

TrueSkill and AdPredictor: Machine Learning in the Wild

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WAPA 2010 – Cumberland Lodge

Outline

The Role of Applications in Machine Learning Research

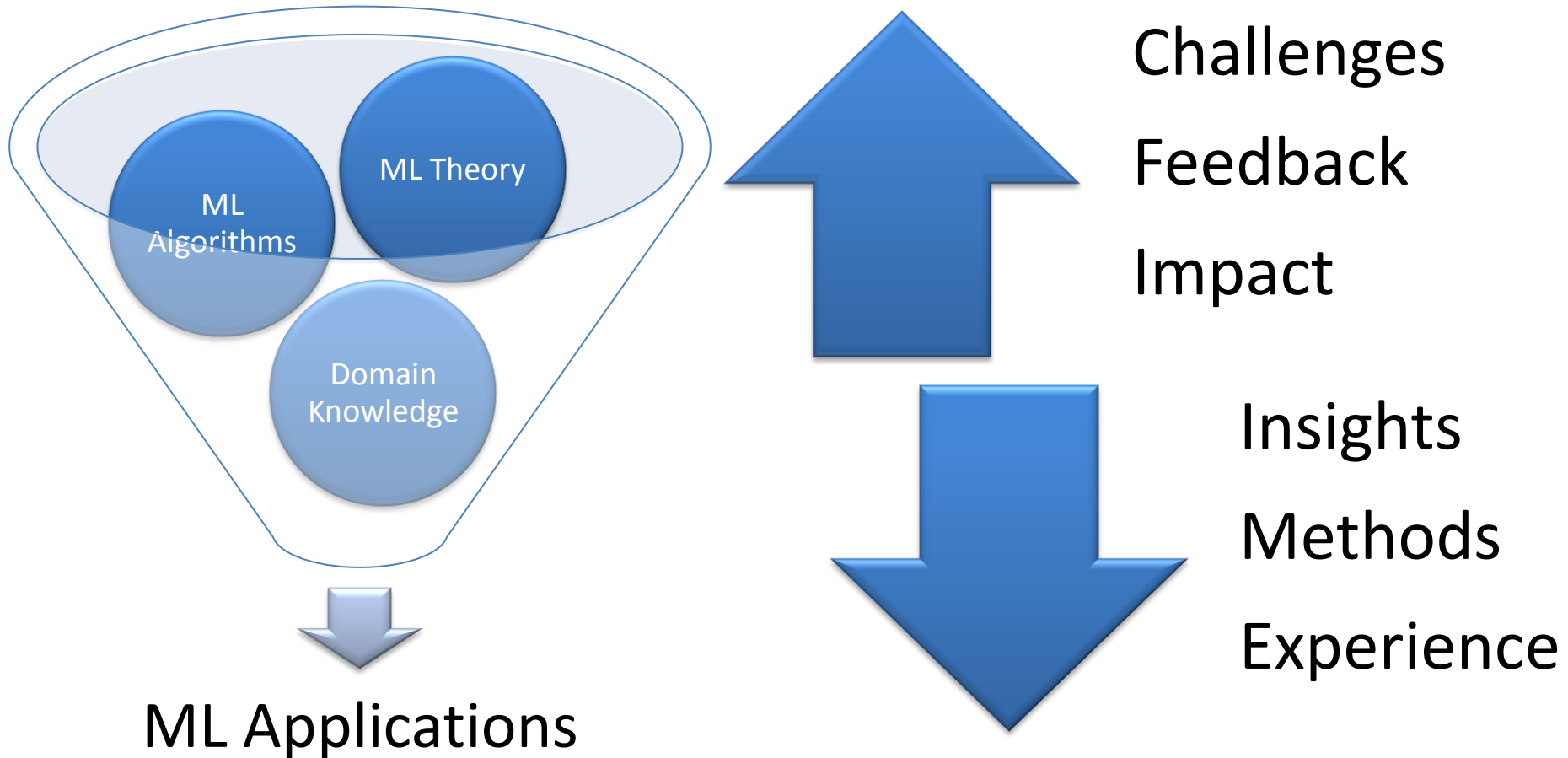
TrueSkill™: Ranking and Matchmaking in Online Games

- Ranking and Matchmaking Task
- TrueSkill Model and Inference
- Empirical Results from Xbox Live and Halo 3
- Specific Challenges in Online Gaming

AdPredictor™: Click-Through Rate Prediction for Sponsored Search

- Paid Search Advertising and Click-Through Rate prediction
- AdPredictor Model and Inference
- Results from the Bing Search Engine
- Specific Challenges in Paid Search Advertising

Applications in Machine Learning (ML)



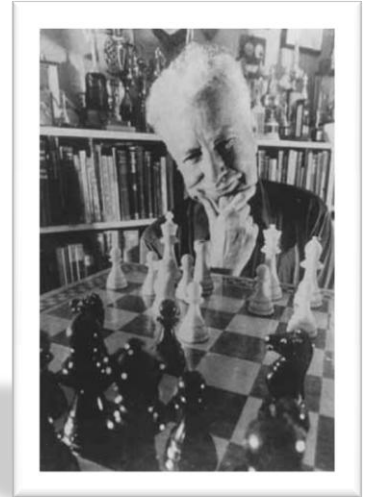
Only real-world impact of ML work is through applications!

Thore Graepel, Ralf Herbrich, Tom Minka, and our friends from Xbox Live

TRUESKILL

Ranking and Matchmaking

- Competition is central to our lives
 - Evolutionary principle
 - 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 consisting of n players, respectively

- **Questions:**

- Skill s_i for each player i

- Global

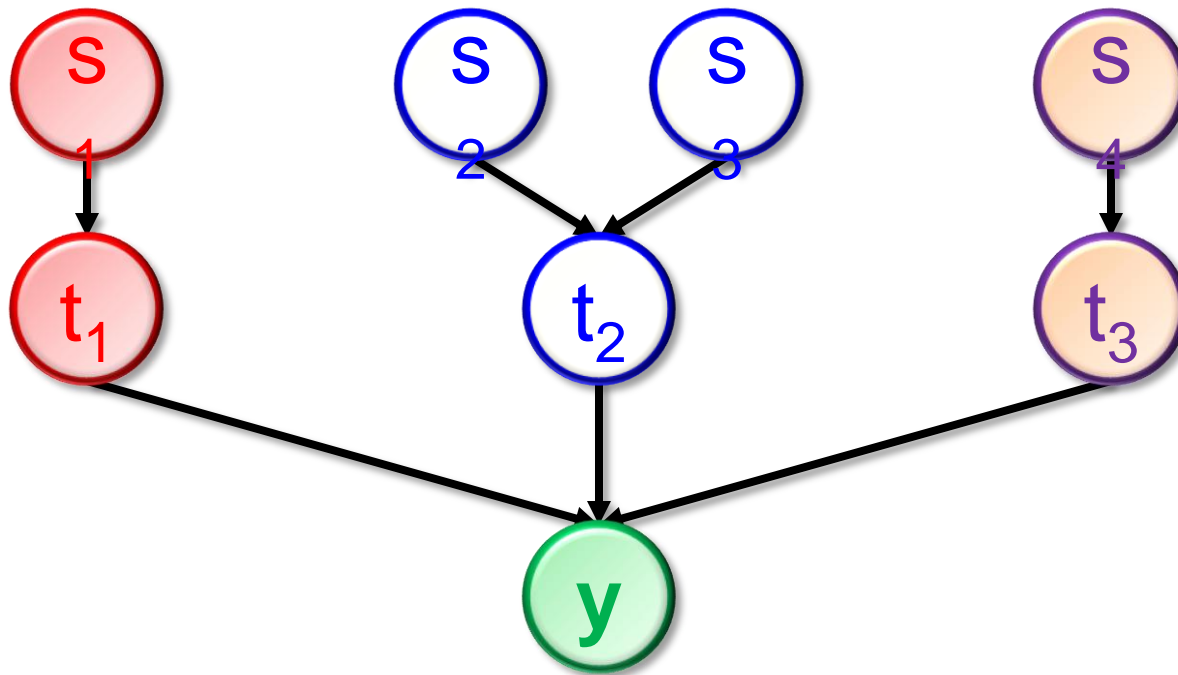
- Fair

The image displays several overlapping data visualizations related to a game:

- Team Score:** A table showing '1st Red Team' with a score of 50.
- Player Performance Table:** A table with columns 'Level', 'Gamertag', 'Avg. Life', and 'Best Spree'. It lists players like SniperEye, xXxHALOxXx, AjaySandhu, Robert115, TurboNegro84(G), and TurboNegro84.
- Ranked Player List:** A vertical list of 17 players with their scores and names, such as SEWICSYDE OWNS (27), FATAL REVENGE (26), Paranoia 1 (25), Paulk (25), IxX OMG Xxl (25), BittyTom (25), brian 2007 (24), SEXY MOZES (24), droplates (24), jaCKdaSaMuRai (24), Il Me Il (24), iamNightMare (24), a retarded007 (24), Perfected Brit (24), THE MUFFIN MANx (24), TheVunit (23), and Mr Sushi87 (23).

Multiple Team Match Outcome Model

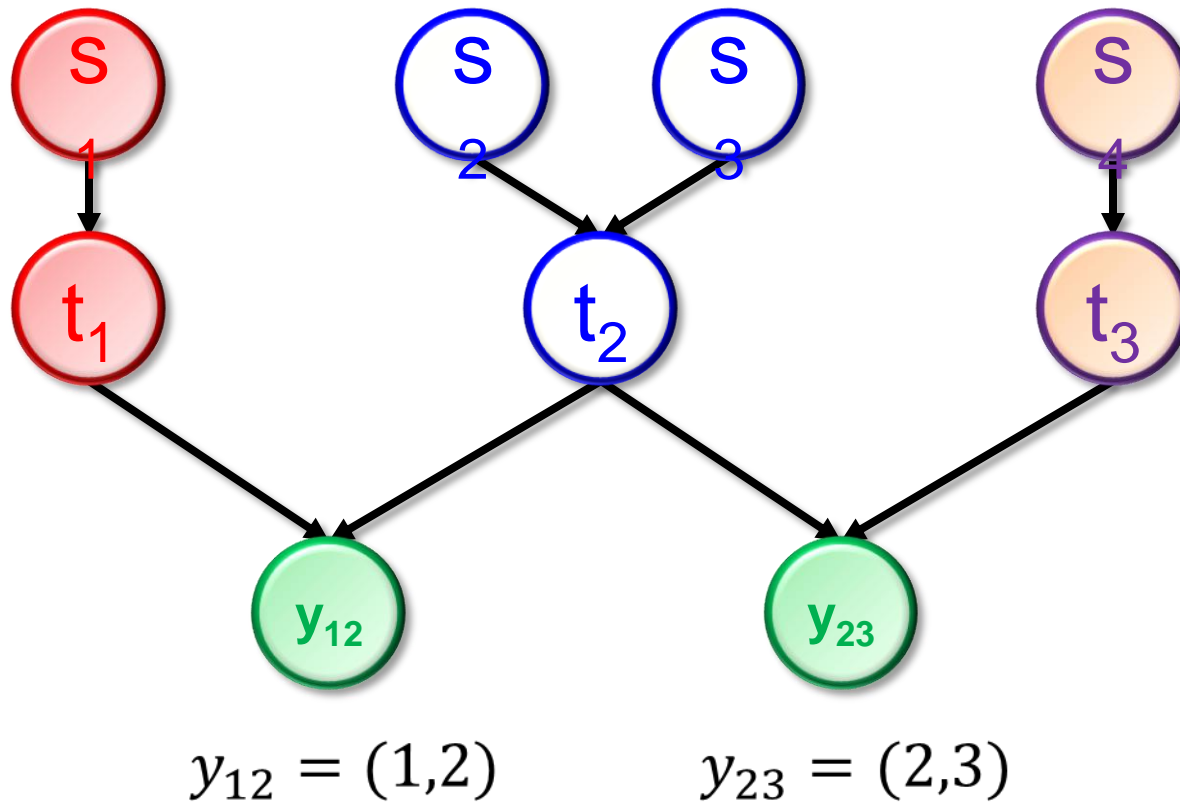
- Possible outcomes: Permutations of the teams



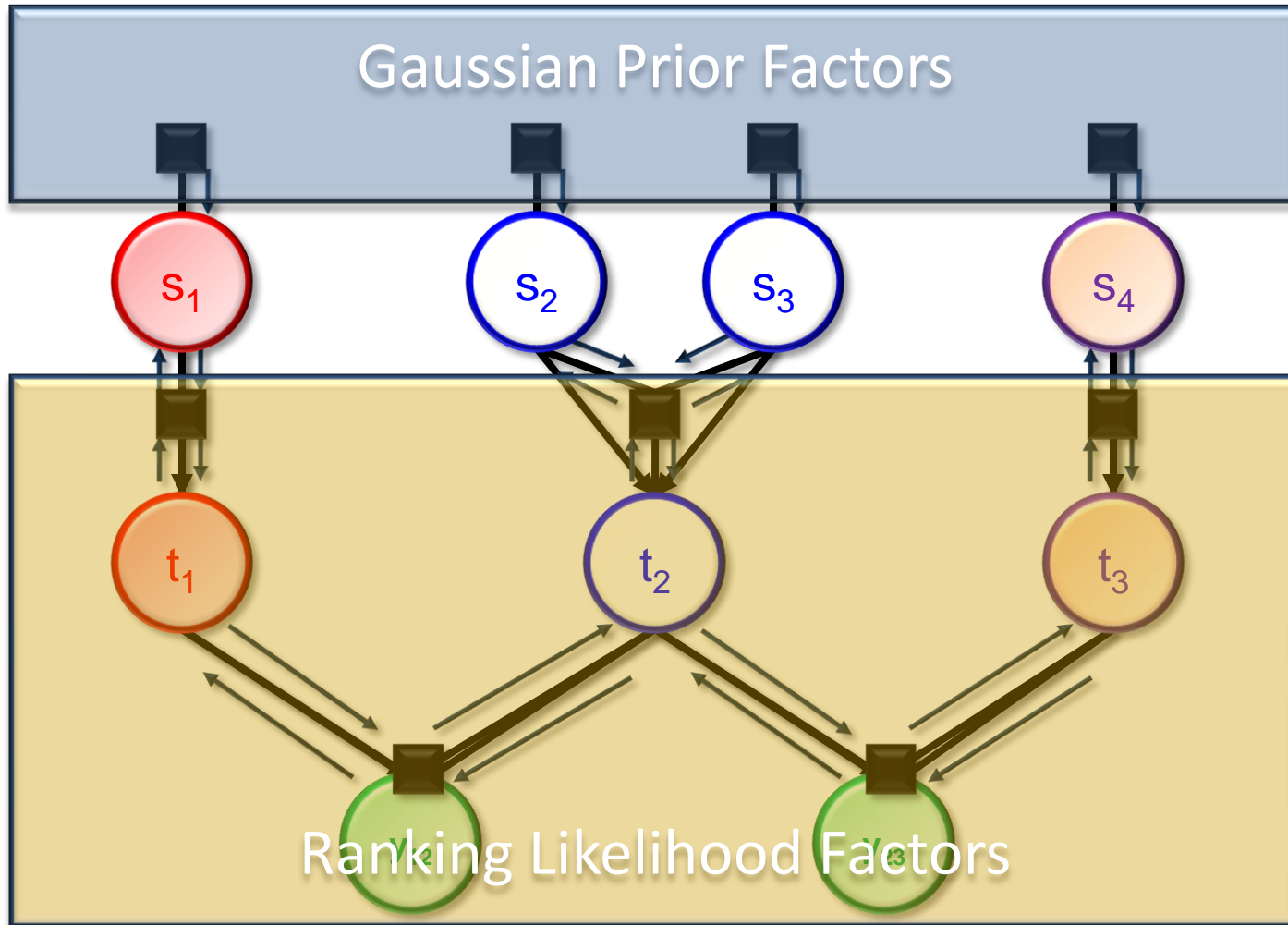
$$P(y|t_1, t_2, t_3) = \mathbb{I}(y = (i, j, k)) \text{ s.t. } t_i > t_j > t_k$$

Multiple Team Match Outcome Model

- Observed outcome (1,2,3), use transitivity!
- Skill posterior $P(s_i|y = (1,2,3)) \approx N(\mu_i, \sigma_i^2)$



Efficient Approximate Inference



Applications to Online Gaming

- **Leaderboard**

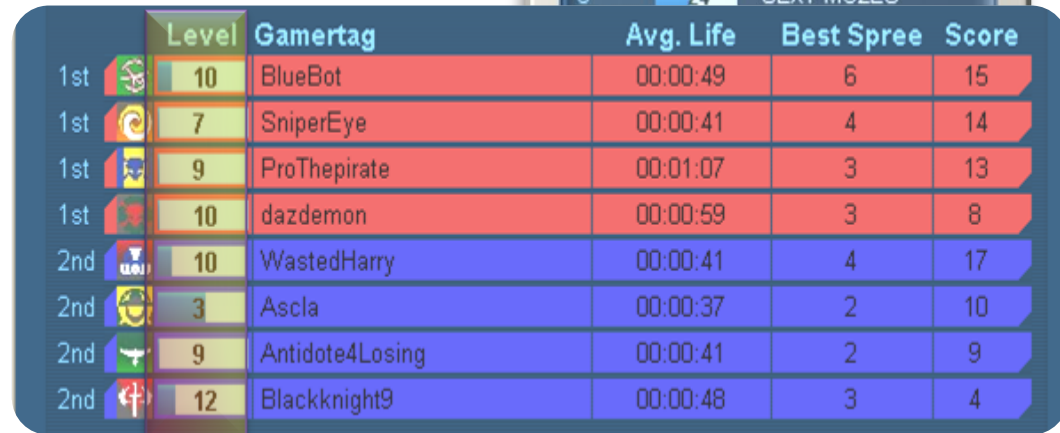
- Global ranking of all players
- Rank conservatively according to $\mu_i - 3 \cdot \sigma_i$

- **Matchmaking**

- For gamers: Most uncertain outcome
- For inference: Most informative
- Equivalent!

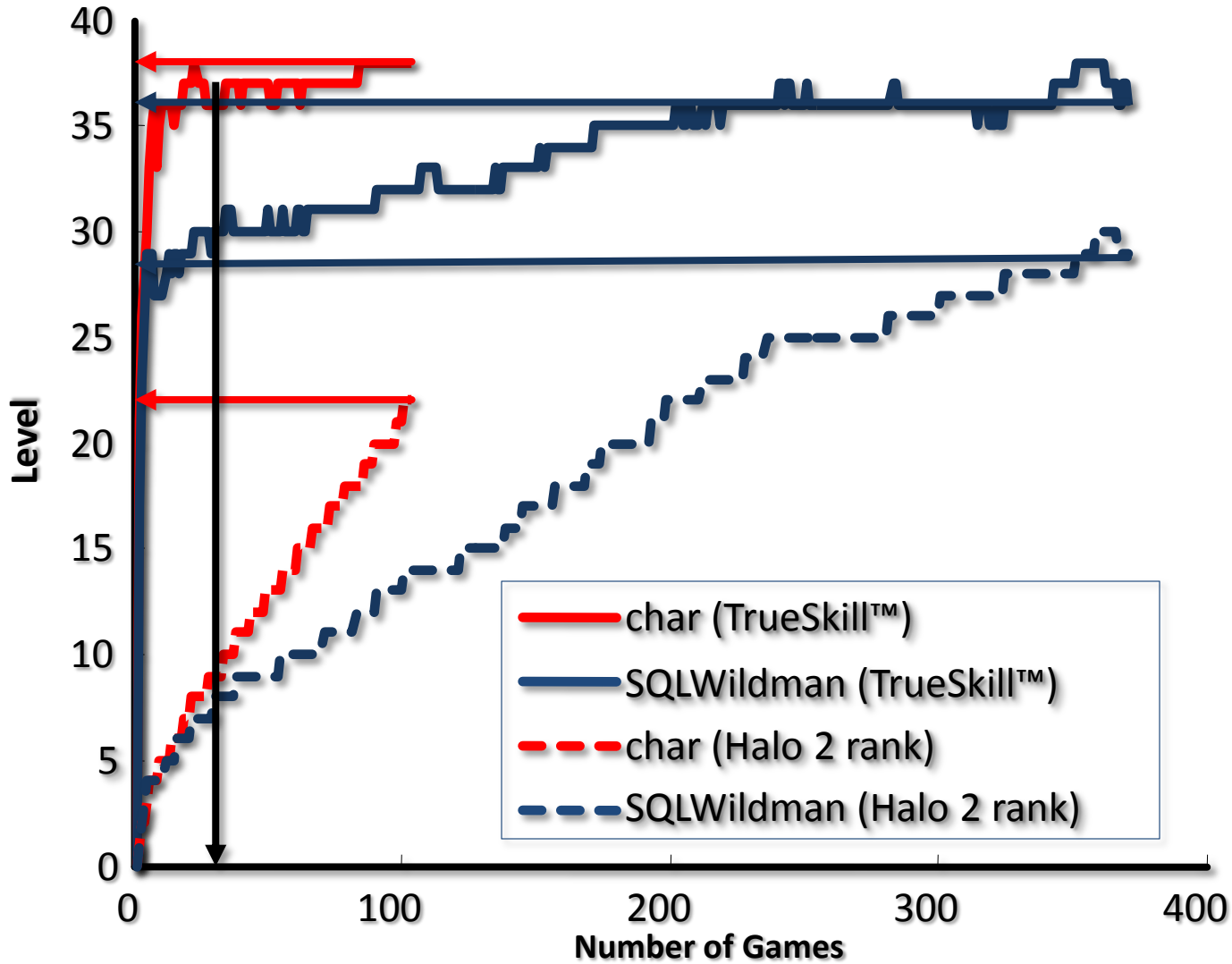


1	27	SEWICSYDE OWNS
2	26	FATAL REVENGE
3	25	Paranoia 1
4	25	Paulk
5	25	IxX OMG Xxl
6	25	BittyTom
7	24	brian 2007
8	24	SEXY MOZES



	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	Blackknight9	00:00:48	3	4

Convergence Speed



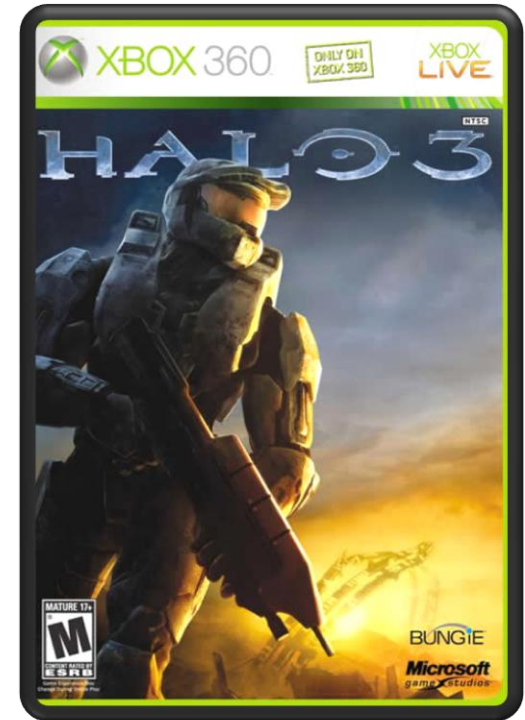
Xbox 360 & Halo 3

- **Xbox 360 Live**

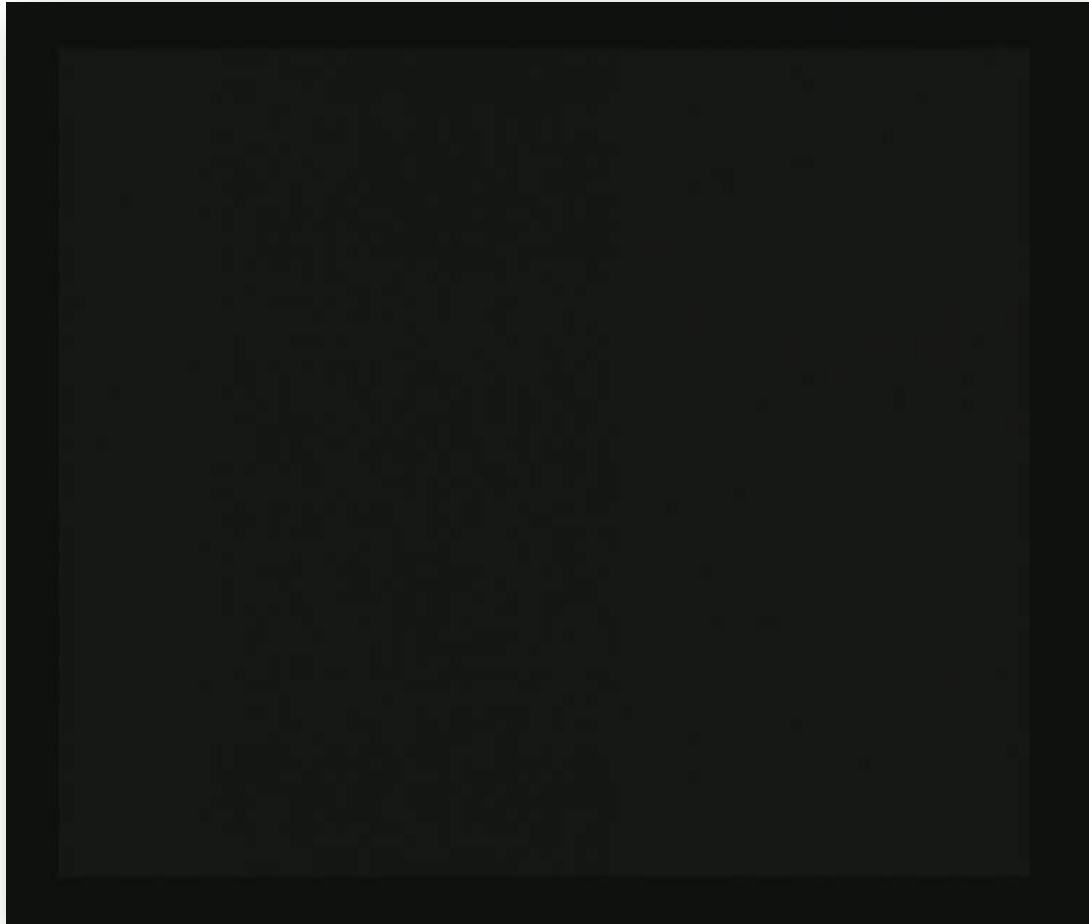
- Launched in September 2005
- Every game uses TrueSkill™ to match players
- > 20 million players
- > 2 million matches per day
- > 2 billion hours of game play

- **Halo 3**

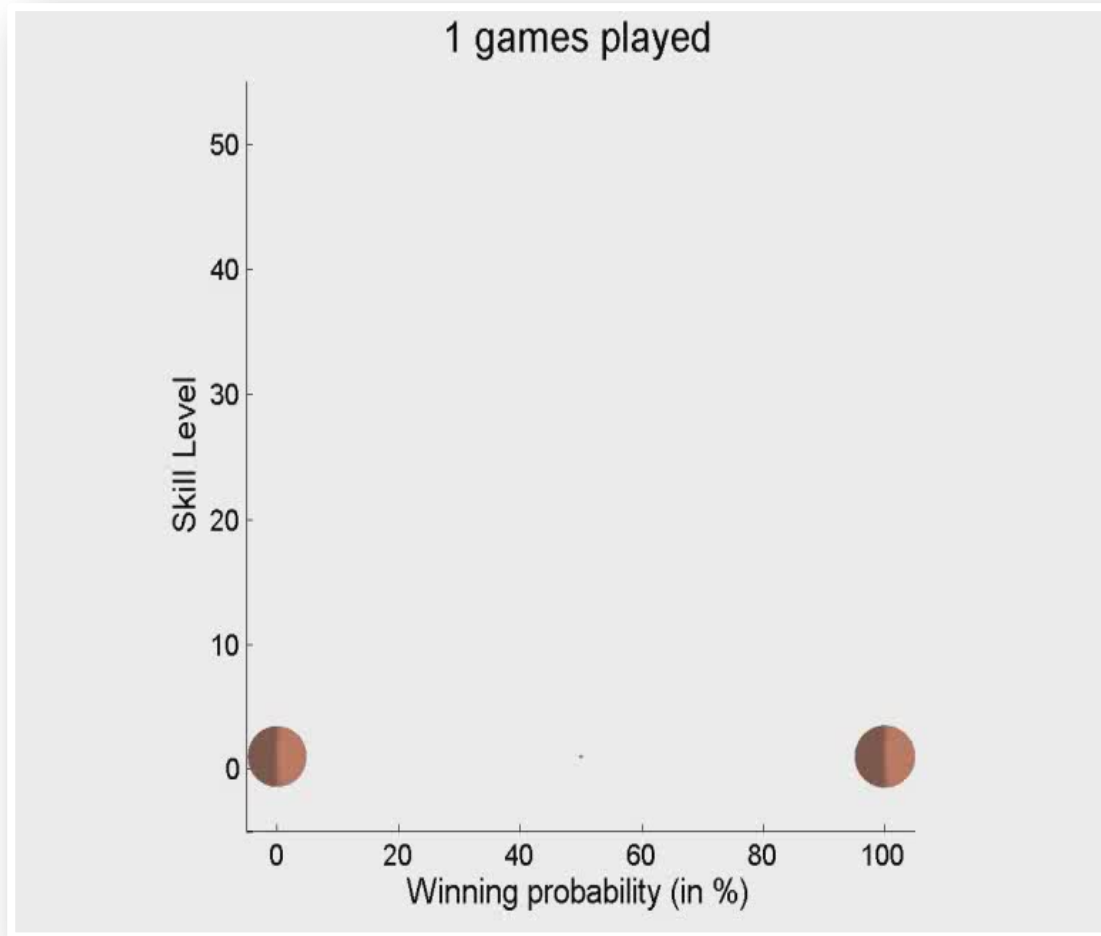
- Launched on 25th September 2007
- Largest entertainment launch in history
- > 200,000 player concurrently (peak: 1,000,000)



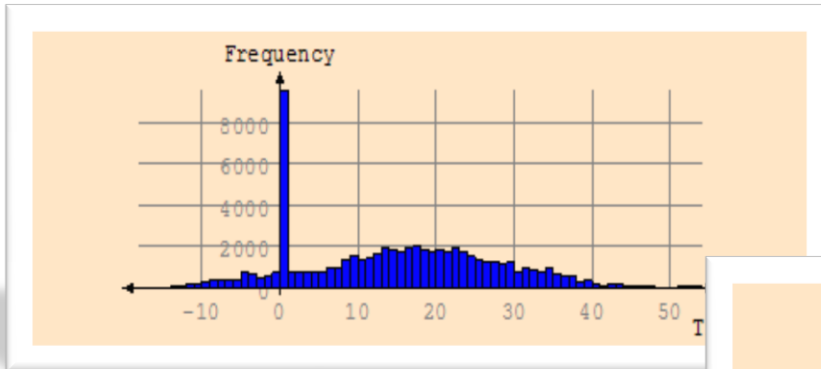
Halo 3 in Action



Halo 3 Analysis: Fair Matches?

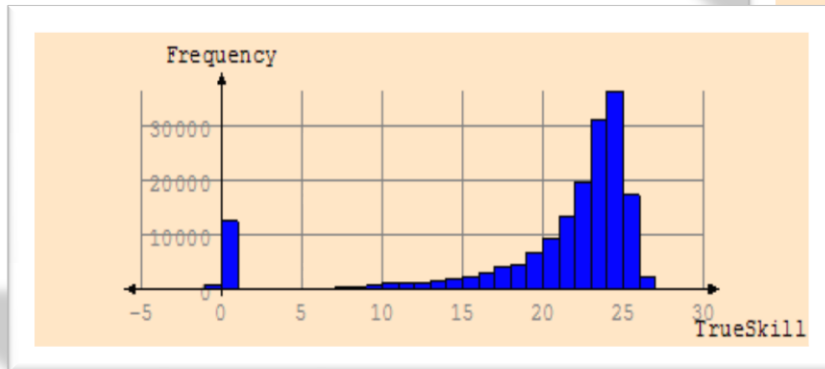
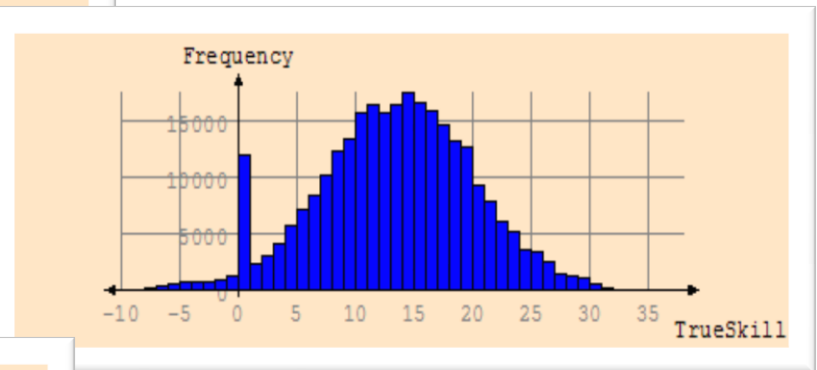


Skill Distributions of Online Games



Golf (18 holes): 60 levels

Car racing (3-4 laps): 40 levels



UNO (chance game): 10 levels

Special Requests from Bungie

- Great, but could you please
 - create a flat skill distribution for more plausible matchmaking!
 - make the skill convergence slower for hill-climbing experience!
 - reduce the updates if low quality matches or bad connections are detected!
 - factor in the time a player actually participates in a match?

Adversarial Behaviour

- Skill Boosting
 - Players collude by choosing a common, but rare language that ensures they are matched and can arrange the game outcome.
 - Players “de-rank” accounts and play in teams with the de-ranked account. When their team wins, their other account’s rank is boosted!
- Now paid services available for boosting players ranks!

Incentive Alignment

- TrueSkill only takes into account the final game outcome at team level
 - No individual performance is counted
 - No proxies for skill (e.g., number of kills, flags etc) are taken into account.
- Why?
 - TrueSkill is universal and can be applied to almost any known game
 - Ratings are aligned with the objective of the game. In team games, players have no incentives to promote their own ranking at the cost of the team.

Closed Training Loop

- TrueSkill was developed and tested based on real-world training data from Halo 2.
- Since TrueSkill's estimates are used for deciding which players to match next:
 - The composition of the training sample is changed by the earlier estimates of the system
 - A loop is created in which TrueSkill feeds on data from matches it has created
 - The prediction performance of TrueSkill may go down over time because it creates harder and harder prediction tasks for itself!

My former boss Bill...

Why are they
wasting their
time on
computer
games?



Great stuff, guys, but
how about online
advertising? Are the
ads not competing
for the attention of
the users just like
players in a game?!

Thore Graepel, Joaquin Quiñonero Candela, Thomas Borchert, Ralf Herbrich & our friends from Microsoft adCenter

ADPREDICTOR

Web Images Videos Shopping News Maps More MSN Windows Live Sign in United States Extras

bing fast flowers

ALL RESULTS 1-10 of 34,900,000 results - [Advanced](#) Sponsored sites

RELATED SEARCHES
 Flowers Same Day
 FTD
 Color Fast
 Flowers Express
 Fast Easy Flowers To Grow
 Fruit Fast
 People Fast
 Flowers Ch

FlowersFast.co Save Now! Same-t	\$1.00	* 10%	= \$0.10	\$0.80
Flowers at 1-8 Same Day Deliver	\$2.00	* 4%	= \$0.08	\$1.25
Save \$10 On F Surprise Friends M	\$0.10	* 50%	= \$0.05	\$0.05

Fast Flowers
 Flowers delivered Australia wide - whether to Sydney, Melbourne, Brisbane or anywhere in Australia or overseas. Fastflowers for your wedding flowers or any special occasion.

50% Off All Flowers
 Join Others Who Have Saved 50%.
 Flowers From \$29.99 Before Discount.
[www.BloomsToday.com](#)

Send Flowers from \$19.99
 Send Roses, Tulips & other Flowers.
 Best Value - Wall Street Journal
[www.ProFlowers.com](#)

\$19.99 Flowers
 Buy Flowers from \$19.99. Same Day

flowersfast.com - [Cached page](#)

Display to users (expected bid)

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

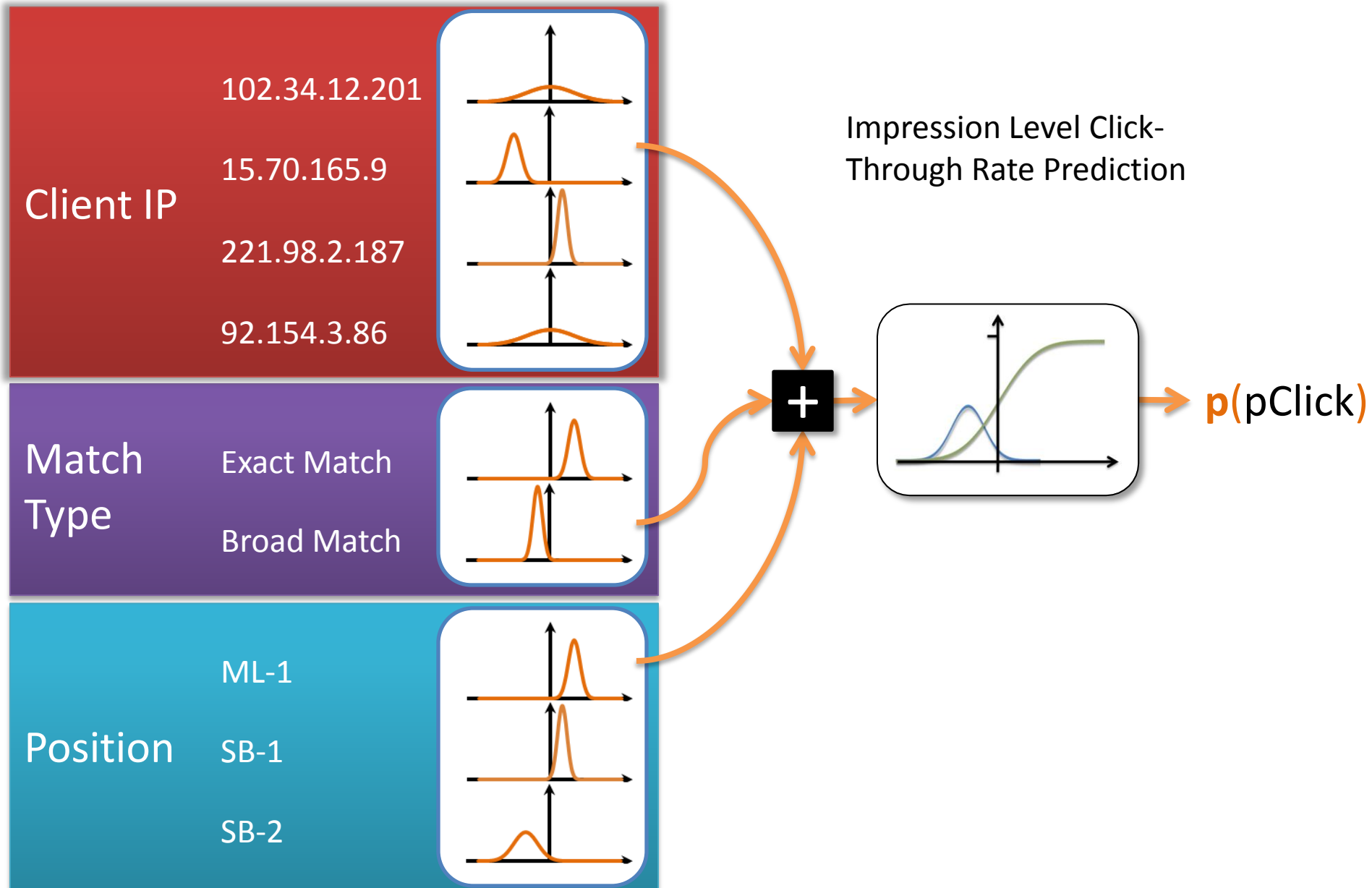
Charge advertisers (per click)

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

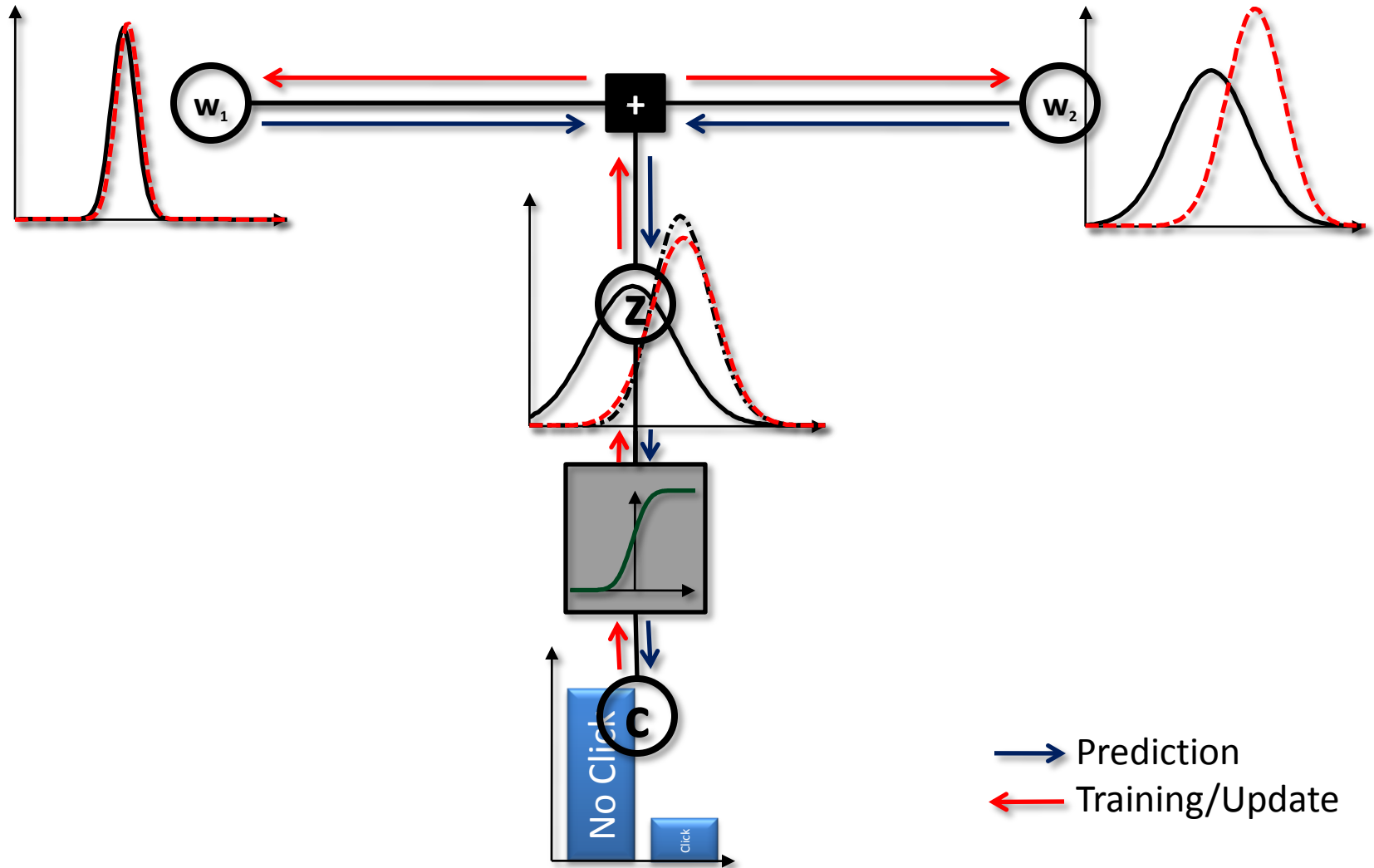
Importance of accurate probability estimates:

- Increase user satisfaction by better targeting
- Provide better deal to advertisers
- Increase revenue by showing ads with high click-thru rate

AdPredictor: Bayesian Probit Regression



Training Algorithm in Action

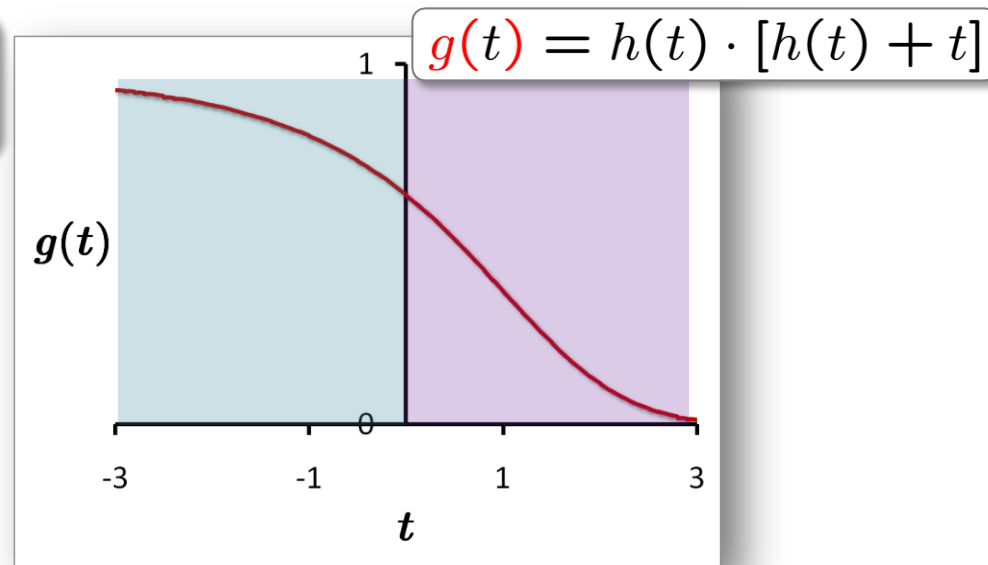
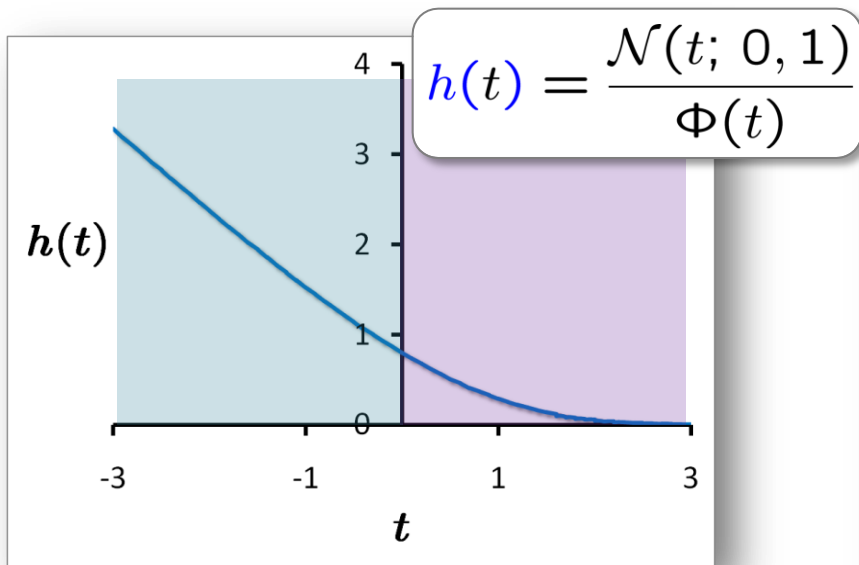


Closed Form Updates for Click

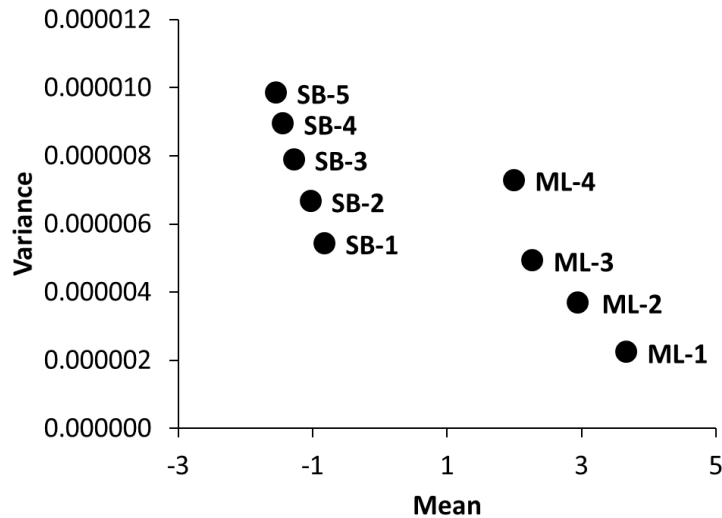
$$\mu_i \leftarrow \mu_i + \frac{\sigma_i^2}{s} \cdot h \left[\frac{\sum_{j=1}^d \mu_j}{s} \right]$$

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

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

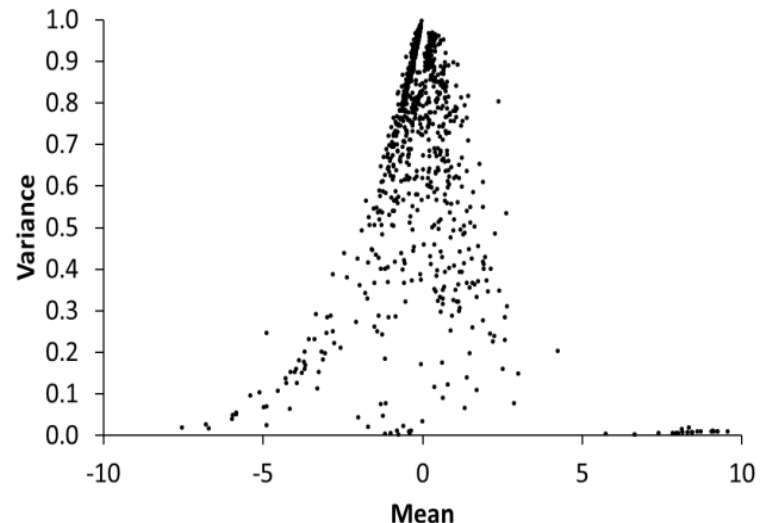


Weight Parameters from Production

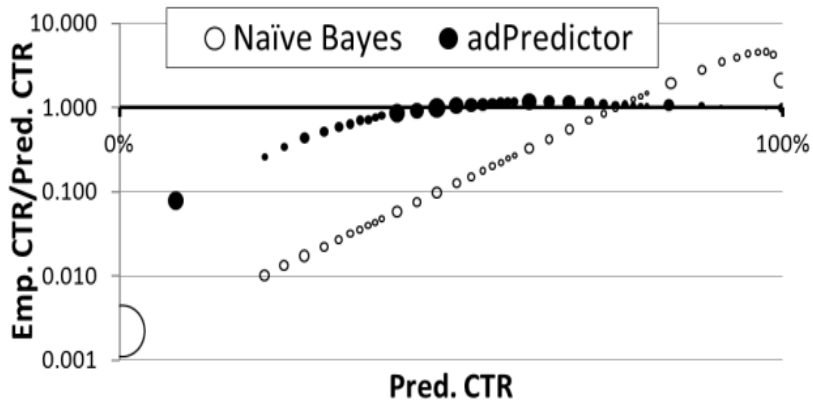


- Means and variances of the display position feature.
- Mainline ML, sidebar SB

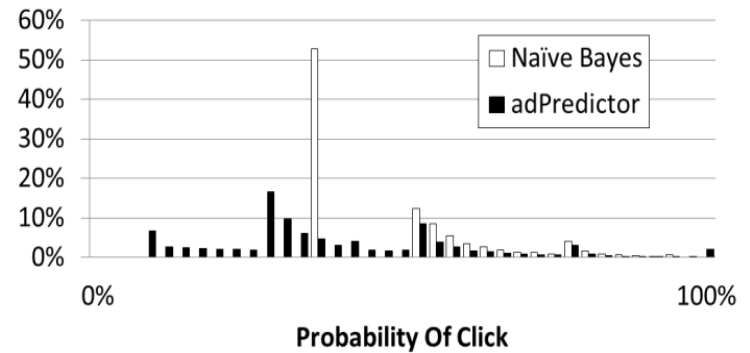
- Means and variances of weights for user ID feature.
- Very high mean may indicate fraud



Comparison with Naïve Bayes



Calibration: AdPredictor vs. Naïve Bayes



Courage: AdPredictor vs. Naïve Bayes

$$RIG := \frac{CE + H(\bar{p})}{H(\bar{p})}$$

$$CE := \frac{1}{T} \sum_{t=1}^T y_t \log \hat{p}_t + (1 - y_t) \log(1 - \hat{p}_t)$$

$$H(\bar{p}) := -(\bar{p} \log \bar{p} + (1 - \bar{p}) \log(1 - \bar{p})).$$

Algorithm	RIG	AUC
adPredictor	61.42%	95.6%
adPredictor (calibrated)	61.35%	95.6%
Naïve Bayes	-41.54%	89.4%
Naïve Bayes (calibrated)	33.86%	89.3%

Web Scale Implementation

AdPredictor drives almost 100% of Bing's sponsored search traffic

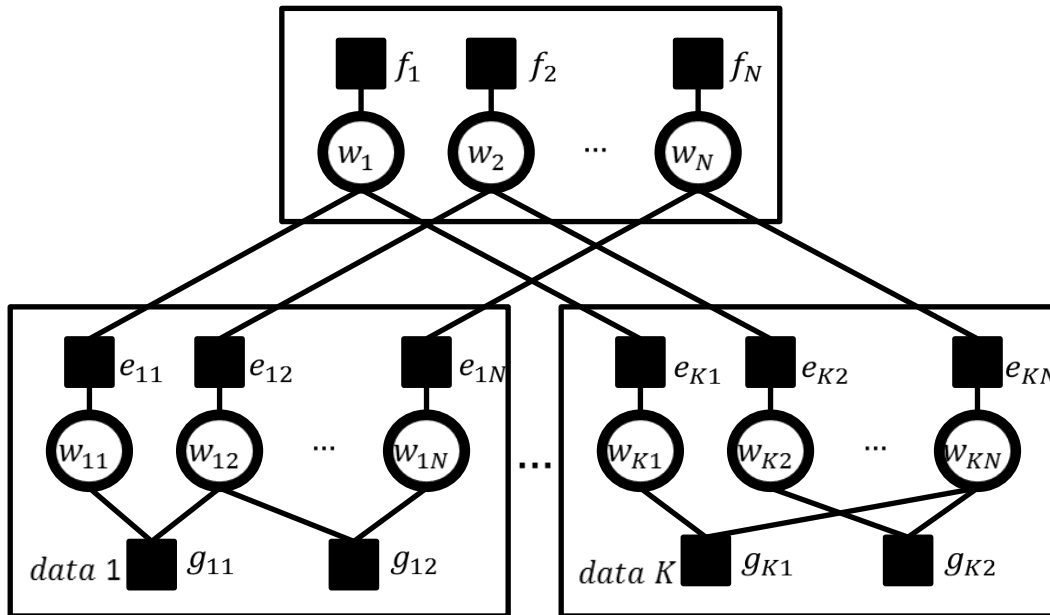
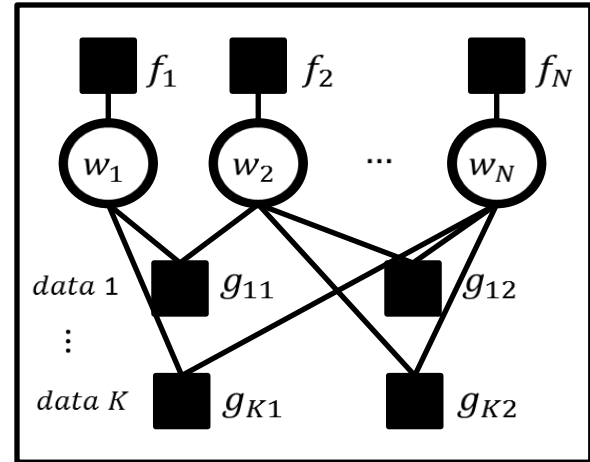
Large volume of data $O(10^9)$ examples per week → Massively parallel training

System's predictions determine composition of future training sample → Exploration

Continuous Model Training → Maintain controlled memory footprint by pruning

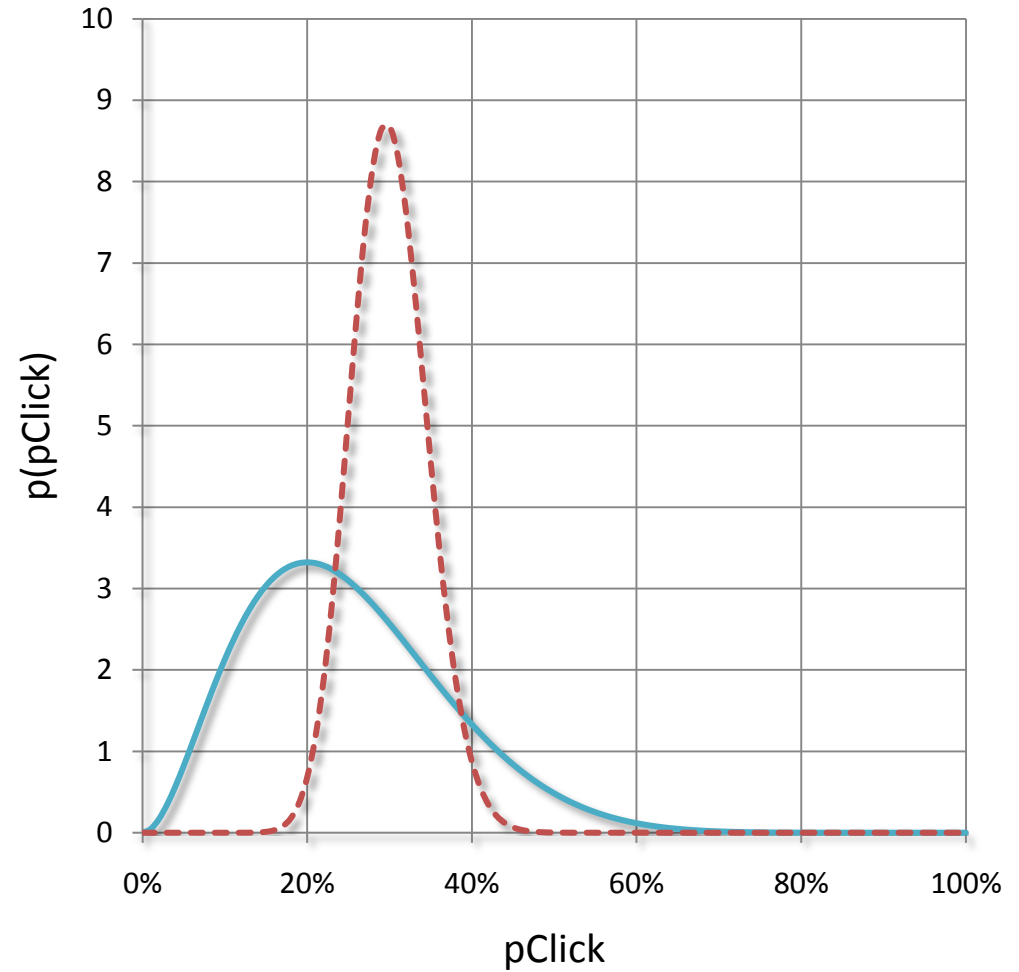
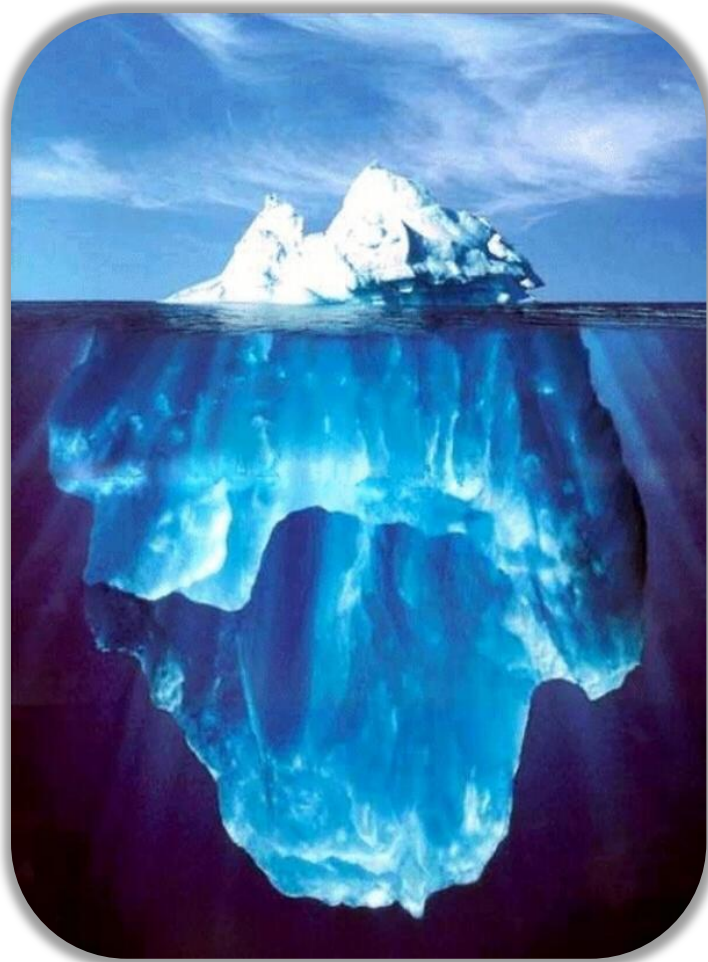
Distributed Training

- Single instance of model leads to inefficient blocking



- Model replication with equality factors for consistency \rightarrow Distributed Training

Principled Exploration



- average: 25% (3 clicks out of 12 impressions)
- - - average: 30% (30 clicks out of 100 impressions)

Adversarial Behaviour

- Click-fraud by using bots or sweat-shops to deplete competitor's budget
- Advertisers may benefit from the in-dubio-pro-reo attitude of the exploration system
- Possible collusion among advertisers by sharing market (phase of the moon) or manipulating bids

Closed Training System

- AdPredictor was designed based on static training data from its predecessor
- Since AdPredictor's CTR estimates are used for deciding which ads to show next:
 - The composition of the training sample is changed by the earlier estimates of the system
 - A loop is created in which AdPredictor feeds on data from ads shown based on its estimates
 - Static performance measures are meaningless in the loopy setting!
 - Difference to TrueSkill: Ads are shown based on high CTR, while matches are created based on similar skill! In both cases: Source entropy up → more difficult tasks

Conclusions

Large Scale Bayesian Models Work in Practice!

- Model uncertainty explicitly
- Automatically adapt learning step size
- Make accurate, calibrated predictions

Online Applications

- Large scale requires parallel training and model pruning
- Closed loop requires active learning and exploration
- Watch out for self-interested agents in the system
- The application is always different from the abstraction!

Thank you!

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