Recommender systems

Alaa BAKHTI - OCTO Technology

Different types of collaborative filtering

Memory-based CF

- Find correlations (similarities) between users or items using the users rating data.
- Rely on simple similarity measures to match similar people or items together.

Model-based CF

- Recommendation as an optimisation problem: use machine learning algorithms to predict ratings.

Model-based CF

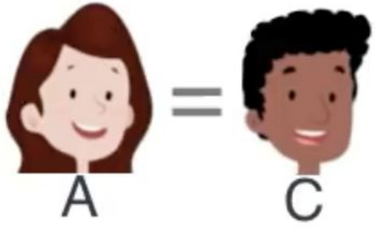
Dimensionality reduction

	M1	M2	M3	M4	M5
	3	1	1	3	1
	1	2	4	1	3
	3	1	1	3	1
	4	3	5	4	4

Credit to [*Luis Serrano - Udacity*]

Dependent rows and columns

	M1	M2	M3	M4	M5
	3	1	1	3	1
					
	3	1	1	3	1
					



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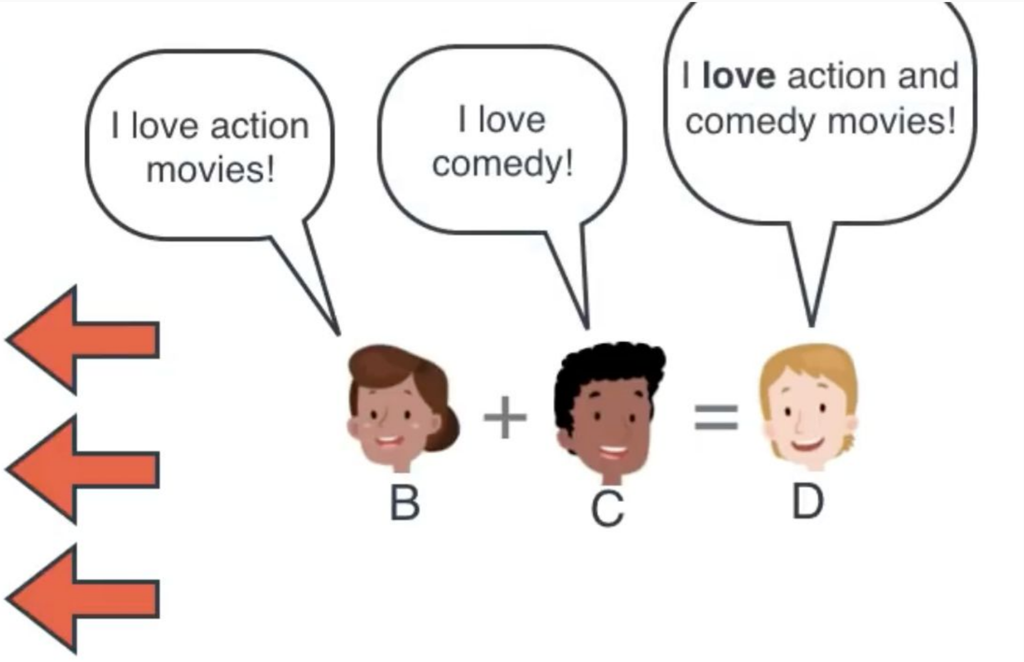


Credit to [*Luis Serrano - Udacity*]

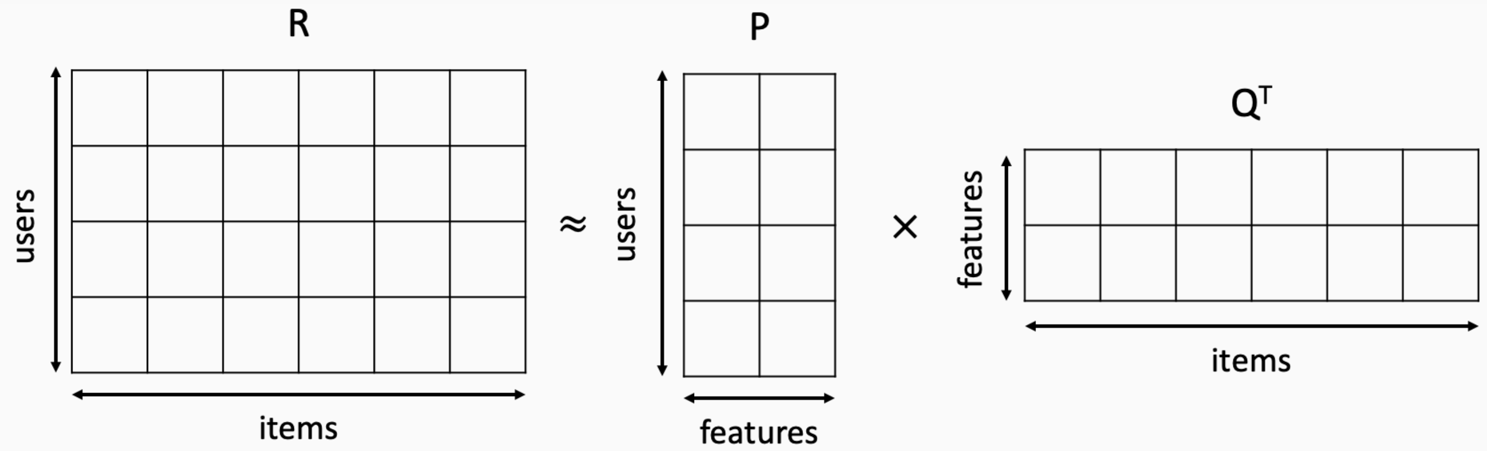
Dependent rows and columns

	M1	M2	M3	M4	M5
		1	1		1
		2	4		3
		1	1		1
		3	5		4

M5 = Average(M2, M3)

Credit to [Luis Serrano - Udacity]

Dimensionality reduction with matrix factorization



Find low dimensional representation of users and movies such that users that are similar are close together.
How to estimate the missing ratings for the matrix R?

Dot product the user and item embeddings.

How to find these 2 matrices ?

What are the methods you know for matrix factorisation?

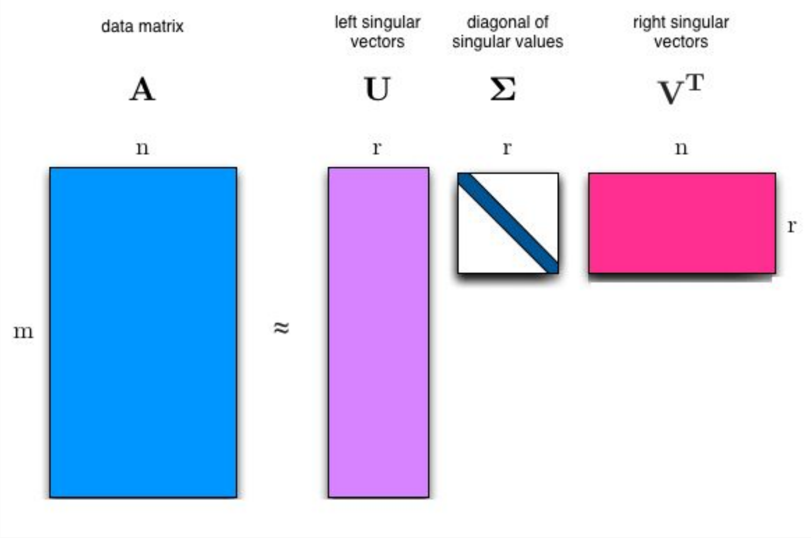
Singular Value Decomposition

- Garanties the minimum reconstruction error.
- Is it the solution?

$$\min_{U,V,\Sigma} \sum_{ij \in A} \left(A_{ij} - [U\Sigma V^T]_{ij} \right)^2$$

Problem

- Assumes that there are no missing values in the matrix R.
- Will consider missing ratings as 0.
- SVD can not deal with these missing entries.
- Imputation of missing values?

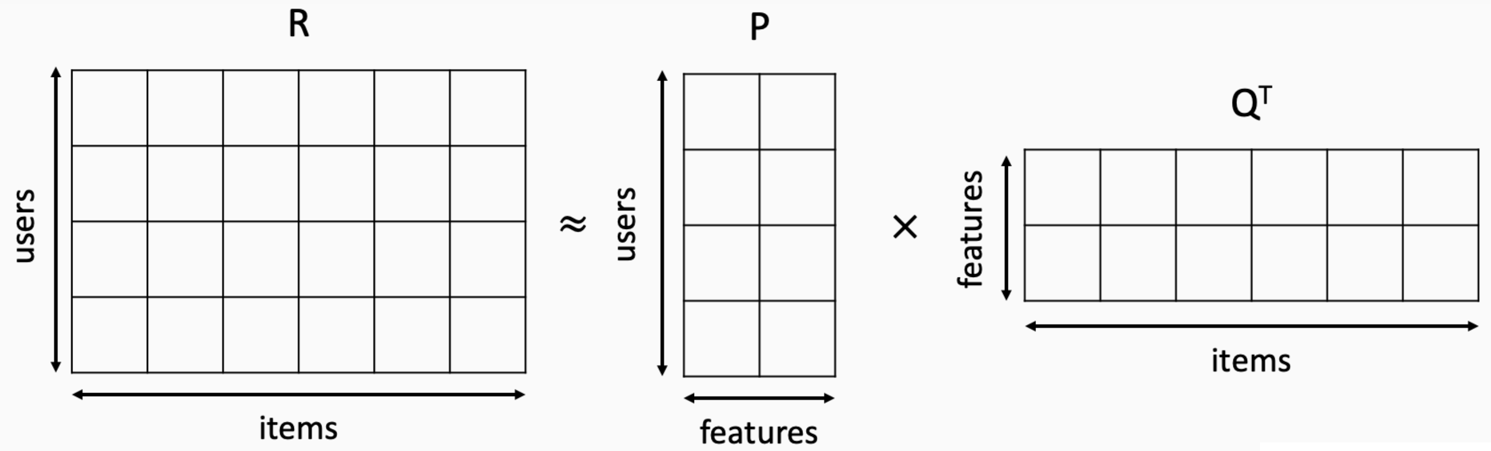


[Source : Fast Randomized SVD - Facebook Research]

Matrix completion

- Matrix completion techniques avoid the necessity of pre-filling missing entries by **reasoning only on the observed ratings**.
- They can be seen as an estimate or an **approximation of the SVD**, computed using application specific optimization criteria.
- **The completion is driven by factorisation**.

Non-negative Matrix Factorisation (NMF)



Dimensions $\approx \sqrt[4]{\text{Possible values}}$

Empirical tradeoff.

$$\min_{P,Q} \sum_{(i,x) \in R} \left(r_{xi} - p_i \cdot q_x^T \right)^2$$

$$\min_{P,Q} \sum_{(i,x) \in R} \left(r_{xi} - p_i \cdot q_x^T \right)^2 + \lambda \left[\sum_i \left\| p_i \right\|^2 + \sum_x \left\| q_x \right\|^2 \right]$$

Advantages and limitations of Collaborative-based filtering

- ➔ No need for domain knowledge
- ➔ Captures the change in user interests over time
- ➔ Diverse and serendipitous (by coincidence) recommendation

- ➔ Hard to add features
- ➔ Item cold start problem

Other types

Knowledge-Based : Ask users for preferences.

- No user interaction data is needed
- Need up to date user data

Popularity-Based : Recommend items that are trending right now.

- Simple implementation
- No personalization (all users will have the same recommendation)

Hybrid recommenders : combine the prediction of multiple recommender systems or the different approaches in the same recommender