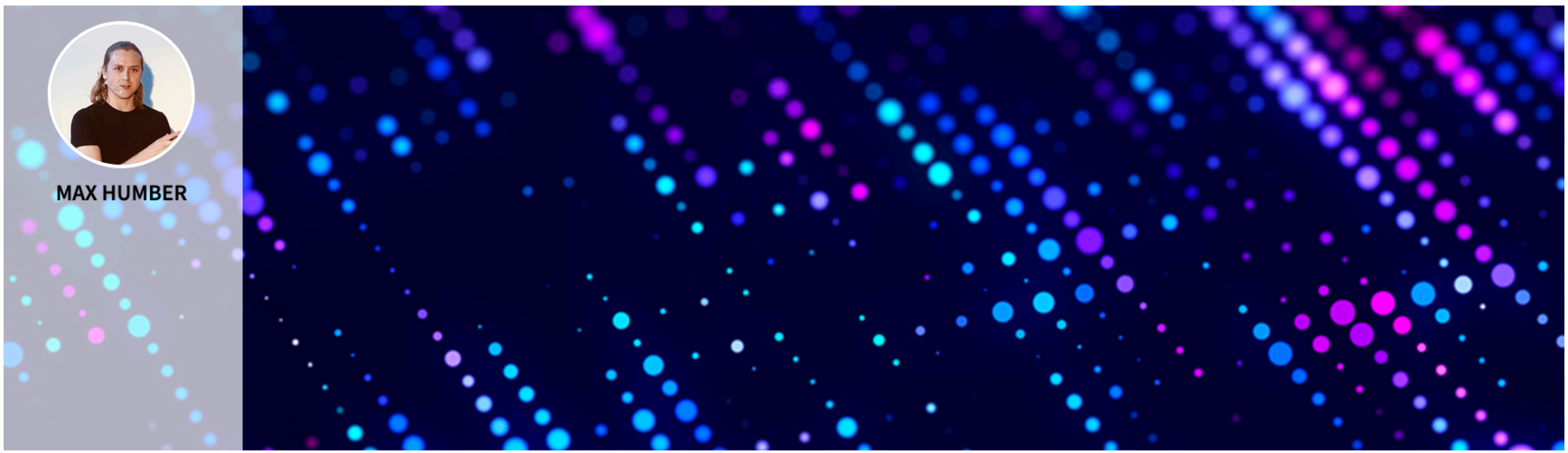
O'REILLY

LIVE ONLINE TRAINING

Building Recommendation Engines in Python

Topic: Data



github.com/maxhumber/BRE

1

Theory

2

Scenarios

3

App

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

vs.

24 samples

40% of shoppers

60% of shoppers

Purchase

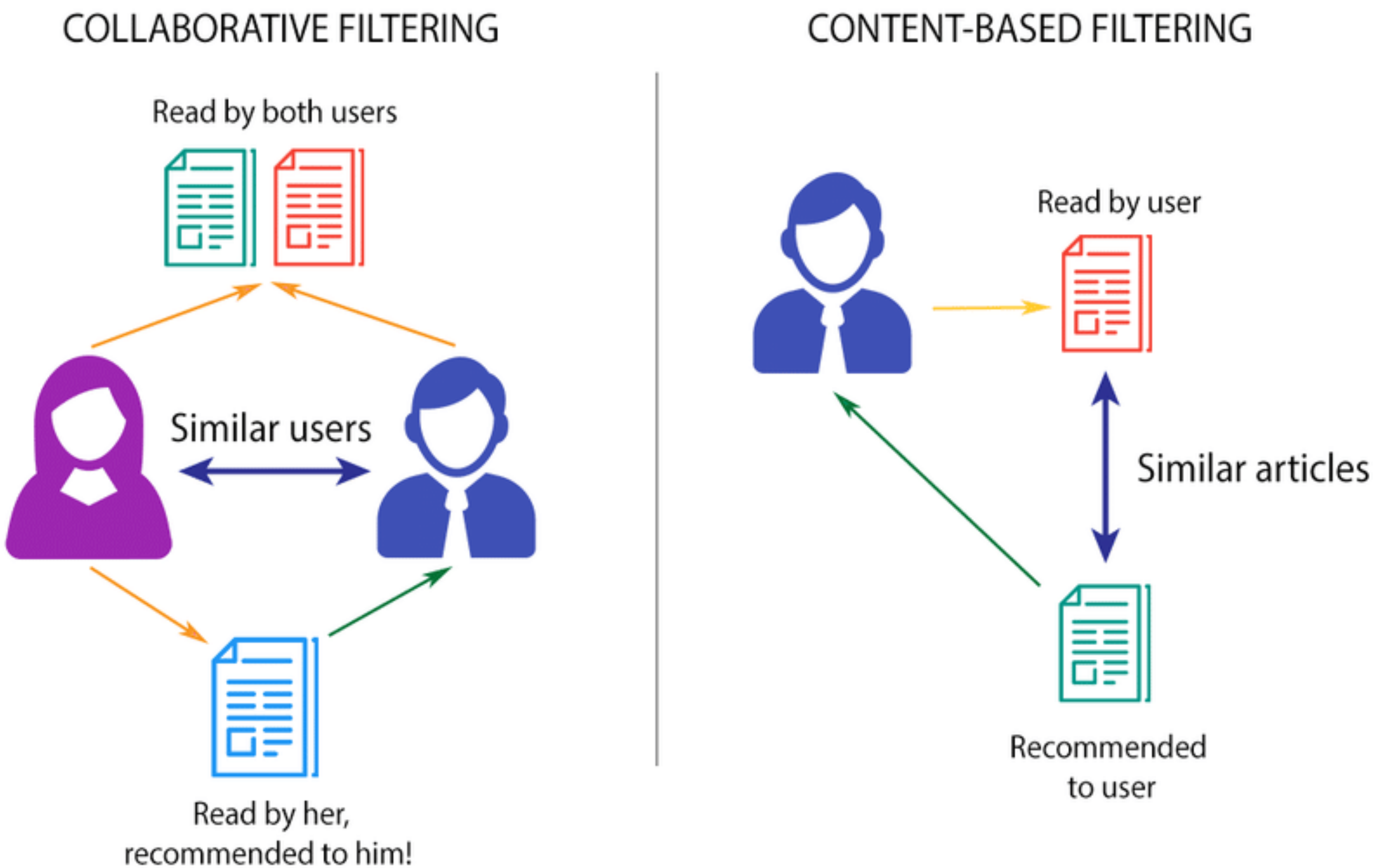
6 samples

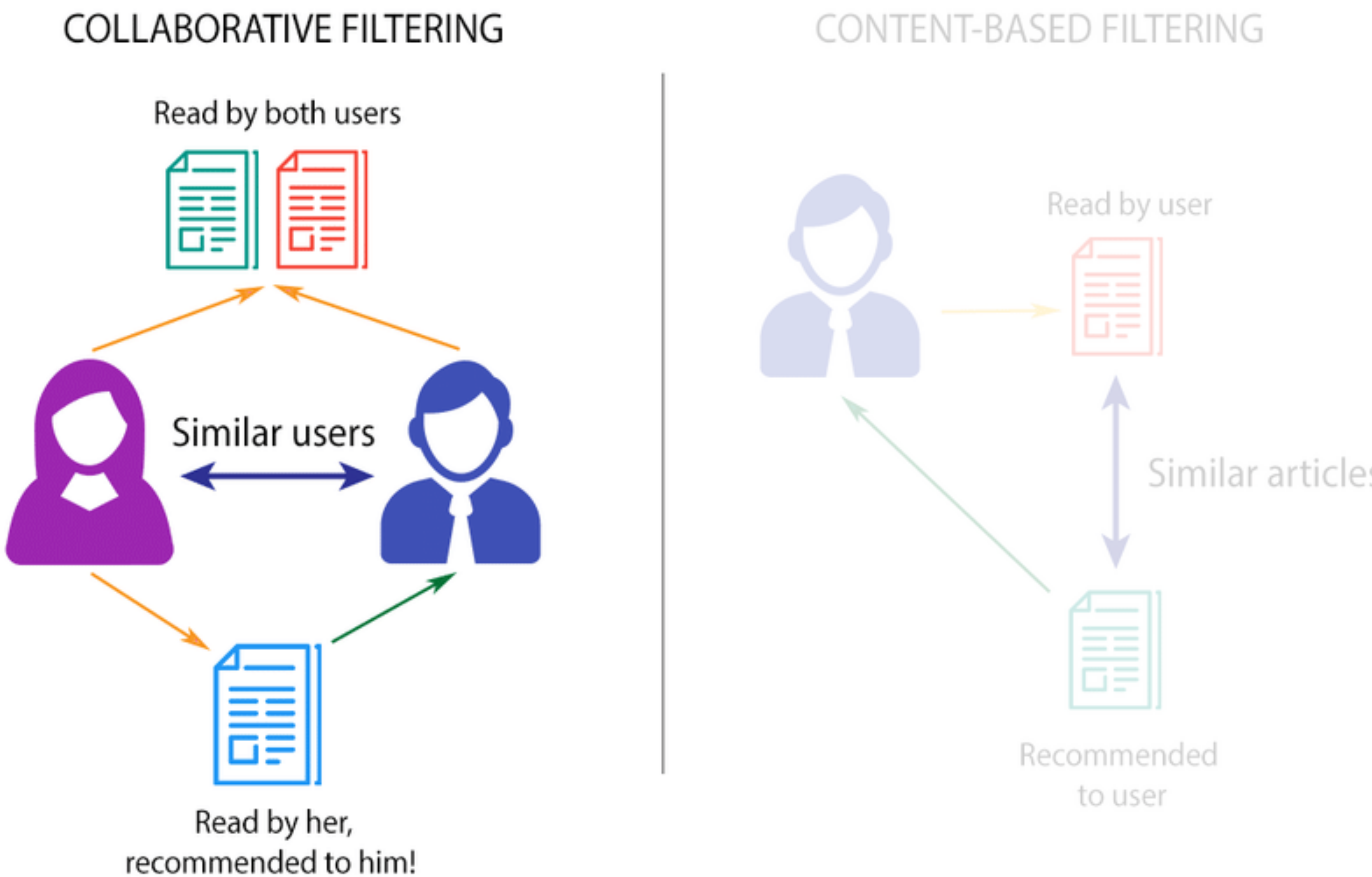
30% conversion

VS.

24 samples

3% conversion


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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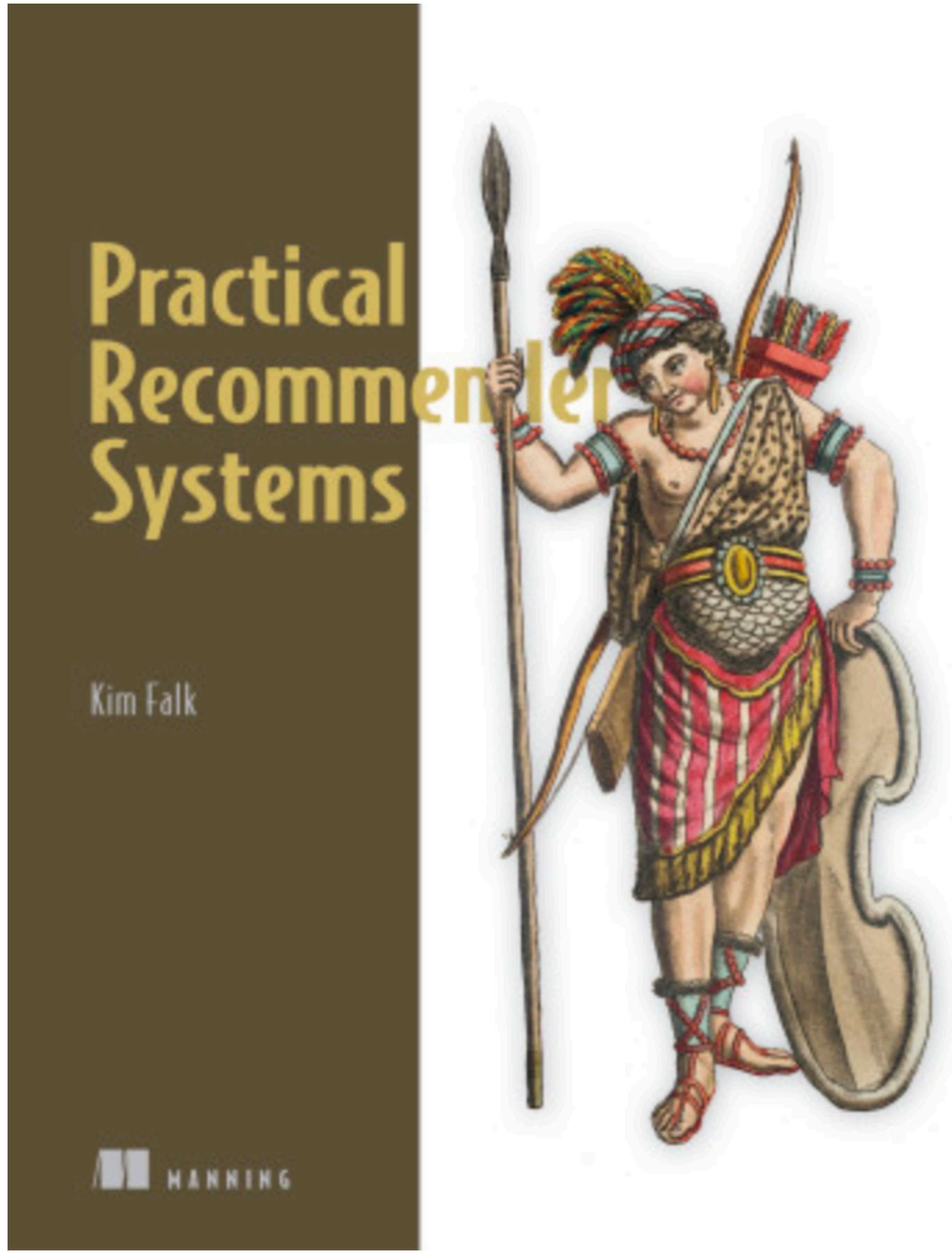
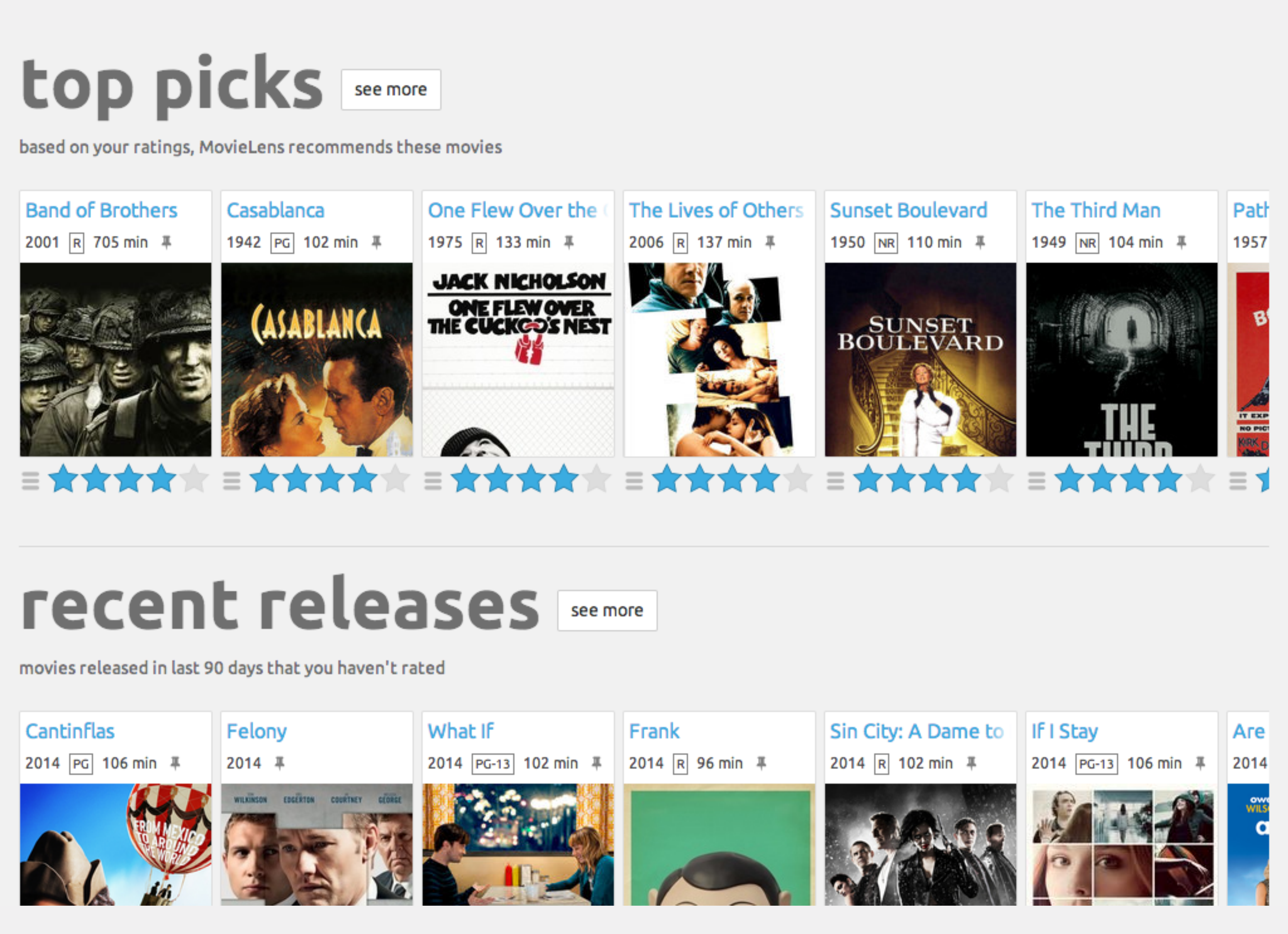
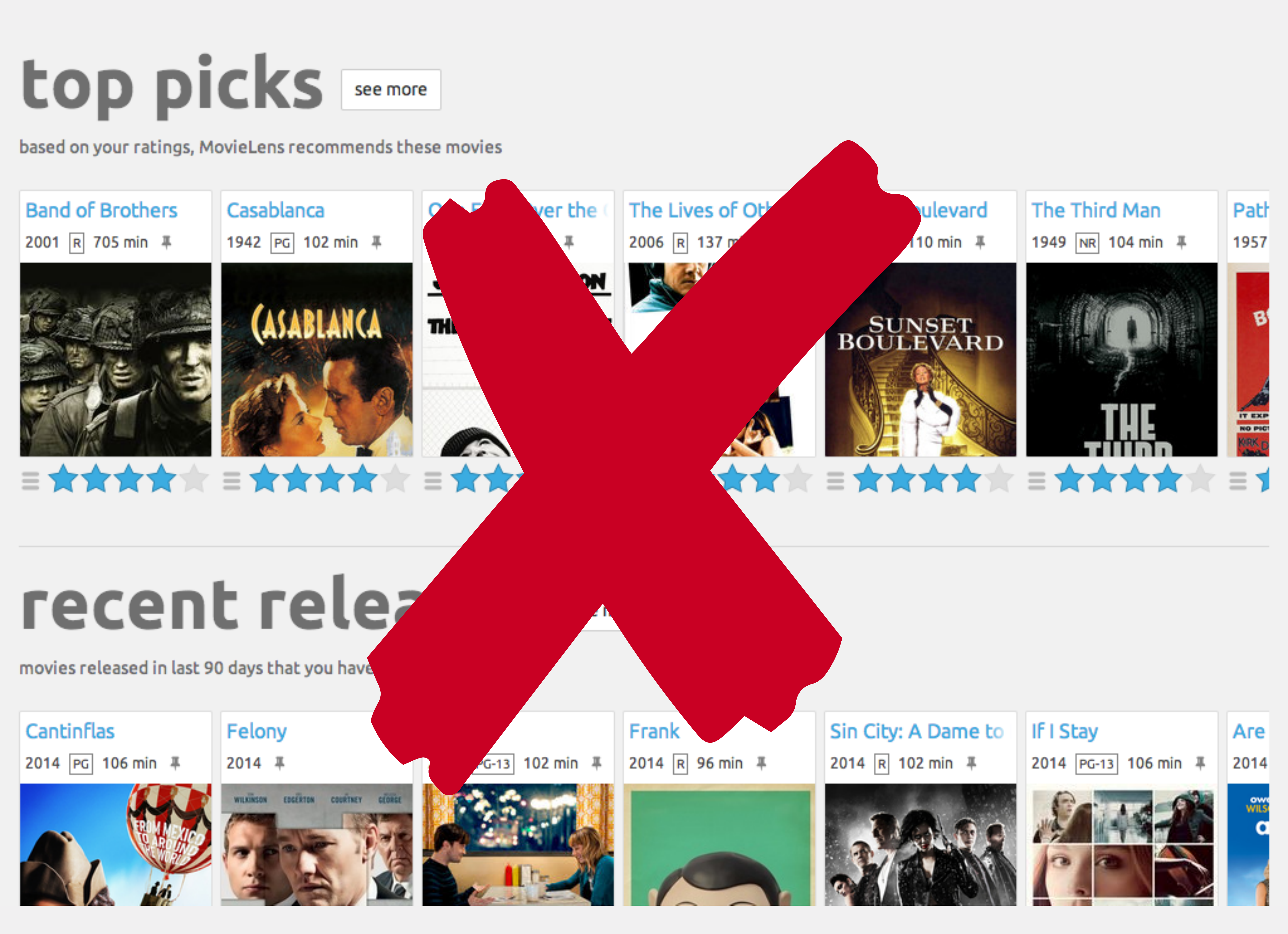


[Practical Recommender Systems]

Data


top picks
see more
based on your ratings, MovieLens recommends these movies
Band of Brothers
2001 R 705 min
Casablanca
1942 PG 102 min
One Flew Over the
1975 R 133 min
The Lives of Others
2006 R 137 min
Sunset Boulevard
1950 NR 110 min
The Third Man
1949 NR 104 min
Path
1957
recent releases
see more
movies released in last 90 days that you haven't rated
Cantinflas
2014 PG 106 min
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
Are
2014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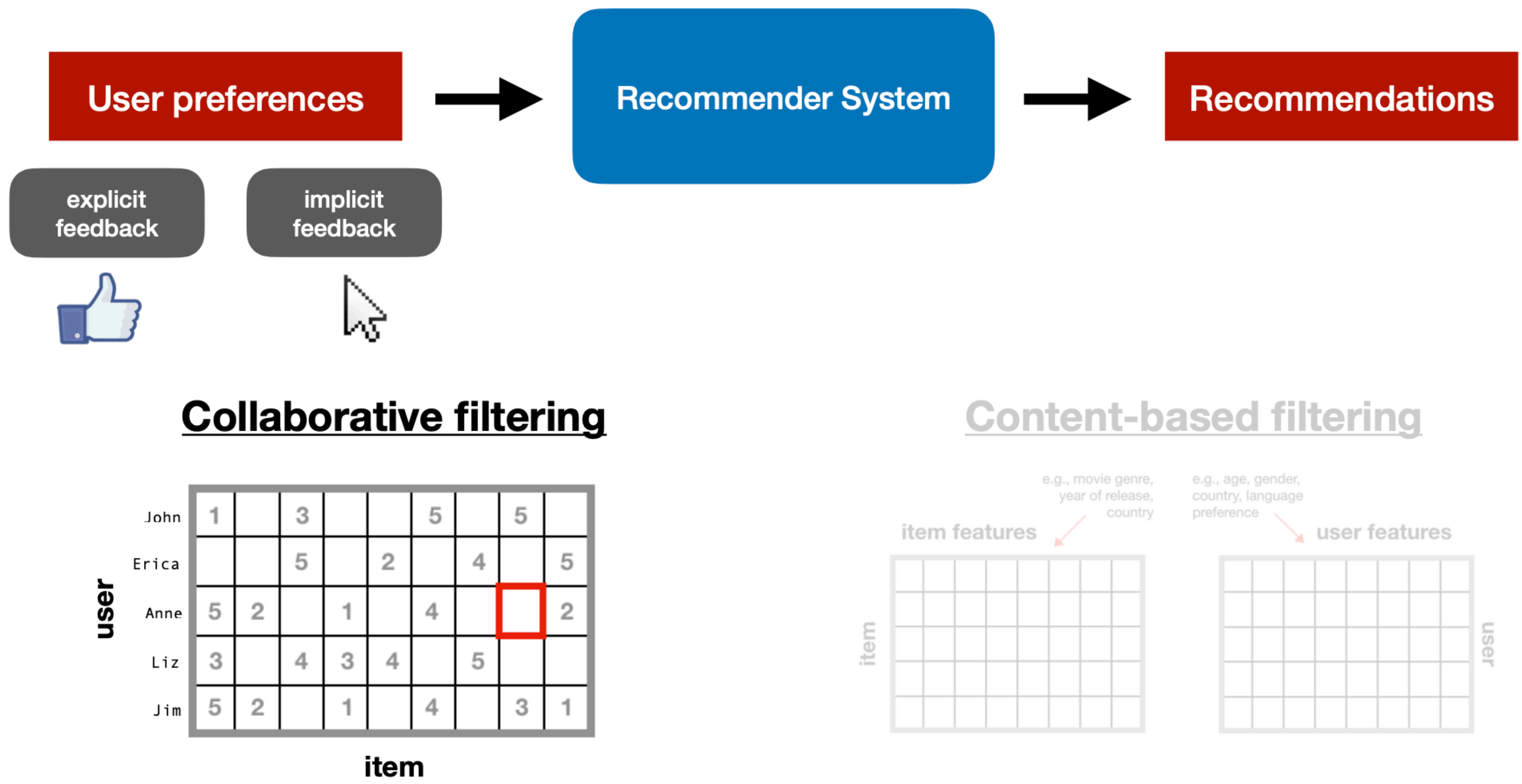
2014 PG 106 min
Felony
2014
102 min
Frank
2014 R 96 min
Sin City: A Dame to
2014 R 102 min
If I Stay
2014 PG-13 106 min
2014

Stars!

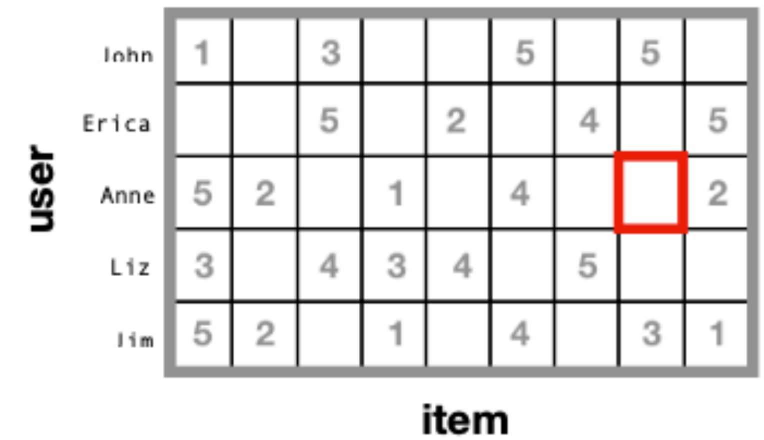
Candy!!

1

Theory


User preferences
Recommender System
Recommendations
explicit feedback
implicit feedback
Collaborative filtering
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
user
item
Content-based filtering
e.g., movie genre, year of release, country
e.g., age, gender, country, language preference
item features
user features
item
user

What are we populating these cells with?



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?

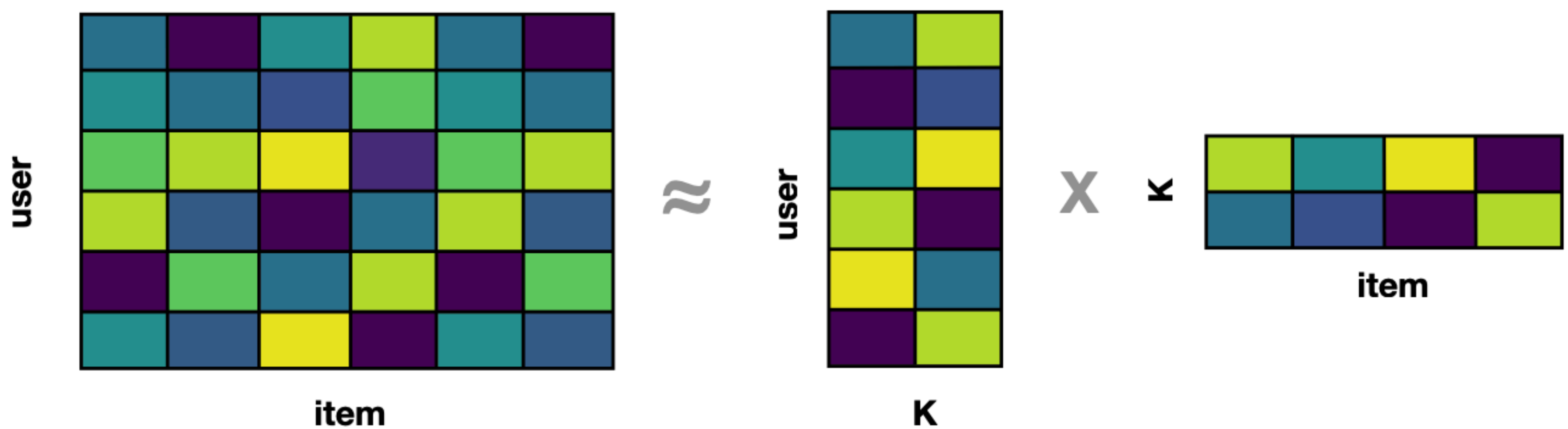
users									
John	1		3			5		5	
Erica			5		2		4		5
Anne	5	2		1		4		$\boxed{3}$	2
Liz	3		4	3	4		5		
Jim	5	2		1		4		3	1

items

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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ABSTRACT

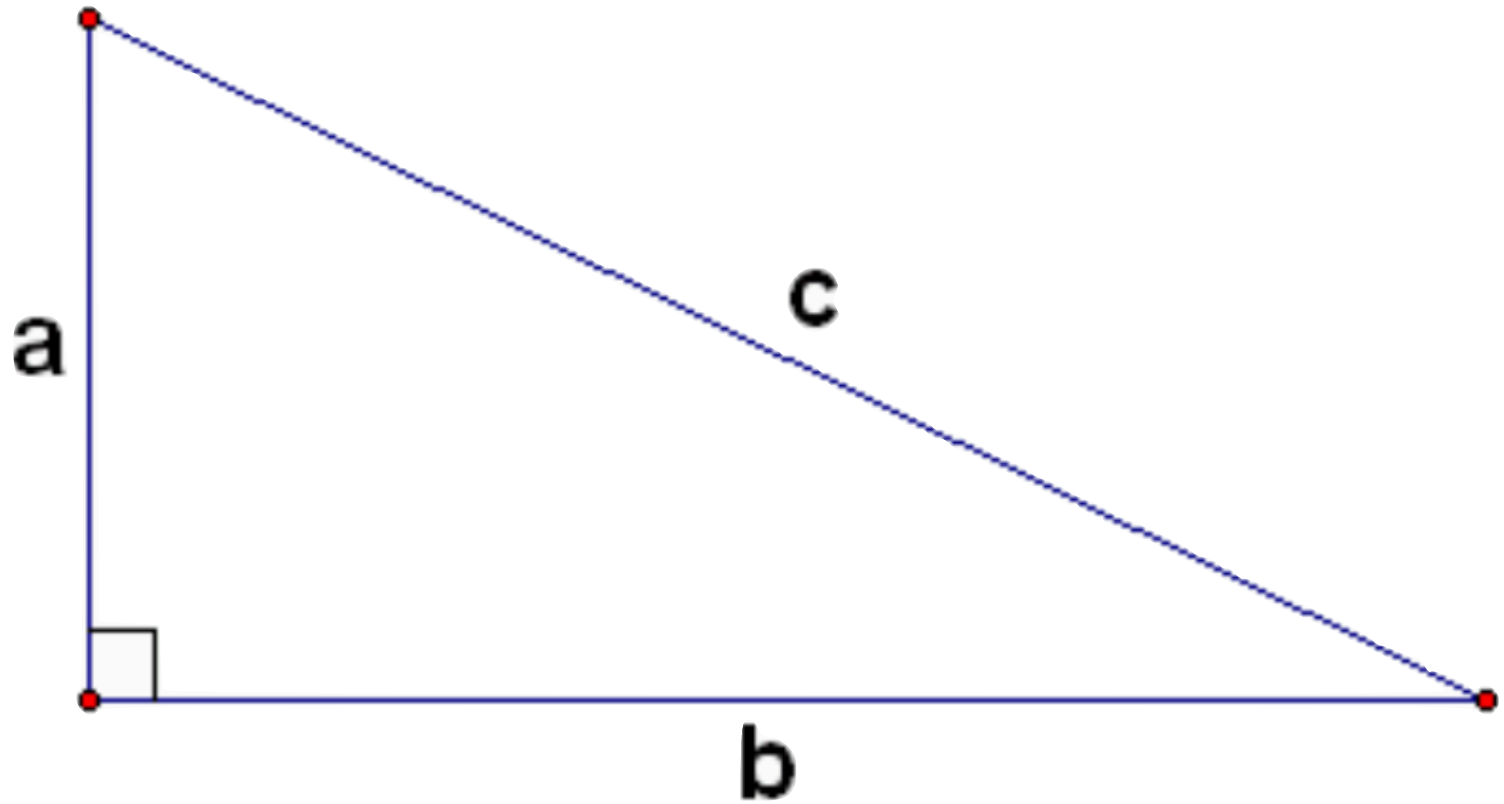
Deep learning techniques have become the method of choice for researchers working on algorithmic aspects of recommender systems. With the strongly increased interest in machine learning in general, it has, as a result, become difficult to keep track of what represents the state-of-the-art at the moment, 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.

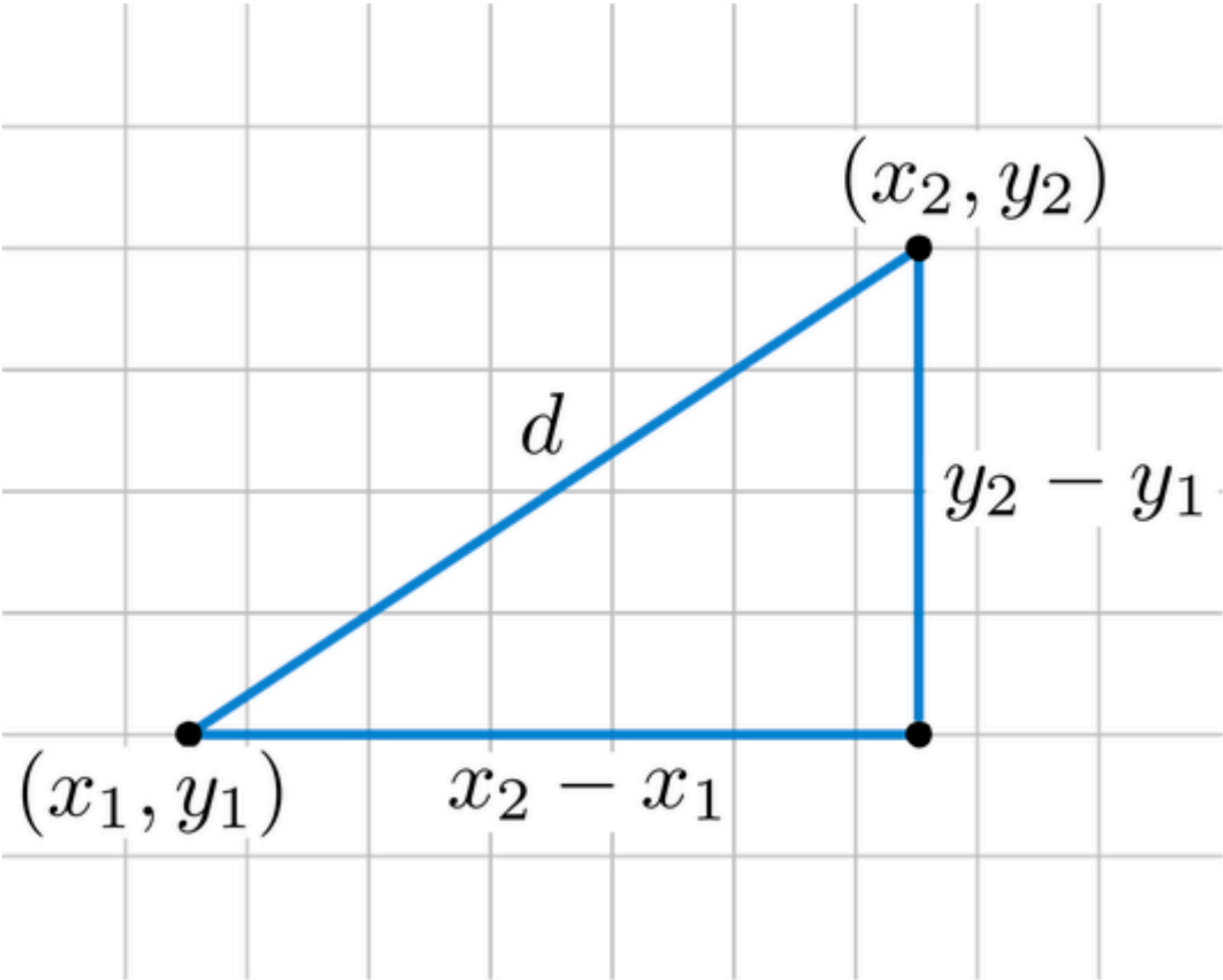
1 INTRODUCTION

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

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Netflix

University of Oxford

Experience

Senior Research Engineer

Netflix

Aug 2016 - Present · 5 yrs 10 mos

Los Gatos, California

Personalization algorithms.

Data Scientist

Lyst

Nov 2012 - Aug 2016 · 3 yrs 10 mos

London, United Kingdom

Recommendations and Personalization.

light fm

https://github.com/lyst/lightfm

light fm

SPOTLIGHT

https://github.com/lyst/lightfm

https://github.com/maciejkula/spotlight

O'REILLY®

Katacoda

Q&A


That's all Folks!