

User-User Collaborative Filtering Quiz

TOTAL POINTS 10

1. Which of the following is a problem with using Pearson correlation (as opposed to other similarity metrics) for computing user similarities in user-user collaborative filtering?

1 point

- ☐ Users may use different portions of the rating scale.
- ☐ Users may not have rated any of the the same items.
- ☐ The user may not know any other users in the system.
- ☒ If users have only rated a small number of the same items, their correlation may be too high.

2.

1 point

Either vector cosine or Pearson correlation are often used to compute a weight in user-user collaborative filtering. What are these metrics trying to measure?

- ☐ These are measures of how much the target user likes popular items.
- ☐ These are measures of how well the recommendations match the user's preferences.
- ☐ These are measures of the number of ratings users have in common.
- ☒ These are measures of the similarity of ratings history between users.

3. A basic user-user collaborative filtering algorithm uses the formula:

1 point

$$P_{a,i} = \frac{\sum_{u=1}^n r_{u,i} \cdot w_{a,u}}{\sum_{u=1}^n w_{a,u}}$$

What is the purpose of the term $w_{a,u}$ in the numerator?

- ☐ It is used to ensure that the resulting prediction is on the same scale as the ratings.
- ☐ It is used to normalize ratings, since users rate on different scales.

- ☐ It is used to make sure that only a limited number of neighbors are part of the computation.
- ☒ It is used to give some neighbors a greater influence on a target user's prediction than others.

4. Resnick discussed a sybil-based shilling attack against a recommender system. Which of these best describes such an attack?

1 point

- ☒ Creating bogus accounts to promote (or demote) particular items
- ☐ Writing a review of a book you wrote with your personal account, but hiding your identity
- ☐ Rating items randomly to confuse the recommender
- ☐ Creating many accounts to overload and slow down or crash the recommender

5.

1 point

Cosley experimented with giving people deliberately inaccurate predictions. He examined three possibilities:

I. People would notice that predictions were wrong

II. People would be biased by the wrong predictions and enter different ratings.

III. People would have lower satisfaction with the system after receiving bad predictions.

Which ones happened?

- ☐ I and II were confirmed, but III was not confirmed.
- ☒ II and III were confirmed, but I was not confirmed
- ☐ All three of the results were confirmed.
- ☐ I and III were confirmed, but II was not confirmed.

6.

1 point

Which of the following would most indicate a situation where user-user collaborative filtering would be strongly preferable to content-based filtering (i.e., filtering based on user preferences of keywords or attributes)?

- ☐ Most users have rated a core set of popular items, though they have different tastes on that core set.
- ☒ The items being recommended don't have good attributes or keywords to describe them (e.g., user-submitted children's drawings without tags).
- ☐ Only implicit ratings are available; users won't provide explicit ratings.
- ☐ There are lots of items to recommend, and relatively few users.

7. Resnick talked about resistance of collaborative filtering recommender systems to attacks from fake accounts (called sybils). Which of these statements about this problem is true

1 point

- ☐ The only way to be resistant to attacks from sybils is to trick them into rating fake movies that reveal that they aren't real users.
- ☒ In order to be resistant to attacks from more sybils, you lose predictive power from genuine raters.
- ☐ If a Pearson correlation-based user-user collaborative filtering recommender is robust against attack from n sybils, a similar system based on Spearman correlation will only be resistant to attack from $(n/2 - 1)$ sybils.
- ☐ There is unfortunately no way to bound the theoretical damage associated with a specific number of sybils -- no matter what you do, three clever sybils can inflict unlimited damage.

8. User-user collaborative filtering depends on certain assumptions. Which of the following IS NOT a requirement for a successful user-user collaborative filtering system

1 point

- ☐ Past agreement between users is predictive of future agreement -- i.e., if you and I have agreed on items before, we mostly still do now.
- ☐ User tastes must either be generally stable (individually) or if changing, they change in sync with other user's tastes.

- ☐ The domain in which we are performing collaborative filtering is scoped such that people who agree within one part of that domain generally agree within other parts of the domain.
- ☒ Users mostly have similar tastes on a set of popular items, though they may have individually different tastes on unpopular items.

9.

1 point

A more advanced user-user collaborative filtering formula is:

$$P_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^n (r_{u,i} - \bar{r}_u) \times w_{a,u}}{\sum_{u=1}^n w_{a,u}}$$

What is the purpose of the \bar{r}_a and \bar{r}_u terms in this version of the formula?

- ☐ These terms specify that we're combining the ratings of lots of other users together.
- ☐ These terms weight the recommendations so closer neighbors count more than distant neighbors.
- ☐ These terms limit the number of neighbors used in the computation
- ☒ These terms normalize the computation to adjust for different users' rating scales.

10. Golbeck explained that trust-based recommenders differ from similarity-based collaborative filtering in all of the following ways EXCEPT which one?

1 point

- ☐ Trust-based systems are harder to get going, because it is often challenging to get trust data.
- ☒ Trust-based systems only consider ratings from users that the target user has a direct trust relationship with, and thus often use many fewer ratings in computing a prediction or recommendation
- ☐ Trust-based systems have an underlying graph of user trust, while similarity-based systems don't need a graph because they only use pairwise similarity scores.
- ☐ Similarity-based collaborative filtering treats all rated items as roughly equivalent in evaluating neighbors, trust-based systems may give very strong weight to the items that a user is most passionate about.

☐ 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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