Recommender System

- What is it?
- How to build it?
- Challenges, new directions and state-of-the-art
- R package: **`recommenderlab`**

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A **recommender system** or a **recommendation system** (sometimes replacing "**system**" with a synonym such as platform or engine) is a subclass of information filtering **system** that seeks to predict the "rating" or "preference" a user would give to an item.

Recommender system - Wikipedia
https://en.wikipedia.org/wiki/Recommender_system

- RS is everywhere: Amazon, Wayfair, Netflix, Google News, Pinterest, Spotify, Facebook, Linkedin, OkCupid ……
- A system that can automatically recommend items to users, which are likely to be of interest to the users, by utilizing historical information.

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Non-personalized RS

Best Selling books

Top Cyber Monday Deals

Most Popular in Electronics

Best Liked

Top 5 Essential Winter Boots

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Two Types of Information

1. Characteristic information about the items
2. User-item interactions

Non-personalized RS

Personalized RS

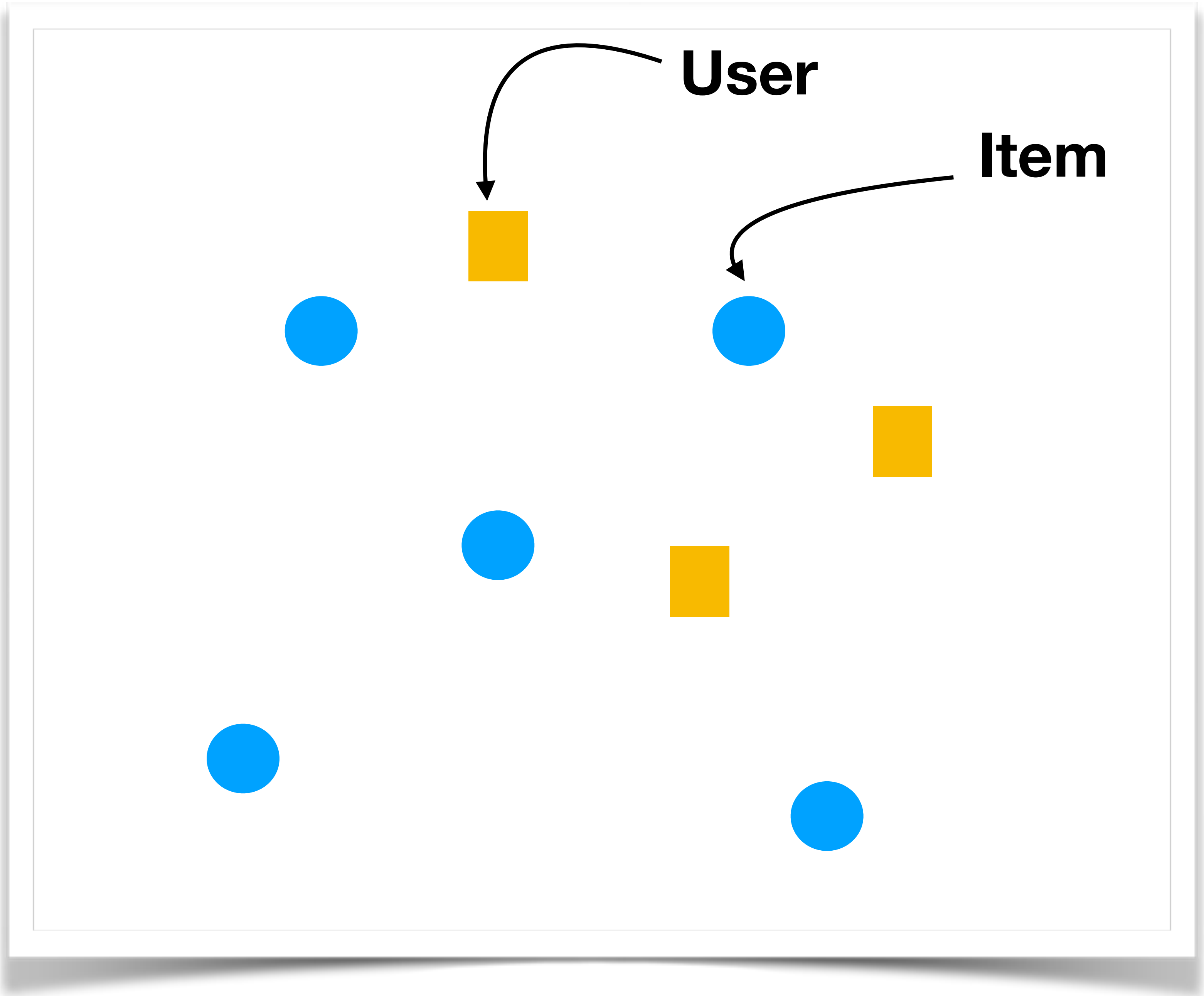
- **Content-based** method
- **Collaborative Filtering** method

  Item-baed CF

  User-baed CF

- **Latent Factor** method
- Hybrid
- **Deep** Recommender System

Content-Based Method



- Item profile: represent each item by a d-dim feature vector. For example, how to characterize a movie/article/product by a feature vector?
- User profile: represent each user by a d-dim feature vector by aggregating the feature vectors of items this user like.

So we embed the m users and n items in a Euclidean space $\mathbb{R}^d$. Then we can recommend items that are close to user i to user i.

Pros

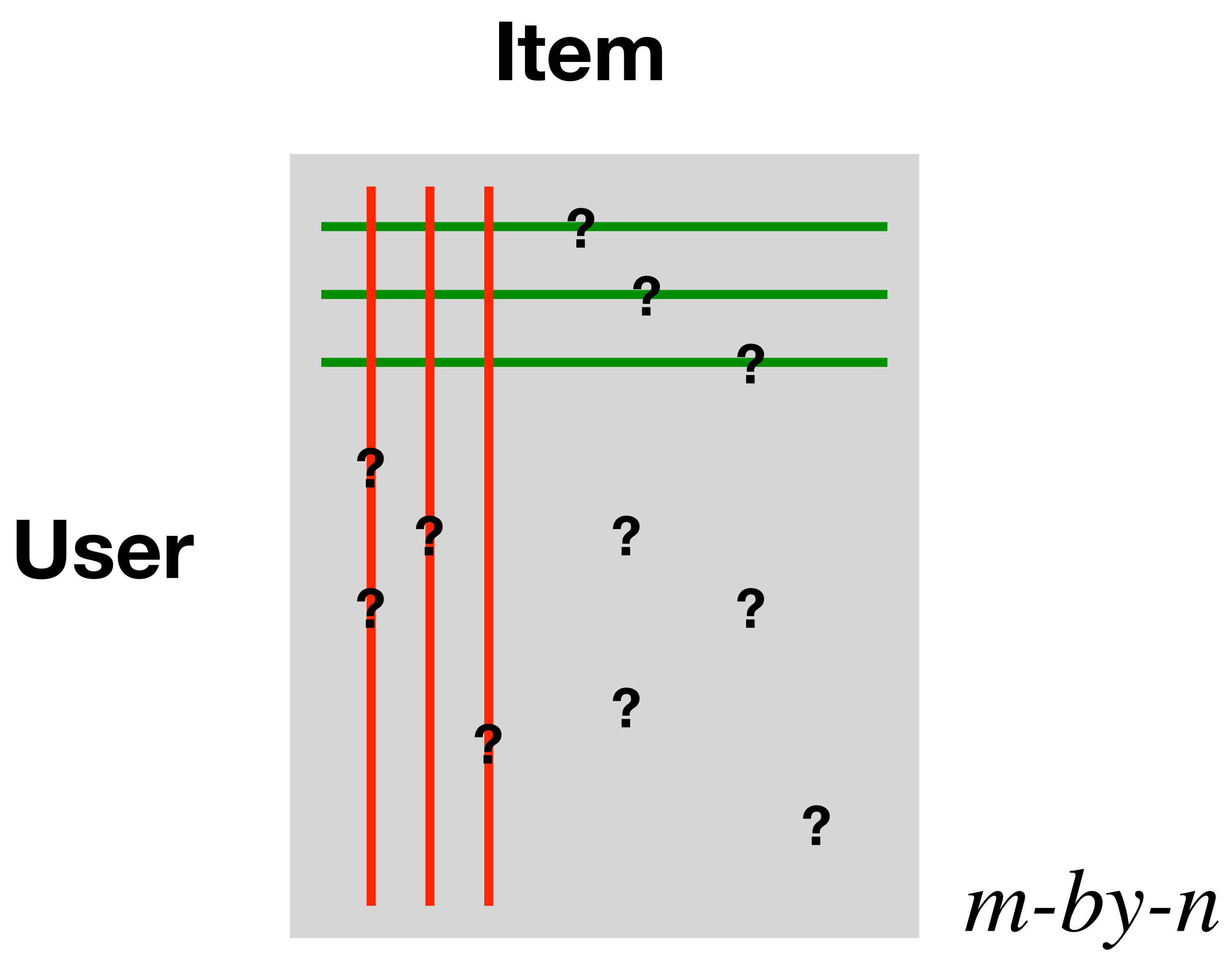
- Do not use user data, so can start recommending on day 1;
- Can recommend new and unpopular items;
- Can recommend to users with unique taste
- Easier to interpret/understand (why we recommend this item to this user)

Cons

- Cannot recommend outside the user's profile
- Recommend substitutes not complements
- **Finding appropriate features is difficult**

Collaborative Filtering (CF) Method

User-Item Rating Matrix: R



How to construct the R matrix?

- Explicit
- Implicit

Challenge: how to differentiate negative vs missing

Collaborative Filtering (CF) Method

User-Item Rating Matrix: R

Item

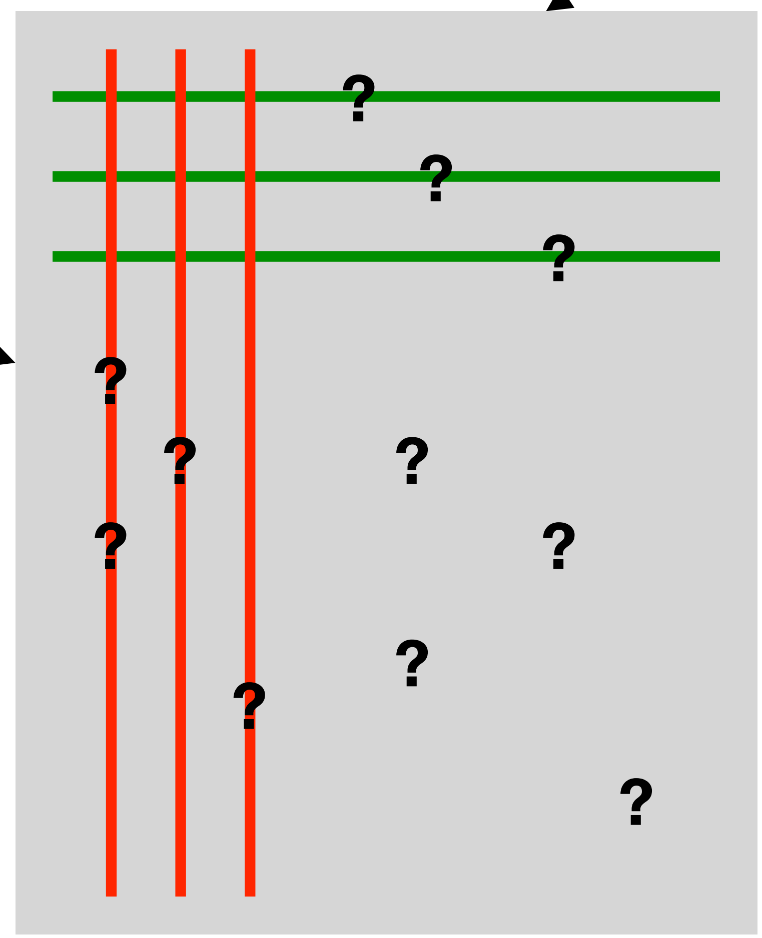
Item-based CF

Users tend to like **similar** items

User-based CF

Items tend to be liked by **similar** users

User



m-by-n

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

Advantage of Centering:

1. Missing = Average instead of zero
2. Handle tough/easy raters

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	$2/3$			$5/3$	$-7/3$		
B	$1/3$	$1/3$	$-2/3$				
C				$-5/3$	$1/3$	$4/3$	
D		0					0

Similarity Measure

- Jaccard similarity: useful for binary ratings

$$\frac{|A \cap B|}{|A \cup B|}, \qquad \text{where } A, B \text{ are two sets.}$$

- Cosine similarity: useful for numerical ratings

$$\frac{u^t v}{\|u\| \cdot \|v\|}, \qquad \text{where } u, v \text{ are two vectors}$$

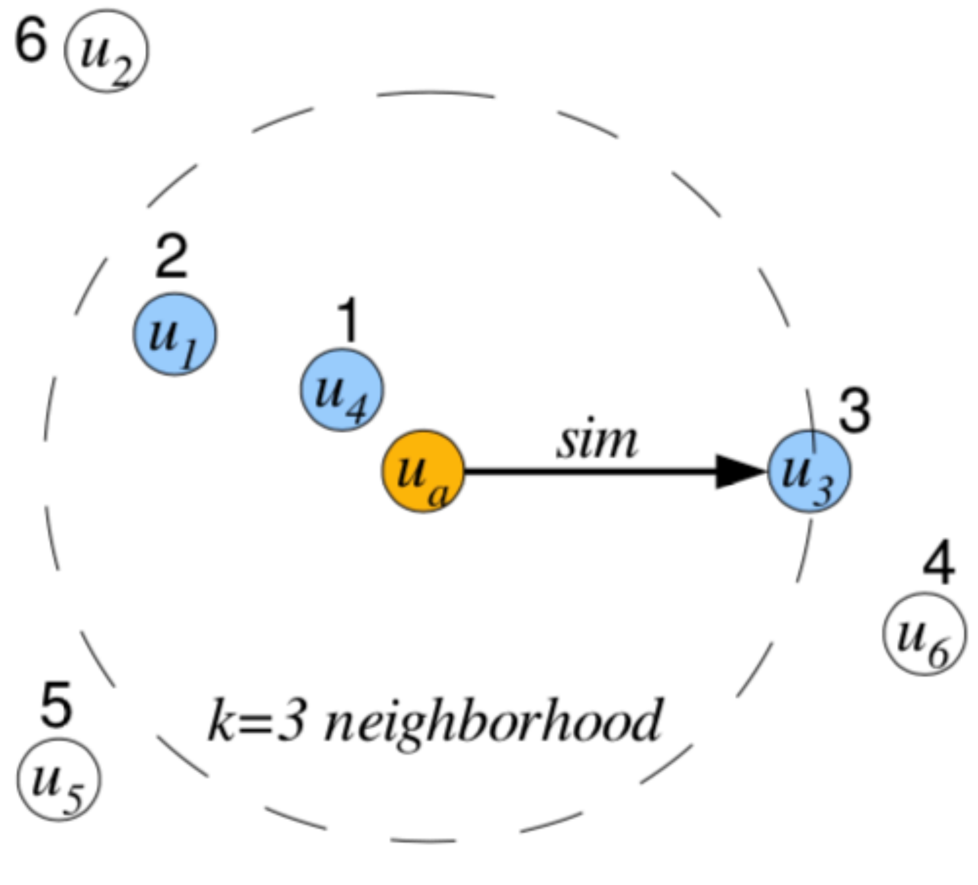
- Centered cosine similarity (Pearson correlation):

$$\frac{(u-\bar{u})^t (v-\bar{v})}{\|u-\bar{u}\| \cdot \|v-\bar{v}\|}, \qquad \text{where } u, v \text{ are two vectors}$$

User-based CF

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8
u_1	?	4.0	4.0	2.0	1.0	2.0	?	?
u_2	3.0	?	?	?	5.0	1.0	?	?
u_3	3.0	?	?	3.0	2.0	2.0	?	3.0
u_4	4.0	?	?	2.0	1.0	1.0	2.0	4.0
u_5	1.0	1.0	?	?	?	?	?	1.0
u_6	?	1.0	?	?	1.0	1.0	?	1.0
u_a	?	?	4.0	3.0	?	1.0	?	5.0
$\hat{r}_a$	3.5	4.0			1.3		2.0	

(a)



(b)

Figure 1: User-based collaborative filtering example with (a) rating matrix and estimated ratings for the active user, and (b) user neighborhood formation.

Source: recommenderlab: A Framework …. By Michael Hahsler (File on Piazza)

= (3.0 + 4.0)/2

=(1.0 + 2.0 + 1.0)/3

Note: We could consider to vary neighborhood with respect items, e.g., choose neighbors who also rated item *i*.

$$\hat{r}_{ai} = \frac{1}{\sum_{j \in \mathcal{S}(i) \cap \{l\,;\,r_{al} \neq ?\}} s_{ij}} \sum_{j \in \mathcal{S}(i) \cap \{l\,;\,r_{al} \neq ?\}} s_{ij} r_{aj}$$

Formula used by Item-based CF (sec 2.2, eq 5), where we compute a weighted average of items that are within kNN and also have been rated by this user.

Item-based CF

$\mathbf{S}$	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	$\hat{r}_a$
i_1	-	0.1	0	**0.3**	**0.2**	**0.4**	0	0.1	-
i_2	0.1	-	**0.8**	**0.9**	0	**0.2**	0.1	0	0.0
i_3	0	**0.8**	-	0	**0.4**	0.1	0.3	**0.5**	4.6
i_4	**0.3**	**0.9**	0	-	0	0.1	0	**0.2**	3.2
i_5	**0.2**	0	**0.4**	0	-	0.1	**0.2**	0.1	-
i_6	**0.4**	**0.2**	0.1	**0.3**	0.1	-	0	0.1	2.0
i_7	0	**0.1**	**0.3**	0	**0.2**	0	-	0	4.0
i_8	**0.1**	0	**0.5**	**0.2**	0.1	0.1	0	-	-
u_a	2	?	?	?	4	?	?	5	

$k=3$

Figure 2: Item-based collaborative filtering

Source: recommenderlab: A Framework …. By Michael Hahsler (File on Piazza)

For the similarity matrix shown on the upper-right,
— the largest three entries in each row are **highlighted in bold** since we only consider 3NN
— columns 1, 5, 8 are highlighted in blue since the test user (whose ratings we aim to predict) has rated only items 1, 5, 8.

When we compute the weighted average, we only need to consider entries **highlighted both in blue and bold**. This is why the prediction for item 2 is missing (i.e., 0).

0.0 = 3NN are missing
4.6 = (0.4/0.9)(4) + (0.5/0.9)(5)
3.2 = (0.3/0.5)(2) + (0.2/0.5)(5)

Content-Based

Pros

- Do not use user data, so can start recommending on day 1;
- Can recommend new and unpopular items;
- Can recommend to users with unique taste
- Easier to interpret/understand (why we recommend this item to this user)

Cons

- Cannot recommend outside the user's profile
- Recommend substitutes not complements
- **Finding appropriate features is difficult**

Computation Challenge for CF: how to efficiently find kNN in a large data set?

Collaborative Filtering (CF)

Cons

- Need enough user data to start recommendation; cannot operate on day 1
- Cannot recommend new, unrated items
- Tend to recommend popular items, against the purpose of personalized RS
- **Cold start** problem for new users/items

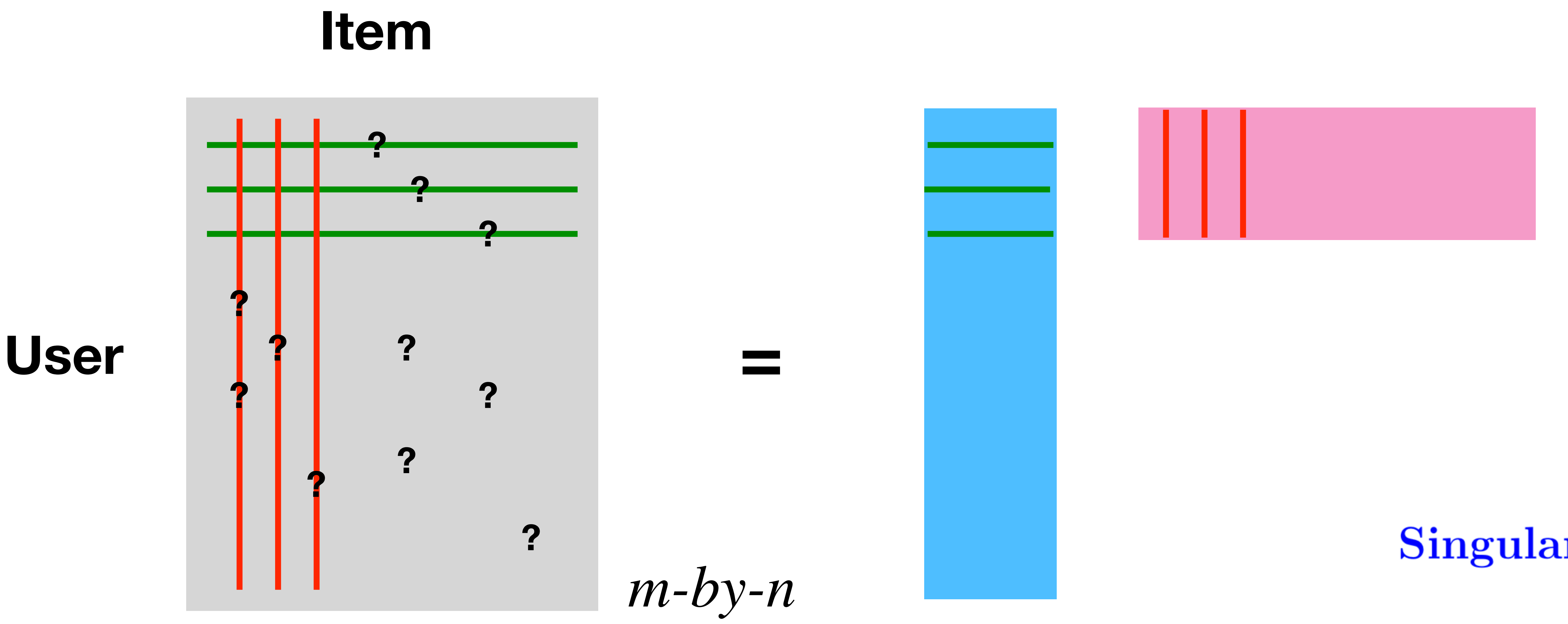
Pros

- No need to define features
- Can recommend outside the user's profile

Item-based performs better in practice: easier to find similar items, but difficult to find similar people

Latent Factor Model

User-Item Rating Matrix: R



Singular Value Decomposition

Approximate $R_{m\times n} \approx U_{m\times d} V^t_{d\times n}$ by minimizing

$$\sum_{R_{ij}\neq \text{NA}} (R_{ij} - u_i^t v_j)^2 + \lambda_1 \text{Pen}(U) + \lambda_2 \text{Pen}(V),$$

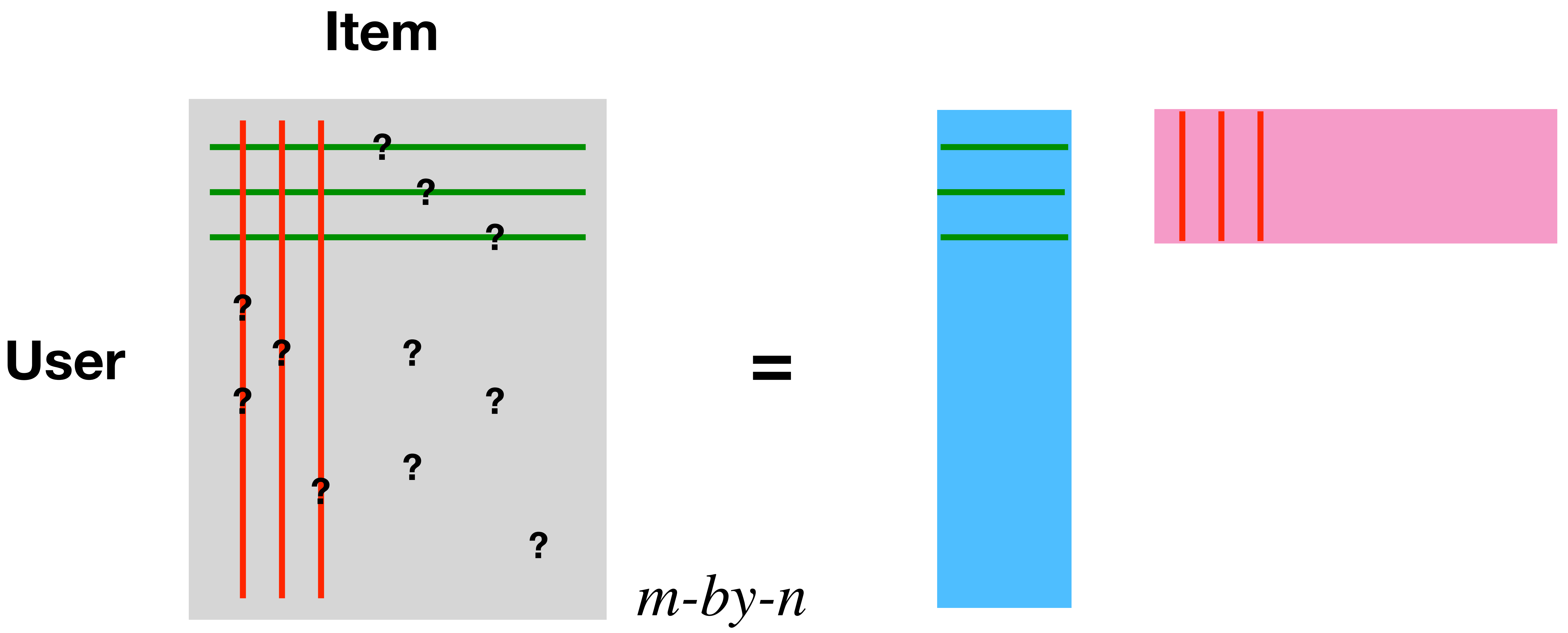
where u_i is the i-th row of matrix U and v_j is the j-th row of matrix V.

Then we can predict any missing entries in R by the corresponding inner product of u_i and v_j.

The classical **SVD** algorithm isn't applicable here due to missing entries, instead algorithms based on **Stochastic Gradient Descent** are employed in practice.

The Global Base Line Model: Correct Bias

User-Item Rating Matrix: R



Over-all Average

Remaining Interaction Term : Collaborative Filtering or Latent Factor model on the Remaining Interaction Term

$$R_{ij} = \mu + a_i + b_j + \tilde{R}_{ij}$$

User effect **Movie effect**

Some Practical Issues

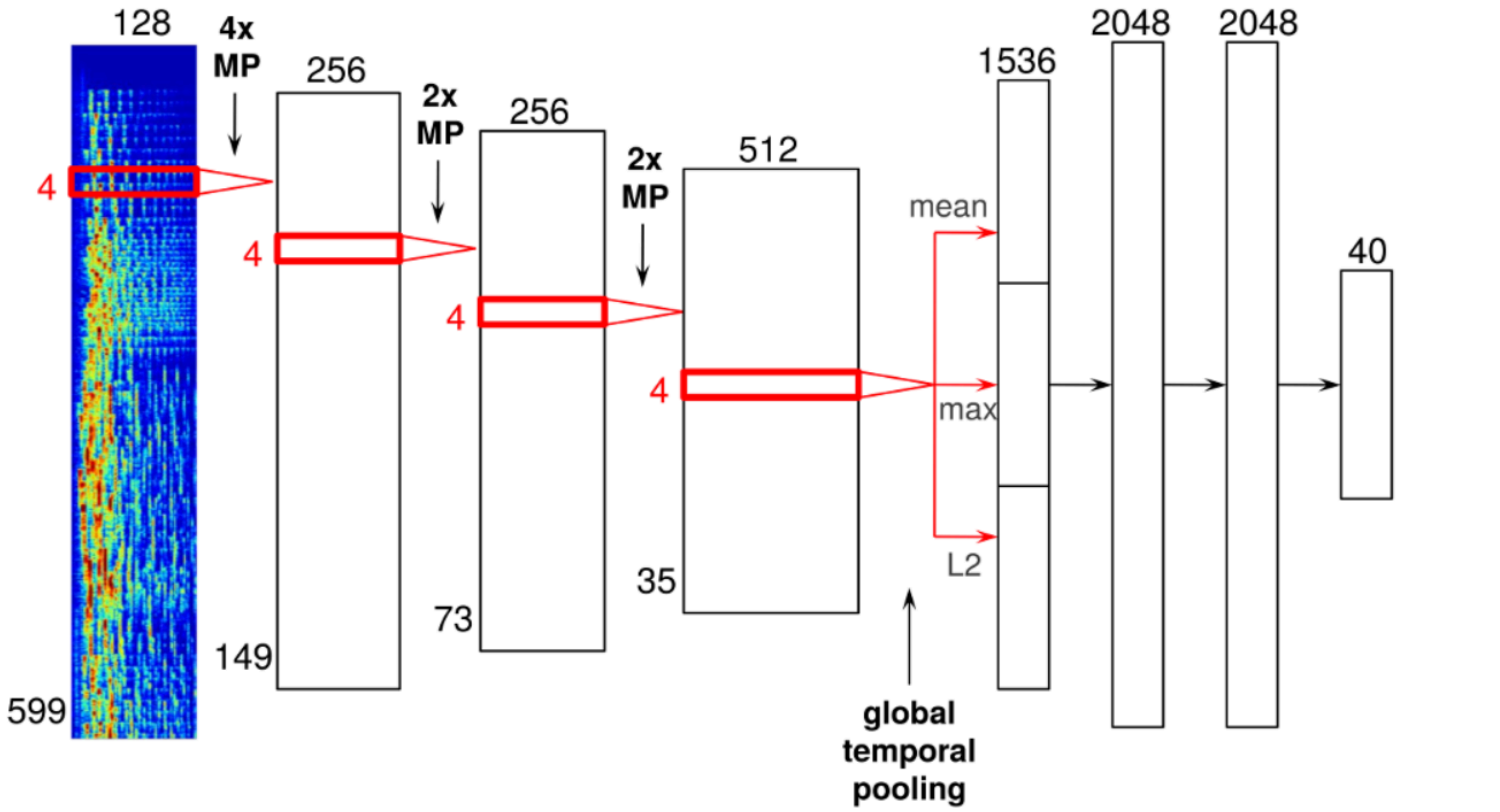
- **Cluster** users and items to reduce computation
- **Hybrid**: combine multiple recommender systems
- Different **contexts** (location, time, device) and **interface** (computer, mobile) need different recommendation systems.
- How to evaluate a recommender system?
  - **RMSE** vs **Top-k**
  - **Serendipity**/**Diversity** versus **Accuracy**
- How to incorporate user **feedback**

Challenges

- **Scalability**: large amount of users and items
- **Sparsity** of the data
- **Utility matrix**: how to construct it based the problem at hand
- **Cold-start**: how to recommend a new item or make recommendation to a new user

Deep Recommender Systems

- Use Deep Learning to construct latent factors for items/users
- Train a Deep Learning model to learn the preference between users and items



http://benanne.github.io/2014/08/05/spotify-cnns.html

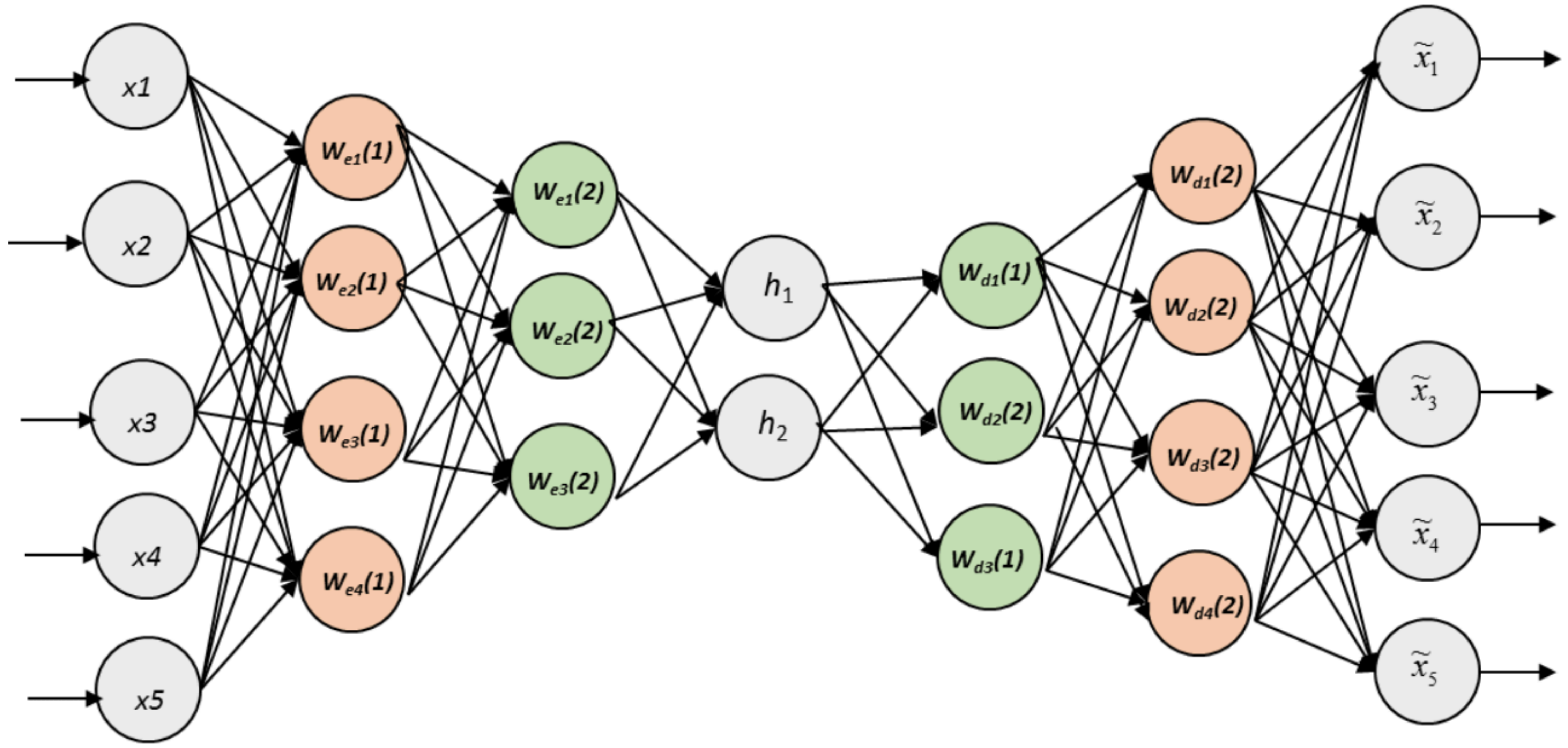


Fig. 2. Deep Autoencoder architecture.

https://towardsdatascience.com/deep-autoencoders-for-collaborative-filtering-6cf8d25bbf1d

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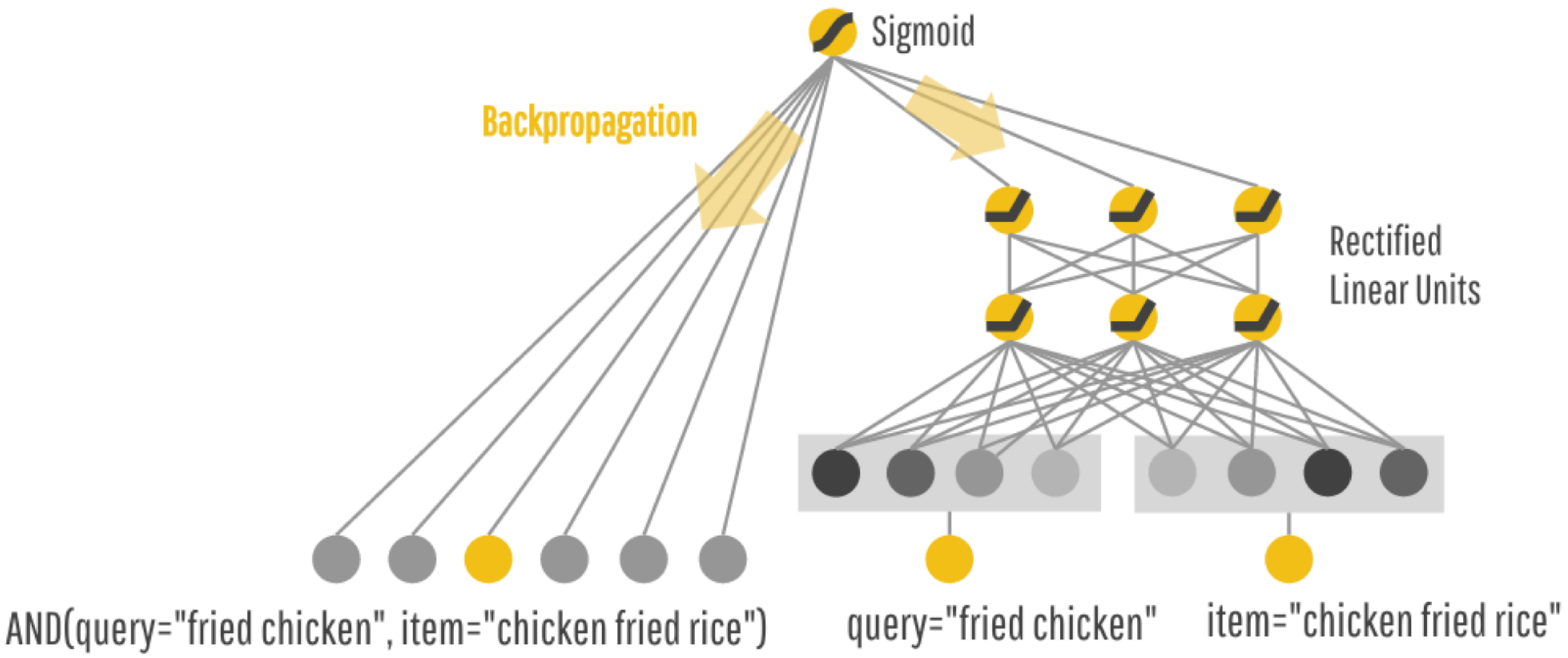

Google's wide-and-deep model

- Wide (sparse) linear model for **memorization**
- Deep neural network model for **generalization**

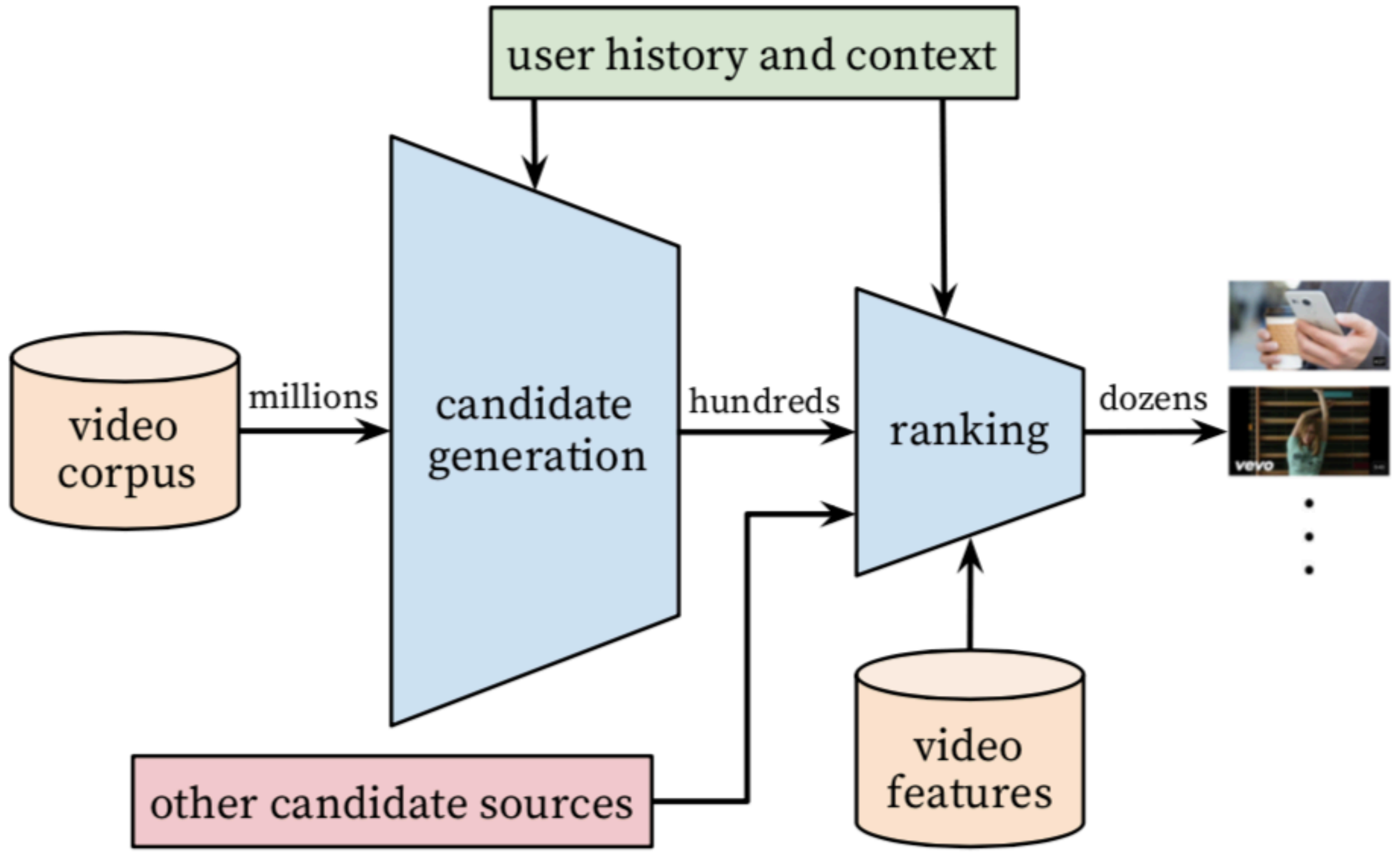

Figure 2: Recommendation system architecture demonstrating the "funnel" where candidate videos are retrieved and ranked before presenting only a few to the user.

Covington et al. (2016)