Recommender Systems and the Netflix Prize

Andreas Töscher, Georg Preßler

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Founding Members

Georg Preßler, Michael Schrotter, Andreas Töscher, Michael Jahrer

Georg Preßler is on site and is prepared to answer your questions

commendo

- specialized in customized recommender systems
- top contender in the Netflix prize
- Netflix Progress Prize 2008

Goal of a recommender system

- building customized websites
- suggestions for interesting products
- improved sorting of search results
- display of similar products

Content vs Collaborative Filter

Content filtering

- based on item meta data
  for example:
  - category or genre
  - actor or director of a movie

Collaborative filtering (CF)

- take taste of many users to infer taste of an individual
- *Assumption:* Users who agreed in the past will agree in the future.

Good recommender systems are mostly a combination of both!

Sources of information for CF

Explicit information

- ratings
- rankings
- comments

Implicit information

- purchase information
- wish list
- clicks
- time spent on a page

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Netflix Prize

NETFLIX

- Netflix is an US online movie rental service
- hiring of movies via mail
- over 100.000 titles
- 55 million DVDs total
- productive start at 1997
- have their own recommendation system called “Cinematch”

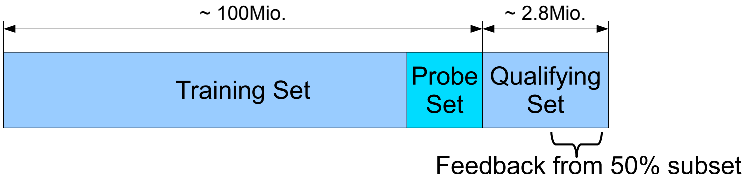
Netflix Prize

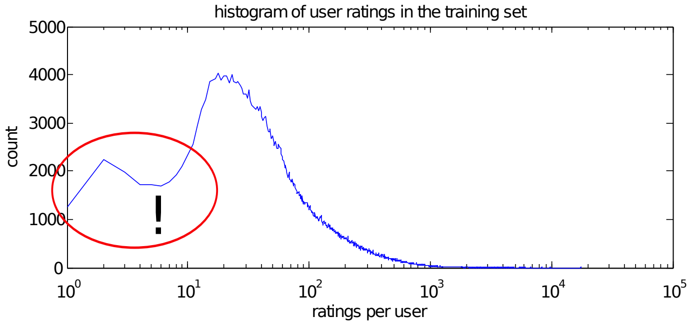
- Grand Prize, 1 Mio. US-Dollar for 10% improvement in prediction accuracy
- Progress Prize, 50.000 US-Dollar, October every year
- started Oct, 2 2006
- ends Oct, 2 2011
  - or when a 10% improvement in RMSE is reached by a team
- www.netflixprize.com

Netflix Prize Facts

- dataset consists of 100 Mio. entries
- quadruples of $< movie, user, rating, date >$
- integer ratings from 1 to 5
- error measure: RMSE (root mean square error)
  $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - t_i)^2}$ $(r_i = prediction \;\; t_i = target)$
- over 45.000 contestants from 180 countries

Dataset Details





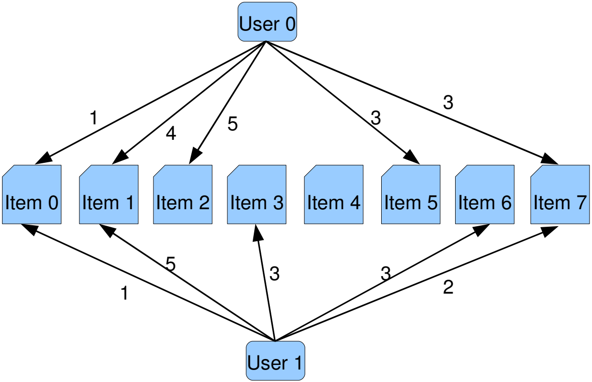
Overview of Models

- Similarity based
  - item based
  - user based
- Latent factor model (e.g. SVD)
- Asymetric factor models
- Neural Networks
- Restricted Boltzmann Machines
- Hybrid approaches

Similarity based methods

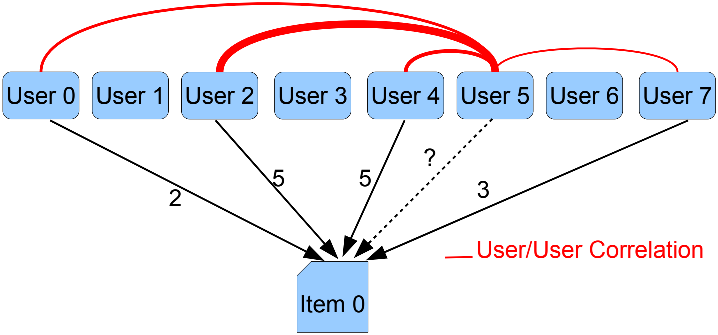
- rating prediction based on neighborhood information
- standard algorithm
- very simple to implement
- easy to understand
- easy to customize

Similarity between users



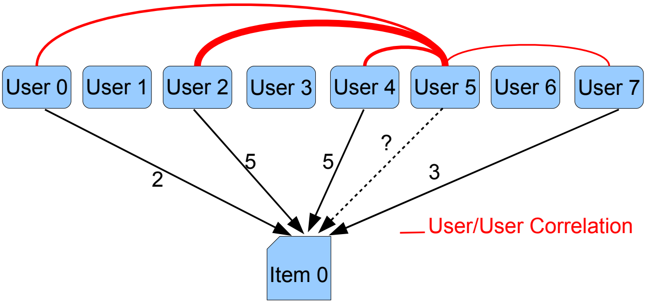
- $U_0 = [1, 4, 3]$
- $U_1 = [1, 5, 2]$

Prediction from user similarity



- Pearson correlation between users
- rating prediction for user 5 on item 0:
  - select k-best correlating users which voted item 0
  - weight the ratings of the k-best users with their correlation to user 5

Prediction from user similarity



- $N(u,i)$ ... k-best correlating users
- c_{uv} ... Pearson correlation between users u and v

$$r_{ui} = \frac{\sum_{v \in N(u,i)} c_{uv} r_{vi}}{\sum_{v \in N(u,i)} |c_{vi}|} \tag{1}$$

Remarks on user similarity models

- in general two users have very few common ratings
- Netflix dataset consists of 500,000 users
- precomputation of all user/user correlations is hard (takes over 1 TByte storage)
- due to sparsity predictions for some user/item combinations are not possible (coverage)

Item/Item Correlations

- in general better defined
- 18,000 movies in the Netflix dataset
- precomputable (for the Netflix dataset)
- predictions are more accurate

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Ranking Quality

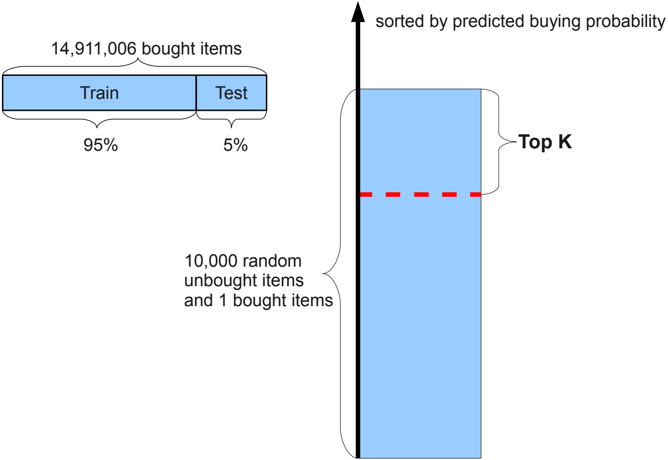
Ranking

- use collaborative filtering for personalized sorting
- small RMSE improvements lead to much better rankings

Dataset details

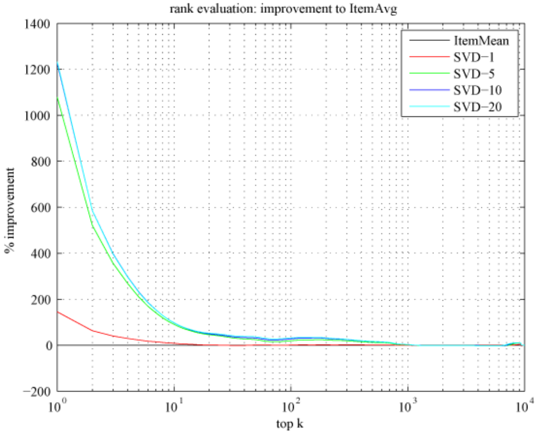
- 855,949 users
- 96,198 items
- 14,911,006 bought items

The Experiment



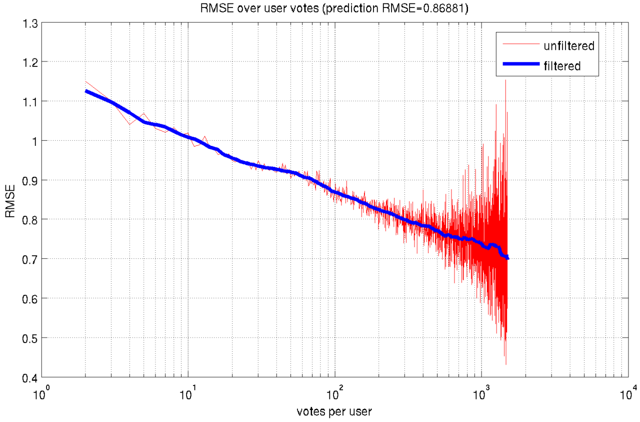
- the experiment is done on the last 5% of rating data

Improved Ranking



	item mean	SVD 1	SVD 5	SVD 10	SVD 20
Improvement over item mean [RMSE]	0.0%	2.14%	6.22%	8%	8.6%
Hit probability for top-1	0.66%	1.6%	7.8%	8.7%	8.8%

Average Error as Function of User Votes



- Netflix Grand Prize level at $\sim$ 100 votes/user

Ways to Increase accuracy

- more sophisticated models
- combining different models
- more information
  - ratings
  - clicks
  - wish list
  - purchase information

Small improvements in accuracy dramatically improves the sorting quality!

An improved RMSE of 8.6% leads to over **1,200%** of improvement on the hit rate for the top-1 item!

Thank you for your attention.

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