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## Main dilemmas facing recommender systems

### The long tail rule

lots of items have little popularity

Can't cater for niche preferences

## Content-based Recommender systems

**Main idea: evaluate main attributes of items to make recommendation**

### How to pick features?

We choose TF-IDF

(Term frequency \* Inverse Doc Frequency)

define:  $f(i,j)$  means "frequency of item(feature) $i$  in doc(item)  $j$ "

$n(i)$  = number of docs that mention term  $i$

$N$  = total number of docs

first, compute two variables:

$$TF(i,j) = f(i,j) / \max(k f(k,j))$$

$$IDF(i) = \log(N / n(i))$$

TF-IDF score,  $w(i,j) = TF(i,j) * IDF(i)$

### How to evaluate similarity between user and item profiles?

use Cosine similarity.

### upsides and downsides

#### upsides:

- not need other users' data
- can meet niche preferences

- able to recommend new items

## **downsides**

- hard to find appropriate features  
In fact, we don't know how accurate the features we choose are.
- never recommend items out of the user profile

# **Collaborative Filtering**

## **User-User collaborative filtering**

**Find other users that give similar ratings compared to the user**

There we choose Pearson correlation.

Formula : See slides1 Page24.

**Biased on other users' ratings**

## **Item-Item collaborative filtering**

**find similar items to the unique item**

**Biased on unique user's ratings**

# **Improvements in the Netflix game**

**The important idea: A three layer structure**

**Upper layer: Global**

**Consider overall deviations of users/movies**

overall deviations of users

**Add bias according to the mean of users/movies**

**Middle layer: Regional**

Factorization: Addressing "regional" effects

**choose SGD to do that**

## **Lower layer: Local**

CF: Extract local patterns

Made model modifications

See slides2Page10

## **Use weight to relace similarity**

$\text{weight}(i,j)$  -> minimize SSE on traing data

Use Convex optimization to do so