



→ **Adapting Ratings in Memory-Based  
Collaborative Filtering using Linear Regression**

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**A|O|T**

Agententechnologien in  
betrieblichen  
Anwendungen  
und der  
Telekommunikation

# Agenda

Collaborative  
Filtering

⇒ **Collaborative Filtering: Rating Prediction**

Baseline  
Algorithm

⇒ **Baseline Algorithm: Pearson Correlation**

Linear  
Regression

⇒ **Linear Regression: Adapting Ratings**

Evaluation

⇒ **Evaluation**

# The Bipartite Rating Graph

Collaborative  
Filtering

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⇒ Database of user and items

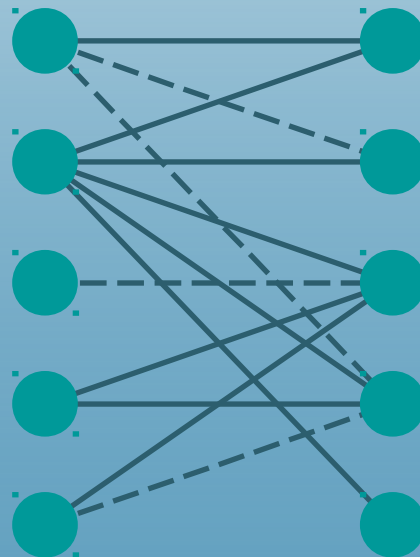
⇒ Users rate items



⇒ Rating database as sparse bipartite graph

Users

Items



Rating values

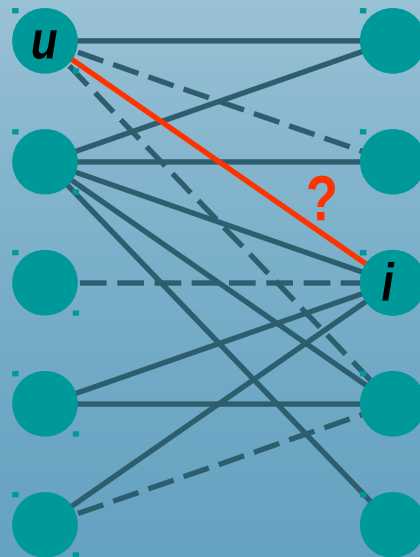
————— > 0

- - - - - < 0

# Collaborative Rating Prediction

- ⇒ Predict a missing rating
- ⇒ Use: Recommend new items (rank unrated items by predicted rating)

Users                      Items



Will user  $u$  like item  $i$  ?

# Weighted Mean of Ratings

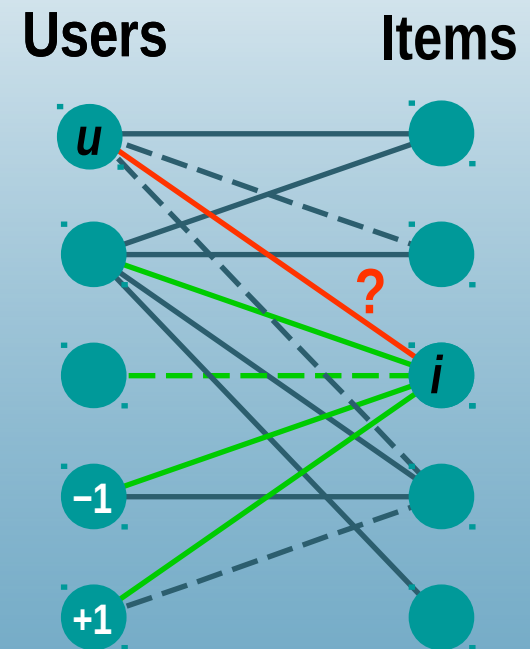
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- ⇒ Item  $i$  has been rated by many users: Take the average of all these ratings
- ⇒ Give high weight to ratings by users similar to  $u$
- ⇒ Similarity measure: use the Pearson correlation between two users' ratings (note: can be negative)
- ⇒ Works also as user-based algorithm



# User Rating Habits and Taste

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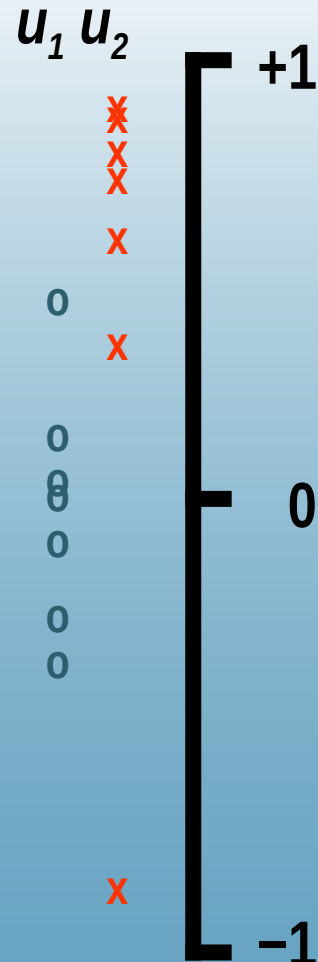
Users have different rating habits:

⇒ Different mean rating

⇒ Different variance

Weighted mean assumes the same rating scale for all users, although the Pearson correlation takes into account different scales

Solution: Weighted means of ratings scaled according to each user's rating mean and variance



# Scaling Ratings

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Two Users  $u$  and  $v$  have common rating vectors  $U$  and  $V$  using linear regression

- ⇒ Determine factors  $a$  and  $b$  minimizing sum of squared errors in  $U - (V \ 1) \begin{pmatrix} a & b \end{pmatrix}^T$
- ⇒ When  $U$  and  $V$  are negatively correlated,  $a$  is negative
- ⇒ Therefore, use absolute value of correlation for weight
- ⇒ Correlation and  $\begin{pmatrix} a & b \end{pmatrix}$  can be calculated in one pass

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**Linear Regression adaptation can be used in variants of weighted mean algorithm:**

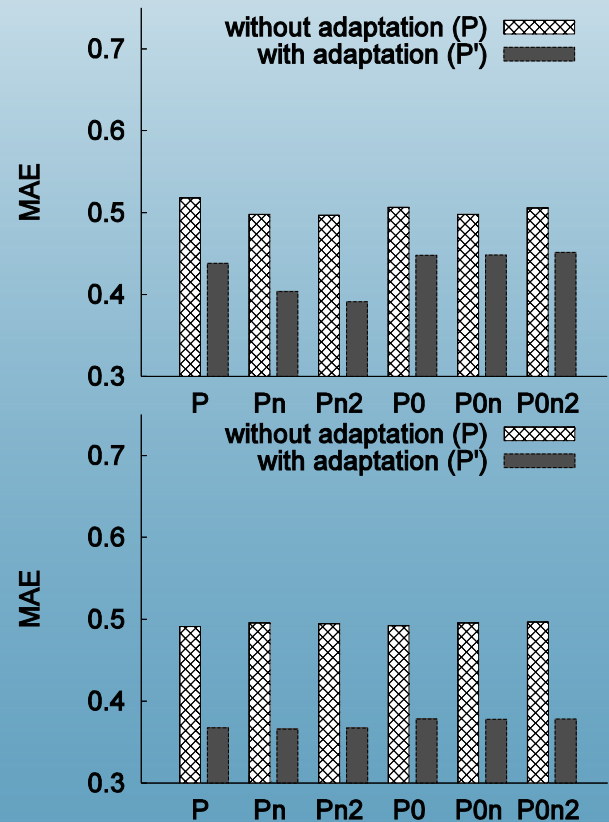
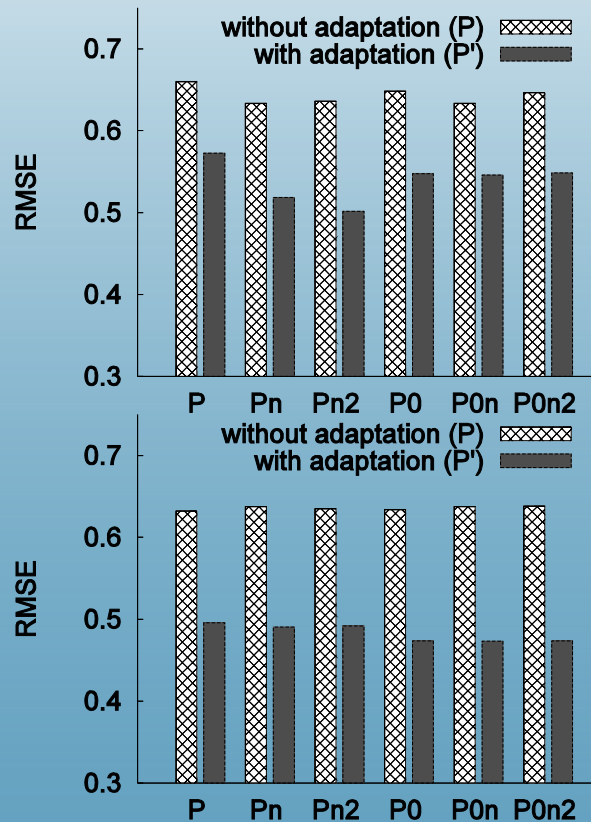
- ⇒ **User-based, item-based**
- ⇒ **With/out normalized ratings**
- ⇒ **Fill missing ratings with default parameter**
- ⇒ **Weight users by number of common ratings ( $1, n, n^2$ )**



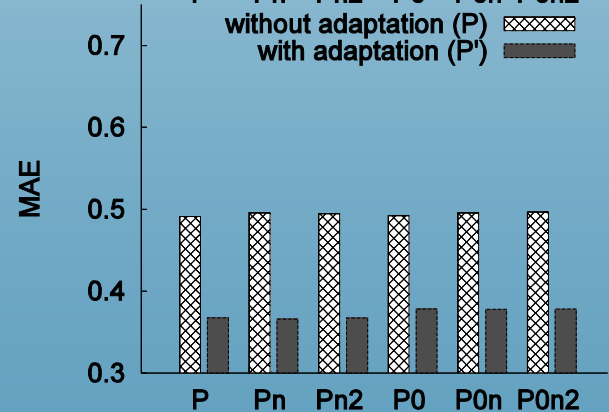
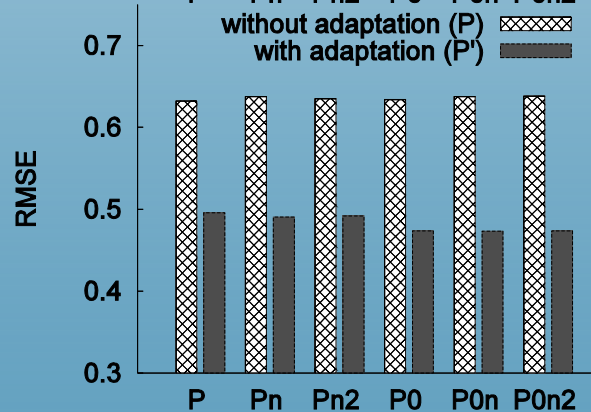
# Evaluation Results

Both error measures (mean average error, mean root squared error) reduced by ~0.1 points

MovieLens



Jester



Collaborative  
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# The End

Collaborative  
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Thank you!

Questions?

Comments?

# Backup

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- ⇒ A: Why doesn't normalization make this obsolete?
- ⇒ Q: Normalization corrects differences in rating habits (scales), whereas regression maps different tastes to each other