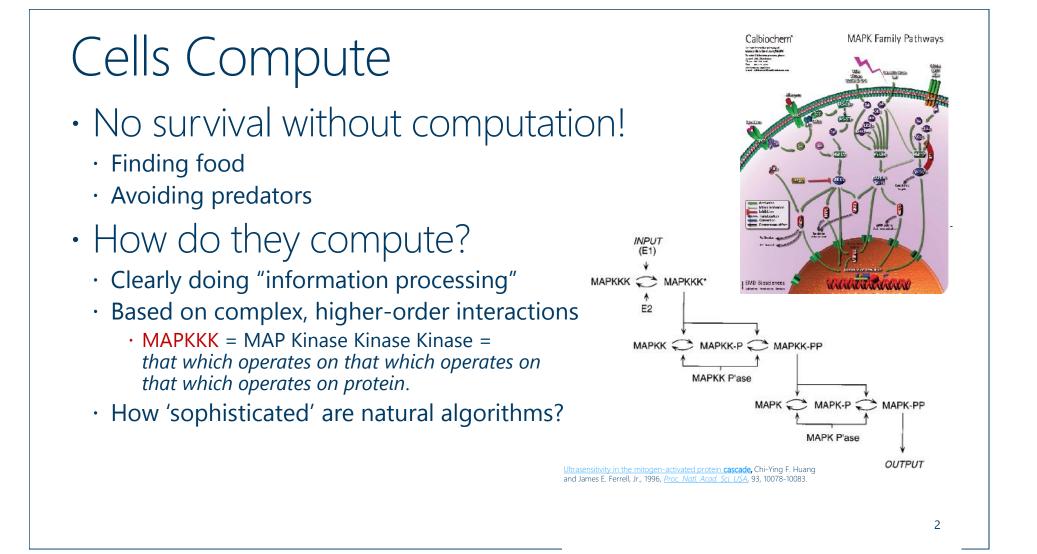
The Cell Cycle Switch Computes Approximate Majority

- Luca Cardelli, Microsoft Research
- Joint work with Attila Csikász-Nagy, CoSBi & King's College London
- Natural Algorithms Workshop, Princeton, 2013-05-21

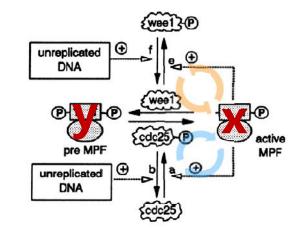


Outline

- Analyzing biomolecular networks
 - $\cdot\,$ Try do understand the function of a network
 - $\cdot\,$ 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:
 - $\cdot\,$ 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, 1155-1168 (1994) 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: Repartment of Agricultural Chemical Tachnology, Tachnical University of Budapest, 15/1 Budapest Gellet Ter 4, Hungary Yauhor tor conseptodence

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

- $\cdot\,$ 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?

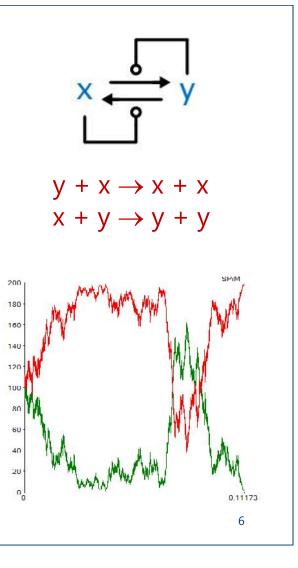
- We need first a **bistable** system: one that has two *distinct* and *stable* states. I.e., given any initial state the system must settle into one of two states
- The settling must be fast (not get stuck in the middle for too long) and robust (must not spontaneously switch back)
- \cdot Finally, we 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
 - $\cdot\,$ x catalyzes the transformation of y into x
 - $\cdot\,$ y catalyzes the transformation of x into y
 - \cdot 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

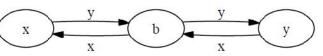
- Approximate Majority (AM)
 - $\cdot\,$ Decide which of two populations is in majority
- A fundamental 'population protocol'
 - · Agents in a population start in state x or state y
 - A pair of agents is chosen randomly at each step, they interact ('collide') and change state
 - The whole population 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.

 $\begin{array}{cccc} x & b & y \\ x & (x,x) & (x,x) & (x,b) \\ b & (b,x) & (b,b) & (b,y) \\ y & (y,b) & (y,y) & (y,y) \end{array}$



Third 'undecided' state

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

Properties

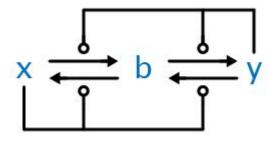
[Angluin et al., http://www.cs.yale.edu/homes/aspnes/papers/disc2007-eisenstat-slides.pdf]

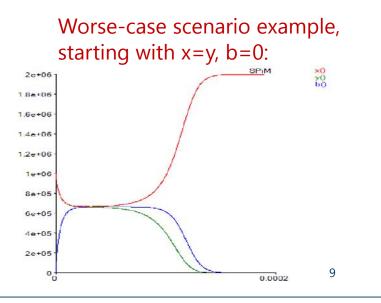
- With high probability, for *n* agents
 - The total number of interactions before converging is O(n log n)
 ⇒ fast
 - The final outcome is correct if the initial disparity is $\omega(sqrt(n) \log n)$ \Rightarrow solution states are robust to perturbations
- Logarithmic time bound in parallel time
 - *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!

 $x + y \rightarrow y + b$ $y + x \rightarrow x + b$ $b + x \rightarrow x + x$ $b + y \rightarrow y + y$





Bistable Even when x=y! (stochastically)

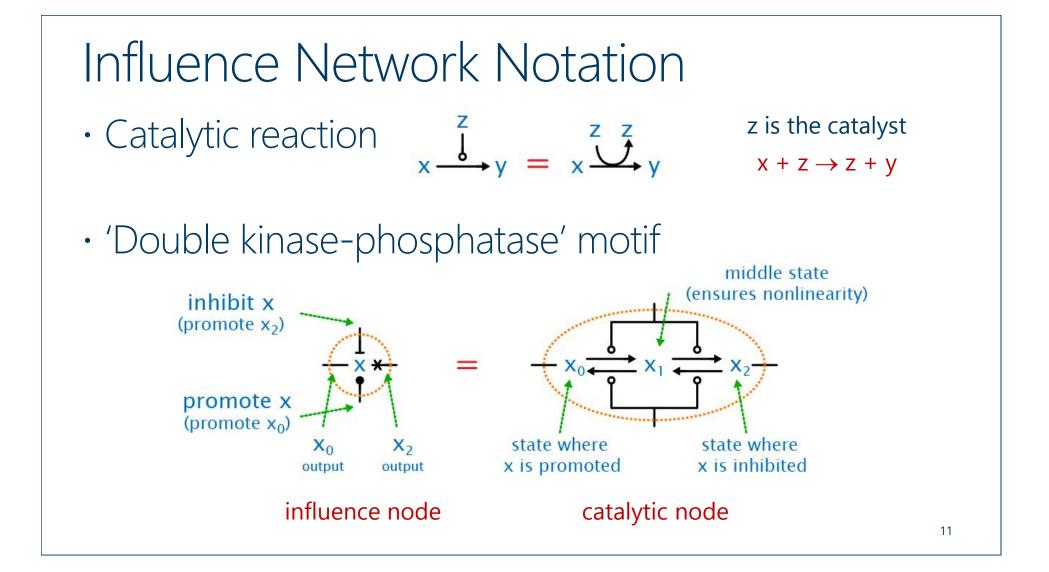
Fast

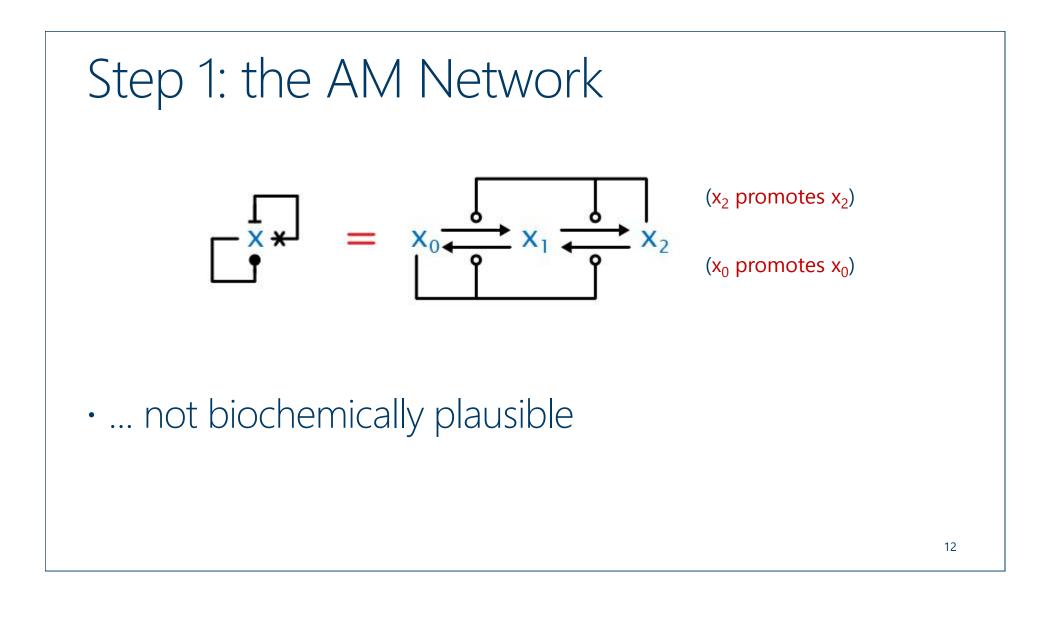
O(log n) convergence time

Robust to perturbation above a threshold, initial majority wins *whp*

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?

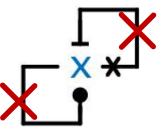


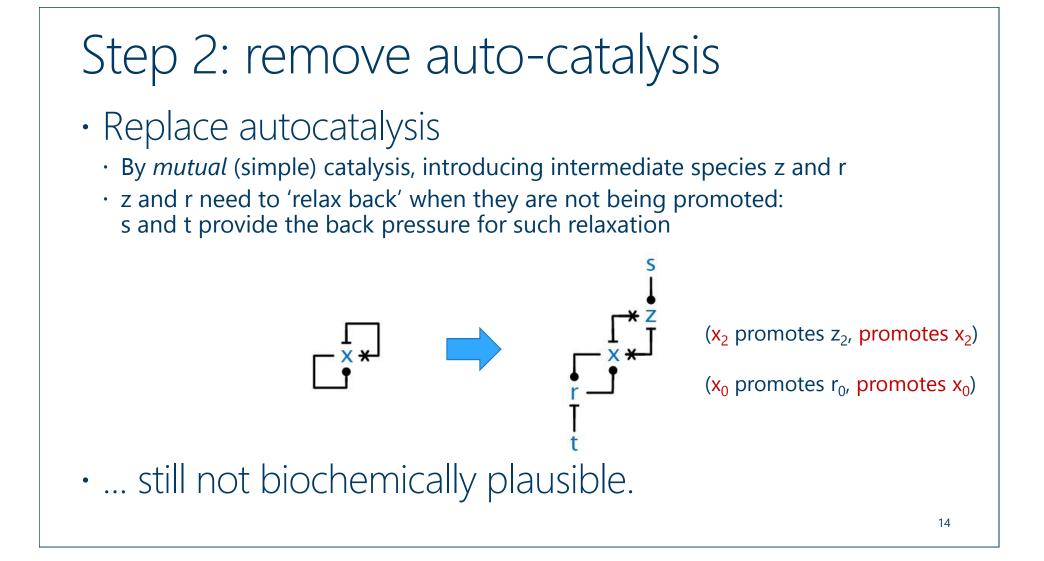


Natural Constraint #1

Direct autocatalysis is not commonly seen in nature

$$\begin{aligned} \mathbf{x}_1 + \mathbf{x}_0 &\to \mathbf{x}_0 + \mathbf{x}_0 \\ \mathbf{x}_1 + \mathbf{x}_2 &\to \mathbf{x}_2 + \mathbf{x}_2 \end{aligned}$$

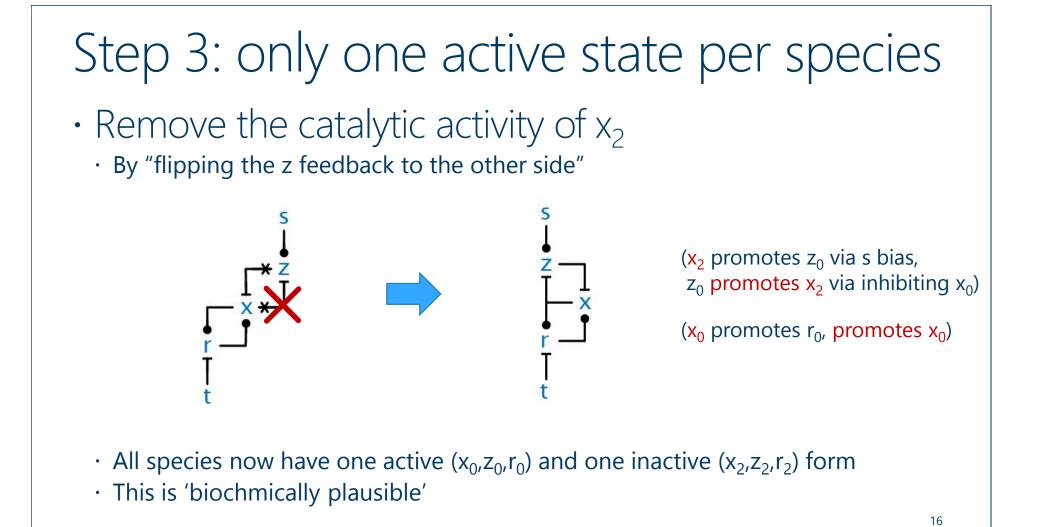


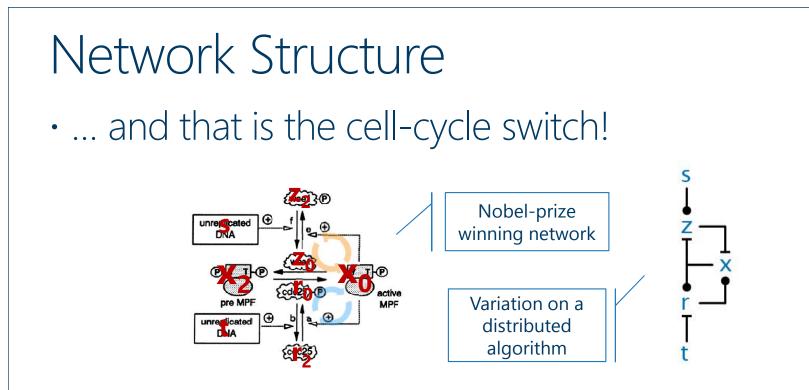


Natural Constraint #2

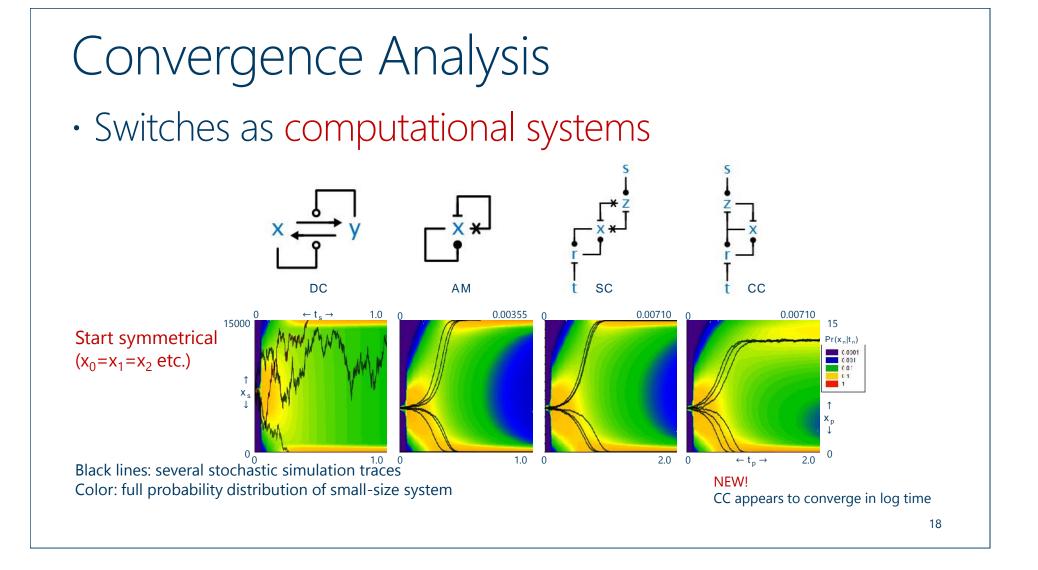
- x_0 and x_2 (usually two states of the same molecule) are both active catalysts in that network
- That is not commonly seen in nature

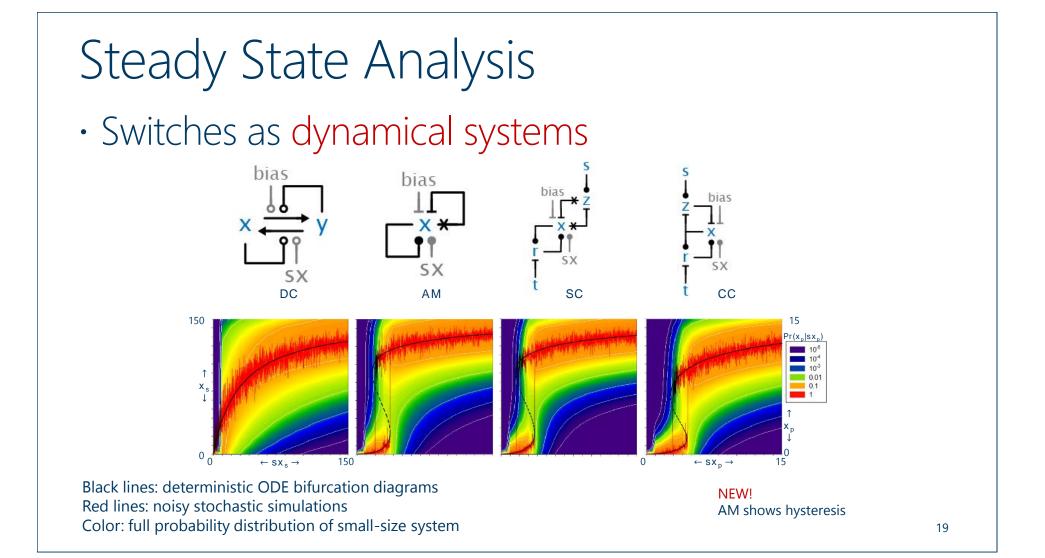
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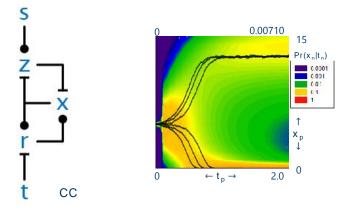
- But did we preserve the AM function through our network transformations?
- Ideally: prove either that the networks are 'contextually equivalent' or that the transformations are 'correct'
- Practically: compare their 'typical' behavior





Evidence that CC is 'similar' to AM

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

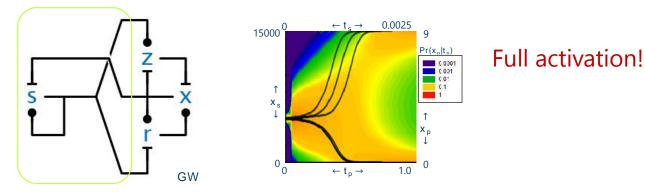


- Because s continuously inhibits x through z, so that x cannot fully express
- \cdot Q: Why didn't nature do better than that?

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Nature fixed it!

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

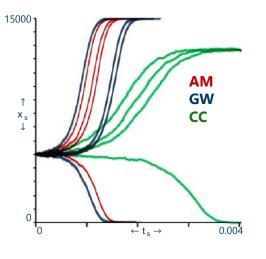


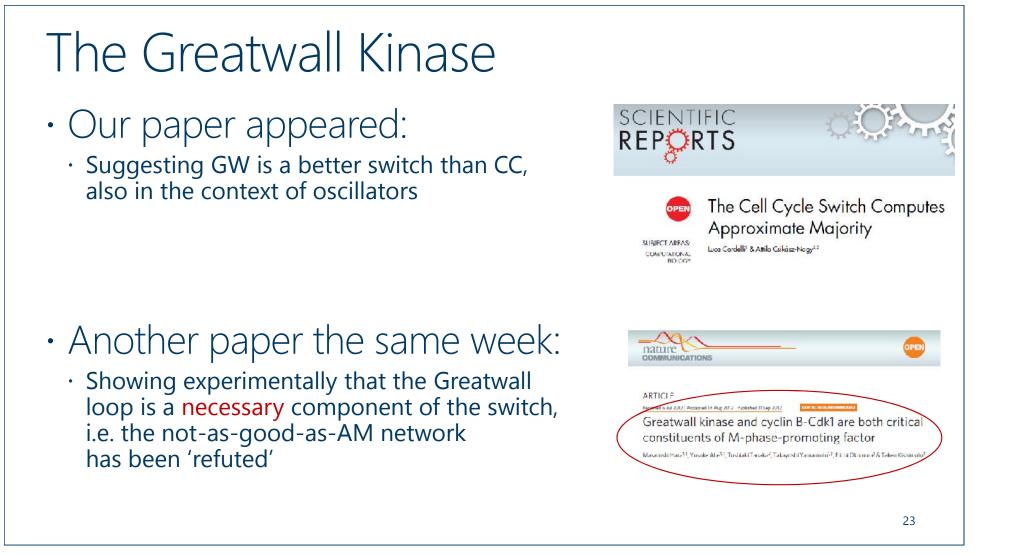
 (As usual, there are many more details in real biological networks; this is one of the many details people knew about without fully understanding its function)

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!





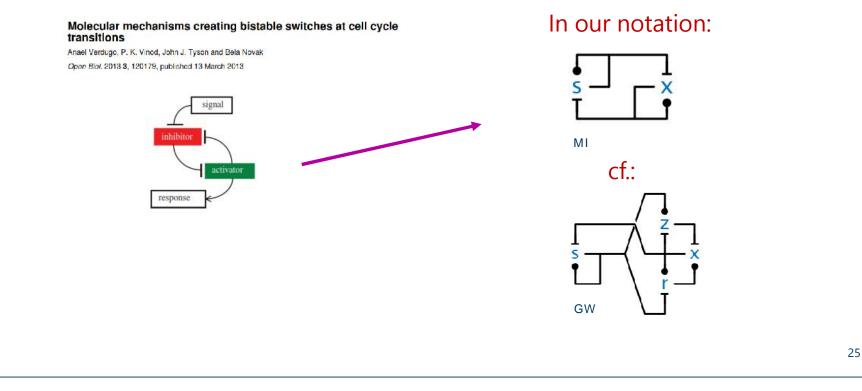
But what about network equivalence?

• Our evidence is empirical

- · Although quantitative and covering both kinetic and steady state behavior
- \cdot 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

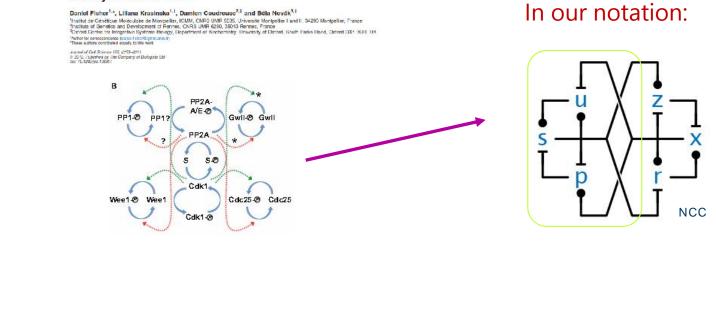
• A new paper suggests that all cellular switches in all phases of the cell cycle follow (abstractly) a mutual inhibition pattern:

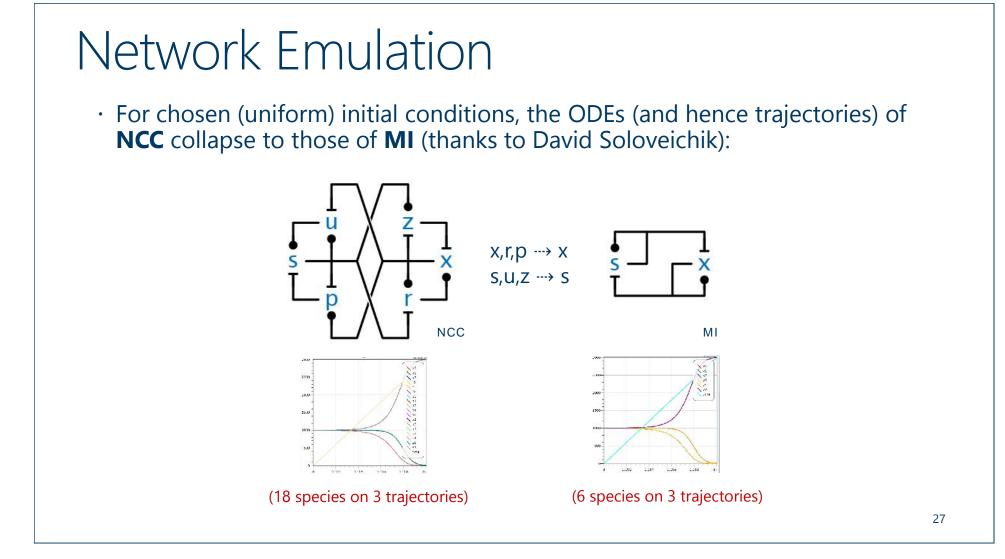


New Cell Cycle Network

- 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

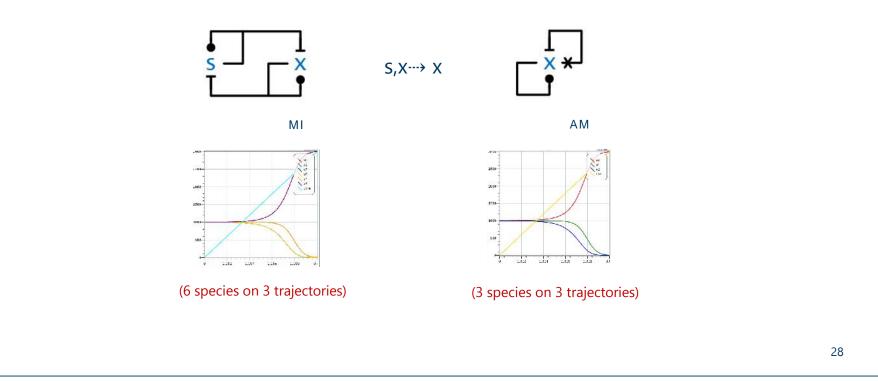
Phosphorylation network dynamics in the control of cell cycle transitions





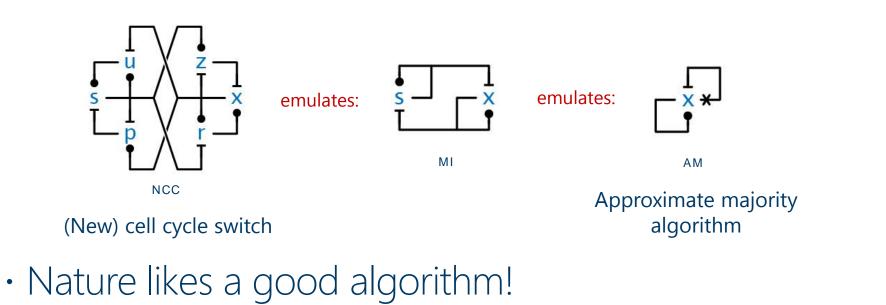
Network Emulation

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



Conclusions

• The cell cycle switch *can* exactly emulate AM





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

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