

# 16: Recommender Systems

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## Recommender systems - introduction

- Two motivations for talking about recommender systems
  - Important application of ML systems**
    - Many technology companies find recommender systems to be absolutely key
    - Think about websites (amazon, Ebay, iTunes genius)
      - Try and recommend new content for you based on passed purchase
      - Substantial part of Amazon's revenue generation
    - Improvement in recommender system performance can bring in more income
    - Kind of a funny problem
      - In academic learning, recommender systems receives a small amount of attention
      - But in industry it's an absolutely crucial tool
  - Talk about the big ideas in machine learning
    - Not so much a technique, but an idea
    - As soon, features are really important
      - There's a big idea in machine learning that for some problems you can learn what a good set of features are
      - So not select those features but learn them
    - Recommender systems do this - try and identify the crucial and relevant features

### Example - predict movie ratings

- You're a company who sells movies
  - You let users rate movies using a 1-5 star rating
    - To make the example nicer, allow 0-5 (makes math easier)
- You have five movies
- And you have four users
- Admittedly, business isn't going well, but you're optimistic about the future as a result of your truly outstanding (if limited) inventory

Movie	Alice (1)	Bob (2)	Carol (3)	Dave (4)
Love at last	5	5	0	0
Romance forever	5	?	?	0
Cute puppies of love	?	4	0	?
Nonstop car chases	0	0	5	4
Swords vs. karate	0	0	5	?



- To introduce some notation
  - $n_u$  - Number of users (called  $n_u$  occasionally as we can't subscript in superscript)
  - $n_m$  - Number of movies
  - $r(i, j)$  - 1 if user  $j$  has rated movie  $i$  (i.e. bitmap)
  - $y^{(i,j)}$  - rating given by user  $j$  to movie  $i$  (defined only if  $r(i, j) = 1$ )
- So for this example
  - $n_u = 4$
  - $n_m = 5$
  - Summary of scoring
    - Alice and Bob gave good ratings to rom coms, but low scores to action films
    - Carol and Dave gave good ratings for action films but low ratings for rom coms
  - We have the data given above

- The problem is as follows
  - Given  $r(i,j)$  and  $y^{(i,j)}$  - go through and try and predict missing values (?'s)
  - Come up with a learning algorithm that can fill in these missing values

## Content based recommendation

- Using our example above, how do we predict?
  - For each movie we have a feature which measure degree to which each film is a
    - Romance ( $x_1$ )
    - Action ( $x_2$ )

Movie	Alice (1)	Bob (2)	Carol (3)	Dave (4)	$x_1$ (romance)	$x_2$ (action)
Love at last	5	5	0	0	0.9	0
Romance forever	5	?	?	0	1.0	0.01
Cute puppies of love	?	4	0	?	0.99	0
Nonstop car chases	0	0	5	4	0.1	1.0
Swords vs. karate	0	0	5	?	0	0.9

- If we have features like these, each film can be recommended by a feature vector
  - Add an extra feature which is  $x_0 = 1$  for each film
  - So for each film we have a  $[3 \times 1]$  vector, which for film number 1 ("Love at Last") would be

$$x^{(1)} = \begin{bmatrix} 1 \\ 0.9 \\ 0 \end{bmatrix}$$

- i.e. for our dataset we have
  - $\{x^1, x^2, x^3, x^4, x^5\}$ 
    - Where each of these is a  $[3 \times 1]$  vector with an  $x_0 = 1$  and then a romance and an action score
  - To be consistent with our notation,  $n$  is going to be the number of features NOT counting the  $x_0$  term, so  $n = 2$
- We could treat each rating for each user as a separate linear regression problem
  - For each user  $j$  we could learn a parameter vector
  - Then predict that user  $j$  will rate movie  $i$  with
    - $(\theta^j)^T x^i = \text{stars}$
    - inner product of parameter vector and features
  - So, lets take user 1 (Alice) and see what she makes of the modern classic Cute Puppies of Love (CPOL)
    - We have some parameter vector  $(\theta^1)$  associated with Alice
      - We'll explain later how we derived these values, but for now just take it that we have a vector

$$\theta^{(1)} = \begin{bmatrix} 0 \\ 5 \\ 0 \end{bmatrix}$$

- CPOL has a parameter vector ( $x^3$ ) associated with it

$$x^{(3)} = \begin{bmatrix} 1 \\ 0.99 \\ 0 \end{bmatrix}$$

- Our prediction will be equal to
  - $(\theta^1)^T x^3 = (0 * 1) + (5 * 0.99) + (0 * 0)$
  - $= 4.95$

- Which may seem like a reasonable value
- All we're doing here is applying a linear regression method for each user
  - So we determine a future rating based on their interest in romance and action based on previous films
- We should also add one final piece of notation
  - $m^j$ , - Number of movies rated by the user (j)

### How do we learn ( $\theta^j$ )

- Create some parameters which give values as close as those seen in the data when applied

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

- Sum over all values of i (all movies the user has used) when  $r(i,j) = 1$  (i.e. all the films that the user has rated)
- This is just like linear regression with least-squared error
- We can also add a regularization term to make our equation look as follows

$$\min_{\theta^{(j)}} \frac{1}{2m^j} \sum_{i:r(i,j)=1} \left( (\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right)^2 + \frac{\lambda}{2m^j} \sum_{k=1}^n (\theta_k^{(j)})^2$$

- The regularization term goes from  $k=1$  through to  $m$ , so  $(\theta^j)$  ends up being an  $n+1$  feature vector
  - Don't regularize over the bias terms ( $\theta_0$ )
- If you do this you get a reasonable value
- We're rushing through this a bit, but it's just a linear regression problem
- To make this a little bit clearer you can get rid of the  $m^j$  term (it's just a constant so shouldn't make any difference to minimization)
  - So to learn  $(\theta^j)$

$$\min_{\theta^{(j)}} \frac{1}{2} \sum_{i:r(i,j)=1} \left( (\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right)^2 + \frac{\lambda}{2} \sum_{k=1}^n (\theta_k^{(j)})^2$$

- But for our recommender system we want to learn parameters for *all* users, so we add an extra summation term to this which means we determine the minimum  $(\theta^j)$  value for every user

$$\min_{\theta^{(1)}, \dots, \theta^{(n_u)}} \frac{1}{2} \sum_{j=1}^{n_u} \sum_{i:r(i,j)=1} \left( (\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right)^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^n (\theta_k^{(j)})^2$$

- When you do this as a function of each  $(\theta^j)$  parameter vector you get the parameters for each user
  - So this is our optimization objective  $\rightarrow J(\theta^1, \dots, \theta^{n_u})$
- In order to do the minimization we have the following gradient descent

$$\theta_k^{(j)} := \theta_k^{(j)} - \alpha \sum_{i:r(i,j)=1} \left( (\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right) x_k^{(i)} \quad (\text{for } k = 0)$$

$$\theta_k^{(j)} := \theta_k^{(j)} - \alpha \left( \sum_{i:r(i,j)=1} \left( (\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right) x_k^{(i)} + \lambda \theta_k^{(j)} \right) \quad (\text{for } k \neq 0)$$

- Slightly different to our previous gradient descent implementations
  - $k = 0$  and  $k \neq 0$  versions

- We can define the middle term above as

$$\frac{\partial}{\partial \theta_k^{(j)}} J(\theta^{(1)}, \dots, \theta^{(n)}) = \left( \sum_{i:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) x_k^{(i)} + \lambda \theta_k^{(j)} \right)$$

- Difference from linear regression
  - No  $1/m$  terms (got rid of the  $1/m$  term)
  - Otherwise very similar
- This approach is called content-based approach because we assume we have features regarding the content which will help us identify things that make them appealing to a user
  - However, often such features are not available - next we discuss a non-contents based approach!

## Collaborative filtering - overview

- The collaborative filtering algorithm has a very interesting property - does feature learning
  - i.e. it can learn for itself what features it needs to learn
- Recall our original data set above for our five films and four raters
  - Here we assume someone had calculated the "romance" and "action" amounts of the films
    - This can be very hard to do in reality
    - Often want more features than just two
- So - let's change the problem and pretend we have a data set where we don't know any of the features associated with the films

Movie	Alice (1)	Bob (2)	Carol (3)	Dave (4)	$x_1$ (romance)	$x_2$ (action)
Love at last	5	5	0	0	?	?
Romance forever	5	?	?	0	?	?
Cute puppies of love	?	4	0	?	?	?
Nonstop car chases	0	0	5	4	?	?
Swords vs. karate	0	0	5	?	?	?

- Now let's make a different assumption
  - We've polled each user and found out how much each user likes
    - Romantic films
    - Action films
  - Which has generated the following parameter set

$$\theta^{(1)} = \begin{bmatrix} 0 \\ 5 \\ 0 \end{bmatrix}, \theta^{(2)} = \begin{bmatrix} 0 \\ 5 \\ 0 \end{bmatrix}, \theta^{(3)} = \begin{bmatrix} 0 \\ 0 \\ 5 \end{bmatrix}, \theta^{(4)} = \begin{bmatrix} 0 \\ 0 \\ 5 \end{bmatrix}$$

- Alice and Bob like romance but hate action
  - Carol and Dave like action but hate romance
- If we can get these parameters from the users we can infer the missing values from our table
  - Lets look at "Love at Last"
    - Alice and Bob loved it
    - Carol and Dave hated it
  - We know from the feature vectors Alice and Bob love romantic films, while Carol and Dave hate them
    - Based on the factor Alice and Bob liked "Love at Last" and Carol and Dave hated it we may be able to (correctly) conclude that "Love at Last" is a romantic film
- This is a bit of a simplification in terms of the maths, but what we're really asking is
  - "What feature vector should  $x^1$  be so that

- $(\theta^1)^T x^1$  is about 5
- $(\theta^2)^T x^1$  is about 5
- $(\theta^3)^T x^1$  is about 0
- $(\theta^4)^T x^1$  is about 0
- From this we can guess that  $x^1$  may be

$$x^1 = \begin{bmatrix} 1 \\ 1.0 \\ 0.0 \end{bmatrix}$$

- Using that same approach we should then be able to determine the remaining feature vectors for the other films

### Formalizing the collaborative filtering problem

- We can more formally describe the approach as follows
  - Given  $(\theta^1, \dots, \theta^{n_u})$  (i.e. given the parameter vectors for each users' preferences)
  - We must minimize an optimization function which tries to identify the best parameter vector associated with a film

$$\min_{x^{(i)}} \frac{1}{2} \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{k=1}^n (x_k^{(i)})^2$$

- So we're summing over all the indices  $j$  for where we have data for movie  $i$
- We're minimizing this squared error
- Like before, the above equation gives us a way to learn the features for one film
  - We want to learn all the features for *all* the films - so we need an additional summation term

### How does this work with the previous recommendation system

- Content based recommendation systems
  - Saw that if we have a set of features for movie rating you can learn a user's preferences
- Now
  - If you have your users preferences you can therefore determine a film's features
- This is a bit of a chicken & egg problem
- What you can do is
  - Randomly guess values for  $\theta$
  - Then use collaborative filtering to generate  $x$
  - Then use content based recommendation to improve  $\theta$
  - Use that to improve  $x$
  - And so on
- This actually works
  - Causes your algorithm to converge on a reasonable set of parameters
  - This is collaborative filtering
- We call it collaborative filtering because in this example the users are collaborating together to help the algorithm learn better features and help the system and the other users

## Collaborative filtering Algorithm

- Here we combine the ideas from before to build a collaborative filtering algorithm
- Our starting point is as follows
  - If we're given the film's features we can use that to work out the users' preference

Given  $x^{(1)}, \dots, x^{(n_m)}$ , estimate  $\theta^{(1)}, \dots, \theta^{(n_u)}$ :

$$\min_{\theta^{(1)}, \dots, \theta^{(n_u)}} \frac{1}{2} \sum_{j=1}^{n_u} \sum_{i:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^n (\theta_k^{(j)})^2$$

- If we're given the users' preferences we can use them to work out the film's features

**Given  $\theta^{(1)}, \dots, \theta^{(n_u)}$ , estimate  $x^{(1)}, \dots, x^{(n_m)}$ :**

$$\min_{x^{(1)}, \dots, x^{(n_m)}} \frac{1}{2} \sum_{i=1}^{n_m} \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^n (x_k^{(i)})^2$$

- One thing you could do is
  - Randomly initialize parameter
  - Go back and forward
- But there's a more efficient algorithm which can solve  $\theta$  and  $x$  simultaneously
  - Define a new optimization objective which is a function of  $x$  and  $\theta$

**Minimizing  $x^{(1)}, \dots, x^{(n_m)}$  and  $\theta^{(1)}, \dots, \theta^{(n_u)}$  simultaneously:**

$$J(x^{(1)}, \dots, x^{(n_m)}, \theta^{(1)}, \dots, \theta^{(n_u)}) = \frac{1}{2} \sum_{(i,j):r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^n (x_k^{(i)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^n (\theta_k^{(j)})^2$$

$$\min_{\substack{x^{(1)}, \dots, x^{(n_m)} \\ \theta^{(1)}, \dots, \theta^{(n_u)}}} J(x^{(1)}, \dots, x^{(n_m)}, \theta^{(1)}, \dots, \theta^{(n_u)})$$

- Understanding this optimization objective
  - The squared error term is the same as the squared error term in the two individual objectives above

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

- So it's summing over every movie rated by every users
  - Note the ":" means, "for which"
    - Sum over all pairs (i,j) for which r(i,j) is equal to 1
- The regularization terms
  - Are simply added to the end from the original two optimization functions
- This newly defined function has the property that
  - If you held  $x$  constant and only solved  $\theta$  then you solve the, "Given  $x$ , solve  $\theta$ " objective above
  - Similarly, if you held  $\theta$  constant you could solve  $x$
- In order to come up with just one optimization function we treat this function as a function of both film features  $x$  and user parameters  $\theta$ 
  - Only difference between this in the back-and-forward approach is that we minimize with respect to both  $x$  and  $\theta$  simultaneously
- When we're learning the features this way
  - Previously had a convention that we have an  $x_0 = 1$  term
  - When we're using this kind of approach we have no  $x_0$ ,
    - So now our vectors (both  $x$  and  $\theta$ ) are  $n$ -dimensional (not  $n+1$ )
  - We do this because we are now learning all the features so if the system needs a feature always = 1 then the algorithm can learn one

## Algorithm Structure

- **1)** Initialize  $\theta^1, \dots, \theta^{n_u}$  and  $x^1, \dots, x^{n_m}$  to small random values
  - A bit like neural networks - initialize all parameters to small random numbers
- **2)** Minimize cost function ( $J(x^1, \dots, x^{n_m}, \theta^1, \dots, \theta^{n_u})$ ) using gradient descent
  - We find that the update rules look like this

$$x_k^{(i)} := x_k^{(i)} - \alpha \left( \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) \theta_k^{(j)} + \lambda x_k^{(i)} \right)$$



$$\theta_k^{(j)} := \theta_k^{(j)} - \alpha \left( \sum_{i:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) x_k^{(i)} + \lambda \theta_k^{(j)} \right)$$

- Where the top term is the partial derivative of the cost function with respect to  $x_k^i$  while the bottom is the partial derivative of the cost function with respect to  $\theta_k^i$
- So here we regularize EVERY parameters (no longer  $x_0$  parameter) so no special case update rule
- **3)** Having minimized the values, given a user (user  $j$ ) with parameters  $\theta$  and movie (movie  $i$ ) with learned features  $x$ , we predict a start rating of  $(\theta^j)^T x^i$ 
  - This is the collaborative filtering algorithm, which should give pretty good predictions for how users like new movies

## Vectorization: Low rank matrix factorization

- Having looked at collaborative filtering algorithm, how can we improve this?
  - Given one product, can we determine other relevant products?
- We start by working out another way of writing out our predictions
  - So take all ratings by all users in our example above and group into a matrix  $Y$

$$Y = \begin{bmatrix} 5 & 5 & 0 & 0 \\ 5 & ? & ? & 0 \\ ? & 4 & 0 & ? \\ 0 & 0 & 5 & 4 \\ 0 & 0 & 5 & 0 \end{bmatrix}$$

- 5 movies
- 4 users
- Get a  $[5 \times 4]$  matrix

- Given  $[Y]$  there's another way of writing out all the predicted ratings

$$\begin{bmatrix} (\theta^{(1)})^T(x^{(1)}) & (\theta^{(2)})^T(x^{(1)}) & \dots & (\theta^{(n_u)})^T(x^{(1)}) \\ (\theta^{(1)})^T(x^{(2)}) & (\theta^{(2)})^T(x^{(2)}) & \dots & (\theta^{(n_u)})^T(x^{(2)}) \\ \vdots & \vdots & \vdots & \vdots \\ (\theta^{(1)})^T(x^{(n_m)}) & (\theta^{(2)})^T(x^{(n_m)}) & \dots & (\theta^{(n_u)})^T(x^{(n_m)}) \end{bmatrix}$$

- With this matrix of predictive ratings
- We determine the  $(i,j)$  entry for EVERY movie

- We can define another matrix  $X$ 
  - Just like matrix we had for linear regression
  - Take all the features for each movie and stack them in rows

$$X = \begin{bmatrix} -(x^{(1)})^T \\ -(x^{(2)})^T \\ \vdots \\ -(x^{(n_m)})^T \end{bmatrix}$$

- Think of each movie as one example

- Also define a matrix  $\Theta$

$$\Theta = \begin{bmatrix} - (\theta^{(1)})^T - \\ - (\theta^{(2)})^T - \\ \vdots \\ - (\theta^{(n_u)})^T - \end{bmatrix}$$

- Take each per user parameter vector and stack in rows
- Given our new matrices  $X$  and  $\theta$ 
  - We can have a vectorized way of computing the prediction range matrix by doing  $X * \theta^T$
- We can give this algorithm another name - **low rank matrix factorization**
  - This comes from the property that the  $X * \theta^T$  calculation has a property in linear algebra that we create a **low rank** matrix
    - Don't worry about what a low rank matrix is

### Recommending new movies to a user

- Finally, having run the collaborative filtering algorithm, we can use the learned features to find related films
  - When you learn a set of features you don't know what the features will be - lets you identify the features which define a film
  - Say we learn the following features
    - $x_1$  - romance
    - $x_2$  - action
    - $x_3$  - comedy
    - $x_4$  - ...
  - So we have  $n$  features all together
  - After you've learned features it's often very hard to come in and apply a human understandable metric to what those features are
    - Usually learn features which are very meaning full for understanding what users like
- Say you have movie  $i$ 
  - Find movies  $j$  which is similar to  $i$ , which you can recommend
  - Our features allow a good way to measure movie similarity
  - If we have two movies  $x^i$  and  $x^j$ 
    - We want to minimize  $||x^i - x^j||$ 
      - i.e. the distance between those two movies
  - Provides a good indicator of how similar two films are in the sense of user perception
    - NB - Maybe ONLY in terms of user perception

### Implementation detail: Mean Normalization

- Here we have one final implementation detail - make algorithm work a bit better
- To show why we might need mean normalization let's consider an example where there's a user who hasn't rated *any* movies

Movie	Alice (1)	Bob (2)	Carol (3)	Dave (4)	Eve (5)
Love at last	5	5	0	0	?
Romance forever	5	?	?	0	?
Cute puppies of love	?	4	0	?	?
Nonstop car chases	0	0	5	4	?
Swords vs. karate	0	0	5	?	?

$$Y = \begin{bmatrix} 5 & 5 & 0 & 0 & ? \\ 5 & ? & ? & 0 & ? \\ ? & 4 & 0 & ? & ? \\ 0 & 0 & 5 & 4 & ? \\ 0 & 0 & 5 & 0 & ? \end{bmatrix}$$

- Lets see what the algorithm does for this user
  - Say  $n = 2$



- We now have to learn  $\theta^5$  (which is an n-dimensional vector)
- Looking in the first term of the optimization objective
  - There are *no* films for which  $r(i,j) = 1$
  - So this term places no role in determining  $\theta^5$
  - So we're just minimizing the final regularization term

$$\min_{\substack{x^{(1)}, \dots, x^{(n_m)} \\ \theta^{(1)}, \dots, \theta^{(n_u)}}} \frac{1}{2} \sum_{(i,j): r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^n (x_k^{(i)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^n (\theta_k^{(j)})^2$$

This term is irrelevant We're only minimizing this

Which can for our single example be simplified to this  $\frac{\lambda}{2} [(\theta_1^{(5)})^2 + (\theta_2^{(5)})^2]$

- Of course, if the goal is to minimize this term then

$$\theta^{(5)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

- Why - If there's no data to pull the values away from 0 this gives the min value
- So this means we predict ANY movie to be zero
  - Presumably Eve doesn't hate all movies...
  - So if we're doing this we can't recommend any movies to her either
- Mean normalization should let us fix this problem

### How does mean normalization work?

- Group all our ratings into matrix Y as before
  - We now have a column of ?s which corresponds to Eves rating

$$Y = \begin{bmatrix} 5 & 5 & 0 & 0 & ? \\ 5 & ? & ? & 0 & ? \\ ? & 4 & 0 & ? & ? \\ 0 & 0 & 5 & 4 & ? \\ 0 & 0 & 5 & 0 & ? \end{bmatrix}$$

- Now we compute the average rating each movie obtained and stored in an  $n_m$  - dimensional column vector

$$\mu = \begin{bmatrix} 2.5 \\ 2.5 \\ 2 \\ 2.25 \\ 1.25 \end{bmatrix}$$

- If we look at all the movie ratings in [Y] we can subtract off the mean rating

$$Y = \begin{bmatrix} 2.5 & 2.5 & -2.5 & -2.5 & ? \\ 2.5 & ? & ? & -2.5 & ? \\ ? & 2 & -2 & ? & ? \\ -2.25 & -2.25 & 2.75 & 1.75 & ? \\ -1.25 & -1.25 & 3.75 & -1.25 & ? \end{bmatrix}$$

- Means we normalize each film to have an average rating of 0
- Now, we take the new set of ratings and use it with the collaborative filtering algorithm
  - Learn  $\theta^j$  and  $x^i$  from the mean normalized ratings

- For our prediction of user  $j$  on movie  $i$ , predict
  - $(\theta^j)^T x^i + \mu_i$ 
    - Where these vectors are the mean normalized values
    - We have to add  $\mu$  because we removed it from our  $\theta$  values
  - So for user 5 the same argument applies, so
 

$$\theta^5 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$
  - So on any movie  $i$  we're going to predict
    - $(\theta^5)^T x^i + \mu_i$ 
      - Where  $(\theta^5)^T x^i = 0$  (still)
      - But we then add the mean ( $\mu_i$ ) which means Eve has an average rating assigned to each movie for here
- This makes sense
  - If Eve hasn't rated any films, predict the average rating of the films based on everyone
    - This is the best we can do
- As an aside - we spoke here about mean normalization for users with no ratings
  - If you have some movies with no ratings you can also play with versions of the algorithm where you normalize the columns
  - BUT this is probably less relevant - probably shouldn't recommend an unrated movie
- To summarize, this shows how you do mean normalization preprocessing to allow your system to deal with users who have not yet made any ratings
  - Means we recommend the user we know little about the best average rated products