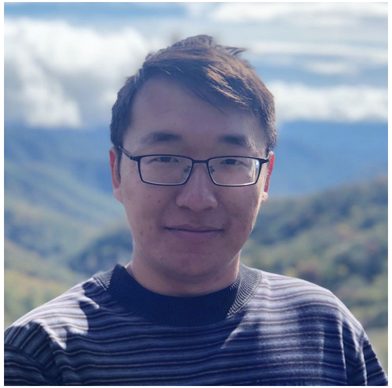
Search and Recommendation

Hao Sheng

August 9th, 2023

hello!



Hao Sheng

ICME Summer Workshop Instructor

Rui Yan

ICME Summer Workshop Assistant

Requirements

- Laptop with networks
- Attention is all you need

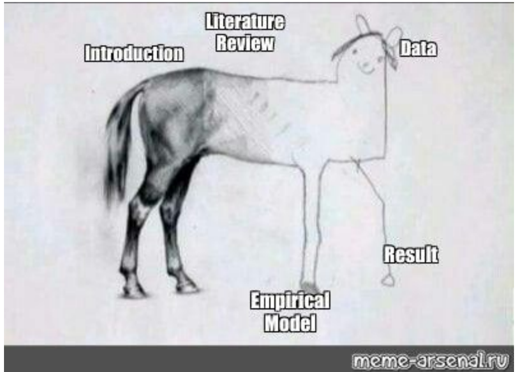
Mentimeter

Agenda

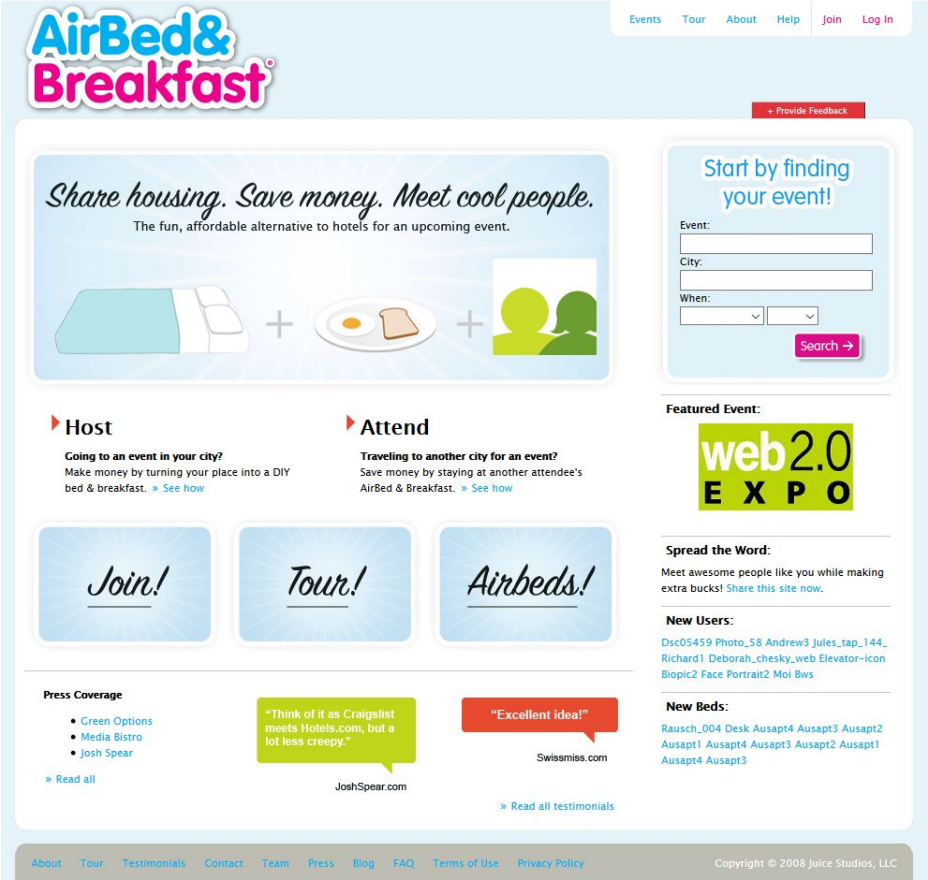
- **Introduction**
- **Lecturing:** The history of recommendation system
- **Break-out:** Recommendation system in daily life
- **Lecturing**: Recommendation as an ML problem
- **Lecturing**: Evaluate recommendation systems
- **Lab:** Recommendation system notebook I

60% Lecturing → 25% Lab → 10% Discussion

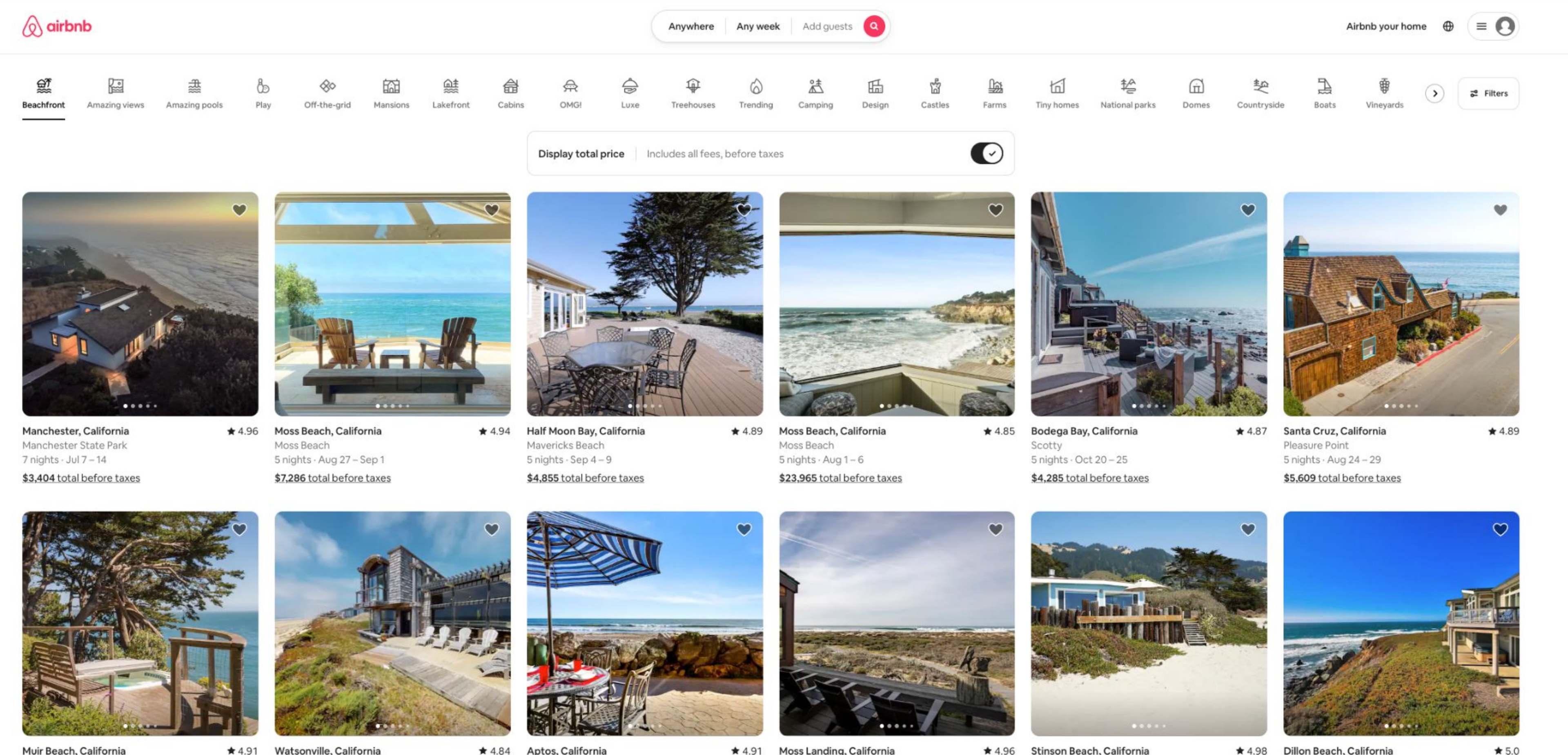
Introduction



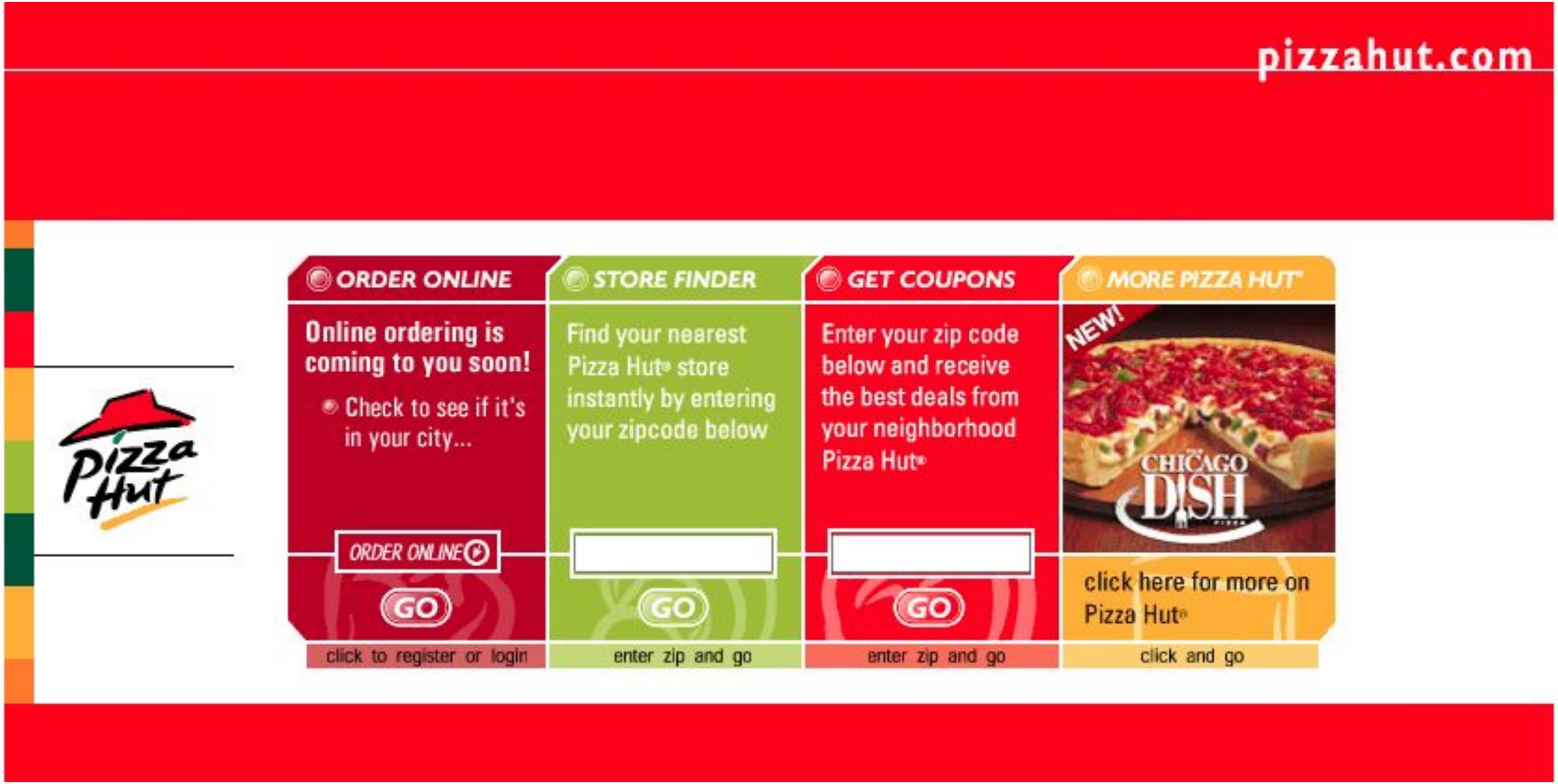
Introduction - AirBnb @ 2008



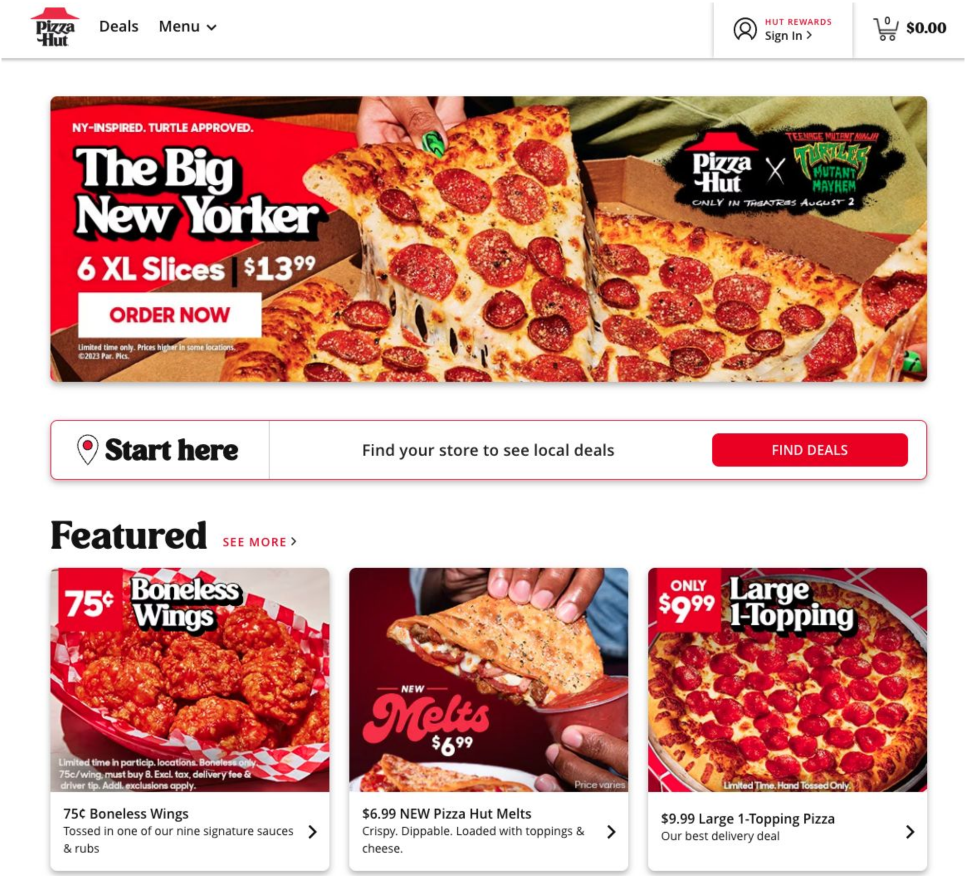
Introduction - AirBnb @ 2023



Introduction - Pizza Hut @ 2002



Introduction - Pizza Hut @ 2023



Introduction - YouTube @ 2005

Home | My Videos | My Favorites | My Messages | My Profile

Sign Up | Log In | Help

YouTube

Your Digital Video Repository

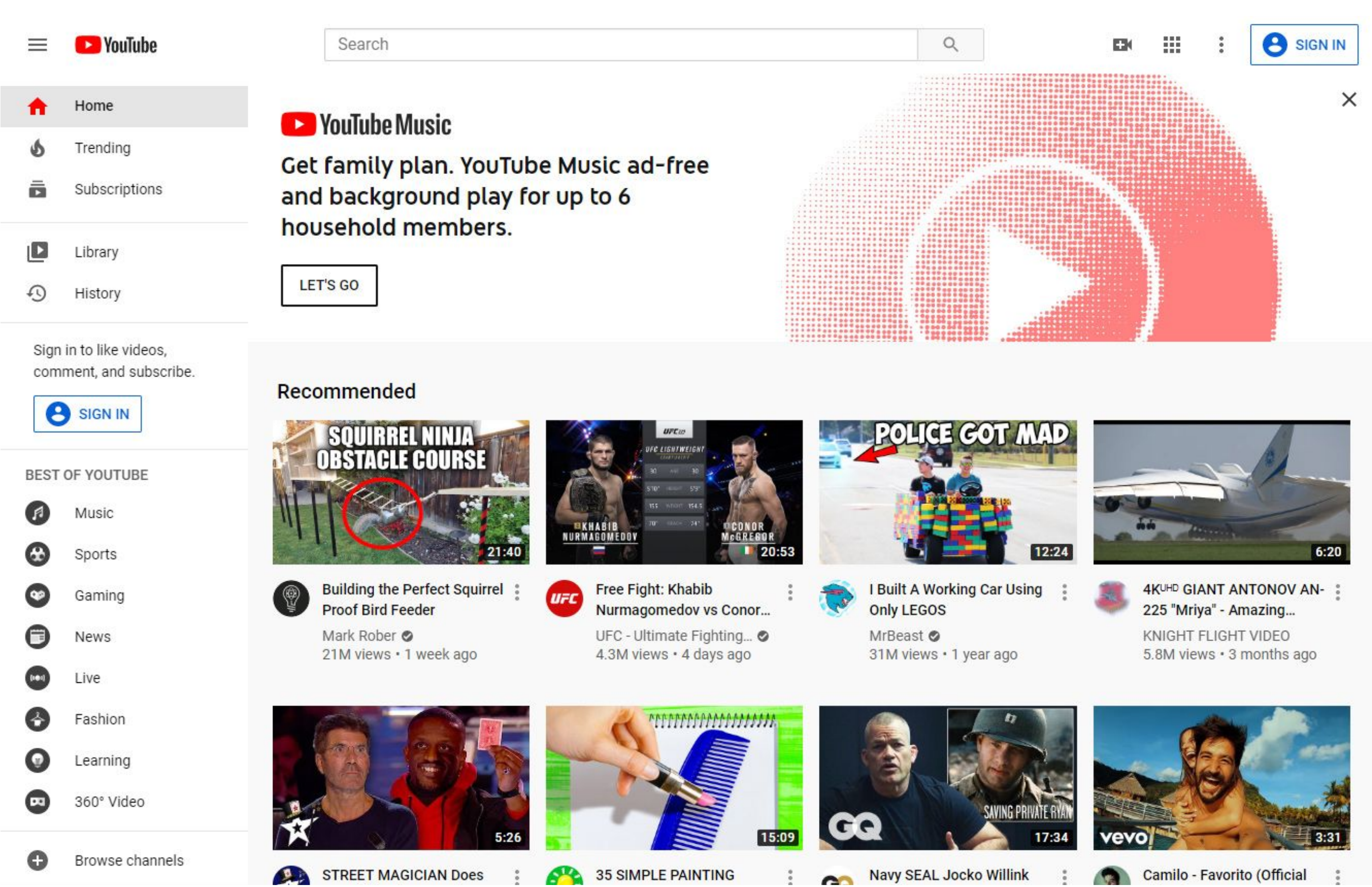
Search Videos

Upload Your Videos

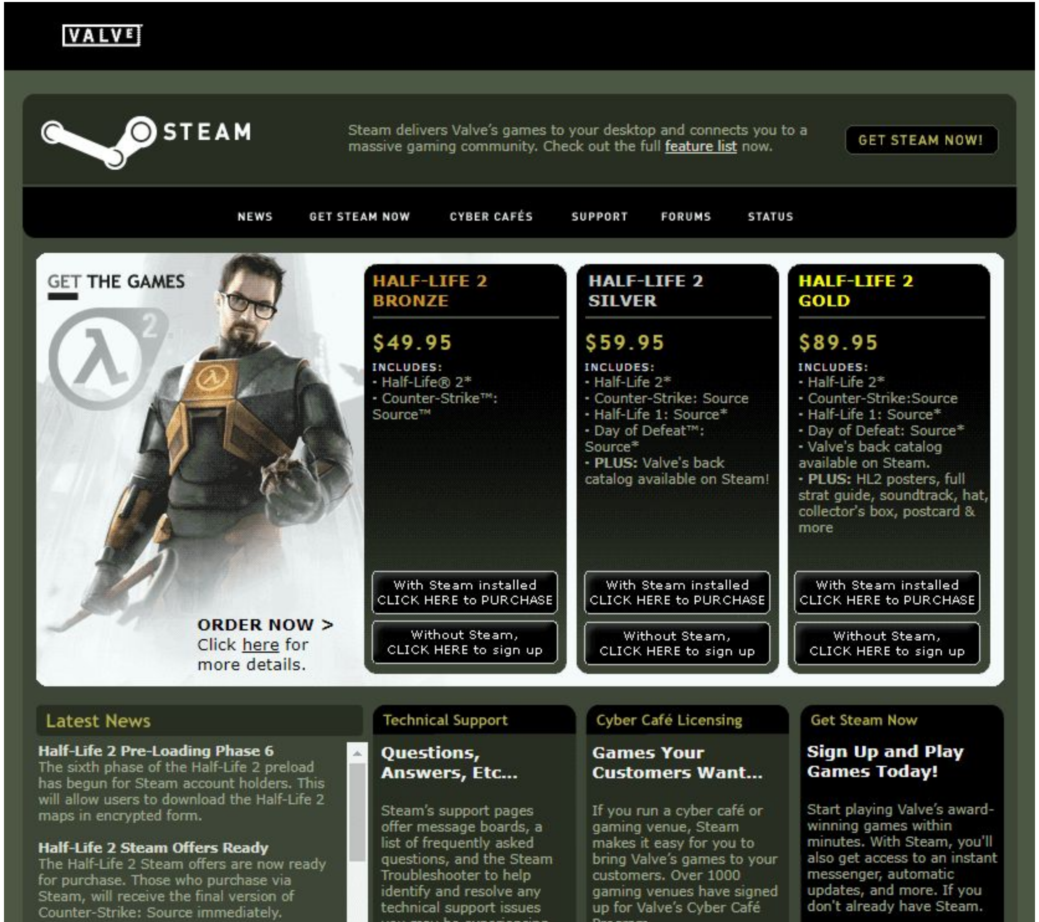
nansheng : azlan : wereldband : ny : superbike : japan : sinceretheory : jozef : party : amazon : board : skate : buckley : shubs : falls : de : stockshot : cubbyhole : burnout : satellite : poughkeepsie : cruise : heritage : orgel : chin : themed : mill : music : new : live : to : farmer : mtv : puenbrouck : sicily : fairfield : musical : coffeehouse : bud : 2005 : trip : jfk : woordjes : death : xlanz : skill : olle : nature : ads : dance :

See More Tags

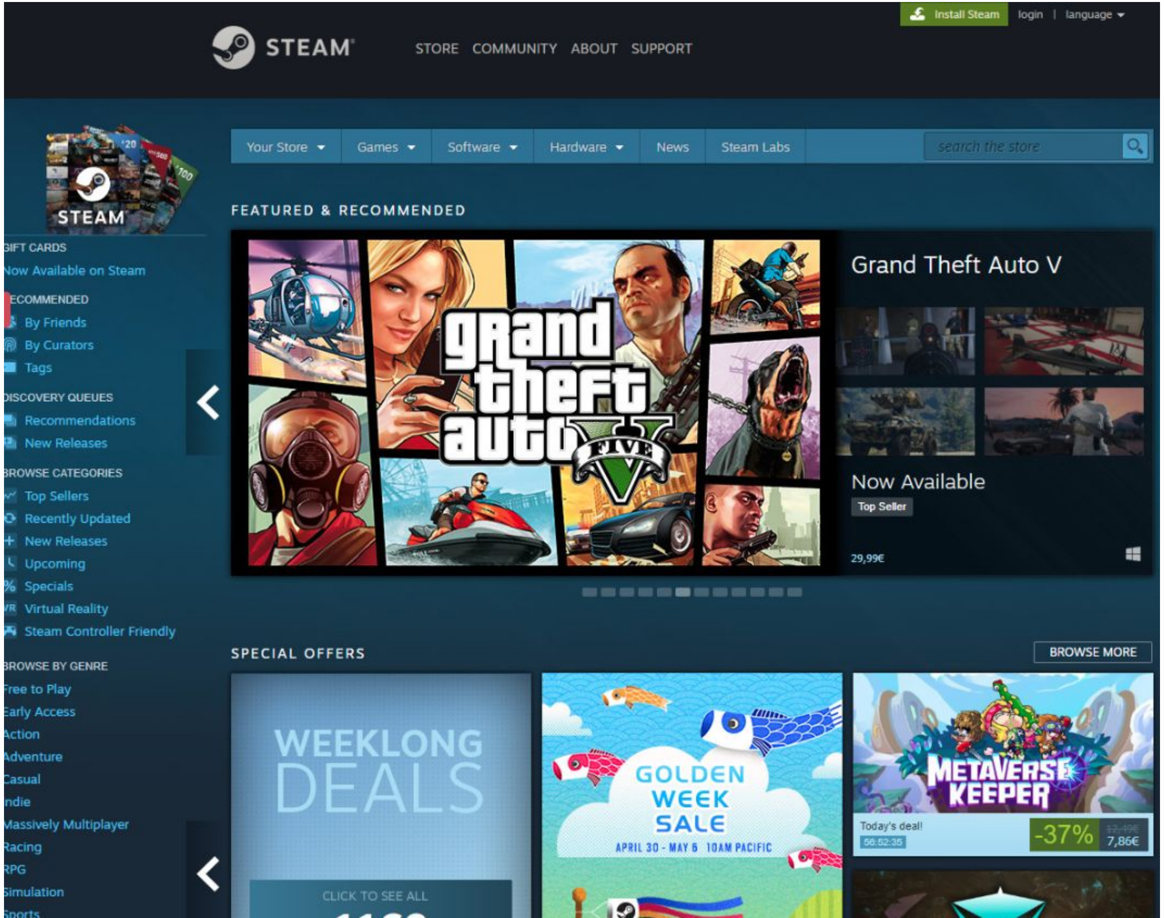
Introduction - YouTube @ 2020



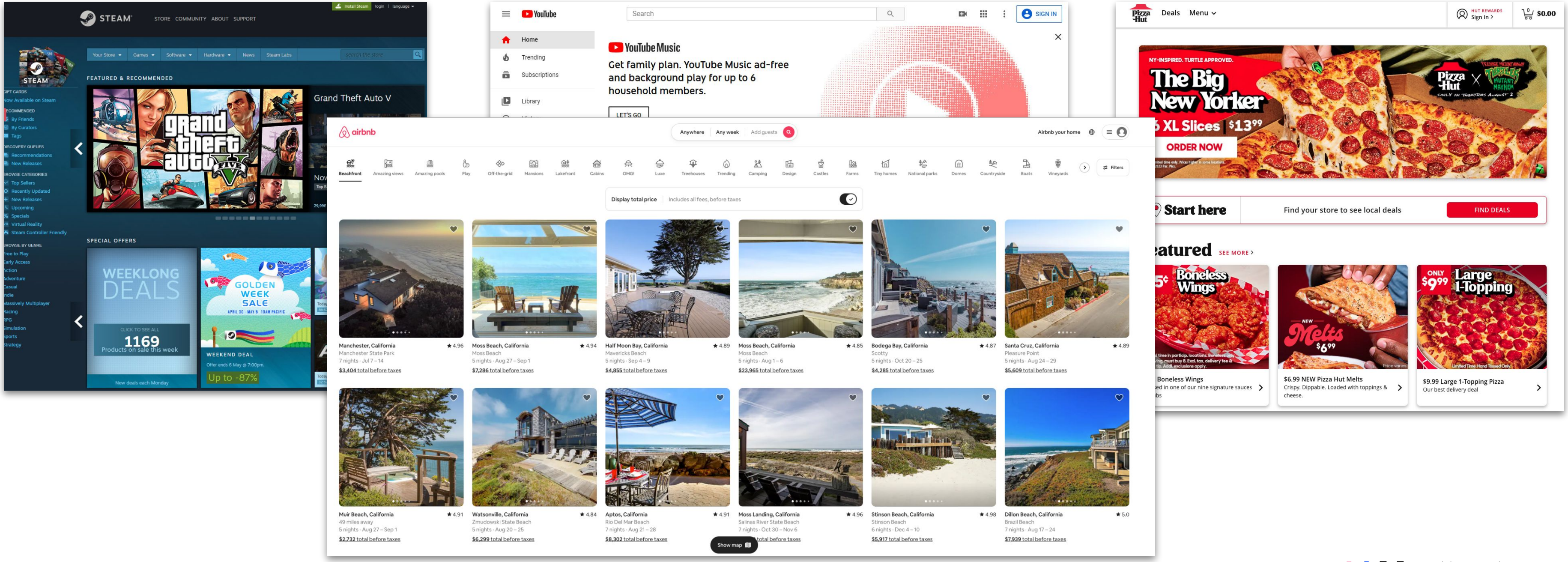
Introduction - Steam @ 2004



Introduction - Steam @ 2023



Homepages @ 2023



Everyone gives user recommendations on the first impression!

Introduction

- Every website gives user recommendations right on visiting.
- The recommendation is getting very “aggressive”?
  - 8 videos from 800 millions videos [1] on YouTube (used to recommend categories only)
  - 8-10 cities (and all in CA) from 100,000 cities [2] on AirBnb
  - GTA V from more than 50k games [3]
  - The Big New Yorker Pizza from 10 crusts x 21 toppings x 6 sources

[1] https://www.globalmediainsight.com/blog/youtube-users-statistics
[2] https://www.searchlogistics.com/learn/statistics/airbnb-statistics
[3] https://backlinko.com/steam-users

Introduction

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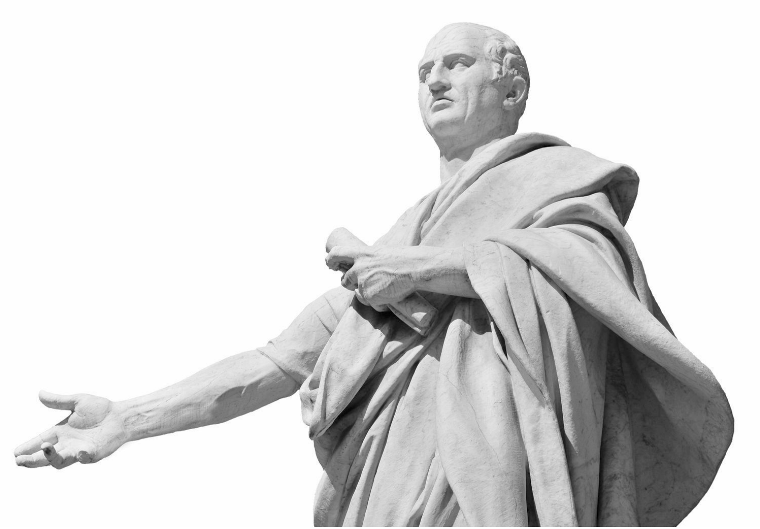
    - GTA V from more than 50k games
    - The Big New Yorker Pizza from 10 crusts x 21 toppings x 6 sources
- What makes them so confident that it is a good suggestion?

The History of Recommendation System

Recommendation and Divination

"I know of no people … that does not consider that future things are indicated by signs and that it is possible … to recognize those signs and predict what will happen."

--- Marcus Tullius Cicero (44 BC)



Divinetech: 1500 BC - 500 BC, China

Oracle bones (Chinese: 甲骨; pinyin: *jiǎgǔ*) are pieces of ox scapula and turtle plastron, which were used for pyromancy – a form of divination – in ancient China, mainly during the late Shang dynasty. *Scapulimancy* is the specific term if ox scapulae were used for the divination, *plastromancy* if turtle plastrons were used.

Divinetech: 1400 BC - 800 BC, Delphi, Greece

- Step 1: **Journey to Delphi**
- Step 2: **Preparation of the supplicant**
- Step 3: **Visit to the Oracle**
- Step 4: **Return home**

Divinetech: 450 BC - Today?

Aquarius
January 20 - February 18

Aries
March 21 - April 19

Cancer
June 22 - July 22

Capricorn
December 22 - January 19

Gemini
May 21 - June 21

Leo
July 23 - August 22

Libra
September 23 - October 22

Pisces
February 19 - March 20

Sagittarius
November 22 - December 21

Scorpio
October 23 - November 21

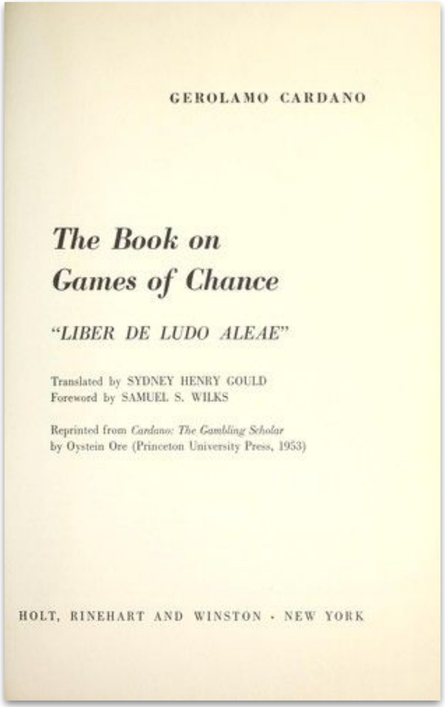
Taurus
April 20 - May 20

Virgo
August 23 - September 22

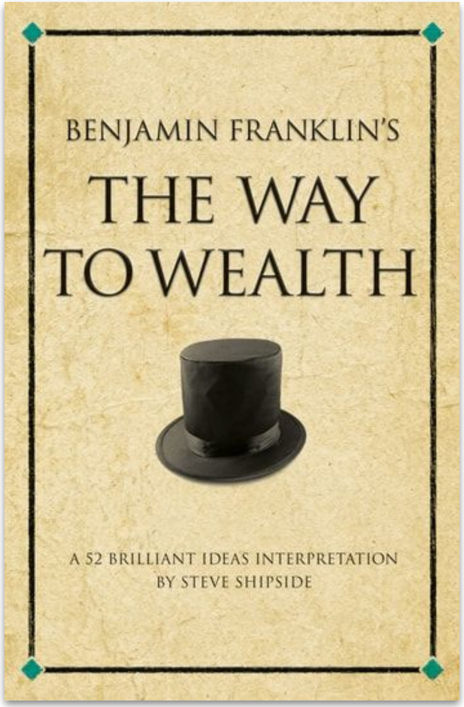
Aries March 21 - April 19

Today you should put good conversation at the top of your priority list! But in order to make it happen, you have to be ready to take things to a deeper level than you usually do with people you don't usually talk to. Small talk is for small minds right now, and since you certainly don't have one of those, why not prove it? Instead of asking about someone's weekend, ask them how they feel about international politics. You might get an odd look, but you'll also get great insight into another person.

Divinetech to Recommendation Literature: 1663 AD - 1859 AD



Cardano, 1663



Benjamin Franklin, 1757

Samuel Smiles, 1859

Recommendation Literature: 1859 AD - Today

- How to Win Friends and Influence People (1936)
- Think and Grow Rich (1937)
- …
- Oracle of the Coffee House (1972)
- The 7 Habits of Highly Effective People (1989)
- Awaken the Giant (1992)
- Chicken Soup of the Soul (1993)
- …
- The One Minute Manager (2001)
- A Guide to the Good Life (2009)
- Personal Development for Smart People (2009)

Recommendation (System): 1500 BC - Today

- People all over the world seek tools/techniques in their personal quest for actionable advice.
- Personalization and quantitative models are introduced.
- Self-help literature reflect the historical strand of recommendation: Curation.

Recommendation System: Definition?

“.. is a subclass of information filtering system that provide suggestions for items that are most pertinent to a particular user.” --- *Wikipedia*

“Recommender systems (RSs) are software tools and techniques that provide suggestions for items that are most likely of interest to a particular user. ” --- *Introduction to Recommender Systems Handbook*

“A recommender system can be described as a system which automatically selects personally relevant information for users based on their preferences.” --- *Intelligent and Relevant*

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First Recommendation System -- Grundy: 1979

COGNITIVE SCIENCE 3, 329-354 (1979)

User Modeling via Stereotypes *

ELAINE RICH

The University of Texas at Austin

This paper addresses the problems that must be considered if computers are going to treat their users as individuals with distinct personalities, goals, and so forth. It first outlines the issues, and then proposes stereotypes as a useful mechanism for building models of individual users on the basis of a small amount of information about them. In order to build user models quickly, a large amount of uncertain knowledge must be incorporated into the models. The issue of how to resolve the conflicts that will arise among such inferences is discussed. A system, Grundy, is described that builds models of its users, with the aid of stereotypes, and then exploits those models to guide it in its task, suggesting novels that people may find interesting. If stereotypes are to be useful to Grundy, they must accurately characterize the users of the system. Some techniques to modify stereotypes on the basis of experience are discussed. An analysis of Grundy's performance shows that its user models are effective in guiding its performance.

1. INTRODUCTION

Scene I

Someone walks into a large library, tells the librarian that he is interested in China, and asks for some books. What sort of books does the librarian recommend? That depends. Is the person a small child who just saw a TV show about China and wants to see more pictures of such an exotic place? Is the person a high school student doing a term paper? Or maybe a prospective tourist? Or a scholar interested in Eastern thought? Can the person read Chinese? The librarian needs to know these things before he can point the reader to the right books. Some of what he needs to know he'll know before he even thinks about it, such as the approximate age of the person. Some things he'll assume until he has evidence to the contrary, such as that the person does not read Chinese. To find out other things, he'll ask a few specific questions. Only after he has a rough model of the person he's talking to can he answer the question.

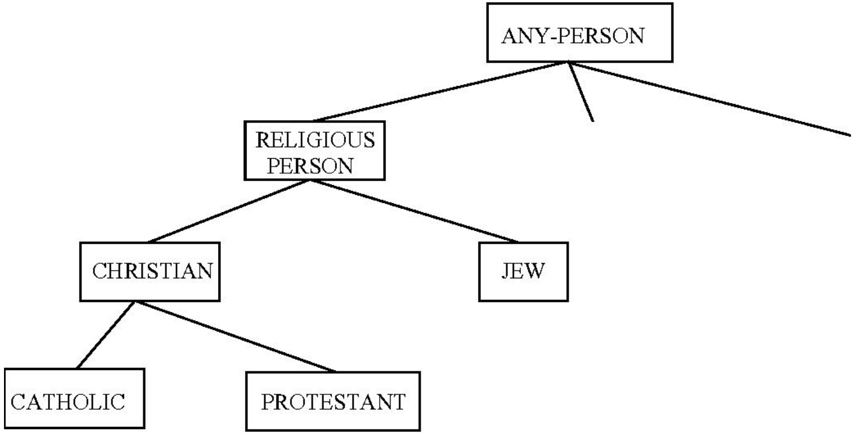
Scene II

The phone rings in the information division of a large pharmaceutical firm. The caller wants information about a drug the company makes. What sort of information should be provided? That depends. Is the caller a doctor, a patient, or an FDA representative? To provide the right information, the person answering the phone needs to know some facts about the caller.

The scenes above illustrate some kinds of situations in which people need to form a *model* of the person with whom they are dealing before they can behave appropriately. They form their model by collecting a few specific pieces of information and then invoking the knowledge they have about the groups to which the current person belongs, such as scholar or medical patient.

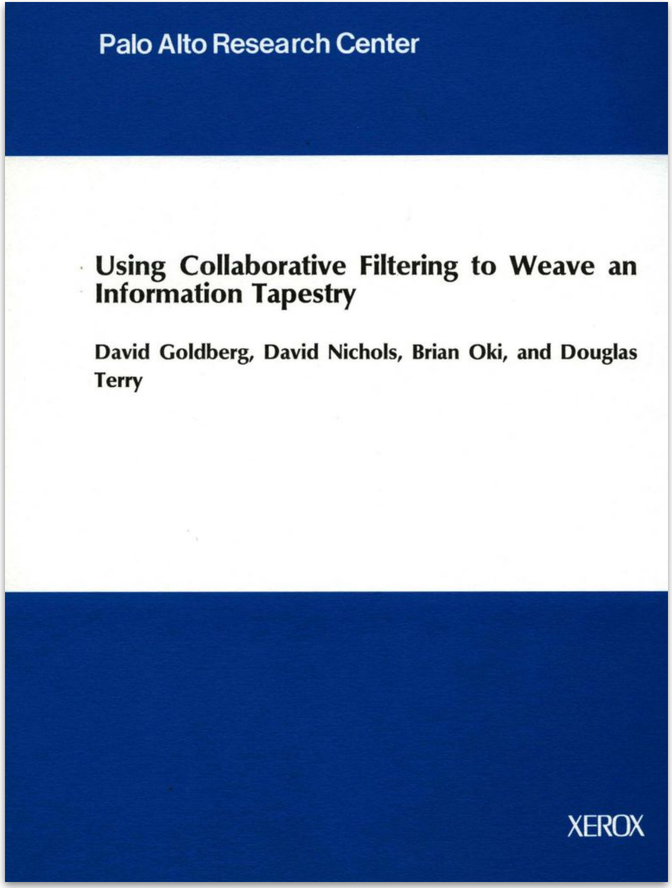
As computers come to be used by a larger number of people to help perform a great variety of tasks, it is becomming more and more important for them to be easy for people to use. There are many factors than can contribute to the ease of use of a computer system, ranging from the good design of input devices such as terminals to the speed of the system's response, the appropriateness of its response, and the naturalness of its input and output languages. Appropriate models of the users of a system can be an important contribution because they can simultaneously affect several of those factors, such as speed and quality of response and habitability of the language interface.

Most systems that interact with human users contain, even if only implicitly, some sort of model of the creatures they will be dealing with. For example, the central assumption behind the mini-max strategy used by game playing programs is that the opponent is trying to win and will therefore make his best possible move. Although it is almost always valid to assume that the opponent wants to win, it is much less often true that he will therefore make the best move. He may, and probably does, have idiosyncracies of style or strategy that preclude that. Of course, human players know that and watch for evidence of such quirks in their opponents.
The term "user model" can be used to mean several different things. The three major dimensions along which user models can be classified are:



Rich, Elaine. "User modeling via stereotypes." *Cognitive science* 3.4 (1979): 329-354.

First Recommendation System Used: 1992, Palo Alto



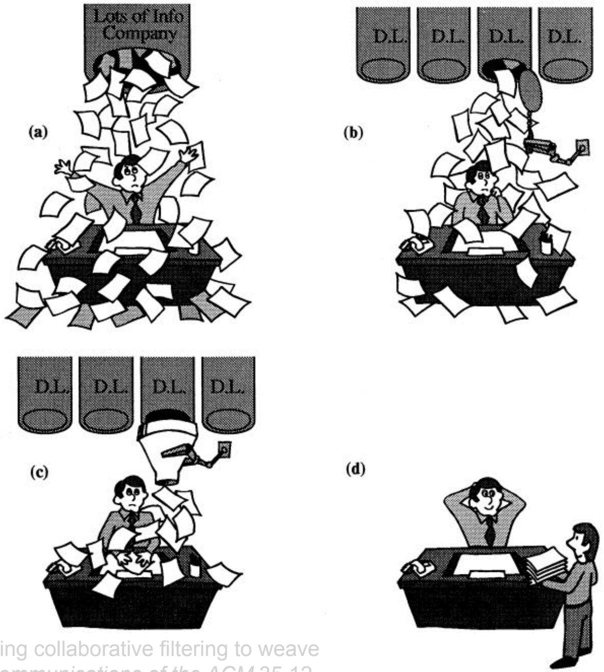
Palo Alto Research Center

Using Collaborative Filtering to Weave an Information Tapestry

David Goldberg, David Nichols, Brian Oki, and Douglas Terry

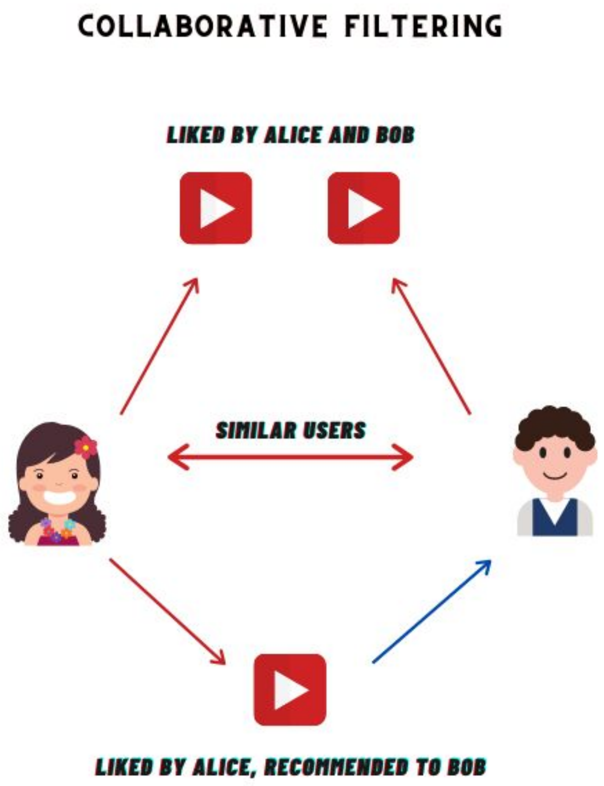
XEROX

Figure 1.
(a) electronic mail overload
(b) using distribution lists
(c) conventional filtering
(d) collaborative filtering



Goldberg, David, et al. "Using collaborative filtering to weave an information tapestry." *Communications of the ACM* 35.12 (1992): 61-70.

Collaborative Filtering: More to come after the break



First-generation “Real” Recommendation System: 1992, Palo Alto

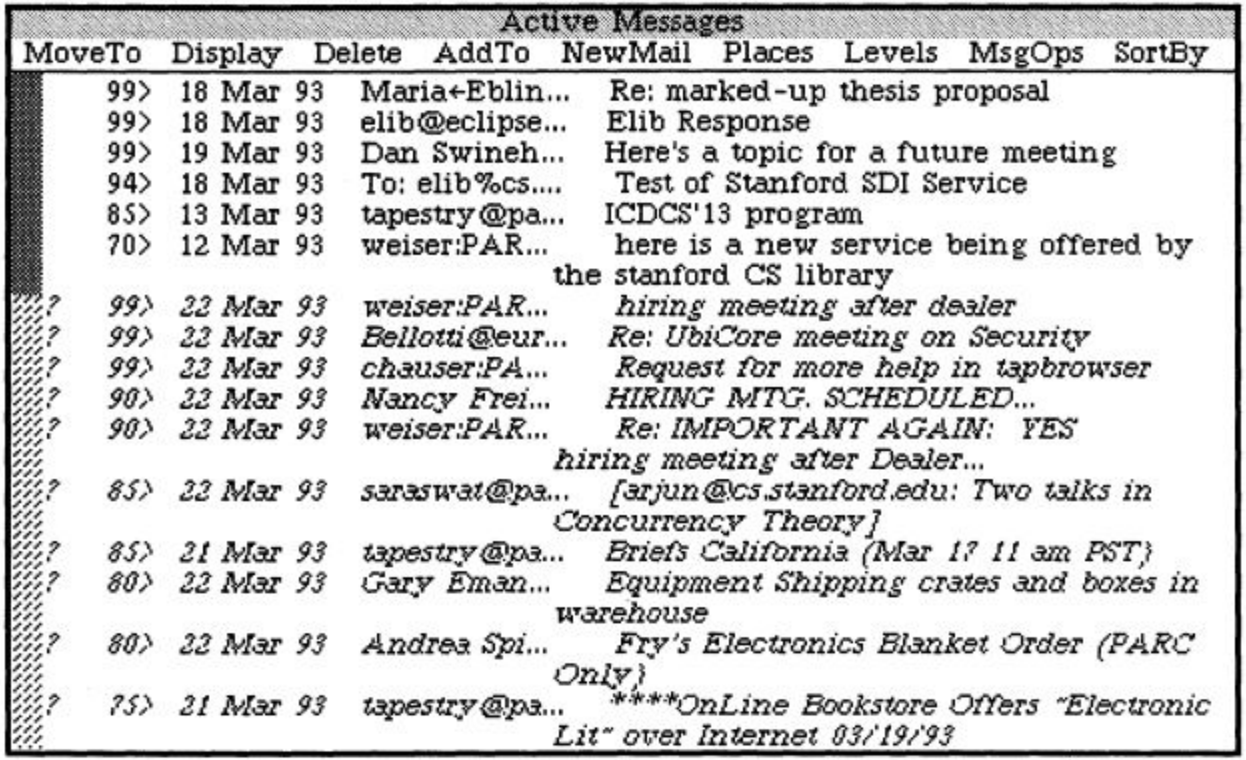


Figure 1. My Active folder showing old messages followed by prioritized new mail.

Goldberg, David, et al. "Using collaborative filtering to weave an information tapestry." *Communications of the ACM* 35.12 (1992): 61-70.

First-generation “Real” Recommendation System: 1992, Palo Alto

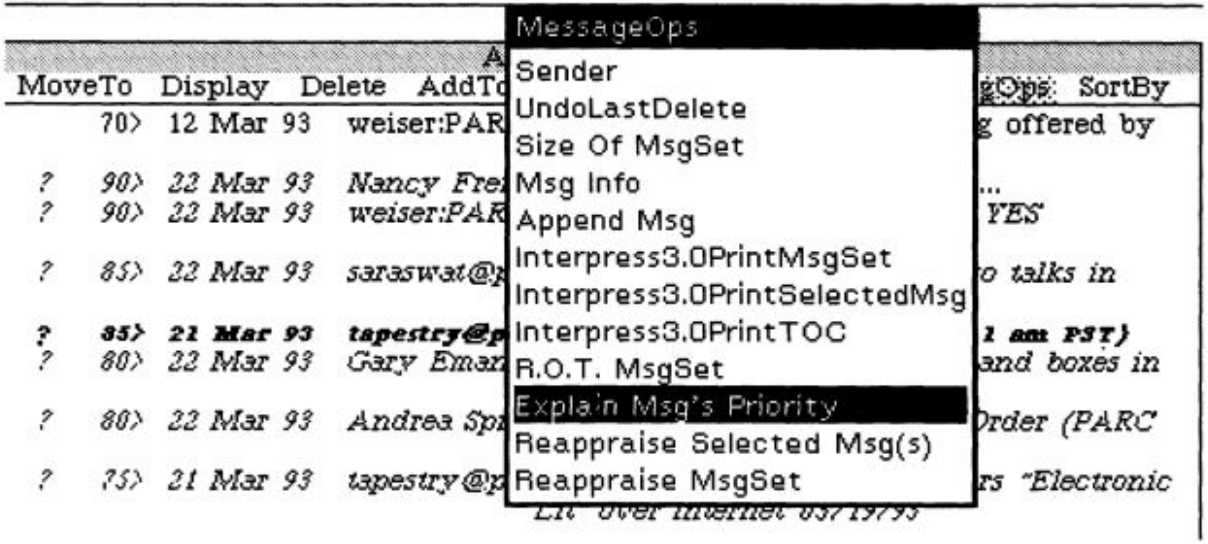


Figure 2. Requesting an explanation for a message's priority.

Annotations for message $ XNS-SMTP-Gateway:Parc:Xerox
appraiser terry $text:Bakersfield => priority 85
appraiser terry $Subject:Briefs←California => priority 55
appraiser terry $sender:tapestry => priority 10

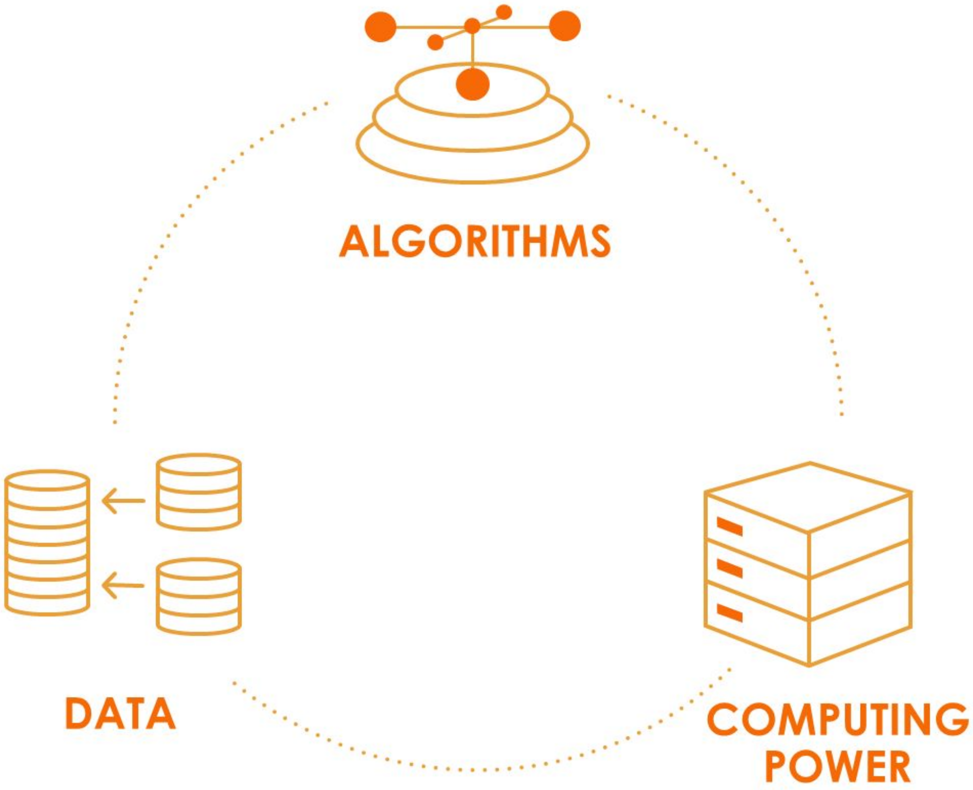
Figure 3. An explanation of priorities assigned to a message by various appraisers.

Goldberg, David, et al. "Using collaborative filtering to weave an information tapestry." *Communications of the ACM* 35.12 (1992): 61-70.

Earlier Recommendation Systems

- Recommendation system: RS automatically selects personalized information based on users’ preferences.
- Grundy:
    - Ask user questions and assign stereotype.
    - **Content-based filtering.**
- Tapestry:
    - Find similar users and recommend their choices.
    - **Collaborative filtering.**

Backbone of Recommendation System: Not Only the Algorithm



Coffee Break

Take a 10 minute break

At Your Service:
Coffee Beans Recommendation
From a Robot Assistant

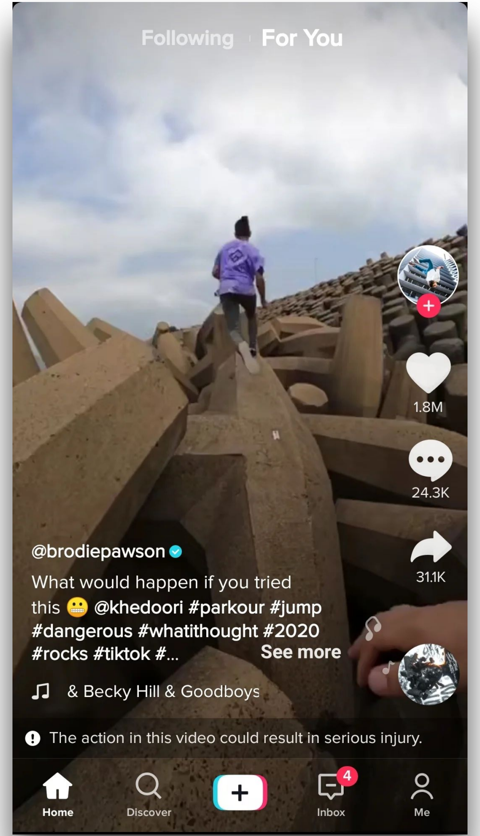
Jacopo de Berardinis*, Gabriella Pizzuto†, Francesco Lanza‡, Antonio Chella ‡, Jorge Meira §, Angelo Cangelosi*
*School of Engineering, The University of Manchester
†School of Informatics, The University of Edinburgh
‡Department of Engineering, University of Palermo
§Department of Computer Science and Information Technologies, University of A Corua

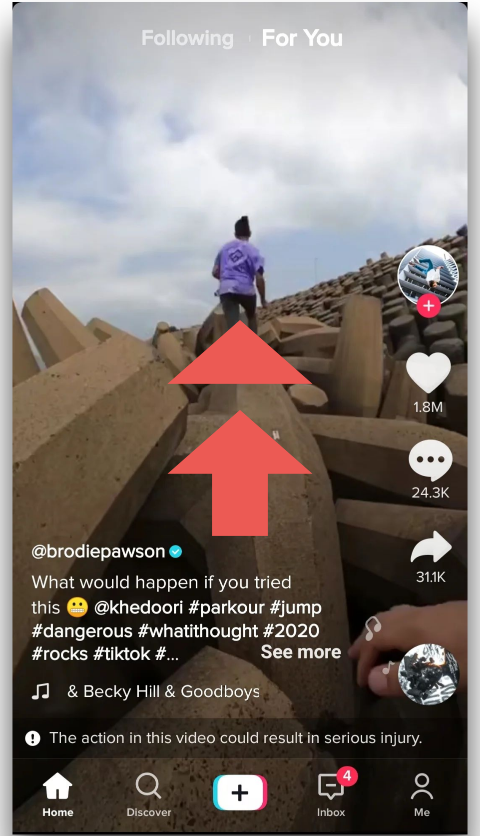
2020

Recommendation System in Daily Life

Recommendation System in Daily Life

- **Q:** What is the input/outputs of the system?
- **Q:** Why is this useful?
- **Q:** Can you guess what’s behind the system?


Following
For You
1.8M
24.3K
31.1K
@brodiepawson
What would happen if you tried this 😬 @khedoori #parkour #jump #dangerous #whatithought #2020 #rocks #tiktok #...
See more
& Becky Hill & Goodboys
The action in this video could result in serious injury.
Home
Discover
4
Inbox
Me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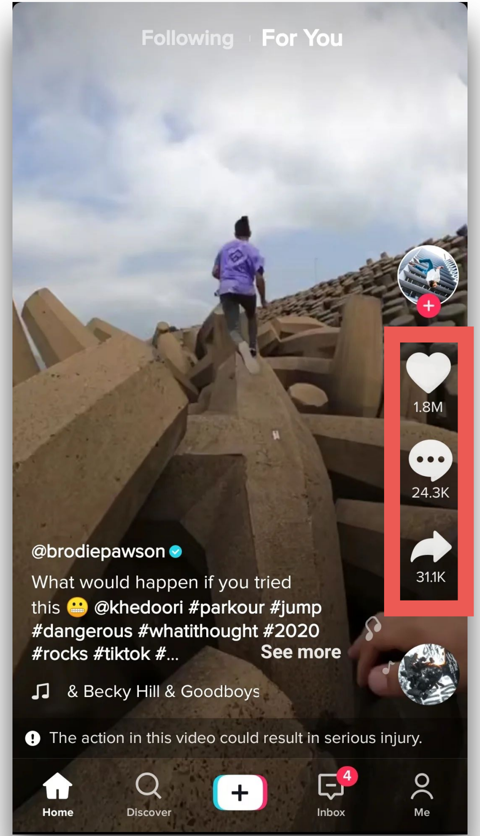

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Recommendation System in Daily Life: TikTok

- **Q:** What is the input/outputs of the system?
  - Input: Historical user behavior (e.g. like/comment/share or not; How long did I stay; Did I finish the video)
  - Outputs: Next short video I would like to watch. Or some Ads that I have high chance to spend my money on.
- **Q:** Why is this useful?
  - Well, it helps to.. kill my time more effectively(?). I don’t need to search for videos I am interested in. Moreover, I explored my interests in a way I could never think about.
- **Q:** Can you guess what’s behind the system?
  - Hmm. Maybe just like the Grundy example? They assigned me a “stereotype”?

Recommendation as an ML Problem

Recommendation System an ML Problem

- How to model recommendation problem mathematically.
- Classic recommendation algorithms
  - Collaborative filtering
    - Memory-based filtering
    - Model-based filtering
  - *Content-based filtering
- How to evaluate recommendation modeling.

Recommendation System an ML Problem

	1	2	3	4	5	6
a	5		1	1		2
b		2		4		4
c	4	5		1	1	2
d			3	5	2	
e	2		1		4	4

prediction: $r_{u,i}$

↓

recommend top-N items

Recommendation System an ML Problem

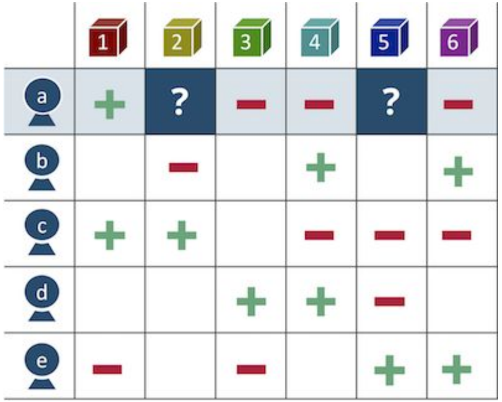
	1	2	3	4	5	6
a	+	?	−	−	?	−
b		−		+		+
c	+	+		−	−	−
d			+	+	−	
e	−		−		+	+

prediction: $r_{u,i}$

↓

recommend top-N items

Recommendation System an ML Problem



prediction: $r_{u,i}$

⬇

recommend top-N items

Recommendation System an ML Problem

Sara	5	3		2	2	2
Jesper	4	3	4		3	3
Therese	5	2	5	2	1	1
Helle	3	5	3		1	1
Pietro	3	3	3	2	4	5
Ekaterina	2	3	2	3	5	5

Recommendation System an ML Problem

Recommendation System an ML Problem

- How to model recommendation problem mathematically.
- Classic recommendation algorithms
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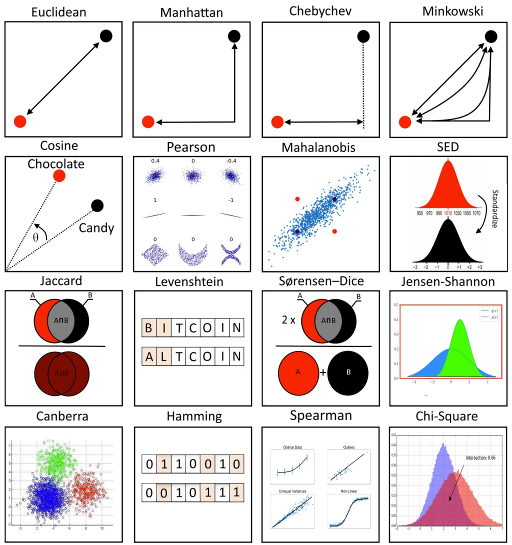
Collaborative Filtering: Similarity Function

You can calculate similarity in many ways, but the overall problem can be defined as follows: Given two items, i_1 and i_2, the similarity between them is given by the function sim(i_1, i_2).



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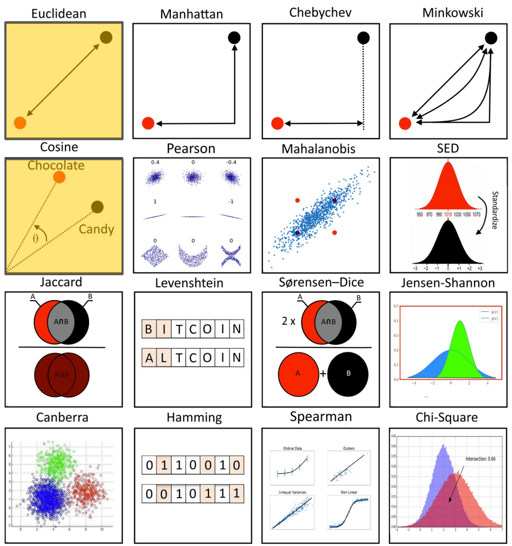
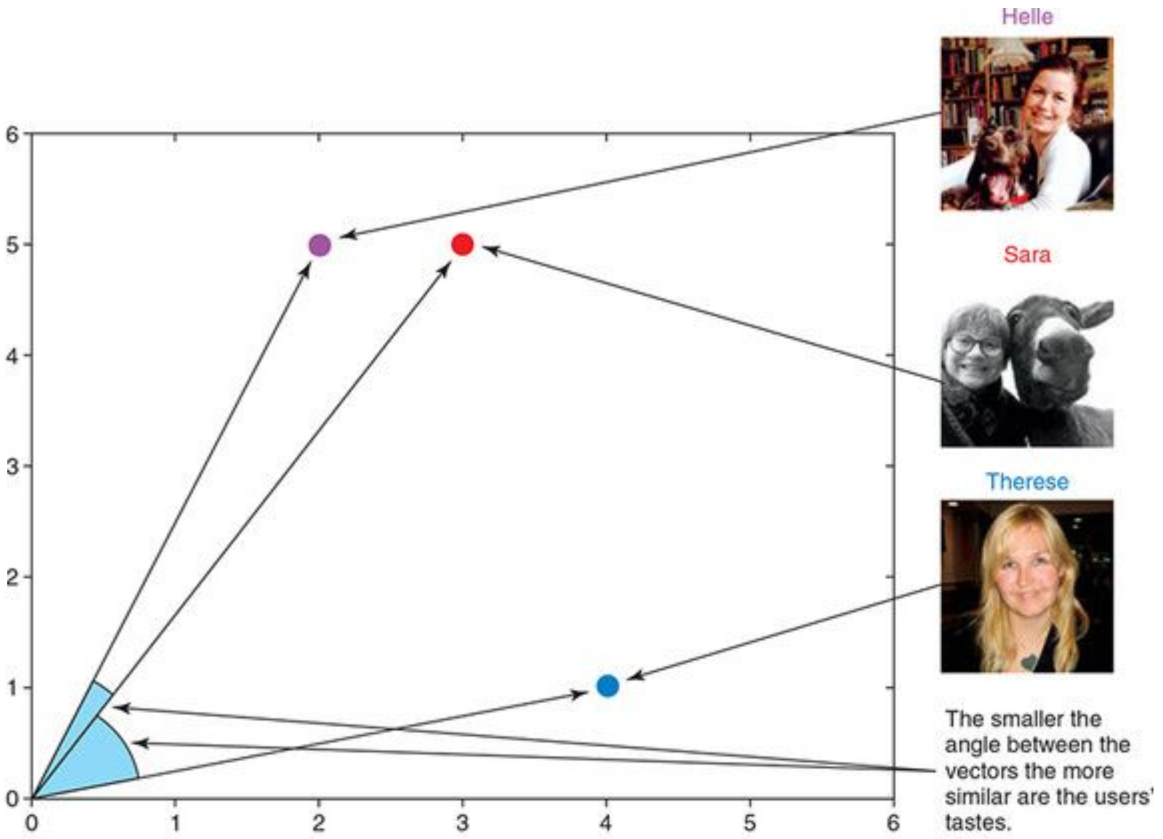


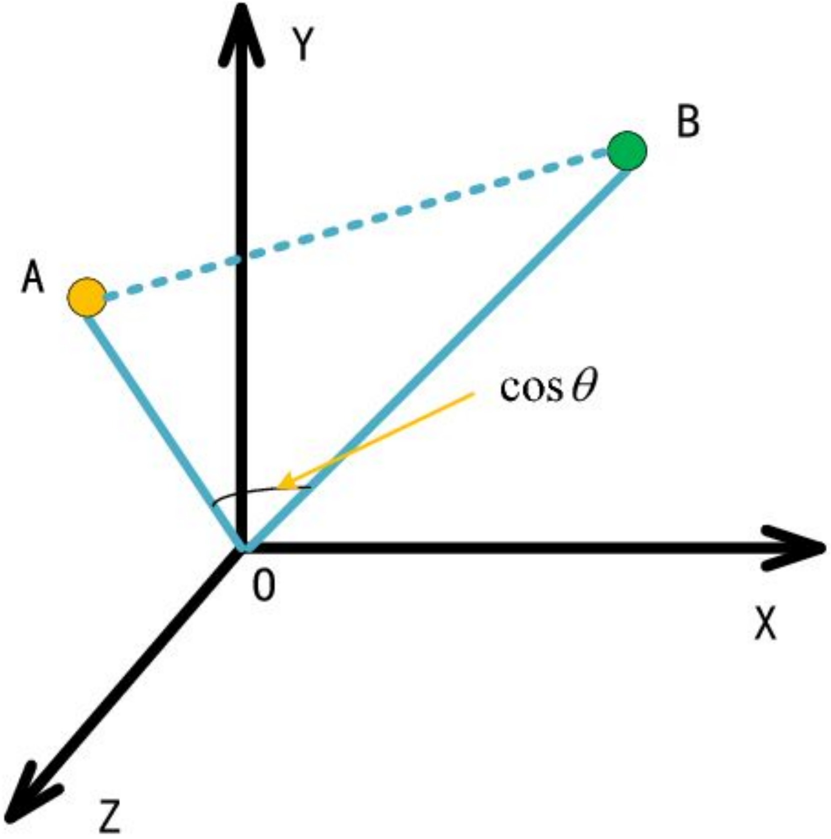
Collaborative Filtering: Cosine Similarity

	Barbie	Oppenheimer
Helle	5	2
Sara	5	3
Therese	1	4

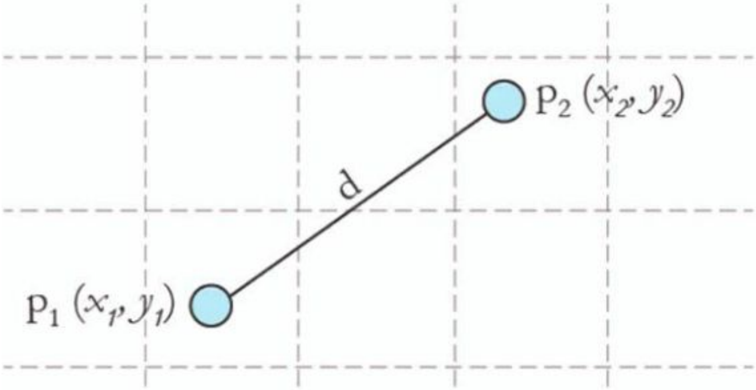


Collaborative Filtering: Cosine Similarity

	Barbie	Oppenheimer	Spider-Man: Across the Spider-Verse
Helle	5	2	3
Sara	5	3	4
Therese	1	4	3



Collaborative Filtering: Euclidean Similarity



$$\text{Euclidean distance (d)} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Collaborative Filtering: Scale-up Similarity Calculation

What if we have 20 million active users?

Calculate similarities of current user <-> 20 million users?

Collaborative Filtering: Scale-up Similarity Calculation

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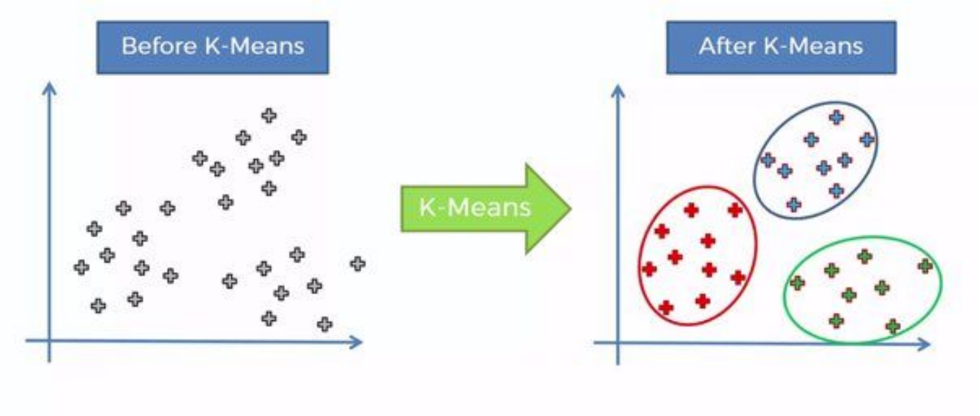
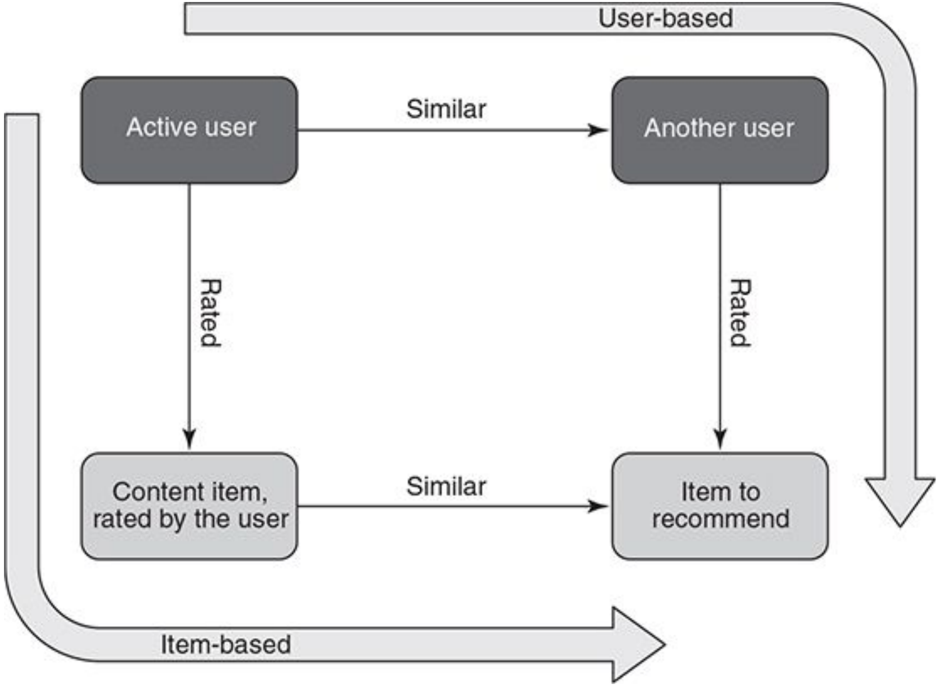


K-Means Clustering in Python: A Practical Guide: https://realpython.com/k-means-clustering-python/

Collaborative Filtering: Memory-based



Collaborative Filtering: Model-based Filtering

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    - Memory-based filtering
    - Model-based filtering
  - *Content-based filtering

Collaborative Filtering: Motivation of Model-based Filtering

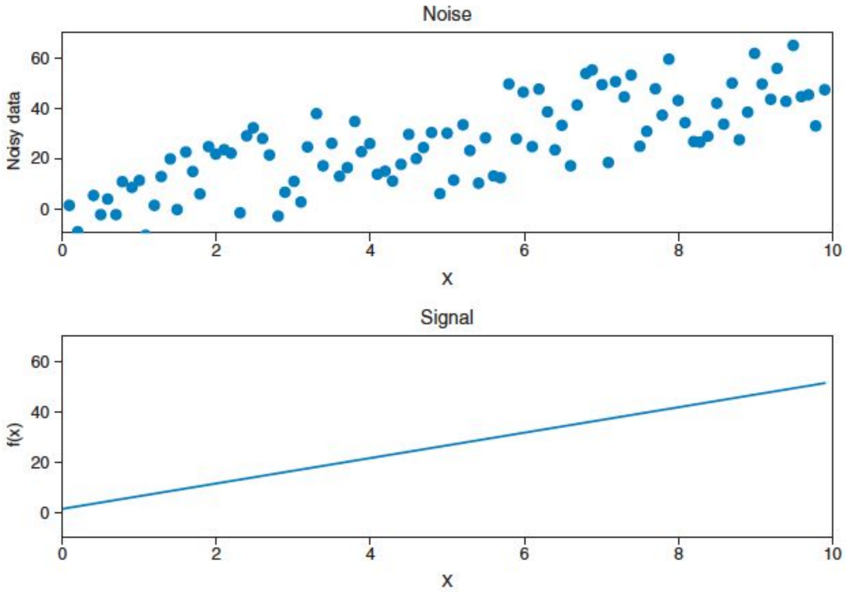


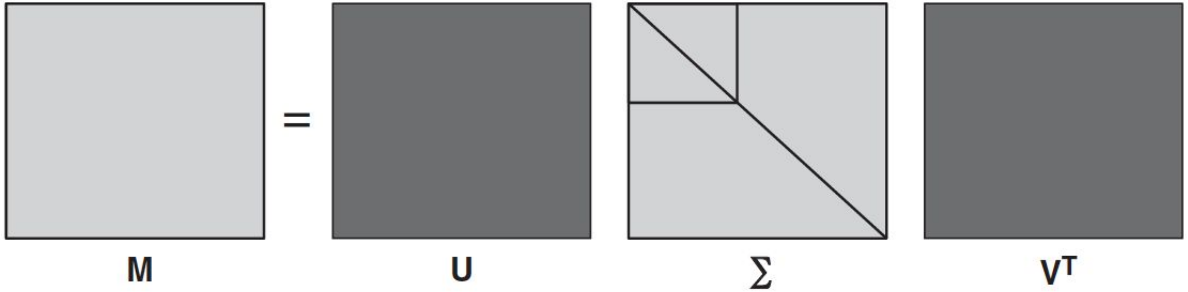
Figure 11.1 A scatter plot of noisy data (top) and the signals that uncover the information in the data (bottom)

Collaborative Filtering: Factorization

Sara	5	3		2	2	2
Jesper	4	3	4		3	3
Therese	5	2	5	2	1	1
Helle	3	5	3		1	1
Pietro	3	3	3	2	4	5
Ekaterina	2	3	2	3	5	5

$$R = \begin{bmatrix} 5 & 3 & 0 & 2 & 2 & 2 \\ 4 & 3 & 4 & 0 & 3 & 3 \\ 5 & 2 & 5 & 2 & 1 & 1 \\ 3 & 5 & 3 & 0 & 1 & 1 \\ 3 & 3 & 3 & 2 & 4 & 5 \\ 2 & 3 & 2 & 3 & 5 & 5 \end{bmatrix}$$

Collaborative Filtering: SVD Factorization



$$
\begin{bmatrix}
5 & 3 & 0 & 2 & 2 & 2 \\
4 & 3 & 4 & 0 & 3 & 3 \\
5 & 2 & 5 & 2 & 1 & 1 \\
3 & 5 & 3 & 0 & 1 & 1 \\
3 & 3 & 3 & 2 & 4 & 5 \\
2 & 3 & 2 & 3 & 5 & 5
\end{bmatrix}
=
$$

-0.34	0.05	0.91	0.11	0.19	-0.00
-0.43	0.16	-0.31	-0.12	0.74	0.35
-0.39	0.56	-0.19	0.63	-0.32	0.02
-0.33	0.42	0.02	-0.76	-0.37	-0.05
-0.48	-0.34	-0.18	0.03	0.10	-0.78
-0.46	-0.61	-0.06	0.02	–0.40	0.51

U

17.27	0	0	0	0	0
0	5.84	0	0	0	0
0	0	3.56	0	0	0
0	0	0	3.13	0	0
0	0	0	0	1.67	0
0	0	0	0	0	0.56

Σ

-0.50	-0.44	-0.41	-0.22	-0.40	-0.43
0.46	0.17	0.42	-0.22	-0.49	-0.55
0.50	0.22	-0.78	0.26	-0.08	-0.13
0.34	-0.77	0.17	0.51	-0.02	-0.01
0.41	-0.36	-0.16	-0.76	0.19	0.25
-0.01	-0.03	0.01	-0.02	0.75	-0.66

V^t

Collaborative Filtering: SVD Factorization

```
def rank_k(k):
    U_reduced= np.mat(U[:,:k])
    Vt_reduced = np.mat(Vt[:k,:])
    Sigma_reduced = Sigma_reduced = np.eye(k)*Sigma[:k]

        return U_reduced, Sigma_reduced, Vt_reduced,

    U_reduced, Sigma_reduced, Vt_reduced = rank_k(4)

    M_hat = U_reduced * Sigma_reduced * Vt_reduced
```

Returns the reduced matrices

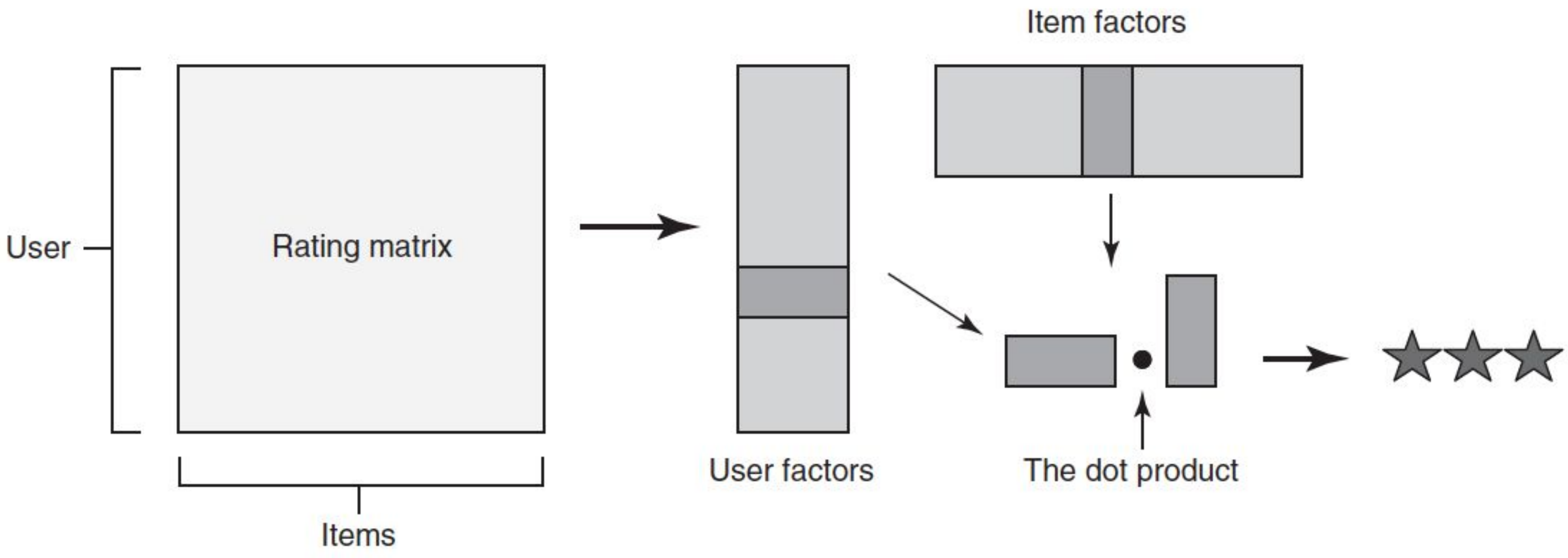
Uses rank_k to return the reduced matrices

Calculates the deduced matrix M_hat

$$R = \begin{bmatrix} 5 & 3 & \boxed{0} & 2 & 2 & 2 \\ 4 & 3 & 4 & \boxed{0} & 3 & 3 \\ 5 & 2 & 5 & 2 & 1 & 1 \\ 3 & 5 & 3 & \boxed{0} & 1 & 1 \\ 3 & 3 & 3 & 2 & 4 & 5 \\ 2 & 3 & 2 & 3 & 5 & 5 \end{bmatrix}$$

Sara	4.87	3.11	0.05	2.24	1.94	1.92
Jesper	3.49	3.46	4.19	0.95	2.62	2.82
Therese	5.22	1.80	4.92	1.59	1.10	1.14
Helle	3.25	4.77	2.90	-0.47	1.14	1.13
Pietro	2.93	3.05	3.03	2.11	4.30	4.67
Ekaterina	2.27	2.77	1.89	2.50	4.92	5.35

Collaborative Filtering: Model-based



Collaborative Filtering: Funk Factorization

$$\begin{bmatrix} 5 & 3 & 0 & 2 & 2 & 2 \\ 4 & 3 & 4 & 0 & 3 & 3 \\ 5 & 2 & 5 & 2 & 1 & 1 \\ 3 & 5 & 3 & 0 & 1 & 1 \\ 3 & 3 & 3 & 2 & 4 & 5 \\ 2 & 3 & 2 & 3 & 5 & 5 \end{bmatrix} = \begin{bmatrix} u_{1,1} & u_{1,2} \\ u_{2,1} & u_{2,2} \\ u_{3,1} & u_{3,2} \\ u_{4,1} & u_{4,2} \\ u_{5,1} & u_{5,2} \\ u_{6,1} & u_{6,2} \end{bmatrix} \begin{bmatrix} v_{1,1} & v_{1,2} & v_{1,3} & v_{1,4} & v_{1,5} & v_{1,6} \\ v_{2,1} & v_{2,2} & v_{2,3} & v_{2,4} & v_{2,5} & v_{2,6} \end{bmatrix}$$

$$RMSE = \sqrt{\frac{1}{|known|} \sum_{(u,i) \in known} (r_{ui} - u_u v_i)^2}$$

Collaborative Filtering: More about Funk

Netflix provided a *training* data set of 100,480,507 ratings that 480,189 users gave to 17,770 movies

[<< | Prev | Index | Next | >>]

Monday, December 11, 2006

Netflix Update: Try This at Home

At one point Simon Funk was #3 on the list.
However, Simon is an independent software developer who works on Netflix prize in his spare time between his trips around New Zealand!
He freely published his code and ideas – the first top leader to do so!

More to read:
https://www.thrillist.com/entertainment/nation/the-netflix-prize
https://sifter.org/simon/journal/20061211.html
https://www.kdd.org/exploration_files/simon-funk-explorations.pdf

Collaborative Filtering: Pros & Cons

- No domain knowledge necessary
- Exploratory

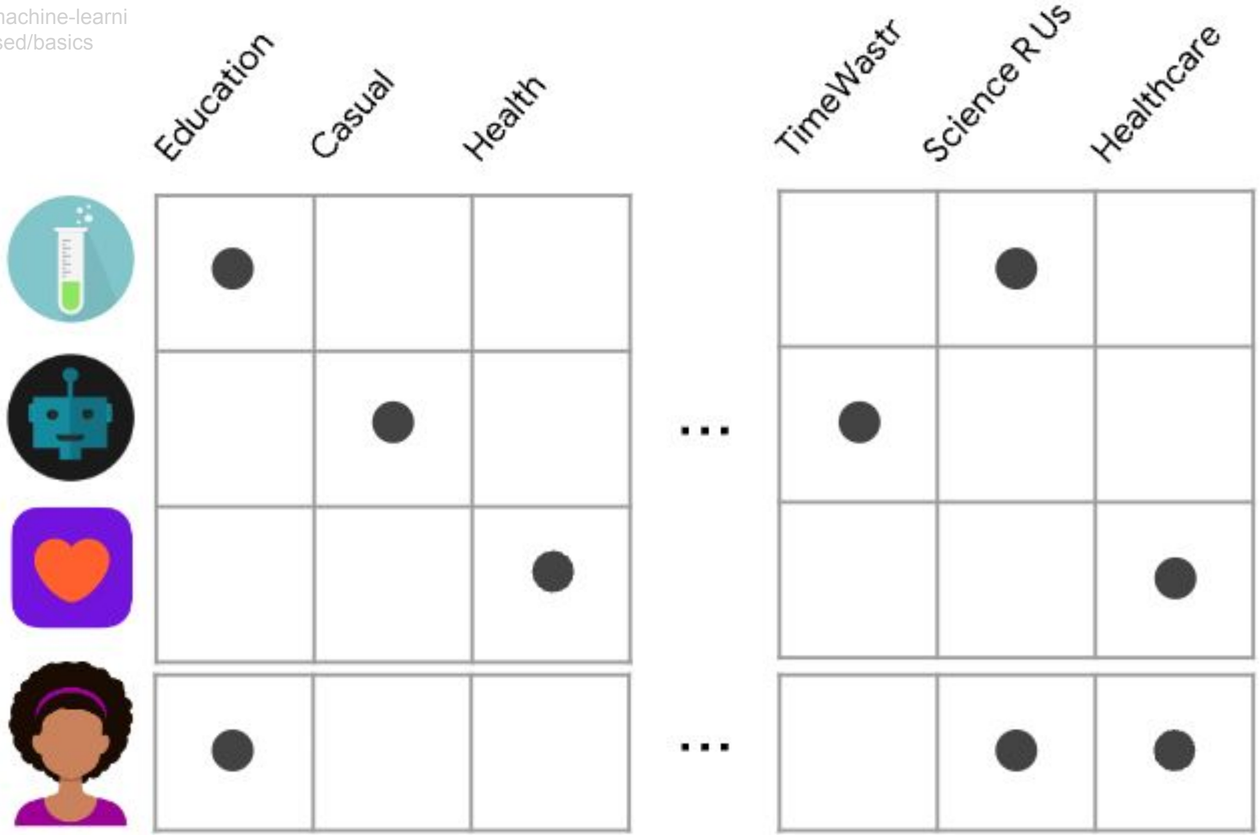
- Sparsity
- Side features
- Cold start
- Gray sheep
- Not using popularity

Content-based Filtering

- How to model recommendation problem mathematically.
- Classic recommendation algorithms
  - Collaborative filtering
    - Memory-based filtering
    - Model-based filtering
  - *Content-based filtering

Content-based Filtering

Example from: https://developers.google.com/machine-learning/recommendation/content-based/basics



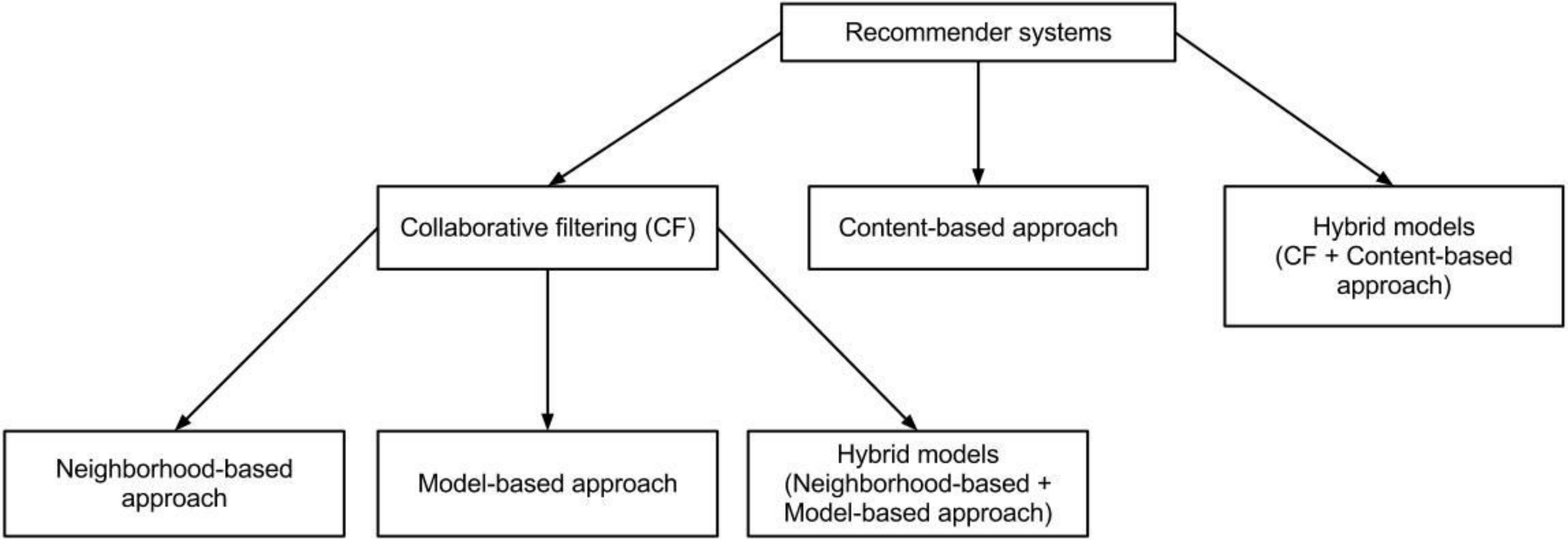
Mentimeter

Content-based Filtering: Pros & Cons

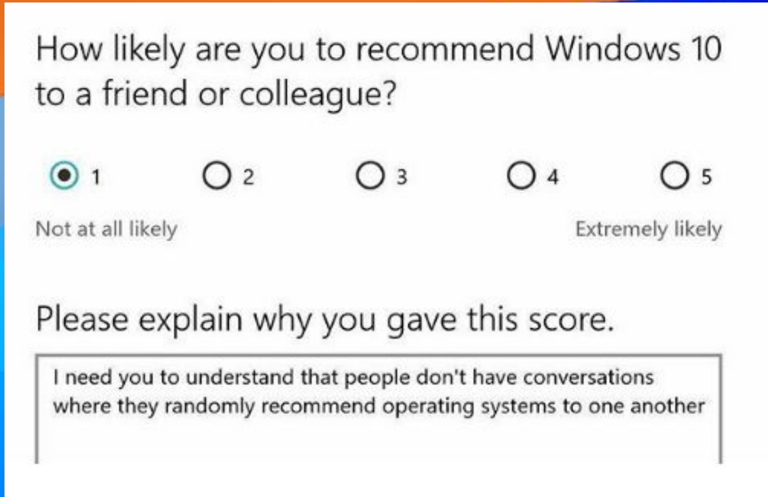
- Easy to scale
- Explainable

- Hand-engineered features
- Not exploratory

Recommendation System an ML Problem



Evaluate Recommendation Systems


How likely are you to recommend Windows 10 to a friend or colleague?

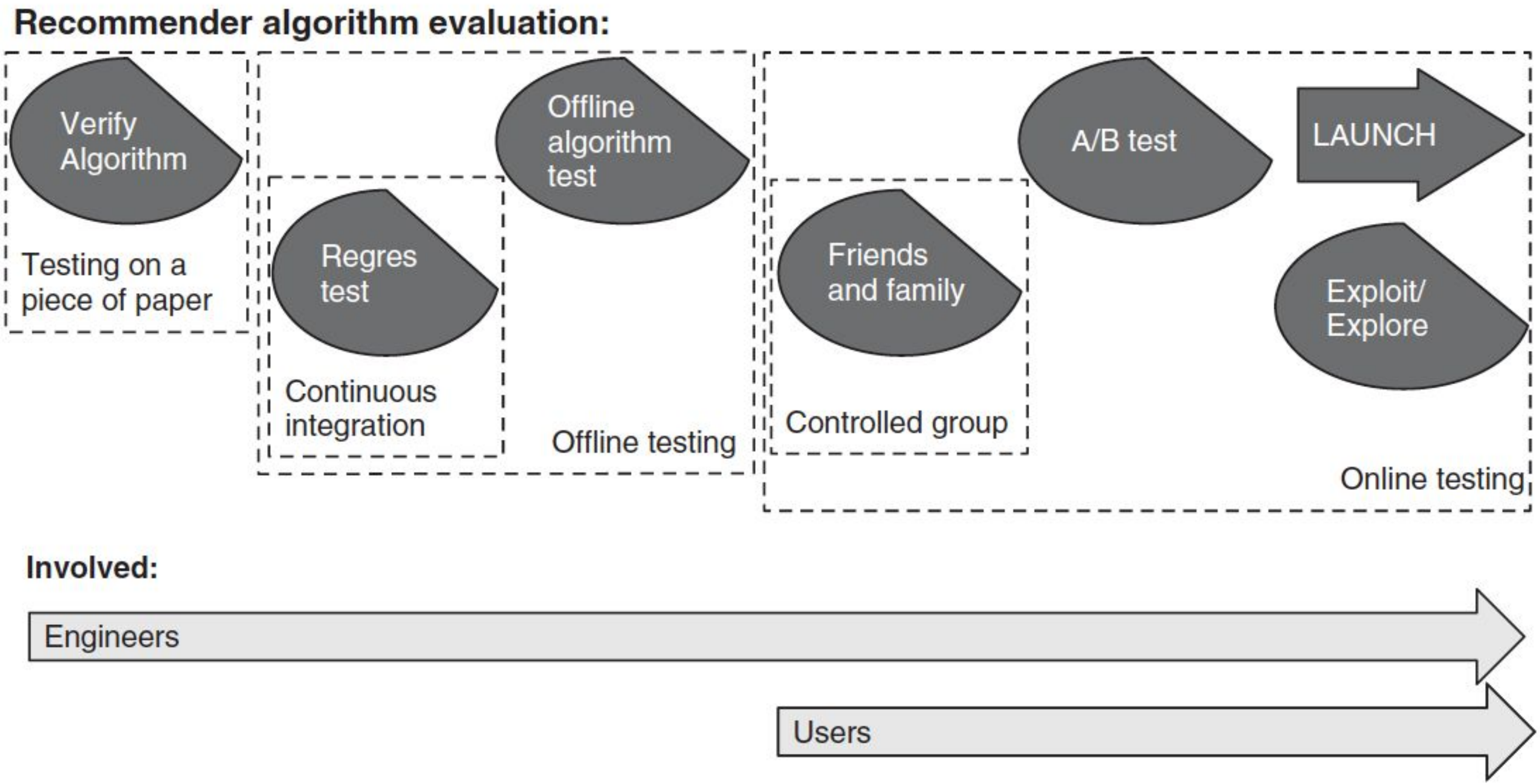
1 2 3 4 5

Not at all likely — Extremely likely

Please explain why you gave this score.

I need you to understand that people don't have conversations where they randomly recommend operating systems to one another

Evaluate Recommendation Systems



Evaluate Recommendation Systems

- Goals and Metrics
- Offline Evaluation
- Online Evaluation

Evaluate Recommendation Systems: Goals

- Accuracy
- Diversity and coverage
- Serendipity
- Scalability

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE = mean squared error
n = number of data points
Y_i = observed values
$\hat{Y}_i$ = predicted values

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n}$$

MAE = mean absolute error
y_i = prediction
x_i = true value
n = total number of data points

Evaluate Recommendation Systems: Goals

- Accuracy
- Diversity and coverage
- Serendipity
- Scalability

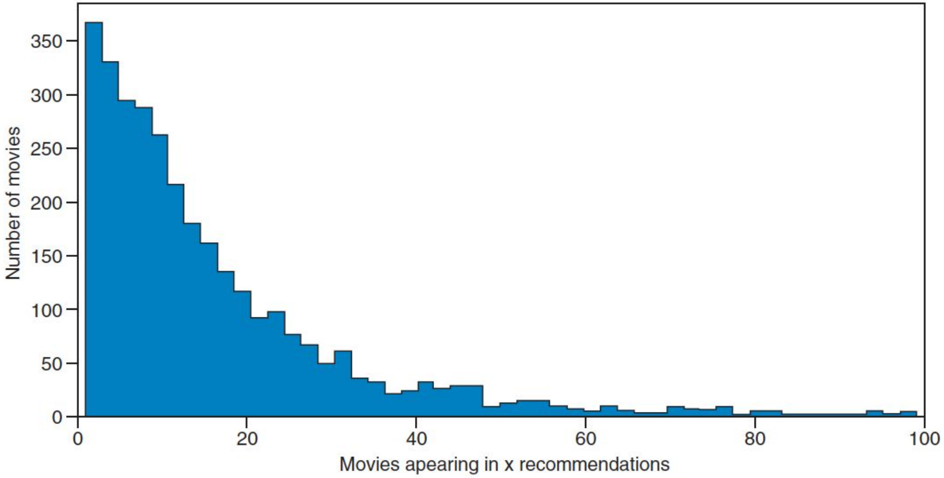
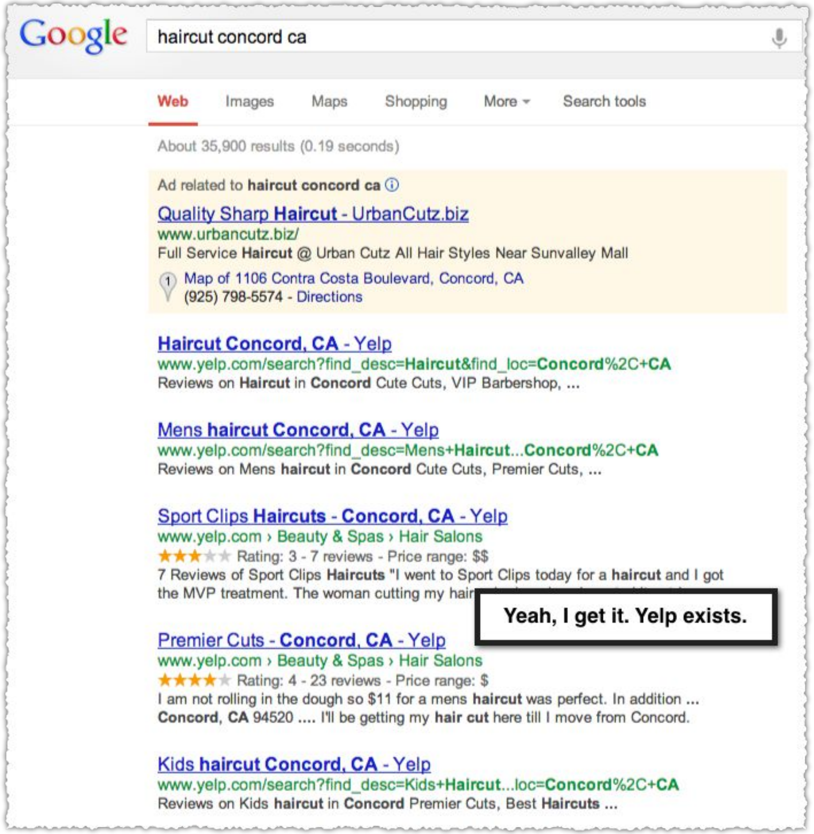


Figure 9.3 How many movies are shown *X* number of times. More than 350 movies are shown in only one recommendation. Counterintuitively, the movies that are most popular are the ones that are in the long tail.

Evaluate Recommendation Systems: Goals

- Accuracy
- **Diversity and coverage**
- Serendipity
- Scalability



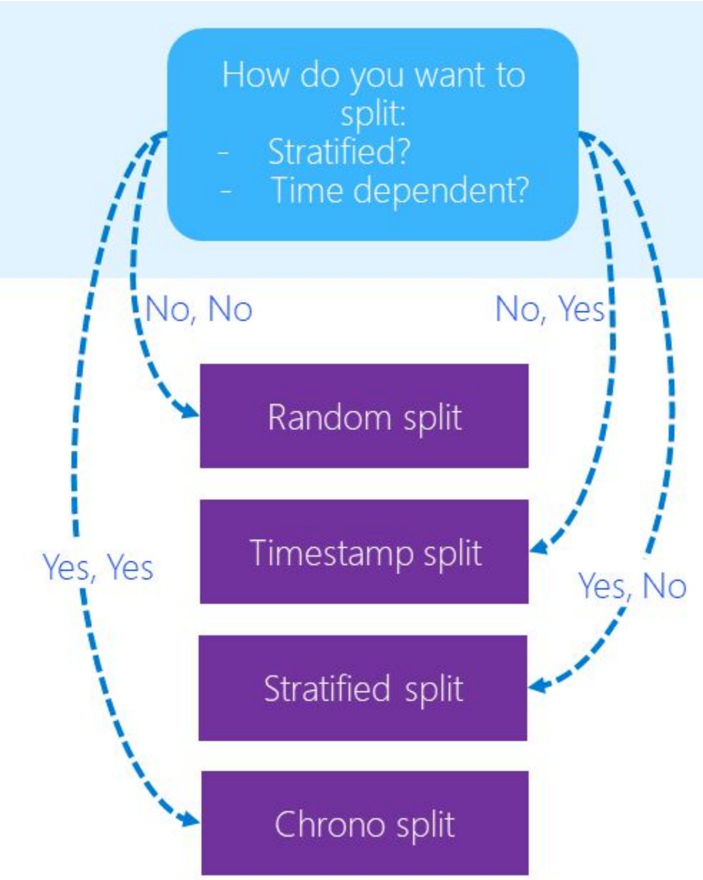
Evaluate Recommendation Systems: Goals

- Accuracy
- Diversity and coverage
- Serendipity
- Scalability

Evaluate Recommendation Systems: Goals

- Accuracy
- Diversity and coverage
- Serendipity
- Scalability -> More to come tomorrow!

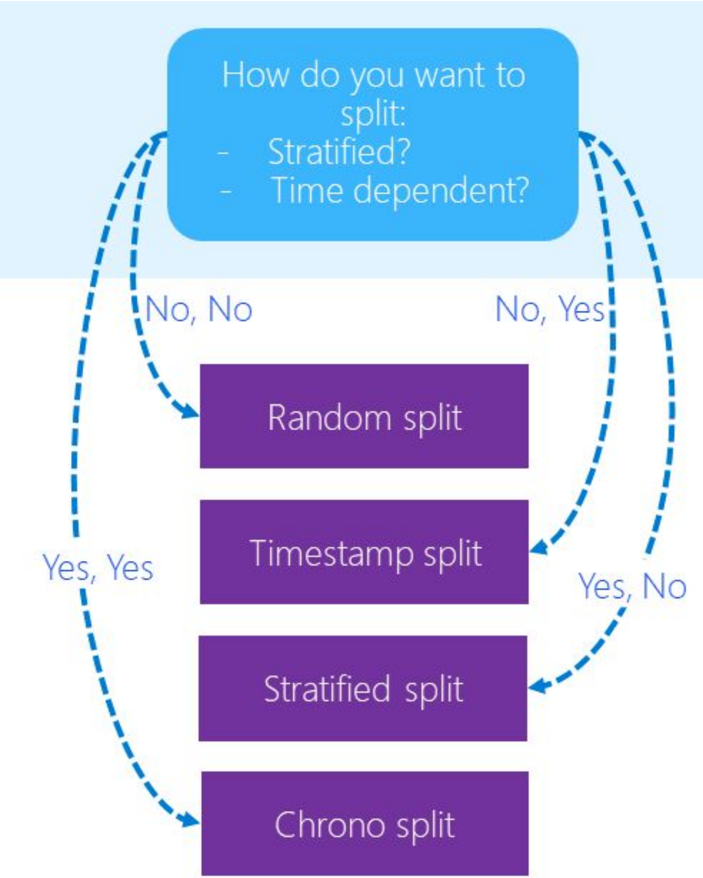
Evaluate Recommendation Systems: Offline Evaluation - Split



Left diagram:
https://github.com/microsoft/recommenders/tree/main/examples

						
Sara	5	3		2	2	2
Jesper	4	3	4		3	3
Therese	5	2	5	2	1	1
Helle	3	5	3		1	1
Pietro	3	3	3	2	4	5
Ekaterina	2	3	2	3	5	5

Evaluate Recommendation Systems: Offline Evaluation - Split



Sara	5	3		2	2	2
Jesper	4	3	4		3	3
Therese	5	2	5	2	1	1
Helle	3	5	3		1	1
Pietro	3	3	3	2	4	5
Ekaterina	2	3	2	3	5	5

Evaluate Recommendation Systems: Online Evaluation

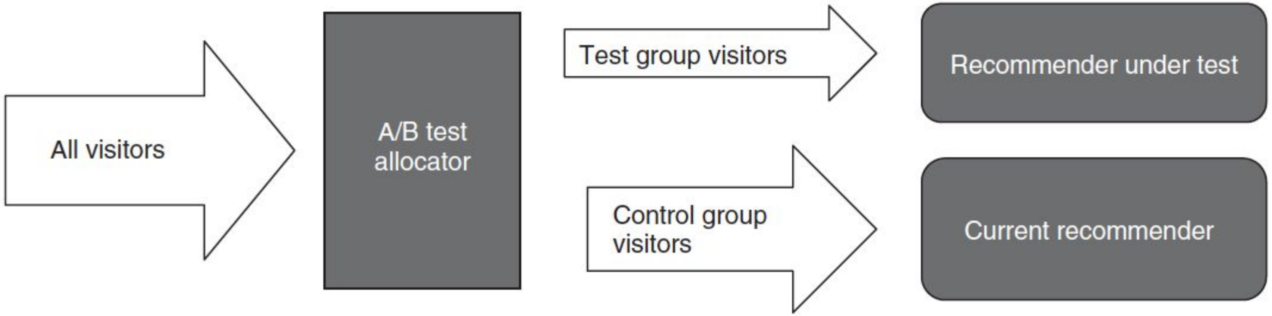
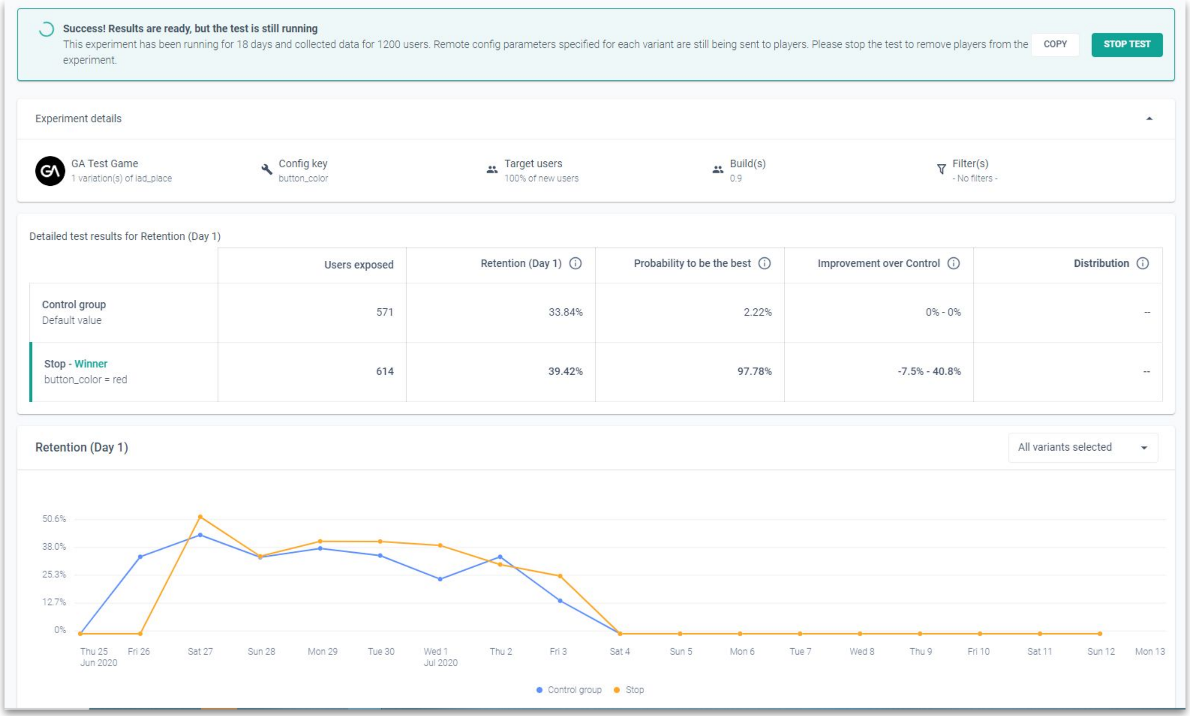


Figure 9.16 In an A/B test, visitors are split into two groups: the test group that sees the new feature and a control group that continues as usual.

Evaluate Recommendation Systems: Online Evaluation



Evaluate Recommendation Systems: Online Evaluation

RETENTION REPORT

Report Settings

Media Source: All

Geo: All

Date

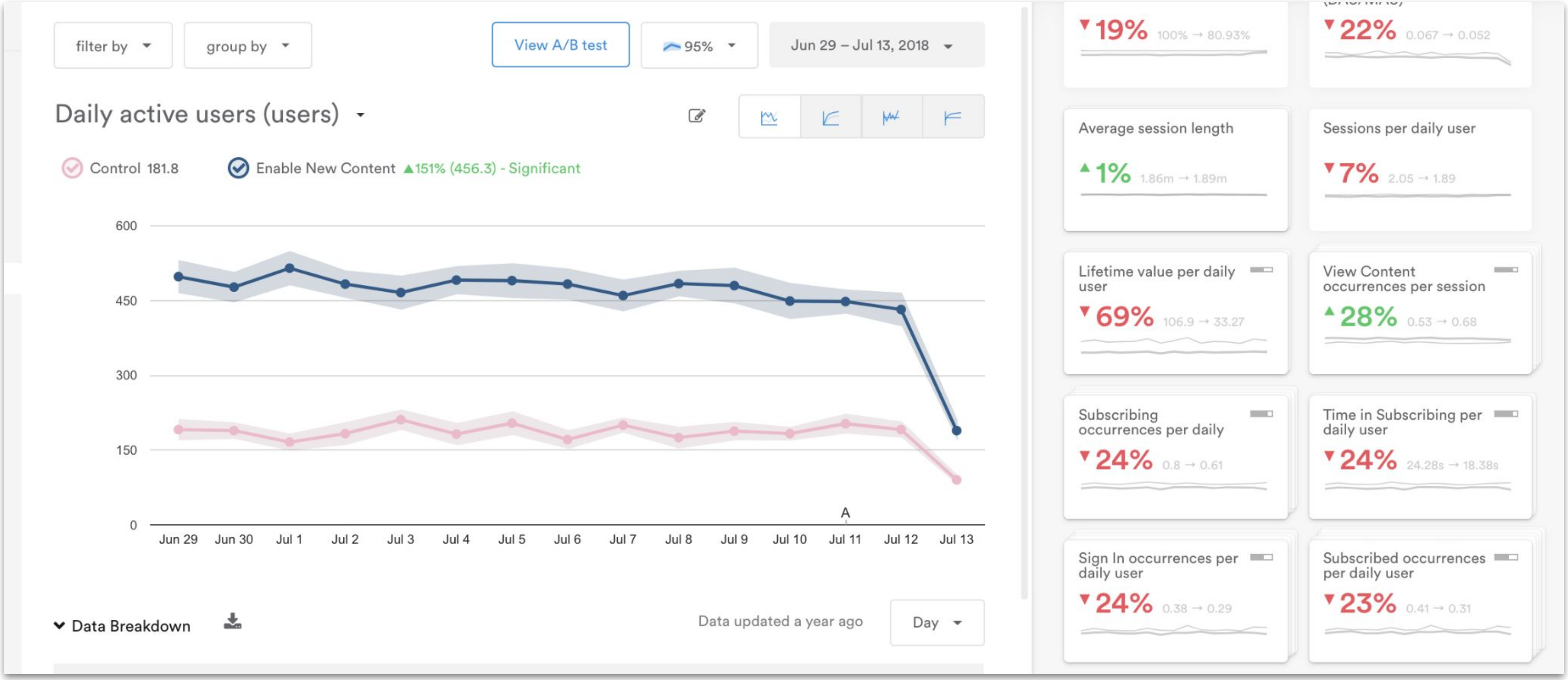
Group By: × Media Source × Campaign × Adset × Ad

Min Cohort Size 10

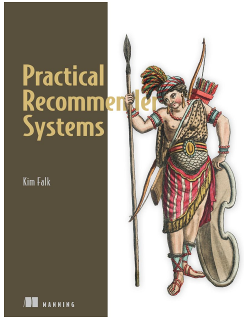
Add More Filters

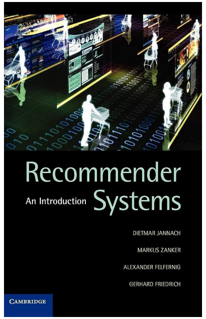
Media Source	Campaign	Adset	Ad	Install Day	Day 1	Day 2	Day 3	Day 4
organic	N/A	N/A	N/A	100% 5,212	17.19% 896	10.57% 551	8.65% 451	7.77% 405
liftoff_int	iphone	N/A	1 320x480_[illegible]_3...	100% 651	15.36% 100	8.45% 55	7.22% 47	6.3% 41
liftoff_int	iphone	N/A	2 320x480_[illegible]_3...	100% 649	15.41% 100	9.24% 60	6.78% 44	4.31% 28
Facebook Ads	iOS	iOS Interest AEP	3 20190404_MWC_2k1...	100% 544	12.68% 69	6.99% 38	4.78% 26	3.86% 21

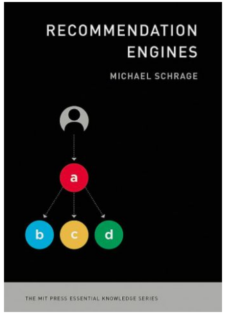
Evaluate Recommendation Systems: Online Evaluation

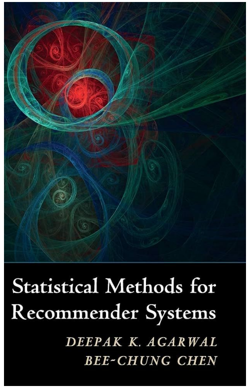


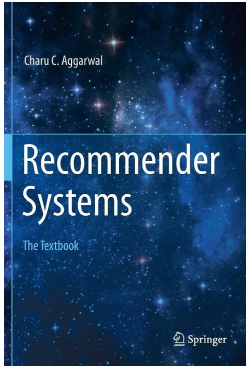
Reference









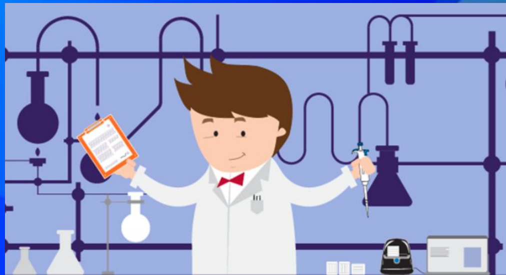


	PRS	IRS	RE	SERS	RST
Related Chap.	Chap. 7-11.	Chap. 2, 7	Chap. 1-5.	Chap. 1, 2, 4.	Chap 1-4.
Hao's Rating	5	3	4	2	4

Coffee Break

Take a 5 minute break

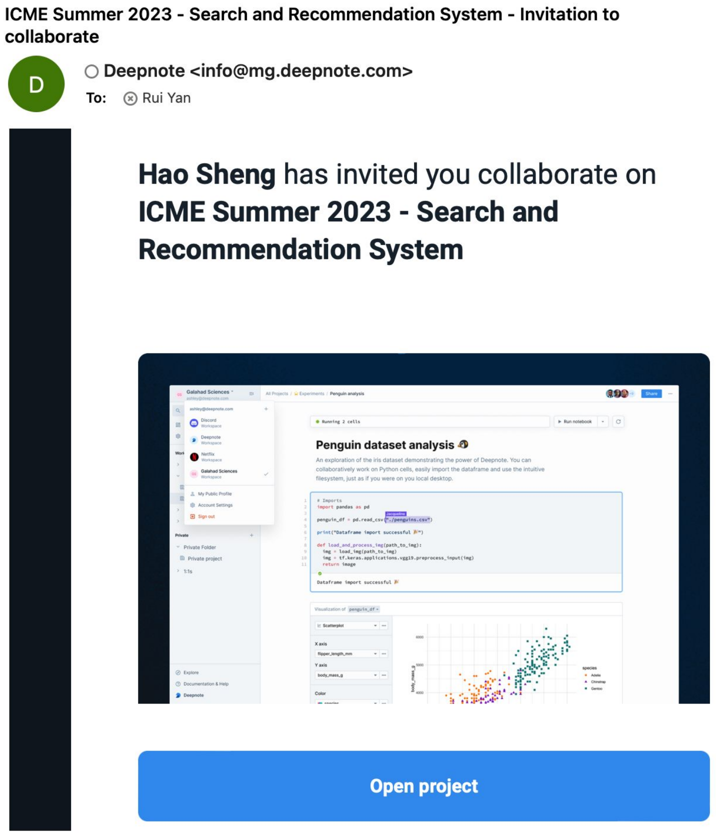
Lab Time!



Instruction for running notebooks on Deepnote

Please click on the "Open project" button found in the email titled "ICME Summer 2023 - Search and Recommendation System - Invitation to Collaborate."

If you don't have a Deepnote account already, you might need to sign up for one.



Instruction for running notebooks on Deepnote

Once you have a Deepnote account, create a workspace with any name you prefer and duplicate the project to your own workspace and run the notebook.