



# Probabilistic Approximations of Bio-Pathways Dynamics

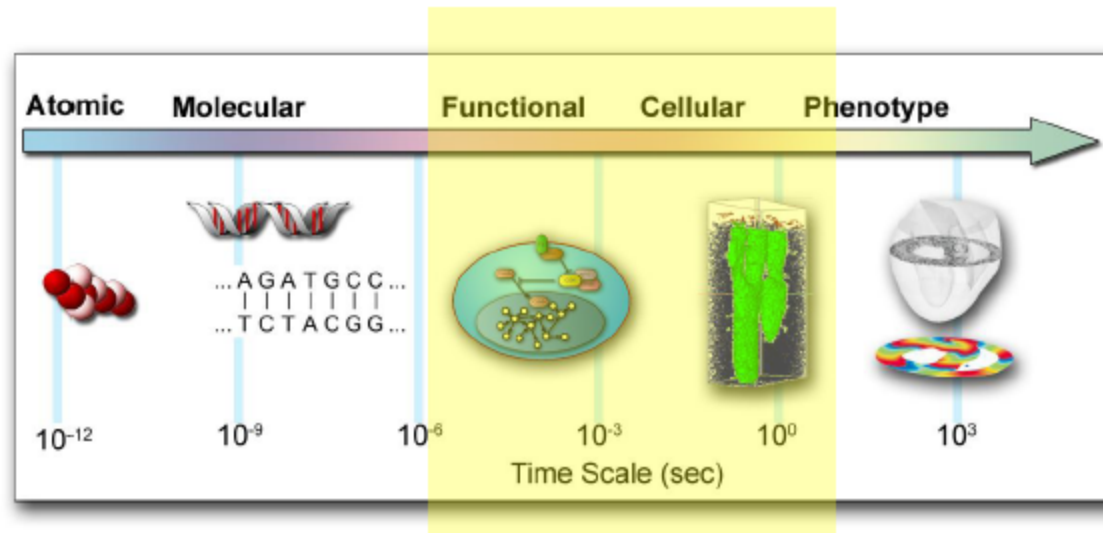
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**School of Computing, National University of Singapore**

**Joint Work with: Liu Bing, David Hsu**

# Granularities

- Several levels of complexity in biological systems



- Our research focuses on the:
  - Intra- **Cellular level**
  - **Bio-pathways**



# A Common Modeling Approach

- Bio-pathway: A network of bio-chemical reactions
- A system (network) of ODEs
  - One for each molecular species
  - Mass action, Michelis-Menten, Hill, etc.
- Study the ODE system to understand the dynamics of the bio-chemical network

# Our work: The main features

- ***ODE systems to describe the dynamics of the bio-chemical networks***
- Decompose → Compute → Compose (ISMB'06, WABI'07)
- Probabilistic models and methods to:
  - update models (RECOMB'10)
  - ***approximate the ODE dynamics***(CMSB'09, TCS'11).

# An Example

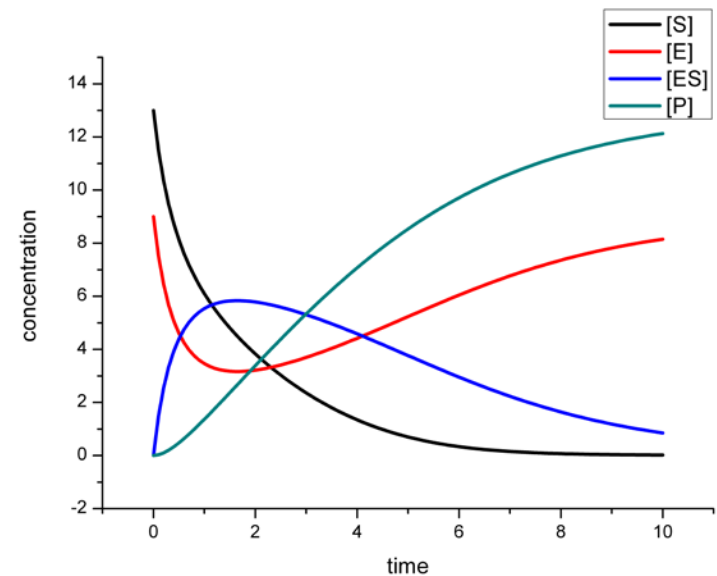


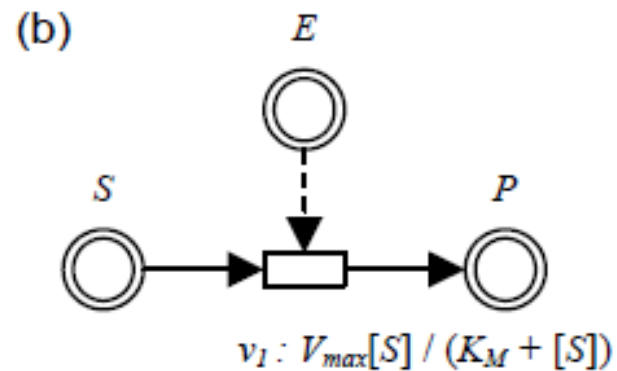
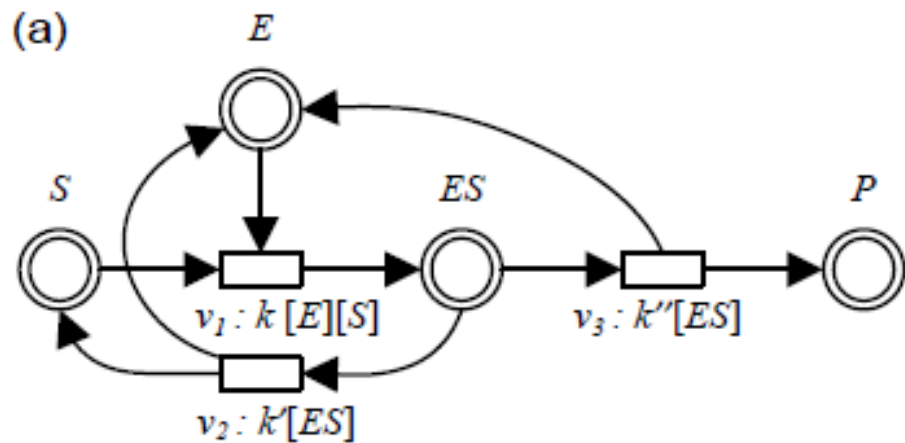
$$\frac{d[S]}{dt} = -k_1[S][E] + k_{-1}[ES]$$

$$\frac{d[ES]}{dt} = k_1[S][E] - (k_{-1} + k_2)[ES]$$

$$\frac{d[E]}{dt} = -k_1[S][E] + (k_{-1} + k_2)[ES]$$

$$\frac{d[P]}{dt} = k_2[ES]$$





# Many Hurdles

- Many rate constants not known
  - must be estimated
  - noisy data; limited precision; population-based
- High dimensional system
  - closed-form solutions are impossible
  - Must resort to numerical simulations
  - *A set (Interval of values) of initial states must be dealt with;*
  - ***a large number of numerical simulations needed for answering each question***

# The “Opinion Poll” Idea

- Discretize the time and value domains.
- Assume a (uniform) distribution of initial states
- Generate a “sufficiently” large number of “typical” trajectories by
  - sampling the initial state and numerical simulations.
- ***Synthesize from this collection of trajectories a dynamic Bayesian network.***
  - **ODEs → DBN**





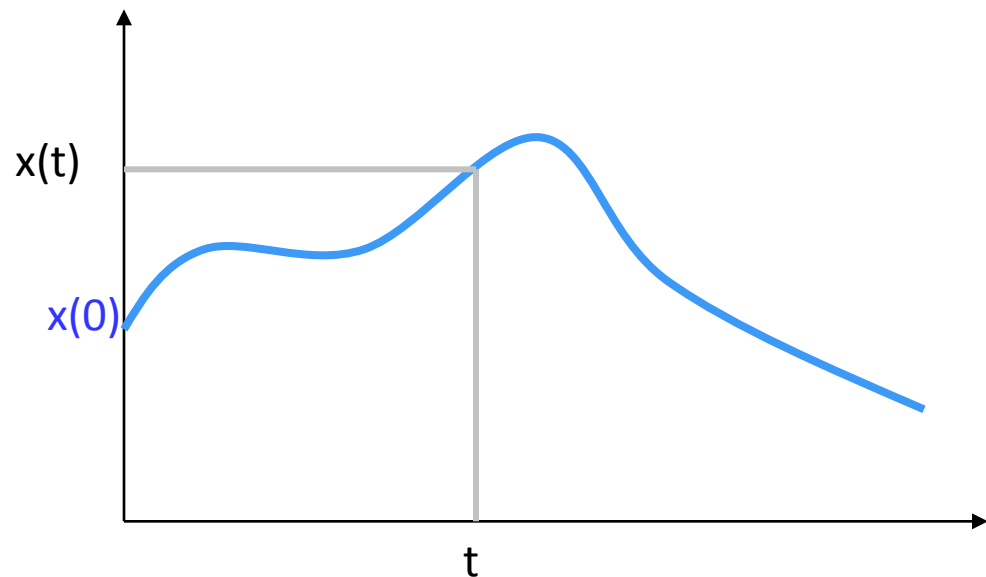
# The “opinion poll” Idea

- Pay the one-time cost of constructing the Bayesian network.
- Amortize this cost by performing multiple analysis tasks using the Bayesian network representation.
  - Using inferencing algorithms for DBNs.

# The Technique

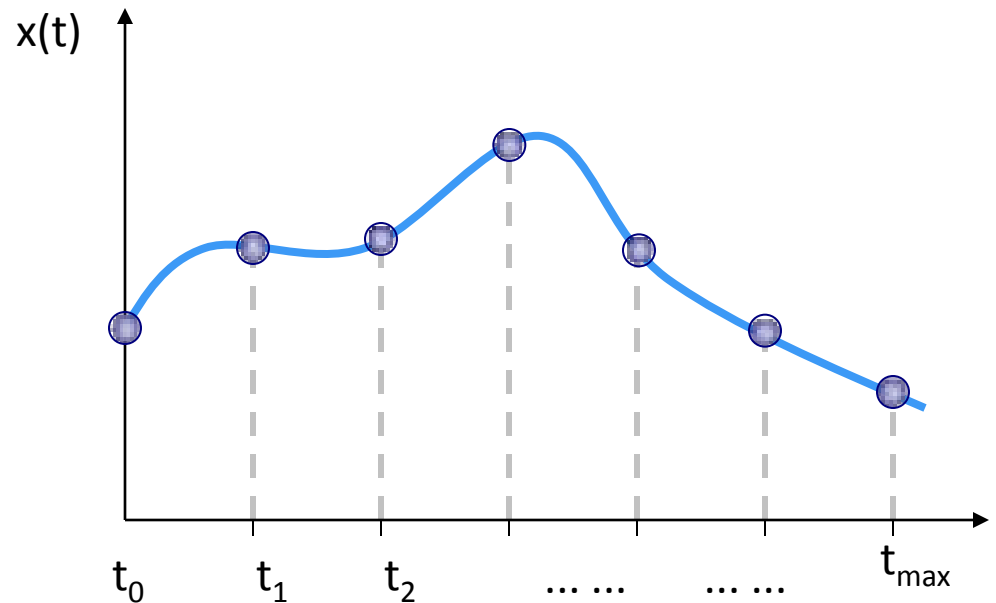
$$\frac{dx}{dt} = 3t^2 + 4$$

- We want to study  $x(t)$  the “solution” to the above equation.  
[  $x(t) = t^3 + 4t + x(0)$  ]



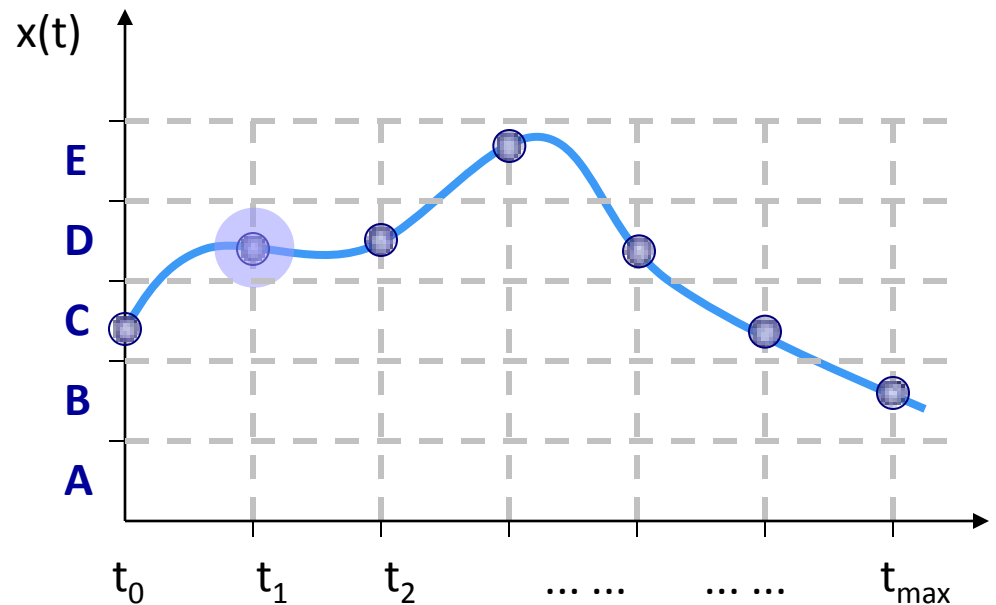
# The Technique

- Observe the system only at discrete time points; in fact, only at finitely many time points



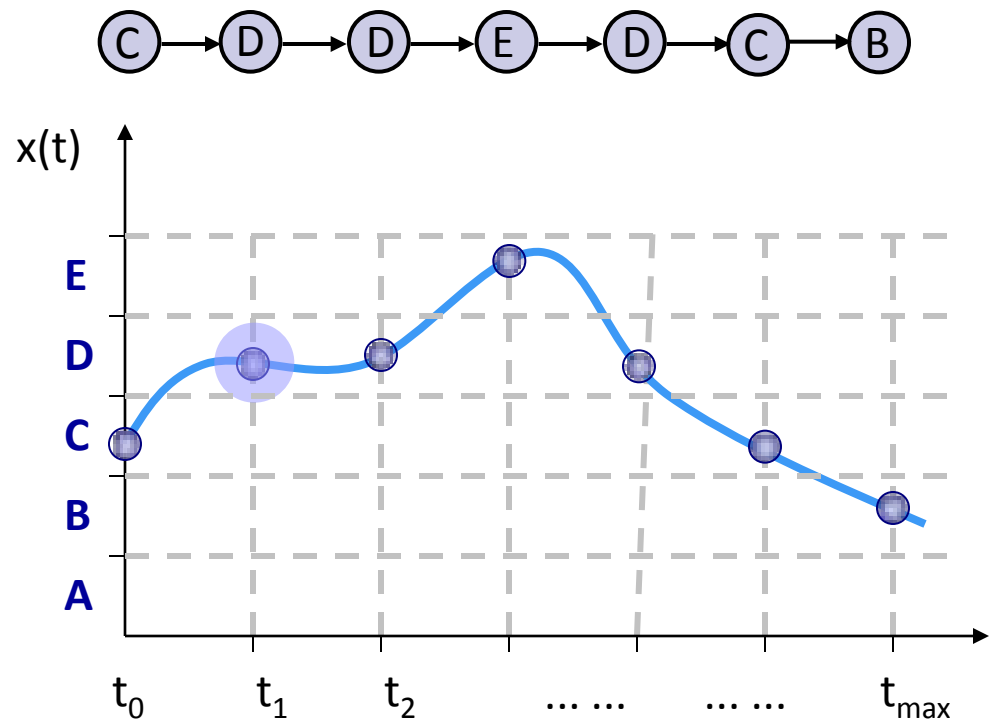
# The Technique

- Observe only with bounded precision



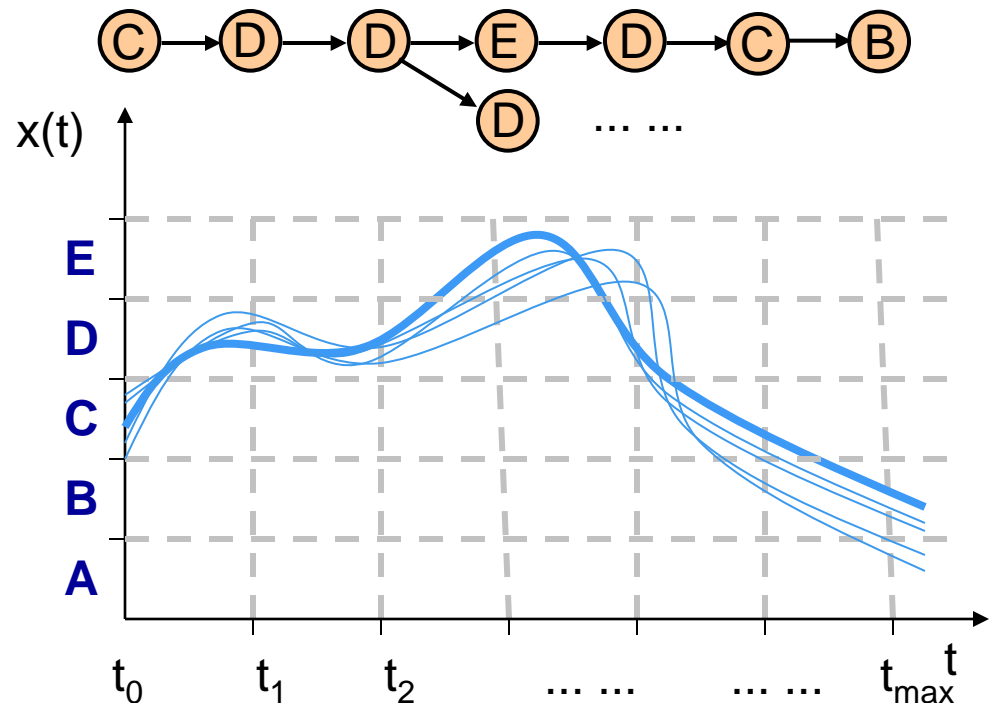
# The Technique

- A trajectory now is sequence of *discrete values*



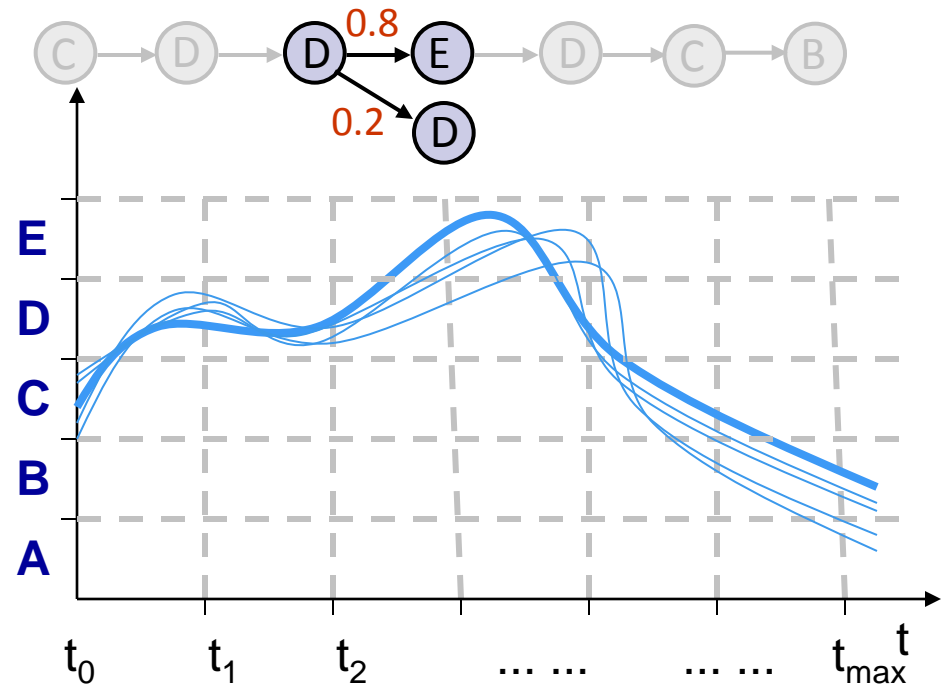
# Main Idea

- With a prior distribution of the initial states
- Many sequences of **discrete values**!



# The Technique

- In fact, a Markov chain.
- $\Pr( (D, 2) \longrightarrow (E, 3) )$  is the “fraction” of the trajectories residing in D at  $t = 2$  that land in E at  $t = 3$ .



# The Technique

- The value space of the variables is assumed to be a compact subset  $C$  of  $\mathcal{R}^n$
- In  $\mathbf{Z}' = F(\mathbf{Z})$ ,  $F$  is assumed to be differentiable everywhere in  $C$ .
  - Mass-law, Michaelis-Menton,...
- Then the solution (flow)  $\Phi_t : C \rightarrow C$  (for each  $t$ ) exists, is unique, is a bijection, is continuous and hence ***measurable***.



$(s, i)$  – States;

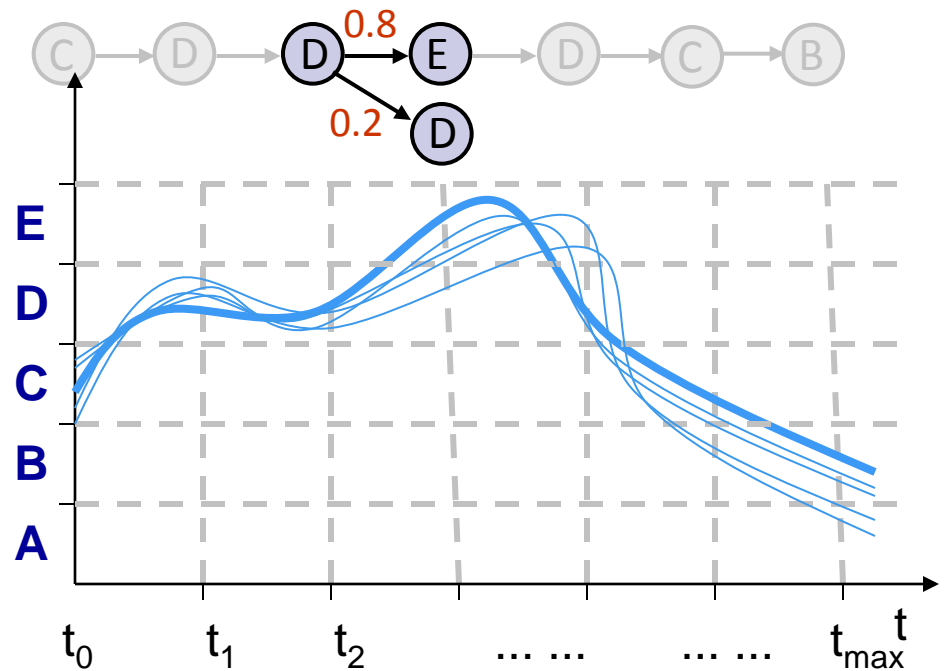
$(s, i) \rightarrow (s', i+1)$  -- Transitions

Sample, say, 1000 times the initial states.

Through numerical simulation, generate 1000 trajectories.

$\Pr(s, i)$  is the fraction of the 1000 trajectories that are in the discrete state  $s$  at  $t_i$ .

$\Pr((s, i) \rightarrow (s', i+1))$  is the fraction of the trajectories that are in  $s$  at  $t_i$  which land in  $s'$  at  $t_{i+1}$ .



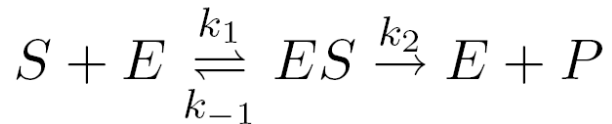
# The Technique

- But the *Markov chain* will be huge.
  - $O(T \cdot k^n)$
  - 50 variables ( $n$ ) , each with two ( $k$ ) intervals,  $T$  time points
  - $T \times 2^{50}$  states !

# The Technique

- Exploit the network structure (additional independence assumptions) to construct a dynamic Bayesian network instead.
  - Sampling + numerical + simulations + counting
- The DBN is a ***factored*** form of a Markov chain.

# The Technique

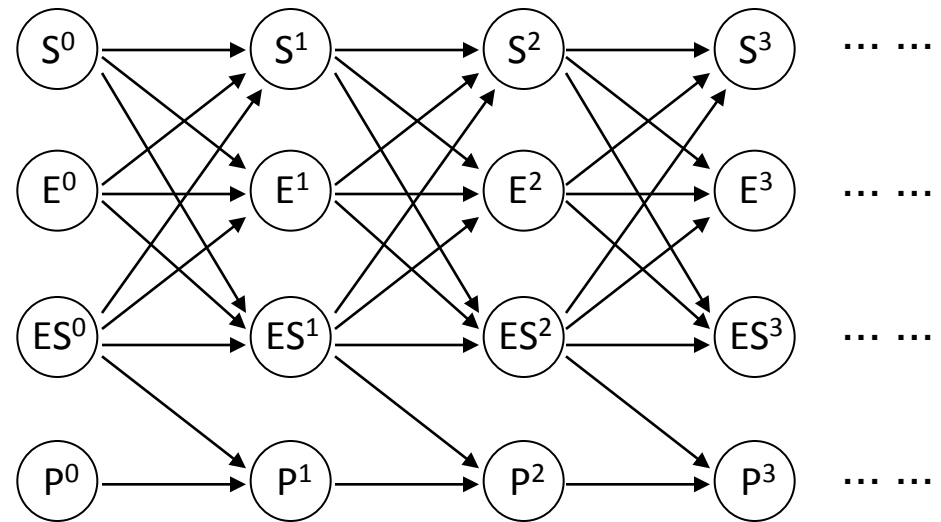


$$\frac{d[S]}{dt} = -k_1[S][E] + k_{-1}[ES]$$

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$$\frac{d[P]}{dt} = k_2[ES]$$



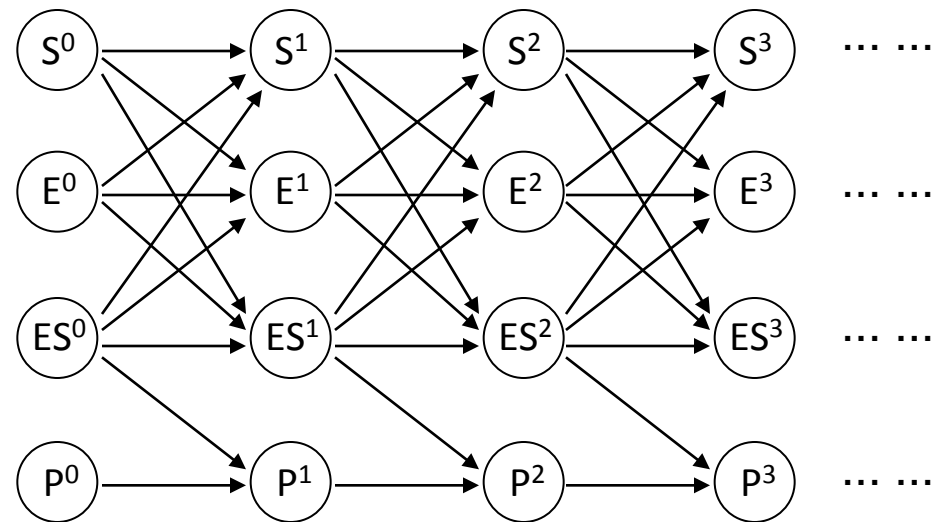
$P(S^1=0 | S^0=0, E^0=0, ES^0=0) = 0.2$   
 $P(S^1=0 | S^0=1, E^0=0, ES^0=0) = 0.4$   
 ... ..

# The Technique



Fill up the entries in the CPTs by sampling, simulations and counting as before.

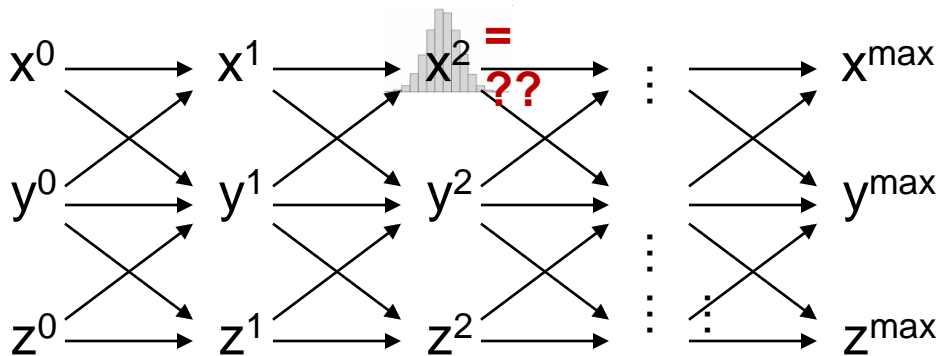
$O(T \cdot n \cdot k^d)$



$P(S^1=0   S^0=0, E^0=0, ES^0=0) = 0.2$ $P(S^1=0   S^0=1, E^0=0, ES^0=0) = 0.4$ ... ..
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# Method

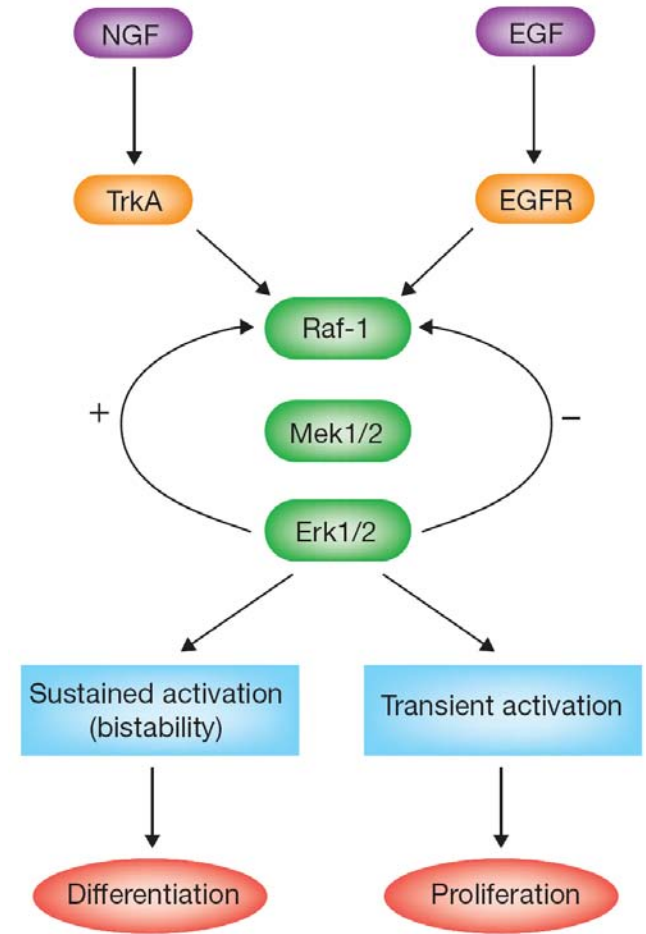
- Model analysis  $\rightarrow$  Bayesian inference
- Approximate inference algorithm (Factored Frontier algorithm)  
(Murphy & Weiss)
- $O(T \cdot n \cdot k^d)$



$$\Pr(x^{i+1}) = \sum_{x^i, y^i} \Pr(x^{i+1} | x^i, y^i) \Pr(x^i) \Pr(y^i)$$

# Two Synthetic Models

- PC12 cells
- The EGF-NGF signaling pathway
- Distinct signals dictate different cellular outcomes by activating the same signaling cascade



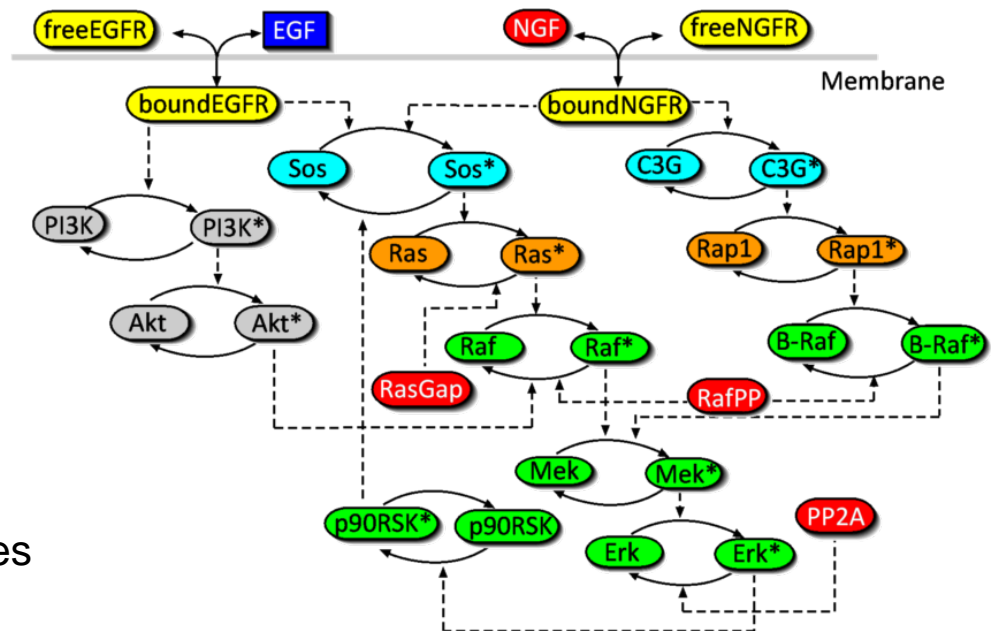
# EGF-NGF Pathway

- ODE model (*Brown et al. 2004*)

- 32 species
- 48 parameters
- Features:
  - Good size
  - Feedback loops

- DBN construction

- Settings
  - 5 intervals
  - 1 min time-step, 100 minutes
  - $3 \times 10^6$  samples
- Runtime
  - 4 hours on a cluster of 10 PCs

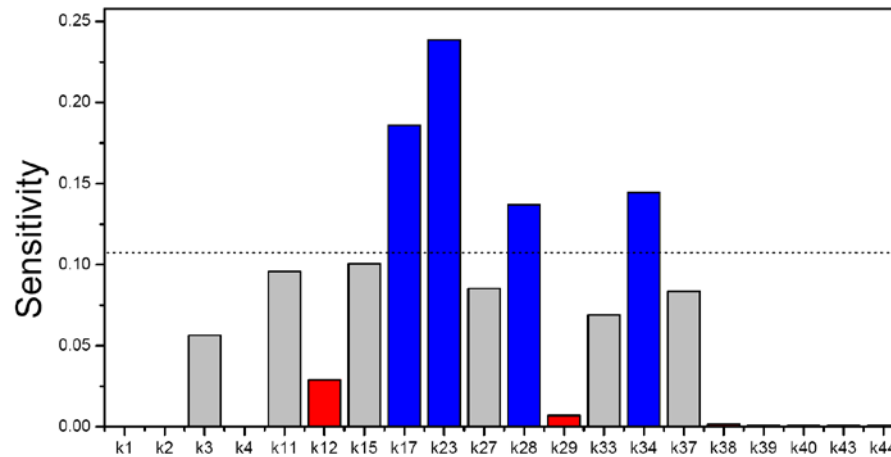




# Global Sensitivity Analysis

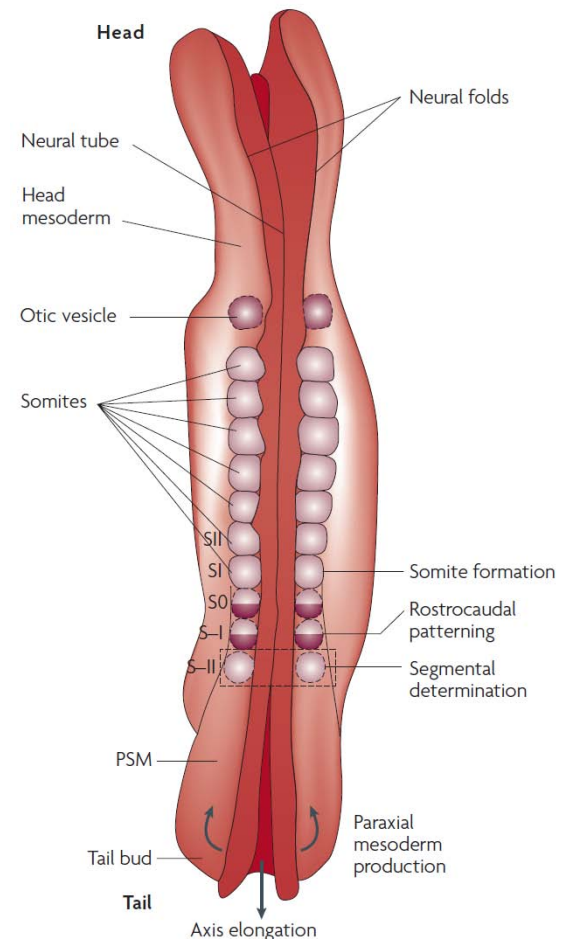
## ■ Running time

- ODE based: 22 hours
- DBN based: 34 minutes

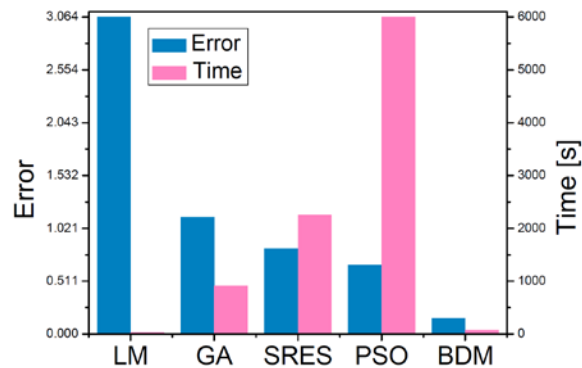


# Segmentation Clock Network

- A nice example of biological rhythms
- Governs the periodic formation process of somites during embryogenesis
- The underlying signaling network couples three oscillating pathways consisting of the FGF, Wnt and Notch signaling pathways



# Results



LM: Levenberg–Marquardt

GA: Genetic Algorithm

SRES: Evolutionary Strategy

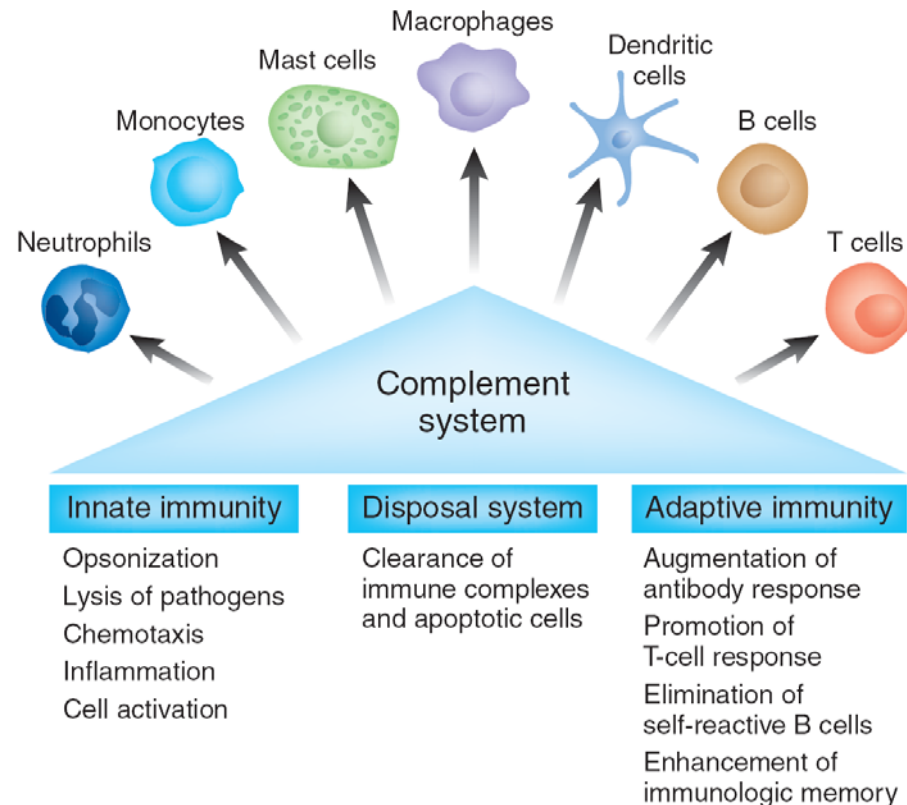
PSO: Particle Swarm Optimization

**BDM: our method**

- Global sensitivity analysis
  - ODE based: 81 hours
  - DBN based: 3 hours

# Complement System

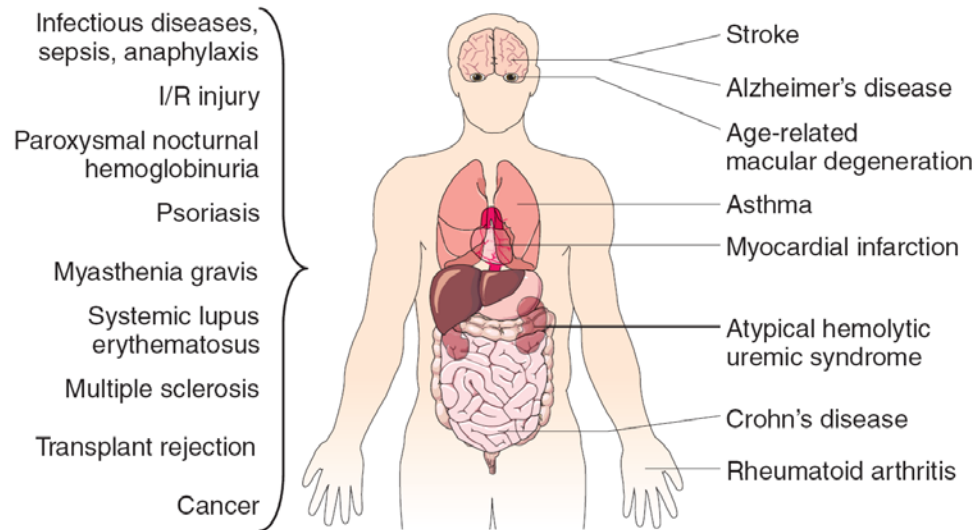
- Complement system is a critical part of the immune system



Ricklin et al. 2007

# Complement System

- Adequate complement activation is necessary
- Excessive complement activation is harmful
- Dysregulation of the balance between activation and inhibition can lead to many diseases



# Motivation

- Quantitatively understand the regulatory mechanisms of complement system
  - How is the complement activity enhanced under inflammation condition?
  - How is the excessive response of the complement avoided?
- The model:
  - Classical pathway + the lectin pathway
    - enhancement
  - Inhibitory mechanisms
    - C4BP

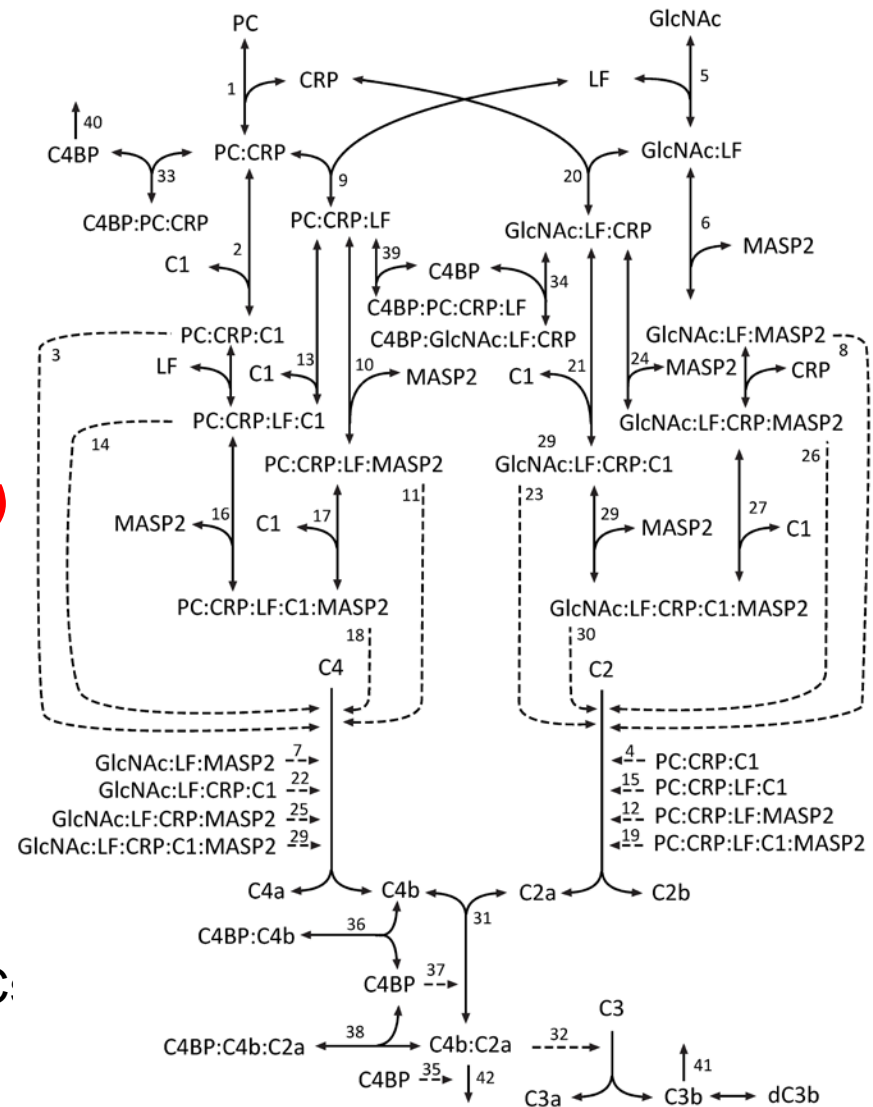
# Complement System

- ODE Model

- 42 Species
- 45 Reactions
  - Mass law
  - Michaelis-Menten kinetics
- 92 Parameters (*71 unknown!*)

- DBN Construction

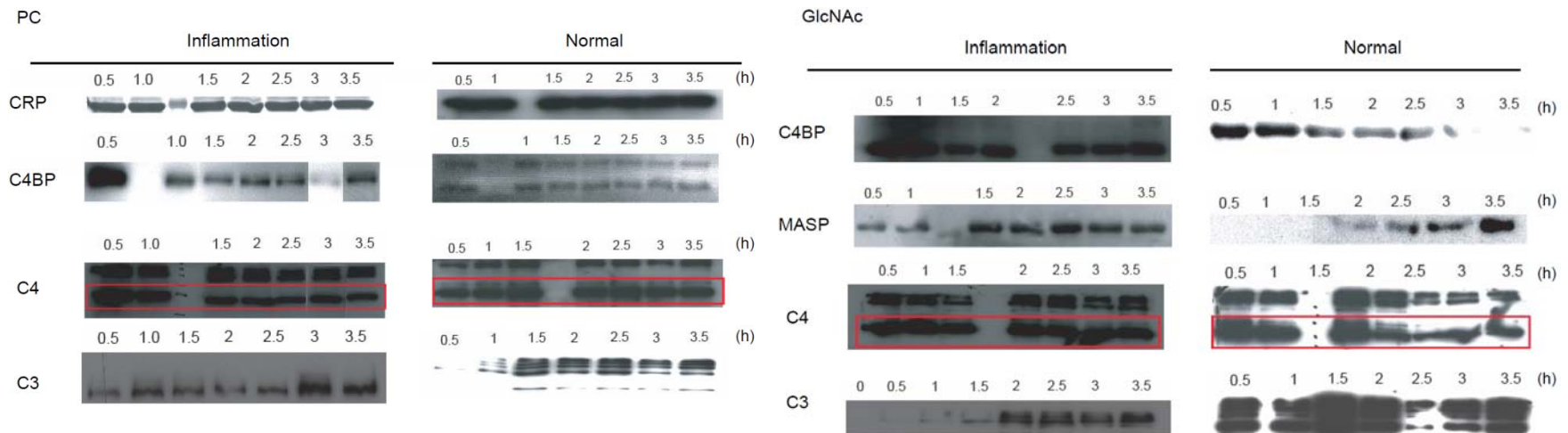
- Settings
  - 6 intervals
  - 100s time-step, 12600s
  - 1.2 x 10<sup>6</sup> samples
- Runtime
  - 12 hours on a cluster of 20 PC:



# Parameter estimation

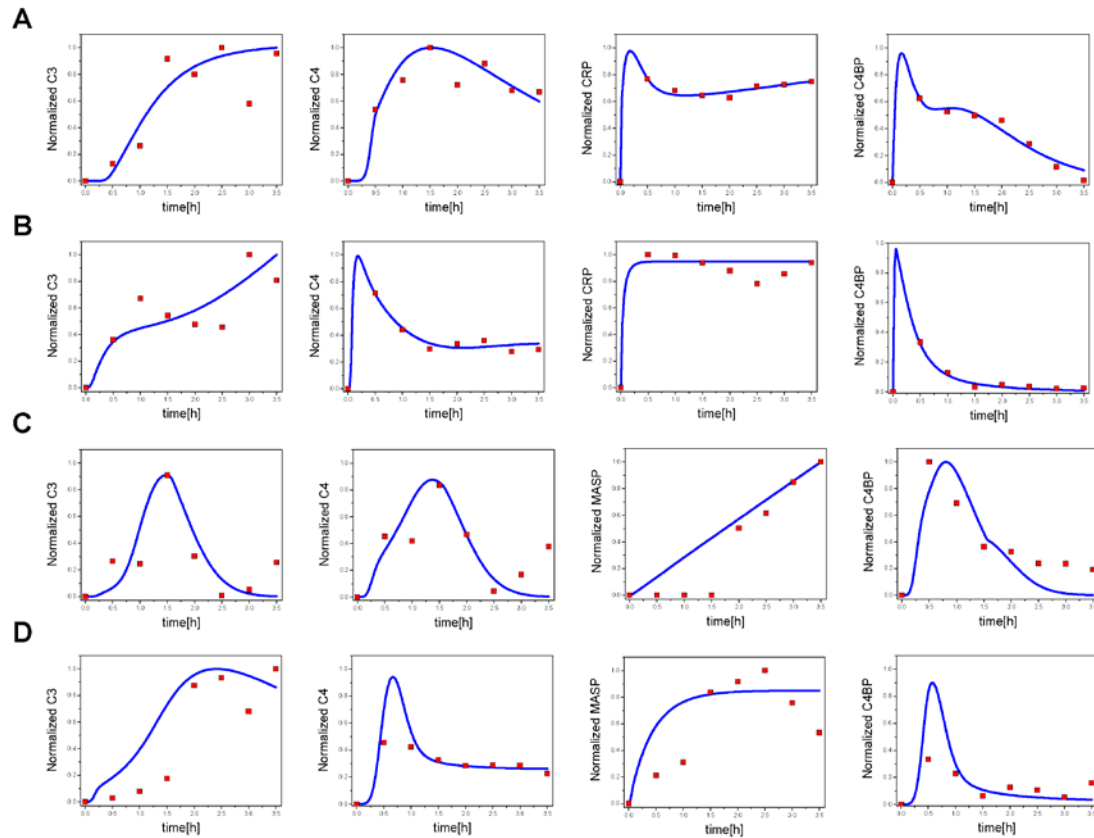
- Training data

- 4 proteins, 7 time points, 4 conditions



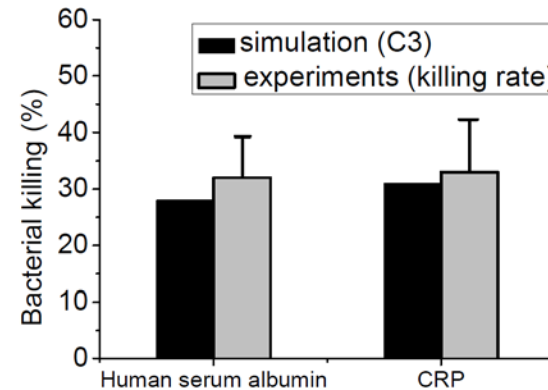
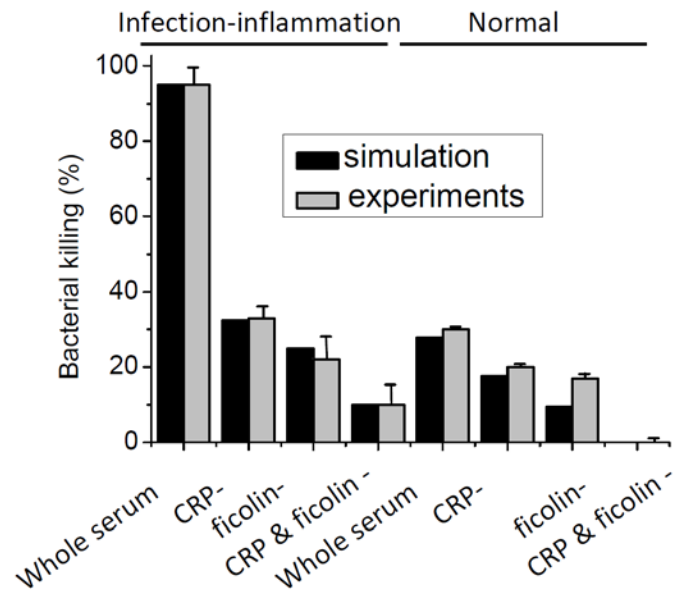


# Model Calibration



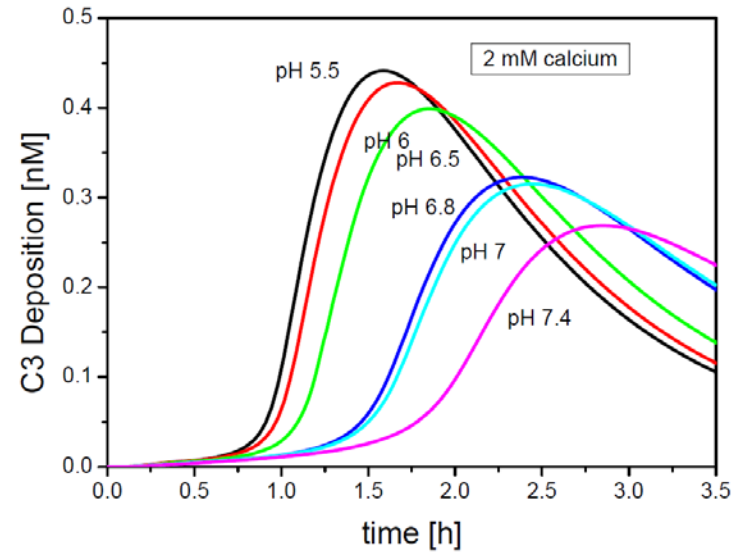
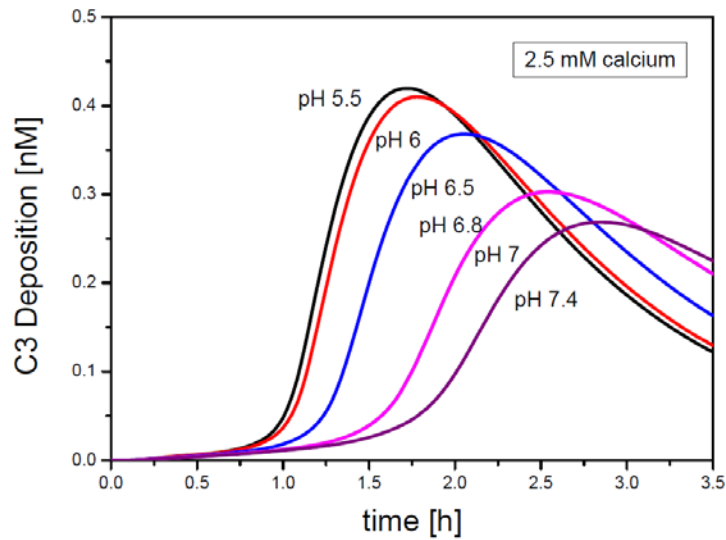
# Model validation

- Validated the model using previous published data (*Zhang et al 2009*)



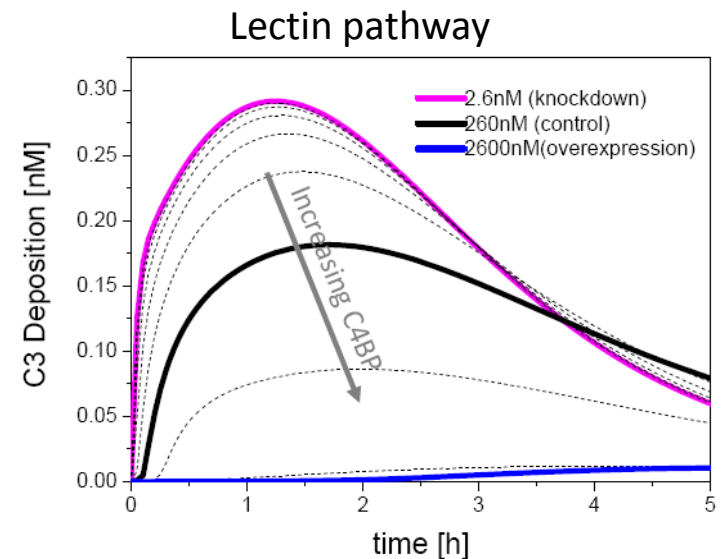
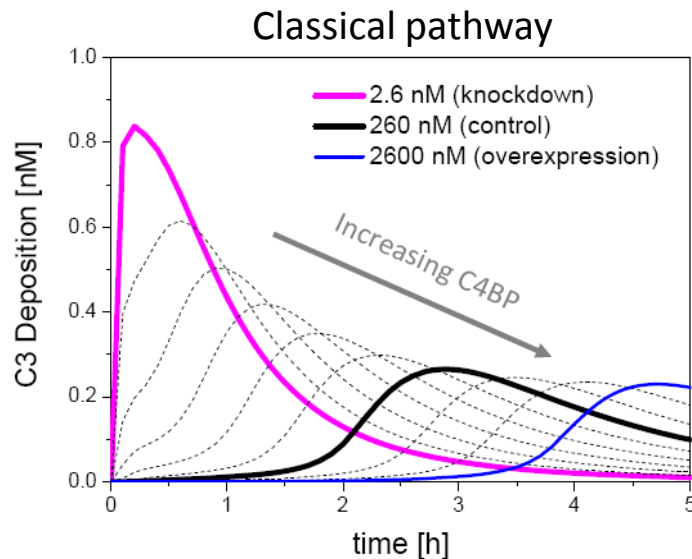
# Enhancement mechanism

- The antimicrobial response is sensitive to the pH and calcium level



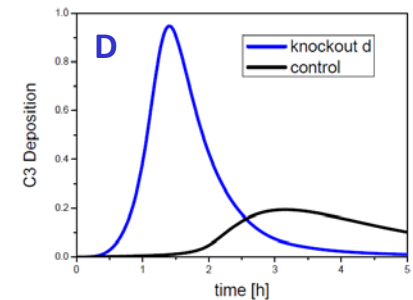
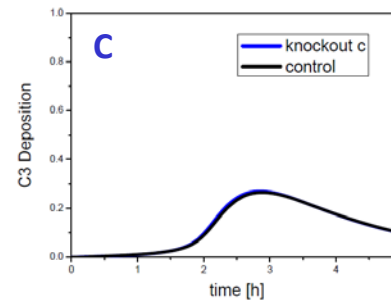
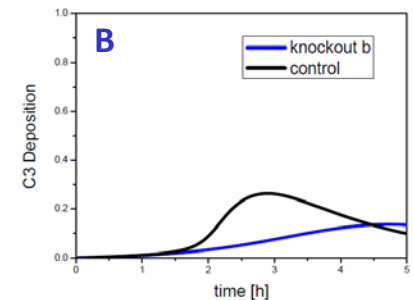
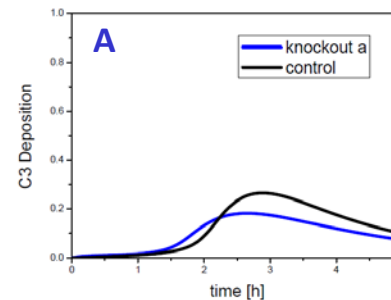
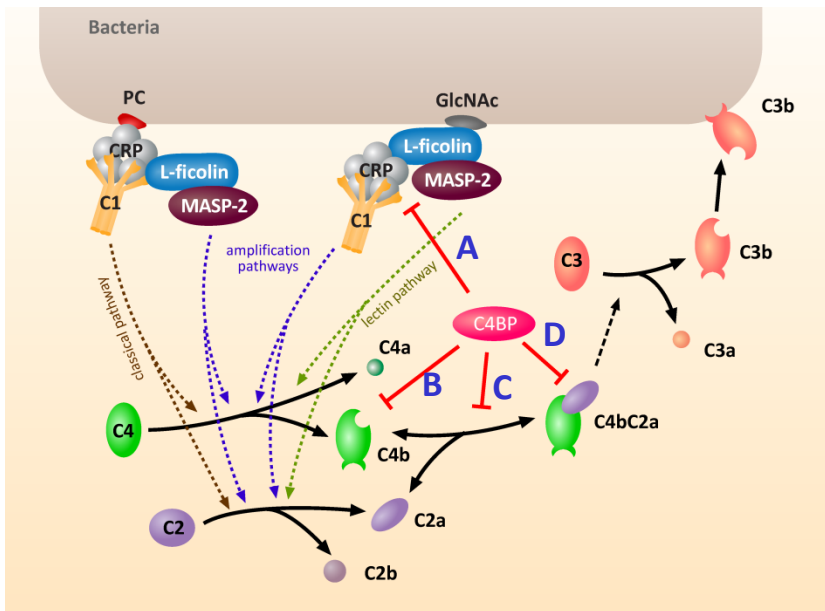
# Model prediction: The regulatory effect of C4BP

- C4BP maintains classical complement activation but delays the maximal response time.
- But attenuates the lectin pathway activation.



# The regulatory mechanism of C4BP

- The major inhibitory role of C4BP is to facilitate the decay of C3 convertase



# Results

- Both predictions concerning C4BP were experimentally verified.
- *“A Computational and Experimental Study of the Regulatory Mechanisms of the Complement System”*
  - Bing Liu, Jing Zhang, Pei Yi Tan, David Hsu, Anna M. Blom, Benjamin Leong, Sunil Sethi, Bow Ho, Jeak Ling Ding, P.S. Thiagarajan

*PLoS Computational Biology Vol. 7, Issue.1 (2011)*

# Conclusion

- The DBN approximation technique is useful and realistic.
- (Approximate) probabilistic verification methods
- Implementation on a GPU platform.
- Error analysis.
- A general abstraction scheme?
  - When is it effective?

# Current Collaborators

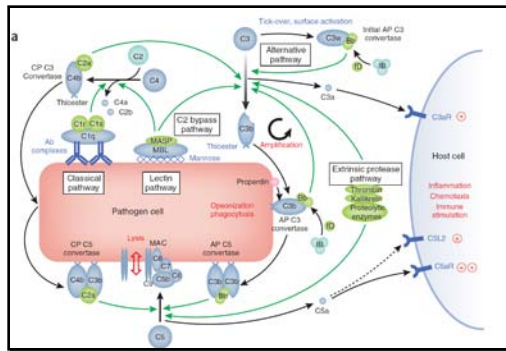
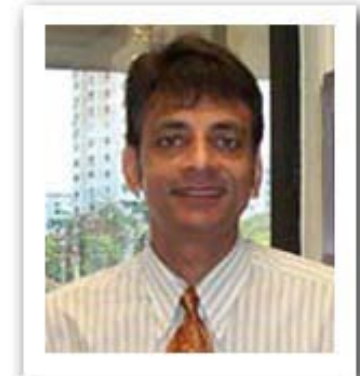
Ding Jeak Ling



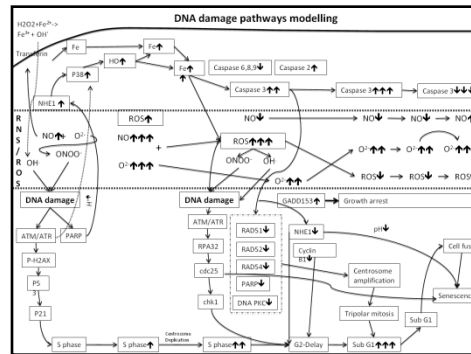
Marie-Veronique Clement



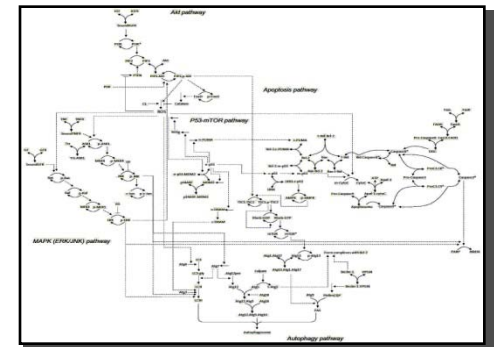
Shazib Pervaiz



Complement pathway



DNA damage pathway



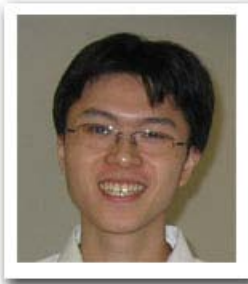
Apoptosis-Autophagy-pathway



# Our group:



S. Akshay



Liu Bing



Abhinav Dubey



Blaise Genest



Benjamin Gyori



David Hsu



Suchee  
Palaniappan



P.S.  
Thiagarajan



Wang Junjie



Gireedhar  
Venkatachalam