Recommendation Systems

推荐系统

You need to recommend a financial product to your users. There are countless financial products available for users to choose from. Which financial product would you recommend to your users? Why?

你要推荐一款理财产品给你的用户。有无数种理财产品供用户选择，你将推荐哪一款理财产品给你的用户呢？为什么？

Here are some movie ratings.

这里是一些电影评分

	Movie 1	**Movie 2**	**Movie 3**	**Movie 4**
Alice	4	4		1
Bob		2	2	3
Carol	1	5	3	
Dennis	3		4	1
Emma	5	2	1	4
Flora	3	1		5

Recommendation is everywhere!

推荐无处不在！

amazon.com

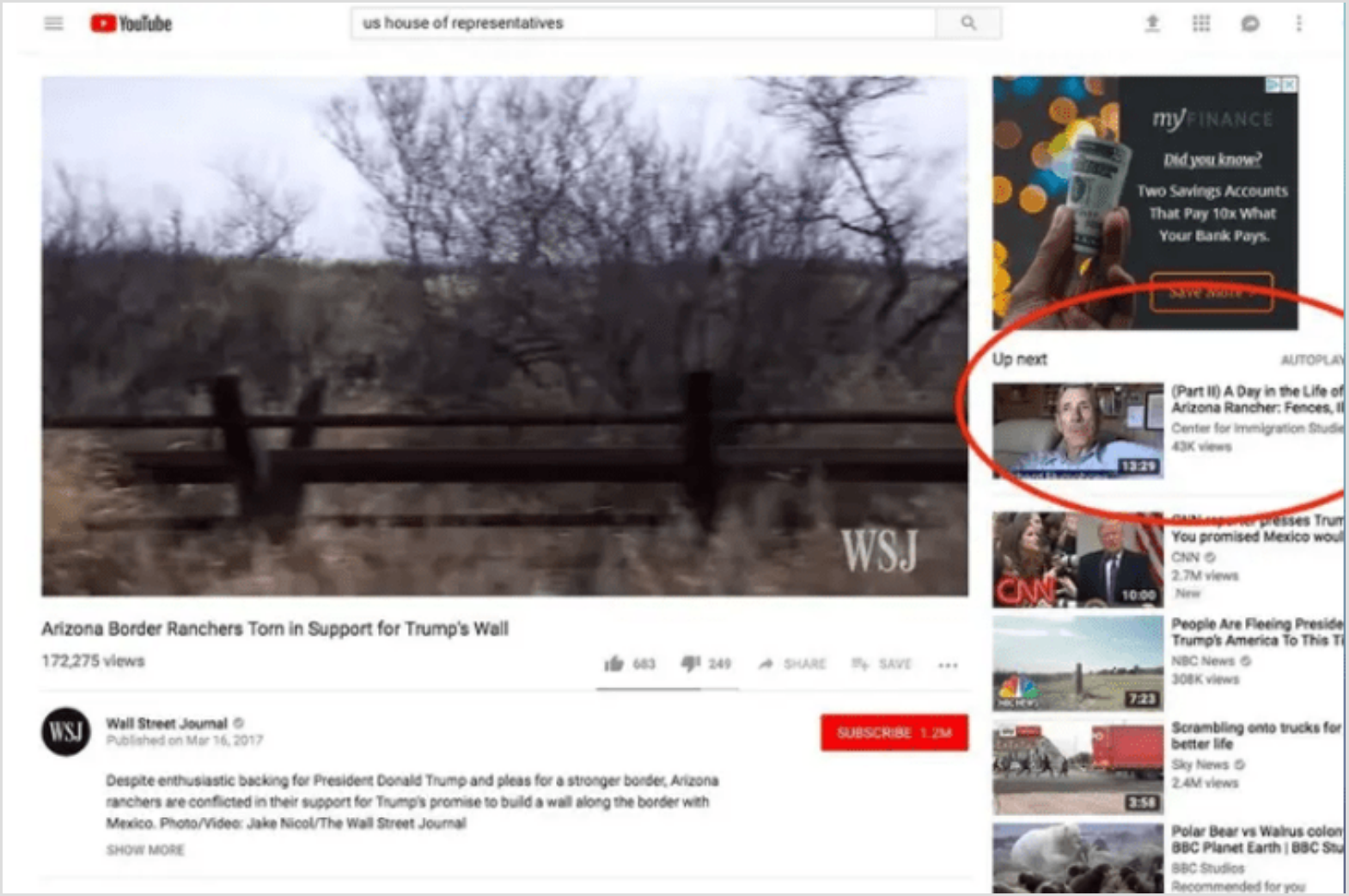
Recommended for You

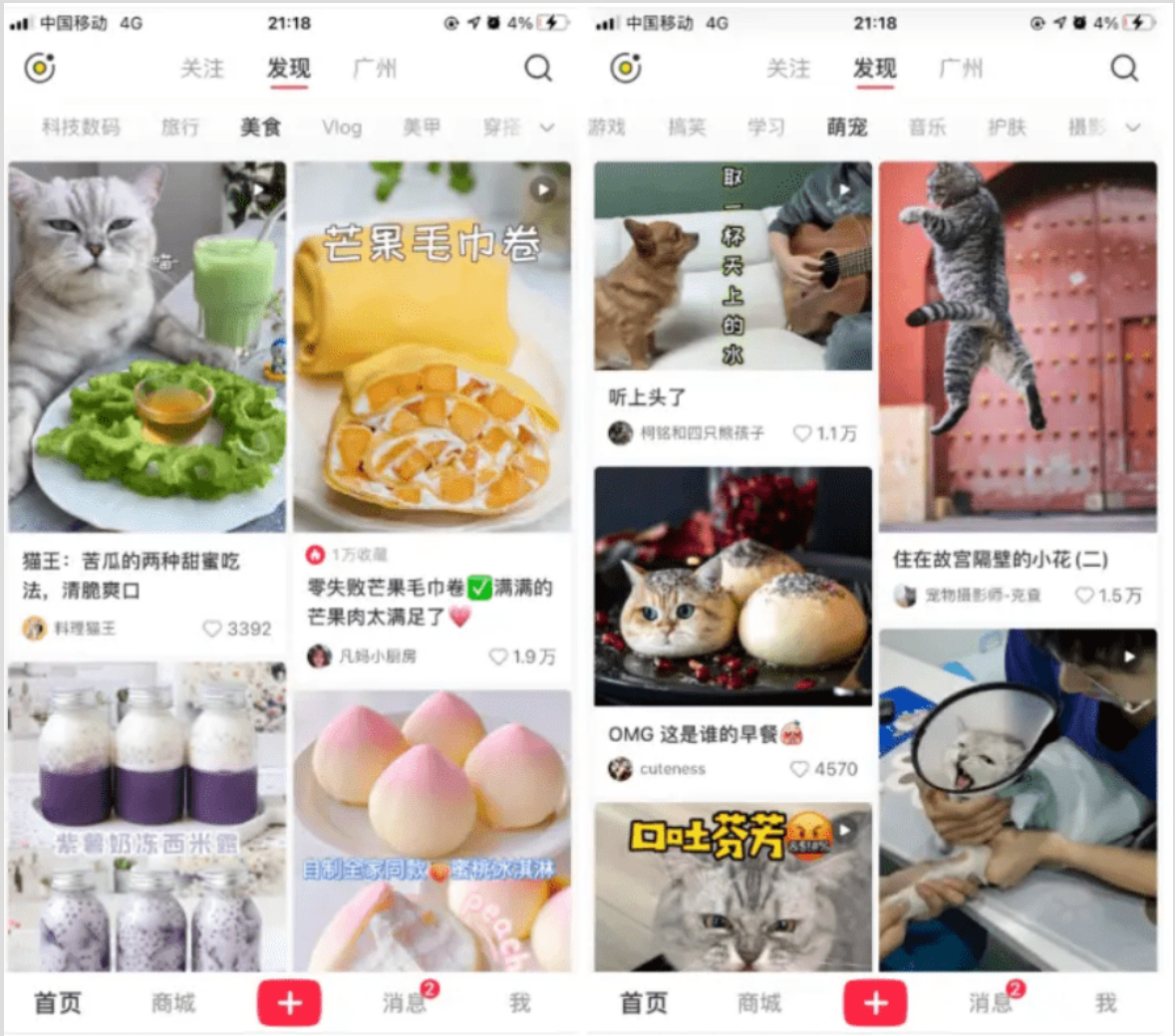
Amazon.com has new recommendations for you based on items you purchased or told us you own.

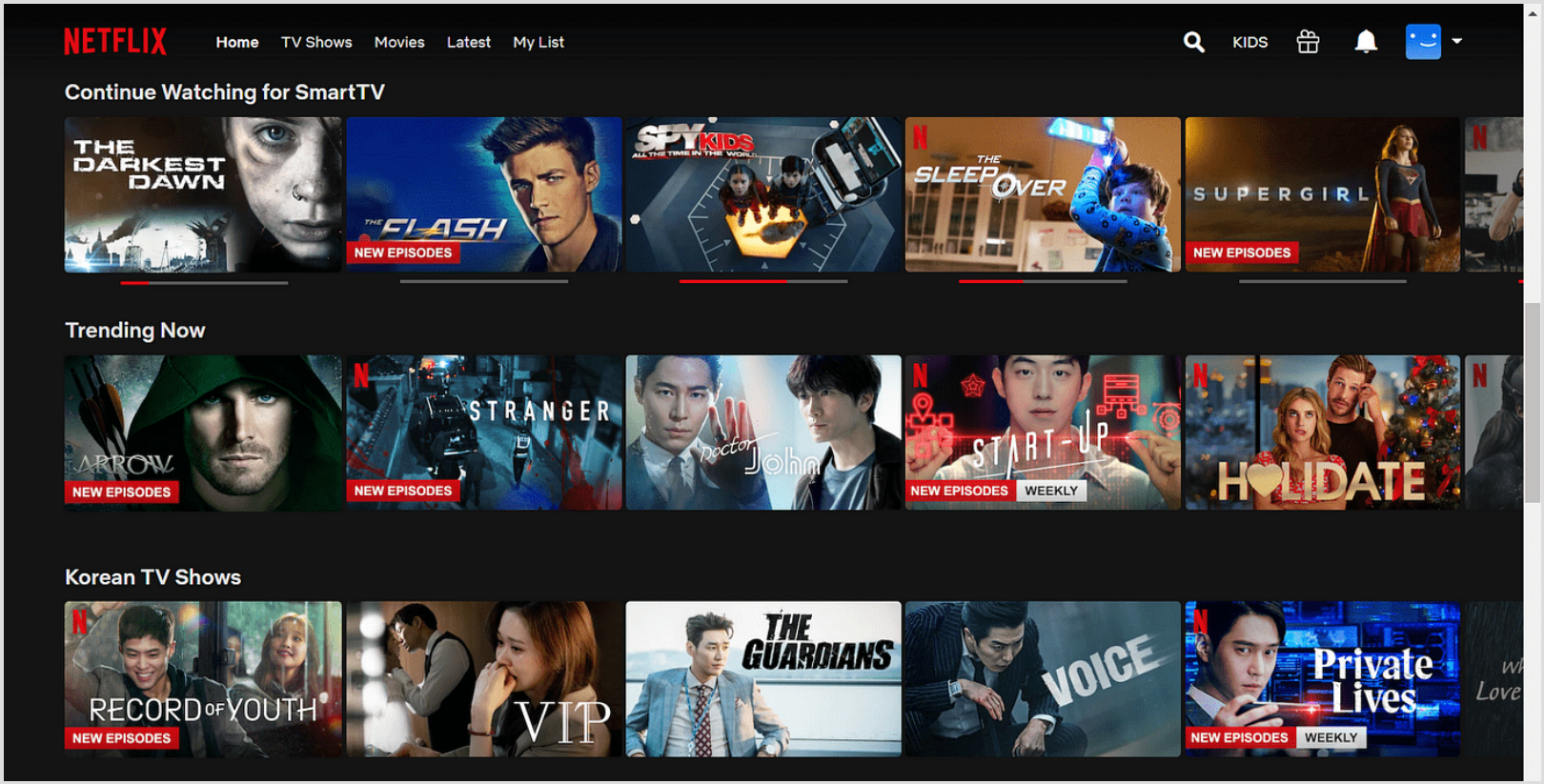
Google Apps Deciphered: Compute in the Cloud to Streamline Your Desktop

Google Apps Administrator Guide: A Private-Label Web Workspace

Googlepedia: The Ultimate Google Resource (3rd Edition)


YouTube
us house of representatives
WSJ
Arizona Border Ranchers Torn in Support for Trump's Wall
172,275 views
683
249
SHARE
SAVE
Wall Street Journal
Published on Mar 16, 2017
SUBSCRIBE 1.2M
Despite enthusiastic backing for President Donald Trump and pleas for a stronger border, Arizona ranchers are conflicted in their support for Trump's promise to build a wall along the border with Mexico. Photo/Video: Jake Nicol/The Wall Street Journal
SHOW MORE
myFINANCE
Did you know?
Two Savings Accounts That Pay 10x What Your Bank Pays.
Up next
AUTOPLAY
(Part II) A Day in the Life of Arizona Rancher: Fences, II
Center for Immigration Studies
43K views
13:29
You promised Mexico woul
CNN
2.7M views
New
10:00
People Are Fleeing Preside Trump's America To This Ti
NBC News
308K views
7:23
Scrambling onto trucks for better life
Sky News
2.4M views
3:58
Polar Bear vs Walrus colon BBC Planet Earth | BBC Stu
BBC Studios
Recommended for you


中国移动 4G
21:18
4%
关注
发现
广州
科技数码
旅行
美食
Vlog
美甲
穿搭
芒果毛巾卷
猫王：苦瓜的两种甜蜜吃法，清脆爽口
料理猫王
3392
1万收藏
零失败芒果毛巾卷✅满满的芒果肉太满足了❤️
凡妈小厨房
1.9万
紫薯奶冻西米露
自制全家同款🍑蜜桃冰淇淋
peach
首页
商城
消息
我
关注
发现
广州
游戏
搞笑
学习
萌宠
音乐
护肤
摄影
取一杯天上的水
听上头了
柯铭和四只熊孩子
1.1万
住在故宫隔壁的小花(二)
宠物摄影师-克意
1.5万
OMG 这是谁的早餐
cuteness
4570
口吐芬芳
首页
商城
消息
我


NETFLIX
Home
TV Shows
Movies
Latest
My List
KIDS
Continue Watching for SmartTV
THE DARKEST DAWN
THE FLASH
NEW EPISODES
SPY KIDS
THE SLEEPOVER
SUPERGIRL
NEW EPISODES
Trending Now
ARROW
NEW EPISODES
STRANGER
NEW EPISODES
doctor John
START-UP
NEW EPISODES
WEEKLY
HOLIDATE
Korean TV Shows
RECORD OF YOUTH
NEW EPISODES
VIP
THE GUARDIANS
VOICE
Private Lives
NEW EPISODES
WEEKLY

BBC
Home News Sport Business Innovation Culture Travel Earth Video Live
Netflix: How did it know I was bi before I did?
13 August 2023
By Ellie House, BBC Long Form Audio
Share

The Importance of Recommendation

- Netflix: 2/3 of the movies watched are recommended.
- Google News: recommendations generate 38% more click-throughs.
- Amazon: 35% sales from recommendations.
- ChoiceStream: 28% of the people would buy more music if they found what they liked.

推荐的重要性

- Netflix: 观看的电影中有2/3是根据推荐的。
- Google News: 推荐产生了比例高达38%的点击率。
- 亚马逊: 35%的销售额来自推荐。
- ChoiceStream: 如果找到自己喜欢的音乐，28%的人会购买更多。

How to recommend?

A recommendation system must have three inputs:

- Items to be recommended: songs, movies, products, restaurants etc. (often many thousands)
- Users of the items: watchers, listeners, purchasers, shoppers etc. (often many millions)
- Feedback of users on items: 5-star ratings, upvotes/downvotes, clicking “next” or “skipping the ad”, purchases or clicks.

如何进行推荐?

一个推荐系统必须有三个输入:

- 要推荐的物品: 歌曲、电影、产品、餐馆等（通常有成千上万个）
- 使用这些物品的用户: 观看者、听众、购买者、购物者等（通常有数百万人）
- 用户对物品的反馈: 5星评级、赞成/反对、点击“下一个”或“跳过广告”、购买或点击等。

Collaborative Filtering

Collaborative filtering is not something new. We have done it in many places in the past. Here are a few examples:

- Bestseller list for books
- Top 50 music list
- The “recent returns” shelf at libraries

The intuition behind: People’s tastes are correlated.

协同过滤

协同过滤并非什么新鲜事物。我们在过去的许多地方都使用过它。以下是一些示例：

- 畅销书榜单
- 前50名音乐榜单
- 图书馆的“最近归还”书架

背后的思路是：人们的口味是相关的。

Collaboratives Filtering

However, in the above examples, recommendations are not personalized, i.e., everybody receives the same recommendation. How to make recommendations personalized?

The intuition: If Alice and Bob both like X and Alice also likes Y, then Bob is more likely to like Y, especially when Alice and Bob know each other.

协同过滤

然而，在上述例子中，推荐并不是个性化的，即每个人都会收到相同的推荐。如何使推荐个性化?

直觉：如果 Alice 和 Bob 都喜欢 X，并且 Alice 还喜欢Y，那么 Bob 更有可能喜欢 Y，尤其是当 Alice 和 Bob 互相认识时。

Suppose that you want to recommend a movie to Emma, which movie will you recommend?

	1	**2**	**3**	**4**	**5**	**6**
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

假设你想向 Emma 推荐一部电影，你会推荐哪部电影?

	1	**2**	**3**	**4**	**5**	**6**
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

User-Based Collaborative Filtering: The Neighbourhood Method

基于用户的协同过滤： 邻域方法

Step 1: Find all the movies rated by Emma before, we get movies 3 and 6

步骤 1：找到 Emma 之前评过的所有电影，我们得到了电影 3 和 6。

	1	**2**	**3**	**4**	**5**	**6**
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Step 2: Identify other users that have rated the same movie, we get Bob, Carol, and Dennis

步骤 2：识别其他评过同一部电影的用户，我们得到了Bob, Carol, 和 Dennis

	1	**2**	**3**	**4**	**5**	**6**
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Step 3: Compare the similarity between Emma and her "neighbors" to see who are close to Emma.

步骤 3：比较 Emma 与她的"邻居"之间的相似性，以确定谁与 Emma 接近。

	1	**2**	**3**	**4**	**5**	**6**
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Step 4: Select the top k most similar neighbors and use their average ratings to predict Emma's rating.

步骤 4：选择最相似的前 k 个邻居，并使用他们的平均评分来预测艾玛的评分。

	1	**2**	**3**	**4**	**5**	**6**
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Item-Based Collaborative Filtering

基于物品的协同过滤

Item-based collaborative filtering

基于物品的协同过滤

Suppose that we are predicting the who will like movie 5.

假设我们正在预测谁会喜欢电影 5

Step 1: Who have rated movie 5 before? We get Alice and Carol.

步骤 1：谁之前评过电影 5？我们得到了 Alice 和 Carol

	1	**2**	**3**	**4**	**5**	**6**
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Step 2: Identify other movies that have rated the same users, we get movies 1 and 3.

步骤 2：识别这些用户评过的其他电影，我们得到了电影 1 和 3

	1	2	3	4	5	6
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Step 3: Compare the similarity between movie 5 and its "neighbors" to see which movie is close to movie 5.

步骤 3：比较电影 5 与其"邻居"之间的相似性，以确定哪部电影接近电影 5

	1	2	3	4	5	6
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Step 4: Select the top k most similar neighbors and use their average ratings to predict movie 5's rating.

步骤 4：选择最相似的前 k 个邻居，并使用他们的平均评分来预测电影 5 的评分。

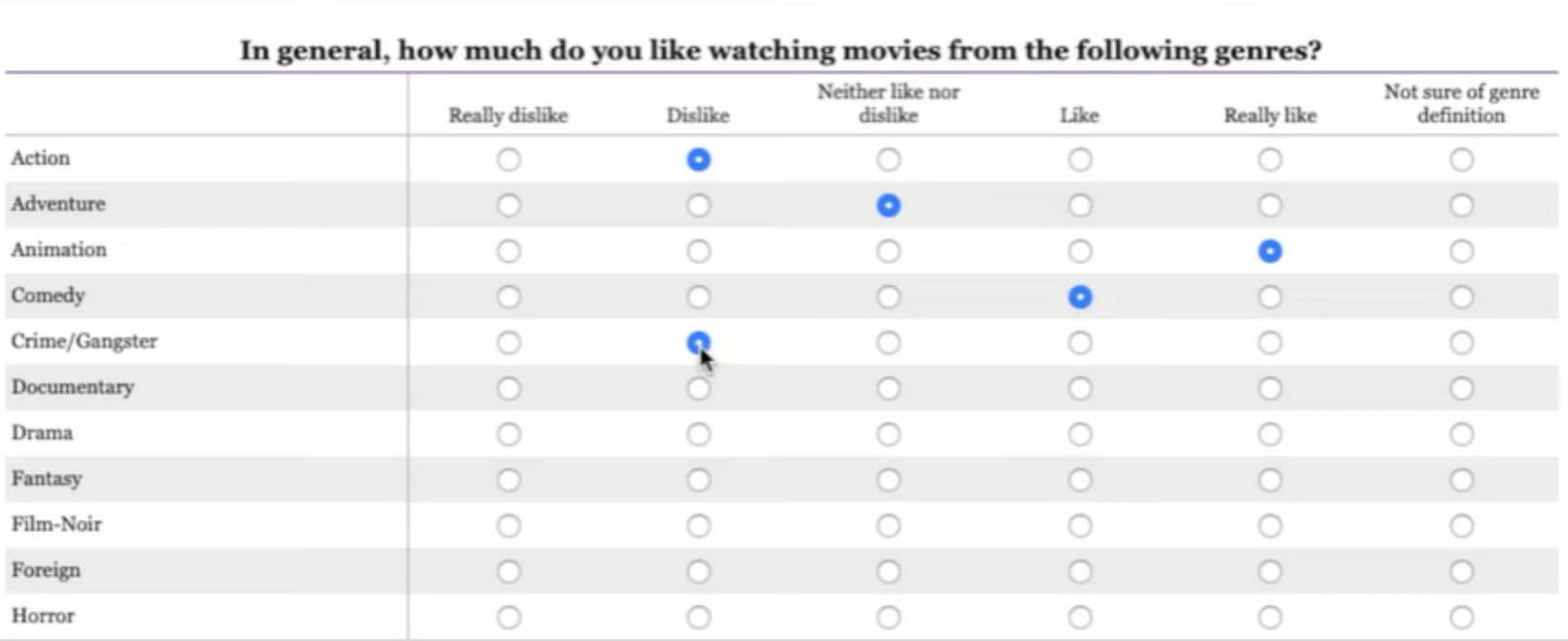
	1	2	3	4	5	6
Alice	2			4	5	
Bob	5		4			1
Carol			5		2	
Dennis		1		5		4
Emma			4			2
Flora	4	5		1		

Model-based Collaborative Filtering

基于模型的协同过滤

What did Netflix do to make recommendations?

Netflix 早年是如何进行推荐的?



In general, how much do you like watching movies from the following genres?

	Really dislike	Dislike	Neither like nor dislike	Like	Really like	Not sure of genre definition
Action	○	●	○	○	○	○
Adventure	○	○	●	○	○	○
Animation	○	○	○	○	●	○
Comedy	○	○	○	●	○	○
Crime/Gangster	○	●	○	○	○	○
Documentary	○	○	○	○	○	○
Drama	○	○	○	○	○	○
Fantasy	○	○	○	○	○	○
Film-Noir	○	○	○	○	○	○
Foreign	○	○	○	○	○	○
Horror	○	○	○	○	○	○

The Matrix Factorization Method

矩阵分解方法

Matrix Factorization

Here, we assume that each movie has a number of “latent” or “hidden” factors that affect user preferences. Examples of the factors include the length of the movie, the amount of actions in the movie, the seriousness of the movie, the orientation of the movie for children etc.

The factors are “latent” or “hidden,” implying that we do not know which these factors are, and we do not need to know either.

矩阵分解

在这里，我们假设每部电影都有一些影响用户偏好的“潜在”或“隐含”因素。这些因素的例子包括电影的时长、电影中的动作量、电影的严肃程度、电影是否适合儿童等。

这些因素是“潜在”或“隐含”的，意味着我们不知道这些因素具体是什么，也不需要知道。

Matrix Factorization

Each user also has his or her own preference for each factor. For instance, some users prefer long movies over short movies, and some users prefer to have more actions in their movie. If we know the preferences of a user and a movie's attribute values, we can match the movie with the user to see whether the user will like the movie.

矩阵分解

每个用户对每个因素也有自己的偏好。例如，有些用户更喜欢长电影而不是短电影，有些用户则更喜欢电影中有更多动作。如果我们知道用户的偏好以及电影的属性值，就可以将电影与用户匹配，以判断用户是否会喜欢这部电影。

Matrix Factorization

For instance, suppose that a movie is long and contains a lot of actions. We also know that

- Alice likes short movies and hates action movies,
- Bob prefers long movies and enjoys action movies.

Then, we can predict that Alice will hate the movie and Bob will like the movie.

矩阵分解

例如，假设一部电影很长且包含很多动作。我们还知道：

- Alice 喜欢短电影并讨厌动作电影，
- Bob 更喜欢长电影并喜欢动作电影。

那么，我们可以预测 Alice 会讨厌这部电影，而 Bob 会喜欢这部电影。

Mathematically, our model is as follows:

$$\begin{aligned}\text{Your rating} = &\text{ Your preference for length} \times \text{Movie's length} \\ &+ \text{Your preference for action} \times \text{Movie's amount of action}\end{aligned}$$

Suppose that the movie's length is 1 and amount of action is 2. Alice's preference for length is 0.5, for action is 0; Bob's preference for length is 1, for action is 1.5. We can predict:

- Alice's rating: $0.5 \times 1 + 0 \times 2 = 0.5$.
- Bob's rating: $1 \times 1 + 1.5 \times 2 = 4$.

在数学上，我们的模型如下：

$$\text{你的评分} = \text{你对时长的偏好} \times \text{电影时长} + \text{你对动作的偏好} \times \text{电影动作含量}$$

假设这部电影的时长为 1，动作量为 2。Alice 对时长的偏好为 0.5，对动作的偏好为 0；Bob 对时长的偏好为 1，对动作的偏好为 1.5。我们可以预测：

- Alice 的评分: $0.5 \times 1 + 0 \times 2 = 0.5$.
- Bob 的评分: $1 \times 1 + 1.5 \times 2 = 4$.

Let's generalize the above discussion. Suppose that Alice, Bob, Carol's preferences for length and action are as follows:

	Length	**Action**
Alice	0.5	0
Bob	1	1.5
Carol	1.5	0.5

There are two movies, whose length and action values are

	Length	**Action**
1	1	2
2	0	3

让我们对上述讨论进行概括。假设 Alice, Bob, Carol 对时长和动作的偏好如下：

	Length	**Action**
Alice	0.5	0
Bob	1	1.5
Carol	1.5	0.5

有两部电影，它们的时长和动作值分别为：

	Length	**Action**
1	1	2
2	0	3

We can multiply the two matrix to get user-movie ratings:

我们可以将这两个矩阵相乘以获得用户-电影评分：

$$\begin{bmatrix} 0.5 & 0 \\ 1 & 1.5 \\ 1.5 & 0.5 \end{bmatrix} \times \begin{bmatrix} 1 & 0 \\ 2 & 3 \end{bmatrix} = \begin{bmatrix} 0.5 & 0 \\ 4 & 4.5 \\ 2.5 & 1.5 \end{bmatrix}$$

In other words, our prediction is as follows.

	Movie 1	**Movie 2**
Alice	0.5	0.0
Bob	4.0	4.5
Carol	2.5	1.5

Overall, if we know the user matrix and the movie matrix, we can multiply the two to get the user-movie rating matrix. The issue is: We do not yet know the user matrix and the movie matrix.

换句话说，我们的预测如下

	Movie 1	**Movie 2**
Alice	0.5	0.0
Bob	4.0	4.5
Carol	2.5	1.5

总体来说，如果我们知道用户矩阵和电影矩阵，我们可以将两者相乘以获得用户-电影评分矩阵。问题是：我们尚不知道用户矩阵和电影矩阵。

But how to get the user matrix and the movie matrix?

The short answer is, we can guess. We guess different user matrices and movie matrices, and see if the predicted rating matrix is close to the actual rating given by users. When the two are close enough, we can use the two matrices to construct the new rating matrix. This is known as matrix factorization.

但是如何获得用户矩阵和电影矩阵呢?

简短的回答是，我们可以进行猜测。我们猜测不同的用户矩阵和电影矩阵，然后查看预测的评分矩阵是否接近用户给出的实际评分。当两者足够接近时，我们可以使用这两个矩阵来构建新的评分矩阵。这被称为矩阵分解。

We can do better than guessing. There are some advanced statistical methods for estimating the user matrix and movie matrix, but this is beyond the scope of our class. If you are interested, you can search for "stochastic gradient descent."

我们可以做得比单纯猜测更好。有一些高级统计方法可以用来估计用户矩阵和电影矩阵，但这超出了我们课程的范围。如果你感兴趣，可以搜索"随机梯度下降"。

The matrix factorization algorithm

矩阵分解算法

```
1  matrix_factorization <- function(R, P, Q, K, steps=5000, alpha=0.0002,
   beta=0.02) {
2    Q <- t(Q)
3    for (step in 1:steps) {
4      for (i in 1:nrow(R)) {
5        for (j in 1:ncol(R)) {
6          if (R[i, j] > 0) {
7            eij <- R[i, j] - sum(P[i,] * Q[,j])
8            for (k in 1:K) {
9              P[i, k] <- P[i, k]+alpha*(2*eij*Q[k, j] - beta*P[i, k])
10             Q[k, j] <- Q[k, j]+alpha*(2*eij*P[i, k] - beta*Q[k, j])
11           }}}}
12     eR <- P %*% Q
13     e <- 0
14     for (i in 1:nrow(R)) {
15       for (j in 1:ncol(R)) {
16         if (R[i, j] > 0) {
17           e <- e + (R[i, j] - sum(P[i,] * Q[,j]))^2
18             for (k in 1:K) {
19             e <- e + (beta/2) * (P[i, k]^2 + Q[k, j]^2)
20           }}}}
21     if (e < 0.001){break}}
22   return(list(P = P, Q = t(Q)))
23 }
```

```r
set.seed(123)
R <- matrix(c(5, 3, 0, 1,
              4, 0, 0, 1,
              1, 1, 0, 5,
              1, 0, 0, 4,
              0, 1, 5, 4,
              2, 1, 3, 0), nrow = 6, ncol = 4, byrow = TRUE)
# N: num of User
N <- nrow(R)
# M: num of Movie
M <- ncol(R)
# Num of Features
K <- 2
P <- matrix(runif(N * K), nrow = N, ncol = K)
Q <- matrix(runif(M * K), nrow = M, ncol = K)
result <- matrix_factorization(R, P, Q, K)
nP <- result$P
nQ <- result$Q
nR <- nP %*% t(nQ)
print(nP)
print(nQ)
print(nR)
```

Back to our example...

回到我们的例子……

	Movie 1	**Movie 2**	**Movie 3**	**Movie 4**
Alice	4	4		1
Bob		2	2	3
Carol	1	5	3	
Dennis	3		4	1
Emma	5	2	1	4
Flora	3	1		5

$$\begin{bmatrix} 4 & 4 & ? & 1 \\ ? & 2 & 2 & 3 \\ 1 & 5 & 3 & ? \\ 3 & ? & 4 & 1 \\ 5 & 2 & 1 & 4 \\ 3 & 1 & ? & 5 \end{bmatrix} \approx \begin{bmatrix} 1.71 & 0.74 \\ 0.84 & 1.35 \\ 1.92 & -0.69 \\ 2.05 & 0.46 \\ 0.70 & 1.95 \\ 0.13 & 1.93 \end{bmatrix} \times \begin{bmatrix} 1.24 & 2.44 & 1.77 & -0.20 \\ 1.83 & 0.14 & 0.10 & 2.32 \end{bmatrix}$$

$$= \begin{bmatrix} 3.47 & 4.28 & 3.09 & 1.37 \\ 3.52 & 2.26 & 1.63 & 2.97 \\ 1.14 & 4.63 & 3.34 & -1.99 \\ 3.41 & 5.09 & 3.67 & 0.66 \\ 4.48 & 1.99 & 1.43 & 4.40 \\ 3.69 & 0.60 & 0.43 & 4.46 \end{bmatrix}$$

https://www.youtube.com/embed/n3RKsY2H-NE?enablejsapi=1

How to recommend financial products using the methods above?

如何用上述方法推荐理财产品?

How to recommend financial products using the methods above?

如何用上述方法推荐理财产品?

Feedback: Whether the user clicks on the ad or whether the consumer user asks for additional information.

反馈：用户是否点击广告，或者消费者用户是否仔细询问。

The Cold Start Problem

冷启动问题

The cold start problem

The collaborative filtering algorithm works very well in generally, yet it suffers from the issue of cold start. Recall that in the recommendation algorithm, we need to know the users' past interaction with the items to make recommendations. However, if a user or an item is completely new without any historical interactions, what would you do to make recommendations?

冷启动问题

协同过滤算法通常效果很好，但它面临着冷启动问题。回想一下，在推荐算法中，我们需要了解用户与项目的过去互动才能进行推荐。然而，如果一个用户或一个项目是全新的，没有任何历史互动，你会如何进行推荐呢？

Question 问题

Both market basket analysis and collaborative filtering can help us make recommendations. When should we use market basket analysis and when should we use collaborative filtering?

购物篮分析和协同过滤都可以帮助我们进行推荐。我们应该在什么情况下使用购物篮分析，在什么情况下使用协同过滤？

Review

Basic Operations in R: Coefficients and Significances

Heisenberg's Uncertainty Principle

Fixed Effects

- What are fixed effects?
- When should we use fixed effects?
- How to use and how to interpret fixed effects?

课程回顾

R语言的基本操作，系数和统计显著性

海森堡不确定原理：观测消费者本身会改变消费者的行为。

固定效应

- 什么是固定效应?
- 什么时候用固定效应?
- 我们应该如何使用和解读固定效应?

Review

Discrete Choice Models

- Logistic regression
- Probit regression
- Multinomial logit model
- Conditional logit model

Which model should we use?

How to interpret the results of a model?

课程回顾

离散选择模型

- 逻辑回归
- Probit 回归
- 多项式逻辑回归(MNL)
- 条件逻辑回归(Conditional Logit)

我们应该选择哪个模型进行分析?

如何解读一个模型输出的结果?

Review

Causality vs Correlation

- Omitted Variable Bias
- Reversed Causality

AB Tests

- Why does AB test solve the issue of causality?
- t-test and χ^2-test
- Tricks and limitations

课程回顾

因果关系和相关性的区别

- 遗漏变量偏差
- 反向因果关系

AB 测试

- 为什么AB测试可以验证因果关系?
- t检测和卡方检测（χ^2-test）
- AB测试的技巧和局限性

Review

Simpson's Paradox: Different results may emerge when you segment your data

k-means algorithm and latent class analysis

- Which algorithm should we use?
- What are the inputs and outputs of the algorithms?
- How does the algorithm work?
- How to determine the number of groups?

课程回顾

辛普森悖论: 当你把数据细分之后，可能会发现不同的结论

k聚类算法和潜在类别分析

- 我们应该选择哪个算法?
- 算法的输入和输出应该是什么?
- 算法背后的逻辑是什么?
- 如何决定聚类或者分组的数量?

Review

Market Basket Analysis

- Support, Confidence, and Lift
- How to make recommendations based on MBA?

Using Conjoint Analysis to set prices

Be aware of the selection bias

课程回顾

购物篮分析

- 支持度，置信度和提升度怎么计算
- 如何利用购物篮分析做出产品推荐

通过联合分析帮助我们进行定价

理解什么是选择偏差

Review

Recommendation Systems

- User-based collaborative filtering
- Item-based collaborative filtering
- Model-based collaborative filtering
- Cold start problem

课程回顾

推荐系统

- 基于用户的协同过滤
- 基于物品的协同过滤
- 基于模型（矩阵分解）的协同过滤
- 如何应对冷启动问题

Final Exam 结课考试

5月25日[星期六]

- 具体考试时间待定
- 考试题目为50道单项选择题；无其他题目
- 考试时间预计为60分钟
- 同时提供英文版和中文版题目

Sample Questions

You want to understand how consumers choose between Air China, China Southern Airline, Hainan Airline, and China Eastern Airline based on the ticket price, flight duration, and departure time. Which model should you use? 你想根据机票价格，飞行时间和起飞时间分析消费者是如何在国航，南航，海航和东航之间做出选择的。你应该选择哪个模型？

A. Linear regression 线性回归

B. Multinomial logit model 多项式逻辑回归

C. Conditional logit model 条件逻辑回归

D. Matrix Factorization 矩阵分解

Sample Questions

You want to predict how consumers choose between CCB, ABC, BOC and ICBC, where a consumer can choose more than one banks based on their age, gender, etc. Which model should you choose? 你想分析用户是如何根据他们的年龄性别等因素在建行，农行，中行和工行之间做出选择的。这里一个用户可以选择多个银行。你应该选择哪个模型？

A. Linear regression 线性回归

B. Multinomial logit model 多项式逻辑回归

C. Conditional logit model 条件逻辑回归

D. Logistic Regression 逻辑回归

Sample Questions

You want to compare means in an AB test. Which model should you choose? 在AB测试中，你想比较两组平均值的大小。你应该选择哪个模型?

A. Linear Regression 线性回归

B. t test t检验

C. Logistic Regression 逻辑回归

D. χ^2 test 卡方检验

Sample Questions

The following table shows the items purchased by each consumer: 下表中列出了每个消费者购买了哪些产品

Consumer 消费者	**Items Purchased 产品**
Alice	{1, 3, 5}
Bob	{1, 4, 5}
Carol	{2, 4}
Denis	{1, 2, 6}

Sample Questions

Calculate the value of support({1}): 计算support({1})的值

A. 1

B. 1/2

C. 3/4

D. 3/11

Sample Questions

Calculate the value of confidence({1}->{5}):

计算confidence({1}->{5})的值

A. 2/3

B. 1/2

C. 1

D. 2

You conducted a linear regression. The dependent variable is car sales, and the independent variable is the color of the car, which is treated as a fixed effect (blue is benchmark). The coefficients and their significances are:

Color 颜色	Coefficient 系数	Significance 显著性
Black 黑色	12.31	0.00
Grey 灰色	0.18	0.21
Yellow 黄色	-7.14	0.02
White 白色	5.15	0.01

Which of the following statements is FALSE?

A. The coefficient and significance for Blue are 0.

B. Color gray does not have significant effect on car sales.

C. Consumers prefer black color over white color when making purchases.

D. Yellow color is least popular among all colors.

你进行了线性回归，你的因变量是汽车销量，自变量是汽车的颜色(固定效应；其中蓝色为基准)。你回归的结果(系数和统计显著性)如下表所示

Color 颜色	Coefficient 系数	Significance 显著性
Black 黑色	12.31	0.00
Grey 灰色	0.18	0.21
Yellow 黄色	-7.14	0.02
White 白色	5.15	0.01

下面的哪个说法是错误的?

A. 蓝色的系数的显著性都是0

B. 灰色不显著影响汽车的销量

C. 相对于白色，消费者更喜欢黑色的汽车

D. 黄色是所有汽车颜色中最不受欢迎的

Sample Questions

Omitted variable bias can be an issue in

在以下哪个模型分析中，我们可能遇到遗漏变量偏差的问题?

A. Linear Regression 线性回归

B. Multinomial Logit Regression 多项式逻辑回归

C. t-test t 检验

D. All of the above 以上均可能

Sample Questions

k-means is an interactive algorithm which updates information in each round. Which of the following information will not be updated? Select D if all will be updated. k聚类是一个循环算法，每一轮都会更新信息。下面哪项信息不会被循环更新？如果都会被更新请选D

A. Number of clusters 聚类数

B. Location of centers 聚类中心位置

C. Cluster membership 每个点的聚类归属

D. All of the above will be updated 以上信息均会被更新

Sample Questions

Which of the following statements on model-based collaborative filtering is FALSE?

A. We need to have the feedback from users as the input.

B. The method is based on matrix factorization.

C. Recommendation is made using market basket analysis.

D. For new users and items, we have the cold start problem.

Sample Questions

下列哪个关于基于模型的推荐系统的描述是错误的?

A. 我们的输入必须包含用户对产品的反馈
B. 该方法基于矩阵分解
C. 我们通过购物篮分析向用户做推荐
D. 对于新的用户或者新的产品，我们有冷启动的问题

Sample Questions

You are building a model to predict which types of consumers are more likely to default in their loans. However, your analysis is subject to the selection/survival bias because your bank does not offer loans to all applicants. One way to alleviate this issue is to

A. Collect data even from applicants who did not get loans

B. Collaborate with other banks to obtain data of their borrowers

C. Offer loans to some borrowers even if we believe they will default

D. Decline loans to some borrowers even if we believe they will pay back

例题

你构造一个模型分析哪一类消费者更容易信用违约。但因为你的银行并不是给所有的申请者都发放贷款，你的数据面临选择偏差的问题。一个缓解选择偏差的方法是：

A. 收集那些申请贷款失败用户的数据

B. 和其他银行合作共享他们的数据

C. 即使我们预测一类用户会信用违约，仍然给其中其中一部分用户发放贷款

D. 即使我们预测一类用户会按时还款，仍然拒绝给其中一部分用户发放贷款

课后讨论问题：

在日常的推荐中，我们认为熟人(例如同一IP地址或者互为好友)往往具有更多的相似性。如何把这一特点融入到我们的推荐系统模型中更好的做推荐？