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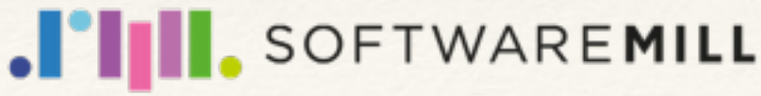
Recommendation systems

Introduction using Mahout



Agenda

- What is a recommender?
- Types of recommenders, input data
- Recommendations with Mahout: single node
- Recommendations with Mahout: multiple nodes

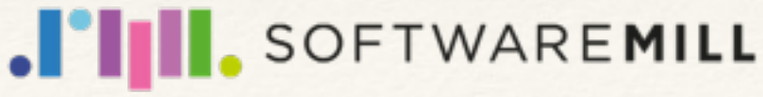
Who Am I?

- **Day**: coding @ SoftwareMill
- **Afternoon**: playgrounds, Duplos, etc.
- **Evenings**: blogging, open-source
  - Original author of Hibernate Envers
  - ElasticMQ, Veripacks, MacWire
  - http://www.warski.org

Me + recommenders

- Yap.TV
- Recommends shows to users basing on their favorites
  - from Yap
  - from Facebook
- Some business rules

Some background



Information ...

- **Retrieval**
  - given a query, select items
- **Filtering**
  - given a user, filter out irrelevant items

What can be recommended?

- Items to users
- Items to items
- Users to users
- Users to items

Input data

- (user, item, rating) tuples
  - rating: e.g. 1-5 stars
- (user, item) tuples
  - **unary**

Input data

- Implicit
  - clicks
  - reads
  - watching a video
- Explicits
  - explicit rating
  - favorites

Prediction vs recommendation

- Recommendations
  - suggestions
    - top-N
- Predictions
  - ratings

Collaborative Filtering

- Something more than search keywords
  - tastes
  - quality
- Collaborative: data from many users

Content-based recommenders

- Define features and feature values
- Describe each item as a vector of features

Content-based recommenders

- User vector
  - e.g. counting user tags
    - sum of item vectors
- Prediction: cosine between two vectors
  - profile
  - item

User-User CF

- Measure similarity between users
- Prediction: weighted combination of existing ratings

User-User CF

- Domain must be scoped so that there's agreement
- Individual preferences should be stable

User similarity

- Many different metrics
- Pearson correlation: $w_{au} = \frac{\sum_{i=1..m}(r_{ai} - \bar{r_a})(r_{ui} - \bar{r_u})}{\sigma_a * \sigma_u}$

User neighbourhood

- Threshold on similarity
- Top-N neighbours
  - 25-100: good starting point
- Variations:
  - trust networks, e.g. friends in a social network

Predictions in UU-CF

$$P_{ai} = \bar{r_a} + \frac{\sum_{u=1..n}(r_{ui} - \bar{r_u}) * w_{au}}{\sum_{u=1..n} w_{au}}$$

Item-Item CF

- Similar to UU-CF, only with items
- Item similarity
  - Pearson correlation on item ratings
  - co-occurences

Evaluating recommenders

- How to tell if a recommender is good?
  - compare implementations
    - are the recommendations ok?
- Business metrics
  - what leads to increased sales

Leave one out

- Remove one preference
- Rebuild the model
- See if it is recommended
- Or, see what is the predicted rating

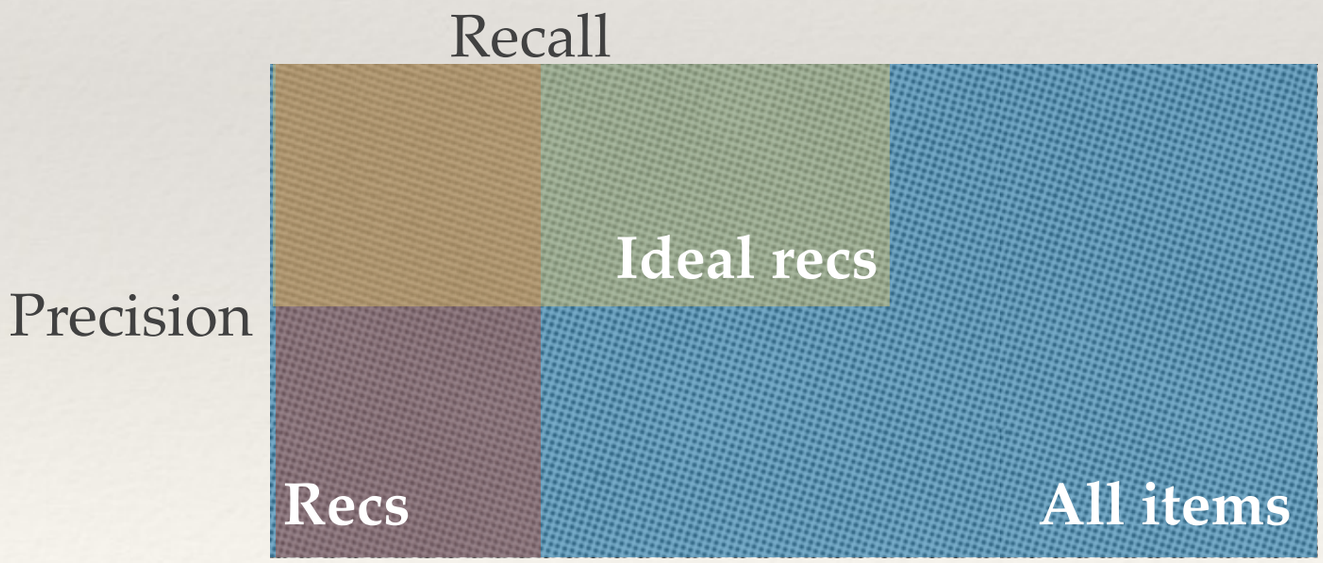
Some metrics

- Mean absolute error: $\frac{\Sigma_i |R_i - P_i|}{ratings}$
- Mean squared error

Precision/recall

- Precision: % of recommended items that are relevant
- Recall: % of relevant items that are recommended

- Precision@N, recall@N



SOFTWAREMILL

Problems

- Novelty: hard to measure
  - leave one out: punishes recommenders which recommend **new** items
- Test on humans
  - A/B testing

Diversity/serendipity

- Increase diversity:
  - top-n
    - as items come in, remove the ones that are too similar to prior items
- Increase serendipity:
  - downgrade popular items

Netflix challenge

- $1m for the best recommender
- Used mean error
- Winning algorithm won on predicting low ratings

Mahout single-node

Mahout
IN ACTION

Sean Owen
Robin Anil
Ted Dunning
Ellen Friedman

MANNING

Requires Adobe Acrobat Reader to play audio and video links

grouplens.org/datasets/movielens/

MovieLens

GroupLens Research has collected and made available rating data sets from the MovieLens web site (http://movielens.org). The data sets were collected over various periods of time, depending on the size of the set. Before using these data sets, please review their README files for the usage licenses and other details.

MovieLens 100k

100,000 ratings from 1000 users on 1700 movies.

- README.txt
- ml-100k.zip
- Index of unzipped files

MovieLens 1M

1 million ratings from 6000 users on 4000 movies.

- README.txt
- ml-1m.zip

MovieLens 10M

10 million ratings and 100,000 tag applications applied to 10,000 movies by 72,000 users.

- README.html
- ml-10m.zip

Datasets

MovieLens

HetRec 2011

WikiLens

Book-Crossing

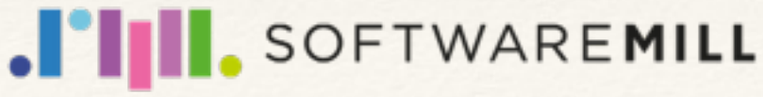
Jester

EachMovie

Mahout single-node

- User-User CF
- Item-Item CF
- Various metrics
  - Euclidean
  - Pearson
  - Log-likelihood
- Support for evaluation

Let's code



Mahout multi-node

- Based on Hadoop
- Pre-computed recommendations
  - Item-based recommenders
    - Co-occurrence matrix
  - Matrix decomposition
    - Alternating Least Squares

Running Mahout w/ Hadoop

```
hadoop jar mahout-core-0.8-job.jar
    org.apache.mahout.cf.taste.hadoop.item.RecommenderJob
    --booleanData
    --similarityClassname SIMILARITY_LOGLIKELIHOOD
    --output output
    --input input/data.dat
```

Links

- http://www.warski.org
- http://mahout.apache.org/
- http://grouplens.org/
- http://graphlab.org/graphchi/
- https://class.coursera.org/recsys-001/class
- https://github.com/adamw/mahout-pres

Thanks!

- Questions?
- Stickers ->
- adam@warski.org