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## 6. Alternating Minimization

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Exercises due Mar 8, 2023 08:59 -03 Completed

**Alternating Minimization****Video**
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**Alternating Minimization Concept Question**

1/1 point (graded)

As in the video above, we now want to find  $U$  and  $V$  that minimize our new objective

$$J = \sum_{(a,i) \in D} \frac{(Y_{ai} - [UV^T]_{ai})^2}{2} + \frac{\lambda}{2} \left( \sum_{a,k} U_{ak}^2 + \sum_{i,k} V_{ik}^2 \right).$$

In order to break a big optimization problem into smaller pieces that we know how to solve, we first find the best  $V$  for that  $U$ . But a subtle and important point is that even if  $V^*$  is best for  $U$ , then  $U$  for  $V^*$  might not be the original  $U$ ! It's like how we might be some lonely person's best friend, but we are not our best friend. In light of this, we repeat, like this: we fix  $U$  and solve for  $V$ , then we take  $V^*$  from the previous step and solve for  $U$ , and repeat this alternate process until we find the best  $U$  and  $V$ . This is an example of iterative optimization, where we greedily take steps in a good direction, but we don't know when to stop.

$$\sum_{(a,i) \in D} \frac{(Y_{ai} - u_a v_i)^2}{2} + \frac{\lambda}{2} \sum_i (v_i)^2$$



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You have used 1 of 3 attempts

## Fixing V and Finding U

0/2 points (graded)

Now, assume we have 2 users, 3 movies, and a 2 by 3 matrix  $Y$  given by

$$Y = \begin{bmatrix} 1 & 8 & ? \\ 2 & ? & 5 \end{bmatrix}$$

Our goal is to find  $U$  and  $V$  such that  $X = UV^T$  closely approximates the observed ratings; we encourage  $U, V$  to be 'simple' in the sense that their entries are small; we quantify the encouragement by a parameter  $\lambda$ , so that our optimal solution  $(U, V)$  depends on  $\lambda$ . (BEC encouragement resolves cases that are strictly ambiguous (for example, in














$$\begin{bmatrix} ? & ? & 16 \\ 2 & 3 & ? \end{bmatrix}$$

that 16 could be a product of  $4 \times 4$  or a product  $(0.00004) \times (400000)$ ; we regard the former unless special domain knowledge suggests otherwise). Moreover, this encouragement and  $V$  entries toward zero, even in non-ambiguous cases. It's like a TA tells you they enjoyed a movie just happened to like that movie's particulars. So there are multiple explanations. Seeing a TA's belief in that data's explanation(s); but when there are multiple explanations for the data, our belief increases over the multiple explanations. So we don't increase our belief in a particular explanation unless we would increase it if other explanations were unavailable. In the case of unknown  $U$  and  $V$ , we would **approximately** multiply to be some known  $Y$  does **not** mean we should guess values of  $U, V$  that multiply to  $Y$ , even if we impose no low-rank constraints. To guess values of  $U, V$  that explain the TA's horror-film fanhood that maximally explain the TA's comment, to do so fails to account for inherent plausibility and the presence of competing explanations.

Assume we start by fixing  $V$  to initial values of  $[4, 2, 1]^T$ . Find the optimal  $2 \times 1$  vector  $U$  (your answer in terms of  $\lambda$ ).

The first element of  $U$  is:

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-  How can we model temporal effect/dynamics in collaborative filtering along with what was ta  
How can we model temporal effect/dynamics in collaborative filtering along with what was taught ? for e.g. n
-  Is there a missed "/2" in loss function in video at 1:21?  
Just noticed that while writing the 1st part of loss function (at 1:21) Prof. Barzilay missed the dividing by 2 in
-  why not explaining the next steps in calculating the v's?  
Its a pity that the next steps are not explained. How do we continue now for calculating the v's knowing the
-  I don't understand how we got  $66 / (68 + \lambda)$  from  $-66 + 68 + \lambda u_1 = 0$   
what is wrong in the train of thought that if  $-66 + 68 + \lambda u_1 = 0$  then  $\lambda u_1 = -2$  hence  $U_1 = -2 /$
-  How does  $X_{ai}^2 = U_a^2 + V_i^2$ ?  
If  $X=UV$  how does  $X_{ai}^2 = U_a^2 + V_i^2$ ? Shouldn't  $X_{ai}^2 = (U_a V_i)^2$ ?
-  Matrix rank  
Hello, I have a question, maybe someone can help. In the video the teacher assumes that the range is equal
-  Sidenote placed ambiguously  
I understand that this is my own fault, but sidenote is definitely placed in a way to confuse two matrices: the
-  Question about partial derivatives and critical points  
I have a bit of a naive question about the reason behind equating the partial derivative of the objective funct
-  Clarity on the last question - Error Message - Invalid Input: '\lambda', '\u\_1' not permitted in an  
So, I followed the lecture and calculated the appropriate derivatives. My derivatives are in the term of lamda
-  Meaning of the last part of the sidenote  
Is the last part of the sidenote talking about how not to choose initial values for one of the vectors or is it's s
-  Need help on last question  
Hi, I don't understand how the professor got the solution at 9:05 in the video. Can anybody explain it to me?
-  What are typical real world values for lambda and k?  
I am wondering what are typical real world values of lambda and k for an online store recommendation engin
-  Reviewing what the first part of the objective function represents  
Hi, I've successfully answered the final question by imitating the professor's work. My question, as a coder w

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