CSCI4622 Machine Learning

2020 Spring

Unsupervised Learning

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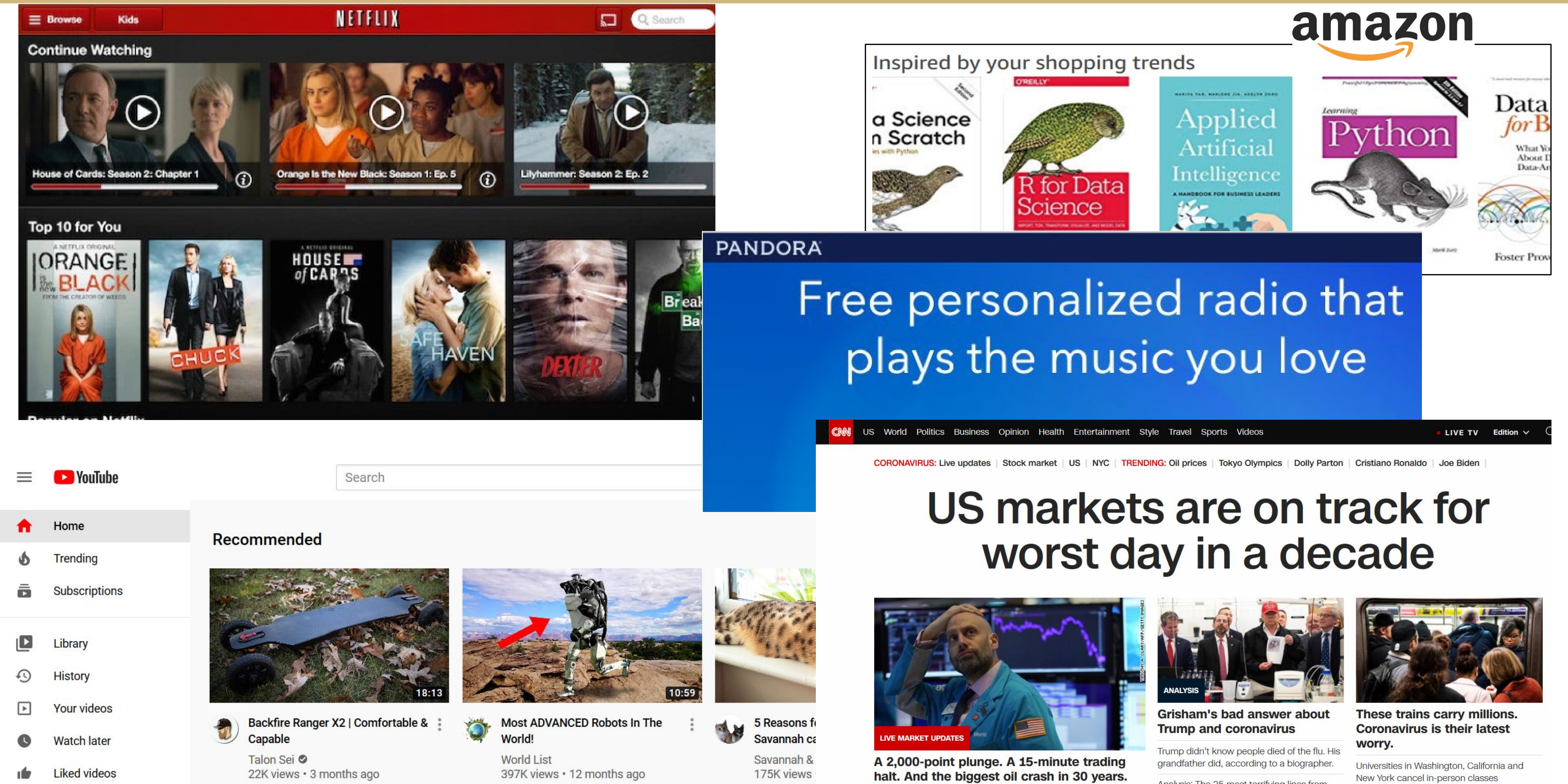
Recommender System

- What is Recommender System
- Content-based Filtering
- Collaborative Filtering
- Matrix Factorization

What is a Recommender System?



Business Goals

What will the user **Like**?

What will the user **Buy**?

What will the user **Click**?

Goal of recommender

- Predict missing ratings
- May be sufficient to just predict a subset of items with high expected rankings
- May be sufficient to just predict general trends, such as *trending* news

Recommendation approaches

Popularity:

● Make the **same** recommendation to **every** user, based only on the popularity of an item.
● E.g. Twitter “Moments”

Content-based (Content filtering):

● Predictions are made based on the properties/characteristics of an item.
● User behavior is **not** considered. (There can be hybrid)
● E.g. Pandora Radio

Recommendation approaches

Collaborative filtering:

● Only consider past user behavior. (**not** content properties...)
● User-User similarity
● Item-Item similarity
● E.g.
○ Netflix & Amazon Recommendations,
○ Google Ads,
○ Facebook Ads, Search, Friends Rec., News feed, Trending news, Rank Notifications, Rank Comments

Similarity-based Collaborative Filtering:

● Use similarity metric between users or items

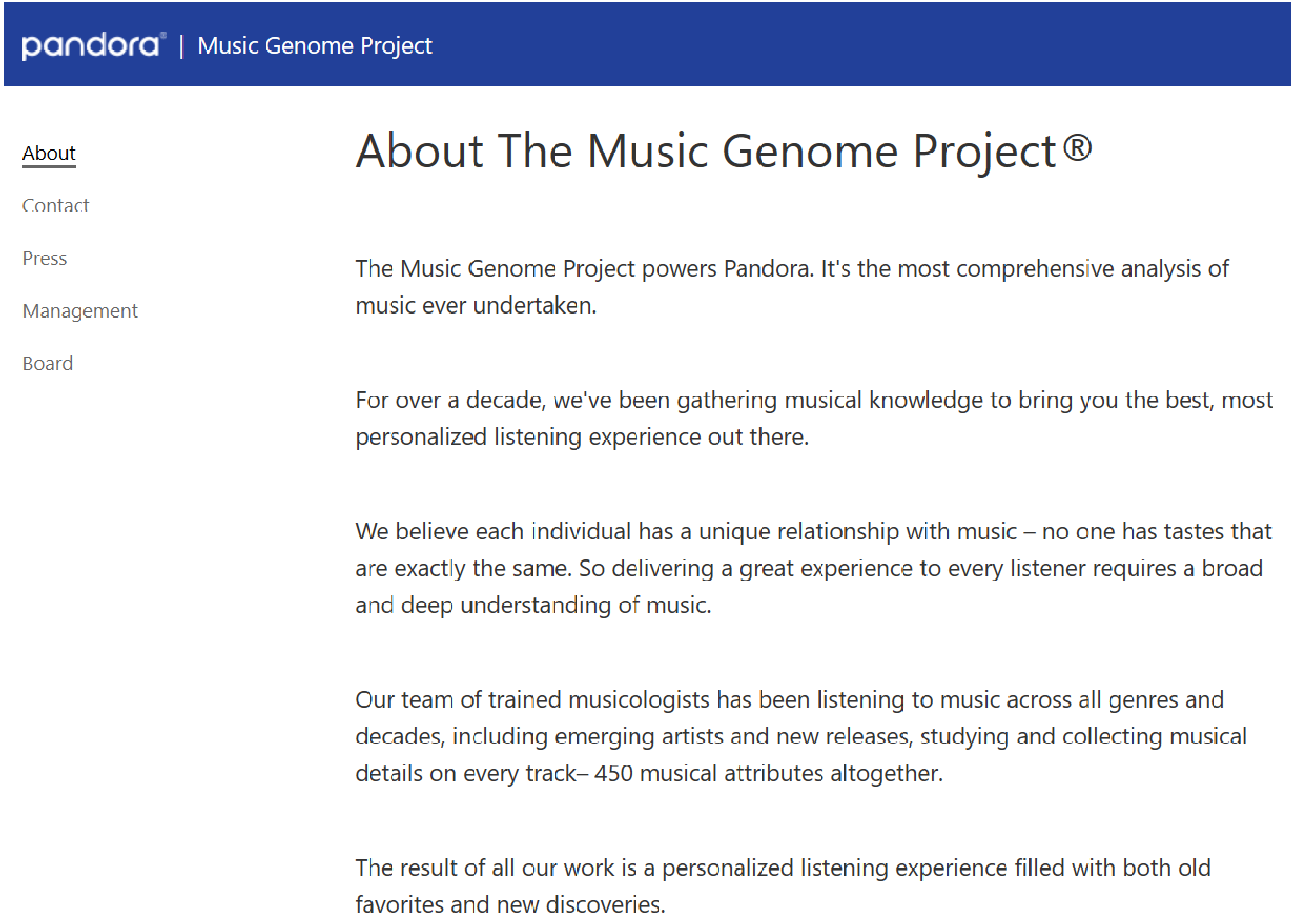
Matrix Factorization Methods:

● Find latent features/factors

Content-Based Filtering

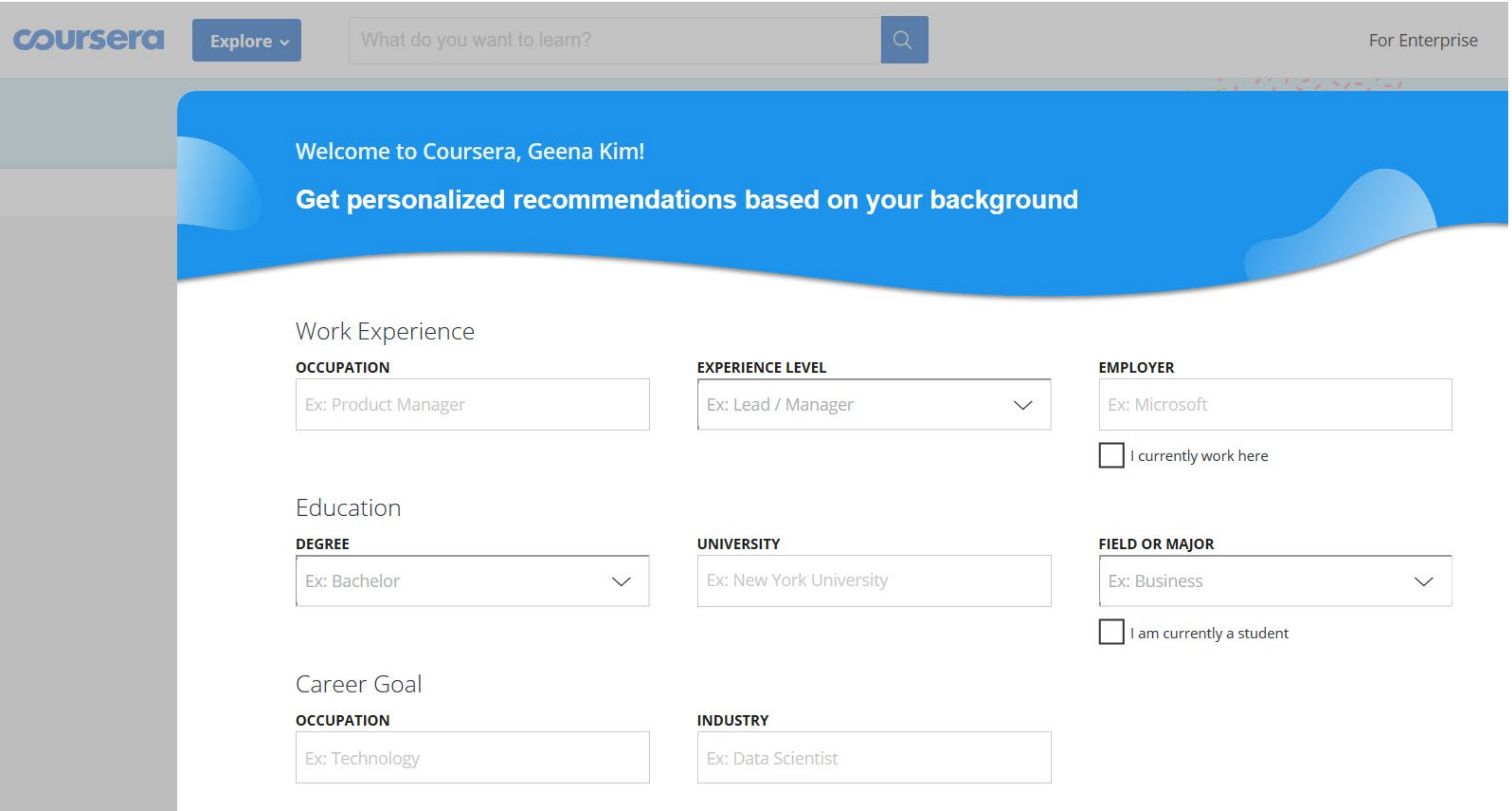
- Creates profile of each user and items
- Need to collect user demographics or questionnaire
- Need domain-specific info about the items
- Features are hand-engineered by the domain experts

Content-Based Filtering Examlpe



User profiling

Oftentimes Recommender systems collect user data

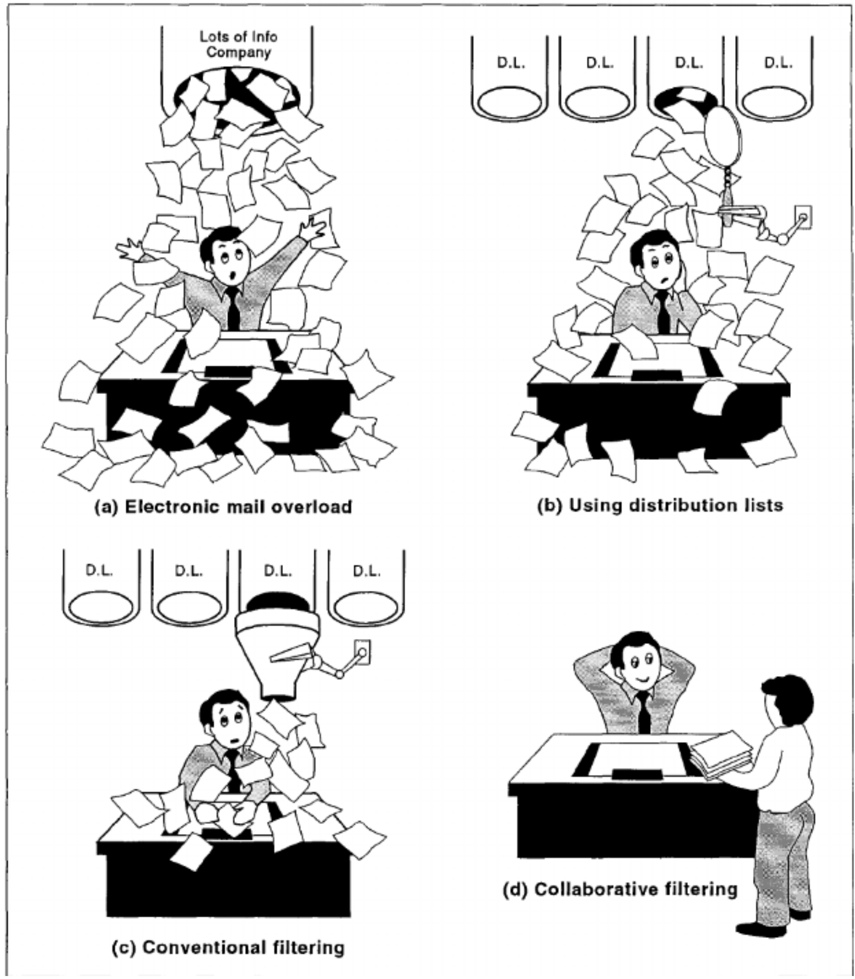


Collaborative Filtering

- No need of hand-engineered features
- Domain-free
- Can learn latent info that are hard to profile using content filtering
- Generally more accurate about user preference
- May suffer from "cold-start" problem

Tapestry

The origin of the name: filtering documents in emails



Goldberg et. al., (1992)

Collaborative Filtering Approaches

Memory-based

- Customers who bought this item also bought ….

Using Similarity

- item-item similarity
- user-user similarity
- Can be combined with clustering

Using Latent factor modeling

- Matrix Factorization
- Tries to explain the rating patterns

Other

- Deep learning

Similarity

What does the data look like?

movie

user

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1	?	
B	5	5	4		?		
C	?		?	2	4	5	
D	?	3	?	?			3

Utility Matrix

User explicitly rate the movie or product

Explicit ratings

Similarity

What does the data look like?

User / Item

	A	B	C	D	...
Al	0	1	0	1	
Bob	0	0	1	0	
Cat	0	1	1	1	
Dan	1	0	0	1	
Ed	0	1	0	0	
...					

User buy or not buy the product

Implicit ratings

Similarity

	A	B	C	D	…
Al	1	?	2	?	
Bob	?	2	3	4	
Cat	3	?	1	5	
Dan	?	2	?	?	
Ed	2	?	?	1	
…					

Item: n 600M

User: m 100M

$_mC_2 \sim O(m^2)$

User-user similarity : $O(m^2 \times n)$

Item-item similarity : $O(n^2 m)$

Calculation cost

Let:
m = #users,
n = #items

User-User: $O(m^2n)$
Item-Item: $O(mn^2)$

Similarity

$0 \sim 1$

Distance-based $0 \sim \text{inf}$

- Manhattan distance $c=1$
- Euclidean distance $c=2$
- Minkowski distance

$\left(\sum_i (x_A^i - x_B^i)^c\right)^{1/c}$

$$\text{similarity}(a, b) = \frac{1}{1 + \text{dist}(a, b)}$$

$+\infty$

1

0

Similarity

Pearson Correlation

a

b

$$\frac{\mathrm{cov}(a,b)}{\mathrm{std}(a)*\mathrm{std}(b)} = \frac{\sum_i (a_i-\bar{a})(b_i-\bar{b})}{\sqrt{\sum_i (a_i-\bar{a})^2}\sqrt{\sum_i (b_i-\bar{b})^2}}$$

$-1 \sim 1$

$$\mathrm{similarity}(a,b) = 0.5 + 0.5 * \mathrm{pearson}(a,b)$$

$0 \sim 1$

Similarity

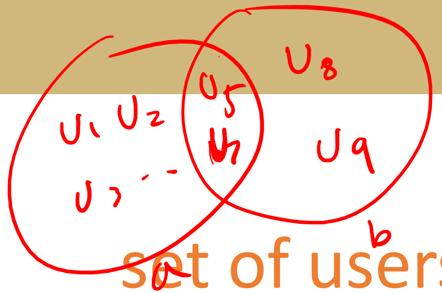
√ Cosine similarity

$$\frac{a \cdot b}{||a||||b||} = \frac{\sum_i a_i b_i}{\sqrt{\sum_i a_i^2}\sqrt{\sum_i b_i^2}}$$ −1 ~ 1

$$\text{similarity}(a, b) = 0.5 + 0.5 * \cos(\theta_{a,b})$$

Similarity

Jaccard similarity



set of users who rated item a

$$\text{similarity}(a, b) = \frac{|U_a \cap U_b|}{|U_a \cup U_b|}$$

Similarity Matrix

	item 1	item 2	item 3	...
item 1	1	0.3	0.2	...
item 2	0.3	1	0.7	...
item 3	0.2	0.7	1	...
...	...	...	...	...

similarity measures

Similarity Matrix

	A	B	C	D	...
Al	1	?	2	?	
Bob	?	2	3	4	
Cat	3	?	1	5	
Dan	?	2	?	?	
Ed	2	?	?	1	
...					

Item

User

	item 1	**item 2**	**item 3**	**...**
item 1	1	0.3	0.2	...
item 2	0.3	1	0.7	...
item 3	0.2	0.7	1	...
...	...	...	...	...

$$\text{rating}(u, i) = \frac{\sum_{j \in I_u} \text{similarity}(i, j) * r_{u,j}}{\sum_{j \in I_u} \text{similarity}(i, j)}$$

$$I_u = \text{ set of items rated by user } u$$
$$r_{u,j} = \text{ user } u\text{'s rating of item } j$$

Latent factor model

		Item				
User		A	B	C	D	...
	Al	1	?	2	?	
	Bob	?	2	3	4	
	Cat	3	?	1	5	
	Dan	?	2	?	?	
	Ed	2	?	?	1	
	...					

$$R_{m \times n} \approx U_{m \times k} V_{k \times n}$$

$$r_{ij} \approx u_{i:} \cdot v_{:j}$$

k:
# of latent features
is a hyperparameter

UV decomposition

$$\begin{bmatrix} 5 & 2 & 4 & 4 & 3 \\ 3 & 1 & 2 & 4 & 1 \\ 2 & & 3 & 1 & 4 \\ 2 & 5 & 4 & 3 & 5 \\ 4 & 4 & 5 & 4 & \end{bmatrix} = \begin{bmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \\ u_{31} & u_{32} \\ u_{41} & u_{42} \\ u_{51} & u_{52} \end{bmatrix} \times \begin{bmatrix} v_{11} & v_{12} & v_{13} & v_{14} & v_{15} \\ v_{21} & v_{22} & v_{23} & v_{24} & v_{25} \end{bmatrix}$$

References

[1] Goldberg, D., Nichols, D., Oki, B., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. *Communications of the Association of Computing Machinery, 35*(12), 61–70.

[2] Leskovec, J., Rajaraman, A., & Ullman, J. D., Mining Massive Datasets Ch.9 Recommender Systems http://infolab.stanford.edu/~ullman/mmds/ch9.pdf