CSE 8803RS: Recommendation Systems

Cold Start

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A. Schein, A. Popescul, L. Ungar and D. Pennock 2002

University of Pennsylvania and NEC

Problem: Collaborative filtering cannot recommend movies that have no ratings.

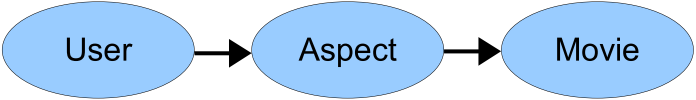
Key idea: Use actors in a new movie to identify similar movies that have been rated.

Other contributions: Use of modified ROC curves for cold-start evaluation.

Advocates uses of heuristic baselines.

Item Cold-Start

- Item-based collaborative filtering: recommend items that are similar to ones the user has rated.
- New movies have no rating history. . . .
- How can we recommend new movies to users in a meaningful way?



$$P(user, movie) = \sum_{aspect} P(user)P(aspect|user)P(movie|aspect) \qquad (1)$$

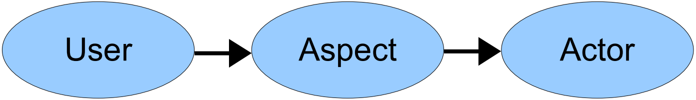
Advantages

- Latent aspects improve generalization.
- Suggestive.

Disadvantage

- Latent aspect of new movie cannot inferred.

Latent Content Aspects



$$P(user, movie) = \sum_{aspect} P(user)P(aspect|user)P(actor|aspect) \qquad (2)$$

EM is used to fit the model.

Folding In New Movies

Recommendations require

$$P(user|movie) = \sum_{aspect} P(user|aspect)P(aspect|movie) \tag{3}$$

Estimate $P(aspect|movie)$ using EM:
Estimation:

$$P(aspect|actor, movie) \propto P(actor|aspect)P(aspect|movie) \tag{4}$$

Maximization:

$$P(aspect|movie) \propto \sum_{actor \in movie} P(aspect|actor, movie) \tag{5}$$

ROC Curves for Evaluation

Complementary Evaluations

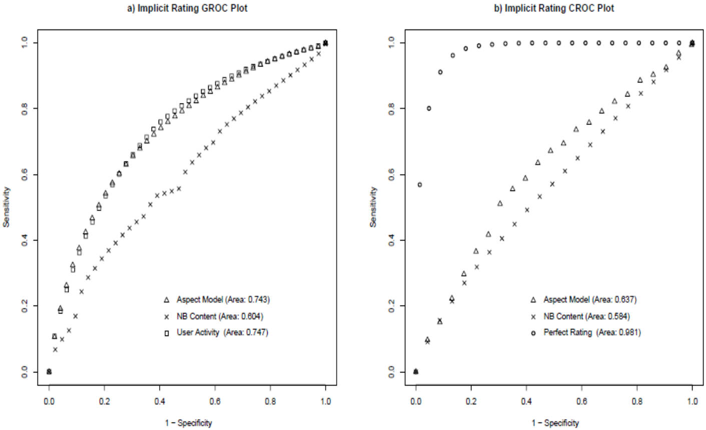
Global ROC (GROC)

- Order all (*user*, *movie*) by the model.
- Recommend the movie in each of the top-k pairs to the corresponding user.
- Plot sensitivity against specificity as k is varied.
- Reflects "easy" cases.

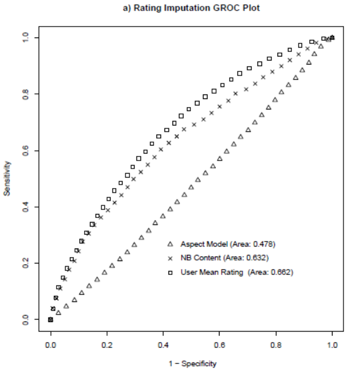
Customer ROC (CROC)

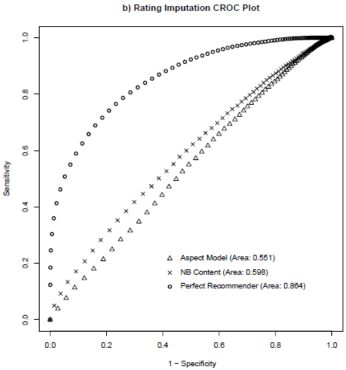
- For each user, order all movies by the model.
- Recommend the top-k movies for each customer.
- Plot sensitivity against specificity as k is varied.
- Reflects "hard" (heavy tail) cases.

Predicting What Will Be Rated



Predicting the Ratings





Discussion

- GROC does not completely describe model performance.
- Aspect model best at predicting what will be rated, but does not know the rating.
- Naïve Bayes provides a weak baseline.
- A well chosen heuristic baseline is ideal for comparison.

Using Structural Content Information for Learning User Profiles

J Huete, L de Campos, J Fernandez-Luna and M Rueda-Morales 2007
University of Granada, Spain

Problem:

- Items in collaborative filtering typically have associated features.
- Existing methods neglected the features in favor of latent profiles.

Key idea: The structure of the features can induce an equivalent and useful structure in the user profile.

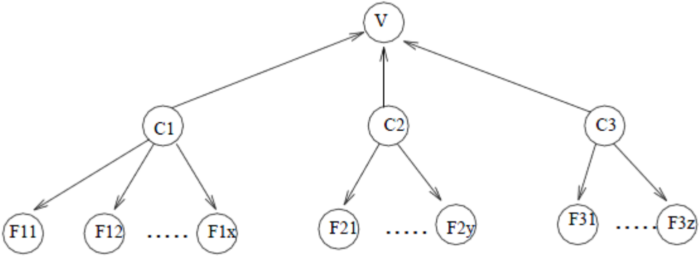
Categories of Features

Assumptions:

- The features can be grouped into categories.
- The user's rating is independent of the features when conditioned on the categories.
- The user's rating is a mixture of the user's ratings for the values of the categories for an item.

Example categories for movies: title, genre, actors, keywords. Features are all boolean, e.g. one feature per possible actor.

Probability Model



- V: Value (rating) of item for user.
- C_i: Value (rating) of category i for this user and item.
- F_{ij}: Feature j of category i for this item.

Algorithm

Estimation: The model is fixed, so if we observed C_i we could easily compute the MLE with Laplace smoothing.
EM is used to simultaneously estimate C_is and model.

Accuracy

Model	%Succ.	Recall	Prec.	F1
Generative	68%	0.7179	0.5714	0.6364
Learning Parameter	64%	0.7692	0.5357	0.6316
Naive Bayes	71%	0.6668	0.5778	0.6190
Learning Profile from Hidden Components	71%	0.6668	0.6190	0.6420

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Rating Patterns

	SP			
LAR	11	12	21	22
111	1.0	1.0	1.0	0.76
112	1.0	1.0	1.0	0.49
121	0.99	0.87	0.86	0.05
122	0.92	0.36	**0.61**	0.20
211	1.0	**0.22**	0.99	0.0
212	0.99	0.44	**0.55**	0.0
221	**0.33**	**0.58**	0.0	0.0
222	0.11	0.47	0.0	0.0

Discussion

- Evaluation is weak (only small synthetic problem).
- Rating pattern problem is an experimental design issue.
- Structural model improves precision—ideal for recommendation.