

Understanding Recommendation Systems

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February 22, 2010

Recommendation Systems

Netflix and **goodreads.com** allow users to rate movies and books.

We have ratings for *user / item* pairs (e.g., *Eric* rated *The Departed* a 5).

Clearly, we do not know ratings for items the user has not rated.

We could recommend an item if we believe a user would rate it highly. Therefore, the ability to predict a rating that a user would give an item can be used for recommendation systems.

Recommendation Systems

We collect the known ratings into a matrix \widehat{M} .

		Movies																				
		1	2	3	4	5	6	7	8	9	10											
Users	1																					
	2																					
	3																					
	4																					
	5																					
	6																					
	7																					
	8																					
	9																					
	10																					

We assume there is a **true matrix** M that is completely filled with the ratings every user would give each item.

Recommendation Systems

Netflix hosted a \$1 million prize to a team that could make a substantial improvement in accuracy over their method to fill in the “missing entries”. They withheld known entries to measure how well participants’ did.

A number of researchers have developed new methodology to make such predictions. One popular method is the so-called low rank matrix completion problem. Here, we assume M is low rank and try to approximate it based only on the known entries in \widehat{M} such that

$$M \approx UV^T$$

where the matrices U and V are low rank and UV^T approximates the known entries \widehat{M} .

Recommendation Systems

This project will be two-fold.

1. We will implement a low rank matrix completion system for predicting user ratings on books. It will have a web front end and allow users to enter a handful of ratings and return book recommendations. The training data will consist of data from a portion of the *Book-Crossing* user/book rating dataset (<http://www.informatik.uni-freiburg.de/cziegler/BX>).
2. Additionally, we are interested in studying the effect of rounding ratings. We assume that users truly rate movies with real numbers between 1 and 5 (e.g., 3.77), but are forced to round to the nearest integer (viz., 1, 2, 3, 4, or 5). We see rounding as inducing error and are interested in studying its effect on the low rank matrix approximation.