Matrix Factorization Quiz

TOTAL POINTS 4

1. What is the basic intuition behind matrix factorization dimensionality reduction algorithms?

1 point

- ( ) The user-user and item-item correlations are more efficiently computed by factoring matrices.
- ( ) That content-based and collaborative filtering are really just two different factorizations of the same ratings matrix.
- ( ) That factoring user and item matrices can partition the users and items into clusters that can be treated identically, reducing the complexity of making recommendations.
- (●) That user-item relationships can be well-described in a lower-dimensional space (latent taste space) that can be computed from the ratings matrix.

2. Most values of the user-item rating matrix are unknown, but traditional SVD-solving algorithms need a complete matrix. Three of the following answers are reasonable ways to fill the matrix. Which is **not** a good way to satisfy this requirement in a situation where the user ratings are on a 1 to 5 scale?

1 point

- ( ) Use the user’s mean rating.
- ( ) Use the item's mean rating.
- ( ) Normalize the ratings and set missing values to 0.
- (●) Set all the missing values to 5, the maximum value.

3. What do we mean by "folding in" when referring to SVD or Gradient Descent algorithms?

1 point

- ( ) Folding in refers to the process of making the matrix into a diagonal (essentially a vector of singular values).
- (●) Folding in refers to using the existing factorization/dimensionalization for new data (e.g., it is a way to add new movies or items with minimal computation).
- ( ) Folding in is a matrix computation shortcut where we reduce the rank of the matrix first by removing all values close to zero.

- ( ) Folding in refers to the process of computing a prediction as a dot product between the vector-space representations of a user and of an item.

4. Probabilistic LSA breaks the process of predicting the probability that a user u will like/buy an item i into what two steps?

1 point

- ( ) First computing the usual prediction of how much the user will like/consume the item (the vector dot product of the user and item vectors), and then computing a "personalization factor" of how much the user is likely to make a personal selection vs. just taking the most popular choices. The resulting probability is a weighted average of the personalized prediction and non-personalized popularity score, weighted by the personalization factor.
- ( ) Predicting the probability that a user will select any item at all, and then the probability that the user will pick each particular item, if any item is picked. These two are multiplied to produce the resulting probability.
- (x) Predicting the user-specific probability that the user will like/select each feature z, and then the probability that item i would be selected if feature z is selected. The products of these are summed across all features.

- [ ] I, **BAL KRISHNA NYAUPANE**, understand that submitting work that isn't my own may result in permanent failure of this course or deactivation of my Coursera account.

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