CS276B

Text Information Retrieval, Mining, and Exploitation

Lecture 10

Feb 18, 2003

Recap – last time

- Vector space classification
- Nearest neighbor classification
- Support vector machines
- Hypertext classification

Today's topics

- Recommendation systems
- What they are and what they do
- A couple of algorithms
- Going beyond simple behavior: context
- How do you measure them?
  - Begin: how do you design them "optimally"?

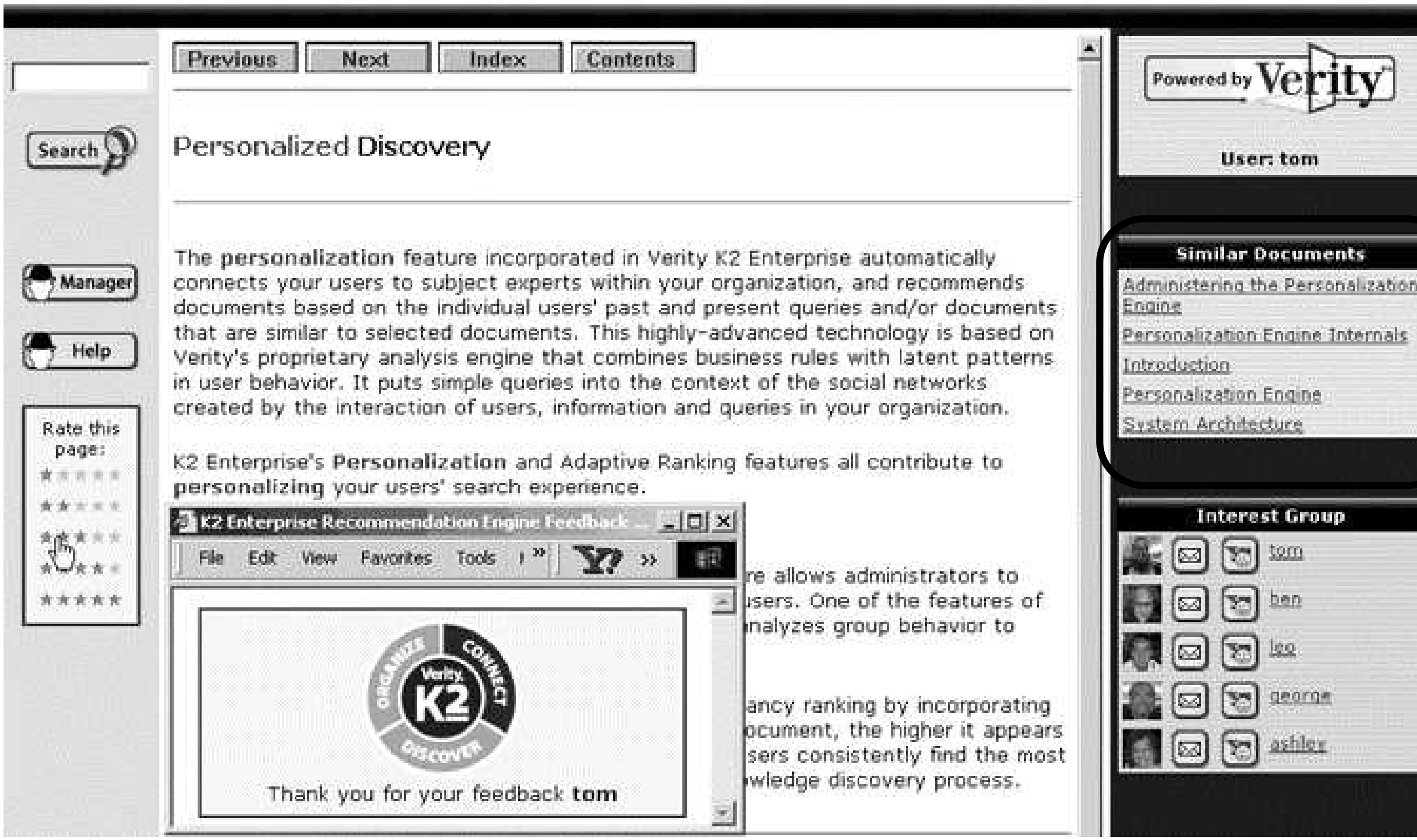
Recommendation Systems

- Given a set of *users* and *items*
  - items could be documents, products, other users …
- Recommend items to a user based on
  - past behavior of this and other users
  - additional information on users/items.

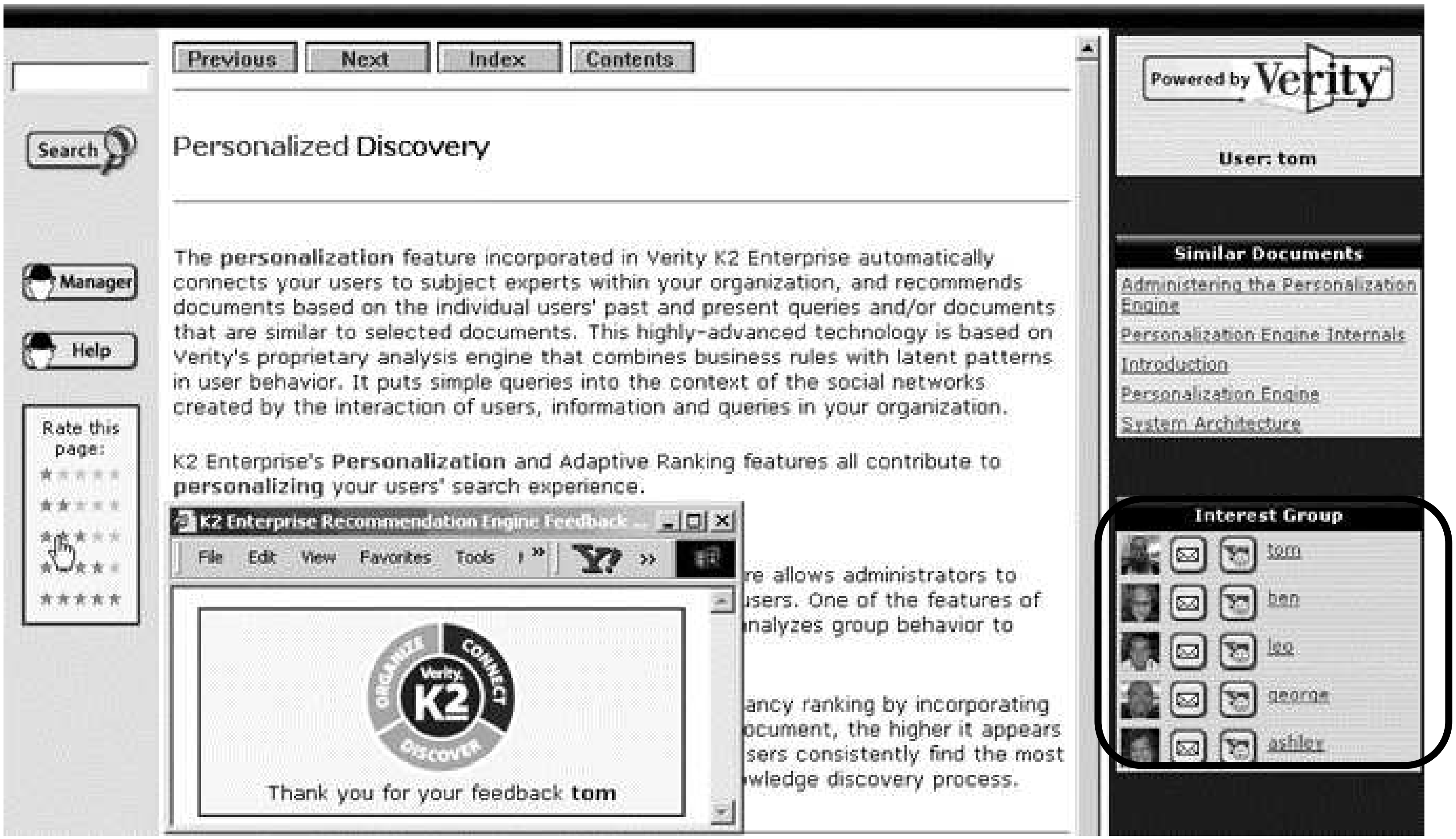
Sample Applications

- Corporate Intranets
  - Recommendation, finding domain experts, …
- Ecommerce
  - Product recommendations - amazon
- Medical Applications
  - Matching patients to doctors, clinical trials, …
- Customer Relationship Management
  - Matching customer problems to internal experts in a Support organization.

Corporate intranets - document recommendation



Corporate intranets - “expert” finding



Inputs to system

- Behavior
  - users' historical "transactions"
- Context
  - what the user appears to be doing now
- Role/domain
  - additional info about users, documents

    …

Inputs - more detail

Past transactions from users:

- which docs viewed
- content/attributes of documents
- which products purchased
- pages bookmarked
- explicit ratings (movies, books …)

Current context:

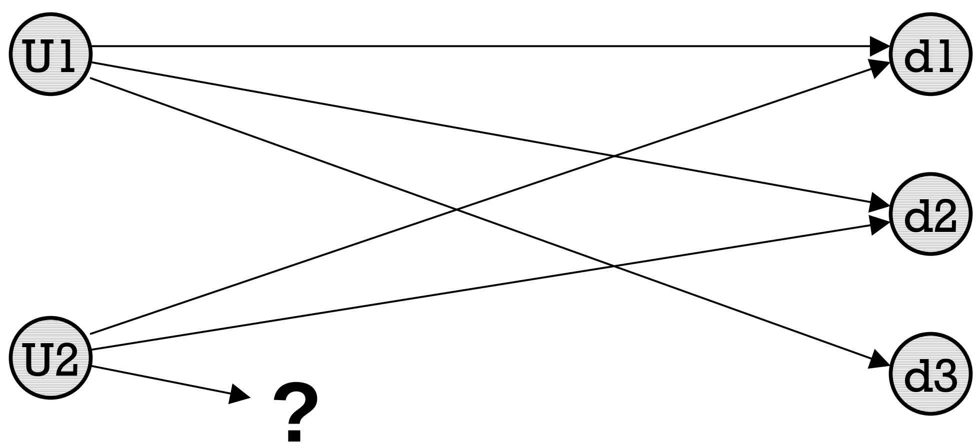
- browsing history
- search(es) issued

Explicit role/domain info:

- Role in an enterprise
- Document taxonomies
- Interest profiles

Example - behavior only

Users Docs viewed

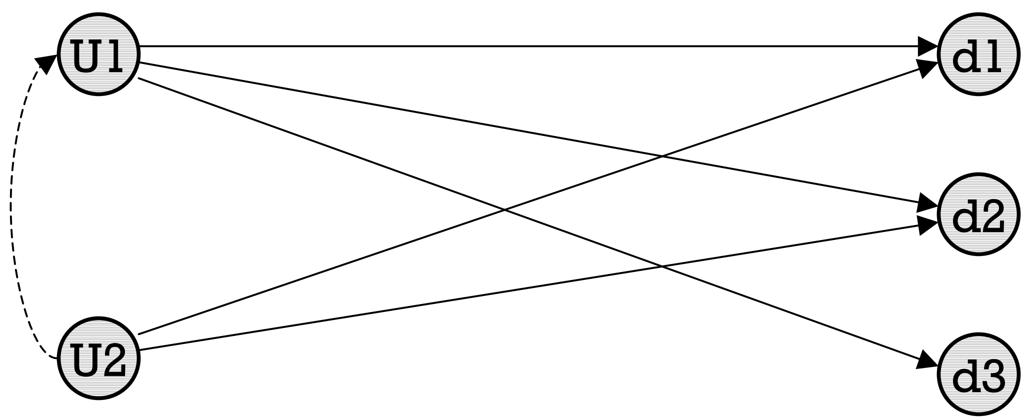


U1 viewed d1, d2, d3.

U2 views d1, d2.

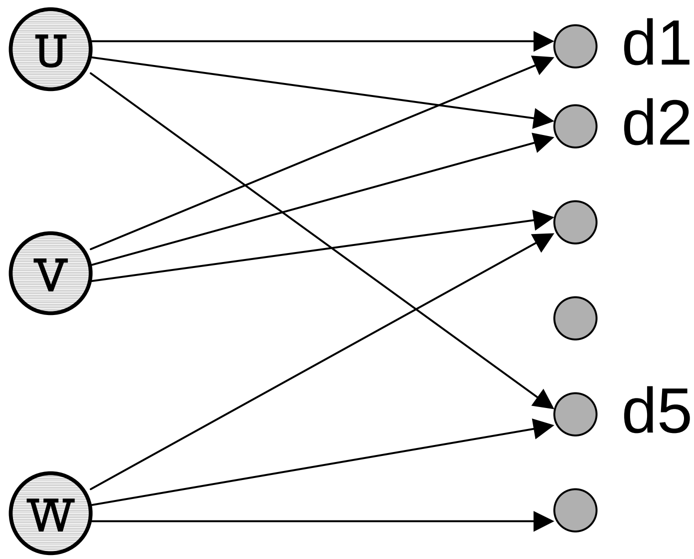
Recommend d3 to U2.

Expert finding - simple example



Recommend U1 to U2 as someone to talk to?

Simplest Algorithm



U viewed d1, d2, d5.

Look at who else viewed d1, d2 or d5.

Recommend to U the doc(s) most "popular" among these users.

Simple algorithm - shortcoming

- Treats all other users as equally important
- Ignores the fact that some users behaved more like me in the past

Measuring collaborative filtering

- How good are the predictions?
- How much of previous opinion do we need?
- Computation.
- How do we motivate people to offer their opinions?

Other aspects

- Rule-based recommendation
- Working in user space vs. item space
- Build regression models of user

Rule-based recommendations

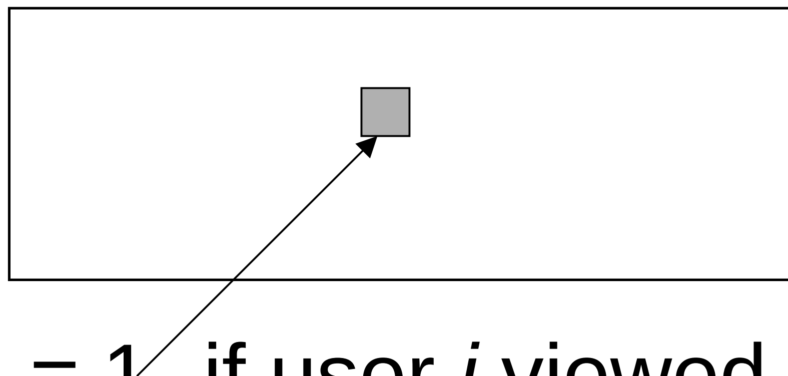
- In practice – rule-based systems in commerce engines
  - Merchandizing interfaces allow product managers to promote items
  - Criteria include inventory, margins, etc.
- Must reconcile these with algorithmic recommendations

User space vs. item space

- Should we work with user similarity or item similarity?
- As with general clustering
  - Recommendations could come from similar users
  - Or opinions could come from items similar to the one we seek an opinion on
    - Similar based on what?
- In some cases, can use both cues

Matrix view

Docs

A = Users 

A_{ij} = 1 if user i viewed doc j,

= 0 otherwise.

AA^t : Entries give # of docs commonly viewed by pairs of users.

Voting Algorithm

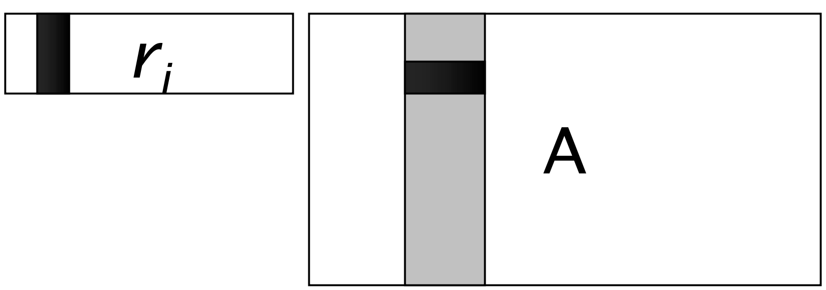
- Row i of AA^t : Vector whose j^{th} entry is the # of docs viewed by both i and j.
- Call this row r_i, e.g., (0, 7, 1, 13, 0, 2, ….)

What's on the diagonal of AA^t?

Voting algorithm

- Then $r_i \circ A$ is a vector whose k^{th} entry gives a weighted vote count to doc k
  - emphasizes users who have high weights in r_i .
- Recommend doc(s) with highest v ounts.

How does this differ from the simple algorithm?



Voting Algorithm - implementation issues

- Wouldn't implement using matrix operations
  - use weight-propagation on compressed adjacency lists
- Need to log and maintain “user views do” relationship.
  - typically, log into database
  - update vote-propagating structures periodically.
- For efficiency, discard all but the heaviest weights in each r_i
  - only in fast structures, not in back-end database.

Write pseudo code

Exercise

- The voting algorithm may be viewed as <u>one</u> iteration of the Hubs/Authorities algorithm from CS276a (as in Lecture 3).
- Derive the extension to the full Hubs/Authorities algorithm with convergence.
  - Make sure all users don't get the same recommendations!
- How do you interpret the top "Hubs"?

Different setting/algorithm

- Each user *i* rates some docs (products, …)
  - say a real-valued *rating* U_{ik} for doc *k*
  - in practice, one of several ratings on a form
- Thus we have a ratings vector U_i for each user
  - (with lots of zeros)
- Compute a *correlation coefficient* between every pair of users *i,j*
  - dot product of their ratings vectors
  - (symmetric, scalar) measure of how much user pair *i,j* agrees: S_{ij}

Predict user *i*'s utility for doc *k*

- Sum (over users j such that U_{jk} is non-zero)

  $S_{ij}\, U_{jk}$

- Output this as the predicted utility for user i on doc k.

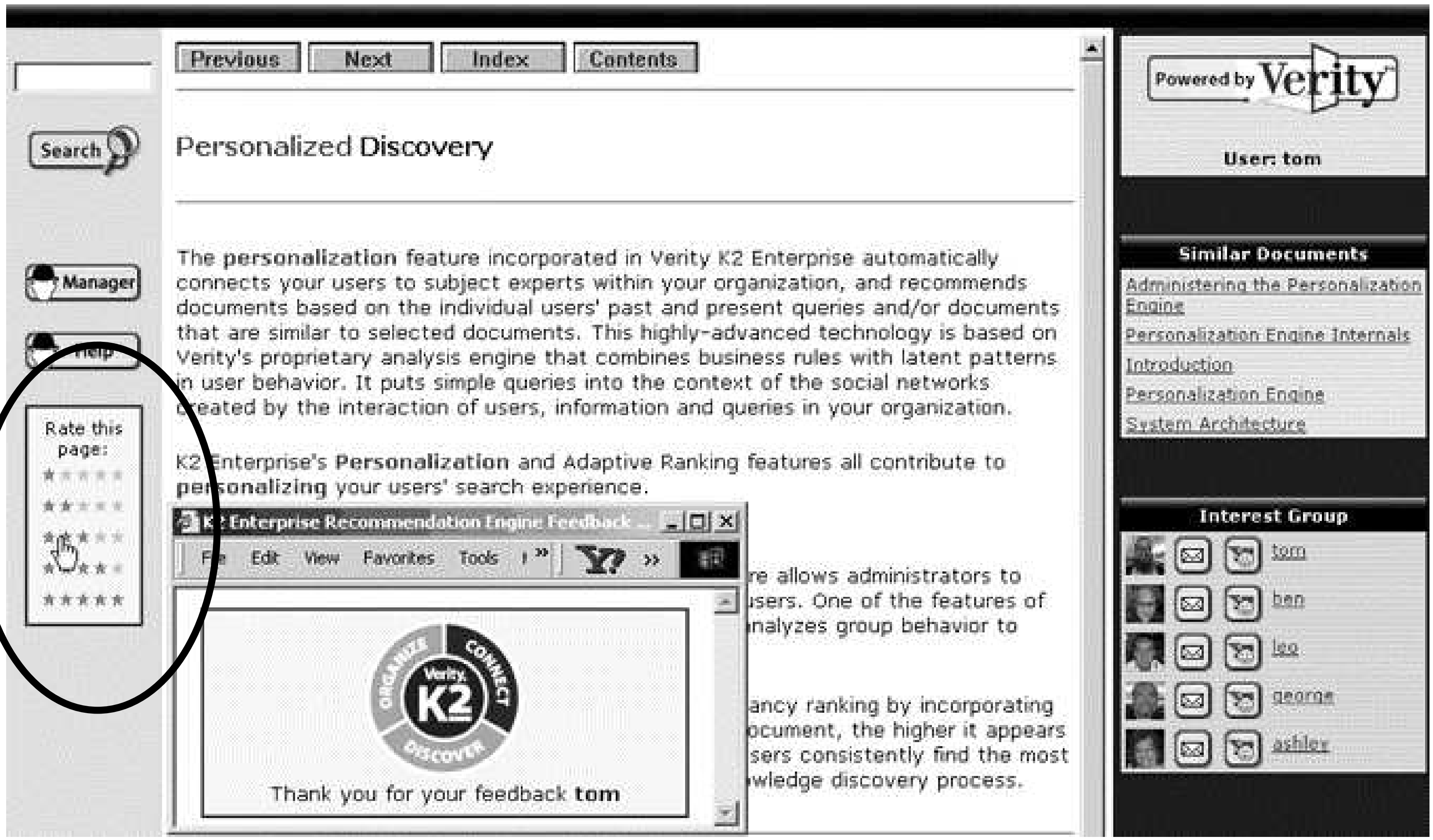
So how does this differ from the voting algorithm?

It really doesn't …

Same algorithm, different scenario

- Implicit (user views doc) vs. Explicit (user assigns rating to doc)
- Boolean vs. real-valued utility
  - In practice, must convert user ratings on a form (say on a scale of 1-5) to real-valued utilities
  - Can be fairly complicated mapping
    - Likeminds function (Greening white paper)
  - Requires understanding user's interpretation of form

Rating interface



Early systems

- GroupLens (U of Minn) (Resnick/Iacovou/Bergstrom/Riedl)
  - netPerceptions company
- Tapestry (Goldberg/Nichols/Oki/Terry)
- Ringo (MIT Media Lab) (Shardanand/Maes)
- Experiment with variants of these algorithms

Recap slide 6 - Inputs

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The next level - modeling context

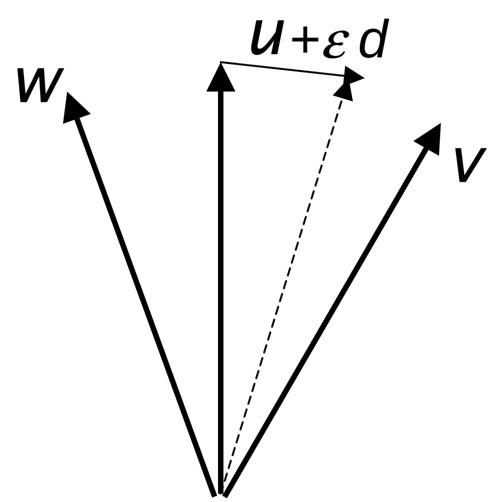
- Suppose we could view users and docs in a common vector space of terms
  - docs already live in term space
- How do we cast users into this space?
  - Combination of docs they liked/viewed
  - Terms they used in their writings
  - Terms from their home pages, resumes …

Context modification

- Then "user *u* viewing document *d*" can be modeled as a vector in this space: $u+\varepsilon\, d$
- User *u* issuing search terms *s* can be similarly modeled:
  - add search term vector to the user vector
- More generally, any term vector (say recent search/browse history) can offset the user vector

Using a vector space

- Similarities in the vector space used to derive correlation coefficients between user context and other users

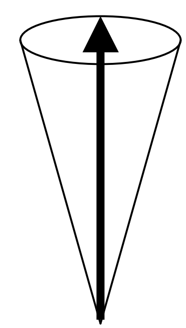


Recommendations from context

- Use these correlation coefficients to compute recommendations as before
- Challenge:
  - Must compute correlations at run time
- How can we make this efficient?
  - Restrict each user to a sparse vector
  - Precompute correlations to search terms
  - Compose $u + \varepsilon s$

Correlations at run time

- Other speedup
  - If we could restrict to users “near” the context
  - Problem - determining (say) all users within a certain “ball” of the context
  - Or *k* nearest neighbors, etc.



Modified vectors

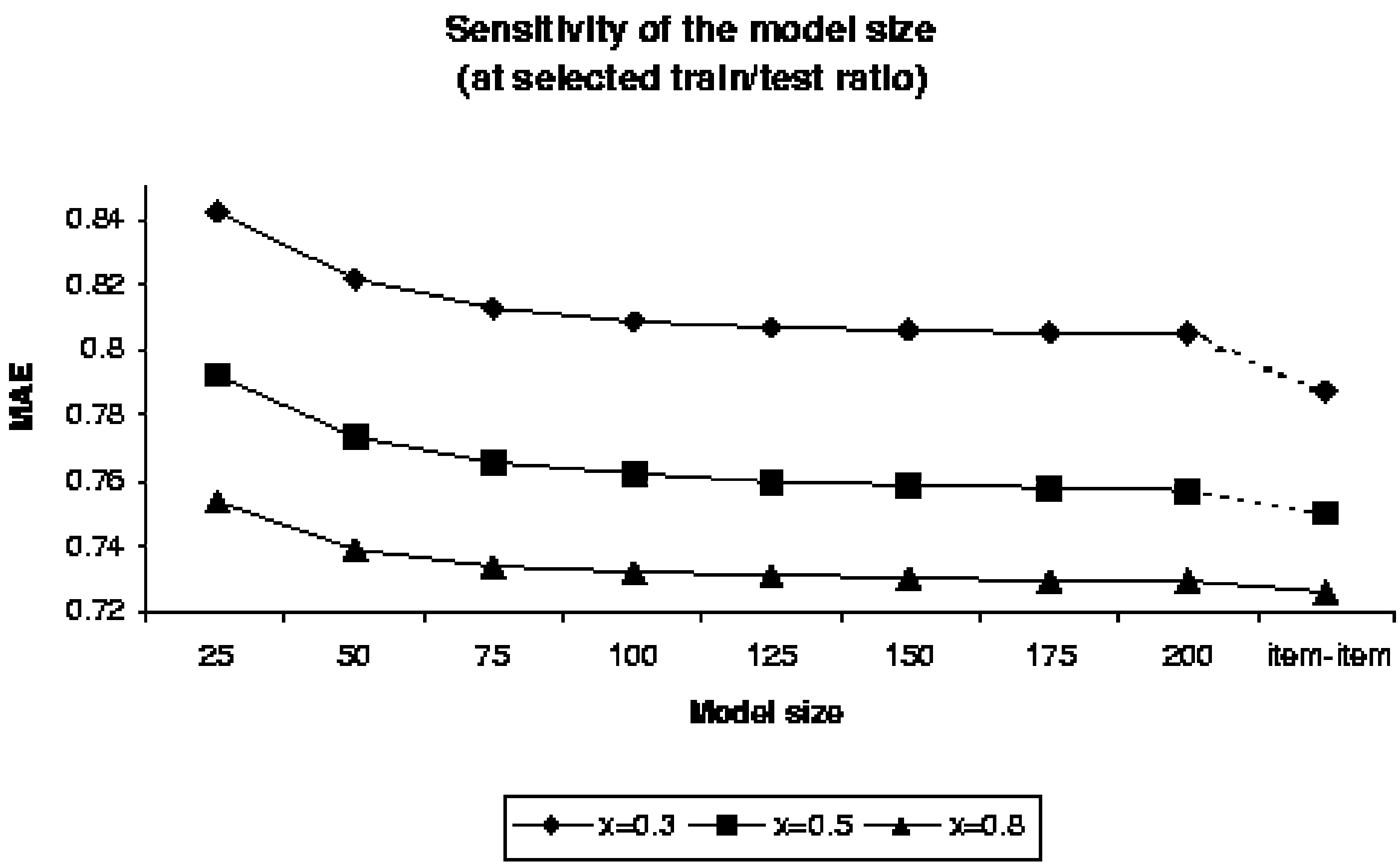
- Should context changes to vector be made permanent?
- Exponential decay?
- Can retain some memory of recent search/browse history

Think of how to do this efficiently.

Measuring recommendations

- Typically, machine learning methodology
- Get a dataset of opinions; mask “half” the opinions
- Train system with the other half, then validate on masked opinions
  - Studies with varying fractions $\neq$ half
- Compare various algorithms (correlation metrics)

k nearest neighbors - efficacy



Source: Sarwar/Karypis/Konstan/Riedl

Summary so far

- Content/context expressible in term space
- Combined into inter-user correlation
  - This is an algebraic formulation, but
  - Can also recast in the language of probability
- What if certain correlations are "constrained"
  - two users in the same department/zip code
  - two products by the same manufacturer?

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Capturing role/domain

- Additional axes in vector space
  - Corporate org chart - departments
  - Product manufacturers/categories
- Make these axes “heavy” (weighting)
- Challenge: modeling hierarchies
  - Org chart, product taxonomy

Measuring recommendations

- Unclear how to design correlation metric to yield good results
- How can we tune the algorithm "up front"?
- Need a formulation of what the system is trying to do

Utility formulation

- Microeconomic view again
- Assume that each user has a real-valued *utility* for each item
- $m \times n$ matrix of utilities for each of m users for each of n items
  - not all utilities known in advance
  - (which ones *do* we know?)
- Predict which (unseen) utilities are highest for each user

User types

- If users are arbitrary, all bets are off
  - typically, assume matrix is of low rank
  - say, a constant *k* independent of *m,n*
  - some perturbation is allowable
- I.e., users belong to *k* well-separated types
  - (almost)
  - Most users' utility vectors are close to one of *k* well-separated vectors

Matrix reconstruction

- Given some utilities from the matrix
- Reconstruct missing entries
  - Suffices to predict biggest missing entries for each user
  - Suffices to predict close to biggest
  - For most users
- This is the formulation we will begin with next time

Resources

- GroupLens
  - http://citeseer.nj.nec.com/resnick94grouplens.html
- Shardanand/Maes
  - http://citeseer.nj.nec.com/shardanand95social.html
- Sarwar et al.
  - http://citeseer.nj.nec.com/sarwar01itembased.html