# **Special Topic: Recommender Systems**

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## Recommender Systems (Personalization, Curation)

- □ Too many items, limited time
- Recommender system analyzes preferences of each user, and provides personalized top-N items with users







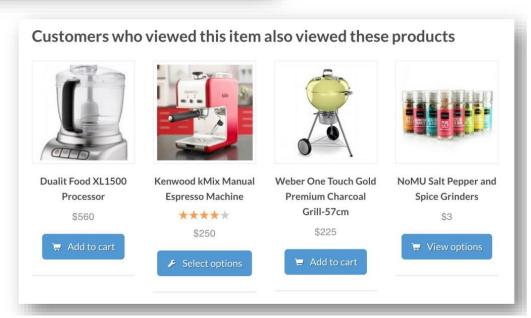




#### Amazon

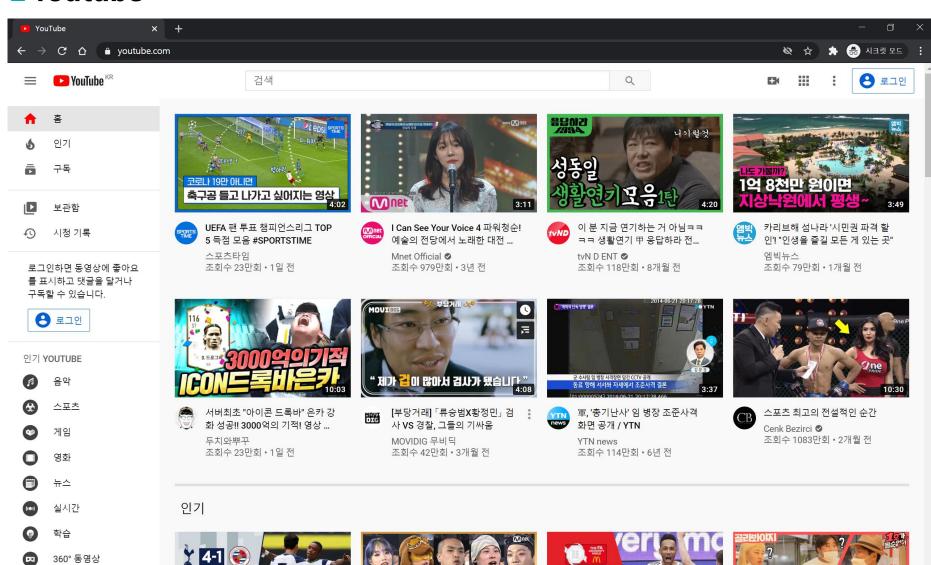


#### **Amazon product recommendation**





#### Youtube





#### ■ Netflix





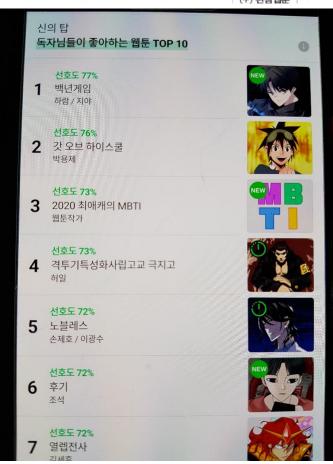
#### Cartoon



#### 신의 탑 SIU

자신의 모든 것이 그리고 그런 소년 스토리, 판타지 |

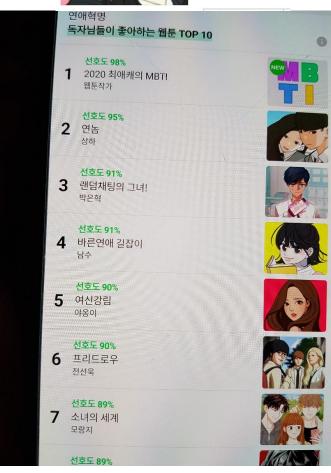
(+) 관심웹툰





#### 연애혁명 2

로맨스, 그런 건 신개념 개그 로민 스토리, 드라마





#### News recommendation





## **Many Applications**

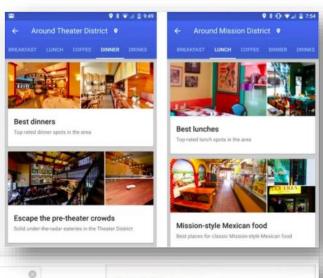
#### □ Etc...

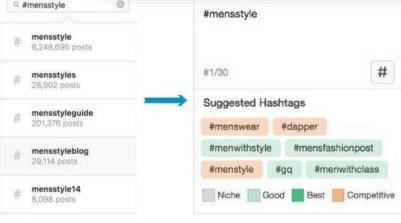
#### Social recommendation





#### Restaurant recommendation





App recommendation

Tag recommendation



# **Many Applications**

□ **Etc...** 























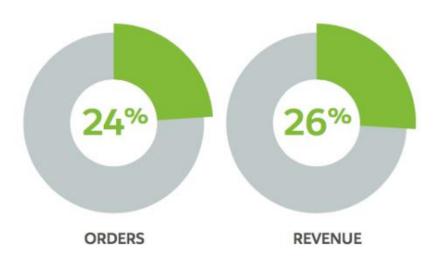
**WATCHA** 



## Why Recommender Systems?

### ■Importance of accurate recommendation

- 35% of the purchases on Amazon are the result of their recommender systems
- 75% of watching on Netflix comes from recommendations
- □ <u>70%</u> of the traffics are driven by "suggested videos" on **YouTube**.







### **Contents**

- 1. Netflix Prize
- 2. Recommendation and Collaborative Filtering
- 3. KNN-based Methods
- 4. Matrix Factorization
- 5. Recent Recommenders
- 6. Case Study



#### ■ 1 million dollar!

### **Netflix Challenge (2006)**

# **Netflix Prize**

The Netflix Prize sought to substantially improve the accuracy of predictions about how much someone is going to enjoy a movie based on their movie preferences.

On September 21, 2009 we awarded the \$1M Grand Prize to team "BellKor's Pragmatic Chaos". Read about their algorithm, checkout team scores on the Leaderboard, and join the discussions on the Forum.

We applaud all the contributors to this quest, which improves our ability to connect people to the movies they love.

#### **Competition**

- \$1 million
- Prize for 10% improvement on Netflix



http://www.netflixprize.com/



Problem setting

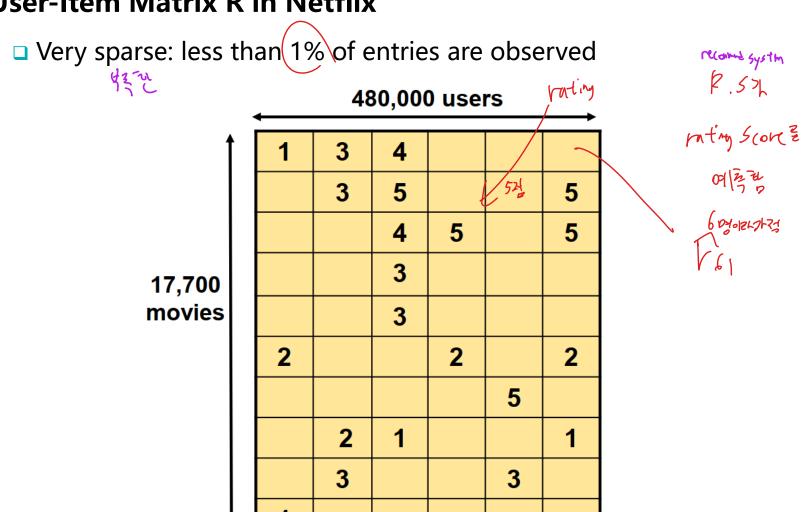
- rating fredictly task
- □ Training data whendown
  - 100 million ratings, 480,000 users, 17,770 movies
  - 6 years of data: 2000-2005
- □ Test data (lose duta
  - Last few ratings of each user (2.8 million)
- □ Evaluation criteria: Root Mean Square Error (RMSE)

$$\frac{1}{|R|} \sqrt{\sum_{(i,x) \in R} (\hat{r}_{xi} - r_{xi})^2}$$

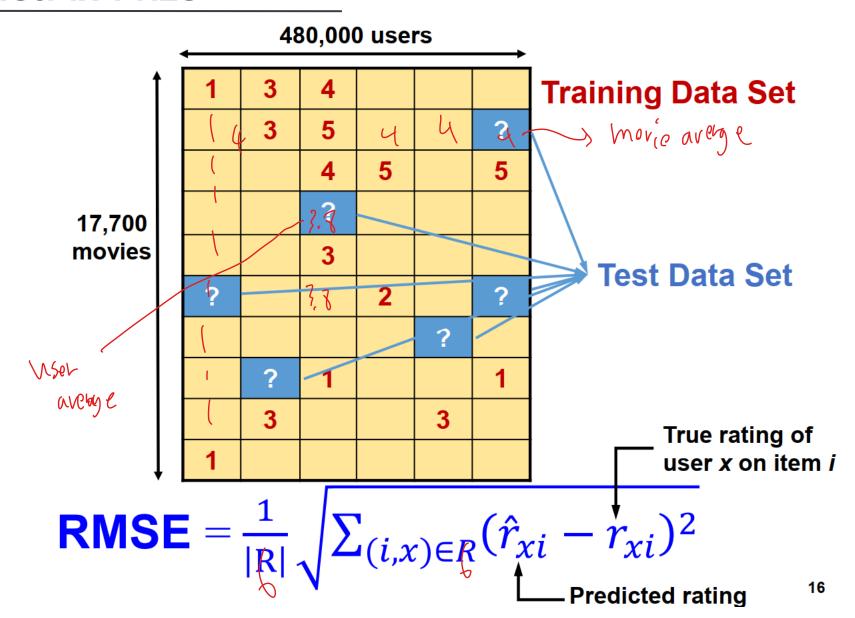
$$|R| \sqrt{\sum_{(i,x) \in R} (\hat{r}_{xi} - r_{xi})^2}$$



#### **□** User-Item Matrix R in Netflix

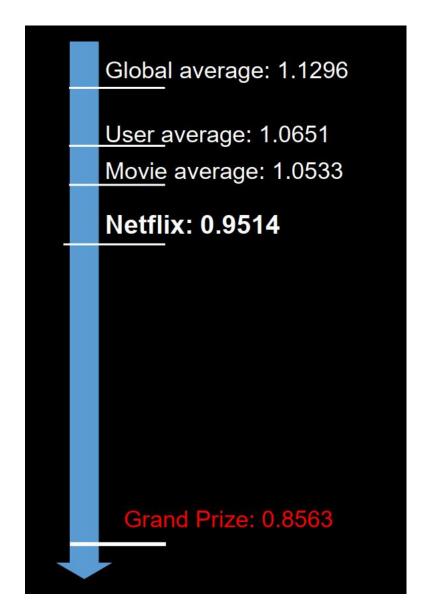








□ RMSE score overview

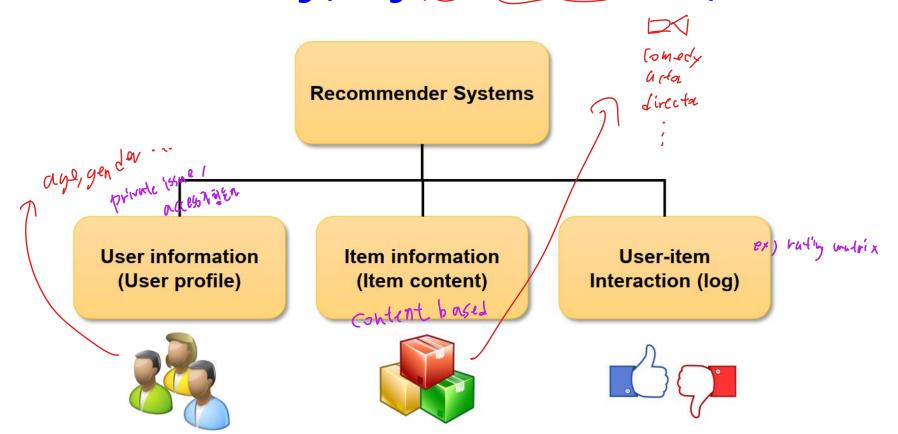


~ 2009



# **Category of Recommendation Algorithms**

- User profile matching
- Content-based recommendation
- □ Collaborative filtering (using user-item interactions)





Contents-based VS Collaborative Filtering Why collaborative filtering is more popular? □ It is domain-agnostic! amazon うみやれなど Collaborative NETFLIX **Flixster Filtering** Algorithm adidas



# Background

- **□ Types** of user-item matrix data
  - □ Explicit feedback: ratings, thumb up, like & dislike, etc... difful to set
  - Implicit feedback: click, purchase, bookmark, etc... (popularized from 2008)

	Item							
	1			3				
		3			2			
User		4			4			
	4		3			1		
		5			5			
			2			5		

**Rating matrix** 

	Item							
		1			1			
			1					
User	1			1				
			1			1		
		1			1			
			1			1		

**Interaction matrix** 



## Background

- How to evaluate a recommendation method?
  - Rating prediction perspective: RMSE (most popular until 2009)
    - How a predicted rating score is similar with the true rating

$$MAE = \frac{1}{N} \sum |predicted - actual|$$

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$$RMSE = \sqrt{\frac{1}{N} \sum (predicted - actual)^2}$$

- Classification perspective: Precision, recall, F-measure (F1 score)
  - How many a top-N recommendation list contains the true items  $\bigcirc$   $\bigcirc$   $\bigcirc$

$$P = \frac{\text{\# of our recommendations that are relevant}}{\text{\# of items we recommended}}$$

$$P = \frac{\# \text{ of our recommendations that are relevant}}{\# \text{ of items we recommended}} \qquad r = \frac{\# \text{ of our recommendations that are relevant}}{\# \text{ of all the possible relevant items}}$$

- Ranking perspective: NDCG (Normalized Discounted Cumulative Gain), **MRR** (Mean Reciprocal Rank)
  - How much the true items are highly ranked in the top-N recommendation list

# Thank You

