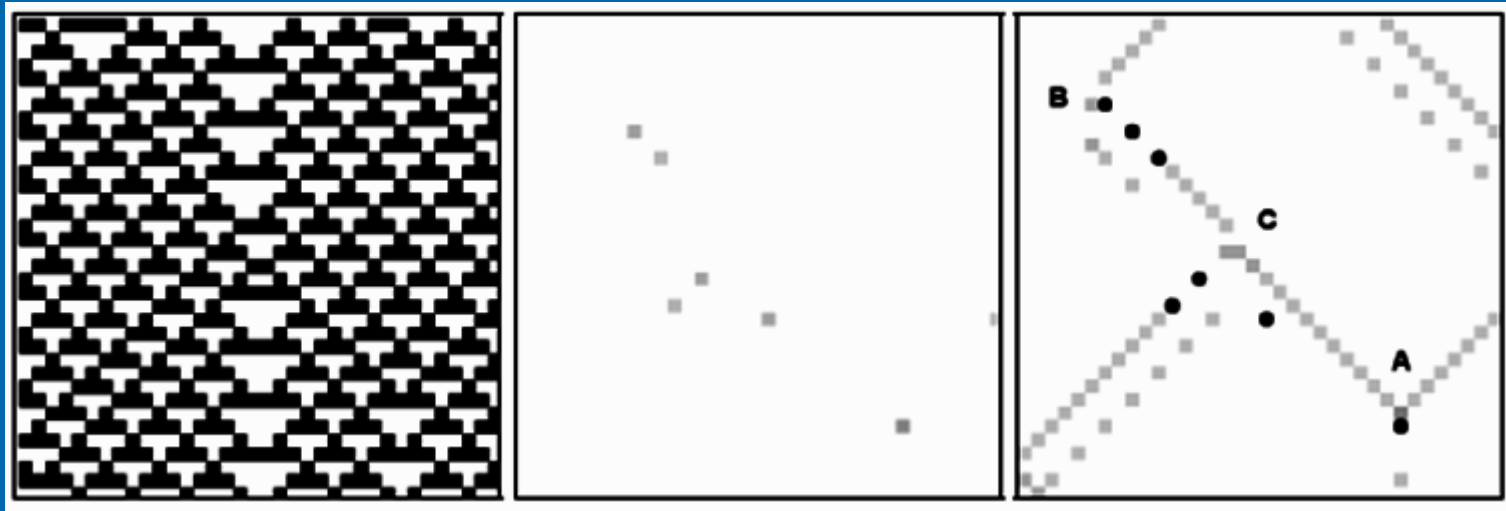


➤ Local Separable Information is:

$$s_X(n) = a_X(n) + \sum_{Y \in V, Y \neq X} t_{Y \rightarrow X}(n)$$

- $s > 0$: trivial info modification.
- $s < 0$: non-trivial info modification, where sources interact.

Local separable information in CAs



ECA rule 54

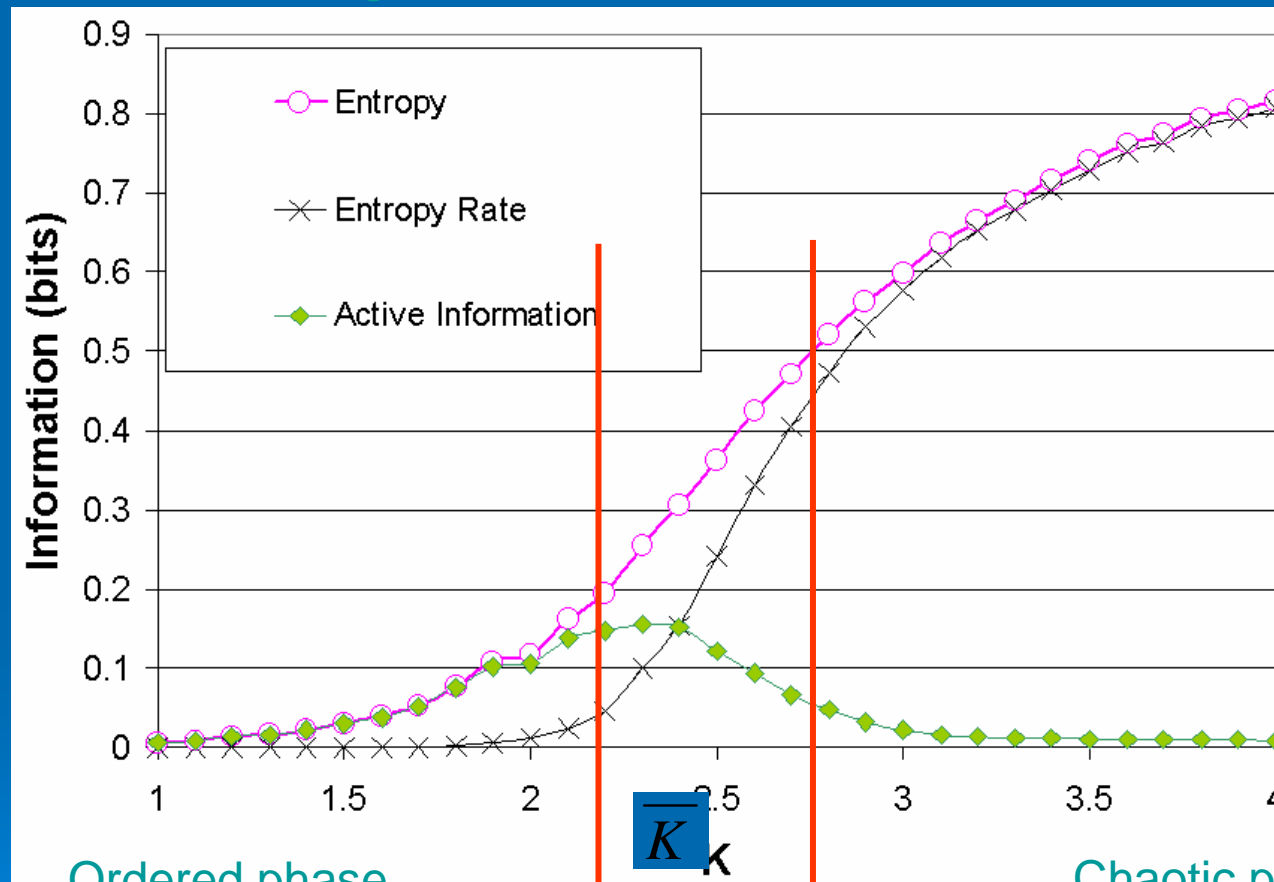
$s(n, k=16) < 0$

Locations of $s(n, k=16) < 0$

- Glider collisions are dominant information modification events (non-trivial information processing).
- Collision points are not where one would trivially identify them.

Average info dynamics in phase transitions

e.g. in Random Boolean Networks



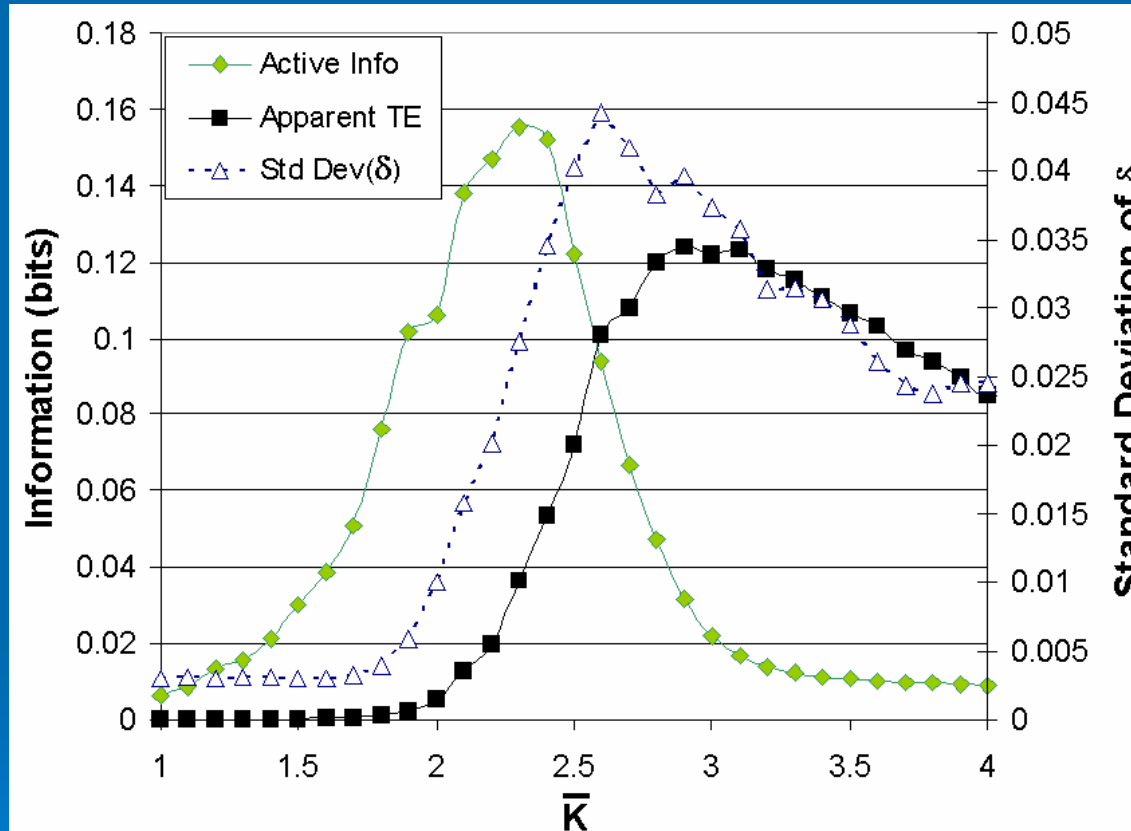
Ordered phase
dominated by
information
storage

Balance near
critical phase

Chaotic phase
dominated by
information
transfer

Average info dynamcs in phase transitions

e.g. in Random Boolean Networks



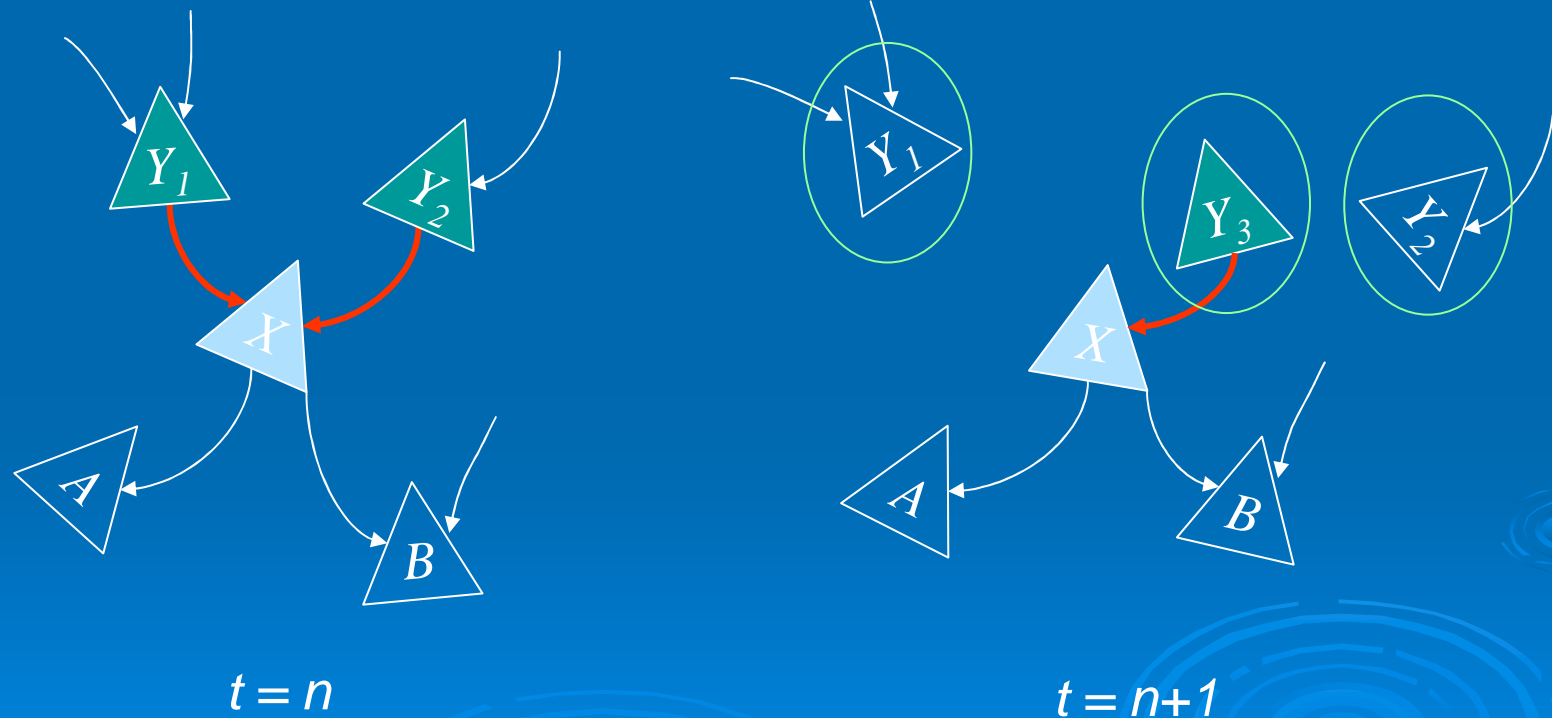
- Information storage peaks slightly within the ordered regime.
- (Coherent) Information transfer peaks slightly within the chaotic regime.

Information dynamics applications

Application	Homogeneous topology of causal links	Fixed topology of causal links
CAs	✓	✓
RBNs	✗	✓
Flocking	✗	✗

Info dynamics of Flocking: challenges

1. Fluidity of causal links
2. Not enough observations for info theoretic calculations

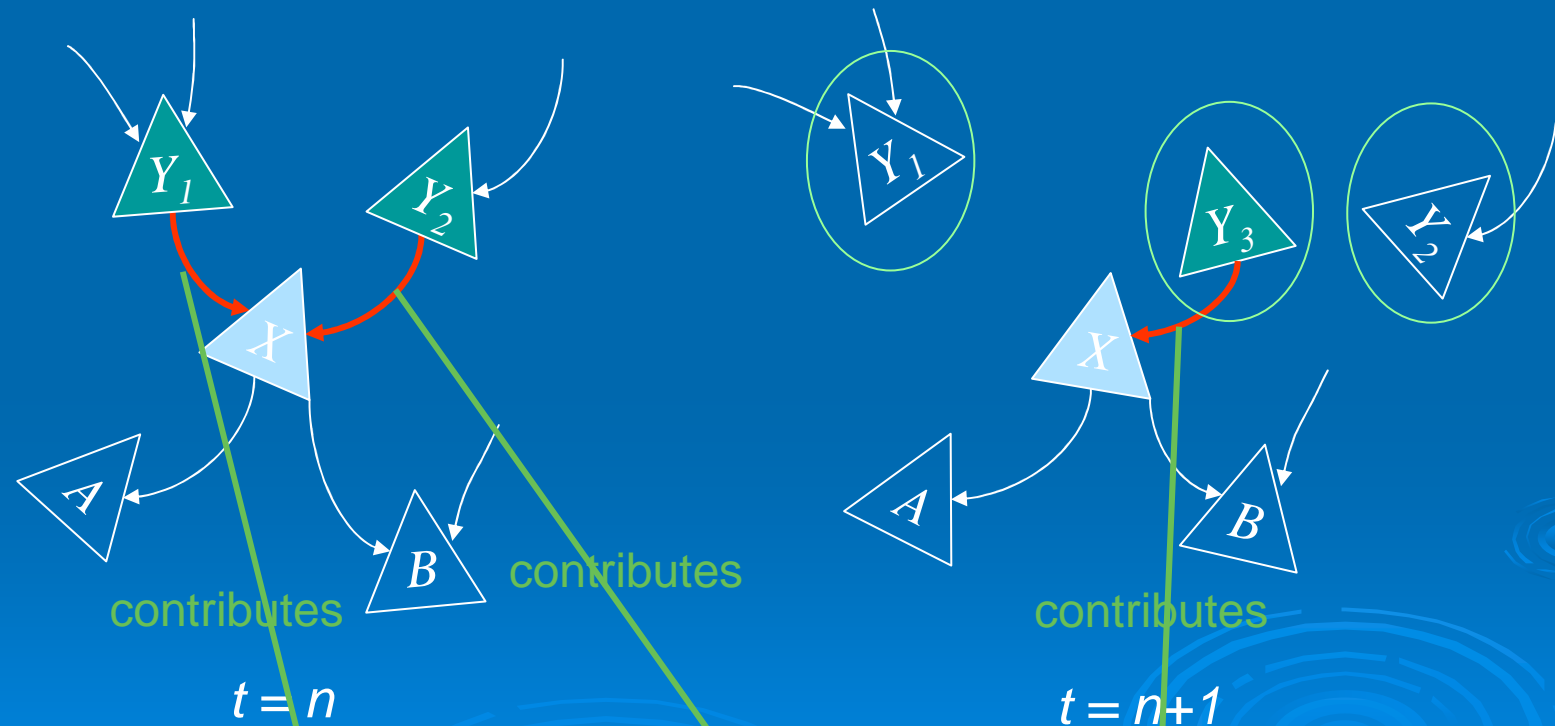


Information dynamics applications

Application	Homogeneous topology of causal links	Fixed topology of causal links	Homogeneous agent logic
CAs	✓	✓	✓
RBNs	✗	✓	✗
Flocking	✗	✗	✓

Info dynamics of Flocking: challenges

1. Fluidity of causal links? ✓
2. Not enough observations? ✓



$$t_{Y \rightarrow X}(n+1, k) = \log_2 \frac{p(x_{n+1} | x_n^{(k)}, y_n)}{p(x_{n+1} | x_n^{(k)})}$$

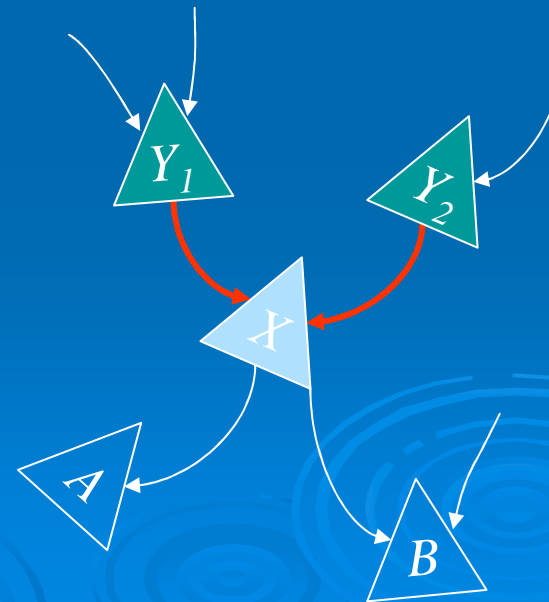
Info dynamics of Flocking: challenges

3. What are the agent states?

1. Past and next state of destination:
 1. Heading? ✗
 2. Change of heading ✓
2. Previous state of info source:
 1. Relative heading and ✓
 2. Relative separation ✓

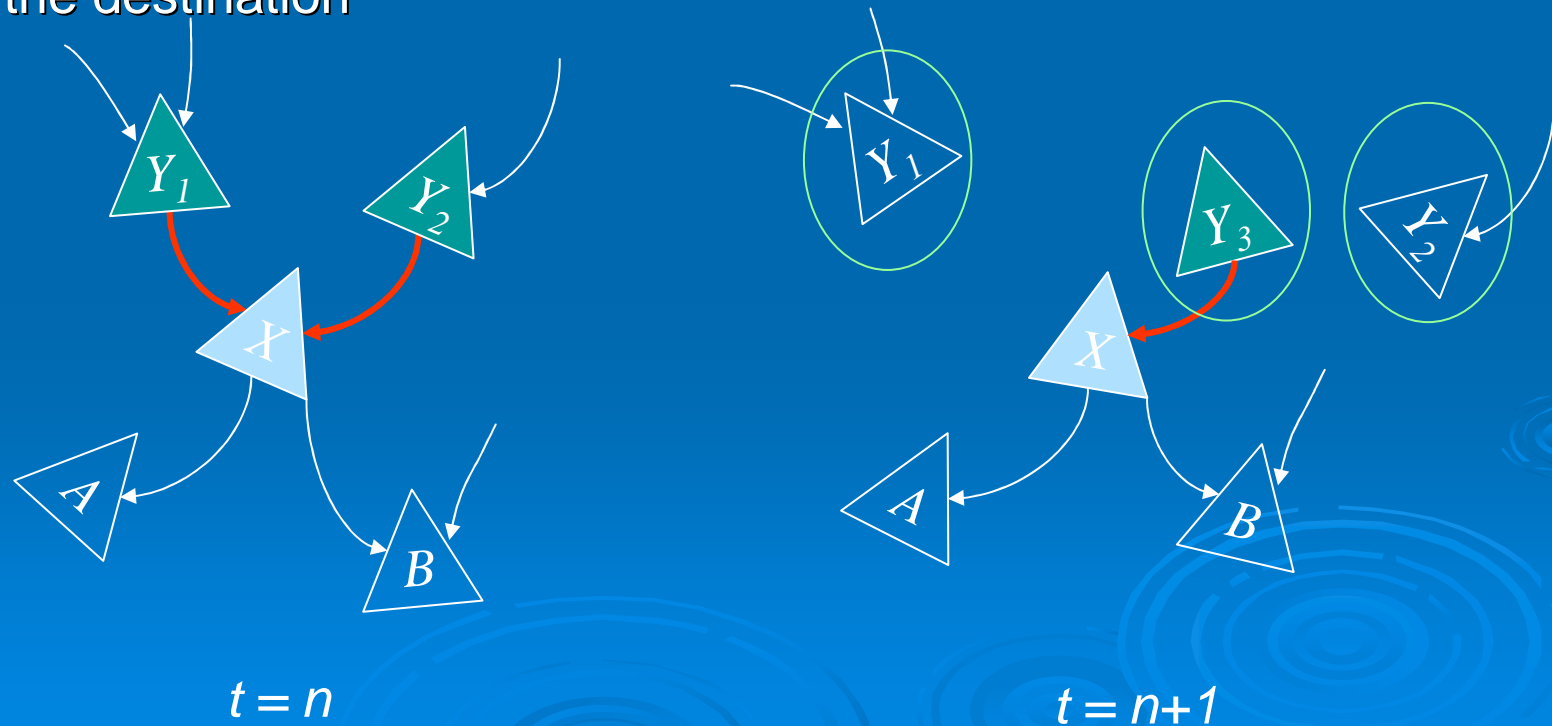
4. Handle continuous variables:

1. Discretize
2. Use kernel estimation



Info dynamics of Flocking: challenges

5. Can we really put all pair-wise interactions into the one set for estimation of the PDFs?
- e.g. Use different PDFs for different number of causal links into the destination



Conclusions

- Demonstrated guidelines on how to apply this framework for the information dynamics of computation to a flocking model
 - Key property: **homogeneous agent functional logic**
 - Allows one to accumulate observations across all transient causal interactions
- Expect the framework to provide insight into:
 - the **local** information dynamics in flocking
 - The **average** information dynamics in a phase transition of flocking behaviour