CIS 635 Knowledge Discovery & Data Mining

Association Learning

Association Learning

- **Market basket analysis**
- Collaborative filtering

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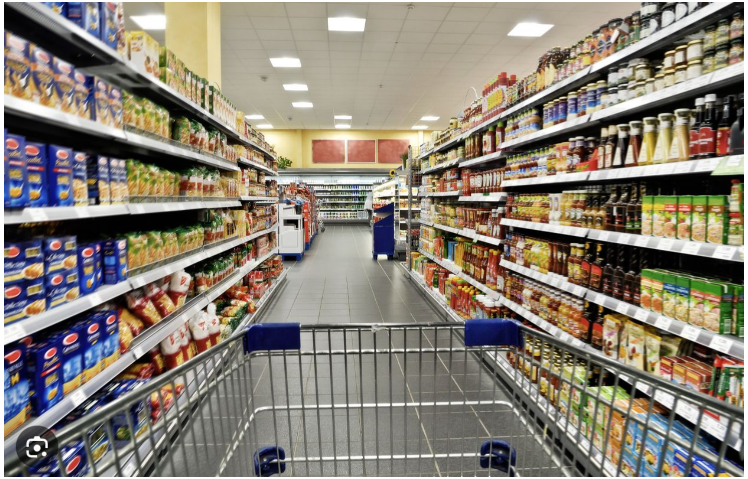
- Market basket analysis

Introduction

- Supermarket items are displayed not random, they follow some patterns



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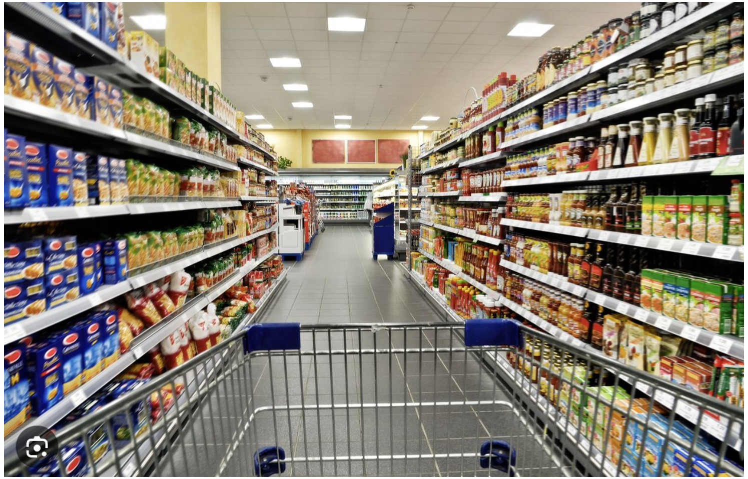
  - **The objective is, clients can access/find items easily**



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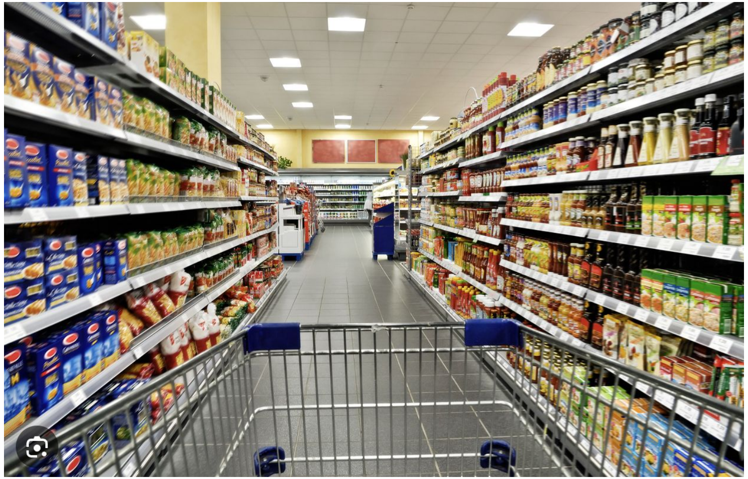
  - **More importantly, the business goal is to increase sales; the more the sales the higher the profit**



Introduction

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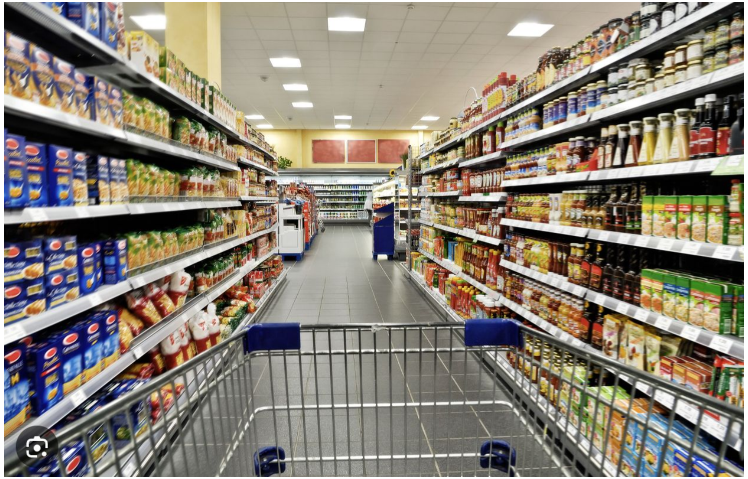
  - The objective is, clients can access/find items easily
  - More importantly, the business goal is to increase sales; the more the sales the higher the profit
- **This is a known concept for years**



Beer Diaper Story

Beer and Diapers – the Perfect Couple

Jim Borden   family, humor, technology   December 7, 2018   3 Minutes

The topic for my class today
we discussed was data mini

The **story goes something like this**:

2002

"One Midwest grocery chain used the data mining capacity of Oracle software to analyze local buying patterns. They discovered that when men bought diapers on Thursdays and Saturdays, they also tended to buy beer. Further analysis showed that these shoppers typically did their weekly grocery shopping on Saturdays. On Thursdays, however, they only bought a few items. The retailer concluded that they purchased the beer to have it available for the upcoming weekend. The grocery chain could use this newly discovered information in various ways to increase revenue. For example, they could move the beer

[Ref: Article published in 2018]

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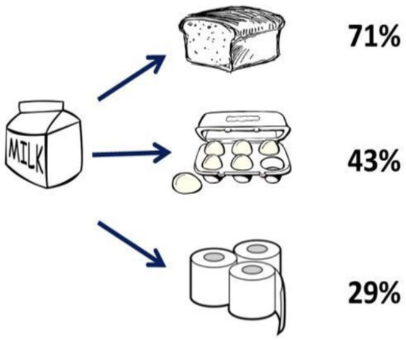

Association rule learning

To create the association rules, we use some evaluation metrics:

Support: Percentage of that sequence of items appearing in orders

$$\frac{\{\text{Diapers, Beer}\}}{\text{count transactions}} = \frac{3}{5} = 60\%$$

ID	Items
1	{Bread, Milk}
2	{Bread, Diapers, Beer, Eggs}
3	{Milk, Diapers, Beer, Cola}
4	{Bread, Milk, Diapers, Beer}
5	{Bread, Milk, Diapers, Cola}
...	...

market basket transactions

{Diapers, Beer} Example of a frequent itemset

{Diapers} → {Beer} Example of an association rule

X Y

Ref: Notebook presentation

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$$\frac{\text{Confidence}\{\text{Diapers, Beer}\}}{\text{Support}\{\text{Beer}\}} = \frac{\frac{(3 \div 5)}{(4 \div 5)}}{3 \div 5} = 1.25$$

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Lift Value:

value = *1* implies no association between items.
value > *1* means that item Y is likely to be bought if the X is bought.
value < *1* means that item Y is unlikely to be bought if item X is bought.

Ref: Notebook presentation

Similar cases

- The purchase patterns of clients/users when they buy items together
- **Restaurant orders.**

Notebook presentation!

- Market basket analysis of two restaurants menus (what items people ordered together)
- Comparison of their business in terms of their menus offering, etc!

Association Learning

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- Collaborative filtering

Recommender Systems

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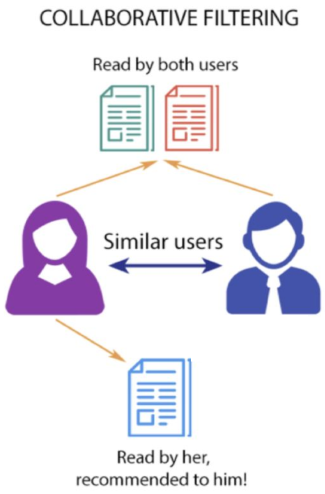
Recommender Systems



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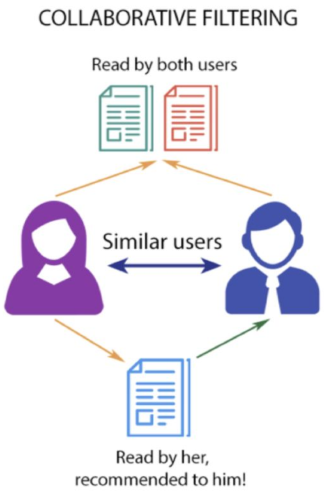

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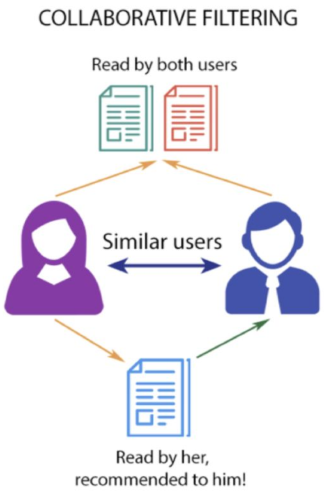

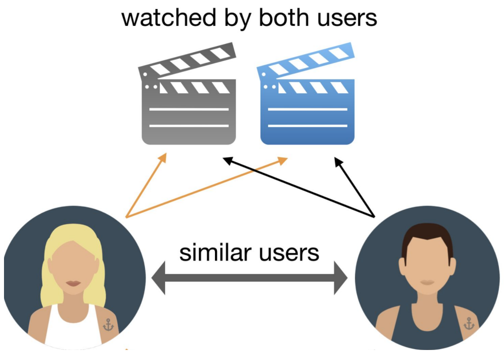

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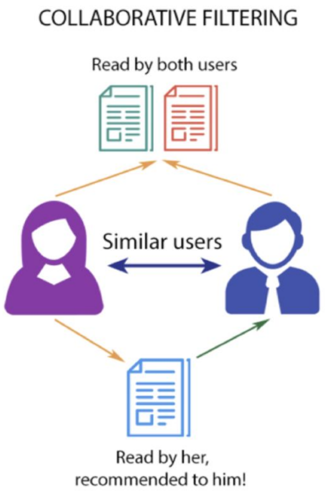

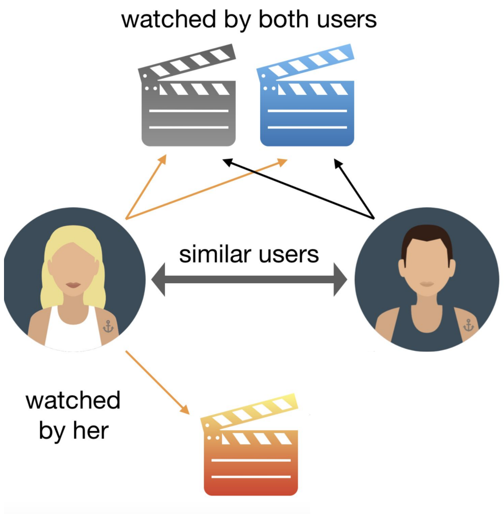

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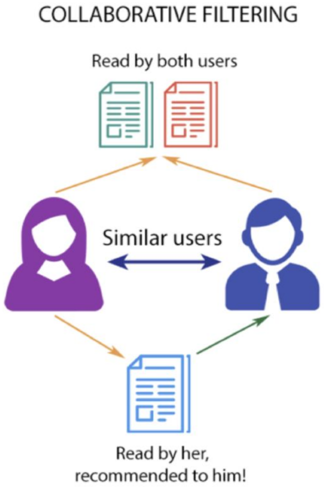

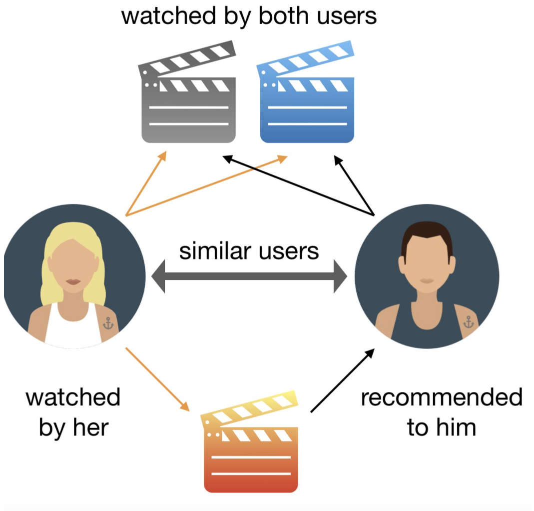

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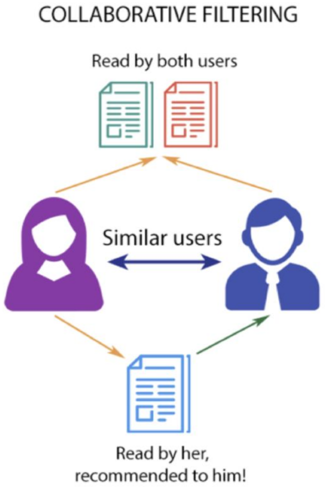
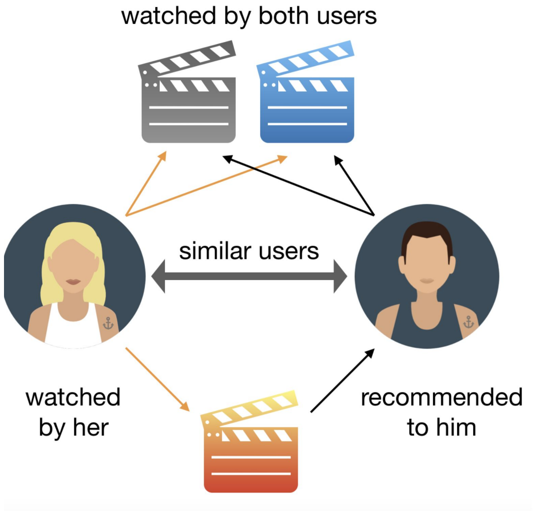


Collaborative filtering



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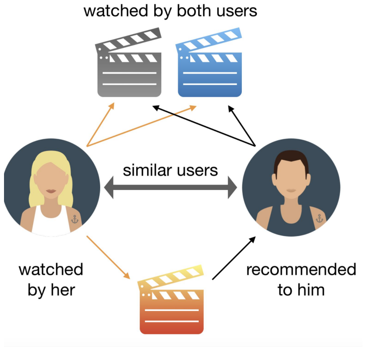

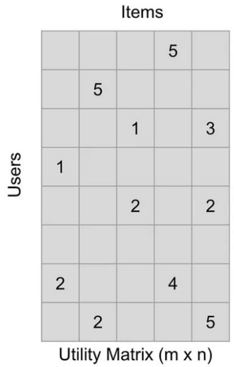

Matrix factorization (numbers are random for the sake of illustration) (Image by author)

- Our data matrix, sometimes called as utility matrix

Recommender Systems

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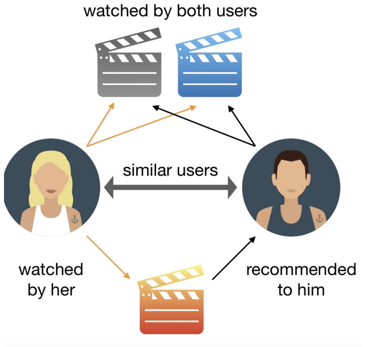


Items

Users

			5	
	5			
		1		3
1				
		2		2
2			4	
	2			5

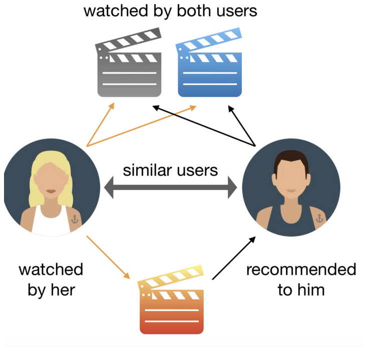
Utility Matrix (m x n)

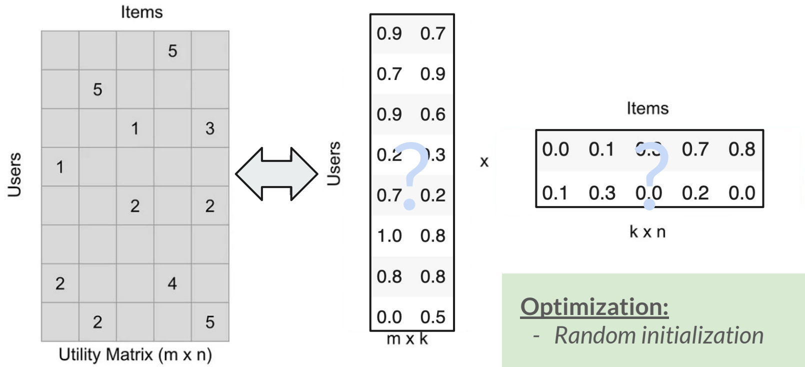
Matrix factorization (numbers are random for the sake of illustration) (Image by author)

- Our data matrix, sometimes called as utility matrix
- **We will talk about a matrix factorization collaborative filtering technique**

Recommender Systems

Collaborative filtering





Optimization:
- *Random initialization*

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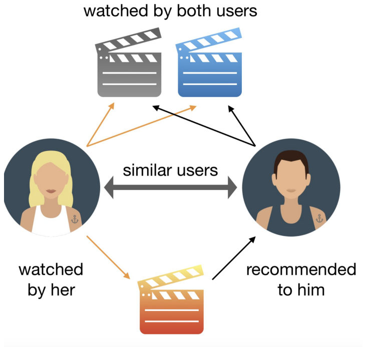

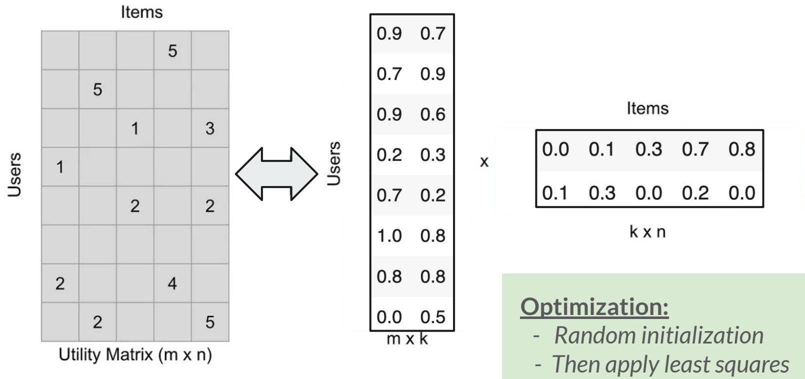

Optimization:
- *Random initialization*
- *Then apply least squares*

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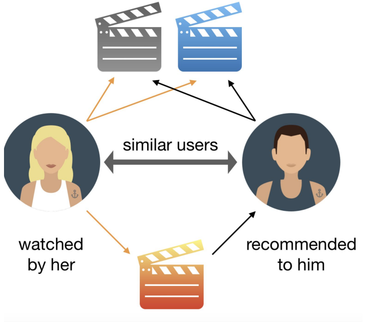
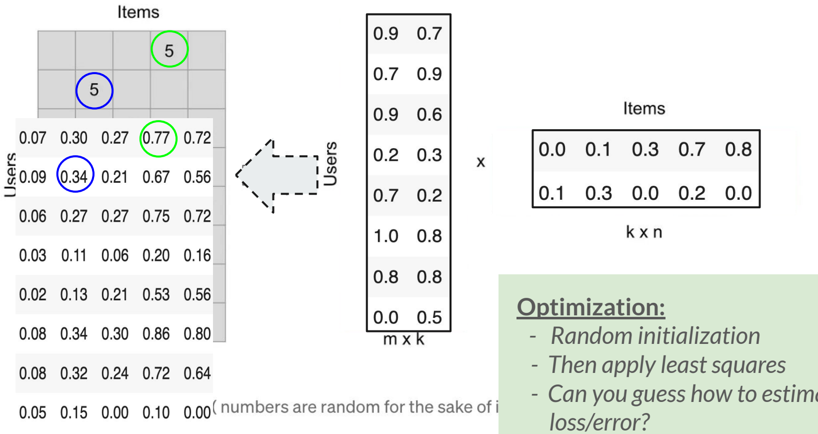


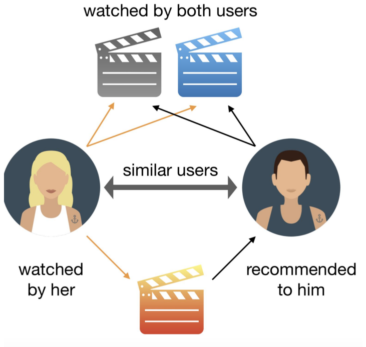


Optimization:

- *Random initialization*
- *Then apply least squares*
- *Can you guess how to estimate loss/error?*

Recommender Systems

Collaborative filtering



Items

?			5	
	5			

Users

0.07	0.30	0.27	0.77	0.72
0.09	0.34	0.21	0.67	0.56
0.06	0.27	0.27	0.75	0.72
0.03	0.11	0.06	0.20	0.16
0.02	0.13	0.21	0.53	0.56
0.08	0.34	0.30	0.86	0.80
0.08	0.32	0.24	0.72	0.64
0.05	0.15	0.00	0.10	0.00

(numbers are random for the sake of i

Users

0.9	0.7
0.7	0.9
0.9	0.6
0.2	0.3
0.7	0.2
1.0	0.8
0.8	0.8
0.0	0.5

m x k

x

Items

0.0	0.1	0.3	0.7	0.8
0.1	0.3	0.0	0.2	0.0

k x n

Optimization:

- *Random initialization*
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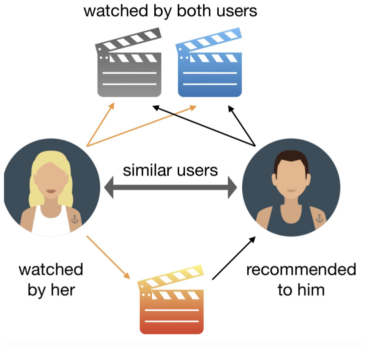
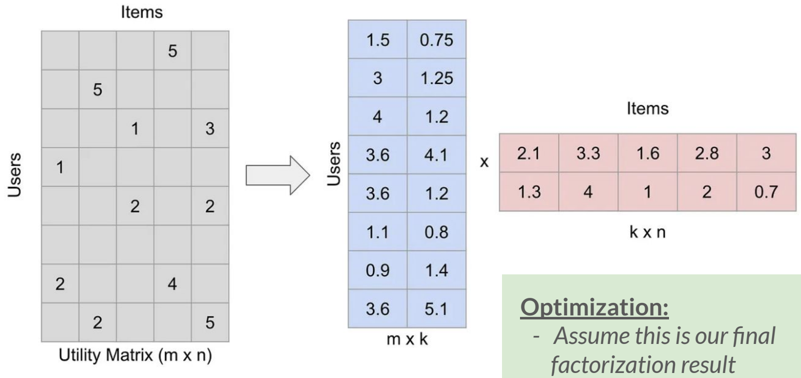




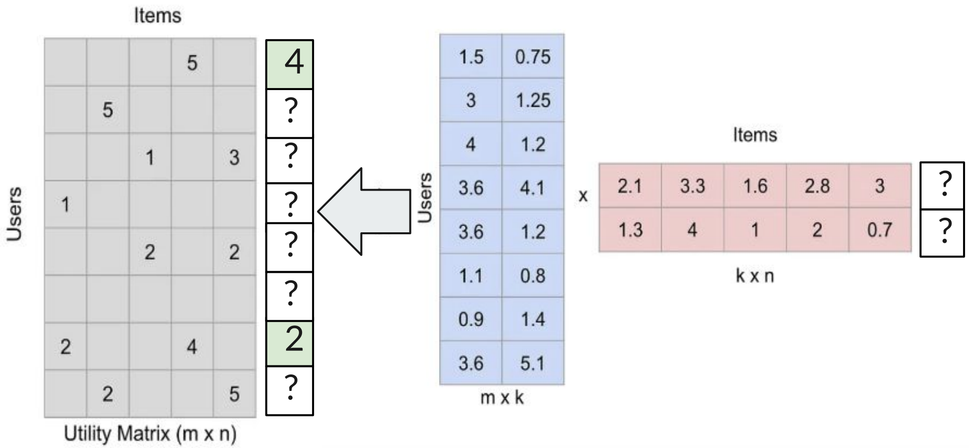
Matrix factorization (numbers are random for the sake of i

Optimization:
- *Assume this is our final factorization result*

A new movie, lets rated by 2 users

Optimize for new ratings of an item

- Given by 2 users
- And for previously learned users and items
- What item values {=(?, ?) can explain the two new ratings given that users are fixed (learned).



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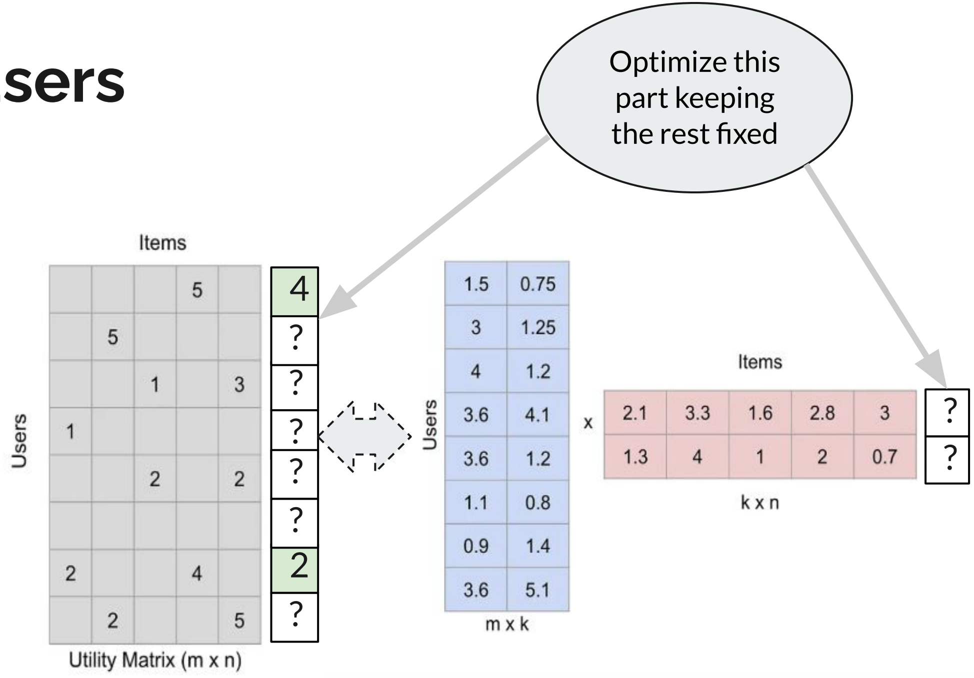

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Optimize for new ratings of an item

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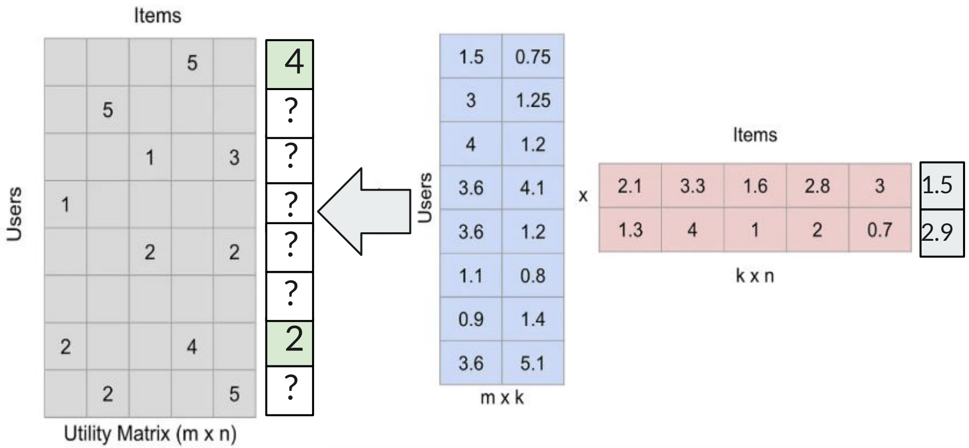
- What item values {=(?, ?) can explain the two new ratings given that users are fixed (learned).
- Then fill the ?? is in the utility matrix.



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