# **Recommendation System**

**Part I: Basic Concepts** 

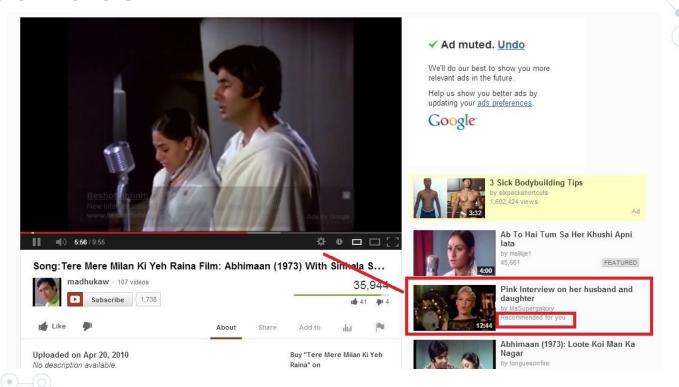
Duc-Trong Le (PhD), VNU-UET
November 2022

# **Outline**

- Real-life Examples
- Introduction to Recommendation Systems (RSs)
  - Item, User, Behavior
  - Role of RSs? How do RSs work?
- Types of Recommendation Systems
- Learning Principles
  - Learning User-Item Associations
  - Learning Item-Item Associations
- Evaluation & Metrics
  - Introduction to Cornac, a Recommendation Framework

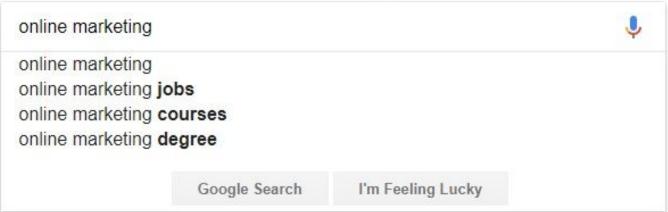


# YouTube

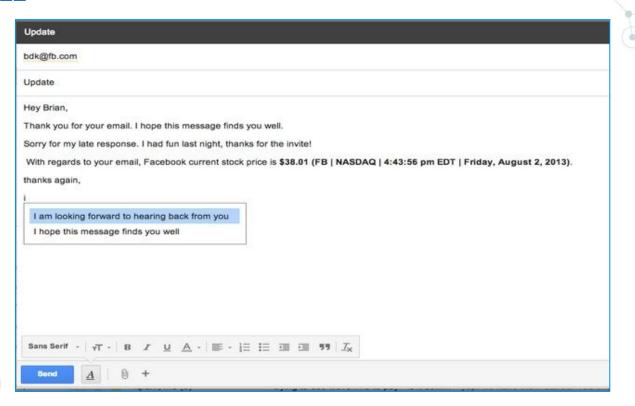


# **Google Search**





# **Gmail**



## **Amazon**

#### Frequently Bought Together









Add all three to Cart | Add all three to Wish List

Show availability and shipping details

- ▼ This item: Beginning Ruby: From Novice to Professional (Expert's Voice in Open Source) by Peter Cooper Paperback \$27.78
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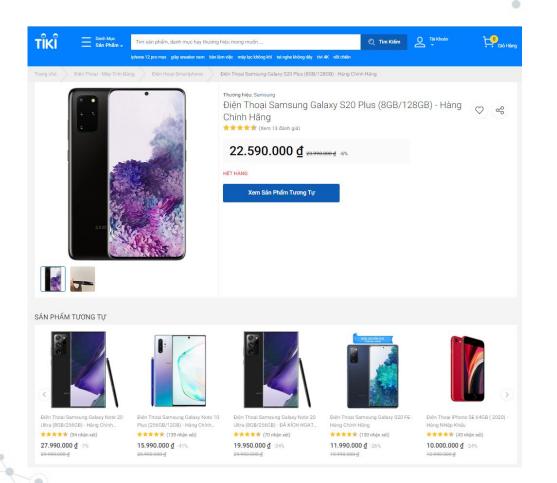
\*\*\*\* 19

#1 Best Seller (in Ruby **Programming Computer** 

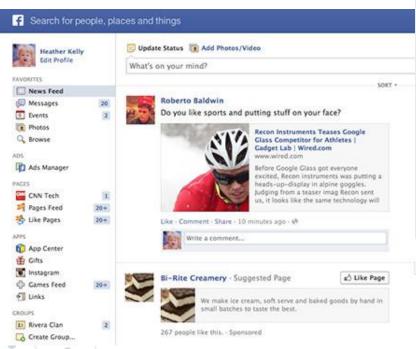
Paperback

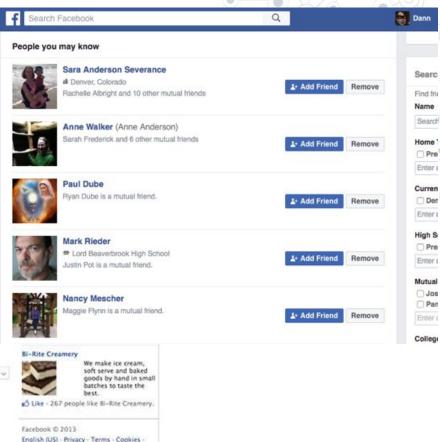
\$29.67 Prime

# Tiki



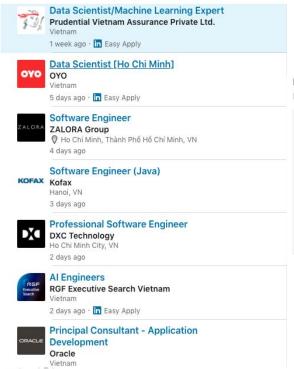
# **Facebook**





# LinkedIn

Jobs you may be interested in



#### Because you viewed

Assoc Research Scientist

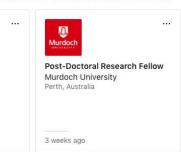
Richmond, VA, US

( Be an early applicant

PPIT

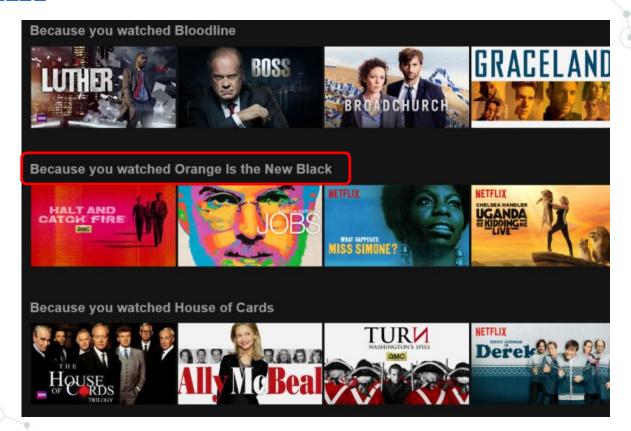
3 weeks ago

IBM Research Scientist - Health Al Postdoc FTH 24Months Melbourne at IBM





# **Netflix**



# **Medium**

# **Medium**

BASED ON YOUR READING HISTORY

#### Visualizing Data with Pairs Plots in Python

How to quickly create a powerful exploratory data analysis visualization

Will Koehrsen in Towards Data Science

Apr 7, 2018 - 8 min read

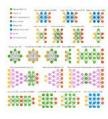


ARTIFICIAL INTELLIGENCE

#### Cheat Sheets for AI, Neural Networks, Machine Learning, Deep Learning & Big Data

The Most Complete List of Best Al Cheat Sheets

Stefan Kojouharov in Becoming Human: Artificial Intelligence Magazine



ARTIFICIAL INTELLIGENCE

#### A Conceptual Explanation of Bayesian Hyperparameter Optimization for Machine Learning

The concepts behind efficient hyperparameter tuning using Bayesian optimization

Will Koehrsen in Towards Data Science

Jun 24, 2018 · 14 min read





### **BaoMoi**

Tăng ni, Phật tử cầu siêu

cho đồng bào tử nạn

trong dịch COVID-19

Núi sạt lở, mặt đường

người dân Trà Leng bị

đứt gãy, hàng ngàn



ĐT Việt Nam đối mặt

lịch thi đấu dày đặc ở

AFF Cup 2020

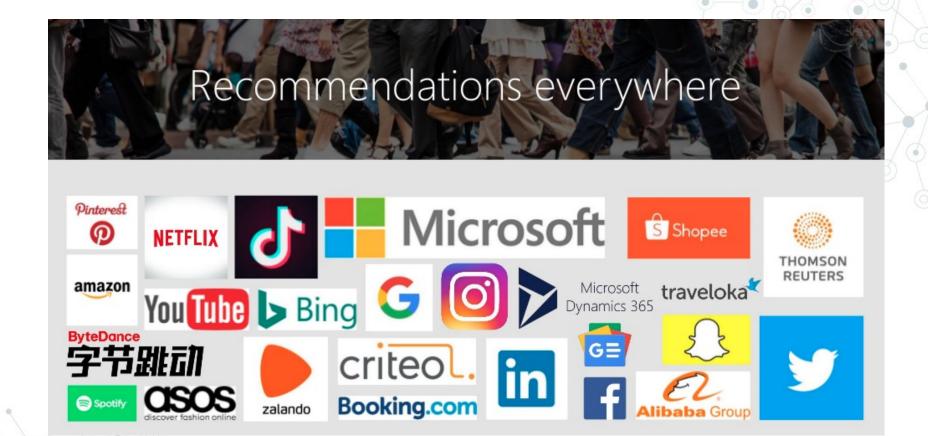
SAIGON 15 phút

Cao tốc dài gần 188 km nối 4 tỉnh

được trình Quốc hội vào tháng 5-

đồng bằng sông Cửu Long sẽ



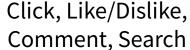


# Introduction to **Recommendation Systems**

# Item, User & Behavior

**Behavior** 

Item



**Video** 



**Customer A** 

Search, Click, Add-to-cart, Purchase, Review, Rate

**Product** 



You Tube

Search, Click, Rate, Like

Movie

Báo Méi.com

Search, Read, Duration, Comment News

• • •

# Why do we need Recommendation?



Millions of Items ...

# **Roles of Recommendation Systems**

Recommender Systems



**Users** 

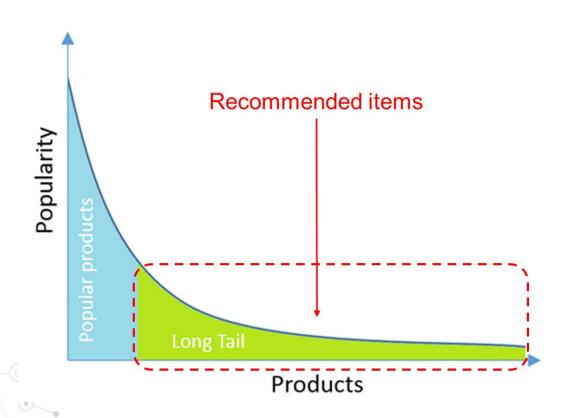
Items

(e.g., video, product, news)

#### Advantages of RS:

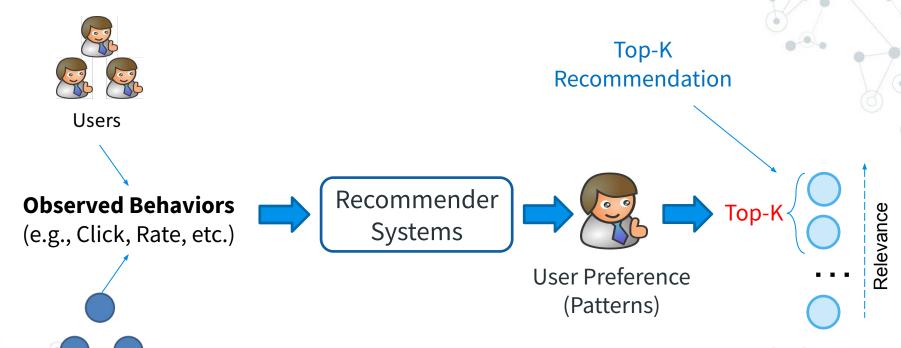
Enterprise Perspective	Customer Perspective
<ul> <li>Reduce search costs</li> <li>Increase customer satisfaction</li> <li>Educate customers about product domains.</li> <li>Optimize sales and profit</li> </ul>	<ul> <li>Easy to find what he/she might want</li> <li>Having an assistant in websites/systems</li> </ul>

# **Long-tail Recommendation**



# How does RS work?

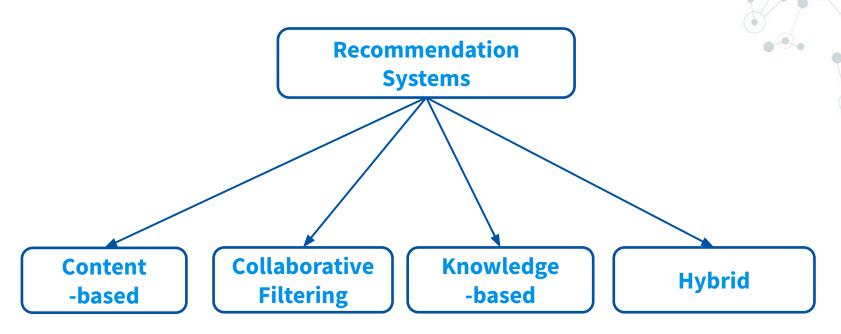
**Items** 



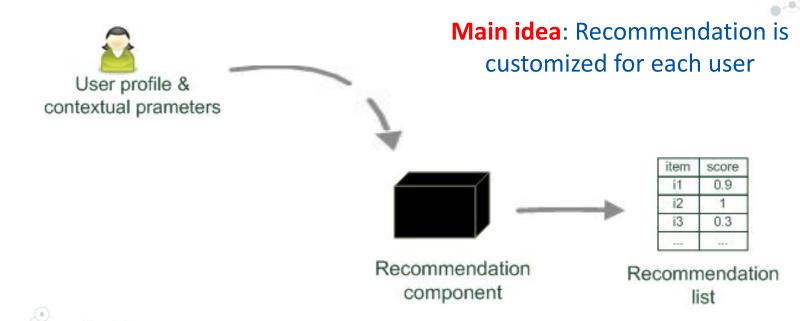
**Ranked Item List** 



# **Types of Recommendation Systems**



# **Personalized Recommendation**



# **Content-based Recommendation (1)**



Main idea: Recommended items are similar to what a user adopted



item score i1 0.9 i2 1 i3 0.3

Product features

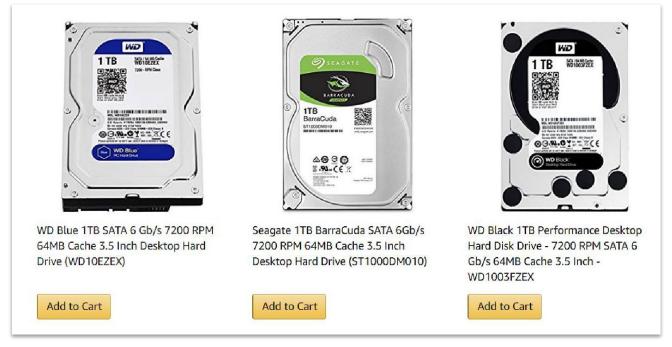
Actors

Genre

Recommendation component

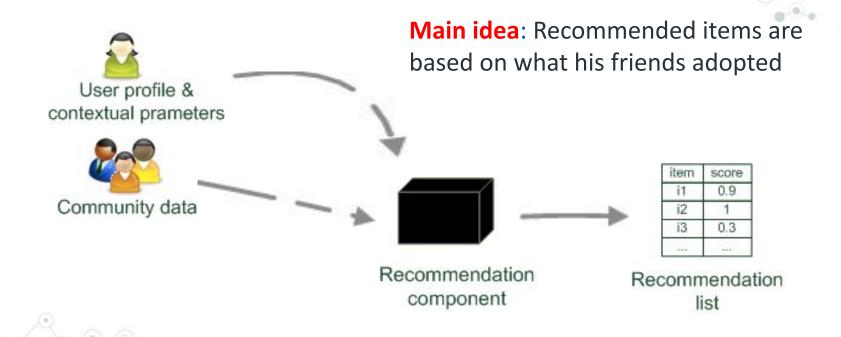
Recommendation list

# **Content-based Recommendation (2)**

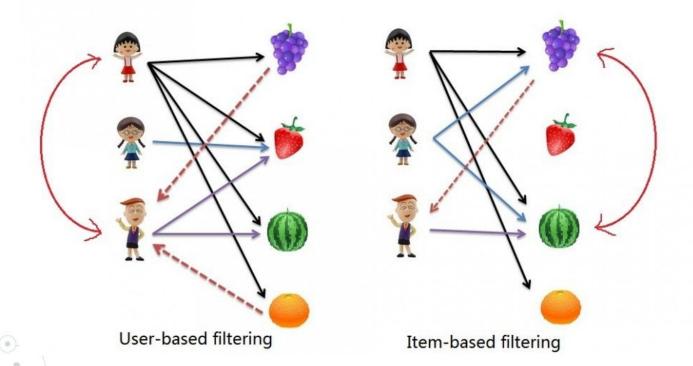


Recommendations for 1TB HDD on Amazon

# **Collaborative Filtering (1)**



# **Collaborative Filtering (2)**



# **Netflix Prize**



	Movie 1	Movie 2	Movie 3
Ted	4	5	5
Carol		5	5
Bob		5	?

#### Leaderboard

Showing Test Score. Click here to show quiz score

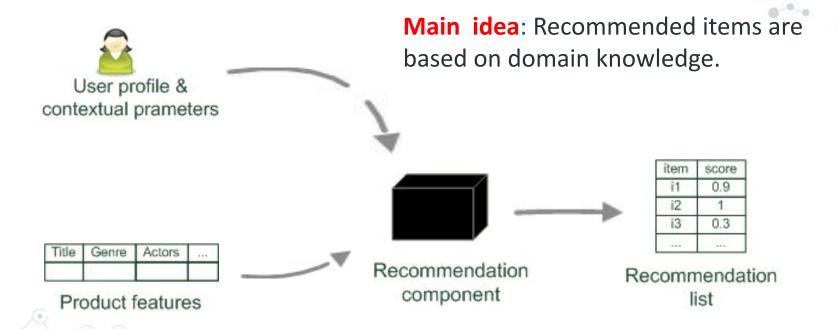
Display top 20 ▼ leaders.

Rank	Team Name	Best Test Score	e <u>%</u> Improvem
Grand	<u>1 Prize</u> - RMSE = 0.8567 - Winning 1	eam: BellKor's Pr	agmatic Chaos
1	BellKor's Pragmatic Chaos	0.8567	10.06
2	The Ensemble	0.8567	10.06
3	Grand Prize Team	0.8582	9.90
4	Opera Solutions and Vandelay United	0.8588	9.84
5	Vandelay Industries!	0.8591	9.81
6	PragmaticTheory	0.8594	9.77
7	BellKor in BigChaos	0.8601	9.70
8	Dace	0.8612	9.59

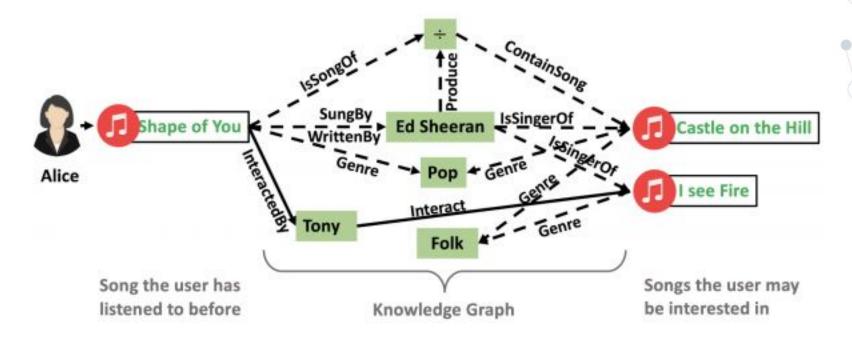
Netflix 1M \$ challenge



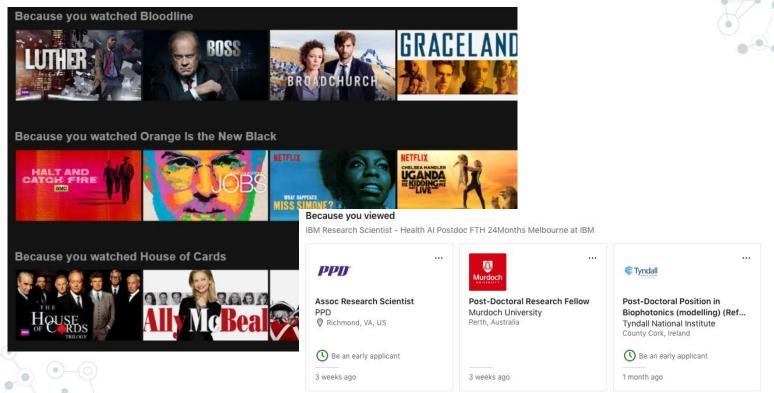
# **Knowledge-based Recommendation (1)**



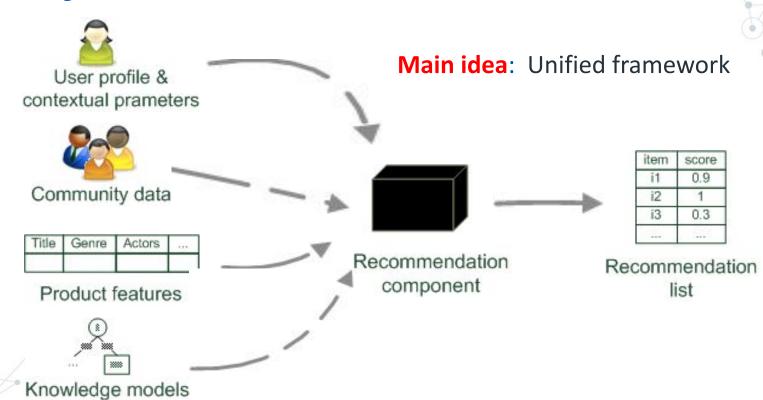
# **Knowledge-based Recommendation (2)**



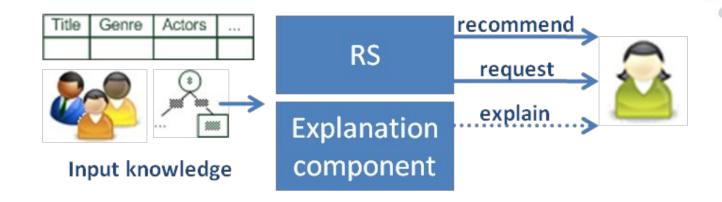
# **Knowledge-based Recommendation (3)**



# **Hybrid Recommendation**



# **Explainable Recommendation**



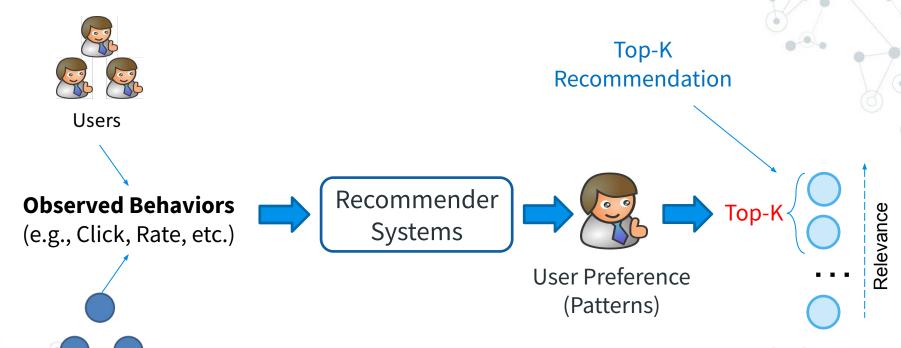
Main idea: Recommendation with explanation



# **Learning Principles**

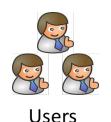
## How does RS work?

**Items** 



**Ranked Item List** 

# **Top-K Recommendation**



<u>Main idea</u>: Learning user preferences via modeling associations to generate top-K recommendations.

#### **Observed Data:**

User-Item & Item-Item
Associations



Recommender Systems







**User Preference** 

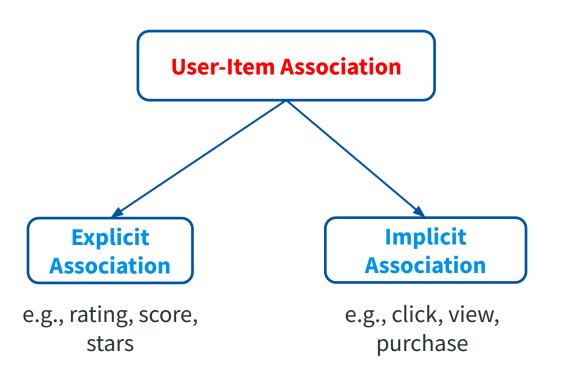


Ranked Item List

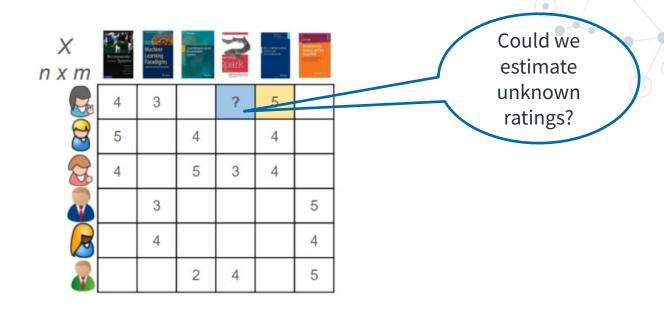


Relevance

## **User-Item Association**

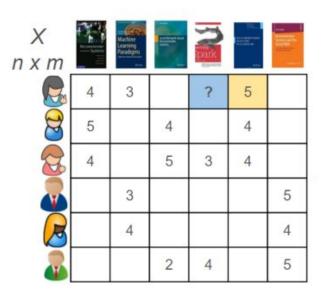


## **Explicit Association-based Recommendation**



Main idea: Recommended items are high rating ones.

## **Rating Prediction**

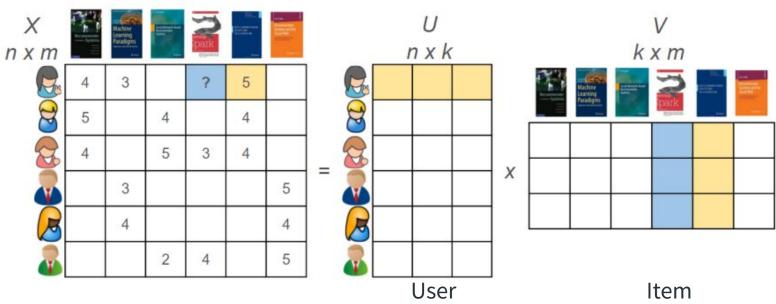


$$\hat{y}_{i,u} = rac{\sum_{u_j \in \mathcal{N}(u,i)} ar{y}_{i,u_j} ext{sim}(u,u_j)}{\sum_{u_j \in \mathcal{N}(u,i)} | ext{sim}(u,u_j)|}$$

Main idea: Rating is computed via similar users.



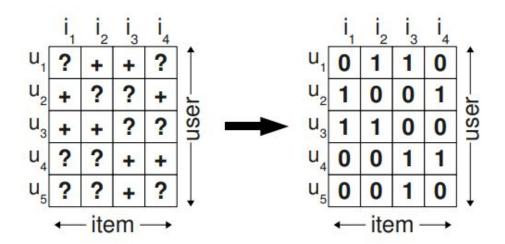
## **Rating Prediction with Matrix Factorization**



latent representation latent representation

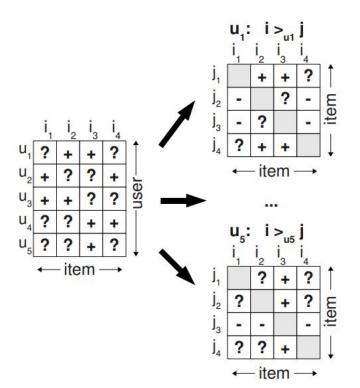
**Learning Objective**: Minimize  $(X_{ij} - U_i \times V_j^T)^2 + \lambda(||U||_2 + ||V||_2)$ 

## **Implicit Association-based Recommendation**



Main idea: Recommended items are popular (Counting)

## Bayesian Personalized Ranking (BPR)

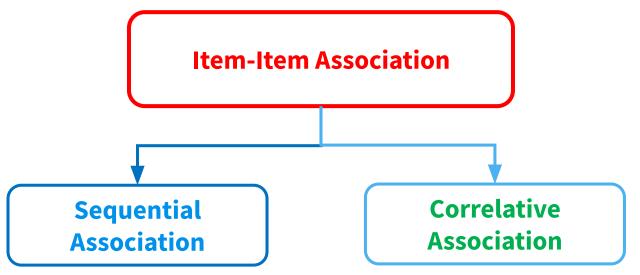


$$\prod_{u \in U} p(>_u |\Theta) = \prod_{(u,i,j) \in D_S} p(i>_u j|\Theta)$$
$$p(i>_u j|\Theta) := \sigma(\hat{x}_{uij}(\Theta))$$
$$\hat{x}_{uij} := \hat{x}_{ui} - \hat{x}_{uj}$$

Main idea: Learn the relative ranking for each user

### **Item-Item Association**

<u>Hypothesis:</u> The adoption of a user on an item might be influenced by his past adoptions on other items.



### **Correlative Association**

**Data:** Basket – Items are adopted at the same time.





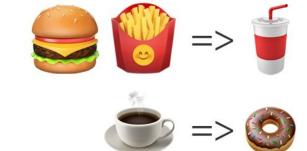
<u>Hypothesis:</u> Items within the same basket are correlated, refers to as *correlative dependencies*.

### **Association Rule-based Recommendation**





https://www.instacart.com/



#### Source:

https://www.quora.com/How-is-association-rule-compared-with-collaborative-filtering-in-recommender-systems



## An Example of Amazon RS

#### Frequently Bought Together









Add all three to Cart | Add all three to Wish List

Show availability and shipping details

- ☑ This item: Beginning Ruby: From Novice to Professional (Expert's Voice in Open Source) by Peter Cooper Paperback \$27.78
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\*\*\*\* 19

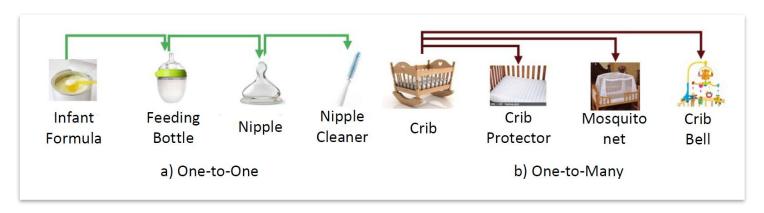
#1 Best Seller (in Ruby **Programming Computer** 

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## **Sequential Association**

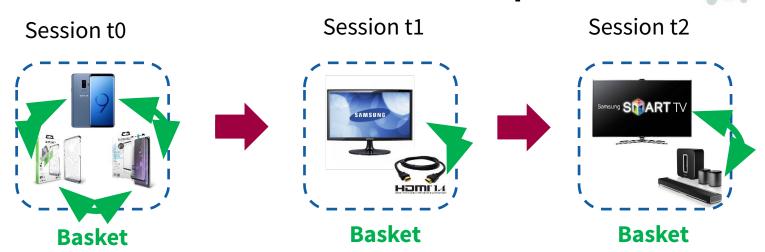
**<u>Data:</u>** Sequence – Items are adopted sequentially by time.



<u>Hypothesis:</u> The next selection (item) of a user is affected by his preceding adoptions

## One more thing ...

#### **The notion of Basket Sequence**

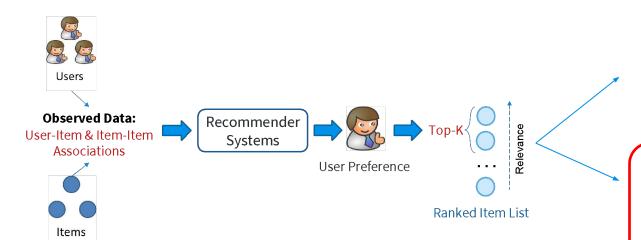


**Correlative associations** among items in a basket **Sequential associations** across baskets in a sequence

## **Evaluation and Metrics**

"Recommender systems are systems that help users discover items they may like."

## **Evaluation Strategy**



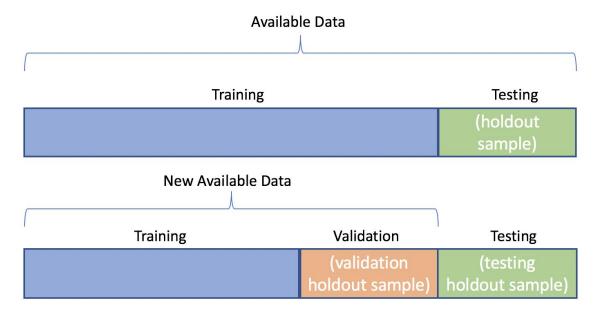
#### **Online Evaluation**

(User Study, A/B Testing)

#### **Offline Evaluation**

(Evaluation metrics on observed data)

## **Offline Evaluation**



**Note**: If the available data consists of item/basket sequence, the train/val/test should be split from non-overlapping consecutive periods

## **Error-based Metrics**

$$ext{MAE} = rac{\sum_{i=1}^{n}|y_i-x_i|}{n}$$

$$ext{MSE} = rac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y_i})^2.$$

$$ext{RMSD} = \sqrt{rac{\sum_{t=1}^T (\hat{y}_t - y_t)^2}{T}}.$$

#### Recommendation via Rating Prediction

	Actual	
	1: Toy Story (1995)	
755	2	
5277	1	
1577		
4388	2	
1202		
3823	3	
5448		
5347	2	
4117	4	
2765	4	

	Pedicted	
1: 1	1: Toy Story (1995)	
	4	
	2	
	3	
	2	
	2	
	5	
	4	
	3	
	5	
	4	

Absolute Error	Squared Error	
Toy Story (1995)	1: Toy Story (1995)	
2		
1		
3		
0		
2		
2		
4		
1		
1		
0		
0		

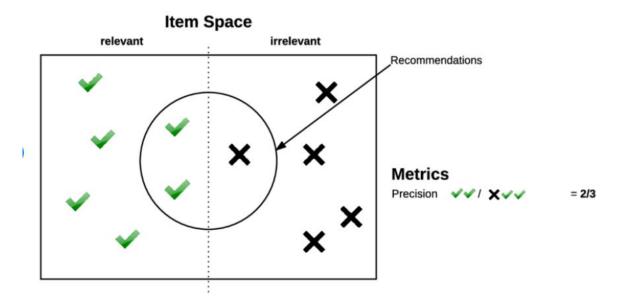
MAE	
1.6	

MSE	Ĩ
4	

RMSE	3
2.0	

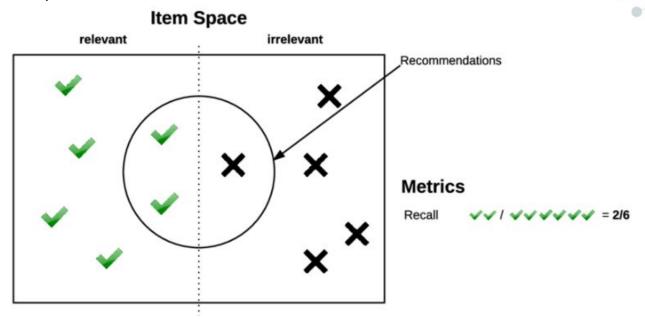
## **Classification-based Metrics (1)**

**Precision@K** for Top-K Recommendation



## **Classification-based Metrics (2)**

Recall@K for Top-K Recommendation



## **Ranking-based Metrics (1)**

Normalized Discounted Cummulative Gain (nDCG@K) for Top-K Recommendation

$$ext{nDCG}_{ ext{p}} = rac{DCG_p}{IDCG_p}, \hspace{0.5cm} ext{DCG}_{ ext{p}} = \sum_{i=1}^p rac{rel_i}{\log_2(i+1)} \hspace{0.5cm} ext{CG}_{ ext{p}} = \sum_{i=1}^p rel_i$$

$$ext{DCG}_{ ext{p}} = \sum_{i=1}^p rac{rel_i}{\log_2(i+1)}$$

$$ext{CG}_{ ext{p}} = \sum_{i=1}^{P} rel_i$$

Items Ranking Relevancy Score	
Movie 1	1
Movie 3	2
Movie 2	2
Movie 5	0
Movie 4	1

Perfect Ranking	Relevancy Score
Movie 3	2
Movie 2	2
Movie 1	1
Movie 4	1
Movie 5	0

CG =	6	
DCG =	12.1	

CG (p) =	6	
DCG (p) =	13.9	

$$nDCG = DCG/DCG (P) = 0.87$$

## Ranking-based Metrics (2)

Mean Reciprocal Rank (MRR) for Top-K Recommendation

$$MRR = rac{1}{N} \sum_{i=1}^{N} rac{1}{rank_i}$$

Items Ranking	Relavent Items	Reciprocol Ranking
Movie 1	No	0
Movie 3	Yes	1/2
Movie 2	Yes	1/3
Movie 5	No	0
Movie 4	Yes	1/5

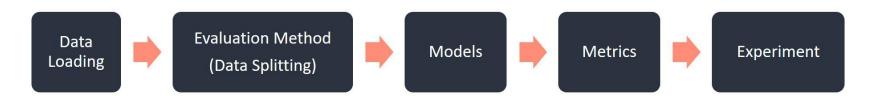
100000000000000000000000000000000000000	and the second s	100000000	
MRR =	1/2+1/3+1/5 =	1.03	





### Cornac

**Cornac** is a comparative framework for multimodal recommender systems, which focuses on making it **convenient** to work with models leveraging **auxiliary data** (e.g., item descriptive text and image, social network, etc.)



Flow of an Experiment in Cornac

Website: <a href="https://cornac.preferred.ai/">https://cornac.preferred.ai/</a>

Tutorials: <u>Github Repo</u>

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# Thanks!

trongld@vnu.edu.vn

