

MPRI 2.19 Biochemical Programming

Rule-based Modeling

Model reduction

Jérôme Feret

DI - ÉNS



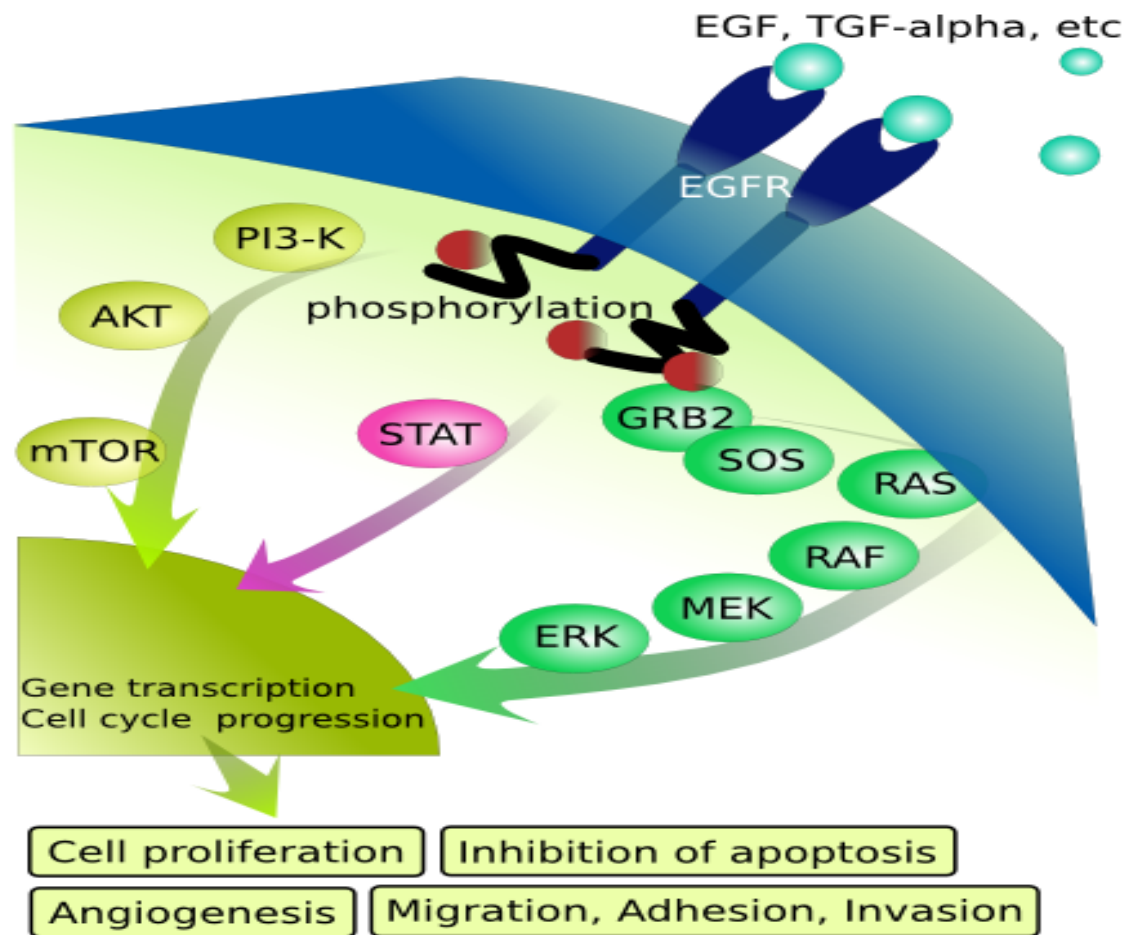
<http://www.di.ens.fr/~feret>

Tuesday, the 11th of January, 2022

On the menu today

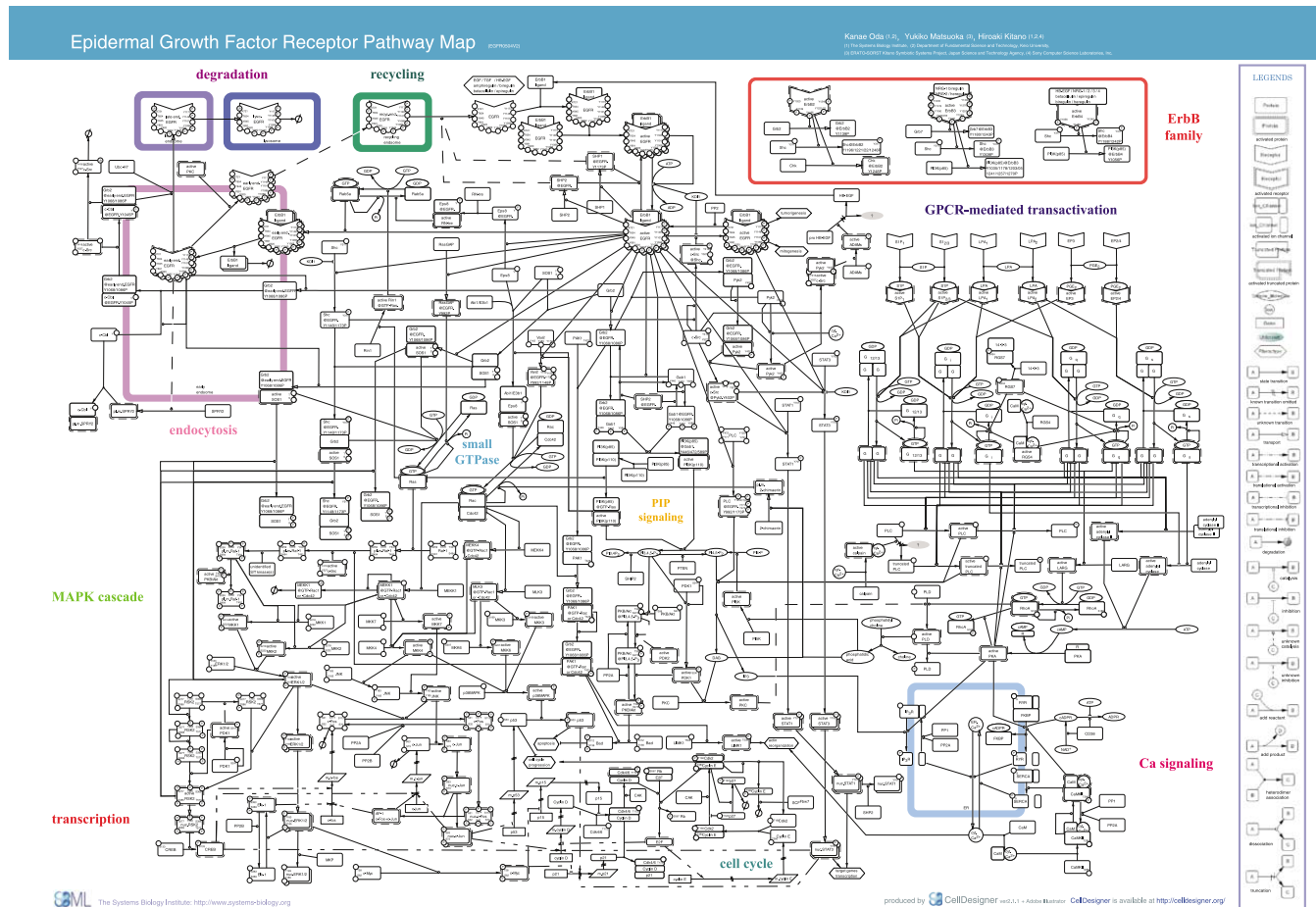
1. Context and motivations
2. Case studies
3. Reduction of ordinary differential equations
4. Abstraction of the information flow
5. Model reduction
6. Conclusion

Intra-cellular signalling pathways



Eikuch, 2007

Interaction maps

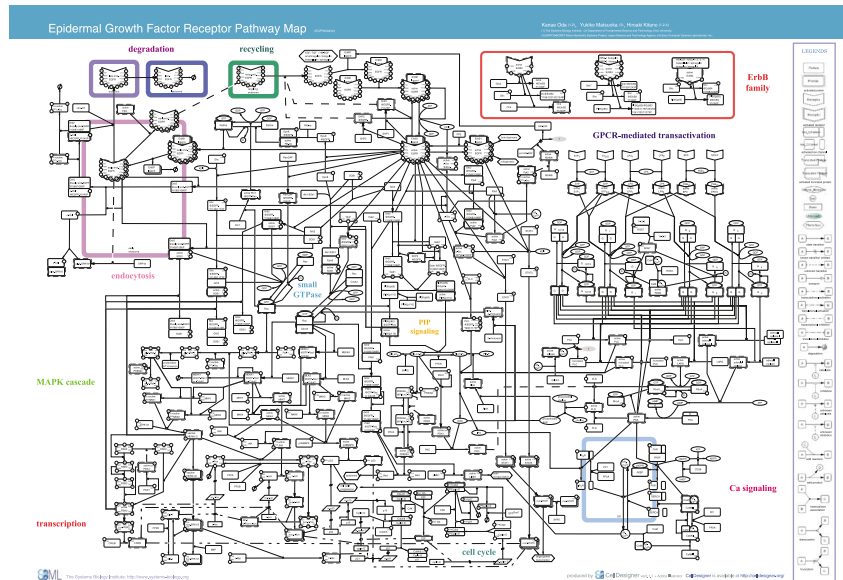


Oda et al, 2005

Models of the behaviour of the system

$$\left\{ \begin{array}{l} \frac{dx_1}{dt} = -k_1 \cdot x_1 \cdot x_2 + k_{-1} \cdot x_3 \\ \frac{dx_2}{dt} = -k_1 \cdot x_1 \cdot x_2 + k_{-1} \cdot x_3 \\ \frac{dx_3}{dt} = k_1 \cdot x_1 \cdot x_2 - k_{-1} \cdot x_3 + 2 \cdot k_2 \cdot x_3 \cdot x_3 - k_{-2} \cdot x_4 \\ \frac{dx_4}{dt} = k_2 \cdot x_3^2 - k_2 \cdot x_4 + \frac{v_4 \cdot x_5}{p_4 + x_5} - k_3 \cdot x_4 - k_{-3} \cdot x_5 \\ \frac{dx_5}{dt} = \dots \\ \vdots \\ \frac{dx_n}{dt} = -k_1 \cdot x_1 \cdot c_2 + k_{-1} \cdot x_3 \end{array} \right.$$

Bridge the gap between...



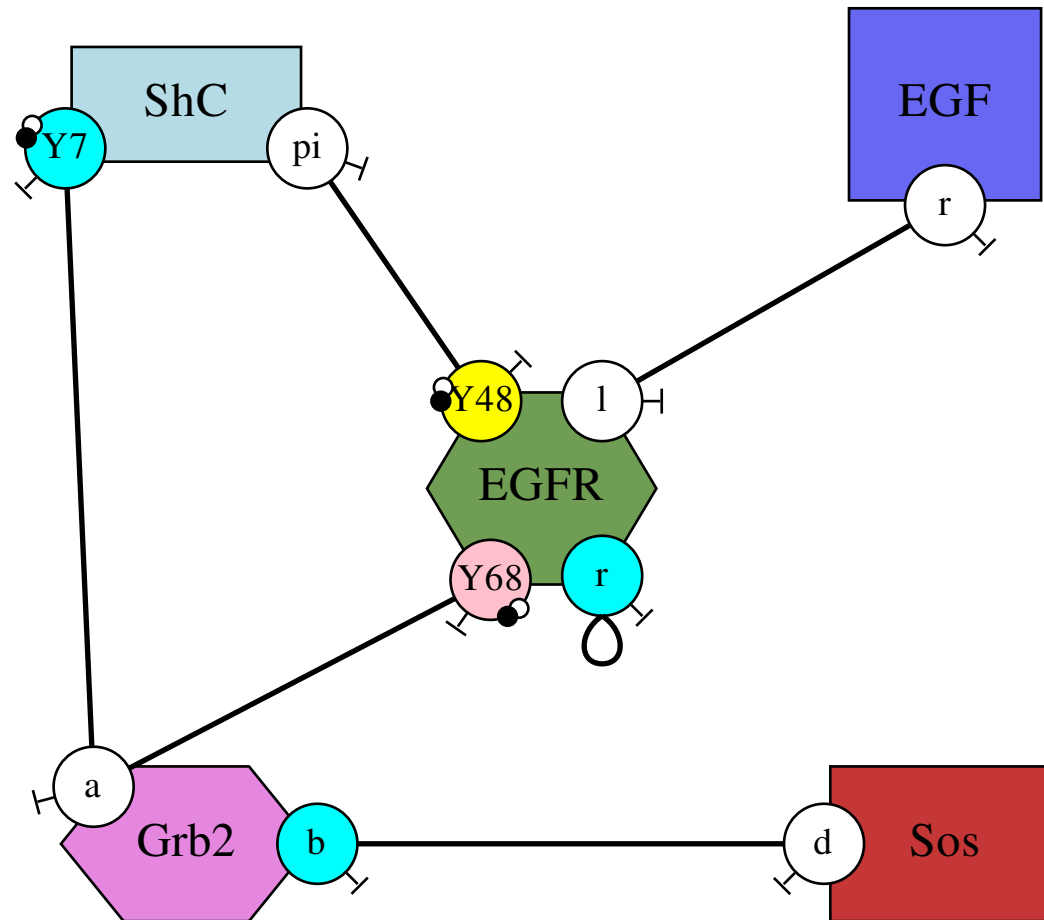
$$\left\{ \begin{array}{l} \frac{dx_1}{dt} = -k_1 \cdot x_1 \cdot x_2 + k_{-1} \cdot x_3 \\ \frac{dx_2}{dt} = -k_1 \cdot x_1 \cdot x_2 + k_{-1} \cdot x_3 \\ \frac{dx_3}{dt} = k_1 \cdot x_1 \cdot x_2 - k_{-1} \cdot x_3 + 2 \cdot k_2 \cdot x_3 \cdot x_3 - k_{-2} \cdot x_4 \\ \frac{dx_4}{dt} = k_2 \cdot x_3^2 - k_2 \cdot x_4 + \frac{v_4 \cdot x_5}{p_4 + x_5} - k_3 \cdot x_4 - k_{-3} \cdot x_5 \\ \frac{dx_5}{dt} = \dots \\ \vdots \\ \frac{dx_n}{dt} = -k_1 \cdot x_1 \cdot c_2 + k_{-1} \cdot x_3 \end{array} \right.$$

knowledge
representation

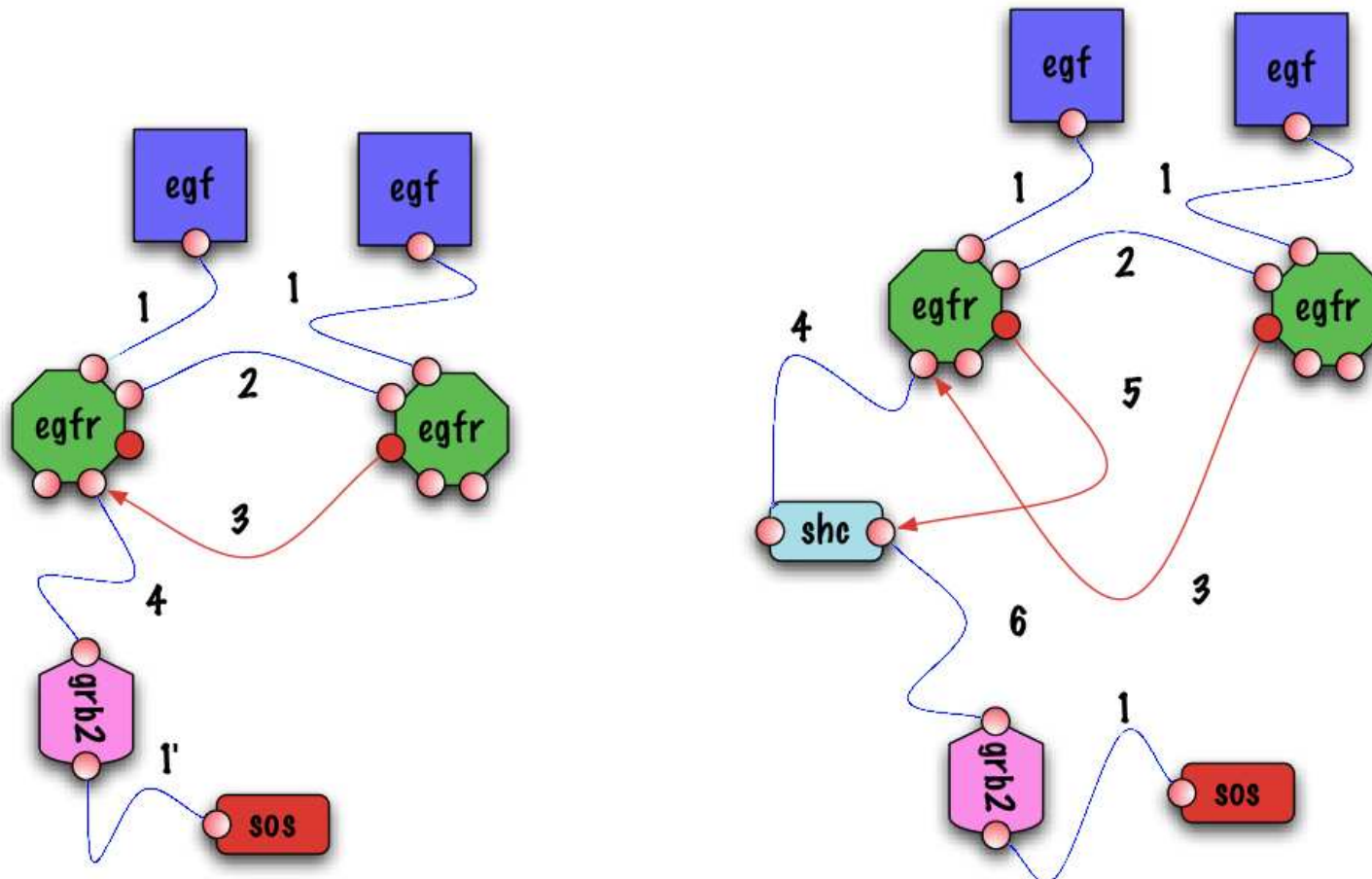
and

models of the
behaviour of systems

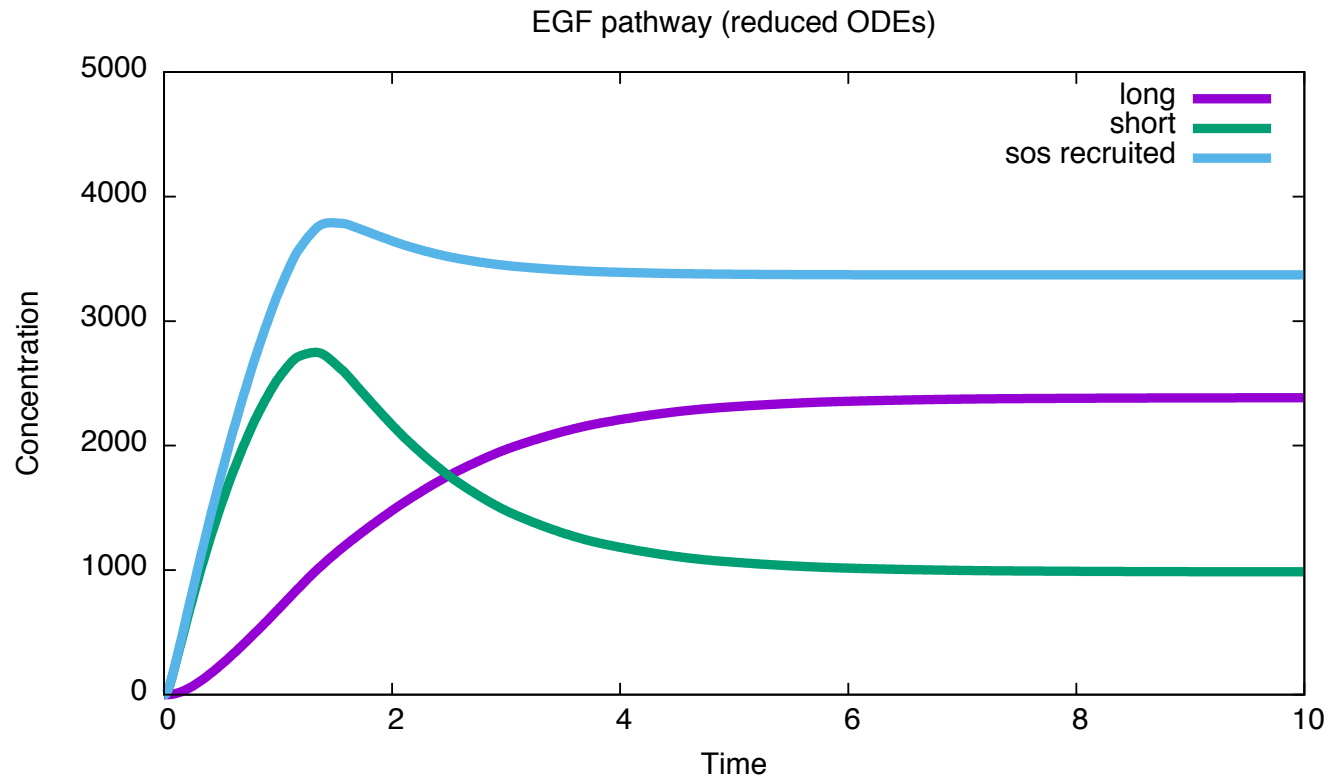
Contact map



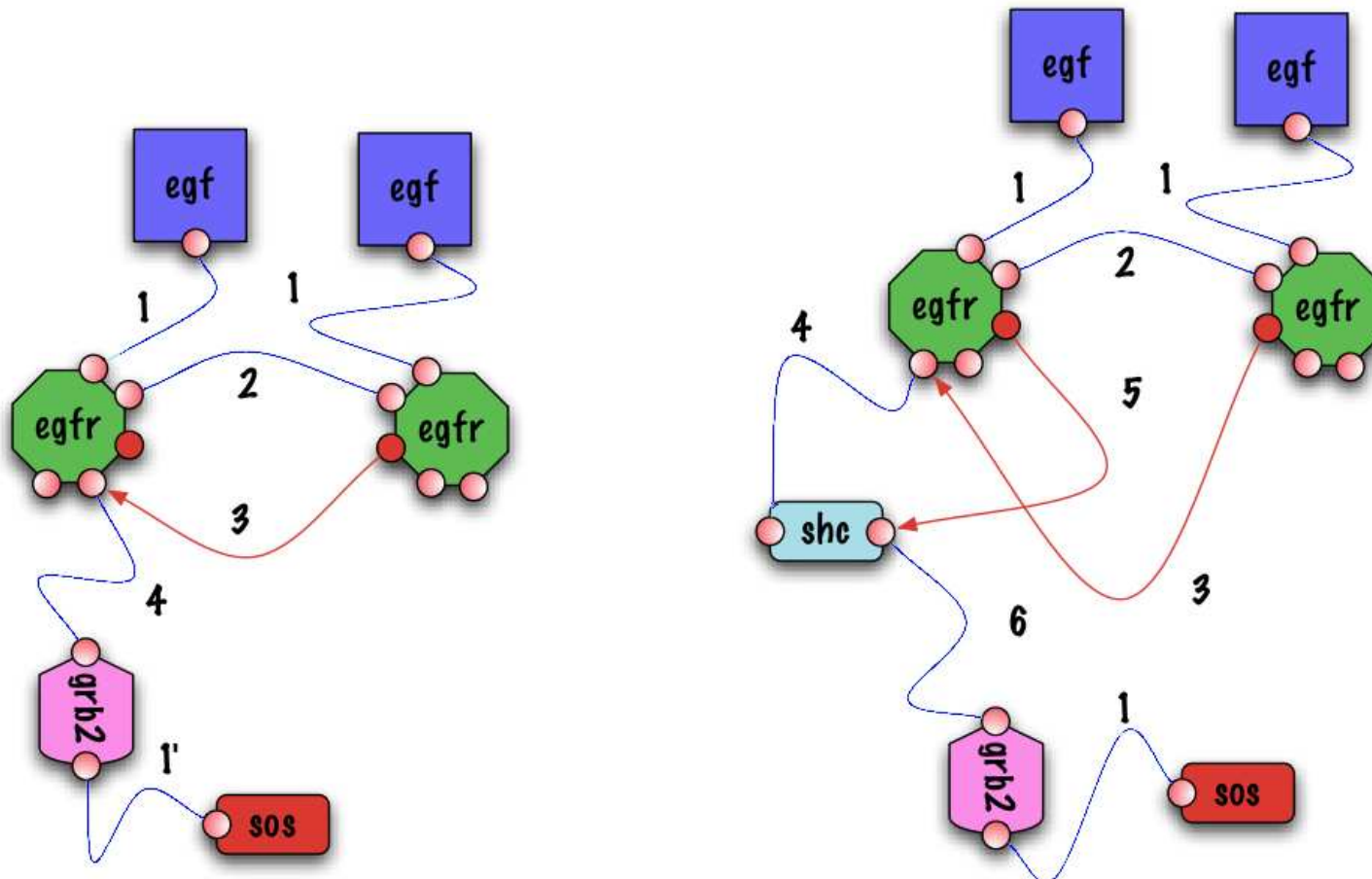
Causal traces



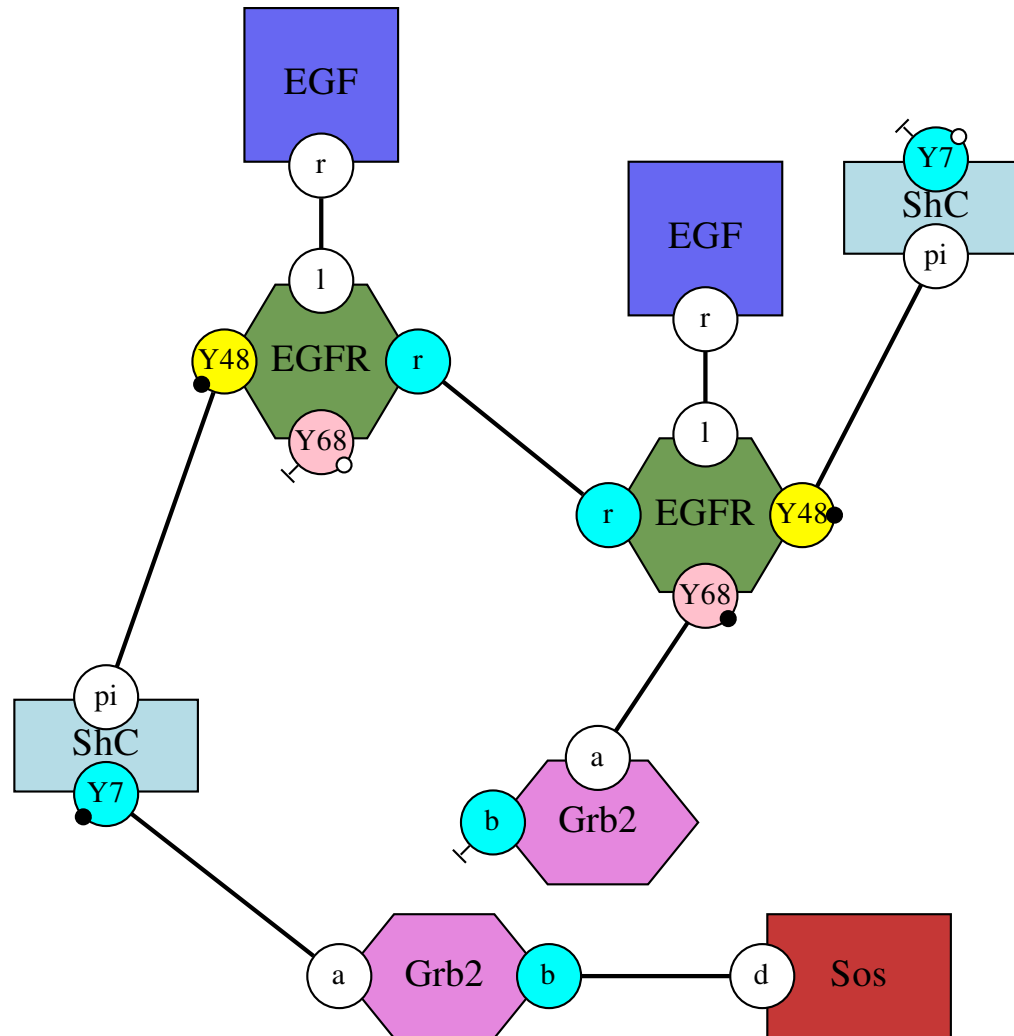
ODE semantics



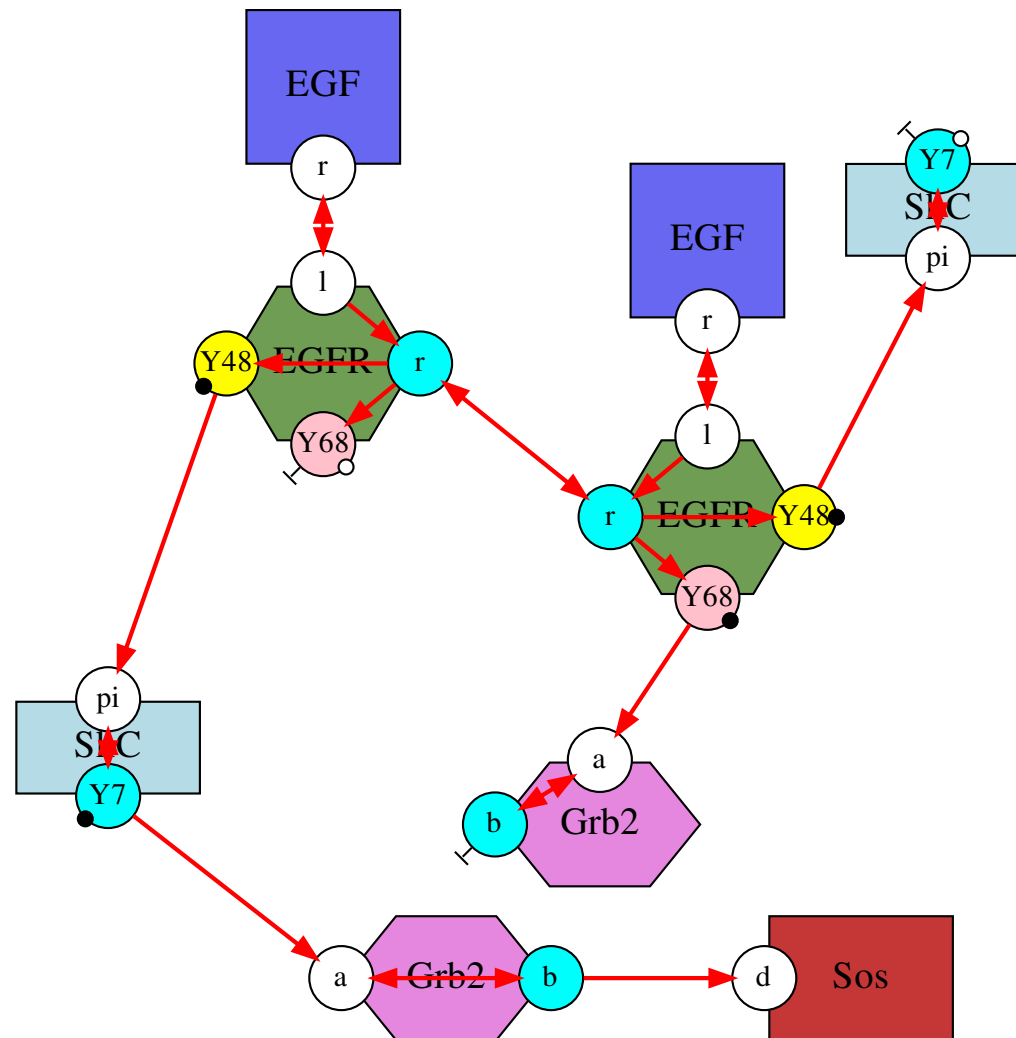
Causal traces



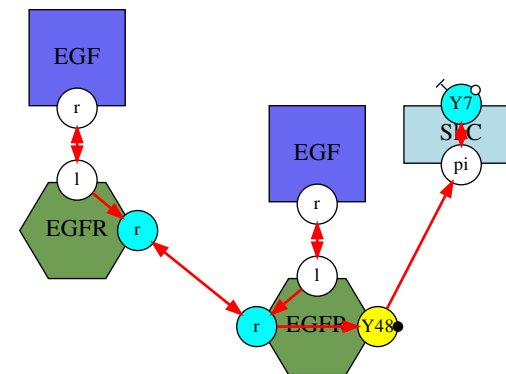
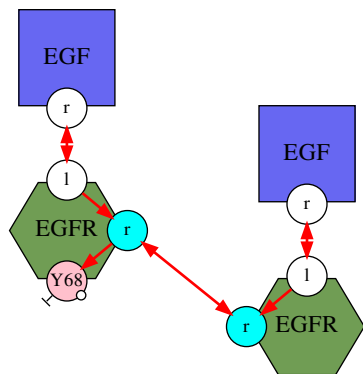
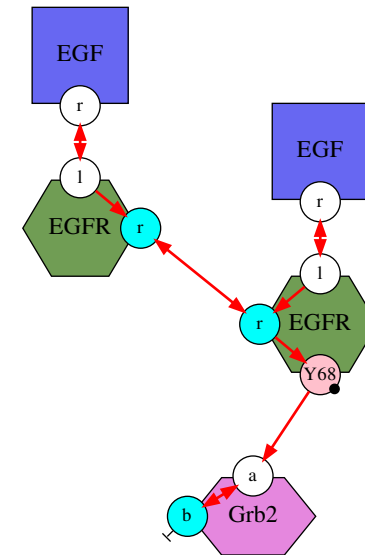
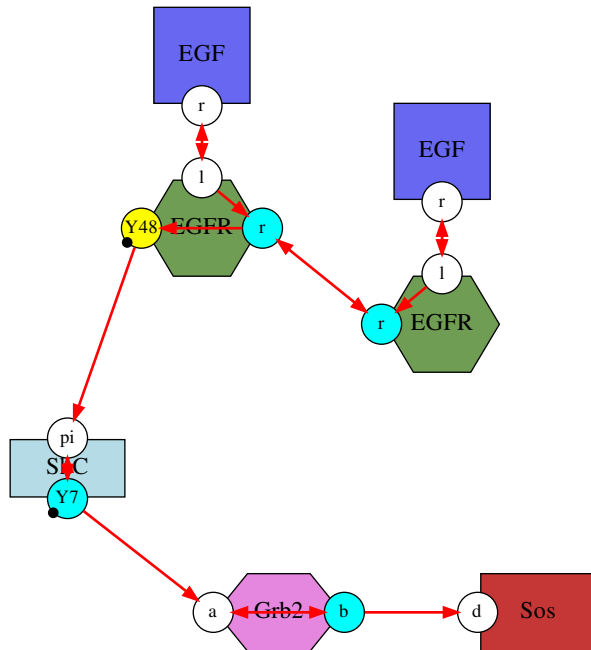
Combinatorial wall



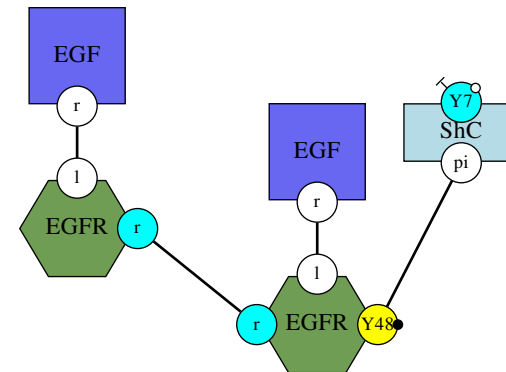
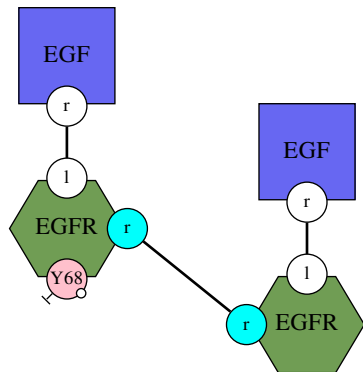
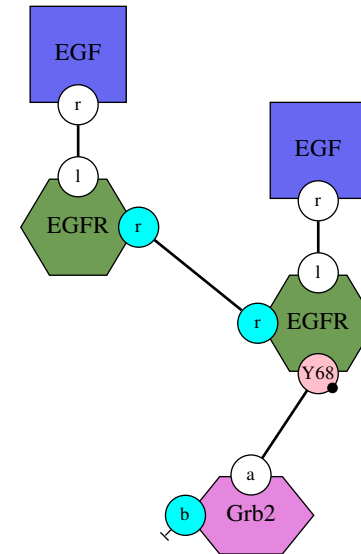
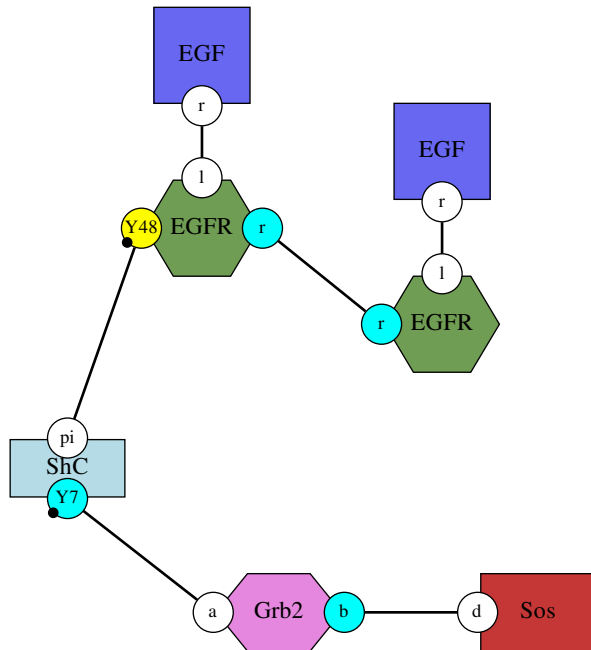
Information flow



A potential breach



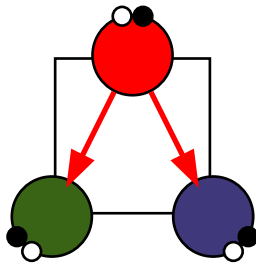
A potential breach



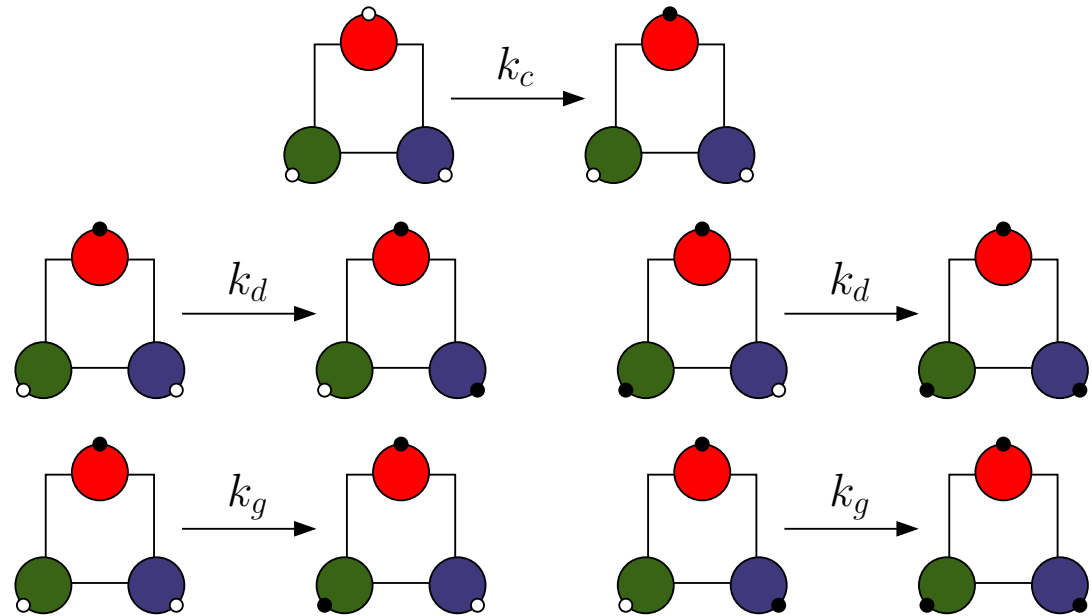
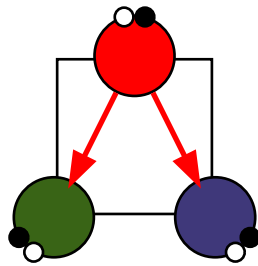
On the menu today

1. Context and motivations
2. **Case studies**
3. Reduction of ordinary differential equations
4. Abstraction of the information flow
5. Model reduction
6. Conclusion

Case study



Case study



Law of mass action

We consider that chemical species are elementary particles without any volume, and that they are diffusing in an infinite, perfectly fluid and homogeneous medium without borders.

Let \mathcal{X} be a set of chemical species.

A reaction network is a set of reactions \mathcal{R} .

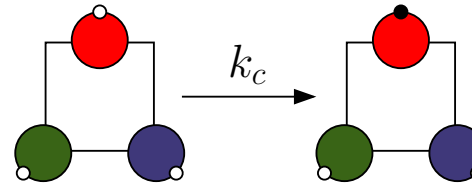
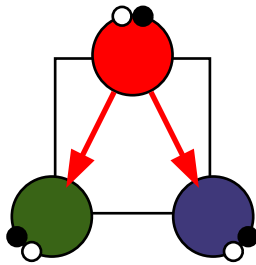
Each reaction r is defined by:

1. α_r , a function from \mathcal{X} to \mathbb{N} (the reactants);
2. β_r , a function from \mathcal{X} to \mathbb{N} (the products);
3. k_r , a non negative real number (the kinetic rate).

With these notations, the law of mass action defines the behaviour of the concentration $[X]$ of each chemical species X :

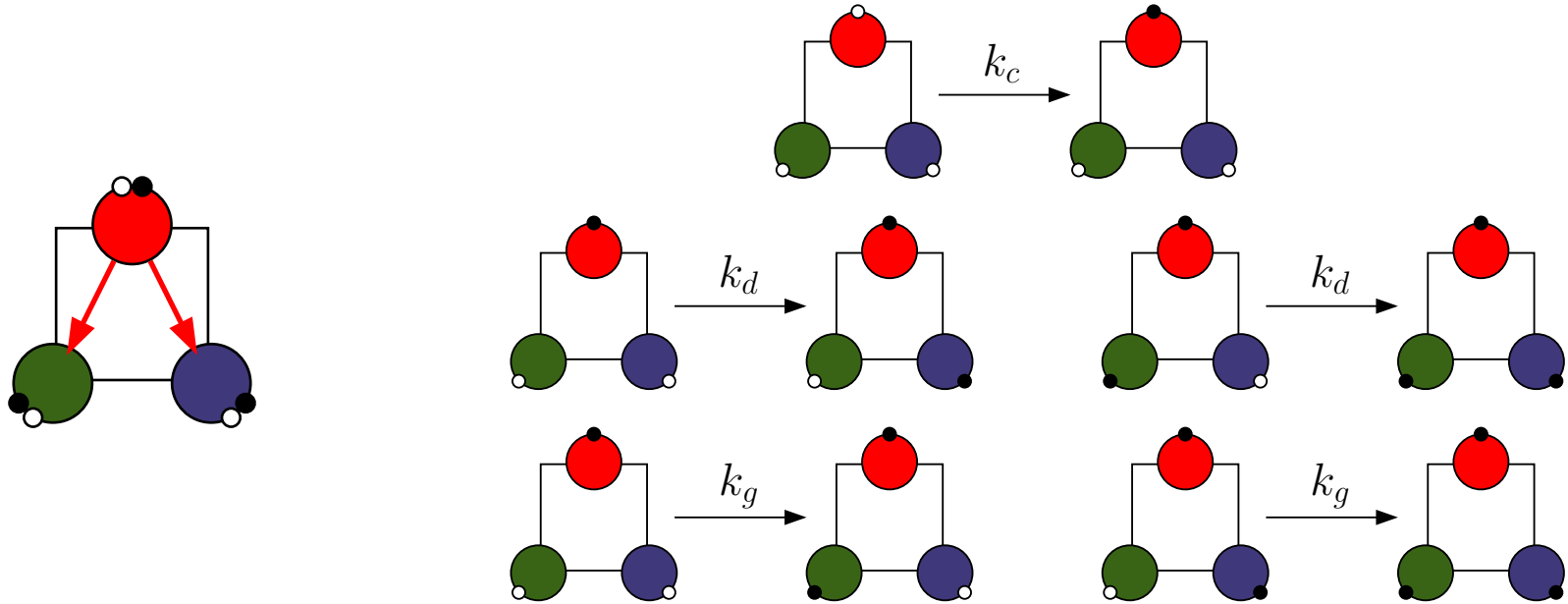
$$\frac{d[X]}{dt} = \sum_{r \in \mathcal{R}} k_r \cdot (\beta_r(X) - \alpha_r(X)) \cdot \prod_{X' \in \mathcal{X}} [X']^{\alpha_r(X')}.$$

Case study



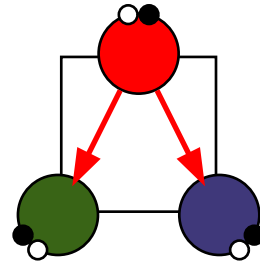
$$\left\{ \begin{array}{l} \frac{d[(u,u,u)]}{dt} = -k_c \cdot [(u,u,u)] \\ \frac{d[(u,\textcolor{red}{p},u)]}{dt} = k_c \cdot [(u,u,u)] \end{array} \right.$$

Case study

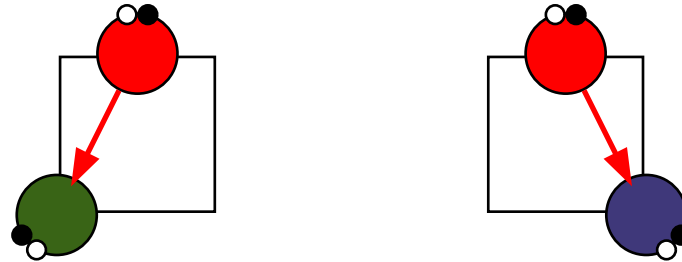


$$\begin{cases} \frac{d[(u,u,u)]}{dt} = -k_c \cdot [(u,u,u)] \\ \frac{d[(u,\textcolor{red}{p},u)]}{dt} = -k_g \cdot [(u,\textcolor{red}{p},u)] + k_c \cdot [(u,u,u)] - k_d \cdot [(u,\textcolor{red}{p},u)] \\ \frac{d[(u,\textcolor{red}{p},\textcolor{blue}{p})]}{dt} = -k_g \cdot [(u,\textcolor{red}{p},\textcolor{blue}{p})] + k_d \cdot [(u,\textcolor{red}{p},u)] \\ \frac{d[(\textcolor{green}{p},\textcolor{red}{p},u)]}{dt} = k_g \cdot [(u,\textcolor{red}{p},u)] - k_d \cdot [(\textcolor{green}{p},\textcolor{red}{p},u)] \\ \frac{d[(\textcolor{green}{p},\textcolor{red}{p},\textcolor{blue}{p})]}{dt} = k_g \cdot [(u,\textcolor{red}{p},\textcolor{blue}{p})] + k_d \cdot [(\textcolor{green}{p},\textcolor{red}{p},u)] \end{cases}$$

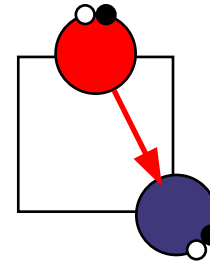
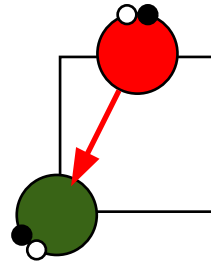
Case study



Case study



Case study



$$[(u, u, u)] = [(u, u, u)]$$

$$[(u, \textcolor{red}{p}, ?)] \triangleq [(u, \textcolor{red}{p}, u)] + [(u, \textcolor{red}{p}, \textcolor{blue}{p})]$$

$$[(\textcolor{green}{p}, \textcolor{red}{p}, ?)] \triangleq [(\textcolor{green}{p}, \textcolor{red}{p}, u)] + [(\textcolor{green}{p}, \textcolor{red}{p}, \textcolor{blue}{p})]$$

$$\begin{cases} \frac{d[(u, u, u)]}{dt} = -k_c \cdot [(u, u, u)] \\ \frac{d[(u, \textcolor{red}{p}, ?)]}{dt} = -k_g \cdot [(u, \textcolor{red}{p}, ?)] + k_c \cdot [(u, u, u)] \\ \frac{d[(\textcolor{green}{p}, \textcolor{red}{p}, ?)]}{dt} = k_g \cdot [(u, \textcolor{red}{p}, ?)] \end{cases}$$

$$[(u, u, u)] = [(u, u, u)]$$

$$[(?, \textcolor{red}{p}, u)] \triangleq [(u, \textcolor{red}{p}, u)] + [(\textcolor{green}{p}, \textcolor{red}{p}, u)]$$

$$[(?, \textcolor{red}{p}, \textcolor{blue}{p})] \triangleq [(u, \textcolor{red}{p}, \textcolor{blue}{p})] + [(\textcolor{green}{p}, \textcolor{red}{p}, \textcolor{blue}{p})]$$

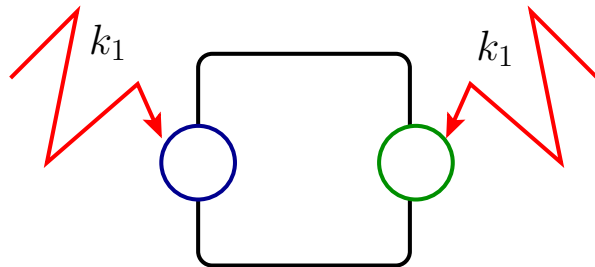
$$\begin{cases} \frac{d[(u, u, u)]}{dt} = -k_c \cdot [(u, u, u)] \\ \frac{d[(?, \textcolor{red}{p}, u)]}{dt} = -k_d \cdot [(?, \textcolor{red}{p}, u)] + k_c \cdot [(u, u, u)] \\ \frac{d[(?, \textcolor{red}{p}, \textcolor{blue}{p})]}{dt} = k_d \cdot [(?, \textcolor{red}{p}, u)] \end{cases}$$

What we have learned so far:

We can use the absence of information flow to detect useless correlations between the states of sites in chemical species. We can use this to cut chemical species into fragments.

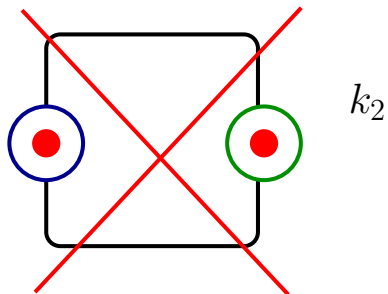
This transformation loses some information: we cannot compute the concentration of each chemical species anymore.

A model with symmetries



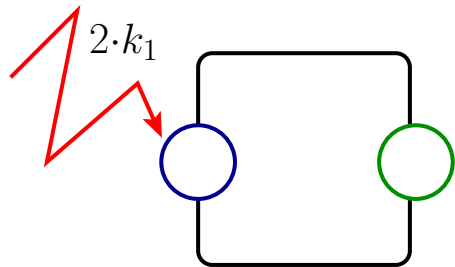
$$\begin{array}{lcl} P & \longrightarrow & {}^*P \quad k_1 \\ P & \longrightarrow & P^* \quad k_1 \end{array}$$

$$\begin{array}{lcl} P^* & \longrightarrow & {}^*P^* \quad k_1 \\ {}^*P & \longrightarrow & {}^*P^* \quad k_1 \end{array}$$

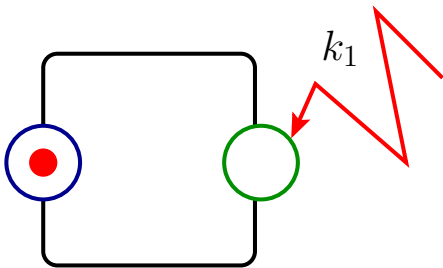


$${}^*P^* \longrightarrow \emptyset \quad k_2$$

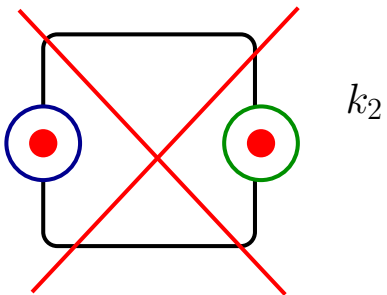
Reduced model



$$P \longrightarrow {}^*P \quad 2 \cdot k_1$$



$${}^*P \longrightarrow {}^*P^* \quad k_1$$



$${}^*P^* \longrightarrow \emptyset \quad k_2$$

Differential equations

- Initial system:

$$\frac{d}{dt} \begin{bmatrix} P \\ {}^*P \\ P^* \\ {}^*P^* \end{bmatrix} = \begin{bmatrix} -2 \cdot k_1 & 0 & 0 & 0 \\ k_1 & -k_1 & 0 & 0 \\ k_1 & 0 & -k_1 & 0 \\ 0 & k_1 & k_1 & -k_2 \end{bmatrix} \cdot \begin{bmatrix} P \\ {}^*P \\ P^* \\ {}^*P^* \end{bmatrix}$$

- Reduced system:

$$\frac{d}{dt} \begin{bmatrix} P \\ {}^*P + P^* \\ 0 \\ {}^*P^* \end{bmatrix} = \begin{bmatrix} -2 \cdot k_1 & 0 & 0 & 0 \\ 2 \cdot k_1 & -k_1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & k_1 & 0 & -k_2 \end{bmatrix} \cdot \begin{bmatrix} P \\ {}^*P + P^* \\ 0 \\ {}^*P^* \end{bmatrix}$$

Invariant

We wonder whether or not:

$$[\star P] = [P^{\star}],$$

Thus we define the difference X as follows:

$$X \triangleq [\star P] - [P^{\star}].$$

We have:

$$\frac{dX}{dt} = -k_1 \cdot X.$$

So the property ($X = 0$) is an invariant.

Thus, if $[\star P] = [P^{\star}]$ at time $t = 0$, then $[\star P] = [P^{\star}]$ forever.

Conclusion

We can abstract away the distinction between chemical species which are equivalent up to symmetries (with respect to the reactions).

1. If the symmetries are satisfied in the initial state:
 - + the abstraction is invertible:
 - we can recover the concentration of any species,
(thanks to the invariants).
2. Otherwise:
 - some information is abstracted away:
 - we cannot recover the concentration of any species;
 - + the system converges to a state which satisfies the symmetries.

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Differential semantics

A system of ordinary differential equations is a pair $(\mathcal{V}, \mathbb{F})$ where:

- \mathcal{V} is a finite set of variables,
- \mathbb{F} is a continuous function from $\mathcal{V} \rightarrow \mathbb{R}^+$ to $\mathcal{V} \rightarrow \mathbb{R}$.

Elements of $\mathcal{V} \rightarrow \mathbb{R}^+$ are called states.

The differential semantics maps each initial state $X_0 \in \mathcal{V} \rightarrow \mathbb{R}^+$ to the solution $X_{X_0} \in [0, T_{X_0}^{\max}[\rightarrow (\mathcal{V} \rightarrow \mathbb{R}^+)$ of the following equation:

$$X_{X_0}(T) = X_0 + \int_{t=0}^T \mathbb{F}(X_{X_0}(t)) \cdot dt.$$

that is defined over the widest time interval as possible.

Back to the case study

$$1. \mathcal{V} \triangleq \{[(u,u,u)], [(u,p,u)], [(p,p,u)], [(u,p,p)], [(p,p,p)]\},$$

$$2. \mathbb{F}(\rho) \triangleq \begin{cases} [(u,u,u)] \mapsto -k_c \cdot \rho([(u,u,u)]) \\ [(u,p,u)] \mapsto -k_g \cdot \rho([(u,p,u)]) + k_c \cdot \rho([(u,u,u)]) - k_d \cdot \rho([(u,p,u)]) \\ [(u,p,p)] \mapsto -k_g \cdot \rho([(u,p,p)]) + k_d \cdot \rho([(u,p,u)]) \\ [(p,p,u)] \mapsto k_g \cdot \rho([(u,p,u)]) - k_d \cdot \rho([(p,p,u)]) \\ [(p,p,p)] \mapsto k_g \cdot \rho([(u,p,p)]) + k_d \cdot \rho([(p,p,u)]). \end{cases}$$

Abstraction

An abstraction is a 5-uple $(\mathcal{V}, \mathbb{F}, \mathcal{V}^\#, \psi, \mathbb{F}^\#)$, where:

- $(\mathcal{V}, \mathbb{F})$ is a system of ordinary equations,
- $\mathcal{V}^\#$ is a finite set of observables,
- ψ is a function from the set $\mathcal{V} \rightarrow \mathbb{R}$ into the set $\mathcal{V}^\# \rightarrow \mathbb{R}$,
- $\mathbb{F}^\#$ is a function \mathcal{C}^∞ from the set $\mathcal{V}^\# \rightarrow \mathbb{R}^+$ into the set $\mathcal{V}^\# \rightarrow \mathbb{R}$;

such that:

- ψ is linear with positive coefficients only and such that each variable $v \in \mathcal{V}$ occurs in the image of at least one observable $v^\# \in \mathcal{V}^\#$ with a non-zero coefficient;
- the following diagram commutes:

$$\begin{array}{ccc}
 (\mathcal{V} \rightarrow \mathbb{R}^+) & \xrightarrow{\mathbb{F}} & (\mathcal{V} \rightarrow \mathbb{R}) \\
 \psi \downarrow & & \downarrow \psi \\
 (\mathcal{V}^\# \rightarrow \mathbb{R}^+) & \xrightarrow{\mathbb{F}^\#} & (\mathcal{V}^\# \rightarrow \mathbb{R})
 \end{array}$$

that is to say that $\psi \circ \mathbb{F} = \mathbb{F}^\# \circ \psi$.

Back to the case study

1. $\mathcal{V} \triangleq \{[(u,u,u)], [(u,\textcolor{red}{p},u)], [(\textcolor{green}{p},\textcolor{red}{p},u)], [(u,\textcolor{red}{p},\textcolor{blue}{p})], [(\textcolor{green}{p},\textcolor{red}{p},\textcolor{blue}{p})]\}$
2. $\mathbb{F}(\rho) \triangleq \begin{cases} [(u,u,u)] \mapsto -k_c \cdot \rho([(u,u,u)]) \\ [(u,\textcolor{red}{p},u)] \mapsto -k_g \cdot \rho([(u,\textcolor{red}{p},u)]) + k_c \cdot \rho([(u,u,u)]) - k_d \cdot \rho([(u,\textcolor{red}{p},u)]) \\ [(u,\textcolor{red}{p},\textcolor{blue}{p})] \mapsto -k_g \cdot \rho([(u,\textcolor{red}{p},\textcolor{blue}{p})]) + k_d \cdot \rho([(u,\textcolor{red}{p},u)]) \\ \dots \end{cases}$
3. $\mathcal{V}^\# \triangleq \{[(u,u,u)], [(\textcolor{red}{?},\textcolor{red}{p},u)], [(\textcolor{red}{?},\textcolor{red}{p},\textcolor{blue}{p})], [(u,\textcolor{red}{p},\textcolor{red}{?})], [(\textcolor{green}{p},\textcolor{red}{p},\textcolor{red}{?})]\}$
4. $\psi(\rho) \triangleq \begin{cases} [(u,u,u)] \mapsto \rho([(u,u,u)]) \\ [(\textcolor{red}{?},\textcolor{red}{p},u)] \mapsto \rho([(u,\textcolor{red}{p},u)]) + \rho([(\textcolor{green}{p},\textcolor{red}{p},u)]) \\ [(\textcolor{red}{?},\textcolor{red}{p},\textcolor{blue}{p})] \mapsto \rho([(u,\textcolor{red}{p},\textcolor{blue}{p})]) + \rho([(\textcolor{green}{p},\textcolor{red}{p},\textcolor{blue}{p})]) \\ \dots \end{cases}$
5. $\mathbb{F}^\#(\rho^\#) \triangleq \begin{cases} [(u,u,u)] \mapsto -k_c \cdot \rho^\#([(u,u,u)]) \\ [(\textcolor{red}{?},\textcolor{red}{p},u)] \mapsto -k_d \cdot \rho^\#([(\textcolor{red}{?},\textcolor{red}{p},u)]) + k_c \cdot \rho^\#([(u,u,u)]) \\ [(\textcolor{red}{?},\textcolor{red}{p},\textcolor{blue}{p})] \mapsto k_d \cdot \rho^\#([(\textcolor{red}{?},\textcolor{red}{p},u)]) \\ \dots \end{cases}$

Let us apply the abstraction function

Let:

1. $(\mathcal{V}, \mathbb{F}, \mathcal{V}^\#, \psi, \mathbb{F}^\#)$ be an abstraction,
2. and $X_0 \in \mathcal{V} \rightarrow \mathbb{R}^+$ be an initial state.

We have, at any time T within the time interval $[0, T_{X_0}^{\max}[$:

$$X_{X_0}(T) = X_0 + \int_{t=0}^T \mathbb{F}(X_{X_0}(t)) \cdot dt.$$

So:

$$\psi(X_{X_0}(T)) = \psi \left(X_0 + \int_{t=0}^T \mathbb{F}(X_{X_0}(t)) \cdot dt \right).$$

Let us push ψ towards the right

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So:

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We have, at any time T within the time interval $[0, T_{X_0}^{\max}[$:

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So:

$$\psi(X_{X_0}(T)) = \psi(X_0) + \int_{t=0}^T \mathbb{F}^\#(\psi(X_{X_0}(t))) \cdot dt.$$

Abstract semantics

Let $(\mathcal{V}, \mathbb{F}, \mathcal{V}^\#, \psi, \mathbb{F}^\#)$ be an abstraction.

The couple $(\mathcal{V}^\#, \mathbb{F}^\#)$ is a system of differential equations.

Let us denote by Y its semantics.

For each state $Y_0 \in \mathcal{V}^\# \rightarrow \mathbb{R}^+$, we denote by $[0, T_{Y_0}^{\# \max}[$ the domain of the function Y_{Y_0} . We have, at any time $T^\# \in [0, T_{X_0}^{\# \max}[$,

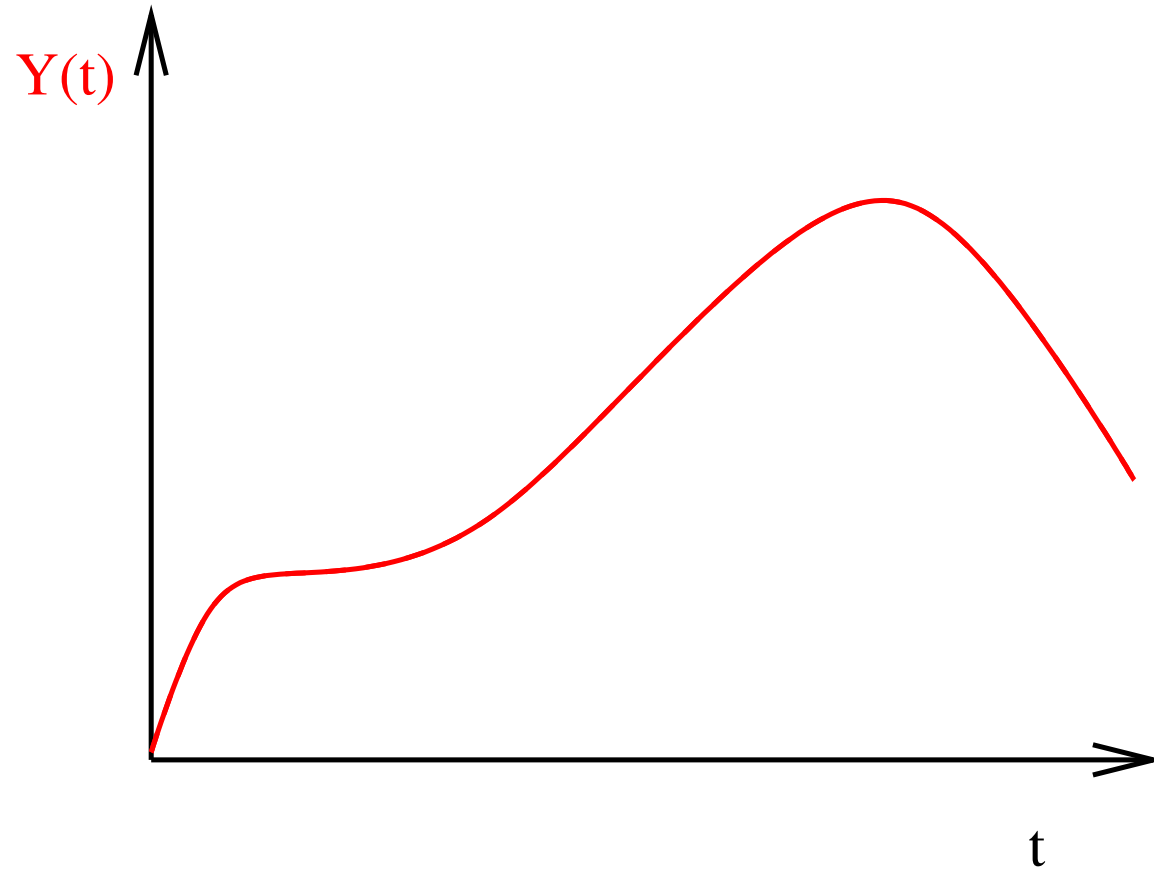
$$Y_{Y_0}(T^\#) = Y_0 + \int_{t=0}^{T^\#} \mathbb{F}^\#(Y_{Y_0}(t)) \cdot dt.$$

Theorem 1 For each initial state $X_0 \in \mathcal{V} \rightarrow \mathbb{R}^+$, we have:

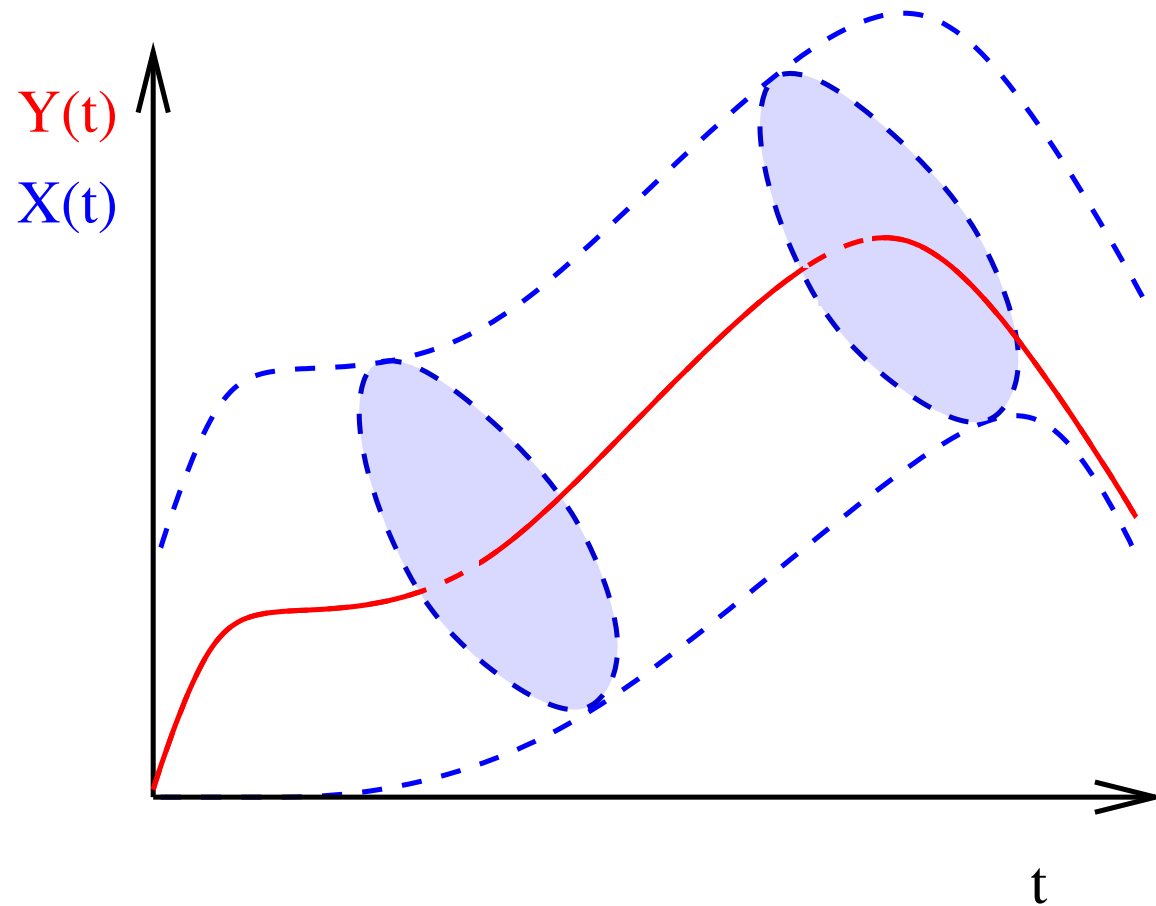
1. $T_{\psi(X_0)}^{\# \max} = T_{X_0}^{\max}$;
2. at any time $T \in [0, T_{X_0}^{\max}[$, $\psi(X_{X_0}(T)) = Y_{\psi(X_0)}(T)$.

That is to say that the abstract semantics is the image of the concrete semantics by the abstraction function.

Abstract trajectories



Concrete trajectories



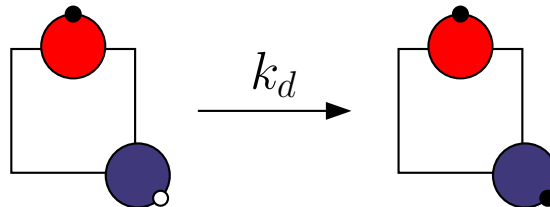
On the menu today

1. Context and motivations
2. Case studies
3. Reduction of ordinary differential equations
4. **Abstraction of the information flow**
5. Model reduction
6. Conclusion

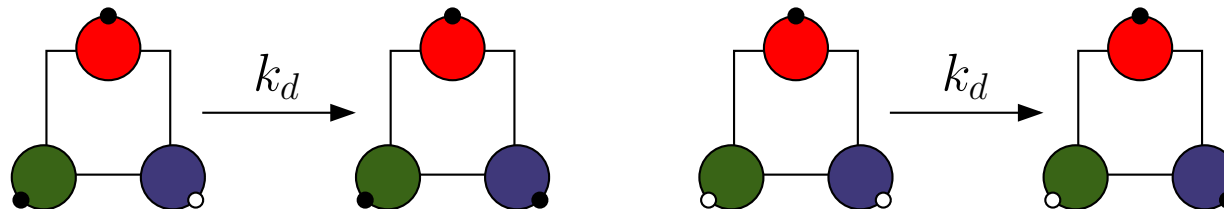
Concrete semantics

A rule is a symbolic representation of a multi-set of reactions.

For instance, the rule:



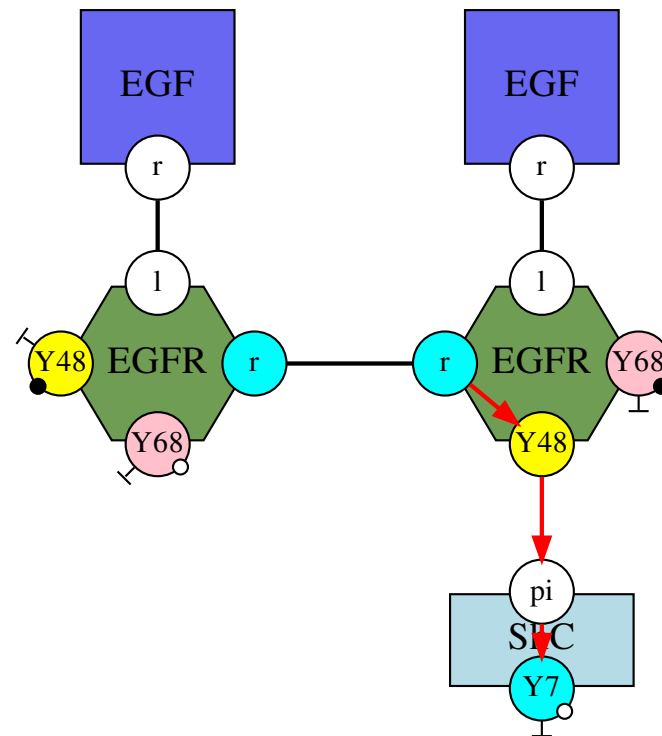
denotes the following two rules:



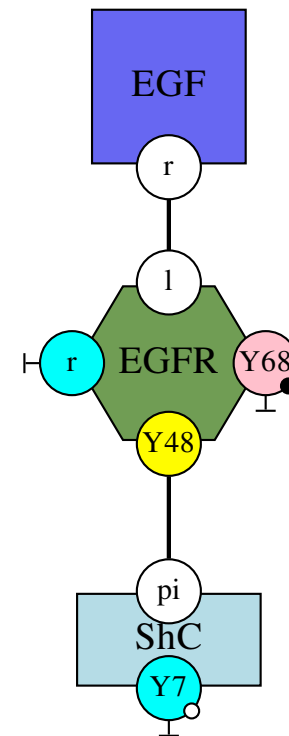
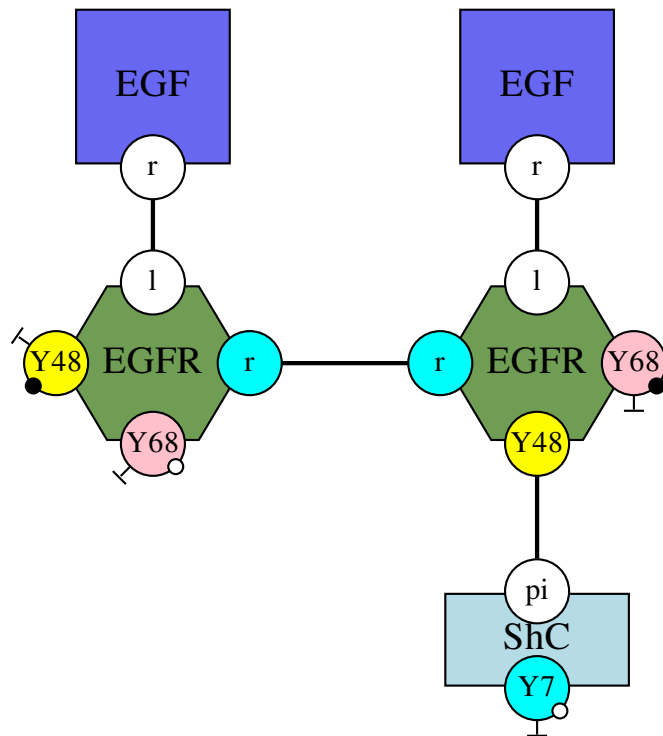
The semantics of a set of rules is the semantics of the underlying multi-set of reactions.

Flow of information (in the concrete)

Does the state of a given site influence the capability to modify another site?

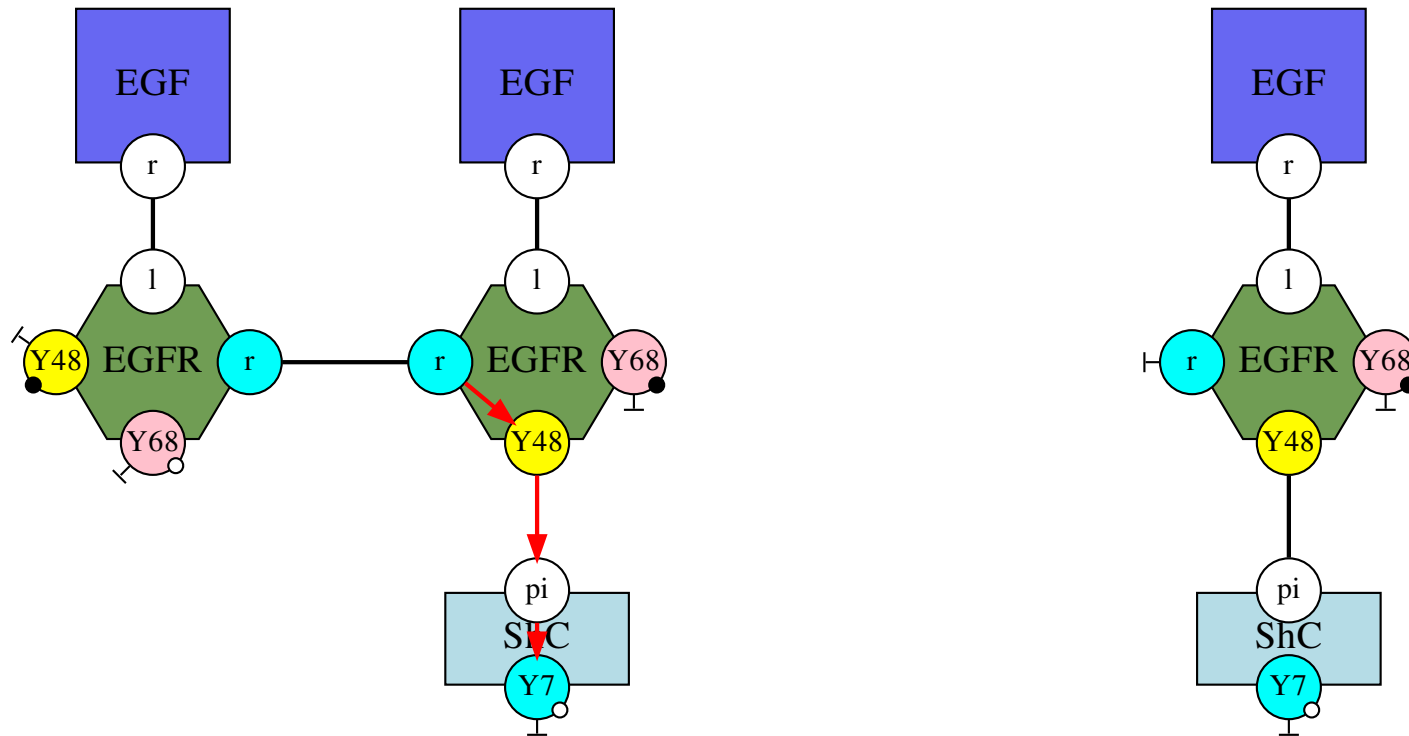


Flow of information (in the concrete)

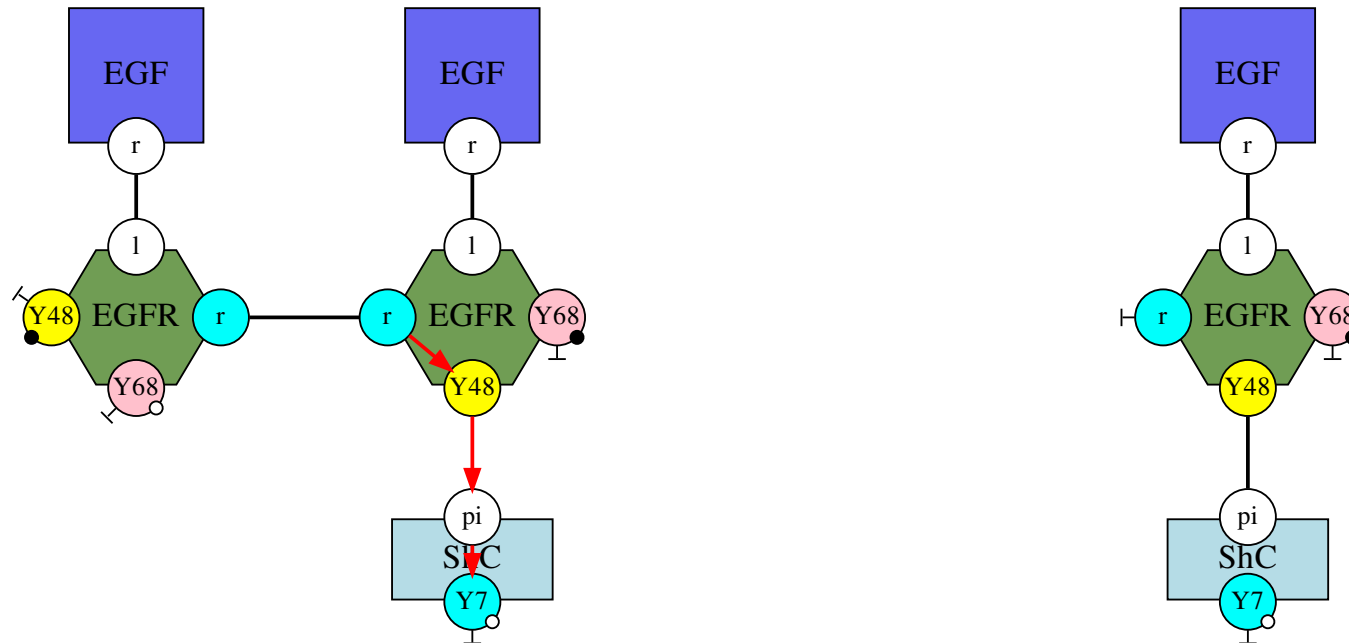


Flow of information (in the concrete)

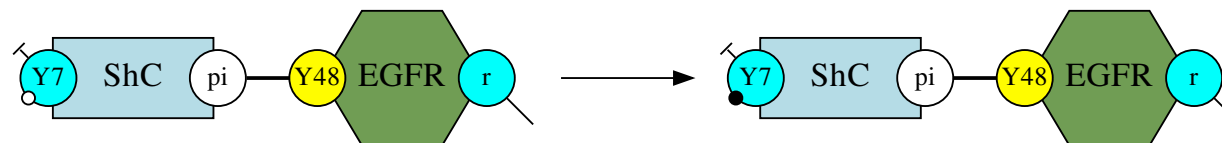
If there exists a soup of chemical species in which the activation rate of the site of *ShC* is different in these two contexts, then there may be a flow of information.



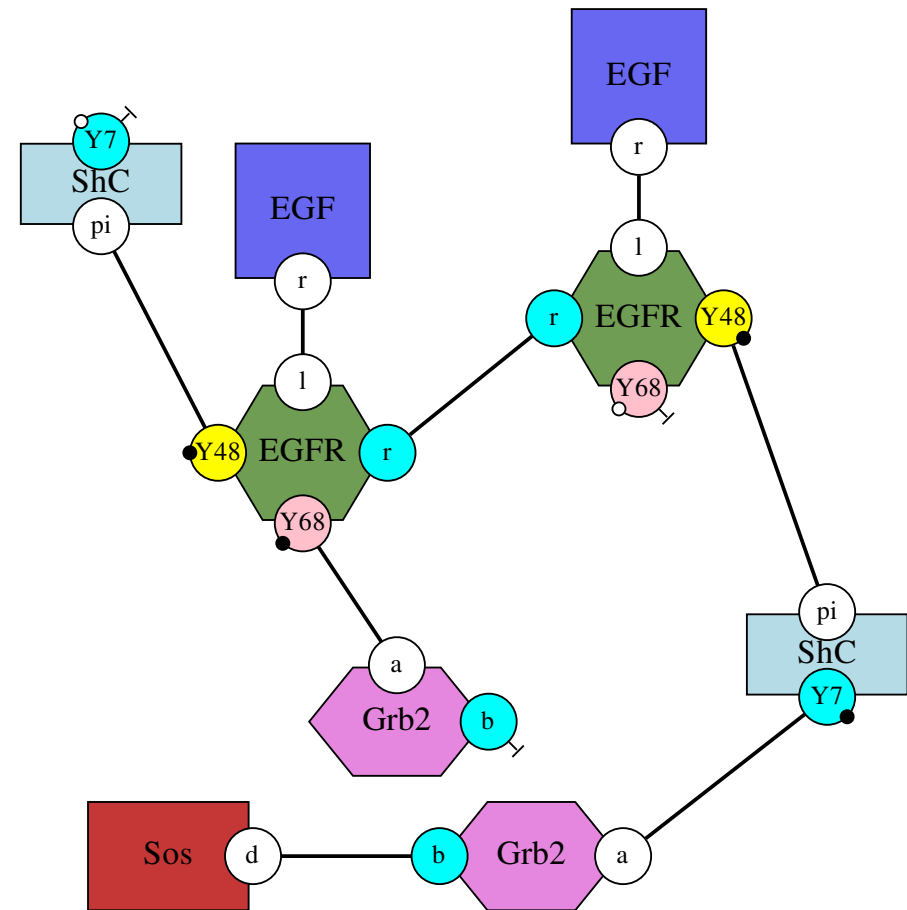
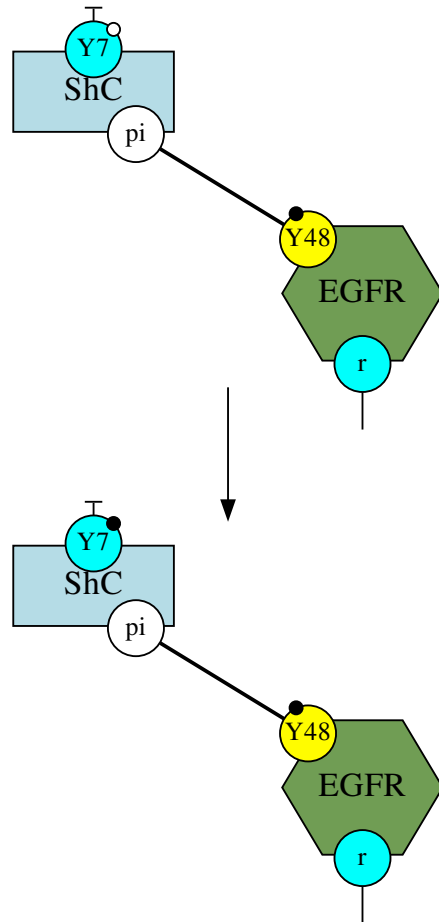
Discrimination by a rule



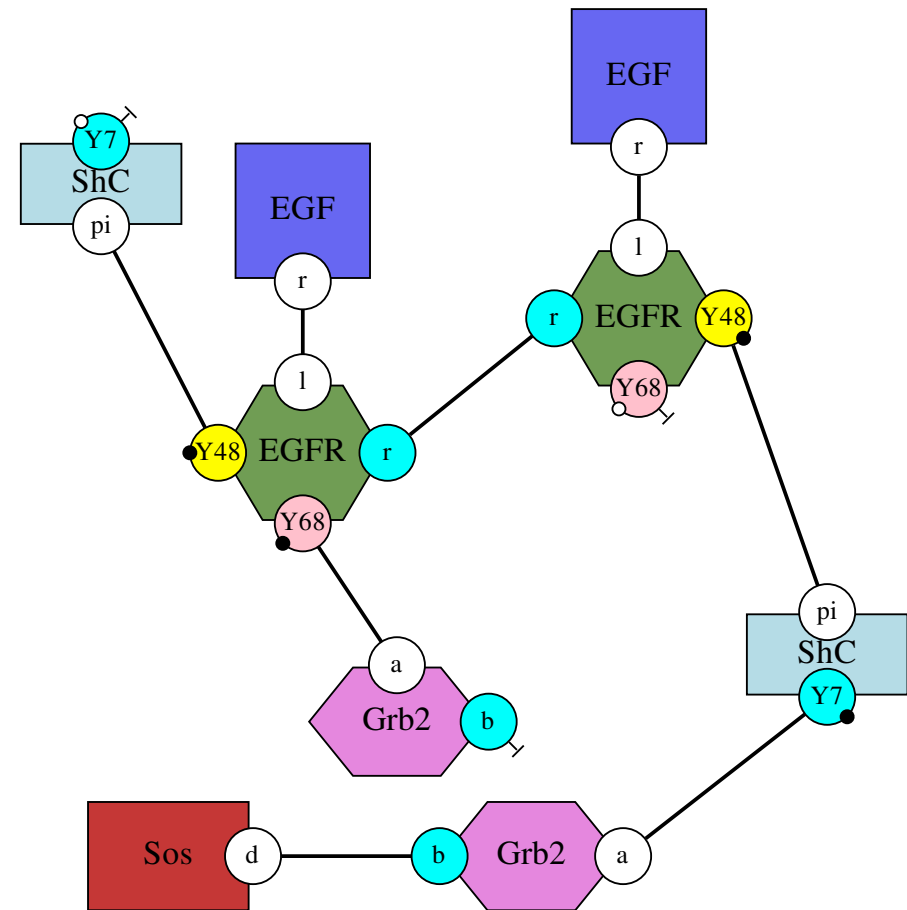
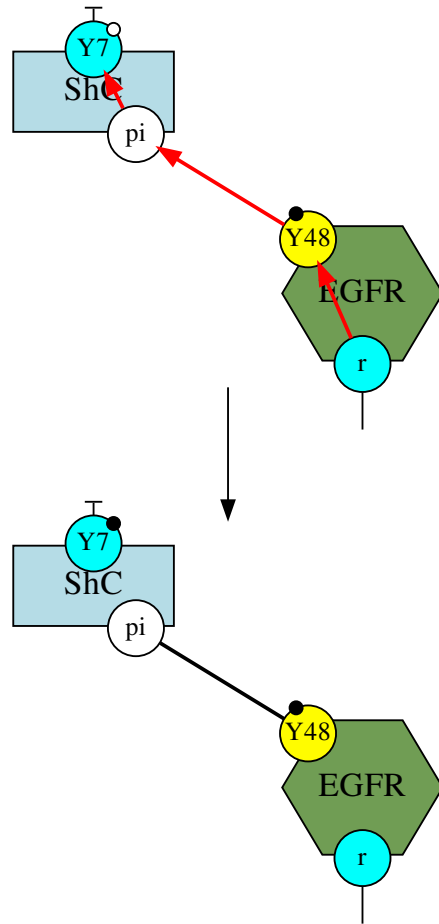
In this case, there exists a rule which makes a difference between these two contexts, for instance the following one:



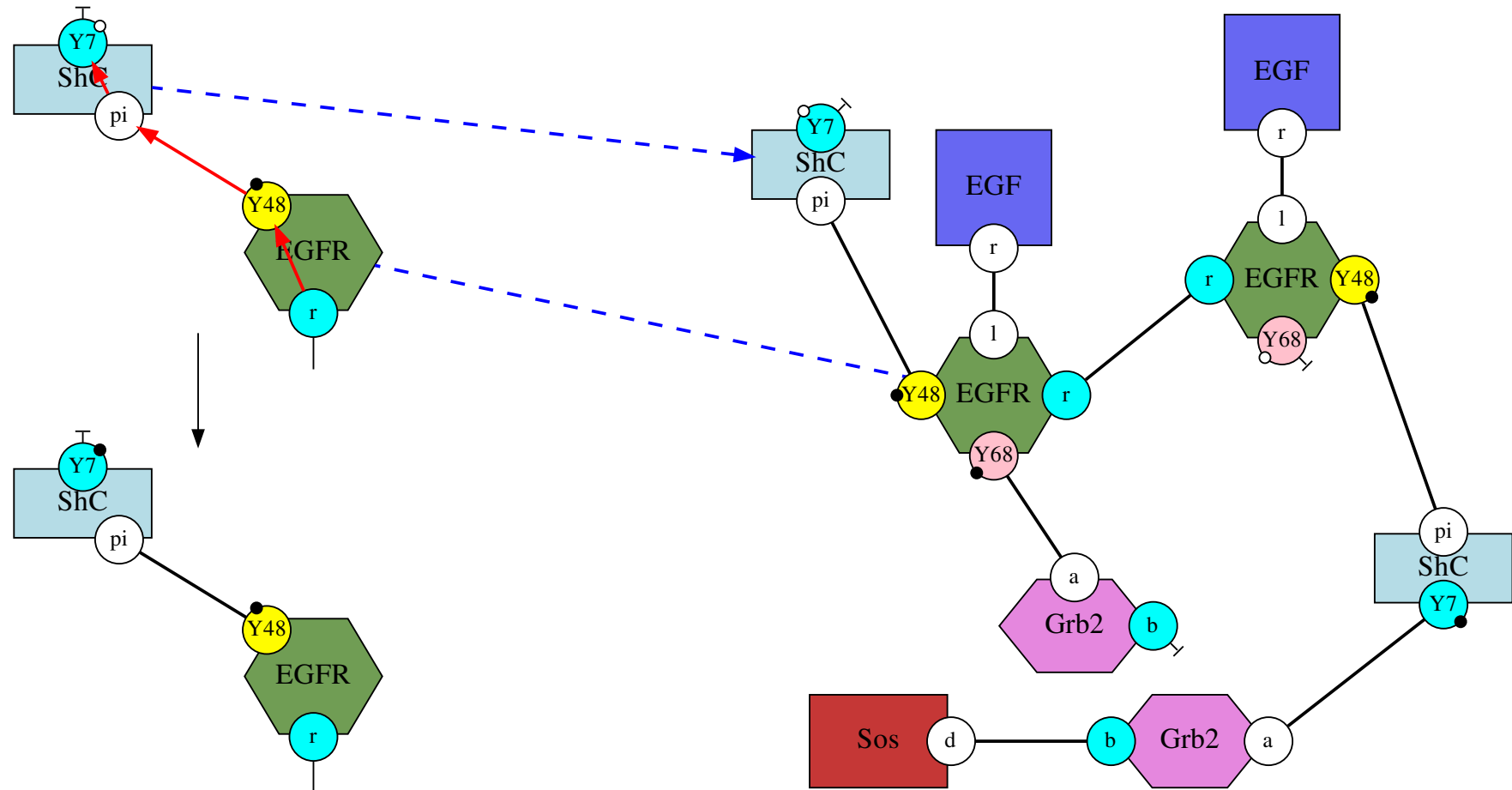
Flow of information due to a rule



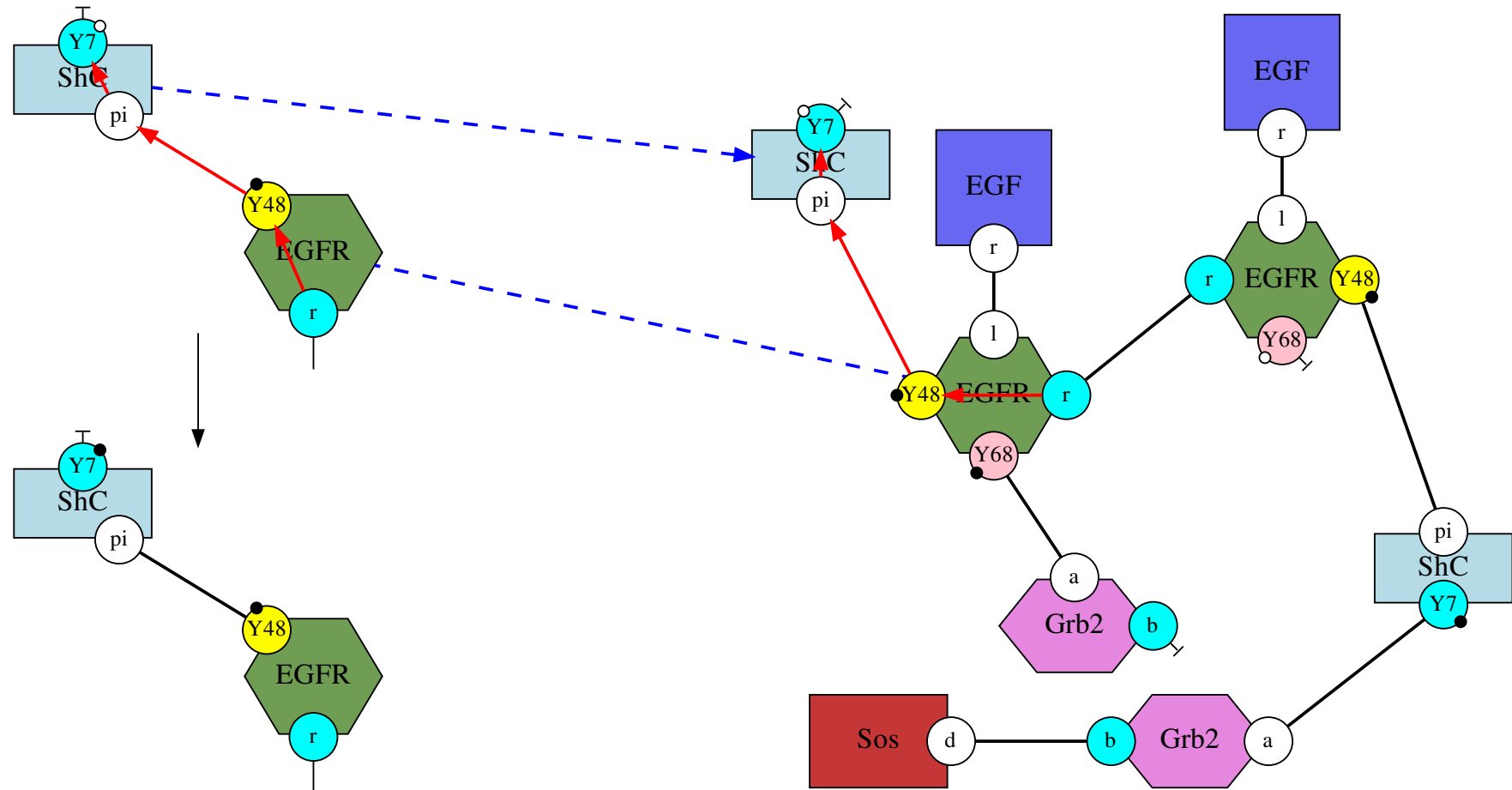
Flow of information due to a rule



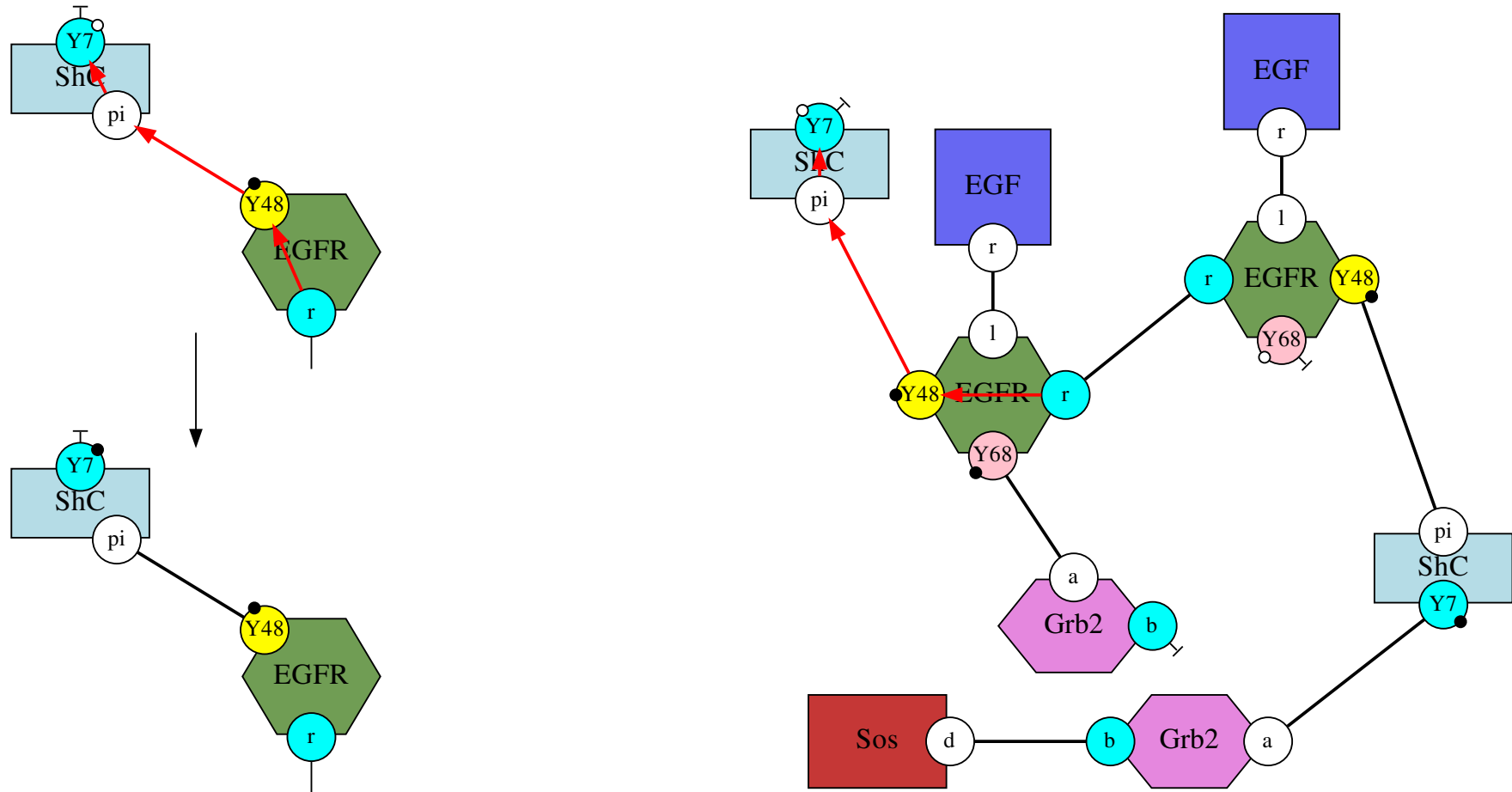
Flow of information due to a rule



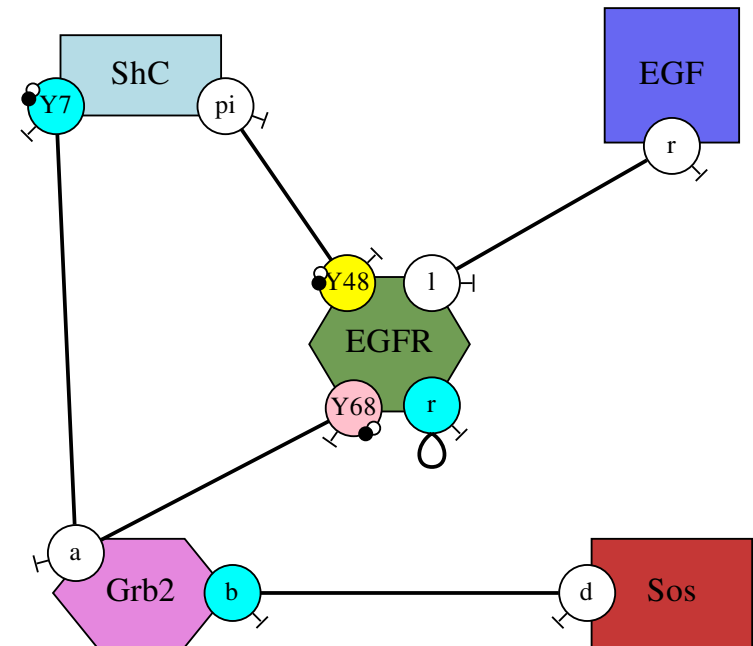
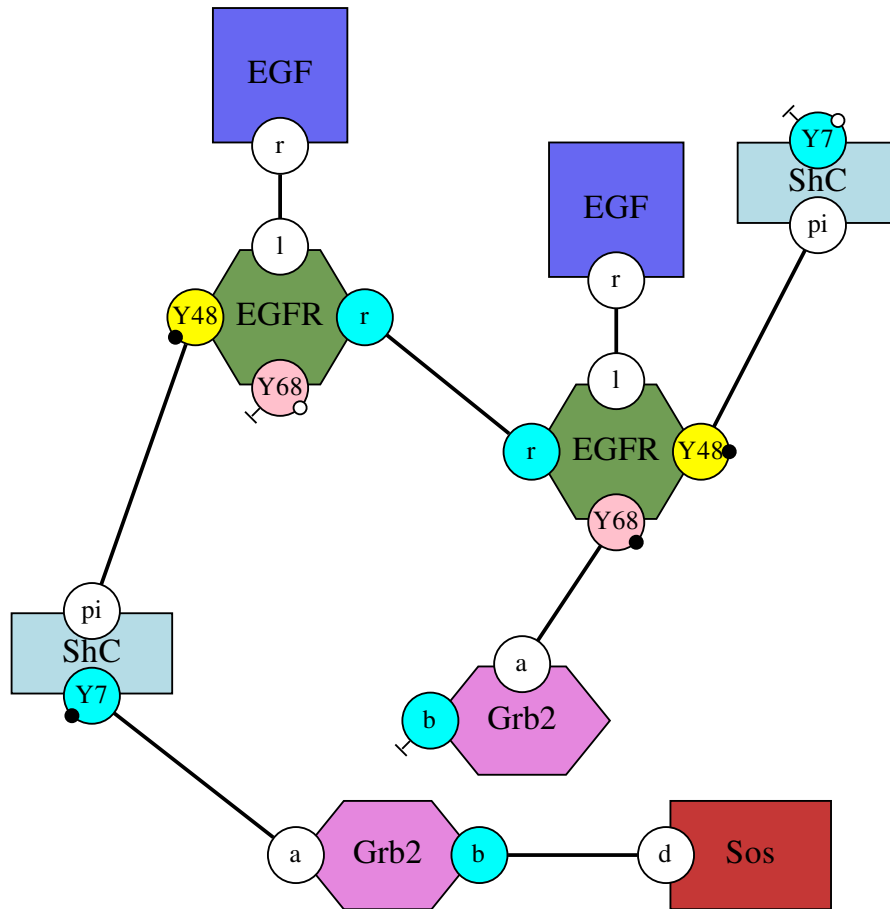
Flow of information due to a rule



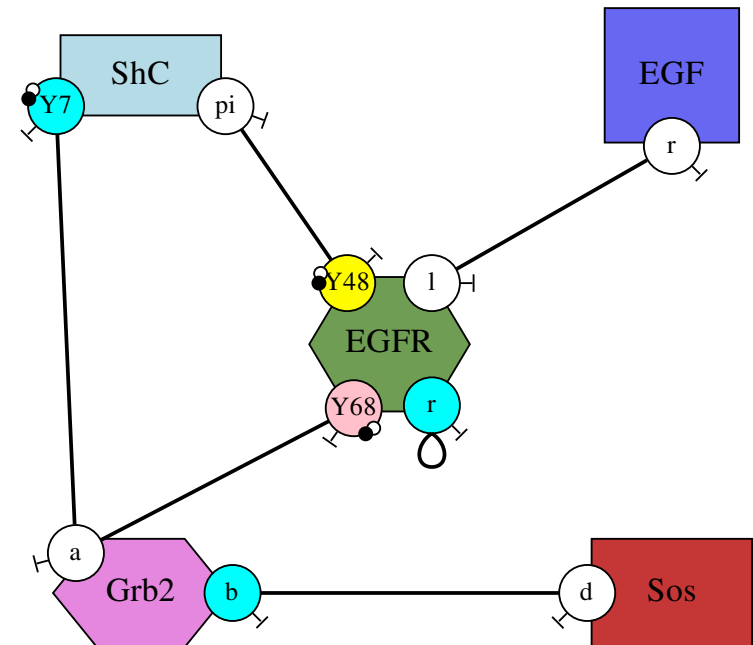
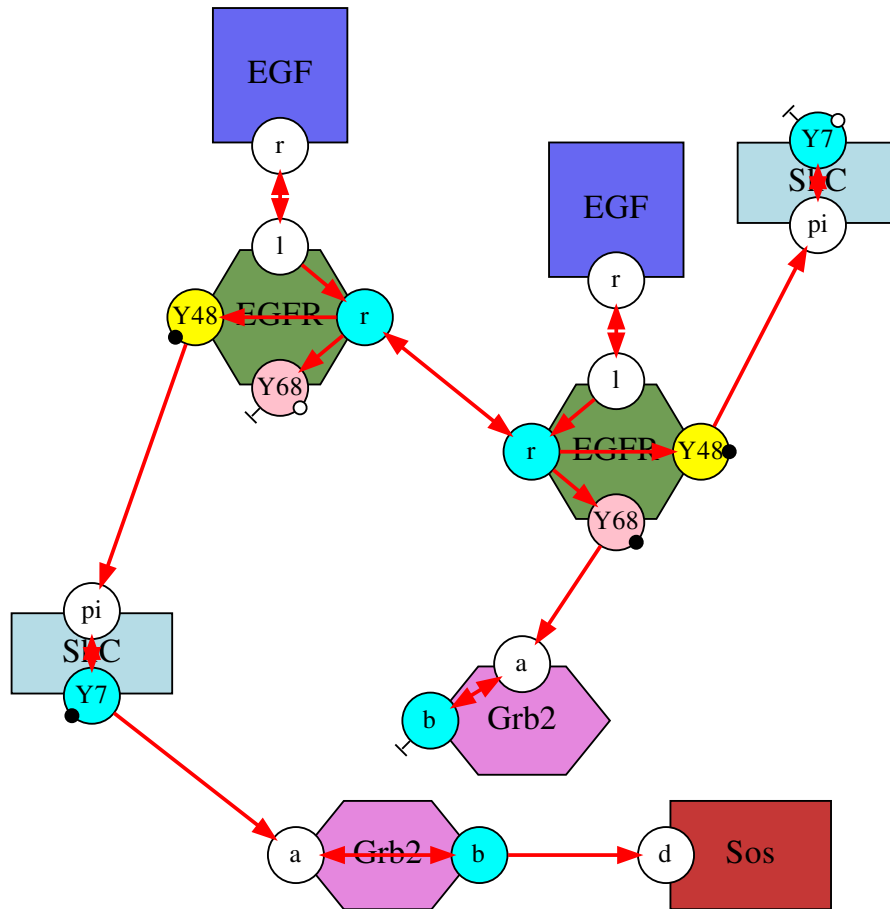
Flow of information due to a rule



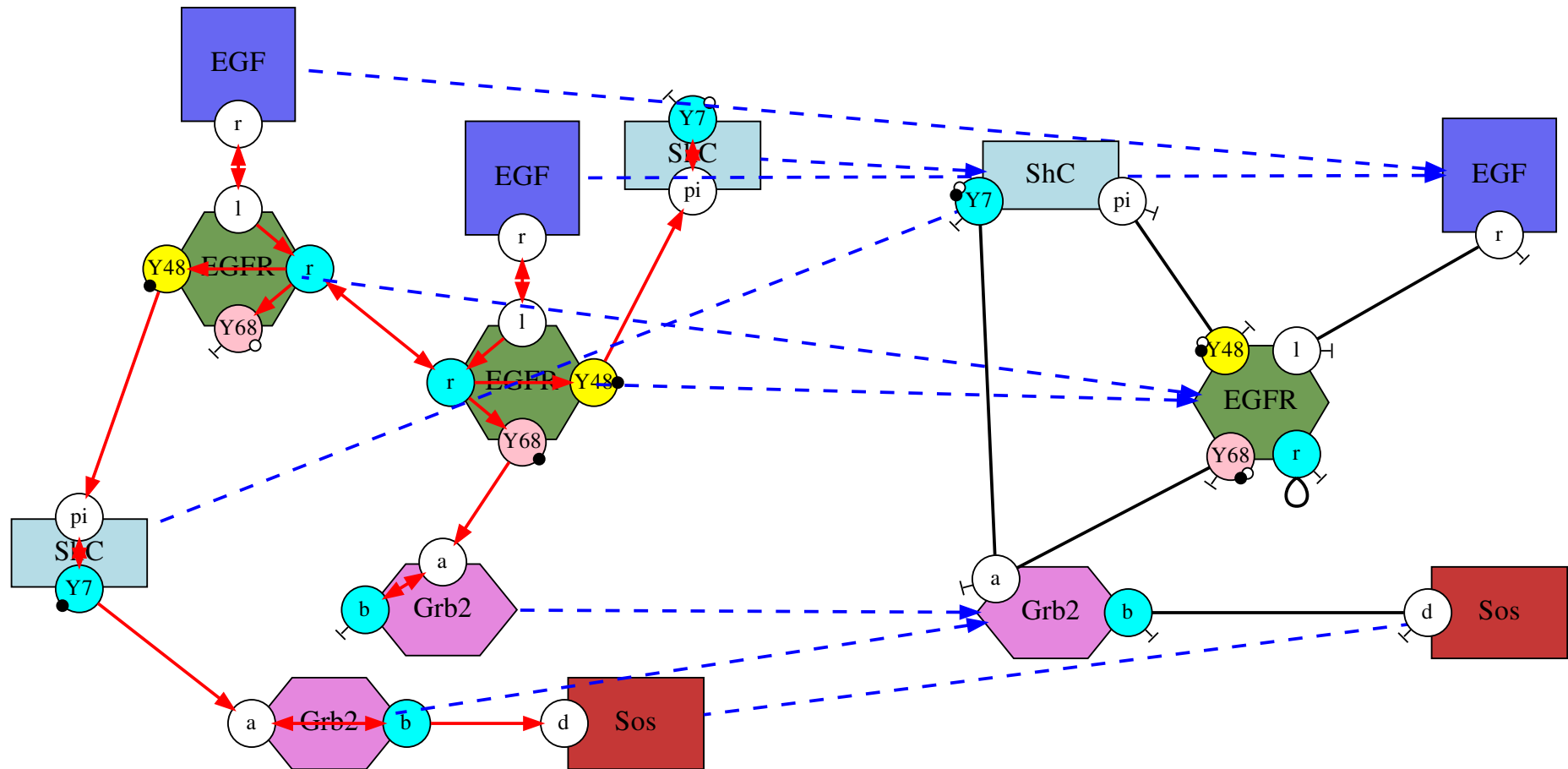
Projection on the contact map



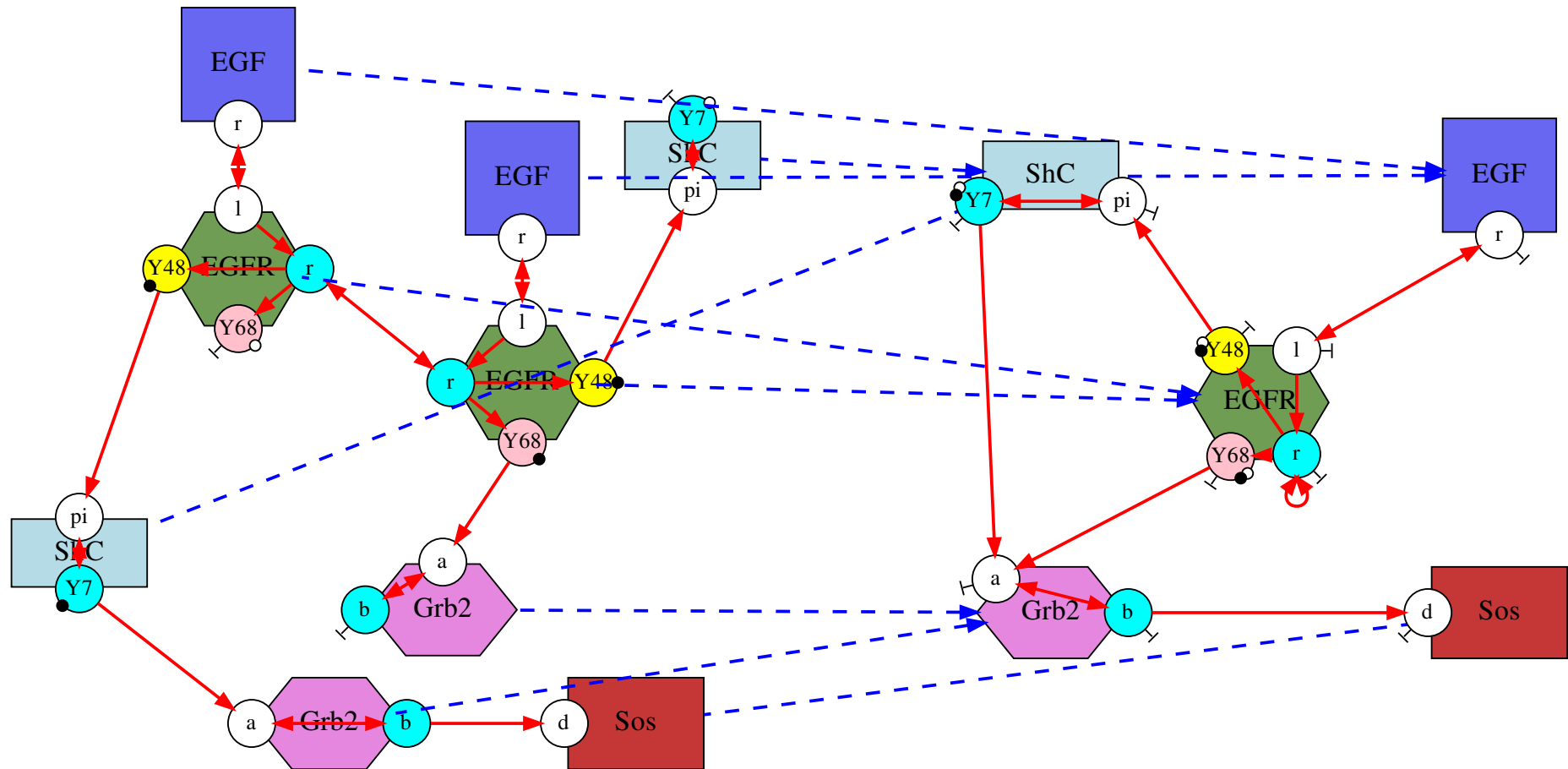
Projection on the contact map



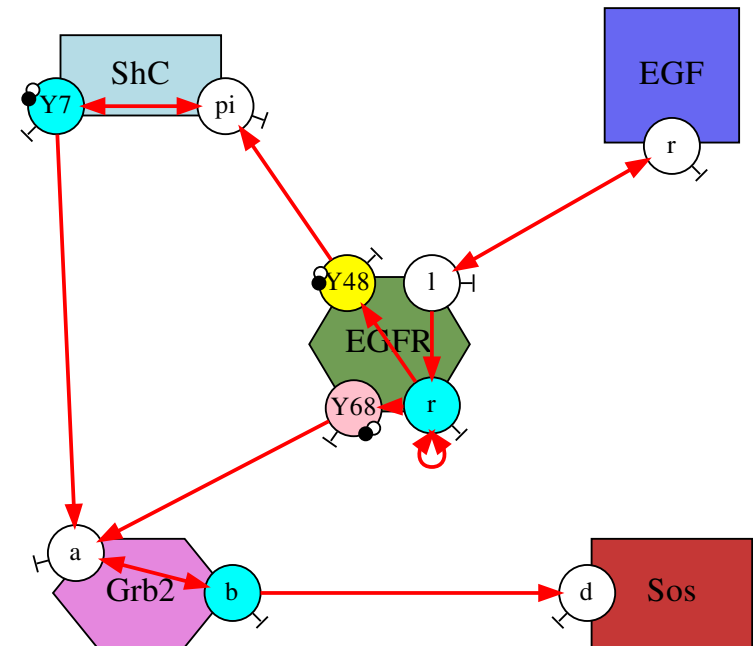
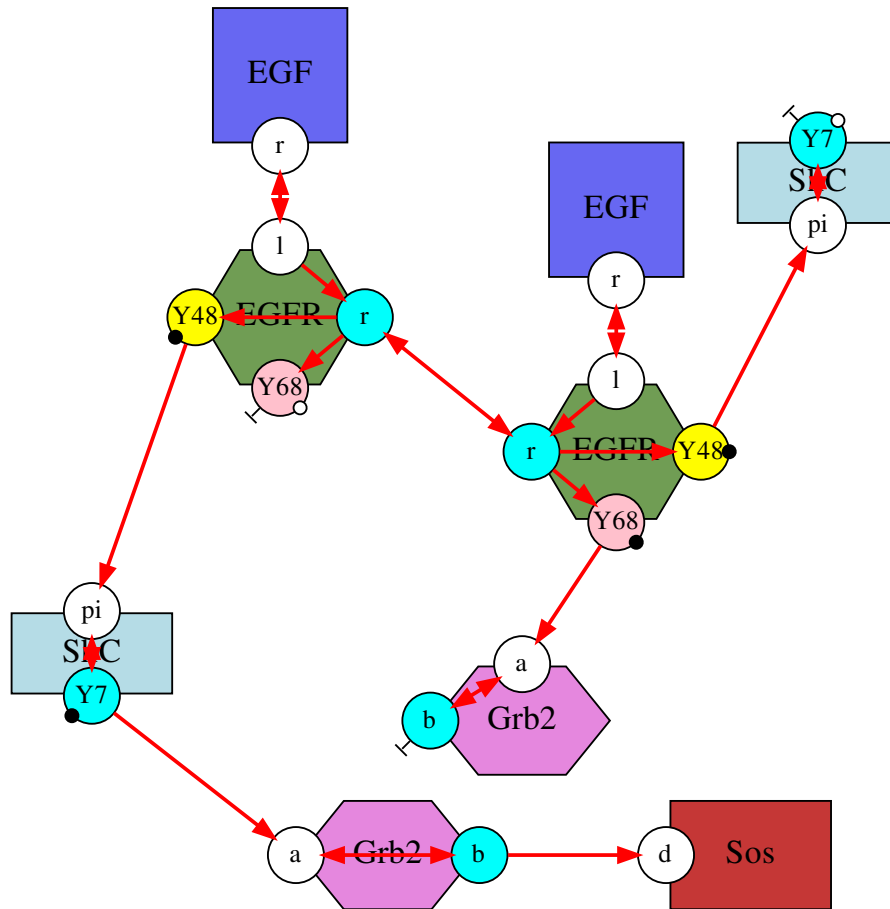
Projection on the contact map



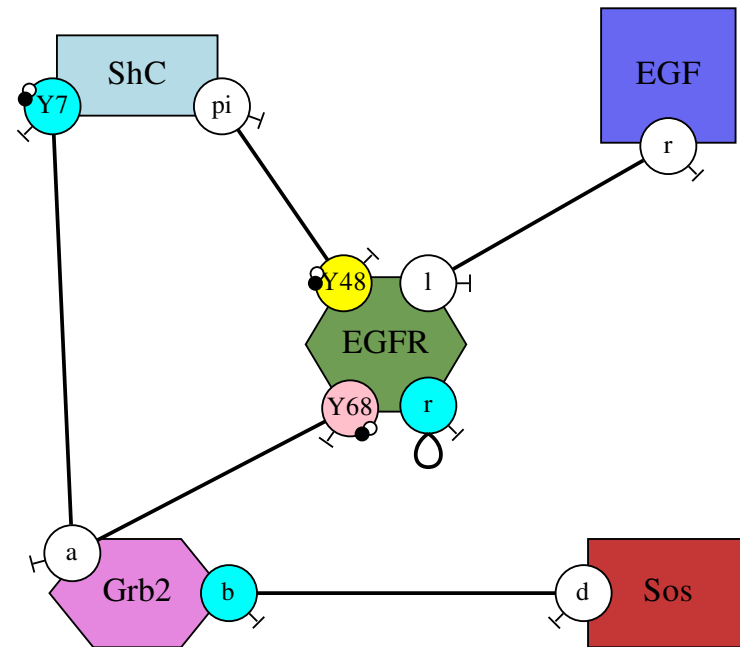
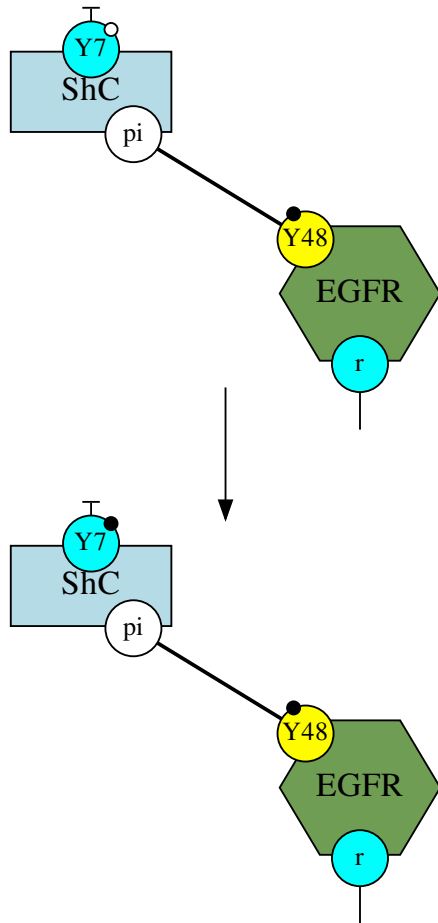
Projection on the contact map



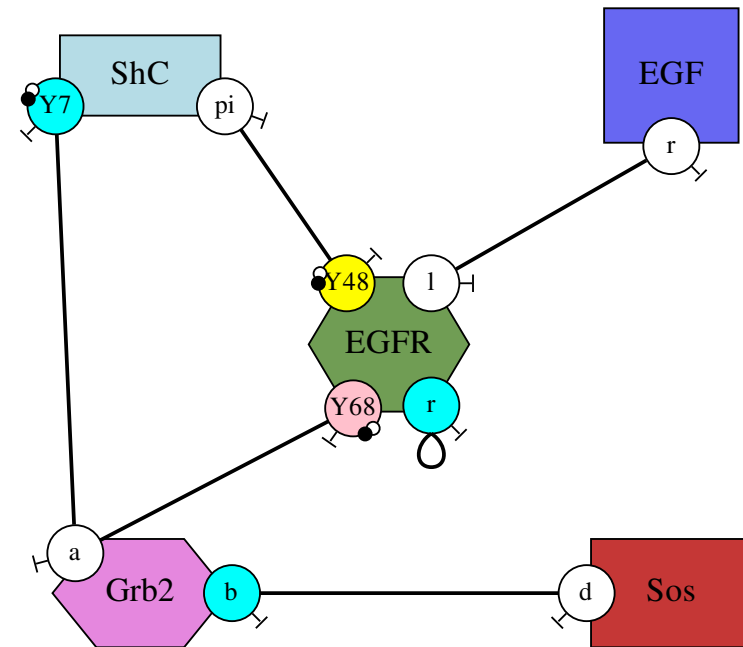
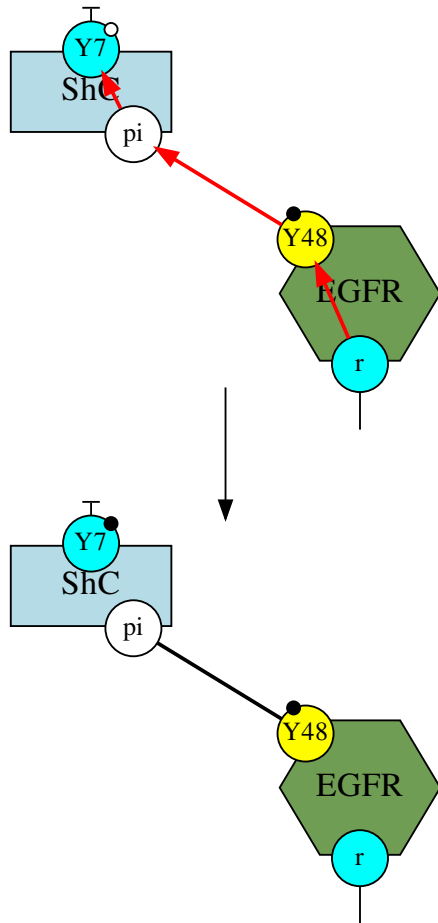
Projection on the contact map



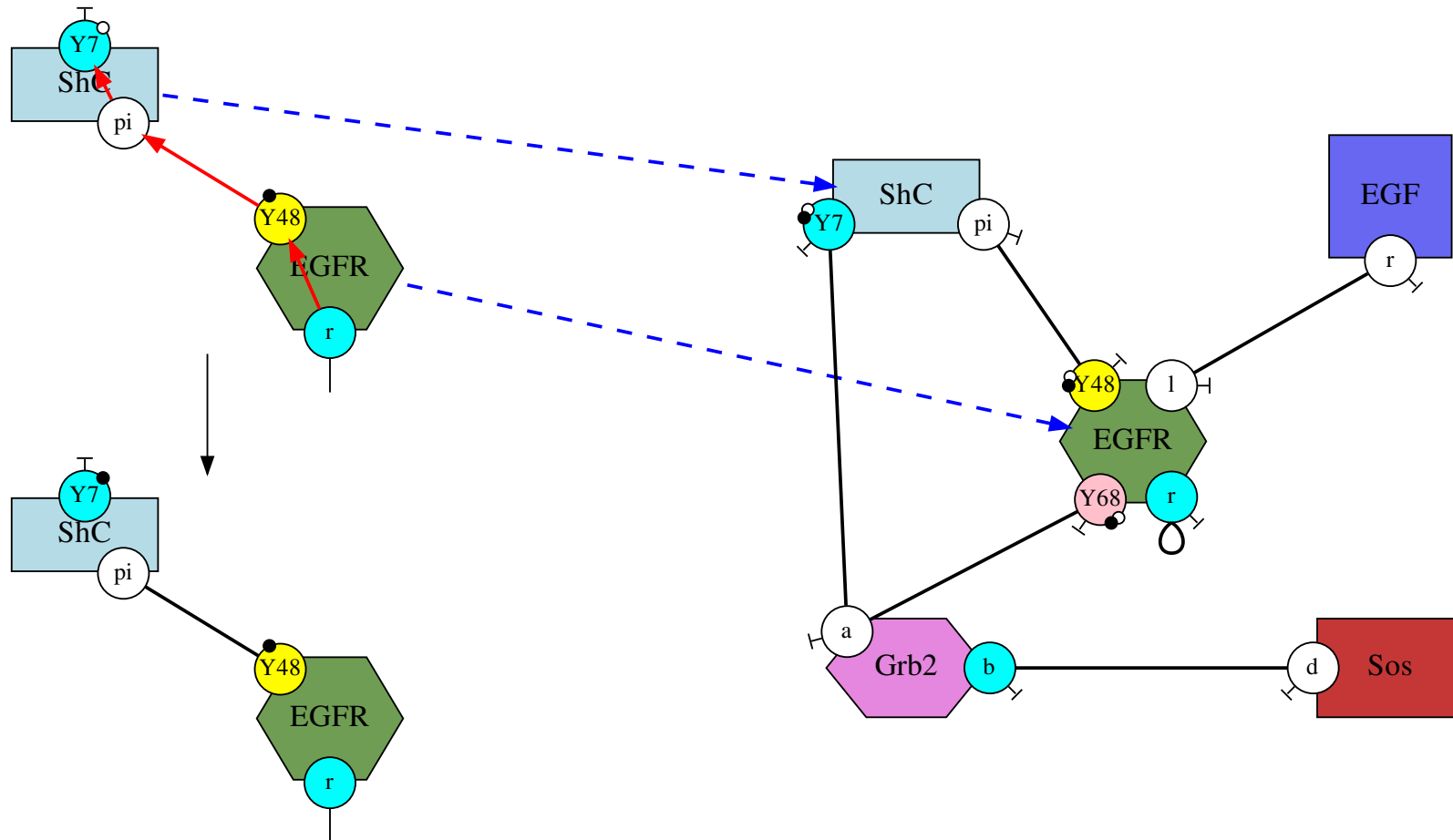
Direct computation



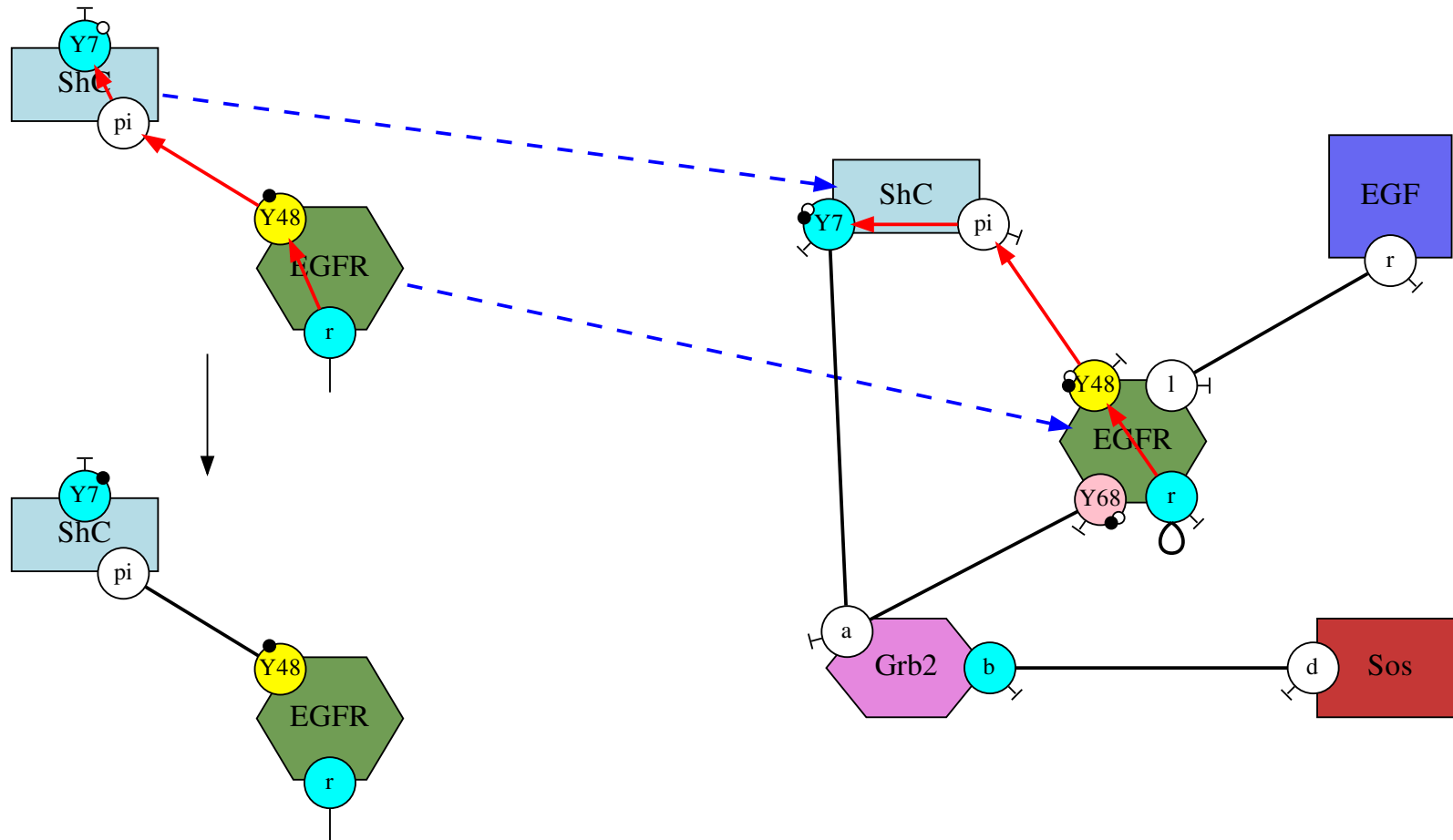
Direct computation



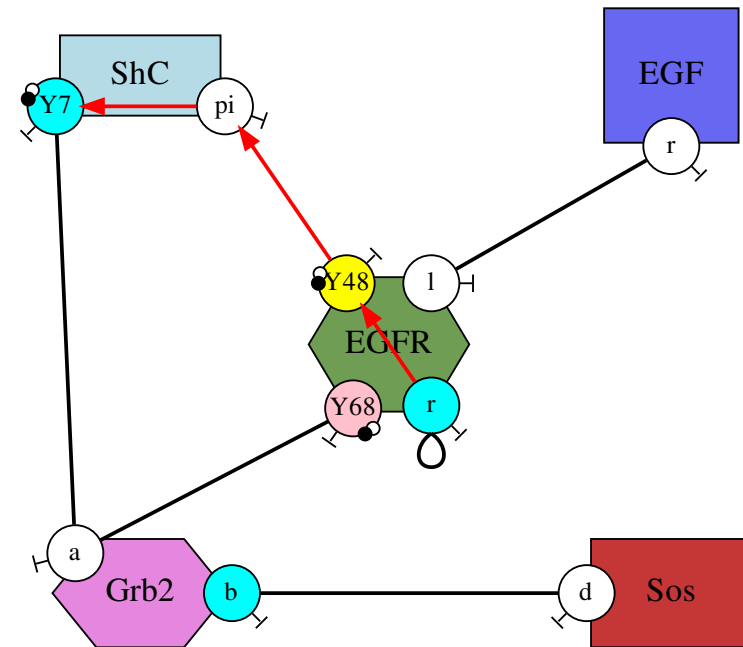
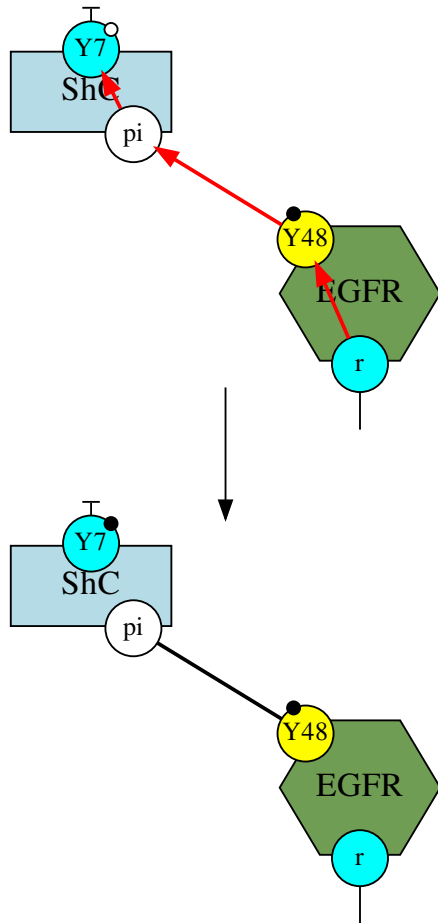
Direct computation



Direct computation



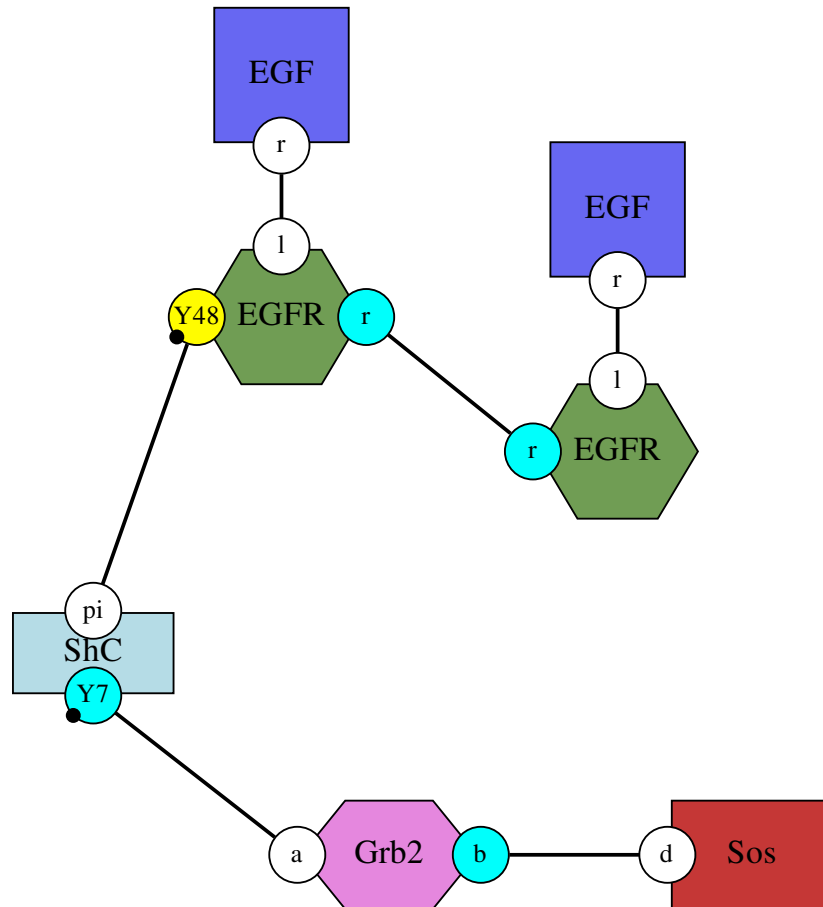
Direct computation



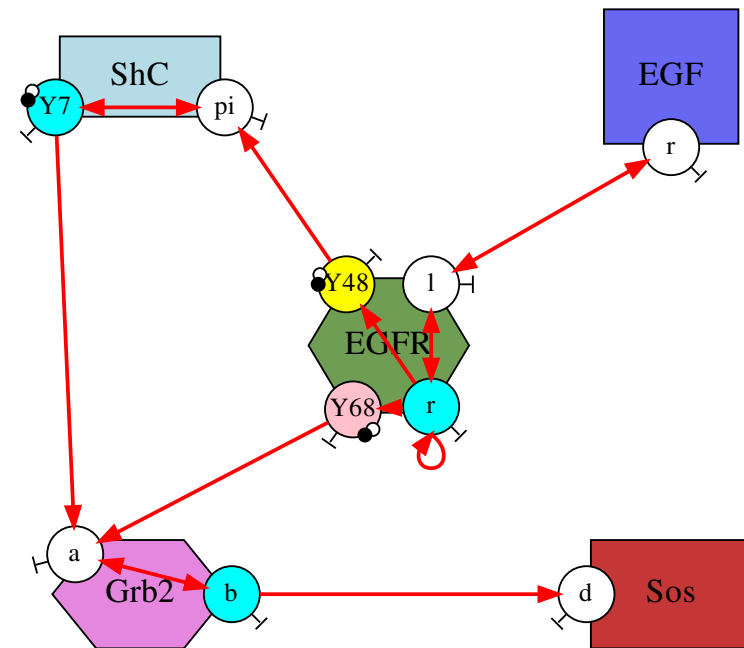
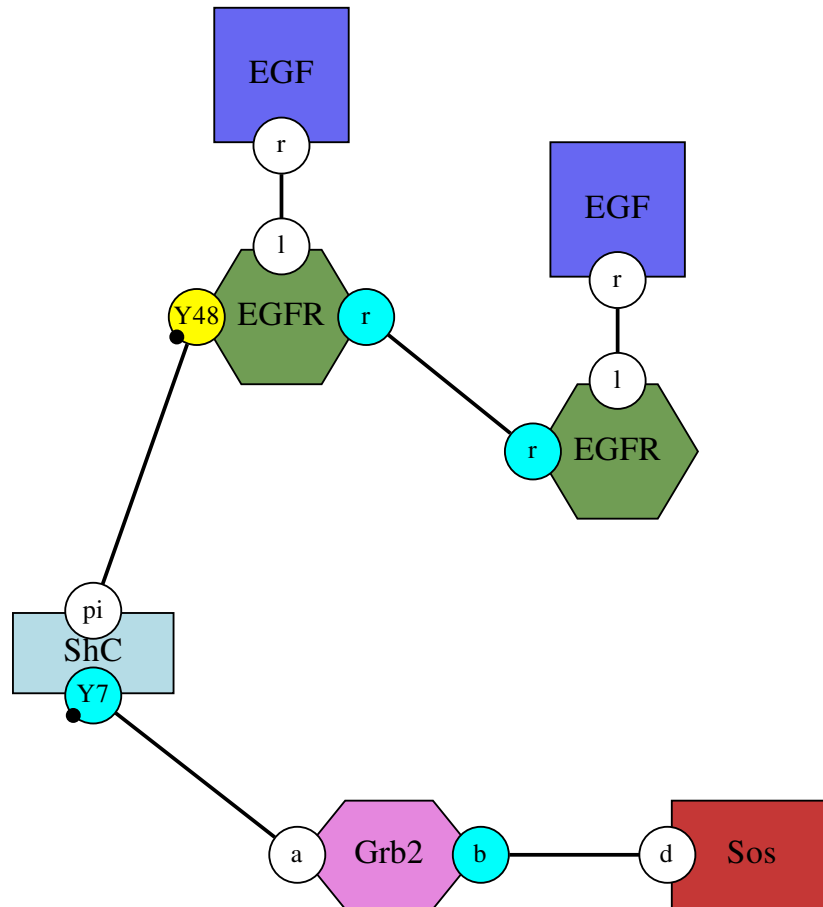
On the menu today

1. Context and motivations
2. Case studies
3. Reduction of ordinary differential equations
4. Abstraction of the information flow
5. **Model reduction**
6. Conclusion

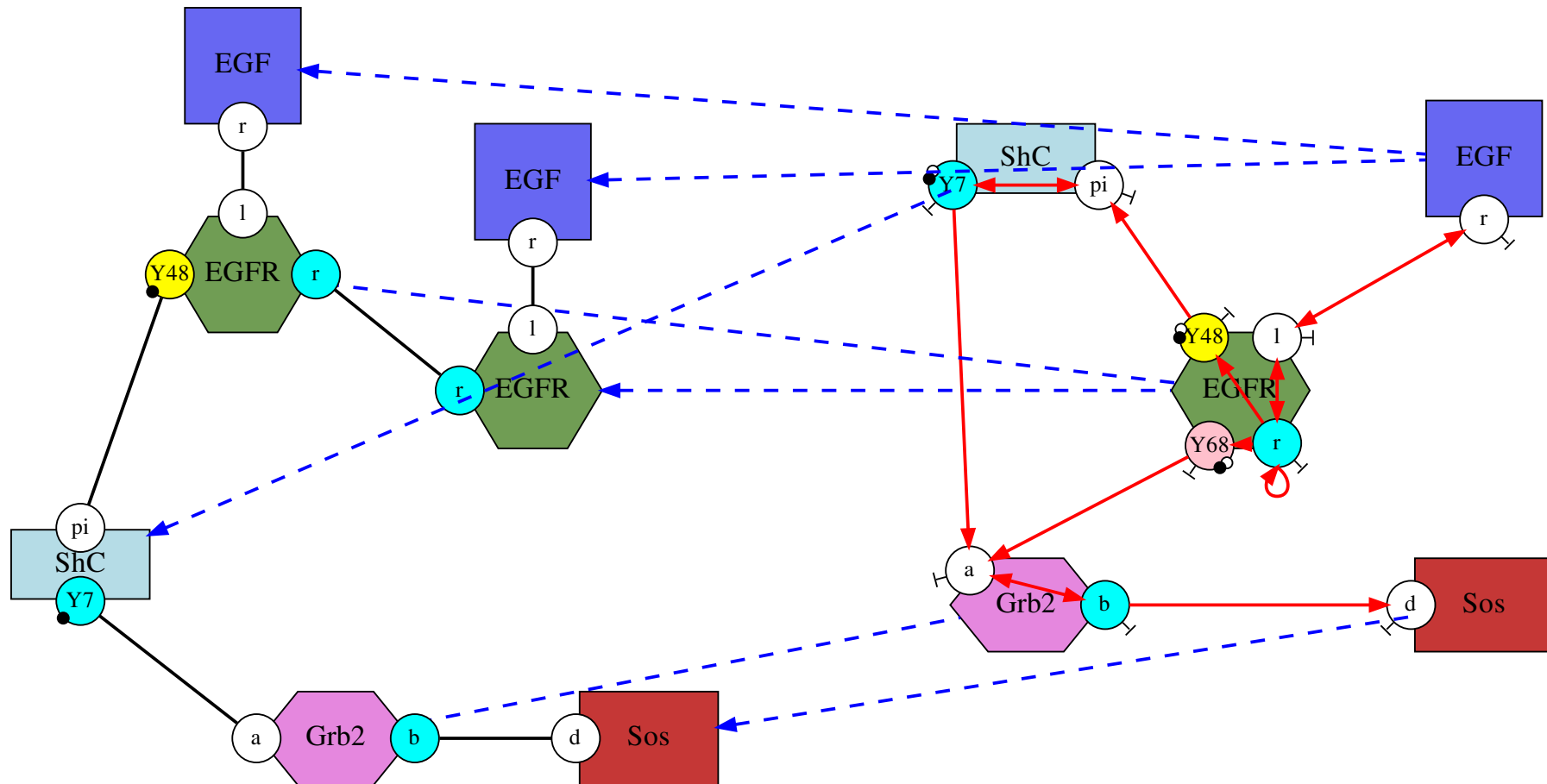
Which patterns shall we keep?



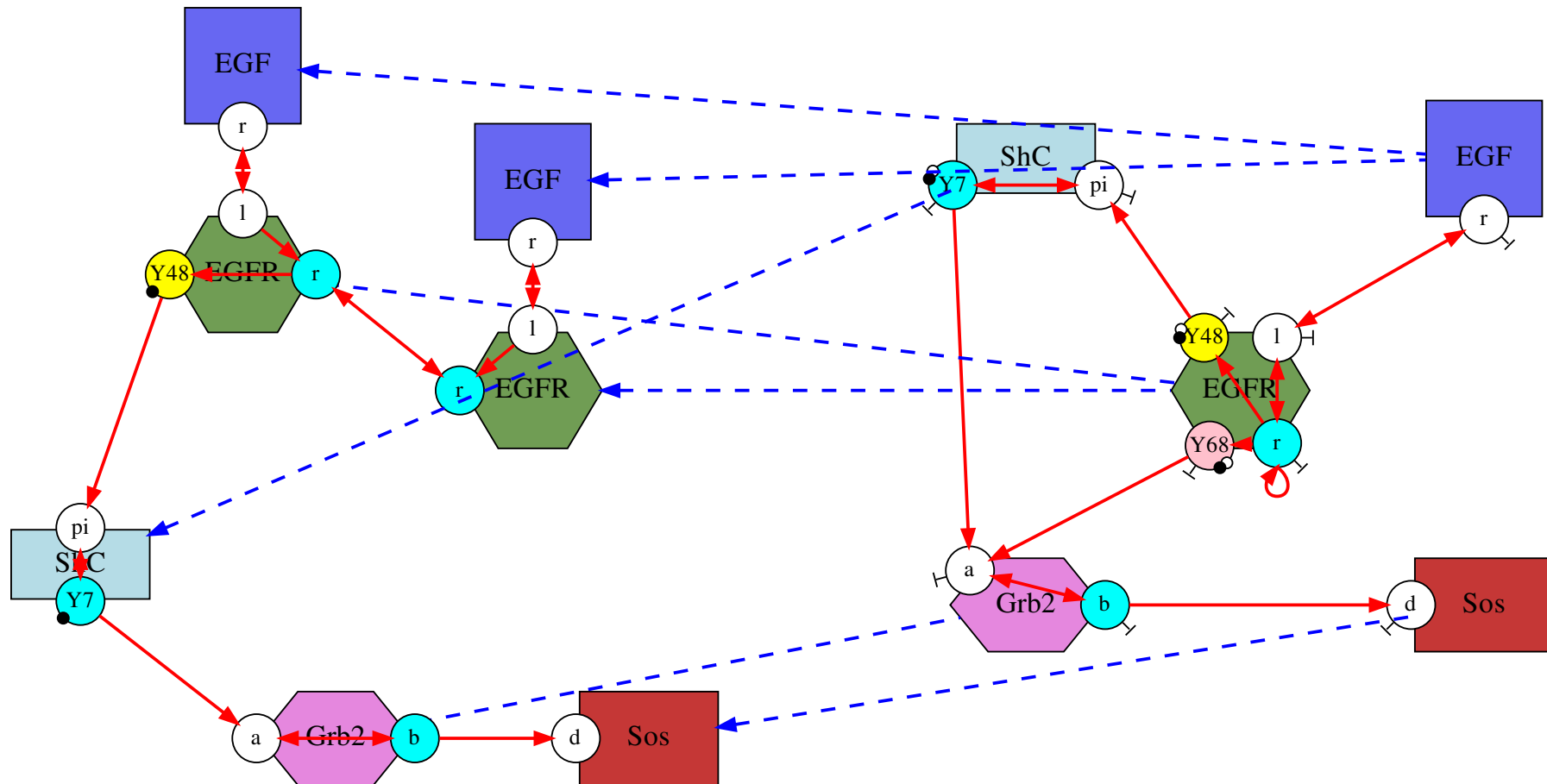
Which patterns shall we keep?



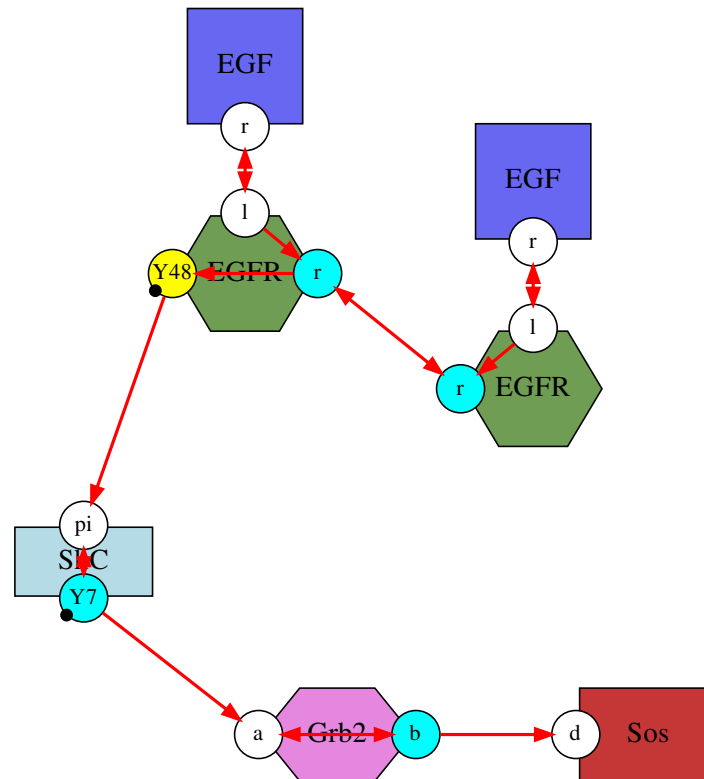
Pattern annotation



Pattern annotation

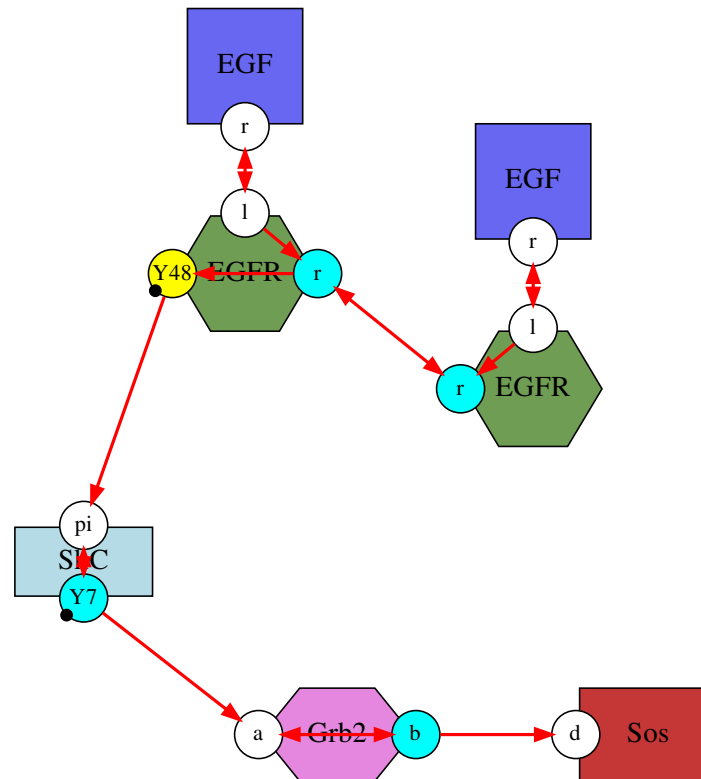


Prefragment



Definition 1 (prefragment) A pattern is a prefragment if, in its annotated form, there exists a site that it is reachable from every site (following the flow of information).

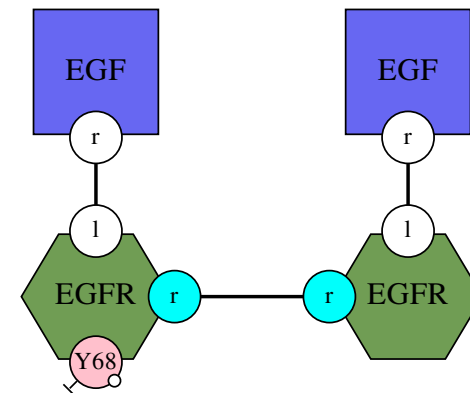
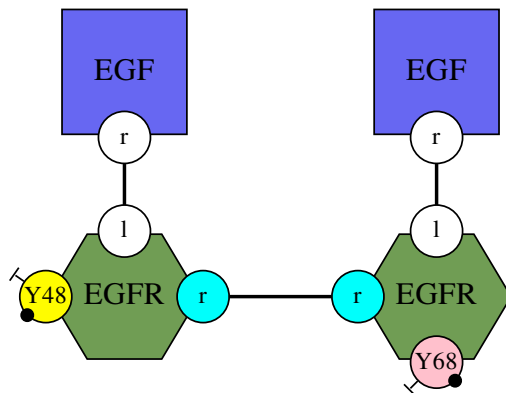
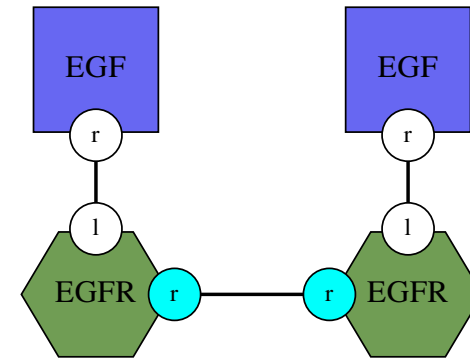
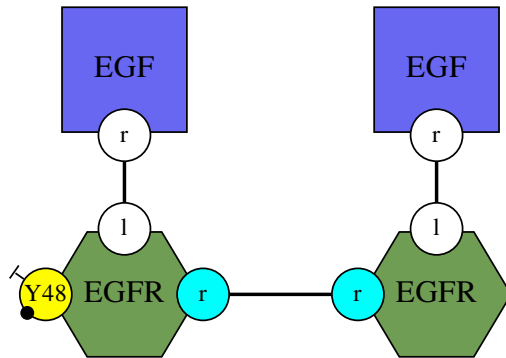
Fragments



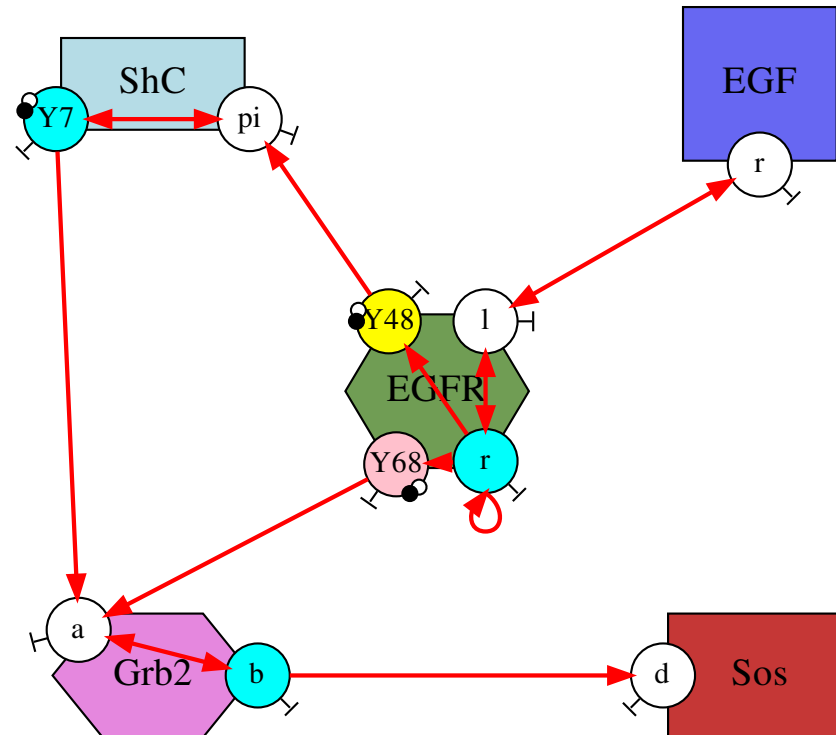
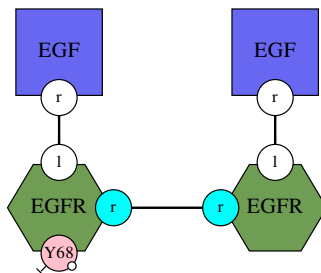
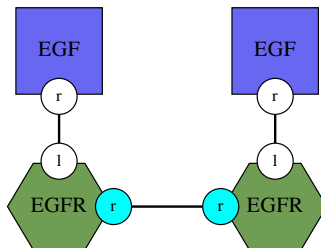
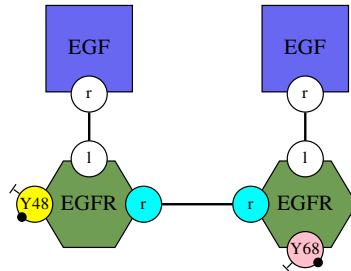
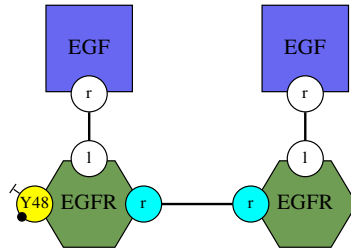
Definition 2 (fragment) A fragment is a prefragment that cannot be embedded in any bigger prefragment.

Examples

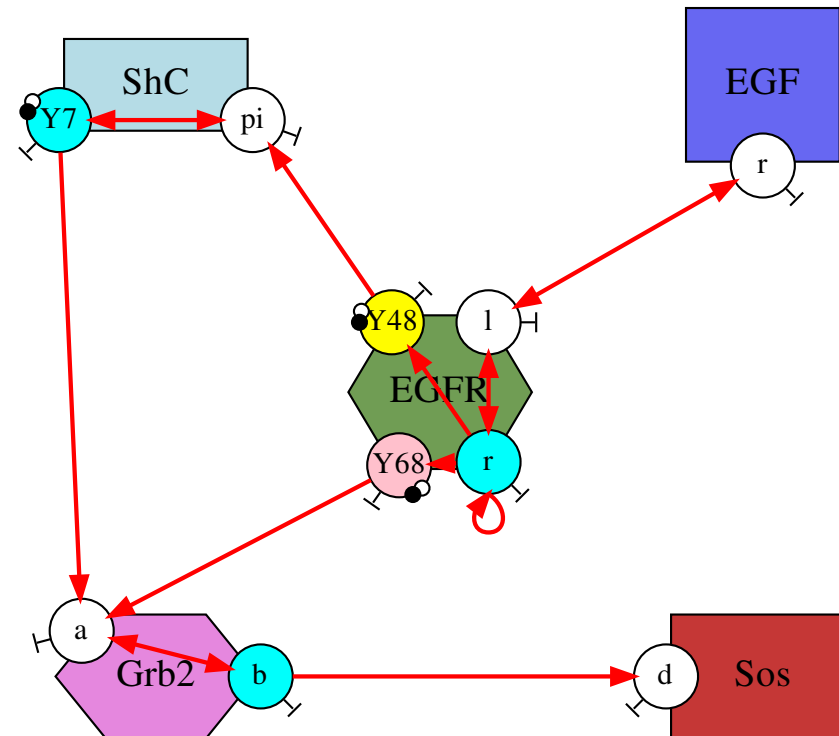
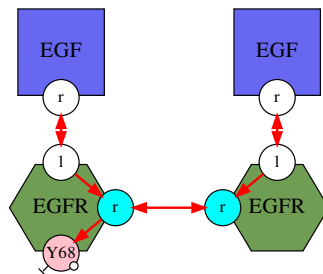
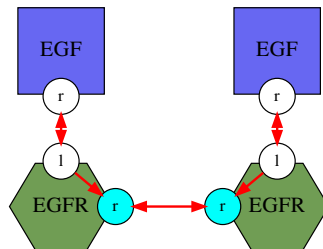
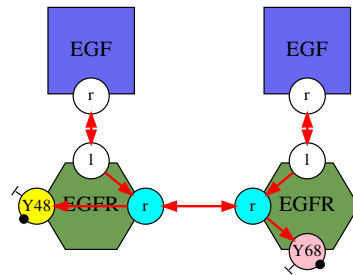
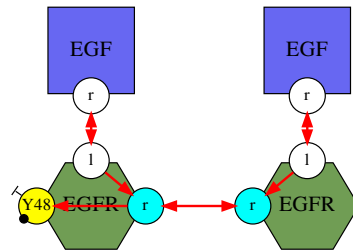
Which patterns are fragments?



Examples : annotated map

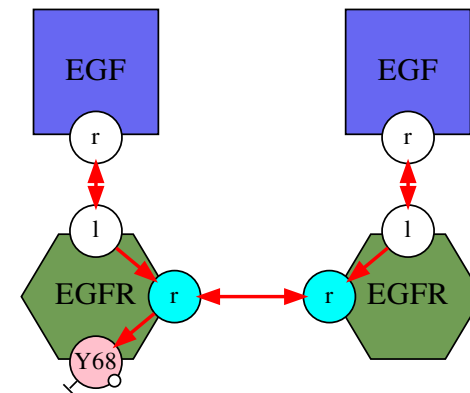
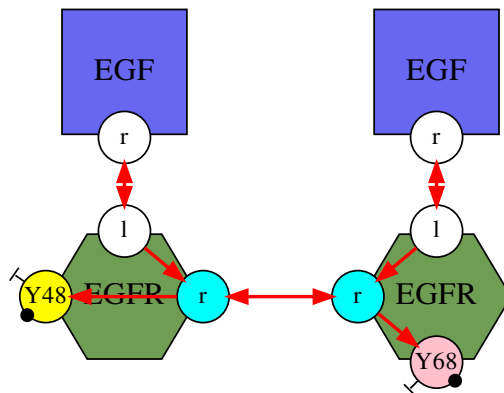
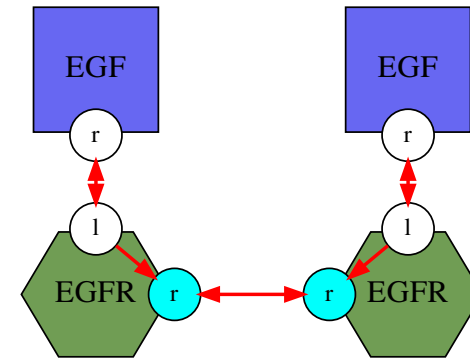
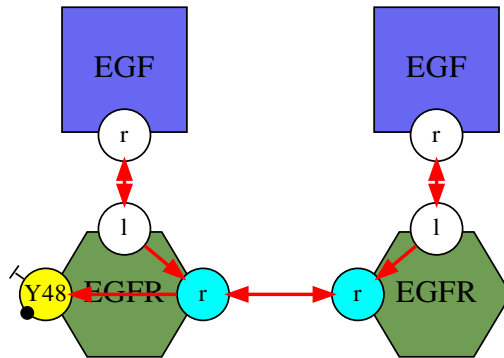


Examples : pattern annotation



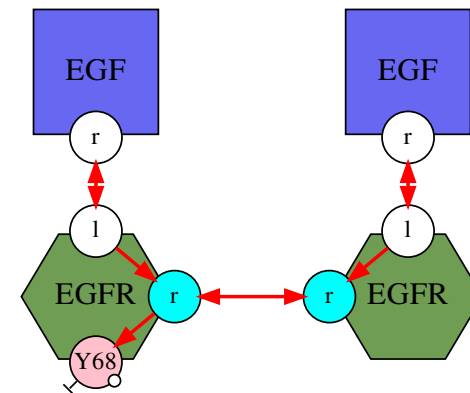
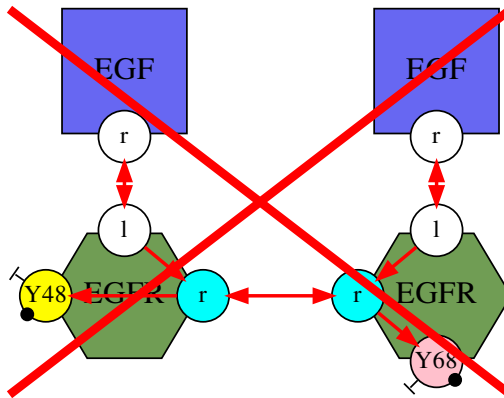
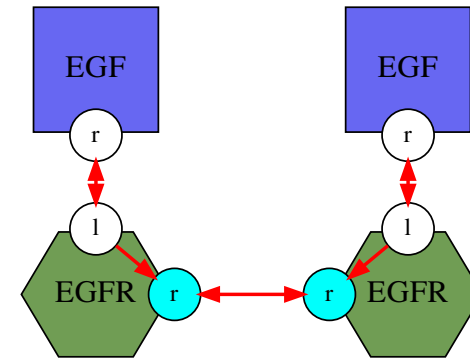
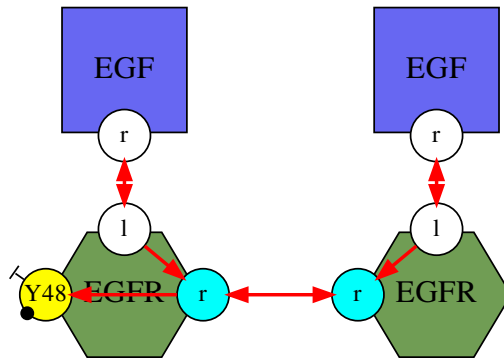
Examples

Which patterns are prefragments?



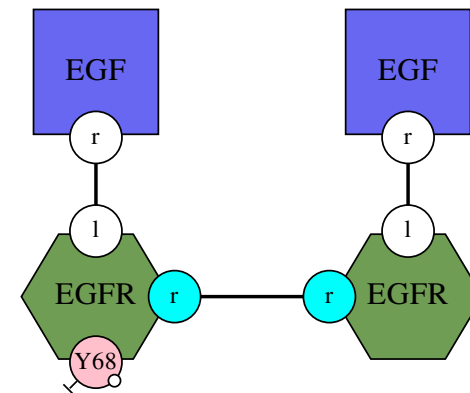
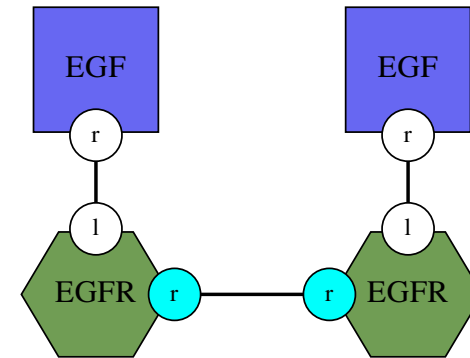
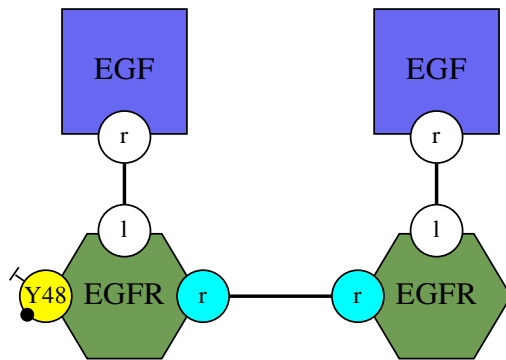
Examples

Prefragments



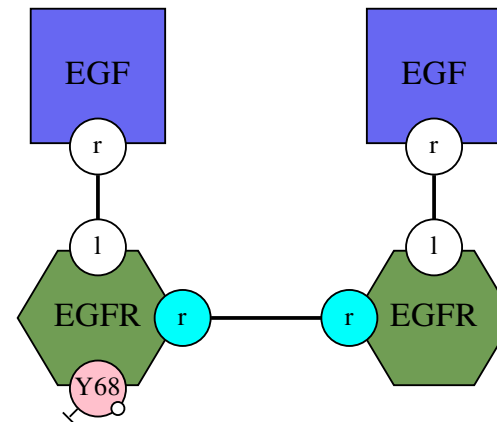
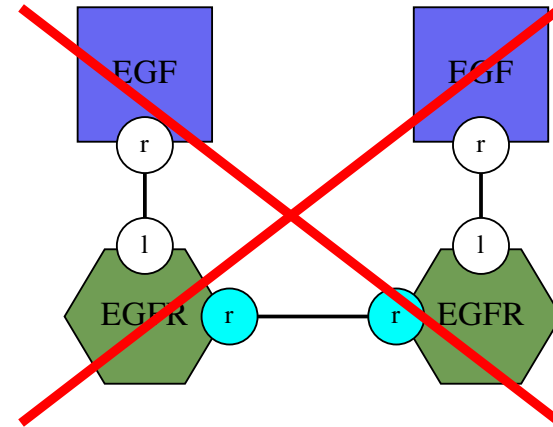
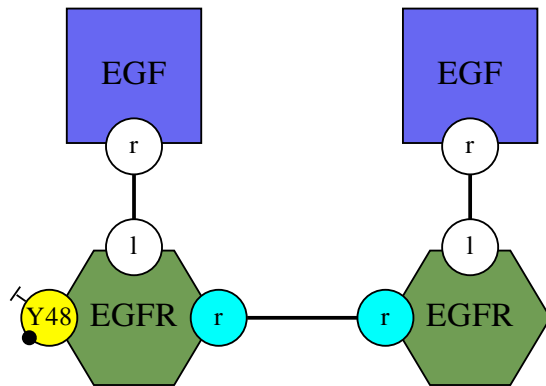
Examples

Which patterns are fragments?

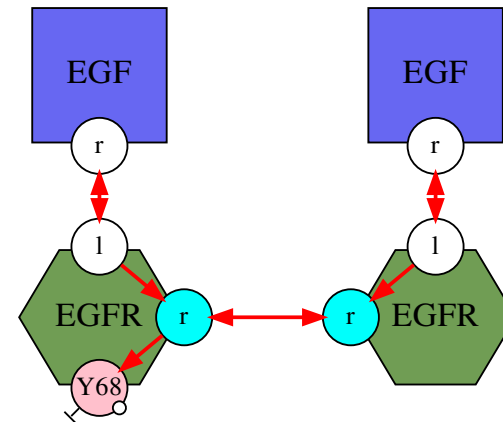
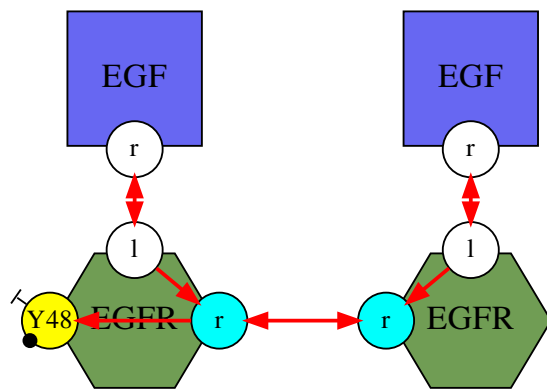


Examples

Fragments



Examples : fragments

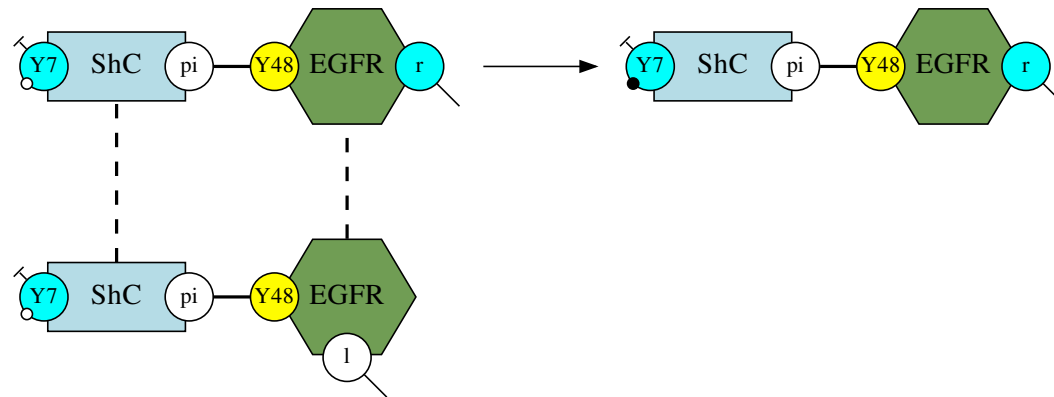


Almost done...

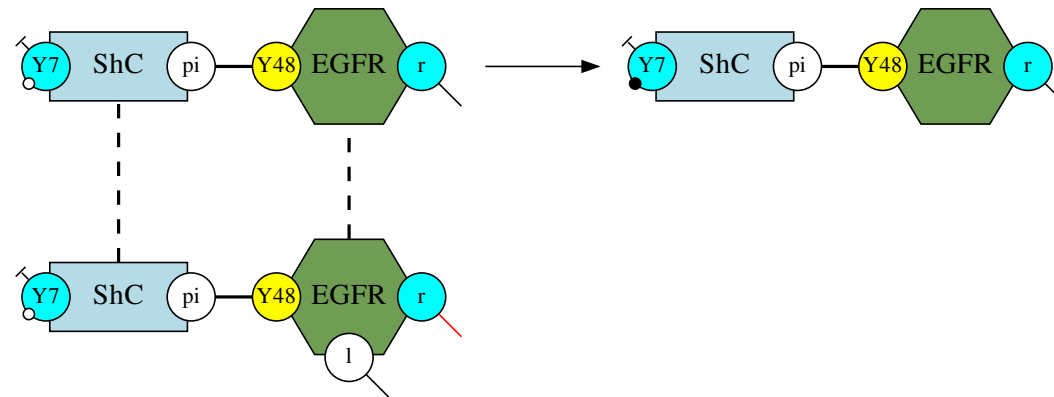
We are left to express the consumption and the production (in concentration) of each fragment as expressions of the concentration of fragments.

Firstly, we notice that the concentration of each prefragment can be expressed as a linear combination of the concentration of the fragments.

Fragments consumption

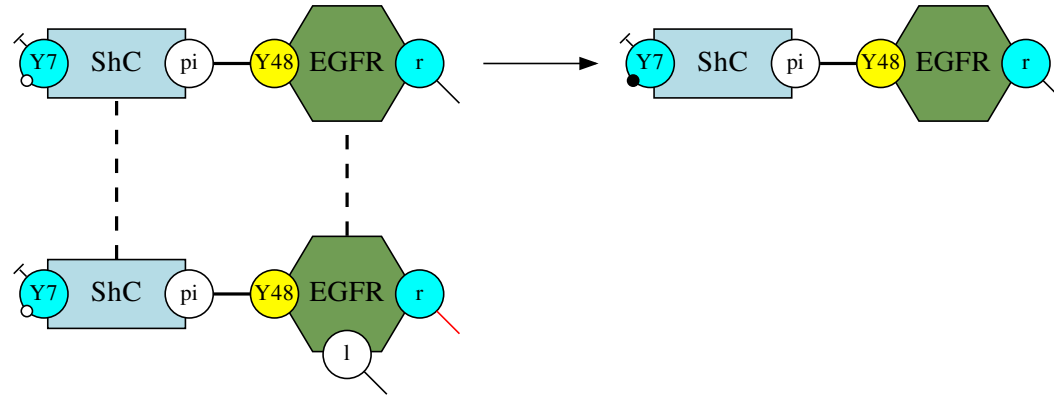


Fragments consumption



Whenever there is an overlap between a fragment and a connected component in the left hand side of a rule such that the common region contains a site that is modified by the rule, then the connected component embeds in the fragment.

Fragments consumption



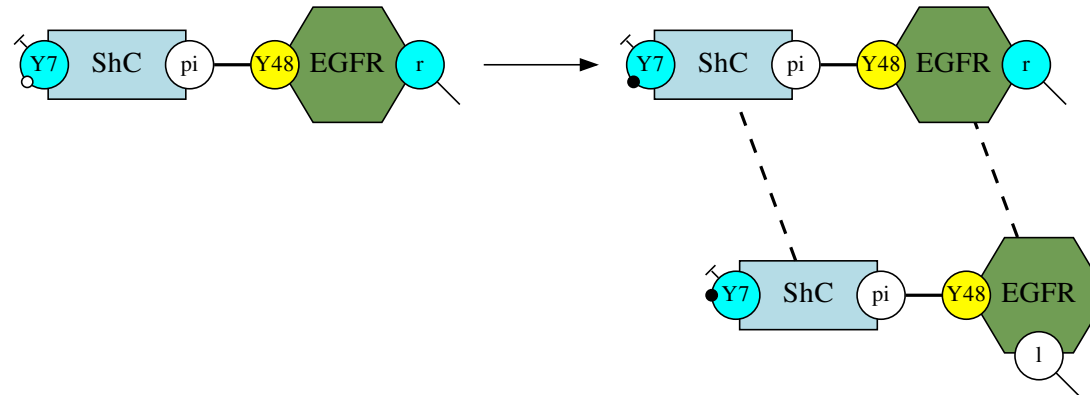
For each fragment F , for each rule:

$$r: C_1, \dots, C_n \rightarrow rhs \quad k$$

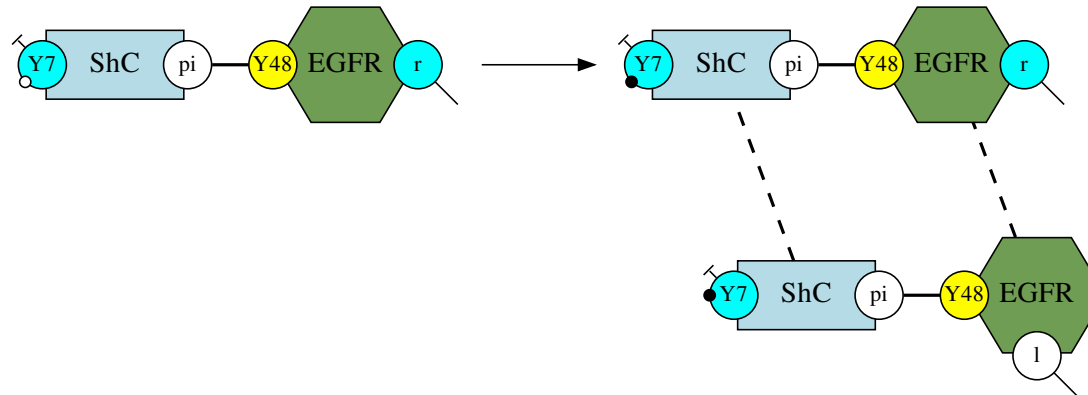
and for each occurrence of a connected component C_j that is modified by the rule, in a the fragment F , we have the following contribution:

$$\frac{d[F]}{dt} = \frac{k \cdot [F] \cdot \prod_{i \neq j} [C_i]}{\text{SYM}[C_1, \dots, C_n] \cdot \text{SYM}[F]}.$$

Fragments production

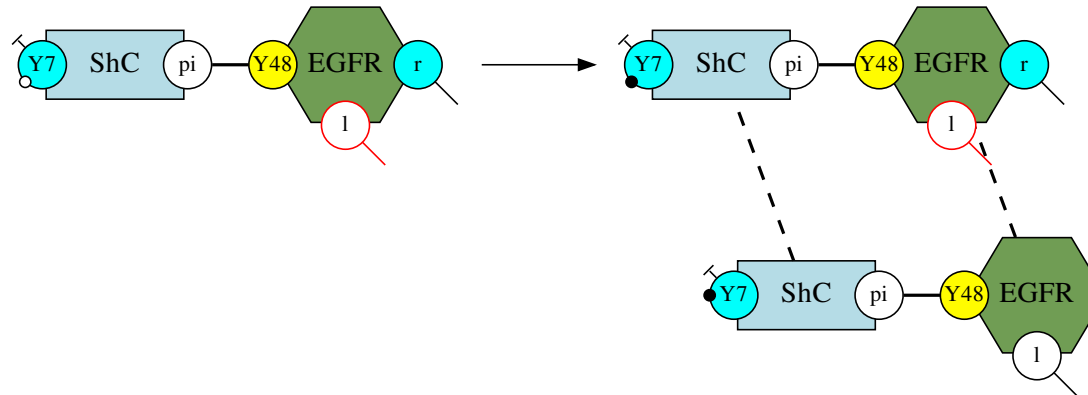


Fragments production



Whenever there is an overlap between a fragment and the right hand side of a rule, such that the common region contains a site that is modified by the rule. . .

Fragments production



Whenever there is an overlap between a fragment and the right hand side of a rule such that the common region contains a site that is modified by the rule, each connected component in the left hand side of the refined rule, is a prefragment.

Fragment production

For each overlap *ch* between a fragment and the right hand side of a rule, such that the common region contains a site that is modified by the rule:

$$r : C_1, \dots, C_m \rightarrow \text{right hand side} \quad k,$$

we have the following contribution:

$$\frac{d[F]}{dt} \stackrel{+}{=} \frac{k \cdot \prod_i [C'_i]}{\text{SYM}[C_1, \dots, C_m] \cdot \text{SYM}[F]}.$$

where C'_1, \dots, C'_n is the left hand side of the refined rule.

On the menu today

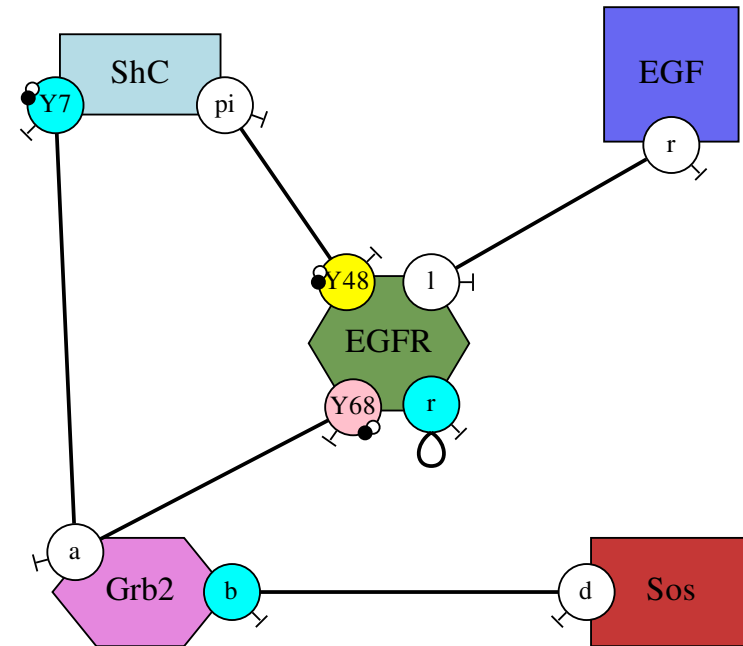
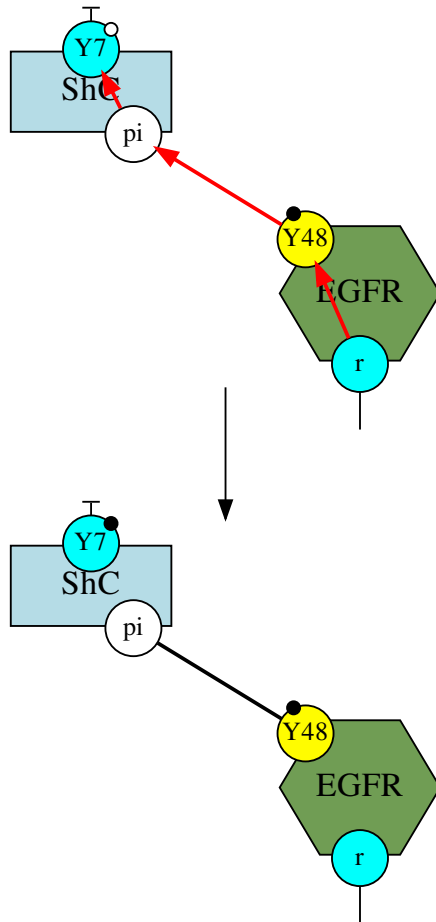
1. Context and motivations
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Benchmark

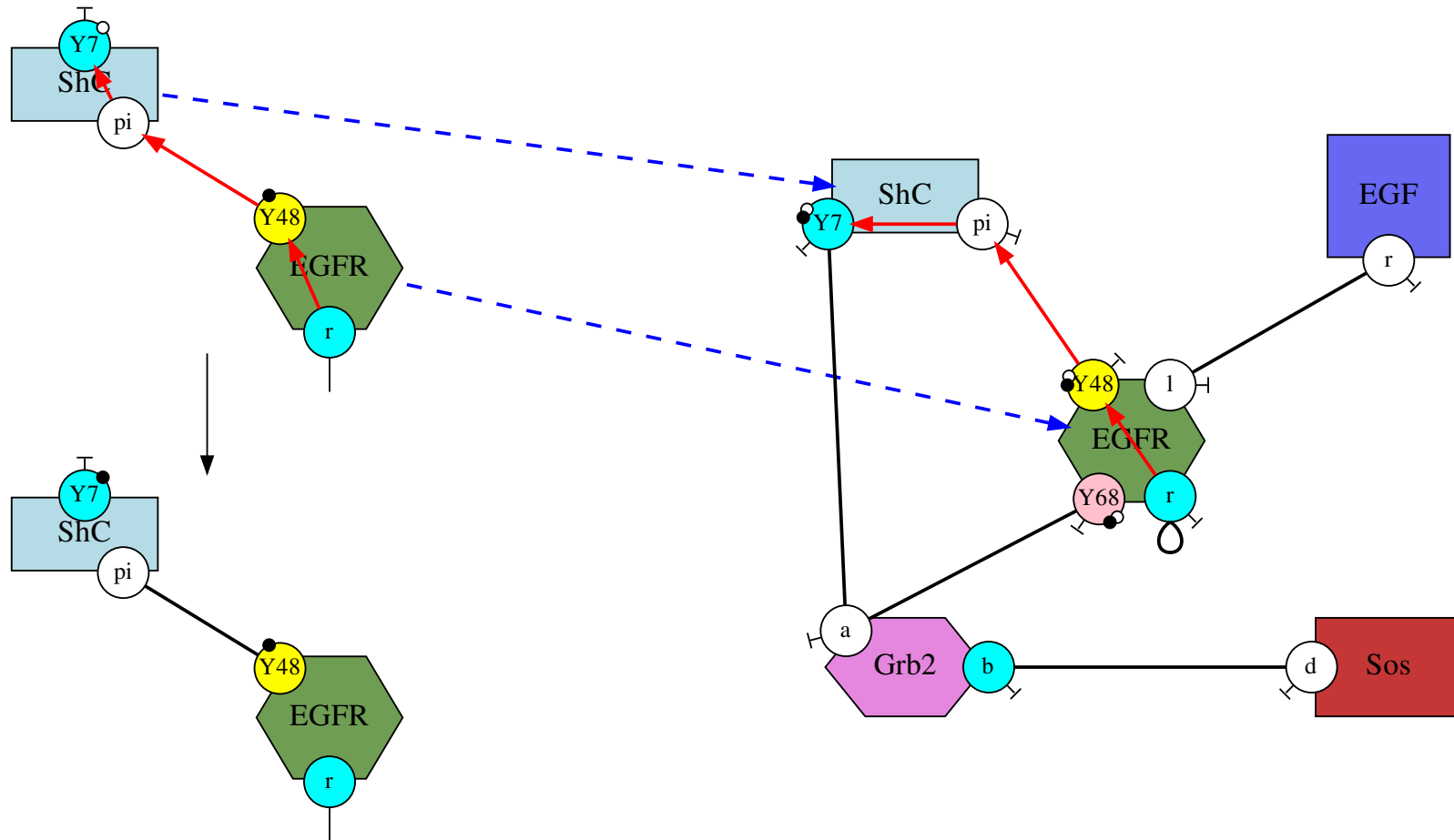
Model	early EGF	EGF/Insulin	SFB
Number of molecular species	356	2899	$\sim 2.10^{19}$
Number of fragments (ODEs semantics)	38	208	$\sim 2.10^5$
Number of fragments (CTMC semantics)	356	618	$\sim 2.10^{19}$

In short

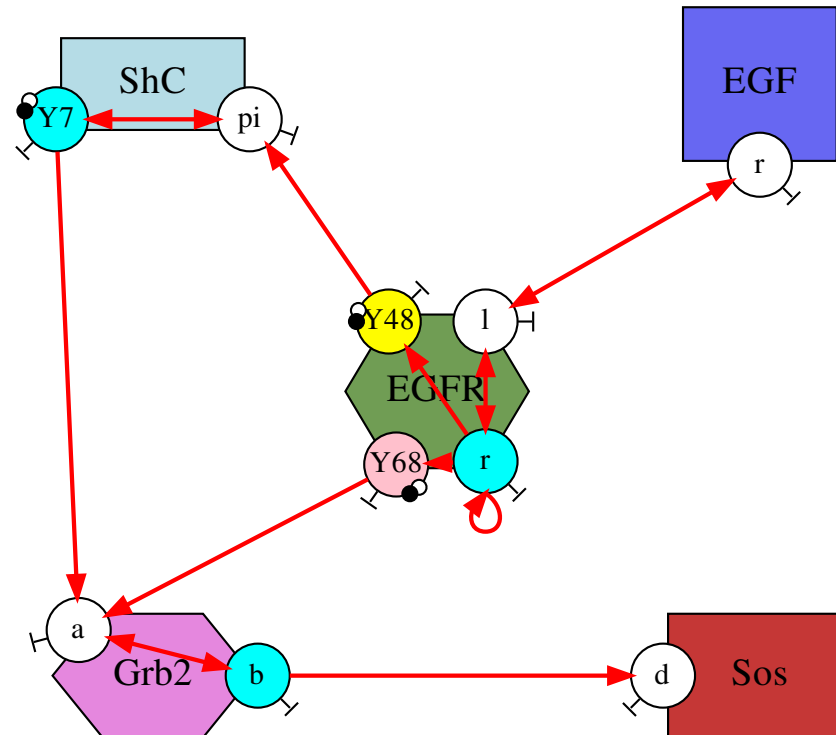
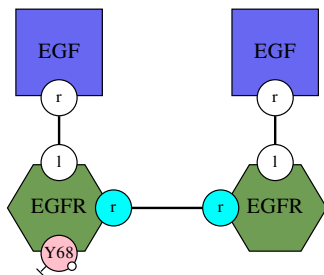
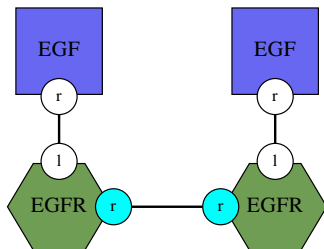
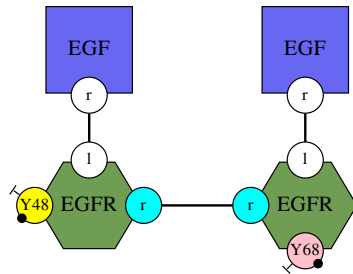
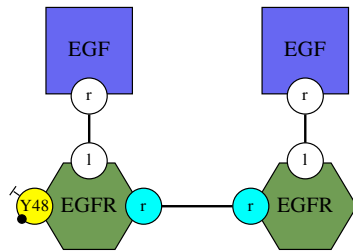
Abstraction of the information flow



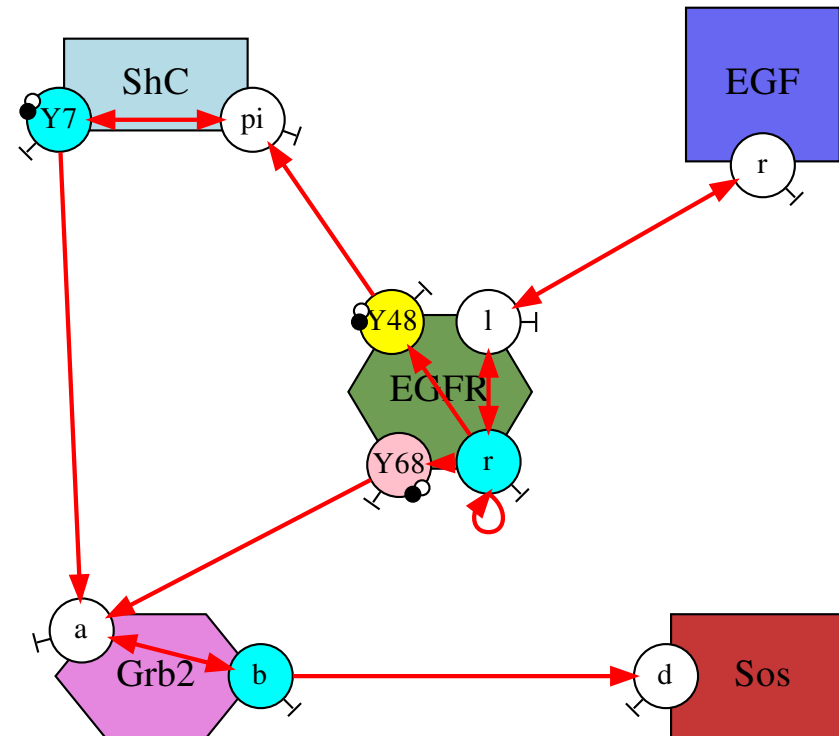
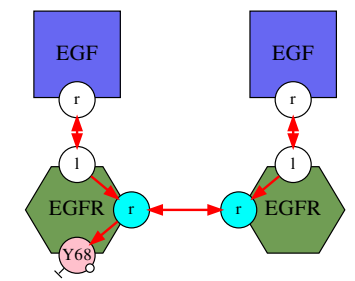
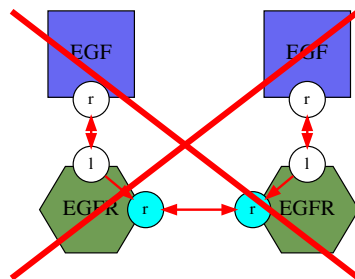
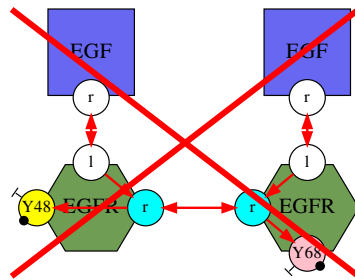
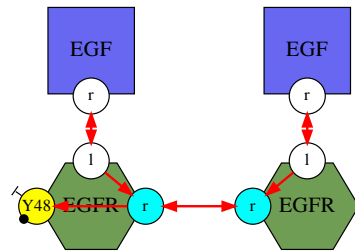
Abstraction of the information flow



Patterns of interest



Patterns of interest



Related topics and acknowledgements

- Model reduction (ODEs semantics)
Vincent Danos, Walter Fontana, Russ Harmer, Jean Krivine
- Context-sensitive abstraction of information flow
Ferdinanda Camporesi
- Model reduction (CTMC semantics)
Tatjana Petrov, Heinz Koepl, Tom Henzinger
- Bisimulations metrics
Norm Ferns.



“AbstractCell”
(2009-2013)



“Big Mechanism” (2014-2017)
“CwC” (2015-2018)



“TGF β SysBio”
(2015-2018)