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APPROACH FOR OUR PROJECT

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CRITIC POINTS

PROBLEM DEFINITION

► Title:

Representation, similarity measures and aggregation methods using fuzzy sets for content-based recommender systems

- ► Movie recommendation
 - ► Build on top of Yager(2003)
- ► Collaborative vs Content-based

PROBLEM DEFINITION

- ► Movie ratings are subjective, imprecise, vague
- ► Same for movie genres

Movies representation in space of genres

	Crime	Horror	Mystery
I_1	1	0	1
G_1	1	0	0.44
I_2	0	1	1
G_2	0	1	0.41

Figure: Fuzzification movie genres

PROPOSED SOLUTION

Different similarity measures

$$S_1(I_k, I_j) = \frac{\sum_{\mathbf{i}} \min(\mu_{x_i}(I_k), \mu_{x_i}(I_j))}{\sum_{\mathbf{i}} \max(\mu_{x_i}(I_k), \mu_{x_i}(I_j))},$$

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Different aggregation methods

$$R_1(I_j) = \sum_k \mu_E(I_k) S(I_k, I_j),$$

$$R_2(I_j) = \underbrace{\max}_{k} \{ \min(S(I_j, I_k), \mu_E(I_k)) \},$$

APPLICATION / BENCHMARK

- ► The algorithm was tested on a widely used movie dataset including 100.000 ratings from 1-5 from 943 users on 1682 movies.
- ► The descriptions of the movies included a IMDB url.
- ► Evaluation based on precision/recall/F1-score
- ► A rating of 4-5 is considered to be 'liked'

- 1. For each user, it randomly splits the movie ratings dataset into a training set and a test set.
- Using the training set, it computes recommendation confidence score for each item in the test set using the different similarity measures and aggregation strategies.
- 3. For each user, using the movies in the testing set, it generates Top-N recommendations and computes the precision, recall, and F1 measure.
- 4. Using different random selection of the movies into testing and training sets, 10 different runs are executed to avoid sensitivity to sampling bias, and the mean results are reported.

RESULTS

Assumption: users prefer movies with specific genres.

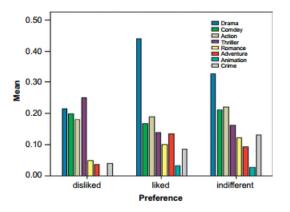


Fig. 1. Genre preferences distribution for user 7: (age = 57, Male, Administrator).

RESULTS

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Result comparison CSM - different similarity measures.

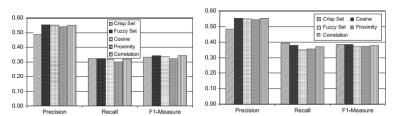


Fig. 2. Mean recommendation accuracy by similarity measures for weighted-sum.

Fig. 3. Mean recommendation accuracy by similarity measures for max-min.

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RESULTS

Difference in precision for fixed recall.

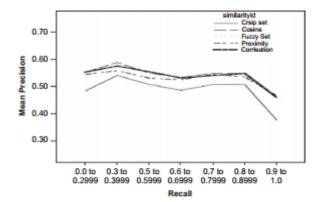


Fig. 4. Mean precision by recall using the weighted-sum.

ADDITIONS

- ► This paper focuses on content-based recommendation
- ► We will extend the FTM method to support collaborative filtering

DATA SET

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Table: Variables in the provided dataset

Attribute	Value
MovieID	Integer [1 17770]
CustomerID	Integer [1 2649429]
Rating	Integer [1 5]
Title	String
YearOfRelease	Integer [1890 2005]
Date	Date [1998-11-01 2005-12-31]
NetflixID	Integer

APPROACH

- Divide the data set in a sufficient training set and test set
- ► Group movies and users in order to get better perspective of rating
- ► Fuzzify the groups to fuzzy sets
- Construct sufficient fuzzy rules as suggested in literature (besides this paper; Yager, 2003)
- Defuzzify and calculate error test set.

- ► Negative: Inclusion of additional attributes (actors/actresses and directors) may improve the performance of the system.
- ► Positive: The researchers see the successful application of the proposed method for the movie recommendation system in a bigger picture