## DNA 17 Tutorial 2:

The Programming Language of Chemical Kinetics, and How To Discipline Your DNA Molecules with Strand Displacement Cascades

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## Living cells are controlled by the most complex signaling networks. Can we (I) understand the function of these networks, (2) be able to engineer new ones with desired function?

The protein interaction network of Syphilis bacteria (Treponema pallidum). Each circle in the figure represents a protein while each line indicates a direct physical interaction.


Drug Discovery \& Development magazine: Vol. 11, No. 8, August, 2008, pp. 22-25.

Living cells are controlled by the most complex signaling networks. Can we (I) understand the function of these networks, (2) be able to engineer new ones with desired function?
in vitro data

model of phosphorylation reactions between $A=K a i A, B=K a i B, C=K a i C$

$$
\begin{align*}
& \tilde{\mathrm{C}}_{i}+\mathrm{B} \underset{\mathrm{k}_{\mathrm{p}}^{\mathrm{Bb}}}{\stackrel{2 \mathrm{k}^{\mathrm{Br}}}{\rightleftarrows}} \mathrm{~B} \widetilde{\mathrm{C}}_{i}, \mathrm{BC} \widetilde{\mathrm{C}}_{i}+\mathrm{B} \underset{2 k_{p}^{\mathrm{B}}}{\stackrel{k^{\mathrm{Br}}}{\rightleftarrows}} \mathrm{~B}_{2} \widetilde{\mathrm{C}}_{i} \tag{1}
\end{align*}
$$

$$
\begin{align*}
& \mathrm{C}_{i} \underset{k_{\text {dep }}}{\stackrel{k_{\text {en }}}{\rightleftarrows}} \mathrm{C}_{i+1}, \widetilde{\mathrm{C}}_{i} \underset{k_{\text {dep }}}{\stackrel{k_{\text {en }}}{\rightleftarrows}} \widetilde{\mathrm{C}}_{i+1} \tag{3}
\end{align*}
$$

Najajima et al, Science, 308, 414-415, 2005 van Zon et al, PNAS, 104: 7420-7425, 2007

Living cells are controlled by the most complex signaling networks. Can we (I) understand the function of these networks, (2) be able to engineer new ones with desired function?

Want to notice patterns in biological signaling/regulatory networks

Engineer embedded controllers for artificial biochemical systems, "wet robots", smart drugs, etc

http://www.artbywicks.com

## Part 1 of 2:

## The Programming Language of Chemical Kinetics

## Using the language of Chemical Reaction Networks (CRNs) prescriptively as a "programming language" rather than descriptively as a modeling language for existing systems



## Outline of Part I

- Stochastic CRN model
- Mass-action CRN model
- Stochastic CRNs:
- illustrative examples: arithmetic operations
- characterizing deterministic behavior
- allowing error permits much more complex behavior (Turing universality)
- Mass-action CRNs:
- dynamical systems
- circuits


## Chemical Reaction Networks (CRN)

syntax:

\[

\]

## two possible semantics:

stochastic: discrete state space, continuous time Poisson process

mass-action: continuous ODEs


## Stochastic CRNs model

- Finite set of species $\{A, B, C, D \ldots\}$. A state is a vector of nonnegative integers, specifying the molecular counts of each species. We also write molecular counts as $\# A, \# B$...
- Finite set of reactions. Each reaction is specified in chemical notation; for example:

$$
A+B \xrightarrow{k} C
$$

indicates a reaction in which the counts of $A$ and $B$ are decreased by 1 , and the count of $C$ is increased by 1 . Each reaction has an associated rate constant $k$. (Unimolecular rate constants have units of $\mathrm{sec}^{-1}$, bimolecular rate constants have units of liters $\cdot$ molecules $^{-1} \cdot \mathrm{sec}^{-1}$ )

## Stochastic CRNs model

-The system evolves via a continuous time Poisson process:
reaction type

$$
\begin{array}{rlll}
A & \xrightarrow{k} & \ldots & k \cdot \# A \\
A+B & \xrightarrow{k} & \ldots & k \cdot \# A \cdot \# B / v \\
A+A & \xrightarrow{k} & \ldots & k \cdot \# A(\# A-1) / v
\end{array}
$$

time until next reaction is exponential random variable with rate $\sum a_{j}$
probability that next reaction is $j^{*}$ is $a_{j^{*}} / \sum a_{j}$

## Scaling from stochastic to mass-action

Increase solution volume $v$ and the molecular counts of all species such that for each species \#X/v stays constant. (Because we measure mass-action concentration in moles/ liter, we have to multiply bimolecular rate constants by Avogadro's number.)

In this way we get mass-action regime in the limit $v \rightarrow \infty$.


## Mass-action CRNs model

-Finite set of species $\{A, B, C, D \ldots\}$. A state is a vector of nonnegative real numbers, specifying the concentrations of each species. We also write concentrations as $[A],[B] \ldots$
-Finite set of reactions. Each reaction is specified in chemical notation; for example:

$$
A+B \xrightarrow{k} C
$$

Each reaction has an associated (mass-action) rate constant $k$. (Unimolecular rate constants have units of $\mathrm{sec}^{-1}$, bimolecular rate constants have units of molar${ }^{-1} \cdot \mathrm{sec}^{-1}$ )

## Mass-action CRNs model

- In any state reaction fluxes are as follows:
reaction type

$$
\begin{array}{rlll}
A & \xrightarrow{k} & \ldots & k \cdot[A] \\
A+B & \xrightarrow{k} & \ldots & k \cdot[A] \cdot[B] \\
A+A & \xrightarrow{k} & \ldots & k \cdot[A]^{2}
\end{array}
$$

- The system behaves according to the ODEs:

$$
\frac{d}{d t}[X]=\sum_{\text {reaction } j} a_{j} \cdot[\text { net stoichiometry change of } X \text { in reaction } i]
$$

$$
\begin{aligned}
& \text { example: } \\
& \begin{array}{rll}
A & \xrightarrow{k_{1}} & B \\
B+B & \xrightarrow{k_{2}} & C
\end{array} \quad \square \frac{d t}{d[B]}=k_{1}[A]-2 k_{2}[B]^{2} \\
& \frac{d[C]}{d t}=k_{2}[B]^{2} \\
& \frac{d[A]}{d t}=-k_{1}[A]
\end{aligned}
$$

## Physical justification for CRNs

## Assumptions for stochastic:

- well-mixedness
- bouncing ball interactions
- instantaneous reactions


McQuarrie 1967, van Kampen, Gillespie 1977, I992, etc

## Extra assumptions for mass-action:

- large molecular counts of all species

Kurtz,"The relationship between stochastic and deterministic models for chemical reactions",J Chem Phys 57:2976, 1972

## What about thermodynamics, conservation of mass?

- thermodynamics says all reactions must be reversible
- if a reaction can occur with a catalyst, it must occur without it (at a slower rate)
- closed system must satisfy Gibbs free energy
- molecules are made of atoms; must be consistent with atomic decomposition and conservation of mass
open systems, implicit energy and mass sources, effectively irreversible reactions, high energy barriers


## Abstract CRNs have been extensively theoretically investigated

- simulation: accuracy, computation time
- equilibrium analysis: number of steady states, bistability?, oscillation?, limit cycle?, chaos?
- deviant behavior of stochastic compared to mass-action
- derived models: Michaelis-Menten, Hill functions, GRNs, S-Systems, NHCA, etc
- time-separation arguments
- network motifs: search and in-silico evolution


## But designing molecular algorithms? Not so much...

## Judging speed of chemical "algorithms"

- Can speed up any behavior by a factor of $\alpha$ if we multiply all rate constants by $\alpha$.
not meaningful
- Can speed up behavior by increasing molecular counts but keeping volume the same. This translates to increasing concentration in mass-action.
impossible: must remain well-mixed, respect finite density of matter

Thus for meaningful analysis of speed of chemical "algorithms":

- fix largest rate constant (say $k=1$ )
- asymptotically, volume $v=O$ (total molecular count). This translates to bounding maximum concentrations in mass-action.


## Programming exercises with stochastic CRNs

> Programming exercise I: $$
\# B:=2 \cdot \# A
$$

Eventually produce the right number of B's

expected time for one instance of reaction
whose propensity is $\# A=n$

## Programming exercise 2:

Detect a molecule of $A$ among $n$ molecules in solution volume $v \approx n$

## Whole test-tube eventually "turns Yellow" if and only if there is at least one molecule of $A$

## start with $\mathrm{n} X$

$$
\begin{aligned}
& A+X \xrightarrow{1} A+Y \\
& X+Y \xrightarrow{1} Y+Y
\end{aligned}
$$

expected time of this algorithm: $1+\Theta(\log n)=\Theta(\log n) \quad$ (fast!)
expected time for one instance of first reaction
whose propensity is $(\# A \cdot \# X) / v=(1 \cdot n) / n=1$
expected time for $n$ instances of second reaction whose propensity is $(\# X \cdot \# Y) / v$

# Programming exercises with stochastic CRNs 

## Programming exercise 3 : <br> $$
\# A:=2 \cdot \# A
$$

$$
n A^{\prime} \mathrm{s}
$$

$$
\text { volume } v \approx n
$$

## Even in the limit $\mathrm{t} \rightarrow \infty$ must be some probability of error.

## Programming exercise 4: <br> Is \#A even?

$n$ A's
volume $v \approx n$

## Eventually converge to the right answer.

start with $1 T$ and $n A$

$$
\begin{aligned}
& A+T \xrightarrow{1} F \\
& A+F \xrightarrow{1} T
\end{aligned}
$$



Expected time for the last $A$ to react with $T$ or $F$. Propensity of this reaction is $(\# A \cdot \# T, F) / v=(I \cdot I) / n$

## How can stochastic CRNs compute "deterministically"?

## Let's start with computing predicates (well-studied).

Species $\boldsymbol{T}$ and $\boldsymbol{F}$ representing output.
YES is absorbing set of states with $\# \mathbf{T}>0, \# F=0$.
$\mathbf{N O}$ is absorbing set of states with $\# \mathbf{T}=0, \# \mathbf{F}>0$.
Everything else (not in YES or NO) can have arbitrary \#T, \#F.
YES is reachable from any state that is reachable from a yes-input, but is not reachable from any no-input.
NO is reachable from any state that is reachable from a no-input, but is not reachable from any yes-input.
(For simplicity assume finite state space for any input. Need to be more careful for infinite state spaces (eg. $A \rightarrow 2 A$ ), but intuition is the same.)

# How can stochastic CRNs compute "deterministically"? 

## Examples of computing a predicate in this way:

Predicate: \#A > \#B
start with $1 F$ and input amounts of $A, B$
$A+F \rightarrow T$
$B+T \rightarrow F$

Predicate: \#A is even start with $1 T$ and input amount of $A$
$A+T \rightarrow F$
$A+F \rightarrow T$

Predicate: $\# A>\# B$ and $\# A$ is even
start with 1 FI, 1 T2, 1 F and input amounts of $A, B$
$A+T 2 \rightarrow A^{\prime}+F 2$
$A^{\prime}+F I \rightarrow T I$
$A+F 2 \rightarrow A^{\prime}+T 2$
$B+T I \rightarrow F I$
$T I+T 2 \leftrightarrow T T$
$T T+F \rightarrow T T+T$
$\mathrm{FI}+\mathrm{T} \rightarrow \mathrm{FI}+\mathrm{F}$
$F 2+T \rightarrow F 2+F$
$B+T I \rightarrow F$

## How can stochastic CRNs compute "deterministically"?

Then the class of predicates that can be computed is well-characterized:

Boolean combination of threshold predicates and modulo predicates:
threshold predicate: $\{\boldsymbol{x} \mid \mathbf{X} \cdot \mathbf{v} \geq r\}$
modulo predicate: $\{\boldsymbol{x} \mid \boldsymbol{x} \cdot \mathbf{v} \equiv \mathrm{r}(\bmod \mathrm{m})\}$

## Stochastic CRNs are Turing Universal, allowing an (arbitrarily small, non-zero) error probability

- Arbitrarily small, non-zero error probability over all time. Error probability controlled by initial molecular count of "accuracy species"
- Two kinds of constructions: Register Machine simulation, Turing Machine simulation
- Turing universal computation can be made fast: $\mathrm{t}=$ poly(number of TM steps).
- But: Register machine or Turing machine simulation just doesn't feel natural for CRNs. Information is stored in unary. Register machine: slow;Turing machine: too many reactions. Has a feeling of shoehorning existing paradigms to a very different system.


## Which dynamical systems can be implemented with mass-action CRNs?



Rössler (chaotic)


## Which dynamical systems can be implemented with mass-action CRNs?

Some ODEs cannot be directly implemented Example (linear oscillator): $\quad \begin{array}{ll}\dot{x}=-y \\ & \dot{y}=x\end{array}$


Problems:
(1) Chemical concentrations cannot be negative.
(2) A species must appear as a reactant to be consumed. Thus the rate of its consumption must be proportional to its concentration.

Solution with representation change: $x=[X p]-[X n] \quad y=[Y p]-[Y n]$

$$
X p \xrightarrow{1} Y_{p}+X p
$$

$$
X_{n} \xrightarrow{1} Y_{n}+X n
$$

$$
\begin{aligned}
& X_{p}+X_{n} \xrightarrow{\text { fast }} \varnothing \\
& \left.\begin{array}{l}
Y_{p} \xrightarrow{1} X_{n}+Y_{p} \\
Y_{n} \xrightarrow{\rightarrow} X_{p}+Y_{n}
\end{array}\right] \quad \dot{X}=[\dot{X p}]-[\dot{X} n]=\left[Y_{n}\right]-\left[Y_{p}\right]=-y
\end{aligned}
$$

## Which dynamical systems can be implemented with mass-action CRNs?

## Korzuhin's theorem:

It is always possible to construct a CRN in which the concentration of some species coincides with any desired accuracy for any desired period of time with the behavior of a given system of polynomial ODEs with non-negative integer powers.
(Applies only to the behavior of the ODEs in the positive orthant.)

Constructed CRN has the following properties -conservation of mass
-reactions of very simple form: at most two reactants and at most two products -no autocatalysis

## Logic circuits with mass-action CRNs



## Problems:

-no signal restoration
-not dynamic or reusable: can't change input values to get new output
-slow: for a single gate, if $[A]=[B]$ then $[A](t)=[B](t)=O(I / t)$ not $O\left(e^{-t}\right)$

Seelig and Soloveichik,"Time complexity of multilayered DNA strand displacement circuits" in DNA I5

## Dynamic logic circuits with mass-action CRNs

| $\mathbf{x}$ | $\mathbf{y}$ | $\mathbf{z}$ |
| :---: | :---: | :---: |
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 0 |
| 1 | 1 | 0 |


dual rail
representation:
species value

| $\mathrm{x}(0) \times(1)$ | x |
| :--- | :--- |
| high low | 0 |
| low high | 1 |

logic
thresholding

$$
\begin{array}{cl}
x(0)+y(1)+w(0) \rightarrow x(0)+y(1)+w(1) & w(0)+w(0)+z(1) \rightarrow w(0)+w(0)+z(0) \\
x(1)+w(1) \rightarrow x(1)+w(0) & w(1)+w(1)+z(0) \rightarrow w(1)+w(1)+z(1) \\
y(0)+w(1) \rightarrow y(0)+w(0) &
\end{array}
$$

## 2-bit pulse counter

 (digital circuit)


Soloveichik, Seelig, Winfree,"DNA as a universal substrate for chemical kinetics", PNAS, 107: 5393-5398 (2010)

# Dynamic logic circuits with mass-action CRNs: signal restoration 

## Cooperativity

$w(0)+w(0)+z(1) \xrightarrow{1} w(0)+w(0)+z(0)$
$w(1)+w(1)+z(0) \xrightarrow{\rightarrow} w(1)+w(1)+z(1)$


Majority Algorithm

$$
\begin{aligned}
& w(0)+w(I) \xrightarrow{1} s w \\
& s w+w(0) \xrightarrow{\rightarrow} 3 w(0) \\
& s w+w(1) \xrightarrow{\rightarrow} 3 w(I)
\end{aligned}
$$

Jiang, Riedel and Parhi, "Digital Logic with
Molecular Reactions," submitted.

# Artificial Biochemistry 

Luca Cardelli

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## Abstract

We model chemical and biochemical systems as collectives of interacting stochastic automata, with each automaton representing a molecule that undergoes state transitions. In this artificial biochemistry, automata interact by the equivalent of the law of mass action. We investigate several simple but intriguing automata collectives by stochastic simulation and by ODE analysis.


Luca Cardelli,"Artificial Biochemistry", in Algorithmic Bioprocesses. Springer (2009) ( http://lucacardelli.name/Papers/Artificial\ Biochemistry.pdf )

# Part 2 of 2: <br> <br> How To Discipline Your DNA Molecules with Strand <br> <br> How To Discipline Your DNA Molecules with Strand Displacement Cascades 

 Displacement Cascades}

## Strand Displacement Cascades is a flexible technology for implementing complex nucleic-acid reaction networks in the laboratory

## Engineering artificial signaling networks

## Long-term goals:

-Insert desired control module into cells? Medical applications? Smart drugs?
-Abiological systems: control modules for nanomotors, self-assembly, polymerization, other kind of chemistries? "Wet robot"?
-Develop clarity of thought for understanding biological signaling networks

Approach: No "alien" technology: only what we can understand and build


## The strand displacement reaction


enzyme-free strand displacement aka branch migration
Green, C \& Tibbetts, C. (1981) Nucleic Acids Research 9, 1905
Weinstock, P \& Wetmur, J. (1990) Nucleic Acids Research 18, 4207
Panyutin, I \& Hsieh, P. (1993) Journal of molecular biology 230, 413
first systematic use in DNA nanotechnology
Yurke, B \& Mills, A. P. (2003) Genetic Programming and Evolvable Machines 4, 111

## Cascading of strand displacement reactions



Dirks, Pierce, "Triggered amplification by hybridization chain reaction," PNAS 101, 15275 (2004).


Seelig, Soloveichik, Zhang, Winfree, "Enzyme-free nucleic acid logic circuits," Science 314, 1585 (2006).

## Strand Displacement Cascades

- Bind two complementary domains
possible moves: • Release any strand held by only a short domain
- Displace a domain by an identical domain if this extends existing hybridization



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## Strand Displacement Cascades example: Catalyst



Zhang, Turberfield, Yurke, Winfree, Science 318: 1121-1125, 2007

## AND Logic Gate


based on Seelig, Soloveichik, Zhang, Winfree, Science 314: 1585-1587 (2006)

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based on Seelig, Soloveichik, Zhang, Winfree, Science 314: 1585-1587, 2006

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## AND Logic Gate


based on Seelig, Soloveichik, Zhang, Winfree, Science 314: 1585-1587, 2006

## AND Logic Gate


based on Seelig, Soloveichik, Zhang, Winfree, Science 314: 1585-1587 (2006)

## Translator Gates: complete sequence independence



## Experimental technique: Fluorescent readout



## Experimental Data for One AND Gate and an II-gate Logic Circuit





Seelig, Soloveichik, Zhang, Winfree, Science 314: 1585-1587, 2006

## Experimental Data for Catalyst



Zhang, Turberfield, Yurke, Winfree, Science 318: 1121-1125, 2007 <br> \title{
VisualDSD:A formal language for describing and modeling <br> \title{
VisualDSD:A formal language for describing and modeling strand displacement cascades
} strand displacement cascades
}


# Rich Snider, Dmitry Danilov and Zoran Popovic collaboration with Georg Seelig, David Baker 

## Flash Game Demo

## You can play it too: http://games.cs.washington.edu/DNA_Game/DNA.html

Play the introductory levels to get to the exponential amplifier challenge. You can submit your solution to the challenge through the game website.

The largest strand displacement cascades implemented in the laboratory used "see-saw" gates

4 simple element types:


## Logic circuits with see-saw gates



130 DNA strands
74 initial DNA species (excluding inputs)

## Neural networks with see-saw gates



112 DNA strands
72 initial DNA species
d Q1: Did the scientist study neural networks?
Q2: Was the scientist British?
Q3: Was the scientist born in the $20^{\text {th }}$ century?
Q4: Was the scientist a mathematician?
Answers: Yes (1), No (0), or I don't know (?)

| 0110 | Rosalind Franklin |
| :--- | :--- |
| 1111 | Alan Turing |
| 0011 | Claude Shannon |
| 1000 | Santiago Ramon y Cajal |







$\cdots x_{1}^{0}-x_{1}^{1} \quad \cdots x_{2}^{0}-x_{2}^{1} \quad \cdots x_{3}^{0}-x_{3}^{1} \quad \cdots x_{4}^{0}-x_{4}^{1}$

## Goal: Be able to take any mass-action CRN and implement it in the test tube

| $1:$ | $X_{1}$ | $\xrightarrow{30}$ | $2 X_{1}$ |
| :--- | ---: | :--- | :--- |
| $2:$ | $2 X_{1}$ | $\xrightarrow{0.5}$ | $X_{1}$ |
| $3:$ | $X_{2}+X_{1}$ | $\xrightarrow{1}$ | $2 X_{2}$ |
| $4:$ | $X_{2}$ | $\xrightarrow{10}$ |  |
| $5:$ | $X_{1}+X_{3}$ | $\xrightarrow{1}$ |  |
| $6:$ | $X_{3}$ | $\xrightarrow{16.5}$ | $2 X_{3}$ |
| $7:$ | $2 X_{3}$ | $\xrightarrow{0.5}$ | $X_{3}$ |



- implicit energy/mass source (no conservation restrictions)
- can use auxiliary species to help mediate reactions
- desired behavior up to scaling in time and concentration
- allow degree of approximation: correct behavior in some limit

David Soloveichik, Georg Seelig, Erik Winfree,"DNA as a Universal Substrate for Chemical Kinetics", PNAS I07:5393-5398, 2010

## Format of formal species


invariant: species is active if species identifier is entirely single-stranded

## Unimolecular reaction $X \rightarrow Y$


and unreactive waste

## Unimolecular reaction $X \rightarrow Y$


intermediate output


## Bimolecular reaction $X+Y \rightarrow Z$



## Bimolecular reaction $X+Y \rightarrow Z$



# Complex self-generated behavior with strand displacement cascades (simulations) 



Predator-prey

$$
\begin{aligned}
& \text { 1: } X_{1}+X_{2} \xrightarrow{k_{1}} 2 X_{2} \\
& \text { 2: } \quad X_{1} \xrightarrow{k_{2}} 2 X_{1} \\
& \text { 3: } \quad X_{2} \xrightarrow{k_{3}} \emptyset \\
& \begin{array}{|ccc|}
\hline \begin{array}{cc}
\text { unscaled } & \text { scaled } \\
k_{1} & 1.5 \\
k_{2} & 1 \\
k_{3}-10 / \mathrm{M} / \mathrm{s} \\
k_{3} & 1
\end{array} & 1 / 300 / 30 / \mathrm{s} \\
\hline
\end{array}
\end{aligned}
$$


--- simulation of ideal CRN

- simulation of DNA implementation

Dynamic logic circuits and state machines with strand displacement cascades (simulations)


-     -         - simulation of ideal CRN
_- simulation of DNA implementation


## Toward laboratory implementation of CRN $\Rightarrow$ strand displacement cascades (work in progress)

Ideal autocatalytic oscillator

$$
\begin{aligned}
& A+B \xrightarrow{1} 2 B \\
& B+C \xrightarrow{+} 2 C \\
& C+A \xrightarrow{\rightarrow} 2 A
\end{aligned}
$$



Recent laboratory experiment



## The Programming Language of Chemical Kinetics

Using the language of Chemical Reaction Networks (CRNs) prescriptively as a "programming language" rather than descriptively as a modeling language for existing systems
stochastic and mass-action

# How To Discipline Your DNA Molecules with Strand Displacement Cascades 

Strand Displacement Cascades is a flexible technology for implementing complex nucleic-acid reaction networks in the laboratory
artificial analogs of signaling networks $\quad 3$ rules description catalytic amplifier, circuits, neural networks theoretically can implement any CRNs

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