Matrix Factorization Recommendations

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Matrix Factorization

- Why Singular Value Decomposition
- Latent Factors
- Singular Value Decomposition
- Extras

Why Singular
Value Decomposition?

Why Singular Value Decomposition (one popular form of Matrix Factorization)?

- Singular Value Decomposition (SVD) was shown during the popular Netflix competition of 2006 to outperform many of the best recommendation algorithms.

- Computationally more efficient than many other recommendation algorithms.

- Link to source.

Latent Factors

Latent Factors

- In order to understand conceptually how SVD works, it is important to understand latent factors.
- Latent factors are not directly observable in the data.
- For an example of user ratings associated for each movie, there is a latent factor associated with each user and each movie.

Latent Factors

- Movie Latent Factors
  - Weights associated with the movie’s:
    - Genre
    - Types of actors/actresses
    - Happiness levels
    - Rating (G-PG-PG13-R)

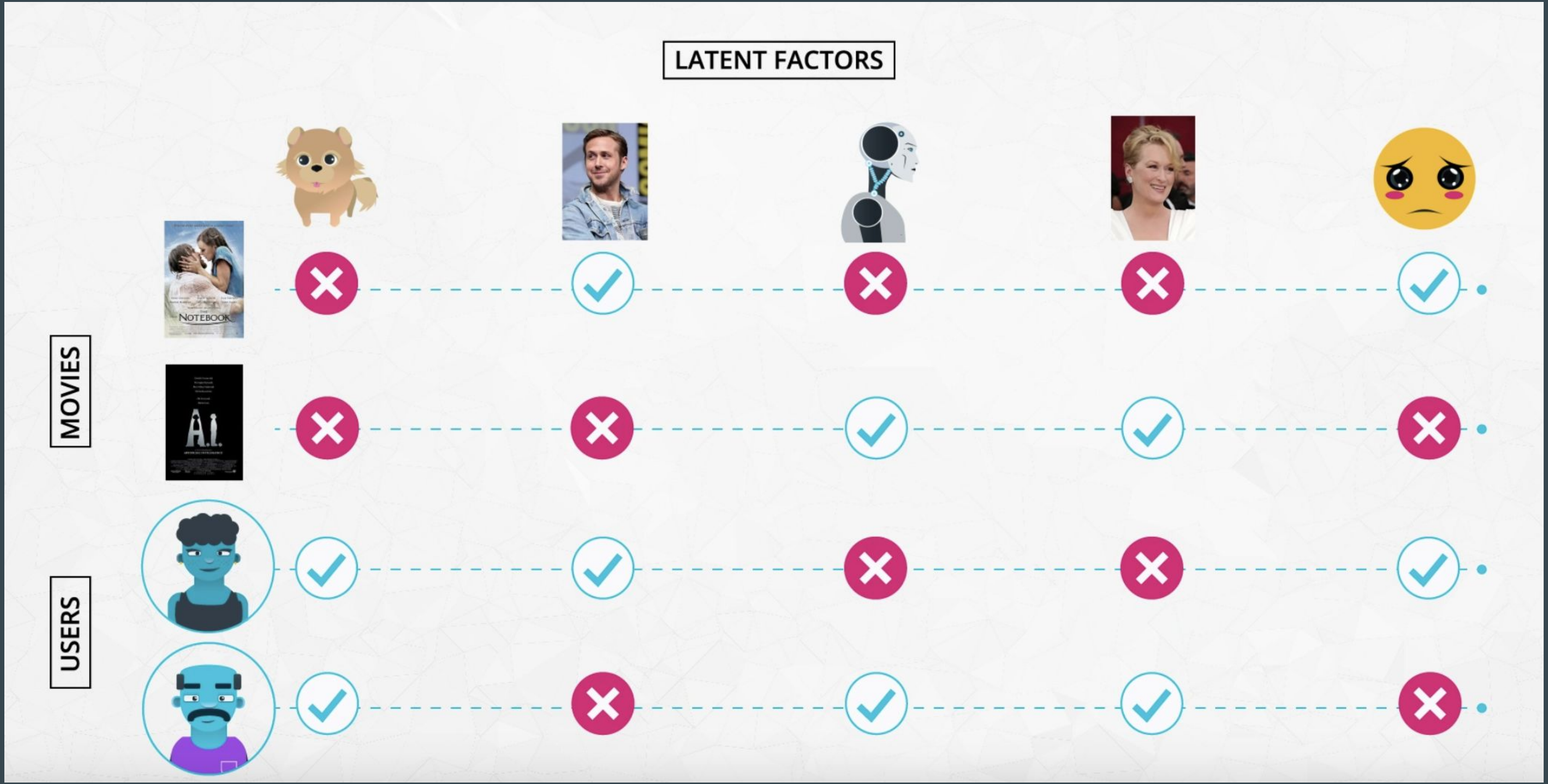
- Notice none of the above would be numbers directly available from user-movie ratings

Latent Factors

- User Latent Factors
  - Weights associated with the user's feelings toward:
    - Movie genre
    - Types actors/actresses
    - Happiness level of the movie
    - Rating of the movie (G-PG-PG13-R)

- Notice none of the above would be numbers directly available from user-movie ratings

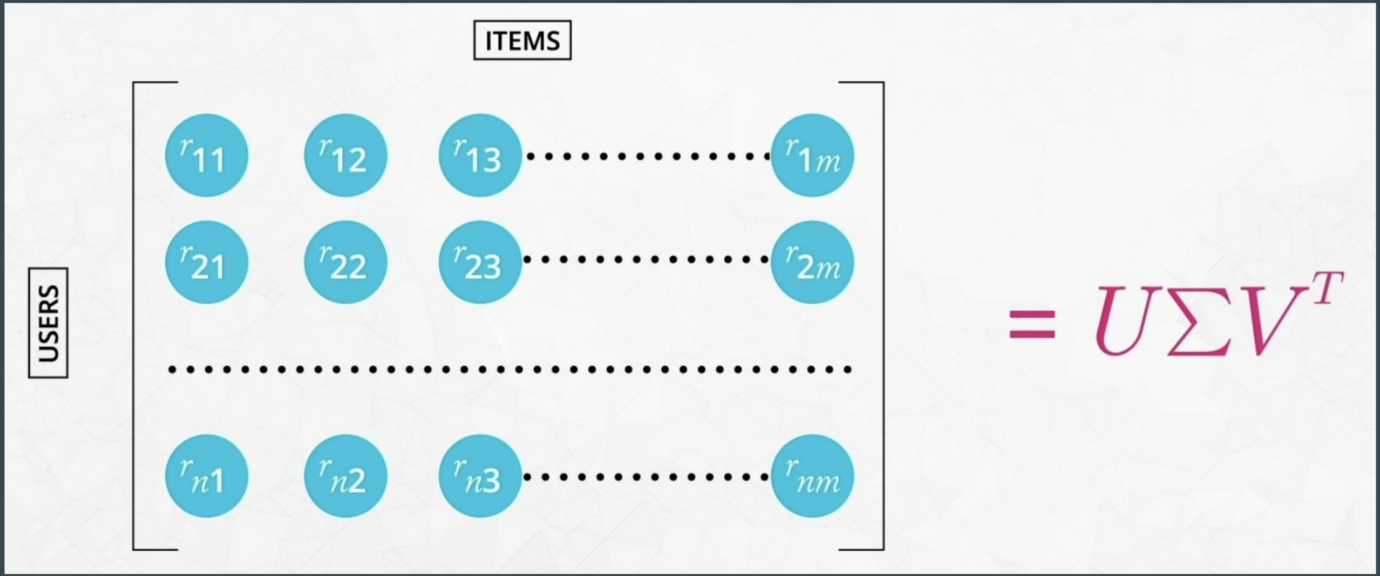
Latent Factors Example



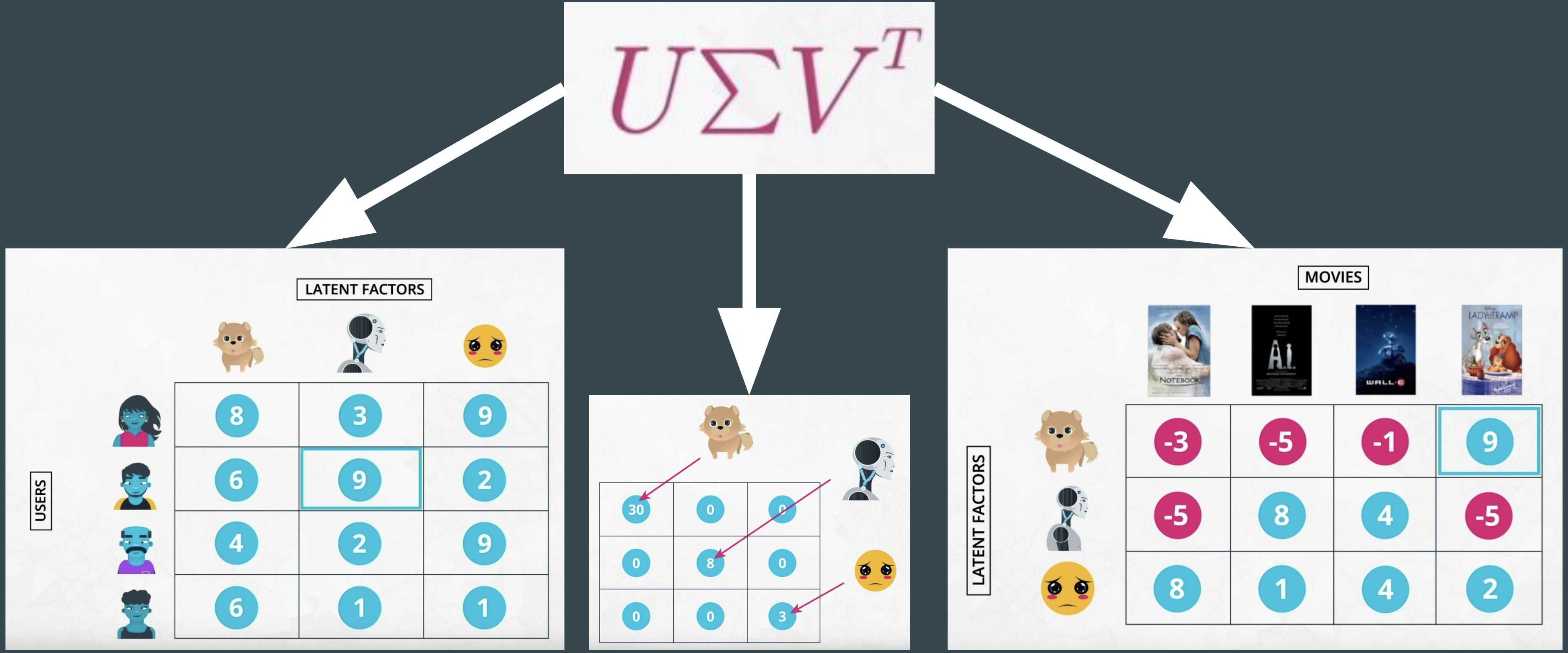
Singular Value Decomposition

Singular Value Decomposition (SVD)

- For recommendations, using SVD means breaking the user-item matrix into three other matrices:



Singular Value Decomposition (SVD)



Extras

Extras

- One of the most popular methods of matrix factorization used with recommendation systems is FunkSVD - the original paper is here.

- The derivation of this method is available in the Coursera course here, which uses gradient descent.

- Other methods of matrix factorization have two matrices and use an alternative least squares method.

Recap

- Using matrix factorization is one of the best ways to make recommendations.

- Matrix factorization involves breaking one matrix into multiple matrices.

- Each matrix then contains latent factors, which help us (latently) understand the underlying relationships that exist between users and items.

- There are two major methods for solving for these matrices: Gradient Descent or Alternating Least Squares.