GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

RECOMMENDATION SYSTEMS

I. CONTENT-BASED FILTERING
II. COLLABORATIVE FILTERING
III. A MATRIX FACTORIZATION MODEL
IV. THE NETFLIX PRIZE

EXERCISE:
V. RECOMMENDING WITH PYTHON

A **recommendation system** will predict a *rating* that a *user* will give an *item* that they have not yet rated.

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

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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*.

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In **content-based filtering**, items are mapped into a featur
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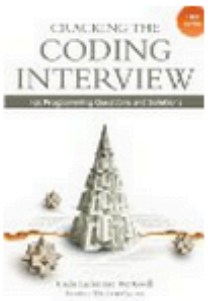
NOTE

Collaborative filtering strategies can still be item-based!

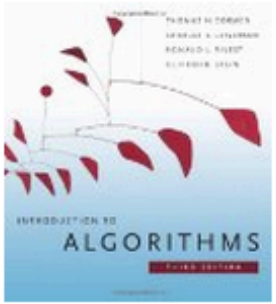
In contrast, the only data under consideration in **collaborative filtering** are user-item ratings, and recommendations depend on *user preferences*.

EXAMPLES – AMAZON

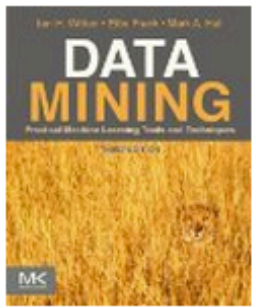
Recommendations for You in Books



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

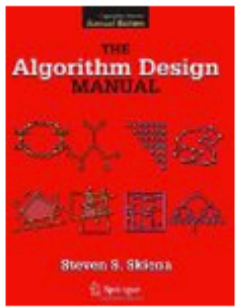


Introduction to Algorithms
Thomas H. Cormen, Charles E...
Hardcover
★★★★☆ (85)
~~$92.00~~ $80.00
Why recommended?



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

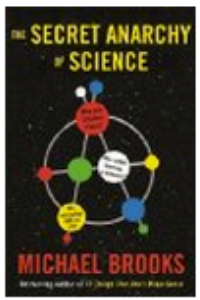
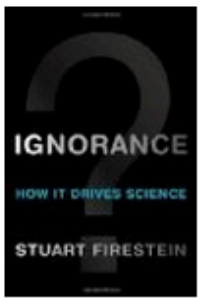
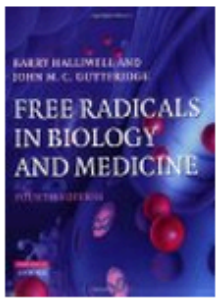
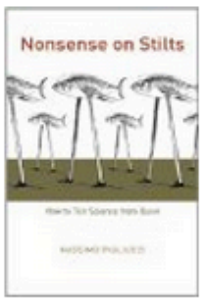
Elements of Programming Interviews...
› Amit Prakash, Adnan Aziz, Tsung-Hsien Lee
Paperback
★★★★½ (25)
~~$29.99~~ $26.18
Why recommended?



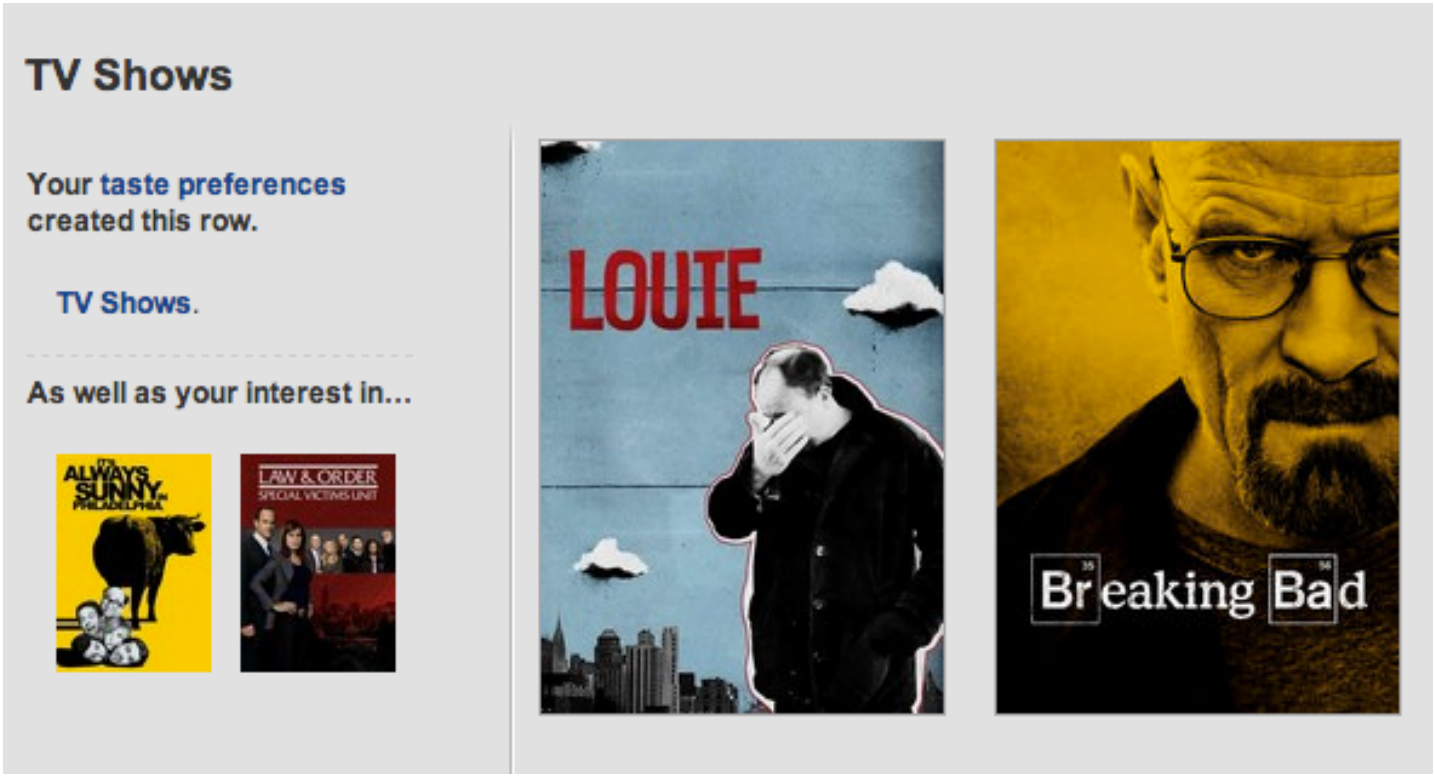
The Algorithm Design Manual
› Steve Skiena
Paperback
★★★★½ (47)
~~$89.95~~ $71.84
Why recommended?

EXAMPLES – AMAZON

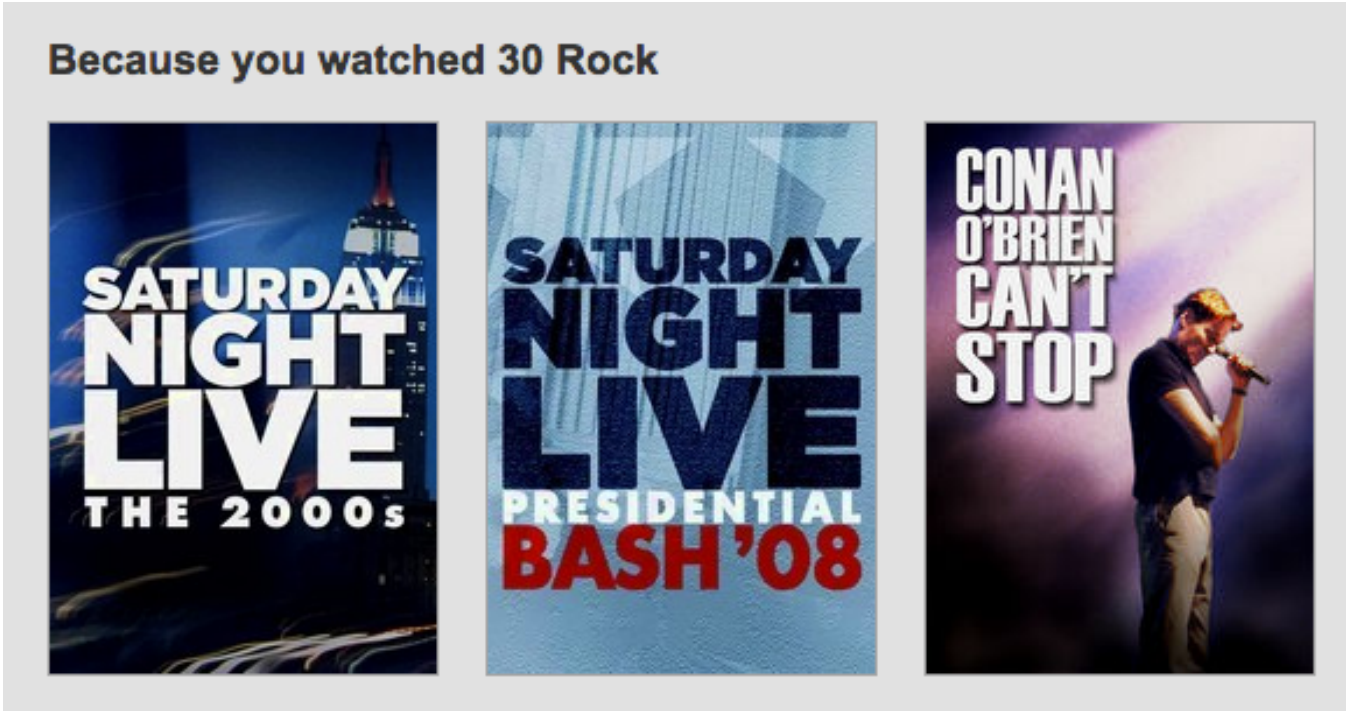
Inspired by Your Wish List

You wished for	Customers who viewed this also viewed			
				
The Secret Anarchy of Science	Ignorance: How It Drives Science	13 Things that Don't Make Sense: The...	Free Radicals in Biology and Medicine	Nonsense on Stilts: How to Tell...
› Michael Brooks	› Stuart Firestein	› Michael Brooks	Barry Halliwell, John Gutteridge	› Massimo Pigliucci
Paperback	Hardcover	Paperback	Paperback	Paperback
★★★★☆ (6)	★★★★½ (31)	★★★★☆ (65)	★★★★★ (6)	★★★½☆ (35)
	~~$21.95~~ $13.02	~~$15.95~~ $12.49	~~$90.00~~ $75.78	~~$20.00~~ $11.94

EXAMPLES – NETFLIX



EXAMPLES – NETFLIX



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

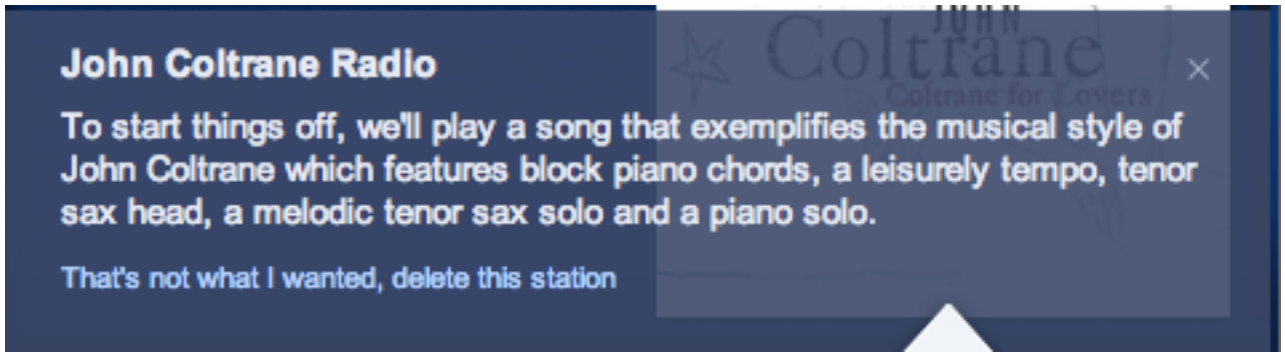
Bill Evans Portrait in Jazz (Full Album)
by hansgy1 · 854,086 views

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:


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

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

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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NOTE

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

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

users:
Alice = (-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.

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 has some difficulties:

Content-based filtering has some difficulties:

- 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

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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NOTE

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

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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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Item-based CF uses ratings data to create an item-item *similarity matrix*.

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NOTE

This is similar 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.

Customers Who Bought This Item Also Bought

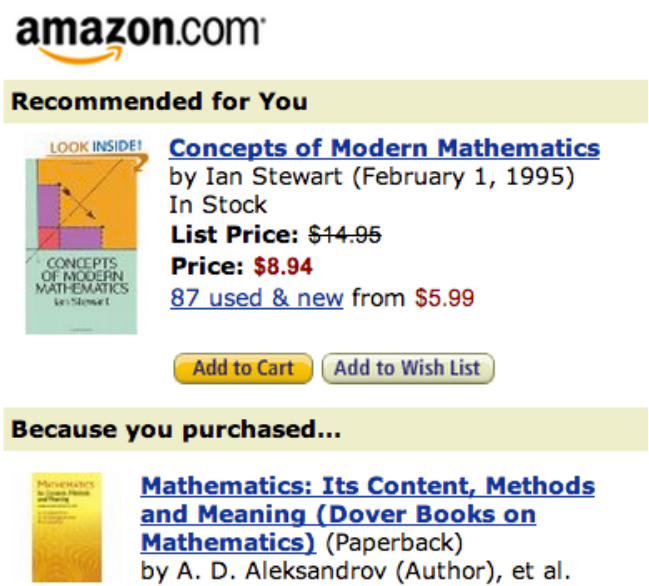
Pitch Dark (NYRB Classics)
› Renata Adler
Paperback
$11.54

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

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



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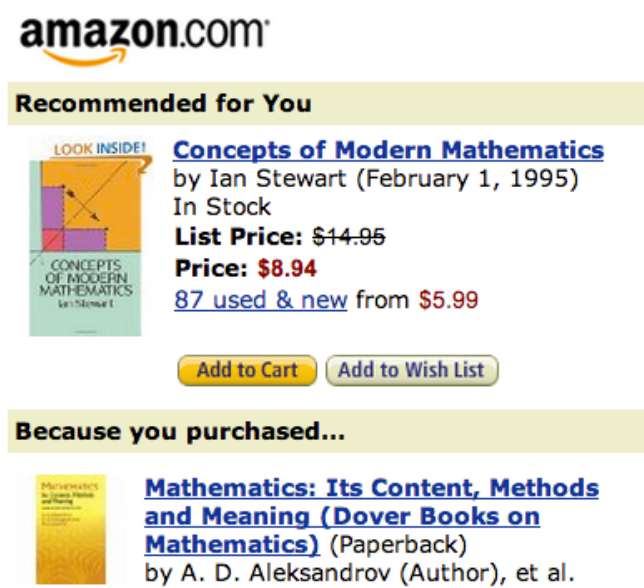

NOTE

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.

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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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As before, values in the item vectors represent the degree to which an item *exhibits* a given feature, and values in the user vectors represent user *preferences* for a given feature.

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

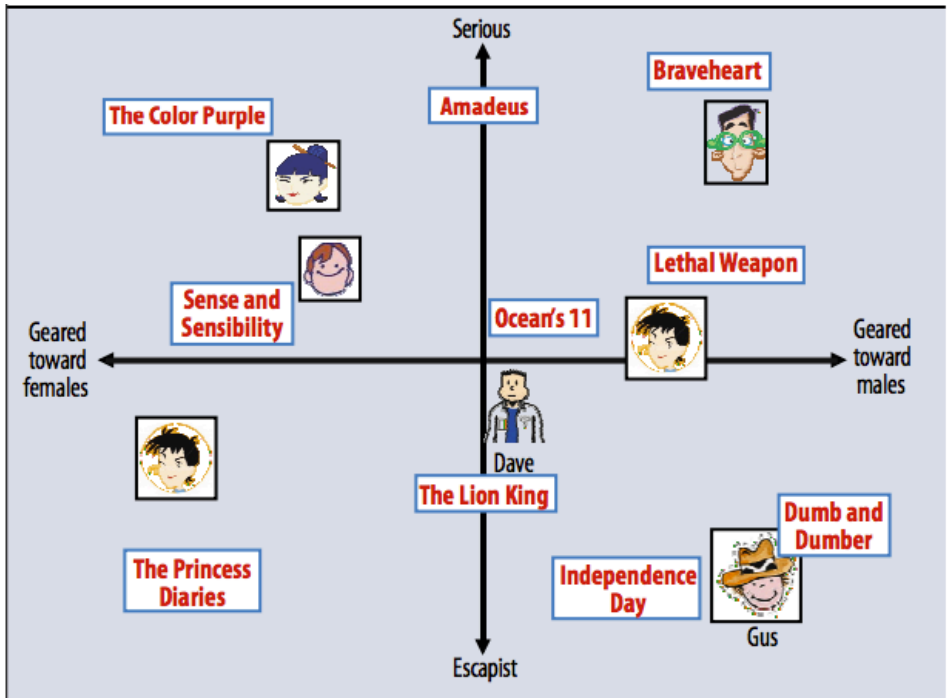

Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

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

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.

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)
- susceptible to fraud (e.g., *shilling attacks*)
- **cold start problem**: need lots of data on new user or item before recommendations can be made

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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 (e.g., 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 (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.

III. A MATRIX FACTORIZATION MODEL

Matrix factorization decomposes the ratings matrix and maps users and items into a low-dimensional vector space spanned by a basis of latent factors.

Matrix factorization decomposes the ratings matrix and maps users and items into a low-dimensional vector space spanned by a basis of latent factors.

Predicted ratings are given by inner products in this space, so for user *u* and item *i* we can write:

$$\hat{r}_{ui} = q_i^T r_u$$

Factoring the ratings matrix via SVD leads to difficulty, since the matrix is typically sparse and therefore our information about the data is incomplete.

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Interpolating missing values is an expensive process and can lead to inaccurate predictions, so we need another way to perform this factorization.

One possibility is to learn the feature vectors using the observed ratings only. Since this dramatically reduces the size of the ratings matrix, we have to be careful to avoid overfitting.

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We can learn these feature vectors by minimizing the loss function:

$$\min_{q,p} \sum_{(u,i)\in\kappa} (r_{ui} - q_i^T p_u)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

where κ denotes the set of known ratings, and λ is a hyperparameter.

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NOTE

The loss function has two unknowns (q, p) and so is not convex!

This can be minimized using a method called *alternating least squares*.

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We can capture these biases in our model by generalizing $\hat{r}_{ui}$:

$$\hat{r}_{ui} = \mu + b_i + b_u + q_i^T r_u$$

Here μ is a global average rating, b_i is the item bias, b_u is the user bias, and $q_i^T r_u$ is the user-item interaction.

With this generalization, our minimization problem becomes:

$$\min_{q,p,b} \sum_{(u,i)\in\kappa} (r_{ui} - \mu - b_u - b_i - q_i^T p_u)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2 + b_u^2 + b_i^2)$$

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Further modifications can be made to this model (incorporating implicit feedback, capturing temporal effects, attaching confidence scores to predictions), and you can find some of the details in the readings.

IV. THE NETFLIX PRIZE

The Netflix prize was a competition to see if anyone could make a 10% improvement to Netflix's recommendation system (accuracy measured by RMSE).

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The ratings matrix contained >100mm numerical entries (1-5 stars) from ~500k users across ~17k movies. The data was split into train/quiz/test sets to prevent overfitting on the test data by answer submission (this was a clever idea!)

The competition began in 2006, and the grand prize was eventually awarded in 2009. The winning entry was a stacked ensemble of 100's of models (including neighborhood & matrix factorization models) that were blended using boosted decision trees.

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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).

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The competition did much to spur interest and research advances in recsys technology, and the prize money was donated to charity.

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?

V. EXERCISE