

# Improving the Quality of Top-N Recommendation

Modern Approaches with a special focus on  
Similar Users/Items



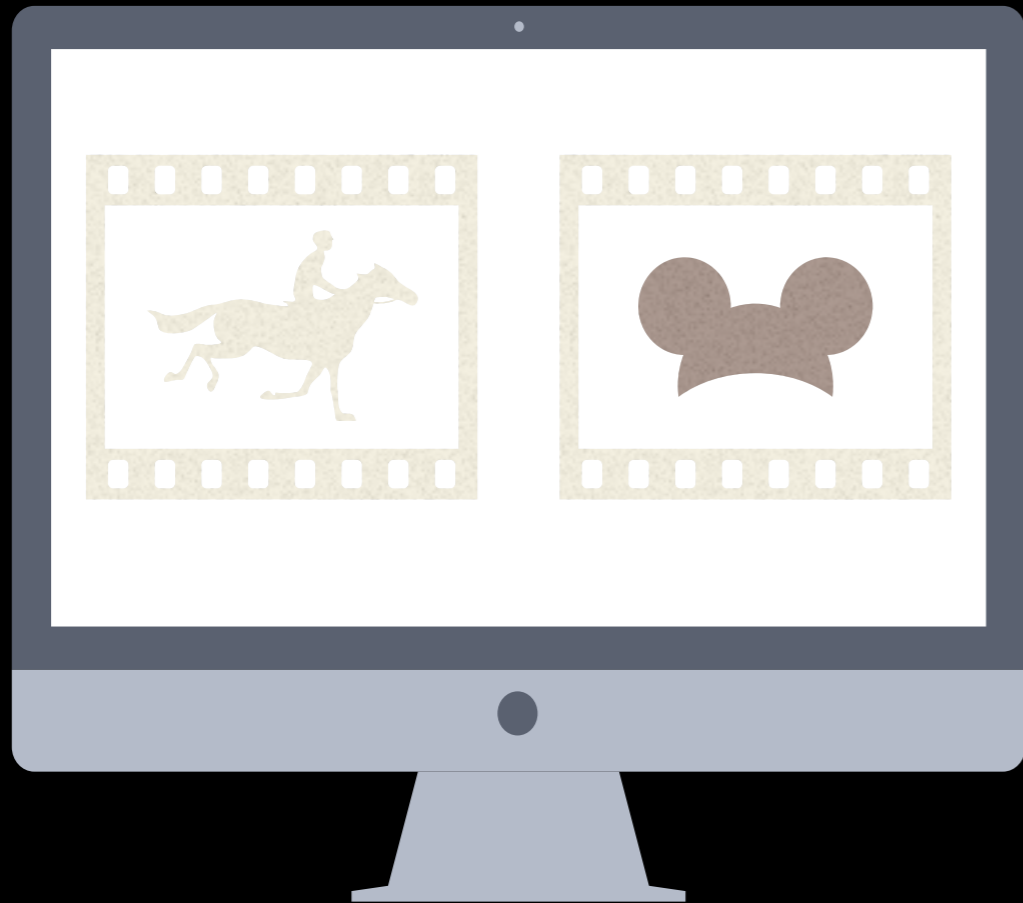
**“Average users spend 18 mins browsing before selecting what program to watch.”**

*Reelgood and Learndipity Data Insights. Wire 2016*

**“Users spend 51 mins a day looking for something to entertain them.”**

*Ericsson Consumer Lab Media Report 2017*

# The art of recommendation



# Latent Space Approaches

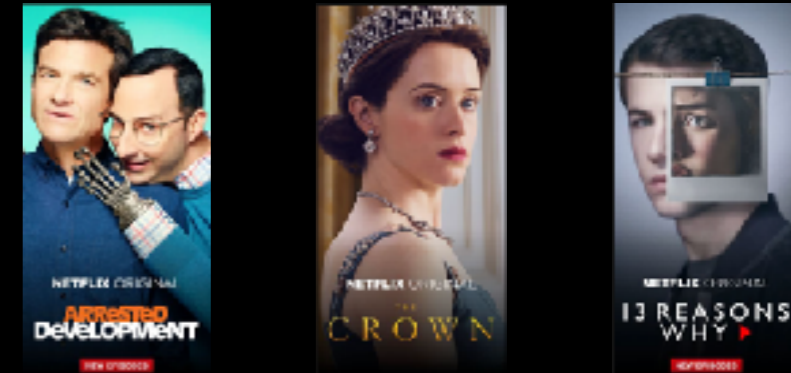


1			
	1		
1	1	1	1

$R$

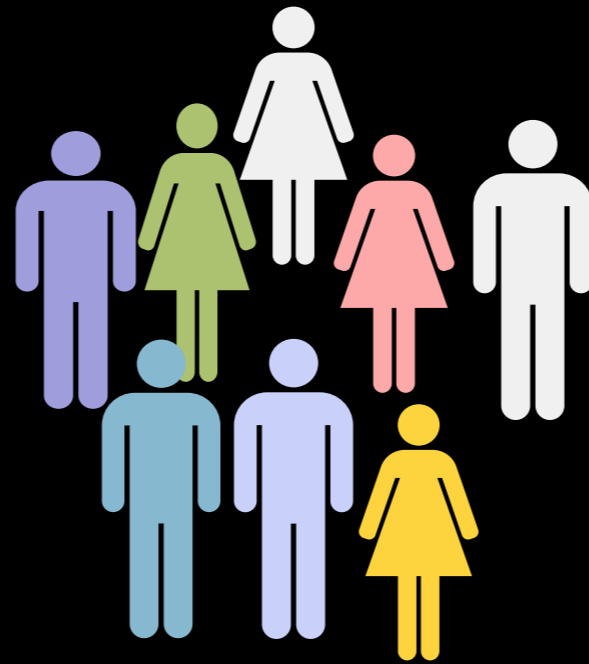
$\approx$

Drama Affinity  
Comedy Affinity  
Award Winning

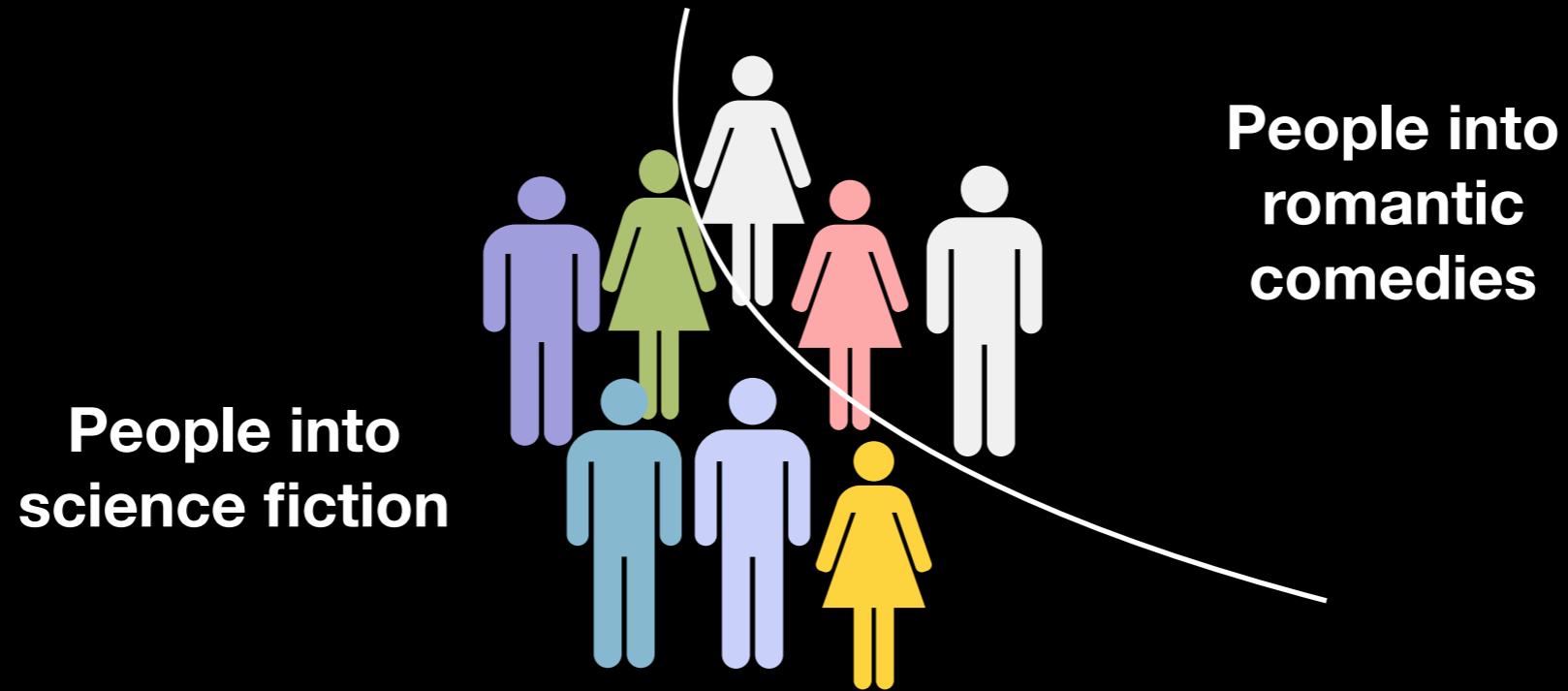


0.7	0.7	1.2
0.4	0.5	
0.3 0.4		

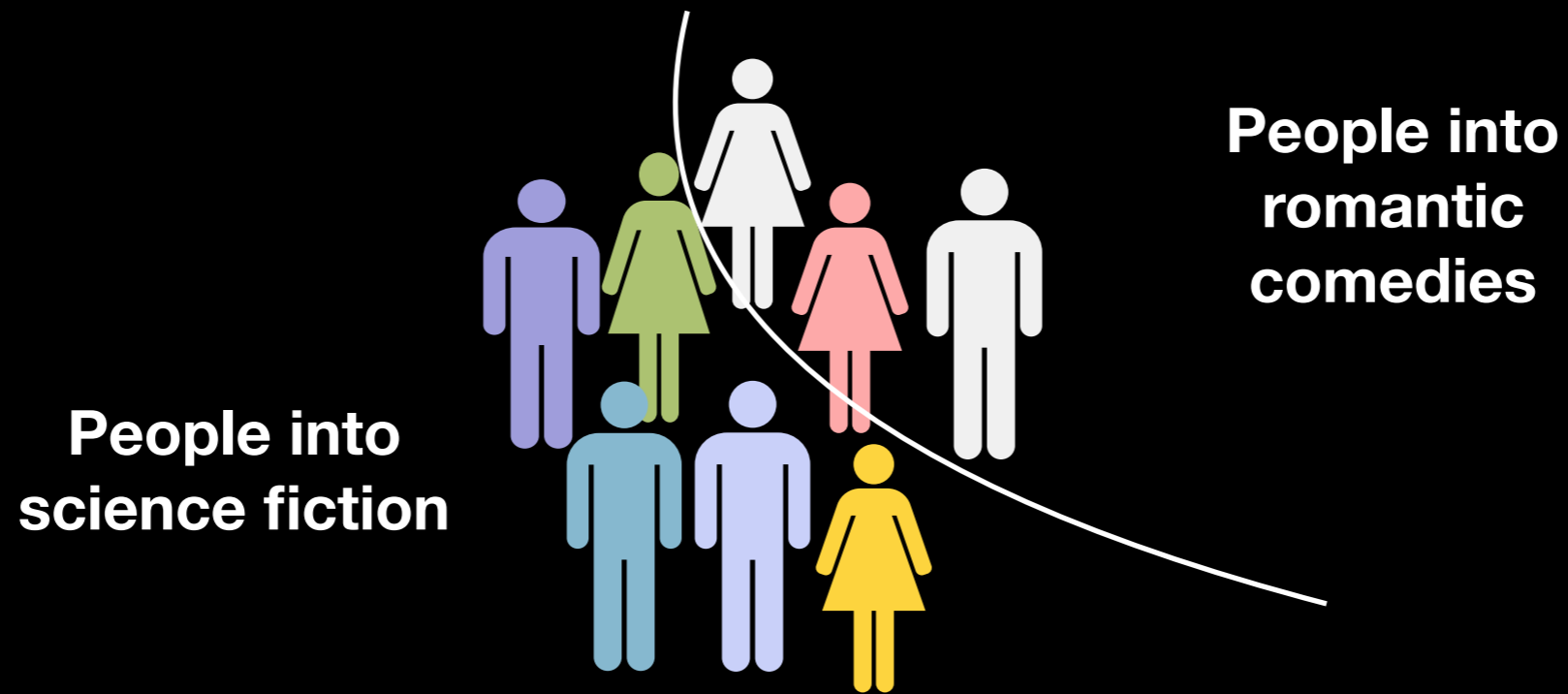
# Star Wars vs Star Trek



# Star Wars vs Star Trek

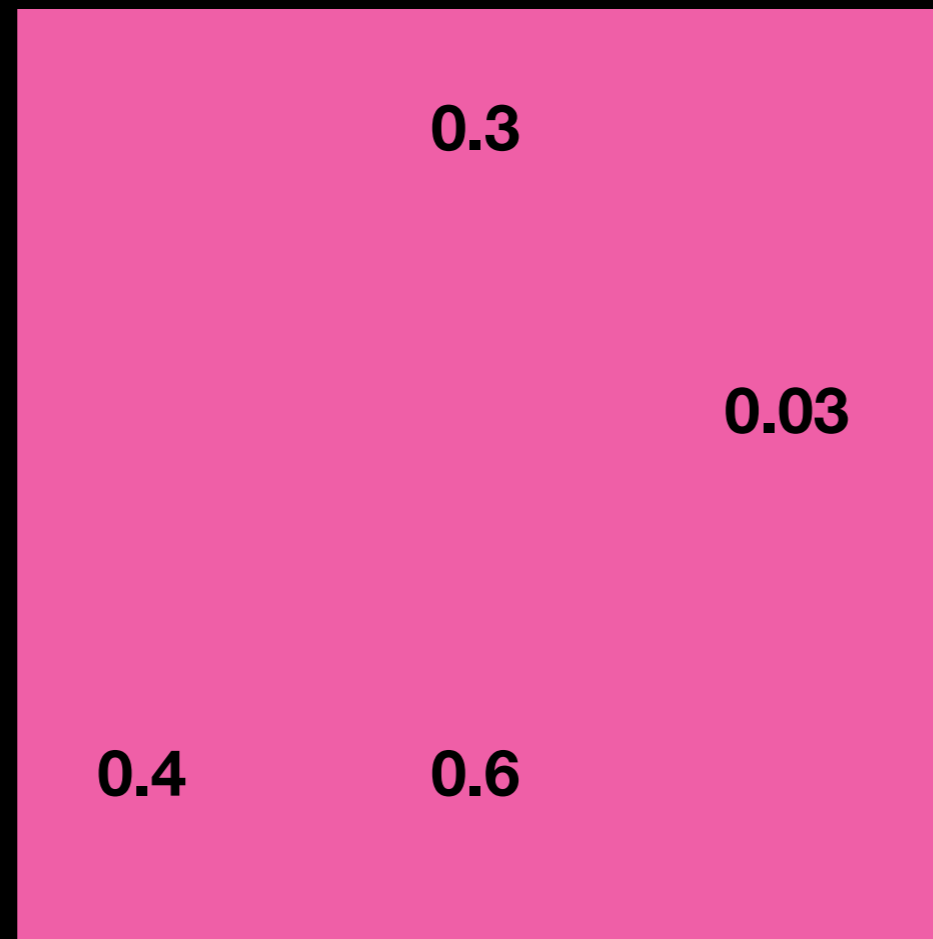
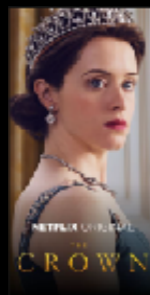


# Star Wars vs Star Trek



Would this be solved by just increasing the number of latent factors?

# Item-item Approaches





# Are two items similar?



1	1	1	1	1		
	1	1	1	1		
1	1		1			
1	1	1		1		
1	1	1			1	1
	1	1			1	1
1	1					1

# Are two items similar?



1

1

1

1

1



1

1

1

1



1

1

1



1

1

1

1



1

1

1

1

1



1

1

1

1



1

1

1

---

1	1	1	1	1		
	1	1	1	1		
1	1		1			
1	1	1		1		
1	1	1			1	1
	1	1			1	1
1	1					1

# Are two items similar?



1	1	1	1	1	1	
	1	1		1	1	
1	1			1		
1	1	1			1	
1	1	1				1
	1	1			1	1
1	1					1

# Are two items similar?




1	1	1	1	1	1		
	1	1		1	1		
1	1			1			
1	1	1			1		
1	1	1				1	1
	1	1				1	1
1	1						1

# Are two items similar?

							
	1	1	1	1	1		
		1	1	1	1		
	1	1			1		
	1	1	1			1	
	1	1	1			1	1
		1	1			1	1
	1	1					1

# Are two items similar?



	1	1	1	1	1	
		1	1	1	1	
	1	1		1		
	1	1	1		1	
	1	1	1			1
		1	1			1
	1	1				1

# Are two items similar?




1	1	1	1	1		
	1	1	1	1		
1	1			1		
1	1	1	1			
1	1	1			1	1
	1	1			1	1
1	1					1

# Are two items similar?

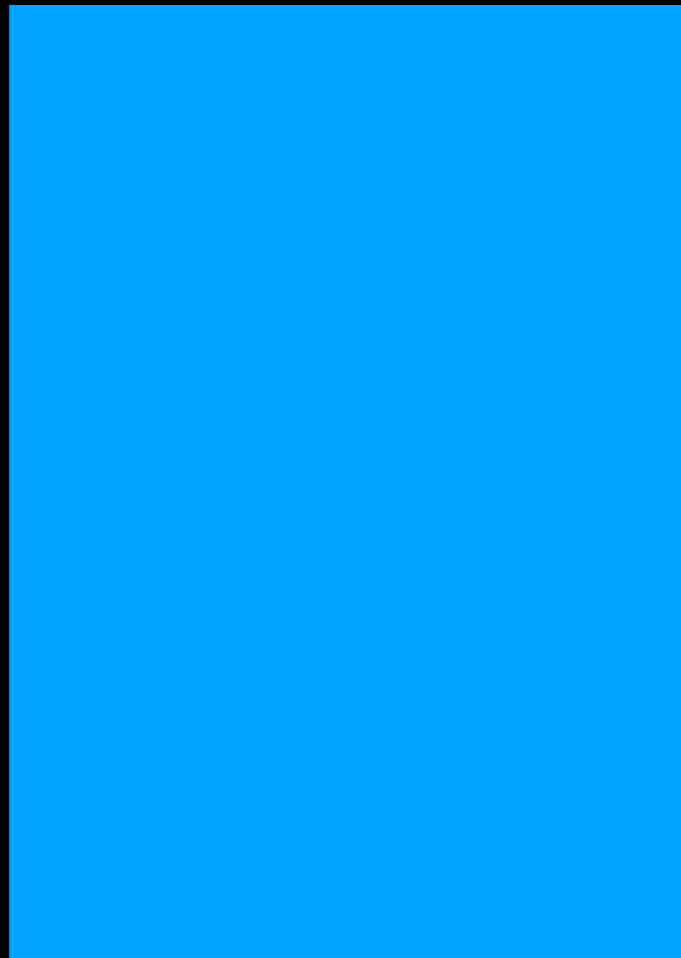
							
	1	1	1	1	1		
		1	1	1	1		
	1	1		1			
	1	1	1		1		
	1	1	1			1	1
		1	1			1	1
	1	1					1



# Are two items similar?

							
	1	1	1	1	1		
		1	1	1	1		
	1	1		1			
	1	1	1		1		
	1	1	1			1	1
		1	1			1	1
	1	1					1

# Global & Local Approaches

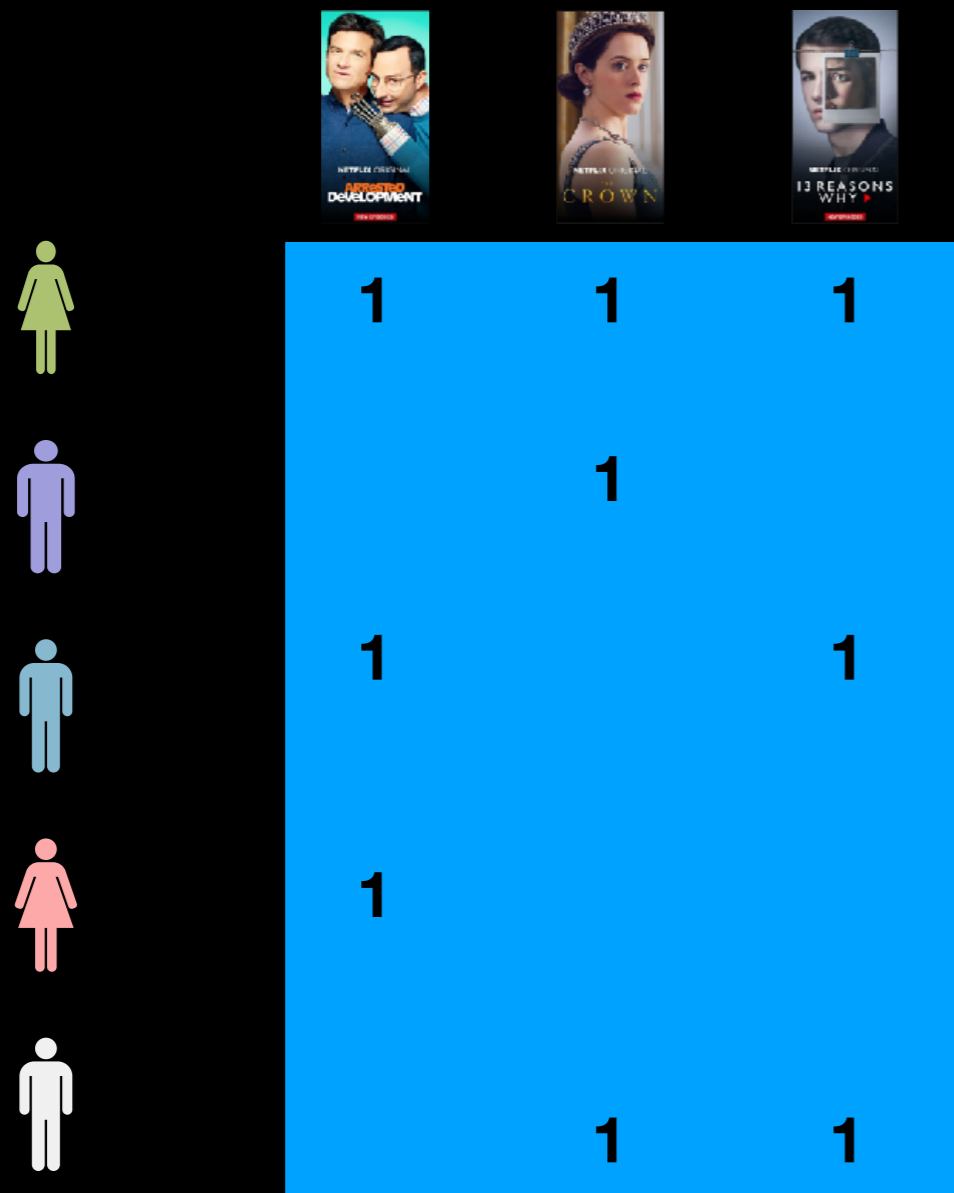


Global











Local

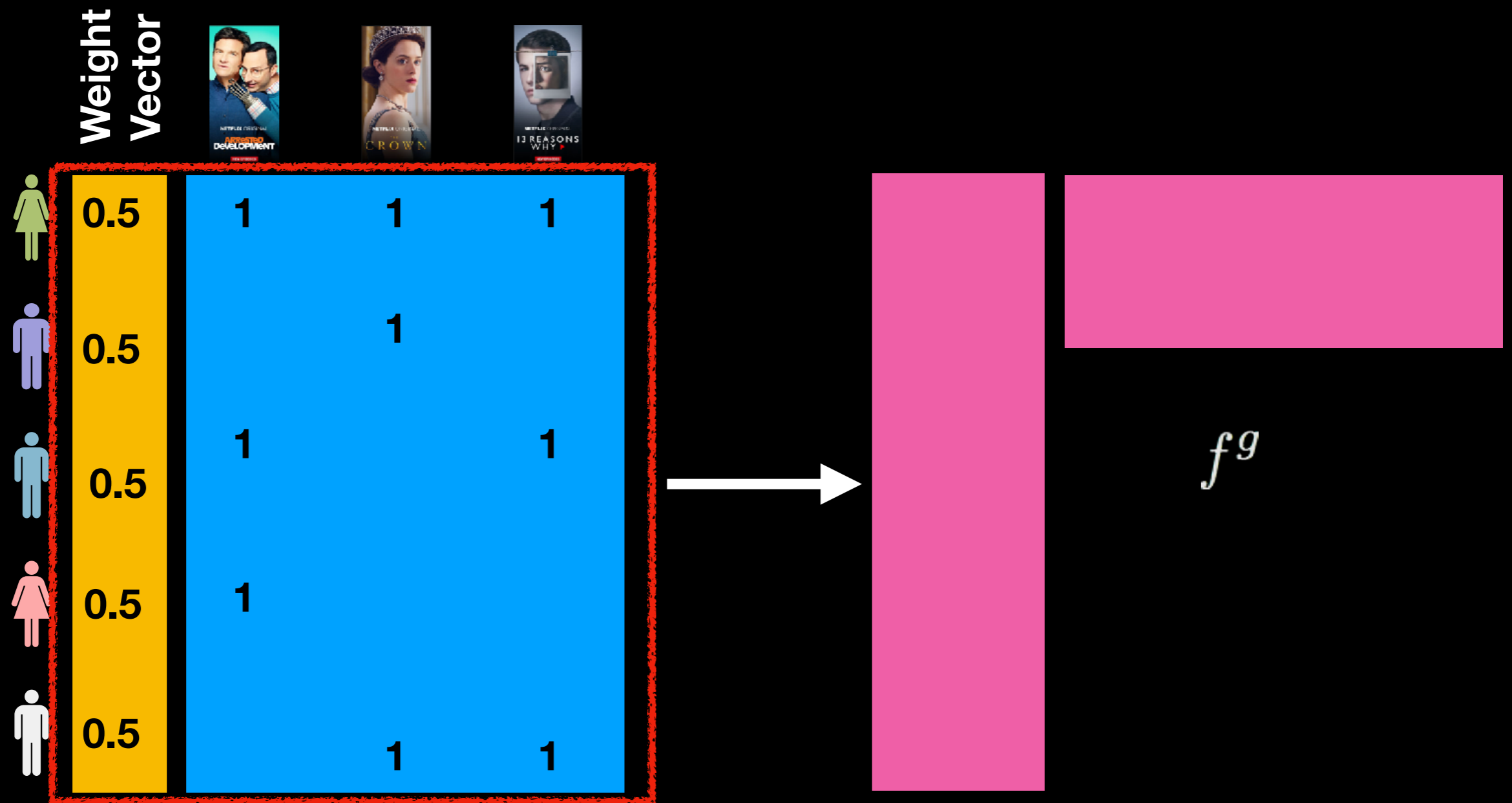
# Global & Local SVD with varying Ranks



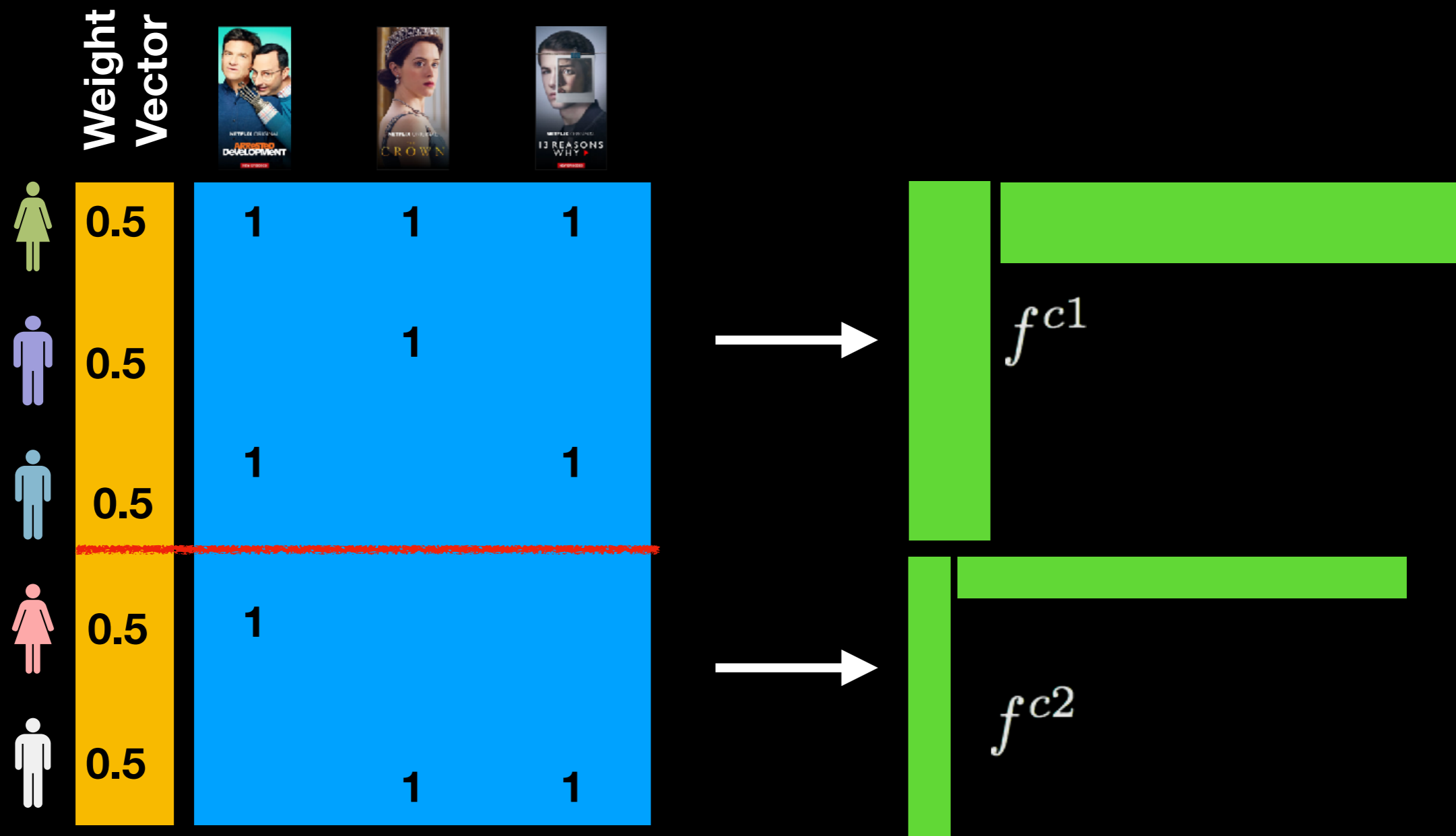
# Global & Local SVD with varying Ranks

	Weight Vector			
	0.5	1	1	1
	0.5		1	
	0.5	1		1
	0.5	1		
	0.5		1	1









# Global & Local SVD with varying Ranks



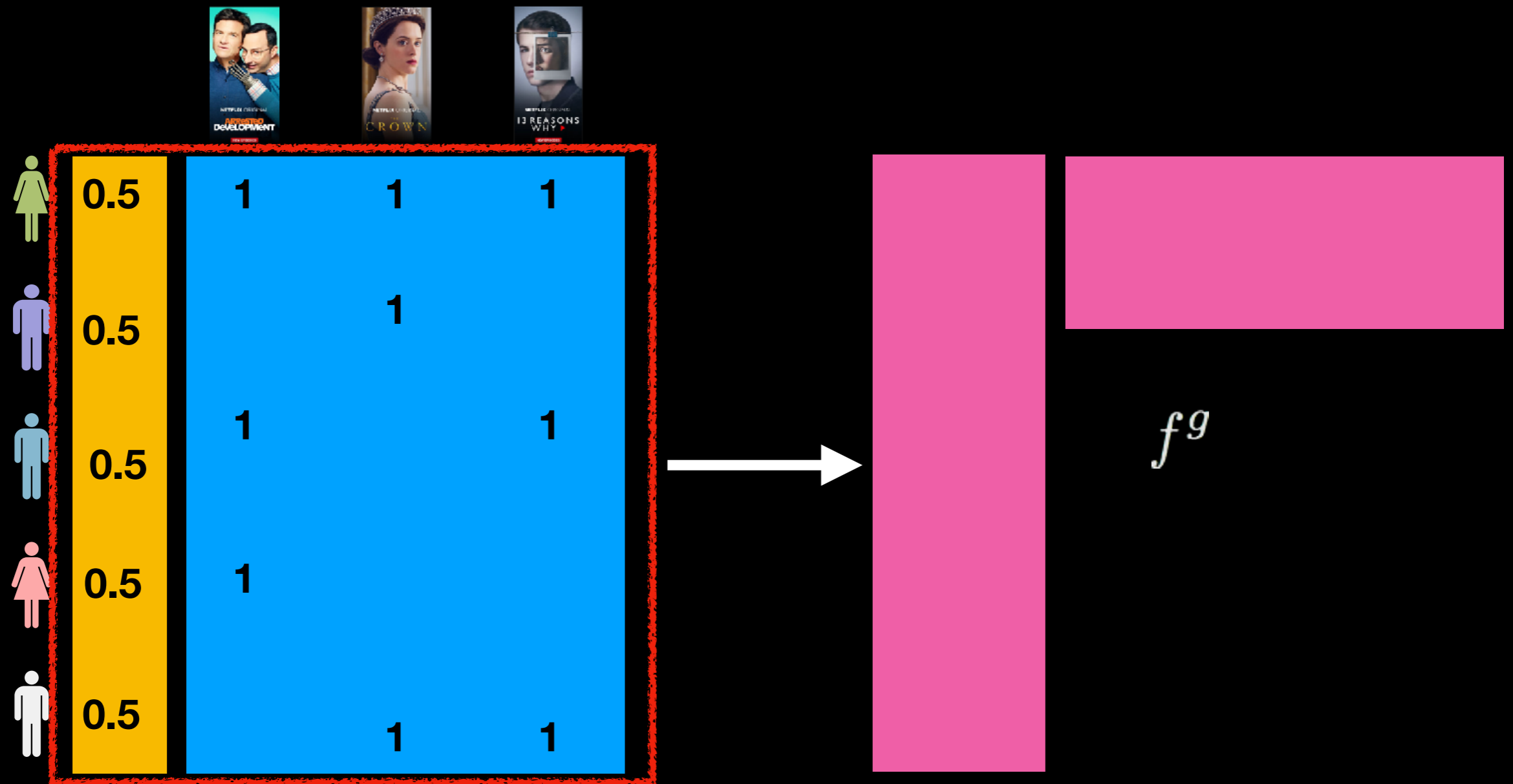
# Global & Local SVD with varying Ranks



# Global & Local SVD with varying Ranks

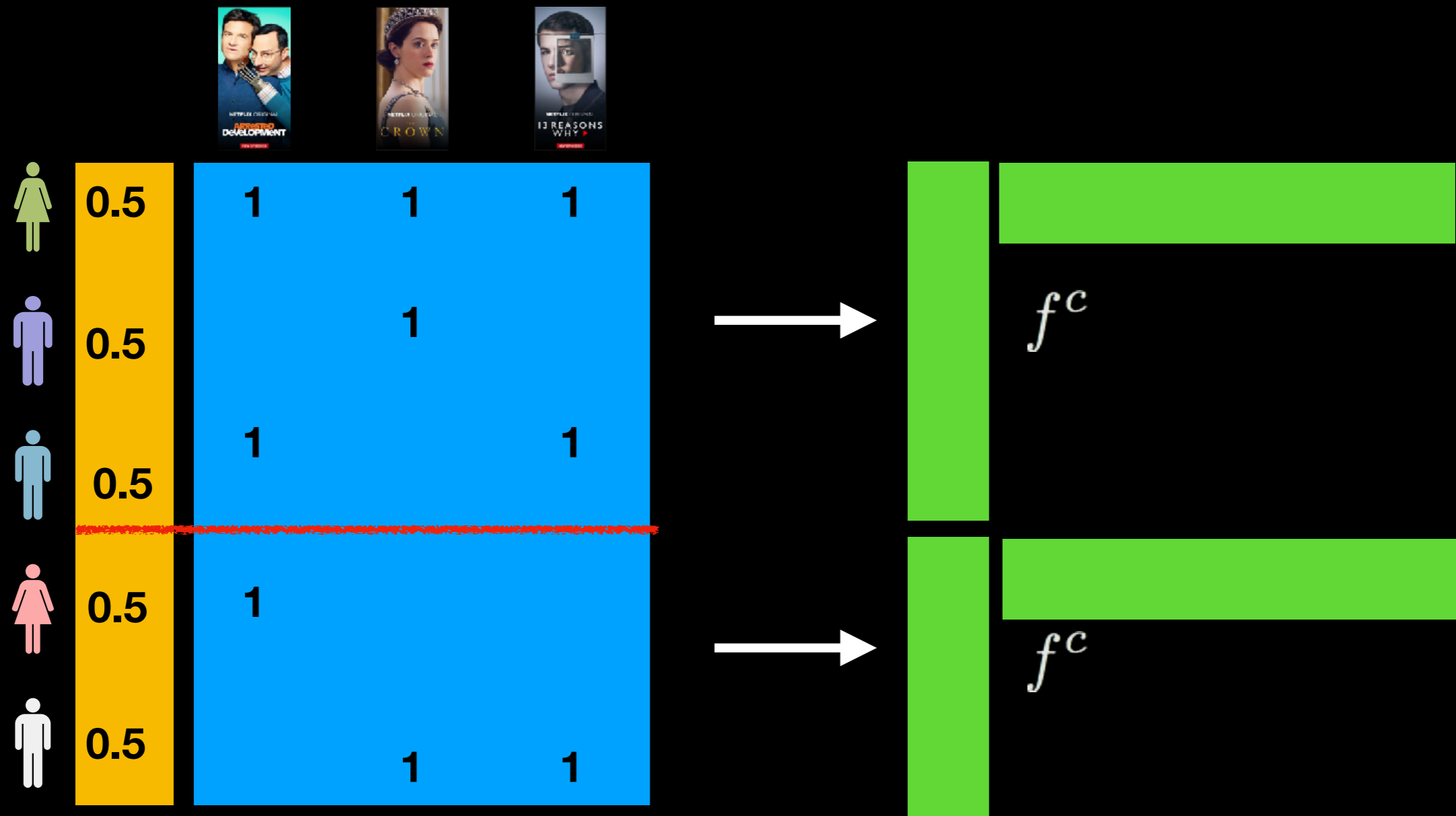
	Weight Vector			
	0.7	1	1	1
	0.3		1	
	0.4	1		1
	0.1	1		
	0.3		1	1

# Global & Local SVD with varying Subsets

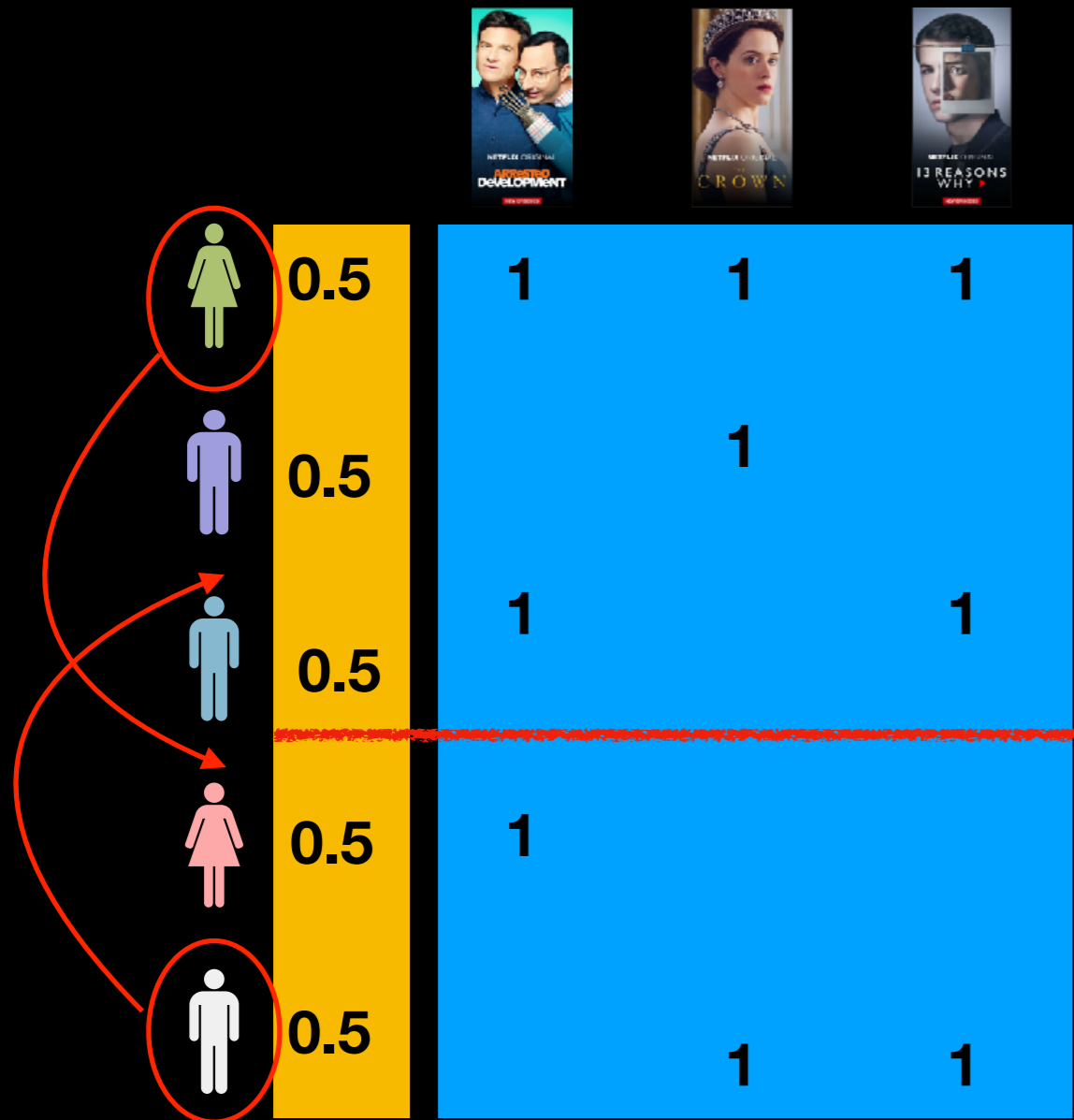




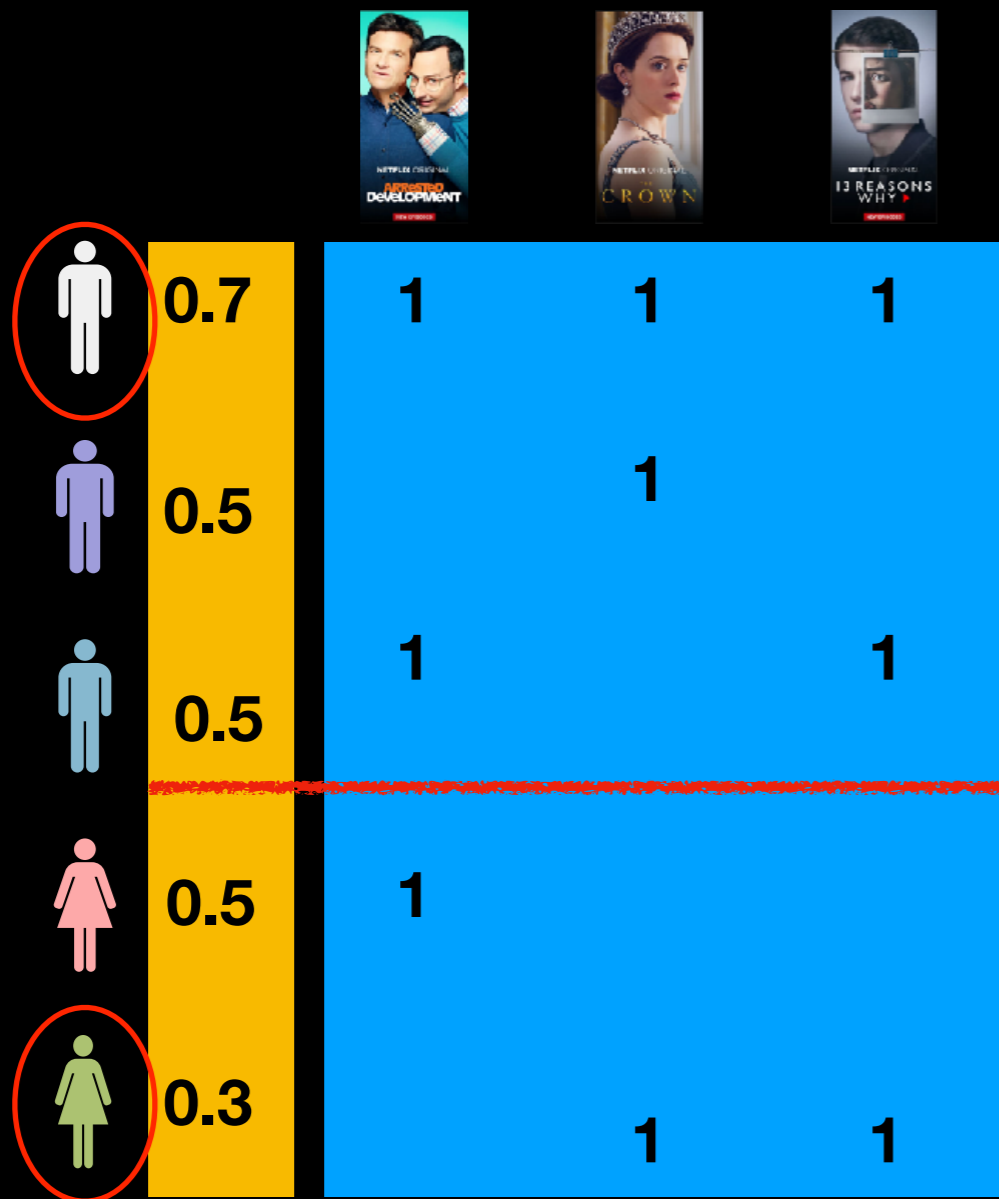
# Global & Local SVD with varying Subsets



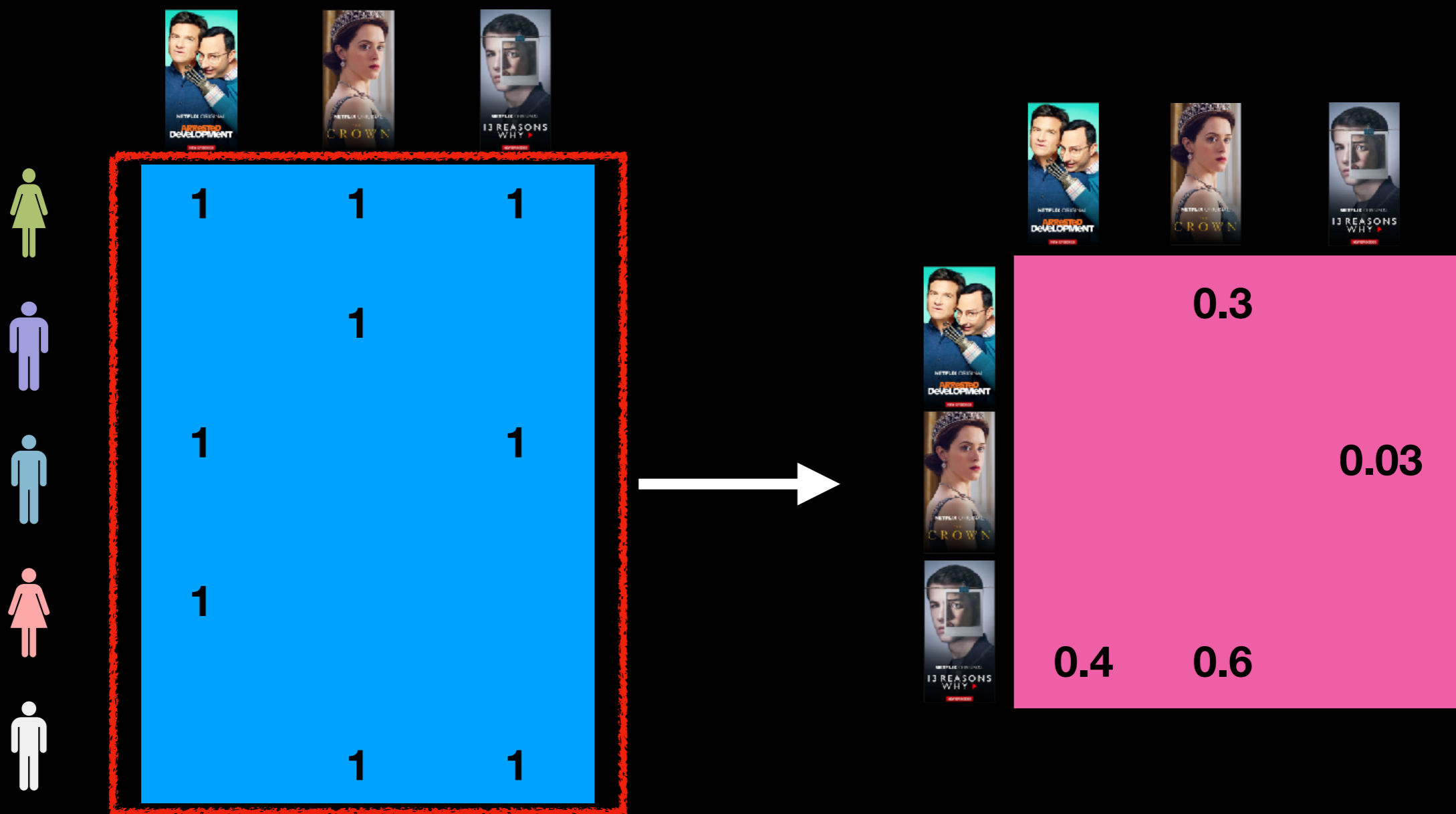
# Global & Local SVD with varying Subsets



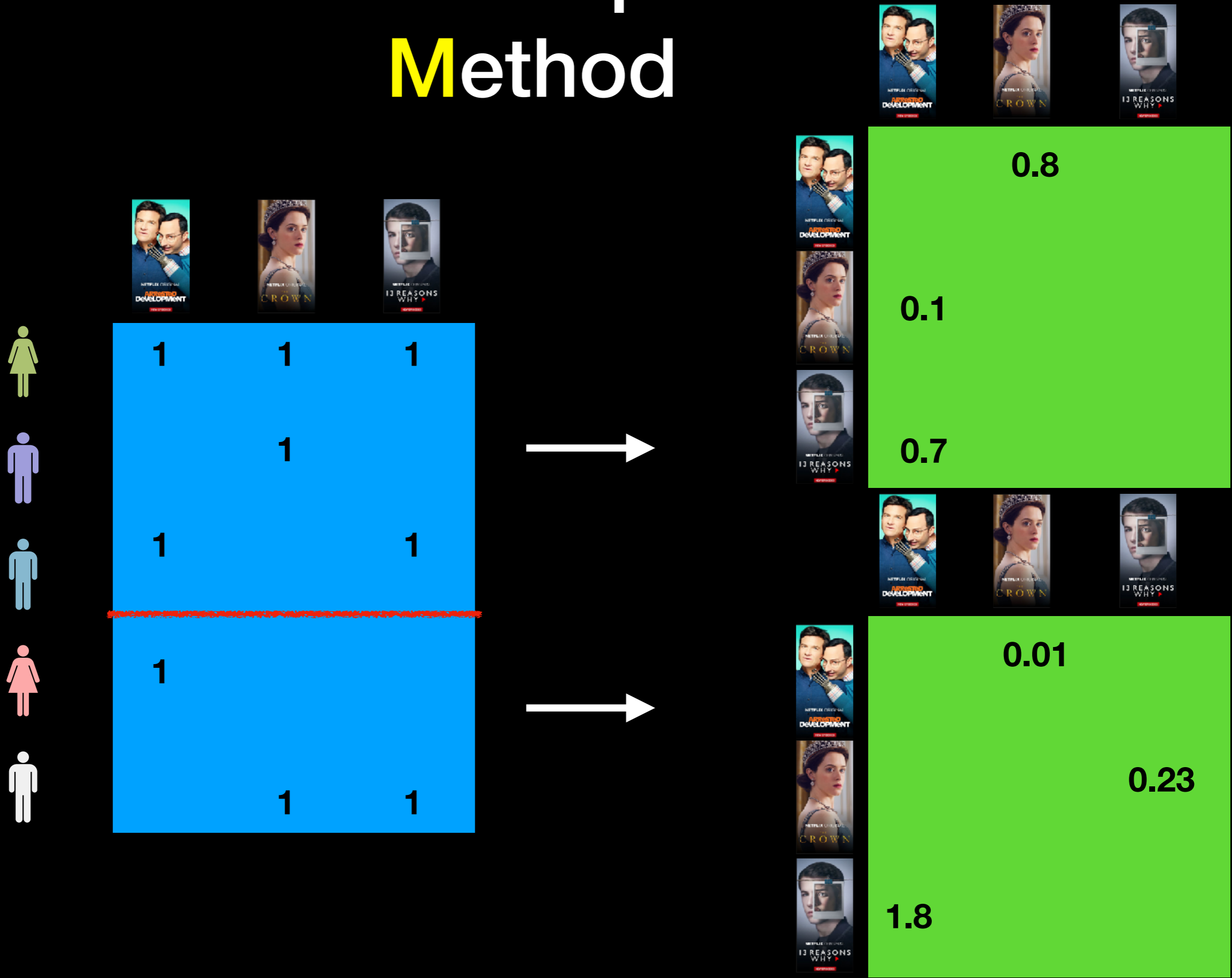
# Global & Local SVD with varying Subsets



# Global & Local Sparse Linear Method

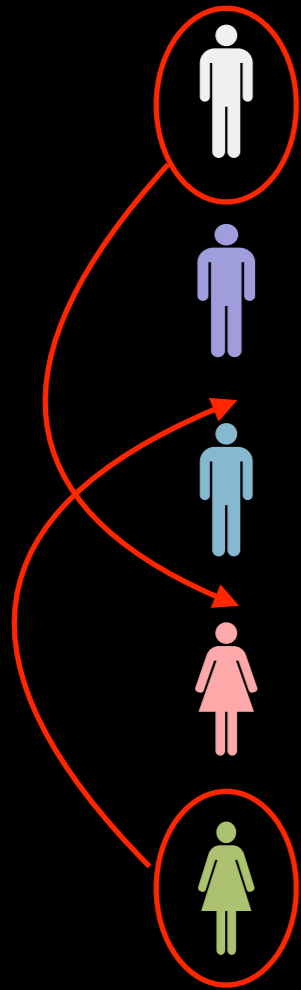


# Global & Local Sparse Linear Method



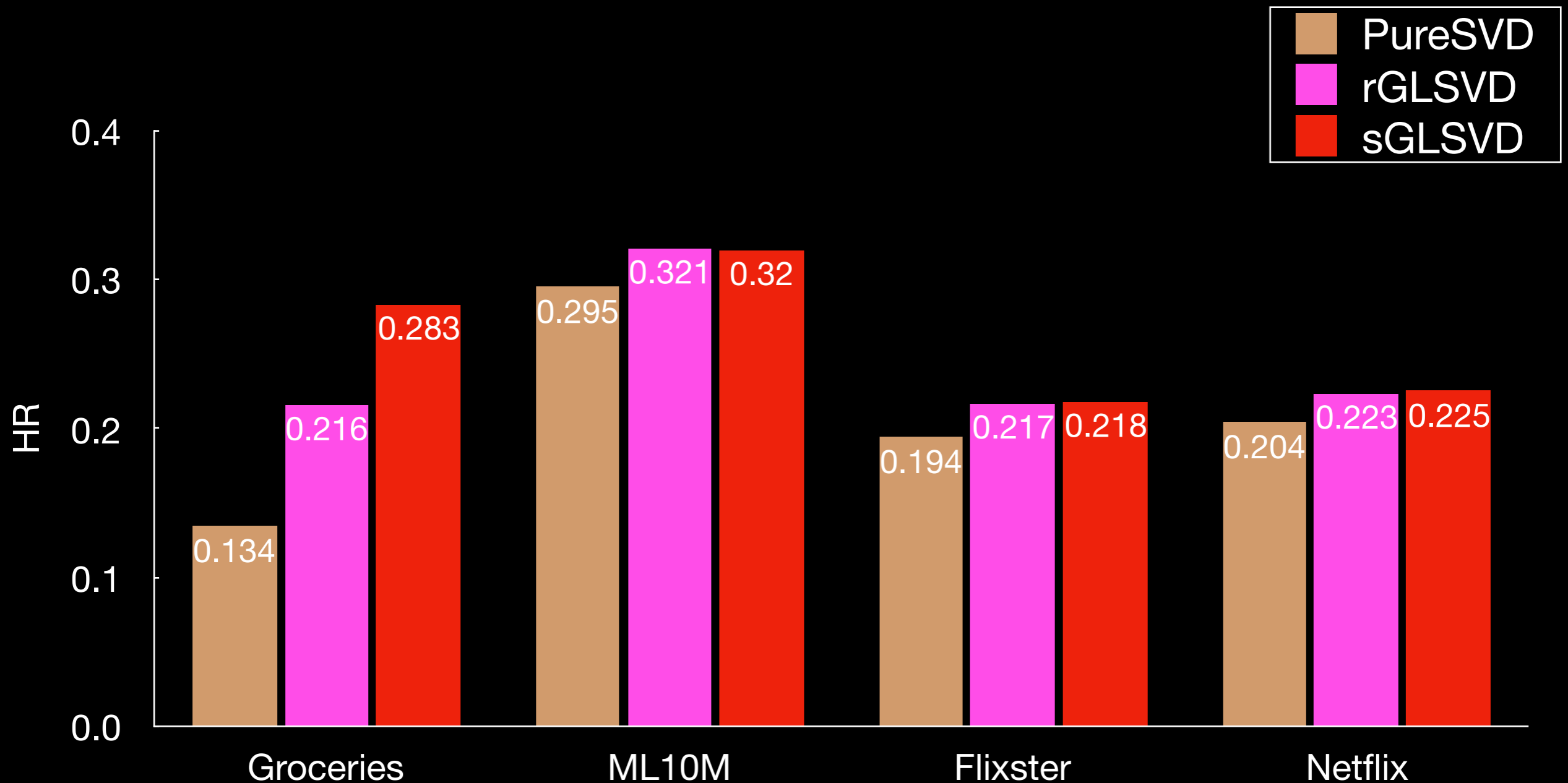
# Global & Local Sparse Linear Method

Updated weight.

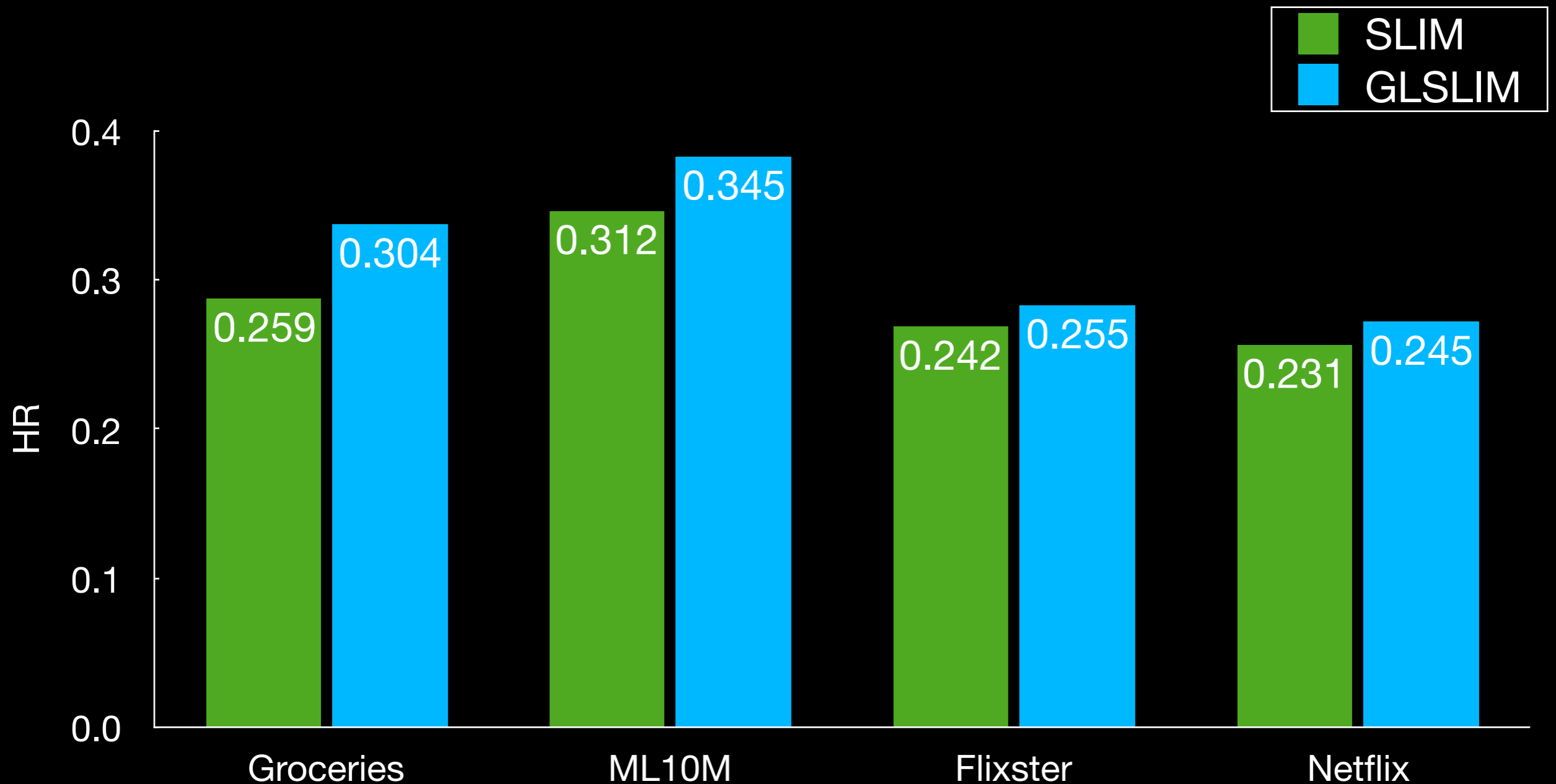


1	1	1
	1	
1		1
<hr/>		
1		
	1	1

# Comparison of PureSVD with sGLSVD and rGLSVD

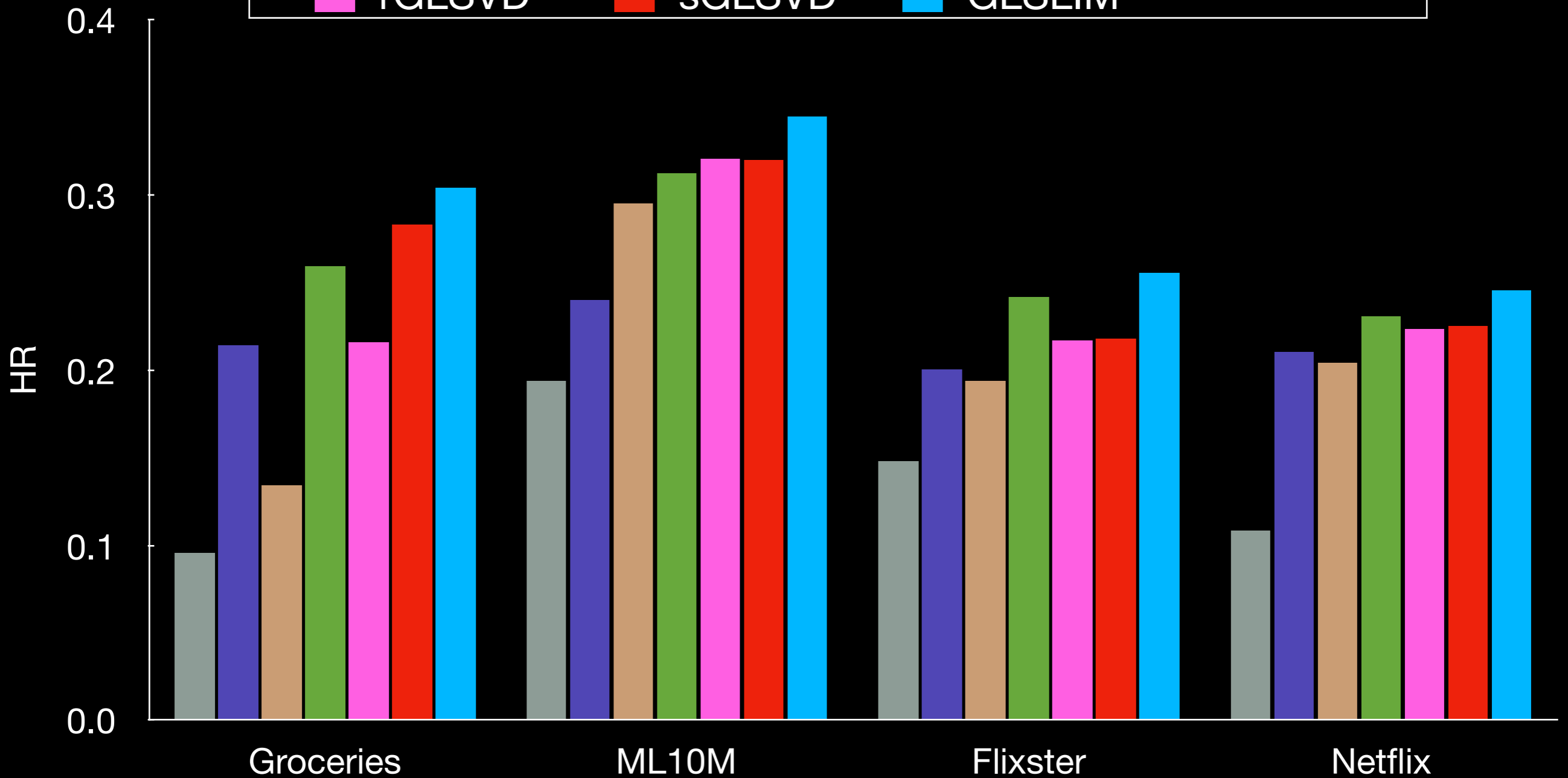


# Comparison of SLIM with GLSLIM





# Comparison with Competing Approaches



# Error in Top-N Recommendation



1	1	1
	1	
1		1
1		
	1	1

# Error in Top-N Recommendation



1

1

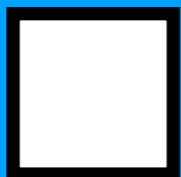
1



1



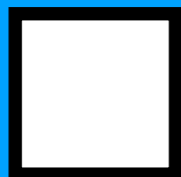
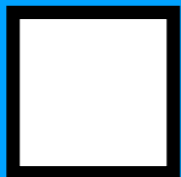
1



1



1



1

1

	1	1	1
		1	
	1		1
	1		
		1	1

# Error in Top-N Recommendation



1

1

1



0.2

1

0.9



1

0.8

1



1

0.03

0.4



1.2

1

1

	1	1	1
	0.2	1	0.9
	1	0.8	1
	1	0.03	0.4
	1.2	1	1

# Error in Top-N Recommendation



1

1

1



0.2

1

0.9



1

0.8

1



1

0.03

0.4



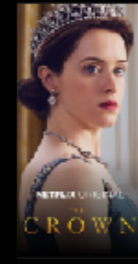
1.2

1

1

	1	1	1
	0.2	1	0.9
	1	0.8	1
	1	0.03	0.4
	1.2	1	1

# Error in Top-N Recommendation



1

1

1



0.2

1

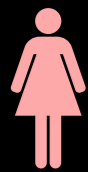
0.9



1

0.8

1



1

0.03

0.4



1.2

1

1



1

1

1



0

1

0



1

0

1



1

0

0



0

1

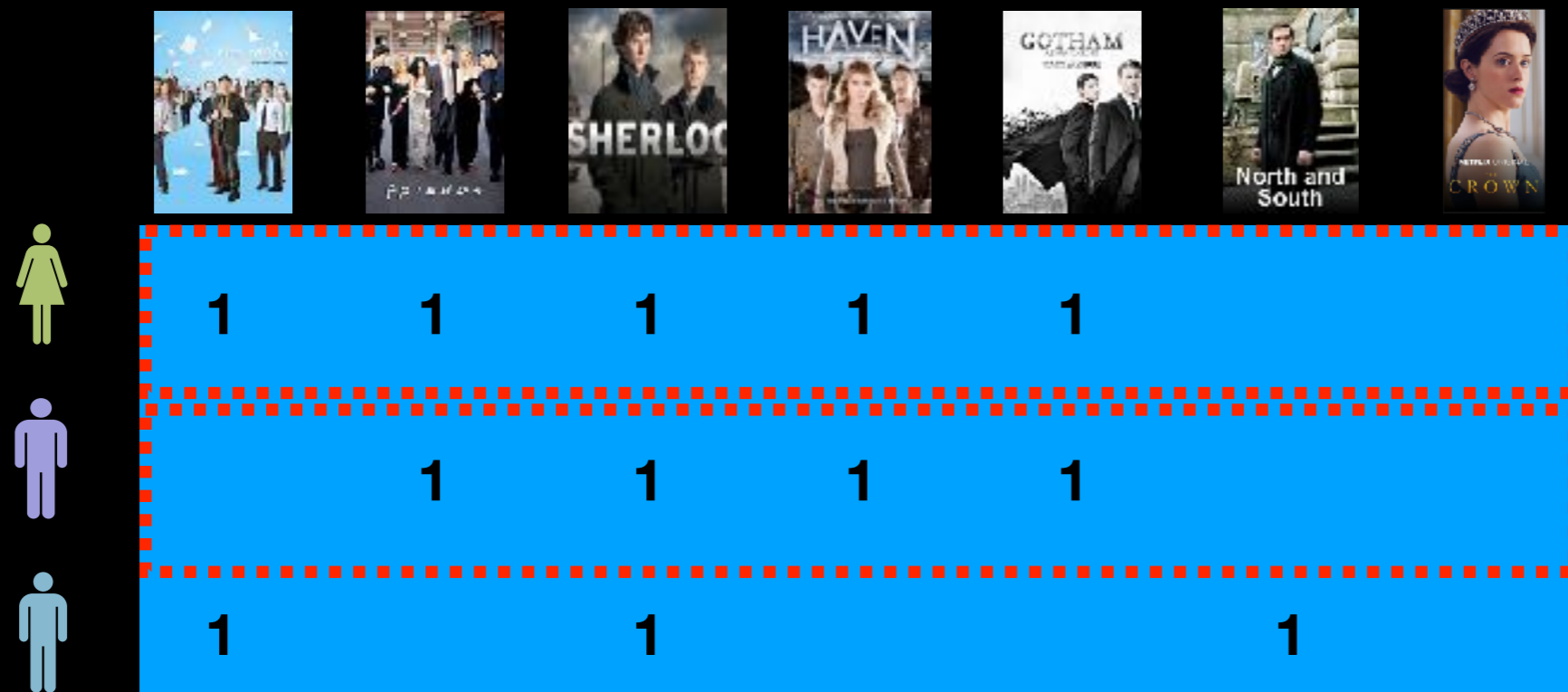
1

# Exploring similar users

The visualization shows a grid of user preferences for seven TV shows. The rows represent three different users, and the columns represent the TV shows. A '1' indicates a preference, and a '0' indicates no preference.

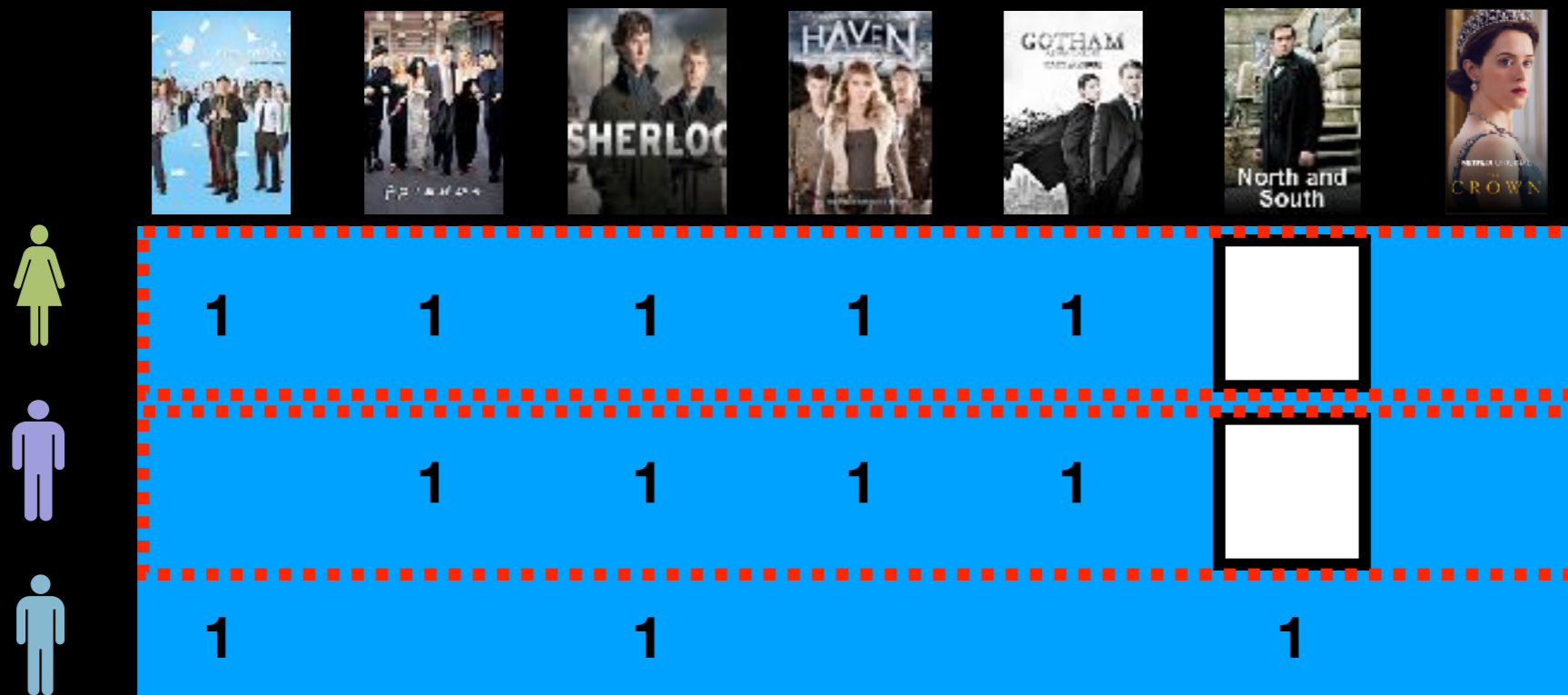
							
	1	1	1	1	1	0	0
	0	1	1	1	1	0	0
	1	0	1	0	0	1	0

# Exploring similar users

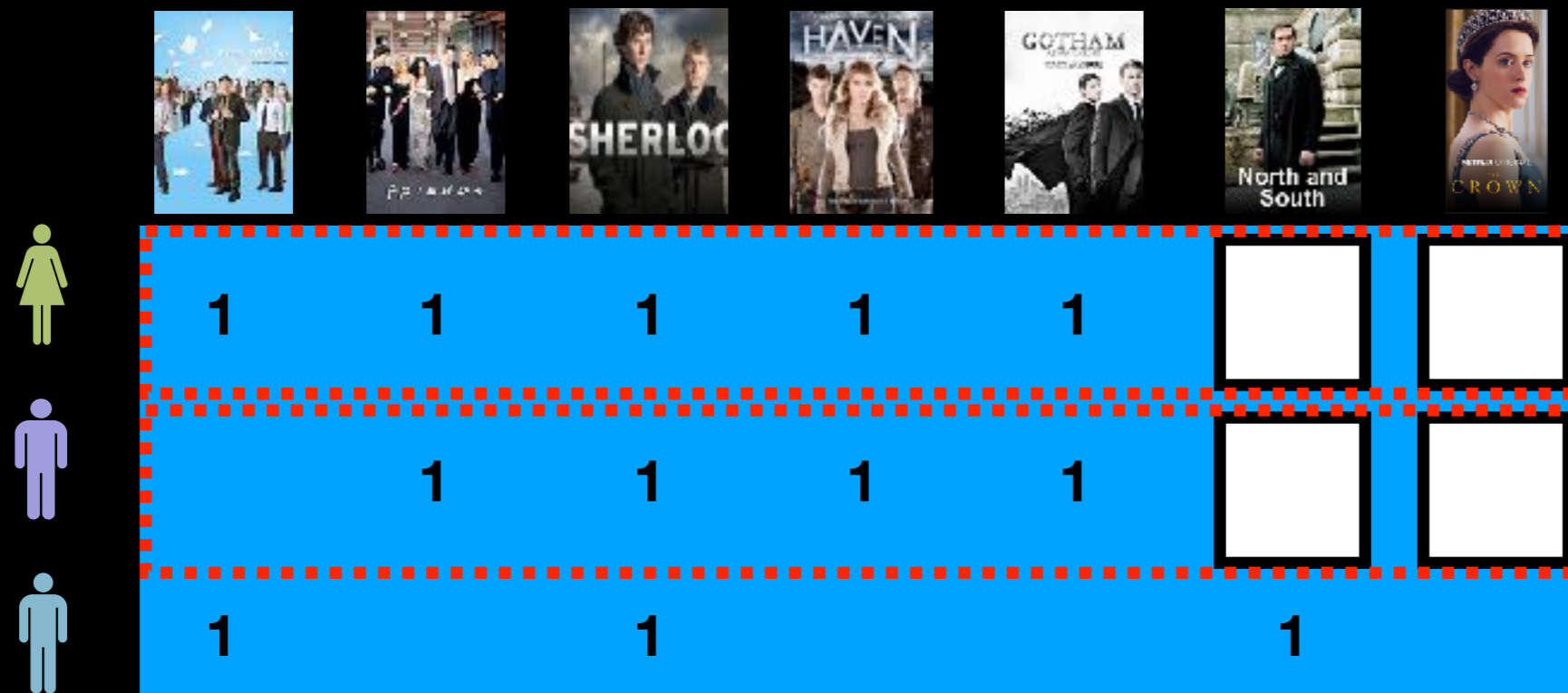




# Exploring similar users



# Exploring similar users



# User Similarity Matrices

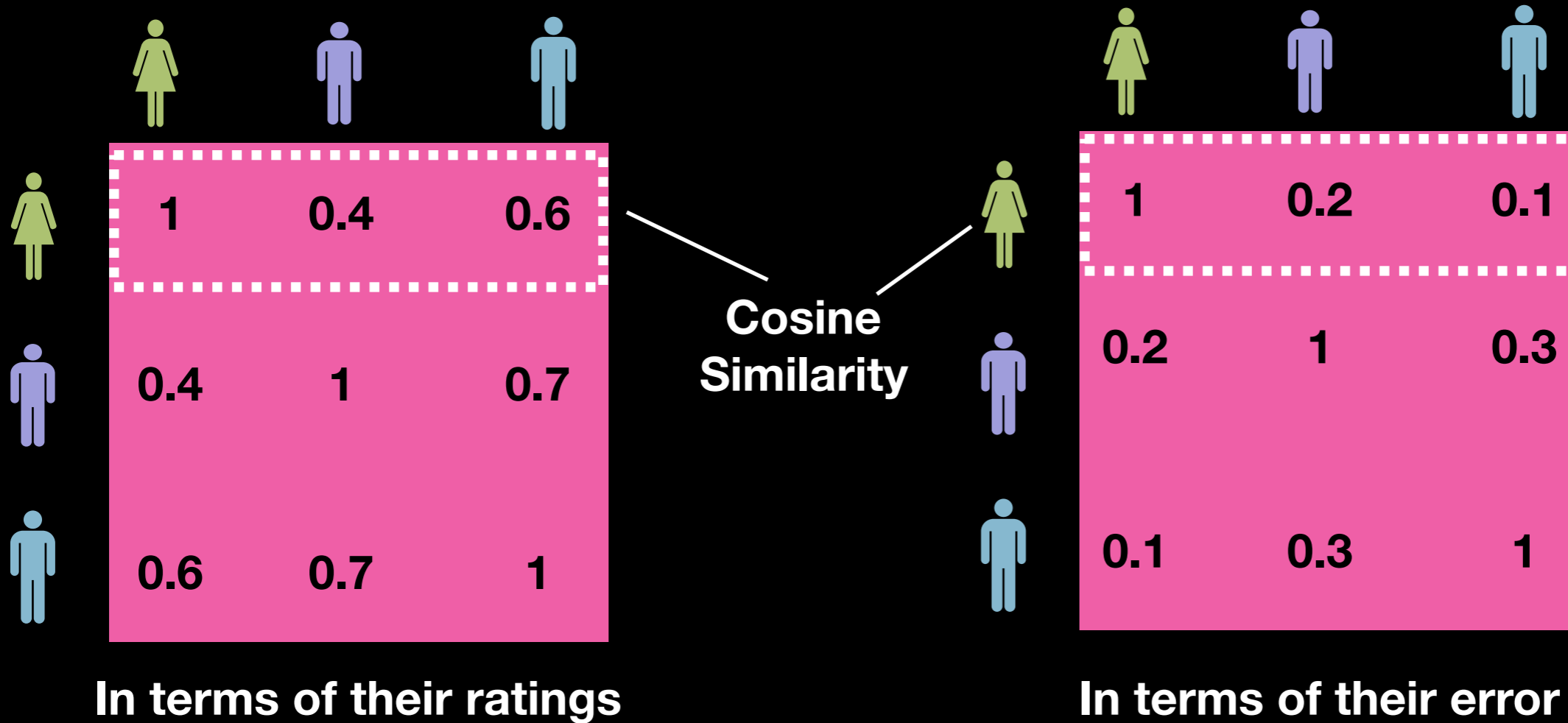


In terms of their ratings

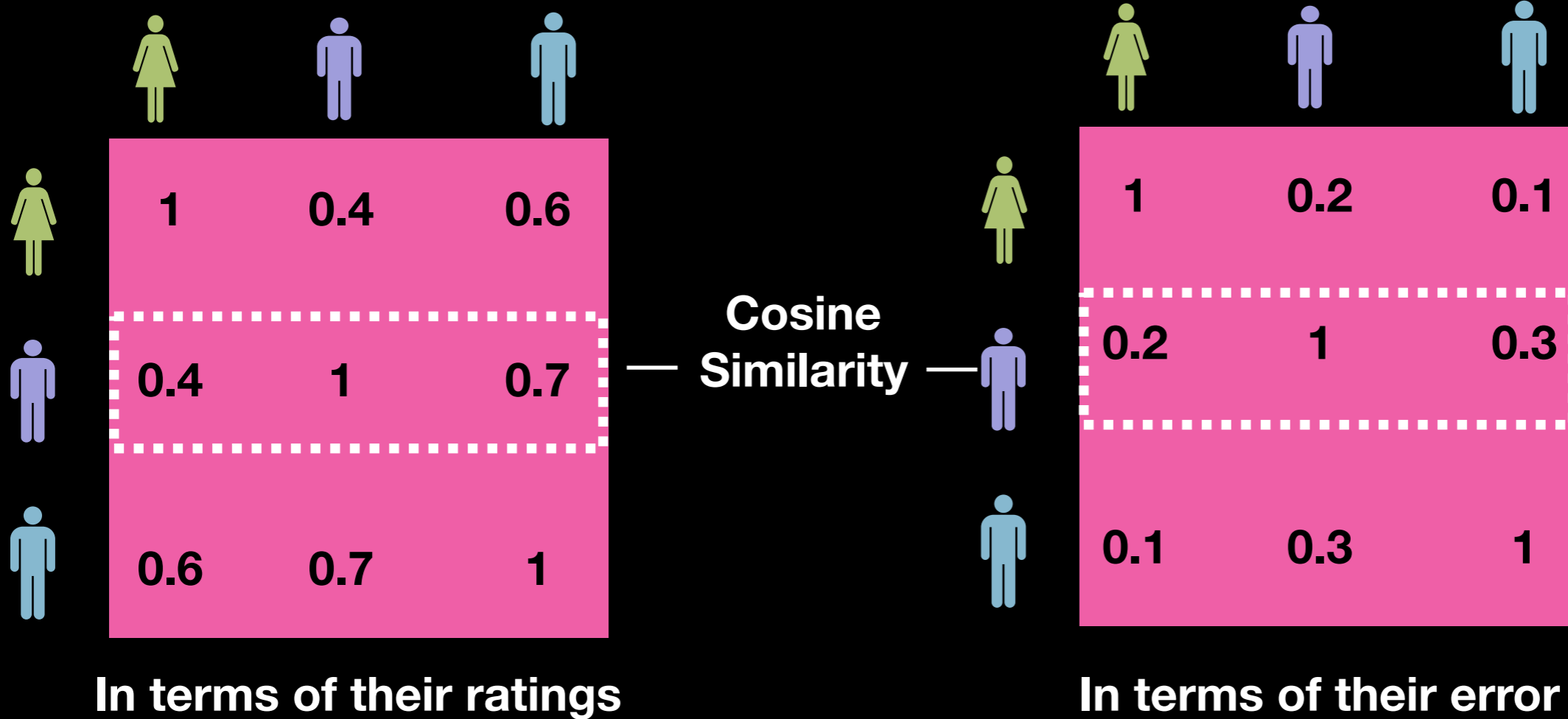


In terms of their error

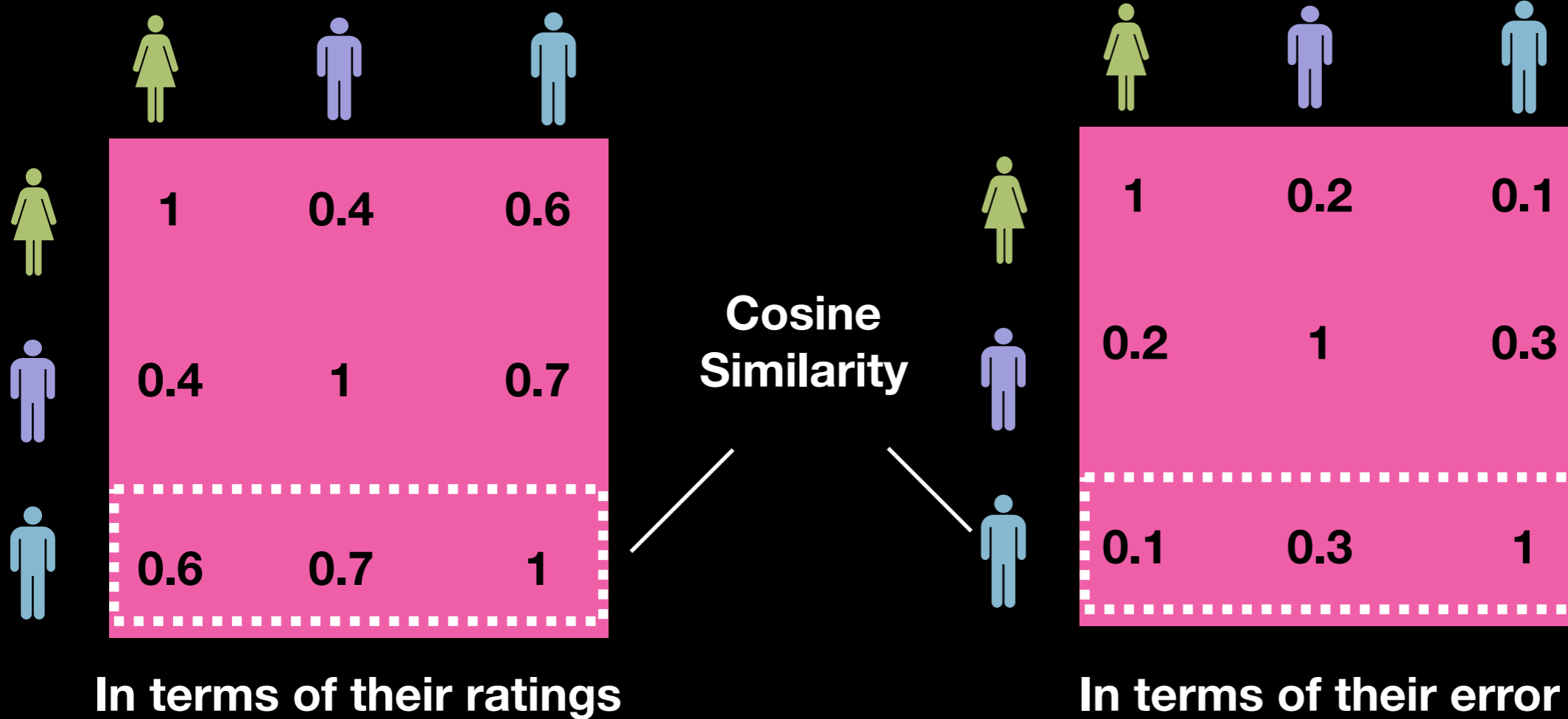
# User Similarity Matrices



# User Similarity Matrices



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# User Similarity Matrices



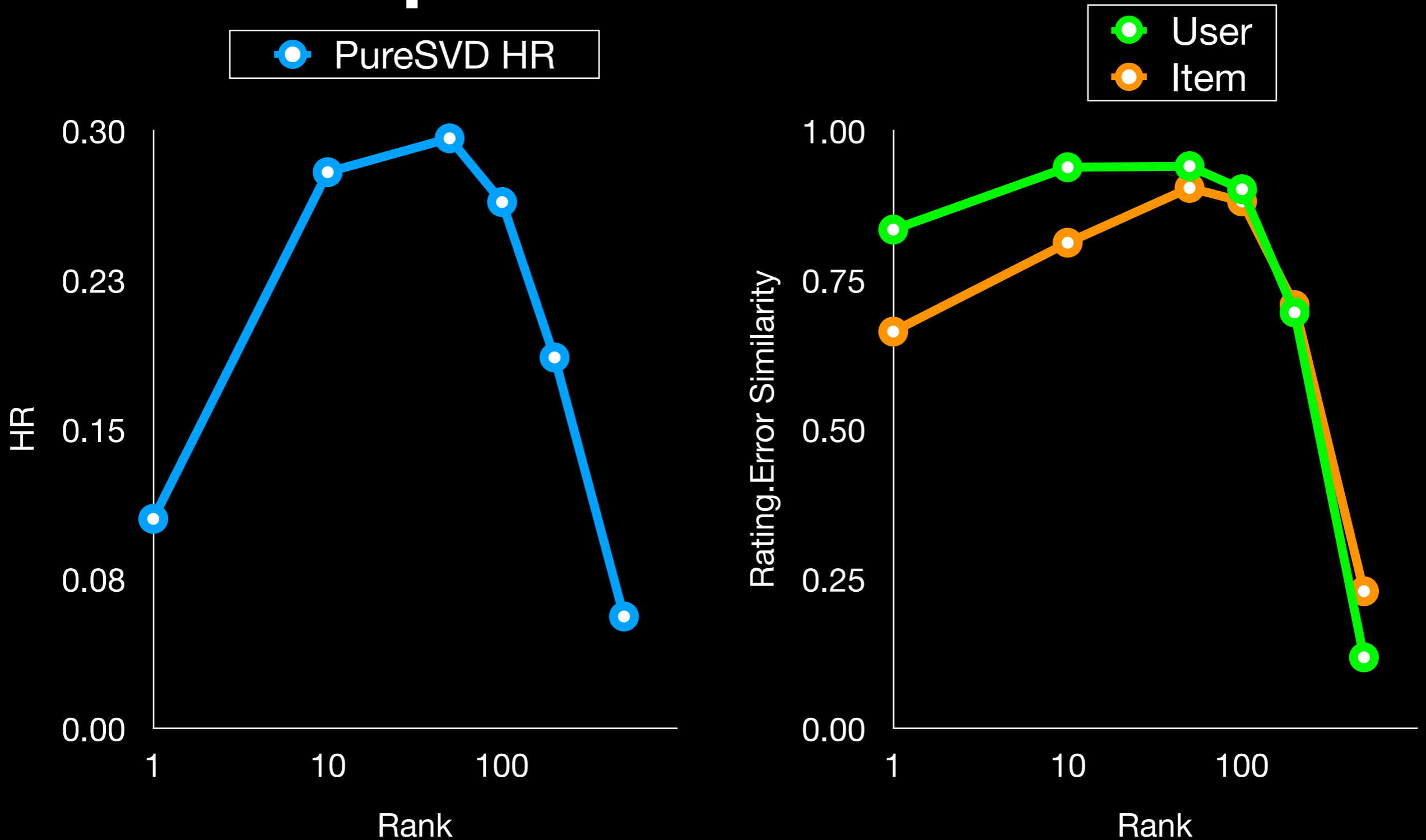
In terms of their ratings

Cosine  
Similarity



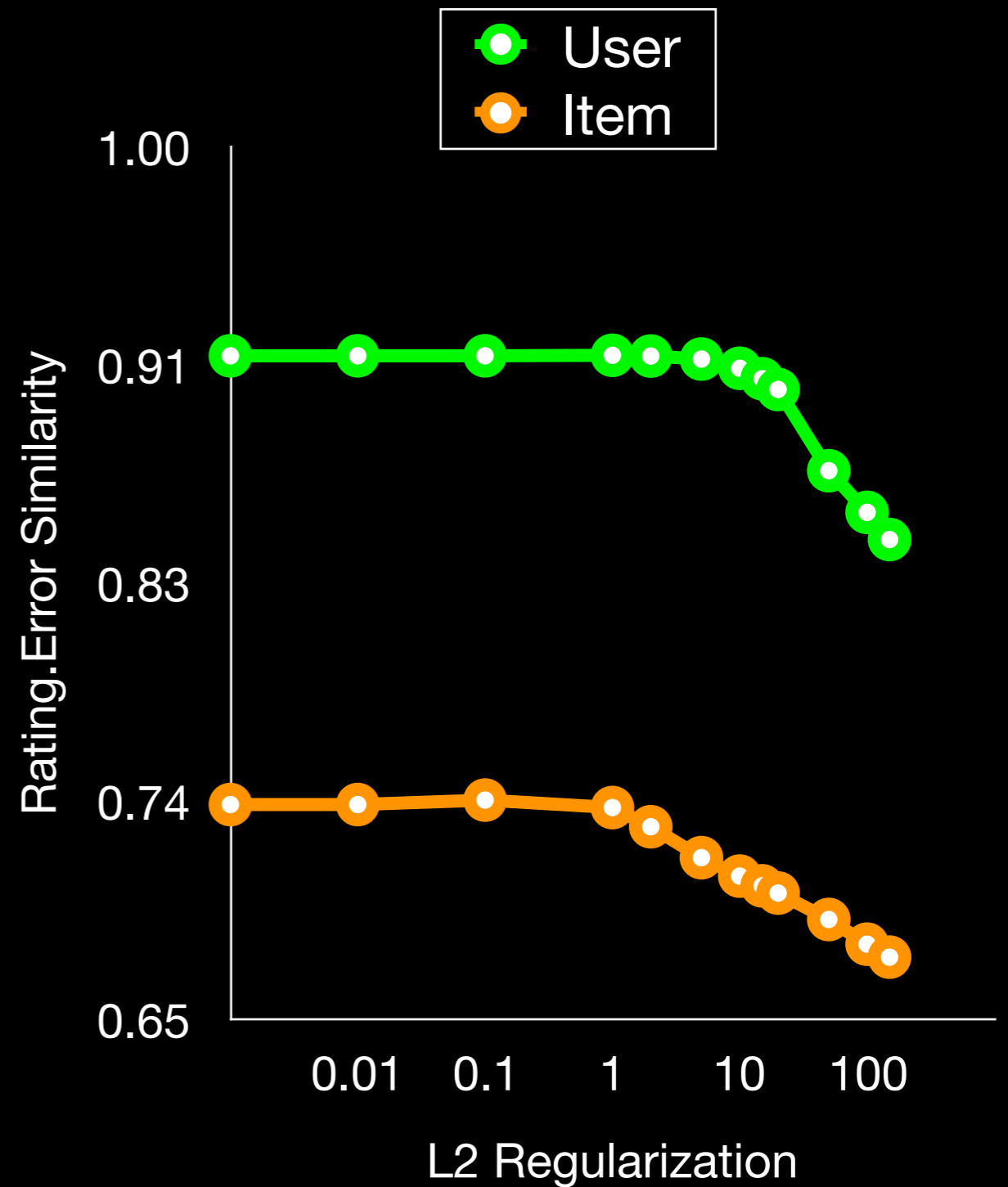
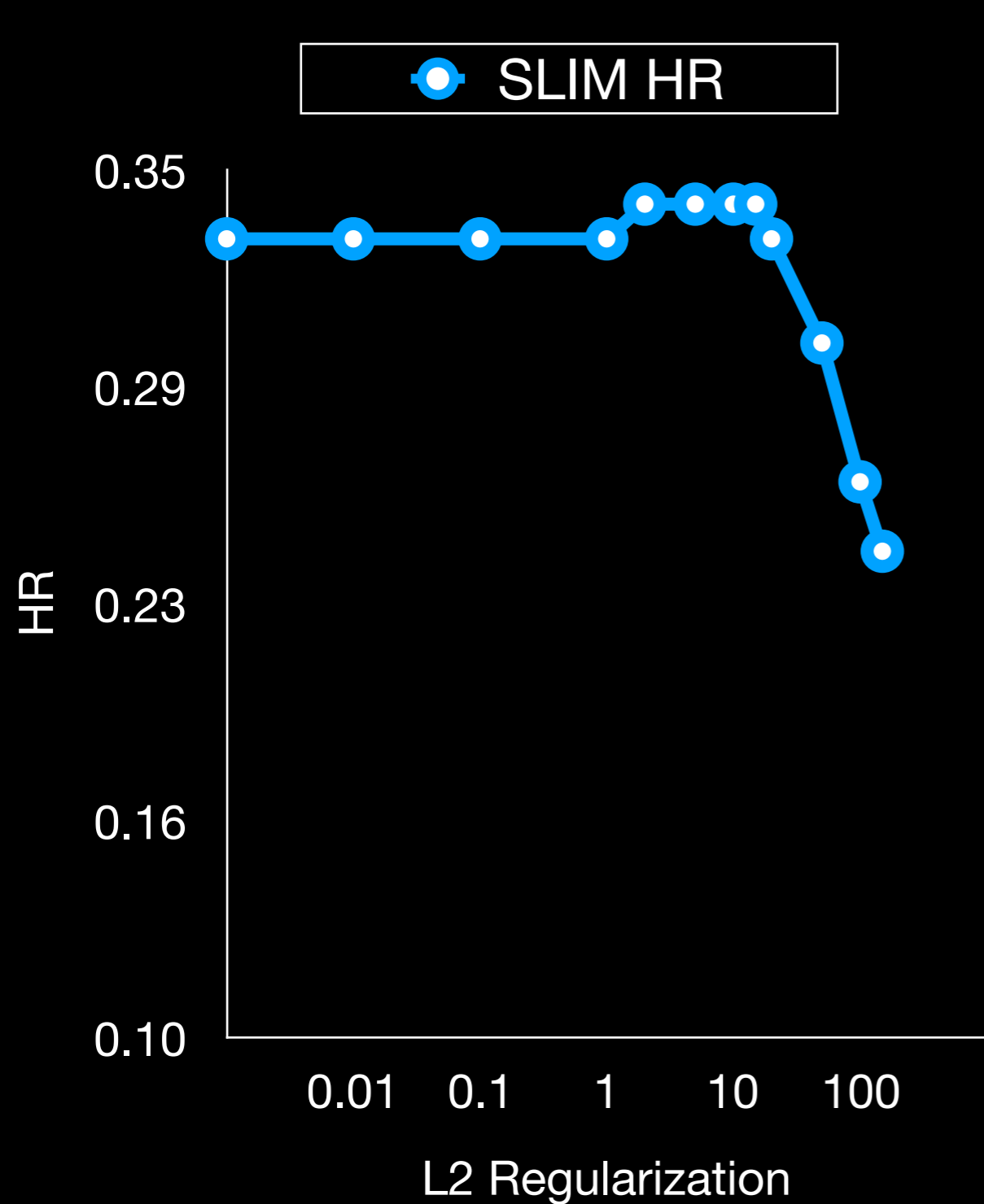
In terms of their error

# Rating.Error Similarities vs Top-N Performance

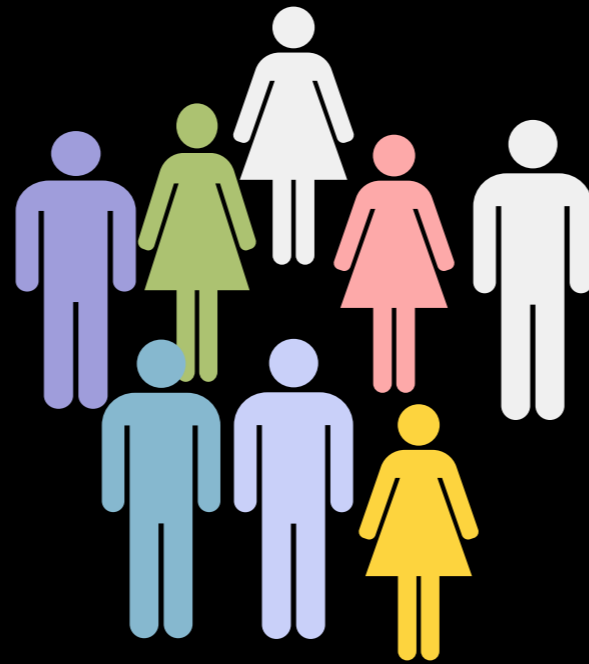




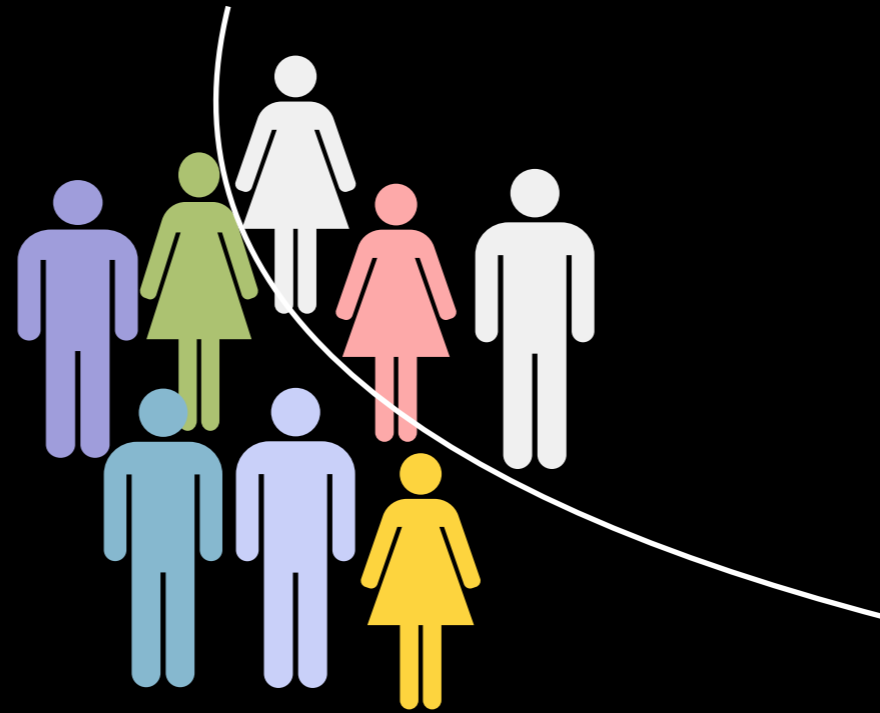
# Rating.Error Similarities vs Top-N Performance



# Focus on similar users

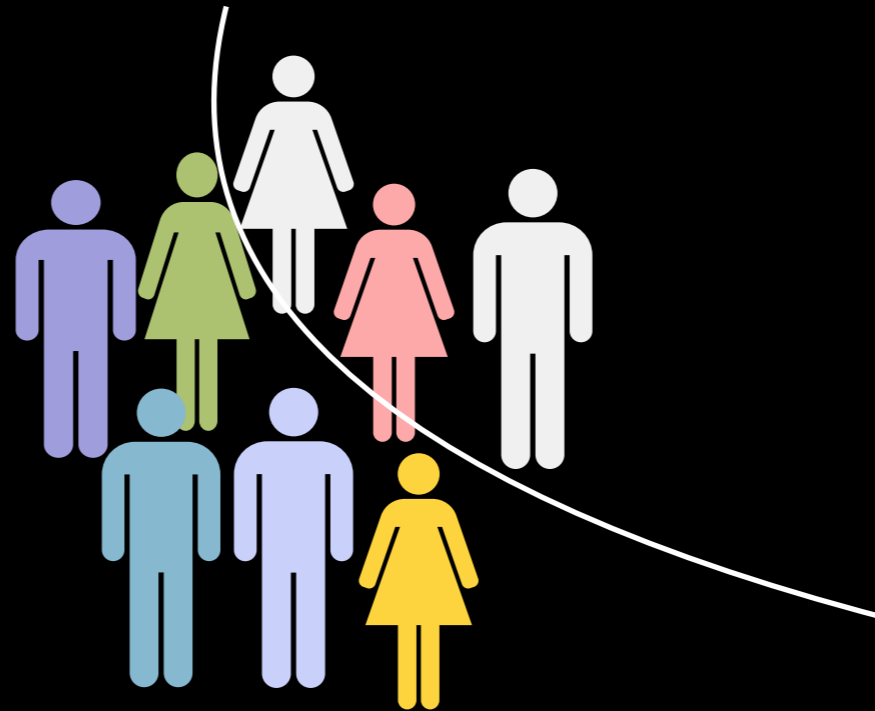


# Focus on similar users



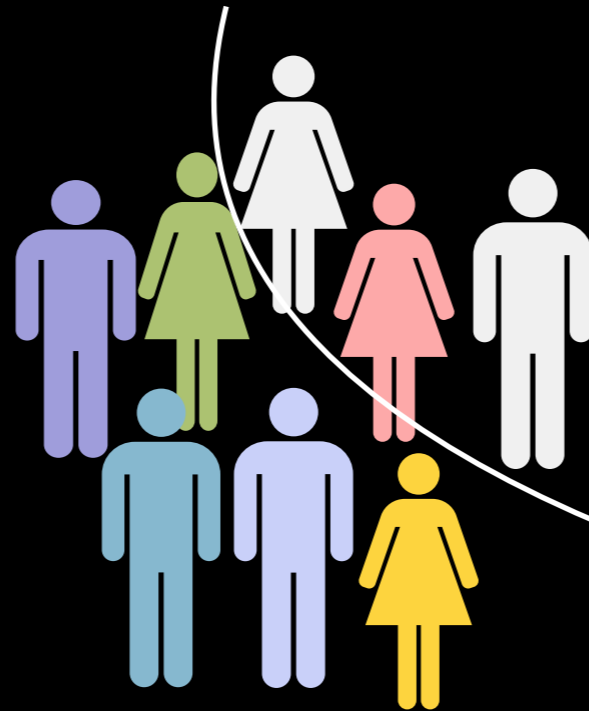
# Focus on similar users

Local Models



# Focus on similar users

Local Models



Similar users =>  
Similar performance

# More details

- ***Local Item-Item Models for Top-N Recommendation***  
Evangelia Christakopoulou and George Karypis, RecSys 2016
- ***Local Latent Space Models for Top-N Recommendation***  
Evangelia Christakopoulou and George Karypis, KDD 2018
- ***Investigating & Using the Error in Top-N Recommendation***  
Evangelia Christakopoulou and George Karypis, Under Review
- <https://www-users.cs.umn.edu/~chri2951/code.html>

Thank you!!

