The GroupLens Research Project:
Collaborative Filtering Recommender Systems

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About me …

Associate Professor of Computer Science & Engineering, Univ. of Minnesota
Ph.D. (1993) from U.C. Berkeley
  • GUI toolkit architecture
Teaching Interests: HCI, GUI Tools
Research Interests: General HCI, and …
  • Collaborative Information Filtering
  • Multimedia Authoring and Systems
  • Web Automation
  • Visualization and Information Management

The Problem:
Information Overload

Too many
  • research papers
  • books
  • Usenet News articles
  • web pages
  • … even movies!

History of Recommender Systems

The Early Years …

Why cave dwellers survived
Critics, critics, everywhere
Editors and publishers, bishops and kings

Recommenders

Tools to help identify worthwhile stuff
  • Filtering interfaces
    ➔ E-mail filters, clipping services
  • Recommendation interfaces
    ➔ Suggestion lists, “top-n,” offers and promotions
  • Prediction interfaces
    ➔ Evaluate candidates, predicted ratings
**Information Filtering**

Information retrieval
- Dynamic information need
- Static content base

Information filtering
- Static information need
- Dynamic content base

**Collaborative Filtering**

Premise
- Information needs more complex than keywords or topics: quality and taste

Small Community: Manual
- Tapestry – database of content & comments
- Active CF – easy mechanisms for forwarding content to relevant readers

**Usenet Trial**

(Miller et al. Usenet ’97; Konstan et al. CACM Mar. ’97)

Medium-scale Usenet trial
- seven weeks
- 250 users; 47,569 ratings; over 600,000 predictions
- variety of newsgroups
  - moderated and unmoderated
  - technical and recreational
- gathered reading activity as well as ratings

**Automated CF**

The GroupLens Project
(Resnick et al. CSCW ’94)
- ACF for Usenet News
  - users rate items
  - users are correlated with other users
  - personal predictions for unrated items
- Nearest-Neighbor Approach
  - find people with history of agreement
  - assume stable tastes

**Does it Work?**

Yes: The numbers don’t lie!
- Usenet trial: rating/prediction correlation
  - rec.humor: 0.62 (personalized) vs. 0.49 (avg.)
  - comp.os.linux.system: 0.55 (pers.) vs. 0.41 (avg.)
  - rec.food.recipes: 0.33 (pers.) vs. 0.05 (avg.)
- Significantly more accurate than predicting average or modal rating.
- Higher accuracy when partitioned by newsgroup
It Works
Meaningfully Well!

Relationship with User Behavior
- Twice as likely to read 4/5 than 1/2/3

Users Like GroupLens
- Some users stayed 12 months after the trial!

ACF Blossomed

1995
- Ringo (later Firefly)
- Bellcore Video Recommender

1996 Recommender Systems Workshop

Early commercialization
- Agents Inc. (later Firefly)
- Net Perceptions
  new issues of scale and performance!

Today

Broad research community
- live research systems
- substantial integration with machine learning, information filtering

Increasing commercial application
- available commercial tools
Recommender Systems

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How It Works
GroupLens Model of Information Filtering

- Users rate Items.
- Users are correlated with other users.
- Predictions made for an item’s value to a particular user by combining ratings of highly correlated users who rated it.
- Recommendations for items for a particular user by identifying popular items among correlated users.
**Understanding the Computation**

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**Broader Approaches to Recommendation**

**Information Retrieval**

Assumptions:
- Usable “keywords” or content features
- Relatively stable information base
- Ephemeral information need

Approach:
- Map query into index of information base
  - TFIDF – term frequency inverse document frequency
Information Filtering

Assumptions:
- Usable keywords or content features
- Stream of information
- Relatively stable information need

Approach
- “Standing queries” against which new content is passed
- Feedback mechanisms to form/update/validate queries

Content-Space Navigation

Assumptions:
- Well-structured content spaces
- Navigation along dimensions

Approach
- Get user into space
- Navigate in sensible directions

Intelligent Agents

Interface model
- “Agent” watches behavior, may also be explicitly instructed or programmed.
- Takes action on behalf of user: finding, sorting, or discarding information.

Approach
- Variety of approaches from pure IF and machine learning to collaborative and hybrid systems
Social Navigation

Assumptions:
- Awareness of others (current or past) helps user find relevant path
- Paths/location of others is distinctive enough for user to recognize

Approach
- Make history or present visible

Recent and Current Research

Other Collaborative Filtering Models

Pull-active CF
- Database of ratings
- User can query
- Tapestry system

Push-active CF
- Easy mechanisms for recommendation
- Maltz/Ehrlich Lotus Notes system
- Joke-forwarding

Interfaces and User Experience

Explaining Recommendations

Ephemeral Recommendations

The Value-of-Information Challenge

PolyLens: Multi-User Recommendations

MetaLens: Multi-Source Recommendations
Other Research (not covered in this talk)
- Algorithm Performance and Metrics (Herlocker)
- Dimensionality Reduction (Sarwar)
- Filterbots (Sarwar, Good)
- Distributed Recommenders (Sarwar)
- E-Commerce Recommender Applications (Schafer)
- User and Usage Studies

Two Studies

Pilot study of explanation feature
- Users liked explain
- Unclear whether they become more effective decision-makers

Comprehensive study of different explanation approaches
- Wide variation of effectiveness
- Some explanations hurt decision-making

Interfaces and User Experience

Explaining Recommendations
(Herlocker et al. CSCW 2000)

Challenge: Belief
- Why should users believe the recommendations?
- When should users believe the recommendations?

Approach
- Explain recommendations
  - Reveal data, process
  - Corroborating data, track record

Most Compelling Interfaces

- Simple visual representations of neighbors ratings
- Statement of strong previous performance “MovieLens has predicted correctly 80% of the time for you”

Less Compelling Interfaces

- Anything with even minimal complexity
  - More than two dimensions
- Any use of statistical terminology
  - Correlation, variance, etc.
Addressing Ephemeral Needs
(Herlocker)

What is an ephemeral interest need?
- Immediate, temporary, dynamic

Current systems don’t support this
- Assume interests will remain relatively constant
- Recommendations are relative to all your interests as a whole

One Simple Approach

User submits “theme” query
- Theme contains examples of items similar to those desired by the user

Set of potentially similar items identified
- Using item-to-item correlation in ratings space

Potentially similar items ranked based on traditional ACF predictions

Theme Selection

Users were very positive about the theme query interface
Relevance of results were dependent on the “support threshold”
- Low support threshold => fewer relevant results
When results were relevant, users were positive overall
Even the users in the low support threshold groups indicated they would like to have the interface added to MovieLens

Query Results

Theme Creation

Results of Theme Query Study
The VOI Challenge

Context:
- What movies should we ask new users about?
  - Popular movies?
  - Contentious movies?
  - Movies we think the user has seen?

Value of Information

Value is higher when contentious
- More information content

Value to community may be high for rare
- Recommend something new to others

Popular movies build neighborhoods faster
- More overlap with other users

Users want to be able to rate
- Too unpopular may turn away users

Recent Experiments

Looked at several alternatives:
- Random movies
- Entropy (information-theoretic value)
- Popularity (number of ratings)
- Mix of entropy and popularity
- Movies we predict the user has seen (item-to-item correlations)

Results

Item-item picks well, but the resulting profile recommends poorly
- Not balanced view
- Ate the low-hanging fruit

Random and entropy overly frustrated pilot users
Mix of popularity and entropy seems good

PolyLens: A Group Recommender

(O’Connor et al. ECSCW 2001)

Challenge: People watch movies together
Solution: A recommender for groups

Issues
- Group formation, rules, composition
- Recommender algorithm for groups
- User interface

Goals

Explore group recommender design space
See if users would want and use a group recommender, at least for movies

Study behavior changes in group members
- Group vs. other users
- New users via groups vs. other new users

Learn lessons about group recommenders
Design Issues

Characteristics of groups
- public or private
- many or few
- permanent or ephemeral

Formation and evolution of groups
- joining policy
- administration and rights

Design Issues

What is a group recommendation?
- group user vs. combined individuals
- social good functions

Privacy and interface issues
- control over joining groups
- withholding and recommendations
- balancing between info overload and support

Survey and Usage Results

Satisfaction (95% like, 77% more useful)
Privacy not an issue (94% see, 93% share)
- individual recommendations “essential”

Groups reflect “real life” groups
New users via groups stayed 1.5x as often
- group vs. other users a wash
Many stillborn groups

PolyLens

Design choices
- private, small, administered, invited groups
- combine individual recs with minimum misery
- high-information interface with opt-out

External invitations added by popular demand

Field Test Results and Lessons

Users like and use group recommenders
- groups have value for all members
- groups can help with outreach to new members

Users trade privacy for utility
Groups are both permanent and ephemeral
Users must be able to find each other
**MetaLens: A Meta- Recommender**  
(Schafer)

Integrating multiple sources of information into a single recommendation list

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**Sources of Data**

- Genre
- MPAA ratings
- Film length
- Objectionable Content
- Distributor
- Release Date
- Start/End Time
- Critical Reviews
- Average User Rating
- User’s personalized MovieLens prediction
- Distance to the Theater
- Special Accommodations
- Discounted Shows

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**What is the problem?**

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**One solution**

Meta-recommendation system

MetaLens
What Have We Learned?

- Meta-recommenders can be built.
- Anecdotally, users like them.
- Some users make heavy use of them, and heavy users are most likely to make some use of them.

Conclusions and Future Work

Conclusions

Collaborative filtering works!

Lots of important issues:
- Algorithms
- Interfaces and User Experience
- Privacy
- Applications

Future Work

- Better integration of collaborative and content filtering
- Better support for community
- Better understanding of user rewards, social role of recommenders

CF Under Diminishing Returns

Original goal of CF was to help people sift through the junk to find the good stuff.

Today, there may be so much good stuff that you need to sift even more.

Certain types of content yield diminishing returns, even with high quality

Portfolios of Content

What if my recommender knows which articles I’ve read, and can identify articles by topic?

What if it sees that I experience marginal returns from reading similar articles on a topic?

Could we downgrade some articles based on “lack of new content?” Could we discover which articles using collaborative filtering?
Temporal Collaborative Filtering

Today’s CF systems may expire or degrade ratings, but do little to detect or predict changes in preference.

Ripe area with lots of commercial applications …

Wine for the Time

Seasonal taste – can we detect that a particular customer shifts wine tastes during hot and cold weather? Can we learn either the content, or separate profiles, reflecting these different tastes?

Evolving taste – can we help a wine newcomer build her palate? Could we identify wines that take her a step or two beyond her current ones? Can we do so by augmenting regular collaborative filtering with temporal models?

Acknowledgements

• This work is being supported by grants from the National Science Foundation, and by grants from Net Perceptions, Inc.

• Many people have contributed ideas, time, and energy to this project.