

# User's Satisfaction Modeling in Personalized Recommendations

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## Idea

context-aware recommenders brings better results  
context strengthen other context's types  
context influences the rating prediction

## Algorithm

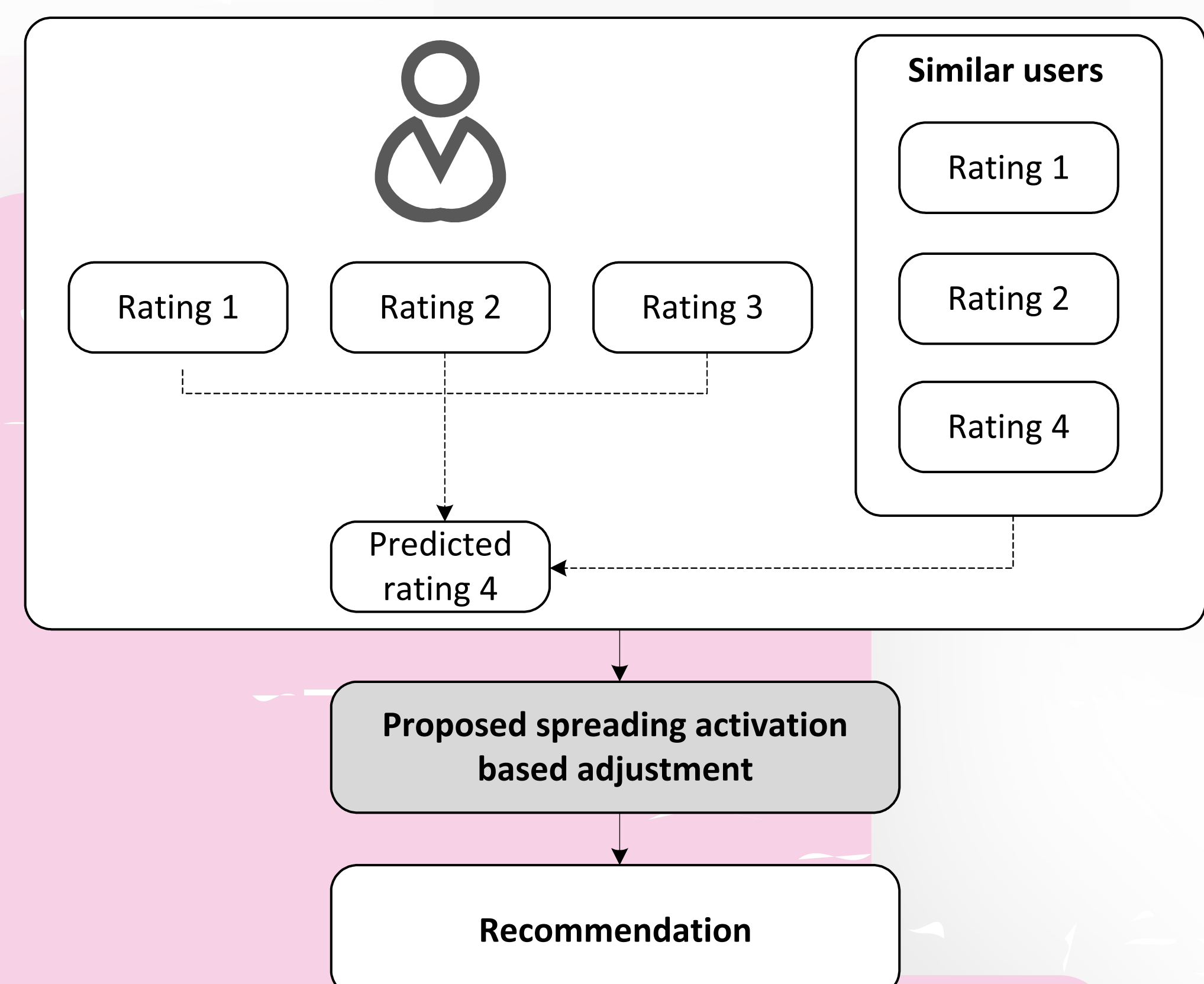
1. predict ratings for unrated items
2. spread activation through user's item specific influence graph
3. combine user's ratings history and result of influence graph

## Results

rating prediction  
average improvement MAE-0,28, RMSE-0,30  
recommendation  
average P@1 improvement 0,02

## Evaluation

LDO5-CoMoDa  
10-fold cross validation  
2296 ratings  
1232 movies  
121 users



$$\text{Rating}_{u \in \text{Users}, i \in \text{Items}} = \kappa n \left( \frac{\sum_{j=1}^{|\mathcal{I}|-1} ((\log_{|\mathcal{I}|-1} \sqrt{j} + 1) \text{history}(u))}{|\mathcal{I}| - 1} \right) + (1 - n) \text{sp}(i, u)$$

Similar users	MAE		RMSE	
	ARP	PM	ARP	PM
3	1,12	<b>0,79</b>	1,24	<b>0,91</b>
5	1,11	0,79	1,23	0,91
10	<b>1,01</b>	0,80	1,23	0,92
20	1,06	0,80	<b>1,20</b>	0,92
Avg.	1,08	0,79	1,23	0,91

P@	Number of similar users							
	3		5		10		20	
	SC	PM	SC	PM	SC	PM	SC	PM
1	0,023	0,040	0,028	0,046	0,027	0,041	0,017	0,045
3	0,022	0,023	0,025	0,025	0,017	0,018	0,014	0,021
5	0,022	0,022	0,024	0,021	0,016	0,017	0,013	0,014
10	0,019	0,020	0,021	0,014	0,015	0,015	0,012	0,011
Avg.	0,021	0,026	0,024	0,027	0,019	0,023	0,014	0,022

