

# Recommender Systems

## lecture 1: introduction

Alexey Grishanov

Moscow Institute of Physics and Technology

Spring 2025

## «What is recommender system?» evolution:

In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients. In some cases the primary transformation is in the aggregation; in others the system's value lies in its ability to make good matches between the recommenders and those seeking recommendations.

● **Resnick, P. and Varian, H. R.: 1997, 'Recommender Systems'. Communications of the ACM**

More formally, the recommendation problem can be formulated as follows: Let  $C$  be the set of all users and let  $S$  be the set of all possible items that can be recommended. Let  $u$  be a utility function that measures the usefulness of item  $s$  to user  $c$ , that is,  $u: C \times S \Rightarrow \mathbb{R}$ , where  $\mathbb{R}$  is a totally ordered set (for example, nonnegative integers or real numbers within a certain range). Then, for each user  $c \in C$ , we want to choose such item  $s' \in S$  that maximizes the user's utility.

● **Adomavicius, G., and Tuzhilin, A. 2005. Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. IEEE Transactions on Knowledge and Data Engineering**



The screenshot shows the Netflix Prize Leaderboard interface. At the top, there's a yellow banner with the 'Netflix Prize' logo. Below it, a navigation bar contains links: Home, Rules, Leaderboard, Register, Update, Submit, and Download. The main heading is 'Leaderboard' in blue. To the right of the heading is a 'Display top' dropdown menu set to '20' and a 'leaders.' label. The table below lists the top 20 teams. The first two rows are highlighted in red, indicating the Grand Prize winners. The table has five columns: Rank, Team Name, Best Score, % Improvement, and Last Submit Time. The teams listed include The Ensemble, BellKor's Pragmatic Chaos, Grand Prize Team, Qora Solutions and Vandelay United, Vandelay Industries I, PragmaticTheory, BellKor in BigChaos, Qora, Qora Solutions, BellKor, BigChaos, Feeds2, Progress Prize 2008 - RMSE = 0.8616 - Winning Team: BellKor in BigChaos, xianxiang, Grady, Cms, Invisible Ideas, Just a guy in a garage, Craig Carmichael, J.Dennis Su, and acutwill. The bottom of the table shows the Progress Prize 2007 - RMSE = 0.8712 - Winning Team: KorBell and a Cinematch score on a split subset - RMSE = 0.9514.

Rank	Team Name	Best Score	% Improvement	Last Submit Time
1	<a href="#">The Ensemble</a>	0.8553	10.10	2009-07-26 18:38:22
2	<a href="#">BellKor's Pragmatic Chaos</a>	0.8564	10.09	2009-07-26 18:18:28
<b>Grand Prize - RMSE &lt;= 0.8563</b>				
3	<a href="#">Grand Prize Team</a>	0.8571	9.91	2009-07-24 13:07:49
4	<a href="#">Qora Solutions and Vandelay United</a>	0.8573	9.89	2009-07-25 20:05:52
5	<a href="#">Vandelay Industries I</a>	0.8579	9.83	2009-07-26 02:49:53
6	<a href="#">PragmaticTheory</a>	0.8582	9.80	2009-07-12 15:09:53
7	<a href="#">BellKor in BigChaos</a>	0.8590	9.71	2009-07-26 12:57:25
8	<a href="#">Qora</a>	0.8603	9.58	2009-07-24 17:18:43
9	<a href="#">Qora Solutions</a>	0.8611	9.49	2009-07-26 18:02:08
10	<a href="#">BellKor</a>	0.8612	9.48	2009-07-26 17:19:11
11	<a href="#">BigChaos</a>	0.8613	9.47	2009-06-23 23:06:52
12	<a href="#">Feeds2</a>	0.8613	9.47	2009-07-24 20:06:46
<b>Progress Prize 2008 - RMSE = 0.8616 - Winning Team: BellKor in BigChaos</b>				
13	<a href="#">xianxiang</a>	0.8633	9.26	2009-07-21 02:04:40
14	<a href="#">Grady</a>	0.8634	9.25	2009-07-26 15:58:34
15	<a href="#">Cms</a>	0.8642	9.17	2009-07-25 17:42:38
16	<a href="#">Invisible Ideas</a>	0.8644	9.14	2009-07-20 03:28:12
17	<a href="#">Just a guy in a garage</a>	0.8650	9.08	2009-07-22 14:10:42
18	<a href="#">Craig Carmichael</a>	0.8656	9.02	2009-07-25 16:00:54
19	<a href="#">J.Dennis Su</a>	0.8658	9.00	2009-03-11 09:41:54
20	<a href="#">acutwill</a>	0.8659	8.99	2009-04-16 06:29:35
<b>Progress Prize 2007 - RMSE = 0.8712 - Winning Team: KorBell</b>				
<b>Cinematch score on split subset - RMSE = 0.9514</b>				

One of the first RecSys competitions  
(02.10.2006 - 26.06.2009)  
[netflixprize.com/leaderboard](http://netflixprize.com/leaderboard)

# Motivation: business value

## Amazon

- 35% of sales estimated to be generated from recommendation system
- billions of dollars in revenue generated through personalized product recommendations

## Netflix

- 80% of content watched on Netflix is a result of recommendation
- "the combined effect of personalization and recommendations save us more than \$1B per year".<sup>a</sup>

---

<sup>a</sup><https://www.businessinsider.com/netflix-recommendation-engine-worth-1-billion-per-year-2016-6>

# Motivation: users value

- 1 **Better discovery & diversity of recommendations:** broaden users' perspectives, encourage them to try new things, and create a more inclusive and diverse experience.
- 2 **Increased user engagement:** provide personalized and relevant experience for users to help users find what they're looking for and engage with the service.
- 3 **Better use of data:** provide insights into user behavior which helps businesses make more informed decisions.

connect **listeners** and **creators** in a unique and enriching way

Example mission (Spotify), from: <https://www.youtube.com/watch?v=Ysh0CXUbXsU>

# Recommender Systems taxonomy

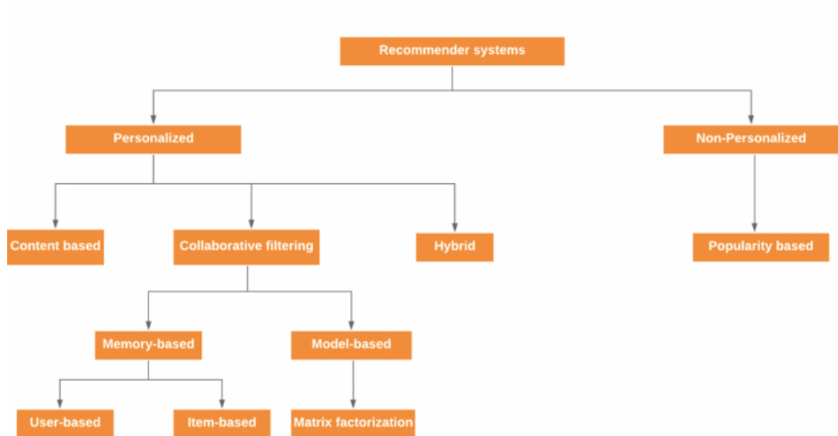


image credit: <https://thingsolver.com/introduction-to-recommender-systems>

# Problem statement

## Given:

- $U = \{u_j | j \in 1, \dots, n_{users}\}$  — set of users
- $I = \{i_j | j \in 1, \dots, n_{items}\}$  — set of items.
- $R = \|r_{ui}\|$  — relation matrix of shape  $n_{users} \times n_{items}$ ,

$r_{ui} \in \begin{cases} \text{typically } \{0, 1\} \text{— implicit feedback} \\ \text{typically } \{1, 2, 3, 4, 5\} \text{— explicit feedback} \end{cases}$

## Possible tasks:

### Rating prediction

- Predict unknown  $r_{ui}$  — regression or (multi-class) classification

### Top-k ranking

- Rank top-k recommendations for items — item2item
- Rank top-k recommendations for users — **item2user (course focus)**

# Evaluation metrics (item2user)

## 1 nDCG

$$DCG@k(u) = \sum_{j=1}^k \frac{2^{r_{uj}} - 1}{\log_2(j+1)}$$

$$IDCG@k(u) = \max(DCG@k(u))$$

$$nDCG@k(u) = \frac{DCG@k(u)}{IDCG@k(u)}$$

$$nDCG@k = \frac{\sum_{u=1}^{n_{users}} nDCG@k(u)}{n_{users}}$$

## 2 Mean Average Precision

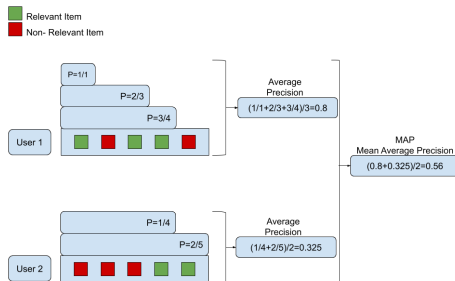
$$p@m(u) = \frac{\sum_{j=1}^m [r_{uj} > 0]}{m}$$

$$ap@k(u) = \frac{\sum_{j=1}^k [r_{uj} > 0] p@j(u)}{\min(k, |r_u|)}$$

$$MAP@k = \frac{\sum_{u=1}^{n_{users}} ap@k(u)}{n_{users}}$$

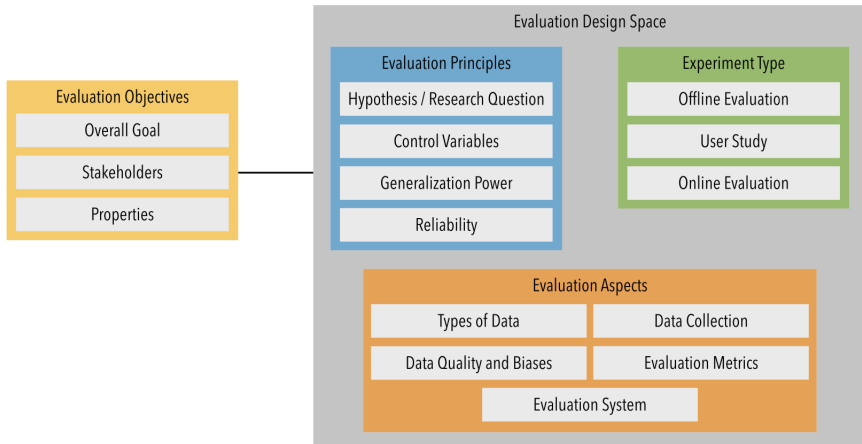
## 3 etc.

image credit:



<https://medium.com/swlh/rank-aware-recsys-evaluation-metrics-5191bba16832>

# Overall evaluation



Evaluation framework example

image credit: <https://dl.acm.org/doi/10.1145/3556536>



- ① *Charu C. Aggarwal*. (2016). Recommender Systems: The Textbook.
- ② *F. Ricci, L. Rokach, B. Shapira*. (2011). Recommender Systems Handbook.
- ③ *Adomavicius, G., Tuzhilin, A.* (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6), 734-749.
- ④ *Eva Zangerle, Christine Bauer* (2022). Evaluating Recommender Systems: Survey and Framework. *ACM Computing Surveys*, Volume 55, Issue 8, Article No.: 170, pp 1–38