Social Recommender Systems
Methods and User Issues

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Outline

1. Motivation
2. Definitions and Examples
3. Recommendation clues on Social Web
4. Case study
5. Evaluation Methods
6. Research Questions
7. Recommending to Groups
8. Discussions
Motivation

Let us recall types of recommender systems we have covered!

- Knowledge-based
- Utility-based
- Demographic-based
- Content-based
- **Collaborative Filtering (CF)**
Motivation

Let us recall types of recommender systems we have covered!

- Knowledge-based
- Utility-based
- Demographic-based
- Content-based
- Collaborative Filtering (CF)

Don’t underestimate: The Power of the Many and The Wisdom of the Crowd!
Amazon says:

"People who bought Book A and B also bought Book C."
Thanks to Collaborative Filtering …

Amazon says:

”People who bought Book A and B also bought Book C.”

Delicious says:

”These are the tastiest bookmarks being saved on Delicious right now by people like you.”
Moreover, thanks to social networks... 

Google recently says:

"Let us include the social circle in your search results!"

The impact of social networks\textsuperscript{2} ...

- 66% of people on social sites have asked friends or followers to help them make a decision

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- 88% of links that 14-24 year olds clicked were sent to them by a friend

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- 40% of all searches are real time "what’s going on now?"
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- 78% of consumers trust peer recommendations over ads and Google SERPs

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66% of people on social sites have asked friends or followers to help them make a decision

40% of all searches are real time “what’s going on now?”

88% of links that 14-24 year olds clicked were sent to them by a friend

78% of consumers trust peer recommendations over ads and Google SERPs

24 of the 25 largest newspapers are experiencing record declines in circulation because we no longer search for the news, the news finds us.

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\textsuperscript{a}Social Recommender Systems Ido Guy, David Carmel IBM Research-Haifa, Israel WWW 2011, March 28th - April 1st, Hyderabad
Definition

Social Recommender Systems (SRSs) are recommender systems that target at social media domain\(^a\).

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The goal of SRSs:

- Improve quality of recommendation
Social Recommender Systems

Definition

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*Social Recommender Systems* Ido Guy, David Carmel IBM Research-Haifa, Israel WWW 2011, March 28th - April 1st, Hyderabad

The goal of SRSs:

- Improve quality of recommendation
- Solve the problem of social information overload
Definition

Social media are media for social interaction and content sharing. Social media is the use of web-based and mobile technologies to turn communication into interactive dialogue.\(^a\)

\(^a\)http://en.wikipedia.org/wiki/Social_media
We are familiar with social recommenders...
We are familiar with social recommenders...
We are familiar with social recommenders...
We are familiar with social recommenders...
More ...
<table>
<thead>
<tr>
<th>Targets</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>People</td>
<td>ReferralWeb (Kautz et al., 1997), Expertise Recommender (McDonald and Acerman, 2000), SonarBuddies (Guy et al. 2008), Do You Know (DYK) (Guy et al. 2009b)</td>
</tr>
<tr>
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<td>PHOAKS (Terveen et al., 1997)</td>
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<td>Multimedia</td>
<td>Flickr, Youtube, Flixter, FilmTrust (Golbeck and Hendler 2006)</td>
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<tr>
<td>Web pages</td>
<td>Del.icio.us, Digg</td>
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<td>Cool Content</td>
<td>StumbleUpon</td>
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<tr>
<td>Groups</td>
<td>Facebook’s Fan Page, LinkedIn Group</td>
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<tr>
<td>Food recipes</td>
<td>Kalas (Svensson et al. 2005)</td>
</tr>
<tr>
<td>Ski tracks</td>
<td>Moleskiing</td>
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</tbody>
</table>
Recommendation clues on Social Web

- Familiarity
Recommendation clues on Social Web

- Familiarity
- Similarity
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Familiarity shows clues when people know each other.
Familiarity on Social Web

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Example
- Explicit connection on social web
Familiarity shows clues when people know each other.

**Example**
- Explicit connection on social web
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Example

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Familiarity on Social Web

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- **A social software recommender** (Guy et. al 2009a). Recommendations based on social relations
Activities on social web reflects **similarities** between users who may actually be strangers.

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**Example**

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Example

- **Same people**: friending, tagged by, tag person
- **Same thing**: tag with, tag used, bookmarks, interest
- **Same place**: communities, forums, blogs

---

Similarity features on Facebook

Choose your interests
Connect with your favorite celebrities, businesses and brands to hear the latest news from them. You can choose more than one.

- Lil Wayne
  6,227,483 people like this.
- Justin Bieber
  6,002,986 people like this.
- Facebook
  20,880,558 people like this.
- The Twilight Saga
  7,372,391 people like this.
- Barack Obama
  5,520,779 people like this.
- Lady Gaga
  10,601,682 people like this.
- True Blood
  2,388,776 people like this.
- Kevin Hart
  411,318 people like this.
- Maya Angelou
  2,030 people like this.
- Michael Jackson
  2,053,162 people like this.
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- True Blood: 2,388,776 people like this.
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- Miley Cyrus: 2,216,814 people like this.

**Friends similar to you**
- 4 mutual likes
- 4 mutual likes
- 3 mutual likes
- 3 mutual likes
- 3 mutual likes
- 3 mutual likes
Example

- **Digg** (Lerman 2006). Stories submitted, read or liked by people with similar interest
- **ReferralWeb** (Kautz 1997). Co-occurrence of names in close proximity in any documents publicly available on the Internet
- **Kalas** (Svensson et al. 2005). Comments and ratings from social members who share same interest
Trust on Social Web

Generate recommendations based on **user trust** on social web. Usually important in risk-high domains.

**Example**

- **Moleskiing** (Avesani et. al 2005). Trust values of users providing comments or ratings
- **FilmTrust** (Golbeck and Hendler 2006). Trust values of users who provided ratings
- **PITTCULT** (Lee 2008). Trust values of friends and non-friend users who have similar interests
Hybrid resources

Recommendation could also base on **Hybrid resources**.

**Example**

- **Do You Know (DYK)** (Guy et. al 2009b). 1) Explicit connections on a SNS, collaboration on wiki pages, or public message exchanges. 2) Similar activities, e.g. rating a same item or commenting on a same blog post.

- **People recommender Widget on Beehive** (Guy et. al 2010a). Shared contents plus shared social link.

- **A social media recommender** (Guy et. al 2010b). Social connections and similar tagging activities.
A Case Study - China’s Sina Microblog

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- Twitter-like Microblog service
- One of the largest Chinese Microblog service

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Twitter-like Microblog service
One of the largest Chinese Microblog service
140 million registered users, out of 457 million Internet users (by May 12, 2011)
"Microblog, Macroprofit"

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A Case Study - China’s Sina Microblog

Features

- Write, reply, forward, save microblog
- Following, Followers
- Joining groups
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People recommendation

- Recommendation based on common connections
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Content recommendation

Two types of content arrangement:

- Chronologically shown
- Filter tweets, due to information overload
  - By time: published time of tweet
  - By content: interest tags,
  - By friends: interaction frequency with friends, i.e., tweets from friends that interact most will be recommended
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Evaluation

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  3. **content-plus-link:** plus friend connection

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  4. SONAR: aggregates social relationship information from different public data sources within IBM, e.g. organizational chart, publication database, friending system, tagging system, blogging system etc.

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- **Two experiment**: personalized survey and controlled field study

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How effective are different algorithms in recommending people as potential friends, and what are their characteristics in terms of recommending known versus unknown people?
Evaluation - goal

1. How effective are different algorithms in recommending people as potential friends, and what are their characteristics in terms of recommending known versus unknown people?

2. Can a people recommender system effectively increase the number of friends a user has, and what would be the overall impact of such a recommender system on the site?
Personalized survey

- 500 active users in a within-subject study
- Each user was exposed to all four algorithms
- Criteria for users:
  1. Logged into Beehive during the week preceding the start of the survey.
  2. Have enough data in Beehive
  3. Have at least 5 words in their associated content
Personalized survey

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  3. Have at least 5 words in their associated content
- Show 12 recommendations for each user on a web page
- Individual recommendations presented in a regular and mirrored Latin square sequence
  - Photo, job title, work location, explanation generated by the algorithm.
Personalized survey

Survey questions

- Do you already know this person?
- Is it a good recommendation?
- Did the reason we chose this person help you make your decision?
Personalized survey

Survey questions

- Do you already know this person?
- Is it a good recommendation?
- Did the reason we chose this person help you make your decision?
- What action would you like to take?
  - Connect to this person
  - Be introduced to this person
  - Nothing
Personalized survey

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- Did the reason we chose this person help you make your decision?
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  - Nothing

Additional feedback?

Other general questions:

- Is finding the people to connect to difficult
- Are you interested in meeting new people on the site?
- The kind of information that would make them more likely connect to someone they do not know
- Whether they consider people recommendations a desired feature.
Results

- 415 logged in, 258 submitted survey form, 230 valid samples
- User needs
- Known vs. unknown; Good vs. not good
- Immediate actions resulted from recommendations
Personalized survey

Results: User needs

- 95% users considered people recommendation useful as a feature on the site
- 61.6% people are interested in connecting to weak ties and meeting new people
- What types of information make them more interested in connecting to an unknown person?
  - 75.2% said common friends
  - 74.4% said common content
  - 39.2% indicated geographical location
  - 27% choose division within IBM
Personalized survey

Results: Known vs. unknown; Good vs. not good
Personalized survey

Results: Immediate actions resulted from recommendations

![Bar chart showing results](chart.png)
Controlled filed study

- 3000 users, with similar criteria in Exp. 1, logged in Beehive 60 days before
- Between-subject study of 5 groups (600 users each)
  - 4 experiment groups, each using one algorithm
  - 1 controlled group, without recommendation
Controlled filed study

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- Between-subject study of 5 groups (600 users each)
  - 4 experiment groups, each using one algorithm
  - 1 controlled group, without recommendation
- Users in experiment groups saw 1 recommendation at a time
- After responding, users will be provided with another recommendation
- Send daily/weekly email notification messages via email
Controlled filed study

UI for controlled field study

**expand your network**

We recommend the following member to you:

Amy Schneller  
Technical Solutions Architect  
Poughkeepsie, NY US  
[view Amy's profile](opens in a new window)

You and Amy have the following 10 keyword(s) in common:

- january, craft, people, boston, meet, rome, dad, halloween, master

Your path to Amy:

You are connected through **Francesco Drew**,  
who is connected with **Amy Schneller**.

- [Get introduced to Amy](what's this?)  
- Add Amy as a connection now  
- Not good for me, show me another
Controlled filed study

Results:
- 1710 logged in, 620 responded to 7451 recommendations, distributed as follows:
  - 122 from content
  - 131 from CpL
  - 157 from FoF
  - 210 from SONAR
Controlled filed study

Results: Effectiveness of recommender algorithms
Good recommendation resulting in connection

<table>
<thead>
<tr>
<th></th>
<th>SONAR</th>
<th>FoF</th>
<th>CplusL</th>
<th>Content</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>59.7%</td>
<td>47.7%</td>
<td>40.0%</td>
<td>30.5%</td>
</tr>
</tbody>
</table>
Controlled filed study

Results: impact of people recommendations
All 4 algorithms significantly increased the number of friends compared to the controlled group.
Experiment conclusions

- Two categories of algorithms: social relationship based and content based
- Relationship based outperformed content based
- Relationship based algorithms better at finding known contacts, content similarity algorithms stronger at discovering new friends
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If we start from social matching systems\(^6\)

**Definition**

**Social matching** (SM) is recommender systems that recommend people, instead of music, movies, or books.

**Research problems for SM**

- *Terveen* and *McDonald* have defined 8 claims for SM.
- We apply them to SRSs.

---

Claim 1. SRSs need to use - and users will be willing to supply - relatively sensitive personal information.
Research problems for SRSs

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- **Claim 2.** SRSs necessarily embody a model of what makes a good match; making that model explicit leads to better matches.
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- **Claim 4.** Creating effective introductions between users is crucial, but requires balancing the effectiveness of introduction and the disclosure of personal data.
Claim 5. Size does matter for a SRS but not as much as you might think.
Research problems for SRSs

- **Claim 5.** Size does matter for a SRS but not as much as you might think.

- **Claim 6.** Designers must consider possible contexts of interaction between matched users.
Research problems for SRSs

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Claim 7. User feedback for a SRS must be relative to a specific role or context; obtaining feedback is much harder than getting user ratings for books, movies, music, etc.
Research problems for SRSs

- **Claim 5.** Size does matter for a SRS but not as much as you might think.
- **Claim 6.** Designers must consider possible contexts of interaction between matched users.
- **Claim 7.** User feedback for a SRS must be relative to a specific role or context; obtaining feedback is much harder than getting user ratings for books, movies, music, etc.
- **Claim 8.** Evaluations of SRSs should focus on users and their goals.
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**Definition**

**Group Recommender Systems (GRSs)** provide recommendations to a group of people.

**Example**

- **Pages**: Let’s Browse (Lieberman et al., 1999); GAIN (Pizzutilo et al. 2005); I-Spy (Smyth et al. 2005)
- **Tourism**: Intrigue (Ardissono et al. 2003); CATS (McCarthy et al. 2006); Travel Decision Forum (Jameson 2004); PocketRestaurantFinder (McCarthy 2002)
- **Music**: MusicFX (McCarthy and Anagnost 1998); Flytrap (Crossen et al. 2002); In-vehicle recommender (Yu et al. 2005); Adaptive Radio (Chao et al. 2005)
- **TV & Movies**: FIT (Goren-Bar and Glinansky, 2002); TV program recommender (Yu et al. 2006); PolyLens (O’Connor et al. 2001)
**Mutual Awareness** is an important measure for enhancing coordination and collaboration.

### Definition

**Mutual Awareness** enables members to be aware of the presence of the others so that they share mutual knowledge and can interact with each other.

- Membership Awareness
- Preference Awareness
- Decision Awareness
**Definition**

**Membership Awareness** allows users to check which users are in the group. Being aware of members in a group facilitates users to decide how to **behave** and thus enhances **trust** in a group recommender.

**Example**

- **TV4M** (Yu et al. 2006): multiple group members log into the system in one common user interface
- **PolyLens** (O'Connor 2001): all group members can view the membership list and remove themselves from the group.
- **CATS** (McCarthy et al. 2006): users cooperate around a common workspace and discuss about a topic.
Recommendation to Groups

Definition

Preference Awareness enables users to be aware of the preferences of other members.

Example

- **Zero awareness**: MusicFX, Flytrap and In-Vehicle music recommender (McCarthy et al. 1998; Crossen et al. 2002; Yu et al. 2005)

- **Partial awareness**

- **Full awareness**: (Collaborative Preference Specification). CATS (McCarthy et al. 2006), PocketRestaurantFinder (McCarthy 2002) and TravelDecisionForum (Jameson 2004).
  - enables users to persuade other members to specify similar preferences
  - supports explaining and justifying a members preference
  - encourages assimilation to facilitate conflict minimization
Recommending to Groups

Figure: Collaborative Preference Specification in Travel Decision Forum

Yu Chen (HCI, EPFL)

Social Recommender Systems

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Recommending to Groups

**Definition**

**Decision Awareness** helps users to make the final decision

**Example**

- **Zero awareness**: simply translating the most highly rated solution into action without the consent of any user (e.g. in MusicFX)

- **Partial awareness**: one or a selected set of representatives of the group are responsible for making the final decisions (e.g. in INTRIGUE and PolyLens)

- **Full awareness**: arriving at final decision through face-to-face discussions (CATS) or mediated discussions MIAU (Kudenko et al. 2003).
Son: I am willing to change SPEED from 200.0 to 100.0. What can you offer me in return?
Father: I am willing to change GSM from 8.0 to 10.0.
Mother: I am willing to change BHP from 40.0 to 70.0.
Daughter: I am willing to change SPEED from 150.0 to 100.0.

Figure: Decision making and negotiation in MIAU
Current SRSs focus on recommendation to individuals in the context of social media.
1. Current SRSs focus on recommendation to individuals in the context of social media.
2. Existing GRSs mainly recommend for off-line groups,
1. Current SRSs focus on recommendation to individuals in the context of social media.

2. Existing GRSs mainly recommend for off-line groups, except PolyLens
Current SRSs focus on recommendation to individuals in the context of social media.

Existing GRSs mainly recommend for off-line groups, except PolyLens.

Would social media help, for recommending for on-line groups?
Thank you!
Questions?