

# Part 1: Chemical Reaction Networks — what, where, why?

- What are Chemical Reaction Networks?
- Where can you use them?
- Why they are hard to analyze?
- Why they are interesting, mathematically and practically?
- Levels at which one can use them as a modeling framework

#### What are Chemical Reaction Networks (loose)

- Models of chemical systems + much more
- Discrete-state Markovian stochastic processes
- Topologically interesting graph systems
- Laboratories in which to study:
  - the consequences of concurrency in transformations
  - how topology controls dynamics or possibilities for order

#### What are Chemical Reaction Networks (tighter)

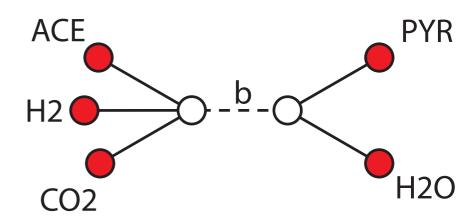
- Sets of reactions that act on sets of species and:
  - reactions can fire independently and randomly
  - convert sets of reactants to sets of products all at once
- Hopping on simple graphs is a degenerate case
- More generally one requires multi-hypergraphs
   (we will represent these with doubly-bipartite graphs)

#### Stochastic processes with or without concurrency

Stochastic process on a simple graph:



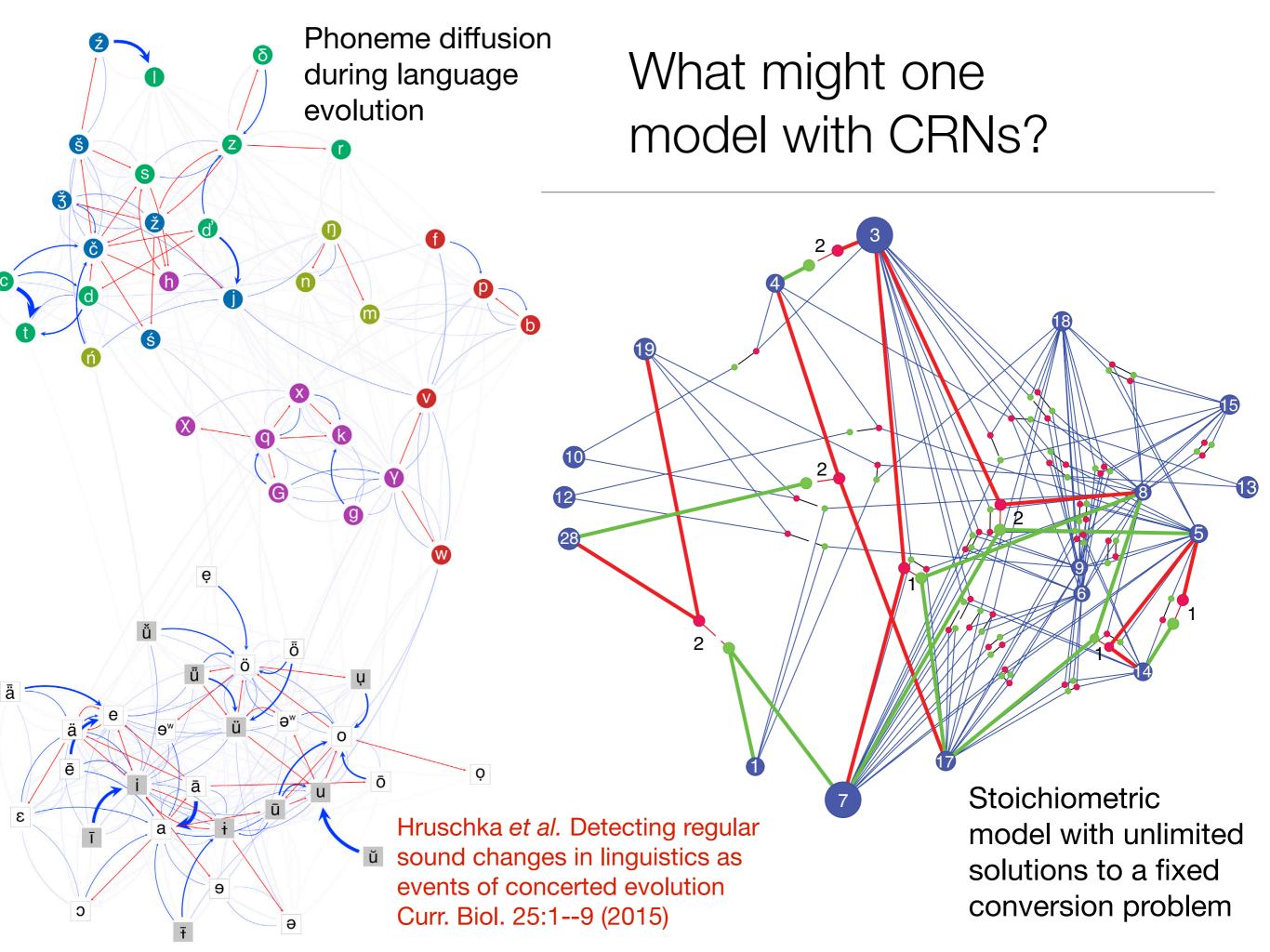
- nodes are "all alike"; particles can occupy anywhere
- particles hop over links simple diffusion on the graph
- CRN: reactions are conditional on all inputs' being available and all outputs' being formed



Reactions are independent like those on the simple graph.
 But moves in the state space are not independent.

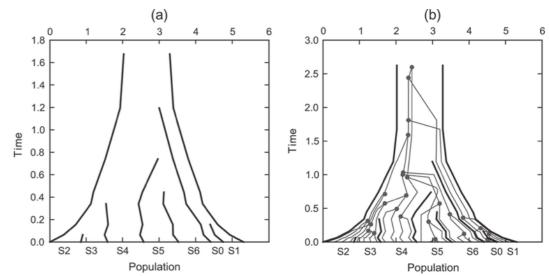
#### Pause to emphasize what is the MAIN POINT

- It is the species that carry state information from one moment to the next in a Markov CRN
- For simple graphs, events that change state are independent species-by-species
- For non-simple hypergraphs, independence is lifted to the reaction level, but may not hold species-by-species
- This difference is the source of complexity



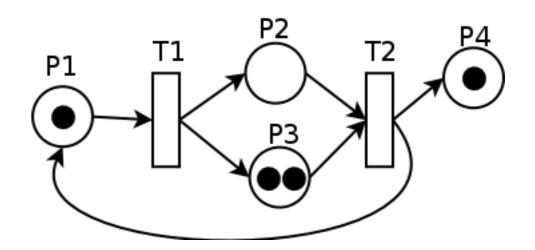
### Other applications and other names for CRNs and closely-related systems

 Population processes such as birth-death processes, including evolutionary games and lots of genetics cases



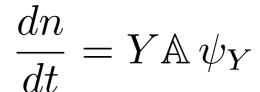
www.researchgate.net/publication/38083310

 In computer science the same concept of concurrency is captured by Petri Nets for process calculus



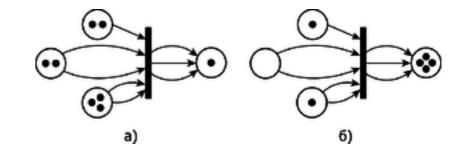
#### Levels at which CRN models can be defined and studied

- Chemical rate equation
- Stochastic process for counts
- "Petri-net proof" counting individuals

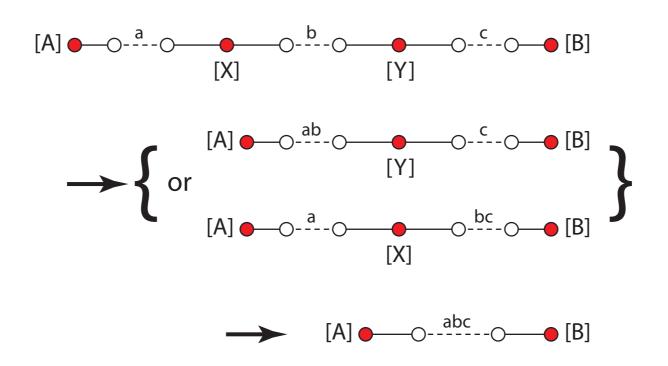


$$\frac{dn}{dt} = Y \mathbb{A} \psi_Y$$

$$\frac{d}{dt} \rho_{n} = \sum_{n'} T_{nn'} \rho_{n'}$$



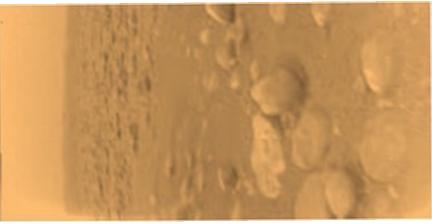
Category-theoretic CRN-composition (J. Baez & students)



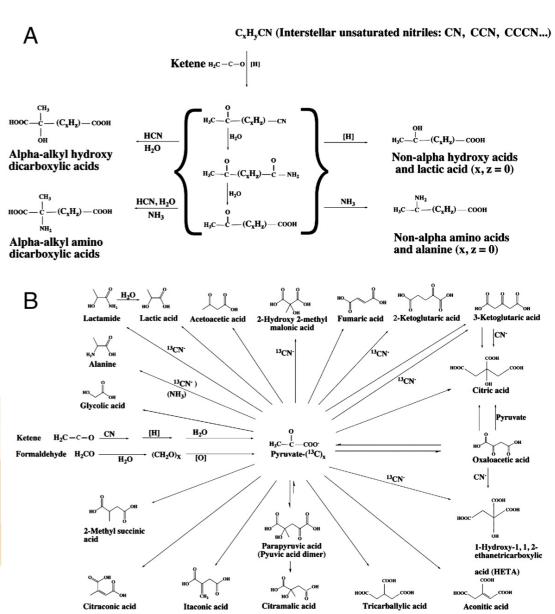
## Graph-grammar methods to generate CRNs, and associated analysis tools for them

- Why do this?
- Actual networks can be too large to write down (Murchison, Titan atmosphere), or too large to even know (OOL as an example)





Huygens image: credit NASA

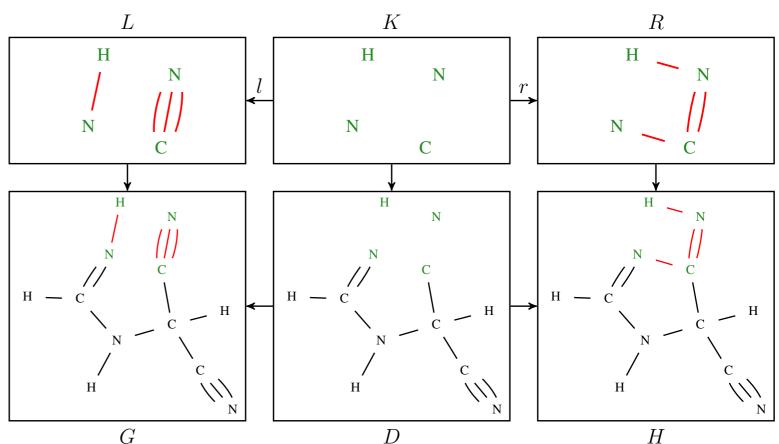


Cooper et al. PNAS 108:14051 (2011)

 Graph-grammars allow you to express an indefinitely-large network recursively from a finite set of generators

### Example of a graph, graph fragment, common pattern, and rewrite rule

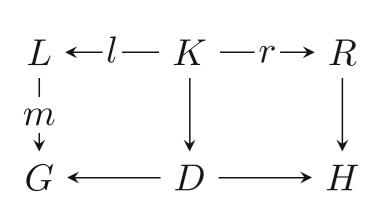
- Molecules themselves are written as graphs
- Maps among sets of molecules become graph morphisms in category theory
- Reaction mechanisms are graph-fragment morphisms
- Reaction application is a graph-embedding map



Key point: finite generator set can produce unlimited CRNs

### The double-pushout formalism for graph re-write rules

 The important thing to say here properly is that there is a commutativity requirement which defines these morphisms

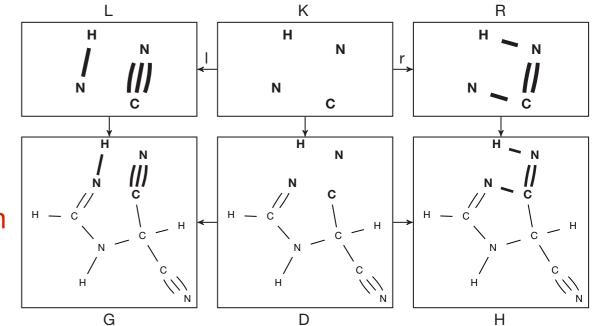


I — left pushout(adds bonds to form L)

r — right pushout(adds bonds to form R)

m — matching morphism

D — gluing condition

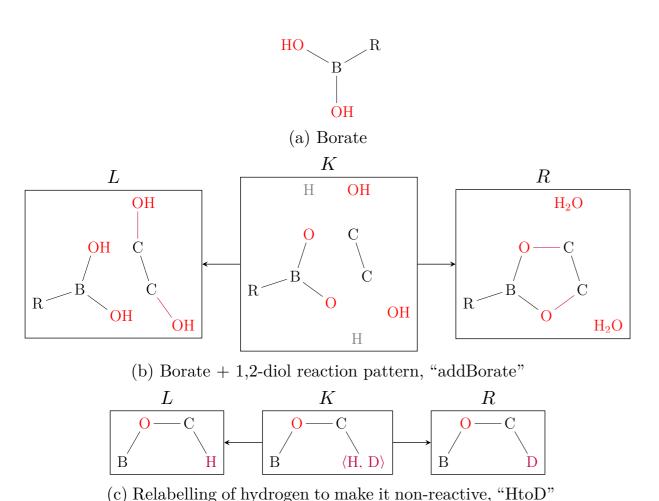


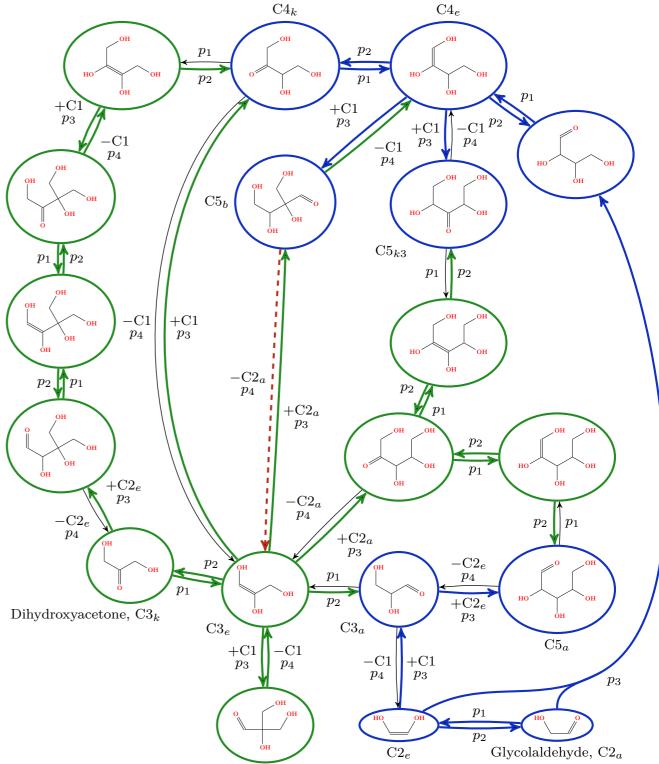
 Morphisms admit partial or full rule composition — think of β-reduction in λ-calculus, or Curried functions in Haskell

Dependency graph for rule composition

# Some examples of the kinds of applied problems graph-grammars have been used to solve

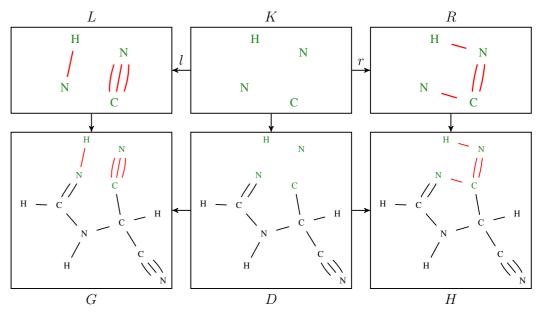
 Steven Benner's pruning of the formose network with Borate to yield Ribose

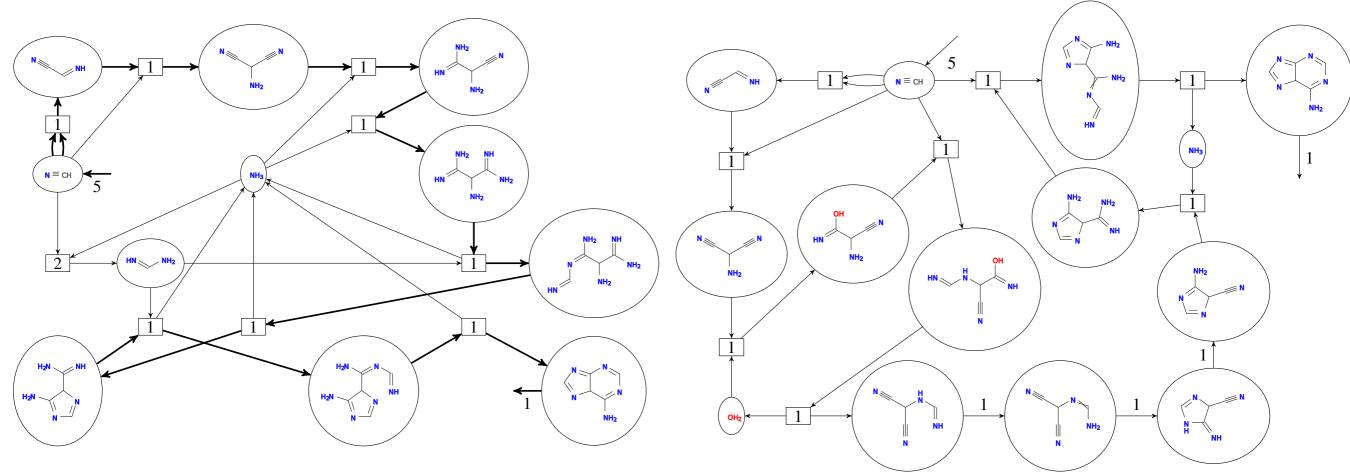




### Some examples of the kinds of applied problems graph-grammars have been used to solve

A network for HCN
 polymerization calibrated
 against Mass Spectroscopy
 molecule concentrations





#### Another example application

Albert Eschenmoser's glyoxylate scenario relating HCN polymerization and hydrolysis to TCA-cycle metabolites

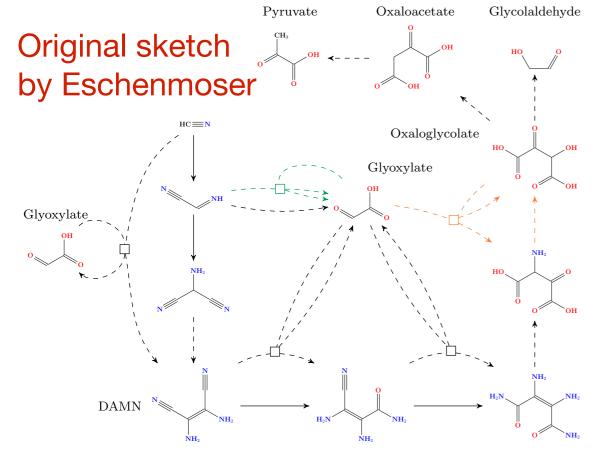


Figure 2: Overview of Eschenmoser's hypothetical chemical space.

This work suggests a role for "path entropies".

Full cascade of optimal solutions

#### The MedØlDatschgerl (MØD) package including a

#### Live Playground

#### http://cheminf.imada.sdu.dk/mod/

- Software package for graphbased cheminformatics
- Even more important: a welldefined representation system for what constitutes a molecule / reaction / pathway
- Tools for hard network search / optimization problems

6/18/2017

MedØlDatschgerl - Cheminformatics 1 documentation



**IMADA** 

#### MedØlDatschgerl

#### Overview

MedØlDatschgerl (MØD) is a software package developed for graph-based cheminformatics. It includes a general graph transformation system for automatically generating reaction networks from graph grammar formulations of chemistries.

The software is primarily implemented in C++, but the package includes comprehensive Python 3 binding that provides easy access most functionality. The package also includes a large visualisation module that makes it possible to automatically visualise molecules, reactions, and reaction networks. Examples of how to use the Python interface and the visualisation capabilities can be seen in the examples section, and they can all be accessed interactively in the Live Playground.

#### **Source Code and Documentation**

Each release is available at GitHub. Please also use GitHub for reporting bugs, suggesting features, and contributing code. The documentation can be found at the GitHub Page.

#### References

If you use MØD in your research, you may want to cite some of the following papers. You may also be interested in the Graph Grammar Library, which has been used in early versions of MØD.

(As BibTeX)

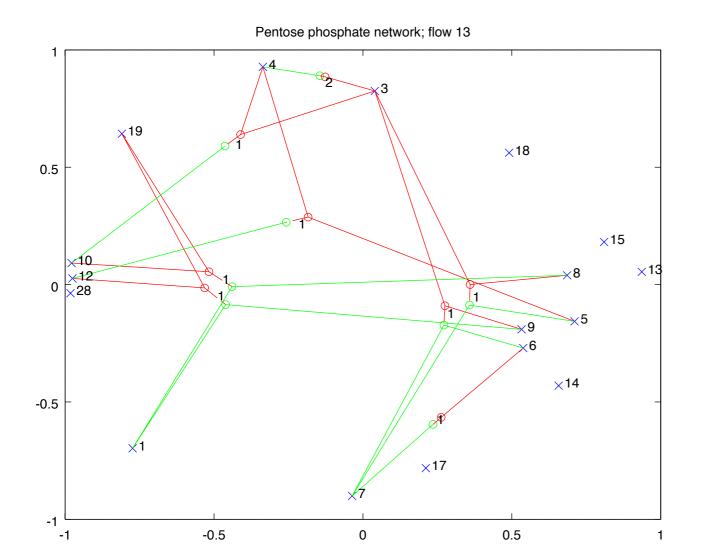
- A Software Package for Chemically Inspired Graph Transformation
   Jakob L. Andersen, Christoph Flamm, Daniel Merkle, and Peter F. Stadler. Graph Transformation 9th International Conference, ICGT 2016, 73-88, 2016 [ DOI | TR ]
- In silico Support for Eschenmoser's Glyoxylate Scenario
   Jakob L. Andersen, Christoph Flamm, Daniel Merkle, and Peter F. Stadler. Israel Journal of Chemistry, 55(8):919-933, 2015. [ DOI | TR ]
- 50 Shades of Rule Composition From Chemical Reactions to Higher Levels of Abstraction
   Jakob L. Andersen, Christoph Flamm, Daniel Merkle, and Peter F. Stadler. Formal Methods in Macro-Biology, 8738:117-135, 2014. [DOI]
- Conference version: Towards an Optimal DNA-Templated Molecular Assembler
   Jakob L. Andersen, Christoph Flamm, Martin M. Hanczyc, and Daniel Merkle. ALIFE 14: The Fourteenth
   Conference on the Synthesis and Simulation of Living Systems, 14:557-564, 2014. [ DOI I http ]
   Journal version: Towards Optimal DNA-Templated Computing
   Jakob L. Andersen, Christoph Flamm, Martin M. Hanczyc, and Daniel Merkle. International Journal of Unconventional Computing, 11(3-4):185-203, 2015. [ http ]
- Generic Strategies for Chemical Space Exploration
   Jakob L. Andersen, Christoph Flamm, Daniel Merkle, and Peter F. Stadler. International Journal of Computational Biology and Drug Design, 7(2/3):225-258, 2014. [DOI | TR]
- Navigating the Chemical Space of HCN Polymerization and Hydrolysis: Guiding Graph Grammars by Mass Spectrometry Data.
   Jakob L. Andersen, Tommy Andersen, Christoph Flamm, Martin M. Hanczyc, Daniel Merkle, and Peter F.

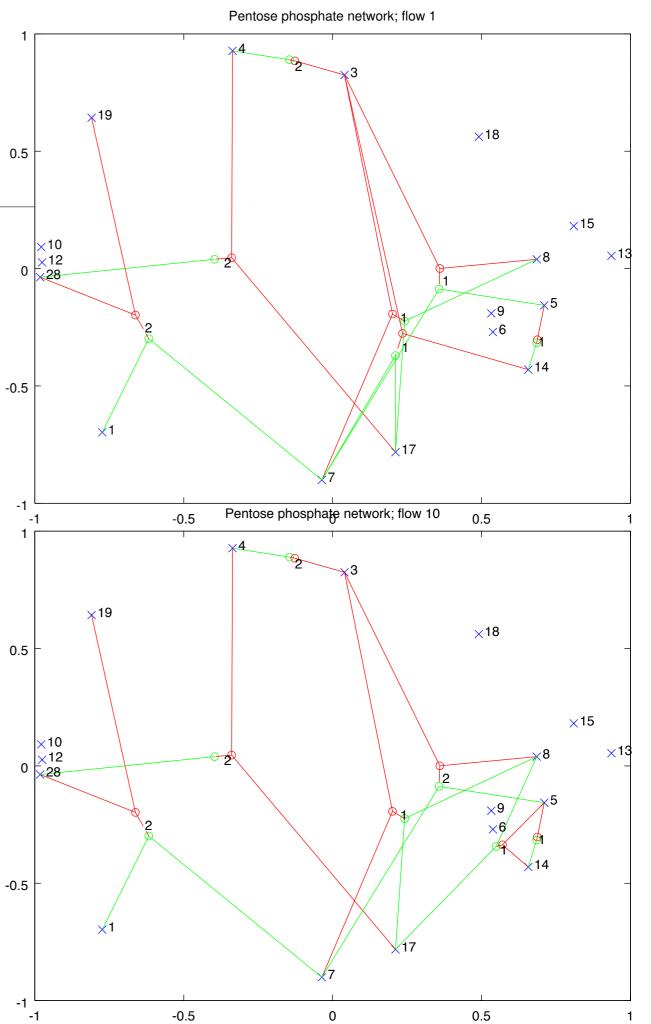
Stadler. Entropy, 15(10):4066-4083, 2013. [DOLI http]

- Inferring chemical reaction patterns using rule composition in graph grammars.
   Jakob L. Andersen, Christoph Flamm, Daniel Merkle, and Peter F. Stadler. *Journal of Systems Chemistry*, 4(1):4, 2013. [ DOI I http ]
- Maximizing output and recognizing autocatalysis in chemical reaction networks is NP-complete.
   Jakob L. Andersen, Christoph Flamm, Daniel Merkle, and Peter F. Stadler. *Journal of Systems Chemistry*, 3(1):1, 2012. [ DOI I http ]

# The concept of Balanced Integer Hyperflows

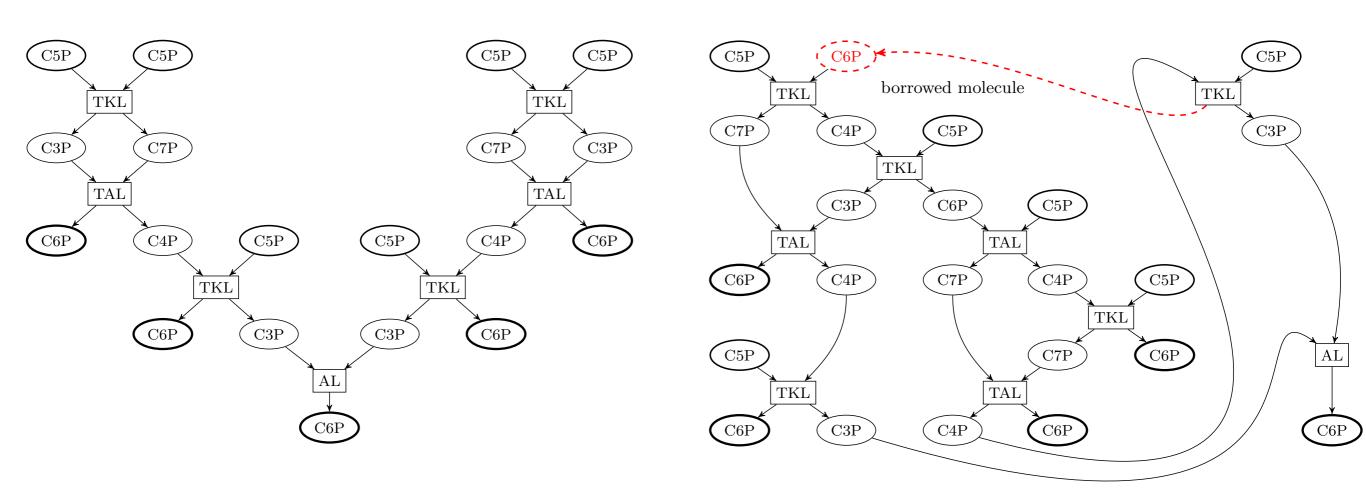
 What combined flux rates balance concentrations at all species? Integer Linear Programming problem





# One finer level than hyperflows: Interpretations (also known as "Petri net proofs")

#### Net conversion in the integer hyperflow: 6C5 -> 5C6



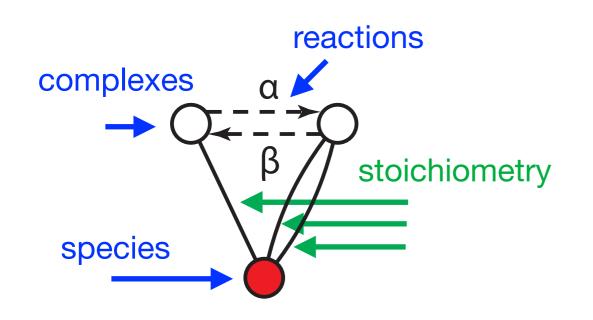
## The hard math that a good computational platform helps you do

- Equivalence of molecules under different pathways: must solve graph isomorphism problem very many times
- Many search and optimization problems that are loworder polynomial on simple graphs are NP complete on hypergraphs
   Andersen et al. J. Sys. Chem. 3:1 (2012)
- For brute-force networks, need Integer-Linear-Programming help
- For networks beyond brute force, good heuristics become essential

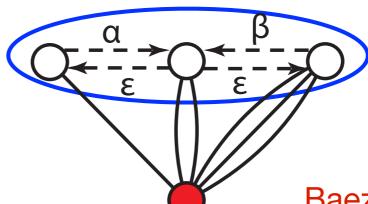
### Part 2: The discrete math (topology, graph theory) of CRNs

- Main concepts, terminology, and graphical notations for CRNs
- The largest component of a CRN on which dynamics behaves the same way as a random walk on a simple graph

#### CRN basics: terms and concepts (graphics)



complex graph (or network)

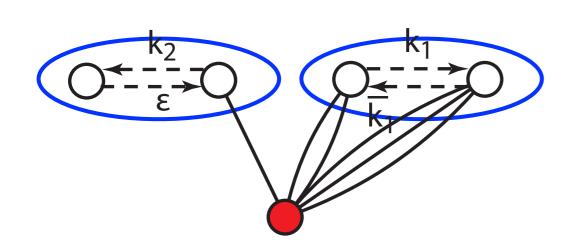


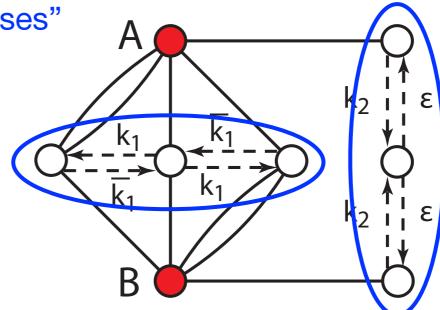
Baez and Biamonte (2017) Gunawardena (2003)

Feinberg (1979, 1983)

Horn and Jackson (1972)

connected components of the complex graph = "linkage classes"





#### CRN basics: terms and concepts (quantities)

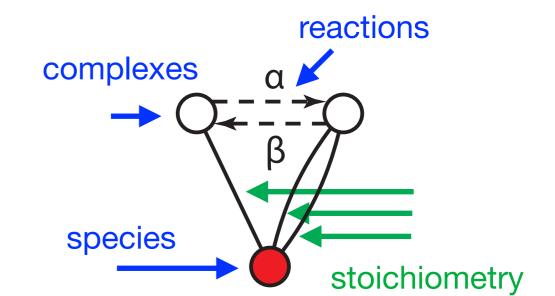
Species index

$$p \in 1, \ldots, P$$

Complex index  $i, j \in 1, \ldots, C$ 

$$i, j \in 1, \ldots, C$$

Reactions (ordered) (i,j) rate const



- Concentrations (column vector)  $n \equiv [n_p]$
- Stoichiometry (complexes to species)

$$Y \equiv \left[ y_p^j \right]$$

Activities (column vector on complexes)  $\psi_Y \equiv \left[\psi_Y^i\right] \quad \psi_Y^i \equiv \prod n_p^{y_p^i}$ 

$$\psi_Y \equiv \begin{bmatrix} \psi_Y^i \end{bmatrix} \quad \psi_Y^i \equiv \prod_p n_p^{y_p^i}$$

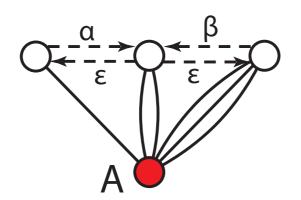
Adjacency/Rate matrix (btw. complexes)

$$\mathbb{A} = \sum_{(i,j)} \left( w_j - w_i \right) k_{ji} w_i^T$$

The rate law

$$\frac{dn}{dt} = Y \mathbb{A} \, \psi_Y$$

#### Example



$$\frac{dn}{dt} = Y \mathbb{A} \, \psi_Y$$

$$Y = \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}$$

$$Y = \left[ \begin{array}{ccc} 1 & 2 & 3 \end{array} \right] \qquad \mathbb{A} = \left[ \begin{array}{ccc} -\alpha & \epsilon & & \\ \alpha & -2\epsilon & \beta \\ & \epsilon & -\beta \end{array} \right] \quad \psi_Y = \left[ \begin{array}{ccc} n & & \\ n^2 & & \\ n^3 & & \end{array} \right]$$
 stoichiometric matrix

activities

$$\mathbb{A} = \sum_{(i,j)} (w_j - w_i) k_{ji} w_i^T$$

means 
$$\mathbb{A} = \left[ \begin{array}{c} -1 \\ 1 \\ 0 \end{array} \right] \alpha \quad \left[ \begin{array}{ccc} 1 & 0 & 0 \end{array} \right] \quad + \left[ \begin{array}{c} 1 \\ -1 \\ 0 \end{array} \right] \epsilon \quad \left[ \begin{array}{ccc} 0 & 1 & 0 \end{array} \right] \quad + \cdots$$

$$\begin{bmatrix} \\ + \end{bmatrix}$$

$$+ \left| \begin{array}{c} 1 \\ -1 \\ 0 \end{array} \right|$$

$$\begin{bmatrix} 0 & 1 \end{bmatrix}$$

## The Complex Network: the largest sub-system that is a simple graph

If this had been a simple graph, the rate law would have been

$$\frac{d}{dt} \begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix} = \mathbb{A} \begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix}$$

$$\mathbb{A} = \begin{bmatrix} -\alpha & \epsilon \\ \alpha & -2\epsilon & \beta \\ \epsilon & -\beta \end{bmatrix}$$

- The Key Difference between simple graphs and CRNs:
  - The species always carry the memory of state
  - In graphs, A acts directly on species
  - In CRNs, A acts on complexes, which have no state

### Part 3: What does topology ensure about dynamics without fine constraints on rates?

- Two classic results (one now, one in the next section)
  - Feinberg's "deficiency-0" theorem for existence, uniqueness, stability, and properties of classical steady states
  - The Anderson-Craciun-Kurtz theorem for steadystate distributions on deficiency-0 networks

#### What are the issues?

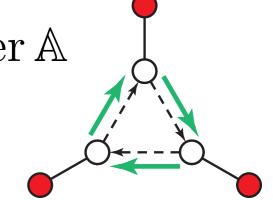
• In general, the rate equation is ugly:  $\dfrac{dn}{dt} = Y \mathbb{A} \, \psi_Y$ 

To what extent does topology allow us to draw conclusions about possible dynamics or steady states?

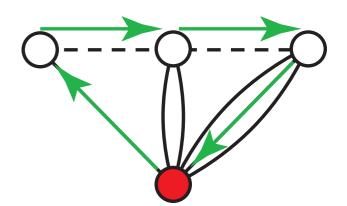
 Reaction stoichiometry can be "clumpy" — we might expect that, independent of the behavior of the classical rate law, that clumpiness might lead to complicated distributions

### The three types of flows that determine the character of solutions

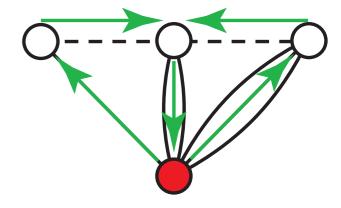
- Balanced flows within the complex network:  $\ker \mathbb{A}$ 



• Flows that change concentration:  $Im(Y\mathbb{A})$ 



• Balanced flows outside  $\ker A$ :  $\ker Y \cap \operatorname{Im} A$ 



### For non-obvious reasons, introduce the concept "deficiency" for a CRN

Stoichiometric subspace:

$$S = \operatorname{Im}(Y\mathbb{A}) \quad s \equiv \dim(S)$$

Deficiency:

$$\delta \equiv \dim (\ker (Y) \cap \operatorname{Im}(\mathbb{A}))$$

• Two identities:  $\dim (\operatorname{Im}(\mathbb{A})) = \dim (\operatorname{Im}(Y\mathbb{A})) + \dim (\ker Y \cap \operatorname{Im}(\mathbb{A}))$   $= s + \delta$   $C = \dim (\operatorname{Im}(\mathbb{A})) + \dim (\ker (\mathbb{A}))$   $= s + \delta + \dim (\ker (\mathbb{A}))$ 

Lead to a counting rule for deficiency:  $\delta = C - s - l$ 

(complexes) (linkage classes)

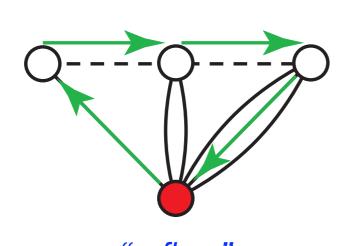
### Remarkable result of topology for existence, uniqueness, stability, interiority of steady states

Theorem (Martin Feinberg)

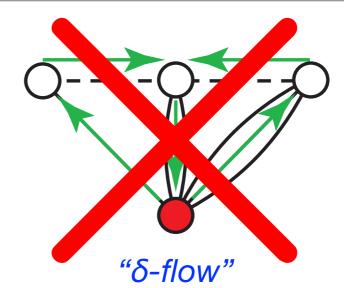
"If a CRN with  $\delta=0$  is weakly reversible then, for mass action kinetics, the rate equations will have precisely one steady state, within each positive stoichiometric compatibility class. This steady state is asymptotically stable." [and has strictly positive concentrations]

Feinberg and Horn 1974; Horn 1973; Feinberg1977,1980

# Intuition for the proof: if deficiency = 0, there can only be mean-regressing flows



"s-flow"
changes some concentration
shifts activities to resist change



balanced (integer) hyperflow preserves concentrations & activities

- If  $\delta = 0$ , there can be no flows that don't change concentration of species
- But if species pile up or are depleted, the greater activity drives flows in the opposite direction (interiority)

### Part 4: Stochastic CRNs, with a tiny mention of generating-function methods

Anderson-Craciun-Kurtz Theorem:

"For a CRN with  $\delta = 0$ , weakly reversible, with mass action kinetics — no matter how clumpy the reactions — the steady-state distributions will be products of Poissons, or slices through them if there are conserved quantities."

D. Anderson, G. Craciun, T. Kurtz 2010

### Discrete-state, continuous-time stochastic processes: Master Equation and a taste of ACK

Probability density function:

$$\rho_{\mathrm{n}}$$

Master equation:

$$\frac{d}{dt}\rho_{\rm n} = \sum_{\rm n'} T_{\rm nn'}\rho_{\rm n'}$$

Expected numbers:

$$n \equiv \langle \mathbf{n} \rangle$$

 Sampling without replacement leads to mass-action rates

$$\Psi_Y(\mathbf{n}) = \left[\Psi_Y^i(\mathbf{n})\right]$$

$$\Psi_Y^i \equiv \prod_p \frac{\mathbf{n}_p!}{(\mathbf{n}_p - y_p^i)!}$$

**Factorial moments** 

• A new rate equation:  $\frac{d}{dt}\langle \mathbf{n}\rangle = Y\mathbb{A}\langle \Psi_Y(\mathbf{n})\rangle$ 

$$\frac{d}{dt} \langle \mathbf{n} \rangle = Y \mathbb{A} \langle \Psi_Y(\mathbf{n}) \rangle$$

### Generating-function methods for discrete-state stochastic processes

• Moment-generating function:  $\phi(z) = \sum_{n} z^{n} \rho_{n}$ 

• If  $\rho$  evolves w/ a master equation:  $\frac{d}{dt}\rho_{\rm n}=\sum_{\rm n'}{\rm T}_{{\rm nn'}}\rho_{{\rm n'}}$ 

• Then  $\phi$  evolves under a PDE called a Liouville equation:  $\frac{\partial}{\partial t}\phi(z) = -\lambda$ 

$$\frac{\partial}{\partial t}\phi(z) = -\mathcal{L}\left(z, \frac{\partial}{\partial z}\right)\phi(z)$$

# Factorial moments and Poisson distributions: least-information null models for steady states

- Poisson distribution:  $\rho_{\rm n} = e^{-\xi} \frac{\xi^{\rm n}}{{\rm n}!}$
- · All factorial moments are simple functions of the mean:

$$\left\langle \frac{\mathbf{n}!}{(\mathbf{n}-k)!} \right\rangle = \sum_{\mathbf{n}} \rho_{\mathbf{n}} \frac{\mathbf{n}!}{(\mathbf{n}-k)!} = \xi^k$$

The generating functions are exponentials:

$$\phi_{\xi}(z) \equiv \sum_{\mathbf{n}} e^{-\xi} \frac{z^{\mathbf{n}} \xi^{\mathbf{n}}}{\mathbf{n}!} = e^{(z-1)\xi}$$

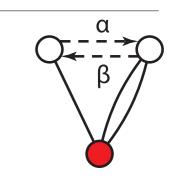
They are eigenstates of the derivative operator:

$$\frac{\partial}{\partial z}\phi_{\xi}(z) = \xi\phi_{\xi}(z)$$

# Example at $\delta = 0$ , and elegant proof that a Poisson distribution is a steady-state solution

Master equation:

$$\frac{d\rho_{\rm n}}{dt} = \left\{ \left( e^{-\partial/\partial n} - 1 \right) \alpha n + \left( e^{\partial/\partial n} - 1 \right) \beta n \left( n - 1 \right) \right\} \rho_{\rm n}$$



Liouville function:

$$\mathcal{L} = \begin{bmatrix} z & z^2 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \begin{bmatrix} \alpha & -\beta \end{bmatrix} \begin{bmatrix} \frac{\partial}{\partial z} \\ \frac{\partial^2}{\partial z^2} \end{bmatrix}$$

$$= z (1 - z) \frac{\partial}{\partial z} \left( \alpha - \beta \frac{\partial}{\partial z} \right)$$

• But on a Poisson distribution:  $\left(\alpha - \beta \frac{\partial}{\partial z}\right) \phi_{\xi}(z) = (\alpha - \beta \xi) \phi_{\xi}(z)$ 

• So steady-state condition  $\mathcal{L}\phi_{\xi}(z) = 0$  whenever  $\xi = \alpha/\beta$ 

#### Getting general ACK from Feinberg's deficiency-0

• More general form for  $\mathcal{L}$ :  $\mathcal{L} = -\psi_Y^T(z) \, \mathbb{A} \, \psi_Y \left( \frac{\partial}{\partial z} \right)$ 

General behavior on a gen. fn. 
$$\psi_Y\left(\frac{\partial}{\partial z}\right)\phi_\xi(z)\bigg|_{z=1}=\langle\Psi_Y(\mathbf{n})\rangle$$

For a Poisson, remember factorial moments:

 $=\psi_Y(\langle \mathbf{n} \rangle)$ 

The derivative just pulls out the coherent-state parm.  $=\psi_Y(\xi)$ 

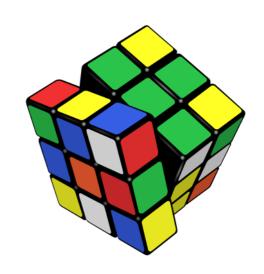
$$\mathcal{L}\phi_{\xi}(z) = -\psi_{Y}^{T}(z) \wedge \psi_{Y}(\xi) \phi_{\xi}(z)$$

• This is just the condition in the rate equation that Feinberg shows can always be solved at  $\delta=0$ . END PROOF

#### More that can be done

- Beyond deficiency-0? When (else) are CRNs simple?
- Duality and fluctuation theorems (Jarzynski, Crooks)
- Develop stat. mech. of concurrency further:
  - Systems-biology language Kappa (Fontana, Danos)
  - Large-Deviations for stochastic Rubik's Cube?





#### Concluding remarks

- Diffusion on ordinary graphs is a restrictive framework, but has still be extremely useful
- Adding concurrency and clumpiness with CRNs is a natural next step, but adds considerable mathematical difficulty
- This ties in well with macro-worlds, and the area of overlap contains a lot of interesting work to do