## Programming Chemical Systems

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## Outline

1. From "any" Digital or Analog system to a Chemical Reaction Network
2. From (made-up) Chemical Reaction Networks to (real) Molecules that implement them (skipped)
3. Languages for Chemical Reaction Networks

Part 1
From (almost) any algorithm and (almost) any dynamical system to a Chemical Reaction Network

## Chemical Reaction Networks (CRN)

$$
X+Y->r Z+W
$$

- A phenomenological model of kinetics in the natural sciences

By (only) observing naturally occurring reactions

- A programming language, finitely encoded in the genome

By which living things manage the unbounded processing of matter and information

- A mathematical structure, rediscovered in many forms

Vector Addition Systems, Petri Nets, Bounded Context-Free Languages, Population Protocols, ...

- A description of mechanism ("instructions" / "interactions") rather than behavior ("equations" / "approximations")

Although the two are related in precise ways
Enabling, e.g., the study of the evolution of mechanism through unchanging behavior

Part 1a

## "Digital" computation = algorithms

## Programming Examples

spec
$Y:=2 X$
$Y:=\lfloor X / 2\rfloor$
$Y:=X 1+X 2$
$X 1->Y$
$X 2->Y$
$Y:=\min (X 1, X 2)$
$X 1+X 2$-> Y

## Advanced Programming Examples

spec
Y := max(X1, X2)
program

$$
\begin{array}{ll}
X 1->L 1+Y & \max (X 1, X 2)= \\
X 2->L 2+Y & (X 1+X 2)-\min (X 1, X 2) \\
L 1+L 2->K & \text { (but is not computed } \\
Y+K->0 & \text { "sequentially") }
\end{array}
$$

Approximate Majority
$(X, Y):=$
if $X \geq Y$ then $(X+Y, 0)$
if $Y \geq X$ then $(0, X+Y)$
$X+Y->Y+B$
$Y+X \rightarrow X+B$
$B+X \rightarrow X+X$
$B+Y->Y+Y$

## CRN Semantics (discrete state space)*

- No-time (concurrent) semantics
- Ignore rates. The multisets of molecules are rewritten according to the reactions, which may fire concurrently when not in resource conflict. This results in a Petri Net.
- Discrete time semantics
- Reaction rates determine the probability with which reactions fire at discrete time intervals, then they behave as multiset rewrites at each discrete time interval.
This results in a Discrete Time Markov Chain (DTMC).
- Continuous time semantics of CRNs
- Reaction rates determine the propensity with which reactions fire (both the probability of firing and the inter-firing intervals), then they behave as multiset rewrites.
This results in a Continuous Time Markov Chain (CTMC).
- These CRNs are called FSCRN (finite stochastic CRN).
*Discrete state space means that each chemical species has a number of molecules (a nonnegative integer);
then time can be modeled as one of the above.


## Programming any algorithm as a FSCRN

A FSCRN is a finite set of reactions over a finite set of species

FSCRNs are not Turing complete
Like Petri nets: reachability is decidable

But unlike Petri nets, FSCRNs are approximately Turing complete
Computation with Finite Stochastic Chemical Reaction Because reactions have also rates
This make it possible to approximate Turing completeness by approximating test-for-zero in a register machine
The probability of error (in test-for-zero) can be made arbitrarily small over the entire (undecidably long) computation.

Adding polymerization to the model makes it fully Turing complete but the syntax becomes considerably more complex

Formal Molecular Biology
Vincent Danos*

## Register Machines (almost...)

i: INC R ${ }_{1}$; JMP j<br>i: $\operatorname{DEC} R_{1}$; JMP j<br>i: IF $R_{2}>0\left\{I N C R_{1} ; J M P j\right\}$<br>i: IF $R_{2}=0 \ldots$

$P C_{i}->R_{1}+P C_{j}$
$P C_{i}+R_{1}->P C_{j}$

$$
P C_{i}+R_{2}->R_{2}+R_{1}+P C_{j}
$$

??? Whatever trick we use will have some error

## - Turing-complete up to an arbitrarily small error

- The error bound is set in advance uniformly for any computation of arbitrary length (because we cannot know how long the computation will last), and the machine will progressively "slow down" to always stay below that bound.


## CRN Semantics (continuous state space/deterministic)*

- ODE semantics of CRNs
- The chemical Law of Mass Action says that the flux of a reaction is determined by the product of the concentrations of the reagents, times the reaction rate.

Definition (CRN Flux) Let $(\mathcal{A}, \mathcal{R})$ be a $C R N$. Let $F(V, T) \in \mathbb{R}_{\geq 0}^{|\mathcal{A}|} \rightarrow \mathbb{R}^{|\mathcal{A}|}$ be the flux of the $C R N$ at volume $V \in \mathbb{R}_{\geq 0}$ and temperature $T \in \mathbb{R}_{\geq 0}$. For a concentration vector $\mu \in \mathbb{R}_{\geq 0}^{|\mathcal{A}|}$ we assume $F(V, T)(\mu)=\sum_{\tau \in \mathcal{R}} v_{\tau} \alpha_{\tau}(V, T, \mu)$ with stoichiometric vector $v_{\tau}$ and rate function $\alpha_{\tau}$.

Law of Mass Action $F(V, T)$ makes up the r.h.s. of an ODE system $\partial \mathcal{A}=F(V, T)$
State produced by a CRN $\mathcal{C}=(\mathcal{A}, \mathcal{R}) \quad$ (species $\mathcal{A}$, reactions $\mathcal{R}$ )
with flux $F$ (r.h.s. of its mass action ODEs) at time $t$,
from initial state ( $x_{0}, V, T$ ) (initial concentrations $x_{0}$, volume $V$, temperature $T$ ):

$$
\begin{aligned}
& \llbracket\left(\left(\mathcal{A}, \mathcal{R}, x_{0}\right), V, T\right) \rrbracket(H)(t)=(G(t), V, T) \\
& \quad \text { let } G:[0 \ldots H) \rightarrow \mathbb{R}^{|\mathcal{A}|} \text { be the solution of } G\left(t^{\prime}\right)=x_{0}+\int_{0}^{t^{\prime}} F(V, T)=(G(s)) d s
\end{aligned}
$$

[^0] concentrations are approximations of the number of molecules via the Avogadro constant.

## CRN Semantics (continuous state space/stochastic)*

## - CME semantics of CRNs (Chemical Master Equation)

- Kolmogorov forward equation of the Markov Chain produced by the CRN.
- Unfeasible to solve or even simulate (to compute the distribution of outcomes)
- The Gillespie algorithm produces individual samples (traces) of the CME distribution


## - LNA semantics of CRNs (Linear Noise Approximation)

Gaussian state (mean \& variance) produced by a $\operatorname{CRN} \mathcal{C}=(\mathcal{A}, \mathcal{R})$ (species $\mathcal{A}$, reactions $\mathcal{R}$, with flux $F$ (r.h.s. of its mass action ODEs) at time $t$, with $\boldsymbol{\mu}_{\mu}(0)=\mu$ and $\Sigma_{\mu, \Sigma}(0)=\Sigma$.
$\llbracket\left(\left(\mathcal{A}, \mathcal{R}, x_{0}\right), V, T\right) \rrbracket(H)(t)=\left(\boldsymbol{\mu}_{\mu}(t), \boldsymbol{\Sigma}_{\mu, \Sigma}(t), V, T\right)$

$$
\begin{aligned}
& \boldsymbol{\mu}_{\mu}(t)=\mu+\int_{0}^{t} F(V, T)\left(\boldsymbol{\mu}_{\mu}(s)\right) d s \\
& F(V, T)(\mu)=\sum_{\tau \in \mathcal{R}} v_{\tau} \alpha_{\tau}(V, T, \mu) \text {, with stoichiometric vector } v_{\tau} \text { and rate function } \overline{\alpha_{\tau}} \text {. We call } J_{F} \\
& \boldsymbol{\Sigma}_{\mu, \Sigma}(t)=\Sigma+\int_{0}^{t} J_{F}\left(\boldsymbol{\mu}_{\mu}(s)\right) \boldsymbol{\Sigma}_{\mu, \Sigma}(s)+\boldsymbol{\Sigma}_{\mu, \Sigma}(s) J_{F}^{\top}\left(\boldsymbol{\mu}_{\mu}(s)\right)+W(V, T)\left(\boldsymbol{\mu}_{\mu}(s)\right) d s
\end{aligned}
$$

A Language for Modeling And Optimizing Experimental Biological Protocols
*Continuous state space means each species has a concentration (a real number);

## Chemistry as a Concurrent Language

- A connection with the theory of concurrency
- Via Process Algebra and Petri Nets



## Finally, Some Bad Bad Programs

$X->Y$
Violates thermodynamics.
(No biggie, assume there is a tiny reverse reaction.)
$X->X+X$
Violates conservation of mass.
(No biggie, assume there is inflow/outflow.)
$X+X->X+X+X$
Violates finite density.
(This is really bad.)


## Part 1b

"Analog" computation = dynamical system

## "Elementary" (NOT!) dynamical systems

A dynamical systems is anything characterized by a system of differential equations (ODEs).
Elementary dynamical systems are those that include on the r.h.s. only polynomials, trigonometry, exponentials, fractions, and their inverses.
E.g., physics: the equation of the simple pendulum has trigonometry on the r.h.s.:

$$
\partial^{2} \theta=-g / l \sin (\theta)
$$

E.g., biology: the enzyme kinetics equation has fractions on the r.h.s.:

$$
\partial[P]=V_{\max }[S] /\left(K_{M}+[S]\right)
$$

E.g., metereology: the chaotic Lorenz attractor has just 3 polynomial equations:

$$
\partial x=a y-a x \quad \partial y=c x-x z-y \quad \partial z=x y-b z
$$


E.g., chemistry: the law of mass action for CRNs implies that their ODEs are
(a restricted "Hungarian" class) of polynomials

STEP 1, Polynomization: All elementary ODEs can be exactly reduced to polynomial ODEs.

MATHEMATICAL THEORY OF THE DIFFERENTIAL

## Abstraction of Elementary Hybrid Systems by Variable Transformation

Jiang Liu ${ }^{1}$, Naijun Zhan ${ }^{2}$, Hengjun Zhao ${ }^{1}$, and Liang Zou ${ }^{2}$

## Programming any dynamical system as a CRN

## Consider the canonical polynomial oscillator: sine/cosine



A very simple elementary ODE system.
But variables go negative: we can't have that in a CRN (no negative concentrations).
STEP 2, Positivation: Split potentially negative variables of polynomial ODEs into the difference of two positive variables. Obtain the same trajectories as differences.

Biomolecular implementation of linear I/O systems

## Programming any dynamical system as a CRN

## Translate positive ODEs to chemical reactions



The Law of Mass Action tells us how to produce polynomial ODEs from CRNs.
The inverse process is called Hungarization, it works for Hungarian ODEs
(polynomial ODEs where each negative monomial has the I.h.s. differentiated variable as a factor).
STEP 3, Hungarization: Translate polynomial ODEs to chemical reaction networks:
each monomial on the r.h.s. produces one reaction.
ON THE INVERSE PROBLEM OF REACTION KINETICS
V. HARS - J. TOTH

Subject to the ODEs being Hungarian, but that is always satisfied after positivation!
E.g. the Lorenz chaotic attractor is already polynomial but not Hungarian,
it cannot be translated to mass action reactions without first doing positivation.

## Programming any dynamical system as a CRN

## Translate those CNRs to (real, DNA) molecules



Chemistry tells us (sometimes) what reactions molecules obey.
The inverse process is possible for DNA molecules, because we can "program" them.
STEP 4, Molecular programming: Translate any mass action chemical reaction network into a set of DNA molecules that obey those reactions.

Works up to an arbitrarily good approximation of Mass Action kinetics,

DNA as a universal substrate for chemical kinetics
David Soloveichik, Georg Seelig, and Erik Winfree
PNAS March 23, 2010 107 (12) 5393.5398; htps://doi.org10.1073/Pnas.0909380107 and up to time rescaling.

## Programming any 'dynamical system as a CRN

Thus, CNRs are "Shannon complete", and can by physically realized


## Summarizing

- Chemistry is (also) a formal language that we can use to implement any algorithm and any dynamical system with real (DNA) molecules
- Turing complete and "Shannon complete"
- ANY collection of abstract chemical reactions can be implemented with specially designed DNA molecules, with accurate kinetics (up to time scaling).
- Approaching a situation where we can "systematically compile" (synthesize) a model to DNA molecules, run an (automated) protocol, and observe (sequence) the results in a closed loop.

Part 3
Languages for CRNs

## Obviously...

Yes of course, there are CRN packages in Python, Matlab, Mathematica, etc. etc.
Yes of course, there are scripting languages, and even operating systems, for all kinds of lab equipment and for Digital Microfluidics, like PurpleDrop [Stephenson et al. 2020]

Yes of course, there are domain specific languages like CRN++ [Vasic et al. 2018]
I wanted to investigate "closing the loop" between mathematical modeling and lab protocols, based on a language for CRNs.

## CMSB'2020 Best Tool Paper Award

Kaemika* app
Integrating protocols and chemical simulation

## Xaemika /'kimika/



Android
Windows
$\overbrace{\text { GitHub }}$
Search "Kaemika" in the app stores http://lucacardelli.name/kaemika.html

Article
A Language for Modeling and Optimizing Experimental Biological Protocols

Luca Cardelli ${ }^{*}$ ©, Marta Kwiatkowska and Luca Laurenti ${ }^{\dagger}$
An integrated language for chemical models \& experimental protocols

Deterministic (ODE) and stochastic (LNA) simulation

Chemical reaction networks (CRNs) and liquid-handling protocols

Reaction scores
Functional scripting


GUI

## Main features

- Species and reactions
- Characterized by initial values and rates
- "Samples" (compartments) and Protocols
- Isolate species and reactions in a compartment, and mix compartments
- Kinetics (simulation)
- Deterministic (ODE) or stochastic (LNA) for chemical models
- Digital microfluidics for chemical protocols
- Programming abstractions
- Assemble models and protocols as compositions of modules


## Species and Reactions

```
//======================================
// Lotka 1920, Volterra }192
// (simplified with all rates = 1)
//======================================
```

number $\times 1_{0}$ <- uniform $(0,1) / /$ random $\times 1_{0}$
number $\times 2_{0}<-$ uniform $(0,1) / /$ random $\times 2_{0}$

```
species x1 @ x10.M
```

// prey
// predator
x1 -> x1 + x1
x1 + x2 -> x2 + x2
x2 -> $\emptyset$
equilibrate for 40 ACTION.
By Alpred J. Lotza.
Received June $2,1920$.


## x $\times 2$ 世

## Stochastic (LNA) simulation

## - For all programs (any CRN, any Protocol)

## 2AM Oscillator

$\partial \mathrm{lo} 1=-\mathrm{hi} 1 \cdot \mathrm{lo} 1-0.5 \cdot \mathrm{hi} 2 \cdot \mathrm{lo} 1+\mathrm{lo} 1 \cdot \mathrm{md}+0.5 \cdot \mathrm{lo} 2 \cdot \mathrm{md}$ $\partial \mathrm{hi} 2=-0.5 \cdot \mathrm{hi} 1 \cdot \mathrm{hi} 2-\mathrm{hi} 2 \cdot \mathrm{lo} 2+\mathrm{hi} 2 \cdot \mathrm{md} »_{1}+0.5 \cdot \mathrm{lo} 1 \cdot \mathrm{md} »_{1}$ $\partial \mathrm{lo} 2=0.5 \cdot \mathrm{hi} 1 \cdot \mathrm{md} »_{1}-\mathrm{hi} 2 \cdot \mathrm{lo} 2-0.5 \cdot \mathrm{lo} 1 \cdot \mathrm{lo} 2+\mathrm{lo} 2 \cdot \mathrm{md} »_{1}$ дhi1 $=-\mathrm{hi} 1 \cdot \mathrm{lo} 1-0.5 \cdot \mathrm{hi} 1 \cdot \mathrm{lo} 2+\mathrm{hi} 1 \cdot \mathrm{md}+0.5 \cdot \mathrm{hi} 2 \cdot \mathrm{md}$ $\partial \mathrm{md}=2 \cdot \mathrm{hi} 1 \cdot \mathrm{lo} 1+0.5 \cdot \mathrm{hi} 1 \cdot \mathrm{lo} 2+0.5 \cdot \mathrm{hi} 2 \cdot \mathrm{lo} 1-\mathrm{hi} 1 \cdot \mathrm{md}-0.5 \cdot \mathrm{hi} 2 \cdot \mathrm{md}-\mathrm{lo} 1 \cdot \mathrm{md}-0.5 \cdot \mathrm{lo} 2 \cdot \mathrm{md}$ $\partial \mathrm{md}>_{1}=0.5 \cdot \mathrm{hi} 1 \cdot \mathrm{hi} 2-0.5 \cdot \mathrm{hi} 1 \cdot \mathrm{md} »_{1}+2 \cdot \mathrm{hi} 2 \cdot \mathrm{lo} 2+0.5 \cdot \mathrm{lo} 1 \cdot \mathrm{lo} 2-\mathrm{hi} 2 \cdot \mathrm{md}>_{1}-0.5 \cdot \mathrm{lo} 1 \cdot \mathrm{md} »_{1}-\mathrm{lo} 2 \cdot \mathrm{md} »_{1}$


 $\operatorname{cov}(\mathrm{lo} 1, \mathrm{hi} 2) \cdot \mathrm{lo} 2+0.5 \cdot \operatorname{cov}(\mathrm{md}, \mathrm{hi2}) \cdot \operatorname{lo2}+\operatorname{cov}(\mathrm{lo1}, \mathrm{hi} 2) \cdot \mathrm{md}+0.5 \cdot \operatorname{cov}(\mathrm{lo} 2, \mathrm{hi} 2) \cdot \mathrm{md}+\operatorname{cov}(\mathrm{lo} 1, \mathrm{hi} 2) \cdot \mathrm{md}>_{1}-0.5 \cdot \mathrm{lo} 1 \cdot \operatorname{var}(\mathrm{hi} 2)+0.5 \cdot \mathrm{md}>_{1} \cdot \operatorname{var}(\mathrm{lo} 1)$
 $\operatorname{lo1}-\operatorname{cov}(\mathrm{lo1} 1, \mathrm{hi} 2) \cdot \operatorname{lo2}-\operatorname{cov}(\mathrm{lo} 1, \mathrm{lo} 2) \cdot h i 1-1.5 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{lo} 2) \cdot \mathrm{hi} 2+\operatorname{cov}(\mathrm{lo} 1, \mathrm{lo} 2) \cdot \mathrm{md}+\operatorname{cov}(\mathrm{lo} 1, \mathrm{lo} 2) \cdot \mathrm{md}>_{1}-0.5 \cdot \mathrm{lo} 2 \cdot \operatorname{var}(\mathrm{lo} 1)+0.5 \cdot \mathrm{md} \cdot \operatorname{var}(\mathrm{lo} 2)$
$\partial \operatorname{cov}(\mathrm{lo} 1, \mathrm{hi} 1)=\operatorname{cov}(\mathrm{lo} 1, \mathrm{md}) \cdot \mathrm{hi1}+0.5 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{md}) \cdot \mathrm{hi2}-\operatorname{cov}(\mathrm{lo} 1, \mathrm{hi1}) \cdot \operatorname{lo1}+\operatorname{cov}(\mathrm{md}, \mathrm{hi1}) \cdot \operatorname{lo1}-0.5 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{hi1}) \cdot \operatorname{lo2}-0.5 \cdot \operatorname{cov}(\mathrm{lo1} 1, \mathrm{lo} 2) \cdot \mathrm{hi} 1-0.5 \cdot \operatorname{cov}(\mathrm{hi2}, \mathrm{hi} 1) \cdot \operatorname{lo} 1-\operatorname{cov}(\mathrm{lo} 1, \mathrm{hi1}) \cdot \mathrm{hi1}-0.5$ $\operatorname{cov}(\mathrm{lo} 1, \mathrm{hi1}) \cdot \mathrm{hi} 2+0.5 \cdot \operatorname{cov}(\mathrm{md}, \mathrm{hi1}) \cdot \mathrm{lo} 2+2 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{hi1}) \cdot \mathrm{md}+0.5 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{hi} 2) \cdot \mathrm{md}+0.5 \cdot \operatorname{cov}(\mathrm{lo} 2, \mathrm{hi1}) \cdot \mathrm{md}-\mathrm{lo} 1 \cdot \operatorname{var}(\mathrm{hi} 1)-\mathrm{hi1} \cdot \operatorname{var}(\mathrm{lo} 1)$
 $\cdot \operatorname{cov}(\mathrm{hi} 2, \mathrm{md}) \cdot \operatorname{lo} 1+0.5 \cdot \operatorname{cov}(\mathrm{lo1} 1, \mathrm{hi}) \cdot \operatorname{lo} 1-0.5 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{hi2}) \cdot \mathrm{md}-0.5 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{lo} 2) \cdot \mathrm{md}-2 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{md}) \cdot \mathrm{hi1}-\operatorname{cov}(\mathrm{lo1} 1, \mathrm{md}) \cdot \mathrm{hi} 2+\operatorname{cov}(\mathrm{lo1} 1, \mathrm{md}) \cdot \mathrm{md}+0.5 \cdot \operatorname{cov}(\mathrm{lo} 2, \mathrm{md}) \cdot \mathrm{md} \cdot \operatorname{lo} 1 \cdot \mathrm{md}-0.5 \cdot \operatorname{lo} 2$ $\mathrm{md}+2 \cdot \mathrm{hi} 1 \cdot \operatorname{var}(\mathrm{lo} 1)+0.5 \cdot \mathrm{hi} 2 \cdot \operatorname{var}(\mathrm{lo} 1)+\mathrm{lo} 1 \cdot \operatorname{var}(\mathrm{md})+0.5 \cdot \mathrm{lo} 2 \cdot \operatorname{var}(\mathrm{md})-\mathrm{md} \cdot \operatorname{var}(\mathrm{lo} 1)$
$\partial \operatorname{cov}\left(\operatorname{lo} 1, \mathrm{md}>_{1}\right)=0.5 \cdot \operatorname{cov}(\mathrm{lo} 1, \mathrm{hi1}) \cdot \mathrm{hi} 2-\operatorname{cov}\left(\mathrm{hi1}, \mathrm{md}>_{1}\right) \cdot \operatorname{lo} 1-0.5 \cdot \operatorname{cov}\left(\mathrm{lo} 1, \mathrm{md}>_{1}\right) \cdot \operatorname{lo} 1-\operatorname{cov}\left(\mathrm{lo} 1, \mathrm{md}>_{1}\right) \cdot \operatorname{lo} 2+\operatorname{cov}\left(\mathrm{md}, \mathrm{md}>_{1}\right) \cdot \operatorname{lo} 1+0.5 \cdot \operatorname{cov}\left(\mathrm{md}, \mathrm{md}>_{1}\right) \cdot \operatorname{lo} 2-0.5 \cdot \operatorname{cov}(\operatorname{lo} 1, \mathrm{hi1}) \cdot \mathrm{md}>_{1}+0.5$
 $\operatorname{cov}\left(\mathrm{lo} 1, \mathrm{md} »_{1}\right) \cdot h i 1-1.5 \cdot \operatorname{cov}\left(\mathrm{lo} 1, \mathrm{md} »_{1}\right) \cdot h i 2+\operatorname{cov}\left(\mathrm{lo} 1, \mathrm{md} »_{1}\right) \cdot \mathrm{md}+0.5 \cdot \mathrm{lo} 2 \cdot \operatorname{var}(\mathrm{lo} 1)-0.5 \cdot \mathrm{md} »_{1} \cdot \operatorname{var}(\mathrm{lo} 1)$

## Writing Models Compositionally

- Embedded chemical notation

Programs freely contain both chemical reactions and control flow
Can generate unbounded-size reaction networks

- Rich data types
numbers, species, functions, networks, lists, flows (time-courses)
flows are composable functions of time used in rates, plotting, and observation
- Modern abstractions

Functional: programs take data as parameters and produce data as results Monadic: programs also produce effects (species, reactions, liquid handling)
Nominal: lexically scoped chemical species (species are not "strings")

## Ex: Predatorial

```
```

function Predatorial(number n) {

```
```

function Predatorial(number n) {
if n = 0 then
if n = 0 then
define species prey @ 1 M
define species prey @ 1 M
prey -> 2 prey // prey reproduces
prey -> 2 prey // prey reproduces
report prey
report prey
yield prey
yield prey
else
else
define species predator @ 1/n M
define species predator @ 1/n M
species prey = Predatorial(n-1)
species prey = Predatorial(n-1)
prey + predator ->{n} 2 predator // predator eats
prey + predator ->{n} 2 predator // predator eats
predator -> Ø // predator dies
predator -> Ø // predator dies
report predator
report predator
yield predator
yield predator
end
end
}
}
species apexPredator = Predatorial(5)
species apexPredator = Predatorial(5)
equilibrate for 50

```
```

equilibrate for 50

```
```

```
//======================================
// Creates a stack of predator-prey
// relationships in Lotka-Volterra style,
// and returns the apex predator.
//=======================================
```



prey

## —— predator. 4

predator• 3
predator•2
predator•1 predator

## Mass Action Compiler

- Lorenz chaotic attractor




## References

Integrated modeling

Of chemical reaction networks and protocols
How the Kaemika app supports it
Why it needs a new language for smooth integration

Closed-loop modeling, experimentation and analysis For complete lab automation
To "scale up" the scientific method

Experimental biological protocols with formal semantics Alessandro Abate, Luca Cardelli, Marta Kwiatkowska, Luca Laurenti, Boyan Yordanov. CMSB 2018.

Kaemika app - Integrating protocols and chemical simulation Luca Cardelli. CMSB 2020.

## Kaemika User Manual

http://lucacardelli.name/Papers/Kaemika\ User\ Manual.pdf

## Conclusions

## Chemical reaction networks

- A fun language to program with
- Compilable to real molecules
- Executable "in your kitchen"
- Still relative primitive, we need to build more programming abstractions


[^0]:    *Continuous state space means each chemical species has a concentration (a real number);

