Recommendation Systems

Slides by: Anand Rajaraman, Jeffrey D. Ullman
Search Recommendations

Items

Products, web sites, blogs, news items, …
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
Recommendation Types

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

- $C = \text{set of Customers}$
- $S = \text{set of Items}$
- Utility function $u: C \times S \rightarrow R$
- $R = \text{set of ratings}$
- $R$ is a totally ordered set
- e.g., 0-5 stars, real number in $[0,1]$
<table>
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<th></th>
<th>King Kong</th>
<th>LOTR</th>
<th>Matrix</th>
<th>Nacho Libre</th>
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<td>0.2</td>
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<td>Carol</td>
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<td>David</td>
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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

recommend

likes

match

User profile

Item profiles

Red
Circles
Triangles
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 TFIDF (Term Frequency times Inverse Doc Frequency)
**TF.IDF**

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

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

$n_i = \text{number of docs that mention term } i$

$N = \text{total number of docs}$

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

**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 $\mathbf{c}$ and item profile $\mathbf{s}$, estimate $u(\mathbf{c}, \mathbf{s}) = \cos(\mathbf{c}, \mathbf{s}) = \frac{\mathbf{c} \cdot \mathbf{s}}{||\mathbf{c}|| ||\mathbf{s}||}$
  
  • 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,
- Apply classifier to each item to find recommendation candidates
- Problem: scalability -- will not investigate further
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

• $\text{sim}(x,y) = \cos(r_x, r_y)$

• Pearson correlation coefficient

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

• $S_{xy} =$ items rated by both users $x$ and $y$
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
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 $R = P \times Q$
Computing Latent Factors

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

- 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:**

\[
\min_{V, \Sigma, U} \sum_{(i, j) \in R} (R(i, j) - (U\Sigma V^T)(i, j))^2
\]

\[
P = U \quad Q = \Sigma V^T
\]
Dealing with missing entries

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

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

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