Introduction to Recommender Systems

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These notes will be posted next week at:
http://www.umn.edu/~konstan

While you’re waiting, please jot down:
– Where you are from
– Your experience with recommenders
– What you want to get out of this tutorial

A Bit of History

• Ants, Cavemen, and Early Recommender Systems
  – The emergence of critics
• Information Retrieval and Filtering
• Manual Collaborative Filtering
• Automated Collaborative Filtering
• The Commercial Era
A Bit of History

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Information Retrieval

- Static content base
  - Invest time in indexing content
- Dynamic information need
  - Queries presented in “real time”

- Common approach: TFIDF
  - Rank documents by term overlap
  - Rank terms by frequency
Information Filtering

- Reverse assumptions from IR
  - Static information need
  - Dynamic content base
- Invest effort in modeling user need
  - Hand-created “profile”
  - Machine learned profile
  - Feedback updates
- Pass new content through filters

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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

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Automated CF

• The GroupLens Project (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!
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Historical Challenges

• Collecting Opinion and Experience Data

• Finding the Relevant Data for a Purpose

• Presenting the Data in a Useful Way

A Few Challenges Specifically Relevant to SIGMOD Folks

(we’ll come back to these)

• Building database systems that can compute recommendations efficiently

• Scaling up to processing entire streams of transactions
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

Scope of Recommenders

- Purely Editorial Recommenders
- Content Filtering Recommenders
  - Collaborative Filtering Recommenders
- Hybrid Recommenders
Wide Range of Algorithms

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

Tutorial Goals and Outline
Goals

• When you leave, you should …
  – Understand recommender systems and their application
  – Know enough about recommender systems technology to evaluate application ideas
  – Be familiar with a variety of recommendation algorithms
  – See where recommender systems have been, and where they are going
  – Have seen a large number of recommender system example cases from research and practice

Outline

• Introduction
• Recommender Application Space
  – Dimensions of Analysis
  – Case Examples
• Algorithms
• Issues / Current Research / Advanced Topics
• Discussion and Questions
  – also encouraged throughout
• Bonus content on slides
Introductions

- Recommender systems
- This tutorial
- Me
- You

About Me

- Professor of Computer Science
  - University of Minnesota
- Background: Human-Computer Interaction
- Recommender Systems Experience
  - Started on GroupLens project in late 1994
  - co-founded Net Perceptions
  - co-authored *Word of Mouse*
  - Still actively working on RS research
    - applications to digital libraries
    - also work on online community; e-Public Health
About You

- Name
- What you do
- Who you work for / where you study
- Briefly
  - Your experience with recommender systems
  - One key thing you want to get out of this tutorial

Recommender Application
Space
Recommender Application Space

- Dimensions of Analysis
  - Domain
  - Purpose
  - Whose Opinion
  - Personalization Level
  - Privacy and Trustworthiness
  - Interfaces
  - <Algorithms Inside>

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
Casa Lapostolle, a partnership between French and Chilean winemaking families, is one of the newer wineries in Chile but they clearly know how to make fine wine. A red that rewards regular visits, Casa Lapostolle’s 1997 Cabernet Sauvignon is so pure, easy to drink, and affordable that you may want to buy it by the case. Ripa flavors of raspberries and plums that are aligned within a delicate frame of oak and a long silky-tannin finish that’s perfect for everyday historic comfort foods. The tannins are soft enough and the

People Helping One Another Know Stuff

Together, we know it all.

Feedback

Top

Related Sites

Wine.com Expert Recommendations

Casa Lapostolle Sauvignon, Rapel Valley, Chile

1997 Casa Lapostolle Cabernet Sauvignon, Rapel Valley, Chile

Lapostolle’s 1997 Cabernet Sauvignon is quite ripe and delicious, showing soft tannins and an easy-drinking profile needed to pair with everything from meatloaf to spaghetti and meatballs.

$9.95

Add to My Wish List

Peter’s Tasting Chart

intensity

delicate

medium

powerful

dry or sweet

bone dry

medium sweet

dessert

body

light body

medium body

very full body

acidity

high acidity

medium acidity

very crisp

tannins

none

low tannins

heavy tannins

completeness

direct

indirect

very complex

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Personalization Level

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

It makes looking good look easy.

*The slimming Faille Tankini – just $58!*

**AS SEEN ON TV!**

The magic word is Faille (say it “fay-le”), it’s a revolutionary ribbed fabric that feels slimming and comfortable. With a liberating-yet-discreet 2-piece style, our Faille Tankini works its magic at a very down-to-earth price: $59.

Want a pair of failles? See all of our slimming Faille favorites.

Let Swim Finder locate your perfect suit!

Quickly sorts through hundreds of suits by:
- Body Shape
- Anxiety Zones
- Leg Height
- Bra Style
- J•B•W•D•W
- Mastectomy
- and more!

It’s fast... it’s fun! Try Swim Finder today! Or, visit SwimFinder to see new styles, swim suits, and more.
Brooks Brothers

Linen

Light, luxurious linen on men's and women's apparel through 5.27.

Become a Member & Save

Up to 80% off

To View the Collection

Cdnow album advisor

Alternative/Indie
Pop/R&B
Hip-Hop
Electronic/Dance
Jazz
Country
Folk/Blues
World
Latin
Classical
New Age
Christian/Gospel
Vocal/Theatrical
Soundtracks
Comed/Spoken
Folk/Alt.
MTV CD Lounge
WHL Music Shop

Album Advisor

Tell us what you like and we'll make some recommendations. Great for buying gifts or broadening your musical horizons.

To start, enter the names of up to three artists below and click on the Recommend button.

- Gordon less
- **
- Recommend

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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
    • Agent/Discussion Interface

• Types of Input
  – Explicit
  – Implicit
Collaborative Filtering: Techniques and Issues

Collaborative Filtering Algorithms

- Non-Personalized Summary Statistics
- K-Nearest Neighbor
- Dimensionality Reduction
- Content + Collaborative Filtering
- Graph Techniques
- Clustering
- Classifier Learning
Teaming Up to Find Cheap Travel

- Expedia.com
  - “data it gathers anyway”
  - (Mostly) no cost to helper
  - Valuable information that is otherwise hard to acquire
  - Little processing, lots of collaboration
Zagat: 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

CF Classic: K-Nearest Neighbor User-User
CF Classic: Submit Ratings

CF Classic: Store Ratings
CF Classic: Compute Correlations

C.F. Engine

pairwise corr.

Ratings
Correlations

CF Classic: Request Recommendations

C.F. Engine

request

Ratings
Correlations
CF Classic: Identify Neighbors

C.F. Engine

find good ...
Ratings
Correlations
Neighborhood

CF Classic: Select Items; Predict Ratings

C.F. Engine

predictions
recommendations
Ratings
Correlations
Neighborhood
## Understanding the Computation

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**Table: Movie Preferences**

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**Image: MovieLens Website**

Welcome to MovieLens!

- **Advanced Search** now allows you to search for movies by director and/or actors in addition to its other features: multiple genres, exclude genres, date ranges, language, hide predictions, and more! Check it out.
- Also, don't forget about the new **publish** feature that lets you publish predictions in HTML/RSS 2.0 format. This and other info about recently added features is available in our archived announcements.

**Did you know...?** 4000 people joined MovieLens the same day you did.

- **New movies:**
  - Shrek 2 (2004)
  - Zathura (2005)

- **New DVDs:**
  - Great Expectations (1932)
  - Road, The (1969)
  - Field of Dreams (1989)
  - Suddenly, Last Summer (1959)
User-User Collaborative Filtering

1. Find a buddy
2. Query the buddy
3. Weighted Sum
4. Combine with own ratings
5. Recommend movies

Target Customer
A Challenge: Sparsity

- Many E-commerce and content applications have many more customers than products
- Many customers have no relationship
- Most products have some relationship

Another challenge: Synonymy

- Similar products treated differently
  - Have skim milk? Want whole milk too?
- Increases apparent sparsity
- Results in poor quality
Item-Item Collaborative Filtering

Item-Item Collaborative Filtering
Item-Item Collaborative Filtering

\[
\begin{align*}
\text{Item Similarities} & = s_{ij} \\
& \text{Used for similarity computation}
\end{align*}
\]
Item-Item Matrix Formulation

- Target item
- 5 closest neighbors
- Raw scores for prediction generation
- Approximation based on linear regression

Item-Item Discussion

- Good quality, in sparse situations
- Promising for incremental model building
  - Small quality degradation
    - Nature of recommendations changes
  - Big performance gain
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
SVD: Mathematical Background

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

SVD for Collaborative Filtering

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

2. Direct Prediction
Singular Value Decomposition

Reduce dimensionality of problem
  – Results in small, fast model
  – Richer Neighbor Network

Incremental Update
  – Folding in
  – Model Update

Trend
  – Towards use of probabilistic LSI

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
Issues in Collaborative Filtering

Research Issues in Collaborative Filtering

- Confidence and Explanation
- Social Navigation
- Recommending for Groups
- Reducing Rating Effort
- New Items and Users
- Evaluation
- Some Challenges
Trust/Acceptance

- Part of the problem is external – eliciting trust in the customer
- Part of the problem is that people don’t understand the basis for a recommendation

Some Stories

Where do users think MovieLens recommendations come from?
Confidence

- Why would someone distrust a recommendation?
  - Can I trust the provider?
  - How does this work, anyway?
  - Does the system know enough about me?
  - Does the system know enough about the item it is recommending?
  - How sure is it?

Trusting the Provider

- Concern about ulterior motives
  - Amazon’s pricing experiments
- Concern about external tampering
  - Easier with pseudonyms and rapid sign-up
- Possible approaches
  - Codes of conduct / disclosed policies
  - External auditing of recommenders
  - “Recommender in your pocket”
The Confidence Challenge

• Why should users believe recommendations?
• When should users believe them?
• Approaches
  – Confidence indicators
  – Explain the recommendations
    • Reveal data, process
    • Corroborating data, track record
  – Offer opportunity to correct mistaken data

A Simple Confidence Display

<table>
<thead>
<tr>
<th>Your Top 5 Recommendations</th>
<th>Recent Box Office</th>
</tr>
</thead>
<tbody>
<tr>
<td>5. Sum of All Fears, The (2002)</td>
<td>★★★★★</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Recent DVDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Red Beard (Akahige) (1965)</td>
</tr>
<tr>
<td>3. From Hell (2001)</td>
</tr>
<tr>
<td>5. Horse’s Mouth, The (1956)</td>
</tr>
</tbody>
</table>

| Recent Home Videos |
Explanation 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.

Explanation: Key Lessons

- Persuasion vs. Information

- Complex explanations often don’t work

- Users often have wrong mental models
  - We don’t sit in a room picking movie recommendations!
**Amazon Improve Your Recommendations**

To improve your recommendations on Amazon, you can provide feedback on items you've rated. This helps Amazon refine its recommendations for you.

### Feedback

You can rate items on a scale from 1 to 5, indicating your level of satisfaction. Higher ratings mean you like the item, while lower ratings mean you don't like it.

### Why Was I Recommended This?

Amazon recommends items based on your browsing and purchase history. By providing feedback, you can help Amazon understand your preferences better.

### Purchased or Rated Items

<table>
<thead>
<tr>
<th>Item Name</th>
<th>Rating</th>
<th>Recommendation</th>
<th>Exclude Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conklin by Shirley D. Cemper</td>
<td>?</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Essential Talmud by John Steinbeck</td>
<td>?</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Still Pumped from Using the Mouse by Scott Adams</td>
<td>?</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Where Wizards Stay Up Late by Kate Hafer, Matthew Lyon</td>
<td>?</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

By providing this feedback, you can help Amazon improve your recommendations.
Issues in Collaborative Filtering

- Confidence and Explanation
- Social Navigation
- Recommending for Groups
- Reducing Rating Effort
- New Items and Users
- Evaluation
- Some Challenges
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

• Applications
  – Real-World (baggage claim)
  – On-Line (footprints)
  – Virtual (GeoNotes)
Issues in Collaborative Filtering

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Recommending for Groups

- Problem: 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
  - 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
Issues in Collaborative Filtering

- Confidence and Explanation
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- New Items and Users
- Evaluation
- Some Challenges
Overview

- Gather “Work Product” Data
- Less User Effort
- Faster Start-Up
- Potentially More Accurate

Google PageRank

- Ranks pages based on incoming links
- Links from higher ranked pages matter more
- Combines text analysis with importance to decide which pages to show you
- Runs on network of thousands of PCs!
- Works to be hard to trick (e.g., citation trading)
GOOGLE

PHOAKS

• Read Usenet news to find web sites!
  – Implicit ratings
  – Filter URLs to find endorsements
  – Create top-n lists of web sites for a Usenet newsgroup community

• Links to endorsements (with age shown)
• Tested against hand-maintained FAQ lists
MITRE’s OWL

• Recommender for word processors
  – Monitored word processor command use
  – Identified common patterns of use
  – Recommended commands to learn
Issues in Collaborative Filtering

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- Some Challenges
Recommending New Items?

Collaborative filtering cannot recommend new items: no one has rated them
- Random
- Content analysis
- Filterbots

What About New Users?

- Collaborative filtering cannot match new users: they have rated nothing
  - Provide average ratings
  - User agents collect implicit ratings [Wasfi]
  - Put users in categories [Haddaway et al.]
  - Carefully select items for users to rate [Pennock & Horvitz, Kohrs & Merialdo]
Goals for New Users

- User effort
- User satisfaction
- Recommendation accuracy
- System utility
## Selling Demographics: DoubleClick

- Ad delivery service
  - Inventory management problem
  - “value” of a page view
- Collect demographic information across sites
  - Use to choose ads to show on new site
  - Cookies on browser
- Consumer resistance
  - Ignored
  - But eventually too expensive to continue

## Selling Demographics: Angara

- *Service* to sell demographics of “new” user to web sites
- Personalize to first-time user
- Claimed substantial improvements in purchase rates
- Out of business in Web bust (merged with Personify)
Selling Demographics: Lessons Learned

• Customers hate cross-site tracking
• Sharing data about millions of customers is expensive
• Effective solutions will require privacy protection and data reduction
Issues in Collaborative Filtering

• Confidence and Explanation
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Evaluating Recommenders
How do we Evaluate Recommenders -- today?

- Industry outcome
  - Add-on sales
  - Click-through rates

Real-world Experience

- Large international catalog retailer
  - 17% hit rate, 23% acceptance rate in call center
- Medium European outbound call center
  - 17% hit rate, 6.7% acceptance rate from an outbound telemarketing call
  - $350.00 price of average item sold
  - Items were in an electronics over-stocked category and were sold-out within 3 weeks
- Medium American online toy store (e-mail campaign)
  - 19% click-thru rate vs. 10% industry average
  - 14.3% conversion to sale vs. 2.5% industry average
How do we Evaluate Recommenders -- today?

- Industry outcome
  - Add-on sales
  - Click-through rates
- Research measures
  - User satisfaction
- Metrics
  - To anticipate the above beforehand (offline)

Evaluating Recommendations

- Prediction Accuracy
  - MAE, MSE,
- Decision-Support Accuracy
  - Reversals, ROC
- Recommendation Quality
  - Top-n measures (e.g., Breese score)
- Item-Set Coverage

What’s Wrong with This Approach?

• What is the purpose of recommenders?
  – to help people find things they don’t already know – and that they’ll like/value/use
  – to serve as a useful advisor
• What are we measuring, mostly?
  – how well the recommenders perform at finding things the users already know
  – performance on individual recommendations

There are Alternatives!

• The “easy” alternative
  – test on real users, real situation
  – have them consume and evaluate
• The “hard” alternative
  – extend our knowledge and understanding about metrics
Extending our Knowledge …

From Items to Lists

• Do users really experience recommendations in isolation?

Making Good Lists

- Individually good recommendations do not equal a good recommendation list
- Other factors are important
  - Diversity
  - Affirmation
  - Appropriateness
- Called the “Portfolio Effect”
  [ Ali and van Stam, 2004 ]

Topic Diversification

- Re-order results in a rec list
- Add item with least similarity to all items already on list
- Weight with a ‘diversification factor’
- Ran experiments to test effects
Experimental Design

- Books from BookCrossing.com
- Algorithms
  - Item-based CF
  - User-based CF
- Experiments
  - On-line user surveys
  - 2125 users each saw one list of 10 recommendations

Online Results

![Graphs showing single-vote averages and overall list value vs. diversification factor.](Image)
Diversity is Important

- User satisfaction more complicated than only accuracy
- List makeup is important to users
- 30% change enough to alter user opinion
- Change not equal across algorithms

Next Steps …

WARNING: Work in Progress
Human- Recommender Interaction

• Three premises:
  – Users perceive recommendation quality in context; users evaluate lists
  – Users develop opinions of recommenders based on interactions over time
  – Users have an information need and come to a recommender as a part of their information seeking behavior

HRI

• A language for communicating user expectations and system behavior
• A process model for customizing recommenders to user needs
• An analytic theory to help designers focus on user needs
HRI Pillars and Aspects

Recommendation Dialogue
- Correctness
- Transparency
- Saliency
- Serendipity
- Quantity
- Usefulness
- Spread
- Usability

Recommender Personality
- Personalization
- Risk Taking / Aversien
- Boldness
- Affirmation
- Adaptability
- Pigeonholing
- Freshness
- Trust

End User’s Information Seeking Task
- Concreteness of Task
- Expectations of Recommender Usefulness
- Task Compromising
- Recommender Importance in Meeting Need

Recommendation Dialog
- The individual recommender interaction
- Historical Aspects
  - Correctness, Quantity, Spread
- New Aspects
  - Transparency
  - Saliency
  - Serendipity
  - Usefulness
  - Usability
Recommendation Personality

- Experience over repeated interactions
- Nature of recommendations
  - Personalization, Boldness, Freshness, Risk
- Progression over time
  - Adaptability, Pigeonholing
- Relationship
  - Affirmation, Trust

Information-Seeking Task

- One of the current limits of HRI
- Concreteness
- Compromise
- Appropriateness of Recommender
- Role of Recommender
- Expectation of Usefulness
HRI Process Model

- Makes HRI Constructive
  - Links Users/Tasks to Algorithms
- But, Needs New Metrics

Developing New Metrics

- Identify candidate metrics
- Benchmark a variety of algorithms
  - and datasets?
  - establish that metric can distinguish algorithms
- Establish link to HRI aspects
  - definitional links; user studies
- Detailed Examples:
  - Ratability, Boldness, Adaptability
Metric Experimental Design

• ACM DL Dataset
  – Thanks to ACM!
  – 24,000 papers
  – Have citations, titles, authors, & abstracts
  – High quality

• Algorithms
  – User-based CF
  – Item-based CF
  – Naïve Bayes Classifier
  – TF/IDF Content-based
  – Co-citation
  – Local Graph Search
  – Hybrid variants

Ratability

• Probability a user will rate a given item
  – “Obviousness”
  – Based on current user model
  – Independent of liking the item

• Many possible implementations
  – Naïve Bayes Classifier
**Ratability Results**

![Bar chart showing ratability results for different methods: Local Graph, Bayes, Item, 50 nbrs, TFIDF, User, 50 nbrs. The x-axis represents different methods, and the y-axis shows mean ratability. The chart indicates that Local Graph and User, 50 nbrs have the highest ratability, while TFIDF has the lowest.](image)

**Boldness**

- **Measure of “Extreme Predictions”**
  - Only defined on explicit rating scale
  - Choose “extreme values”
  - Count appearance of “extremes” and normalize

- **For example, MovieLens movie recommender**
  - 0.5 to 5.0 star scale, half-star increments
  - Choose 0.5 and 5.0 as “extreme”
Adaptability

- Measure of how algorithm changes in response to changes in user model
  - How do users grow in the system?
- Perturb a user model with a model from another random user
  - 50% each
  - See quality of new recommendation lists
Adaptability Results

Adaptability, Even-Split

mean % adaptable

Local Graph Bayes Item, 50 nbrs TFIDF User, 50 nbrs

top-10 top-20 top-30 top-40
Adaptability Results

Adaptability, Even-Split

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Some Challenges

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

• Temporal Recommendation
  – Beyond reacting …

• Processing Transaction Streams

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?

Deeper Criteria than Accuracy

- Understanding user tasks and needs in context
  - Reassurance
  - Novelty
  - Risk Tolerance
  - Set Usage
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

• 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?
Processing Transaction Streams

- Leaving privacy aside for a minute …
  - Imagine you’re a large credit-card processor (or other large transaction processor), who is trying to provide enhanced service through recommendation …
  - What can you do to each transaction when it comes through to build more effective user models, product models, etc.? 

Conclusions, Resources, Discussion
Conclusions

- Broad area of research and practice
  - across HCI, IR, Machine Learning, Data Mining
- Simple techniques work fairly well
  - the key challenges are often scale and sparsity
- Complex design issues

Resources

- Where are papers published?
  - CSCW, SIGIR, CHI, AAAI, UM/AH, ICDM, and many other venues
  - ACM Recommender Systems 2008!! (Lausanne)
    - recsys.acm.org
- Bibliography of relevant work
  - A fairly good one (though 3-4 years old) by Vaclav Petricek (University College London); search Google for 'recommender systems annotated bibliography'
  - Start of one at www.grouplens.org
Resources

• Software to try this yourself
  – COFE - http://eecs.oregonstate.edu/iis/CoFE/
  – SUGGEST -
    http://gjaros.dtc.umn.edu/gkhome/suggest/overview

• Data Sets (www.grouplens.org)
  – MovieLens
  – Jester
  – BookCrossing

Discussion
Extra Slides as Time Permits

Nine Principles for Recommender Application Design
Be a Product Expert
Be a Customer Agent
Many Touchpoints, One Business
Box Products, Not People
Watch What I Do, Not What I Say
ReferralWeb
Click-by-Click Marketing
Customers who bought this item also bought

  by David A. Grossman
  [3.00](4) $25.48

- **Information Retrieval: Data Structures and Algorithms**
  by William S. Frakes
  [3.00](4) $59.65

- **Managing Gigabytes: Compressing and Indexing Documents and Images (The Morgan Kaufmann Series in Multimedia and Information Systems)**
  by Jan H. Witten
  [3.00](4) $46.99

- **Mining the Web: Discovering Knowledge from Hypertext Data**
  by Saamer Chakrabarti
  [3.00](4) $65.95

- **The Geometry of Information Retrieval**
  by C. J. van Rijsbergen
  [3.00](4) $45.00

**Editorial Reviews**

**David D. Lewis, AT&T Labs**

“This is a marvelous collection. The papers have been selected with care, and provide an unprecedented concentration of knowledge about information retrieval. The introductory material, by two of the leading researchers in IR, is itself a valuable reference to the history and status of the field and the important ideas in it. This book will instantly become the most important reference in the field.

**Review**

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—David D. Lewis, AT&T Labs

See all Editorial Reviews
Community Filtering
Community Creates Content
Information retrieval

Information retrieval (IR) is the science of searching for information in documents, searching for document versions, searching for metadata which describe documents, or searching within databases, whether relational stand-alone databases or hypertextually-networked databases such as the World Wide Web. There is a common confusion, however, between data retrieval, document retrieval, information retrieval, and text retrieval, and each of these has its own body of literature, theory, practice and technologies. IR is, like most nascent fields, interdisciplinary, based on computer science, mathematics, library science, information science, cognitive psychology, linguistics, statistics, physics.

Automated IR systems are used to reduce information overload. Many universities and public libraries use IR systems to provide access to books, journals, and other documents. IR systems are often related to object and query. Queries are formal statements of information needs that are put to an IR system by the user. An object is an entity which keeps or stores information in a database. User queries are matched to objects stored in the database. A document is, therefore, a data object. Often the documents themselves are not kept or stored directly in the IR system, but are instead represented in the system by document surrogates.

In 1992 the U.S. Department of Defense, along with the National Institute of Standards and Technology (NIST), cosponsored the Text Retrieval Conference (TREC) as part of the TIPSTER test program. The aim of this was to look into the information retrieval community by supplying the infrastructure that was needed for such a huge evaluation of text retrieval methodologies.

Web search engines such as Google, Yahoo search, or Live.com are the most visible IR applications.

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**Contents (hide)**

- 1. Performance measures
  - 1.1 Precision
  - 1.2 Recall
  - 1.3 Fall-Out
  - 1.4 F-measure
  - 1.5 Average precision
- 2. Model bases

**Promoted Videos**

- Passionate About This: Lisboa
- Sony Bravia Mock TV: EmotivMediaTV
- Armored Core 4 PS3 (Launch Trailer)
- Steinmetz Fans: Test TIme

**Featured Videos**

- **Soundwave: The Touch**
  - An out of work actor puts the call that may bring him back to trendy-style, but has the world moved on?
  - From: 9412

- **to dream**
  - From: editors
  - Views: 26,574

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Community is Content
Facebook

Meetup

Whatever your interest. Wherever you are.

Some of May’s 54,179 Meetups:

San Francisco Scrapbooking Meetup

“Weekly crafternoon... it’s the best networking group I’ve experienced.”

Silicon Valley Technology Meetup

“Interesting... will come again.”

Boston Social Justice Meetup

“A convenient, rain-sheltering way to connect to other people who share similar interests and live nearby.”

New York Meditation Meetup

“Nice group of people.”

http://www.meetup.com/

Enter an interest:

- e.g. knitting, moms, dogs, baseball

Country

ZIP Code

Or, browse all interests or all cities

“TIME”

“Newsweek”

“SUN”

“TIME”

“Newsweek”

“SUN”
Current Research & Advanced Topics

Recommending Research Papers
Recommending Research Papers

• Using Citation Webs
• For a full paper, we can recommend citations
  – A paper “rates” the papers it cites
  – Every paper has ratings in the system
• Other citation web mappings are possible, but many are have problems

Demonstration #1

• Steps
  – Select user
  – Select paper
  – Select algorithm
  – See recommendations
What We Found

• Results published in McNee et al. (CSCW 2002):
  – Yes, we can make recommendations this way!
    • offline analysis showed that best algorithms could find half of
      recommendable withheld references in top 10, ¾ in top 40 recs
    • online experiments showed best algorithms gave recommendations
      more than half of which were relevant, and more than half of which
      were novel
  – Users like it!
    • more than half of users felt useful (1/4 to 1/3 said not)
    • 1-2 good recs out of 5 seemed sufficient for use
  – Different algorithms have different uses
• Further exploration in Torres et al. (JCDL 2004)

Phase II

• Shifted our focus to ACM Digital Library
• Greater exploration of user tasks:
  – awareness services
  – keeping track of a community
• More automation
  – find own bibliography from citations
  – find collaborators
• Thinking about “researcher’s desktop”
Moving Forward

- Collaboration
  - Computer Scientists (HCI, recommenders)
  - Librarians (field work, domain expertise, “real-life” service deployment)
- Research methods
  - Offline data gathering and feasibility studies
  - Online pilots and controlled experiments
  - Online field studies (including random-assignment studies)

What’s Next?

- Short-Term Efforts
  - Task-specific recommendation
  - Understanding personal bibliographies
  - Privacy issues
- Longer-Term Efforts
  - Toolkits to support librarians and other power users
  - Exploring the shape of disciplines
  - Rights issues