SI 583 - Recommender Systems, Winter 2009

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Lecture 10:
Singular Value Decomposition; Evaluation Metrics
SI583: Recommender Systems
Software modules
Fitting the weights: SVD

- Model weights from SVD \((U, S, V)\):

  - Weight (item \(j\), feature \(f\)) = \(\sqrt{s_{ff}} \cdot V_{fj}\)
  - Weight (user \(i\), feature \(f\)) = \(\sqrt{s_{ff}} \cdot U_{if}\)

Alternative: get software package to calculate weights directly.
SVD-based CF: Summary

- Pick a number of features $k$
- Normalize ratings
- Use SVD to find best fit with $k$ features
- Use fitted model to predict value of Joe’s normalized rating for item X
- Denormalize (add Joe’s mean) to predict Joe’s rating for X
SVD Practicalities

- SVD is a common mathematical operation; numerous libraries exist
- Efficient algorithms to compute SVD for the typical case of sparse ratings
- A fast, simple implementation of an SVD-based recommender (by Simon Funk/Brandyn Webb) was shown to do very well on the Netflix challenge
SVD and Content Filtering

- Similar idea: Latent Semantic Indexing used in content-filtering
  - Fit item descriptions and keywords by a set of features
  - Related words map onto the same feature
  - Similar items have the similar feature vectors

- Useful to combine content+collaborative filtering
  - Learn some features from content, some from ratings
Where we are in the course

Up to this point:
- Eliciting ratings
- Using implicit information
- Software architecture
- Collaborative filtering algorithms

Next:
- Evaluation
- Scalable software (briefly)
- Interface extensions
- Manipulation and defenses
- Privacy
Evaluation of Recommendation Quality
Recommendation Presentation

- Predicted score
- (Ordered) list of recommended items
- Filter threshold based on score
Fast! (Score:5, Funny)
by bablefisk (115988) on Tuesday February 10, @06:02AM (#26795395)

November 2007 was a bit optimistic, but september 2008 is still a really fast fix!

Reply to This

That's more than just a typo... (Score:5, Funny)
by Arancaytar (966377) <arancaytar.iyaran@gmail.com> on Tuesday February 10, @06:06AM (#26795419) Hon

That entire news item is outdated. :P

Reply to This

Confusion about Dates (Score:2, Insightful) by Zephiris (788562) The article [bbc.co.uk] apparently fails to

Re: (Score:2) by harry666t (1062422) ...and you should also always specify whether it's AD or BC, whe

Re: (Score:2) by Gandalf_Greyhame (44144) Of course it's AD. You don't have to say it's AD. It's
Assessing Quality of a Threshold

- Many metrics derived from the “confusion matrix”:
Assessing Quality of a Threshold

- **Precision** $p$
  \[ \frac{TP}{(TP+FP)} \]

- **Recall** $r$
  \[ \frac{TP}{(TP+FN)} \]
Assessing Quality of a Threshold

- Precision $p$
  \[ \frac{TP}{TP+FP} \]
- Recall $r$
  \[ \frac{TP}{TP+FN} \]
- Combinations, e.g., $2pr/(p+r)$ \{F1-measure\}

Which metric is best?
Assessing Quality of a Threshold

- Precision $p$
  \[ TP/(TP+FP) \]

- Recall $r$
  \[ TP/(TP+FN) \]

- Combinations, e.g.,
  \[ 2pr/(p+r) \] \{F1-measure\}

- Which metric is best?
- Depends on scenario..
- Ultimately, all are special cases of cost-benefit analysis
  - cost of inspecting an item
  - benefit from seeing a good item
  - (perhaps) penalty for missing a good item
Assessing Quality of a Threshold

- Other charts you might see:
  - ROC (receiver operator characteristic) curve
  - precision-recall curve
  - both are different ways of showing how the tradeoff changes with the threshold
Example ROC curve
Learn Your School Facts
www.SchoolDataDirect.org Comprehensive Data on Your Students and School District For Free!

Free School Information
www.thebeehive.org/FreeSchoolInfo Everything schools from finding to homework. All free!

School of Information - University of Michigan: The iSchool at ...
The School of Information (SI) at the University of Michigan educates professionals to lead in the information age, offering the PhD and master's degree in ...
www.si.umich.edu/ - 27k - Cached - Similar pages

School of Information
UC Berkeley School of Information ... Workshop Unites Ph.D. Students From UC Information Schools. First-ever student-run workshop brings together doctoral ...
www.ischool.berkeley.edu/ - 34k - Cached - Similar pages

School of Information - University of Texas
The mission of The University of Texas at Austin School of Information is to shape information realities for human and social benefit by: 1) Discovering new ...
www.ischool.utexas.edu/ - 32k - Cached - Similar pages

Great Schools - Public and Private School Ratings, Reviews and ...
School information by state (click to expand)School information by city (click to expand)School information by district (click to expand) ...
www.greatschools.net/ - 35k - Cached - Similar pages
Assessing quality of a list

- On/off correctness; see previous slide
- Number of swaps necessary to get correct ordering
- Is there anything good on the list?
- Some scoring/point function
  - E.g. 10 points if top choice on the list, etc.
Rating predictions

![NetflixFrontpage](https://www.gizmodo.com/schoolofinformation/1761637021)

*www.gizmodo.com*
Assessing quality of score predictions

- Mean Absolute Error

\[
\frac{|\text{pred} - \text{actual}|}{N}
\]
Assessing quality of score predictions

- Mean Absolute Error

\[
\frac{\sum |\text{pred} - \text{actual}|}{N}
\]

- Mean Squared Error

\[
\frac{\sum (\text{pred} - \text{actual})^2}{N}
\]
Choice of error metric

- Why did Netflix choose MSE instead of MAE?
- What other metrics could they have used, and what impact would they have had?
Minimizing MAE and MSE

- Given beliefs, probability distribution over ratings
  - E.g., 0, 4, or 5, each with probability 1/3
- What should you predict in order to minimize MAE?
- What should you predict in order to minimize MSE?