Lecture Notes for

Managing and Mining Multiplayer Online Games

Summer Term 2019

Chapter 8: Ranking Skill

http://www.dbs.ifi.lmu.de/cms/VO_Managing_Massive_Multiplayer_Online_Games

Chapter Overview

- calculating the skill level from win statistics
- ELO-Ranking
- True Skill
- Team Skill

Models for play level

idea: Skill level can be deduced from past victories and defeats.

model: Every player *i* has a skill level s_i. If $s_i > s_j$ then s_i is very likely to win in a competition.

applications:

- **matchmaking**: choose interesting opponents with comparable skill level
- **ladders/rankings**: creating public rankings as an expression of prestige (compare Tennis, SC2, WOW arena, Halo2, …)
- **organizing tournaments**: assistance for draw, qualification, clearing disputes.

#	Spieler	Punkte	Win%	Leave%	Total	W-D-L (Leaves)
1.	ku5h ._.	440 VS	74%	0.0%	34	25 - 0 - 9 (0)
2.	KevKev	367 VS	53%	0.0%	43	23 - 2 - 18 (0)
3.	GAMEBUG	343 VS	63%	0.0%	24	15 - 4 - 5 (0)
4.	Scasyy	342 VS	54%	0.0%	39	21 - 1 - 17 (0)
5.	FATAL	337 VS	63%	0.0%	30	19 - 1 - 10 (0)
12.	bueli	278 VS	65%	0.0%	23	15 - 0 - 8 (0)
20.	powerhead	244 VS	56%	0.0%	34	19 - 1 - 14 (0)
12.	bueli	278 VS	65%	0.0%	23	15 - 0 - 8 (0)
41.	random	216 VS	63%	0.0%	16	10 - 1 - 5 (0)
48.	afr0	205 VS	59%	0.0%	29	17 - 0 - 12 (0)

Letzte Aktualisierung 02 Jul 2008 — Nächste Veröffentlichung 06 Aug 2008

Rang	Team	P Jul 08	+/- Rang Jun 08	+/- P Jun 08
1	Spanien	1557	3	254
2	Italien	1404	1	-20
3	Deutschland	1364	2	90
4	Brasilien	1344	-2	-169
5	Niederlande	1299	5	188
6	Argentinien	1298	-5	-261
7	Kroatien	1282	8	265
8	Tschechische Republik	1146	-2	-100
9	Portugal	1104	2	10
10	Frankreich	1053	-3	-90

The ELO System

Introduced by Arpad Elo in 1970 and adopted by the *World Chess Federation*.

Assumption: player *i*'s performance p_i is normal distributed around his skill level with variance β^2.

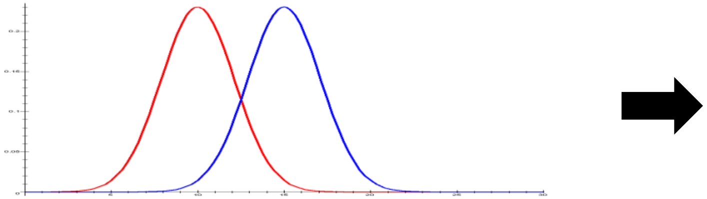
$\Rightarrow$ s_i: $p_i = N(s_i, \beta^2)$

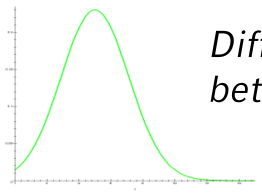
$\Rightarrow$ $s_i > s_j$ *does not necessarily mean i is* losing against *j*

but rather $Pr(i$ wins against $j) > 50\%$

task: compute $Pr(p_i > p_j \mid s_i, s_j)$ (probability of *i* playing better than *j*)

=> Difference of 2 normal distributed variables with the same variance β^2 is normal distributed with mean $(s_i - s_j)$ and variance β^2.





Difference distribution between p_i and p_j

Let Φ be the accumulated density function of a normal distribution with anticipated value of 0 and a variance of 1, then follows:

$$P\left(p_1 > p_2 \mid s_1, s_2\right) = \Phi\left(\frac{s_1 - s_2}{\sqrt{2}\beta}\right)$$

Updating the ELO Ranking

- positions have to be adjusted as soon as new results are available.
- changes follow the zero-sum principle. $s_1^{new} + s_2^{new} = s_1 + s_2$
- difference Δ is supposed to increase the likelihood of the observation within the model
- match result: y $\in$ {0,-1,1} (Win:1, Loss:-1, Draw:0)
- updating ELO Scores with the result y_l: $\Delta = \alpha\beta\sqrt{\pi}\left(\frac{y_l+1}{2} - \Phi\left(\frac{s_1 - s_2}{\sqrt{2}\beta}\right)\right)$

  α : weighing factor for a match 0< α <1 (approx. 0.07 for chess)
- ELO scores need comparatively many matches to stabilize. (ca. 20)
- properties:
  - chronological order of updates is important: good for long intervals between measurements, but bad performance for tournaments, where a players skill presumably stays constant.
  - ELO system does not allow for conclusions about individual performance in team games.
  - restricted representation of results. No differentiated treatment of events with a ranking for result (e.g. racing, …).

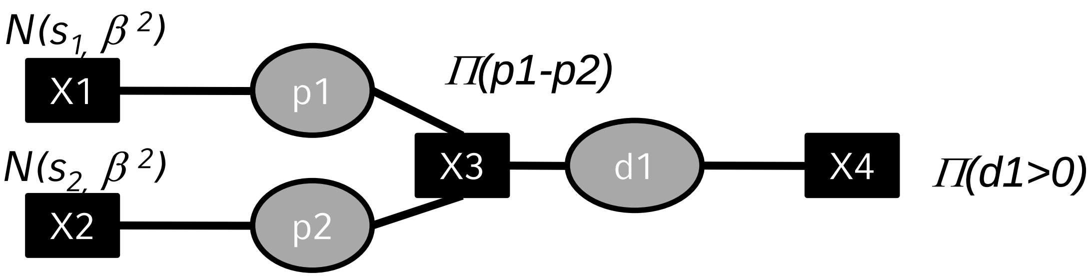
True Skill

factor graphs

bi-partite graph with factor nodes and variable nodes.

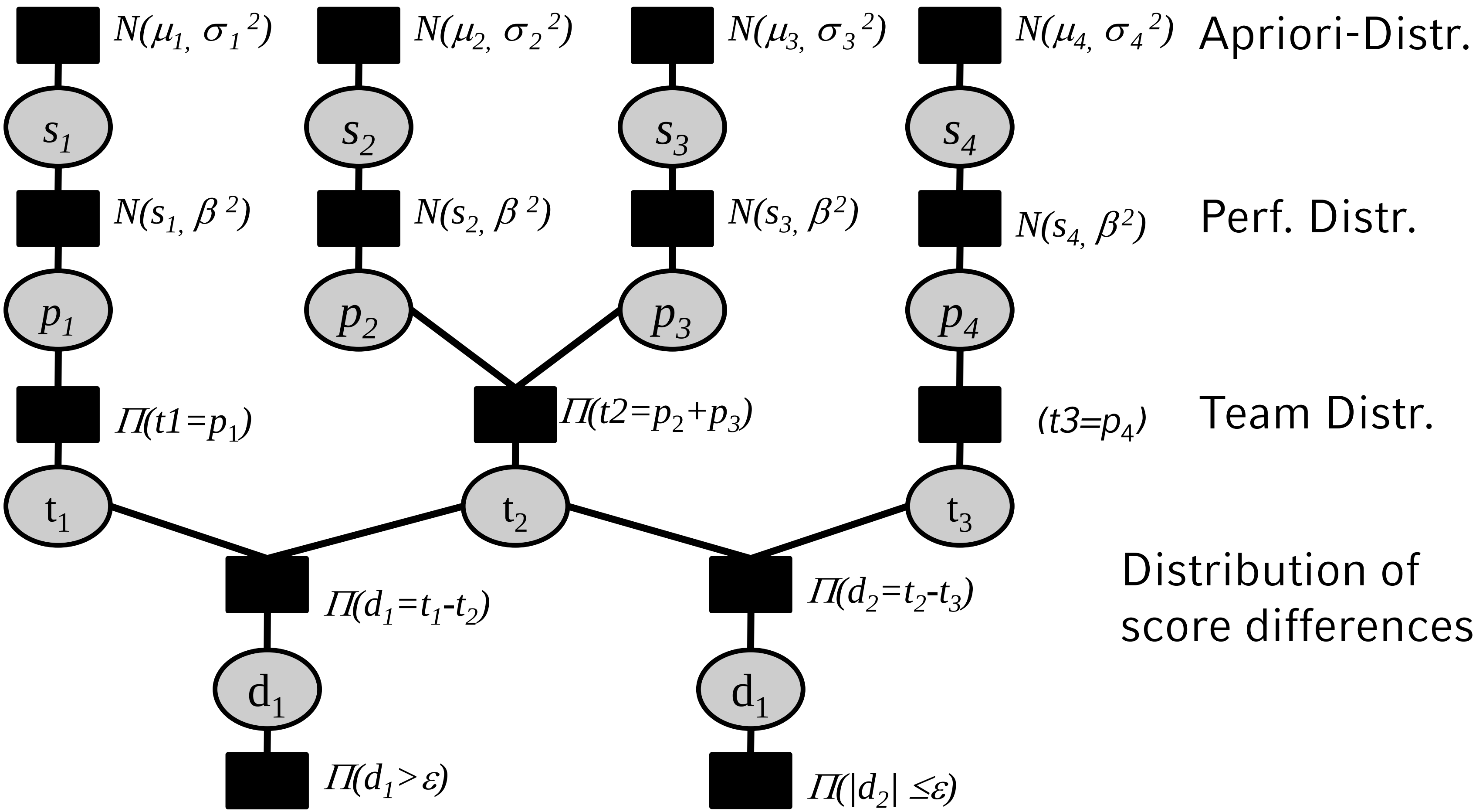
- variable nodes: describe distribution functions
- factor nodes: model the interaction of variables
- edges: description of variables interacting for a factor

example: Factor Graph for ELO System



- **True Skill**: extension of ELO Systems used for XBOX360 Live (e.g. HALO2 ranking)
- **considers**:
  - skill uncertainty
  - allows conclusions for team-members in team games (additive performance t_1)
  - result presentation as order of play results ($t_1 \geq t_2 \geq .. \geq t_m$)

Factor graph for True Skill



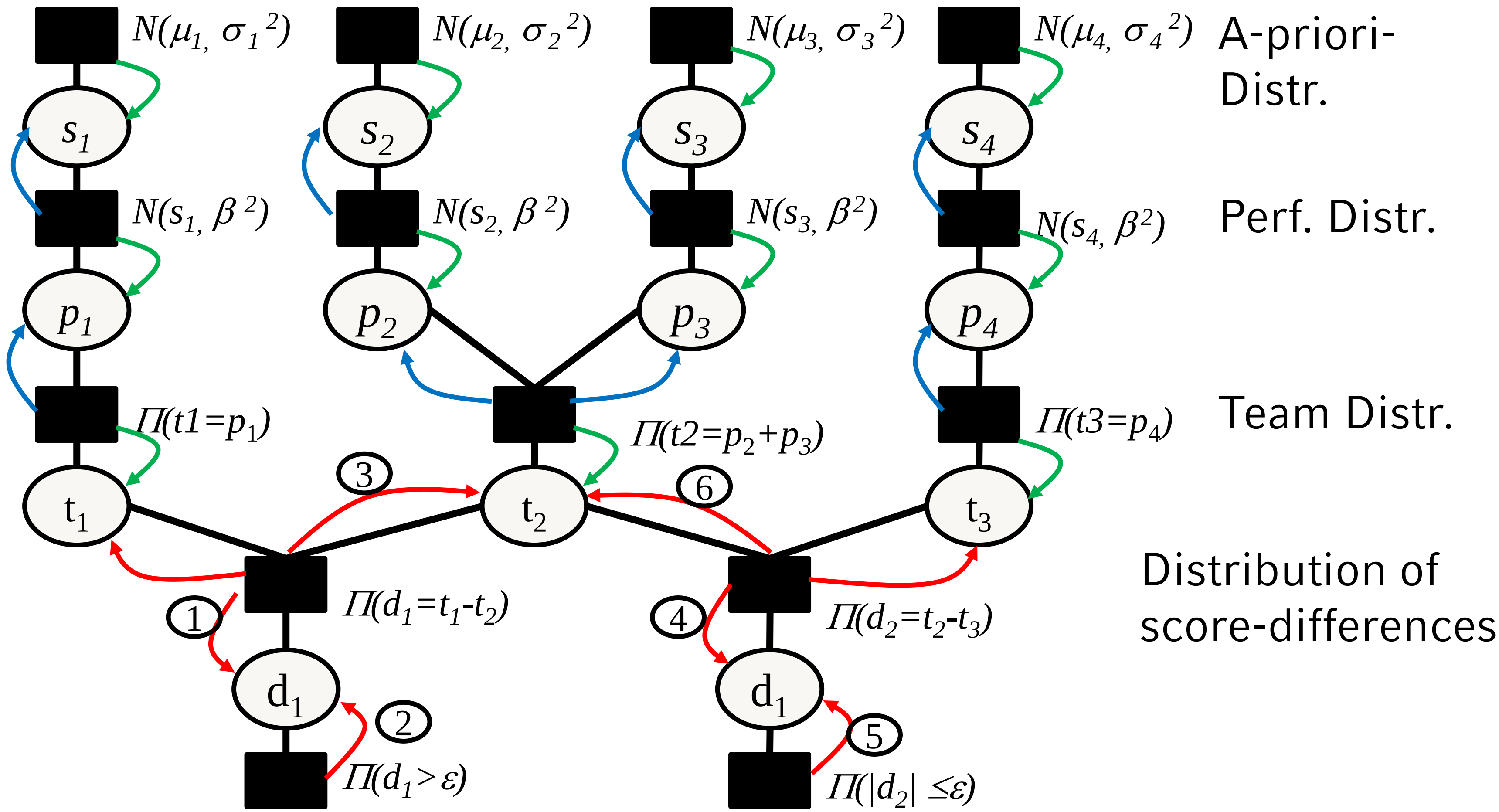
Example: 4 Players, 3 Teams: $\{(s_{1)}, (s_2,s_3),(s_4)\}$
Result: $t_1 > \varepsilon+t_{2\,,}$ $t_1 > \varepsilon+t_3,$ $\varepsilon > |t_2 - t_2|$

Factor Graph use for True Skill

- factor graph represents the distribution for $Pr(s,p,t|r,A)$
  - **r**: ranking result, **A**: team composition
  - **s**: player skill, **p**: player performance, **t**: team rating
- compute the distribution of player skill s conditional to the observations r and A: $$\Pr(s \mid r, A) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \Pr(s, p, t \mid r, A) dp\, dt$$

  s_i is normal distributed with mean value μ_i and standard deviation σ_i
- With the given factor graph and the current values of μ and σ for the participating players $\Pi(d_1 > \varepsilon)$ and $\Pi(|d_2| \leq \varepsilon)$ can be estimated.
- Comparing the prediction with the actual result, one can propagate the error back to μ and σ and adapt the model accordingly.
- Propagating probabilities and parameter updates on a factor graph are also called message-passing or belief propagation.

Training scheme for True Skill



1. **Forward propagation:** estimate the results
2. **Update of Team-performance**: redistribution of results to teams
3. **Update of a-posteriori Distributions**: propagates update-messages as far as parameters μ and σ.

Discussion True Skill

- Improves the ELO system by:
  - expansion of result representation
  - converges faster using a priori distributions
    for particular players
  - team assessment

- Disadvantages of True Skill:
  - chronological order is important, even though one can assume
    that skill does not change between two matches.
    (Expansion: True Skill Trough Time 2008)
  - team skill is considered as the sum of player skills
    But: In reality player synergy is much more complicated:
    “Having 5 carries in a Moba does not work!!”

Team Skill

idea: Considering not only individual play level, but also team chemistry.

=> Viewing a player's joint performance compared to his single performance.

=> Some player's performance increases when combined with specific players.

given: A Team $T=\{p_1,..,p_K\}$ with K players. Let t_k be a sub-team of T with k-elements. ($t_k \subseteq T \wedge |t_k|=k$). $Skill(t_k)$ constitutes sub-team t_k's skill level. (For example, calculated with ELO or True-Skill.)

task: Skill level of team T considering team chemistry?

approach: calculating average over computed sub-team ranking

Team Skill-k

- average play level of a sub team of size k scaled to team size K.

$$TS_k(T) = K \cdot \frac{1}{k} \cdot \frac{1}{\binom{K}{k}} \cdot \sum_{i=1}^{\binom{K}{k}} Skill(s_{ki}) = \frac{(k-1)!(K-k)!}{(K-1)!} \cdot \sum_{i=1}^{\binom{K}{k}} Skill(s_{ki})$$

example:

k=1 and K=5 $$TS_k(T) = \frac{5}{1} \cdot \frac{1}{\binom{5}{1}} \cdot \sum_{i=1}^{\binom{5}{1}} Skill(s_{1_i}) = \sum_{i=1}^{5} Skill(s_{1_i})$$

k=2 and K=5 $$TS_k(T) = \frac{5}{2} \cdot \frac{1}{\binom{5}{2}} \cdot \sum_{i=1}^{\binom{5}{2}} Skill(s_{2_i}) = \frac{1}{4} \sum_{i=1}^{10} Skill(s_{2_i})$$

Team Skill-AllK-LS

Challenges for improving Team Skill-*k*:

- determining *k* is hard => take all possible sub-teams.
- we don't have sample observations for all existing sub-teams => only consider sub-teams with a reliable skill estimation.

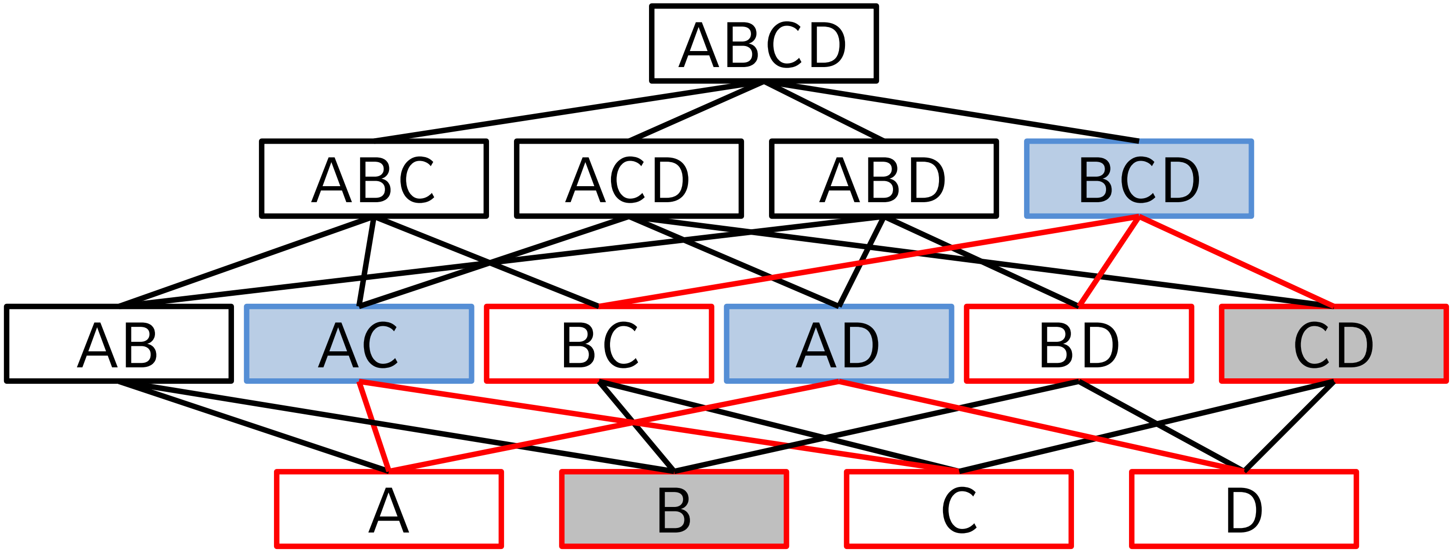
Idea: Consider all sub-teams with a reliable estimate and which are not a sub-team of a larger reliably estimated sub-team.

Approach: Consider all sub-teams $t^*_{k,i}$ for which $Skill(t_{k,i})$ can be reliably computed and for which no sub-team $t_{k+l,j} \supset t_{k,i}$ exists.

Calculate team performance as k times the mean of the single player performance.

$$TS_{ALL-LS}(T) = \frac{K}{\sum_{m \in \{m | \exists t^*_m \neq \{\}\}} |m|} \left(\sum_{m \in \{m | \exists t^*_m \neq \{\}\}} E(t^*_m) \right) = \frac{K}{\sum_{m \in \{m | \exists t^*_m \neq \{\}\}} m \,|} \left(\sum_{m \in \{m | \exists t^*_m \neq \{\}\}} \left(\frac{1}{l} \cdot \sum_{i=1}^{l} Skill(t^*_{m,i}) \right) \right)$$

Example: Team Skill ALL-LS



red: pruned area, blue: used sub-teams, grey: pruned sub-teams.

$$TS_{ALL-LS}(T) = \frac{4}{3+2}\left(Skill(t_{BCD}) + \frac{1}{2}\left(Skill(t_{AC}) + Skill(t_{AD})\right)\right)$$

Conclusion

- method for capturing increased success of teams with good chemistry.

- team skill depends on data of as many different team compositions as possible

- approaches for improvement:
  - roles within the team are not required explicitly
  - confidence of the underlying skill estimation is not treated
  - correlation between team skill and player skill is assumed to be uniform
- Team Skill, True Skill and ELO symmetrically value wins and losses.

=> in many casual games a win awards more to the player skill than a loss would reduce it to keep players motivated to play.

Alternative Approach

- rating players not by success, but by skillful behavior:
  1. collect and describe spatial-temporal behavior over the full spectrum of skill.
  2. learn a regression model.
  3. rate player, while playing, for his *k* last actions.

- this approach is used for dynamic play level adjustment in PVE.

- very suitable if it is known what constitutes successful behavior in the game. (e.g. accuracy in FPS Games, DPS/HPS Numbers in MMORPGS)

Learning goals

- Scope of application for player ranking and matchmaking
- ELO
- True Skill
- Team Skill

Literature

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- Pierre Dangauthier, Ralf Herbrich, Tom Minka, Thore Graepel **TrueSkill Through Time: Revisiting the History of Chess,** In Advances in Neural Information Processing Systems 20 (NIPS), 2008.
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- Colin DeLong, Nishith Pathak, Kendrick Erickson, Eric Perrino, Kyong Shim, Jaideep Srivastava:**TeamSkill: Modeling team chemistry in online multi-player games,** on Proc. of the 15th Pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining (PAKDD2011), 2011.