

# Kinetic Models and Qualitative Abstraction for Relational Learning in Systems Biology

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# Introduction

Problems: **exploit** experimental data, **learn** what rules the cell.

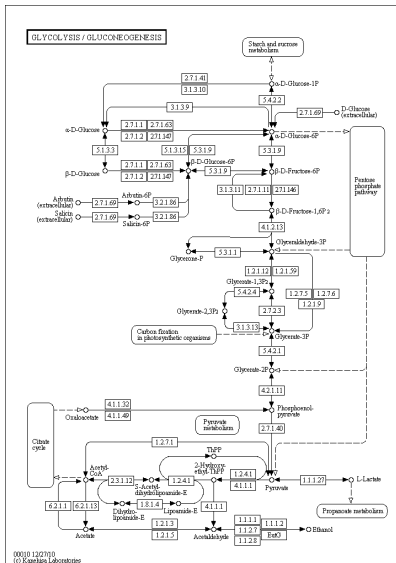
Method: **discretize** metabolites concentration, **combine** with existing pathways structures, use **kinetic models** with **inductive logic programming**.

- 1 Previous works
  - Metabolic Pathways
  - Inductive Logic Programming
  - Bibliography
- 2 A finer logic modeling
  - The trap
  - Kinetic modeling
  - Implementation
- 3 Results and further
  - Ranked Results
  - Where next?

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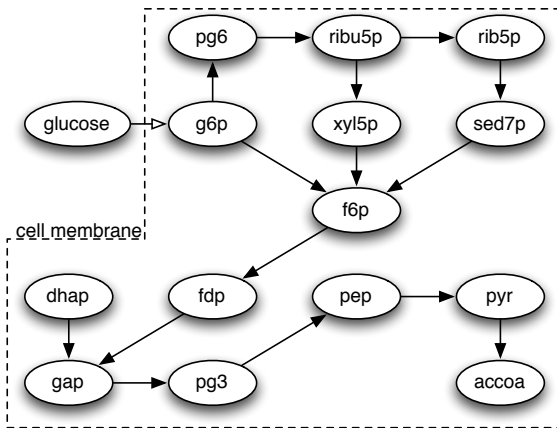
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# (Metabolic) Pathways



- Graphs of interconnected reactions
- Glucose enters  $ATP \Rightarrow ADP$  G6P
- Chain of reactions to take energy and store it in ATP/NADH (2 per molecule of Glucose)
- Acetyl CoA is at the origin of the Krebs cycle (part of cellular respiration)

# Glycolysis and Pentose Phosphate of *E. Coli*



# Abduction & Induction

ILP strength lies in the fact that learnt rules/clauses are directly useable in a logical program.

## Induction & Abduction

From  $\mathcal{B}$  Background Knowledge  $\wedge$   $\mathcal{E}$  examples

◊ Find  $\mathcal{H}$  hypotheses satisfying  $\mathcal{B} \wedge \mathcal{H} \models \mathcal{E}$  and  $\mathcal{B} \cup \mathcal{H} \not\models \perp$

**Abduction:** ground (or  $\exists$  quant.) formulae, direct causes of observations that are called explanations.

**Induction:** universally ( $\forall$ ) quantified formulae (small  $\mathcal{B}$ ), more general hypotheses.



R. J. Mooney: Integrating abduction and induction in machine learning. IJCAI97 Workshop on Abduction and Induction in AI, 37–42 (1997).



Flach P. A., Kakas A. C.: Abduction and induction: Essays on their relation and integration. Kluwer (2000).






# Inverse Entailment (Consequence Finding)

ILP is interested in the formulas derived from  $B \wedge \neg \mathcal{E}$  that are not derived from  $B$  alone.

## Inverse Entailment

The previous definition is equivalent to  $B \wedge \neg \mathcal{E} \models \neg \mathcal{H}$  and  $B \not\models \neg \mathcal{H}$ .

We can then use a consequence finding procedure (resolution, tableaux) to find  $\neg \mathcal{H}$  (SOLAR).

-  Inoue, K.: Linear resolution for consequence finding. Artificial Intelligence 56:301-353 (1992).
-  Inoue K.: Induction as consequence finding. Machine Learning, 55:109-135 (2004).
-  Nabeshima H., Iwanuma K., and Inoue K.: SOLAR: A Consequence Finding System for Advanced Reasoning. TABLEAUX 2003, LNAI, Vol. 2796, pp. 257-263, Springer (2003).

# New age began there

The point for automatic **qualitative reasoning** through **ILP** has been made.



King, R., Whelan, K., Jones, F., Reiser, P., Bryant, C., Muggleton, S., Kell, D., and Olivier, S. (2004). Functional genomic hypothesis generation and experimentation by a robot scientist. *Nature*, 427:247–252.



King, R., Garrett, S., and Coghill, G. (2005). On the use of qualitative reasoning to simulate and identify metabolic pathways. *Bioinformatics*, 21(9):2017–2026.

# Inhibitory effect of toxins

**Metabolic flux analysis** through **induction**: rules that explain the concentration changes (up or down) between 2 experiments, with and w/o toxin.



Doncescu, A., Inoue K., Yamamoto Y.: Knowledge Based Discovery in Systems Biology Using CF-Induction. LNCS N.4570, pages 395-404 (2007).

# Dealing with kinetics?

Main complete models use **ordinary differential equations**.

**Temporal logic** combined with **stochastic logic programming**  $\Rightarrow$  **kinetic models**.



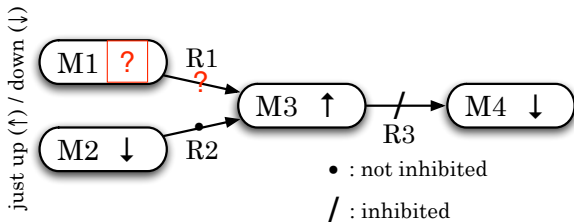
Franco R. and Canela E.: Computer simulation of purine metabolism. European Journal of Biochemistry, 144:305-315 (1984).



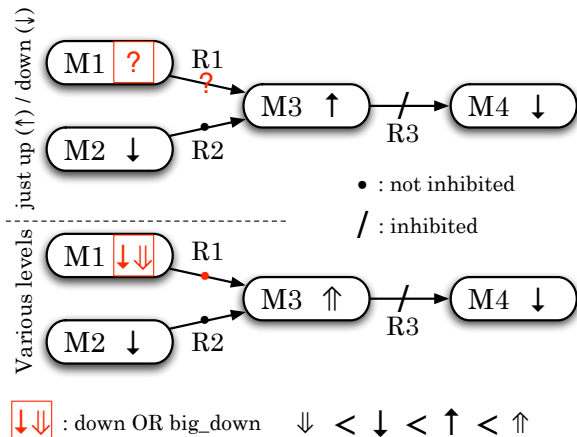
Fages, F., Soliman, S., and France, I. R. (2008). Model revision from temporal logic properties in systems biology. In: Probabilistic Inductive Logic Programming. LNAI, volume 4911, pages 287–304.

# Limits of The Previous Models

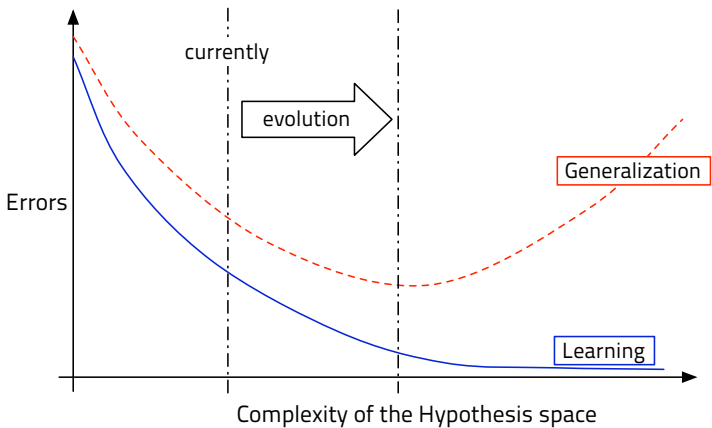
- No models for **dynamic transitions**
- Not enough information to be **precise** enough:



# Dealing With More Knowledge



# Be More Precise but Avoid Overfitting

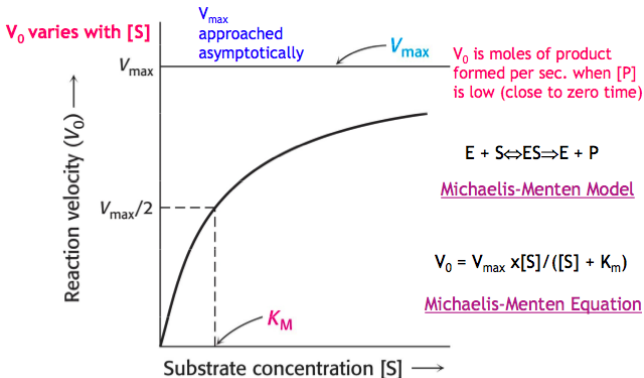


# Michaelis-Menten Kinetics

## Speed of a one-way reaction

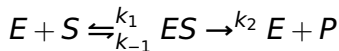
$v = \# \{ \text{products per second per mole of the enzyme} \}$

$$sS \rightarrow pP \Rightarrow v = -\frac{1}{s} \frac{d[S]}{dt} = \frac{1}{p} \frac{d[P]}{dt}$$





# Simplification of Michaelis-Menten Equation



Michaelis – Menten equation : 
$$\frac{d[P]}{dt} = V_m \frac{[S]}{[S] + K_m} \quad (1)$$

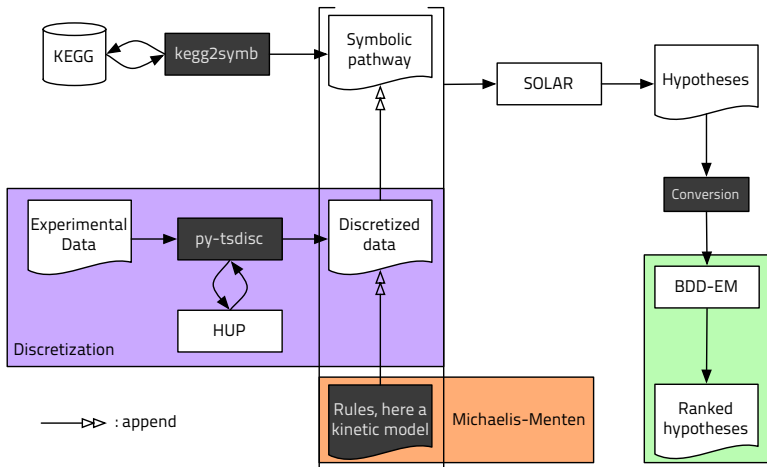
$$\frac{d[P]}{dt} \xrightarrow{\text{disc.time}} \frac{[P]_{T+\text{timestep}} - [P]_T}{(T + \text{timestep}) - T} \quad (2)$$

$$(1) \text{ and } (2) \Rightarrow V_m \frac{[S]_T}{[S]_T + K_m} \approx \frac{[P]_{T+\text{timestep}} - [P]_T}{(T + \text{timestep}) - T}$$

We chose to work with a constant timestep :

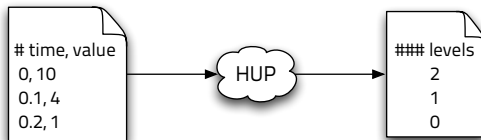
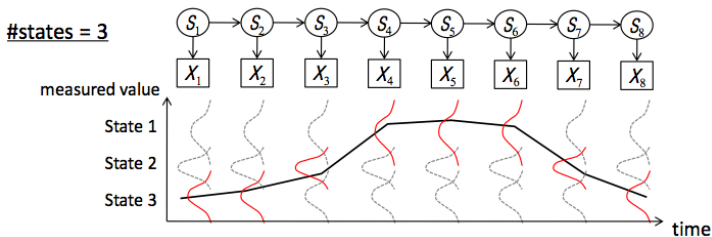
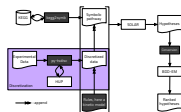
$$\Rightarrow [P]_{T+1} = V_m \frac{[S]_T}{[S]_T + K_m} + [P]_T \quad (3)$$

# Additional work and tools

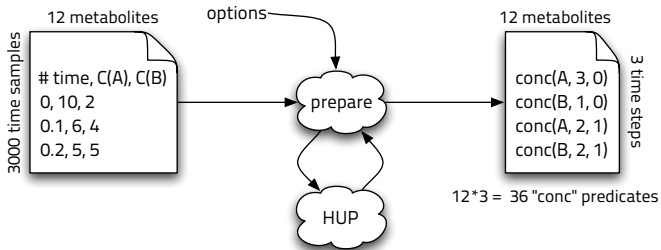
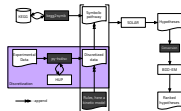


# HUP: HMM Utility Program

Clustering method that uses  
Continuous Hidden Markov Model +  
Bayesian Score:



# Wrapping HUP



# Logical Kinetic Modeling



**Approximations for extreme values in:**

$$[P]_{T+1} = V_m \frac{[S]_T}{[S]_T + K_m} + [P]_T$$

# Logical Kinetic Modeling (rules)

$$\underline{[S] \ll K_m}$$

reaction(S, P, Km)  $\wedge$  concentration(S, 0, 0)  $\wedge$   
 concentration(Km, 2, 0)  $\wedge$  concentration(P, L, 0)  $\rightarrow$   
 concentration(P, L, 1)

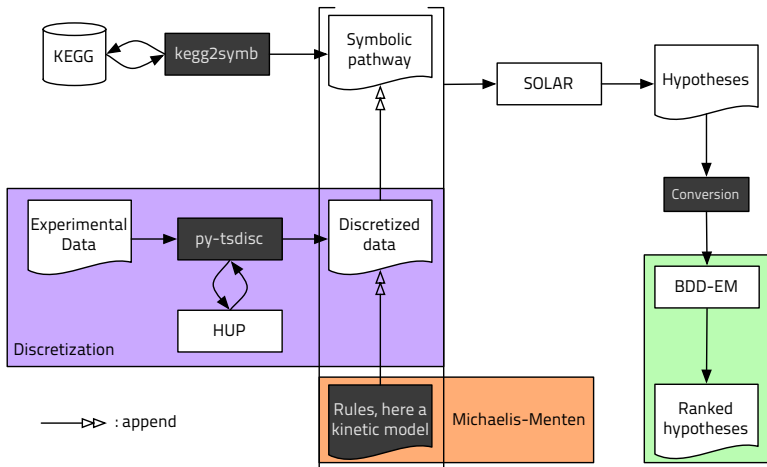
$$\underline{[S] \simeq K_m}$$

reaction(S, P, Km)  $\wedge$  concentration(S, 1, 0)  $\wedge$   
 concentration(Km, 1, 0)  $\wedge$  concentration(P, L, 0)  $\rightarrow$   
 concentration(P, L, 1)

$$\underline{[S] \gg K_m}$$

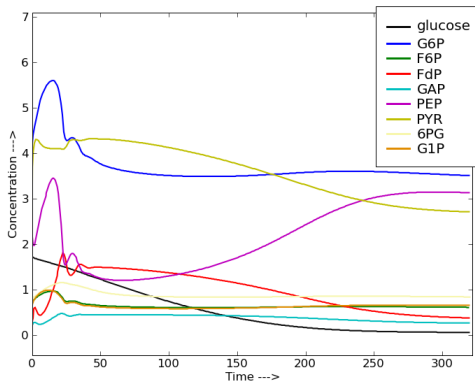
reaction(S, P, Km)  $\wedge$  concentration(S, 2, 0)  $\wedge$   
 concentration(Km, 0, 0)  $\rightarrow$  concentration(P, 2, 1)

# Data-centric schema



# Inputs

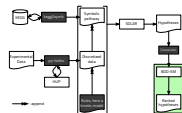
## Structure of the pathway(s) + Background knowledge (MM) + Metabolites concentrations





# Ranking the hypotheses with BDD-EM

Hyp. no.	Probability	Abducted concentrations levels at T=0
H130	$\approx 1.0$	pg3: 2, adp: 0
H392	$4.879.E^{-1}$	sed7p: 0, e4p: 2, f6p: 0, pg3: 2, adp: 0
H216	$7.567.E^{-2}$	pg3: 2, adp: 0, pep: 0, atp: 2, pyr: 2
H196	$6.930.E^{-2}$	fdp: 0, dhap: 2, gap: 0, pg3: 2, adp: 0
H356	$5.621.E^{-2}$	pg3: 2, adp: 0, g6p: 1, nadph: 1
H94	$3.692.E^{-2}$	sed7p: 0, e4p: 2, f6p: 0, pg3: 2, adp: 0, pep: 0, atp: 2, pyr: 2
H251	$3.497.E^{-2}$	glucose: 2, adp: 0, pg3: 2
H286	$3.382.E^{-2}$	sed7p: 0, e4p: 2, f6p: 0, fdp: 0, dhap: 2, gap: 0, pg3: 2, adp: 0
H405	$2.796.E^{-2}$	pg3: 2, adp: 0, pep: 2, atp: 0
H167	$2.743.E^{-2}$	sed7p: 0, e4p: 2, f6p: 0, pg3: 2, adp: 0, g6p: 1, nadph: 1
.	.	.
H378	$1.974.E^{-8}$	glucose: 2, adp: 0, sed7p: 0, e4p: 2, f6p: 0, fdp: 0, dhap: 2, gap: 0, pg3: 2, pep: 0, atp: 2, pyr: 2, g6p: 0, nadph: 2, pg6: 1



# Is is correct?

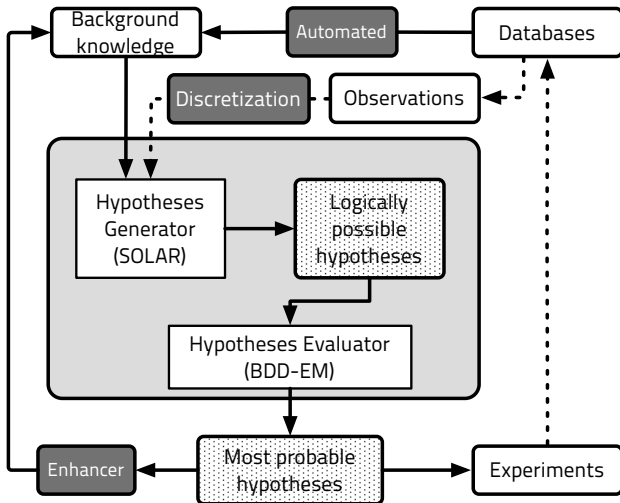
Ok with:  $glucose + 2ADP + 2P + 2NAD^+ \rightarrow$   
 $2\ pyruvate + 2ATP + 2(NADH, H^+) + 2H_2O$

Agree with:



Peters-Wendisch, P., Schiel, B., Wendisch, V., and et al., E. K. (2001). Pyruvate carboxylase is a major bottleneck for glutamate and lysine production by corynebacterium glutamicum. *Molecular Microbiol. Biotechnol.*, 3(2).

# Full system



## Future tracks:

- **Enhancing of the knowledge base**, 2 simple and sound algorithms (one in the paper):
  - most probable hypotheses first
  - smallest number of hypothesis additions (biggest abducibles coverage first)
- **Finer discretization**: trivial with our **continuous HMMs with parameter tying**.
- **Automatic** generation of MM rules (for orders  $> 3$ ).

# Conclusion

We presented and validated a **method** and **tools** to work on **real data**.

Working with **other experiments** on **more complex** organisms and pathways (for instance *S. Ce*) will require:

- Enhancing of the KB
- Finer discretization
- Kinetic rules

# Thanks

Thank you for your attention.

# Any questions?

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Prof. Inoue: [ki@nii.ac.jp](mailto:ki@nii.ac.jp)