User Validation of Recommendation Serendipity Metrics

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1 INTRODUCTION

Serendipity has been increasingly recognized as an important objective of recommender systems, because it can help overcome the over-specialization problem (also called “filter bubble” phenomenon since users are likely trapped in a subspace of options if the recommendation is purely accuracy-oriented) [14, 16, 17]. Being different from the other beyond-accuracy objectives (such as novelty and diversity) that may compromise accuracy to a certain degree, serendipity has been targeted to preserve relevance (i.e., usefulness to the user) but evoke a surprised feeling of users about the recommended item. In a recent work, it was demonstrated to significantly lead to user satisfaction with recommendations and purchase intention on an industrial mobile e-commerce platform [6].

However, measuring recommendation serendipity is complex, since it includes multiple dimensions to be assessed, such as unexpectedness, novelty, and relevance [8]. Moreover, it is difficult to objectively define “unexpectedness” (also called “surprise”), because it is an emotional response of the user [8, 14, 17]. To address these challenges, various offline metrics have been proposed in recent years based on researchers’ assumptions. For instance, the metrics proposed in [13, 25, 30] emphasize on a specific component of serendipity (e.g., surprise in [13] and novelty in [25, 30]), which consider either the current recommendation’s distance from items in the user profile (i.e., the items s/he has previously visited or rated), or its general unpopularity among the available options (e.g., less frequently clicked by all of the users). Some related work, on the other hand, has aimed to develop a full metric for evaluating serendipity as a whole, which mainly multiplies unexpectedness prediction with a relevance score that indicates the recommendation’s relation to the user’s preferences [9, 11, 24].

Unfortunately, these metrics have rarely been validated due to the lack of users’ feedback data. Simply adopting them to evaluate a particular recommender algorithm is hence unreliable, since it is not evident whether the recommended item is truly serendipitous as perceived by the user, even though the objective metric estimates it [14]. The other limitation is that there is little work to empirically compare different evaluation metrics, so it is still unclear which metric(s) could be more accurate [17].

Therefore, in this work, based on a large-scale collection of user feedback data (involving over 10,000 users’ records), we have tested a number of serendipity metrics as well as their possible variations. To be more specific, we plugged a user survey into a popular mobile
For example, in [13, 14], serendipity was defined with two components: relevance and surprise, where surprise refers to the recommendation’s dissimilarity to user profile. Two pair-wise similarity metrics, respectively based on point-wise mutual information and item content labels, were proposed to measure the surprise. [2] suggested a metric called “general unexpectedness” that assumes an item accommodating a rare co-occurrence of features is unexpected. In [30], two generic forms of novelty metric were presented: one is based on the distance of the recommended item from those consumed by the user, and the other based on the item’s unpopularity. [25] also developed a novelty metric, which is particularly based on the item taxonomy to calculate the smallest distance from the recommendation’s class and those of items in the user profile.

The related works on full metrics mostly presented a multiplication formula that combines unexpectedness (or novelty) and relevance. In [24], the authors considered the item not easily predicted by a primitive prediction method (PPM) with high unexpectedness (low ratatability) degree, and multiplied it with the item’s relevance score to indicate its serendipity. [10] modified this formulation, by subtracting those items generated by a PPM from a list of recommendations to calculate the list’s overall serendipity level. [1] further added a set of expected items to be subtracted, which include items rated by the user plus those similar to the rated ones. Different from this series of approaches that are sensitive to the choice of PPM, [9, 11] developed a serendipity metric that considers items’ metadata attributes (e.g., genres) for distance measurement between the currently recommended item and the user profile.

2.2 User Study

User study means that the evaluation on recommendation serendipity involves real users to interact with the system (a prototype or a deployed online system) to provide their feedback [8, 20, 26, 28, 34].

For instance, [34] conducted a small-scale user study (with 21 participants) to evaluate user reactions to a serendipity-enhancing system that recommends music artists. Each participant was asked to evaluate two recommendation lists respectively generated by a baseline and the serendipity-enhancing version in a random order. The post-task questionnaire contains questions about their perceived enjoyment (from “dislike the song” to “will definitely listen again”) and serendipity (from “exactly what I listen to normally” to “something I would never have listened to otherwise”) on a 5-point Likert scale. [26] recruited 9 users to evaluate a fusion-based recommender system that allows users to experience extrinsic and intrinsic accidents to discover serendipitous books. By comparing with the standard Amazon interface, they found users perceived their system more capable of “exciting my interest and enabling me to discover something new” that is related to serendipity. [8] combined the questionnaire and facial expression detection approach in a preliminary user experiment (involving 40 subjects) performed on their serendipity-oriented algorithm. Two questions were asked to respectively assess a user’s perceived relevance of the recommended movie (“Do you like this movie?”) and its unexpectedness (“Have you ever heard about this movie?”). If a user likes a movie and s/he has never heard about it, it is assumed to be a serendipitous recommendation. The user’s facial expression was detected.
Table 1: Description of our collected user data

| # of users (after filtering) | 11,429 (female: 7,793, male: 3,636) |
|-----------------------------|-----------------------------------|
| Distribution of algorithm assignment | HOT: 2,819, Rel-CF: 2,817, Nov-CF: 2,895, Ser-CF: 2,898 |
| # of items in those users' profiles | 7,739,262 |
| Average number of items in the user profile | 1,522 (min = 5, max = 14,932) |
| # of item categories in those users' profiles | 12,875 |

Note: The user profile refers to the set of items clicked by the user in the past three months. Each item can belong to multiple categories as shown in the item taxonomy (see Figure 1).

simultaneously to implicitly infer her/his surprised feeling when s/he saw the item.

More recently, [16] conducted a user survey (participated by 475 users) to acquire users’ responses to eight different serendipity definitions in a movie recommender (e.g., one definition is the combination of questions “I expected to enjoy this movie before watching it for the first time” and “[The system] influenced my decision to watch this movie”). By running a regression model on users’ answers with some dependent variables, the authors found that most definitions of serendipity can help broaden user preferences.

3.3 Limitations of Related Work
Although user study can be more reliable and accurate to evaluate recommendation serendipity, it is demanding and costly to conduct [14]. In comparison, offline measurement is easier and quicker to perform [11, 17], but so far the proposed serendipity metrics have rarely been validated due to the lack of large-scale user feedback data. To the best of our knowledge, only the Movielens Serendipity dataset is relatively large (with 481 users’ feedback) [16], but it does not include users’ personal information (such as curiosity that may affect their serendipity preference), and only has totally 2,150 serendipity records over 1,678 movies.

The novelty of our work lies in filling this vacancy by collecting a large amount of user data, which contain over 10,000 users’ opinions on recommendations from various angles (i.e., unexpect- edness, novelty, serendipity, relevance, timeliness) as well as their own curiosity values. This dataset was then used to test different serendipity metrics. The results are constructive for enhancing the adequacy of serendipity measurement in the offline environment.

3 USER DATA COLLECTION
3.1 Experimental Setup
We conducted a user survey on a popular mobile e-commerce application in China (Mobile Taobao) starting from Dec. 21, 2017. The users were able to access the survey after they logged in the system. If a user volunteered to join, s/he first received a recommended product with its name, image, short description, and price (that was generated by one of four recommender algorithms; see Section 3.3). The user then completed a questionnaire that assessed her/his immediate feedback on the recommendation. S/he was also asked to fill out a psychological curiosity quiz. As the incentive, all participants were placed in a lottery draw with customized presents as awards given to the winners.

Till March 17, 2018, we accumulated 13,741 records. Each record contains a user’s opinions on one recommended product. We carefully checked their responses in order to filter out invalid answers. For example, if a user did not answer all of the questions, or gave the same rating to all the questions (as some were asked in the reversed way), her/his response was deleted. In addition, we only kept the user’s first record if s/he took the experiment more than once. We also tried to ensure that the recommendation was not clicked by the user in the past1. As a result, 11,446 users remained (7,806 females, with ages ranging from 20 to 60), among whom we further removed some outlier cases (9 users who clicked less than 5 items previously, and 8 users who clicked more than 15,000 items). The final dataset includes 11,429 users (see Table 1 of their descriptive statistics).

3.2 Survey Questions
Because the survey was completed on users’ mobile devices, in order to reduce its duration (as users are usually less patient in responding to a lengthy mobile questionnaire [31]), we adopted a short version of ResQue (a widely used user-centric evaluation framework for recommenders [27]), which, as claimed by the authors, can provide a fast and reliable way to assess user perceptions of a recommendation. Specifically, we asked three serendipity-specific questions (see Table 2): unexpect edness, novelty, and serendipity. It is worth noting that “serendipity” was asked directly because there is a popularly used Chinese word “œ” (relevant) which makes it intuitive for Chinese users to understand what “serendipity” means.

We also enquired about each user’s curiosity. According to the psychological theory [3, 18, 29], curiosity is an intrinsic human trait, triggered when there is a gap between the person’s current knowledge level and the desired level. Our previous study revealed that more curious users are more likely to perceive a novel item as serendipitous [6]. It is hence interesting to study whether curiosity could be usefully integrated into the serendipity metric. In our survey, we asked users to respond to a popular curiosity instrument: Curiosity and Exploration Inventory-II (CEI-II) [15]. It is a 10-item self-report scale embodying a person’s “motivation to seek out knowledge and new experiences” and “willingness to embrace the novel, uncertain, and unpredictable nature of everyday life” [15]. This instrument has been shown to have acceptable internal reliability and stable validity across time. It is also short enough to be possibly completed within two minutes [7]. Moreover, it was validated as having good psychometric properties in a Chinese context [33].

3.3 Recommender Algorithms
As mentioned before, each user was randomly assigned one algorithm’s recommendation. We concretely implemented four algorithms: one is popularity-based, and three are variants of the
Table 2: Assessment of user perceptions of recommendation and descriptive statistics

| Assessment question | Mean (Std) | K-S test |
|---------------------|-----------|----------|
| Unexpectedness:     |           |          |
| "The item recommended to me is unexpected." | 3.153 (1.456) | 0.208*** |
| Novelty:            |           |          |
| "The item recommended to me is novel." | 2.941 (1.427) | 0.229*** |
| Serendipity:        |           |          |
| "The item recommended to me is a pleasant surprise." | 2.656 (1.455) | 0.200*** |
| Relevance:          |           |          |
| "The item recommended to me matches my interests." | 3.157 (1.452) | 0.252*** |
| Timeliness:         |           |          |
| "The item recommended to me is very timely." | 2.836 (1.492) | 0.195*** |
| Curiosity:          |           |          |
| Curiosity and Exploration Inventory-II (CEI-II) [15] | 3.139 (0.819) | 0.035*** |

Note: All of the questions were responded on 5-point Likert scale, and accompanied by Chinese translations. ***p < 0.001 for Kolmogorov-Smirnov (K-S) test.

collaborative filtering (CF) based method tailored to respectively emphasize recommendation relevance, novelty, and serendipity. Therefore, by comparing these algorithms through both user evaluation and approximation metrics, we could verify the metrics’ actual performance. A brief introduction to each algorithm is given below (details can be referred to [6]).

(1) HOT: The product with the most clicks is recommended, so it is not personalized to individual preferences.

(2) Rel-CF: It is a variant of the standard user-based CF by including the item’s timestamp information (i.e., the time when the user clicked it). To be more specific, if two users have often clicked the same item within the same domain (domain is the top-level category of items such as “clothes,” “toys,” “home appliances”; see Figure 1) and their clicking time is close, the two items’ similarity score will be enhanced.

(3) Nov-CF: It also considers the timestamp info, but is more targeted to recommend an item unfamiliar to the user. For this purpose, the item-based CF was adjusted to calculate two items’ similarity if they belong to two different categories (that refer to all domains and subordinate level categories as shown in Figure 1), so that the recommended item will be likely from a category that the user has rarely visited.

(4) Ser-CF: It is more serendipity oriented, because its recommendation’s relevance to the target user’s preferences is more strengthened on top of Nov-CF. In particular, when calculating two items’ similarity, it considers their time sequence as well as the other items clicked by the same user, by summing the similarities between any two adjacent items positioned from \( p_{ui} \) to \( p_{uj} \) \( (p_{ui} \) is the position of item \( i \) within the time sequence of items user \( u \) has clicked). Besides, a user’s weight will be higher if her/his distance from the other users (who also clicked items \( i \) and \( j \)) is larger, in order to increase the recommendation’s unexpectedness.

The numbers of users distributed to the four algorithms are respectively: 2,819 for HOT, 2,817 for Rel-CF, 2,895 for Nov-CF, and 2,898 for Ser-CF.

4 SERENDIPITY METRICS

To implement the serendipity metrics, each user record was first converted into a tetrad: \( (u, r, F_{ur}, I_u) \), where \( u \) is the user’s ID, \( r \) is the recommendation’s ID, \( F_{ur} \) is the user’s feedback on \( r \) \( (F_{ur} = \{ f_{aur} \( (1) \), ..., \( f_{aur}(k) \} \) \), where \( k \) refers to one specific question in the questionnaire; see Table 2), and \( I_u \) is the user’s profile \( (I_u = \{ i_{u1}, i_{u2}, ..., i_{um} \} \) \), where \( i_{um} \) is one clicked item). For each item, we only require the categories it belongs to: \( C_1 = \{ c_{11}, c_{12}, ..., c_{1m} \} \) (e.g., one item’s categories are “Clothes”, “Women’s clothing”, “Suit”, “Work uniform”), but no other auxiliary information is needed.

Therefore, with a serendipity metric, we are able to estimate a recommendation \( r \)’s serendipity degree for user \( u \) based on her/his profile \( I_u \), which can then be compared with the user’s actual feedback \( F_{ur} \) to validate the metric’s adequacy. We implemented in total 22 component metrics and 4 kinds of full metrics\(^3\). Some of them consider the target user’s profile (so it is user dependent) and some are based on the item’s general popularity (so user independent). Besides, as for full metric, in addition to multiplying the result of component metric with the relevance score as proposed in related work [9, 24], we incorporated some new elements, such as *timeliness* and *user curiosity*, to further improve it.

4.1 Component Metrics

Component metric primarily assesses the “surprising” aspect of a recommendation. As for the metrics based on user profile, most of them stress to calculate the distance between the current recommendation \( r \) and user profile \( I_u \), under the assumption that if \( r \) is largely dissimilar from the items the user has already visited, it will be more likely surprising from the user’s perspective. In comparison, the popularity-based metrics aim to disclose whether \( r \) will be unlikely familiar (known) to the user given that it is unpopular among all users (e.g., infrequently clicked). Note that we did not classify these component metrics according to their original definitions, because for some metrics, though the terms are different (e.g., called surprise in [13] and novelty in [30]), the formulas are essentially similar. Table 3 lists the typical component metrics that we have implemented.

4.1.1 User Profile Based. There are four major types of formulation that consider user profile:

- **Distance-based approach** that mainly computes the minimal or average distance between the current recommendation \( r \)

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\(^3\)Note that we have focused on a single recommendation’s serendipity in this paper, so the metrics specific to evaluating a whole list of recommendations’ serendipity [1, 10] were not included.
Table 3: List of state-of-the-art serendipity component metrics that we have implemented, based on user profile or item popularity

| Name                          | Metric                                                                 | Explanation                                                                 |
|-------------------------------|------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| **User profile based**        |                                                                        |                                                                             |
| \( su_{1,2}^{\text{cos}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Minimal content-based Cosine distance (\( r \) denotes \( i \)'s category vector); |
| \( su_{2}^{\text{cos}} (u, r) \) | \( \frac{1}{|I_u|} \sum_{r \in I_u} 1 - \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \) | Average content-based Cosine distance;                                      |
| \( su_{1,2}^{\text{collab}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Minimal collaborative-based Cosine distance;                                |
| \( su_{2}^{\text{collab}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Average collaborative-based Cosine distance;                                |
| **Jaccard based**             |                                                                        |                                                                             |
| \( su_{1,2}^{\text{jaccard}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Minimal content-based Jaccard distance;                                     |
| \( su_{2}^{\text{jaccard}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Average content-based Jaccard distance;                                     |
| \( su_{1,2}^{\text{collab jaccard}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Minimal collaborative-based Jaccard distance;                               |
| \( su_{2}^{\text{collab jaccard}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Average collaborative-based Jaccard distance;                               |
| \( su_{1}^{\text{dist}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Minimal class distance;                                                    |
| \( su_{2}^{\text{dist}} (u, r) \) | \( \min \{ \frac{r \cdot \text{profile}}{\sqrt{\text{profile}^2}} \} \) | Average class distance;                                                    |
| **Popularity based**          |                                                                        |                                                                             |
| \( sp_{1,2} (u, r) \) | \( \frac{1}{|I_u|} \sum_{r \in I_u} \frac{1}{|r|} \) \[\text{num of users who have clicked r and } |I_u| \text{ is the total number of users;] | Popular items are the top-1000 items with the largest amount of users who have clicked it; |
| \( sp_{3} (u, r) \) | \( 1 - \log_{|I_u|} \frac{|r|}{|I_u|} \) \[\text{num of clicks on r and } |I_u| \text{ is the total number of clicks on all items;] | Popular items are the top-1000 items with the largest amount of clicks; |
| \( sp_{1,2}^{\text{click}} (u, r) \) | \( 1 - \frac{|\text{click}|}{|r|} \) \[\text{click} \text{ is the number of clicks} | And the user’s profile items \( I_u \) [13, 14, 30]: \( su_{1}^{\text{dist}} (u, r) = \min \{ \text{dist} (r, i) \} \) (1) Higher values are supposed to signify better surprise results. \( \text{dist} (r, i) \) can be computed through classical Cosine or Jaccard distance metrics [17] (see Table 3). For each, there can be two variations: **content-based** that considers the item’s content (such as categories \( C_i \) in our case) to compute two items’ difference (i.e., \( su_{1,2}^{\text{cos}_\text{dist}}, su_{1,2}^{\text{jaccard}_\text{dist}} \), and **collaborative-based** that counts on the set of users who clicked both items (\( su_{1,2}^{\text{collab}_\text{cos}_\text{dist}}, su_{1,2}^{\text{collab}_\text{jaccard}_\text{dist}} \)). We also implemented the content-based **class distance** proposed in [25]: \( su_{1,2}^{\text{class}_\text{dist}} (u, r) \), which is particularly based on the item taxonomy (see Figure 1) to determine how many hops it requires to move from \( c_r \) to \( c_i \) (\( c_r \) is \( r \)'s immediate category; see Table 3).  
- **Point-wise mutual information (PMI) based approach** [13, 14], which is to check the probability that two items are seen by the same user, under the assumption that if the current recommendation is rarely observed together with the items in the user’s profile, it will be more surprising to her/him. It has two variations, which respectively take the lower bound of the surprise and the average surprise value across all items in \( I_u \):  
  \[ sp_{1}^{\text{pmi}} (u, r) = \min \{ \text{PMI} (r, i) \} \] (3)  
  \[ sp_{2}^{\text{pmi}} (u, r) = \frac{1}{|I_u|} \sum_{i \in I_u} \frac{1}{\text{PMI} (r, i) + \text{PMI} (r, i)} \] (4)  
  where \( \text{PMI} (r, i) = \log_{|I_u|} \frac{|r \cap i|}{|r| |i|} \) (in which \( p(r) \) is the probability that item \( r \) is to be clicked by any user, and \( p(r, i) \) is the probability that the same user clicks both items \( r \) and \( i \)).  
- **Deviation from the result by primitive prediction method (PPM)** [24], which original form is\[^4\]  
  \[ sp_{\text{ppm}} (u, r) = \max \{ \text{PMII} (r) - \text{PMII} (r, 0) \} \] (5)  
  where \( \text{PMII} (r) \) indicates how confidently the system recommends item \( r \) to user \( u \), and \( \text{PMII} (r) \) denotes whether the item can be easily predicted by a primitive method, so the assumption is that if \( \text{PMII} (r) \) is much higher than \( \text{PMII} (r) \), the recommendation is more unexpected. [24] suggested three candidates for \( \text{PMII}(r) \) that are all based on contents of items in user profile (see Table 3 with our implementations \( sp_{1,2,3}^{\text{ppm}} \)). Because in our case the algorithm’s confidence of recommending \( r \) is 1 (as it is the single item recommended by that algorithm) and the output of \( \text{PMII}(r) \) is binary, the formula can finally be rewritten as \( sp_{\text{ppm}} (u, r) = 1 - \text{PMII}(r) \).  
- **Attribute co-occurrence method** [9, 11], which mainly counts the occurrence of items within the user profile \( I_u \) that share the same attributes (categories in our case) with those of recommendation \( r \). If \( r \)'s categories less frequently occur in \( I_u \), it is supposed to be more surprising:  
  \[ sp_{\text{attri-occ}} (u, r) = \frac{1 + n_{I_u, \text{max}} - n_{I_u, c_r}}{1 + n_{I_u, \text{max}}} \] (6)  
  where \( n_{I_u, c_r} \) refers to the number of items in \( I_u \) that are described by the same attributes of \( r \), and \( n_{I_u, \text{max}} \) is the maximal number of items in \( I_u \) that share a single attribute with \( r \).

Therefore, PMI-based approach can be classified as collaborative-based, while deviation from PPM and attribute co-occurrence method are content based.

4.1.2 Popularity Based. As mentioned above, popularity-based metrics are user independent, because they just rely on the item’s general popularity without taking into account the target user’s profile. There are mainly two variations [30]:  
- **Popularity based**\[^5\]  
  \[ sp_{1,2}^{\text{pop}} (u, r) = 1 - \text{Popularity} (r) \] (7)  
  \[ sp_{2}^{\text{pop}} (u, r) = -\log_{|I_u|} \text{Popularity} (r) \] (8)  
  \[^4\]This metric, and the next attribute co-occurrence method, was originally part of a full metric [9, 24]. We took it out because it inherently measures the “surprising” aspect.
The first formula takes the inverse of an item’s popularity, while the second emphasizes highly novel items with the log of the inverse popularity. Table 3 lists various ways to calculate Popularity(r), e.g., based on the number of users who have clicked it (sur_{user,pop}), or the total number of clicks placed on it (sur_{click,pop}).

4.2 Full Metrics

Full metric is aimed to evaluate serendipity as a whole. Its generic form is [9, 24]:

\[
\text{serendipity}(u, r) = \text{sur}(u, r) \cdot \text{rel}(u, r)
\]  

(9)

where sur(u, r) is the result of component metric (from the previous section) and rel(u, r) is the item’s relevance score that can be judged by the user or approximated by accuracy metrics [24]. Because we got each user’s rating on the recommendation’s relevance (see Table 2), we used it to indicate rel(u, r).

In addition, we extended the metric to incorporate two new elements. One is *timeliness* that indicates whether the item is recommended at the right time. In our previous work [6], it was found that timeliness is significantly related to users’ serendipity perception, which even behaves more actively than the other predictors (such as relevance and unpredictedness). Thus, we added *timeliness* as a potential effect into the full metric:

\[
\text{serendipity}(u, r) = \text{sur}(u, r) \cdot \text{rel}(u, r) \cdot \text{tim}(u, r)
\]  

(10)

where tim(u, r) is the user’s real rating on timeliness.

The second new element is *user curiosity*. Still, as shown in our previous work, highly curious users are more inclined to perceive a novel item as serendipitous, because they tend to embrace uncertain situations. Therefore, we thought it might take certain role in serendipity measurement:

\[
\text{serendipity}(u, r) = \text{sur}(u, r) \cdot \text{rel}(u, r) \cdot \text{tim}(u, r) \cdot \text{cur}(u)
\]  

(11)

where cur(u) can be either obtained from the user’s answers to a psychological curiosity quiz (such as CEI-II [15] used in our survey), or simulated based on the user’s history data. For the latter, [20] suggested to use the number of unique categories that appear in the user profile lq to estimate her/his coping potential check (a curiosity appraisal according to [29]), given that the more diverse categories of items the user has visited, the more likely s/he would be able to deal with new and complex things. We hence use notations cur_{quiz}(u) and cur_{sim}(u) to respectively denote the two ways of acquiring a user’s curiosity value.

5 RESULTS ANALYSIS

We first conducted normality testing for each variable assessed in the user survey. The p values of the Kolmogorov-Smirnov test (suitable for sample size greater than 2,000 [21]) are all less than 0.001 (see Table 2), showing that the null hypothesis of normal distribution is rejected for each variable. Therefore, we chose non-parametric tests that do not assume normality for the following correlation and comparison analyses.

5.1 Metrics Validation

5.1.1 Correlation Results. We applied all of the component metrics to the recommendation that a user received in the survey, and compared their results with the user’s actual feedback (in terms of unpredictedness, novelty, and serendipity). We found most of the results returned by the component metrics are significantly positively correlated with users’ perceived unpredictedness (p < 0.05 by Spearman’s correlation)5; see Table 4), among which the correlations of user profile based metrics are higher than those of popularity-based metrics. Moreover, among the profile-based metrics, content-based metrics overall perform better than collaborative-based. The metrics based on class distance (sur_{class_dist}) actually achieve the highest correlation among all, followed by content-based Cosine/Jaccard distance metrics (sur_{cont}_cos_dist and sur_{cont}_jaccard_dist). Relatively, the deviation from PPM (sur_{ppm}) and attribute co-occurrence method (sur_{attri_occ}) get slightly lower correlations.

As for novelty and serendipity, mainly the results by class distance metric (sur_{class_dist}) are positively correlated with them, but very weakly (r_s = 0.059 w.r.t. novelty and r_s = 0.037 w.r.t. serendipity), suggesting that it might be difficult to directly predict them by using those component metrics.

For the next step, we tried full metrics by first integrating the item’s *relevance* score. It shows the correlations can be largely increased after relevance was incorporated. Especially, when combining each of the five component metrics (i.e., sur_{collab_cos_dist}, sur_{cont}_jaccard_dist, sur_{cont}_cos_dist, sur_{class_dist}, and sur_{attri_occ}, among the ten best metrics that are significantly related to unpredictedness) with relevance, the correlation with serendipity can reach 0.50 (or above; p < 0.01). The correlations with novelty are also increased, but lower than those with serendipity. We further incorporated timeliness into the full metrics, which return even higher correlations with serendipity (above 0.67), inferring that timeliness can be very useful to help improve the serendipity’s estimation accuracy.

The last element we incorporated is *user curiosity*. It shows the correlations can be higher than those without the curiosity (above 0.68), if it was explicitly acquired from the psychological quiz (cur_{quiz}). However, if the curiosity was simulated based on the number of unique categories in user profile (cur_{sim}), the correlations are obviously decreased, which suggests that user curiosity

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5Spearman’s correlation is a nonparametric test used to measure the degree of association between two variables that are measured on an ordinal or continuous scale.
Table 5: Full metric’s correlation (with user feedback), accuracy, and precision results

| Unexpect- | Novelty | Serendipity | Unexpect- | Novelty | Serendipity | Unexpect- | Novelty | Serendipity | Unexpect- | Novelty | Serendipity | Unexpect- | Novelty | Serendipity |
|----------------|----------|-------------|----------------|----------|-------------|----------------|----------|-------------|----------------|----------|----------|-------------|----------------|----------|-------------|
| Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric | Full Metric |
| \(\text{user\_lab\_cos\_dist}\) | 0.14��55% 58% | 0.07��51% 76% | 0.64��73% 88% | 0.17��58% 56% | 0.71��65% 69% | 0.72��66% 64% | 0.85��84% 86% | 0.07��55% 39% | 0.51iciel% 73% 69% | 0.08��55% 36% | 0.52iciel% 73% 67% | 0.09��55% 36% | 0.52iciel% 73% 69% | 0.10��55% 36% | 0.52iciel% 73% 69% |
| \(\text{user\_jaccard\_dist}\) | 0.14��55% 58% | 0.07��51% 76% | 0.64��73% 88% | 0.17��58% 56% | 0.71��65% 69% | 0.72��66% 64% | 0.85��84% 86% | 0.07��55% 39% | 0.51iciel% 73% 69% | 0.08��55% 36% | 0.52iciel% 73% 67% | 0.09��55% 36% | 0.52iciel% 73% 69% | 0.10��55% 36% | 0.52iciel% 73% 69% |
| \(\text{user\_cos\_dist}\) | 0.13��55% 59% | 0.07��51% 77% | 0.59��70% 81% | 0.17��59% 52% | 0.55��73% 68% | 0.71��68% 64% | 0.73��81% 80% | 0.09��58% 38% | 0.56iciel% 49% 56% | 0.06��55% 36% | 0.52iciel% 73% 69% | 0.10��55% 38% | 0.56iciel% 49% 56% | 0.11��55% 36% | 0.56iciel% 49% 56% |
| \(\text{user\_attri\_occ}\) | 0.15��56% 57% | 0.07��51% 77% | 0.57��71% 80% | 0.17��59% 52% | 0.55

Figure 2: Impact of user profile size on serendipity feedback and measurement (the result is normalized in [0,1], and all users are evenly divided into ten bins). Cosine distance, class distance, and attribute co-occurrence), which verifies that the chance of finding an item dissimilar to those the user has seen before will be smaller if her/his profile is larger.

5.2 Algorithm Comparison

We further applied those metrics to compare several recommender algorithms and contrasted the results from user evaluation. Table 6 lists the metrics whose results are exactly in agreement with user perceptions. First of all, from users’ perspective, there is very strong evidence of differences among the four algorithms: Ser-CF is significantly better than Nov-CF, Rel-CF, and HOT, in terms of

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\[\text{User Validation of Recommendation Serendipity Metrics Conference'17, July 2017, Washington, DC, USA}\]

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\[\text{Each metric’s result was first normalized before being classified into a binary output according to its mean value.}\]

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\[\text{We used Kruskal-Wallis 1-way ANOVA test for overall comparison and Mann Whitney Wilcoxon test for pairwise comparison, which are both nonparametric tests used to compare the mean ranks of independent groups [22].}\]
Table 6: Algorithm comparison through user evaluation and approximation metrics

|                  | Mean Rank | Sig.   |
|------------------|-----------|--------|
| **Unexpectedness** |           |        |
| TRBF             | 610.84**  | 579.19* |
| Rel-CF           | 549.02    |        |
| Nov-CF           | 543.62    |        |
| Ser-CF           | 548.57    |        |
| **Novelty**      |           |        |
| TRBF             | 5166.05   |        |
| Rel-CF           | 5376.43   |        |
| Nov-CF           | 6037.15†  |        |
| Ser-CF           | 6474.02‡  |        |
| **Serendipity**  |           |        |
| TRBF             | 4942.21   |        |
| Rel-CF           | 5376.43   |        |
| Nov-CF           | 6037.15†  |        |
| Ser-CF           | 6474.02‡  |        |

Note: The superscript indicates that the corresponding algorithm significantly outperforms the numbered one, with p < 0.05 adjusted by the Bonferroni correction. Due to the space limit, we only list metrics that return exactly same significant differences as those of user evaluation.

distance metric) can achieve better correlation and accuracy results than the corresponding minimal distance approach (minimal content-based Cosine/Jaccard/class distance metric).

In addition, the comparison among various formulations of full metric reveals the added values of relevance, timeliness and curiosity in evaluating recommendation serendipity. In particular, it shows curiosity as a personal characteristic, can be helpful for enhancing the estimation of a recommendation’s serendipity. However, our results also suggest that it should be carefully simulated if no psychological quiz could be conducted.

The application of those metrics to multiple recommender algorithms demonstrates their actual performance in algorithm comparison, because the results are exactly consistent with those of user evaluation. Specifically, it verifies the function of some component metrics to compare algorithms in terms of their unexpectedness aspect, and the function of some full metrics to measure their novelty and serendipity aspects.

Besides, we find novelty and serendipity are closely related in several results, which can be explained by a strong correlation that exists between users’ perceptions of them ($r_s = 0.586, p < 0.01$), much higher than the correlation between unexpectedness and serendipity ($r_s = 0.341, p < 0.01$). Given that some full metrics can much more accurately estimate serendipity than novelty, while the popularity-based component metrics (originally proposed to indicate novelty [30]) do not show positive correlation with it, further investigation is indeed needed to identify more dedicated metric for novelty.

7 CONCLUSIONS AND FUTURE WORK

To the best of our knowledge, this is the first work that has conducted a large-scale user validation of a number of existing serendipity metrics. The major findings are: 1) The component metrics that consider a user’s own clicking history can be more useful to estimate an item’s unexpectedness, in comparison to those purely considering the item’s popularity; and those based on the clicked item’s content (such as categories in our case) can be more effective than the collaborative-based metrics. 2) Full metrics that involve unexpectedness (as predicted by the component metric), relevance, timeliness, and user curiosity can more precisely assess recommendation serendipity, relative to those that do not combine all of them. 3) The metrics’ practical performance in algorithm comparison is also demonstrated, because the results are in agreement with user evaluation.

However, this work also has some limitations. First, we did not include metrics specific to measure a whole list of recommendations’ overall serendipity [1, 10]. Second, the metric validation was conducted on our collected data, for which the domain is restricted to mobile e-commerce. Third, the popularity-based metrics did not perform well, which may be partially because our dataset just contains a subset of users’ historical data (over three months). Ideally, an item’s popularity should be determined based on all users’ behavior across a longer period of time. Fourth, we did not test state-of-the-art recommender algorithms [8, 19, 20, 35], because we attempted to tailor the classical methods to stress unexpectedness, relevance, novelty, and serendipity respectively.

novelty and serendipity ($p < 0.05$), while HOT returns significantly more unexpected recommendations relative to the other three; as for the difference between Nov-CF and Rel-CF, the former is perceived more novel and serendipitous.

The measurement via some component and full metrics exhibits similar pattern. Specifically, the algorithm comparison through most of component metrics reveals that HOT is significantly higher than the other three, which is consistent with users’ evaluation on the unexpectedness facet. As for full metrics, they primarily project users’ novelty and serendipity perceptions, because the ones (that were shown significantly related to novelty and serendipity in the above analysis) also give the highest score on Ser-CF, followed by Nov-CF, Rel-CF, and HOT. It hence implied that they can be properly used to assess an algorithm’s relative serendipity degree.

On the other hand, as these four algorithms were designed with different properties, it shows the recommendation by Ser-CF is in practice perceived more serendipitous by users, demonstrating that curiosity, as a personal characteristic, can be helpful for enhancing the estimation of a recommendation’s serendipity. However, our results also suggest that it should be carefully simulated if no psychological quiz could be conducted.

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6 DISCUSSION

Thus, this experiment shows that component metrics can be more useful for indicating users’ unexpectedness feedback than novelty and serendipity feedback. In this regard, user profile based metrics behave more actively than popularity-based metrics; and furthermore content-based metrics (i.e., class distance, content-based Cosine/Jaccard distance, attribute co-occurrence) are of higher correlations with unexpectedness, than collaborative-based distance, deviation from PPM, and PMI-based metrics. Moreover, some component metrics (that are positively correlated with unexpectedness) can be well allied with relevance, timeliness, and user curiosity to estimate recommendation novelty and serendipity, among which we find still content-based metrics in general perform better than others. Another interesting observation is that the average content-based Cosine/Jaccard/class

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We will address the above limitations in our future work. Moreover, given the content-based metrics can potentially more effectively disclose a recommendation's unexpectedness, we may further strengthen them by considering the inherent semantic structure of item content (such as knowledge graph [5]). On the other hand, in order to apply full metrics in real offline measurement, we will find appropriate metrics to approximate timeliness (to consider the item's compatibility with the user's current contexts) and curiosity (to embody the user’s intrinsic propensity towards surprising items). We will then test the metrics’ applicability to more recent serendipity-oriented algorithms, as well as their adequacy in other product domains.

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