Multiverse Recommendation:

N-dimensional Tensor Factorization for Context-aware Collaborative Filtering

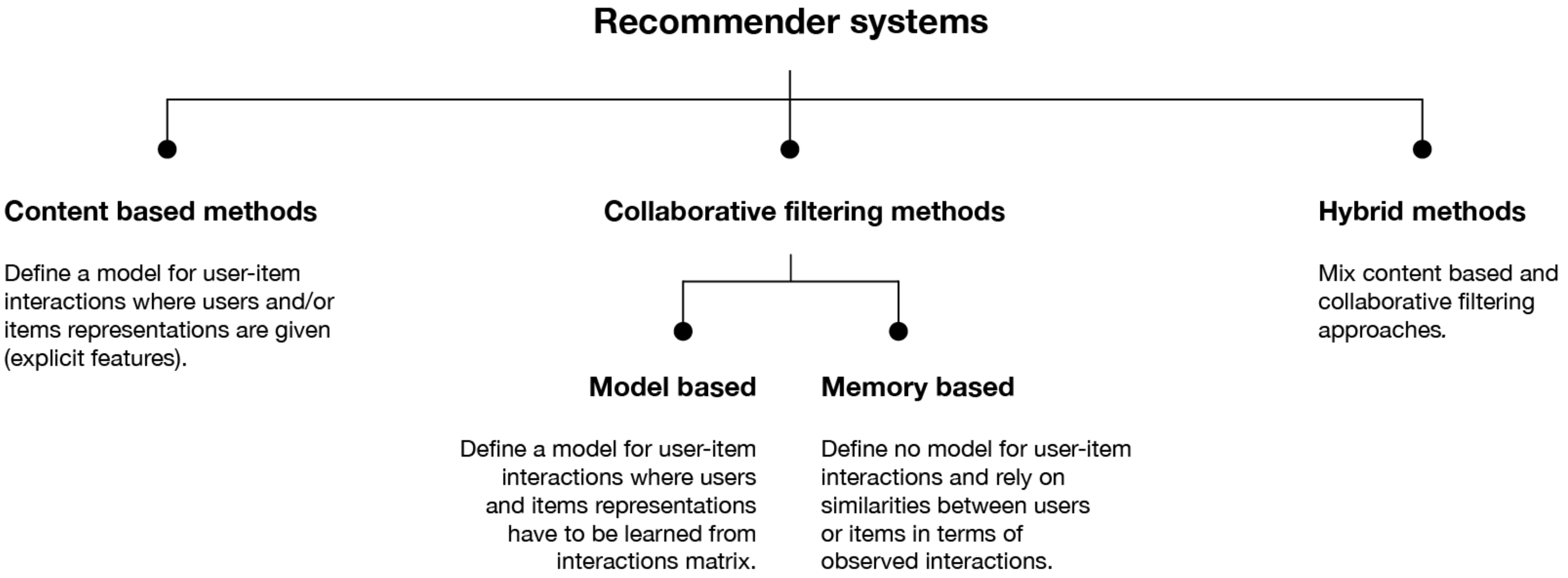
Karatzoglou et. al., (ACM Recommender Systems `10)

Hyunji Choi

May 1st, 2021

Contents

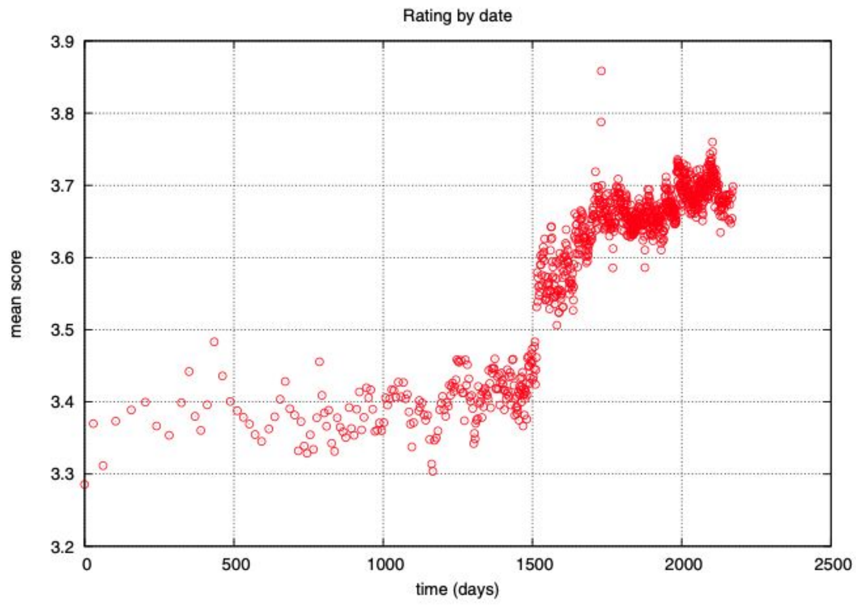
Content-based and Collaborative Filtering Recommendation

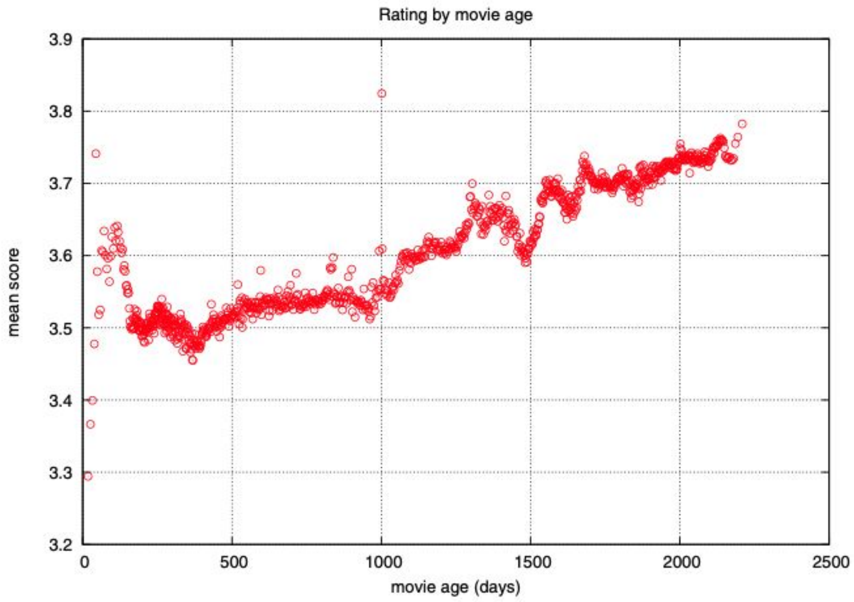


https://towardsdatascience.com/introduction-to-recommender-systems-6c66cf15ada

Context-aware Recommendation

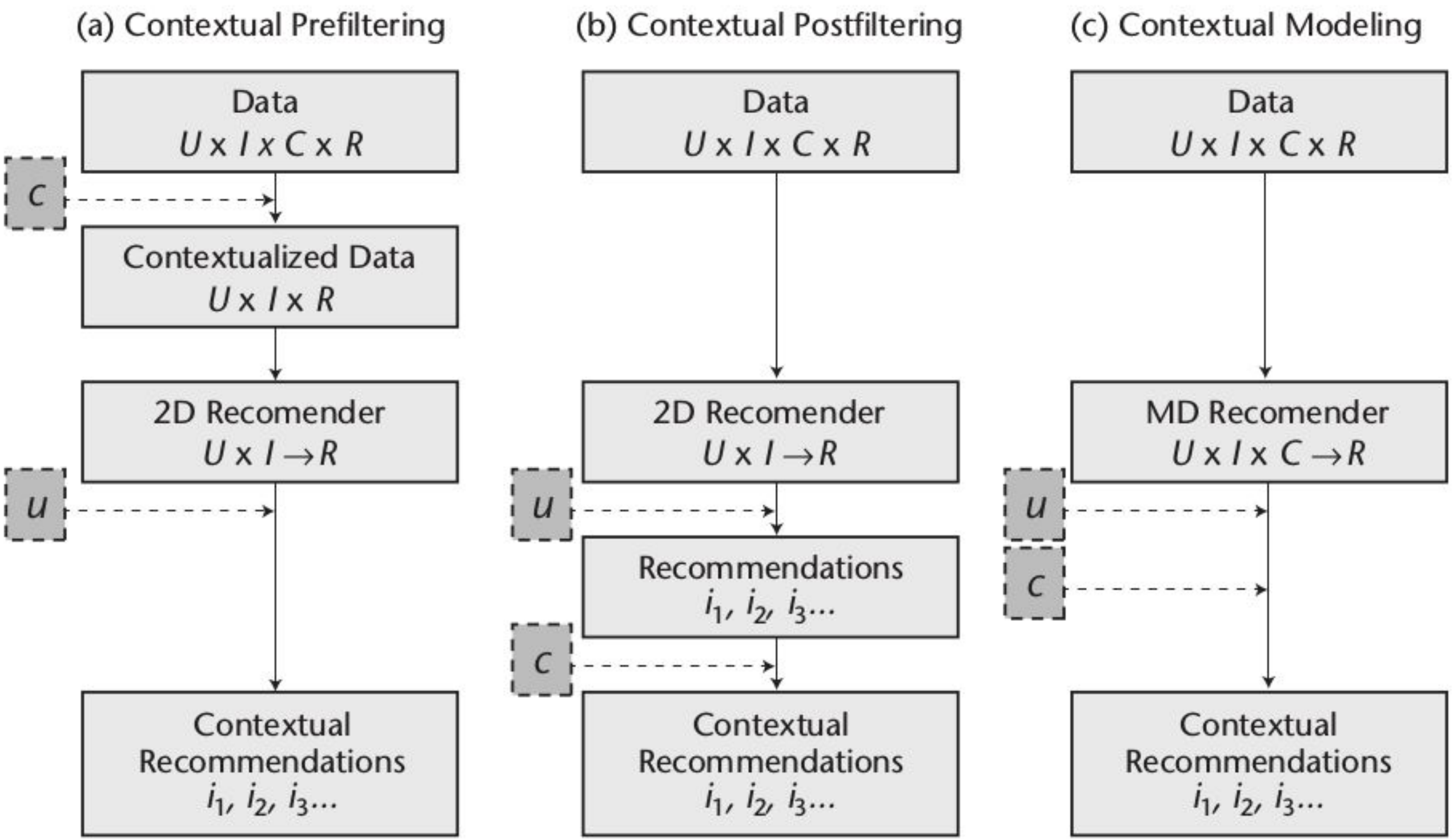
- **Time matters!**





Collaborative Filtering with Temporal Dynamics

Early models of Context-aware Recommendation



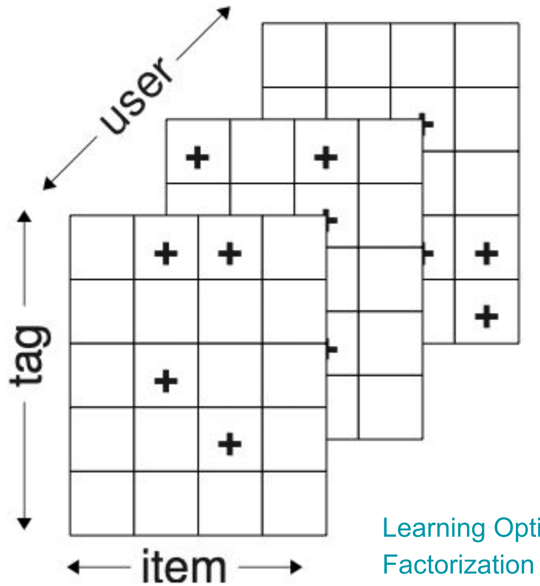
https://medium.com/@andresespinosapc/the-basics-of-context-aware-recommendations-5dd7a939049b

Contextual Modeling

- **timeSVD++**

$$b_{ui}(t) = \mu + b_u + \alpha_u \cdot \text{dev}_u(t) + b_{u,t} + b_i + b_{i,\text{Bin}(t)}$$

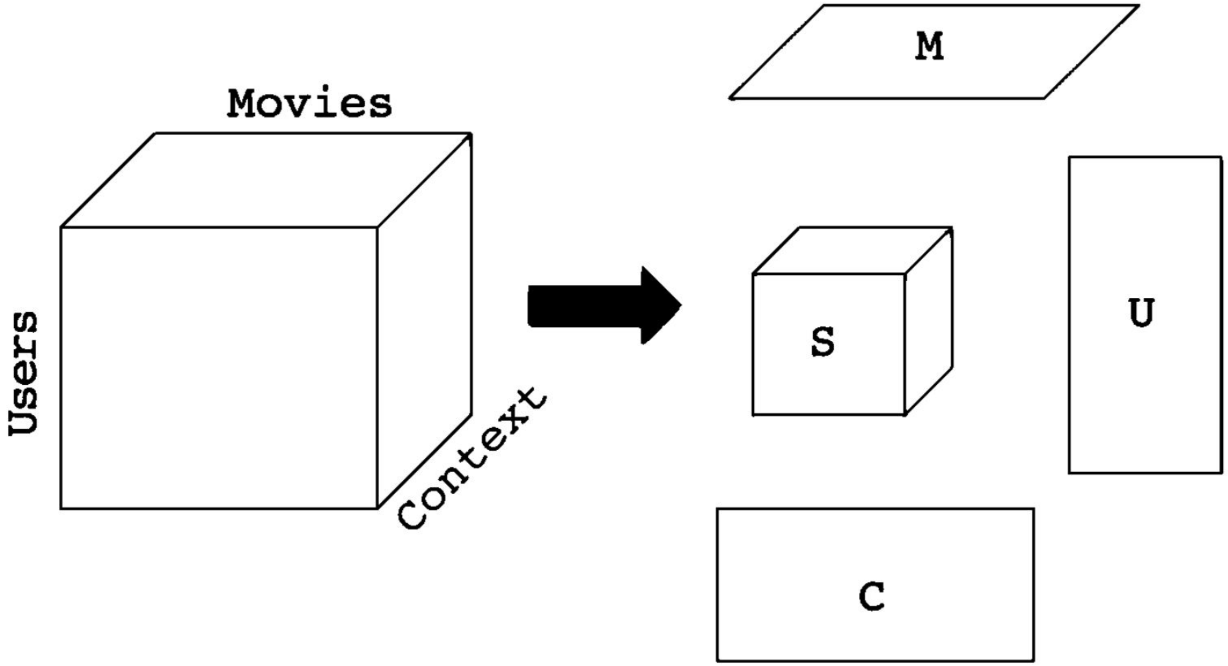
- **RTF**



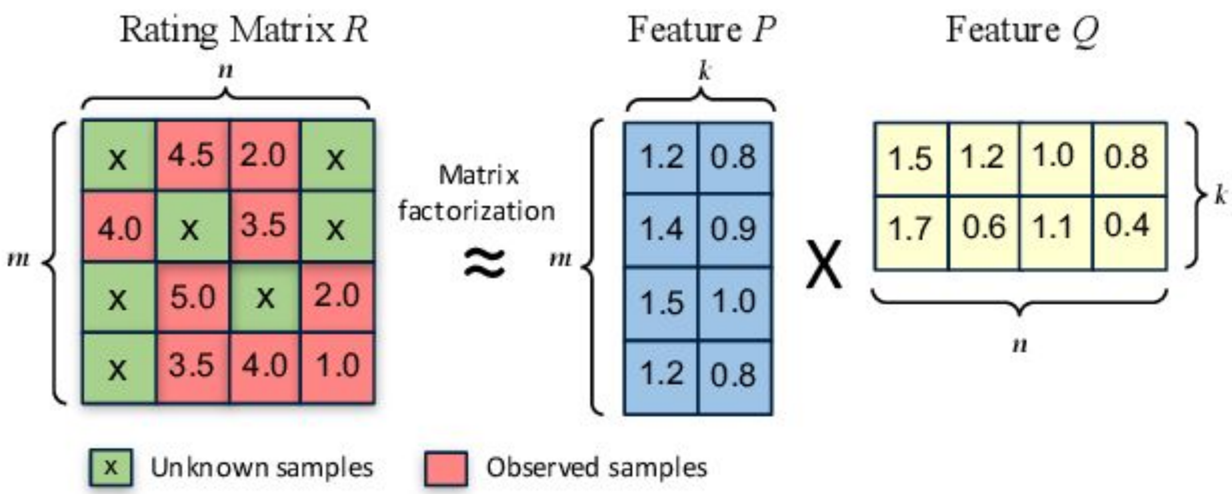
Learning Optimal Ranking with Tensor Factorization for Tag Recommendation

Approach

- **Generalize matrix factorization to model multiple variables.**



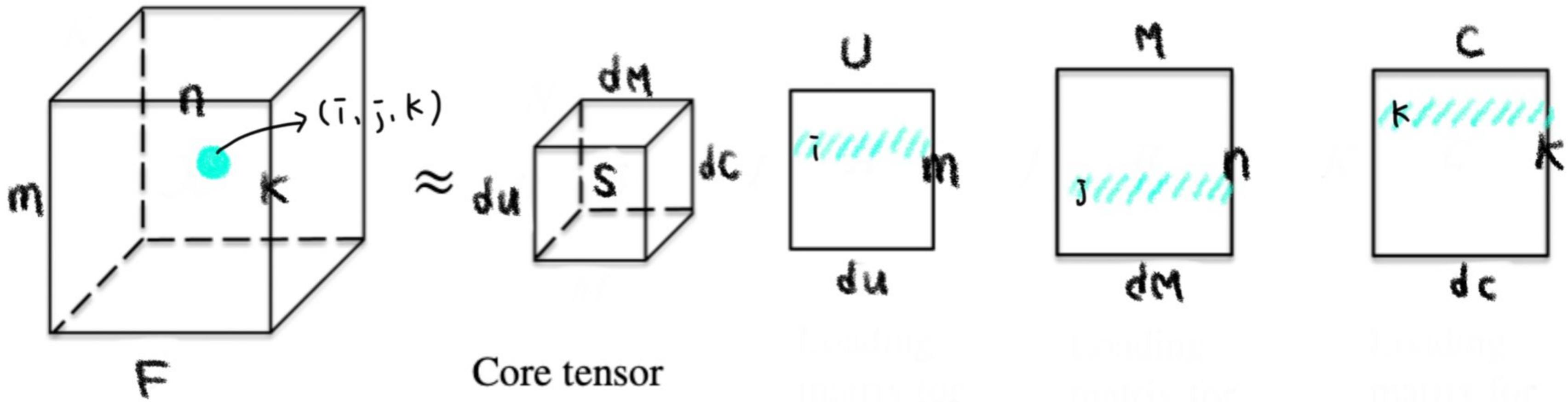
Matrix Factorization



CuMF_SGD: Fast and Scalable Matrix Factorization

- **Minimize loss(R-PQ).**

Tensor Factorization



$$F_{ijk} = S \times_U U_{i*} \times_M M_{j*} \times_C C_{k*}$$

- **Minimize loss(Y-F).**

Tensor Factorization for Collaborative Filtering

- **HOSVD requires dense matrix.**
- **Unrated initialized to zero tends to learn near-zero values (bias).**
- **Do not use unrated cell in training.**

Multiverse Recommendation

- **Loss function**

$$L(F,Y) := \frac{1}{\|S\|_1} \sum_{i,j,k} D_{ijk} l(F_{ijk}, Y_{ijk})$$

- **With Regularization: Prevent overfitting and set boundary.**

$$R[U,M,C,S] := L(F,Y) + \Omega[U,M,C] + \Omega[S]$$

SGD based Training Algorithm

Algorithm 1 Tensor Factorization

Input Y, d

Initialize $U \in \mathbb{R}^{n \times d_U}$, $M \in \mathbb{R}^{m \times d_M}$, $C \in \mathbb{R}^{c \times d_C}$ and $S \in \mathbb{R}^{d_U \times d_M \times d_C}$ with small random values.

Set $t = t_0$

while (i, j, k) in observations Y **do**

$\quad \eta \longleftarrow \frac{1}{\sqrt{t}}$ and $t \longleftarrow t + 1$

$\quad F_{ijk} = S \times_U U_{i*} \times_M M_{j*} \times_C C_{k*}$

$\quad U_{i*} \longleftarrow U_{i*} - \eta \lambda_U U_{i*} - \eta \partial_{U_{i*}} l(F_{ijk}, Y_{ijk})$

$\quad M_{j*} \longleftarrow M_{j*} - \eta \lambda_M M_{j*} - \eta \partial_{M_{j*}} l(F_{ijk}, Y_{ijk})$

$\quad C_{k*} \longleftarrow C_{k*} - \eta \lambda_C C_{k*} - \eta \partial_{C_{k*}} l(F_{ijk}, Y_{ijk})$

$\quad S \longleftarrow S - \eta \lambda_S S - \eta \partial_S l(F_{ijk}, Y_{ijk})$

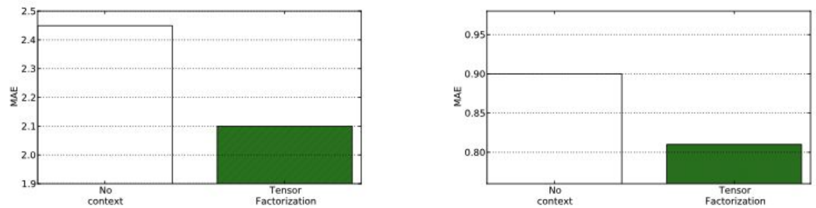
end while

Output U, M, C, S

Performance - Data and Metric

- **Yahoo! Webscope**
  - Increase rating if c=1 and decrease if c=0.
- **Movie Survey**
- **Food Survey**
- **MAE**

Effect of Context



(a) Adom data (b) Food data

Figure 2: Comparison of matrix (no context) and tensor (context) factorization on the Adom and Food data.

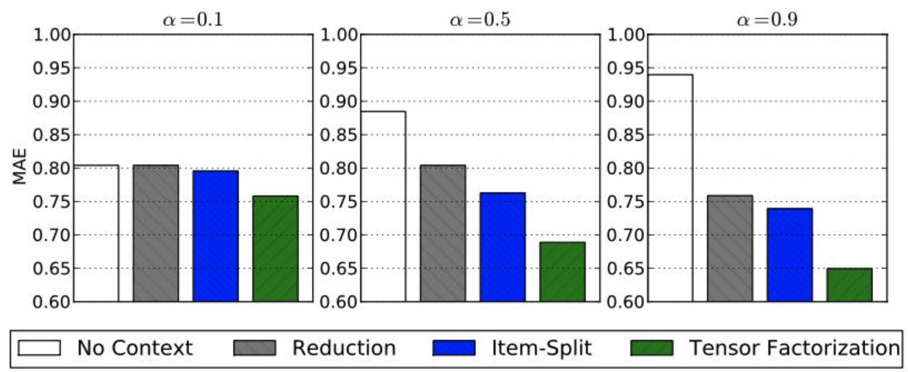


Figure 3: Comparison of context-aware methods on artificial data

Comparison with pre-filtering

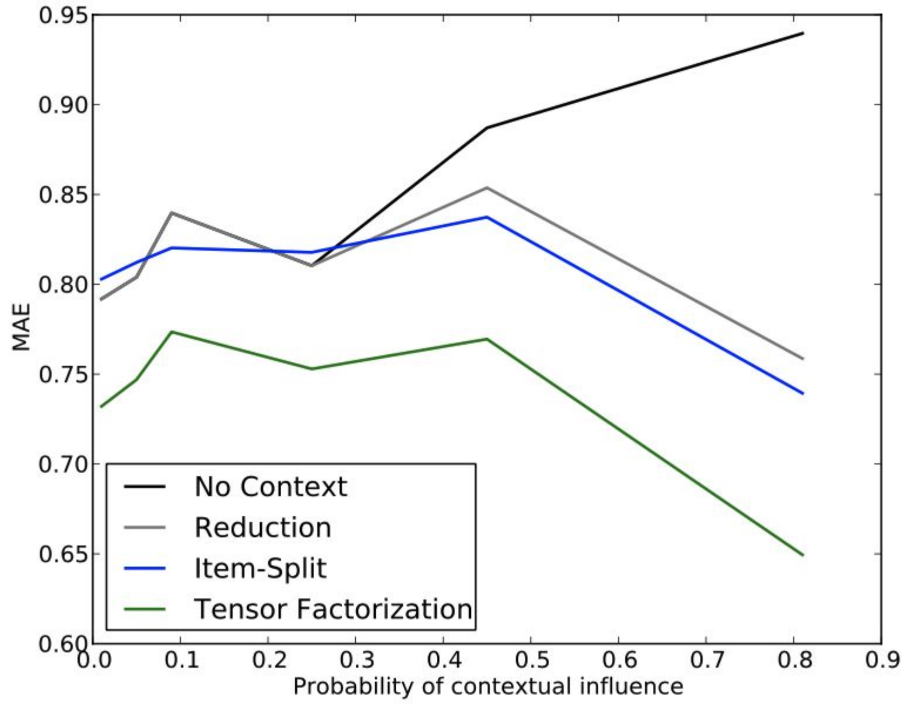


Figure 4: Evolution of MAE values for different methods with increasing influence of the context variable

Conclusion

- **Integrated generic Tensor Factorization approach to CF.**
- **Higher recommendation accuracy.**