Computational Challenges in Large-Scale Pathway Modeling

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Scientific Computing and Mathematical Modeling GlaxoSmithKline

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Scientific Computing and Mathematical Modeling

Agenda

Biological pathways

- simple example of a pathway
- simple example of pharmaceutical interest
- Building a mathematical model of biological networks
- Computational challenges



Motivation

- Build as complete a model of as much of a cell or organism as possible
 - E. coli is the archetypical prototype
- Figure out what to do with it once we get it What if we had a perfect model? Then what?





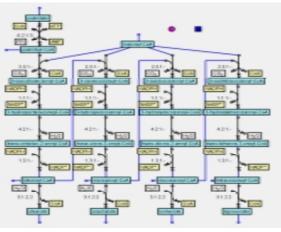


What is a Pathway?

For the purposes of this talk:

A network of interaction biological entities represented as a directed graph.

So network and pathway are equivalent under this definition.



Saturated Fatty Acid Elongation



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Pharmaceutical Interest in Pathways

- Predicting culture conditions for overproduction of biopharmaceuticals and drug targets, bioengineering of target assays, enzymes, receptors, etc.
- Understanding compound modes of action
- Identifying novel behaviors and new behaviors of known pathways
 - clues to new intervention approaches
 - selecting and prioritizing of new targets
- Identifying and validating bio-markers
 - ♦ animal ⇔ human correlation
- Interpreting and integrating system biology data:
 - transcriptomics, proteomics and metabolomics and other 'omics'



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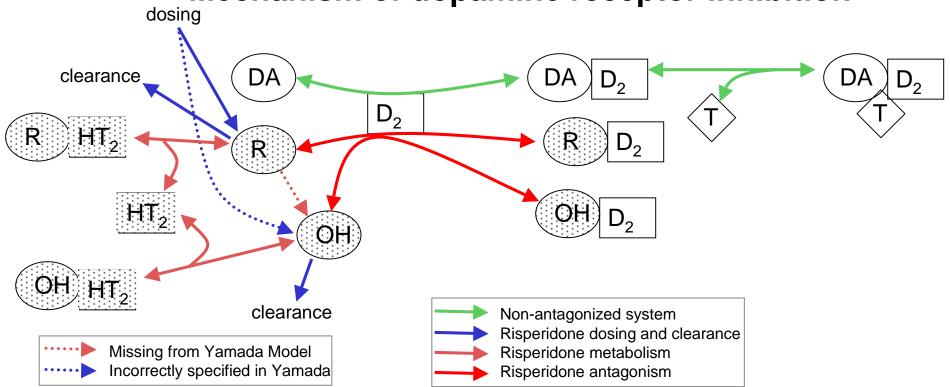
A Simple Pharmaceutical Pathway Example

- Risperidone is a psychotropic agent used for treating schizophrenia or psychosis
- 2.1% of patients develop extrapyramidal symptoms:
 - involuntary movements
 - tremors and rigidity
 - body restlessness
 - muscle contractions
 - changes in breathing and heart rate
- Hypothesis for the extrapyramidal symptoms: Dopamine receptor antagonism Yamada, et al, Synapse 46, 32-37 (2002)



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Mechanism of dopamine receptor inhibition



Receptor Binding:

Formation of active complex:

Risperidone conversion to 9-hydroxyrisperidone Binding to D_2 and 5-HT₂ receptors

 $\begin{array}{l} \mathsf{D}\mathsf{A} + \mathsf{D}_2 \Leftrightarrow \mathsf{D}\mathsf{A} \bullet \mathsf{D}_2 \\ \mathsf{D}\mathsf{A} \bullet \mathsf{D}_2 + \mathsf{T} \Leftrightarrow \mathsf{D}\mathsf{A} \bullet \mathsf{D}_2 \bullet \mathsf{T} \\ \mathsf{R} \to \mathsf{O}\mathsf{H} \\ \mathsf{R} + \mathsf{D}_2 \Leftrightarrow \mathsf{R} \bullet \mathsf{D}_2 \\ \mathsf{R} + \mathsf{H}\mathsf{T}_2 \Leftrightarrow \mathsf{R} \bullet \mathsf{H}\mathsf{T}_2 \\ \mathsf{O}\mathsf{H} + \mathsf{D}_2 \Leftrightarrow \mathsf{O}\mathsf{H} \bullet \mathsf{D}_2 \end{array}$

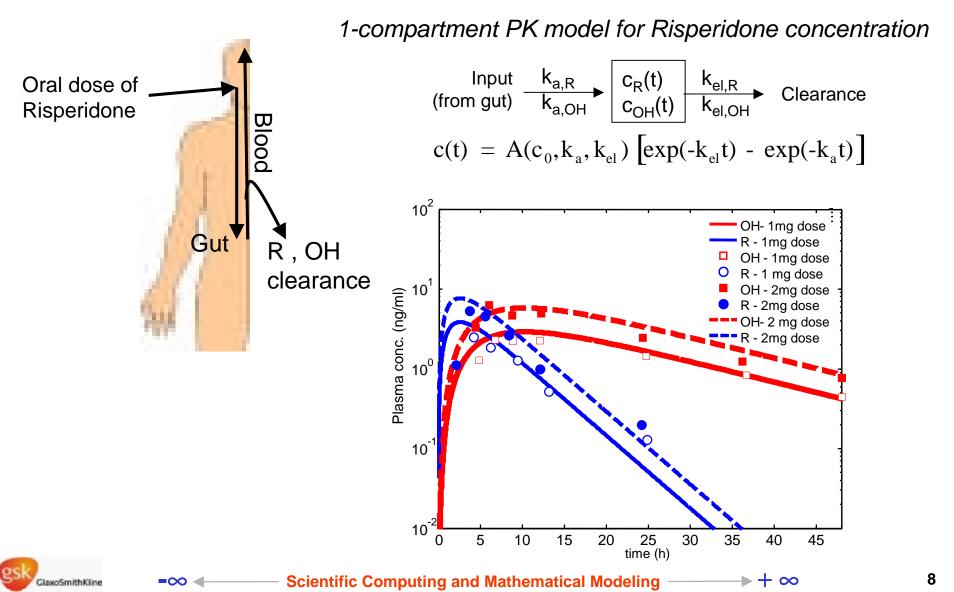
 $OH + HT_2 \Leftrightarrow OH \bullet HT_2$

DA: Dopamine
D₂: Receptor
T: Transmitter
R: Risperidone
OH: 9-hydroxyR
HT₂: Receptor

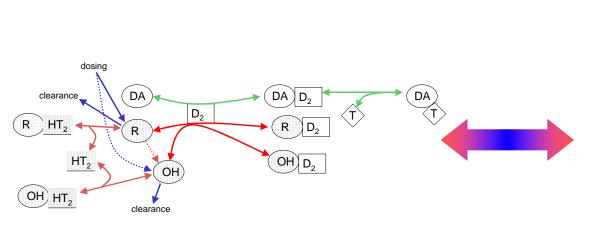


Yamada model for Risperidone PK

Yamada et al, 2002, Synapse, 46:32-37



The ODE Model Approach



Biological model

$$\begin{split} \frac{d[\mathbf{R}]^{\text{get}}}{dt} &= -\mathbf{k}_{a}^{\text{R}} \; [\mathbf{R}]^{\text{get}} \\ \frac{d[\mathbf{OH}]^{\text{get}}}{dt} &= -\mathbf{k}_{a}^{\text{OH}} \; [\mathbf{OH}]^{\text{get}} \\ \frac{d[\mathbf{R}]}{dt} &= \mathbf{k}_{a}^{\text{R}} \; \mathbf{R}^{\text{get}} - \mathbf{k}_{d}^{\text{R}} \; [\mathbf{R}] \\ \frac{d[\mathbf{OH}]}{dt} &= \mathbf{k}_{a}^{\text{R}} \; [\mathbf{OH}]^{\text{get}} - \mathbf{k}_{d}^{\text{OH}} \; [\mathbf{OH}] \\ \frac{d[\mathbf{DAgD}_{2}]}{dt} &= \mathbf{k}_{a}^{\text{DAgD}_{2}} \; [\mathbf{DA}][\mathbf{D}_{2}] - \mathbf{K}_{A}^{\text{DAgD}_{2}} \mathbf{k}_{a}^{\text{DAgD}_{2}} \; [\mathbf{DAgD}_{2}] \\ \frac{d[\mathbf{DAgD}_{2}gT]}{dt} &= \mathbf{k}_{a}^{\text{DAgD}_{2}gT} \; [\mathbf{DAgD}_{2}][\mathbf{T}] - \mathbf{K}_{A}^{\text{DAgD}_{2}gT} \mathbf{k}_{a}^{\text{DAgD}_{2}gT} \; [\mathbf{DAgD}_{2}gT] \\ \frac{d[\mathbf{RgD}_{2}]}{dt} &= \mathbf{k}_{a}^{\text{RgD}_{2}} \; \boldsymbol{\beta}_{\text{R}} [\mathbf{R}][\mathbf{D}_{2}] - \mathbf{K}_{A}^{\text{RgD}_{2}} \mathbf{k}_{a}^{\text{RgD}_{2}} \; [\mathbf{RgD}_{2}] \\ \frac{d[\mathbf{RgD}_{2}]}{dt} &= \mathbf{k}_{a}^{\text{OH}gD_{2}} \; \boldsymbol{\beta}_{\text{OH}} [\mathbf{OH}][\mathbf{D}_{2}] - \mathbf{K}_{A}^{\text{RgD}_{2}} \mathbf{k}_{a}^{\text{RgD}_{2}} \; [\mathbf{OHgD}_{2}] \\ \frac{d[\mathbf{RgHT}_{2}]}{dt} &= \mathbf{k}_{a}^{\text{OH}gD_{2}} \; \boldsymbol{\beta}_{\text{OH}} [\mathbf{OH}][\mathbf{D}_{2}] - \mathbf{K}_{A}^{\text{RgHT}_{2}} \mathbf{k}_{a}^{\text{RgHT}_{2}} \; [\mathbf{RgHT}_{2}] \\ \frac{d[\mathbf{OH}g\mathbf{HT}_{2}]}{dt} &= \mathbf{k}_{a}^{\text{OH}g\mathbf{HT}_{2}} \; \boldsymbol{\beta}_{\text{OH}} [\mathbf{OH}][\mathbf{HT}_{2}] - \mathbf{K}_{A}^{\text{OH}g\mathbf{HT}_{2}} \; [\mathbf{OH}g\mathbf{HT}_{2}] \\ \frac{d[\mathbf{OH}g\mathbf{HT}_{2}]}{dt} &= \mathbf{k}_{a}^{\text{OH}g\mathbf{HT}_{2}} \; \boldsymbol{\beta}_{\text{OH}} [\mathbf{OH}][\mathbf{HT}_{2}] - \mathbf{K}_{A}^{\text{OH}g\mathbf{HT}_{2}} \; [\mathbf{OH}g\mathbf{HT}_{2}] \\ [\mathbf{DA}]_{\text{total}} &= [\mathbf{DA}] + [\mathbf{DA}g\mathbf{D}_{2}gT] \\ [\mathbf{DA}]_{\text{total}} &= [\mathbf{DA}] + [\mathbf{DA}g\mathbf{D}_{2}gT] \\ [\mathbf{D}_{2}]_{\text{total}} &= [\mathbf{T}] + [\mathbf{D}Ag\mathbf{D}_{2}gT] \\ [\mathbf{D}_{2}]_{\text{total}} &= [\mathbf{D}_{2}] + [\mathbf{D}Ag\mathbf{D}_{2}] + [\mathbf{D}Ag\mathbf{D}_{2}gT] + [\mathbf{OH}g\mathbf{D}_{2}] \\ [\mathbf{HT}_{3}]_{\text{total}} &= [\mathbf{HT}_{3}] + [\mathbf{R}g\mathbf{HT}_{3}] + [\mathbf{OH}g\mathbf{HT}_{3}] \end{aligned}$$

Mathematical model Numerical simulations

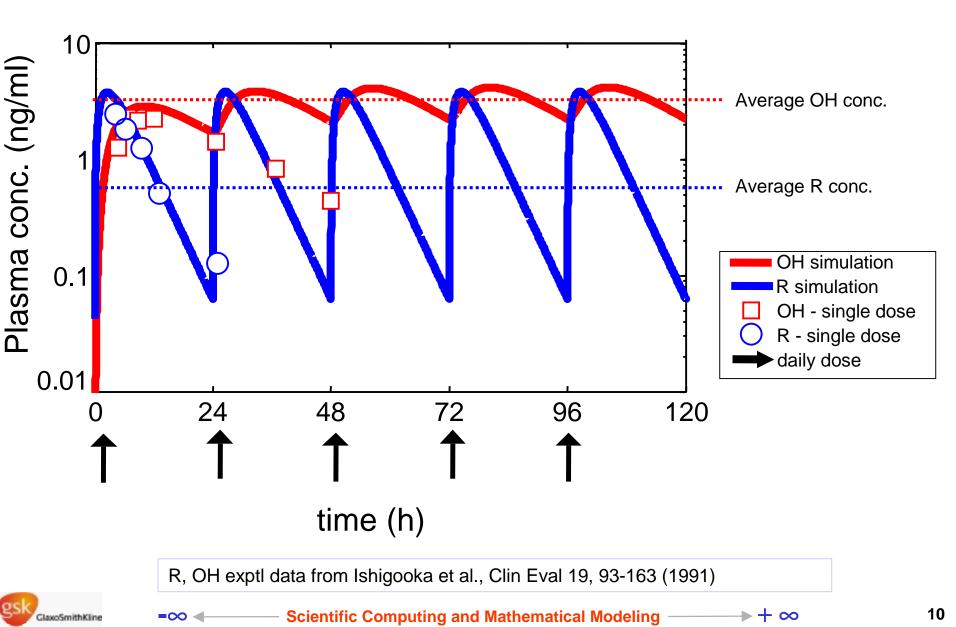
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$$\mathbf{x'} = \mathbf{f}(\mathbf{x}, \lambda) + D(t)$$

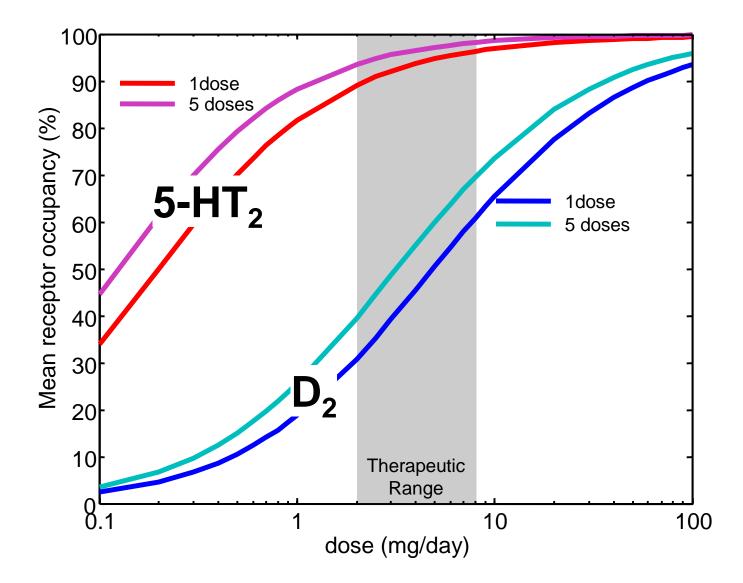
ODEs

gsk

Daily Dosing Differs from a Single Dose Plasma Concentration



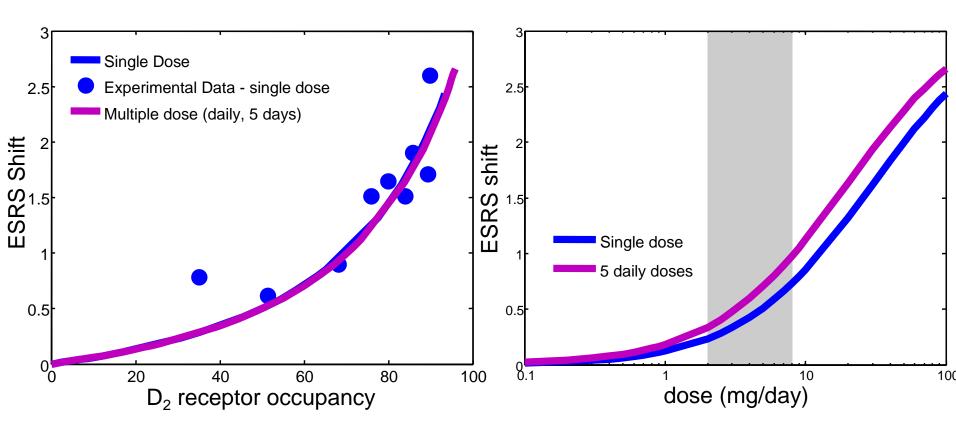
Effect of multiple dosing on receptor occupancy





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Daily dosing causes differences in predicted side-effects

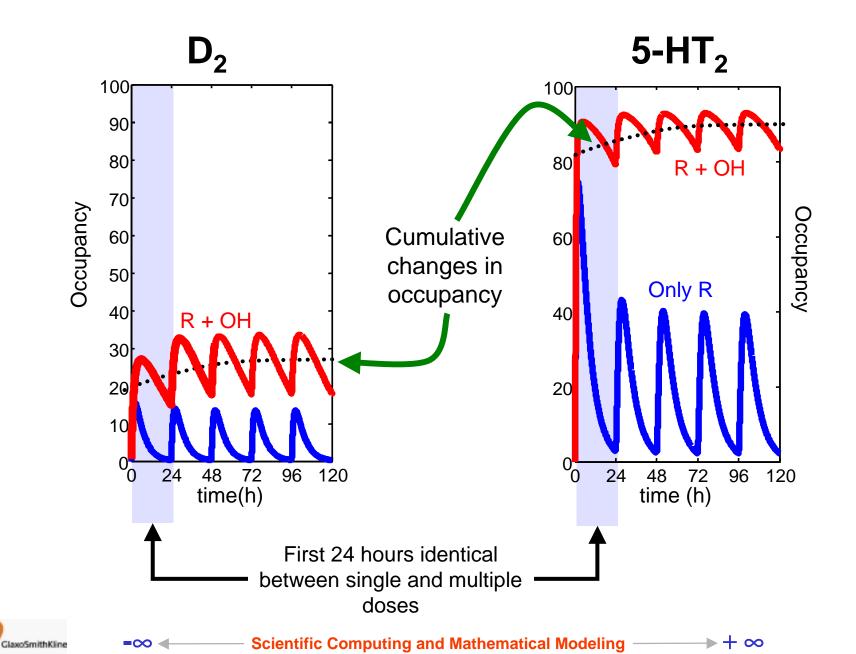


Multiple dosing results in increased ESRS shift, increasing with daily dose administered

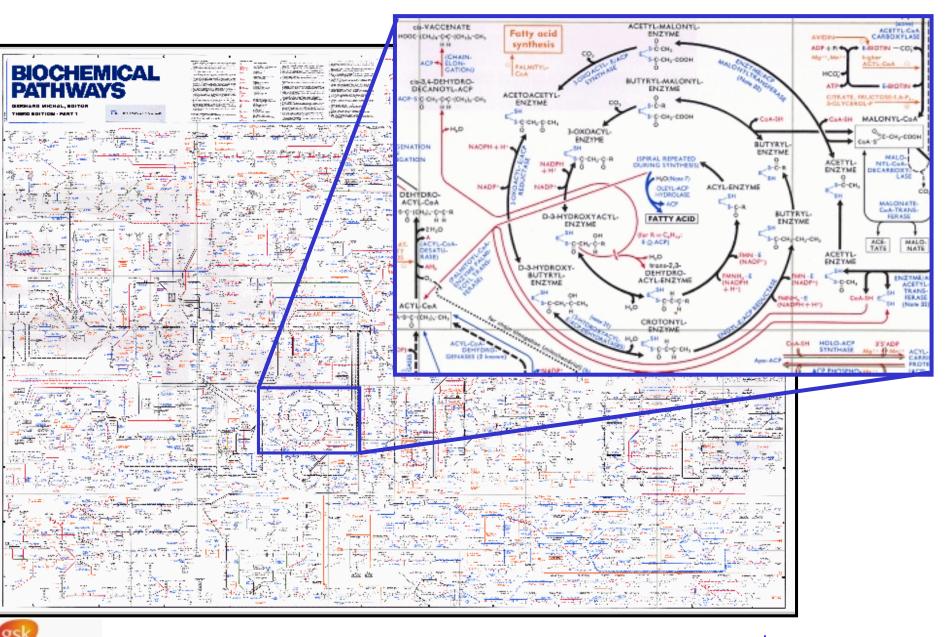


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Receptor Occupancy as a function of cumulative dosing



Real Pathways are More Complex



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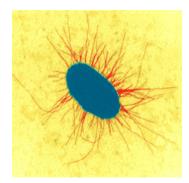
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Mathematical Complexity

- Consider a small, relatively unsophisticated bacterium: Escherichia coli

 - 2500 proteins

- at least several hundred small molecules
- 3 interactions per entity X 5000 entities
- 3 parameters per equation
- \approx 15 000 equations with 45 000 parameters!



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 $X' = F(X;\lambda)$ continuous, discrete, stochastic $0 = G(X;\lambda)$ analytic constraints $0 = H(X;\lambda)$ non – analytic constraints

• Now add on spatial change - 15 000 PDEs!



The Modeling P	rocess
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1A Building the model -- forward problem

- Static
- Kinetic
 - Rate law determination
 - Parameter determination

1B Reconstructing the model -- inverse problem

2 Validating the model

- Experimental data comparison
- Plausible biology from analytic analysis/simulation
- Examining and assertions testing results

3 Simulation

- Hypothesis testing
- Hypothesis generation

Building the model

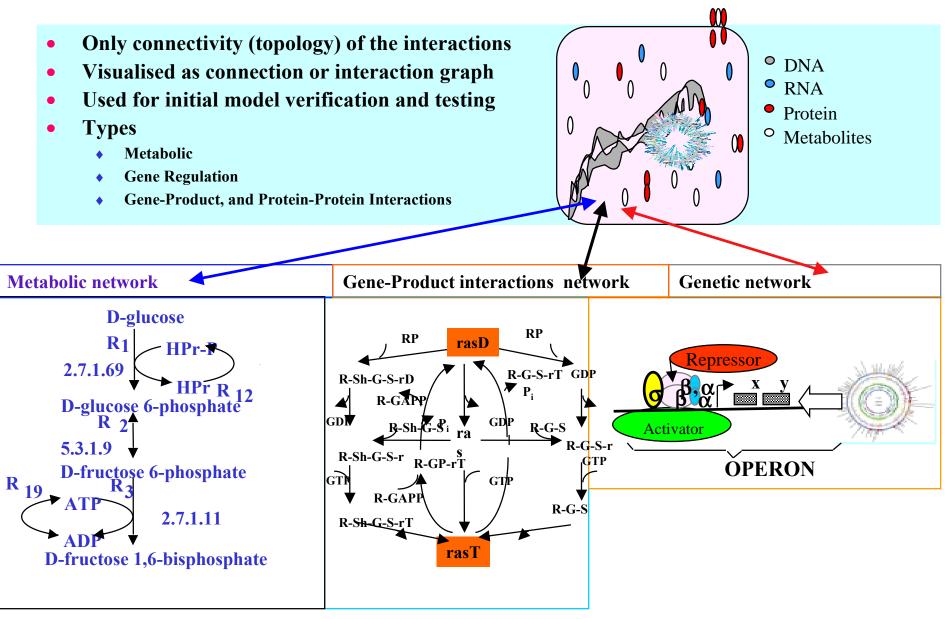
Getting it right

Getting value out of it

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Static Model



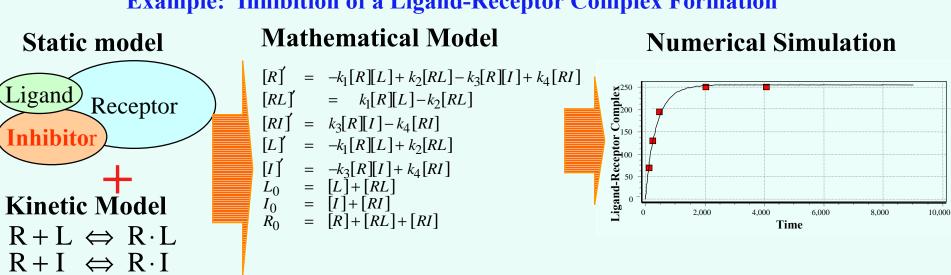
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Kinetic Model

•	First phase:	Kinetic models - time dependency incorporated	
		 Kinetic behaviour (rate laws) added to static model 	
		 May or may not obey mass action kinetics 	
•	Second phase:	Kinetic constants determined from experimental data	
•	Third phase	Mathematical model - equations generated	
		 Time variation of all concentrations and fluxes can be simulated 	
		 Model analyses possible: sensitivity, linear stability theory, asymptotic analysis, etc. 	

Example: Inhibition of a Ligand-Receptor Complex Formation



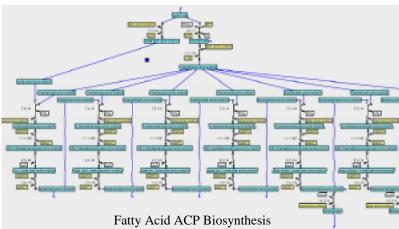
The Resulting System Very Large, Flawed, and Damned Useful!

- The resulting system of equations:
 - x' = F(x,l)

 $0 = \mathbf{I}(x, l)$

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- 0 = G(x, l) algebraic relationships
- 0 = H(x,l) analytic constraints
 - non analytic constraints
- Very large dimensionalities in:
 - the number of species, X
 - the number of interactions
 - the number of parameters, λ
 - the number of constraint equations



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• Uncertainty, error, ambiguity, approximations, etc

As the pathways grow large, the nature of the problems change.

Building the model

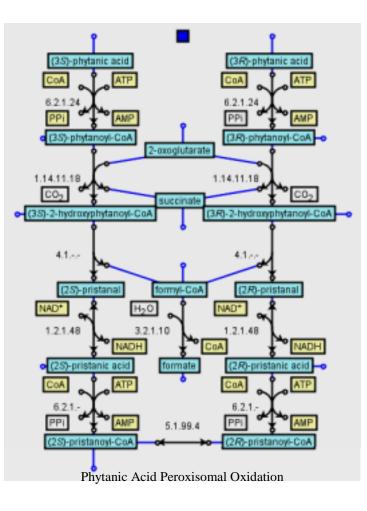
- knowledge management
- knowledge updating
- incomplete knowledge
- Automation
- Updating the model versioning
- Analysis of the model
 - Too much for a human to peruse
 - Theory gaps
 - Automation

Analysis of the simulation results

- Too much for a human to peruse
- New techniques

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Automation





Automation

• No human intervention whatsoever

- None, nada, zip!
- If it takes a human to setup, run or analyze its not automated

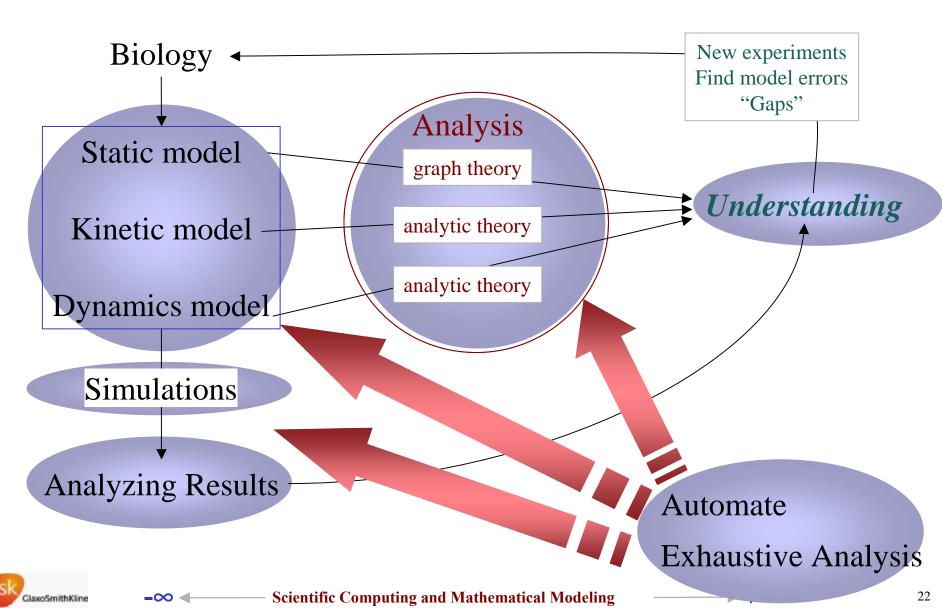
Robust algorithms

- Graceful failure
- Knowledge of domain of applicability
- Pathological data happens very often Murphy is omnipresent
- Not as easy as it main seem at first
- Many existing algorithms are not automatable in current usage



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The Compatibution as topping Ritides map



Theory Gap for Large Systems

- Large but not infinite dimensionality is the problem
- Analytical and numerical determination:
 - Finding 'true' null states there may be a great number
 - Finding linear null states- there may be a great number
 - Asymptotic behaviors
 - Controllability, predictability, integrability, ...
 - Steady state, non-linear behaviors
 - Bifurcation analyses
 - Perturbed behaviors drug dosing, environment, mutants, etc.
 - ...
- How to calculate in a computationally efficient manner
- Can't afford to calculate everything
- Need to a priori determine which are to be done

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Continuousness / Stochasticity/ Discreteness / Ambiguity

• Continuous approximation breaks down

- Need to use master equations or some other form of involving stochasticity
- May need to dynamically switch as system evolves

• Some processes are truly discrete

- Consider cellular automatons, Petri Nets, discrete events, etc.
- Some parts of the model are only known qualitatively
 - Qualitative simulation techniques.

• Uncertainty and variation in the system

- Initial conditions
- Rate constants and rate laws
- Population variations
- Interval or fuzzy integration
- Multiscale time, length, concentration, etc.
- Constraints DAEs

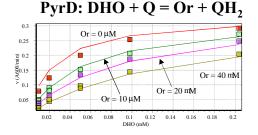
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The challenge: one hybrid integrator

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Parameter challenges

- The larger the model:
 - the more parameters compared to the experiments
- Static guessing filling in the gaps
 - guessing gene function by analogy
 - looking for missing reactions i.e. enzyme

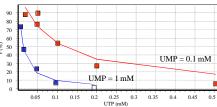


- Kinetic guessing integrating kinetic islands guessing plausible rate laws and parameters
 - Analogy approaches, similarity across species('multiple alignment')
 - From flux analysis?
- Do we need to know all parameters? Accuracy?



Parameter challenges

- Determine parameters of rate laws from an optimization to fit experimental kinetics data
 - noisy and incomplete data
 - ill-posed, possibly severely



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- How do we scale this up as the model gets bigger?
 - One huge model fitting? Can we even afford this approach?
 - One sub-systems at a time fitting?
 - Hierarchical fitting? Stitching together pieces individually calibrated does not a priori mean the model is calibrated
- What's the best way to optimize?
 - Is L₂ the best objective function?
 - Constraints incorporating and coming up with better ones
- How do we know how well we've done?



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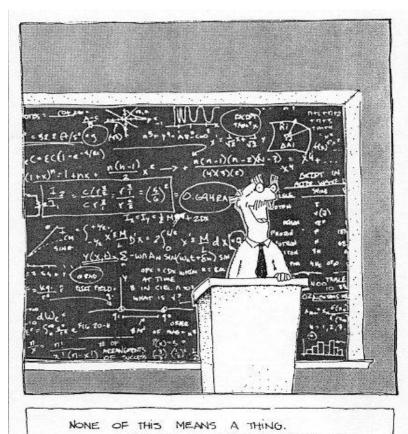
Inverse Problems and Biological Plausibility

• What makes a model more biological than another?

- thermodynamic constraints
- numerical integrity semi-definite solutions
- asymptotic behaviors
- stability properties
- information theory constraints
- physico-chemical constraints
- environmental constraints
- evolution constraints

- flux distributions
- mass and energy balance

Parameter determination needs also



WHAT DO YOU THINK OF THAT? HA!

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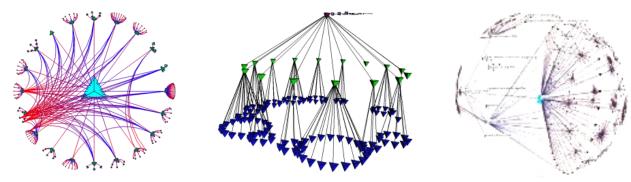


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Visualization Challenges

• Visualization in a large graph with too much detail

- Analysis of results what's interesting?
- Drill down, hyperbolic viewers, database driven for large models
- Visualizing fluxes in a meaningful way
- How do you visualize huge networks?



Experiments By T. Munzer, UBC, for visualizing Web connections

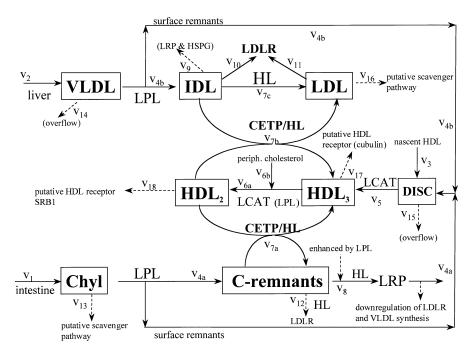
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- Tools needed for panning, zooming, drill-down, scalable, incrementally updatable from a database, etc.
- Pathway editors for input

• Animation - visualizing temporal fluxes

Discovering "New" Biology

Assumption: if we didn't know anything any biology per se, could we rediscover it from the model?



Caveat:

if we can find *"old"* biology, then presumably we could find *"new"* biology



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Discovering "New" Biology

• Finding new *cooperative* or *emergent* phenomena:

- pathways and "distinguishable" sub-systems
- cycles and "clocks"
- oscillatory systems
- regulatory systems
- "states" or "modes" of the system

• The resulting biology acts as plausible checks on the model

• Some ideas:

- Persistent pathway behavior *is* or *is not* independent of initial conditions
- Conditional pathway is active only for certain initial conditions the nub of course is how to identify this
- Model \Rightarrow graph \Rightarrow matrix \Rightarrow permutation matrix reordering
 - \Rightarrow structure \Rightarrow biology?
- Pattern recognition approaches. Model comparison? Different organisms/species?
- Some type of flux or domain decomposition?



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How do you know they're right? Assertions checking

- Provide a means to formally represent biology that went into the model
 - aspects of computer language parsing, AI-knowledge representation, inference
- Purposes
 - as a formal computer language for incorporation into software
 - for automation of the biology knowledge comparisons against data
 - allow checking model accuracy
 - used as criteria for optimisation e.g. parameter determination of rate laws
- Consequences of the assertions
 - require certain behaviours to be present in the model
 - expect, but not require some behaviours
 - search for speculative behaviours
 - provide diagnostic tools for examining the quality of the data

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Assertions - Bacterial Aerobicity Example

Different genes are expressed under different environments conditions - temperature, media composition, pH, and oxygen. Regulatory systems control expression, but assertions can be used to ensure the basic regulatory processes of the model are accurate.

Find the time when the system changes from anaerobic to aerobic behaviour and then # make sure that the key regulations appear to be happening

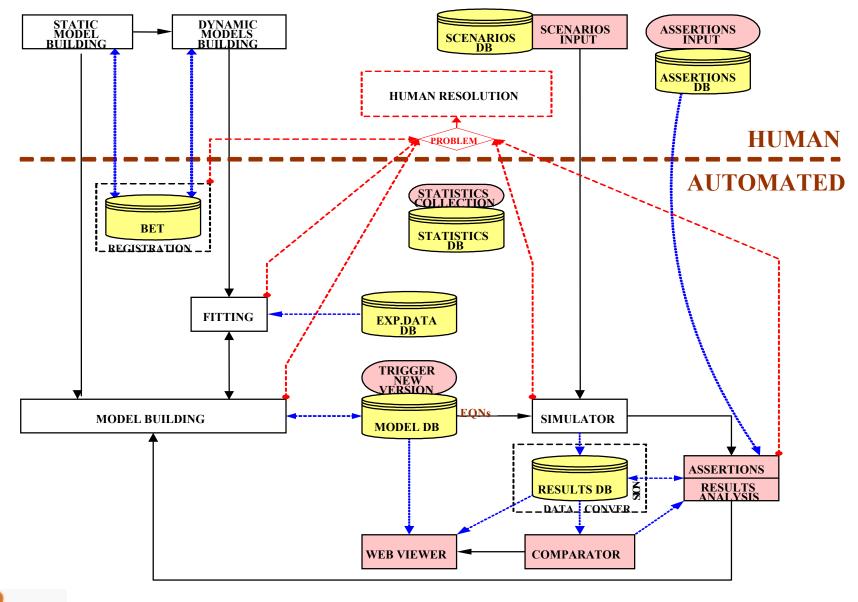
Regulation_time =	time > change.time('ANAEROBIC', 'AEROBIC')		
	AND	'ArcA-P' >> 'ArcA'	#positive regulation (activation) of ArcA by ArcA-P
	OR	'FNR-ox' >> 'FNR-red'	#FNR repressed aerobically

#Then, if regulation appears to be happening, for each protein behaving aerobically:

ForEach aerobic_protein=aerobic(*)	#look at each aerobic protein, one at a time				
{					
b = flux.value(aerobic_protein);	#get the flux of each aerobic protein concentration				
c = gene.name(aerobic_protein);	#time course of expression of the parent gene				
if (regulation_time AND (b > 0))					
{					
Success Action:	#if the assertion for this protein is true				
Message ("'AerobicityState' confirmed by the expre	Message ("'AerobicityState' confirmed by the expression profile of gene %s",c)				
Failure Action:	#if the assertion for this protein is false				
Message ("Gene %s does not have the expected 'AerobicityState' expression pattern",c)					
Status = WARNING	#indicate a non-fatal problem				
}					
}					

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The Pathway Modeling Factory Concept

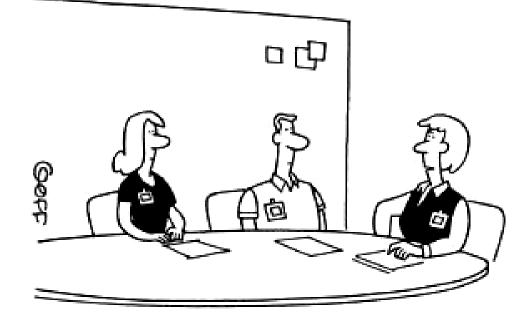


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What Else Is There? Much, Much More !

Only limited by our imaginations



"Come on, people. We need a creative epiphany right now. Who has one?"



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Acknowledgements

