Making Matches – Recommending the right Personalities



Current Tpoics in Web Applications, Information

Management and Semantics

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KOM - Multimedia Communications Lab Prof. Dr.-Ing. Ralf Steinmetz (Director) Dept. of Electrical Engineering and Information Technology Dept. of Computer Science (adjunct Professor) TUD – Technische Universität Darmstadt Merckstr. 25, D-64283 Darmstadt, Germany Tel.+49 6151 166150, Fax. +49 6151 166152

Presented by: Paul Schweiger

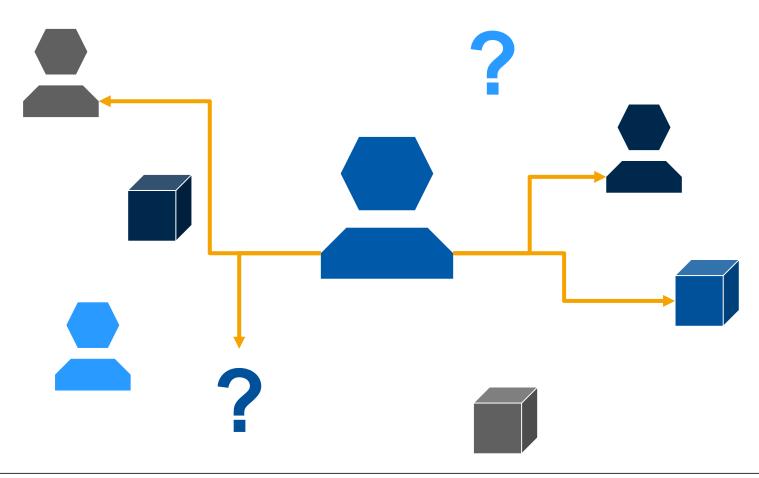
Paul.schweiger@stud.tu-darmstadt.de

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Introduction

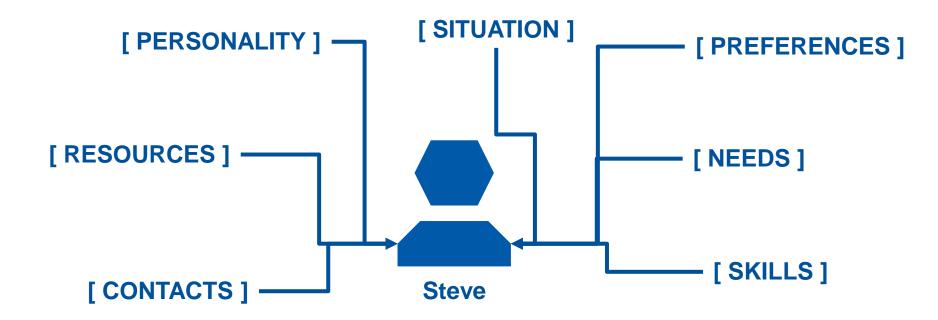


Recommender Systems help people to engage in meaningful ways



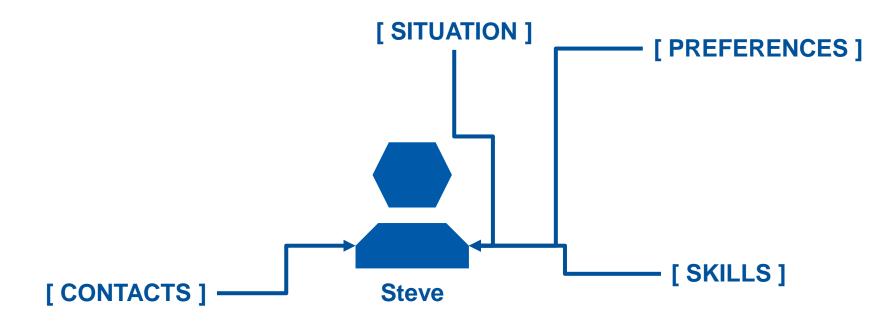


- Recommendations have to be adjusted for an individual user
- User Models encompass everything we deem relevant about our user



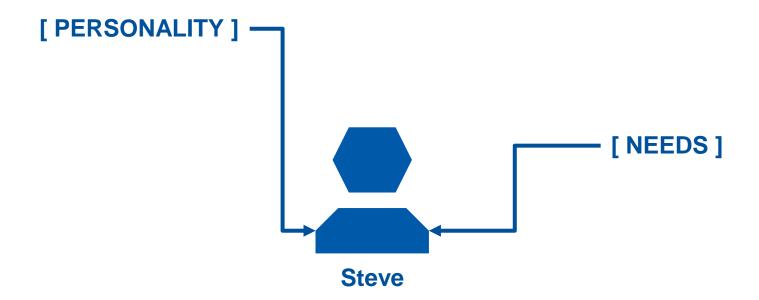


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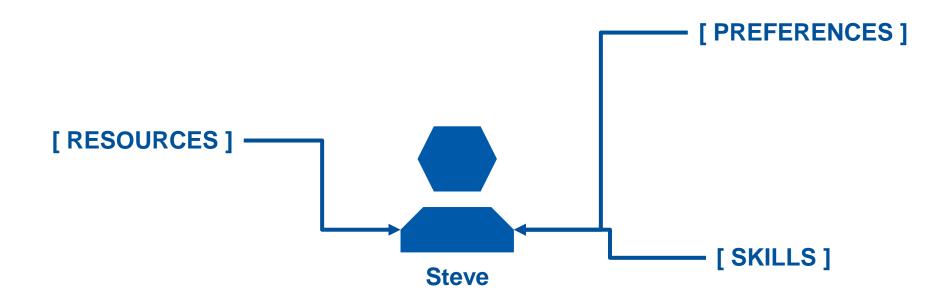


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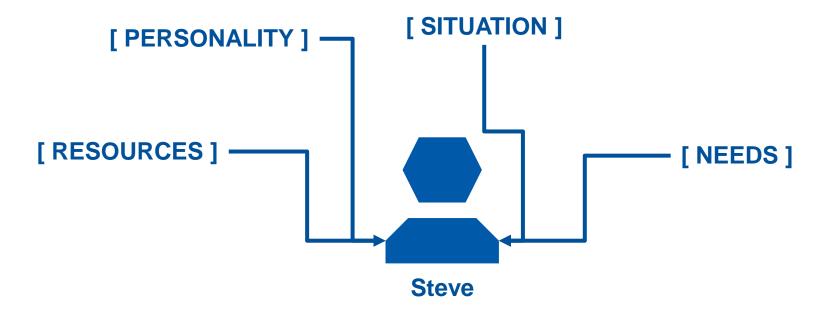


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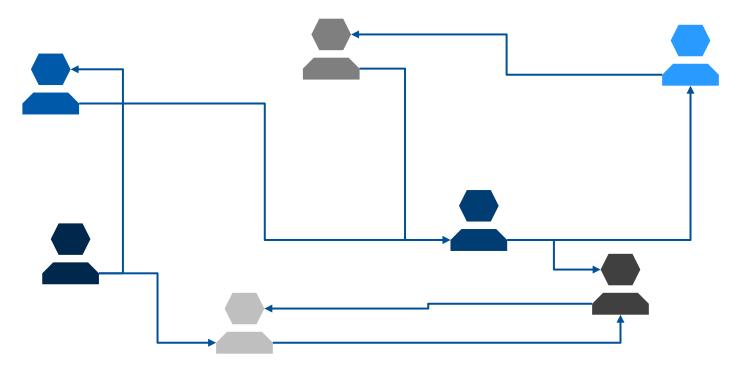


Core Concepts: Reciprocal Recommendations



Reciprocal Recommendations

- Users receive users as recommendations and is in turn a recommended item
- Truly reciprocal when a user is recommended to his own recommended users
- Online dating, gaming matchmaking, social networks, group formation, ...

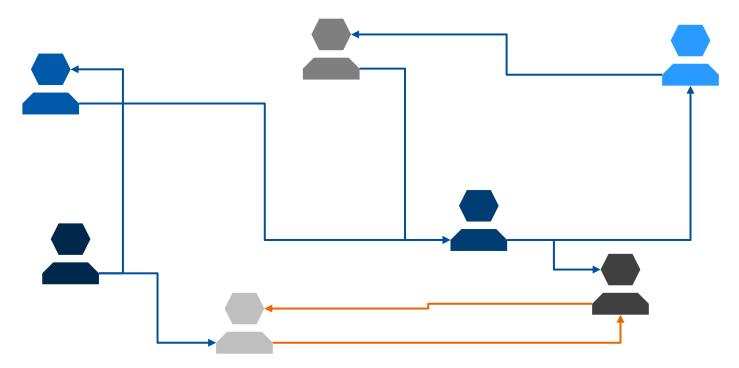


What is this talk about?



Reciprocal Recommendations

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Reciprocal Peer Recommendation for Learning Purposes



System

- adaptive, web-based, student-facing, multi-purpose learning platform
- Classical e-learning platform capabilities and recommendation of learning capabilities
- RiPPLE -> "Recommendation in Personalized Peer Learning Environments"

User Model

- Topic-wise competency (derived from e-learning results)
- Available timeslots
- Roles: Topics in which a user would like to
 - Find a learning partner
 - Receive peer support
 - Give peer support
- Preferences regarding competency differences for each role

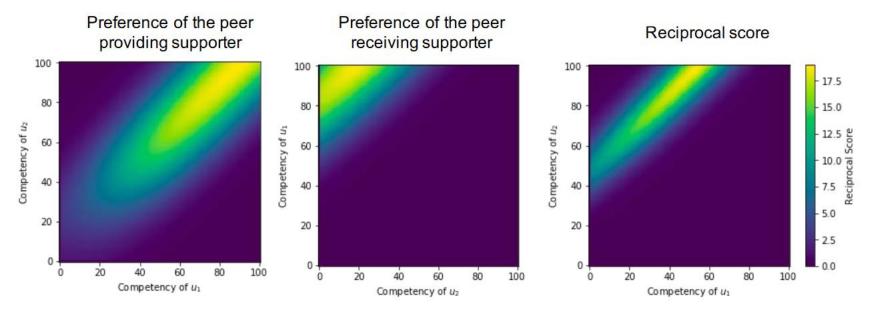
Combine user's learning needs and capabilities

Reciprocal Peer Recommendation for Learning Purposes



Recommendations

- If their timeslots and roles are compatible, calculate two one-directional scores for every pair of users
- Calculate the harmonic mean of these two values, leading to a reciprocal, symmetric score for each match
- Return a list of k recommendations to each user



Reciprocal Peer Recommendation for Learning Purposes



Evaluation

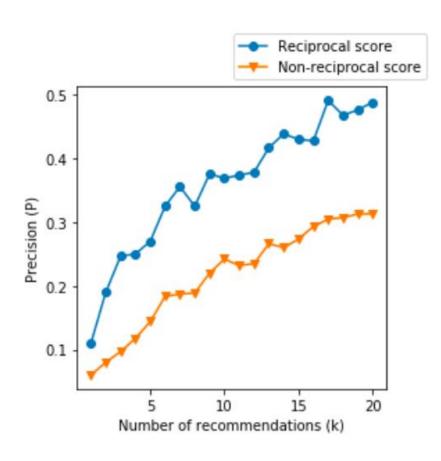
- Completely artificial data
- Main question: How would the system perform in real life?
- Quality metrics:
 - Scalability
 - Reciprocality
 - Coverage
 - Quality
- No specific goals set

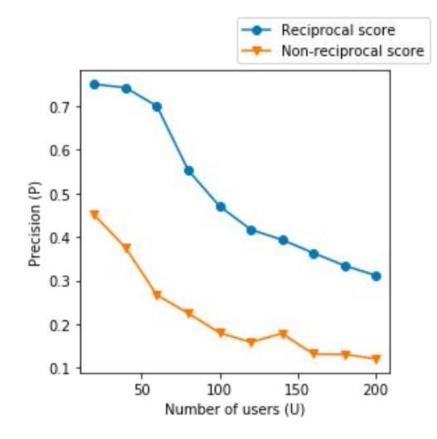
Future Plans

Practical evaluation in college courses during 2018

Reciprocality

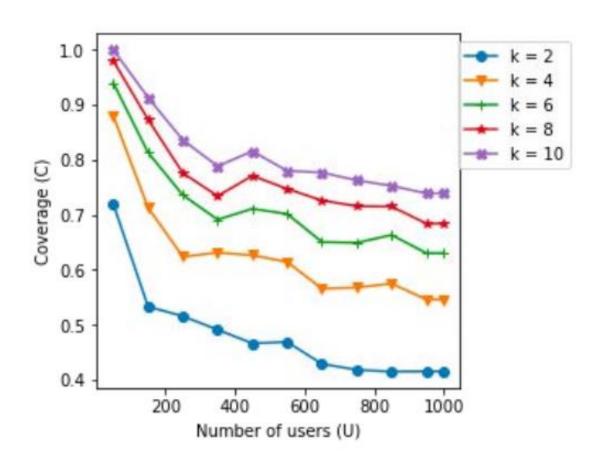






Coverage





Discussion



RiPPLE's shortcomings

- No consideration of abandoned users
- No learning groups, only pairing
- How would users know their competency difference preferences?

- Especially important in reciprocal scenarios, where users are items
- Overspecification leads to random recommendations
- Data Collection Problems [See next slide]

Discussion – Data Collection Problems



Explicit user data

- Self-reported by users about themselves (e.g. feedback, ratings, ...)
- biased by inability to properly report information
 - Source: Dude, trust me. [Doing my Masters in Psychology in IT]
- Psychology was founded to collect information about people, e.g. via tests

Implicit user data

- Online data collected during usage
- Cold start problem: Users would have to be randomly assigned at first
- Operationalization problems:
 - How do we measure "fun" in games? How do we measure sympathy between users?
 - Source: Dude, trust me.

Summary



User Modeling

- Highly important to be able to properly recommend items
- Depending on many different factors
- Data can be hard to acquire

Reciprocal Recommendations

- Valuable mechanism to help people find meaningful engagements
- Ensure benefits for all participants

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- Aaaand lots more, found in the paper. Seriously, I couldn't list them here.

new social connections The applications of reciprocal peer recommendation are manifold and generally beneficial in a highly social and connected modern world. Bringing different people together and providing opportunities to engage with one another yields [15] J. Riegelsberger, S. Counts, S. D. Farnham, and B. C. Philips, "Personmany advantages and teaches meaningful skills. However, human factors need to be incorporated in the algorithms to
account for the dualistic role of users as both recommended
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method for providing feedback or game plays and enhancing social
method for providing feedback or game plays and enhancing social items and recipients of recommendations. Many experiments items and recipients of recommendations. Many experiments with explicitly and implicitly collected data have uncovered a relative state of the navigated. Especially due to the many problems associated with measuring humans, algorithms are still unreliable when hundling people in recipiencal situations. However, skillif design can circumvent some of these problems and create systems that are far from professions of these problems and create systems that are far from the problems and create systems that are far from the problems and create systems that are far from the problems and create systems that are far from the problems and create systems that are far from the problems and create systems that are far from the problems and create systems that are far from the problems are considered to the problems and create systems that are far from the problems are considered to the consideration and the considered to the problems are considered to the consideration and the considered to the problems are considered to the consideration and the consideration are considered to the consideration are considered to the consideration and the consideration are considered to the consideration are consideration and the consideration are consideration and the considerati if RiPPLE's streamlined user model and up-front evaluation of technical measures have made it a platform fit for practical use. Until then, further research is required.

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