Recommender Systems

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Recommender Systems. . . what?

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Information filtering systems that seek to predict the 'rating' or 'preference' that a user would give to an item (such as music, books, or movies) or social element (e.g. people or groups) they had not yet considered, using a model built from the characteristics of an item or the user's social environment.

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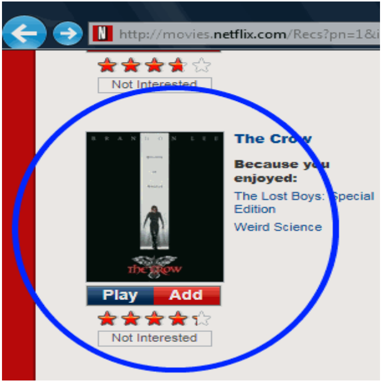
This is how they make more MONEY !!!

Images to prove the point. . .

Movie recommendations on Netflix



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Book recommendations on Amazon

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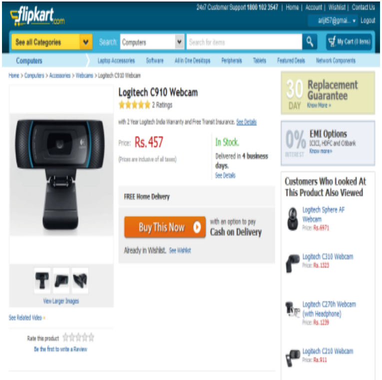
Recommendations on Flipkart



What is Collaborative filtering?

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Collaborative filtering is...

A machine learning algorithm that predicts movie ratings for new users (speaking in the context of the movie recommendations system) based on some (possibly none) movies in the database that they have already rated and also based on movie ratings by other users in the systems social environment. These predicted ratings can then be used to recommend top rated movies to the new user.

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- Allows us to predict movie ratings for new users even when they have not rated any movies. The most intuitive prediction in this case would be to predict the average rating for each movie.
- Allows us to predict ratings for new movies even when no user has rated those movies. So you don't need someone to watch every new film and rate it when it is first released.

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$$\mathbf{Y} = \text{movies} \begin{array}{c} \text{users} \\ \begin{array}{|c|c|c|c|} \hline 4 & 3 & 3 & ? \\ \hline 4 & 1 & ? & 1 \\ \hline 2 & 5 & 4 & 1 \\ \hline 2 & ? & 5 & 3 \\ \hline \end{array} \end{array}$$

movie ratings
on scale 1 - 5

n_m X n_u matrix

n_m = number of movies in DB

n_u = number of users in DB

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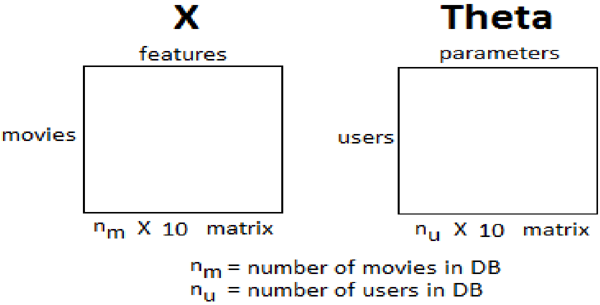

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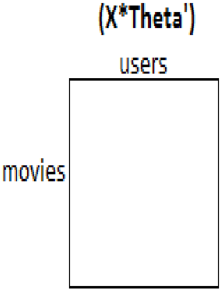
Theta is a n_u X 10 matrix

X is a n_m X 10 matrix

$\therefore$ (X*Theta') is a n_m X n_u matrix



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- One method would be to randomly initialize 'X' and find 'Theta' that minimizes the Cost Function(will be described soon). Then, use this 'Theta' to find 'X' that minimizes the Cost Function. Many iterations like this are carried out. But, this is sort of a chicken-and-egg problem.

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- The solution to this is to randomly initialize both 'X' and 'Theta' and learn them simultaneously (this actually works !!!).

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Our ultimate goal is to learn 'X' and 'Theta' such that the predicted values in (X*Theta') are not very far from the real ratings in matrix 'Y'. Thus, we want to minimize the Cost Function 'J' which is nothing more than the sum of squared error between the actual and predicted ratings and is defined below :

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$$J = \frac{1}{2} \sum_{(i,j):r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2$$

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$$\text{X\_grad} = \frac{\partial J}{\partial x_k^{(i)}} = \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})\theta_k^{(j)}$$

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- Large 'alpha' - optimization may never converge.
- Small 'alpha' - takes too long to converge.

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$$X = \frac{X - (\text{mean})}{\text{variance}}$$

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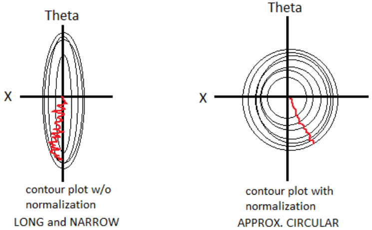

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$$Y_i = Y_i - \text{mean}$$

for each rating Y_i in the database

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$$J = J + \left(\frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^{n} (\theta_k^{(j)})^2 \right) + \left(\frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^{n} (x_k^{(i)})^2 \right)$$

$$X\_grad = X\_grad + \lambda x_k^{(i)}$$

$$\theta\_grad = \theta\_grad + \lambda \theta_k^{(j)}$$

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Thus, Recommendation engines are a must-have in every e-commerce establishment these days to grow economically themselves as well as help the customers choose the best possible products on sale according to their likings and preferences, at the same time making the whole process accurate, fast and most importantly fun. Collaborative filtering, no doubt deserves its place as a popular algorithm in this age of advanced social interactions.

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THANK YOU