

Mining Novelty-Seeking Trait Across Heterogeneous Domains

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ABSTRACT

An incisive understanding of personal psychological traits is not only essential to many scientific disciplines, but also has a profound business impact on online recommendation. Recent studies in psychology suggest that novelty-seeking trait is highly related to consumer behavior. In this paper, we focus on understanding individual novelty-seeking trait embodied at different levels and across heterogeneous domains. Unlike the questionnaire-based methods widely adopted in the past, we first present a computational framework, Novel Seeking Model (**NSM**), for exploring the novelty-seeking trait implied by observable activities. Then, we explore the novelty-seeking trait in two heterogeneous domains: check-in behavior in location based social networks, which reflects mobility patterns in the physical world, and online shopping behavior on e-commerce sites, which reflects consumption concepts in economic activities. To demonstrate the effectiveness of **NSM**, we conducted extensive experiments, with a large dataset covering the two-domain activities for hundreds of thousands of individuals. Our results suggest that **NSM** offers a powerful paradigm for 1) presenting an effective measurement of a personality trait that can explicitly explain the deviation of individuals from the habits of individuals and crowds; 2) uncovering the correlation of novelty-seeking trait at different levels and across heterogeneous domains. The proposed method provides emerging implications for personalized cross-domain recommendation and targeted advertising.

Categories and Subject Descriptors

H.2.8 [Database Applications]: Data Mining; J.4 [Social and Behavioral Sciences]: Psychology

Keywords

Novelty Seeking, Human Behavior, Check-in, Online Shopping

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1. INTRODUCTION

"Towering genius despairs a beaten path. It seeks regions hitherto unexplored."

—Abraham Lincoln

Novelty seeking is a personal trait described as the search for unfamiliar experiences and feelings that are “varied, novel, complex, and intense”, and by the readiness to take “physical, social, legal, and financial” risks for the sake of such experiences. Novelty seeking, as well as harm avoidance and reward dependence, has been regarded as the basic requirement for human activities [4].

Follow a crawling baby around and you will see that starting from birth, nothing excites us more than something new and different. According to the uncovered genetic roots and relations to the dopamine system [6], our unique brains are biologically primed to engage with and even generate novelty, from our ancestors’ first bow and arrow to the latest smart phone. This neophilia has always been a key human survival skill, whether adapting to climate change on the ancestral African savanna or coping with the latest digital toy from Silicon Valley. For individuals, despite the anti-conformity property of novelty-seeking behavior, if this adventurousness and curiosity are combined with persistence, it will lead to personal growth and the kind of creativity that benefits society as a whole. Given its importance, understanding an individual’s novelty-seeking propensity has been essential to many scientific disciplines as varied as psychology [1], sociology [16], biomedicine [6], and economics [12]. In consumer behavior and recommender system research, understanding this personality trait is particularly crucial since consumers’ attributes are strong indicators of their purchasing behaviors [34]. Hence, if you know more about whether your consumer loves trying new things, you can recommend your product more reasonably according to consumer’s taste and reach your targets faster and more effectively.

In the last few decades, to measure this personality trait, researchers have developed and proposed numerous scales. For example, on one side, Kirton and Michael [18] proposed KAI (Kirton’s innovators-adaptors inventory), which focuses on the propensity to innovate at a general level and describes attraction to any kind of newness; on the other side, Raju [27], Goldsmith and Hofacker [13] proposed the so-called adoptive innovativeness scales, which measure domain-specific novelty with regards to the adoption of new products. In spite of the importance of the previous research into the measurement of novelty-seeking trait, the tradition-

tional survey-based approaches rely on retrospective self-reporting and thus are vulnerable to memory error (e.g., subjects might misremember the adoption time of a product), not to mention the well-known experimenter effects [31]. In addition, the time and money cost, as well as the data granularity, limit the effectiveness and efficiency of survey-based approaches for understanding novelty-seeking in both individual and population.

During the past few years, with the proliferation of mobile devices, ubiquitous sensing technologies, and various kinds of social media, the emerging era of “big data” has provided unprecedented potential for us to uncover the personality traits implied by our everyday lives. Based on data collected in a single domain (e.g., the purchasing history of an individual at an online shopping website can span several years, which would have been nearly impossible to obtain in the past), we can explore individual novelty-seeking trait in a complete data-driven way. Such an approach can analyze data at a much larger scale than questionnaire-based methods. For instance, if a person frequently purchases latest-launched digital products on Amazon, this propensity for neophilia would clearly imply she might be a novelty-lover in the online shopping domain. Given a person’s variety of footprints, we can validate whether her novelty-seeking behavior is consistent across heterogeneous domains. For example, if we observe a person prefers to explore new places on Foursquare, can we conclude that she also possesses high novelty-seeking in her buying behavior on Amazon? This issue is crucial to cross-domain recommendation, especially in the situation where one domain suffers from the cold-start problem.

Given the heterogeneous behavioral data of individuals across various domains, the major challenges of this work are:

- How to computationally model the novelty-seeking trait of an individual in a general way, given both the individual behavior as well as mass behavior.
- How to analyze and compare the novelty-seeking trait at different levels and across heterogeneous domains.

To address the above challenges, in this paper, we first give a comprehensive description of novelty-seeking measured in two respects: *self novelty*, which exploits the desire for diversity and *crowd novelty*, which exploits the degree of anti-conformity. We then propose a complete data-driven framework termed **NSM** to understand the novelty-seeking trait at a general level. This model is flexible enough to characterize novelty-seeking at different granularities and in various domains. Further more, we delve into the exploration of domain-specific novelty-seeking in check-in behaviors, which reflect mobility patterns in the physical world, and online shopping behaviors, which reflect consumption in economic activity. Our evaluation consists of multiple parts. First, we conducted several experiments to analyze and compare the novelty-seeking propensity at different levels in a single domain, and tested the performance of prediction results in various situations. Next, we explicitly discovered users with behavioral data across two domains, to compare the consistency of their novelty-seeking traits in terms of both individual and social aspects.

To the best of our knowledge, our work is the first attempt to investigate and model human novelty-seeking in a computational way, based on the heterogeneous behavioral data

of hundreds of thousands of people. The main contributions of this paper include the following:

- We have developed a Bayesian approach to computationally model the individual sequential behavior. This method provides an automatic and data-driven way of generating observable behaviors according to novelty-seeking trait and preference.
- We present in-depth analytics for exploring the novelty-seeking trait in heterogeneous domains and at different levels. The domain-specific activities reveal their novelty-seeking trait in different aspects of life.
- We conducted extensive experiments on large-scale datasets to validate the effectiveness and flexibility of our method. We investigated the performance on domain-specific novelty-seeking exploration, novelty-related prediction results, and cross-domain novelty-seeking comparison.

2. RELATED WORK

2.1 Novelty Seeking Research

Novelty Seeking, which can also be termed sensation seeking or neophilia, has long been studied in psychology, consumer behavior, and health science [38, 16, 6]. In 1967, Acker and McReynolds [1] proposed that the basic notion of novelty seeking appears to be that through some internal drive or motivating force, the individual is motivated to seek out novel information. The primary aspect of this is to seek new and potentially discrepant information. This is the most emphasized aspect in studies by psychologists, such as McClelland [22], Fiske and Maddi [9], who discussed varied experience, Rogers [30], who discussed the notion of venturesomeness. The second aspect is the extent to which individuals vary their choices in familiar contexts, for example, by alternating their purchases of previously sampled brands or styles [21]. This aspect of novelty seeking is perhaps better described as variety seeking or stimulus variation. The stimuli are already known and thus rotating their use may serve to reduce boredom or fatigue.

Since the mid-1970s, the emergence of a research direction has led to the design of novelty seeking scales through a structured validation process. The most representative scales are presented in two groups: “life innovativeness” scales and “adoptive innovativeness” scales. Leavitt and Walton [19], Kirton’s [18], and Hurt et al.’s [17] are included in the category of “life innovativeness” scales due to the fact that their scopes go beyond the sole adoption of new products; while “adoptive innovativeness” scales, which primarily include Raju’s [27], Goldsmith et al. [13], and Baumgartner et al. [2], are specifically designed to measure the novelty seeking as a tendency to buy new products.

Compared to these previous works, our work can primarily be differentiated in two aspects: 1) we consider the novelty-seeking trait of an individual by comparing her personal behavior with her own history as well as mass behavior; 2) we develop a data-driven framework to figure out novelty-seeking trait computationally and automatically.

2.2 Recommender System

In recent years, recommender systems have been extensively studied due to their wide application in business [29].

Plenty of sequential methods have been proposed and we only concentrate on listing several typical ones. Zimdars et al. [36] investigated how to extract sequential patterns to learn the next state with a standard predictor, e.g., a decision tree. Mobasher et al. [24] adopted pattern mining methods to extract sequential patterns that are used for generating recommendations. Shani et al. [33] introduced a recommender system according to a Markov decision process and a Markov chain based recommender. To enhance the maximum likelihood estimates of the Markov chain transition graphs, they described several heuristic approaches such as clustering and skipping. Rendle et al. [28] proposed the factorized personalized Markov chains, which brought together personalized transition graphs and the benefits of sequential time-invariant user taste. In short, the main difference in our work from previous approaches is that our model considers user behavior characterized by preference and novelty-seeking, which provides a better explanation for personalized recommendations.

In another aspects, cross-domain recommendations have also been widely discussed, e.g., Zhang et al. [35] leveraged user profiles in social media to help prediction and recommendation on e-commerce sites, Berkovsky et al. [3] addressed the sparsity issue of recommendation in one domain by applying cross-domain mediation of collaborative user models. Different from existing mainstream methods, such as transfer learning approaches [26] that only transfer user preferences or interests, we are associating heterogeneous domains with an explicit psychological trait that guides human behavior at an intrinsic level.

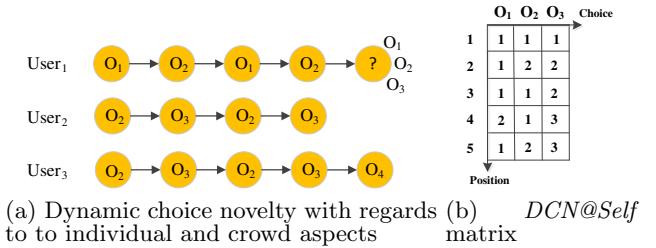
3. MODELING GENERAL NOVELTY SEEKING TRAIT

In this section, we present a framework to explore the general novelty-seeking trait embodied in an individual’s behavioral data. But first, we explicitly clarify some of the terms commonly used in this article, and then tackle the challenge of modeling and inferring an individual’s novelty-seeking trait.

3.1 Preliminary

Action and Choice : An action x taken by an individual is a domain-specific activity, which discriminately describes the observable behavior of this individual on one particular domain at a specific time. $x \in \{o_1, \dots, o_M\}$ indicates the optional choices for an action, the granularity of the choice can vary according to different demands and the data format obtained from the data provider. For example, an action on Foursquare refers to a check-in where the choice can be represented with geo-coordinates or a POI category, such as “restaurant” and “shopping mall”; an action on Amazon refers to the purchase of an item, where the choice can be the exact name or the category, e.g., “women’s wear”. The action sequence $\mathbf{x} = (x_1, x_2, \dots, x_N)$ of an individual refers to the actions taken in chronological order, where N is the number of actions.

Dynamic Choice Novelty (DCN) : DCN is a $N \times M$ (length of sequence \times number of choices) matrix, where each element is an integer ranging from 1 to M . Before we explore the novelty-seeking trait of an individual, we first describe the novelty degree related to a particular action this individual takes. At each position of the action sequence, the



(a) Dynamic choice novelty with regards to individual and crowd aspects (b) $DCN@Self$ matrix

Figure 1: Dynamic choice novelty of individuals w.r.t an example of $DCN@Self$ matrix

individual faces M choices, and the comparison among the novelty degree of these choices at that moment determines a partial order. Thus, we use **DCN** to represent the comparison at each position, where the i th row measures the partial order of the M choices at the i th position of the action sequence. As shown in Figure 1(a), given $user_1$ faces three choices at the last position, the vector corresponding to this position indicates, at this moment, which choice is more novel. At any particular position, we consider two factors that determine the ordering: given historical observation, popularity of the choice itself and popularity of the choice transition, the more popular the two factors, the lower ranking the choice.

We discuss two ways to calculate popularity: a) *self novelty* ($DCN@Self$) calculates the popularity according to an individual’s historical behavior. This term embodies the propensity of exploring new things when considering the individual’s personal experience and can be interpreted as a measurement of variety; b) *crowd novelty* ($DCN@Crowd$) calculates the popularity according to the historical behavior of all users. This measurement reveals the propensity for exploring new things when considering mass behavior and can be interpreted as the degree of anti-conformity [20].

For example, regarding $user_1$ in Figure 1(a), on one hand, if we consider this individual’s personal historical behavior, the novelty ($DCN@Self$) order of the choices at the last position is $o_3 > o_2 > o_1$ since o_3 never appears before, $o_2 > o_1$ is because that given her previous choice o_2 , the transition $o_2 \rightarrow o_1$ has appeared while $o_2 \rightarrow o_2$ has not, thus $DCN@Sel_{5o_3} = 3$, $DCN@Sel_{5o_2} = 2$ and $DCN@Sel_{5o_1} = 1$ (Note that 1 indicates the lowest ranking and vice versa). Figure 1(b) gives an intuitive display of the $DCN@Self$ matrix for $user_1$. On the other hand, if we consider that $user_2$ and $user_3$ frequently conduct $o_2 \rightarrow o_3$, the novelty ($DCN@Crowd$) ranking of that position might be $o_2 > o_1 > o_3$. Formally, given the previous action x_{i-1} , we rank the choices for $DCN@Self$ ($DCN@Crowd$) according to

$$DCN@Sel_{fix_i} \propto \frac{1}{(\#x_i^{Sel} + 1) \cdot (T_{x_{i-1}x_i}^{Sel} + 1)} \quad (1)$$

$$DCN@Crowd_{fix_i} \propto \frac{1}{(\#x_i^{Crowd} + 1) \cdot (T_{x_{i-1}x_i}^{Crowd} + 1)}$$

where $\#x_i^{Sel}$ refers to the frequency of x_i before the i th position in this individual’s sequence, and it measures the choice popularity at that moment in view of this individual. $T_{x_{i-1}x_i}^{Sel}$ refers to the transition probability of $x_{i-1} \rightarrow x_i$ before the i th position in this individual’s sequence, and it measures the choice transition popularity at that moment in

view of this individual. The notation for crowd novelty is similar, except that the frequency and transition probability are calculated according to the mass behavior. Notice that at a position, if two choices are equally popular according to Equation (1), they have the same order in the matrix (e.g., the last two columns of the second row in Figure 1(b)). Thus, matrices $DCN@Self$ and $DCN@Crowd$ are calculated separately, and both of them clearly describe the dynamic property of the novelty comparison among the choices (a different position has a different choice ordering).

Novelty-Seeking Level: The novelty-seeking level $z \in \{1, 2, \dots, K\}$ is an integer, where a larger value indicates a higher novelty-seeking propensity and vice versa. In the action sequence of an individual, each position relates to a specific novelty-seeking level, e.g., if $user_1$ choose o_3 at the last position, it is more likely she has a high novelty-seeking propensity at that moment and wants to explore something new.

Novelty-Seeking Trait (NST): Novelty-seeking trait is a real number ranging from 1 to K , which is represented as the mean of a multinomial distribution $\theta = \{\theta_1, \dots, \theta_K\}$, where θ_k refers to the probability of having novelty-seeking level k . Since the novelty-seeking level is an instant status related to one action, NST measures temperament, which is implied by the integrated behaviors the individual has conducted. The larger the NST , the greater the novelty-seeking propensity the individual possesses and vice versa.

3.2 Constructing Novelty Seeking Model

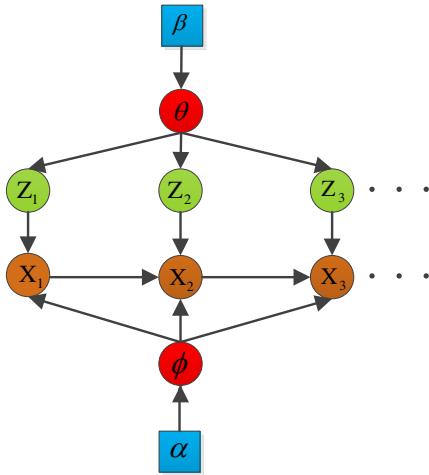


Figure 2: A graphical representation of our general novelty seeking model

How are an individual's observable actions generated sequentially? We tackle this problem from the perspective of combining choice utility and novelty-seeking tendency [12]. To address this issue, we leverage graphical modeling to express how to generate observable actions. All the symbols we use in this model are summarized in Table 1. It shows in Figure 2, Z_i is a latent variable that represents the novelty-seeking level at position i . Explicitly, we assume each novelty-seeking level is sampled from the multinomial novelty-seeking distribution θ . In addition, we use a latent variable $\phi = \{\phi_1, \dots, \phi_M\}$ to represent the utility of each choice, which can also be interpreted as this individ-

Table 1: Summary table of symbols

	Symbol Description
K	number of optional values for novelty-seeking level
M	number of optional choices for an action
N	length of action sequence
$\mathbf{x} = (x_1, \dots, x_N)$	a vector indicates action sequence
$\mathbf{z} = (z_1, \dots, z_N)$	a vector indicates novelty-seeking level sequence
$\boldsymbol{\theta} = \{\theta_1, \dots, \theta_K\}$	novelty-seeking level distribution
$\boldsymbol{\phi} = \{\phi_1, \dots, \phi_M\}$	choice utility distribution
$DCN_{N \times M}$	dynamic choice novelty matrix
α, β	hyperparameters relate to ϕ and θ separately

ual's preference for each choice. α and β are the relevant hyper-parameters to ϕ and θ separately. X_i is a variable representing the observable choice for the i th action and as shown in the figure, the value of X_i relies on the novelty-seeking level at that moment, the choice utility distribution ϕ , and the previously chosen actions. For simplicity and computational feasibility, we consider the first-order dependency of the action sequence. Given the dynamic choice novelty matrix DCN precomputed according to the individual's behavior ($DCN@Self$) or mass behavior ($DCN@Crowd$), and incorporating both the utility and novelty-seeking factors, the conditional probability is given as

$$P(X_i = x_i | x_{i-1}, z_i, \phi) = \frac{\phi_{x_i} \cdot f(z_i, DCN_{ix_i})}{\sum_{x_i} (\phi_{x_i} \cdot f(z_i, DCN_{ix_i}))} \quad (2)$$

where the first-order dependency between x_{i-1} and x_i is embodied in the fact that when we compute DCN_{ix_i} , the popularity of $x_{i-1} \rightarrow x_i$ is required.

Since we actually expect the fact at each position, when the novelty of a choice is consistent with the novelty-seeking level, this individual will accept the choice with a higher probability. For example, if an individual is at the highest novelty-seeking level K at a moment, we expect that she is more likely to accept a choice with the largest novelty in the partial ordering, or if she is at the middle novelty-seeking level at a moment, we expect she is more likely to accept a choice with middle novelty in the partial ordering, and so on for other conditions. Considering these constraints, we give the function adopted in this paper as follows:

$$f(z_i, DCN_{ix_i}) = \exp \left(-\left(z_i - \frac{DCN_{ix_i}}{\max(DCN_i)} \cdot K \right)^2 \right) \quad (3)$$

where $\max(DCN_i)$ indicates the maximum value in the i th row of matrix DCN .

Specifically, the generative process of our novelty seeking model (NSM) is as follows:

1. Draw novelty-seeking level distribution $\theta \sim Dirichlet(\beta)$
2. Draw choice utility distribution $\phi \sim Dirichlet(\alpha)$
3. For the i th position in the sequence
 - (a) Draw novelty-seeking level $z_i \sim \theta$
 - (b) Draw item $x_i \sim P(X_i | x_{i-1}, \phi, z_i)$

3.3 Inference

There are a variety of algorithms that perform inference and estimate parameters in graphical models. The EM algorithm does not perform well due to local maxima. Following [10, 32] for HMM inferences and [15] for topic model inference, we apply explicit pointwise Gibbs sampling by repeatedly drawing novelty-seeking level z , novelty-seeking level distribution θ , and choice utility distribution ϕ . The sampling process is summarized as follows:

Given the current state of the sampler, $\{\mathbf{z}, \theta, \phi\}$, iteratively for each position i ,

1. Randomly draw z_i from

$$P(z_i | \mathbf{z}_{-i}, \mathbf{x}, \phi, \theta) \propto P(\mathbf{z}, \mathbf{x} | \phi, \theta) \\ \propto \theta_{z_i} \cdot \phi_{x_i} \cdot f(z_i, DCN_{ix_i}) \quad (4)$$

2. Randomly draw θ from

$$\theta \sim Dirichlet(\theta | \beta') \quad (5)$$

where β' is a vector that increases the position k by n_k for β , n_k is the number of novelty-seeking level with value k in the current state of the sampler.

3. Randomly draw ϕ from

$$P(\phi | \mathbf{z}, \mathbf{x}, \theta) \propto P(\mathbf{x} | \phi, \mathbf{z}) \cdot P(\phi | \alpha) \\ \propto \frac{\prod_{i=2}^N (\phi_{x_i} \cdot f(z_i, DCN_{ix_i}))}{\prod_{i=2}^N \sum_{x_i} (\phi_{x_i} \cdot f(z_i, DCN_{ix_i}))} \quad (6)$$

To sample vector ϕ from the pseudo probability in Equation (6), we use Gibbs sampling again and iteratively use the rejection sampling method [11] to sample ϕ_j from conditional probability $p(\phi_j | \phi_{-j})$.

Finally, after obtaining θ and ϕ , the *NST* of this individual is calculated as the mean of θ . We use novelty matrix $DCN@Self$, representing self novelty, and novelty matrix $DCN@Crowd$, representing crowd novelty, to explore an individual's *NST* separately, and the results are denoted as $NST@Self$ and $NST@Crowd$. Next, to predict the next action x_{N+1} (we will test the performance of prediction in the experiments section), the conditional probability for x_{N+1} is given as

$$P(X_{N+1} = x | x_N, z_i, \phi) \\ = \sum_{k=1}^K (\theta_k \cdot \frac{\phi_x \cdot f(k, DCN_{(N+1)x})}{\sum_x (\phi_x \cdot f(k, DCN_{(N+1)x}))}) \quad (7)$$

4. NOVELTY-SEEKING IN HETEROGENEOUS DOMAINS

This section details the individual novelty seeking behavior in two heterogeneous domains: mobility and online shopping. For mobility, we consider users' check-in behavior as represented by their movement in the physical world. For online shopping, we consider users' purchase behavior as it reveals their economic consumption.

4.1 Novelty-Seeking in Mobility

In recent decades, the widespread use of mobile devices and wireless networks has offered the opportunity to gain insight on human mobility at an unprecedented scale, using

data from Bluetooth [5], cellular [14] or Online Location-based Social Networks (LBSN) [25]. In particular, we investigate an individual's novelty-seeking trait as reflected in mobility patterns according to the shared check-ins on Sina Weibo (the most popular social media website in China, which also provides location-based services such as check-in). The online check-ins contain abundant information of users' physical movements in daily lives, e.g., the point-of-interest (POI) indicates the geo-location and activity category, while the timestamp reveals the chronological order.

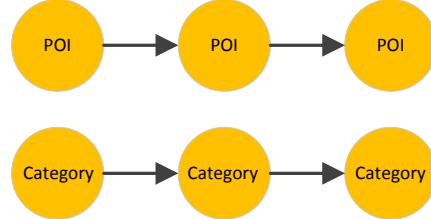


Figure 3: Different granularities considered in the check-in sequence

For check-in behavior, the time-ordered check-in history of an individual corresponds to her action sequence in our general model. Since novelty-seeking measured at different granularities of the observation might reflect a distinct propensity related to different aspects [23], we explicitly analyze an individual's *NST* at both the POI and category levels.

If we consider that the choice corresponds to the POI (the finest granularity described as a unique location ID, geo-coordinates, and a category), then the observable sequence corresponds to the POI sequence as shown in the top row of Figure 3. As the statistics show in Figure 4(a), except for a few routinely visited POIs such as office and home, most POIs are visited less than 100 times, which account for more than 90% of the total visited POIs. It indicates that most POIs are visited occasionally. Figure 4(b) shows that the long tail phenomenon is more obvious for the transitions, which implies both an individual and the crowd would rarely repeat previous transition patterns (visiting B right after visiting A) at the POI level. Thus at the POI level, we can infer that an individual tends to be both high *NST@Self* and high *NST@Crowd*, which will be validated in the experiment section.

If we consider that the choice is related to POI category, which clearly implies the activity engaged in at that place, we can acquire a better understanding of both an individual's lifestyle and the comparison between personal behav-

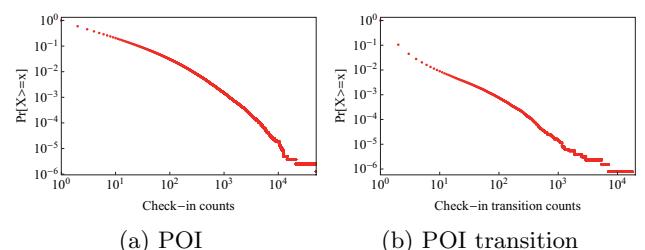


Figure 4: Check-in probability vs. counts

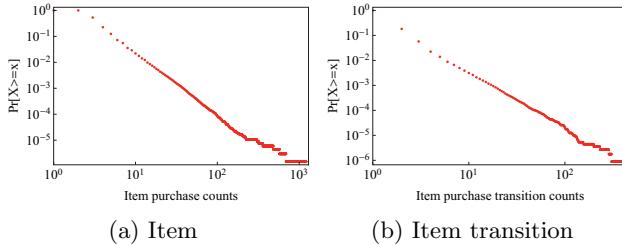


Figure 5: Online purchase probability vs. counts

ior and mass behavior. Taking *NST@Crowd* for example, if a group of users frequently checks in at their individual offices, which refer to different POIs, even though they actually share a common pattern, at the POI granularity they will be treated as novelty-seeking individuals since the specific locations vary. Thus, it makes more sense that they are non-novel persons when the comparison is made at the category level. In the experiment section, the comparison of results at the two levels will be discussed in detail.

4.2 Novelty-Seeking in Online Shopping

Shopping is one of the essential activities of daily life. With the prevalence of e-commerce, a growing number of people have developed an affinity for online shopping due to its diversity and convenience. It has been reported that online shoppers in China have reached 194 hundred million¹ and their online shopping behavior actually offers a wealth of information about economic activities. We explore the novelty-seeking trait related to online shopping behavior by investigating the purchasing behavior on Taobao, the largest e-commerce platform for online shopping in China. The description of a purchased item on Taobao typically contains the item name, category, brand, price, seller information and product summary. The online purchase history provides an in-depth understanding of consumption behavior, e.g., the product category indicates demand and interest, the price implies financial situation, and the rating refers to satisfaction, etc.

For online shopping behavior, an individual's action sequence described in the general model reflects her time-ordered purchase history. Similar to check-in behaviors, we explicitly compare *NST* measured at item and item category levels. As shown in Figure 5, an item purchase and a transition purchase (purchase B right after purchase A) also follow the power law distribution, which implies at the item granularity, people tend to present high novelty-seeking propensity.

5. EXPERIMENTS

In this section, we first describe and analyze the data we collected for two domains. Based on this huge dataset, we conducted extensive experiments to measure the novelty-seeking trait under different granularities in check-in behavior and online shopping behavior and validated the performance for the prediction results. Next, we determined the users who explicitly shared their connections across do-

Table 2: Basic statistics of SinaWeibo check-in and Taobao online shopping dataset

Dataset	Statistics	
Weibo	#User	123,865
	#Check-in	8,455,878
	#Ave. Check-in	68.3
	#POI	804,720
	#Ave. POI	53.2
	#Category (Second Level)	187
Taobao	#Ave. Category	18.3
	#User	79,959
	#Purchase	11,918,688
	#Ave. Purchase	149.1
	#Item	1,385,130
	#Ave. Item	136.3
	#Category (First Level)	112
	#Ave. Category	34

mains and compared their *NST* to test the consistency of the novelty-seeking trait across heterogeneous domains.

5.1 Data Collection and Description

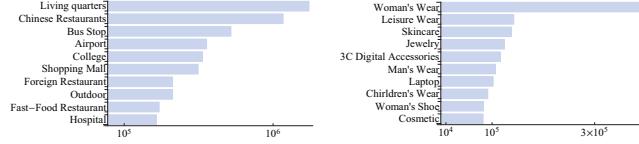
We measured the novelty-seeking trait and evaluated the model on the two publicly available websites: SinaWeibo and Taobao.



Figure 6: An user's partial obtained ratings from sellers

SinaWeibo, the largest social network in China, also provides location-based services. By using public APIs, we crawled user information including all check-in histories with timestamp and POI details. Then, we collected an individual's online shopping data on Taobao according to the publicly available credit ratings of an individual. Specifically, if a user has purchased a product on Taobao, the seller will always rate on this consumer unless this individual explicitly opts out to indicate that she needs to purchase the product anonymously (if the seller does not provide a rating herself, the system will assign a default rating to the buyer for this transaction several days later). In most cases, the role of the rating from the seller is to show the seller's appreciation of the transaction. All the ratings will be shown on the individual's credit rating page. An example of individual's partial ratings from several sellers are shown in Figure 6, where each record contains the purchased item, the rating content, the rating time, and the corresponding seller. The ratings explicitly obtained from sellers imply the online purchasing history. Due to the fact that a seller usually gives the rating right after the consumer purchases the item, we regard the rating time as the purchase time. For each item in our Taobao dataset, we also obtained the item information

¹<http://www.1.cnnic.cn/IDR/ReportDownloads/201209/P020120904421720687608.pdf>



(a) Top 10 Categories visted in check-in data (b) Top 10 Categories purchased in online shopping data

Figure 7: Most popular categories in two datasets

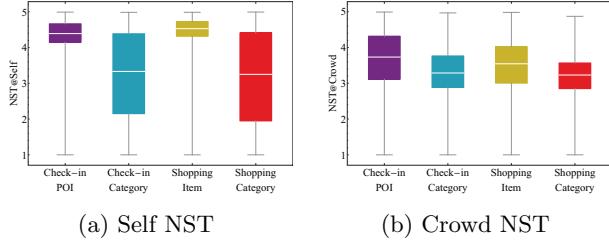


Figure 8: Self NST and crowd NST in check-in data and online shopping data

by using the APIs provided. Moreover, to validate whether the data obtained from the rating pages well represent this individual’s purchasing history on Taobao, we asked 25 persons to provide coverage of items included in the ratings by comparing the actual total number. The results show that the average coverage was 86.4%, which we believe is representative enough for users’ online shopping behavior.

To remove outliers and clean up the data, we first filter the noisy data, e.g., repeated check-ins at the same place in quite a short interval, and then require that every user on SinaWeibo has at least 30 check-ins and that every user on Taobao has made purchases at least 30 times. The basic statistics of the collected data is summarized in Table 2, e.g., “#Ave. Check-in” and “#Ave. POI” indicate that an individual would possess 68.3 check-ins and visit 53.2 different POIs on average. This table shows Taobao users buy an average of 136.3 different items. Considering the 149.1 average purchase times, we can see that an individual would rarely buy products they have bought before. For the description of POI, we concentrate on the second level of category, which gives a comprehensive and significant representation of user activities, such as Subway Station, Hospital, Chinese Restaurant, etc. Figure 7(a) shows the top-10 visited categories. We can see that the popular activities such as Living Quarters and Restaurants appropriately represent the demand for mobility. For online shopping, we consider category description at the first level, which contains 112 types in total, and this granularity provides sufficient information for understanding purchasing behavior. The most purchased categories are listed in Figure 7(b), which shows that Woman’s Wear has dominated consumption to some extent.

5.2 Novelty-Seeking Trait in a Single Domain

In this subsection, we first analyze and compare the measured novelty-seeking trait in each domain. Next, we discuss the evaluation metrics for prediction and present the results for two domains separately.

5.2.1 Novelty-Seeking Trait

When exploring the *NSM* model for an individual, we pre-calculated that individual’s self novelty matrix $DCN@Self$ and crowd novelty matrix $DCN@Crowd$ according to her observable sequence as well the collective sequences of the whole group of people. We then infer her $NST@Self$ and $NST@Crowd$ separately. Referring to the five-point partition of consumers in the innovation adoption lifecycle [30], we set the number of optional values for the novelty-seeking level as $K = 5$ in the reported results. Thus for an individual, $NST = 5$ indicates she has the highest propensity for novelty seeking, while $NST = 1$ indicates she is the most conservative.

For check-in data, we compared the results at the POI and category levels separately, and the same comparison was done for online-shopping data. Figure 8 gives an intuitive display of the NST distribution in two domains and at two levels. As shown in Figure 8(a), compared to $NST@Self$ at the category level, $NST@Self$ at the POI level is much higher and most of the people tend to show a high novelty-seeking propensity. The reason is that the power law property of visited POIs indicates an individual frequently visits new POIs, and therefore at a certain position, most of the optional POIs are places she occasionally visits later. At that moment, these unvisited POIs are different from previous ones and all of them indicate the same highest novelty value. Choosing one of them indicates this individual exhibits the highest novelty-seeking level at that moment. At the category level, more behavior patterns appear repeatedly and thus individuals exhibit lower aspirations for novelty seeking. The $NST@Self$ distribution of online shopping shows similar pattern. The figure shows $NST@Self$ of item in online shopping is a little higher than that of POI in check-in. The reason might be that $\frac{\#Avg.\text{Item}}{\#Avg.\text{Purchase}} > \frac{\#Avg.\text{POI}}{\#Avg.\text{Check-in}}$, which indicates purchasing behavior is more decentralized than check-in behavior and thus exhibits high tendency for novelty-seeking. Figure 8(b) shows the results of $NST@Crowd$. For check-in behavior at the POI level, we see that $NST@Crowd$ was a little lower than $NST@Self$. The reason is that when an individual chose a POI, the optional candidates actually had been visited by others and their crowd novelty could be clearly differentiated. If an individual did not always choose the POI with the highest crowd novelty, she would not always demonstrate the highest level of novelty-seeking. For $NST@Crowd$, the similar distribution between POI level and category level implies that the propensity for accepting popular things at different granularities is consistent, e.g., if a person tends to eat Chinese food, which is popular at the category level, she might also prefer the most popular restaurant at the POI level. The two figures show that even at different granularities, both $NST@Self$ and $NST@Crowd$ present similar patterns in check-in data and online shopping data, which implies that novelty-seeking trait distribution tends to show consistency across heterogeneous domains.

Furthermore, since $NST@Self$ actually measures an individual’s aspiration for variety, we compared two model-free methods widely adopted in information theory: shannon en-

Table 4: Prediction Results nDCG@10 for check-in and online shopping

Dataset	Level	NSM@Self	NSM@Crowd	OF	MC	FPMC
Check-in	POI	0.158	0.154	0.147	0.153	0.161
	Category	0.503	0.501	0.479	0.495	0.507
Shopping	Item	0.009	0.008	0.004	0.008	0.011
	Category	0.353	0.349	0.340	0.347	0.356

Table 3: Spearman's rho between *NST@Self* and shannon entropy, LZ separately

Check-in		<i>NST@Self</i> POI	<i>NST@Self</i> Category
	shannon entropy	0.613	0.686
Shopping		<i>NST@Self</i> Item	<i>NST@Self</i> Category
	shannon entropy	0.601	0.717
	LZ	0.613	0.774

tropy and Lempel-Ziv estimators [37], which calculates the conditional entropy. We made use of Spearman's rho [8], which measures the monotonic consistency between two variables, to test whether *NST@Self* stays in line with model-free methods. The results are shown in Table 3, which indicate that an individual's *NST@Self* shows an obvious positive correlation with both shannon entropy and LZ, i.e., when an individual's behavior is more random (higher shannon entropy or LZ) compared to other people, her *NST@Self* will be ranked higher in the crowd. However, the LZ method shows a more intense correlation since our model has considered the conditional situations.

5.2.2 Prediction

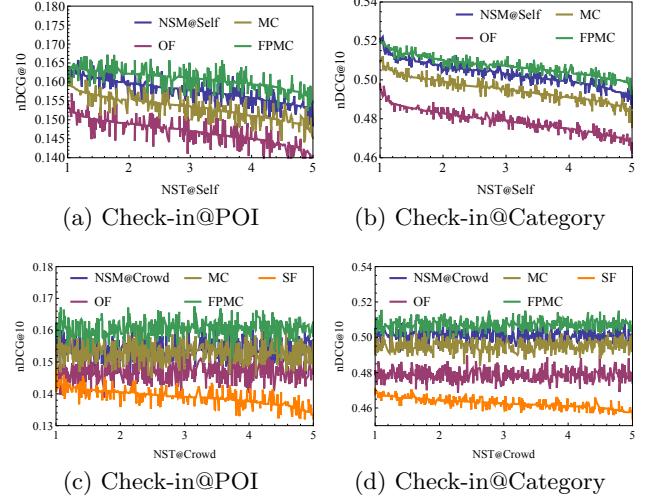
Taking check-ins at the POI level for example, to evaluate the predictability of our proposed model, the experiment was tested as follows: when we predicted a check-in, all previous check-in history was used as training data. We obtained the prediction probability for the next check-in as described in Equation (7) and tested the check-ins at the last positions of a sequence. In our experiment, we used nDCG, a widely adopted metric in information retrieval, to evaluate the performance. We first listed prediction probabilities of optional candidates in ascending order, and used rel_i as a binary value indicating whether the i th predicted POI was just the one visited by the user. Then we used nDCG@p to evaluate the performance, given by:

$$nDCG@p = \frac{DCG_p}{IDCG_p} \quad (8)$$

$$\text{where } DCG_p = \sum_{i=1}^p \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

We compared our model with the following methods:

1. **OF** (Order by Frequency): OF method always gives a recommendation list of the POIs according to the individual's visit frequency in the past
2. **MC** (Markov Chain): The MC method models sequential behavior by learning a transition graph over POIs that is used to predict the next check-in based on the


Figure 9: Prediction results vs. NST

recent check-ins of a user. The recommendation list is then ordered by transition probability given the previous location.

3. **FPMC** (Factorized personalized Markov Chain): This method proposed by [28] is a state-of-the-art model embedding users' preferences and their personalized Markov chains to provide the next POI recommendation. In our reported results, the factorization dimension was set at 20 for comparison.

In the reported results, we used nDCG@10 to compare the results as shown in Table 4. The comparisons at different situations show that **FPMC** usually performed best, while our methods, both **NSM@Self** and **NSM@Crowd**, performed better than **MC** and **OF**. On the one hand, **FPMC** performed better due to the fact that the purpose of **FPMC** is to predict the next item accurately while the main purpose of our model is to figure out the reason behind the observed behavior, e.g., a user's choice of an item is partially due to her current novelty-seeking level (there might exist some other personality traits influencing the behavior), apart from the individual preference for this item. On the other hand, our methods outperformed **MC** and **OF**, because item frequency as well as first-order transition probability has been captured as the dynamic choice novelty matrix in our model. Therefore, when the prediction gap with **FPMC** is acceptable, our model could give a better explanation for the psychology of decision-making and thus move a step closer to persuasive recommendations [7].

Furthermore, all the users were divided into 500 groups according to their *NST* and we compared the prediction results for different groups. Due to space limitations, we only



(a) Bind Taobao account to SinaWeibo in Taobao's personal setting



(b) A tweet in SinaWeibo refers to the binding

Figure 10: Link Taobao account to Weibo

Table 5: Basic statistical information of users who explicitly connected their account across two domains

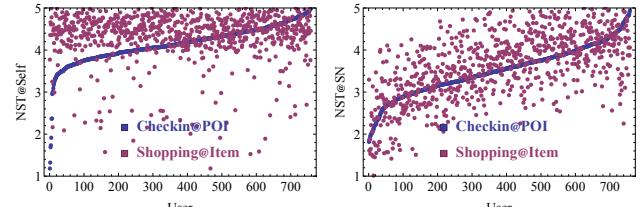
#User	758
#Ave. Check-in	57.9
#Ave. POI	45.6
#Ave. POI Category	17.7
#Ave. Purchase	184.8
#Ave. Item	166.1
#Ave. Item Category	41

include the results of the check-in data, which is similar to that of the online shopping data. For example, Figure 9(a) shows that as $NST@Self$ increases, the individuals of that group intend to explore new places and thus it is more difficult for all the tested models to correctly predict behavior. Figure 9(b) shows the pattern is similar for prediction results related to $NST@Self$ at the category level. In view of this, a precise estimation of $NST@Self$ will provide insights for personalized recommendation. However, if we consider the crowd novelty propensity $NST@Crowd$, since it focuses less on an individual's historic patterns, prediction results of the four methods on different groups do not show significant difference as shown in Figure 9(c) and Figure 9(d). We compared our results with another method named **SF**, which gives the recommendation list of POIs or categories according to the frequency visited by the crowd (**OF** is based on an individual's own visit frequency) and the prediction results are shown in Figure 9(c) and Figure 9(d). The figures demonstrate that it is more difficult to recommend popular things if the group has a higher $NST@Crowd$, which implies these individuals are more likely to reject popular things. At this point, exploring $NST@Crowd$ will provide guidance for whether to recommend popular things, especially in the cold-start stage in recommender systems.

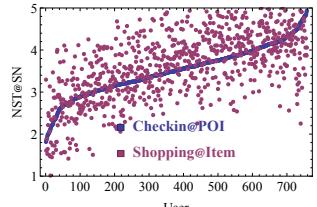
5.3 Novelty-Seeking Trait Across Heterogeneous Domains

In this subsection, we first identify users who explicitly connected their accounts on Sina Weibo and Taobao, and then analyze their NST consistency across the two heterogeneous domains.

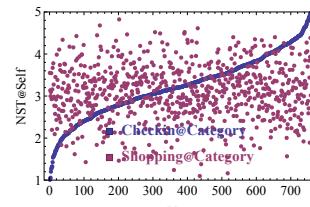
As shown in Figure 10(a), a user can explicitly connect her Taobao account to her SinaWeibo account in the personal settings page. After they are connected, the system will recommend that the user post on SinaWeibo by default. Figure 10(b) shows this post contains unique keywords "I have just binded my account on Taobao", hence we used the "tweet content search" function on SinaWeibo to find users



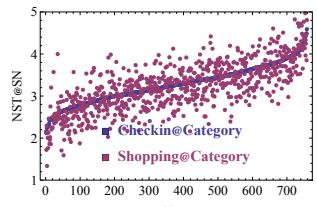
(a) $NST@Self$ Comparision



(b) $NST@Crowd$ Comparision



(c) $NST@Self$ Comparision



(d) $NST@Crowd$ Comparision

Figure 11: NST comparison across two domains at different levels

Table 6: Spearman's rho of NST across two domains

Comparison level	$NST@Self$	$NST@Crowd$
Check-in@POI vs. Shopping@Item	-0.137	0.526
Check-in@Category vs. Shopping@Category	0.041	0.731

who explicitly published such posts. The short url in the post indicates this user's Taobao homepage and thus we can connect their SinaWeibo account with their Taobao ID.

For those users, we collected their check-in data and online shopping data as mentioned above. After reducing the noise and filtering out users with less than 30 check-ins or 30 purchases, we finally found 758 users and their information is summarized in Table 5. To explicitly compare their NST across two domains, as shown in Figure 11, we ordered users (from left to right in the horizontal axis) by their NST in the check-in data, and plotted their NST in the check-in data and shopping data separately. Figure 11(a) and Figure 11(c) indicates that both at the POI and category level, there was not significant evidence to show that $NST@Self$ was consistent across these two domains, which implies that even though an individual was adventurous in one domain, he might be quite conservative in another domain. However, Figure 11(b) and Figure 11(d) show that in terms of following crowd behavior, these users' $NST@Crowd$ were significantly consistent, especially at the category level, which provides insight for the potential of cross-recommendation strategies according to this propensity for consistency. For example, being aware of an individual's historical movement can imply whether to recommend the most popular products on an e-business website. In addition, Spearman's rho is also presented in Table 6, where the positive values for $NST@Crowd$ validate the significant consistency across two

domains at both levels, while the tiny values for *NST@Self* show the inconsistency of *NST@Self*.

6. DISCUSSION

- **Limitations.** While showing the potential to leverage a massive amount of behavioral data to understand individual novelty-seeking related to both personal and social factors, we are aware that this method has several limitations. First, human behavior is complicated. We consider that an individual’s behavior is influenced by her *NST* and preference. However, there may be many other factors that affect the final choice of activities, such as contexts, other personality traits, etc. Second, the novelty is rated on the basis of repeated patterns in an individual’s experience or mass behavior, and this strategy is limited to analyze the behaviors themselves. In the future, we can expand our focus to include the content of the conducted activities, e.g., the geographic distance between POIs might also imply an individual’s novelty-seeking propensity for exploration. Third, the targeted population mainly consists of people who use online shopping and online social networks extensively, which implies they have up-to-date lifestyles and they may be biased towards higher novelty-seeking groups.
- **Privacy issues.** We want to reemphasize that in this work we only collected the publicly available data, i.e., check-ins provided by SinaWeibo APIs, ratings of online shopping published in users’ credit rating pages (visible to every one on the web) and the detailed description of products provided by Taobao APIs. The connection between user accounts was also identified from their self-disclosed content. However, we still remind that users might not have enough intention for their published data, and the connection of their different accounts might cause undesired consequences, i.e., a user might not expect her SinaWeibo friends to notice her purchasing history on Taobao. Thus, we suggest both the users and social network sites re-consider their privacy policy in terms of the linkage between multiple accounts.

7. CONCLUSIONS

In this paper, we have presented **NSM**, a complete data-driven framework for exploring individual novelty-seeking trait with a consideration of two aspects: self novelty related to a personal desire for diversity and crowd novelty related to noncompliance with mass behavior. Following this framework, we investigated check-in behavior and online shopping behavior to explore an individual’s *NST* at various levels across heterogeneous domains. We conducted a series of experiments to validate the usability and flexibility of this framework. The results show that, in terms of large populations, both *NST@Self* and *NST@Crowd* showed a consistent distribution of collective behavior while from the individual perspective on a smaller dataset, we observed a consistent *NST@Crowd* and an inconsistent *NST@Self*.

Please note that our work is not designed to replace traditional methods of novelty seeking. Instead, we believe that these methods can complement each other to enable a better and more comprehensive understanding of how novelty-seeking trait connects cross-domain human activities, which is not only important for advancing the understanding of

novelty-seeking trait in psychological science, but also essential to personalized recommendation and targeted advertising.

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