# Improving model consistency by qualitative equations

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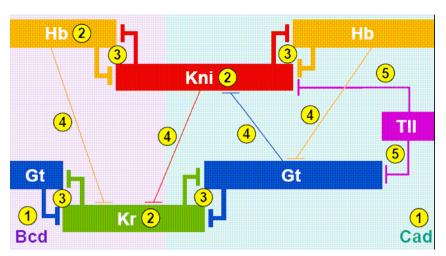


LA BRETAGNE

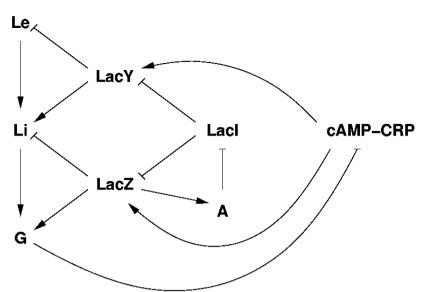


# Summary

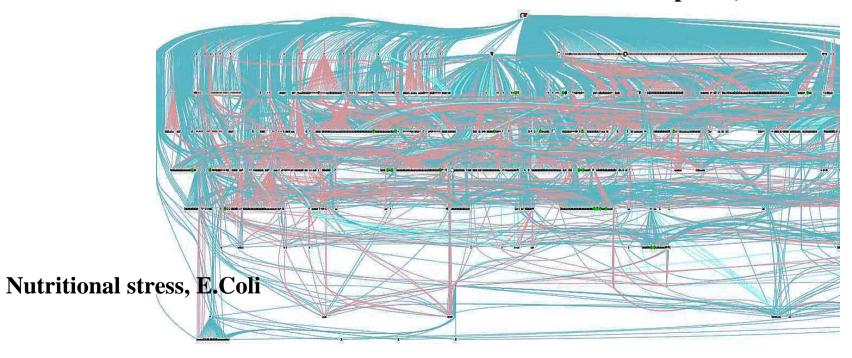
- Large scale models and data
- Qualitative equations
- Prediction and correction, a case study: nutritional stress in *Escherichia Coli*
- Reverse engineering: interaction sign inference
  - ✓ Feasability study: random solutions, *Escherichia Coli* network
  - ✓ Application: transcriptional regulatory network in Saccharomyces cerevisiae
- Conclusion



Gap genes, first 3 hours of Drosophila



Lactose operon, E.Coli



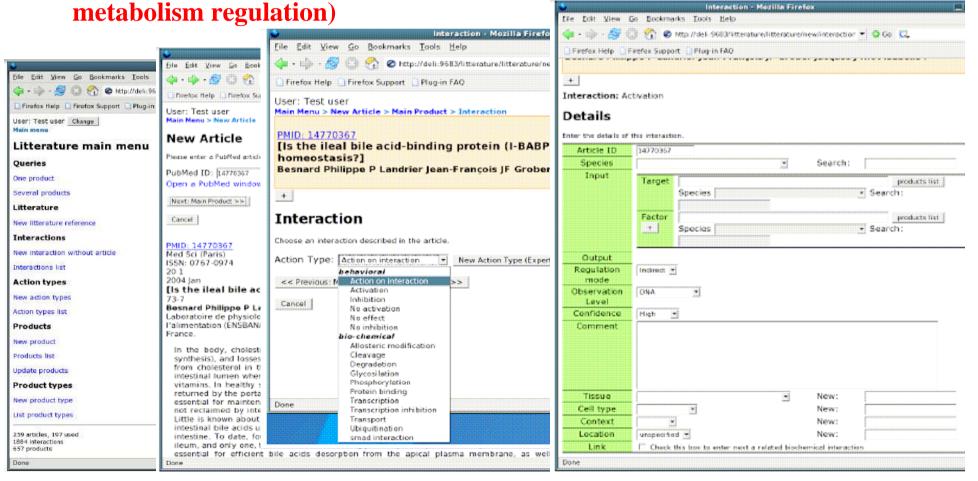
Network models : oriented graphs + signs

#### Knowledge databases: RegulonDB, KEGG, Ingenuity, BioBase, etc.

Transcriptional interactions: ChIP/chip, promoter analysis

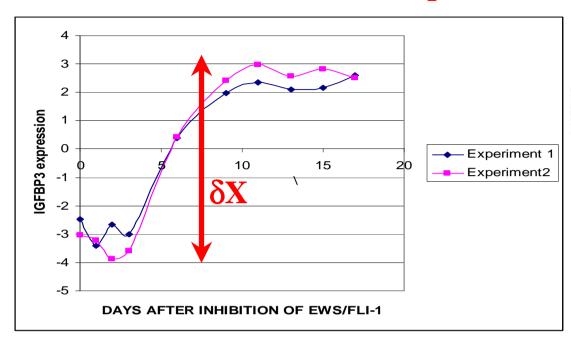
**Interaction signs: well controlled experiments** 

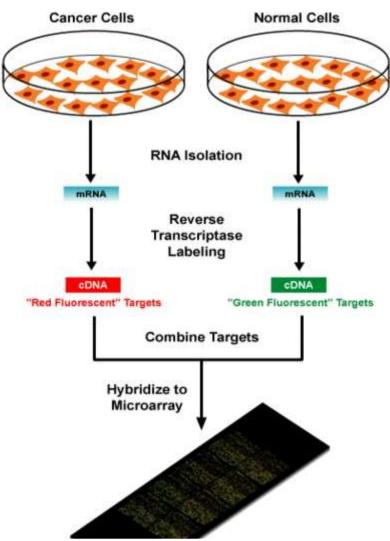
GARDON: our database (lipid



#### Time series, switch-like response

#### Differential data





$$|\delta \log X| < \theta$$
, sign=0  
 $\delta \log X > \theta$ , sign=+  
 $\delta \log X < -\theta$ , sign=-  
else sign=?

Qualitative transcriptional data: signs of differences of concentrations between two states

# Exploit model-data consistency

#### Data prediction:

• Propose gene variation signs consistent with a model and with relatively reliable data

#### Data correction:

• Detect and correct false positives and false negatives

#### Model reverse engineering:

- Do not start from scratch
- Infer signs of interactions
- Infer new interactions

#### Experiment design:

• Guide data collection

# Qualitative equations: define consistency

#### Biological problem:

Following a perturbation (stress, signal) the state of the cell changes. Variations of hundreds or thousands of variables can be monitored. How to use this information?

#### Steps:

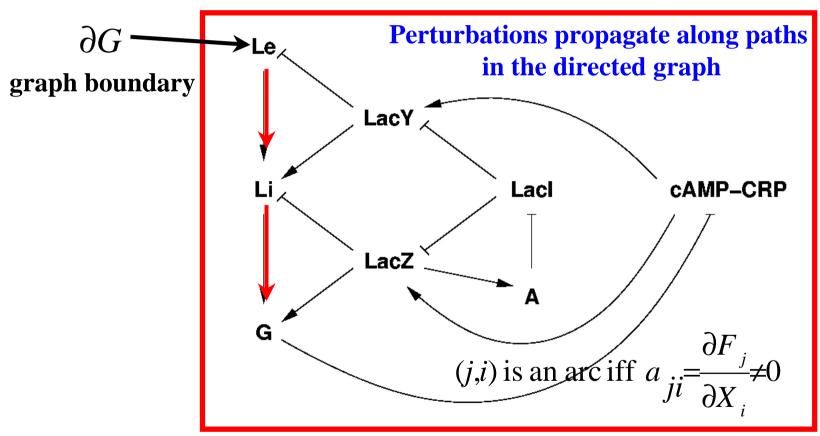
- develop an "elasticity" theory of graphs (O.Radulescu et al. J.R.Soc.Interface 2006)
- translate this theory into qualitative equations (with A.Siegel et al. Biosystems 2006)
- polynomial algorithms for solving systems of qualitative equations (with Ph.Veber, M.leBorgne et al. Complexus 2006)
- application to large networks (E.Coli with C.Guziolowski et al., proc. RIAMS 2006, S. Cerevisiae with Ph.Veber, C.Guziolowski in work)

# Elasticity of graphs

$$\frac{dX}{dt} = F(X,P)$$
 dynamics

F(X,P)=0 Steady state equation

Steady state is perturbed  $\delta P \rightarrow \delta X$ 



Dirichlet solution: 
$$\delta X_i = \sum_{j \in \partial G} \sum_{j \to i} \frac{a_{j \to i}}{C_{j \to i}} \delta X_j$$
Soc.Interface 2006)

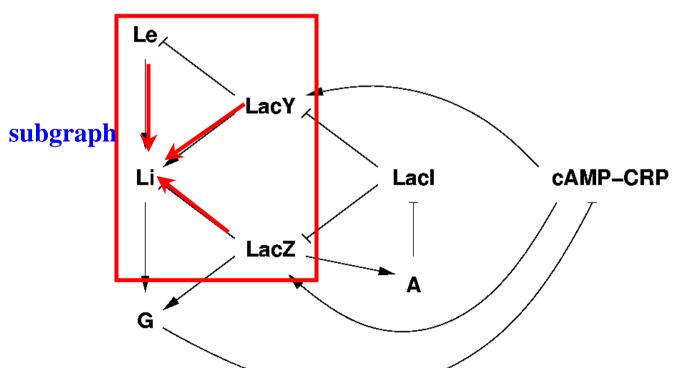
#### Qualitative equations

$$\delta X_{i} = -\left(\frac{\partial F_{i}}{\partial X_{i}}\right) - 1 \sum_{j \in pred(i)} a_{ji} \delta X_{j}$$
 Dirichlet solution for subgraph

$$sign(\delta X_i) = \sum_{j \in pred(i)} sign(a_{ji}) sign(\delta X_j)$$
 Qualitative equation

 $sign \in \{-,+,?\}$  Sign algebra



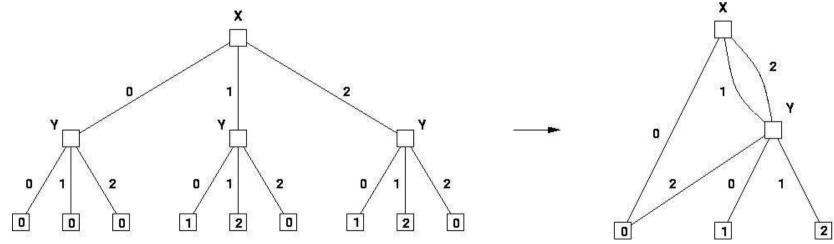


$$++-=?$$
  $+++=+$   
 $+\times-= +\times+=+$   
 $?+-=?$   $?++=?$   
 $?\times-=?$   $?\times+=?$ 

(with A.Siegel et al.Biosystems 2006, with Ph.Veber, M.LeBorgne Complexus 2006)

## Algorithm for solving qualitative equations

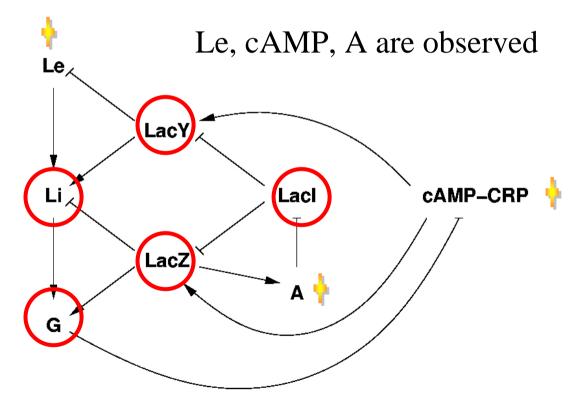
- •Map signs to elements of the finite field Z/3Z
- •Map qualitative equations to polynomial equations over Z/3Z
- •NP complete problem
- •Ternary Decision Trees contracted to directed acyclic graphs and systematic use of cache memory for non-redundant computation
- •Obtain exhaustive lists of solutions within minutes for 1000 nodes



#### Predictions of a model

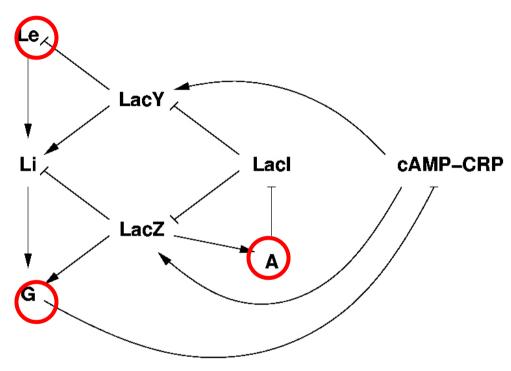
hard components: variables whose values are the same (+ or -) in any solution

the hard components are the predictions of the model



Li,G,LacZ,LacY, LacI are hard components

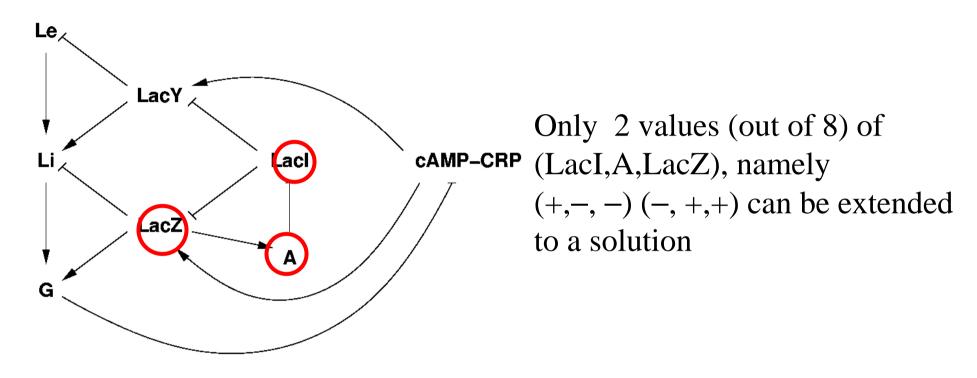
# Experiment design



Any value of the triplet (Le,G,A) can be extended to a solution

These variables have no validation power

## Use validation power for experiment design



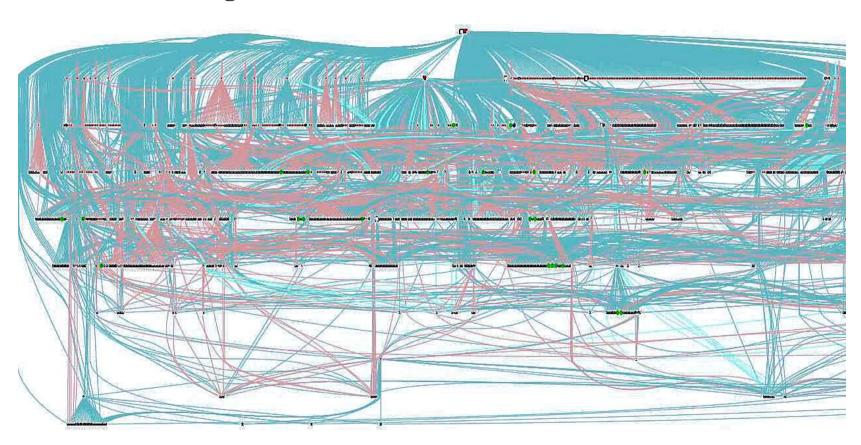
Define validation power as:

$$\tau(X_1, \dots X_p) = 1 - \frac{\text{val}(X_1, \dots X_p)}{2^p}$$

Choose high validation power sets for optimal design

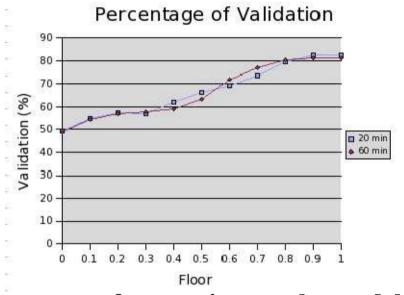
#### Large scale application: nutritional stress of E.Coli

1258 nodes, 2526 interactions,  $10^{600}$  states,  $10^{16}$  solutions Source: RegulonDB (March 2006)



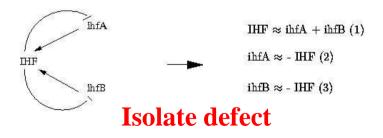
#### We have obtained:

• a set of predictions: from 40 observations in the stationary phase, 401 hard components, 26% of the network; these where compared to expression data



Number of genes compared 325 300 275 250 compared 225 0 200 175 20 m in 150 ♦ 60 m in 125 100 75 50 0.1 0.2 0.3 0.4 0,5 0.6 0.7 0.8 0.9 Floor

• a set of corrections to the model





**Propose correction** 

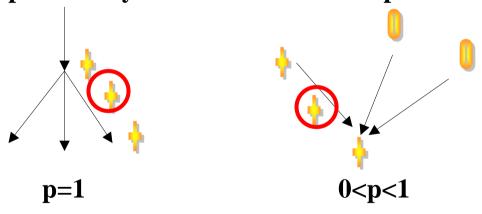
• a set of corrections to data: minimality with respect to Hamming distance

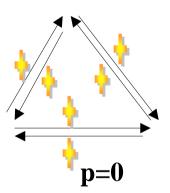
#### Reverse engineering: interaction sign inference

**Problem:** ChIP/chip data provide unsigned interactions. Which proportion of signs can be infered from expression data? Use QEs with interaction signs as variables.

Numerical feasibility study: Generate random, consistent observations, from them compute hard components (predicted signs).

**Analytical approximate guess:** three classes of interactions. p=probability of inference in one experiment

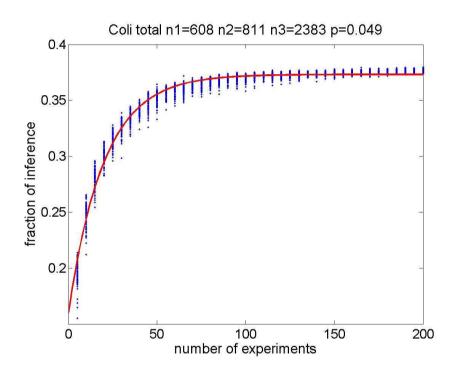




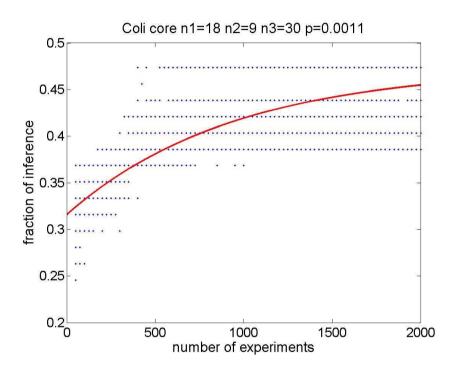
$$n = n_1 + n_2 \left[ 1 - (1 - p)^n \exp \right]$$

#### Sign reverse engineering: numerical feasibility study

# type of experiments: generate gene and TF variations compatible with the network constraints



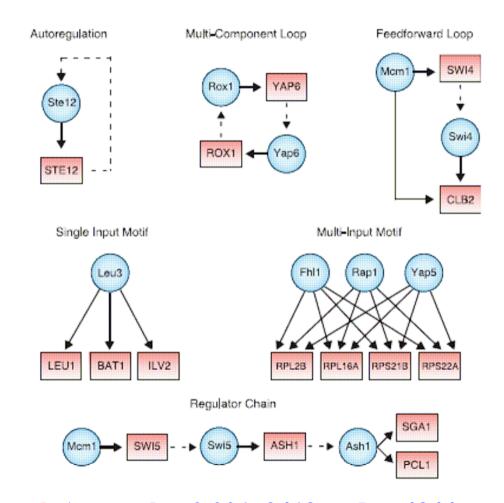
Total network: need few experiments, randomly chosen



Core network: need more experiments, eventually well chosen; experiment design useful

#### Transcriptional regulation network in S.Cerevisiae

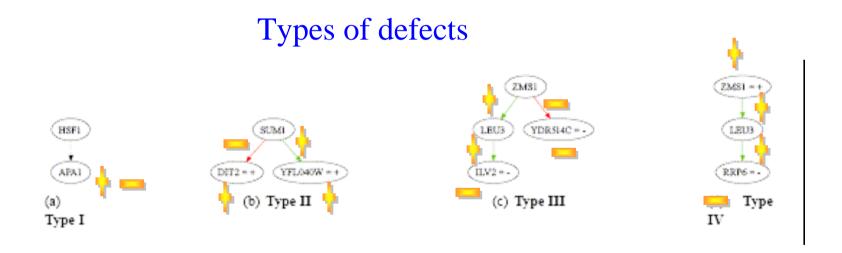
Sources:Lee et al. (2002), MacIsaac et al. (2005), Harbinson et al. (2004)



global network (at p-value 0.001, 2419 nodes, 4344 interactions) and core network (at p-value 0.001, 70 nodes, 96 interactions)

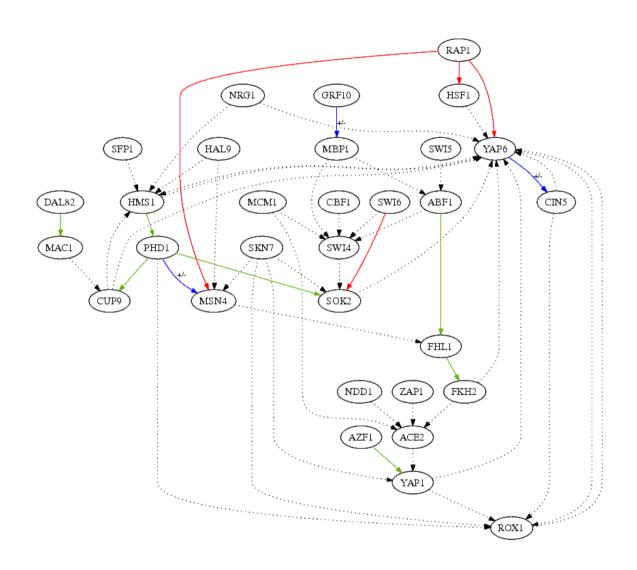
#### Inferred signs and defects

Interaction network	Nodes	Edges	Number of Experiments	Input/Output obs. simult.	Inferred signs	MBM Int. TypeI	MBM Int. TypeII,III,IV	Total Inf. rate
Core of Lee transcriptional network Lee et al. 2002, Kauffman et al. 2003	31	52	15	46	11 (21.1%)	3 (5.7%)	0	26.8%
Extended Lee transcriptional network Lee at al. 2002	70	96	15	70	29 (30.2%)	7 (7.2%)	0	37.4%
Global transcriptional network Lee at al. 2002, p-value = 0.001	2419	4344	14	2270	631 (14.5%)	281 (6.5%)	463 (11%)	32%
Inferred network  MacIsaac et al. 2005, Harbinson et al. 2004  threshold = 0.001; bindings=2	83	131	14	91	21 (16%)	4 (3%)	0	19%

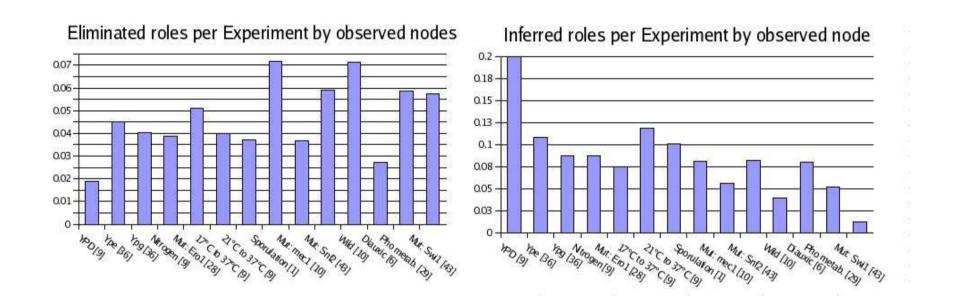


Iterations short range defects → inference → longer range defects

#### Inferred signs for core of Lee et al. (2002)



#### Inference per type of experiment



YPD: Broth to stationary phase Gash et al 2000

#### Conclusion

- Qualitative equations suitably describe consistency between data and models
- Our rules are over-approximations of boolean rules: they produce robust predictions
- Sign reverse engineering is possible with a small number of experiments (10-15); nevertheless limits exist, specially for core network; use experiment design (choice of experiments)
- Future work:
  - ✓ Diagnosis: better characterization of defects, propose corrections
  - ✓ Experiment design, useful for core network
  - ✓ Model other types of data : project in cancer genomics CGH, microRNA silencing, expression time series

# Acknowledgements

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