Making Matches - Recommending the right personality

Paul Schweiger

TECHNISCHE UNIVERSITÄT DARMSTADT

1 Topic Summary

As globalization and connectedness advance, online communities grow in importance and the offline world embraces online opportunities. A surplus of possible contacts emerges, making it challenging to have an optimal online experience by engaging with fitting personalities. This interaction between users is a cornerstone of many different activities, such as multiplayer gaming, social networks, crowdsourcing communities or online dating platforms, making matchmaking efforts important to further financial and social goals. Recommender Systems that account for an adequate operationalization of the relevant personality traits can be used to improve said goals all across different domains of usage.

The ever-growing market of multiplayer gaming experiences have created online spaces where different personalities are forced to work together. While forming an effective team is the apparent goal of competitive online gaming, for the most part of the community *having fun* is even more important. At the same time, the internet's anonymity makes it a great place for trolls and toxic players, resulting in intra-community problems and a âĂIJsaltyâĂİ experience. Not only toxic players, but a combination of different player goals and styles can lead to bad experiences: a single aggressive player in a defensive team will not have the needed support in battle, while players aiming for a story-driven experience wonâĂŹt be able to cooperate with performance-oriented hardcore gamers.

Considering the fact that a large amount of players is available at any given moment, it should be possible to incorporate such preferences in the matchmaking process - which is currently mainly driven by player experience and performance.

A recent study by Wang et al. [WYS15] looked at the enjoyment of multiplayer sessions in League of Legends (LoL) based on player personality. They followed a subset of Sternberg's [Ste99] problem-solving styles in order to categorize the playstyle of different users. While others tried to gain player personality knowledge by simply asking them [RCFP07] or other players [PLBH11], Wang et al. automated this process with gameplay statistics. They assigned specific in-game actions to each of their player categories and determined a player's style based on his action profile. Choosing the data used to calculate a "good" experience is highly domain specific and depends on available objective game statistics.[DCTL+12] Match enjoyment for LoL was modeled as a function of game length, with shorter games being less enjoyable due to one team dominating the other. The results show a clear tendency of specific globally-active and risk-taking players to positively influence the overall game enjoyment. A neural network tasked with predicting match enjoyment achieved better scores when player style data was included, suggesting that this might benefit matchmaking algorithms. However, it is important to note that the used measures are highly subjective to LoL, as interviews with players of both LoL and other games confirm.

Most Online Dating Services experience comparable problems: Learning who goes good with one another is a major success criterion for dating applications. Possible matchups need to be built according to their preferences rather based upon global performance. Studies predicting user tastes based on the tastes of similar users, a technique called "Collaborative Filtering", showed better results than global matchmaking. [BP07]

Proper personality-based matchmaking in online environments has a positive influence on overall user satisfaction. Successful Recommender Systems need to incorporate personal and detailed data, rather than just performance measurements. On the other hand the limiting effect of Recommender Systems on content diversity needs to be considered, especially in this social use case. [NHH+14]

2 Introduction

Oben klauen, aber Learning-Bezug: In the globalized world, it is more and more important to stay connected: To stay connected with lots and lots of humans both virtually and phisically, and to stay in touch with recent technological advancements and to learn meaningful things. The world has a plethora of opportunities, topics, people, products, ... and people have a limited amount of attention and time to spend on those - this is why recommender Systems are important Focus on E-Learning and Reciprocal Recommendation, because...

Introduction to Recommendation in E-Learning (How good is research? Overlap with other topics -> shorten this section)

Introduction to Recommendation in Reciprocal environments (How good is this researched? How many things do we know?)

This report will discuss possible solutions to improve learning via reciprocal peer recommendation in Learning-Environments. As one of the first (???) and the most recent implementation of such an endeavor, the report will provide a detailed overview of XXXXXXXXX by XXXXXXXX. Important findings leading up towards the work, possible extensions and research in other fields that might prove to be beneficial to this study will be discussed.

3 Research leading towards the paper

3.1 Learning

TODO: Provide overview of modern learning:

- learner types
- E-Learning vs. offline learning
- peer learning
- recommender systems for e-learning so far

3.2 Recommender Systems

TODO: Provide short overview of RS
Where do they come from, what have they been used for?
REMARK: This section might be removed due to overlap with other sections. Maybe RS for E-Learning and reciprocal RS will be enough

3.3 Reciprocal Recommendation

TODO: Provide Overview of Reciprocal Recommendation

- Goal of recirpocal recommendation
- different ways to do this: Just a score for other people, or actual reciprocal recommendations, where bothpartners see each other as a recom.
- Other fields (Gaming, Dating)
- Common methods (Collaborative Filtering)
- Common problems encountered when doing this (operationalize personality / relevant aspects, acquire personal information about people, self-reported vs. implicit, ...)

4 Reciprocal Recommendation for E-Learning (Paper Title!)

4.1 Introduction

Introduction: Motivation for this specific study. What did they want to accomplish?
Explain goals and problems of XXX et al. implemented Ripple [capitalization!] to prove their theories.

4.2 Ripple

Explain Ripples aspects and assumptions and how people get matched.
Ripple will be evaluated in live conditions in the course of this year. To check whether the implementation could work under real conditions, XXXX conducted an evaluation using randomly generated data. This will be discussed in the upcoming section

4.3 Evaluation

Goals of evaluation
How random data was designed
Quality Measures
Results in every measure
Use images?

4.4 Discussion

Recap of their discussion
Current results are scientifically weak: Lots of assumptions about initial values (e.g. for T), no aims of bounds set to determine whether final values are actually good.
Does not consider buy-in by users. This is okay for the tool, it will still recommend people, but the actual use of this whole measure will get undermined.
self-evaluating data about students is prone to errors and was not checked or detailed: misleading competency values might spoil results.
Abandoned users due to edge-cases: Someone with low competency prefering to teach, high competency preferring to get teached. Ripple does account for these cases by only recommending the best fits, so even low fits can still be recommended.
Transparency: Will students know how good their matching value is?
Possible error for highly compatible users who appear in many recommendations: They have few reciprocal recs, but will get lots of meeting requests.
ARE THERE ANY DISCUSSIONS ABOUT THIS PAPER YET?

5 Extensions

TODO: Include possible follow-up research, directions for further research or innovative ideas from other fields to include in future recirpocal peer recommendation for elearning studies.

Bibliography

[BP07] Lukas Brozovsky and Vaclav Petricek. Recommender system for online dating service. *arXiv preprint cs/0703042*, 2007.

[DCTL+12] Olivier Delalleau, Emile Contal, Eric Thibodeau-Laufer, Raul Chandias Ferrari, Yoshua Bengio, and Frank Zhang. Beyond skill rating: Advanced matchmaking in ghost recon online. *IEEE Transactions on Computational Intelligence and AI in Games*, 4(3):167–177, 2012.

[NHH+14] Tien T Nguyen, Pik-Mai Hui, F Maxwell Harper, Loren Terveen, and Joseph A Konstan. Exploring the filter bubble: the effect of using recommender systems on content diversity. In *Proceedings of the 23rd international conference on World wide web*, pages 677–686. ACM, 2014.

[PLBH11] WO'Kelley II Patrick, Steven D Lamb, Michal Bortnik, and Johan Peter Hansen. System and method for providing feedback on game players and enhancing social matchmaking, November 29 2011. US Patent 8,066,568.

[RCFP07] Jens Riegelsberger, Scott Counts, Shelly D Farnham, and Bruce C Philips. Personality matters: Incorporating detailed user attributes and preferences into the matchmaking process. In *System Sciences, 2007. HICSS 2007. 40th Annual Hawaii International Conference on*, pages 87–87. IEEE, 2007.

[Ste99] Robert J Sternberg. *Thinking styles*. Cambridge University Press, 1999.

[WYS15] Hao Wang, Hao-Tsung Yang, and Chuen-Tsai Sun. Thinking style and team competition game performance and enjoyment. *IEEE Transactions on Computational Intelligence and AI in Games*, 7(3):243–254, 2015.