Recommender Systems

CS246: Mining Massive Datasets
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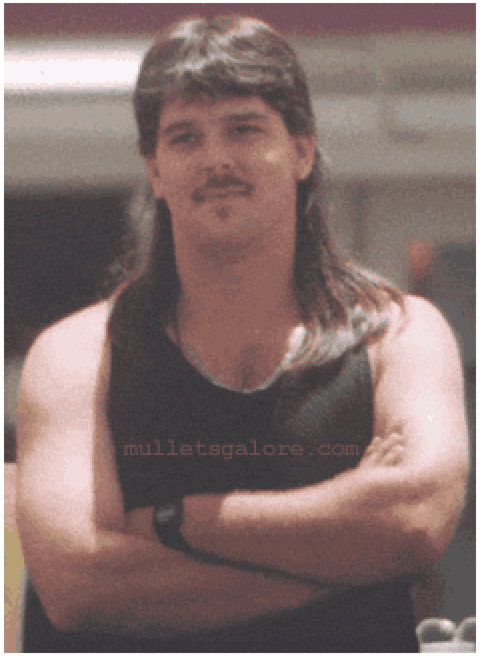
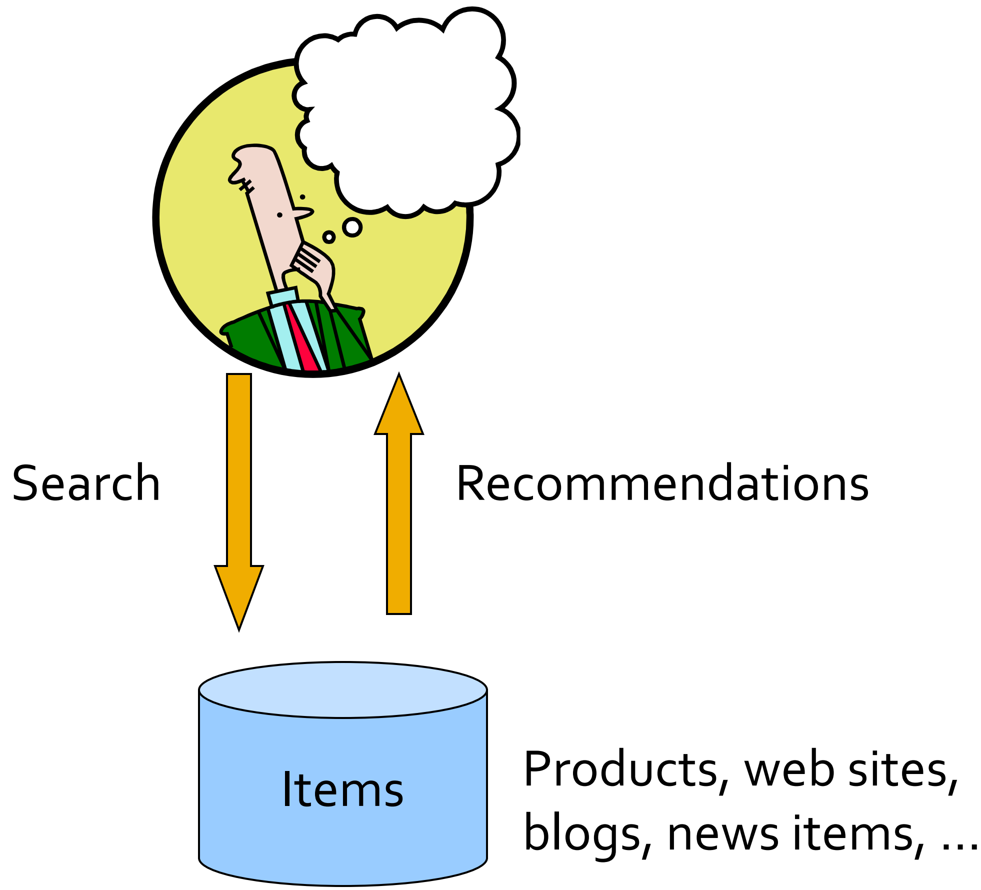
Example



- Customer A
  - Buys Metalica CD
  - Buys Megadeth CD

- Customer B
  - Does search on Metalica
  - Recommender system suggests Megadeth from data collected from customer A

Recommendations



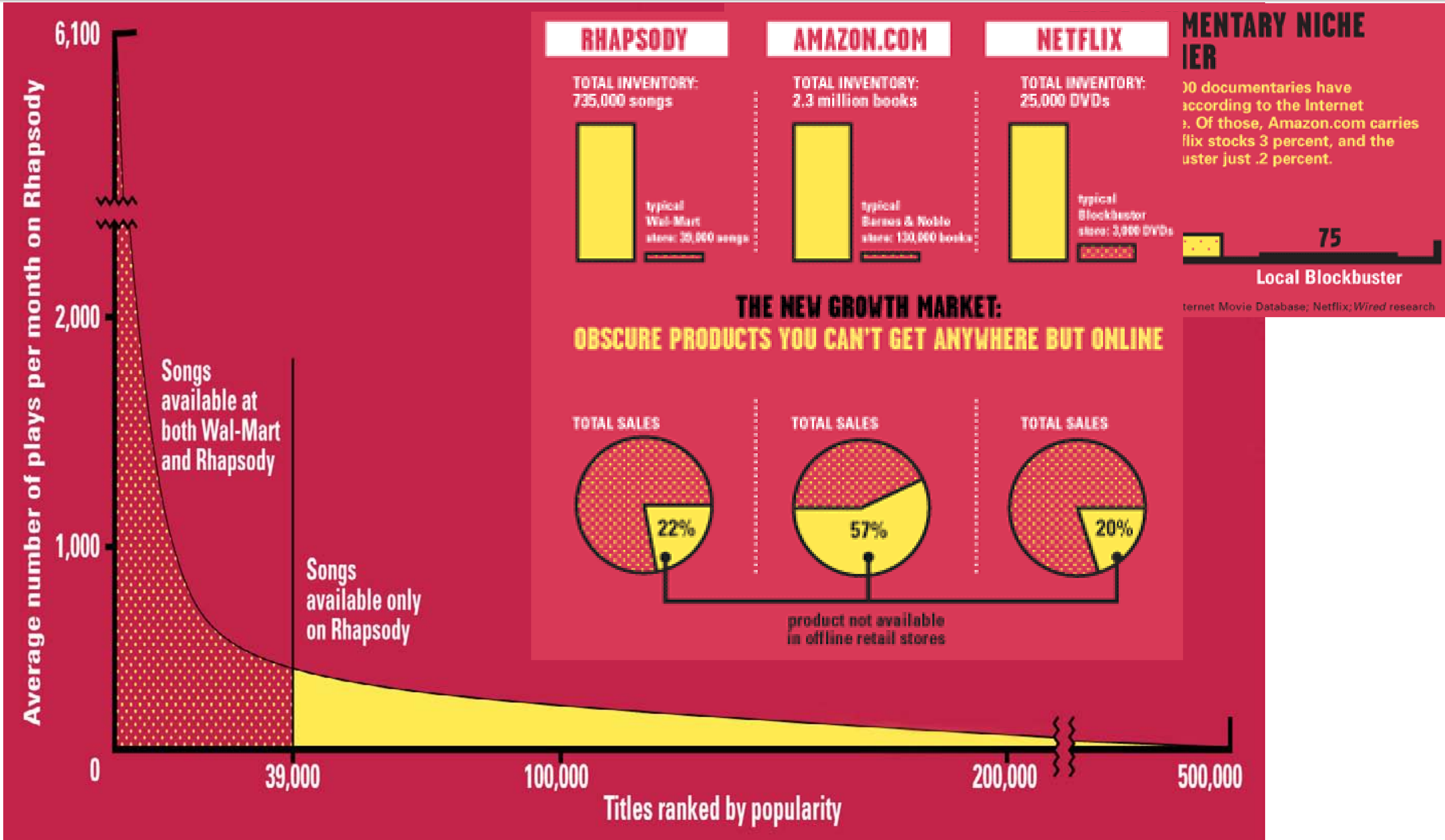
Examples:

amazon.com
PANDORA
StumbleUpon
del.icio.us
NETFLIX
movielens
helping you find the *right* movies
last.fm
the social music revolution
Google News
YouTube
XBOX LIVE

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:
    - http://www.wired.com/wired/archive/12.10/tail.html

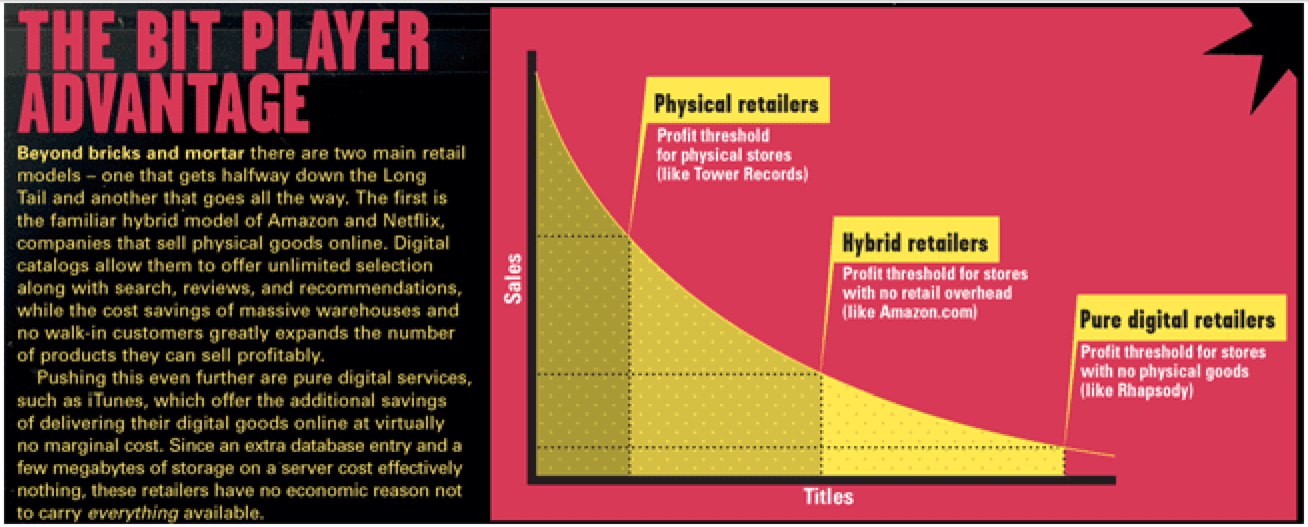
The Long Tail



Source: Chris Anderson (2004)

Sources: Erik Brynjolfsson and Jeffrey Hu, MIT, and Michael Smith, Carnegie Mellon; Barnes & Noble; Netflix; RealNetworks

Physical vs. Online



Read http://www.wired.com/wired/archive/12.10/tail.html to learn more!

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

	Avatar	LOTR	Matrix	Pirates
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?

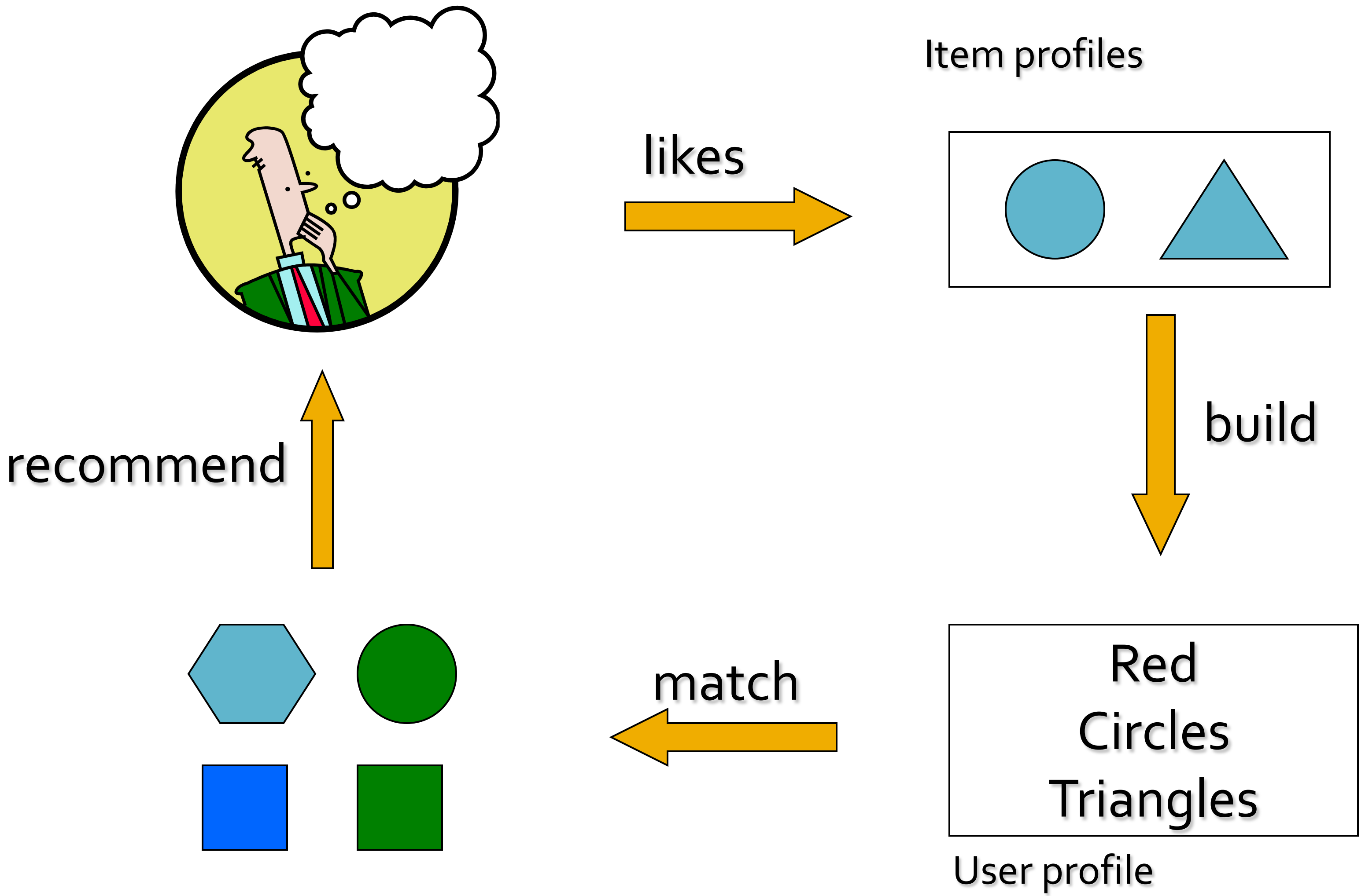
Extrapolating Utilities

- Key problem: matrix U is sparse
  - most people have not rated most items
  - Cold start: new items have no ratings
- 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 $u(\mathbf{c},\mathbf{s}) = \cos(\mathbf{c},\mathbf{s}) = \mathbf{c}.\mathbf{s}/(|\mathbf{c}||\mathbf{s}|)$
  - Need efficient method to find items with high utility: later

Pros: Content-based approach

- No need for data on other users.
  - No cold-start or sparsity problems.
- Able to recommend to users with unique tastes.
- Able to recommend new and unpopular items
  - No first-rater problem
- Can provide explanations of recommended items by listing content-features that caused an item to be recommended

Cons: 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
  - Unable to exploit quality judgments of other users
- 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):
  - $r_{cs} = 1/k \sum_{d \text{ in } D} r_{ds}$
  - $r_{cs} = (\sum_{d \text{ in } D} sim(c,d)\ r_{ds})/(\sum_{d \text{ in } D} sim(c,d))$
  - Other options?
- Many tricks possible…

Complexity

- Expensive step is finding k most similar customers
  - $O(|U|)$
- Too expensive to do at runtime
  - Could pre-compute
- Naïve precomputation takes time $O(N|U|)$
  - Stay tuned for how to do it faster!
- 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

Example: Item-Item based

	Avatar	LOTR	Matrix	Pirates
Alice	1		0.2	
Bob		0.5		0.3
Carol	0.2		1	
David				0.4

- What do we recommend for Avatar?
  - cos(Avatar, Matrix) =0.38
  - cos(Avatar, Lotr) =0.0

Pros & cons of collaborative filtering

- Works for any kind of item
  - No feature selection needed
- Cold Start:
  - Need enough users in the system to find a match.
- Sparsity:
  - The user/ratings matrix is sparse. Hard to find users that have rated the same items.
- First Rater:
  - Cannot recommend an item that has not been previously rated.
  - New items, Esoteric items
- Popularity Bias:
  - Cannot recommend items to someone with unique tastes.
  - Tends to recommend popular items.

Hybrid Methods

- Implement two or more different recommenders and combine predictions
  - Perhaps using a linear model
- Add content-based methods to collaborative filtering
  - item profiles for new item problem
  - demographics to deal with new user problem

Evaluation

movies

users

1	3	4			
	3	5			5
		4	5		5
		3			
		3			
2			2		2
				5	
	2	1			1
	3			3	
1					

Evaluation

movies

users

1	3	4			
	3	5			5
		4	5		5
		3			
		3			
2			?		?
				?	
	2	1			?
	3			?	
1					

Test Data Set
(most recent ratings)

Evaluating Predictions

- Compare predictions with known ratings
  - Root-mean-square error (RMSE)
  - Precision at top 10: % of those in top10
  - Rating of top 10: Average rating assigned to top 10
  - Rank Correlation: Spearman's, r_s, between system's and user's complete rankings.
- 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

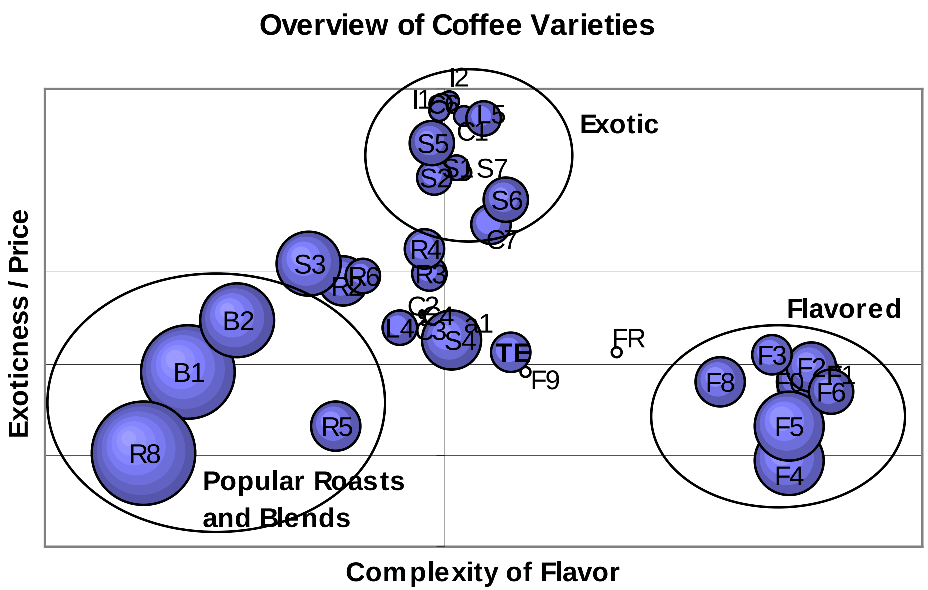
Problems with Measures

- Narrow focus on accuracy sometimes misses the point
  - Prediction Diversity
  - Prediction Context
  - Order of predictions
- In practice, we care only to predict high ratings:
  - RMSE might penalize a method that does well for high ratings and badly for others

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 similarity
  - e.g., user profiles, item profiles
- We already know how to do this!
  - Near-neighbor search in high dimensions (LSH)
  - Dimensionality reduction

Dimensionality reduction



The bubbles above represent products sized by sales volume. Products close to each other are recommended to each other.