# RECOMMENDER SYSTEMS

Mirko Polato, PhD
University of Turin
Computer Science Department
mirko.polato@unito.it

# SCHEDULE

01 RECOMMENDER SYSTEMS
What is a recommender systems and why it is important

02 RECSYS ALGORITHMS
Is accuracy the sole metric we care?

03 EVALUATING RECOMMENDER SYSTEMS
Is accuracy the sole metric we care?

04 CHALLANGES IN RECSYS
Other challenges in the recsys research field

01

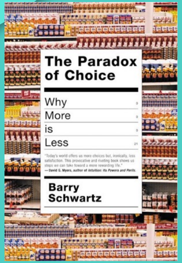
# RECOMMENDER SYSTEMS

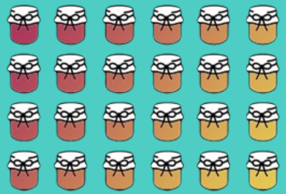
What is a recommender systems and
why it is important

«We are leaving the Information Age and entering the **Recommendation Age** [...] Information gathering is no longer the issue - making smart decisions based on the information is now the trick [...] So recommendations act as shortcuts through the information mass, getting us to the right, or "right enough" answer.»

—CHRIS ANDERSON (THE LONG TAIL, 2006)

# THE PARADOX OF CHOICE – WHY MORE IS LESS



**24 flavors of jam**

- **60%** of the customers stopped at the booth;
- On average, 2 tastes;
- Only the **3%** of the customers purchased.

**6 flavors of jam**

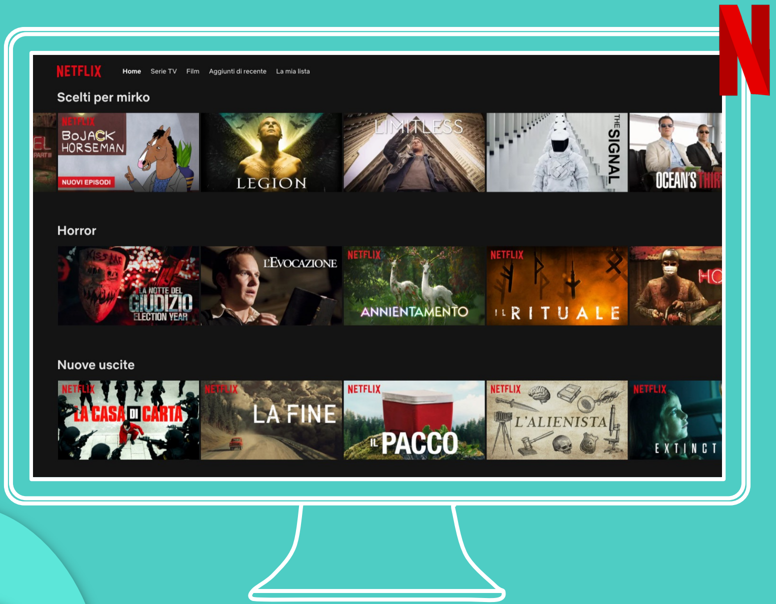
- **40%** of the customers stopped at the booth;
- On average, 2 tastes;
- **30%** of the customers purchased.

# WHAT IS A RECOMMENDER SYSTEM?

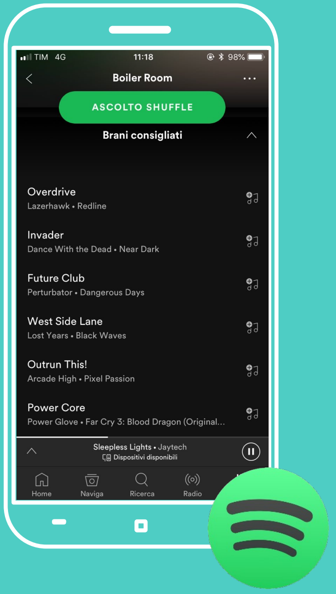
A recommender system is a subclass of information filtering system that seeks to predict the preference a user would give to an item.

—WIKIPEDIA

# RECSYS IN EVERYDAY LIFE







# RECSYS INGREDIENTS

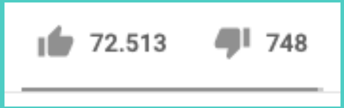
USERS

ITEMS

RATINGS

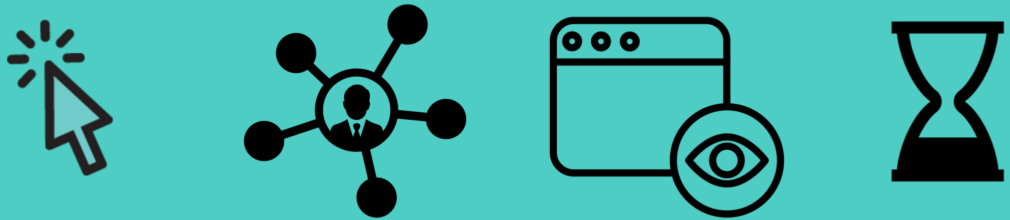
# USER FEEDBACK

## EXPLICIT FEEDBACK



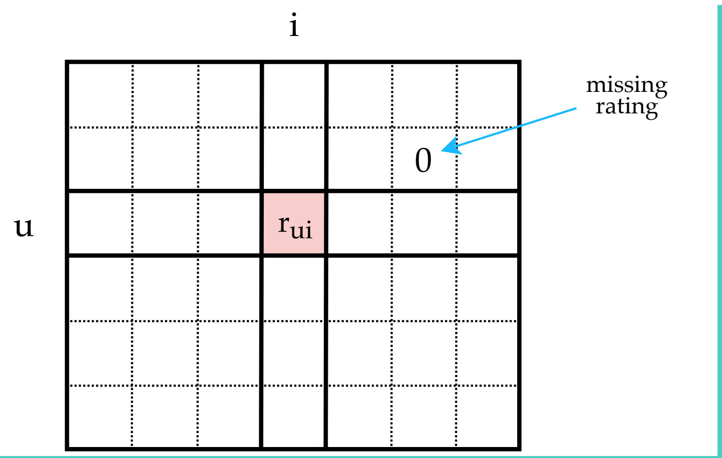


## IMPLICIT FEEDBACK



# RATING MATRIX

- **Explicit feedback:** the rating is expressed inside a range of values, e.g., [1,5] like in the 5 stars rating systems;
- **Implicit feedback:** usually the rating is binary (either 0 or 1), where 1 means an interaction and 0 a missing interaction.



# CONTEXT

- DATE/TIME
- LOCATION
- WEATHER
- MOOD

03

# RECSYS ALGORITHMS

How to make recommendation using machine laerning

# MOST COMMON APPROACHES

## COLLABORATIVE

Similar users like similar items. The similarity is computed on the basis of historical choices

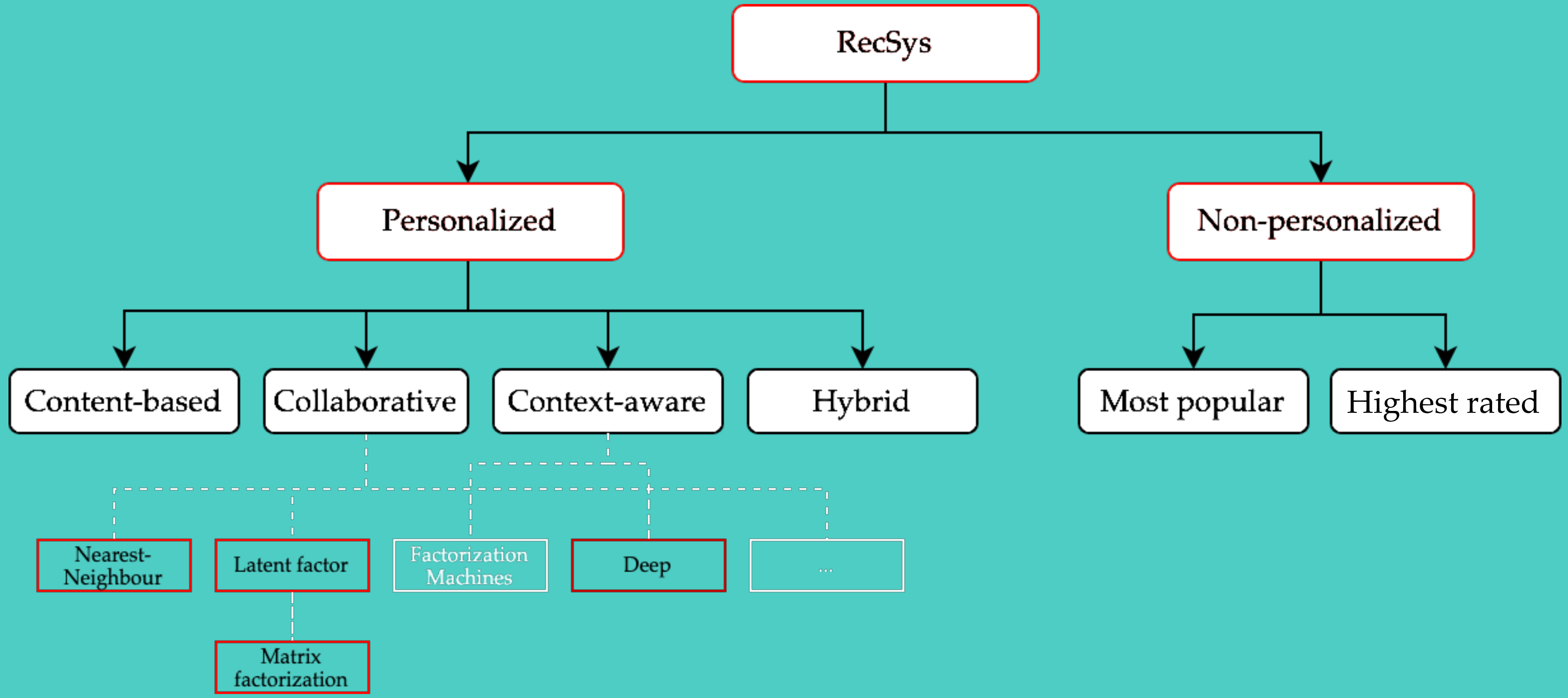
## CONTENT-BASED

User likes items with similar content (i.e., features) to the ones liked in the past

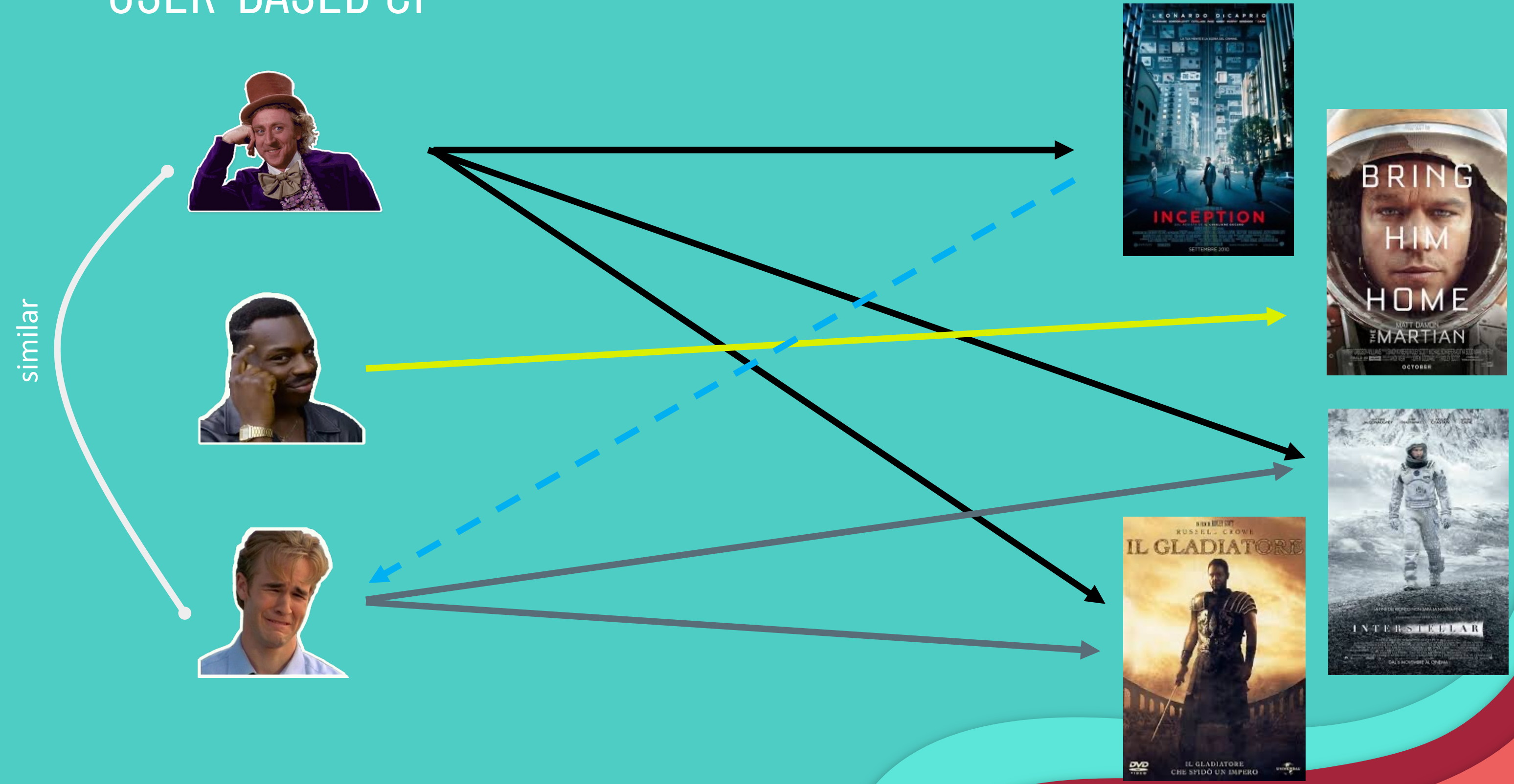
## HYBRID

Merges the PROS of both CF and CB

# RECSYS TAXONOMY

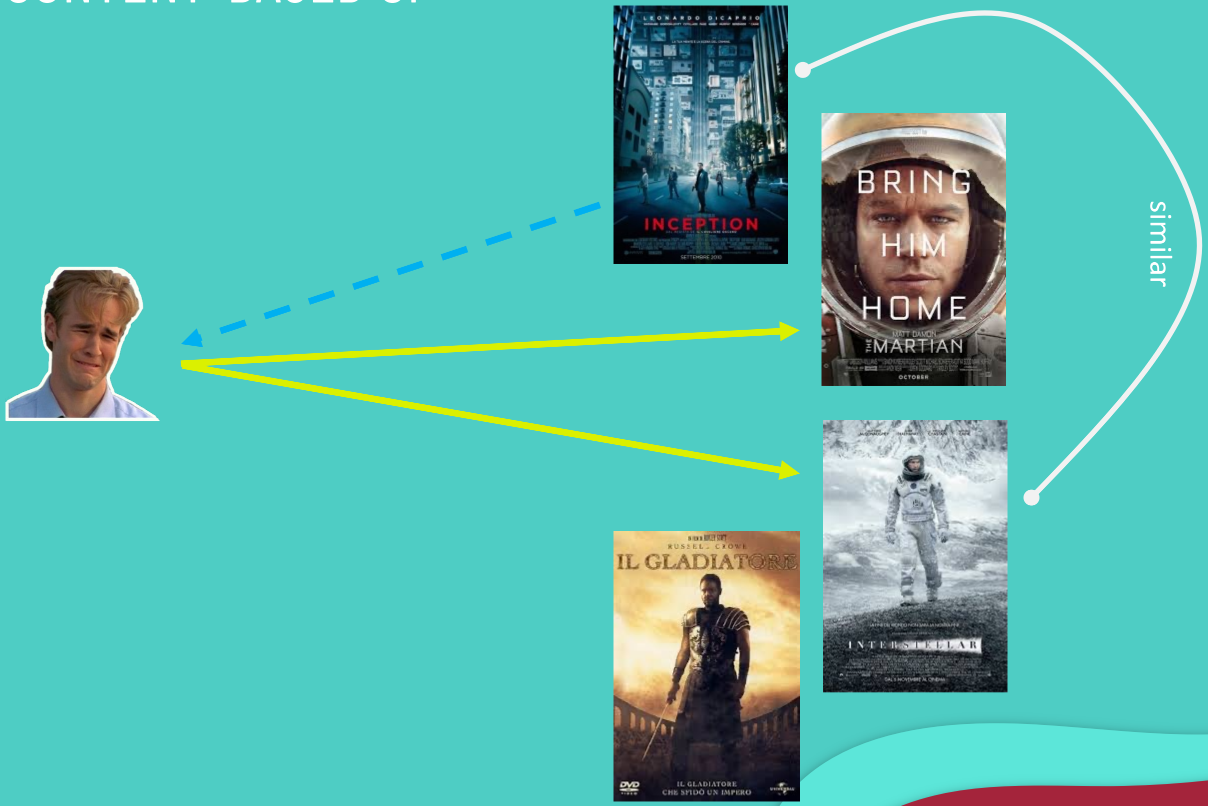


# USER-BASED CF



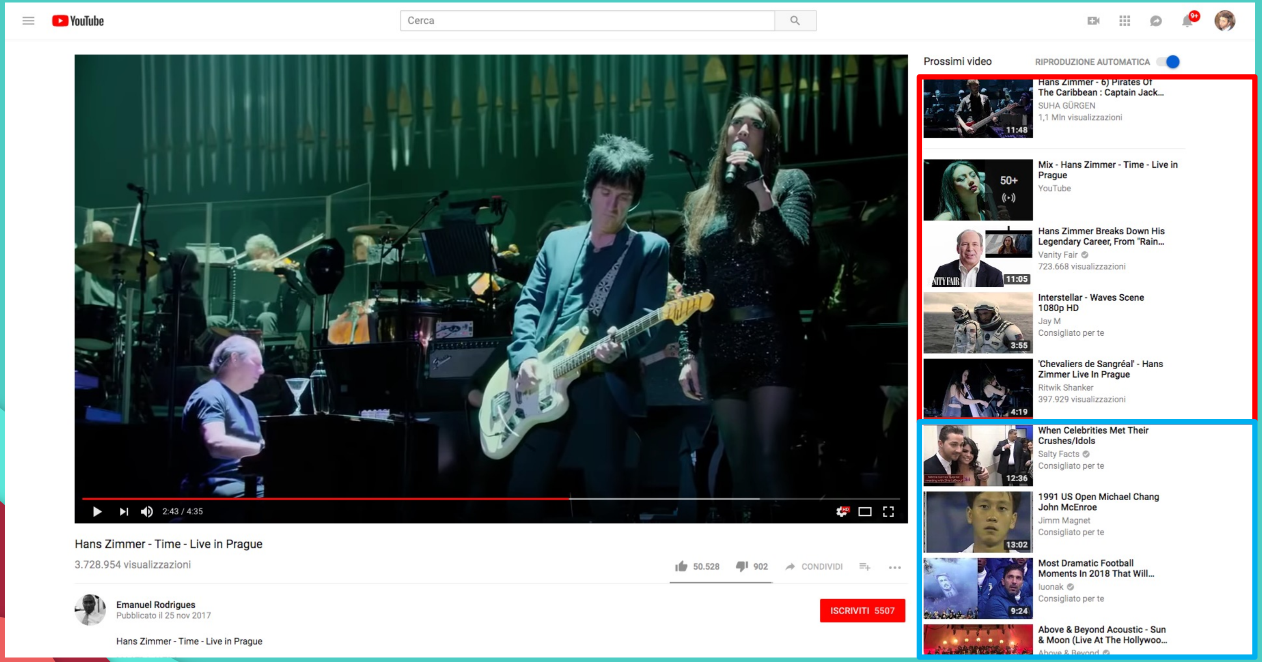
# ITEM-BASED CF

# CONTENT-BASED CF




Genre: Sci-Fi
Director: C. Nolan
OST: H. Zimmer
Starring: M. Caine

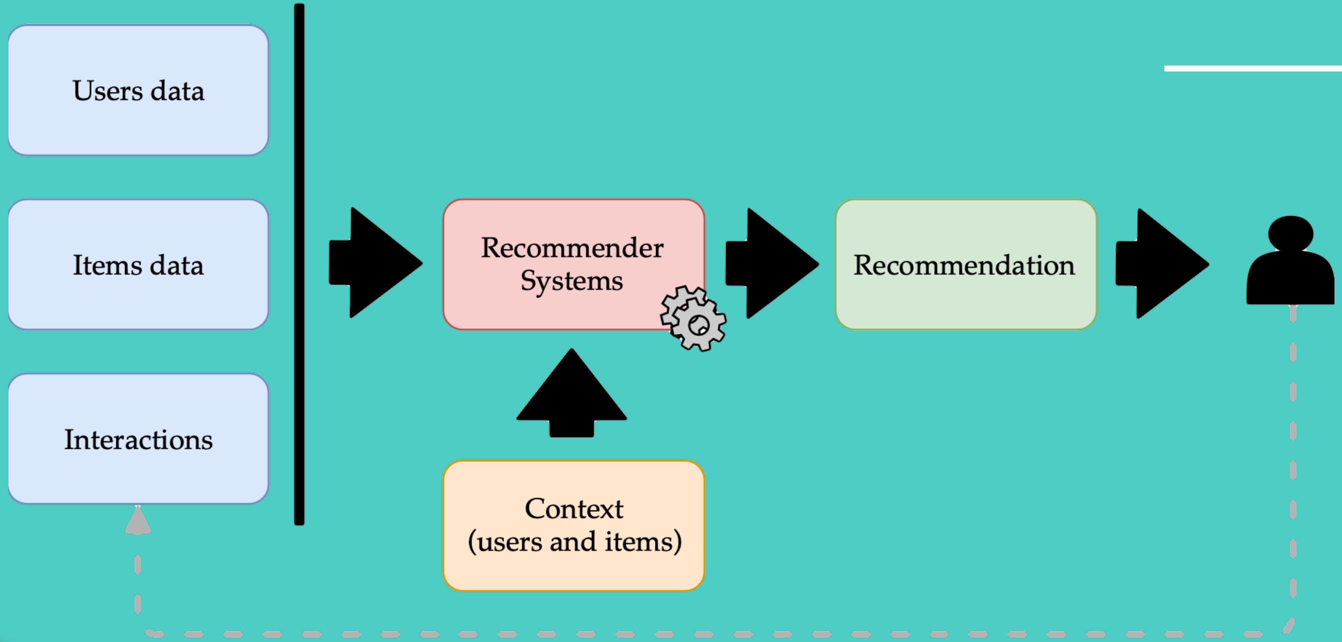
# AN EVERYDAY EXAMPLE




CF ITEM-BASED + CONTENT-BASED

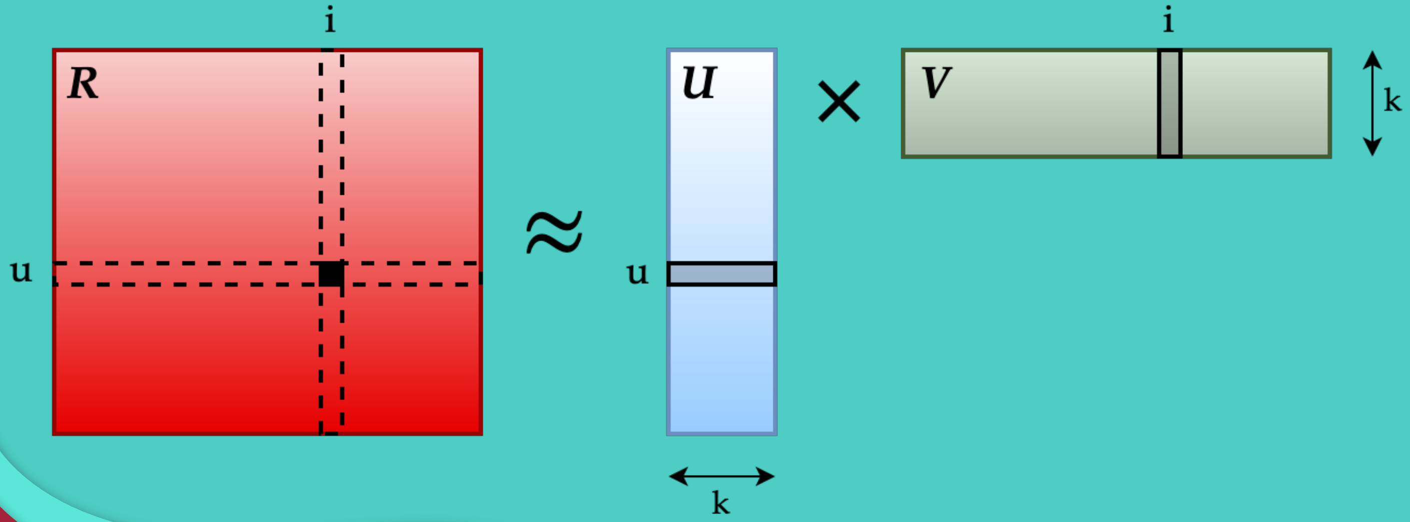
CF USER-BASED

# RECSYS STANDARD PIPELINE

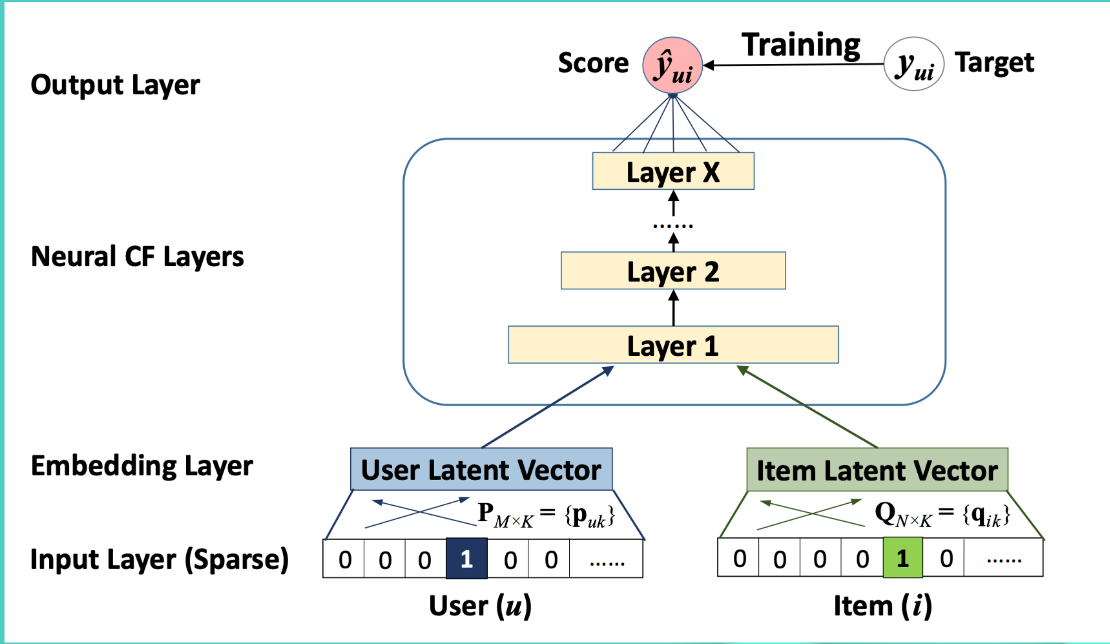


# MATRIX FACTORIZATION

$$\mathbf{R} \approx \mathbf{P}\mathbf{Q}^\top \quad \mathbf{R} \in \mathbb{R}^{m\times n}, \mathbf{P} \in \mathbb{R}^{n\times k}, \mathbf{Q} \in \mathbb{R}^{m\times k}$$

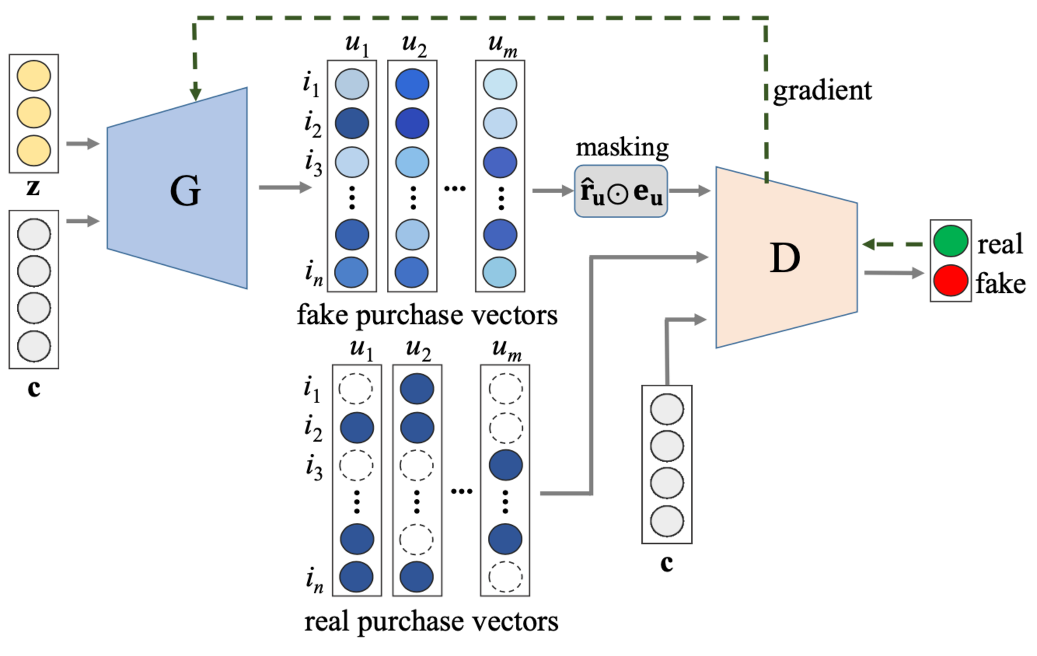


# DEEP NEURAL NETWORK



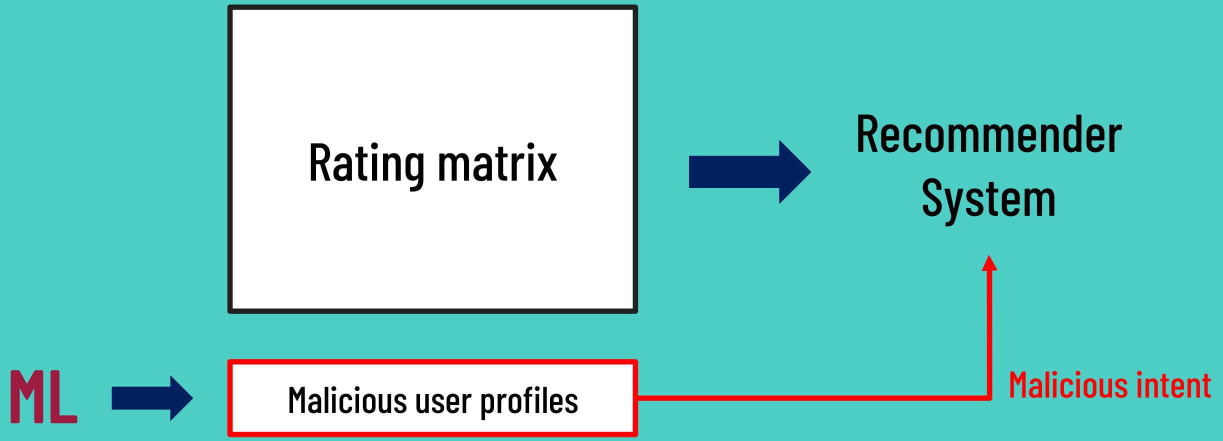

Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural Collaborative Filtering. In Proceedings of the 26th International Conference on World Wide Web (WWW '17). International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE, 173–182. https://doi.org/10.1145/3038912.3052569

# GENERATIVE APPROACHES



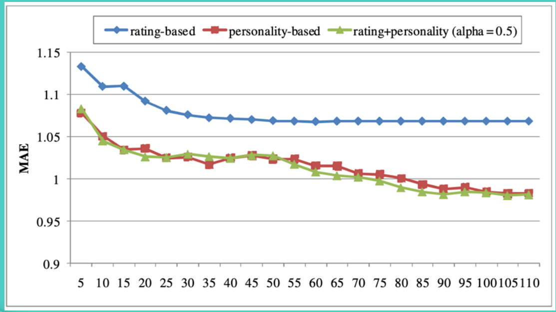

Dong-Kyu Chae, Jin-Soo Kang, Sang-Wook Kim, and Jung-Tae Lee. 2018. CFGAN: A Generic Collaborative Filtering Framework based on Generative Adversarial Networks. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM '18). Association for Computing Machinery, New York, NY, USA, 137–146

# SECURITY & PRIVACY IN RECSYS



# PERSONALITY IN RECSYS

## Personality as similarity [1]




## Personality and MF [2]

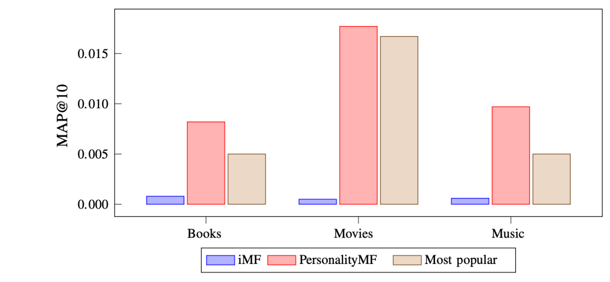



**Fig. 3** MAP@10 in the extreme cold-start scenario

## Personality and ratings [3]

**Table 4. A summary of proportions of consumptions across various categories. (p < 0.001: *** p < 0.01 ** p < 0.05 *)**

| | Openness | Conscientiousness | Extroversion | Agreeableness | Neuroticism |
|---|---|---|---|---|---|
| **Action** | | low > high (+2%) * | | | low > high (+2%)** |
| **Adventure** | low > high (+1%) * | | | | low > high (+1%) * |
| **Comedy** | | | | | high > low (+2%) * |
| **Drama** | high > low (+4%) ** | | | | |
| **Fantasy** | low > high (+1%) *** | | | | low > high (+1%) * |
| **Romance** | high > low (+1%) ** | high > low (+2%) ** | low > high (+1%)* | | high > low (+1%) * |
| **Thriller** | low > high (+1%) * | low > high (+2%) * | | | low > high (+1%) * |

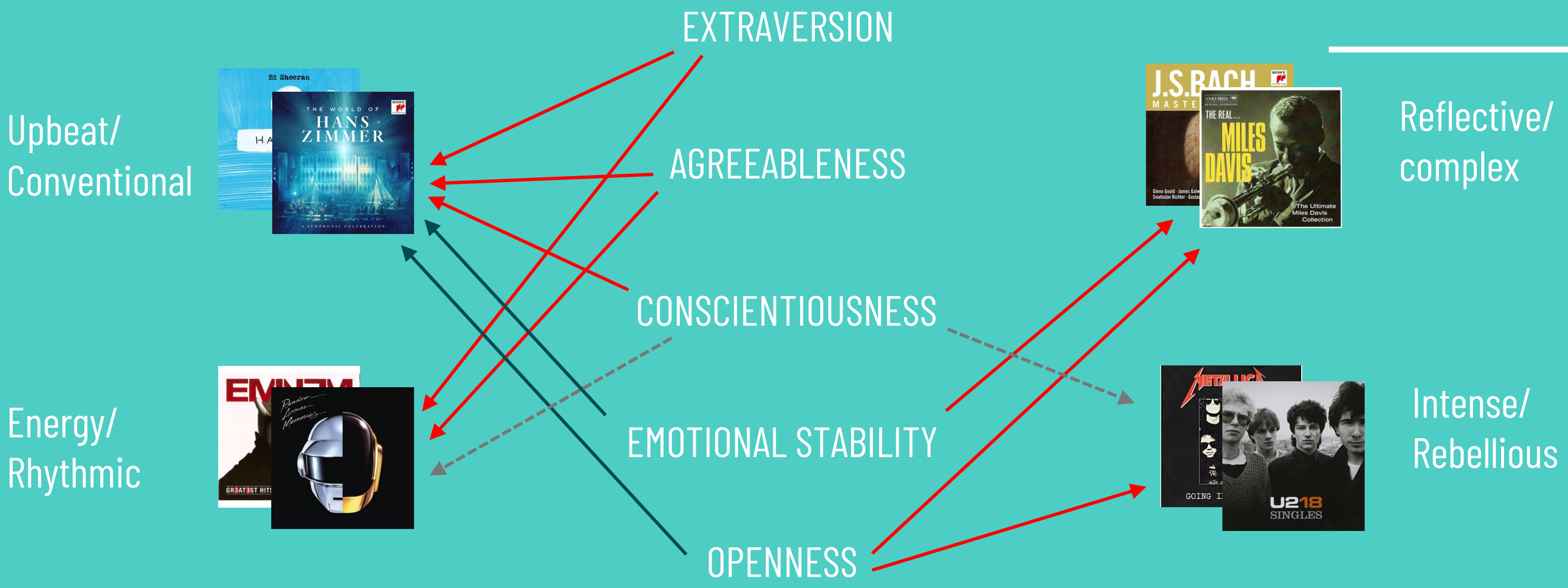

[1] Hu, R., and Pu, P. (2010). Using Personality Information in Collaborative Filtering for New Users. In Proceedings of the 2nd ACM RecSys'10 Workshop on Recommender Systems and the Social Web (pp. 17–24).

[2] Fernández-Tobías, I., Braunhofer, M., Elahi, M., Ricci, F., and Cantador, I. (2016). Alleviating the new user problem in collaborative filtering by exploiting personality information. User Modeling and User-Adapted Interaction, 26(2), 1-35.

[3] Karumur, R. P., Nguyen, T. T., and Konstan, J. A. (2016). Exploring the Value of Personality in Predicting Rating Behaviors. In Proceedings of the 10th ACM Conference on Recommender Systems - RecSys '16 (pp. 139–142).

# PERSONALITY AND MUSIC PREFERENCES

## BIG 5




[1] Rentfrow, P. J., and Gosling, S. D. (2003). The do re mi's of everyday life: The structure and personality correlates of music preferences. Journal of Personality and Social Psychology, 84(6), 1236-1256.

[2] Tkalčič, M., Ferwerda, B., Hauger, D., and Schedl, M. (2015). Personality Correlates for Digital Concert Program Notes. In UMAP 2015, Lecture Notes On Computer Science 9146 (Vol. 9146, pp. 364-369).

# EMOTIONS IN RECSYS

## Emotion as implicit feedback [2]

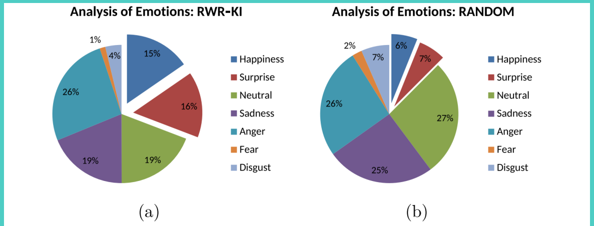



**Fig. 13.** Analysis of emotions associated with serendipitous recommendations.

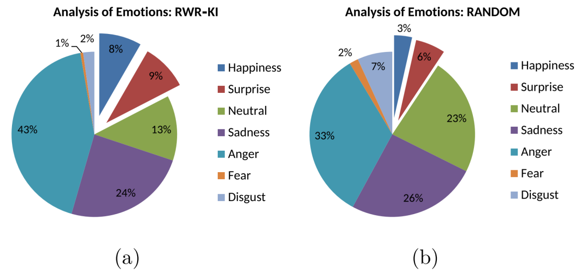
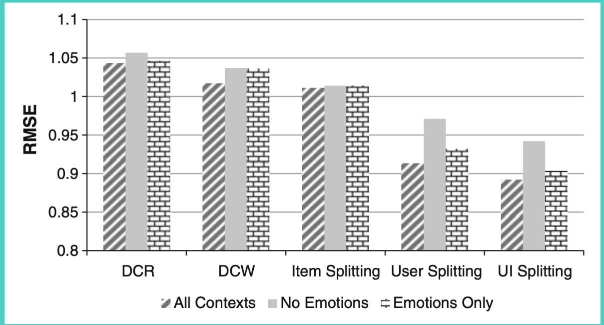



**Fig. 14.** Analysis of emotions associated with non-serendipitous recommendations.

## Emotion as context [1]





[1] Zheng, Y., Mobasher, B., and Burke, R. (2016). Emotions in Context-Aware Recommender Systems (pp. 311-326). In M. Tkalčič, B. De Carolis, M. de Gemmis, A. Odić, and A. Košir (Eds.), Emotions and Personality in Personalized Services: Models, Evaluation and Applications

[2] Gemmis, M. De, Lops, P., Semeraro, G., and Musto, C. (2015). An investigation on the serendipity problem in recommender systems. Information Processing and Management, 51(5), 695-717.

03

# EVALUATING RECOMMENDER SYSTEMS

Is accuracy the sole metric we care?

# EVALUATING RECSYS

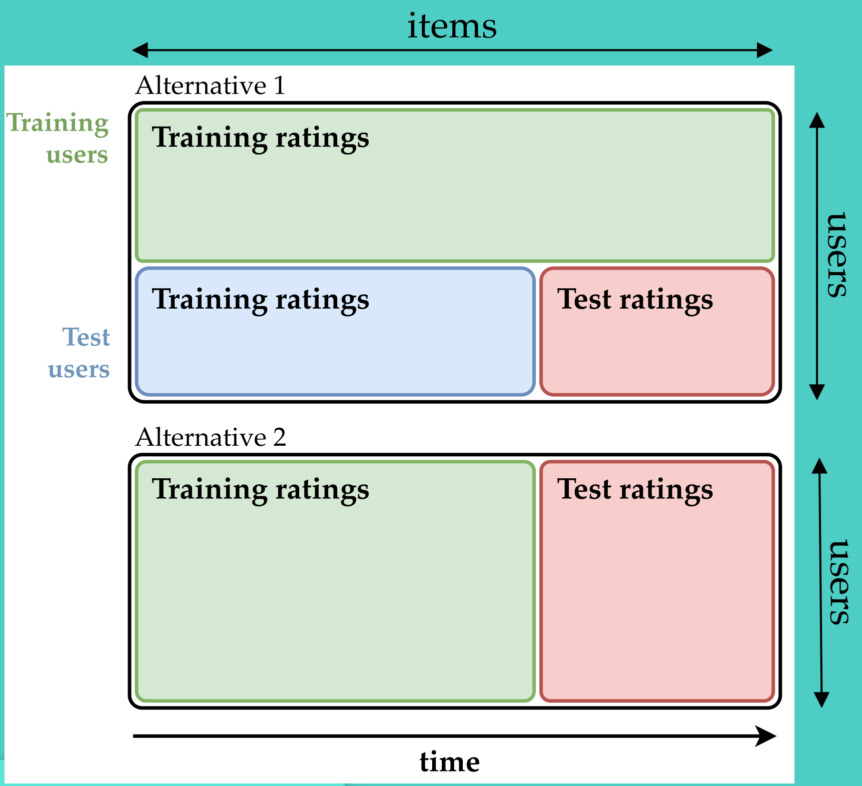
## Precision-oriented

- Standard metrics borrowed from Information Retrieval and dal Machine learning
- E.g., Precision, Recall, AUC, Hit@k, AP@k, MRR, …

## Experience-oriented

- Focus on **user-experience**
  - Novelty
  - Diversity
  - Serendipity

# HOW TO PARTITION A DATASET



# EXPERIENCE-ORIENTED MEASURES

## DIVERSITY

- Internal difference in the current experience (recommendation)
- Assessed inside the set of recommended items independently from the user history
- Useful to offer/show diverse items

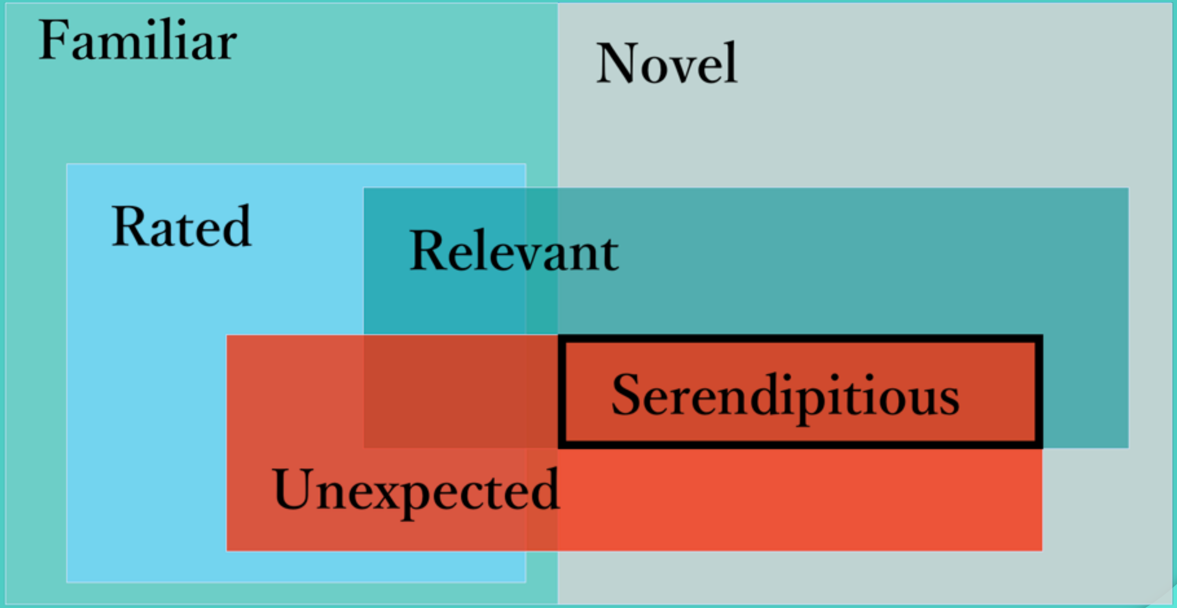
## NOVELTY

- Difference of the current experience w.r.t. the past ones
- Globally speaking is the **opposite of the popularity**
- Useful to offer/show nevel items

## SERENDIPITY

- Special case of novelty: relevant + novel + **unexpected**
- Includes an **emotional component**
- Not clear how to evaluate

# VISUAL INTUITION



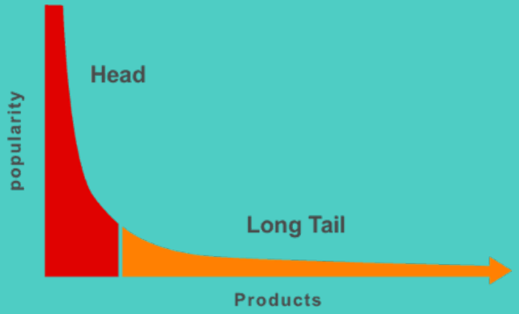
04

# CHALLENGES IN RECSYS

Other challenges in the recsys research field

# TYPICAL CHALLENGES

LONG-TAIL DISTRIBUTION




DATA SPARSITY

COLD START

# VISUALIZATION CHALLENGES IN RECSYS

Considering different situations, such as mood, time, individual, or collaborative scenarios

CTX-AWARENESS

# VISUALIZATION CHALLENGES IN RECSYS

Presenting visualizations to browse the entire information space

EXPLORABILITY

CTX-AWARENESS

# VISUALIZATION CHALLENGES IN RECSYS

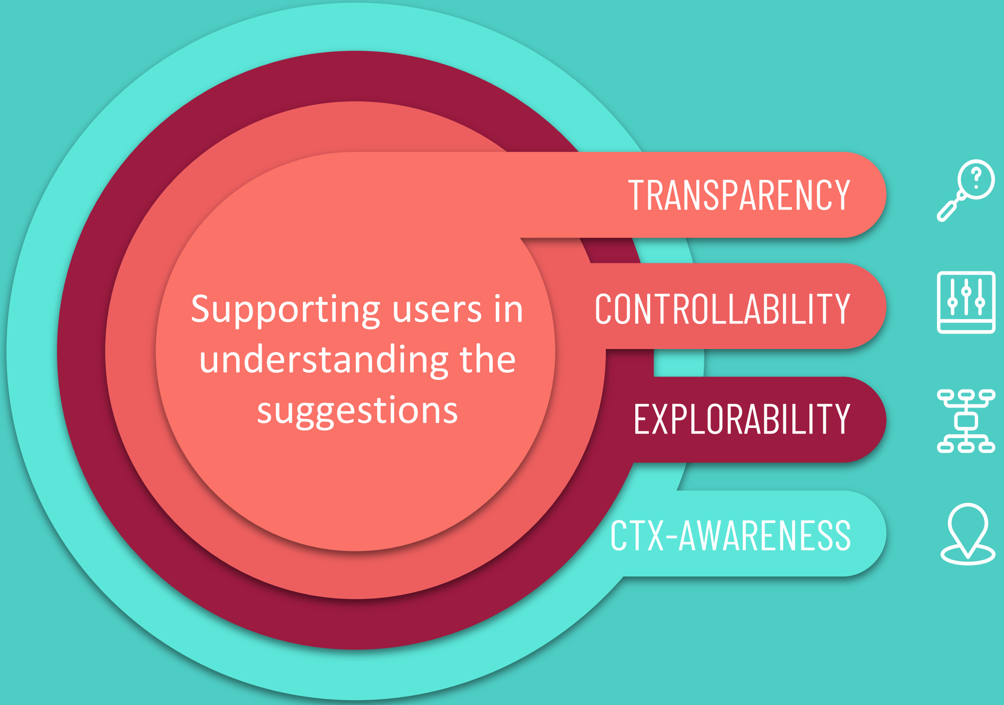
Providing users control over features that influence the algorithm

CONTROLLABILITY

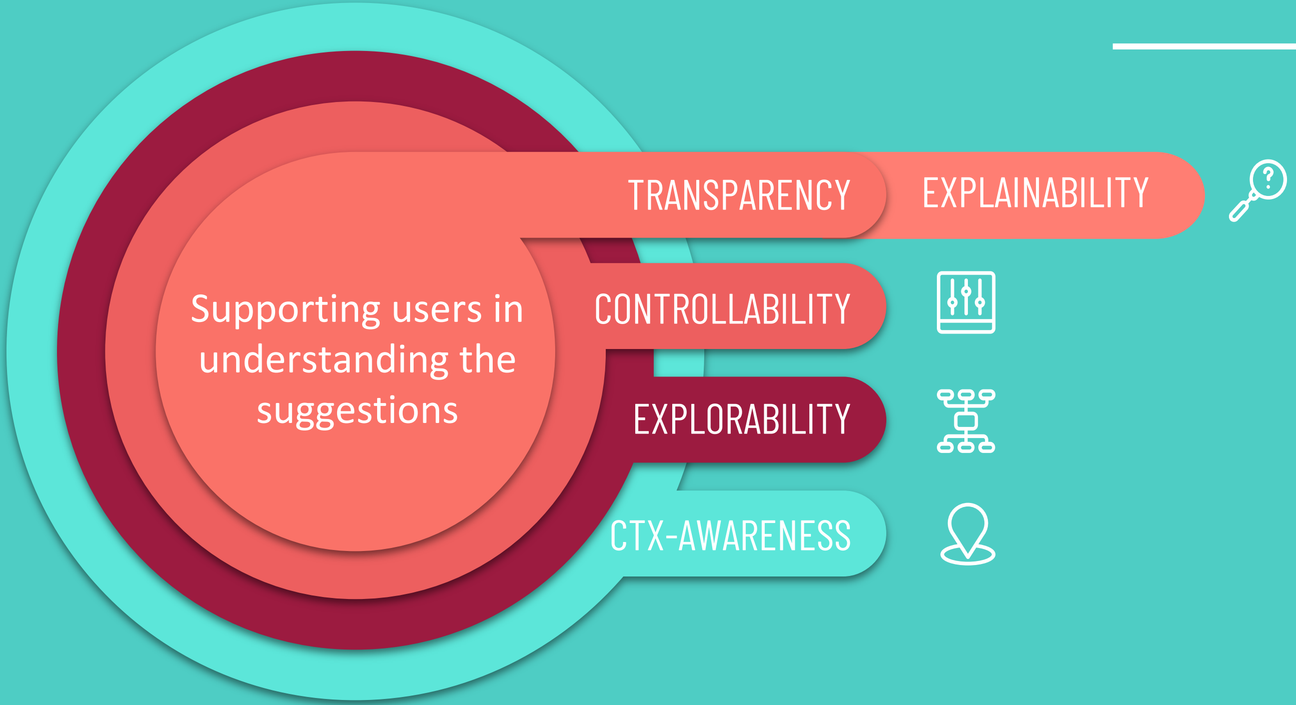
EXPLORABILITY

CTX-AWARENESS

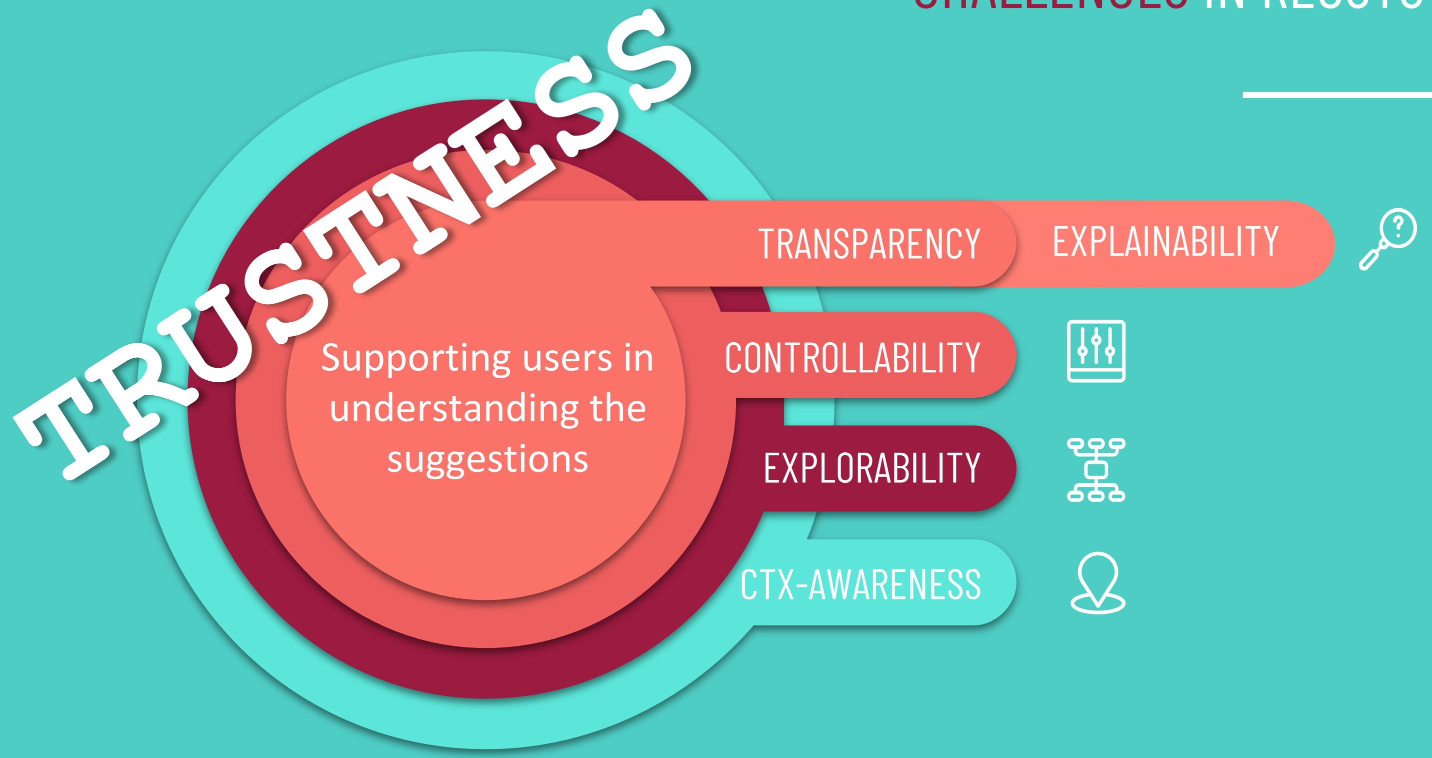
# VISUALIZATION CHALLENGES IN RECSYS



# VISUALIZATION CHALLENGES IN RECSYS



# VISUALIZATION CHALLENGES IN RECSYS



# THANKS!

Any questions?

Mirko Polato, PhD
mirko.polato@unito.it