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# CIS 678 Machine Learning

Association Learning

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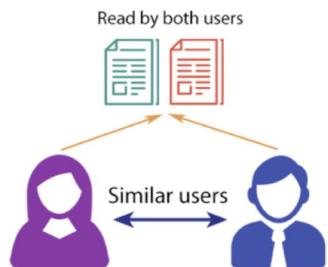
## Association Learning

- Market basket analysis
- Collaborative filtering

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# Recommender Systems

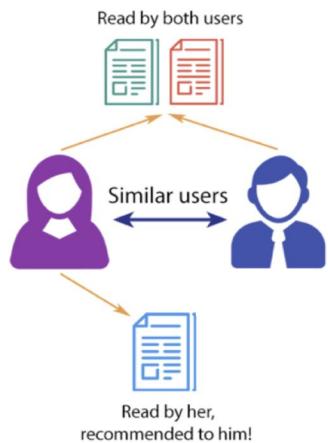
## COLLABORATIVE FILTERING



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# Recommender Systems

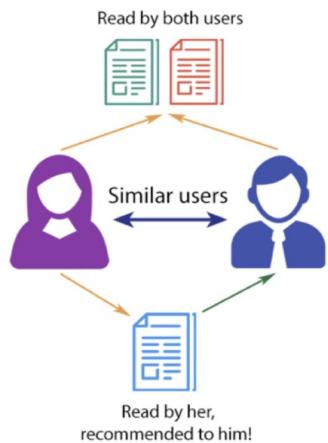
## COLLABORATIVE FILTERING



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# Recommender Systems

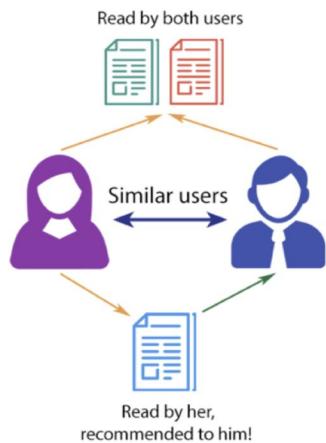
## COLLABORATIVE FILTERING



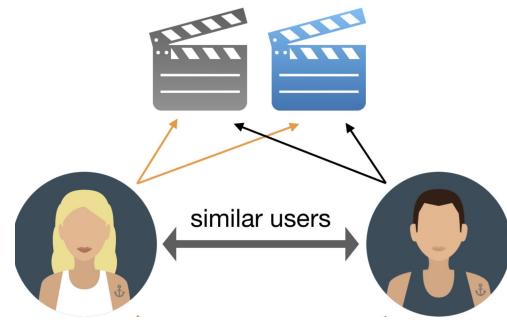
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# Recommender Systems

COLLABORATIVE FILTERING

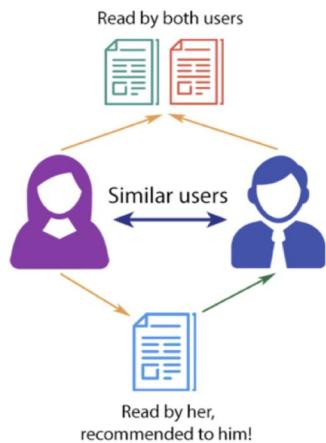


watched by both users

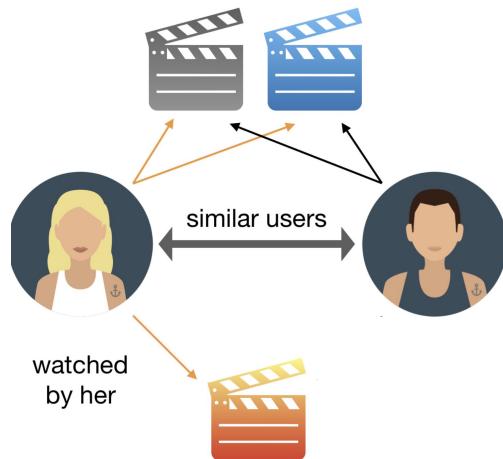


# Recommender Systems

COLLABORATIVE FILTERING

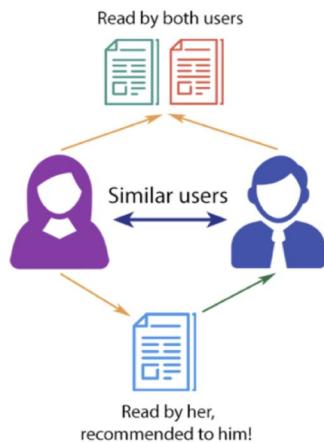


watched by both users

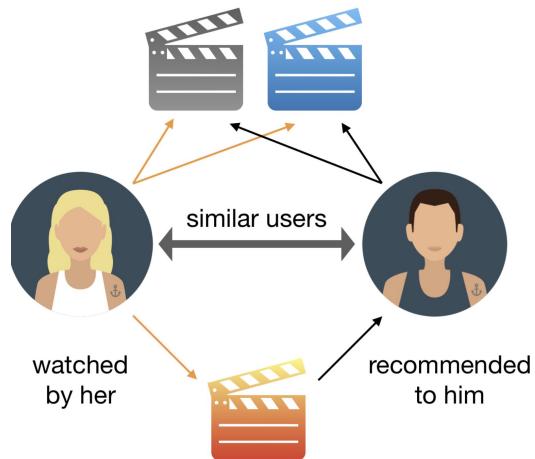


# Recommender Systems

COLLABORATIVE FILTERING

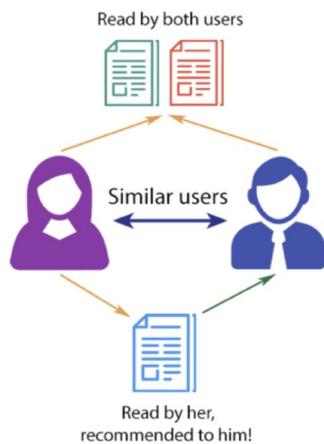


watched by both users



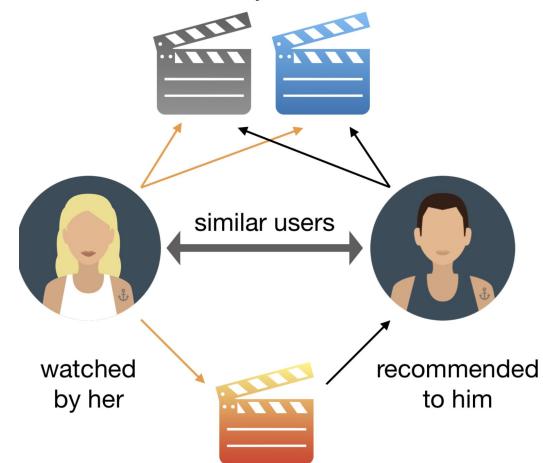
# Recommender Systems

## COLLABORATIVE FILTERING



Collaborative  
filtering

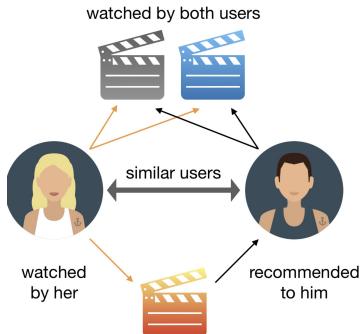
## watched by both users



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# Recommender Systems

## Collaborative filtering



		Items		
		5		
		5	1	3
1				
		2	2	2
2			4	
		2		5

Utility Matrix ( $m \times n$ )

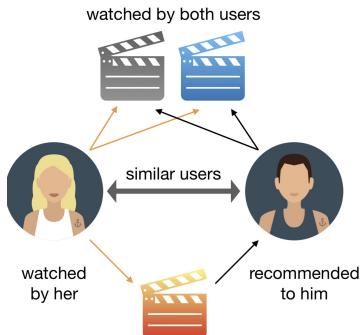
- Our data matrix, sometimes called as utility matrix

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

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# Recommender Systems

## Collaborative filtering



		Items		
		5		
		5	1	3
1				
		2	2	2
2			4	
		2		5

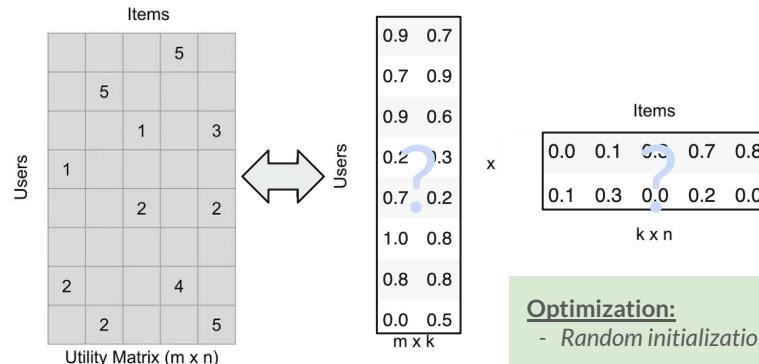
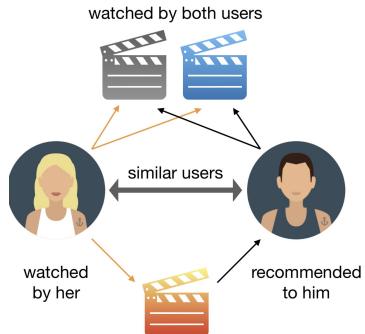
Utility Matrix ( $m \times n$ )

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

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

# Recommender Systems

## Collaborative filtering

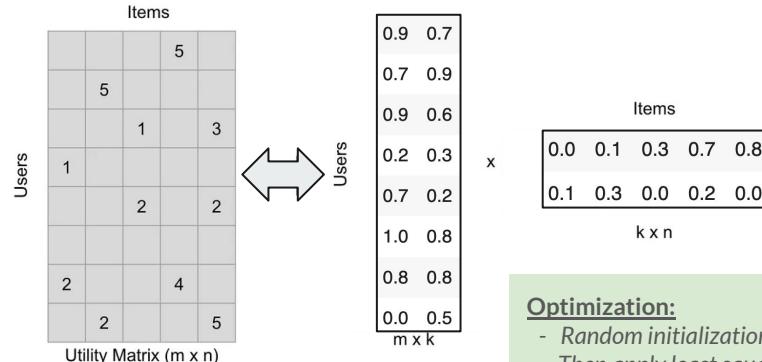
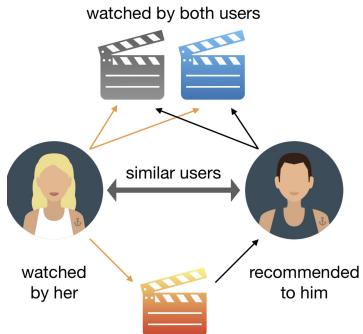


**Optimization:**  
- Random initialization

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

# Recommender Systems

## Collaborative filtering



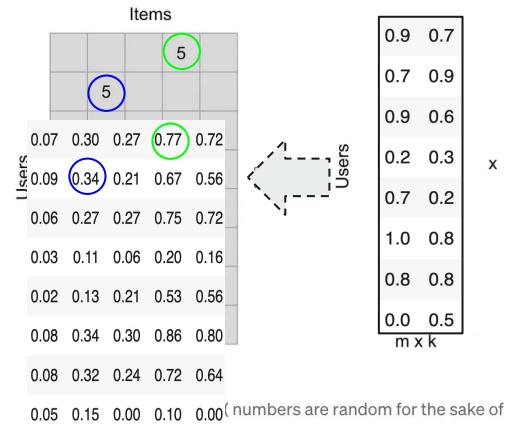
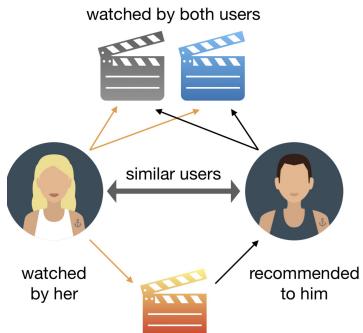
**Optimization:**

- Random initialization
- Then apply least squares

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

# Recommender Systems

## Collaborative filtering



Items

k x n

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

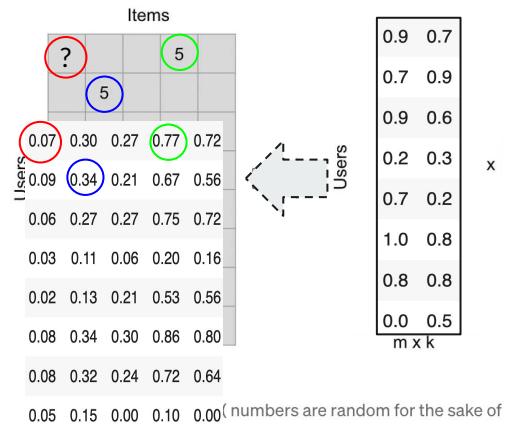
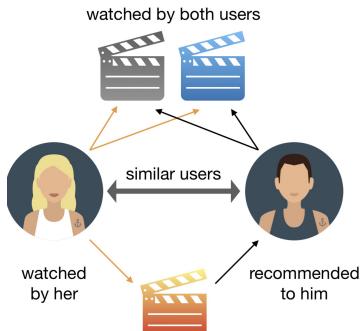
m x k

### Optimization:

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

# Recommender Systems

# Collaborative filtering

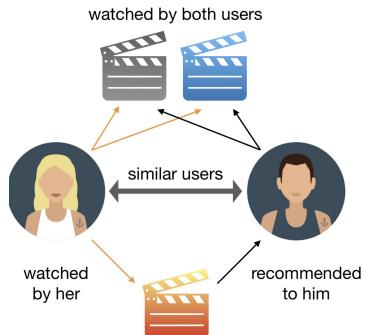


## Optimization

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

# Recommender Systems

## Collaborative filtering



Users	Items		
	5	1	3
1	5		
		1	3
2		2	2
		2	
2		4	
		2	5

Utility Matrix ( $m \times n$ )

$\rightarrow$

Users	Items				
	2.1	3.3	1.6	2.8	3
x	1.3	4	1	2	0.7
	2.1	3.3	1.6	2.8	3
	1.3	4	1	2	0.7

$m \times k$

$k \times n$

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

Matrix factorization (numbers are random for the sake of i)

# 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).

The diagram illustrates a utility matrix and its multiplication with another matrix. On the left, a utility matrix is shown with rows labeled 'Users' and columns labeled 'Items'. The matrix contains numerical values and question marks. A large arrow points from this matrix to the right, where it is multiplied by another matrix. The second matrix has columns labeled 'Items' and rows labeled 'Users'. The result of the multiplication is a matrix with dimensions  $m \times k$ , which also contains numerical values and question marks.

		Items		
		5	1	3
Users	1	5		
			1	3
2		2	2	
2			4	
		2		5

Utility Matrix ( $m \times n$ )

$\times$

		Items				
		2.1	3.3	1.6	2.8	3
Users	1	2.1	3.3	1.6	2.8	3
		1.3	4	1	2	0.7
2						?

$m \times k$

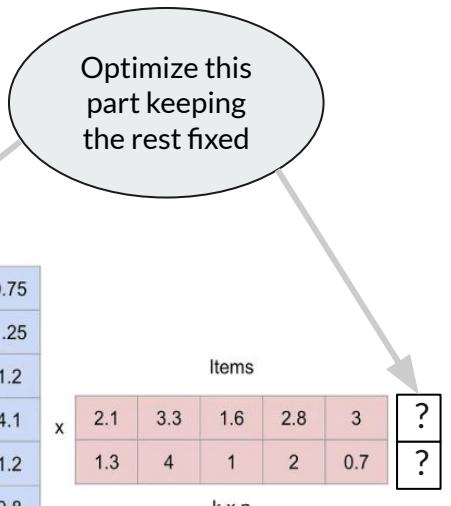
# A new movie rated by 2 users

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).

		Items		
		5	1	3
Users	5			4
	1			?
1	2		2	3
	2		4	2
2	2			5
	2			?

Utility Matrix ( $m \times n$ )



# A new movie 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).
  - Then fill the ?? is in the utility matrix.

Items			Users	Users	
	5			1.5	0.75
	5			3	1.25
	1	3		4	1.2
1				3.6	4.1
	2	2		3.6	1.2
				1.1	0.8
2		4		0.9	1.4
	2			3.6	5.1
		5		m x k	
Utility Matrix (m x n)			4	?	?
			?	?	?
			?	?	?
			2	2	?
			?	?	?

Items					
x	2.1	3.3	1.6	2.8	3
	1.3	4	1	2	0.7
					2.9



**QA**

