



## *Recommender Systems: Advanced Concepts in Research and Practice*

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<http://www.grouplens.org>

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## *A Bit of History*


- Ants, Cavemen, and Early Recommender Systems
  - The emergence of critics
- Information Filtering and User Modeling
- Manual Collaborative Filtering
- Automated Collaborative Filtering
  - Social Navigation and other approaches
- The Commercial Era



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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



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## *Introductions*


- Me
- You
- This tutorial



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## *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
  - Still actively working on RS research



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## *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



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## About This Tutorial

Background

- I have taught an introductory tutorial on RS about a dozen times (often with John Riedl, Anthony Jameson)

The idea:


- A venue to go beyond the introductory material to explore newer knowledge and current problems
- Inherently biased by what I find to be interesting (for better or for worse)
- Assumes basic understanding of RS (e.g., k-nearest-neighbor collaborative filtering – if not, let’s fix that!)



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## Goals of this Tutorial

- To understand the state of research and practice in recommender systems:
  - Algorithms
  - Interface Design
  - Evaluation
- To explore the future of user-centered recommender system design
- To have fun while doing so!




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## Where do Recommenders Fail?

Your experiences


- Where have recommenders really missed the mark?
- Where have they looked dumb?
- And why????



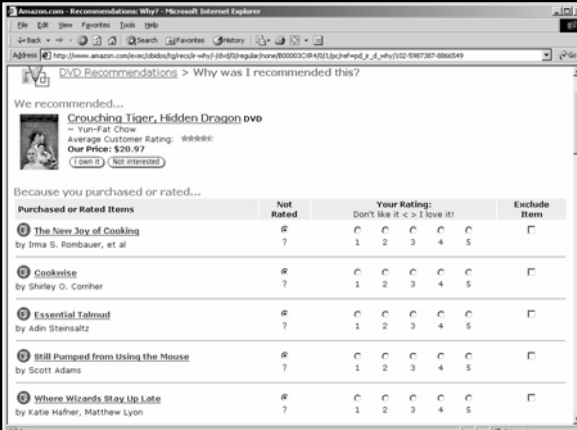
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## My Examples

- Recommending without enough data (weak confidence)
- Recommending items ignorant of context
- Ignoring overall interest or balance
- Just plain wrong!



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Amazon.com - Recommendations: Why? - Microsoft Internet Explorer

Address: http://www.amazon.com/recommendations/why?pf\_rd\_p=4010444e-904e-4151-bc1f-9d71d1e97367-8966549

DVD Recommendations > Why was I recommended this?

We recommended...

**Crouching Tiger, Hidden Dragon DVD**  
by Yuen Fat Chow  
Average Customer Rating:   
Our Price: \$20.97

Because you purchased or rated...

Purchased or Rated Items	Not Rated	Your Rating: Don't like it < > I love it!	Exclude Item
<b>The New Joy of Cooking</b> by Irma S. Rombauer, et al	?	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/>	<input type="checkbox"/>
<b>Cookwise</b> by Shirley O. Corbher	?	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/>	<input type="checkbox"/>
<b>Essential Talmud</b> by Adin Steinsaltz	?	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/>	<input type="checkbox"/>
<b>Still Dumped from Using the Mouse</b> by Scott Adams	?	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/>	<input type="checkbox"/>
<b>Where Wizards Stay Up Late</b> by Katie Hafner, Matthew Lyon	?	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/>	<input type="checkbox"/>



Amazon.com - Recommendations: Why? - Microsoft Internet Explorer

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DVD Recommendations > Why was I recommended this?

We recommended...

**The History of Middle-earth: The Hobbit**  
by J.R.R. Tolkien, Christopher Tolkien (Editor)  
Average Customer Review:   
Our Price: \$19.40 Used \$8.99 from \$9.99

**The History of Middle-earth: The Silmarillion**  
by J.R.R. Tolkien, Christopher Tolkien (Editor)  
Average Customer Review:   
Our Price: \$11.99 Used \$8.99 from \$9.99

**The History of Middle-earth: The Rings**  
by J.R.R. Tolkien, Christopher Tolkien (Editor)  
Average Customer Review:   
Our Price: \$11.99 Used \$8.99 from \$9.99

**The History of Middle-earth: The Fall of Gondolin**  
by J.R.R. Tolkien, Christopher Tolkien (Editor)  
Average Customer Review:   
Our Price: \$6.99 Used \$8.99 from \$9.99

The screenshot shows a list of four articles from the Tolkien Estate website, each recommended by a system. The articles are:

- Sauron Defeated** By J.R.R. Tolkien, Editor
- The War of the Ring** By J.R.R. Tolkien, Editor
- Treason of Isengard** By J.R.R. Tolkien, Editor
- Shaping of Middle Earth** By J.R.R. Tolkien, Editor

Each article entry includes a small thumbnail image, the title, author, and a 'Recommender Systems' label. The browser's address bar shows 'http://www.tolkienestate.com/'.

The screenshot shows a news aggregator page with several headlines. A 'Recommender Systems' label is overlaid on the page. The headlines include:

- House rejects timetable for Iraq pullout
- House takes away Jefferson committee seat
- Grand jury declines to indict McKinney
- Bush boosts fundations for modern vote
- U.S. prosecutors apologize to Conn. mayor
- Bush Plans Visit Protected Sea Area in Hawaii
- Duck Look-Alike Reveals Birds' Evolution
- The DNA Age: That Wild Strain? Maybe It Began in Family
- Columbia Chemistry Professor Is Extracting 4 More Papers
- Gates' step-back pressures Microsoft execs
- Foundation says Gates, wife involved
- Video Foots help Rockies ready for game
- Gates to lessen his Microsoft role in 2008
- Apple eyes labor conditions at iPod plant
- Poll shows city divided over smoking ban
- Entertains pressed on wife's ties to United
- BATBOY CHEERED FOR OUT AT HOME
- Legislators urge steps after theft of laptops
- High speed a factor in gram-night crash

The screenshot shows a 'Please Refine Your Basket of Papers' page. It contains two columns of paper titles:

- Your Publications:**
  - 1. PocketNet: Toward a personal recommender system
  - 2. Evaluating collaborative filtering recommender systems
  - 3. Are informal tools better? comparing DEMAIS, pencil and paper, and software for early multimedia design
  - 4. Meta-recommendation systems: user-controlled integration of diverse recommendations
  - 5. Explaining collaborative filtering recommendations
  - 6. Commands as media design and implementation of a command stream
  - 7. DEMAIS: designing multimedia applications with interactive storyboards
  - 8. Is seeing believing? how recommender system interfaces affect users' opinions
  - 9. Enhancing digital libraries with TechLeas+
  - 10. Getting to know you: learning new user preferences in recommendation systems
  - 11. On the recommending of citations for research papers
- Your Citations:**
  - 1. Aggarwal, C., Wolf, J., Wu, K., and Yu, P. 1999. Horting hatches an egg: A new graph-theoretic approach to collaborative filtering. In Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 201-212.
  - 2. Amato, B., Terveen, L., Hill, W., Hill, D., and Scholman, R. 2003. Experiments in social data mining. The Top-Shop System. ACM Trans. Computer-Human Interact. 10, 1 (Mar.), 34-45.
  - 3. Amato, B., Terveen, L., Hill, D., and Ju, P. 1999. An empirical evaluation of user interfaces for topic management of web sites. In Proceedings of the 1999 Conference on Human Factors in Computing Systems (CHI 99). ACM, New York, 552-559.
  - 4. Bosch, A., Kuchinsky, A., and Bhan, N. 2002. Quality is in the eye of the beholder: Meeting users' requirements for internet quality of service. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM Press, 297-304.
  - 5. Klemmer, S., et al. The Designers' Output: A Tangible Interface for Collaborative Web Site Design. In Proceedings of UIST, 2001, pp. 1-10.
  - 6. Greff, W. R., and Pente, J. The Maximum Entropy Approach and Probabilistic IR Methods. ACM Transactions on Information Systems 18(3): 248-287.
  - 7. Chan, J. 2003. Collaborative filtering with privacy via factor analysis. In Proceedings of the 25th Annual International ACM SIGIR Conference on Research and Development in Information Systems.

This screenshot is similar to the previous one, but with a vertical stack of labels overlaid on the right side of the page:

- Recommender Systems
- Multimedia toolkits
- Recommender Systems
- Multimedia toolkits
- Recommender Systems
- User Interface Design

The screenshot shows a 'Your Recommendations' page with two lists of research papers:

- List A:**
  - [1] Deshpande, M. and Karypis, G. 2004. Item-based top-N recommendation algorithms. ACM Trans. Inf. Syst. 22, 1 (Jan. 2004), 143-177. DOI=http://doi.acm.org/10.1145/963770.963776.
  - [2] Mooney, R. J. and Roy, L. 2000. Content-based book recommending using learning for text categorization. In Proceedings of the Fifth ACM Conference on Digital Libraries (San Antonio, Texas, United States, June 02 - 07, 2000). DL '00. ACM Press, New York, NY, 195-204. DOI=http://doi.acm.org/10.1145/336597.336602.
  - [3] Lin, J., Newman, M. W., Hong, J. I., and Landay, J. A. 2001. DENDIM: an informal tool for early stage web site design. In CHI '01 Extended Abstracts on Human Factors in Computing Systems (Seattle, Washington, March 31 - April 05, 2001). CHI '01. ACM Press, New York, NY, 465-467. DOI=http://doi.acm.org/10.1145/434067.434190.
  - [4] Ginsberg, A. and Ahuja, S. 1995. Automating environment of virtual meeting room histories. In Proceedings of the Third ACM International Conference on Multimedia (San Francisco, California, United States, November 05 - 09, 1995). MULTIMEDIA '95. ACM Press, New York, NY, 65-75. DOI=http://doi.acm.org/10.1145/217279.215123.
  - [5] Curtis, P., Dixon, M., Frederick, R., and Nichols, D. A. 1995. The Tiptop audio-video architecture: secure multimedia in network places. In Proceedings of the Third ACM International Conference on Multimedia (San Francisco, California, United States, November 05 - 09, 1995). MULTIMEDIA '95. ACM Press, New York, NY, 79-90. DOI=http://doi.acm.org/10.1145/217279.215128.
- List B:**
  - [1] Ritchie, D. M. and Thompson, K. 1974. The UNIX time-sharing system. Commun. ACM 17, 7 (Jul. 1974), 365-375. DOI=http://doi.acm.org/10.1145/360311.360316.
  - [2] Sherwood, T., Perelman, E., Hansen, G., and Calder, B. 2002. Automatically characterizing large-scale program behavior. SIGARCH Comput. Architec. News 30, 3 (Dec. 2002) DOI=http://doi.acm.org/10.1145/635508.604403.
  - [3] Valder, A., Lebeck, A., and Ellis, C. S. 2000. Every joule is precious: the case for revisiting operating system design for energy efficiency. In Proceedings of the 9th Workshop on ACM SIGOPS European Workshop: Beyond the PC: New Challenges For the Operating System (Kolding, Denmark, September 17 - 20, 2000). EW '00. ACM Press, New York, NY, 337-341. DOI=http://doi.acm.org/10.1145/406726.587835.
  - [4] Liu, B., Hsu, W., and Ma, Y. 1999. Mining association rules with multiple minimum supports. In Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (San Diego, California, United States, August 15 - 18, 1999). KDD '99. ACM Press, New York, NY, 337-341. DOI=http://doi.acm.org/10.1145/331229.332274.
  - [5] Dink, R. P., Lakshminarayana, G., Raghunathan, A., and Raj, N. K. 2000. Power analysis of embedded operating systems. In Proceedings of the 37th Conference on Design Automation (Las Vegas, California, United States, June 05 - 09, 2000). DAC '00. ACM Press, New York, NY, 312-315. DOI=http://doi.acm.org/10.1145/337292.337427.

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- Recommender Systems
- Multimedia toolkits
- Recommender Systems
- User Interface Design

*More Generally ...*

- Recommenders fail when ...
  - they lack awareness of their own knowledge
  - they don't consider the context of recommendation
  - they don't consider the user's goals and needs

### How do we Evaluate Recommenders -- today?

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



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### 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



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### 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)



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### Evaluating Recommendations

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



J. Herlocker et al. Evaluating Collaborative Filtering Recommender Systems. *ACM Transactions on Information Systems* 22(1), Jan. 2004.



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### 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



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### 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



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## Extending our Knowledge ...



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## From Items to Lists


- Do users really experience recommendations in isolation?



C. Ziegler et al. "Improving Recommendation Lists through Topic Diversification", in Proc. WWW2005.  
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## 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 ]



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## 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



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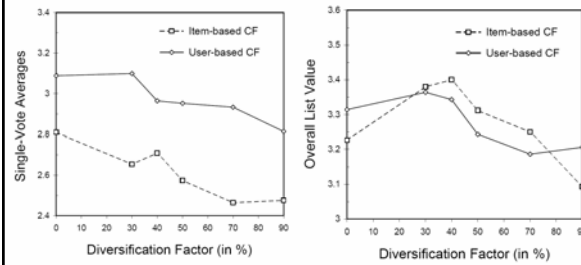
## Experimental Design

- 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




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## Online Results



Diversification Factor (in %)	Item-based CF	User-based CF
0	2.80	3.05
10	2.75	3.05
20	2.65	3.05
30	2.65	3.05
40	2.70	2.95
50	2.55	2.95
60	2.50	2.95
70	2.45	2.95
80	2.45	2.90
90	2.45	2.85


Diversification Factor (in %)	Item-based CF	User-based CF
0	3.25	3.30
10	3.30	3.30
20	3.35	3.35
30	3.35	3.35
40	3.40	3.35
50	3.30	3.25
60	3.25	3.20
70	3.20	3.20
80	3.20	3.15
90	3.15	3.15



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### *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



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### *Next Steps ...*


WARNING: Work in Progress

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### *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




➡ S. McNee et al. "Making Recommendations Better: An Analytic Model for Human-Recommender Interaction" in *Ext. Abs. CHI 2006*

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### *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



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### *HRI Pillars and Aspects*


Recommendation Dialogue	Recommender Personality	End User's Information Seeking Task
Correctness	Personalization	Concreteness of Task
Quantity	Risk Taking/Aversion	Expectations of Recommender Usefulness
Transparency	Boldness	Task Compromising
Usefulness	Affirmation	Recommender Importance in Meeting Need
Saliency	Adaptability	Recommender Appropriateness
Spread	Pigeonholing	
Serendipity	Freshness	
Usability	Trust	



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### *Recommendation Dialog*


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



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### *Recommendation Personality*


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



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### *Information-Seeking Task*

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




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### *HRI Process Model*

```

    graph LR
      A[Users & Tasks] -- Analyze --> B[HRI]
      B -- Create Mapping --> C[Metrics]
      C -- Benchmark --> D[Recommender Algorithms]
    
```


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



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### *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



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### *Metric Experimental Design*


<ul style="list-style-type: none"> <li>• ACM DL Dataset                             <ul style="list-style-type: none"> <li>▪ Thanks to ACM!</li> <li>▪ 24,000 papers</li> <li>▪ Have citations, titles, authors, &amp; abstracts</li> <li>▪ High quality</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>• Algorithms                             <ul style="list-style-type: none"> <li>▪ User-based CF</li> <li>▪ Item-based CF</li> <li>▪ Naïve Bayes Classifier</li> <li>▪ TF/IDF Content-based</li> <li>▪ Co-citation</li> <li>▪ Local Graph Search</li> <li>▪ Hybrid variants</li> </ul> </li> </ul>
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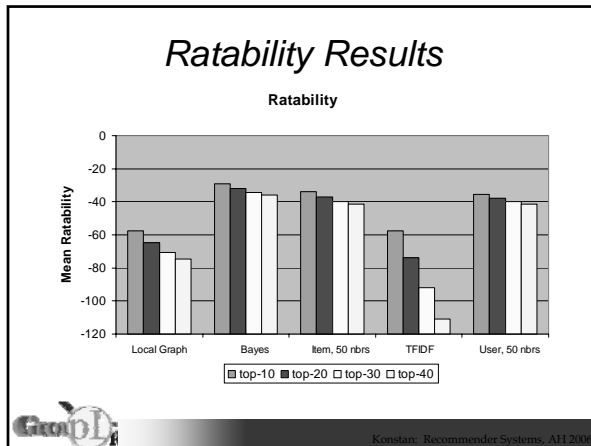
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### *Ratability*

- 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



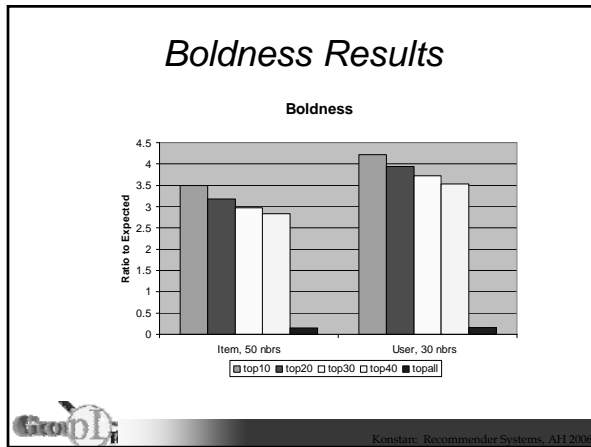
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### Boldness

- 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”

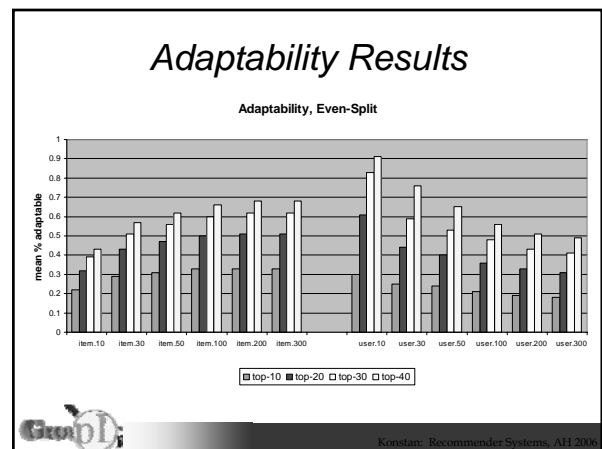
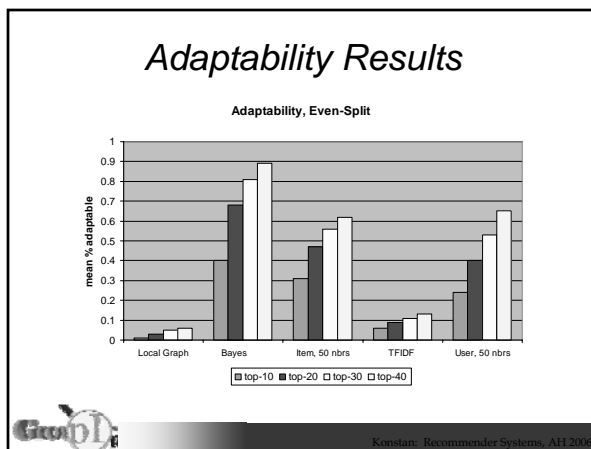
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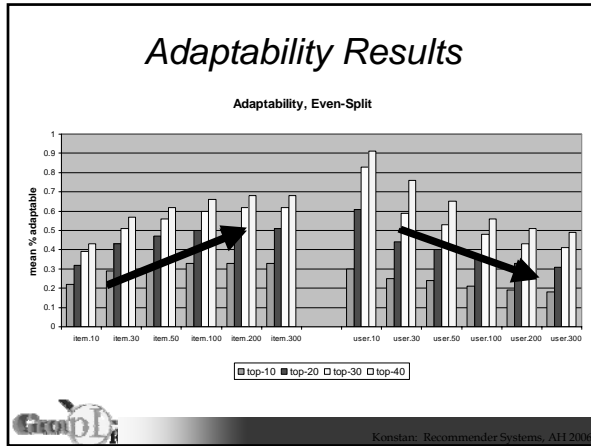


### Adaptability

- 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

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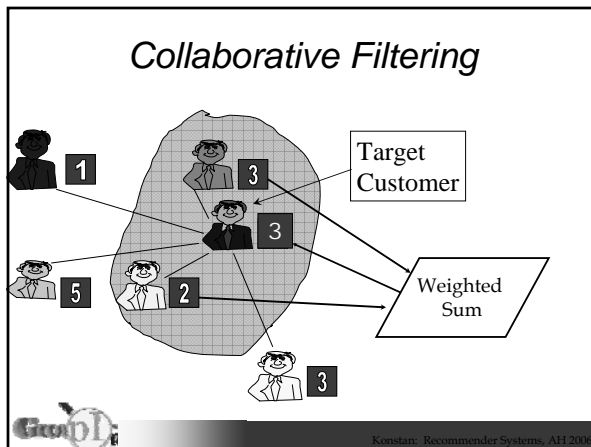
### More Generally ...

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### Recommender Algorithms

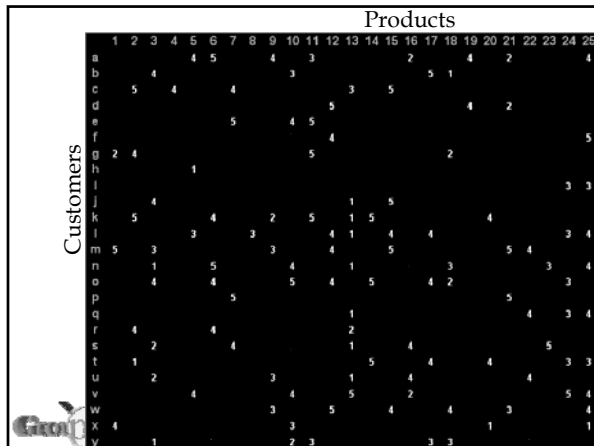
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### E-Commerce Scale

- Millions of Products
- Millions of Customers
- Thousands of Clicks per Second
- Scalability!

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### Sparsity

- Many customers have no relationship
- Many products have no relationship
- Synonymy
  - Similar products treated differently
  - Increases sparsity, loss of transitivity
  - Results in poor quality

### Collaborative Filtering Algorithms

- Non-Personalized Summary Statistics
- K-Nearest Neighbor
  - user-user
  - item-item
- Dimensionality Reduction
  - LSI
  - PLSI
  - Factor Analysis
- Content + Collaborative Filtering
  - Burke's Survey of Hybrids
- Graph Techniques
  - Horting
- Clustering
- Classifier Learning
  - Naïve Bayes
  - Bayesian Belief Networks
  - Rule-induction

Screenshot of a ZAGAT SURVEY web page for La Forêt restaurant in San Jose. It shows a review, ratings for Food, Decor, and Service, and a 'VOTE' section.

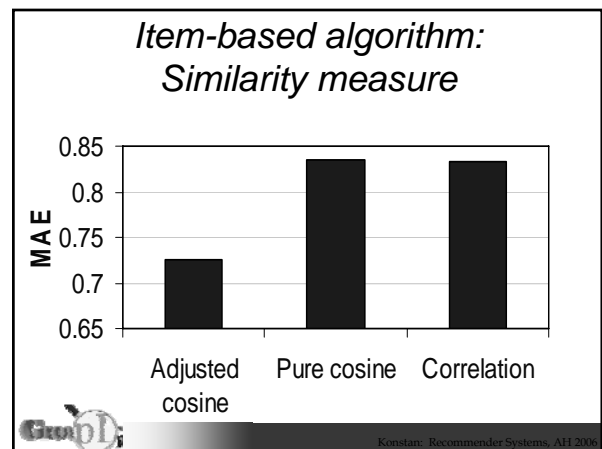
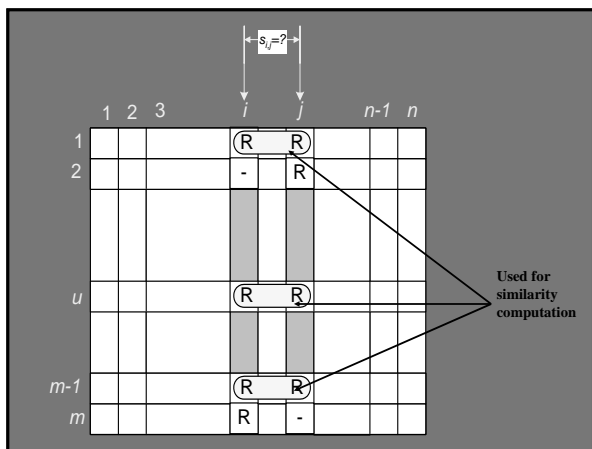
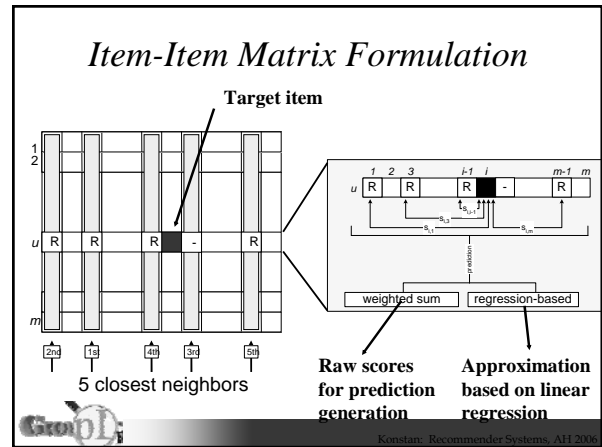
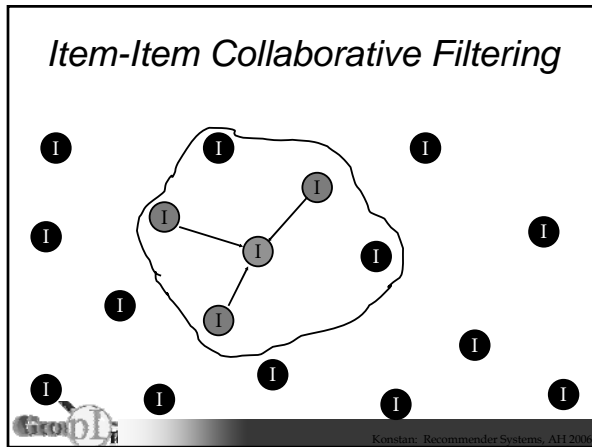
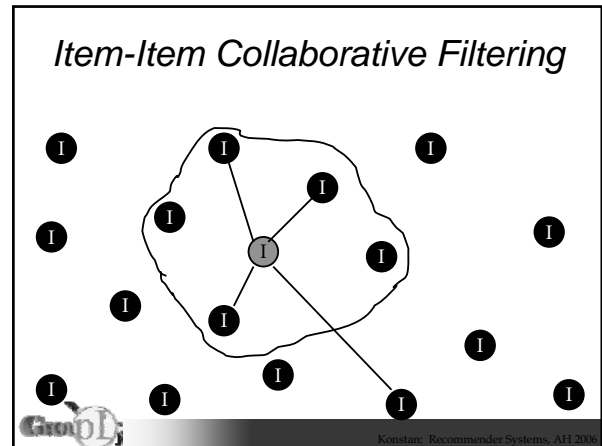
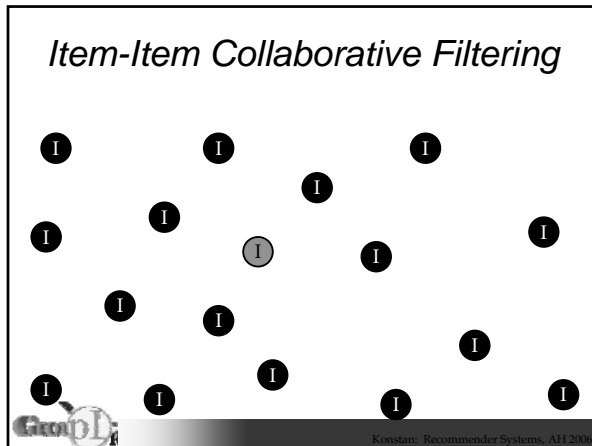
### Collaborative Filtering Algorithms

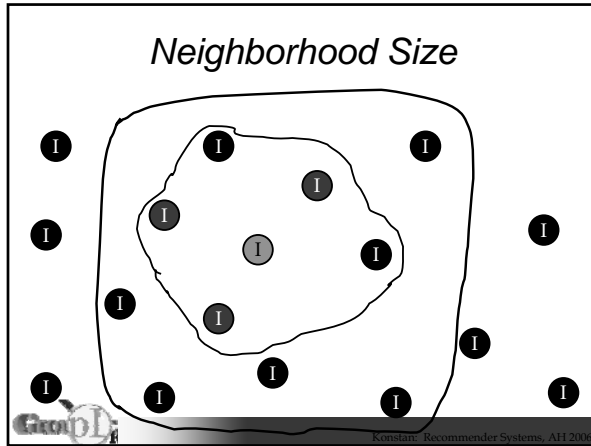
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- Content + Collaborative Filtering
  - Burke's Survey of Hybrids
- Graph Techniques
  - Horting
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  - Naïve Bayes
  - Bayesian Belief Networks
  - Rule-induction

### Item-Item Collaborative Filtering

A diagram illustrating item-item collaborative filtering with scattered circles labeled 'I' representing items.

B. Sarwar et al. Item-based collaborative filtering recommendation algorithms. Proc. WWW 2001.

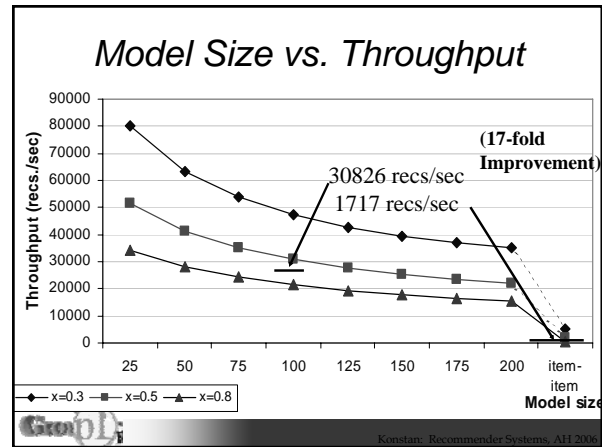
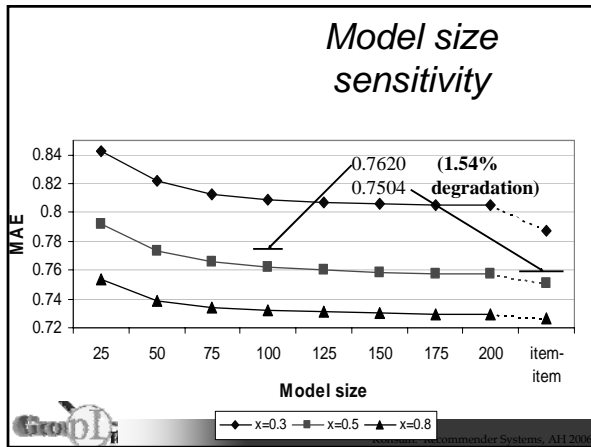




### Incremental Item-Item Algorithm

- Model Building
  - Compute similarity between items
  - Record  $p$  most similar items for each item
    - $p$  is model size
- Prediction Generation
  - $p'$  is subset of  $p$  rated by  $u$
  - Use  $\min(p', k)$  items for prediction
    - $k$  is neighborhood size

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### Item-Item Discussion

- Good quality, in sparse situations
- Promising for incremental model building
  - Small quality degradation
  - Big performance gain

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### Collaborative Filtering Algorithms

<ul style="list-style-type: none"> <li>• Non-Personalized Summary Statistics</li> <li>• K-Nearest Neighbor                             <ul style="list-style-type: none"> <li>▪ user-user</li> <li>▪ item-item</li> </ul> </li> <li>• Dimensionality Reduction                             <ul style="list-style-type: none"> <li>▪ LSI</li> <li>▪ PLSI</li> <li>▪ Factor Analysis</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>• Content + Collaborative Filtering                             <ul style="list-style-type: none"> <li>▪ Burke's Survey of Hybrids</li> </ul> </li> <li>• Graph Techniques                             <ul style="list-style-type: none"> <li>▪ Horting</li> </ul> </li> <li>• Clustering</li> <li>• Classifier Learning                             <ul style="list-style-type: none"> <li>▪ Naive Bayes</li> <li>▪ Bayesian Belief Networks</li> <li>▪ Rule-induction</li> </ul> </li> </ul>
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Konstan, Recommender Systems, AH 2006

### 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

B. Sarwar et al. Incremental SVD-Based Algorithms for Highly Scalable Recommender Systems, Proc ICIT 2002.  
Konstan, Recommender Systems, AH 2006

### SVD: Mathematical Background

$R_k$  (m x n) =  $U$  (m x k)  $S_k$  (k x k)  $V'$  (k x n)

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

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### SVD for Collaborative Filtering

1. Low dimensional representation  
 $O(m+n)$  storage requirement  
 2. Direct Prediction

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### Experimental Setup

- MovieLens Data (www.movielens.umn.edu)
  - Size 943 x 1,682; 100,000 ratings entry
  - Ratings are from 1-5
  - Used for Prediction and Neighborhood experiments
- E-Commerce Data
  - Size 6,502 x 23,554; 97,045 purchase entry
  - Purchase entries are dollar amounts
  - Used for Neighborhood experiment
- Training and Test Portions
  - Percentage of Training data, x
  - 10x cross-validation

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### Experimental Setup

- Benchmark Systems
  - CF-Predict
  - CF-Recommend
- Evaluation Metrics
  - Prediction
    - Mean Absolute Error (MAE)
  - Top-N Recommendation
    - Recall and Precision
    - Combined score F1

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### Dimension Sensitivity

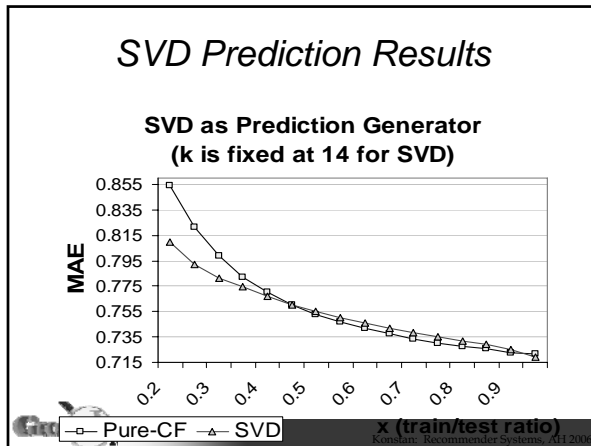
Sensitivity of No. of Dimensions

MAE

Number of Dimensions, k

$\diamond$  x=0.5     $\square$  x=0.8

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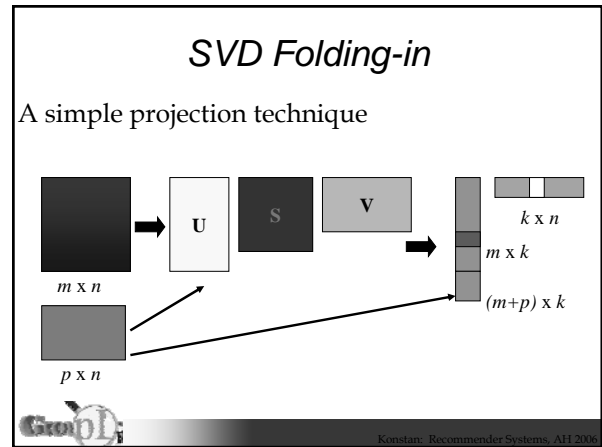


- ### Discussion
- Pros:
    - SVD addresses sparsity
    - Comparable quality with only 14 features
    - Storage space:  $O(mn)$  vs.  $O(m+n)$
  - Cons:
    - Problem with dynamic database
    - SVD computation is expensive

### SVD Performance Issues

	Traditional CF	SVD-based CF
<b>Model Building</b>	Relatively Fast	Slow
<b>Prediction Generation</b>	Slow	Very Fast

Annotations: Offline performance (points to Slow in Model Building), Online performance (points to Very Fast in Prediction Generation)



- ### Singular Value Decomposition
- Reduce dimensionality of problem
    - Results in small, fast model
    - Richer Neighbor Network
  - Incremental Update
    - Folding in
    - Model Update

- ### Collaborative Filtering Algorithms
- Non-Personalized Summary Statistics
  - K-Nearest Neighbor
    - user-user
    - item-item
  - Dimensionality Reduction
    - LSI
    - PLSI
    - Factor Analysis
  - Content + Collaborative Filtering
    - Burke's Survey of Hybrids
  - Graph Techniques
    - Horting
  - Clustering
  - Classifier Learning
    - Naive Bayes
    - Bayesian Belief Networks
    - Rule-induction


### Algorithm Exercise

Recommender Application (choose one)

- Personalized newspaper
- Music streaming application
- Dentist recommender



The exercise

- Identify sources of data for recommendation
  - content and/or ratings
- Identify 2 user situations
- Explore recommender algorithms for application



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### Thinking About User Experience

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### Recommender Application Space


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



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### Domains of Recommendation

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

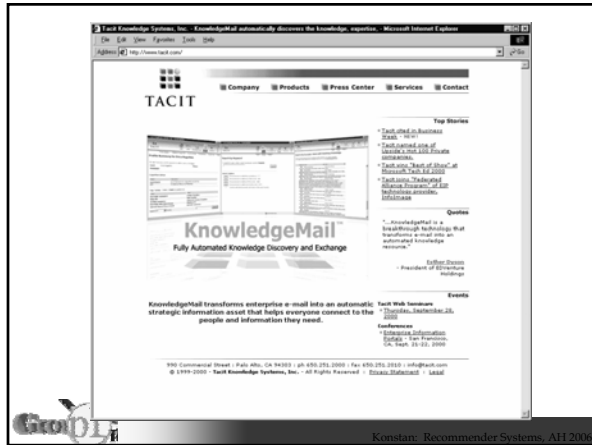
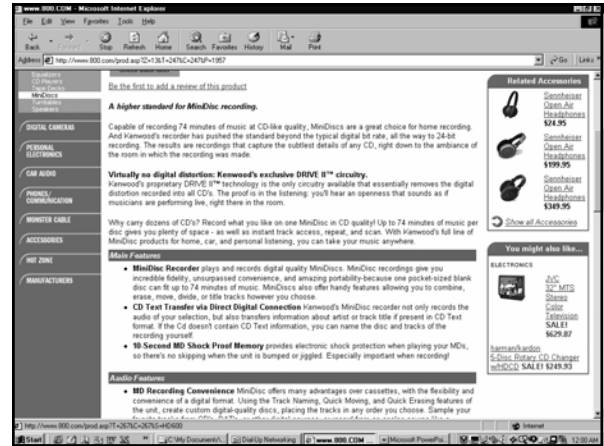


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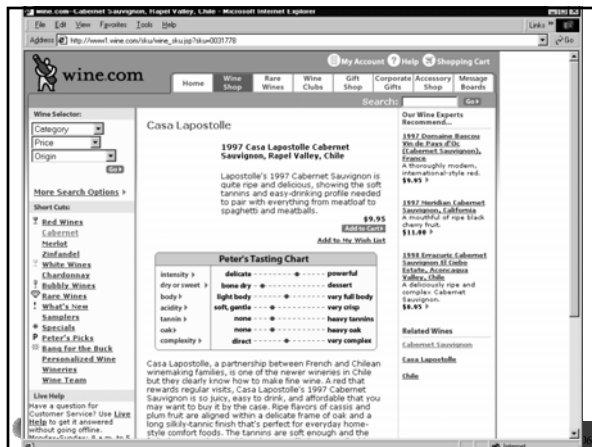
### Purposes of Recommendation

- The recommendations themselves
  - Sales
  - Information
- Education of user/customer
- Build a community of users/customers around products or content



### Whose Opinion?

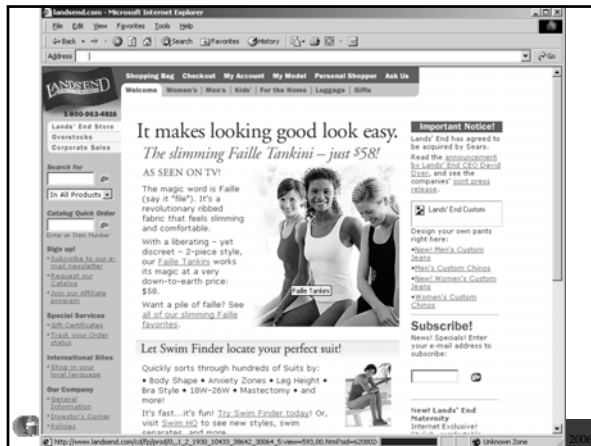
- “Experts”
- Ordinary “phoaks”
- People like you



### Personalization Level

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





## Privacy and Trustworthiness

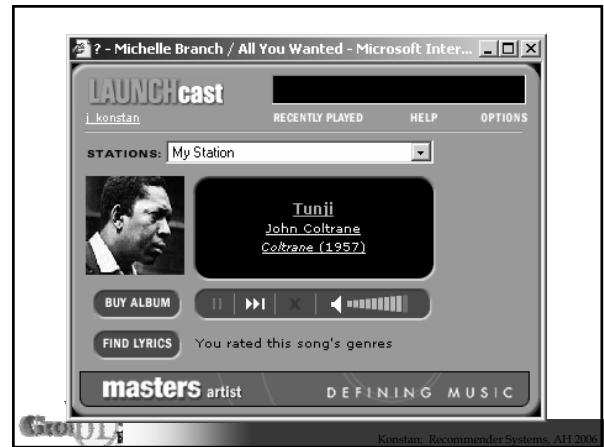
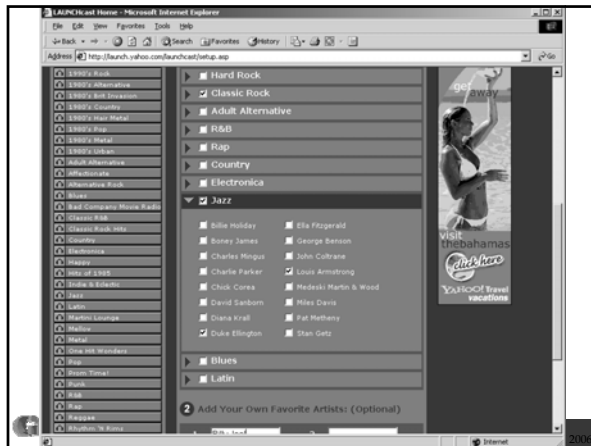
- Who knows what about me?
  - Personal information revealed
  - Identity
  - Deniability of preferences
- Is the recommendation honest?
  - Biases built-in by operator
    - “business rules”
  - Vulnerability to external manipulation

## Interfaces

- Types of Output
  - Predictions
  - Recommendations
  - Filtering
  - *Organic vs. explicit presentation*
- Types of Input
  - Explicit
  - Implicit


## Launching Organic Interfaces

- Launch.yahoo.com – a truly personal radio station
  - Observes play limits
  - Mixes different inputs, different recommenders
  - Kill a song – once and forever
  - Nice information on why a song is playing



### Application Critiques

- Consider the following recommender-powered application
  - What's good?
  - What's bad?
  - Why?



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### Summary and Discussion



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