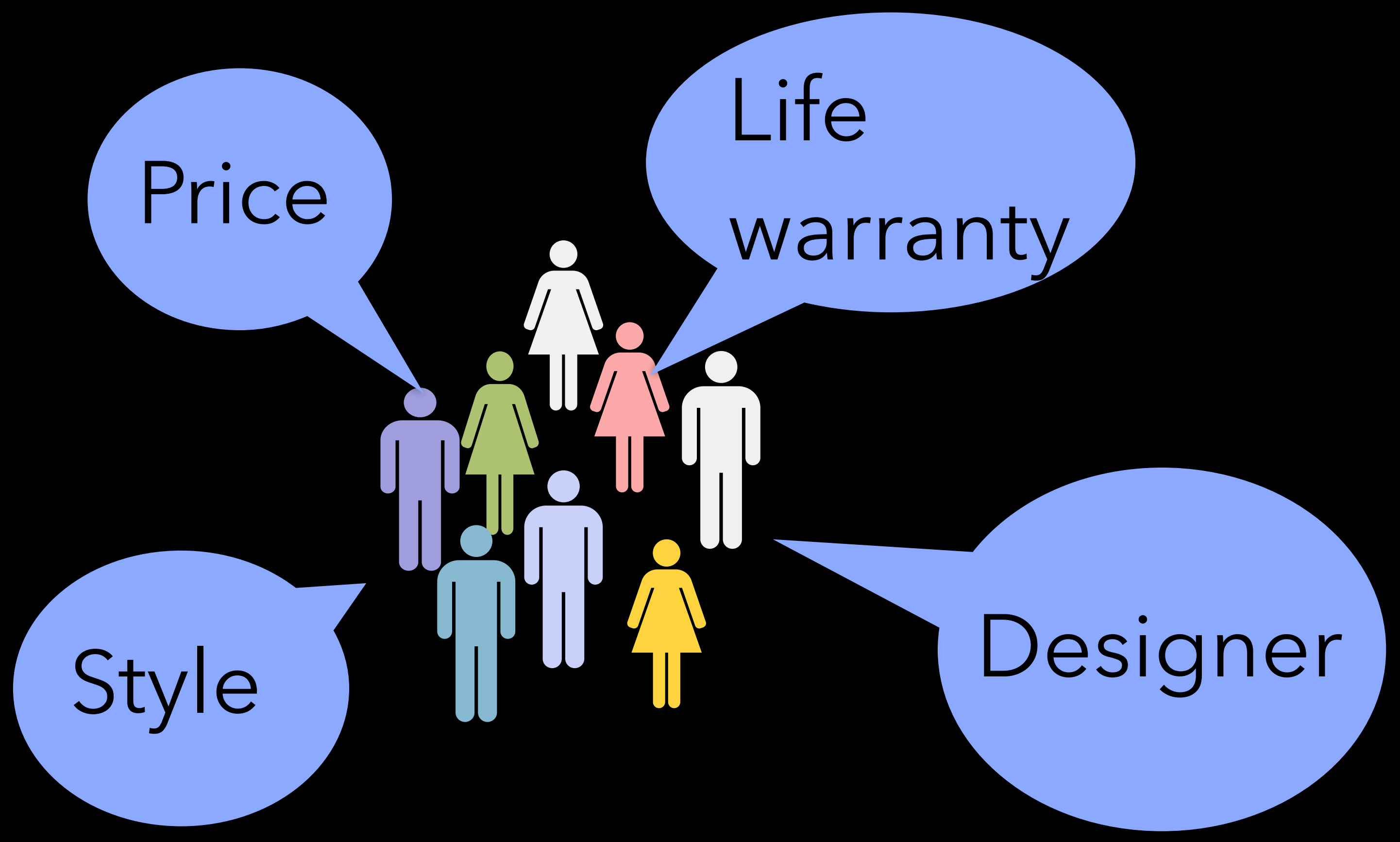
# Local Latent Space Models for Top-N Recommendation

Evangelia Christakopoulou and George Karypis

# Motivation

# Latent space approaches - user model

Users' behaviors are driven by their preferences across various aspects.



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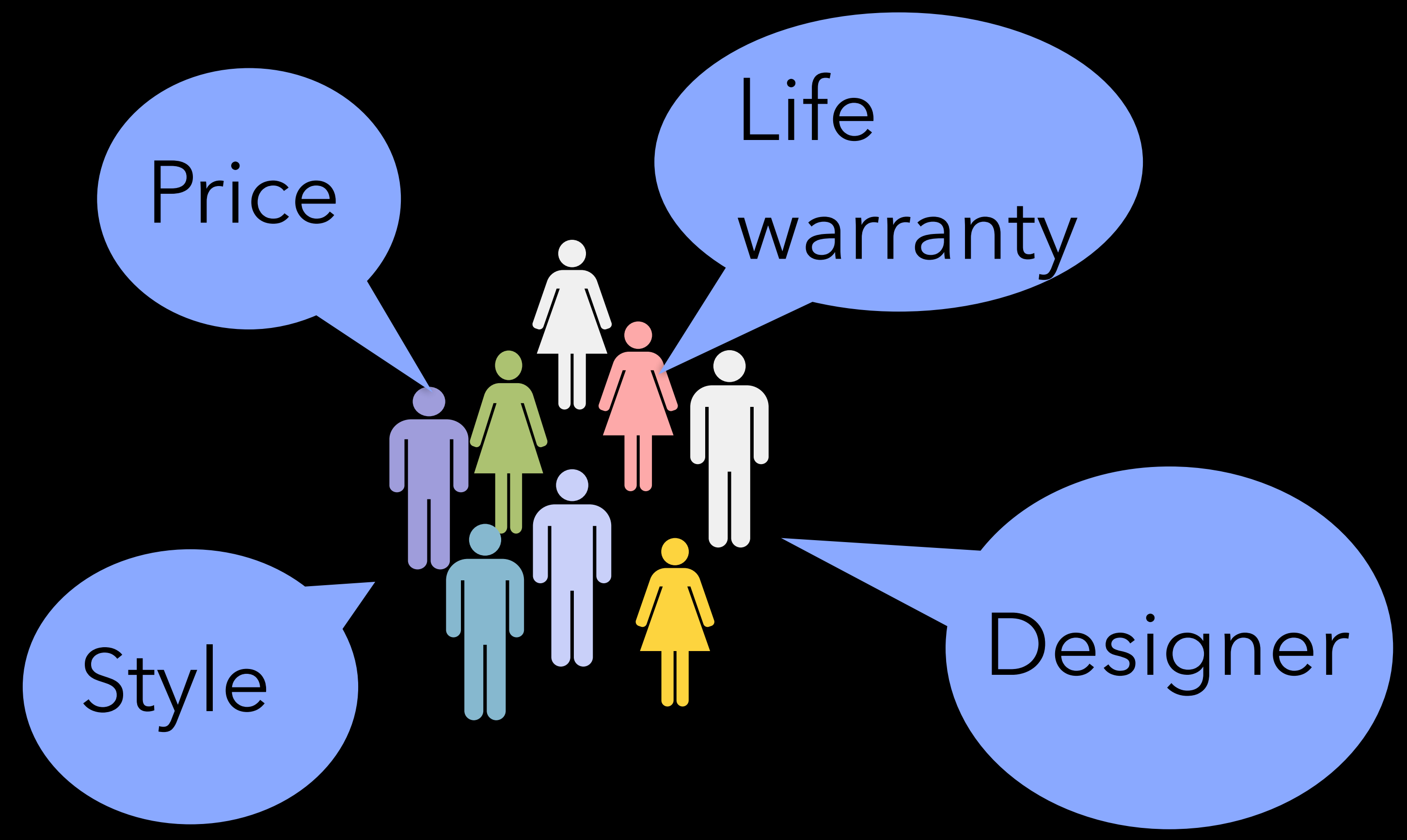
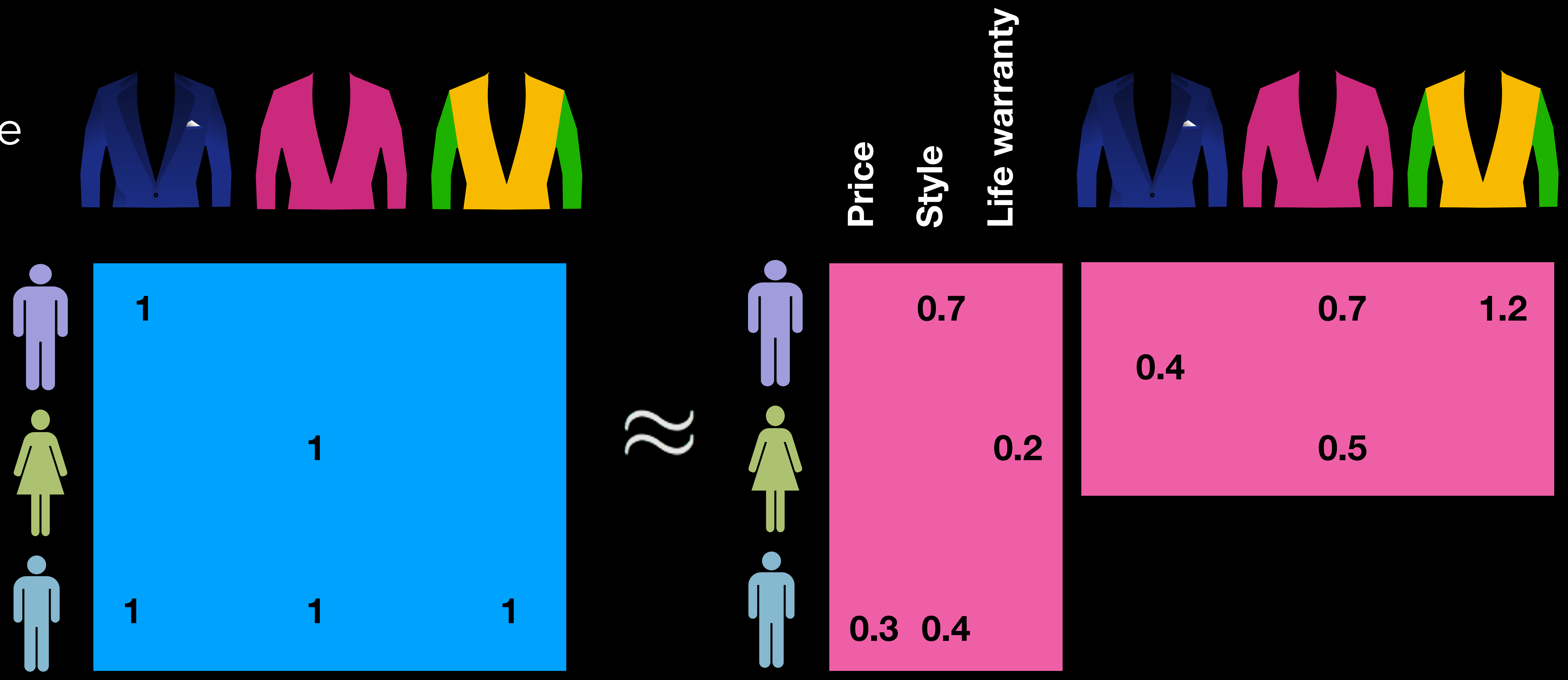
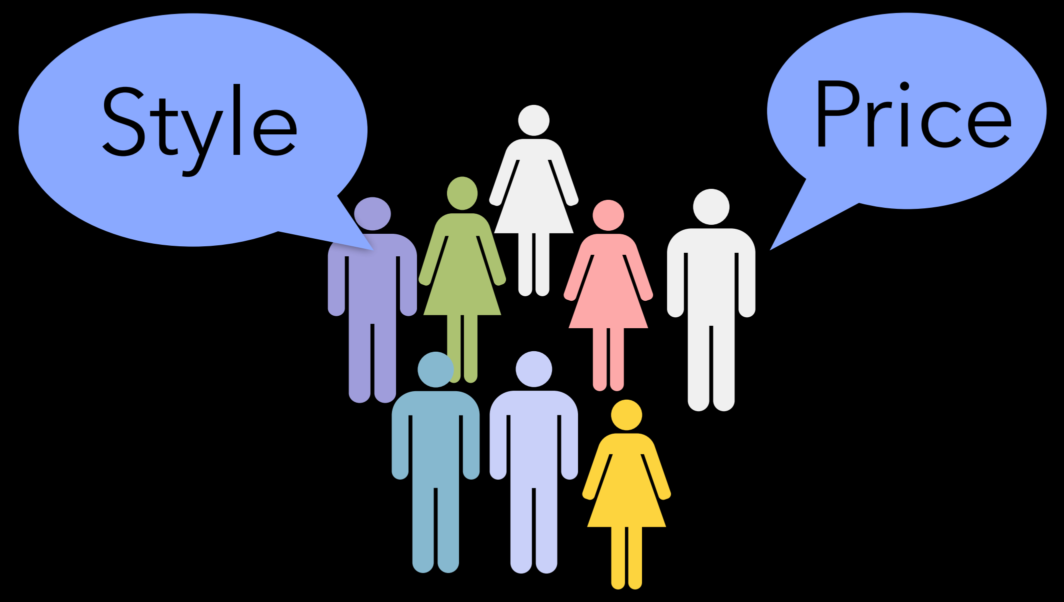



Latent space approaches model these aspects as factors shared by all.



# Limitations of existing user model

Some aspects are shared by all
(global aspects)



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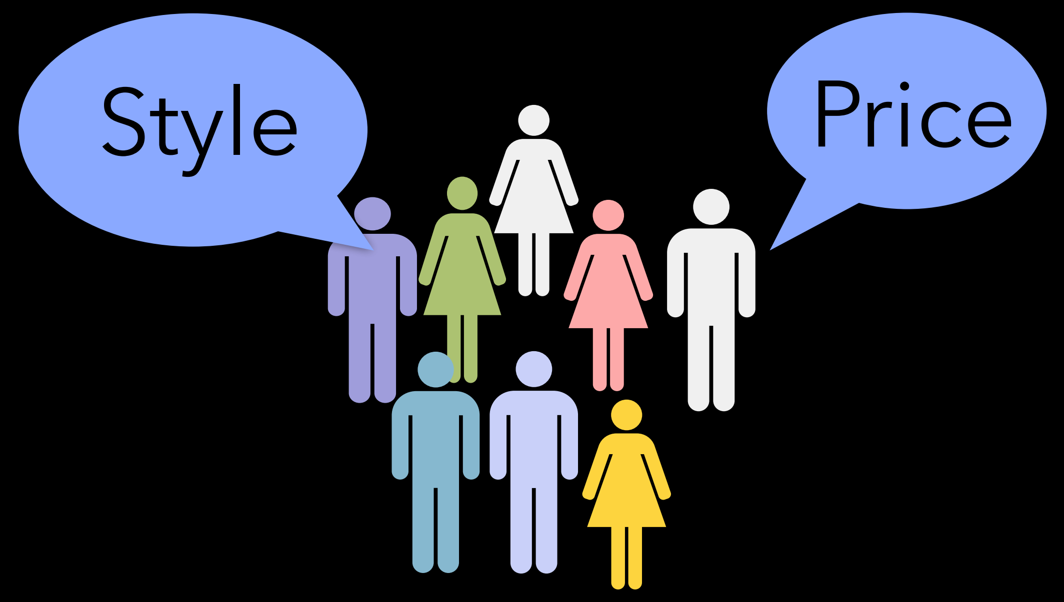
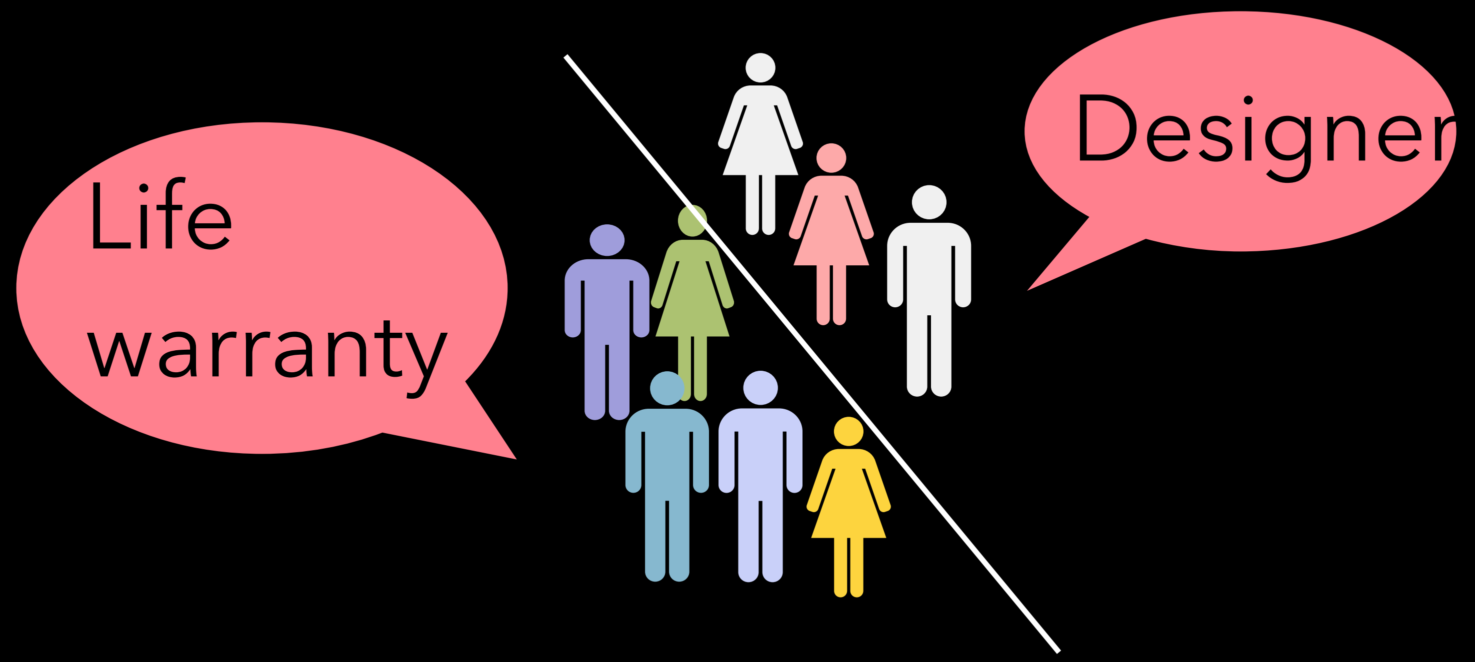
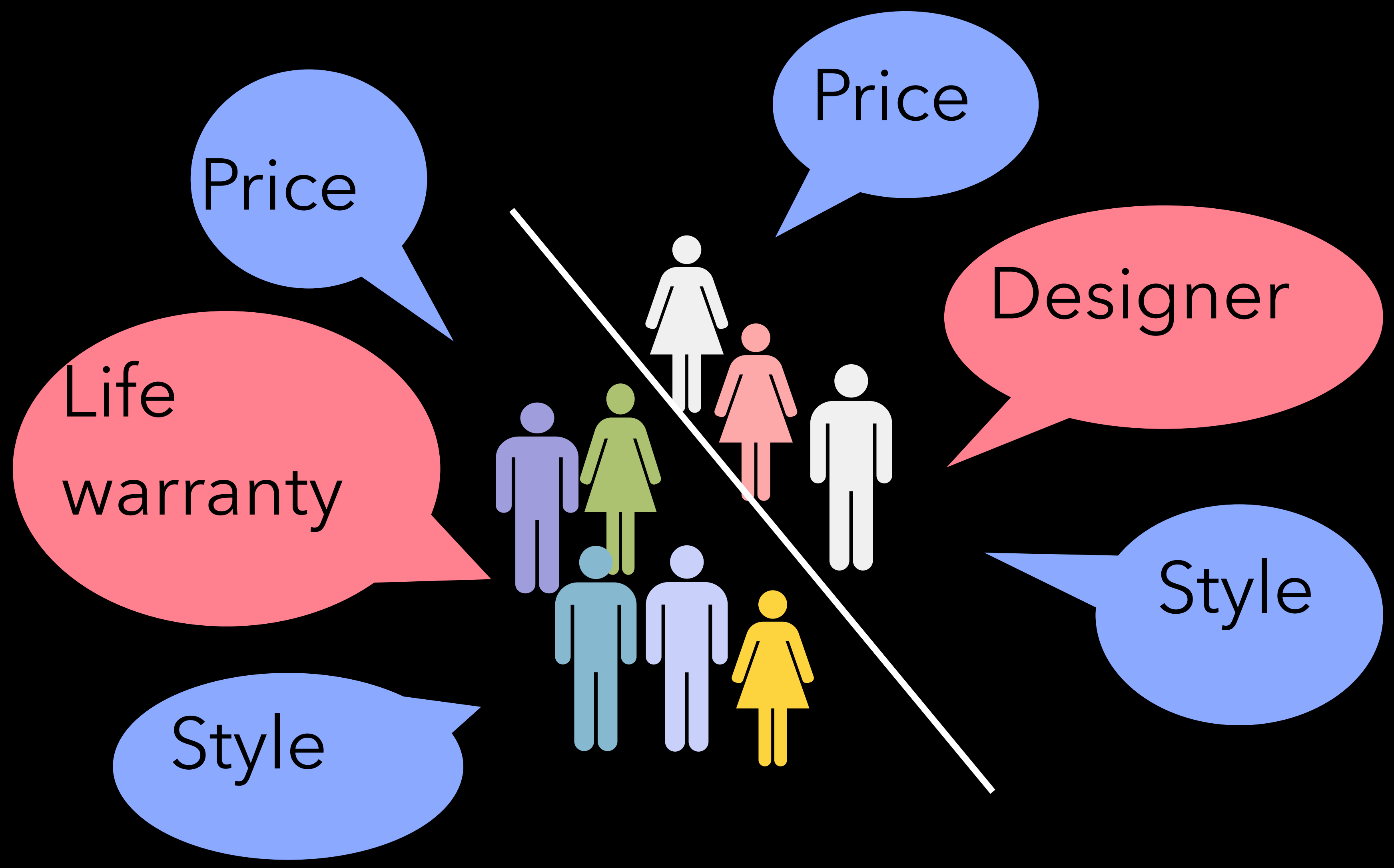



Some interest only some groups of
like-minded people (**local aspects**)



# Proposed user model




We explicitly encode such structure by estimating both a global low-rank model and multiple user-subset specific low-rank models.

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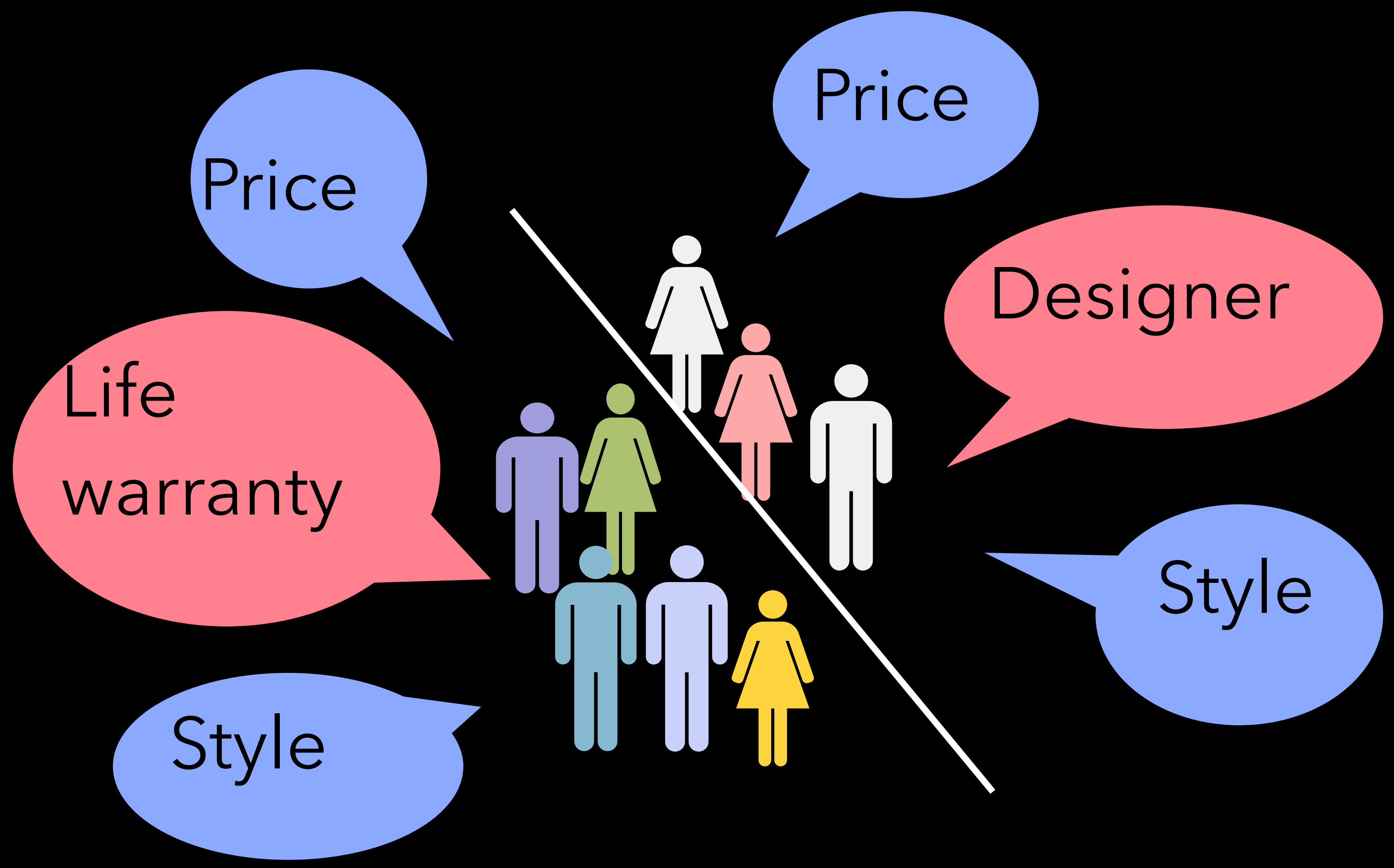
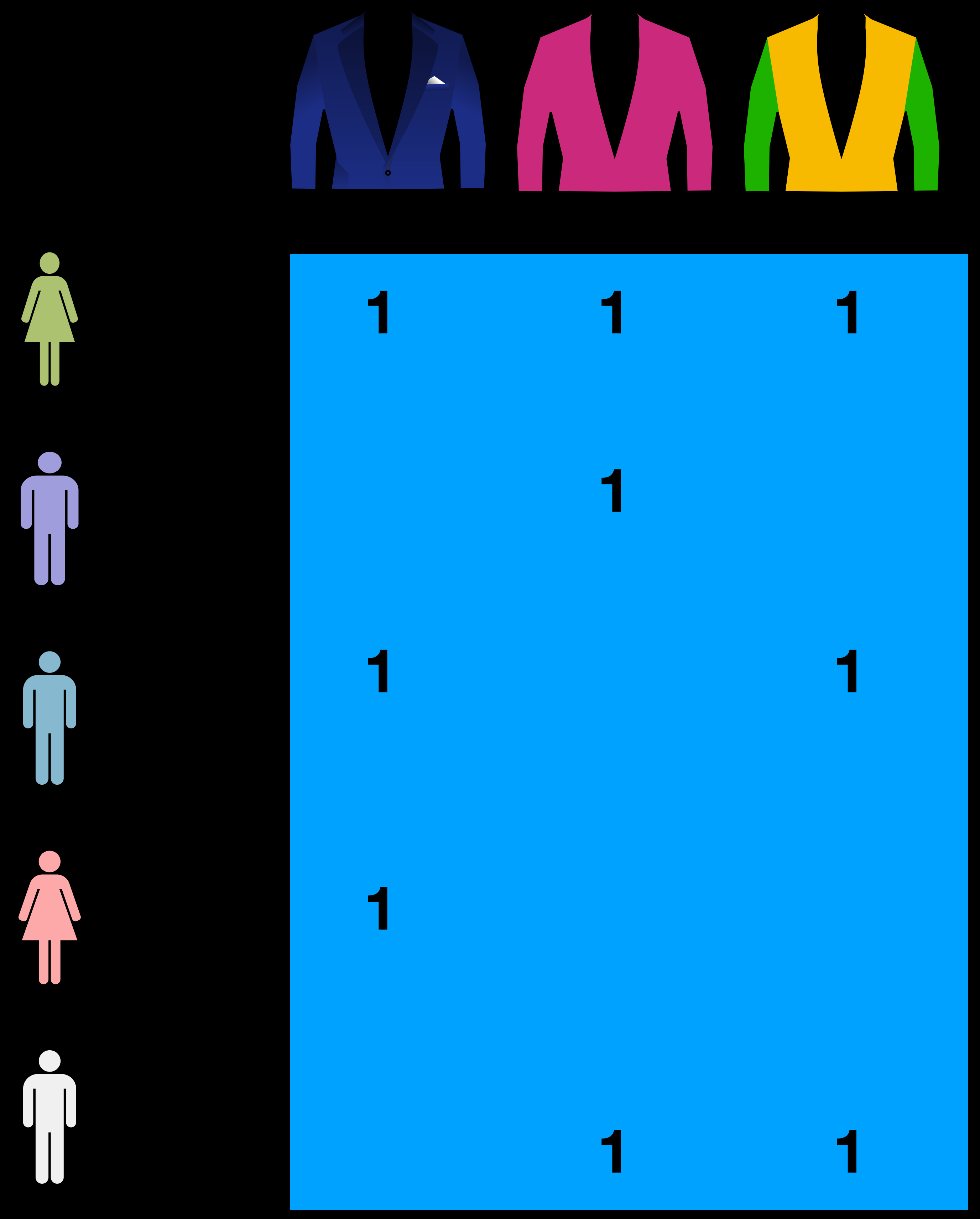



We explicitly encode such structure by estimating both a global low-rank model and multiple user-subset specific low-rank models.

Why not increase the rank?

# Methods

# Global & Local SVD with varying Ranks (rGLSVD)



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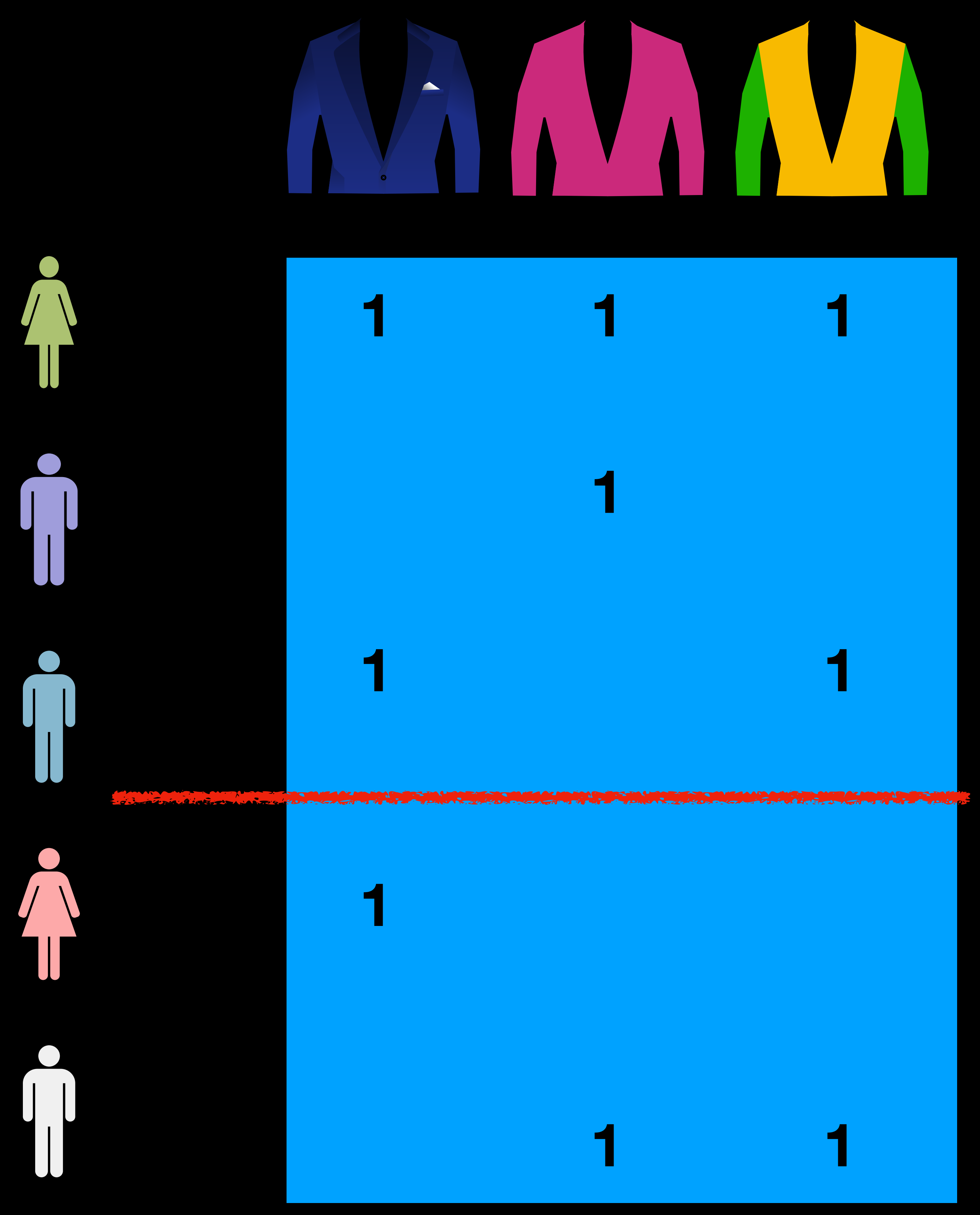

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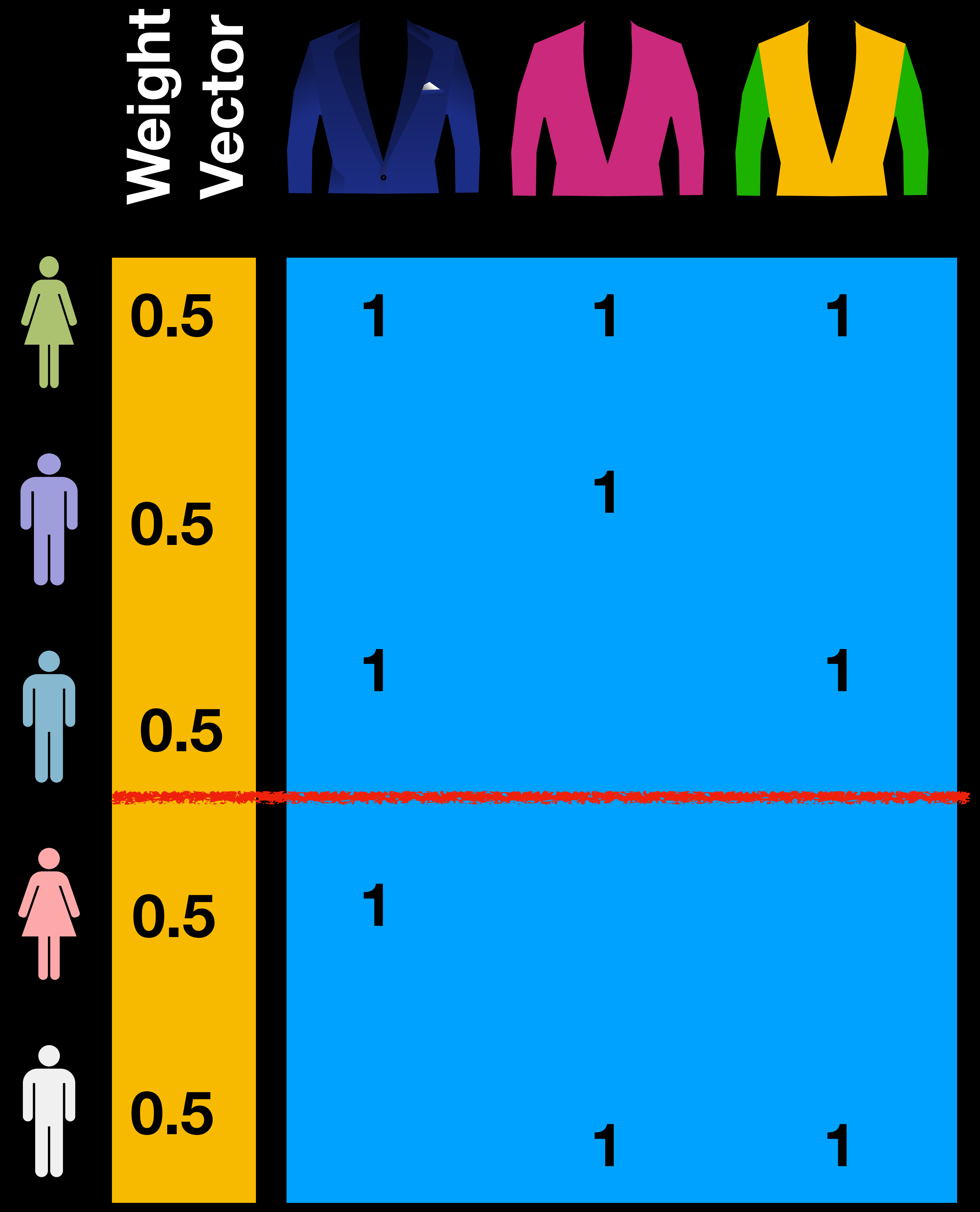

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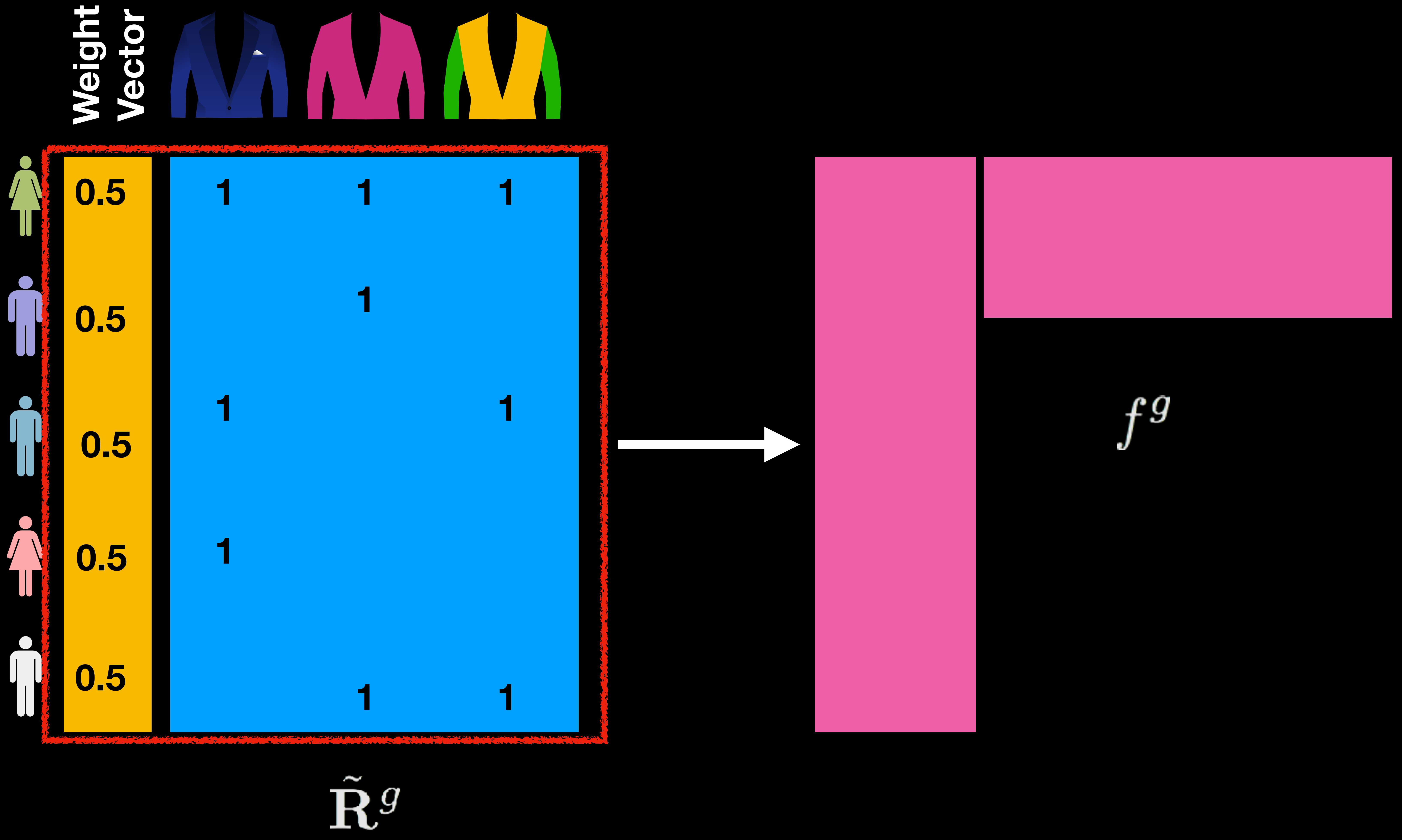


$$\tilde{\mathbf{R}}^g = \mathbf{P}\boldsymbol{\Sigma}_{f^g}\mathbf{Q}^T$$

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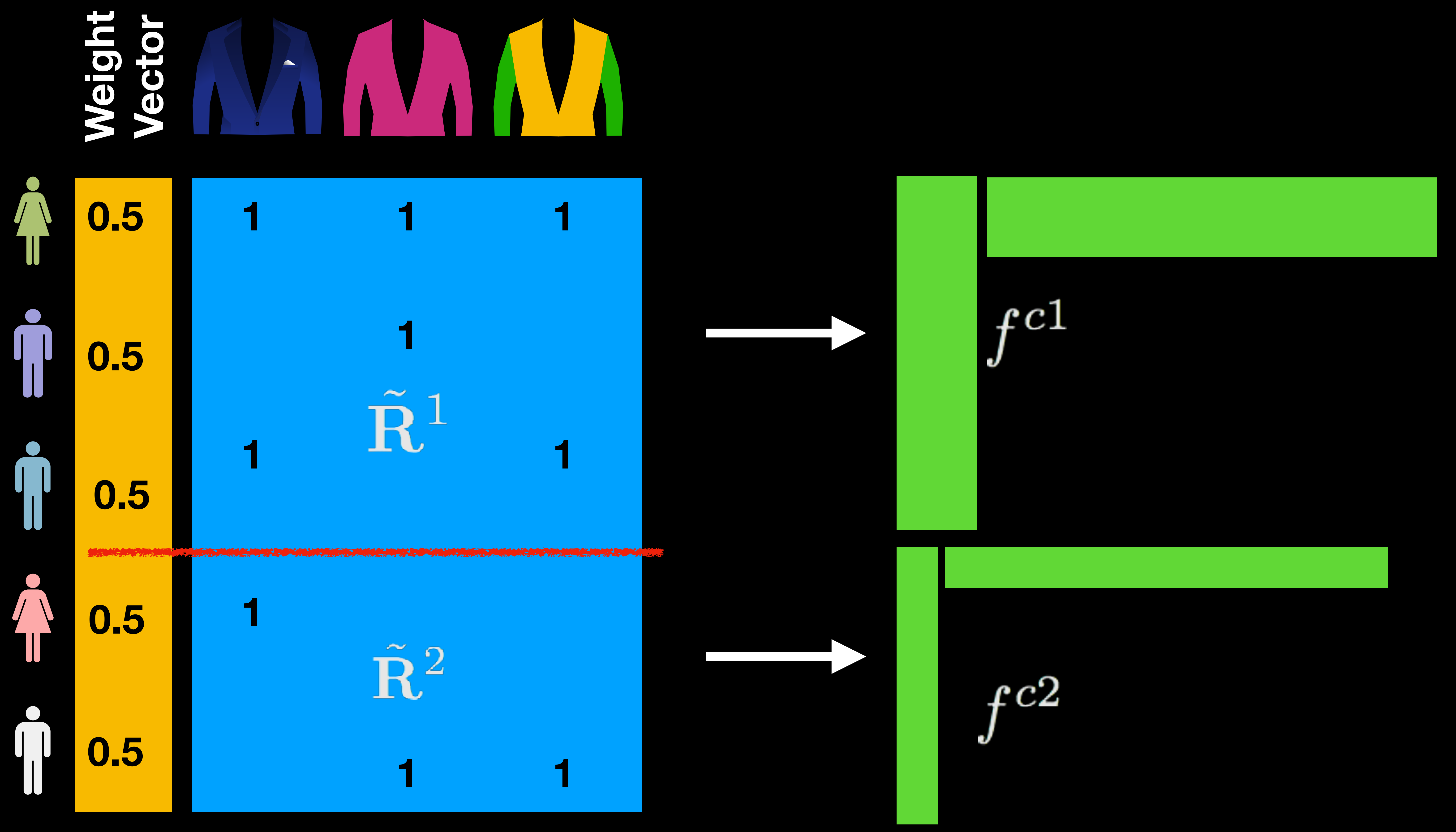


$$\tilde{\mathbf{R}}^c = \mathbf{P}^c \boldsymbol{\Sigma}_{f^c} \mathbf{Q}^{cT}$$

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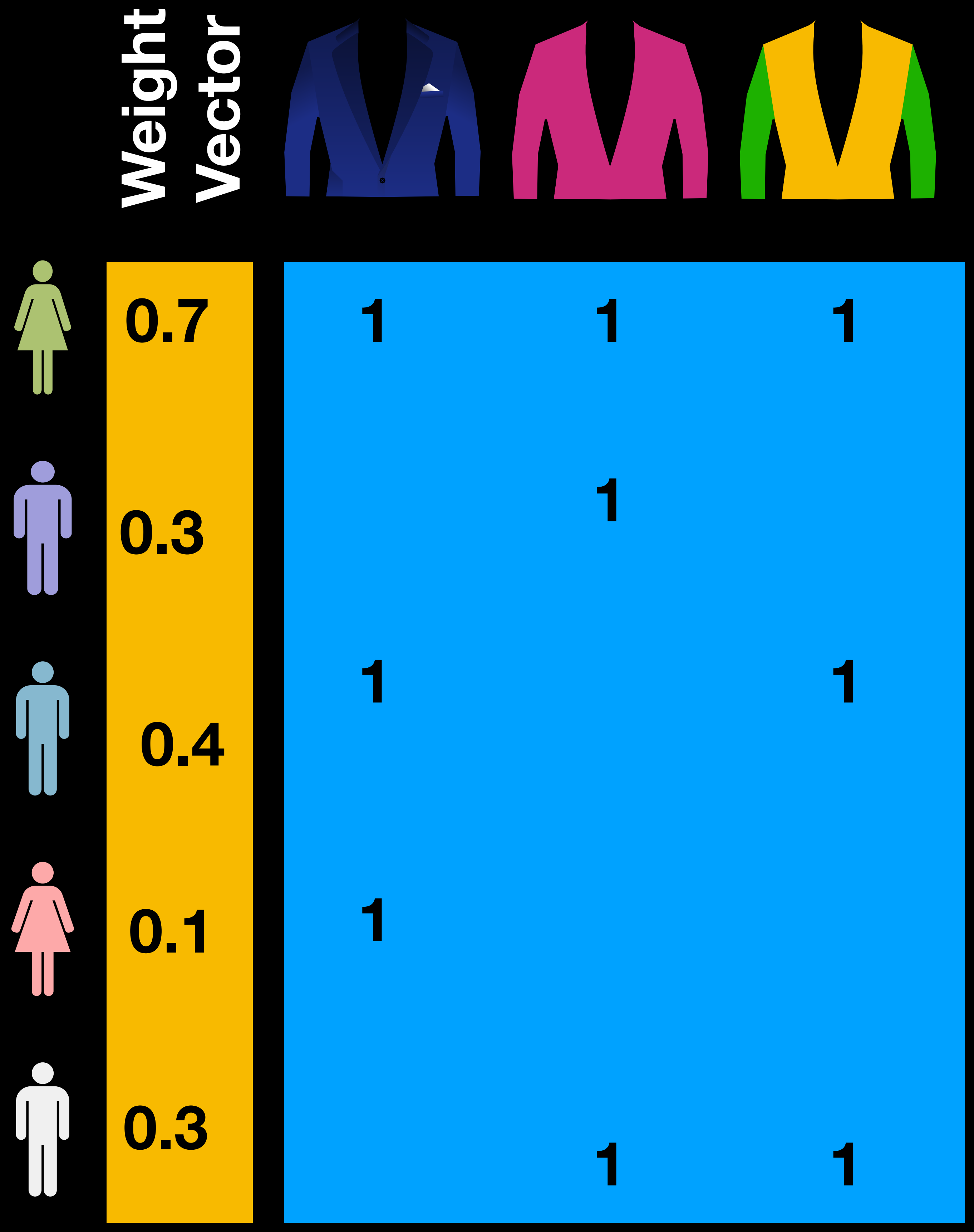
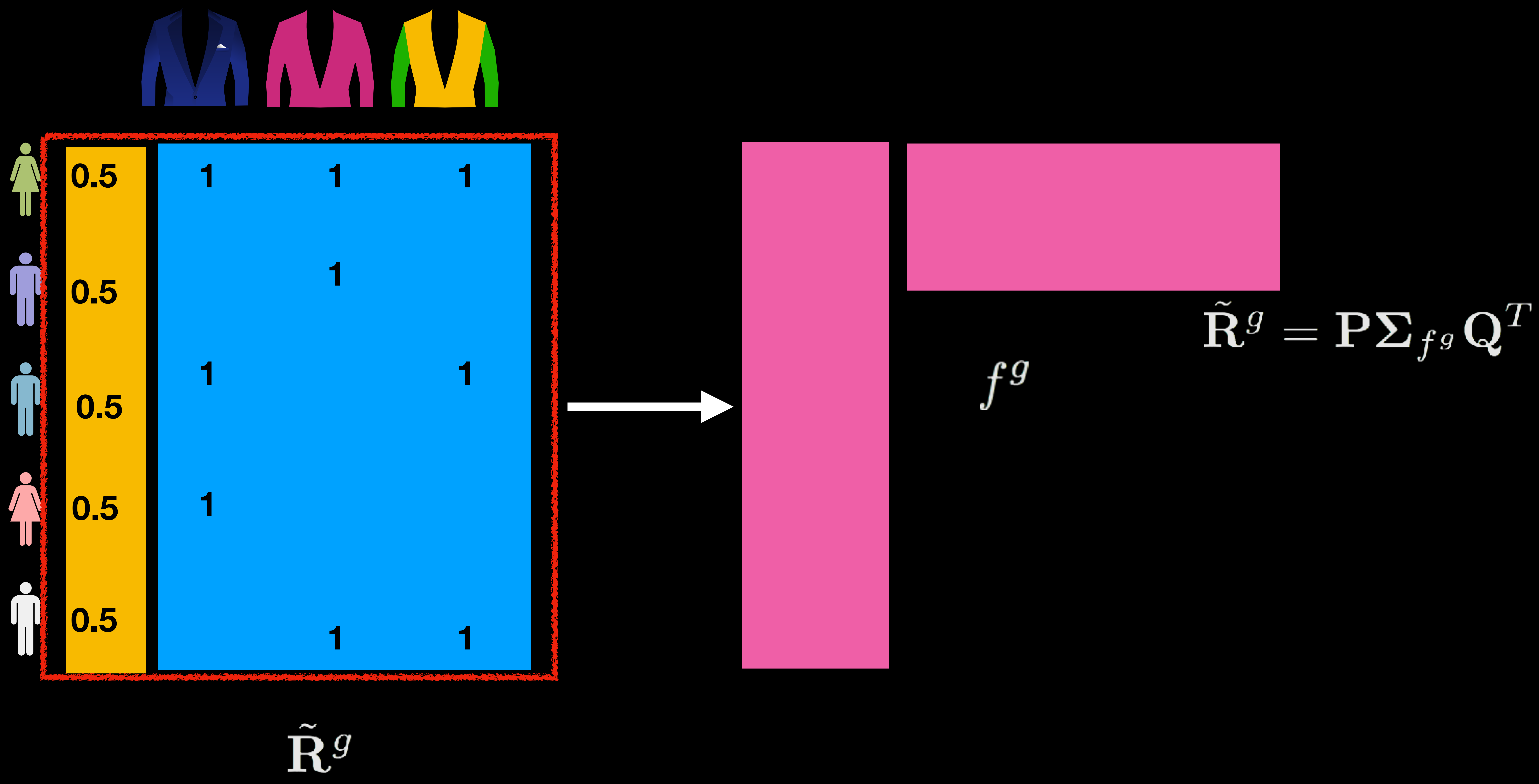


| | | | |
|---|---|---|---|
| **Weight Vector** | | | |
| 0.7 | 1 | 1 | 1 |
| 0.3 | | 1 | |
| 0.4 | 1 | | 1 |
| 0.1 | 1 | | |
| 0.3 | | 1 | 1 |

# Global & Local SVD with varying Subsets (sGLSVD)



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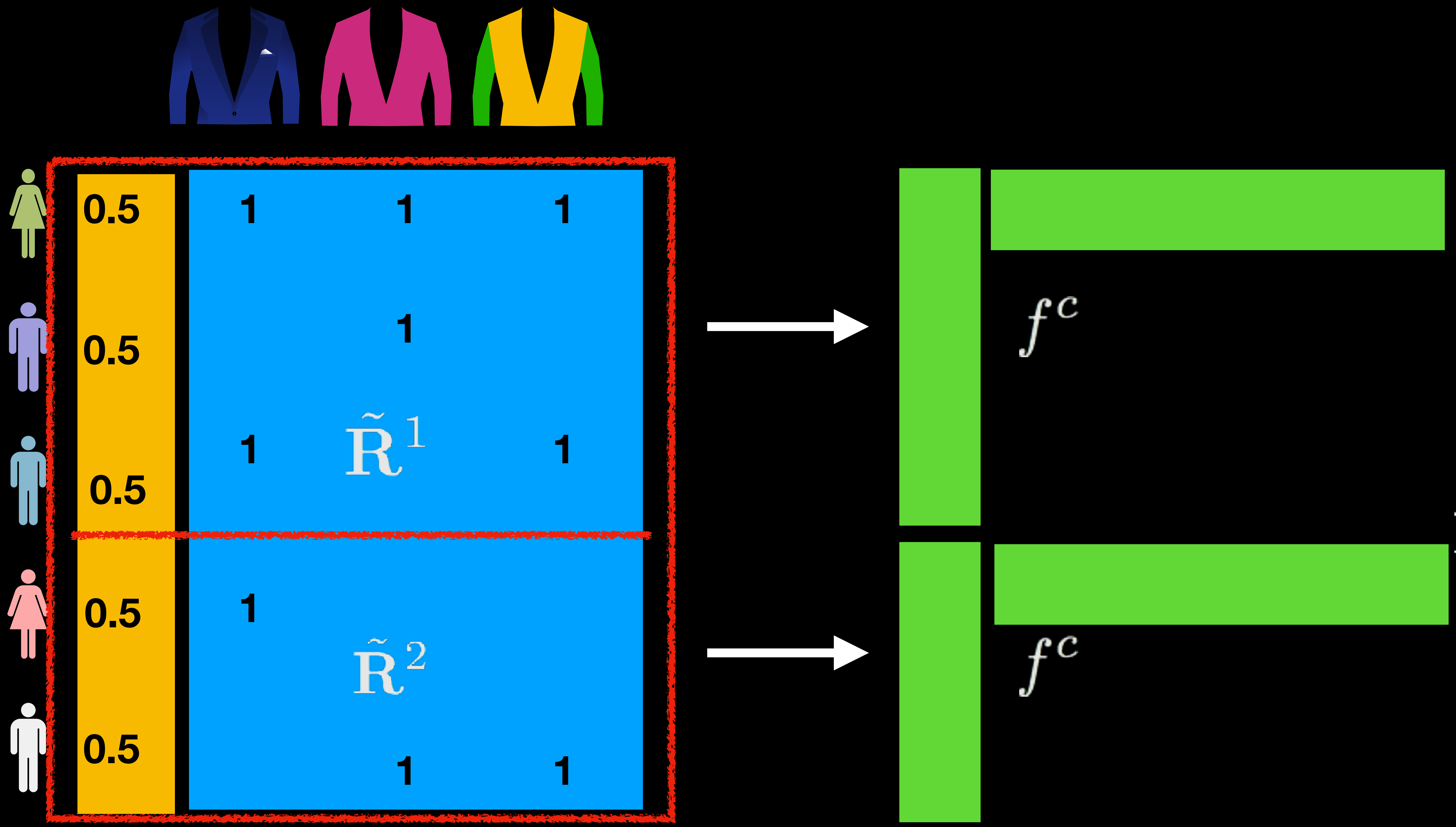


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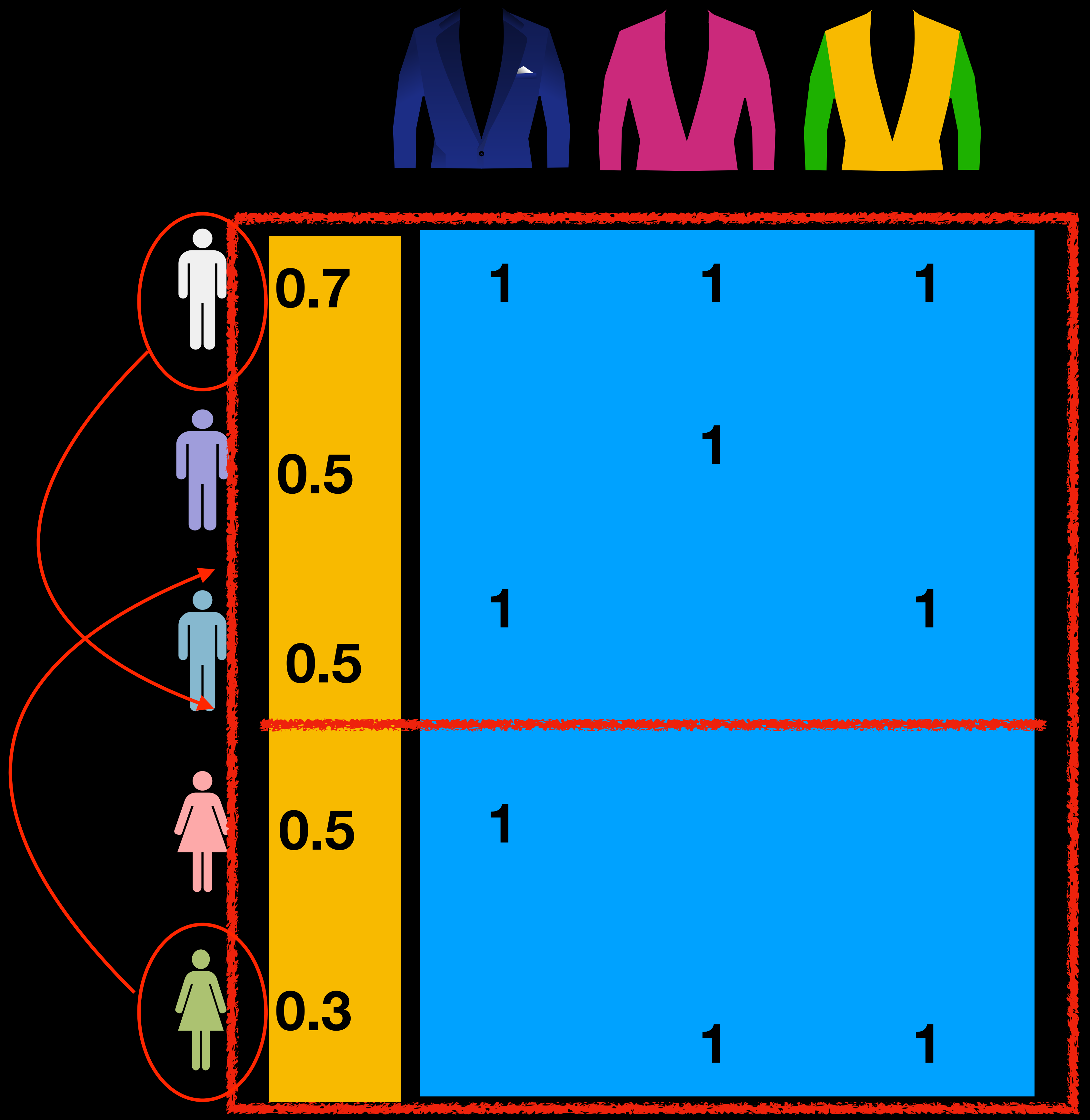

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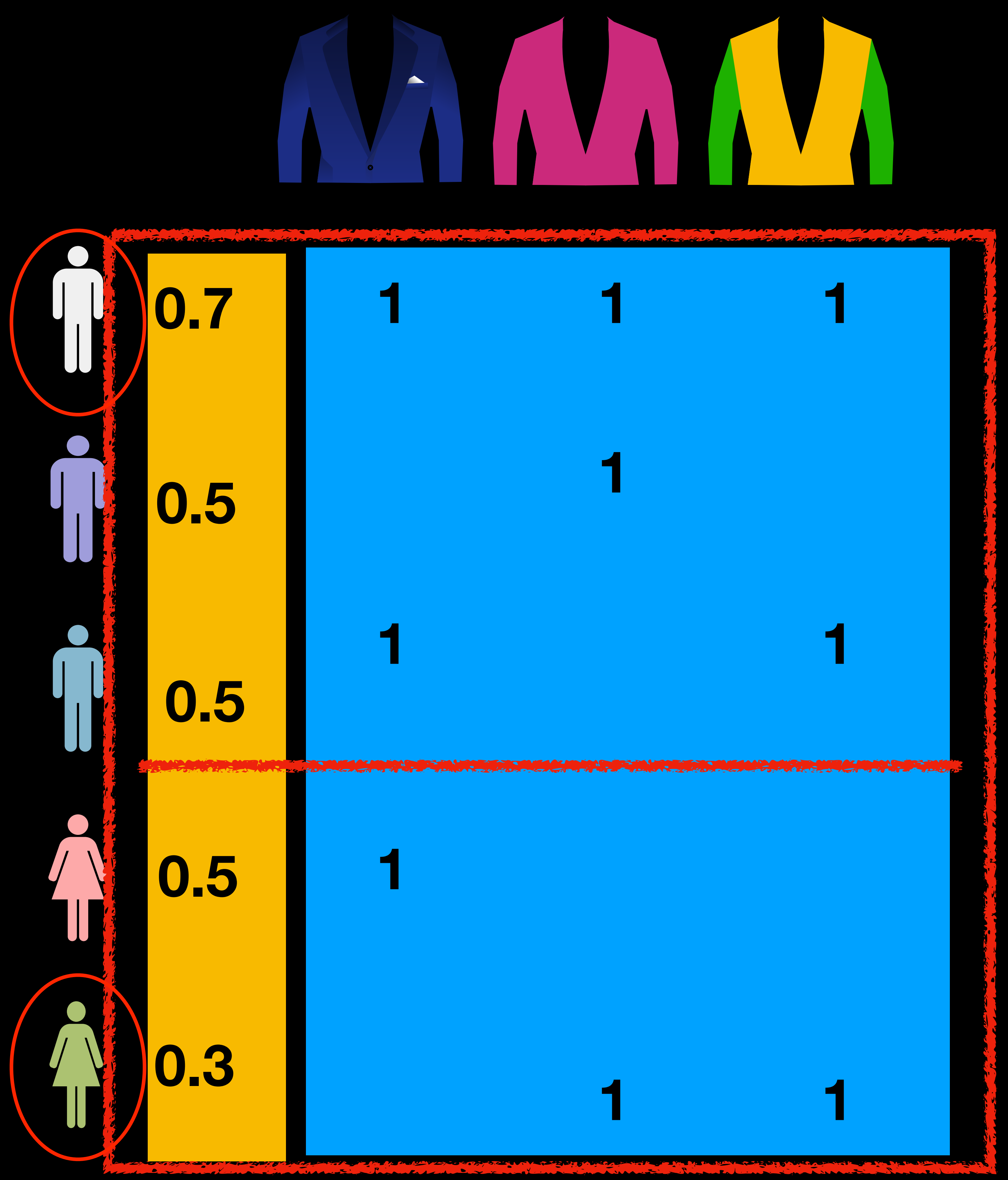


# Recommendation

- Estimate the values of the missing entries

$$\tilde{r}_{ui} = \mathbf{p}_u^T \mathbf{\Sigma}_{f^g} \mathbf{q}_i + \mathbf{p}_u^{cT} \mathbf{\Sigma}_{f^c} \mathbf{q}_i^c$$

- Sort them and recommend the N highest.

# Experimental evaluation

# Datasets

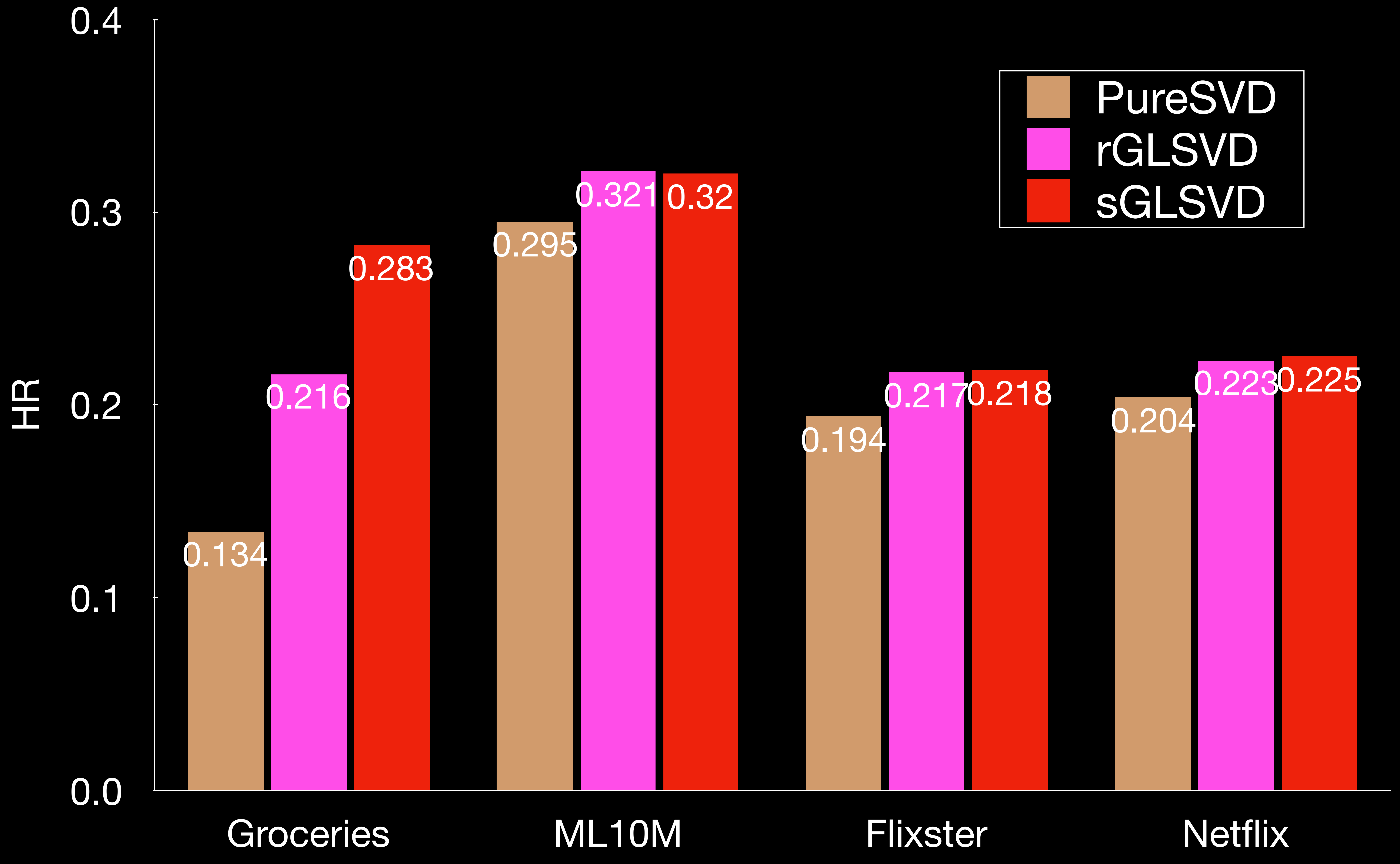
| Name | #Users | #Items | #Transactions | Density |
|---|---|---|---|---|
| Groceries | 63,034 | 15,846 | 2,060,719 | 0.21% |
| ML10M | 69,878 | 10,677 | 10,000,054 | 1.34% |
| Flixster | 29,828 | 10,085 | 7,356,146 | 2.45% |
| Netflix | 274,036 | 17,770 | 31,756,784 | 0.65% |

# Evaluation Methodology

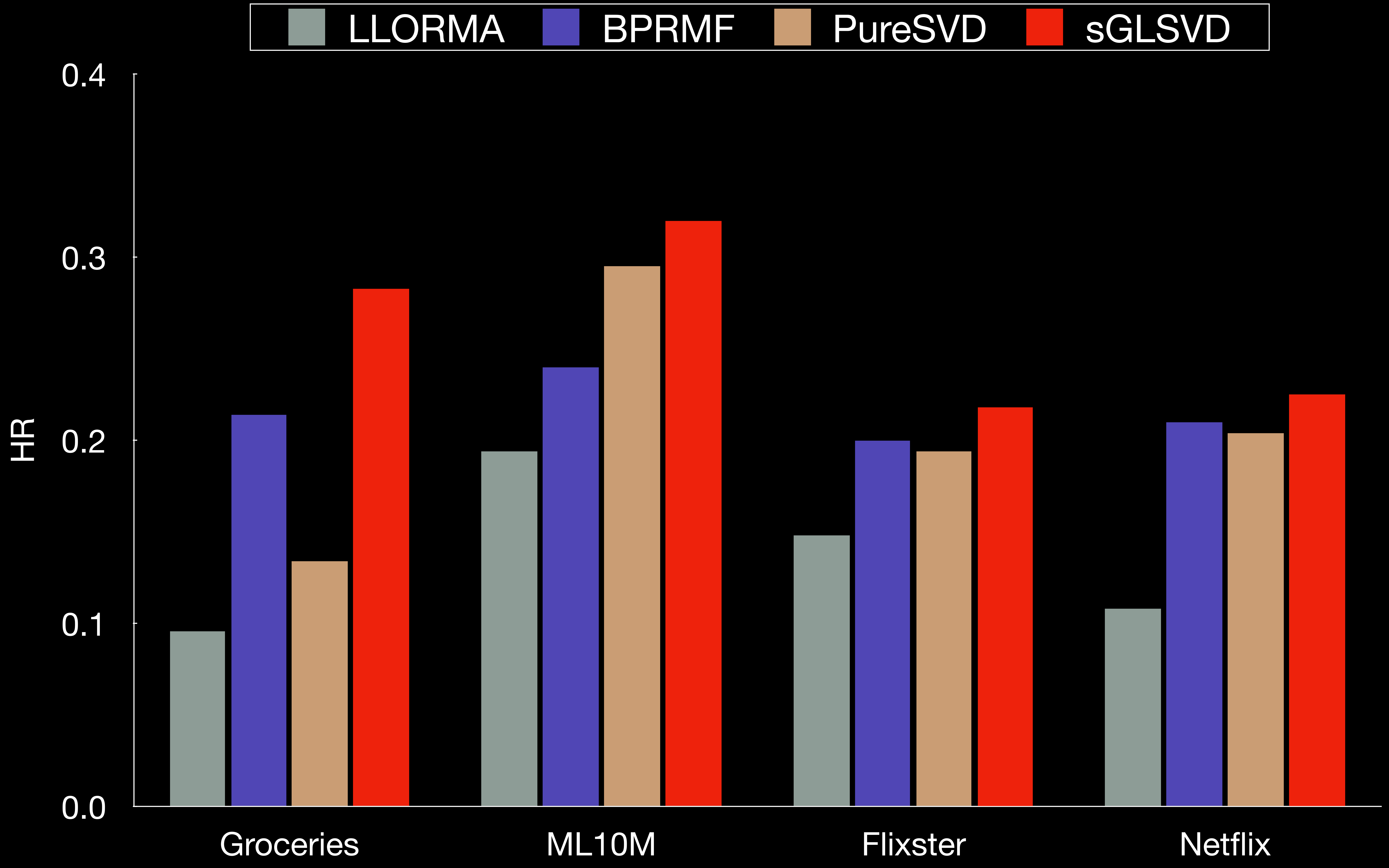
- Leave-one-out cross validation
- Hit Rate (HR), Average Reciprocal Hit Rank (ARHR)
- Search over parameter space

# Experimental results

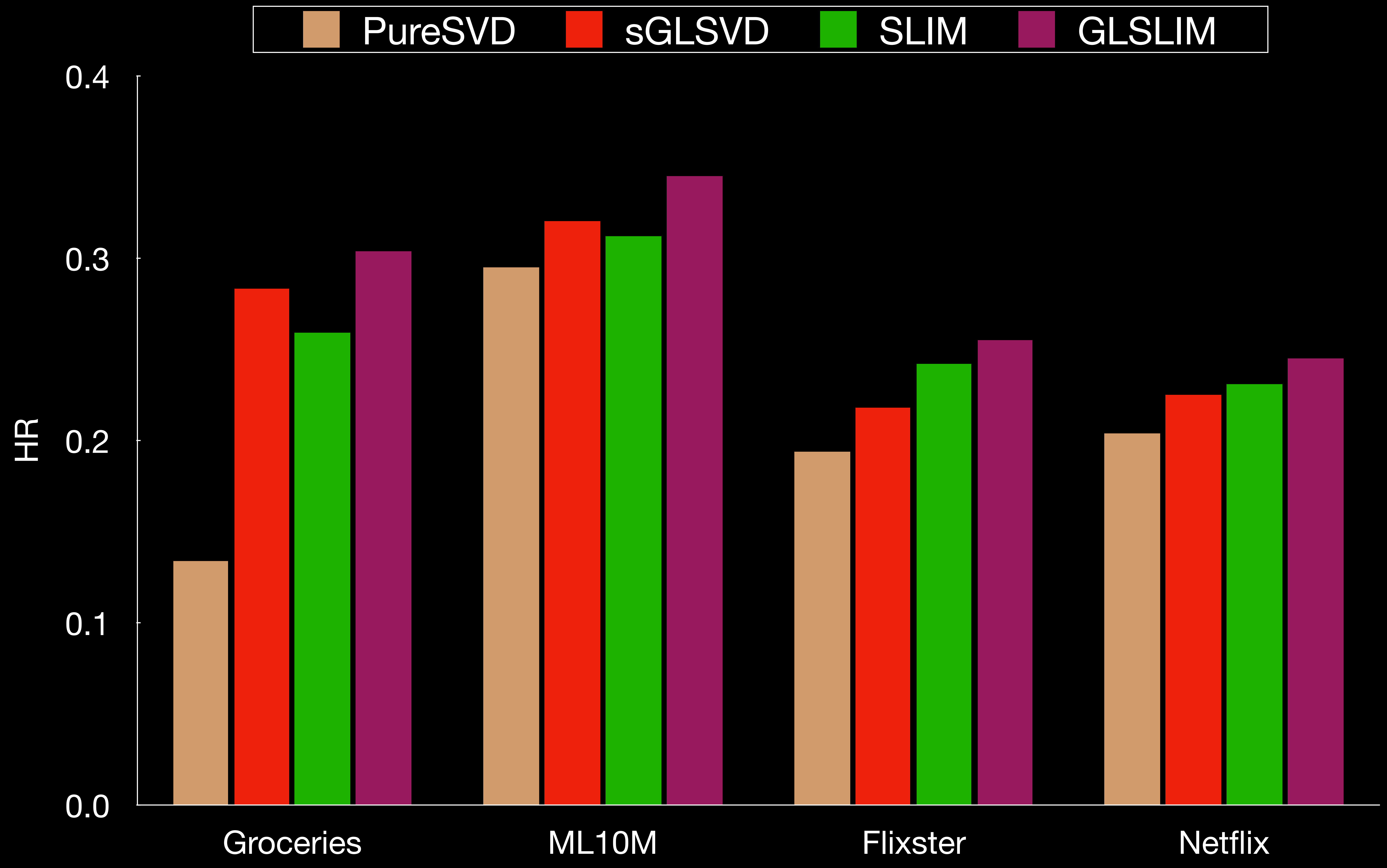
# Performance against competing global approach



# Performance against competing latent space approaches



# Global & local against global approaches



# Global & local against global approaches

| Method | Mins |
|---|---:|
| sGLSVD | 9.3 |
| GLSLIM | 199.2 |
| GLSLIM - warm | 53.7 |

# Conclusion

# Key messages

- Merits of the proposed user model.
- Estimation of better latent representations that lead to significant improvements of 13% on average and up to 37%.

# Thank you!