Building a Recommendation Engine

agenda

1. an introduction to recommendation engines & how they work (three types!)

2. how can we code a recommendation engine?

// part 1: an introduction to recommendation engines

types of recommendation engines, and **why**???

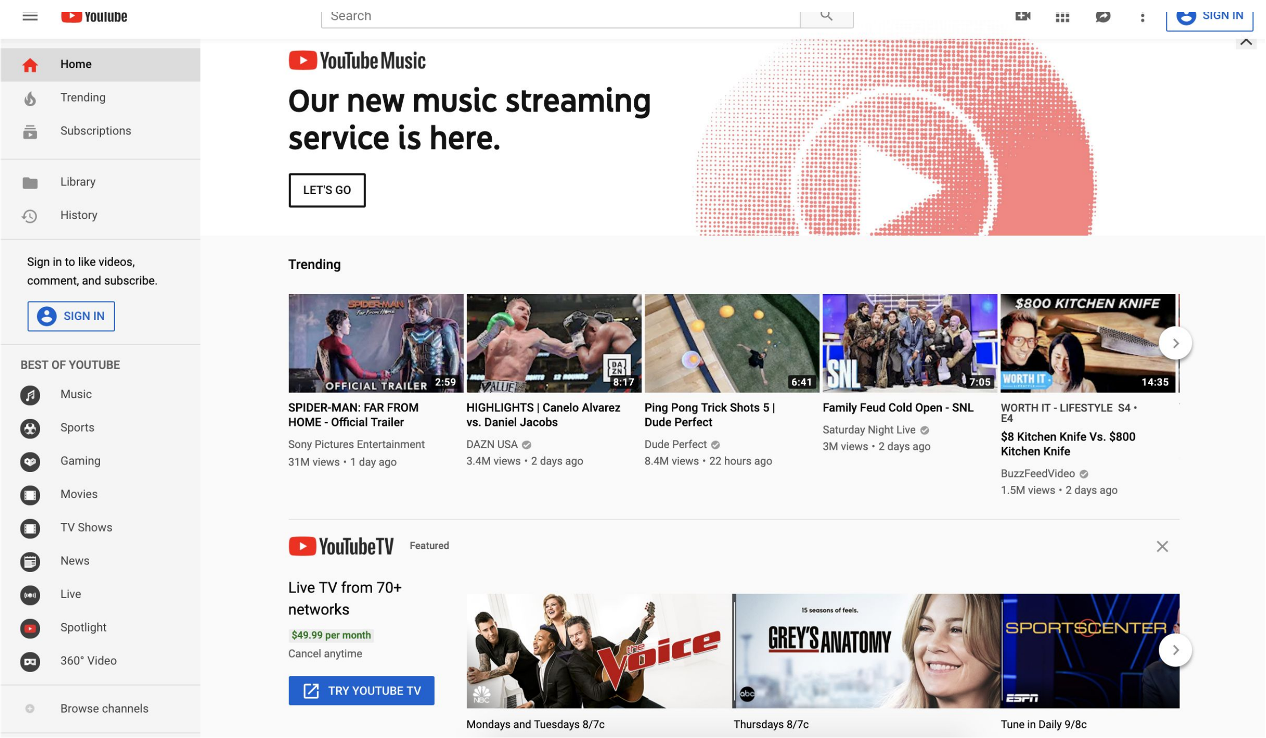
- why do we need recommendation engines + what are some examples?

types of recommendation engines, and **why**???

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

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

non-personalized recommendation engines



content-based recommendation engines

- makes recommendations based on an item’s **features**

movies	Genre	Actor	Director	Year	IMDB	Rotten Tomatoes	...
1							
2							
3							
4							
5							
...							

similarity metrics

- euclidean distance
- jaccard index
- cosine similarity

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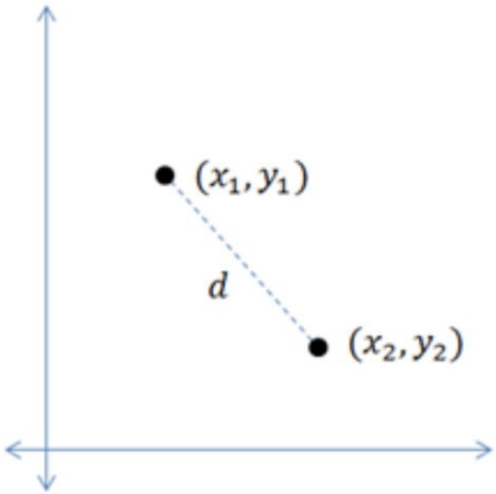
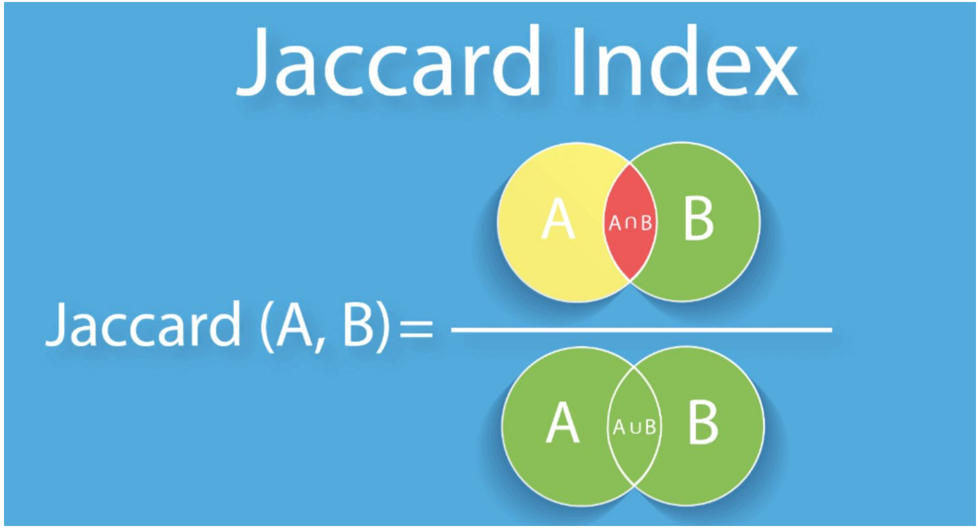


$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

similarity metrics

- euclidean distance
- **jaccard index**
- cosine similarity



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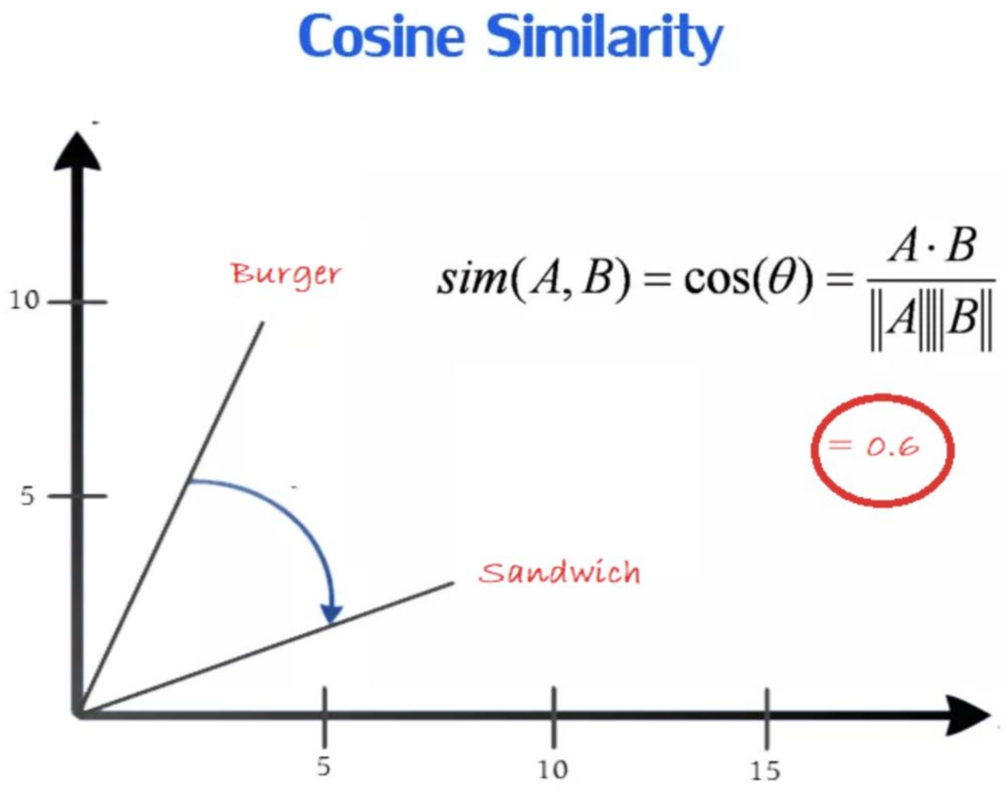

similarity metrics

- Now that we have learned how to calculate distance metrics, how do we calculate that for documents?
- Two options:
  - Bag of words
  - tf-idf

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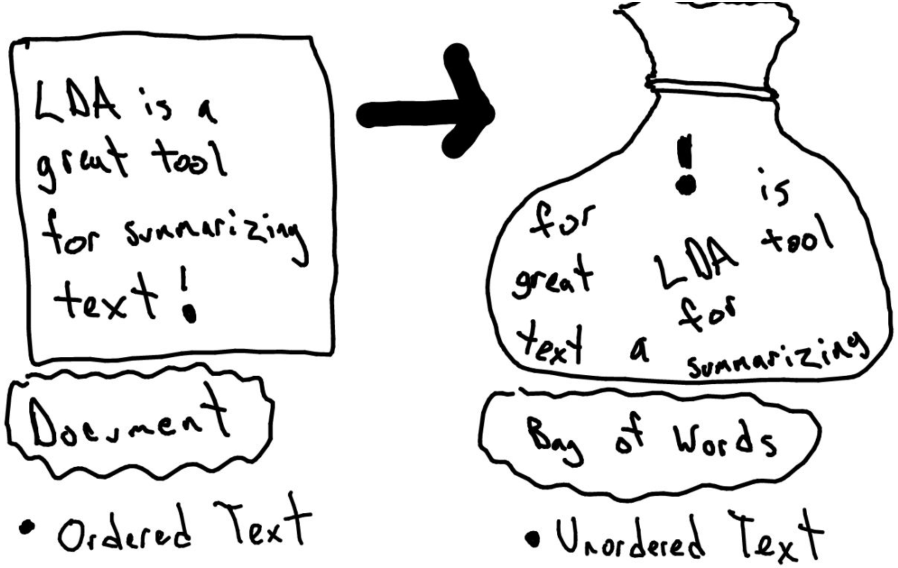


similarity metrics

Example:

1. “I love dogs”
2. “Dogs are awesome pets”
3. “I have four pets, two dogs, a guinea pig, and a cat, and i love them” →

i	love	dogs	are	awesome	pets	have	four	two	a	guinea	pig	cat
1	1	1	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	1	0	0	0	0	0	0	0
2	1	1	0	0	1	1	1	1	2	1	1	1

similarity metrics

- Now that we have learned how to calculate distance metrics, how do we calculate that for documents?
- Two options:
  - Bag of words
  - **Tf-idf**
    - **TF: Term Frequence:**
      TF(t) = (Number of times term t appears in a document) / (Total number of terms in the document).
    - **IDF: Inverse Document Frequency:**
      IDF(t) = log_e(Total number of documents / Number of documents with term t in it)
    - TF-IDF = TF * IDF

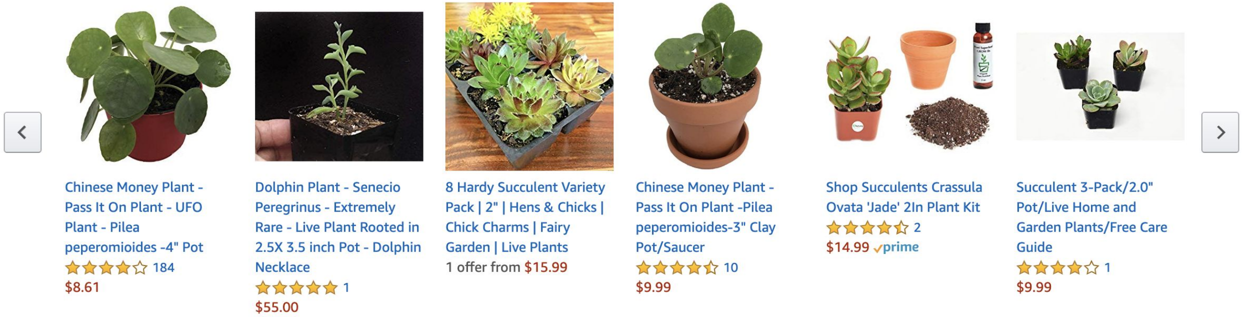
similarity metrics

- Now that we have learned how to calculate distance metrics, how do we calculate that for documents?

- Documents will then be turned into tf-idf matrix, where each document is an observation, and each column represent a token
- Each document can then be represented as a vector in an n dimensional space, where n stands for number of tokens
- We can then calculate a cosine similarity matrix of p x p, where p is the number of documents

content-based recommendation engines

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



collaborative filtering

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

- different ways to do collaborative filtering:
    - Memory-based(aka neighborhood based):
        - Item-item similarity
        - User-user similarity
    - model-based: Singular Vector Decomposition (SVD)

collaborative filtering -- the **utility matrix**

- a utility matrix shows user ratings of different items

- the idea is to fill in the blanks

	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

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**

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**

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)?

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

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

$\approx$

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

$\cdot$

U1	U2	U3	U4
x	x	x	x
x	x	x	x

collaborative filtering -- pros and cons

- personalized for each user!

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

stuff we've learned

recommendation engines!!!

1. non-personalized		
2. content-based		
collaborative filtering	memory-based	**3. user-user**
		4. item-item
	model-based	**5. SVD**

// part 2: coding our own recommendation engine!

stuff we've learned

recommendation engines!!!

1. non-personalized
2. content-based
3. model-based collaborative filtering with SVD

code-along: https://github.com/jessicafangfanglee/hotel-recommendation