Chapter 9: Collaborative and Antagonistic Behavior

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

- Calculating play level from win statistics
- ELO-Ranking
- True Skill and the Microsoft-Model
- Team Skill: Taking team chemistry into account
- Outlook on network analysis in games
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.

**Use:**

- **matchmaking:** Choosing 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.
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 \( \beta^2 \). \( s_i; p_i = N(s_i, \beta^2) \)

\[ s_i > s_j \text{ does not necessarily mean } i \text{ is losing against } j \]

**rather:** \( Pr(i \text{ wins against } j) > 50\% \)

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

\( \Rightarrow \) Difference of 2 normal distributed variables with the same variance \( \beta^2 \) is normal distributed with an anticipated value of \( s_i - s_j \) and variance \( \beta^2 \).

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

\[
P(p_1 > p_2 | s_1, s_2) = \Phi\left(\frac{s_1 - s_2}{\sqrt{2\beta}}\right)
\]
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 $\Delta$ 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 $y_i$: 
  $$\Delta = \alpha \beta \sqrt{\pi} \left( \frac{y_i + 1}{2} - \Phi \left( \frac{s_1 - s_2}{\sqrt{2} \beta} \right) \right)$$

  $\alpha$ : weighing factor for a match $0< \alpha <1$ (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. motor 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 ($t_1 \geq t_2 \geq \ldots \geq t_m$)
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 $\mu_i$ and standard deviation $\sigma_i$
- With the given factor graph and the current values of $\mu$ and $\sigma$ 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 $\mu$ and $\sigma$ 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 $\mu$ and $\sigma$.

```
N(\mu_1, \sigma_1^2) \quad N(\mu_2, \sigma_2^2) \quad N(\mu_3, \sigma_3^2) \quad N(\mu_4, \sigma_4^2)
N(s_1, \beta^2) \quad N(s_2, \beta^2) \quad N(s_3, \beta^2) \quad N(s_4, \beta^2)
```


1. $\Pi(t_1=p_1)$
2. $\Pi(d_1=t_1-t_2)$
3. $\Pi(t_2=p_2+p_3)$
4. $\Pi(d_2=t_2-t_3)$
5. $\Pi(|d_2| \leq \varepsilon)$
6. $\Pi(t_3=p_4)$

\[\Pi(d_1=t_1-t_2) \quad \Pi(t_2=p_2+p_3) \quad \Pi(t_3=p_4)\]
Discussion True Skill

• Improves the ELO Systems 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 Through Time 2008)
  • team skill is considered as the sum of player skills (In reality player synergy is much more complicated: 11 Messis ≠ world’s best soccer team)
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. ($t_k \subseteq T \land |t_k|=k$). $\text{Skill}(t_k)$ constitutes sub-team’s $t_k$ skill level (for example calculated with ELO or True-Skill)

**task:** Skill level of team $T$ considering team chemistry?

**approach:** Calculating average over determined sub-team ranking.
Team Skill-k

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

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

example:

k=1 and K=5

$$TS_1(T) = \frac{5}{1} \cdot \frac{1}{\binom{5}{1}} \cdot \sum_{i=1}^{\binom{5}{1}} \text{Skill}(s_{1i}) = \sum_{i=1}^{\binom{5}{1}} \text{Skill}(s_{1i})$$

k=2 and K=5

$$TS_2(T) = \frac{5}{2} \cdot \frac{1}{\binom{5}{2}} \cdot \sum_{i=1}^{\binom{5}{2}} \text{Skill}(s_{2i}) = \frac{1}{4} \sum_{i=1}^{\binom{5}{2}} \text{Skill}(s_{2i})$$
Team Skill-AIIK-LS

Means of improvement towards Team Skill $k$:

- Determining $k$ is hard => take all possible sub-teams.
- Separate results do not exist for all sub-teams => Only consider sub-teams with a reliable ranking.

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

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

Calculate team performance as a $k$-multiple of average single performance.

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

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

rot: pruned Area, blau: used sub-teams, grey: pruned sub-teams.
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

• Skill in Team Skill, True Skill and ELO symmetrically values win and loss.

=> in many casual games an win award more increase to player score than losses reduces the skill level (keep players motivated to play)
Alternative Approach

• Rating players not by success, but by his behavior matching a successful player’s 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)
Network Analysis in Games

• Many MMO-games include analyzable social structures: 
  \textit{Who plays with whom and for how long?}

• modeling team-strategies

• response profile to an opponent’s actions

• finding criminal associations (e.g. gold-farmer trusts)

• tools to create pick-up groups
Learning goals

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


- Pierre Dangauthier, Ralf Herbrich, Tom Minka, Thore Graepel
  *TrueSkill Through Time: Revisiting the History of Chess*,
