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

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Two Types of Information

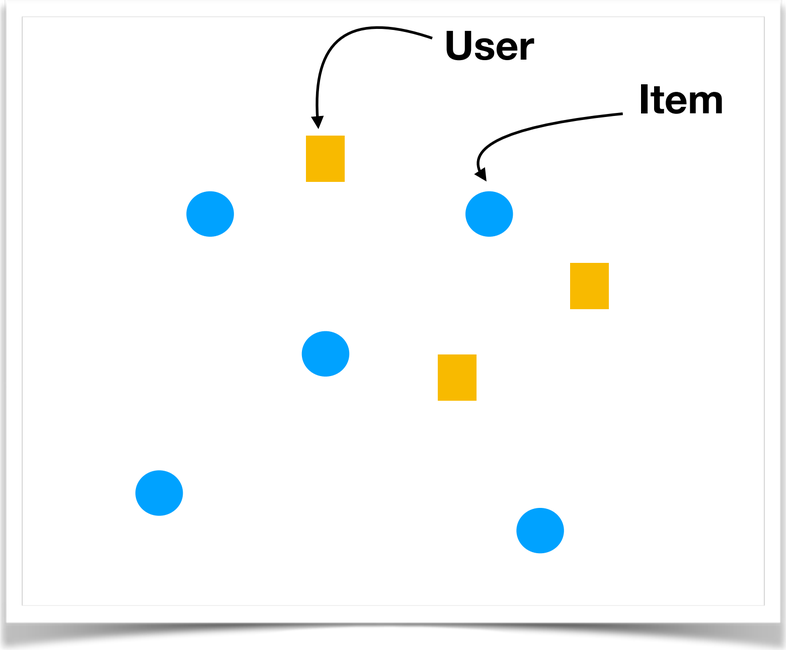
1. Characteristic information about the items
2. User-item interactions

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

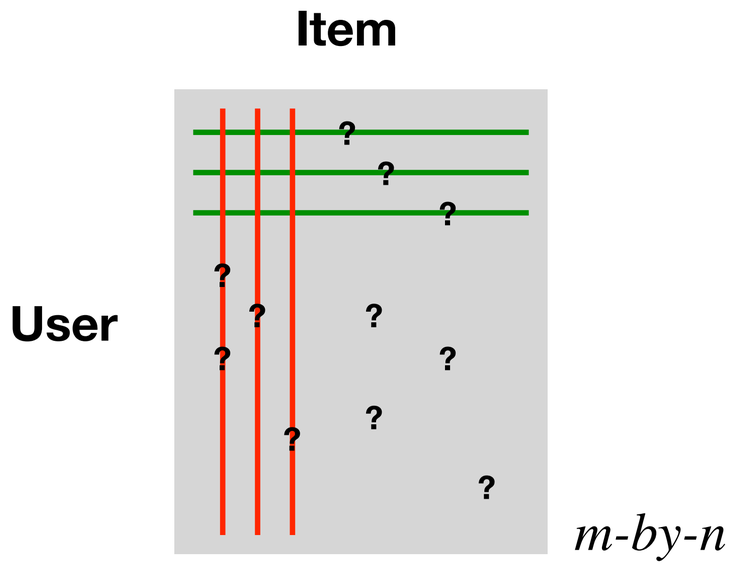
- Do not use user data, so can start recommending on day 1;
- Can recommend new and unpopular items;
- Can recommend to users with unique taste
- Easier to interpret/understand (why we recommend this item to this user)

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



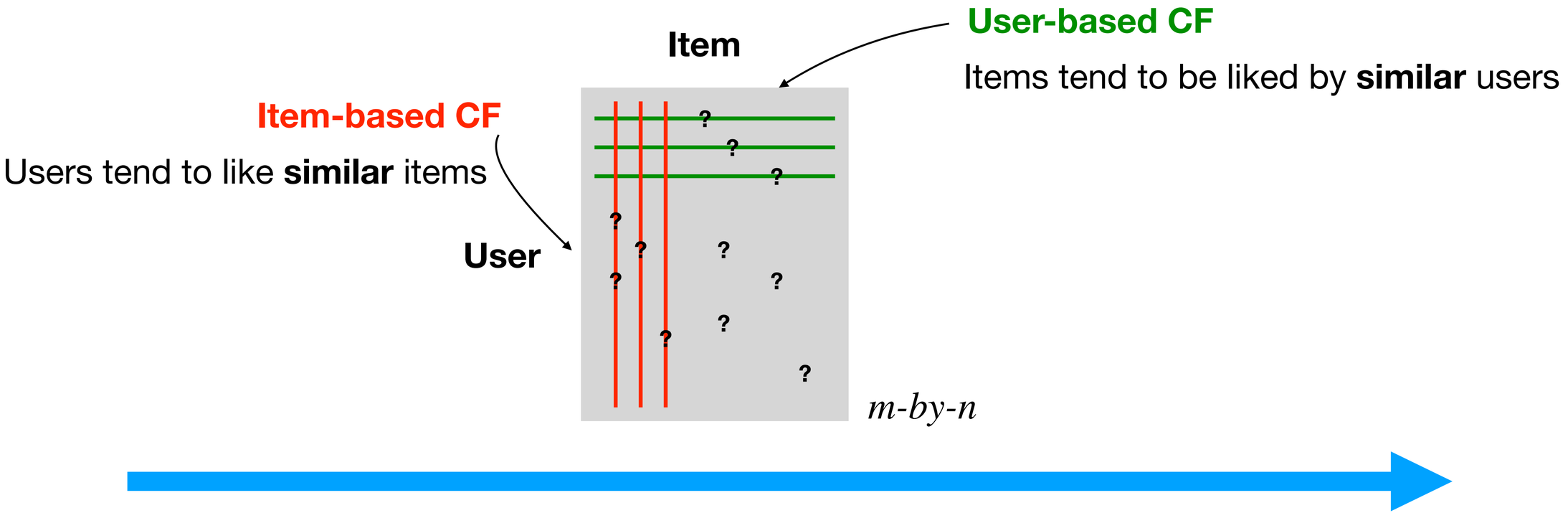
How to construct the R matrix?

- Explicit
- Implicit

Challenge: how to differentiate negative vs missing

Collaborative Filtering (CF) Method

User-Item Rating Matrix: R



Popularity Based Recommendation: **Five top rated movies**

Item Based Recommendation: **Show me more of the same I've liked**

User Based Recommendation: **Tell me what's popular among my peers**

Collaborative Filtering (CF) Method

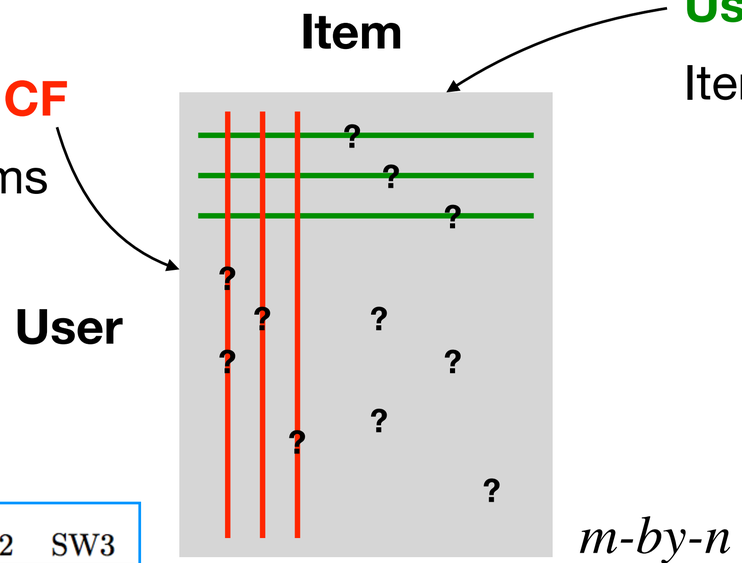
User-Item Rating Matrix: R

User-based CF

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

Item-based CF

Users tend to like **similar** items



	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

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

- Cosine similarity: useful for numerical ratings

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

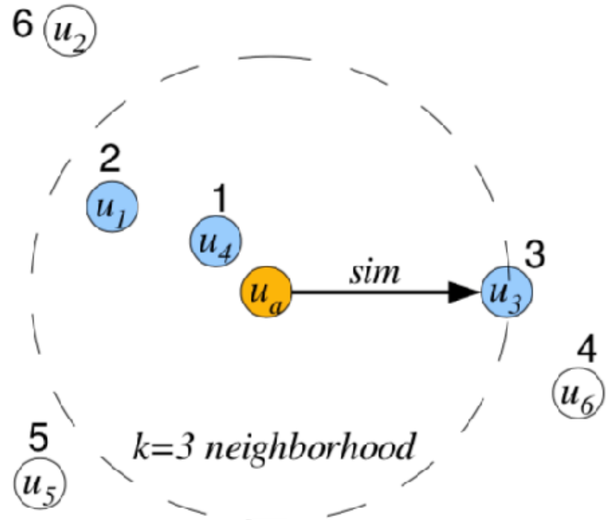
- Centered cosine similarity (Pearson correlation):

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

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

= (3.0 + 4.0)/2

=(1.0 + 2.0 + 1.0)/3

Note: We could use different neighborhood for different items, e.g., when computing the rate for item i, choose kNN among users who have rated item i, instead of using the same kNN neighborhood for all items.

Item-based CF

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

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.

S	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	$\hat{r}_a$	$k=3$
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		

Figure 2: Item-based collaborative filtering

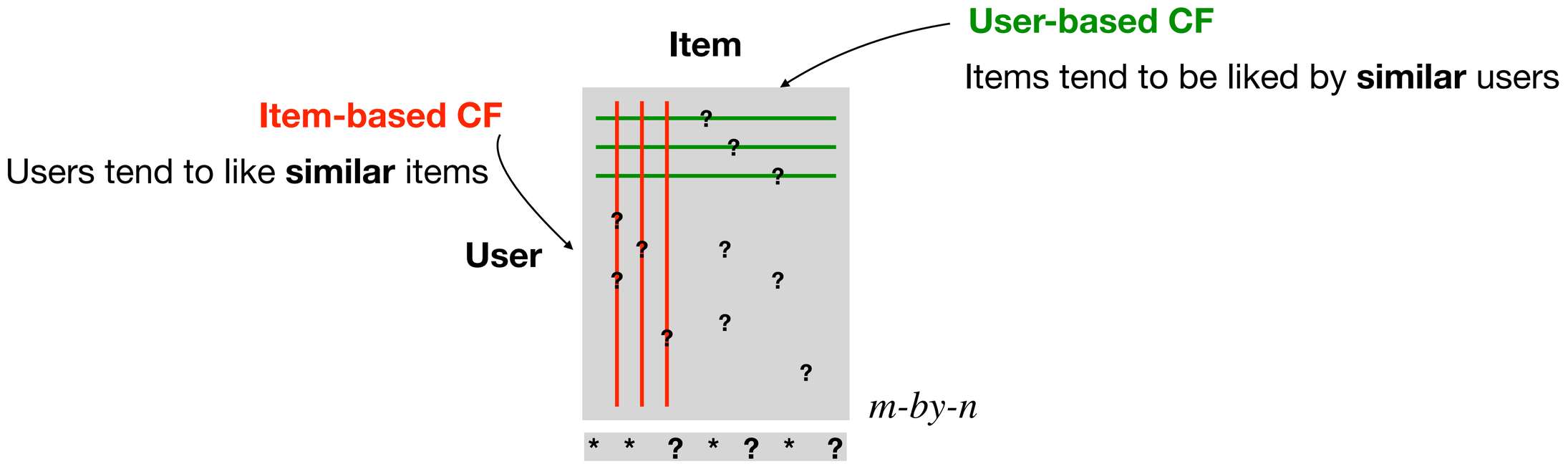
Source: recommenderlab: A Framework …. By Michael Hahsler

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)

IBCF vs UBCF

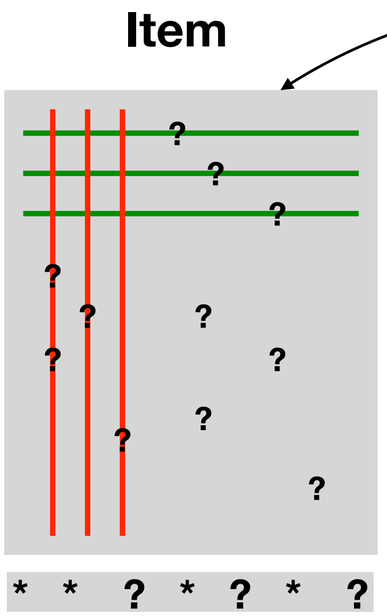


Computation Cost

- when filling all ? entries
- when predicting one new user

Which one would Amazon choose?

IBCF vs UBCF



User-based CF

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

Item-based CF

Users tend to like **similar** items

m-by-n

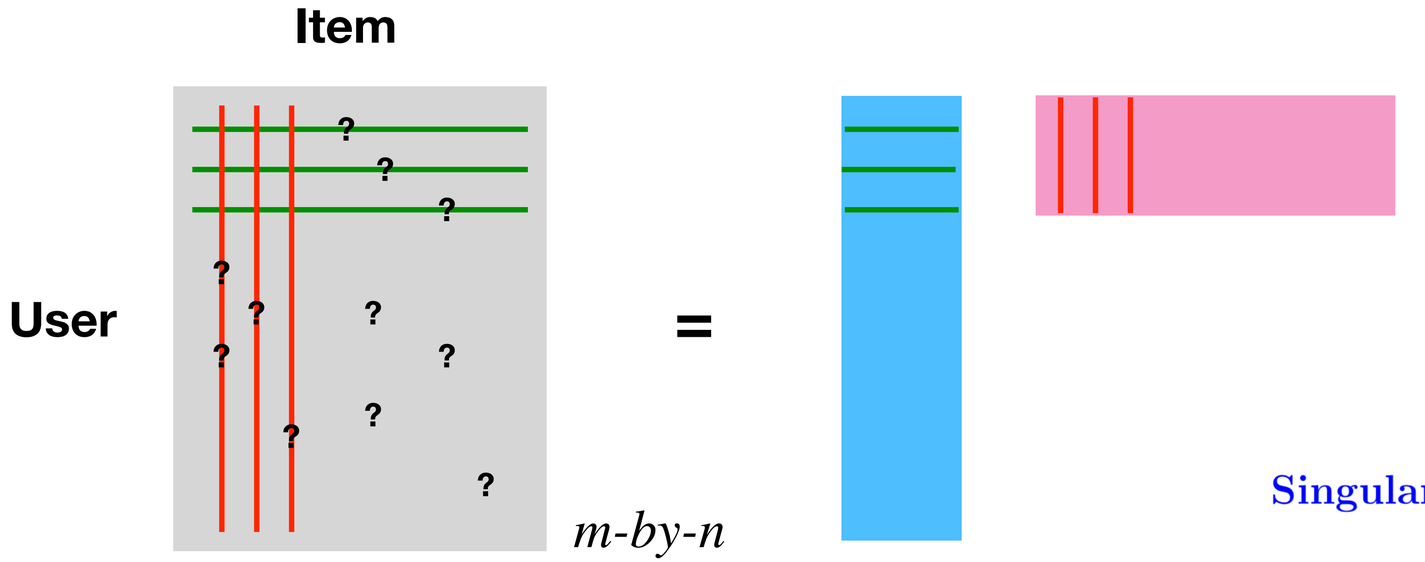
Computation Cost

- when filling all ? entries
- when predicting one new user

- **UBCF**: no training; computation is needed at the prediction stage
- **IBCF**: main computation occurs in the training (compute the item-to-item M-by-M similarity matrix as well as the related sorting); memory challenge at the prediction stage

Latent Factor Model

User-Item Rating Matrix: R



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

Singular Value Decomposition

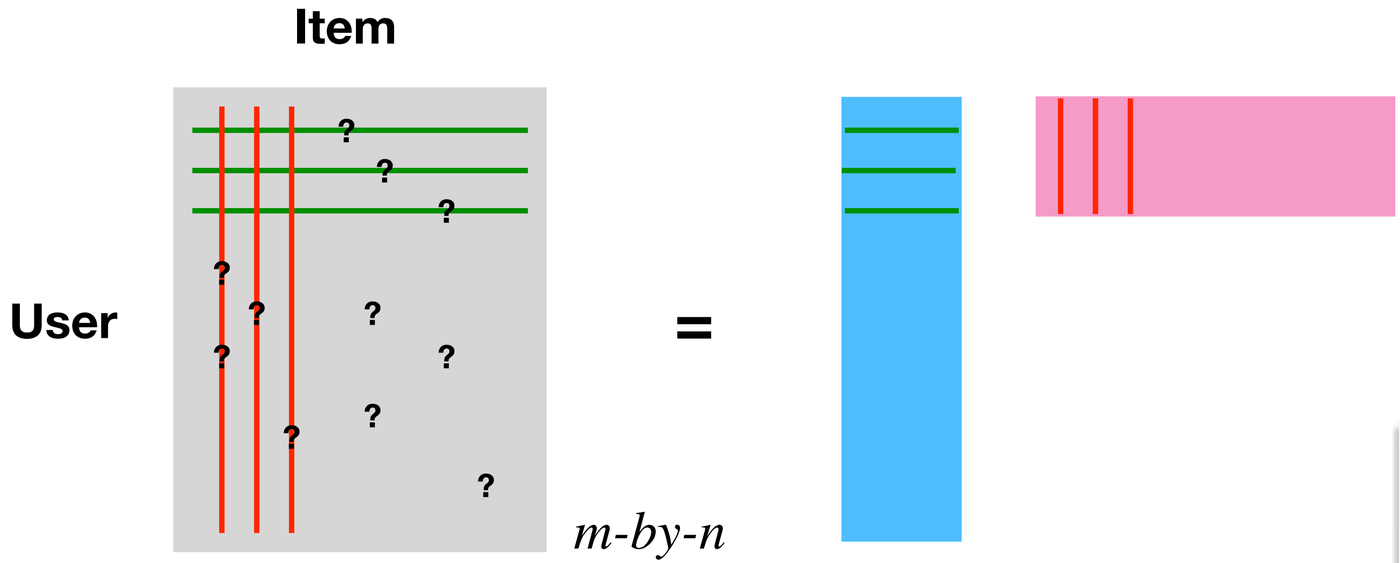
Approximate $R_{m\times n} \approx U_{m\times d} V^t_{d\times n}$ by minimizing

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

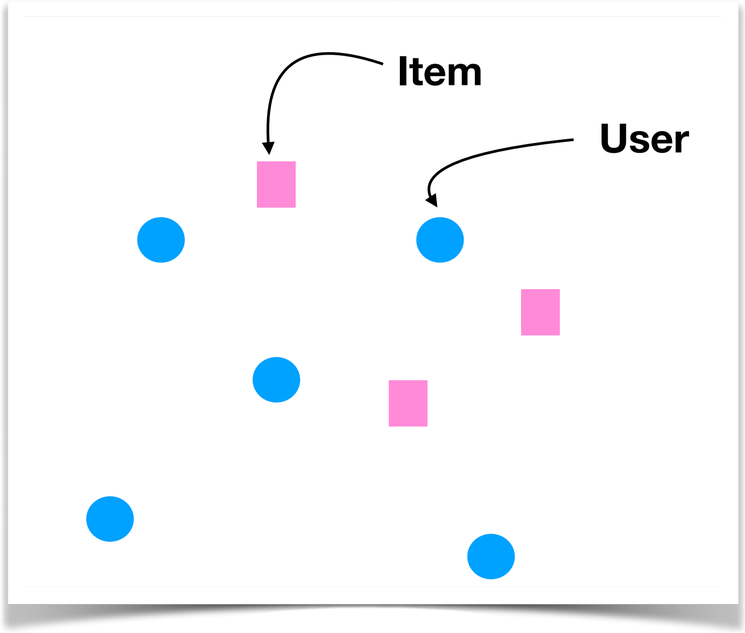
where u_i is the i-th row of matrix U and v_j is the j-th row of matrix V. Then we can predict any missing entries in R by the corresponding inner product of u_i and v_j.

Latent Factor Model

User-Item Rating Matrix: R

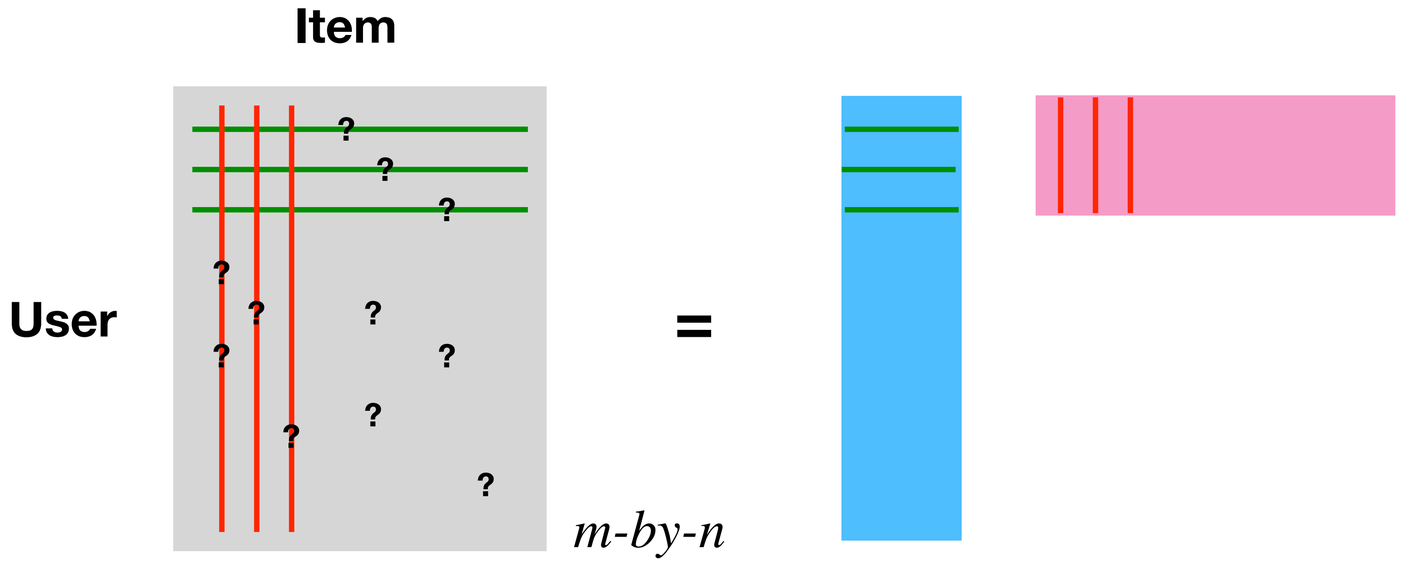


We **embed** the n users and m items in a Euclidean space. Then for each user, we can recommend items that are closer to that user.



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

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

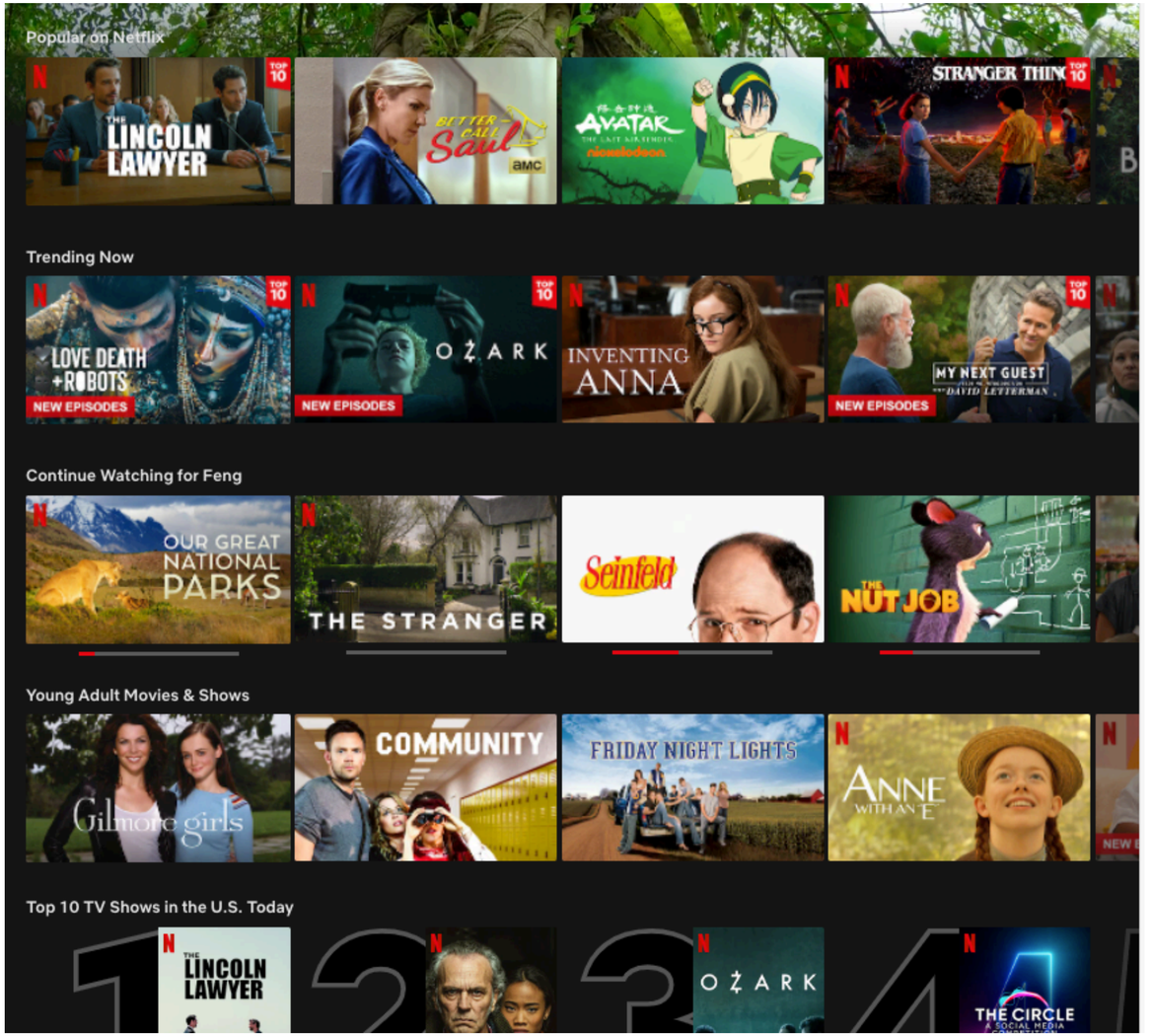
User effect

Movie effect

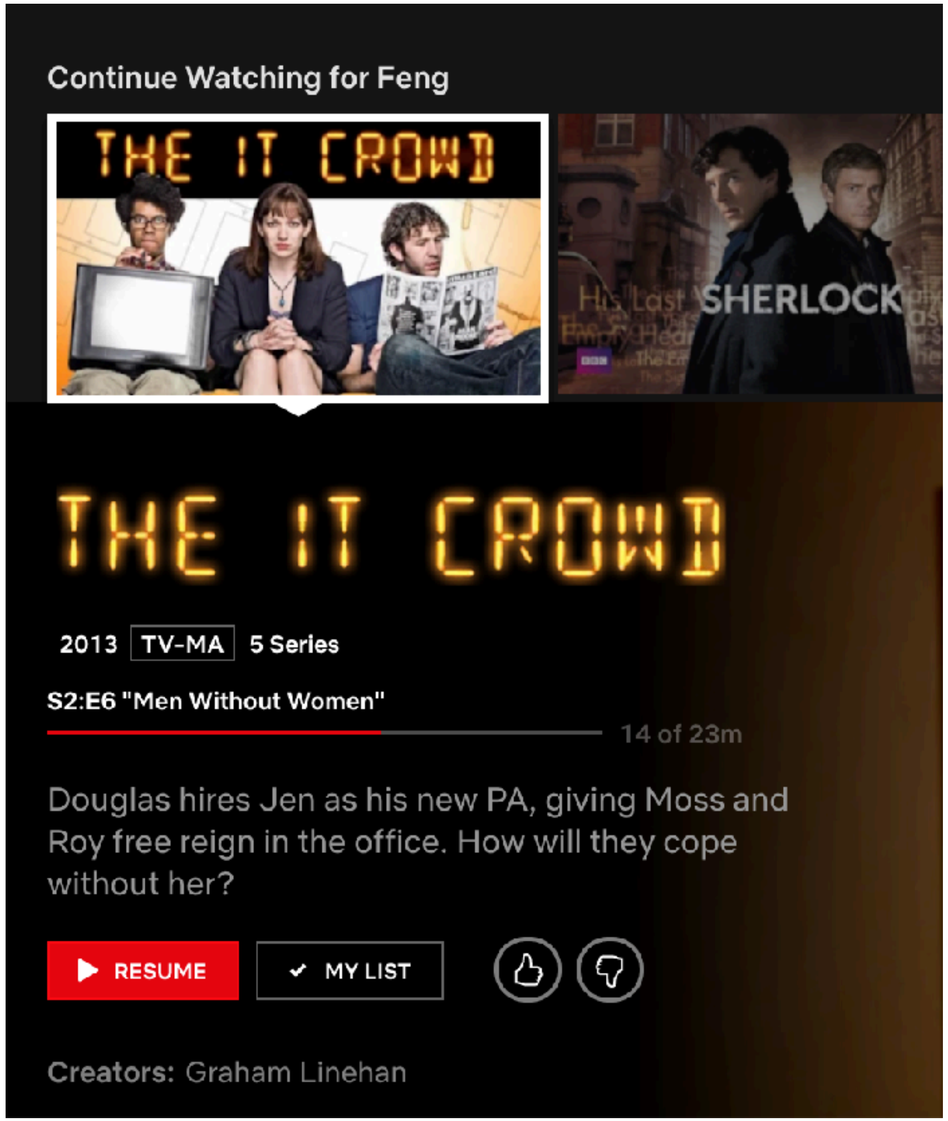
Practical Challenges & Issues

- **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**
- **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

Practical Issues: Hybrid of Recommender Systems



Practical Issues: Beyond the Five Star Ratings



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JULY 6, 2018 7:26AM PT

Netflix Is Shutting Down User Reviews This Summer

"According to Netflix, thumbs-based ratings deliver more accurate recommendations and they're easier for people to understand than the five-star scale. The company said that in testing, it saw a 200% increase in ratings by users with the thumbs-up/thumbs-down system."

Netflix will kill its 5-star rating system in favor of 'thumbs-up, thumbs-down' — here's why

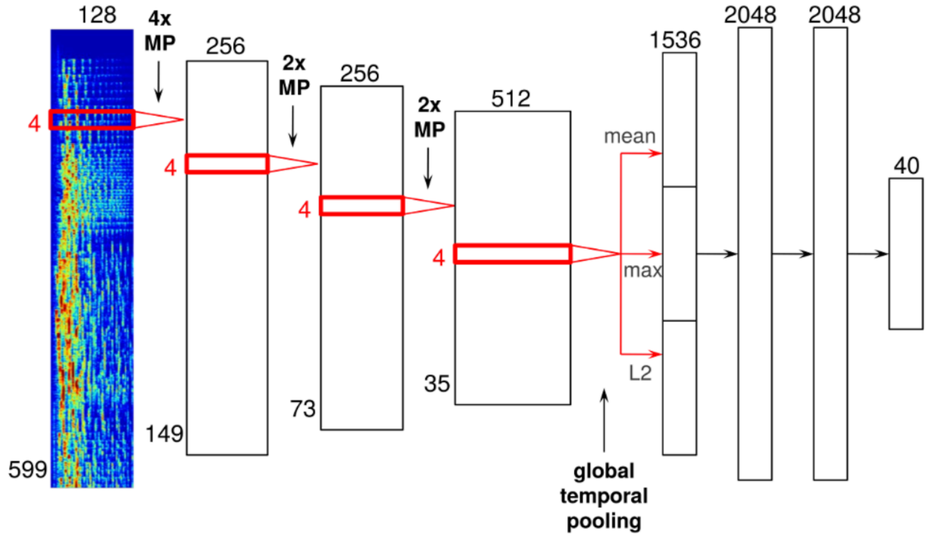
Nathan McAlone Mar. 16, 2017, 6:16 PM

"Netflix CPO Neil Hunt told Business Insider that Netflix wanted to do away with the stars, since it considered them a **poor method** of understanding what shows and movies people liked.

The problem, Hunt said at the time, is that people subconsciously try to be critics. When they rate a movie or show from one to five stars, they fall into trying to objectively assess the "quality," instead of basing the stars on how much "enjoyment" they got out of it.

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

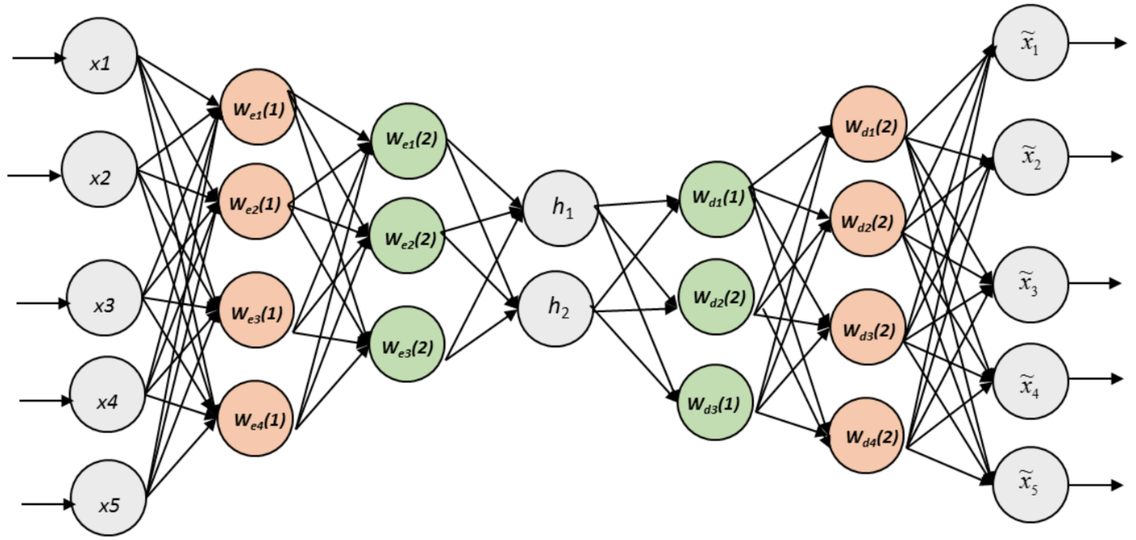


Fig. 2. Deep Autoencoder architecture.

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

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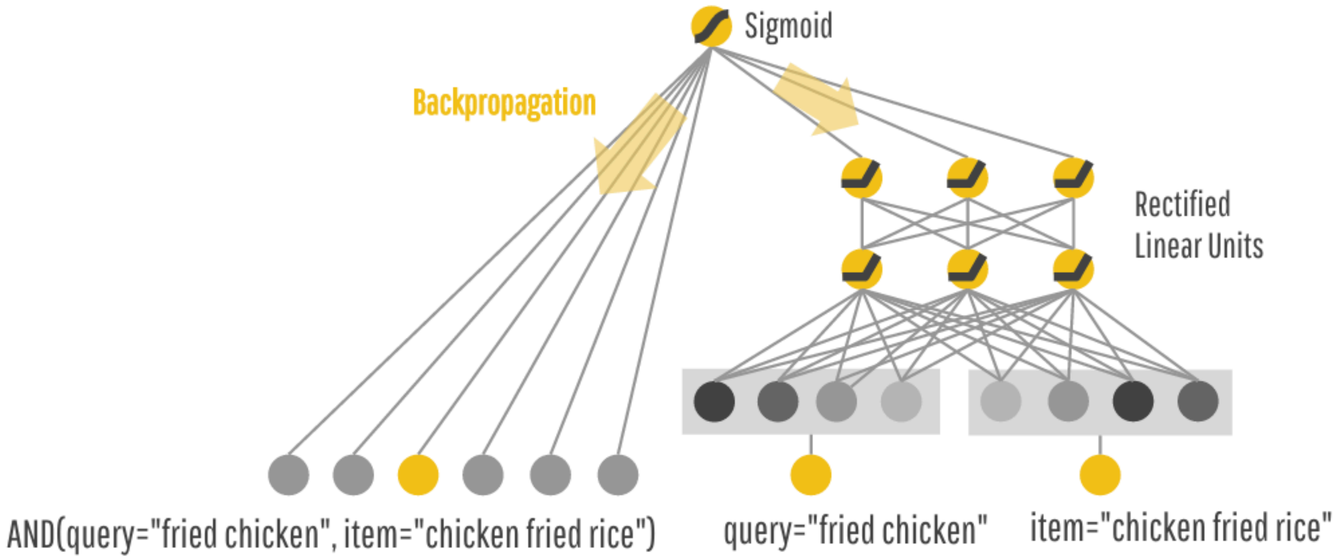

Google's wide-and-deep model

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

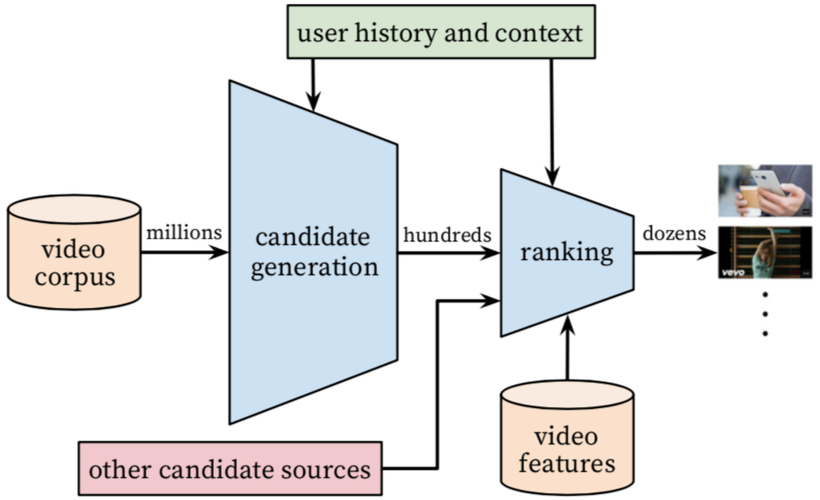

Figure 2: Recommendation system architecture demonstrating the "funnel" where candidate videos are retrieved and ranked before presenting only a few to the user.

Covington et al. (2016)