Recommender Systems:
User Experience and System Issues
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Scope of Recommenders
- Purely Editorial Recommenders
- Content Filtering Recommenders
- Collaborative Filtering Recommenders
- Hybrid Recommenders

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
  - Visualization and Information Management
  - Interesting Applications and their Delivery

Wide Range of Algorithms
- Simple Keyword Vector Matches
- Pure Nearest-Neighbor Collaborative Filtering
- Machine Learning on Content or Ratings

A Quick Introduction
What are recommender systems?
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

Classic Collaborative Filtering
- MovieLens*
- K-nearest neighbor algorithm
- Model-free, memory-based implementation
- Intuitive application, supports typical interfaces
*Note – newest release uses updated architecture/algorithm
### Understanding the Computation

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**Talk Roadmap**

- Introduction
- Application Space
- Algorithms
- Influencing Users
- Group Recommenders
- Recommending Research Papers

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**Recommender Application Space**

Dimensions of Analysis
- Domain
- Purpose
- Whose Opinion
- Personalization Level
- Privacy and Trustworthiness
- Interfaces
- Algorithms Used

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**Domains of Recommendation**

- Content to Commerce
  - News, information, “text”
  - Products, vendors, bundles
Purposes of Recommendation

The recommendations themselves

- Sales
- Information

Education of user/customer

Build a community of users/customers around products or content
ReferralWeb

Whose Opinion?

“Experts”
Ordinary “phoaks”
People like you

Personalization Level

Generic
- Everyone receives same recommendations
Demographic
- Matches a target group
Ephemeral
- Matches current activity
Persistent
- Matches long-term interests
Privacy and Trustworthiness

Who knows what about me?
- Personal information revealed
- Identity
- Deniability of preferences

Is the recommendation honest?
- Biases built-in by operator
  - "business rules"
- Vulnerability to external manipulation

Interfaces

Types of Output
- Predictions
- Recommendations
- Filtering
- Organic vs. explicit presentation

Types of Input
- Explicit
- Implicit
Collaborative Filtering Algorithms

Non-Personalized Summary Statistics
K-Nearest Neighbor
Dimensionality Reduction
Content + Collaborative Filtering
Graph Techniques
Clustering
Classifier Learning

Is Non-Personalized Good Enough?

What happened to my favorite guide?
◆ They let you rate the restaurants!

What should be done?
◆ Personalized guides, from the people who “know good restaurants!”

Collaborative Filtering Algorithms

Non-Personalized Summary Statistics
K-Nearest Neighbor
◆ user-user
◆ item-item
Dimensionality Reduction
Content + Collaborative Filtering
Graph Techniques
Clustering
Classifier Learning

Item-Item Collaborative Filtering
Item-Item Collaborative Filtering

Item-Item Matrix Formulation

Item-Item Discussion

Collaborative Filtering Algorithms

Non-Personalized Summary Statistics
K-Nearest Neighbor
Dimensionality Reduction
- Singular Value Decomposition
- Factor Analysis
Content + Collaborative Filtering
Graph Techniques
Clustering
Classifier Learning
Dimensionality Reduction

Latent Semantic Indexing
- Used by the IR community
- Worked well with the vector space model
- Used Singular Value Decomposition (SVD)

Main Idea
- Term-document matching in feature space
- Captures latent association
- Reduced space is less-noisy

Singular Value Decomposition

Reduce dimensionality of problem
Results in small, fast model
Richer Neighbor Network
Incremental Update
Folding in
Model Update

SVD: Mathematical Background

\[ R_{m \times n} = U_{m \times k} S_{k \times k} V'_{k \times n} \]

The reconstructed matrix \( R_k = U_k S_k V'_k \) is the closest rank-\( k \) matrix to the original matrix \( R \).

Collaborative Filtering Algorithms

Non-Personalized Summary Statistics
K-Nearest Neighbor
Dimensionality Reduction
Content + Collaborative Filtering
Graph Techniques
  - Horting: Navigate Similarity Graph
Clustering
Classifier Learning
  - Rule-Induction Learning
  - Bayesian Belief Networks

SVD for Collaborative Filtering

1. Low dimensional representation
   \( O(m+n) \) storage requirement

2. Direct Prediction

Talk Roadmap

- Introduction
- Application Space
- Algorithms
  - Influencing Users
    - Cosley et al., CHI 2002
  - Group Recommenders
  - Recommending Research Papers
Does Seeing Predictions Affect User Ratings?

RERATE: Ask 212 users to rate 40 movies

- 10 with no shown prediction
- 30 with shown predictions (random order):
  - 10 accurate, 10 up a star, 10 down a star

Compare ratings to accurate predictions

- “Prediction” is user’s original rating
- Hypothesis: users rate in the direction of the shown prediction

The Study

<table>
<thead>
<tr>
<th>PREDICTED RATING</th>
<th>YOUR RATING</th>
<th>GENRE</th>
<th>TITLE</th>
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Accuracy Matters

Accuracy Matters

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<th>Ratings %</th>
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Domino Effects?

Seeing Matters

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<th>Ratings %</th>
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<td>Not shown</td>
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Rated, Unrated, Doesn’t Matter

Recap of RERATE effects:

- Showing prediction changed 8% of ratings
- Altering shown prediction changed 12%

Similar experiment, UNRATED movies

- 137 experimental users, 1599 ratings
- Showing prediction changed 8% of ratings
- Altering shown prediction changed 14%
But Users Notice!

Users are often insensitive…
UNRATED part 2: satisfaction survey
  ◆ Control group: only accurate predictions
  ◆ Experimental predictions accurate, useful?
  ◆ ML predictions overall accurate, useful?
Manipulated preds less well liked
Surprise: 24 bad = MovieLens worse!

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

Talk Roadmap

✓ Introduction
✓ Application Space
✓ Algorithms
✓ Influencing Users
  ◆ Group Recommenders
    O’Conner et al, ECSCW 2001
  ◆ Recommending Research Papers

Design Issues

Characteristics of groups
  ◆ public or private
  ◆ many or few
  ◆ permanent or ephemeral
Formation and evolution of groups
  ◆ joining policy
  ◆ administration and rights

Recommend for Groups

Problem: People watch movies together
Solution: A recommender for groups
Issues
  ◆ Group formation, rules, composition
  ◆ Recommender algorithm for groups
  ◆ User interface

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
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

Subsequent Redesign

Move from groups to buddies
- Hybrid permanent/ephemeral
- Lower overhead for subgroups

Support e-mail based invitation
- Viral marketing
- No need for ML logins

Remove most privacy settings
- Buddy model supports person-to-person rather than person-to-group

Talk Roadmap

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  McNeel et al, CSCW 2002

Citation Webs

- Wonderful network already exists between research papers
- Papers link to other papers
- ACI in ResearchIndex (Lawrence, 1999)
- A ‘citation’ versus a ‘full paper’
- Citations are “pointers to papers”
- Leverage in CF System?
**CF using Citation Webs**

- Map the citation web directly onto the ratings matrix
  - Full papers are “users”
  - Citations are “items”
GroupLens Model

C.F. Engine

Ratings

Correlations

Votes

Request

GroupLens Model

C.F. Engine

Ratings

Correlations

Votes

Request

CF using Citation Webs

- For a full paper, we can recommend citations
- Every paper has ratings in the system
- Other citation web mappings are possible, but many are have problems
Informal Results

Off-line studies showed promise
On-line study showed different algorithms met different needs
- General positive attitude from users
- Typically one or two useful recommendations in a set of five
  - That’s enough to be useful
A lot of work remains to be done!

Talk Roadmap

- Introduction
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- Recommending Research Papers
  - Conclusions!

Two Grand Challenges

Diminishing Marginal Returns
- Why today’s recommenders won’t be enough ten years from now

Temporal Recommendation
- Beyond reacting ...
**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.

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**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?

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**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 …

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**Wine for the Time**

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?

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**Acknowledgements**

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

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