Enhancing Recommender Systems With a Stimulus-Evoked Curiosity Mechanism

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Abstract—Classical algorithms in recommender systems (RS) mainly emphasis on achieving high accuracy and thus recommend items precisely matching a user's past choices. However, the user may gradually lose interest and crave something more inspiring. In psychology, curiosity is a critical human nature and can be efficient bootstrap exploratory behaviors, thus this phenomenon can be explained as insufficient stimulation to induce curiosity regard to recommended items. Inspired from the above, this work proposes a Curiosity-drive Recommendation Framework (CdRF) which incorporates a highly innovative Stimulus-evoked Curiosity mechanism (SeCM) together with a basic accuracy-oriented algorithm via Borda count. In SeCM, we first estimate the stimulus intensity appearing on each item for each user and then model personalized curiosity among the calculated intensities using Wundt curve. For the target user, the output of CdRF is a ranked list of N items which are both relevant and highly curiousness. We conduct extensive experiments using four public datasets to evaluate the performance of each specification of SeCM as well as the whole framework CdRF. The results reveal that SeCM can flexibly generate diversified items and CdRF can increase diversity in terms of ILS, Newness and AD while compromising very little Precision. This kind of research also offers a way to understand both individual differences in curiosity and how curiosity contributes to item exploration at the level of RS.

Index Terms—Recommender systems, novelty, conflict, stimulus-evoked curiosity mechanism, relevance preference, diversity

1 Introduction

Most work in recommender systems (RS) adopt accuracy-centric design which provide a candidate list composing highly relevant items. Over time, the user may get bored and have difficulty in concentrating on the current activities [1]. This universal phenomenon raises two open questions about RS enhancement: "why is this happening?" and "how to alleviate it?". From the perspective of psychology, the first question may be explained by "insufficient stimulation to evoke users curiosity regard to the pushed items." This line of thinking encourages the design of additional curiosity mechanism to enrich existing accuracy-oriented RS with the capacity of recommending items that stimulate curiosity. The curiosity mechanism mentioned becomes a plausible alleviation to the second question and also what we concerned with in this paper.

In the literature, there were only four work have been devoted to this topic [2], [3], [4], [5]. Santos [2] collected CEI-II questionnaires from a group of volunteers and then calculated the curiosity level of a given user based on those statistics. A major limitation of Santos's work is it requires manual intervention. Quite apart from Santos's questionnaire-type work, Wu *et al.* separately and automatically modeled surprise-drive curiosity [3] and uncertainty-drive curiosity [4] for recommendation tasks. Unlike Wu's work that tried to maximize the diversification of the recommended items, Zhao, *et al.* [5] presented a curiosity-based RS, called *CBRS*, which leverages a novelty-drive curiosity model to recommend relevant-yet-diverse music tracks. However, it cannot handle the case if data is not Beta distributed and hence severely limits its large-scale application. In addition, *CBRS* ignores the fact that curiosity is usually evoked by a number of factors instead of novelty alone. Similar problems exist in other curiosity models as well. In the light of shortcoming highlighted above, this work therefore aims to design a more general and comprehensive curiosity mechanism.

A pressing challenge resides on curiosity research is to dig out its underlying cause. Fortunately, psychological theories of Curiosity-drive, Social Conflict and Intermediate Arousal Potential (IAP) bring us some enlightenments: 1) a number of stimulus simultaneously present on an item rather than separately appears. That is, each item appears an overall stimulus intensity to the user; 2) usually, the moderate level of stimulation governs the arousal of curiosity; 3) curiosity appetite is not identical across individuals. In these regards, there are actually two sub-tasks should be considered at the level of curiosity mechanism. One is to give quantitative analysis for stimulus intensities. Another is to model personalized curiosity for each user with respect to their tolerances in those intensities. Providing solutions to these sub-tasks result in a newly Stimulus-evoked Curiosity Mechanism, termed *SeCM*.

To complete the recommendation circle, *SeCM* is incorporated into the proposed Curiosity-drive Recommendation Framework, namely *CdRF*, together with an existing accuracy-oriented algorithm via Borda Count method. So that, *CdRF* is able to enhance RS in maintaining acceptable

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relevance to a user's selection in the past (i.e., hight accuracy in the form of Precision) while achieving considerable gain in diversity (i.e., hight diversity in the form of ILS, Newness and AD). Summarizing, our main contributions lie in:

- We adopt a psychologically inspired view to explore the effect of curiosity and its underlying cause on recommendation problems. So far, little work have recognized the importance of curiosity and its effect on RS, this study is meant to contribute to such seldom explored area.
- We design a novel stimulus-evoked curiosity mechanism *SeCM*. It provides not only a way of measuring novelty but also a way of measuring conflict since both of them are key factors that necessarily induce curiosity. To the best of our knowledge, this is the first effort to gauge conflict in the context of RS, as well as, the first attempt to merge the study of novelty with conflict for curiosity research.
- As the core of *SeCM*, personalized curiosity is modeled using Wundt curve coupled with Avoidance of Boredom (AoB) and Avoidance of Anxiety (AoA) rules. To be specific, the modeling task is treated as an optimization problem based on Saunders's definition of Wundt curve [6]. *SeCM* outputs a series of curiousness scores on items for users. As far as we know, it is the first work to creatively grant Saunders's Wundt curve with learning capacity as well as extend it to RS case.
- To obtain a Top-N ranked list of potential items, we propose a general recommendation framework *CdRF*. It generally incorporates an accuracy-oriented method, a curiosity mechanism, and a ranking optimization method together so as to gain a more comprehensive RS.
- Extensive experiments on two movie datasets and two book datasets with more than ten competitors (specifications) verify the effectiveness of *SeCM* and *CdRF* on recommending relevant and diverse items.

2 Preliminaries

Due to the inter-discipline of our research, we preface curiosity-related theories and terminologies widely used in psychological field and also adopted in our work.

2.1 Curiosity-Drive Theory

Psychologist Berlyne defined curiosity as a drive that promotes exploratory behaviors to learn more about a source uncertainty, mainly induced by novelty and conflict, with the goal of acquiring sufficient knowledge to reduce the uncertainty. Berlyne also suggested that curiosity appears to be evoked by a stimulus or a set of stimuli, such as novel-stimulus, conflict-stimulus, etc., and usually more than one types of stimulus coexist instead of independently exists [7]. In this paper, we mainly focus on a compound of novel- and conflict- stimulus evoked curiosity and leverage it to enhance RS for Top-N item recommendation.

2.2 Social Conflict Theory

Everyday experience suggests that decision-making is often accompanied by conflict [8]. Debra Gerardi suggested that conflict engagement creates connection and cultivates curiosity. Kurt Lewin was among the first to bring together the concepts of decision-making and psychological conflict [9], [10]. Depending on the valences of the choice alternatives, conflict has been classified as approach-approach conflict, avoidance-avoidance conflict, and approach-avoidance conflict (AAC) [11]. In approach-avoidance conflict situations, a decision is made between desirable and undesirable outcomes. For example, whether to or not to watch the movie of "Jurassic Park" since social peers provide incompatible votes (e.g., in the case of higher ratings coexist with lower ratings) can generate AAC. As commented by Lewin that people are frequently placed in an AAC situation, conflict during this work has been linked to AAC.

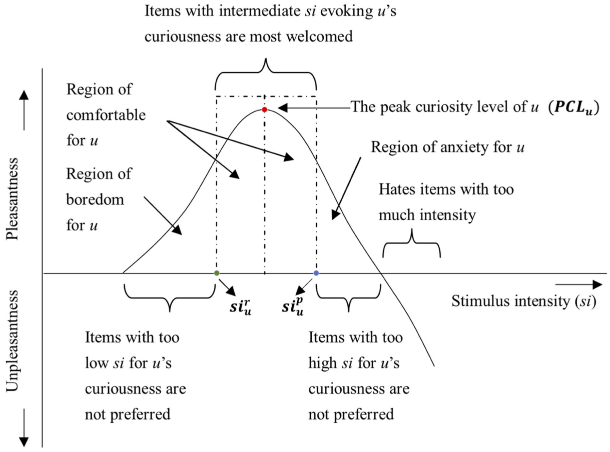


Fig. 1. Illustration of user u's Wundt curve.

2.3 Intermediate Arousal Potential Theory

In the 1870s, Wilhelm Wundt introduced the concept of "optimal level of stimulation" and postulated an inverted-U relationship between stimulation level and hedonic tone, well-known as the "Wundt curve". It states that many forms of stimulation level are pleasant at medium intensities and become unpleasant when the intensities are too high [12]. Based on Wundt's theory, Berlyne formed the theory of "Intermediate arousal potential" (IAP). It suggests that people sometimes withdraw from objects and sometimes approach and inspect them, the actual exploration is more likely to occur when arousal potential is only slightly around optimal and thus easily brought back to its optimum [13].

For illustration, we introduce the IAP process under the context of our curiosity-drive recommendation task as described in Fig. 1. The x-axis refers to the intensity of stimulus (si), and the y-axis refers to the user u's pleasant feedback (above x-axis) or unpleasant feedback (below x-axis). We can observe that u's pleasantness initially increases until it reaches a peak curiosity level (short for PCL), while additional si becomes welfare reducing. This phenomenon can be explained by the fact that the user u (1) prefers items with intermediate si evoking her curiousness; (2) feels boring with items that are well learnt or trivial; (3) is anxious to items that are unlearnable or random; and (4) hates items with too much si. In summary, the Wundt curve posits that individuals normally strive to maintain intermediate amount of stimulating arousal, shying away from boredom and anxiety [14]. Accordingly, there are two ends of the spectrum: AoB and AoA, separately reflecting the rules in stimulus selection. The AoB states items that below a certain stimulus threshed (si_u^r), the user will feel boring owing to scanty stimulation. The AoA says that beyond a certain stimulus threshed (si_u^p), the user will become anxious due to overwhelming stimulation. This offers a new angle and cut-in point to our recommendation task: for the target user u the most pleasing items are those presenting intermediate stimuli; and for RS, it's more practical to recommend items appearing stimulus intensities within the range of $[si_u^r, si_u^p]$.

Besides, another key point is there must also be individual differences in stimulus responses because of their different level in stimulus tolerance [15]. For example, conservative users enjoy items with lower level of stimulus, whereas radical users may appreciate relatively high stimulating items. This also provides a striking requirement of personalized curiosity modeling.

3 Problem Definition

The original data is organized by (u, i, r, t) quadruples, which denotes user u rates item i with score r at time t. We denote $\mathcal{U}$ and $\mathcal{I}$ as the set of users and items, respectively, where $|\mathcal{U}| = m$, $|\mathcal{I}| = n$. Symbols (u, v, w) and (i, j, k) are separately preserved for individual users and items. $\mathbf{R}$ represents $m \times n$ user-item rating matrix. An entry (u, i) in $\mathbf{R}$ is denoted by $r_{u,i}$. We use $\mathcal{I}_u$ to define a set of items that rated by u while use $\mathcal{U}_i$ to denote a set of users that rated i. In practice, we have ordered the (u, i, r, t) quadruples by timestamp t for each user in advance. Therefore, given chronically ordered $\langle u, i, r \rangle$ triples, the problem discussed in this paper is how to model individual curiosity as well as combine with a existing accuracy-oriented RS to output a ranked list containing N relevant-yet-diverse items.

4 The Proposed Stimulus-Evoked Curiosity Mechanism (SeCM)

Guided by the psychological theories introduced in Section 2, we design *SeCM* which qualifies the overall stimulus intensity, models personalized curiosity with Wundt curve, and finally generates curiousness scores on each item for each user. These will be described in the next three subsections.

4.1 Measure Overall-Stimulus Intensity

Berlyne identified several key factors that may arouse curiosity: one of them is novelty, another of them is conflict. A distinction that calls for consideration is that between novelty and conflict. Novelty would be one with some quality that differs from the user's previous experiences while conflict would be one associates with incompatible responses. They are separately quantified by novel-stimulus intensity si^{Nov} and conflict-stimulus intensity si^{Conf}. In particular, considering that a number of stimulus simultaneously present on an item rather than separately appears, together with the fact that human beings are more likely to balance all the cases comprehensively for decision-making, we are therefore compelled to focus mainly on a compound-stimulus case in this work. To be specific, we use $si_{u,i}$ to denote the overall stimulus intensity appearing on item i for u, which is formulated as follow, where α is a trade-off parameter

$$si_{u,i} = \alpha \times si_{u,i}^{Nov} + (1 - \alpha) \times si_{u,i}^{Conf}. \tag{1}$$

4.1.1 Compute Novel-Stimulus Intensity

Novelty denotes something new. Berlyne presumed that the novel-stimulus intensity is inversely proportional to how similar and how recently the stimulus compared to previous experience [7]. Based on such criterion, we present a formal definition to estimate novel-stimulus intensity presenting on i for u (denoted by $si_{u,i}^{Nov}$) as follow:

$$si_{u,i}^{Nov} = \sum_{z=1}^{\rho} [e^{-\mu z} \times \underset{(\mathcal{I}_u)_{i-z} \mapsto j}{dissim_{i,j}}]. \tag{2}$$

In (2), we introduce a forgetting coefficient μ. Term $e^{-\mu k}$ is used to depict the fact that a user's memory is decaying with time. The value of μ is associated with ρ while ρ indicates only the 1th to ρth nearest items accessed in the past by u are considered for the calculation of $si_{u,i}^{Nov}$.

We use $dissim_{i,j}$ to denote the degree of dissimilarity between items i and j, which is formally described in (3)

$$dissim_{i,j} = \frac{1 - pcc_{i,j}}{2}. \tag{3}$$

Here, $pcc_{i,j}$ refers to Pearson correlation coefficient (PCC) [16] between i and j. Due to characteristic of PCC that its values range from -1 to 1, $dissim_{i,j}$ is bounded into [0,1]. Look back to (2), the assignment of the actual item j in term $dissim_{i,j}$ is determined by $(\mathcal{I}_u)_{i-z} \mapsto j$, where $(\mathcal{I}_u)_{i-z}$ denotes the zth item priors to i in set $\mathcal{I}_u$. Note that $\mathcal{I}_u$ is already arranged in a chronological order. $(\mathcal{I}_u)_{i-z} \mapsto j$ means j is replace by any value on the left of the arrow.

Generally, $dissim_{i,j}$ is assigned decaying weights through multiplied by $e^{-\mu z}$ along with the varied j from near to far. By doing so, we have identified $si_{u,i}^{Nov}$ as a quantity that increase both with "dissimilarity" and "recency", which coincides with Berlyne's criterion on novel-stimulus.

4.1.2 Compute Conflict-Stimulus Intensity

Conflict has been defined in various ways [17]. Berlyne suggested that conflict-stimulus intensity is positively related to the nearness to equality in the strengths of the competing responses [7]. For the purpose of this study, we provisionally assume that conflict-stimulus intensity presents on i for u (denoted by $si_{u,i}^{Conf}$) can be reflected by the nearness to equality in the competing strengths between positive and negative responses on the same i received from u's close social peers. Specifically, we 1) regard ratings higher than $\bar{r}$ are positive responses while ratings less than or equal to $\bar{r}$ are negative responses. Here, $\bar{r}$ indicates the average value of the whole scale; 2) simply estimate the closeness between a user and one of her social peers via a PCC value in the absence of explicit user-user friend relationships.

Let $po_{u,i}$ and $ne_{u,i}$ be the strength of positive responses and negative responses on i voted by u's social peers, respectively. $po_{u,i}$ and $ne_{u,i}$ are formulated as follows:

$$po_{u,i} = \frac{\sum_{v \in \mathcal{U}_{u,i}^{po}} \left[pcc_{u,v} \times (r_{v,i} - \bar{r})\right]}{\sum_{v \in \mathcal{U}_{u,i}^{po}} pcc_{u,v}} \tag{4}$$

$$ne_{u,i} = \frac{\sum_{w \in \mathcal{U}_{u,i}^{ne}} \left[pcc_{u,w} \times (\bar{r} - r_{w,i})\right]}{\sum_{w \in \mathcal{U}_{u,i}^{ne}} pcc_{u,w}}. \tag{5}$$

In (4), the numerator can be regard as a member of nearest neighbors methods (KNN), which computes the strength of positive responses for u on i based on the combination of other users' ratings weighted by their closeness with u. The calculation of $ne_{u,i}$ is likewise manipulated in (5). We use $\mathcal{U}_{u,i}^{po}$ and $\mathcal{U}_{u,i}^{ne}$ to denote the two sets organizing u's close social peers who give positive responses on i and negative responses on i, respectively. In practice, $\mathcal{U}_{u,i}^{po}$ ($\mathcal{U}_{u,i}^{ne}$) is sorted by the descending order of $pcc_{u,v}$ ($pcc_{u,w}$) values. To lower the time complexity, we restrict the max size of $|\mathcal{U}_{u,i}^{po}|$ and $|\mathcal{U}_{u,i}^{ne}|$ to γ where $\gamma \ll m$. Hence, at most u's γ close social peers who gave positive (negative) ratings on i would be considered in calculating $po_{u,i}$ ($ne_{u,i}$), bounded by the constraint of $pcc_{u,v} > 0$ ($pcc_{u,w} > 0$).

Intuitively, the more close $po_{u,i}$ is to $ne_{u,i}$, the higher incompatibility of the two responses on i among u's social peers, which strengthen the stimulation of conflict for u. Accordingly, the estimation of $si_{u,i}^{Conf}$ is given by

$$si_{u,i}^{Conf} = 1 - \left|\frac{po_{u,i} - ne_{u,i}}{po_{u,i} + ne_{u,i}}\right|. \tag{6}$$

From (6), we can see that $si_{u,i}^{Conf}$ maximumly lifts when $po_{u,i}$ and $ne_{u,i}$ were more nearly equal, which corresponds to Berlyne's criterion on conflict-stimulus. Note that the value range of $si_{u,i}^{Conf}$ is [0,1].

4.2 Model Stimulus-Evoked Curiosity With Wundt Curve

Considering that a user's curiosity can be evoked from a stimulus and generally behaves like an inverse U-shape pattern, the central task now is how to appropriately depict such stimulus-evoked curiosity using Wundt curve.

Following AOB and AOA rules mentioned in Section 2.3, Saunders approximately modeled the Wundt curve via a sum of two sigmoid functions [6]: a reward function regarding to AoB and a punishment function regarding to AoA. Sketched in Fig. 2, the hedonic function $H(si)$ is used to calculate hedonic values given in a solid curve, the reward and punishment sigmoidal curves shown dashed [12].

Building on Saunders's work, we model u's curiosity with Wundt curve by regarding the original hedonic function as a user's predictive curiosity function, denoted by $\hat{C}_u(si)$, which calculates the predictive curiousness scores for u. And the domain of $\hat{C}_u$ is the stimulus intensity. Following the idea, $\hat{C}_u(si)$ is defined as the sum of a reward function $R_u(si)$ and a punishment function $P_u(si)$. They are formulated as follows:

$$\hat{C}_u(si) = R_u(si) + P_u(si) \tag{7}$$

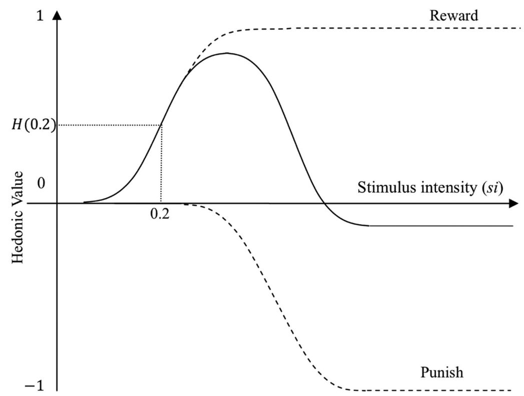


Fig. 2. Illustration of Saunders's modeling of Wundt curve.

$$R_u(si) = \frac{1}{1 + e^{-\theta_r(si - si_u^r)}} \tag{8}$$

$$P_u(si) = -\frac{1}{1 + e^{\theta_p(si - si_u^p)}}. \tag{9}$$

In (8) and (9), si occurs as an exponent. The physical meaning of θ_r is the slope of R_u at point $(si_u^r, R_u(si_u^r))$ while θ_p is the slope of P_u at point $(si_u^p, P_u(si_u^p))$. As mentioned in Section 2.3, si_u^r and si_u^p are two important thresholds, separately denotes the minimum si to be rewarded and the minimum si to be punished for u [12]. Note that to simplify this work, we directly set $\theta_r = 20, \theta_p = -20$ as suggested by Ref. [18] and leave si_u^r and si_u^p are the two parameters.

4.3 Estimate the Wundt Curve

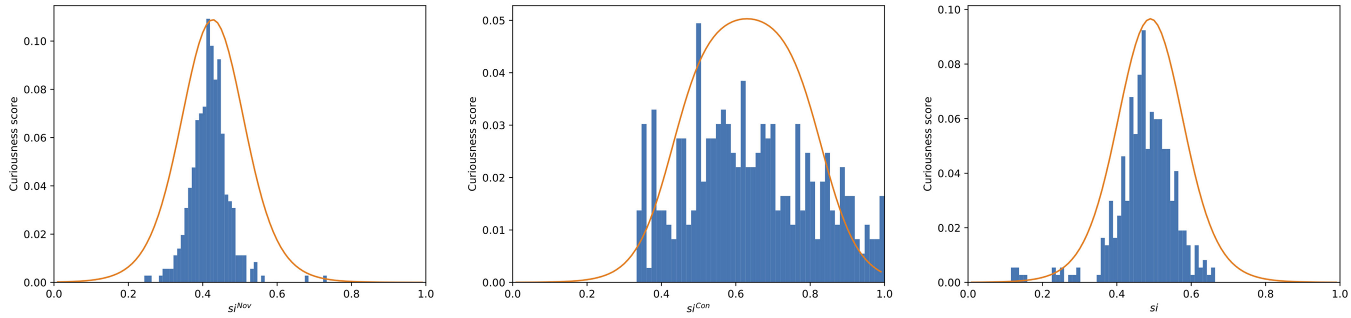
In what follows, we shall estimate the Wundt curve. The task can alternatively be catered as an optimization problem. To be specific, we define a loss function and minimizes it to learn parameters si_u^r and si_u^p.

Given $\langle u, i, r\rangle$ triples in the training set, we can obtain a list of u's accessed $si_{u,i}$ via (1). It is denoted by $\mathcal{L}_u^{si} = \{si_{u,i}\}$. Let us imaging the distribution of those intensities, in statistics data distribution alike can be approximated and graphically represented in histograms. To construct histograms, we divide the entire range of si ([0,1]) into 50 equal intervals: itv_0 ((0,0.02]), itv_1 ($(0.02, 0.04]$), $\ldots, itv_{49}$ ((0.98,1]) by step 0.02 in the first step. Then, for a target user u, we count how many $si_{u,i}$ values fall into each interval, denoted by $Count(itv_x)$ via (10)

$$Count(itv_x) = \sum_{si_{u,i} \in \mathcal{L}_u^{si}} \left(\left\lfloor \frac{si_{u,i}}{0.02} \right\rfloor == x?1:0\right), \tag{10}$$

where x is the indicator of the interval and its value is taken from 0 to 49. The decimal portion of $\frac{si}{0.02}$ value is rounded by $\lfloor\ \rfloor$ operator. The ternary operator $\lfloor\frac{si}{0.02}\rfloor == x?1:0$ means that if the condition $\lfloor\frac{si}{0.02}\rfloor == x$ is true, the value 1 in front of semicolon is returned, otherwise return 0.

In the second step, we introduce a histogram function $C_u(si)$ to describes u's stimulus interaction probability. It is formally defined by the ratio of the $\lfloor\frac{si}{0.02}\rfloor$th interval's count value to the sum of all the intervals' count values



(a) (b) (c)

Fig. 3. Illustrations of the user u's actual stimulus-evoked curiosity and predicted stimulus-evoked curiosity. (a) Blue histograms summarize the distributions of u's accessed $si_{u,i}^{Nov}$ and orange Wundt curve represents u's predicted $\hat{C}_u(si^{Nov})$. (b) Blue histograms summarize the distributions of u's accessed $si_{u,i}^{Conf}$ and orange Wundt curve represents u's predicted $\hat{C}_u(si^{Conf})$. (c) Blue histograms summarize the distributions of u's accessed $C_u(si)$ and orange Wundt curve represents u's predicted $\hat{C}_u(si)$.

$$C_u(si) = \frac{Count(itv_{\lfloor \frac{si}{0.02} \rfloor})}{\sum_{x \in 0,1,\ldots,49} Count(itv_x)}. \tag{11}$$

Through (11), $C_u(si)$ can be regarded as the likelihood that curiosity will be evoked. In more detail, larger $C_u(si_{u,i})$ indicates that more of u's accessed items appear stimulus intensities in the range of $(0.02 \times \lfloor \frac{si_{u,i}}{0.02} \rfloor, 0.02 + 0.02 \times \lfloor \frac{si_{u,i}}{0.02} \rfloor]$, so we may assume that u shows more curiousness on those items, and vise versa. In these regards, we creatively propose to consider $C_u(si)$ as the actual curiosity function of u since it follows a similar idea. The advantage of doing so are 1) its simplicity and ability to provide comparative histograms for the learning of Wundt curve; and 2) its effectively to make good use of rich interaction data for curiosity modeling.

Before we delve into cost function definition, we would like to give examples to facilitate our explanation and discussion. See Fig. 3, three types of intensities (si^{Nov}, si^{Conf} and si) related to u are used in three sub-figures, respectively. u's actual and predicted curiosity are incorporated into the same sub-figure. As it can be seen from all the sub-figures, blue histograms match our intuition as we expect intermediate stimulus intensities contribution to the actual explorative behaviors be larger than the contribution of the remaining regions. Most importantly, these observations could not only give practical evidence for the existence of the Wundt curve, but also confirm our idea on regarding $C_u(si^{Nov})/C_u(si^{Conf})/C_u(si)$ as the actual stimulus-evoked curiosity function of u corresponding to $si^{Nov}/si^{Conf}/si$.

With regard to si, our estimation task is to make the orange curve approximate to the Blue histograms. Following this, we define the loss function $Loss_u$ as the relative difference between C_u and $\hat{C}_u$ for u, given by:

$$Loss_u = \sum_{si_{u,i} \in \mathcal{L}_u^{si}} (\hat{C}_u(si_{u,i}) - C_u(si_{u,i}))^2. \tag{12}$$

In the learning process, we adopt gradient descent (GD) to learn about the variables si_u^r and si_u^p with minimum loss function $Loss_u$. For each user, the detailed training procedure is provided in Algorithm 1. Lines 1-3 compute the $Count(\cdot)$ values for each interval, which takes $O(1)$ complexity. $C_u(\cdot)$ values are calculated in Lines 4-6. Its time complexity is around $O(\overline{n})$, where $\overline{n}$ is the average number of items accessed by a user in the training set. For each iteration, see lines 9-10, the gradients and update rules are computed over the two variables, thus the computational time is $O(1)$. The total time complexity is then $O(\overline{n}+t)$ where t is the number of iterations. We can see that learning individual Wundt curve for all the users dose not need higher runtime as taking only $O(m \times (\overline{n}+t))$ time complexity, because t and $\overline{n}$ are usually very small, allowing the proposed curiosity model to be applied in real-time.

Algorithm 1. Training Procedure of Wundt Curve

input: $\mathcal{L}_u^{si}$, List of u's accessed si in the training set;
η, Learning rate of the SGD.
output: Parameters si_u^r and si_u^p

1: **for** $x = 0$ *to* $x \leq 49; x++$ **do**
2: Compute $Count(itv_x)$ using (10)
3: **end for**
4: **for** $si \in \mathcal{L}_u^{si}$ **do**
5: Compute $C_u(si)$ using (11)
6: **end for**
7: Initialize $si_u^r = 0$, $si_u^p = 1$
8: **while** $Loss_u$ not converged or $\leq$ max_iterations **do**
9: $si_u^r = si_u^r - \eta \times \frac{\partial Loss_u}{\partial si_u^r}$
10: $si_u^p = si_u^p - \eta \times \frac{\partial Loss_u}{\partial si_u^p}$
11: **end while**

Once Wundt curve is estimated, we obtain u's predicted curiousness score on item i (denoted by $cur_{u,i}$) by feeding $si_{u,i}$ into the Wundt curve. Formally, $cur_{u,i} = \hat{C}(si_{u,i})$.

To stress our contribution, it is worthwhile to make a distinction between Saunders' and our's modeling for the Wundt curve. Saunders assumed that Wundt curve stays the same and does not or cannot vary since it limits si_u^r and si_u^p as pre-given constants. However, this hypothesis always does not hold. On the one hand, it's difficult for all the users to share a set of fixed parameters in advance. Because different people accompanies with different curiosity level even if confronting the same stimulus. On the other hand, curiosity is not a static result but a dynamic status which requires continuous learning. In these regards, we creatively arm Saunders' modeling with learning capacity. By doing so, we facilitate the use of web-scale interaction data to estimate the Wundt curve so as to depict individuals curiosity more

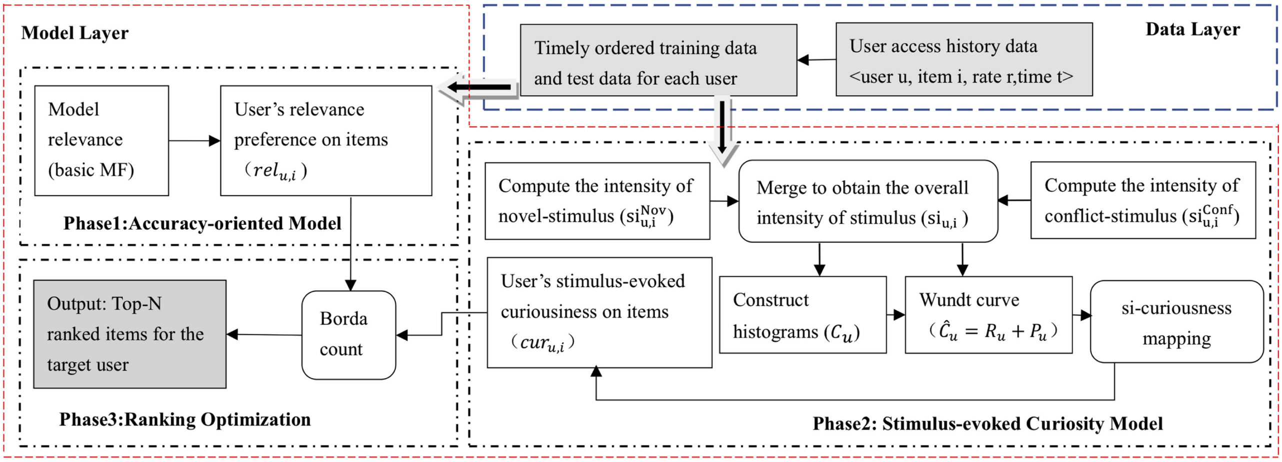


Fig. 4. Overview of the proposed framework *CdRF*.

appropriately. This idea largely enhance the applicability and feasibility of Saunders' modeling. Other cases that follow the pattern of inverted-U shaped Wundt curve, such as relations between real estate price and consumption, etc., can also be depicted and learnt alike. So that, our modeling method exhibits high flexibility and promising potential.

5 The Overall Curiosity-Drive Recommendation Framework (CdRF)

The overall framework of *CdRF* is illustrated in Fig. 4. *CdRF* takes two layers: data layer and model layer. Once user historical records are built, data layer provides timely ordered training data and test data for model layer. Model layer mainly consists of three Phases. Phase 1 computes user relevance preference scores on items (denoted by $rel_{u,i}$) via conducting existing accuracy-oriented method (*AoM*). Phase 2 calculates $cur_{u,i}$ through the proposed *SeCM*. Phase 3 sorts a candidate list by Borda count so as to balance between $rel_{u,i}$ and $cur_{u,i}$, and finally outputs items that dominates the first N places for the target user u. Considering that Phase 2 is throughly detailed in Section 4, in what follows, we are going to introduce Phase 1 and Phase 3, respectively.

5.1 Accuracy-Oriented Method (AoM)

MF models have gained popularity and proved to achieve high accuracy in RS [19]. To generate accurate recommendation, a plausible choice for *CdRF* would be *IF-MF* [20] since it is one of the most successful and widely used MFs tailored to Top-N item ranking. Technically, let $\mathbf{P}$ is a $m \times n$ dimensional matrix, and each entry is given by $p_{u,i}$

$$p_{u,i} = \begin{cases} 1 & r_{u,i} > 0 \\ 0 & otherwise \end{cases}. \tag{13}$$

We then use $confidence_{u,i}$ to indicate our confidence in u's rating on item i, which is given by:

$$Confidence_{u,i} = 1 + \ log\Big(1 + \frac{r_{u,i}}{\epsilon}\Big), \tag{14}$$

where ϵ is a small constant for log scaling. Following *IF-MF*, we minimize $\sum_{u,i}[Confidence_{u,i} \times (p_{u,i} - \mathbf{x}_u^{\tau}\mathbf{y}_i)^2] + \lambda(\sum_u |\mathbf{x}_u|^2 + \sum_u |\mathbf{y}_i|^2)$ to obtain latent matrices $\mathbf{X}^{m\times d}$ and $\mathbf{Y}^{d\times n}$. λ is a regularization parameter. $\mathbf{X}$ ($\mathbf{Y}$) denotes the mappings of users (items) into d reduced latent space and $\mathbf{x}_u$ ($\mathbf{y}_i$) is the latent feature vector in $\mathbf{X}$ ($\mathbf{Y}$). Consequently, $rel_{u,i}$ is calculated by the inner product between $\mathbf{x}_u$ and $\mathbf{y}_i$, which measures how much u's relevance preference on i

$$rel_{u,i} = \mathbf{x}_u \cdot \mathbf{y}_i. \tag{15}$$

5.2 Ranking Optimization

In the last phase, we try to balance a user's curiosity with her relevance preference for recommendation via a ranking optimization utility. In practice, we adopt weighted Borda count [4], [21] since it favors candidates supported by a broad consensus among voters. Mapping to our case, the voters refer to two ranked lists: $\mathcal{L}_u^R$ which is sorted by the descending order of relevance preference scores $rel_{u,i}$, and $\mathcal{L}_u^C$ which is sorted by the descending order of curiousness scores $cur_{u,i}$. Accordingly, Borda count assigns $score^R_{u,i}$ and $score^C_{u,i}$ to i, which are defined in (16) and (17), respectively

$$score^R_{u,i} = t + 1 - pos(\mathcal{L}_u^R, i) \tag{16}$$

$$score^C_{u,i} = t + 1 - pos(\mathcal{L}_u^C, i), \tag{17}$$

where t denotes the size of the candidate list and $|\mathcal{L}_u^R| = |\mathcal{L}_u^C| = t$. We separately use $pos(\mathcal{L}_u^R, i)$ and $pos(\mathcal{L}_u^C, i)$ to represent the i's position in $\mathcal{L}_u^R$ and $\mathcal{L}_u^C$. Having done this, the final score $F\_score_{u,i}$ is calculated via (18)

$$F\_score_{u,i} = \beta \times score^C_{u,i} + (1 - \beta) \times score^R_{u,i}. \tag{18}$$

Trade-off β is used to decide the influence proportion of u's curiosity and relevance preference on $F\_score_{u,i}$. Ultimately, the proposed *CdRF* generates a Top-N list of items for the target user u, which is arranged in a descending order by $F\_score_{u,i}$.

6 Experimental Evaluations

In this section, we describe experimental datasets, evaluation metrics and competitors.

TABLE 1
Statistics of the Four Experimental Datasets

Statistic	ML-100K	ML-1M	Abooks	Lthing
No. of Ratings	100,000	1,000,209	128,643	115,628
No. of Users	943	6,040	1,627	1,178
No. of items	1,682	3,952	4,779	2,833
Matrix Density	6.30%	4.19%	1.65%	3.46%
Avg Ratings per User	106	166	79	98

6.1 Experimental Datasets and Evaluation Metrics

We conduct experiments on two movie datasets from MovieLens-1M and MovieLens-100 K,[1] and two book datasets from Amazon Books [22], [23] and Librarything [24]. For short, these datasets are abbreviated as ML-1M, ML-100 K, ABooks, and Lthing. Except for Lthing which ratings value in range [0.5,5] with step 0.5, other datasets value in range [1,5] with step 1. Since the book datasets are extremely sparse, in our experiments, we preprocessed them in the following order: 1) intercepted with a time span of about 1.5 years 2) randomly selected 10 percent users on Abooks 3) removed items with less than 50 rated users; 4) discarded users with less than 50 rated items. The main statistics of the four datasets are summarized in Table 1. In order to learn the Wundt curve, it is inevitably to order the data according to the time sequence. For each user, the previous 2/3 (4/5) data are used as training data and the rest 1/3 (1/5) are used as testing set on movie (book) datasets. We report the average results over 5 runs for all methods.

We provide two series of metrics to separately estimate accuracy and diversity performance in this work. On the one hand $Precision$ is employed to evaluate the accuracy performance, on the other hand three diversity metrics (ILS [5], $Newness$ [25], [26] and AD [27]) are adopted.

6.2 Competitors

We provide three groups of competitors (14 in total), ranging from basic competitors to components of *CdRF*, and various specifications of *SeCM*.

Basic Competitors. *CdRF* is compared with the baseline *IF-MF* [20] and various ranking competitors, including *SC* [3], *UC* [4], *CBRS* [5], and *PopRec*. Note that accuracy-oriented technique used in *SC*, *UC* and *CdRF* is $IF-MF$ whereas *SC* adopts *R-MF* [29].

Components of CdRF. To study the effect of the components of *CdRF*, we provide two competitors:

1) *AoM* or *IF-MF*. *AoM* discovers relevant items preferred by users. The recommendation can be achieved by removing the effect of *SeCM* via setting a Borda count weight $\beta = 0$ in (18). It is specified to *IF-MF* since we select *IF-MF* as a realization of *AoM*.
2) *SeCM*. It depicts personalized curiosity for users. The recommendation can be performed by eliminating the effect of AoM via setting $\beta = 1$ in (18).

Specifications of SeCM. To better explore *SeCM*, we also compare several specifications of *SeCM*:

1) *Compound*. It is our highly suggested specification of *SeCM*, which considers a compound stimulus to learn users' curiosity via Wundt curve. As discussed in Section 4.3, $cur_{u,i} = \hat{C}(si_{u,i})$. Particularly, to analysis the effect of the inner component of the *Compound*, we further provide three detailed specifications of *Compound* for comparison. They are $\alpha = 0.3$, $\alpha = 0.5$ and $\alpha = 0.7$, which present *conflict_bias*, *equal_weight* and *novelty_bias* situations, respectively.
2) *Novelty_only*. It merely considers the novel-stimulus to learn users' curiosity via Wundt curve. It is achieved by setting $\alpha = 1$ in (1).
3) *Conflict_only*. It merely considers the conflict-stimulus to learn users' curiosity via Wundt curve. It is achieved by setting $\alpha = 0$ in (1).
4) *Compound_max*. It directly uses the compound-stimulus intensity as curiosity score. $cur_{u,i} = si_{u,i}$.
5) *Novelty_max*. It directly uses the novel-stimulus intensity as curiosity score. $cur_{u,i} = si^{Nov}_{u,i}$.
6) *Conflict_max*. It directly uses the conflict-stimulus intensity as curiosity score. $cur_{u,i} = si^{Conf}_{u,i}$.

7 Experiments and Results Analysis

In order to validate the benefits of the proposed *CdRF* as well as its core component *SeCM*, we conduct extensive experiments across the four datasets. We use LibRec library [28] for *IF-MF*, *R-MF* and *PopRec* while the remaining algorithms are implemented using Python. All the experiments are conducted on a machine containing an Intel Xeon CPU E5-2620 with 2.30 GHz, 64 GB RAM, Linux Ubuntu 16.04 OS.

7.1 Parameters Setting

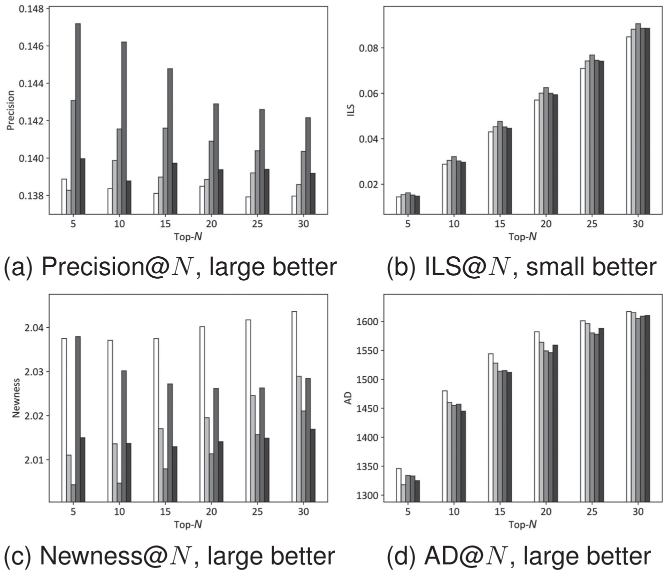
For the Phase 1 regards to $IF - MF$, we set the regularization parameters $\lambda = 0.01$ and the number of latent factors $d = 15$. Meanwhile, we experimentally set $\epsilon = 10^4$. For the Phase 2 associates with *SeCM*, to compute novel-stimulus intensity, we set $\rho = 10$. To compute conflict-stimulus intensity, except for ABooks which γ is set to 3, other datasets is set to 5. For the Phase 3, t is fixed by 50 as suggested in work [5].

7.2 Exp.1 Estimate the Specifications of SeCM

The purpose of this first series of experiments is to investigate the impact of different specifications of *SeCM* on recommendation performance and determine the best combination for *Compound* on each dataset. Concretely, we compare 1) three specifications: *Compound*, *Novelty_only* and *Conflict_only* in *SeCM*; 2) three inner specifications of *Compound*: *conflict_bias*, *equal_weight* and *novelty_bias* situations. Technically, we tune α to obtain each specification. Figs. 5, 6, 7 and 8 separately present the performance at four measures on the four datasets, where N varies from 5 to 30 given $\beta = 1$. To improve readability, a change from light to darkness is reported to reinforce novelty while weaken conflict.

We have the following findings on ML-1M dataset: 1) in the form of Precision@N, *novelty_bias* consistently achieves significant performance than other specifications. *equal_weight* takes the second place (Fig. 5a). These suggest the equal treatment of novel-stimulus intensity and conflict-stimulus intensity or more consideration is put on novel-stimulus intensity in *compound* can largely enhance Precision@N. On the opposite side,

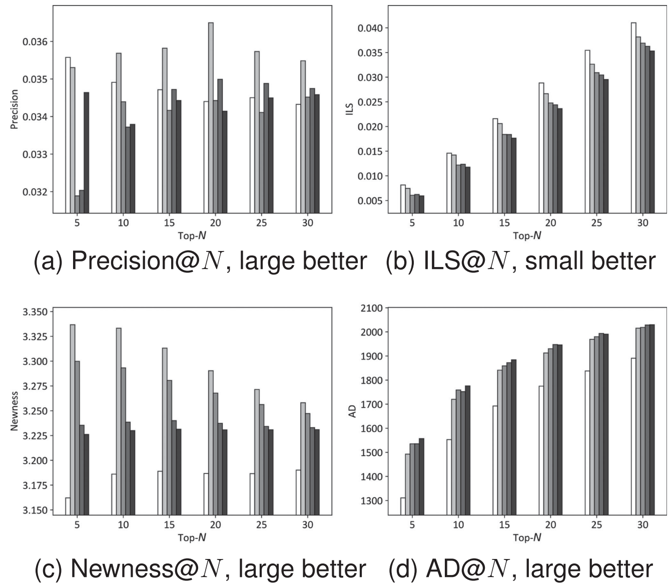
1. https://grouplens.org/datasets/movielens/



(a) Precision@N, large better (b) ILS@N, small better

(c) Newness@N, large better (d) AD@N, large better

Fig. 5. Performance of specifications of $SeCM$ in ML-1M dataset.



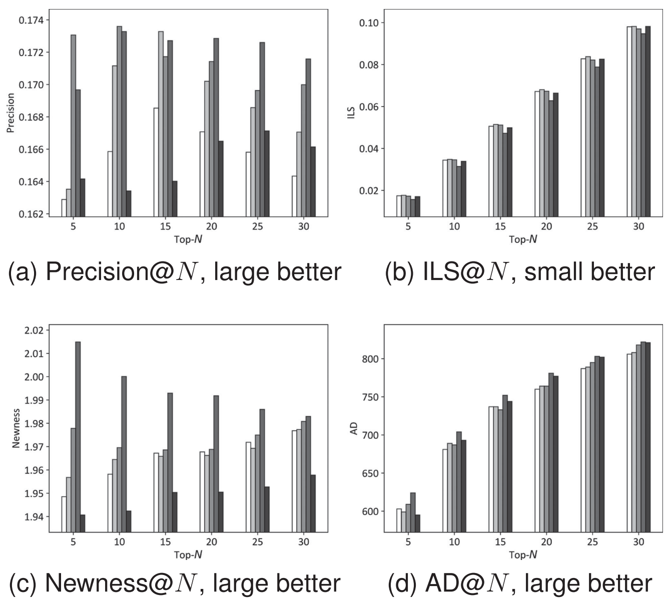
(a) Precision@N, large better (b) ILS@N, small better

(c) Newness@N, large better (d) AD@N, large better

Fig. 7. Performance of specifications of $SeCM$ in ABooks dataset.

Conflict_only has the worst Precision@N in general, the reduces reflect the disadvantage of conflict-stimulus-evoked curiosity on accuracy since *Conflict_only* gives predominant emphasis to conflict-stimulus intensity; 2) there is a slight advantage of *Conflict_only* and *Novelty_only* on ILS@N compared with either specifications of the *Compound* (Fig. 5b); 3) On Newness@N (Fig. 5c), *Conflict_only* performs best, followed by *novelty_bias*; 4) The AD@N performance of *Conflict_only* is the best and others is varied and tend to approaching each other as N increases (Fig. 5d).

We also obtain the following observations from ML-100 K dataset: 1) in the form of Precision@N, both *Novelty_only* and *Conflict_only* are lower than all the inner specifications of *Compound* (Fig. 6a), indicating that balance of novel- and conflicting- stimulus can bring more accuracy compared with either of the two; 2) *novelty_bias* is the most eye-catching specification since it achieves consistently the best performance on all the diversity measures (Figs. 6b, 6c and 6d), reflecting its superiority and stability.



(a) Precision@N, large better (b) ILS@N, small better

(c) Newness@N, large better (d) AD@N, large better

Fig. 6. Performance of specifications of $SeCM$ in ML-100K dataset.

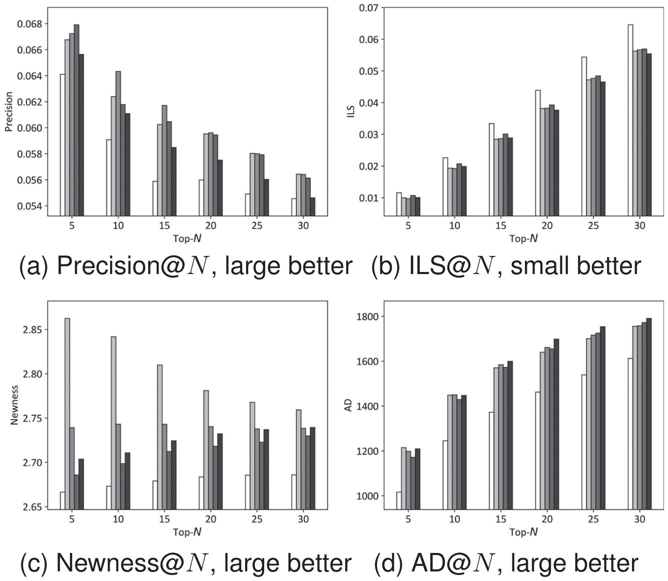
Fig. 7 shows the results of the ABooks dataset. Among the data, we observe that 1) for the Precision@5, *conflict_only* achieves the best accuracy, followed by *conflict_bias*. However, with larger N values, the performance of *conflict_bias* improves, enabling it to outperform all the other specifications (Fig. 7a); 2) *conflict_bias* is significantly better than other specifications on Newness (Fig. 7c); 3) except for *conflict_only*, the gap among the remains is getting smaller with the growth of N on ILS and AD (Figs. 7b and 7d).

Fig. 8 reports the results of the Lthing dataset. Observe that in the form of Precision (Fig. 8a), the three hybrid specifications always outperform specifications that model conflict-stimulus-evoked curiosity or novel-evoked curiosity alone (Fig. 8a). Moreover, *conflict_bias* achieves best Newness (Fig. 8c).

In conclusion, balance is felt to be so essential since we can take advantage of both novelty and conflict induced curiosity. Moreover, as mentioned earlier in this article, a user's curiosity is usually evoked depending upon a series of factors instead of a single factor. Therefore, the *Compound* is more practical. Importantly, it's worthy to mention that we purely report *Compound* in the case of $\alpha = 0.7$ ($\alpha = 0.3$) on the movie (book) datasets in the rest of the experiments because this inner specification *novelty_bias* (*conflict_bias*) is found to be the best performing combination.

7.3 Exp.2 Effect of β for CdRF and Effect of Wundt Curve for SeCM

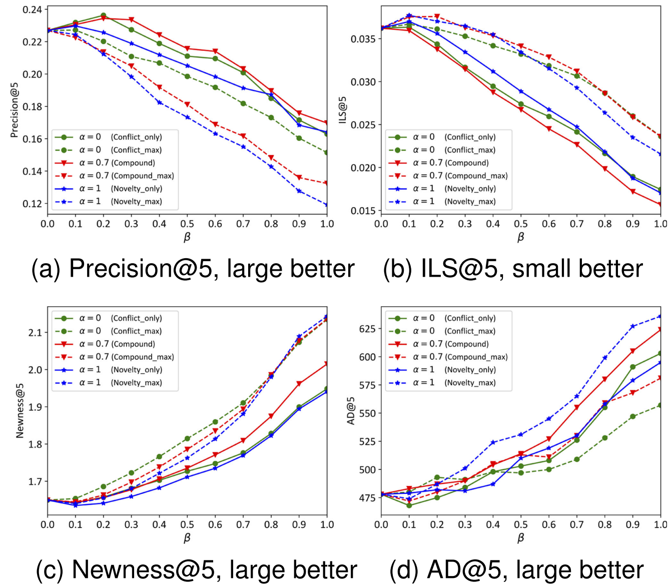
As well as tuning the Borda count trade-off β to investigate the dilemma between curiosity and relevance preference, the second series of experiments are mainly performed to get an estimate of how recommendation performance is affected by Wundt curve. Technically, we compare those specification of *SeCM* with and without Wundt curve. To facilitate discussion, specifications using Wundt curve (*Compound*, *Novelty_only* and *Conflict_only*) are introduced in solid lines while "max" specifications without Wundt



(a) Precision@N, large better (b) ILS@N, small better

(c) Newness@N, large better (d) AD@N, large better

Fig. 8. Performance of specifications of $SeCM$ in Lthing dataset.



(a) Precision@5, large better (b) ILS@5, small better

(c) Newness@5, large better (d) AD@5, large better

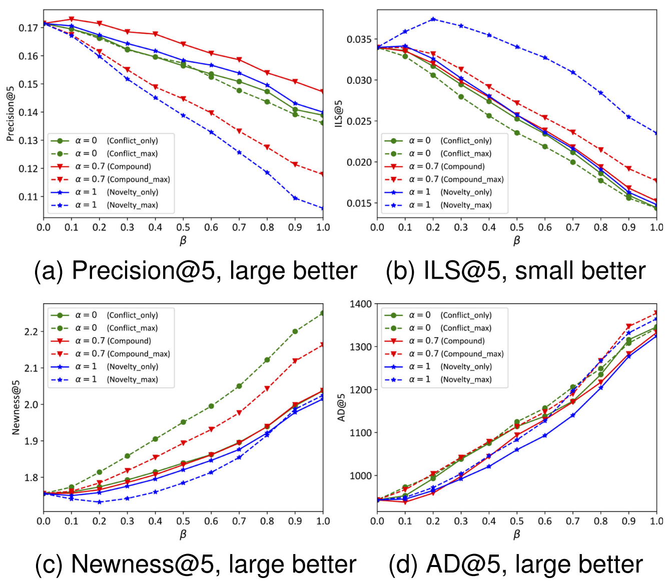
Fig. 10. Effect of Wundt curve for SeCM in ML-100 K dataset.

curve (*Compound_max*, *Novelty_max* and *Conflict_max*) are introduced in dashed lines. Each pair of them is painted in the same color with the same marks, eg. red lines with triangles are used for *Compound* and *Compound_max*. Experimental results with the four datasets when $N = 5$ are reported in Figs. 9, 10, 11, and 12, respectively.

Taken as a whole, a degree of relevance preference is decreased when β is tuned from 0 to 1. Accordingly, in most situations, diversity performance gets better as the amount of curiosity factors increase on the four datasets. This phenomenon verifies that curiosity evoked by novel-stimulus, conflict-stimulus, or a compound of them are valuable in allowing RS to discover and recommend diverse items. Also, the trade-off β adopted in Borda count manages to satisfy the requirements of relevance preference, diversity or both more efficiently and flexibility.

Observing from Figs. 9a, 10a, 11a, and 12a, methods with solid lines generally outperform methods with dotted lines on Precision@5. We attribute this to the fact that *Compound*, *Novelty_only* and *Conflict_only* accommodate AOA and AOB via Wundt curve bring more informative stimuli, and thus have the capacity to recommend both relevant and diverse items. Whereas, *Compound_max*, *Novelty_max* and *Conflict_max* follow a single AOB rule and thus pursue highly diverse items while regardless of relevance preference. Moreover, this phenomenon also proves the effectiveness of the fitness adaption of personal inverted-U shaped curiosity by leveraging Wundt curve.

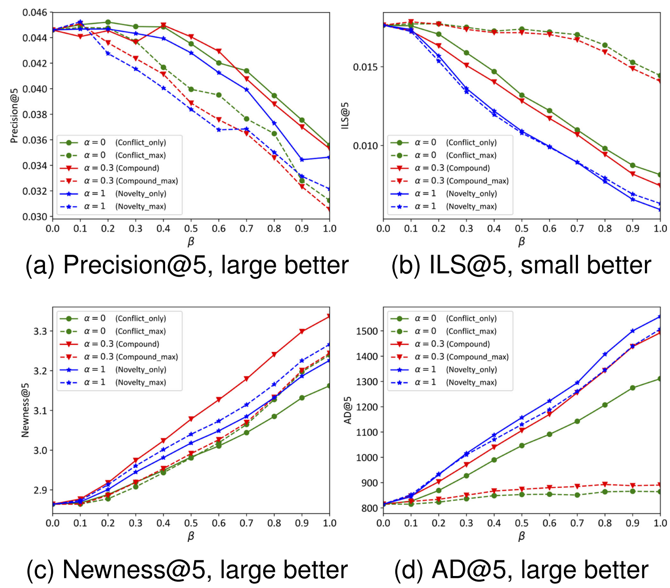
Remaining sub-figures report the differences of diversity measures@5 among competitors on the four datasets, respectively. On the movie datasets, not surprisingly, methods in the absence of Wundt curve can produce higher degree of diversity than methods with Wundt curve in general, especially under the circumstances of AD@5 on ML-1M (Fig. 9d) and Newness@5 on ML-100K (Fig. 10c).



(a) Precision@5, large better (b) ILS@5, small better

(c) Newness@5, large better (d) AD@5, large better

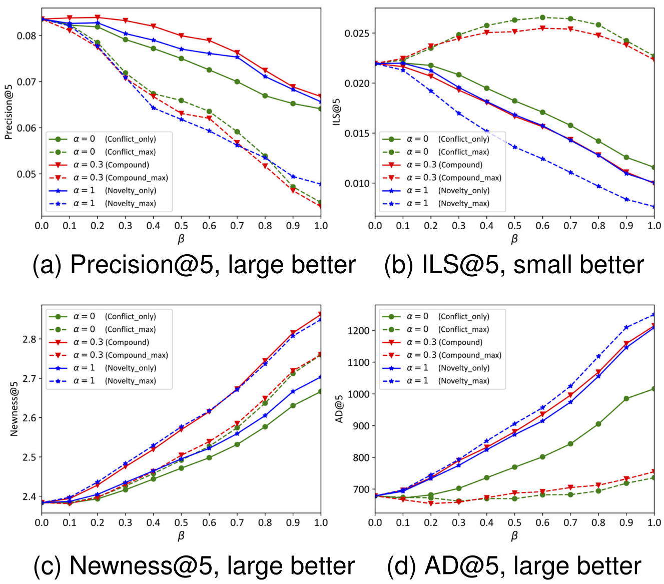
Fig. 9. Effect of Wundt curve for SeCM in ML-1M dataset.



(a) Precision@5, large better (b) ILS@5, small better

(c) Newness@5, large better (d) AD@5, large better

Fig. 11. Effect of Wundt curve in ABooks dataset.



(a) Precision@5, large better (b) ILS@5, small better

(c) Newness@5, large better (d) AD@5, large better

Fig. 12. Effect of Wundt curve in Lthing dataset.

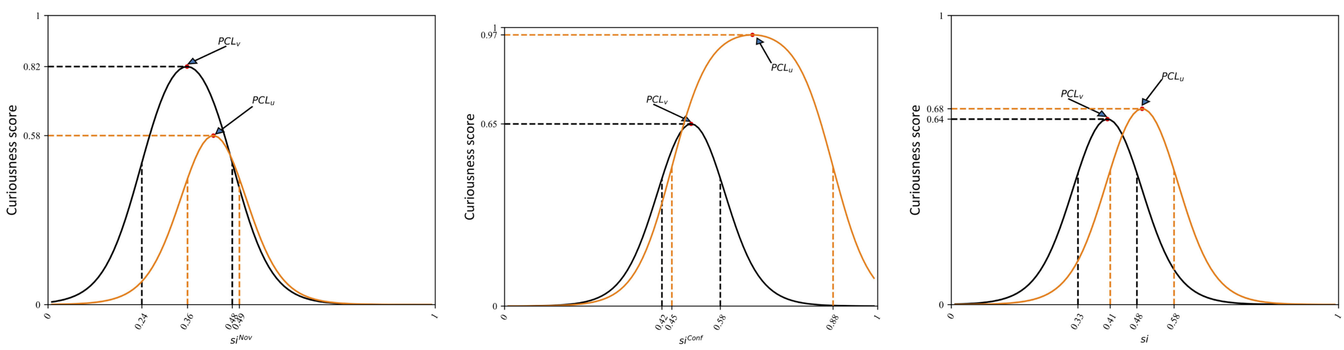
However, there are still some sparkles appearing on methods using Wundt curve. For example, on ML-100K, *Compound*,*Conflict_only*, and *Novelty_only* superiors to their max methods at ILS@5 (Fig. 10b). This can be explained by the effect of Wundt curve guiding personalized level of curiosity for generating the recommendation lists and hence leads to higher ILS. On the book datasets, the above situation is somewhat different. First, *Compound* is superior to others on Newness including methods without Wundt curve (see Fig. 11c); Second, *Conflict_max* and *Compound_max* perform worst on ILS and AD (Figs. 11b and 11d). These indicate that diversity is generally improved with Wundt curve.

From the above results, we conclude that *compound* is the most effective method than others because of maintaining excellent precision while providing relatively satisfactory diversity. These also indicate that simultaneously taking novel- and conflict- stimulus into account by Wundt curve surpasses either alone.

To have a deep understanding of Wundt curve coming from IAP theory, we next investigate simulated Wundt curve based on stimulus intensities either alone (si^{Nov}, si^{Conf}) or in conjunction with each other (si) for curiosity. Accordingly, three plots are depicted in Fig. 13, where we present three realistic illustrations. Users u is the 10th user and user v is the 3979th user listed in ML-1M dataset. The number of items u and v have rated in the training set is 267 and 64, respectively. The estimated Wundt curve of u (orange curve) and v (black curve), separately defined by $\hat{C}_u(\cdot)$ and $\hat{C}_v(\cdot)$, are incorporated into the same plots. From the plots, we can draw the following points:

First of all, the curiosity level varied from one user to another. For instance, u and v expose themselves merely to novel-stimuli (Fig. 13a), their novel-stimuli evoked curiosity would be modeled by $\hat{C}_u(si^{Nov})$ and $\hat{C}_v(si^{Nov})$, respectively. The peak curiosity level of u, denoted by PCL_u is the point $(\frac{(0.24+0.48)}{2}, 0.82)$ of $\hat{C}_u(si^{Nov})$. Where, 0.24 is the learnt parameter of si_u^r and 0.48 is the learnt parameter of si_u^p. Similarly, v's PCL_v is the point $(\frac{(0.36+0.49)}{2}, 0.58)$ while $si_v^r = 0.36$ and $si_v^p = 0.49$. These results indicate u (v) is more willing to spend most of her time on items appearing intermediate intensities between 0.24 and 0.48 (0.36 and 0.49) due to the evoked curiosity. Our curiosity mechanism would assign higher curiousness scores on items which presents novel-stimulus intensities in the range of [0.24, 0.48] ([0.36, 0.49]) for u (v) via the Wundt curve. It is worthy to note that the other two plots (Figs. 13b and 13c) provide judgment of curiousness in much the same way. Obviously, our modeling of curiosity using Wundt curve has the advantage of interpretability.

Furthermore, users associate with different responses when confronting different types of stimulus. Taking v as an example, v can tolerant extremely high conflict-stimulus intensities ($si^{conf} = 1$, see Fig. 13b) than that of novel-stimulus intensities and compound-stimulus intensities. This reflects that even if v received equal strength of positive responses and negative responses on the same item from her social peers, v may have a certain probability of selecting the item. However, the cases alike can not be depicted from Beta distribution presented in Ref. [5], because the two ends ($si^{conf} = 0$ and si^{conf}=1) are not actually part of the domain of the density function. In practice, nearly two thirds users (2,064 out of 6,040) fail to obtain their Wundt curve via using Beta distribution. Therefore, a significant advantage of our modeling with Wundt curve is it in general more accurately reflect users' responses on stimulus intensities, makes it an appropriate and practical approach for future research.



(a) (b) (c)

Fig. 13. Illustration of stimulus-evoked curiosity of u and v depicted by Wundt curve. (a) Novel-stimulus-evoked curiosity, (b) Conflict-stimulus-evoked curiosity, and (c) Compound-stimulus-evoked curiosity.

TABLE 2
Percentage Improvement of *Compound* Compared to other Competitors on the Four Datasets

Algorithm	Percentage improvement of *Compound* in terms of measures@5 and @10 (% Improv.)							
	Precision@5	ILS@5	Newness@5	AD@5	Precision@10	ILS@10	Newness@10	AD@10
UC	-1.54	82.12	43.29	55.36	-0.89	71.92	30.50	22.97
SC	6.38	-28.27	-14.17	-36.16	6.28	-35.51	-17.13	-47.25
CBRS	1.48	1.38	0.20	-0.52	1.36	0.26	-0.06	-0.32
IF-MF	-2.43	55.19	16.10	41.36	-1.52	41.72	12.73	18.38
PopRec	-3.21	96.53	111.07	1726.03	-1.68	93.79	93.96	1206.86
Compound	Precision@5: 0.147, ILS@5:0.015, Newness@5:2.038, AD@5: 1333 Precision@10: 0.148, ILS@10: 0.0317, Newness@10: 2.011, AD@10: 1445							

(a) ML-1M dataset

Algorithm	Percentage improvements of CdRF in terms of measures@5 and @10 (% Improv.)							
	Precision@5	ILS@5	Newness@5	AD@5	Precision@10	ILS@10	Newness@10	AD@10
UC	-0.32	87.12	58.14	89.43	-0.88	75.44	36.87	42.89
SC	10.29	37.30	12.40	33.69	11.29	24.80	6.20	14.29
CBRS	2.63	23.03	3.63	2.79	2.60	15.41	1.14	2.74
IF-MF	-5.98	56.11	21.89	33.40	-4.36	44.89	16.51	23.83
PopRec	1.21	96.20	140.40	1392.86	1.87	93.24	107.01	995.38
Compound	Precision@5:0.169, ILS@5: 0.016, Newness@5: 2.015, AD@5: 624 Precision@10: 0.173, ILS@10: 0.032, Newness@10: 2.000, AD@10:704							

(b) ML-100K dataset

Algorithm	Percentage improvements of CdRF in terms of measures@5 and @10 (% Improv.)							
	Precision@5	ILS@5	Newness@5	AD@5	Precision@10	ILS@10	Newness@10	AD@10
UC	-0.06	70.70	20.74	58.67	-0.23	56.70	15.81	36.46
SC	1.16	36.73	3.77	34.85	1.33	15.03	0.17	13.54
CBRS	0.23	79.69	3.18	62.79	0.68	55.59	2.46	20.83
IF-MF	-0.93	57.79	16.50	83.17	-0.76	44.28	12.65	51.35
PopRec	1.90	99.01	79.44	9852.00	2.05	98.17	69.22	7067.50
Compound	Precision@5:0.035, ILS@5: 0.007, Newness@5: 3.337, AD@5: 1492 Precision@10: 0.036, ILS@10: 0.014, Newness@10: 3.333, AD@10:1723							

(c) ABooks dataset

Algorithm	Percentage improvements of CdRF in terms of measures@5 and @10 (% Improv.)							
	Precision@5	ILS@5	Newness@5	AD@5	Precision@10	ILS@10	Newness@10	AD@10
UC	-0.79	84.18	39.11	121.40	-0.54	74.10	27.85	73.09
SC	4.35	26.80	6.85	18.50	4.25	7.76	1.61	1.47
CBRS	1.40	56.96	6.53	38.68	1.44	39.36	5.67	21.39
IF-MF	-1.68	54.61	20.07	78.99	-1.10	45.36	15.31	53.50
PopRec	-1.00	98.39	106.35	5180.87	0.27	97.14	87.36	3923.33
Compound	Precision@5:0.067, ILS@5: 0.010, Newness@5: 2.862, AD@5: 1214 Precision@10: 0.062, ILS@10: 0.019, Newness@10: 2.842, AD@10:1448							

(d) Lthing dataset

Where, positive values indicates the advantage of Compound *while negative values indicate the advantage of the competitors.*

7.4 Exp.3 Comparison of *SeCM* With Existing Techniques on Recommendation

Our next analyses focus on comparing the proposed *SeCM* on recommendation with a number of state-of-the-art approaches. The results are reported in Table 2 along with the percentage of relative improvements (% Improv.), where the *Compound* of *SeCM* is selected as the baseline.

The recommendation performance on ML-1M dataset can be found in Table 2a, from which we have the following findings: 1) Among all the curiosity-drive methods, *Compound* is most effective. *SC* beating *SeCM* on all diversity measures but under-performs on accuracy losing by as much as 6.38 percent Precision@5 and 6.28 percent Precision@10. *Compound* performs comparably *UC* on Precision and also obtains significant advantages, such as 82.12 percent improvement on ILS@5 and 55.36 percent improvement on AD@5. Although, *Compound* performance on AD and Newness is sometimes not as good as *CBRS*. Those tiny differences (0.03 percent on average) may be overshadowed by *Compound*'s 1.48 percent increase in Precision@5 and 1.36 percent increase in Precision@5. 2) When employing Precision as the evaluation metric, *PopRec* performs best, followed by *IF-MF*. The advantage however, comes at the large expense of diversity. Related to *Compound*, *PopRec* suffers 1,726 percent drop in AD@5 and 1206 percent drop in AD@10. These could be attributed to the fact that *PopRec* inherently push same recommendation lists for all the users. 3) *Compound* increases *IF-MF* in the form of average diversity by 48.45 percent on ILS, 14.41 percent on Newness and 29.87 percent on AD. These results could imply that promising diversity results still be achieved from *Compound* in the case of Phase 3 is entirely removed from

TABLE 3
Comparison of Curiosity-Drive Methods With the Baseline *IF-MF* on the Four Datasets

Precision@5 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5
1	29.75	6.04	19.83	-129.91	-16.17	-4.88	6.58	1.51	7.42
1.5	42.91	10.48	29.03	-	-	-	12.51	2.90	12.73
2	50.52	13.87	36.06	-	-	-	25.13	5.84	20.47
2.5	55.19	16.10	41.36	-	-	-	31.92	7.70	23.01
Baseline: IF-MF	Precision@5: 0.1747, ILS@5: 0.0336, AD@5: 949, Newness@5:1.7608								

Precision@10 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10
1	31.32	7.22	21.85	-93.87	-13.62	-3.73	8.75	2.12	9.33
1.5	45.57	12.30	29.40	-	-	-	22.57	5.43	19.96
Baseline: IF-MF	Precision@10: 0.1647 , ILS@10: 0.0526 , AD@10: 1136 , Newness@10: 1.8133								

(a) ML-1M dataset

Precision@5 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5
1	26.18	5.20	7.53	-127.40	-13.83	-9.00	-3.44	0.94	4.81
2	37.43	9.68	16.11	-172.02	-17.15	-14.02	-	-	-
3	45.21	13.65	21.34	-229.06	-21.20	-21.13	1.55	2.67	2.93
Baseline: IF-MF	Precision@5: 0.2269, ILS@5: 0.0362, AD@5: 478, Newness@5: 1.6495								

Precision@10 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10
1	26.27	6.46	8.40	-62.52	-9.05	-5.71	-1.88	0.13	0.67
2	33.48	9.59	11.43	-87.21	-11.40	-7.39	-0.07	1.26	1.01
3	39.48	12.70	14.96	-111.57	-13.79	-12.44	4.50	3.16	3.19
Baseline: IF-MF	Precision@10: 0.2154 , ILS@10: 0.0587 , AD@10: 595 , Newness@10: 1.7127								

(b) ML-100K dataset

Precision@5 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5
0.1	30.27	39.09	8.22	-17.06	-1.91	-1.75	0.47	-0.32	0.11
0.3	36.53	48.44	10.07	-24.53	0.00	-2.33	0.82	0.12	0.45
0.3	-	-	-	-33.79	5.74	-2.94	-	-	-
0.4	39.40	54.09	11.01	-38.10	7.75	-3.17	0.89	2.40	1.04
Baseline: IF-MF	Precision@5: 0.045, ILS@5: 0.018, AD@5: 815, Newness@5: 2.8641								

Precision@10 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10
0.1	18.53	24.60	5.22	-16.76	-1.55	-1.68	-	-	-
0.2	24.76	31.04	6.85	-21.78	0.21	-2.16	-0.54	-0.09	0.18
0.3	-	-	-	-24.38	1.90	-2.38	-	-	-
0.4	27.90	34.79	7.77	-26.87	4.26	-2.59	-0.44	1.67	0.89
Baseline: IF-MF	Precision@10: 0.0433, ILS@10: 0.0255, AD@10: 1136, Newness@10: 2.959								

(c) ABooks dataset

Precision@5 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5	ILS@5	AD@5	Newness@5
0.1	-	-	-	-6.39	-1.27	-0.79	-0.24	0.41	0.03
0.2	17.76	22.58	5.68	-	-	-	-	-	-
0.3	20.73	25.73	6.60	-53.79	-7.19	-5.37	-	-	-
0.4	26.07	33.04	8.61	-131.19	-13.91	-10.53	-0.42	0.18	0.11
Baseline: IF-MF	Precision@5: 0.084, ILS@5: 0.022, AD@5: 678, Newness@5: 2.384								

Precision@10 Loss	**CdRF** (% Improv.)			**UC** (% Improv.)			**CBRS** (% Improv.)		
(% reduction)	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10	ILS@10	AD@10	Newness@10
0.1	21.45	25.73	6.46	-82.80	-9.03	-7.69	-0.23	-0.17	-0.04
0.2	24.93	29.16	7.62	-	-	-	-0.57	-0.00	-0.07
0.3	28.56	33.81	8.83	-94.56	-10.34	-8.59	-1.14	0.66	-0.06
0.4	32.06	38.30	10.11	-104.82	-11.45	-9.33	-	-	-
Baseline: IF-MF	Precision@10: 0.0734, ILS@10: 0.0353, AD@10: 943, Newness@10: 2.464								

(d) Lthing dataset

Where, positive values indicates the advantage of the curiosity-based methods while negative values indicate the advantage of IF-MF.

CdRF, at the same time, only lost 2.43 percent Precision@5 and 1.52 percent Precision@10. We attribute these to *Compound*'s superiority, which successfully depict individuals curiosity, leads to reaching a compromise between relevance and diversity.

From Tables 2b, 2c and 2d, experimental results show that *Compound* consistently performs better than all other competitors regarding various diversity measures. Meanwhile, *Compound* also maintains impressive Precision which is ranked just behind *IF-MF* and *UC* (and *PopRec* in Precision@5 on Lthing dataset). However, such difference seems to be negligible, since small precision loss brings great improvement in diversity. For example on ABooks dataset, *Compound* lost 0.06 percent on Precision@5 compared with *UC*, but achieves significant improvements in diversity (eg., 70.70 percent on ILS@5, 58.67 percent on AD@5, etc). Similar improvement is found with precision loss compared with *IF-MF* and *PopRec*, showing the superiority of *Compound*.

In summary, our proposed *SeCM* (in *Compound* situation) either performs comparably or outperforms other counterparts across datasets. It achieves very strong performance on diversity on the four datasets, proving it indeed recommends items more diversely. In these regards, it is suitable as a useful supplement to traditional accuracy-oriented RS.

7.5 Exp.4 Comparison of *CdRF* With Existing Curiosity Techniques

Taking *IF-MF* as the baseline, the fourth series of experiments aim to investigate accuracy loss (% reduction in Precision) suffered by the proposed *CdRF* and existing curiosity-drive methods (*UC* and *CBRS*) in gaining diversity (% Improv. in ILS, AD and Newness). Table 3 report the detailed results on the four datasets, respectively. Note that we exclude *SC* from the comparison because it is intuitively based on $R-MF$ not *IF-MF*, where *R-MF* is used to accurately predict ratings.

From the results across the four datasets, we have the following findings: 1) with equal amount of accuracy loss, *CdRF* is always successful in providing diversity compared to others. For instance on ML-1M dataset (Table 3a), in the case of 1 percent reduction at Precision@5, *CdRF* can achieve 29.75 percent improvement in the form of ILS@5 over *IF-MF*. Whereas, *CBRS* only increase 6.58 percent ILS@5, at the same time, *UC* even sacrifices 129.91 percent ILS@5. This clearly shows that *CdRF* can be effective in recommending more diverse items; 2) it is only *CdRF* that consistently outperforms the baseline on all the diversity measures. This observation coincides with the intuition that the proposed *SeCM* can help enhance diversity for RS. However, *CBRS* and *UC* also adopt curiosity mechanism, their results are not satisfactory. On the one hand, though following AOA and AOB rules, *CBRS* dose not perform very stable across the datasets and fails to outperform *IF-MF* some cases especially on Lthing dataset. The main reason may be its modeling method of Wundt curve which hampers to accurately capture personal curiosity. On the other hand, *UC* performs worst. We partly attribute the loss to its computational method, which may inevitably promote hot items showing in recommendation lists and thus pulls diversity performance down. These comparisons also confirm that *CdRF* is effective even in cases when the curiosity baselines perform poorly; 3) *CdRF* can obtain diversity enhancement even if compromise very little accuracy. For example, on ML-100K dataset, compared to *IF-MF*, *CBRS* achieves diversity advantages until lost 3 percent Precision. Whereas, *CdRF* quickly gains more diversity since sacrificing only 1 percent precision loss (Table 3b). In fact, we can also conclude that if RS is allowed to tolerate more accuracy loss, *CdRF* can achieve much more diversity.

Comprehensively, the proposed *CdRF* outperforms considered rivals on the four datasets, which supports the point that the overall quality of recommendation can be improved by simultaneously capturing a user's relevance preference and individual curiosity. More importantly, these results also support the conclusion that *CdRF* can be used to quickly generate diverse items with acceptable accuracy, exhibiting its advantages of stability, superiority and flexibility in recommending relevant-yet-diverse items. In addition, experiments also suggest that *CdRF* is very general, it not only performs well on movie recommendation, but also works well on book recommendation. These properties promote *CdRF* more readily to be applied in reality.

8 Related Work

8.1 Recommendation on Diversity Improvement

Oh *et al.* in Ref. [30] presented Personal Popularity Tendency Matching (*PPTM*) to recommend novel items based on the discovered Personal Popularity Tendency (PPT). Zhang *et al.* of Ref. [31] presented a novelty-seeking based dinning recommender system (*NDRS*), by leveraging historical dinning pattern, socio-demographic characteristics and restaurants attributes. Pathak *et al.* in Ref. [32] introduced a clustering based framework (*KRCF*) to increase novelty and diversity. Gogna *et al.* proposed [1] and [33] for the issue with a single stage method. Among them, Ref. [1] incorporated additional diversity enhancing constraints into MF. Ref. [33] leveraged ratings and item metadata via a single (joint) optimization model based on the matrix completion framework to achieve accuracy-diversity balance.

8.2 Curiosity-Drive Recommendation

Although curiosity has been widely studied in psychology and gradually applied in neuroscience as well as sociology fields [34], [35], [36], to the best of our knowledge, this topic has been approached only by the following four work in the context of RS.

Santos [2] presented a hybrid RS considering the curiosity level of each individual as a decisive factor to recommend sites of South America. The first requirements was to collect CEI-II questionnaires from volunteers. It then performed content-based recommendation for lower curiosity users and executed collaborative-based recommendation for higher curiosity users. However, additional manual intervention is required beyond the normal use of the RS service.

Wu *et al.* of Ref. [3] modeled surprise-evoked curiosity. The same authors also proposed another approach in Ref. [4] for curiosity-drive recommendation. They first modeled user uncertainty curiosity built over Shannon entropy and Damster-Shafter theory, and then ranked items by consolidating both user preference and uncertainty. However, Wu's work recommended items with the strongest stimulation and ignored the individual differences in curiosity.

Lee *et al.* [5] proposed a curiosity-based recommendation system (*CBRS*) which generated recommendation with a personalized amount of novelty to fit the users curiosity level. It presented a computational model of user curiosity, called Probabilistic Curiosity Model (*PCM*) to model a users curiosity with Beta distribution function. However, *CBRS* suffers from several limitations: it 1) fails to utilize social factors since curiosity is also connected with social context except for personal context [6]; 2) lacks interpretability and generalization since it is always out of work if the characteristics of beta distribution is not satisfied; 3) in many scenarios the information is limited to ratings or access information of items, and item features such as music genres may not be available or incomplete [37].

9 Conclusion and Future Work

Traditional RS suffers from accuracy over-fitting problem which dampens a user's enthusiasm towards the pushed items. In psychology, curiosity is the heart and motive force to drive explorative behaviors. Inspired by this, we propose a curiosity-drive recommendation framework (*CdRF*). It flexibly manages to tie a novel stimulus-evoked curiosity mechanism (*SeCM*) with an existing accuracy-oriented MF method via Borda count to recommend relevant-yet-diverse items, and therefore promotes user engagement in RS.

SeCM is essentially a vital constituent part of *CdRF*, which is designed to capture the curiosity appetite for individuals. The rational behind *SeCM* is exploration is more likely to occur when the intensity of stimulus appearing on an item is only slightly supra optimal regarding to a target user. To be concrete, *SeCM* qualifies the compound of novel- and conflict- stimulus intensity, and models personalized curiosity using Wundt curve accompanied by AOA and AOB rules. Experiments two movie and two book datasets demonstrated that 1) *SeCM* ensures recommendation matches individual curiosity level, meanwhile, helps to diversify recommendation; 2) *CdRF* not only outperforms state-of-the-art curiosity-based approaches, but also maximizes the variety in recommendation for an (given) acceptable loss in accuracy.

Although the question of curiosity-drive exploration is vast, we believe this work serves as a step forward and provides some key ideas to reinforce RS performance. There are several possible extensions can be pursued in future work. The first is to breaking the equivalently assignment of α to all the users because individuals actually hold different sensitivity to different stimulus. For example, one may be more disturbed by a conflicts-stimulus compared with a novel-stimulus. Another interesting extension is to take dangers originated in curiosity (as expressed by "curiosity kills the cat" [36]) into considerations, which may also influences a user's online behaviors. Furthermore, other factors that evoke curiosity, such as complexity, incongruity, etc., will be investigated and incorporated to upgrade overall recommendation results. Also, there is an urgent need for designing combined metrics to simultaneously measure accuracy and diversity.

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References

[1] A. Gogna and A. Majumdar, "DiABlO: Optimization based design for improving diversity in recommender system," *Inf. Sci.*, vol. 378, pp. 59–74, 2017.
[2] A. M. dos Santos, "A hybrid recommendation system based on human curiosity," in *Proc. 9th ACM Conf. Recommender Syst.*, 2015, pp. 367–370.
[3] Q. Wu, S. Liu, C. Miao, Y. Liu, and C. Leung, "A social curiosity inspired recommendation model to improve precision, coverage and diversity," in *Proc. IEEE/WIC/ACM Int. Conf. Web Intell.*, 2016, pp. 240–247.
[4] Q. Wu, S. Liu, and C. Miao, "Modeling uncertainty driven curiosity for social recommendation," in *Proc. Int. Conf. Web Intell.*, 2017, pp. 790–798.
[5] P. Zhao and D. L. Lee, "How much novelty is relevant? It depends on your curiosity," in *Proc. 39th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval*, 2016, pp. 315–324.
[6] R. Saunders, "Curious design agents and artificial creativity a synthetic approach to the study of creative behaviour," PhD dissertation, Dept. Architectural Des. Sci., University of Sydney, Sydney, Australia, 2002.
[7] D. E. Berlyne, *Conflict, Arousal and Curiosity*. New York, NY, USA: McGraw-Hill, 1960.
[8] A. Diederich, "Decision making under conflict: Decision time as a measure of conflict strength," *Psychonomic Bull. Rev.*, vol. 10, pp. 167–176, 2003.
[9] K. Lewin, "The conflict between Aristotelian and Galileian modes of thought in contemporary psychology," *J. Gen. Psychol.*, vol. 23, no. 2, pp. 517–554, 1931.
[10] K. Lewin, "Field theory in social science," *Amer. Catholic Sociol. Rev.*, vol. 12, no. 2, 1951, Art. no. 103.
[11] N. E. Miller, *Experimental Studies of Conflict*. New York, NY, USA: Ronald Press, 1944.
[12] Q. Wu, "Computational curiosity (a book draft)," *Comput. Sci.*, 2015, pp. 14–23. [Online]. Available: http://arxiv.org/abs/1502.04780v1
[13] J. A. Litman, "Curiosity and the pleasures of learning: Wanting and liking new information," *Cognition Emotion*, vol. 19, no. 6, pp. 793–814, 2005.
[14] S. Sreenivasan, "Quantitative analysis of the evolution of novelty in cinema through crowdsourced keywords," *Sci. Rep.*, vol. 3, no. 5, pp. 2758–2758, 2013.
[15] P.-Y. Oudeyer, "Computational theories of curiosity-driven learning," *Comput. Sci.*, 2018, pp. 1–24. [Online]. Available: http://arxiv.org/abs/1802.10546v2
[16] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, "GroupLens: An open architecture for collaborative filtering of netnews," in *Proc. ACM Conf. Comput. Supported Cooperative Work*, 1994, pp. 175–186.
[17] L. A. Coser, *The Functions of Social Conflict*. New York, NY, USA: Routledge, 2001.
[18] K. E. Merrick, A. Isaacs, M. Barlow, and N. Gu, "A shape grammar approach to computational creativity and procedural content generation in massively multiplayer online role playing games," *Entertainment Comput.*, vol. 4, pp. 115–130, 2013.
[19] K. Xu *et al.*, "Improving user recommendation by extracting social topics and interest topics of users in uni-directional social network," *Knowl.-Based Syst.*, vol. 140, pp. 120–133, 2018.
[20] Y. Hu, Y. Koren, and C. Volinsky, "Collaborative filtering for implicit feedback datasets," in *Proc. 8th IEEE Int. Conf. Data Mining*, 2008, pp. 263–272.
[21] M. van Erp and L. Schomaker, "Variants of the Borda count method for combining ranked classifier hypotheses," in *Proc. 7th Int. Workshop Front. Handwriting Recognit.*, 2000, pp. 443–452.
[22] J. McAuley, C. Targett, Q. Shi, and A. v den Hengel, "Image-based recommendations on styles and substitutes," in *Proc. 38th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval*, 2015, pp. 43–52.
[23] R. He and J. McAuley, "Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering," in *Proc. 25th Int. Conf. World Wide Web*, 2016, pp. 507–517.
[24] T. Zhao, J. McAuley, and I. King, "Improving latent factor models via personalized feature projection for one class recommendation," in *Proc. 24th ACM Int. Conf. Inf. Knowl. Manage.*, 2015, pp. 821–830.
[25] S. Vargas and P. Castells, "Rank and relevance in novelty and diversity metrics for recommender systems," in *Proc. ACM Conf. Recommender Syst.*, 2011, pp. 109–116.
[26] T. Zhou, Z. Kuscsik, J.-G. Liu, M. Medo, J. R. Wakeling, and Y.-C. Zhang, "Solving the apparent diversity-accuracy dilemma of recommender systems," *Proc. Nat. Academy Sci. United States America*, vol. 107, no. 10, 2010, Art. no. 4511.
[27] G. Adomavicius and Y. Kwon, "Improving aggregate recommendation diversity using ranking-based techniques," *IEEE Trans. Knowl. Data Eng.*, vol. 24, no. 5, pp. 896–911, May 2012.
[28] G. Guo, J. Zhang, Z. Sun, and N. Yorke-Smith, "LibRec: A java library for recommender systems," in *Proc. 23rd Conf. User Modelling, Adaptation Personalization*, 2015.
[29] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Comput.*, vol. 42, pp. 30–37, 2009.
[30] J. Oh, S. Park, H. Yu, M. Song, and S.-T. Park, "Novel recommendation based on personal popularity tendency," in *Proc. IEEE 11th Int. Conf. Data Mining*, 2011, pp. 507–516.
[31] K. Z. Fuzheng Zhang, N. J. Yuan, X. Xie, E. Chen, and X. Zhou, "A novelty-seeking based dining recommender system," in *Proc. 24th Int. Conf. World Wide Web*, 2015, pp. 1362–1372.
[32] A. Pathak and B. K. Patra, "A knowledge reuse framework for improving novelty and diversity in recommendation," in *Proc. 2nd ACM IKDD Conf. Data Sci.*, 2015, pp. 11–19.
[33] A. Gogna and A. Majumdar, "Balancing accuracy and diversity in recommendation using matrix completion framework," *Knowl.-Based Syst.*, vol. 125, pp. 83–95, 2017.
[34] G. Loewenstein, "The psychology of curiosity: A review and reinterpretation," *Psychol. Bull.*, vol. 116, pp. 75–78, 1994.
[35] J. Gottlieb, P.-Y. Oudeyer, M. Lopes, and A. Baranes, "Information-seeking, curiosity and attention: Computational and neural mechanisms," *Trends Cogn. Sci.*, vol. 17, no. 11, pp. 585–593, 2013.
[36] C. Kidd and B. Y. Hayden, "The psychology and neuroscience of curiosity," *Neuron*, vol. 88, no. 3, pp. 449–460, 2015.
[37] S. Vargas, "Novelty and diversity enhancement and evaluation in recommender systems and information retrieval," in *Proc. 37th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval*, 2014, pp. 1281–1281.

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