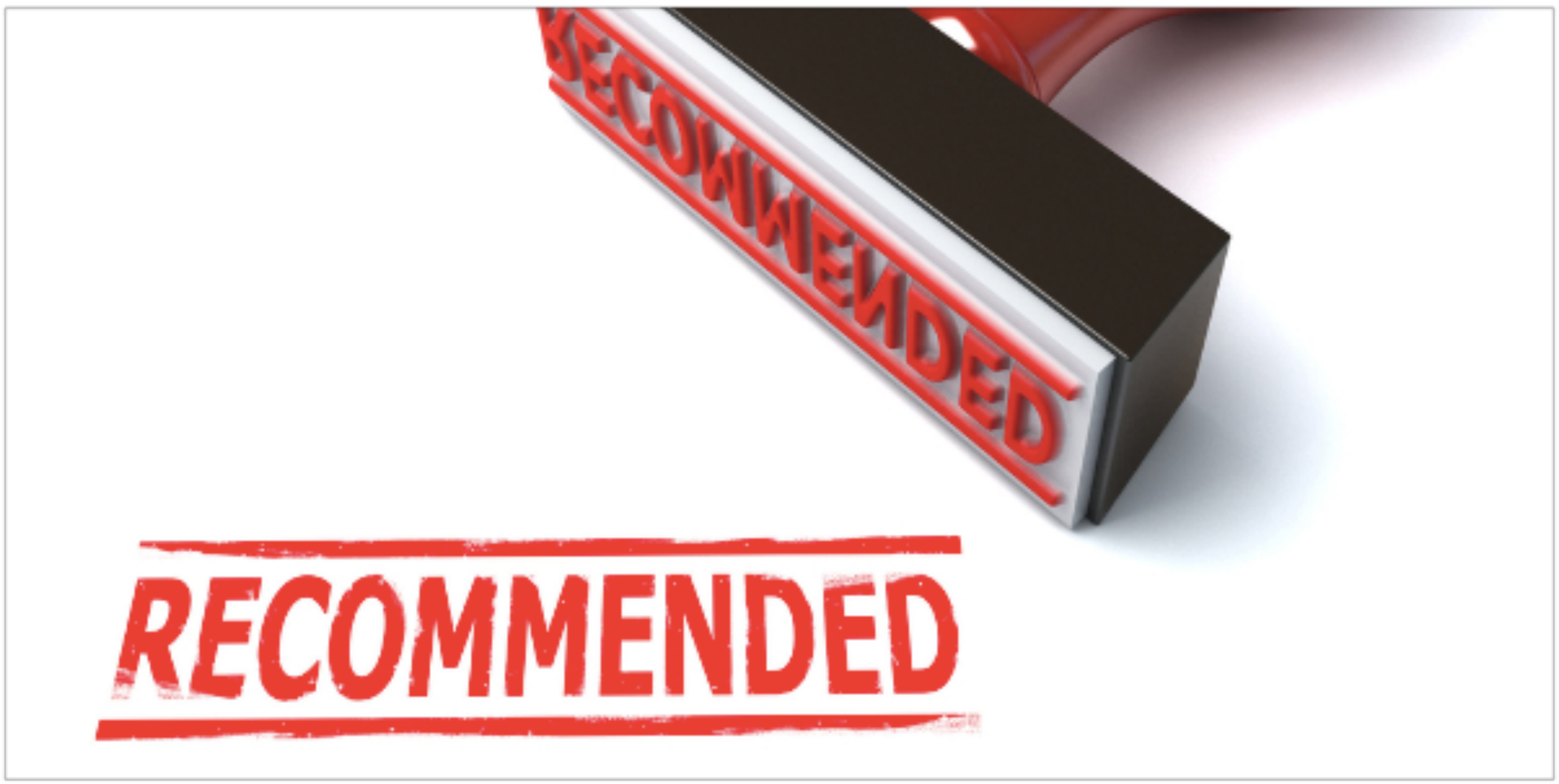
UNIVERSITAT DE BARCELONA

Master on Foundations of Data Science

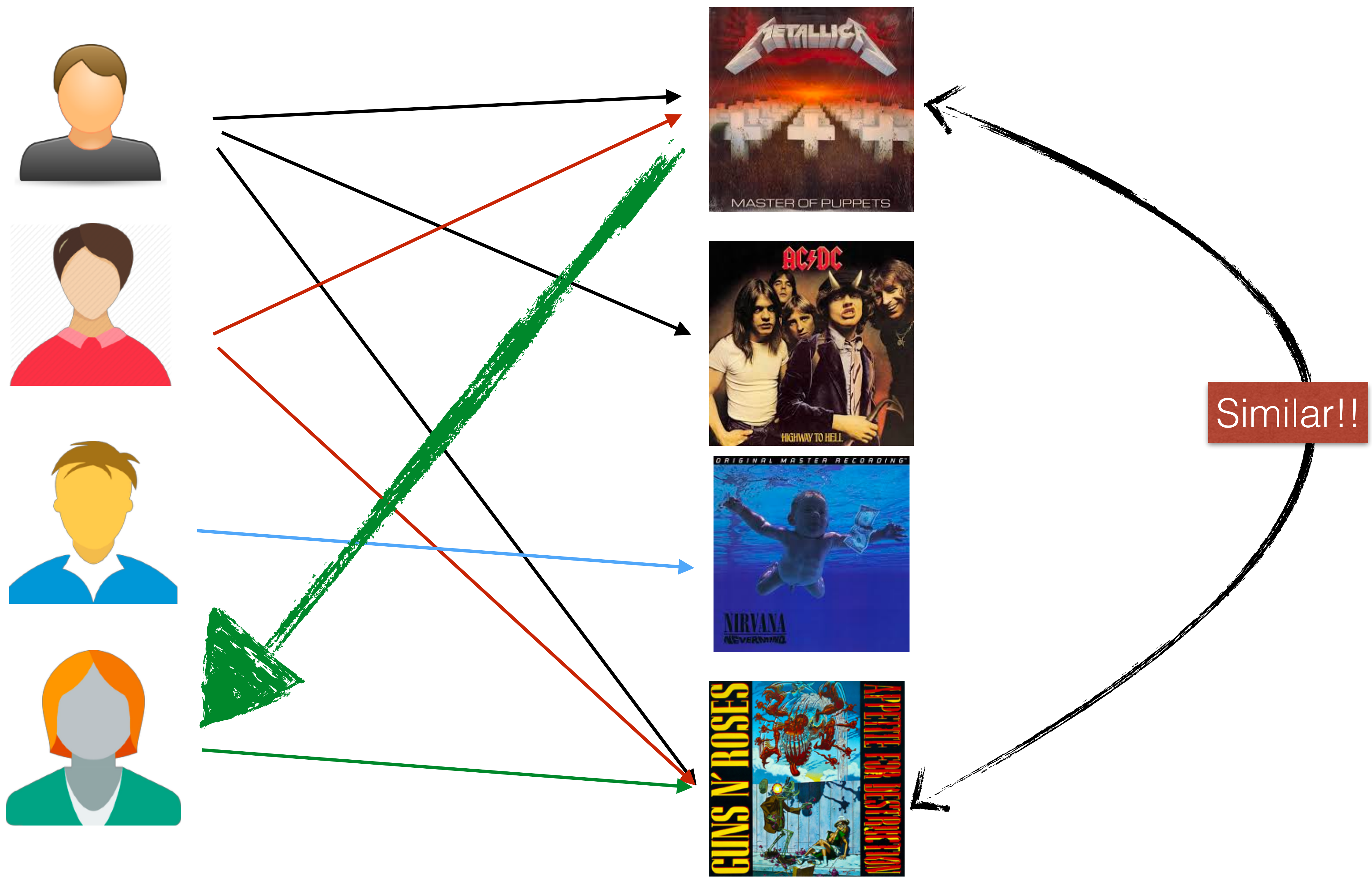


Recommender Systems

Collaborative Recommender Systems (II)

Santi Seguí | 2017-2018

Item-Based Recommender



Let's see how we can create a **Item-Based CF** for Movie recommendations.

Item-Based Recommender

- Instead on relying on the user similarity, prediction can rely on **item similarities**.
- Item similarity used to be **more stable** than user-similarity. So, the the update frequency of the items similarity is not as critical than user-similarity
  - Item-similarities are more static, while user-similarities are more dynamic

Item-based collaborative filtering recommendation algorithms B Sarwar, G Karypis, J Konstan, J Riedl Proceedings of the 10th international conference on World Wide Web, 285-295	5944	2001

Similarity Measures
What happens with item-based systems?

- Pearson Correlation

$$sim(a,b) = \frac{\sum_{p \in P}(r_{a,p} - \bar{r_a})(r_{b,p} - \bar{r_b})}{\sqrt{\sum_{p \in P}(r_{a,p} - \bar{r_a})^2}\sqrt{\sum_{p \in P}(r_{b,p} - \bar{r_b})^2}}$$

- Cosine distance

$$sim(a,b) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| * |\vec{b}|}$$

Where:

- $sim(a,b)$ is the similarity between user "a" and user "b"
- P is the set of common rated movies by user "a" and "b"
- $r_{a,p}$ is the rating of movie "p" by user "a"
- $\bar{r_a}$ is the mean rating given by user "a"

Are these measures good?

Item Based CF
Pearson Correlation

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

- Similarities are computed between items.

- Before computing the similarities between columns, each row of the rating matrix is centered to a mean zero.

Adjusted Cosine Similarity

- Computing similarity using basic cosine measure in item-based case has one important drawback: **The differences in rating scale between different users are not taken into account.**

- The Adjusted Cosine Similarity offsets this drawback by subtracting the corresponding user average from each co-rated pair:

$$sim(i,j) = \frac{\sum_{u \in U}(R_{u,i} - \bar{R_u})(R_{u,j} - \bar{R_u})}{\sqrt{\sum_{u \in U}(R_{u,i} - \bar{R_u})^2}\sqrt{\sum_{u \in U}(R_{u,j} - \bar{R_u})^2}}.$$

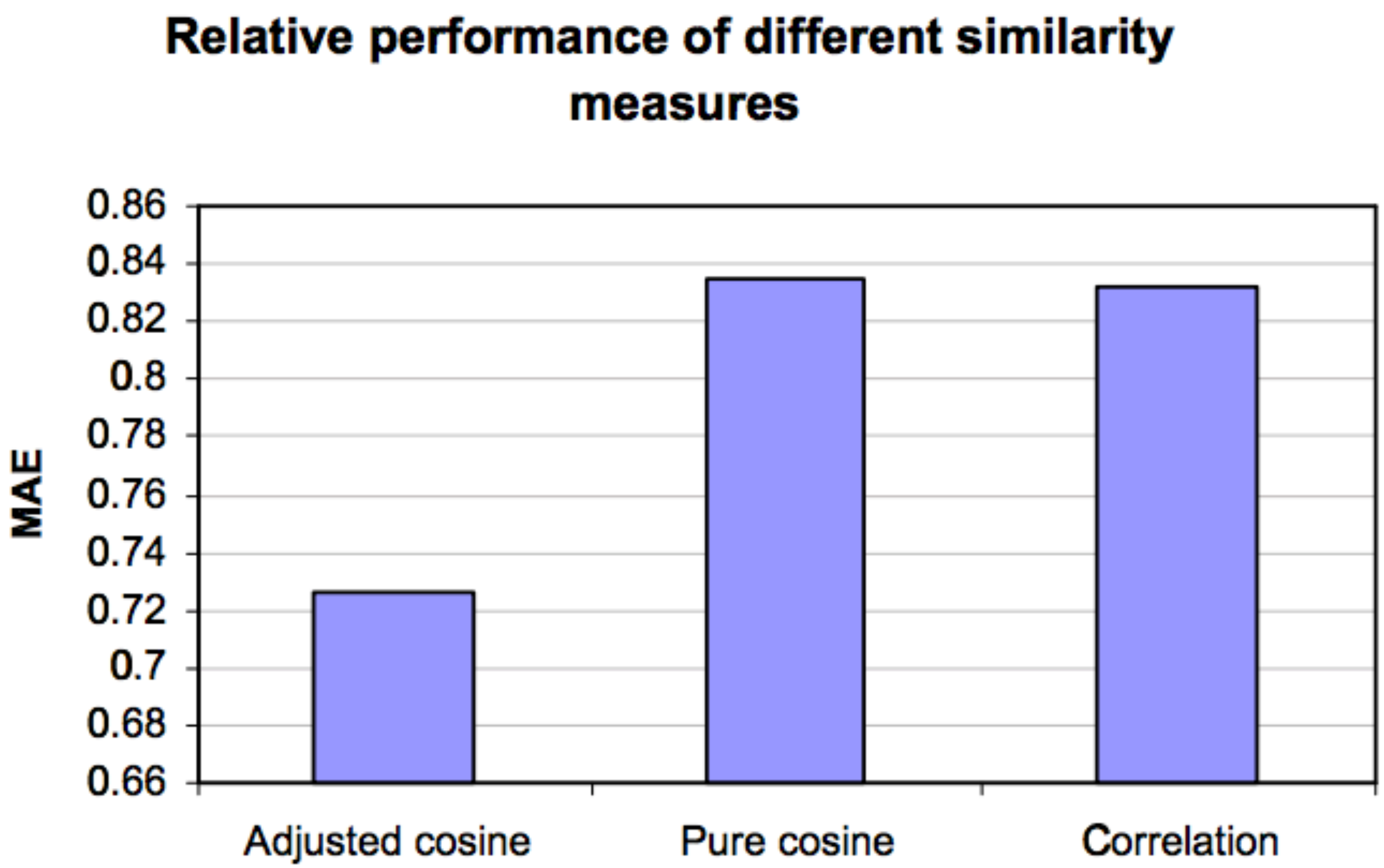


Figure 4: Impact of the similarity computation measure on item-based collaborative filtering algorithm.

Item-based collaborative filtering recommendation algorithms
B Sarwar, G Karypis, J Konstan, J Riedl
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5944 2001

Item-Based
How do we generate a prediction?

$$\hat{r}_{u,j} = \bar{r}_u + \frac{\sum_{v \in P_u(j)} sim(u,v) \times (r_{v,j} - \bar{r}_v)}{\sum_{v \in P_u(j)} sim(u,v)}$$

Why not another equation?

Exercice:

I want to create a Recommender System for **NETFLIX** using MovieLens dataset.

I have to decide which aproach to use:

a) Non-Personalized

b) User-Based CF

c) Item-Based CF

Plan an implementation plan, think about which is the best under all possibles scenarios you can find.

What should we do in order to say which is best?

User-Based vs. Item-Based

- m = #users ; n = #items
- Normally, the number of users is much bigger than the number of items.

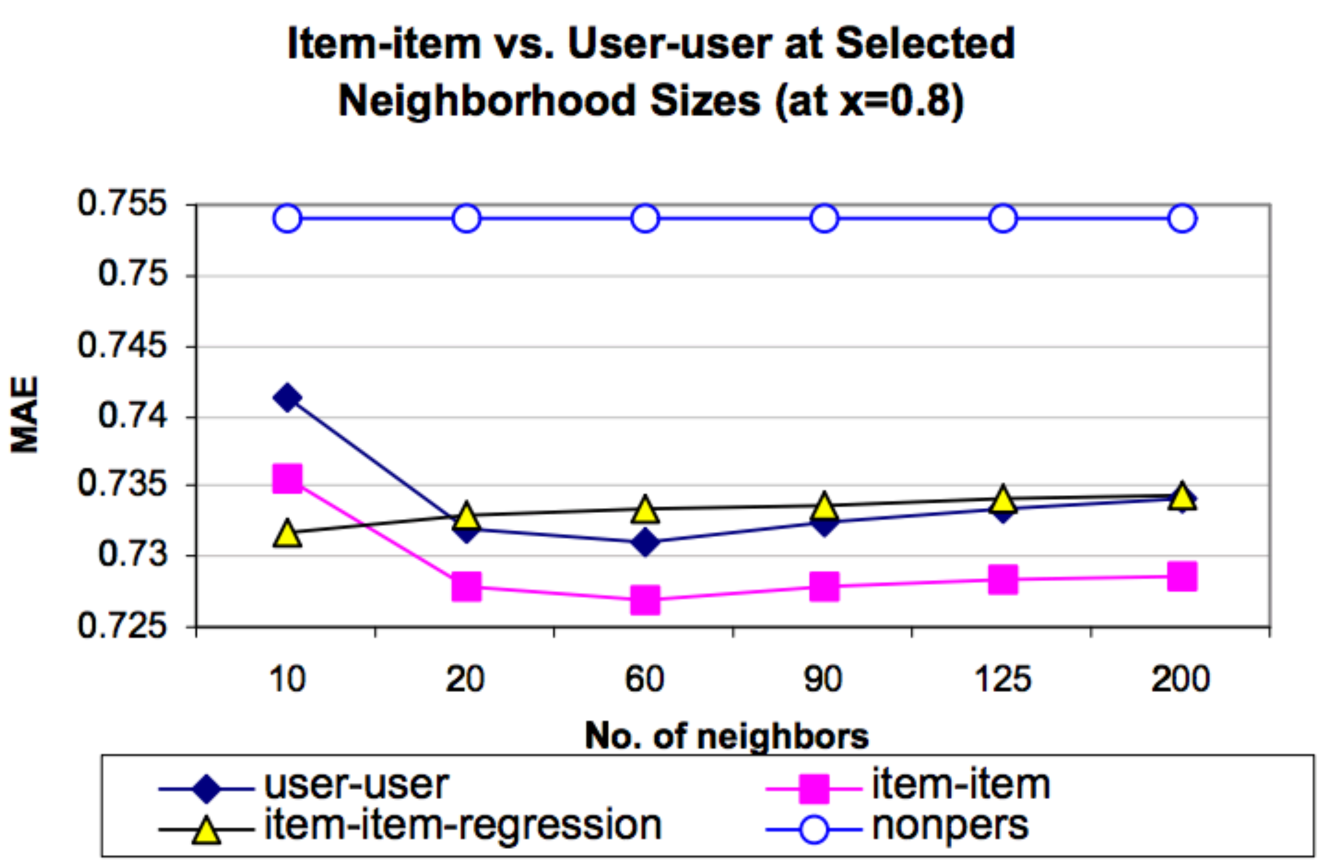
Computational time:

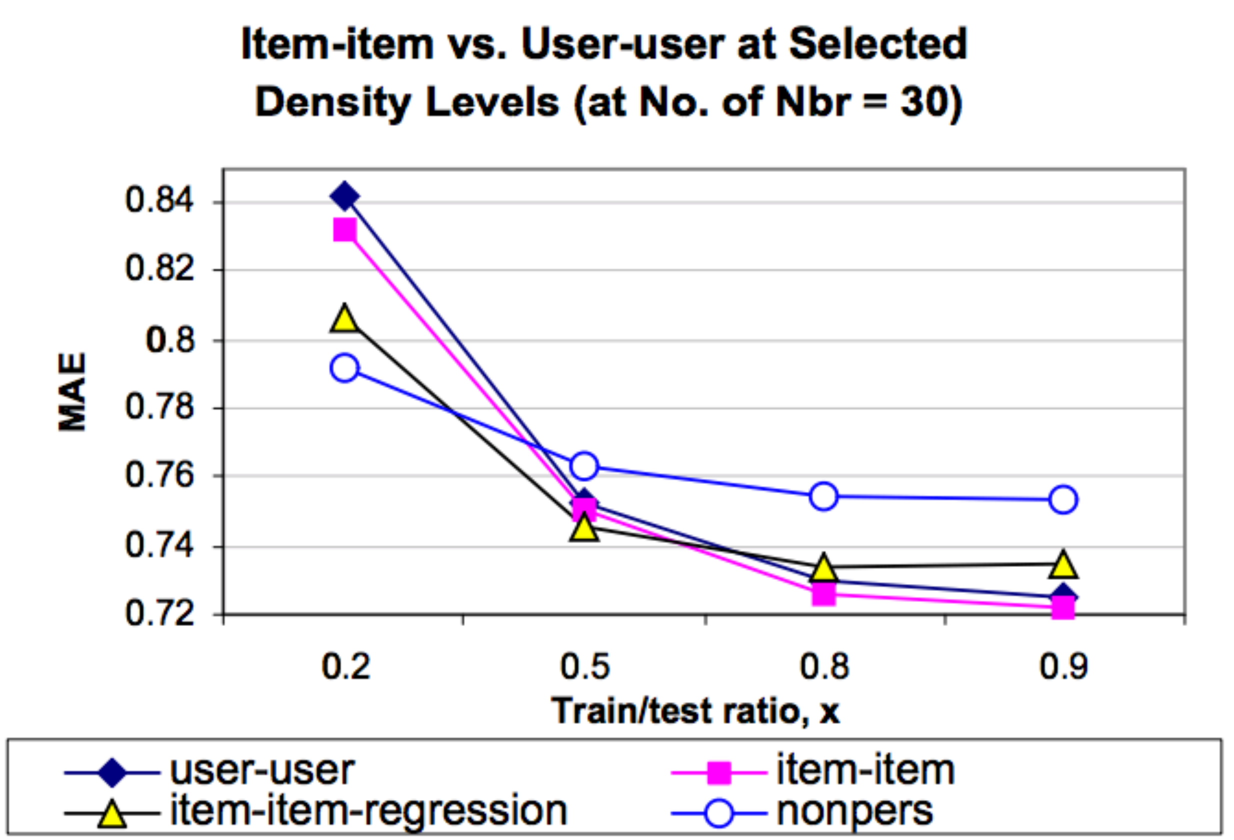
O(m^2 n) O(n^2 m)

Memory Requirements:

O(m^2) O(n^2)

User-Based vs. Item-Based





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User-Based vs. Item-Based

- **Pros User-based**
  - Tend to provide higher diversity (more serendipity)
- **Pros Item-based**
  - Better results (in terms of RMSE)
  - More stable to changes

User-Based vs. Item-Based

	User-Based	Item-Based
Scalability		
Explanation		
Novelty		
Coverage		
Cold start		
Performance		

User-Based vs. Item-Based

	User-Based	Item-Based
Scalability	Bad when #users is huge	Bad when #items is huge
Explanation	Bad	Good
Novelty	Bad	Good
Coverage	Bad	Good
Cold start	Bad for new users	Bad for new items
Performance	Need to get many users history	Only need to get current users's history

Item-Based Nearest Neighbor Regression

- We can replace the (normalized) similarity coefficient AdjustedCosine(j,i) with a unknown parameter w_{ji}^{item} to model the rating prediction of a user u for target item i.

$$\hat{r}_{ui} = \sum_{j \in Q_i(u)} w_{ji}^{item} \cdot r_{uj}$$

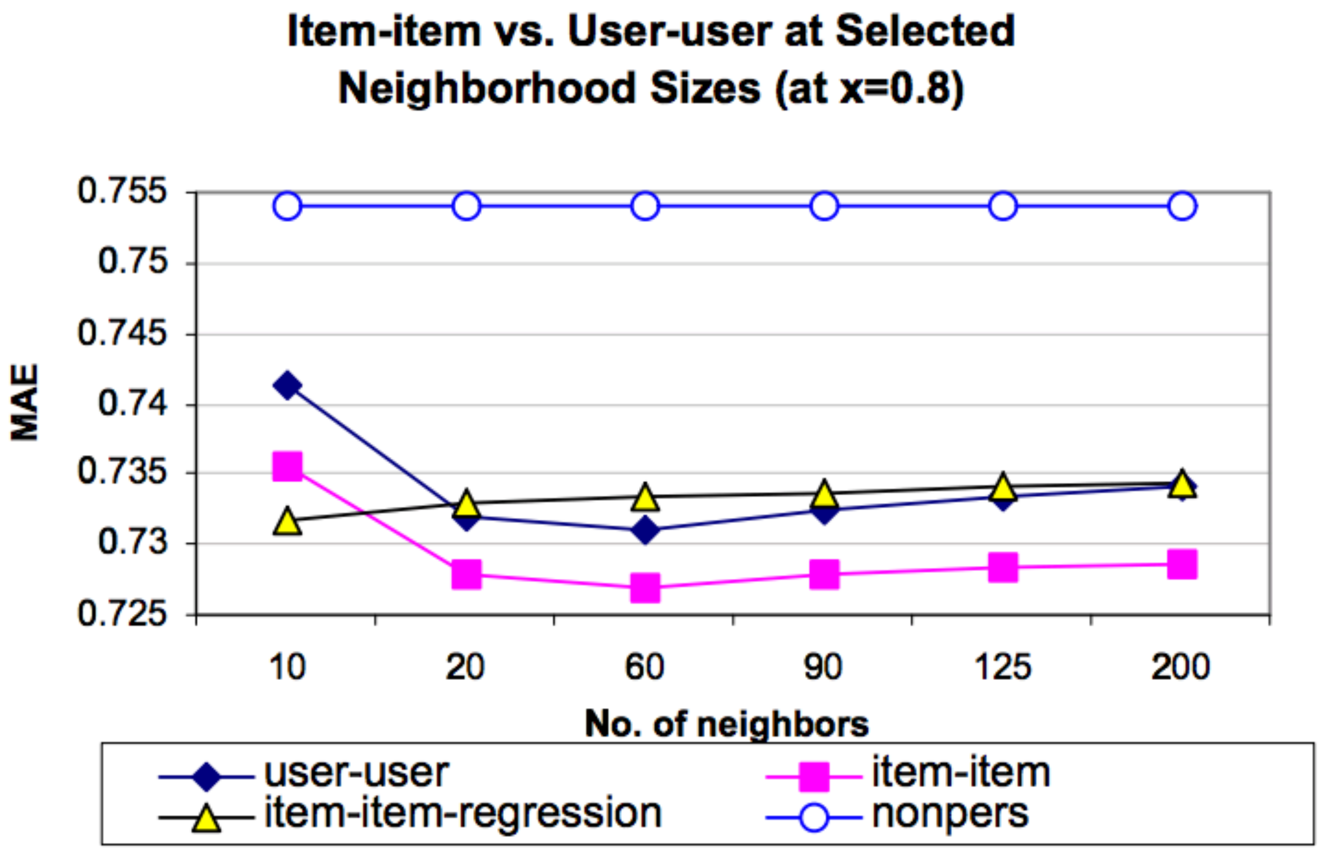
The nearest items in Qi(u) can be determined using the adjusted cosine

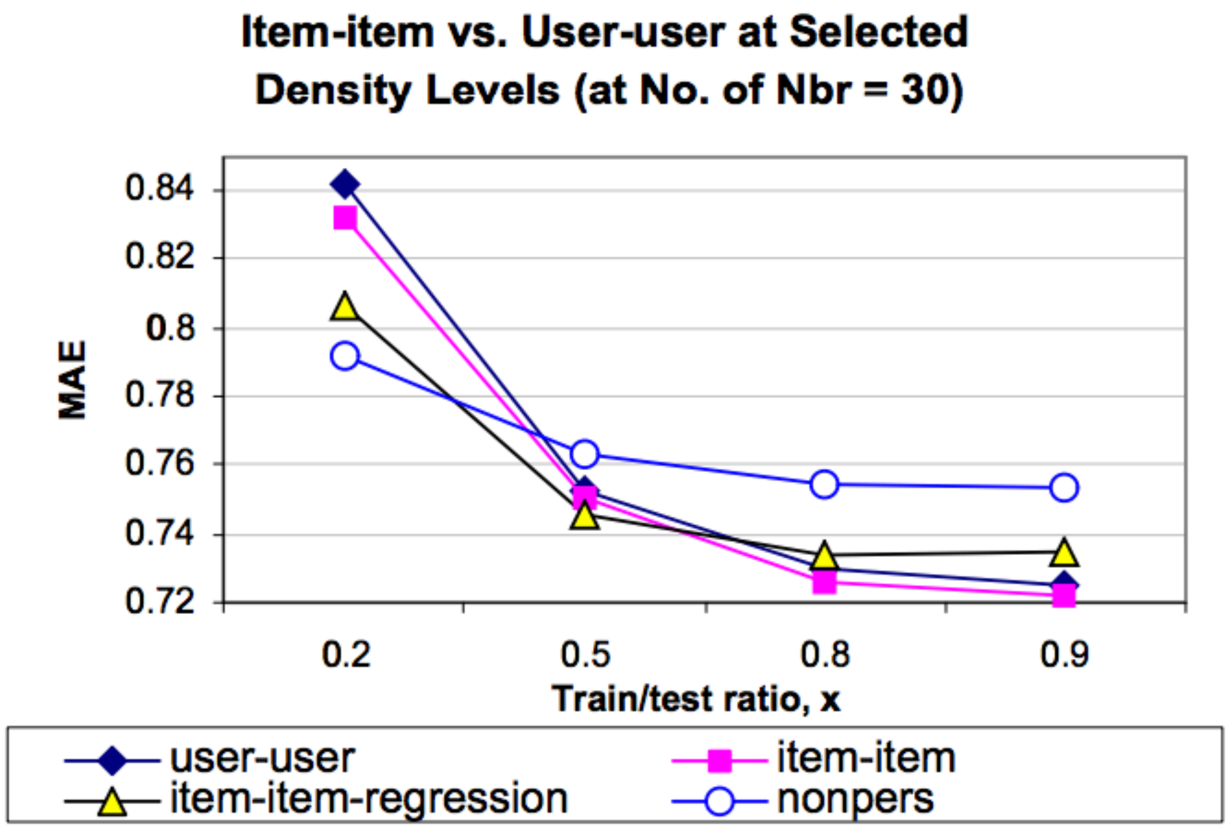
Item-Based Nearest Neighbor Regression

$$Minimize\ J_t = \sum_{u \in U_t} (r_{ut} - \hat{r}_{ut})^2$$

$$= \sum_{u \in U_t} \left(r_{ut} - \sum_{j \in Q_t(u)} w_{jt}^{item} \cdot r_{uj} \right)^2$$

User-Based vs. Item-Based





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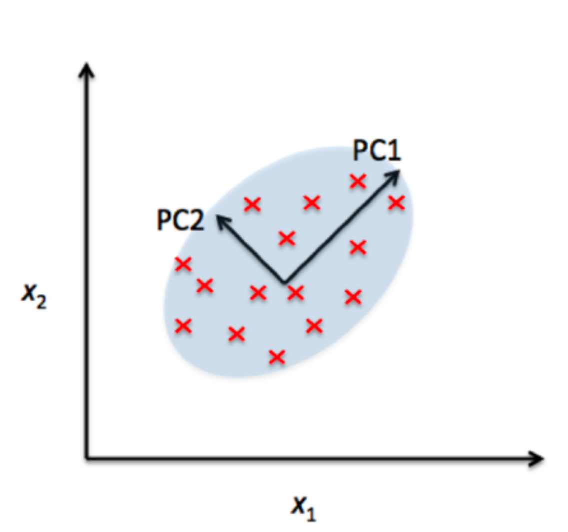
Dimensionality Reduction

- Pairwise similarities are hard to robustly be computed in sparse matrices.
- Dimensionality reduction can be used to **improve** neighborhood-based methods both in terms of **quality** and in terms of **efficiency**
- A reduced representation of the data can be created in terms of either row-wise latent factors or in terms of column-wise latent factors.

Dimensionality Reduction



Items

Latent Factors

users

≈

users

m x n **sparse matrix**

m x d **matrix**
where d<<n

Dimensionality Reduction

- The low-dimensional representation can be computed using **PCA** or **SVD-Like** methods.
- After the d-dimensional representation of each user is estimated, the similarity between users can be computed
- Cosine or dot product on the reduced vectors can be used in order to compute the similarity
- More robust since the feature vector is fully specified
- More efficient

Dimensionality Reduction

- How to **obtain** the **d-dimensional representation** on the sparse matrix?
- **SVD Method**. Steps:
    - Augment the *m x n* incomplete rating matrix R -> R_f
        - Mean-user rating or mean-item rating for each row/column
    - Lets define the similarity matrix S as $\mathbf{S = R_f^T R_f}$. S is a positive semi-definite of size *n x n*
    - Determine the dominat basis vectors of R_f by computing the diagonalization of the similarity matrix S.
        - $S = P \Lambda P^T$, where P is an *n x n* matrix, whose columns contain the orthonormal eigenvectors of S. Λ is a diagonal matrix containing the non-negative eigenvalues of S along its diagonal.
    - Let denote P_d the *n x d* matrix only containing the columns of P with the largest eigenvalues
    - The low representation of R is obtained by the multiplication of $\mathbf{R_f P_d}$

Dimensionality Reduction

- How to **obtain** the **d-dimensional representation** on the sparse matrix?
- **PCA Method**. Steps:
  - Augment the *m x n* incomplete rating matrix R -> R_f
    - Mean-user rating or mean-item raring for each row/column
  - Lets define the similarity matrix S as **the Covariance Matrix of Rf**
  - Determine the dominat basis vectors of R_f by computing the diagonalization of the similarity matrix S.
    - $S = P\Lambda P^T$, where P is an *n x n* matrix, whose columns contain the orthonormal eigenvectors of S. Λ is a diagonal matrix containing the non-negative eigenvalues of S along its diagonal.
  - Let denote P_d the *n x d* matrix only containing the columns of P with the largest eigenvalues
  - The low representation of R is obtained by the multiplication of $\mathbf{R_f P_d}$

Challenges on Factorization

- Challenges:
  - Missing Values
    - Need a way to fill it
    - Several alternatives, including clever averages and predictions
  - Computational Complexity
  - Lack of transparency/explainability

TASK 1
Trivago Recommender System

Create:

1) A recommender system
2) Submit at least one approach
3) Explain your conclusions in class (5 minutes)

You can work with **teams** from **up to 3 members**

Deadline: 7th April (23.55)

RecSys Challenge 2019

Welcome ACM RecSys Community! For this year's challenge from the online travel domain, build a context-aware accommodation recommendation system that utilises live user interactions.

About the RecSys 2019 Challenge

The goal of the challenge is to use user signals within a session to detect the intent of the user and to update the recommendation of accommodations provided to the user. Given a dataset of the interactions of the users on our website and metadata for the items they interacted with, the participants are tasked with predicting what items have been clicked in the later part of a session.

More about the challenge →
Dataset →

Current Leaderboard

Team	Score
CustomerSuccess	0.3713
trivago	0.288448
Sharknado	0.288448
Grubhub Personalization	0.288448
Team Buctù	0.288448