




Inspire…Educate…Transform.

Recommendation Systems

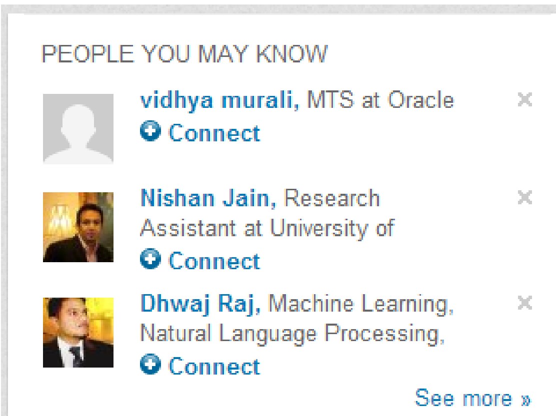
Dr. Manish Gupta

Sr. Mentor – Academics, INSOFE

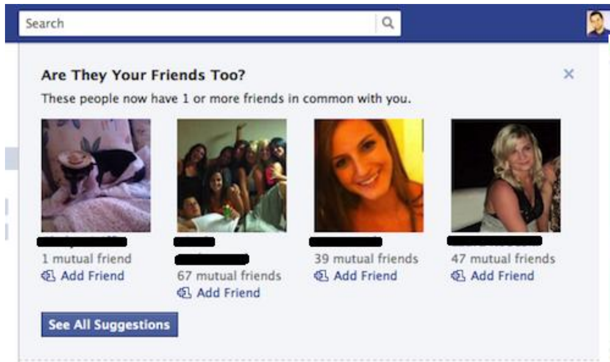
Slides borrowed (and modified) from http://www.slideshare.net/idoguy/social-recommender-systems-tutorial-www-2011-7446137

Recommendation Systems Everywhere

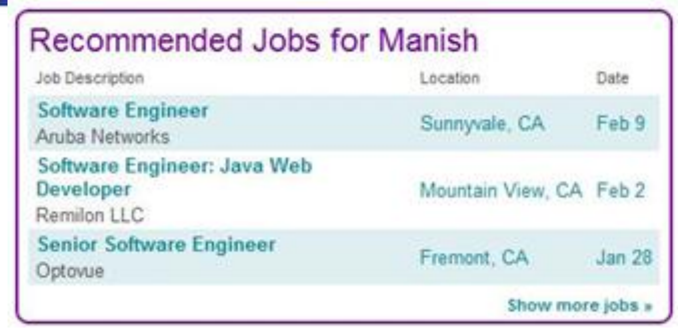
LinkedIn People Recommendations



Facebook People Recommendations

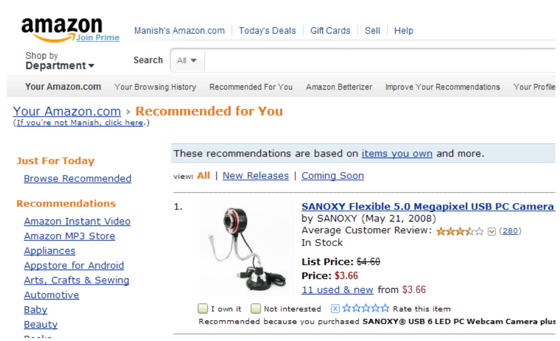


HotJobs Job Recommendations

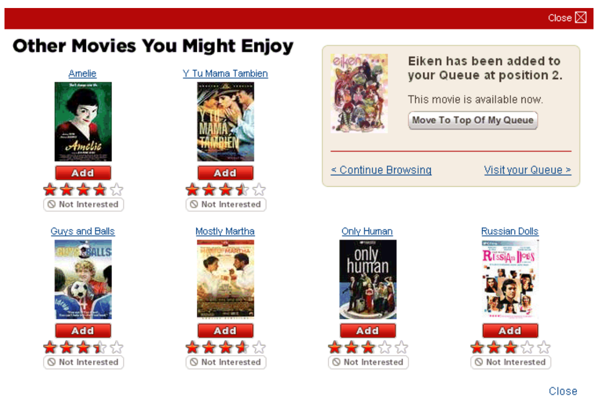


Bing Query Recommendations

Amazon Product Recommendations



Netflix Movie Recommendations



CSE 7306c

Social Overload

- Information Overload
  - Blogs, microblogs, forums, wikis, news, bookmarked webpages, photos, videos, etc.
- Interaction Overload
  - Friends, followers, followees, commenters, co-members, voters, likers, taggers, review writers, etc.

CSE 7306c

Social Recommender Systems

- Recommender Systems that target the social media domain
- Aim at coping with the challenge of social overload by presenting the most attractive and relevant content
- Also aim at increasing adoption and engagement
- Often apply personalization techniques

Collaborative Filtering

- In the real world we seek advices from our trusted people (friends, colleagues, experts)
- CF automates the process of "word-of-mouth"
  - Weight all users with respect to similarity with the active user.
  - Select a subset of the users (neighbors) to use as recommenders
  - Predict the rating of the active user for specific items based on its neighbors' ratings
  - Recommend items with maximum prediction

User-based CF Algorithm

- The User x Item Matrix

	Shrek	Snow-white	Superman
Alice	Like	Like	Dislike
Bob	?	Dislike	Like
Chris	Like	Like	Dislike
John	Like	Like	?

- Shall we recommend Superman for John?
- John's taste is similar to both Chris and Alice tastes ⇒ Do not recommend Superman to Jon

CSE 7306c

User-based CF Algorithm

- Let R be the rating matrix
  - r_{uj} is then the vote of user u for item j
- I_u be the set of items for which user u has provided the rating
- Voting
  - Mean vote for user u: $\bar{r_u} = \frac{1}{|I_u|}\sum_{i \in I_u} r_{ui}$
  - Prediction rating: $p_{uj} = \bar{r_u} + \gamma \sum_{v=1}^{n} w(u,v)(r_{vj} - \bar{r_v})$
    - $w(u,v)$ = similarity between users u and v
    - γ is a normalization constant $\gamma = \frac{1}{\sum_{v=1}^{n} w(u,v)}$

CSE 7306c

User-based CF Algorithm

- Cosine based similarity between users
  - $w(u,v) = \frac{\sum_{i \in I} r_{ui} r_{vi}}{\sqrt{\sum_{i \in I} r_{ui}^2} \sqrt{\sum_{i \in I} r_{vi}^2}}$
- Pearson based similarity between users
  - $w(u,v) = \frac{\sum_{i \in I} (r_{ui} - \overline{r_u})(r_{vi} - \overline{r_v})}{\sqrt{\sum_{i \in I} (r_{ui} - \overline{r_u})^2} \sqrt{\sum_{i \in I} (r_{vi} - \overline{r_v})^2}}$

CF - Practical Challenges

- Ratings data is often sparse, and pairs of users with few co-ratings are prone to skewed correlations
- Fails to incorporate agreement about an item in the population as a whole
  - Agreement about a universally loved item is much less important than agreement for a controversial item
    - Some algorithms account for global item agreement by including weights inversely proportional to an item’s popularity
- Calculating a user’s perfect neighborhood is expensive – requiring comparison against all other users
  - Sampling: a subset of users is selected prior to prediction computation
  - Clustering: can be used to quickly locate a user's neighbors

Enhancing CF with Friends

- The user's network of friends and people of interest has become more accessible in the Web 2.0 era (Facebook, LinkedIn, Twitter,...)
- Such social relationships can be very effective for recommendation compared to traditional CF
  - Recommendation from people the user knows
  - Spare explicit feedback such as ratings
  - Effective for new users
- Various works have shown the effectiveness of friend-based recommendation over CF, e.g.:
  - Movie and book recommendation - Comparing Recommendations Made by Online Systems and Friends [Sinha & Swearingen, 2001]
  - Friends as trusted recommenders for movies [Golbeck, 2006]
  - Club recommendation within a German SNS - Collaborative Filtering vs. Social Filtering [Groh & Ehmig, Group 2007]

Item-Based Nearest Neighbor Algorithms

- The transpose of the user-based algorithms
  - Generate predictions based on similarities between items
  - The prediction for an item is based on the user's ratings for similar items

	Shrek	Snow-white	Superman
Alice	Like	Like	Dislike
Bob	?	Dislike	Like
Chris	Like	Like	Dislike
John	Like	Like	?

- Bob dislikes Snow-white (which is similar to Shrek) ⇒ do not recommend Shrek to Bob
- Predicted rating: $p_{uj} = \gamma \sum_{i=1}^{m} w(i,j) r_{ui}$
- Traverse over all m items rated by user u and measure their rating, averaged by their similarity to the predicted item
- w(i,j) is a measure of item similarity - usually the cosine measure
- Average correction is not needed because the component ratings are all from the same target user

Dimensionality Reduction Algorithms

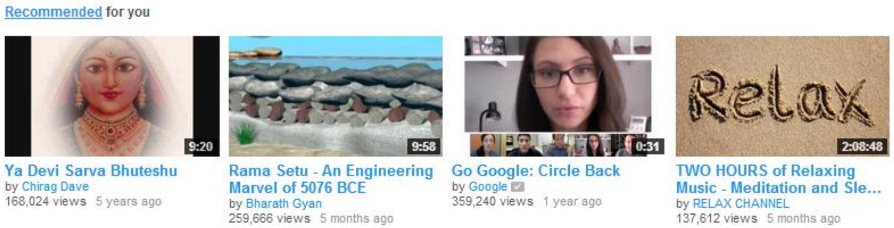
- Reduce domain complexity by mapping the item space to a smaller number of underlying “dimensions”
  - Represent the latent topics present in those items
  - Improve accuracy in predicting ratings in most cases
  - Reduce run-time performance needs and lead to larger numbers of co-rated dimensions
- Popular techniques: Singular Value Decomposition and Principal Component Analysis
  - Require an extremely expensive offline computation step to generate the latent dimensional space

Hybrid Recommendation Methods

- Any Recommendation approach has pros and cons
  - e.g. CF & CB both suffer from the cold start problem
  - but CF can recommend "outside the box" compared to Content-based approaches
- Hybrid recommender system combines two or more techniques to gain better performance with fewer drawbacks
- Hybrid methods:
  - Weighted: scores of several recommenders are combined together
  - Switching: switch between recommenders according to the current situation
  - Mixed: present recommendations that are coming from several recommenders
  - Cascade: One recommender refines the recommendations given by another

Content Recommendation: Videos

- The YouTube Video Recommendation System [Davidson et al., RecSys '10]



- Goals
  - recent and fresh
  - diverse
  - relevant to the user's recent actions
  - users should understand why a video was recommended to them
- Based on user’s personal activities (watched, favorited, liked)
- Using co-visitation graph of videos
- Ranking based on a variety of signals for relevance and diversity

The Cold Start Problem

- The Cold Start problem concerns the issue where the RS cannot draw inferences for users or items for which it has not yet gathered sufficient information
- New items
  - e.g., a newly created document w/o tags or bookmarks
  - e.g., a newly created community w/o members
- New users
  - e.g., a user that has just signed up to a new site
  - e.g., a new member or employee
- Typically addressed by applying a hybrid approach

The Cold Start Problem of New Items

- Traditional CF systems are based on item ratings
  - Until rated by a substantial number of users, the system will not be able to recommend the item
- a.k.a the "early rater" problem – first person to rate an item gets little benefit
- Same for implicit feedback over items – clicks, searches, comments, tags
- Even more acute for activity streams, where items quickly come and go
- Typically addressed by integrating CB similarity measurements
  - Recommendation based on the data of older similar items

The Cold Start Problem for New Users

- Sometimes also referred to as the “New User Problem”
- User needs to rate sufficient items for a CB recommender to really understand the user’s preferences
- Mitigated by CF – similar users who rated more items can yield more recommendations
- Traditional CF still faces an issue if the user did not provide any explicit feedback (or very small amount of feedback)
- Typically resolved through building a user profile by integrating other user activity (implicit feedback)
  - Browsing history, click-through data, searches
- Social media introduces new ways to learn about the user from external sources
  - Friends (“social filtering”), tags, communities, …
  - More public information which is less sensitive to privacy issues

CSE 7306c

Trust in Recommendation (by Explanations)

- MoviExplain: A Recommender System with Explanations (Symeonidis 09)
- Good explanations could help inspire user trust and loyalty, increase satisfaction, make it quicker and easier for users to find what they want, and persuade them to try or purchase a recommended item

Our Justified Recommendations

[Movie id]	[Movie title]	[The reason is]	[because you rated]
1526	Witness (1985)	Ford, Harrison (I)	21 movies with this feature
1273	Color of Night (1994)	Willis, Bruce	7 movies with this feature
1004	Geronimo: An American Legend (1993)	Hackman, Gene	7 movies with this feature
1442	Scarlet Letter, The (1995)	Oldman, Gary	7 movies with this feature
1044	Paper, The (1994)	Close, Glenn	7 movies with this feature
693	Casino (1995)	De Niro, Robert	6 movies with this feature
274	Sabrina (1995)	Pollack, Sydney	6 movies with this feature
1092	Dear God (1996)	Kinnear, Greg	5 movies with this feature

Explanation Types

- Nearest neighbor explanation
  - Customers who bought item X also bought items Y, Z
  - Item Y is recommended because you rated related item X
- Content based explanation
  - This story deals with topics X, Y which belong to your topic of interest
- Social based explanation
  - People leverage their social network to reach information and make use of trust relationships to filter information
    - Your friend X wrote that blog
    - 50% of your friends liked this item (while only 5% disliked it)

Evaluation Goals

- An application designer who wishes to add a recommendation system to her application must make a decision about the most appropriate algorithm for her goals
- Most evaluation methods rank systems based on
  - Prediction power — the ability to accurately predict the user's choices
  - Classification accuracy – the ability to differentiate good items from bad ones.
  - Novelty and Exploration ability -discovering new items, and exploring diverse items
  - Other features
    - Preserving the user privacy
    - Fast response
    - Ease of interaction with the recommendation engine

Offline Evaluation

- Based on a pre-collected data set of users choosing or rating items
  - Usually done by recording historical user data, and then hiding some of these interactions in order to compare the user predicted rating with her actual rating
- No interaction with real users, thus allow comparing a wide range of candidate algorithms at a low cost
- Mostly useful for evaluating the prediction power of the system and for system tuning

Online Evaluation

- Evaluate the system by real users that perform real tasks
  - Provides the strongest evidence for the true value of the system to its users
  - The real effect of the recommendation system depends on a variety of user's dependent factors that are changed dynamically
    - The user current intent
    - The user's current context
- Feedback from the users is collected by observing their feedback to the system's recommendation
  - Systems are evaluated according to the acquired vs. non-acquired ratio
- Such a live user experiment may be controlled
  - Randomly assign users to different conditions
    - e.g. test a new version of your system on a test set of users
  - A/B testing: split users to test groups and measure effectiveness of different conditions/algorithms on the groups
- On-line evaluation studies are done on a regular basis by commercial Recommendation Systems

International School of Engineering

Plot 63/A, 1st Floor, Road # 13, Film Nagar, Jubilee Hills, Hyderabad - 500 033

For Individuals:	+91-9502334561/63 or 040-65743991
For Corporates:	+91-9618483483
Web:	http://www.insofe.edu.in
Facebook:	https://www.facebook.com/insofe
Twitter:	https://twitter.com/Insofeedu
YouTube:	http://www.youtube.com/InsofeVideos
SlideShare:	http://www.slideshare.net/INSOFE
LinkedIn:	http://www.linkedin.com/company/international-school-of-engineering

This presentation may contain references to findings of various reports available in the public domain. INSOFE makes no representation as to their accuracy or that the organization subscribes to those findings.