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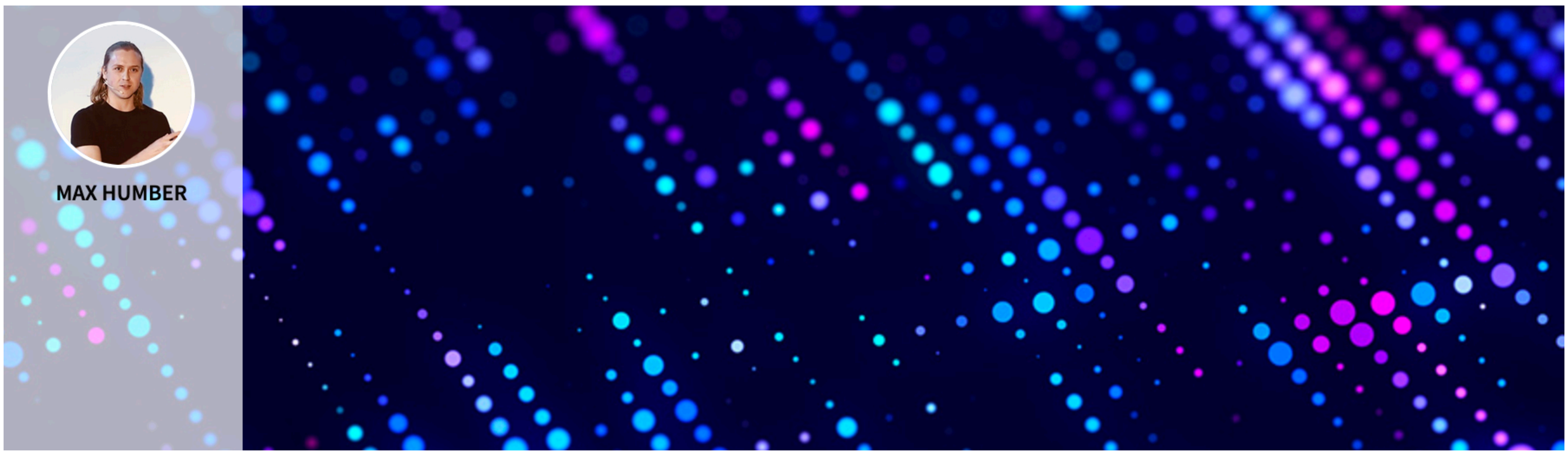
LIVE ONLINE TRAINING

Building Recommendation Engines in Python

Topic: Data



github.com/maxhumber/BRE

November 18, 2020

10:00am – 12:00pm EST

1 Theory

2 Scenarios

3 App

POLLS
(REMOVE)

- Poll: Have you ever built a recommendation engine? {Y/N}
- Poll: Is your interest personal or professional? {personal/professional}

NETFLIX

amazon

When Choice is Demotivating: Can One Desire Too Much of a Good Thing?

Sheena S. Iyengar
Columbia University

Mark R. Lepper
Stanford University

6 samples

VS.

24 samples

Interest

6 samples

40% of shoppers

VS.

24 samples

60% of shoppers

Purchase

6 samples

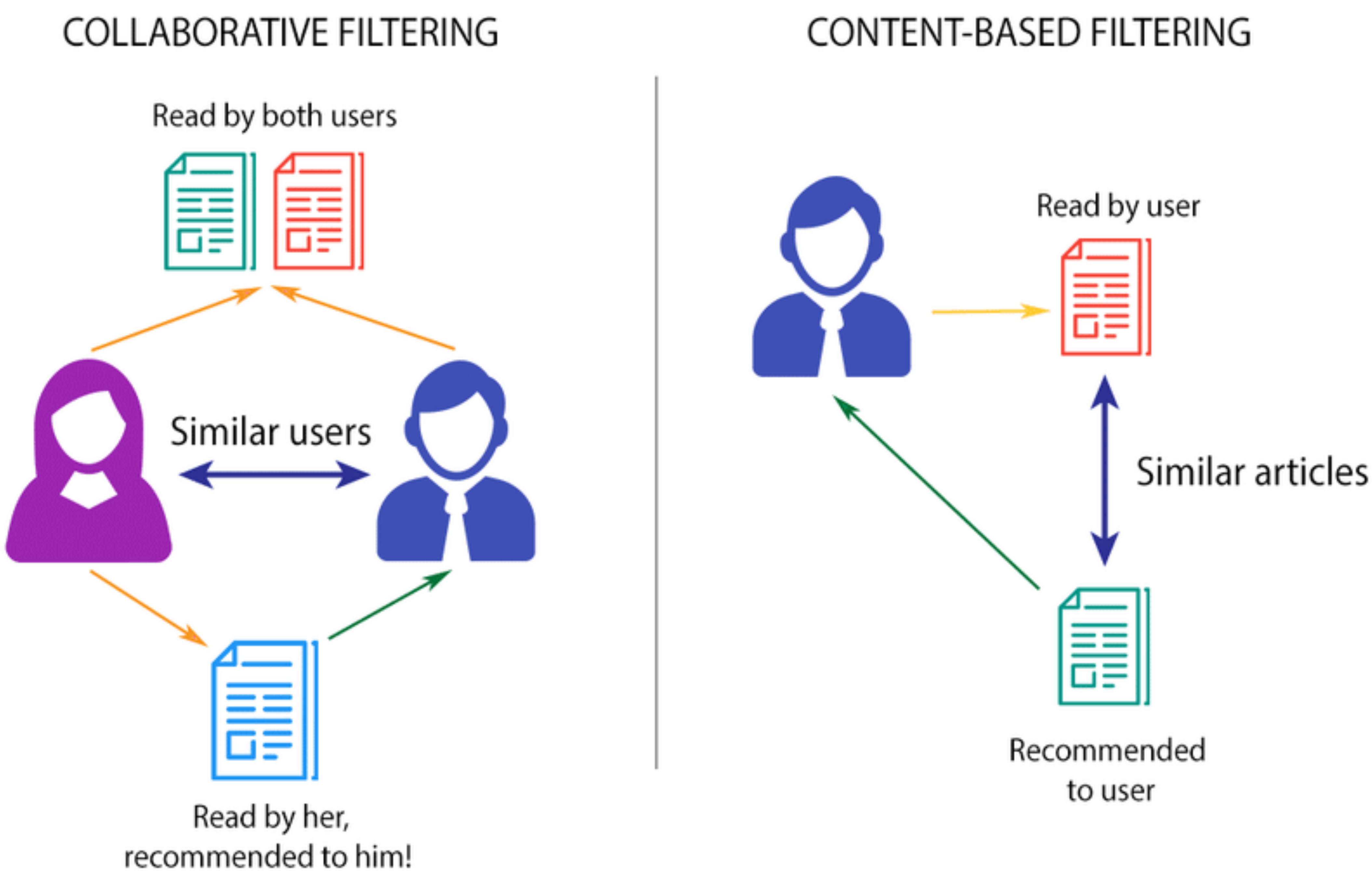
VS.

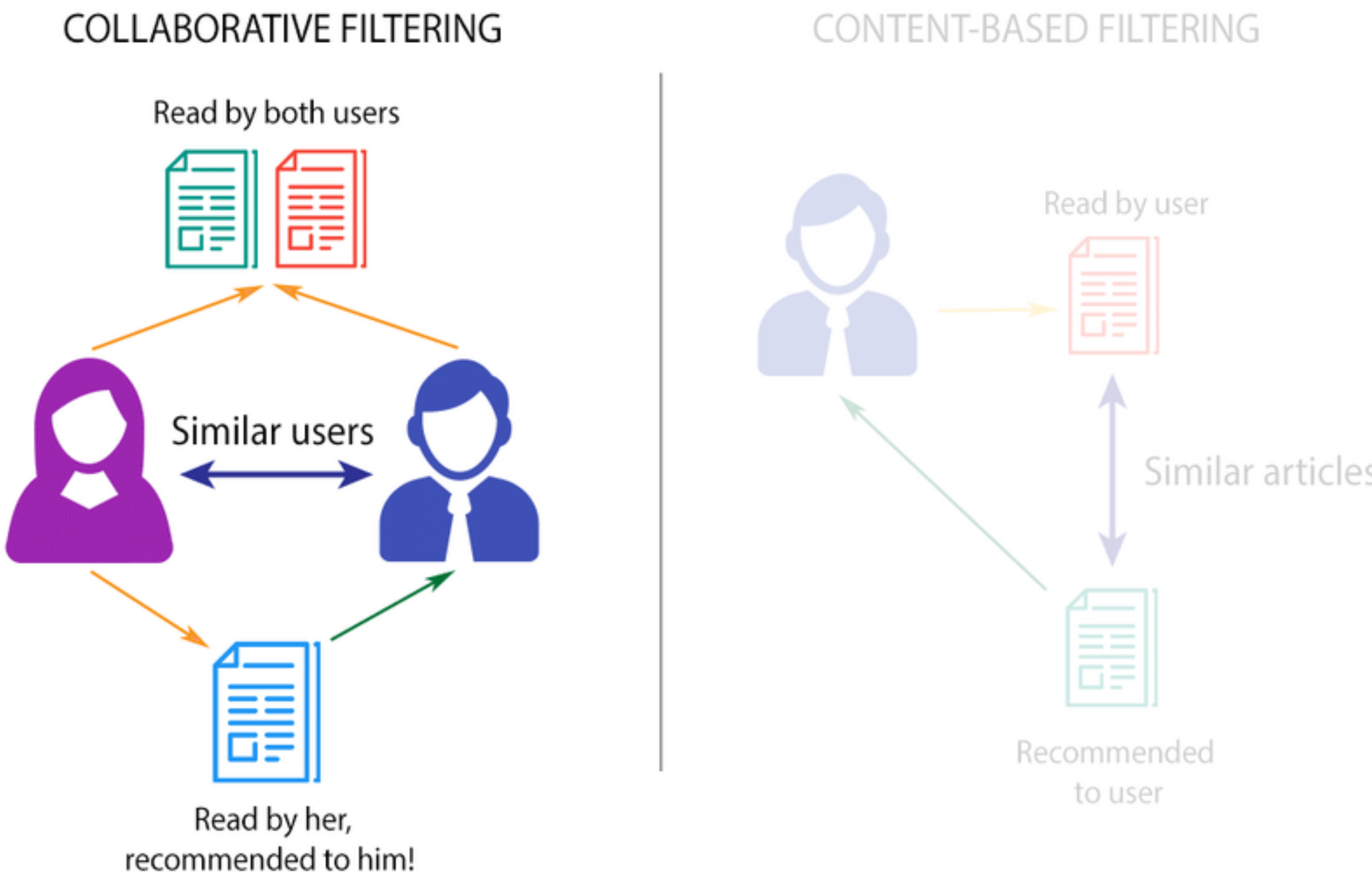
24 samples

30% conversion

3% conversion

2 hours…


COLLABORATIVE FILTERING
Read by both users
Similar users
Read by her,
recommended to him!
CONTENT-BASED FILTERING
Read by user
Similar articles
Recommended
to user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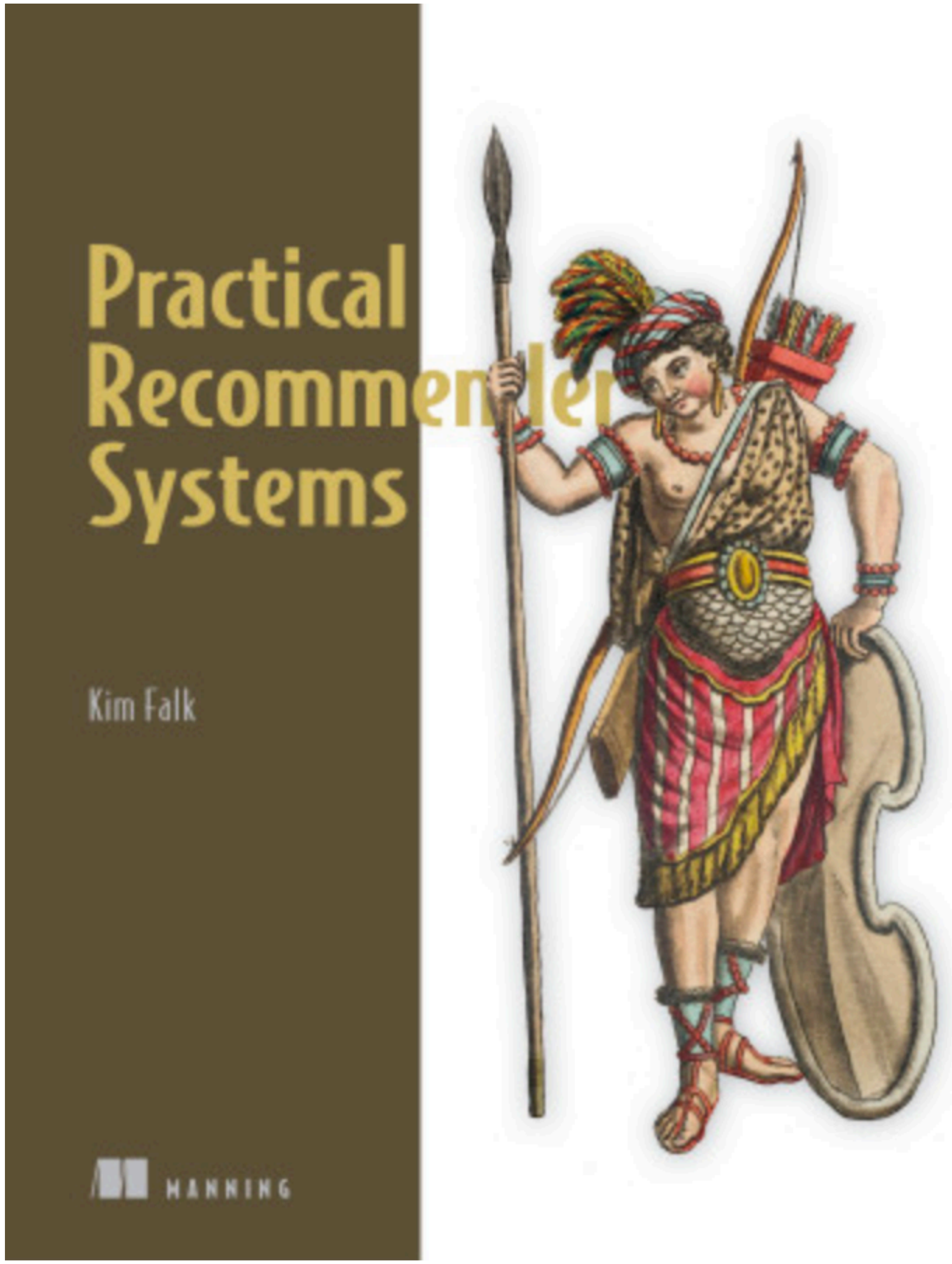

Practical Recommender Systems

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Data

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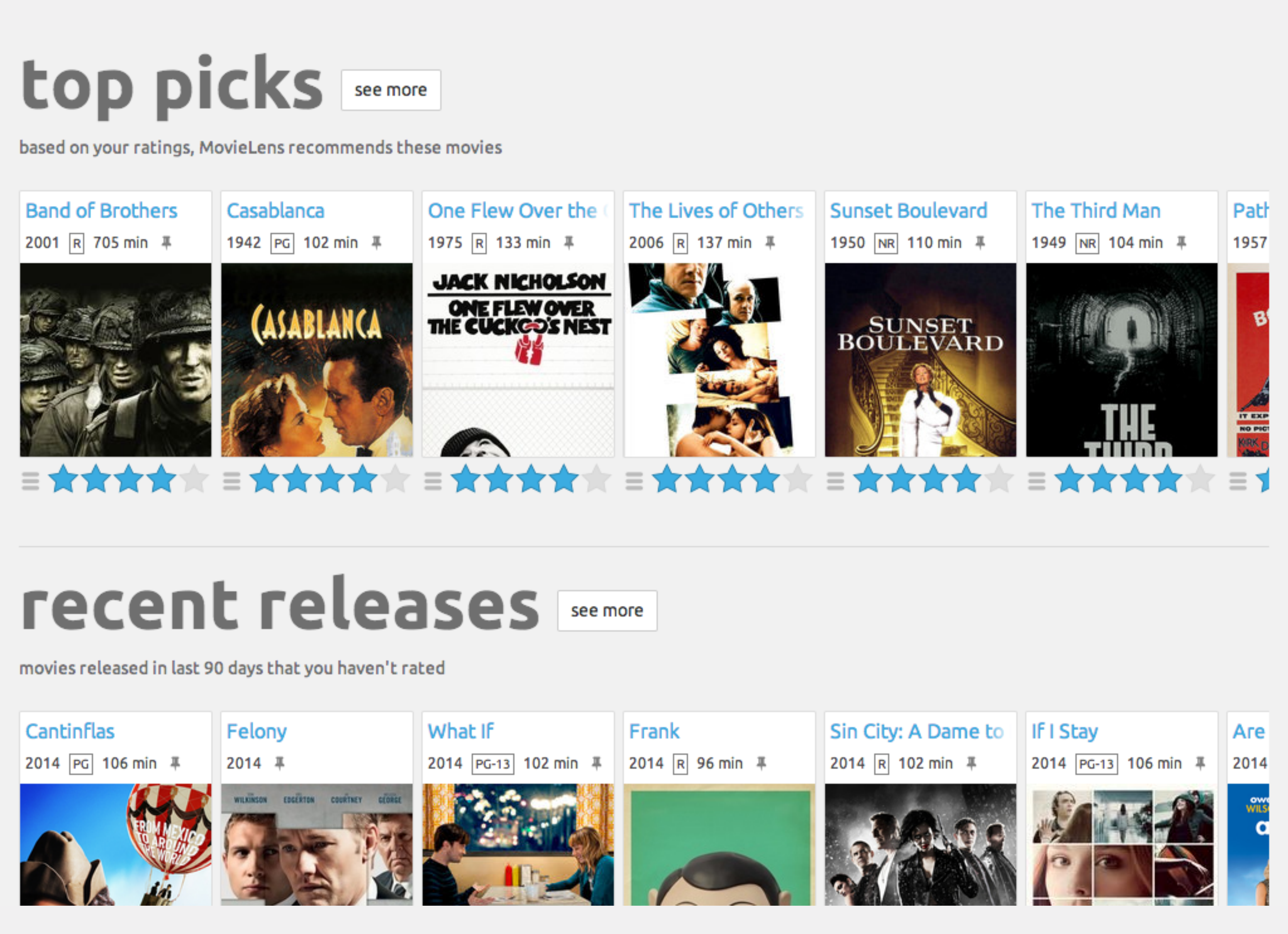
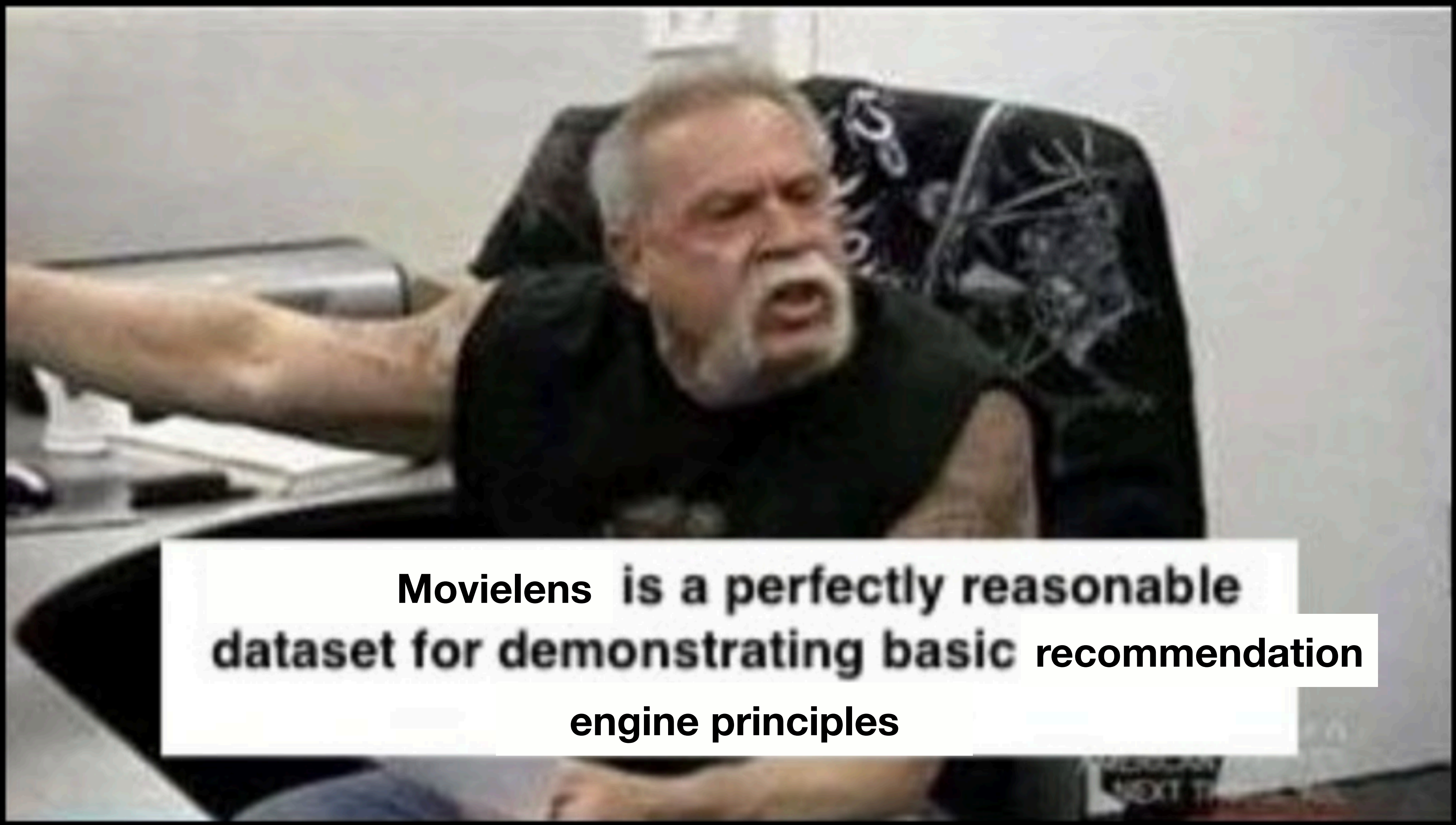

top picks
see more
based on your ratings, MovieLens recommends these movies
Band of Brothers
2001 R 705 min
Casablanca
1942 PG 102 min
CASABLANCA
One Flew Over the
1975 R 133 min
JACK NICHOLSON
ONE FLEW OVER THE CUCKOO'S NEST
The Lives of Others
2006 R 137 min
Sunset Boulevard
1950 NR 110 min
SUNSET BOULEVARD
The Third Man
1949 NR 104 min
THE
1957
recent releases
see more
movies released in last 90 days that you haven't rated
Cantinflas
2014 PG 106 min
FROM MEXICO TO AROUND THE WORLD
Felony
2014
What If
2014 PG-13 102 min
Frank
2014 R 96 min
Sin City: A Dame to
2014 R 102 min
If I Stay
2014 PG-13 106 min
2014

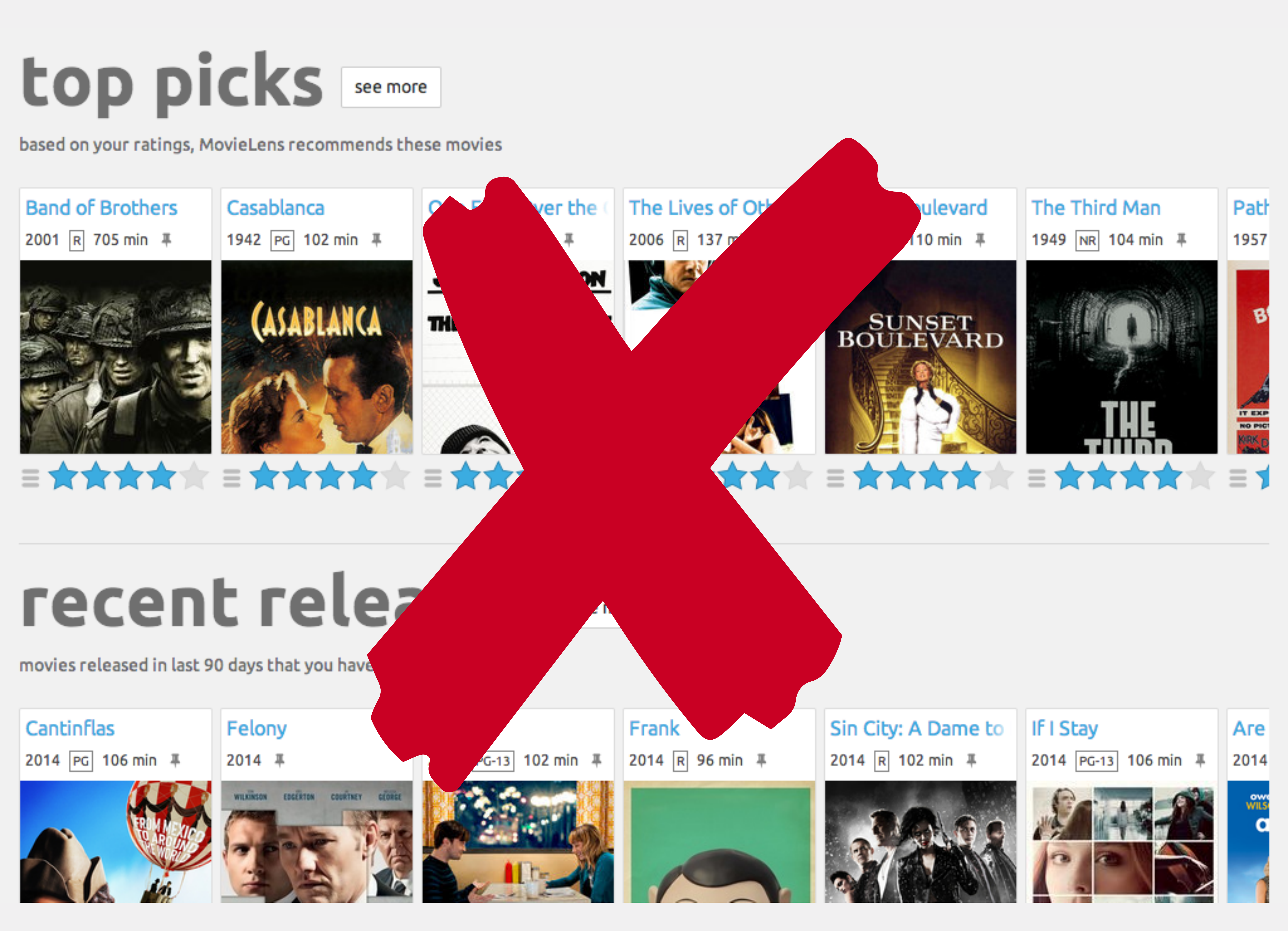

Movielens is a perfectly reasonable dataset for demonstrating basic recommendation engine principles


It lulls beginners into falsely thinking working with data is easy


EVERYONE NEEDS TO START
SOMEWHERE


IT'S THE WRONG PLACE FOR BEGINNERS TO START


YOU DON'T
REMEMBER
WHAT IT'S LIKE
TO BE A
BEGINNER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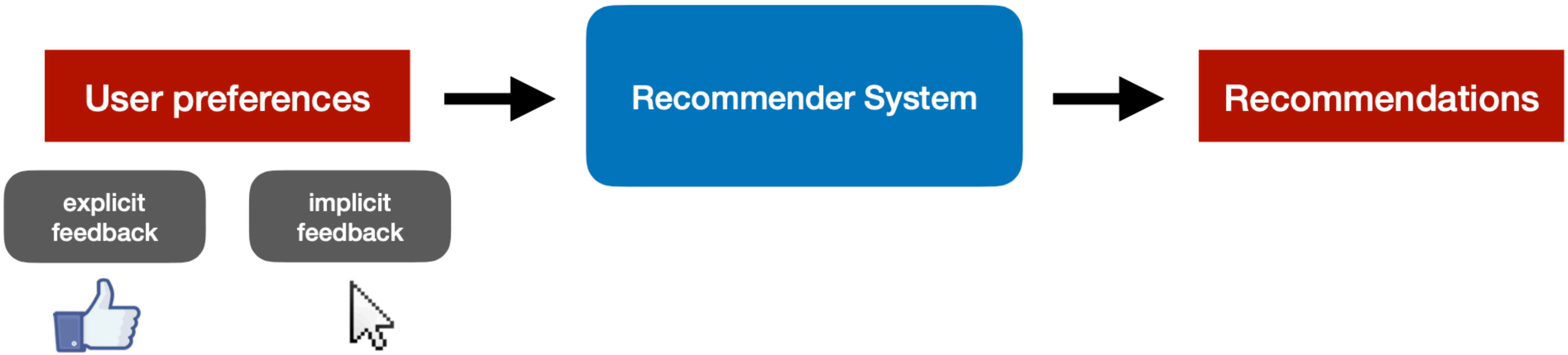
2014
WILKINSON EDGERTON COURTNEY GEORGE
PG-13 102 min
Frank
2014 R 96 min
Sin City: A Dame to
2014 R 102 min
If I Stay
2014 PG-13 106 min
Are
2014

Stars!

Candy!!

1

Theory



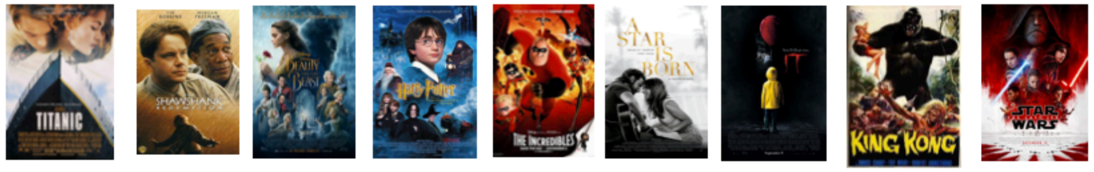
Collaborative filtering

user									
John	1		3			5		5	
Erica			5		2		4		5
Anne	5	2		1		4			2
Liz	3		4	3	4		5		
Jim	5	2		1		4		3	1

item

Content-based filtering

Similar people like similar things



users									
John	1		3			5		5	
Erica			5		2		4		5
Anne	5	2		1		4		$\boxed{3}$	2
Liz	3		4	3	4		5		
Jim	5	2		1		4		3	1

items

User-item (“utility”) matrix

users									
John	1		3			5		5	
Erica			5		2		4		5
Anne	5	2		1		4		$\boxed{3}$	2
Liz	3		4	3	4		5		
Jim	5	2		1		4		3	1

items

What are we populating these cells with?

user

John	1		3			5		5	
Erica			5		2		4		5
Anne	5	2		1		4			2
Liz	3		4	3	4		5		
Jim	5	2		1		4		3	1

item

Explicit feedback

Likert-scale rating (1-5)
Liked or not (boolean)

Implicit feedback

Browsing behaviour
Purchased? Read? Watched?

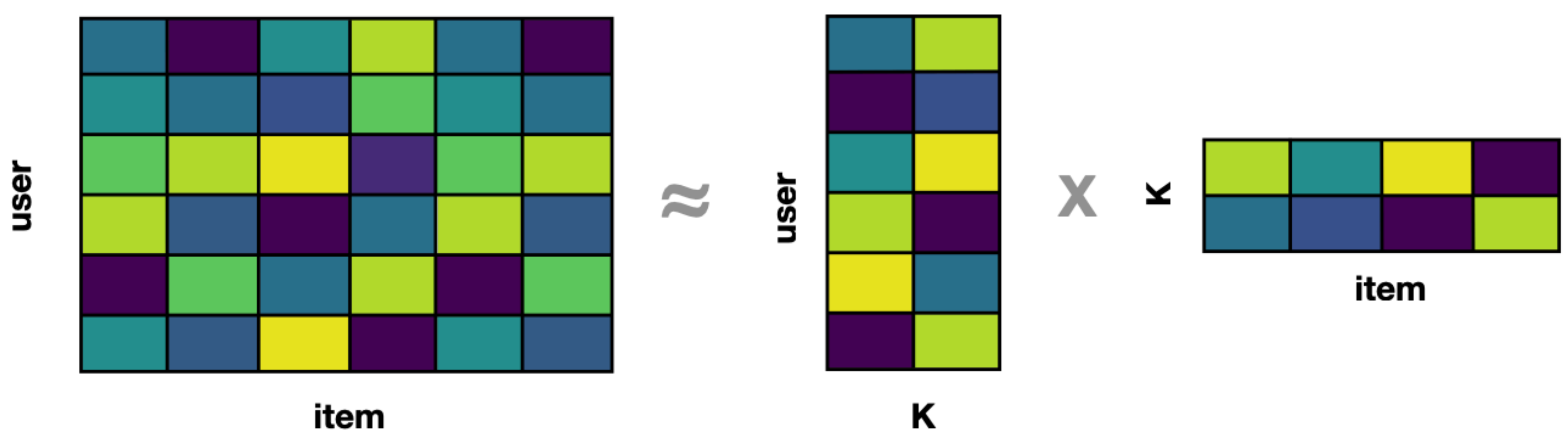
Developing a user feedback score

- Dwell time
- Recent vs. old interactions
- Negative implicit feedback
- What behaviour are you trying to drive?

Matrix Factorization

- Dimensionality reduction
- Factorize the user-item matrix to get 2 latent factor matrices:
  - User-factor matrix
  - Item-factor matrix
- Missing ratings are predicted from the inner product of these two factor matrices

$$X_{mn} \approx P_{mk} \times Q_{nk}^{T} = \hat{X}$$



Are We Really Making Much Progress? A Worrying Analysis of Recent Neural Recommendation Approaches

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902v3 [cs.IR] 16 Aug 2019

ABSTRACT

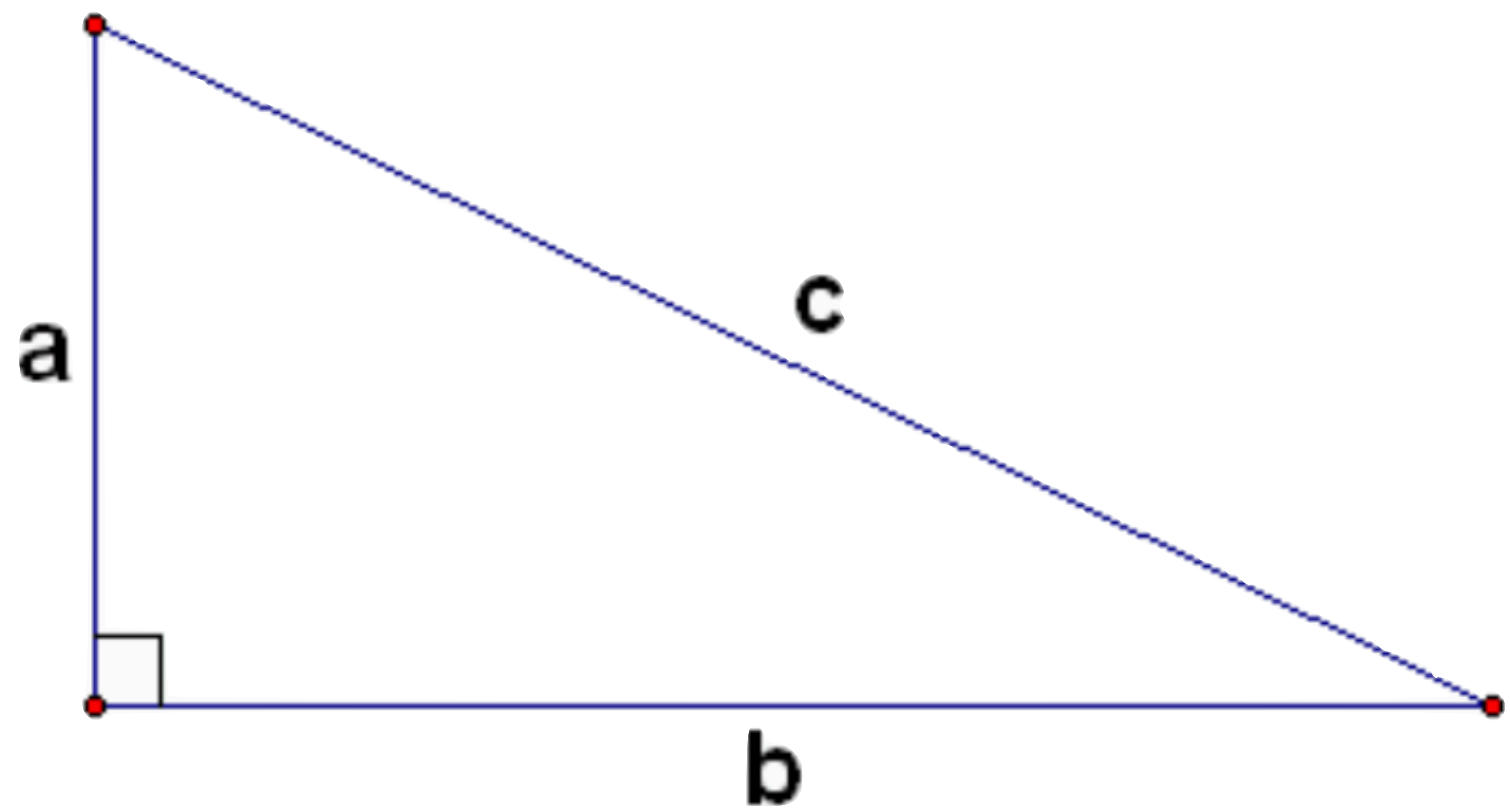
Deep learning techniques have become the method of choice for researchers working on algorithmic aspects of recommender systems. With the strongly increased interest in machine learning in general, it has, as a result, become difficult to keep track of what represents the state-of-the-art at the moment, e.g., for top-n recommendation tasks. At the same time, several recent publications point out problems in today's research practice in applied machine learning, e.g., in terms of the reproducibility of the results or the choice of the baselines when proposing new models.

In this work, we report the results of a systematic analysis of algorithmic proposals for top-n recommendation tasks. Specifically, we considered 18 algorithms that were presented at top-level research conferences in the last years. Only 7 of them could be reproduced with reasonable effort. For these methods, it however turned out that 6 of them can often be outperformed with comparably simple heuristic methods, e.g., based on nearest-neighbor or graph-based techniques. The remaining one clearly outperformed the baselines but did not consistently outperform a well-tuned non-neural linear ranking method. Overall, our work sheds light on a number of potential problems in today's machine learning scholarship and calls for improved scientific practices in this area.

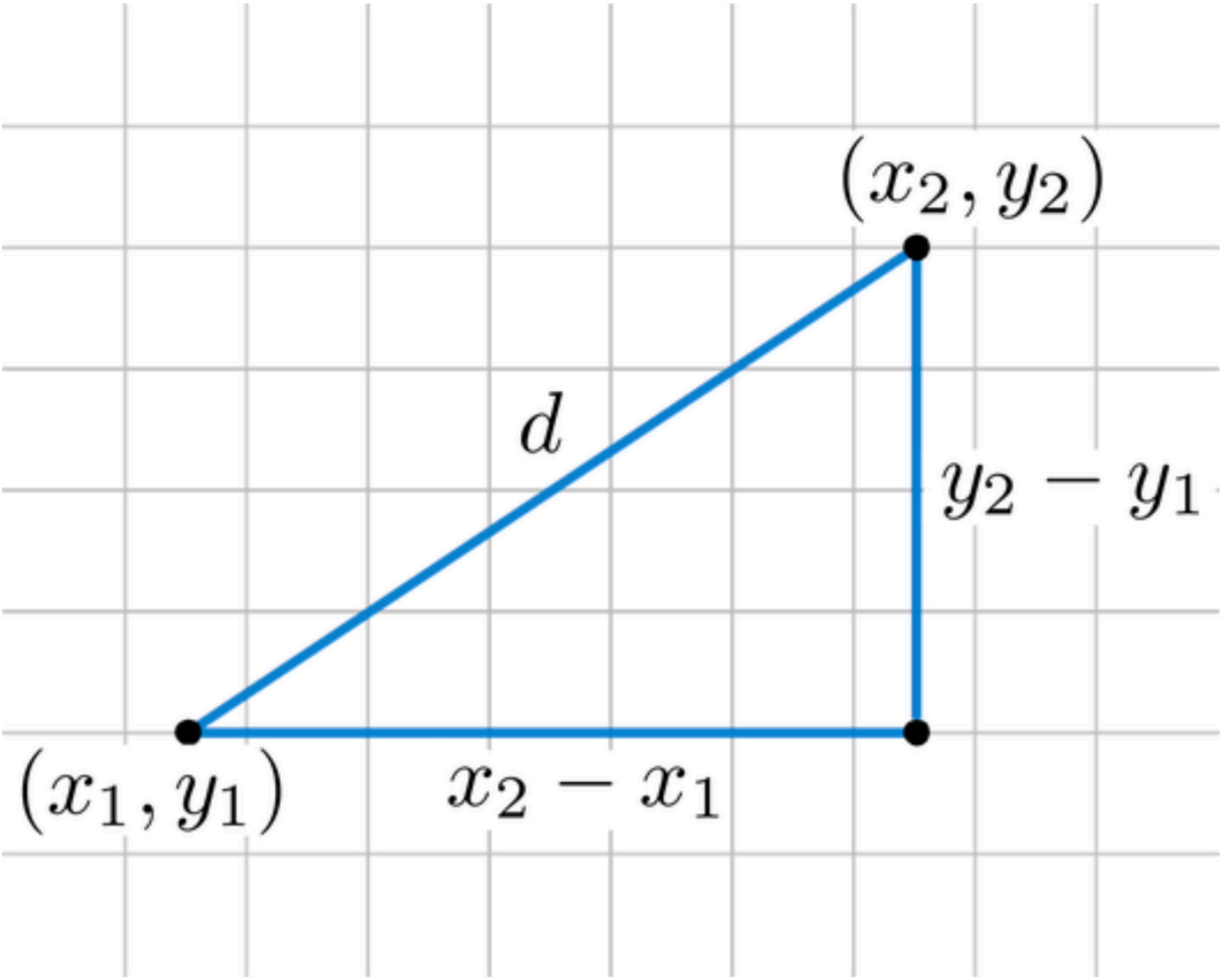
1 INTRODUCTION

Within only a few years, deep learning techniques have started to dominate the landscape of algorithmic research in recommender systems. Novel methods were proposed for a variety of settings and algorithmic tasks, including top-n recommendation based on long-term preference profiles or for session-based recommendation scenarios [36]. Given the increased interest in machine learning in general, the corresponding number of recent research publications, and the success of deep learning techniques in other fields like vision or language processing, one could expect that substantial progress resulted from these works also in the field of recommender systems. However, indications exist in other application areas of machine learning that the achieved progress—measured in terms of accuracy improvements over existing models—is not always as strong as expected.

Lin [25], for example, discusses two recent neural approaches in the field of information retrieval that were published at top-level conferences. His analysis reveals that the new methods do *not* significantly outperform existing baseline methods when these are carefully tuned. In the context of recommender systems, an in-depth analysis presented in [29] shows that even a very recent neural method for session-based recommendation can, in most cases, be outperformed by very simple methods based, e.g., on nearest-



$$a^2 + b^2 = c^2$$



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

distance.ipynb

Q&A

2

Scenarios

Maciej Kula · 3rd

London, United Kingdom · 396 connections · Contact info

Message

More...

Netflix

University of Oxford

Experience

Senior Research Engineer
Netflix
Aug 2016 – Present · 3 yrs 8 mos
Los Gatos, California

Personalization algorithms.

Data Scientist
Lyst
Nov 2012 – Aug 2016 · 3 yrs 10 mos
London, United Kingdom

Recommendations and Personalization.

https://github.com/lyst/lightfm

light fm

SPOTLIGHT

https://github.com/lyst/lightfm

https://github.com/maciejkula/spotlight

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Katacoda

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Q&A

Flask

model.ipynb

app.py

Q&A


That's all Folks!

max humber

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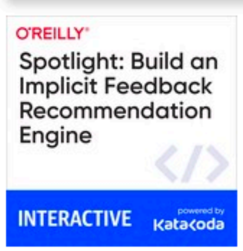

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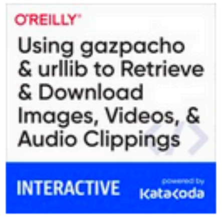
Spotlight: Build an Implicit Feedback Recommendation Engine

By Max Humber

RECOMMENDER SYSTEMS

O'Reilly Media, Inc. July 2020

Use Spotlight to build a collaborative filtering model on user behavior max humber



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MACHINE LEARNING

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github.com/maxhumber/gazpacho

github.com/maxhumber/gif

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