

AI Techniques for Personalized Recommendation

Tutorial presented at AAAI 2002

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Introduction

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What Are Recommender Systems?

Preview

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What are Recommender Systems?

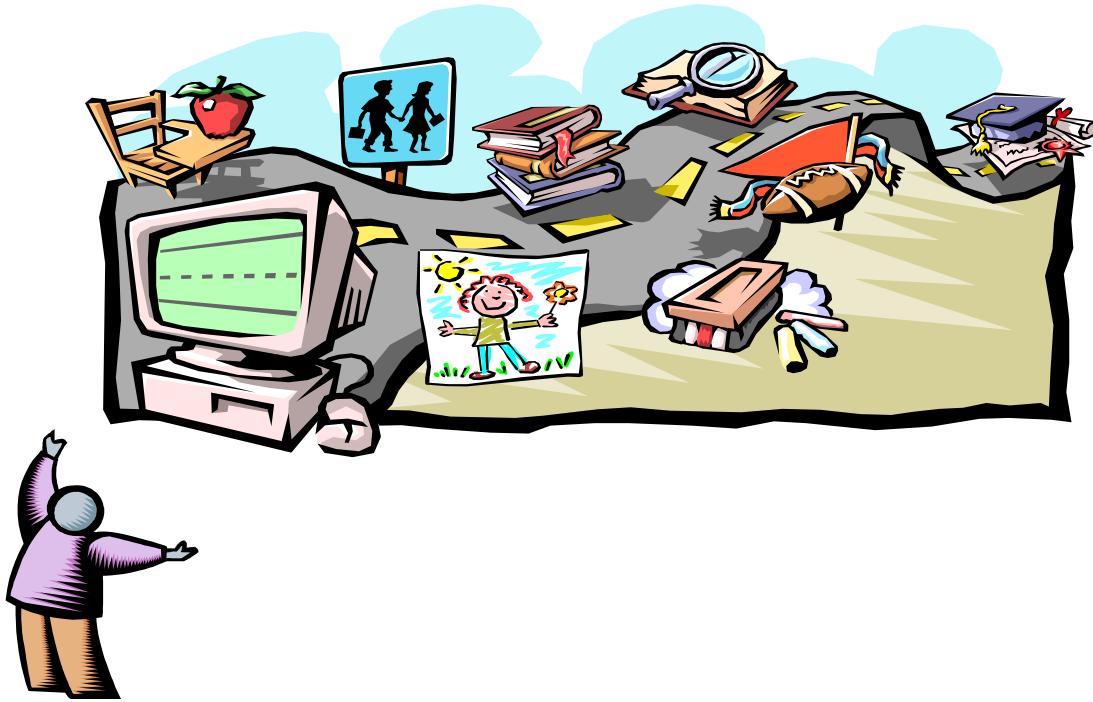
Goals of this Tutorial

Brief History of Recommender Systems



7

The Problem: Overload



Too Much Stuff!

8

Too many messages!

Too many journal articles!

Too many movies!

Too much content!

9

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

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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

Tutorial Goals and Outline Goals⁽¹⁾

12

When you leave, you should ...

- Understand recommender systems and their application
- Know enough about recommender systems technology to evaluate application ideas
- Be able to design and critique recommender application designs

Goals (2)

- Be familiar with a variety of recommendation algorithms
- Understand the privacy issues in recommender systems and approaches to addressing them
- See where recommender systems have been, and where they are going

Outline (1)

Introduction

Applications and Interfaces

- E-commerce
- Documents
- Off-web
- Case studies

Outline (2)

Algorithms and Techniques

- Overview
- Collaborative Filtering
 - Algorithms
 - Interfaces
 - Case Studies

Lunch

Outline (3)

Algorithms and Techniques II

- Case-Based Reasoning
- Other Content-Based Methods
- Demographically Based Methods
- Hybrid Methods
- Utility-Based Methods
- Knowledge-Based Methods
- Case Studies

Recommender System Design Exercise

Outline (4)

Advanced Topics

- Anthropomorphism
- Group Decision Making Support
- Mobile/Wireless Recommenders
- Privacy Issues
- Diminishing Marginal Returns
- Temporal Recommenders

Conclusions and Questions

History of Recommender Systems

The Early Years ...

Why cave dwellers survived

Critics, critics, everywhere

How editors are like cave dwellers

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

Collaborative Filtering

Premise

- Information needs more complex than keywords or topics: quality and taste

Small Community: Manual

- Tapestry – database of content & comments
- Active CF – easy mechanisms for forwarding content to relevant readers

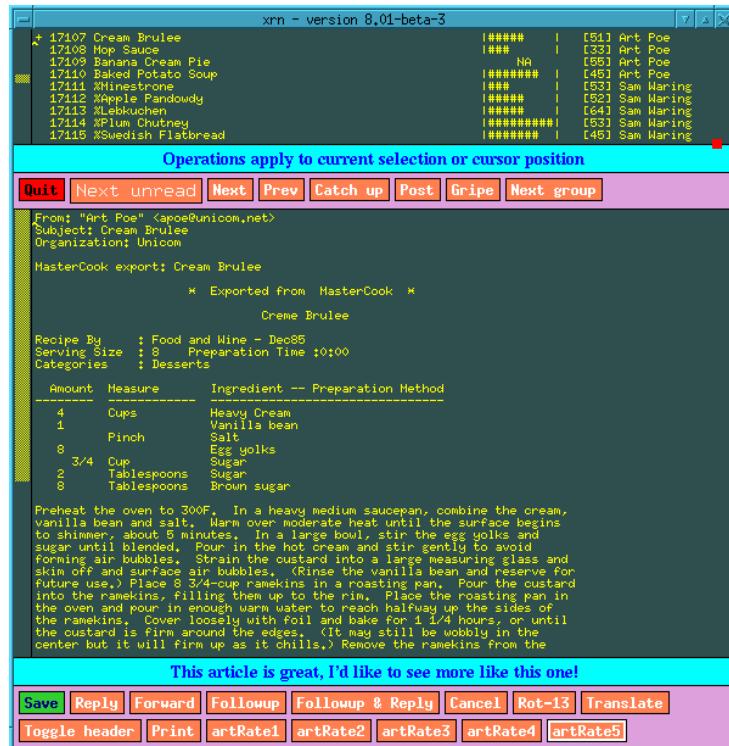
Automated CF

The GroupLens Project (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

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Usenet Interface



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ACF Blossomed

1995

- Ringo (later Firefly)
- Bellcore Video Recommender

1996 Recommender Systems Workshop

Early commercialization

- Agents Inc. (later Firefly)
- Net Perceptions

new issues of scale and performance!

Today

Broad research community

- live research systems
- substantial integration among:
 - collaborative filtering
 - machine learning
 - non-ML information filtering

Increasing commercial application

- available commercial tools

Introductions Presenters

Joe Konstan

- Human-computer interaction

John Riedl

- Collaborative computing

Anthony Jameson

- User modeling

Disclaimers ...

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About You ...

Where you're from

Your experience with recommenders

What you want to get out of this tutorial

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Recommender Application Space

Dimensions of Analysis

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

Domains of Recommendation

Domains of Recommendation

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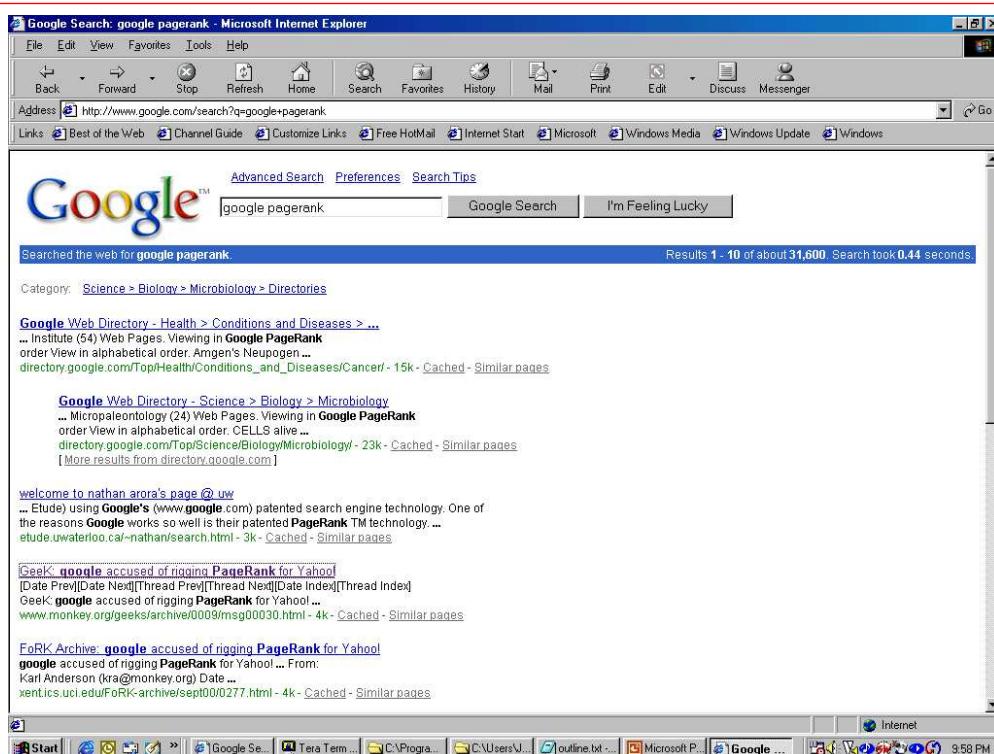
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Content to Commerce

- News, information, “text”
- Products, vendors, bundles

Google: Content Example

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101 Guides



Purposes of Recommendation

Purposes of Recommendation

34

The recommendations themselves

- Sales
- Information

Education of user/customer

Build a community of users/customers around products or content

35

800.com You Might Also Like

A higher standard for MiniDisc recording.

Capable of recording 74 minutes of music at CD-like quality, MiniDiscs are a great choice for home recording. And Kenwood's recorder has pushed the standard beyond the typical digital bit rate, all the way to 24-bit recording. The results are recordings that capture the subtlest details of any CD, right down to the ambiance of the room in which the recording was made.

Virtually no digital distortion: Kenwood's exclusive DRIVE II™ circuitry.

Kenwood's proprietary DRIVE II™ technology is the only circuitry available that essentially removes the digital distortion recorded into all CDs. The proof is in the listening: you'll hear an openness that sounds as if musicians are performing live, right there in the room.

Why carry dozens of CDs? Record what you like on one MiniDisc in CD quality! Up to 74 minutes of music per disc gives you plenty of space - as well as instant track access, repeat, and scan. With Kenwood's full line of MiniDisc products for home, car, and personal listening, you can take your music anywhere.

Main Features

- **MiniDisc Recorder** plays and records digital quality MiniDiscs. MiniDisc recordings give you incredible fidelity, unsurpassed convenience, and amazing portability-because one pocket-sized blank disc can hold up to 74 minutes of music. MiniDiscs also offer handy features allowing you to combine, erase, move, divide, or title tracks however you choose.
- **CD Text Transfer via Direct Digital Connection** Kenwood's MiniDisc recorder not only records the audio of your selection, but also transfers information about artist or track title if present in CD Text format. If the CD doesn't contain CD Text information, you can name the disc and tracks of the recording yourself.
- **10-Second MD Shock Proof Memory** provides electronic shock protection when playing your MDs, so there's no skipping when the unit is bumped or jiggled. Especially important when recording!

Audio Features

- **MD Recording Convenience** MiniDisc offers many advantages over cassettes, with the flexibility and convenience of a digital format. Using the Track Naming, Quick Moving, and Quick Erasing features of the unit, create custom digital-quality discs, placing the tracks in any order you choose. Sample your favorite tracks from CDs, DATs, or other digital sources, or record from a radio source.

Epinions Sienna Overview

36

Average rating: ★★★★ (62 Member Opinions)

Recommended 93% of the time

2000 Toyota Sienna

Current Est. Price: \$20730-27334
Manufacturer: Toyota
Class: Van & Minivan
Model Year: 2000
Model Picture: XLE 4 Dr Pass Van

Get Updates

Send me email alerts when new opinions on "2000 Toyota Sienna" appear

Help others decide. Write an opinion.

Go Shopping!

Find out where to buy this item.

Related Items

- 2001
- 2000

Member Opinions

Toysota Sienna: Try to Find a better minivan by **JMB623** (Aug 30 '99)
Product rating: ★★★★★
We bought the 1998 Sienna, knowing that it's usually sheer stupidity to buy the first year release of most vehicles. But Toyota R & D'd this one...

Quiet, comfortable ride by **istrickl** (Dec 22 '99)
Product rating: ★★★★★
My husband and I bought this vehicle because we were ready to give ourselves and our almost teenage boys more room on trips. We have an SUV and love...

a great mini-van by **dannels** (May 16 '00)
Product rating: ★★★★★
When we were shopping for a mini-van, we had a lot of input from friends. I have owned 2 Toyota Camry's and I was very satisfied with the quality...

Opinion Highly Recommended by an advisor

Opinion Highly Recommended by an advisor

Opinion Highly Recommended by an advisor

Read all 62 Member Opinions -->

Professional Reviews

1999 Toyota Sienna XLE by **ArchivellUSA.com**

Suggest a Link

Highly Recommended

See What's New

Latest Reviews

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OWL Tips

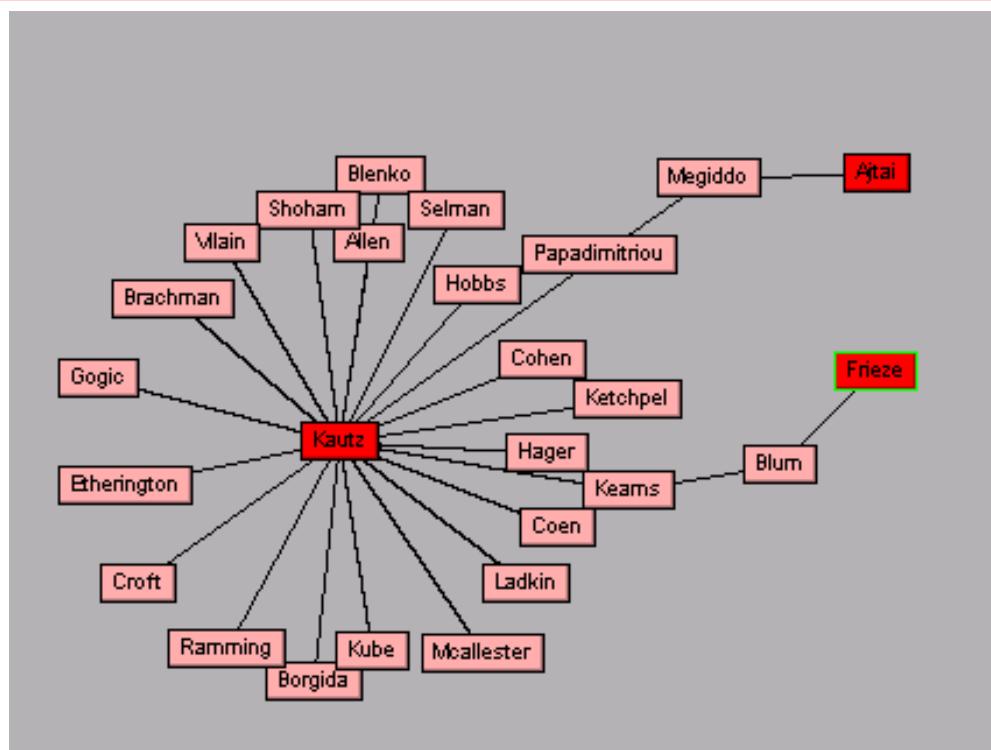
OWL Tips

Date	Word Commands	Comments	Priority
9/30/98	EditFind	Use Find more to search for text in file	88
	EditDeleteWord	Learn the shortcut keys to delete words	87
	FormatUnderline	Try using underlining for formatting text	80
	FileClose	Try different ways to close your file	74
	EditReplace	Use Replace more for finding and replacing text	72
	ViewZoom	Learn how to enlarge or reduce the display	69
	ViewShowAll	FYI-more than average use for Show All commar	67
	FormatBulletsAndNumbering	Learn how to automatically add bullets and num	64
	ToolsWordCount	Use Word Count to look up statistics on files	61
	ViewPage	Use Page Layout to view files before printing	57

User: M06375 OWL Version: 5.0c [OWL Help](#) [OK](#)

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ReferralWeb



Whose Opinion? Whose Opinion?

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“Experts”

Ordinary “phoaks”

People like you

Wine.com Expert Recommendations

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The screenshot shows a Microsoft Internet Explorer window displaying the wine.com website. The URL in the address bar is http://www1.wine.com/sku/wine_sku.jsp?sku=0031778. The page title is "wine.com-Cabernet Sauvignon, Rapel Valley, Chile - Microsoft Internet Explorer".

The main content area displays a product page for "1997 Casa Lapostolle Cabernet Sauvignon, Rapel Valley, Chile". The price is listed as \$9.95. There are "Add to Cart" and "Add to My Wish List" buttons.

To the right of the product details, there is a sidebar titled "Our Wine Experts Recommend..." listing three wines:

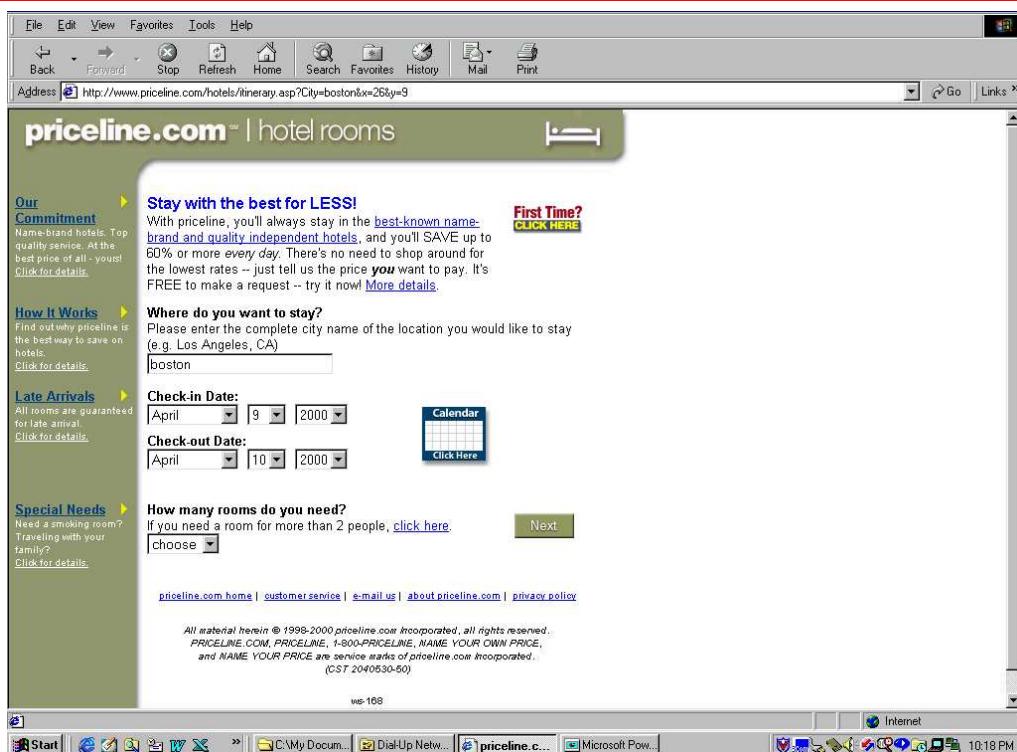
- 1997 Domaine Bascou**
Vin de Pays d'OC (Cabernet Sauvignon), France
A thoroughly modern, international-style red.
\$9.95 ▶
- 1997 Meridian Cabernet**
Sauvignon, California
A mouthful of ripe black cherry fruit.
\$11.00 ▶
- 1998 Errazuriz Cabernet**
Sauvignon El Cielo Estate, Aconcagua Valley, Chile
A deliciously ripe and complex Cabernet Sauvignon.
\$8.95 ▶

Below the sidebar, there is a section titled "Peter's Tasting Chart" with a grid of wine characteristics and descriptions.

The left sidebar contains a "Wine Selector" with dropdown menus for Category, Price, and Origin, and a "Go" button. It also includes a "More Search Options" section with links to Red Wines, White Wines, Rare Wines, What's New, Samplers, Specials, Peter's Picks, Bang for the Buck, Personalized Wine, Wineries, and Wine Team. At the bottom of the sidebar, there is a "Live Help" section with instructions for getting customer service help.

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Priceline.com Screenshot



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Phoaks

The screenshot shows a Microsoft Internet Explorer browser window displaying the Phoaks website. The URL in the address bar is http://www.phoaks.com/cgi-bin/get-page?NEWSGROUP=rec.music.dylan&QUERY_TYPE=url-frequency&DISPLAY_RANGE=1-10&DISPLAY_TYPE=html_lol.

People Helping One Another Know Stuff
Freq "Together, we know it all." Pheedback

[Recency](#) [Top Posters](#) [Area Summary](#) [Help](#)

Search
* Searches for posted web pages that contain any of the above words

Navigate Up: [PHOAKS Home Page](#) : [Newsgroup Areas](#) : [rec](#) . [music](#) . [dylan](#)

Frequently Mentioned Resources

Resource Title	Distinct Posters	Click on Bars for Message Context(s) *
1) Bob Dylan - Bob Links	23	...
2) Bob Dylan Chords	9	[dark bar]
3) RemarQ - The Internet's Best Collaboration...	8	[medium bar]
4) bobdylan.com: Bob Dylan	7	[light bar]
5) CDNOW	6	[dark bar]
6) Mailing List WWW Gateway	6	[dark bar]
7) Deja.com	4	[medium bar]
8) LC Z39.50 Server Soft Reference	4	[light bar]
9) Resource at www.cs.umass.edu	4	[dark bar]
10) Sidewalk	4	[light bar]

* Note: each square represents the posting of one resource (e.g., URL) by one person. The lighter the square, the more recent the post. Click on a square to view messages where this resource was mentioned. Posting a web resource does not necessarily imply endorsing that resource. Sometimes it may actually mean the opposite. Consult the relevant netnews messages to obtain context.

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MovieLens: Product Example

The screenshot shows a Microsoft Internet Explorer window displaying the MovieLens website. The address bar shows the URL: http://movielens.umn.edu/search.cgi. The page title is "movielens" with the tagline "helping you find the right movies". The navigation menu includes Home, Your Ratings, To-See List, Account Info, Groups, Reviews, Help, Privacy, and Logoff. Below the menu, there are search fields for "Search For Movie Title:" and "Select group:", both currently set to "NO GROUP". A "Get Recommendations:" button is also present. A message at the top says "Rating more movies improves your predictions; you've rated 36 so far. Currently displaying Comedy movies released anytime." Below this, a legend defines rating levels: [5] = Must See, [4] = Will Enjoy, [3] = It's OK, [2] = Fairly Bad, [1] = Awful. The main content area displays a table of movie recommendations. The columns are PREDICTED RATING, YOUR RATING, GENRE, TITLE, REVIEWS, and TO-SEE LIST (3 movies). The table lists various classic and modern comedies like "Trouble in Paradise", "Bank Dick", "Freedom for Us", "City Lights", "Still Breathing", "General, The", "Gold Rush", "Vie est belle", "Shop Around the Corner", "Bringing Up Baby", "Yojimbo", "Modern Times", "Almost Famous", "Wrong Trousers", "Jonah Who Will Be 25 in the Year 2000", "Little Big Man", "Tampopo", and "Close Shave". Most movies have a checked checkbox in the "To-See List" column.

Personalization Level Personalization Level

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Generic

- Everyone receives same recommendations

Demographic

- Matches a target group

Ephemeral

- Matches current activity

Persistent

- Matches long-term interests

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Lands' End

The screenshot shows the Lands' End website in Microsoft Internet Explorer. The header includes a logo, a phone number (1-800-963-4816), and a search bar. The main navigation menu at the top has links for Shopping Bag, Checkout, My Account, My Model, Personal Shopper, Ask Us, Welcome, Women's, Men's, Kids', For the Home, Luggage, and Gifts. A sidebar on the left offers links for Lands' End Store Overstocks, Corporate Sales, Search for, Catalog Quick Order, Sign up!, Special Services, and International Sites. The main content area features a headline about a slimming Faille Tankini for \$58, followed by a photograph of three women in tankinis. To the right, there's an 'Important Notice' about the company being acquired by Sears, a 'Lands' End Custom' section for designing pants, and a 'Subscribe!' form. A sidebar on the right promotes 'New! Lands' End Maternity'.

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Brooks Brothers

The screenshot shows the Brooks Brothers website in Microsoft Internet Explorer. The header includes a logo and a search bar. The main navigation menu at the top has links for men, women, clearance, specialtyshops, and shoppingbag. The main content area features a large advertisement for 'light, luxurious linen' with a 25% discount. To the right, there are promotional boxes for 'THE GOLDEN FLEECE POLO NOW 3 FOR \$85', 'BECOME A MEMBER & SAVE', and 'MEN'S & WOMEN'S CLEARANCE UP TO 80% OFF'. The footer includes links for brooks.buys, gifts, top ten, boys, brooks.mail, about us, and a phone number (1.800.556.7039). There are also links for emailsignup, submit, stores, catalog, brooks card, privacy, help, members, and sign-in.

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CDNow Album Advisor

The screenshot shows the CDNow Album Advisor page. At the top, there's a banner for 'Folk & Blues up to 30% off' and a link to 'Stay Awake at Work with Non-Stop Music from CDNOW Radio'. The menu bar includes File, Edit, View, Favorites, Tools, Help, and a 'Links' button. The address bar shows the URL: http://www.cdnnow.com/cgi-bin/mserver/SID=1648068516/pagename=/RP/AI/album_advisor.html. Below the menu is a navigation bar with links to MUSIC, VIDEO, GIFTS, MY CDNOW, and HELP. A 'Shopping Cart' icon shows 0 items. A search bar has 'Artist' selected and a 'search' button. To the right of the search bar is a link to 'Search Classical'. On the left, there's a sidebar with categories like Rock, Alternative/Indie, Pop/R&B, Hip-Hop, Electronic/Dance, Jazz, Country, Folk/Blues, World, Latin, Classical, and New Age. Below these are links for Christian/Gospel, Vocal/Theatrical, Soundtracks, Comedy/Spoken, and Kids/Family. At the bottom of the sidebar are links for MTV CD Lounge and VH1 Music Shop. The main content area contains a section titled 'Album Advisor™' with the sub-section 'Album Advisor™'. It says 'Tell us what you like and we'll make several recommendations. Great for buying gifts or broadening your musical horizons.' Below this is a form where users can enter artist names. Two names have been entered: 'gordon bok' and 'enya'. A 'Recommend' button is below the input fields. At the bottom of the page, there are language links: 日本語, Deutsch, Español, Français, Italiano, Nederlands, Português, and a menu bar with Music, Video, Gifts, My CDNOW, Help, and Shopping Cart.

CDNow Album Advisor Recommendations

The screenshot shows the CDNow Album Advisor Recommendations page. The address bar is the same as the previous screenshot. The main content displays three recommended albums:

- Ace Of Base - Cruel Summer**: Includes a thumbnail image of the album cover, a 'Listen' button, and download links for "Cruel Summer" via Real Audio and Windows Media. It also includes a link to "See complete track list and more album info." and purchase links: "Add to Cart \$12.99".
- Erasure - Abba-Esque**: Includes a thumbnail image, a 'Listen' button, and download links for "Lay All Your Love On Me" via Real Audio and Windows Media. It also includes a link to "See complete track list and more album info." and purchase links: "Add to Cart \$6.99".
- Vangelis - Opera Sauvage**: Includes a thumbnail image, a 'Listen' button, and download links for "Hymne" via Real Audio and Windows Media. It also includes a link to "See complete track list and more album info." and purchase links: "Add to Cart \$11.97".

At the bottom of the page, there are 'Done' and 'Internet' buttons.

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My CDnow

The screenshot shows the 'My CDnow' summary page. At the top, there's a navigation bar with links for MUSIC, VIDEO, GIFTS, MY CDNOW, and HELP. Below the navigation is a shopping cart icon showing 0 items, a search bar, and a 'CDNOW Recommends' section featuring a recommendation for 'John Coltrane Love Supreme'.

ORDER HISTORY: Order #14856068 placed on December 25, 1999, Status: Order Shipped. Get additional order information.

REWARDS: Current Program: None. You are not currently signed up for any rewards program. Start earning rewards for FREE CDs and more right now!

PREFERENCES: Customize your

CDNOW RECOMMENDS: John Coltrane Love Supreme, List Price \$27.97, Add to Cart \$13.99. More items recommended for you!

WISH LIST: Want to keep track of items you might like to purchase at a later date? Start your list today!

FAVORITE ARTISTS: Bok*Gordon / Muir*Ann Mayo / Trickett*Ed. Go to Artist. Modify your options and check for Advance Orders and New Releases from your favorite artists.

ACCOUNT INFORMATION & ADDRESS BOOK: Modify your Account Information, change your Primary Address or set up Express Checkout.

RATE YOUR MUSIC: You have 3 items that you haven't rated yet. Tell us [redacted] about the music you own and help us make better recommendations!

Privacy and Trustworthiness

Privacy and Trustworthiness

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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

Applications and Interfaces

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Interfaces

Types of Output

- Predictions
- Recommendations
- Filtering
- *Organic vs. explicit presentation*

Types of Input

- Explicit
- Implicit

Domains in Depth

Web-based e-commerce

Recommending documents and people

Off-web applications

For each domain:

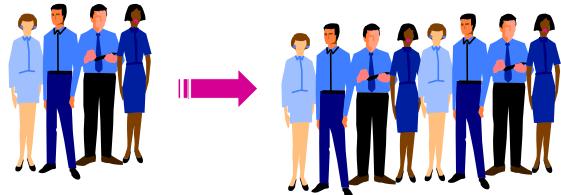
- Interface issues
- Examples
- Privacy issues

E-Commerce

E-Commerce Personalization

- ◆ Increased traffic at your site

- more customers
- more visits each



- ◆ Increased value per customer
- more purchases
- cross-sell
- up-sell

eMarketing Opportunity

Browsers

- Personalized browsing
- Target and attract profitable customers

Seekers

- Increase purchase success
- Enhance customer loyalty

Directed buyers

- Focused cross-sell

E-Commerce Recommenders

Key issues:

- How to get preference information
 - Implicit measures (purchase, navigation)
 - Explicit request
 - Pay (status or money)
- How to display recommendations
 - Call attention
 - Blend in
- “Business Rules”

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Clinique

Which Products Are Right For You? - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address http://www.clinique.com/app/nph-consult.cgi Go

CLINIQUE | shop online | world of clinique | for men only | site map | SIGN IN / MY PROFILE

 which products
are right for you?

We can recommend skin care and colour just for you. First please tell us a little about yourself. So we can determine your skin type. If this is your first consultation, your answers will be remembered and used to provide you with personalized information on products custom fit for you.

Please select the choice that describes you. Not Sure? Click the "?" buttons for help.

If you are a registered user and you have already taken a personal consultation and would like to call up your information before you have another consultation please [click here to sign in](#).

Please select an answer for each question and then click the "tell me my skin type" button.

COLOUR OF EYES			
<input type="radio"/> BLUE	<input type="radio"/> GREEN, GREY OR GOLDEN	<input type="radio"/> HAZEL	<input type="radio"/> BROWN OR BLACK
<input type="radio"/> BLOND	<input type="radio"/> RED	<input type="radio"/> LIGHT BROWN	<input type="radio"/> DARK BROWN OR BLACK
<input type="radio"/> ALWAYS BURNS	<input type="radio"/> BURNS, THEN TANS	<input type="radio"/> TANS	<input type="radio"/> TANS EASILY
<input type="radio"/> VERY FAIR	<input type="radio"/> MODERATELY FAIR	<input type="radio"/> MEDIUM	<input type="radio"/> DARK OR OLIVE
PORE SIZE			
<input type="radio"/> INVISIBLE	<input type="radio"/> SMALL	<input type="radio"/> MEDIUM	<input type="radio"/> LARGE
<input type="radio"/> NEVER	<input type="radio"/> RARELY	<input type="radio"/> OCCASIONALLY	<input type="radio"/> FREQUENTLY
<input type="radio"/> DRY OR QUITE DRY	<input type="radio"/> OILY IN AREAS	<input type="radio"/> OILY	<input type="radio"/> VERY OILY
SURFACE FACIAL LINES			
<input type="radio"/> MANY	<input type="radio"/> SEVERAL	<input type="radio"/> FEW	<input type="radio"/> VERY FEW

Epinions Sienna Overview

58

Epinions.com - Reviews of 2000 Toyota Sienna - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address http://www.epinions.com/auto_Make-2000_Toyota_Sienna Go

Home > Autos & Motorcycles > Autos > 2000 Toyota Sienna

Average rating: ★★★★ (62 Member Opinions)

Recommended 93% of the time



2000 Toyota Sienna

Current Est. Price: \$20730-27334
 Manufacturer: Toyota
 Class: Van & Minivan
 Model Year: 2000
 Model Pictured: XLE 4 Dr Pass Van

[More Detailed Information](#)

Get Updates
[Send me email alerts when new opinions on "2000 Toyota Sienna" appear](#)

Help others decide.
[Write an opinion](#)

Go Shopping!
[Find out where to buy this item](#)

Related Items

- [2001](#)
- [2000](#)

Member Opinions

Toysota Sienna: Try to Find a better minivan by [JMB623](#) (Aug 16 '99)
 Product rating: ★★★★★
 We bought the 1998 Sienna, knowing that it's usually sheer stupidity to buy the first year release of most vehicles. But Toyota R & D'd this one...

Quiet, comfortable ride by [jstrickl](#) (Dec 22 '99)
 Product rating: ★★★★★
 My husband and I bought this vehicle because we were ready to give ourselves and our almost teenage boys more room on trips. We have an SUV and love...

a great mini-van by [dannels](#) (May 16 '00)
 Product rating: ★★★★★
 When we were shopping for a mini-van, we had a lot of input from friends. I have owned 2 Toyota Camry's and I was very satisfied with the quality...

[Read all 62 Member Opinions -->](#)

Professional Reviews

1999 Toyota Sienna XLE by [ArchivelUSA.com](#)

Suggest a Link

Highly Recommended

Opinion Highly Recommended by an advisor

Opinion Highly Recommended by an advisor

Opinion Highly Recommended by an advisor

The site just changed.

NEW OPINIONS arrive around the clock at Epinions.com!

See What's New

Latest Reviews

59

Epinions Profile

Epinions.com - Reviews of JMB623 - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address: http://www.epinions.com/user/jmb623

JMB623's Public Profile

Opinions written: 73 | Member visits: 4712 | Total visits: 30108

Epinions ID: JMB623
Gender: Male
Member since: Jul 12, 1999
Email: jmblaw@mindspring.com



Get Updates

Send me email alerts on opinions by JMB623

Send me alerts when JMB623 writes new comments

Web of Trust

Trust JMB623's opinions!

Distrust JMB623's opinions!

JMB623 trusts:

1. vinay
2. Mike Speiser
3. tom
4. icare
5. Collectoronian
- 24 other members

more...

JMB623 distrusts:

none yet

JMB623 is trusted by:

1. HonestIsKey
2. Idaved
3. asdd
4. chris9b
5. jmb623
- 204 other members
- 15 hidden members

more...

Whom should I trust?

Favorite Web Sites:

- http://www.pcwin.com
- http://www.epinions.com
- http://www.pcmag.com/utilities

Interests:

My almost 4-year old daughter, technical writing, computers, Internet, motorcycles.

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 Deskjet 895C on HP's 895C

Epinions Profile Bottom

60

Epinions.com - Reviews of JMB623 - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address: http://www.epinions.com/user/jmb623

Love It		Hate It	
> Autos & Motorcycles	> Autos & Motorcycles	> Computers & Internet	> Computers & Internet
1. 20th Century	1. State Farm	2. Ford Festiva	2. Nationwide
2. Ford Festiva	3. Toyota Sienna	3. Microsoft Outlook 98	4. AT&T (TCI)
3. Toyota Sienna	4. BMW K Series	5. 2000 Harley Davidson FXST	5. Electronics
4. BMW K Series	5. 2000 Harley Davidson FXST	6. Nasr Software Paint Shop ProVr	6. EarthlinkVr
more...	more...	7. NetObjects FusionVr	7. AOL (AOL)
> Web Services	> Web Services	8. It UtilitiesVr	8. AOL (AOL)
1. Stamps.com	2. Stamps.com	9. Adaptec GoBackVr	9. Magellans Corporation Winboost 2000Vr
2. Eletter	more...	10. Magellans Corporation Winboost 2000Vr	10. AOL (AOL)

Opinions written by JMB623

Date	Title	Reviewed Product	Product Rating	Category	Opinion Rating
08/20/00	ACDSee 3.0: Professional Image Slinger	ACDSee	*****	Computers & Internet	Highly Recommended
08/13/00	HP 6300 Series: Fastest Scan in the West	HP ScanJet 6300C	*****	Computers & Internet	Highly Recommended
07/16/00	Plextor's Fast And Reliable CD-RW Reads 32X, W 8X, RW 4X	Plextor PlexWriter 8/4/32	*****	Computers & Internet	Highly Recommended
07/04/00	Powersitch Can Make An Artist Out of Almost Anyone!!	Powerswitch	*****	Computers & Internet	Highly Recommended
06/29/00	Internet Cleanup Obliterates Your Trail	Internet Cleanup	*****	Computers & Internet	Highly Recommended
04/17/00	Paramanus			Computers & Internet	Highly Recommended
04/17/00	Speednet or Science Fiction???	Development Speednet 4	****½	Computers & Internet	Highly Recommended
04/07/00	BullsEye 2 Pro: Meta-search King of the Hill	BullsEye	*****	Computers & Internet	Highly Recommended
03/28/00	Pretty-up Your Monitor Display	Displaymate	*****	Computers & Internet	Highly Recommended

61

Epinions Earnings

The screenshot shows the Epinions.com user account interface for a member named johntr. The main banner features a large '\$100' and the text 'In Calling Card Calls!'. The left sidebar contains 'Account options' with links like Account Summary, Opinions & Earnings, Email alerts, Content filters, Web of Trust, Love It/Hate It, Edit personal info, Edit public profile, Change password, and View public profile. Below this is the 'System Status' section, which indicates 'No known system problems at this time.' and a 'Status Archive...'. The 'Earnings summary' section shows the following data:

Opinions		Earnings Summary	
Opinions written:	2	Opinion Eroyalties:	\$0.14
Member visits:	6	Income Share:	\$0.12
Total visits:	8	Other:	\$0.00
		Total Earnings: \$0.26	

The 'Opinions summary' section also lists 'Opinions written: 2', 'Member visits: 6', and 'Total visits: 8'. The 'Site settings' section includes 'Requested email alerts: 4' (Members alerted to your: - New opinions: 0, - New comments: 0), 'Content Filters' (Displayed opinions: - Highly Recommended, - Recommended), and 'Web of Trust' (you trust: [edit] 1. JMB623, you distrust: [edit] none yet, you are trusted by: none yet). The 'Love It / Hate It' section notes that the list is currently empty.

62

TM Hockey

The screenshot shows the ticketmaster.com ticket purchase page for a Minnesota Wild game at the Xcel Energy Center on Friday, September 29, 2000, at 7:00PM. The page displays the following information:

- BEST AVAILABLE TICKETS**
- Event:** MINNESOTA_WILD
XCEL ENERGY CENTER
Friday, September 29, 2000 7:00PM
- Area:** END OF ICE THAT OPPONENT SHOOTS AT TWICE
PRICE LEVEL 4
LOWER LEVEL SEATING
- Selected Tickets:** SECTION 103, ROW 26, SEATS 8 TO 9
- Seating Chart or Map:** Click Here (Chart Will Open In A New Browser)
- Selected Pricing:**

Tix/City	Type	Face Value per ticket	Ticketmaster Convenience Charge per ticket	Building Facility Charge	per ticket Total
2	A	64.00	3.75	0.00	67.75
Subtotal: 2 128.00 7.50 0.00 135.50					
Ticketmaster Handling Charge: 3.00					
Total Charge: 138.50					
- Delivery Method:** Will-Call
- Do you want to purchase these tickets? Yes No**
- BILLING INFORMATION**

63

Priceline 1

priceline.com Hotels - Region - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address: http://www.priceline.com/hotels/region.asp?session_key=050111AC660111AC20000922004830146201706090 Go

priceline.com™ | hotel rooms

Select the areas in Minneapolis - St. Paul where you'd be willing to stay. Priceline will search for a hotel at your price in the area(s) you select. Remember, you'll always stay in a nationally recognized name-brand or well-known independent hotel.

Airport (MSP) - Mall of America [Details](#)

Downtown Minneapolis [Details](#)

Eagan [Details](#)

Minneapolis North [Details](#)

Minneapolis West [Details](#)

Roseville [Details](#) Improve your chances choose 2 or more areas

Southwest Minneapolis [Details](#)

St. Paul [Details](#)

University - Metrodome [Details](#)

Woodbury [Details](#)

Select All Zones

See full area map below

NEXT >

The areas in Minneapolis - St. Paul are highlighted in the map below. You can click on an area for a closer look.

Priceline 2

64

priceline.com Hotels - Star Level Information - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address: http://www.priceline.com/hotels/include/star_info.asp?session_key=050111AC660111AC20000922004830146201706090 Go

The following price guidelines show you what you might pay if you did not book your hotel room through priceline. The range of rates shown below should be used as a general guideline only. Actual available rates may be higher or lower than the ranges stated. Factors such as holidays, major events, and the day of the week can all influence rates. Remember, at priceline we want you to save by getting your hotel room(s) at the best price of all - yours!

Star Level	Rating	Average rates that you would expect to pay in Minneapolis without using priceline
1 Star	Economy	\$58 - \$72
2 Star	Moderate	\$86 - \$105
3 Star	Upscale	\$122 - \$145
4 Star	Deluxe	\$121 - \$151

Here are the 4 easy steps we recommend to name your own price:

1. Shop around for the lowest available hotel rates before you name your price.
2. If the lowest rate you find fits your budget in a hotel you want to stay in, we recommend that you reserve those rooms, since rates and availability change constantly.
3. If not, let priceline try to find available high quality hotel rooms for you, at the price you want to pay.
4. Remember, the more reasonable your price, the better your chance of getting hotel rooms through priceline.com.

Priceline.com Incorporated is a seller of travel in the State of California (CST 2040530-50). Registration as a seller of travel does not constitute approval by the State of California.

1 STAR Hotels: Economy

Priceline's 1 Star hotels are national name-brand and well known independent hotels. These hotels are generally 2-4 stories high and are located near major attractions or convenient intersections, often in close vicinity to restaurants and business/shopping centers. [Back](#)

2 STAR Hotels: Moderate

Priceline's 2 Star hotels are national name-brand and well known independent hotels with a reputation for offering a consistent level of quality and amenities. Participating hotels are well-regarded, with high

Privacy Issues

Identity

- Require login?
- Cookies?
- Require “real” login or pseudonym?

Ratings and reviews

- Revealed to other members/customers?
- Visible to marketer?

Honesty vs. business rules

Document Recommendation Personalized Knowledge Management

Recommending documents

- Easier to “keep up to date”
- Automatic routing of content to people
- More effective research
- More valuable portals and services
 - Advertising revenue!

Recommending people

- More efficient organizations
- Social stickiness

Documents and People

Key issues:

- Many techniques for analyzing data (keywords, associations, etc.)
- Control and data privacy
- Getting honest data when users have ulterior motives

Ebay Feedback Profile



The screenshot shows an Internet Explorer window displaying the eBay Feedback Profile for user 'dutypaid'. The address bar shows the URL: <http://cgi2.ebay.com/aw-cgi/eBaySAPI.dll?ViewFeedback&userid=dutypaid>.

The page includes the eBay header with links to home, my eBay, site map, and sign in. It also features a search bar and a link to the eBay ID card.

Overall profile makeup:

- 1606 positives. 1553 are from unique users and count toward the final rating.
- 5 neutrals. 1 are from users [no longer registered](#).
- 14 negatives. 14 are from unique users and count toward the final rating.

eBay ID card for dutypaid (1539):

Member since Friday, Dec 11, 1998

Summary of Most Recent Comments			
	Past 7 days	Past month	Past 6 mo.
Positive	48	131	1152
Neutral	0	2	4
Negative	0	1	13
Total	48	134	1169
Bid Retractions	0	0	0

[Auctions by dutypaid](#)

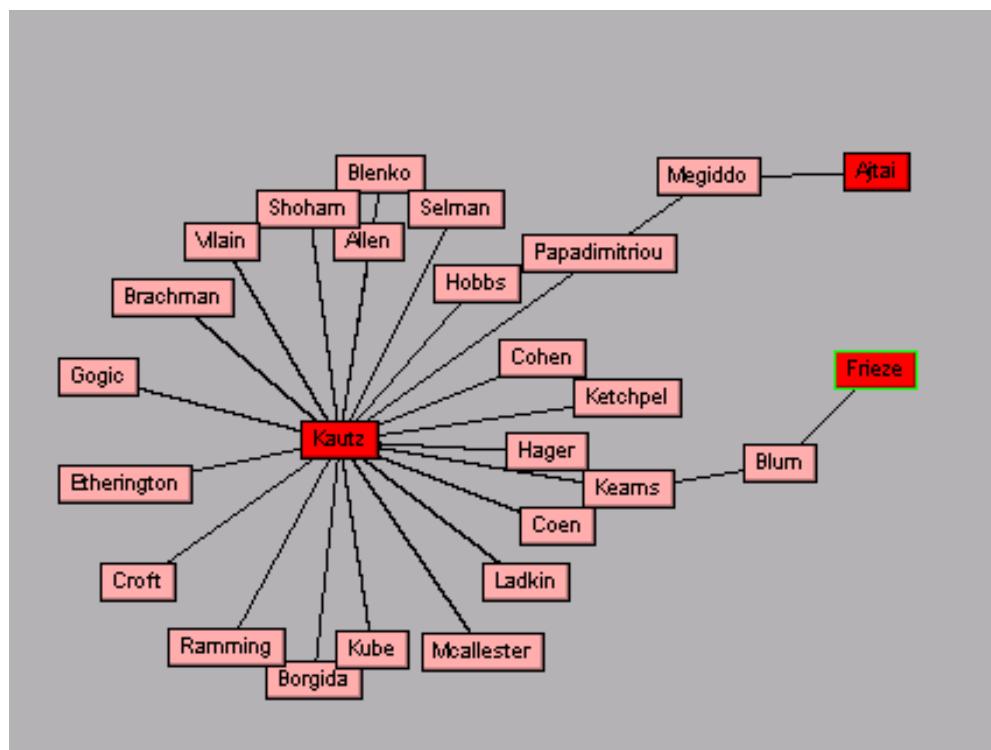
Note: There is 1 comment that was converted to neutral because the commenting user is [no longer registered](#).

You can [leave feedback](#) for this user. Visit the [Feedback Forum](#) for more info on feedback profiles.

If you are [dutypaid \(1539\)](#) ★, you can [respond to comments](#) in this Feedback Profile.

69

ReferralWeb



70

Tacit

Tacit Knowledge Systems, Inc. - KnowledgeMail automatically discovers the knowledge, expertise, - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address <http://www.tacit.com/>

TACIT

Company Products Press Center Services Contact

Top Stories

- Tacit cited in **Business Week** - **NEW!**
- Tacit named one of **Upside's Hot 100 Private companies.**
- Tacit wins "Best of Show" at Microsoft Tech Ed 2000
- Tacit joins "Federated alliance" of EIP technology providers **InfoImage**

Quotes

"...KnowledgeMail is a breakthrough technology that transforms e-mail into an automated knowledge resource."

Esther Dyson
- President of EDventure Holdings

Events

KnowledgeMail transforms enterprise e-mail into an automatic strategic information asset that helps everyone connect to the people and information they need.

Tacit Web Seminars
• Thursday, September 28, 2000

Conferences
• Enterprise Information Portals - San Francisco, CA, Sept. 21-22, 2000

990 Commercial Street | Palo Alto, CA 94303 | ph 650.251.2000 | fax 650.251.2010 | info@tacit.com
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Privacy Issues

Same as E-commerce, plus

- Extra sensitivity of profile data
 - E.g., Tacit's dual profiles

Honesty/openness vs. edited content

Off-Web Interfaces Kiosks

Alienware PC's Now Offered
on Best Buy ``Computer
Creation Stations''

Blockbuster
customer identity
privacy issues

Music Store
sampling versus "listening"



73

Increasing Cross-Sell



With traditional cross-sell methods

With Net Perceptions' realtime recommendations

Avg Cross-Sell Value \$19.50*

60%
higher
50%
higher

Cross Sell Success Rate 9.8%

* Converted from British Pounds

Call Centers

74

Inbound

- “screen-pops”
- Legacy systems
- appropriateness

Outbound

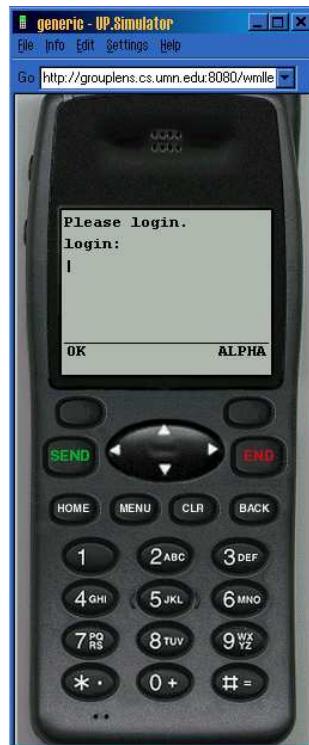
- Predict who will buy
- Predict what they will buy
- Predict when to contact them
- Online campaign management

Mail

Personalize offers
What is appropriate?

- Who?
- What?
- What price?
- Vulnerable?

WMLLens Login



Case Studies of Applications and Interfaces

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Expedia.com

Expediating Cheap Travel

Expedia.com saves “data it gathers anyway” to turn every travel searcher into a set of eyes helping other customers.

- (Mostly) no cost to helper
- Valuable information that is otherwise hard to acquire
- Little processing, lots of collaboration

79

Expedia

The screenshot shows a Microsoft Internet Explorer window displaying the Expedia.com homepage. The main content area is titled "Deals found by other Expedia.com customers" for a trip from Minneapolis, MN (MSP) to Amsterdam, Netherlands (AMS-Schiphol). The search parameters are set for trips between 9/21/2000 and 3/5/2001, sorted by price. The results table lists various flight options with their airline names (Icelandair or Northwest), travel dates, lengths, and lowest fares. A legend indicates that yellow stars next to fares represent the best deals found by other customers for that route.

Departure/Return	Length	Airline	Lowest fare
Wed 1-Nov / Wed 8-Nov	7 days	Icelandair	\$463 ★
Wed 15-Nov / Wed 29-Nov	14 days	Icelandair	\$463 ★
Wed 13-Dec / Thu 21-Dec	8 days	Icelandair	\$463 ★
Thu 14-Dec / Thu 21-Dec	7 days	Icelandair	\$463 ★
Wed 18-Oct / Mon 23-Oct	5 days	Northwest	\$472 ★
Thu 19-Oct / Mon 23-Oct	4 days	Northwest	\$472 ★
Tue 24-Oct / Tue 31-Oct	7 days	Northwest	\$472 ★
Tue 31-Oct / Thu 9-Nov	9 days	Northwest	\$473 ★
Wed 22-Nov / Tue 28-Nov	6 days	Northwest	\$473 ★
Mon 11-Dec / Mon 18-Dec	7 days	Northwest	\$473 ★
Tue 12-Dec / Mon 18-Dec	6 days	Northwest	\$473 ★

Zagat

Zagat What it Takes

80

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!"

81

Zagat

The screenshot shows a Microsoft Internet Explorer window displaying a Zagat review for "LA BELLE VIE". The review is categorized under "Out of Town" and includes the address: 312 S. Main St.(Nelson St.) Stillwater, MN, 55082-5169 (651) 430-3545. The review text describes it as "Supercreative" French-Mediterranean cuisine with two former D'Amico Cucina chefs. It notes a "charming" newcomer with enthusiastic foodie support and a "historic" storefront setting. Some speak of "great promise" while others find it "could be outstanding"; converts are convinced it's already a "very special" "escape".

At the top right, there are rating buttons for F, D, S, C, and E, with 26, 25, 23, \$43, and a red "VOTE" button below them. Below the review, there are links for "INVITE FRIENDS" and "E-MAIL THIS REVIEW".

On the left, there is a sidebar titled "features list" with a list of restaurant features like Credit Cards Accepted, Game In Season, Noteworthy Newcomers, Open Sunday, Party Spaces, Quiet Conversation, Romantic Spots, Visitors on Expense Accounts, Wine/Beer Only, Winning Wine Lists, and Worth a Trip.

The main search interface on the right allows users to refine their search by including or excluding certain criteria. The "INCLUDE THESE IN MY REVISED SEARCH" section includes checkboxes for food, decor, service, cost, neighborhood, and cuisine. The "ADJUST THE CRITERIA TO BROADEN OR NARROW MY SEARCH" section shows dropdown menus for each of these criteria, with "Out of Town" selected for neighborhood and "French" selected for cuisine. A "show me more like this" button is at the bottom.

Launch.com Launching Organic Interfaces

82

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

83

Launch (1)

LAUNCHcast Home - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address: http://launch.yahoo.com/launchcast/setup.asp

1990's Rock
1980's Alternative
1980's Brit Invasion
1980's Country
1980's Hair Metal
1980's Pop
1980's Metal
1980's Urban
Adult Alternative
Affectionate
Alternative Rock
Blues
Bad Company Movie Radio
Classic R&B
Classic Rock Hits
Country
Electronica
Happy
Hits of 1985
Indie & Electric
Jazz
Latin
Martini Lounge
Mellow
Metal
One Hit Wonders
Pop
Prom Time!
Punk
R&B
Rap
Reggae
Rhythm 'N Rims

Hard Rock
Classic Rock
Adult Alternative
R&B
Rap
Country
Electronica
Jazz
Billie Holiday
Ella Fitzgerald
Boney James
George Benson
Charles Mingus
John Coltrane
Charlie Parker
Louis Armstrong
Chick Corea
Medeski Martin & Wood
David Sanborn
Miles Davis
Diana Krall
Pat Metheny
Duke Ellington
Stan Getz

2 Add Your Own Favorite Artists: (Optional)

get away
visit thebahamas
click here
YAHOO! Travel vacations

84

Launch (2)

LAUNCHcast Home - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address: http://launch.yahoo.com/launchcast/member.asp

Hi, konstan | Yahoo! | LAUNCH Home | Sign Out | Help

SEARCH All GO

INTERNET RADIO MUSIC VIDEOS ARTISTS STYLES SONGS

LAUNCHcast internet radio local radio LAUNCHcast help local radio help

LAUNCHcast Home

LAUNCH STATIONS

Listen to our radio stations:

- 1990's Rock (LISTEN)
- Listen to the best rock of the 90's
- 1960's Rock
1970's Rock
1980's Alternative
1980's Brit Invasion
1980's Country
1980's Hair Metal
1980's Pop
1980's Metal
1980's Urban
Adult Alternative
Affectionate

MY STATION

j_konstan's Station (LISTEN)

Featuring: Louis Armstrong, The Bee Gees, Chicago, Phil Collins, The Eagles, Duke Ellington, Elton John, Madonna

Abba (My Station Page)

LAUNCHcast NEWS

The hottest music is on LAUNCHcast!

Check out these hot new tracks, albums, and artists now on LAUNCHcast!

Click and rate them highly using the rating tool to increase the likelihood that they will play on your station.

Bad Co. Movie Radio (Music From the Bad Company Movie)
Rap Radio (Ludacris, Ja Rule, etc.)

ADVERTISEMENT

Bahamas
7 nights all inclusive with air, hotel & more from \$959
get away

85

Launch (3)



86

Launch (4)



Real-World Experience

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

Recommender System for User

88

Find what I want

Know I will like it

Trust system to help me

Team up with my friends to defeat evil
marketers

89

Recommender System for Marketer

Show people what they will buy

Learn what people want so you have it

Learn how much they want it so you get
as much as possible

Who Will Prevail?

90

Who is deploying recommender systems?

Who has the money?

Consumers will react if tricked

Alternatives exist, and will be deployed if
necessary

Privacy Issues in CF Algorithms

Actual user identity isn't needed

- A pseudonym works fine
- A session ID plus a profile can work
 - Challenges helping others

Noise can add deniability

- Adding some random ratings doesn't seem to hurt much

Still have inference problem

- Gee, Xmen got a recommendation, and then John bought the product!

Case Studies of Applications and Interfaces

An Active Buyer Guide

- During the tutorial, we will briefly try looking for a product with the help of an Active Buyer Guide
- The emphasis here is on the nature of the user experience
- The techniques underlying this type of system will be discussed in a later section



<http://www.activebuyerguide.com/>

The Notebook Expert

Self–Description of Soliloquy (1)

94

From the Corporate Fact Sheet

"Soliloquy's Dialogue Experts allow shoppers to interact with a website in the most natural and intuitive way: by using their own words"

"And the Dialogue Experts' knowledge about products is vast and available instantly, at any time"

"Shoppers benefit from an enhanced user experience, better service and instant response time"

"E-commerce websites benefit from higher sales, lower costs and invaluable market intelligence gained from the Dialogue Mining of shoppers' conversations"

See the Corporate Fact Sheet, which is available via <http://www.soliloquy.com>. A similar upper description of the firm is given in the following article: Lucente, M. (2000). Conversational interfaces for e-commerce applications. *Communications of the ACM*, 43(9), 59–61.

Self–Description of Soliloquy (2)

Clients

- The example dialogs with the Notebook Expert that are presented on the following slides were conducted at <http://www.buy.com> in December, 2000
- At that time, the Notebook Expert was also deployed at <http://www.cnet.com>
- At both sites, the Notebook Expert has apparently since been taken out of the site
- Similarly, other earlier clients of Soliloquy (Acer, Hewlett–Packard, and Hardware Street) have apparently discontinued use of the Notebook Expert

Examples of Possible Inputs

According to the web site, the Notebook Expert can deal with user inputs of the following types, among others:

Statements about the planned use of the system

- I travel a lot
- I need a laptop for school
- I need a laptop for accounting
- I do desktop publishing
- I trade in stocks, shares, options and futures
- I play games on the computer
- I need a laptop for graphics
- Show me one for spreadsheets

Specification of preferences

- I want a cheap notebook
- I plan to spend around \$2000
- Show me a notebook with a big screen
- Show me a really fast laptop computer

Questions about concepts

- What is USB?
- What is a sound card?

97

Dialog With the Notebook Expert (1)

The screenshot shows the buy.com website's 'Computers' section, specifically the 'Notebooks' category. The main content area displays three featured notebooks: NEC Computers Versa FXi, HP Omnibook 6000, and Sony VAIO PCG-F650. Each entry includes a small image of the laptop, its price, and a 'Buy Wishlist' link. To the right, there is a sidebar titled 'Portable Products' with a section for the 'Notebook Expert'. This section contains a question mark icon and text explaining that it helps users find the right notebook based on specifications like MHz, RAM, and HD.

When \mathcal{U} arrives at buy.com's main notebook page, she can see the link (on the right) to the page of the Notebook Expert

Dialog With the Notebook Expert (2)

The screenshot shows the 'notebook expert' application interface. At the top, there is a welcome message: 'Welcome to the Notebook Expert! I can help you select a laptop, or I can try to answer your questions about computers. Please tell me some of the features you're looking for in a notebook--something fast, inexpensive, light-weight, or with a large hard drive.' Below this, there is a text input field containing the text 'I need a lot of memory.' and a 'help' button. To the right, there is a 'start over' button and a 'Quick Summary' section which currently says 'Your configuration hasn't been specified yet.' At the bottom, there is a note 'Your notebook choices will appear here.' and a small 'educated by Soliloquy™' logo.

Here, S starts by asking about the features that \mathcal{U} would like. In some cases, S starts with a question about how \mathcal{U} intends to use the notebook (see the examples above)

99

Dialog With the Notebook Expert (3)

There are 76 laptops that satisfy your requirements. Here are some examples.

How much money (USD) can you spend?
Choose something between 2299.99 and 4217.95 dollars.
Any choice in this range will make it simpler for me to narrow your search.

I can spend about \$3000.

product name	price	more info	memory
SONY SYSTEMS VAIO PCG-SR17	\$2299.99	more info	128Mb
COMPAQ CONSUMER Presario Portable 17XL365	\$2399	more info	128Mb
ACER AMERICA TravelMate 735TLV	\$2429.95	more info	128Mb
ACER AMERICA TravelMate 343TV	\$2458.95	more info	128Mb
IBM OFFICE COMPUTING ThinkPad X20 2662	\$2491.95	more info	128Mb
IBM OFFICE COMPUTING ThinkPad T20 2647	\$2573.95	more info	128Mb
IBM OFFICE COMPUTING ThinkPad X20 2662	\$2594.95	more info	128Mb

educated by Soliloquy™

 start over help

Soliloquy Quick Summary
Main Memory Capacity Above 64 Megabyte;

As we can see in the Quick Summary on the right, the vague specification "a lot of memory" (see the previous slide) was translated into the internal specification "> 64 Megabyte"

Dialog With the Notebook Expert (4)

100

examples.

The faster the processor, the better your computer will run.
Nowadays, fast is considered to be at least 500 MHz. What speed do you want?
The range for the items selected is 600 to 800 mhz.
If you choose something in this range I can narrow your search.

I don't need more than 600 mhz.

product name	price	more info	memory
IBM OFFICE COMPUTING ThinkPad T20 2647	\$3016.95	more info	128Mb
ACER AMERICA TravelMate 737TLV	\$2950.95	more info	256Mb
NEC COMPUTERS Versa SXi	\$2936.95	more info	128Mb
IBM OFFICE COMPUTING ThinkPad X20 2662	\$2931.95	more info	128Mb
IBM OFFICE COMPUTING ThinkPad T21 2647	\$2931.95	more info	128Mb
SONY SYSTEMS VAIO PCG-XG38	\$2899.99	more info	128Mb
SONY SYSTEMS VAIO PCG-75051 S	\$2899.99	more info	128Mb

educated by Soliloquy™

 start over help

Soliloquy Quick Summary
Laptop Price Approximately 3000 Dollar; Main Memory Capacity Above 64 Megabyte;

The value "\$3000" in the vague specification "I can spend about \$3000" (previous slide) was interpreted not as an upper limit but as a desired price

At any time, *U* can click on one of the hyperlinks in the window listing the notebooks to go to a web page about that specific notebook

101

Dialog With the Notebook Expert (5)

I don't need more than 600 mhz.
There are 25 laptops that satisfy your requirements. Here are some examples.
Which laptop manufacturer do you want?
 Some choices are nec, hp and sony.
 Just choose what you like best.

Tell me about nec.

product name	price	more info	memory	speed
IBM OFFICE COMPUTING ThinkPad T21 2647	\$2732.95	more info	128Mb	750Mhz
IBM OFFICE COMPUTING ThinkPad T21 2647	\$2759	more info	128Mb	750Mhz
IBM OFFICE COMPUTING ThinkPad T20 2647	\$2779.95	more info	128Mb	650Mhz
TOSHIBA Tecra 8100	\$2779.95	more info	128Mb	750Mhz
NEC TECHNOLOGIES Versa SXi	\$2796.95	more info	128Mb	650Mhz
HP SYSTEMS OmniBook 6000	\$2799	more info	128Mb	650Mhz
IBM OFFICE COMPUTING ThinkPad T20 2647	\$2829.95	more info	128Mb	700Mhz

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Soliloquy

Quick Summary
 Laptop Price At Least 2700.0
 Dollar AND At Most 3300.0 Dollar;
 Central Processing Unit Speed
 Above 600 MHz; Main Memory
 Capacity Above 64 Megabyte

Here we can see how \mathcal{S} interpreted the vague specification "I don't need more than 600 mhz"

Dialog With the Notebook Expert (6)

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Just choose what you like best.

Tell me about nec.
The manufacturer is the company that makes a product.
So then, let's get back to our conversation.
Which laptop manufacturer do you want?

Any manufacturer except nec.

product name	price	more info	memory	speed
IBM OFFICE COMPUTING ThinkPad T21 2647	\$2732.95	more info	128Mb	750Mhz
IBM OFFICE COMPUTING ThinkPad T21 2647	\$2759	more info	128Mb	750Mhz
IBM OFFICE COMPUTING ThinkPad T20 2647	\$2779.95	more info	128Mb	650Mhz
TOSHIBA Tecra 8100	\$2779.95	more info	128Mb	750Mhz
NEC TECHNOLOGIES Versa SXi	\$2796.95	more info	128Mb	650Mhz
HP SYSTEMS OmniBook 6000	\$2799	more info	128Mb	650Mhz
IBM OFFICE COMPUTING ThinkPad T20 2647	\$2829.95	more info	128Mb	700Mhz

educated by Soliloquy™



Soliloquy

Quick Summary
 Laptop Price At Least 2700.0
 Dollar AND At Most 3300.0 Dollar;
 Central Processing Unit Speed
 Above 600 MHz; Main Memory
 Capacity Above 64 Megabyte

Here is an example of an attempt by \mathcal{S} to answer a question by \mathcal{U} about a particular concept (here: a particular manufacturer)

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Dialog With the Notebook Expert (7)

The screenshot shows a search interface for laptops. The user has typed "I need to walk around with the laptop a lot." into the input field. A "start over" button is visible above the input field, and an "enter" button is to the right. To the right of the input field is a "Quick Summary" section with the following text:

Laptop Price At Least 2700.0
Dollar AND At Most 3300.0 Dollar;
Manufacturer Name Is NEC OR Is
EXCEL; Central Processing Unit
Speed Above 600 MHz;

The main area displays a table of search results:

product name	price	more info	memory	speed
NEC TECHNOLOGIES Versa LXi	\$3296.95	more info	128Mb	700Mhz
NEC COMPUTERS Versa SXi	\$3199	more info	128Mb	750 Mhz
NEC TECHNOLOGIES Versa LXi	\$3195.95	more info	128Mb	650 Mhz
NEC TECHNOLOGIES Versa LXi	\$3096.95	more info	128Mb	700 Mhz
NEC COMPUTERS Versa LXi	\$3017.95	more info	128Mb	650 Mhz
NEC COMPUTERS Versa SXi	\$2936.95	more info	128Mb	700 Mhz
NEC COMPUTERS Versa SXi	\$2835.95	more info	128Mb	650 Mhz

At the bottom left of the interface, it says "educated by Soliloquy™".

Here is another example of S 's natural language understanding capabilities

Dialog With the Notebook Expert (8)

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The screenshot shows a search interface for laptops. The user has typed "I need to walk around with the laptop a lot." into the input field. A "start over" button is visible above the input field, and an "enter" button is to the right. To the right of the input field is a "Quick Summary" section with the following text:

Your configuration hasn't been specified yet.

The main area displays a table of search results:

product name	price	more info	memory	speed
NEC TECHNOLOGIES Versa LXi	\$3296.95	more info	128Mb	700Mhz
NEC COMPUTERS Versa SXi	\$3199	more info	128Mb	750Mhz

S is actually capable of processing some statements of this general sort

E.g., "I go to conferences a lot"

It would be unreasonable to expect S to be able to understand every possible statement of this type, since this capability would require a great deal of world knowledge

Still, an interpretation problem should obviously not have such drastic consequences for the course of the dialog

Collaborative Filtering Techniques

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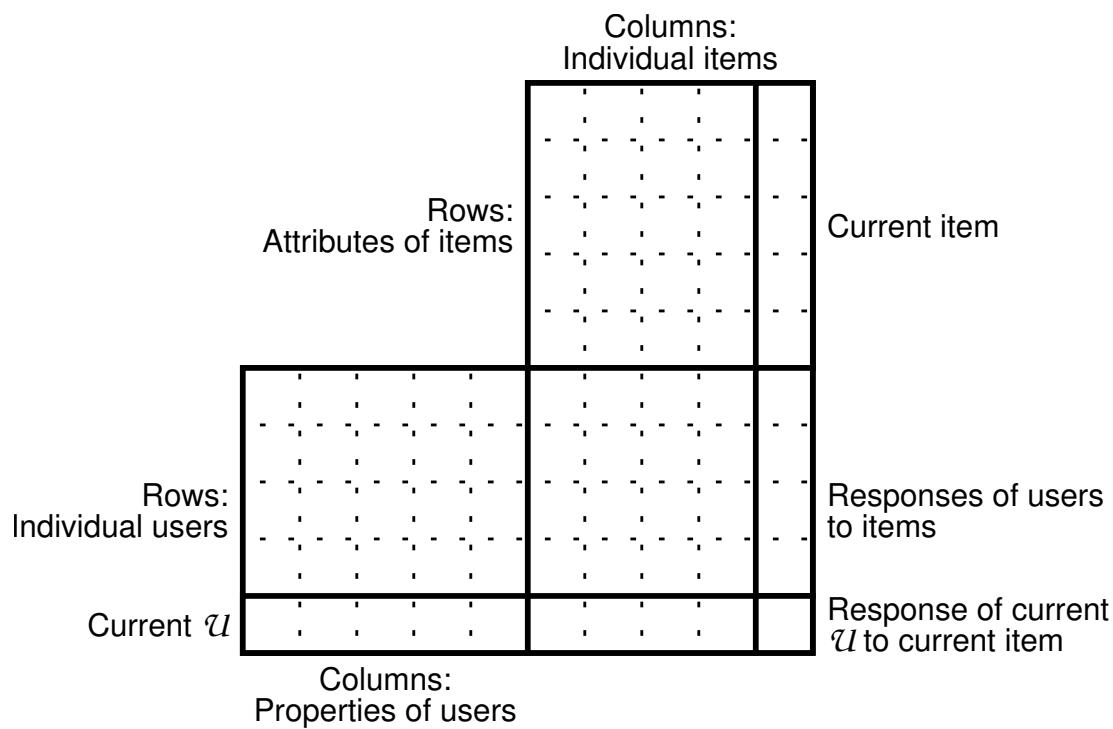
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Overview of Recommendation Techniques

Types of Information

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107 Overview of Recommendation Techniques (1)

The remaining slides in this section are based largely on Tables I–III of the following highly recommended article: Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User Modeling and User-Adapted Interaction*, 12(2), 1–53. <http://cbeblade.fullerton.edu/~rburke/pubs/burke-umui-ip.pdf>

Technique	Typical background	Typical Input	Typical Process
Collaborative	Ratings from U of items in I	Ratings from \mathcal{U} of items in I	Identify users in U similar to \mathcal{U} , and extrapolate from their ratings of I
Content-based	Features of items in I	\mathcal{U} 's ratings of items in I	Generate a classifier that fits \mathcal{U} 's rating behavior and use it on I
Demographic	Demographic information about U and their ratings of items in I	Demographic information about \mathcal{U}	Identify users that are demographically similar to \mathcal{U} , and extrapolate from their ratings of I

 U / I = sets of users / items \mathcal{U} / I = an individual user / item

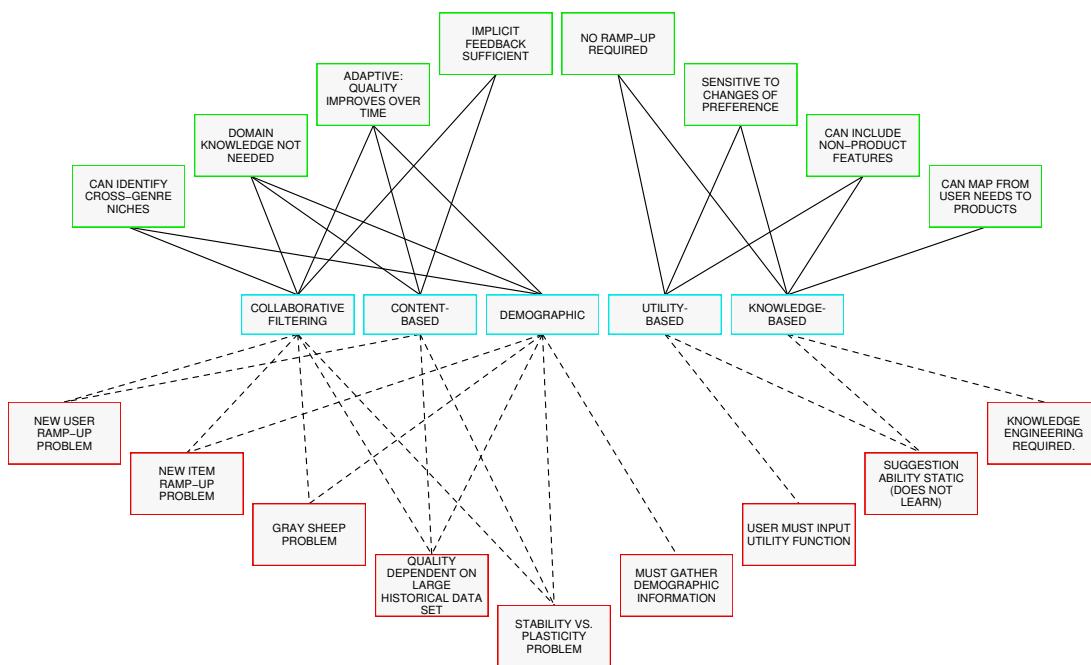
Overview of Recommendation Techniques (2)

Technique	Typical background	Typical Input	Typical Process
Utility-based	Features of items in I	A utility function over items in I that describes \mathcal{U} 's preferences	Apply the function to the items and determine I 's rank
Knowledge-based	Features of items in I ; knowledge of how these items meet a user's needs	A description of \mathcal{U} 's needs or interests	Infer a match between I and \mathcal{U} 's need.

 U / I = sets of users / items \mathcal{U} / I = an individual

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Approaches, Pros, and Cons



Five approaches to recommendation and their positive (above) and negative (below) aspects, according to Burke (2002)

Importance of Hybrids

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Motivation

- As the previous slide indicates, different techniques have partly complementary strengths and weaknesses
- ⇒ Increasingly, hybrids combining two or more techniques are being explored

Ways of combining techniques (preview)

1. Weighted
2. Switching
3. Mixed
4. Feature combination
5. Cascade
6. Feature augmentation
7. Meta-level

K-Nearest-Neighbor Algorithms

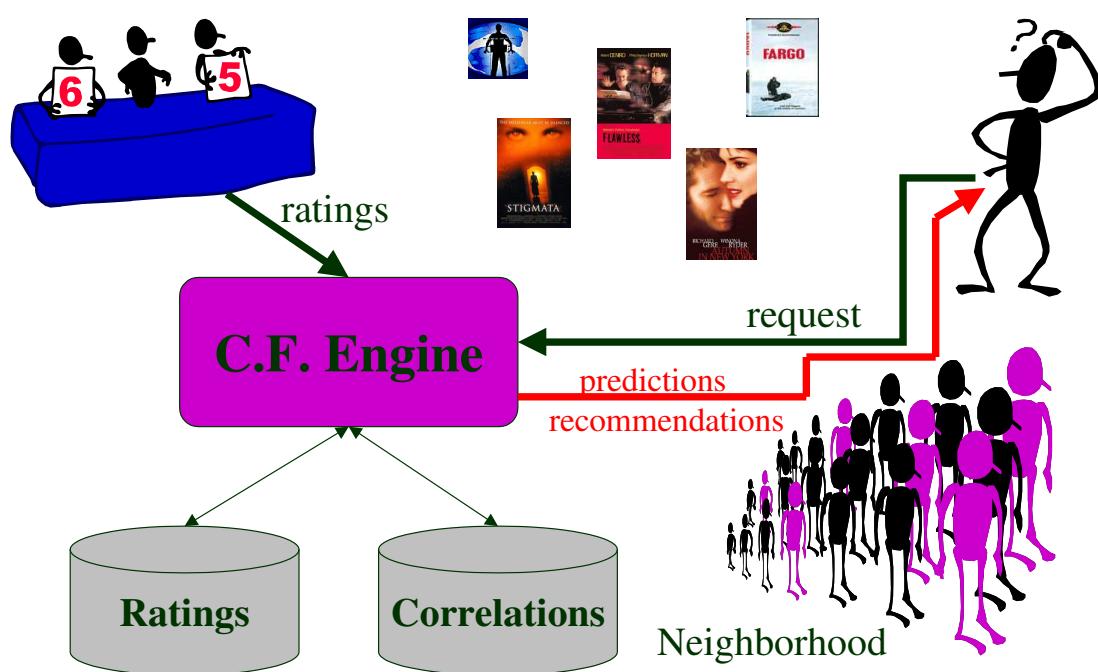
K Nearest Neighbor

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AI, CF, data mining, other algorithms

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How It Works



Collaborative Filtering

Premise

- Information needs more complex than keywords or topics: quality and taste

Small Community: Manual

- Tapestry – database of content & comments
- Active CF – easy mechanisms for forwarding content to relevant readers

Automated Collaborative Filtering

The GroupLens Project (CSCW '94)

- Users like recommendations
- Recommendations change behavior
- Users willing to share data to get recommendations

Ringo (CHI '95)

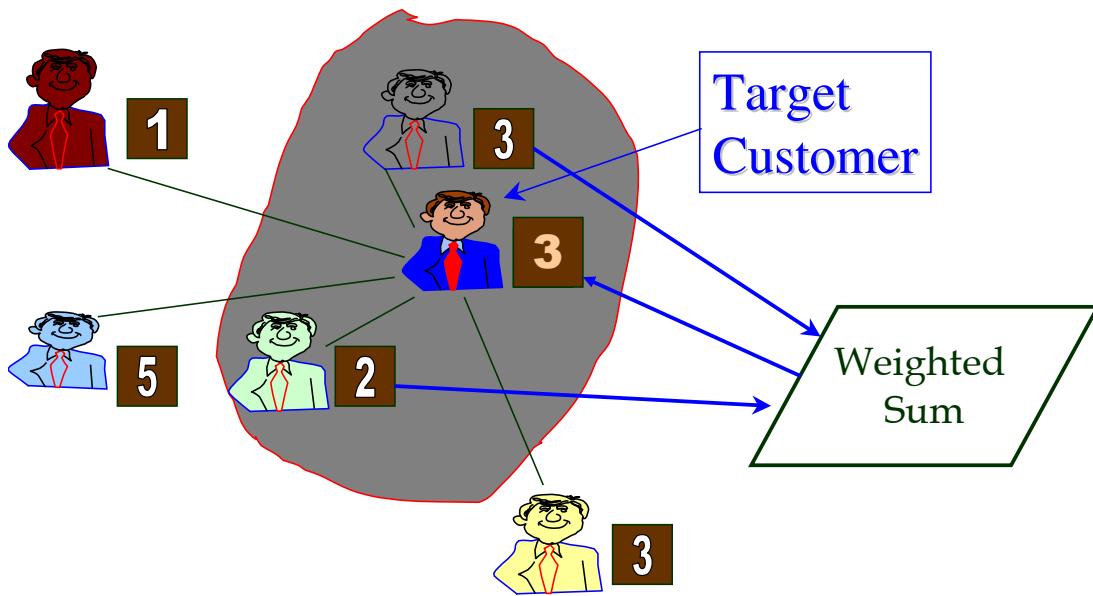
- Community building in recommenders

PHOAKS (CSCW '96)

- Implicit ratings in recommenders

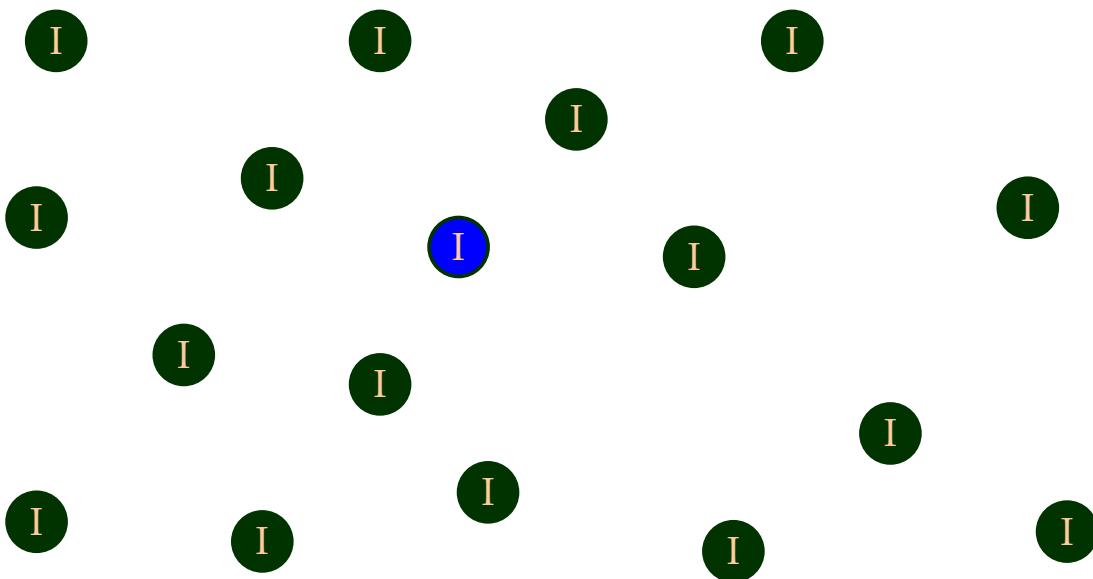
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Collaborative Filtering



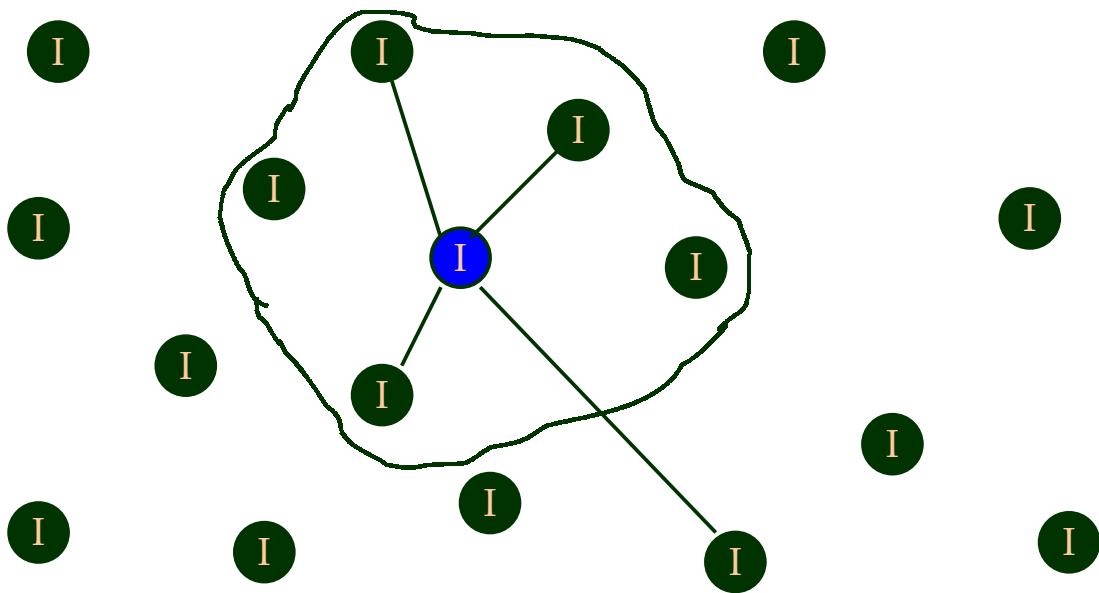
Item-Item Item-Item Collaborative Filtering ⁽¹⁾

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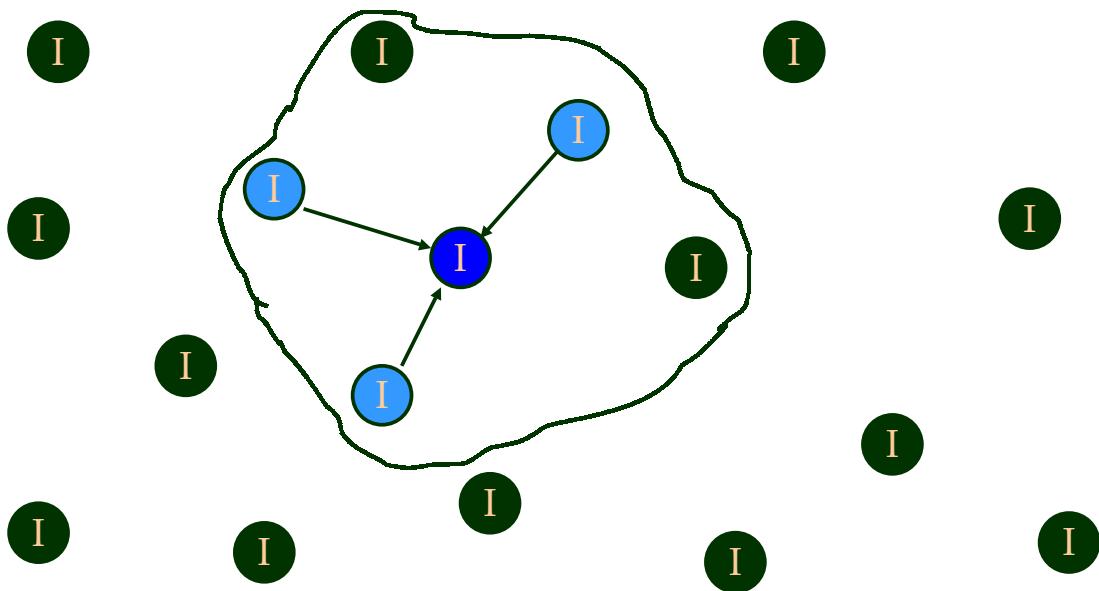
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Item–Item Collaborative Filtering (2)



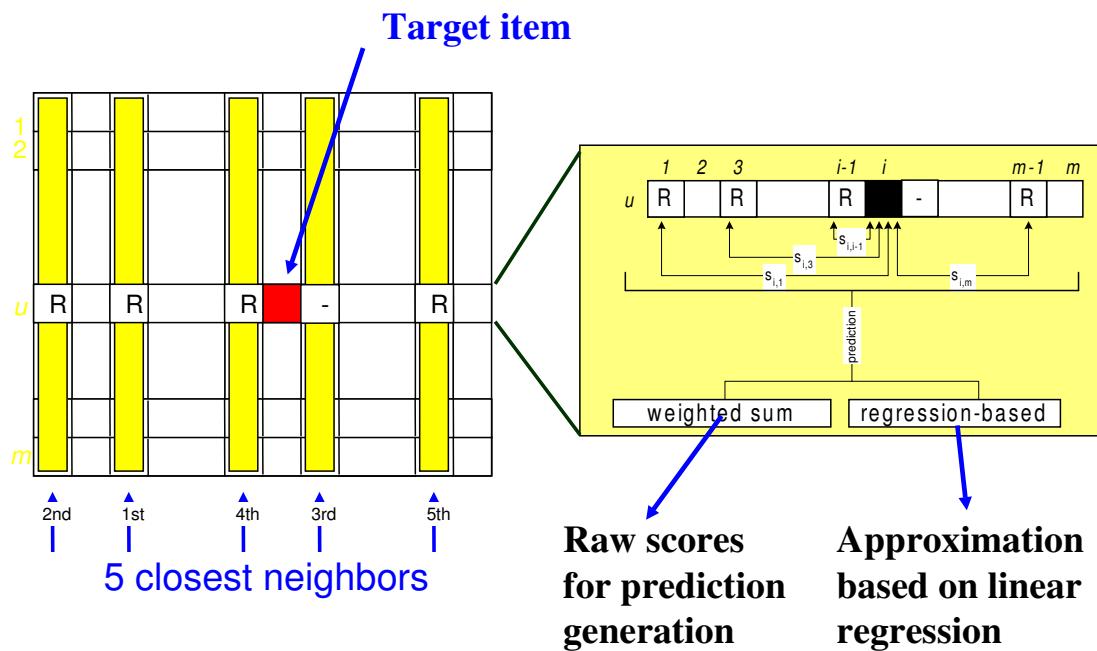
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Item–Item Collaborative Filtering (3)



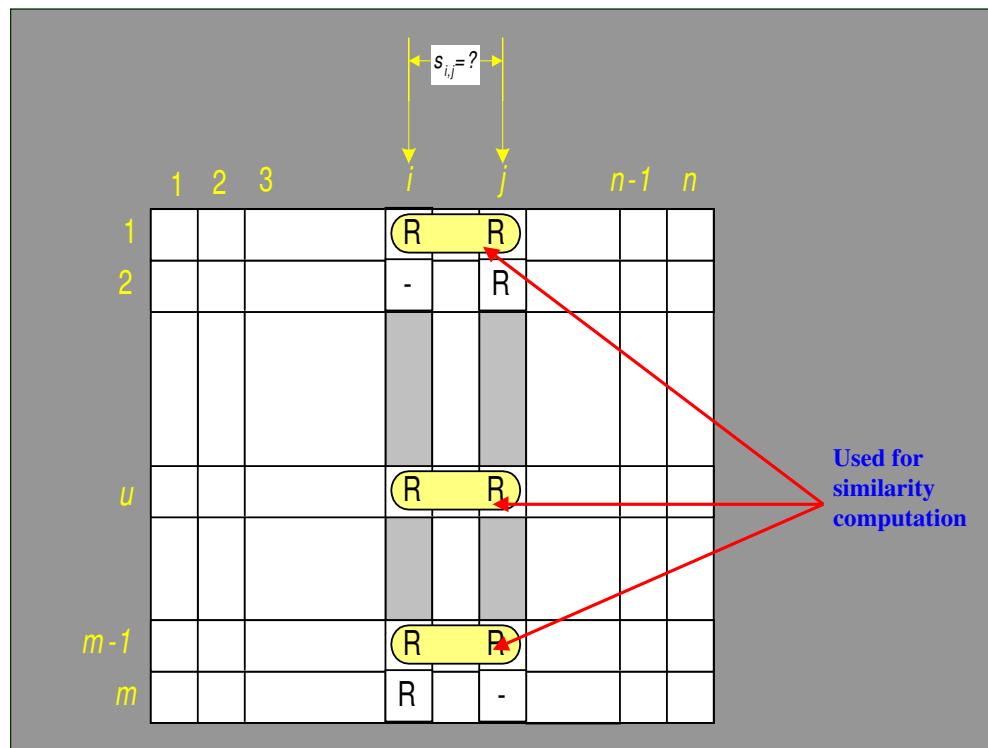
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Item-Item Matrix Formulation



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Item Similarities



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Item–Item Discussion

Good quality, in sparse situations

Promising for incremental model building

- Small quality degradation
- Big performance gain

Dimensionality Reduction Algorithms Other CF Algorithms

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K-Nearest Neighbor

Bayesian Belief Network

Clustering

Horting: Navigate similarity graph

Eigenvectors

Content + Collaborative Filtering

Item-Item

Association Rules

¹²³Possible Solution: 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

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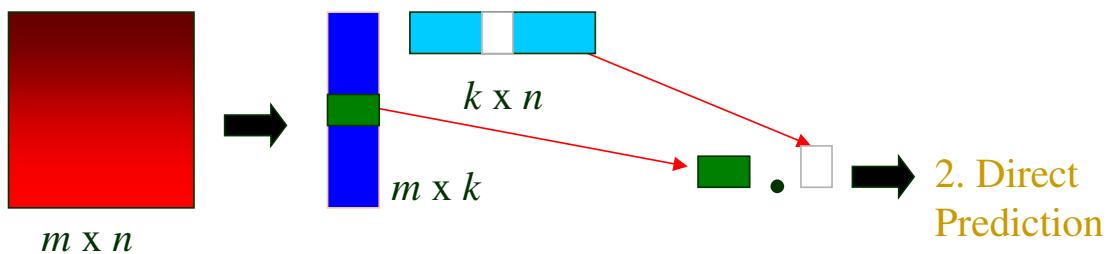
$$\begin{array}{c}
 \text{R}_k \\
 \text{---} \\
 m \times n
 \end{array}
 =
 \begin{array}{c}
 \text{---} \\
 \text{U}_k \\
 \text{---} \\
 m \times k
 \end{array}
 \begin{array}{c}
 \text{---} \\
 S \\
 \text{---} \\
 k \times k
 \end{array}
 \begin{array}{c}
 \text{---} \\
 V_k' \\
 \text{---} \\
 k \times n
 \end{array}$$

The reconstructed matrix $R_k = U_k \cdot S \cdot V_k'$ is the closest *rank-k* matrix to the original matrix R .

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SVD for Collaborative Filtering

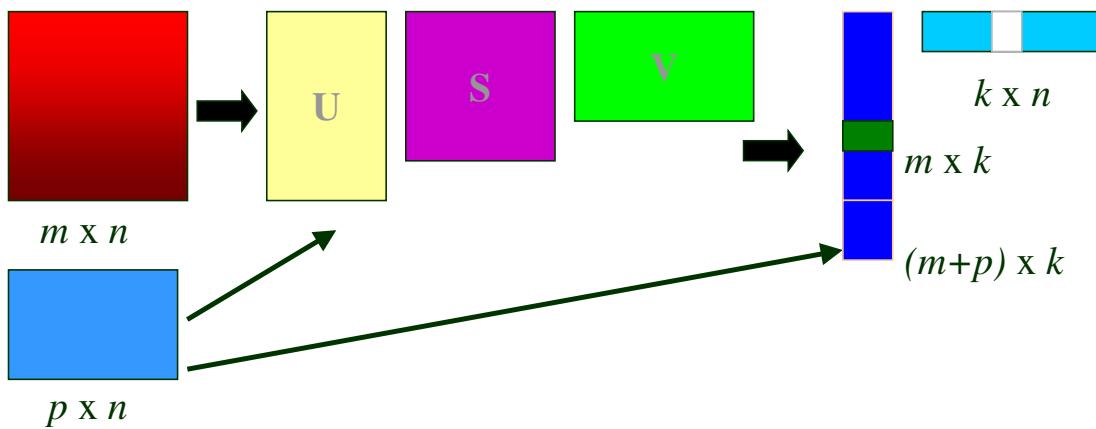
1. Low dimensional representation
 $O(m+n)$ storage requirement



SVD Folding-in

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A simple projection technique



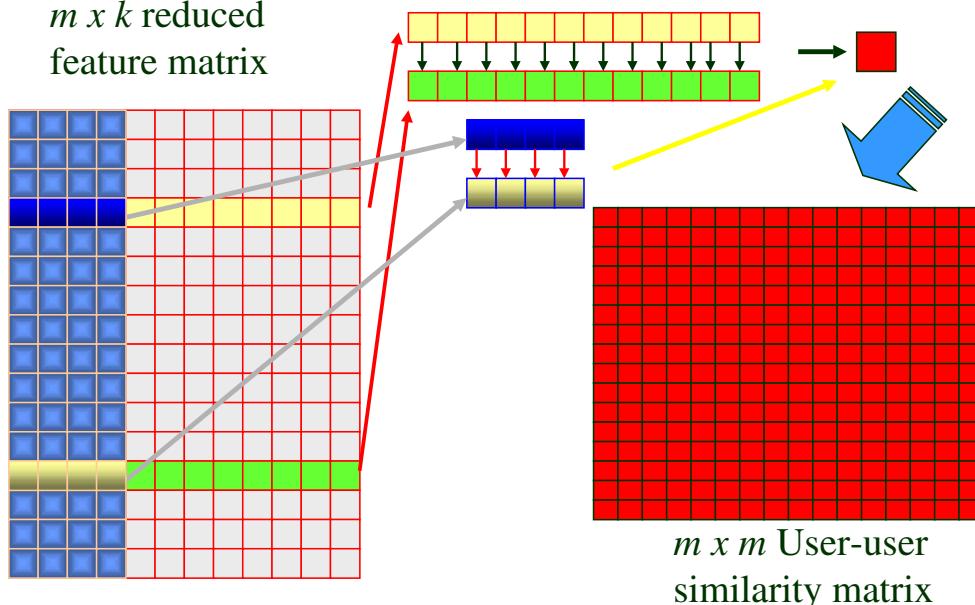
¹²⁷ Neighborhood in Low Dimensional Space (1)

$m \times n$ User-item matrix

$$O(m^2k) \approx O(m^2)$$

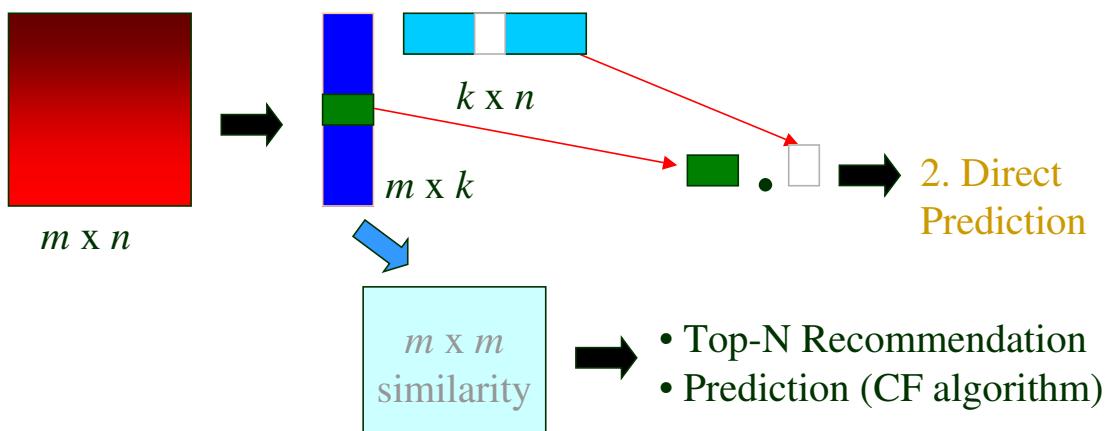
$m \times k$ reduced feature matrix

$$O(m^2n) \approx O(m^3)$$



Neighborhood in Low Dimensional Space (2) ¹²⁸

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



3. Neighborhood Formation

Conclusion

SVD results are promising

- Provides better Recommendations for Movie data
 - Provides better Predictions for $x < 0.5$
- Not as good for the E-Commerce data
 - Even up to 700 dimensions!
- Need incremental algorithms

SVD provides better online performance

SVD is capable of meeting RS challenges

- Sparsity
- Scalability
- Synonymy

Explanation and Confidence Trust / Acceptance

Part of the problem is external – eliciting trust in the customer (Bailey et al., HFWeb 2001)

Part of the problem is that people don't understand the basis for a recommendation

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Some Stories

Where do users think MovieLens recommendations come from?

Confidence

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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?

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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"

Explaining Recommendations

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 Challenge: Belief

- *Why* should users believe the recommendations?
- *When* should users believe the recommendations?

Approach

- Explain recommendations
 - Reveal data, process
 - Corroborating data, track record

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Two Studies

Pilot study of explanation feature

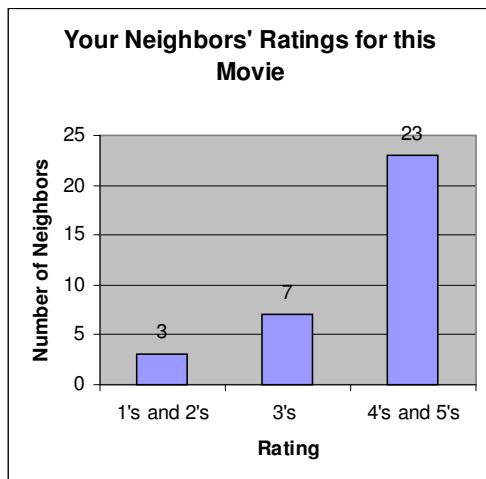
- Users liked explain
- Unclear whether they become more effective decision-makers

Comprehensive study of different explanation approaches

- Wide variation of effectiveness
- Some explanations hurt decision-making

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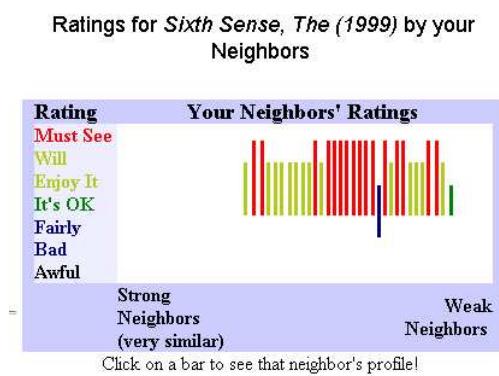
Most Compelling Interfaces



- *Simple* visual representations of neighbors ratings
- Statement of strong previous performance
“MovieLens has predicted correctly 80% of the time for you”

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Less Compelling Interfaces



- Anything with even minimal complexity
 - More than two dimensions
- Any use of statistical terminology
 - Correlation, variance, etc.

Explanation: Key Lessons

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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!

Collaborative Filtering Case Studies Contents

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Improve Your Recommendations **Amazon Improve Your Recommendations**

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The screenshot shows a Mozilla Firefox browser window displaying the Amazon.com 'Improve Your Recommendations' page. The URL in the address bar is <http://www.amazon.com/rec/lobdos/g/recc/r-collection-edt/-1/1/unrated/all/104-2814376-0523900?cont-page=recs/signed-in-continues/cont-type=collection>. The page title is 'Your Recommendations > Improve Your Recommendations'. The main content area lists five items for rating, each with a small thumbnail, the item name, the author, and a rating scale from 1 to 5 stars. Each item row includes a checkbox labeled 'Use to make recommendations'.

Show: Items not rated All items in: All Products	Not Rated	Your Rating:
Don't like it < I love it!		
? 1 2 3 4 5		
1. Stupid White Men...and Other Sorry Excuses for the State of the Nation by Michael Moore	? 1 2 3 4 5	<input type="checkbox"/> Use to make recommendations
2. The Harry Diaries by Emma McLaughlin, Nicola Kraus	? 1 2 3 4 5	<input type="checkbox"/> Use to make recommendations
3. Atonement by Ian McEwan	? 1 2 3 4 5	<input type="checkbox"/> Use to make recommendations
4. The Ultimate French Review and Practice by David M. Stillman, Rónná L. Gordon	? 1 2 3 4 5	<input type="checkbox"/> Use to make recommendations
5. Irish Heartbeat ~ Van Morrison & The Chieftains	? 1 2 3 4 5	<input type="checkbox"/> Use to make recommendations

Commercial Explanations

Amazon Explanation

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DVD Recommendations > Why was I recommended this?

We recommended...

Crouching Tiger, Hidden Dragon dvd
 ~ Yun-Fat Chow
 Average Customer Rating: ★★★★
 Our Price: \$20.97

Because you purchased or rated...

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

Launch Exp

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With Flashcom DSL there's no wait to connect!

LAUNCH Discover New Music

LAUNCHcast now available in REAL™

LAUNCHcast Stations **jkonstan's Station**

Who's on LAUNCHcast

- eidenb** Saddle In The Rain John Prine
- ckoebler** Distant Voices Bush
- soulmatesclub** Billie Jean Michael Jackson

Top 10 Videos

LAUNCHcast Stations **jkonstan's Station**

CONNECTION 300k Cable, LAN

To customize your station, visit the **Station Manager**, where you can rate your favorite artists, albums and songs, subscribe to DJs who share your tastes, edit your genre, mood, bandwidth preferences, and more.

Play your station directly from your desktop [Download the LAUNCHcast Desktop Application \(beta\) >](#)

Modern Rock Station **Ja Rule Fan Station**

New Order, Shina, U2, Creed, Candi Lauper, Hole, more... Dr. Dre, DMX, Eminem, Jay-Z, Juvenile, 2Pac, and more...

listen **watch** **listen** **watch** **listen** **watch**

more GENRE stations > **more FAN stations >**

LAUNCHcast Playing 00:03 / 04:57

Fast Car Tracy Chapman Tracy Chapman (1988)

Recommended by fans of Elton John

Fans: xrayx, garyrinker, chris, EITopo, Almost_Famous, All 1,138 Fans...

Genres: Mainstream Pop, Adult Alternative

edit **history** **share** **buy**

to win...

Group Recommenders

143

PolyLens: A Group Recommender

Problem: People watch movies together

Solution: A recommender for groups

Issues

O'Connor, M., Cosley, D., Konstan, J., & Herlocker, J. (2001). PolyLens: A recommender system for groups of users. In *Proceedings of the European Conference on Computer-Supported Cooperative Work*.

- Group formation, rules, composition
- Recommender algorithm for groups
- User interface

Goals

144

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

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Design Issues (1)

Characteristics of groups

- public or private
- many or few
- permanent or ephemeral

Formation and evolution of groups

- joining policy
- administration and rights

Design Issues (2)

146

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

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PolyLens

Design choices

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

Group: Dantest		Back To Individual Recommendations				
TITLE	GENRE	REVIEWS	GROUP	YOUR	cosley@cs.umn.edu	cosley@quasar
Pixote (1981)	Drama	★★★★★	★★★★★	★★★★★	★★★★★	★★★★★
Wrong Trousers, The (1993)	Animation, Comedy	★★★★★	★★★★★	★★★★★	★★★★★	★★★★★
After Life (1998)	Drama	★★★★★	★★★★★	★★★★★	★★★★★	★★★★★
King of Masks, The (Bian Lian) (1996)	Drama	★★★★★	★★★★★	★★★★★	★★★★★	★★★★★

External invitations added by popular demand

Field Test Results and Lessons

148

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

New Users Some Stories

149

Do I have to re-enter my 2000 movie ratings?

What About New Item

150

Collaborative filtering cannot recommend new items: no one has rated them

- Random
- Content analysis
- Filterbots

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What About New Items?

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]

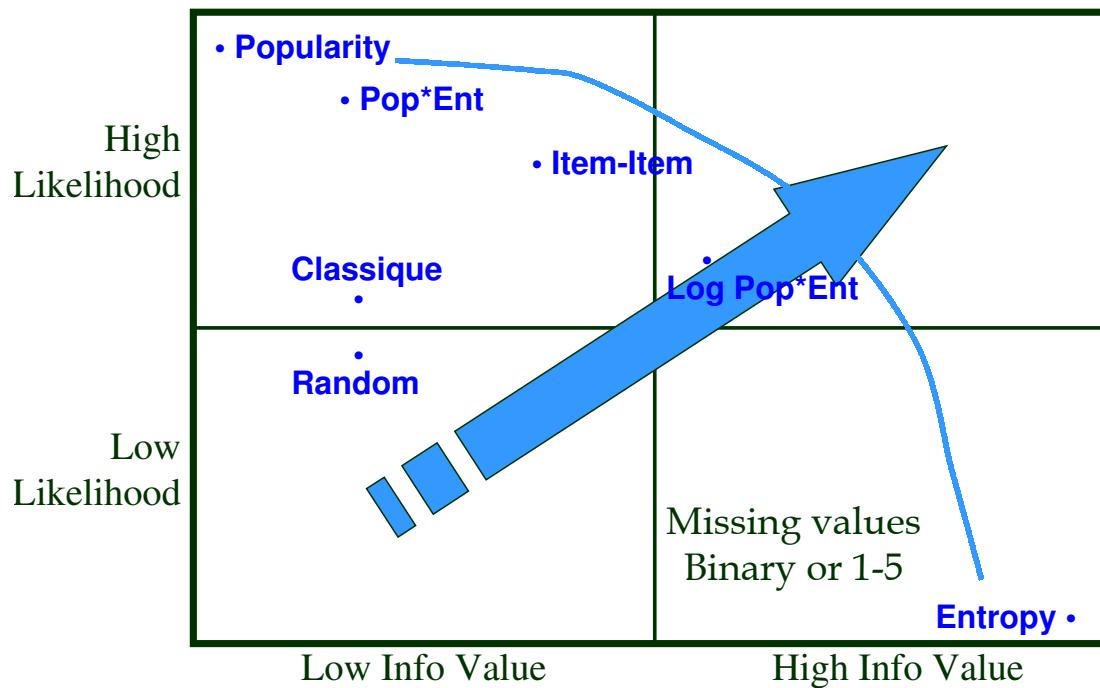
Goals for New Users

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- ➡ User effort
- ➡ User satisfaction
- ➡ Recommendation accuracy
- ➡ System utility

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Dimensions of Value



Non-CF Techniques

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Case-Based Reasoning

Personalization in a Job Finding System (1)

Basic idea of CASPER

- Underlying retrieval system: JobFinder, an Irish recruitment web site
- JobFinder provides conventional search-engine functionality over a database of job offers
- Limitation: \mathcal{U} 's search query seldom reflects all of her actual criteria
- \mathcal{U} 's ratings of jobs previously retrieved by JobFinder represent an additional source of information on \mathcal{U} 's needs
- These previous "cases" are used to filter further cases retrieved by the system


 user profiling for
 content personalisation. In P. Brusilovsky,
 (Eds.), *Adaptive hypermedia and adaptive Web-based systems:*
Proceedings of AH 2000 (pp. 62–72). Berlin: Springer.

Personalization in a Job Finding System (2)

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Procedure

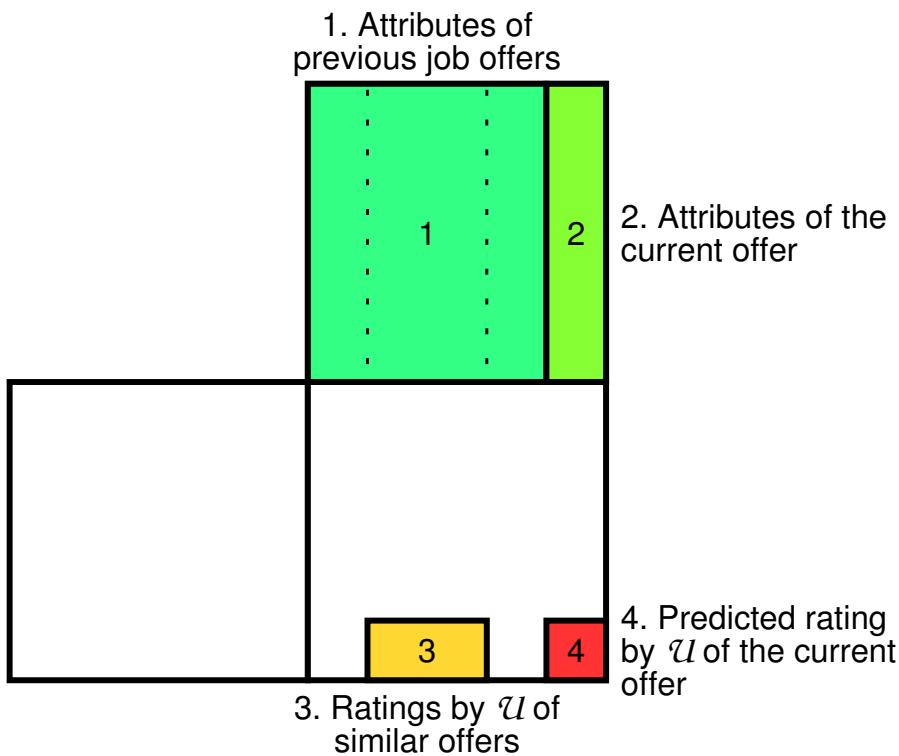
- \mathcal{U} is asked to rate each job offer she retrieves from the database
- These offers and their ratings are stored as cases that reflect \mathcal{U} 's preferences
- The relevance of a new job offer is predicted on the basis of the ratings of the k (here: 5) most similar previous cases ("nearest neighbors")
- \mathcal{S} 's criteria for assessing the similarity between two cases takes into account the domain-specific significance of the various attributes
 - Example: Java programming is more similar to C++ programming than it is to Pascal programming
- Each of these previous ratings is weighted by the similarity of the case to the current job offer

Evaluation results (summary)

- About 70% correct classifications, using for each \mathcal{U} a case base of 57 job offers previously rated by that \mathcal{U}

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Case-Based Reasoning: Schema



Naive Bayes Classifiers Naive Bayes in NewsDude

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Function of NewsDude

- The system NewsDude selects news stories for presentation in accordance with its models of \mathcal{U} 's long-term and short-term interests

Basic equation

- $p(\text{interesting} | \text{word}_1 \dots \text{word}_n) = p(\text{interesting}) \prod_i^n p(\text{word}_i | \text{interesting})$

Intuitive formulation

- "A story is likely to be interesting to \mathcal{U} if it contains words that occur frequently in stories that are interesting to \mathcal{U} "

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Nearest Neighbor and Naive Bayes

- In addition to the long-term user model just described, NewsDude employs a short-term user model based on the nearest neighbor algorithm (cf. CASPER)

Advantages of nearest neighbor in this context

Short ramp-up time

- A prediction can sometimes be made about a story even if only one similar story has been rated previously by \mathcal{U}

Tracking of short-term interests

- Example: \mathcal{U} may now be intensely interested in following a particular developing story

Taking into account special cases

- Example: \mathcal{U} has already heard (almost) exactly the same story

Evaluation

- Empirical comparisons confirmed that the hybrid user model performed better than either of its components alone

Demographically Based Methods The Lifestyle Finder⁽¹⁾

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Elicitation

- The Lifestyle Finder, in the form of a clairvoyant named Waldo, elicits demographic information in a playful fashion that does not require \mathcal{U} to supply identifying information
- 93% of the users surveyed agreed that the Lifestyle Finder's questions did not invade their privacy

Exploitation

- After \mathcal{U} has answered a few lifestyle-related questions, the Lifestyle Finder presents its guess about the demographic cluster to which \mathcal{U} belongs
- It then recommends web pages with information about products that should be of interest to persons within this cluster

The Lifestyle Finder was freely available on the web long enough to collect data from 20,000 users, but it is no longer available. See Krullwich, B. (1997). Lifestyle Finder: Intelligent user profiling using large-scale demographic data. *AI Magazine*, 18(2), 37–45.

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The Lifestyle Finder (2)

Procedure of "demographic generalization"

- The Lifestyle Finder assigns \mathcal{U} to one or more of 62 demographic clusters from a commercial demographic system employed for consumer marketing
- If \mathcal{U} 's answers match more than one cluster, the predictions that are common to all matched clusters form the basis for recommendations for \mathcal{U}
- S may ask further questions that efficiently narrow down the set of possible clusters for \mathcal{U}

Evaluation

- Users gave positive responses to more than 40% of the web pages recommended in this way, compared with about 30% of the randomly recommended pages
- This level of accuracy is lower than that attainable through other methods
 - This method is accordingly proposed as a complement to methods that require more input from each user

Selling Demographics: DoubleClick

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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

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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

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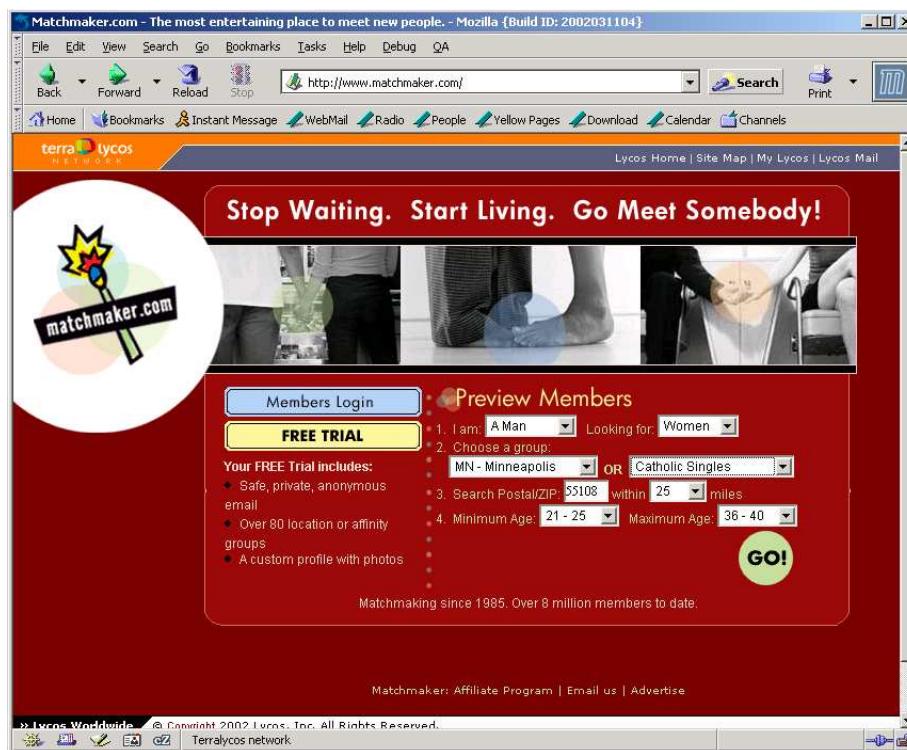
Customers hate cross-site tracking

Sharing data about millions of customers is expensive

Effective solutions will require privacy protection and data reduction

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Matchmaker: Seeker Features



Content and Demographic Information Example Restaurant Domain

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Method

Users

- 44 students at the University of California at Irvine

Items

- 58 restaurants in Orange County, California
 - – each as described on a web page
- Content of typical description
 - Short overview, cuisine, atmosphere, location, detailed menu

Ratings

- "Would you like to eat at this restaurant?" (+ or -)
- Each user rated each restaurant
- Overall, 53.4% of all ratings were +
- In each experiment, half of the ratings of each user were randomly deleted

The slides in this subsection are based on Pazzani, M. J. (1999). A framework for collaborative, content-based and demographic filtering. *Artificial Intelligence Review*, 13, 393–408. <http://www.ics.uci.edu/~pazzani/Publications/Publications.html>

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Person-Person CF

Computation

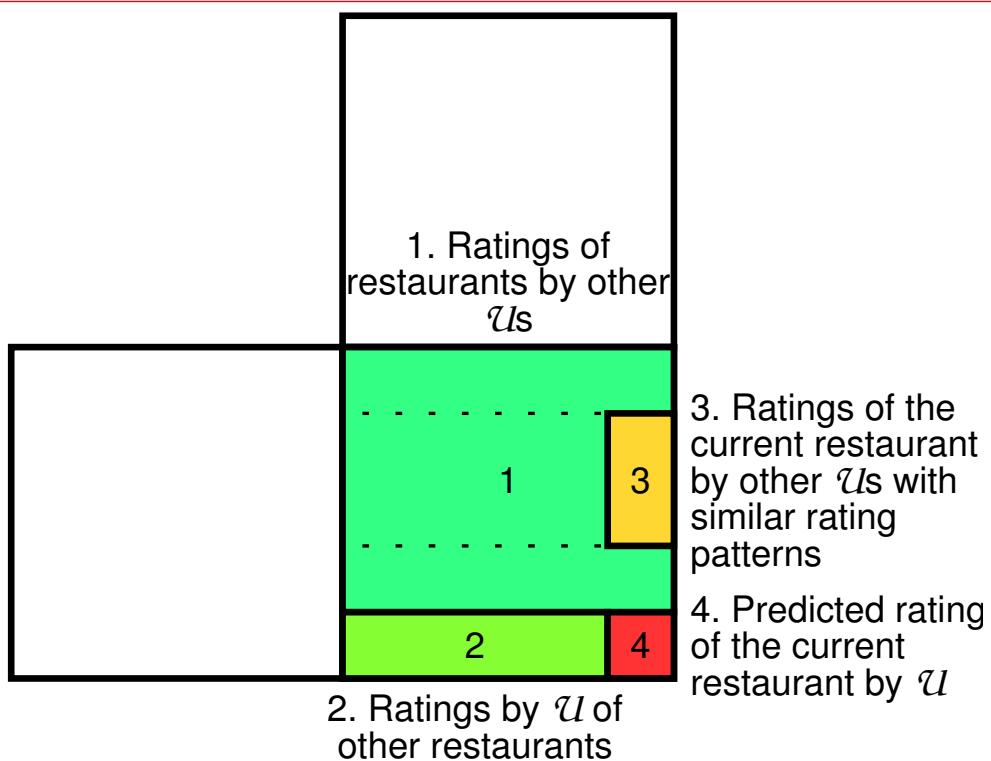
- Prediction based on weighted average of other users' ratings
 - Each weight based on Pearson r correlation

Result

- 67.9% ($\pm 0.58\%$) of top 3 recommended restaurants were in fact positively rated

Person-Person CF: Schema

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Item–Item CF

Computation

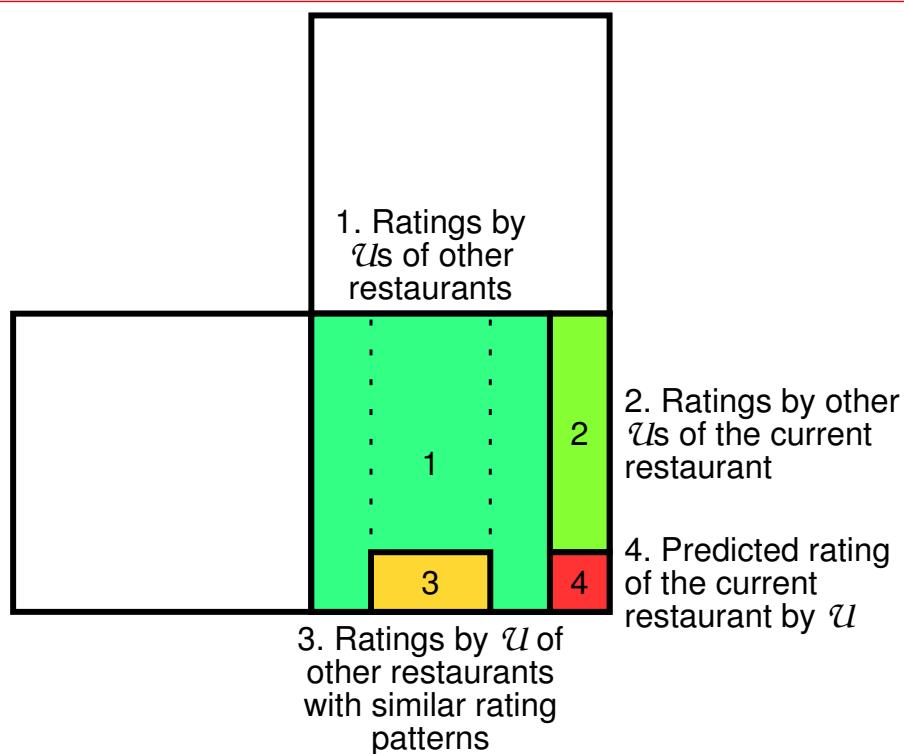
- Prediction based on weighted average of other restaurants' ratings

Result

- 59.8% ($\pm 1.00\%$) of top 3 recommended restaurants were positively rated

Item–Item CF: Schema

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Content-Based Recommendation (1)

Algorithm

- WINNOW (Blum et al., 1995)

Features of restaurant descriptions

- Presence vs. absence of each possible word (or pairs of adjacent words) occurring in the text
 - Terms associated with liking for one user:
`farm, sirloin, private, milk, exquisitely`
`prime rib, old English, charbroiled served`

Basic prediction formula

- \mathcal{U} is expected to like a restaurant r iff
- $\sum_t weight_t \cdot presence_{tr} > threshold$

 Blum, A., Hellerstein, L., & Littlestone, N. (1995). Learning in the presence of finitely or infinitely many irrelevant attributes. *Journal of Computer and System Sciences*, 50(1), 32–40.

Content-Based Recommendation (2)

174

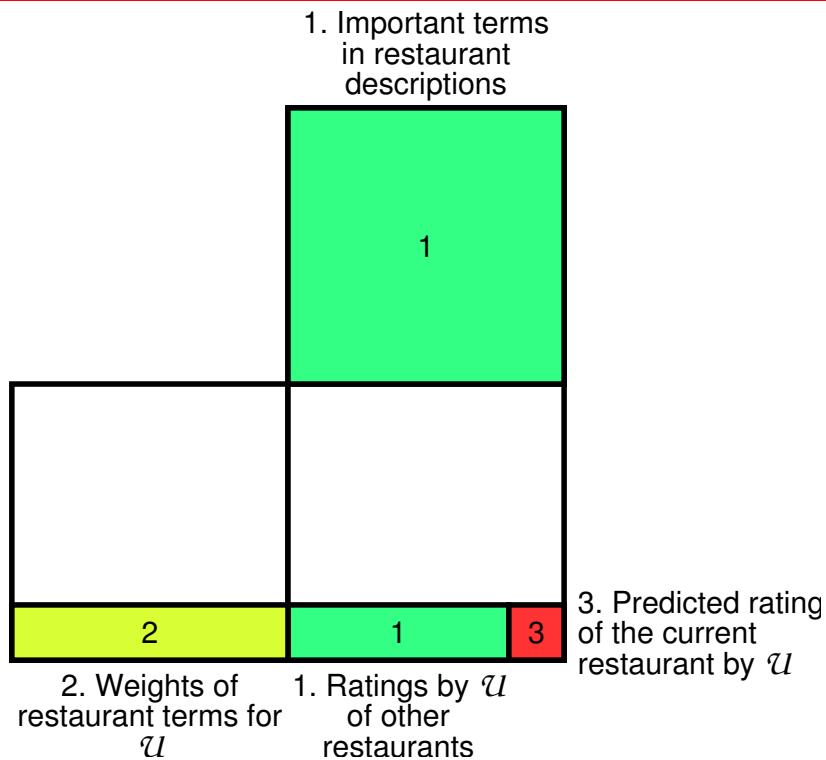
Adjusting weights for each individual \mathcal{U}

- Set all word weights to 1.0
- In each iteration through all documents
 - For each document
 - If document is incorrectly predicted to be liked,
divide the weight of each word in the document by 2
 - If document is incorrectly predicted to be disliked,
multiply the weight of each word in the document by 2
 - Stop when the weights no longer change

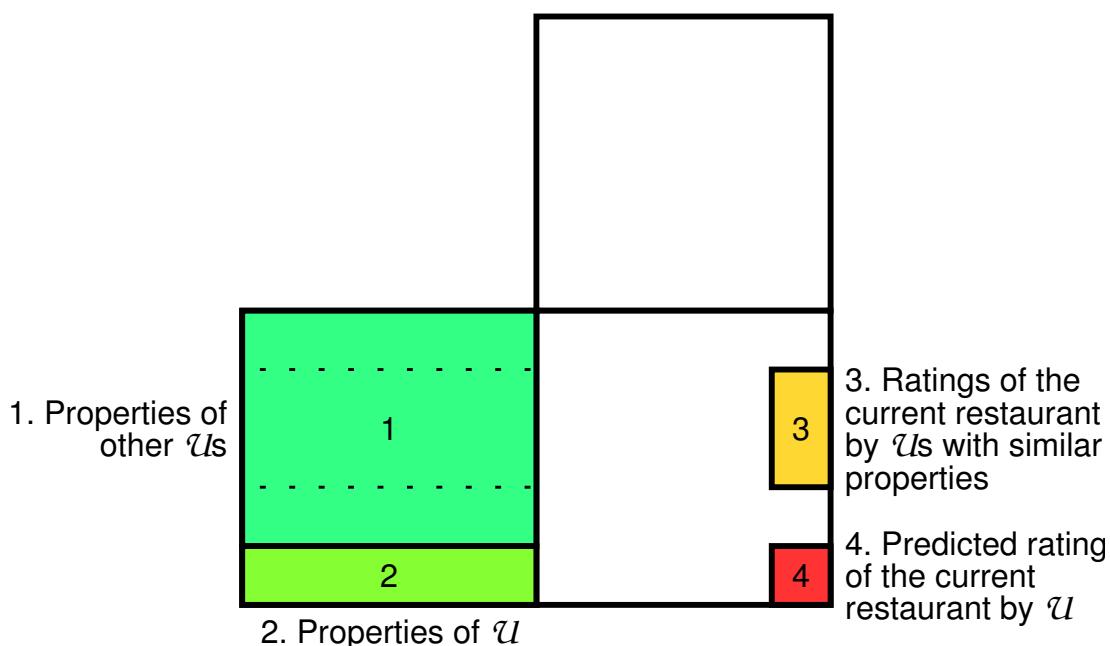
Results

- 61.2% ($\pm 0.56\%$) of top 3 recommendations were liked
- Using pairs of adjacent terms (e.g., *shrimp appetizer*): 61.5% ($\pm 0.84\%$)

175 Content-Based Recommendation: Schema



Demographic Prediction via Similarity



A simpler approach to demographic prediction than the one taken in the study of Pazzani (1999)

¹⁷⁷

Demographic Prediction via Classification

Source of demographic data

- Words in users' web home pages

Computation

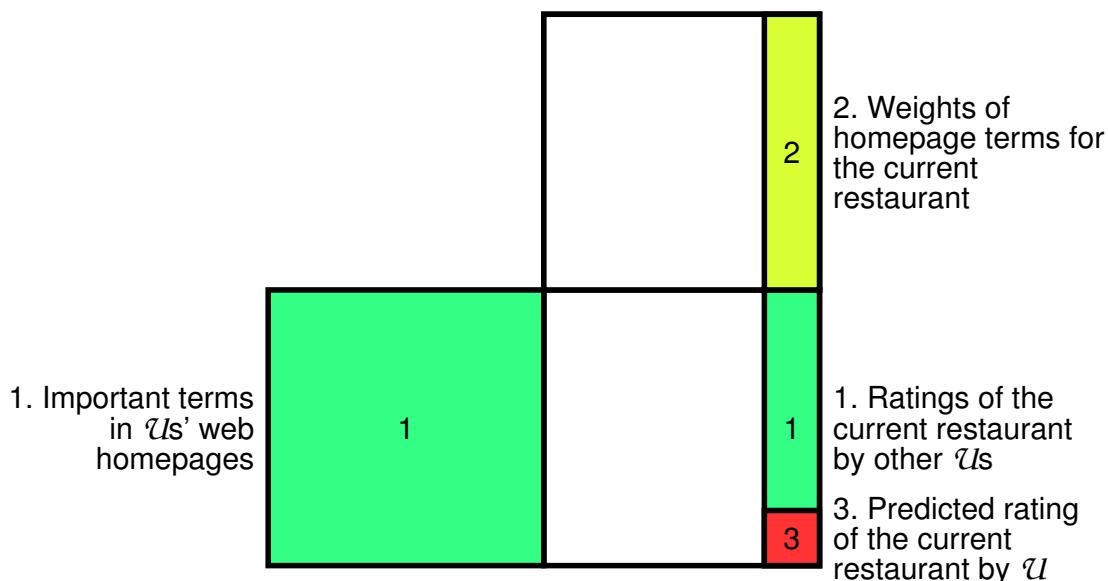
- Analogous to content-based prediction:
 - For each restaurant \mathcal{R}
Use Winnow to learn a classifier for \mathcal{R} that takes users' homepages as input

Results

- 57.5% (± 0.76) of top 3 recommendations were liked

Demographic Prediction: Schema

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Collaboration by Content

Basic idea

- Additional user attributes:
 - Weights of terms in \mathcal{U} 's content-based profile
After elimination of terms found to have little value for classification
- Finding neighbors of \mathcal{U}
 - As with the collaborative filtering computation,
– but using the term weights instead of the ratings

Results

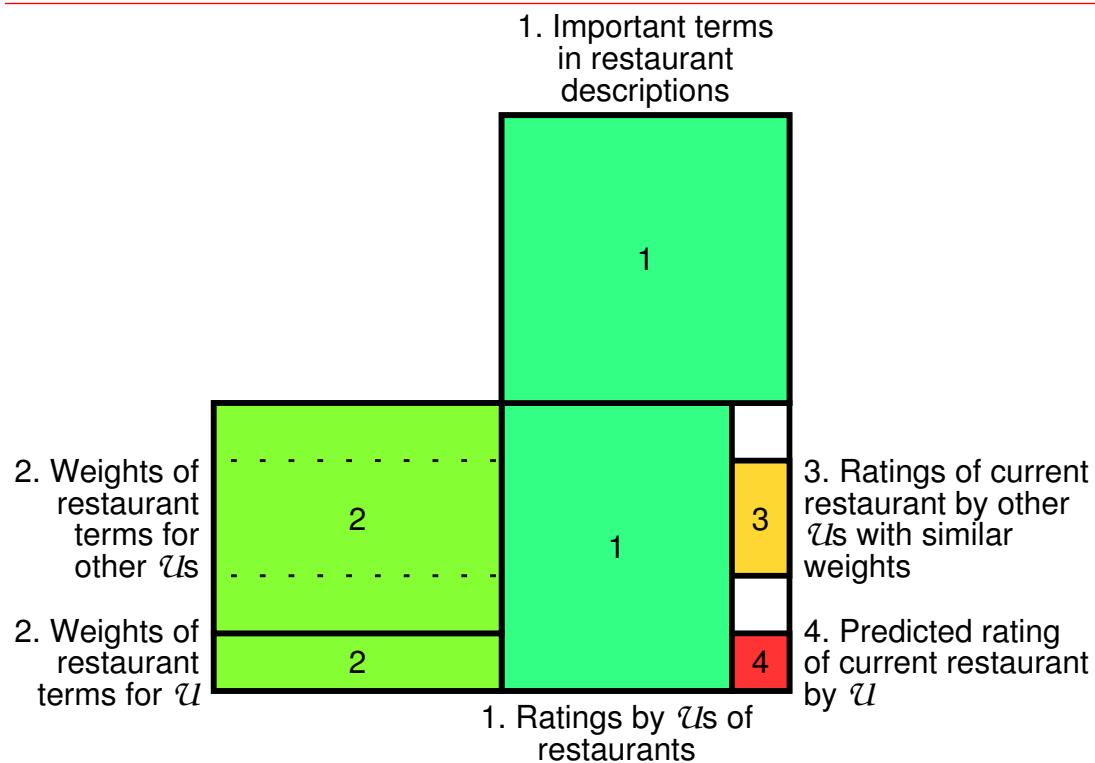
- 70.1% ($\pm 0.60\%$) of top 3 recommendations were liked

Advantages

- Over normal collaborative filtering
 - More information for computation of similarity among users
- Over pure content-based filtering
 - Sensitive to other users' overall evaluation

Collaboration by Content: Schema

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Combining All Prediction Methods

Computation

- All of the five methods discussed above were applied simultaneously
- For each prediction:
 - For each method:
 - the 5 highest-rated restaurants are determined
 - the restaurant with the N th highest rating gets $6-N$ points
 - The total rating of a restaurant is determined by the sum of its points

Results

- 72.1% ($\pm 0.44\%$) of top 3 recommendations were liked
- \Rightarrow the best results of this study

Exploiting All Three Types of Data A Bayesian Mixed-Effects Model ⁽¹⁾

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Learning a general model

- For each of the N users encountered so far
 - Learn a Naive Bayes classifier for predicting responses on the basis of item features
 - E.g., "This \mathcal{U} likes comedies and dislikes horror films"
- For the entire group of users encountered so far
 - Learn a model for predicting the parameters of a \mathcal{U} 's classifier on the basis of that \mathcal{U} 's demographic characteristics
 - E.g., "Female users over 60 tend not to like horror films, though some do"

The discussion in this subsection is based on: Condellif, M. K., Lewis, D. D., Madigan, D., & Posse, C. (1999). Bayesian Mixed-Effects Models for Recommender Systems. ACM SIGIR '99 Workshop on Recommender Systems: Algorithms and Evaluation, Berkeley, CA. <http://www.cs.umbc.edu/~ian/sigir99-rec.html>

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A Bayesian Mixed-Effects Model (2)

Learning about each individual \mathcal{U}

- When a new \mathcal{U} is encountered
 - On the basis of \mathcal{U} 's demographic characteristics, determine the prior expectations concerning \mathcal{U} 's naive Bayes classifier
 - On the basis of \mathcal{U} 's responses to items, update the parameters of her classifier

Predicting for a given \mathcal{U} and I

- Apply \mathcal{U} 's current classifier to the features of I

Evaluation With Beverage Preferences (1)

184

Data

16 beverages:

- Coke, Diet Coke, Sprite, Dr. Pepper, root beer, sparkling water, orange juice, grapefruit juice, apple juice, tomato juice, cranberry juice, coffee, tea, hot chocolate, beer, wine

10 beverage attributes

- Carbonated, sweet, juice, hot, alcoholic, caffeinated, low-calorie, fruit-derived, highly advertised, citrus drink

8 user attributes

- Female, less than 21 years old, 21–30 years old, over 30 years old, white, Asian, not White or Asian, from the U.S.

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Evaluation With Beverage Preferences (2)

Methods compared with

Simple non-Bayesian methods

- E.g., conventional collaborative filtering

Simpler Bayesian methods

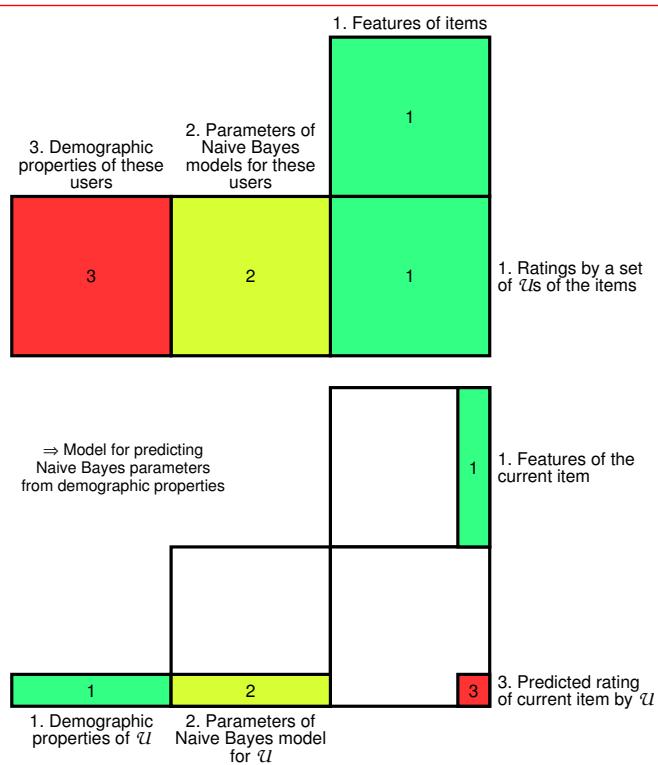
- 3 simpler ways of determining prior distributions for each \mathcal{U}
 - E.g., take mean of all previous users

Results

- User attributes had little predictive value in this domain
- Better than normal collaborative filtering
- Not better on this task than simpler Bayesian models

Bayesian Mixed-Effects Model: Schema

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Types of Hybrid Model

Hybridization Methods (1)

Weighted

- The scores (or votes) of several recommendation techniques are combined together to produce a single recommendation
⇒ Pazzani's (1999) combination of all of his methods (Slide 181)

Switching

- The system switches between recommendation techniques depending on the current situation
⇒ NewsDude's Naive Bayes and Nearest Neighbor models (Slide 161)

Mixed

- Recommendations from several different recommenders are presented at the same time
⇒ Amazon's web pages

Based on Table III of Burke, R. (2002). Hybrid recommender systems:
Survey and experiments. *User Modeling and User-Adapted Interaction*.
<http://cbeblade.fullerton.edu/~rburke/pubs/burke-umail-ip.pdf>

Hybridization Methods (2)

Feature combination

- Features from different recommendation data sources are thrown together into a single recommendation algorithm
- ⇒ Case-based recommendation: Use both item features and responses of other users

Cascade

- One recommender refines the recommendations given by another
- ⇒ Content-based restaurant recommendation + tie-breaking on the basis of responses of similar users

Feature augmentation

- Output from one technique is used as an input feature to another
- ⇒ (Slides 189 – 191)

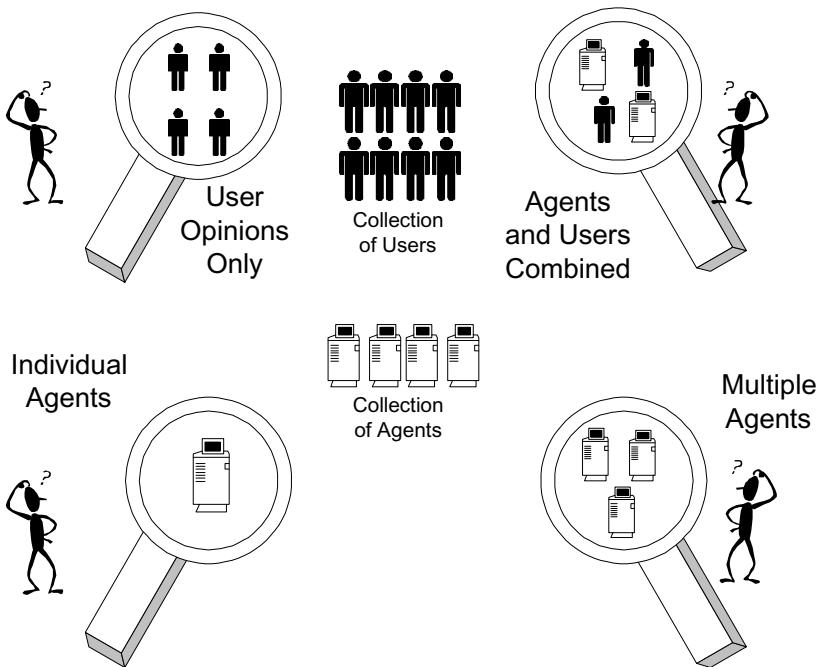
Meta-level

- The model learned by one recommender is used as input to another
- ⇒ Pazzani's Collaboration by Content (Slides 179–180)

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Example of Feature Augmentation (1)

Figure 1 from Good, N., Schafer, J. B., Konstan, J. A., Borchers, A., Sawar, B., Herlocker, J., & Riedl, J. (1999). Combining collaborative filtering with personal agents for better recommendation. In *Proceedings of the Sixteenth National Conference on Artificial Intelligence*, Orlando, FL, pp. 439–446. <http://www.cs.umn.edu/Research/GroupLens/research.html>



Good et al. (1999) compared various combinations of individual recommending agents and collaborative filtering methods

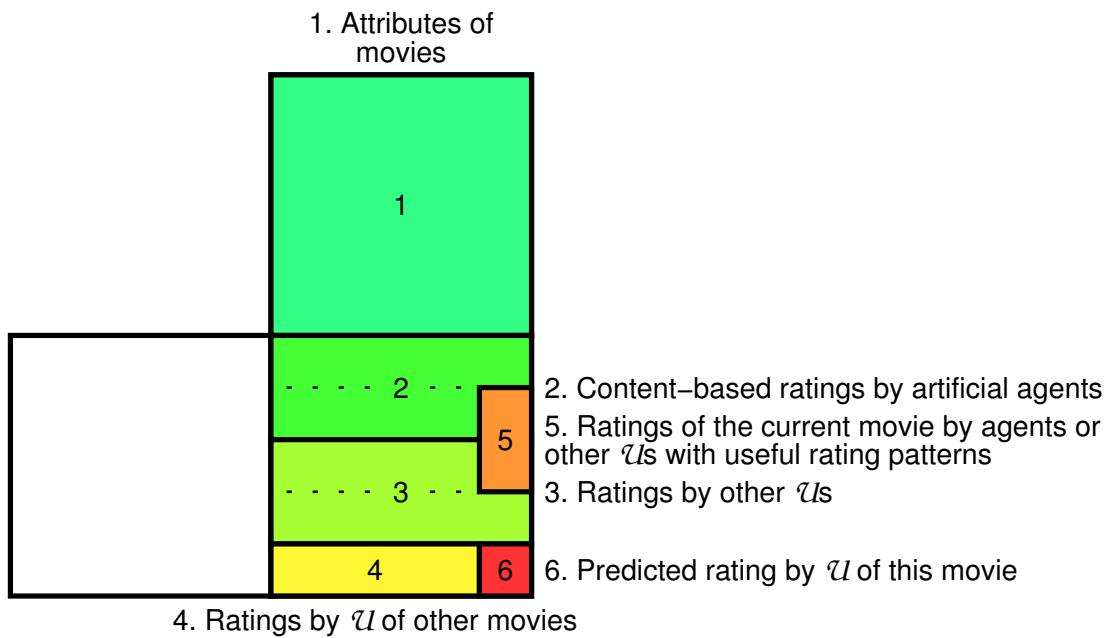
190

Example of Feature Augmentation (2)

Inclusion of other methods as neighbors

- Realize one or more other methods as "agents"
- Include the agents as "neighbors" in the collaborative filtering, along with real users
- Allow the collaborative algorithm to determine, for each \mathcal{U} , what weight to give to these agents' predictions

Artificial Agents: Schema

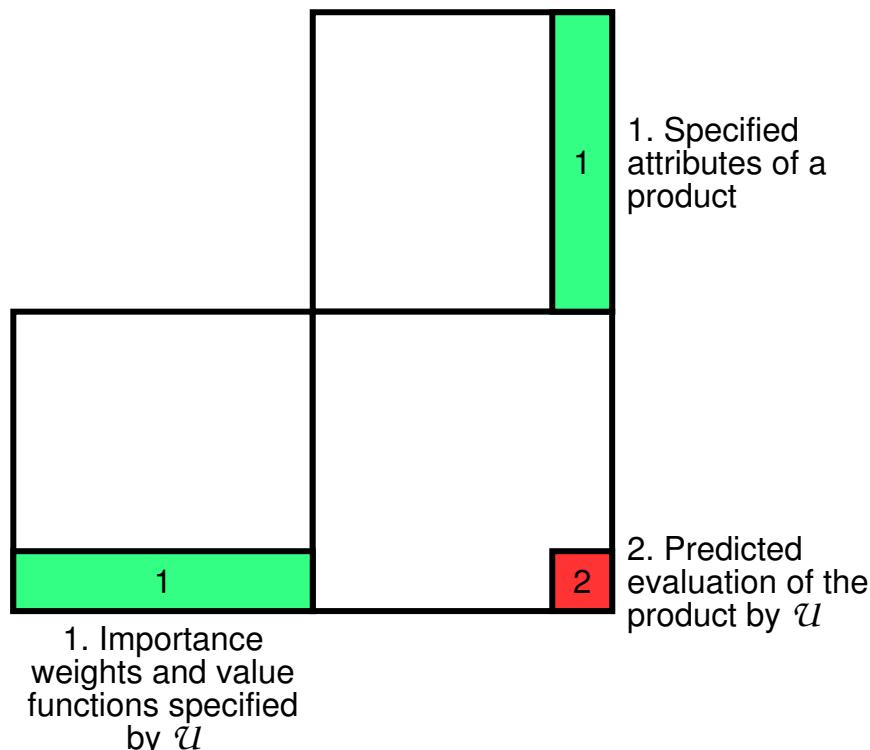


Explicit Preference Elicitation Introduction

- Frictionless.com created a web-based system (\mathcal{S}) called PurchaseSource
- On-line vendors can use this system to help customers locate suitable products
- What we will see on the following slides is a walkthrough of a demonstration of this system
- What is of interest is the basic system itself, not the specific information that has been entered on the particular type of product that our hypothetical \mathcal{U} is looking for (backpacks)

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Explicit Preferences: Schema



Overview of Types of Sports Articles

194

- \mathcal{U} has already indicated that he is interested in sports articles
- \mathcal{U} now clicks on "Backpacks" under "Outdoors"

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Choosing a "Profile"

**PURCHASESOURCE™
RETAIL**

YOUR PROFILE
SELECT A SHOPPING PROFILE

1. SELECT A PROFILE
2. SELECT YOUR PREFERENCES
3. SEE AND COMPARE YOUR RESULTS

Choose the shopping profile that best describes you or select Custom Profile if none of them fit. Then, click on "Next Step" or "Select Your Preferences" to continue shopping.

- ◆ **Day Hiker** – You are looking for a small pack to take with you on day hikes. Use this profile to compare small backpacks.
- ◆ **Car Camper** – You are looking for a backpack for one- or two-day hikes. Use this profile to compare full-size packs that are designed for average use.
- ◆ **Explorer** – You are an avid hiker and your backpack is very important to you. Use this profile to compare expedition-quality packs.
- ◆ **Budget Shopper** – You are looking for a backpack, but you do not want to pay for features you will not use. Use this profile to compare less expensive packs.
- ◆ **Custom Profile** – Select the features that best fit your needs. This profile will not select any preferences for you.

SEARCH THIS CATEGORY

- By choosing the profile "Day Hiker", \mathcal{U} allows S to make guesses about many of \mathcal{U} 's preferences
- \mathcal{U} will now need to specify only the preferences that S has not guessed correctly

Specifying Preferences

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PREFERENCES
SELECT YOUR PREFERENCES

1. SELECT A PROFILE
2. SELECT YOUR PREFERENCES
3. SEE AND COMPARE YOUR RESULTS

The product and retailer preferences below were chosen based on your selected shopping profile. If any of these features are more or less important to you than we've indicated, you can easily change them. The choices you make here will determine the individual results and rankings you will see. Click "Next Step" or "See and Compare Your Results" to continue shopping.

Basic Features	Preferences	Importance Rating
		Must Have Very Important Not Important
Capacity learn more	EDIT 1,000 cu.in - 1,500 cu.in	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Loading learn more	EDIT No Preference	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Manufacturer learn more	EDIT No Preference	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Price learn more	EDIT \$40.00 - \$100.00	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Type learn more	EDIT Daypack, Fannypack	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Weight learn more	EDIT 1.00 lbs - 5.00 lbs	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

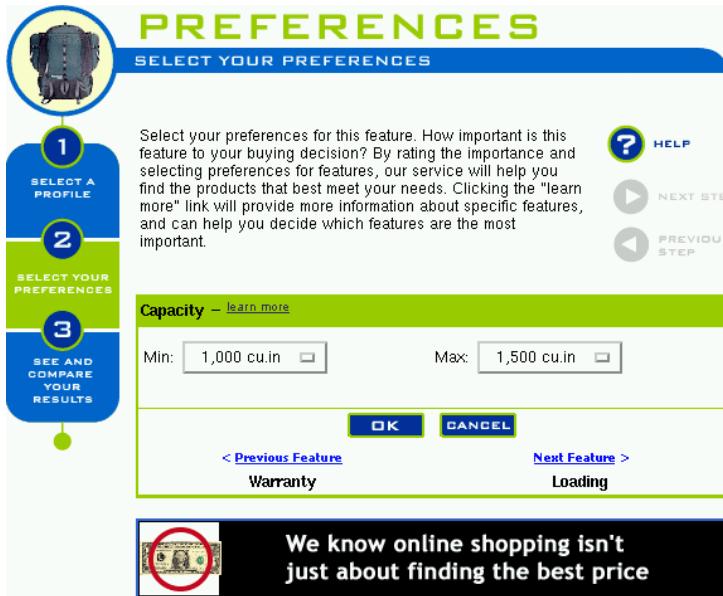
Advanced Features	Preferences	Importance Rating
		Must Have Very Important Not Important
Additional Features learn more	EDIT No Preference	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Color learn more	EDIT No Preference	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Material learn more	EDIT No Preference	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Size learn more	EDIT No Preference	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

Merchant Features	Preferences	Importance Rating
		Must Have Very Important Not Important

- For each attribute, \mathcal{U} can specify how *important* it is that the product should fall into the specified range
- \mathcal{U} can learn more about the attribute by clicking the "learn more" button
 - For the attribute "Capacity", see the result on the slide after next
- \mathcal{U} can also "edit" the range itself
 - Here, our \mathcal{U} chooses to edit the range for "Capacity" by clicking on the first "Edit" button

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Editing the Range for an Attribute



- Before editing the range, our \mathcal{U} chooses to "learn more" about the attribute "Capacity"

Learning More About an Attribute

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- After reading this information, our \mathcal{U} goes "back" to the previous screen
- There, \mathcal{U} uses the right-hand pop-up menu to change the maximum capacity to 2,500 cu. in

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Overview of the Recommended Products (1)

YOUR RESULTS
PRODUCTS THAT MATCH YOUR PREFERENCES

Below are all the products that meet (even partially) one or more of your preferences. Right now, they are sorted by the Frictionless™ ValueScore, with the best matches at the top of the list. You can resort your results by price or other criteria by clicking on the drop-down menu.

You can also compare up to three products side-by-side, feature-for-feature, by simply clicking on the checkboxes to the left of the product names, and then clicking the "Compare" button.

There are **50 Total Matches** to your search from the [34 Merchants Searched](#).

Profile: Day Hiker

Results are sorted by [Value Score](#). Sort Results by selecting from the drop-down menu and clicking the [GO](#) button:

Value Score [GO](#)

Pages: [1](#) [2](#) [3](#) [4](#) [5](#)

	Product	Merchant	Frictionless™ Value Score	Price
<input type="checkbox"/>	Recreational Equipment Inc. Alpine	Recreational Equipment Inc.	██████████ 100	\$42.99 buy
<input type="checkbox"/>	Eureka Gemini Technical Daypack	iQVC <input checked="" type="checkbox"/>	██████████ 98	\$74.95 buy
<input type="checkbox"/>	Eureka Diablo Technical Daypack	iQVC <input checked="" type="checkbox"/>	██████████ 97	\$92.50 buy
<input type="checkbox"/>	Eureka Freebird Technical Daypack	iQVC <input checked="" type="checkbox"/>	██████████ 97	\$97.50 buy
<input type="checkbox"/>	Camp Trails Canoe Pack	Eastern Mountain Sports <input checked="" type="checkbox"/>	██████████ 96	\$120.00 buy

- Each recommended product is summarized here in a single line

Overview of the Recommended Products (2)

	Product	Merchant	Frictionless™ Value Score	Price
<input type="checkbox"/>	Osprey Finesse	Mountain Gear	██████████ 96	\$199.00 buy
<input type="checkbox"/>	Osprey Impala	Mountain Gear	██████████ 96	\$239.00 buy
<input type="checkbox"/>	Jansport Locker Pack	Eastern Mountain Sports <input checked="" type="checkbox"/>	██████████ 96	\$48.60 buy
<input type="checkbox"/>	Eureka Monterey Daypack	iQVC <input checked="" type="checkbox"/>	██████████ 96	\$62.93 buy
<input type="checkbox"/>	Jansport Couloir	The Sports Authority	██████████ 95	\$110.00 buy

Select up to 3 items and click **Compare** to see a side-by-side comparison. Click the Value Bars (████) to see an analysis of the scores.

COMPARE

Pages: [1](#) [2](#) [3](#) [4](#) [5](#)

SEARCH THIS CATEGORY

I [GO](#)

To narrow your search within these results enter a product or merchant name:

Key:

Value Bars
 = This product meets all of your preferences
 = One or more preferences are not met

The [Frictionless™ Value Score](#) (shown in red, next to the Value Bars) represents how well a product, offered by a specific merchant, meets the preferences that you selected

Click the Value Score or Value Bars (████) to see an analysis of Value Scores based on your preferences

- Our *U* clicks on the light-colored bar for the last product listed ("Jansport Couloir") to find out more about the reasons for the recommendation

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Summary for a Single Product

The **Value Icons** (● ●) depict how well each option matches your preferences. The more blue an icon is, the better it meets your preferences. A yellow icon (✖) means that a preference is not met.

Analysis of the Frictionless SM Value Score

Product: Jansport Couloir – sold by The Sports Authority

Frictionless SM
Value Score 95

Hits

1 "Must Have" preferences are satisfied:

Feature	Your Preferences:	This Product:
Type – learn more	Daypack, Fannypack	Daypack

2 of 3 important preferences are met. Your most important features are displayed below:

Feature	Your Preferences:	This Product:
Capacity – learn more	1,000 cu.in – 2,500 cu.in	2,400 cu.in
Weight – learn more	1.00 lbs – 5.00 lbs	3.00 lbs

Misses

There are several preferences that are not met, causing the yellow Value Bar to appear.

Feature	Your Preferences:	This Product:
Price – learn more	\$40.00 – \$100.00	\$110.00

Additional Information

-20 of your important preferences contained no data
-You did not express a preference, or chose "Not Important" for 20 features
To see how each feature measured up to the preferences you selected, click the Details button.

BACK **DETAILS**

- This page refers to a single product, but it still doesn't include all of the detailed considerations underlying S 's rating of this product
- Our \mathcal{U} wants to know these details, so he clicks on "Details"

Details for a Single Product

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Your personal comparison chart. See how your selections stack up, feature-by-feature.

The round icons will tell you whether a product meets your preferences – fully (●), partially (● & ○), or not at all (✖). For more information about the icons, [click here](#) to jump to the key. You'll also notice a "BUY" button above our Value Score for each product. When you're ready to do it, click it. We'll connect you to the right site.

General Features

	Couloir	
Manufacturer	○	Jansport
Merchant	○	The Sports Authority
Price	✖	\$110.00
PurchaseSource	Retail Merchant Network	—

Basic Features

	Couloir	
Capacity	●	2,400 cu.in
Loading	—	n/a
Loading Type	—	n/a
Pockets	—	n/a
Type	●	Daypack
Weight	●	3.00 lbs

**Frictionless SM
Value Score** 95

BUY

NEXT STEP **PREVIOUS STEP**

- Here, \mathcal{U} can see, for each attribute, how S rated this product with respect to this attribute
- (Only the first part of the long screen is shown here)

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Comparison of Three Products

General Features						
	Alpine	Gemini Technical Daypack	Diablo Technical Daypack			
Manufacturer	<input type="radio"/> Recreational Equipment Inc.	<input type="radio"/> Eureka	<input type="radio"/> Eureka			
Merchant	<input type="radio"/> Recreational Equipment Inc.	<input type="radio"/> iQVC	<input type="radio"/> iQVC			
Price	<input checked="" type="radio"/> \$42.99	<input checked="" type="radio"/> \$74.95	<input checked="" type="radio"/> \$92.50			
Purchase Source	—	<input checked="" type="radio"/>	<input checked="" type="radio"/>			
Retail Merchant Network	—	<input type="radio"/>	<input checked="" type="radio"/>			
	BUY	BUY	BUY			
Frictionless™ Value Score	■ 100	■ 98	■ 97			
Basic Features						
Capacity	<input type="radio"/>	2,930 cu.in	<input type="radio"/>	2,540 cu.in	<input type="radio"/>	2,900 cu.in
Loading	—	n/a	<input type="radio"/>	Top Load	<input type="radio"/>	Top Load
Pockets	—	n/a	—	n/a	<input type="radio"/>	Extra Pockets
Type	<input checked="" type="radio"/>	Daypack	<input checked="" type="radio"/>	Daypack	<input checked="" type="radio"/>	Daypack
Weight	<input checked="" type="radio"/>	2.50 lbs	<input checked="" type="radio"/>	2.40 lbs	<input checked="" type="radio"/>	2.10 lbs
Advanced Features						
Additional Features	—	n/a	<input type="radio"/>	Ice Axe Loops, Daisy Chain	<input type="radio"/>	Daisy Chain
Color	—	n/a	—	n/a	—	n/a
Material	—	n/a	—	n/a	—	n/a

- Later, our \mathcal{U} chooses to request a comparison of three other backpacks, which were more highly rated

- In each column of this screen, essentially the same information is presented as in the screen with details for a single product (see the previous slide)

Non-CF Case Studies

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Incremental Preference Elicitation

Automated Travel Assistant Domain

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Example of dialog ultimately desired

- Client:* I want to fly from Seattle to Newark next Tuesday afternoon.
- Agent:* I've got a United flight at 3:30pm for \$500 and an American flight at 12:30pm for \$520.
- Client:* I can't leave before 3:00pm but I do prefer American.
- Agent:* I have another American flight through Denver at 4:00pm for \$530.
- Client:* That's pretty expensive. I'd be willing to go on a later flight or another airline if it'd be much cheaper.
- Agent:* The cheapest flight is USAir at 8pm for \$490.
- Client:* In that case, the American flight is fine.

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Candidate Critique Agents

Goals of a Candidate Critique Agent

- Suggest optimal and near-optimal solutions on the basis of S 's current model of \mathcal{U} 's preferences
- Elicit and refine the user model
 - Perhaps by displaying bad candidates to encourage \mathcal{U} to refine her criteria
- Indicate the range of available solutions in the dataset

Style of interaction

- S presents a short, carefully selected list of candidate solutions to \mathcal{U}
- \mathcal{U} either
 - accepts one of these options or
 - critiques one or more of them
- Critiques provide additional information about \mathcal{U} 's preferences, which lead to new and better candidates

Formalization (1)

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Definition of a problem domain

- In terms of a predefined set of attributes:
 - A_1, A_2, \dots, A_n
- Each attribute takes on values from an underlying set:
 - $\text{dom}(A_i) = \{v(i, 1), v(i, 2), \dots, v(i, k)\}$
- A candidate solution can be described with a tuple of the form:
 - (v_1, v_2, \dots, v_n)

Example in the travel domain

- Dataset: all currently available flights
- Attributes of each flight:
 - Cost, airline, departure and arrival cities, time and date of travel,
 - ...

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Formalization (2)

Representation of preferences

- \mathcal{U} 's preferences: soft constraints on the values of attributes
- Constraint function:
 - $C_i(v) : \text{dom}(A_i) \rightarrow [0, 1]$
- 0 = "fully satisfied", 1 = "fully unsatisfied"

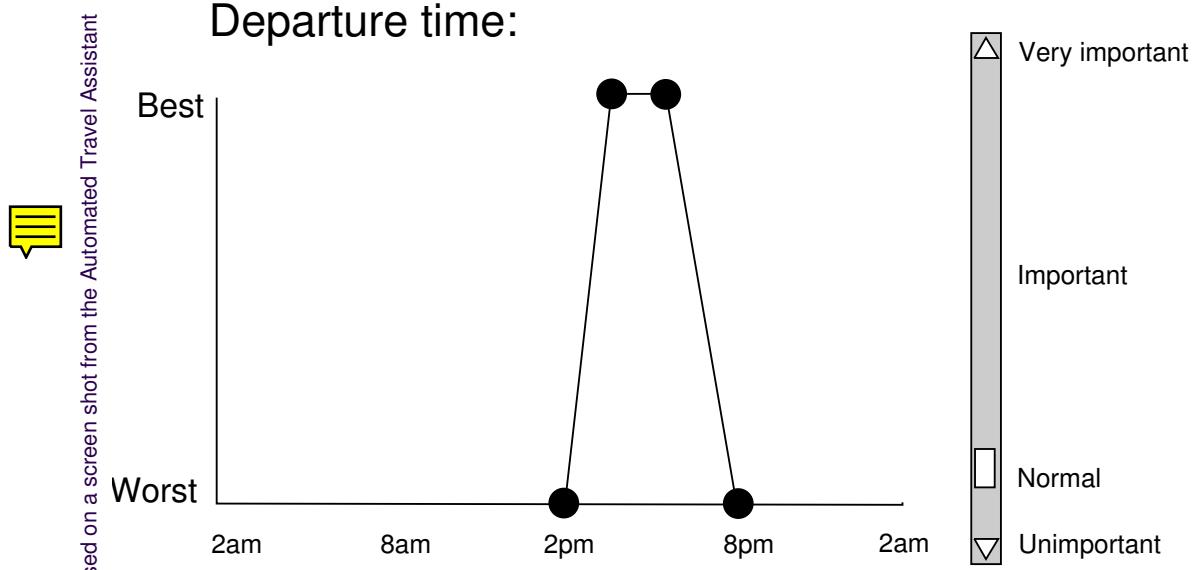
Simplifying assumption here

- Preferences are *additive independent*:
 - A preference concerning one attribute does not depend on the level of any other attribute

Formalization (3)

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Departure time:



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Formalization (4)

User model

$$(\{C_1, \dots, C_n\}, \{w_1, \dots, w_n\})$$

where C_i is a constraint and w_i is the weight, a real number in [0,1], of constraint C_i

Error of a candidate solution

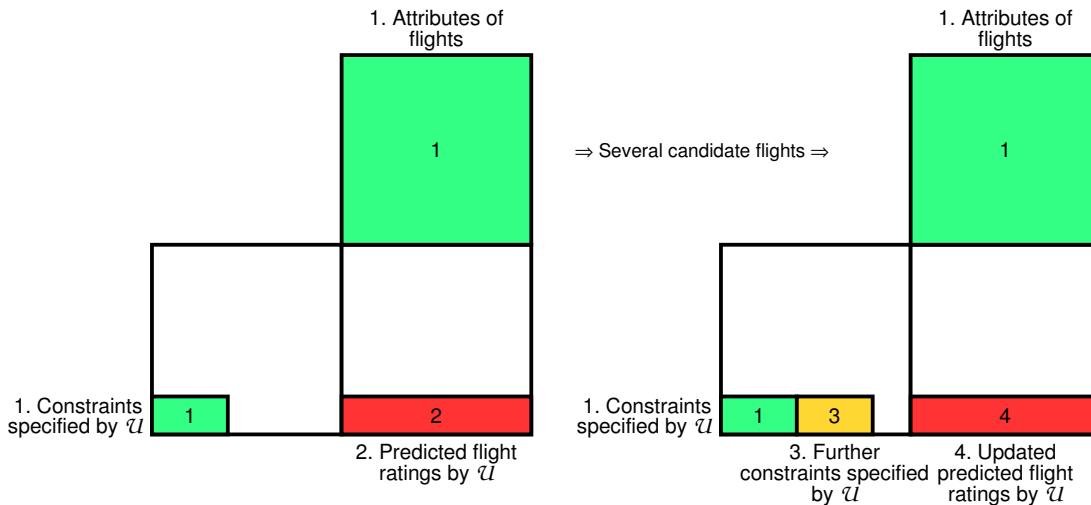
$$E((v_1, \dots, v_n)) = \sum_{i=1}^n C_i(v_i) \cdot w_i$$

Simplest Control Algorithm

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1. \mathcal{U} specifies initial constraints
2. \mathcal{S} displays the N solutions that best satisfy \mathcal{U} 's constraints
3. If \mathcal{U} accepts one of these solutions, finish
4. \mathcal{U} critiques these solutions by
 - adding or modifying constraints and/or
 - changing previously specified weights
5. Go to Step 2

Candidate Critique Agents: Schema



Improvements on Simplest Algorithm (1)

1. Start with some default preferences

Examples

- \mathcal{U} is moderately price sensitive
- \mathcal{U} prefers fewer stops to more stops
- \mathcal{U} prefers to fly on as few different airlines as possible

Benefit

- Most \mathcal{U} s get better suggestions without having to specify these preferences

2. Do not show dominated candidates

Principle

- Do not present a candidate if some other presented candidate satisfies each of \mathcal{U} 's assumed constraints at least as well (and for at least one constraint, better)

Benefit

- \mathcal{U} is not shown candidates that he is unlikely to choose

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Improvements on Simplest Algorithm (2)

3. Present significantly different candidates

Formalization

- The attribute values of objects 1 and 2 are significantly different iff:

$$\cdot \sum_i w_i |v_{i,1} - v_{i,2}| \geq \delta$$

Benefit

- A varied set of candidates is more likely to elicit significant new constraints from \mathcal{U}
- E.g., "no afternoon flights"

4. Present extreme candidates

Examples

- Cheapest possible flight
- Nonstop flight (if any) that best satisfies \mathcal{U} 's other constraints

Benefit

- \mathcal{U} gets a better overview of the full range of possibilities

Example Interaction (1)

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\mathcal{U} states that he wishes to travel between San Jose and Philadelphia, leaving any time on September 25 and returning any time on October 6

Best Trips:

San Jose {American}	Philadelphia	San Jose	\$503
San Jose {USAir}	Philadelphia	San Jose	\$523
San Jose {American}	Philadelphia	San Jose	\$503

Cheapest Trip:

San Jose {USAir, Reno Air, United}	Philadelphia	San Jose	\$353
--	--------------	----------	-------

Best Nonstop:

None

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Example Interaction (2)

Being interested in nonstops, \mathcal{U} modifies the preference concerning the departure city, stating that San Francisco is almost as acceptable as San Jose

Best Trips:

San Francisco {USAir}	Philadelphia	San Francisco	\$518
San Francisco {United}	Philadelphia	San Francisco	\$518
San Francisco {United}	Philadelphia	San Francisco	\$513

Cheapest Trip:

San Francisco {America West}	Philadelphia	San Francisco	\$318
---------------------------------	--------------	---------------	-------

Best Nonstop:

San Francisco {USAir}	Philadelphia	San Francisco	\$518
--------------------------	--------------	---------------	-------

Example Interaction (3)

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It occurs to \mathcal{U} that he prefers United to USAir, so he modifies his airline preference accordingly

Best Trips:

San Francisco {United}	Philadelphia	San Francisco	\$518
San Francisco {United}	Philadelphia	San Francisco	\$518
San Jose {United}	Philadelphia	San Jose	\$503

Cheapest Trip:

San Francisco {America West, United}	Philadelphia	San Francisco	\$348
--	--------------	---------------	-------

Best Nonstop:

San Francisco {United}	Philadelphia	San Francisco	\$518
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The FindMe Systems Introduction

219

Burke, R. D., Hammond, K. J., & Young, B. C. (1997). The FindMe approach to assisted browsing. *IEEE Expert*, 12(4), 10.

Burke, R. D. (2001). Knowledge-based recommendation systems. *Encyclopedia of Library and Information Science*, 69, 1-10. <http://cbeblade.fullerton.edu/~rburke/pubs/>

The FindMe family

- Burke and his colleagues developed several related systems that are based on the "FindMe" approach to recommendation
- The basic principles are illustrated here with the restaurant recommendation system "Entree", which is available on the web

Overview of Entree

Specification of preferences

- At the beginning of a session, \mathcal{U} has two options:
 1. \mathcal{U} specifies her preferences by choosing a few properties of restaurants
 2. \mathcal{U} enters the name of some other restaurant that she knows (in Chicago or another city) which exemplifies her preferences

Criticism of the initial results

- \mathcal{S} presents some restaurants that correspond to \mathcal{U} 's specifications
- \mathcal{U} can then specify how the set of candidates can be improved

Entree: Examples (1)

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The screenshot shows the Entree Chicago interface. At the top is a logo featuring a silver dome with a city skyline silhouette inside. Below the logo, the text "Entree Chicago" is displayed. The interface is divided into sections for specifying preferences:

- I would like to eat at a restaurant that has:** This section contains four dropdown menus: "Cuisine" (with options like Italian, Mexican, etc.), "Price" (with options like Cheap, Moderate, Expensive), "Style" (with options like Casual, Formal), and "Atmosphere" (with options like Quiet, Noisy, etc.).
- I would like to eat at a restaurant just like:** This section contains two dropdown menus: "Michael Jordan's" and "Chicago".
- Action buttons:** At the bottom are two buttons: "New Query" and "Submit".

\mathcal{U} specifies her interests

The Entree System is (sometimes) available under
<http://infolab.lis.nwu.edu/entree/pub/>

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Entree: Examples (2)

Entree Results

The Chicago restaurant you chose is:
Michael Jordan's
 500 N. LaSalle St. (Grand Ave. & Illinois St.), Chicago, 312-644-3865
 American (New) \$15-\$30
 Excellent Decor, Good Service, Good Food, Business Scene, Hip Place To Be, Private Rooms Available, Private Parties, People Keep Coming Back, Parking/Valet, Great for People Watching, See the Game, Singles Scene, Pub Feel, Weekend Brunch

We recommend:
Planet Hollywood (map)
 633 N. Wells St. (Ohio St.), Chicago, 312-266-7827
 American (New) \$15-\$30
 Excellent Decor, Good Service, Good Food, Traditional, Hip Place To Be, Private Rooms Available, Private Parties, No Reservations, Place for Singles, For the Young and Young at Heart, People Keep Coming Back, Late Night Menu, After Hours Dining, Parking/Valet, Great for People Watching, See the Game, Singles Scene, Pub Feel, Weekend Brunch, Tourist Appeal

less *ss* *nicer* *cuisine*
traditional *creative* *livelier* *quieter*

For other suggestions, select:

Planet Hollywood	Goose Island Brewing Co.	Northside Cafe
Gordon	Hubbard Street Grill	Pandl's in Bayside
Charlie Trotter's	Pump Room	Zealous
Winnetka Grill		

S offers an initial result, further results, and an opportunity to criticize the results

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Entree: Examples (3)

Entree Results

I would like to eat at a restaurant just like:

Planet Hollywood (map)
 633 N. Wells St. (Ohio St.), Chicago, 312-266-7827
 American (New)
 Excellent Decor, Good Service, Good Food, Traditional, Hip Place To Be, Private Rooms Available, Place for Singles, For the Young and Young at Heart, People Keep Coming Back, Late Night Menu, After Hours Dining, Parking/Valet, Great for People Watching, See the Game, Singles Scene, Pub Feel, Weekend Brunch

that has:

Cuisine
American	
Cajun/Creole	
Californian	
Southern	
Southwestern	
.....	
Latin	
Caribbean	
Mexican	
South American	
.....	
British	
French	
Italian	
German	
Greek	
Slavic	
Spanish	
.....	
Asian	
Chinese	
Japanese	
Korean	
Thai	
Vietnamese	
.....	
African	
Ethiopian	
More...	

U would prefer a similar restaurant with South American cuisine

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Entree: Examples (4)

For a restaurant like this one, but serving South American food:

Planet Hollywood

633 N. Wells St. (Ohio St.), Chicago, 312-266-7827

American (New)

\$15-\$30

We recommend:

Rio Latin Tapas ([map](#))

546 N. Wells St. (Ohio St.), Chicago, 312-923-9333

South American, Tapas

below \$15

Good Decor, Excellent Service, Extraordinary Food, Entertainment, Dancing, Little Known But Well Liked

less \$\$ nicer cuisine

traditional creative livelier quieter

For other suggestions, select:

Rio Latin Tapas

[Julio's Latin Cafe](#)

Gypsy's Cove

[Rinconcito Sudamericano](#)

[El Nandu](#)

[Machu Picchu](#)

[Dixie Que](#)

[El Presidente](#)

[Wishbone](#)

[Campeche](#)

Faced with this result, *U* clicks on the button "Creative" in order to find a similar but more creative restaurant

Entree: Examples (5)

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For a more creative restaurant than:

Rio Latin Tapas

546 N. Wells St. (Ohio St.), Chicago, 312-923-9333

South American, Tapas

below \$15

We recommend:

Santa Fe Tapas ([map](#))

1962 N. Halsted St. (Armitage Ave.), Chicago, 312-404-9168

Tapas, Southwestern

\$15-\$30

Good Decor, Good Service, Excellent Food, Creative, Weekend Brunch

less \$\$ nicer cuisine

traditional creative livelier quieter

For other suggestions, select:

Santa Fe Tapas



By now the set of candidates has been reduced to a single restaurant

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Key Methods (1)

This example illustrates some of the methods that are applied in the FindMe approach:

Retrieval by similarity

1. At first, \mathcal{U} specifies either
 - An example product; or
 - A small set of attributes that correspond to various *goals*
 - Examples: "cuisine" = "French", "style" = "casual"
2. \mathcal{S} orders all of the products in the database according to their *similarity* to the given example or attribute set
 - For each goal, a similarity metric has to be defined
 - For example, \mathcal{S} needs to know how similar French and Japanese cuisine are
 - Defining these similarity metrics is one of the main tasks that has to be handled when a system like Entree is introduced in a new domain

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Key Methods (2)

Different orderings of goals

- When restaurants are sorted, the various goals are taken into account in a particular order
- Example:
 - First they are sorted in terms of the similarity of their cuisine to \mathcal{U} 's specification
 - Then restaurants that are equally similar with respect to cuisine are sorted with respect to "atmosphere"
 - Assumption here: cuisine is a more important criterion than atmosphere
- Handling differences among users in the importance of goals
 - In some of the FindMe systems, \mathcal{U} can specify the relative importance of the goals herself
 - She can choose from several prespecified "retrieval strategies" (e.g., "Money is no object")

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Key Methods (3)

Criticizing (tweaking) of the candidate restaurants by \mathcal{U}

- After a critique by \mathcal{U} , \mathcal{S} simply removes from the candidate set all restaurants that do not satisfy the specified constraint
 - Example: All restaurant that are not "more creative" than the most recently suggested one

Use of familiar concepts

- \mathcal{S} makes it possible for \mathcal{U} to employ concepts that are more familiar and less concrete than the attributes stored in the database (e.g., *casual*)

Key Methods (4)

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Explaining conflicts among specifications

- \mathcal{U} may sometimes specify a combination of desired attributes that (almost) never occurs
 - Example from the automobile domain: powerful motor combined with low gas consumption
- In this case \mathcal{S} calls attention to the conflict
 - Note: This functionality is not realized in Entree, but it is realized in the related system Car Navigator (Burke et al., 1997)

Social Navigation

Social Navigation (1)

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

Social Navigation (2)

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[MODIFY this page](#)
[To the Top](#)
[Recently Modified](#)
[Recently Accessed](#)

Recent Changes

14 January 1999

- [Groundhog Day checklist](#)   ...anx3-11.dialup.emory.edu
- [Groundhog Day Logo and T-shirt Design](#)   ...juggler2.cc.emory.edu
- [What are these funny markers for](#)   ...juggler2.cc.emory.edu
- [News](#)   ...170.140.164.100

13 January 1999

- [Groundhog Day 1999](#)   ...209.86.62.75
- [Yo Yo Letter](#)  ...209.86.62.75
- [People needing crash space for GHD99](#)   ...juggler2.cc.emory.edu

12 January 1999

- [Rumors exchange](#)   ...anx52-130.dialup.emory.edu
- [Juggler's Pages](#)   ...205.219.180.52
- [AJA address list](#)   ...pc253.netzip.com
- [Ideas and suggestions for the festival](#)   ...pc253.netzip.com
- [Formatting Rules](#)   ...170.140.37.49
- [What is a Swiki server](#)   ...170.140.37.49

Designing Recommender Applications

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Reminders and Instructions

The O–I–P Model

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Outputs

- Presenting recommendations

Inputs

- Gathering preference and product data

Process

- Producing recommendations from inputs

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Outputs

Types

- Suggestions, predictions, ratings, reviews

Delivery

- Push, pull, organic/pассив

Presentation

- Lists, annotations, annotations

Inputs

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From the targeted user

- Explicit vs. implicit
- Ratings, purchase history, keyword/attribute, navigation

From the community

- Product attributes, popularity, ratings, purchase histories, reviews, navigation

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Process

- Manual recommendation – editors
- Statistical summarization
- Collaborative filtering
 - User-to-user correlation
 - Item-to-item correlation
- Content-based recommendation
- Demographically based recommendation
- Utility-based recommendation
- Knowledge-based recommendation

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Instructions

Work in groups of 3-4

Identify a recommender application

- E-commerce application (broadly defined)
- Ideally tied to one of your businesses

Outline desired outputs, available inputs,
and an appropriate process

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Debriefing **Design Exercise Debriefing**

From each group:

- What was the application?
- What were the inputs, outputs, process?

- What were the hardest choices?
- What were the easiest choices?

Advanced Topics Contents

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Anthropomorphism and Group Decisions **Anthropomorphism and Group Decisions**

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- During the tutorial, we will look at a demo from the ongoing project MIAU
- Distinguishing characteristics of this system:
 - Product decision support for a group of cooperating users
E.g., members of a family who are planning a vacation together
 - Asynchronous interaction (via the web) in a situation where face-to-face discussion is more customary and convenient
 - Support for user collaboration during the phase of preference specification
 - Users can help each other – and copy from each other – so as to:
 - ease the burden of preference specification
 - ensure relatively complete and conflict-free specification of preferences
 - Use of animated agents as representatives of the users during the phase of conflict resolution



Mobile / Wireless Recommender Systems Wherever



WMLLens Login (1)

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WMLLens Login (2)



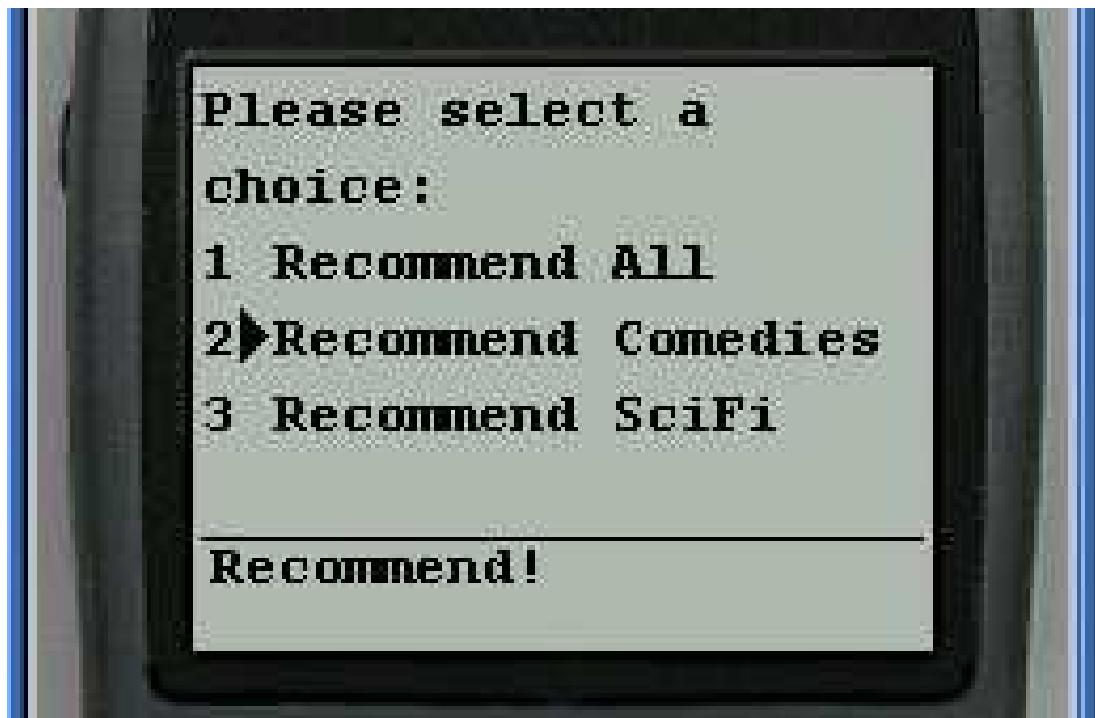
WMLLens Password

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WMLLens Menu



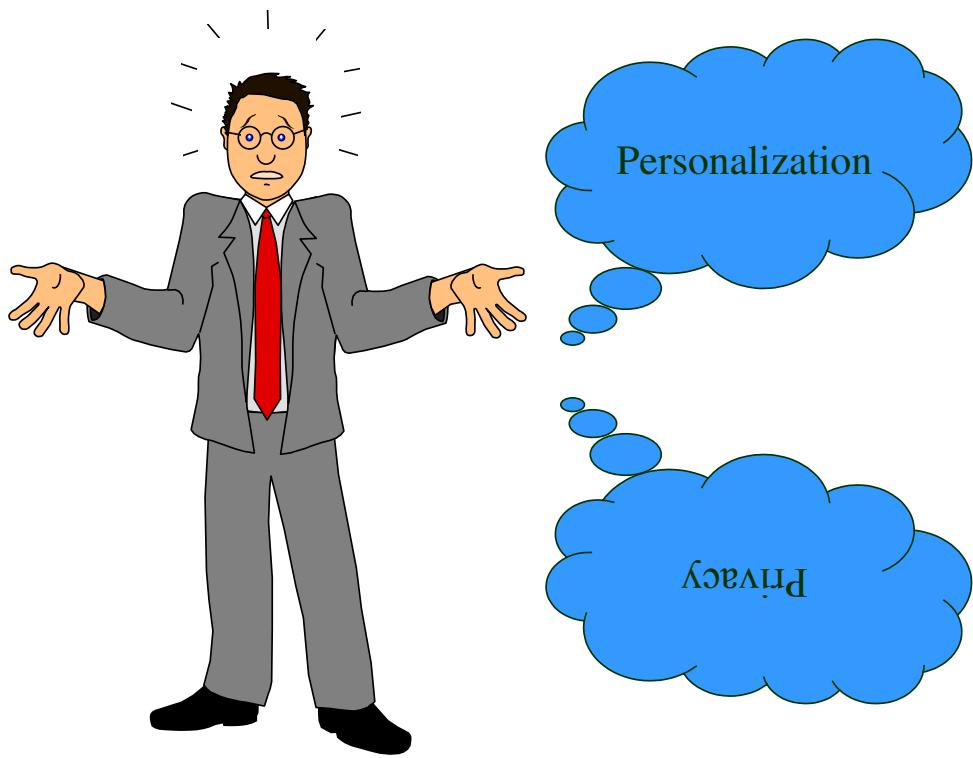
246

WMLLens Comedies



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Privacy versus Personalization



Some Stories

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Cdnow email

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Privacy

- No business has failed because of privacy
 - but ...
- Consumers beginning to wake up
- Government beginning to wake up
- EU has protections in place already

Consumer Profiles

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Microsoft Wallet

Remembers logins
Credit cards and addresses, too
Sites must support

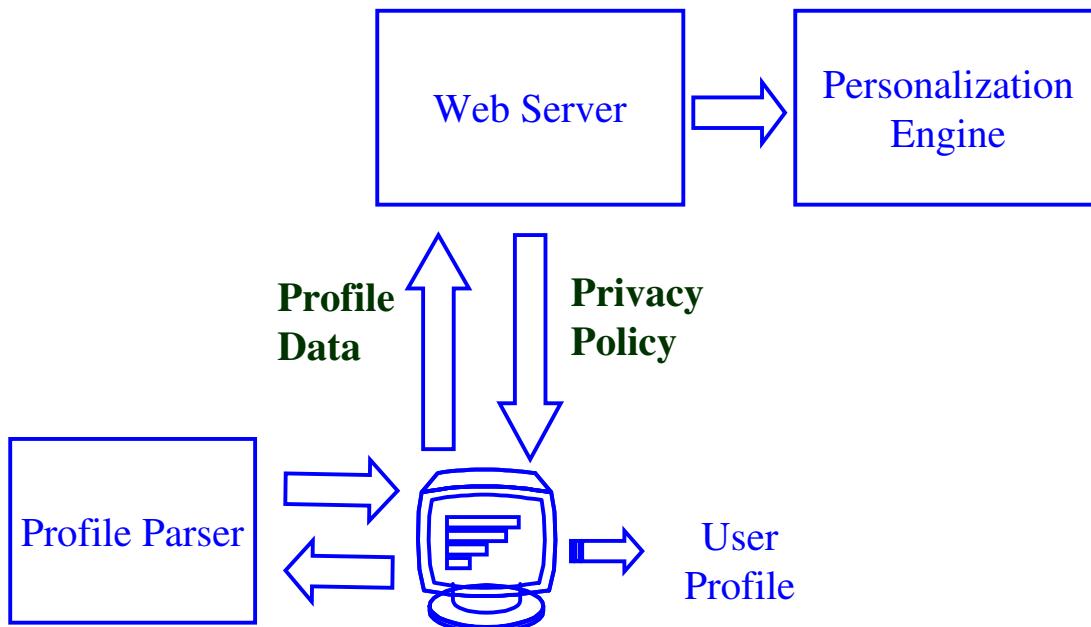
Novell DigitalMe

Remembers logins
Recognizes forms on sites, and fills them out

Product preference information, too!

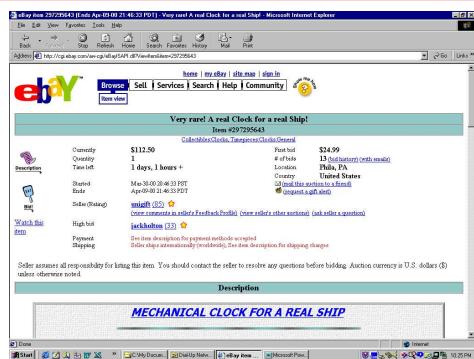
251

P3P from W3C

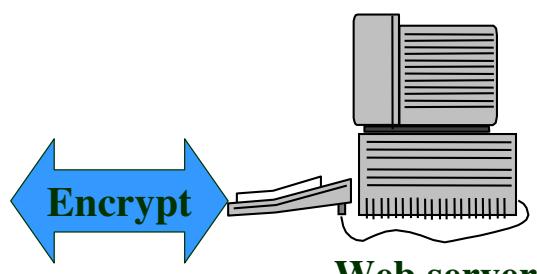


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Where are the Profiles?



Web client



Web server



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Who Pays the Agents?

Price Bots

- Junglee (Excite), Jango (Amazon), MySimon

Opinion Leaders

- Deja.com (Half.com), AskIlda (Best Buy), Epinions

Recommenders

- Owned by businesses

Microsoft Hailstorm

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P3P approach to Privacy

Microsoft volunteers to keep the profiles

Consumer response?

- Noone cares

Business response!

- Not with our customers!

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Consumer Desires (1)



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Consumer Desires (2)

Recommendations wherever I am
Recommendations that I can trust
Control over what preferences I share
Control over who I share with

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Recommendations Unplugged



Wireless PDA

Experimental questions

- How do users interact?
- What usage patterns?
- What happens as users gain experience?
- How do different modalities compare?
- How does usage compare with web?



WML



Avant Go



Voice

Peer-to-Peer Recommenders

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Builds on model based item-item algorithm

Separate model construction from usage

Key Question: How to find neighbors?

Incrementally build a model just for me

Portfolios and Temporal CF

Two Grand Challenges

Diminishing Marginal Returns

- Why today's recommenders won't be enough ten years from now

Temporal Recommendation

- Beyond reacting ...

CF Under Diminishing Returns

Original goal of CF was to help people sift through the junk to find the good stuff.

Today, there may be so much good stuff that you need to sift even more.

Certain types of content yield diminishing returns, even with high quality

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Portfolios of Content

What if my recommender knows which articles I've read, and can identify articles by topic?

What if it sees that I experience marginal returns from reading similar articles on a topic?

Could we downgrade some articles based on "lack of new content?" Could we discover which articles using collaborative filtering?

Temporal Collaborative Filtering

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Today's CF systems may expire or degrade ratings, but do little to detect or predict changes in preference.

Ripe area with lots of commercial applications ...

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Wine for the Time

Seasonal taste – can we detect that a particular customer shifts wine tastes during hot and cold weather? Can we learn either the content, or separate profiles, reflecting these different tastes?

Evolving taste – can we help a wine newcomer build her palate? Could we identify wines that take her a step or two beyond her current ones? Can we do so by augmenting regular collaborative filtering with temporal models?

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Commercial Tools

Tools

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- Data mining for offline analytics
- Campaign management so marketer has something to do
- Personalization for real-time decision-making
- Dynamic content for Web site Dynamic Content + Personalization
- Approach: Goals, Relate to Recommender Systems, Sample Vendors

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Commercial Tools: Goals (1)

Data
Mining

Campaign
Mgmt

Personalize

Dynamic
Content



- Analyze customer and traffic data to drive business decisions
- Simplify deployment of analytic solutions
- “Close the loop” between the marketer and the customer

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Commercial Tools: Goals (2)

Data
Mining

Campaign
Mgmt

Personalize

Dynamic
Content



- Run inbound and outbound campaigns
- Derive more revenue from customers
- Evaluate campaign performance

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Commercial Tools: Goals (3)

Data
Mining

Campaign
Mgmt

Personalize

Dynamic
Content



- Recommend products or content to site visitors
- Help customers find value from site
- Create strong relationships with customers

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Commercial Tools: Goals (4)

Data
Mining

Campaign
Mgmt

Personalize

Dynamic
Content



- Produce HTML content from database
- Simplify authoring, editing, and management of site
- Support interactivity and personalization

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Commercial Tools and Personalization (1)

Data
Mining

Campaign
Mgmt

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Content



- Similar analytic techniques
- Migrating towards real-time solutions
- Lessons learned: human-in-the-loop stops the loop

Commercial Tools and Personalization (2)

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Data
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- Choose people to campaign at
- Choose products to offer
- Work “for” rather than “at” customers

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Commercial Tools and Personalization (3)

Data
Mining

Campaign
Mgmt

Personalize

Dynamic
Content



- Recommender systems can be used to personalize
- Personalization has very broad meaning: “Hello John” to “I know what you did last summer”

Commercial Tools and Personalization (4)

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Data
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- Often provide simple rules to decide how to deliver content
- Other vendors must work in dynamic content environment

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Sample Vendors (1)

Data
Mining

Campaign
Mgmt

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Content



- digiMine (Usama Fayyad)
- Accrue (+NeoVista)

Sample Vendors (2)

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- E.piphany (www.epiphany.com)
- Broadbase (www.broadbase.com)

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Sample Vendors (3)

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- Net Perceptions (+KD1)
(www.netperceptions.com)
- LikeMinds (+Andromedia)
(www.macromedia.com)

Sample Vendors (4)

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- Vignette (+ DataSage)
(www.vignette.com)
- ATG (www.atg.com)

Holy Grail

Combine technologies across entire spectrum

- Data mining for offline analytics
- Campaign management to drive marketing decisions to customers
- Personalization for real-time decision-making
- Dynamic content for Web site

Further Resources **Web Page for Tutorial Participants**

- The following web page contains supplementary material for this tutorial:
 - <http://dfki.de/~jameson/aaai02-tutorial>
- Types of supplementary material
 - An annotated bibliography listing many of the key articles in this field
 - Links to electronic versions of selected articles
 - Links to interesting recommender systems that are accessible via the web