recommendation engines

stuff to learn today:

1. name different kinds of recommendation engines
2. explain the concepts behind each kind of engine
3. pros and cons of the different engines + when to use which

part 1: types of recommendation engines, and **why**???

- three main types of recommendation engines:
  a. non-personalized
  b. content-based
  c. collaborative filtering

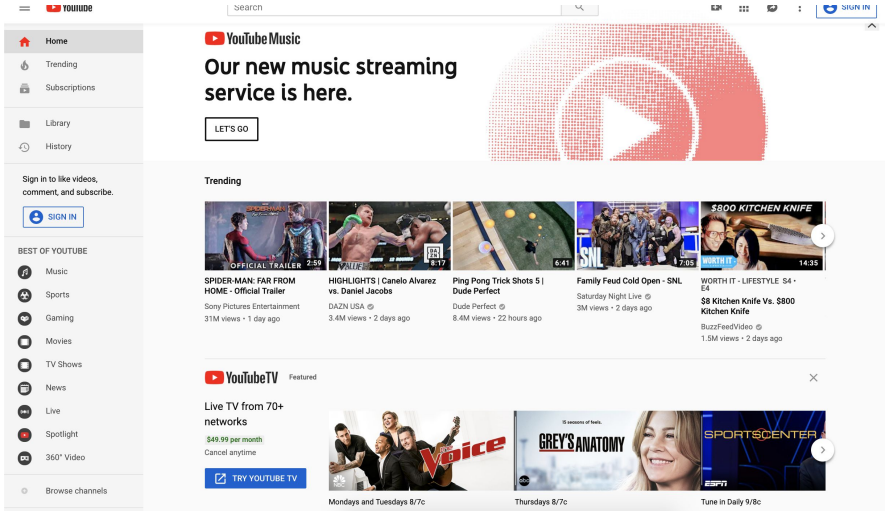
- why do we need recommendation engines + what are some examples?

part 2: non-personalized recommendation engines

- top-rated items
- most bought/watched/consumed items
- items who will give companies highest ROI

- easy to make recommendations (same recommendations for everyone)

- is it the most effective?



part 3: content-based recommendation engines

- makes recommendations based on an item's **features**
- models we already know that can do this!!

- how would you build a recommendation engine using models you already know?

		Items				
		A	**B**	**C**	**D**	**...**
Features	**Genre**	2	3	5	1	...
	Actor	5	4	2	1	...
	Director	1	1	1	3	...
	Year	3	4	5	2	...
	IMDB Ratings	5	4	1	2	...

similarity metrics

- euclidean distance
- jaccard index
- cosine similarity
- adjusted cosine similarity
- pearson correlation

		Items				
		A	**B**	**C**	**D**	**...**
Features	**Genre**	2	3	5	1	...
	Actor	5	4	2	1	...
	Director	1	1	1	3	...
	Year	3	4	5	2	...
	IMDB Ratings	5	4	1	2	...

part 3: content-based recommendation engines

- what are some pros and some pitfalls of content-based recommendations?

part 4: collaborative filtering -- the **utility matrix**

- a utility matrix shows user ratings of different items (usually sparse 😞)
- the idea is to fill in the blanks, and recommend items with the highest predictions

	Movie 1	Movie 2	Movie ...	Movie N
User 1	1	BLANK	BLANK	3
User 2	BLANK	5	BLANK	3
User 3	BLANK	BLANK	1	BLANK
User 4	2	3	BLANK	BLANK
User 5	BLANK	BLANK	1	BLANK
User 6	4	BLANK	5	BLANK
User 7	BLANK	4	BLANK	BLANK
User ...	BLANK	3	BLANK	BLANK
User m	BLANK	BLANK	BLANK	4

	Movie 1	Movie 2	Movie ...	Movie N
User 1	1	4	2	3
User 2	1	5	3	3
User 3	2.5	2.8	1	3.5
User 4	2	3	2	3.5
User 5	2.5	2.8	1	3.1
User 6	4	1.2	5	1.4
User 7	1	4	2.5	3
User ...	2	3	2	3
User m	1	4	2	4

part 4: collaborative filtering

- recommends items **based on ratings of other users**

- different ways to do collaborative filtering:

  - memory-based (aka neighborhood-based)
    - user-user similarity
    - item-item similarity

  - model-based (matrix factorization)

part 4a: user-user collaborative filtering

filling up the utility matrix based on **user** similarities

to get recommendations for user X:

1. get user similarity values
2. the predicted rating for item A is a weighted average of others' ratings

	U1	U2	U3	U4
I1	4	2	3	5
I2	3	2	4	2
I3	?	4	5	4
I4	3	2	4	4

cos	U1
U2	0.65
U3	0.76
U4	0.83

sum = 2.24

? = (0.65*4 + 0.76*5 + 0.83*4)/2.24
= **4.34**

part 4a: collaborative filtering -- pros and cons

- personalized for each user

- computationally heavy
- popularity bias
- the **cold start** problem

part 4b: item-item collaborative filtering

filling up the utility matrix based on **item** similarities

to get recommendations for user X:

1. get ITEM similarity values
2. the predicted rating for item A is a weighted average of other **items**

	U1	U2	U3	U4
I1	4	2	3	5
I2	3	2	4	2
I3	?	4	5	4
I4	3	2	4	4

cos	I3
I1	0.78
I2	0.83
I4	0.87

sum = 2.48

? = (0.78*4 + 0.83*3 + 0.87*3)/2.48
= **3.31**

part 4b: user-user vs item-item

which is better?????

- in general, item-item has proven to be more effective
- it's hard to predict users' *unique* tastes

time complexity (for ***m*** users and ***n*** items)

- user-user: $O(m^2n)$
- item-item: $O(mn^2)$
- which would be faster if **m > n** (more users than items)?

similarity metrics:

- experimentally, **Pearson correlation** has demonstrated to be the best

part 4c: model-based collaborative filtering

singular value decomposition:

- another way to fill in the utility matrix via matrix factorization

modified SVD in recommendation engines:

- breaks down the utility matrix into a **user matrix** and an **item matrix**
- the other dimensions are latent features
- gradient descent using Alternating Least Squares to preserve the relationship between items and between users (parallelizable)

very math, but best-in-class models use some form of SVD

part 4c: modified SVD for filling in utility matrices

	U1	U2	U3	U4
I1	4	2	3	5
I2	3	2	4	2
I3	?	4	5	4
I4	3	2	4	4

≈

I1	×	×
I2	×	×
I3	×	×
I4	×	×

latent features

•

U1	U2	U3	U4
×	×	×	×
×	×	×	×

latent features

part 4c: gradient descent with Alternating Least Squares

I1	1	1
I2	1	1
I3	1	1
I4	1	1

•

U1	**U2**	**U3**	**U4**
1	1	1	1
1	1	1	1

=

	U1	**U2**	**U3**	**U4**
I1	2	2	2	2
I2	2	2	2	2
I3	2	2	2	2
I4	2	2	2	2

OG	**U1**	**U2**	**U3**	**U4**
I1	4	2	3	5
I2	3	2	4	2
I3	?	4	5	4
I4	3	2	4	4

RMSE = 1.75

part 4c: gradient descent with Alternating Least Squares

I1	x	1
I2	1	1
I3	1	1
I4	1	1

•

U1	U2	U3	U4
1	1	1	1
1	1	1	1

=

	U1	U2	U3	U4
I1	x+1	x+1	x+1	x+1
I2	2	2	2	2
I3	2	2	2	2
I4	2	2	2	2

OG	U1	U2	U3	U4
I1	4	2	3	5
I2	3	2	4	2
I3	?	4	5	4
I4	3	2	4	4

Finding **x** to minimize:

$(4-(x+1))^2 + (2-(x+1))^2 + (3-(x+1))^2 + (5-(x+1))^2$

setting d/dx = 0, x = **2.5**

part 4c: gradient descent with Alternating Least Squares

I1	2.5	1
I2	1	1
I3	1	1
I4	1	1

•

U1	**U2**	**U3**	**U4**
1	1	1	1
1	1	1	1

=

	U1	**U2**	**U3**	**U4**
I1	3.5	3.5	3.5	3.5
I2	2	2	2	2
I3	2	2	2	2
I4	2	2	2	2

OG	**U1**	**U2**	**U3**	**U4**
I1	4	2	3	5
I2	3	2	4	2
I3	?	4	5	4
I4	3	2	4	4

RMSE = 1.58!!

part 4c: gradient descent with Alternating Least Squares

I1	?	?
I2	?	?
I3	?	?
I4	?	?

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U1	**U2**	**U3**	**U4**
?	?	?	?
?	?	?	?

=

	U1	**U2**	**U3**	**U4**
I1	3.55	2.91	3.68	3.85
I2	3.25	2.66	3.37	3.08
I3	3.7	3.42	4	3.85
I4	3.32	2.86	3.6	3.49

OG	**U1**	**U2**	**U3**	**U4**
I1	4	2	3	5
I2	3	2	4	2
I3	?	4	5	4
I4	3	2	4	4

RMSE = 1.15

stuff we've learned

recommendation engines!!!

<table>
<tr><td colspan="3">1. non-personalized</td></tr>
<tr><td colspan="3">2. content-based</td></tr>
<tr><td rowspan="3">collaborative filtering</td><td rowspan="2">memory-based</td><td>3. user-user</td></tr>
<tr><td>4. item-item</td></tr>
<tr><td>model-based</td><td>5. SVD</td></tr>
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