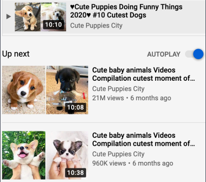
» Recommender Systems

Personalised recommendations are the application of machine learning most of us experience daily. Many examples:

- Shopping, e.g. amazon:

- Videos, Music, e.g. youtube:



- News
- Apps
- Adverts

» Quick Class Poll

On a scale of 1-5 (1=v good, 5=v bad), how useful do you find the recommendations you receive for:

* Videos e.g. youtube
* Movies e.g. netflix
* Music e.g. spotify
* Shopping e.g. amazon
* Adverts e.g. in google search

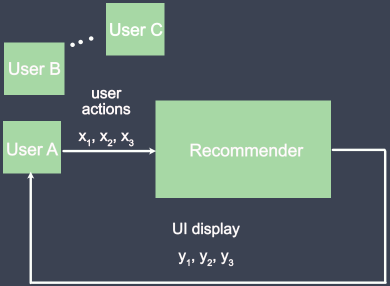
And:

* Do you use an ad blocker?

» Recommender Systems

- Deciding whether an image contains a cat or not is an objective "technical" kind of problem – its fixed and well defined, fairly easy to agree when we've succeeded .
- In contrast making personalised recommendations are:
  - *Subjective*:
    - *Personal*. No ground truth, what I like you might dislike
    - *Time-varying*. What I like today I might be bored by in a months time
    - *Feedback*. Recommendations can change user behaviour/steer users, and recommender leanrs user behaviour → filter bubbles etc
  - *Hard to evaluate performance* → this is a whole research topic!
- Often conflicting objectives:
  - *User* wants useful suggestions
  - *Operator* of recommender system is providing the service for a reason. E.g. operator might prefer to recommend:
    - Most profitable movie rather than the one user would most like
    - News headline mostly likely be clicked rather than the one most likely to be informative
  - *Content producers* may want to manipulate recommendations to promote their content
- Often privacy concerns → surveillance capitalism
- Not such clear progress as in image processing → due to intrinsic noise or lack of data? Emperor's new clothes?

» Recommender Systems



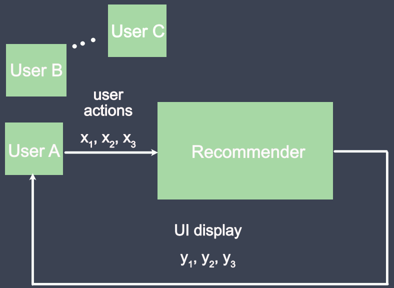
* Repeat

  System displays info y_t to user

  User takes action x_t

* *User actions* x_t
  * Clicks, ratings, time spent watching a video or reading news, purchase of an item, tweeting a link etc
* *Displayed info* y_t
  * Image of product, price, reviews, ratings by other users etc
* *Sequence* of displays to user and corresponding user actions e.g. recommendations update as user explores displayed products by clicking on links

» Recommender Systems



- *Multiple users* of system, so can learn from population of users
- *Context* e.g.
  - User's current situation and short-term intents and interest.
  - Time → recent news, newer movies, videos of more interest
  - Price → are some items discounted/on sale?
  - Ordering → if buy camera may be interested in memory card
  - Recommend only unseen items or repeatedly recommend past ones → "Repeated recommendations as reminders"?
- Have less data on some users than others, especially:
  - *Cold start*: New users, new items e.g news articles, videos

Let's simplify:

- *User actions*. Map user action to a rating value e.g. between 0 and 1.
  - We know which items a user has rated and which they have not.
  - Have negative feedback: a rating of 0 tells us a user didn't like an item, its *not* the same as not rating an item (which might occur because they don't know an item exists, or for other reasons)
- *Display info*. Have a set V of items
- *Sequence*. Ignore sequence information
- *Multiple users*. Have set U of users.
- *Context*. Ignore.
- *Cold start*. Ignore.

So what we observe is a set of triplets (user, item, rating). This is a minimal setup, not realistic but hopefully captures the essence of the recommender task.

» Content-based Recommendation

Task: predict the top N items for user (the N most highly rated items not already seen).

* Idea 1: recommend items to user that are similar to items previously rated highly by user
    1. How to measure similarity of items?
    2. How to predict rating for unseen items?

Measuring similarity:

* Map from details of item v to feature vector $x(v)$ E.g.
    * Map item category/genre to feature using one-hot encoding
    * Map text description to feature vector using bag of words model and TF-IDF
* Calc cosine similarity of items v, w. For feature vectors $x(v)$ and $x(w)$ cosine similarity is $s(v,w) = \frac{\sum_{j=1}^{n} x_j(v)x_j(w)}{\sqrt{\sum_{j=1}^{n} x_j^2(v)}\sqrt{\sum_{j=1}^{n} x_j^2(w)}}$

Predict user u rating for unseen item v using kNN approach

* Find set N_k of k items seen/rated by user u and most similar to unseen item v
* Predicted rating $\hat{R}_{uv} = \frac{\sum_{w \in N_k} s(v,w) R_{uw}}{\sum_{w \in N_k} s(v,w)}$

» Content-based Recommendation

Cosine similarity:

* Suppose feature vector for item v is $[1, 0, 0, 1]$ and for item w is $[1, 0, 1, 0]$, then

$$\sum_{j=1}^{n} x_j(v)x_j(w) = 1 \times 1 + 0 \times 0 + 0 \times 1 + 1 \times 0 = 1$$

and

$$\sqrt{\sum_{j=1}^{n} x_j^2(v)} = \sqrt{2}, \ \sqrt{\sum_{j=1}^{n} x_j^2(w)} = \sqrt{2}$$

so $s(v, w) = \frac{1}{2}$

* Suppose now feature vector for item w is $[1, 0, 0, 1]$, then

$$\sum_{j=1}^{n} x_j(v)x_j(w) = 1 \times 1 + 0 \times 0 + 0 \times 0 + 1 \times 1 = 2$$

and $s(v, w) = 1$

* For the product $x_j(v)x_j(w)$ to be large we need *both* $x_j(v)$ and $x_j(w)$ large

» Item-based Collaborative Filtering

Task: predict the top N items for user (the N most highly rated items not already seen).

* Idea 2: recommend items that similar users previously rated highly $\rightarrow$ *collaborative filtering* since using info from population of users

Measuring similarity of users:

* Let M_u be set of items rated by user u and R_{uv} be rating of item $v \in M_u$ by user u. Then $M_{uu'} = M_u \cap M_{u'}$ is the set of items rated by both users. Cosine distance between users u, u':

$$s(u,u') = \frac{\sum_{v \in M_{uu'}} R_{uv} R_{u'v}}{\sqrt{\sum_{v \in M_{uu'}} R_{uv}^2} \sqrt{\sum_{v \in M_{uu'}} R_{u'v}^2}}$$

  i.e sum the product of the user ratings for items rated by both user u and user u'. Will tend to be large when users *both* rate same items highly

* Problems: (i) usually each user rates only a small number of items so $M_u \cap M_{u'}$ might be small/empty, (ii) computationally expensive to calc for all user pairs u, u' when have many users

» Item-based Collaborative Filtering

Idea 3: Measure similarity of items collaboratively

- Item-Based Collaborative Filtering Recommendation Algorithms 2001 http://files.grouplens.org/papers/www10_sarwar.pdf
- For two items v and w let U_v be the set of users who have rated item v and U_w the set of users who have rated item w. Then $U_{vw} = U_v \cap U_w$ is the set of users who have rated both u and v. Collaborative cosine similarity between items v and w is:

$$s(v, w) = \frac{\sum_{u \in U_{vw}} R_{uv} R_{uw}}{\sqrt{\sum_{u \in U_{vw}} R_{uv}^2} \sqrt{\sum_{u \in U_{vw}} R_{uw}^2}}$$

$s(v, w)$ large when users tend to rate items v and w similarly

Predict user u rating for unseen item v using kNN approach

- Find set N_k of k items seen/rated by user u and most similar to unseen item v
- Predicted rating $\hat{R}_{uv} = \frac{\sum_{w \in N_k} s(v,w) R_{uw}}{\sum_{w \in N_k} s(v,w)}$

Note: (i) if enough users then U_{vw} should be pretty large, (ii) #items usually much smaller than #users so calc for all item pairs v, w not too expensive to compute

» Item-based Collaborative Filtering

Collaborative cosine similarity:

* We can gather ratings data into ratings matrix R, element R_{uv} is equal to rating given by user u to item v, e.g. $R_{12} = 4$

$$R = \begin{bmatrix} 5 & 4 & 0 & 0 \\ ? & 5 & ? & 0 \\ 5 & ? & ? & ? \\ 0 & 0 & 5 & ? \\ 0 & 0 & 5 & 4 \end{bmatrix}$$

* Users rating both items 1 and 2:

$$R = \begin{bmatrix} 5 & 4 & 0 & 0 \\ ? & 5 & ? & 0 \\ 5 & ? & ? & ? \\ 1 & 0 & 5 & ? \\ 0 & 1 & 5 & 4 \end{bmatrix}$$

So $U_1 = \{1,3,4,5\}$, $U_2 = \{1,2,4,5\}$ and $U_{12} = U_1 \cap U_2 = \{1,4,5\}$ and

$$\sum_{u \in U_{12}} R_{u1} R_{u2} = 5 \times 4 + 0 \times 5 + 0 \times 1, \quad \sqrt{\sum_{u \in U_{12}} R_{u1}^2} = \sqrt{5^2 + 1^2 + 0^2}, \quad \sqrt{\sum_{u \in U_{12}} R_{u2}^2} = \sqrt{4^2 + 0^2 + 1^2$$

and $s(1,2) = \frac{20}{\sqrt{26}\sqrt{16}} = 0.98 \rightarrow$ items 1 and 2 are pretty similar wrt ratings.
Repeat calc for items 2 and 3, $s(2,3) = \frac{5}{\sqrt{17}\sqrt{50}} = 0.17 \rightarrow$ much less similar

» Example: Item-Based Movie Recommender

Python Lenskit package https://lkpy.readthedocs.io/en/stable/index.html implements many common recommender approaches, including item-based collaborative filtering:

```
from lenskit.datasets import ML100K
from lenskit import batch, topn, util
from lenskit import crossfold as xf
from lenskit.algorithms import Recommender, als, item_knn as knn
from lenskit.metrics.predict import rmse
import pandas as pd

algo_ii = knn.ItemItem(20)

def eval(aname, algo, train, test, all_preds):
    fittable = util.clone(algo)
    fittable = Recommender.adapt(fittable)
    fittable.fit(train)
    # predict ratings
    preds = batch.predict(fittable, test)
    preds['Algorithm'] = aname
    all_preds.append(preds)

def main():
    all_preds = []; test_data = []
    for train, test in xf.partition_users(ratings[['user', 'item', 'rating']], 5, xf.SampleFrac(0.2)):
            test_data.append(test)
            eval('II', algo_ii, train, test, all_preds)
    preds = pd.concat(all_preds, ignore_index=True)
    preds_ii = preds[preds['Algorithm'].str.match('II')]
    print(preds_ii.head())
    test_data = pd.concat(test_data, ignore_index=True)
    print('RMSE II:', rmse(preds_ii['prediction'],preds_ii['rating']))

if __name__ == '__main__':
    ml100k = ML100K('ml-100k')
    ratings = ml100k.ratings; print(ratings.head())
    main()
```

» Example: Item-Based Movie Recommender

* Download data using:
  wget http://files.grouplens.org/datasets/movielens/ml-100k.zip
  unzip -f ml-100k.zip
* Typical output:

```
user item rating timestamp
0 196 242 3.0 881250949
1 186 302 3.0 891717742
2 22 377 1.0 878887116
3 244 51 2.0 880606923
4 166 346 1.0 886397596
user item rating prediction Algorithm
4059 3 354 3.0 3.371460 II
4060 3 319 2.0 3.028429 II
4061 3 345 3.0 3.250216 II
4062 3 355 3.0 2.331747 II
4063 3 294 2.0 2.898721 II

RMSE II: 0.9004012551052291
```

» Session-based Recommendation

- Useful recommendations often depend on user's current situation and short-term intents and interest
- Often users interact with a system in a "session" e.g. go to retailer web site to look for a coffee machine. Then come back and this time look for a jacket.

- Can use recent user interactions to improve recommendations
- Unsurprisingly, can give a significant boost in performance e.g. see:
  - Session-based Item Recommendation in E-Commerce 2017 https://web-ainf.aau.at/pub/jannach/files/Journal_UMUAI_2017.pdf
  - Effective Nearest-Neighbor Music Recommendations 2018 https://web-ainf.aau.at/pub/jannach/files/Workshop_RecSys_Challenge_2018.pdf
- How to extend previous approach to use sessions?

» Session-based Collaborative Filtering

How to extend previous approach to use sessions?

- Define a user session e.g. last N interactions with a user
- Use nearest neighbours on sessions rather than single items:
  - Set S of past sessions for all users. Each session $a \in S$ consists of a set I_a of items and their ratings $r_a(v)$, $v \in I_a$.
  - Measure similarity between two sessions a and b using:

$$s(a,b) = \frac{|I_a \cap I_b|}{\sqrt{|I_a||I_b|}}$$

    where $I_a \cap I_b$ is set of items that appear in both sessions a and b.
  - Let N_k be the set of k sessions in S closest to current session, e.g. use $k = 500$
  - Predicted rating of item v by user u is:

$$\hat{R}_{uv} = \frac{\sum_{b \in N_k} s(a,b) 1_b(v)}{\sum_{w \in N_k} s(a,b)}$$

    where $1_b(v) = 1$ when session b contains item v and otherwise $1_b(v) = 0$
  - Many tweaks possible. E.g. replace $1_b(v) = 1$ by the rating $r_a(v)$ of item v by the user in session b, in $s(a,b)$ give greater weight to more recent items in session

» Session-based Recommendation

Session similarity;

- Suppose two previous sessions with items $I_1 = \{5, 4, 1, 10\}$ and $I_2 = \{1, 5, 10, 9, 20\}$. Then $I_1 \cap I_2 = \{1, 5, 10\}$ and session similarity is:

$$s(1,2) = \frac{|I_1 \cap I_2|}{\sqrt{|I_1||I_2|}} = \frac{3}{\sqrt{4 \times 5}} = 0.67$$

- Suppose current session 3 has $I_3 = \{4, 5\}$ and set of k nearest sessions is $N_k = \{1, 2\}$. Then $1_1(10) = 1$ and $1_2(10) = 1$, $s(3,1) = \frac{2}{\sqrt{2\times 4}} = 0.7$, $s(3,2) = \frac{1}{\sqrt{2\times 5}} = 0.31$. Predicted rating for item 10 is:

$$\hat{R}_{u10} = \frac{s(3,1)1_1(10) + s(3,2)1_2(10))}{s(3,1) + s(3,2)} = \frac{0.7 \times 1 + 0.31 \times 1}{0.7 + 0.31} = 1$$

and for item 7 is

$$\hat{R}_{u7} = \frac{0.7 \times 0 + 0.31 \times 0}{0.7 + 0.31} = 0$$

» Collaborative Filtering With Implicit user feedback

- So far we assumed that user's rate an item and we know which items have been rated.
- What about clicks?
  - A click probably indicates some interest an item, but a single click is a weak signal as to whether a user likes an item or not
  - Main problem: lack of negative feedback. Absence of a click might mean two things. (i) user saw item but wasn't interested in it, (ii) user doesn't know item exists
- One way to measure similarity between items v and w is:

$$s(v, w) = \frac{|U_{vw}|}{\sqrt{|U_v||U_w|}}$$

  where U_{vw} is the set of users who have clicked on both items v, w, U_v the set of users who have clicked item v and U_w the set of users who have clicked item w
- Observing repeated clicks is more informative, so keep can track of #clicks and use that as a surrogate rating
- Lack of negative feedback still a problem though

» Summary

- With item-based approaches its easy to incorporate context information by modifying similarity. E.g. to include:
  - Time between when two videos/news articles were posted
  - Difference in price
  - Review text sentiment
- Item-based approaches are easy to understand, easy to implement
- Widely used, a decent baseline
  - Two Decades of Recommender Systems at Amazon.com 2017 https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7927889
- For collaborative filtering it's essential to have enough users so that U_{vw} is not small/empty $\rightarrow$ otherwise use a content-based approach e.g. use bag of words+TFIDF to find items with similar descriptions, type etc
- Thorny problems:
  - *Cold start*. (i) New user who hasn't rated anything yet. Typically fall back to recommending most popular items until get more info about new user. (ii) Collaborative filtering also has item cold-start problem i.e. new item has no ratings yet
  - *Implicit feedback*. Clicks don't provide negative feedback