

# Collaborative Filtering

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- 3) Steps we took in our experimental approach
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# 1) Purpose of the study and approaches we used

## Goal of our Study

- We want to compare different options to perform collaborative filtering on two distinct database.
- We need to compare the following things:
  - Memory-based Algorithm(based on neighbors)
    - ✓ Different combinations of components
  - Model- based Algorithm
    - ✓ Choose the best meta-parameters

## Experimental Approach

Here are the different steps of our experimental approach:

- 1 Find the best Memory-based Algorithm(based on neighbors)
  - ✓ Do predictions based on different combination of components
  - ✓ Evaluate the test data to find best combinations of components
- 2 Find the best Model-based Algorithm
  - ✓ Do predictions based on different parameters
  - ✓ Evaluate the test data to find the best parameters
- 3 Compare the two and come up with a recommended algorithm for a specific usage.

## 2) How to evaluate the performance of our different algorithms ?

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### 1 Web Dataset

Web Dataset: Ranked Scoring: we default  $\alpha=5$ ,  $d=0.5$

$$R_a \models \sum_j \frac{\max(v_{a,j} - d, 0)}{2^{(j-1)/(\alpha-1)}}$$
$$R = 100 \frac{\sum_a R_a}{\sum_a R_a^{max}}$$

### 2 Movie Dataset

1. MAE = ABS(Estimation – real score)
2. Multi-class ROC:

We extend the definition of ROC defined by Hand and Till, to more than 2 classes by averaging pairwise comparisons. This measure reduces to the standard form in the two class case.

### 3) Steps we took in our experimental approach

1

#### Memory-based Algorithm

##### Similarity Weight:

- Pearson Correlation
- Entropy: 1,2
- Mean-Square-difference: 1,2
- SimRank: 1

dis-similarity to similarity.

##### Significance Weighting: 1,2

##### Selecting Neighbors:

- Weight Threshold: 1,2
- Best-n-estimator: 1,2
- Combined: 1,2

##### Rating Normalization:

- Deviation for Mean: 1,2

**Evaluation: Ranked Scoring for d1, MAE for d2**

2

#### Model-based Algorithm

##### EM Algorithm(Log-likelihood Function )

**Score Estimation**

**Evaluation: MAE, ROC**

## 4) Finding the best Memory-based Model

### 1 MAE for movie Data of Memory-based Algorithm

| Similarity Weighting | Significance Weighting | Selecting Neighbors    | MAE  |
|----------------------|------------------------|------------------------|------|
| Pearson              | F                      | Best-N(10)             | 3.03 |
| Pearson              | F                      | Best-N(15)             | 2.97 |
| Pearson              | T                      | Weight Threshold(0.4)  | 2.64 |
| Pearson              | T                      | Weight Threshold(0.5)  | 2.43 |
| Pearson              | T                      | Combined               | 2.43 |
| MSE                  | F                      | Best-N(10)             | 3.28 |
| MSE                  | F                      | Best-N(15)             | 3.24 |
| MSE                  | F                      | Combined               | 3.18 |
| MSE                  | T                      | Best-N(10)             | 2.66 |
| MSE                  | T                      | Best-N(15)             | 2.62 |
| MSE                  | T                      | Weight Threshold(0.85) | 2.42 |
| MSE                  | T                      | Combined               | 2.57 |
| Entropy              | F                      | Best-N(10)             | 3.41 |
| Entropy              | F                      | Weight Threshold(0.3)  | 2.9  |
| Entropy              | F                      | Combined               | 3.31 |
| Entropy              | T                      | Best-N(10)             | 2.83 |
| Entropy              | T                      | Best-N(15)             | 2.64 |
| Entropy              | T                      | Weight Threshold(0.3)  | 2.6  |
| Entropy              | T                      | Combined               | 2.7  |

### Analysis

- For the Movie Dataset, Significance Weighting seems to be a need to reduce MAE in every combination. In terms of Selecting Neighbors, Weight Threshold outperforms Best-N and Combined Method. For best-N, n=15 outperform n=10.
- Specifically, MSE+Significance Weighting+Weight Threshold(0.85) performs the best. Pearson+Significance Weighting+Weight Threshold(0.5) and Pearson+Significance Weighting+Combined also perform well.

# 4) Finding the best Memory-based Model

## 2 Ranked Scoring for Web Dataset

| Similarity Weighting | Significance Weighting | Selecting Neighbors    | Ranked Score |
|----------------------|------------------------|------------------------|--------------|
| Pearson              | F                      | Best-N(10)             | 53.07335993  |
| Pearson              | F                      | Best-N(15)             | 53.88041758  |
| Pearson              | F                      | Combined               | 54.82918581  |
| Pearson              | F                      | Weight Threshold(0.4)  | 61.05223056  |
| Pearson              | F                      | Weight Threshold(0.5)  | 58.98323061  |
| Pearson              | F                      | Weight Threshold(0.6)  | 52.6233943   |
| Pearson              | T                      | Best-N(10)             | 53.07335993  |
| Pearson              | T                      | Best-N(15)             | 53.88041758  |
| Pearson              | T                      | Weight Threshold(0.5)  | 58.98323061  |
| Pearson              | T                      | Weight Threshold(0.6)  | 52.6232261   |
| Pearson              | T                      | Combined               | 55.83386888  |
| MSE                  | F                      | Best-N(10)             | 57.43879672  |
| MSE                  | F                      | Best-N(15)             | 62.59660348  |
| MSE                  | F                      | Weight Threshold(0.08) | 69.10069659  |
| MSE                  | F                      | Weight Threshold(0.1)  | 59.65513169  |
| MSE                  | F                      | Combined               | 69.13923115  |
| MSE                  | T                      | Best-N(10)             | 57.29309379  |
| MSE                  | T                      | Best-N(15)             | 61.86672917  |
| MSE                  | T                      | Weight Threshold(0.1)  | 58.38028125  |
| MSE                  | T                      | Combined               | 68.70204497  |
| Entropy              | F                      | Best-N(10)             | 51.77175435  |
| Entropy              | F                      | Best-N(15)             | 53.78706305  |
| Entropy              | F                      | Weight Threshold(0.8)  | 61.44838698  |
| Entropy              | F                      | Combined               | 55.57004837  |
| Entropy              | T                      | Best-N(10)             | 51.77175435  |
| Entropy              | T                      | Best-N(15)             | 53.78706305  |
| Entropy              | T                      | Weight Threshold(0.7)  | 74.0076065   |
| Entropy              | T                      | Combined               | 55.94488558  |

## Analysis

- For the Microsoft Dataset, in terms of Similarity Weighting, MSE and Entropy outperforms Pearson Correlation in general. In terms of Selecting Neighbors, Weight Threshold seems to be the best in most combinations.
- Specifically, Entropy+Significance Weighting+Weight Threshold(0.7) performs the best. MSE+Combined and MSE+Weight Threshold(0.7) also perform well.

# 5) Finding the best Cluster Model

- Before comparing the Cluster model with the memory-base algorithms respective performance on the Movie Data set we need to train the Cluster model

## 1 Idea of the Cluster model

- **idea:** there are certain groups or types of users capturing a common set of preferences and taste.
  - Given a unobserved class variable  $C$ , the votes of users for a particular movie are iid
  - We can use the EM algorithm to learn the parameters

$$\mu_c := P(\Delta_i = c), \quad \text{for } c = 1, \dots, C;$$
$$\gamma_{c,j}^{(k)} := P(V_j^{(i)} = k | \Delta_i = c), \quad \text{for } \forall c, j, k.$$

## 2 Training the Cluster Model:

- **Method to find the best number of cluster  $C$** 
  - We divide the training set into a sub-training set and a validation set. In the validation set, 70% of the each user's votes are known, the remaining 30% are predicted.
  - For each value of  $C$  we run the EM algorithm on the sub-training set, and we evaluate the performance metrics on the validation set.
  - We obtain the following results, the best parameter is  $C=7$

| C   | 3       | 5       | 7       | 9        |
|-----|---------|---------|---------|----------|
| MAE | 1.01345 | 1.00694 | 1.00455 | 1.021888 |
| ROC | 0.2474  | 0.2467  | 0.2445  | 0.2535   |

- **Testing performance:**

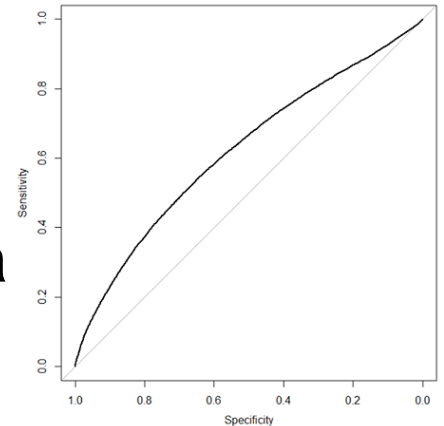
- We ultimately test the performance of the model on the test set with  $C=7$

# 6) Results & Analysis: Comparing all the models

## 1 Cluster Models Performance

- We choose  $C=7$ , train on the whole training set, and evaluate on the testing set.
- The results are: **MAE=0.99195, ROC=0.2397**

## 2 Comparing the performance of all the methods on the Movie Data



| Similarity Weighting    | Significance Weigh | Selecting Neighbo    | MAE   |
|-------------------------|--------------------|----------------------|-------|
| Pearson                 | F                  | Best-N(10)           | 3, 03 |
| Pearson                 | F                  | Best-N(15)           | 2, 97 |
| Pearson                 | T                  | Weight Threshold(0.4 | 2, 64 |
| Pearson                 | T                  | Weight Threshold(0.5 | 2, 43 |
| Pearson                 | T                  | Combined             | 2, 43 |
| MSE                     | F                  | Best-N(10)           | 3, 28 |
| MSE                     | F                  | Best-N(15)           | 3, 24 |
| MSE                     | F                  | Combined             | 3, 18 |
| MSE                     | T                  | Best-N(10)           | 2, 66 |
| MSE                     | T                  | Best-N(15)           | 2, 62 |
| MSE                     | T                  | Weight Threshold(0.8 | 2, 42 |
| MSE                     | T                  | Combined             | 2, 57 |
| Entropy                 | F                  | Best-N(10)           | 3, 41 |
| Entropy                 | F                  | Weight Threshold(0.3 | 2, 9  |
| Entropy                 | F                  | Combined             | 3, 31 |
| Entropy                 | T                  | Best-N(10)           | 2, 83 |
| Entropy                 | T                  | Best-N(15)           | 2, 64 |
| Entropy                 | T                  | Weight Threshold(0.3 | 2, 6  |
| Entropy                 | T                  | Combined             | 2, 7  |
| Cluster-Model using C=7 |                    |                      | 0. 99 |

## Recommendations

The best collaborative filtering algorithm on this data set is our **Cluster Model with 7 latent classes**.

Let's note that might not be the case on the Web Data Set, for which our better **tested** algorithm is the memory-based Entropy+Significance Weighting+Weight Threshold(0.7). We will need to run our cluster model on this data base to conclude.