# Recommender Systems
# lecture 1: introduction

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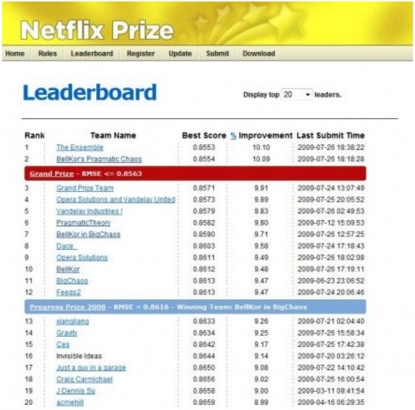
# Historical note

«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 x S ⇒ R, where 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**


Netflix Prize

Home Rules Leaderboard Register Update Submit Download

Leaderboard

Display top 20 leaders.

| Rank | Team Name | Best Score | % Improvement | Last Submit Time |
|---|---|---|---|---|
| 1 | The Ensemble | 0.8553 | 10.10 | 2009-07-26 18:38:22 |
| 2 | BellKor's Pragmatic Chaos | 0.8554 | 10.09 | 2009-07-26 18:18:28 |
| Grand Prize - RMSE <= 0.8563 | | | | |
| 3 | Grand Prize Team | 0.8571 | 9.91 | 2009-07-24 13:07:49 |
| 4 | Opera Solutions and Vandelay United | 0.8573 | 9.89 | 2009-07-25 20:05:52 |
| 5 | Vandelay Industries ! | 0.8579 | 9.83 | 2009-07-26 02:49:53 |
| 6 | PragmaticTheory | 0.8582 | 9.80 | 2009-07-12 15:09:53 |
| 7 | BellKor in BigChaos | 0.8590 | 9.71 | 2009-07-26 12:57:25 |
| 8 | Dace_ | 0.8603 | 9.58 | 2009-07-24 17:18:43 |
| 9 | Opera Solutions | 0.8611 | 9.49 | 2009-07-26 18:02:08 |
| 10 | BellKor | 0.8612 | 9.48 | 2009-07-26 17:19:11 |
| 11 | BigChaos | 0.8613 | 9.47 | 2009-06-23 23:06:52 |
| 12 | Feeds2 | 0.8613 | 9.47 | 2009-07-24 20:06:46 |
| Progress Prize 2008 - RMSE = 0.8616 - Winning Team: BellKor in BigChaos | | | | |
| 13 | xiangliang | 0.8633 | 9.26 | 2009-07-21 02:04:40 |
| 14 | Gravity | 0.8634 | 9.25 | 2009-07-26 15:58:34 |
| 15 | Ces | 0.8642 | 9.17 | 2009-07-25 17:42:38 |
| 16 | Invisible Ideas | 0.8644 | 9.14 | 2009-07-20 03:26:12 |
| 17 | Just a guy in a garage | 0.8650 | 9.08 | 2009-07-22 14:10:42 |
| 18 | Craig Carmichael | 0.8656 | 9.02 | 2009-07-25 16:00:54 |
| 19 | J Dennis Su | 0.8658 | 9.00 | 2009-03-11 09:41:54 |
| 20 | acmehill | 0.8659 | 8.99 | 2009-04-16 06:29:35 |

One of the first and most notable RecSys competitions (2006-2009)

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

# Motivation: money

## Amazon

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

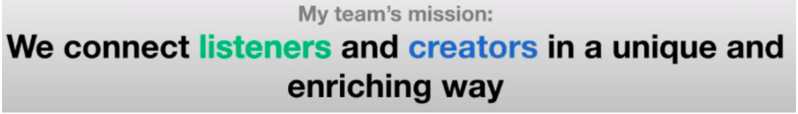
## Netflix

- 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".[a]

[a] https://www.businessinsider.com/netflix-recommendation-engine-worth-1-billion-per-year-2016-6

# Motivation: beyond money

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.




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

# Recommender Systems taxonomy

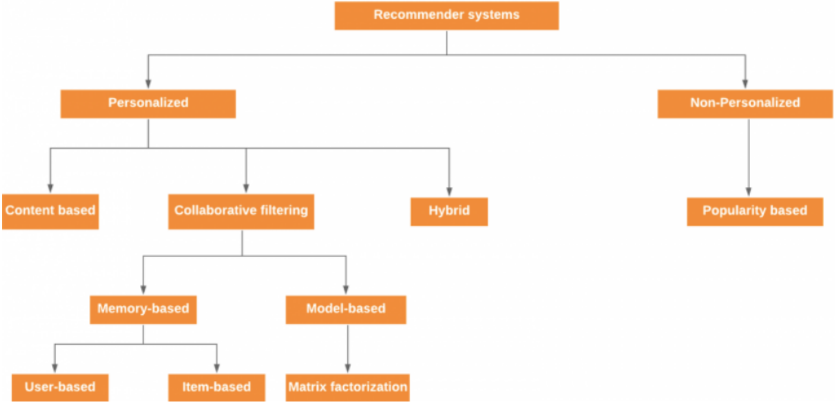



image credit: https://thingsolver.com/introduction-to-recommender-systems

# 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 $n_{users} \times n_{items}$,

$$r_{ui} \in \left[ \begin{array}{c} \text{typically } \{0,1\} \text{— implicit feedback} \\ \text{typically } \{1,2,3,4,5\} \text{— explicit feedback} \end{array} \right.$$

**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**

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

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

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

3. etc.

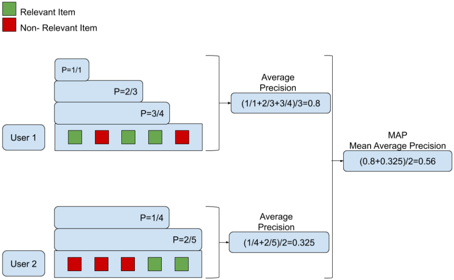
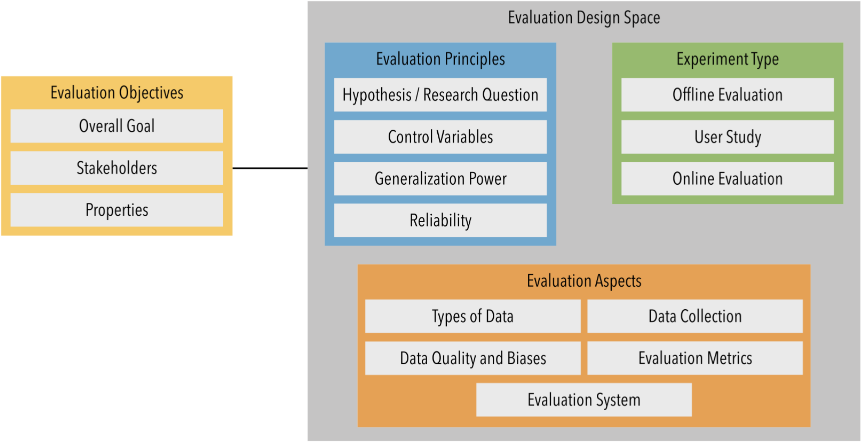



image credit:

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

# Literature


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