

# The Cell Cycle Switch Computes Approximate Majority

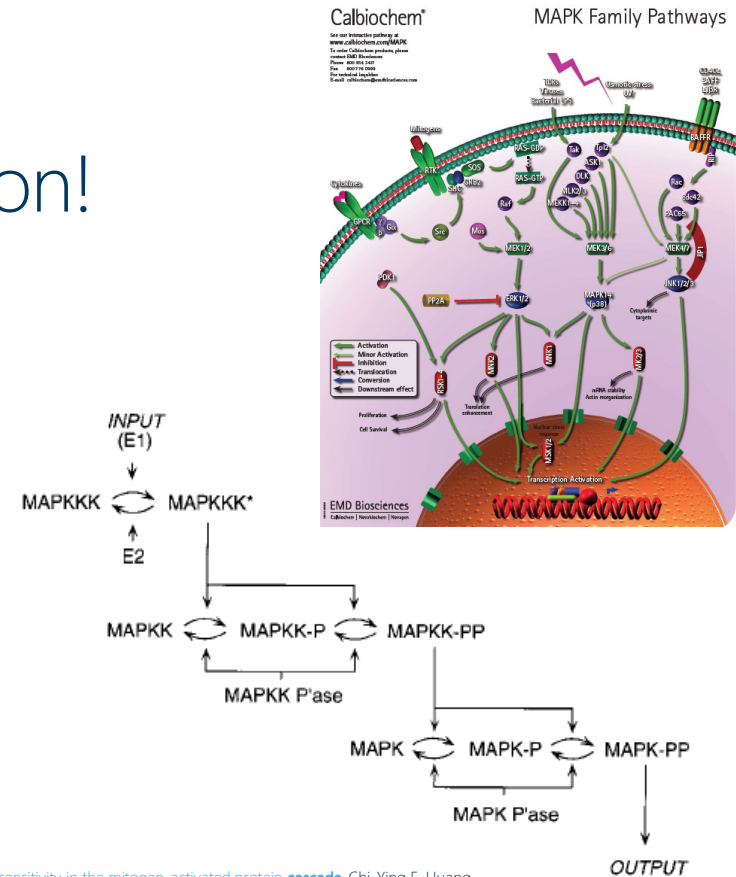
Luca Cardelli, Microsoft Research

Joint work with Attila Csikász-Nagy, CoSBI & King's College London

Aalborg, 2013-08-07

# Cells Compute

- No survival without computation!
  - Finding food
  - Avoiding predators
- How do they compute?
  - Clearly doing “information processing”
  - Based on complex, higher-order interactions
    - **MAPKKK** = MAP Kinase Kinase Kinase = *that which operates on that which operates on that which operates on protein.*
  - How ‘sophisticated’ are natural algorithms?



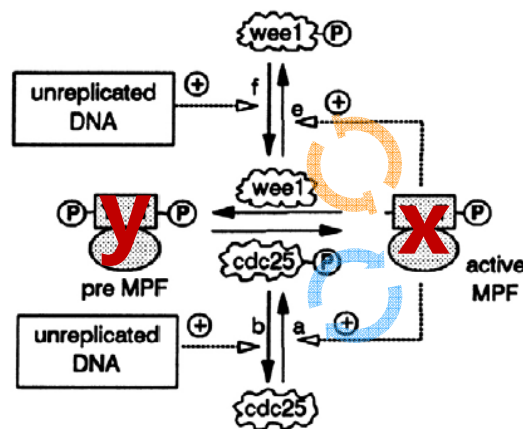
[Ultrasensitivity in the mitogen-activated protein cascade](#), Chi-Ying F. Huang and James E. Ferrell, Jr., 1996, *Proc. Natl. Acad. Sci. USA*, 93, 10078-10083.

# Outline

- Analyzing biomolecular networks
  - Try do understand the function of a network
  - But also try to understand its *structure*, and what determines it
- The Cell-Cycle Switches
  - Some of the best studied molecular networks
  - Important because of their fundamental function (cell division) and the stability of the network across evolution
- We ask:
  - What does the cell cycles switch compute?
  - How does it compute it?

# The Cell Cycle Switch

- This network is **universal in all Eukaryotes** [P. Nurse]
  - I.e., the **network** at the core of cell division is *the same* from yeast to us
  - *Not the components of the network, nor the rates*



Journal of Cell Science 106, 1153-1168 (1993)  
Printed in Great Britain © The Company of Biologists Limited 1993

**Numerical analysis of a comprehensive model of M-phase control in *Xenopus* oocyte extracts and intact embryos**

**Bela Novak\* and John J. Tyson†**

Department of Biology, Virginia Polytechnic Institute and State University, Blacksburg, Virginia 24060-0406, USA

\*Permanent address: Department of Agricultural Chemical Technology, Technical University of Budapest, 1521 Budapest Gellert Ter 4, Hungary  
†Author for correspondence

Double positive feedback on x  
 Double negative feedback on x  
 No feedback on y  
 What on earth ... ???

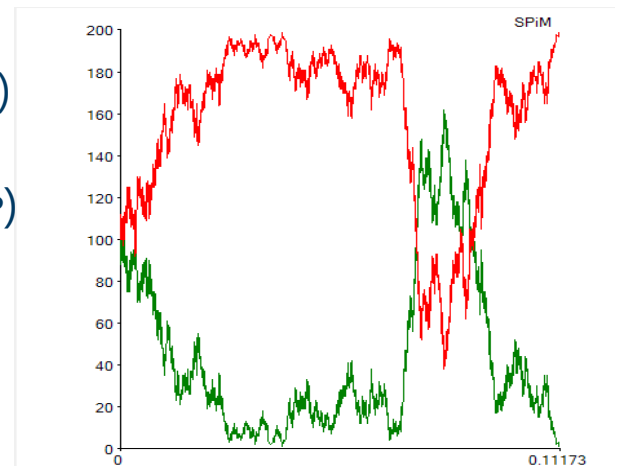
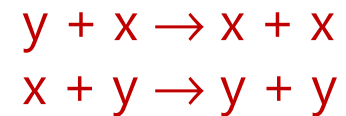
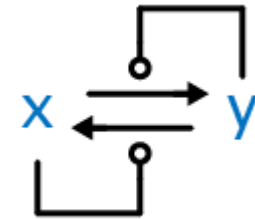
- The function is very well-studied. But why this structure?
- I.e., **why this algorithm?**

# How to Build a Good Switch

- What is a “good” switch?
  - We need first a **bistable** system: one that has two *distinct* and *stable* states. I.e., given any initial state the system must settle into one of two states
  - The settling must be **fast** (not get stuck in the middle for too long) and **robust** (must not spontaneously switch back)
  - Finally, we need to be able to **flip** the switch by external inputs
- “Population” Switches
  - Populations of identical agents (molecules) with the whole population switching from one state to another as a whole
  - Highly concurrent (**stochastic**)

# A Bad Algorithm

- Direct Competition
  - x catalyzes the transformation of y into x
  - y catalyzes the transformation of x into y
  - when all-x or all-y, it stops
- This system has two end states, but
  - Convergence to an end state is slow (a random walk)
  - Any perturbation of an end state can start a random walk to the other end state (hence not really *bistable*)



# A Very Good Algorithm

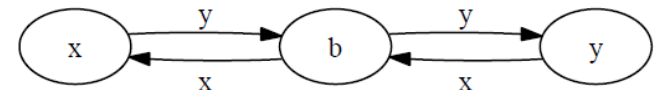
- Approximate Majority (AM)
  - Decide which of two populations is in majority
- A fundamental 'population protocol'
  - Agents in a population start in state  $x$  or state  $y$
  - A pair of agents is chosen randomly at each step, they interact ('collide') and change state
  - The whole population must eventually agree on a majority value (all- $x$  or all- $y$ ) with probability 1

Dana Angluin · James Aspnes · David Eisenstat

## A Simple Population Protocol for Fast Robust Approximate Majority

We analyze the behavior of the following population protocol with states  $Q = \{b, x, y\}$ . The state  $b$  is the **blank** state. Row labels give the initiator's state and column labels the responder's state.

	$x$	$b$	$y$
$x$	$(x, x)$	$(x, x)$	$(x, b)$
$b$	$(b, x)$	$(b, b)$	$(b, y)$
$y$	$(y, b)$	$(y, y)$	$(y, y)$



### Third 'undecided' state

- 1) Disagreements cause agents to become undecided
- 2) Undecided agents believe any non-undecided agent they meet

# Properties

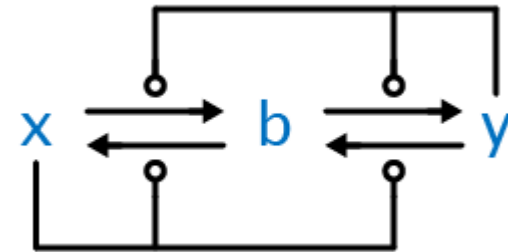
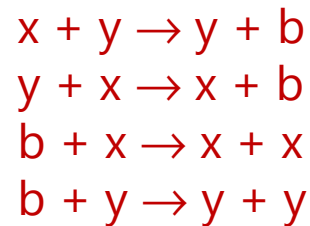
[Angluin et al., <http://www.cs.yale.edu/homes/aspnes/papers/disc2007-eisenstat-slides.pdf>]

- With high probability, for  $n$  agents
  - The total number of interactions before converging is  $O(n \log n)$   
⇒ fast
  - The final outcome is correct if the initial disparity is  $\omega(\sqrt{n} \log n)$   
⇒ solution states are robust to perturbations
- Logarithmic time bound in parallel time
  - *Parallel time* is the number of steps divided by the number of agents
  - In parallel time the algorithm converges with high probability in  $O(\log n)$



# Chemical Implementation

Chemistry as a programming language for population algorithms!



Bistable

Even when  $x=y$ ! (stochastically)

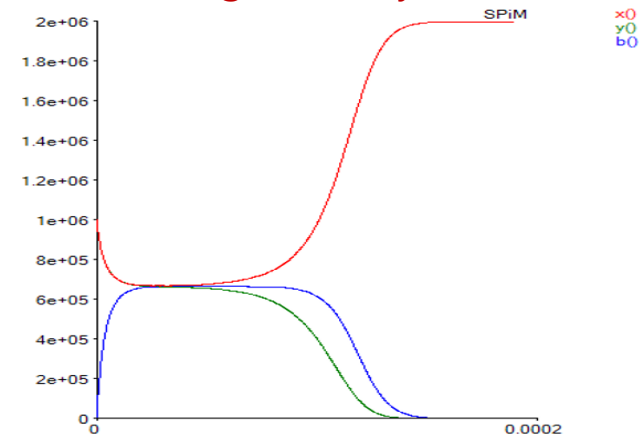
Fast

$O(\log n)$  convergence time

Robust to perturbation

above a threshold, initial majority wins *whp*

Worse-case scenario example, starting with  $x=y$ ,  $b=0$ :



# Correspondence PP $\leftrightarrow$ (normalized)CRN

[Soloveichik., <http://arxiv.org/abs/0803.1030> Appendix A.4 + personal communication]

- Suppose we have a Chemical Reaction Network with:
  - All the reactions are unit-rate, bimolecular, with two products:  $A + B \rightarrow^1 C + D$
  - At most one reaction with the same reactants.
  - “Saturated” with null reactions  $E + F \rightarrow^1 E + F$  and  $G + G \rightarrow^1 G + G$  for all the other possible reactants among existing species (these null reactions have no effect on the kinetics).
  - So there is a one-to-one reaction/interaction correspondence with a Population Protocol (which also has null interactions).
- Consider the sum  $\lambda$  of the Gillespie propensities of all reactions in any state
  - It is always the same (everything interacts with everything else at rate 1): for  $n$  molecules in volume  $v$ ,  $\lambda = n(n-1)/2v$  \*
  - By Gillespie, the time to the next (possibly null) reaction is an exponential random variable with rate  $\lambda$ .
  - There are on average  $1/\lambda$  (possibly null) reactions per unit time. And since  $n/v$  (“concentration”) is assumed constant,  $\lambda$  is  $O(n)$ .
- Transferring Population Protocols Results
  - PPs measure time complexity in expected number of interactions. E.g.: AM converges in  $O(m \log m)$  interactions WHP.
  - But there is now a correspondence with CNR time: let  $E(m)$  be the expected number of interactions of the PP, then  $E(m/\lambda) = E(m)/\lambda$  is the expected running time of the CRN. This can be bounded tightly with Chernoff bounds.
  - For AM,  $E(m)$  is  $O(m \log m)$ , and  $\lambda$  is  $O(n)$ , hence the expected running time of its CRN,  $E(m/\lambda)$ , is logarithmic in the system size.

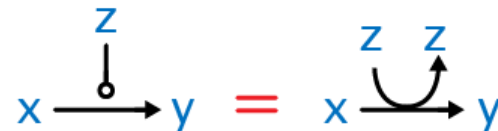
\* Just to confirm, splitting the reactions between the same species and between different species, the sum of the propensities is  $\sum_i \frac{x_i(x_i-1)}{2V} + \sum_{i < i'} \frac{x_i x_{i'}}{V} = \frac{1}{2V} (\sum_i x_i x_i - \sum_i x_i + 2 \sum_{i < i'} x_i x_{i'}) = \frac{1}{2V} (\sum_{i, i'} x_i x_{i'} - \sum_i x_i) = \frac{n(n-1)}{2V}$  using the fact that  $2 \sum_{i < i'} x_i x_{i'} = \sum_{i \neq i'} x_i x_{i'}$  and  $\sum_i x_i x_i + \sum_{i \neq i'} x_i x_{i'} = \sum_{i, i'} x_i x_{i'}$ .

# Back to the Cell Cycle

- The AM algorithm has ideal properties for settling a population into one of two states
- But that is not what the cell cycle uses
- Or is it?

# Influence Network Notation

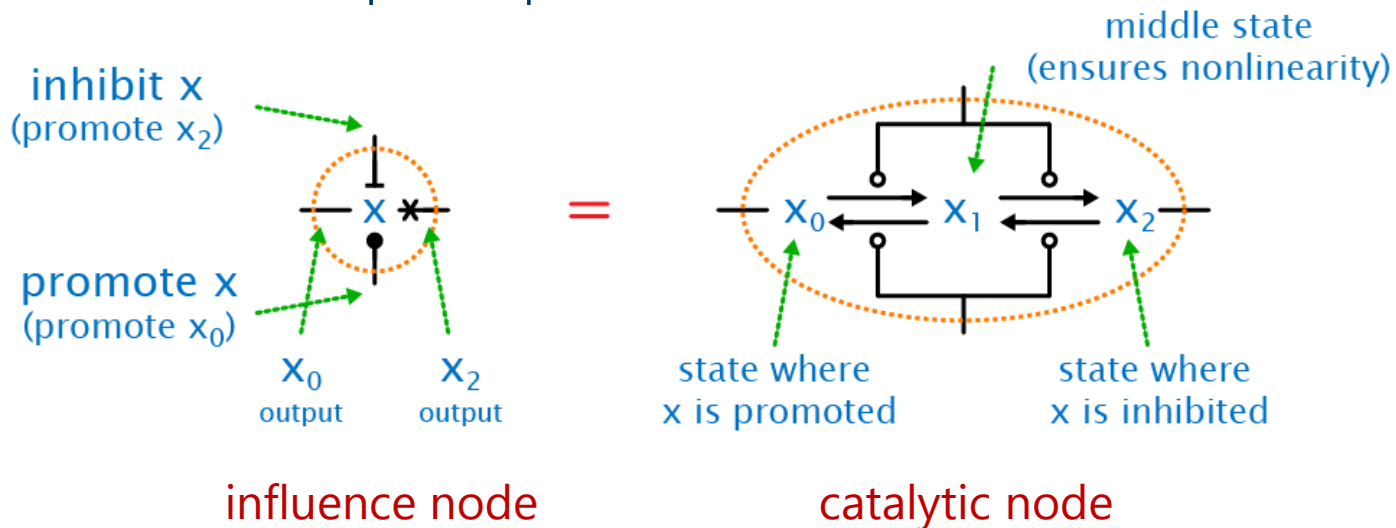
- Catalytic reaction



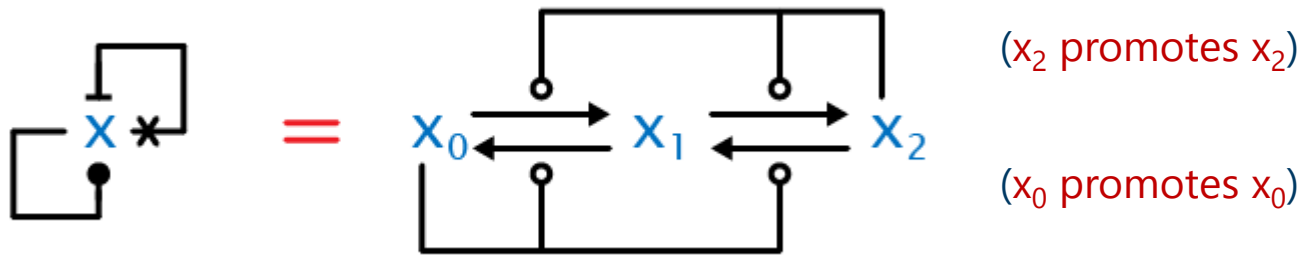
z is the catalyst



- 'Double kinase-phosphatase' motif



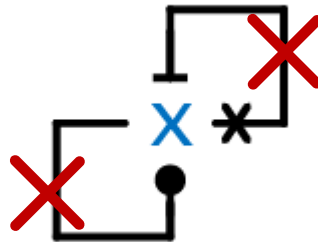
# Step 1: the AM Network



- ... not biochemically plausible

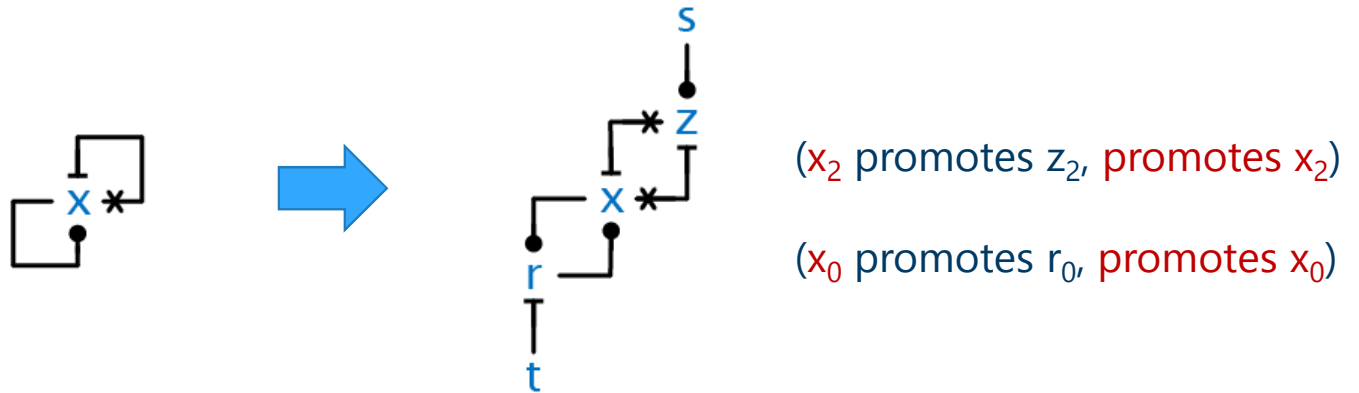
# Natural Constraint #1

- Direct autocatalysis is not commonly seen in nature



## Step 2: remove auto-catalysis

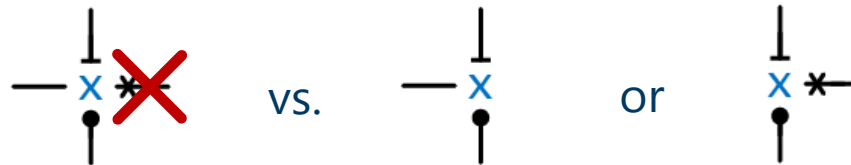
- Replace autocatalysis
  - By *mutual* (simple) catalysis, introducing intermediate species z and r
  - z and r need to 'relax back' when they are not being promoted: s and t provide the back pressure for such relaxation



- ... still not biochemically plausible.

## Natural Constraint #2

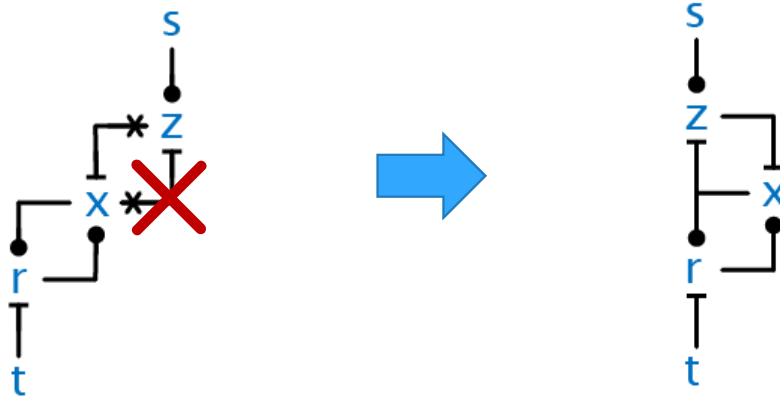
- $x_0$  and  $x_2$  (usually two states of the same molecule) are both active catalysts in that network
- That is not commonly seen in nature





# Step 3: only one active state per species

- Remove the catalytic activity of  $x_2$ 
  - By "flipping the z feedback to the other side"

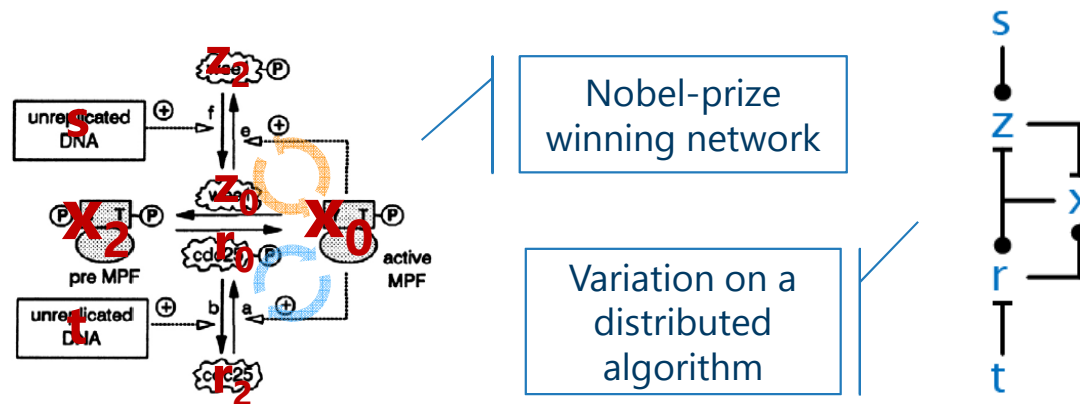


( $x_2$  promotes  $z_0$  via s bias,  
 $z_0$  promotes  $x_2$  via inhibiting  $x_0$ )  
( $x_0$  promotes  $r_0$ , promotes  $x_0$ )

- All species now have one active ( $x_0, z_0, r_0$ ) and one inactive ( $x_2, z_2, r_2$ ) form
- This is 'biochemically plausible'

# Network Structure

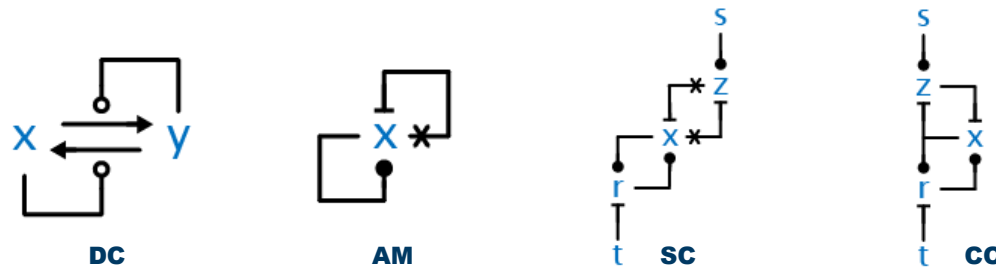
- ... and that is the cell-cycle switch!



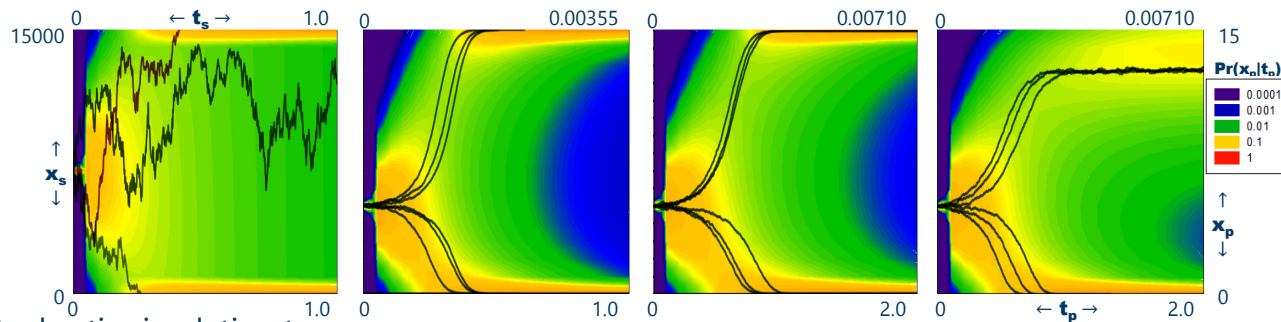
- But did we preserve the AM function through our network transformations?
- Ideally: prove either that the networks are 'contextually equivalent' or that the transformations are 'correct'
- Practically: compare their 'typical' behavior

# Convergence Analysis

- Switches as computational systems



Start symmetrical  
( $x_0 = x_1 = x_2$  etc.)

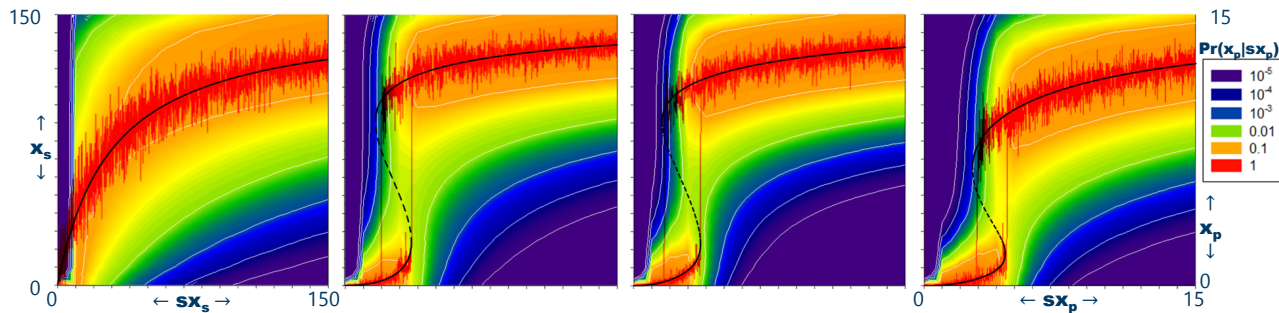
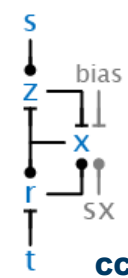
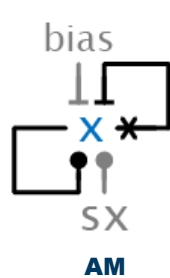
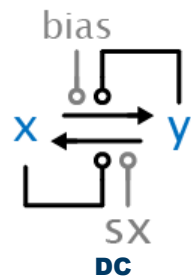


Black lines: several stochastic simulation traces  
Color: full probability distribution of small-size system

**NEW!**  
CC appears to converge in log time

# Steady State Analysis

- Switches as dynamical systems

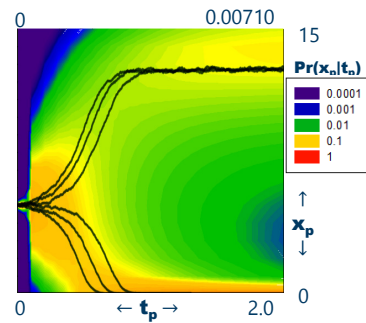


Black lines: deterministic ODE bifurcation diagrams  
 Red lines: noisy stochastic simulations  
 Color: full probability distribution of small-size system

**NEW!**  
 AM shows hysteresis

# Evidence that CC is 'similar' to AM

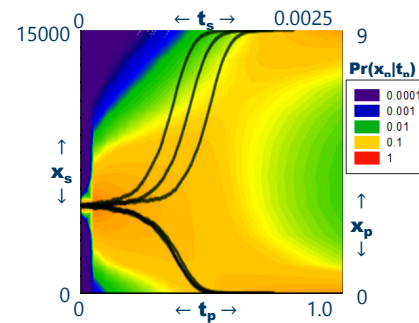
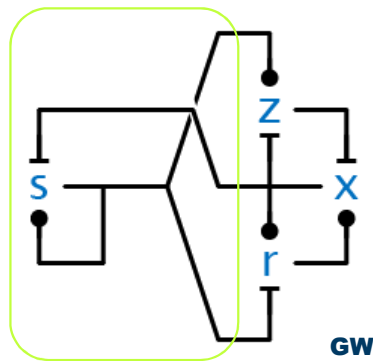
- But there was a difference
  - The output of CC does not go 'fully on' like AM:



- Because s continuously inhibits x through z, so that x cannot fully express
- Q: Why didn't nature do better than that?

# Nature fixed it!

- There is another known feedback loop
  - By which  $x$  suppresses  $s$  "in retaliation" via the so-called **Greatwall** loop
  - Also,  $s$  and  $t$  happen to be the same molecule



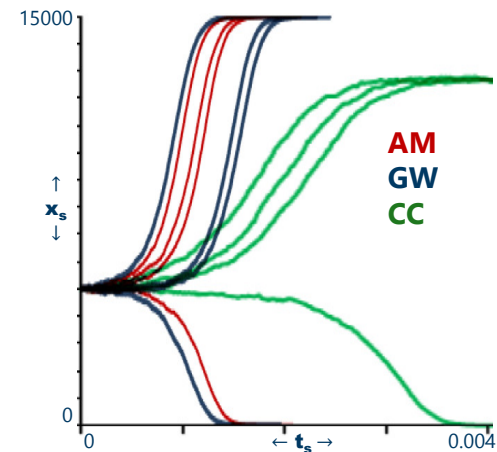
Full activation!

- (As usual, there are many more details in real biological networks; this is one of the many details people knew about without fully understanding its function)

# More surprisingly

- Made it faster too!
  - The extra feedback also speeds up the decision time of the switch, making it about as good as the 'optimal' AM switch:

Conclusion (in our published paper):  
Nature is trying as hard as it can to  
implement an AM-class algorithm!



# The Greatwall Kinase

- Our paper appeared:
  - Suggesting GW is a better switch than CC, also in the context of oscillators
  
- Another paper the same week:
  - Showing experimentally that the Greatwall loop is a **necessary** component of the switch, i.e. the not-as-good-as-AM network has been 'refuted'



The Cell Cycle Switch Computes Approximate Majority

SUBJECT AREAS:  
COMPUTATIONAL  
BIOLOGY

Luca Cardelli<sup>1</sup> & Attila Csikász-Nagy<sup>2,3</sup>



ARTICLE

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Greatwall kinase and cyclin B-Cdk1 are both critical constituents of M-phase-promoting factor

Masatoshi Hara<sup>1,†</sup>, Yusuke Abe<sup>1,†</sup>, Toshiaki Tanaka<sup>2</sup>, Takayoshi Yamamoto<sup>1,†</sup>, Eiichi Okumura<sup>1</sup> & Takeo Kishimoto<sup>1</sup>



# But what about network equivalence?

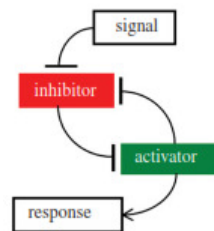
- Our evidence is empirical
  - Although quantitative and covering both kinetic and steady state behavior
  - Also, contextual equivalence holds in the context of oscillators (see paper)
- Analytical evidence is harder to obtain
  - The proof techniques for the AM algorithm are hard and do not generalize easily to more complex networks
  - Quantitative theories of behavioral equivalence and behavioral approximation, e.g. in process algebra, are still lacking (although rich qualitative theories exist)

# Mutual Inhibition

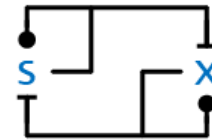
- A new paper suggests that all cellular switches in all phases of the cell cycle follow (abstractly) a mutual inhibition pattern:

## Molecular mechanisms creating bistable switches at cell cycle transitions

Anael Verdugo, P. K. Vinod, John J. Tyson and Bela Novak  
*Open Biol.* 2013 3, 120179, published 13 March 2013

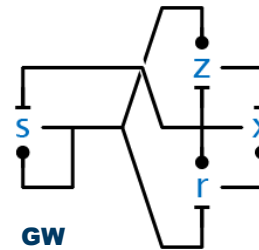


In our notation:



MI

cf.:



GW

# New Cell Cycle Network

- A new paper presents a more complete view of the cell cycle switch
- N.B. “phosphorylation network dynamics” is the same as our  $x_0-x_1-x_2$  motif

## Phosphorylation network dynamics in the control of cell cycle transitions

Daniel Fisher<sup>1\*</sup>, Lilliana Krasinska<sup>1,2</sup>, Damien Coudreuse<sup>2,3</sup> and Béla Novák<sup>3,2</sup>

<sup>1</sup>Institut de Génétique Moléculaire de Montpellier, IGMM, CNRS UMR 5535, Université Montpellier I and II, 34293 Montpellier, France

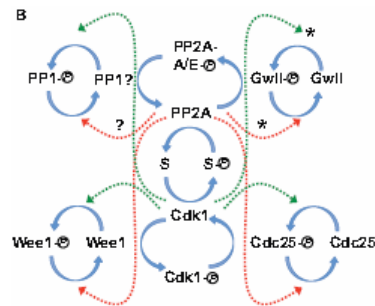
<sup>2</sup>Institute of Genetics and Development of Rennes, CNRS UMR 6290, 35043 Rennes, France

<sup>3</sup>Oxford Centre for Integrative Systems Biology, Department of Biochemistry, University of Oxford, South Parks Road, Oxford OX1 3QU, UK

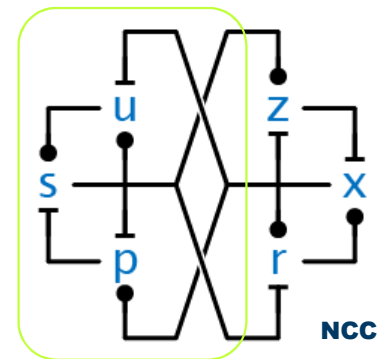
\*Author for correspondence (daniel.fisher@igmm.cnrs.fr)

<sup>†</sup>These authors contributed equally to this work.

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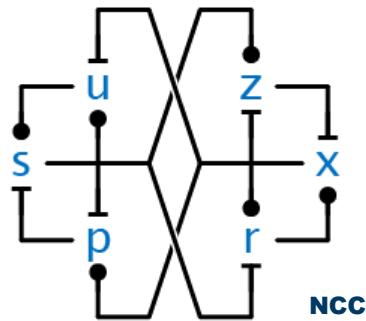


In our notation:

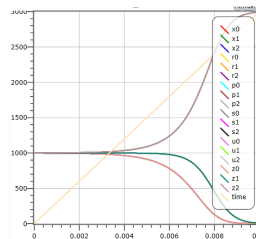
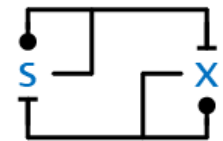


# Network Emulation

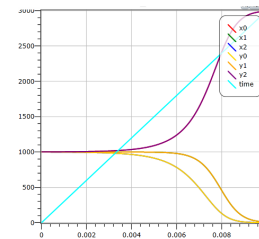
- For chosen (uniform) initial conditions, the ODEs (and hence trajectories) of **NCC** collapse to those of **MI** (thanks to David Soloveichik):



$x, r, p \rightarrow x$   
 $s, u, z \rightarrow s$



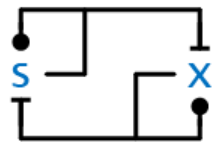
(18 species on 3 trajectories)



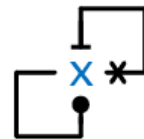
(6 species on 3 trajectories)

# Network Emulation

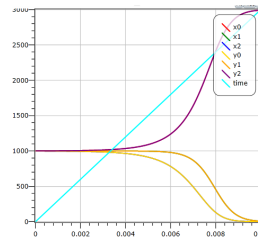
- For chosen (uniform) initial conditions, the ODEs (and hence trajectories) of **MI** collapse to those of **AM**:



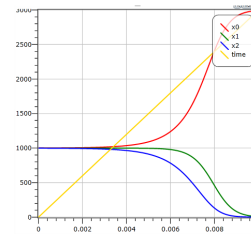
**MI**



**AM**



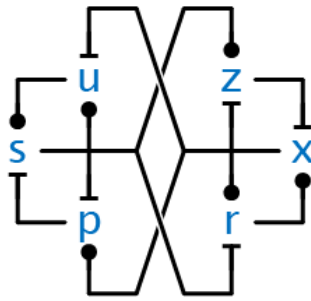
(6 species on 3 trajectories)



(3 species on 3 trajectories)

# Conclusions

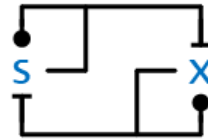
- The cell cycle switch *can exactly* emulate AM



**NCC**

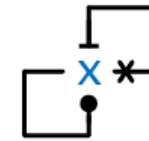
(New) cell cycle switch

emulates:



**MI**

emulates:



**AM**

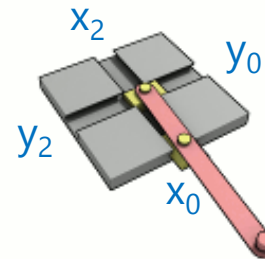
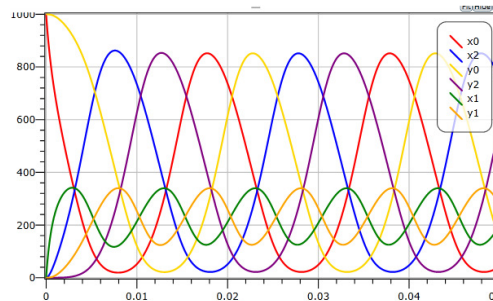
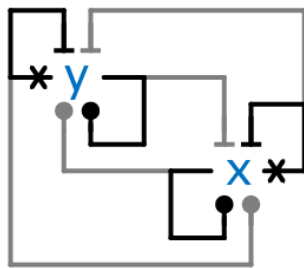
Approximate majority  
algorithm

- Nature likes a good algorithm!

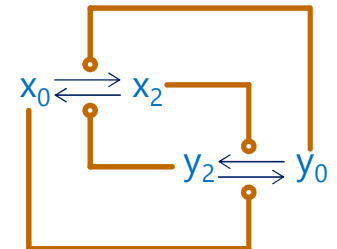
Extra

# Cell Cycle Oscillator

- The cell cycle switch is part of an oscillator network
  - The cell cycle oscillation: grow-divide-grow-divide...
- The principle of the oscillator
  - Two interconnected switches yield a limit-cycle oscillator; e.g. two AM switches
  - In a Trammel of Archimedes configuration (gray rates < black rates)
  - (The biological network lacks some of these links and still oscillates)



[en.wikipedia.org/wiki/Trammel\\_of\\_Archimedes](http://en.wikipedia.org/wiki/Trammel_of_Archimedes)





# In separate work...

- We have a chemical implementation of AM using DNA gates
- I.e., a 'synthetic reimplementation' of the central cell-cycle switch.

## Programmable chemical controllers made from DNA

Yuan-Jyue Chen<sup>1</sup>, Neil Dalchau<sup>2</sup>, Niranjan Srinivas<sup>3</sup>, Andrew Phillips<sup>2</sup>, Luca Cardelli<sup>2</sup>, David Soloveichik<sup>4</sup>, and Georg Seelig<sup>1,5</sup>

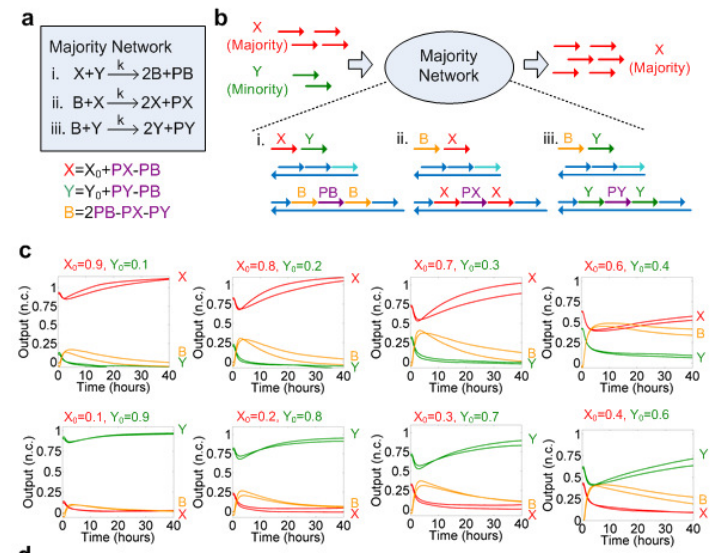
<sup>1</sup> Department of Electrical Engineering, University of Washington, Seattle

<sup>2</sup> Microsoft Research, Cambridge (UK)

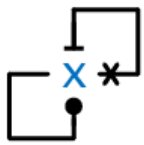
<sup>3</sup> Computation and Neural Systems, California Institute of Technology, Pasadena

<sup>4</sup> Center for Systems and Synthetic Biology, University of California, San Francisco

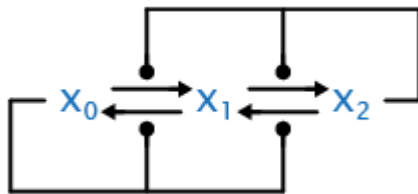
<sup>5</sup> Department of Computer Science & Engineering, University of Washington, Seattle



# Collapse in detail

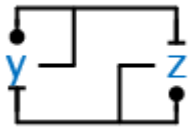


AM

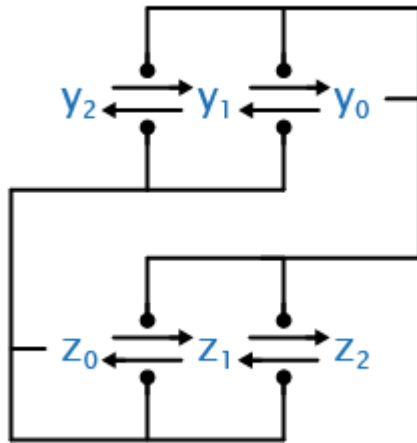


$$\begin{aligned} dx_0/dt &= x_0 * x_1 - x_0 * x_2 \\ dx_1/dt &= x_0 * x_2 + x_2 * x_0 - x_1 * x_0 - x_1 * x_2 \\ dx_2/dt &= x_1 * x_2 - x_2 * x_0 \end{aligned}$$

$$x_{tot} = x_0 + x_1 + x_2$$



MI



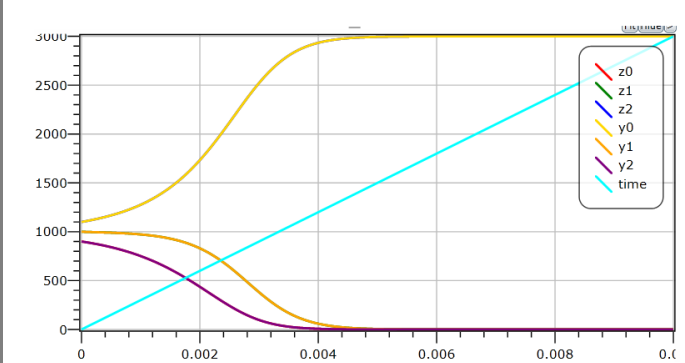
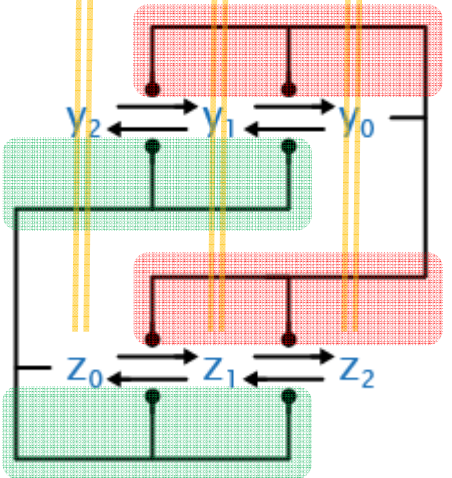
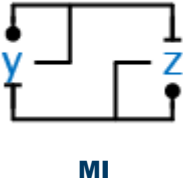
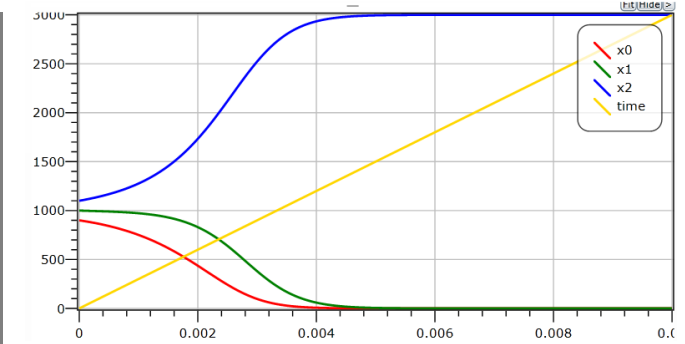
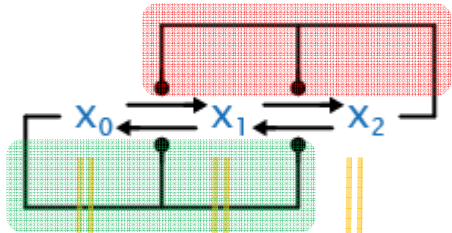
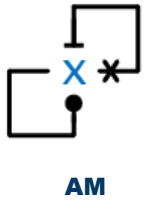
$$\begin{aligned} dz_0/dt &= z_1 * z_0 - z_0 * y_0 \\ dz_1/dt &= z_2 * z_0 + z_0 * y_0 - z_1 * z_0 - z_1 * y_0 \\ dz_2/dt &= z_1 * y_0 - z_2 * z_0 \end{aligned}$$

$$\begin{aligned} dy_0/dt &= y_1 * y_0 - y_0 * z_0 \\ dy_1/dt &= y_0 * z_0 + y_2 * y_0 - y_1 * z_0 - y_1 * y_0 \\ dy_2/dt &= y_1 * z_0 - y_2 * y_0 \end{aligned}$$

$$y_{tot} = y_0 + y_1 + y_2$$

$$z_{tot} = z_0 + z_1 + z_2$$

# Collapse in detail



$$x_0(0) = y_2(0) = z_0(0)$$

$$x_1(0) = y_1(0) = z_1(0)$$

$$x_2(0) = y_0(0) = z_2(0)$$

(at time 0)

# Collapse in detail

[David Soloveichik]

Assume that at some time  $t$ , in **MI**:

$$\begin{aligned}y_2(t) &= z_0(t) \\y_1(t) &= z_1(t) \\y_0(t) &= z_2(t)\end{aligned}\quad (\text{at time } t)$$

then, e.g.:

$$\begin{aligned}(\frac{dy_2}{dt})(t) &= y_1(t) * z_0(t) - y_2(t) * y_0(t) \\&= z_1(t) * z_0(t) - z_0(t) * y_0(t) \\&= (\frac{dz_0}{dt})(t)\end{aligned}$$

this implies that  $y_2(t+dt) = z_0(t+dt)$  and so on at any future time; i.e.  $y_2 = z_0$ .

Similarly  $y_1 = z_1$  and  $y_0 = z_2$ . So the trajectories of **MI** overlap in pairs.

Now assume at some time  $t$  in **AM** and **MI**:

$$\begin{aligned}x_0(t) &= y_2(t) = z_0(t) \\x_1(t) &= y_1(t) = z_1(t) \\x_2(t) &= y_0(t) = z_2(t)\end{aligned}\quad (\text{at time } t)$$

we again have that, e.g.:

$$\begin{aligned}(\frac{dx_0}{dt})(t) &= x_0(t) * x_1(t) - x_0(t) * x_2(t) \\&= z_0(t) * z_1(t) - z_0(t) * y_0(t) \\&= (\frac{dz_0}{dt})(t)\end{aligned}$$

so  $x_0 = z_0 (= y_2)$  at any future time,  
and similarly  $x_1 = z_1 (= y_1)$  and  $x_2 = z_2 (= y_0)$

And if we start with initial conditions satisfying:

$$\begin{aligned}x_0(0) &= y_2(0) = z_0(0) \\x_1(0) &= y_1(0) = z_1(0) \\x_2(0) &= y_0(0) = z_2(0)\end{aligned}\quad (\text{at time } 0)$$

then we have the same time evolution for **AM** and **MI**.



# Question (Cris Moore)

- Is it true that any trajectory of the 'bigger' system converges to a trajectory of the 'smaller' system?
  - This is more than ability to simulate or approximate the smaller system. (We already know from the ODEs that the bigger system can in fact simulate the small one *exactly*.)
  - If the above is true, it further means that the bigger system, even though it has a richer state space and many more trajectories, cannot in fact "stay away" from the behavior of the smaller systems, even if it starts in a state that is not representable in the smaller system.
- "Hi Luca. I have been trying to wrestle with the 18-dimensional (actually 12-dimensional) system all at once. Establishing linear stability of the manifold equivalent to AM seems fairly easy, but I want to show it's globally stable, at least over a large range of initial conditions. Just wanted to let you know. - Cris" [Last I heard.]

