Master on Foundations of Data Science

Recommender Systems

Collaborative Recommender Systems

Santi Seguí | 2019-2020

Generalization of Supervised Classification

Features

	x1	x2	x3	x4	x5	x6	x7
U1	13,1	4	2,34	1	5,3	0,32	?
U2	1,1	3	2	4,5	4,5	9,9	?
U3	4	4,4	4,5	0,3	7,4	2,3	?
U4	9,3	32	3	5	3,2	7.54	?
U5	-2	3	5.3	5,3	3,5	9,9	?
U6	-6,3	46,3	6,2	5	8,3	4,5	?
U7	3,5	5	3,2	5,3	6,2	7,8	?

Items

	I1	I2	I3	I4	I5	I6	I7
U1	1	?	?	?	?	?	3
U2	?	3	?	4,5	4,5	?	?
U3	4	?	4,5	?	?	?	4
U4	?	?	3	5	?	?	?
U5	?	3	?	?	3,5	?	?
U6	?	?	?	5	?	4,5	3
U7	3,5	5	?	5	?	?	3

Collaborative-based methods

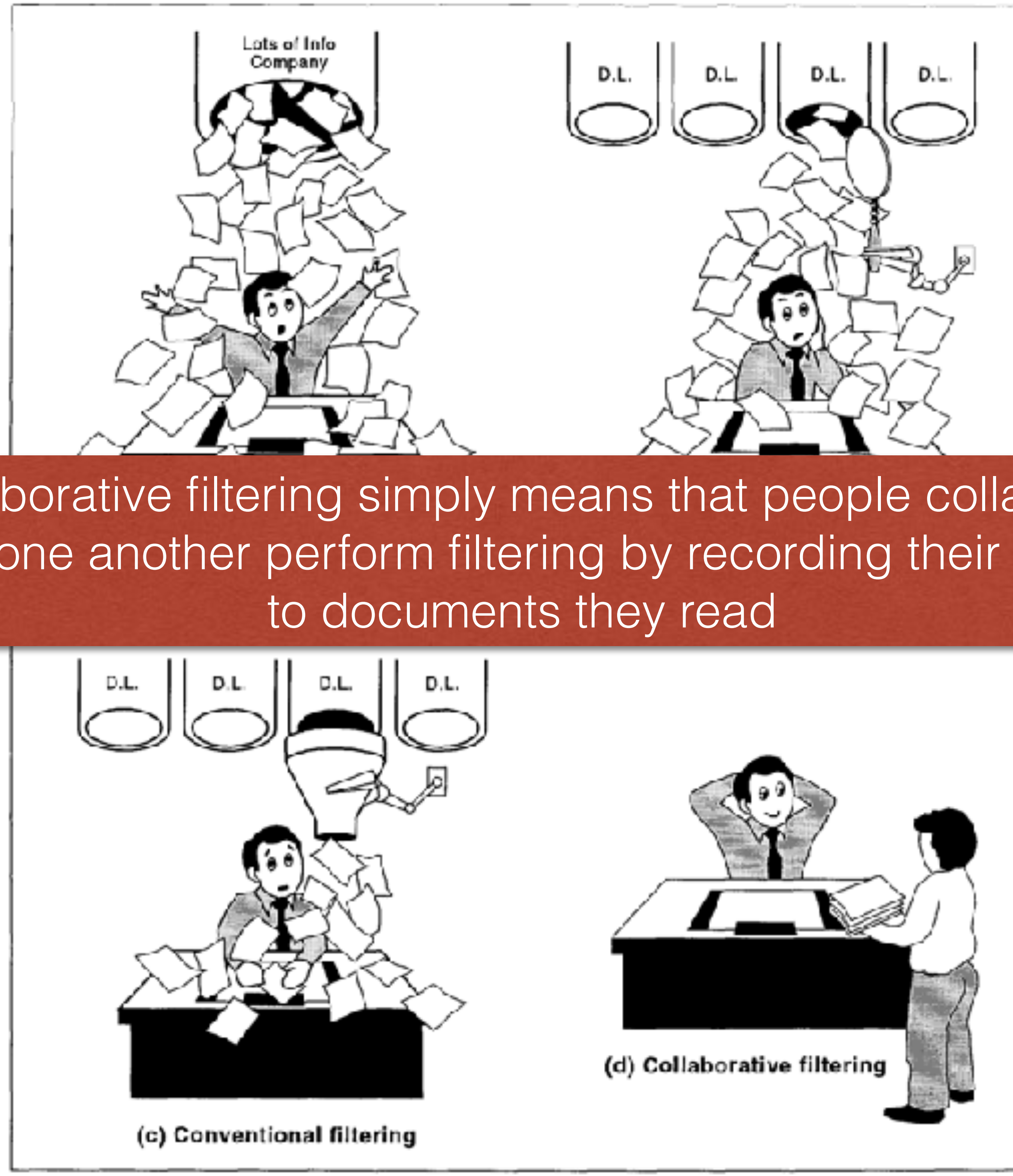
Conceptual goal:
Give me recommendation based on a collaborative approach that leverages the ratings and actions of my peers and myself

Input:
User ratings + community ratings

Using COLLABORATIVE FILTERING to Weave an Information TAPESTRY

David Goldberg, David Nichols, Brian M. Oki, and Douglas Terry

Tapestry is an experimental mail system developed at the Xerox Palo Alto Research Center. The motivation for Tapestry comes from the increasing use of electronic mail, which is resulting in users being inundated by a huge stream of incoming documents [2, 7, 12]. One way to handle large volumes of mail is to provide mailing lists, enabling users to subscribe only to those lists of interest to them. However, as illustrated in Figure 1, the set of documents of interest to a particular user rarely map neatly to existing lists. A better solution is for a user to specify a *filter* that scans all lists, selecting interesting documents no matter what list they are in. Several mail systems support filtering based on a document's contents [3, 5, 6, 8]. A basic tenet of the Tapestry work is that more effective filtering can be done by involving humans in the filtering process.



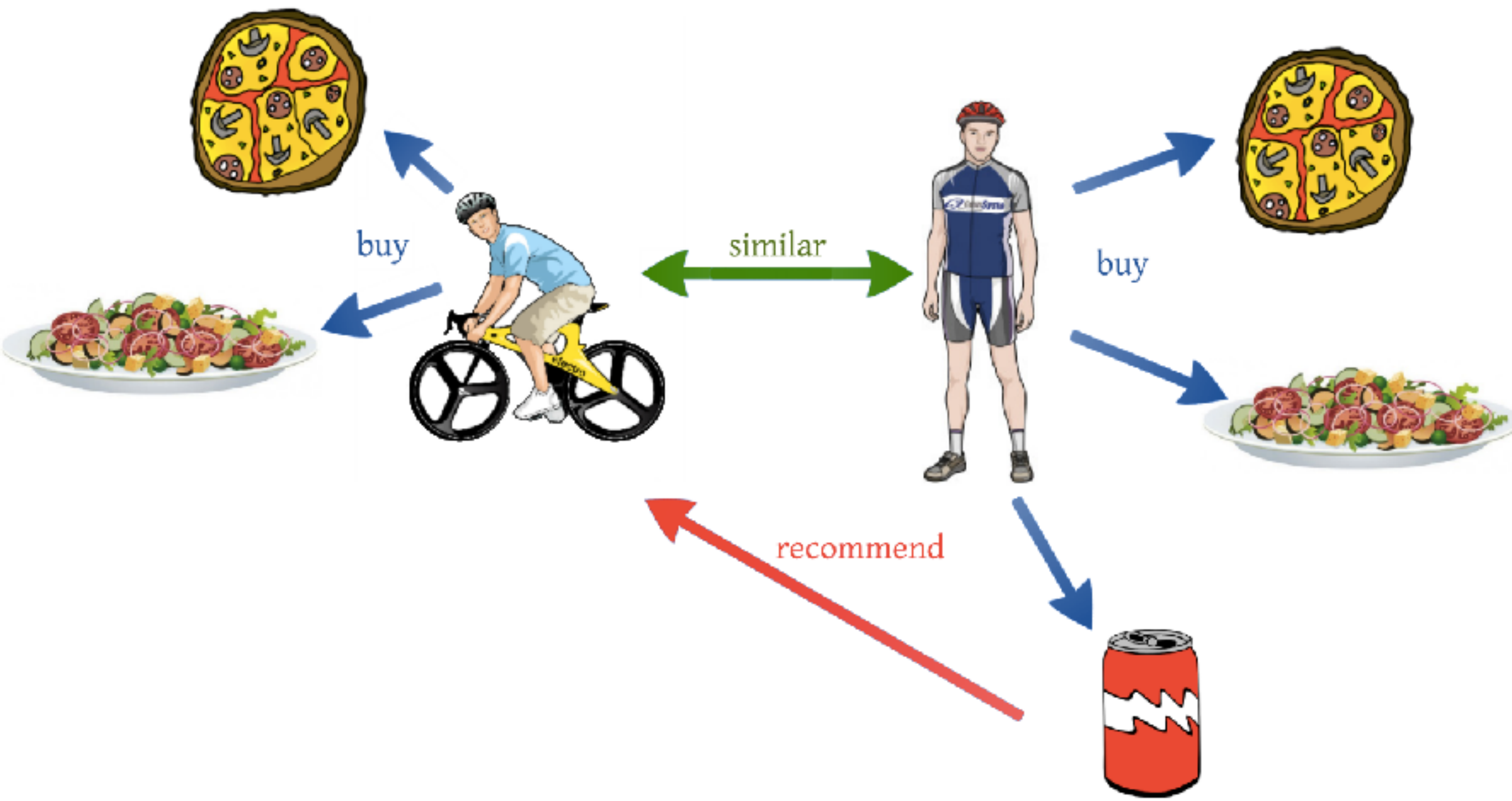
Collaborative filtering simply means that people collaborate to help one another perform filtering by recording their reactions to documents they read

Image from : http://dl.acm.org/citation.cfm?id=138867

Using collaborative filtering to weave an information tapestry
D Goldberg, D Nichols, BM Oki, D Terry
Communications of the ACM 35 (12), 61-70 — 3887 — 1992

UNIVERSITAT DE BARCELONA

Collaborative filtering



Collaborative filtering

- Collaborative filtering methods are based on collecting and **analyzing a large amount of information** on users' behaviors, activities or preferences and predicting what users will like based on their **similarity to other users**.

- Hypothesis: **Similar users tend to like similar items**.

- Requires a user community.

Rating Matrices

- *R* is the ***m x n*** rating matrix where ***m*** is the number of users and ***n*** the number of items.

- Rating can be defined in a variety of ways:

  - **Continuous ratings**: from -10 to 10

  - **Interval-based ratings**: 5 stars, 3 stars

  - **Ordinal ratings**: {strongly disagree, disagree, neutral, agree and strongly agree}

  - **Binary ratings**: Like/dislike

  - **Unary ratings**: Buy

Collaborative filtering

- **Cold Start**: There needs to be enough other users already in the system to find a match.
- **Sparsity**: If there are many items to be recommended, even if there are many users, the user/ratings matrix is sparse, and it is hard to find users that have rated the same items.
- **First Rater**: Cannot recommend an item that has not been previously rated.
  - New items
  - Esoteric items
- **Popularity Bias**: Cannot recommend items to someone with unique tastes.
  - Tends to recommend popular items.

Two main approaches

1. **Memory-based methods**
    - Neighborhood-based methods
2. **Model-based methods**
    - Machine learning and data mining

Neighborhood-based methods

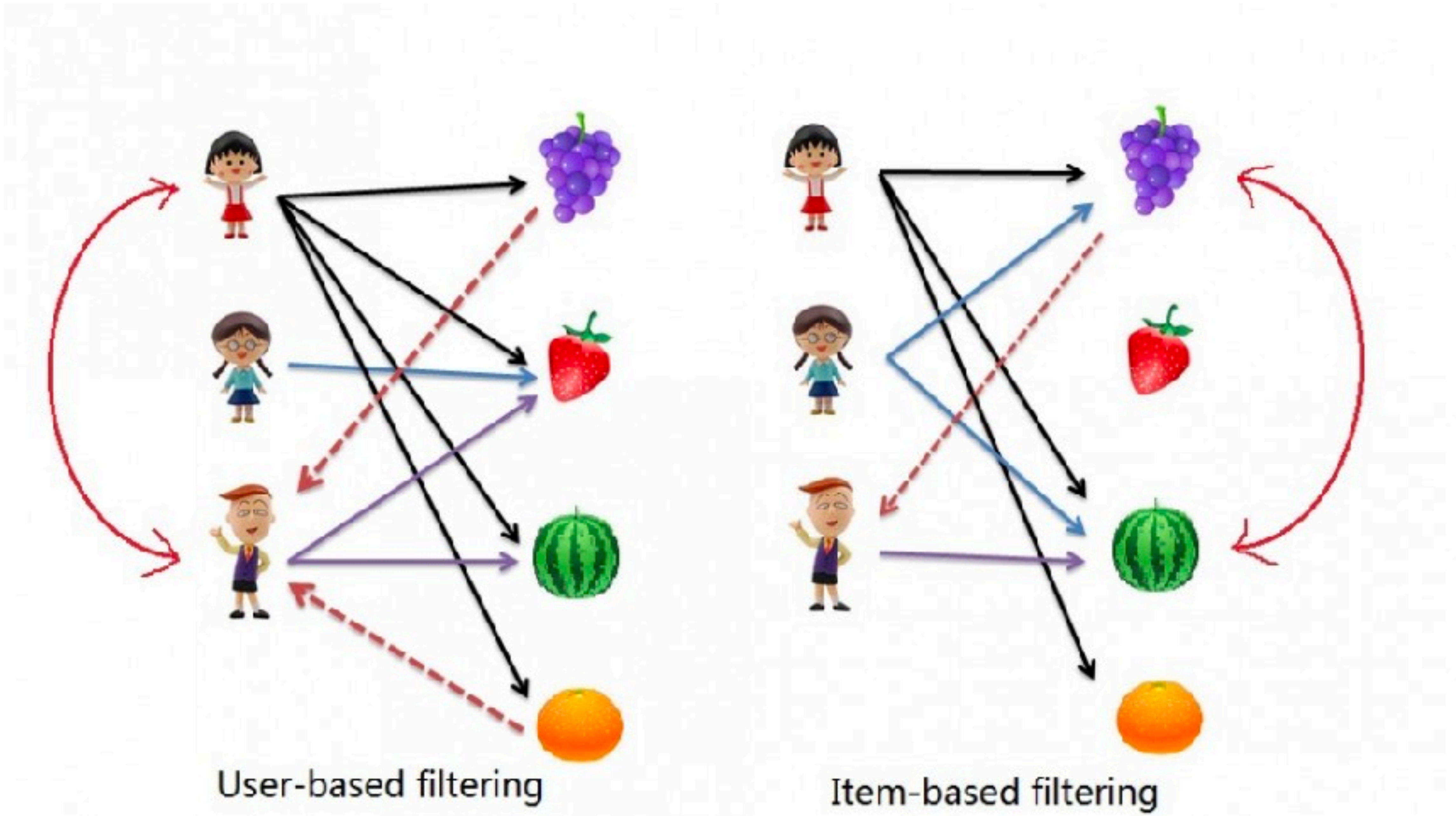
- Neighborhood-based methods were among the earliest algorithms developed for collaborative filtering. These methods are based on the fact that similar users display similar patters or rating behaviors and similar items receive similar ratings.

- There are two primary types of neighborhood -based algorithms:

  - **User-based** CF works like this: take a user U and a set of other users D whose ratings are similar to the ratings of the selected user U. And, use the ratings from those like-minded users to calculate a prediction for the selected user U.

  - In **Item-based** CF you build an item-item matrix determining relationships between pairs of items and using this matrix and data on the current user, infer the user's taste.

Neighborhood-based methods



Let’s see how we can create a **User-Based CF** for Movie recommendations.

EXAMPLE: Movie Recommender System. User-Based Collaborative Filtering

- Given an "active **user**" and an **item** that has not been seen by the **user**, the goal is to estimate the rating for the **item**.

	Superman	Star Wars 1	Matrix	Spiderman
Santi	3	3.5	4.5	¿?
User1	3.5	4	5	5
User2	3	¿?	4.5	3
User3	3.5	5	3.5	2

The basic technique

- User-based nearest-neighbor collaborative filtering
  - Given an **"active user" (e.g. Santi)** and the items not yet seen (**e.g. Spiderman**) the goal is to estimate Santi's rating for the those (e.g. **Spiderman)** items,
    - find a set of users (peers) who has similar tates than the active user (Santi) in the past **and** who have rated the item (Spiderman)
    - use, e.g. the **weighted averaged** of their ratings to predict, if Santi will like them
    - do this for all items Santi has not seen and recommend the best-rated

	Superman	Star Wars 1	Matrix	Spiderman
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How to measure similarity between users?

- The computation of the **similarity** between the items is one **critical step** in the CF algorithms.
- The basic idea in similarity computation between two users *a* and *b* is to first isolate the items commonly rated by both users (set *P*), and then to apply a similarity computation technique to determine the similarity.

Similarity Measures

- Euclidean Distance
- Pearson Correlation
- Person Correlation corrected
- Spearman Correlation
- Cosine Distance

How to measure similarity between users?

- Euclidean distance

$$sim(a,b) = \sqrt{\sum_{p \in P} (r_{a,p} - r_{b,p})^2}$$

- Pearson Correlation

$$sim(a,b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r_a})(r_{b,p} - \bar{r_b})}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r_a})^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r_b})^2}}$$

- Cosine distance

$$sim(a,b) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| * |\vec{b}|}$$

Where:

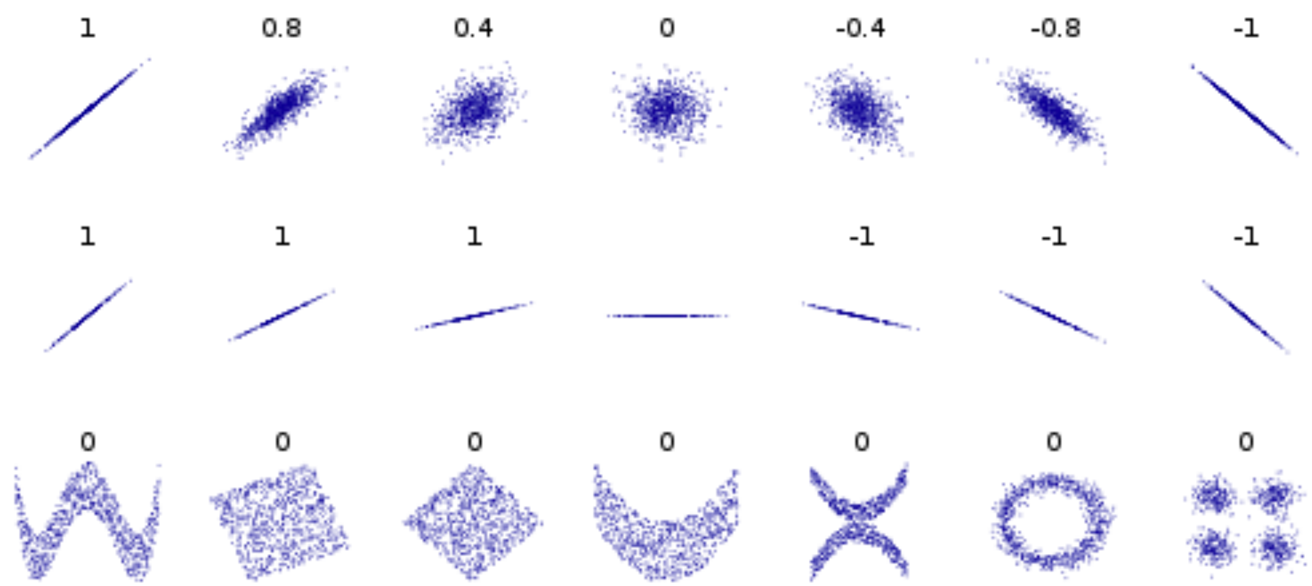
- $sim(a,b)$ is the similarity between user "a" and user "b"
- P is the set of common rated movies by user "a" and "b"
- $r_{a,p}$ is the rating of movie "p" by user "a"
- $\bar{r_a}$ is the mean rating given by user "a"

Similarity Measures Euclidean distance

$$sim(u,v) = \sqrt{\sum_{j \in P} (r_{uj} - r_{vj})^2}$$

CAUTION: if the users use to rate with a different mean and standard deviation euclidean distance can give some problems

Similarity Measures
Pearson Correlation



Negative Values?

Strange correlations are rare,
and do not carries interesting information

Which is the best measure?

Hands on time!

Which is the best similarity function?

- …. there is not a clear answer…but, there are some tips:
  - Pearson Correlation used to work better than euclidean distance since it is based more on the ranking than on the values.
  - In general, Pearson Correlation coefficient is preferable to the raw cosine because of the bias adjustment effect of mean-centering
  - Cosine distance is usually used when our data is binary/unary, i.e. “like vs. not like” or “buy vs. not buy”.

Similarity Measures

- *Significance weighting*: When two users (or items) have **very few** items (or users) **in common** the **reliability** of the similarity scores if **low**. In this cases the similarity score should be reduced with a discount factor to de-emphasize the importance of that pair the importance of that user pair.

$$sim_c(u,v) = sim(u,v) \times \frac{min(50, |I_u \cap I_v|)}{50}$$

How do we generate a prediction from the neighbor's ratings?

$$\hat{r}_{u,j} = \frac{\sum_{v \in P_u(j)} sim(u,v) \times r_{v,j}}{\sum_{v \in P_u(j)} sim(u,v)}$$

Where *Pu(j)* is denoted to the set of the top-k similar users to target user *u,* sim(u,v) the similarity between user u and v and $r_{u,j}$ the rating of the user *u* to the movie *j*

How do we generate a prediction from the neighbor's ratings?

Example:

Critic	$sim(a,b)$	Rating Movie1: r_{b,p_1}	$sim(a,b) * (r_{b,p_1})$	Rating Movie2: r_{b,p_2}	$sim(a,b) * (r_{b,p_2})$
User1	0.99	3	2.97	2.5	2.48
User2	0.38	3	1.14	3	1.14
User3	0.89	4.5	4.0	-	-
User4	0.92	3	2.77	3	2.77
$\sum_{b \in N} sim(a,b) * (r_{b,p})$			10.87		6.39
$\sum_{b \in N} sim(a,b)$			3.18		2.29
$pred(a,p)$			3.41		2.79

Other prediction functions

- Different users may provide ratings on different scales. Some users rate all items highly, whereas another rate all items negatively

$$\hat{r}_{u,j} = \bar{r}_u + \frac{\sum_{v \in P_u(j)} sim(u,v) \times (r_{v,j} - \bar{r}_v)}{\sum_{v \in P_u(j)} sim(u,v)}$$

Caution: predicted scores can goes outside the range. However, the rank is correct.

Other prediction functions

$$\hat{r}_{u,j} = \bar{r}_u + \sigma_u \frac{\sum_{v \in P_u(j)} sim(u,v) \times z_{v,j}}{\sum_{v \in P_u(j)} |sim(u,v)|}$$

Where z_{vj} is the standardized rating computed as follows:

$$z_{uj} = \frac{r_{uj} - \bar{r}_u}{\sigma_u} = \frac{s_{uj}}{\sigma_u}$$

and $$\sigma_u = \sqrt{\frac{\sum_{j \in I_u} (r_{uj} - \bar{r}_u)^2}{|I_u| - 1}}$$

Caution: predicted scores can goes outside the range. However, the rank is correct.

Some tricks (I)

- **Top-k** most similar users to the target user in order to do the predictions.
  - Weakly correlated users might add to the error in prediction, as well as, negative correlations often do not have a predictive value.

Some tricks (II)

Recursive methods: In order to avoid cold-start we can apply a recursive method for new users or for sparse data sets.

Some tricks (III)

Similarlity amplificaton:

$$sim(u, v) = Pearson(u, v)^{\alpha}$$

Where $\alpha > 1$

Some tricks (IV)

Clustering applied as a “first step” for **shrinking** the candidate set of users.

Long Tail Problem

- Difficult to provide good rating prediction for those item in the long tail.
- Popular items does not provide the same information about tastes than non-popular items
- Usually, popular items provide less profit than non-popular.
- Usually, non-popular items generates more surprise to the user

Impact of the long Tail

Some movies are really popular since other very unpopular. **Popular items** can sometimes **worsen the quality** of the recommendations since they tend to be **less discriminative** across different users

Each item *j* can be weighted by w_j as follows

$$w_j = log\left(\frac{m}{m_j}\right)$$

where *m* is the total number of users, and m_j is the number of users who have rated the item j

$$Pearson(u,v) = \frac{\sum_{k \in I_u \cap I_v} w_k (r_{uk} - \bar{r}_u)(r_{vk} - \bar{r}_v)}{\sqrt{\sum_{k \in I_u \cap I_v} w_k (r_{uk} - \bar{r}_u)^2} \sqrt{\sum_{k \in I_u \cap I_v} w_k (r_{vk} - \bar{r}_v)^2}}$$

Clustering

- Computing the similarity between users is computationally expensive.
- Clustering is cheaper to than computing the ***mxm*** similarity matrix
- Redefine top similar users using only the subset of users in the same cluster
- Problem: ***MxN*** is an incomplete, really sparse, matrix.

Dimensionality Reduction and Neighborhood Methods

- Dimensionality reduction can **improve** neighborhood methods in terms of **accuracy** and also in terms of **efficiency**.
- Similarities are hard to be computed in huge dimensional sparse rating matrices.
    - Latent factor models

Explaining recommendations

- Help on:
  - Transparency
  - Trust

A survey of explanations in recommender systems
N Tintarev, J Masthoff
Data Engineering Workshop, 2007 IEEE 23rd International Conference on, 801-810

226 2007

What is an Explanation

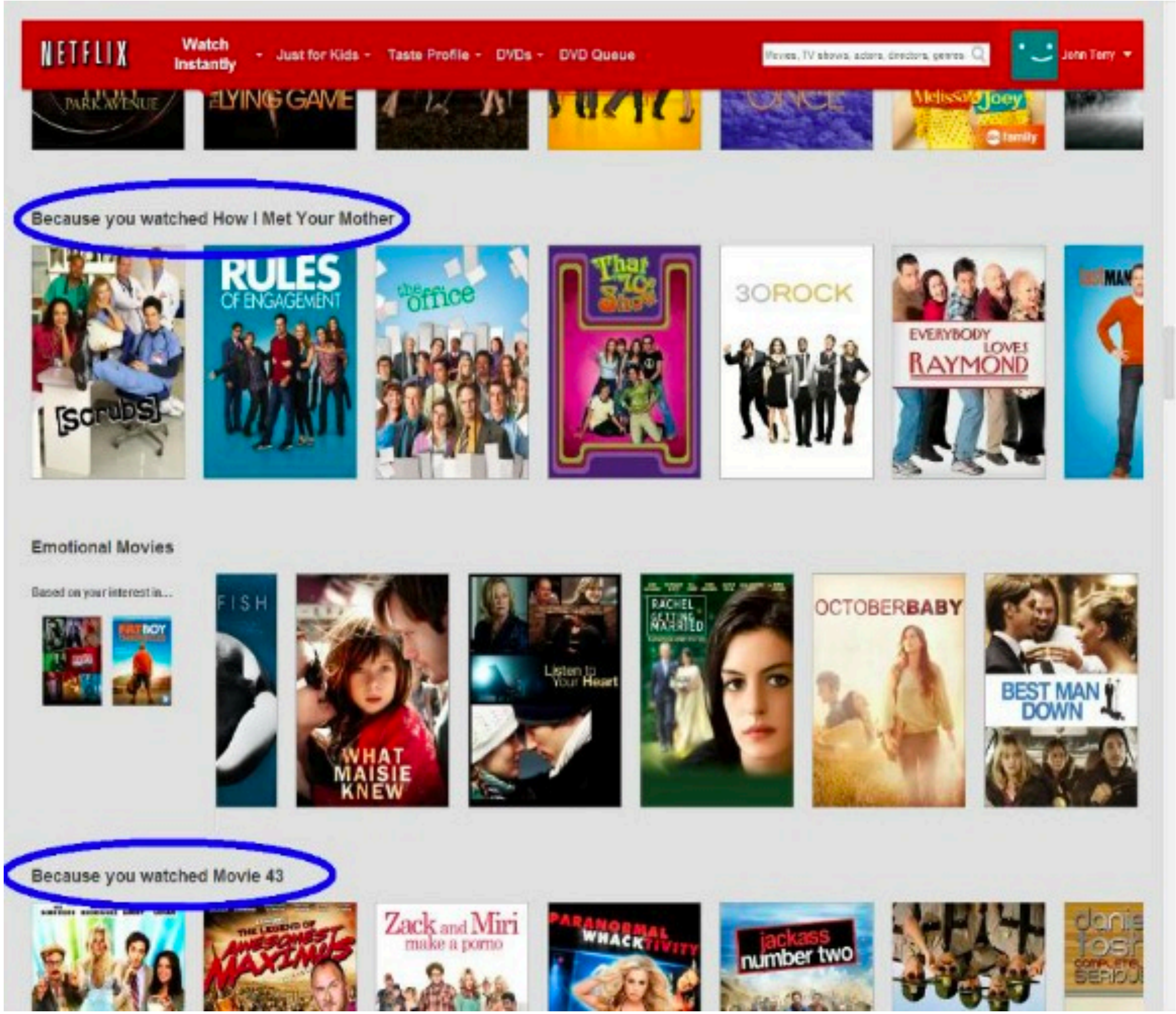
- Additional data to help users understand a specific recommendation
    - It is totally separate from an explanation how the system works as a whole
- Some explanation are confidence values
- Show distributions
- Sometimes tied to ability to edit profile to **improve recommendations**

#		N	Mean Response	Std Dev
1	Histogram with grouping	76	5.25	1.29
2	Past performance	77	5.19	1.16
3	Neighbor ratings histogram	78	5.09	1.22
4	Table of neighbors ratings	78	4.97	1.29
5	Similarity to other movies rated	77	4.97	1.50
6	Favorite actor or actress	76	4.92	1.73
7	MovieLens percent confidence in prediction	77	4.71	1.02
8	Won awards	76	4.67	1.49
9	Detailed process description	77	4.64	1.40
10	# neighbors	75	4.60	1.29
11	No extra data – focus on system	75	4.53	1.20
12	No extra data – focus on users	78	4.51	1.35
13	MovieLens confidence in prediction	77	4.51	1.20
14	Good profile	77	4.45	1.53
15	Overall percent rated 4+	75	4.37	1.26
16	Complex graph: count, ratings, similarity	74	4.36	1.47
17	Recommended by movie critics	76	4.21	1.47
18	Rating and %agreement of closest neighbor	77	4.21	1.20
19	# neighbors with std. deviation	78	4.19	1.45
20	# neighbors with avg correlation	76	4.08	1.46
21	Overall average rating	77	3.94	1.22

Table 1. Mean response of users to each explanation interface, based on a scale of one to seven. Explanations 11 and 12 represent the base case of no additional information. Shaded rows indicate explanations with a mean response significantly different from the base cases (two-tailed $\alpha = 0.05$).

Figure 1. One of the twenty-one different explanation interfaces given shown in the user survey. Notice that the title has been encoded, so that it does not influence a user's decision to try a movie.

Example



NETFLIX
Watch Instantly
Just for Kids
Taste Profile
DVDs
DVD Queue
Because you watched How I Met Your Mother
Emotional Movies
Based on your interest in...
Because you watched Movie 43