GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

RECOMMENDATION SYSTEMS, COLLABORATIVE FILTERING

AGENDA

- Recommendation Systems
- Collaborative Filtering
- Demo

RECOMMENDATION SYSTEMS

RECOMMENDATION SYSTEMS

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

Bleeding Edge
Thomas Pynchon
Hardcover
$18.05

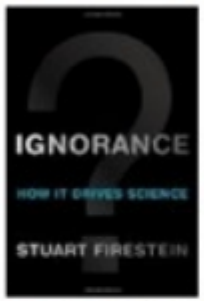
The Flamethrowers: A Novel
› Rachel Kushner
★★★½☆ (17)
Hardcover
$15.79

RECOMMENDATION SYSTEMS

Inspired by Your Wish List

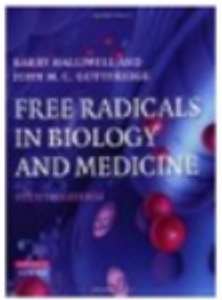
You wished for | Customers who viewed this also viewed

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



Ignorance: How It Drives Science
› Stuart Firestein
Hardcover
★★★★½ (31)
~~$21.95~~ $13.02

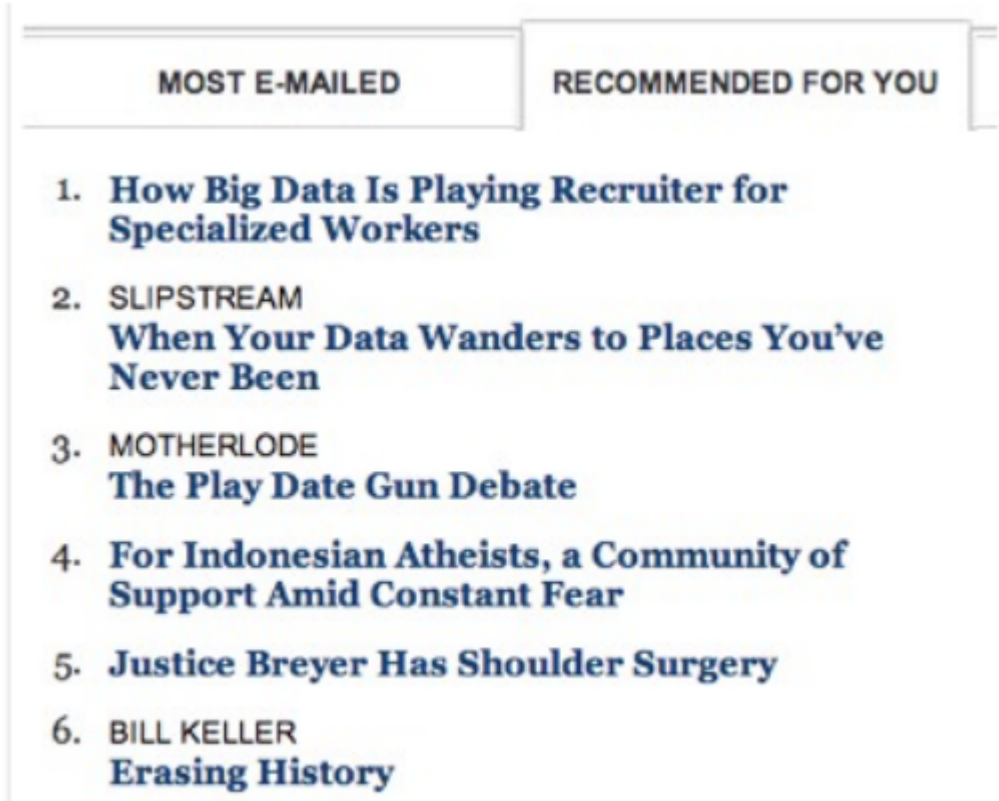
13 Things that Don't Make Sense: The...
› Michael Brooks
Paperback
★★★★☆ (65)
~~$15.95~~ $12.49



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
★★★½☆ (35)
~~$20.00~~ $11.94

RECOMMENDATION SYSTEMS



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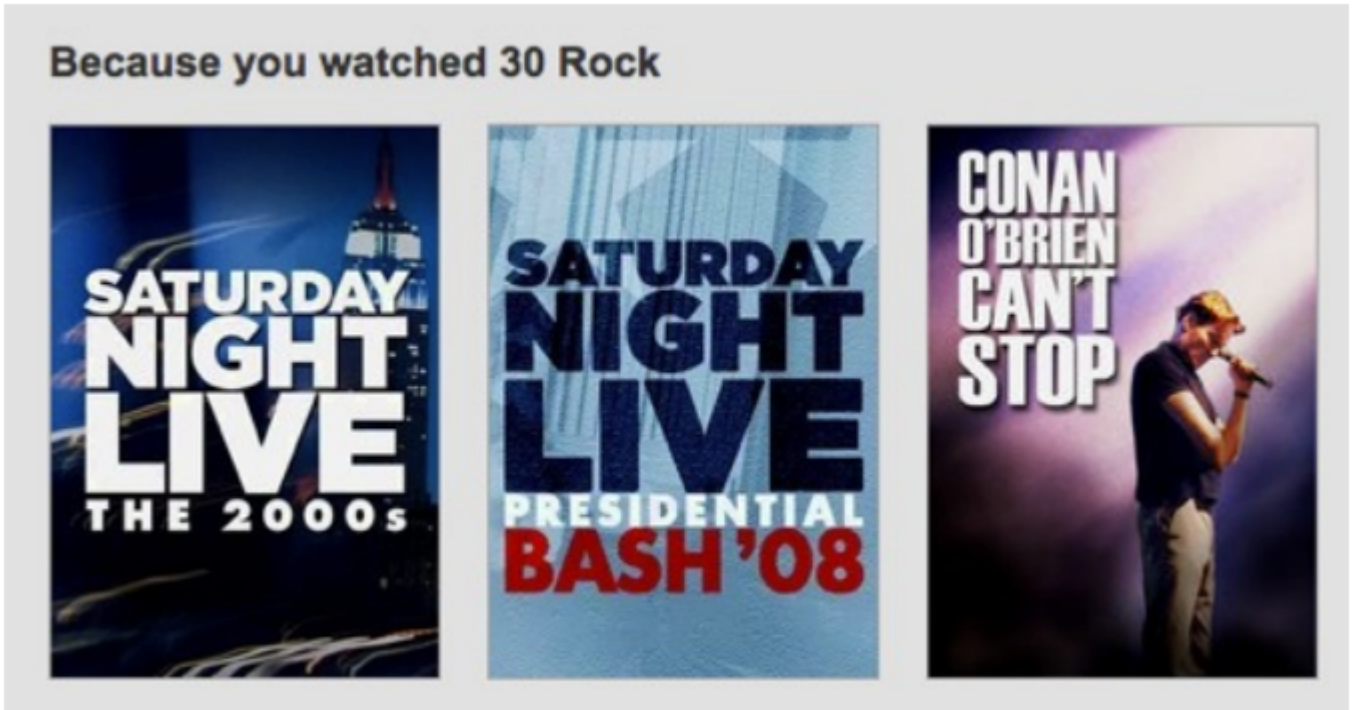

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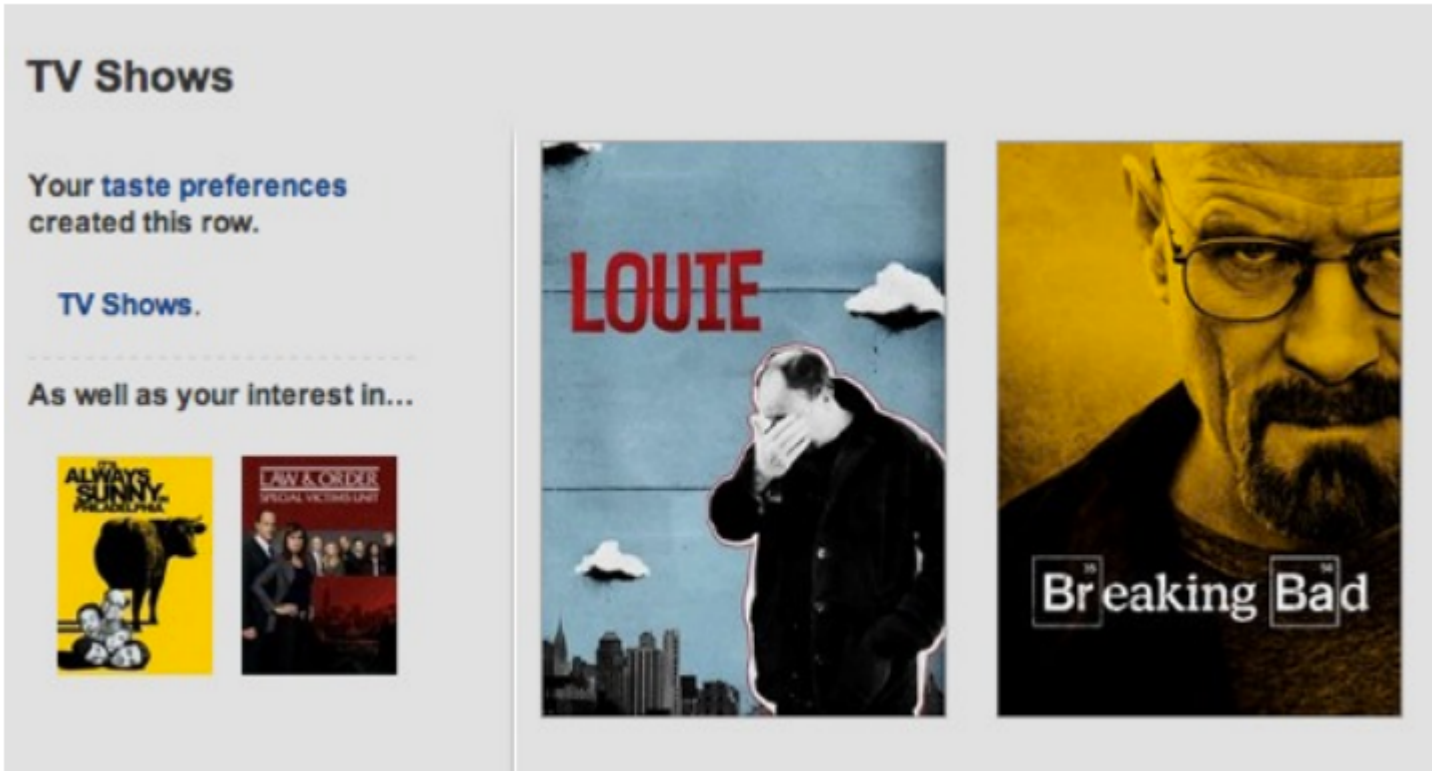

RECOMMENDATION SYSTEMS

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- Items may be products, events, movies, songs, etc.
- Recommendation can be accomplished by predicting ratings of items for users, or by predicting whether or not the user will be interested in the item
- Recommendation is ***not*** a machine learning task like multi-class classification or clustering

RECOMMENDATION SYSTEMS

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- In ***content-based filtering*** systems, items and users are mapped into a feature space, and recommendations are learned from these feature representations
- In contrast, the only data under consideration in ***collaborative filtering*** systems are the users' ratings for items

CONTENT-BASED FILTERING

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One of the main approaches to content-based filtering:

- Map users and items to same feature space, compute distance between a user and item

CONTENT-BASED FILTERING

Item vectors measure the degree to which the item is described by each feature, and user vectors measure a user's preference for each feature.

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Toy Story -> (Comedy: 1, Animated: 1, Mafia: 0)
Godfather -> (Comedy: 0, Animated: 0, Mafia: 1)

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Toy Story -> (Comedy: 1, Animated: 1, Mafia: 0)
Godfather -> (Comedy: 0, Animated: 0, Mafia: 1)

User 1 -> (Comedy: 1, Animated: 0, Mafia: 0)

CONTENT-BASED FILTERING

features = (big box office, intended for kids, famous actors)

Finding Nemo = (5, 5, 2)

Mission Impossible = (3, -5, 5)

Jiro Dreams of Sushi = (-4, -5, -5)

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CONTENT-BASED FILTERING

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Finding Nemo = (5, 5, 2) (-3*5 + 2*5 -2*2) = -9

Mission Impossible = (3, -5, 5) (-3*3 - 2*5 -2*5) = -29

Jiro Dreams of Sushi = (-4, -5, -5) (3*4 - 2*5 + 2*5) = +12

Jason = (-3, 2, -2)

EXAMPLES OF CONTENT-BASED FILTERING

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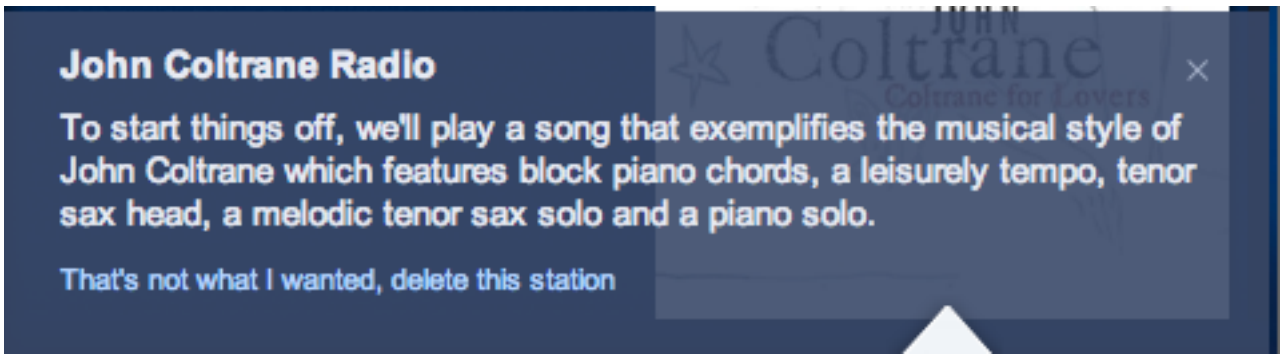
- Pandora maps songs into a feature space using “genes” designed by the Music Genome Project.
- Songs similar to the initial selection are assigned to the station.

Pandora


John Coltrane Radio
To start things off, we'll play a song that exemplifies the musical style of John Coltrane which features block piano chords, a leisurely tempo, tenor sax head, a melodic tenor sax solo and a piano solo.
That's not what I wanted, delete this station

ADVANTAGES OF CONTENT-BASED FILTERING

- Previous ratings are not required

DISADVANTAGES OF CONTENT-BASED FILTERING

- You must map each item into a feature space

DISADVANTAGES OF CONTENT-BASED FILTERING

- You must map each item into a feature space
- It is hard to create cross-content recommendations (e.g., books/music/films)

COLLABORATIVE FILTERING

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With Collaborative Filtering the goal is to predict how users will rate items that they have not yet rated.

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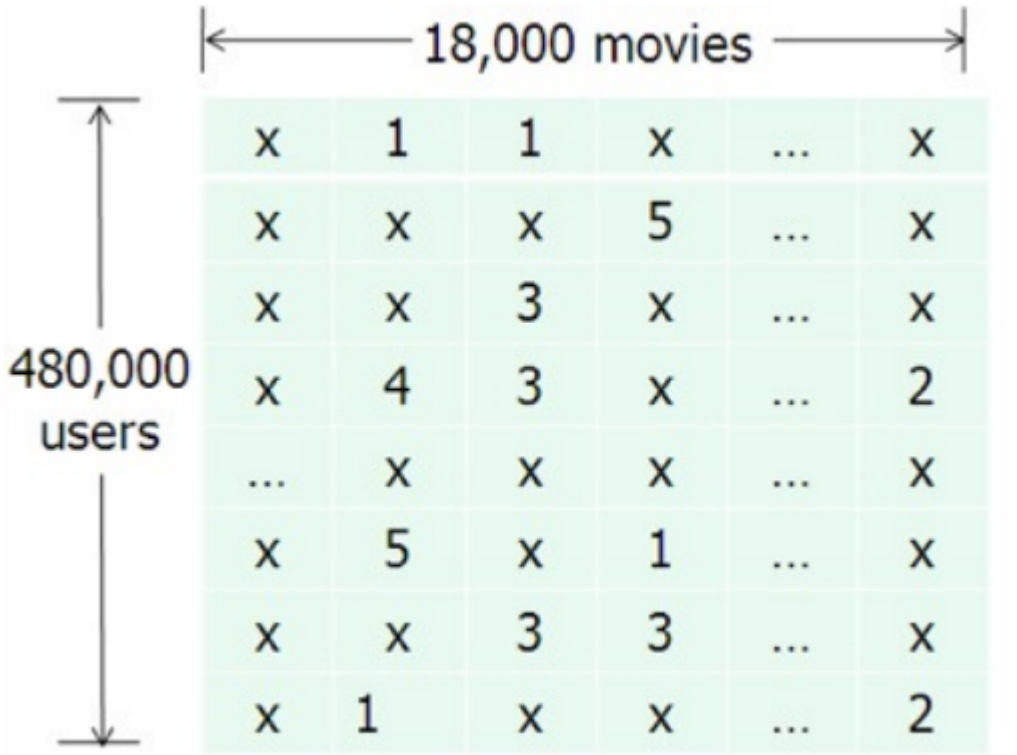
Collaborative filtering methods do not represent the users and items in a feature space; they only use the existing user-item ratings.

COLLABORATIVE FILTERING

In the typical CF system, the dataset is a ratings matrix whose columns correspond to items, and whose rows correspond to users.

COLLABORATIVE FILTERING



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	Item1	Item2	...	ItemN
Item1	1	.8	0	0
Item2	0.1	1	0	0
...	0.6	0	1	0.1
ItemN	0	0	0.3	1

COLLABORATIVE FILTERING

Similarity could be as simple as the % of users who liked X who also liked Y.

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Recommendations are then made to a user for items most similar to those that the user has already rated highly.

COLLABORATIVE FILTERING

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→ An item-item similarity matrix can get pretty big!

e.g. for all of Amazon's products, the number of 2-combinations of a set of N items = N! / (2! * N-2!)

COLLABORATIVE FILTERING

Model-based CF techniques use matrix decomposition to find deeper structure in the ratings data.

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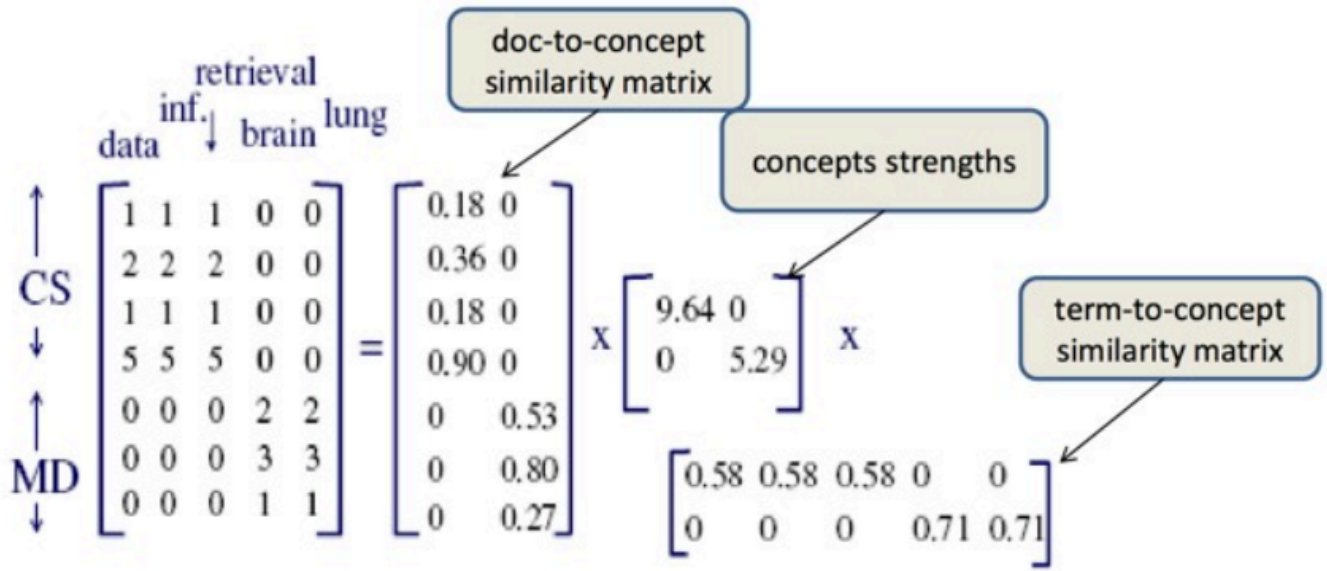
$$\underset{(n \times d)}{A} = \underset{(n \times k)}{U} \; \underset{(k \times k)}{\Sigma} \; \underset{(k \times d)}{V^T}$$

COLLABORATIVE FILTERING



COLLABORATIVE FILTERING

Once we identify the latent variables in the ratings matrix, we can express both users and items in terms of these latent variables.

COLLABORATIVE FILTERING

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

COLLABORATIVE FILTERING

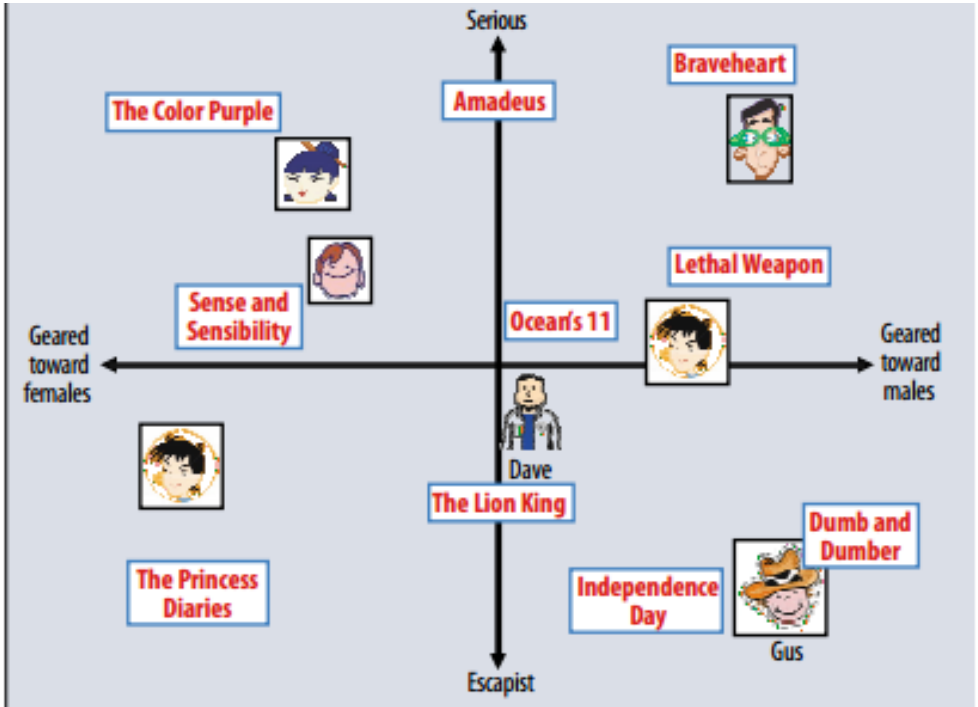

Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

ADVANTAGES OF COLLABORATIVE FILTERING

- CF is domain independent and requires no explicit user or item profiles to be created.

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- Domain independent and requires no explicit user or item profiles to be created
- Combines predictive accuracy and (relative) scalability

ADVANTAGES OF COLLABORATIVE FILTERING

- Won the Netflix prize!
- Collaborative filtering methods are generally regarded as the state-of-the-art in recommendation technology

DISADVANTAGES OF COLLABORATIVE FILTERING

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DISADVANTAGES OF COLLABORATIVE FILTERING

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

COLD START PROBLEM

The cold start problem arises because we've been relying only on ratings data, or on explicit feedback from users

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

COLD START PROBLEM

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.

Implicit feedback leads to less accurate ratings, but the data is much denser (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 METHODS

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

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

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

DEMO