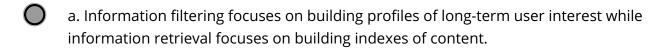
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Midterm Part 2

12 questions

1 point 1. Which of these statements about information filtering and information retrieval is NOT TRUE?



O b. Information filtering involves matching a user-entered query to document terms or item attributes.

c. Information filtering evaluates new content items for match against user profiles.

d. Information retrieval often uses the TFIDF approach where terms are more relevant if they occur in few documents, but frequently in the matched document.

1 point 2. In our taxonomy of recommender systems, what do we mean by "ephemeral personalization?"

a. Ephemeral personalization means that you may get different recommendations the next time you log in.

O b. Ephemeral personalization is based on demographics or similar characteristics rather than on actions or purchases.

c. Ephemeral personalization is based on the products preferred by people like you -- your neighborhood of users.

 d. Ephemeral personalization is based on your current navigation or market basket, but not a long-term profile of your preferences.

In the Hacker News scoring algorithm, the net upvotes is raised to a small (≤1) power. Why? point a. To demote old items. b. To decrease the weight of later upvotes, so votes 900-1000 have less individual impact than 90-100. c. To keep overall-popular items from being pinned at the top of the page. d. Because the relative importance of votes and age differences shift as items get older Amazon.com has many recommender systems. Which of the following techniques did we NOT see in our tour of Amazon.com? point a. Recommenders based on demographics such as age and zip code b. Product association recommenders based on the page currently viewed c. Recommenders based on your recent shopping history d. Recommenders based on a long-term profile of purchases and ratings Why might we prefer product-association recommenders to average-rating recommenders? point a. Product associations are based on user ratings. b. Product associations involve fancy math. c. Product associations allow recommendations that are relevant to a current context. d. Product associations are personalized to a user's full history, while averageratings are not.

point

When is "inverse document frequency" least useful as part of a content-filtering recommender? point a. When attributes that apply only rarely are not all that helpful in making decisions (e.g., extras in a movie). b. When certain items have many more attributes than other items. c. When certain items are much more popular than other items. d. When users are most interested in receiving recommendations for less popular items. The vector space model is quite useful for modeling document needs (i.e., what a user requests in a query) or item preferences (i.e., attribute preferences), but it has some point limitations. Which of the following is a serious limitation of the model? a. It only works in domains where liking is a yes-no decisions; it can't handle degrees of preference. b. It limits preferences to a linear combination of attributes -- it can't specify that you either want Tom Hanks and Meg Ryan together, or neither of them, but not one without the other. c. It results in profiles that are nearly impossible to explain to an ordinary user because they are based on complex combinations of attributes that don't make intuitive sense. d. It cannot produce top-n lists -- only predictions for individual item preferences. Which of these statements DOES NOT describe the Entrée Style Recommenders?

a. They build a model of user preferences that can be used to provide personalized

b. They require a substantial collection of information about the items being

recommendations.

recommended.

requesting items that differ in a certain way from the current recommendation. d. They don't use individual users' ratings of the items anywhere in the recommendation process. The Herlocker explanations paper explored a variety of explanation interfaces, but it did have one key mistake. What was that mistake? point a. It forgot to use some of the better explanations available. b. The authors didn't realize that some of the explanations were really just made up data. c. The paper really didn't measure usefulness of explanations; it measured persuasiveness of those explanations instead. d. The authors didn't recruit enough test users to get any statistically significant results. 10. Which of the following would most indicate a situation where user-user collaborative filtering would be strongly preferable to content-based filtering? point a. There are lots of items to recommend, and relatively few users. b. Only implicit ratings are available; users won't provide explicit ratings. c. Most users have rated a core set of popular items, though they have different tastes on that core set. d. The items being recommended don't have good attributes or keywords to describe them (e.g., user-submitted children's drawings without tags).

c. They provide an interface that allows the user to refine recommendations by

11. Which of the following types of users have been the source of data for making recommendations in recommender systems?

point

	O	a. People with similar tastes to the target user.		
	0	b. All system users who have expressed opinions.		
	0	c. Experts whose opinions were solicited for the site.		
	0	d. All of the above, sometimes in different systems, sometimes in	the same system	
·		k talked about resistance of collaborative filtering recommender sys		
point	from 1	ake accounts (called sybils). Which of these statements about this pr	roblem is true?	
	0	a. In order to be resistant to attacks from more sybils, you lose predictive power from genuine raters.		
	0	b. 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.		
	0	c. If a collaborative filtering recommender is robust against attack from n sybils, a similar content-filtering recommender will only be resistant to attack from (n/2 - 1) sybils.		
	0	d. 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.		
			Submit Quiz	
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