



# Rule-based Modeling



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# Outline

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1. **The motivation for rule-based modeling**
2. Basic concepts of rule-based modeling
3. An example model specification
4. Methods for simulating a model
5. Suggested exercise

# The need for predictive models of signal-transduction systems

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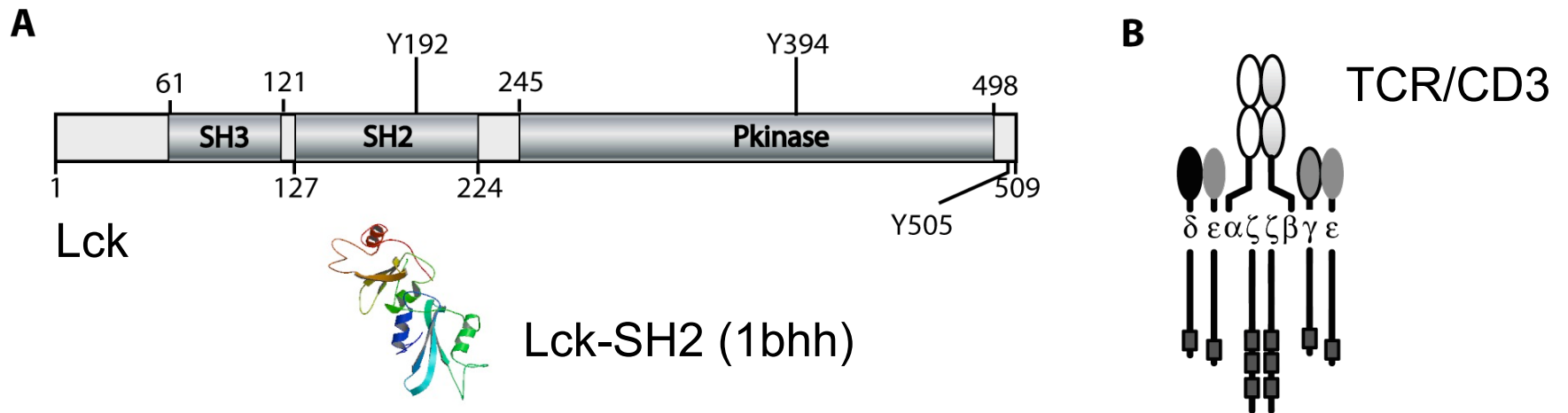
- **These systems mediate cellular information processing and regulate cellular phenotypes**
- **They are complex**
- **Molecular changes that affect cell signaling cause/sustain disease (e.g., cancer)**
- **Numerous drugs that target signaling proteins are currently in clinical trials**
  - Spectacular successes (e.g., imatinib treatment of CML)
  - But results are disappointing for many patients
- **Many clinical trials are underway to test combinations of drugs (clinicaltrials.gov)**
  - There are too many combinations to consider all possibilities in trials

## Value added by modeling

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- **We can use models to organize information about a system with precision**
  - Introduces greater rigor and discipline
- **We can determine the logical consequences of a model specification**
  - Design principles can be elucidated (key for synthetic biology)
  - Certification (essential for personalized medicine)

# A signaling protein is typically composed of multiple components (subunits, domains, and/or linear motifs) that mediate interactions with other proteins

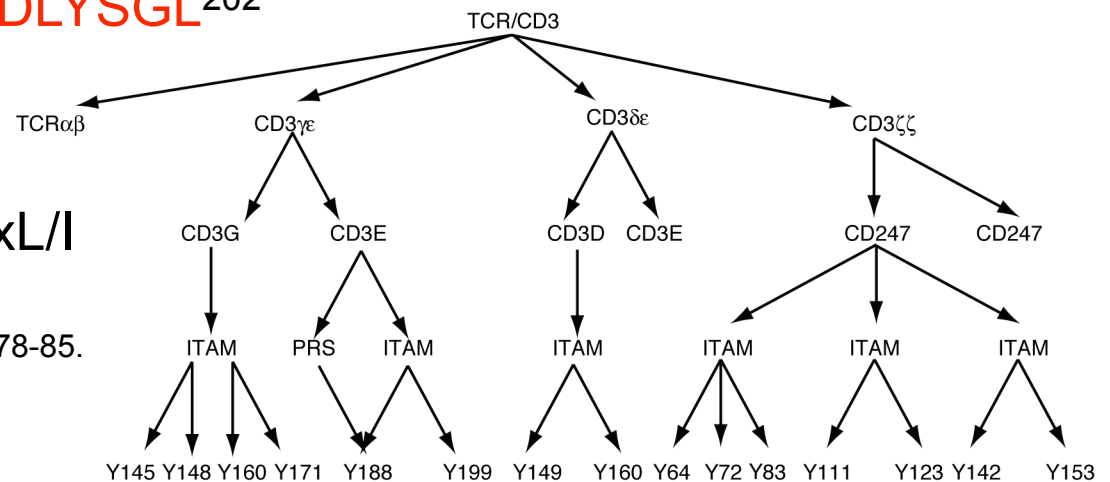


CD3E: 184PNPDYEP<sup>IR</sup>KGQRDL<sup>YS</sup>GL202

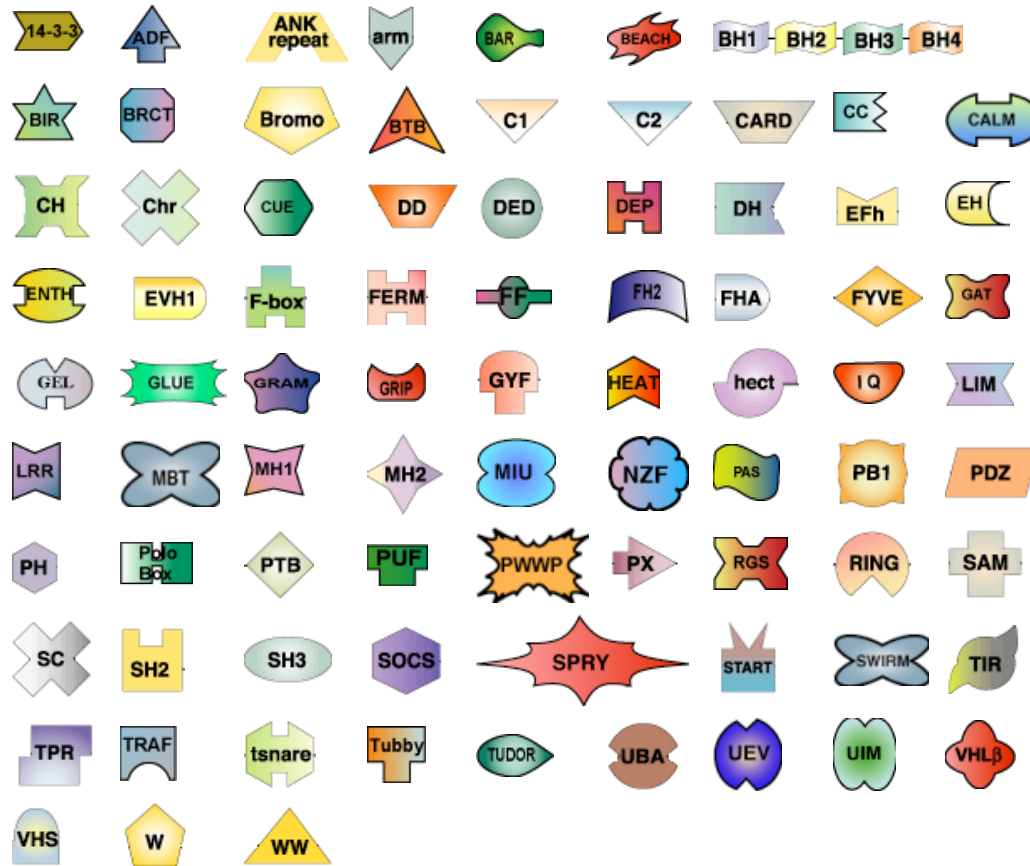
PRS: PxxDY

ITAM: YxxL/I(x<sub>6-8</sub>)YxxL/I

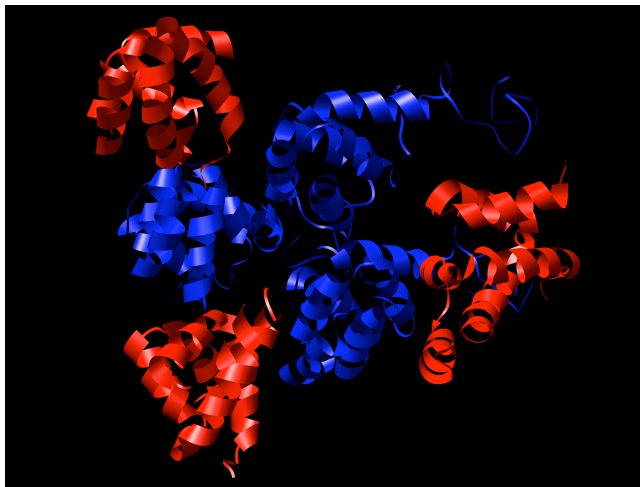
Kesti T et al. (2007) J. Immunol. 179:878-85.



# There are many protein interaction domains



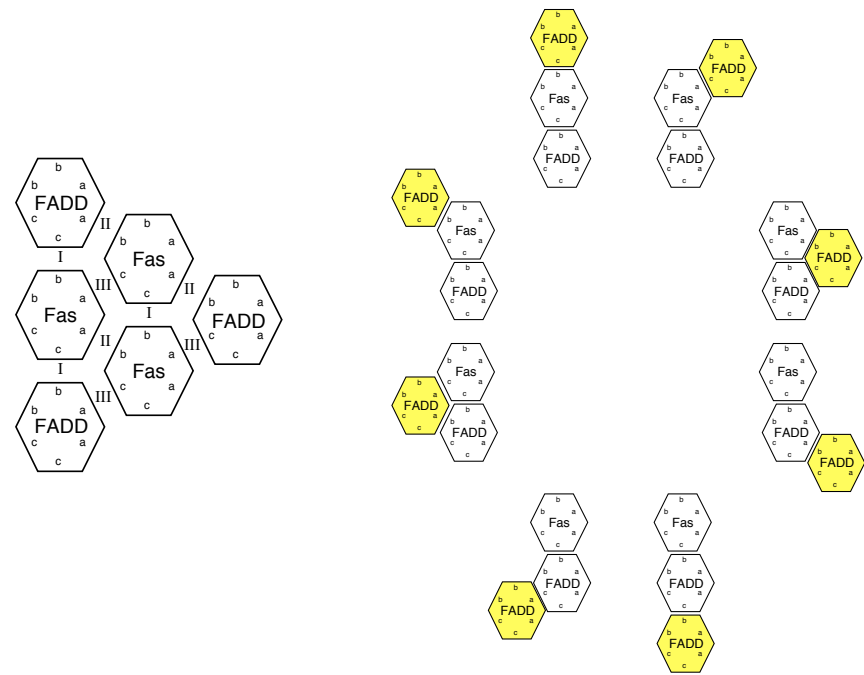
# Some domains are multivalent and mediate oligomerization via domain-domain interactions



A hexamer of death domains

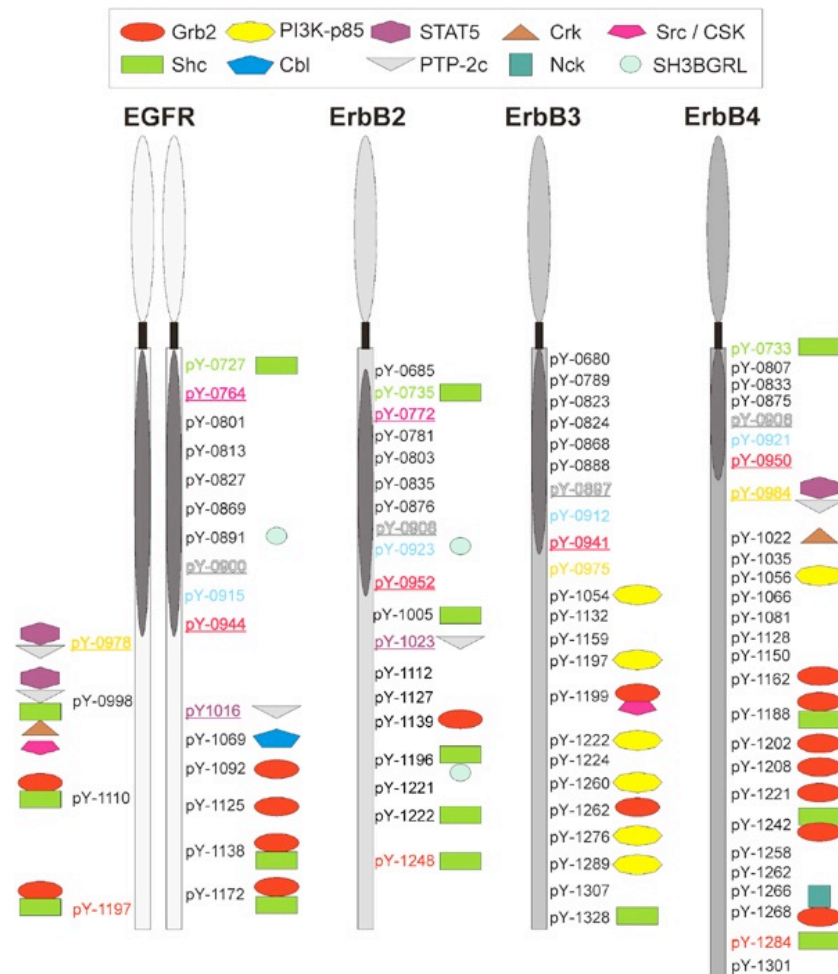
Weber and Vincenz (2001) *FEBS Lett.*

C.-T. Tung (Los Alamos)



**There are many possible protein complexes!**

# Domain-motif interactions are often controlled by post-translational modifications



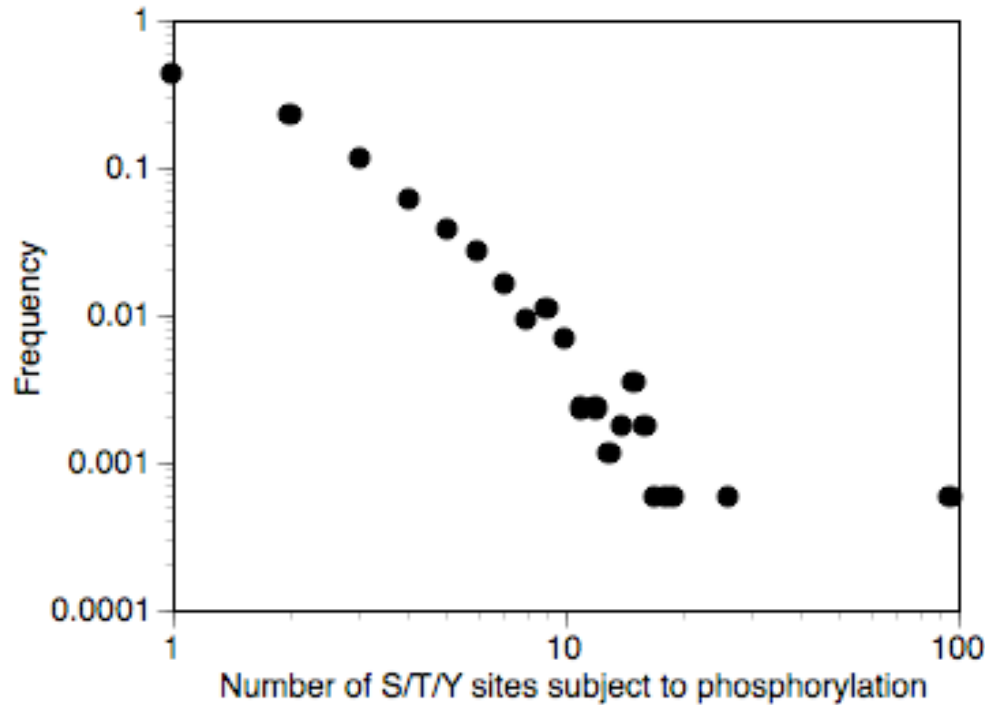
There are many possible protein phosphoforms!





## Signaling proteins typically contain multiple phosphorylation sites (S/T/Y)

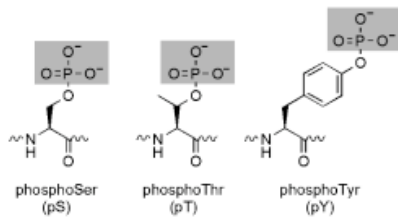
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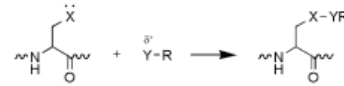
> 50% are phosphorylated at 2 or more sites

Phospho.ELM database v. 3.0 (<http://phospho.elm.eu.org>)

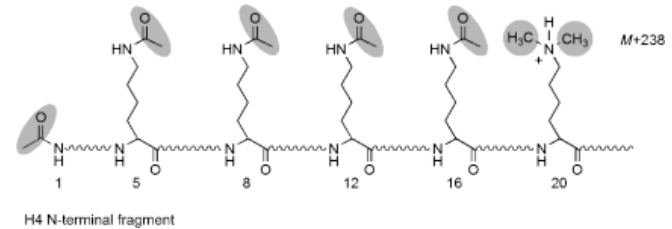
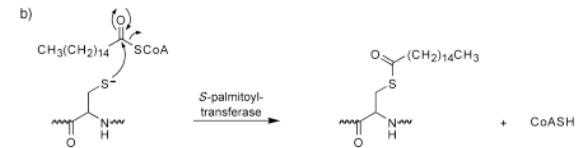
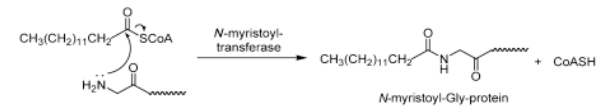
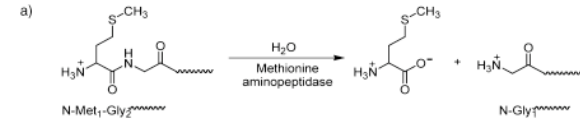
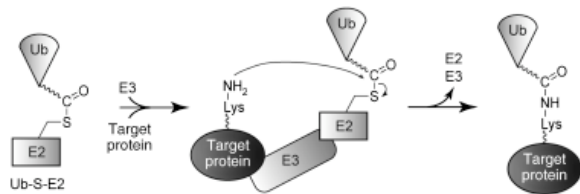
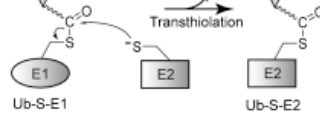
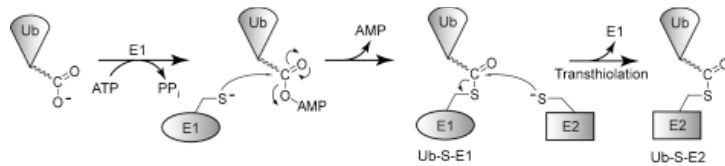
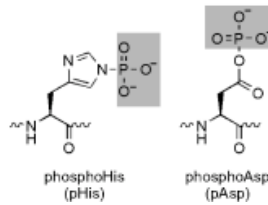
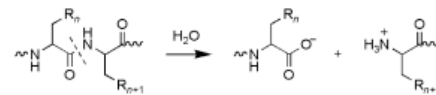
# There are many different kinds of post-translational modifications of proteins



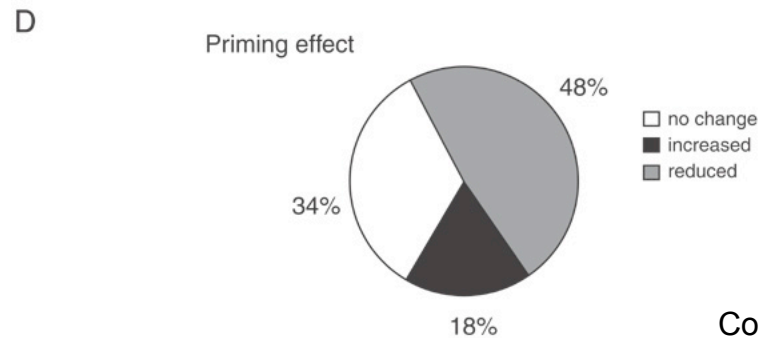
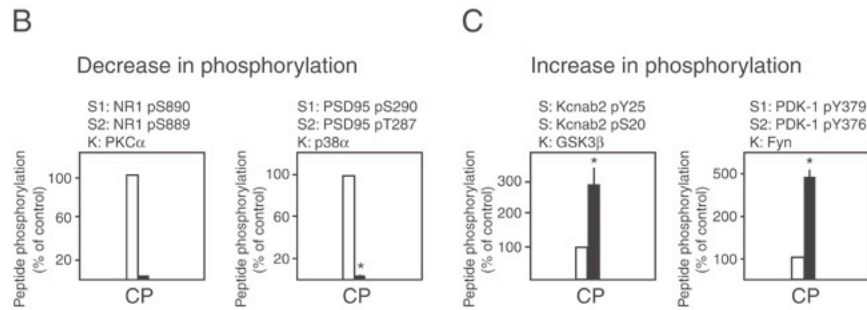
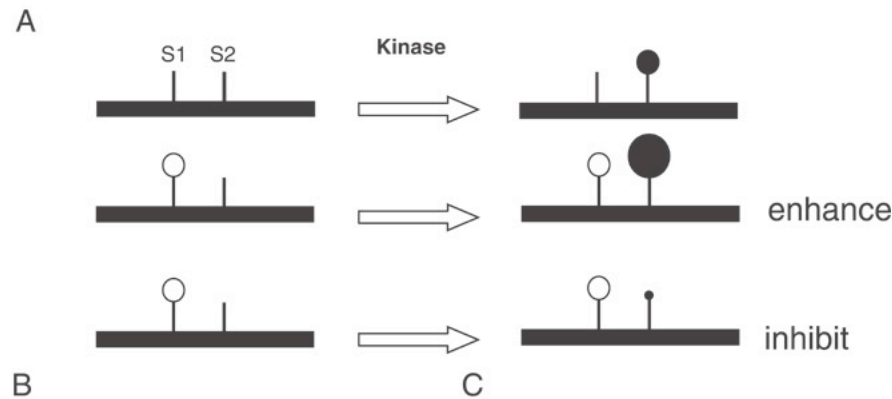
1. Covalent modification



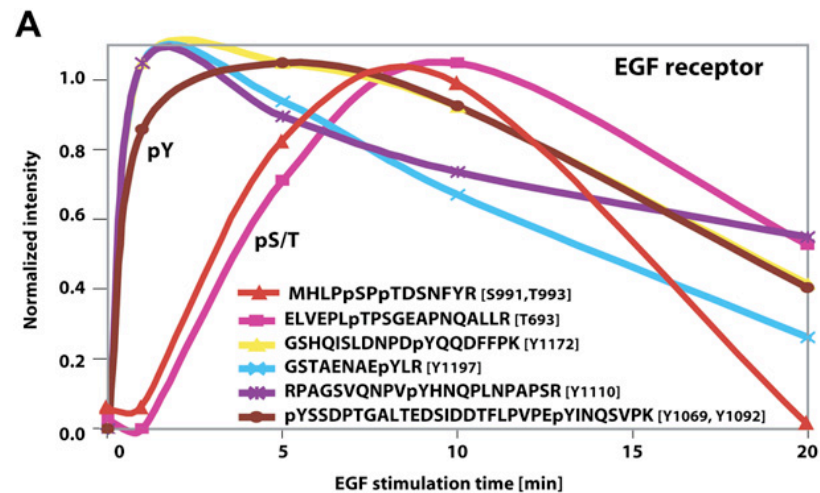
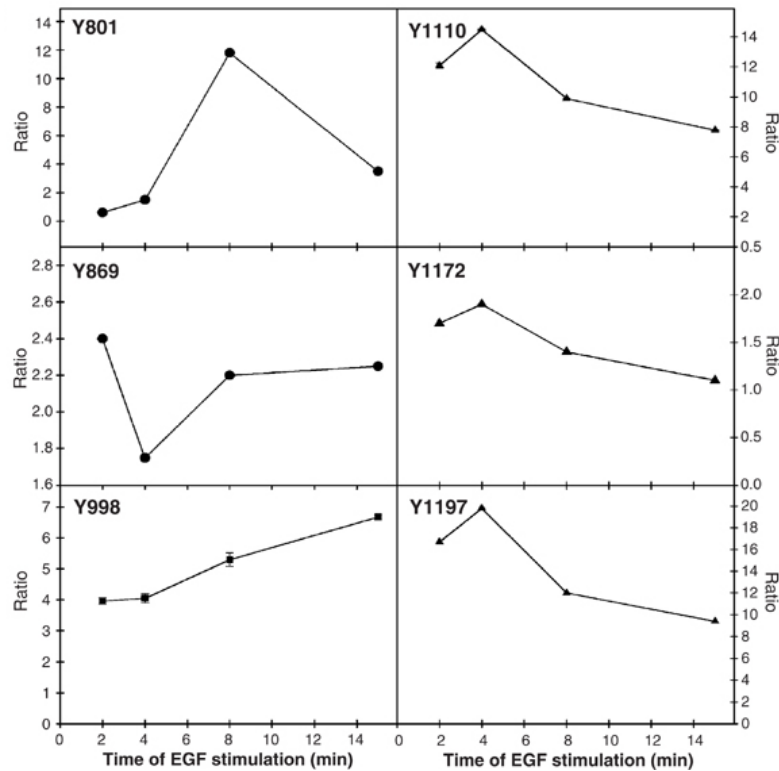
2. Cleavage of protein backbone



# Priming – cooperative phosphorylation of neighboring kinase substrates is common



# Distinct time courses of phosphorylation for different amino acid residues within the same protein



Schulze WX et al. (2005) Mol. Syst. Biol.

Olsen JV et al. (2006) Cell 127:635-48.

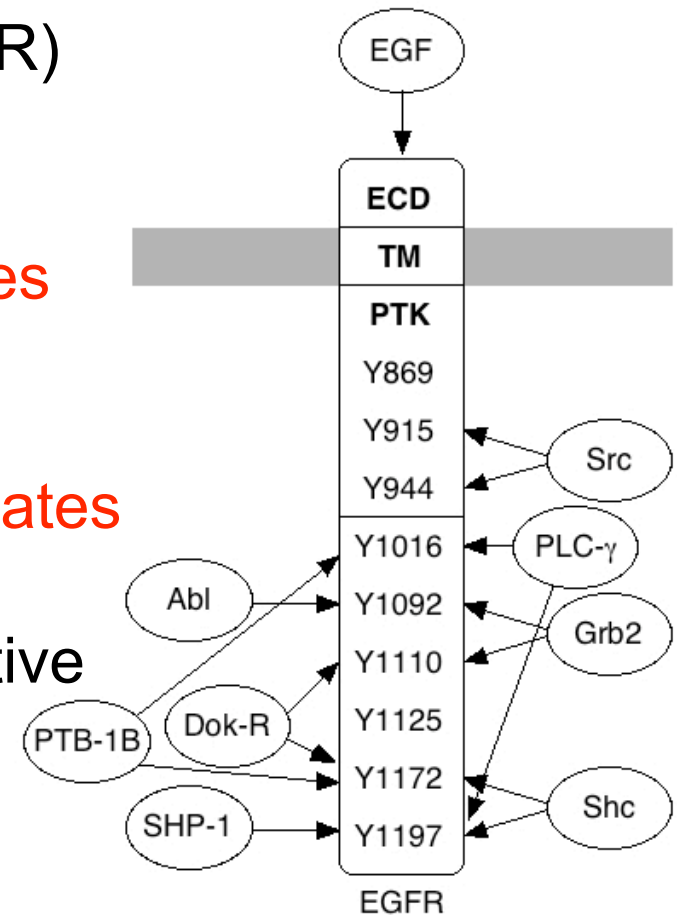
# Combinatorial complexity – a serious problem for the conventional modeling approach

Epidermal growth factor receptor (EGFR)

9 sites =>  $2^9=512$  phosphorylation states

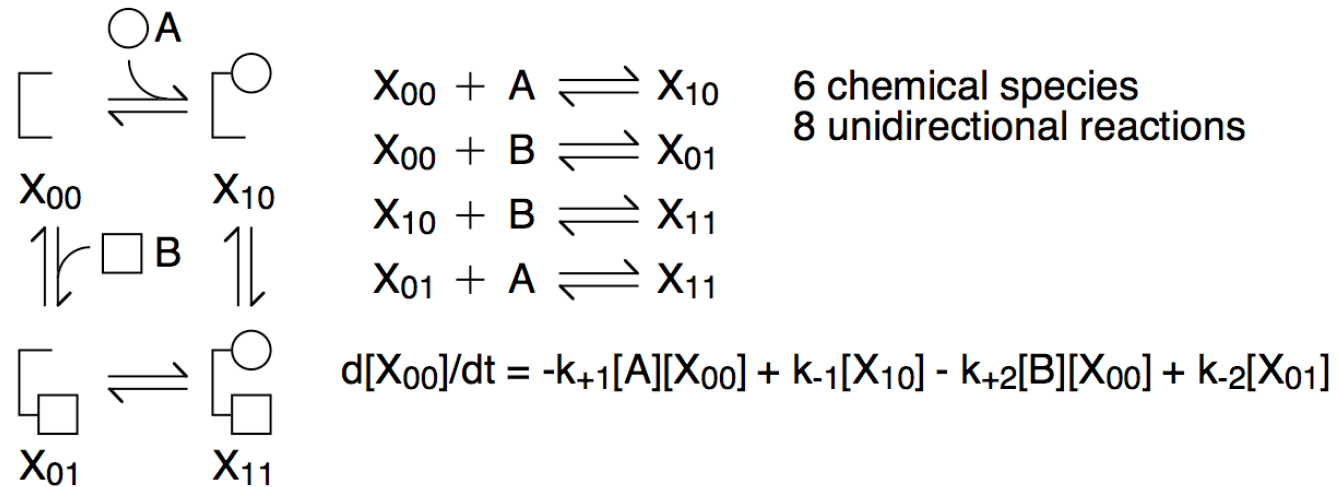
Each site has  $\geq 1$  binding partner  
=> more than  $3^9=19,683$  total states

EGFR must form *dimers* to become active  
=> more than  $1.9 \times 10^8$  states



# The textbook approach

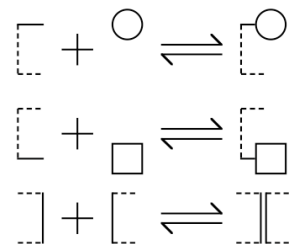
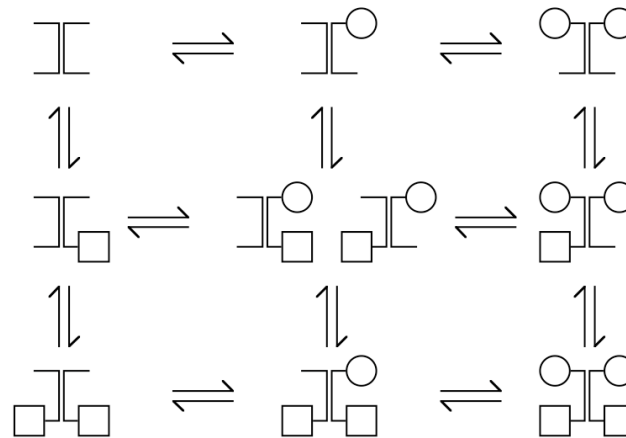
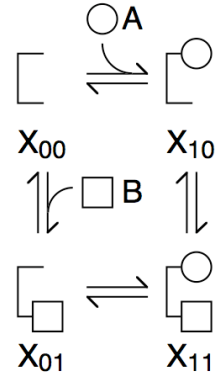
Conventional representation of a biochemical reaction network



# Network (model) size tends to grow nonlinearly (exponentially) with the number of molecular interactions in a system when molecules are structured

Network size increases nonlinearly when an extra interaction is considered

16 chemical species  
60 unidirectional reactions

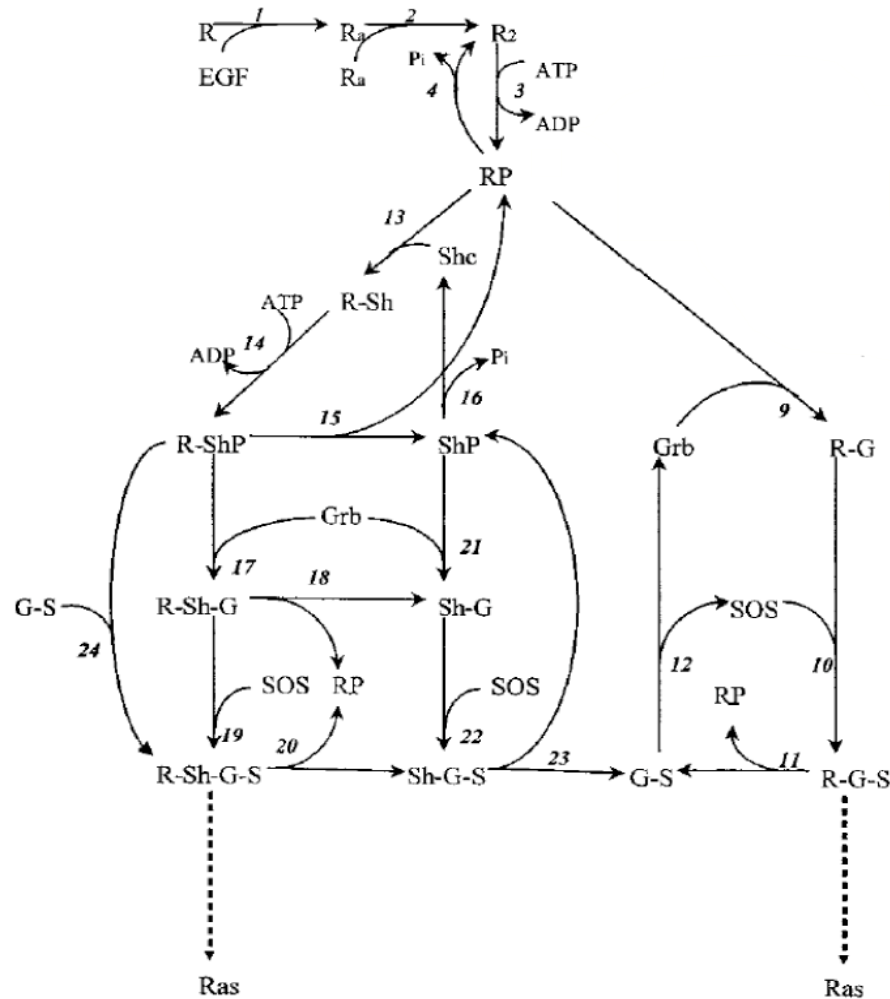


There are only three interactions. We can use a “rule” to model each of these interactions.

*Science's STKE re6 (2006)*



# If you can write the model by hand, it may look like a mechanistic model, but it's probably just a complicated fitting function



A reaction scheme incorporated in many published models of EGFR signaling

# Rule-based modeling solves the problem of combinatorial complexity

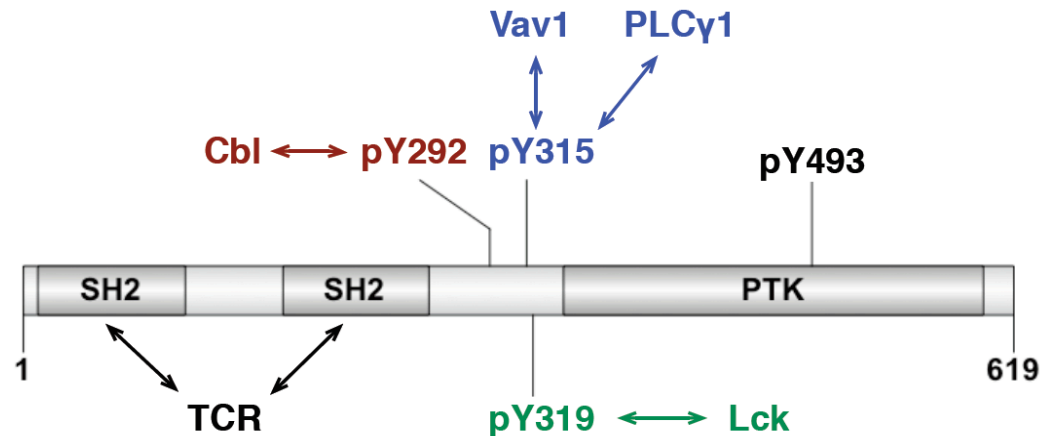
## ■ Inside a Chemical Plant

- Large numbers of molecules...
- ...of a few types
- Conventional modeling works fine (a good idea since 1865)

## ■ Inside a Cell

- Possibly small numbers of molecules...
- ...of many possible types
- Rule-based modeling is designed to deal with this situation (new)

■ ZAP-70



# Outline

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3. An example model specification
4. Methods for simulating a model
5. Suggested exercise

## Rule-based modeling: basic concepts

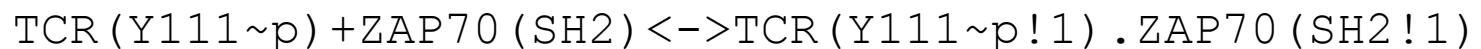
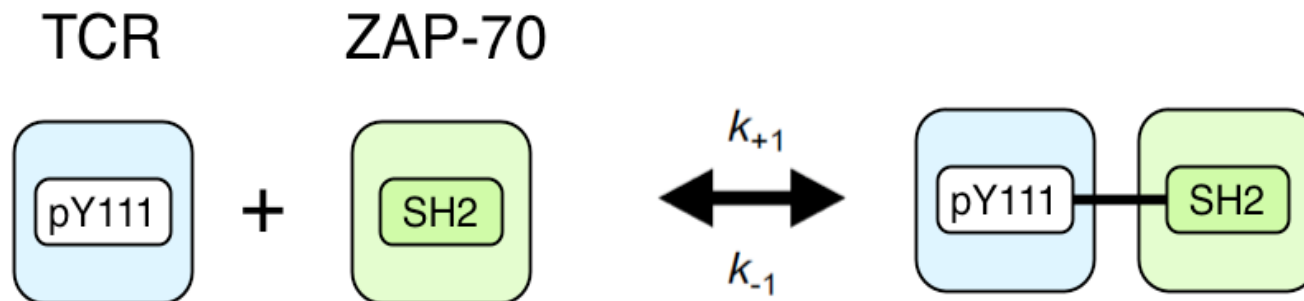
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**Graphs represent molecules, their component parts, and “internal states”**

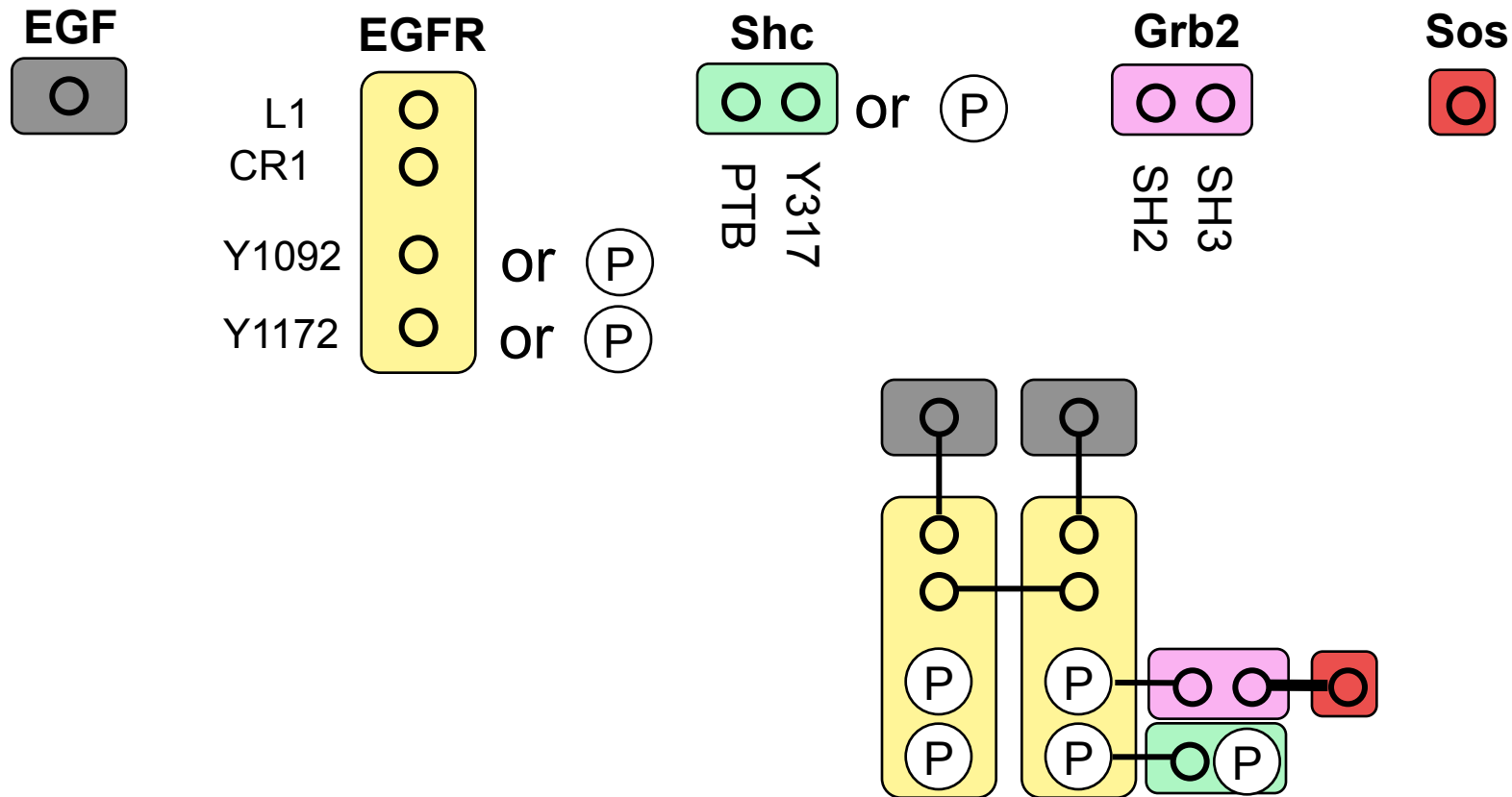
Molecules, components, and states can be directly linked to annotation in databases

**Graph-rewriting rules represent molecular interactions**

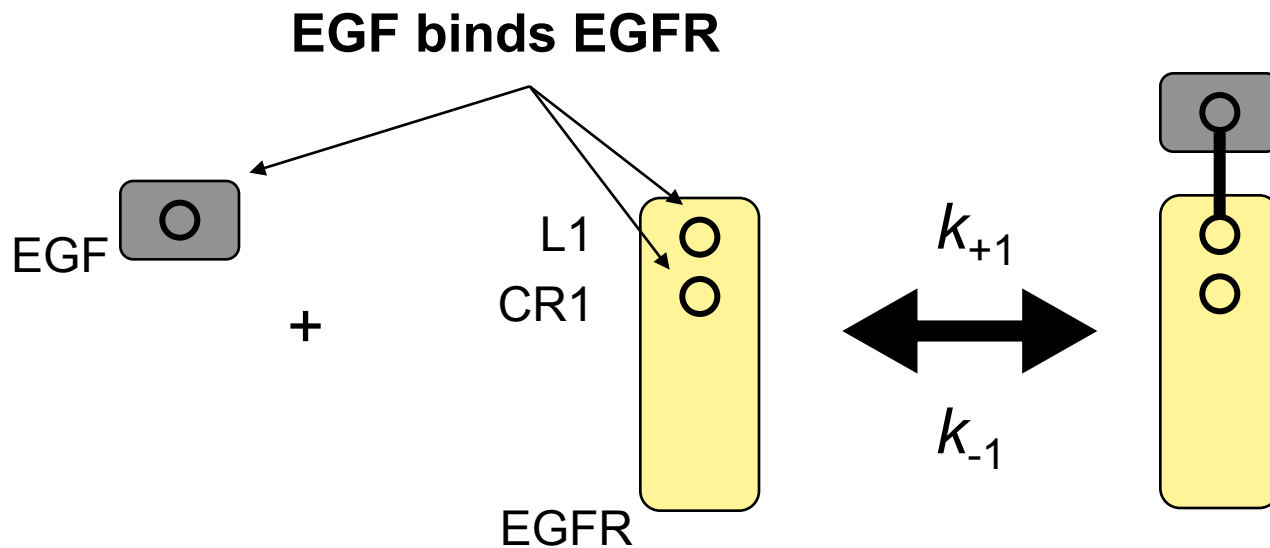
A rule specifies the addition or removal of an edge to represent binding or unbinding, or the change of an internal state to represent, for example, post-translational modification of a protein at a particular site



# Structured objects are naturally represented by graphs, so we use graphs to represent molecules and molecular complexes in signal-transduction systems



# Use graph-rewriting rules to represent interactions



begin reaction rules



end reaction rules

# Outline

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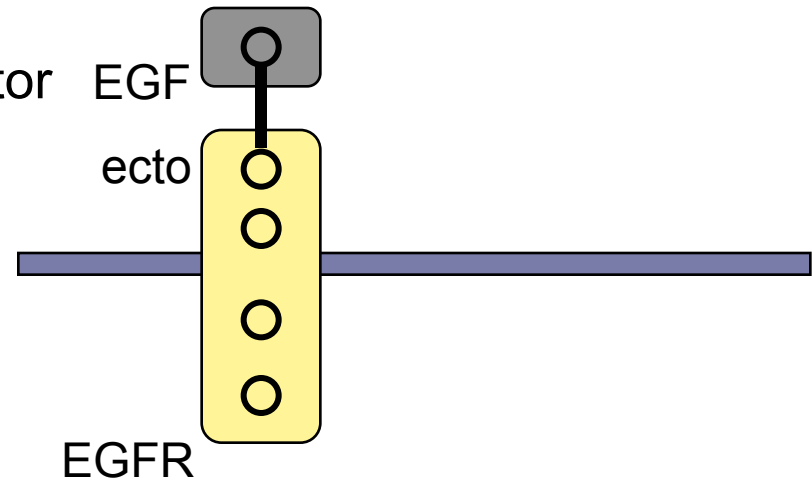
# Early events in EGFR signaling, illustrated with the same (sub)graphs used to specify a rule-based model for these events

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EGF = epidermal growth factor

EGFR = epidermal growth factor receptor

## 1. EGF binds EGFR

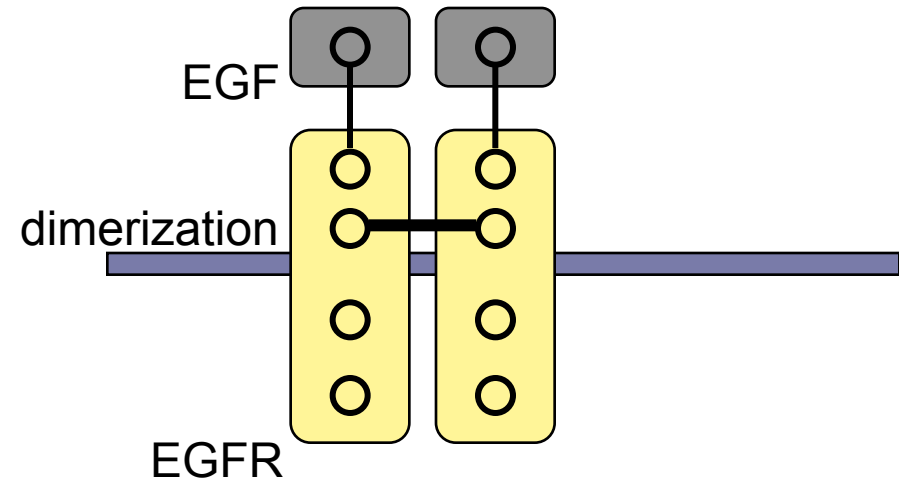




# Early events in EGFR signaling

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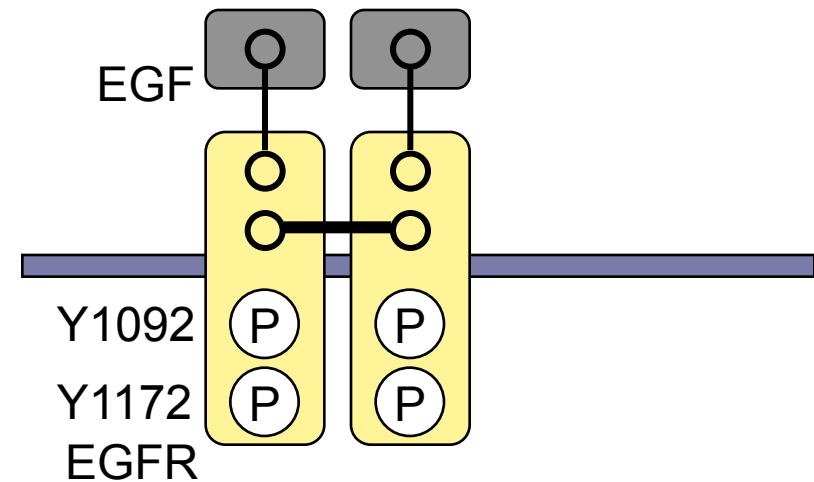
1. EGF binds EGFR
2. **EGFR dimerizes**



## Early events in EGFR signaling

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1. EGF binds EGFR
2. EGFR dimerizes
3. **EGFR transphosphorylates a copy of itself**

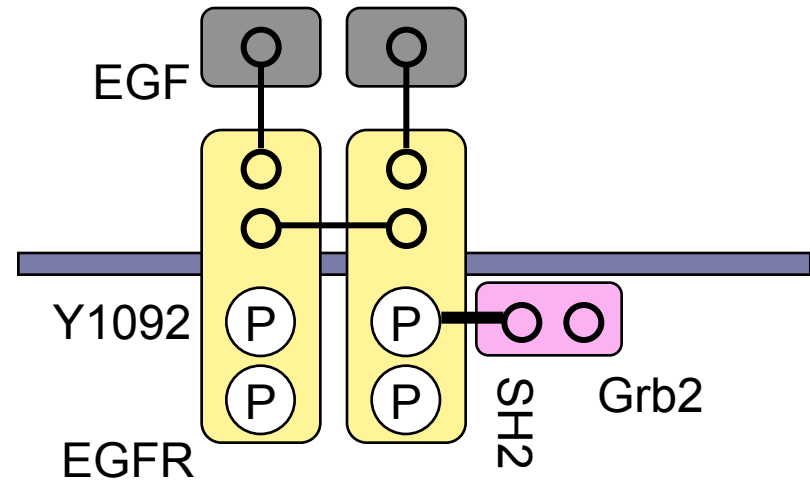


# Early events in EGFR signaling

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## Grb2 pathway

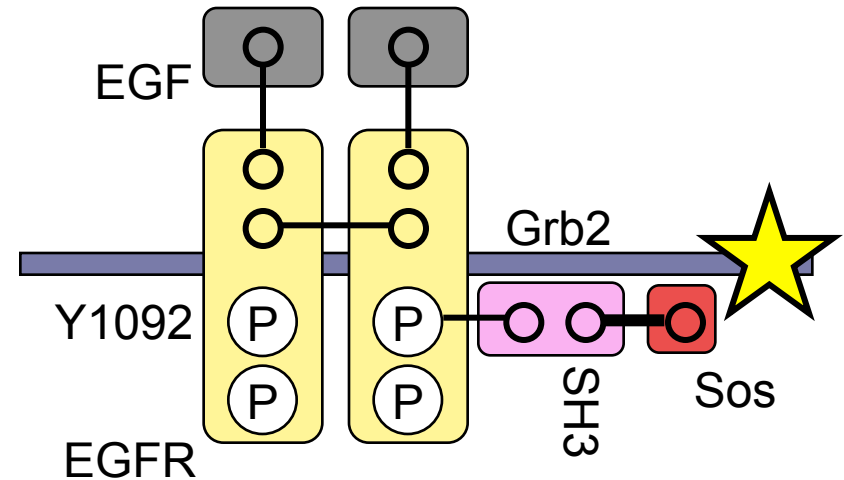
1. EGF binds EGFR
2. EGFR dimerizes
3. EGFR transphosphorylates
4. **Grb2 binds phospho-EGFR**



# Early events in EGFR signaling

## Grb2 pathway

1. EGF binds EGFR
2. EGFR dimerizes
3. EGFR transphosphorylates
4. Grb2 binds phospho-EGFR
5. **Sos binds Grb2 (Activation Path 1)**

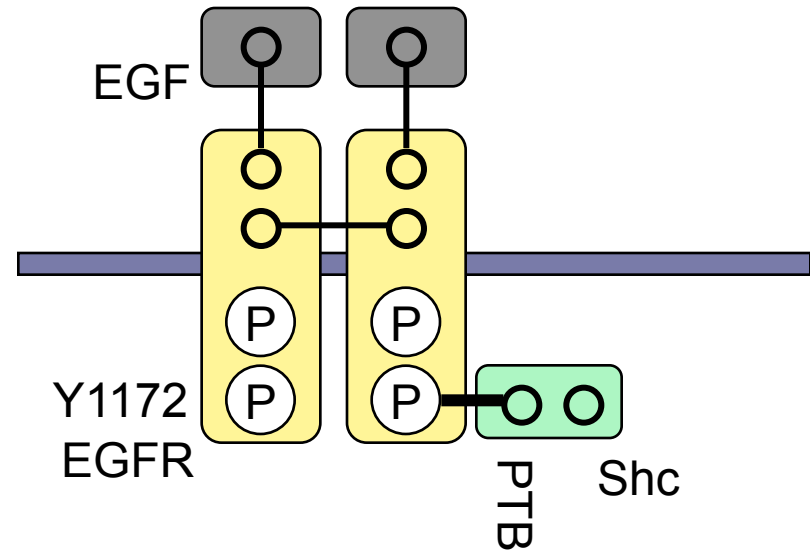


# Early events in EGFR signaling

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## Shc pathway

1. EGF binds EGFR
2. EGFR dimerizes
3. EGFR transphosphorylates
4. **Shc binds phospho-EGFR**

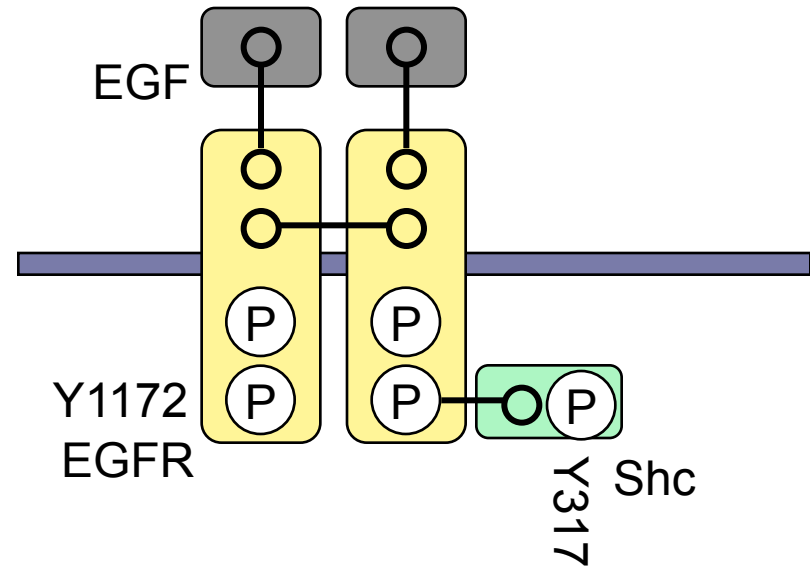


# Early events in EGFR signaling

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## Shc pathway

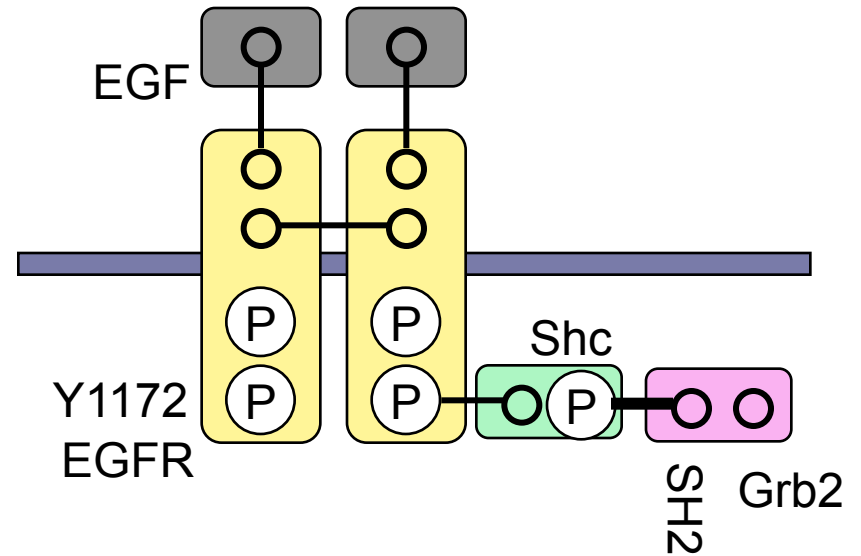
1. EGF binds EGFR
2. EGFR dimerizes
3. EGFR transphosphorylates
4. Shc binds phospho-EGFR
- 5. EGFR transphosphorylates Shc**



# Early events in EGFR signaling

## Shc pathway

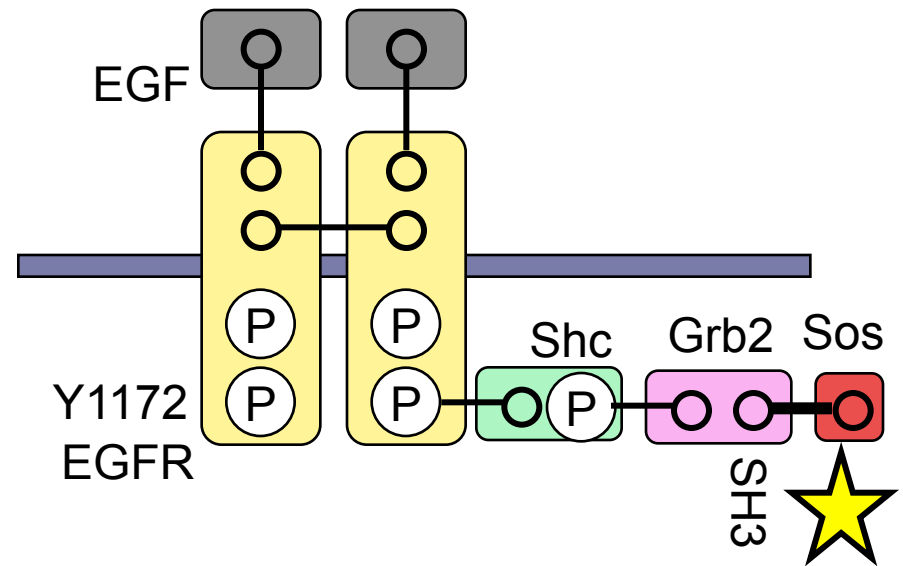
1. EGF binds EGFR
2. EGFR dimerizes
3. EGFR transphosphorylates
4. Shc binds phospho-EGFR
5. EGFR transphosphorylates Shc
6. **Grb2 binds phospho-Shc**



# Early events in EGFR signaling

## Shc pathway

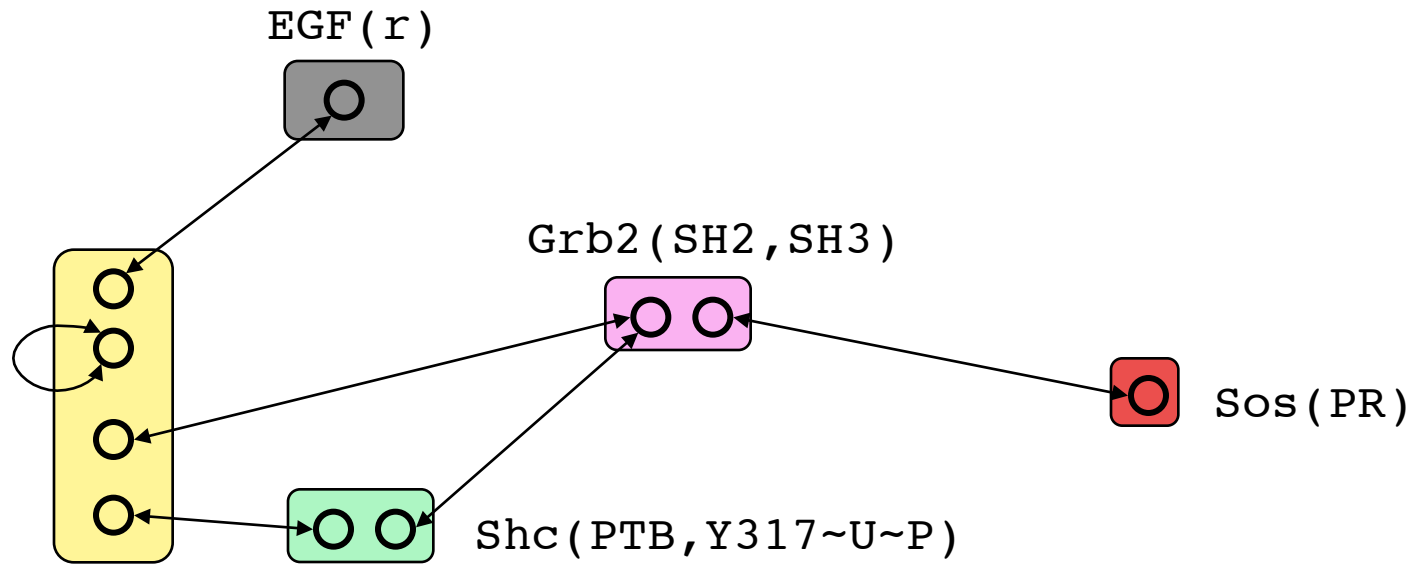
1. EGF binds EGFR
2. EGFR dimerizes
3. EGFR transphosphorylates
4. Shc binds phospho-EGFR
5. EGFR transphosphorylates Shc
6. Grb2 binds phospho-Shc
7. **Sos binds Grb2 (Activation Path 2)**





# Summary of molecules and their interactions in a simple model of early events in EGFR signaling

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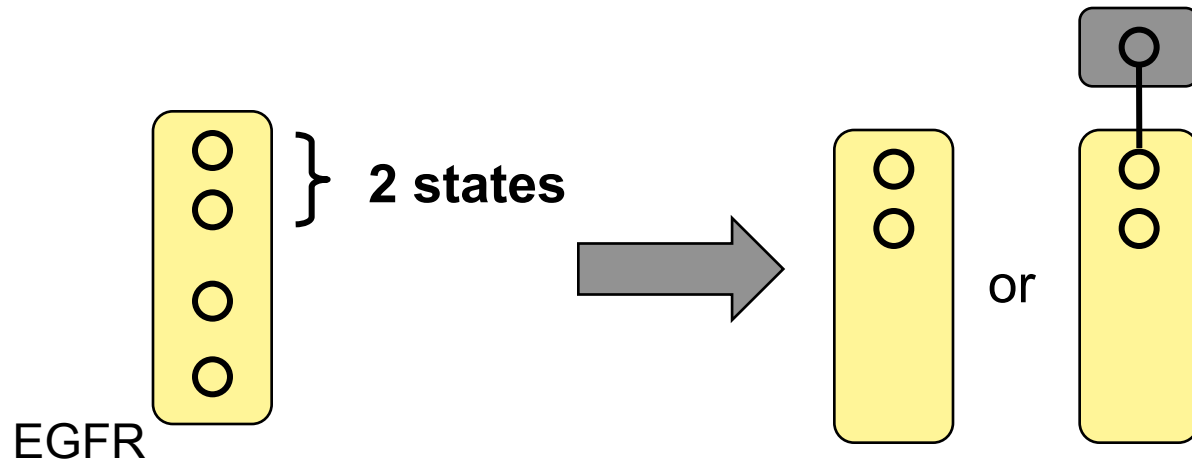
EGFR (l, d, Y1092~U~P, Y1172~U~P)

Blinov et al. (2006)

# Combinatorial complexity of early events

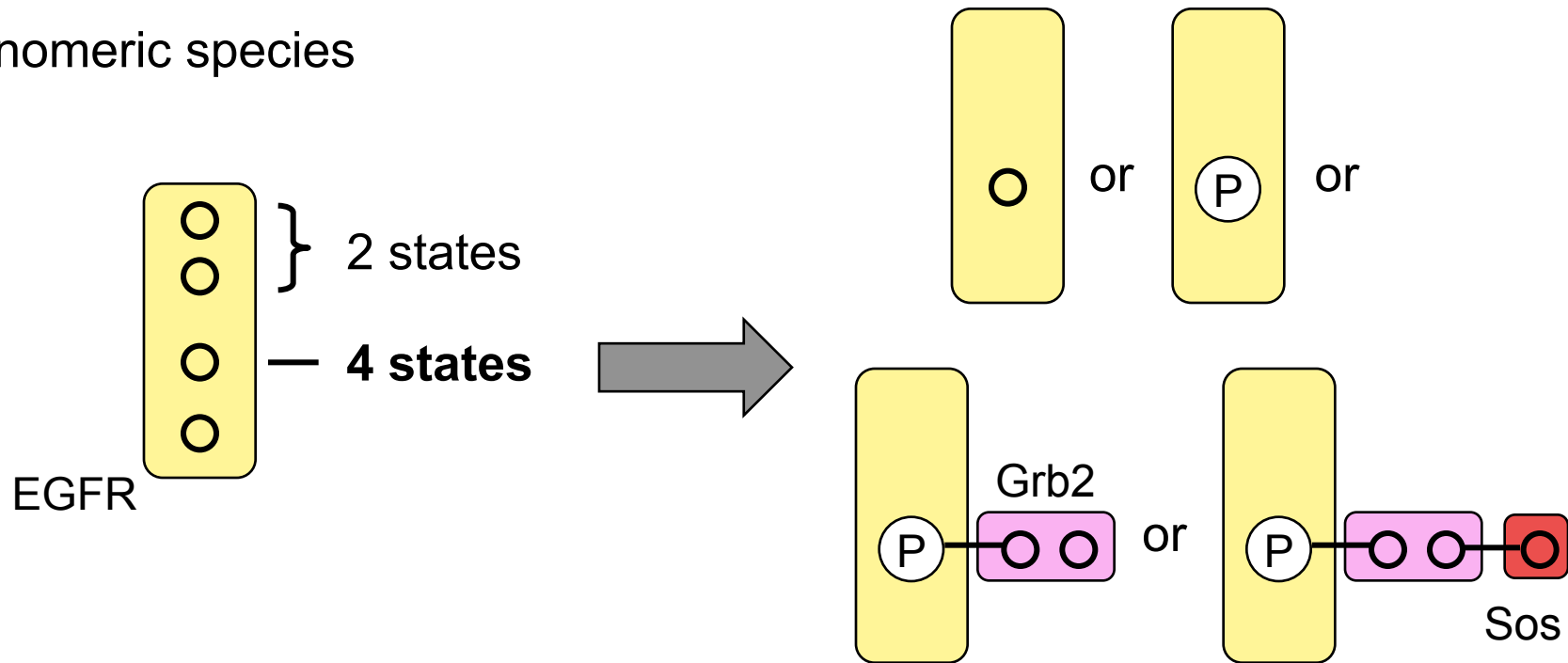
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Monomeric species



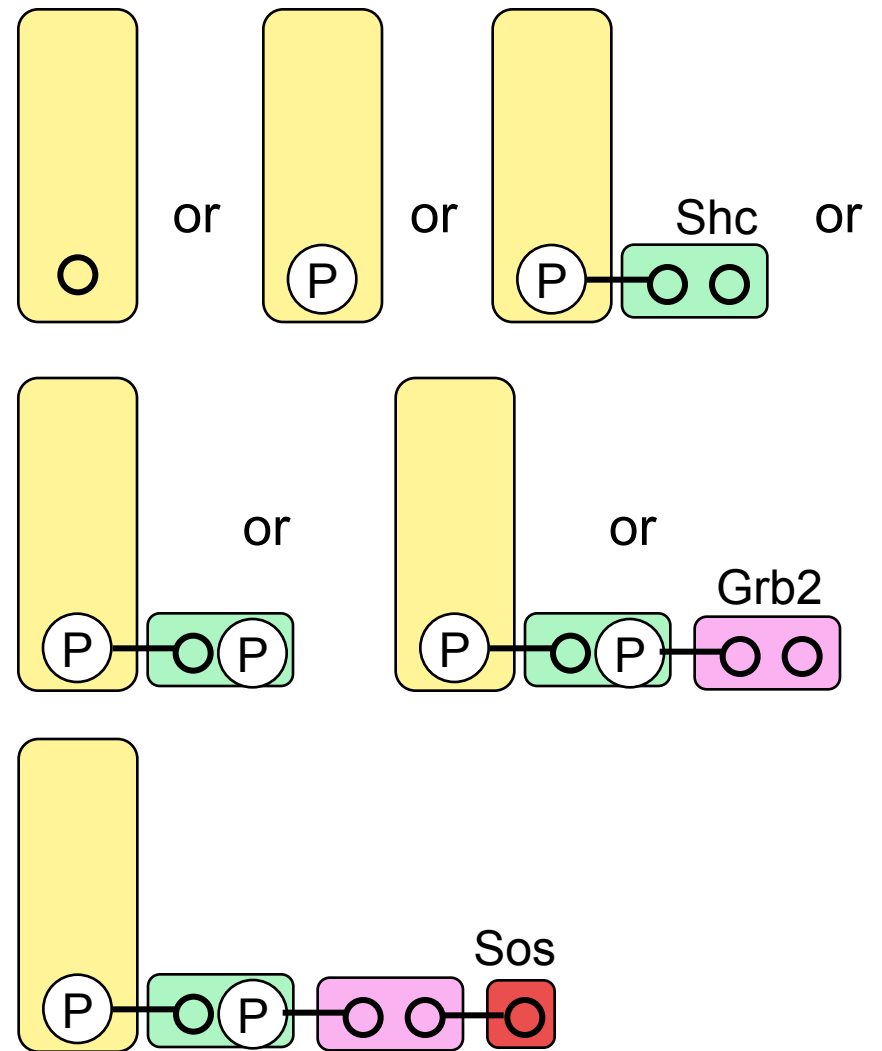
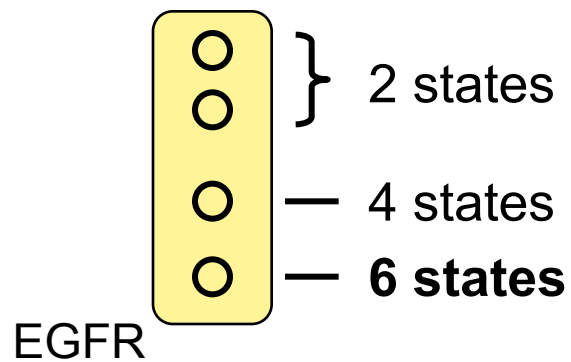
# Combinatorial complexity of early events

Monomeric species



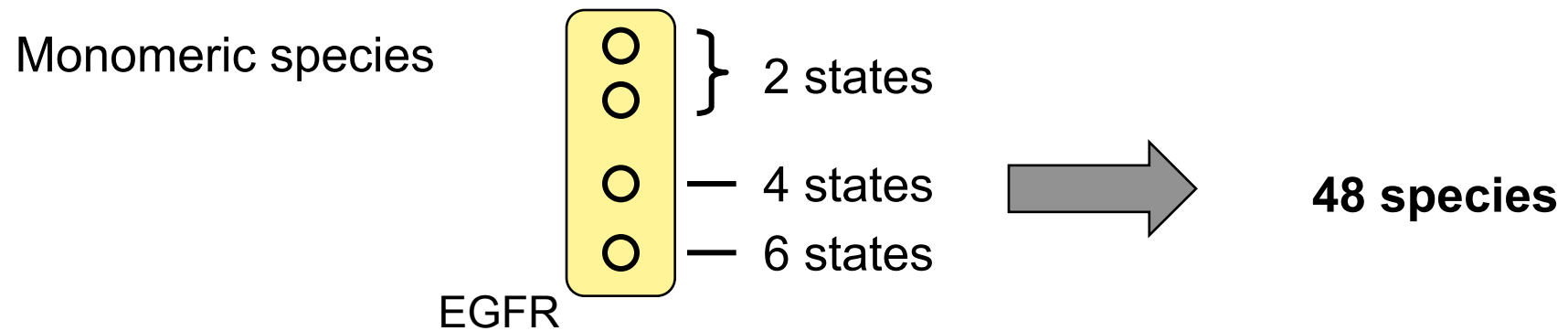
# Combinatorial complexity of early events

Monomeric species

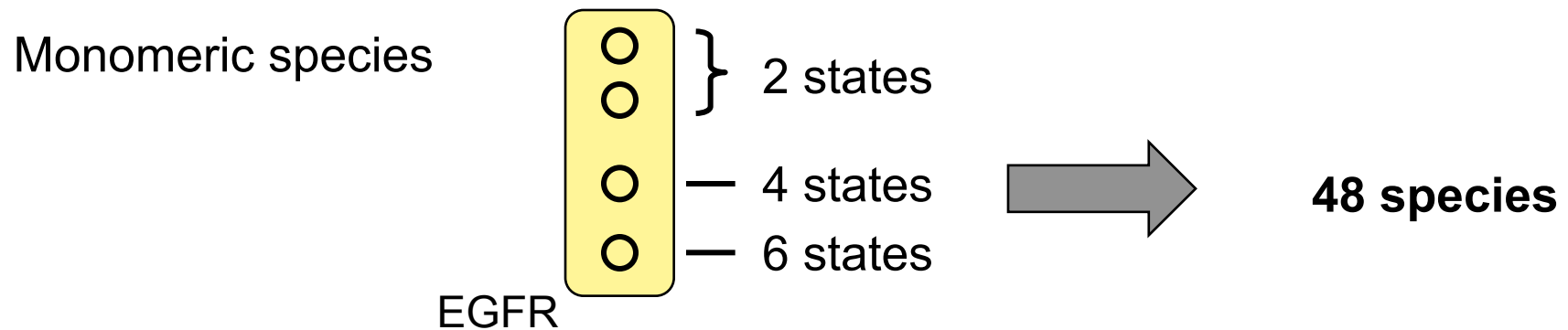


# Combinatorial complexity of early events

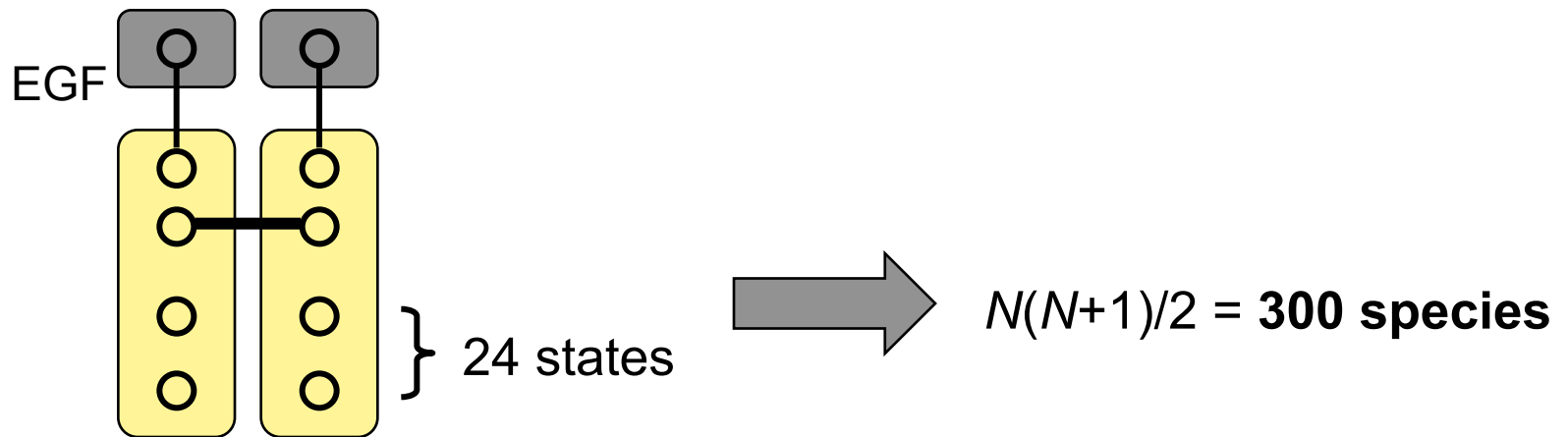
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# Combinatorial complexity of early events



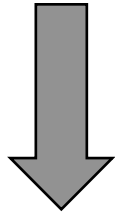
Dimeric species



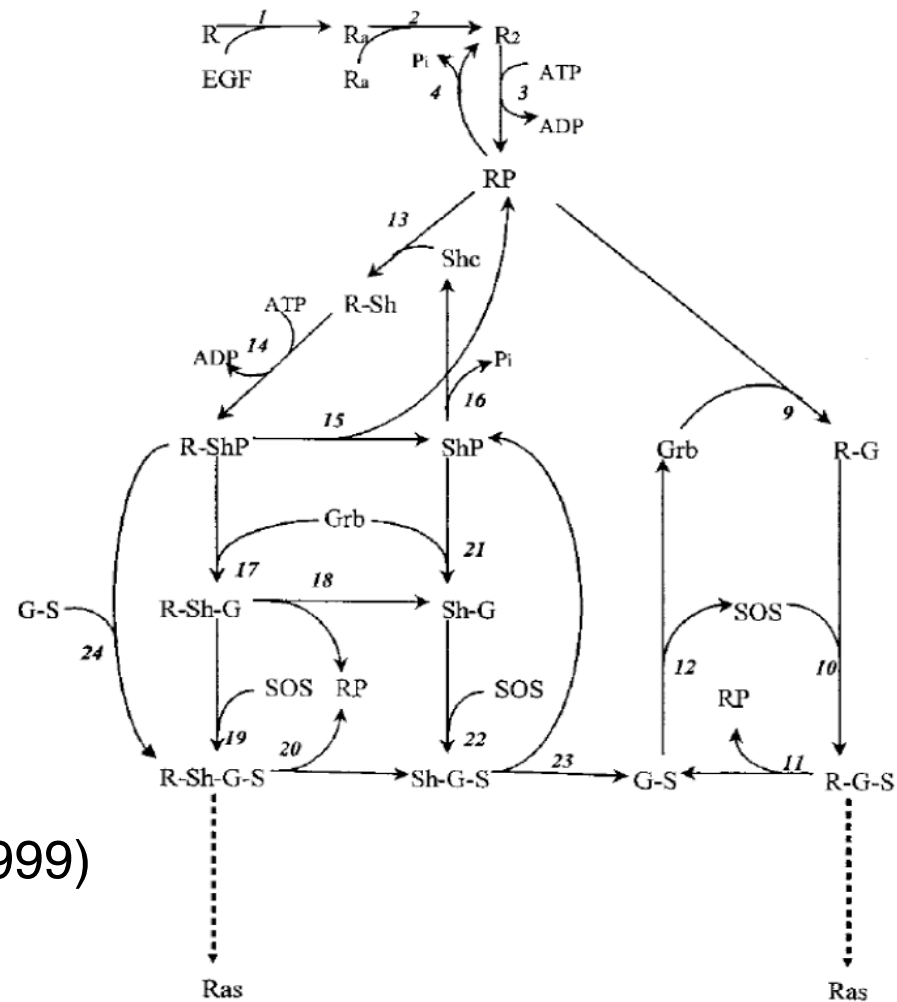
# A conventional model for EGFR signaling

The Kholodenko model\*

5 proteins



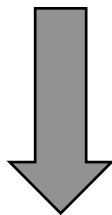
18 species  
34 reactions



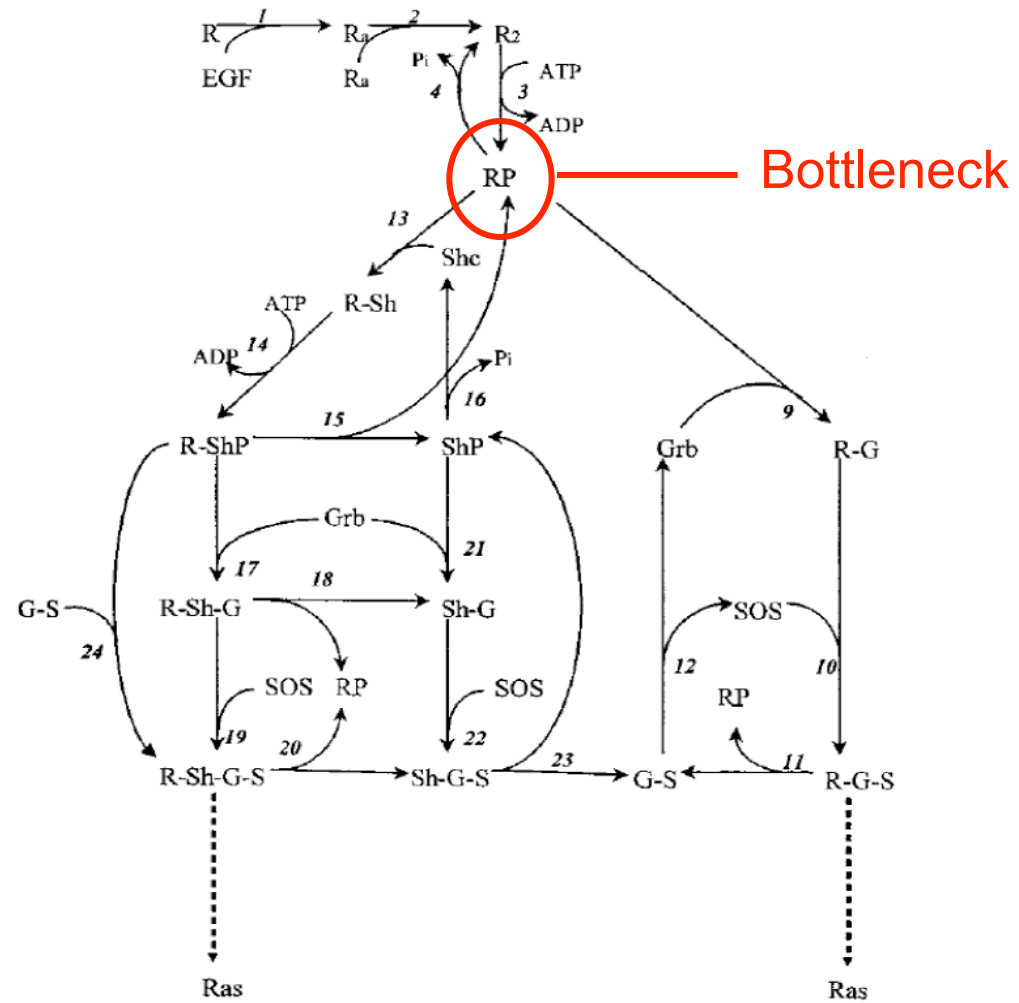
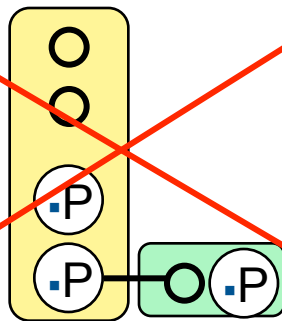
\**J. Biol. Chem.* **274**, 30169 (1999)

# Assumptions made to limit combinatorial complexity

1. Phosphorylation inhibits dimer breakup



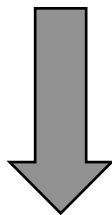
No modified monomers



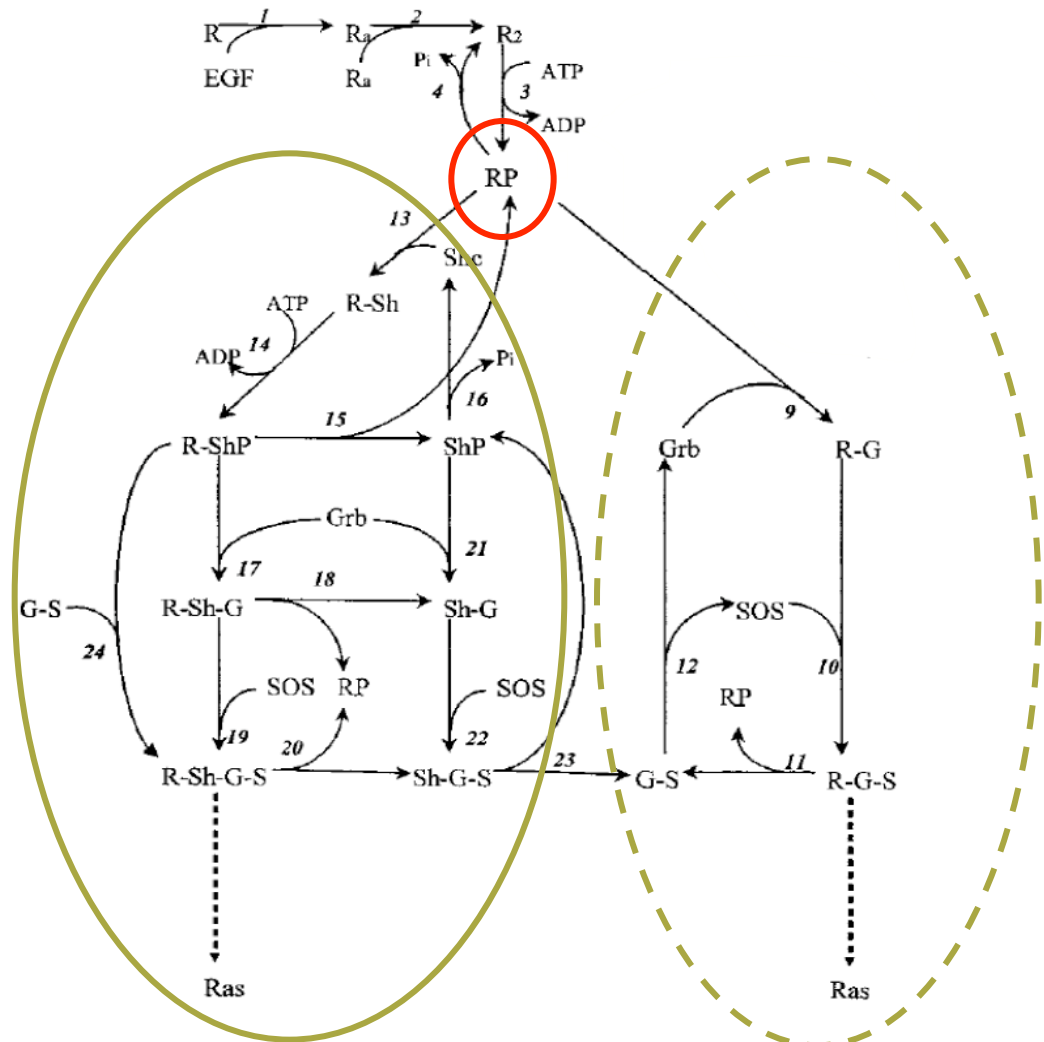
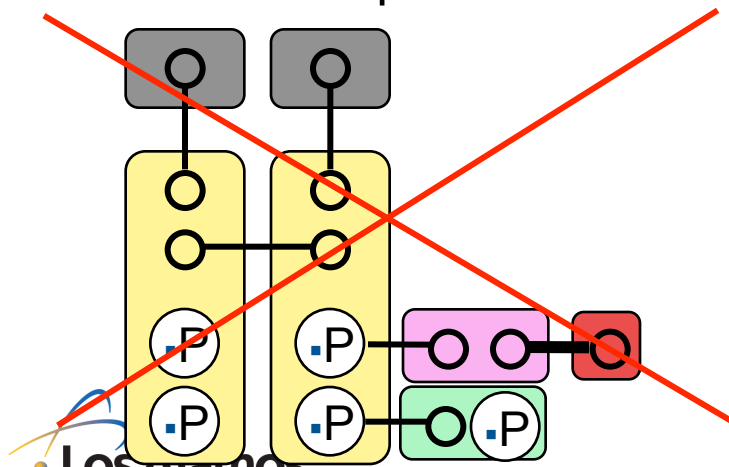


# Assumptions made to limit combinatorial complexity

- Adaptor binding is competitive



No dimers with more than one associated adapter



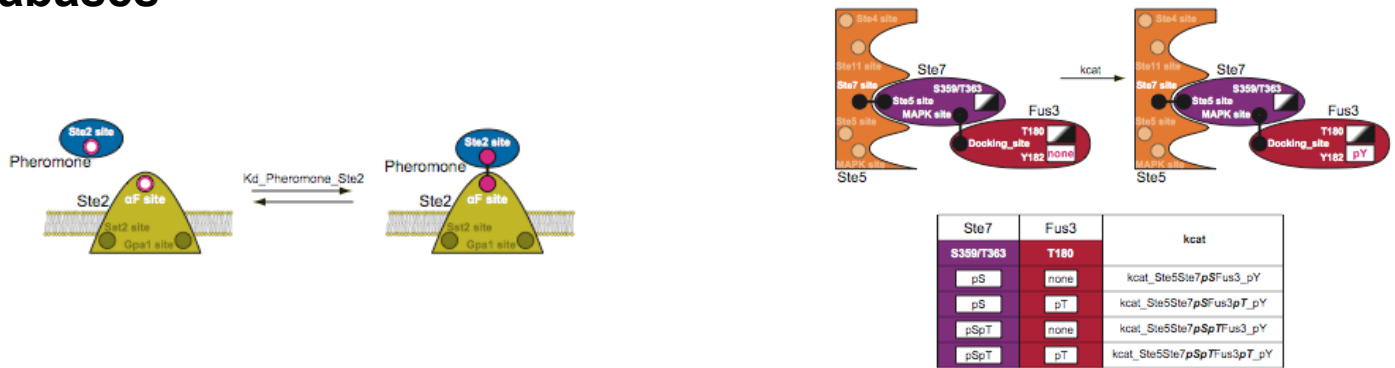
# Reminders

Graphs represent molecules, their component parts, and states

A (graph-rewriting) rule specifies the addition or removal of an edge to represent binding or unbinding, or the change of a state label to represent, for example, post-translational modification of a protein at a particular site

A model specification is readily visualized and compositional

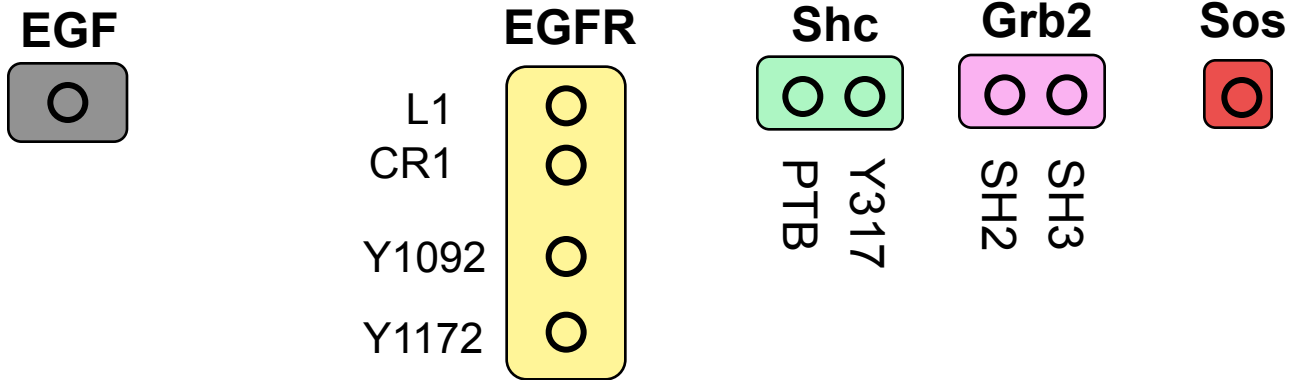
Molecules, components, and states can be directly linked to annotation in databases



# Molecules are modeled as graphs

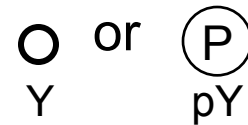
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Molecules



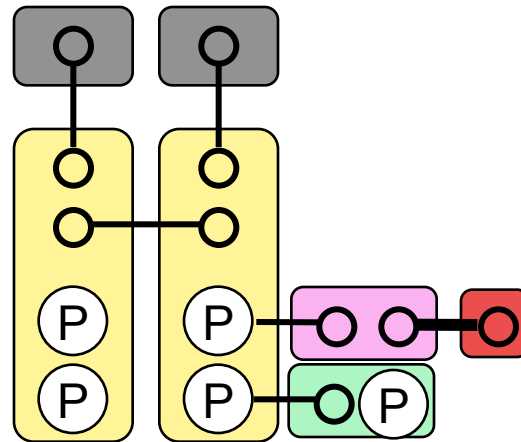
Nodes represent components of proteins

Y components may have labels:



# Molecular complexes are simply connected molecules

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No need to introduce a unique name (e.g.,  $X_{123}$  or ShP-RP-G-Sos) for each chemical species, as in conventional modeling

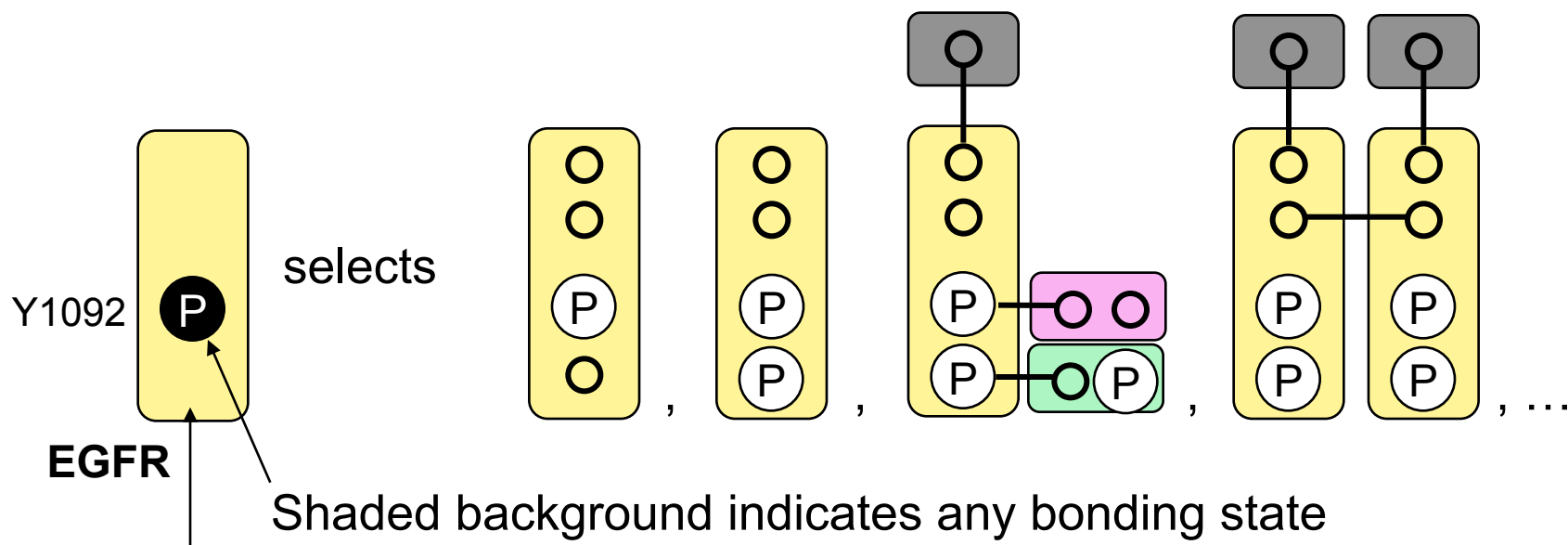
Edges represent bonds between components

Bonds may be intra- or intermolecular

# Patterns (subgraphs) define sets of chemical species with common features

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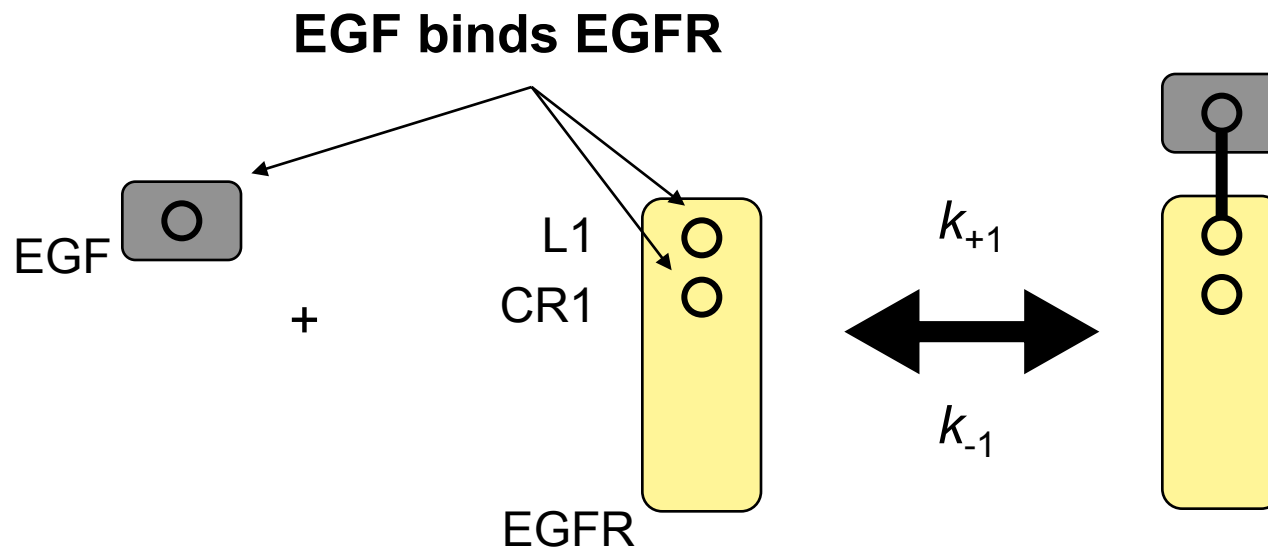
*A pattern that matches EGFR phosphorylated at Y1092*



Suppressed components don't affect match

# A reaction rule, composed of patterns, defines a class of reactions

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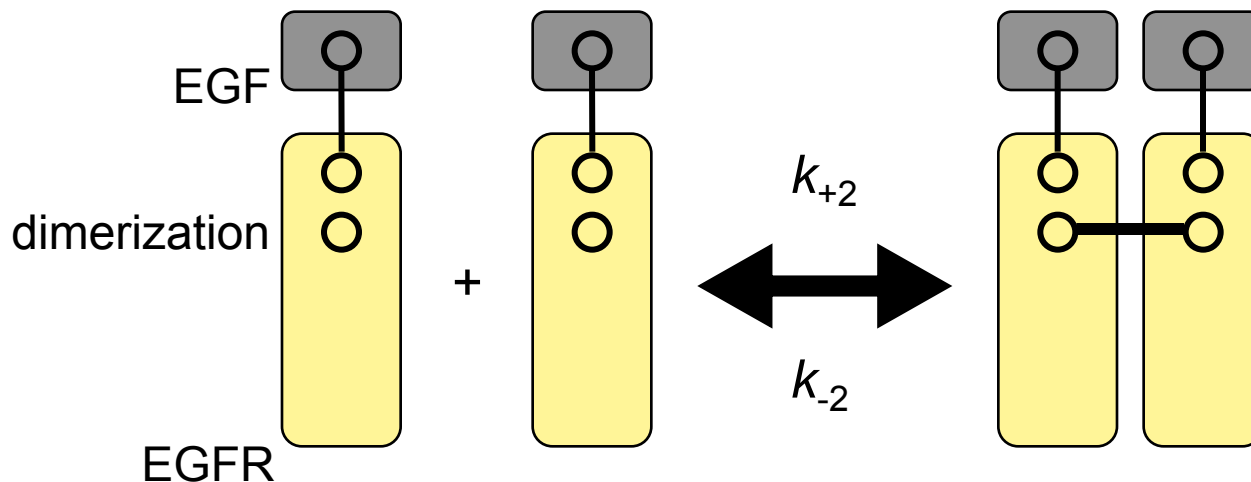


Patterns select reactants (by matching graphs representing chemical species) and specify a transformation of the graphs representing reactants - **Addition of bond between EGF and EGFR in this case**

## Dimerization rule eliminates previous assumption restricting breakup of receptors

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EGFR dimerizes (600 reactions are implied by this one rule)



**No free lunch:** According to this rule, dimers form and break up with the same fundamental rate constants regardless of the states of cytoplasmic domains, which is an idealization.

# Rule-based version of the Kholodenko model

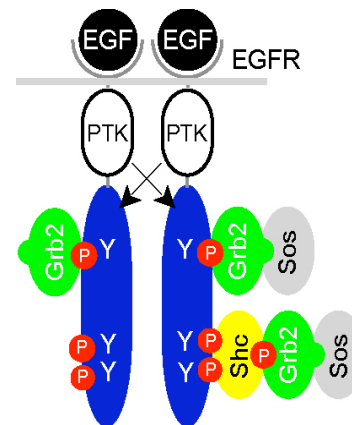
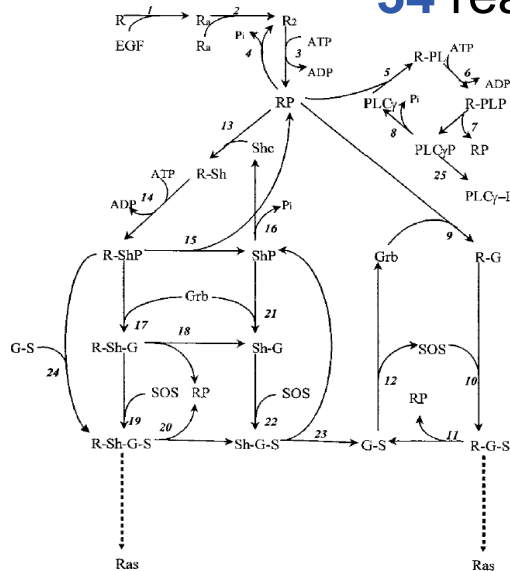
- 5 molecule types
- 23 reaction rules
- No new rate parameters! – Q: How? A: a rule provides a coarse-grained description of the reactions implied by the rule. All these reactions are parameterized by the same fundamental rate constant(s).

18 species

356 species

3749 reactions

34 reactions



Blinov et al. *Biosystems* **83**, 136 (2006).

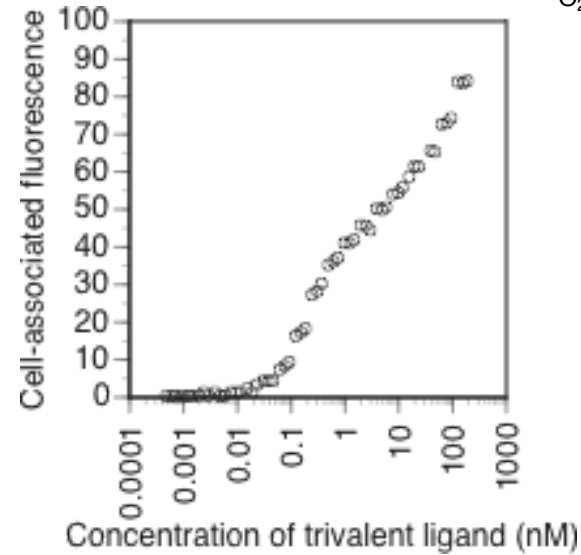
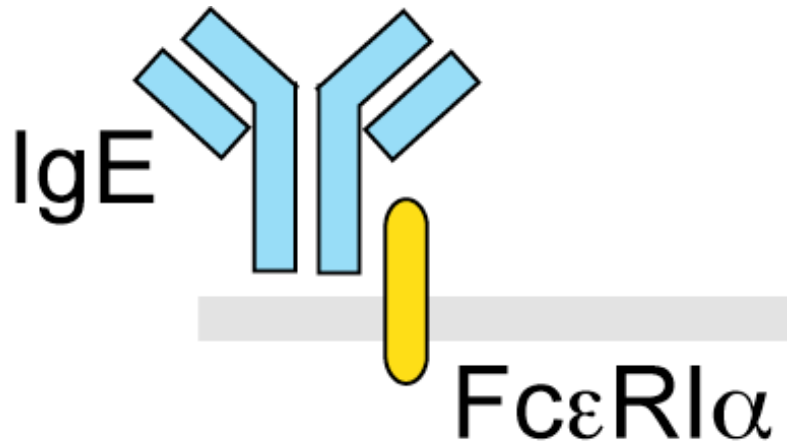
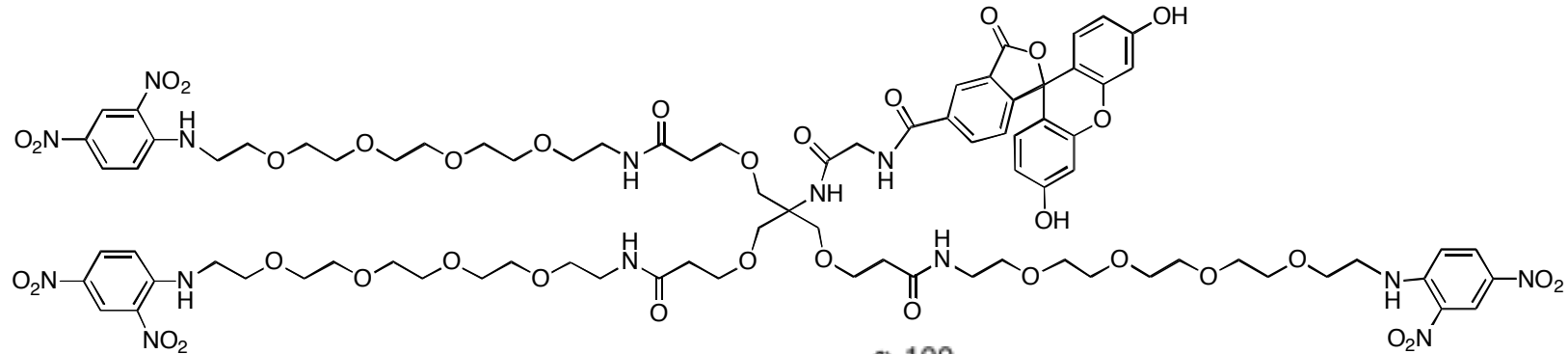


# Outline

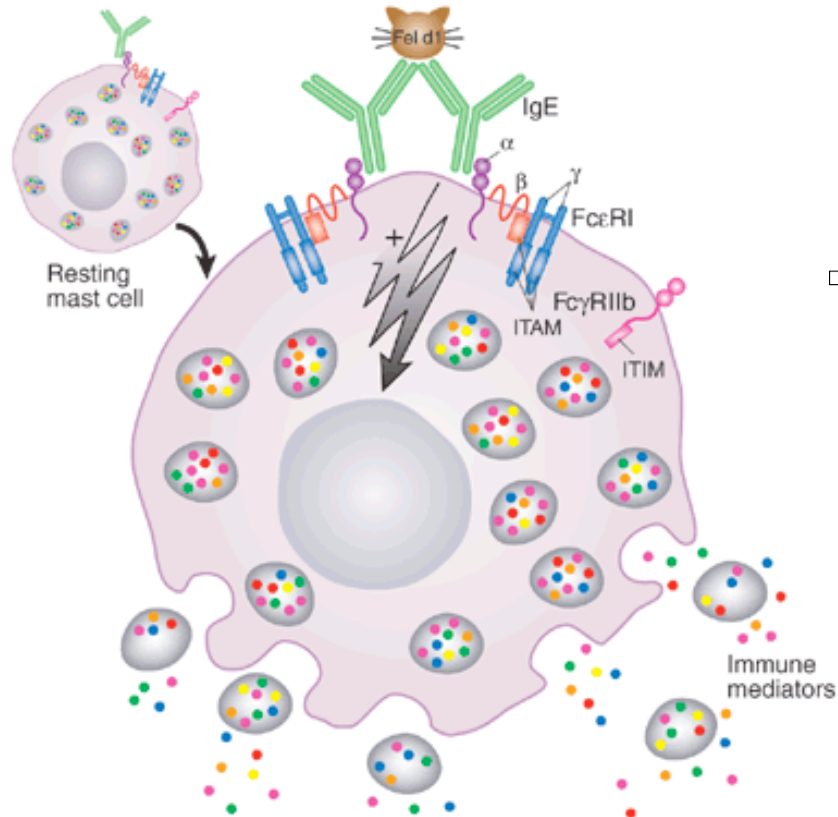
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1. The motivation for rule-based modeling
2. Basic concepts of rule-based modeling
3. An example model specification
4. **Methods for simulating a model**
5. Suggested exercise

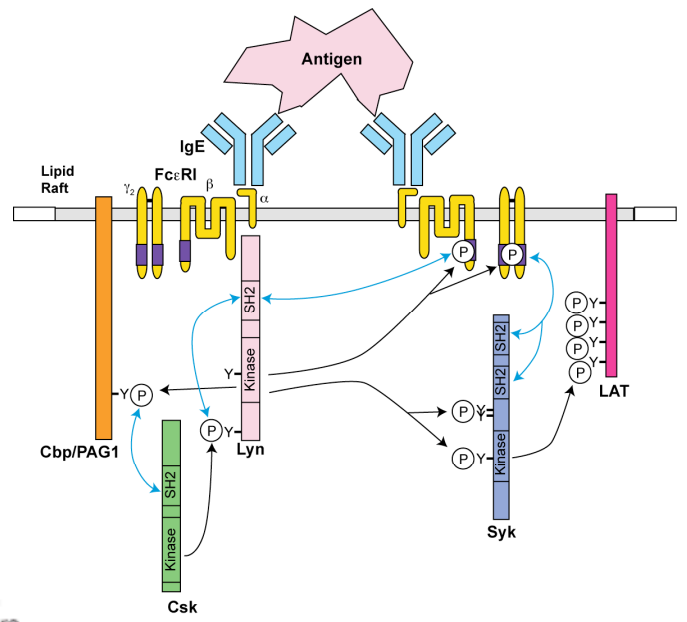
# Consider interaction of a trivalent ligand with a bivalent cell-surface receptor



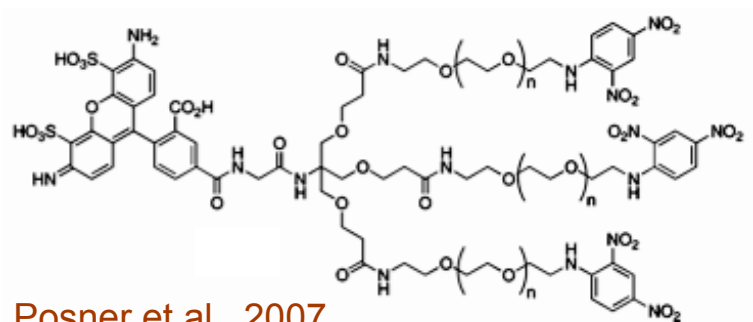
# Signaling by FcεRI begins with ligand-induced receptor clustering



Fc $\epsilon$ RI-dependent mast cell activation:  
 Degranulation (release of histamine, etc.)  
 Cytokine/chemokine release (TNF- $\alpha$ , IL-6, IL-8, etc.)  
 Arachidonic acid metabolite release (LTC $_4$ , PGD $_2$ , etc.)  
 ↓  
 Anaphylaxis, allergy (atopic asthma), etc.

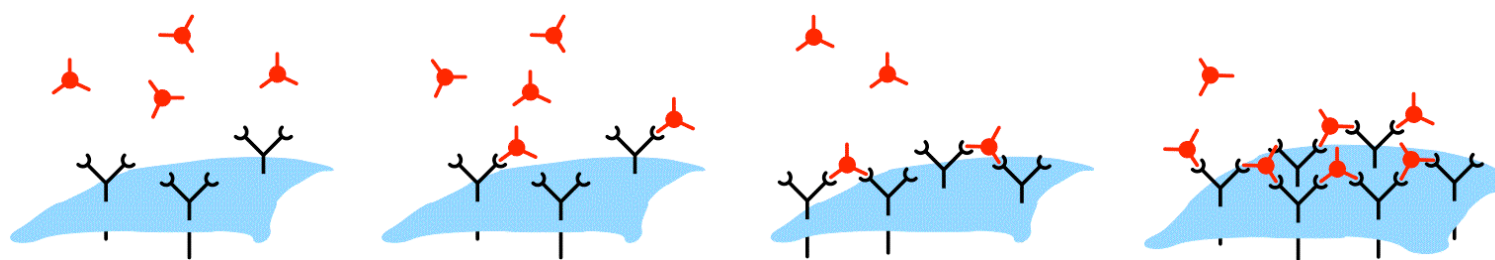
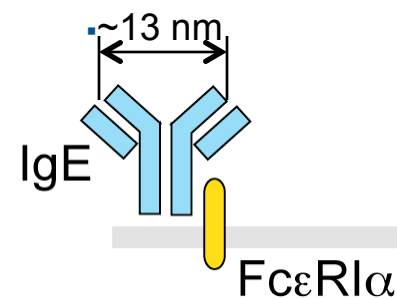


# Trivalent ligands



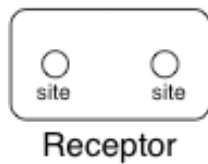
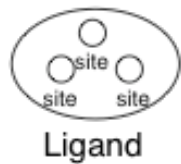
Posner et al., 2007,  
*Org. Lett.*, **9**:3551

• Compound 6a

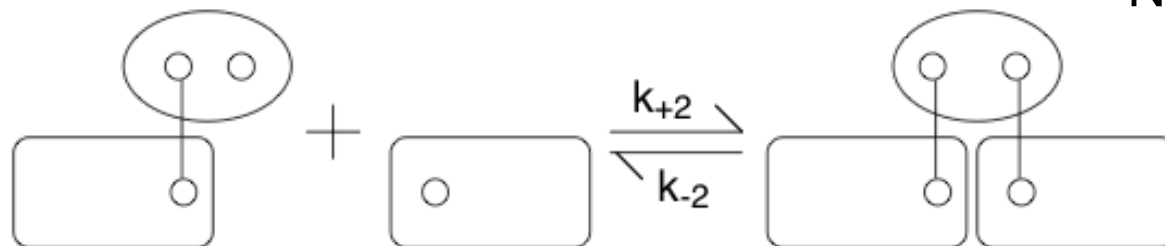
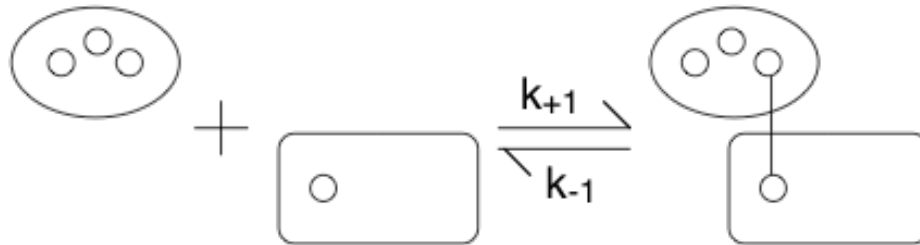


# Rule-based model specification corresponding to equilibrium model of Goldstein and Perelson (1984)

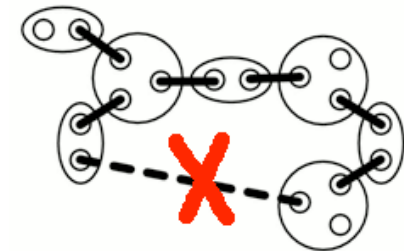
## Molecules      Equivalent-site TLBR model



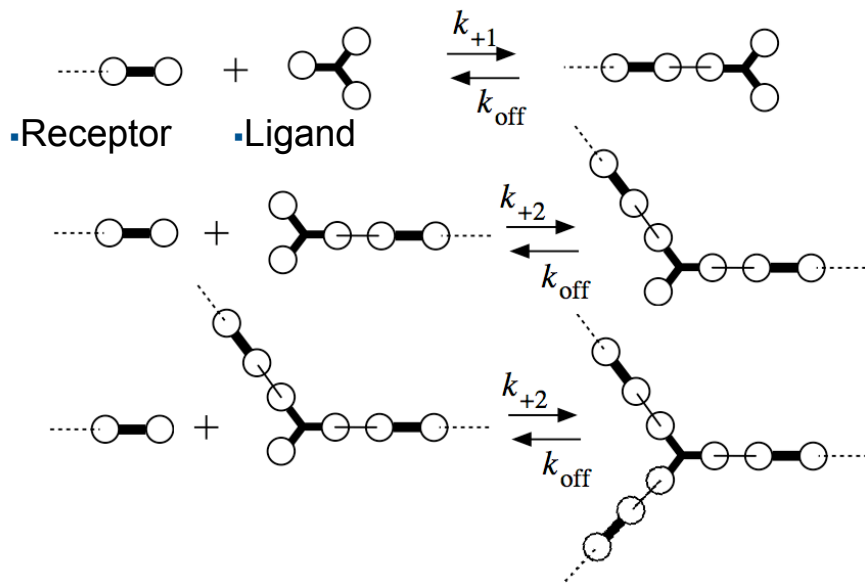
### Interactions (reaction rules)



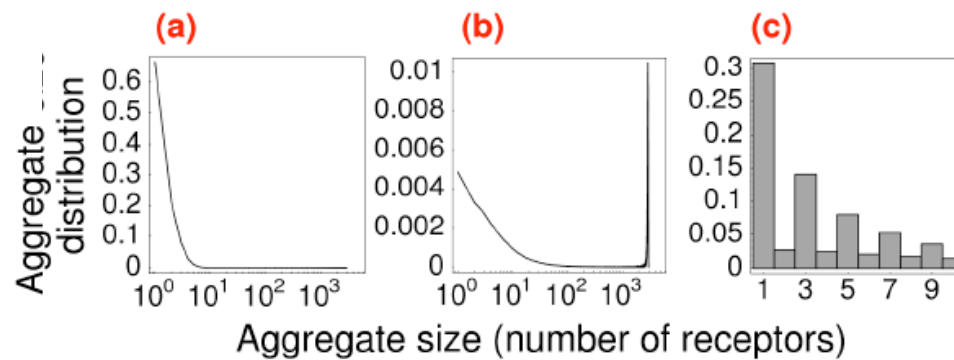
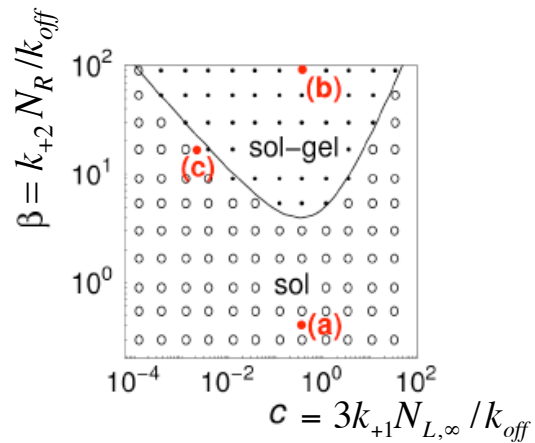
No cyclic aggregates



# Goldstein-Perelson and TLBR models



- Equilibrium properties:



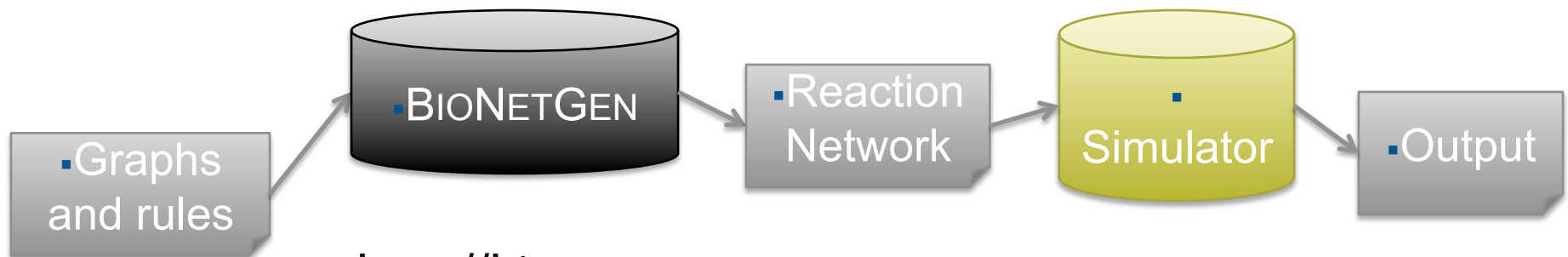
- Goldstein and Perelson (1984) *Biophys. J.*, 45:1109
- Yang et al. (2008) *Phys. Rev. E*, 78:31910

## Protocol for “generate-first” simulation

1. Define molecules as *graphs* and interactions as *graph-rewriting rules*.

2. Specify concentrations and rate constants

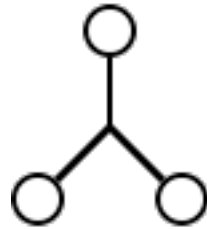
3. Generate the implied reaction network and then simulate the network dynamics using conventional methods



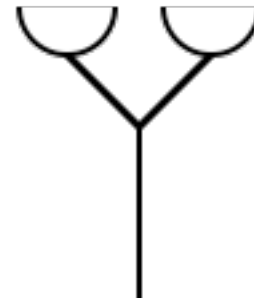
• <http://bionetgen.org>

## “Generate-first” method starts with seed species

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Ligand

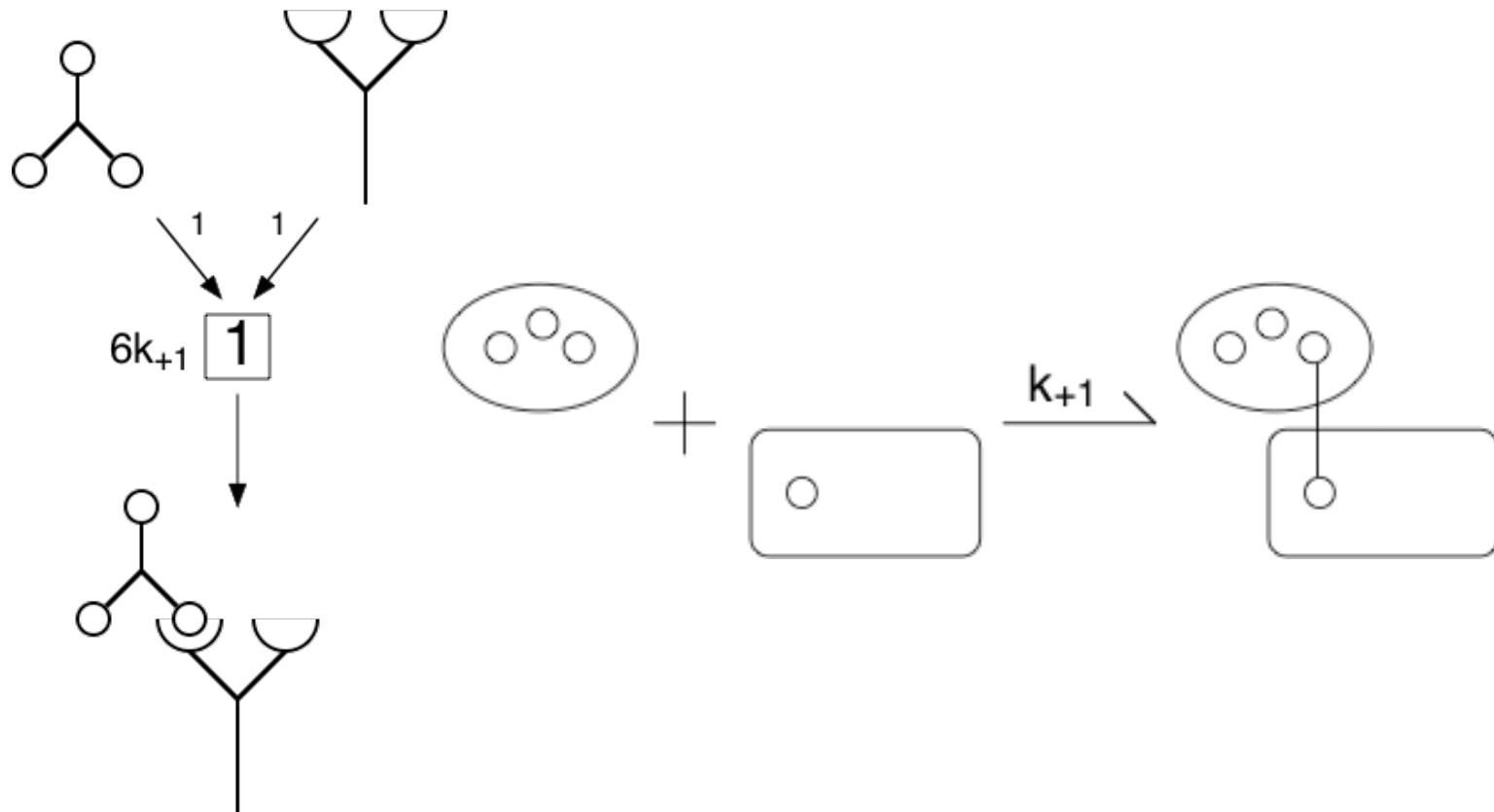


Receptor

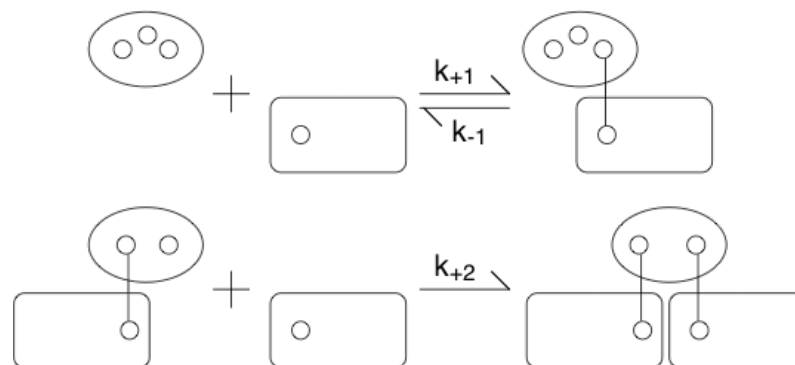
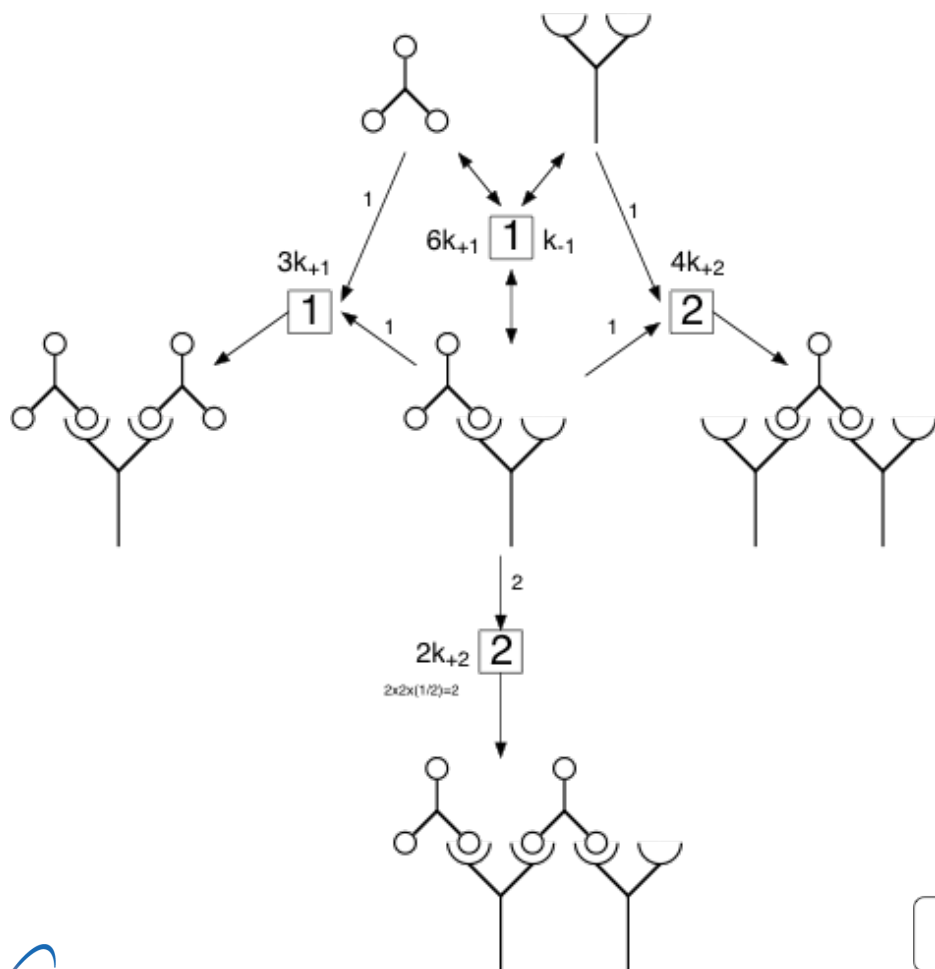


## After first round of rule application

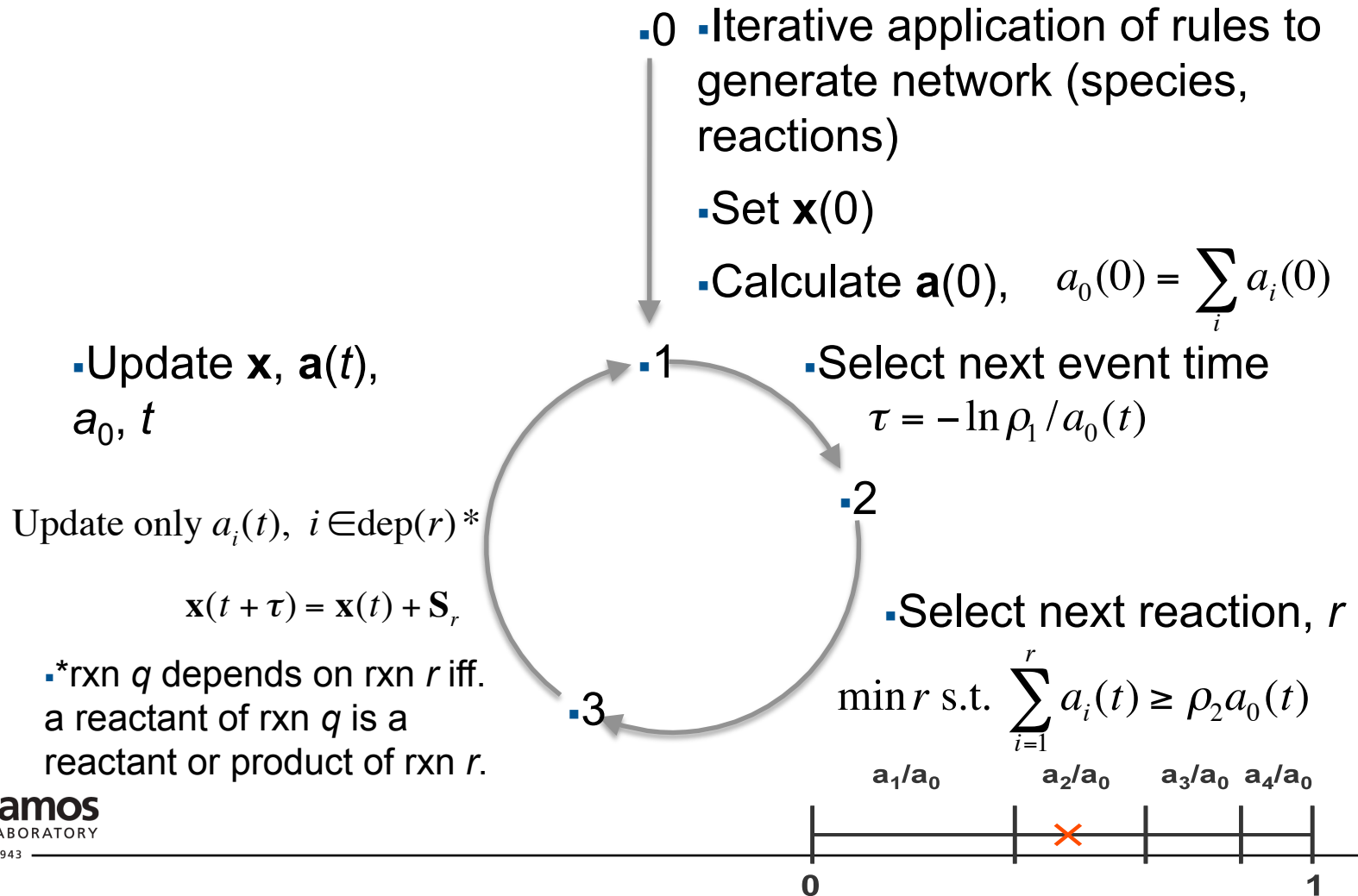
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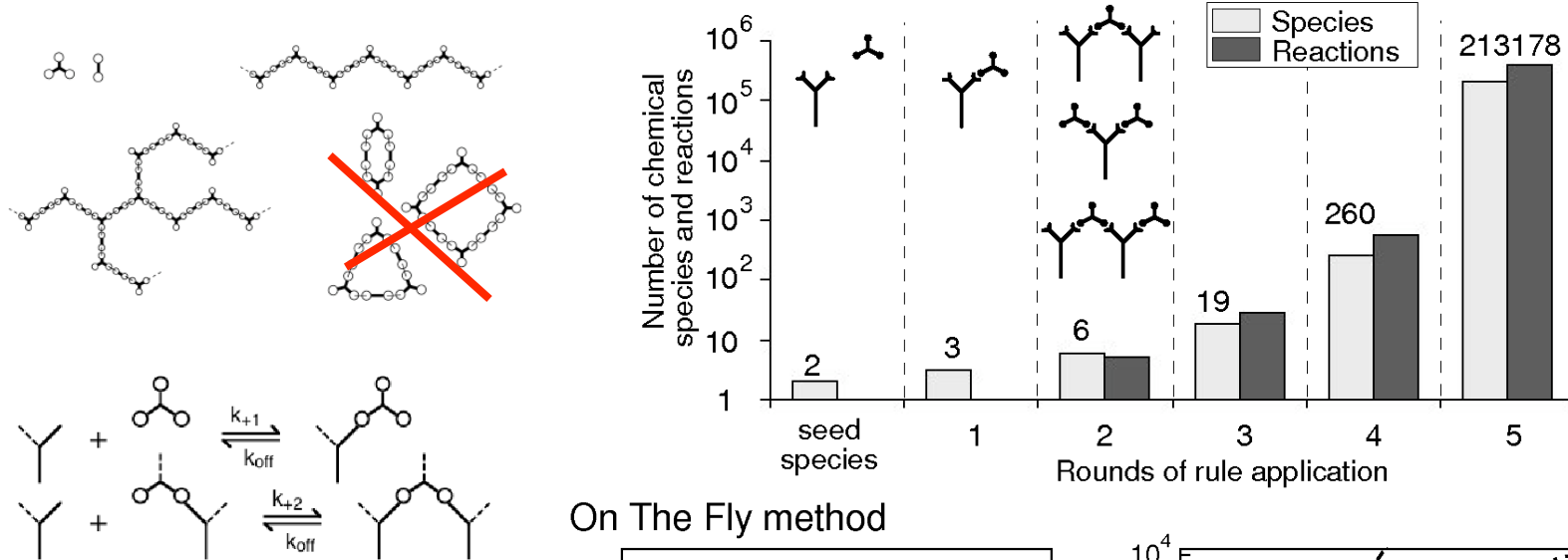
## After the second round of rule application



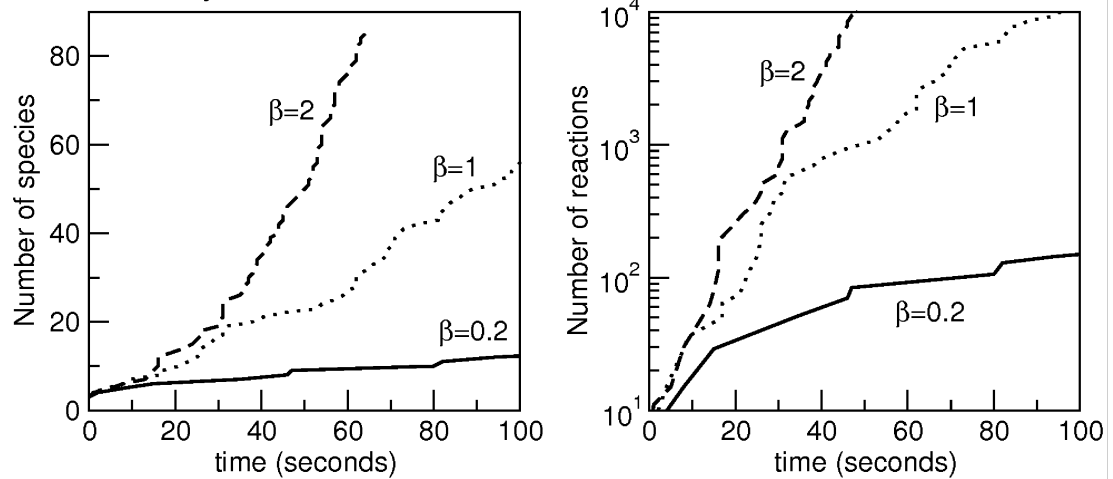
# Gillespie method: generate-first or on-the-fly simulation



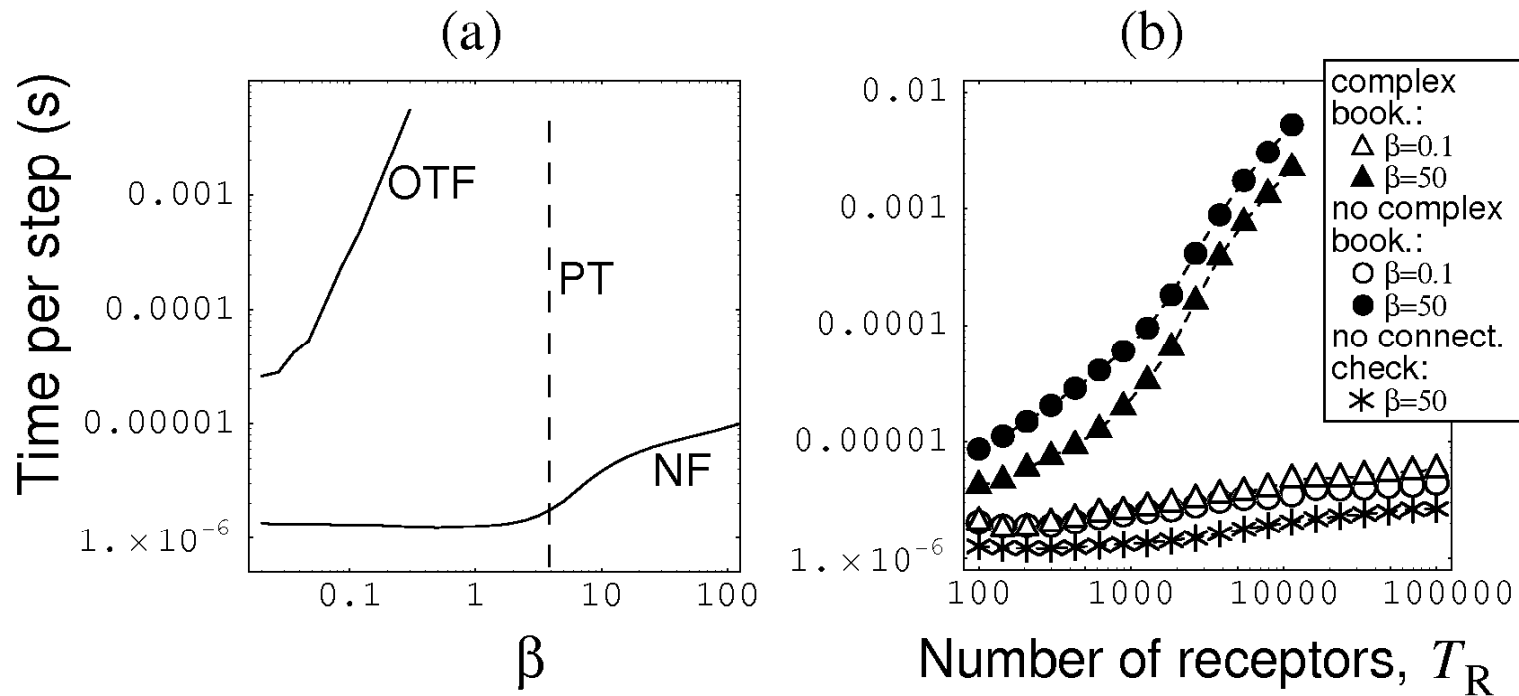
# Rule-derived network can be too large to simulate using conventional population-based methods



On The Fly method



# Performance of on-the-fly (OTF) simulation method

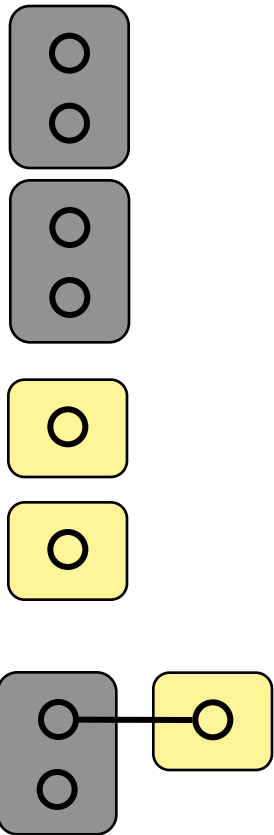


Yang et al. (2008) Phys. Rev. E

# Network-free simulation

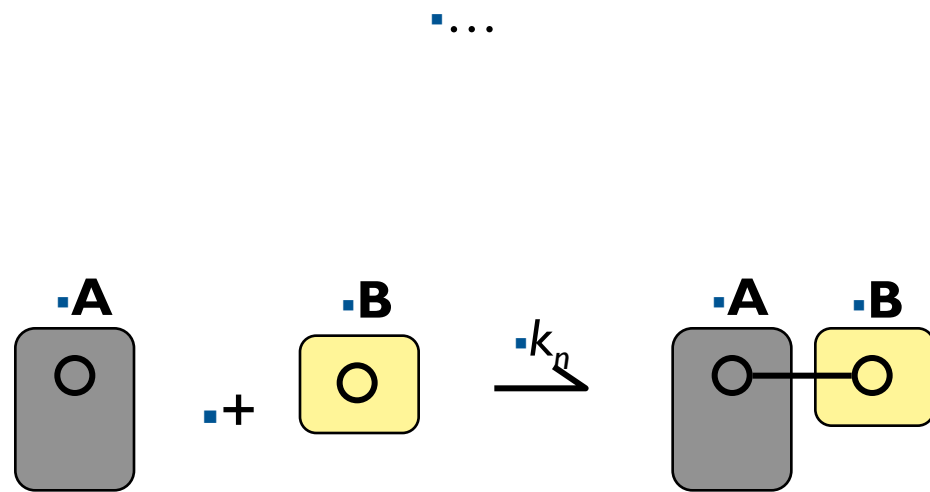
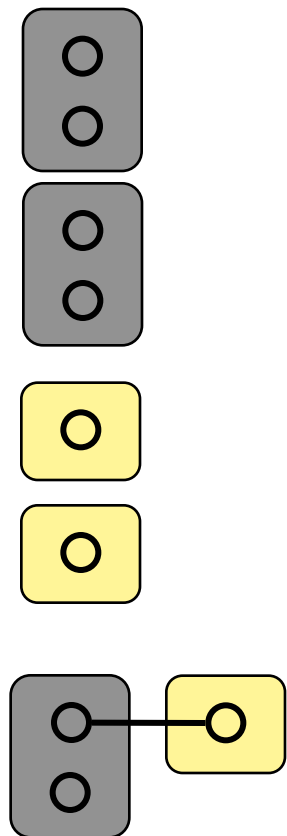
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## Agents/particles in simulation “box”



# Network-free simulation

- Agents/particles
- Rules are event generators



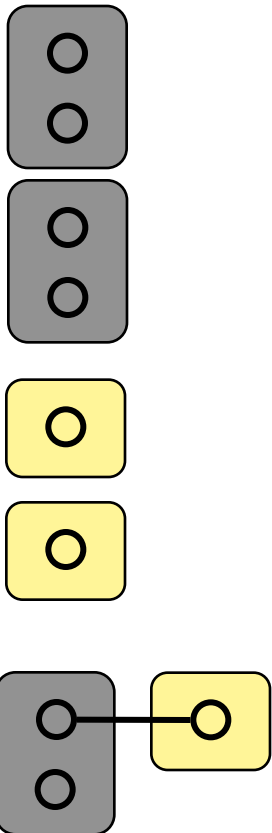
▪Rule  $n$

▪Cumulative rate =  $a_n = k_n [A][B]$

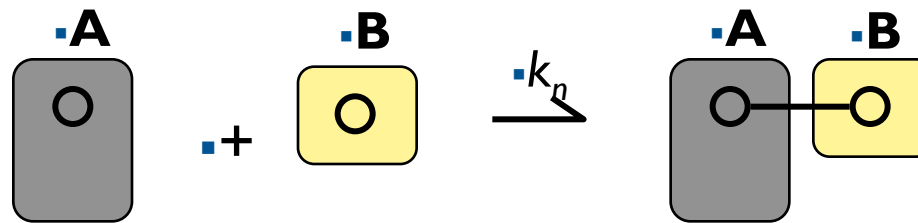
...

# Network-free simulation

## Agents/particles



▪ Event  $n$  is chosen to fire using Gillespie algorithm



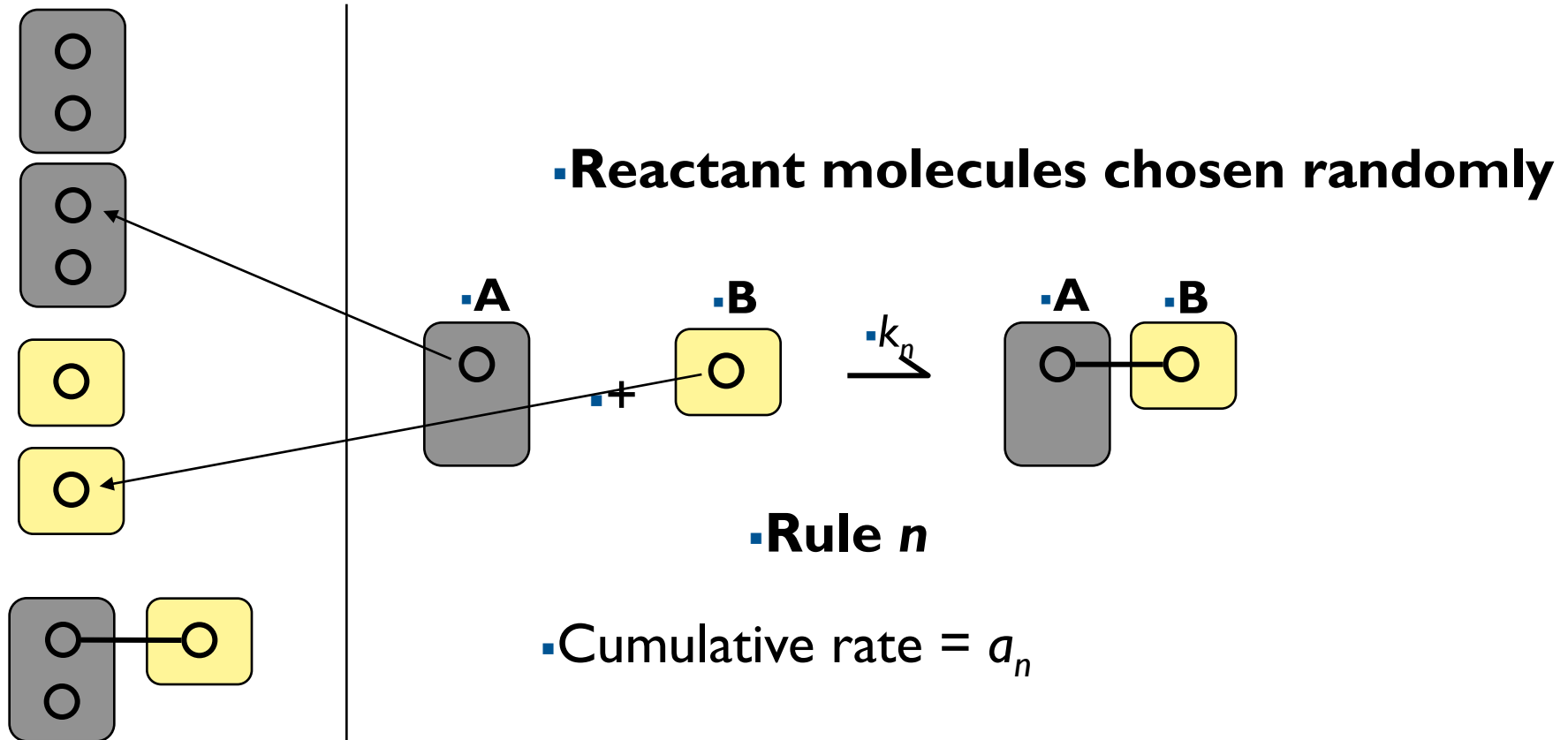
▪ Rule  $n$

▪ Cumulative rate =  $a_n$



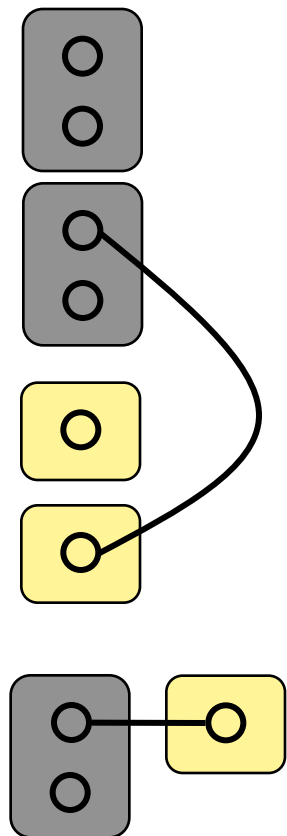
# Network-free simulation

## Agents/particles

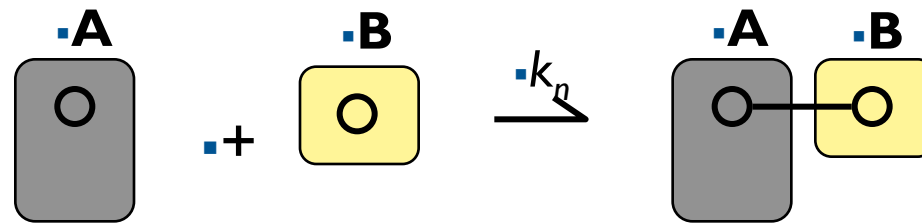


# Network-free simulation

## Agents/particles



Rule transformation is applied



Rule  $n$

Cumulative rate =  $a_n$

# Kinetic Monte Carlo method for “network-free” simulation of rule-based models

1. Instantiate molecules with components and states.
2. Determine cumulative rate for each  $m$ th reaction type,

$$r_m = k_m \prod_n^{n_m} N_n$$

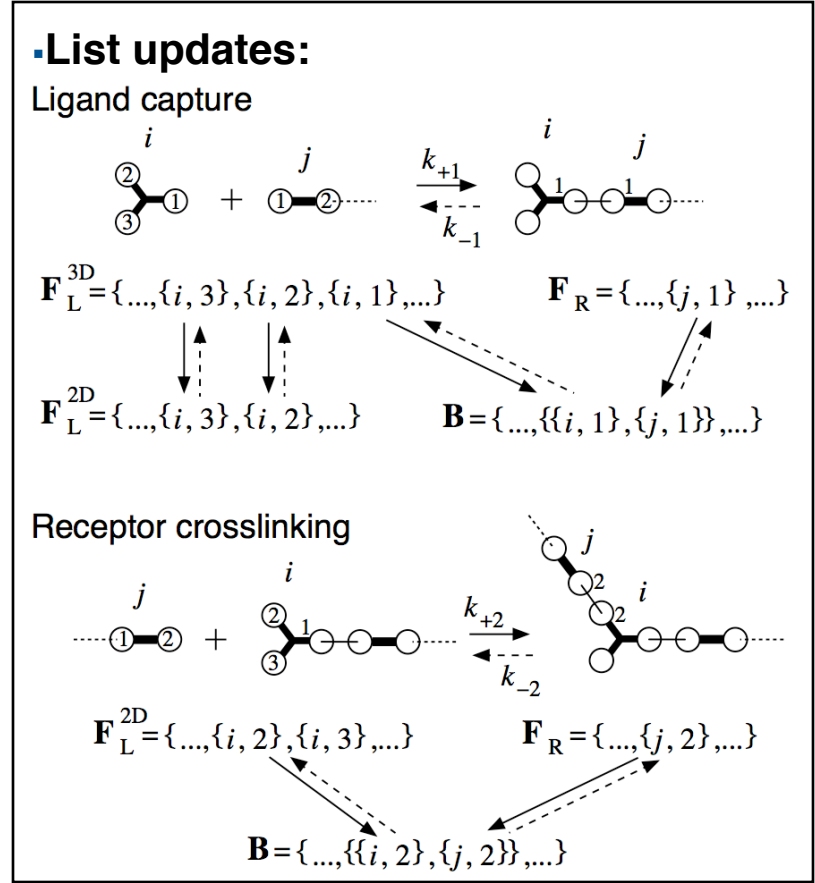
3. Select next reaction time,

$$\Delta t = -\ln(z_1) / r_{tot}$$

4. Select next reaction type using the following condition:

$$\sum_{j=1}^{J-1} r_j < z_2 r_{tot} \leq \sum_{j=1}^J r_j$$

5. Select reactant molecules and **check context**.
6. **Update lists**. Iterate.



Yang et al. (2008) *Phys. Rev. E*, 78:031910

# Conclusions

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- Mechanistic models of cell signaling systems can be formulated via the rule-based modeling approach, simulated and used, for example, to provide a mechanistic interpretation of temporal phosphoproteomic data (not shown)
- Comprehensive models of cell signaling systems (on the way) should serve as launching pads for investigating a wide array of issues related to development of predictive models for cell signaling systems
  - What is required for model validation?
  - What are the best strategies for certification (e.g., model-guided experimental design)?
  - Can we quantify and track how consistent a model is with available knowledge?

# Outline

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