

Recommender Systems: User Experience and System Issues

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<http://www.grouplens.org>



UNIVERSITY OF MINNESOTA

About me ...

- Professor of Computer Science & Engineering, Univ. of Minnesota
- Ph.D. (1993) from U.C. Berkeley
 - GUI toolkit architecture
- Teaching Interests: HCI, GUI Tools
- Research Interests: General HCI, and ...
 - Collaborative Information Filtering
 - Multimedia Authoring and Systems
 - Visualization and Information Management
 - Medical/Health Applications and their Delivery



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A Quick Introduction

- What are recommender systems?
- Tools to help identify worthwhile stuff
 - Filtering interfaces
 - E-mail filters, clipping services
 - Recommendation interfaces
 - Suggestion lists, "top-n," offers and promotions
 - Prediction interfaces
 - Evaluate candidates, predicted ratings



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Scope of Recommenders

- Purely Editorial Recommenders
- Content Filtering Recommenders
- Collaborative Filtering Recommenders
- Hybrid Recommenders



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Wide Range of Algorithms

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



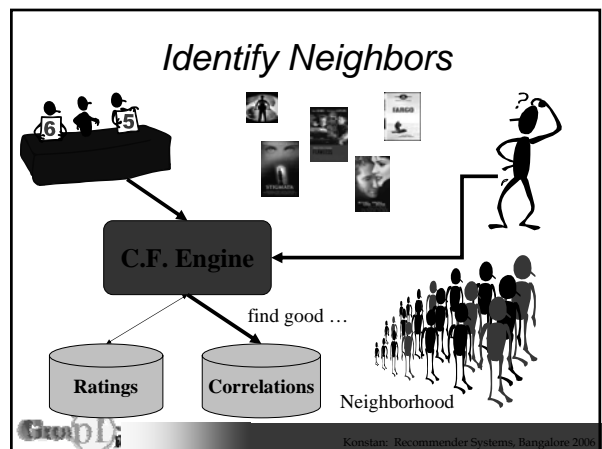
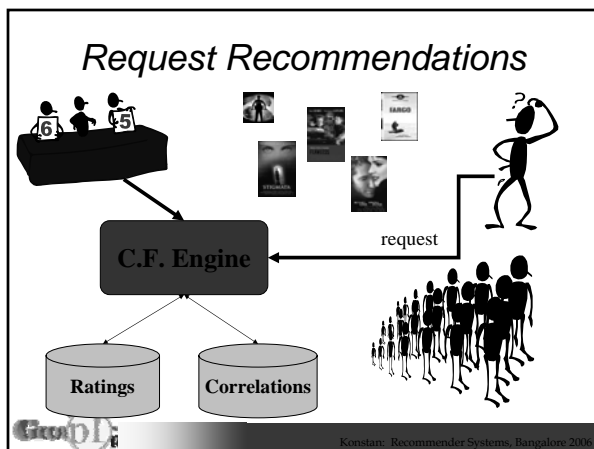
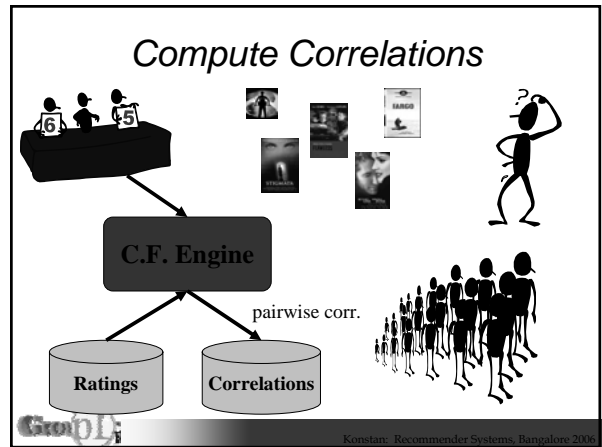
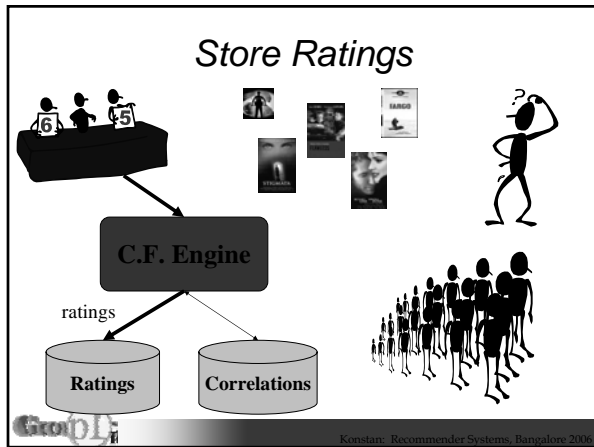
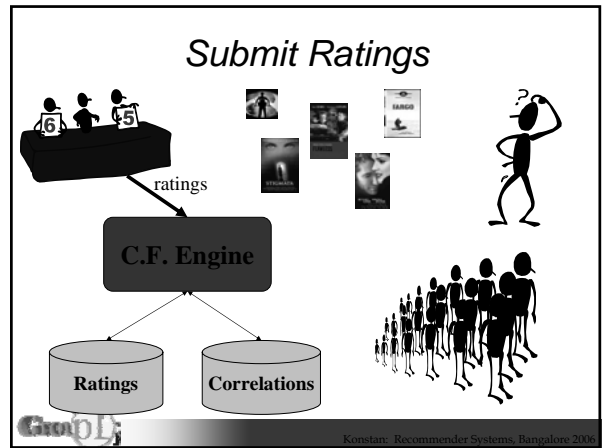
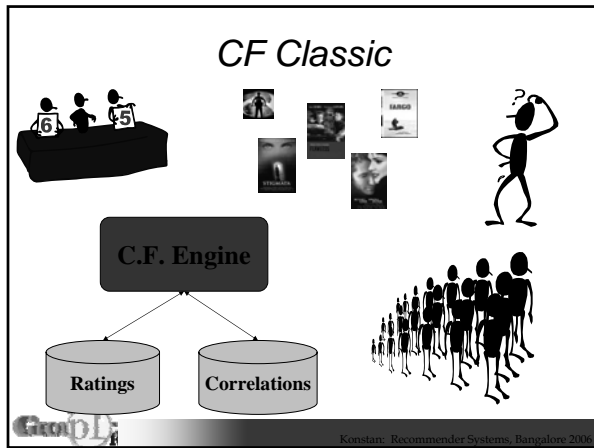
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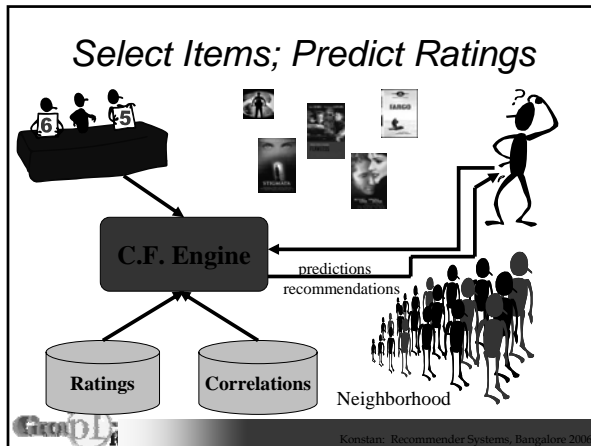
Classic Collaborative Filtering

- MovieLens*
- K-nearest neighbor algorithm
- Model-free, memory-based implementation
- Intuitive application, supports typical interfaces
- *Note - newest releases use updated architecture/algorithm



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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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Understanding the Computation

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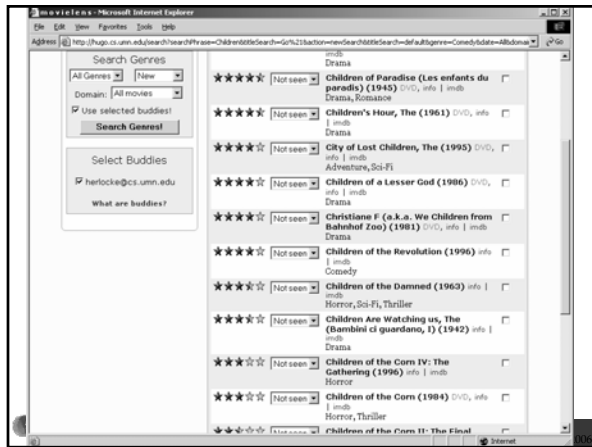
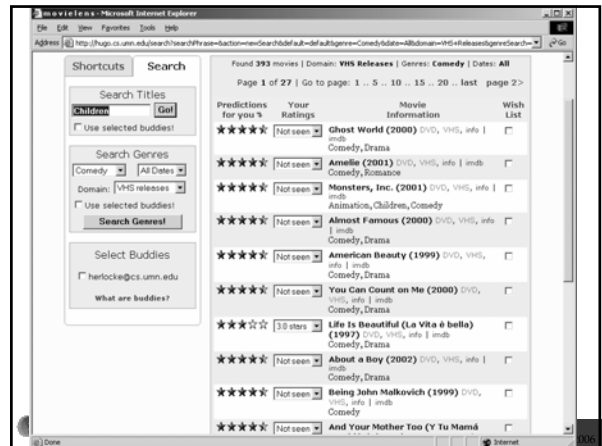
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Jean	A	C	A	C		A
Ben	F	A				F
Nathan	D		A		A	

MovieLens

Freely accessible at: <http://www.movielens.org>



Talk Roadmap

- ✓ Introduction
- Choices
 - Algorithms
 - Application Space Overview
 - Research Overview
 - Influencing Users
 - Recommending Research Papers
 - Rethinking Recommendation
 - 8 Principles for Personalization

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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

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ZAGAT SURVEY: BY POPULAR VOTE - Microsoft Internet Explorer

Address: http://www.zagat.com/SearchDetails.asp?VID=1&PID=1&LID=306L&SID=1826888RW=21&NDPH=San+Jose&RID=30610

ZAGAT SURVEY HOME NEWS BROWSE INDEXES VOTE

location: San Francisco go restaurant search:

ZAGAT SHOP on sale now in the ZAGAT SHOP 2003/04 ATLANTA RESTAURANTS

Prefer MasterCard Click here to start shopping

REVIEW

La Forêt

San Jose
21747 Bertram Rd. (Almaden Rd.) San Jose, CA, 95120-4329 (408) 997-3458

Food 25 Decor 26 Service 26 Cost \$57

VOTE

Please select your ratings for Food, Decor, Service on a scale of 0-3 (0=worst, 3=best). Click here for help.

Food Decor Service

Favorite dish:

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Item-Item Collaborative Filtering

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

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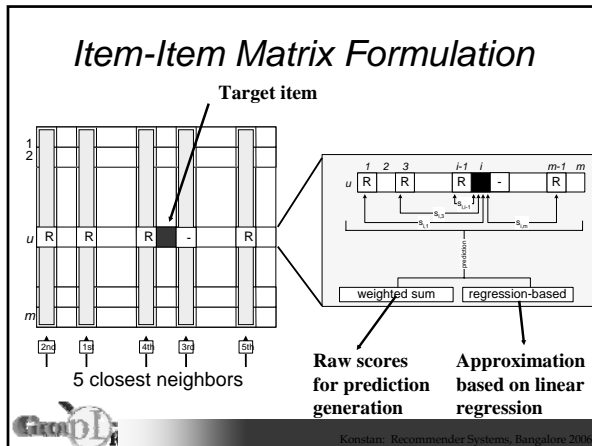
Item-Item Collaborative Filtering

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Item-Item Collaborative Filtering

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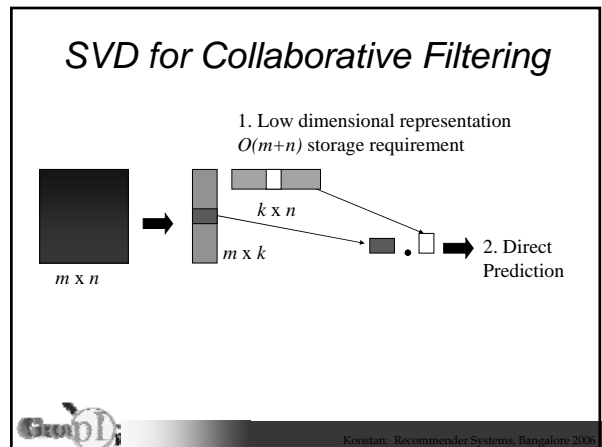
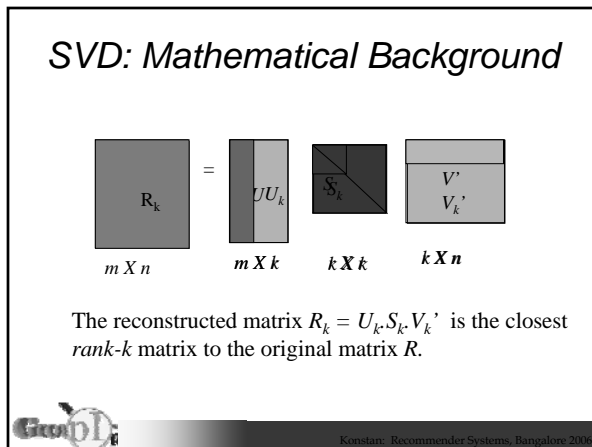
Used for similarity computation



- ### Item-Item Discussion
- Good quality, in sparse situations
 - Promising for incremental model building
 - Small quality degradation
 - Big performance gain
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- ### 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 ICCIT 2002.
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Singular Value Decomposition

Reduce dimensionality of problem

- Results in small, fast model
- Richer Neighbor Network

Incremental Update

- Folding in
- Model Update



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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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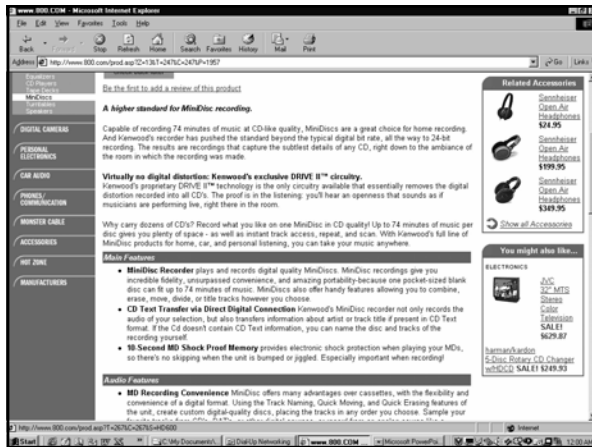


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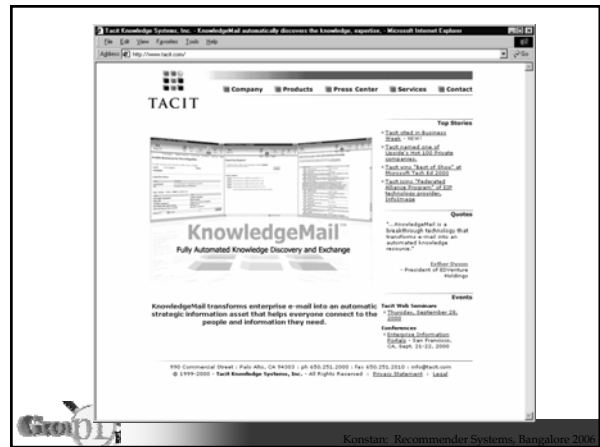
Purposes of Recommendation

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

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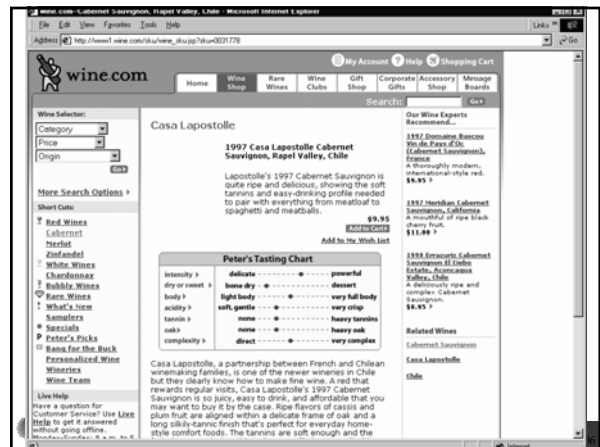


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Whose Opinion?

- "Experts"
- Ordinary "phoaks"
- People like you

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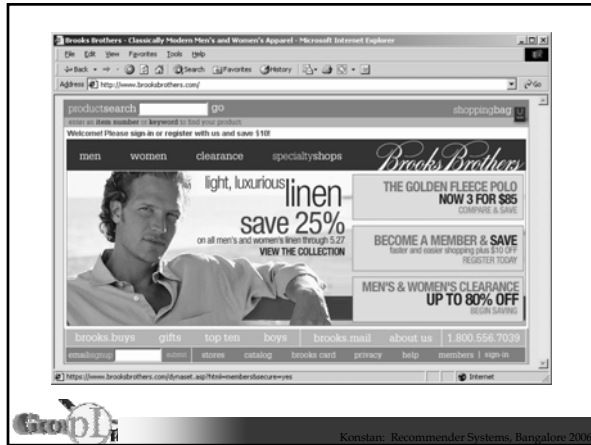
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Personalization Level

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



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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



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Interfaces

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



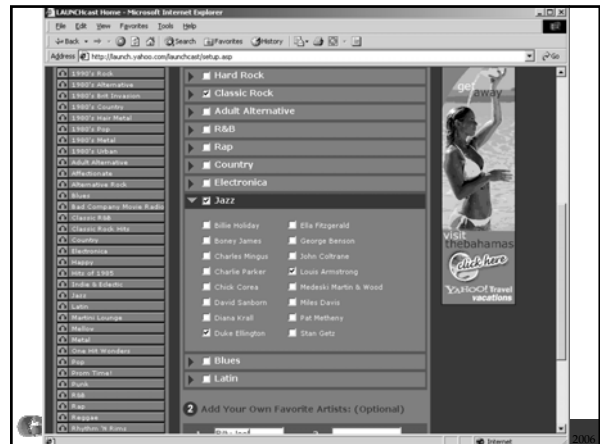
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Launching Organic Interfaces

- 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



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Current and Recent Research

User Experience

- Impact of Ratings on Users
- New User "Orientation"
- Confidence Displays
- Interface Design
- Human-Recommender Interaction

Algorithmic and Systems Issues

- Beyond Accuracy: Metrics and Algorithms
- Buddies and Multi-User Recommendations
- Influence and Shilling

Eliciting Participation in On-Line Communities

- Reinventing Conversation
- User-Maintained Communities

Extending Recommendation to New Domains

- Recommending Research Papers



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Does Seeing Predictions Affect User Ratings?

- RERATE: Ask 212 users to rate 40 movies
 - 10 with no shown prediction
 - 30 with shown predictions (random order):
 - 10 accurate, 10 up a star, 10 down a star
- Compare ratings to accurate predictions
 - "Prediction" is user's original rating
 - Hypothesis: users rate in the direction of the shown prediction



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The Study

Progress - Mozilla (Build ID: 2002021104)

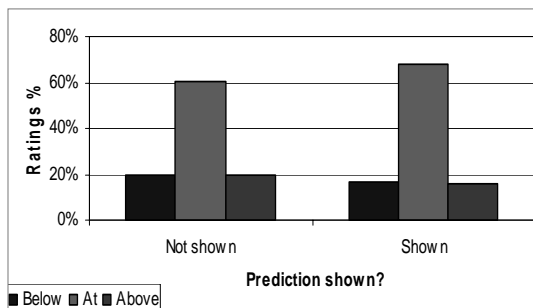
Please rate the movies listed below. These ratings will not be saved to your profile.

PREDICTED RATING	YOUR RATING	GENRE	TITLE
★★★	<input type="text" value="don't know"/>	Action, Adventure Comedy, Horror Sci-Fi	Army of Darkness (1992) (MMA)
★★	<input type="text" value="don't know"/>	Adventure Comedy Fantasy	Bill & Ted's Bogus Journey (1989) (MMA)
★★★★	<input type="text" value="don't know"/>	Drama	Citizen Kane (1941) (MMA)
★★★★	<input type="text" value="don't know"/>	Action, Thriller	Die Hard 2 (1990) (MMA)
★★★★	<input type="text" value="don't know"/>	Horror	Evilwrist The (1973) (MMA)
★★★★	<input type="text" value="1"/>	Crime, Drama	Heist (2001) (MMA)
★★	<input type="text" value="3"/>	Action, Adventure	Knights Tale A (2001) (MMA)
★★★★	<input type="text" value="5"/>	Comedy	Monty Python and the Holy Grail (1975) (MMA)



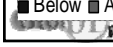
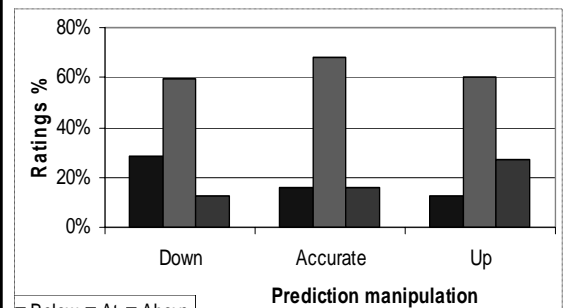
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Seeing Matters



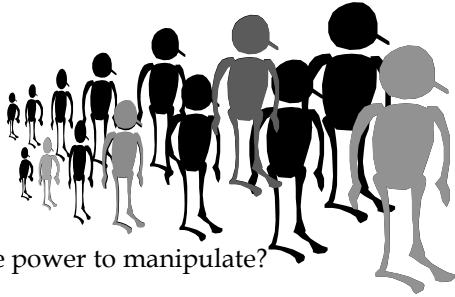
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Accuracy Matters



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Domino Effects?



- The power to manipulate?



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Rated, Unrated, Doesn't Matter

- Recap of RERATE effects:
 - Showing prediction changed 8% of ratings
 - Altering shown prediction changed 12%
- Similar experiment, UNRATED movies
 - 137 experimental users, 1599 ratings
 - Showing prediction changed 8% of ratings
 - Altering shown prediction changed 14%



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But Users Notice!

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



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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



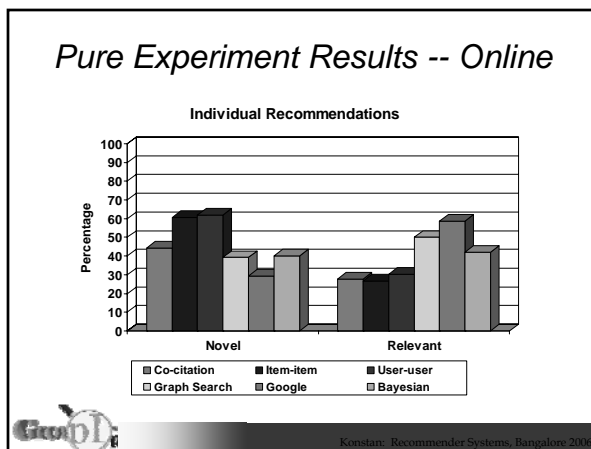
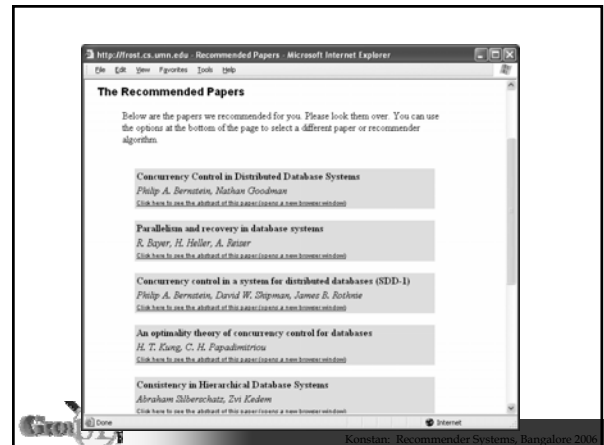
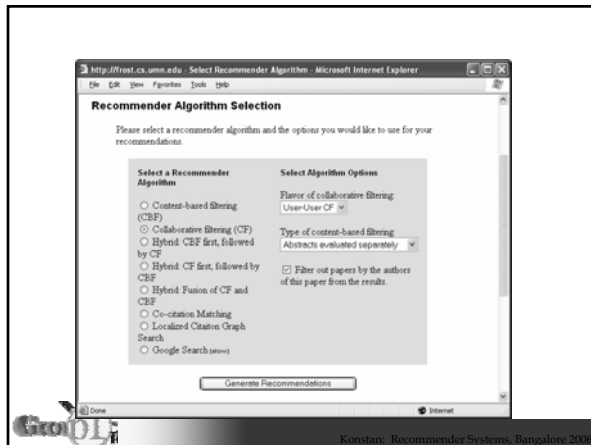
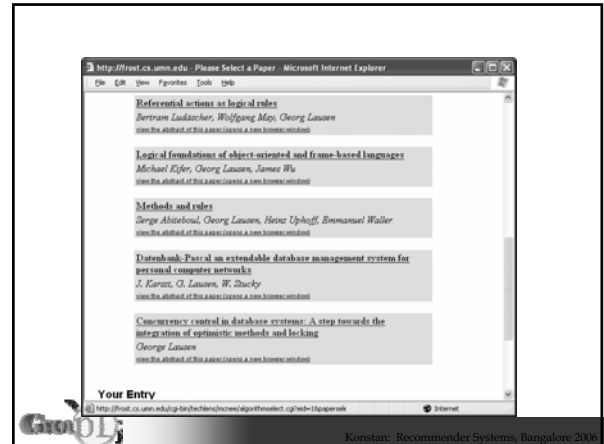
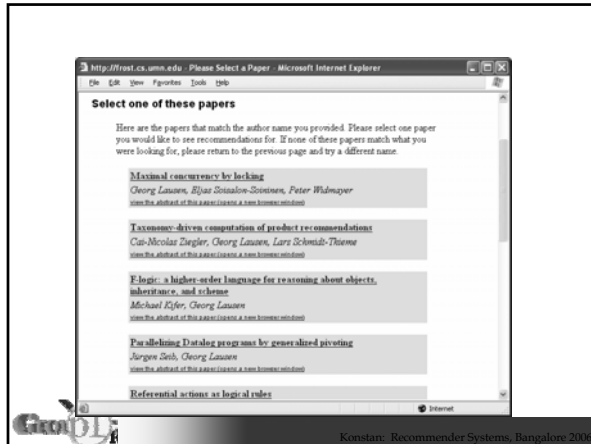
S. McNee et al. "On the Recommending of Citations for Research Papers", in *Proc. CSCIV 2002* and R. Torres et al. "Enhancing Digital Libraries with TechLens+", in *Proc. JCDL 2004*.



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- ### Pure Experiment Results -- Online
- Worst algorithm returned good results over 25% of the time
 - 76% of users got at least one good recommendation
 - Users happy with one good recommendation in list of five
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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



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Task-Specific Recommendations

- Many different user needs
 - awareness in area of expertise
 - find specific work in area of expertise
 - explore peripheral or new area
 - find people with relevant expertise
 - reviewers, program committees, collaborators
 - reading list for students, newcomers
 - individuals or groups
- Different algorithms fulfill different needs



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Evaluating Recommendations

- Prediction Accuracy
 - MAE, MSE,
- Decision-Support Accuracy
 - Reversals, ROC
- Recommendation Quality
 - Top-n measures
- 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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From Items to Lists

- Do users really experience recommendations in isolation?



C. Ziegler et al. "Improving Recommendation Lists through Topic Diversification", in Proc. WWW 2005.



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The screenshot displays a list of four recommended books. Each item includes a small book cover icon, a title, a brief description, and pricing information. The items are:

- War of the Ring (The History of the Lord of the Rings, Part Three)** by J.R.R. Tolkien. Price: \$19.40.
- The War of the Ring (The History of the Lord of the Rings, Part Three)** by J.R.R. Tolkien. Price: \$11.20.
- The Hobbit (The History of the Lord of the Rings, Part Two)** by J.R.R. Tolkien. Price: \$11.20.
- The Shining of Middle-earth (The History of Middle-earth, Volume 12)** by J.R.R. Tolkien. Price: \$4.99.

 Each item has a 'View Details' link and a 'Rate this item' star rating.



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Sauron Defeated
By J.R.R. Tolkien, Christopher Tolkien, Editor
Average Customer Review: 4.8/5.0 (100 reviews)
Our Price: \$20.40 (Used & New from \$1.99)

The War of the Ring
By J.R.R. Tolkien, Editor
Average Customer Review: 4.8/5.0 (100 reviews)
Our Price: \$11.20 (Used & New from \$1.99)

Treason of Isengard
By J.R.R. Tolkien, Editor
Average Customer Review: 4.8/5.0 (100 reviews)
Our Price: \$11.20 (Used & New from \$1.99)

Shaping of Middle Earth
By J.R.R. Tolkien, Editor
Average Customer Review: 4.8/5.0 (100 reviews)
Our Price: \$4.99 (Used & New from \$1.99)

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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

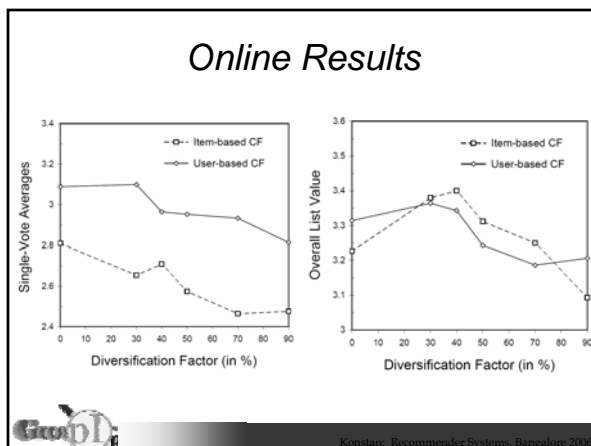
- Re-order results in a rec list
- Add item with *least* similarity to all items already on list
- Weight with a 'diversification factor'
- Ran experiments to test effects

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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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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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Human-Recommender Interaction

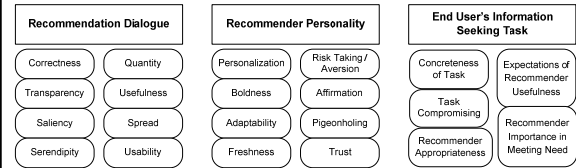
- Three premises:
 - Users perceive recommendation quality in context; users evaluate lists
 - Users develop opinions of recommenders based on interactions over time
 - Users have an information need and come to a recommender as a part of their information seeking behavior



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

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HRI Pillars and Aspects



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HRI Process Model



- Makes HRI Constructive
 - Links Users/Tasks to Algorithms
- Need New Metrics



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New Metrics

- Benchmark a variety of algorithms
- Need several metrics inspired by different HRI Aspects
- Examples:
 - Ratability
 - Boldness
 - Adaptability



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Metric Experimental Design

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



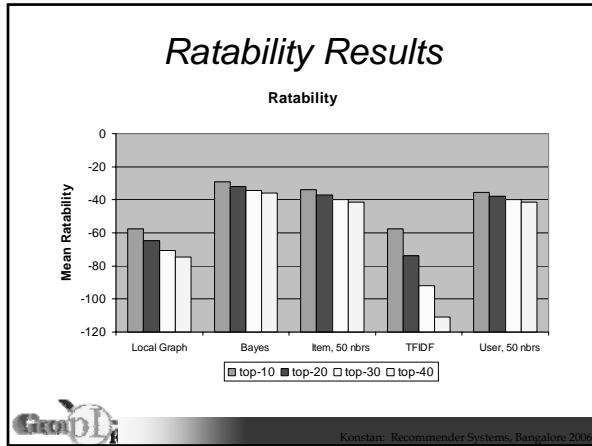
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Ratability

- 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



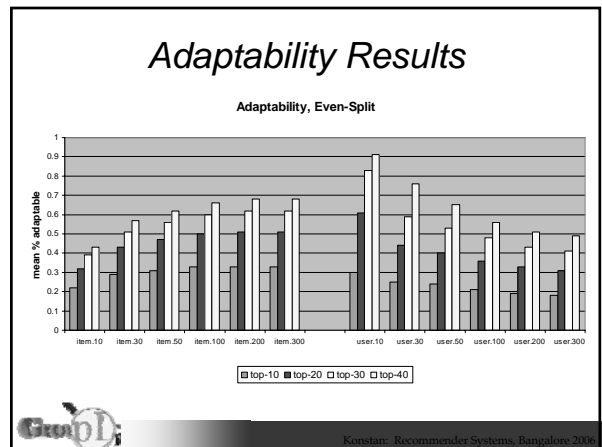
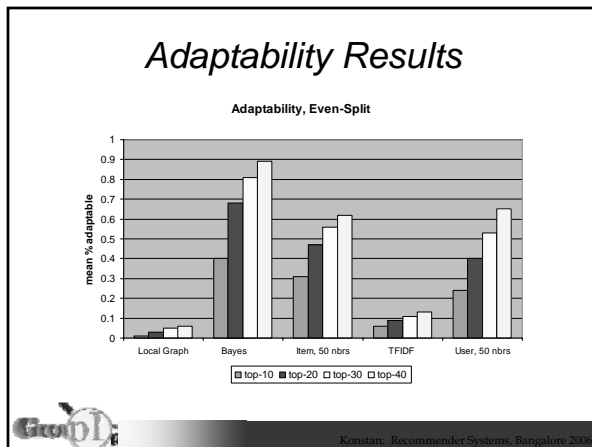
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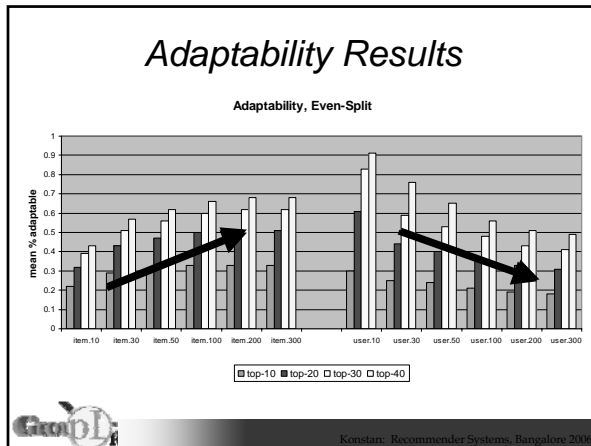


- ### Boldness
- Measure of “Extreme Predictions”
 - Only defined on explicit rating scale
 - Choose “extreme values”
 - Count appearance of “extremes” and normalize
 - For example, MovieLens
 - 0.5 to 5.0 star scale, half-star increments
 - Choose 0.5 and 5.0 as “extreme”
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- ### 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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- ### Talk Roadmap
- ✓ Introduction
 - Choices
 - Algorithms
 - Application Space Overview
 - Research Overview
 - Influencing Users
 - Recommending Research Papers
 - Rethinking Recommendation
 - 8 Principles for Personalization
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Eight Principles for Personalizing Your Business

Illustrated by Case Studies

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- ### The Eight Principles
1. Demonstrate Product Expertise
 2. Be a Customer Agent
 3. Maintain Excellent Service Across Touchpoints
 4. Box Products, Not People
 5. Watch What I Do
 6. Revolutionize Knowledge Management
 7. Use Communities to Create Content
 8. Turn Communities into Content
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Principle 1. Demonstrate Product Expertise

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- ### Key Ideas
- Use expertise and recommenders to build customer trust
 - Provide deep product data, so that customers can make informed decisions
 - Make it fun!
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Principle 3.
Maintain Excellent Service Across Touchpoints



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Key Ideas

- It's still you however your customers get there
- Different strokes for different folks



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Kiosks

- Alienware PC's Now Offered on Best Buy "Computer Creation Stations"
- Blockbuster
 - customer identity
 - privacy issues
- Music Store
 - sampling versus "listening"



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Call Centers

- Inbound
 - "screen-pops"
 - Legacy systems
 - appropriateness
- Outbound
 - Predict who will buy
 - Predict what they will buy
 - Predict when to contact them
 - Online campaign management



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Zagat What it Takes


- 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!"



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Principle 5. Watch What I Do



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Key Ideas


- Actions speak louder than words
- Determine actions by context
- Respond to customers' reactions to your recommendations



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Examples

- Google
- PHOAKS
- Amazon
- My Yahoo




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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)



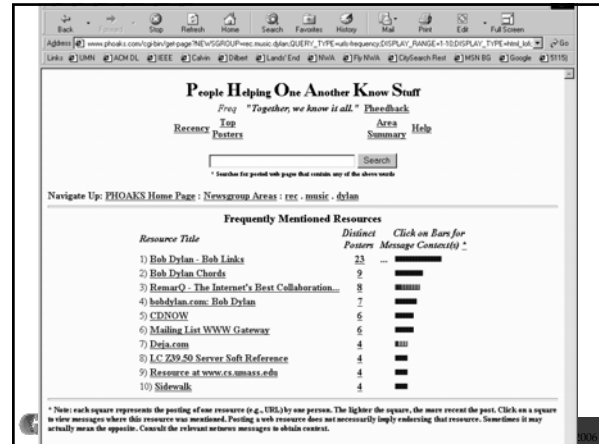
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PHOAKS

- 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



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Principle 7.

Use Communities to Create Content

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Key Ideas

- Editorial process is value added
- Free is better than paying for it
 - customers trust what they produce
- Reward creatively



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Home > Autos & Motorcycles > Autos > 2000 Toyota Sienna

Level II / Hate II

Average rating: 4.5 (62 Member Opinions)

Recommended 93% of the time

2000 Toyota Sienna

Current Est. Price: \$10750-27324
Manufacturer: Toyota
Class: Van & Minivan
Model Year: 2000
Model Platform: LE 4 Dr Pass Van

Get Updates

Help others decide. Write an opinion.

Go Shopping!

Related Items

Professional Reviews

Get Updates

Web of Trust

jmb623's Profile

Opinions written: 75 | Member since: 4712 | Total visits: 39199

Opinions ID: jmb623
Gender: Male
Member since: Jul 12, 1999
Email: jmb623@msn.com

Favorite Web Sites:

Interests:

About jmb623:

I am a lawyer by day and a geek by night. Computers and software became a serious passion a few years ago, and I have immersed myself in fooling with them ever since. I learned a lot about operating systems and device drivers by tweaking Windows 95 until I wiped it out. I replaced it with Windows 98 and wiped that out a few times, but still run it.

I taught myself to do hardware and software installations the hard way (by screwing up), and began to do beta testing and software reviews about a year ago. I have written articles and software reviews for www.pcwin.com. I've also answered a lot of user posted questions for the HP Desigjet 895C on HP's 895C.

Love It

Hate It

Opinions written by jmb623

Date	Title	Reviewed Product	Product Rating	Category	Opinion Rating
08/20/00	MSN 3.0: Professional Outlook Sidebar	MSN	*****	Computers & Internet	Highly Recommended
08/13/00	HP 895C: Review: Fastest Scan in the West	HP ScanJet 8300C	*****	Computers & Internet	Highly Recommended
07/14/00	HP's Fast And Furious: HP's Fast And Furious: HP's Fast And Furious	Printer: HP DeskJet 8300C	*****	Computers & Internet	Highly Recommended
07/04/00	Research: Can Make An Adult Out of Almost Anyone!	Research	*****	Computers & Internet	Highly Recommended
04/29/00	Internet: Can You Make An Adult Out of Almost Anyone!	Internet: Can You Make An Adult Out of Almost Anyone!	*****	Computers & Internet	Highly Recommended
04/17/00	Speedtest: Speedtest at Science Fiction???	Speedtest	*****	Computers & Internet	Highly Recommended
04/07/00	Ballista 2 Pro: MetaSearch Ballista 2 Pro	Ballista 2 Pro	*****	Computers & Internet	Highly Recommended
03/28/00	Ballista 2 Pro: Your Member: Double DoubleDouble	Ballista 2 Pro	*****	Computers & Internet	Highly Recommended

Account options

Account Summary

Opinions & Earnings

Account Summary

Opinions written: 2
Member visits: 4
Total visits: 8

Earnings Summary

Opinion Earnings: \$0.14
Domain Earnings: \$0.12
Other: \$0.00
Total Earnings: \$0.26

System Status

Site Settings

Web of Trust

Love It / Hate It

Matchmaker.com - The most entertaining place to meet new people.™ Matcha (Build ID: 2000031104)

Stop Waiting. Start Living. Go Meet Somebody!

Members Login

Preview Members

FREE TRIAL

Your FREE Trial includes:

- Safe, private, anonymous
- Over 60 location or affinity groups
- A custom profile with photos

Matchmaking since 1995. Over 8 million members to date.

Conclusions

- From humble origins ...
 - Substantial algorithmic research
 - HCI and online community research
 - Important applications
 - Commercial deployment



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Recommender Systems: User Experience and System Issues

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