Steps for User Based Collaborative Filtering – An Example



## User-based nearest-neighbor collaborative filtering

- Example
  - A database of ratings of the current user, Alice, and some other users is given:

	ltem1	Item2	Item3	ltem4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

 Determine whether Alice will like or dislike Item5, which Alice has not yet rated or seen

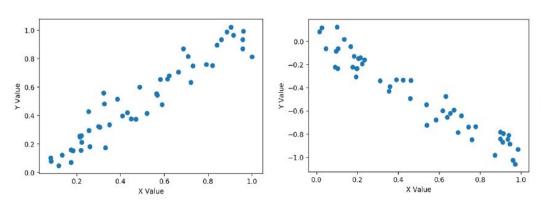


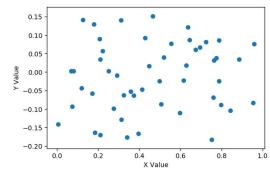
A popular similarity measure in user-based CF: Pearson correlation

$$r(x,y) = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})}}$$

- r represents the Pearson correlation value between 2 numerical arrays x and y
- Value between +1 and -1
- Strength of Linear Relationship







Positive Correlation (0 < r < 1)

Negative Correlation (-1 < r < 0)

Zero Correlation (r = 0)



#### Pearson Correlation between User Rating arrays

a, b: users

 $r_{a,p}$ : rating of user a for item p

 $r_{b,p}$ : rating of user b for item p

P: set of items, rated both by a and b

$$r(x,y) = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})}} \implies sim(a,b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}}$$



•A popular similarity measure in user-based CF: Pearson correlation

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, b : users
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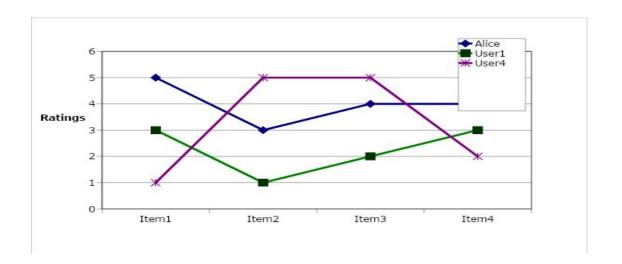
 $r_{a,p}$ : rating of user a for item p $r_{a,p}$ : rating of user b for item p

P: set of items, rated both by a and b

	ltem1	ltem2	Item3	ltem4	ltem5	
Alice	5	3	4	4	?	
User1	3	1	2	3	3	sim = 0.85
User2	4	3	4	3	5	sim = 0.85 sim = 0.70
User3	3	3	1	5	4	sim = 0.00
User4	1	5	5	2	1	sim = -0.79



Takes differences in rating behavior into account





# **Choosing Neighbourhood size**

	ltem1	Item2	Item3	Item4	Item5	
Alice	5	3	4	4	?	
User1	3	1	2	3	3	sim = 0.85
User2	4	3	4	3	5	sim = 0.85 sim = 0.70 sim = 0.00
User3	3	3	1	5	4	sim = 0.00
User4	1	5	5	2	1	sim = -0.79



# Choosing Neighbors & Making predictions

• A common prediction function:

$$pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(a,b)}$$

$$pred(Alice, Item 5) = \overline{r_{alice}} + \frac{\sum_{b \in N} sim(Alice, b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(Alice, b)}$$

$$N = \{User 1, User 2\}$$



# Choosing Neighbors & Making predictions

	ltem1	ltem2	Item3	Item4	Item5		
Alice	5	3	4	4	?		
User1	3	1	2	3	3	sim = 0	.85
User2	4	3	4	3	5	sim = 0 $sim = 0$	.70
User3	3	3	1	5	4	sim = 0	
User4	1	5	5	2	1	sim = -(	).79

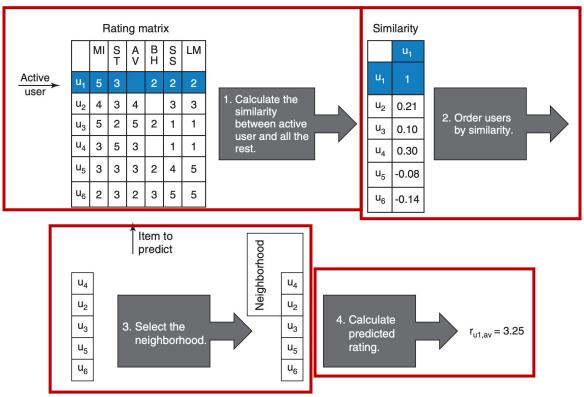
$$pred(Alice, Item \ 5) = \overline{r_{alice}} + \frac{sim(Alice, User \ 1) * \left(r_{User \ 1, item 5} - \overline{r_{User \ 1}}\right) + sim(Alice, User \ 2) * \left(r_{User \ 2, item 5} - \overline{r_{User \ 2}}\right)}{sim(Alice, User \ 1) + sim(Alice, User \ 2)}$$

$$pred(Alice, Item 5) = 3.75 + \frac{0.85 * (3 - 2.4) + 0.70 * (5 - 3.8)}{0.85 + 0.7}$$

pred(Alice, Item 5) = 4.621



# Steps for User-User CF





#### **Design Decisions**

- Neighbourhood Size
  - All users?
  - K users most similar to active user u
- Similarity Function
  - Pearson Correlation
  - Cosine Similarity
  - Spearman Rank Correlation
- Averaging Function
  - Weighted average
  - Simple Average
  - Regression



#### Improving the metrics/prediction function

- Not all neighbor ratings might be equally "valuable"
  - Agreement on commonly liked items is not so informative as agreement on controversial items
  - Possible solution: Give more weight to items that have a higher variance
- Value of number of co-rated items
  - Use "significance weighting", by e.g., linearly reducing the weight when the number of co-rated items is low
- Case amplification
  - Intuition: Give more weight to "very similar" neighbors, i.e., where the similarity value is close to 1.
- Neighborhood selection
  - Use similarity threshold or fixed number of neighbors

