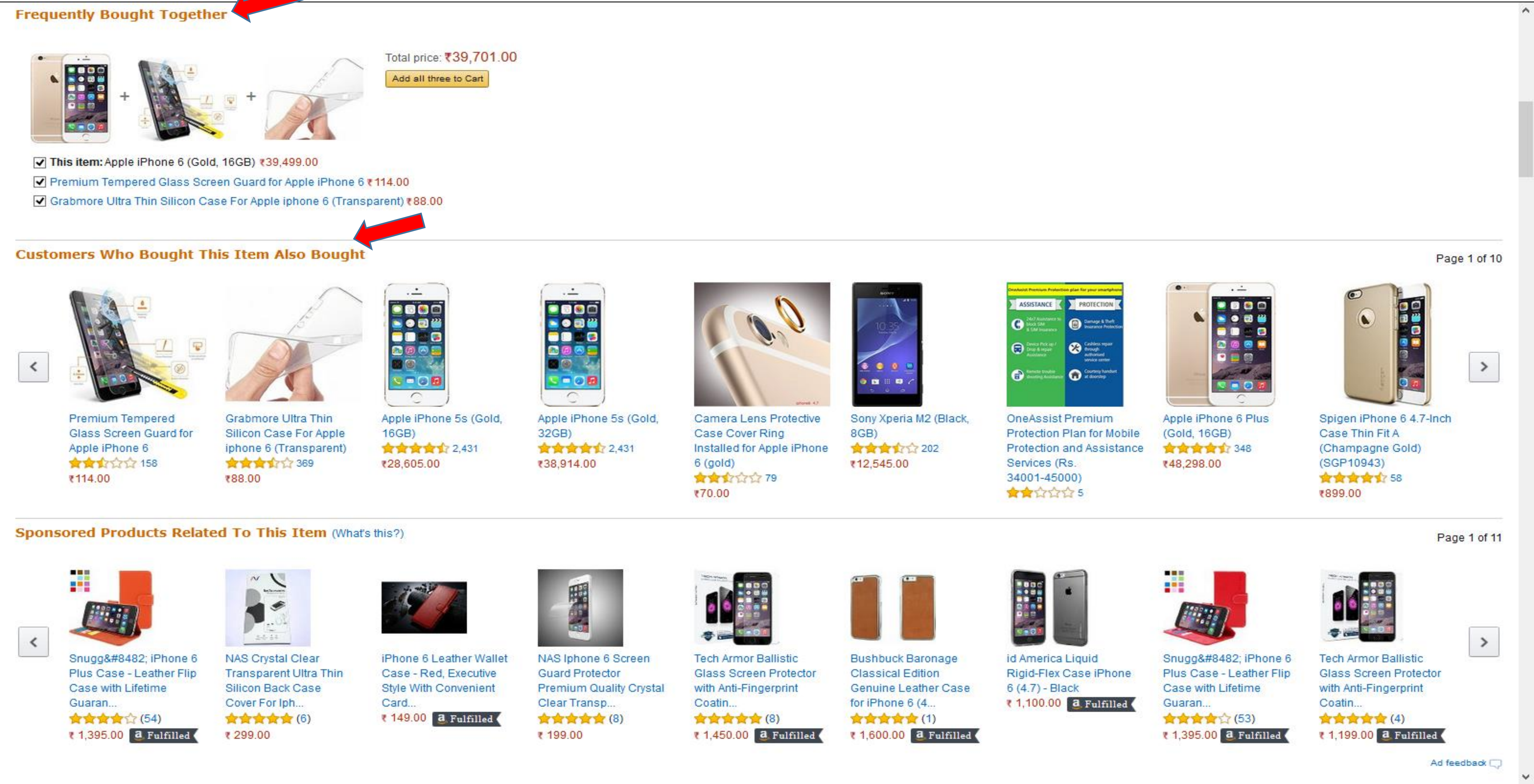
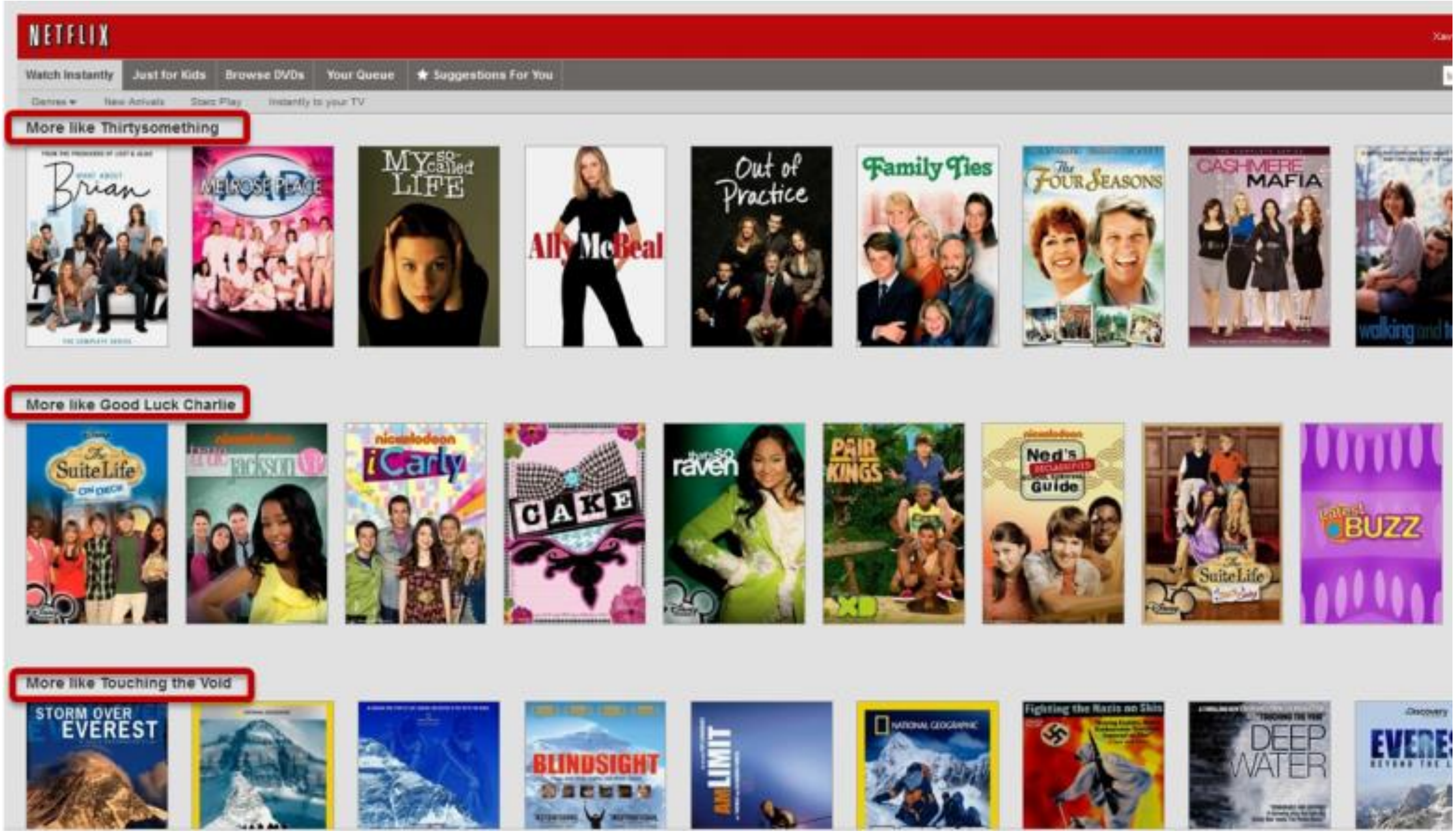
Collaborative Filtering - An Introduction

Online Recommendations



Netflix


NETFLIX
Watch Instantly
Just for Kids
Browse DVDs
Your Queue
Suggestions For You
More like Thirtysomething
More like Good Luck Charlie
More like Touching the Void

Data Mining Methods and Nature of Data

TABLE 1.1 ORGANIZATION OF DATA MINING METHODS IN THIS BOOK, ACCORDING TO THE NATURE OF THE DATA*

	Supervised: Continuous Response	Supervised: Categorical Response	Unsupervised: No Response
Continuous predictors	Linear regression (6) Neural nets (11) k-Nearest neighbors (7) Ensembles (13)	Logistic regression (10) Neural nets (11) Discriminant analysis (12) k-Nearest neighbors (7) Ensembles (13)	Principal components (4) Cluster analysis (15) Collaborative filtering (14)
Categorical predictors	Linear regression (6) Neural nets (11) Regression trees (9) Ensembles (13)	Neural nets (11) Classification trees (9) Logistic regression (10) Naive Bayes (8) Ensembles (13)	Association rules (14) Collaborative filtering (14)

***Numbers in parentheses indicate chapter number.**

Ref: Data Mining for Business Analytics: Concepts, Techniques and Applications in R, by Galit Shmueli et al., Wiley India, 2018.

Collaborative Filtering

- User based methods
- Item based methods

Item-user matrix

- Cells are user preferences, r_{ij}, for items
- Preferences can be ratings, or binary (buy, click, like)

	Item ID			
User ID	I_1	I_2	$\cdots$	I_p
U_1	$r_{1,1}$	$r_{1,2}$	$\cdots$	$r_{1,p}$
U_2	$r_{2,1}$	$r_{2,2}$	$\cdots$	$r_{2,p}$
$\vdots$				
U_n	$r_{n,1}$	$r_{n,2}$	$\cdots$	$r_{n,p}$

More efficient to store as rows of triplets

Each row has the user ID, the item ID, and the user’s rating of that item

(U_u, I_i, r_{ui})

User-based Collaborative Filtering

- Start with a single user who will be the target of the recommendations

- Find other users who are most similar, based on comparing preference vectors

Measuring Proximity

- Like nearest-neighbor algorithm
- But Euclidean distance does not do well
- Correlation proximity does better (Pearson)
- For each user pair, find the co-rated items, calculate correlation between the vectors of their ratings for those items
  - Note that the average ratings for each user are across all products, not just the co-rated ones

$$\mathrm{Corr}(U_1, U_2) = \frac{\sum (r_{1,i} - \overline{r}_1)(r_{2,i} - \overline{r}_2)}{\sqrt{\sum (r_{1,i} - \overline{r}_1)^2}\sqrt{\sum (r_{2,i} - \overline{r}_2)^2}}$$

Example – Tiny Netflix subset

	Movie ID								
Customer ID	1	5	8	17	18	28	30	44	48
30878	4	1			3	3	4	5	
124105	4								
822109	5								
823519	3		1	4		4	5		
885013	4	5							
893988	3						4	4	
1248029	3					2	4		3
1503895	4								
1842128	4						3		
2238063	3								

TABLE 14.8 SAMPLE OF RECORDS FROM THE NETFLIX PRIZE CONTEST, FOR A SUBSET OF 10 CUSTOMERS AND 9 MOVIES

Consider users 30878 and 823519

Correlation between users 30878 and 823519

First find average ratings for each user:

$$\overline{r}_{30878} = (4+1+3+3+4+5)/6 = 3.333$$
$$\overline{r}_{823519} = (3+1+4+4+5)/5 = 3.4$$

Customer ID	1	5	8	17	18	28	30	44	48
30878	4	1			3	3	4	5	
124105	4								
822109	5								
823519	3		1	4		4	5		
885013	4	5							
893988	3						4	4	
1248029	3					2	4		3
1503895	4								
1842128	4						3		
2238063	3								

Movie ID

TABLE 14.8 SAMPLE OF RECORDS FROM THE NETFLIX PRIZE CONTEST, FOR A SUBSET OF 10 CUSTOMERS AND 9 MOVIES

Find correlation using departure from avg. ratings for the co-rated movies (movies 1, 28 and 30):

$$\text{Corr}(U_1, U_2) = \frac{\sum (r_{1,i} - \overline{r}_1)(r_{2,i} - \overline{r}_2)}{\sqrt{\sum (r_{1,i} - \overline{r}_1)^2}\sqrt{\sum (r_{2,i} - \overline{r}_2)^2}}$$

$$\text{Corr}(U_{30878}, U_{823519}) =$$
$$\frac{(4-3.333)(3-3.4) + (3-3.333)(4-3.4) + (4-3.333)(5-3.4)}{\sqrt{(4-3.333)^2 + (3-3.333)^2 + (4-3.333)^2}\sqrt{(3-3.4)^2 + (4-3.4)^2 + (5-3.4)^2}}$$
$$= 0.6/1.75 = 0.34$$

Cosine Similarity

Like correlation coefficient, except do not subtract the means

Use raw ratings instead of departures from averages

$$\text{Cos Sim}(U_{30878}, U_{823519}) = \frac{4 \times 3 + 3 \times 4 + 4 \times 5}{\sqrt{4^2 + 3^2 + 4^2}\sqrt{3^2 + 4^2 + 5^2}}$$
$$= 44/45.277 = 0.972$$

Ranges from 0 (no similarity) to 1 (perfect match)

	Movie ID								
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822109	5								
823519	3		1	4		4	5		
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TABLE 14.8 SAMPLE OF RECORDS FROM THE NETFLIX PRIZE CONTEST, FOR A SUBSET OF 10 CUSTOMERS AND 9 MOVIES

Using the similarity info to make recommendations

- Given a new user, identify k-nearest users
- Consider all the items they rated/purchased, except for the co-rated ones
- Among these other items, what is the best one? "Best" could be
  - Most purchased
  - Highest rated
  - Most rated
- That "best" item is the recommendation for the new user

Cold Start

- Collaborative filtering suffers from what is called a *cold start*: it cannot be used as is to create recommendations for new users or new items.
- For a user who rated a single item, the correlation coefficient between this and other users (in user-generated collaborative filtering) will have a denominator of zero and the cosine proximity will be 1 regardless of the rating.
- In a similar vein, users with just one item, and items with just one user, do not qualify as candidates for nearby neighbors

Item-based collaborative filtering

- When the number of users is huge, user-based calculations pose an obstacle (similarity measures cannot be calculated until user shows up)
- Alternative – when a user purchases an item, focus on similar items

1. Find co-rated (co-purchased) items (by any user)
2. Recommend the most popular or most correlated item

Item-based collaborative filtering

- Similarity is now computed between items, instead of users. For example, in the Netflix sample, the correlation between movie 1 (with average $r1 = 3.7$) and movie 5 (with average $r5 = 3$) is:

$$\mathrm{Corr}(I_1, I_5) = \frac{(4-3.7)(1-3)+(4-3.7)(5-3)}{\sqrt{(4-3.7)^2+(4-3.7)^2}\sqrt{(1-3)^2+(5-3)^2}} = 0$$

	Movie ID								
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TABLE 14.8 SAMPLE OF RECORDS FROM THE NETFLIX PRIZE CONTEST, FOR A SUBSET OF 10 CUSTOMERS AND 9 MOVIES

- Thus we can compute similarity between all the movies.
- This can be done offline.
- In real time, for a user who rates a certain movie highly, we can look up the movie correlation table and recommend the movie with the highest positive correlation to the user's newly rated movie.

Summary – Collaborative Filtering

- User-based – for a new user, find other users who share his/her preferences, recommend the highest-rated item that new user does <u>not</u> have.
  - User-user correlations cannot be calculated until new user appears on the scene… so it is slow if lots of users
- Item-based – for a new user considering an item, find other item that is most similar in terms of user preferences.
  - Ability to calculate item-item correlations in advance greatly speeds up the algorithm
  - The disadvantage of item-based recommendations is that there is less diversity between items (compared to users' taste), and therefore, the recommendations are often obvious.

Association Rules

- focus entirely on frequent (popular) item combinations.
- Data rows are single transactions.
- Ignores user dimension.
- Often used in displays (what goes with what).
- Binary Data
- Two or more items

Collaborative Filtering

- focus is on user preferences.
- Data rows are user purchases or ratings over time.
- Can capture “long tail” of user preferences
- useful for recommendations involving unusual items
- Binary as well as Ratings data
- Between pairs of items or users

Slide Contents - References

- The contents of this presentation were sourced and assembled from
  - Data Mining for Business Analytics: Concepts, Techniques and Applications in R, by Galit Shmueli et al., Wiley India, 2018.