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Beyond Friendship:-

The Art, Science and Applications of Recommending People to People in Social Networks

Luiz Augusto Pizzato (University of Sydney, Australia)

Anmol Bhasin (LinkedIn, USA)

About the speakers

- **Luiz Pizzato** is a research fellow at the University of Sydney. Luiz has done extensive work in the area of reciprocal recommender and have implemented and evaluated a number of reciprocal recommender algorithms to match people to people for a large online dating website. These algorithms have been successfully trialled in a large scale user experiment and have since then been used to find dating partners.

- **Anmol Bhasin** is the Director of Engineering for Recommendations, Personalization and A/B testing systems at LinkedIn (www.linkedin.com). His team's contributions include LinkedIn's various personalized recommendation products (e.g., "Jobs You Might Be Interested In"), social news ("LinkedIn Today"), and systems for ad targeting and click through rate prediction. He and his team also work on enterprise People Recommenders in LinkedIn's product suite such as "People You May Hire" and "Talent Match" for LinkedIn's recruiter product. His team operates the content processing pipeline and online experimentation (A/B) framework used for LinkedIn's suite of data products.

Prior to LinkedIn, Anmol worked at business search engine Business.com, where he developed the crawler, indexing systems, and retrieval algorithms. Anmol has also authored mobile gaming applications, including the award-winning Tecmo Bowl. Anmol received a Masters in Computer Science from the State University of New York at Buffalo, where he focused on text mining and applied machine learning for cross document learning.

Tutorial Overview

- Introduction
  - The basics of Social Recommenders
  - People recommender systems
  - Reciprocity & its quirks

- Cornerstones
  - Motivating Examples
- Special Topics in People Recommenders
  - Intent Understanding
  - Multi-Objective Optimization
  - Evaluation Quirks
- Some Novel approaches & Applications
  - Social Lens & Referrals
  - Virtual Profiles
  - Pathfinding
  - Endorsements
- Conclusions

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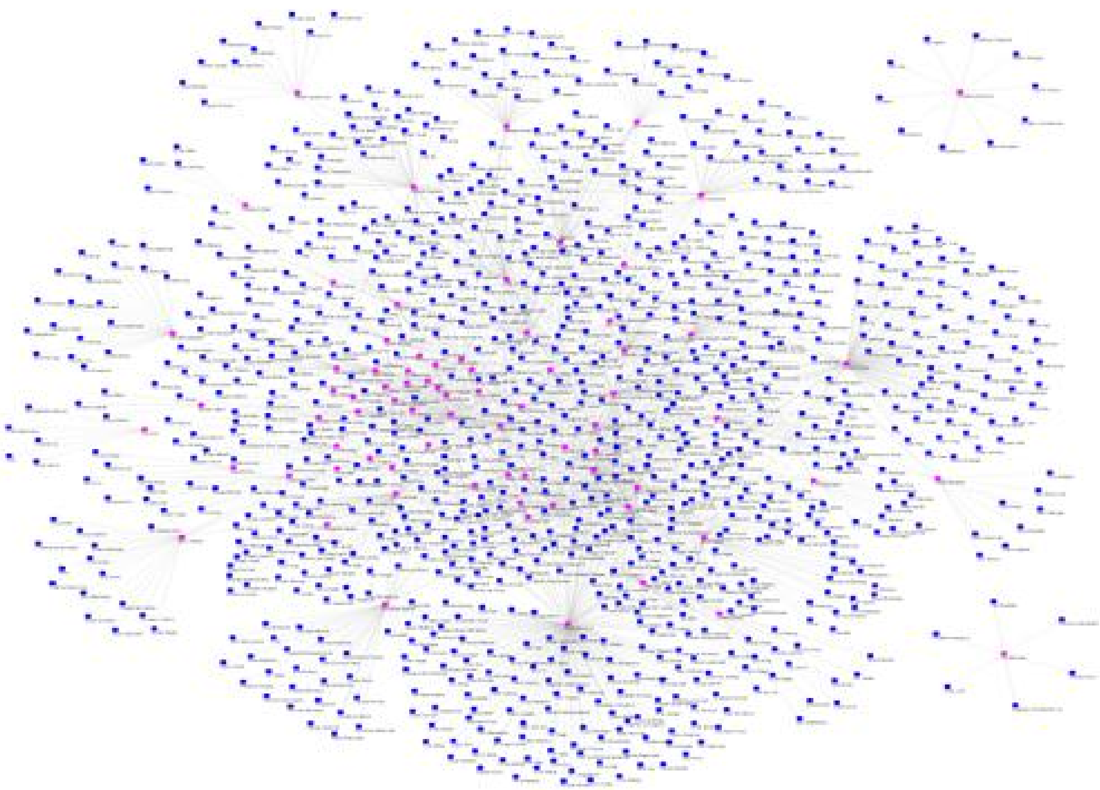
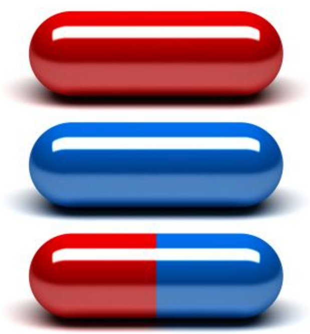
The basics of Social Recommenders

Social recommenders imply the possibility of leveraging social network information to provide recommendations.





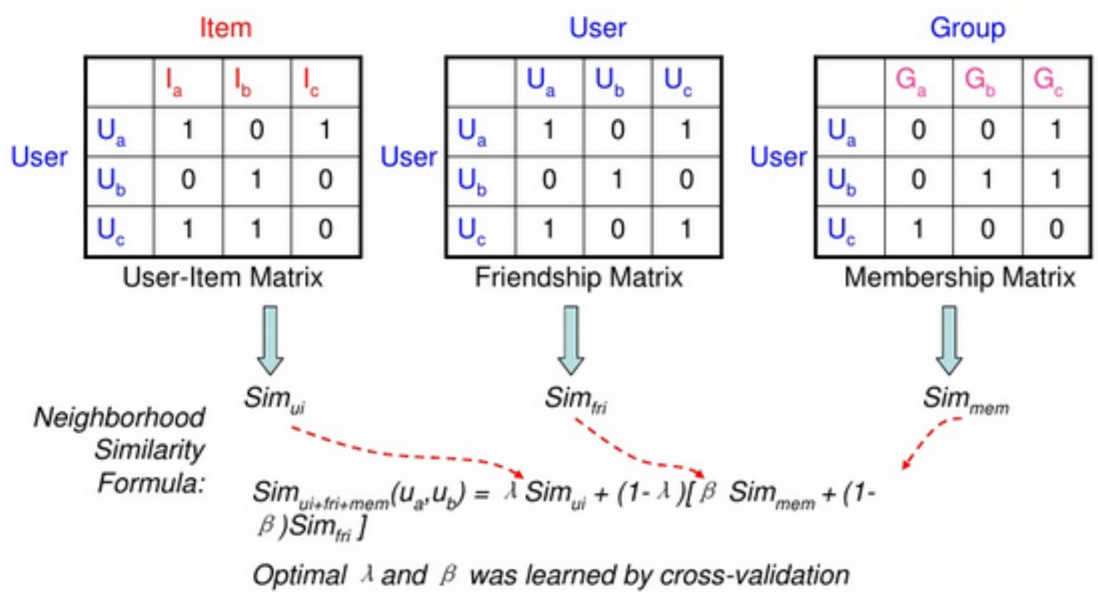
The basics of Social Recommenders

- What are your friends reading?
  - news that are relevant to your network may also be relevant to you

- Does this apply to products, advertisement?

The basics of Social Recommenders

Can we infer who you are and what you like based on your relationships?



User-Item Matrix	I_a	I_b	I_c
U_a	1	0	1
U_b	0	1	0
U_c	1	1	0

Friendship Matrix	U_a	U_b	U_c
U_a	1	0	1
U_b	0	1	0
U_c	1	0	1

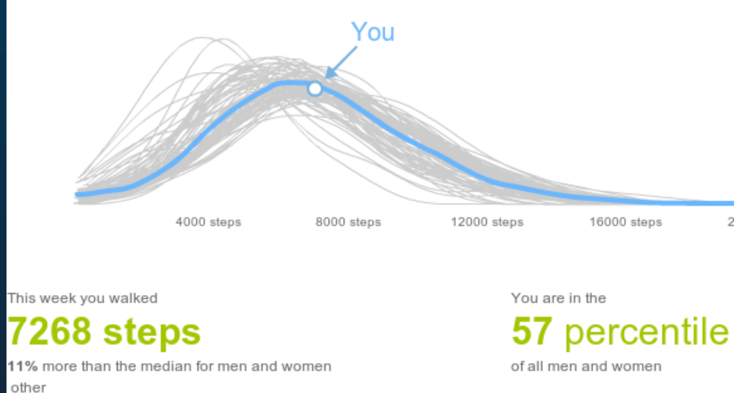
Membership Matrix	G_a	G_b	G_c
U_a	0	0	1
U_b	0	1	1
U_c	1	0	0

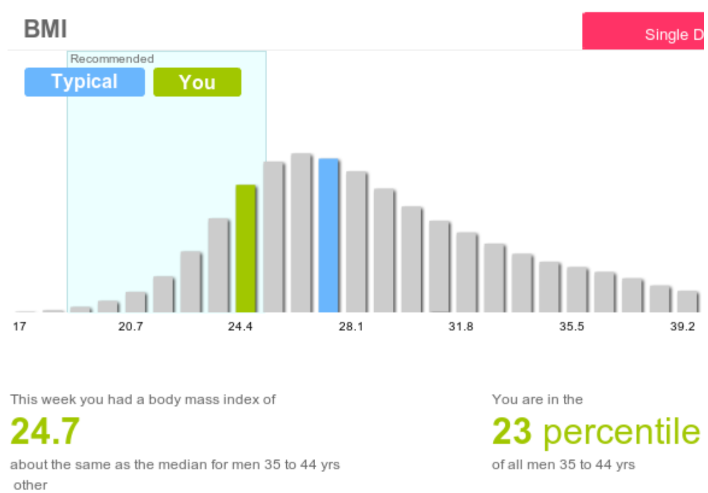
Quan, Yuan. Social Recommendation: http://www.slideshare.net/clickstone/social-recommendation

The basics of Social Recommenders

Leverage global graph and its content to provide advice on your own local graph and content

- Example: Fitness
  - How fit are you in comparison to your peers?
  - How to improve this? What others have done to improve?





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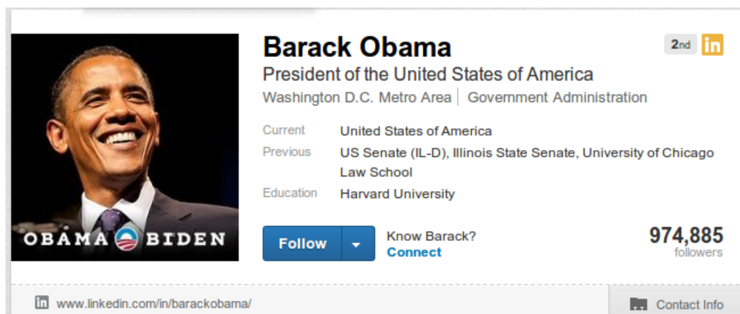
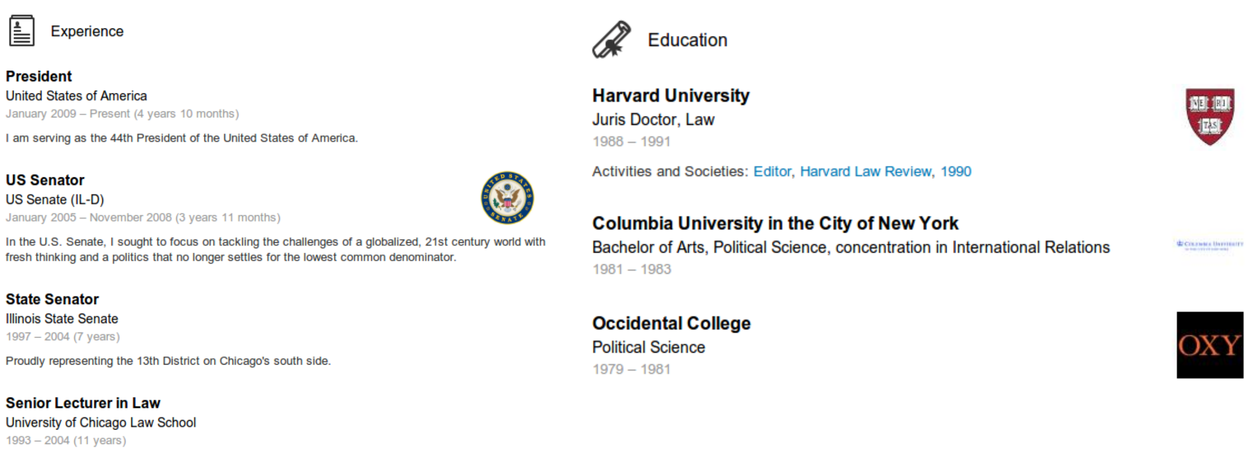
The basics of Social Recommenders

Leverage global graph and its content to provide advice on your own local graph and content

- Example: Career: How to advance in your career?





The basics of Social Recommenders

Recommendations for connections happens when the recommendation focus on the network itself and the interaction between its nodes.

- Friends you may (want to) know
- People you may want to date
- People who can help you
- Jobs you may want to apply
- Groups you might want to join

People recommender systems

- Where can we have people to people recommenders:
  - Social Networks:
  - Online Communities:
  - Online Dating Services:
  - Education Services:
    - Mentor/Mentee matching, MOOCs
  - Employment:
  - Hyperlocal Services:

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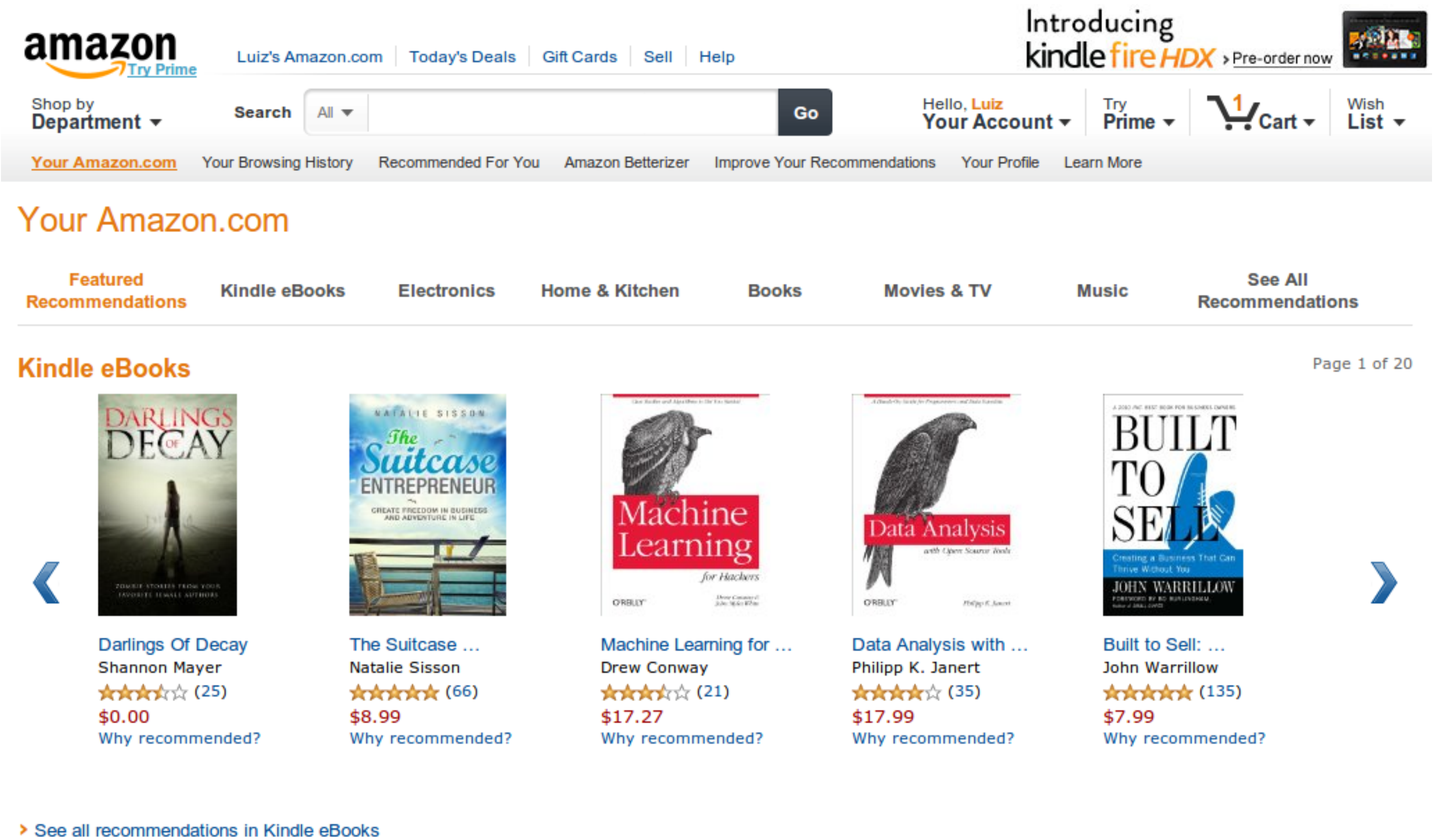
reciprocal (people) recommenders vs traditional (product) recommenders

What is traditional?



reciprocal (people) recommenders vs traditional (product) recommenders

Why reciprocal?

- Both sides of the recommendation need to agree to something;
  - Dating
  - Job matching
  - Adding contacts on Facebook/LinkedIn/G+

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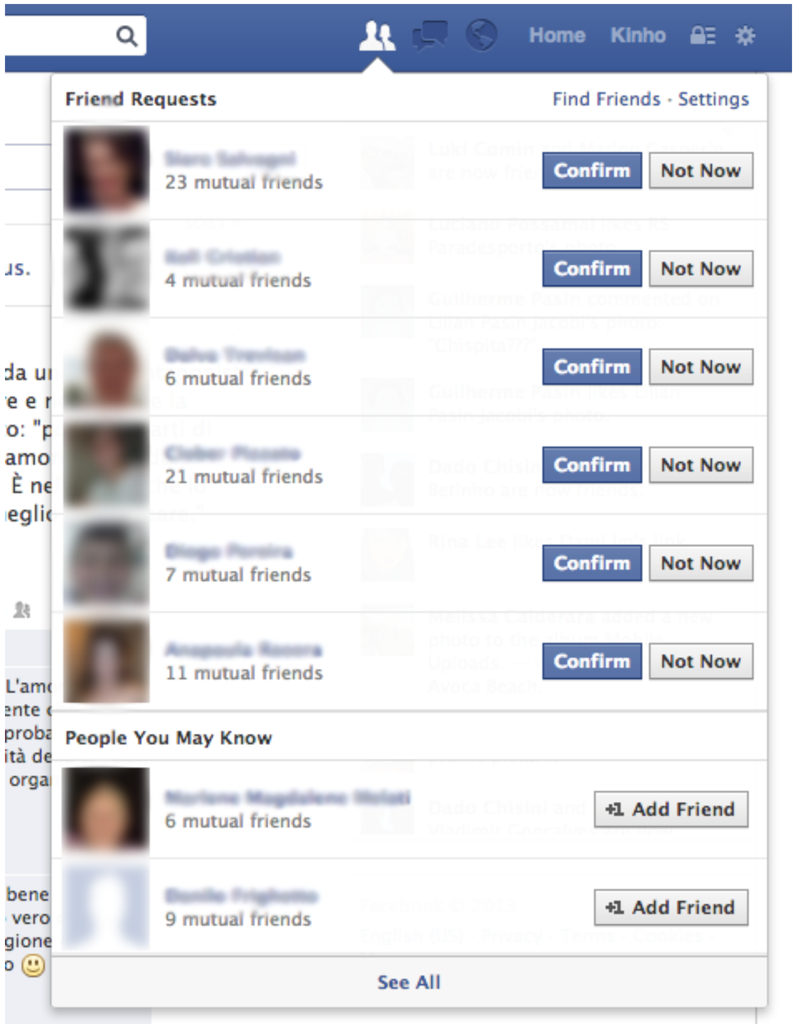
Reciprocity and social networks



Reciprocity and social networks

- What about?
  - Followers @ Twitter / Facebook
  - Likes, +1s

How reciprocity changes the game

A successful recommendation is agreed between the two sides of the recommendation

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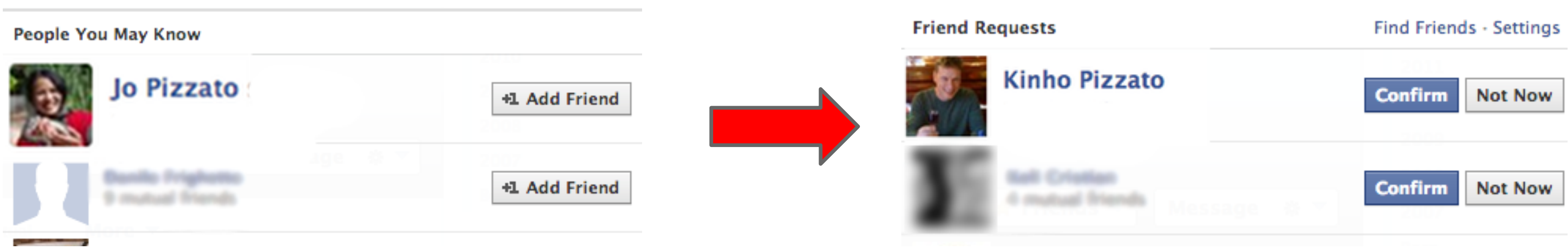

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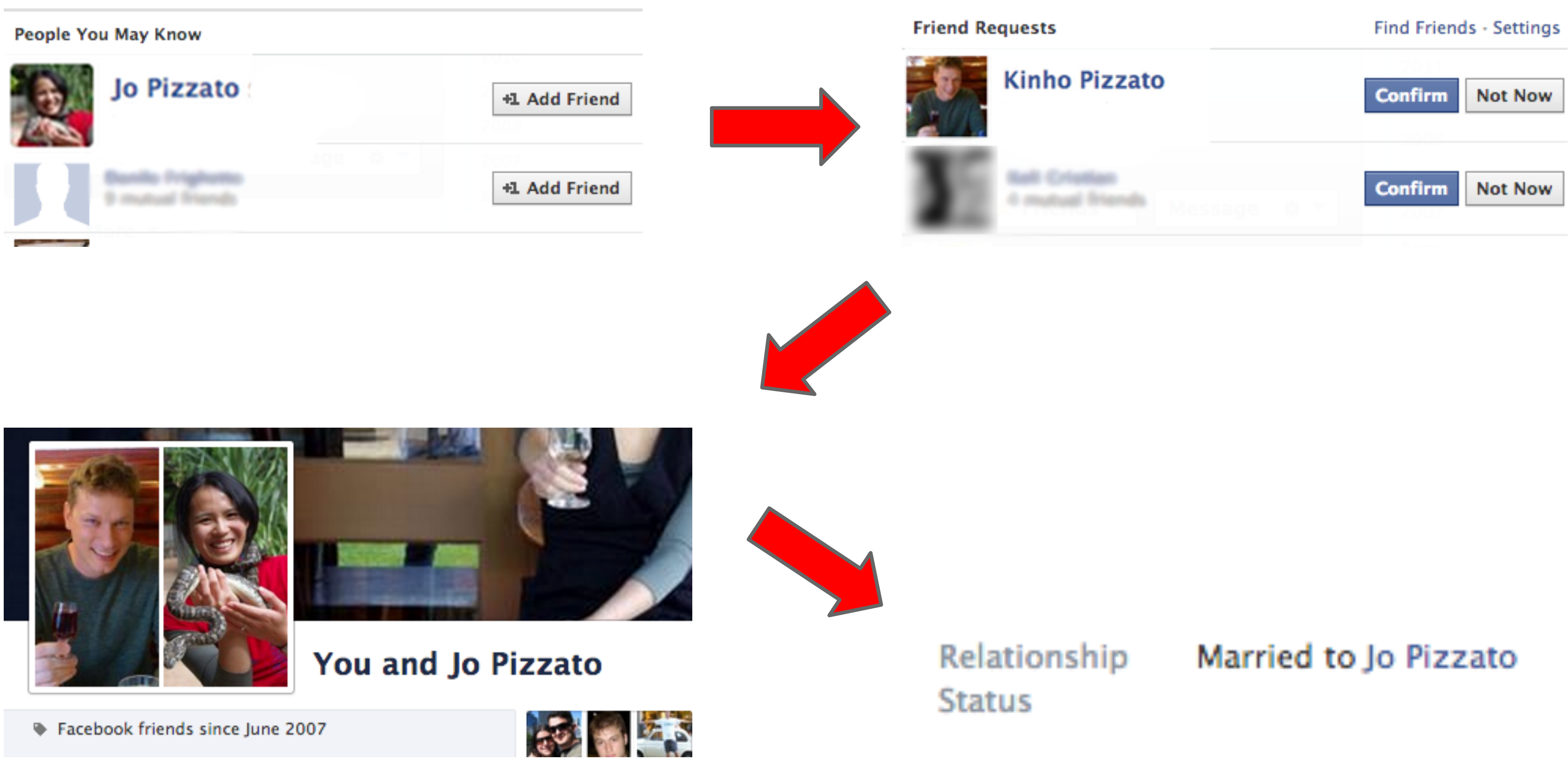
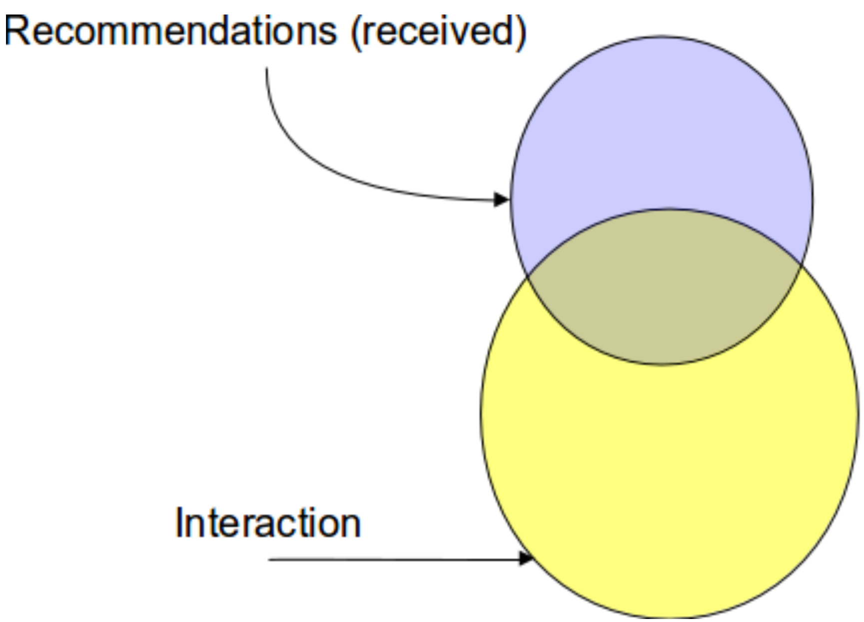
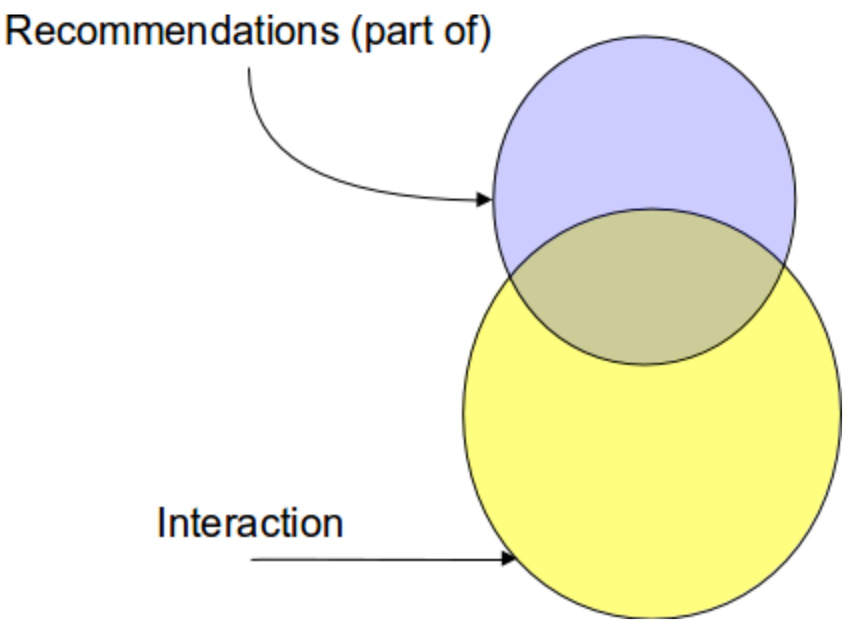


Measuring recommendation success

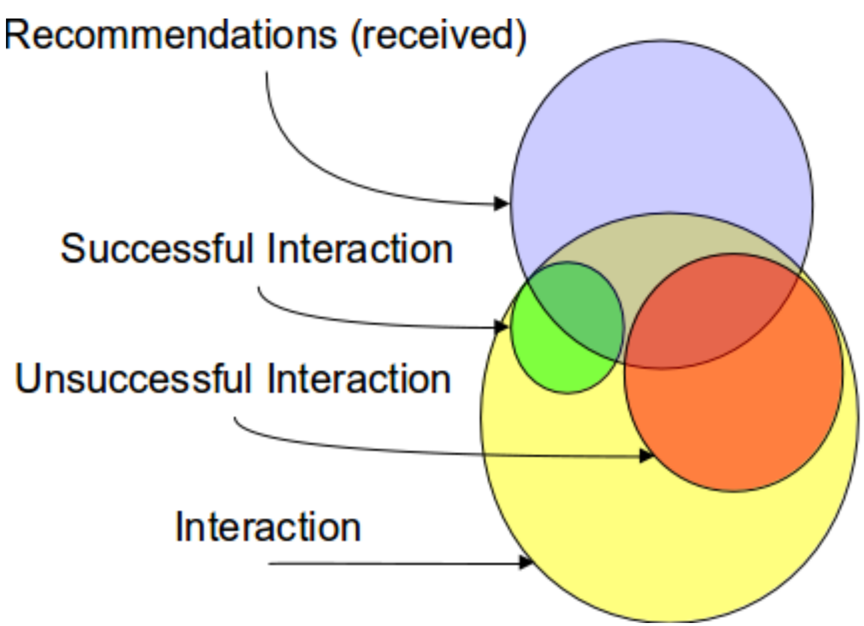
- Traditional:
    - How many recommendations users received and lead to an interaction?
    - How many times an items was recommended and got an interaction?

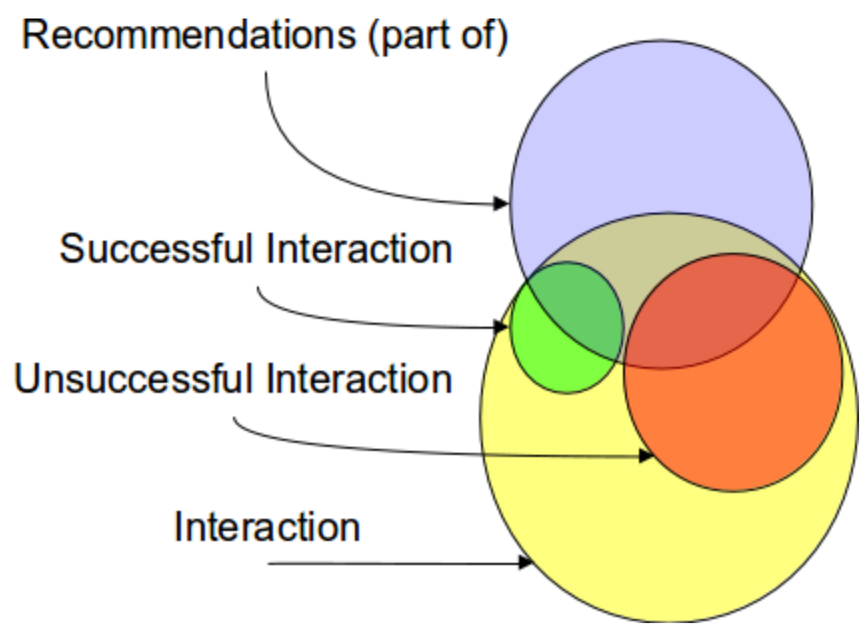




Measuring recommendation success

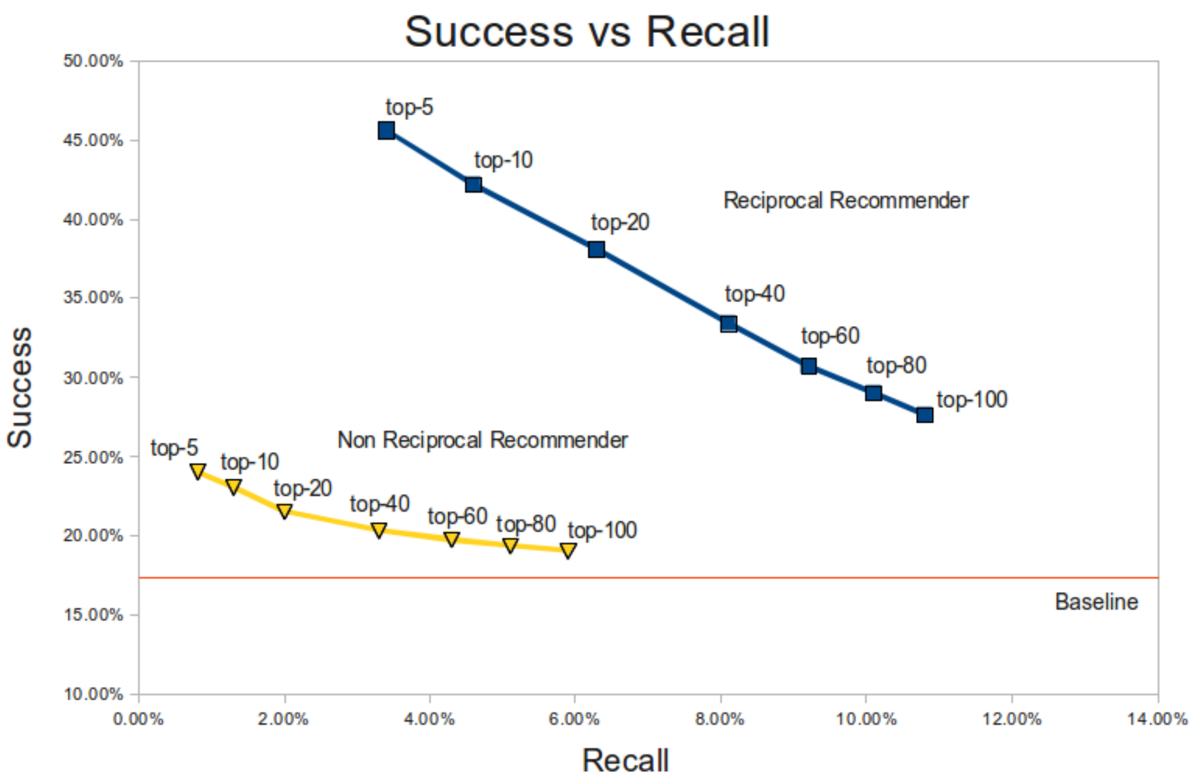
- Reciprocal:
  - Same as before and...
  - How many actions have lead to a successful or unsuccessful connection?





Rec. people vs product: agreement

A successful recommendation is agreed between the two sides of the recommendation



Pizzato et al. 2010, RecSys

Rec. people vs product: awareness

The receiver of the recommendation is aware of that success of a connection is dependent on the other side too

Rec. people vs product: awareness

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Action	views	EOIs	paid communication
Number of actions	39,016	5,692	864
Object matches subject's preferences	27,270 (70%)	4,453 (78%)	650 (75%)
Subject matches object's preferences	21,146 (54%)	3,228 (57%)	578 (67%)

Rec. people vs product: awareness

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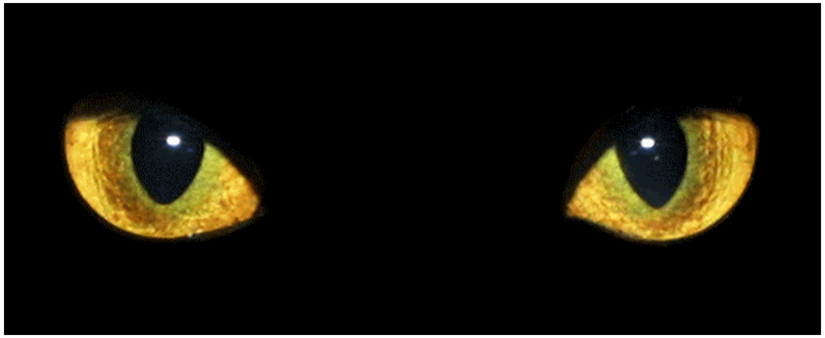
Observer effect:

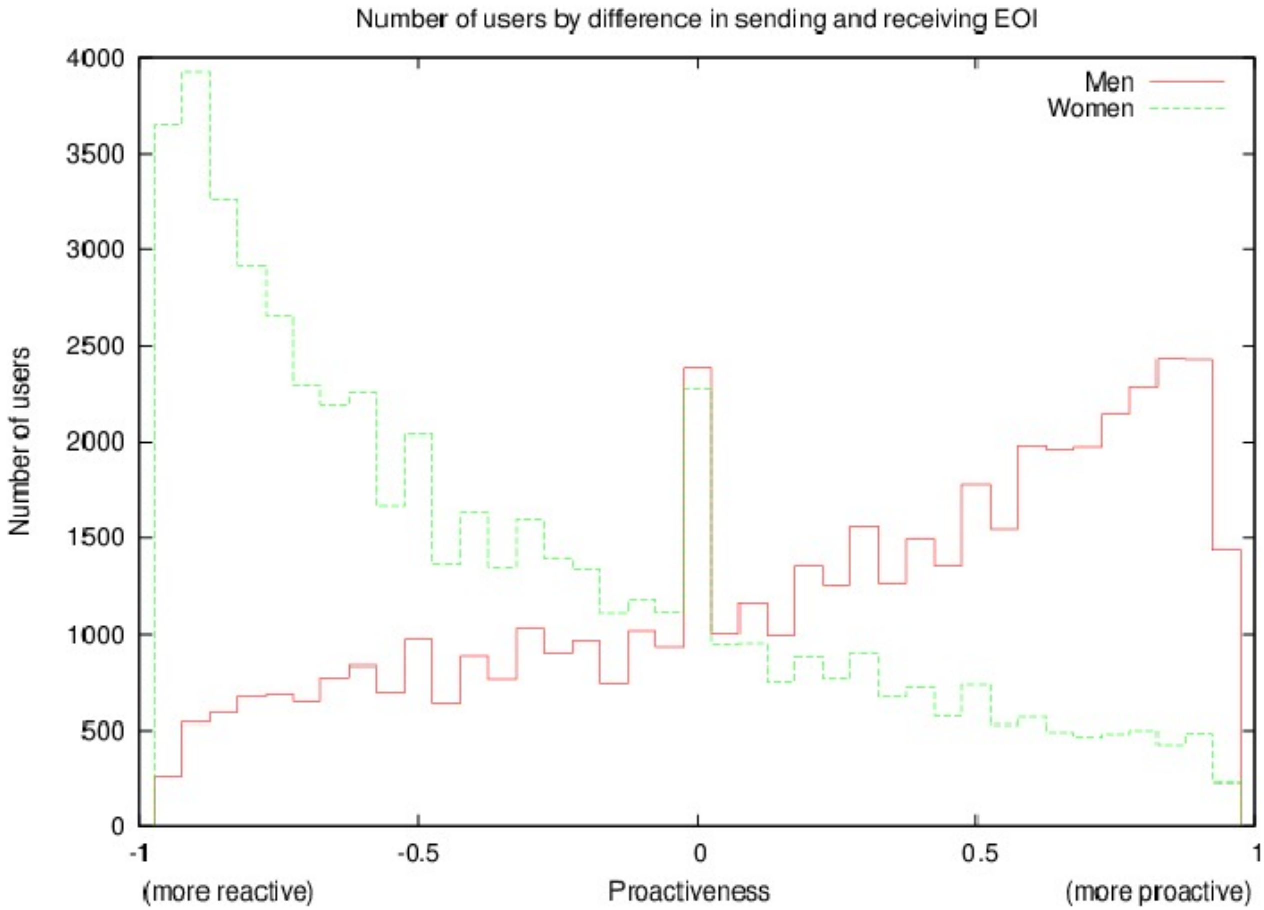


Rec. people vs product: user roles

Users can be proactive and/or reactive

Rec. people vs product: user roles

Users can be proactive and/or reactive



Rec. people vs product: user roles

Users can be proactive and/or reactive

Proactive users may not need to be the object of recommendations; however, strictly reactive users should be recommended to other users.

Rec. people vs product: danger of rejection

Poor recommendations are dangerous as they may lead to the user feeling rejected

Rec. people vs product: danger of rejection

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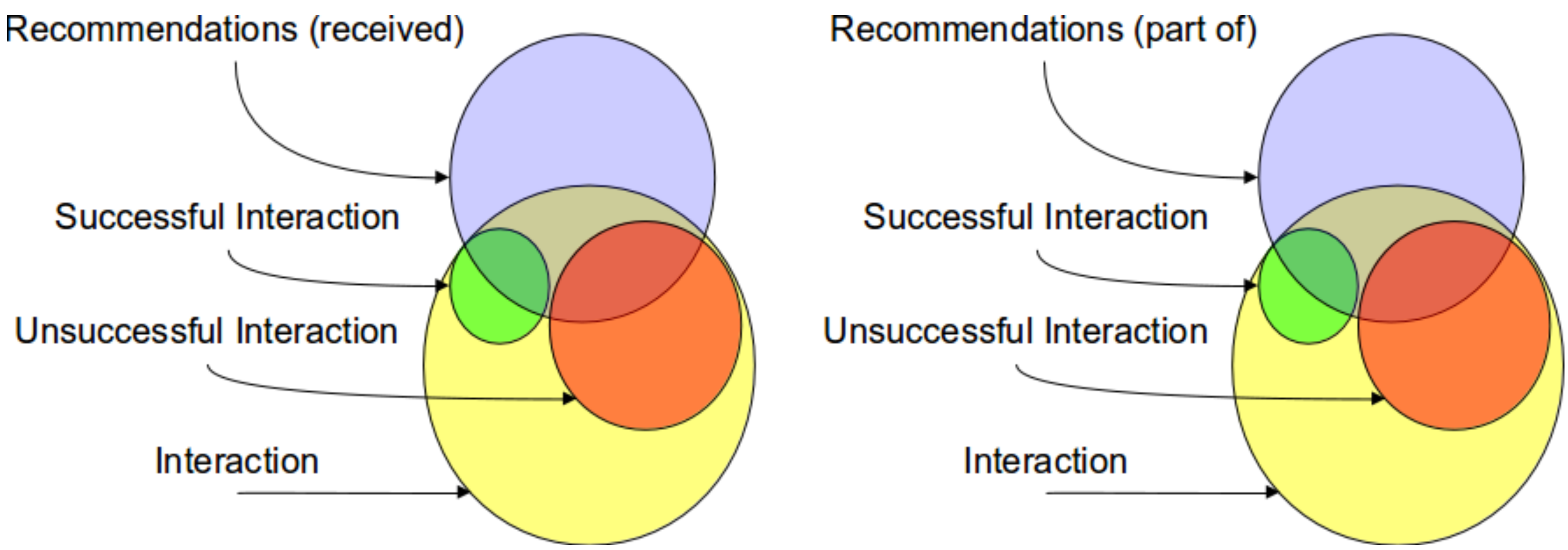
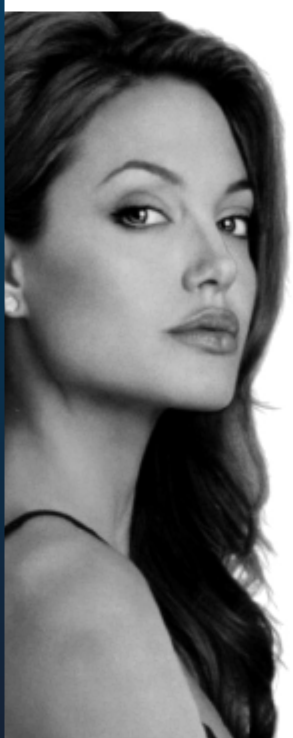


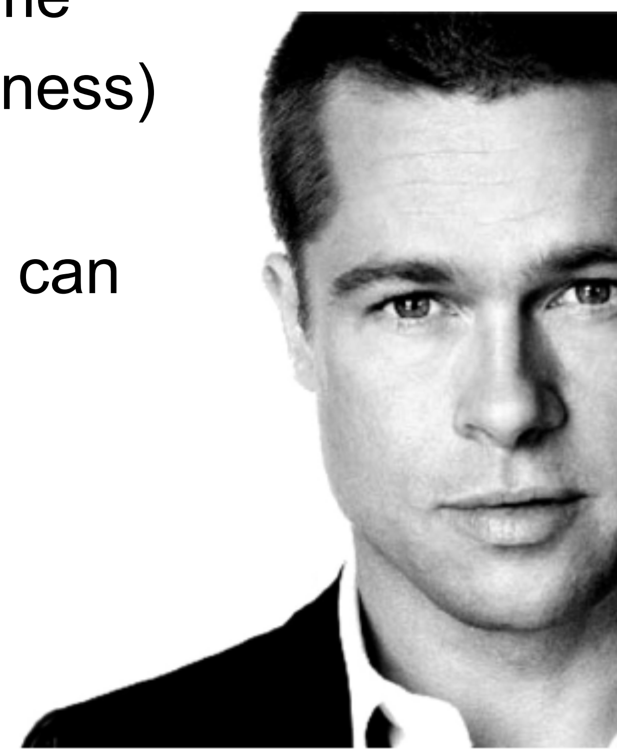
Rec. people vs product: limited availability

Users have a patience level

Some users become very popular (and subsequently they become important for the website/business)

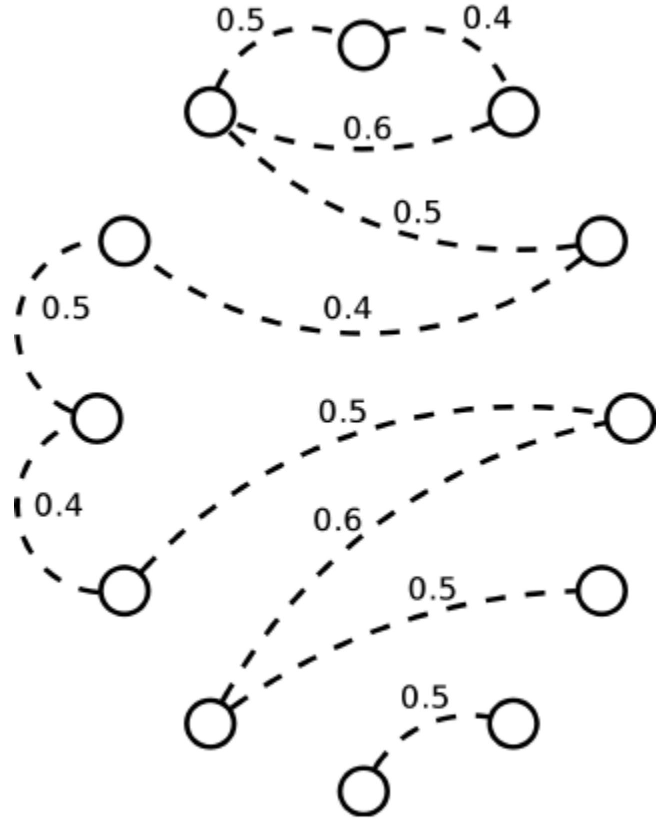
Any bias towards these users can aggravate the problem





Rec. people vs product: limited availability

What are the best n-matches for the whole social network?



Pizzato and Silvestrini, 2011, RecSys

Stochastic Graph

Rec. people vs product: content rich domain

Users provide rich self-profiles, including their preferences (these may be inaccurate)

Rec. people vs product: content rich domain

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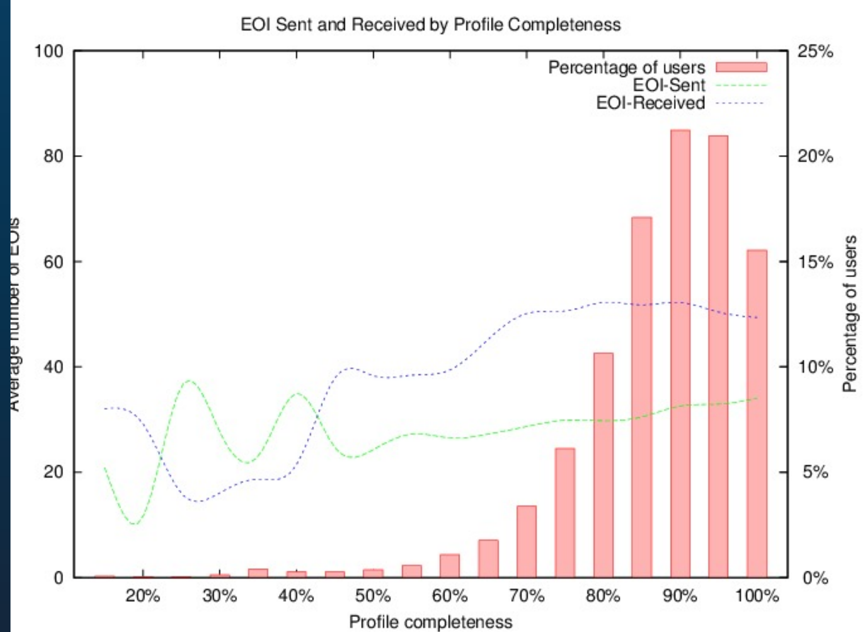
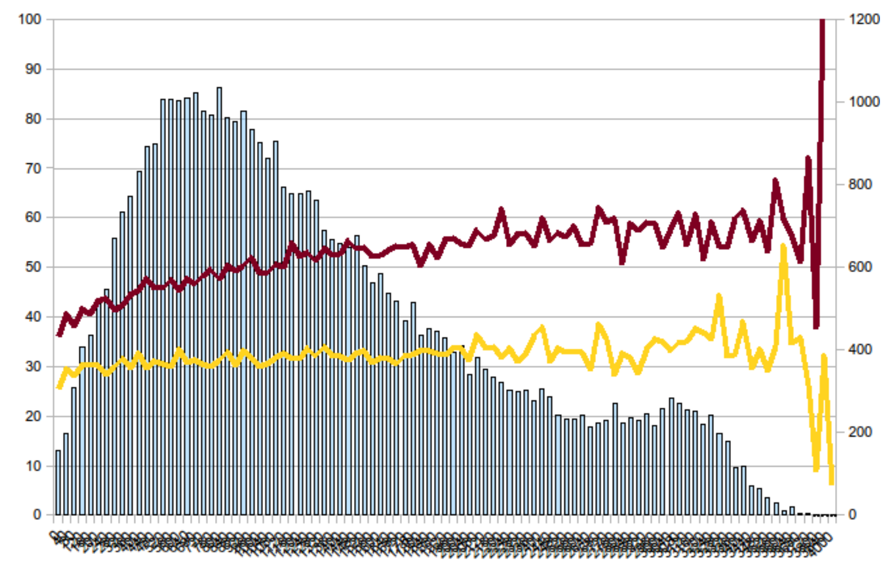




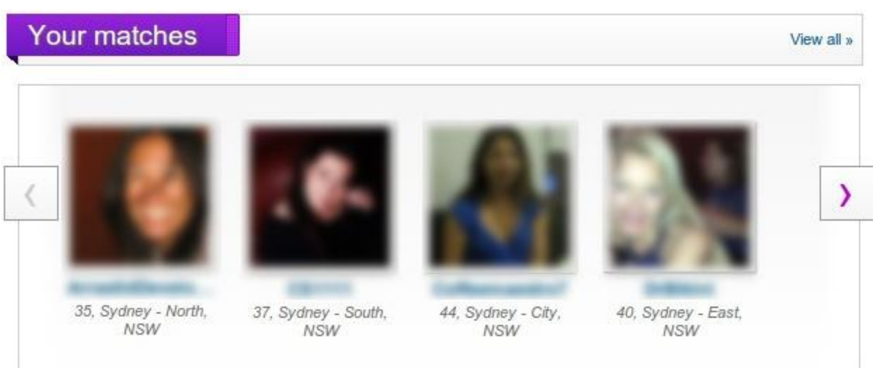
Rec. people vs product: interaction poor

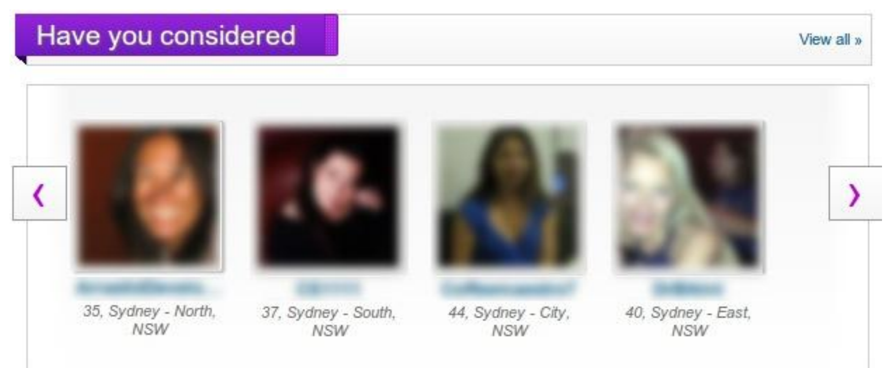
Depending on domain and purpose, users may be looking for only one successful recommendation

Rec. people vs product: interface

What are you trying to achieve with the recommendation?

- Do not confuse users
    - Does the recommendation follow the user's explicit preferences? If not, explain why.





Rec. people vs product: fraud

People to people domain have the risk of social engineering...

What types of fraud are there?

Rec. people vs product: fraud

Man duped $500K in online romance scam

British police arrest man in connection to international scam

CBC News Posted: Sep 26, 2013 5:15 PM PT | Last Updated: Sep 30, 2013 9:38 AM PT

Online romance costs Perth woman $100,000

Sep 19, 2013 | Vote 0 0

Woman duped out of $123k in online dating scam

By Molly Hayes

e than $100,000 in an online "catfish scam"

) in order to trick another person into believing

Woman Loses $50,000 in Online Dating Scam: Deputies

An Ocala woman developed an onl
her out of $50,000, officials said.

Friday, Sep 6, 2013 | Updated 1:49 PM EDT

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Local man shafted NT$180,000 in Nigerian online-dating scam

The China Post news staff
September 5, 2013, 12:34 am TWN

Print Email Tweet Share

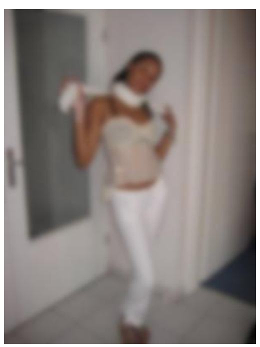
TAIPEI, Taiwan -- A Taiwanese man lost NT$180,000 to a self-proclaimed female British solider in an elaborate online dating scheme, local media reported yesterday.

Rec. people vs product: fraud

Identifying scammers is surprisingly hard in online dating

Male, 56, Medway, United States

I am a loving, kind, romantic, passionate, funny, joyful, fun, person. Looking for the same in my woman. I want chemistry, like to hold hands, affectionate, nice, woman who like to go do. I enjoy boating, swimming, the water, cars, movies, theatre, flying, singing, dancing, and I like to go traveling.



Female, 23, Agery, Australia

I'm very open minded and willing to try anything once, twice if I like it. You must be too. I'm very cute and perky. I am looking for a good person, caring, social and compassionate I like to be treated well and treat others well I love to travel I am genuine and I do not play mind games.

~4K pp, 100g

Rec. people vs product: fraud

Identifying scammers is surprisingly hard in online dating

Scammer behaviour may be biggest give away

This behaviour may influence recommender systems

How recommenders can help preventing/minimizing the risk of fraud?

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