

Mass action networks with the isolation property

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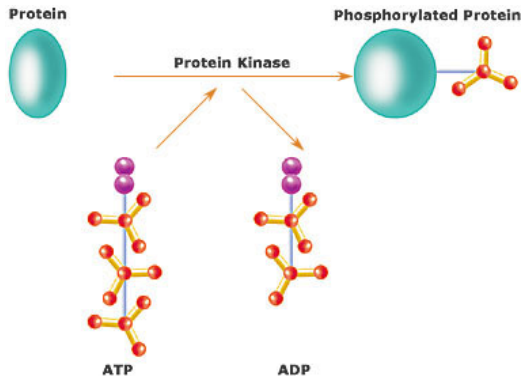
(joint work with Carsten Conradi and Thomas Kahle)

Osnabrück, March 23, 2018

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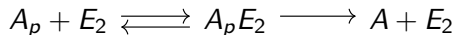
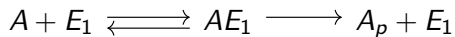
- Example of a chemical reaction network in biology
- Chemical reaction networks with the isolation property

Phosphorylation

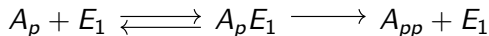
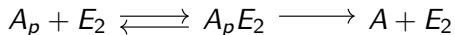
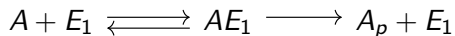


(Wikipedia)

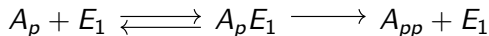
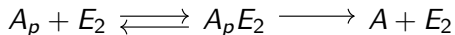
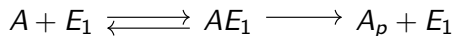
Sequential Distributed Phosphorylations



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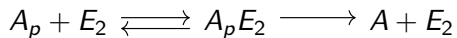
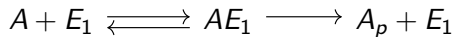


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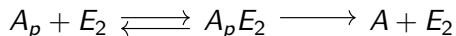
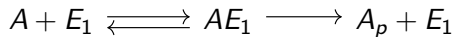


⋮

Eg.: From 1-site Phosphorylation to polynomial Rings

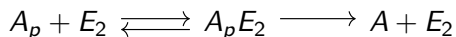


Eg.: From 1-site Phosphorylation to polynomial Rings



- Assume that A, E_1, \dots are in some isolated, homogeneous reactor \mathfrak{R} .

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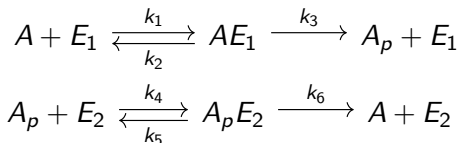


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Law of mass action

The rate of a chemical reaction is directly proportional to the product of concentrations of the reactants.

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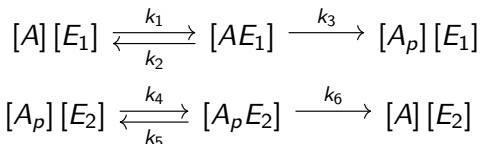


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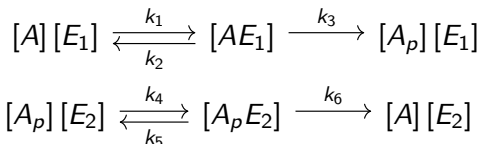


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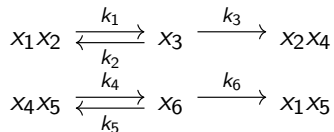
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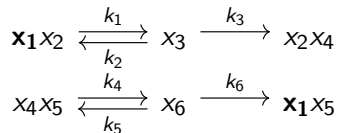
The rate of a chemical reaction is directly proportional to the product of concentrations of the reactants.

Denote: $[A] = x_1, [E_1] = x_2, [AE_1] = x_3, [A_p] = x_4, [E_2] = x_5, [A_pE_2] = x_6$.

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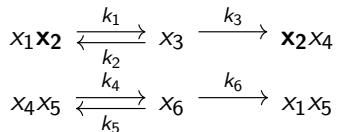
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- Trajectory:

$$\dot{x}_1 = -k_1 x_1 x_2 + k_2 x_3 + k_6 x_6$$

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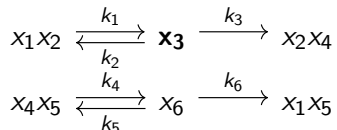


- Trajectory:

$$\dot{x}_1 = -k_1 x_1 x_2 + k_2 x_3 + k_6 x_6$$

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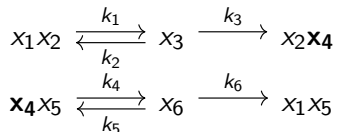
- Trajectory:

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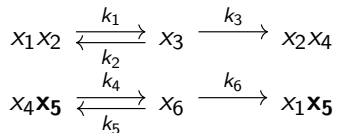
$$\dot{x}_1 = -k_1 x_1 x_2 + k_2 x_3 + k_6 x_6$$

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$$\dot{x}_3 = k_1 x_1 x_2 - k_2 x_3 - k_3 x_3$$

$$\dot{x}_4 = k_3 x_3 - k_4 x_4 x_5 + k_5 x_6$$

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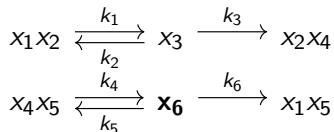
$$\dot{x}_2 = -k_1 x_1 x_2 + k_2 x_3 + k_3 x_3$$

$$\dot{x}_3 = k_1 x_1 x_2 - k_2 x_3 - k_3 x_3$$

$$\dot{x}_4 = k_3 x_3 - k_4 x_4 x_5 + k_5 x_6$$

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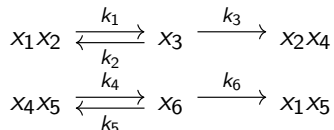
$$\dot{x}_3 = k_1 x_1 x_2 - k_2 x_3 - k_3 x_3$$

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$$\dot{x}_5 = -k_4 x_4 x_5 + k_5 x_6 + k_6 x_6$$

$$\dot{x}_6 = k_4 x_4 x_5 - k_5 x_6 - k_6 x_6$$

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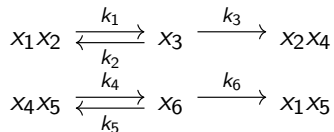
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$$\begin{aligned} \dot{x}_1 &= -k_1 x_1 x_2 + k_2 x_3 + k_6 x_6 \\ \dot{x}_2 &= -k_1 x_1 x_2 + k_2 x_3 + k_3 x_3 \\ \dot{x}_3 &= k_1 x_1 x_2 - k_2 x_3 - k_3 x_3 \\ \dot{x}_4 &= k_3 x_3 - k_4 x_4 x_5 + k_5 x_6 \\ \dot{x}_5 &= -k_4 x_4 x_5 + k_5 x_6 + k_6 x_6 \\ \dot{x}_6 &= k_4 x_4 x_5 - k_5 x_6 - k_6 x_6 \end{aligned}$$

- Steady States ($\dot{x}_i = 0$):

$$\begin{aligned} 0 &= -k_1 x_1 x_2 + k_2 x_3 + k_6 x_6 \\ 0 &= -k_1 x_1 x_2 + k_2 x_3 + k_3 x_3 \\ 0 &= k_1 x_1 x_2 - k_2 x_3 - k_3 x_3 \\ 0 &= k_3 x_3 - k_4 x_4 x_5 + k_5 x_6 \\ 0 &= -k_4 x_4 x_5 + k_5 x_6 + k_6 x_6 \\ 0 &= k_4 x_4 x_5 - k_5 x_6 - k_6 x_6 \end{aligned}$$

Eg.: From 1-site Phosphorylation to polynomial Rings



- Trajectory:

$$\dot{x} = \underbrace{\begin{pmatrix} -1 & 1 & 0 & 0 & 0 & 1 \\ -1 & 1 & 1 & 0 & 0 & 0 \\ 1 & -1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 1 & 0 \\ 0 & 0 & 0 & -1 & 1 & 1 \\ 0 & 0 & 0 & 1 & -1 & -1 \end{pmatrix}}_S \underbrace{\begin{pmatrix} k_1 x_1 x_2 \\ k_2 x_3 \\ k_3 x_3 \\ k_4 x_4 x_5 \\ k_5 x_6 \\ k_6 x_6 \end{pmatrix}}_{\phi(k,x)}$$

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Macaulay2 Experiment 1

```
i1 : needsPackage("Binomials");
i2 : K=QQ[k_1..k_6]; R=K[x_1..x_6];
i3 : I=ideal(-k_1*x_1*x_2+k_2*x_3+k_6*x_6,
            -k_1*x_1*x_2+k_2*x_3+k_3*x_3,
            k_1*x_1*x_2-k_2*x_3-k_3*x_3,
            k_3*x_3-k_4*x_4*x_5+k_5*x_6,
            -k_4*x_4*x_5+k_5*x_6+k_6*x_6,
            k_4*x_4*x_5-k_5*x_6-k_6*x_6);
i4 : associatedPrimes I
o4 : {ideal(k_3*x_3-k_6*x_6,
            k_4*x_4*x_5+(-k_5-k_6)*x_6,
            k_1*x_1*x_2-k_2*x_3-k_6*x_6)}
i5 : isBinomial I
o5 = false
i6 : gens gb I
o6 = | x_3k_3-x_6k_6 x_4x_5k_4-x_6k_5-x_6k_6
      x_1x_2k_1-x_3k_2-x_6k_6 |
```

Macaulay2 Experiment 2

```
i1 : needsPackage("Binomials");
i2 : K=frac(QQ[k_1..k_6]); R=K[x_1..x_6];
i3 : I=ideal(-k_1*x_1*x_2+k_2*x_3+k_6*x_6,
            -k_1*x_1*x_2+k_2*x_3+k_3*x_3,
            k_1*x_1*x_2-k_2*x_3-k_3*x_3,
            k_3*x_3-k_4*x_4*x_5+k_5*x_6,
            -k_4*x_4*x_5+k_5*x_6+k_6*x_6,
            k_4*x_4*x_5-k_5*x_6-k_6*x_6);
i4 : associatedPrimes I
stdio:4:1:(3): error: expected base field to be QQ or ZZ/p
i5 : isBinomial I
o5 = true
i6 : gens gb I
o6 = | x_3-k_6/k_3x_6 x_4x_5+(-k_5-k_6)/k_4x_6
      x_1x_2+(-k_2k_6-k_3k_6)/k_1k_3x_6 |
```

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- Let $V := \{x \in \mathbb{R}^6 : f(x) = 0, \forall f \in I\}$,
 $V_{\geq 0} := V \cap \mathbb{R}_{\geq 0}^6$ and $V_{>0} := V \cap \mathbb{R}_{>0}^6$.

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- As I is binomial, the Zariski closure of $V_{>0}$ is toric.
- Therefore $V_{>0}$ has a monomial parametrization:

$$\begin{array}{l} \mathbb{R}_{>0}^3 \quad \rightarrow \\ (t_1, t_2, t_3) \mapsto \end{array} \left(\frac{k_6(k_2 + k_3)}{k_1 k_3} \frac{t_3}{t_1}, t_1, \frac{k_6}{k_3} t_3, \frac{k_5 + k_6}{k_4} \frac{t_3}{t_2}, t_2, t_3 \right). \quad \mathbb{R}_{>0}^6$$

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 - Primary decomposition is computationally expensive.
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 - Look at simpler cases (e.g., systems with the isolation property)

The kernel of the stoichiometric matrix

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- Let E be a matrix whose columns are the extreme rays of $\ker(S) \cap \mathbb{R}_{\geq 0}^r$. Let n_i denote the i^{th} row of E .

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- Let E be a matrix whose columns are the extreme rays of $\ker(S) \cap \mathbb{R}_{\geq 0}^r$. Let n_i denote the i^{th} row of E .
- If E has p columns, let $\Lambda(E) := \{\lambda \in \mathbb{R}_{\geq 0}^p : E\lambda > 0\}$.

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Clustering the reactions

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- Let \mathfrak{R} denote the union of all preclusters.
- A **cluster** is an element of the maximal partition of \mathfrak{R} induced by the preclusters.

Definition

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Definition

A mass action network has the isolation property when the rows of E indexed by different clusters have disjoint supports.

Theorem [2017; Conradi, I., Kahle]

If a mass action network \mathcal{N} has the isolation property, then the set of positive steady states $V_{>0}$ of \mathcal{N} has a monomial parametrization.

Idea of the proof (definitions)

- Let \mathcal{Y} denote the matrix whose i^{th} column is the exponent vector of the source of the i^{th} arrow.

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- Let U^{doub} denote a matrix with r rows which has a column $e_i - e_j$ for each superdoubling set $\{i, j\}$.
- Let \tilde{U} denote a matrix such that the columns of $(U^{\text{doub}} | \tilde{U})$ span $\ker(\mathcal{Y})$.

Lemma I [2010; Conradi, Flockerzi]

If i and j belong to the same cluster J , then

$$\log \left(\frac{n_i \nu}{n_i \lambda} \right) = \log \left(\frac{n_j \nu}{n_j \lambda} \right) := \psi_J(\nu, \lambda) \text{ for all } \nu, \lambda \in \Lambda(E).$$

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Definition

If \mathcal{N} has γ clusters, J_1, \dots, J_γ , let:

$$\begin{aligned} \psi : \Lambda^2(E) &\rightarrow \mathbb{R}^\gamma \\ (\nu, \lambda) &\mapsto (\psi_{J_1}(\nu, \lambda), \dots, \psi_{J_\gamma}(\nu, \lambda)). \end{aligned}$$

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Lemma II [2010; Conradi, Flockerzi]

If \mathcal{N} has the isolation property then $\text{im} \psi$ is a linear space.

Idea of the proof

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Lemma III [2010; Conradi, Flockerzi]

There are two positive steady states $x^* \neq x^{**}$ with a common k^* if and only if $\exists \kappa \in \text{im} \psi$ with $\mathcal{Y}^T (\log(x^{**}) - \log(x^*)) = \Pi \kappa$ and $\tilde{U}^T \Pi \kappa = 0$.

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Lemma IV [2017; Conradi, I., Kahle]

For every steady state x^* of \mathcal{N} and for every $\kappa \in \text{im} \psi$ and $\mu \in \mathbb{R}^n - \{0\}$ with $\tilde{U}^T \Pi \kappa = 0$ and $\mathcal{Y}^T \mu = \Pi \kappa$, there is another steady state $x^{**} = e^\mu \circ x^*$.

Thank you for your attention!

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