GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

RECOMMENDATION SYSTEMS

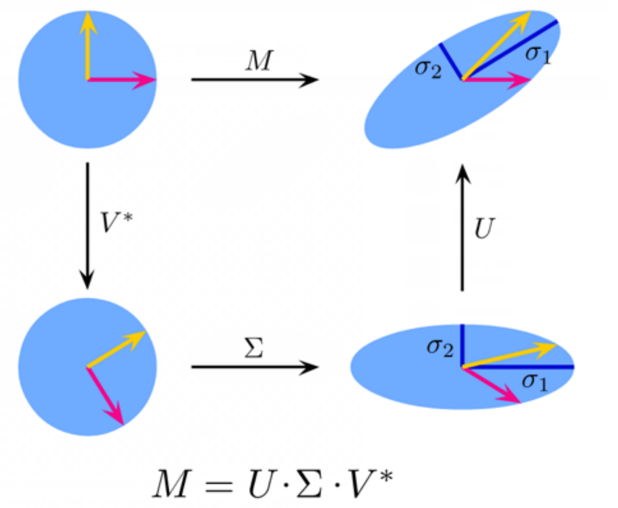
DATA SCIENCE IN THE NEWS

LAST TIME:

I. DIMENSIONALITY REDUCTION

II. PRINCIPAL COMPONENTS ANALYSIS

III. SINGULAR VALUE DECOMPOSITION



EXERCISE:

IV. DIMENSIONALITY REDUCTION IN SCIKIT-LEARN

QUESTIONS?

WHAT WAS THE MOST INTERESTING THING YOU LEARNT?

WHAT WAS THE HARDEST TO GRASP?

I. OVERVIEW
II. CONTENT-BASED FILTERING
III. COLLABORATIVE FILTERING
IV. THE NETFLIX PRIZE

KEY OBJECTIVES

- BE ABLE TO RECOGNIZE RECOMMENDER SYSTEMS IN RW SCENARIOS
- BE ABLE TO DESCRIBE HOW A REC SYS WORKS
- KNOW THE DIFFERENCE BETWEEN CONTENT BASED AND COLLABORATIVE FILTERING REC SYS
- BE ABLE TO IMPLEMENT A RECOMMENDATION SYSTEM IN PYTHON

OVERVIEW

A recommendation system aims to **match users to products/items/brand/etc** that they likely haven't experienced yet.

This rating is produced by analyzing other user/item ratings (and sometimes item characteristics) to provide **personalized recommendations** to users.

Discussion:
Why do we need new methods for recommendation?

There are two general approaches to recsys design:

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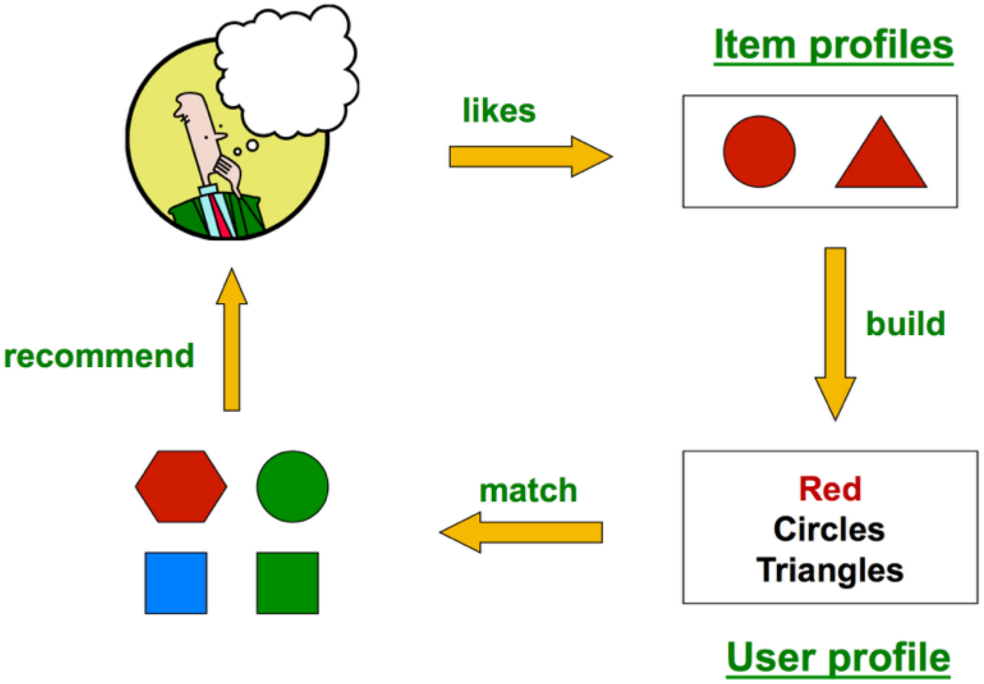
In **content-based filtering**, items are mapped into a feature space, and recommendations depend on *item characteristics*.

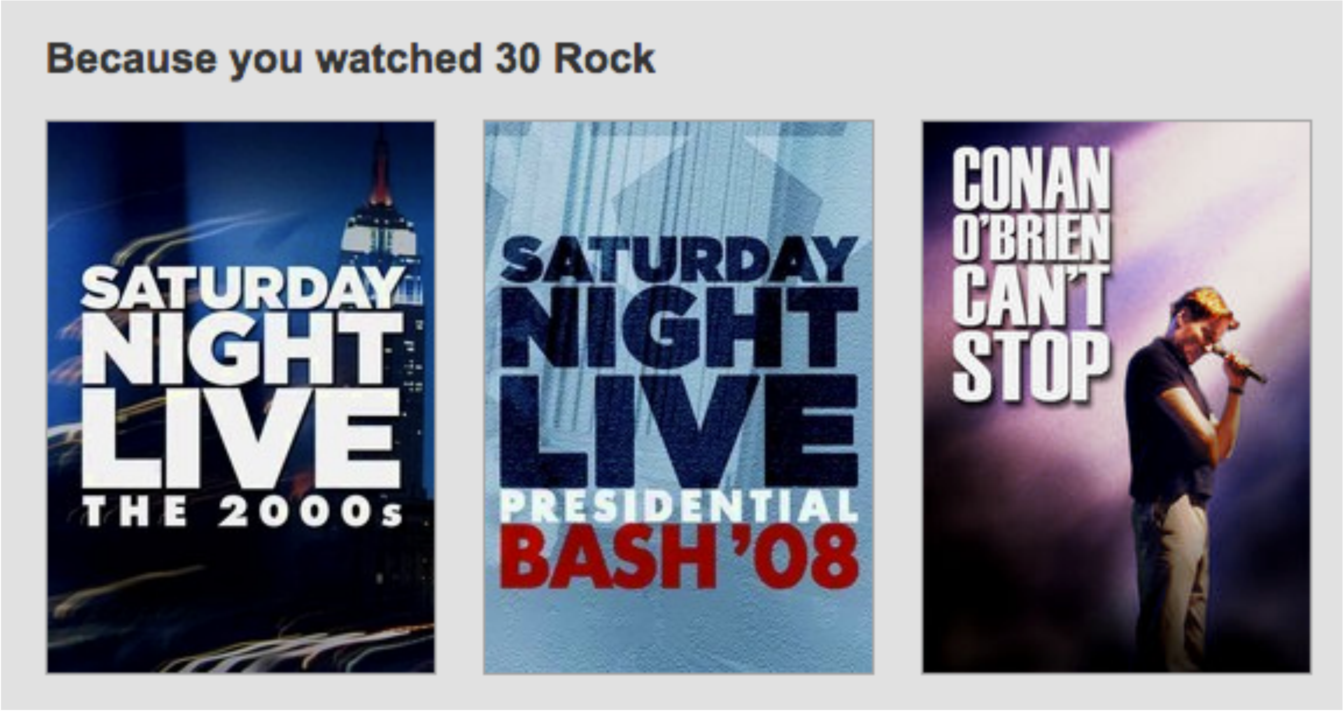
In contrast, the only data under consideration in **collaborative filtering** are user-item ratings, and recommendations depend on *user preferences*.

content-based filtering:

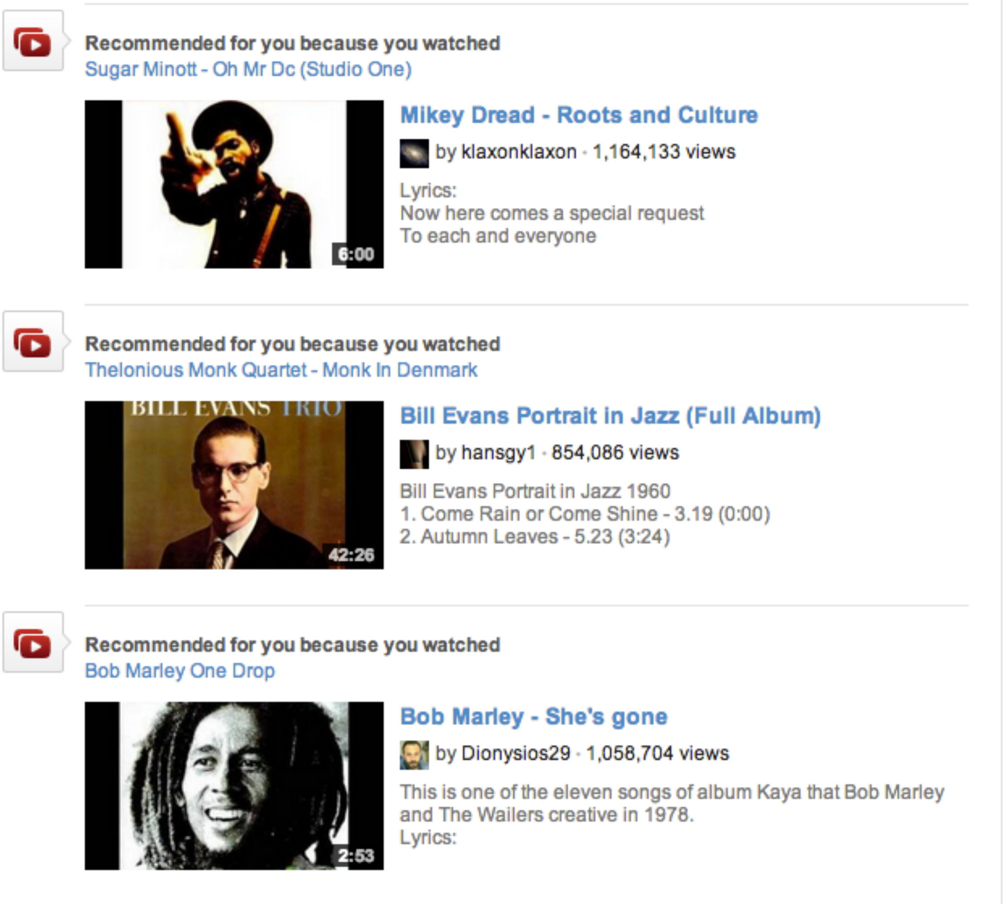


J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

EXAMPLES – NETFLIX



EXAMPLES – YOUTUBE



How can we find good recommendations?

- Manual Curation
- Manually Tag Attributes
- Audio Content, Metadata, Text Analysis
- Collaborative Filtering

EXAMPLES – NYTIMES.COM

MOST E-MAILED | RECOMMENDED FOR YOU

1. **How Big Data Is Playing Recruiter for Specialized Workers**
2. SLIPSTREAM
   When Your Data Wanders to Places You've Never Been
3. MOTHERLODE
   The Play Date Gun Debate
4. **For Indonesian Atheists, a Community of Support Amid Constant Fear**
5. **Justice Breyer Has Shoulder Surgery**
6. BILL KELLER
   Erasing History

EXAMPLES – NYTIMES.COM

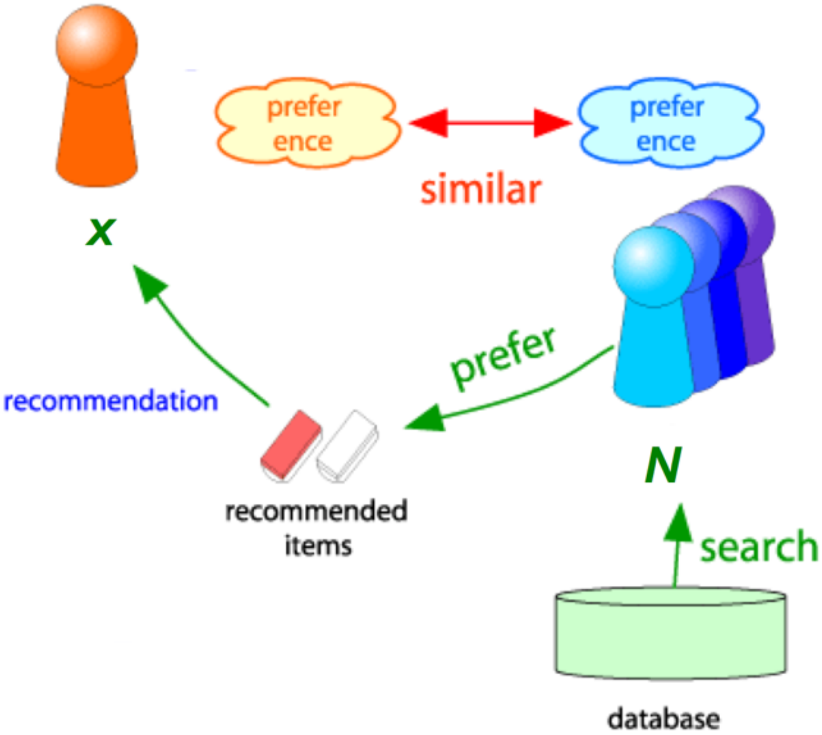
8. How do you determine my Most Read Topics?

Back to top ▲

Each NYTimes.com article is assigned topic tags that reflect the content of the article. As you read articles, we use these tags to determine your most-read topics.

To search for additional articles on one of your most-read topics, click that topic on your personalized Recommendations page. To learn more about topic tags, visit Times Topics.

collaborative filtering:



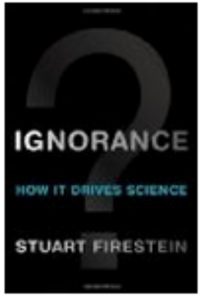
EXAMPLES – AMAZON

EXAMPLES – AMAZON

Inspired by Your Wish List

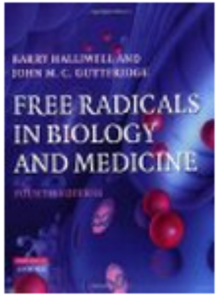
You wished for | Customers who viewed this also viewed

The Secret Anarchy of Science
› Michael Brooks
Paperback
(6)



Ignorance: How It Drives Science
› Stuart Firestein
Hardcover
(31)
~~$21.95~~ $13.02

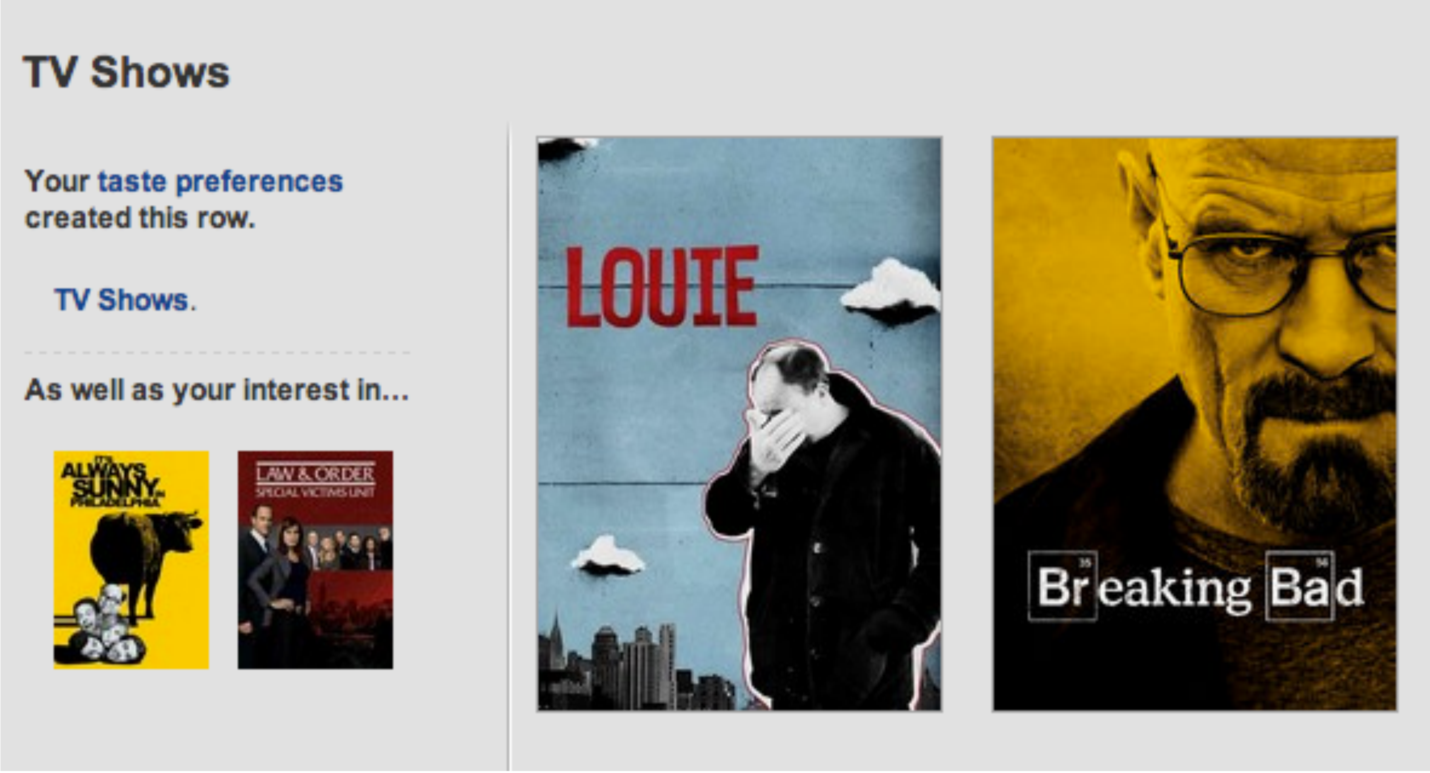
13 Things that Don't Make Sense: The...
› Michael Brooks
Paperback
(65)
~~$15.95~~ $12.49



Free Radicals in Biology and Medicine
Barry Halliwell, John Gutteridge
Paperback
(6)
~~$90.00~~ $75.78

Nonsense on Stilts: How to Tell...
› Massimo Pigliucci
Paperback
(35)
~~$20.00~~ $11.94

EXAMPLES – NETFLIX



Find 3 examples of companies that use recommender systems and figure out if they use content based or collaborative filtering methods

CONTENT-BASED FILTERING

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NOTE

The idea is that users like items that are *similar* to other items they've consumed.

EXAMPLE – CONTENT-BASED FILTERING

features = (big box office, aimed at kids, famous actors)

items (movies):
Finding Nemo = (5, 5, 2)
Mission Impossible = (3, -5, 5)
Jiro Dreams of Sushi = (-4, -5, -5)

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NOTE (*)

In practice, these predictions would be proportional to *deviations* from some global average rating (hence the negative values).

One notable example of content-based filtering is Pandora, which maps songs into a feature space using features (or "genes") designed by the Music Genome Project.

Using song vectors that depend on these features, Pandora can create a station with music having similar properties to a song the user selects.

source: http://www.pandora.com/about/mgp

About The Music Genome Project®

We believe that each individual has a unique relationship with music – no one else has tastes exactly like yours. So delivering a great radio experience to each and every listener requires an incredibly broad and deep understanding of music. That's why Pandora is based on the Music Genome Project, the most sophisticated taxonomy of musical information ever collected. It represents over ten years of analysis by our trained team of musicologists, and spans everything from this past Tuesday's new releases all the way back to the Renaissance and Classical music.

Each song in the Music Genome Project is analyzed using up to 450 distinct musical characteristics by a trained music analyst. These attributes capture not only the musical identity of a song, but also the many significant qualities that are relevant to understanding the musical preferences of listeners. The typical music analyst working on the Music Genome Project has a four-year degree in music theory, composition or performance, has passed through a selective screening process and has completed intensive training in the Music Genome's rigorous and precise methodology. To qualify for the work, analysts must have a firm grounding in music theory, including familiarity with a wide range of styles and sounds.

source: http://www.pandora.com/about/mgp

CONTENT-BASED FILTERING

http://www.music-map.com/

CONTENT-BASED FILTERING

Content-based filtering has some difficulties:

CONTENT-BASED FILTERING

Content-based filtering has some difficulties:

- *need to map each item into a feature space (usually by hand!)*
    - *moreover, need to know what those features are!*

- *limited in scope (items must be similar to each other)*

- *hard to create cross-content recommendations (eg books/music films… requires comparing elements from different feature spaces!)*

COLLABORATIVE FILTERING

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NOTE

The idea here is that users get value from recommendations based on other users with similar *tastes*.

RATINGS MATRIX

18,000 movies

480,000 users

x	1	1	x	...	x
x	x	x	5	...	x
x	x	3	x	...	x
x	4	3	x	...	2
...	x	x	x	...	x
x	5	x	1	...	x
x	x	3	3	...	x
x	1	x	x	...	2

NOTE

This matrix will always be *sparse*!

source: http://www.eecs.berkeley.edu/~zhanghao/main/publications/subfolder/netflix.png

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similarity matrix.

Recommendations are then made to a user for it
similar to those that the user has already rated hi

This is also called **memory-based CF.**

NOTE

This is equivalent to a clustering problem in the space of column vectors (items).

Item-based CF is a *neighborhood method*.

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NOTE

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NOTE

User-based collaborative filtering is possible but less efficient, since there are typically more users than items.

ITEM-BASED COLLABORATIVE FILTERING

Customers Who Bought This Item Also Bought

Pitch Dark (NYRB Classics)
› Renata Adler
Paperback
$11.54

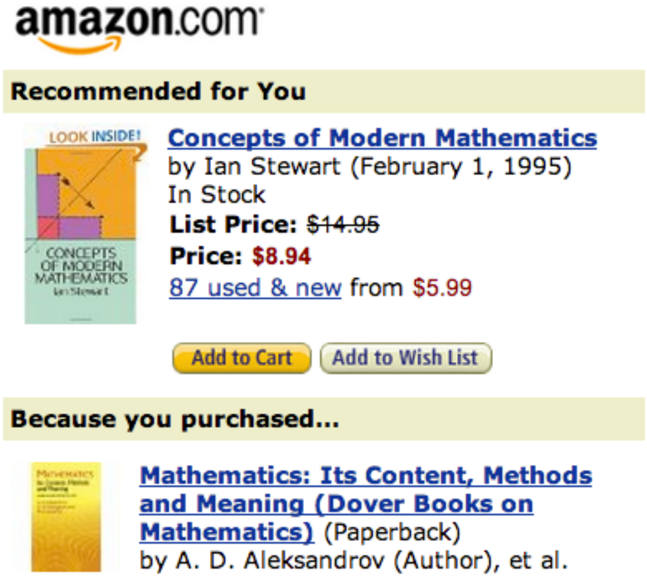
How Literature Saved My Life
› David Shields
(60)
Hardcover
$18.08

No image available

Bleeding Edge
Thomas Pynchon
Hardcover
$18.05

The Flamethrowers: A Novel
› Rachel Kushner
(17)
Hardcover
$15.79

Neighborhood methods such as item-based CF are popular and ***easy to understand****, but they* ***don't scale well.***



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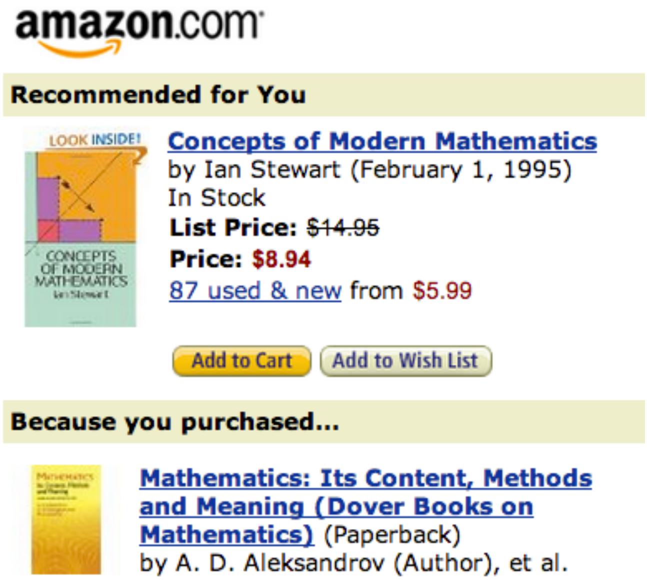

NOTE

Item-based CF is different than content-based filtering!

Though we're making recommendations based on items, we are *not* embedding the items in a feature space.

Model-based *collaborative filtering abandons the neighborhood approach and applies other techniques to the ratings matrix.*

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The most popular model-based CF techniques use ***matrix decomposition techniques*** *to find deeper structure in the ratings data.*

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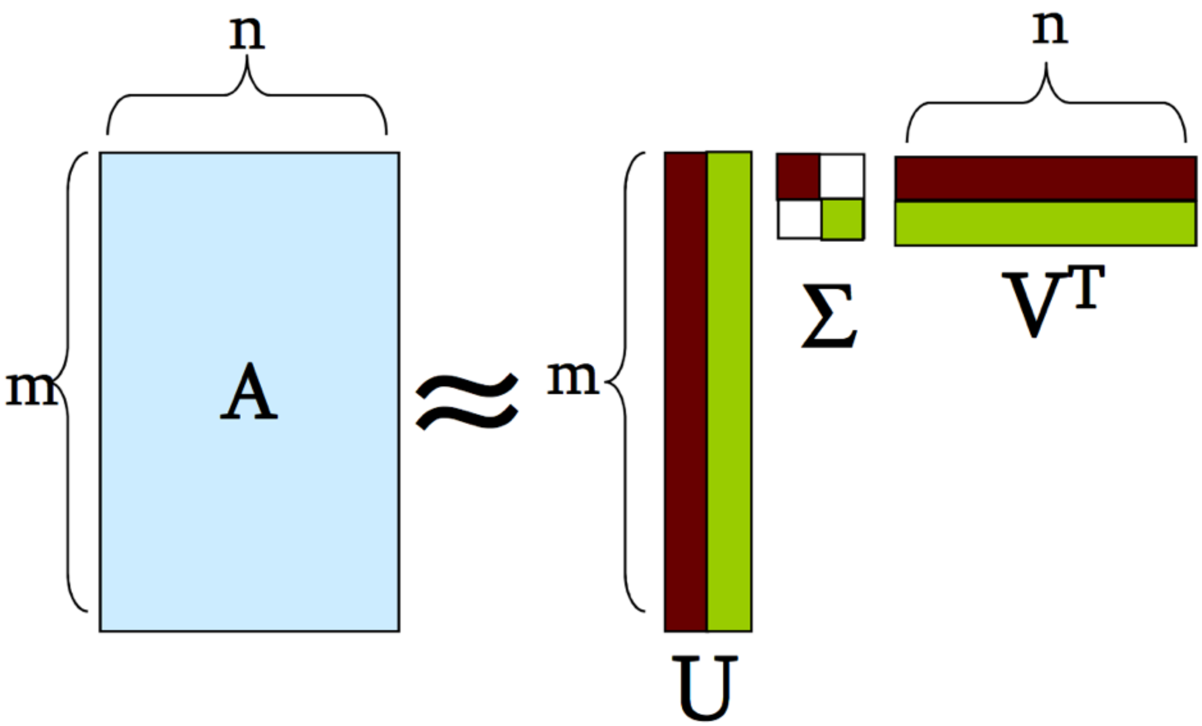
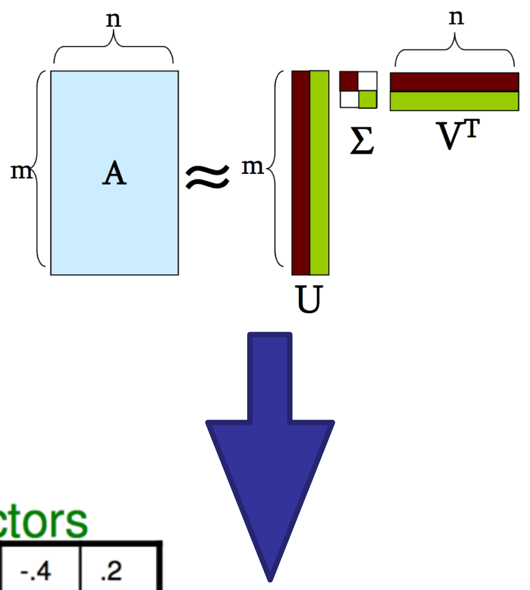
*The most popular model-based CF techniques use **matrix decomposition techniques** to find deeper structure in the ratings data.*

*For example, we could decompose the ratings matrix via **SVD** to reduce the dimensionality and extract* latent variables.

remember SVD?



J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org



users

items

1		3			5			5		4	
		5	4			4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

R

≈

factors

items

.1	-.4	.2
-.5	.6	.5
-.2	.3	.5
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

Q

users

factors

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6

P^T

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

identify the latent variables in the ratings matrix

=> can express both users and items in terms of these

users (columns), items (rows)

1		3			5			5		4	
		5	4			4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

R

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.1	-.4	.2
-.5	.6	.5
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1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

Q

users (columns), factors (rows)

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6

P^T

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NOTE

Only now we didn't have to invent the features, but they emerged from the SVD

Ratings are constructed by taking dot products of user & item vectors in the latent feature space.

COLLABORATIVE FILTERING

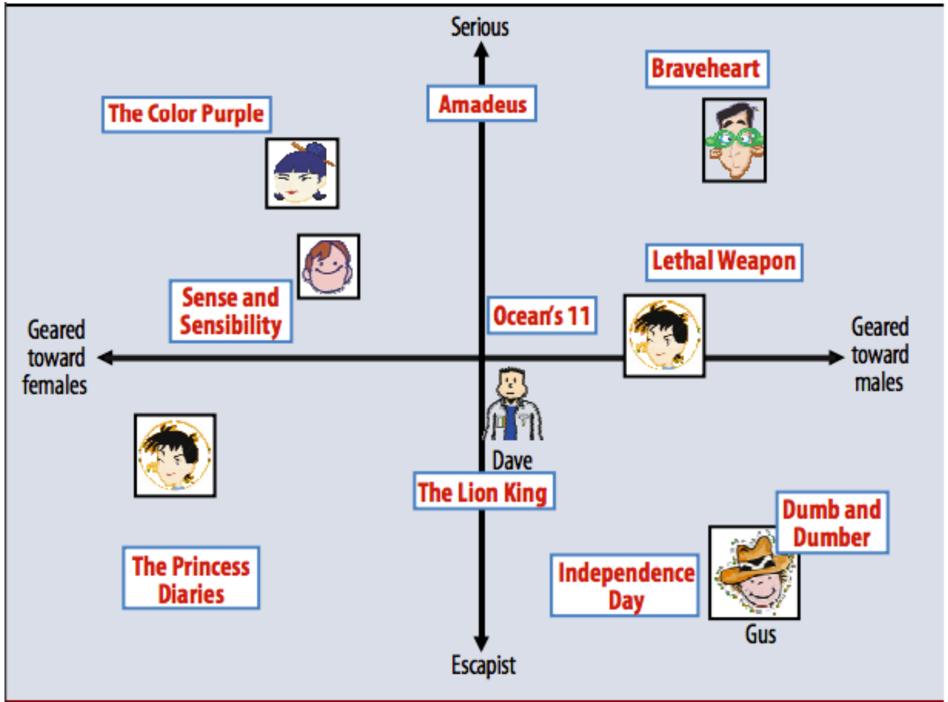

Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

source: http://www2.research.att.com/~volinsky/papers/ieeecomputer.pdf

This approach is domain independent, and requires no explicit user or item profiles to be created.

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Since the conclusion of the Netflix prize, these latent factor methods for collaborative filtering have been regarded as the state-of-the-art in recsys technology.

Quick check

What are the main types of CF Rec Systems?

Pros/Cons

Discuss in pairs

CF Methods have some drawbacks:

- *lots of (high-dimensional) ratings data needed*
- *data is typically very sparse (in the Netflix prize dataset, ~99% of possible ratings were missing)*
- *susceptible to fraud (eg shilling attacks)*
- cold start problem*: need lots of data on new user or item before recommendations can be made*

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Until a user rates several items, we don't know anything about her preferences!

We can get around this by enhancing our recommendations using **implicit feedback***, which may include things like item browsing behavior, search patterns, purchase history, etc.*

*While **explicit feedback** (ratings, likes, purchases) leads to high quality ratings, the data is sparse and cold starts are problematic.*

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*Meanwhile **implicit feedback** (browsing behavior, etc) leads to less accurate ratings, but the data is much more dense (and less invasive to collect).*

Implicit feedback can help to infer user preferences when explicit feedback is not available, therefore easing the cold start problem.

Hybrid filtering methods *provide another way to get around the cold start problem by combining filtering methods (eg, by using content-based info to “boost” a collaborative model).*

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This content-based info can be item-based as above, or even user-based (eg, demographic info).

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Hybrid methods can also make the data sparsity issue easier to deal with, by broadening the set of features under consideration.

THE NETFLIX PRIZE

NETFLIX PRIZE

award $1 million to anyone who can improve movie recommendation by 10%

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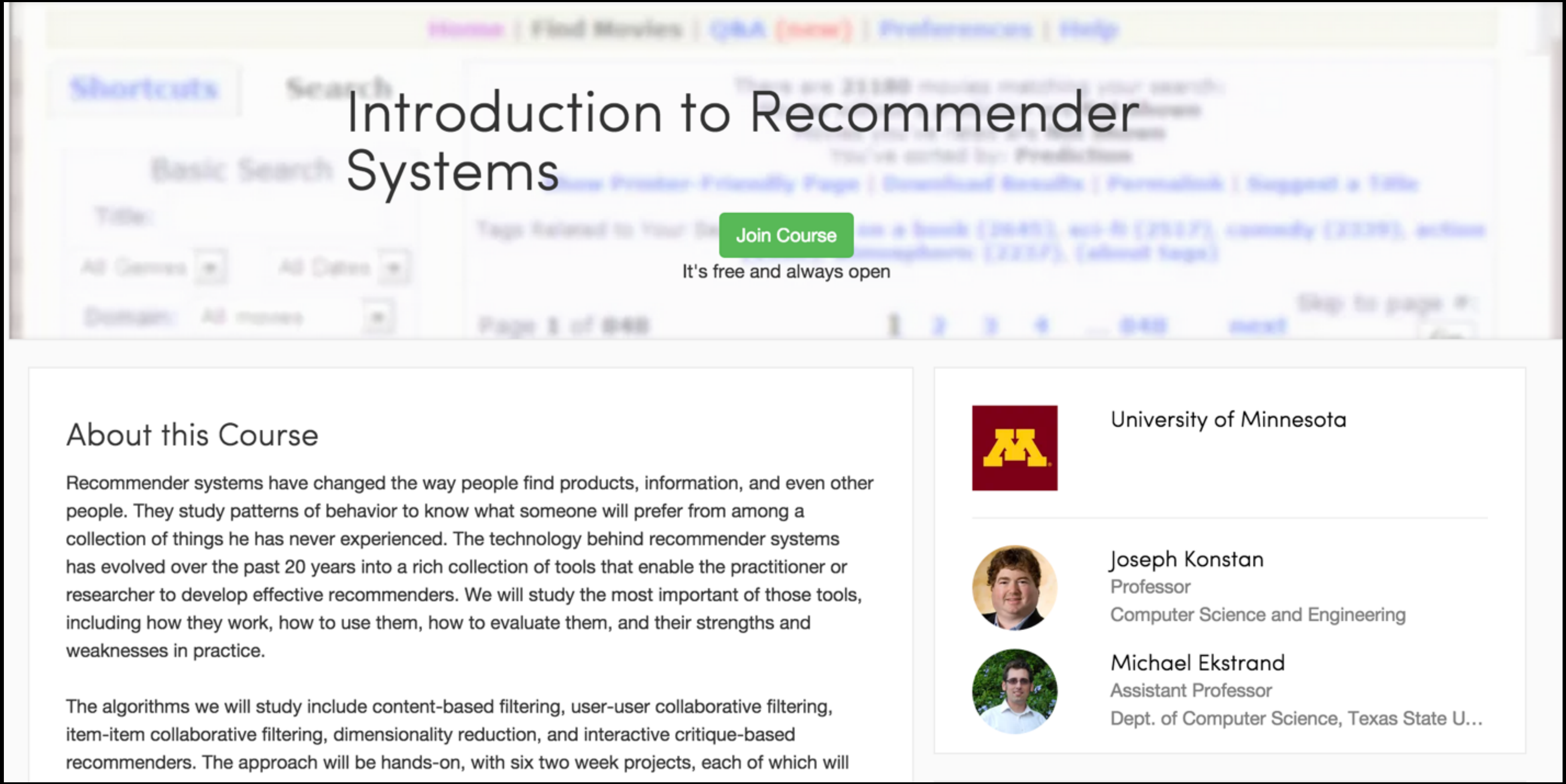
Ultimately, the competition ended in a photo finish. The winning strategy came down to last-minute team mergers & creative blending schemes to shave 3rd & 4th decimals off RMSE (concerns that would not be important in practice).

Though they adopted some of the modeling techniques that emerged from the competition, Netflix never actually implemented the prizewinning solution.

Why do you think that’s true?



Further learning material:
https://www.coursera.org/learn/recommender-systems