



# **DNA** Computing

 Programmable controllers for embedded DNA systems



# Chemical Reaction Networks

- In DNA Strand Displacement we can implement arbitrary chemical reaction networks (CRN)
- CRN has become our "general purpose programming language" for nanotechnology



# Engineered CRNs

- What is the meaning/purpose/effect of an engineered CRN program?
- How can we represent desired behavior (algorithms)
   in the CRN language?
- How can we correctly transform programs written in the CRN language?

# Natural CRNs

- What is the meaning/purpose/effect of a natural CRN program?
- How can nature represent desired behavior (algorithms) in the CRN language?
- How can nature correctly transform programs written
  in the CRN language?

# CRN Morphisms

When are two reaction networks related? For example:

- When do they produce the same behavior?
- When is one more robust than another?
- When has one evolved from another?
- When is one a simplified but representative version of another?
- When are there hidden symmetries within one network?
- A morphism (map) relates two networks
  - $\cdot\,$  Study conditions on morphisms that answer the above questions















# Network Emulation: MI emulates AM

• For *any* rates and initial conditions of AM, we can find *some* rates and initial conditions of MI such that the (6) trajectories of MI retrace those (3) of AM:





# Network Emulation: NCC emulates MI

 For any rates and initial conditions of MI we can find some rates and initial conditions of NCC such that the (18) trajectories of NCC retrace those (6) of MI







## Emulations Compose: NCC emulates AM

• The (18) trajectories NCC can *always* retrace those (3) of AM



## Emulation in Context



**AM-AM Oscillator** 



**AM-MI Oscillator** 





 $m \in MI \rightarrow AM$  is an emulation: it maps  $z \rightarrow x$  and  $\sim w \rightarrow x$ 

We can replace AM with MI in a context. The mapping m tells us how to wire MI to obtain an overall emulation:

Each influence crossing the dashed lines into x is replaced by a similar influence into both z and  $\sim w$ . The latter is the same as an opposite influence into w (shown).

Each influence crossing the dashed lines out of x is replaced by a similar influence from the same side of *either z or*  $\sim w$ . The latter is the same as a similar influence from the opposite side of w (shown), and the same as an opposite influence from the same side of w.

20

## When can a Network Emulate Another?

- What kind of morphisms guarantee emulation?
  - do they preserve network structure?
  - do they preserve stoichiometry?





# Corollaries

- By checking only static network and morphism properties we can learn that:
  - All these networks are (at least) bistable
  - (We do not have to reanalyze the steady states of all these dynamical systems)
  - All these networks can perform *exactly* as fast as AM
  - (We do not have to reprove the complexity bounds for all these networks)











# Cell Cycle Switch





### The "classical" Cell Cycle Switch **CC** approximates AM performance



#### CC converges in O(log n) time (like AM) (but 2x slower than AM, and does not fully switch)

Symmetrical initial conditions (x<sub>0</sub>=x<sub>1</sub>=x<sub>2</sub>)

Black lines: high-count stochastic simulation traces Color: full probability distribution of low-count system

Hor axis is time.

#### AM shows hysteresis (like CC)

Black lines: deterministic ODE bifurcation diagrams Red lines: medium-count stochastic simulations Color: full probability distribution of low-count system

Hor axis is stimulus pushing towards x<sub>0</sub> against fixed bias.

There is an obvious bug in CC performance: let's fix it!



### A Theory of Network Emulation (with thanks to David Soloveichik)

- So far, evidence is empirical
  - Simulations based on a choice of parameters
- But indeed...
  - $\cdot$  We can show that, GW, NCC, etc. are *exactly* and *always* as good as AM
  - Where *exactly* means *numerically* as good, not just in the same complexity class
  - And *always* means for *any* choice of rates and initial conditions





# Interpretations of Network Morphisms

### Explanation of network structure

• E.g. we know that the main function of Delta-Notch is to stabilize the system in one of two states. AM is the quintessential network that embodies fast robust bistability. The stoichiomorphism from Delta-Notch to AM "explains" what Delta-Notch (normally) does, and exactly how well it can do it.

### Robust implementation of simpler function

Redundant symmetries are implicit in the stoichiomorphism relationships

### Neutral paths in network space (evolution)

- If an evolutionary event happens to be a stoichiomorphism, or close to it, it will not be immediately selected against, because it is "kinetically neutral".
- This allows the network to increase its complexity without kinetic penalty.
- · Later, the extra degrees of freedom can lead to kinetic differentiation.
- But meanwhile, the organism can explore variations of network structure.

### Network implementation (not abstraction!)

- Stoichiomorphisms are not about abstraction / coarse-graining that preserve behavior, on the contrary, they are about *refinement / fine-graining* that preserve behavior.
- They describe *implementations* of abstract networks, where the abstract networks themselves may not be (biologically) implementable because of excessive demands on species interactions.

| Population Majo  | ority  |   |    |
|--|--|---|----|
| 2004: Computation in networks of passively mobile finite-state<br>Sensors. Dana Angluin, James Aspnes, Zoé Diamadi, Michael J. Fischer, René Peralta. PODC'04. | Majority.<br>The value of the majority function is 1 if there are more<br>1's than 0's in the input otherwise, it is 0.<br>The states of our protocol consist of a live bit and a<br>counter with values in the set $\{-1, 0, 1\}$ . Initially, the live | <b>Exact</b> Majority - 6-state<br><b>Nondeterministic</b> .<br>(population protocol)   |    |
| 2007: A Simple Population Protocol for Fast Robust<br>Approximate Majority. Dana Angluin, James Aspnes, David Eisenstat. DISC07.                               | x y b y y  | Approximate Majority - 3-state<br>Stochastic, discrete time<br>(DTMC) Fundamental results.  |    |
| 2007: Theoretical Analysis of Epigenetic Cell Memory by<br>Nucleosome Modification. Isn B. Dodd, Mile A. Micheeken, Kim Sneppen, Genevieve Thon, Cell.         |  | Approximate Majority - 3-state<br>Stochastic, discrete time<br>(ad-hoc)   |    |
| 2009. Artificial Biochemistry. Luca Cardelli Algorithmic Bioprocesses, Springer.   | la A 2 2 2 B lb  | Approximate Majority - 3-state<br>Stochastic, <b>continuous time</b><br>(CTMC)  |    |
| 2009: Robust Stochastic Chemical Reaction Networks and<br>Bounded Tau Leaping (Appendix 4), David Soloveichick J.Comput.Biol                                   |  | Transfer complexity results from discrete time population protocols to continuous time <b>stochastic chemical reaction networks</b> . |    |
| 2009. Using Three States for Binary Consensus on Complete Graphs. Etienne Perron, Dinkar Vasudevan, and Milan Vojnovic IEEE Infocom.                           |  | Approximate Majority - 3-state<br>Stochastic, <b>continuous time</b><br>(CTMC) Fundamental results.                                   |    |
| 2010: Convergence Speed of Binary Interval Consensus. Moez Draief,<br>Milan Vojnovic Infocom <sup>1</sup> 10.  |  | <b>Exact</b> Majority - 4-state<br>Stochastic, <b>continuous time</b> .   |    |
| 2012: The Cell Cycle Switch Computes Approximate Majority.<br>Luca Cardeli, Attla Cskász-Nagy. Scientific Reports.   |  | The biological cell cycle switch<br>is a (non-obvious) implementation of<br>approximate majority.                                     |    |
| 2014: Morphisms of Reaction Networks that Couple Structure to Function. Luca Cardelia  | $x \xrightarrow{\bullet} b \xrightarrow{\bullet} y$  | Approximate Majority - 3-state<br><b>Continuous space</b> , continuous time<br>(Deterministic ODE)                                    | 34 |