» Overview

* Recommending = Matrices?
    * Matrix completion
    * Matrix Factorization
    * SLIM
    * BLC
* What do big companies use?
* Content of this lecture is optional - won't be examined

» Recommending = Matrix Completion

Example: users rate books they have read from 0-5.

Book	Alice(1)	Bob(2)	Carol(3)	Dave(4)
Machine Learning for Dummies(1)	5	4	0	0
Hands-On Machine Learning(2)	?	5	?	0
Deep Learning(3)	5	?	?	?
A Kitten Called Holly(4)	0	0	5	?
Kittens 2018 Calendar(5)	0	0	5	4

Define ratings matrix R with element R_{uv} equal to rating given by user u to item v, e.g. $R_{12} = 4$

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

Notation:

* n number of users, $n = 4$
* m number of items, $m = 5$
* $\delta_{uv} = 1$ if item v rated by user u, 0 otherwise, $\delta_{11} = 1$, $\delta_{21} = 0$

» Recommending = Matrix Completion

Ratings matrix R, element R_{uv} equal to rating given by user u to item v, e.g.

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

* The task of the recommender system is to predict the missing values in the ratings matrix (the $?$ elements) $\rightarrow$ *matrix completion*
* To make this task well-defined we need to add some constraints/restrictions on these predictions ...

» Matrix Factorisation

Suppose we have following ratings data:

Book	Alice(1)	Bob(2)	Carol(3)	Dave(4)	$x^{(1)}$=[ML	kittens]
Machine Learning for Dummies(1)	5	4	0	0	1	0
Hands-On Machine Learning(2)	?	5	?	0	?	?
Deep Learning(3)	5	?	?	?	?	?
A Kitten Called Holly(4)	0	0	5	?	?	?
Kittens 2018 Calendar(5)	0	0	5	4	0	1

Rough idea:

* Each book has a topic e.g. machine learning or kittens. Use one-hot encoding to map topic to a feature vector of length $d = 2$ for an item. E.g.
  * Item 1 “Machine Learning for Dummies” has feature vector $x^{(1)} = [1, 0]$
  * Item 5 ‘Kittens 2018 Calendar” has feature vector $x^{(5)} = [0, 1]$
* Each user has a preference for the topics. So represent each user by a weight vector. E.g.
  * User 1 Alice has weight vector $\theta^{(1)} = [5, 0]$
  * User 3 Carol has weight vector $\theta^{(3)} = [0, 5]$
* Predict rating of item v by user u using:

$$\hat{R}_{uv} = (\theta^{(u)})^T x^{(v)} = \sum_{i=1}^{d} \theta_i^{(u)} x_i^{(v)}$$

E.g. Carol’s rating of “A Kitten Called Holly” is $0 \times 0 + 5 \times 1 = 5$ and predicted rating of “Deep Learning” is $0 \times 1 + 5 \times 0 = 0$

» Matrix Factorisation

* Idea: Use linear model of items and user preferences
  * Each item v is characterised by an abstract feature vector $x^{(v)}$ of length d. E.g. $d = 2$ and $x^{(1)} = [1, 4]$
  * Each user's preferences are captured by the weight they place on each element of item feature vector i.e each user u is characterised by a vector $\theta^{(u)}$ of d weights. E.g. $\theta^{(1)} = [1, 0]$
  * Predicted rating of item v by user u is

$$\hat{R}_{uv} = (\theta^{(u)})^T x^{(v)}$$

    E.g. $\hat{R}_{11} = 1 \times 1 + 0 \times 4 = 1$.

* Cost function: square error plus L_2 penalty

$$\sum_{u=1}^{n} \sum_{v=1}^{m} \delta_{uv} (R_{uv} - \hat{R}_{uv})^2 + \sum_{u=1}^{n} (\theta^{(u)})^T \theta^{(u)} / C_1 + \sum_{v=1}^{m} (x^{(v)})^T x^{(v)} / C_2$$

* Select $x^{(v)}$ and $\theta^{(u)}$ to minimise cost function e.g. using stochastic gradient descent
  * Note: cost is non-convex so training might be slow/tricky.
* This approach won the Netflix prize in 2008. Matrix Factorization Techniques For Recommender Systems 2009 https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5197422

» Matrix Factorisation

Extra details:

* Calculate the mean rating μ over all items and users and write predicted rating as:

$$\hat{R}_{uv} = \mu + (\theta^{(u)})^T x^{(v)}$$

  i.e. $(\theta^{(u)})^T x^{(v)}$ estimates deviations from mean rating.

* Some users tend to systematically give higher (or lower) ratings than other users $\rightarrow$ can mean that predictions based on their ratings are inaccurate. Add a bias parameter b_u for user u, so predicted rating of item v by user u becomes:

$$\hat{R}_{uv} = \mu + b_u + (\theta^{(u)})^T x^{(v)}$$

* Similarly for items. Add a bias parameter b_v for item v:

$$\hat{R}_{uv} = \mu + b_u + b_v + (\theta^{(u)})^T x^{(v)}$$

* Estimate parameters b_u, b_v, $\theta^{(u)}$, $x^{(v)}$ by choosing values that minimise the cost function.

» Example: Item-Based Movie Recommender

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

```
from lenskit.algorithms.basic import Bias, Popular, TopN
from lenskit import topn
from lenskit.metrics.predict import rmse
import pandas as pd

algo_pop = Bias(); algo_ii = knn.ItemItem(20)
algo_als5 = als.BiasedMF(5)

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('BIAS', algo_pop, train, test, all_preds)
                eval('II', algo_ii, train, test, all_preds)
                eval('MF', algo_als5, train, test, all_preds)
        preds = pd.concat(all_preds, ignore_index=True)
        preds_ii = preds[preds['Algorithm'].str.match('II')]
        preds_bias = preds[preds['Algorithm'].str.match('BIAS')]
        preds_nf= preds[preds['Algorithm'].str.match('MF')]
        test_data = pd.concat(test_data, ignore_index=True)
        print('RMSE BIAS:', rmse(preds_bias['prediction'],preds_bias['rating']))
        print('RMSE II:', rmse(preds_ii['prediction'],preds_ii['rating']))
        print('RMSE MF:', rmse(preds_mf['prediction'],preds_mf['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 prediction Algorithm
3924 1 143 1.0 4.031989 II
3925 1 6 5.0 4.092580 II
3926 1 211 3.0 4.183012 II
3927 1 157 4.0 4.070335 II
3928 1 190 5.0 4.534220 II
      user item rating prediction Algorithm
7848 1 143 1.0 2.989210 MF
7849 1 6 5.0 3.859588 MF
7850 1 211 3.0 4.437893 MF
7851 1 157 4.0 4.204632 MF
7852 1 190 5.0 4.026473 MF
   user item rating prediction Algorithm
0 1 143 1.0 3.862483 POP
1 1 6 5.0 3.566096 POP
2 1 211 3.0 4.017835 POP
3 1 157 4.0 3.790314 POP
4 1 190 5.0 4.241681 POP

RMSE POP: 0.9403746168971867
RMSE II: 0.899763752505545
RMSE MF: 0.909195791898838
```

» Why "Matrix Factorisation"?

Another way to think about the same thing ...

* Gather user parameter vectors into a matrix U:

$$U = [\theta^{(1)}, \theta^{(2)}, \dots, \theta^{(n)}]$$

  where $[\theta^{(v)}$ is a column vector, so U is a $d \times n$ matrix

* Gather item feature vectors into a $d \times m$ matrix V:

$$V = [x^{(1)}, x^{(2)}, \dots, x^{(m)}]$$

* The transpose U^T of matrix U is

$$U^T = \begin{bmatrix} (\theta^{(1)})^T \\ (\theta^{(2)})^T \\ \vdots \\ (\theta^{(n)})^T \end{bmatrix}$$

  and

$$U^T V = \begin{bmatrix} (\theta^{(1)})^T x^{(1)} & (\theta^{(1)})^T x^{(2)} & \dots & (\theta^{(1)})^T x^{(m)} \\ (\theta^{(2)})^T x^{(1)} & (\theta^{(2)})^T x^{(2)} & \dots & (\theta^{(2)})^T x^{(m)} \\ \vdots & & & \\ (\theta^{(n)})^T x^{(1)} & (\theta^{(n)})^T x^{(2)} & \dots & (\theta^{(n)})^T x^{(m)} \end{bmatrix}$$

* So $\hat{R} = U^T V$ is prediction for rating matrix R. Expressing matrix $\hat{R}$ as the product of two factors U and $V \rightarrow$ *matrix factorisation*

» SLIM

- Idea: use a slightly more flexible/general matrix factorization model
  - SLIM: Sparse Linear Methods for Top-N Recommender Systems 2011 https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6137254
  - ADMM SLIM: Sparse Recommendations for Many Users 2020 https://dl.acm.org/doi/pdf/10.1145/3336191.3371774 (Netflix)
- Rating matrix R. Let R_v be column of R corresponding to item $v \rightarrow$ a vector consisting of all the user ratings of item v.
- Predicted rating of item v by user u:

$$\hat{R}_{uv} = R_v^T(\theta^{(v)}) = \sum_{i=1}^{m} \delta_{uv'} \theta_{v'}^{(v)} R_{uv'}$$

  where $\theta^{(v)}$ is a vector of weights and $\delta_{uv} = 1$ when user u has rated item v and 0 otherwise. So R_{uv} is a weighted linear combination of the user's previous item ratings.
- Cost function:

$$\sum_{u=1}^{n} \sum_{v=1}^{m} \delta_{uv}(R_{uv} - \hat{R}_{uv})^2 + \sum_{v=1}^{m} (\theta^{(v)})^T \theta^{(v)} / C_1 + \sum_{v=1}^{m} \sum_{v'=1}^{m} |\theta_{v'}^{(u)}| / C_1$$

- Constraints: $\theta_{v'}^{(v)} \geq 0,\ \theta_v^{(v)} = 0$. Note: $\theta_{v'}^{(v)} \geq 0$ constraints sometimes dropped to simplify optimisation
- Perrformance of SLIM found to be good (often better than vanilla MF) in many independent tests.

» Clustering Users

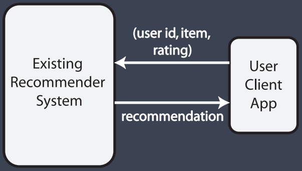
- Vanilla matrix factorization treats the user population as being homogeneous, then tries to patch things up by adding extra b_u parameters.
- But we expect that user's can be grouped into rough clusters $\rightarrow$ e.g. advertisers have known this forever.
- Idea: Have a set of user groups, suppose each user belongs to just one group. For users in same group use matrix factorization to predict ratings (so all users in same group have same predicted ratings).
  - BLC: Private Matrix Factorization Recommenders via Automatic Group Learning 2017 https://arxiv.org/abs/1509.05789
- Predicted rating for all users in group g is

$$\hat{R}_{uv} = (\theta^{(g)})^T x^{(v)}$$

  and parameter $g^{(u)}$ is the group of user u. E.g. $g^{(1)} = 2$ when user 1 is in group 2
- Select parameters $\theta^{(g)}, x^{(v)}, g^{(u)}$ to minimise the usual MF cost
- Tests show state of the art performance with no further tuning.
- Number of groups is a hyperparameter, but typically a small number is sufficient e.g. 32 groups $\rightarrow$ is that surprising or not?

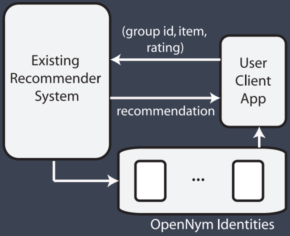
» Clustering Users: Privacy By Design

User accesses system via an account used only by them, so id and user strongly linked.



Conventional

User accesses system via an account shared with other users having similar interests.



OpenNym

» Summary

* Implicit feedback (clicks etc → lack of negative feedback)
  * Plenty of pretty effective approaches for incorprating implicit feedback. E.g.
  * BPR: Bayesian Personalized Ranking from Implicit Feedback 2009 https://arxiv.org/pdf/1205.2618.pdf
  * Collaborative Filtering for Implicit Feedback Datasets 2008 http://yifanhu.net/PUB/cf.pdf
* Context e.g. time, price/discounts, review text
  * Typical approach is to extend the predicted rating to include extra context info:

$$\hat{R}_{uv} = \mu + b_u + b_v + (\theta^{(u)})^T x^{(v)} + \text{context parameters}$$

* Sessions
  * Not really, though idea of using abstract feature vector for users/items carries over.
* Cold-start
  * A thorny problem for all collaborative filtering approaches.
  * For new users can recommend most popular items until know more about user → clustering of users into groups can help
  * For new items one approach is to randomly include them in recommendations to a few users to elicit initial feedback

» What do big companies use ?

Amazon

- Two Decades of Recommender Systems at Amazon.com 2017 https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7927889
  - Item-based collaborative filtering, with tweaks to similarity measure.

Netflix

- ADMM SLIM: Sparse Recommendations for Many Users 2020 https://dl.acm.org/doi/pdf/10.1145/3336191.3371774
  - SLIM variant of matrix factorization

Youtube

- Deep Neural Networks for YouTube Recommendations 2016 https://static.googleusercontent.com/media/research.google.com/en/ /pubs/archive/45530.pdf
  - Basically matrix factorization, with tweaks and implemented using neural net.
- Latent Cross: Making Use of Context in Recurrent Recommender Systems 2018 https://dl.acm.org/doi/pdf/10.1145/3159652.3159727
  - Use recurrent neural net for low-rank (i.e. matrix factorization-like) *session-based* approach. Softmax layer maps from RNN output to probability vector across all videos.

» What do big companies use ?

Facebook

- Recommending Items To More Than A Billion People 2015 https://engineering.fb.com/core-data/recommending-items-to-more-than-a-billion-people/
  - Uses matrix factorization.
  - Article spends a *lot* of time discussing how to make things scalable
- Deep Learning Recommendation Model for Personalization and Recommendation Systems 2019. https://github.com/facebookresearch/dlrm.
  - Map inputs to feature vector using a mix of approaches (incl. matrix factorization and neural nets)
  - Use MLP to map from features to a prediction of probability of a click.
  - Not many other concrete details though ...

Instagram

- Powered by AI: Instagrams Explore Recommender System 2019 https://ai.facebook.com/blog/powered-by-ai-instagrams-explore-recommender-system/
- Map from account info to a feature vector using a neural net approach.
- Keep track of accounts a user has interacted with previously. Use cosine distance between accounts to find similar accounts. Then use those to form list of candidate recommendations.
- Rank candidates by predicting actions (like, save, negative action) that person is likely to take. Use a multi-pass MLP then ConvNet approach for this.

» ConvNets & Recommenders

We haven't talked about using ConvNets/Deep Learning for making recommendations ...

* Session-Based Recommendations With Recurrent Neural Networks 2016
  https://arxiv.org/pdf/1511.06939.pdf
  * Seems to work pretty well in independent evaluations
  * Recurrent neural nets are being used by youtube for making session-based recommendations
  * Recurrent neural net = treat interactions as a time-series, we leave time-series to another module!
* Are We Really Making Much Progress? A Worrying Analysis of Recent Neural Recommendation Approaches 2019
  https://dl.acm.org/doi/pdf/10.1145/3298689.3347058
  * Session-based approaches aside, serious concerns have been raised about claims of performance gains from use of ConvNets $\rightarrow$ item-based and matrix factorization approaches frequently observed to outperform ConvNets when fairly compared.
  * Jury is still out on this, but wise to be cautious about over-hyped claims and motivated reasoning re deep learning.

» Some Known Issues

- Shilling attacks/adversarial data. E.g.
  - A hotel might post fake reviews (or pay someone else to post them) talking itself up, or talking down the opposition
  - Similarly with product reviews
  - Botnets and large-scale click fraud
  - Manipulation on facebook, twitter etc by state actors
- Seems like no easy solutions …
  - Create costly barrier to keep bots etc out e.g. must pay for a room in hotel before a review can be submitted.
  - Create barrier by building reputation over time e.g. stackoverflow
  - Manual moderation/policing (automated statistical ML methods not so effective in adversarial situations)
- Filter bubbles
  - Feedback loop: recommendations$\rightarrow$user actions $\rightarrow$recommendations
  - Commercial pressure: maximising clicks etc
  - Manipulation: fake news?
- Privacy/surveillance capitalism
  - US, Europe and Asia have very different privacy regulations.
  - As access control (couched as “consent”) …
  - Adding noise/perturbing the data (k-anonymity, differential privacy).
  - Hiding in the crowd/clustering
  - Emperors new clothes: maybe we can make equally bad recommendations with far less data?