Department of Algorithms and Programming Technologies

MIPT
MOSCOW INSTITUTE OF PHYSICS AND TECHNOLOGY

Recommender Systems

Materials supplied by BigDataTeam:
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APT dept., FIVT MIPT

Moscow, November-December 2018

Outline of the RS module

Lectures

- Introduction into RecSys (RS). RS classification. Non-Personalised RS. Content-Based RS.

- Collaborative Filtering RS. UU and II CF. Explicit & Implicit Feedback. Matrix Factorisation for RS\

- Advanced RS (guest lecture)

Practice

- 2 seminars and 1 HW

Introduction into RS: Goals

- **explain** basic ideas of Content-Based (**CB**), Collaborative Filtering (**CF**) and Knowledge-Based (**KB**) Recommender System algorithms;
- know steps to **train** simple RS algorithms;
- learn how to **design** RS experiment and **evaluate** it;
- learn how to **overcome** cold-start problem;

Introduction into RS: Outline

- **RS Basics: domains, classification**
- Non-personalised RS
- Content-Based RS
- RS Evaluation

RS: news

НОВОСТИ НАУКИ

Ученые обнаружили «временной туннель» в центре галактики

В центре галактики Млечный Путь находится не черная дыра, а так называемая «кротовья нора», с помощью которой якобы можно путешествовать сквозь пространство и время. Об этом заявил академик Российской академии наук (РАН) Николай Кардашев.

Ученые определили фрукт, способный предотвратить рак

Ученые научились читать мысли человека при помощи смартфона

Стивена Хокинга выписали из больницы

Страдающие ожирением люди считают свой лишний вес нормой

КОМПЬЮТЕРНЫЕ НОВОСТИ

Безопасность Софт Hardware Интернет Игры

Появилось первое фото нового смартфона с клавиатурой от BlackBerry

Непосредственно перед уходом производитель выпустит новый смартфон, оснащенный аппаратной клавиатурой, который получил название Mercury. В сети появились снимки нового смартфона, на которых можно рассмотреть лицевую панель BlackBerry Mercury.

Hisense A2 с E-Ink-экраном на задней панели замечен в TENAA

Беспроводной интернет празднует 25-летие

СМИ: Новый iPad от Apple избавится от кнопки «Домой»

Microsoft обновила функцию символьных ссылок в Windows 10

RS: e-commerce

Хиты продаж

Электромясорубка VITEK VT-3614 G

★★★★½ (3)

~~4990р.~~
2990р.

Электрочайник Scarlett SC - EK18P28

★★★★☆ (23)

~~1390р.~~
990р.

Электрочайник Maxwell MW-1041 GD

★★★☆☆ (19)

~~1990р.~~
1290р.

RS: movie

IMDb

Find Movies, TV shows, Celebrities and more... All

Movies, TV & Showtimes | Celebs, Events & Photos | News & Community | Watchlist

recommended movies

by ordanzala created 25 Oct 2013 | last updated - 3 months ago

Page 1 of 8 (708 Titles) Sort by: List Order (ascel

Log in to copy items to your own lists. View:

1. **Бёрдмэн** (2014)

7.8/10

Illustrated upon the progress of his latest Broadway play, a former popular actor's struggle to cope with his current life as a wasted actor is shown. (119 mins.)

Director: Alejandro G. Iñárritu
Stars: Michael Keaton, Zach Galifianakis, Edward Norton, Andrea Riseborough

Add to Watchlist

2. **Побег из Шоушенка** (1994)

9.3/10

Two imprisoned men bond over a number of years, finding solace and eventual redemption through acts of common decency. (142 mins.)

Director: Frank Darabont
Stars: Tim Robbins, Morgan Freeman, Bob Gunton, William Sadler

RS: music

Слушают сейчас

Lordly feat. Alex Aiono
Feder

My Way 3:39
Calvin Harris

Alone 2:41
Alan Walker

Lost on You Swanky Tunes & Going Deeper Remix; Radio Edit 3:30
L.P.

Туманы 3:26
Макс Барских

Твои глаза 3:53
LOBODA

We Don't Talk Anymore feat. Selena Gomez 3:37
Charlie Puth

RS: what can it be?

RS: domains

- news
- e-commerce
- movie
- music
- finance
- life insurance
- tourism
- job search
- real estate
- …

RS: domains

- news
- e-commerce
- movie
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- …

extras: cross-domain

RS: categories

- Non-Personalised
- Content-Based (CB)
- Knowledge-Based (KB)
- Neighbourhood Models (UU / II CF)
- Collaborative Filtering (CF)

+ Hybrid Recommender Systems

Non-Personalised

most popular items

Top Tech Products & Gadgets

1–6 of 6

Samsung Galaxy S8

Nintendo Switch

Sony Alpha a6000

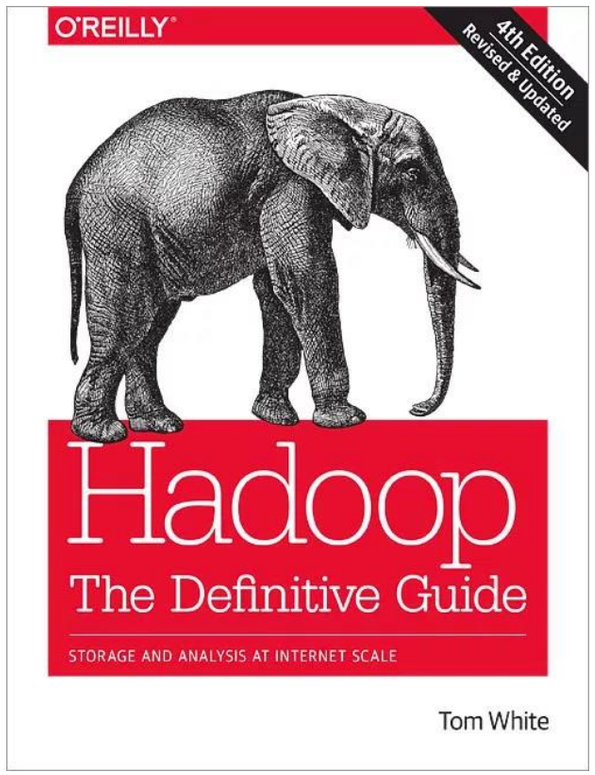
Fitbit Charge 2

Apple MacBook Pro with Touch Bar

Fidget Spinners

from: https://www.google.com/shopping?hl=en

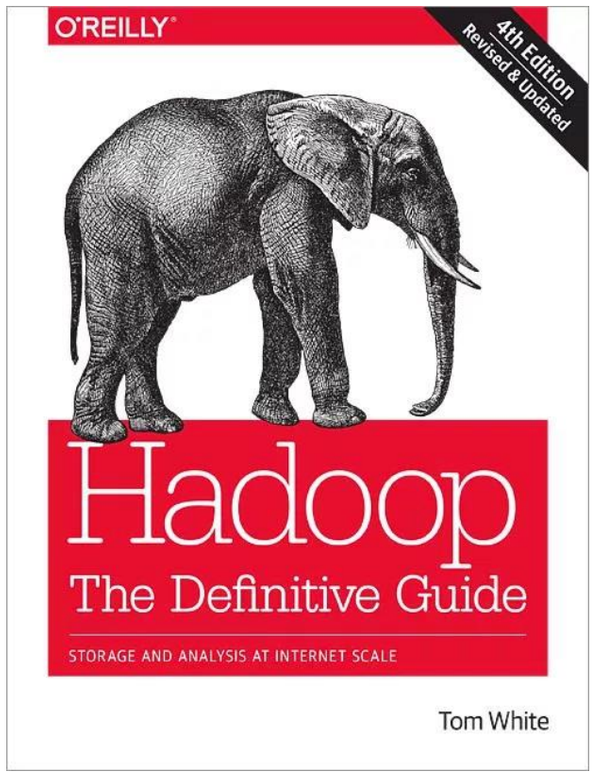
Content Based (CB)



Property	Expected Type	Description
Properties from Book		
`bookEdition`	Text	The edition of the book.
`bookFormat`	BookFormatType	The format of the book.
`illustrator`	Person	The illustrator of the book.
`isbn`	Text	The ISBN of the book.
`numberOfPages`	Integer	The number of pages in the book.

user	book	author	…	target
programmer A	C++	Bjarne Stroustrup	…	**likes**
programmer A	Cooking	Gordon Ramsay	…	**dislikes**
programmer B	Cooking	Gordon Ramsay	…	**likes**
…	…	…	…	…

Content Based (CB)



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user	book	author	…	target
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programmer A	Cooking	Gordon Ramsay	…	**dislikes**
programmer B	Cooking	Gordon Ramsay	…	**likes**
…	…	…	…	…
programmer A	Linux Cookbook	Carla Schroder	…	**???**

Neighbourhood Models (User-User / Item-Item)

likes

dislikes

similar user

likes or dislikes ??

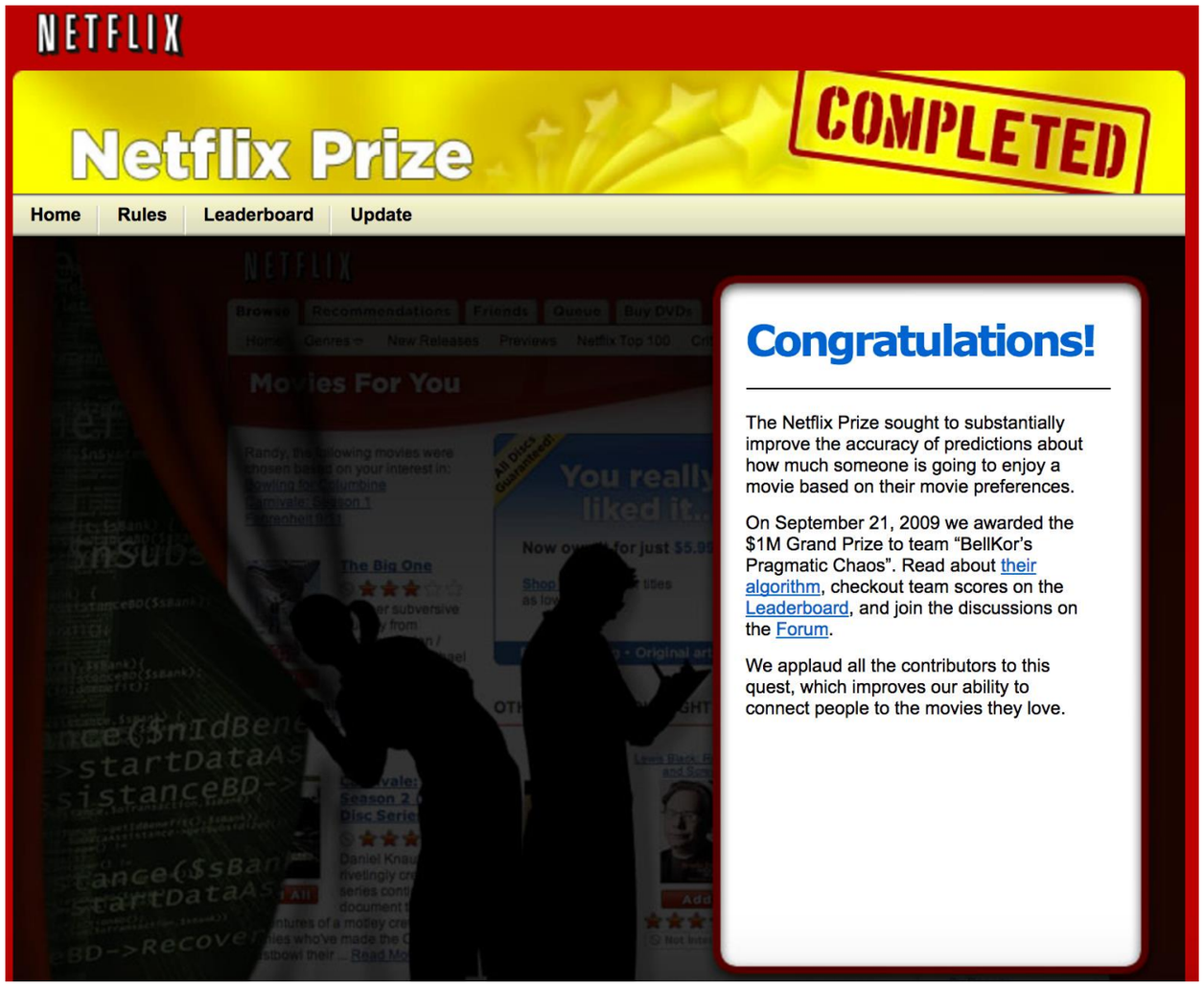
Neighbourhood Models (User-User / Item-Item)

purchase history (yesterday)

Recommender System

Do you want to buy ??

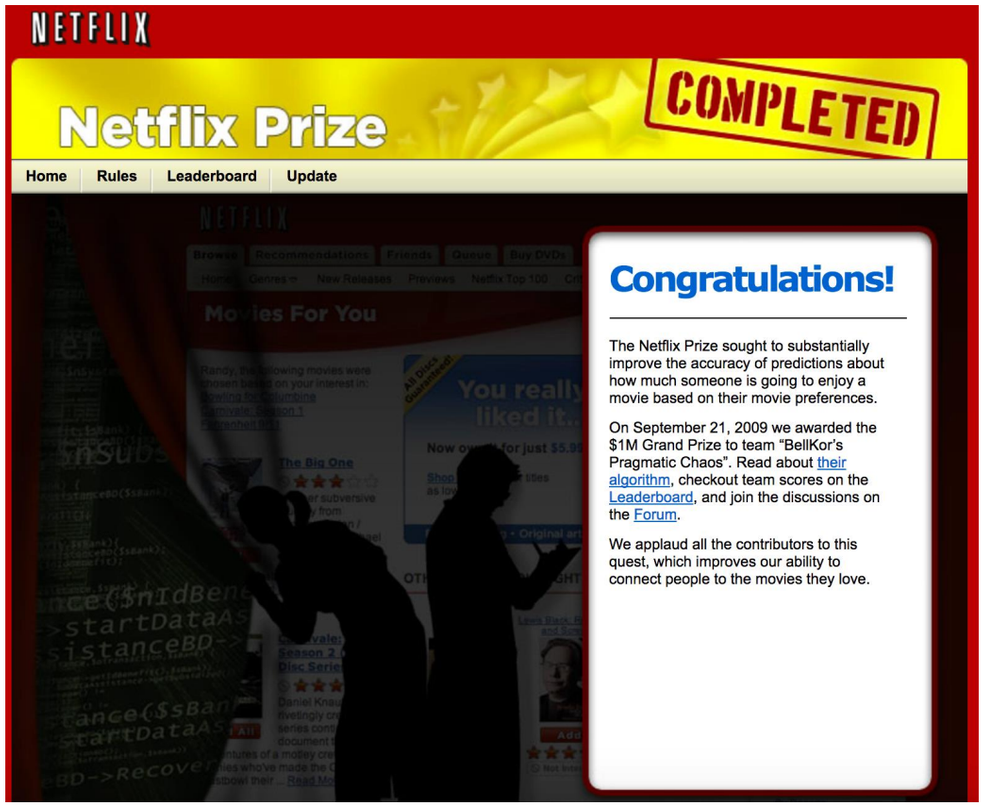
Collaborative Filtering (CF)

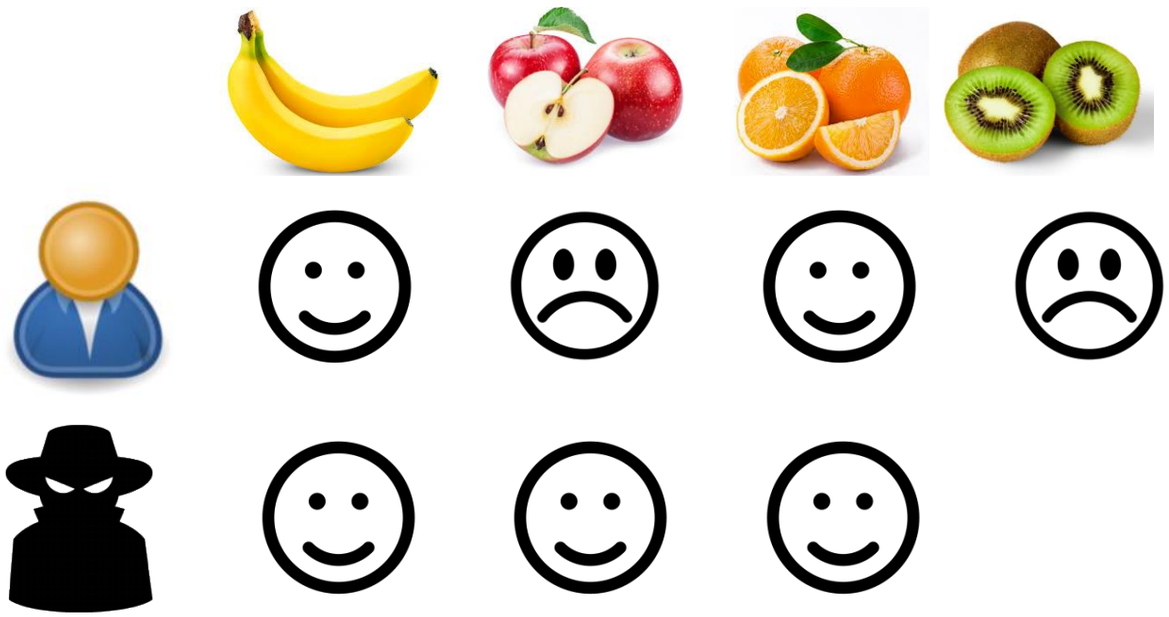


2006, October, 2nd (start)
2007 - progress Prize
2008 - progress Prize
2009 - June/July 25, 10+% (improvement)

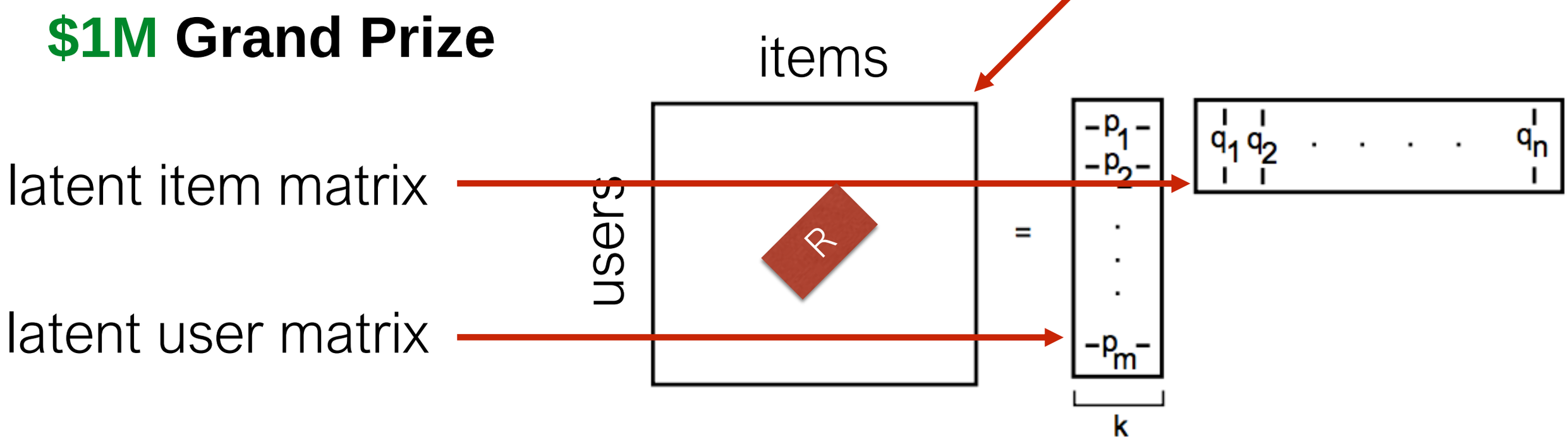
$1M Grand Prize

Collaborative Filtering (CF)





$1M Grand Prize



Knowledge Based (KB)

£165,000 - 2 bedroom ...
First Avenue, Stafford ST16

£1,325,000 - 4 bedroom terraced ...
Howgate Road, London SW14

£149,950 - 3 bedroom terraced ...
Kendal Road, St Annes, ...

Knowledge Based (KB)

£165,000 - 2 bedroom ...
First Avenue, Stafford ST16

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Howgate Road, London SW14

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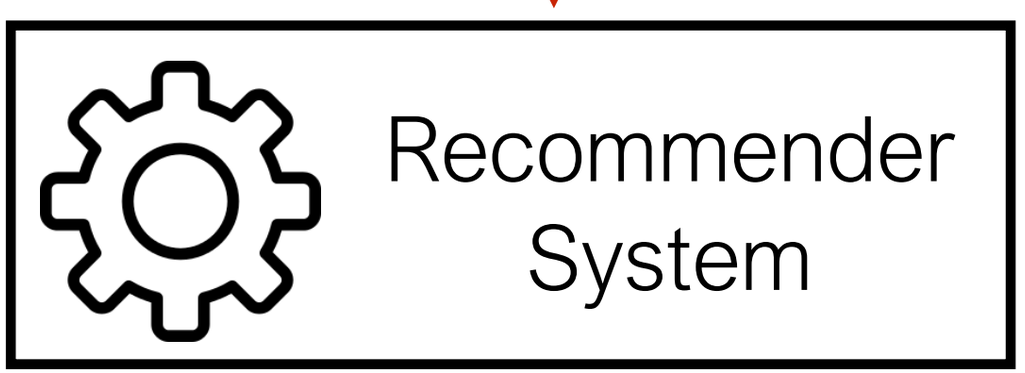
Kendal Road, St Annes, ...

domain knowledge

get suggestions



Hybrid RecSys: Alg_1 + Alg_2 + …

- news **(CB, CF)**
- e-commerce **(CF)**
- movie **(CF)**
- music **(CB / CF)**
- finance **(KB)**
- life insurance **(KB)**
- tourism **(CB, KB)**
- job search **(CB)**
- real estate **(KB)**
- …

What types of Recommender Systems exist?

- [ ] Content-Based
- [ ] Collaborative-Based
- [ ] Content-Filtering
- [ ] Hybrid
- [ ] Knowledge-Based
- [ ] Collaborative Filtering

Evaluation




5 3 4 0

? 2 3 ?

Evaluation

5 3 4 0

? 2 3 ?

4 vs 5

0 vs 1

Prediction (metrics):
- MAE, RMSE, …

Evaluation

5 3 4 0

~~?~~ 2 3 ~~?~~

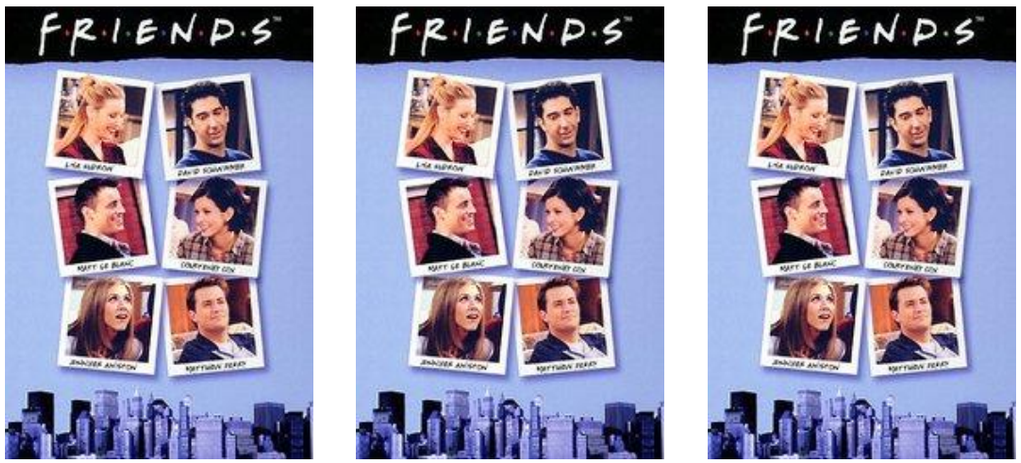
order of recommendations

Prediction (metrics):
- MAE, RMSE, …

Recommendation:
- MRR, DCG, …

Evaluation

recommendations



season#5 season#3 season#9

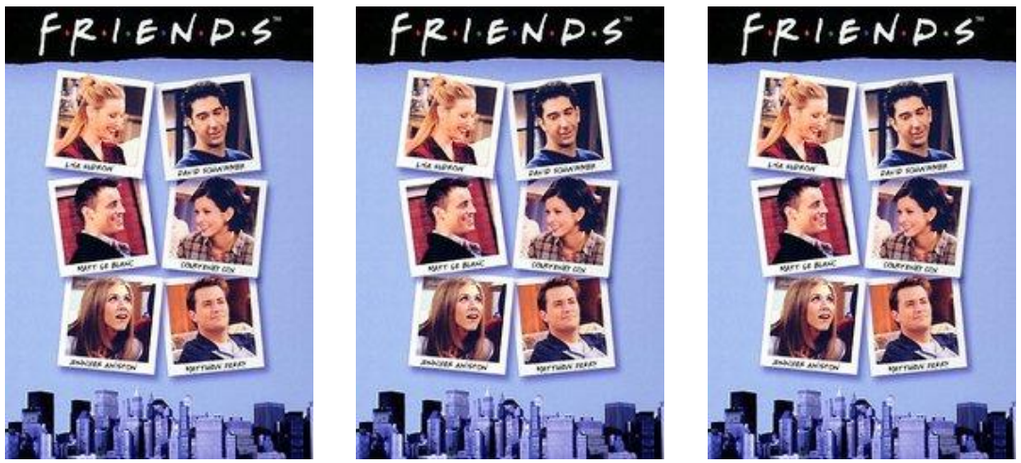
...

Prediction (metrics):
- MAE, RMSE, …

Recommendation:
- MRR, DCG, …

Evaluation

recommendations



season#5 season#3 season#9

...

Prediction (metrics):
- MAE, RMSE, …

Recommendation:
- MRR, DCG, …

extras: coverage, novelty, diversity, serendipity, …

RecSys Challenges

RecSys Challenges

- Cold-Start Problem

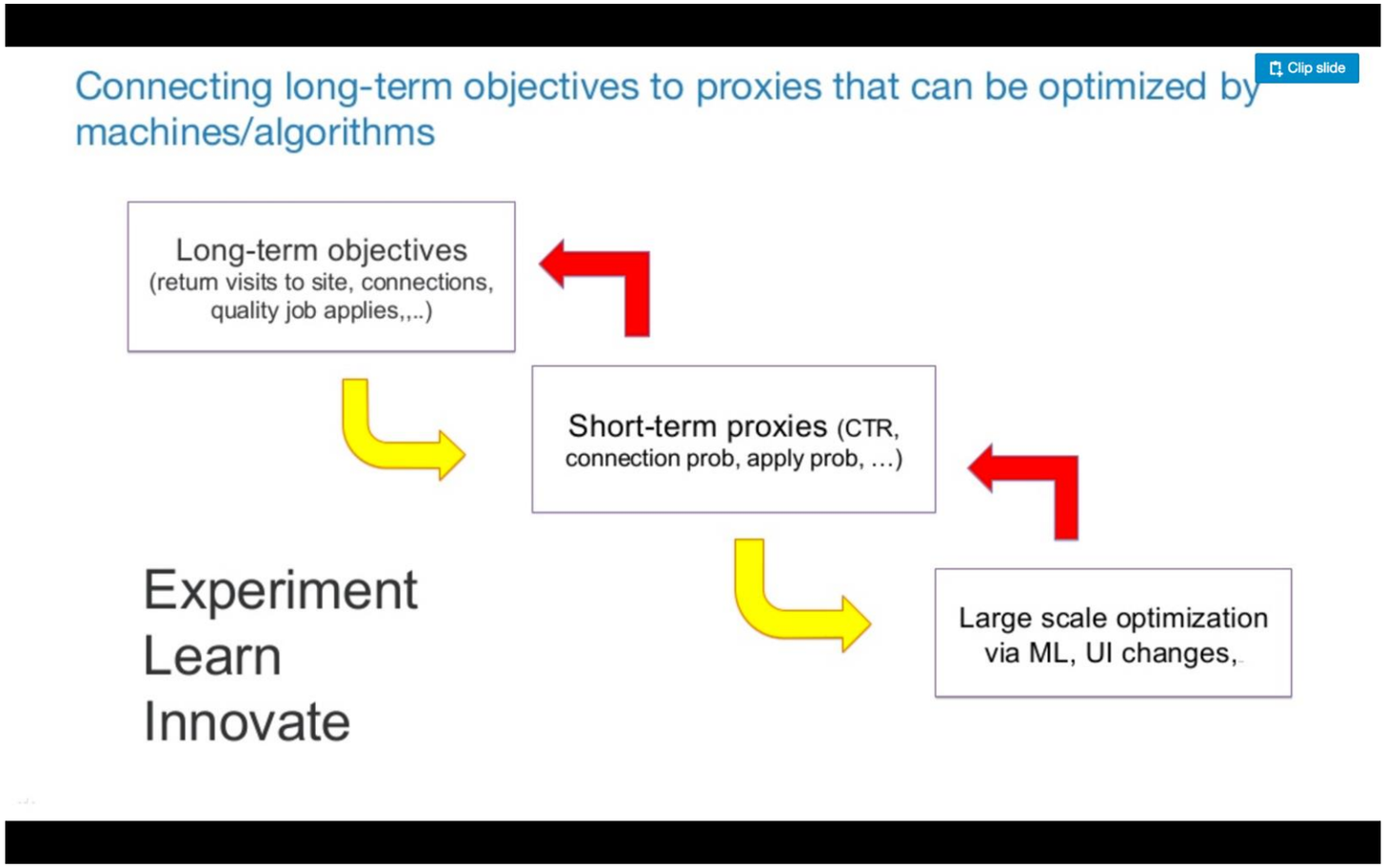
5 3 4 ?

? ? ? ?

RecSys Challenges

- Cold-Start Problem
- Offline / Online correlation

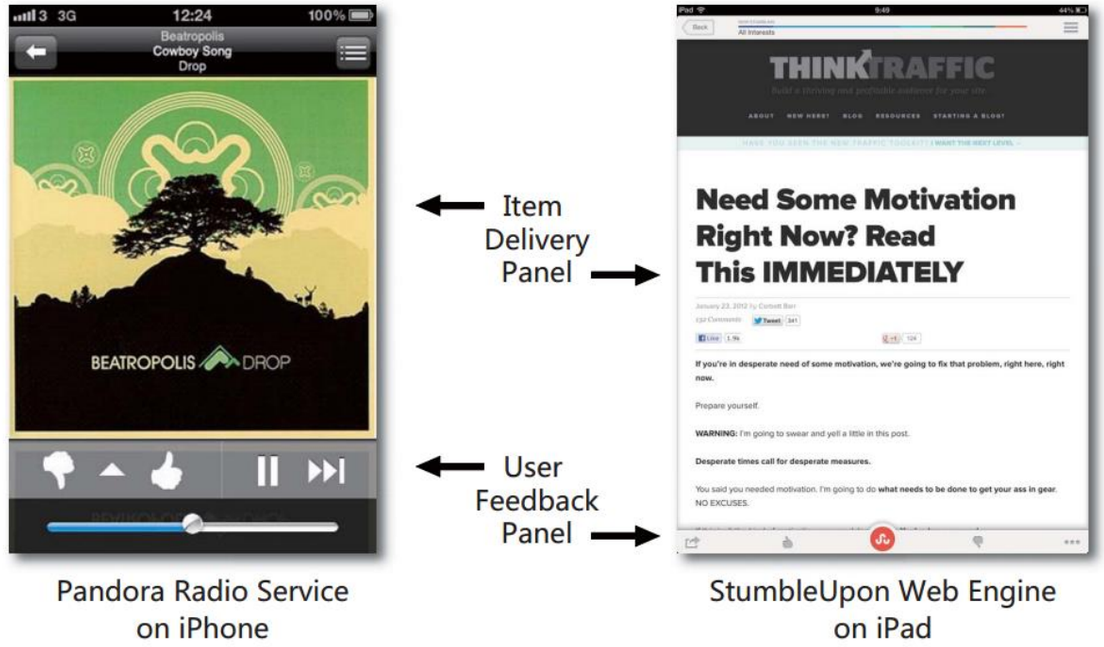
RecSys'16 tutorial: Lessons learned from building real-life recommender systems



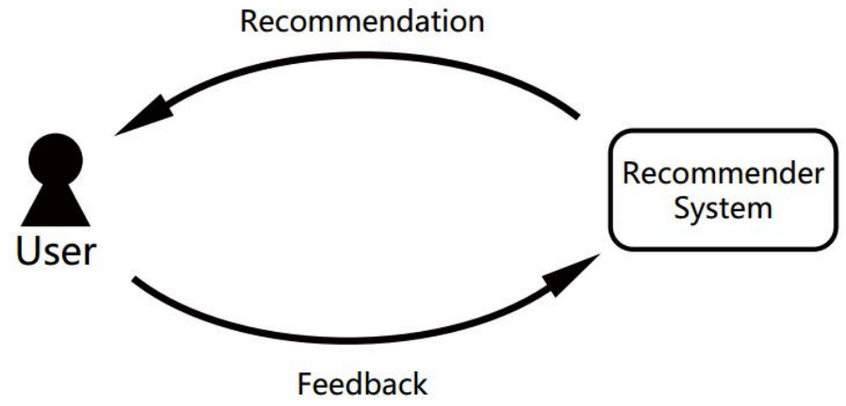
credit: Deepak Agarwal,
Senior Director of Engineering at LinkedIn

RecSys Challenges

- Cold-Start Problem
- Offline / Online correlation
- Interface Design, Exploration / Exploitation dilemma



(a) Two examples of Interactive Recommender Systems.



(b) Non-stop Recommendation-feedback loop.

Xiaoxue Zhao, Weinan Zhang, Jun Wang (2013), Interactive Collaborative Filtering, CIKM

RecSys Challenges

- Cold-Start Problem
- Offline / Online correlation
- Interface Design, Exploration / Exploitation dilemma
- Scalability
- Imbalanced Dataset (activity - power law distribution)

Outline (Introduction into RS)

- RS Basics: domains, classification
- **Non-personalised RS**
- Content-Based RS
- RS Evaluation

movielens

provided by

grouplens is a research lab in the Department of Computer Science and Engineering at the University of Minnesota

movielens

```
$ head ~/path/to/ratings.csv
userId,movieId,rating,timestamp
1,31,2.5,1260759144
1,1029,3.0,1260759179
1,1061,3.0,1260759182
...
```

```
$ head ~/path/to/movies.csv
movieId,title,genres
1,Toy Story (1995),Adventure|Animation|Children|Comedy|Fantasy
2,Jumanji (1995),Adventure|Children|Fantasy
3,Grumpier Old Men (1995),Comedy|Romance
4,Waiting to Exhale (1995),Comedy|Drama|Romance
```

```
from pyspark.mllib import recommendation
from pyspark import SparkContext

def to_rating(ml_latest_row):
   user, movie, rating, timestamp = ml_latest_row.split(",")
   return recommendation.Rating(int(user), int(movie), float(rating))

def skip_header(rdd):
   header = rdd.first()
   rdd = rdd.filter(lambda row: row != header)
   return rdd

if __name__ == "__main__":
   sc = SparkContext(appName="RecSys Non-Personalized")
   data = sc.textFile("./path/to/ratings.csv")
   data = skip_header(data)
   movielens = data.map(to_rating)
   movie_ratings = movielens.map(lambda r: (r.product, r.rating)).groupByKey()
   movie_avg_rating = movie_ratings.map(lambda (movie_id, ratings): (movie_id,
      sum(ratings) / len(ratings)))
   movie_avg_rating.map(lambda (k, v): (v, k)).sortByKey(ascending=False).take(10)
```

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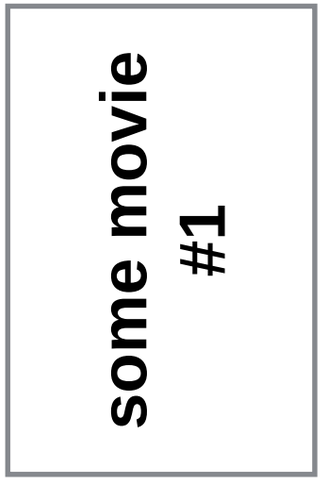
    movie_avg_rating.map(lambda (k, v): (v, k)).sortByKey(ascending=False).take(10)
```

```
movie_titles = sc.textFile("./ml-latest-small/movies.csv")
movie_titles = skip_header(movie_titles)
titles = movie_titles.map(parse_movie_data)
# call several times to see random behaviour
print movie_avg_rating.join(titles) \
    .map(lambda (movie_id, (avg_rating, title)): (avg_rating, (title, movie_id))) \
    .sortByKey(ascending=False).take(15)
```

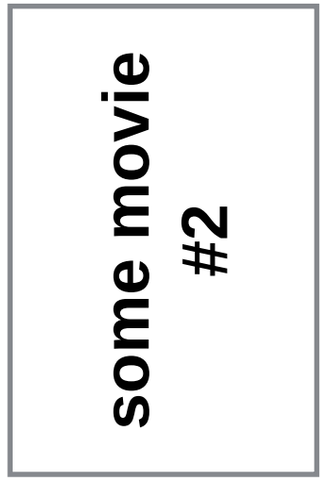
trial#1

trial#2

Damped Means



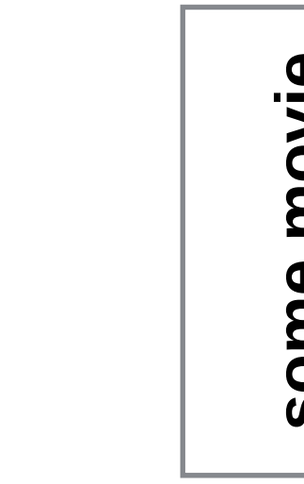
rated by

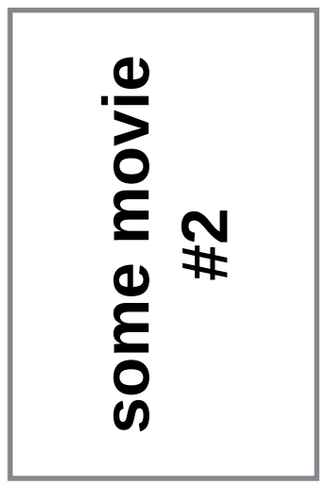


rated by

$$\frac{\sum_{\text{users u who rated movie i}} r_{ui}}{\text{quantity of movie i ratings}}$$

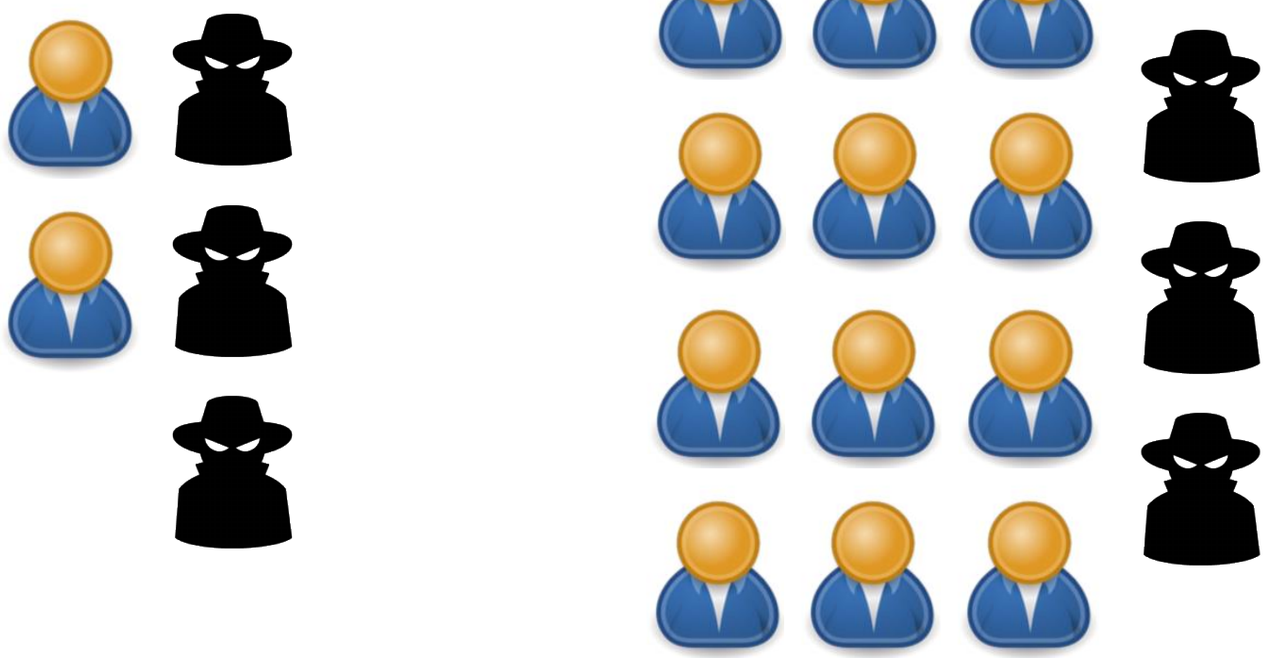
Damped Means





rated by

rated by



$$\frac{\sum_{\text{users u who rated movie i}} r_{ui} + k\mu}{\text{quantity of movie i ratings} + k}$$

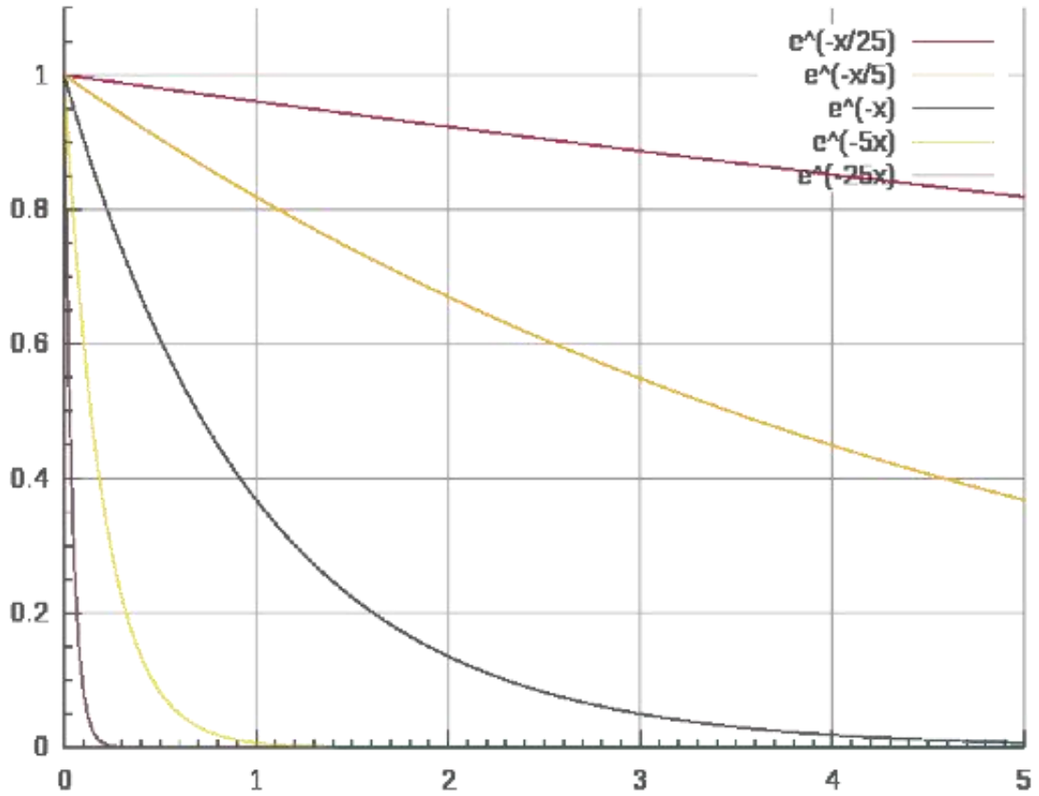
```
...
movie_avg_rating = movie_ratings.map(lambda (movie_id, ratings):
(movie_id, (sum(ratings) + k * mu) / (len(ratings) + k))

)
...
```

movielens

```
$ head ~/path/to/ratings.csv
userId,movieId,rating,timestamp
1,31,2.5,1260759144
1,1029,3.0,1260759179
1,1061,3.0,1260759182
...
```

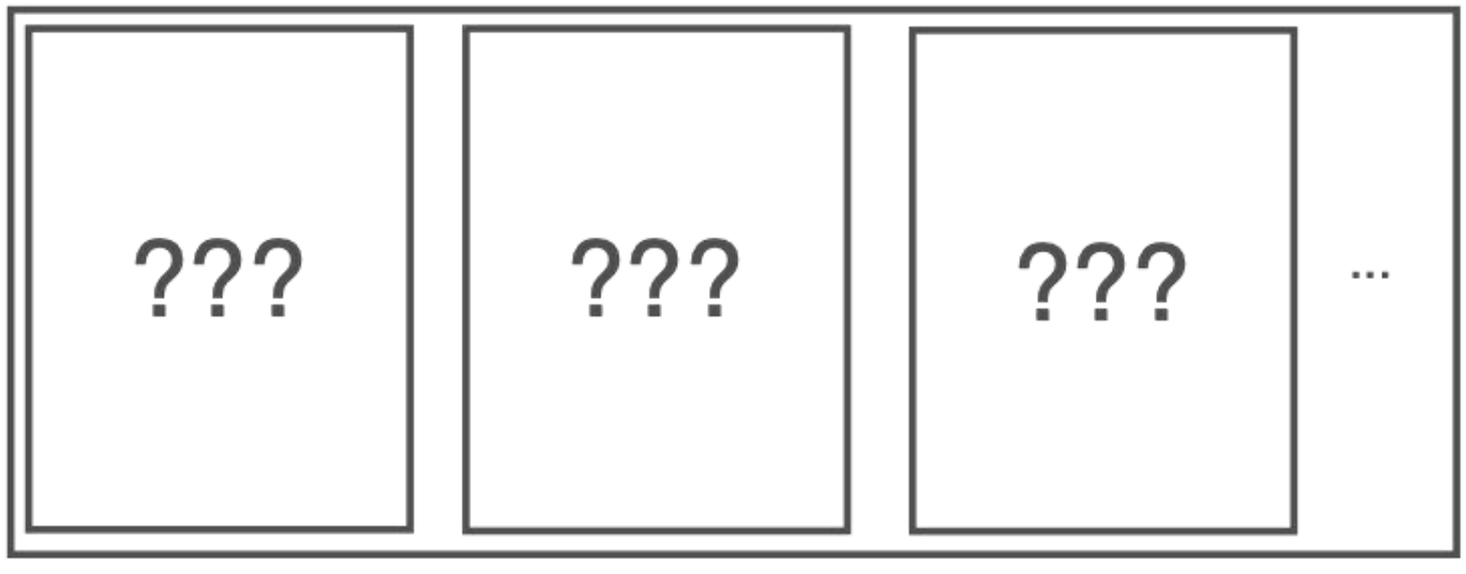
Trending now



see: https://en.wikipedia.org/wiki/Exponential_decay

Trending now

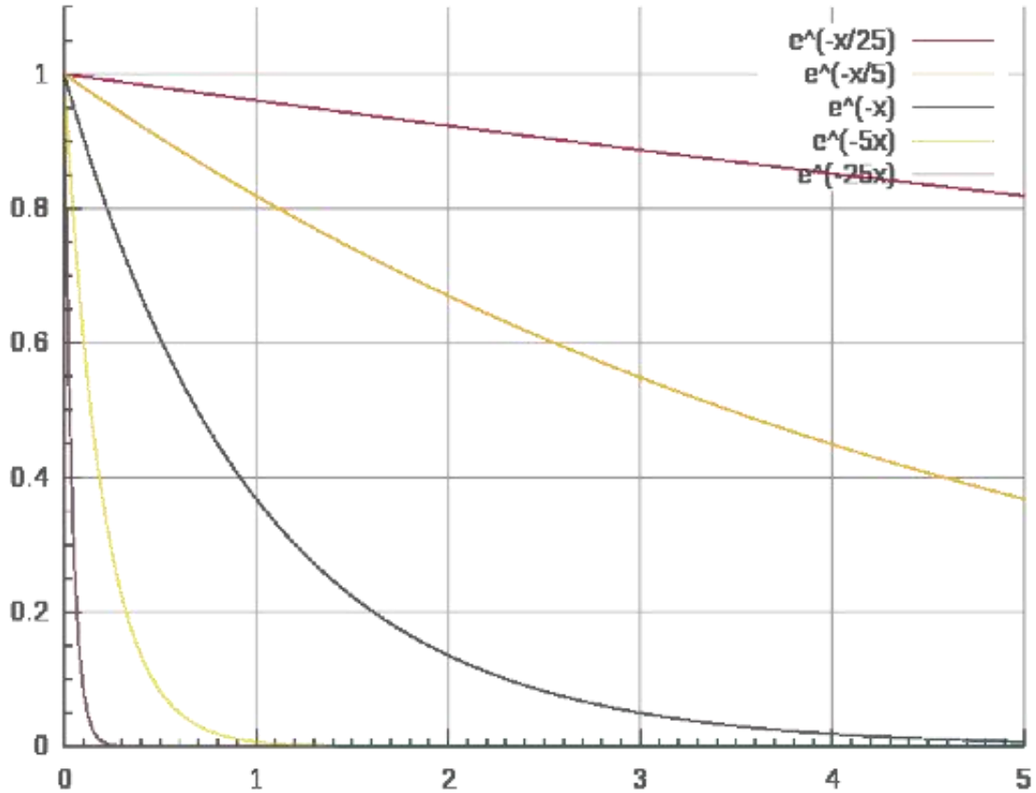
$$decay = e^{-\alpha(now() - rating\ timestamp)}$$



Are movies getting better with time?

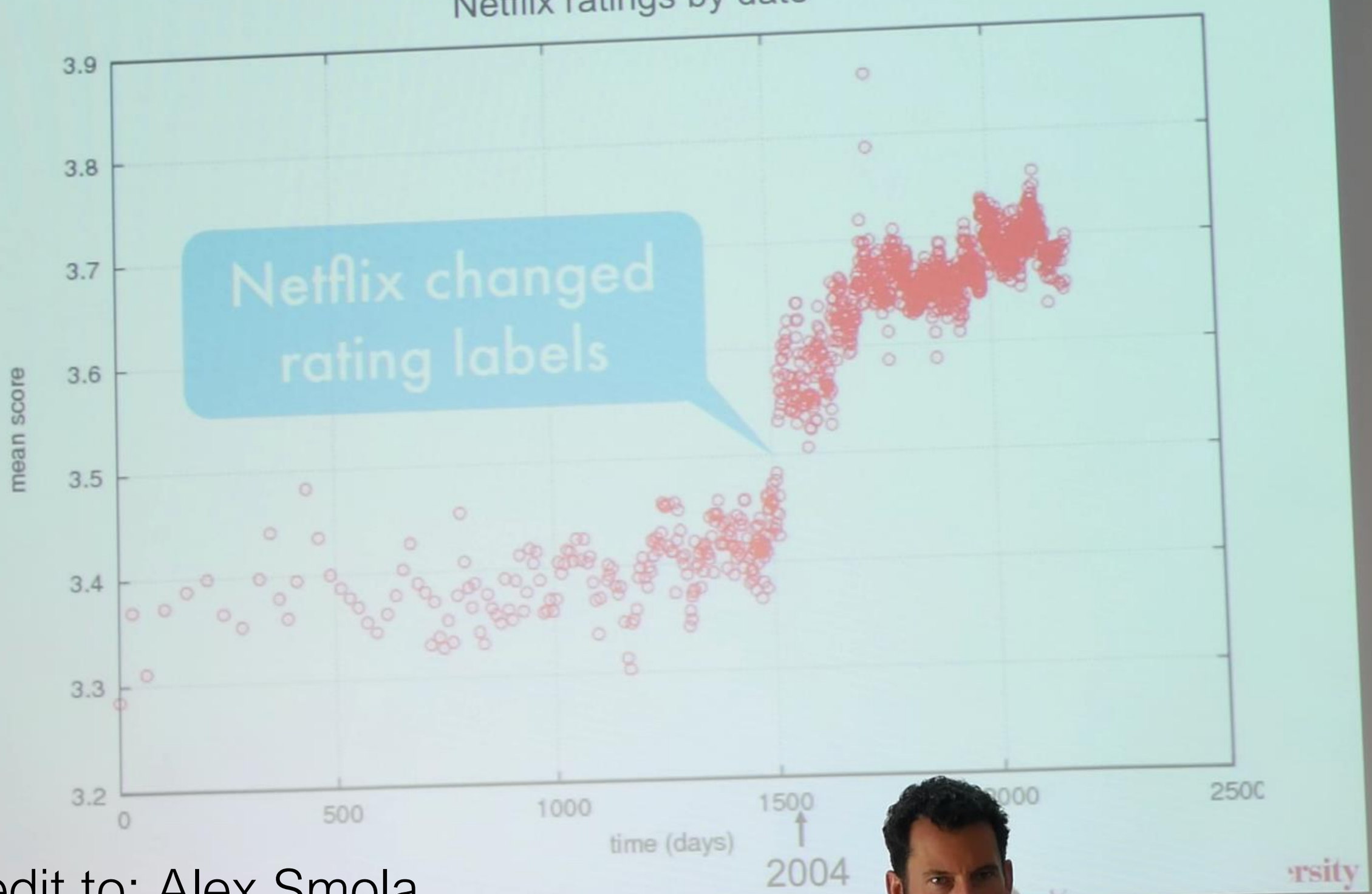
credit to: Alex Smola

Trending now

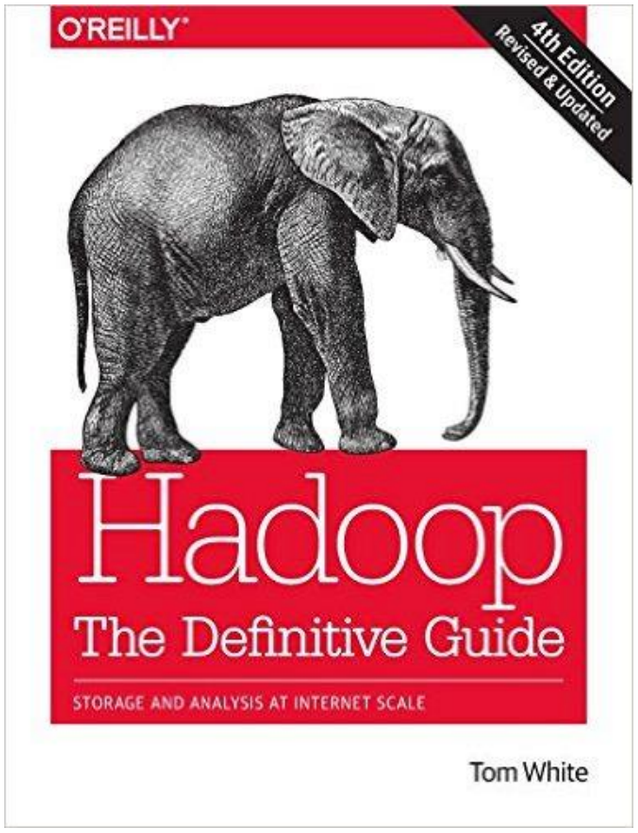


see: https://en.wikipedia.org/wiki/Exponential_decay

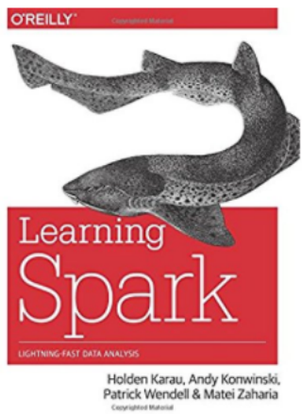
Something Happened in Early 2004…



credit to: Alex Smola



Customers who bought this item also bought



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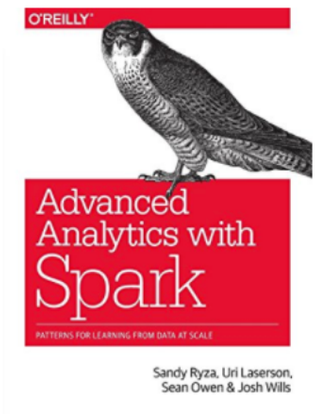

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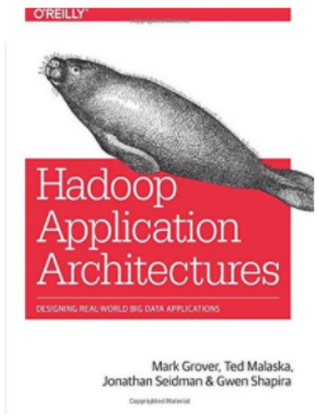

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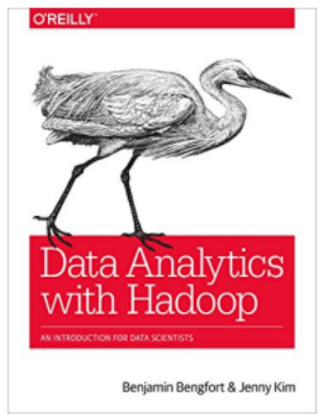

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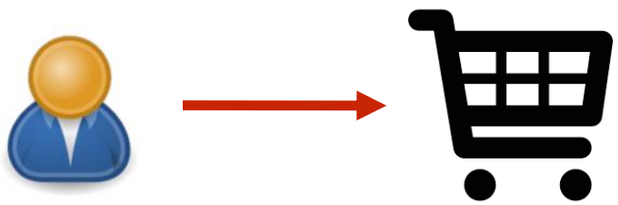
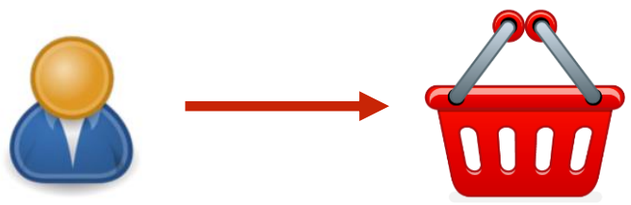
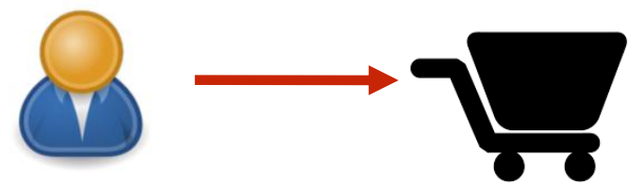






...

...

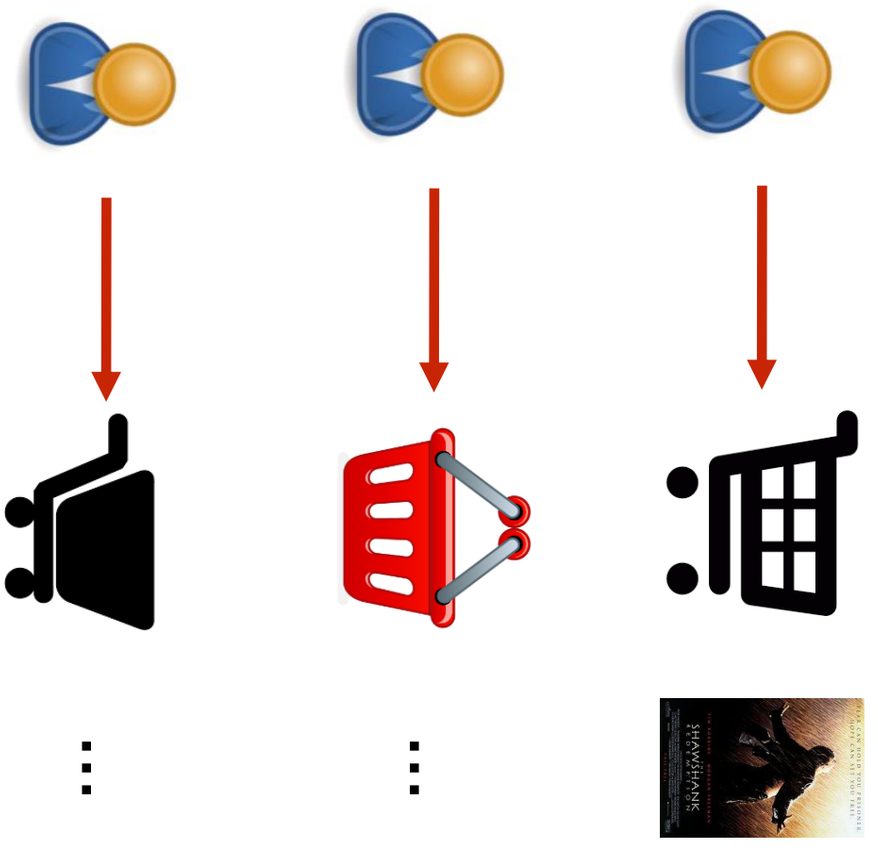
item A

???

???

???

...

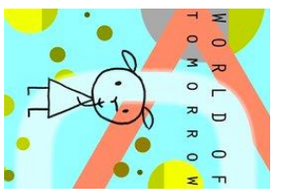


Shawshank … (1994)

Godfather (1972)

… Suspects (1995)

item A



Solving «Bananas» Problem

item A

movie «bananas»

Solving «Bananas» Problem

item A

movie «bananas»

$$\frac{\#A\&B}{\#A} \longrightarrow lift = \frac{\#A\&B}{\#A \times \#B}$$

Solving «Bananas» Problem

item A

movie «bananas»

$$\frac{\#A\&B}{\#A} \longrightarrow lift = \frac{\#A\&B}{\#A \times \#B}$$

$$\frac{P(B|A)}{P(B|\ not\ A)}$$

Solving «Bananas» Problem

item A

movie «bananas»

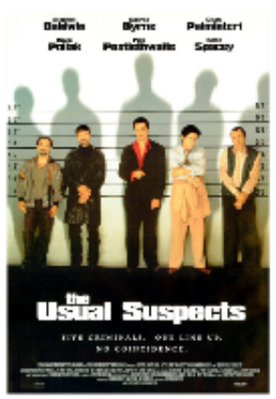
$$\frac{\#A\&B}{\#A} \longrightarrow lift = \frac{\#A\&B}{\#A \times \#B}$$

$$\frac{P(B|A)}{P(B|\ not\ A)}$$

Shawshank (1994)

Godfather (1972)

Suspects (1995)



see (for example): Data-Intensive Text Processing with MapReduce by Jimmy Lin and Chris Dyer. Morgan & Claypool Publishers, 2010. Chapter 3: “Pairs vs Stripes”

Coffee and Tea Break

What is the name of the following problem?

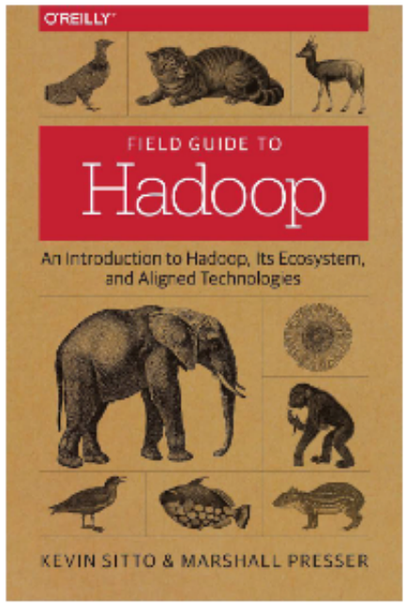
- recommend the most popular items disregard the user's context / behavior / history.

- [ ] Minions Problem
- [ ] Bananas Problem
- [ ] Winnie the Pooh Problem
- [ ] Harry Potter Problem
- [ ] Orange Problem

Outline (Introduction into RS)

- RS Basics: domains, classification
- Non-personalised RS
- **Content-Based RS**
- RS Evaluation

Content Based (CB)



Property	Expected Type	Description
Properties from Book		
`bookEdition`	Text	The edition of the book.
`bookFormat`	BookFormatType	The format of the book.
`illustrator`	Person	The illustrator of the book.
`isbn`	Text	The ISBN of the book.
`numberOfPages`	Integer	The number of pages in the book.

User	Book	Author	...	Target
programmer A	C++	Bjarne Stroustrup	...	**likes**
programmer A	Cooking	Gordon Ramsay	...	**dislikes**
programmer B	Cooking	Gordon Ramsay	...	**likes**
...	...	...	...	...
programmer A	Linux Cookbook	Carla Schroder	...	**???**

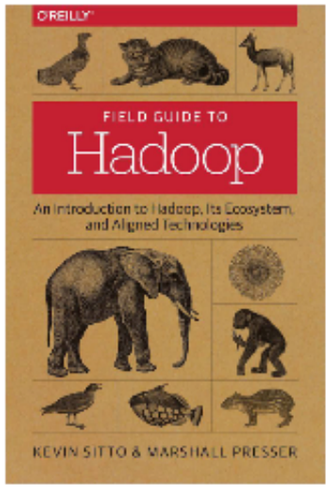
http://schema.org/Book

Questions:

1. Item representation
2. User representation
3. Distance / similarity measure

item

1



$$i \in \mathbb{R}^m$$

2 user

$$u \in \mathbb{R}^m$$

3 $$distance(u, i) : \mathbb{R}^m \times \mathbb{R}^m \mapsto \mathbb{R}$$

Questions:

1. **Item representation**
2. User representation
3. Distance / similarity measure

Movie	Budget (numerical)	Genre (categorical)	...
The Shawshank Redemption	$25,000,000	Crime | Drama	...
The Godfather	$6,000,000	Crime | Drama	...
...	...	...	...

Questions:

1. **Item representation**
2. User representation
3. Distance / similarity measure

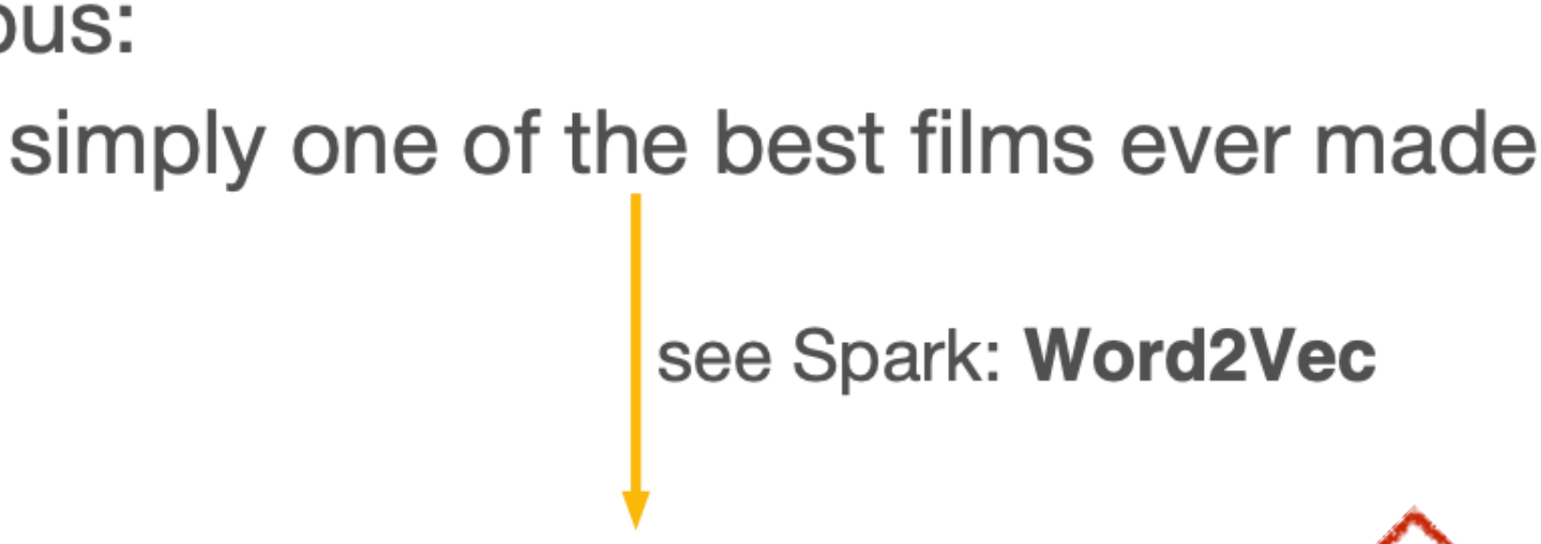
Movie	User Reviews	...
The Shawshank Redemption	… This is simply one of the best films ever made and …	...
The Godfather	… The Godfather is commonly considered to be one of the “greatest films of all time” …	...
...	...	...

Questions:

1. **Item representation**
2. User representation
3. Distance / similarity measure

Text corpus:

… this is simply one of the best films ever made and …



OPEN https://issues.apache.org/jira/browse/SPARK-14864 [doc2vec]

Questions:

1. Item representation
2. **User representation**
3. Distance / similarity measure

$$U\begin{bmatrix} \overset{=i_1}{\diamond} & \overset{=i_2}{\diamond} & \overset{=i_3}{\diamond} & \\ \vdots & \vdots & \vdots & \\ \dots & 5 & 2 & 4 & \dots \\ \vdots & \vdots & \vdots & \end{bmatrix} \longrightarrow U = AVG\begin{pmatrix} 5 \times i_1 \square\square\square\square \\ 2 \times i_2 \square\square\square\square \\ 4 \times i_3 \square\square\square\square \end{pmatrix}$$

Questions:

1. Item representation
2. **User representation**
3. Distance / similarity measure

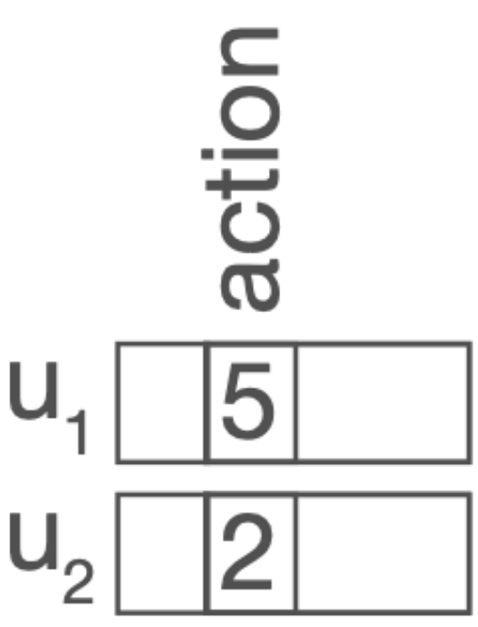
$$U\begin{bmatrix} \dots & \underset{\vdots}{5} & \underset{\vdots}{2} & \underset{\vdots}{4} & \dots \end{bmatrix} \rightarrow U = AVG\begin{pmatrix} 5 \times i_1 \\ 2 \times i_2 \\ 4 \times i_3 \end{pmatrix}$$

$$AVG : \frac{i_1 + i_2 + i_3}{3} \quad AVG : \frac{5i_1 + 2i_2 + 4i_3}{5 + 2 + 4}$$

$$AVG : \frac{decay(ts_1) \times i_1 + \dots}{decay(ts_1) + \dots}$$

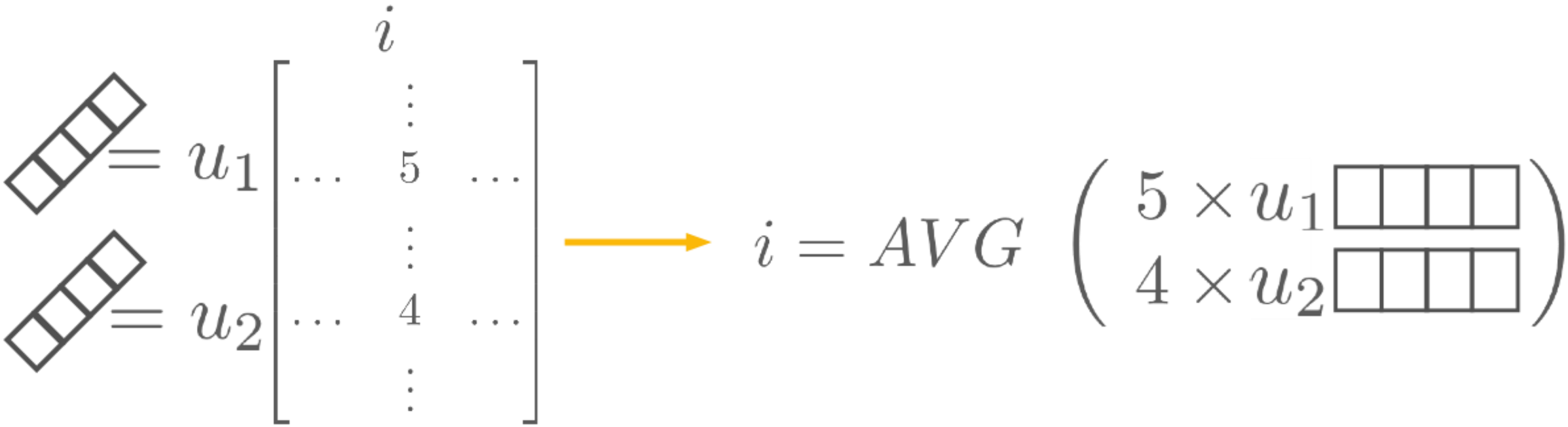
Questions:

1. Item representation
2. **User representation**
3. Distance / similarity measure



Questions:

1. Item representation
2. **User representation (vice versa)**
3. Distance / similarity measure



Questions:

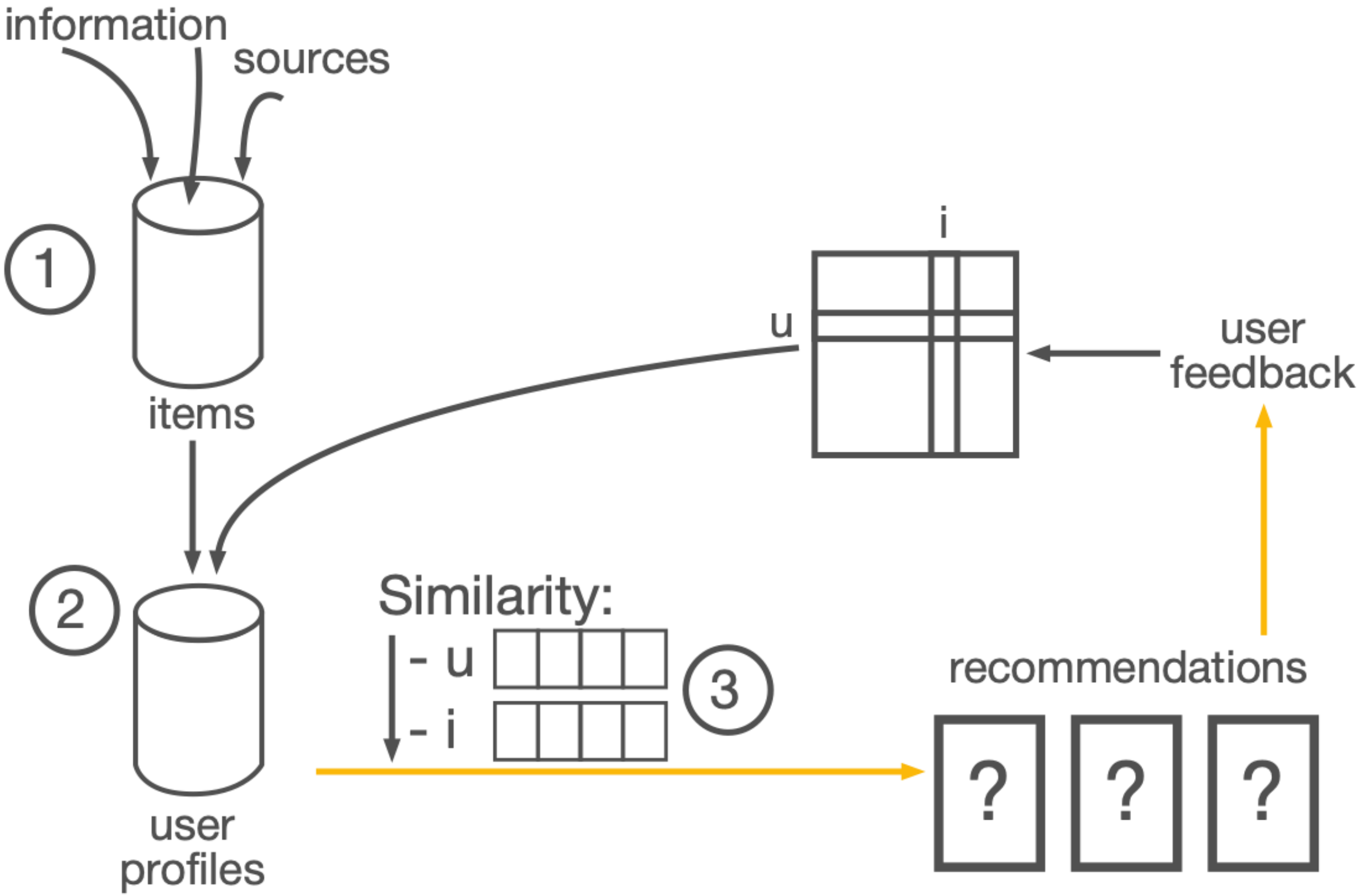
1. Item representation
2. User representation
3. **Distance / similarity measure**

1. Metrics intended for real-valued vector spaces
2. Metrics intended for integer-valued vector spaces
3. Metrics intended for boolean-valued vector spaces

... user-defined distance

http://scikit-learn.org/stable/modules/generated/sklearn.neighbors.DistanceMetric.html

CB RS Cheatsheet



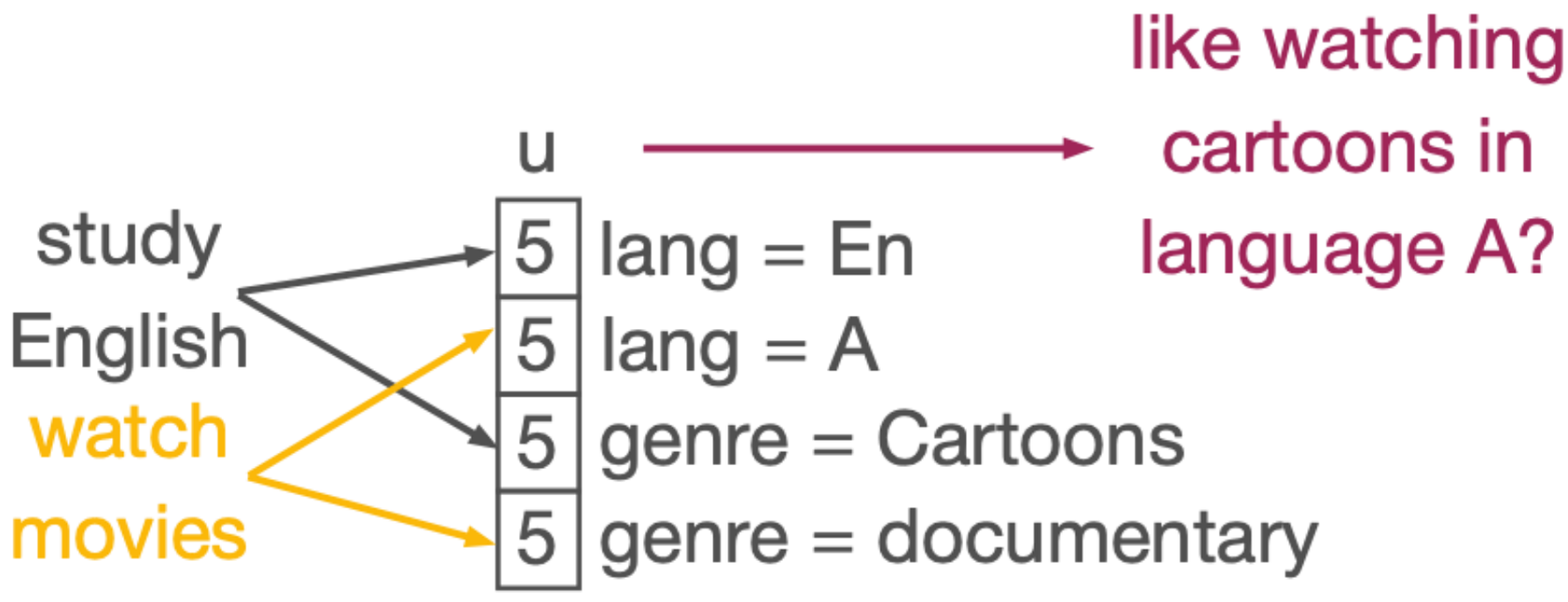
Content-Based RecSys: **Pros** and **Cons**

(+) personalized recommendations

(+/-) cold-start problem (either user or item)

(+/-) profile explanations (except embeddings)

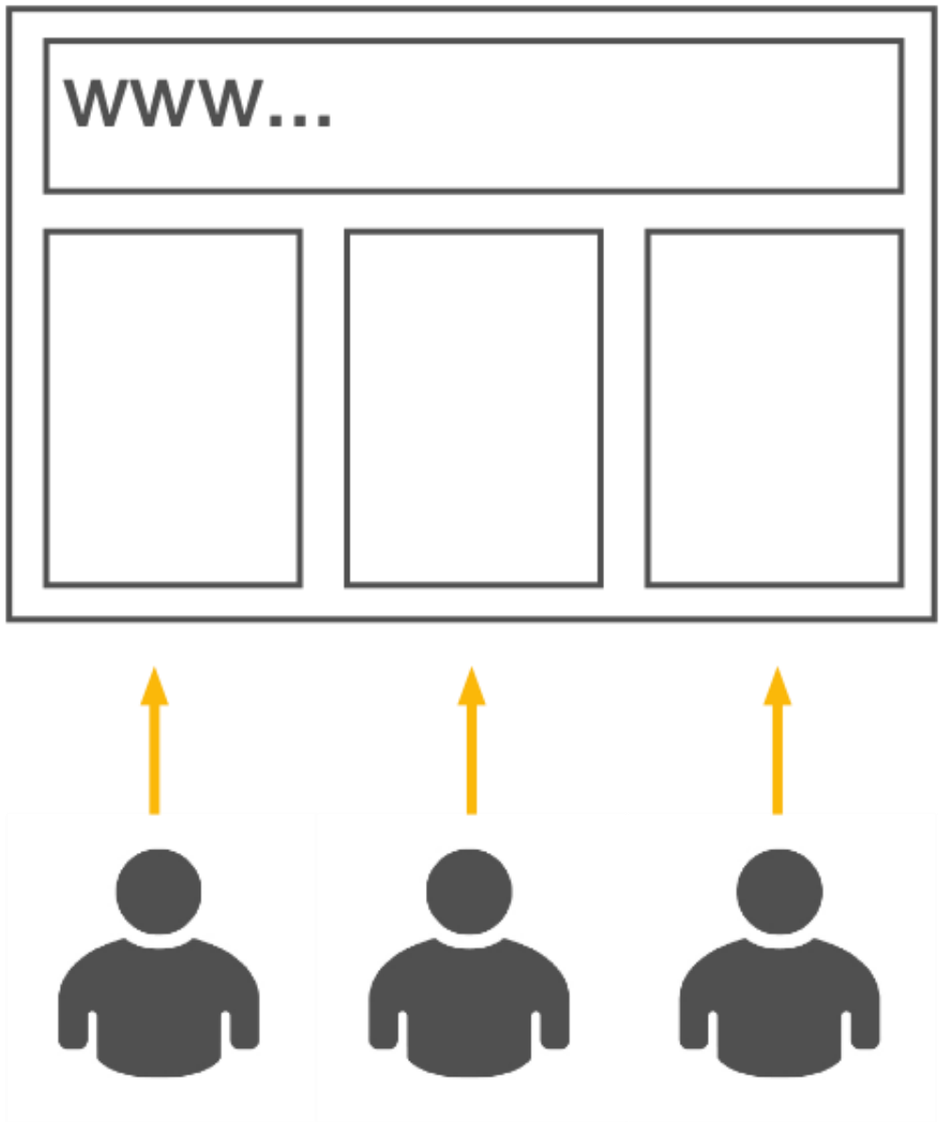
(-) complex interdependencies



Outline (Introduction into RS)

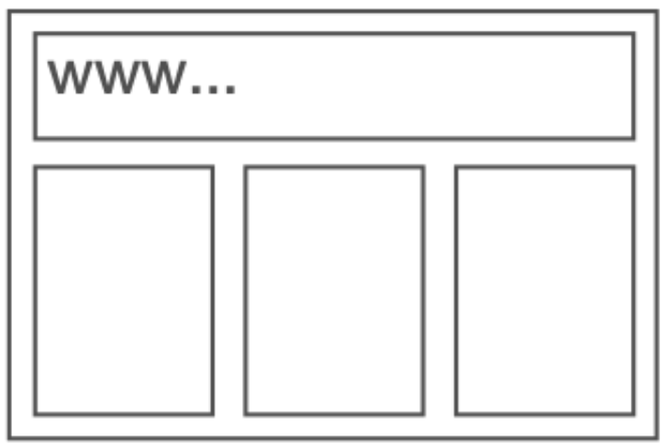
- RS Basics: domains, classification
- Non-personalised RS
- Content-Based RS
- **RS Evaluation**

service provider



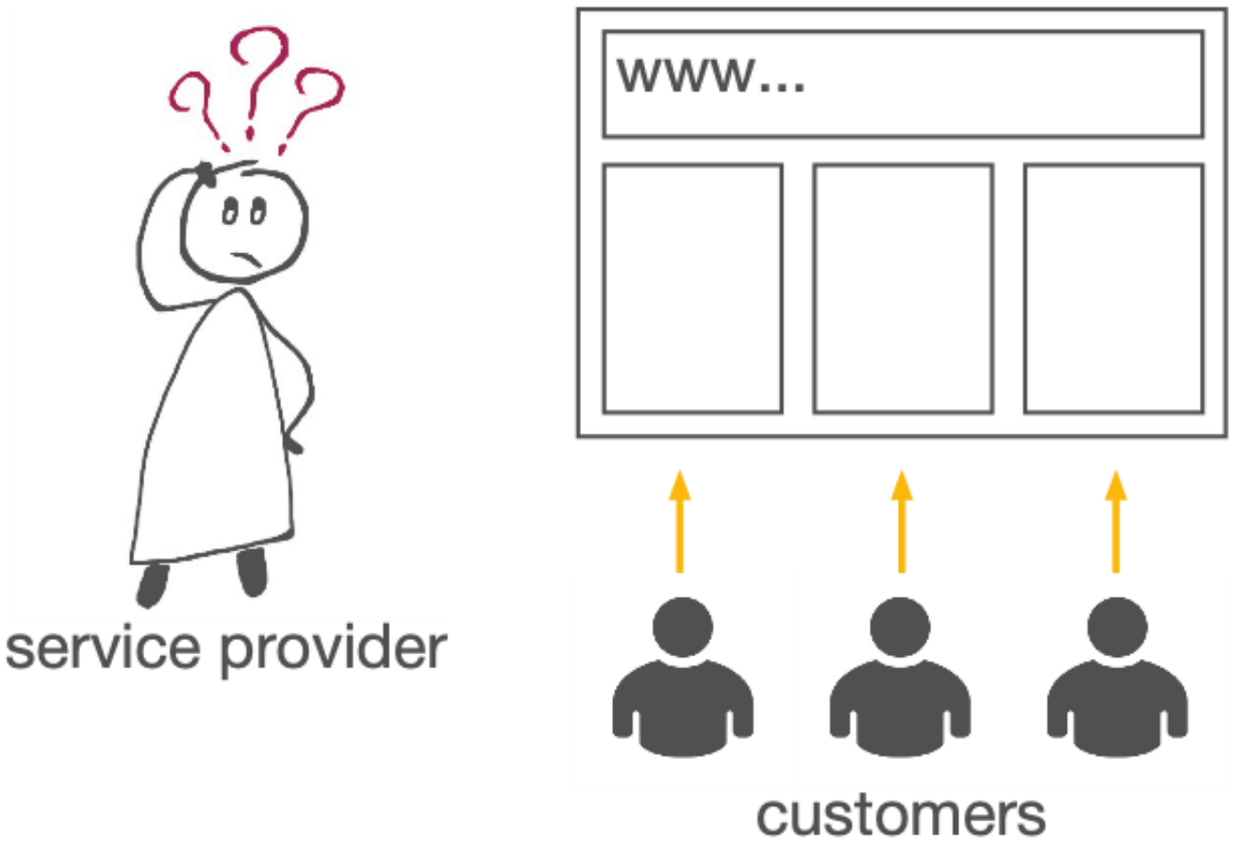
customers

service provider



customers

long-term objective



long-term objective

ПЦК

$$CLV = GC \times \frac{1}{1 + d - r}$$

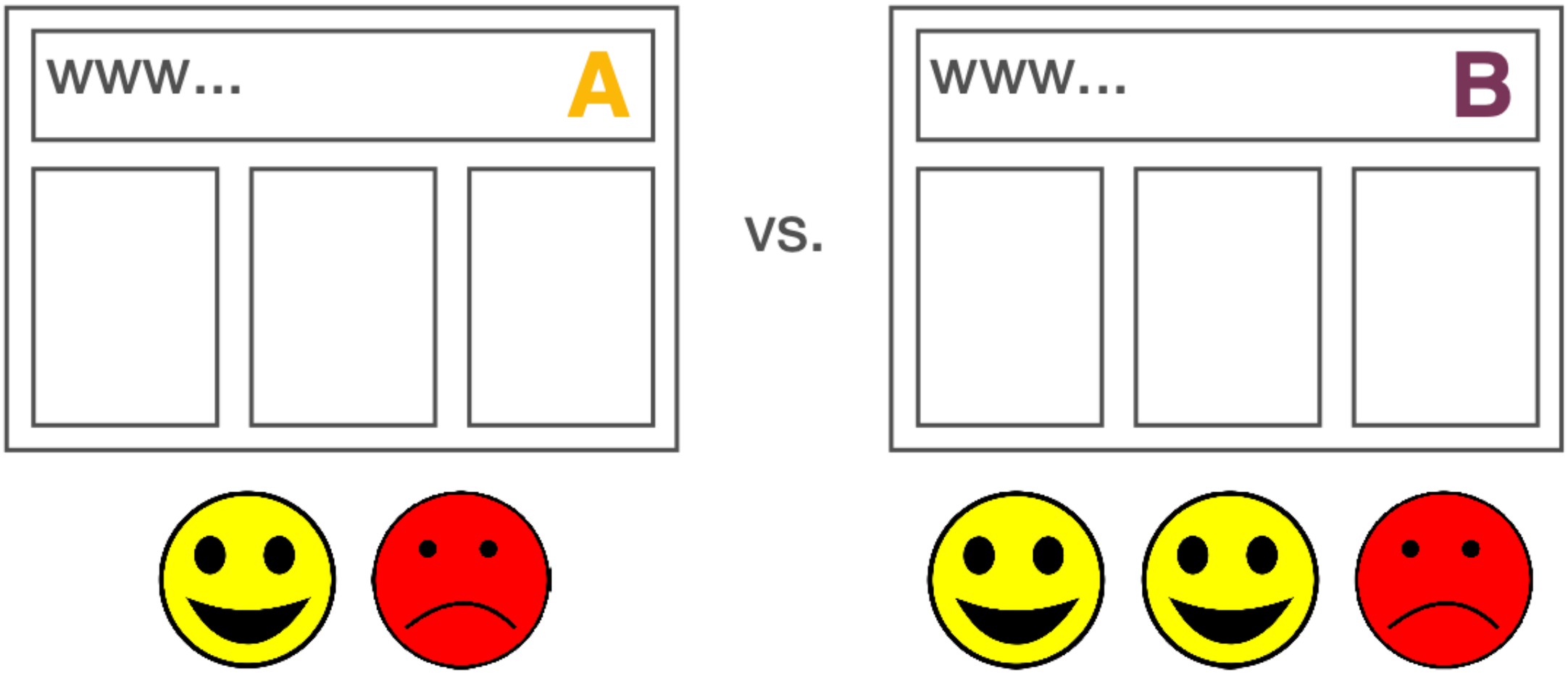
CLV - **C**ustomer **L**ifetime **V**alue

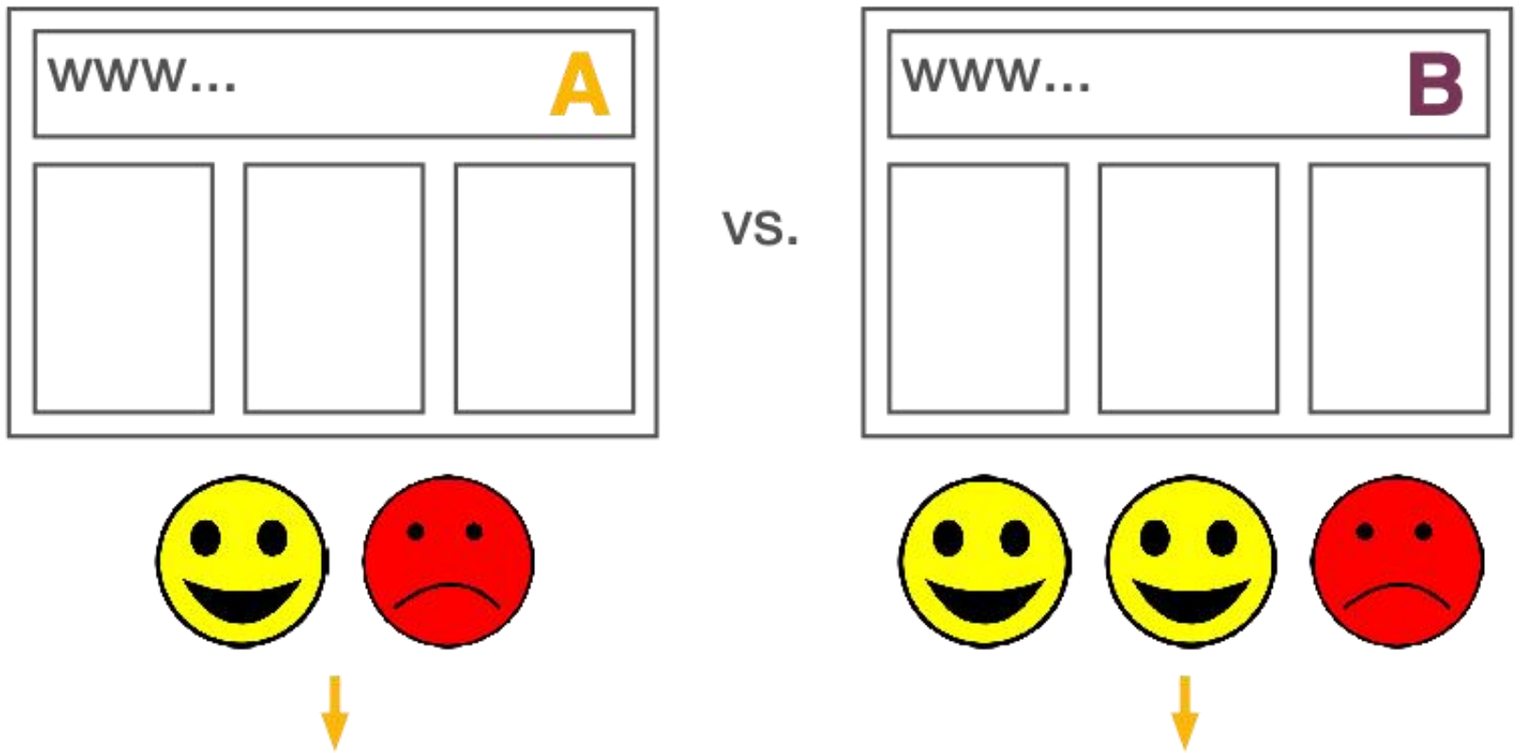
GC - **G**ross **C**ontribution

d - **d**iscount rate

r - **r**etention rate

[пожизненная ценность клиента]


www...
A
vs.
www...
B



monthly LTV (A) vs. monthly LTV (B)

see: sand clock in Budapest

$$CTR = \frac{\#clicks}{\#impressions}$$

long term objective (e.g. LTV)

proxy

short term objective (e.g. CTR)

$$CTR = \frac{\#clicks}{\#impressions}$$

1. High correlation(short term objective, long term objective)

long term objective (e.g. LTV)

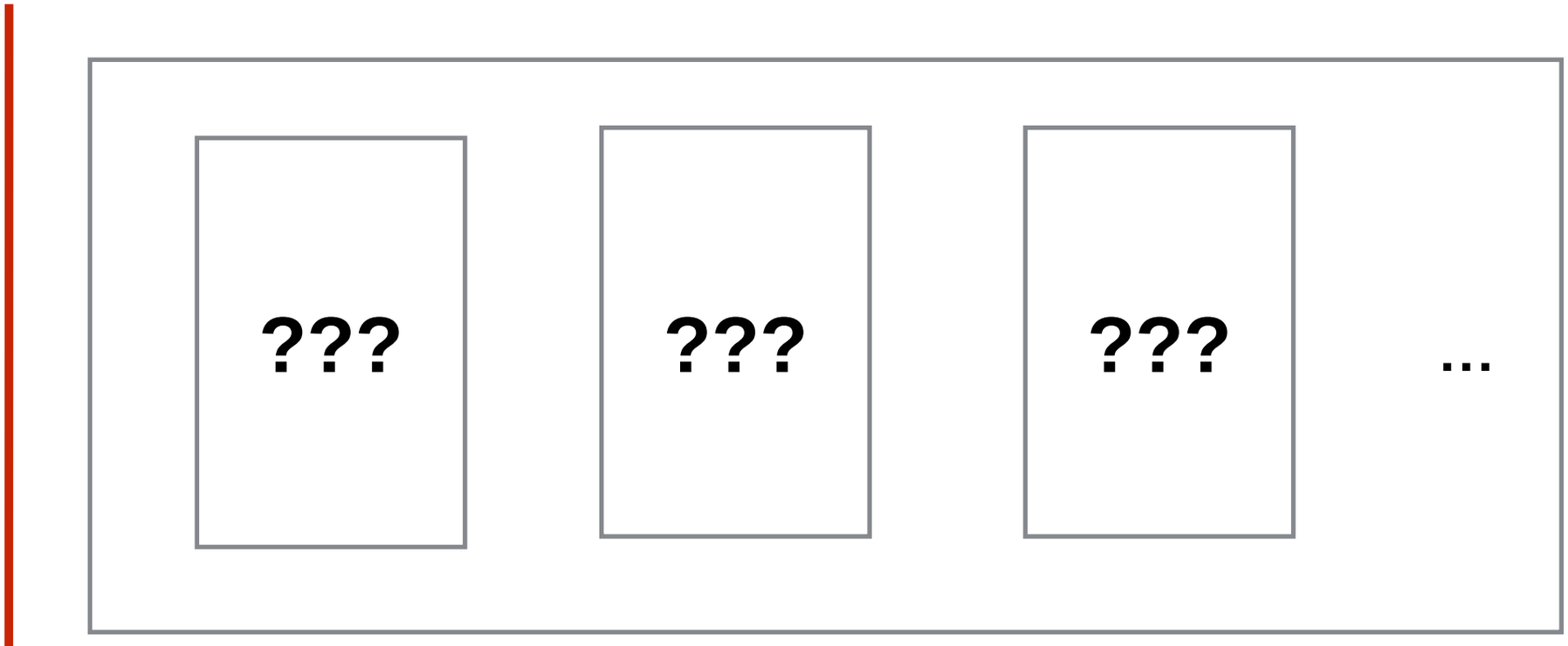
proxy

short term objective (e.g. CTR)

$$CTR = \frac{\#clicks}{\#impressions}$$

1. High correlation(short term objective, long term objective)
2. Faster results

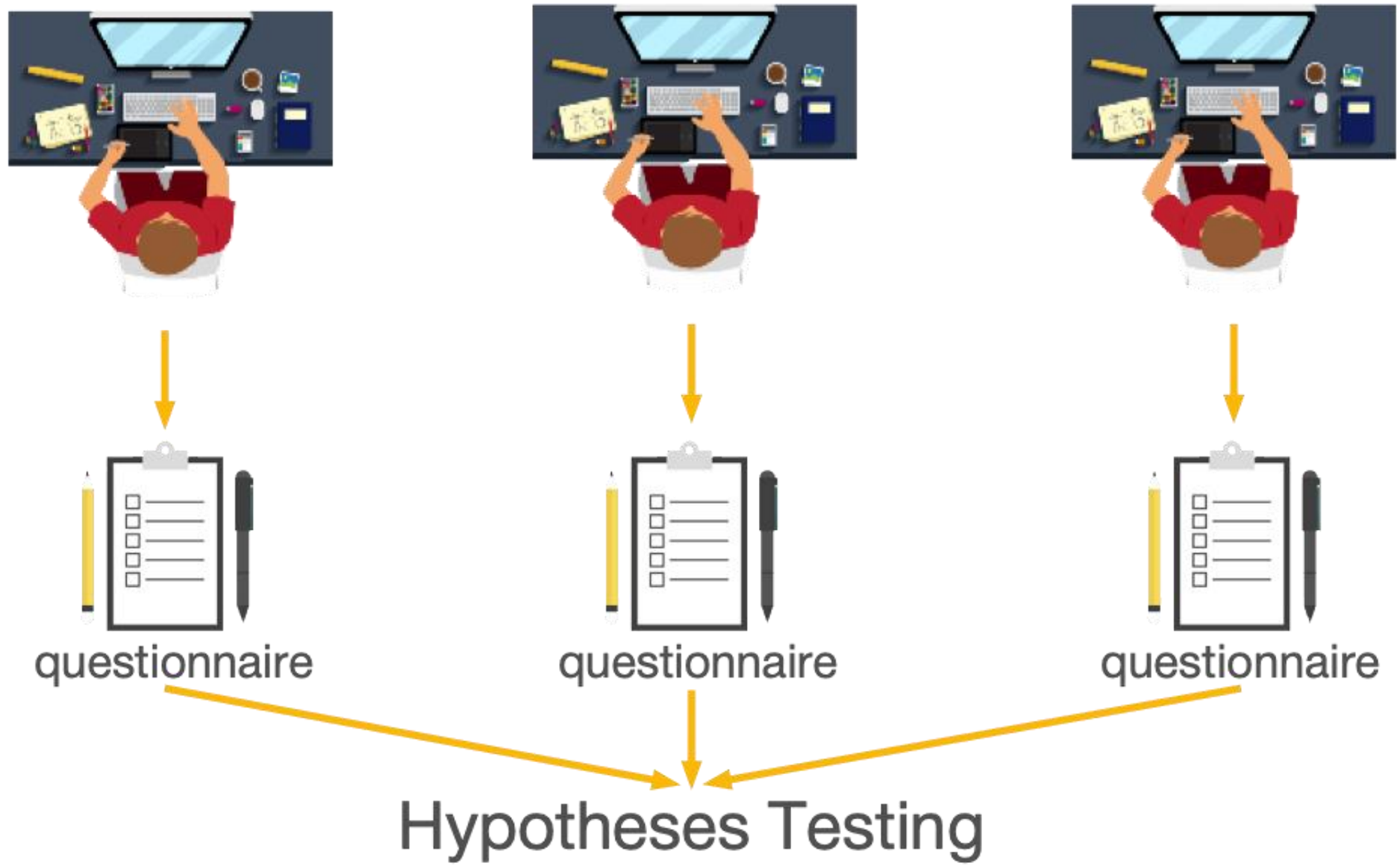
online experiments risks



online experiments risks

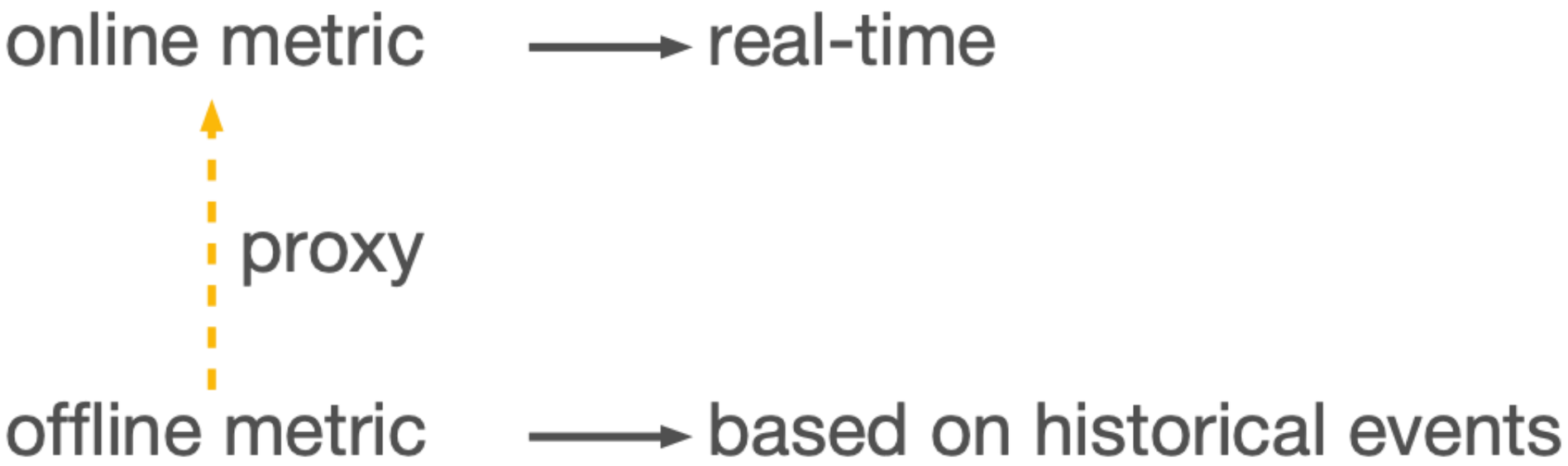
. . .

User studies



see: https://en.wikipedia.org/wiki/Statistical_hypothesis_testing

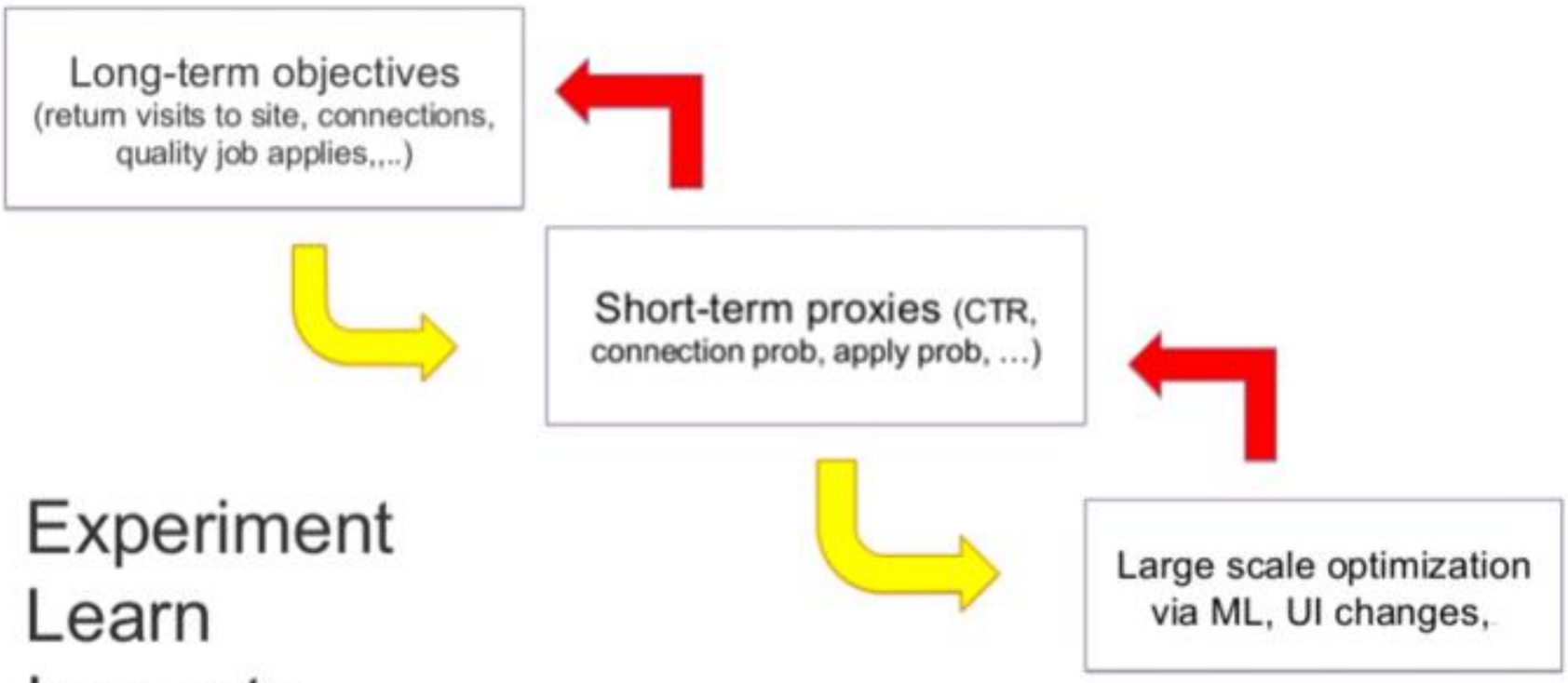
Offline experiments



RecSys'16 tutorial: Lessons learned from building real-life recommender systems

Connecting long-term objectives to proxies that can be optimized by machines/algorithms

Clip slide



credit: Deepak Agarwal, Senior Director of Engineering at LinkedIn

Offline Metrics

$$MAE = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N}$$

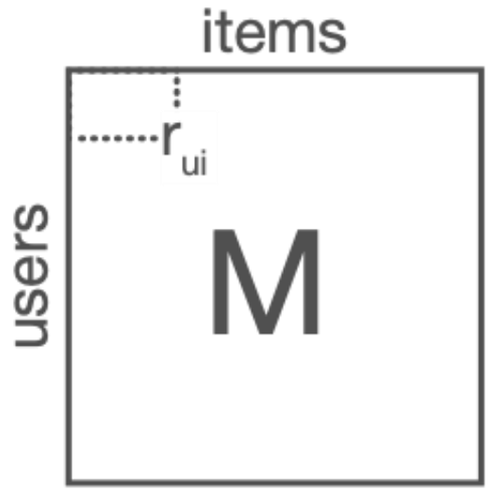
$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (p_i - r_i)^2}{N}}$$

see: https://en.wikipedia.org/wiki/Mean_absolute_error
see: https://en.wikipedia.org/wiki/Root-mean-square_deviation

Offline Metrics

$$\text{GMAE} = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (p_i - r_i)^2}{N}}$$



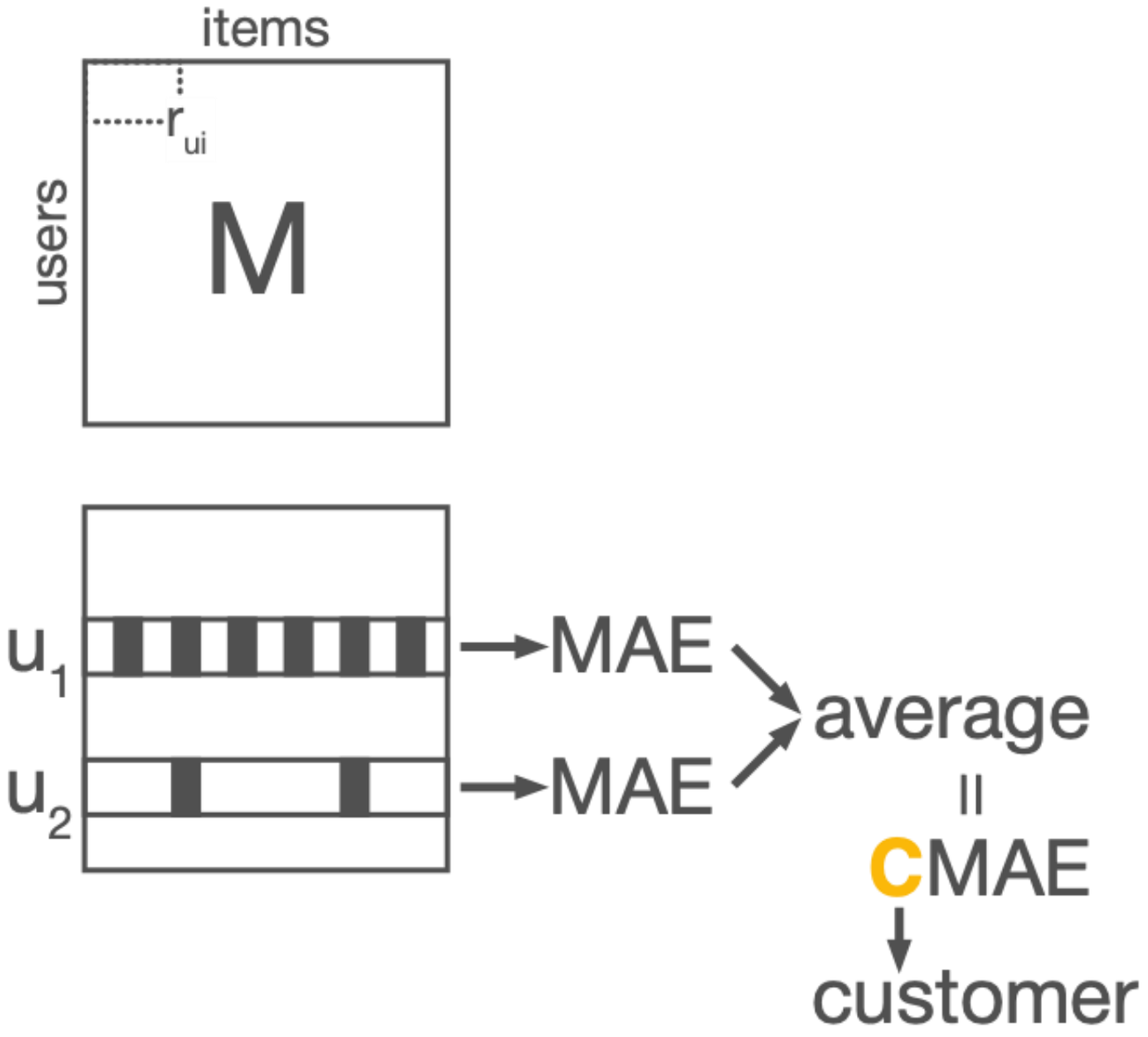
see: https://en.wikipedia.org/wiki/Mean_absolute_error

see: https://en.wikipedia.org/wiki/Root-mean-square_deviation

Offline Metrics

$$\text{GMAE} = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N}$$

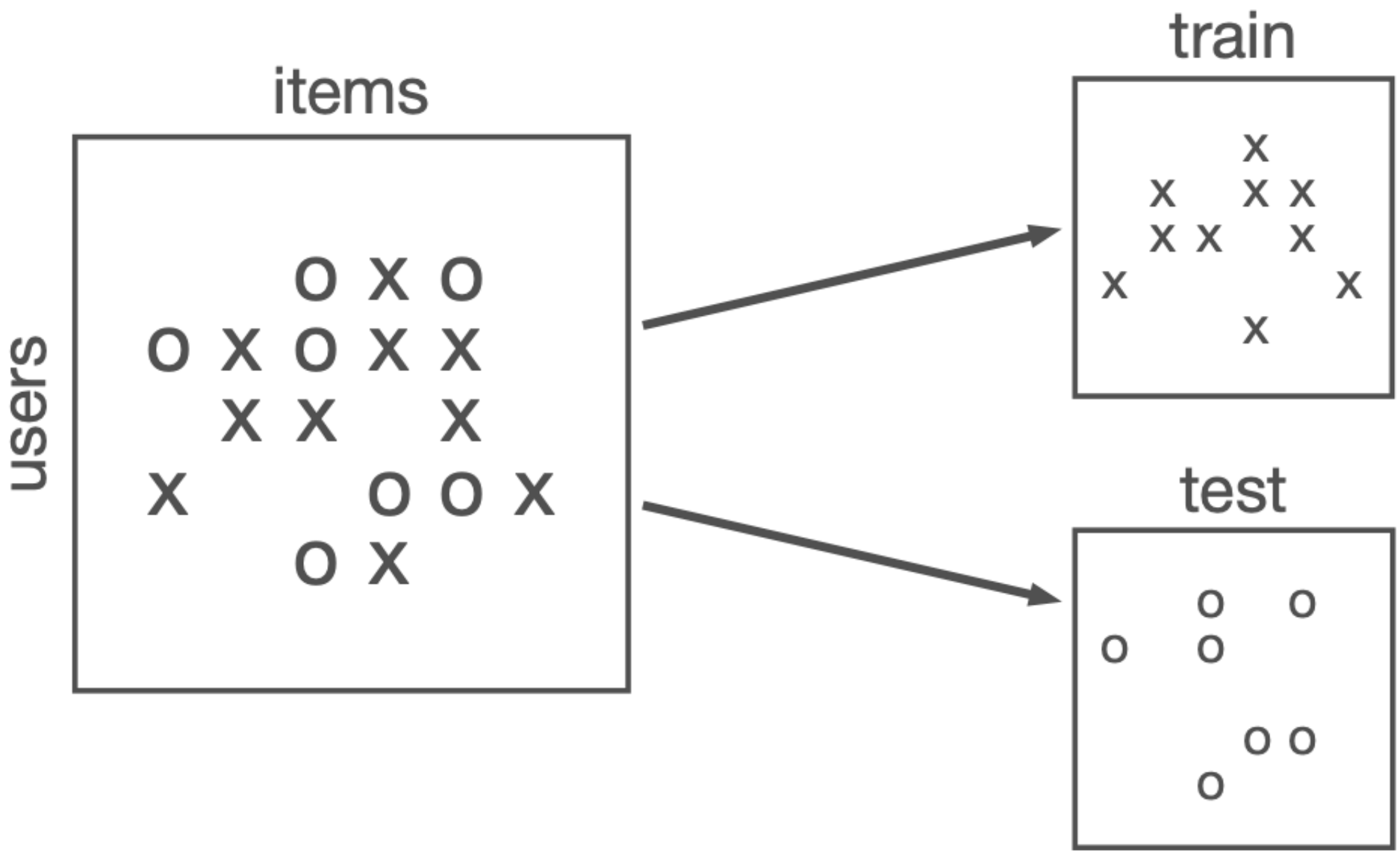
$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (p_i - r_i)^2}{N}}$$



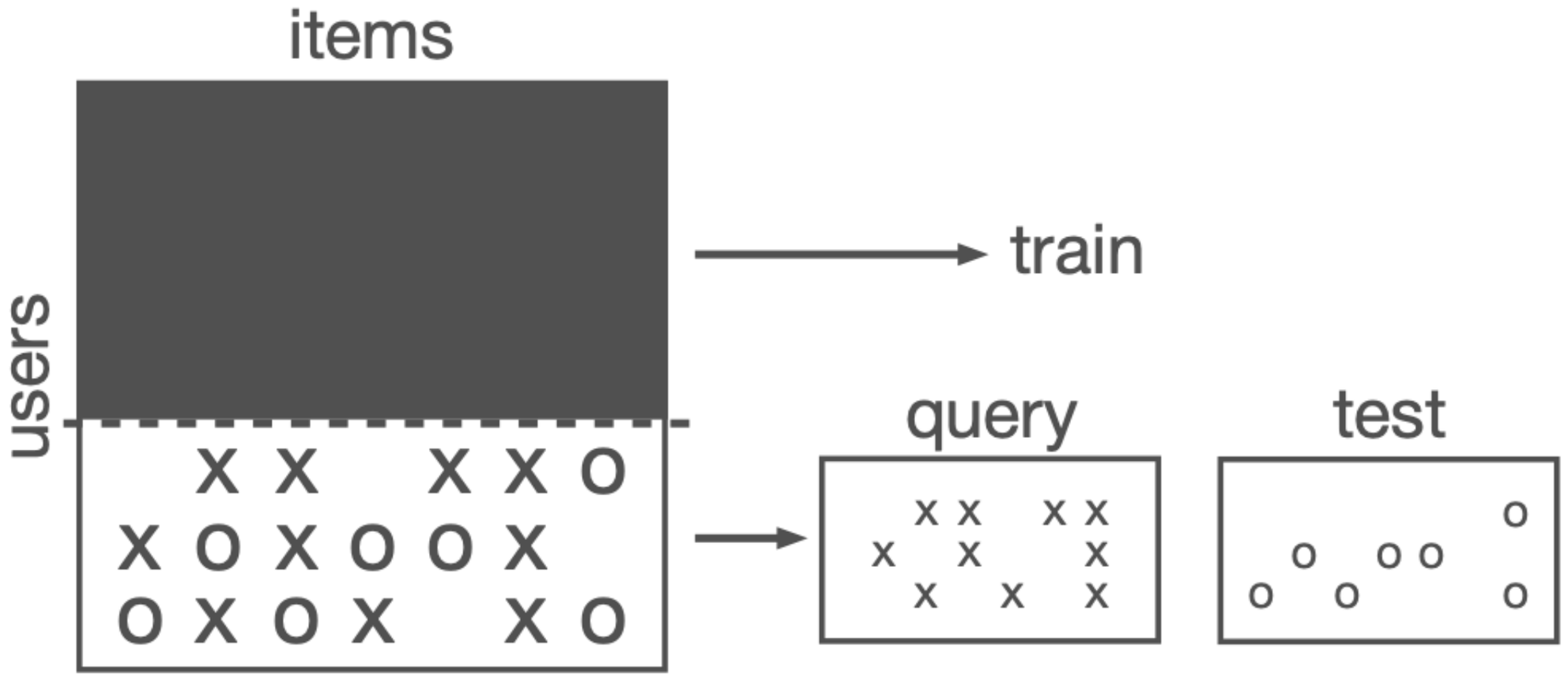
see: https://en.wikipedia.org/wiki/Mean_absolute_error

see: https://en.wikipedia.org/wiki/Root-mean-square_deviation

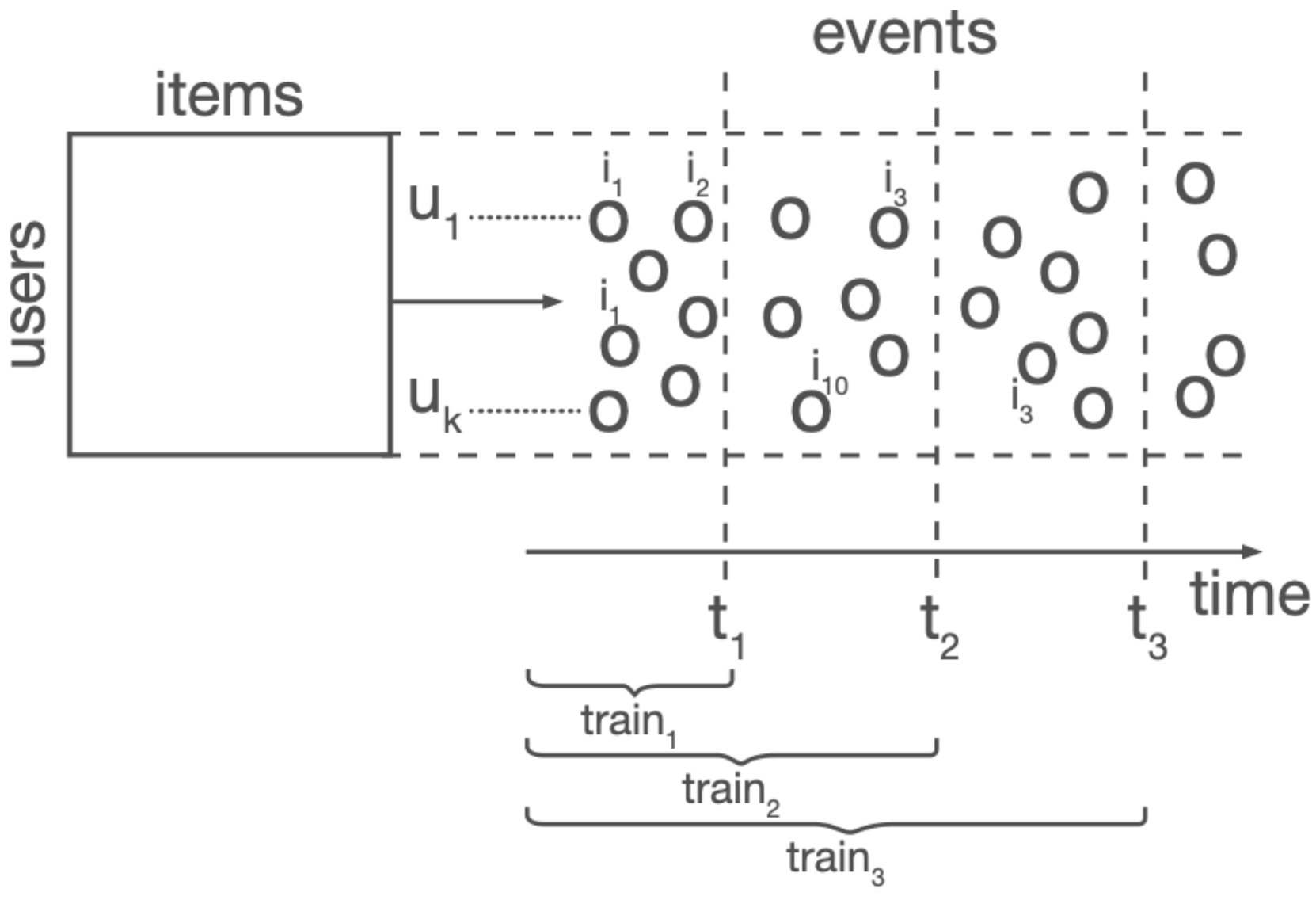
RecSys: Cross Validation



RecSys: Cross Validation



RecSys: Cross Validation



Introduction into RS: Goals

- **explain** basic ideas of Content-Based (**CB**), Collaborative Filtering (**CF**) and Knowledge-Based (**KB**) Recommender System algorithms;
- know steps to **train** simple RS algorithms;
- learn how to **design** RS experiment and **evaluate** it;
- learn how to **overcome** cold-start problem;

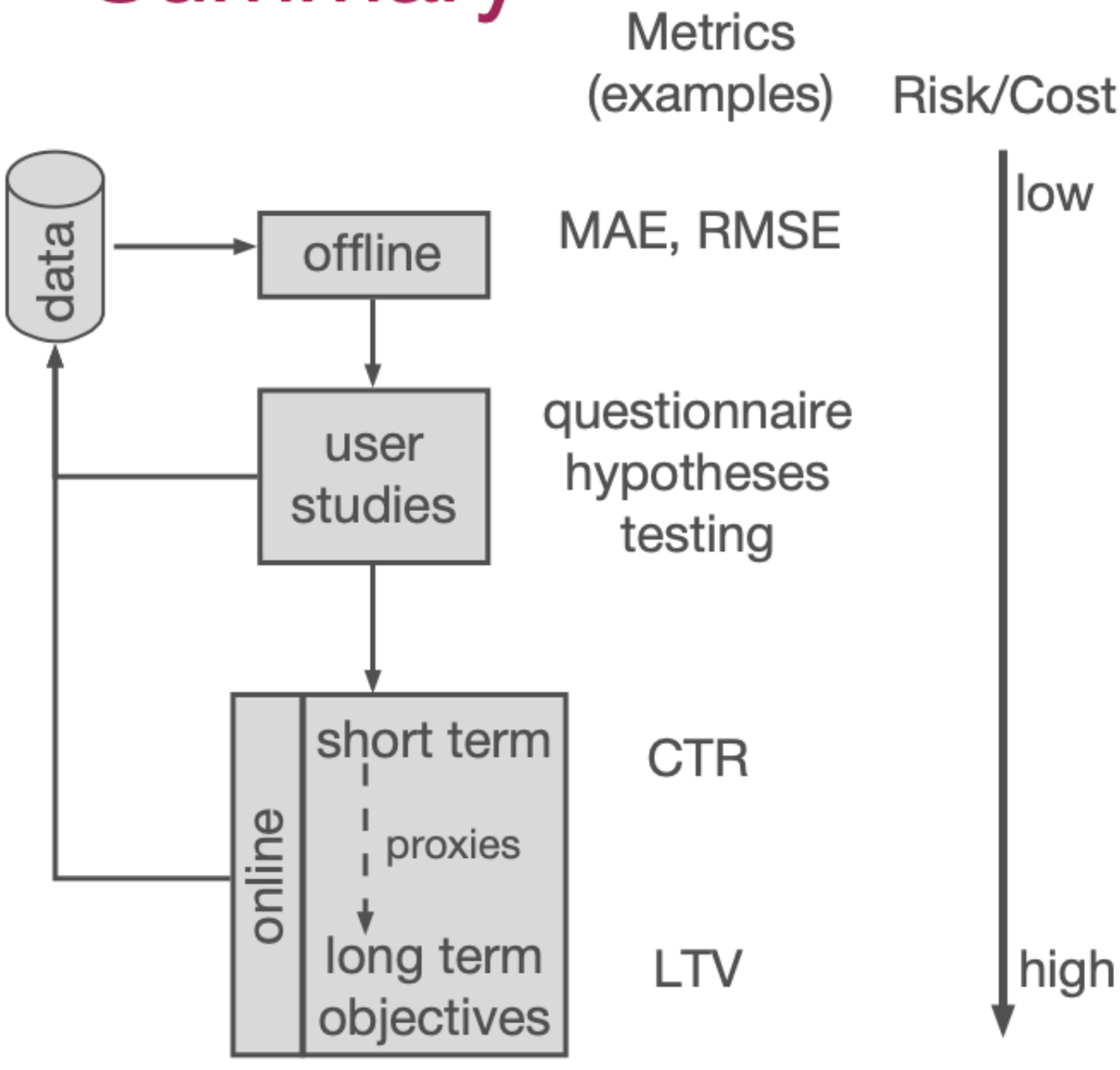
Summary

- you can **build** the following Non-Personalized Recommender System:
  - «Most popular items»
  - «Trending items»
  - «Users who likes A item also likes B item»

Summary

- you can build the following Content-Based Recommender System taking into account:
  - «User / Item representation»
  - «Distance / similarity metric»
- you can explain pros / cons of Content-Based RS

Summary



- you can **explain** the difference between **offline**, **user studies** and **online** experiments
- you can **design** experiments according to your needs
- you can **process** CV in 3 different ways

References

Теоретический минимум:

1. лекция Introduction to Machine Learning 10-701 CMU 2015 (Alex Smola);
2. лекция Воронцова про коллаборативную фильтрацию;

Учебная программа:

1. лекции по RS на Coursera (последняя неделя в рамках курса "Big Data Applications: Machine Learning at Scale”);
2. Xavier Amatriain Lectures 1+2, Lectures 3+4 (2014);

References (Deep Dive)

1. специализация про RS на Coursera (University of Minnesota)

2. книги:

Recommender System Handbook (2015, Ricci, Francesco, Rokach, Lior, Shapira, Bracha (Eds.))

Recommender Systems (2016, Aggarwal, Charu C.)

Practical Recommender Systems (2015-2017, Kim Falk)

3. Блог https://buildingrecommenders.wordpress.com/

4. материалы конференций ACM RecSys

Feedback

лекции: https://goo.gl/forms/TpY4aaojXLszGPQy2

семинары: https://goo.gl/forms/zSEynRUOCIO1SXv02

Thank you! Questions?

Appendix

Applications and Evaluation

Evaluation Metrics (formulas)

Accuracy

$$\mathrm{nDCG_p} = \frac{DCG_p}{IDCG_p}$$

$$\mathrm{DCG_p} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i)}$$

IDCG is the value for the perfect ranking
rel_i is 1 if the user watched the program at rank i or 0 otherwise

Diversity

$$d(i,j) = \text{⅓ } category(i{=}j) + \text{⅓ } subcategory(i{=}j) + \text{⅓ } channel(i{=}j)$$

$$ILD(u) = \frac{1}{|R|(|R|-1)} \sum_{i \in R} \sum_{j \in R} d(i,j) \qquad ILD = \frac{1}{|U|} \sum_{u \in U} ILD(u)$$

Novelty

$$MSI(u) = \frac{1}{|R_u|} \sum_{i \in R} \frac{|\{v \in U \mid i \in W_v\}|}{|U|} \qquad MSI = \frac{1}{|U|} \sum_{u \in U} MSI(u)$$

Serendipity

$$Unexp(u) = \frac{1}{|R||W_u|} \sum_{i \in R} \sum_{j \in W_u} d(i,j) \qquad Unexp = \frac{1}{|U|} \sum_{u \in U} Unexp(u)$$

R_u = list of recommended items for user u
W_u = watching history for user u
U = list of users

credit: Miguel Costa (RecSysTV'16)

Контрольные вопросы

1. Запишите функционал для оптимизации задачи предсказания рейтингов. Какие существуют модификации?

2. Запишите функционал для оптимизации задачи рекомендации ТОП-5 товаров.

3. В каких областях имеет смысл применять Knowledge-Based рекомендательные системы?

4. Запишите формулу для учета "устаревания" рейтингов и приведите пример использования в реальной жизни.

5. Что такое проблема холодного старта? Какие способы борьбы с ним?

6. Запишите 3 формулы для предсказания рейтингов в случае Content-Based рекомендательных систем.