Group 4

Collaborative Filtering Algorithms

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CONTENTS

1. Data Sets
2. Memory Based Algorithm
3. Model Based Algorithm
4. Evaluation
5. Result Analysis

Data Set Info

Data Set 1: Anonymous Microsoft Web Data

Binary (0 for not visited & 1 for visited)

User: User indices range from 10010 to 42708

Feature (web): Site indices ranging from 1000 to 1295

Train: 4151* 85

Test: 665 * 85

Data Set 2: Movies Grading Data

6 Categories (movie rating from 1 to 6)

User: User indices range from 1 to 74418

Feature(Movie):Movie indices range from 1 to 1648

Train: 5055 * 1619

Test: 5055 * 1597

Implementation: Variants being tested

Algorithm	Component	Variants	Data
Memory-based Algorithm	Similarity Weight	Pearson Correlation	1,2
		Mean Square Difference	1,2
		SimRank	1
	Variance Weighting	No	1,2
	Selecting Neighbors	Weight Threshold	1,2
		Best-n-estimator	1,2
		Combined	1,2
	Rating Normalization	Deviation for Mean	1,2
		Z-score	1,2
Model-based Algorithm	Cluster Models		1

Similarity Weight:

Weight all users with respect to similarity with the active user:

- **Pearson Correlation**

Measures the degree to which a linear relationship exists between two variables

$$w_{a,u} = \frac{\sum_{i=1}^{m}(r_{a,i} - \overline{r}_a) * (r_{u,i} - \overline{r}_u)}{\sigma_a * \sigma_u}$$

- **Mean Square Difference**

$$MSD_{a,u} = \frac{\sum_h (r_a - r_u)^2}{n}$$

$$w_{a,u} = \frac{max(MSD_{a,u}) - MSD_{a,u}}{max(MSD_{a.u})}$$

SimRank

For the algorithm of SimRank, we mainly implement these two equations below

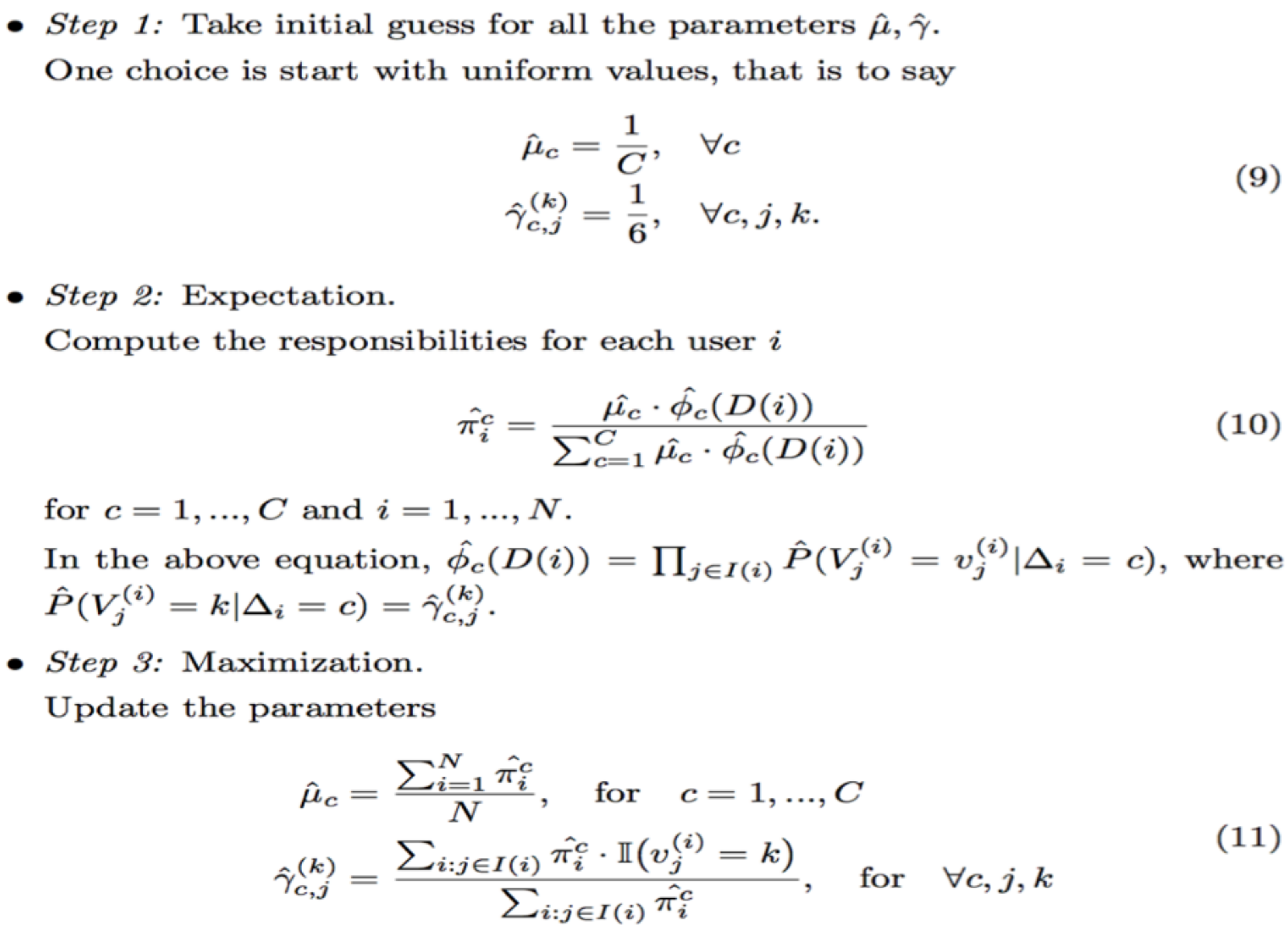
$$s(c,d) = \frac{C_2}{|I(c)||I(d)|} \sum_{i=1}^{|I(c)|} \sum_{j=1}^{|I(d)|} s(I_i(c), I_j(d))$$

$$s(A,B) = \frac{C_1}{|O(A)||O(B)|} \sum_{i=1}^{|O(A)|} \sum_{j=1}^{|O(B)|} s(O_i(A), O_j(B))$$

The way to compute SimRank is the naïve method:

$$R_0(a,b) = \begin{cases} 0 & (\text{if} \quad a \neq b) \\ 1 & (\text{if} \quad a = b) \end{cases} \qquad R_{k+1}(a,b) = \frac{C}{|I(a)||I(b)|} \sum_{i=1}^{|I(a)|} \sum_{j=1}^{|I(b)|} R_k(I_i(a), I_j(b))$$

Model Based Algorithm – Cluster Model



- *Step 1:* Take initial guess for all the parameters $\hat{\mu}, \hat{\gamma}$.

  One choice is start with uniform values, that is to say

$$\begin{aligned} \hat{\mu}_c &= \frac{1}{C}, \quad \forall c \\ \hat{\gamma}_{c,j}^{(k)} &= \frac{1}{6}, \quad \forall c, j, k. \end{aligned} \tag{9}$$

- *Step 2:* Expectation.

  Compute the responsibilities for each user i

$$\hat{\pi_i^c} = \frac{\hat{\mu_c} \cdot \hat{\phi}_c(D(i))}{\sum_{c=1}^{C} \hat{\mu_c} \cdot \hat{\phi}_c(D(i))} \tag{10}$$

  for $c = 1, ..., C$ and $i = 1, ..., N$.

  In the above equation, $\hat{\phi}_c(D(i)) = \prod_{j \in I(i)} \hat{P}(V_j^{(i)} = v_j^{(i)} | \Delta_i = c)$, where $\hat{P}(V_j^{(i)} = k | \Delta_i = c) = \hat{\gamma}_{c,j}^{(k)}$.

- *Step 3:* Maximization.

  Update the parameters

$$\begin{aligned} \hat{\mu}_c &= \frac{\sum_{i=1}^{N} \hat{\pi_i^c}}{N}, \quad \text{for} \quad c = 1, ..., C \\ \hat{\gamma}_{c,j}^{(k)} &= \frac{\sum_{i:j \in I(i)} \hat{\pi_i^c} \cdot \mathbb{I}(v_j^{(i)} = k)}{\sum_{i:j \in I(i)} \hat{\pi_i^c}}, \quad \text{for} \quad \forall c, j, k \end{aligned} \tag{11}$$

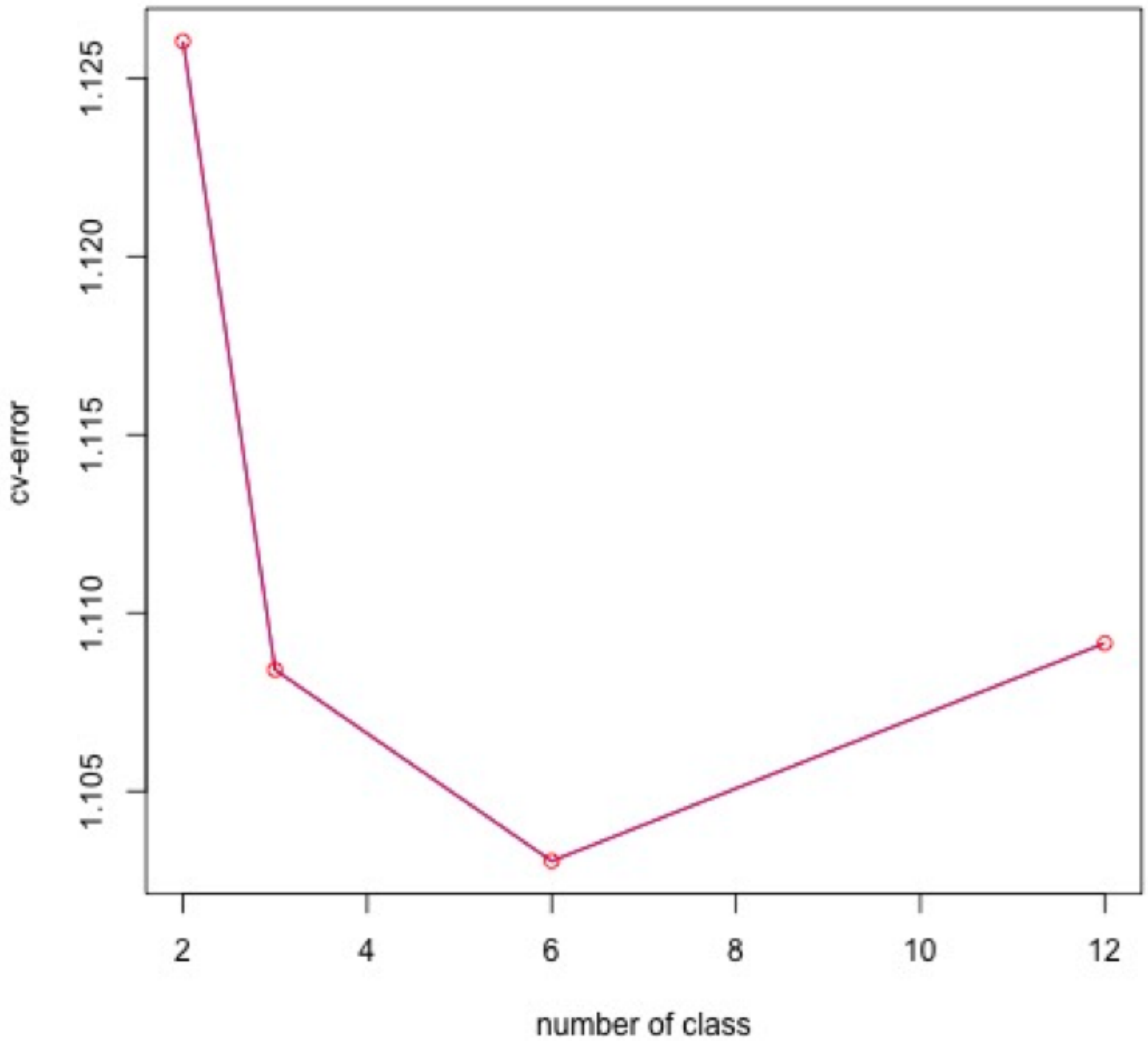
For initialization,

Set parameter γ random variable which sum by class is 1.

For iteration,

We set the iteration as 100; There is also another stop sign which is

$|\pi_i - \pi_{i-1}| \leq 0.05$


cv-error
1.125
1.120
1.115
1.110
1.105
2
4
6
8
10
12
number of class

Rating Normalization

- **Deviation for mean**

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

- **Z-score:**

$$p_{a,i} = \overline{r}_a + \sigma_a * \frac{\sum_{u=1}^{n} \frac{r_{u,i} - \overline{r}_u}{\sigma_u} * w_{a,u}}{\sum_{u=1}^{n} w_{a,u}}$$

Evaluation

For this part, we applied three evaluation methods to compare the results:

For dataset 1 – Rank Score

- Rank Score

❖ It measures the expected utility of a ranked recommendation list Ra and normalized by the maximum achievable utility Ra_max.

❖ The expected utility of a list is simply the probability of viewing a recommanded item times its utility.

For dataset 2 – MAE

- MAE

❖ MAE is simply to calculate the average absolute deviation for a user :

$$S_a = \frac{1}{m_a} \sum_{j \in P_a} |p_{a,j} - v_{a,j}|$$

Results Analysis

Dataset 1: Ranked Scoring					
Selecting Nbors Similarity Weight	Weight Threshold		Best-N-Estimator		Combined
	0.05	0.2	20	40	0.05 + 40
Pearson Correlation	45.7274	44.05147	32.68916	34.62473	33.7009
Mean-Squared-Difference	47.77998	47.77998	33.38771	35.12559	35.04042
SimRank	45.985	32.1453	32.3775	33.39524	35.0523

Dataset 2: MAE

Selecting Nbors Similarity Weight	Weight Threshold		Best-N-Estimator		Combined
	0.05	0.2	20	40	0.05 + 40
Pearson Correlation	1.187658	1.185793	1.167949	1.167326	1.183761
Mean-Squared-Difference	1.168654	1.168654	1.170718	1.169313	1.166298

THANK YOU