MICHIGAN STATE UNIVERSITY

Data Science and Engineering Lab

IJCAI 2021 MONTREAL

# Deep Learning for Recommendations: Fundamentals and Advances

**Wenqi Fan[1], Xiangyu Zhao[2], Dawei Yin[3], Jiliang Tang[4]**

[1]The Hong Kong Polytechnic University, [2]City University of Hong Kong,

[3]Baidu Inc., [4]Michigan State University

**Tutorial website**: https://advanced-recommender-systems.github.io/ijcai2021-tutorial/

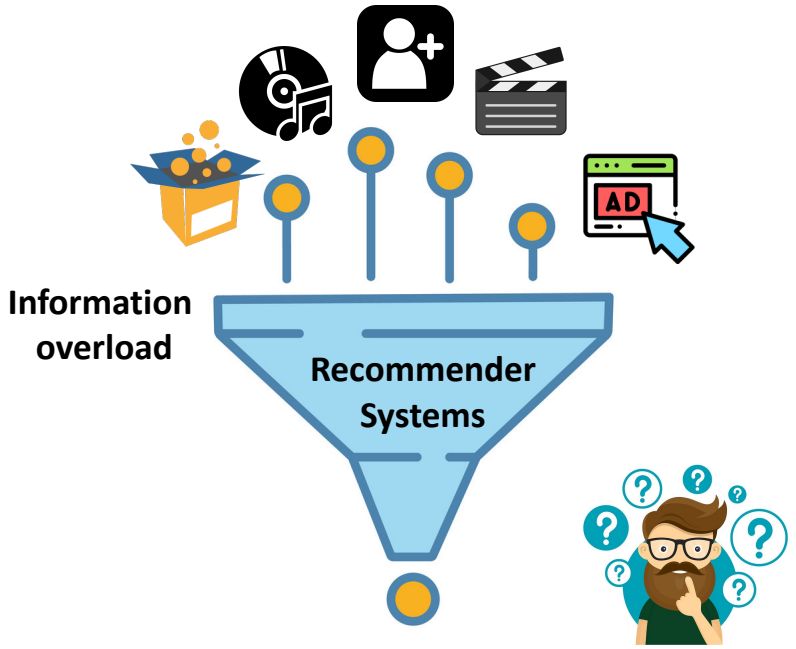
THE HONG KONG POLYTECHNIC UNIVERSITY 香港理工大學

CityU 香港城市大學 City University of Hong Kong

Baidu 百度

# Recommender Systems

**Age of Information Explosion**


**Recommend item X to user**

**Items** can be: Products, News, Movies, Videos, Friends, etc.

# Recommender Systems

**Recommendation has been widely applied in online services:**

- **E-commerce**, Content Sharing, Social Networking ...

amazon

ebay

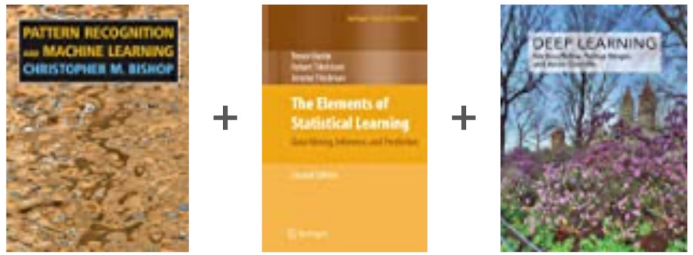
淘宝网 Taobao.com

JD.COM

---

**Product Recommendation**

Frequently bought together




A + B + C

Total price: $208.9

Add all three to Cart

Add all three to List

# Recommender Systems

**Recommendation has been widely applied in online services:**

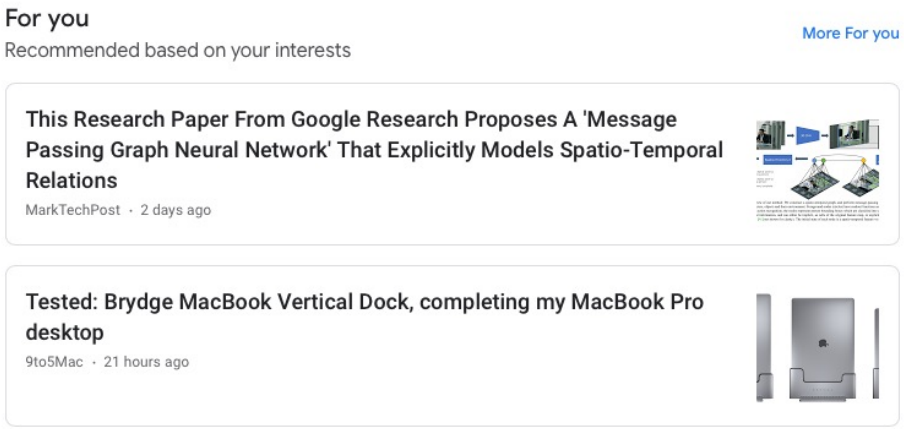
- E-commerce, **Content Sharing**, Social Networking ...

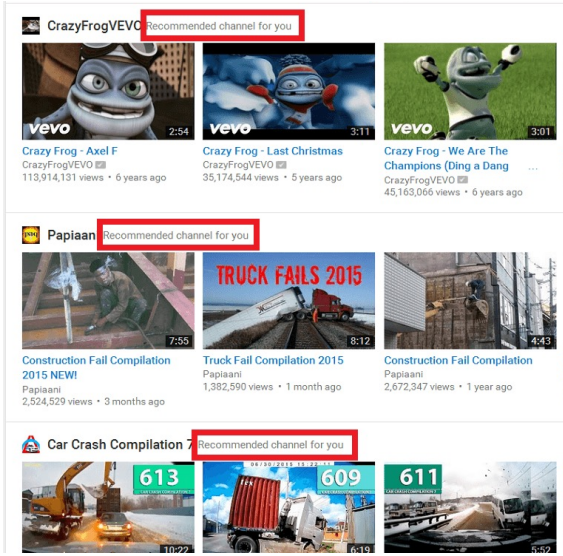




---

**News/Video/Image Recommendation**



# Recommender Systems

**Recommendation has been widely applied in online services:**

- E-commerce, Content Sharing, Social Networking ...

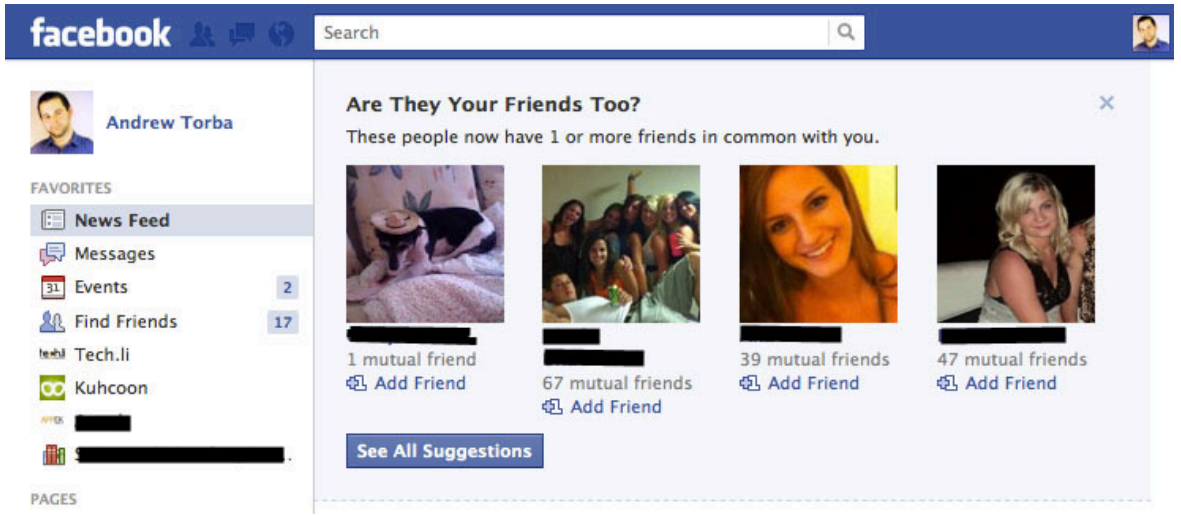
facebook

新浪微博 weibo.com

LinkedIn

---

**Friend Recommendation**



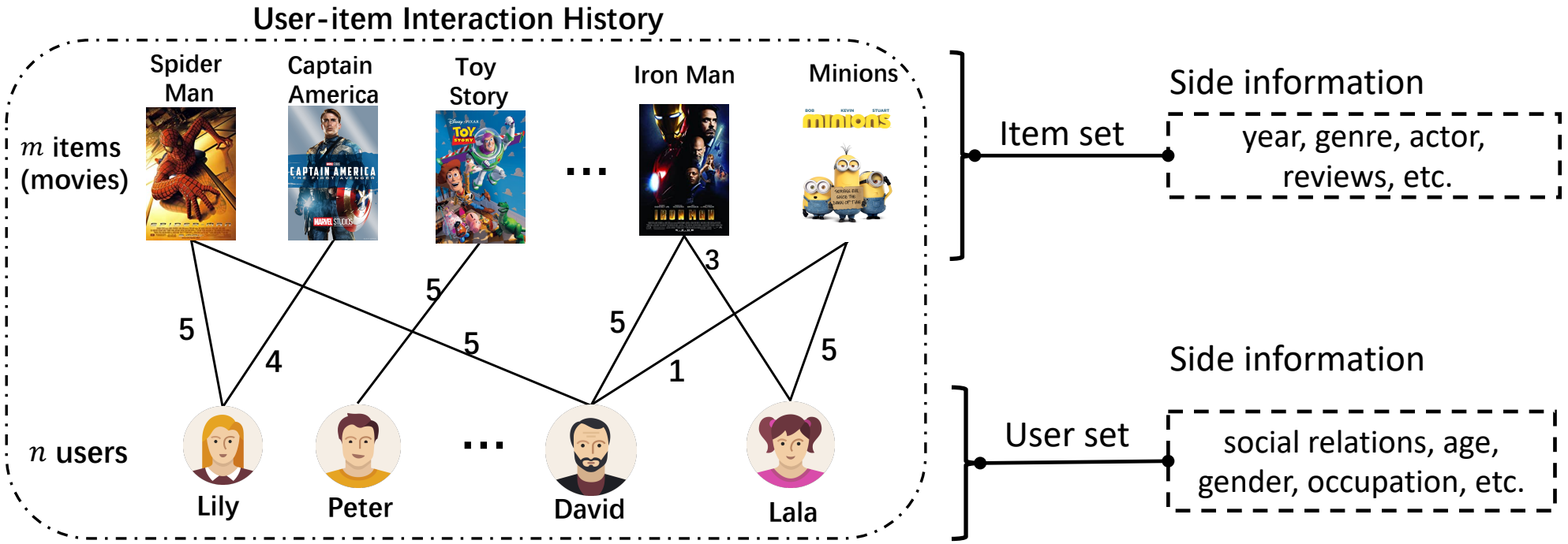
# Problem Formulation

**INPUT**

Historical user-item interactions or additional side information (e.g., social relations, item's knowledge, etc.)

**OUTPUT**

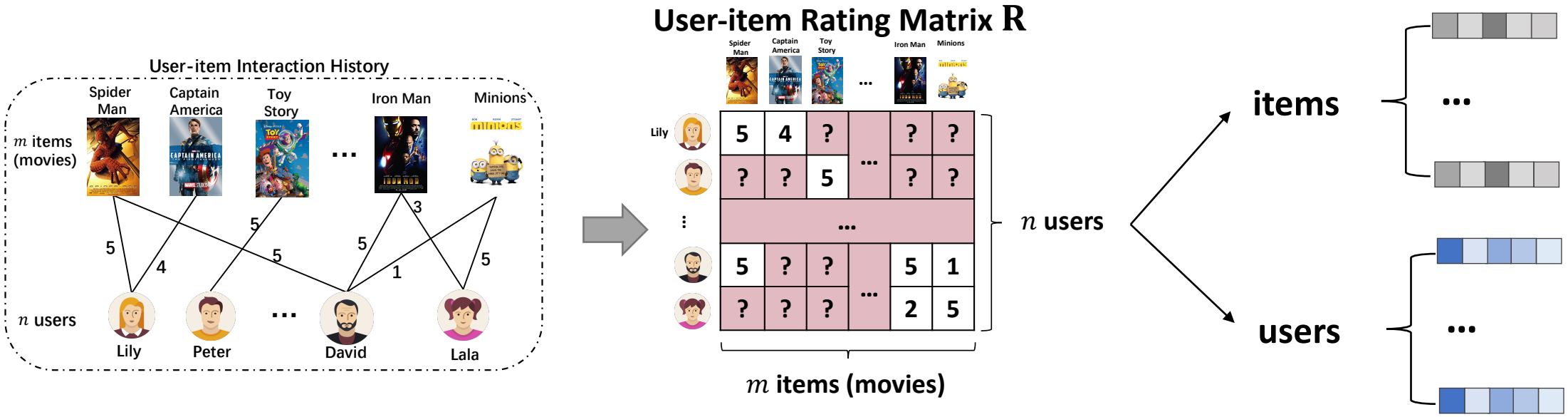
Predict how likely a user would interact with a target Item (e.g., click, view, or purchase)



# Recommender Systems

- **Collaborative Filtering (CF) is the most well-known technique for recommendation.**
  - Similar users (with respect to their historical interactions) have similar preferences.
  - Modelling users' preference on items based on their past interactions (e.g., ratings and clicks).

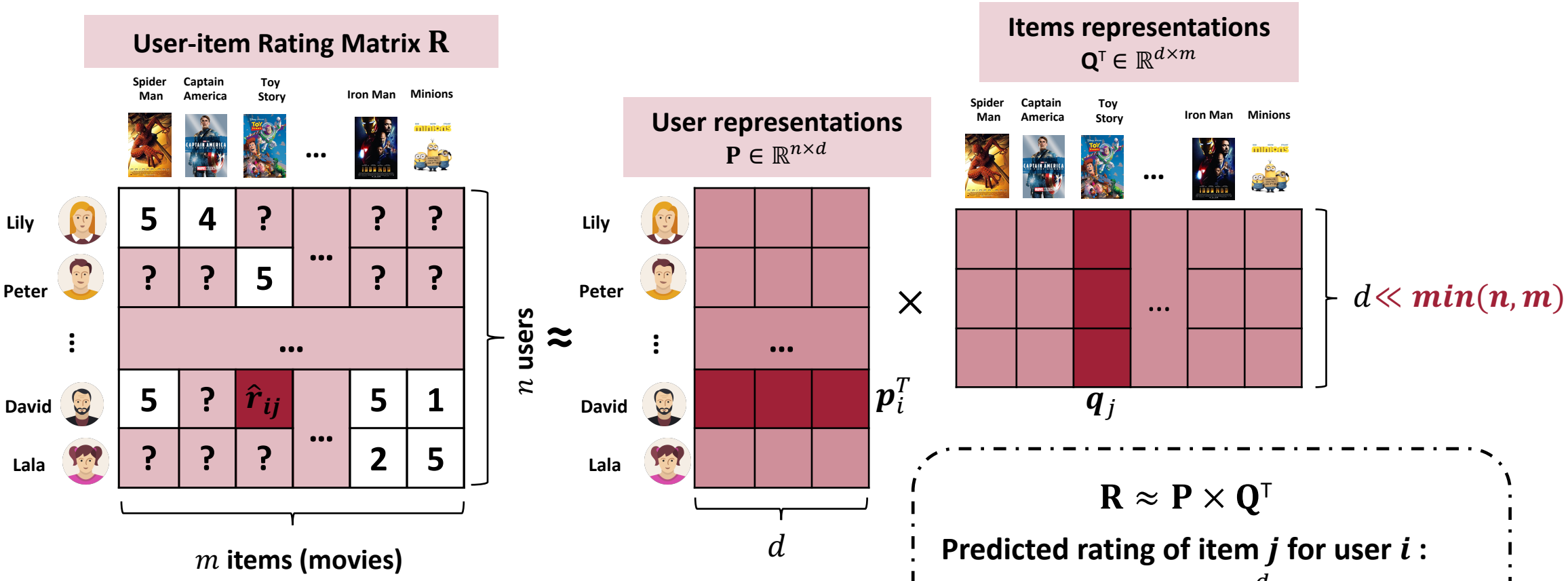
- **Learning representations of users and items is the key of CF.**



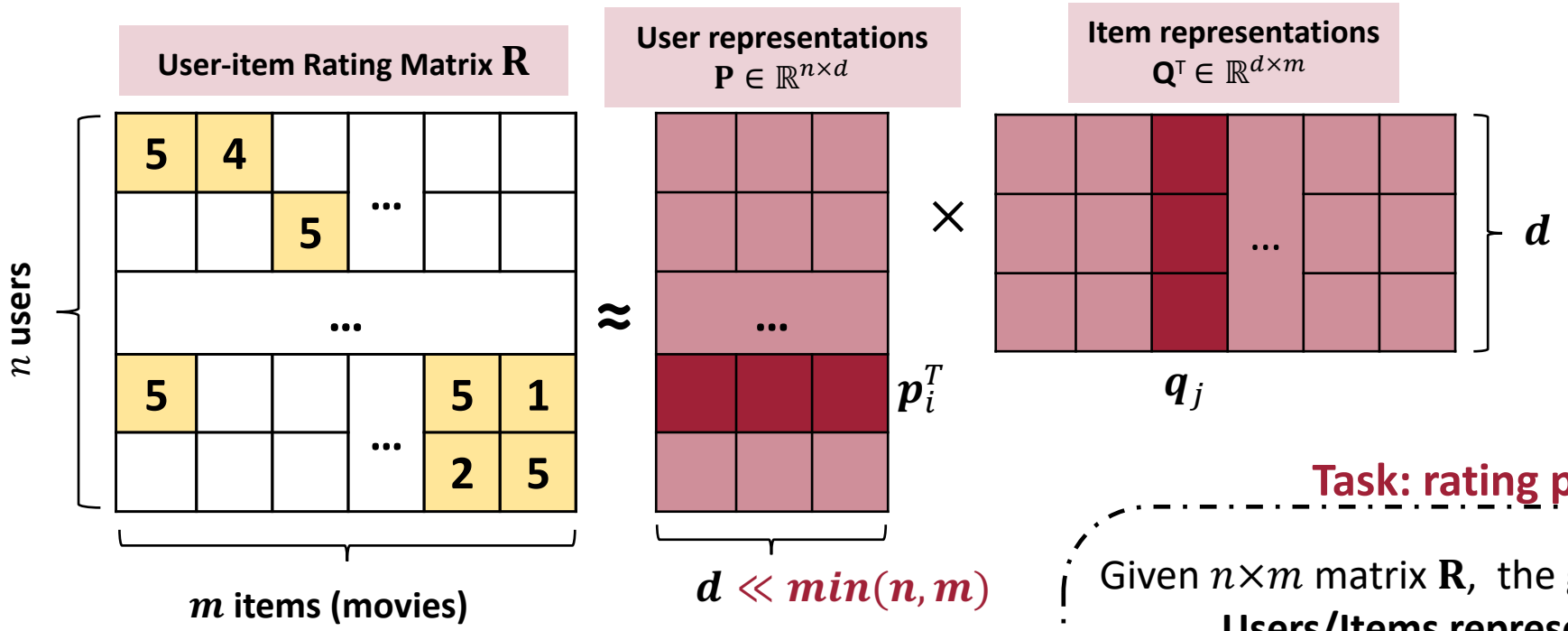

**Task: predicting missing movie ratings in Netflix.**

# Matrix Factorization

- Learn **representations** to describe users and items based on user-item rating matrix $\mathbf{R}$.



# Matrix Factorization




**Task: rating prediction in Netflix**

Given $n \times m$ matrix $\mathbf{R}$, the goal is to learn:

**Users/Items representations**: $\mathbf{P} \in \mathbb{R}^{n \times d}$, $\mathbf{Q} \in \mathbb{R}^{m \times d}$

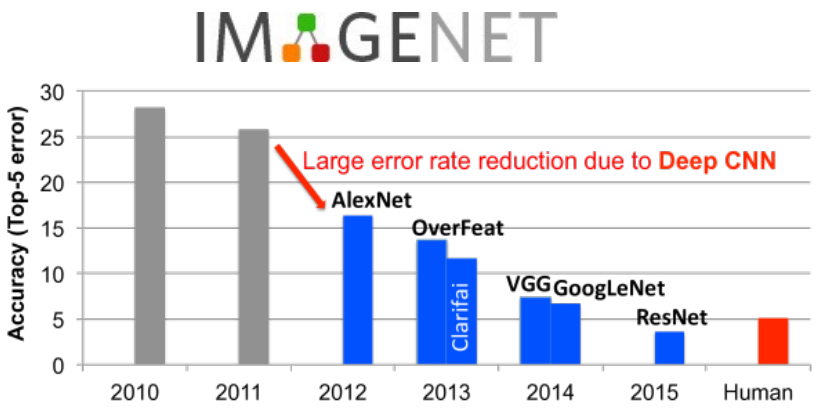
Objective with rating reconstruction error:

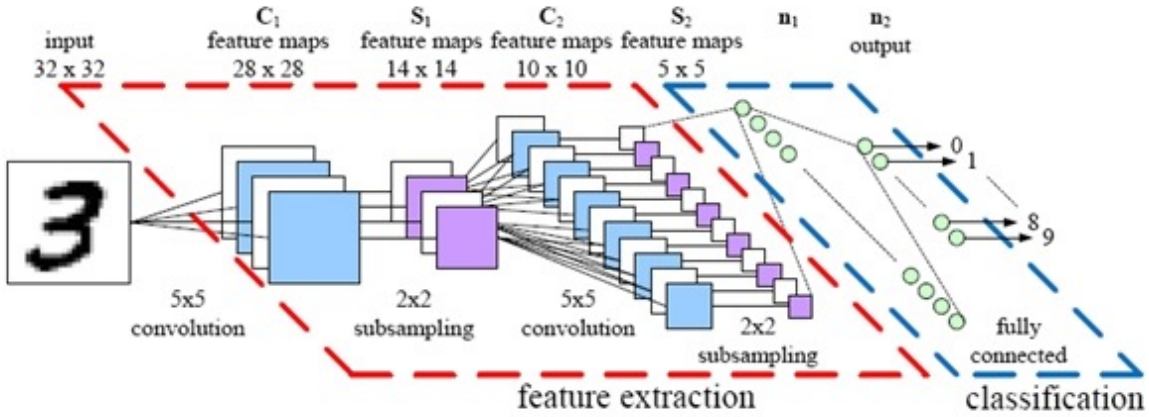
$$min_{\mathbf{P},\mathbf{Q}} \sum_{i,j \in S} (r_{ij} - \hat{r}_{ij})^2 = \sum_{i,j \in S} (r_{ij} - \boldsymbol{p}_i^T \boldsymbol{q}_j)^2$$

observed rating score

predicted rating score

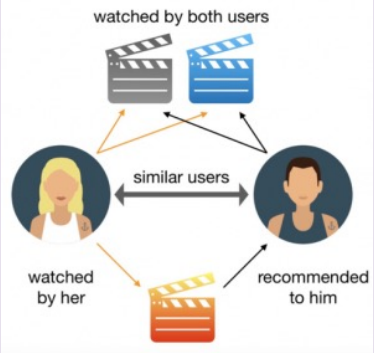
# Deep Learning is Changing Our Lives



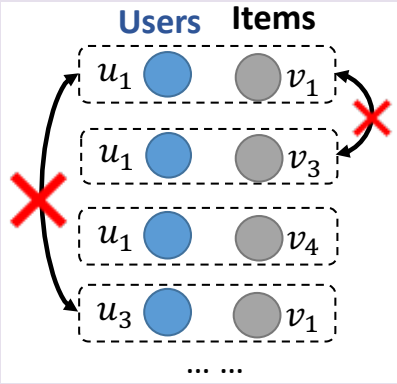

# Deep Recommender Systems

## Fundamentals of Deep Recommender Systems



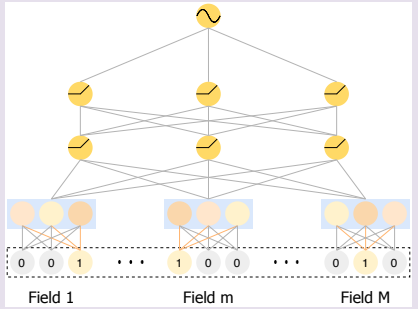

**Recommendation Policies**
- Offline optimization
- Short-term reward

**Reinforcement Learning (RL)**



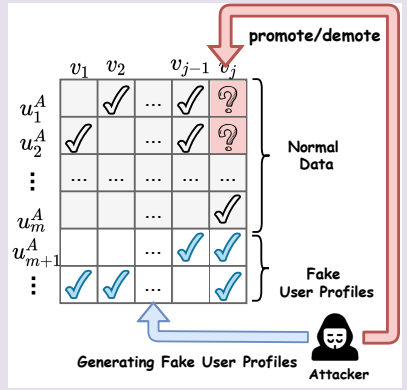

**Graph-structured Data**
- Information isolated island Issue: ignore implicit/explicit relationships among instances

**Graph Neural Networks (GNNs)**




**Manually Deisgned Architectures**
- Expert knowledge
- Time and engineering efforts

**Automated Machine Learning (AutoML)**




**Poisoning attacks:**
- Promote/demote items
- White/grey/black-box attacks

**Adversarial Attacks**

# Agenda

- Introduction to Recommender Systems  (Jiliang Tang)
- Fundamentals of Deep Recommender Systems (Wenqi Fan)
- Reinforcement Learning for Recommendations (Xiangyu Zhao)
- Coffee Break (10 mins)
- Graph Neural Network for Recommendations (Wenqi Fan)
- AutoML for Recommendations (Xiangyu Zhao)
- Adversarial Attacks for Recommendations (Wenqi Fan)
- Future