Collaborative Filtering Algorithms

Group 10

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- Data Set
- Memory-Based Model
- Model-Based Model
- Comparison
- Conclusion

Part 1

Data Set

Data Set

Microsoft Web Data

The data records the use of www.microsoft.com by 38000 anonymous, randomly-selected users.

- implicit
- 1 for visit
- 0 for no visited
- Use Ranked Score to evaluate

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

EachMovie

61265 users entered a total of 2811983 numeric ratings on 1623 movies, i.e. about 2.4% entries are rated by zero-to-five stars.

- explicit
- Score from 1 to 6
- NA for no rated
- Use MAE to evaluate

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

Assignment

Algorithm	Component	Variants	Data
Memory-based Algorithm	Similarity Weight	Pearson	1,2
		Spearman	1,2
		SimRank	1
	Variance Weighting	No	1,2
		Yes	1,2
	Selecting Neighbors	Weight Threshold	1,2
Model-based Algorithm	Cluster Models		2

Part 2

Memory-Based Algorithm

Memory-Based Algorithm

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

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

Similarity Weighting

Pearson Correlation

$$w(a,i) = \frac{\sum_j (v_{a,j} - \bar{v}_a)(v_{i,j} - \bar{v}_i)}{\sqrt{\sum_j (v_{a,j} - \bar{v}_a)^2 \sum_j (v_{i,j} - \bar{v}_i)^2}}$$

Spearman Correlation

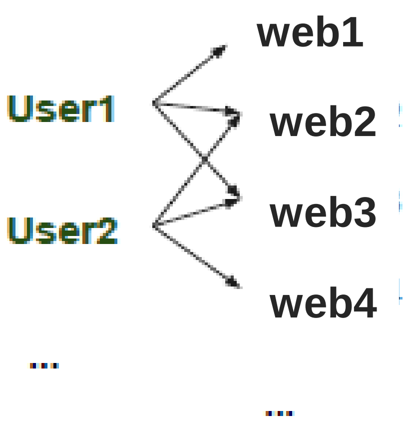
$$w_{a,u} = \frac{\sum_{i=1}^{m} (rank_{a,i} - \overline{rank_a}) * (rank_{u,i} - \overline{rank_u})}{\sigma_a * \sigma_u}$$

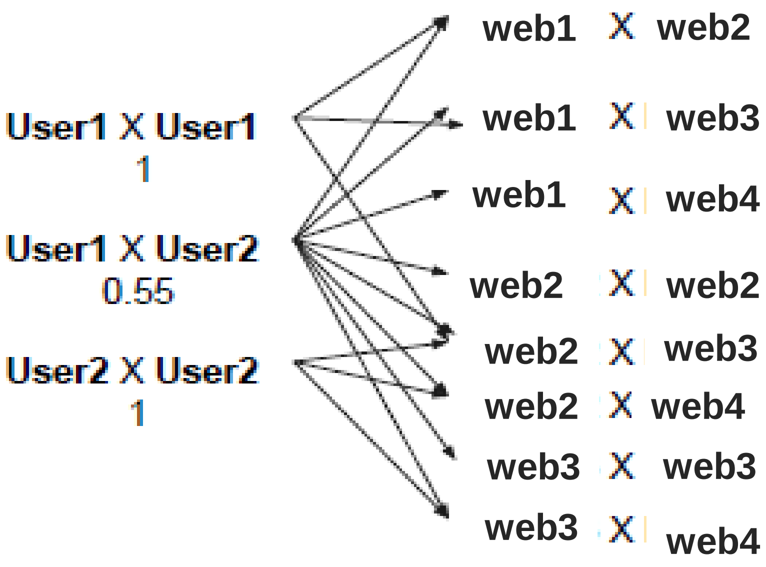
Similarity Weighting

Simrank

$$s_1(a,b) = \frac{C_1}{|O(a)||O(b)|} \sum_{i=1}^{|O(a)|} \sum_{j=1}^{|O(b)|} s_2(O_i(a), O_j(b))$$

$$s_2(a,b) = \frac{C_2}{|I(a)||I(b)|} \sum_{i=1}^{|I(a)|} \sum_{j=1}^{|I(b)|} s_1(I_i(a), I_j(b))$$





Variance Weighting

Vairance Weighting
(Pearson Correlation)

$$w_{a,u} = \frac{\sum_{i=1}^{m} v_i * z_{a,i} * z_{u,i}}{\sum_{i=1}^{m} v_i}$$

Selecting neighbors

Selecting neighbors
(Weight Threshold)

$$W_{a,u} = \begin{cases} \omega_{a,u}, & \omega_{a,u} > threshold, \\ 0 & o.w. \end{cases}$$

Result – Data1

Rank Score		Z-Score				Deviation for Mean			
		Variance=OFF		Variance=ON		Variance=OFF		Variance=ON	
		Pearson	Spearman	Pearson	SimRank	Pearson	Spearman	Pearson	SimRank
					40.77057				40.77628
Weight Threshold	0.2	39.364175 (52.42%)	39.364175 (52.42%)	39.977511 (50.15%)		39.459138 (52.42%)	39.459138 (52.42%)	39.959964 (50.15%)	
	0.3	38.077085 (29.03%)	38.077087 (29.02%)	39.145602 (34.91%)		38.171786 (29.03%)	38.171798 (29.02%)	39.233054 (34.91%)	
	0.4	5.820478 (15.14%)	5.820477 (15.14%)	38.091526 (21.31%)		5.857705 (15.14%)	5.857706 (15.14%)	38.232782 (21.31%)	
	0.5	1.835299 (5.76%)	1.837463 (5.77%)	5.856577 (11.02%)		1.8487 (5.76%)	1.846338 (5.77%)	5.871136 (11.02%)	

Result – Data2

MAE		Z-Score			Deviation for Mean		
		Variance=OFF		Variance=ON	Variance=OFF		Variance=ON
		Pearson	Spearman	Pearson	Pearson	Spearman	Pearson
Weight Threshold	0	1.428475 (100%)	1.593824 (100%)	1.88334 (100%)	1.336934 (100%)	1.319426 (100%)	1.69374 (100%)
	0.2	1.137397 (57.83%)	1.137854 (57.81%)	1.145734 (50.10%)	1.135716 (57.83%)	1.136039 (57.81%)	1.139967 (50.18%)
	0.3	1.147375 (40.65%)	1.149654 (39.92%)	1.159057 (34.82%)	1.140594 (40.64%)	1.142161 (39.92%)	1.140594 (40.64%)
	0.4	1.16645 (24.28%)	1.171506 (23.15%)	1.182244 (21.21%)	1.149662 (24.28%)	1.1532 (23.15%)	1.149662 (24.28%)
	0.5	1.202854 (11.80%)	1.210711 (10.82%)	1.216701 (10.93%)	1.169631 (11.80%)	1.174899 (10.82%)	1.169631 (11.81%)

Part 3

Model-Based Algorithm

Model-Based Algorithm

Score Estimation

$$\mathbb{E}[V_b^{(i)}|v_j^{(i)}, j \in I(i)] = \sum_{k=1}^{5} k \cdot P\big(V_b^{(i)} = k|v_j^{(i)}, j \in I(i)\big),$$

$$= \frac{\sum_{c=1}^{C} P(\Delta_i = c) \cdot P(V_b^{(i)} = k|\Delta_i = c) \cdot \prod_{j\in I(i)} P(V_j^{(i)} = v_j^{(i)}|\Delta_i = c)}{\sum_{c=1}^{C} P(\Delta_i = c) \cdot \prod_{j\in I(i)} P(V_j^{(i)} = v_j^{(i)}|\Delta_i = c)},$$

Log-likelihood Function

$$l(\mu, \gamma|data) = \sum_{i=1}^{N} l_i(\mu, \gamma|data)$$

$$= \sum_{i=1}^{N} \log\Big[\sum_{c=1}^{C} \mu_c \cdot \prod_{j\in I(i)} P(V_j^{(i)} = v_j^{(i)}|\Delta_i = c)\Big],$$

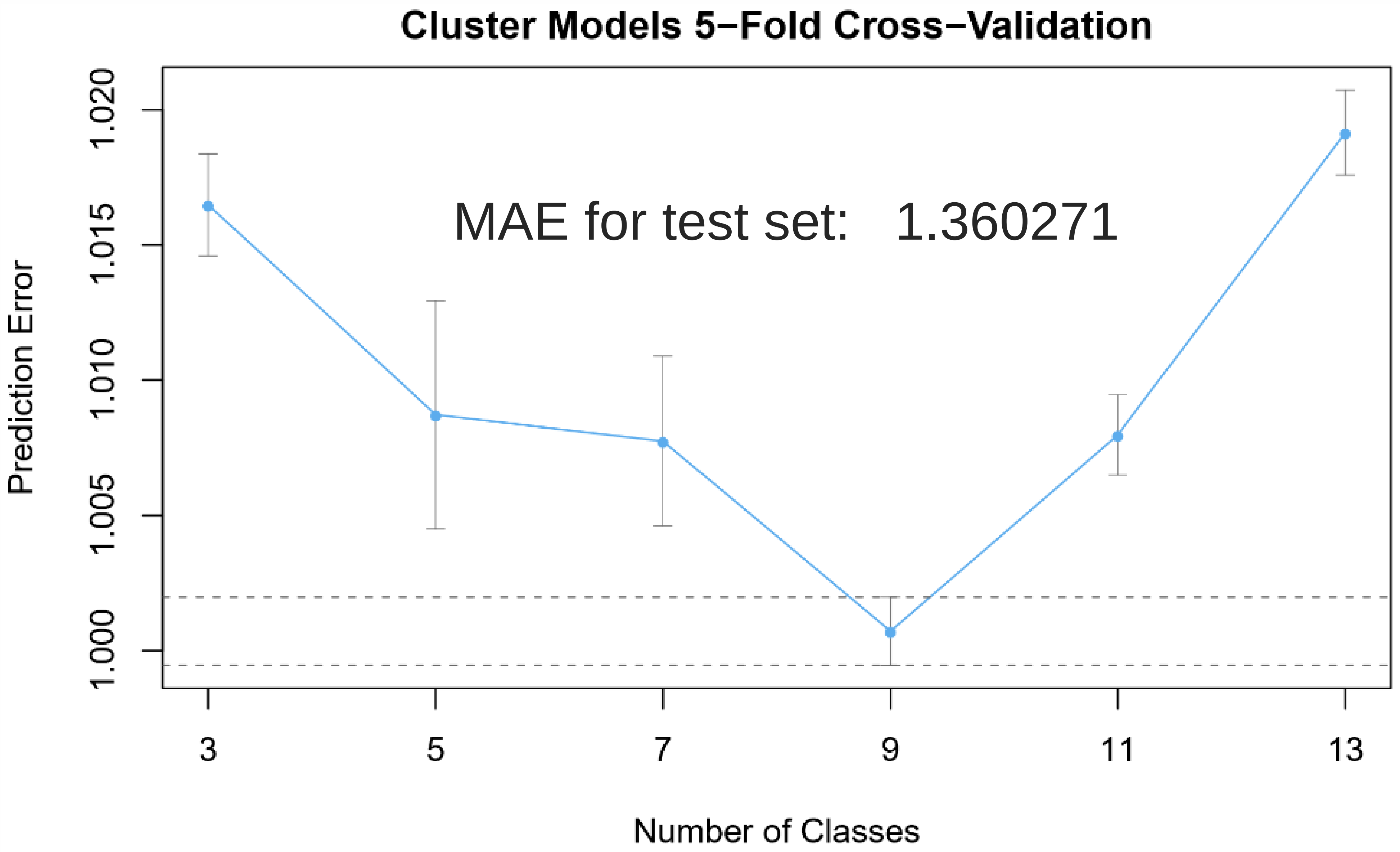
EM Algorithm

$$\hat{\pi}_i^c = \frac{\hat{\mu}_c \cdot \hat{\phi}_c(D(i))}{\sum_{c=1}^{C} \hat{\mu}_c \cdot \hat{\phi}_c(D(i))}$$

$$\hat{\mu}_c = \frac{\sum_{i=1}^{N} \hat{\pi}_i^c}{N}, \quad \text{for} \quad c = 1, \ldots, C$$

$$\hat{\gamma}_{c,j}^{(k)} = \frac{\sum_{i:j\in I(i)} \hat{\pi}_i^c \cdot \mathbb{I}(v_j^{(i)} = k)}{\sum_{i:j\in I(i)} \hat{\pi}_i^c}, \quad \text{for} \quad \forall c, j, k$$

Cross-Validation



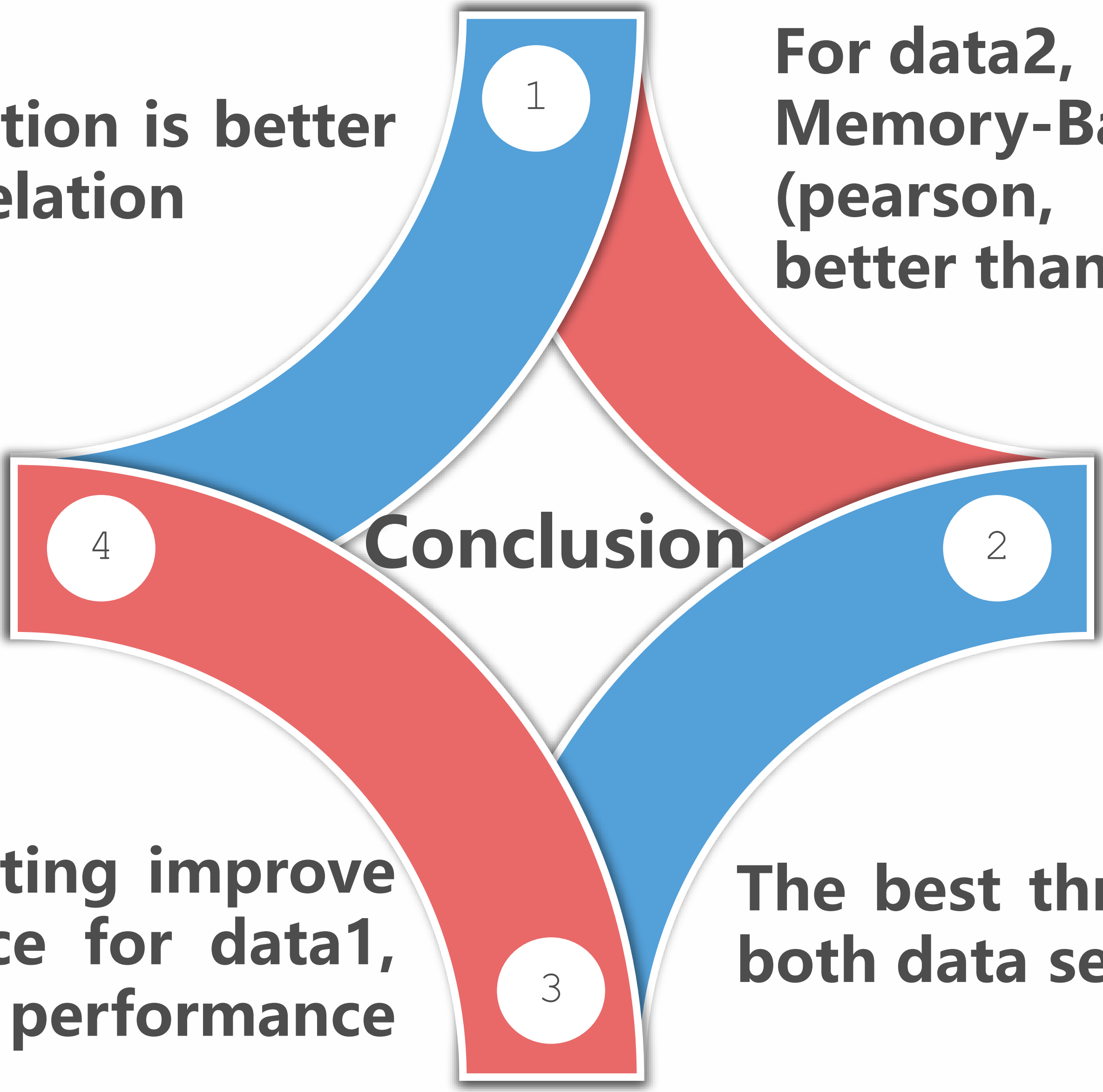
Comparison —— Data 2

	MAE
Cluster Model	1.360271
Memory-Based Model (Corrleation = Pearson Variance = No Threshold =0.2)	1.135716

Conclusion

For data1,
Simrank correlation is better than other correlation

For data2,
Memory-Based Model (pearson, threshold=0.2) is better than Cluster Model



The best threshold is 0.2 for both data sets

Variance Weighting improve the performance for data1, while lower the performance for data2

Thank You!

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