CS345
Data Mining

Recommendation Systems
Netflix Challenge
Course Projects

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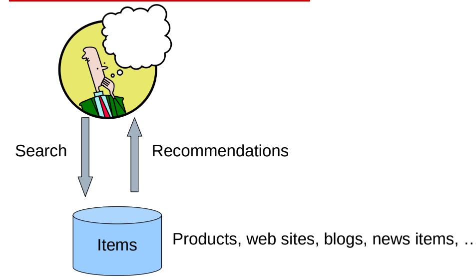
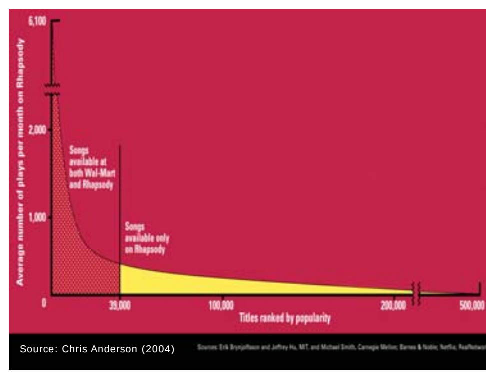
Recommendations



From scarcity to abundance

- Shelf space is a scarce commodity for traditional retailers
  - Also: TV networks, movie theaters,…
- The web enables near-zero-cost dissemination of information about products
  - From scarcity to abundance
- More choice necessitates better filters
  - Recommendation engines
  - How Into Thin Air made Touching the Void a bestseller

The Long Tail



Recommendation Types

- Editorial
- Simple aggregates
  - Top 10, Most Popular, Recent Uploads
- Tailored to individual users
  - Amazon, Netflix, …

Formal Model

- C = set of Customers
- S = set of Items
- Utility function u: $C \times S \rightarrow R$
  - R = set of ratings
  - R is a totally ordered set
  - e.g., 0-5 stars, real number in [0,1]

Utility Matrix

	King Kong	LOTR	Matrix	Nacho Libre
Alice	1		0.2	
Bob		0.5		0.3
Carol	0.2		1	
David				0.4

Key Problems

- Gathering “known” ratings for matrix
- Extrapolate unknown ratings from known ratings
  - Mainly interested in high unknown ratings
- Evaluating extrapolation methods

Gathering Ratings

- Explicit
  - Ask people to rate items
  - Doesn’t work well in practice – people can’t be bothered
- Implicit
  - Learn ratings from user actions
  - e.g., purchase implies high rating
  - What about low ratings?

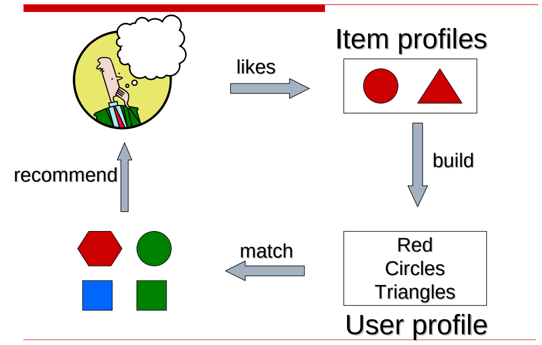
Extrapolating Utilities

- Key problem: matrix U is sparse
  - most people have not rated most items
- Three approaches
  - Content-based
  - Collaborative
  - Hybrid

Content-based recommendations

- Main idea: recommend items to customer C similar to previous items rated highly by C
- Movie recommendations
  - recommend movies with same actor(s), director, genre, …
- Websites, blogs, news
  - recommend other sites with “similar” content

Plan of action



Item Profiles

- For each item, create an item profile
- Profile is a set of features
  - movies: author, title, actor, director,…
  - text: set of "important" words in document
- How to pick important words?
  - Usual heuristic is TF.IDF (Term Frequency times Inverse Doc Frequency)

TF.IDF

f_{ij} = frequency of term t_i in document d_j

$$TF_{ij} = \frac{f_{ij}}{\max_k f_{kj}}$$

n_i = number of docs that mention term i
N = total number of docs

$$IDF_i = \log \frac{N}{n_i}$$

TF.IDF score $w_{ij} = TF_{ij} \times IDF_i$

Doc profile = set of words with highest TF.IDF scores, together with their scores

User profiles and prediction

- User profile possibilities:
  - Weighted average of rated item profiles
  - Variation: weight by difference from average rating for item
  - …
- Prediction heuristic
  - Given user profile **c** and item profile **s**, estimate u(**c**,**s**) = cos(**c**,**s**) = **c**.**s**/(|**c**||**s**|)
  - Need efficient method to find items with high utility: later

Model-based approaches

- For each user, learn a classifier that classifies items into rating classes
  - liked by user and not liked by user
  - e.g., Bayesian, regression, SVM
- Apply classifier to each item to find recommendation candidates
- Problem: scalability
  - Won't investigate further in this class

Limitations of content-based approach

- Finding the appropriate features
  - e.g., images, movies, music
- Overspecialization
  - Never recommends items outside user's content profile
  - People might have multiple interests
- Recommendations for new users
  - How to build a profile?

Collaborative Filtering

- Consider user c
- Find set D of other users whose ratings are "similar" to c's ratings
- Estimate user's ratings based on ratings of users in D

Similar users

- Let r_x be the vector of user x's ratings
- Cosine similarity measure
  - sim(x,y) = $\cos(r_x, r_y)$
- Pearson correlation coefficient
  - S_{xy} = items rated by both users x and y

$$sim(x,y) = \frac{\sum_{s \in S_{xy}} (r_{xs} - \bar{r_x})(r_{ys} - \bar{r_y})}{\sqrt{\sum_{s \in S_{xy}} (r_{xs} - \bar{r_x})^2 (r_{ys} - \bar{r_y})^2}}$$

Rating predictions

- Let D be the set of *k* users most similar to *c* who have rated item *s*
- Possibilities for prediction function (item s):
  - $r_{cs} = 1/k \sum_{d \in D} r_{ds}$
  - $r_{cs} = (\sum_{d \in D} \text{sim}(c,d) \times r_{ds}) / (\sum_{d \in D} \text{sim}(c,d))$
  - Other options?
- Many tricks possible…

Complexity

- Expensive step is finding k most similar customers
  - O(|U|)
- Too expensive to do at runtime
  - Need to pre-compute
- Naïve precomputation takes time O(N|U|)
  - Simple trick gives some speedup
- Can use clustering, partitioning as alternatives, but quality degrades

Item-Item Collaborative Filtering

- So far: User-user collaborative filtering
- Another view
  - For item s, find other similar items
  - Estimate rating for item based on ratings for similar items
  - Can use same similarity metrics and prediction functions as in user-user model
- In practice, it has been observed that item-item often works better than user-user

Pros and cons of collaborative filtering

- Works for any kind of item
  - No feature selection needed
- New user problem
- New item problem
- Sparsity of rating matrix
  - Cluster-based smoothing?

Hybrid Methods

- Implement two separate recommenders and combine predictions
- Add content-based methods to collaborative filtering
  - item profiles for new item problem
  - demographics to deal with new user problem
  - Filterbots

Evaluating Predictions

- Compare predictions with known ratings
  - Root-mean-square error (RMSE)
- Another approach: 0/1 model
  - Coverage
    - Number of items/users for which system can make predictions
  - Precision
    - Accuracy of predictions
  - Receiver operating characteristic (ROC)
    - Tradeoff curve between false positives and false negatives

Problems with Measures

- Narrow focus on accuracy sometimes misses the point
  - Prediction Diversity
  - Prediction Context
  - Order of predictions

Finding similar vectors

- Common problem that comes up in many settings
- Given a large number N of vectors in some high-dimensional space (M dimensions), find pairs of vectors that have high cosine-similarity
- Compare to min-hashing approach for finding near-neighbors for Jaccard similarity

Similarity-Preserving Hash Functions

- Suppose we can create a family **F** of hash functions, such that for any h∈**F**, given vectors x and y:
  - $Pr[h(x) = h(y)] = sim(x,y) = cos(x,y)$
- We could then use $E_{h \in \mathbf{F}}[h(x) = h(y)]$ as an estimate of sim(x,y)
  - Can get close to $E_{h \in \mathbf{F}}[h(x) = h(y)]$ by using several hash functions

Similarity metric

- Let θ be the angle between vectors x and y
- $\cos(\theta) = x.y/(|x||y|)$
- It turns out to be convenient to use $sim(x,y) = 1 - \theta/\pi$
  - instead of $sim(x,y) = \cos(\theta)$
  - Can compute $\cos(\theta)$ once we estimate θ

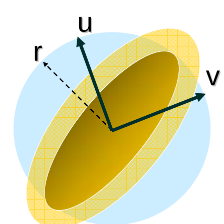
Random hyperplanes

Vectors u, v subtend angle θ

Random hyperplane through origin (normal r)

$h_r(u) = 1$ if $r.u \geq 0$

0 if $r.u < 0$

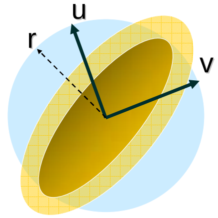


Random hyperplanes

$h_r(u) = 1$ if $r.u \geq 0$

0 if $r.u < 0$

$Pr[h_r(u) = h_r(v)] = 1 - \theta/\pi$



Vector sketch

- For vector u, we can contruct a k-bit sketch by concatenating the values of k different hash functions
  - sketch(u) = $[h_1(u)\ h_2(u)\ \ldots\ h_k(u)]$
- Can estimate θ to arbitrary degree of accuracy by comparing sketches of increasing lengths
- Big advantage: each hash is a single bit
  - So can represent 256 hashes using 32 bytes

Picking hyperplanes

- Picking a random hyperplane in M-dimensions requires M random numbers
- In practice, can randomly pick each dimension to be +1 or -1
  - So we need only M random bits

Finding all similar pairs

- Compute sketches for each vector
  - Easy if we can fit random bits for each dimension in memory
    - For k-bit sketch, we need Mk bits of memory
  - Might need to use ideas similar to page rank computation (e.g., block algorithm)
- Can use DCM or LSH to find all similar pairs

Project Ideas…

- Compare algos for near-duplicates
- Netflix
- Extracting relations, list-building
- Discovering synonyms, spelling variants
- Spam detection
- Identifying website boundaries
- and many, many others…