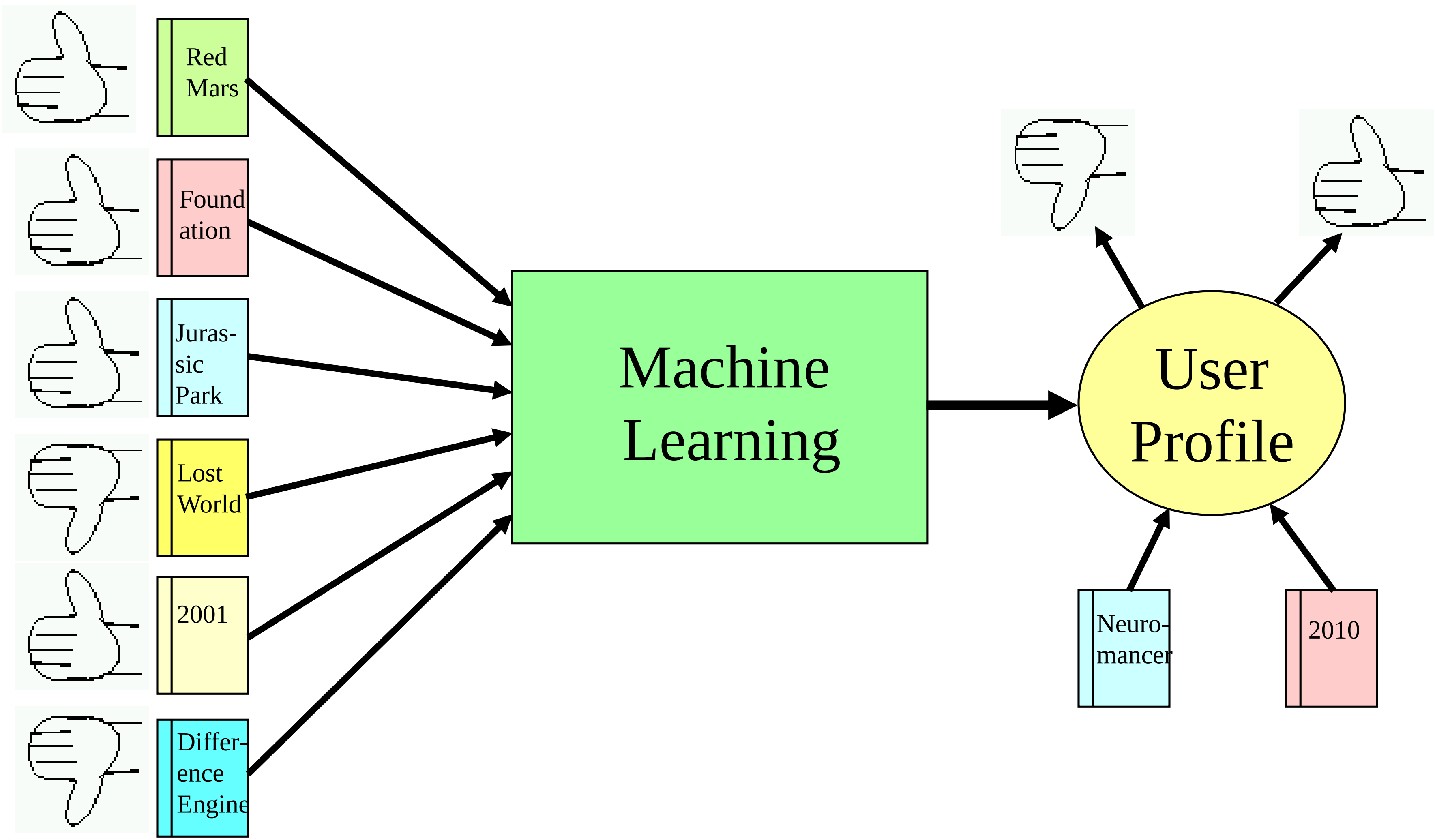
Recommender Systems

Collaborative Filtering &
Content-Based Recommending

Recommender Systems

- Systems for recommending items (e.g. books, movies, CD's, web pages, newsgroup messages) to users based on examples of their preferences.
- Many websites provide recommendations (e.g. Amazon, NetFlix, Pandora).
- 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 (e.g. form or calendar appt. completion)
- From a business perspective, it is viewed as part of Customer Relationship Management (CRM).

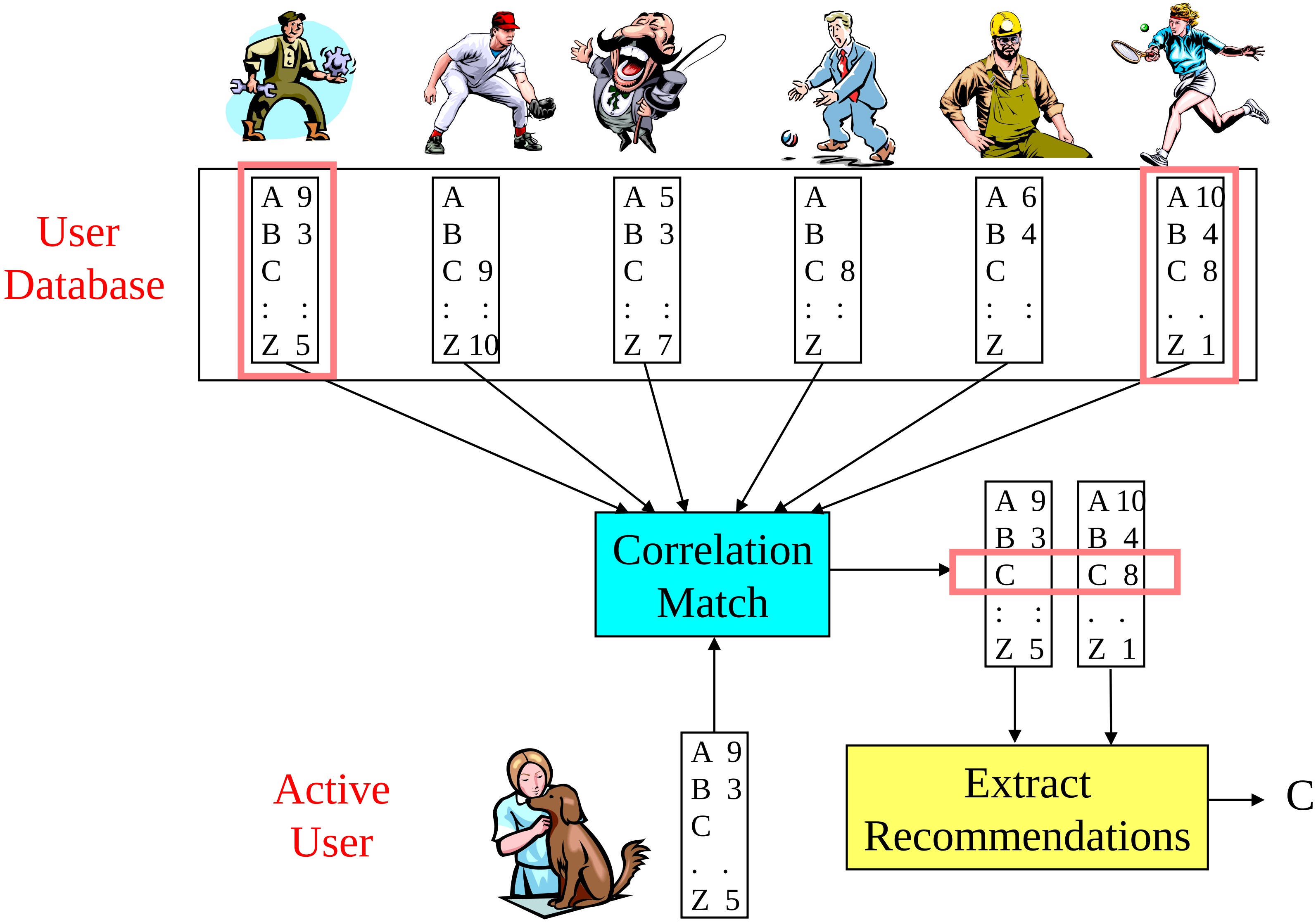
Machine Learning and Personalization

- Machine Learning can allow learning a *user model* or *profile* of a particular user based on:
  - Sample interaction
  - Rated examples
- This model or profile can then be used to:
  - Recommend items
  - Filter information
  - Predict behavior

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

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

Similarity Weighting

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

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

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*

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.

Rating Prediction

- 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.

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.
- Some previous applications:
  - Newsweeder (Lang, 1995)
  - Syskill and Webert (Pazzani et al., 1996)

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

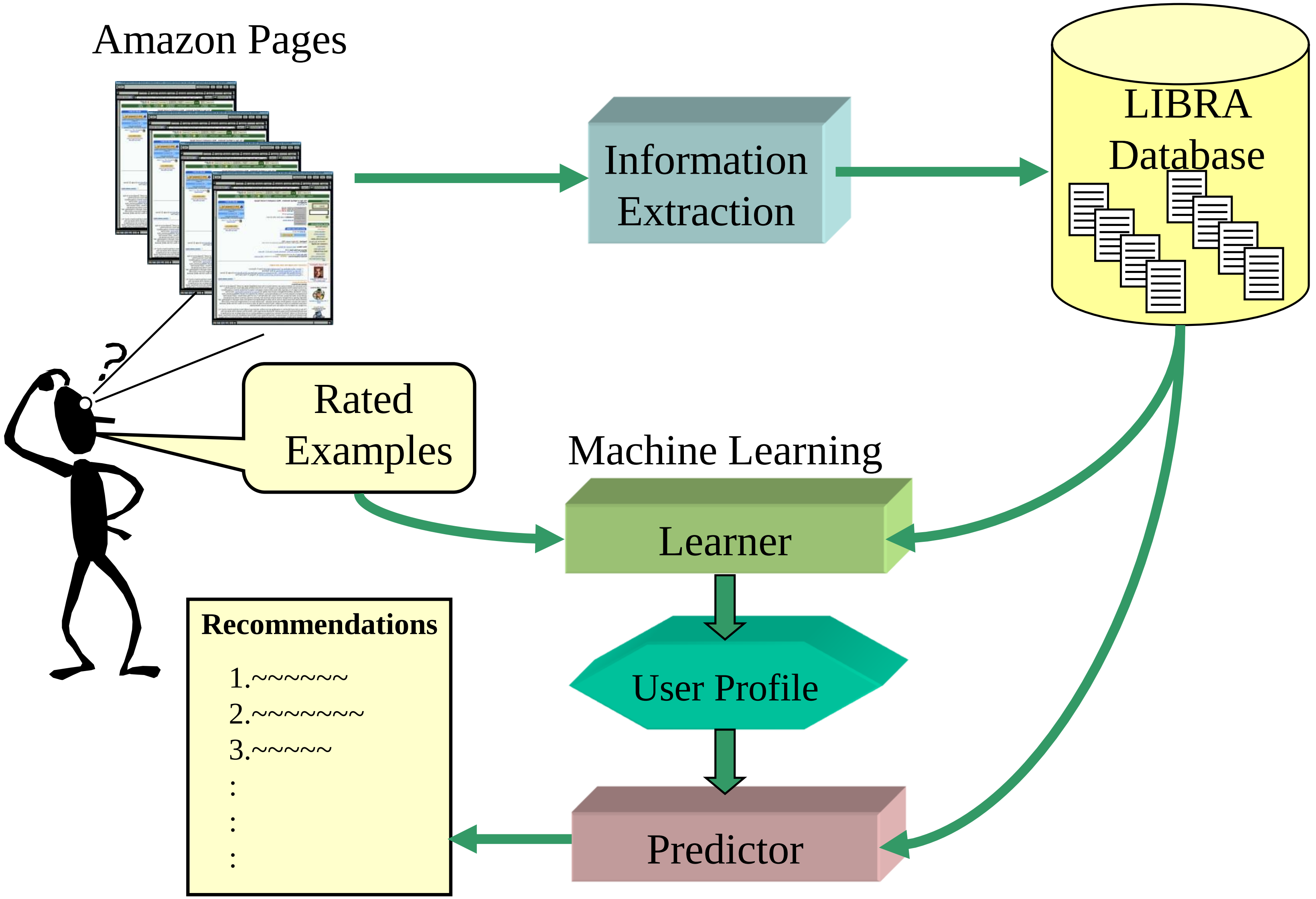
- Requires content that can be encoded as meaningful features.
- Users' tastes must be represented as a learnable function of these content features.
- Unable to exploit quality judgments of other users.
  - Unless these are somehow included in the content features.

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 Amazon Page

Age of Spiritual Machines

Sample Extracted 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.
- Libra uses a naïve Bayesian text-categorization algorithm to learn a profile from these rated examples.
  - Rating 6–10: Positive
  - Rating 1–5: Negative
- The learned profile is used to rank all other books as recommendations based on the computed posterior probability that they are positive.
- 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

- 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.
- Lisp implementation is quite efficient:
  - Training: 20 exs in 0.4 secs, 840 exs in 11.5 secs
  - Test: 200 books per second

Explanations of Profiles and Recommendations

- Feature strength of word w_k appearing in a slot s_j :

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

Experimental Data

- Amazon searches were used to find books in various genres.
- Titles that have at least one review or comment were kept.
- Data sets:
  - Literature fiction: 3,061 titles
  - Mystery: 7,285 titles
  - Science: 3,813 titles
  - Science Fiction: 3.813 titles

Rated Data

- 4 users rated random examples within a genre by reviewing the Amazon pages about the title:
  - LIT1 936 titles
  - LIT2 935 titles
  - MYST 500 titles
  - SCI 500 titles
  - SF 500 titles

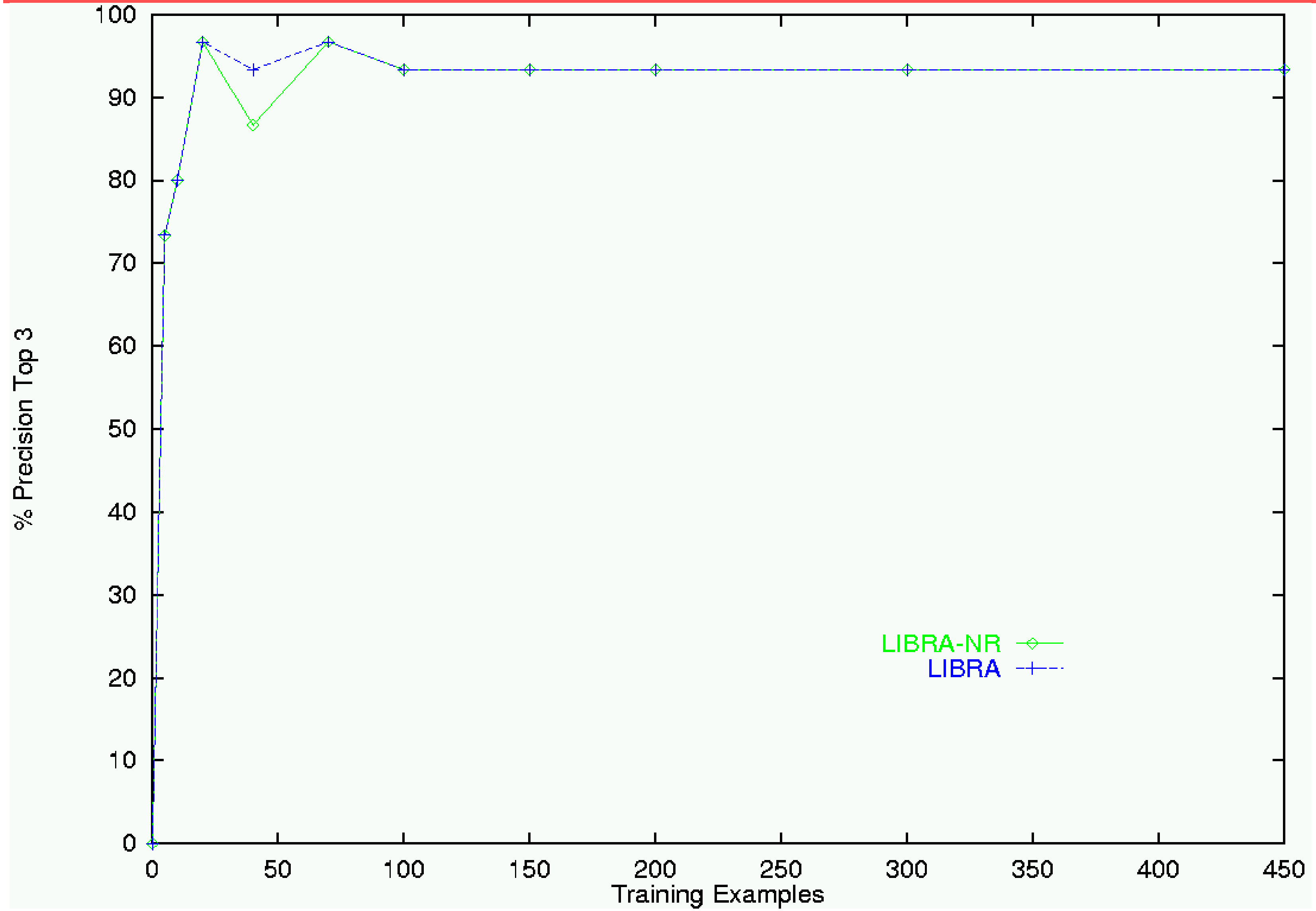
Experimental Method

- 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.

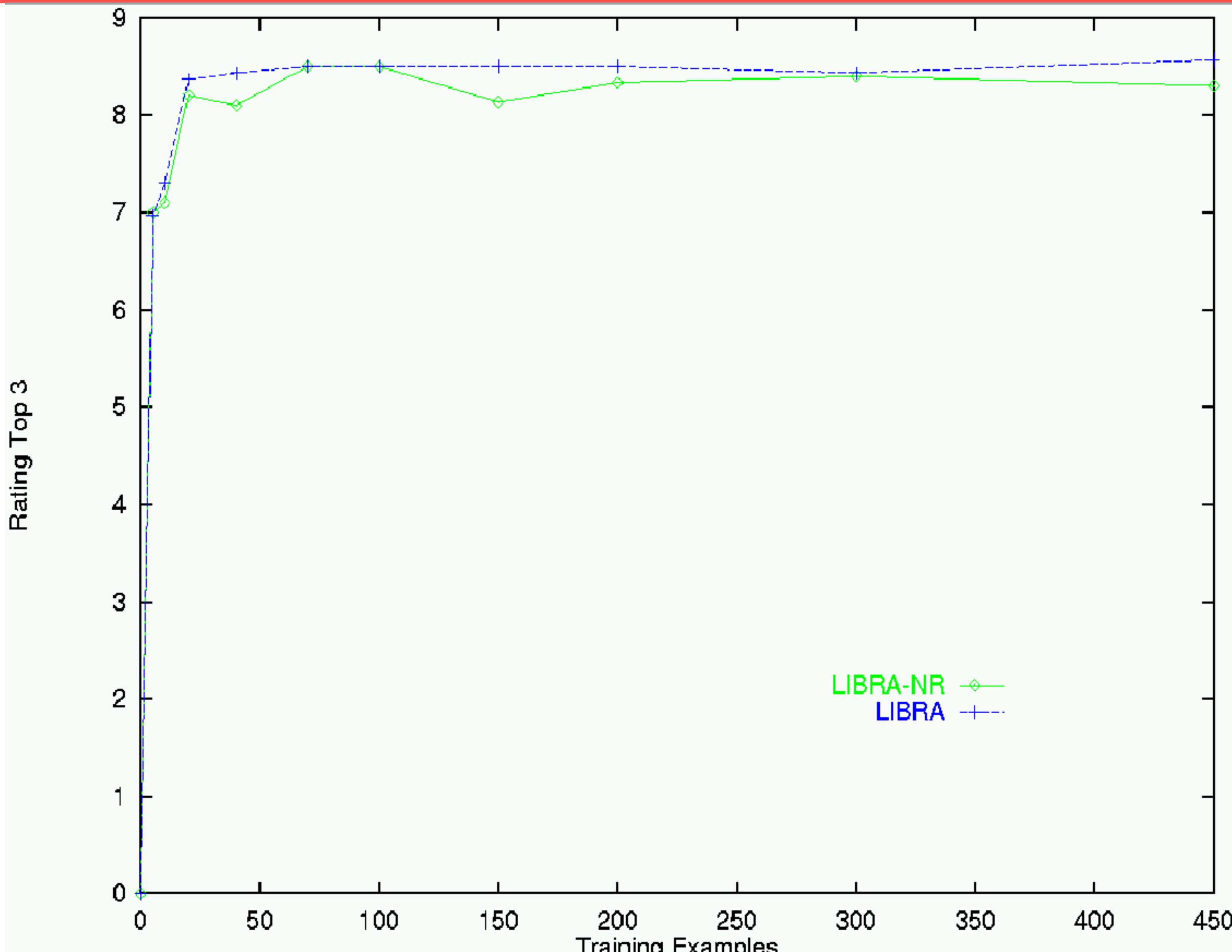
Experimental Result Summary

- 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.

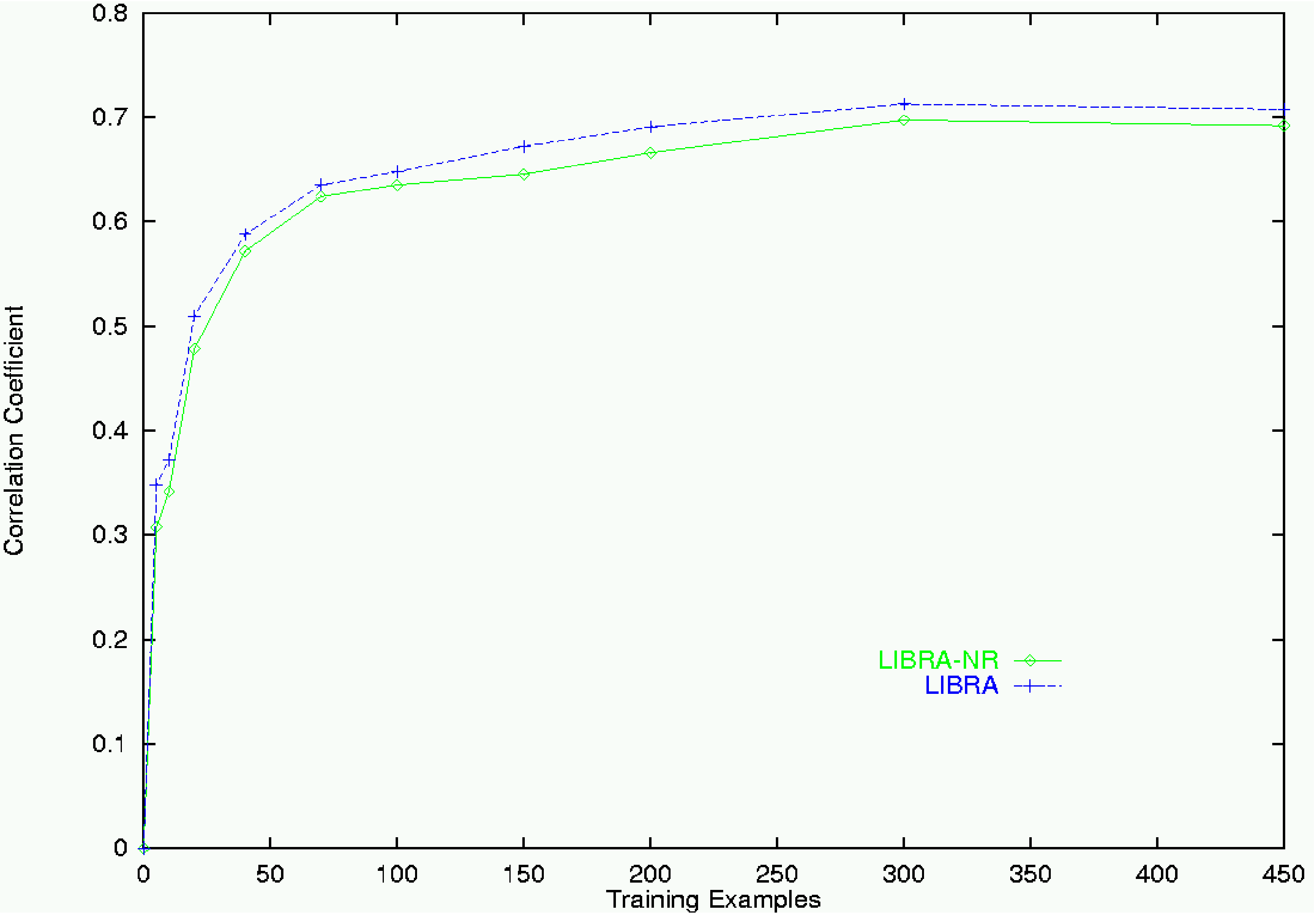
Precision at Top 3 for Science



Rating of Top 3 for Science



Rank Correlation for Science



User Studies

- Subjects asked to use Libra and get recommendations.
- Encouraged several rounds of feedback.
- Rated all books in final list of recommendations.
- Selected two books for purchase.
- Returned reviews after reading selections.
- Completed questionnaire about the system.

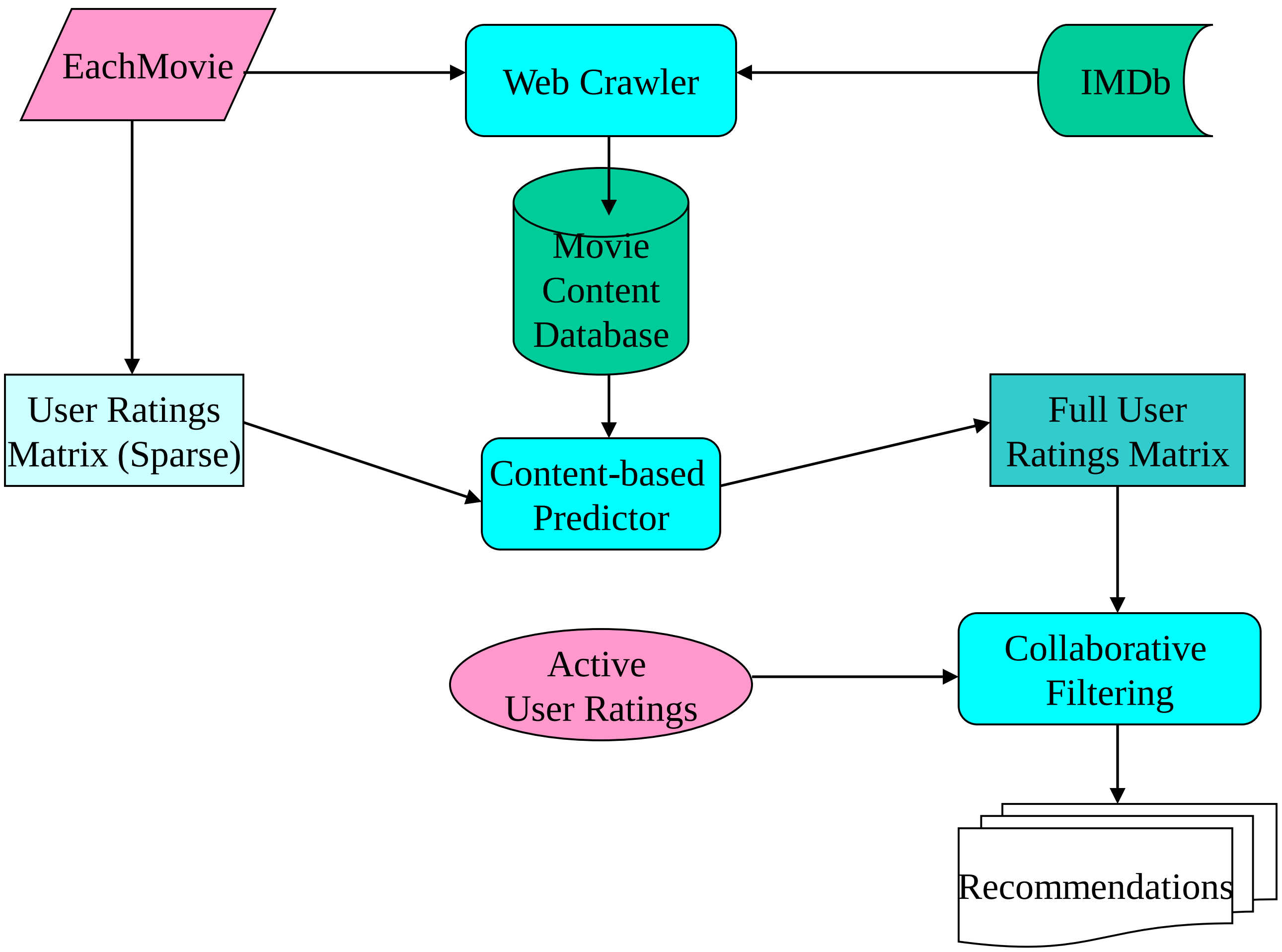
Combining Content and Collaboration

- 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.**

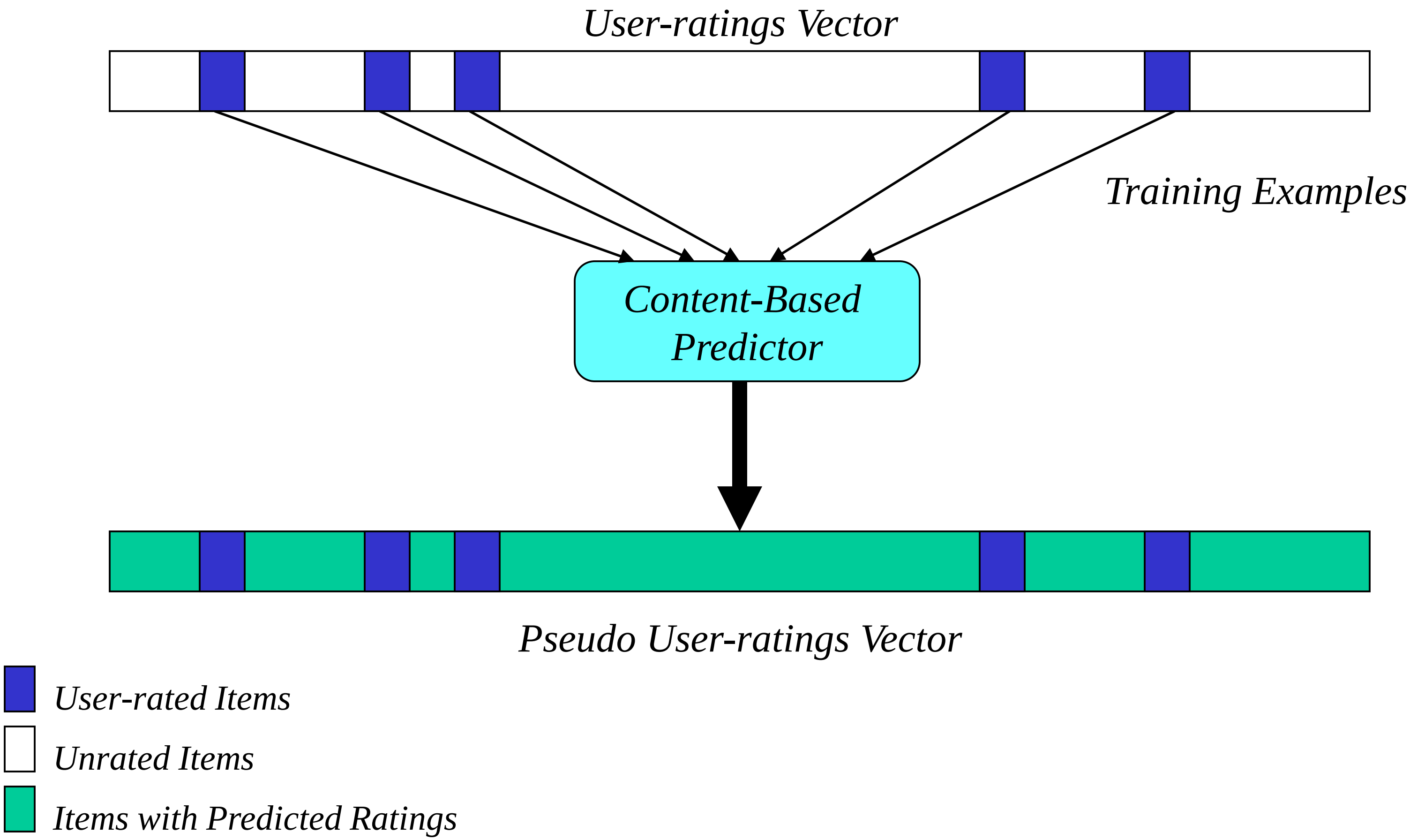
Movie Domain

- *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.

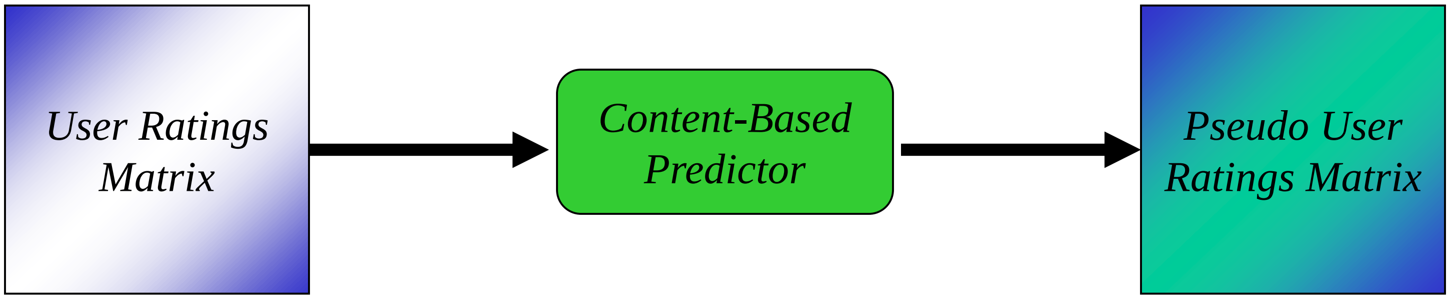
Content-Boosted Collaborative Filtering



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

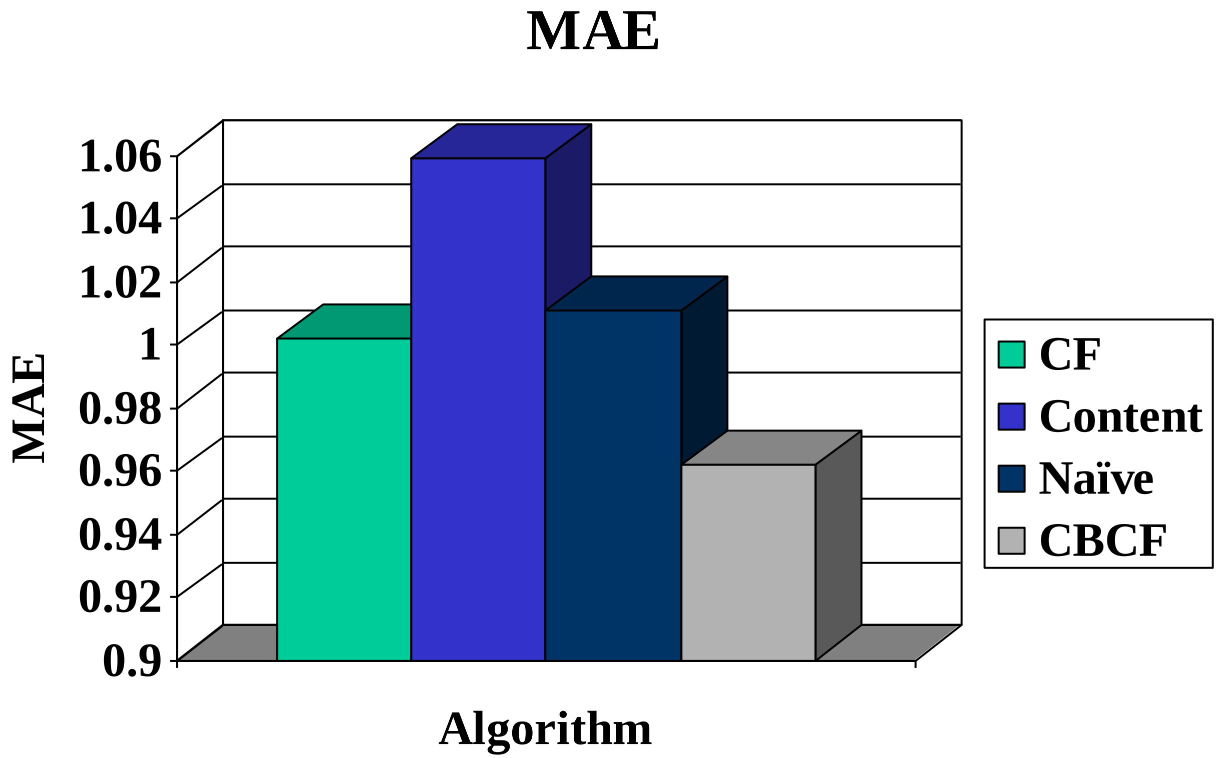
Experimental Method

- 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

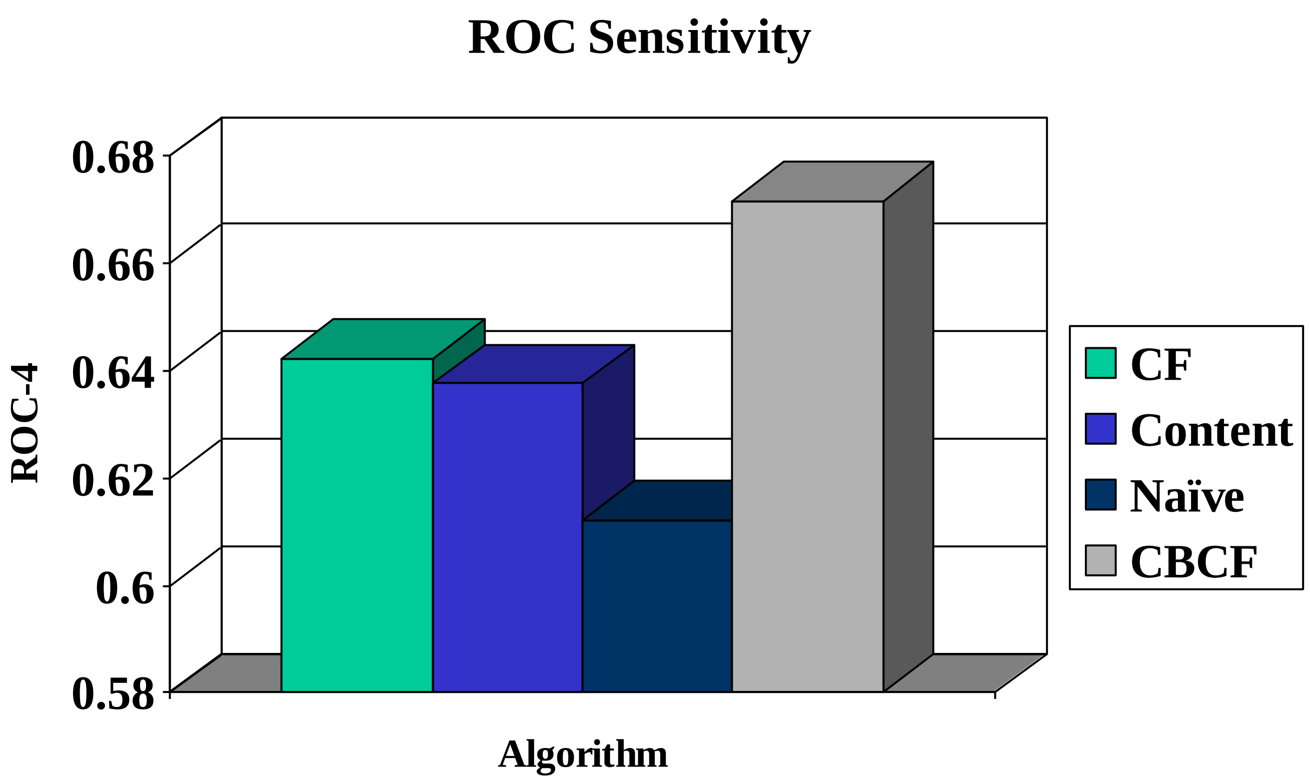
- Mean Absolute Error (MAE)
  - Compares numerical predictions with user ratings
- ROC sensitivity [Herlocker 99]
  - How well predictions help users select *high-quality* items
  - Ratings ≥ 4 considered "good"; < 4 considered "bad"
- Paired t-test for statistical significance

Results - I



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

Results - II



CBCF outperforms rest (5% improvement over CF)

Active Learning
(Sample Section, Learning with Queries)

- Used to reduce the number of training examples required.
- System requests ratings for specific items from which it would learn the most.
- Several existing methods:
  - Uncertainty sampling
  - Committee-based sampling

Semi-Supervised Learning
(Weakly Supervised, Bootstrapping)

- Use wealth of unlabeled examples to aid learning from a small amount of labeled data.
- Several recent methods developed:
  - Semi-supervised EM (Expectation Maximization)
  - Co-training
  - Transductive SVM’s

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.