Analyzing and Modeling User Curiosity in Online Content Consumption: A LastFM Case Study

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***Abstract*—Curiosity is a natural trait of human behavior. When we take into account the time we spend consuming content online, it is expected that at least a fraction of that time was driven by curious behavior. Aiming at understanding how curiosity drives online information consumption, we here propose a model that captures user curiosity relying on several stimulus metrics. Our model relies on the well-established Wundt's curve from psychology and is based on metrics capturing Novelty, Complexity and Uncertainty as key stimuli driving one's curiosity. As a case study, we apply our model on a dataset of online music consumption from LastFM. We found that there are four main types of user behaviors in terms of how the curiosity stimulus metrics drive the user accesses to online music. These are characterized based on the diversity in the songs, artists and musical genres accessed.**

***Index Terms*—User Behavior, Curiosity, Information Consumption, Modeling.**

I. Introduction

Our personality traits naturally emerge as we perform our daily activities, these traits are manifested also in our online interactions. There has been a recent surge of studies on psychological aspects of online behavior thanks to the big data [1]. Such as the Big Five personality test to identify personality traits, which has been the focus of several efforts [2], [3]. By identifying such traits it is possible to tune and enhance services and technologies to better meet one's individual personality, ultimately improving user satisfaction [4].

Several studies have shown that some personality traits are strongly associated with *curiosity* [2], [5]. Indeed, curiosity has been recognized as a critical factor that influences human behavior in positive and negative ways at all stages of life.

As discussed by prior efforts, an individual's curiosity is essentially driven by external stimuli [6], [7] which are captured by collative variables. These variables refer to different characteristics of a stimulus, i.e., external factors that govern how one's curiosity is stimulated [6]. Novelty, complexity, uncertainty and conflict are collative variables that capture aspects related to curiosity stimulation [7].

Starting from the point that stimulus is as a combination of collative variables, the Wundt's curve has been proposed to model one's curiosity. The curve captures curiosity as a function of the stimulus intensity [8]. A Wundt's follows a bell-shape, indicating that too-little or too-much stimuli will respectively lead an individual to relaxation and anxiety. Moderate stimulation leads to curious behavior.

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Curiosity models based on the Wundt's curve have already been applied in the design of artificial creativity systems, to control the behavior of non-player characters in digital games and in reconfigurable robots [9]. In the particular domain of online information consumption, Zhao *et al* [4] recently used it in the design of a personalized recommendation system. Yet, the authors used a single collative variable, namely novelty, as stimulus to curiosity. The use of other collative variables, strongly related to curiosity, has not been investigated yet. The authors applied the model without assessing the extent to which it actually captures user curiosity in their target domain.

Our goal here is to model and analyze user curiosity as a driving force behind user consumption of online content. Building upon existing models [4], we consider all collative variables as sources of stimulus to curiosity. Also, we investigate whether a single Wundt's curve is a reasonably model of user curiosity. As case study, we focus on the consumption of online music from LastFM, as musical tastes are related to personality characteristics [5]. To that end, we analyze a large dataset consisting of over 243M listening events, covering more than 84K users and 9M songs. Specifically, we address two research questions:

- **Research Question 1 (RQ1)**: Are there distinct user behavior profiles in terms of curiosity stimuli, as captured by the collative variables?
- **Research Question 2 (RQ2)**: To which extent user curiosity can be accurately modeled by a Wundt's curve?

Given our focus on online music, we start by proposing stimulus metrics related to songs, artists and their musical genres capturing the collative variables. Next, we find that, though the single Wundt's curve is a reasonable model, for more than 40% of them the curiosity curve is multi-modal, reflecting a mixed behavior. So, it can be well modelled by the combination of two or three Wundt's curves.

In sum, this paper presents a thorough effort of modeling user curiosity as a driving force of online music consumption. Compared to prior studies, our contributions are: (1) the proposition and analysis of a set of metrics that capture different perspectives of the stimuli offered to users as they are exposed to online content; and (2) new models of curiosity that more accurately account for the diversity of user behavior.

The rest of this paper is organized as follows. We briefly review related work in Section II, whereas Section III discusses the modeling of user curiosity. We present our results addressing the aforementioned research questions in Sections

IV and V, and Section VI offers a discussion of the results and possible directions for future work.

II. Related Work

According to Wu et al., the computational model of curiosity has a broad set of applications [8]. Regarding crowd-sourcing, Law et al., used curiosity as a motivational to encourage crowd workers on Amazon's Mechanical Turk [10]. Also, Manyangara et al. conducted a surveyed with curiosity in peoples on multitasking of seeking information and technologies [11].

Saunders propose a approach to implement artificial creativity, he modeling it via curiosity based in Wundt's curve and used Novelty for its purpose [12]. Still on the artificial intelligence setting, Macedo used curiosity as one component from a set in multi-agent systems to exploration of environments [13].

In recommendation systems, Zhao used curiosity as discovery utilities based in Novelty in a framework [4]. Also, Maccatrozzo propose a serendipity in content-based recommender systems measuring the Novelty as cosine similarities among items [14]. Niu personalized the serendipity to stimulate the curiosity in recommendations for health-care articles [15]. Wu model user curiosity in recommendation systems via Uncertainty on Douban and Flixster [16]. At last, Menk introduced a hybrid recommender considering individual's curiosity on sites of South America [3].

III. Modeling User Curiosity

According to the Information Gap Theory [7], one's curiosity arises due to a discrepancy between what one knows and what one wishes to know. It states that one's curiosity will arise spontaneously when external factors alert the individual to the existence of such gap [7].

The arousal of curiosity depends on the appropriate level of stimulation that can be induced by a stimulus. Wundt introduced the concept of "optimal level of stimulation" and postulated a bell-shaped relationship between the stimulation level and the hedonic response [6]. This hedonic response is directly associated with curiosity as it represents the level of pleasure one feels while satisfying her curiosity triggered by the input stimulus. An example Wundt's curve is shown in Figure 1, where the axis x denotes the stimulus degree received by an individual and the axis y denotes the hedonic response. Lower hedonic values (unpleasantness) are achieved if the user receives too much (i.e. anxiety zone) or too little (i.e. boredom zone) stimulation, whereas maximum hedonic value (thus curiosity) is triggered by moderate stimulus.

Within this context, there is an ensemble of collative variables referring to external factors that govern several forms of stimulation selection. In particular, our analysis shall focus on some of the stimuli cited by Berlyne [6], such as:

1) Novelty, which is inversely related to frequency and dissimilarity in the stimulus pattern;
2) Uncertainty, which is related to the difficulty in deciding how to respond to a stimulus. As such, it can be quantified by the entropy [8] of stimulus pattern;

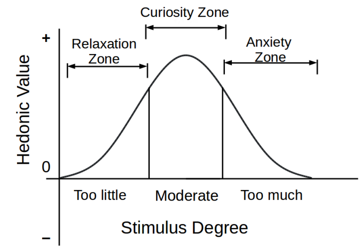


Fig. 1. Wundt's curve and respective zones.

3) Conflict, which occurs when the same stimulus triggers multiple incompatible responses in an individual.
4) Complexity refers to the diversity in a stimulus pattern.

Novelty is inversely related to the frequency, recency and dissimilarity of a stimulus with respect to past experiences of the user. The uncertainty associated with a stimulus is directly related to the difficulty of an individual in responding to it. Beryline proposed to estimate the uncertainty of a stimulus by grouping possible stimuli into classes, each representing an alternative response, and computing class probabilities.

Furthermore, conflict is related to the number of alternative responses the user may give to a stimulus, their strengths and how similar they are. Finally, complexity relates to the amount of information in a given item. In our particular setting, LastFM, songs covering multiple genres are more complex than those with a single genre.

A. Computing Stimuli

Our present goal is to analyze and model user curiosity in the particular context of online music consumption. To that end, we consider the temporal sequence of listening events of a user u. Each event i of user u is associated with a timestamp t_i and a unique song (track) s_i by an artist (singer/band) a_i. Each artist a_i has one or more tracks and is characterized by k_i ($k_i \geq 1$) musical genres $g(a_i) = [g_i^1, g_i^2, \ldots, g_i^{k_i}]$. Thus, each event i is defined by a tuple $(u, t_i, s_i, a_i, g(a_i))$.

We begin by stating that one important factor when understanding user behavior online is time. In fact, temporal aspects such as recency (e.g., last time an item was accessed) will naturally correlate with our variables. In this sense, all metrics are computed for a given user u and specific listening event i, using as input all previous listening events in the window $[t_i - w, t_i]$. Thus, the curiosity of the user for access i depends on every previous access inside the window.

Based on such temporal aspect, it is important to consider that users' curiosity will likely dwindle after long periods. Thus, in our analysis, we consider a $w = 24h$. That is, the curiosity of the user depends **only** on the events from the last 24 hours. We leave the evaluation of other windows as future work. For the sake of readability, we do not explicitly refer the user u and the time window w in our definitions.

All of our metrics will be defined in the unit of *bits*. To do so, we shall take the $\log_2$ of probabilities and compute the surprisal (in bits) [17]. This was a design choice to facilitate the aggregation of metrics. With s_i capturing the current song (track) and a_i the current artist, we define $novelty_s(i)$ and $novelty_a(i)$ as the novelty of tracks and artists. $novelty_s(i)$ is defined as:

$$novelty_s(i) \quad = \quad -\log_2\left(\frac{\sum_{j=1}^{n_l^i} I(s_j, s_i)}{n_l^i}\right) \qquad (1)$$

where $I(a, b)$ is 1 if a and b are the same and 0 otherwise. This indicator function measures the number of previous accesses in the window to the same track/artist. n_l^i captures the number of listening events in the past window. The base-2 logarithm is applied measure the surprisal (in bits) [17]. $novelty_a(i)$ is similarly defined by looking at artists instead of songs. Both metrics captures will be higher for less accessed artists/tracks.

Similarly, we define the novelty of genres at event i as:

$$novelty_g(i) = -\log_2\left(\frac{\sum_{j=1}^{k_i} number(g_i^j)/k_i}{\sum_{g\in\mathcal{G}_i} number(g)/|\mathcal{G}_i|}\right) \qquad (2)$$

where $\mathcal{G}_i$ is the set of distinct musical genres associated with all listening events in the past window, g_i^j is the j^{th} genre associated with listening event i and $j \in \{1, 2, \ldots, k_i\}$, and $number(g)$ is the number of times the user listened to an artist associated with genre g in the past window (i.e., $number(g) = \sum_{j=1}^{n_l^i}\sum_{l=1}^{k_j} I(g_j^l, g)$). Thus $novelty_g(i)$ is taken as the average number of times the user listened to each genre associated with event i during the past window, normalized by the average number of times the user listened to all distinct genres in the same period.

We propose to capture uncertainty and conflict associated with event i based on the probabilities of the user listening to different musical genres, denoted by $P(G)$. The probability of a class denotes the strength of the corresponding response, in which case the uncertainty of a stimulus relates to the Shannon entropy [17] of the classes. Specifically, uncertainty is quantified by the entropy of genres. Let $P(G = g) = number(g)/|\mathcal{G}_i|$, computed for all genres listened by the user in the past window (i.e., genres in set $\mathcal{G}_i$). Uncertainty at event i is given by:

$$uncertainty(i) = -\sum_{g\in\mathcal{G}_i} P(G = g)\log_2 P(G = g), \qquad (3)$$

Similarly, conflict is estimated by the average probability of genre, computed over all genres listened by the user in the past window:

$$conflict(i) = -\log_2\left(\frac{1}{|\mathcal{G}_i|}\sum_{g\in\mathcal{G}_i} P(G = g)\right) \qquad (4)$$

Finally, we define the two complexity metrics, instantaneous and overall complexity, denoted by $instComplex$ and $overallComplex$ respectively, as:

$$instComplex(i) \quad = \quad -\log_2\left(\frac{k_i}{n_g}\right) \quad \text{and} \qquad (5)$$

$$overallComplex(i) \quad = \quad -\log_2\left(\frac{|\mathcal{G}_i|}{n_g}\right), \qquad (6)$$

where n_g is the total number of distinct genres in the complete listening history. The instantaneous complexity is simply the fraction of the number of genres in the current song, k_i, divided by the number of genres consumed so far (including this song), n_g. The overall complexity is measured as fraction of the total number of distinct genres, i.e. $|\mathcal{G}_i|$, that exist inside window divided by the n_g. The instantaneous complexity is related to the current. It answers question's such as: how complex is this item when compared to the other items consumed. In contrast, the overall complexity is related to the window. It answers questions as: How complex is the behavior of the user in the last 24 hours.

TABLE I
STATISTICS OF LFM-1B DATASET.

Item	Number
Users	84,466
Artists	219,055
Albums	4,351,218
Tracks	9,319,305
Listening events	243,555,074
Users with at least 1K listening	43,220

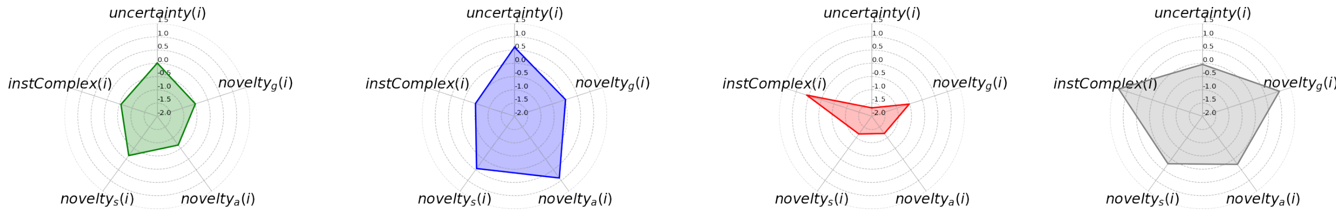
B. The LastFM Dataset

As a case study, we employ the LFM-1B Dataset of [18]. This dataset captures the listening behavior of users on the LastFM website. The data covers the period of January 2013 to August 2014. Each event recorded contains the following features: user, artist, album, track and timestamp of listening. To capture complexity, we incorporate into the dataset the genre of artists (e.g., The Beatles belongs to the rock genre). In particular, we make use of the genres defined in [19]. It is comprised of: *rnb, rap, eletronic, rock, new age, classical, reggae, blues, country, world, folk, easy listening, jazz, vocal, children's, punk, alternative, spoken word, pop* and *heavy metal*. Table I summarizes our dataset.

Recall that we compute the metrics over time windows of 24 hours. In order to avoid data sparsity issues, we consider in our analysis only users with at least 1,000 listening events in the whole period. We also only consider events with at least 30 previous listening events in each 24-hour window between January 2013 to August 2014. After such filtering, we were left with 43,220 users with 149,949,511 stimulus events.

IV. UNDERSTANDING METRICS

Before combining the proposed metrics to build a user curiosity model we first perform a careful exploration of each individual metric. In particular, we identify complementary and redundant metrics, before computing our final stimulus. Moreover, we also present a characterization of user profiles based on the subset of metrics that we consider.



(a) C_0: Underground. (b) C_1: Eclectic. (c) C_2: Niche Radical. (d) C_3: Explorer.

Fig. 2. Radar-chart with normalized stimulus metrics per cluster.

A. Variable Selection

In order to understand how metrics relate to one another, we measured the Spearman correlation coefficient ρ_s between all possible pairs of metrics. Recall that this coefficient ranges from $[-1, 1]$, with each extreme indicating perfect correlations. The Spearman coefficient was measured by creating a vector for each metric considering every access i of a user. Thus, if a user has accessed 10K songs, we have 7 vectors of size 10K to correlate.

Our end goal is to filter out redundant metrics. Thus, with the correlation coefficient we aim to identify metrics where for the majority of users the Spearman correlation exceeds a threshold of ± 0.5. In particular, we determine that two metrics are *redundant* when: over 90% of users have the value ρ_s *outside* of the range: $\rho_s \notin [-0.5, +0.5]$. When correlations are in this range for 90% of the users, we define the pair of metrics as complementary.

We define the operation $A \longleftrightarrow B$ as the relationship of correlation between two variables, where A and B are two variables from stimulus metric. It serves as initial evidence of redundant metrics. After inspecting the figure, we computed our redundancy threshold (above). We found evidence redundant relationships for:

- $conflict(i) \longleftrightarrow uncertainty(i)$;
- $conflict(i) \longleftrightarrow overallComplex(i)$;
- $overallComplex(i) \longleftrightarrow uncertainty(i)$.

To understand these findings, recall that $overallComplex(i)$ is related to the number of genres inside window's period of time. $conflict(i)$ is the probability of genre on the window. In the end, both metrics end up capturing correlated stimuli. Also, $uncertainty(i)$ is the entropy of genres inside window which, by definition, is derived from $conflict(i)$.

Although there are some cases where above correlation are somewhat expected, there are interesting cases of metrics capturing semantically related concepts (e.g., the novelty of artists, songs, and genres) that were not correlated. By filtering out redundant metrics, we can better understand the curiosity of users. Based on these findings, we keep five metrics: $novelty_s(i)$, $novelty_a(i)$, $novelty_g(i)$, $instComplex(i)$ and $uncertainty(i)$.

B. Clustering by Access Profile

We now turn our attention to uncovering the common curiosity patterns in our dataset. According to Section III-B, there are close to 150M listening events when we consider the 43K users with at least 1,000 listening events. In order to understand the common patterns, we employ a clustering approach In particular, measure each one of the five *non-redundant* metrics). In the end, we have a 150M by 5 matrix that we use to cluster *events*.

In our clustering, we make use of the Mini-Batch K-Means that that is suitable for large Web datasets [20]. To define the number of clusters k, we made use the β_{CV} and Average Silhouette score. The former, Average Silhouette score, is an aggregate measure of how similar an element is to its own cluster compared another clusters. The later, β_{CV}, is defined as the ratio of coefficient of variation (CV) of intra-clusters distances and CV of inter-cluster distances. The smallest value of k where β_{CV} remains roughly stable is selected [21].

Before clustering, we re-normalized the metrics using a Z-scale. It is well known that K-Means will lead to poor clustering when values are not normalized. Even though we omit detailed figures due to space constraints, we point out that both strategies (β_{CV} and Average Silhouette score) pointed to $k = 4$ as the more adequate choice.

To interpret our clusters, in Figure 2 we depict the centroids of each cluster. Recall that a centroid is simply the average of each of the 5 metrics. To provide further evidence that our clustering is adequate, we computed the confidence interval of 95% for each metric from the centroids. Based on these intervals, we verified that each cluster is different from the others (there is no overlap in the intervals for each metric).

To better understand our clusters, we adopt the labels used by [22]. In particular, it is important to understand that each cluster summarizes the type of events i, not users. These are labelled as follows:

- C_0 (*Underground*): The access is towards an item with similar stimuli metrics. However, the values are low indicating a tendency to stay in the relaxation zone for every metric. There are $48,627,376$ events in this cluster and it is exhibited in the Figure 2a;
- C_1 (*Eclectic*): Notice that the accesses in this cluster is regularly spread out across each metric. Different from the previous case, the metrics are higher (i.e. higher stimulus). $52,829,351$ events and it is in the Figure 2b;
- C_2 (*Niche Radical*): the Figure 2c exhibits the radar-chart for this cluster, a set of access which the user listening to repeated songs (smaller novelty). Also the songs are more complex. In total, $18,645,990$ events;

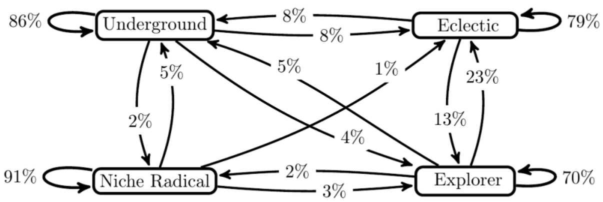


Fig. 3. Typical CBMG from overall user behavior.

TABLE II
STATISTICS OF ACCESS PROFILE VALUES PER USER.

Access Profile	1 Beta	2 Beta mix	3 Beta mix
Underground	35.54%	35.09%	36.11%
Eclectic	34.39%	32.39%	20.49%
Niche Radical	10.70%	15.38%	27.47%
Explorer	20.37%	17.14%	15.93%
Total:	100.00%	100.00%	100.00%

- C_3 (*Explorer*): the Figure 2d shows the *Explorer*. The event is very similar to *Eclectic* with $29,846,794$ events. However, its main difference is the accesses pursuing more complex music (i.e. songs with many genres).

To better understand how users transition across different clusters, we built a Customer Behavior Model Graph (CBMG) [21]. This is shown in Figure 3. The CBMG is a Markovian model. On it, nodes represent the event profile (i.e. *Underground*, *Eclectic*, *Niche Radical* and *Explorer*) and the arcs denote the transitions of specific access's profile to another. The weight of arcs denotes probabilities of transitions pattern occurring. The sum of all outgoing probabilities for each state is 1. We weight each edge as being proportional to the number of transitions across the clusters for every user.

At a first glance, one can clearly see a tendency towards repeated behavior. This is somewhat expected as repeated consumption of songs/artists is common online [23]. What is more interesting is how users tend to have higher transitions across the *Eclectic* and *Explorer* behavior. While the self-loop is high in these cases, there is a tendency (above 13%) to migrate. When the users are in the *Underground* and *Niche Radical* phases, this tendency to migrate decreases.

So far, our results point out that user behavior in terms of curiosity is quite complex. Each cluster represents a different pattern of behavior (metric values). Also, users tend to transition across these patterns. These results motivate the need of Wundt models that are able to capture such complexities. These models are discussed in the next section.

V. Curiosity Models

We now tackle our second research question: To which extent user curiosity can be accurately modelled by a Wundt's curve? Following the approach of to Zhao *et al* [4], we can estimate a *single* Wundt's curve as a Beta distribution. The Beta is a continuous probability distribution with shape parameters $\alpha > 1$ and $\beta > 1$. The probability density function (PDF) of Beta distribution is:

$$b_{\alpha,\beta}(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}, \quad \text{where} \quad B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

and Γ is the Gamma function, α and β are two positive shape parameters. The Beta is a flexible distribution that is able to capture different shapes related to the Wundt curve. In our analysis, the accesses of each user will be used to learn multiple Wundt curves. That is, we shall estimate Beta distributions for each user using as input the access metrics.

To fit the Beta models to our data, we need to map the final value of curiosity to the $[0,1]$ range (the domain of the Beta). Thus, we initially take the mean of the 5 metrics (notice that they are all in bits) for each listening event. Thus, we are capturing the average number of bits of the access. We then map the mean to $[0,1]$ range using a min-max normalization.

One of the fallacies of Zhao *et al* [4] was to assume that each user may be modelled by a single Wundt curve. Here, we shall show that this is not the case. To capture more complex behavior, we employ a mixture of Beta distributions, i.e.:

$$f(x) = \pi_1 b_{\alpha_1,\beta_1}(x) + \ldots + \pi_M b_{\alpha_M,\beta_M}(x) = \sum_{i=1}^{M} \pi_i b_{\alpha_i,\beta_i}(x),$$

where M is the number of mixture components and π_i, α_i and β_i are respectively the i-th mixture component and two shape parameters from Beta mixture distribution. We estimate mixture of betas considering $M \in \{1,2,3\}$. For the estimation of parameters, we used the Iterated Method of Moments [24].

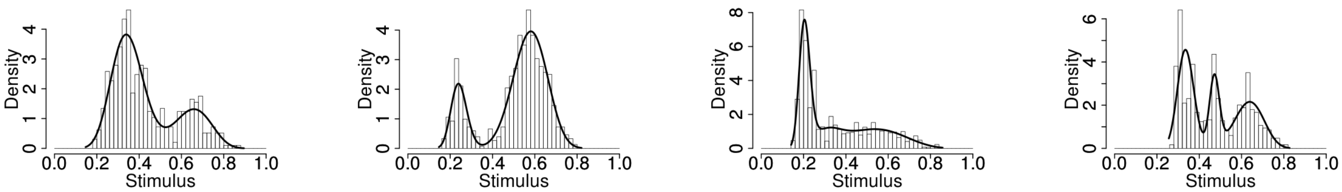
A. Classes of Wundt's Curve

For each user in our dataset, we fit Beta mixtures considering $M \in \{1,2,3\}$. To validate each mixture, we employed the Kolmogorov-Smirnov (KS) Test. Notice that we are fitting thousands of users, and thus are performing thousands of hypothesis (one for each user) tests. Given that this is a multiple comparison setting, to correct our p-values, we employ the Benjamini-Hochberg (BH) method . After p-value correction, we employ a *corrected* significance level of $\alpha^+ = 0.01$. We state the each user is modelled by the smallest mixture of Betas, smallest M, that is validated by the test.

So, when we consider all of the users, for $M \in \{1,2,3\}$ mixture of Betas 57.85% are accurately modelled by a single Beta, 36.46% of users require a two Beta mixture, and 3.96% of users are modelled by three Betas. In the end, only 1.76% were not validated by at least three Betas. These users were discarded. To exemplify our results, in Figure 4 we show four examples of users that were modelled with two and three mixtures. The Figures 4a, 4b and 4d clearly show the multi-modality of curves.

B. Curiosity and Access Patterns

We also correlated the mixture of Betas models with the types of access (clusters). To do so, Table II exhibits the fraction per access profile inside of each mixture model. This fraction is computed over all of the accesses for every user captured with 1, 2 or 3 mixtures (each column sums to 100%). From the table, we can see that *Underground* has almost



(a) 2 Beta: User ID 2349062. (b) 2 Beta: User ID 3058490. (c) 3 Beta: User ID 3058795. (d) 3 Beta: User ID 4432965.

Fig. 4. Mixed Wundt curve: examples of 4 users.

constant presence in each different model (rows). In contrast, *Eclectic* and *Explorer* show a decrease in presence as the number of mixture increases. This indicates that users captured with a single beta will mostly be stimulated by *Underground* and *Eclectic* accesses. More complex users, captured more (2 or 3) Betas, show a higher variation in such behavior. Overall, these findings serve as evidence that users that transition across multiple clusters will require more mixtures.

VI. Conclusions

In this work we provide an in-depth analysis on how to model curiosity in online content consumption. Motivated by advances both in data mining as well as psychology, we model curiosity as a mixture of Beta distribution. Each distribution capturing a Wundt's curve. In particular, we answer two research questions RQ1: Are there distinct user behavior profiles in terms of curiosity stimuli, as captured by the collative variables? and, RQ2: To which extent user curiosity can be accurately modeled by a Wundt's curve?

Our findings are important as it unveils some of the flaws of prior endeavors. In particular, we carefully inspect which collative variables should be used to model curiosity stimuli. Then we show that user curiosity is more complex than it seems, with the same user possibly being curious towards different profiles (clusters) of stimuli (RQ1). Moreover, for a large fraction of users we require more than one Wundt curve to model curiosity (RQ2).

Thus, this work serve as a basis for designing user-centric applications that consider curiosity. For instance, by identifying whether the user is in anxiety or boredom zone it is possible to stimulate the user to move until the curiosity zone recommending the right items. So, the user will achieve higher levels of curiosity score, hence leading to the user to involve more deeply into system. As future work, we can extend the findings in this paper to provide better personalized search results and recommendations. Finally, our results can be naturally extended to other domains besides music since that there is some way to classify the set of items on categories. Thus, it will be possible to compute the stimulus metrics according to collative variables and to fit the user's curiosity.

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References

[1] P. Singer, "Modeling aspects of human trails on the web by philipp singer, with prateek jain as coordinator," *SIGWEB*, no. Winter, 2016.
[2] W. Youyou, M. Kosinski, and D. Stillwell, "Computer-based personality judgments are more accurate than those made by humans," *National Academy of Sciences*, vol. 112, no. 4, pp. 1036–1040, 2015.
[3] A. M. Santos, "A hybrid recommendation system based on human curiosity," in *Proceedings of the 9th ACM RecSys*, 2015.
[4] P. Zhao and D. L. Lee, "How much novelty is relevant?: It depends on your curiosity," in *Proceedings of the 39th SIGIR ACM*, 2016.
[5] A. Greasley, A. Lamont, and J. Sloboda, "Exploring musical preferences: An in-depth qualitative study of adults' liking for music in their personal collections," *Qualitative Research in Psychology*, vol. 10, no. 4, 2013.
[6] D. Berlyne, *Conflict, Arousal and Curiosity*, ser. McGraw-Hill series in psychology. NY, USA: McGraw-Hill, 1960.
[7] G. Loewenstein, "The psychology of curiosity: A review and reinterpretation," *Psychological Bulletin*, vol. 116, no. 1, pp. 75–98, 1994.
[8] Q. Wu and C. Miao, "Curiosity: From psychology to computation," *ACM Computing Surveys*, vol. 46, no. 2, pp. 18:1–18:26, 2013.
[9] K. E. Merrick and M. L. Maher, *Motivated Reinforcement Learning: Curious Characteres for Multiuser Gamers*. Germany: Springer-Verlag Berlin Heidelberg, 2009.
[10] E. Law and et al, "Curiosity killed the cat, but makes crowdwork better," in *Proceedings of the ACM CHI*, 2016.
[11] A. Manyangara and E. G. Toms, "The effect of cognitive style and curiosity on information task multitasking," in *ACM IIiX*, 2010.
[12] R. Saunders and J. S. Gero, "How to study artificial creativity," in *Proceedings of the 4th ACM Creativity & Cognition*, 2002.
[13] L. Macedo and A. Cardoso, "The role of surprise, curiosity and hunger on exploration of unknown environments populated with entities," in *IEEE EPIA*, 2005.
[14] V. Maccatrozzo and et al, "Sirup: Serendipity in recommendations via user perceptions," in *Proceedings of the 22nd ACM IUI*, 2017.
[15] X. Niu and F. Abbas, "A framework for computational serendipity," in *Proceedings of the 25th UMAP ACM*, 2017.
[16] Q. Wu, S. Liu, and C. Miao, "Modeling uncertainty driven curiosity for social recommendation," in *Proceedings of the ACM WI*, 2017.
[17] D. MacKay, *Information Theory, Inference, and Learning Algorithms*. Cambridge, UK: Cambridge University Press, 2005.
[18] M. Schedl, "The lfm-1b dataset for music retrieval and recommendation," in *Proceedings of the ACM ICMR*, 2016.
[19] M. Schedl and B. Ferwerda, "Large-scale analysis of group-specific music genre taste from collaborative tags," in *IEEE ISM*, 2017.
[20] D. Sculley, "Web-scale k-means clustering," in *Proccedings of the ACM WWW*, 2010.
[21] D. A. Menasce and V. Almeida, *Scaling for E Business: Technologies, Models, Performance, and Capacity Planning*. USA: Pren. Hall, 2000.
[22] A. M. Ramos, N. Andrade, and L. B. Marinho, "Exploring the relation between novelty aspects and preferences in music listening," in *Proceedings of the 14th ISMIR*, 2013.
[23] A. R. Benson, R. Kumar, and A. Tomkins, "Modeling user consumption sequences," in *Proceedings of the 25th ACM WWW*, 2016.
[24] C. Schröder and S. Rahmann, "A hybrid parameter estimation algorithm for beta mixtures and applications to methylation state classification," *Algorithms for Molecular Biology*, vol. 12, no. 1, pp. 12–21, 2017.