Introduction

What are Recommender Systems?

Goals of this Tutorial

Brief History of Recommender Systems

The Problem: Overload

Too much stuff!

Too many books!
Too many journal articles!

Too many movies!
Too much content!

Too many product choices!
Heck, even too many people!

Recommenders

Tools to help identify worthwhile stuff

- Filtering interfaces
  - E-mail filters, clipping services
- Recommendation interfaces
  - Suggestion lists, “top-n,” offers and promotions
- Prediction interfaces
  - Evaluate candidates, predicted ratings

Scope of Recommenders

Purely Editorial Recommenders

Content Filtering Recommenders

Collaborative Filtering Recommenders

Hybrid Recommenders
Goals

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
- See where recommender systems have been, and where they are going

Outline

- Introduction
- Recommender Systems Application Space
- MovieLens Case Study
- Recommender Algorithms
- Eight Principles and Case Studies
- Designing Recommender Applications
- Privacy Issues
- Commercial Tool Survey

Highlights and Focus Areas

- E-Commerce Recommenders
- Community Recommenders
- Knowledge Management Recommenders
- Off-The-Desktop Recommenders
- Group Application Design Exercise
- Plenty of Discussion

History of Recommender Systems

- Why cave dwellers survived
- Critics, critics, everywhere
- The dreaded editor
Automation

Information retrieval
- Dynamic information need
- Static content base

Information filtering
- Static information need
- Dynamic content base

Collaborative Filtering

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

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

Automated CF

The GroupLens Project (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

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 commercial application
- Widely used in e-commerce
- available commercial tools

Diverse research community
- live research systems
- substantial integration with machine learning, information filtering, HCI, and more
Introductions

Who are We?

John Riedl
  Collaborative and distributed systems
Joe Konstan
  Human-computer interaction

GroupLens Research
Net Perceptions
Word of Mouse

Who are You?

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

The Recommender Application Space

Dimensions of Analysis

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

Domains of Recommendation

Content to Commerce
  ◆ News, information, “text”
  ◆ Products, vendors, bundles
Purposes of Recommendation

The recommendations themselves
- Sales
- Information

Education of user/customer

Build a community of users/customers around products or content

Whose Opinion?

“Experts”
Ordinary “phoaks”
People like you

Personalization Level

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

Privacy and Trustworthiness

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

Interfaces

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

Types of Input
- Explicit
- Implicit

MovieLens Case Study
Key Concepts

Users
Items – Movies
Ratings – Explicit, 1 to 5 stars
Correlations – Relationships among users
Predictions – Personal predicted ratings
Recommendations – Suggested Items

How It Works

GroupLens Model

C.F. Engine

Ratings
Correlations

GroupLens Model

C.F. Engine

Ratings
Correlations

GroupLens Model

C.F. Engine

Ratings
Correlations

GroupLens Model

C.F. Engine

Ratings
Correlations

request
GroupLens Model

Understanding the Computation

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

Understanding the Computation

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Recommender Algorithms

Collaborative Filtering

Target Customer

Weighted Sum
E-Commerce Scale

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

Sparsity

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

Item-Item Collaborative Filtering

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

\[
R_{m \times n} = U_{m \times r} S_{r \times r} V_{r \times n}^T
\]

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

SVD for Collaborative Filtering

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

2. Direct Prediction

Collaborative Filtering Algorithms

Non-Personalized Summary Statistics
- K-Nearest Neighbor
  - User-User
  - Item-Item

Dimensionality Reduction
- Singular Value Decomposition
- Factor Analysis

Content + Collaborative Filtering

Collaborative Filtering Algorithms

Graph Techniques
- Horting: Navigate Similarity Graph
- Clustering
- Classifier Learning
  - Rule-Induction Learning
  - Bayesian Belief Networks
Case Studies in Personalization

Overview

Commercial Agents that Treat You Right
- Lands' End, Clinique, Launch

We Know (Knew) Who You Are
- DoubleClick, Angarra, and their apps

Looking for An Opportunity?
- Product of the Month Clubs, TiVo

Straight from the Lab
- Calendar Apprentice, Moods, and Effective Interrogation

Lands' End

The Challenge
- Get people to buy clothes at a distance

Some Personal Tools
- My Personal Shopper
  - Learn preferences, recommend, support short-term interests
- My Virtual Model
  - Learn body, use to help customers visualize
The Challenge

- Buy make-up online?
- Attract people to their brand online?

Some Personal Tools

- Personal Consultation
  - Interview to determine skin type
- Looks Maker (of blessed memory)
- Match products you already have
Personalized Radio

Some neat stuff

- Runs with rules of real radio
- Explains why music is playing
- Allows ratings of Artists, Albums, Songs
- Repetition (to a point) is Good!
- Die! Die! Die! Button

Sadly

- Notion of “rating” is a bit strange
What About First Timers?

Doubleclick
- Popular banner ad network
- Decided in early 2002 to abandon full personalization

Angarra
- Tracks users and compiles “non-identifying” personalizing information
- Makes this data available for first-time personalization (to the segment level)
- Includes control cases to test effectiveness
Could Do Better

Product of the Month Clubs
  ◆ Force customers into genre categories
  ◆ Potential of automatic shipment
  ➔ Do you trust Dean and Deluca?

TiVo – Digital Video Recorder
  ◆ Gathers lots and lots of data
  ◆ Still does a lousy job filling “time”

FMRL Movie Recommendations

User submits “theme” query
  ◆ Theme contains examples of items similar to those desired by the user

Set of potentially similar items identified
  ◆ Using item-to-item correlation in ratings space

Potentially similar items ranked based on traditional ACF predictions

From The Laboratory

Mitchell’s Calendar Apprentice
  ◆ Learns rules of how to schedule
  ◆ Takes over as confidence and user permit

Effective Interrogation
  ◆ Value-of-information analysis
  ◆ Which items to ask about?
    ➔ High popularity? High Entropy?
    ➔ Value to individual? Value to Community?
    ➔ System-Driven? User-Driven?

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Principles Learned

Be a Customer Agent
- Listen, Learn, and Use
- Anticipate Pitfalls
- Bring “Inside” Opportunities and Info
- Make the Match

Box Products, Not People
- Individuals, not Demographics
- Evolving Personalization
- Real-Time Updates

Case Studies in Knowledge Management

Overview

Recommending people
- eBay, ReferralWeb

Recommending Documents
- Tacit

Privacy Issues

ReferralWeb
Privacy Issues

Same as E-commerce, plus
- Extra sensitivity of profile data
  - E.g., Tacit’s dual profiles

Honesty/openness vs. edited content

Principles

- 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

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

Case Studies in Expertise

Overview

- Overcoming Reluctance
  - Priceline Hotels, Ticketmaster

- Helping Users Explore Possibilities
  - Entrée, Confidence

- Wasted Opportunity
  - See’s Candies

Priceline

- The Challenge
  - Get you to commit money to a hotel they won’t identify

- The Approaches
  - Reassure that many have succeeded before
  - Demonstrate knowledge of the locale
  - Carefully explain rating system
  - Help users with price guidelines
Recommender Systems: Interfaces and Technology

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CHI 2003 April 7, 2003
Principles Learned

Demonstrate Product Expertise
- Use expertise and recommenders to build customer trust
- Provide deep product data, so that customers can make informed decisions
- Make it fun!

Case Studies in Community Recommenders

Overview

Use Communities to Create Content
- Epinions, Slashdot, Flutter.com, Social Navigation, Filterbots

Turn Communities into Content
- Geocities, MatchMaker, LambdaMoo, MSN Games
Social Navigation

Assumptions:
- Awareness of others (current or past) helps user find relevant path
- Paths/location of others is distinctive enough for user to recognize

Approach
- Make history or present visible

Inspiration

Need selfless, consistent raters

Humans?
No: ratings robots.

Filterbots Alone

Filterbots

Recent Changes
14 January 1999
- Consulting Dev checklist ◁ 323:12 daily rums.edu
- Consulting Dev Tools and Test Date ◁ juggle1.cs.umn.edu
- What are these funny numbers for ◁ juggle1.cs.umn.edu
- History ◁ 170.142.164.160

13 January 1999
- Consulting Dev checklist ◁ 323:12 daily rums.edu
- Yo Yo Letter ◁ 323:12 daily rums.edu
- Don't need en-route setup for CHI02 ◁ juggle1.cs.umn.edu

12 January 1999
- Page address list ◁ 170.142.3:12 daily rums.edu
- Add this page to the list ◁ pr253.rats.com
- Need en-route setup for the list ◁ pr253.rats.com
- Preparing Rights ◁ 170.142.5:12 daily rums.edu
- What is a meta server? ◁ 170.142.57.49
Filterbots Apart

Advantages of the FilterBot model

Combines best of agents and humans
- agents rate frequently, quickly, consistently
- humans add subjective taste and quality

Framework pulls out the best of each
- use only the bots that work; ignore the others
- use only the people who agree; ignore the others
- balance people and bots based on available ratings and agreement

Risks of Filterbots

- What if no humans read certain articles?
  "voluntary" censorship or quality control?
- What about rogue filterbots?
- What if people “prefer” filterbots to humans?

The Filterbot Rainbow

Yahoo & GeoCities
Yahoo bought GeoCities, which then tried to change rules on ownership of content; customers protested by "blacking out" all their content until the site returned to old rules.
Turn Communities into Content

Principles

- Editorial process is value added
- Help customers find interesting information from other customers
- Free is better than paying for it
  - customers trust what they produce
- Reward creatively
- Enable customer control (e.g., social nets)
- Encourage response (e.g., eBay)
Case Studies in Using Implicit Preference Data

Overview

Gather “Work Product” Data
- Google, PHOAKS, OWL

Make Implicit Ratings Visible
- Amazon

Don’t Ignore Me!
- My Yahoo!

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

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

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

Recommender for word processors
- Monitored word processor command use
- Identified common patterns of use
- Recommended commands to learn

Amazon.com

Broad collection of recommenders
Lots of use of purchase data
- But what if it was a gift?
- What if you didn’t like it?
- What if your account is shared?
Makes this data visible
- Improve your recommendations
- Explain a recommendation

My Yahoo!

Typical portal
- User control over “streams” of content
- Streams managed independently
- Doesn’t track usage to update
  ➤ Already seen
  ➤ What I seem to like/dislike
- Doesn’t suggest streams I might like
Principles Learned

Watch What I Do
- Actions speak louder than words
- Determine actions by context
- Make implicitly gathered data visible
- Respond to customers' reactions to your recommendations

Case Studies around Touchpoints

Outline

Kiosks
Call Centers
Mobile
Zagats

Kiosks
Alienware PCs Now Offered on Best Buy "Computer Creation Stations"
Blockbuster
customer identity
privacy issues
Music Store
sampling versus "listening"

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

Consumers call in purchases
Implemented personalization, too
Experiment:
- one group of agents with old method
- one group of agents with personalization

Directed Buyers: Increasing Cross-Sell

<table>
<thead>
<tr>
<th>With traditional cross-sell methods</th>
<th>With realtime recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg Cross-Sell Value</td>
<td>$19.50*</td>
</tr>
<tr>
<td>Cross Sell Success Rate</td>
<td>9.8%</td>
</tr>
<tr>
<td></td>
<td>50% higher</td>
</tr>
<tr>
<td></td>
<td>60% higher</td>
</tr>
</tbody>
</table>

* Converted from British Pounds

Consumer Desires

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

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?

Recommended Unplugged
**Peer-to-Peer Recommenders**

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

**Zagat What it Takes**

What happened to my favorite guide?
- They let you rate the restaurants!

What should be done?
- Personalized guides, from the people who "know good restaurants!"

**Principles Learned**

Maintain excellent service across touchpoints
- It’s still you however your customers get there
- Different strokes for different folks
- Equivalent service does not mean equal service

**Designing Recommender Applications**

**The O-I-P Model**

Outputs
- Presenting recommendations

Inputs
- Gathering preference and product data

Process
- Producing recommendations from inputs
**Outputs**

Types
- Suggestions, predictions, ratings, reviews

Delivery
- Push, pull, organic/passive

Presentation
- Lists, annotations, annotations

**Inputs**

From the targeted user
- Explicit vs. implicit
- Ratings, purchase history, keyword/attribute, navigation

From the community
- Product attributes, popularity, ratings, purchase histories, reviews, navigation

**Process**

Manual recommendation – editors
Statistical summarization
Attribute-based selection

Ephemeris personalization
- Current selection
- Market Basket

Long-Term personalization

**Exercise**

Work in groups of 3-4

Identify a recommender application
- E-commerce or community application (broadly defined)
- Ideally tied to one of your research interests, businesses, or personal interests

Outline desired outputs, available inputs
Discuss appropriate processes

**Privacy**

The conflict between recommender systems and privacy
Some Stories

Toysmart
Amazon Pricing
CDnow email

Privacy or Trust?

Customers are willing to share data
♦ If they trust the recipient
♦ If they know what it is being used for
♦ If they benefit

Customers are very wary
♦ If they fear their data is being sold
♦ If they fear it is being used to take advantage of them

P3P from W3C

Web Server ➔ Personalization Engine
Profile Data ➔ Privacy Policy
Profile Parser ➔ User Profile

Where are the Profiles?

Web client
Web server

Smart Card
PDA

Microsoft Hailstorm

P3P approach to Privacy
Microsoft volunteers to keep the profiles

Consumer response?
♦ Great silence
Business response!
♦ Not with our customers!

Commercial Tools
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
Approach: Goals, Relate to Recommender Systems, Sample Vendors

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

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

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

• digiMine
• Accrue
• SPSS (+NetGenesis)
**Commercial Tools**

**Sample Vendors**

- E.piphany (www.epiphany.com)
- Kana (www.kana.com)
- Teradata (NCR, www.teradata.com)

**Goals**

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

**Goals**

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

**Relate to Personalization**

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

**Relate to Personalization**

- Often provide simple rules to decide how to deliver content
- Other vendors must work in dynamic content environment
Commercial Tools
Sample Vendors
- Vignette (www.vignette.com)
- Broadvision (www.broadvision.com)
- Microsoft CMS

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

Conclusions
Recommendation is essentially task-based
- Tricky issues of balance and focus
  ➔ Correctness vs. Value
  ➔ Diversity
- People notice poor or manipulated recommendations (Amazon, MovieLens)
Interfaces are evolving
- More integrated into task flow

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 children’s product store (e-mail campaign)
- 19% click-thru rate vs. 10% industry average
- 14.3% conversion to sale vs. 2.5% industry average

The Golden Rule
“The one who has the gold, makes the rules.”

Price Bots
- Junglee (Excite), Jango (Amazon), MySimon
Opinion Leaders
- Deja.com (Half.com), AskIda (Best Buy), Epinions
Recommenders
- Owned by businesses
Recommender Systems: Interfaces and Technology

Recommender System for User

Find what I want
Know I will like it
Trust system to help me
Team up with my friends to defeat evil marketers

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?

Who is deploying recommender systems?
Who has the money?

Consumers will react if tricked
Alternatives exist, and will be deployed if necessary
Recommender Systems

- Becoming necessary for e-commerce
- Create value for businesses
- Create value for customers
- Many open research problems
  - Technology
  - Deployment and Interfaces
  - Effectiveness

Discussion