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!

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

History of Recommender Systems

The Early Years …

Why cave dwellers survived

Critics, critics, everywhere

Editors and publishers, bishops and kings

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

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

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

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

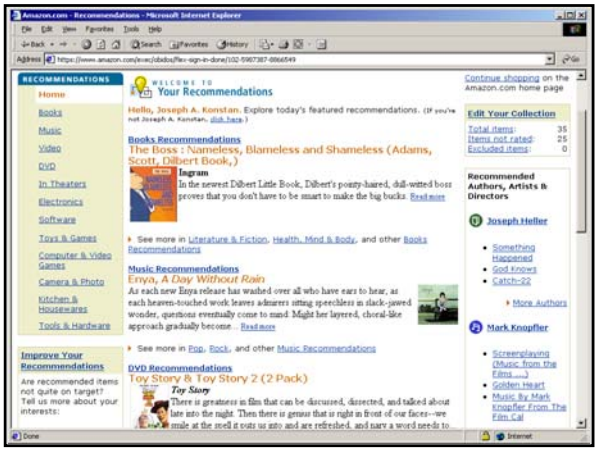
It Works Meaningfully Well!

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

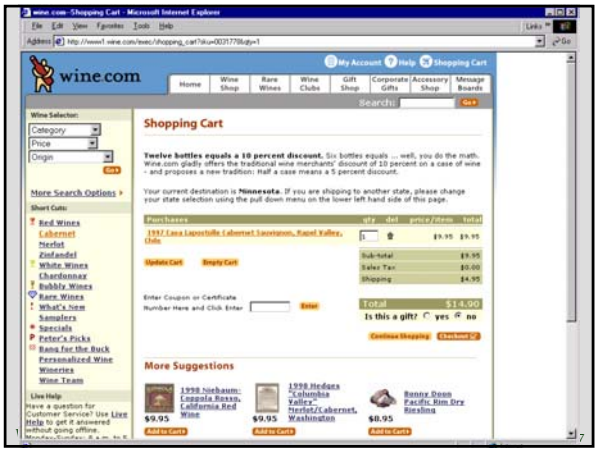
- Ringo (later Firefly)
- Bellcore Video Recommender

1996 Recommender Systems Workshop

Early commercialization

- Agents Inc. (later Firefly)
- Net Perceptions

new issues of scale and performance!



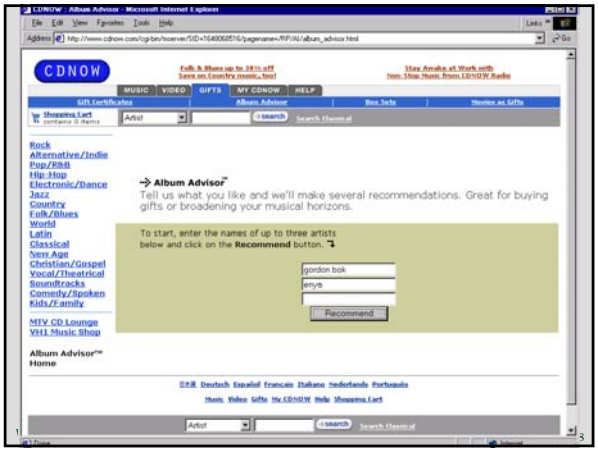
Today

Broad research community

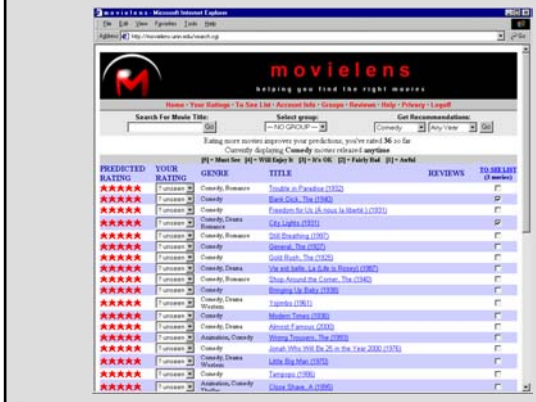
- live research systems
- substantial integration with machine learning, information filtering

Increasing commercial application

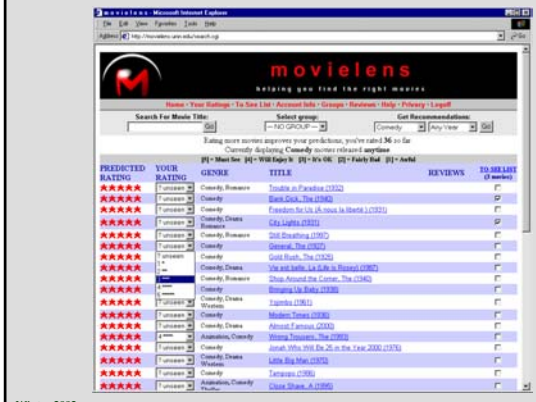
- available commercial tools




CDNOW - Album Advisor - Microsoft Internet Explorer
Ace Of Base
Cruel Summer
List $16.97
Add to Cart $12.99
Listen
"Cruel Summer"
Real Audio
Windows Media
See complete track list and more album info.
Fantasia 2000
Score
List $17.97
Add to Cart $13.99
Listen
"Symphony No.5"
Real Audio
See complete track list and more album info.
Erasure
Abba-Esque
List $6.97
Add to Cart $6.99
Listen
"Lay All Your Love On Me"
Real Audio
Windows Media
See complete track list and more album info.
Vangelis
Opera Sauvage
List $11.97
Listen
"Hymne"


movielens
helping you find the right movies


movielens
helping you find the right movies
Welcome to MovieLens, konstan@cs.umn.edu!
Have you ever wanted to get movie recommendations for a group of friends or relatives? Now you can with MovieLens! Try groups now:
Just want to rate some movies? Use the "Get Recommendations" at the top of the page to select a set of movies you would be interested in rating. Any movie you get a recommendation for, you can rate.
Our privacy statement last changed on April 26, 2000.
We have many movie reviewers in our database, and will be adding more every week!
Here are the 100 most recent additions to our movie database.
MovieLens is a free service provided by GroupLens Research at the University of Minnesota.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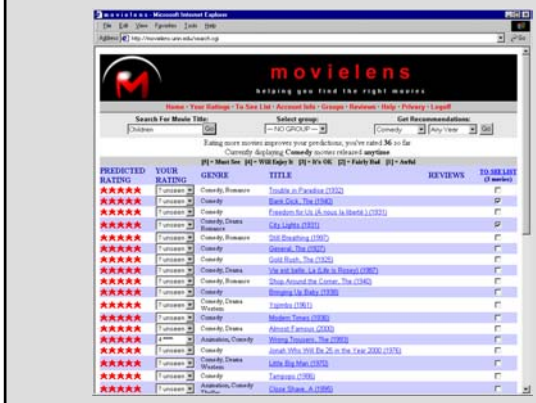
movielens
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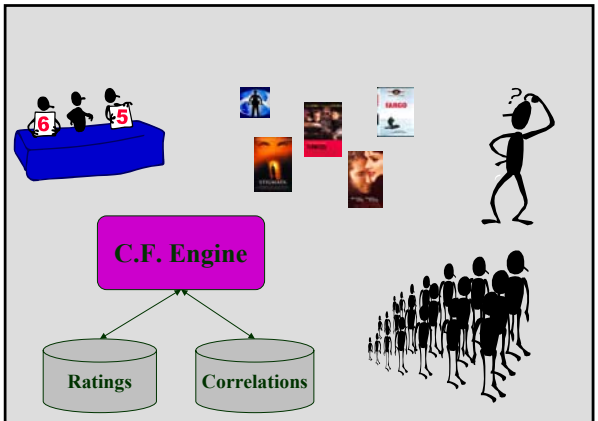
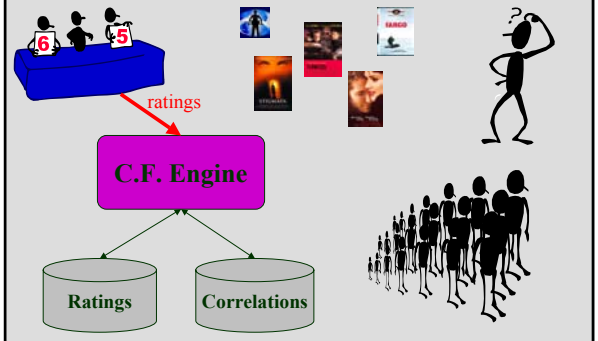
"ANGELA'S ASHES"
All reviews are based on a 5 star rating.

How It Works


6
5
C.F. Engine
Ratings
Correlations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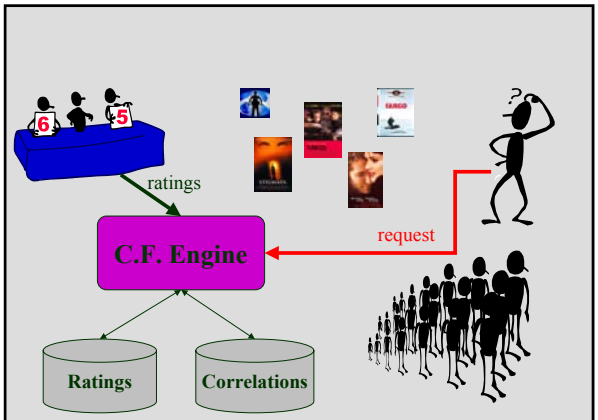
6
5
ratings
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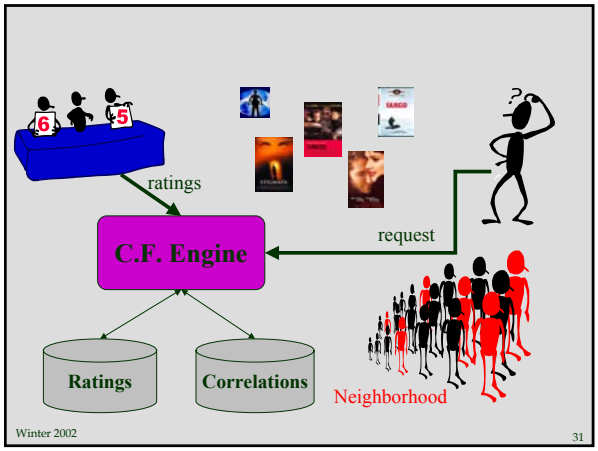
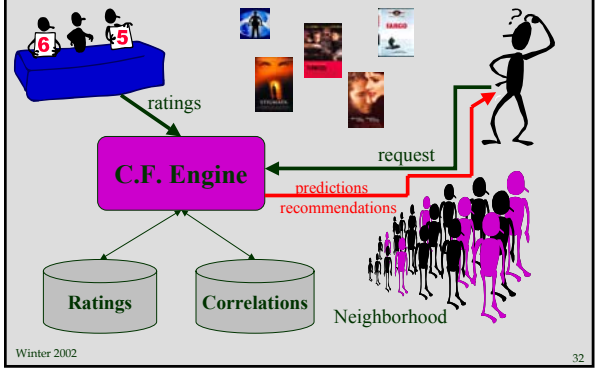
C.F. Engine
Ratings
Correlations



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

	Hoop Dreams	Star Wars	Pretty Woman	Titanic	Blimp	Rocky XV
Joe	D	A	B	D	?	?
John	A	F	D		F	
Susan	A	A	A	A	A	A
Pat	D	A		C		
Jean	A	C	A	C		A
Ben	F	A				F
Nathan	D		A		A	

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Jean	A	C	A	C		A
Ben	F	A				F
Nathan	D		A		A	

Broader Approaches to Recommendation

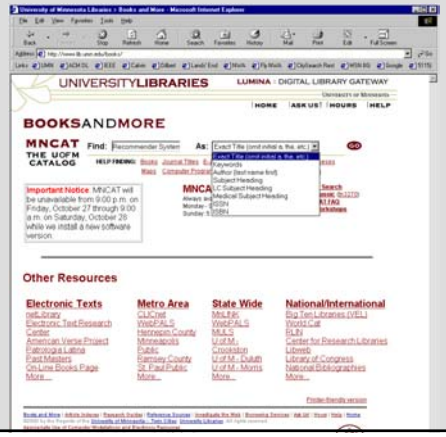
Information Retrieval

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



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

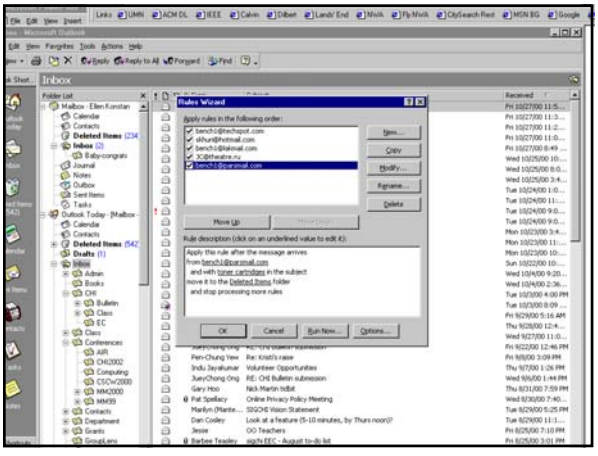
Information Filtering

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

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

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

Recent and Current Research

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

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

Two Studies

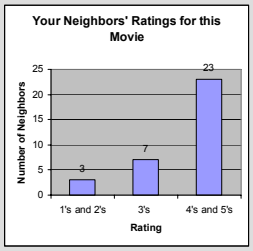
Pilot study of explanation feature

- 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

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 Creation

Theme Selection

Query Results

Results of Theme Query Study

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

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

PolyLens

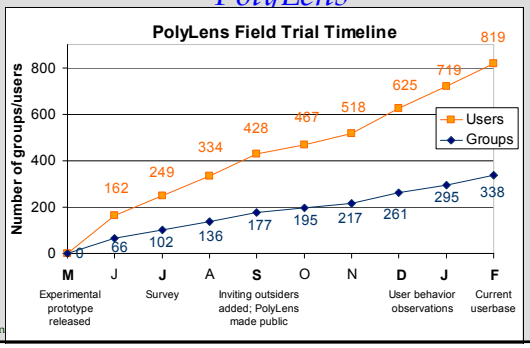
Design choices
- private, small, administered, invited groups
- combine individual recs with minimum misery
- high-information interface with opt-out

Group: Dantest — Back To Individual Recommendations

TITLE	GENRE	REVIEWS	GROUP	YOUR	easley@cs.cornell.edu	easley@gsm.cor
Pirate (1981)	Drama		★★★★★	★★★★★	★★★★★	★★★★★
Wrong Trousers, The (1993)	Animation, Comedy		★★★★★	★★★★★	★★★★★	★★★★★
After Life (1998)	Drama		★★★★½	★★★★½	★★★★½	★★★★★
King of Masks, The (Bian Lian) (1996)	Drama		★★★★½	★★★★★	★★★★½	★★★★★

External invitations added by popular demand

Field Testing PolyLens



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

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

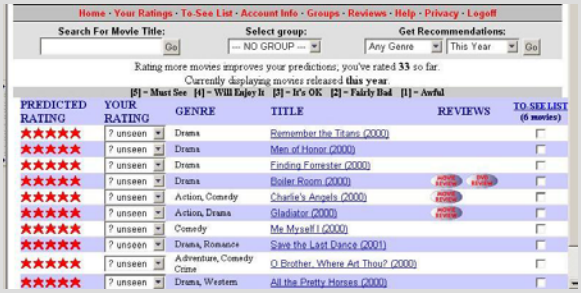
MetaLens: A Meta-Recommender
(Schafer)

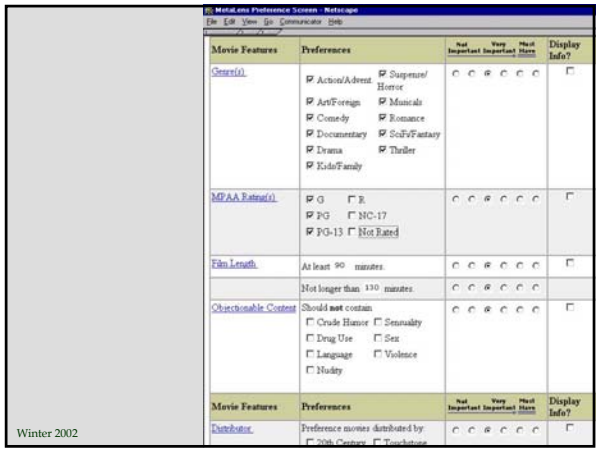
Integrating multiple sources of information into a single recommendation list

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 Accomodations
- Discounted Shows

What is the problem?





One solution

Meta-recommendation system
- MetaLens

Meta-Lens Score	Movie	Theater	Start Time	End Time	Movie-Lens Prediction	Genre	MPAA Rating	Run-time	Avg. User Rating
58.2	Rent in Show (2000)	Riverview Theater	Unavailable	Unavailable	★★★★½	Comedy	PG-13	90	4.0
53.6	Crouching Tiger, Hidden Dragon (2000)	Landmark Lagoon Cinema	7:10	9:10	★★★★★	Romance	PG-13	120	4.5
53.6	You Can Count on Me (2000)	University Film Society	Unavailable	Unavailable	★★★★½	Drama	R	109	4.4
51.5	The Family Man (2000)	Riverview Theater	Unavailable	Unavailable	★★★★½	Comedy and Romance	PG-13	125	3.9
51.2	Enemy at the Gates (2001)	St. Anthony Main	7:20	9:46	★★★	Drama and Romance	R	146	3.8
48.1	Requiem for a Dream (2000)	University Film Society	7:15	8:57	★★★★½	Drama	NR	102	4.3
47.7	Billy Elliot (2000)	Historic Suburban World Cinema Grd Theatre	7:00	8:30	★★★★½	Drama and Musical/Performing Arts	R	90	4.3
47.2	Pollock (2000)	Landmark Lagoon Cinema	7:15	9:12	★★★★	Drama	R	117	3.7
46.9	The House of Mirth (2000)	Landmark Lagoon Cinema	7:00	9:20	★★★★	Drama and Romance	PG	140	3.6
46.3	15 Minutes (2001)	St. Anthony Main	3:30	5:29	★★★★★	Thriller and Comedy	R	119	3.4

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

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

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