Learning at Scale

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Amazon

Overview

- Part 1: Theory
  - Graphical Models
  - Inference in Factor Graphs
  - Approximate Message Passing
  - Distributed Message Passing
- Part 2: Applications
  - TrueSkill: Gamer Rating and Matchmaking
  - TrueSkill Through Time: History of Chess
  - Click-Through Rate Prediction in Online Advertising
  - Matchbox: Recommendation Systems
  - Pattern Learning in Go

Part 1: Theory

http://www.coursera.org

http://www.cs.ubc.ca/~murphyk/MLbook/index.html

http://www.cs.ucl.ac.uk/staff/d.barber/brml/

http://research.microsoft.com/en-us/um/people/cmbishop/PRML/index.htm

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Cox Axioms: Probabilities and Beliefs

- **Design**: System must assign degree of plausability $p(A)$ to each logical statement A.
- **Axiom**:
  1. $p(A)$ is a real number
  2. $p(A)$ is independent of Boolean rewrite
  3. $p(A|C') > p(A|C) \quad \wedge \quad p(B|AC') = p(B|AC)$
     $\Rightarrow \quad p(AB|C') \geq P(AB|C)$

P must be a probability measure!

Infer-Predict-Decide Cycle

Inference:

P(Parameters) + Data → **P**(Parameters|Data)

- Requires a (structural) model **P**(Data|Parameters)
- Allows to incorporate prior information **P**(Parameters|Data)

Prediction:

P(Parameters) + Data → **P**(Data)

- Requires integration/ summation of parameter uncertainty
- Does not change state!

Decision Making:

Loss(Action,Data) + **P**(Data) → Action

- Business-loss not learning-loss!
- Often involves optimization!

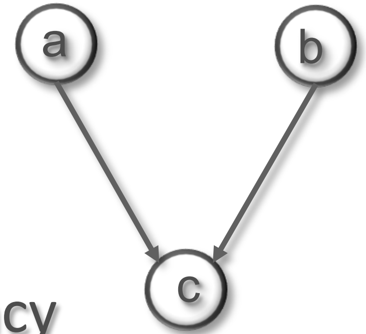
Graphical Models

- **Definition:** Graphical representation of joint probability distribution
  - Nodes:  = Variables
  - Edges: Relationship between variables
- **Variables**:
  - Observed Variables: Data
  - Unobserved Variables: ‘Causes’ + Temporary/Latent
- **Key Questions**:
  - (Conditional) *Dependency*: $p(a,b|c) \stackrel{?}{=} p(a|c) \cdot p(b|c)$
  - *Inference*/Marginalisation: $p(a,b) = \sum_c p(a,b,c)$

Directed Models: Bayesian Networks

- **Definition:** Graphical representation of joint probability distribution (Pearl, 1988)
  - Nodes:  = Variables
  - Directed Edges: Conditional probability distribution

- **Semantic:**



$$p(\mathbf{x}) = \prod_i p\left(x_i | \mathbf{x}_{\text{parents}(i)}\right)$$

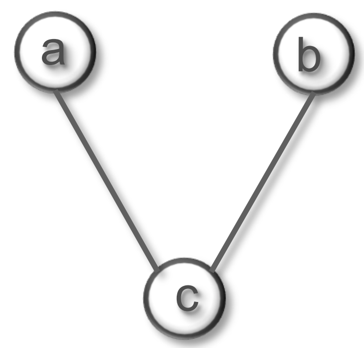
  - Ancestral relationship of dependency

$$p(a, b, c) = p(a) \cdot p(b) \cdot p(c|a, b)$$

Undirected Models: Markov Networks

- **Definition:** Graphical representation of joint probability distribution (Pearl, 1988)
  - Nodes: ○ = Variables
  - Edges: Dependency between variables

- **Semantic:**



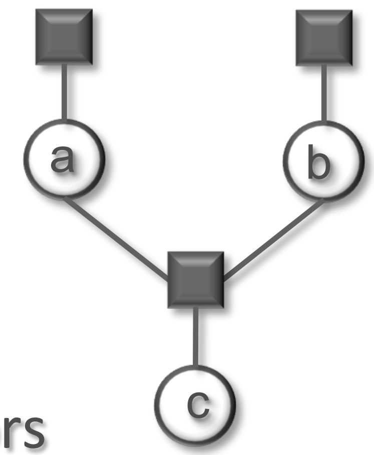
$$p(\mathbf{x}) = \frac{1}{Z} \cdot \prod_{C} \phi(x_C) \qquad \phi \geq 0$$

  - Local potentials over cliques

$$\begin{aligned} p(a,b,c) &= \frac{1}{Z} \cdot \phi_{ac}(a,c) \cdot \phi_{bc}(b,c) \\ Z &= \sum_a \sum_b \sum_c \phi_{ac}(a,c) \cdot \phi_{bc}(b,c) \end{aligned}$$

Factor Graphs

- **Definition:** Graphical representation of product structure of a function (Wiberg, 1996)
  - Nodes: = Factors = Variables
  - Edges: Dependencies of factors on variables.



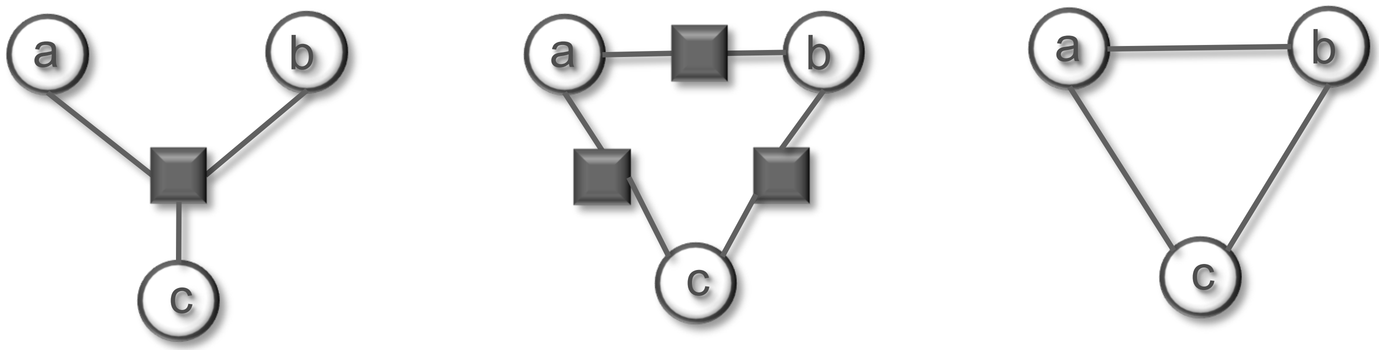
- **Semantic:**

$$p(\mathbf{x}) = \prod_f f\left(\mathbf{x}_{V(f)}\right)$$

  - Local variable dependency of factors

$$p(a,b,c) = f_1(a) \cdot f_2(b) \cdot f_3(a,b,c)$$

Factor Graphs are Powerful!



$f_1(a, b, c)$ $\quad$ $f_1(a, b) \cdot f_2(b, c) \cdot f_3(a, c)$ $\quad$ $\phi(a, b, c)$

Undirected graphical models can hide the factorisation within a clique!

Factor Graphs and Bayes' Law

- Bayes' law

$$p(\mathbf{s}|y) \propto p(y|\mathbf{s}) \cdot p(\mathbf{s})$$

- Factorising prior

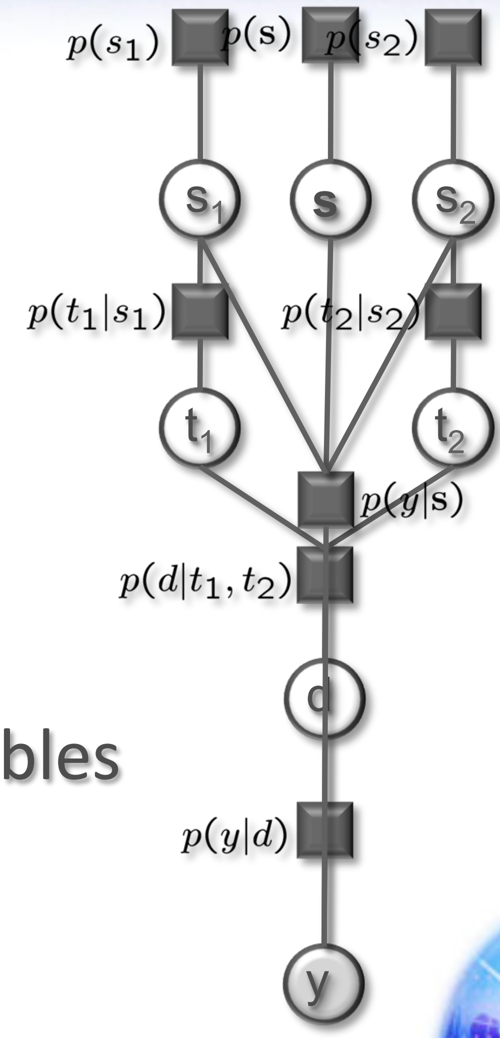
$$p(\mathbf{s}) = p(s_1) \cdot p(s_2)$$

- Factorising likelihood

$$p(y, \mathbf{t}, d|\mathbf{s}) = \prod_i p(t_i|s_i) \cdot p(d|t_1, t_2) \cdot p(y|d)$$

- Inference: Sum out latent variables

$$p(y|\mathbf{s}) = \sum_{\mathbf{t}} \sum_d p(y, \mathbf{t}, d|\mathbf{s})$$



Summary

	Dependency	Efficient Inference	Usage
Bayesian Networks	Yes	Somewhat	Ancestral Generative Process
Markov Networks	Yes	No	Local Couplings and Potentials
Factor Graphs	No	Yes	Efficient, distributed inference

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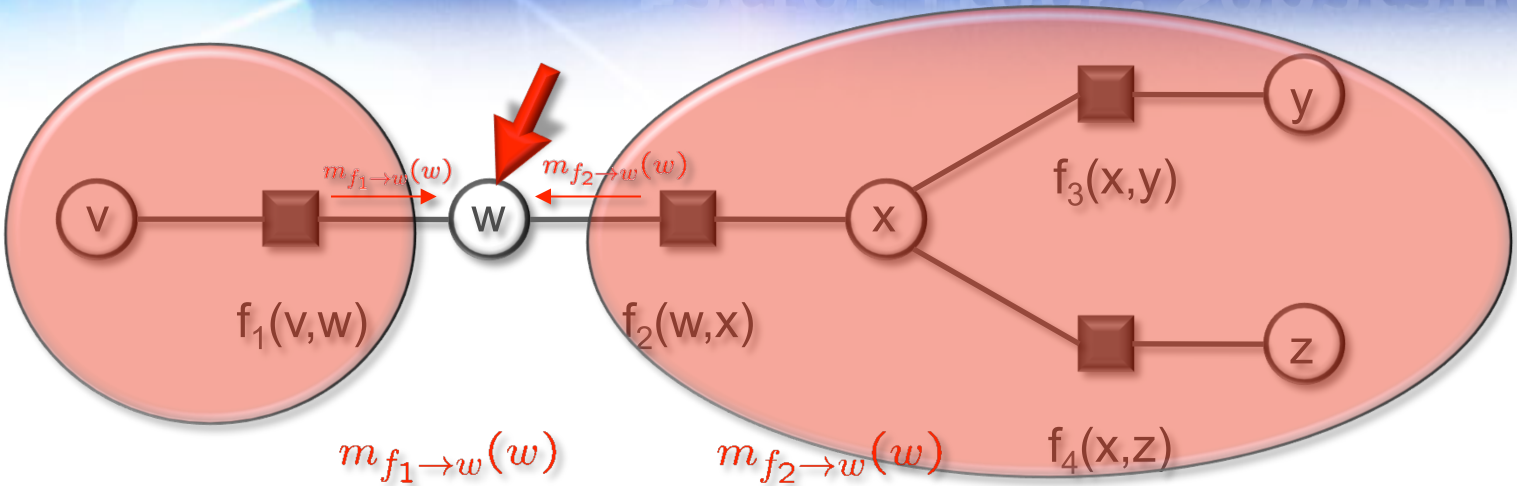
Factor Graphs and Factor Trees

- **Factor Graphs:** Arbitrary functions
  - Bayesian Networks
  - Markov Networks
- **Factor Trees**: Functions where the variable indices never decrease from left to right
- **Factor Graph → Factor Tree**:
  1. Pick an arbitrary node
  2. Build the spanning tree

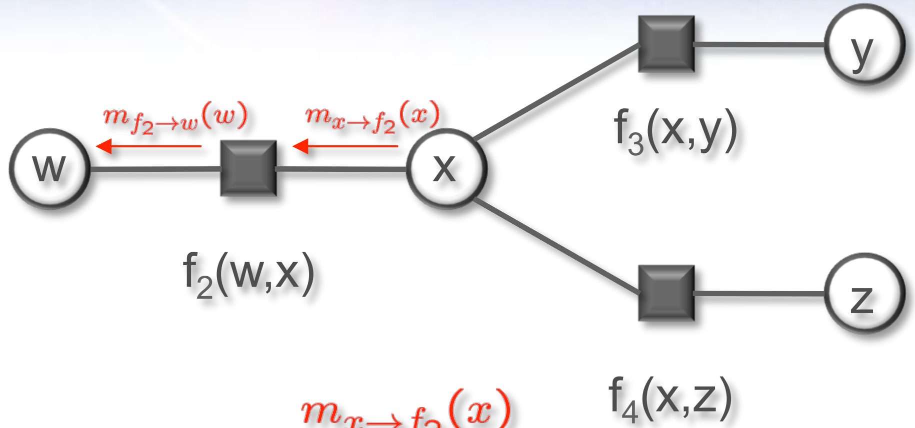
Factor Trees: Separation



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

Observation: Sum of products becomes product of sums of all messages from neighbouring factors to variable!

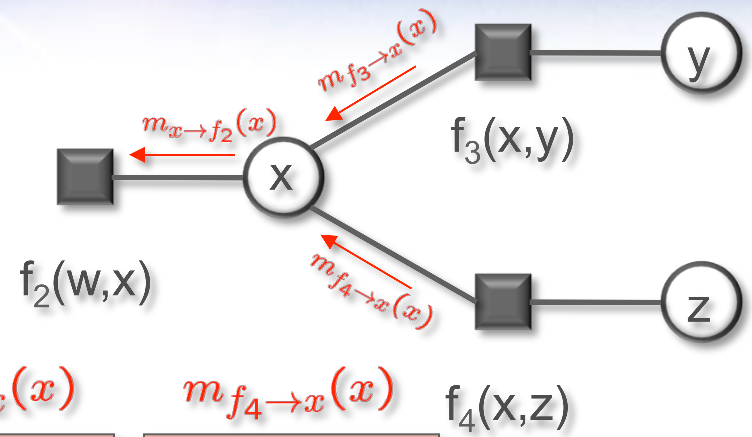
Messages: From Factors To Variables



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

Observation: Factors only need to sum out all their local variables!

Messages: From Variables To Factors



$$m_{x\to f_2}(x) = \overbrace{\boxed{\left[\sum_y f_3(x,y)\right]}}^{m_{f_3\to x}(x)} \cdot \overbrace{\boxed{\left[\sum_z f_4(x,z)\right]}}^{m_{f_4\to x}(x)}$$

Observation: Variables pass on the product of all incoming messages!

The Sum-Product Algorithm

- Three update equations (Aji & McEliece, 1997)

$$
\begin{aligned}
p(t) &= \prod_{f \in F_t} m_{f \to t}(t) \\
m_{f \to t_1}(t_1) &= \sum_{t_2} \sum_{t_3} \cdots \sum_{t_n} f(t_1, t_2, t_3, \ldots) \prod_{i>1} m_{t_i \to f}(t_i) \\
m_{t \to f}(t) &= \prod_{f_j \in F_t \setminus \{f\}} m_{f_j \to t}(t)
\end{aligned}
$$

- Update equations can be directly derived from the distributive law.
- Calculate all marginals at the same time!
- Only need to pass messages twice along each edge!

Practical Considerations I

- **Log-Transform:** $\lambda_{f\to t}(t) := \log\left[m_{f\to t}(t)\right]$

$$\log\left[p(t)\right] = \sum_{f\in F_t} \lambda_{f\to t}(t)$$

$$\lambda_{f\to t_1}(t_1) = \sum_{t_2}\sum_{t_3}\cdots\sum_{t_n} f(t_1,t_2,t_3,\ldots)\exp\left[\sum_{i>1}\lambda_{t_i\to f}(t_i)\right]$$

$$\lambda_{t\to f}(t) = \sum_{f_j\in F_t\setminus\{f\}} \lambda_{f_j\to t}(t)$$

- **Exponential Family Messages:**

$$m(t) \propto \exp\left(\psi(t)\cdot\boldsymbol{\theta}\right)$$

- Message updates are just additions of the parameters $\boldsymbol{\theta}$!

Exponential Families

- (Univariate) Gaussian: $\boldsymbol{\theta} := \left(\frac{\mu}{\sigma^2}, \frac{1}{\sigma^2}\right)$
- Bernoulli: $\boldsymbol{\theta} := \log\left(\frac{p}{1-p}\right)$
- Binomial: $\boldsymbol{\theta} := \log\left(\frac{p}{1-p}\right)$
- Beta: $\boldsymbol{\theta} := (\alpha, \beta)$
- Gamma: $\boldsymbol{\theta} := \left(\alpha, \frac{1}{\beta}\right)$

Practical Considerations II

- **Redundant computations:**

$$p(t) = \prod_{f \in F_t} m_{f \to t}(t)$$

$$m_{t \to f}(t) = \prod_{f_j \in F_t \setminus \{f\}} m_{f_j \to t}(t)$$

$$p(t) = m_{t \to f}(t) \cdot m_{f \to t}(t)$$

- **Caching**: Only store $p(t)$ and $m_{f \to t}(t)$, then

$$m_{t \to f}(t) = \frac{p(t)}{m_{f \to t}(t)}$$

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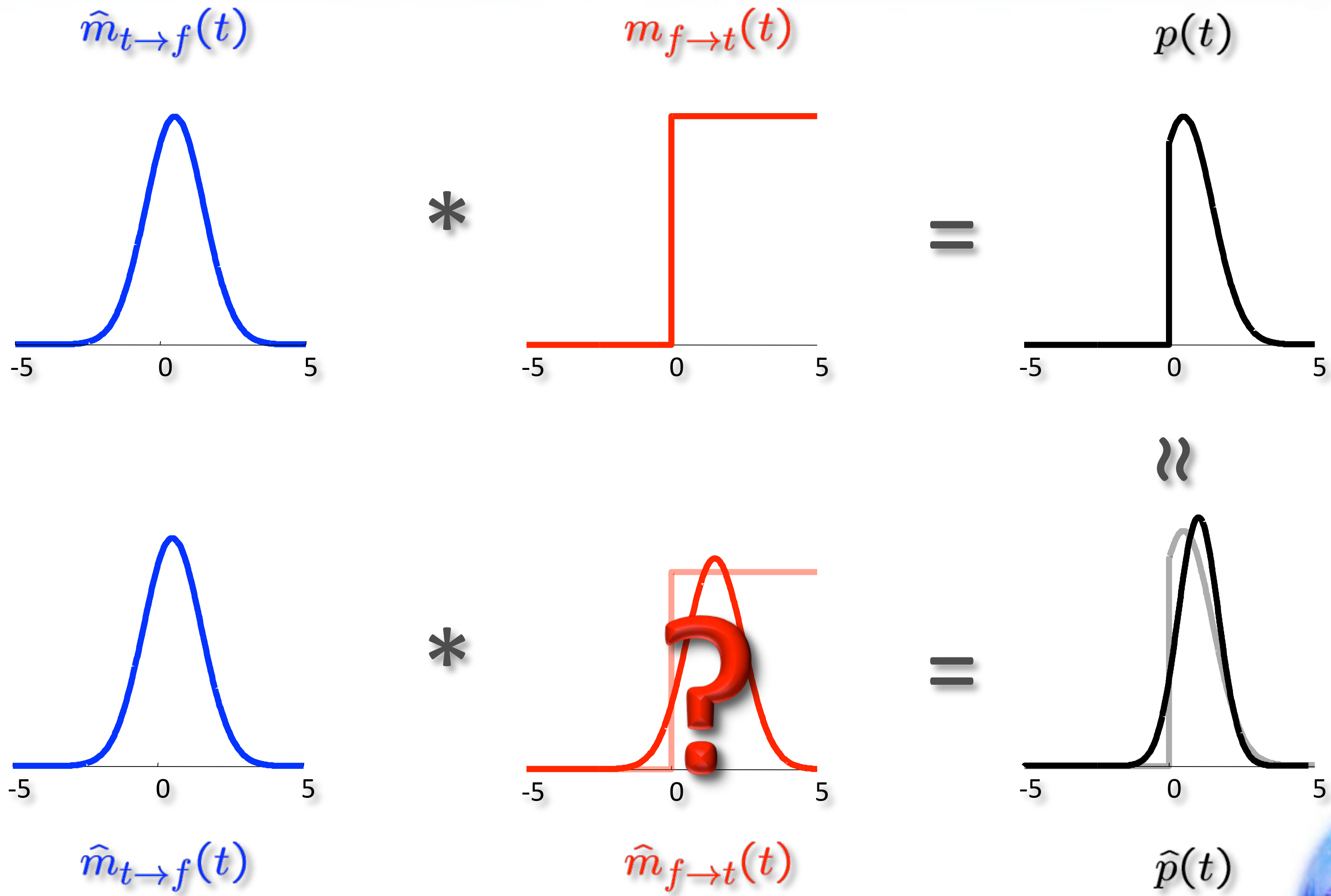
Approximate Message Passing

- **Problem:** The exact messages from factors to variables may not be closed under products.
- **Solution:** Approximate *each* marginal as well as possible in using a divergence measure on beliefs.
- **General Idea:** Leave-one out approximation

$$
\begin{aligned}
\hat{p}(t) &= \mathrm{argmin}_{\hat{p}}\, D\left[\overset{p(t)}{\boxed{m_{f\to t}\cdot \hat{m}_{t\to f}}}, \hat{p}\right] \\
\hat{m}_{f\to t}(t) &= \frac{\hat{p}(t)}{\hat{m}_{t\to f}(t)}
\end{aligned}
$$

Approximate Message Passing



Divergence Measures

- **Kullback-Leibler Divergence:** Expected log-odd ratio between two distributions:

$$\mathsf{KL}(p,q) := \sum_t p(t) \log\left(\frac{p(t)}{q(t)}\right)$$

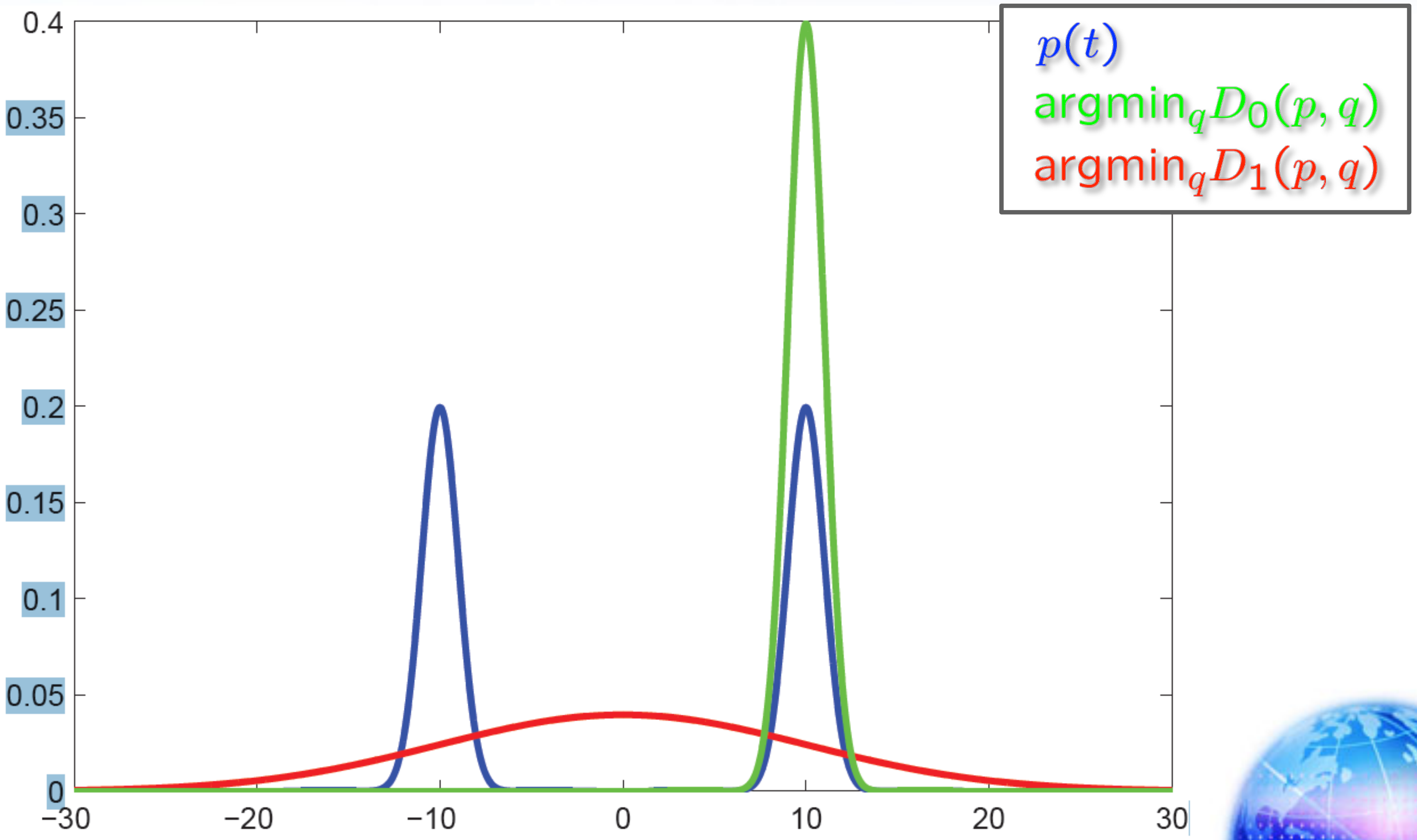
- **Minimizer for Exponential Families:** Matching the moments of the distribution $p(t)$!
- **General α-Divergence:**

$$D_\alpha(p,q) := \frac{1 - \sum_t \frac{p^{\alpha-1}(t)}{q^{\alpha-1}(t)}}{\alpha(1-\alpha)}$$

- **Special Cases:**

$$\begin{aligned} D_0(p,q) &= \mathsf{KL}(q,p) \\ D_1(p,q) &= \mathsf{KL}(p,q) \end{aligned}$$

α-Divergence in Pictures



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Large-Data Challenge

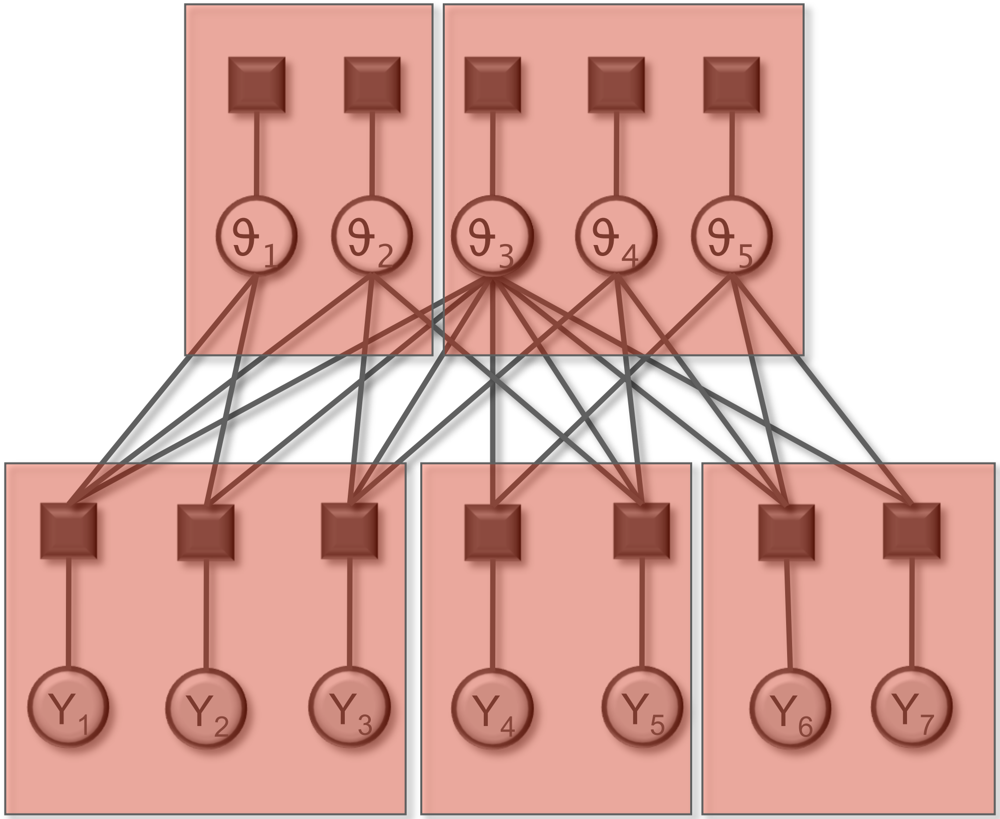
Datasets	Number of Data Items	Number of Variables
Facebook News Feed	100B news stories / day	650M users / day
Facebook Social Graph	130B friends connection	1B users
Google PageRank	~4T web links	1T web pages
Amazon Forecasting	15.6M products/ day (peak)	20+M products
Xbox Gamer Ranking	>1M sessions/game (peak)	20+M users

Important Constants

- Number of seconds / day: 86,400
- Number of RAM read access / day: ~10^{13}
- Number of RAM write access / day: ~10^{12}
- Max network bandwidth: ~8TB / day

Distributed Conditional Models

$$p(\boldsymbol{\theta}|\mathbf{X},\mathbf{Y}) \propto \prod_i p(y_i|\boldsymbol{\theta},\mathbf{x}_i) \cdot \prod_j p(\theta_j)$$



Belief Store ("Memory")

Message Passing ("Communicate")

Data Messages ("Compute")

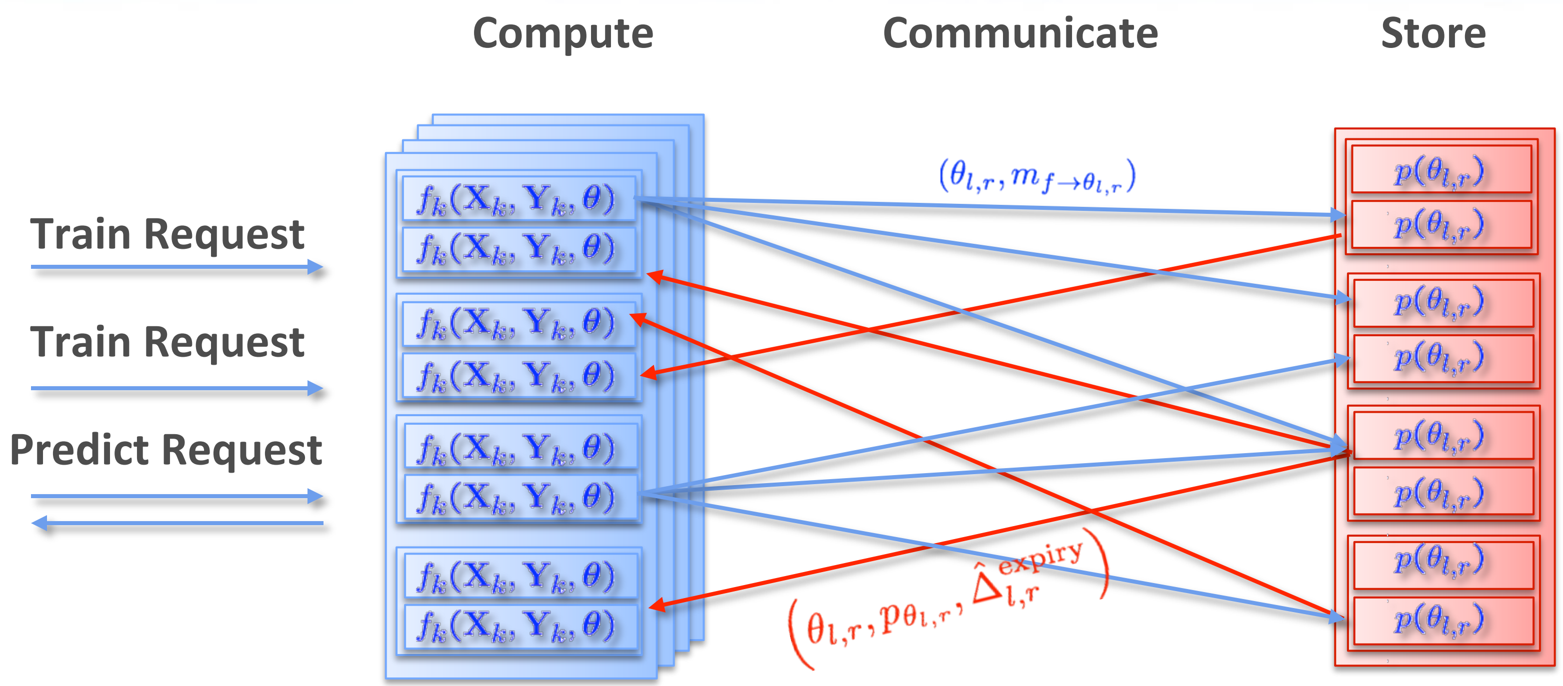
Distributed Message Passing

- **Idea**: Group variables and send messages across system boundaries

$$\prod_i p(y_i|\boldsymbol{\theta}, \mathbf{x}_i) \cdot p(\boldsymbol{\theta}) = \prod_k \underbrace{\boxed{\prod_{j=1}^{n_k} p(y_{k,j}|\boldsymbol{\theta}, \mathbf{x}_{k,j})}}_{f_k(\mathbf{X}_k, \mathbf{Y}_k, \boldsymbol{\theta})} \cdot \prod_l \underbrace{\boxed{\prod_{r=1}^{m_l} p(\theta_{l,r})}}_{g_l(\boldsymbol{\theta}_l)}$$

- **Data factors**: $f_k(\mathbf{X}_k, \mathbf{Y}_k, \boldsymbol{\theta})$
  - Know exactly which model parameter messages get updated
- **Parameter factors**: $g_l(\boldsymbol{\theta}_l)$
  - Need to keep track of which data factors need message update

A Systems Service View



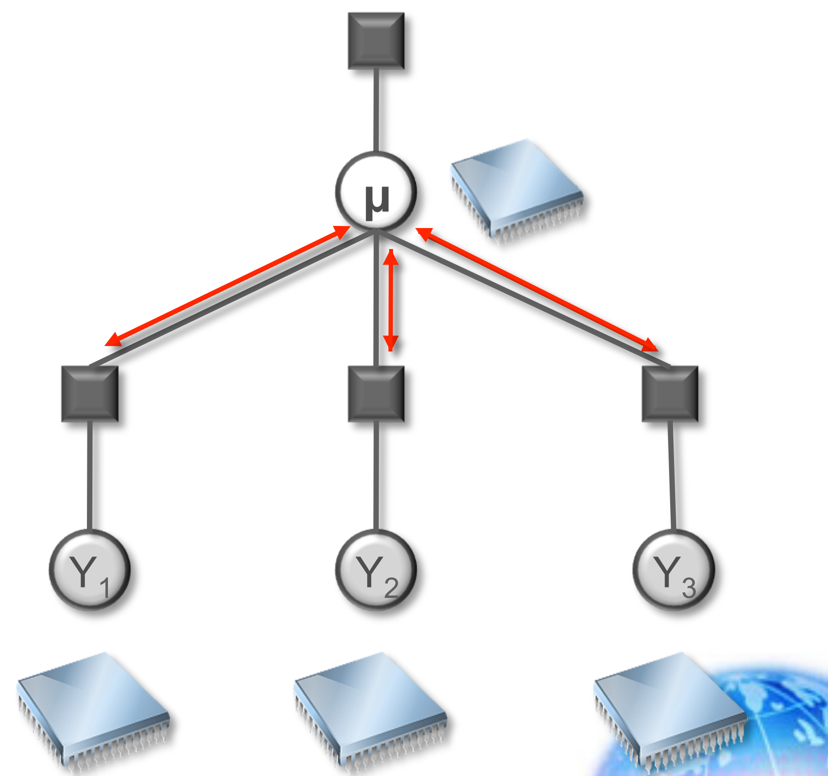
Additional Technical Challenges

- Shard <-> Machine Consistency
- High Performance (Asynchronous programming)
- Reliability, Maintainability
  - **All parameters are stored in RAM → "Checkpoint" or Redundancy**
  - **Canary procedure is unsafe → Traffic proxy**
  - **Central model management and model management tools**

Relation to Map-Reduce

- **Map-Reduce**
  - **Map**: Data nodes compute messages $m_{F_k \to \mu}$ from data y_i and $m_{\mu \to F_k}$
  - **Reduce**: Combine messages $m_{F_k \to \mu}$ into p_{μ} by multiplication
  - Vanilla MR is a single pass only!
- **Caveats**:
  - Approximate data factors need all incoming message $m_{F_k \to \mu}$!
  - Each machine needs to be able to store the belief over μ

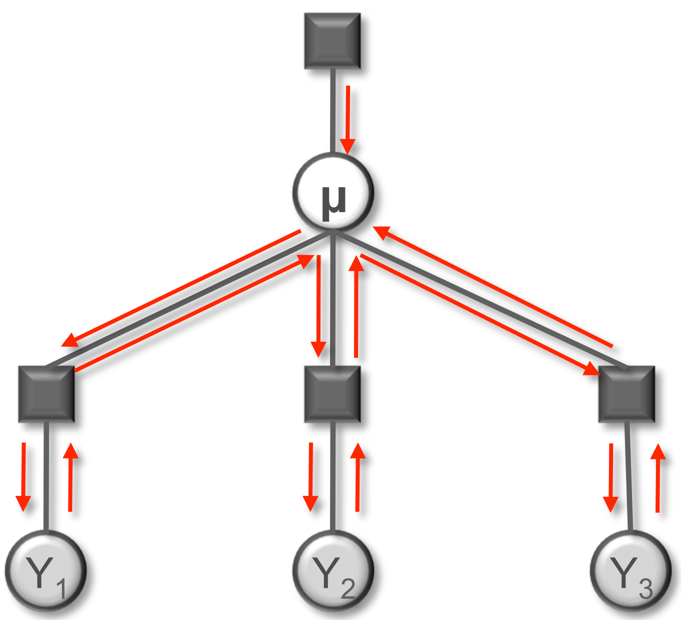
$$p(\boldsymbol{\theta}|\mathbf{x},\mathbf{y}) \propto \prod_k f_k(\mathbf{Y}_k|\boldsymbol{\theta},\mathbf{X}_k) \cdot p(\boldsymbol{\theta})$$



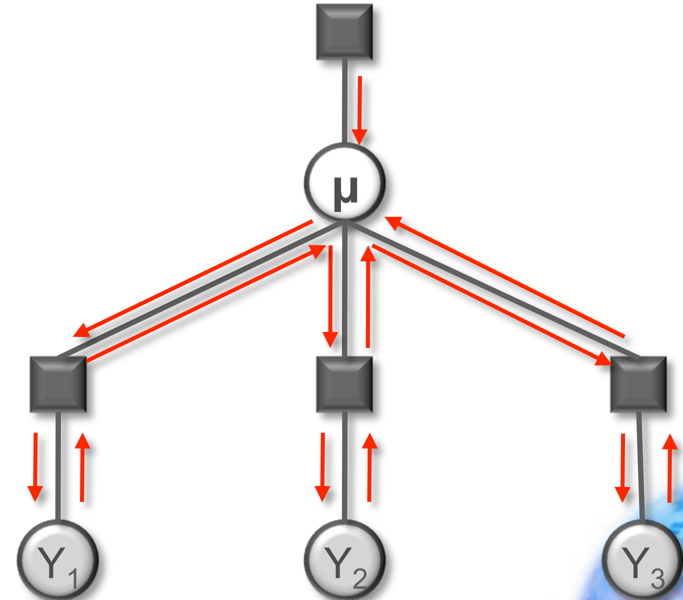
Approximation Quality

$$
\begin{aligned}
p(y_i|\boldsymbol{\theta}, \mathbf{x}_i) &= \Phi(y_i \boldsymbol{\theta}^{\mathrm{T}} \mathbf{x}_i) \\
p(\boldsymbol{\theta}) &= \prod_j \mathcal{N}(\theta_j; \mu_j, \sigma_j^2)
\end{aligned}
$$

Sequential



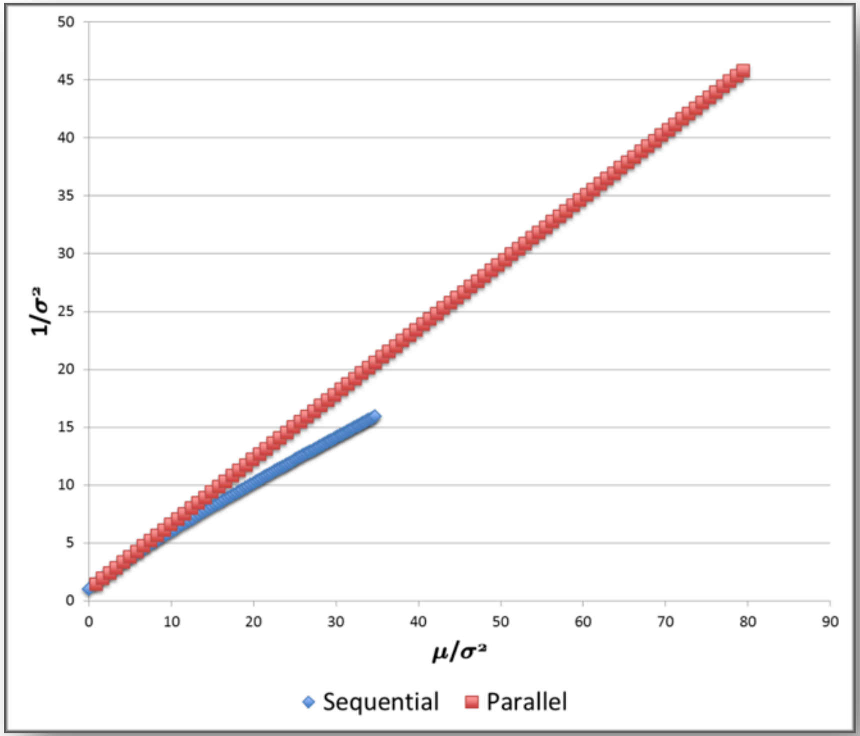
Parallel



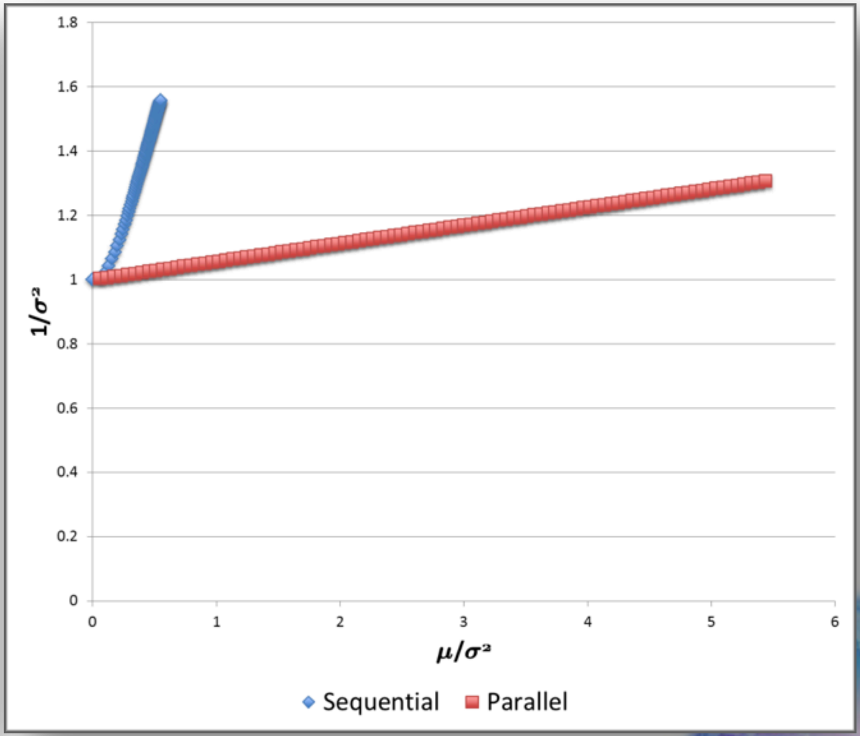
Approximation Quality

$$\mathbf{x} = [1; 1; \ldots; 1]^{\mathrm{T}}$$

Single Bias Feature



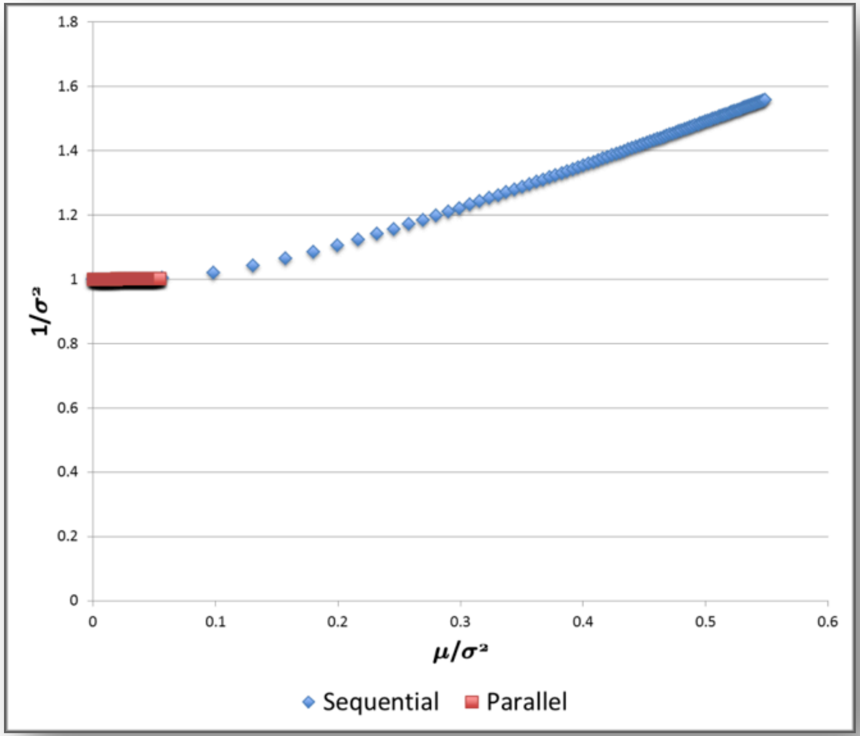
100 Bias Features



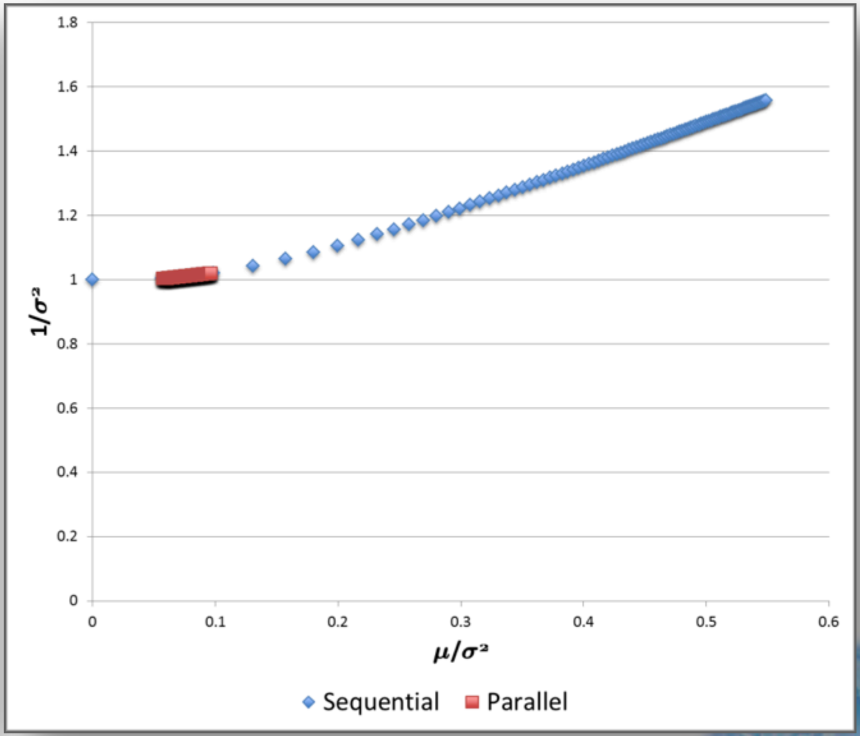
Solution : Dampening!

$$\lambda_{f \to \theta} \Rightarrow \alpha \cdot \lambda_{f \to \theta}$$

First Step



Second Step



Break!

Part 2: Applications

Overview

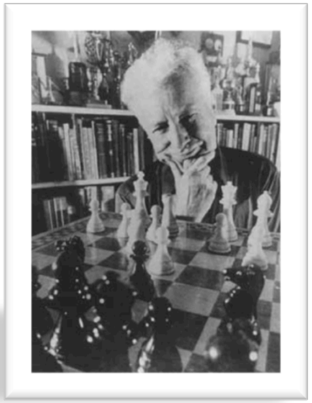
- TrueSkill: Gamer Rating and Matchmaking
- Click-Through Rate Prediction in Online Advertising
- Matchbox: Recommendation Systems
- Pattern Learning in Go

TrueSkill™

Joint work with Thore Graepel, Tom Minka & Phillip Trelford

Motivation

- Competition is central to our lives
  - Innate biological trait
  - Driving principle of many sports
- Chess Rating for fair competition
  - ELO: Developed in 1960 by Árpád Imre Élő
  - Matchmaking system for tournaments
- Challenges of online gaming
  - Learn from few match outcomes efficiently
  - Support multiple teams and multiple players per team

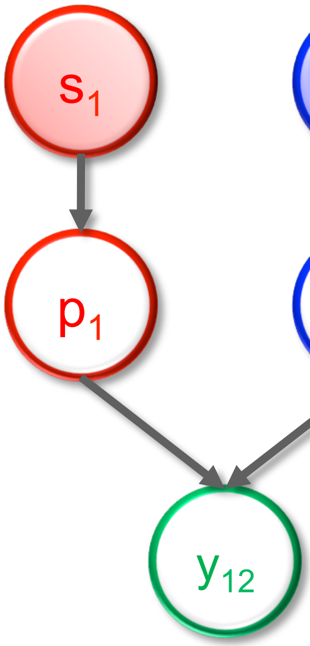


The Skill Rating Problem

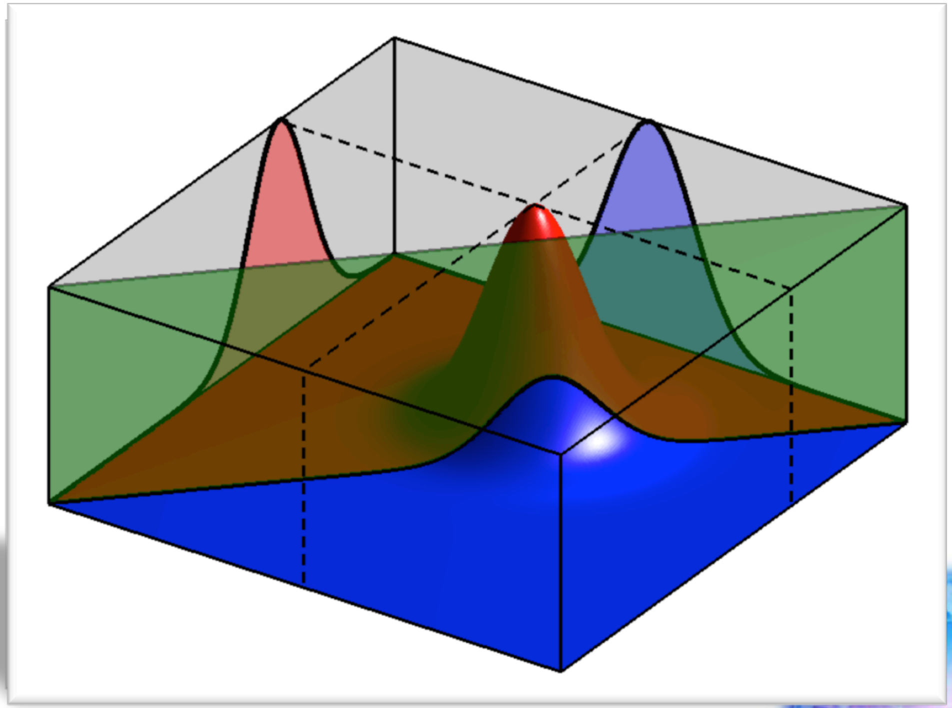
- **Given**:
  - Match outcomes: Orderings among k teams
- **Qu**
  -

Two Player Match Outcome Model

- Latent Gaussian performance model for fixed skills
- Possible outcomes: Player 1 wins over 2 (and vice versa)

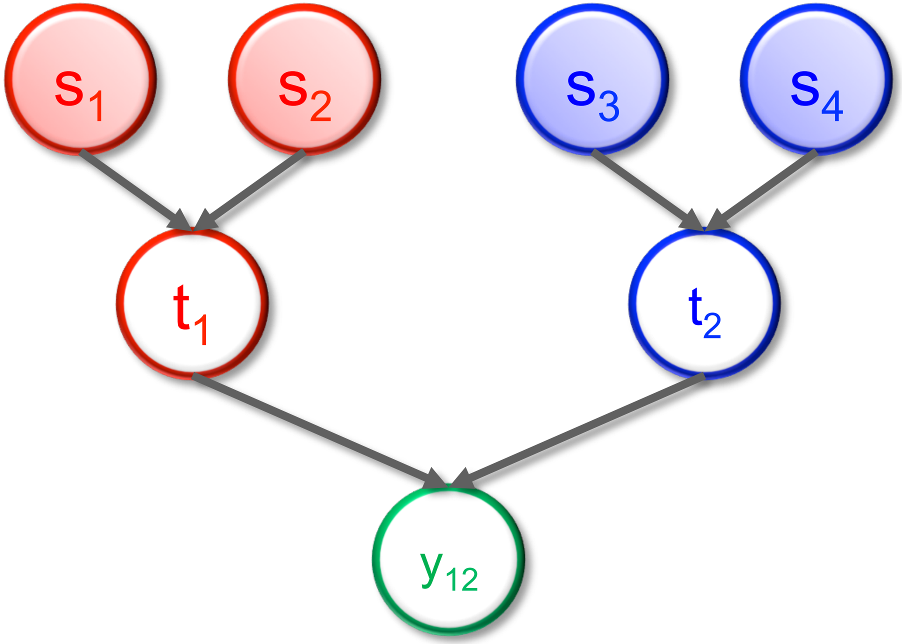


$$\mathbf{P}(y_{12} = (1,2) | p_1, p_2) = \mathbb{I}(p_1 > p_2)$$



Two Team Match Outcome Model

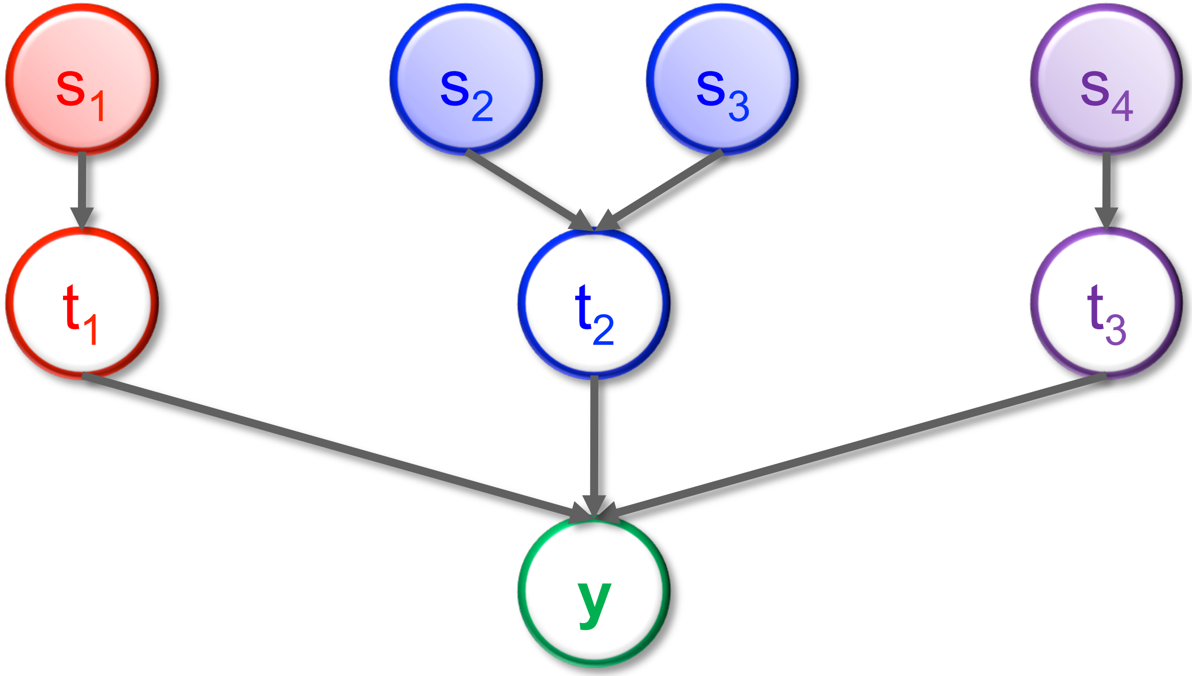
- Skill of a team is the sum of the skills of its members



$$\mathbf{P}(t_1|s_1, s_2) = \mathcal{N}\left(t_1; s_1 + s_2, 2 \cdot \beta^2\right)$$

Multiple Team Match Outcome Model

- Possible outcomes: Permutations of the teams

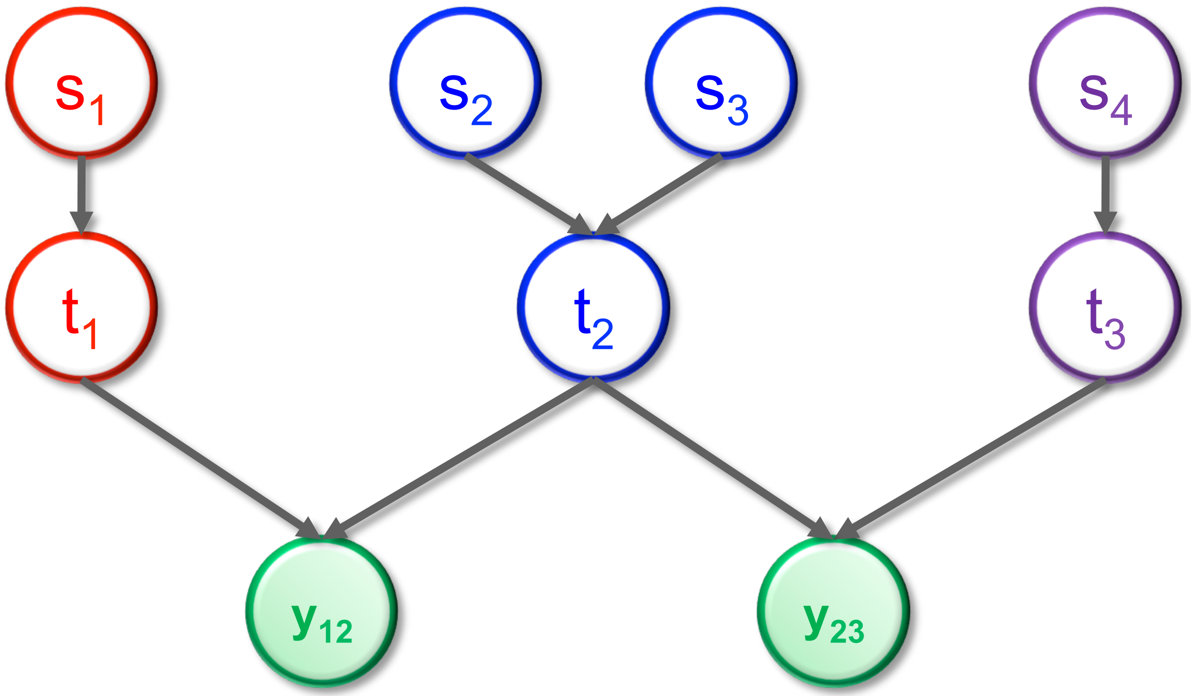


$$\mathbf{P}(\boldsymbol{y}|t_1, t_2, t_3) = \mathbb{I}(\boldsymbol{y} = (i, j, k)) \text{ where } t_i > t_j > t_k$$

Multiple Team Match Outcome Model

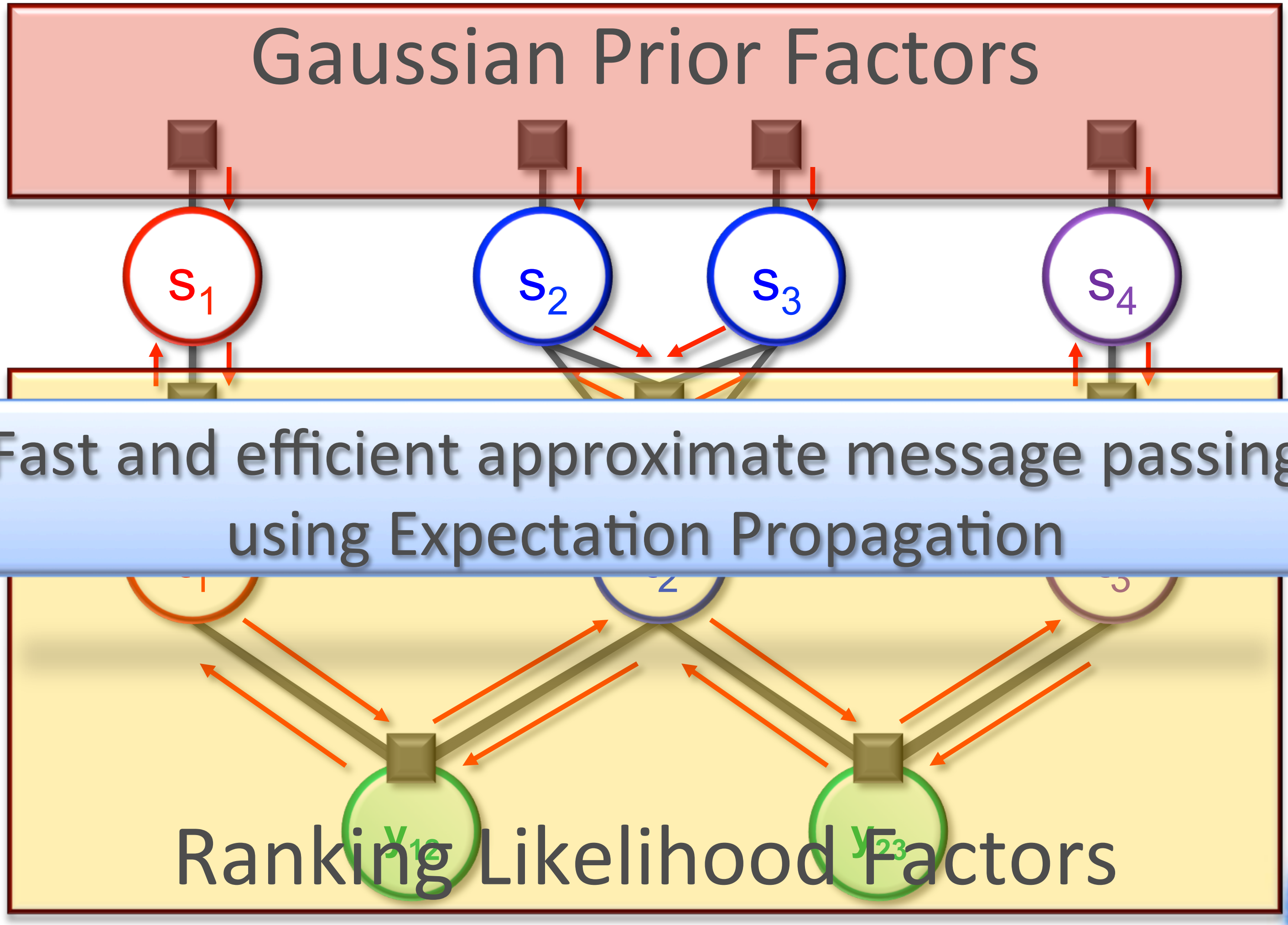
- But we are interested in the (Gaussian) posterior!

$$\mathbf{P}(s_i|\boldsymbol{y} = (1,2,3)) = \mathcal{N}(s_i; \mu_i, \sigma_i^2)$$



$y_{12} = (1,2)$ $y_{23} = (2,3)$

Efficient Approximate Inference



Fast and efficient approximate message passing using Expectation Propagation

Applications to Online Gaming

- **Leaderboard**
  - Global ranking of all players

$$\mu_i - 3 \cdot \sigma_i$$

- **Matchmaking**
  - For gamers: Most uncertain outco

		Level	Gamertag	Avg. Life	Best Spree	Score
1st		10	BlueBot	00:00:49	6	15
1st		7	SniperEye	00:00:41	4	14
1st		9	ProThepirate	00:01:07	3	13
1st		10	dazdemon	00:00:59	3	8
2nd		10	WastedHarry	00:00:41	4	17
2nd		3	Ascla	00:00:37	2	10
2nd		9	Antidote4Losing	00:00:41	2	9
2nd		12	Blackknight19	00:00:48	3	4

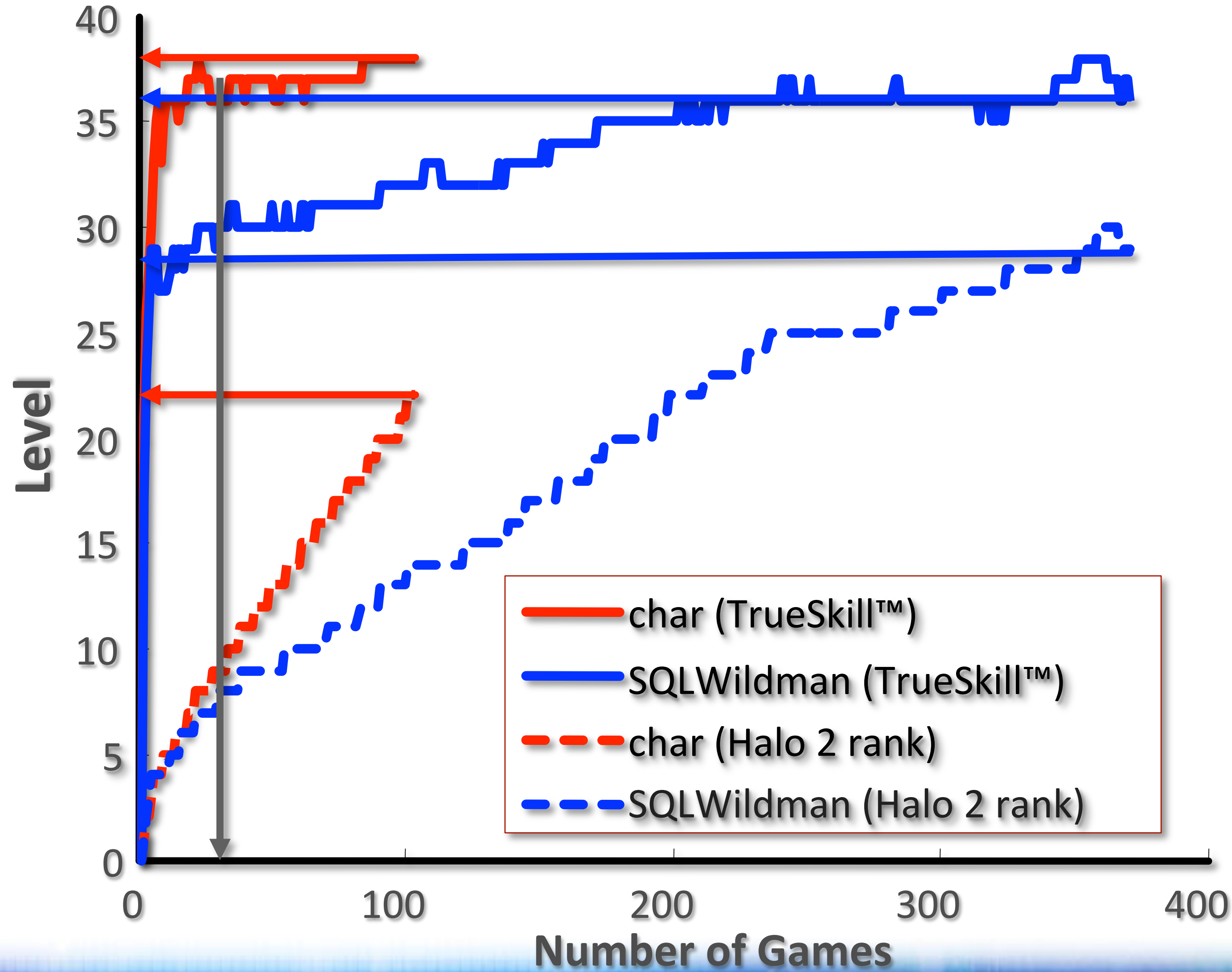
1	27	SEWiCSYDE OWNS
2	26	FATAL REVENGE
3	25	Paranoia 1
4	25	Paulk
5	25	IxX OMG XxI
6	25	BittyTom
7	24	brian 2OO7
		SEXY MOZES
		droplates
		jaCKdaSaMuRai
		II Me II
		iamNightMare
		a retarded007
		Perfected Brit
		THE MUFFIN MANx
		TheVunit
		Mr Sushi87

$$\frac{\mathbf{P}(p_i \approx p_j \,|\, \mu_i - \mu_j, \sigma_i^2 + \sigma_j^2)}{\mathbf{P}(p_i \approx p_j \,|\, \mu_i - \mu_j = 0, \sigma_i^2 + \sigma_j^2 = 0)}$$

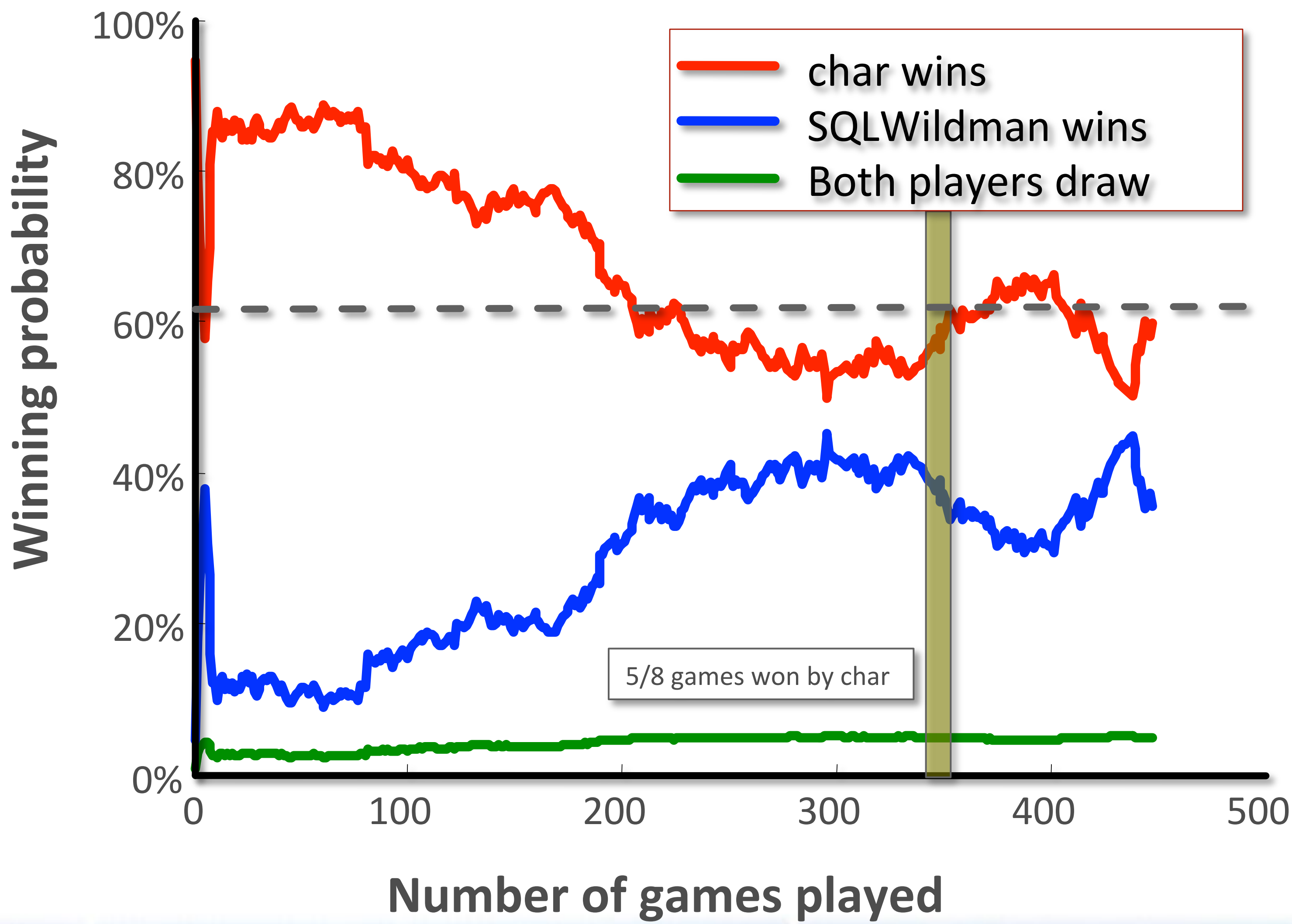
Experimental Setup

- **Data Set: Halo 2 Beta**
  - 3 game modes
    - Free-for-All
    - Two Teams
    - 1 vs. 1
  - > 60,000 match outcomes
  - ≈ 6,000 players
  - 6 weeks of game play
  - Publically available

Convergence Speed



Convergence Speed (ctd.)



Xbox 360 & Halo 3

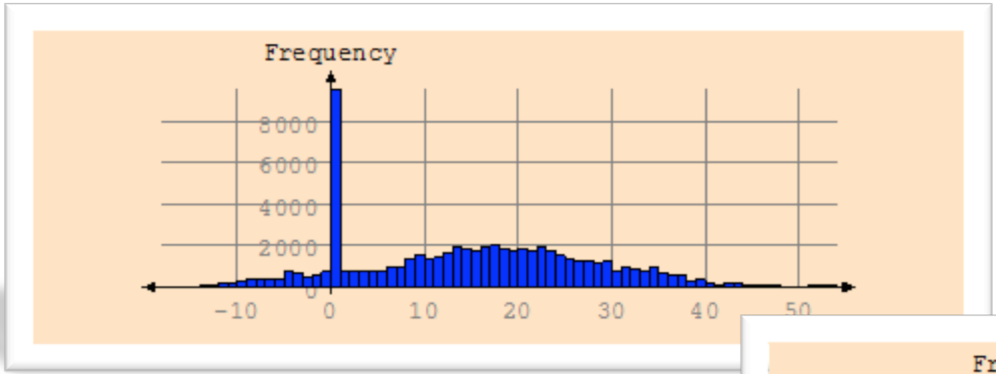
- **Xbox 360 Live**
  - Launched in September 2005
  - Every game uses TrueSkill™ to match players
  - > 10 million players
  - > 2 million matches per day
  - > 2 billion hours of gameplay

- **Halo 3**
  - Launched on 25th September 2007
  - Largest entertainment launch in history
  - > 200,000 player concurrently (peak: 1,000,000)

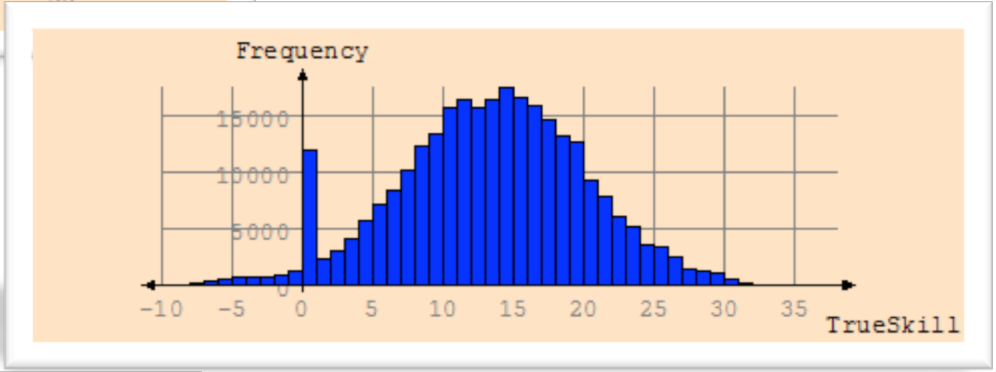
Halo 3 in Action

Halo 3 Public Beta Analysis

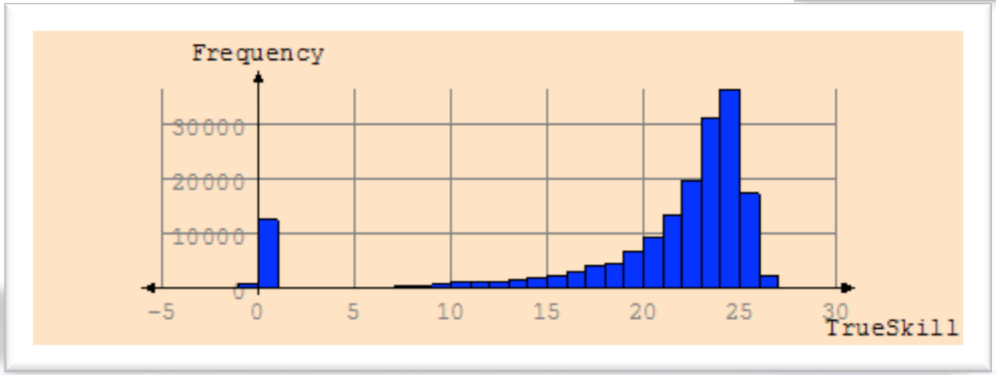
Skill Distributions of Online Games



Golf (18 holes): 60 levels



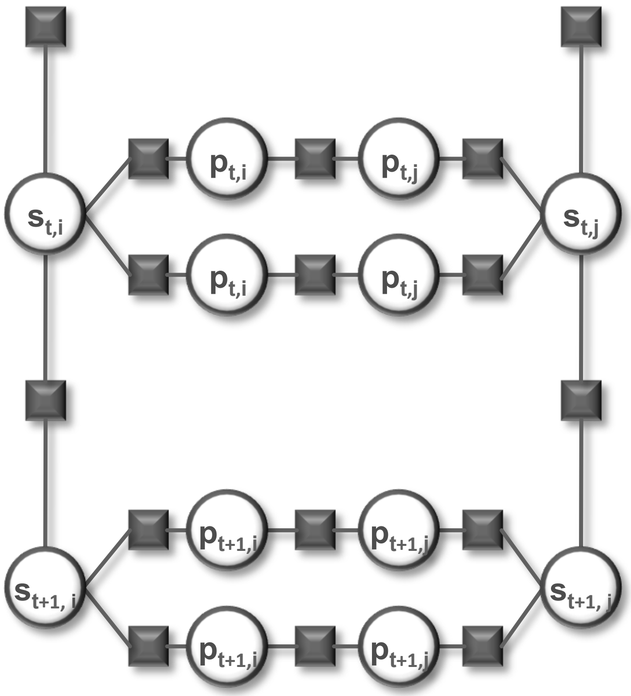
Car racing (3-4 laps): 40 levels



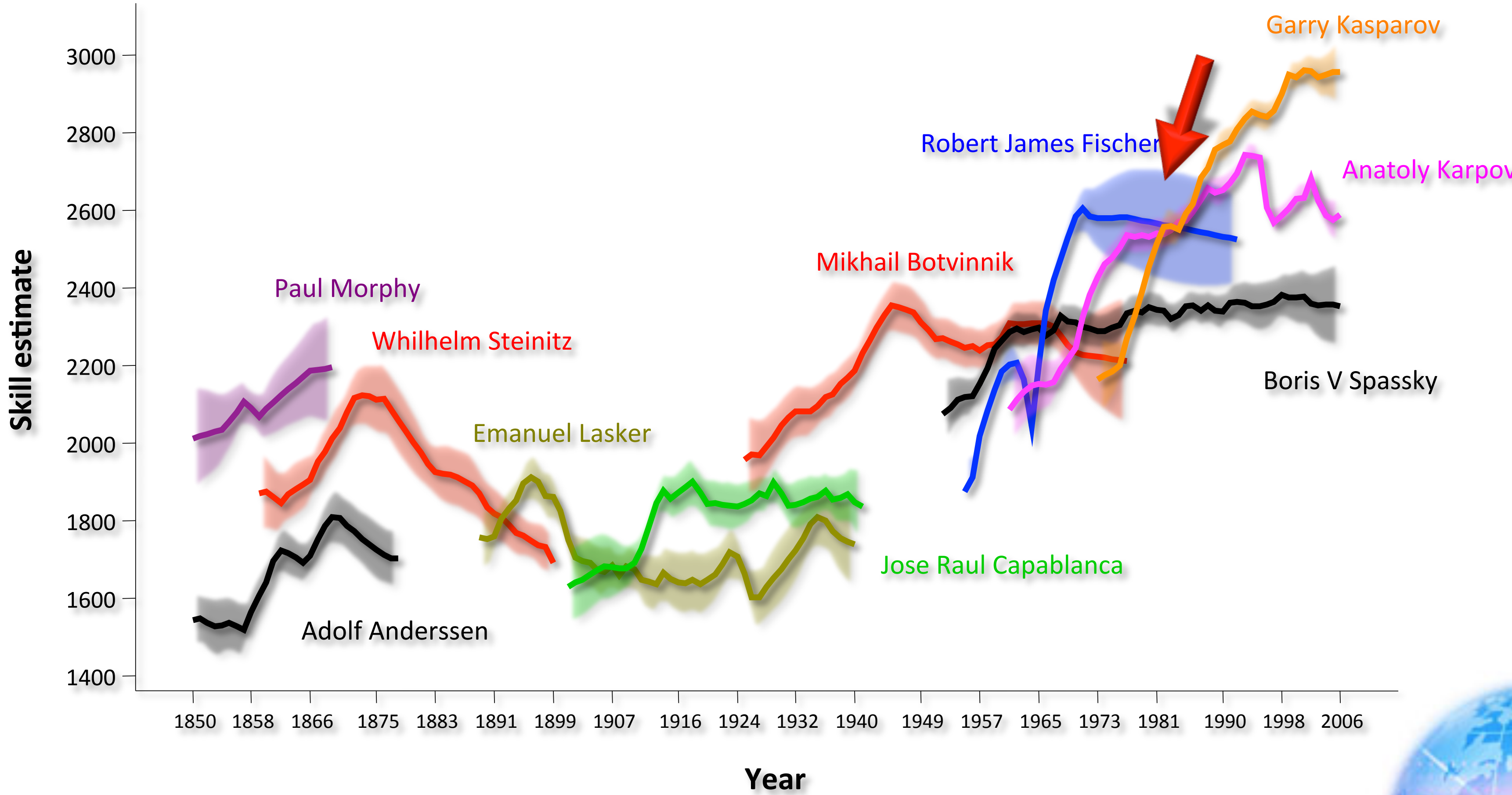
UNO (chance game): 10 levels

TrueSkill™ Through Time: Chess

- Model time-series of skills by smoothing across time
- History of Chess
  - 3.5M game outcomes (ChessBase)
  - 20 million variables (each of 200,000 players in each year of lifetime + latent variables)
  - 40 million factors



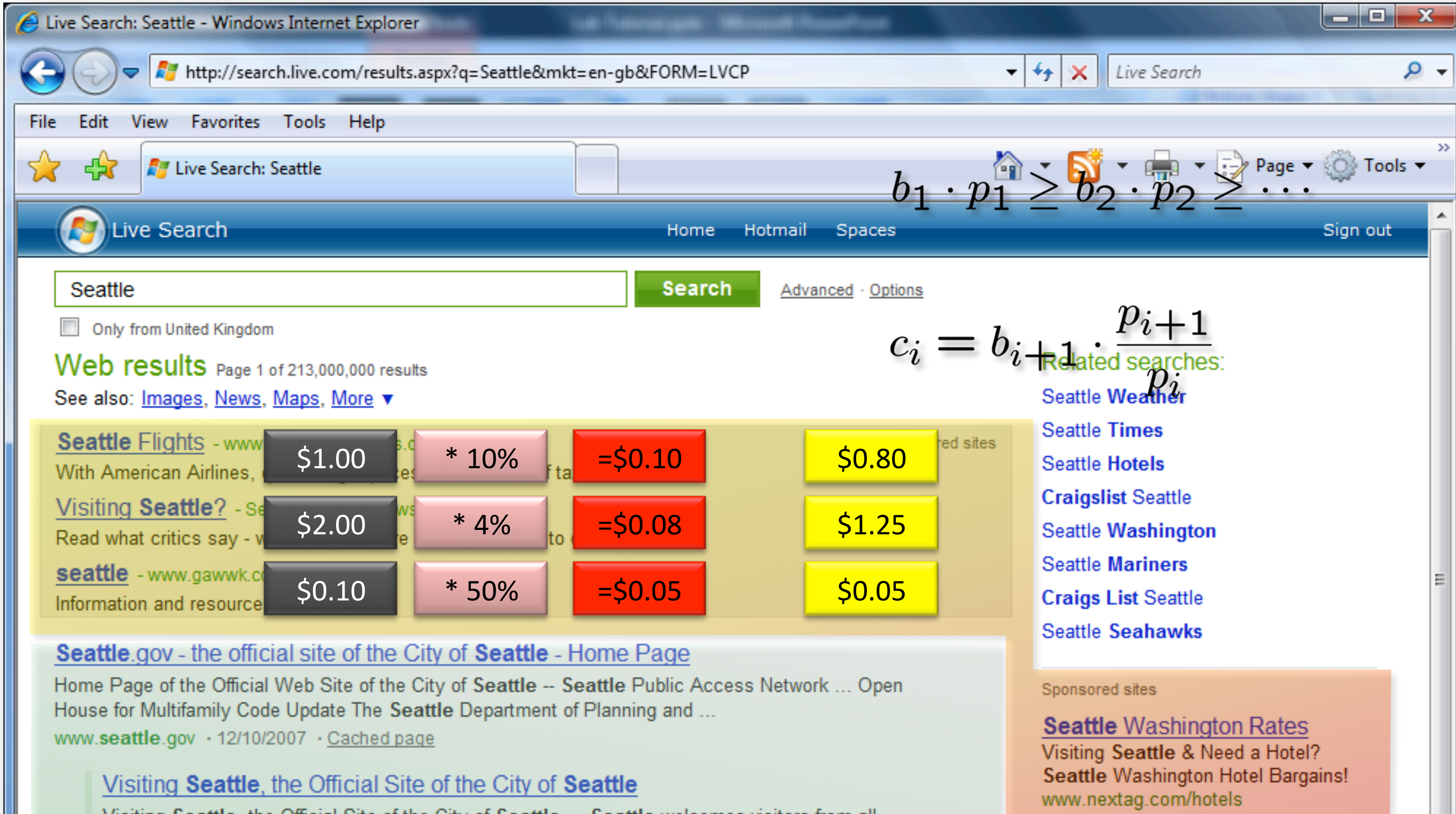
ChessBase Analysis: 1850 - 2006



Online Advertising

Joint work with Thore Graepel, Joaquin Quiñonero Candela, Onno Zoeter, Tom Borchert , Phillip Trelford

Why Predict Probability-of-Click?



$$b_1 \cdot p_1 \geq b_2 \cdot p_2 \geq \cdots$$

$$c_i = b_{i+1} \cdot \frac{p_{i+1}}{p_i}$$

The Scale of Things

- **Several weeks of data in training**:

  7,000,000,000 impressions

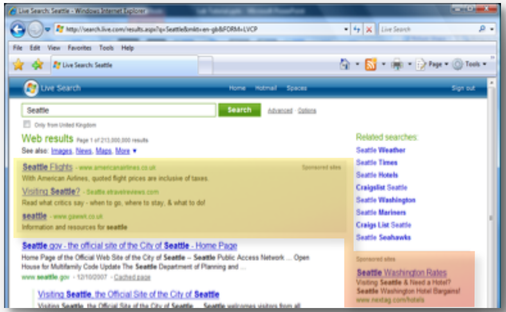
- **2 weeks of CPU time during training**:

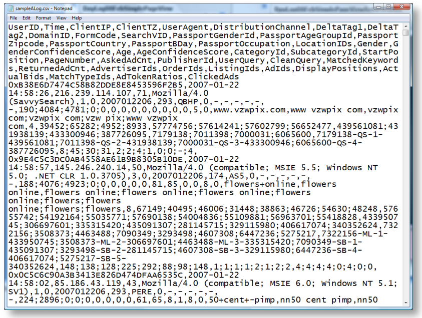
  2 wks × 7 days × 86,400 sec/day =

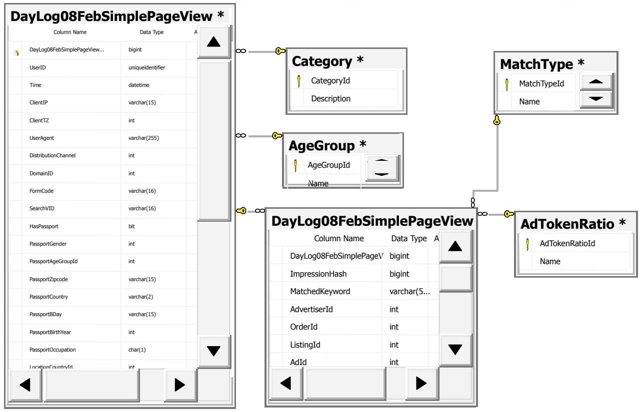
  1,209,600 seconds

- **Learning algorithm speed requirement**:
  - 5,787 impression updates / sec
  - 172.8 μs per impression update

The Flow of Information



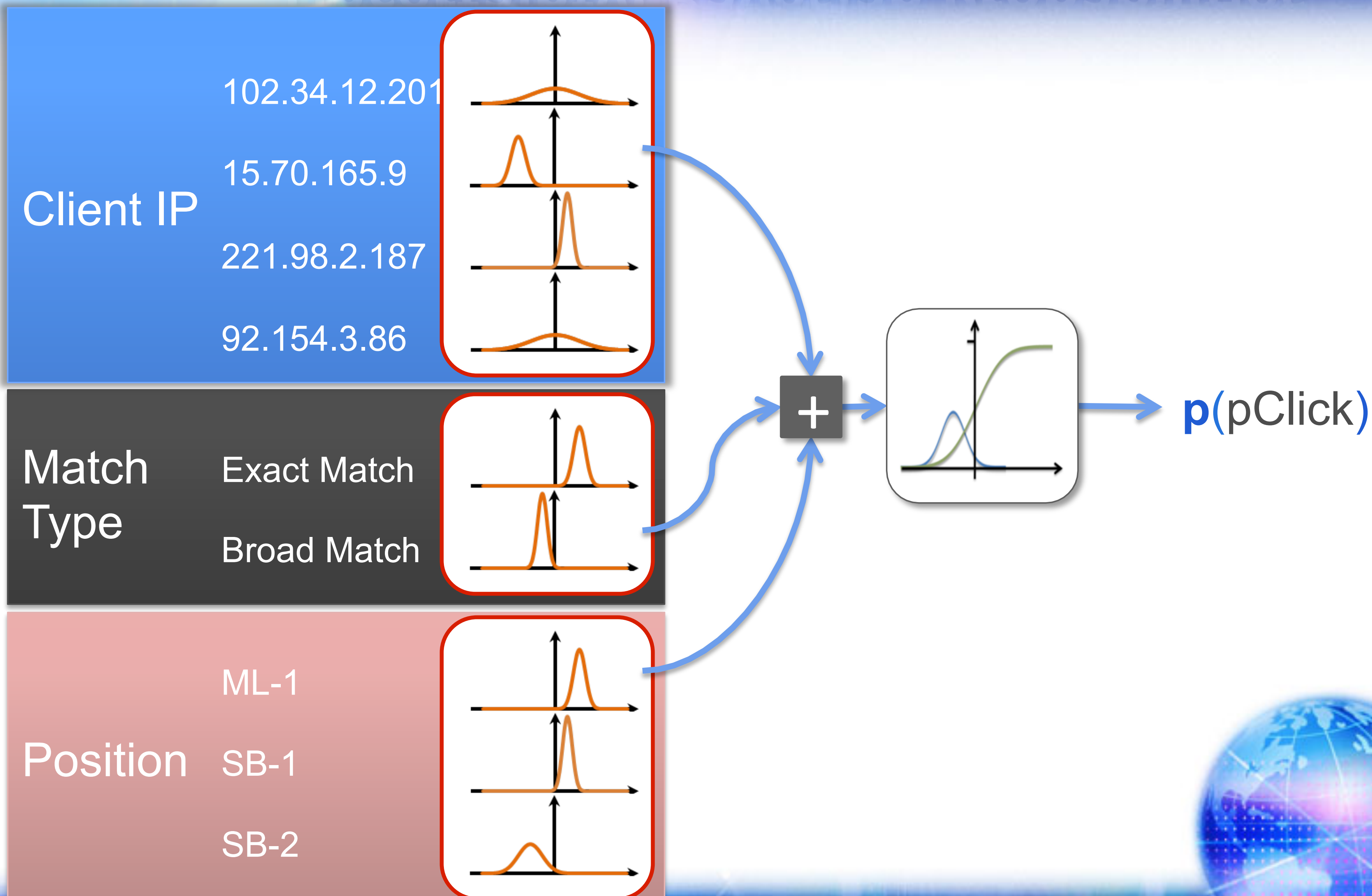




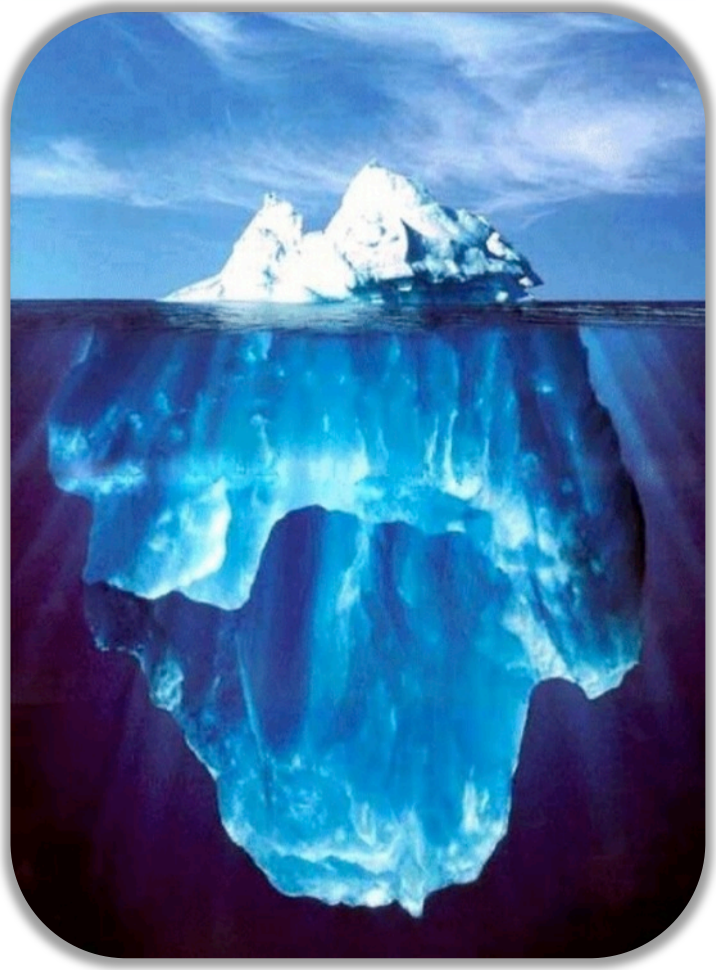
User interaction → Raw Logs → Structured Data

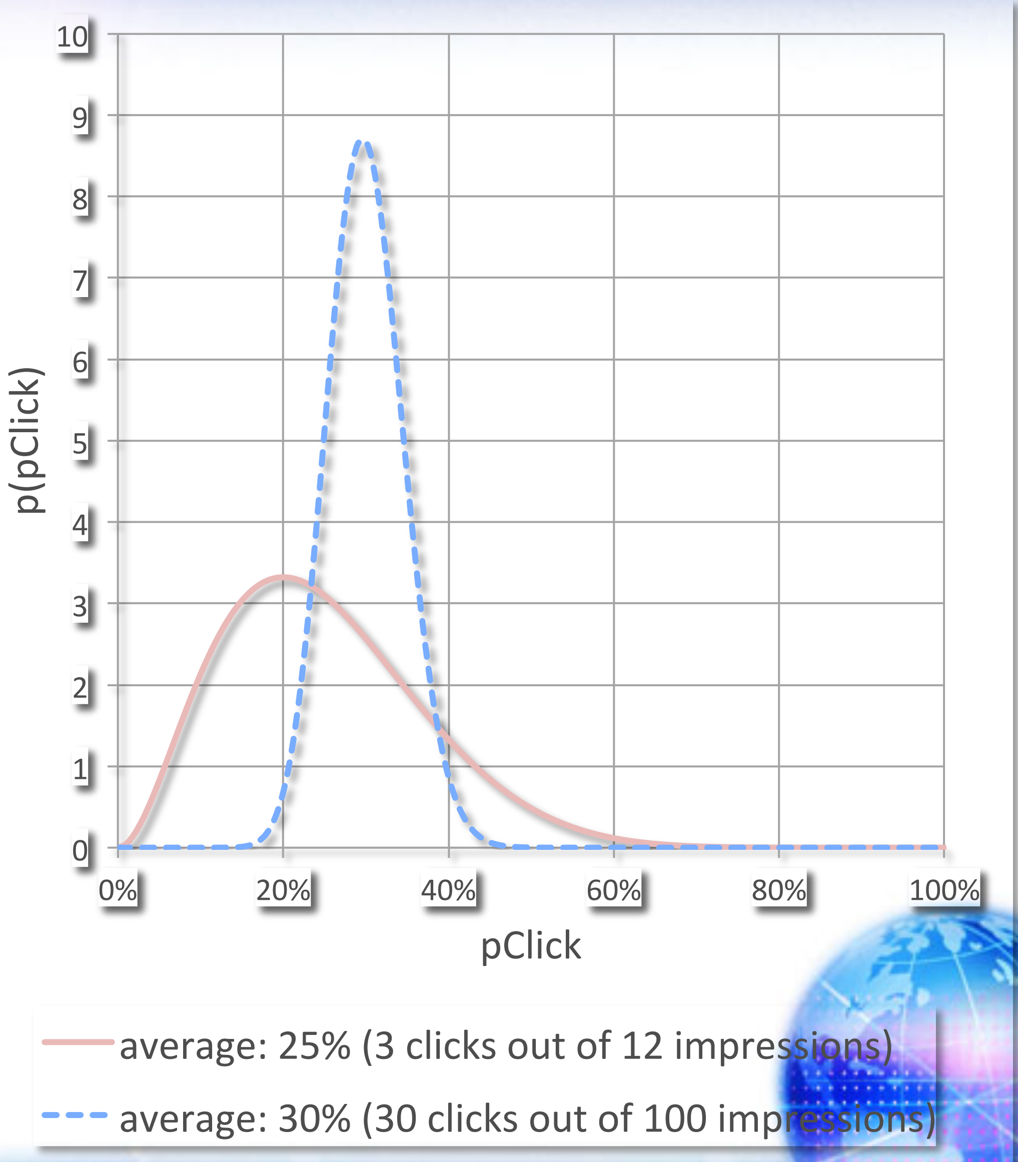
- Why structured data?
  - Data validation and cleaning
  - Principled feature transformations

Uncertainty: Bayesian Probabilities

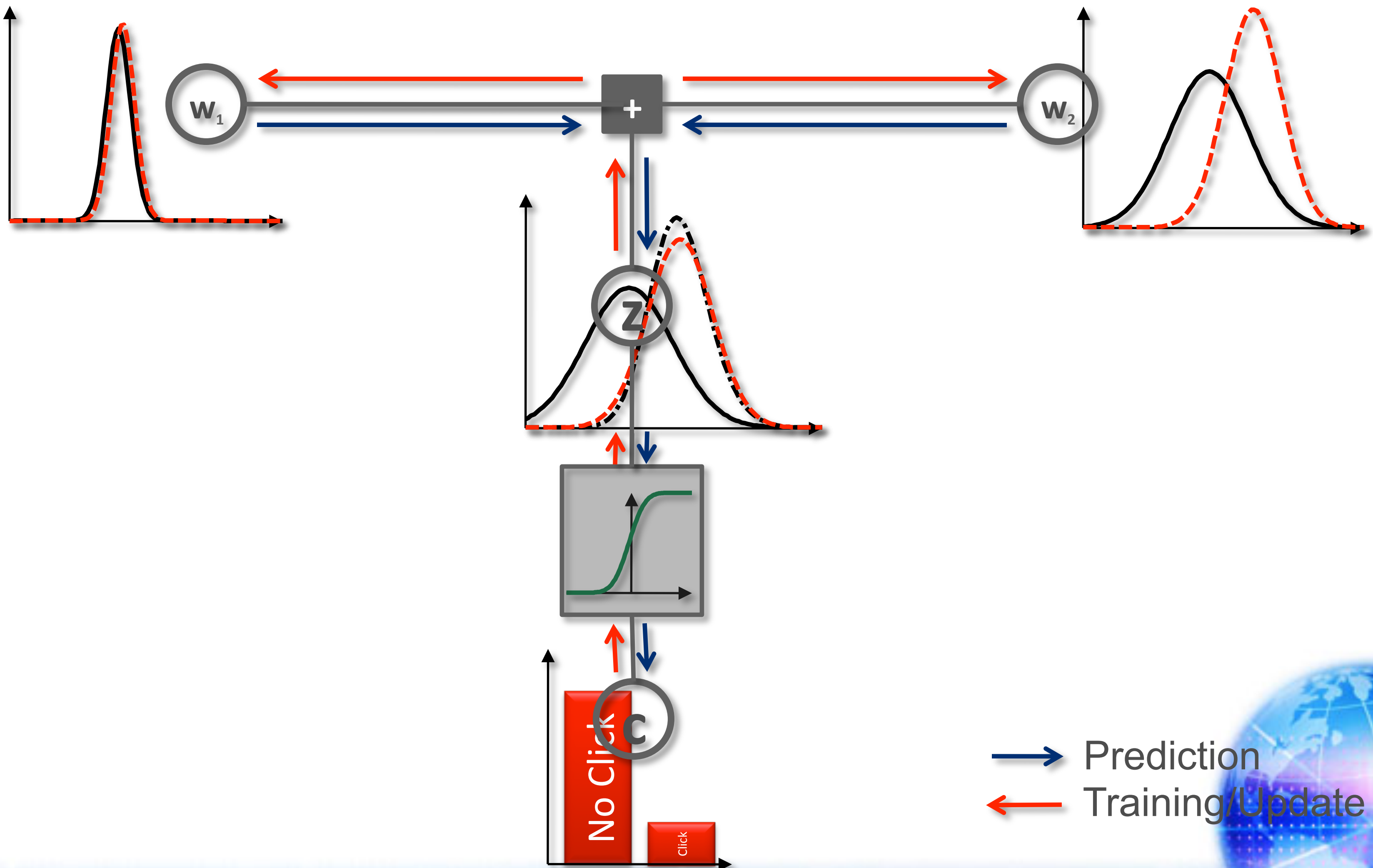


Principled Exploration





Training Algorithm in Action

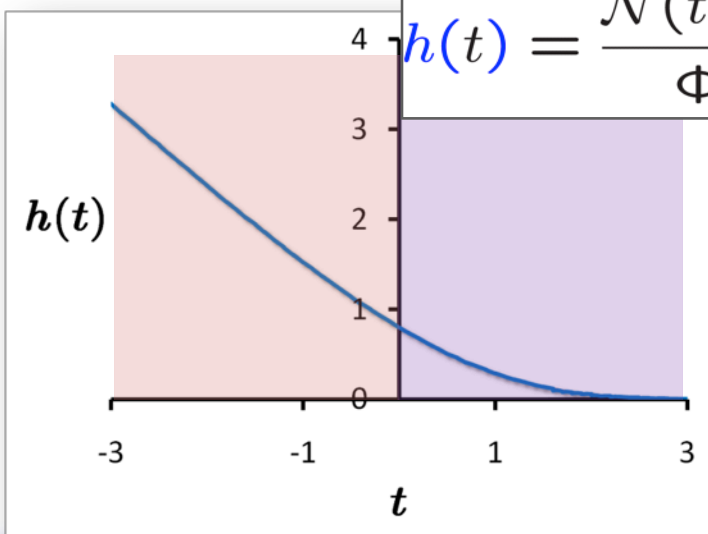


Inference: An Optimization View

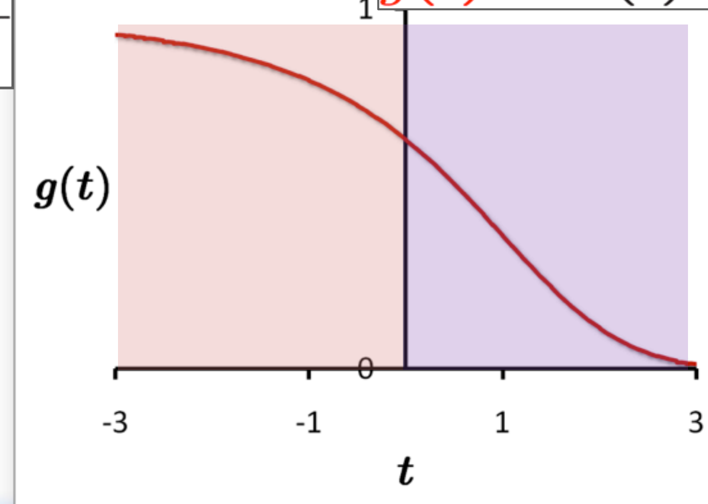
$$\mu_i \leftarrow \mu_i + \frac{\sigma_i^2}{s} \cdot h\left[\frac{\sum_{j=1}^{d} \mu_j}{s}\right] \qquad \sigma_i^2 \leftarrow \sigma_i^2 \left(1 - \frac{\sigma_i^2}{s^2} \cdot g\left[\frac{\sum_{j=1}^{d} \mu_j}{s}\right]\right)$$

$$s^2 = \beta^2 + \sum_{j=1}^{d} \sigma_j^2$$

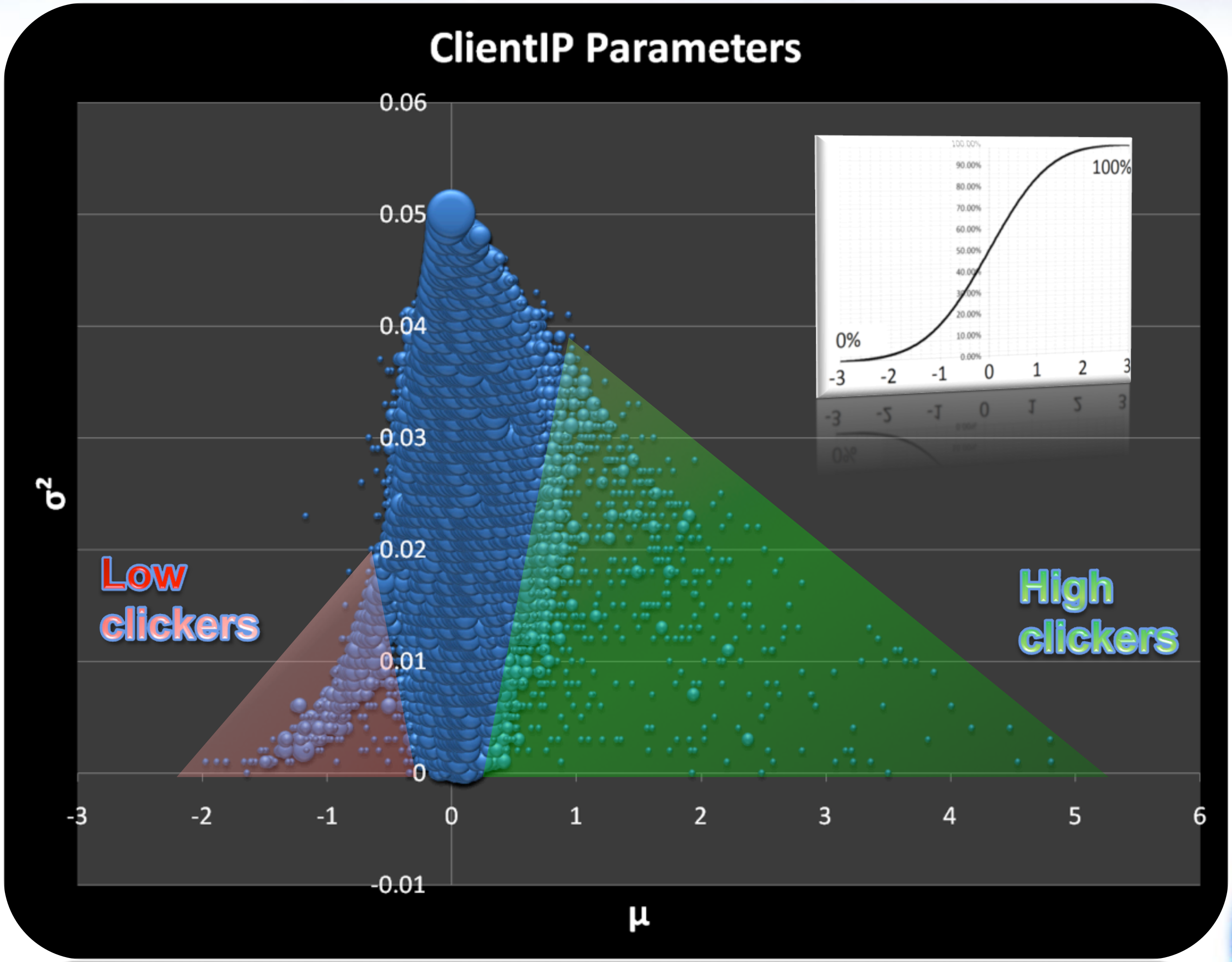
$$h(t) = \frac{\mathcal{N}(t;\, 0, 1)}{\Phi(t)}$$



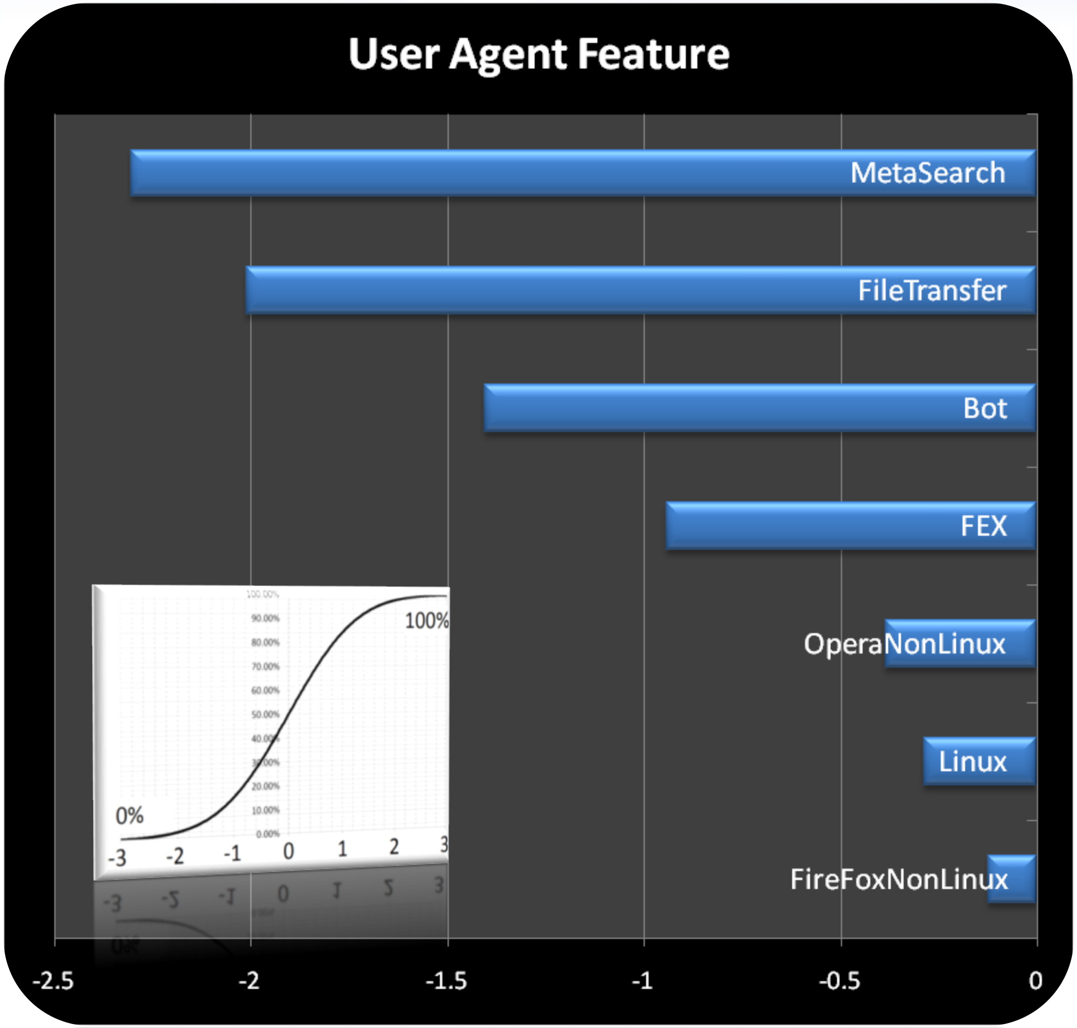
$$g(t) = h(t) \cdot [h(t) + t]$$



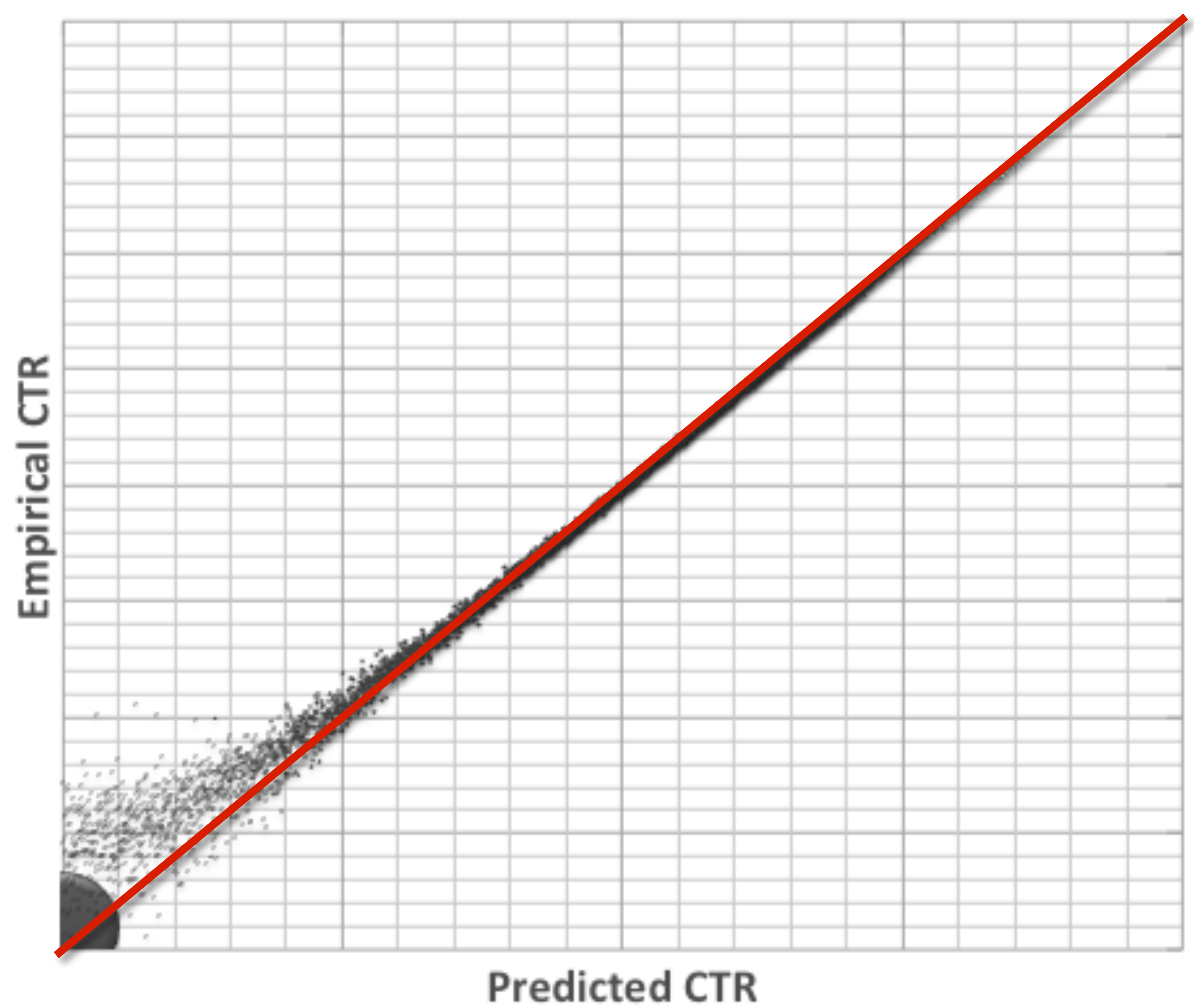
Client IP: Mean & Variance



UserAgent: Mean Posterior Effects

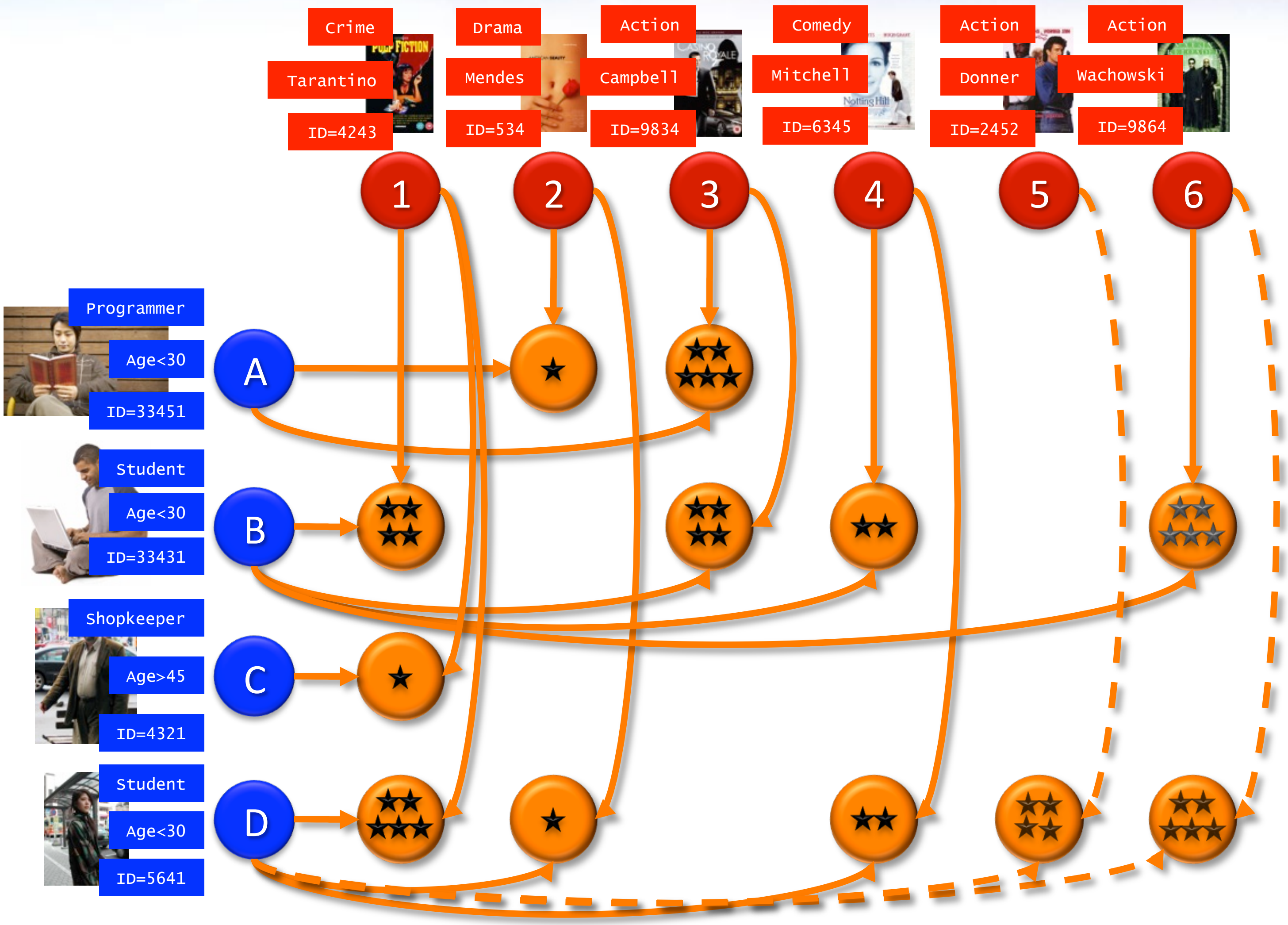


Accuracy



MatchBox

Joint work with Thore Graepel, Joaquin Quiñonero Candela, David Stern


Crime
Tarantino
ID=4243
Drama
Mendes
ID=534
Action
Campbell
ID=9834
Comedy
Mitchell
ID=6345
Action
Donner
ID=2452
Action
Wachowski
ID=9864
1
2
3
4
5
6
Programmer
Age<30
ID=33451
A
Student
Age<30
ID=33431
B
Shopkeeper
Age>45
ID=4321
C
Student
Age<30
ID=5641
D

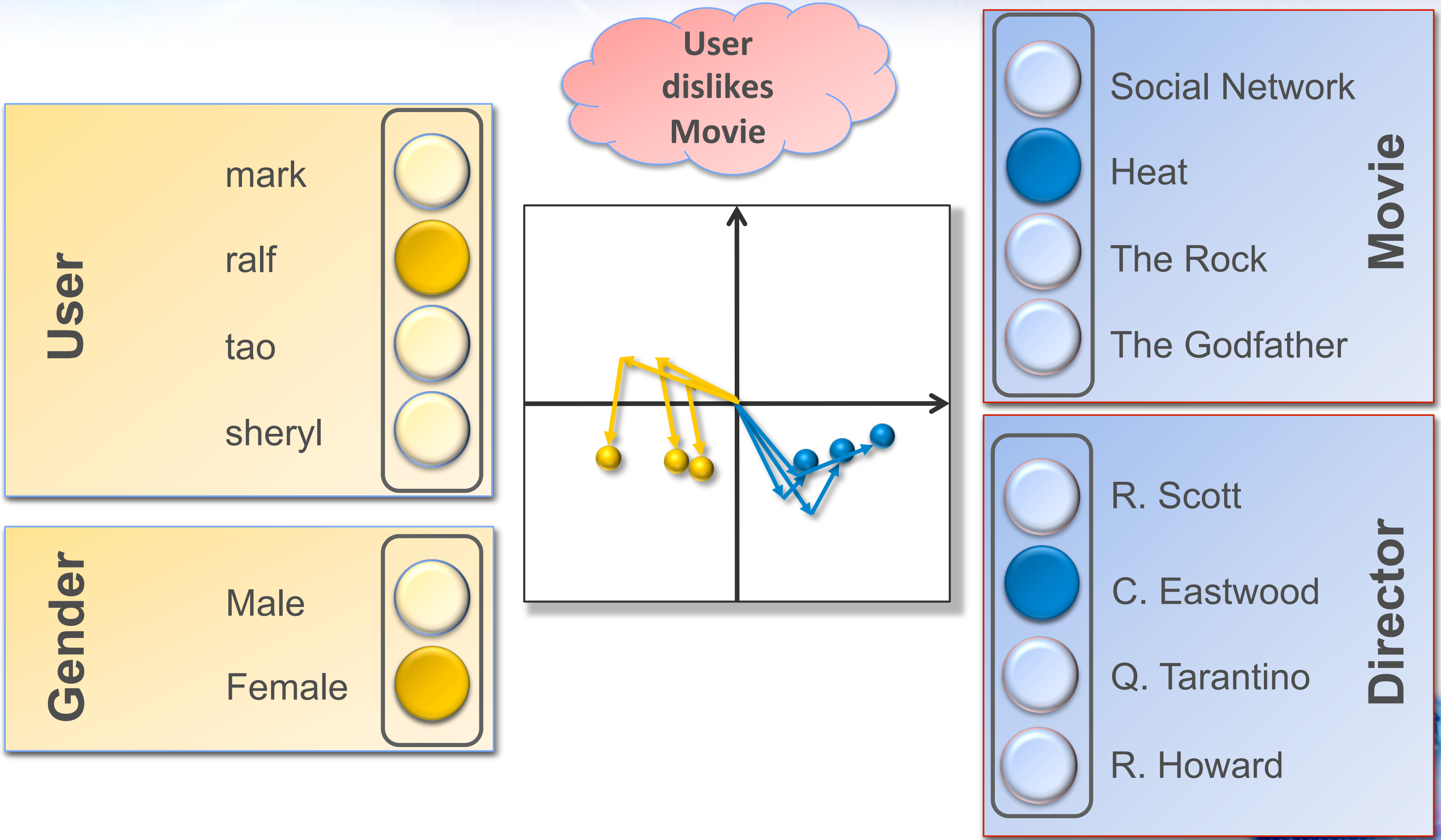
Matchbox With Metadata

User $\mathbf{s} = \mathbf{U}\mathbf{x}$

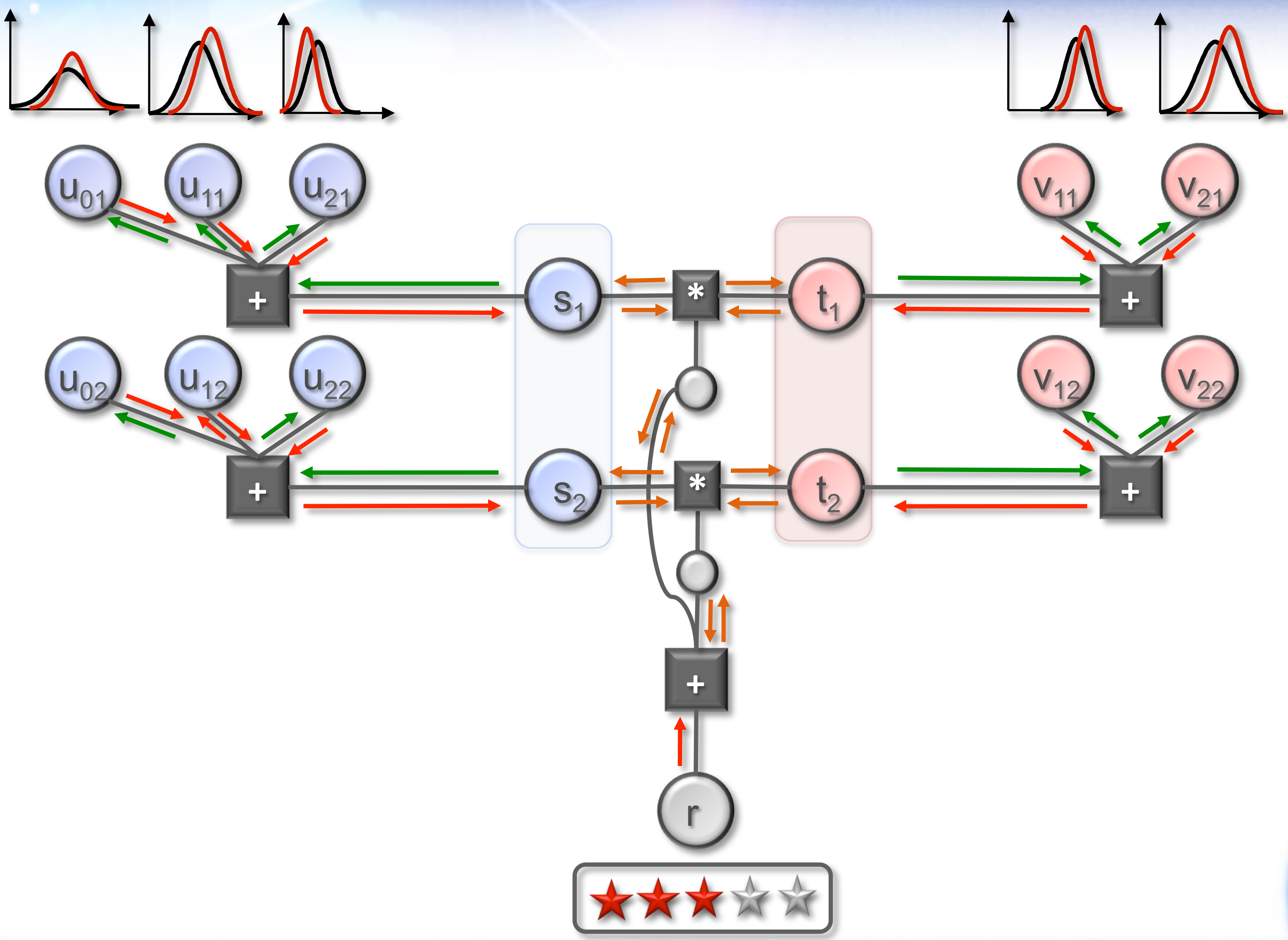
Item $\mathbf{t} = \mathbf{V}\mathbf{y}$

Rating potential ~ $\mathcal{N}(\mathbf{s}^\top \mathbf{t}, \beta^2)$

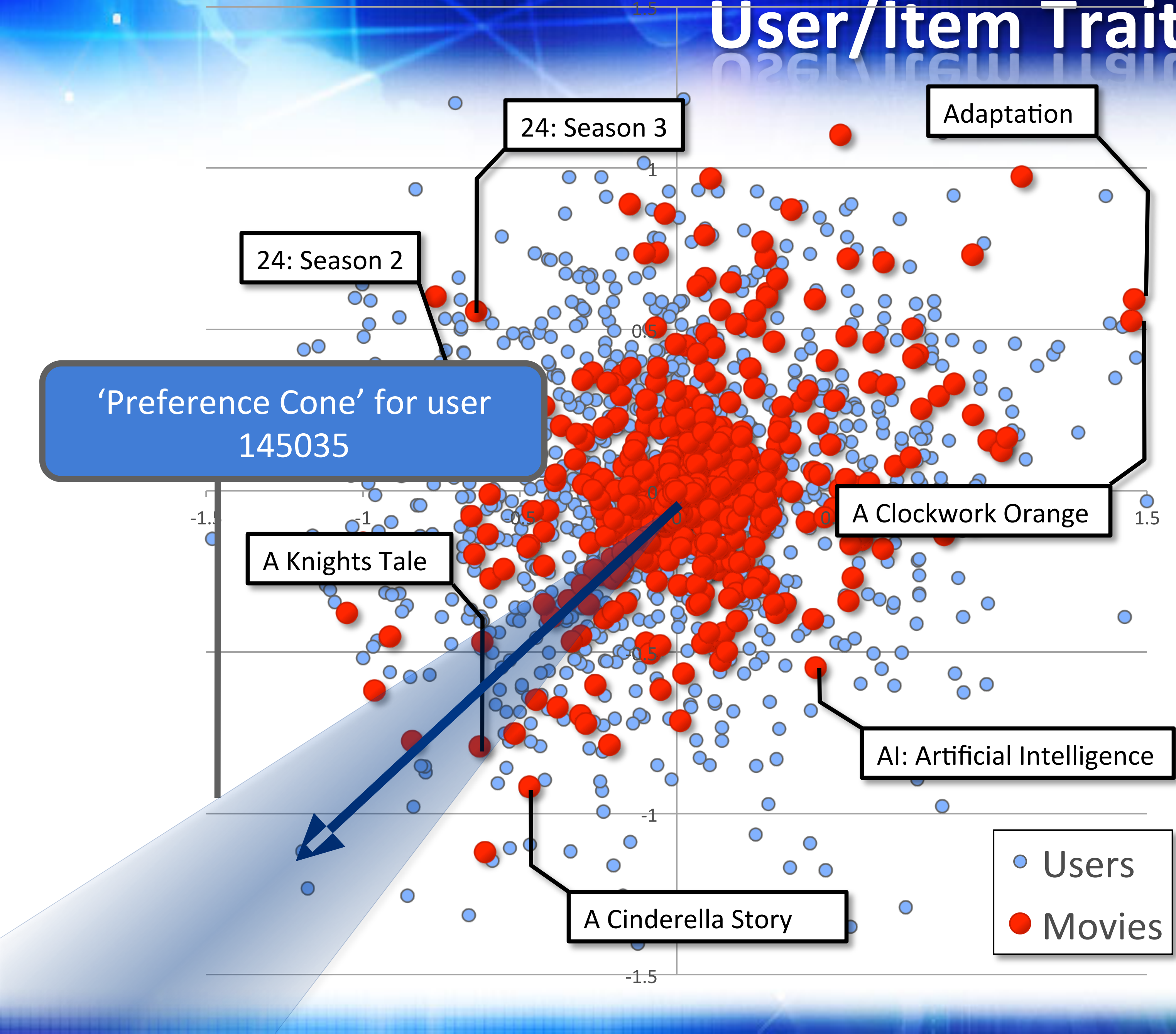
Recommender System: MatchBox



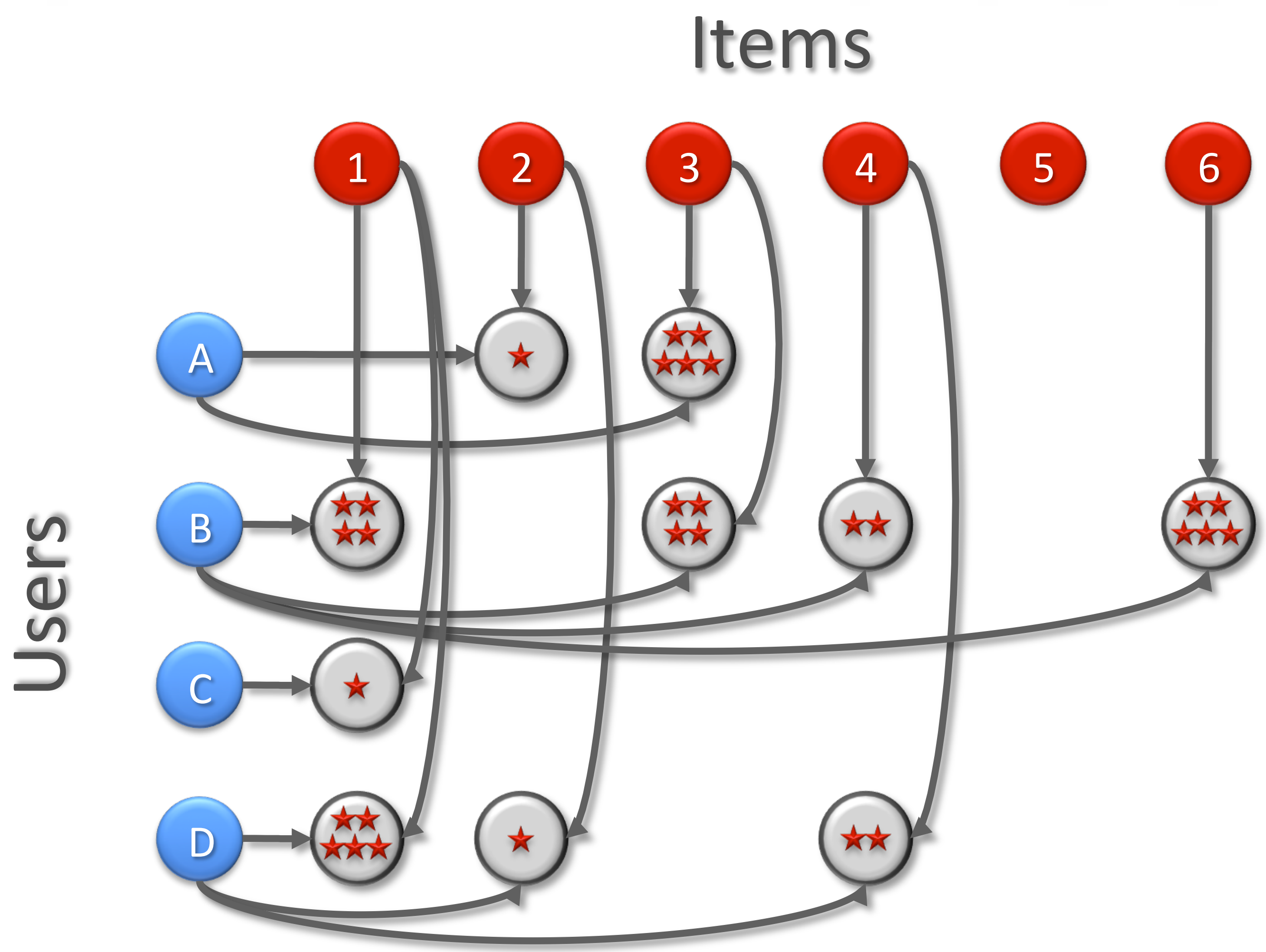
Message Passing For Matchbox



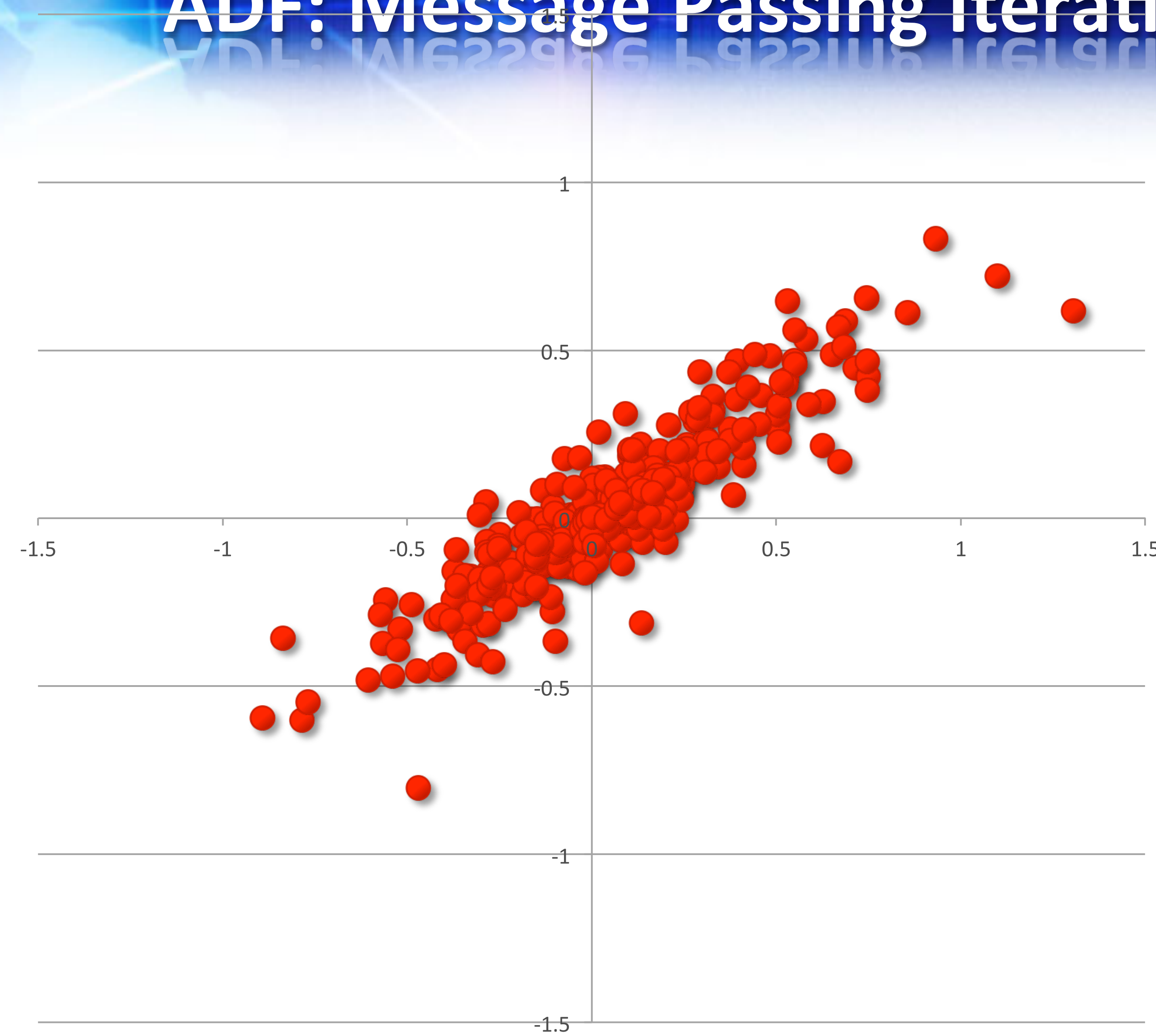
User/Item Trait Space



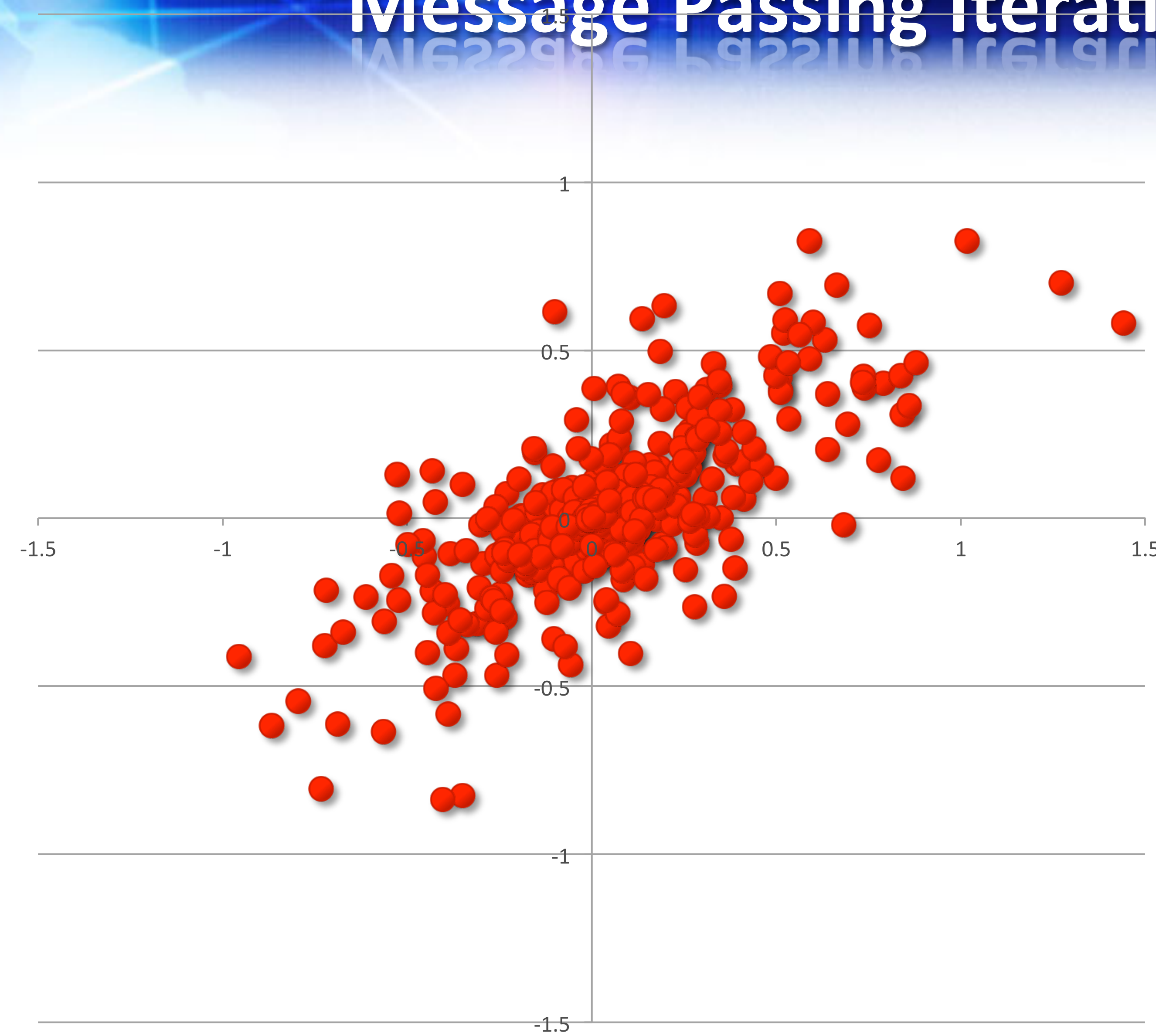
Incremental Training with ADF



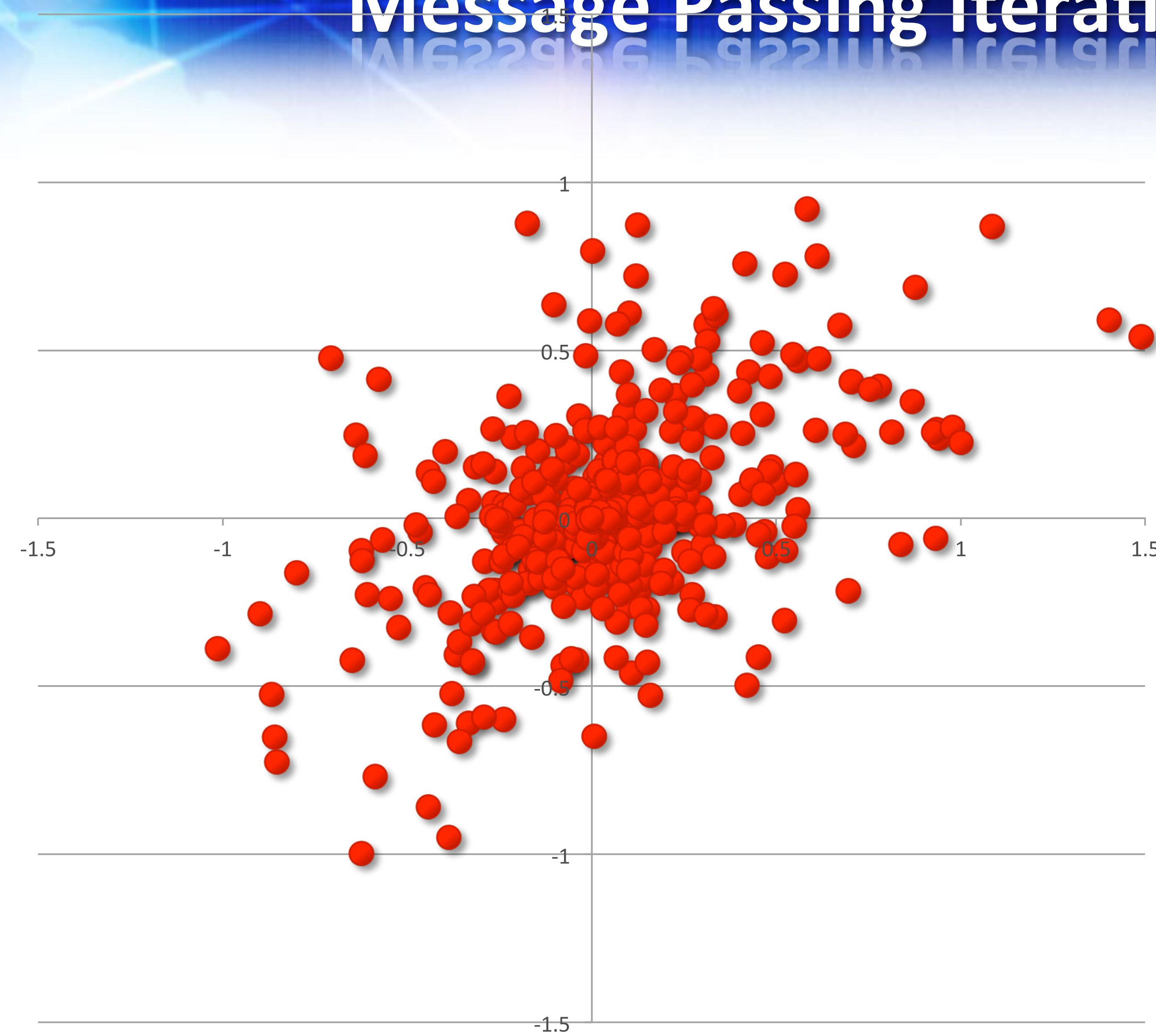
ADF: Message Passing Iteration 1



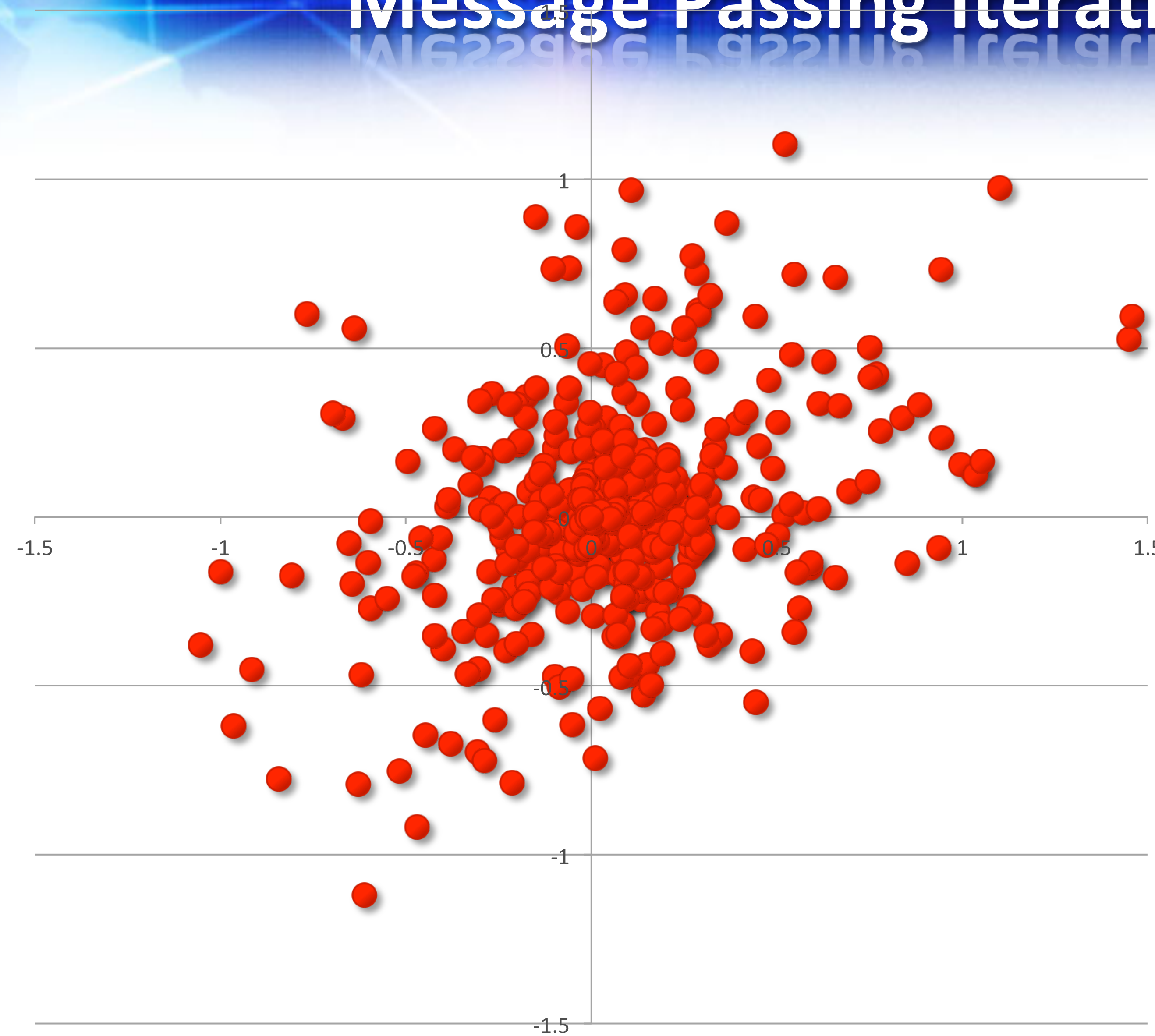
Message Passing Iteration 2



Message Passing Iteration 3

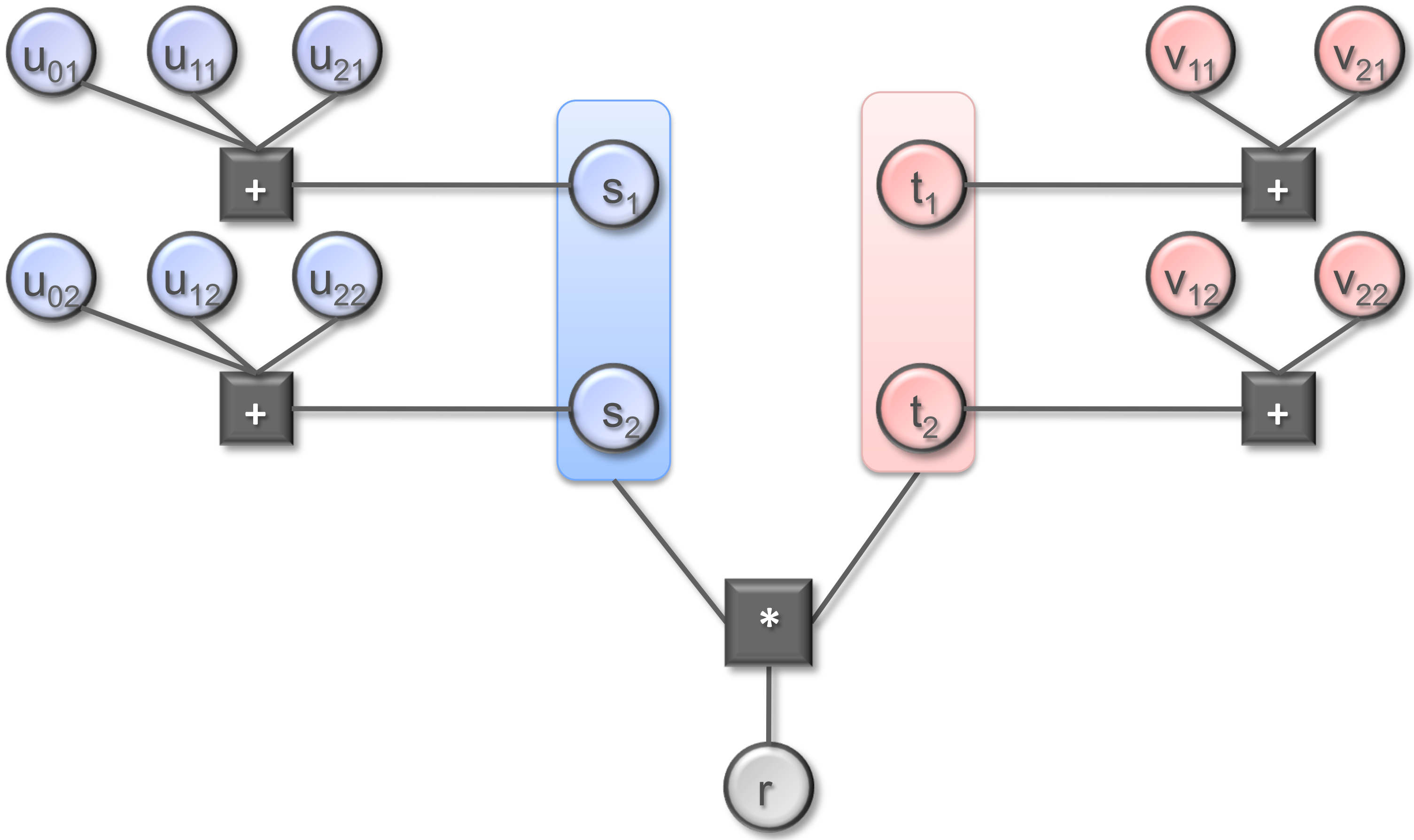


Message Passing Iteration 4

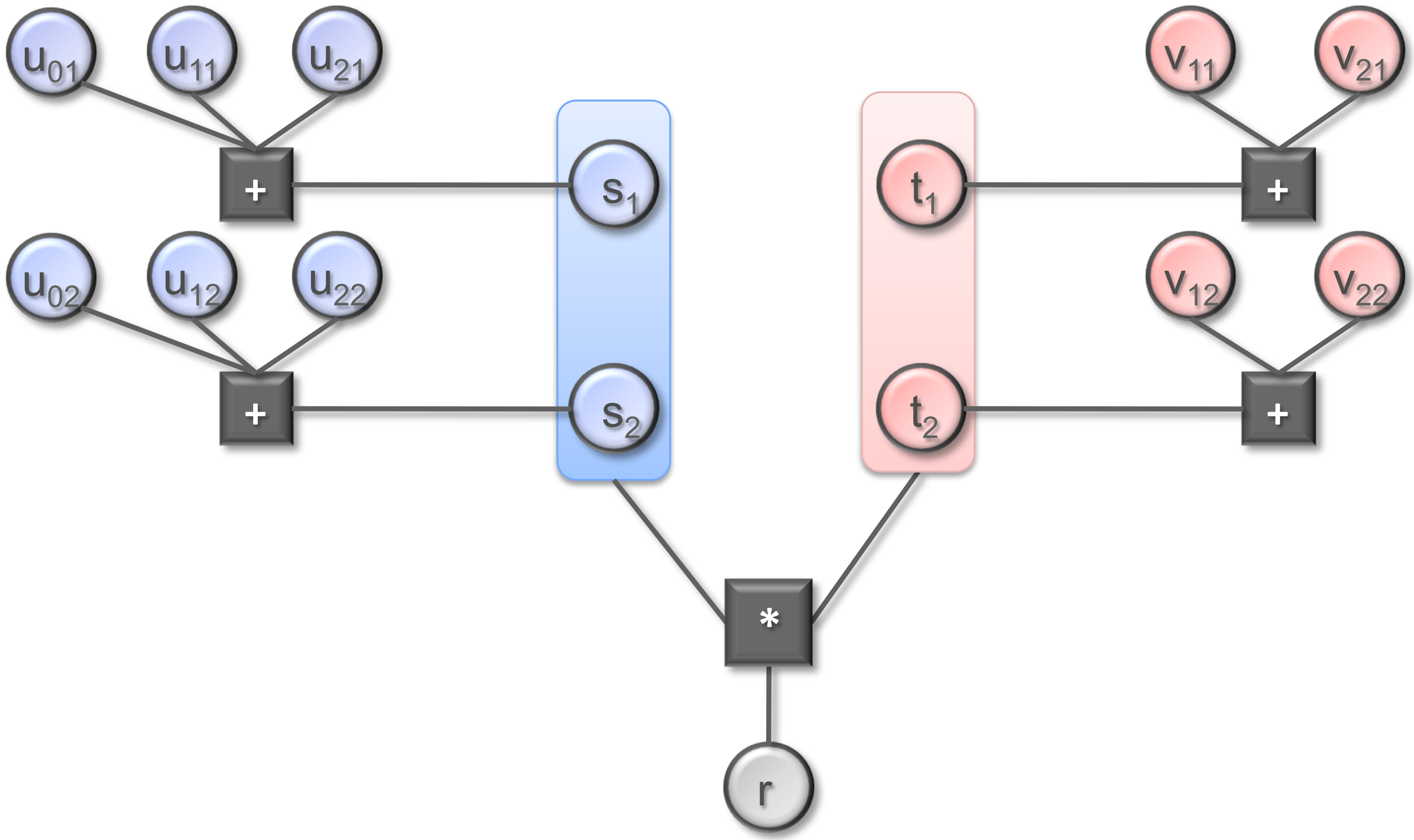


feedback models

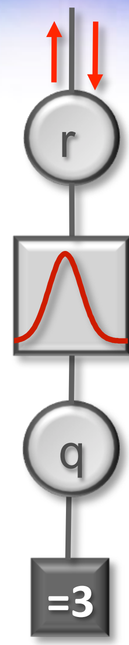
Feedback Models



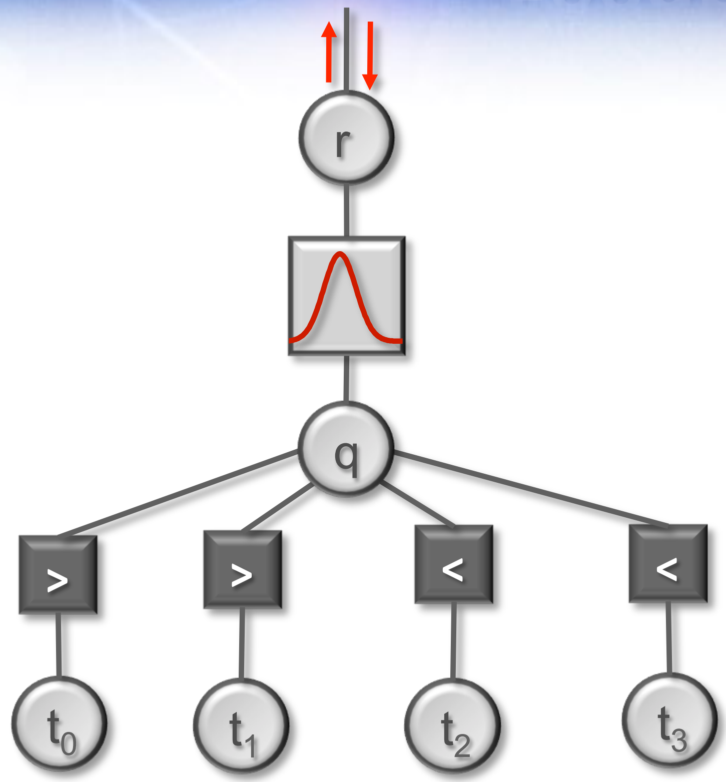
Feedback Models



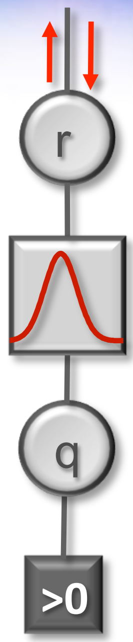
Feedback Models



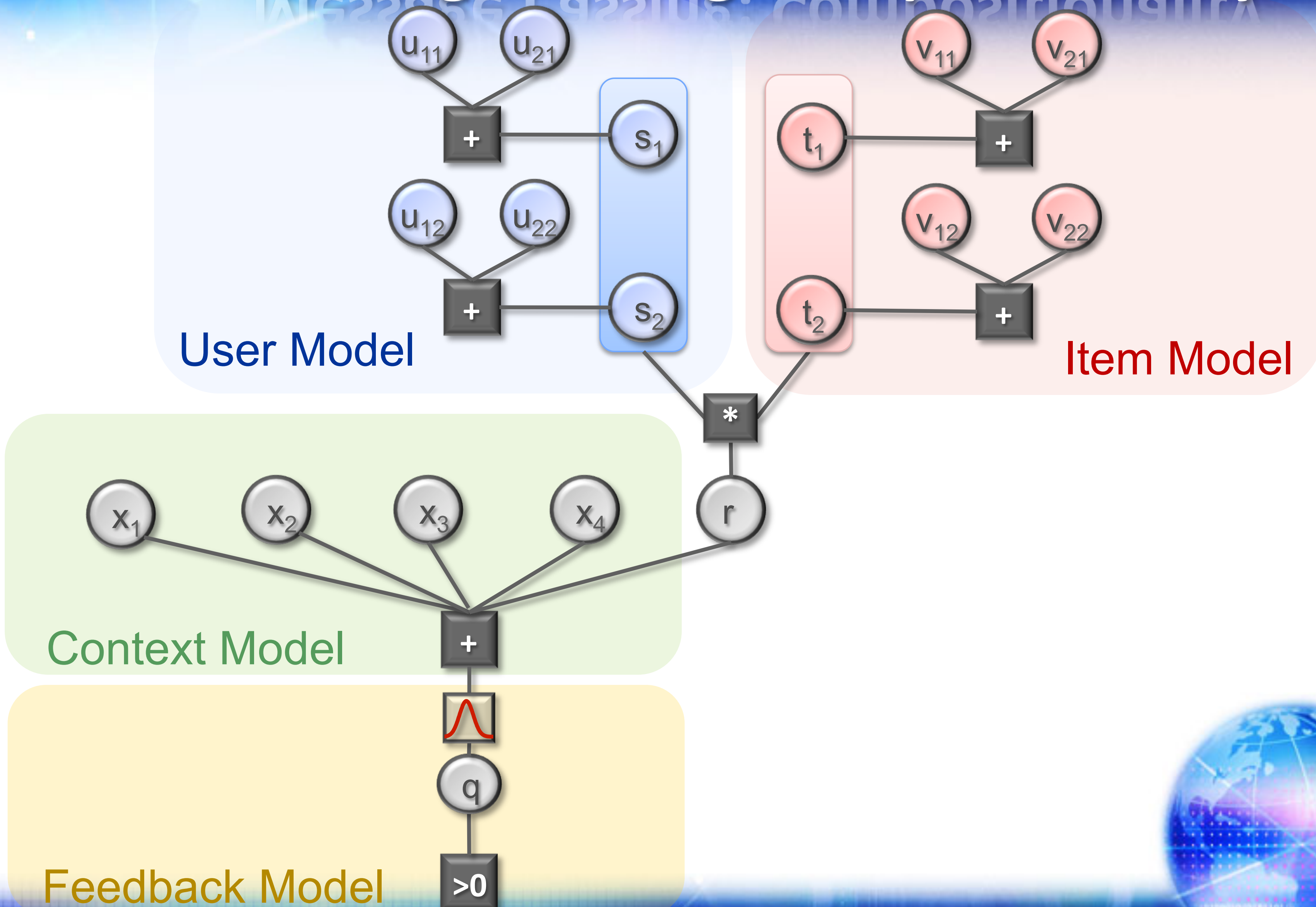
Feedback Models



Feedback Models



Message Passing: Compositionality



accuracy

Performance and Accuracy

MovieLens Data

- 1 million ratings
- 3,900 movies / 6,040 users
- User / movie metadata

MovieLens – 1,000,000 ratings

6,040 users

User ID

User Job	
Other	Lawyer
Academic	Programmer
Artist	Retired
Admin	Sales
Student	Scientist
Customer Service	Self-Employed
Health Care	Technician
Managerial	Craftsman
Farmer	Unemployed
Homemaker	Writer

User Age
<18
18-25
25-34
35-44
45-49
50-55
>55

User Gender
Male
Female

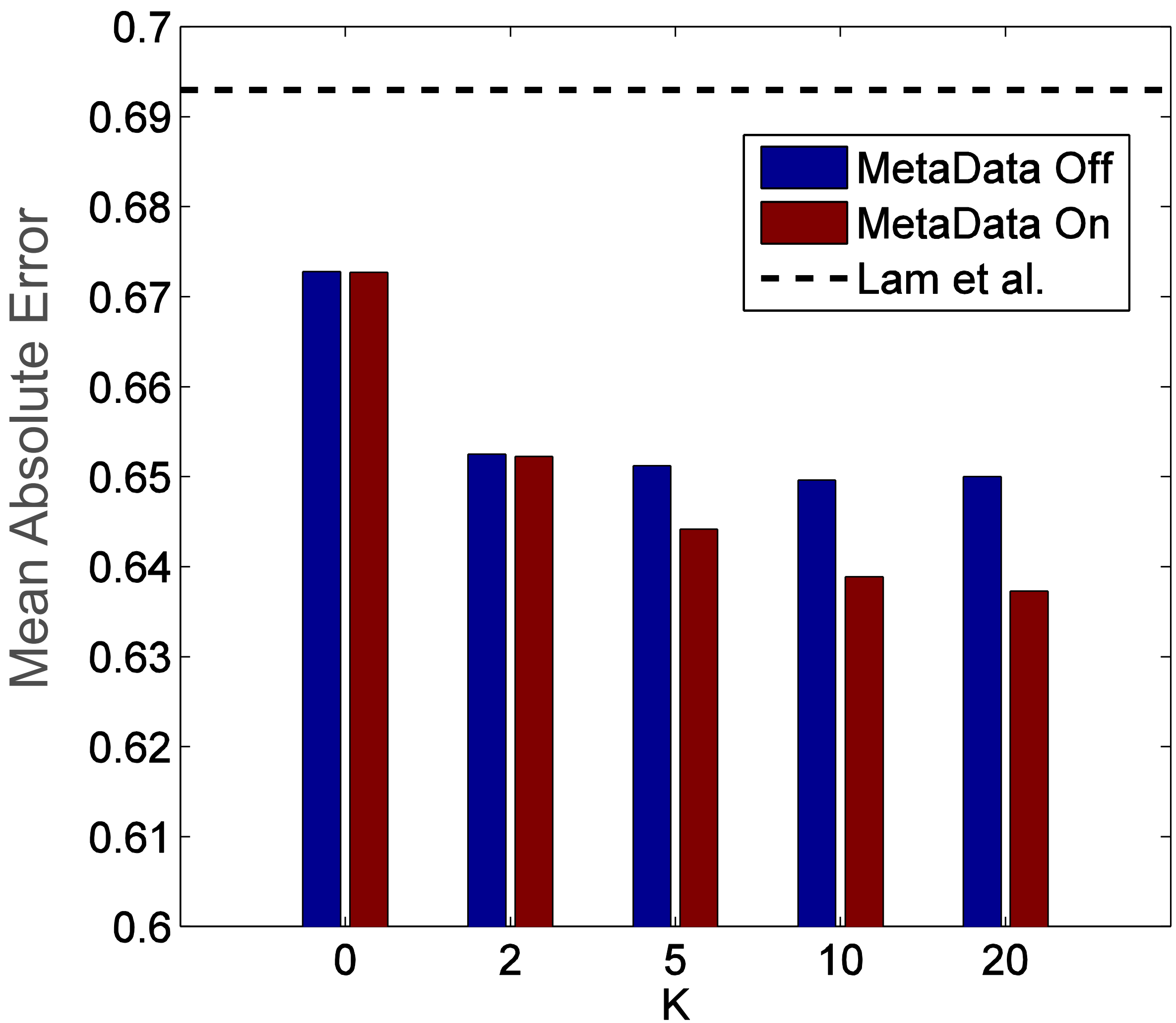
3,900 movies

Movie ID

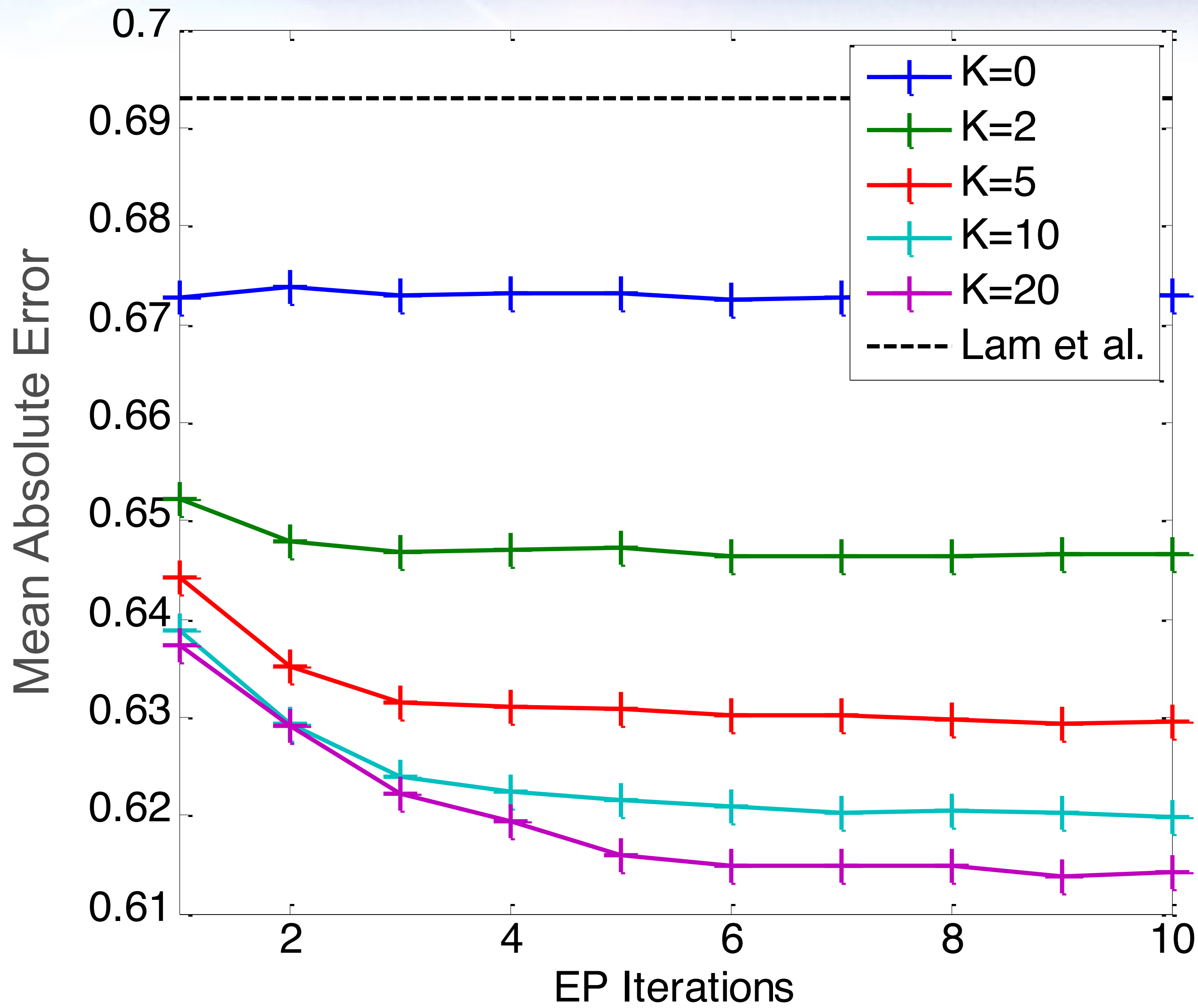
Movie Genre	
Action	Horror
Adventure	Musical
Animation	Mystery
Children’s	Romance
Comedy	Thriller
Crime	Sci-Fi
Documentary	War
Drama	Western
Fantasy	Film Noir

MovieLens with Thresholds Model

(ADF), Training Time= 1 Minute



MovieLens Error with Thresholds



Recommendation Speed

Recommendation Speed

- **Goal:**
  find N items with highest predicted rating.
- **Challenge:**
  potentially have to consider all items.
- Two approaches to make this faster:
  - Locality Sensitive Hashing
  - KD Trees
- Locality Sensitive Hash:

$$P(h(x) = h(y)) = \mathrm{sim}(x, y)$$

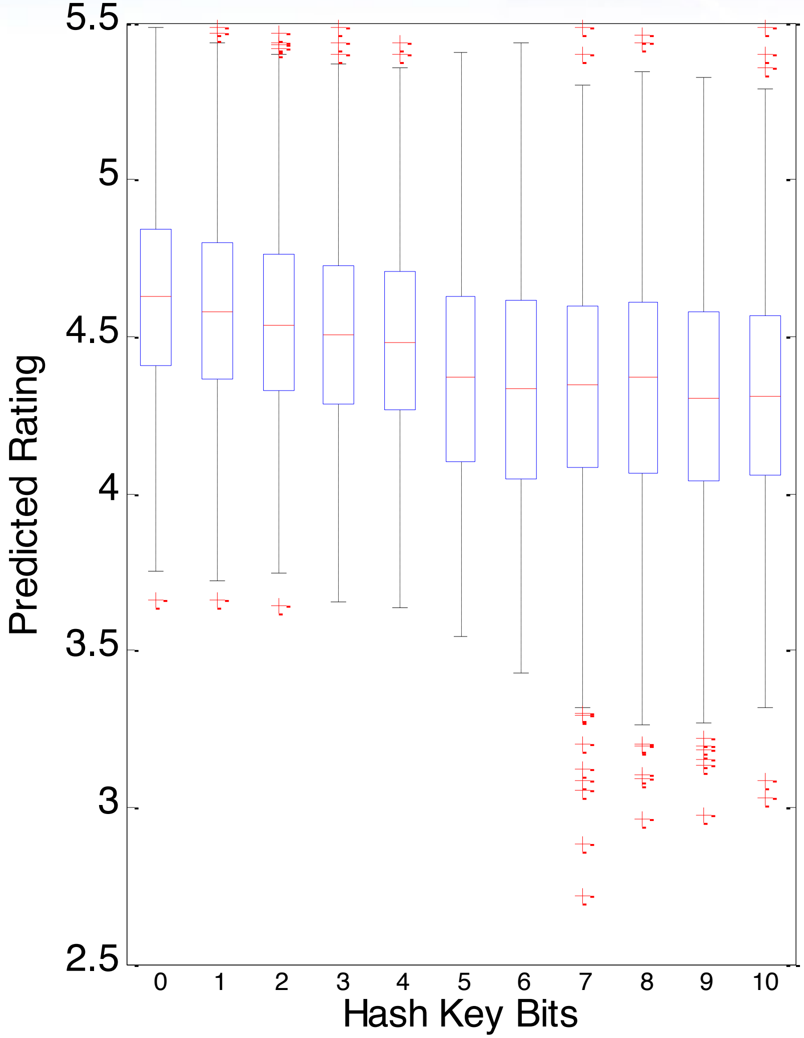
Random Projection Hashing

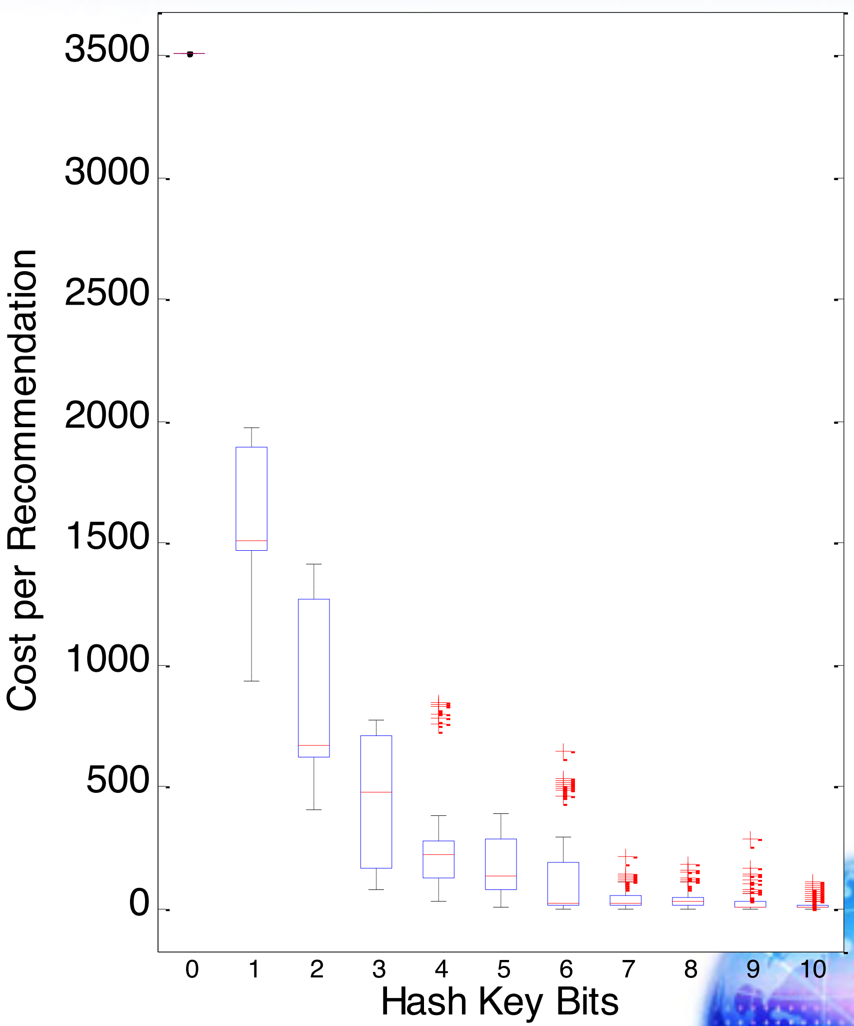
- Random Projections:
  - Generate random hyper planes (m random vectors, a_i).
  - Gives m bit hash, $\{x_0, x_1, \cdots, x_m\}$, by:

$$x_i = \mathbf{1}[\mathbf{a}_i \cdot \mathbf{t} > 0]$$

- p(all bits match) ∝ cosine similarity.
- Store items in buckets indexed by keys.
- Given a user trait vector:
  1. Generate key, q.
  2. Search buckets by hamming distance from q until find N items.

Accuracy and Speedup





Learning to Play Go

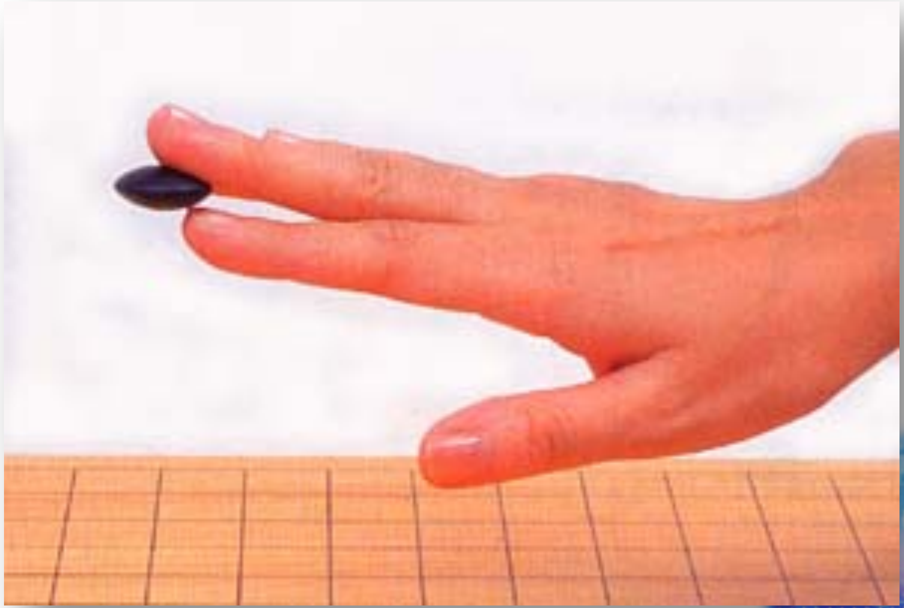
Joint work with Thore Graepel & David Stern

Uncertainty in Go

- Go is game of perfect information.
- Complexity of game tree +
  limited computer speed → uncertainty.
- 味 'aji' = 'taste'.
- Our Approach:
  Represent uncertainty using probabilities.

Machine Learning

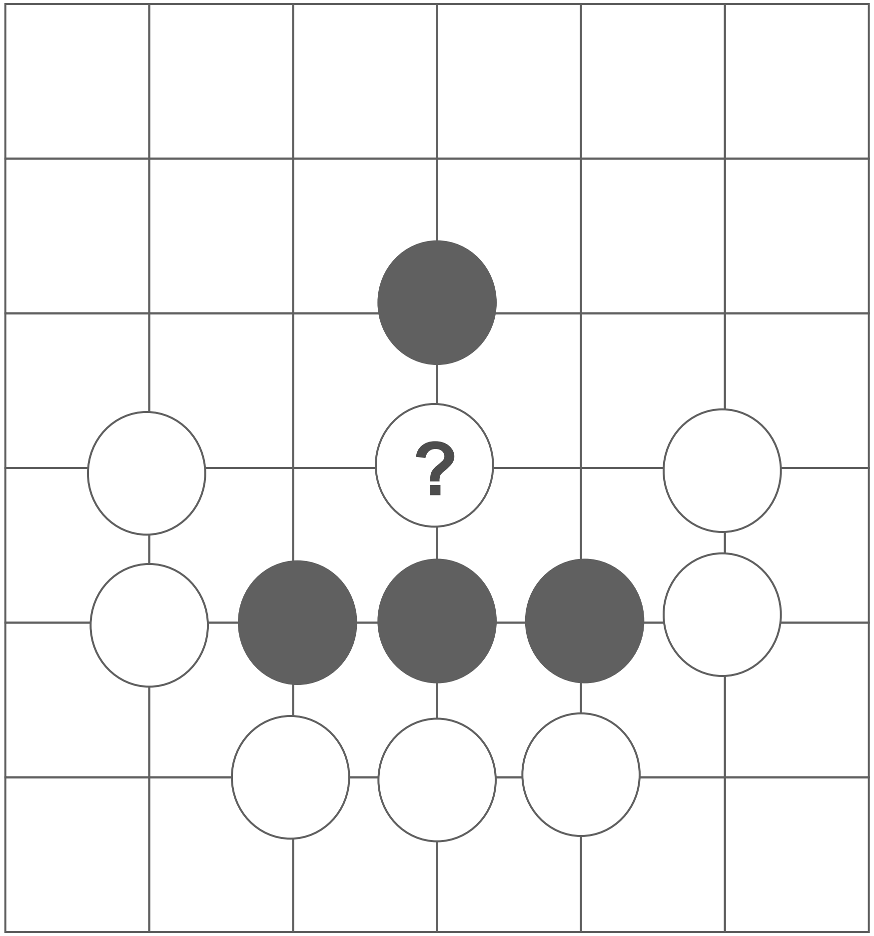
- Automatic knowledge Acquisition.
- Principled management of uncertainty.
- Applications to Go:
  - **Move Prediction.**
  - **Tactical Search.**
  - **Territory Prediction.**
  - **Monte Carlo Go.**



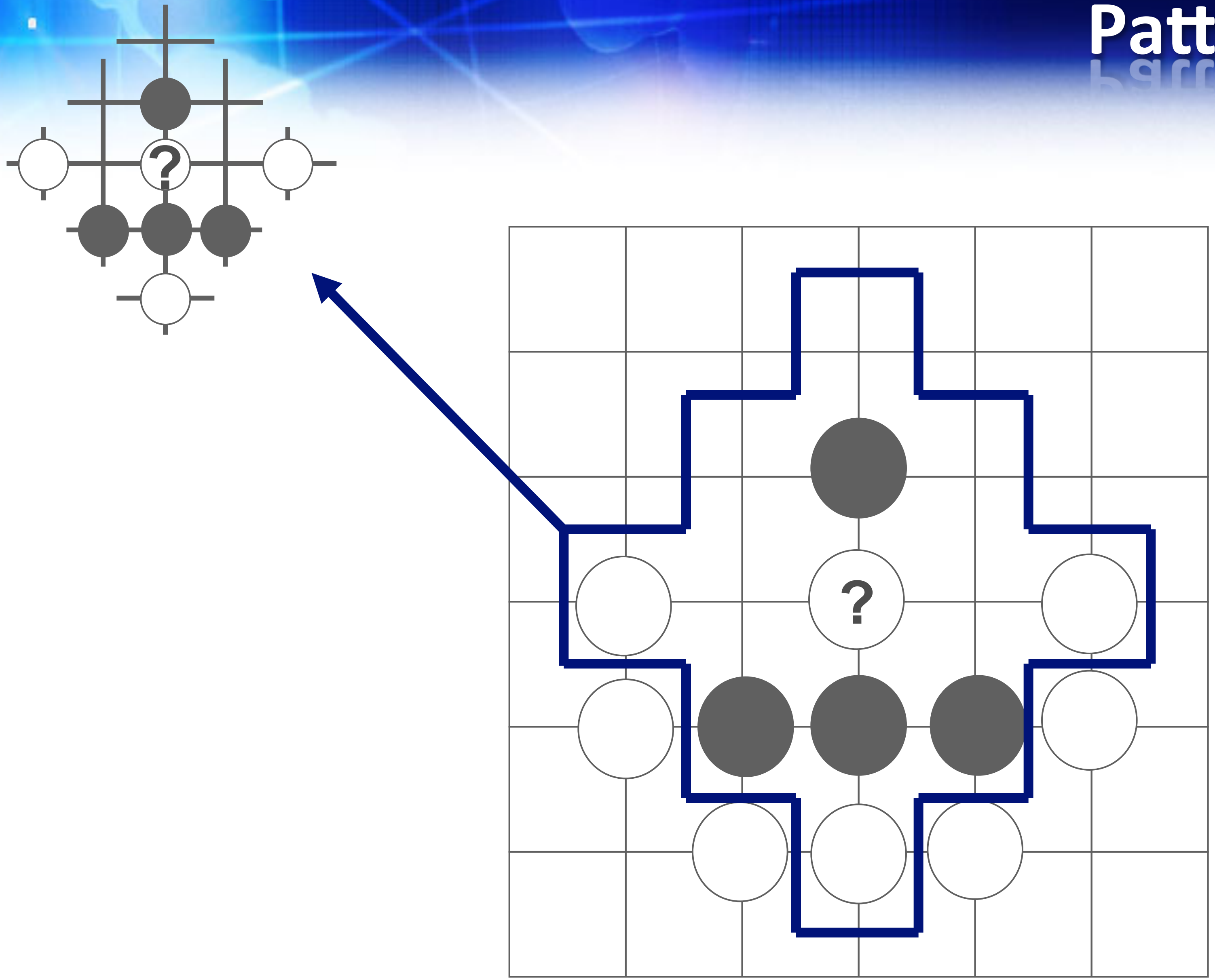
Move Prediction

- Learning from Expert Game Records
- Move associated with a set of patterns.
  - **Exact arrangement of stones.**
  - **Centred on proposed move.**
- Sequence of nested templates.
- Inspired by work by David Stoutamire and Frank de Groot

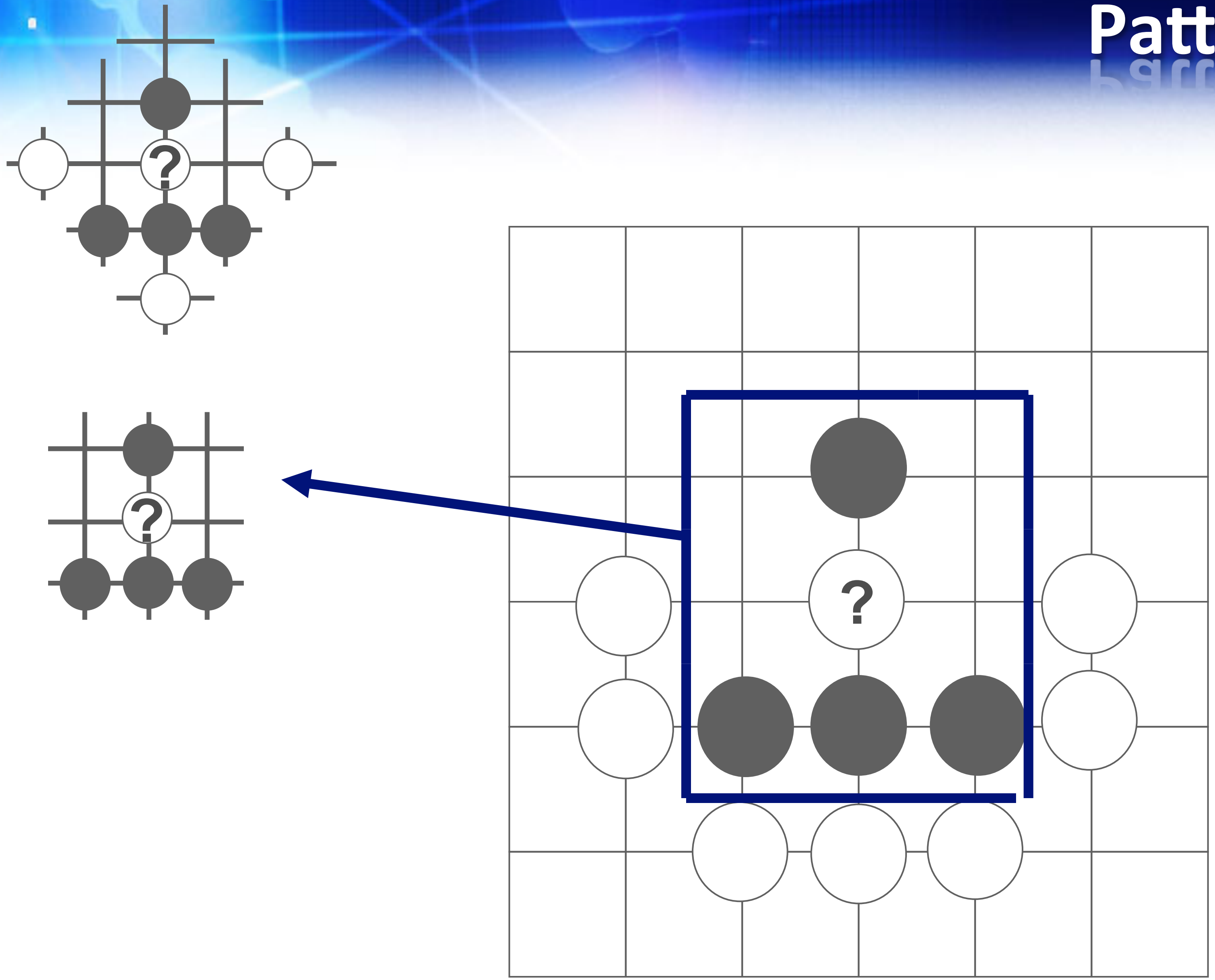
Patterns



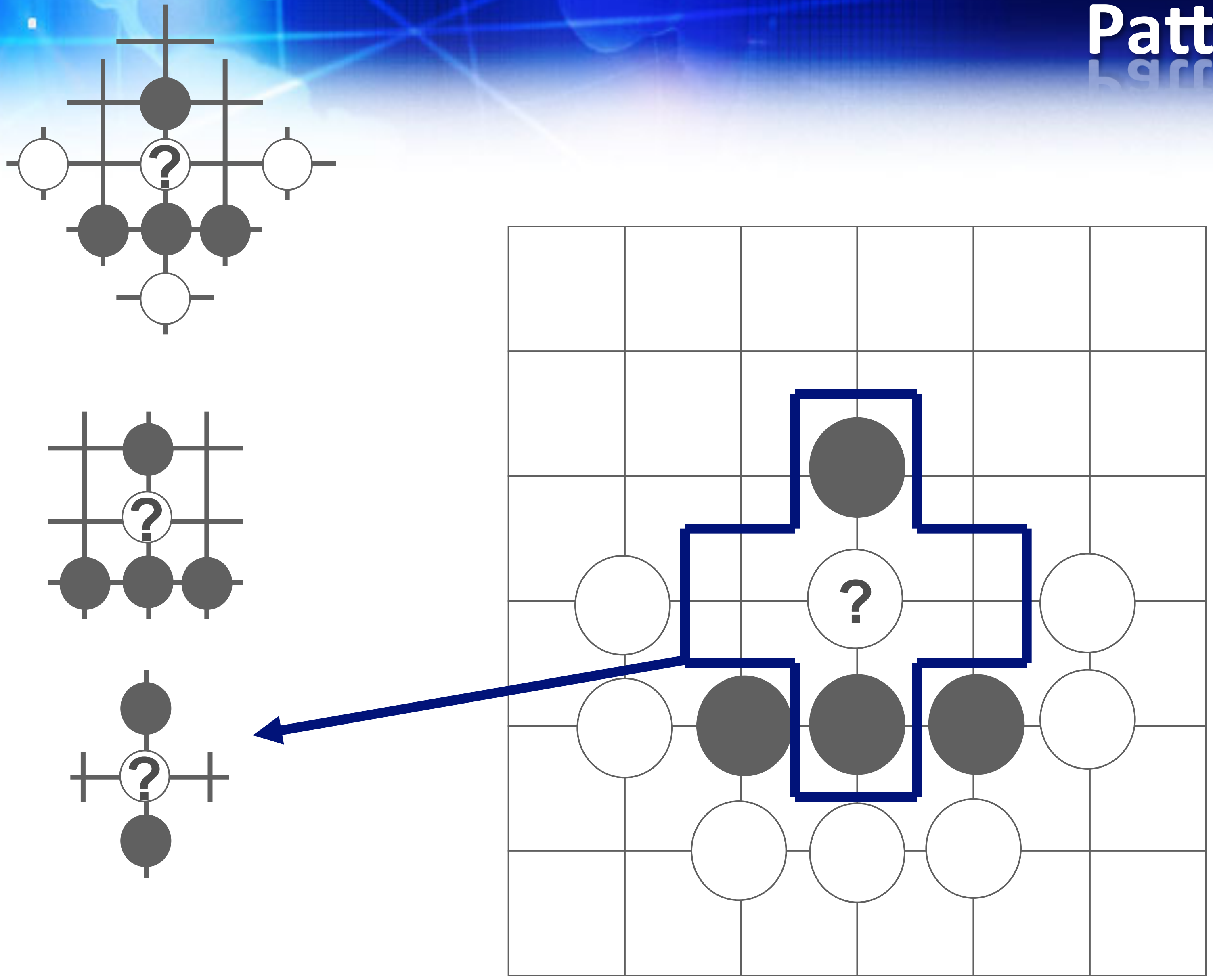
Patterns



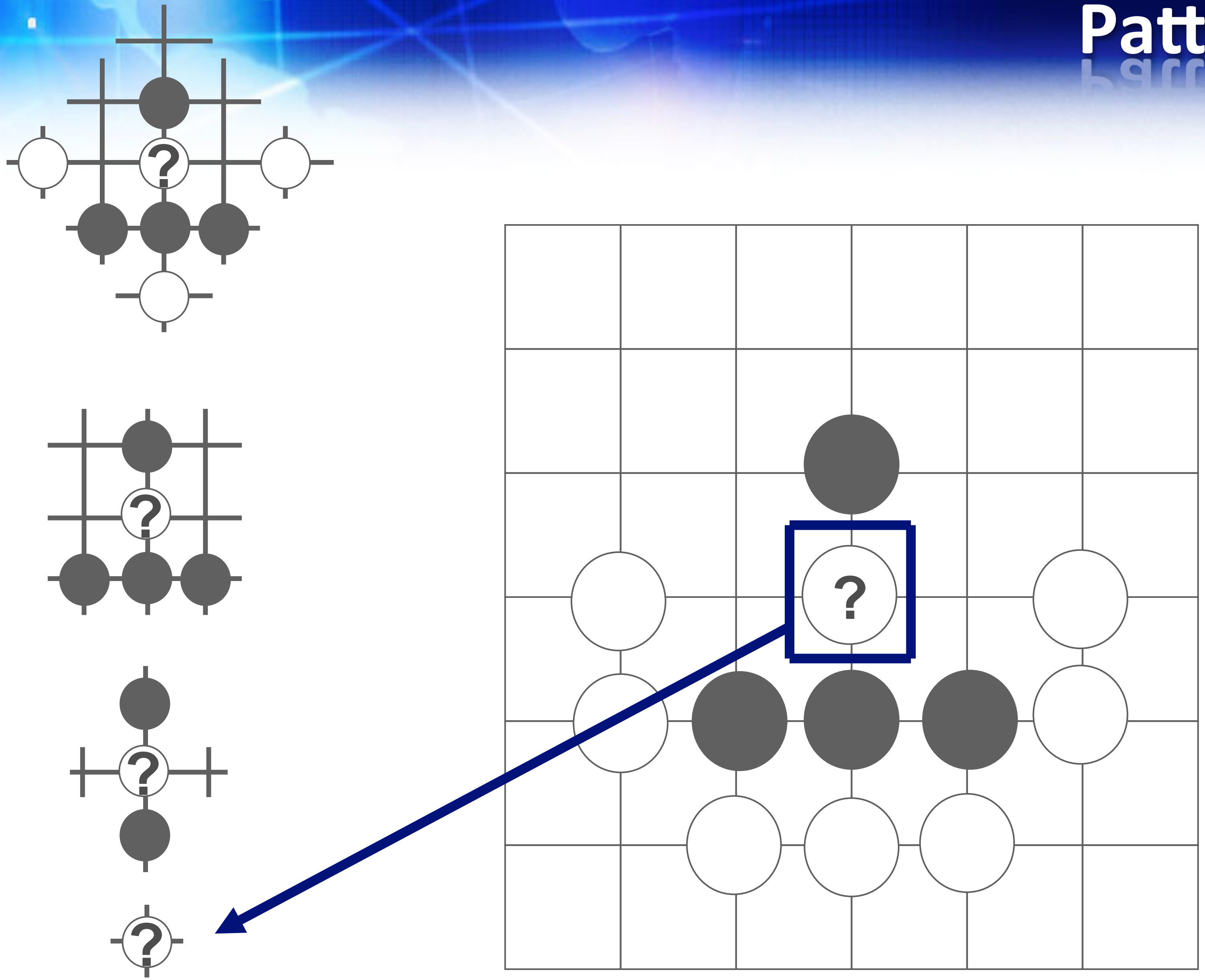
Patterns



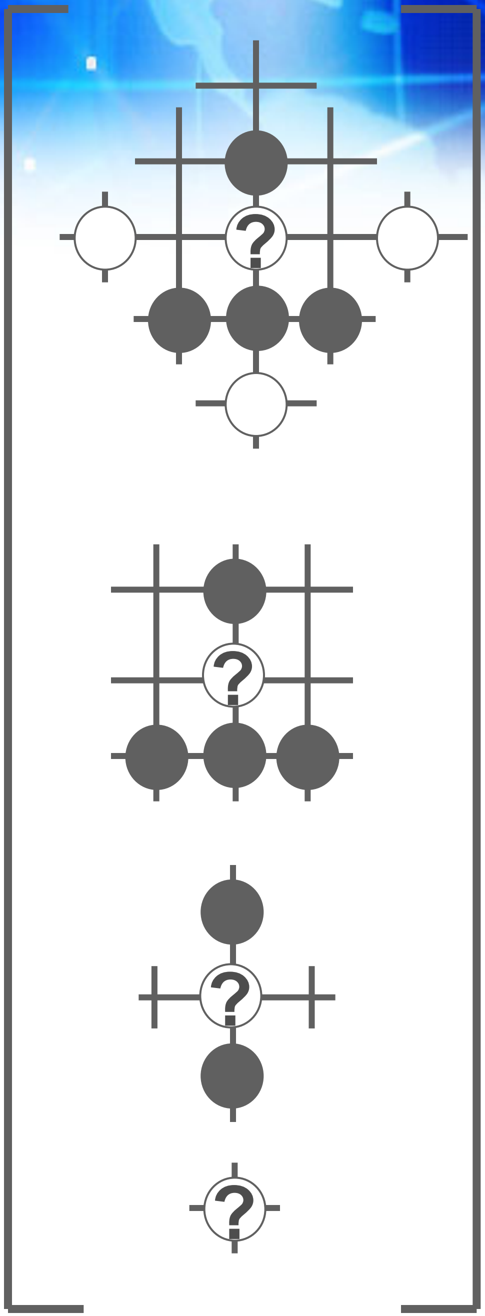
Patterns

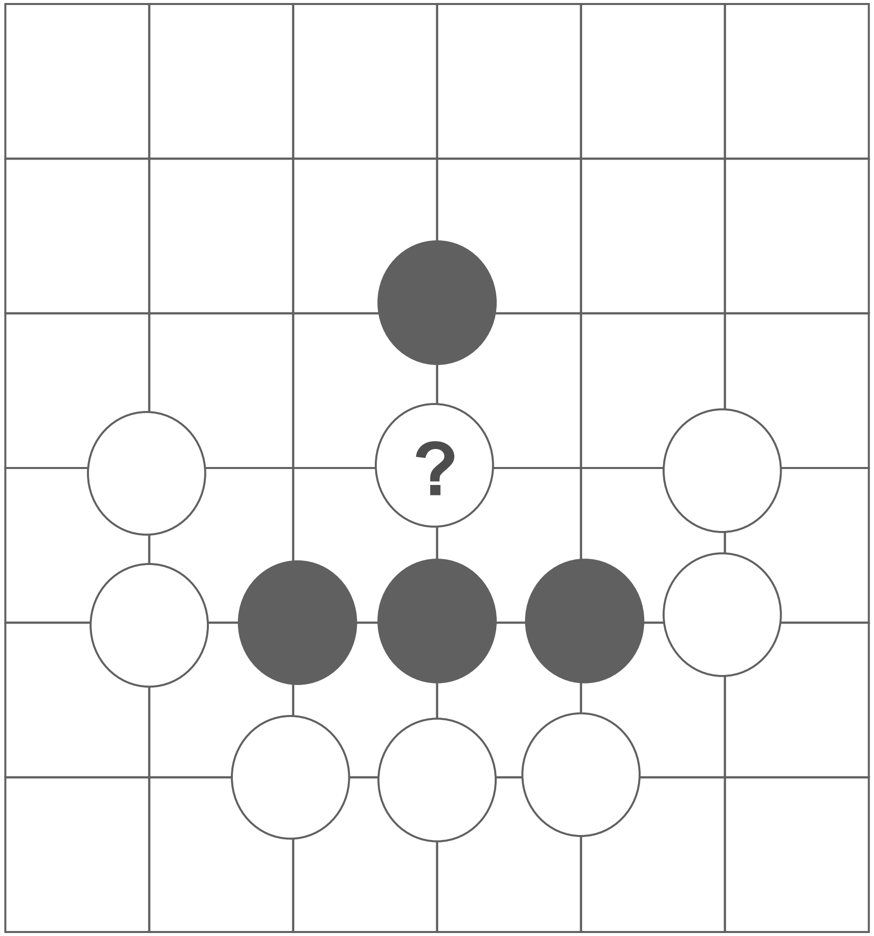


Patterns

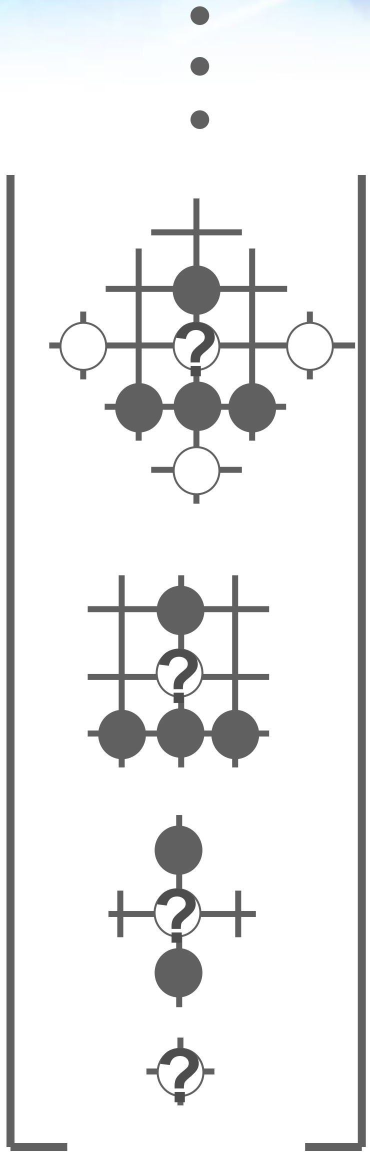


Patterns





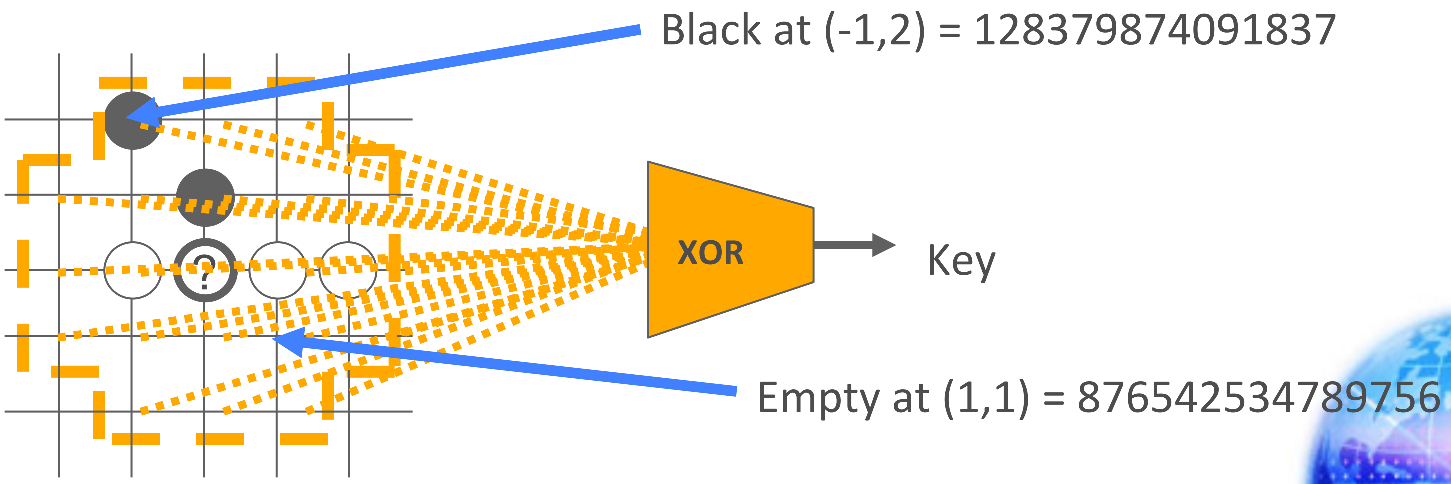
Patterns



- 13 Pattern Sizes
  - **Smallest is vertex only.**
  - **Biggest is full board.**

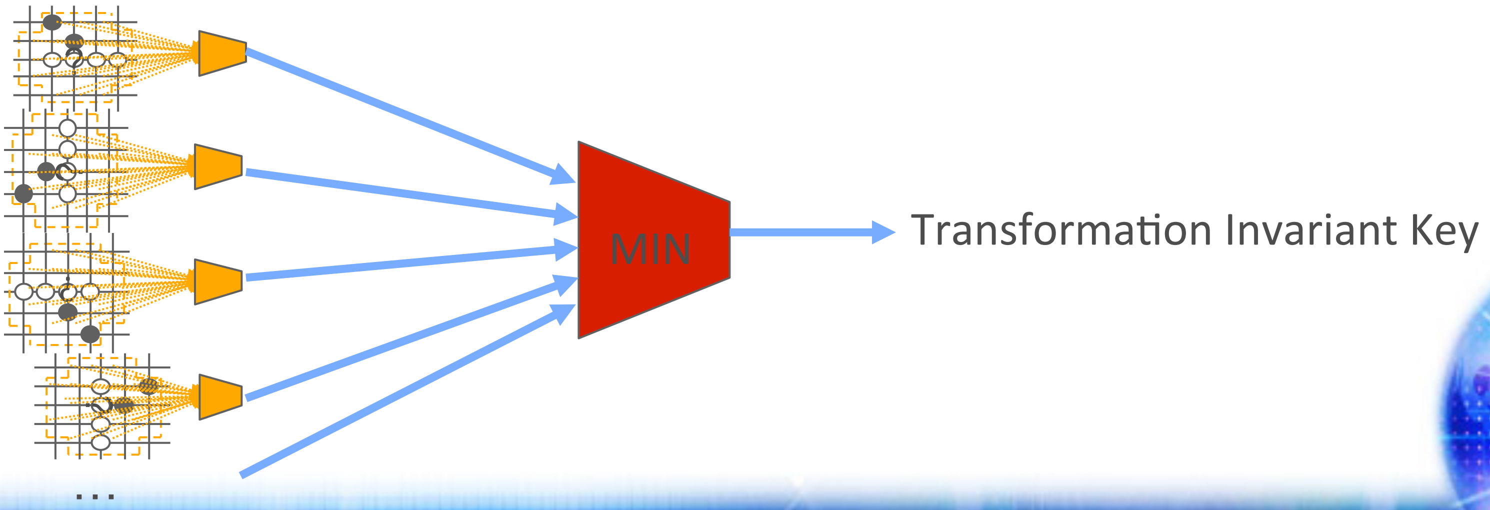
Pattern Matching

- **Goal**: Pattern information stored in hash table.
- **Idea**: 64 bit random numbers for each template vertex: One for each of {black, white, empty, off}.
- Combine with XOR (Zobrist, 1970).



Pattern Hash Key

- **Goal**: Pattern information stored in hash table.
- **Idea**: 64 bit random numbers for each template vertex: One for each of {black, white, empty, off}.
- Combine with XOR (Zobrist, 1970).



Harvesting

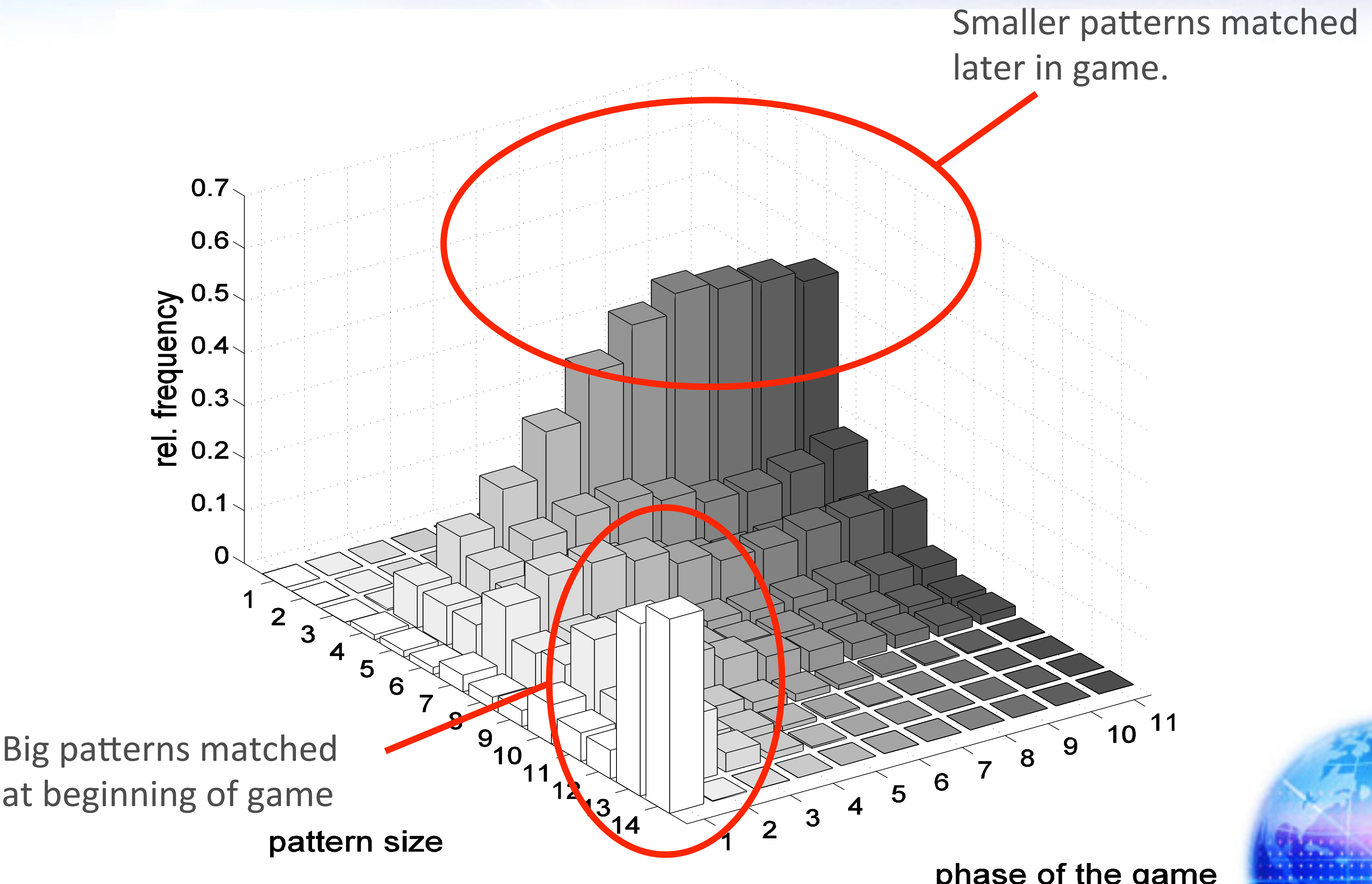
- **Data Size**: 180,000 games × 250 moves × 13 pattern sizes…

  …gives **600 million potential patterns**

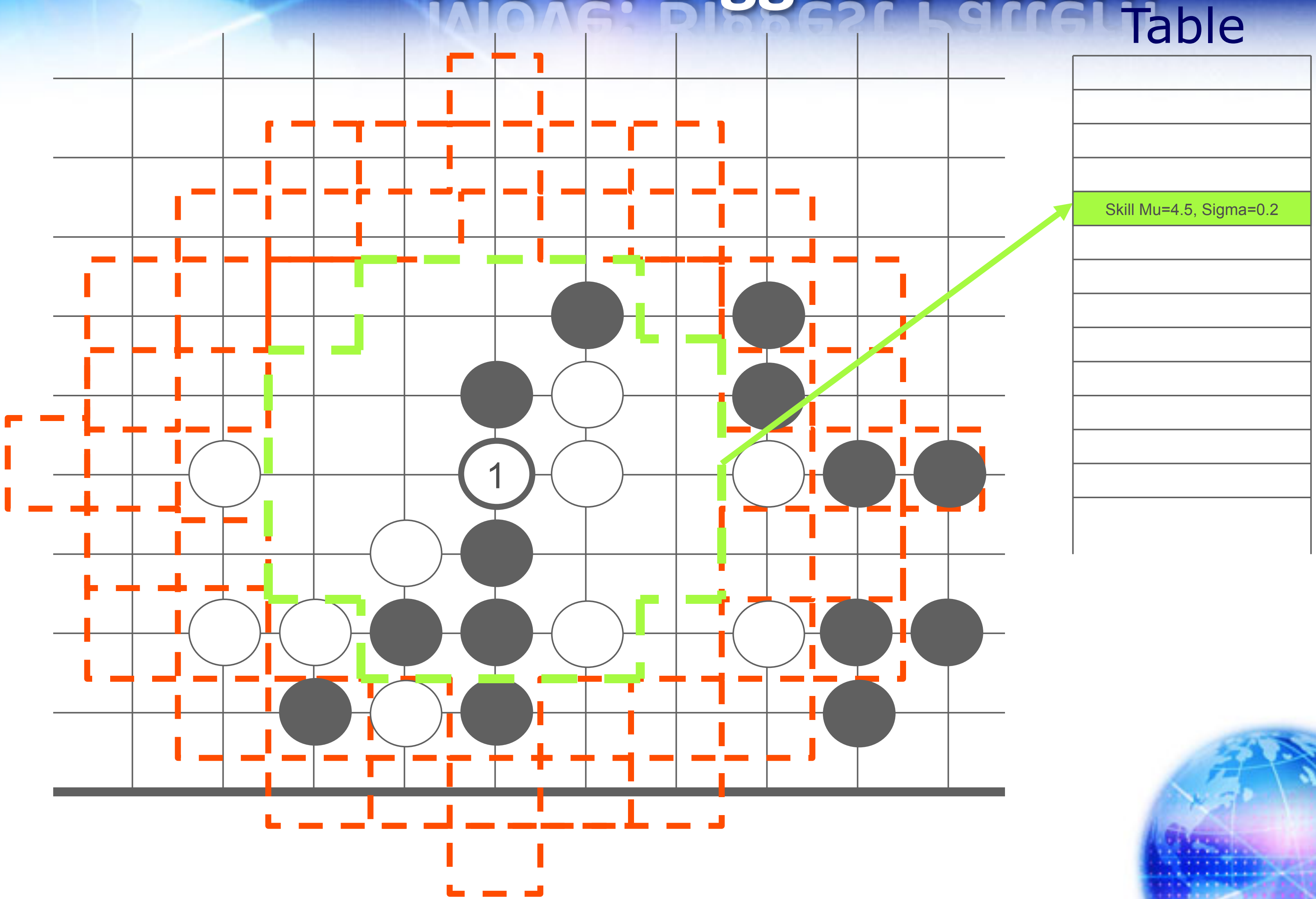
- **Problem**: Need to limit number stored.

- **Idea**: Keep patterns played more than n times.
- **Bloom filter**: Approximate test for set membership with minimal memory footprint.

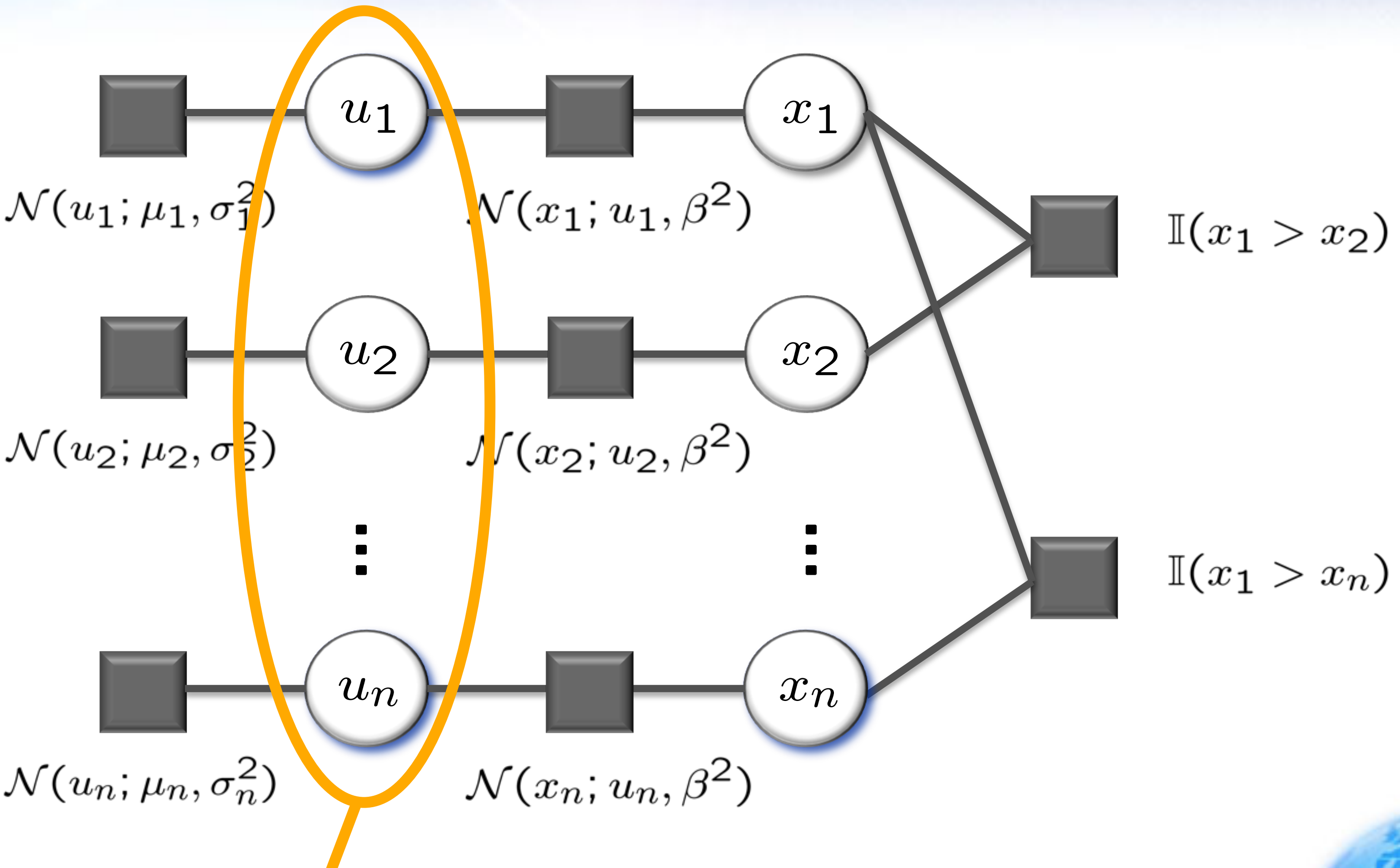
Relative Frequencies of Pattern Sizes



Move: Biggest Pattern

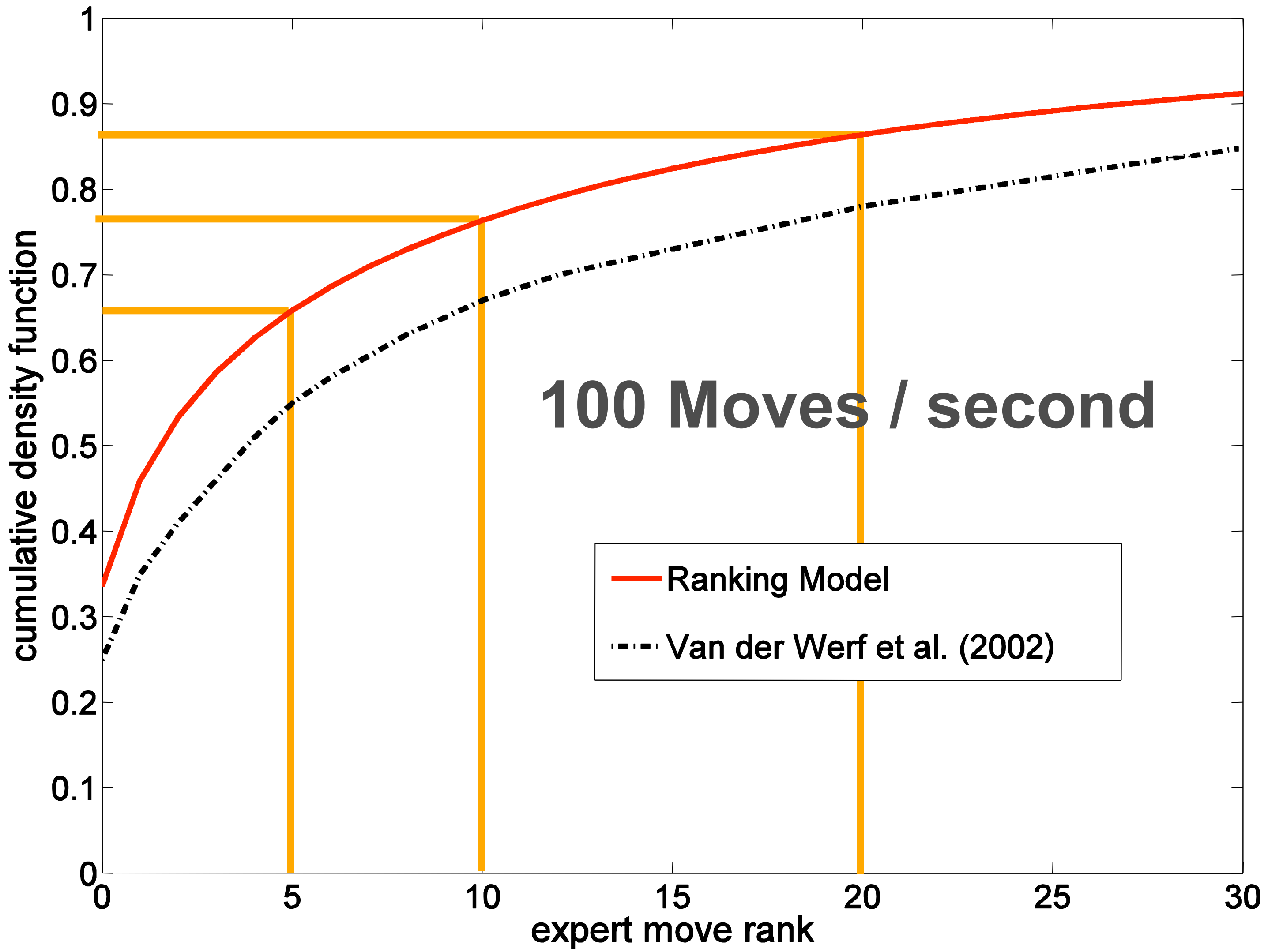


Bayesian Ranking Model

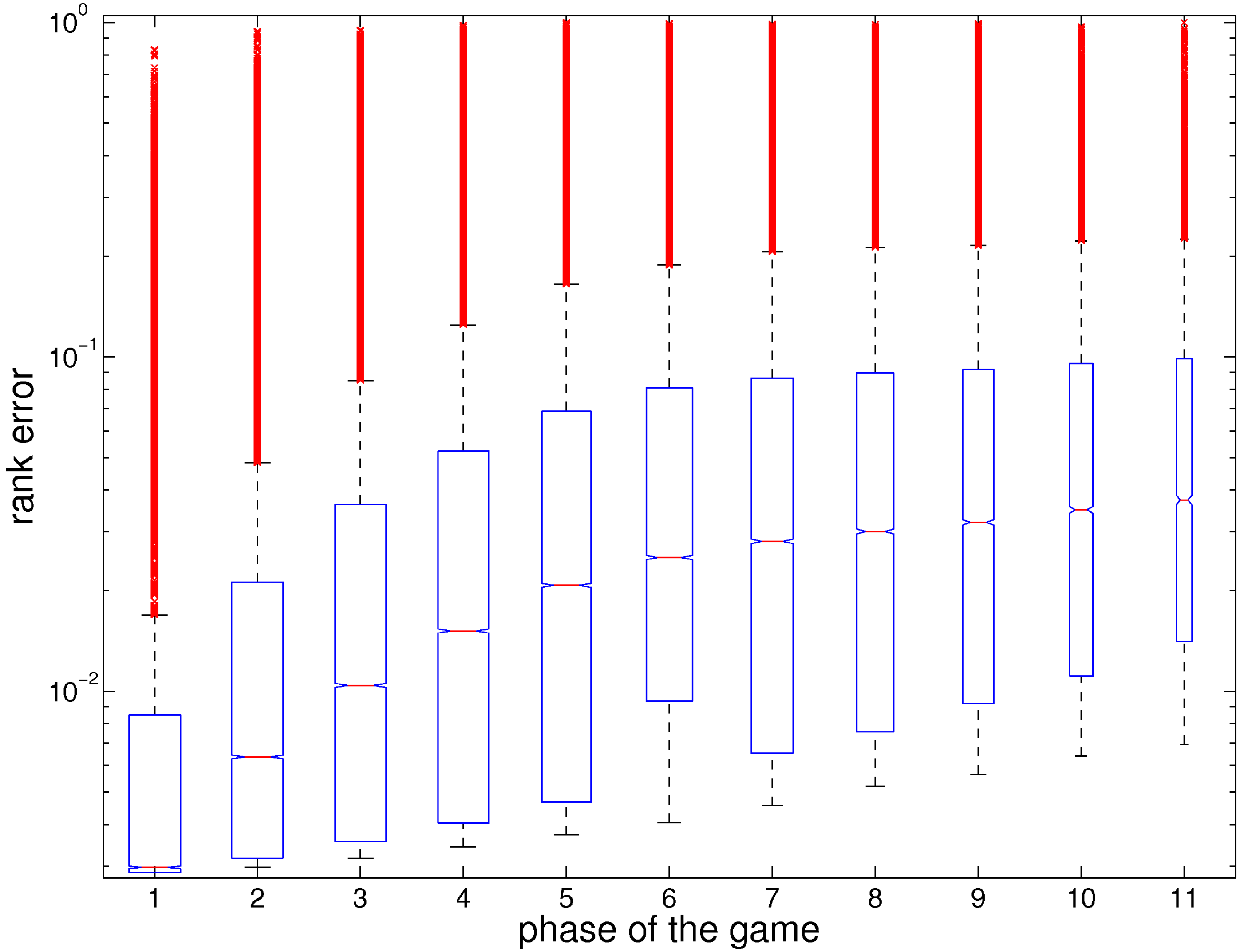


$$p(\mathbf{u}|\text{move, position}) = \int p(\mathbf{u}, \mathbf{x}|\text{move, position}) d\mathbf{x}$$

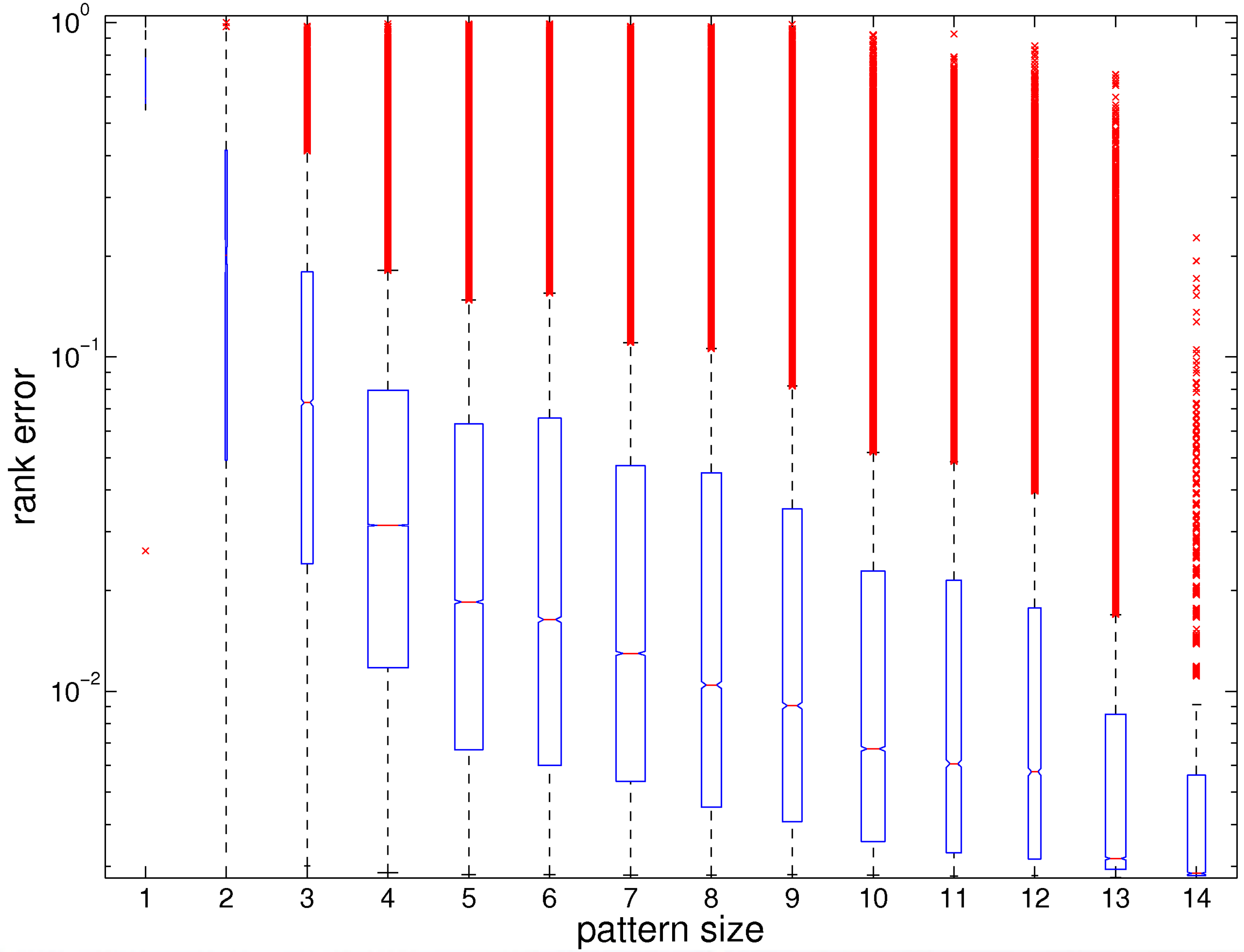
Move Prediction Performance



Rank Error vs Game Phase



Rank Error vs Pattern Size



Thanks!