

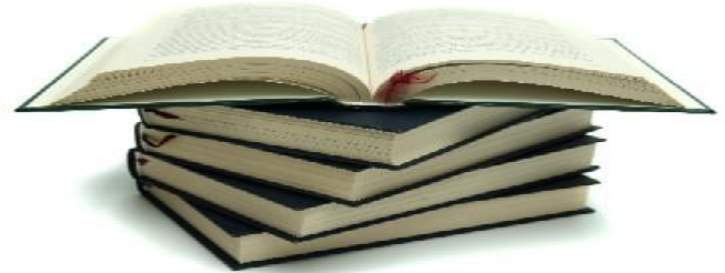
RECOMMENDER SYSTEMS

CSE435: *Intelligent Decision Support Systems*

Alexandra Coman



Sources



MAIN:

- Burke, R., 2002: “Interactive Critiquing for Catalog Navigation in e-Commerce”
- Burke, R., 2002: “Hybrid Recommender Systems: Survey and Experiments”

ADDITIONAL:

- Smyth, B. and McClave, P., 2001: “Similarity vs Diversity”
- McGinty, L. and Smyth, B., 2003: “On the Role of Diversity in Conversational Recommender Systems”
- McSherry, D. 2001: “Increasing Recommendation Diversity Without Loss of Similarity”
- McSherry, D. 2002: “Diversity-Conscious Retrieval”

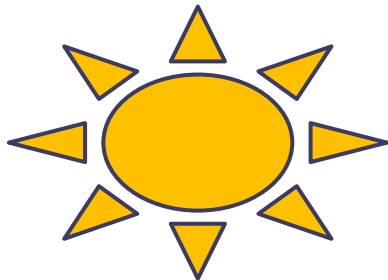
A Definition

“any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options.”

[Burke, 2002]

Recommendation Problem

- *Problem:* user's need



- *Solution:* match between user's need and an available product/service



Recommender Systems

emulate interaction
with a salesperson, in
view of choosing a
product/service from
the set of available ones



Related Systems

- Keyword-based search engines

A screenshot of a search bar interface. It features a blue header bar with the word "Search" on the left. To the right of "Search" is a dropdown menu currently displaying "All Departments". Further right is a text input field containing the text "keyword search". On the far right of the bar is a circular orange button with the word "GO" in white capital letters.

- Other information retrieval systems

What sets recommender systems apart?

A Definition

“any system that produces *individualized* recommendations as output or has the effect of guiding the user in a *personalized* way to *interesting* or *useful* objects in a large space of possible options.”

[Burke, 2002]

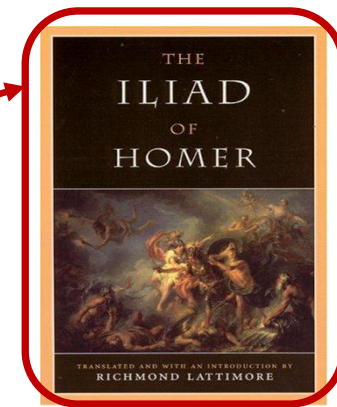
Recommender Systems

INDIVIDUALIZED

USEFUL

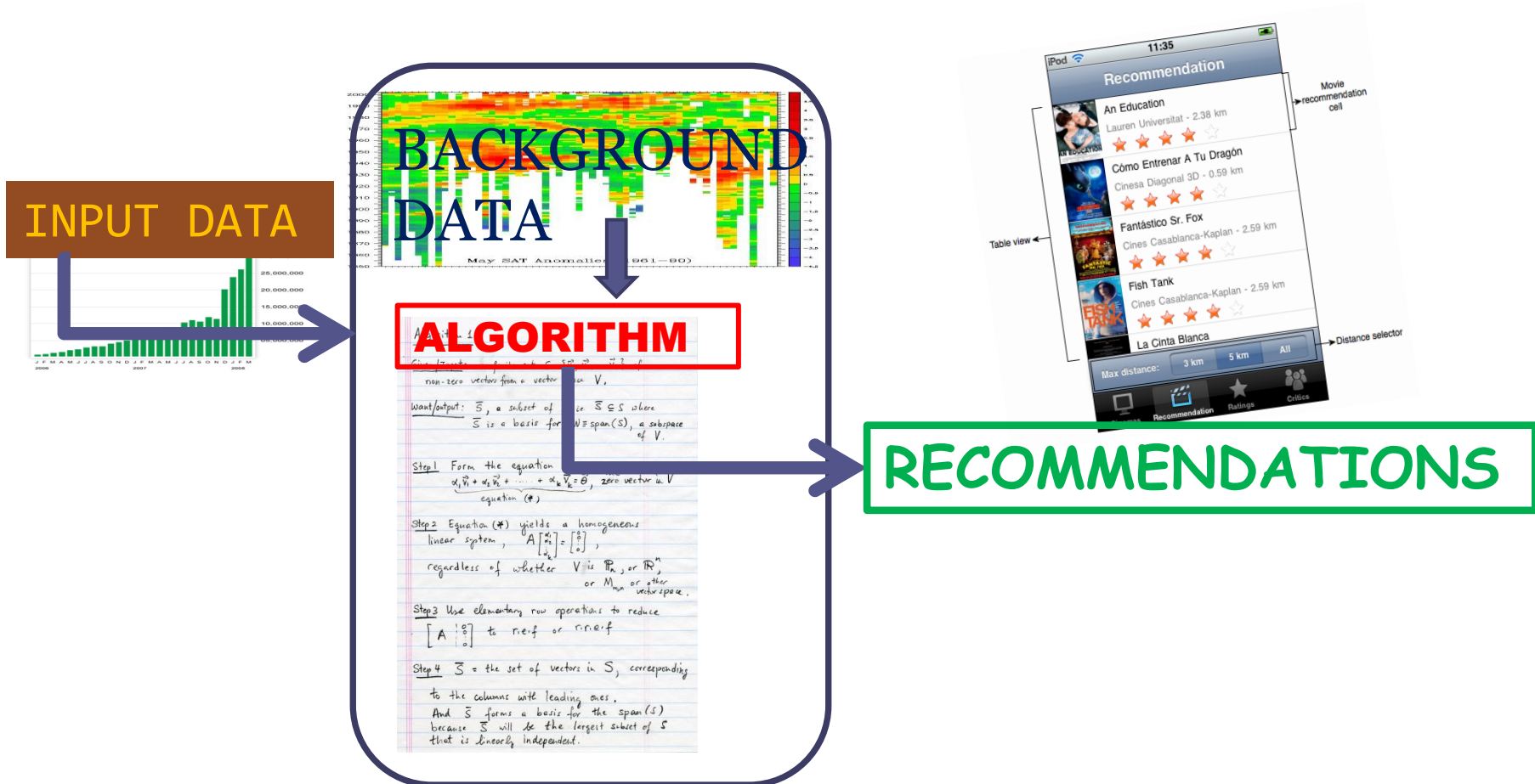
INTERESTING

When Necessary?



- Large, difficult to navigate search spaces
 - E.g. e-commerce inventories: “virtually unbounded”, no shelf-space and paper-catalog cost limits
- Non-expert user, complex products

Recommender System



INPUT DATA

BACKGROUND DATA

ALGORITHM

RECOMMENDATIONS

non-zero vectors from a vector space V .

Want/output: \mathcal{S} , a subset of V or $\mathcal{S} \subseteq S$ where \mathcal{S} is a basis for $W = \text{span}(S)$, a subspace of V .

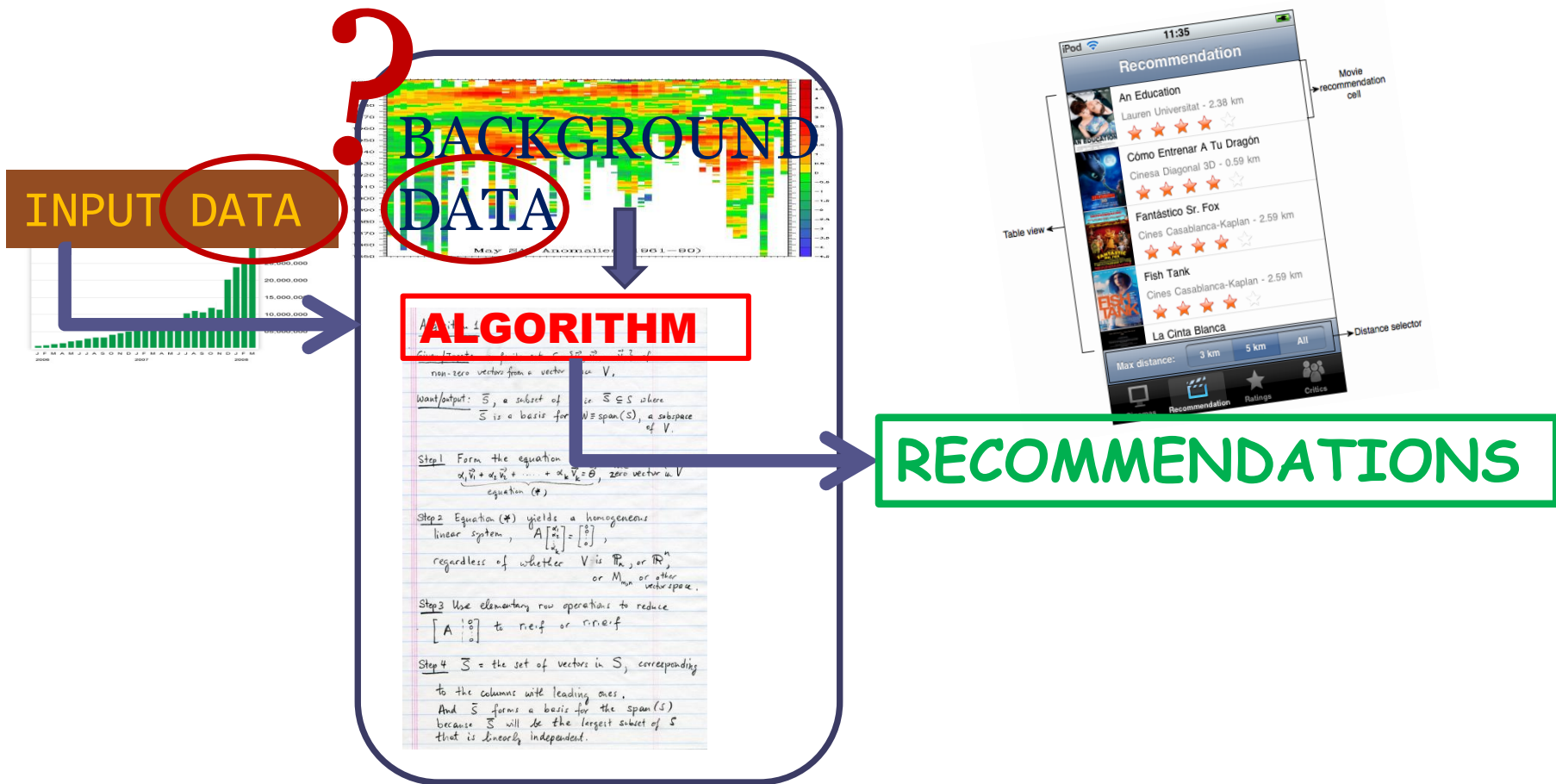
Step 1 Form the equation $\alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n = 0$, zero vector in V equation (*)

Step 2 Equation (*) yields a homogeneous linear system, $A \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$, regardless of whether V is \mathbb{R}^n , or \mathbb{R}^m , or $M_{m,n}$ or other subspace.

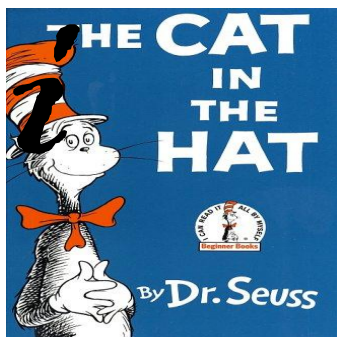
Step 3 Use elementary row operations to reduce $[A \mid 0]$ to r.e.f or r.r.e.f

Step 4 \mathcal{S} = the set of vectors in S , corresponding to the columns with leading ones.
And \mathcal{S} forms a basis for the span(S) because \mathcal{S} will be the largest subset of S that is linearly independent.

Data?



Input: U , u , I and i



\in



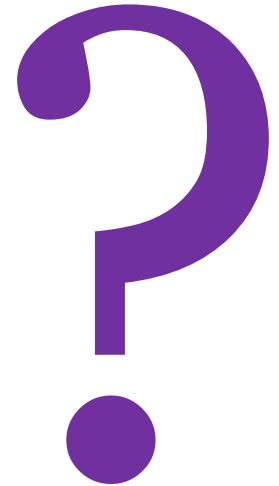
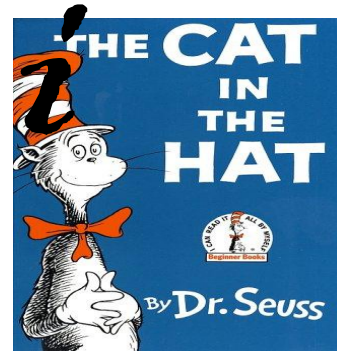
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Input: U , u , I and i

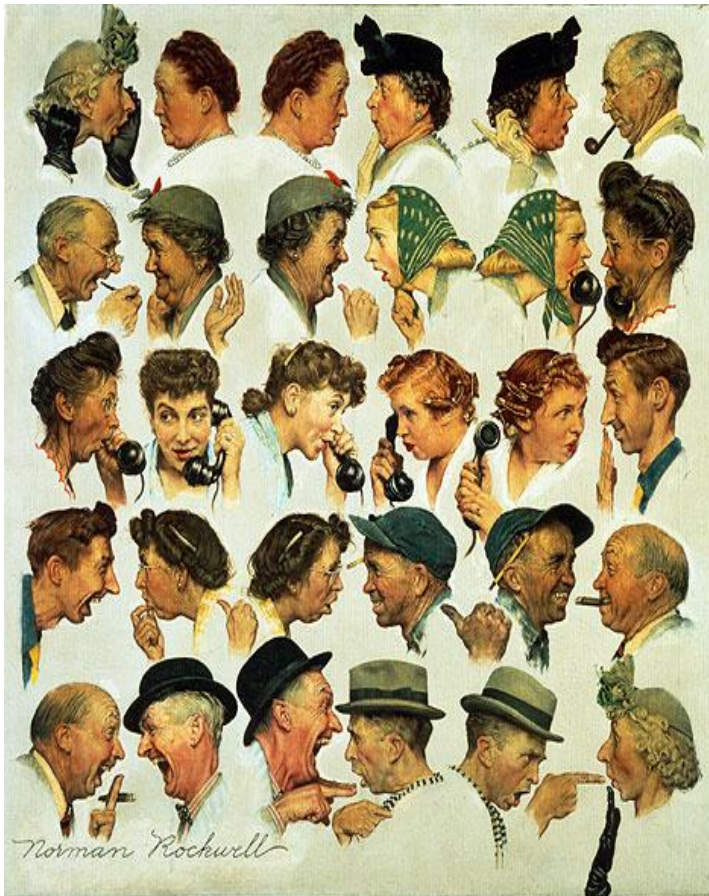
- I : set of items over which recommendations might be made
- U : set of users whose preferences are known
- u : user for whom recommendations need to be generated
- i : item for which we would like to predict u 's preference.

Output?



- Input: $\mathcal{U}, u, \mathcal{I}, i$
- Output: u 's predicted preference for i
 - like/dislike (binary)
 - degree of preference (real)

Types of Recommender Systems



- Collaborative Systems
 - aggregate ratings or recommendations of objects
 - recognize commonalities between users on the basis of their ratings
 - generate new recommendations based on inter-user comparisons
 - possibly, use time-based discounting of ratings

Types of Recommender Systems



- Demographic
 - categorize users based on personal attributes
 - make recommendations based on demographic classes

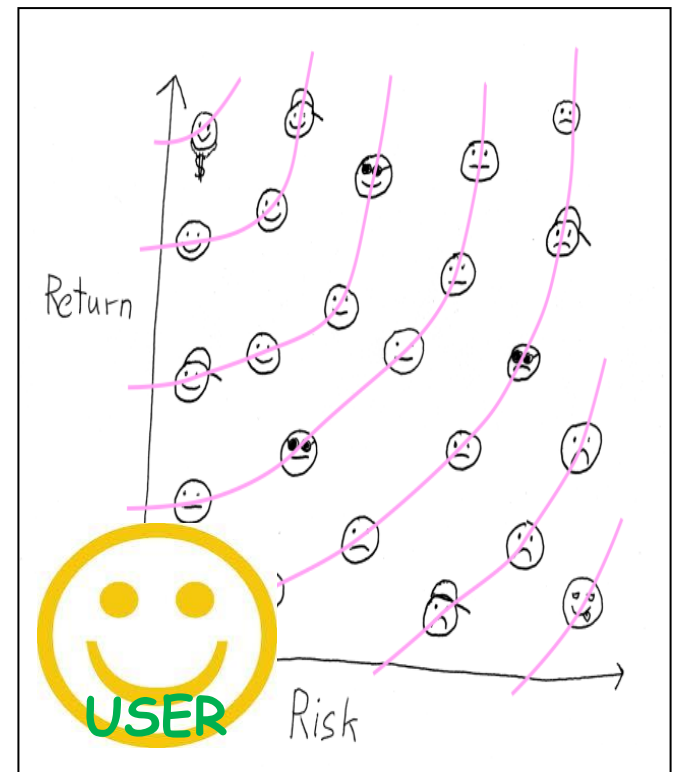
Types of Recommender Systems

- Content-based
 - objects defined by their associated features
 - learn profile of the user's interests based on the features present in objects the user has rated
 - long-term models, updated as more evidence about user preferences is observed

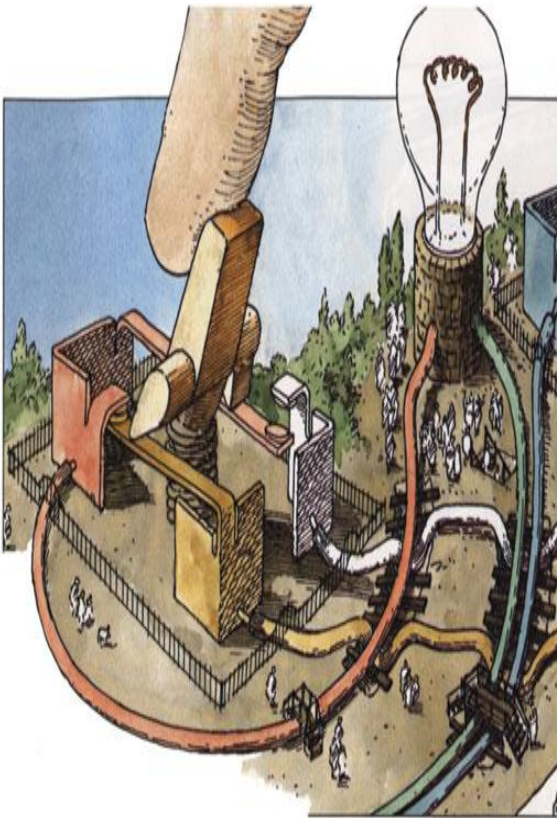


Types of Recommender Systems

- Utility-based
 - make suggestions based on a computation of the utility of each object for the user
 - employ constraint satisfaction techniques to locate the best match
 - no long-term generalizations about users



Types of Recommender Systems



- Knowledge-based
 - functional knowledge: how a particular item meets a particular need
 - can reason about the relationship between a need and a possible recommendation
 - no long-term models

Most popular?

Technique	Background	Input	Process
Collaborative	Ratings from U of items in I .	Ratings from u of items in I .	Identify users in U similar to u , and extrapolate from their ratings of i .
Content-based	Features of items in I	u 's ratings of items in I	Generate a classifier that fits u 's rating behavior and use it on i .
Demographic	Demographic information about U and their ratings of items in I .	Demographic information about u .	Identify users that are demographically similar to u , and extrapolate from their ratings of i .
Utility-based	Features of items in I .	A utility function over items in I that describes 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 u 's needs or interests.	Infer a match between i and u 's need.

Most popular

- Why?

Technique	Background	Input	Process
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Strengths / Weaknesses?

Strengths / Weaknesses

Technique	Pluses	Minuses
Collaborative filtering (CF)	A. Can identify cross-genre niches. B. Domain knowledge not needed. C. Adaptive: quality improves over time. D. Implicit feedback sufficient	I. New user ramp-up problem J. New item ramp-up problem K. "Gray sheep" problem L. Quality dependent on large historical data set. M. Stability vs. plasticity problem
Content-based (CN)	B, C, D	I, L, M
Demographic (DM)	A, B, C	I, K, L, M N. Must gather demographic information
Utility-based (UT)	E. No ramp-up required F. Sensitive to changes of preference G. Can include non-product features	O. User must input utility function P. Suggestion ability static (does not learn)
Knowledge-based (KB)	E, F, G H. Can map from user needs to products	P Q. Knowledge engineering required.

How do we get the most out of strengths and alleviate drawbacks?



Hybrid Recommender Systems

- Combine multiple methods in order to take advantage of strengths and alleviate drawbacks
- Weighted
 - scores/votes of several recommendation techniques combined together to produce a single recommendation
- Switching
 - system switches between recommendation techniques depending on the current situation
- Mixed
 - recommendations from several different recommenders presented at the same time



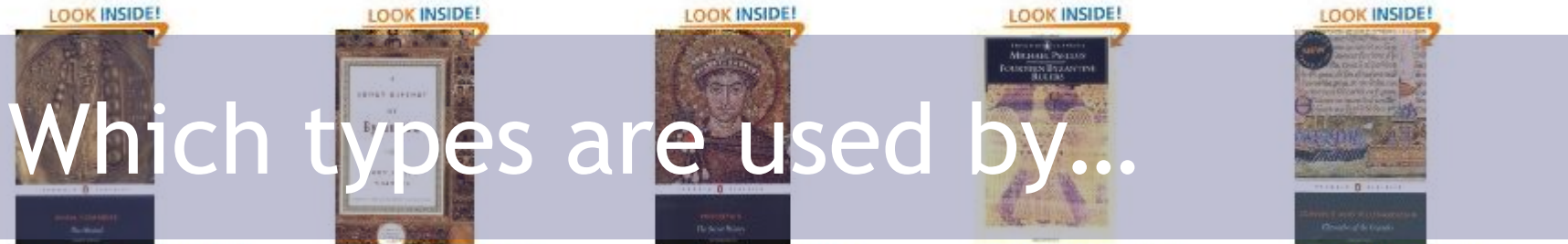
Hybrid Recommender Systems

- Feature combination
 - features from different recommendation data sources thrown together into a single recommendation algorithm
- Cascade
 - one recommender refines the recommendations given by another
- Feature augmentation
 - output from one technique is used as an input feature to another
- Meta-level
 - the model learned by one recommender is used as input to another

Additional Items to Explore

You viewed

Customers who viewed this also viewed



The Alexiad (Penguin Classics) > Anna Comnena
A Short History of Byzantium > John Julius Norwich
The Secret History (Penguin Classics) > Procopius
Fourteen Byzantine Rulers: The... > Michael Psellus
Chronicles of the Crusades
Jean de Joinville, Geffroy

Inspired by Your Shopping Trends

- Netflix?
- Amazon?
- Pandora?
- Last.fm?
- BookLamp?
- Others?

Treatise on the City of God > Thomas Aquinas
The Historians of Ancient Rome
Ron Mellor, Ronald Mellor
200-Thread...
Newpoint Home
Chicago (Related Recordings)

Jane Birkin & Serge Gainsbourg
Similar to: Jane Birkin, Brigitte Bardot, Françoise Hardy

Jacques Dutronc
Similar to: Françoise Hardy, Jacques Brel, Brigitte Bardot

Marianne Faithfull
Similar to: Françoise Hardy, Jane Birkin, Kate Bush

Chantal Goya
Similar to: Françoise Hardy, Brigitte Bardot, Jane Birkin

The Oxford History of Ancient Egypt
> Ian Shaw

PBS HOME VIDEO
King Lear
Because you enjoyed:
Amadeus
Seven Samurai
A Streetcar Named Desire
Play

THE BIG CITY MAHANAGAR
Mahanagar
Because you enjoyed:
Solaris
In the Mood for Love
Ikiru
Play

THE THIN RED LINE
The Thin Red Line
Because you enjoyed:
The New World
Mulholland Dr.
2001: A Space Odyssey
Play

What's Missing?

- So far, we have this:



What's Missing?

- So far, we have this:



What if not the right match?

What's Missing?



If no product of interest in recommended set, start over with reformulated search?

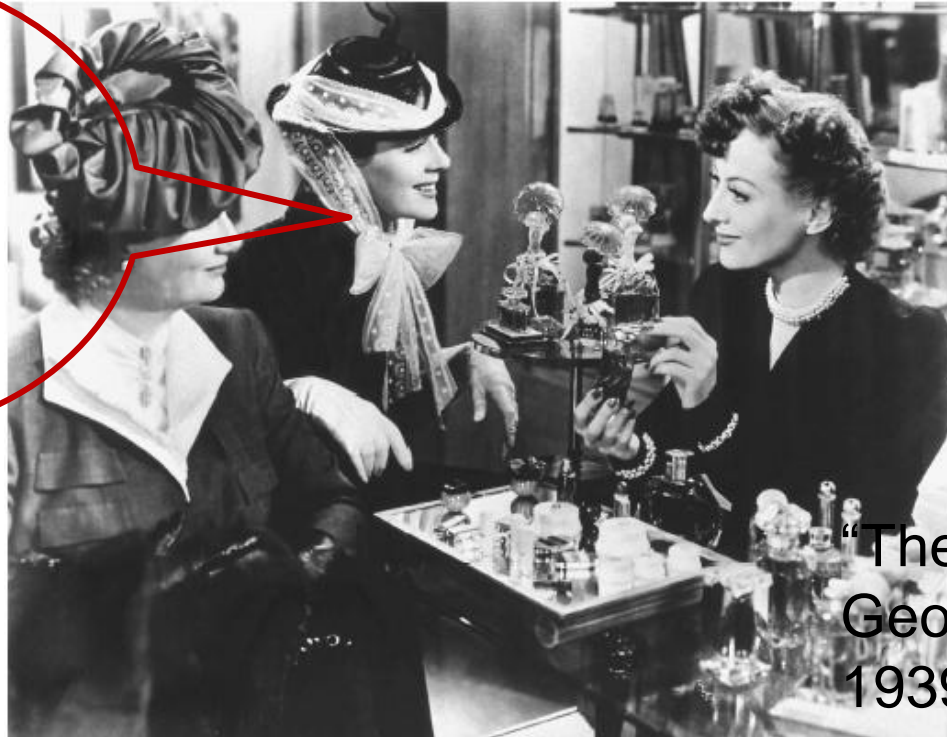


“NARROWING”
PROBLEM

Solution?

- Ongoing interaction:

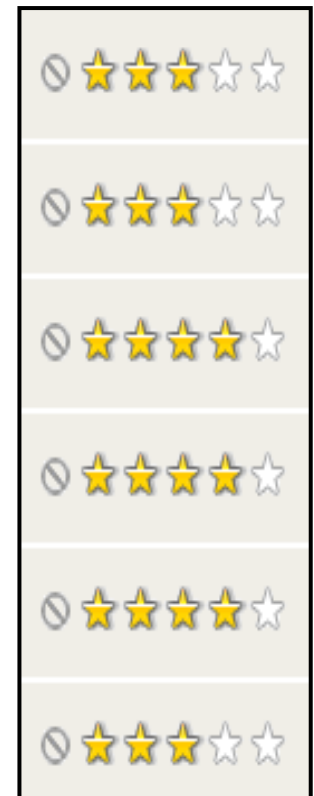
Something similar, but with a sandalwood base note?



“The Women”,
George Cukor,
1939

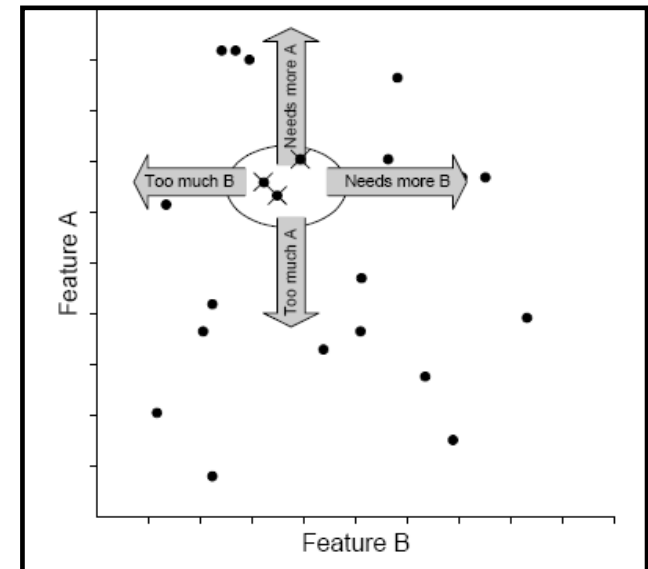
Critiquing

- Navigation of solution space that solves the “narrowing” problem
- Interactive, incremental: does not require that the user have a completely specified need at the start
- Shoppers “learn” by exploring the product space
- Requirements not static, but constantly shifting



“FindMe” Critique-Based Retrieval

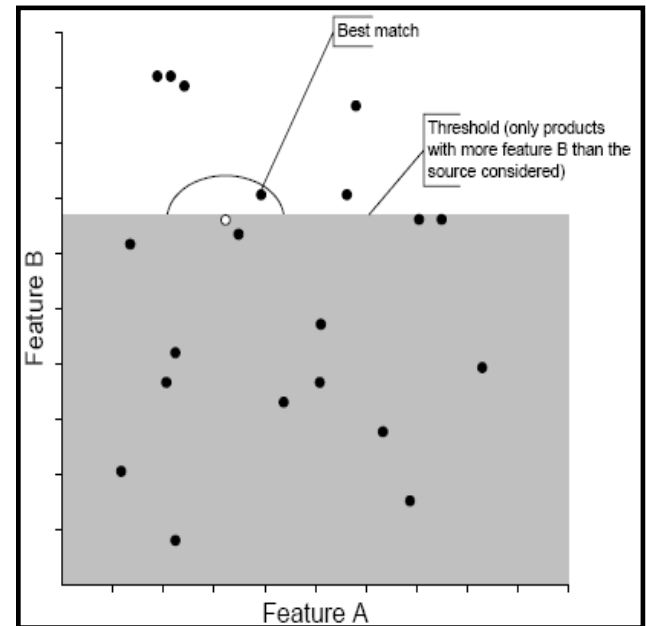
- CBR System
- Navigation system superior to repeated search: intuitive, natural, requires less effort
- Steps:
 - User chooses “source”/”entry point” from catalog (using search or direct name-based identification)
 - Perform case retrieval, find items most similar to source
 - Obtain “critique” of presented examples
 - Use critique to redirect the search, filtering the solution space along specified feature dimension



R.Burke: “Interactive Critiquing for Catalog Navigation in e-Commerce”

“FindMe” Critique-Based Retrieval

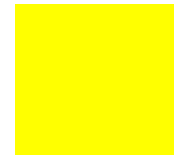
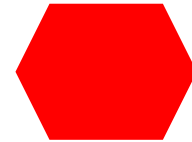
- Steps:
 - User chooses “source”/”entry point” from catalog (using search or direct name-based identification)
 - Perform case retrieval, find items most similar to source
 - Obtain “critique” of presented examples
 - Use critique to redirect the search, filtering the solution space along specified feature dimension (e.g. “more B”)



R.Burke: “Interactive Critiquing for Catalog Navigation in e-Commerce”

Recommendation and Critiquing

- [“Entry point”] A red polygon, please!
- Something with fewer sides?
- ... but equilateral!
(note: “red” feature lost)
- Something similar in green?
- ... and with even fewer sides?



Similarity?

SIM(



,




)=?

Similarity



- Not simple or uniform, situation-specific
 - E.g. $SIM(car, boat)=1$ if location near water
 - $SIM(car, boat)=0$ if location landlocked
- Must capture buyers' intuitive sense of what ought to be considered similar
- “Local Similarity metric”: goal-oriented, multiple goals and their trade-offs considered
- Hierarchy of global similarity metrics : domain-specific

Entrée Chicago



For a cheaper restaurant than:

Yoshi's Cafe	
3157 N. Halsted St. (Belmont Ave.), Chicago, 312-248-6160	
Asian, Japanese, French (New)	\$30-\$50

We recommend:

Lulu's (map)	
626 Davis St (bet. Chicago & Orrington Aves), Evanston, 708-869-4343	
Japanese, Asian	below \$15

Good Decor, Excellent Service, Excellent Food, Creative, No Reservations, Weekend Brunch, Wheelchair Access, Long Drive

- Knowledge-based restaurant recommender
- “FindMe” System:
 - Similarity-based Recommendation
 - Critique-based Navigation

Entrée Chicago

"CRITIQUING"
BUTTONS

We recommend:

Yoshi's Cafe
3257 N. Halsted St. (Belmont Ave.), Chicago, 312-248-6160

Asian, Japanese, French (New) \$30-\$50

Extraordinary Decor, Extraordinary Service, Near-perfect Food, Need To Dress, Prix Fixe Menus, Quiet for Conversation, Very Busy - Reservations a Must, Romantic, Good Out of Town Business, Fabulous Wine Lists, Game, Parking/Valet

less \$5 *nicer* *cuisine*
traditional *creative* *livelier* *quieter*

- Goal hierarchy:
 - cuisine (I), price (II), quality (III), atmosphere (IV)
- Unfortunately, no longer online

A Demo Recommender System

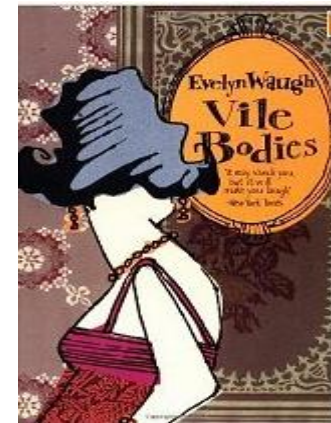
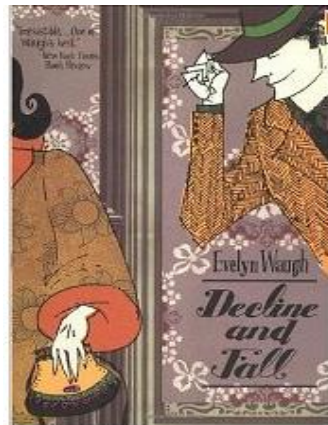
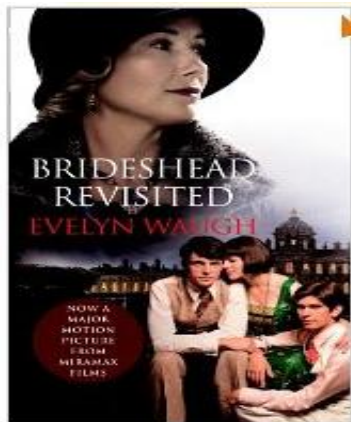
- Movielens
 - <http://www.movielens.org/login>

What's the Potential Problem Here?

- *Query: green, triangular*



- *Query: early twentieth-century novel by British author*

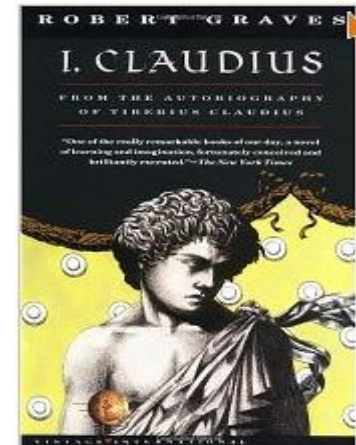
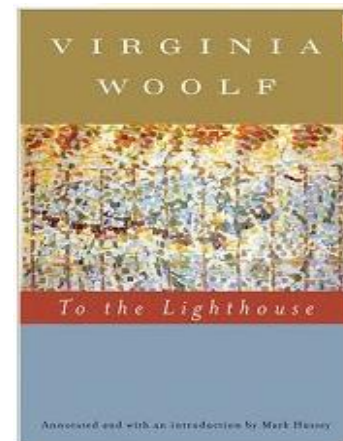
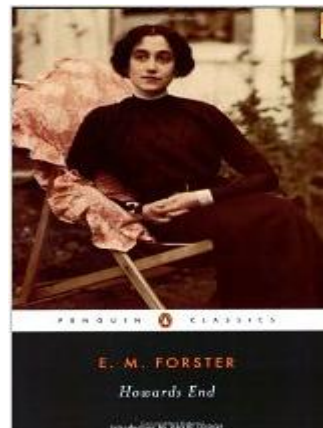
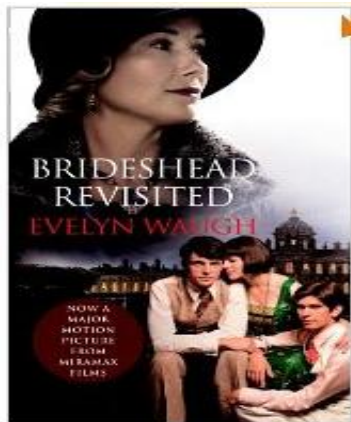


Diversity!!!

- *Query: green, triangular*



- *Query: early twentieth-century novel by British author*



- Variation of retrieved results
- Better sample of solution space
- Genuine alternatives for the user
- “Surprising” options that may otherwise not be considered

MUST be balanced with
similarity!

Diversity

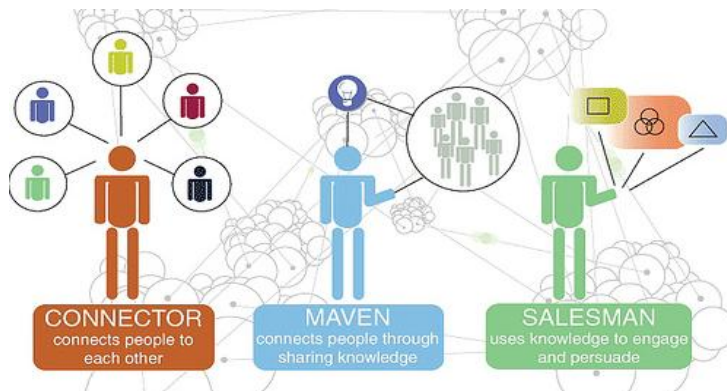


Diversity-Aware Retrieval Algorithms

- No algorithm for optimal balance between Similarity and Diversity
- “Bounded Greedy” [Smyth & McClave]: a heuristic attempt, so far the most popular
- “Similarity Layers” [McSherry]
- “Adaptive Selection” [McGinty and Smyth]
 - doses similarity/diversity intelligently, based on user’s choices on each recommendation cycle

Current and Future Research Directions

- Mobile Recommender Systems (*MobyRek*)
- Recommender systems leveraging and enhancing Social Networks?



F. Ricci and Q. N. Nguyen,
Critique-Based Mobile
Recommender Systems,
OEGAI Journal, 24(4):2005.

Summary

- Recommender systems help navigate vast product spaces, helping locate items that are interesting and useful to individual users
- Mostly used in business-to-person e-commerce contexts
- Multiple types of recommender systems, based on type and source of input/background data (can be combined into “hybrids”)
- “Critiquing” makes navigation intuitive and efficient, emulating interaction with a salesperson; it helps reduce the “narrowing” effect
- Diversity a relevant, currently-explored issue, must be balanced with Similarity