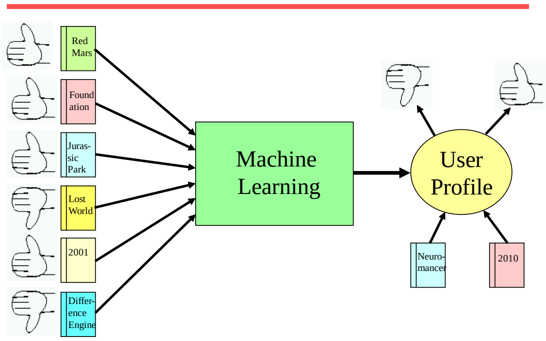
Recommender Systems

Collaborative Filtering &
Content-Based Recommending
Slides based on R. Mooney's class

Recommender Systems

- Systems for recommending items (e.g. books, movies, music, web pages, newsgroup messages) to users based on examples of their preferences.
- Many on-line stores provide recommendations (e.g. Amazon, Netflix).
- Recommenders have been shown to substantially increase sales at on-line stores.
- There are two basic approaches to recommending:
  - Collaborative Filtering (a.k.a. social filtering)
  - Content-based

Book Recommender

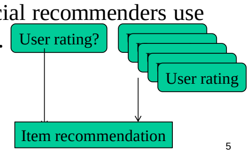


Personalization

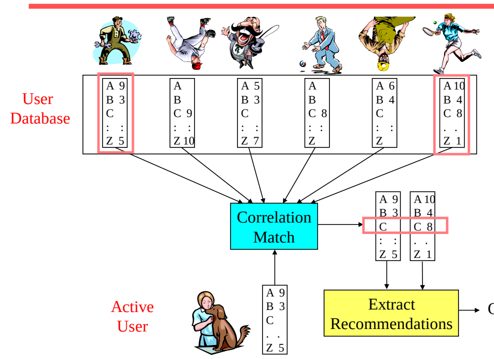
- Recommenders are instances of personalization software.
- Personalization concerns adapting to the individual needs, interests, and preferences of each user.
- Includes:
  - Recommending
  - Filtering
  - Predicting
- From a business perspective, it is viewed as part of Customer Relationship Management (CRM).

Collaborative Filtering

- Maintain a database of many users' ratings of a variety of items.
- For a given user, find other similar users whose ratings strongly correlate with the current user.
- Recommend items rated highly by these similar users, but not rated by the current user.
- Almost all existing commercial recommenders use this approach (e.g. Amazon).



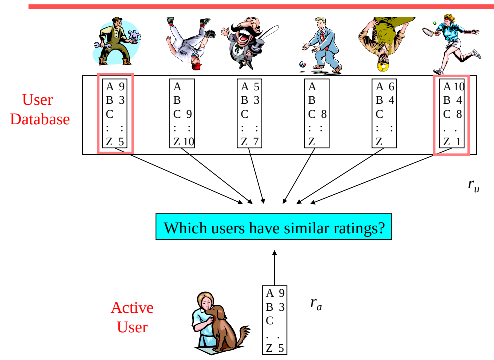
Collaborative Filtering



Collaborative Filtering Method

1. Weight all users with respect to similarity with the active user.
2. Select a subset of the users (*neighbors*) to use as predictors.
3. Normalize ratings and compute a prediction from a weighted combination of the selected neighbors' ratings.
4. Present items with highest predicted ratings as recommendations.

Find users with similar ratings/interests



Similarity Weighting

- Typically use Pearson correlation coefficient between ratings for active user, *a*, and another user, *u*.

$$c_{a,u} = \frac{\text{covar}(r_a, r_u)}{\sigma_{r_a} \sigma_{r_u}}$$

r_a and r_u are the ratings vectors for the m items rated by **both** *a* and *u*

$r_{i,j}$ is user *i*'s rating for item *j*

Covariance and Standard Deviation

- Covariance:

$$\text{covar}(r_a, r_u) = \frac{\sum_{i=1}^{m} (r_{a,i} - \bar{r}_a)(r_{u,i} - \bar{r}_u)}{m}$$

$$\bar{r}_x = \frac{\sum_{i=1}^{m} r_{x,i}}{m}$$

- Standard Deviation:

$$\sigma_{r_x} = \sqrt{\frac{\sum_{i=1}^{m} (r_{x,i} - \bar{r}_x)^2}{m}}$$

Relationship between Covariance and Cosine Similarity

- Covariance:

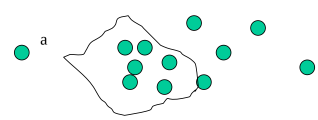
$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y}$$

- Cosine similarity:

$$r = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}}$$

Neighbor Selection

- For a given active user, *a*, select correlated users to serve as source of predictions.
  - Standard approach is to use the most similar n users, *u*, based on similarity weights, $w_{a,u}$
  - Alternate approach is to include all users whose similarity weight is above a given threshold. Sim(r_a, r_u)> t



Significance Weighting

- Important not to trust correlations based on very few co-rated items.
- Include *significance weights*, $s_{a,u}$, based on number of co-rated items, m.

$$w_{a,u} = s_{a,u} c_{a,u}$$

$$s_{a,u} = \begin{Bmatrix} 1 \text{ if } m > 50 \\ \dfrac{m}{50} \text{ if } m \le 50 \end{Bmatrix}$$

Rating Prediction (Version 0)

- Predict a rating, $p_{a,i}$, for each item i, for active user, a, by using the n selected neighbor users, $u \in \{1,2,\ldots n\}$.
- Weight users' ratings contribution by their similarity to the active user.

$$p_{a,i} = \frac{\sum_{u=1}^{n} w_{a,u} r_{u,i}}{\sum_{u=1}^{n} w_{a,u}}$$

Rating Prediction (Version 1)

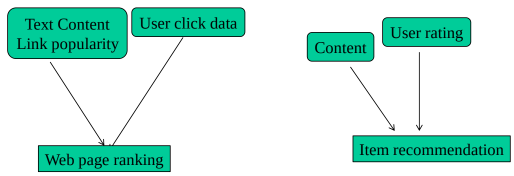
- Predict a rating, $p_{a,i}$, for each item i, for active user, a, by using the n selected neighbor users, $u \in \{1,2,\ldots n\}$.
- To account for users different ratings levels, base predictions on *differences* from a user's *average* rating.
- Weight users' ratings contribution by their similarity to the active user.

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^{n} w_{a,u} (r_{u,i} - \bar{r}_u)}{\sum_{u=1}^{n} w_{a,u}}$$

Problems with Collaborative Filtering

- **Cold Start**: There needs to be enough other users already in the system to find a match.
- **Sparsity**: If there are many items to be recommended, even if there are many users, the user/ratings matrix is sparse, and it is 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.

Recommendation vs Web Ranking



Content-Based Recommending

- Recommendations are based on information on the content of items rather than on other users' opinions.
- Uses a machine learning algorithm to induce a profile of the users preferences from examples based on a featural description of content.
- Applications:
  - News article recommendation

Advantages of 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.

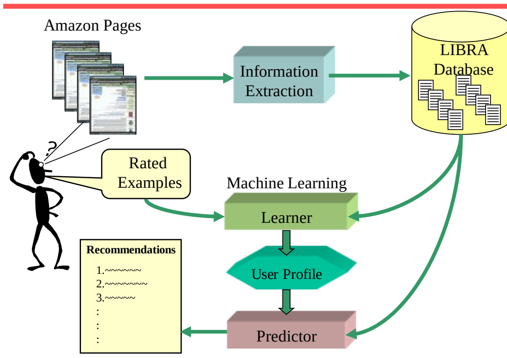
Disadvantages of Content-Based Method

- Requires content that can be encoded as meaningful features.
- Users' tastes must be represented as a learnable function of these content features.
- Unable to exploit quality judgments of other users.
  - Unless these are somehow included in the content features.

LIBRA
Learning Intelligent Book Recommending Agent

- Content-based recommender for books using information about titles extracted from Amazon.
- Uses information extraction from the web to organize text into fields:
  - Author
  - Title
  - Editorial Reviews
  - Customer Comments
  - Subject terms
  - Related authors
  - Related titles

LIBRA System



Sample Extracted Amazon Book Information

Title: <The Age of Spiritual Machines: When Computers Exceed Human Intelligence>
Author: <Ray Kurzweil>
Price: <11.96>
Publication Date: <January 2000>
ISBN: <0140282025>
Related Titles: <Title: <Robot: Mere Machine or Transcendent Mind>
Author: <Hans Moravec> >
…
Reviews: <Author: <Amazon.com Reviews> Text: <How much do we humans…> >
…
Comments: <Stars: <4> Author: <Stephen A. Haines> Text:<Kurzweil has …> >
…
Related Authors: <Hans P. Moravec> <K. Eric Drexler>…
Subjects: <Science/Mathematics> <Computers> <Artificial Intelligence> …

Libra Content Information

- Libra uses this extracted information to form “bags of words” for the following slots:
  - Author
  - Title
  - Description (reviews and comments)
  - Subjects
  - Related Titles
  - Related Authors

Libra Overview

- User rates selected titles on a 1 to 10 scale.
- Use a Bayesian algorithm to learn
  - Rating 6–10: Positive
  - Rating 1–5: Negative
- The learned classifier is used to rank all other books as recommendations.
- User can also provide explicit positive/negative keywords, which are used as priors to bias the role of these features in categorization.

Bayesian Categorization in LIBRA

- Model is generalized to generate a **vector** of bags of words (one bag for each slot).
  - Instances of the same word in different slots are treated as separate features:
    - "Chrichton" in author vs. "Chrichton" in description
- Training examples are treated as *weighted* positive or negative examples when estimating conditional probability parameters:
  - An example with rating $1 \leq r \leq 10$ is given:
    positive probability: $(r - 1)/9$
    negative probability: $(10 - r)/9$

Implementation & Weighting

- Stopwords removed from all bags.
- A book's title and author are added to its own related title and related author slots.
- All probabilities are smoothed using Laplace estimation to account for small sample size.
- Feature strength of word w_k appearing in a slot s_j :

$$\text{strength}(w_k, s_j) = \log \frac{P(w_k \mid \text{positive}, s_j)}{P(w_k \mid \text{negative}, s_j)}$$

Experimental Method

- 10-fold cross-validation to generate learning curves.
- Measured several metrics on independent test data:
  - Precision at top 3: % of the top 3 that are positive
  - Rating of top 3: Average rating assigned to top 3
  - Rank Correlation: Spearman's, r_s, between system's and user's complete rankings.
- Test ablation of related author and related title slots (LIBRA-NR).
  - Test influence of information generated by Amazon's collaborative approach.

Experimental Result Summary

- Precision at top 3 is fairly consistently in the 90's% after only 20 examples.
- Rating of top 3 is fairly consistently above 8 after only 20 examples.
- All results are always significantly better than random chance after only 5 examples.
- Rank correlation is generally above 0.3 (moderate) after only 10 examples.
- Rank correlation is generally above 0.6 (high) after 40 examples.

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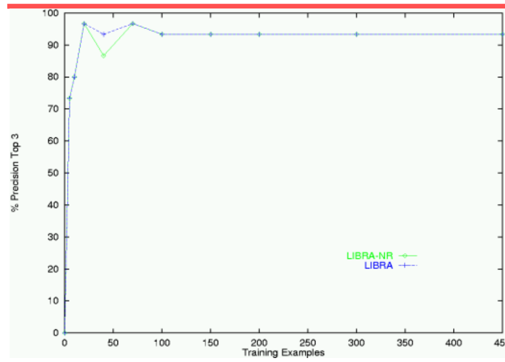
Precision at Top 3 for Science



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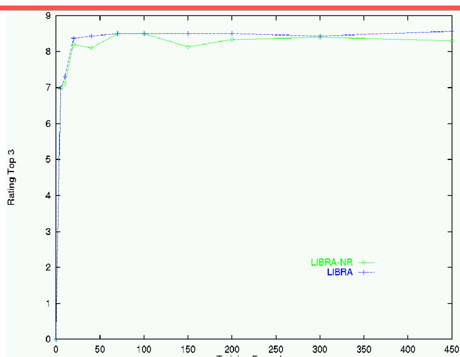
Rating of Top 3 for Science



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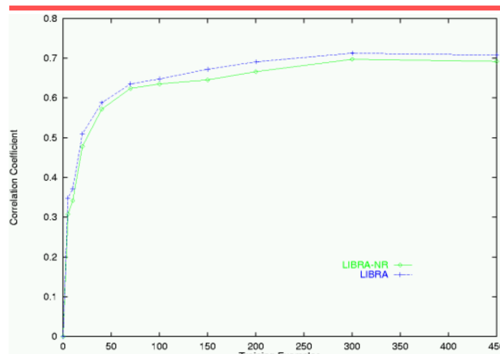
Rank Correlation for Science



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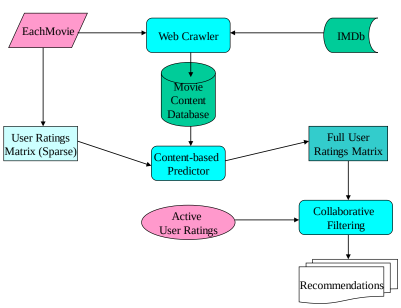
Combining Content and Collaboration

- Content-based and collaborative methods have complementary strengths and weaknesses.
- Combine methods to obtain the best of both.
- Various hybrid approaches:
  - Apply both methods and combine recommendations.
  - Use collaborative data as content.
  - Use content-based predictor as another collaborator.
  - **Use content-based predictor to complete collaborative data.**

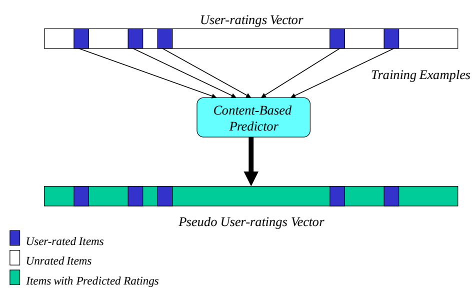
Movie Domain

- *EachMovie* Dataset [Compaq Research Labs]
  - Contains user ratings for movies on a 0–5 scale.
  - 72,916 users (avg. 39 ratings each).
  - 1,628 movies.
  - Sparse user-ratings matrix – (2.6% full).
- Crawled Internet Movie Database (*IMDb*)
  - Extracted content for titles in *EachMovie*.
- Basic movie information:
  - Title, Director, Cast, Genre, etc.
- Popular opinions:
  - User comments, Newspaper and Newsgroup reviews, etc.

Content-Boosted Collaborative Filtering



Content-Boosted CF - I



Content-Boosted CF - II

- Compute pseudo user ratings matrix
  - Full matrix – approximates actual full user ratings matrix
- Perform CF
  - Using Pearson corr. between pseudo user-rating vectors

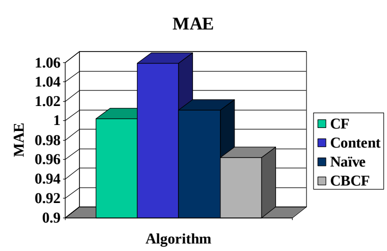
Experimental Method

- Used subset of *EachMovie* (7,893 users; 299,997 ratings)
- Test set: 10% of the users selected at random.
  - Test users that rated at least 40 movies.
  - Train on the remainder sets.
- Hold-out set: 25% items for each test user.
  - Predict rating of each item in the hold-out set.
- Compared CBCF to other prediction approaches:
  - Pure CF
  - Pure Content-based
  - Naïve hybrid (averages CF and content-based predictions)

Metrics

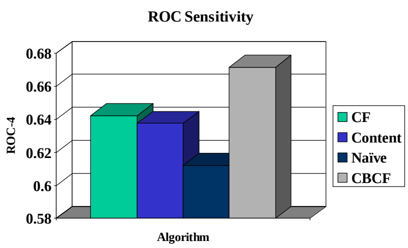
- Mean Absolute Error (MAE)
  - Compares numerical predictions with user ratings
- ROC sensitivity [Herlocker 99]
  - True positive rate: How well predictions help users select *high-quality* items
  - Ratings ≥ 4 considered "good"; < 4 considered "bad"

Results - I



CBCF is significantly better (4% over CF) at (p < 0.001)

Results - II



CBCF outperforms rest (5% improvement over CF)

Conclusions

- Recommending and personalization are important approaches to combating information over-load.
- Machine Learning is an important part of systems for these tasks.
- Collaborative filtering has problems.
- Content-based methods address these problems (but have problems of their own).
- Integrating both is best.