GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 14: RECOMMENDATION SYSTEMS

LAST TIME:

- ENSEMBLE METHODS
- BAGGING
- BOOSTING
- RANDOM FORESTS

QUESTIONS?

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

EXERCISE:
V. RECSYS IN PYTHON WITH MOVIELENS DATA

The purpose of a **recommendation system** *is to 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.

There are two general approaches to recsys design:

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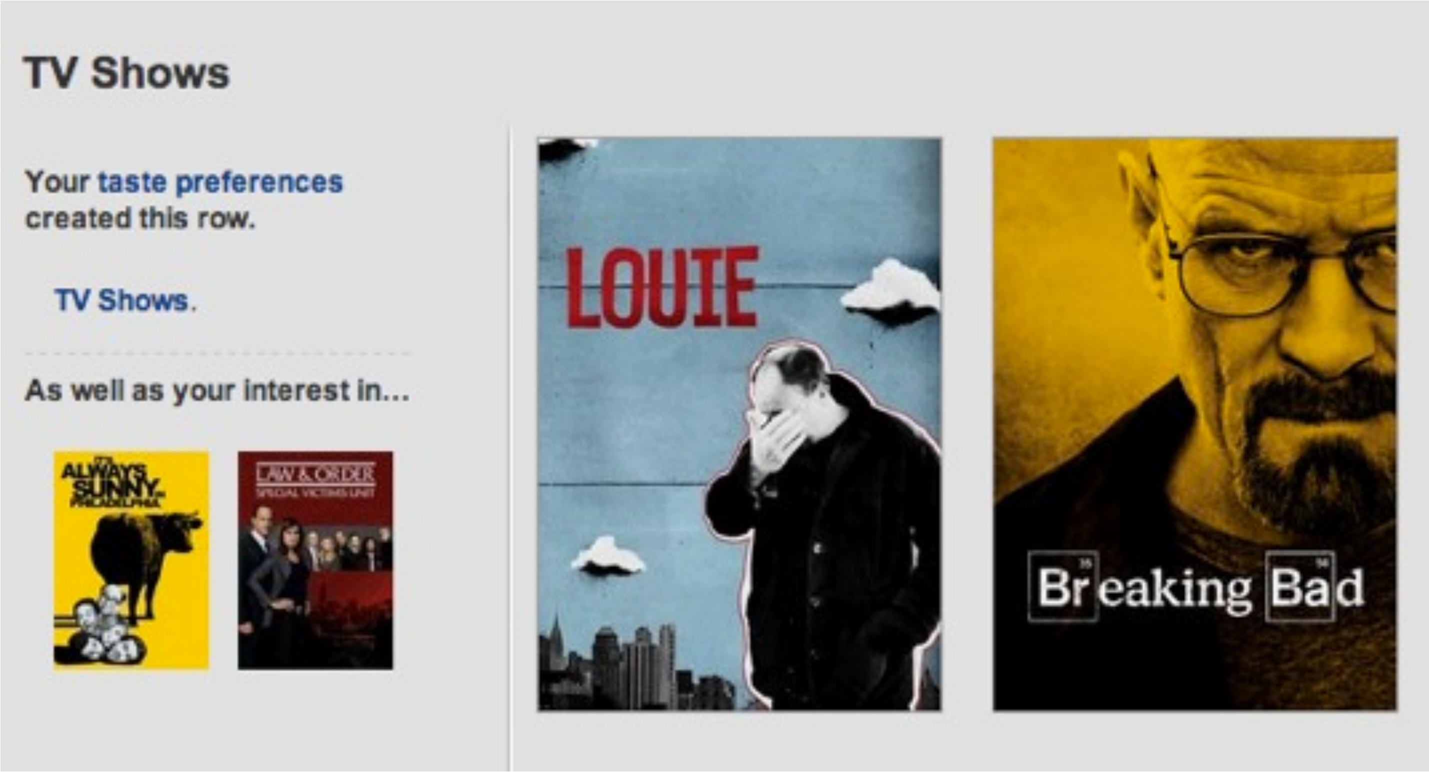
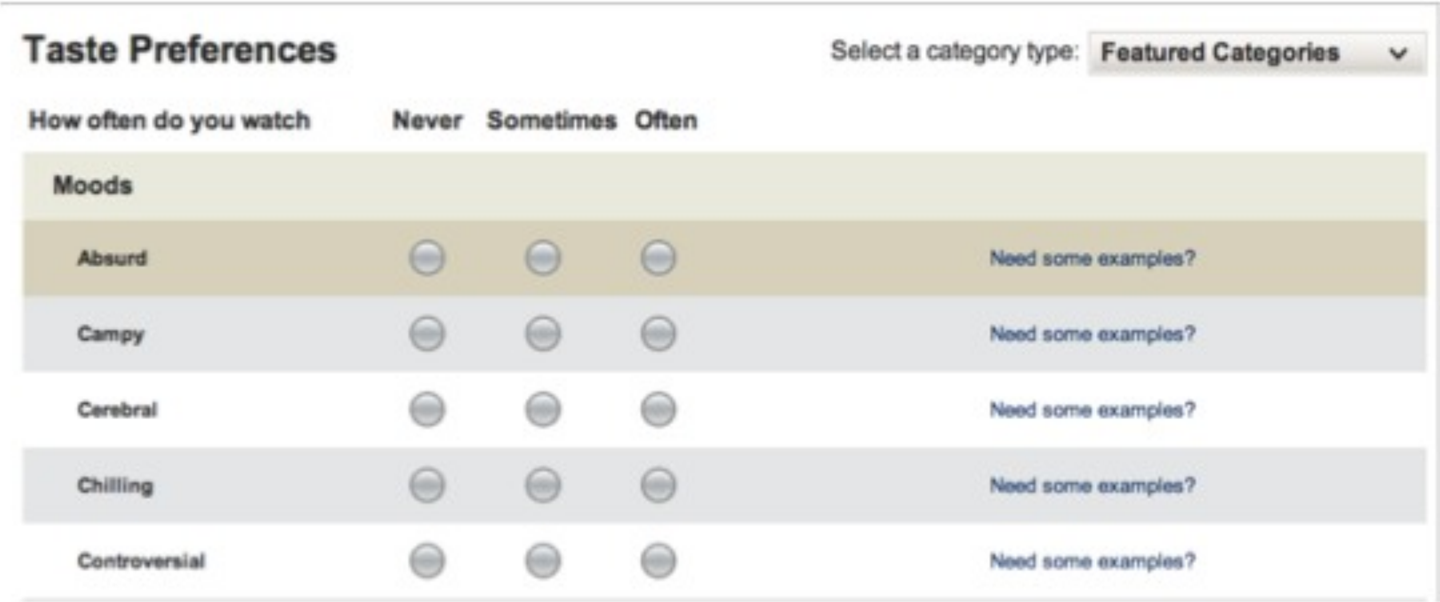
Content-based filtering*: items are mapped into a feature space, and recommendations depend on item characteristics.*

Collaborative filtering: *recommendations are only based on user-ratings*

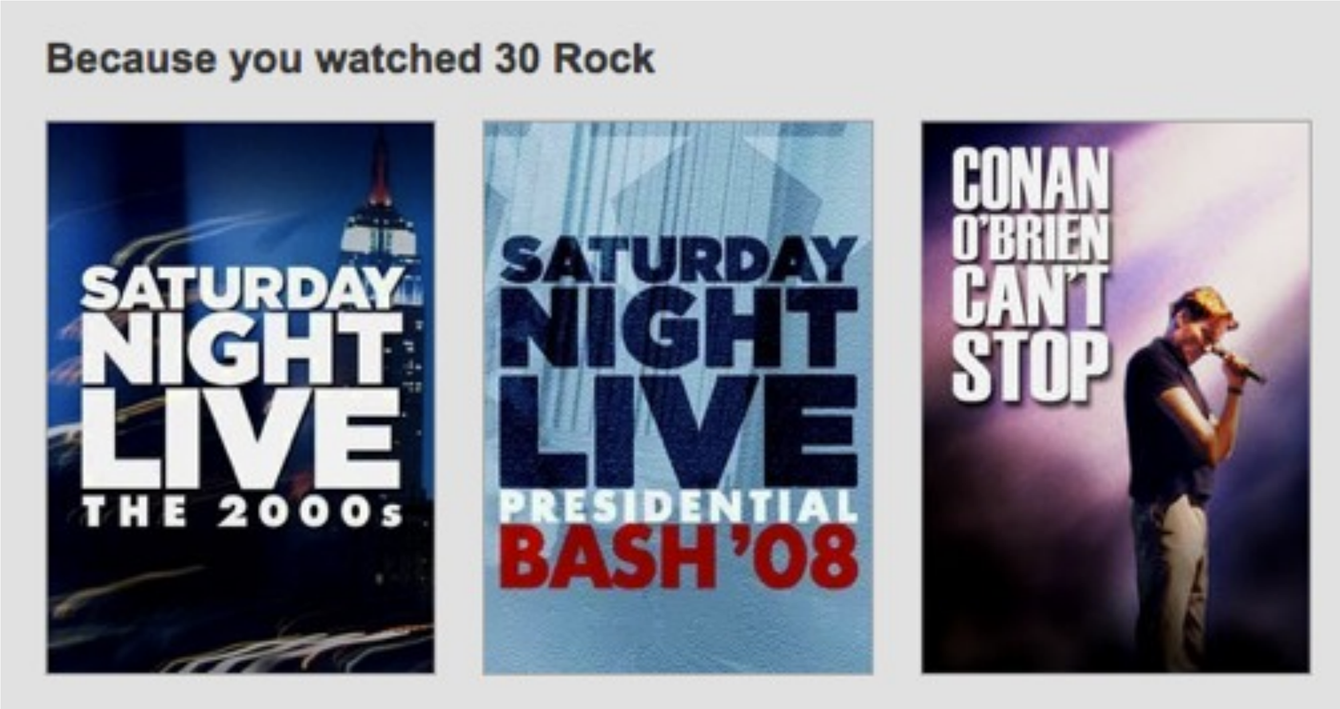
EXAMPLES – NETFLIX



EXAMPLES – NETFLIX: CONTENT-BASED FILTERING

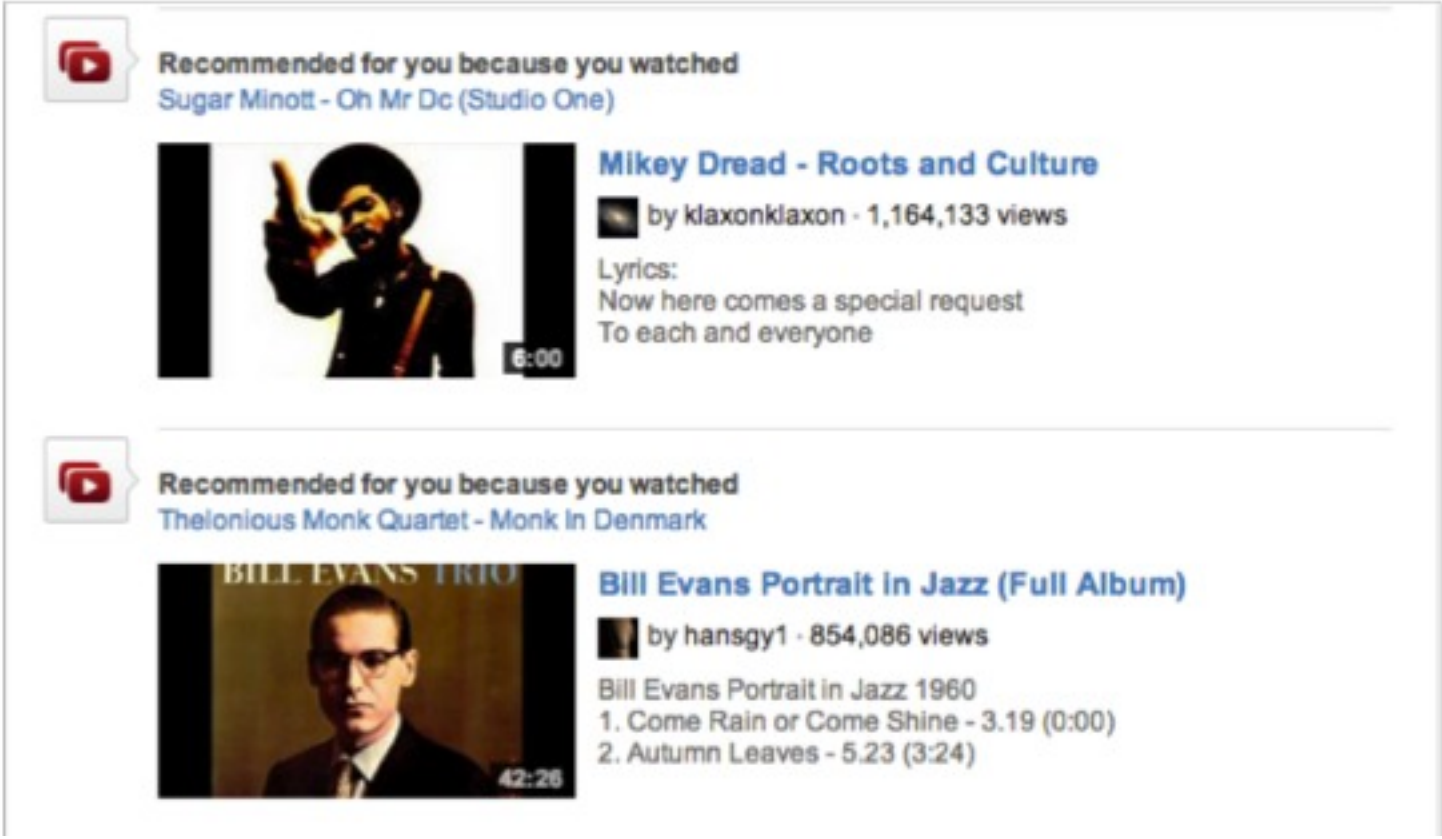


EXAMPLES – NETFLIX: ITEM BASED COLLABORATIVE FILTERING

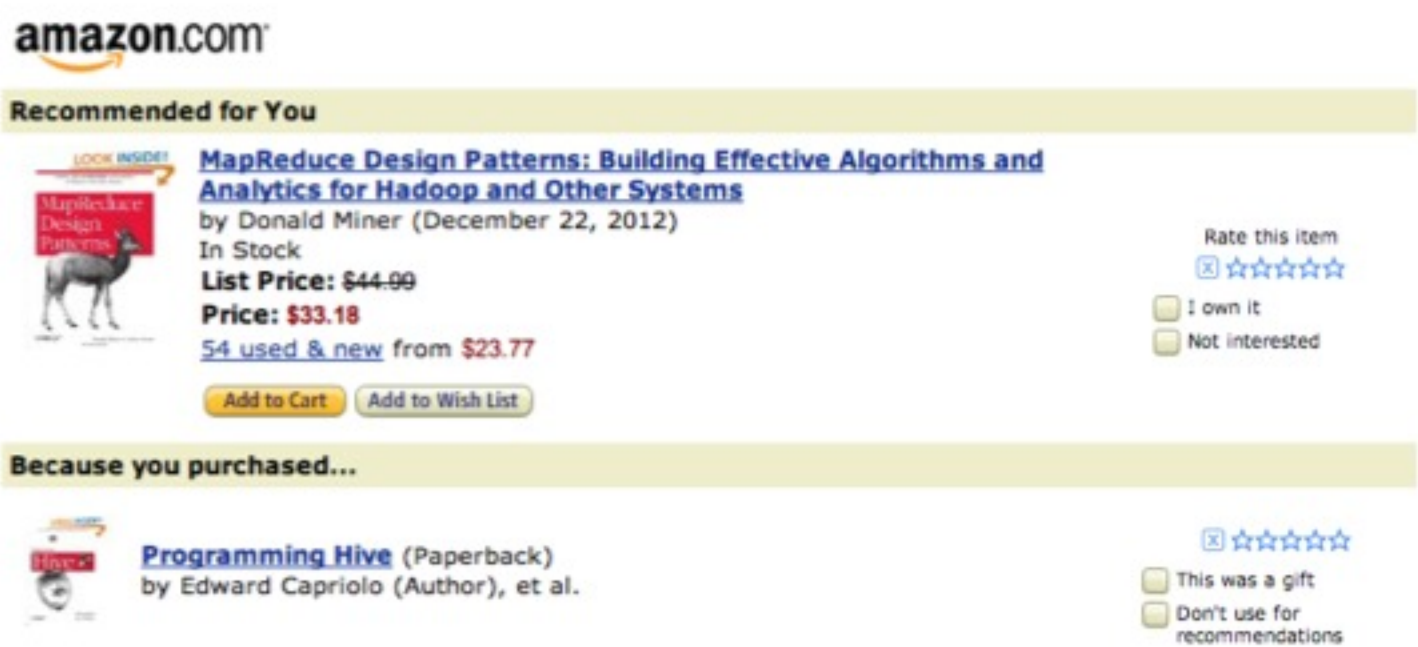


EXAMPLES – NETFLIX: USER BASED COLLABORATIVE FILTERING

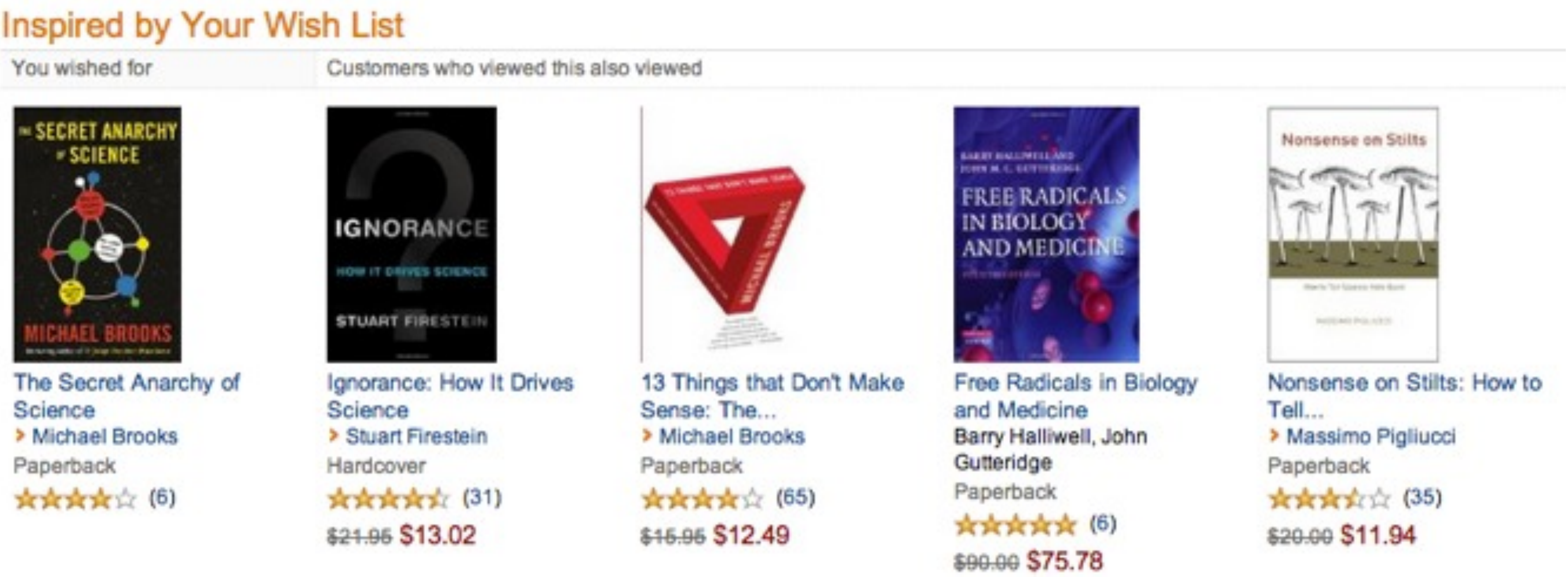
EXAMPLES – YOUTUBE: ITEM-BASED COLLABORATIVE FILTERING

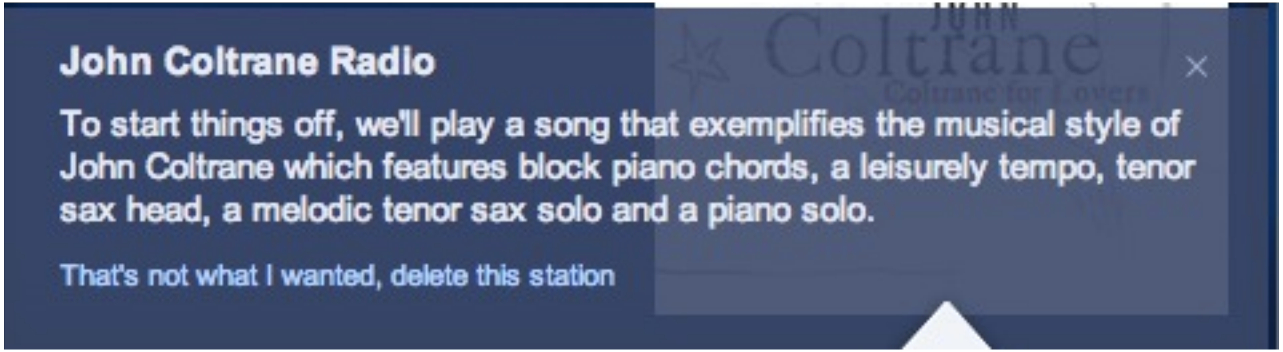


EXAMPLES – AMAZON: ITEM-BASED COLLABORATIVE FILTERING



EXAMPLES – AMAZON: WHAT ABOUT THIS ONE?




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

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.

I. CONTENT-BASED FILTERING

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NOTE

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

Movies	big box office	aimed at kids	famous actors
Finding Nemo	5	5	2
Mission Impossible	3	-5	5
Jiro Dreams of Sushi	-4	-5	-5

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User	Big box office	Aimed at kids	Famous actors
Jayne	-3	2	-2
Bob	5	-4	5

Movies	big box office	aimed at kids	famous actors	
Finding Nemo	5 x -3	5 x 2	2 x -2	= -9
Mission Impossible	3 x -3	-5 x 2	5 x -2	= -29
Jiro Dreams of Sushi	-4 x -3	-5 x 2	-5 x -2	= +12

User	Big box office	Aimed at kids	Famous actors
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Bob	5	–4	5

Movies	big box office	aimed at kids	famous actors	
Finding Nemo	5 x 5	5 x -4	2 x 5	= +15
Mission Impossible	3 x 5	-5 x -4	5 x 5	= +60
Jiro Dreams of Sushi	-4 x 5	-5 x -4	-5 x 5	= -65

User	Big box office	Aimed at kids	Famous actors
Jayne	-3	2	-2
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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 challenges:

- *need to map each item into a feature space (usually by hand!)*
- *recs 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

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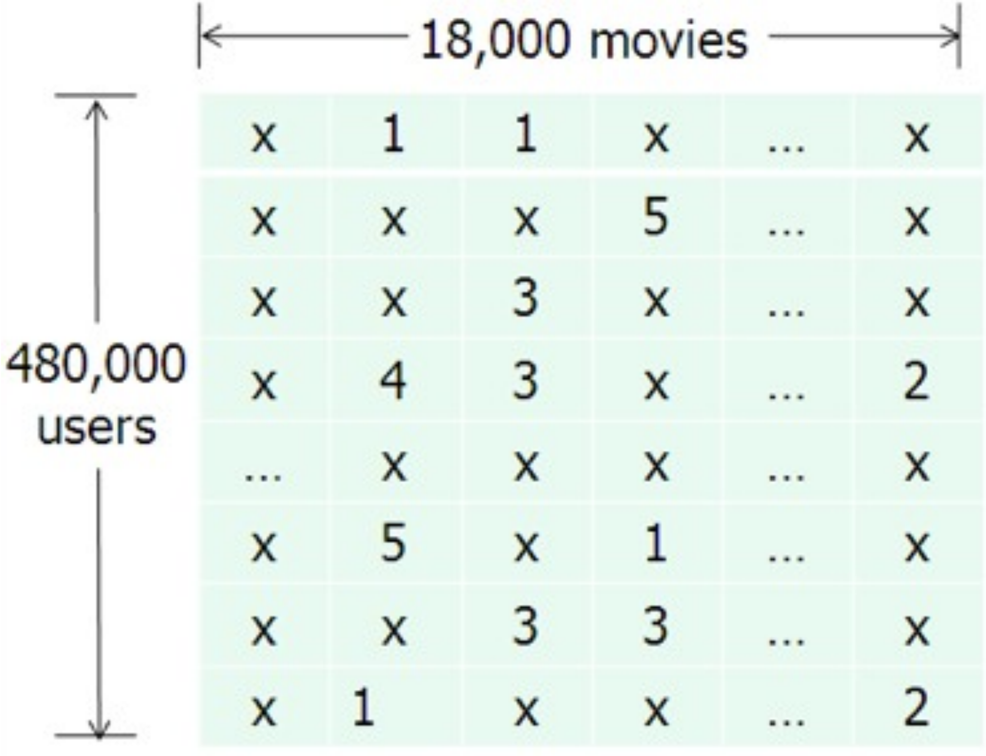
Assumption: users get value from recommendations based on other users with similar tastes

RATINGS MATRIX



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

NOTE

This matrix will always be *sparse*!

Collaborative filtering can be done in two different ways.

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Memory-based: *uses a sample of the users that are most similar to a given user to predict ratings on unrated items.*

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Memory-based: *uses a sample of the users that are most similar to a given user to predict ratings on unrated items.*

Model-based: *extracts complex patterns from the dataset, and uses that as a "model" to make recommendations without having to use the dataset every time*

*For a given user (u_i), find users that are most similar (e.g. **vector similarity** or **Pearson correlation coefficient**)*

For a given item i_j, the predicted rating of u_i is the average of the known ratings of i_j within the group of similar users.

We just talked about user-based CF, but the same process can be done for item-based CF.

Item-based CF is more commonly used that user-based CF, why do you think that is?

Model-based collaborative filtering abandons the neighbor 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.

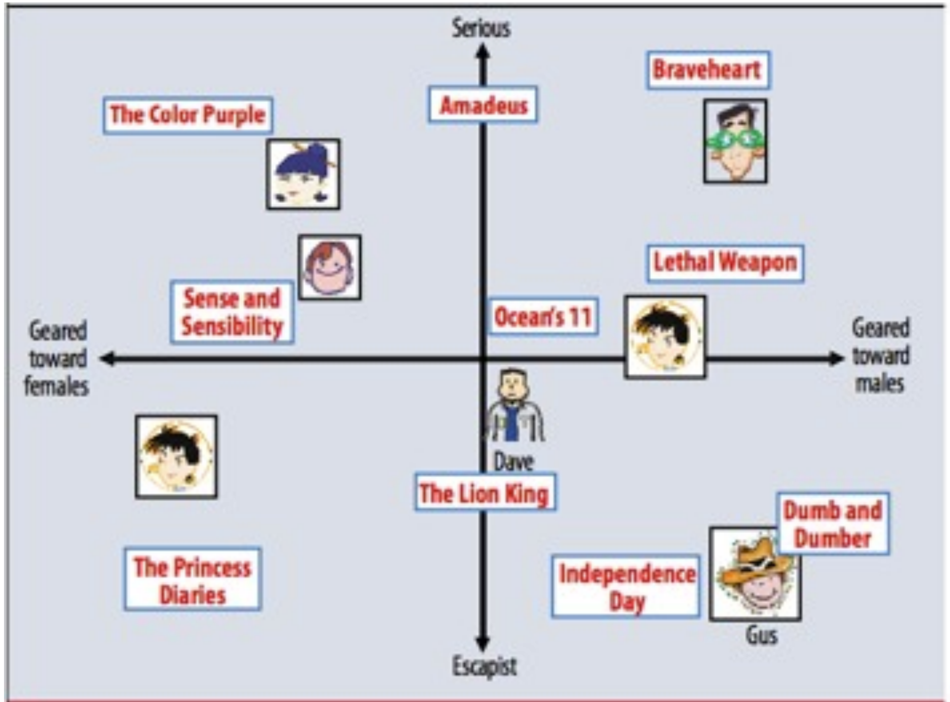

Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

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

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.

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

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

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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 look up the details in the references.

IV. THE NETFLIX PRIZE

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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!)

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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?