Recommender Systems

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June 10, 2024

Crossing Minds

Dauphine | PSL
UNIVERSITÉ PARIS

Outline

1. Introduction
2. The Recommendation Problem
3. User Feedback
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5. Evaluation of RS
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7. Content-Based Filtering
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9. Context-Aware Recommendation
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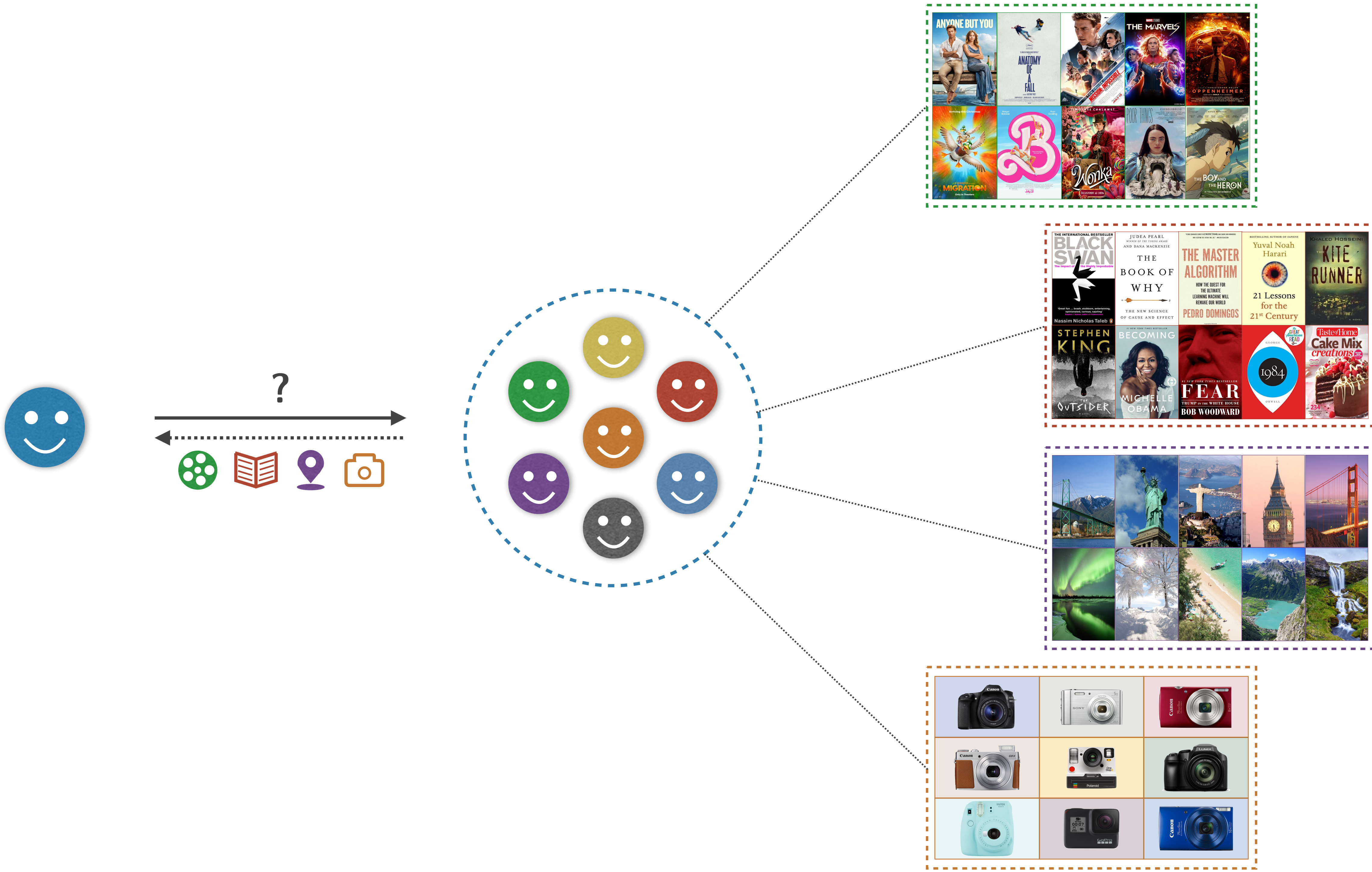
13. A Practical Example: Recommendation in Location-Based Social Networks

Introduction

The (black) art of recommendation



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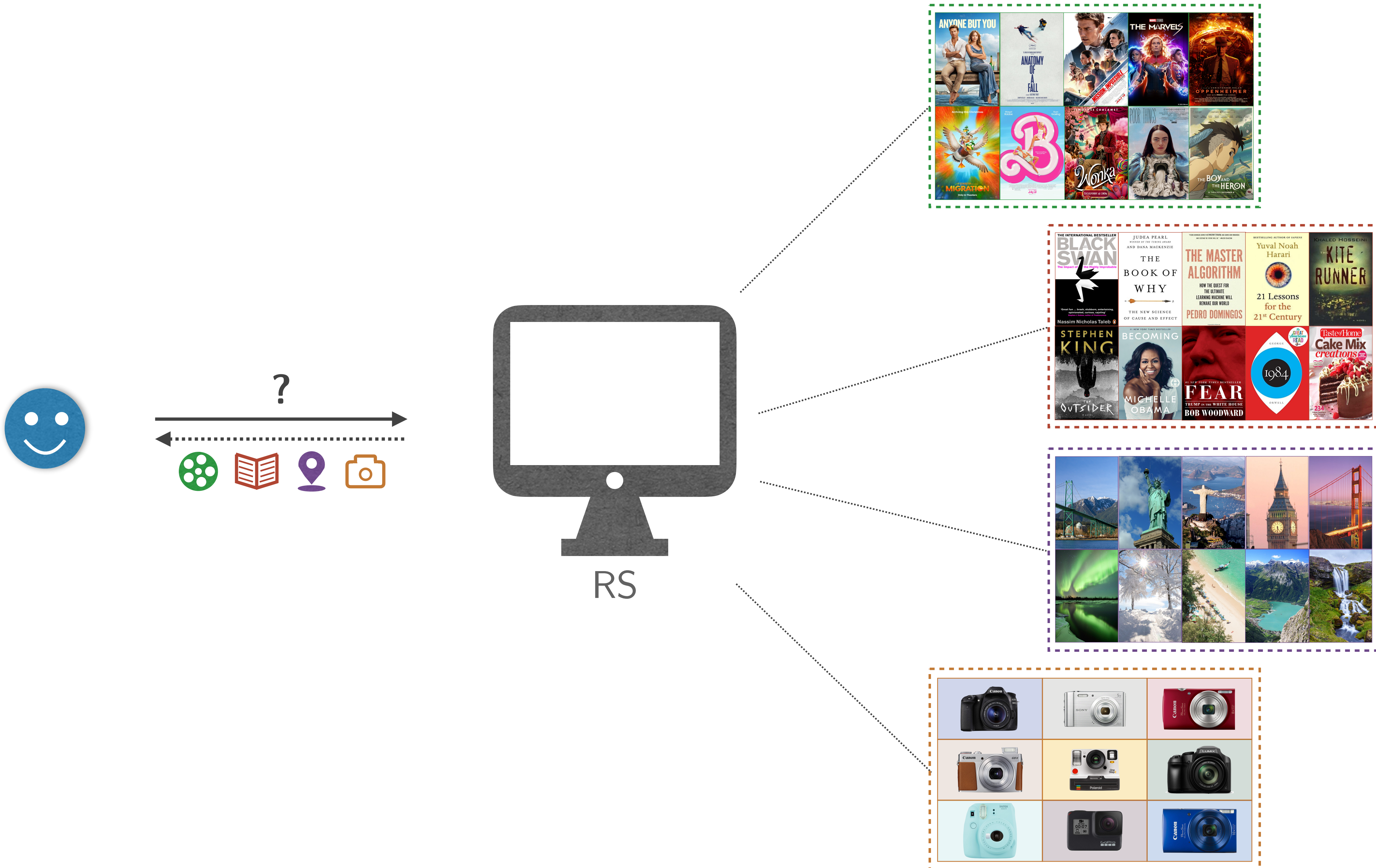


The value of recommender systems

For consumers

- Find good and relevant products
- Improve decision making
- Help them overcome the *information overload*

The value of recommender systems

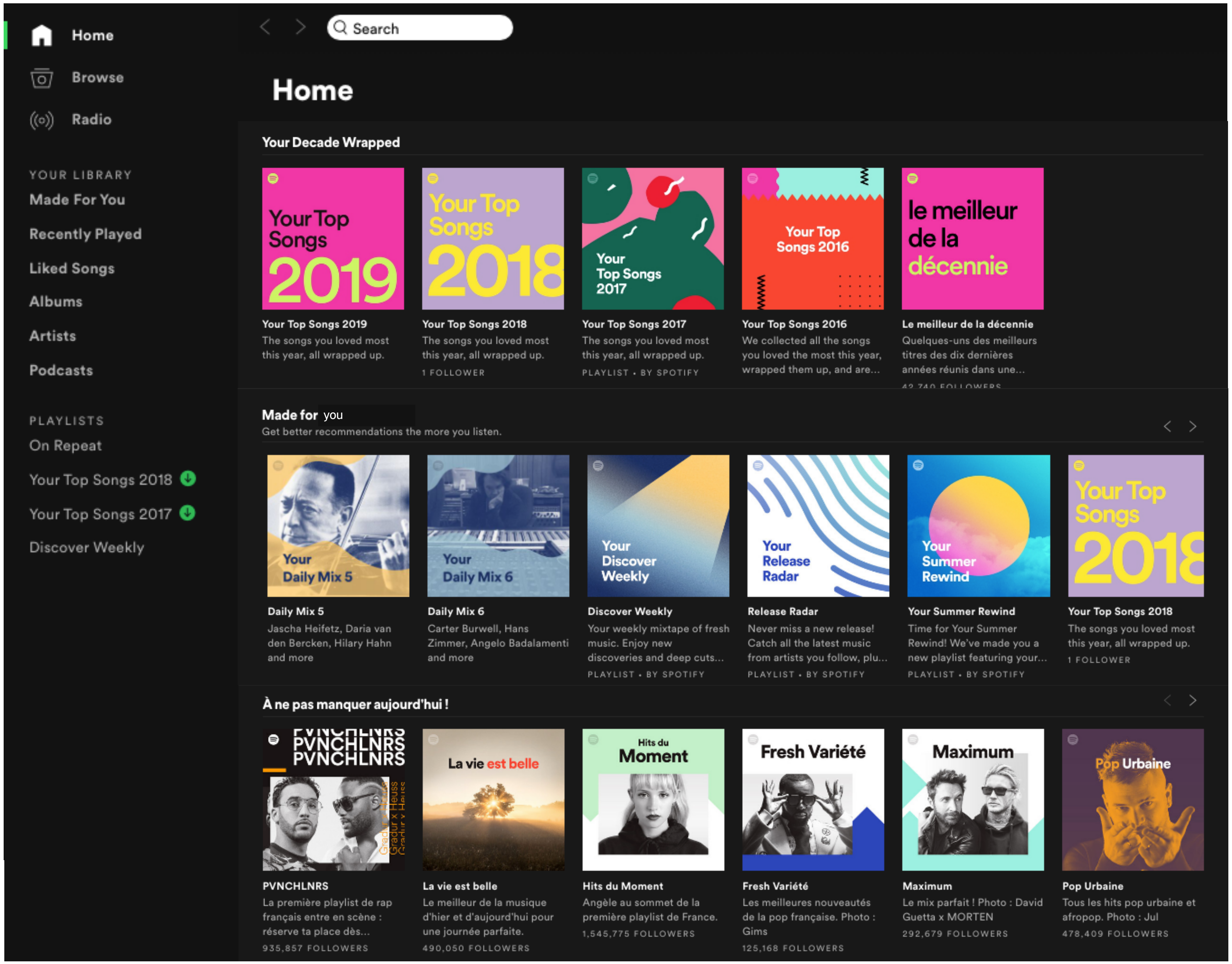
For consumers

- Find good and relevant products
- Improve decision making
- Help them overcome the *information overload*

For service providers

- Increase the number of products sold
- Sell more diverse products
- Increase the user satisfaction and fidelity
- Learn more about consumers

Personalization at Spotify



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A. S. Das et al. *Google News Personalization: Scalable Online Collaborative Filtering.* In WWW '07, 2007.

Measuring the business value of recommender systems

- Click-Through Rate (CTR)

Dietmar Jannach and Michael Jugovac. *Measuring the Business Value of Recommender Systems*. arXiv 2019

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- User engagement and behavior

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What is a recommender system?

→ A Recommender System (RS) provides personalized suggestions of **items** for **users**, the items being drawn from a large catalog, based on knowledge of the user, the items, and **interactions** between users and items.

What is a recommender system?

- Knowledge of the user
  - Historical data - interactions with items
    - Purchases, clicks, views, ratings,...
  - Demographics
    - Age, gender, nationality, political views, income,...
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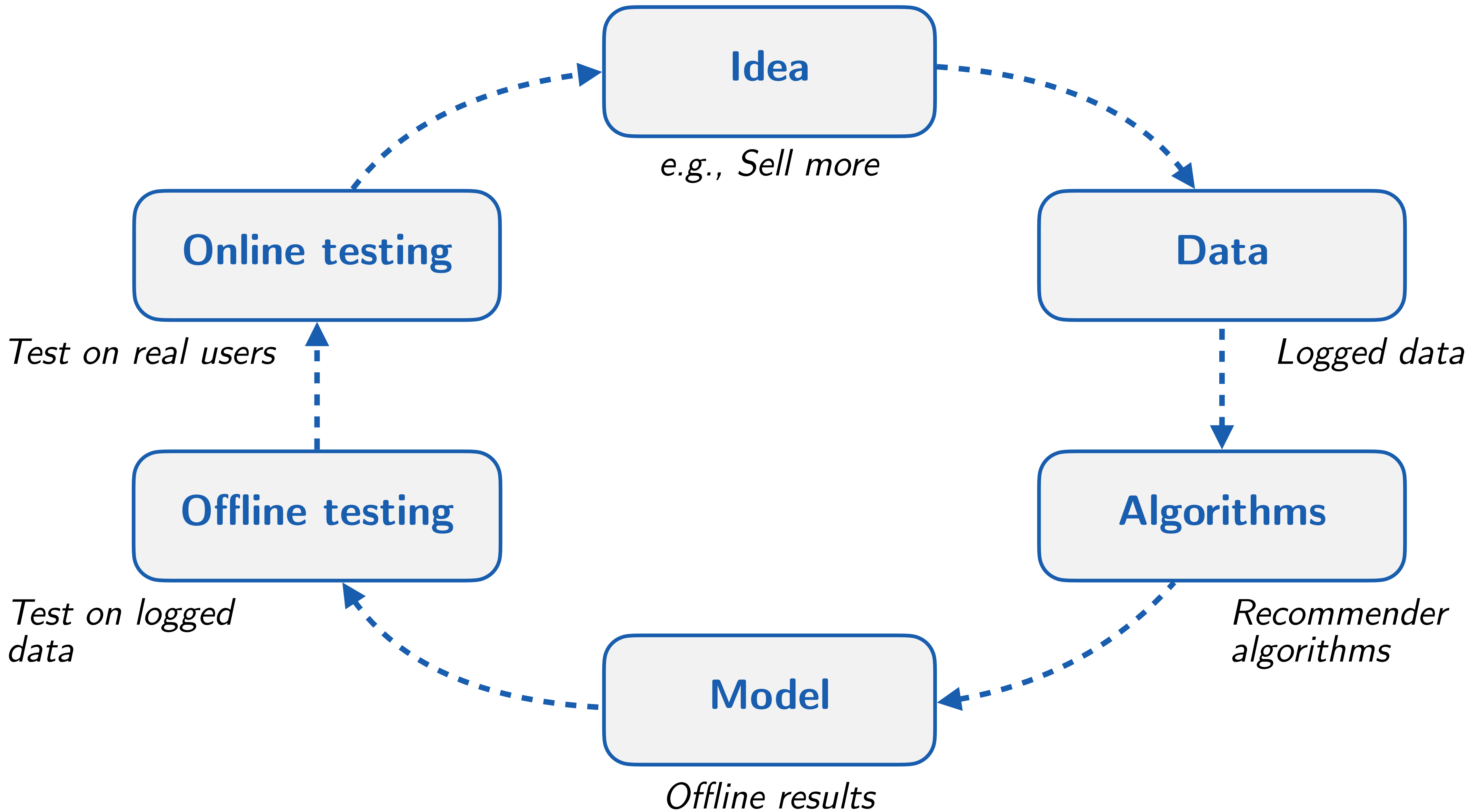
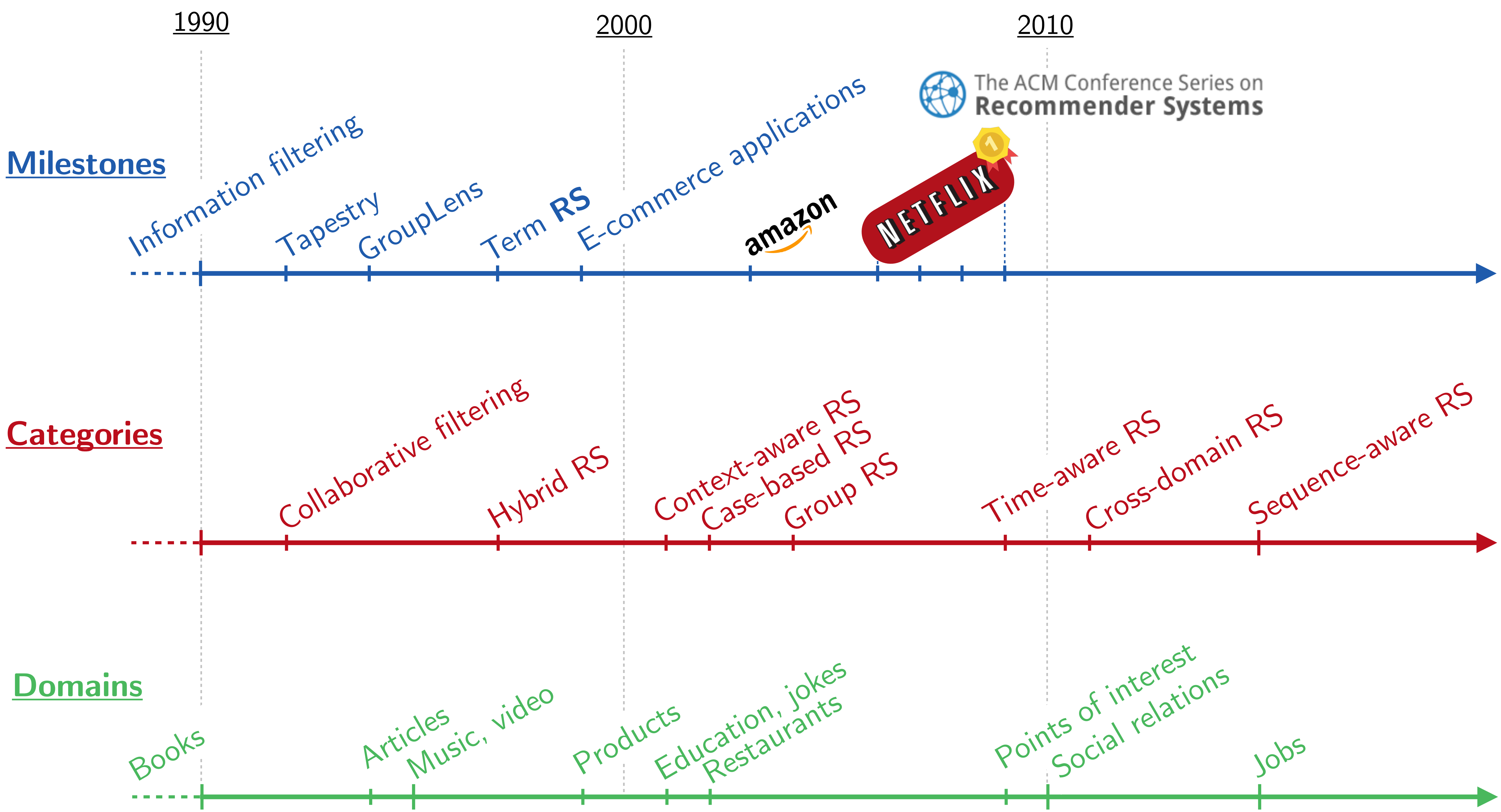
Building a recommender system



Kim Falk. 2019. *Practical Recommender Systems.* Manning, 2019.

Historical perspective on recommender systems



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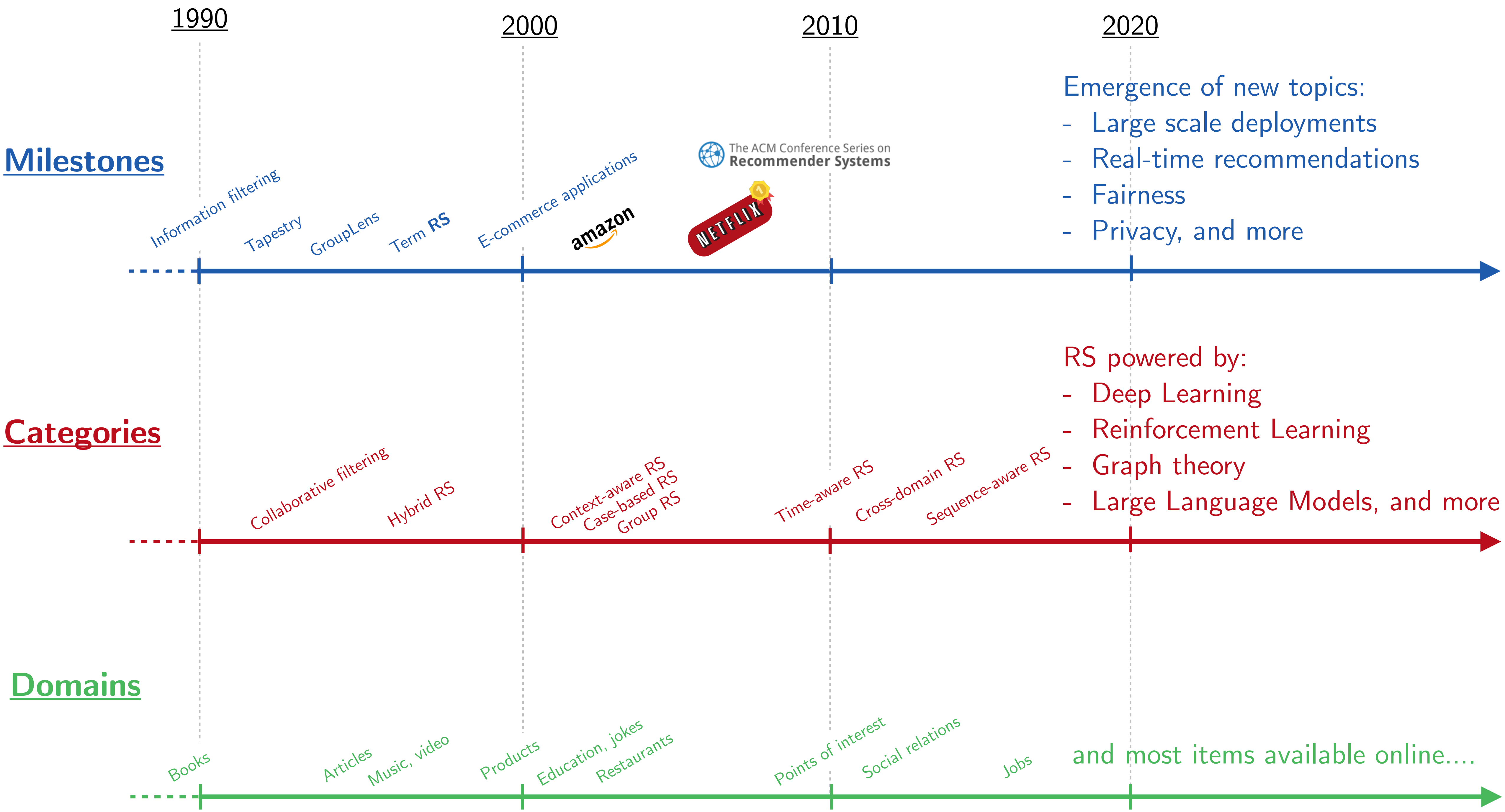

The recommendation problem

The Netflix Prize (2006)

- **End-goal:** Recommend movies to Netflix users
- Competition problem:
  - Predict movie ratings on a 5-star scale
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→ Recommendation problem formulated as **rating prediction**

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Rating prediction

- The task of the RS is to predict the rating that a user will give to an item he did not rate.
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Top-N recommendation

- The task of the RS is to predict the relevance of an item for a user, *i.e.*, predict whether the user will choose an item or not.

General formulation

- Let $\mathcal{U}$ be the set of users and $\mathcal{I}$ the set of items.
- Let f be a utility function that measures the usefulness, e.g., rating or relevance, of an item for a user: $f : \mathcal{U} \times \mathcal{I} \rightarrow \mathcal{R}$, where $\mathcal{R}$ is a totally ordered set.
- For each user $u \in \mathcal{U}$, we recommend the items maximizing f :

$$\forall u \in \mathcal{U}, i^* = \arg\max_{i \in \mathcal{I}} f(u, i)$$

f can represent the rating or the relevance of an item

A recommendation algorithm

Algorithm 1 A recommendation algorithm

Input: user u, number of items to recommend N

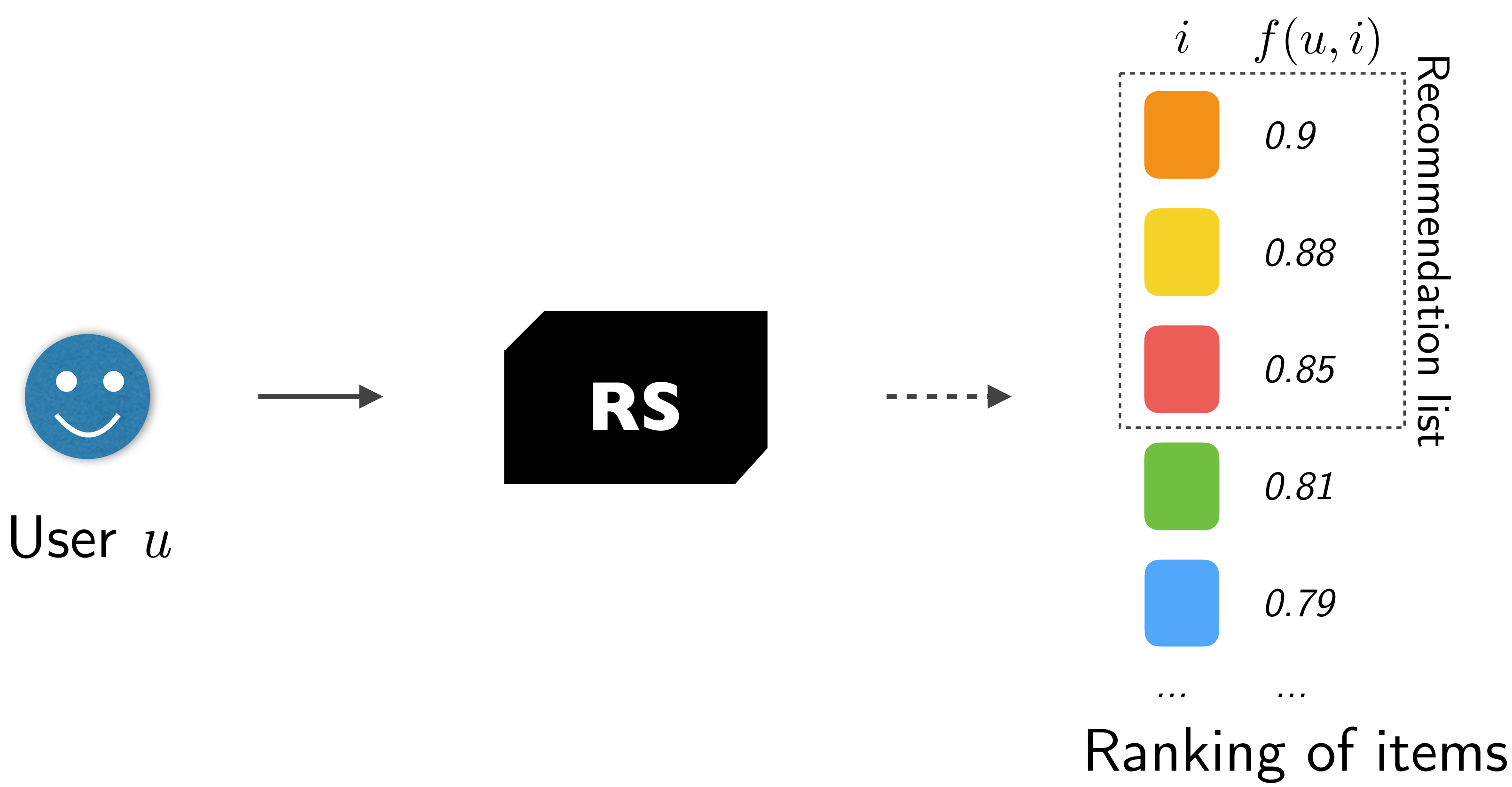
for i in $\mathcal{I} \setminus \mathcal{I}_u$ **do**

  Predict $\hat{r}_{ui}$

end for

Create list of $\mathcal{I} \setminus \mathcal{I}_u$ items ordered by decreasing order of $\hat{r}_{ui}$

Return N first items of the list



User feedback

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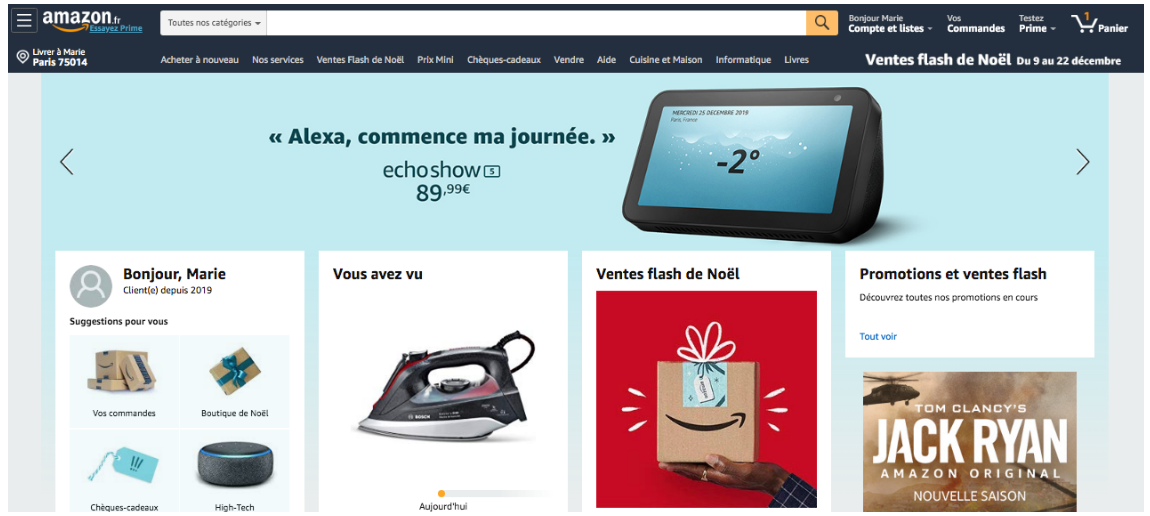
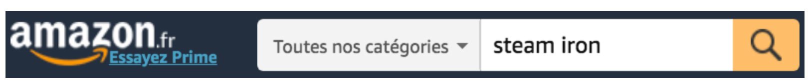
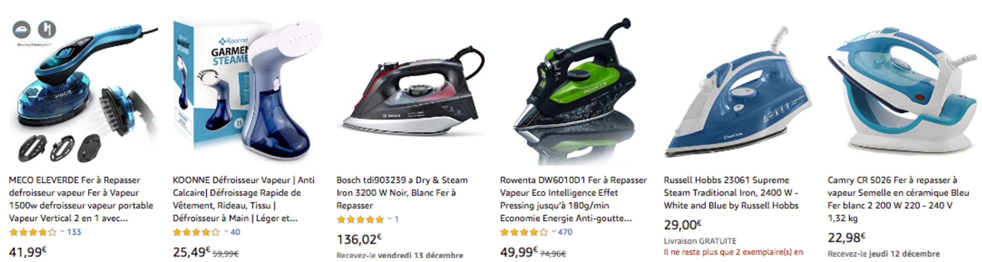
Browsing on Amazon...



Click on card #2



Search with keywords "w_1 w_2"



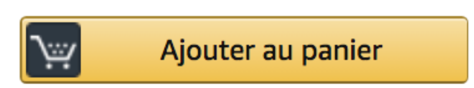
Impression with items #1, 2, 3, 4, 5, 6

Click on item #3

Informations sur le produit

Marque	Bosch
Numéro de modèle	TDI903239A
Couleur	Noir, Blanc
Poids de l'article	2,12 Kg
Dimensions du colis	33,8 x 20,2 x 12,4 cm
Capacité	0.4 litres
Puissance	3200 Watts
Matériau	Aluminium

Read description of item #3



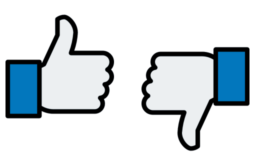
Add item #3 to cart

Rate and review item #3

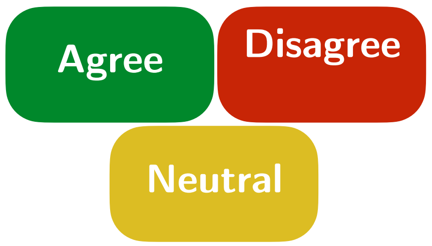
Explicit feedback

- Explicit feedback is a form of feedback directly reported by the user to the system.

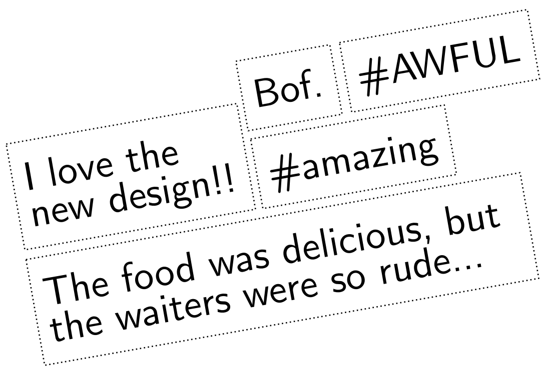
Ratings, 5-star scale



Like/Dislike



Ordinal scale



Textual reviews

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  - Explicit feedback exhibit some biases, e.g., some users tend to give higher ratings than others for a similar level of appreciation.

Implicit feedback

- Implicit feedback is collected by the system without the intervention of the user.

Clicks


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Views of item's description

Purchases

Add to Wishlist

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Views of item's description

Acheter cet article

Purchases

Ajouter à votre liste

Add to Wishlist

$\longrightarrow$ More abundant than explicit feedback

Implicit feedback

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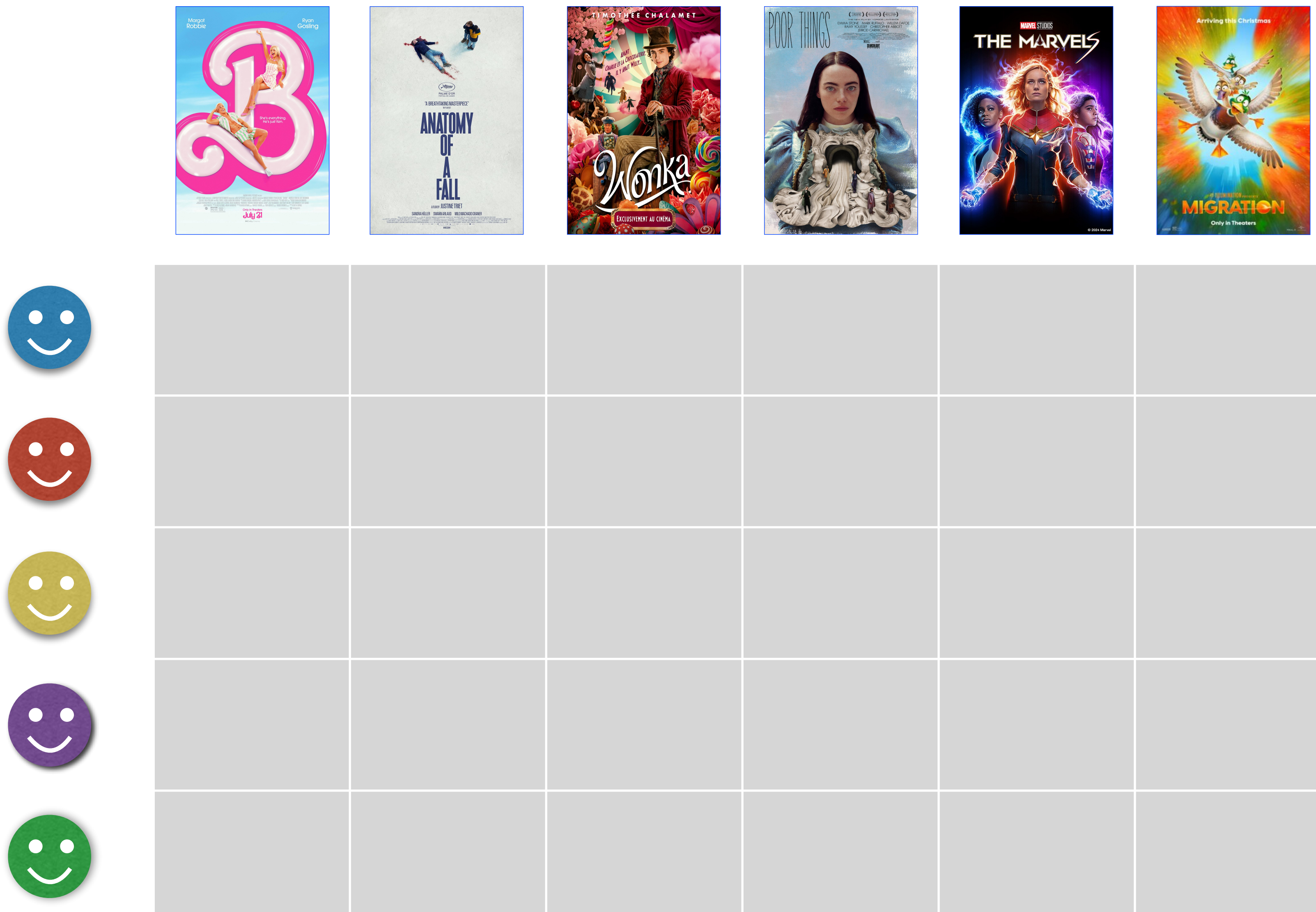
- Challenges:
  - Implicit feedback is inherently noisy.
    - Every *positive item*, i.e., item the user has interacted with, is not necessarily an item liked by the user.
  - There is no negative feedback.
    - Negative items are a mixture of unliked items and unknown items.

Feedback matrix



Feedback matrix - Explicit feedback

	4		5	1		
				5	4	3
		3	1	5		
	2	2			5	4
		5		2		

Feedback matrix - Implicit feedback (Binary)

1		1	1		
			1	1	1
	1	1	1		
1	1			1	1
	1		1		

Feedback matrix - Implicit feedback (Weights)

2		2.8	0.8		
			3.2	2.4	1
	1.2	1	2		
0.4	0.9			2.1	1.3
	3		0		

Challenges

Rating data sparsity

- Users only interact with a small number items selected from a very large catalog of available items.

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Examples of datasets:

NETFLIX

480k users
18k movies
100M ratings
Period of ~7 years

Density: **1.1%**

James Bennett and Stan Lanning. *The Netflix Prize.* In Proc. KDD Cup and Workshop, 2007.

ACCOR HOTELS Feel Welcome

7.8M users
4.5k hotels
34.7M bookings
Period of ~4 years

Density: **0.1%**

Marie Al-Ghossein et al. *Exploiting Contextual and External Data for Hotel Recommendation.* In Proc. UMAP, 2018.

amazon

20.98M users
9.35M items
82.83M ratings
Period of ~18 years

Density: **0.00004%**

https://cseweb.ucsd.edu/~jmcauley/datasets.html#amazon_reviews

Cold-start

- The *cold-start* problem designates the problems of:
  - Recommending items to new users where the historical data is missing,
    - Recommendations cannot be computed before the user has rated a certain number of items, but the user expects to receive suggestions before that.
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  - Recommending new items to existing users.
- A related problem is the *gray sheep* problem:
  - Recommending items to users who have very unique tastes, such that no other user (or very few users) has interacted with the same items.

Overspecialization

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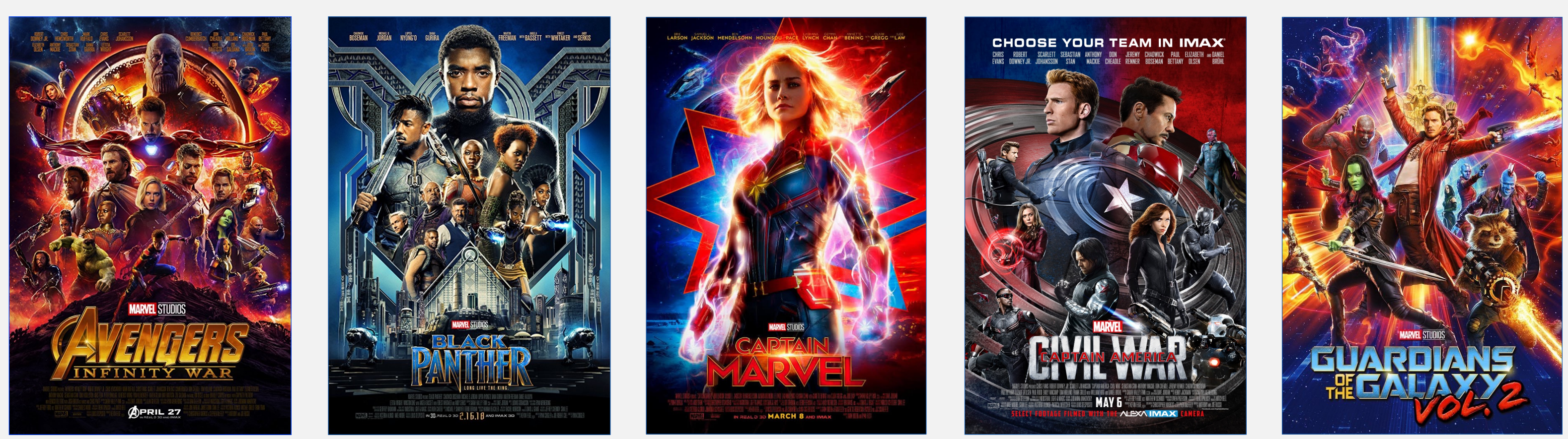
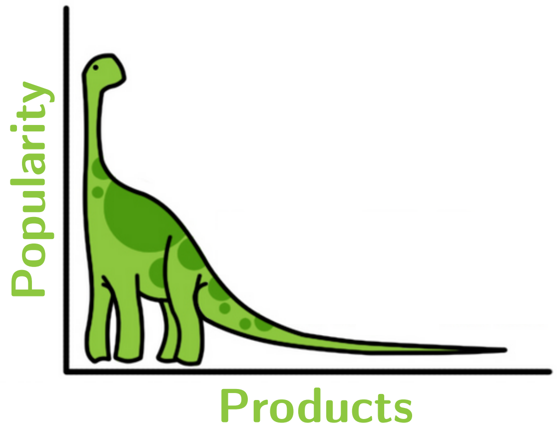


Popularity bias

- Most item catalogs exhibit the *long tail* effect,



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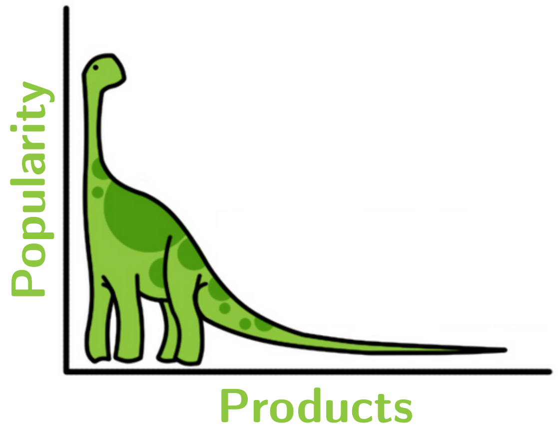

which raises two issues:

- Risk of recommending popular items to everyone,

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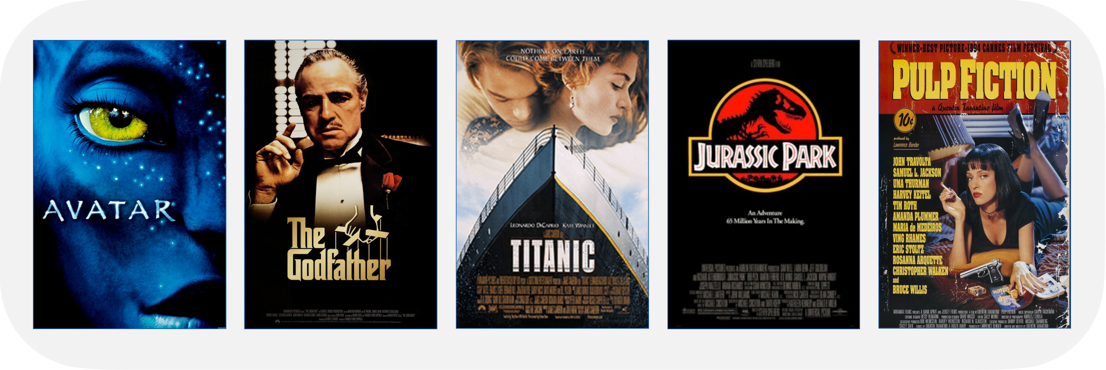

- Difficulty to promote long tail items with little feedback.

Temporal dynamics

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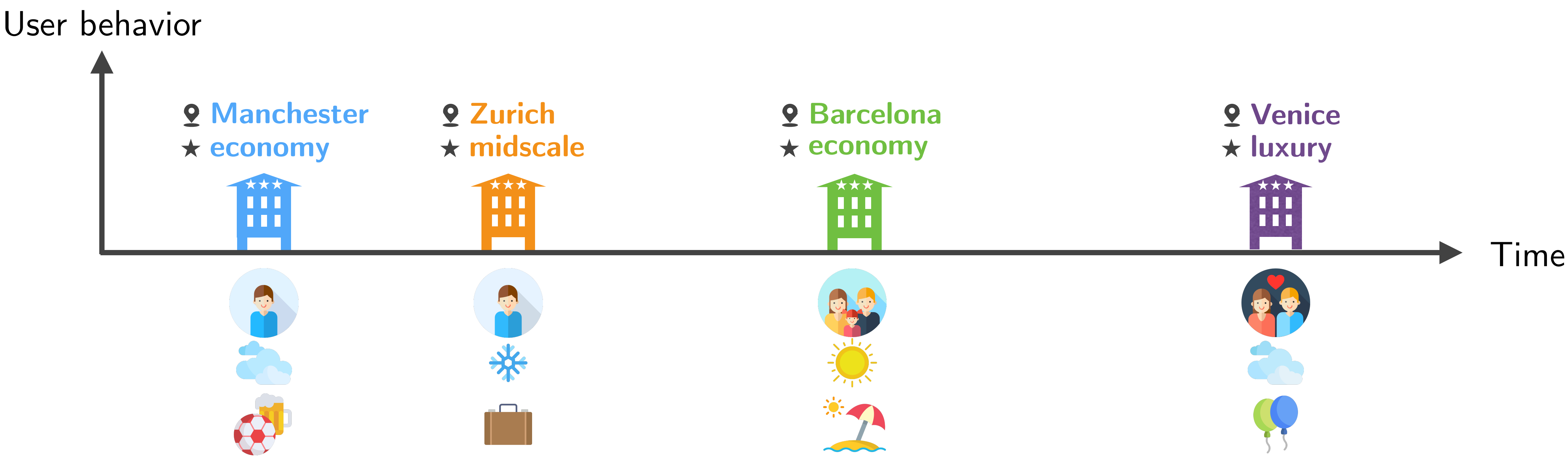

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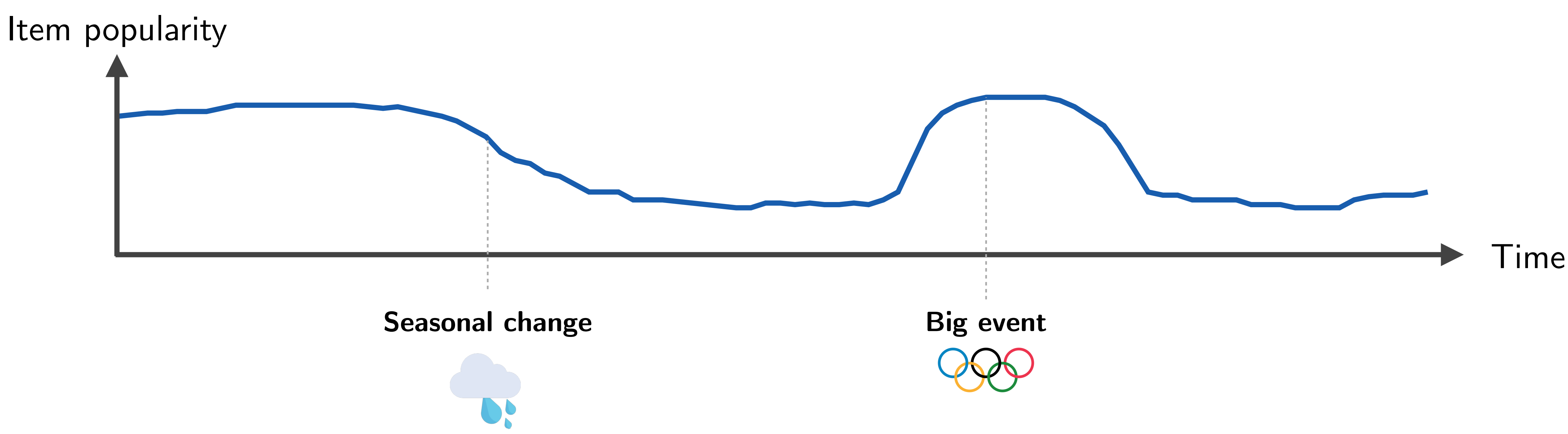
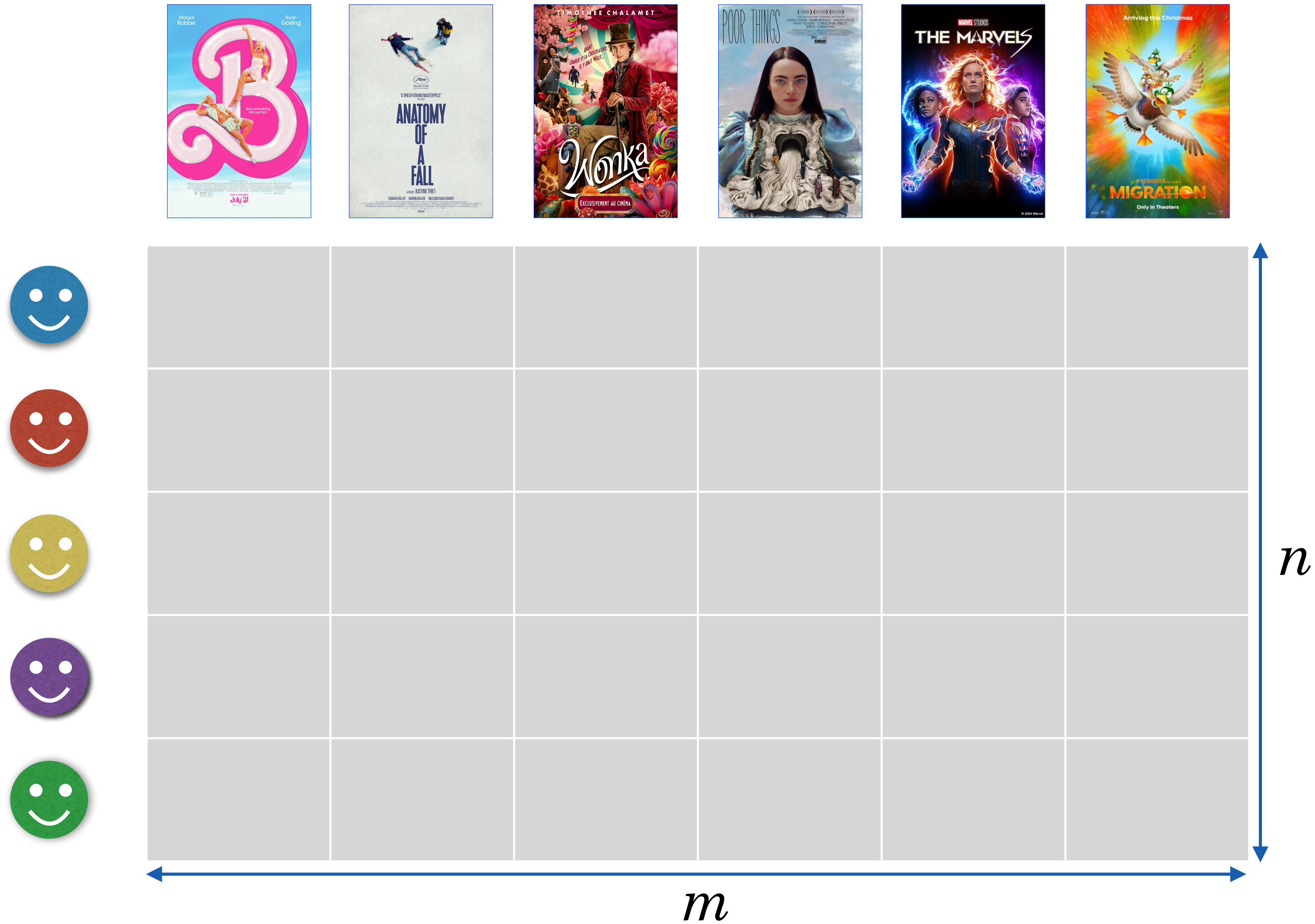


Feedback matrix - Notations

Set of items: $\mathcal{I}$, set of items rated by user u: $\mathcal{I}_u$

Set of users: $\mathcal{U}$



Feedback matrix: R

Rating: r_{ui}, predicted rating: $\hat{r}_{ui}$

Evaluation of RS

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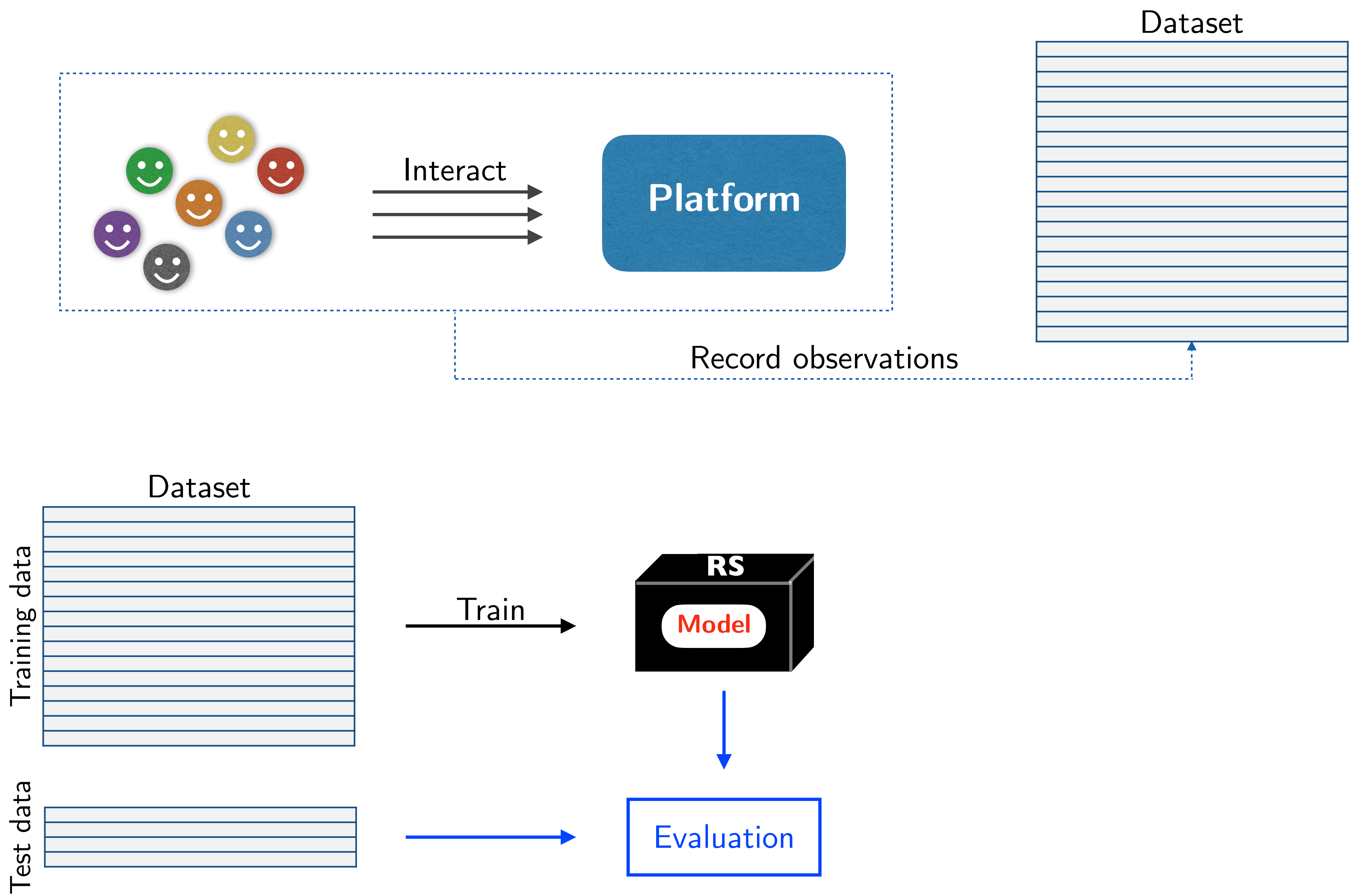
  - Cons: Risk of negatively affecting the real users's experience

Offline evaluation



Offline evaluation

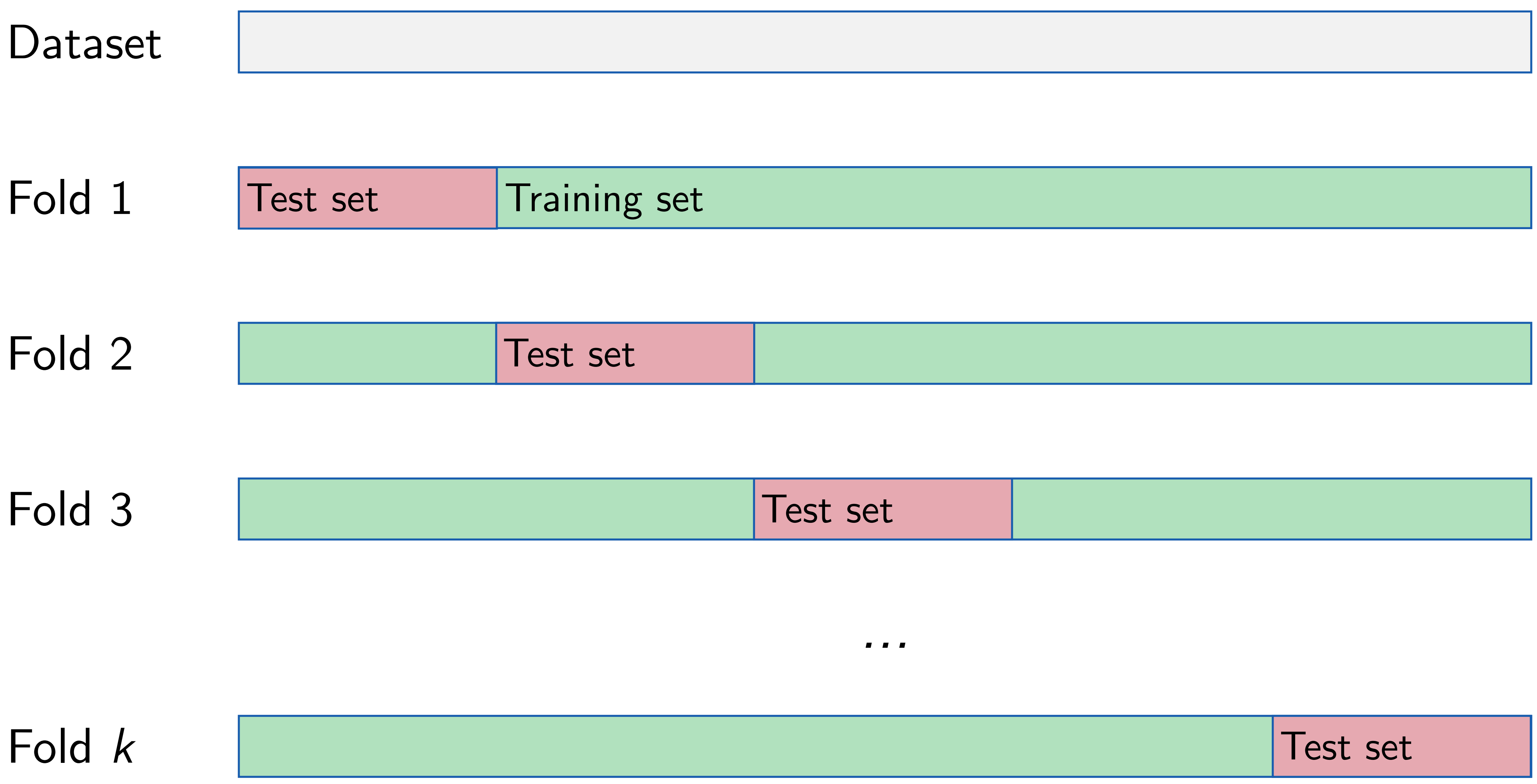
- Random split

4		**5**	1		
			5	**4**	**3**
	3	**1**	5		
2	2			5	4
	5		**2**		

Training set   Test set

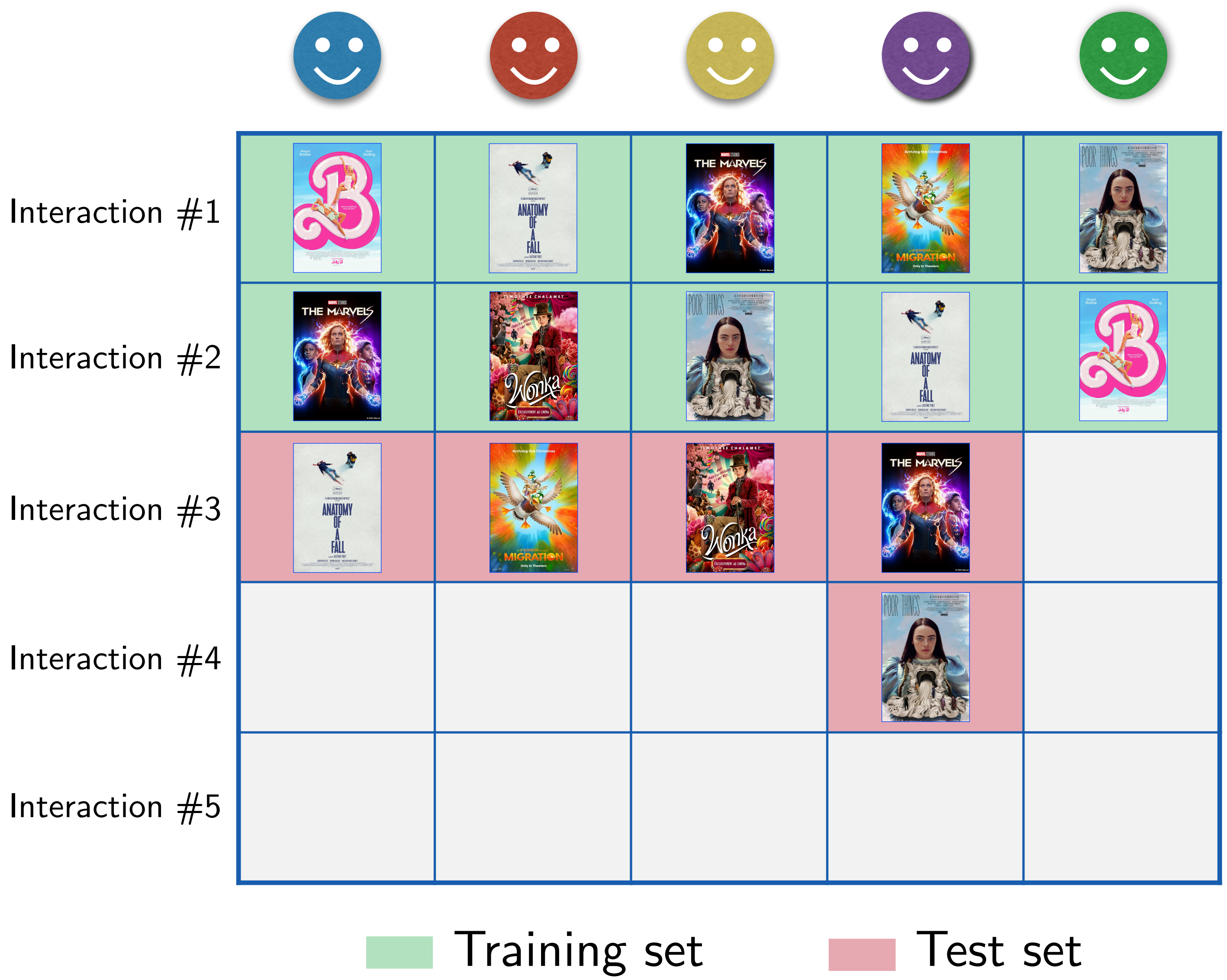
Offline evaluation

- Random split, k-fold cross validation



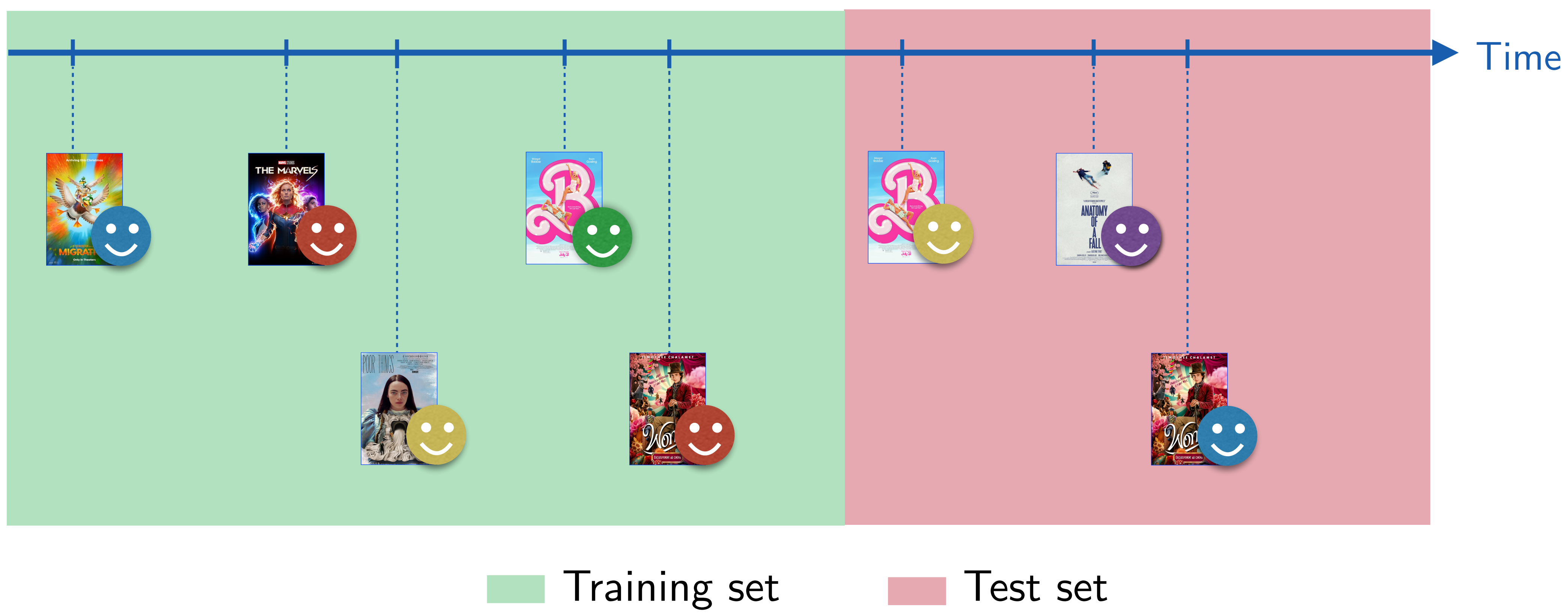
Offline evaluation

- Given-n split



Offline evaluation

- Chronological split



Evaluation criteria

- Accuracy
  - How accurate are the predictions of utility of items?

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  - How surprising are the relevant computed recommendations?

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- Diversity
  - How diverse are the computed recommendations?
- Serendipity
  - How surprising are the relevant computed recommendations?
- Explainability
  - Are we able to explain and justify the recommendations?

Evaluation metrics for accuracy

Measuring the accuracy of the predicted ratings.

- Mean Absolute Error (MAE)

$$MAE = \frac{1}{|\mathcal{T}|} \sum_{(u,i) \in \mathcal{T}} |r_{ui} - \hat{r}_{ui}|$$

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User	Actual rating	Predicted rating	Error
	★★★★★	★★★★☆	★
	★☆☆☆☆	★★★★☆	★★★
	★★★☆☆	★★★★★	★★
	★★★★☆	★★★★☆	
	★★☆☆☆	★☆☆☆☆	★

$$MAE = 1.4$$

Evaluation metrics for accuracy

Measuring the accuracy of the predicted ratings.

- Root Mean Squarred Error (RMSE)

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{|\mathcal{T}|} \sum_{(u,i) \in \mathcal{T}} (r_{ui} - \hat{r}_{ui})^2}$$

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$$RMSE = 3$$

Evaluation metrics for accuracy

Measuring the accuracy of top-N recommendations

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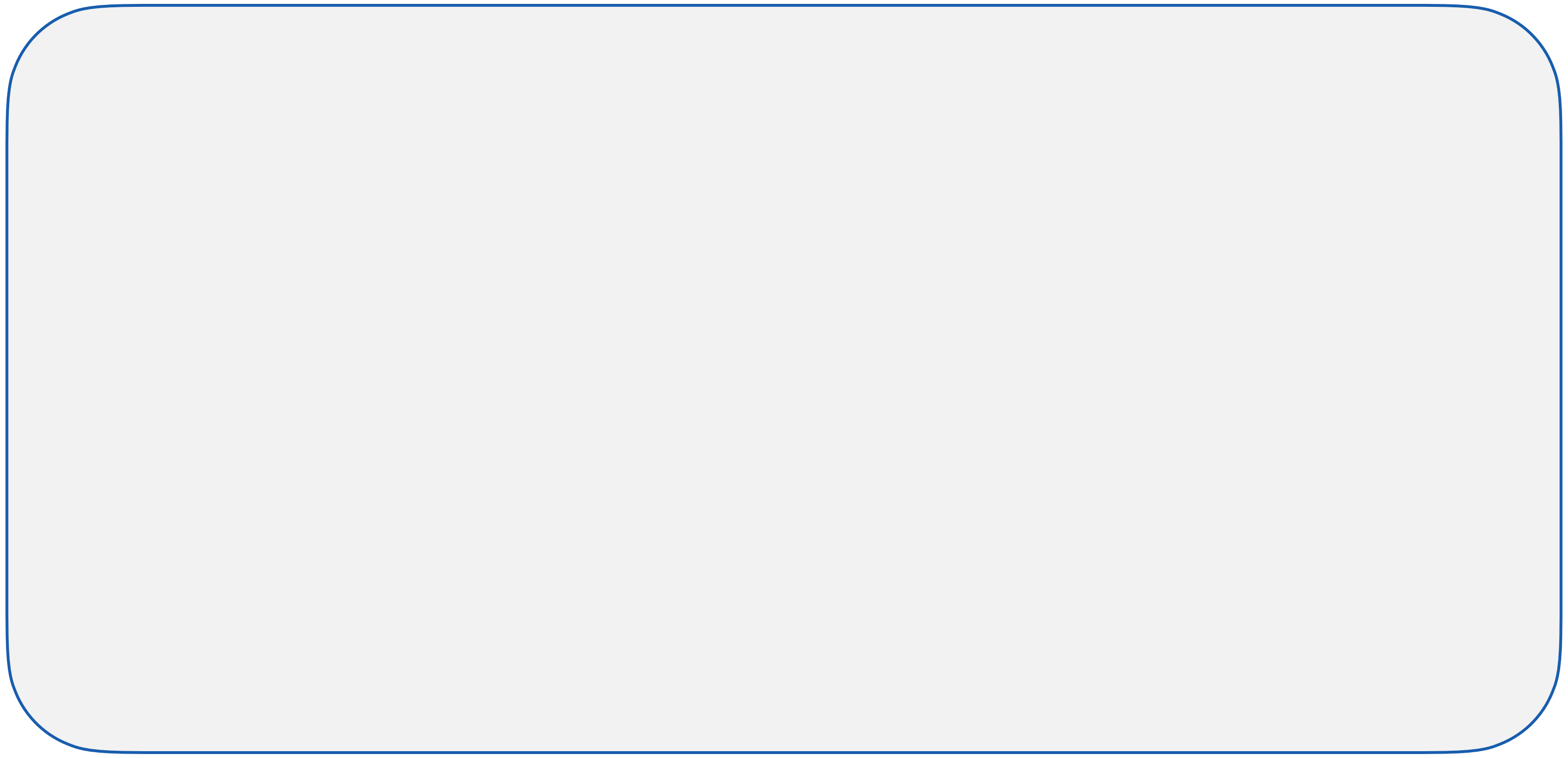
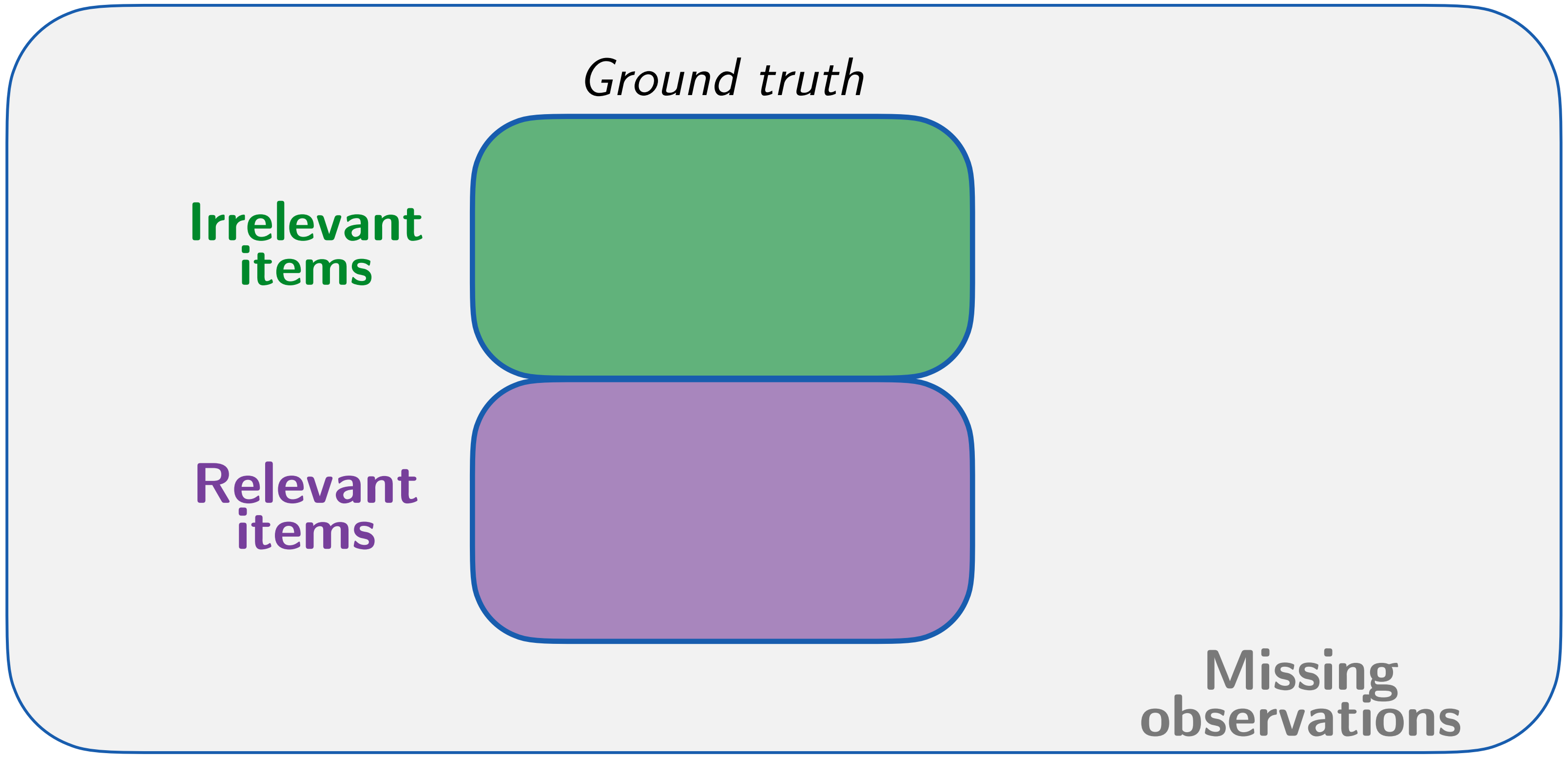


Complete dataset

Evaluation metrics for accuracy

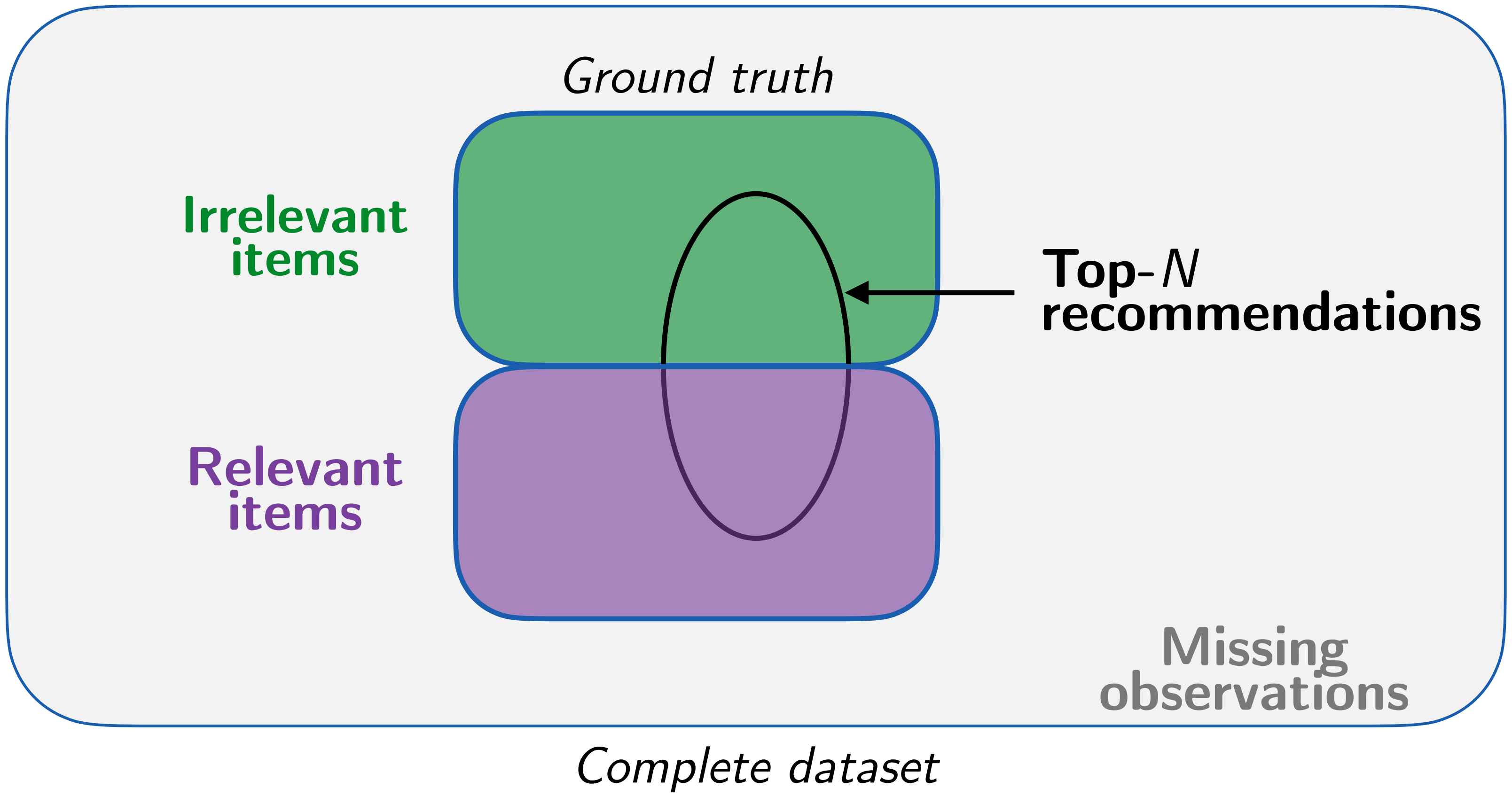
Measuring the accuracy of top-N recommendations



Complete dataset

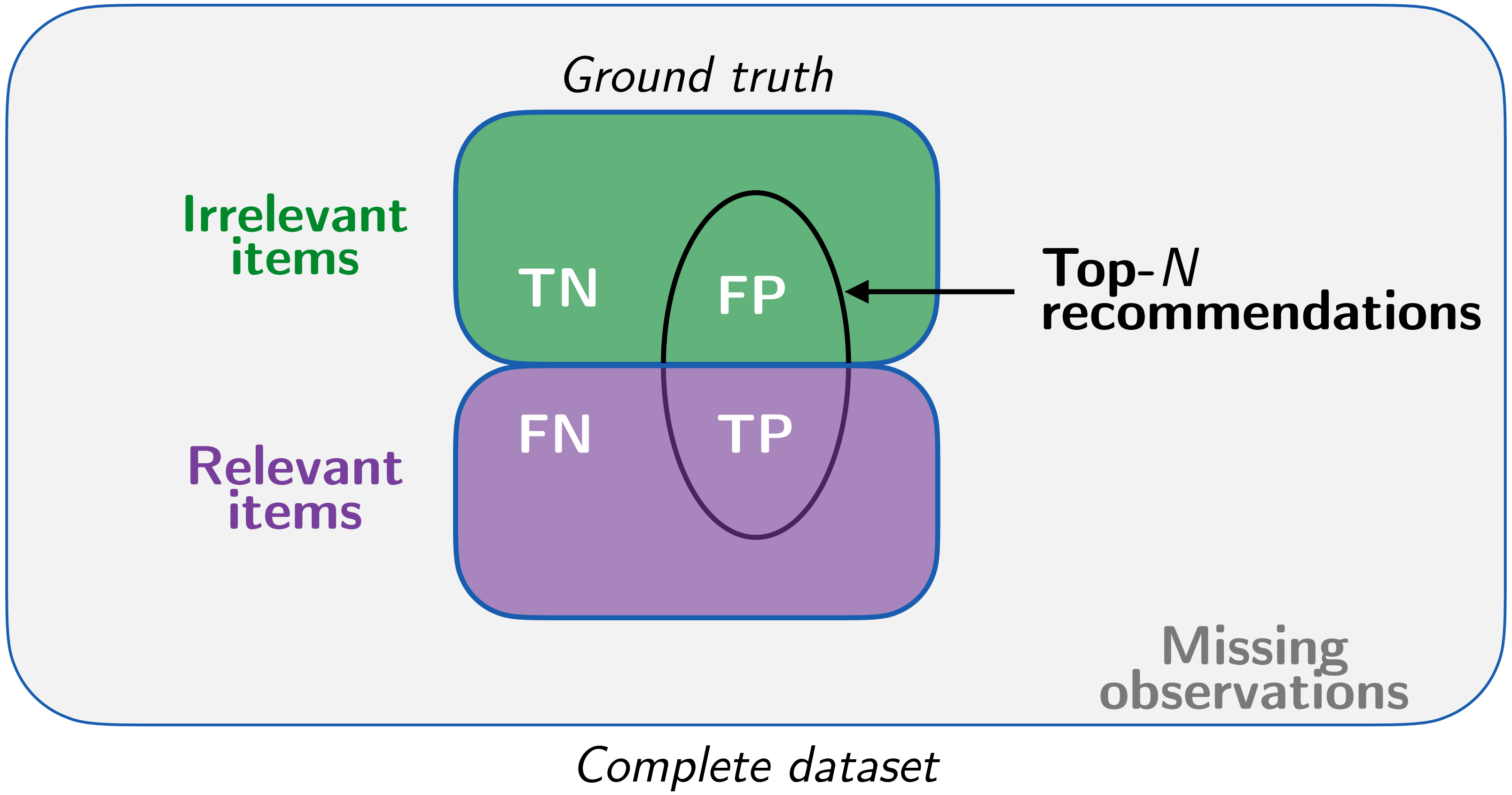
Evaluation metrics for accuracy

Measuring the accuracy of top-N recommendations



Evaluation metrics for accuracy

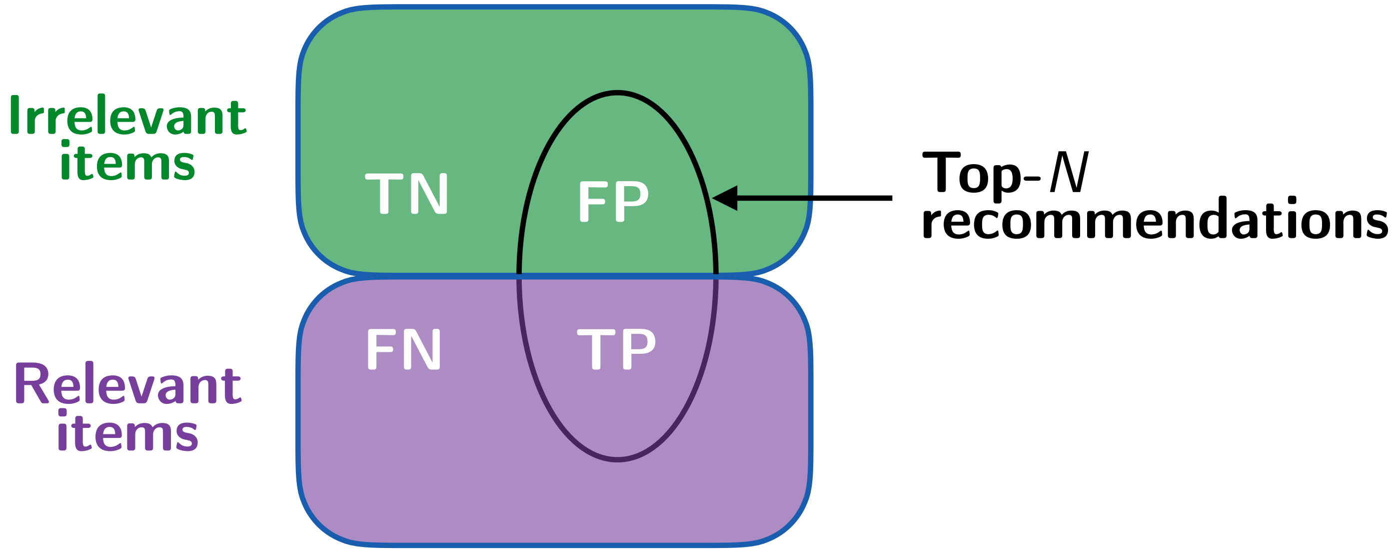
Measuring the accuracy of top-N recommendations



Evaluation metrics for accuracy

Measuring the accuracy of top-N recommendations

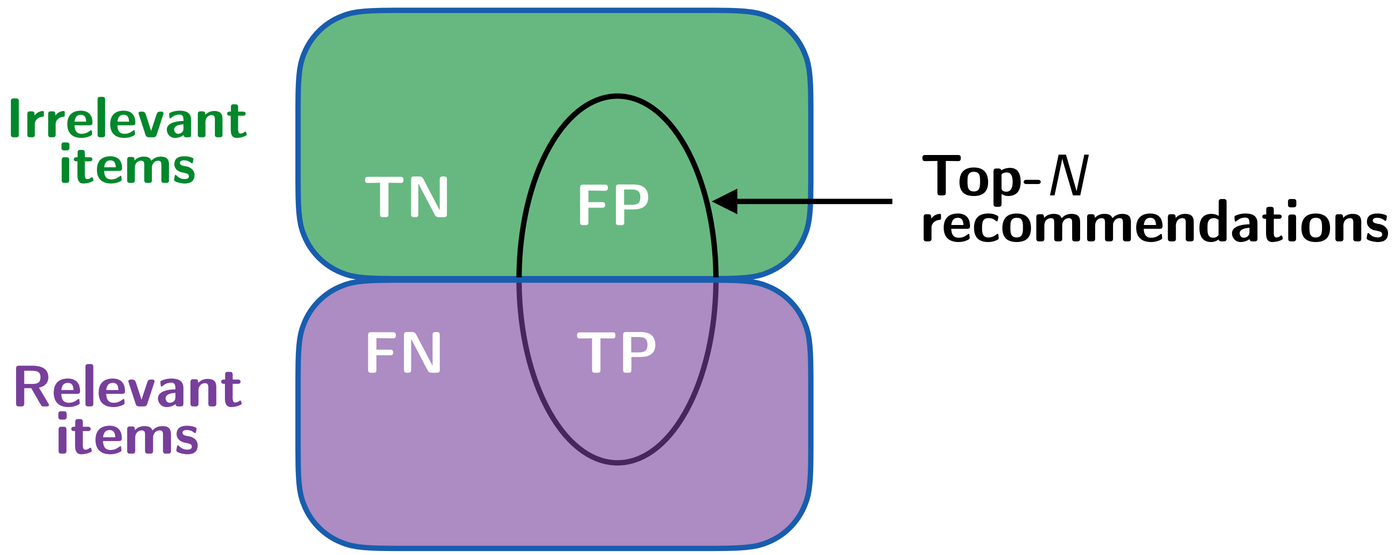
$$Recall_u@N = \frac{TP}{FN + TP} = \frac{\#relevant\ recommended\ items}{\#relevant\ items}$$



Evaluation metrics for accuracy

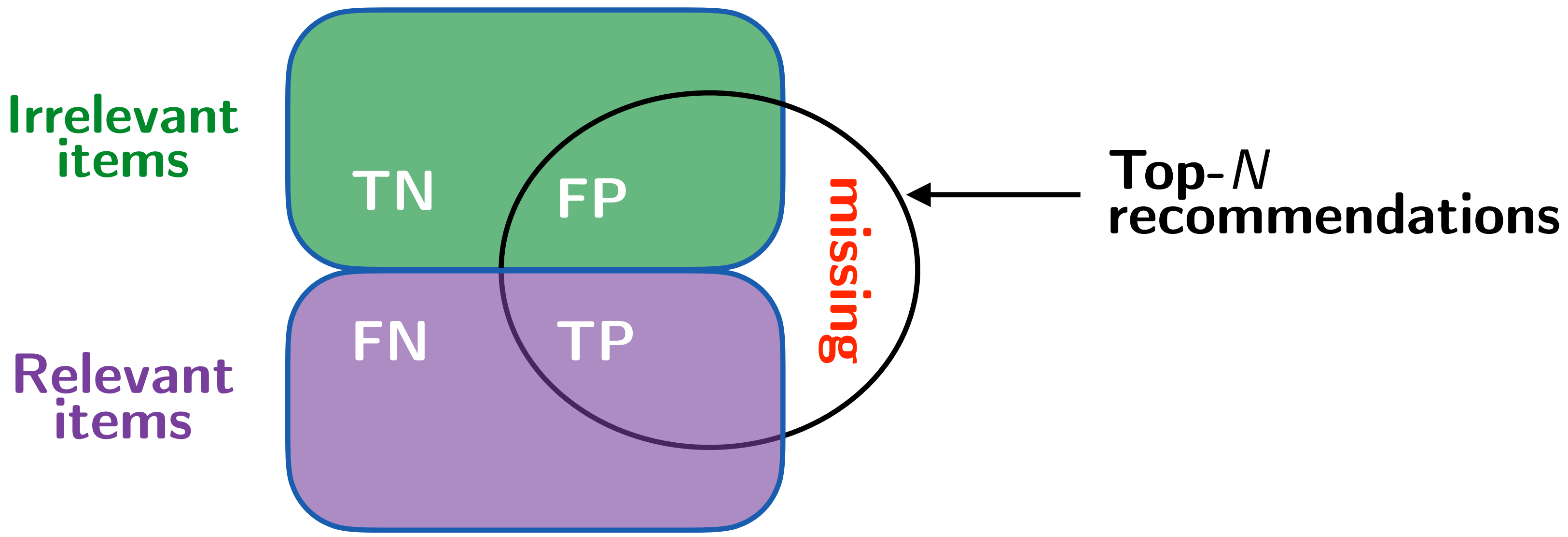
Measuring the accuracy of top-N recommendations

$$Precision_u@N = \frac{TP}{FP+TP} = \frac{\#relevant\ recommended\ items}{\#recommended\ items}$$



Evaluation metrics for accuracy

- Recall: *Missing Not As Random* assumption
  - Non-relevant items are more likely to be missing than relevant items
- Precision: *All Missing As Negative* assumption
  - All missing ratings are irrelevant



Evaluation metrics for ranking

Measuring the quality of ranking of top-N recommendations

- Discounted Cumulative Gain (DCG):

$$DCG_u@N = \sum_{i=1}^{N} \frac{rel_{ui}}{log_2(i+1)}$$

where rel_{ui} = *1* if item at rank i is relevant, *0* otherwise.

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$$DCG_u \quad 1 + 0 + 0 + 0.43 + 0.38$$

Evaluation metrics for ranking

Measuring the quality of ranking of top-*N* recommendations

- Normalized Discounted Cumulative Gain (DCG):

$$NDCG@N = \frac{1}{|\mathcal{T}_u|} \sum_{u \in \mathcal{T}_u} \frac{DCG_u@N}{DCG_u^*@N}$$

where $DCG^*{}_u$ is the best possible DCG_u that can be obtained.

Evaluation metrics for ranking

Measuring the quality of ranking of top-*N* recommendations

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$$NDCG@N = \frac{1}{|\mathcal{T}_u|} \sum_{u \in \mathcal{T}_u} \frac{DCG_u@N}{DCG^*_u@N}$$

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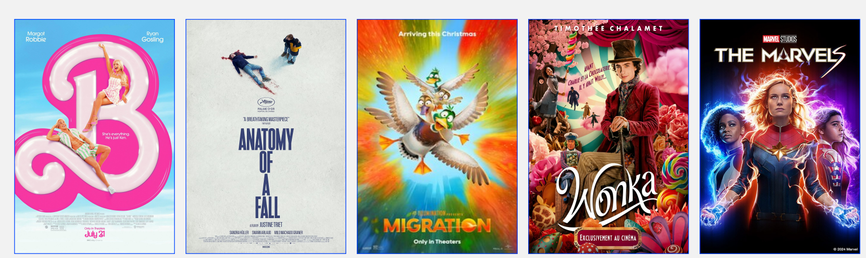
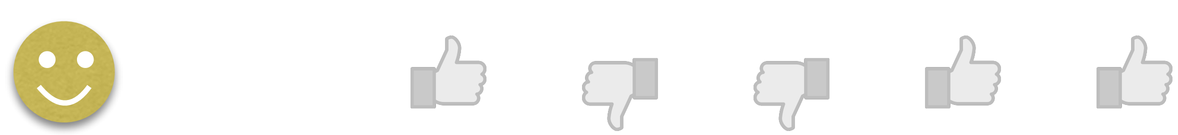
Recommendation list



i = 1 i = 2 i = 3 i = 4 i = 5



$DCG^*{}_u$ $1 + 0.63 + 0.5 + 0.43 + 0.38$

List of other used metrics

- Mean Average Precision (MAP)
- Mean Reciprocal Rank (MRR)
- Area under the ROC Curve (AUC)
- Hit-Rank (HR)
- Average Reciprocal Hit-Rank (ARHR)

  ...

Non-personalized recommendations

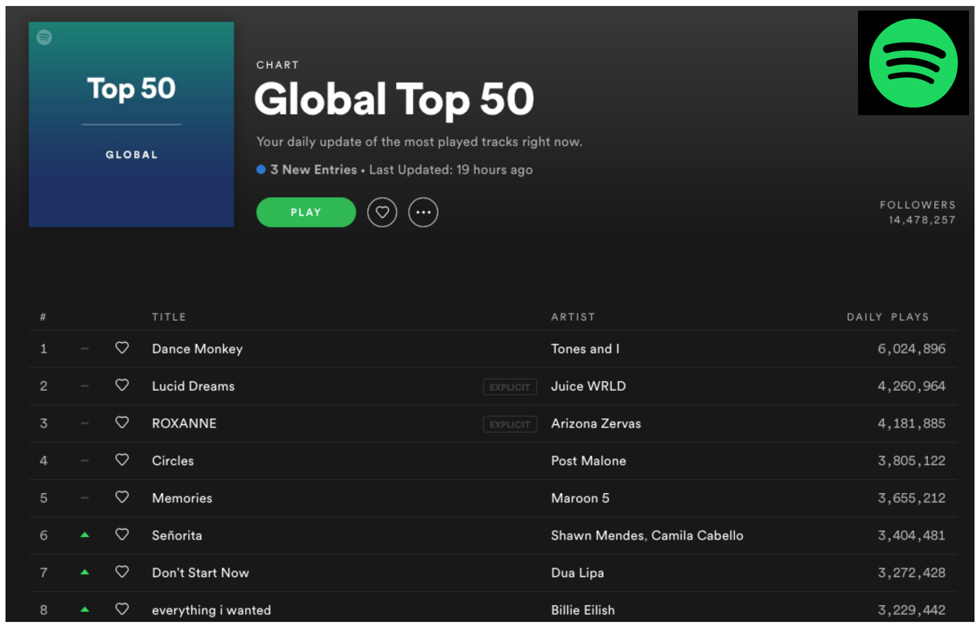
Non-personalized recommendations

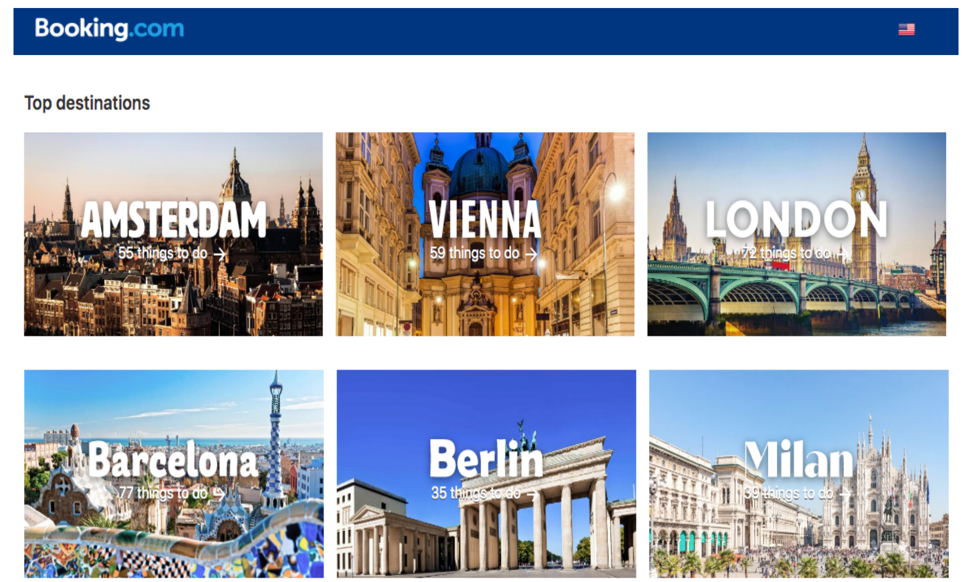
- Personalized recommendations
  - Tailor the recommendation list to a specific individual
  - Using information about the target user and similar users

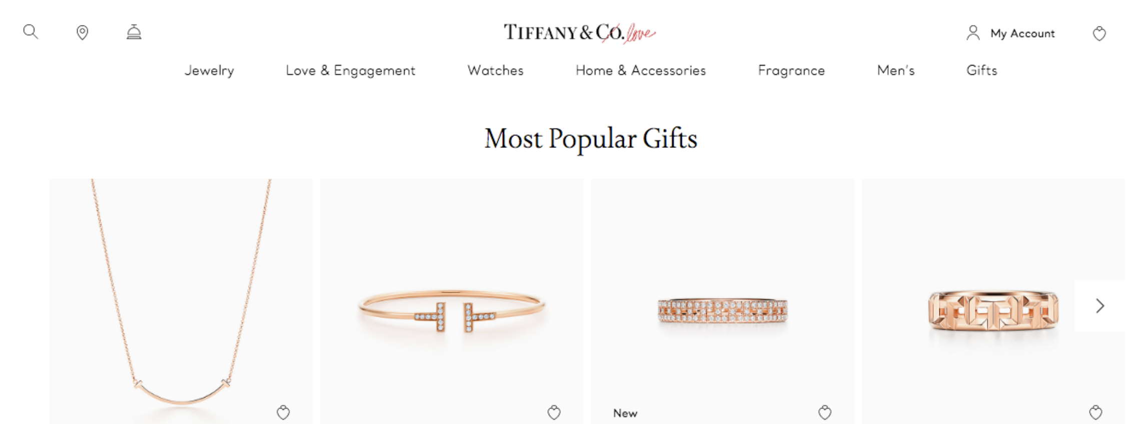
vs.

- Non-personalized recommendations
  - Do not require to know anything about the individual user
  - Using aggregated information about users

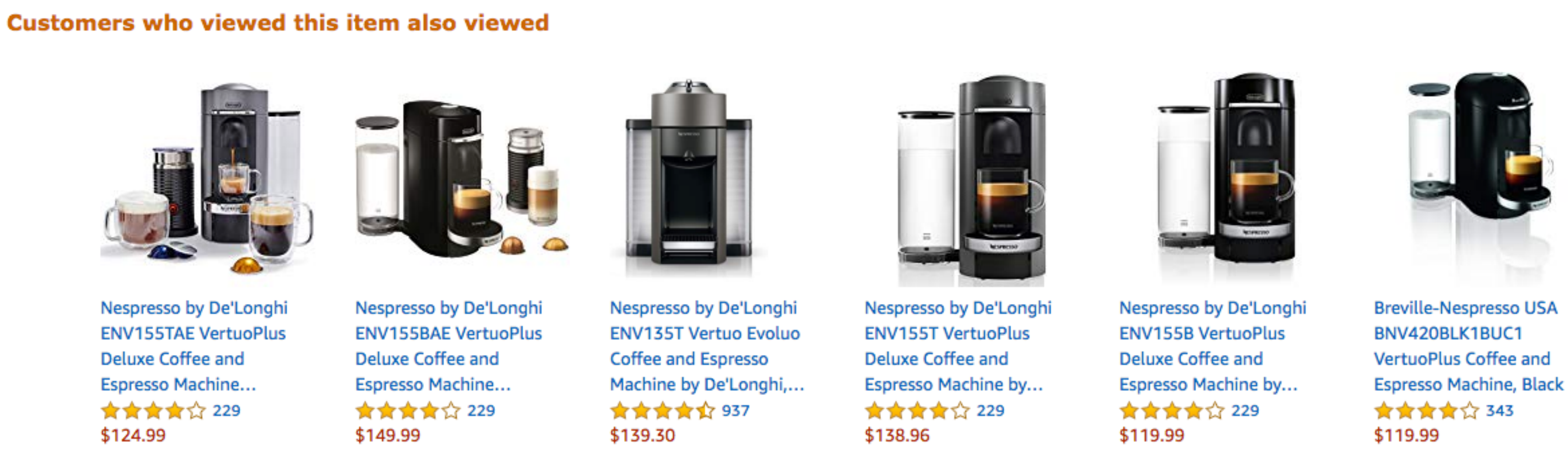
Most popular item recommendation







Association rules

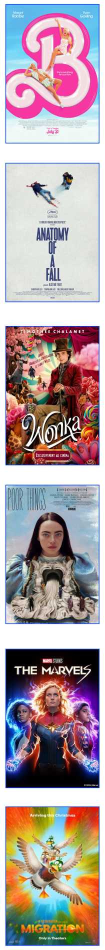


Association rules

1		1	1		
			1	1	1
	1	1	1		
1	1			1	1
	1		1		

Also watched...

Users who watched...



	1	1	1	1	1
1		1	2	1	1
1	1		2	0	0
1	2	2		1	1
1	1	0	1		2
1	1	0	1	2	

Confidence: $c(i \to j) = \dfrac{|\mathcal{U}_i \cap \mathcal{U}_j|}{|\mathcal{U}_i|}$

Support: $S(i \to j) = \dfrac{|\mathcal{U}_i \cap \mathcal{U}_j|}{|\mathcal{U}|}$

Towards personalized recommendations...

- Recommendations approaches
  - Collaborative Filtering approaches
  - Content-Based Filtering approaches
  - Hybrid approaches
  - Context-aware approaches