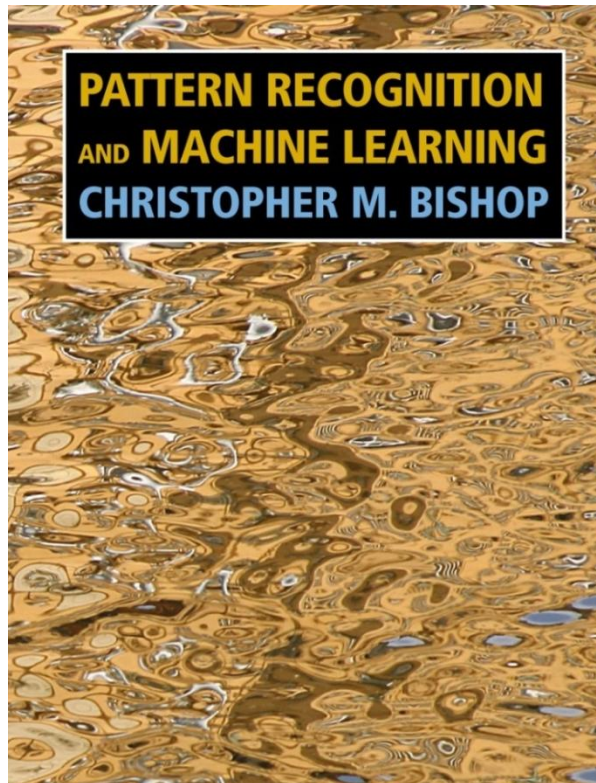


INTRODUCTION TO BAYESIAN INFERENCE – PART 1

CHRIS BISHOP

Please ask questions!



<http://research.microsoft.com/~cmbishop>

First Generation

“Artificial Intelligence” (GOFAI)

*Within a generation ... the problem of creating
‘artificial intelligence’ will largely be solved*

Marvin Minsky (1967)

Expert Systems (1980s)

knowledge-based AI

rules elicited from humans

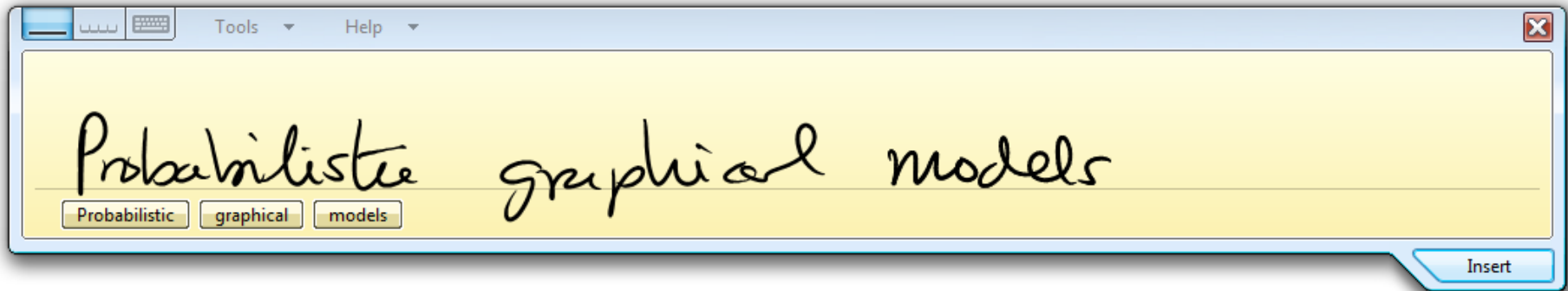
Combinatorial explosion



General theme: hand-crafted rules

Second Generation

Neural networks, support vector machines



Difficult to incorporate complex domain knowledge

General theme: black-box statistical models

Third Generation

General theme: deep integration of domain knowledge and statistical learning

Bayesian framework

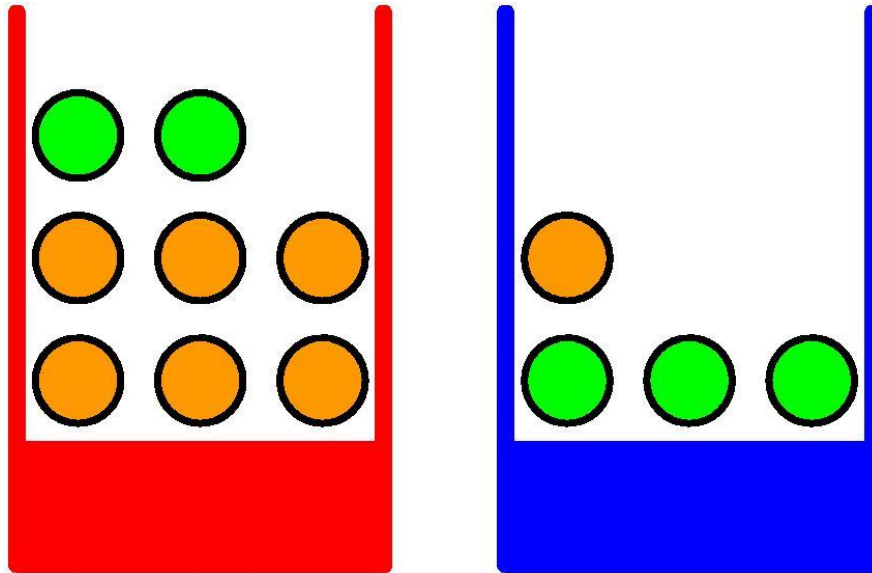
Probabilistic graphical models

Fast inference using local message-passing

Origins: Bayesian networks, decision theory, HMMs,
Kalman filters, MRFs, mean field theory, ...

Probability Theory

Apples and Oranges



Fruit is orange, what is probability that box was blue?

The Rules of Probability

Sum rule

$$p(X) = \sum_Y p(X, Y)$$

Product rule

$$p(X, Y) = p(Y|X)p(X)$$

$$p(X) \geq 0$$

$$\sum_X p(X) = 1$$

Bayes' Theorem

$$\begin{aligned} p(Y|X) &= \frac{p(X, Y)}{p(X)} \\ &= \frac{p(X|Y)p(Y)}{p(X)} \end{aligned}$$

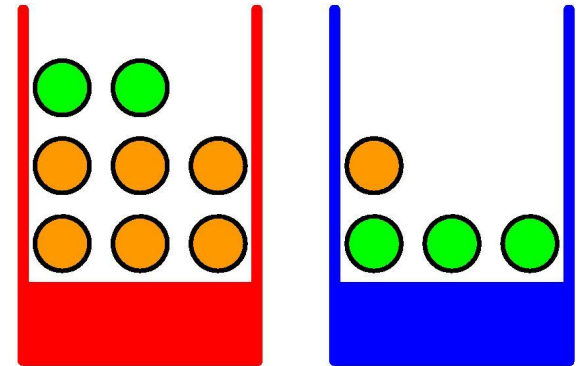
$$\begin{aligned} p(X) &= \sum_Y p(X, Y) \\ &= \sum_Y p(X|Y)p(Y) \end{aligned}$$

Oranges and Apples

Suppose $p(B = r) = 2/5$

Suppose we select an **orange**

Then

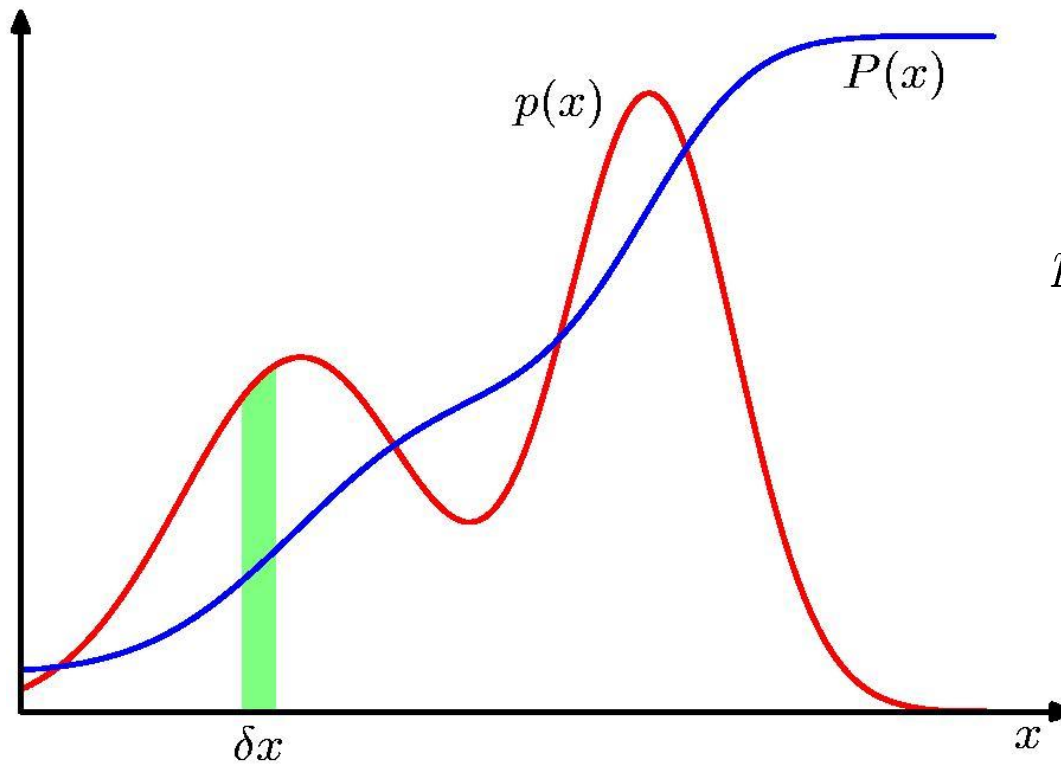


$$\begin{aligned} p(F = o) &= p(F = o|B = r)p(B = r) + p(F = o|B = b)p(B = b) \\ &= 9/20 \end{aligned}$$

and hence

$$\begin{aligned} p(B = r|F = o) &= \frac{p(F = o|B = r)p(B = r)}{p(F = o)} \\ &= 2/3 \end{aligned}$$

Probability Densities



$$p(x \in (a, b)) = \int_a^b p(x) dx$$

$$P(z) = \int_{-\infty}^z p(x) dx$$

$$p(x) \geq 0$$

$$\int_{-\infty}^{\infty} p(x) dx = 1$$

Bayesian Inference

Consistent use of probability to quantify uncertainty

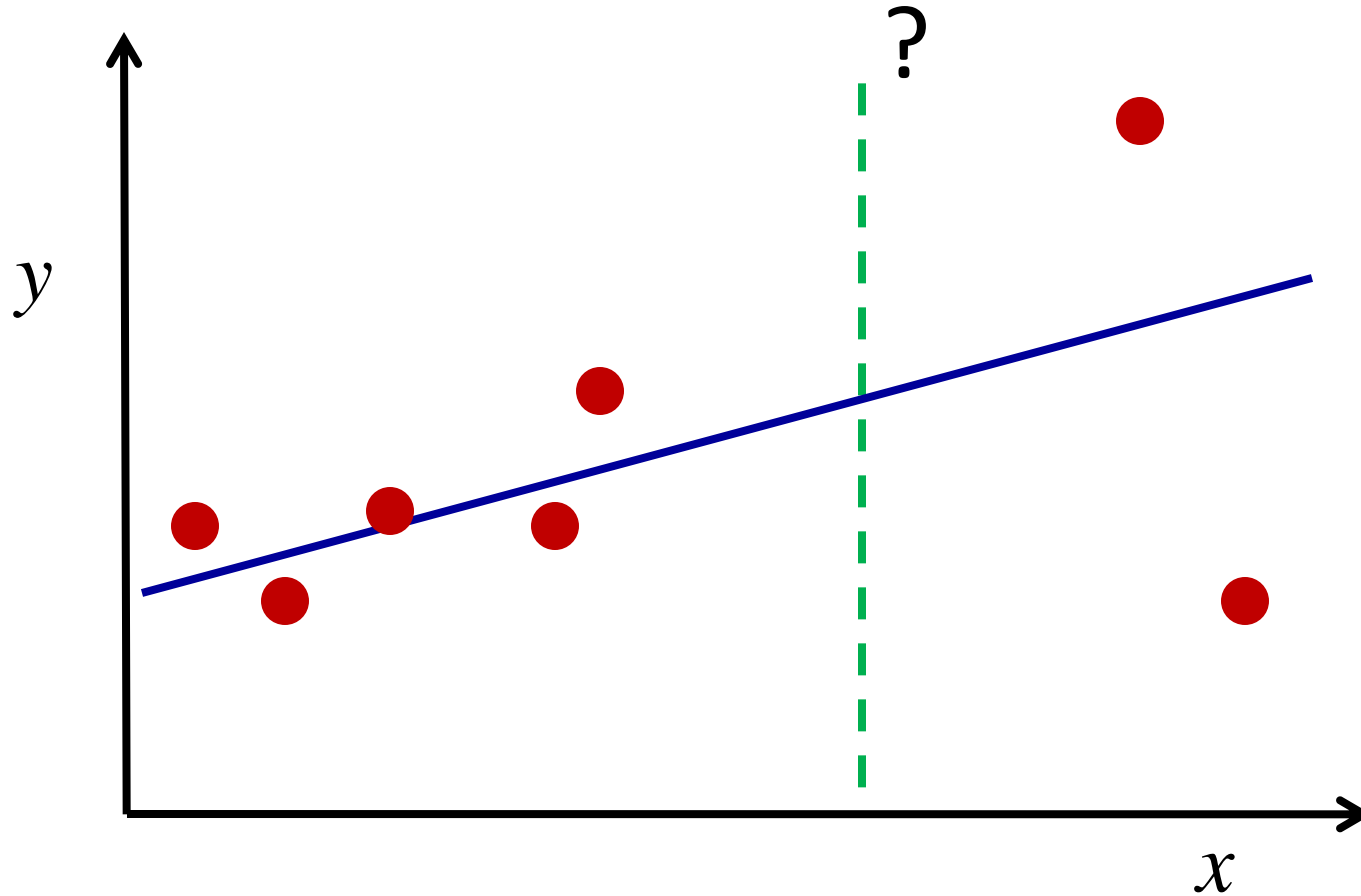
$$p(\boldsymbol{\theta}|\hat{\mathbf{x}}, \mathbf{X}) \propto p(\hat{\mathbf{x}}|\boldsymbol{\theta}) p(\boldsymbol{\theta}|\mathbf{X})$$

posterior likelihood function prior

Predictions involve marginalisation, e.g.

$$p(\mathbf{y}|\mathbf{X}) = \int p(\mathbf{y}|\boldsymbol{\theta})p(\boldsymbol{\theta}|\mathbf{X}) \mathrm{d}\boldsymbol{\theta}$$

Why is prior knowledge important?



Probabilistic Graphical Models

Combine probability theory with graphs

- ✓ new insights into existing models
- ✓ framework for designing new models
- ✓ Graph-based algorithms for calculation and computation (c.f. Feynman diagrams in physics)
- ✓ efficient software implementation

Directed graphs to specify the model

Factor graphs for inference and learning

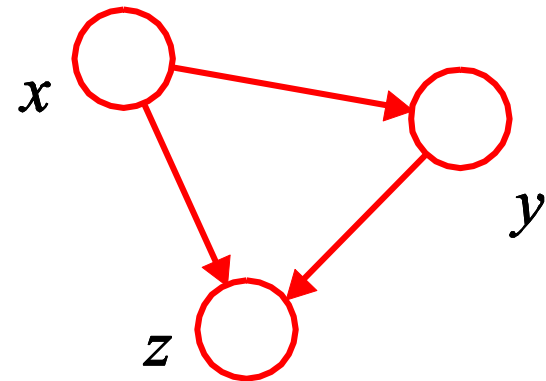
Decomposition

Consider an arbitrary joint distribution

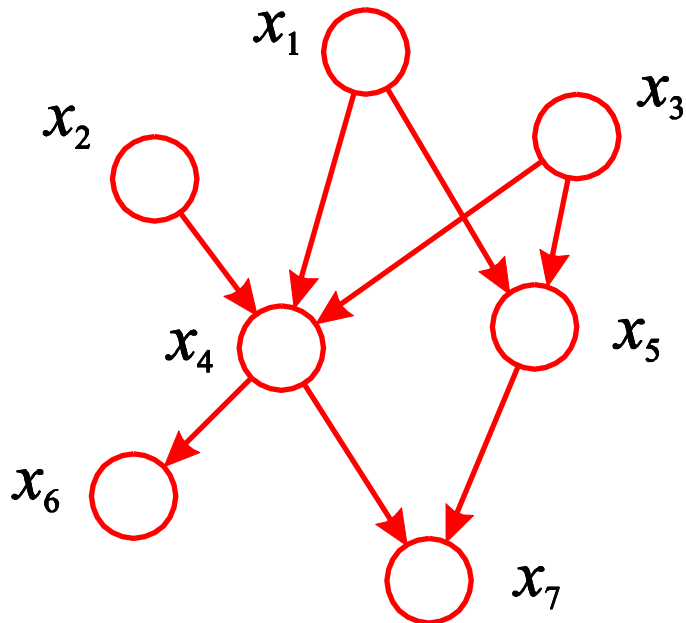
$$p(x, y, z)$$

By successive application of the product rule:

$$\begin{aligned} p(x, y, z) &= p(x)p(y, z|x) \\ &= p(x)p(y|x)p(z|x, y) \end{aligned}$$



Directed Graphs



$$\begin{aligned} p(x_1, \dots, x_7) &= p(x_1)p(x_2)p(x_3) \\ &\quad p(x_4|x_1, x_2, x_3)p(x_5|x_1, x_3) \\ &\quad p(x_6|x_4)p(x_7|x_4, x_5) \end{aligned}$$

Arrows indicate causal relationships

MAAS

Manchester Asthma and Allergies Study

Goal: discover environmental and genetic causes of asthma

1,186 children monitored since birth

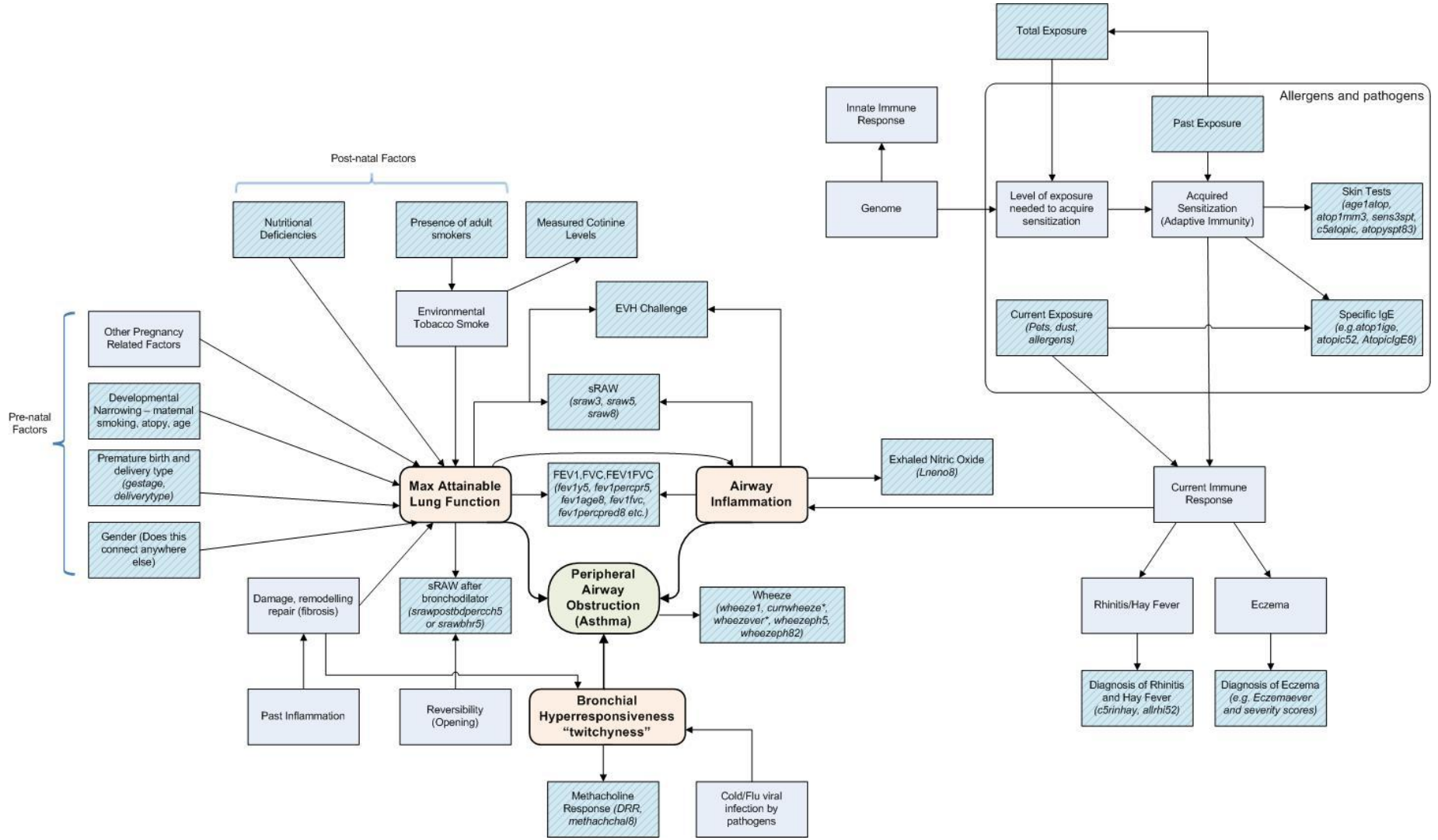
640k SNPs per child

Many environment and physiological measurements:

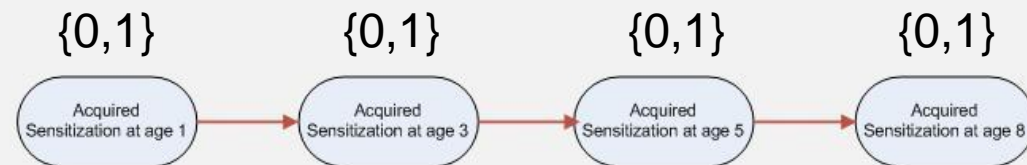
skin and IgE blood tests at age 1, 3, 5, and 8

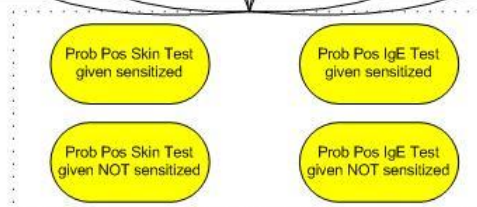
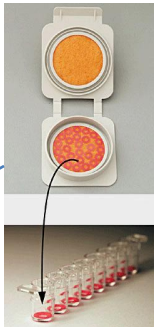
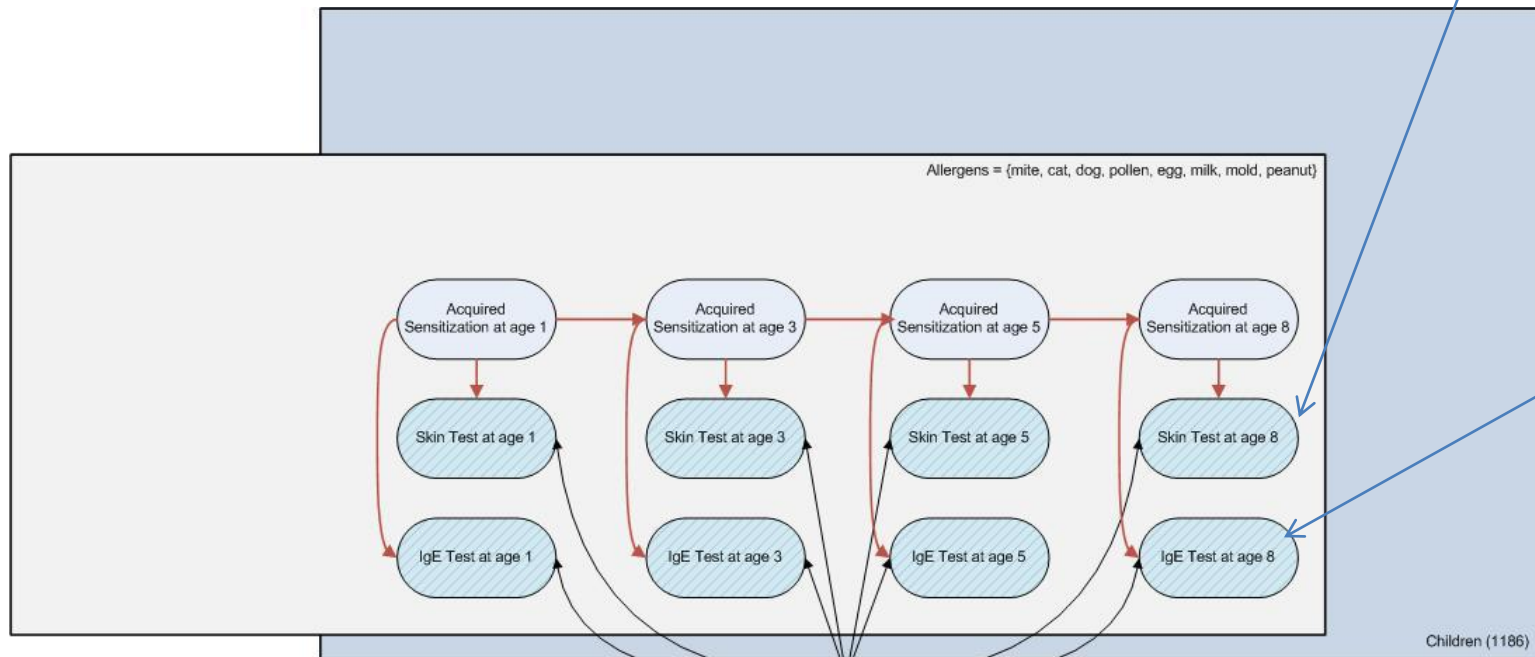
wheezing, methacholine response,

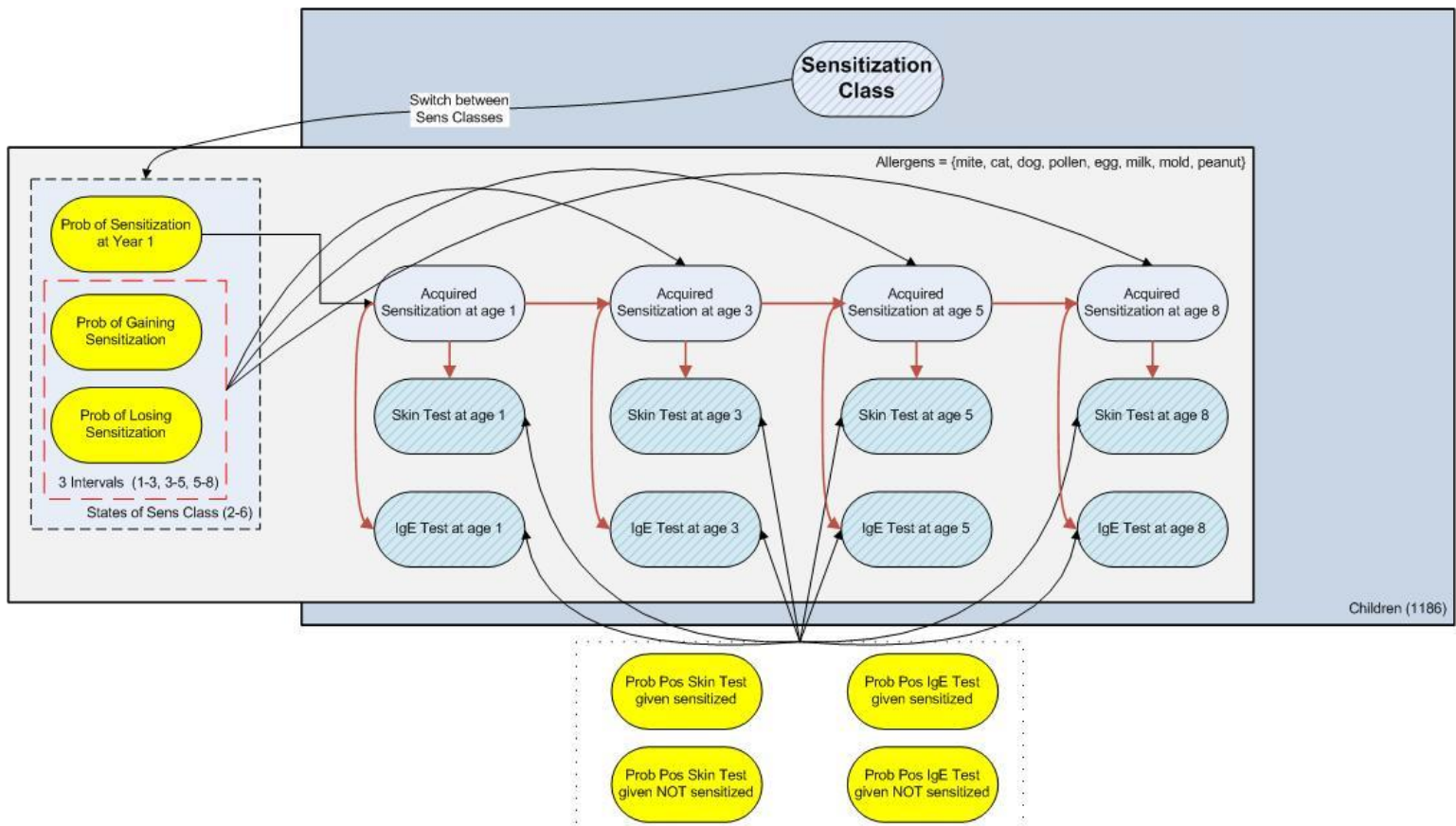
pets, parental smoking, day-care, breast feeding, ...



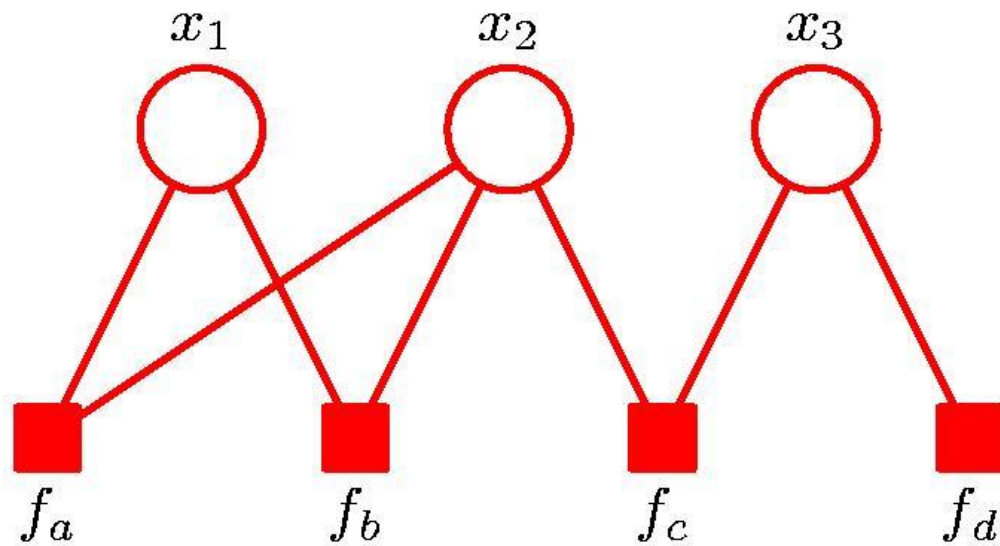
Allergens = {mite, cat, dog, pollen, egg, milk, mold, peanut}







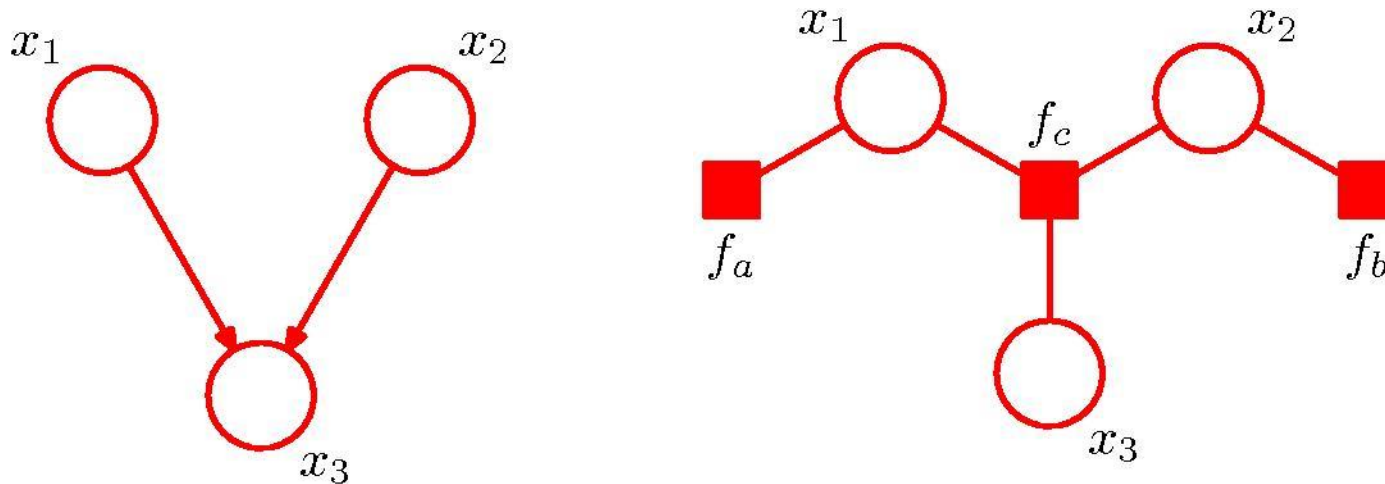
Factor Graphs



$$p(x_1, x_2, x_3) = f_a(x_1, x_2) f_b(x_1, x_2) f_c(x_2, x_3) f_d(x_3)$$

From Directed Graph to Factor Graph

$$p(x_1, x_2, x_3) = p(x_1)p(x_2)p(x_3|x_1, x_2)$$



$$f_a(x_1) = p(x_1)$$

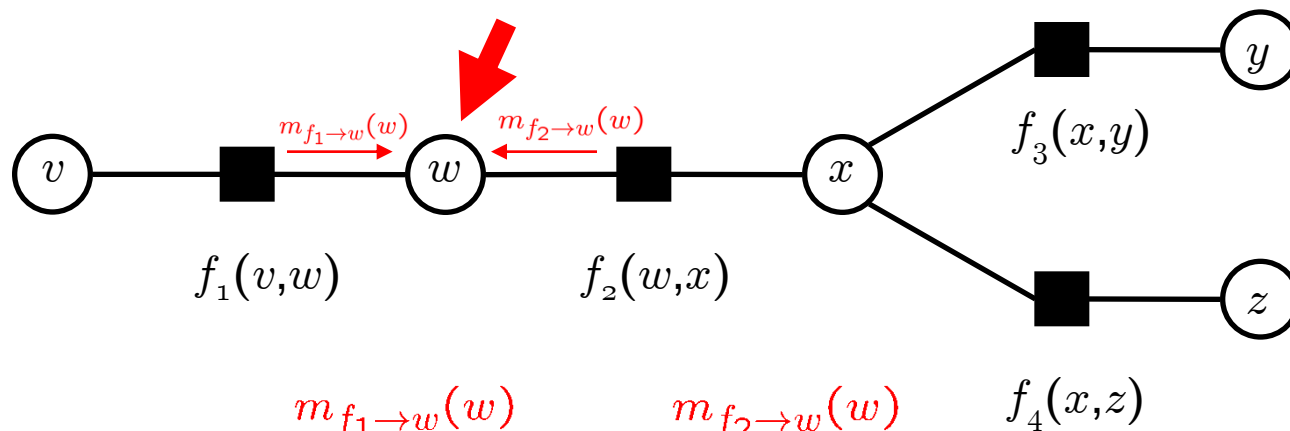
$$f_b(x_2) = p(x_2)$$

$$f_c(x_1, x_2, x_3) = p(x_3|x_1, x_2)$$

Inference on Graphs

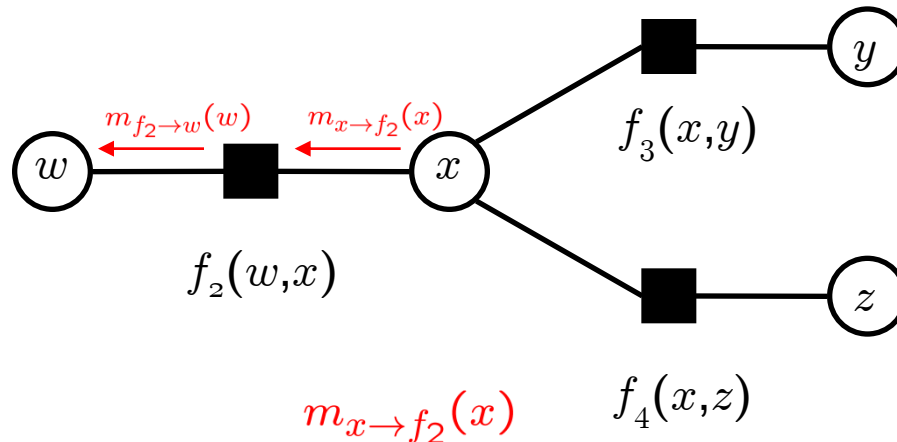
$$ab + ac = a(b + c)$$

Factor Trees: Separation



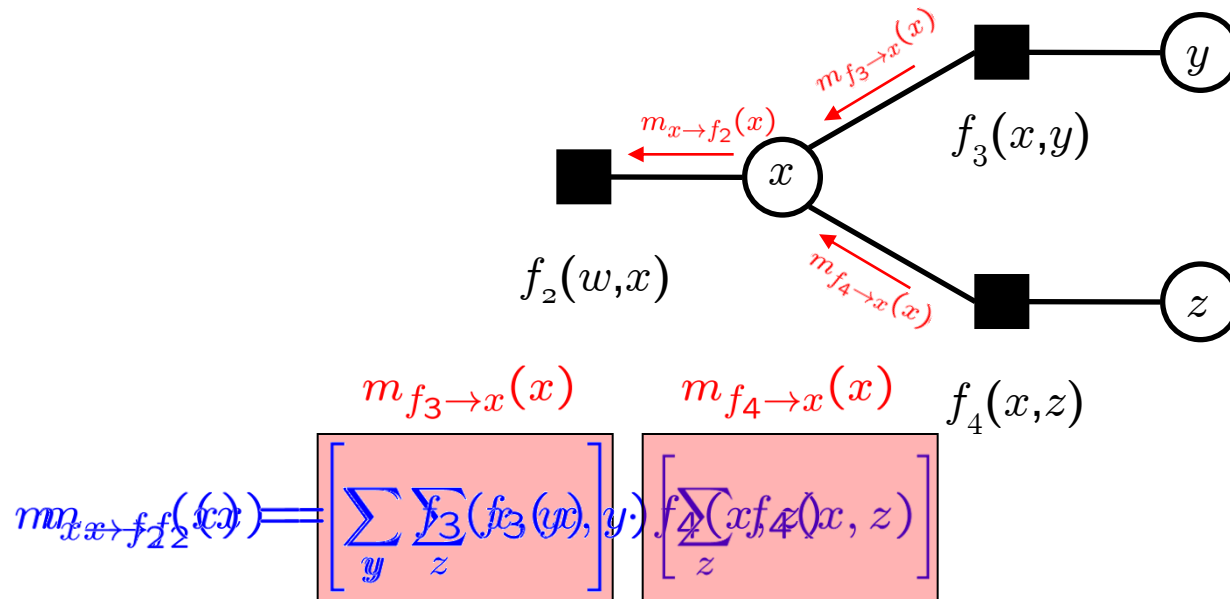
$$p(w) = \left[\sum_v \sum_x \sum_y \sum_z f_1(v, w) f_2(w, x) f_3(x, y) f_4(x, z) \right]$$

Messages: From Factors To Variables



$$m_{f_2 \rightarrow w}(w) = \sum_x \sum_y \sum_z f_2(w, x) \left[\sum_y \sum_z f_3(x, y) f_4(x, z) \right]$$

Messages: From Variables To Factors

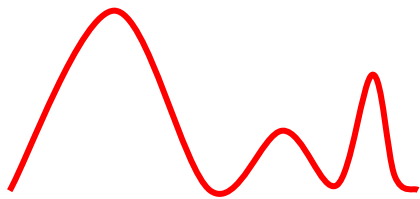


What if the graph is not a tree?

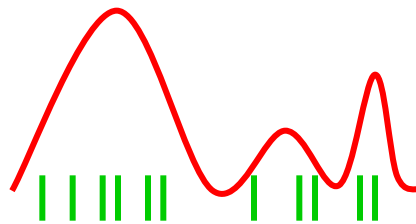
Keep iterating the messages:

loopy belief propagation

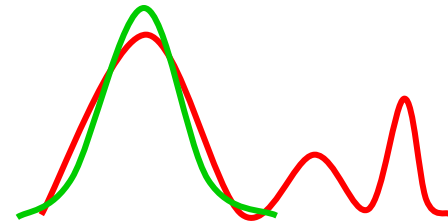
What if marginalisations are not tractable?



True distribution

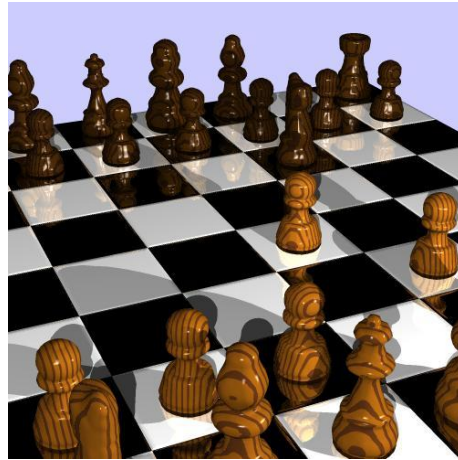


Monte Carlo



VMP / Loopy BP / EP

Illustration: Bayesian Ranking



Ralf Herbrich
Tom Minka
Thore Graepel

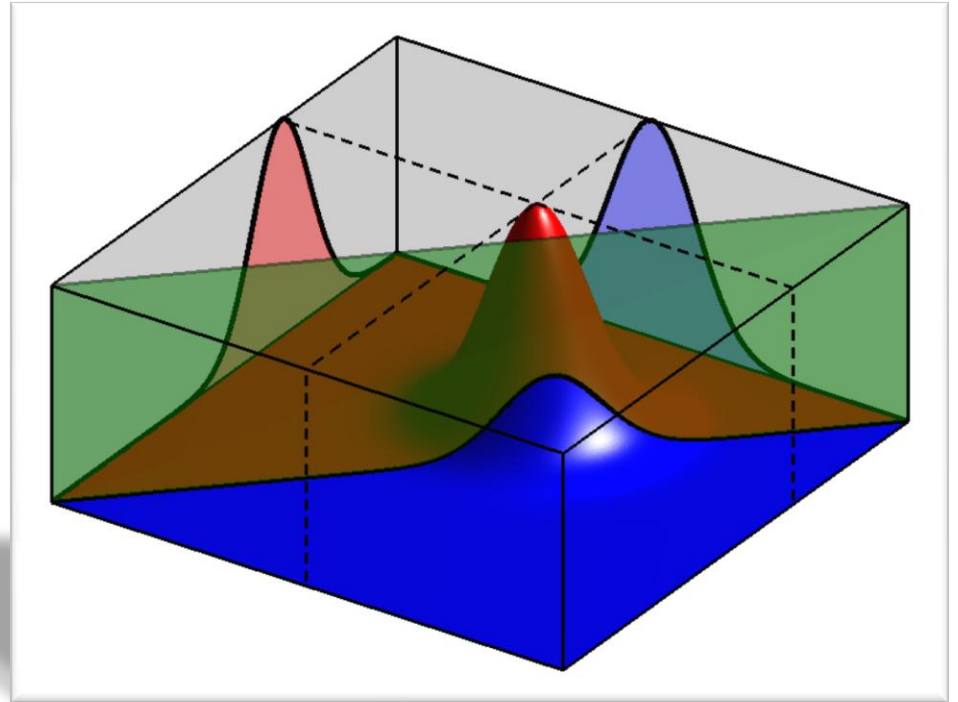
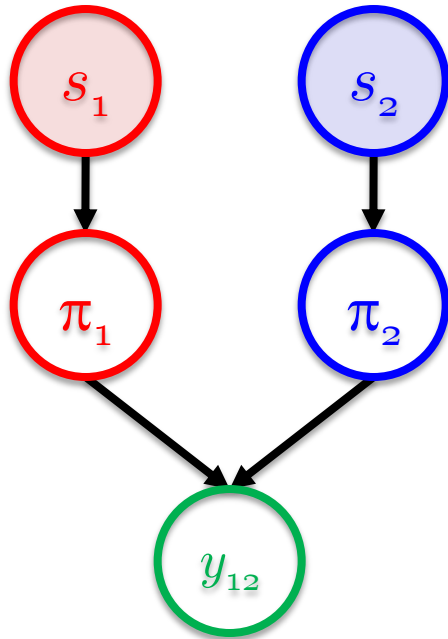
Goal: global ranking from noisy partial rankings

Conventional approach: Elo (used in chess)

- maintains a single strength value for each player

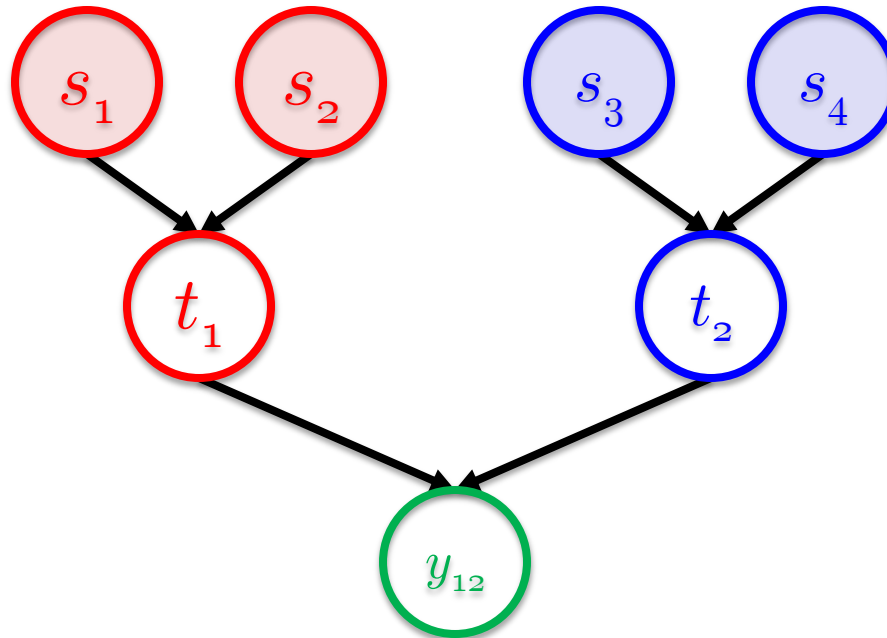
- cannot handle team games, or > 2 players

Two Player Match Outcome Model



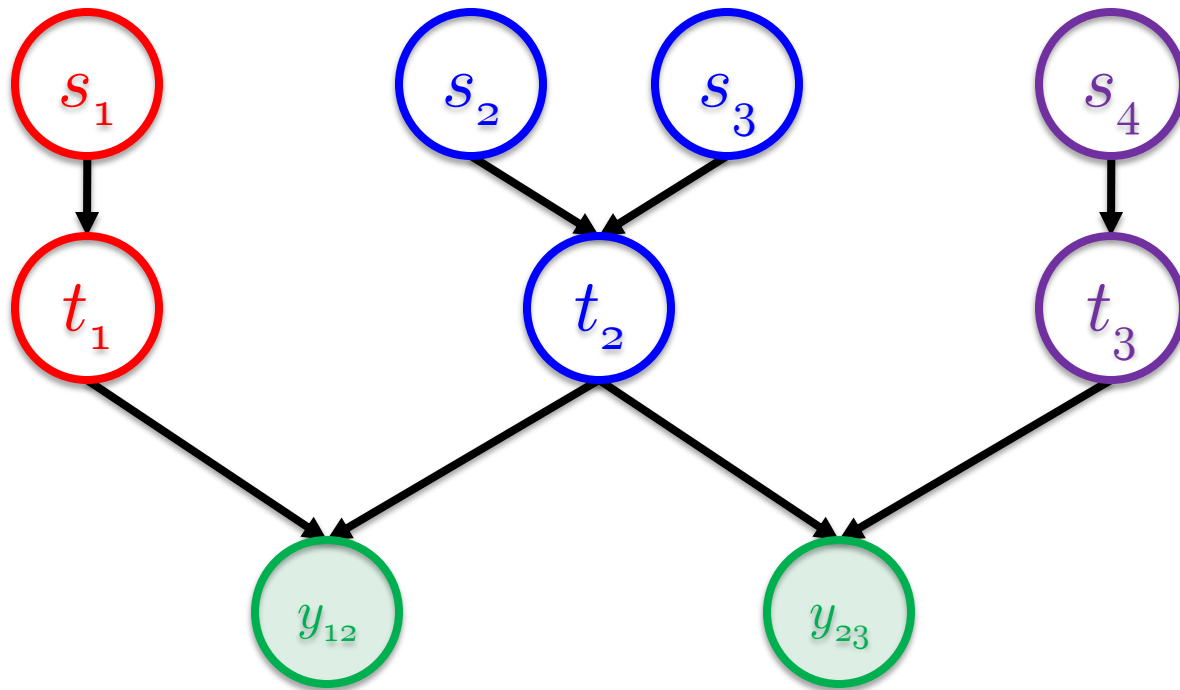
$$p(y_{12} = (1, 2) | \pi_1, \pi_2) = I(\pi_1 > \pi_2)$$

Two Team Match Outcome Model

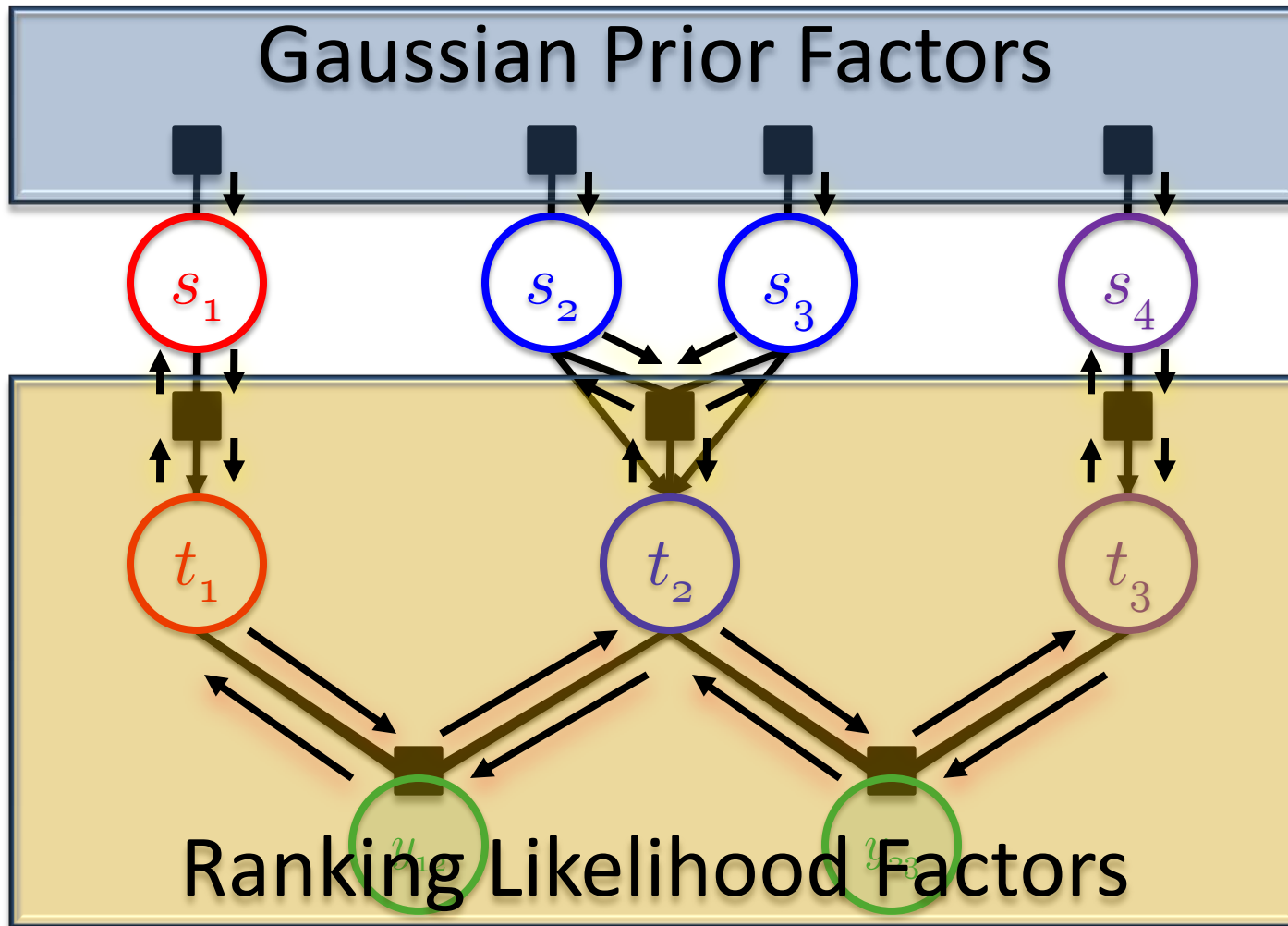


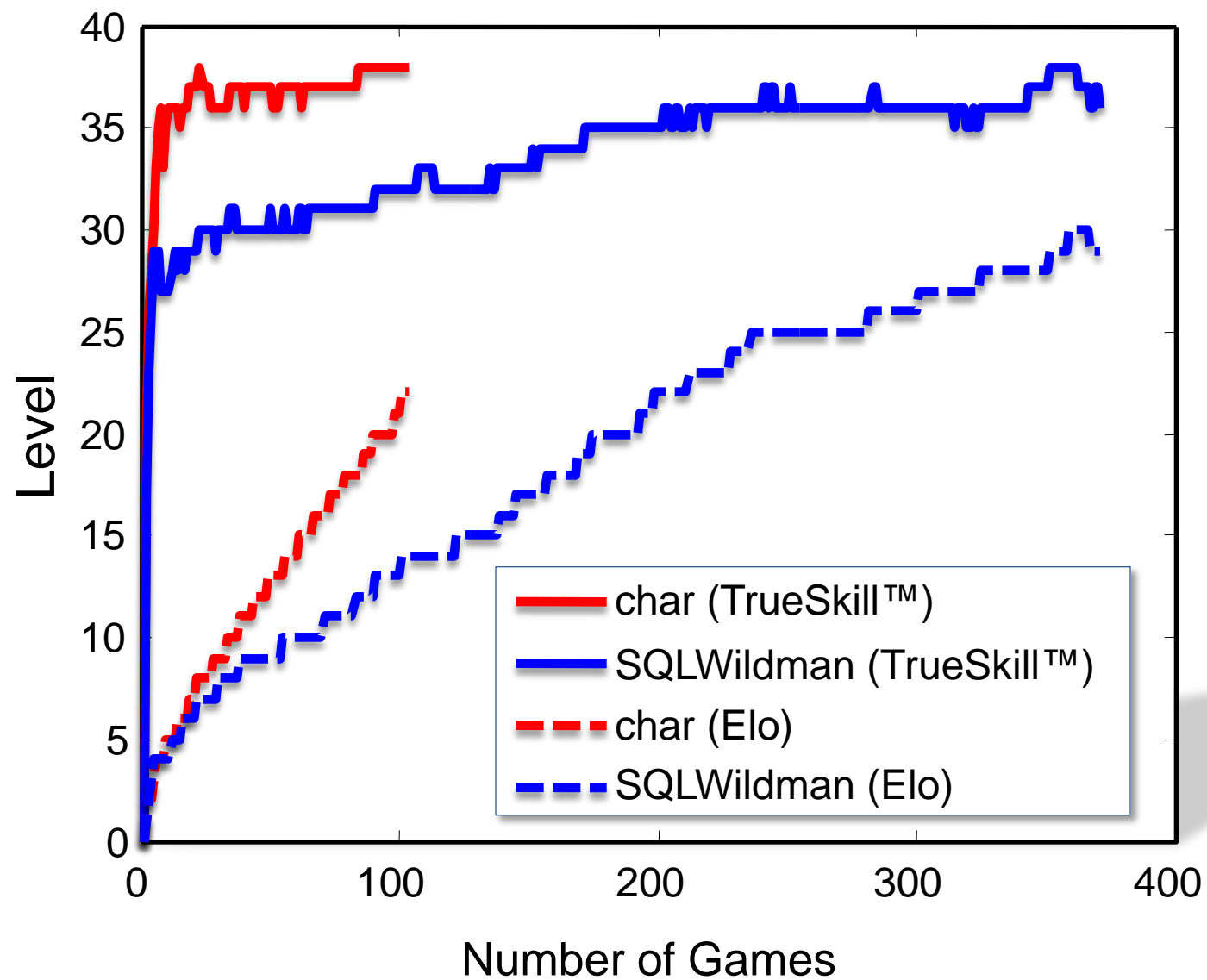
$$p(t_1 | s_1, s_2) = \mathcal{N}(t_1 | s_1 + s_2, 2\beta^2)$$

Multiple Team Match Outcome Model

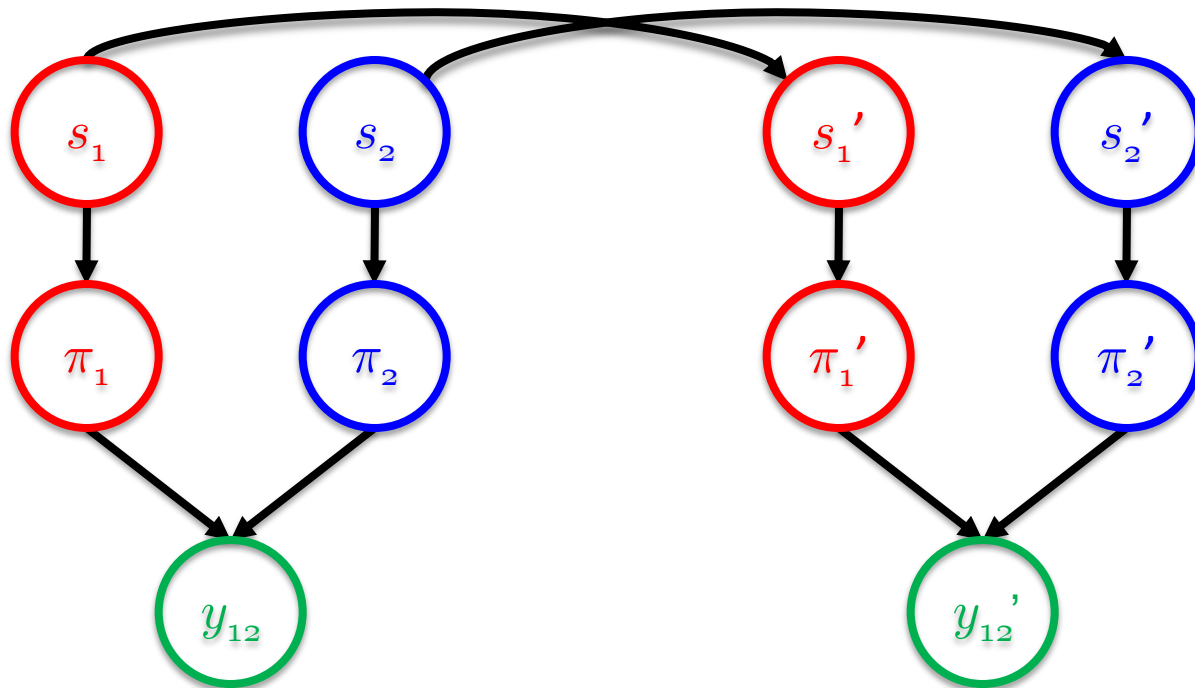


Gaussian Prior Factors





Skill Dynamics



$$p(s'_i | s_i) = \mathcal{N}(s'_i | s_i, \tau^2)$$

*TrueSkill*TM

Xbox 360 Live: launched September 2005

*TrueSkill*TM for ranking and to match players

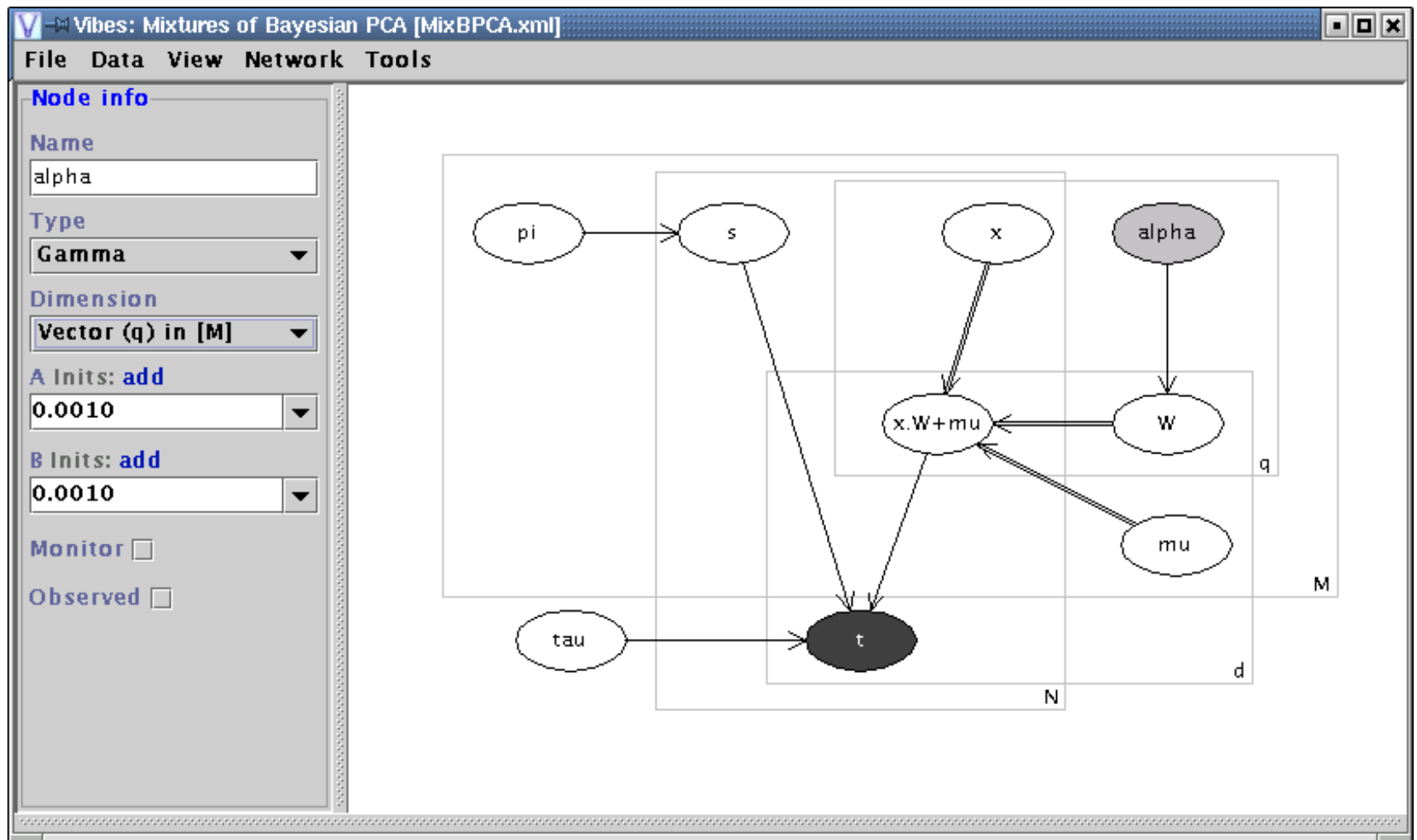
10M active users, 2.5M matches per day

“Planet-scale” application of Bayesian methods



XBOX
LIVE[®]







research.microsoft.com/infernet

Tom Minka
John Winn
John Guiver
Anitha Kannan

Infer.Net demonstration

