Recommender Systems

Mining Massive Datasets

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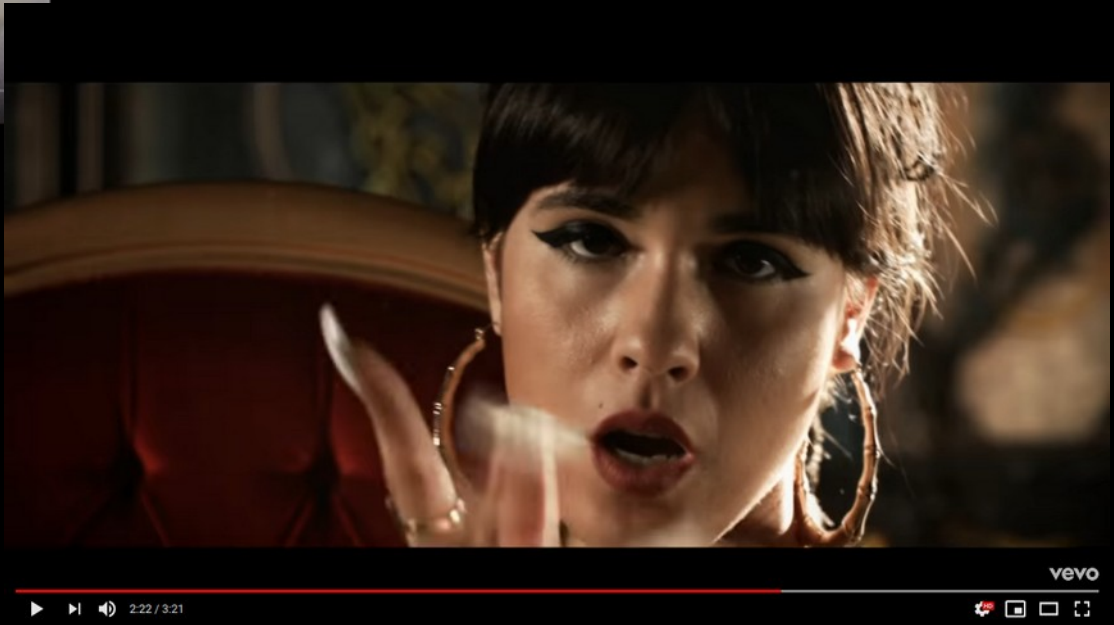
Sources

- Data Mining, The Textbook (2015) by Charu Aggarwal (Section 18.5) – slides by Lijun Zhang
- Mining of Massive Datasets 2nd edition (2014) by Leskovec et al. (Chapter 9) - slides A, B

YouTube's algorithm cares as much about trap as your professor, but manages to produce reasonable recommendations. How?



Recommender systems (purchase)

- Given data from user buying behaviors
  - User profiles, interests, browsing behavior, buying behavior, and ratings about various items
- Leverage such data to make recommendations to customers about possible buying interests

Recommender systems (general)

- Given data from user interests
  - User profiles, interests, browsing behavior, item interaction behavior, ratings about various items
- Leverage such data to make recommendations to users about further interesting items

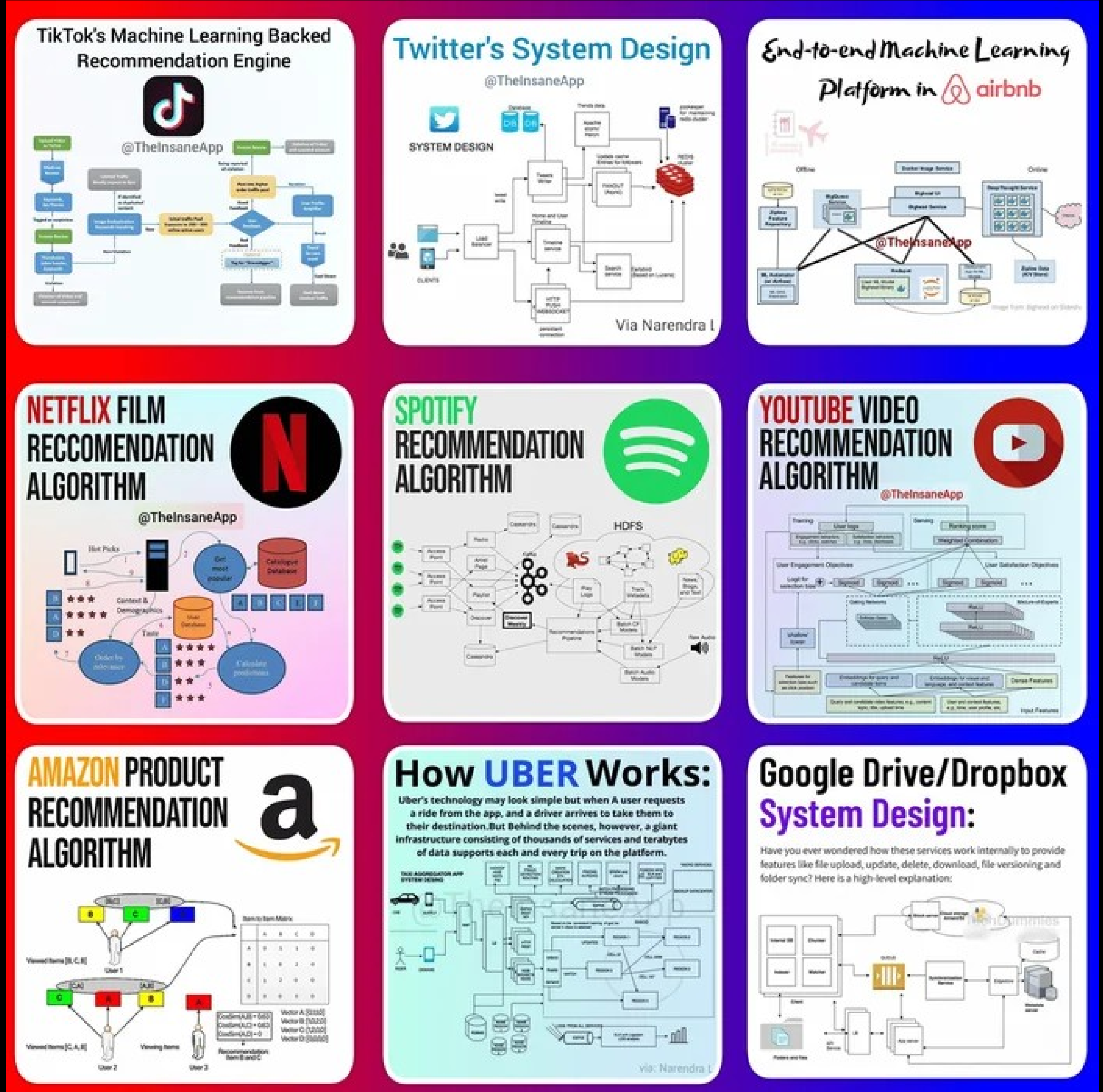
NETFLIX

Spotify®

amazon

YouTube

STEAM®



Large scale engines for recommendation:

- are composed of **multiple layers**,
- use **online** and **offline** (batch) models,
- include complex **data pipelines** to move **behavioral** and **content** signals around.

Source: The Insane App
March 2021

Utility matrix

- For n users and d items, there is a matrix D of **utility** values
  - The utility value for a user-item pair could correspond, e.g., to buying behavior or ratings of the user for the item
  - Typically, a small subset of the utility values are known

Utility matrix (ratings-based, positive preference)

	GLADIATOR	GODFATHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			5		2
U_2		5			4	
U_3	5	3		1		
U_4			3			4
U_5				3	5	
U_6	5		4			

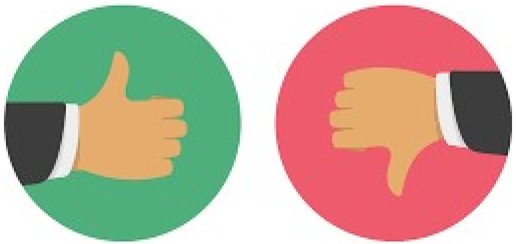
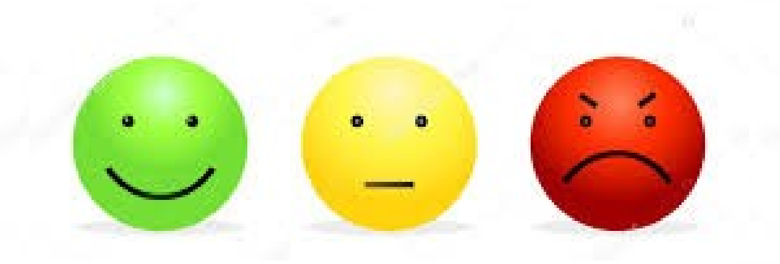
(a) Ratings-based utility

	GLADIATOR	GODFATHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			1		1
U_2		1			1	
U_3	1	1		1		
U_4			1			1
U_5				1	1	
U_6	1		1			

(b) Positive-preference utility

Types of utility

- **Explicit**: we ask users to rate items


- **Implicit**: we take watching/consuming/buying behavior as a positive signal, skip/hide as negative

Sources for a recommendation

- Content-based recommendation
  - Users and items are associated with features
  - Features are matched to infer interest
- Interaction-based recommendations
  - Leverage user preferences in the form of ratings or other behavior
  - Recommend through similarity or latent factors

THE COLD START PROBLEM

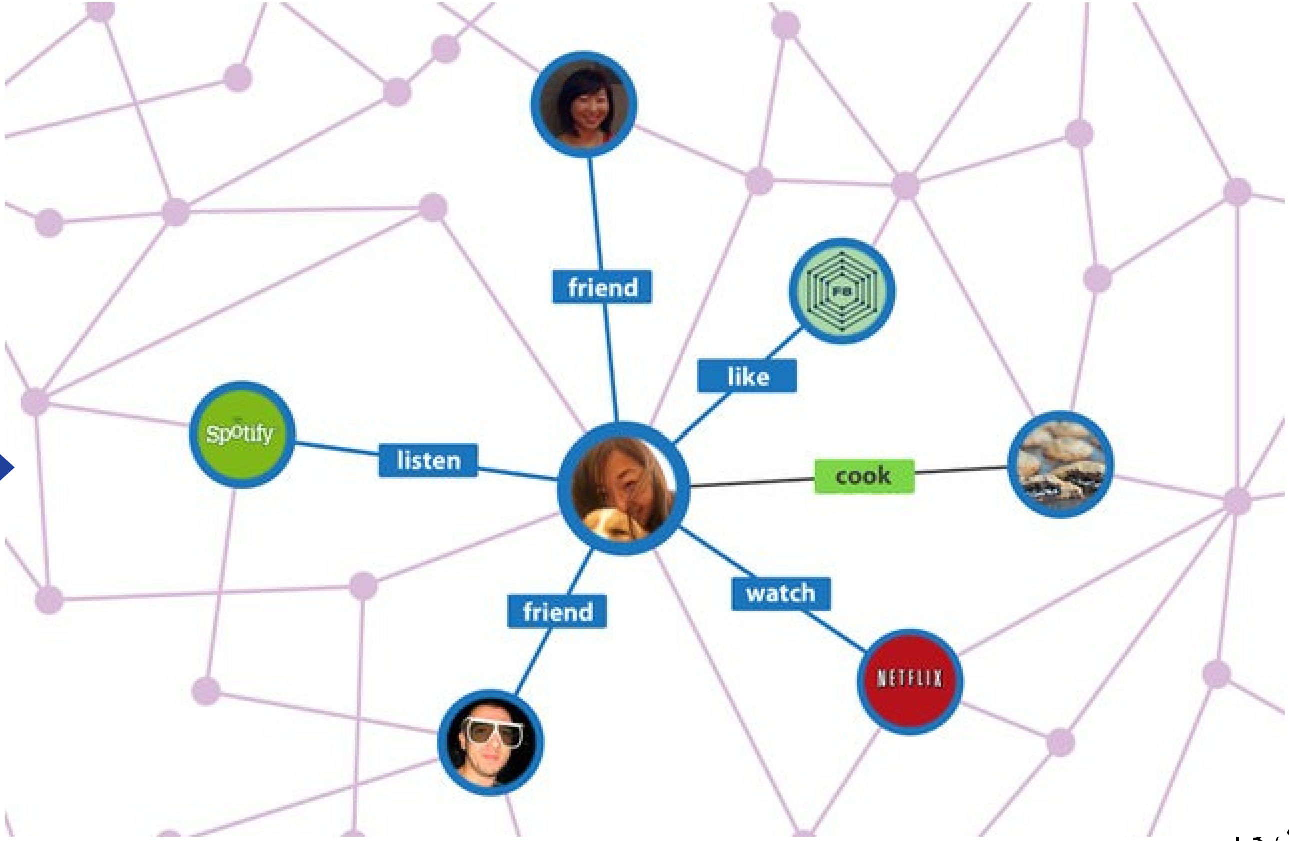
New items have no ratings

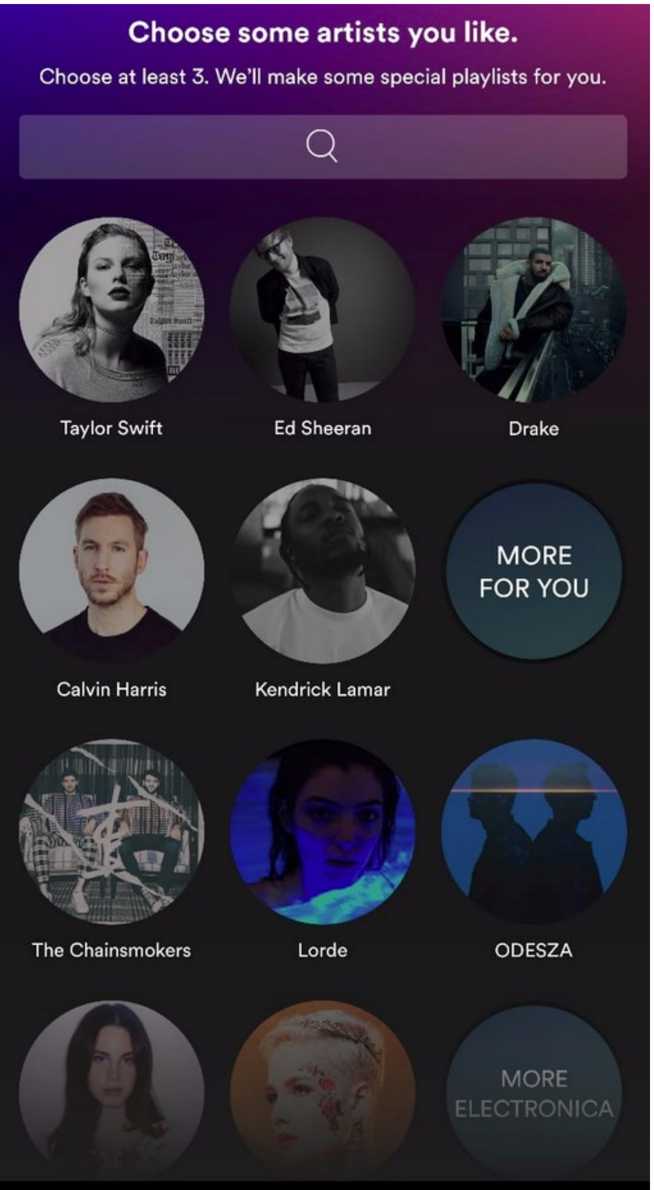
and

New users have no history

Photo: Torque News

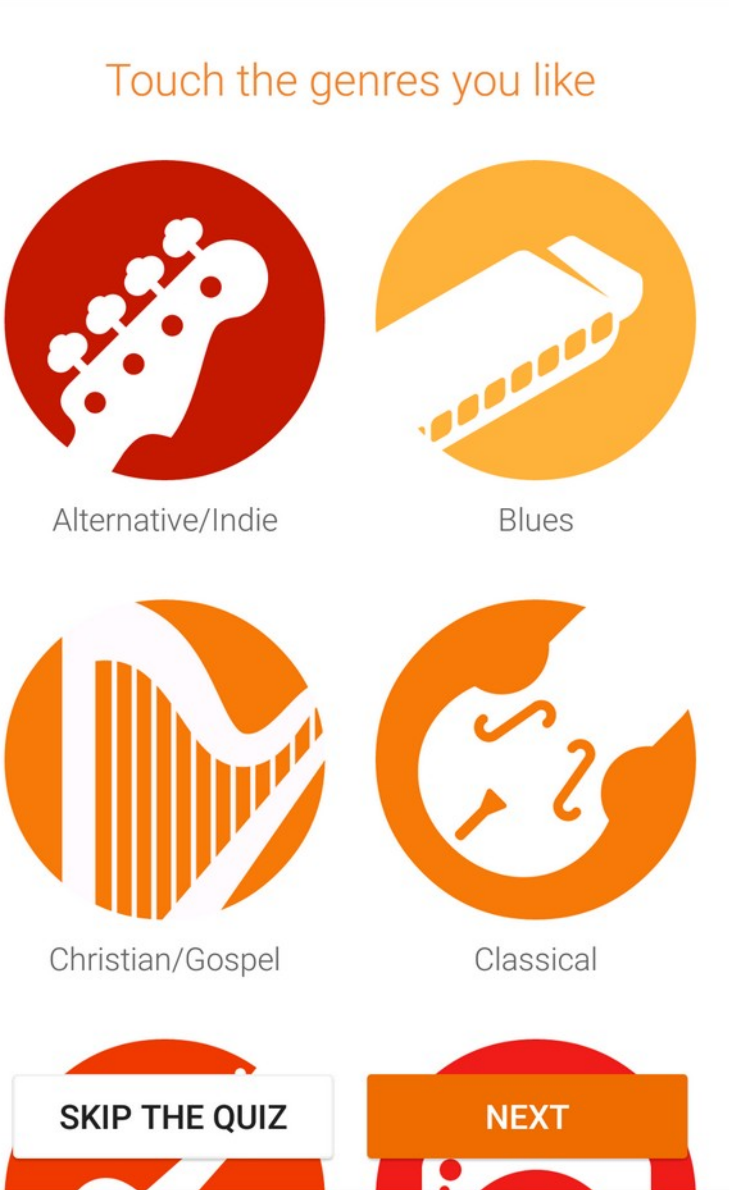
Solution 1. “Side information”





THE COLD START PROBLEM

Solution 2. “On-boarding” users



Content-based recommendations

General idea of content-based recommendations

- Movies: recommend other movies with same director, actor, genre, as viewed ones
- Products: recommend other products in same category, brand, color, as purchased ones

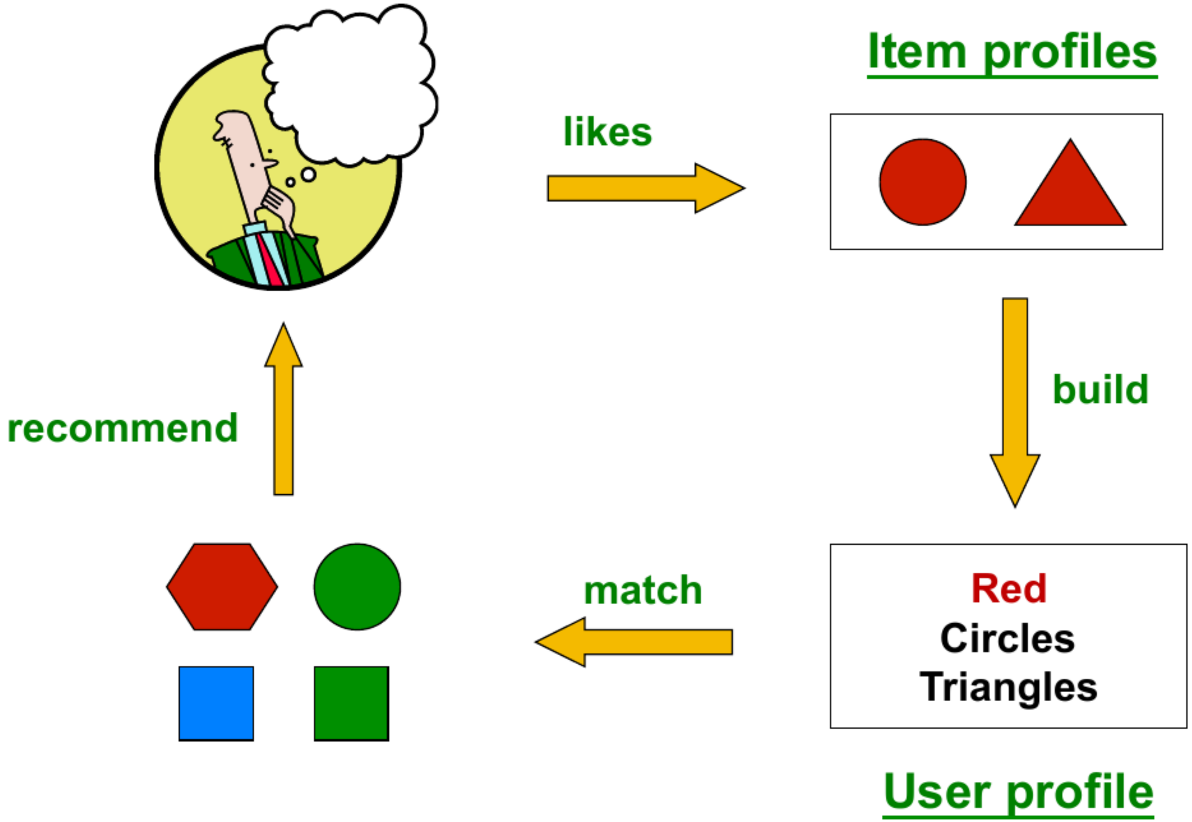
Creating a recommendation

- User is associated with some documents that describe his/her interests
  - Specified demographic profile
  - Specified interests at registration time
  - Descriptions of the items bought
- Items are also associated with semi-structured descriptions

JBL GO lleva el sonido de calidad JBL a todas partes. GO es su solución de altavoz todo en uno y reproduce música en tiempo real vía Bluetooth desde smartphones y tabletas, gracias a su batería recargable. También cuenta con un práctico manos libres.

Potencia	**3 W**
Respuesta de Frecuencia	**180Hz – 20 kHz**
Tipo de altavoz	**Portátil**
Amplificador de sonido	**Integrado**

Creating a recommendation (cont.)



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Possible recommendation methods

- If no utility matrix is available
  - k-nearest neighbor approach
    - Find the top-k items that are closest to the user (when items and users can be represented in the same space, e.g., dating apps)
  - The cosine similarity with tf-idf can be used
- If a utility matrix is available
  - Classification-based approach: training documents are those for which the user has specified utility, labels are utility values
  - Regression-based approach in the case of ratings
- Limitations: depends on the quality of the features

Example: regression-based approach for content-based recommendation

Movie	Adventure	Action	Science-Fiction	Drama	Crime	Thiller		User 1	User 2
Star Wars IV	1	1	1	0	0	0		1	-1
Saving Private Ryan	0	0	0	1	0	0			
American Beauty	0	0	0	1	0	0			
City of Gold	0	0	0	1	1	0		-1	1
Interstellar	0	0	1	1	0	0		1	
The Matrix	1	1	1	0	0	1			1

...

We would do two regressions: one for the ratings of user 1 and another for user 2.
(We can also do this for groups of users, e.g., by city and age)

How many rated movies would we need, as a minimum, to be able to do this?

Exercise: single user recommendation

- Database of ~100 electric scooters, of which 12 have been rated on a scale 1-5
- We have done linear regression on:

  price [$], battery capacity [Wh], range [km]

- Which would be your top-3 recommended ... ng the remaining ones?

Answer in
Google Spreadsheet

Pros and Cons of content-based recommendations

- Pros:
  - No cold-start problem if no utility needed
  - Able to recommend to users with very particular tastes
  - Able to recommend new and obscure items
  - Able to provide explanations that are easily understandable

Pros and Cons of content-based recommendations

- Cons:
  - Finding the correct features might be hard
  - Recommending for new users still challenging if user features are different from item features
  - Overspecialization/"bubble": might reinforce user interests
  - Does not exploit ratings of other users!

Summary

Things to remember

- Content-based recommendations

Exercises for TT16-TT18

- Mining of Massive Datasets 2nd edition (2014) by Leskovec et al. Note that some exercises cover advanced concepts:
  - Exercises 9.2.8
  - Exercises 9.3.4
  - Exercises 9.4.6