Recommender Systems and the next-generation Web
New opportunities

- More types of information available
- More willingness of users to contribute
- New application areas
  - Friends, pictures, movies, tags, bookmarks
Web 2.0

- **Web users connect via social networks**
  - Publish their demographic characteristics and preferences
  - Actively provide and annotate resources such as images or videos
  - Share their knowledge in community platforms

- **New types of public information spaces**
  - Web logs (blogs)
  - Wikis
  - Platforms for sharing multimedia resources

- **New capabilities of Web 2.0 greatly influence the field of recommender systems**
RS and the Social Web

- **The Web 2.0 / Social Web**
  - Facebook, Twitter, Flickr, ...
  - People actively contribute information and participate in social networks

- **Impact on recommender systems**
  - More information about user's and items available
    - Demographic information about users
    - Friendship relationships
    - Tags on resources
  - New application fields for RS technology
    - Recommend friends, resources (pictures, videos), or even tags to users
  
  => Requires the development of new algorithms
  => Currently, many papers published on this topic
Trust-aware recommender systems (TARS)

- **Trust in recommender systems**
  - Get users to believe that the recommendations made by the system are correct and fair
  - Assess the "trustworthiness" of users to discover and avoid attacks on recommender systems
  - Trust relationships between users (our focus)

- **Trust-enhanced nearest-neighbor recommender systems**
  - Exploit trust networks to improve the system performance
  - The accuracy of the recommendations can be increased
  - Alleviate the cold-start problem
  - Improve on the user coverage
Trust-aware recommender systems (TARS)

- **Explicit trust statements between users**
  - Can be expressed on some social web platforms (epinions.com)
  - Could be derived from relationships on social platforms
  - Trust is a multi-faceted, complex concept
  - Goes however beyond an "implicit" trust notion based on rating similarity

- **Exploiting trust information in RS**
  - To improve accuracy (neighborhood selection)
  - To increase coverage
  - Could be used to make RS robust against attacks
**TARS (Massa & Avesani 2007)**

- **Input**
  - Rating matrix
  - Explicit trust network (ratings between 0 – no trust, and 1 – full trust)

- **Prediction**
  - Based on usual weighted combination of ratings of the nearest neighbors
  - Similarity of neighbors is however based on the trust value

**Note**
- Assume standard Pearson CF with min. 3 peers and similarity-threshold = 0.5
- No recommendation for A possible
- However, assuming that trust is transitive and 3 trusted users are sufficient, then the rating of E could be used
- Good for cold-start situations
- Limit transitivity
Trust metrics and effectiveness

- Experiments on an Epinions.com dataset
- Effectiveness of simple algorithms
  - Simple algorithms such as "always predict value 5" or "always predict the mean rating value of a user" (Many 5-star ratings in the dataset)
  - Predict average rating of items, good results for cold-start users. However, for controversial items CF outperforms simple algorithms
- Using direct trust only
  - Uses only the opinions of users for which an explicit trust statement is available
  - Works well for cold-start users, niche items and opinionated users (have a high standard deviation in their ratings),
  - Best method with respect to mean absolute user error (MAUE)
    MAUE: compute the mean error for each user and then average these user errors over all the users. Errors of cold-start users are as influential as errors for heavy rater
  - However coverage is below CF
Trust metrics and effectiveness (cont.)

- **Trust propagation**
  - Increasing propagation distance leads to an increase in rating coverage but decreases prediction accuracy

- **Hybrids**
  - Such a combination quite intuitively leads to increased coverage but the performance did not increase
RS, social networks and trust

- **Hybrids**
  - Information from various sources might be combined to generate personalized information services (Hess et al. 2006), i.e. combine trust networks of researchers and visibility of scientific papers

- **Implicit trust**
  - One will ask friends who have similar tastes for a recommendation.
  - Trustworthiness is measured by how often a user has been a reliable predictor in the past (Massa and Avesani 2007)

- **Recommending new friends**
  - Another form of cold-start problem
  - Many of today's social web platforms aim to increase the connectivity of their members by suggesting other users as friends, e.g. "close a trust triangle" by similarity measures
Folksonomies

- Folk taxonomies
  - Users add tags to resources (such as images)
  - Tags can describe different aspects of a resource such as content, genre but also personal impressions such as *boring*
  - Folksonomies are based on freely-used keywords (e.g. on flickr.com)
  - Not as formal as ontologies, but more easy to acquire

- Semantic Web approaches
  - Formal, defined, and machine-processible annotations
  - Formal ontologies have the advantages of preciseness and definedness, they are hard to acquire

- Recommender systems and folksonomies
  - Exploit the information of how items are tagged by the community
  - Recommend tags to users
Folksonomies and content-based methods

- Recommendations based on tag clouds

- Linguistic methods for tag-based recommendation
  - merge tags assigned by users to descriptions in special slots (Gemmis et al. 2008)
Recommendations based on tag clouds

- \( n_k(u, r) \) .. number of movies annotated by keyword \( k \), assigned a rating \( r \) by user \( u \)
- \( T_{u,r} \) .. tuples \( \langle k, n_k \rangle \) where \( k \) is a keyword and \( n_k \) is the number of how often \( k \) was assigned by \( u \) to movies with rating \( r \)
- Given a user \( u \), a movie \( m^* \) and a rating \( r^* \) the appropriateness of \( r^* \) is:
  \[
  \sigma(u, m^*, r^*) = \sum_{\{\langle k, n_k \rangle \in T_{u, r^*} | k \in K_{m^*}\}} \frac{n_k(u, r^*)}{\log(N_k)}
  \]
  
  \( N_k \) .. global frequency of keyword \( k \)
  
  \( K_{m^*} \) .. set of keywords associated to \( m^* \)
  
  \( \log(N_k) \) .. the usual weighting factor for term frequencies
Recommendations based on tag clouds (cont.)

Weighted average for all possible rating values $R$

$$\overline{\sigma}(u, m^*) = \frac{1}{S(u, m^*)} \sum_{r \in R} r \times \sigma(u, m^*, r)$$

where the normalization factor is:

$$S(u, m^*) = \sum_{r \in R} \sigma(u, m^*, r)$$
Recommendations based on tag clouds (cont.)

\( \bar{r}(m^*) \) .. average rating of users who have rated \( m^* \)

The weighted estimated rating value of a movie \( m^* \) of user \( u \) is

\[
\sigma^*(u, m^*) = 0.5 \bar{r}(m^*) + 0.5 \bar{\sigma}(u, m^*)
\]

Does well for average ratings, improvements possible for extreme ratings
Linguistic methods for tag-based recommendation

(Gemmis et al. 2008)

- Items are described by static slots, e.g. title, painter

- In addition so called dynamic slots
  
  \textit{SocialTags}(I) and \textit{PersonalTags}(U,I) are added

  $I$ is an item, $U$ is a user

  - $\text{SocialTags}(I)$: tags added to $I$
  
  - $\text{PersonalTags}(U,I)$: tags added by user $U$ to $I$

  - Words in slots are replaced by synsets (synonymy set) exploiting WORDNET

  - Word sense disambiguation methods are applied

  - Slots contain a set of synsets (semantic tags)

- Finally, a Bayesian approach is applied for predicting the user rating exploiting the values of the slots
Folksonomies and collaborative filtering methods

- Tag-enhanced "classical" collaborative filtering methods
  - View tags as additional information for discovering similarities between users and items
  - For example, Tso-Sutter et al. (2008) viewed tags as additional attributes providing background knowledge

- Tag-based collaborative filtering and item retrieval
  - Social ranking (Zanardi and Capra 2008), a method that aims to determine a list of potentially interesting items in the context of a user query
  - Social ranking aims to overcome this problem by applying traditional CF ideas in a new way
  - Use user and tag similarities to retrieve a ranked list of items for a given user query
Tag-enhanced collaborative filtering

- **Difference to content-boosted CF**
  - Tags/keywords are not "global" annotations, but local for a user

- **Possible approach, a combined, tag-aware CF method**
  - Remember, in user-based CF
    - Similarity of users is used to make recommendations
    - Here, view tags as additional items (0/1 rating, if user used a tag or not); thus similarity is also influenced by tags
  - Likewise, in item-based CF, view tags as additional users (1, if item was labeled with a tag)

- **Predictions**
  - Combine user-based and item-based predictions in a weighted approach
  - Experiments show that only combination of both helps to improve accuracy
Tag-based CF and item retrieval

- **Item retrieval in Web 2.0 applications**
  - Often based on overlap of query terms and item tags
  - Insufficient for retrieving the "long tail" of items
    - Users may use different terms in their annotations
      - Think of possible tags of a car, "Volkswagen", "beetle", "red", "cool"...

- **One approach, Social Ranking**
  - Use CF methods to retrieve ranked list of items for given query
    - Compute user and tag similarities (e.g., based on co-occurrence)
  - Two-phase retrieval
    - Extend user query with similar tags (improves coverage)
    - Rank items based on
      - Relevance of tags to the query
      - Similarity of taggers to the current user
  - Leads to measurably better coverage and long-tail retrieval
Recommending tags

Tags

outback • australia • silverton • broken hill •
vw • beetle • volkswagen • car • sky •
rusty
Recommending tags

- **Remember, users annotate items very differently**

- **RS technology can be employed to help users finding appropriate tags**
  - Possible approach
    - Derive two-dimensional projections of the \(\langle User, Tag, Resource \rangle\) relation eliminating either tags or resources
    - Determine \(k\) nearest neighbors of a user \(u\) based on one projection
    - Tag \(t\) for an item \(I\) and user \(u\) is rated by counting the usage of tag \(t\) for item \(I\) by the nearest neighbors of \(u\) weighted by the similarity of the neighbors to \(u\)
    - Recommend the top \(n\) tags
  - Evaluation
    - Similarity based on User-Tag projection is better than User-Resource projection
    - Always better than "most-popular (by resource)"-strategy

- **FolkRank**
  - View folksonomy as graph and apply PageRank idea
Recommending content in participatory media

- **Second-generation web, participatory media**
  - Users contribute the content
  - Exploit information if the active user trusts the content providing person.

- **(Seth et al. 2008)**
  - Credibility of messages depend on credibility of authors which depends on topics and the active user and the opinion of her friends
  - Messages are labeled with their authors
  - Users assign a supposed credibility to messages
  - Users are explicitly connected with their "friends"
  - Every user can declare a list of topics in which he or she is interested, i.e. topic specific networks can be generated
  - Bayesian model predicts if the active user will find a new message credible
(Guy et al. 2009)

- Differentiates users in familiar and similar users w.r.t. active user
- Familiar score depends on organizational charts, direct connections in social networks, tagging of persons, co-authorship of content
- Similarity score depends on co-usage of tags, co-bookmarking the same webpage, co-commenting the same blog entry
- Recommendations based on similarity scores and familiarity scores were compared
- Explanations in terms of persons who are similar/familiar were given
- Recommendations based on familiarity scores outperformed similarity scores (user classified the recommended items as interesting, not interesting, already known)
- Effect could be caused by persuasion
- Explanations caused an increase of classifying items as interesting
Ontological filtering

- **Semantic Web community**
  - Describe web resources by languages that can be interpreted by software systems
  - Match the information need of users by exploiting machine interpretable information, e.g. OWL
  - Formulate a domain ontology

- **Apply ontology to improve recommender systems**
  - Knowledge-based techniques such as simple inheritance taxonomies and logical description
  - These recommender systems are actually hybrid systems
  - The aim is to leverage their capabilities by knowledge-based methods
Augmentation of filtering

- **Augmentation of filtering by taxonomies**
  - Hierarchical ontology
  - "sport" is a parent of "soccer" and a grandparent of "world soccer tournaments"
  - Use item profile and user profile to annotate news items and let users directly express interests

- **Augmentation of filtering by attributes**
  - Attributes used to characterize items
  - In the movie domain, attributes are genre, actors, director, and name
  - Use semantic information about items (e.g. genre, actor, etc.) to compute similarities between items
  - Combine semantic similarity and rated similarity to predict user ratings
Example for filtering by taxonomies (Maidel et al. 2008)

- **Given**
  - Item profile: set of concepts associated to items
  - User profile: set of concepts associated to users
  - Taxonomy of concepts (sub-super concept hierarchy, e.g. soccer is a sport)

- **Compute matching scores between user and item concepts**
  - Various cases: perfect match, parent/child and grandparent/grandchild match
    e.g. user is interested in sports, item is a member of soccer items
  - Each match has a score depending on matching case
  - Compute item/user match depending on the weights of the concepts of the
    active user and the matching score of user concepts and item concepts

- **Evaluation**
  - Without concept taxonomy the quality of recommendations drops significantly
  - If user explicitly states the interest in concepts, quality improves significantly
Extracting semantics from the web

- **Semantic information can provide valuable means for improving recommendations**
  - Where does this information come from?
  - How costly and reliable is the acquisition process?

- **Approaches to generate semantic information**
  - Humans are providing semantics by annotating content and by declaring logical sentences
  - Develop software systems that are able to generate semantics with little or no human intervention (particularly attractive)
AllRight system (Jannach et al. 2009)
Discussion – The Filter Bubble
Summary

- Opportunities, current methods, and realizations of Web 2.0

- Semantic Web for recommender systems

- Exploit additional information to contribute more trustworthy and qualitative enhanced recommendations

- Both Web 2.0 and the Semantic Web in combination not only drive new technologies but have huge impacts on society regarding the communication and interaction patterns of humans

- Recommendations shape the users’ behavior in Web++
Literature


