Recommender System

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Why Recommender System?

Introduction to Recommender System

Terminology Explanation

- User
- Item: movies, books, songs, …

- n_u : number of users
- n_m : number of items

=> Rating matrix/Utility matrix: $(n_u \; x \; n_m)$

- Rating information
  - Implicit feedback: number of times website visited, read a book, view a book, heard a song, …
  - Explicit feedback: user rating for a movie

Problem Formulation

	I1	I2	I3	I4
U1	4	?	3	?
U2	?	3	?	?
U3	5	?	?	2
U4	?	1	?	?
U5	?	?	4	5

Item descriptions

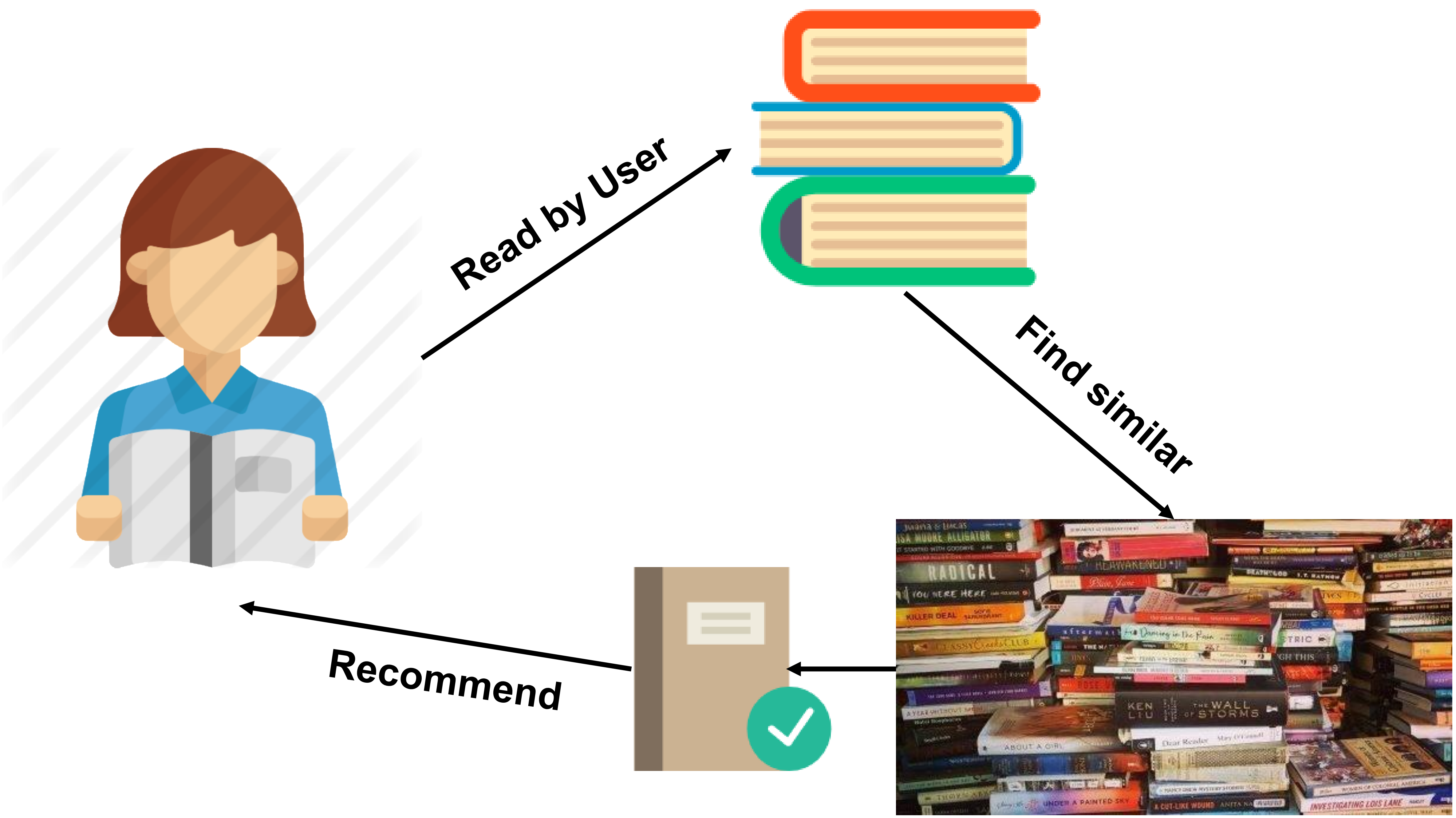
	I1	I2	I3	I4
U1	4	2	3	5
U2	3	3	2	4
U3	5	1	5	2
U4	1	1	3	2
U5	4	3	4	5

Recommender System Approaches

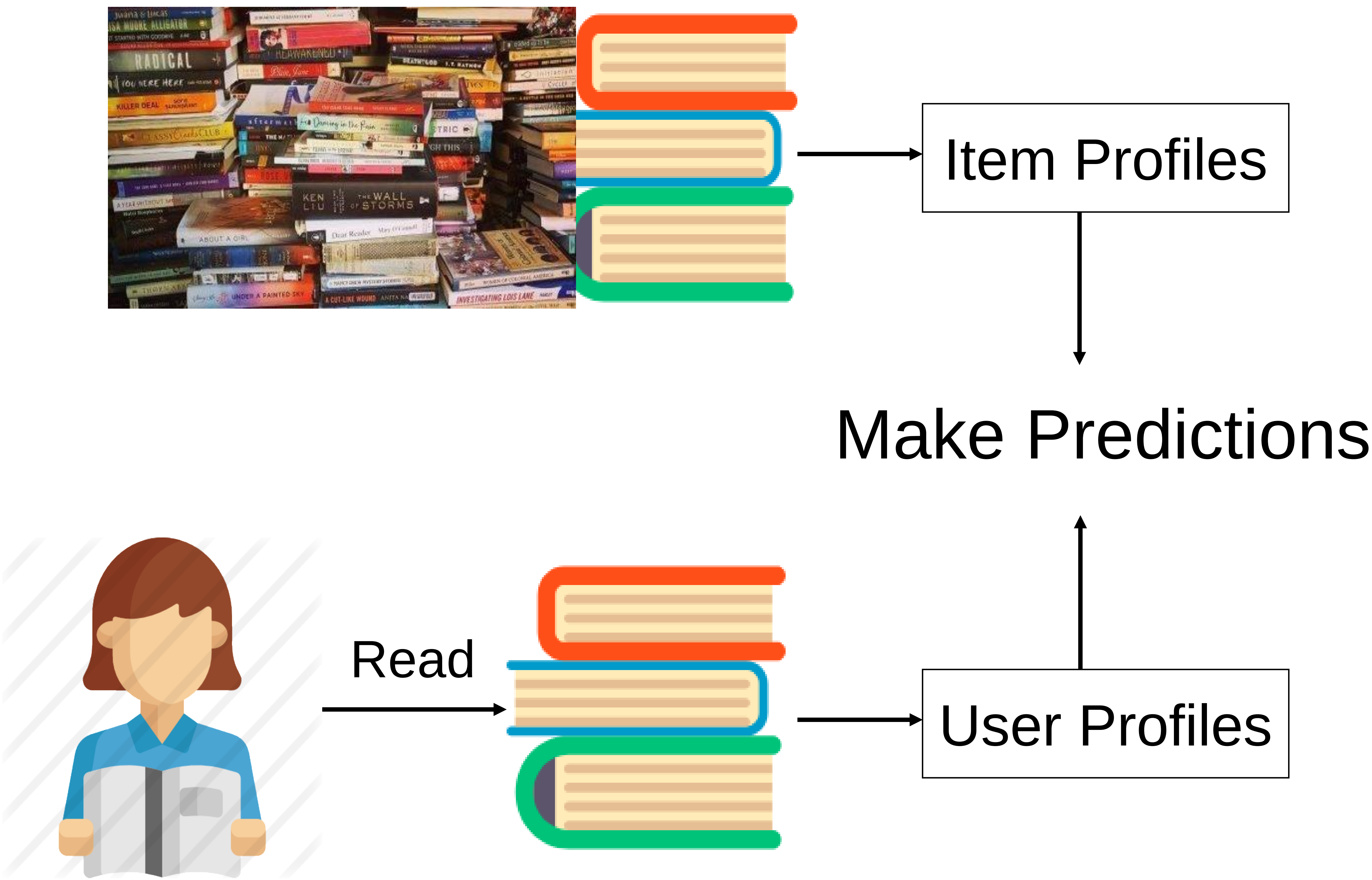
- Content-based
- Collaborative Filtering
- Hybrid methods

Content-based

- **Main idea:** "Recommend items that are similar to those the user liked in the past"



Content-based



Item Profiles

- List of features
  - Movies: actor, title, director, genre, …
  - Songs: singer, year release, musician, …
  - Books: Title, author, genre, …
- Text features
  - List of important words
  - Use TF-IDF

User Profiles and Making Predictions

- User Profiles:
  - User has rated items with profiles $x_1, \ldots, x_n$
  - Simple: average of rated item profiles

- Making Predictions:
  - Item profiles: $x_1, \ldots, x_k$
  - User profile: u_1
  - Prediction: Cosine similarity $\cos(x_q, u_1), q \in [1, k]$

Learning a User Model

- Regression/Classification task
- Training data: item profile and ratings

	I1	I2	I3	I4
U1	4	?	3	?
U2	?	3	?	?
U3	5	?	?	2
U4	?	1	?	?
U5	?	?	4	5

	x1	x2
I1	0.9	0.1
I2	0.4	0.6
I3	0.5	0.5
I4	0.3	0.7

Learning a User Model

- $r(i, j) = 1$ if user i rated movie j (0 otherwise)
- $y^{(i,j)}$ = rating by user i on movie j
- $w^{(i)}$: parameter vector for user i
- $x^{(j)}$: feature vector for movie j
- For user i, movie j, predicted rating: $(w^{(i)})^T x^{(j)}$
- n: number of features in movie

- To learn $w^{(i)}$ parameter for user i:

$$\min_{w^{(i)}} \frac{1}{2} \sum_{j:r(i,j)=1} ((w^{(i)})^T x^{(j)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{k=1}^{n} (w_k{}^{(i)})^2$$

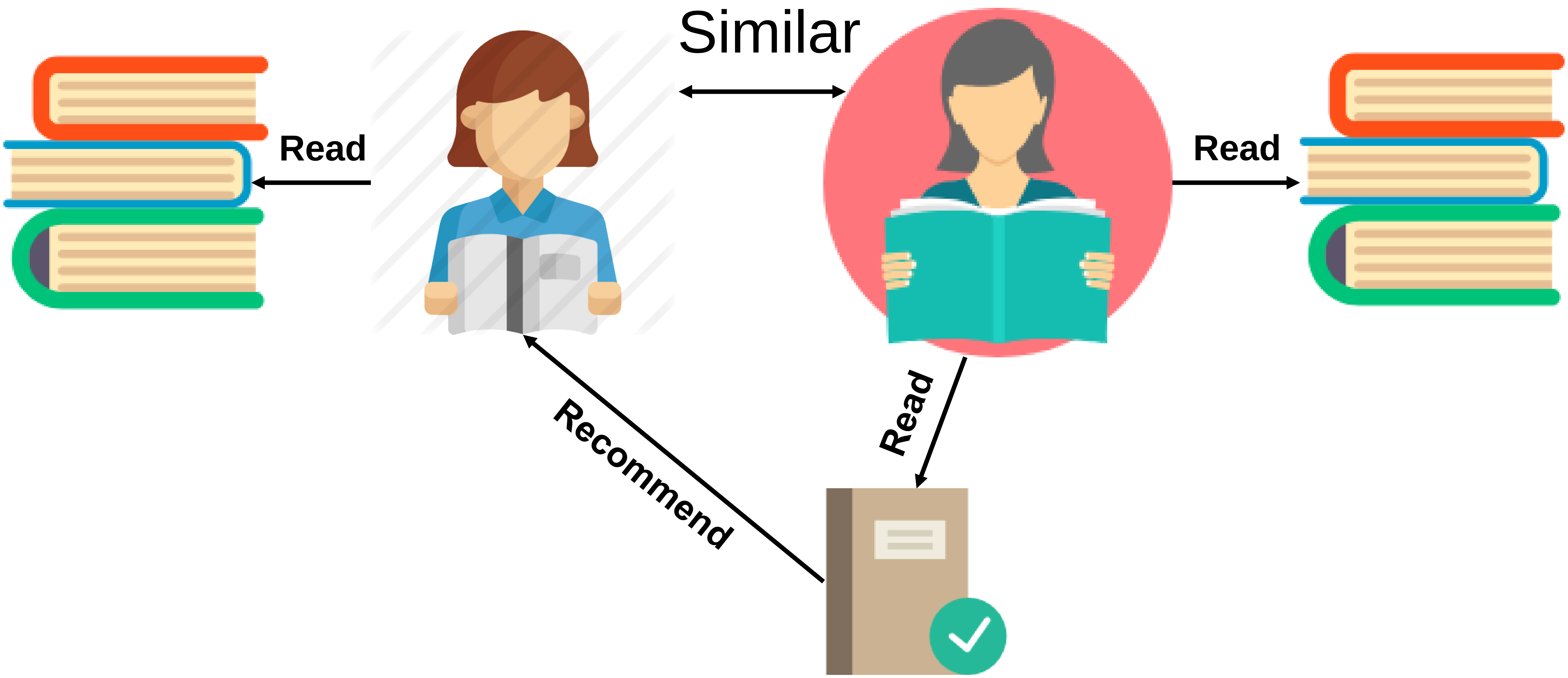
Comments

- Advantages:
  - No need data of other users
  - Able to recommend new and unpopular items
  - Explanations for recommended items

- Disadvantages:
  - Never recommends items outside user's content profile
  - Unable to exploit quality judgments of other users
  - Cold-start problem for new users

Collaborative Filtering

- **Main idea:** “Recommend items that similar users liked”



Collaborative Filtering

- Neighborhood-based
  - **User-user collaborative filtering**
  - Item-item collaborative filtering
- Matrix Factorization

User-user Collaborative Filtering

Step 1: Normalized data

	U1	U2	U3	U4	U5	U6	U7
I1	5	5	2	0	1	?	?
I2	4	?	?	0	?	2	?
I3	?	4	1	?	?	1	1
I4	2	2	3	4	4	?	4
I5	2	0	4	?	?	?	5

3.25	**2.75**	**2.5**	**1.33**	**2.5**	**1.5**	**3.33**

Mean user ratings

	U1	U2	U3	U4	U5	U6	U7
I1	1.75	2.25	-0.5	-1.3	-1.5	0	0
I2	0.75	0	0	-1.3	0	1.5	0
I3	0	1.25	-1.5	0	0	-0.5	-2.3
I4	-1.2	-0.7	0.5	2.67	1.5	?	0.67
I5	-1.2	-2.7	1.5	0	0	0	1.67

Normalized rating matrix

User-user Collaborative Filtering

Step 2: Calculate user similarity: cosine similarity

	u_0	u_1	u_2	u_3	u_4	u_5	u_6
u_0	1	0.83	-0.58	-0.79	-0.82	0.2	-0.38
u_1	0.83	1	-0.87	-0.40	-0.55	-0.23	-0.71
u_2	-0.58	-0.87	1	0.27	0.32	0.47	0.96
u_3	-0.79	-0.40	0.27	1	0.87	-0.29	0.18
u_4	-0.82	-0.55	0.32	0.87	1	0	0.16
u_5	0.2	-0.23	0.47	-0.29	0	1	0.56
u_6	-0.38	-0.71	0.96	0.18	0.16	0.56	1

User similarity matrix

User-user Collaborative Filtering

Step 3: Rating prediction

$$\hat{y}_{i,u} = \frac{\sum_{u_j \in \mathcal{N}(u,i)} \bar{y}_{i,u_j} \mathbf{sim}(u, u_j)}{\sum_{u_j \in \mathcal{N}(u,i)} |\mathbf{sim}(u, u_j)|}$$

	U1	U2	U3	U4	U5	U6	U7
I1	1.75	2.25	-0.5	-1.3	-1.5	0.18	-0.63
I2	0.75	0.48	-0.17	-1.3	-1.33	1.5	0.05
I3	0.91	1.25	-1.5	-1.84	-1.78	-0.5	-2.3
I4	-1.2	-0.7	0.5	2.67	1.5	0.59	0.67
I5	-1.2	-2.7	1.5	1.57	1.56	01.59	1.67

User-user Collaborative Filtering

Step 5: Denormalized

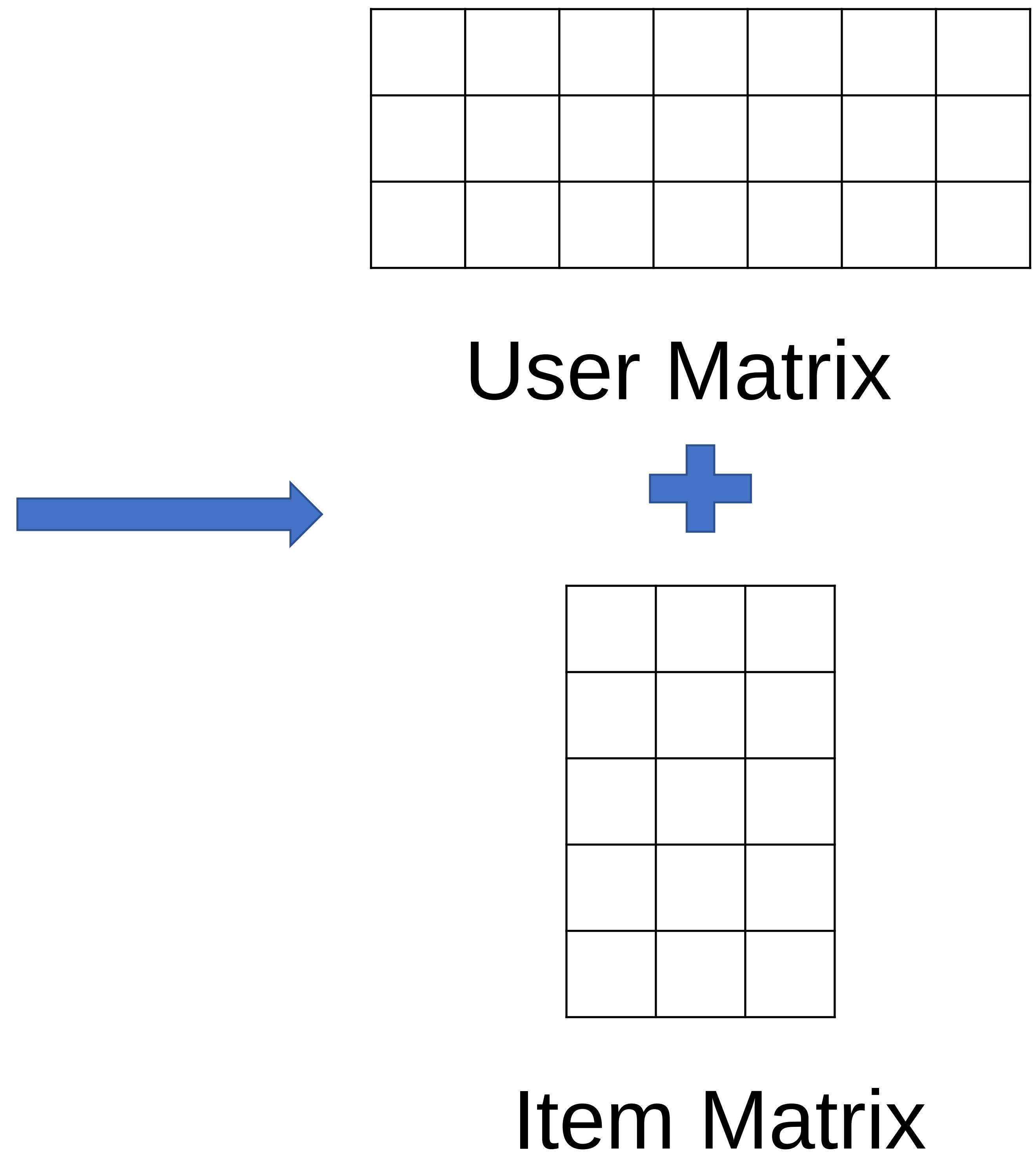
	U1	U2	U3	U4	U5	U6	U7
I1	5	5	2	0	1	1.68	2.70
I2	4	3.23	2.33	0	1.67	2	3.38
I3	4.15	4	1	-0.5	0.71	1	1
I4	2	2	3	4	4	2.10	4
I5	2	0	4	2.9	4.06	3.10	5

Matrix Factorization

- n_u : number of users
- n_m : number of items
- n_u = 7, n_m = 5, K = 3

	U1	U2	U3	U4	U5	U6	U7
I1	5	5	2	0	1	?	?
I2	4	?	?	0	?	2	?
I3	?	4	1	?	?	1	1
I4	2	2	3	4	4	?	4
I5	2	0	4	?	?	?	5

Rating Matrix



Matrix Factorization

- Content-based, for user i:

$$\min_{w^{(i)}} \frac{1}{2} \sum_{j:r(i,j)=1} ((w^{(i)})^T x^{(j)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{k=1}^{n} (w_k{}^{(i)})^2$$

- For n_u users:

$$\min_{w^{(i)},\ldots,w^{(n_u)}} \frac{1}{2} \sum_{i=1}^{n_u} \sum_{j:r(i,j)=1} ((w^{(i)})^T x^{(j)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_u} \sum_{k=1}^{n} (w_k{}^{(i)})^2$$

Matrix Factorization

- For find features vector of items:

$$\min_{x^{(j)},\dots,x^{(n_m)}} \frac{1}{2}\sum_{j=1}^{n_m}\sum_{i:r(i,j)=1}((w^{(i)})^T x^{(j)} - y^{(i,j)})^2 + \frac{\lambda}{2}\sum_{j=1}^{n_m}\sum_{k=1}^{n}(x_k{}^{(j)})^2$$

- For find both features vector of items and users:

$$J(x,w) = \frac{1}{2}\sum_{(i,j):r(i,j)=1}((w^{(i)})^T x^{(j)} - y^{(i,j)})^2 + \frac{\lambda}{2}\sum_{i=1}^{n_u}\sum_{k=1}^{n}(w_k{}^{(i)})^2 + \frac{\lambda}{2}\sum_{j=1}^{n_m}\sum_{k=1}^{n}(x_k{}^{(j)})^2$$

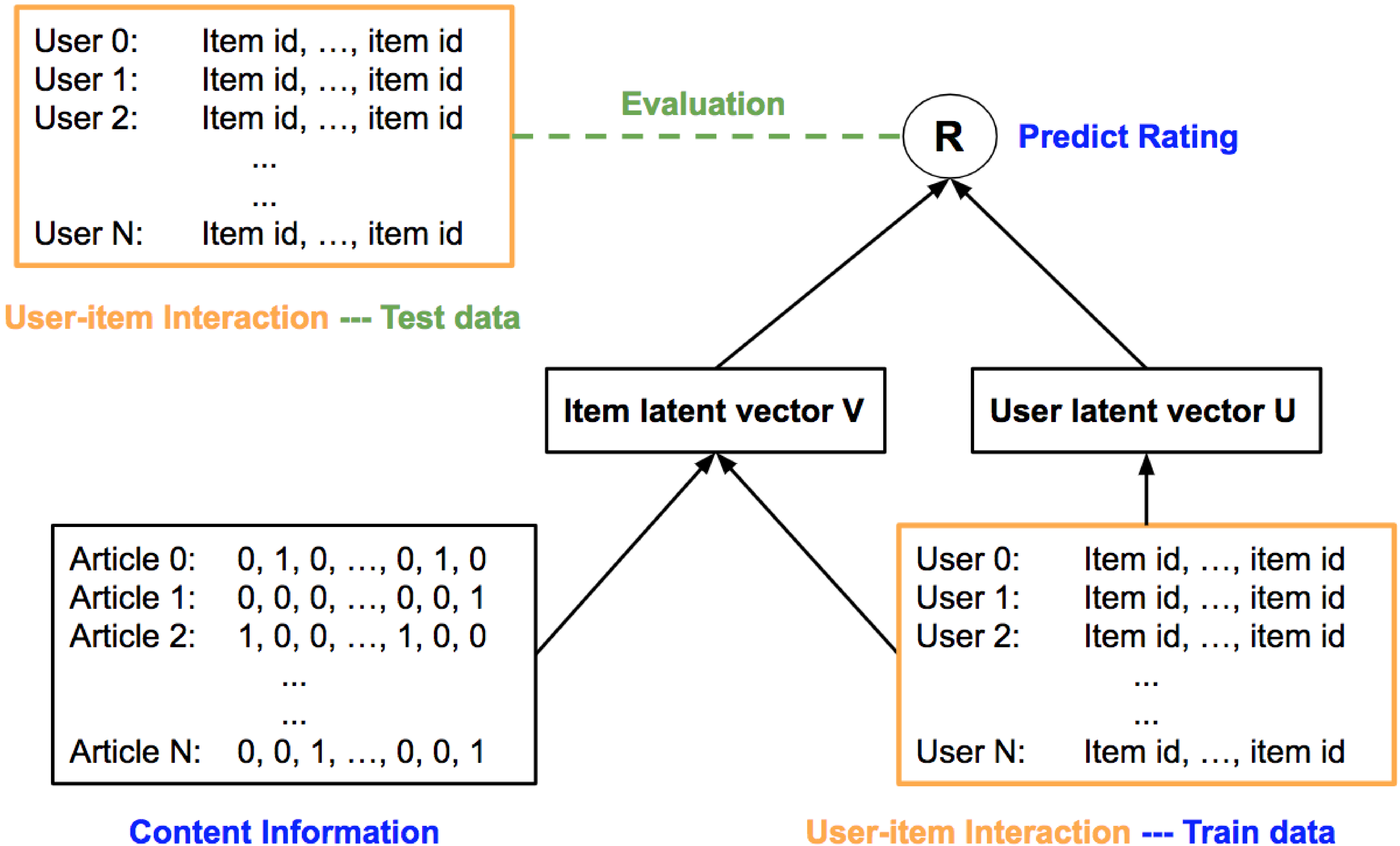
Comment

- Collaborative filtering result > Content-based result

- Issues of Collaborative filtering:
  - Cold-start problems
  - Sparsity problems

=> Hybrid methods: combine both Collaborative filtering and Content-based

Current State-of-the-art Models



Datasets

- Movie
  - Movielens: MovieID, Title, Genre, Rating, Tag
  - Netflix
- Scientific paper
  - CiteULike: Title, abstract, User-item interaction, tag…
  - CiteSeer
- Amazon product data

1. https://movielens.org/
2. http://www.citeulike.org/

Evaluation

- **Rating Prediction Task**
  - Mean Absolute Error (MAE)
  - Mean Square Error (MSE)
  - Root Mean Square Error (RMSE)
- **Top-N Recommendation Task**
  - Precision and Recall
  - Mean Average Precision (MAP)
  - Mean Reciprocal Rank (MRR)
  - Normalized Discounted Cumulative Gain (nDCG)

References

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3. Ruslan Salakhutdinov andAndriy Mnih. Probabilistic Matrix Factorization. In Proceedings of the 20th International Conference on Neural Information Processing Systems (NIPS'07), 2007.
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thank you
danke
謝謝
ngiyabonga
рахмат
teşekkür ederim
Баярлалаа
спасибо
faafetai lava
mersi
kia ora
barka
welalin
tack
spas
mahalo
tapadh leat
vinaka
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terima kasih
ευχαριστώ
diolch
dhanyavadagalu
shukriya
mercê
мерси
তোমাকে ধন্যবাদ
감사합니다
xièxie
merci