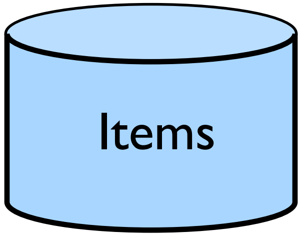
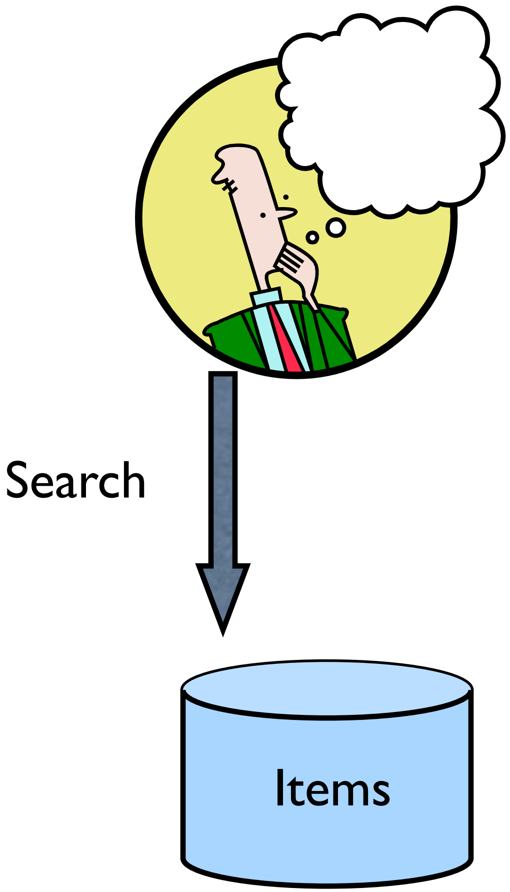
Recommendation Systems

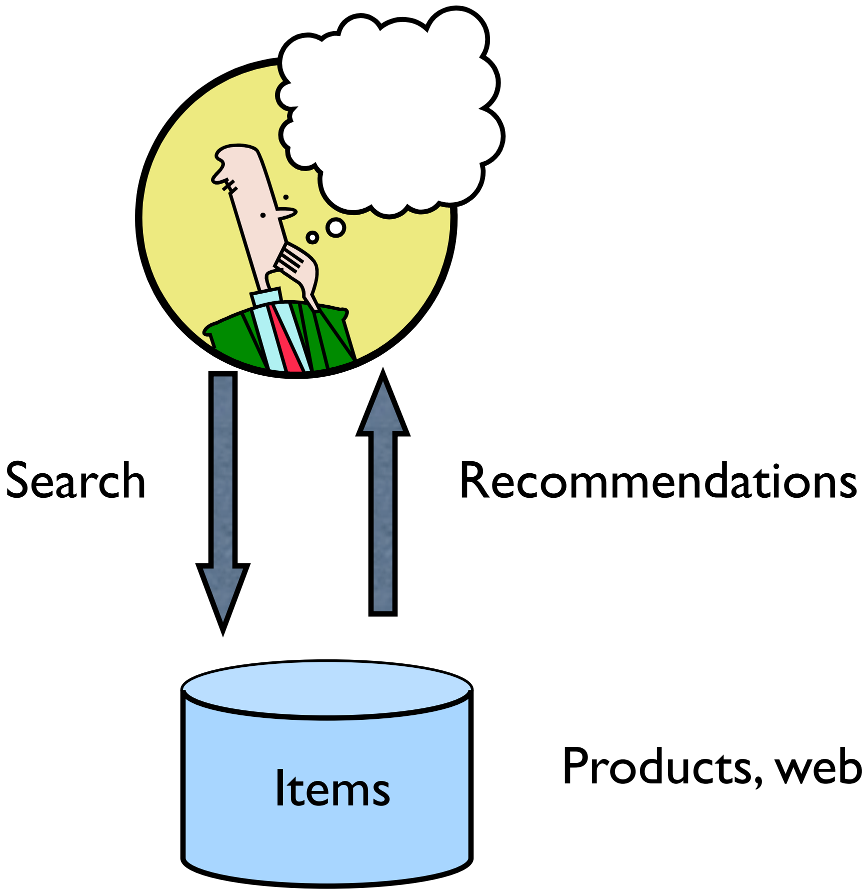
Thanks to: Anand Rajaraman, Jeffrey D. Ullman



Products, web sites, blogs, news items, …



Products, web sites, blogs, news items, …



Products, web sites, blogs, news items, …

From Scarcity to Abundance

From Scarcity to Abundance

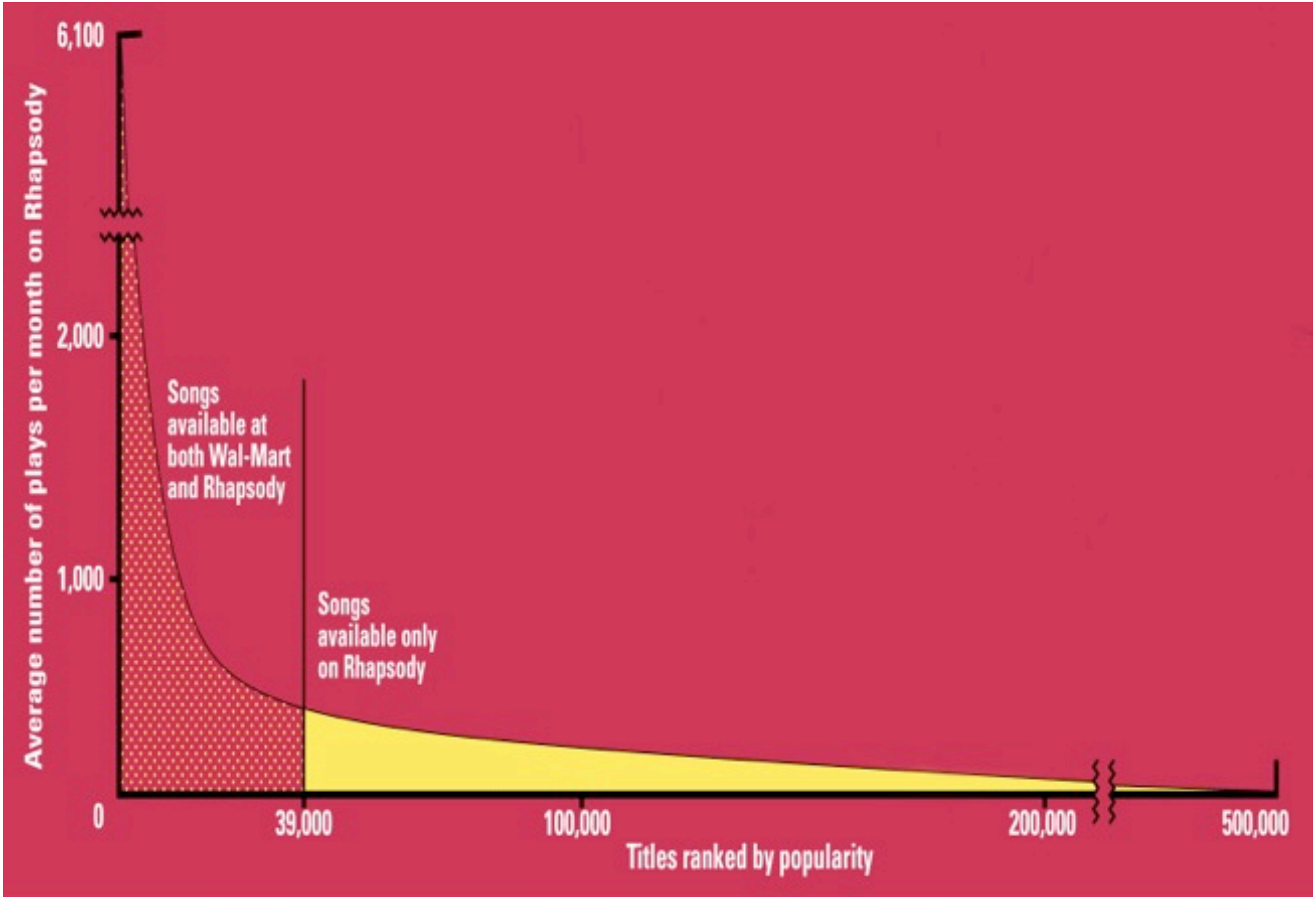
- Shelf space is a scarce commodity for traditional retailers
  - Also: TV networks, movie theaters,…

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

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



Source: Chris Anderson (2004)

Recommendation Types

Recommendation Types

- Editorial

Recommendation Types

- Editorial
- Simple aggregates
  - Top 10, Most Popular, Recent Uploads

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

Key Problems

- Gathering "known" ratings for matrix

Key Problems

- Gathering "known" ratings for matrix
- Extrapolate unknown ratings from known ratings
    - Mainly interested in high unknown ratings

Key Problems

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

Gathering Ratings

Gathering Ratings

- Explicit
    - Ask people to rate items
    - Doesn’t work well in practice – people can’t be bothered

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

Extrapolating Utilities

- Key problem: matrix U is sparse
  - most people have not rated most items

Extrapolating Utilities

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

Content-based recommendations

Content-based recommendations

- Main idea: recommend items to customer C similar to previous items rated highly by C

Content-based recommendations

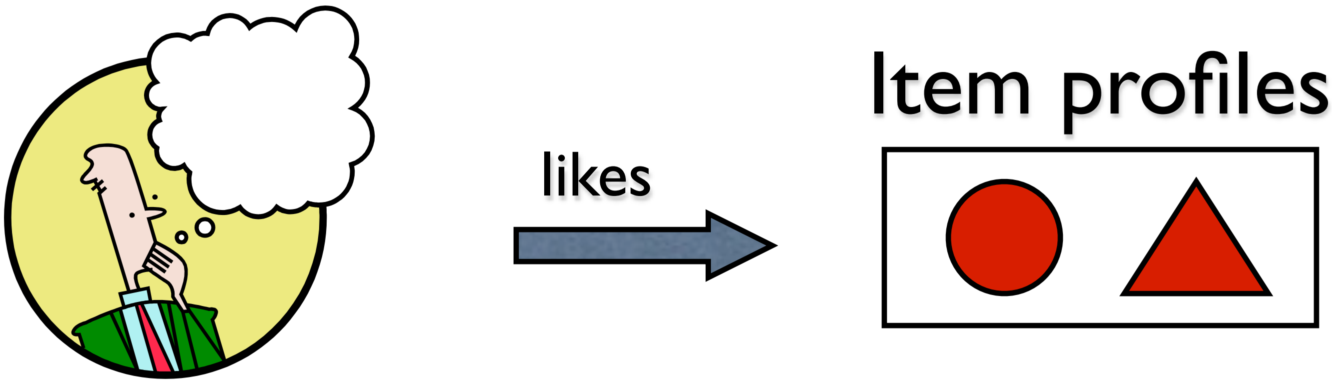
- Main idea: recommend items to customer C similar to previous items rated highly by C
- Movie recommendations
  - recommend movies with same actor(s), director, genre, …

Content-based recommendations

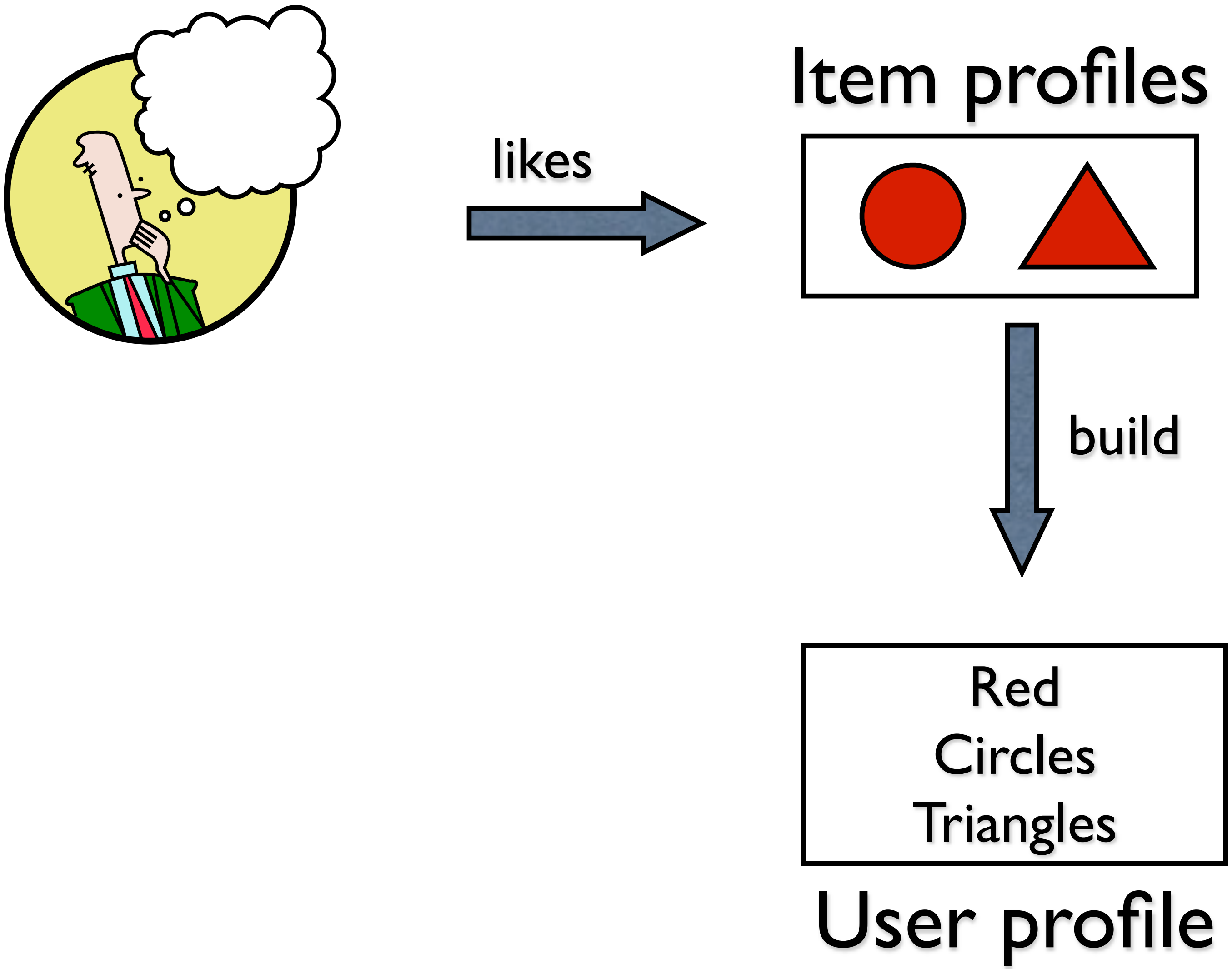
- Main idea: recommend items to customer C similar to previous items rated highly by C
- Movie recommendations
  - recommend movies with same actor(s), director, genre, …
- Websites, blogs, news
  - recommend other sites with "similar" content

Plan of Action

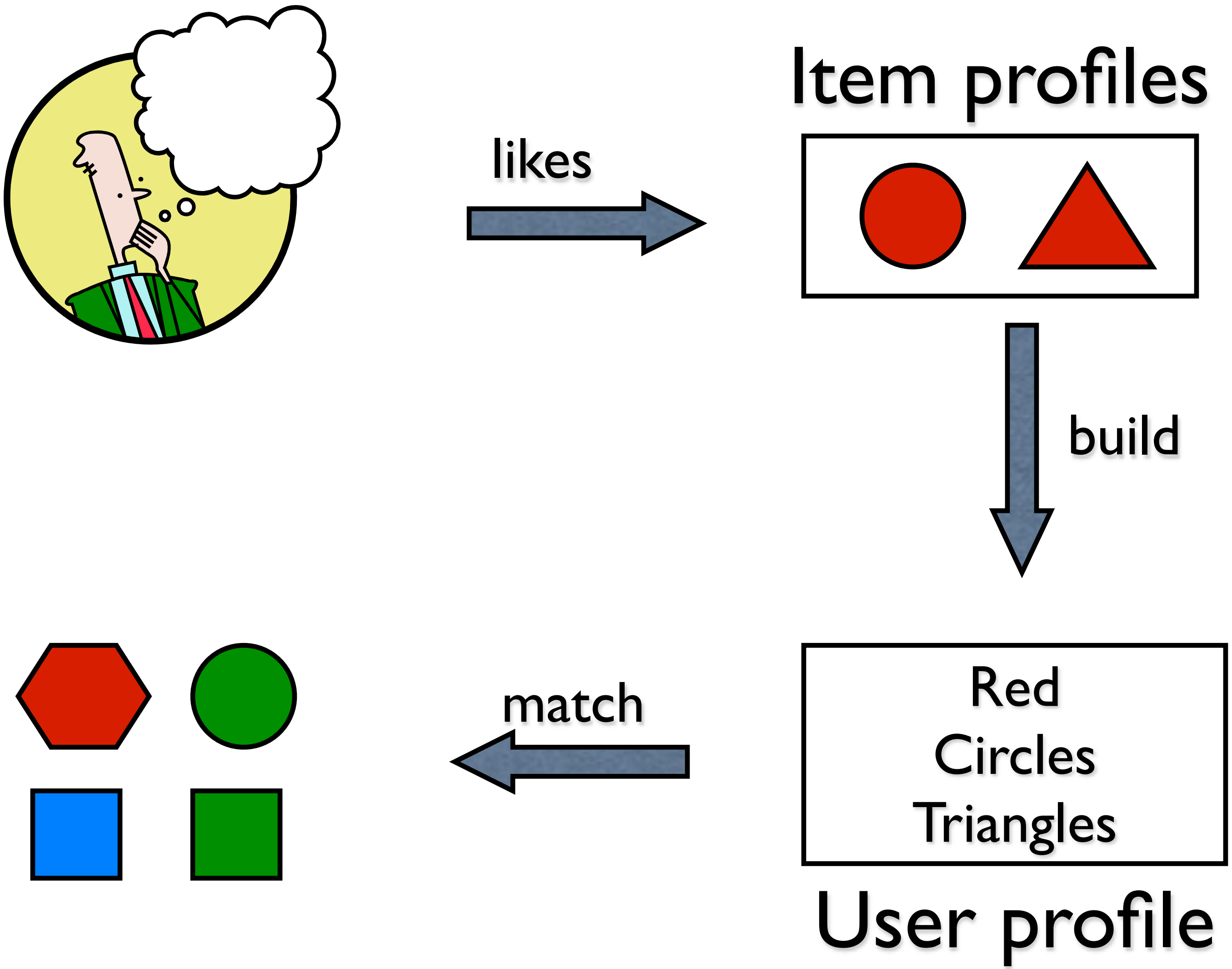
Plan of Action



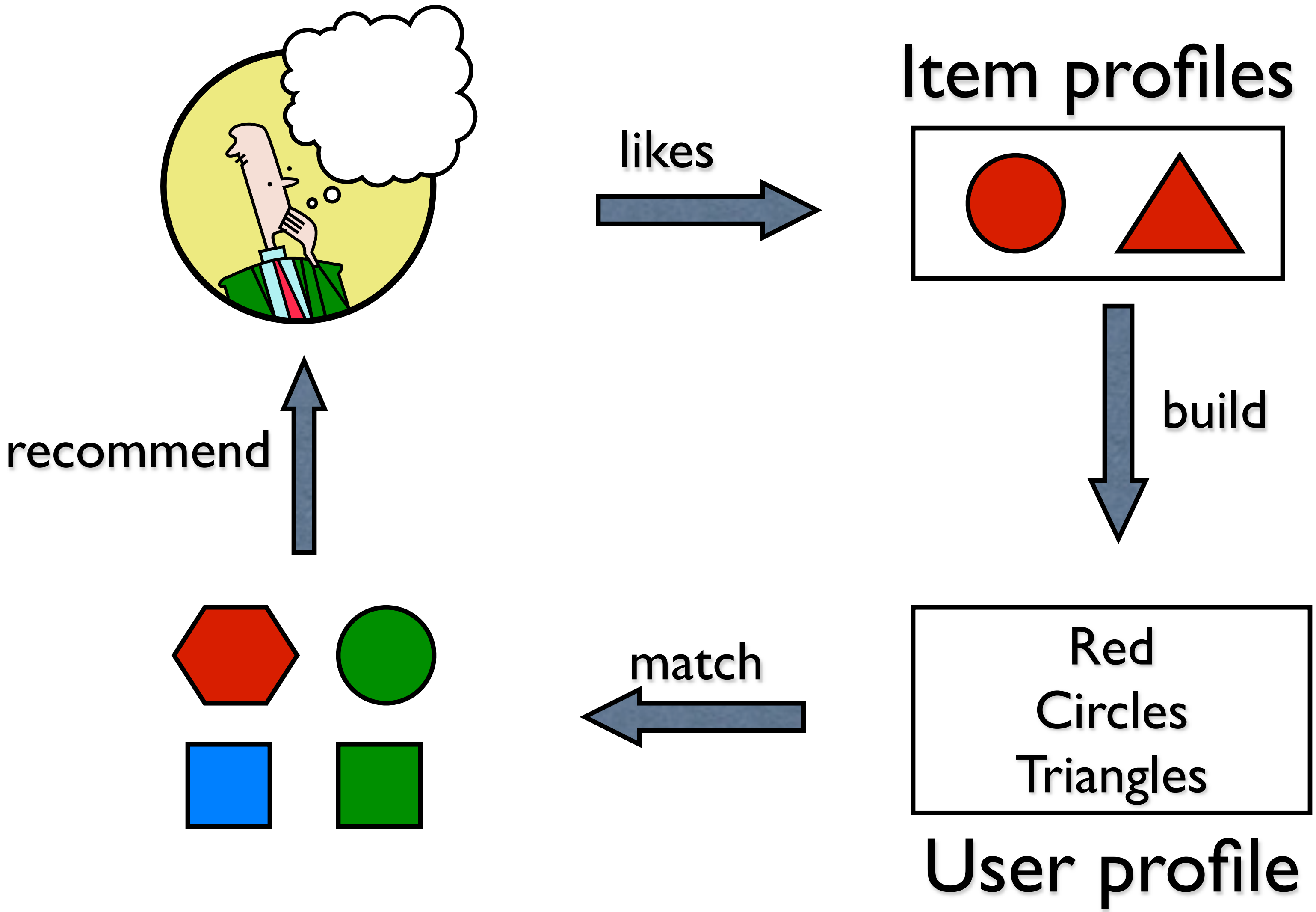
Plan of Action



Plan of Action



Plan of Action



Item Profiles

Item Profiles

- For each item, create an item profile

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

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 profiles and prediction

- User profile possibilities:

User profiles and prediction

- User profile possibilities:
  - Weighted average of rated item profiles

User profiles and prediction

- User profile possibilities:
  - Weighted average of rated item profiles
  - Variation: weight by difference from average rating for item ...

User profiles and prediction

- User profile possibilities:
  - Weighted average of rated item profiles
  - Variation: weight by difference from average rating for item ...
- Prediction heuristic

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**|)

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 $\mathbf{c}$ and item profile $\mathbf{s}$, 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

Model-based approaches

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,

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,
- Apply classifier to each item to find recommendation candidates

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,
- Apply classifier to each item to find recommendation candidates
- Problem: scalability -- will not investigate further

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,
- Apply classifier to each item to find recommendation candidates
- Problem: scalability -- will not investigate further

Limitations of content-based approach

Limitations of content-based approach

- Finding the appropriate features
    - e.g., images, movies, music

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

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

Similar Users

- Let r_x be the vector of user x's ratings

Similar Users

- Let r_x be the vector of user x's ratings
- Cosine similarity measure
  - $sim(x,y) = cos(r_x , r_y)$

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

Similar Users

- Let r_x be the vector of user x's ratings
- Cosine similarity measure
  - sim(x,y) = cos(r_x , r_y)

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

- Pearson correlation coefficient
  - S_{xy} = items rated by both users x and y

Complexity

Complexity

- Expensive step is finding k most similar customers

Complexity

- Expensive step is finding k most similar customers
  - $O(|U|)$

Complexity

- Expensive step is finding k most similar customers
  - O(|U|)
- Too expensive to do at runtime

Complexity

- Expensive step is finding k most similar customers
  - O(|U|)
- Too expensive to do at runtime
  - Need to pre-compute

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 $O(N|U|)$

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

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

Item-item collaborative filtering

- So far: User-user collaborative filtering

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

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

Pros and Cons of Collaborative Filtering

- Works for any kind of item
  - No feature selection needed

Pros and Cons of Collaborative Filtering

- Works for any kind of item
  - No feature selection needed
- New user problem

Pros and Cons of Collaborative Filtering

- Works for any kind of item
  - No feature selection needed
- New user problem
- New item problem

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

Hybrid Methods

- Implement two separate recommenders and combine predictions

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

Evaluating Predictions

Evaluating Predictions

- Compare predictions with known ratings
    - Root-mean-square error (RMSE)

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
- In practice, we care only to predict high ratings
    - RMSE might penalize a method that does well for high ratings and badly for others

Add Data

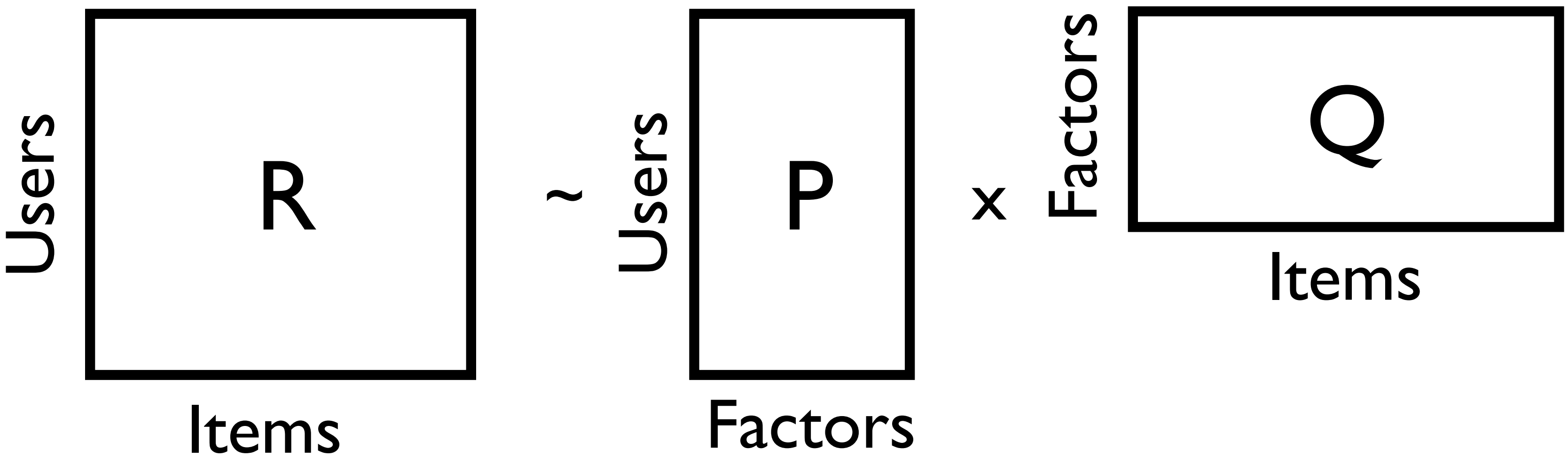
- Leverage all the data
  - Don't try to reduce data size in an effort to make fancy algorithms work
  - Simple methods on large data do best
- Add more data
  - e.g., add IMDB data on genres
- More Data Beats Better Algorithms

http://anand.typepad.com/datawocky/2008/03/more-data-usual.html

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
  - e.g., user profiles, item profiles

Latent Factors



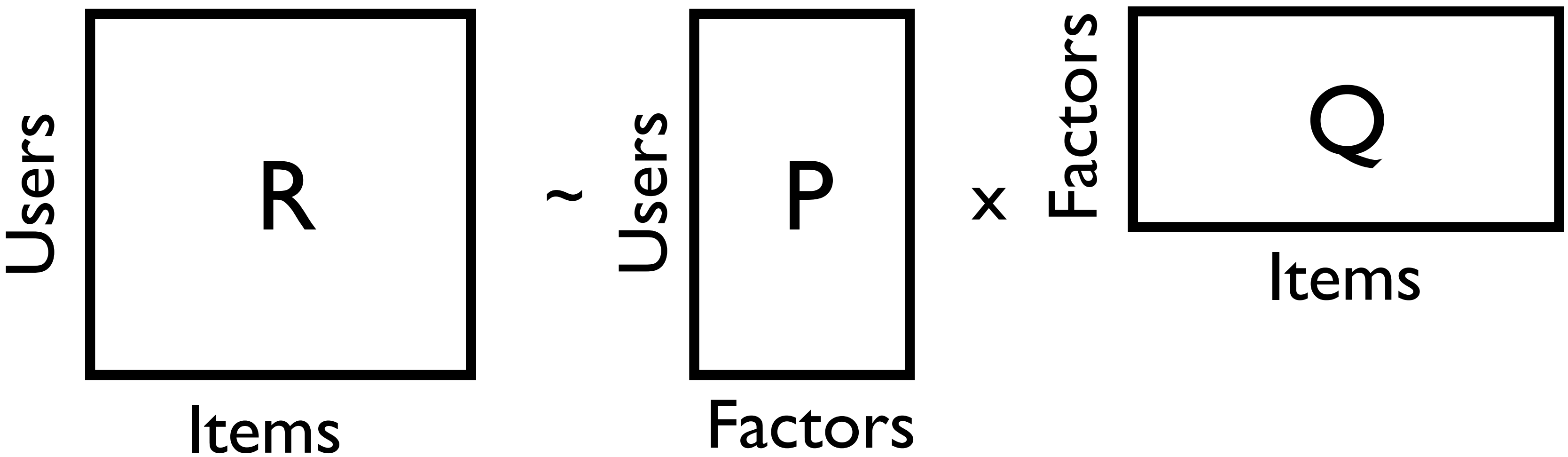
How can we compute matrices P and Q such that R = PxQ

Computing Latent Factors

$$\min_{P,Q} \sum_{(i,j)\in R} \left(R(i,j) - P(i,:)Q(:,j)\right)^2$$

- SVD could be used but we have **missing entries**
- Specialized methods!

Computing Latent Factors



$$\min_{P,Q} \sum_{(i,j)\in R} (R(i,j) - P(i,:)Q(:,j))^2$$

Computing Latent Factors

$$\min_{P,Q} \sum_{(i,j)\in R} (R(i,j) - P(i,:)Q(:,j))^2$$

- SVD:

$$\min_{V,\Sigma,U} \sum_{(i,j)\in R} \left(R(i,j) - (U\Sigma V^T)(i,j)\right)^2$$

$$P = U \quad Q = \Sigma V^T$$

Dealing with missing entries

- **Want to:** minimize Sum Square Error (SSE) on unseen test data

- **Idea:** Minimize SSE on training data

$$\min_{P,Q} \sum_{(i,j)\ \text{Training}} \left(R(i,j) - P(i,:)Q(:,j)\right)^2 + \lambda \left(\sum_{i,j} P(i,j)^2 + \sum_{i,j} Q(i,j)^2 \right)$$