GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 14: RECOMMENDATION SYSTEMS

LAST TIME:

- DIMENSIONALITY REDUCTION
- PCA/SVD

QUESTIONS?

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \\
\begin{array}{c} \\ \\ \text{CS} \\ \\ \\ \text{MD} \\ \\ \end{array} &
\begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
2 & 2 & 2 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 \\
0 & 0 & 0 & 3 & 3 \\
0 & 0 & 0 & 1 & 1
\end{bmatrix}
\end{array}
=
\underbrace{\begin{bmatrix}
0.18 & 0 \\
0.36 & 0 \\
0.18 & 0 \\
0.90 & 0 \\
0 & 0.53 \\
0 & 0.80 \\
0 & 0.27
\end{bmatrix}}_{\text{doc-to-concept similarity matrix}}
\times
\underbrace{\begin{bmatrix}
9.64 & 0 \\
0 & 5.29
\end{bmatrix}}_{\text{concepts strengths}}
\times
\underbrace{\begin{bmatrix}
0.58 & 0.58 & 0.58 & 0 & 0 \\
0 & 0 & 0 & 0.71 & 0.71
\end{bmatrix}}_{\text{term-to-concept similarity matrix}}
$$

Consider a matrix A *with* n *rows and* d *features.*

The **singular value decomposition** *of* A *is given by:*

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

st. U, V *are* **orthogonal** *matrices and* Σ *is a* **diagonal** *matrix.*

→ $UU^T = I_n, \; VV^T = I_d$ → $\Sigma_{ij} = 0 \; (i \neq j)$

I. CONTENT-BASED FILTERING

II. COLLABORATIVE FILTERING

EXERCISE:

IV. BEER RECOMMENDER IN PYTHON

The purpose of a **recommendation system** *is decide whether an item (product, event, movie, song) is something in which a user is highly likely to be interested*

There are two general approaches to recsys design:

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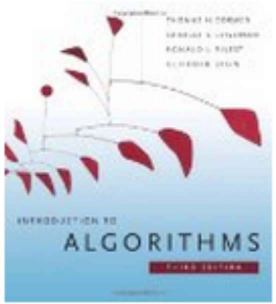
In **content-based filtering**, *items are mapped into a feature space, and recommendations depend on specified characteristics.*

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

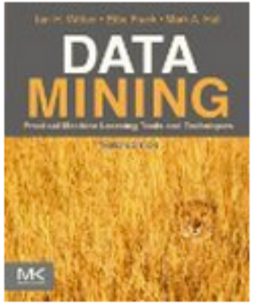
EXAMPLES – AMAZON

Recommendations for You in Books

Cracking the Coding Interview: 150...
› Gayle Laakmann McDowell
Paperback
(166)
~~$39.95~~ $23.22
Why recommended?

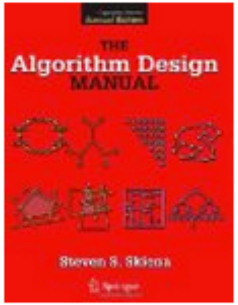


Introduction to Algorithms
Thomas H. Cormen, Charles E...
Hardcover
(85)
~~$92.00~~ $80.00
Why recommended?



Data Mining: Practical Machine...
› Ian H. Witten, Eibe Frank, Mark A. Hall
Paperback
(27)
~~$69.95~~ $42.09
Why recommended?

Elements of Programming Interviews...
› Amit Prakash, Adnan Aziz, Tsung-Hsien Lee
Paperback
(25)
~~$29.99~~ $26.18
Why recommended?



The Algorithm Design Manual
› Steve Skiena
Paperback
(47)
~~$89.95~~ $71.84
Why recommended?

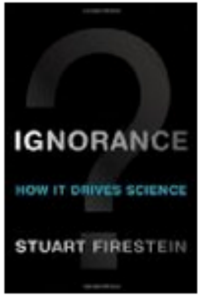
EXAMPLES – AMAZON

Inspired by Your Wish List

You wished for

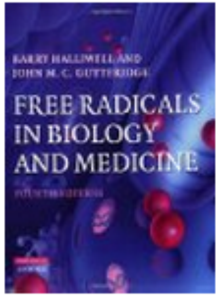
The Secret Anarchy of Science
› Michael Brooks
Paperback
(6)

Customers who viewed this also viewed



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

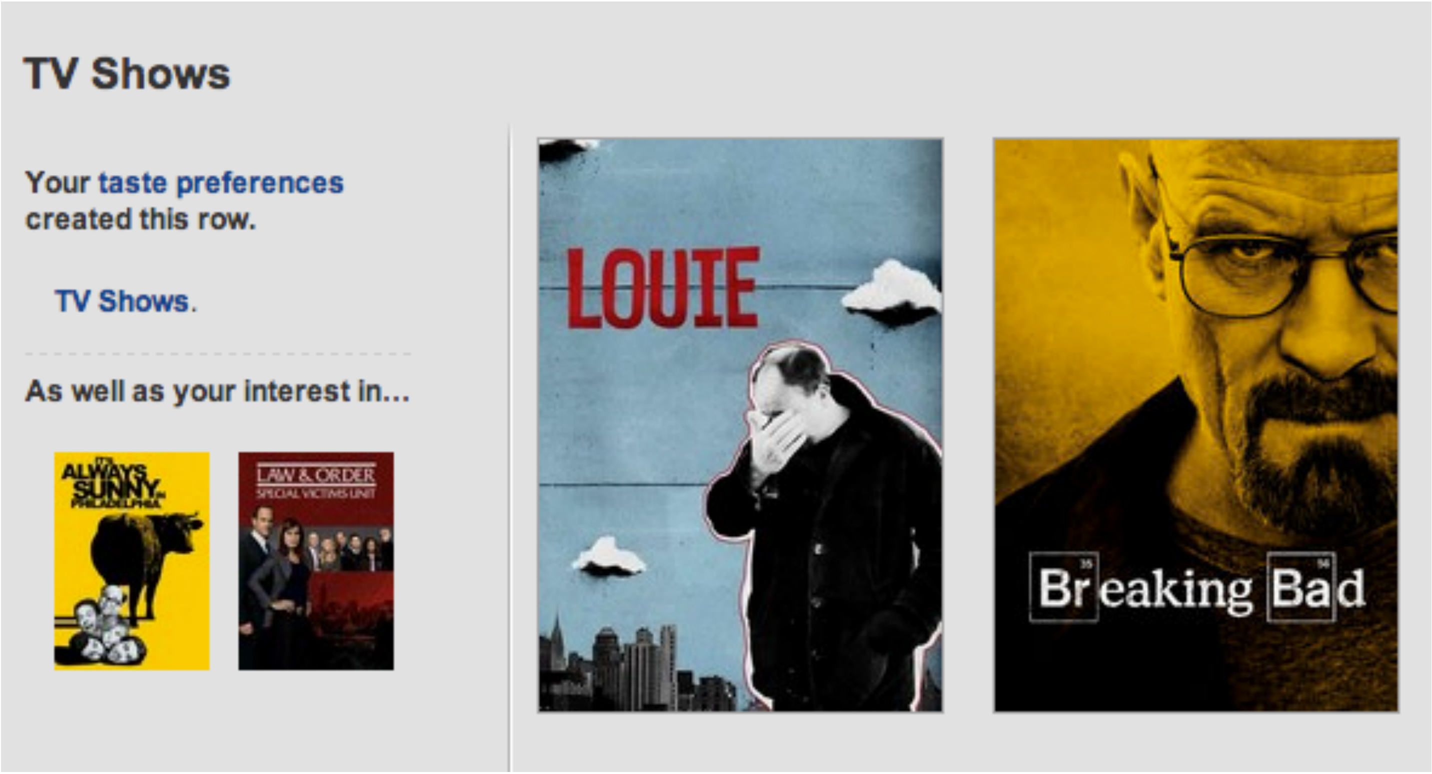
13 Things that Don't Make Sense: The...
› Michael Brooks
Paperback
(65)
~~$15.95~~ $12.49



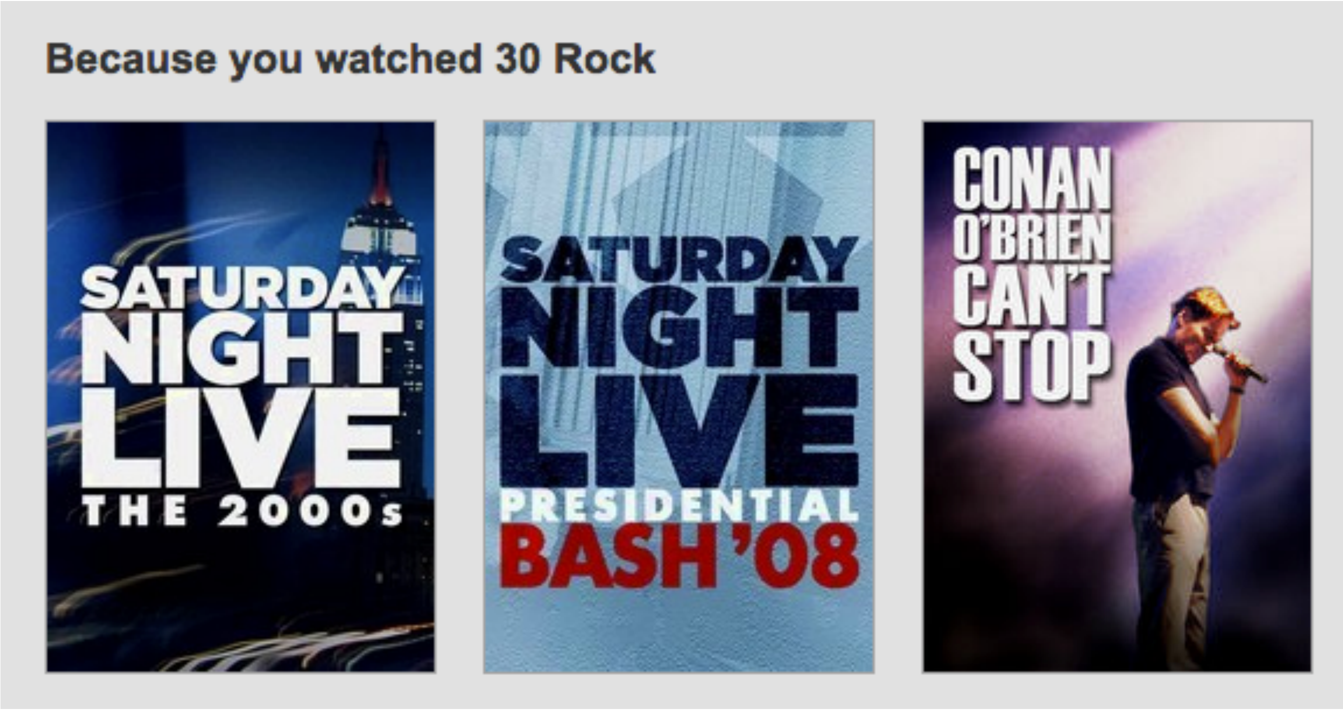
Free Radicals in Biology and Medicine
Barry Halliwell, John Gutteridge
Paperback
(6)
~~$90.00~~ $75.78

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

EXAMPLES – NETFLIX



EXAMPLES – NETFLIX



EXAMPLES – YOUTUBE

Recommended for you because you watched
Sugar Minott - Oh Mr Dc (Studio One)

Mikey Dread - Roots and Culture

by klaxonklaxon · 1,164,133 views

Lyrics:
Now here comes a special request
To each and everyone

Recommended for you because you watched
Thelonious Monk Quartet - Monk In Denmark

Bill Evans Portrait in Jazz (Full Album)

by hansgy1 · 854,086 views

Bill Evans Portrait in Jazz 1960
1. Come Rain or Come Shine - 3.19 (0:00)
2. Autumn Leaves - 5.23 (3:24)

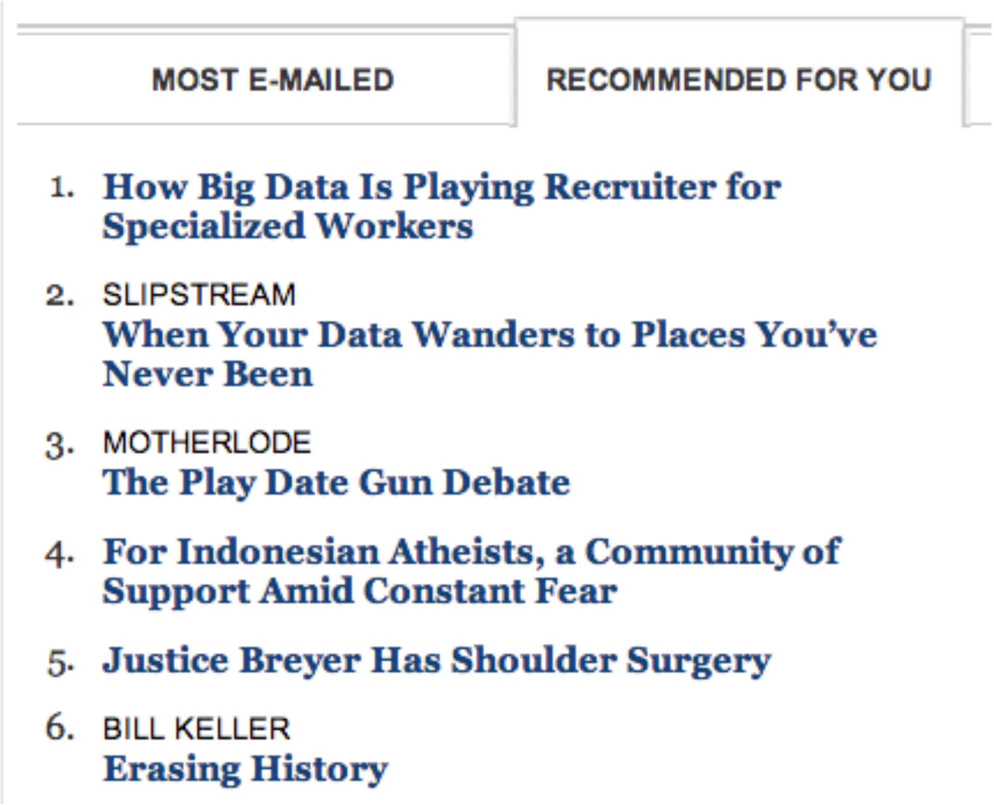
Recommended for you because you watched
Bob Marley One Drop

Bob Marley - She's gone

by Dionysios29 · 1,058,704 views

This is one of the eleven songs of album Kaya that Bob Marley and The Wailers creative in 1978.
Lyrics:

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.

I. CONTENT-BASED FILTERING

Content-based filtering *begins by mapping each item into a feature space. Both users and items are represented by vectors in this space.*

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Two approaches:

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

2) Create features from user+item pairs and use ML algorithm to predict like/dislike

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Each sample/row is a user/item pair with some outcome:

Outcome = Bought
User features - (purchase power, demographics)
Item features - category, metadata
User/Item features - user/item category overlap

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

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

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

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

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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items (movies):

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Mission Impossible = (3, -5, 5)

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

users:

Jason = (-3, 2, -2)

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

items (movies):	*predicted ratings*:*
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*

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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.

Content-based filtering has some difficulties:

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- *need to map each item into a feature space (usually by hand!)*
- *recommendations are limited in scope (items must be similar to each other)*
- *hard to create cross-content recommendations (eg books/music films…this would require comparing elements from different feature spaces!)*

II. COLLABORATIVE FILTERING

The purpose of a **recommendation system** *is decide whether an item (product, event, movie, song) is something a user is highly likely to be interested*

REFRAMED AS:

The purpose of a **recommendation system** *is to predict a rating that a user will give an item that they have not yet rated.*

Collaborative filtering *refers to a family of methods for predicting ratings where instead of thinking about users and items in terms of a feature space, we are only interested in the existing user-item ratings themselves.*

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In this case, our dataset is a ratings matrix whose columns correspond to items, and whose rows correspond to users.

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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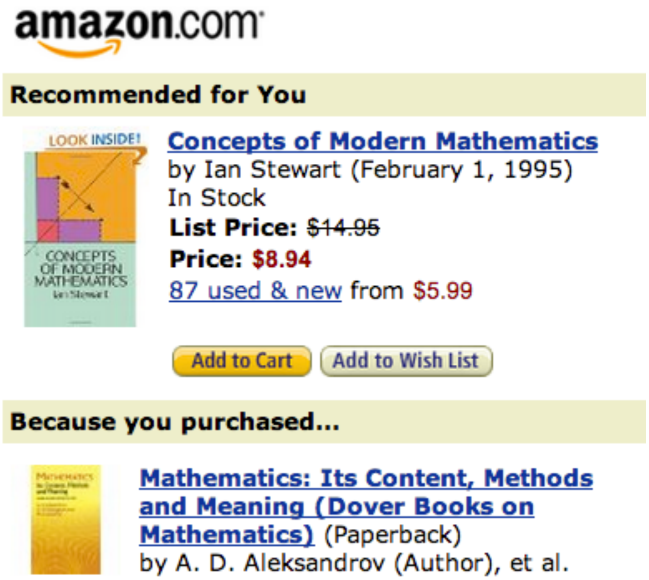
This is also called **memory-based CF** *or* **neighborhood** methods

ITEM-BASED COLLABORATIVE FILTERING

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



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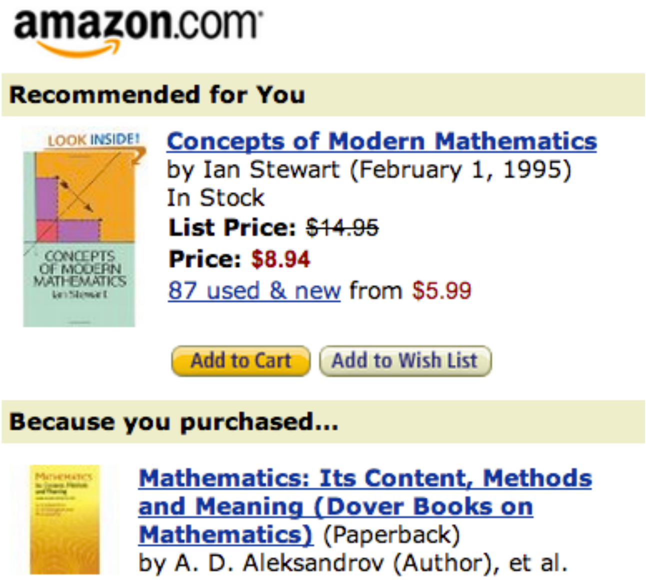

NOTE

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.

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

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

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

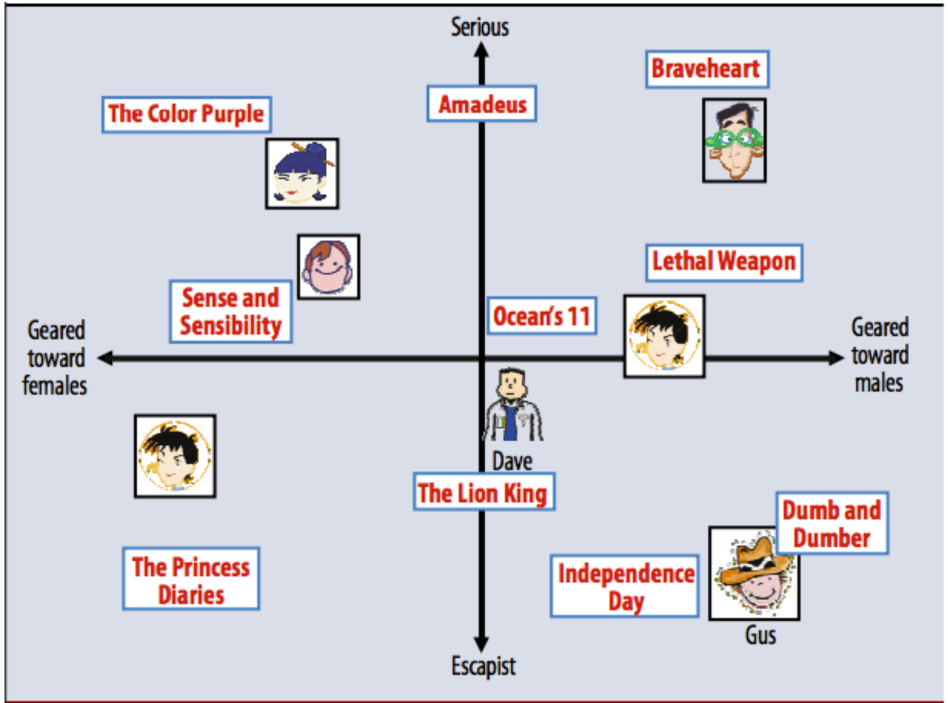

Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

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

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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.

But they do 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)*

- **cold start problem**: *need lots of data on new user or item before recommendations can be made*

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

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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.*

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