A CHARACTERIZATION METHODOLOGY OF EVOLUTIONARY BEHAVIOR IN RECOMMENDER SYSTEMS

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Abstract: Recommender Systems (RSs) have become increasingly important tools for various commercial applications on the Web. Despite numerous efforts, RSs still require improvements to make recommendation more effective and applicable to many real scenarios. Recent studies point out the temporal evolution as a primordial manner for improving RSs without, however, understand in detail how this evolution emerges. Thus, we propose a methodology for evolutive characterization of users and applications in order to provide a better understanding of this temporal dynamic in RSs. Applying our methodology in a real scenario has proved to be useful even to help in the choice of RSs adherents of each scenario.

1 INTRODUCTION

The large volume of data available on the WEB has generated in recent years a challenging scenario for various applications. Users have more options that can effectively handle (Adomavicius and Tuzhilin, 2005). Several commercial applications, such as Amazon, Last.Fm, among others, provide a collection of items with millions of distinct products. Although the availability of a wide range of options has been a desired scenario in the past, nowadays represents a major challenge. In fact, we can state that this large amount of options is "choking" the users, making the simple choice of products of user interest a difficult task. In this context, the Recommender Systems (RSs), which allow filtering this amount of information, showing only what can be useful to user interest, are becoming increasingly important.

Several strategies to recommend products, information and services to users have been proposed recently (Adomavicius and Tuzhilin, 2001a; Burke, 2002; Abbasse and Mirrokni, 2007). The main idea of the RSs is to estimate potentially interesting items to users, based on a prior knowledge of their behavior, as well as relevant characteristics of these items. Although the idea is simple, its implementation presents many computational challenges ranging from how to model the users behavior, to how to use this modeling information to provide the recommendation itself. For instance, user behavior can be represented by any subset of items he has consumed, or even by items not yet consumed but that may be relevant to the system or to the user, given a metric of interest. While there are numerous proposals, current RSs still need improvements to address these challenges and make the recommendation more effective and applicable to a wider range of scenarios, such as trip advice, financial services, among others (Adomavicius and Tuzhilin, 2001b).

Such challenges are being addressed by incorporating some dimensions of analysis into RSs. Currently, particular attention is being given to the temporal dimension (Koren, 2009), due to the dynamic aspect of user behavior. The user taste is not a static characteristic, exhibiting changes over time. A same user may has distinct opinions about the same object in different moments. Several studies agree on the impact of taste shifts to the recommendation (Adomavicius et al., 2005; Adomavicius and Tuzhilin, 2001b; Koren, 2009). As a consequence, the user model-

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ing should be continuously updated to reflect such natural changes. In this sense, a major activity is to understand and measure the variability associated with the user behaviors and with the applications over time, as well as the interaction between them. Despite the relevance of this understanding, we did not find any studies that analyze how this temporal evolution, which we call evolutionary behavior, emerges in RSs.

In this work we present a methodology for evolutionary characterization of users and applications, which is divided into three main steps that represent a hierarchical view of the RS domains. The objective is to measure a not closed set of characteristics that vary over time and that would affect the quality of the RSs. Such information will provide subsidies for the proposal of new techniques in RSs, as well as for proper changes in traditional techniques. For instance, through our methodology we can assess practical issues about RSs, usually disregarded in the literature, such as: How often users tend to consume the same item?; How diverse is the user consumption in a given period of time?; What is the time interval between consecutive accesses of the users in the system?

In order to validate our methodology, we have chosen the *Last.Fm*, one of the largest virtual musical community in the world. The results showed that *Last.Fm* is mainly composed by activities of new users, that present a decreasing consumption trend. Further, the user behaviors are concentrated in few distinct items, exhibiting a high repetition rate in the consumption and a very dynamic behavior, quickly varying their set of favorite songs. Such observations allowed to assist in identifying the most appropriate techniques for recommendation to *Last.Fm* besides to properly redefine some traditional RSs assumptions. In summary, the main contributions of this work can be described as the proposal of a new methodology of evolutionary characterization, and a deeper and useful understanding of an actual recommendation domain.

The remainder of this paper is organized as follows. Section 2 discusses the main related work. Section 3 presents our methodology of characterization. After, in Section 4, we apply the proposal methodology in data derived from the *Last.Fm*. Finally, in Section 5, we conclude and discuss future work.

2 RELATED WORK

Recommender Systems (RSs) play currently an important role in e-commerce systems, assisting users in finding their favorite items and services. At this way, several studies propose new strategies to recommend products, information and services to users in various domains (Burke, 2002). However, several challenges make the effectiveness and applicability of current techniques inadequate for many scenarios (Adomavicius and Tuzhilin, 2005). Some of these challenges have been studied extensively, and metrics that allow to identify and to measure them in real domains are recurrently investigated.

A first challenge consists of modeling the user behavior. Since each user can be modeled through a distinct subset of objects (e.g., only for objects consumed by him, or by objects considered relevant to the domain), identifying the best model represents a complex task. Nevertheless, most studies about user modeling in RSs are done in a simplistic way, without take into account some relevant characteristics of the user behavior, such as the items relevance for each user. For instance, metrics that quantify the consumption diversity of each user may provide useful information about the appropriate size of the object sets that model the users. A second challenge refers to data sparsity, established by the very nature of commercial applications. As the number of distinct objects in these domains is generally huge, users are able to consume only a small portion of the existing items. Moreover, there is a high concentration of users around a few distinct objects followed by a downward concentration around other objects, a phenomenon known as heavy tail (Anderson, 2006), accentuating the data sparsity. In this context, measuring the emergence of new users and items over time in recommendation domain allows to identify the actual impact of sparsity in RSs. Some studies even suggest specific techniques to address this problem in RSs (Wu and Li, 2008).

Another common challenge in RSs consists of providing diversified recommendations (McSherry, 2002; Lathia et al., 2010). Although the domains where the RSs operate have a wide variety of items, the recommendations are generally somewhat diversified. In (Zhang and Hurley, 2008), for example, the authors model the diversity of the recommendation as an optimization problem. We also can point out the so called *Cold Start* problem as a challenge for RSS. The *Cold Start* refers to the difficulty in making recommendations on new items or for new users, since there is little information in the system about such items and users (Schein et al., 2002). In fact, one major challenge is to provide precise recommendations when little is known about the users (Adomavicius and Tuzhilin, 2005).

More recently, a new challenge has been analyzed in RSs: the temporal evolution of the data (Koren, 2009; Cremonesi and Turrin, 2010). Traditionally, RSs are based on the premise that users past behavior repeats in the future. However, this assumption is not always true, since data may change over time. For instance, new objects appear and opinions about the same objects vary over time. Thus, the analysis of these data need to find a balance between penalizing time effects that have low impact on future behavior, while capturing trends that reflect inherent recurring patterns in the data.

Efforts on temporal evolution in RSs can be classified into two groups. The first one includes studies which focus on assessing the quality of the recommendations over time. In (Lathia et al., 2009), the impact of temporal dynamics on the recommendations is evaluated. In (Zhang and Hurley, 2008), the authors assess how the diversity of the recommendation is affected over time. In the second group we have works that propose new recommendation models that take into account the temporal evolution (Cremonesi and Turrin, 2010). In (Koren, 2009), the authors argue that proposing recommendation models that take into consideration the time tends to be more effective than proposing complex models. Thus, variations on the profiles of the users over time have been incorporated to RSs (Stern et al., 2009).

Our work differs from others by analyzing how the temporal dynamics emerges in recommendation scenarios, as well as by evaluating how some metrics related to the aforementioned challenges behave over time. Despite various efforts, we did not find any studies that aim to characterize and to understand the temporal evolution in RSs. We believe that this understanding is relevant not only to propose techniques that address the temporal dynamics properly, but also to provide a better understanding of the other recommendation challenges. Quantifying each of the mentioned challenges, and how they evolve over time, allow us to identify which should be prioritized, and consequently, what techniques are best suited to each domain.

3 METHODOLOGY

In this section we present our characterization methodology of the evolutionary behavior in recommendation environments. In order to characterize different dimensions of each domain, we divide this methodology in three main steps, namely **System Context Analysis**, **Interaction Analysis** and **Users Profile Analysis**. Each step has a not closed set of metrics that can capture relevant aspects of the domain, which vary over time and that may affect the quality of the recommendation. The choice of these metrics is based on their correlation with the main challenges currently studied in RSs, as pointed out by previous studies described in section 2. Further, new metrics can be also incorporated into our methodology as other relevant aspects are identified.

It is noteworthy that, although these steps are independent and can be applied separately, they represent a hierarchical view of the recommendation environments. The objective of the **System Context Analysis** is to evaluate how the supply of items is defined over time as well as to identify the business rules established by the recommendation domain. After, we evaluate in the **Interaction Analysis** how users interact with the system during their lifetime. Finally, in the **Users Profile Analysis**, we characterize how the users behave, regarding the consumption of items available in the domain, and how this behavior changes over time. In the subsequent sections, we describe in detail the goals and major metrics related to each of the above steps of our methodology.

3.1 System Context Analysis

This first step of our methodology aims to understand the evaluated environment. Identifying inherent characteristics of the objects and the interaction pattern between objects and users, defined by the environment, represents the main direction of this analysis. For example, the “consumption” of songs may differ essentially from the “consumption” of videos. It is verified since it is assumed that users listen to the same songs again and again more often than watch the same videos. Another relevant aspect would be the distribution of items popularity in each domain. While in some areas, such as songs and videos, popular items are orders of magnitude more consumed than unpopular items in others, such as restaurant recommendation, this difference is not as prominent. Therefore, we consider how these features define a set of general “parameters” for the recommendation in each domain, by being able to inform the recommender systems aspects that enable them to adapt to each domain. For instance, knowing that a same user often consumes the same item repeatedly may suggest to the recommender that it can make the same recommendation for the same user more than once.

In order to accomplish this analysis, there is a list of metrics in Table 1 that we consider relevant. The choice of such metrics was done through a systematic collection of information that can be directly used by recommender systems. It is important to mention that, as in the other steps, we are not interested in list a closed set of all existing and possible to be measured “parameters”.

Table 1: Metrics for System Context Analysis (CA).

Metric	Description
Distribution of lifetime in the system (**CA-1**)	For each user, we determine his lifetime, from his registration moment until the analysis moment. At this way, we are able to verify if users of a given domain tend to remain in the system for a long time.
Distribution of consumed items (**CA-2**)	For each user, we measure the total number of items consumed throughout his lifetime until the analysis moment. This distribution shows how many items, in general, users consume in the domain.
Distribution of items popularity (**CA-3**)	For each distinct item, we determine the number of different users who have consumed it, at least once, during the period of analysis. Therefore, we evaluate the probability of an item become popular in the system.
Emergence rate of users and distinct consumed items (**CA-4**)	For each moment of analysis, we calculate the number of distinct items and users in the system. Thus, it is possible to identify the diversification trend of the environment in terms of users and objects.
Repetition rate in items consumption (**CA-5**)	For each moment of analysis, we divide the total number of consumed items by the number of distinct consumed items at each moment. This information is particularly useful since it measures the recommender "freedom" in offering repeatedly a same item to a same user.

Table 2: Metrics for Interaction Analysis (IA).

Metric	Description
System usage time (**IA-1**)	It is defined as the amount of temporal units of a user lifetime that he actually have consumed items or have accessed the system.
Interval between accesses over time (**IA-2**)	The interval between accesses is given by the average time interval between consecutive accesses of a same user. An analysis of these intervals over time shows whether users are gradually abandoning the system or not.
Consumption frequency per lifetime (**IA-3**)	It represents the average number of items consumed by users in each distinct moment of their lifetimes. This information may be relevant for evaluating if the system has an increasing trend of consumption. An important issue closely related to this analysis is whether "older" users in the system have a higher consumption profile or not.
Distribution of consumption rate per access (**IA-4**)	It is defined by dividing the number of requests that an item gets by the number of times it was consumed (in scenarios where such distinction is valid).

3.2 Interaction Analysis

Having identified the characteristics of the recommendation domain, our next step consists of understanding how the users use and interact with the system. Aspects such as how often they consume items, the temporal gap between consecutive consumptions, the system usage assiduity, among others, represent important information about how the systems are used. The usefulness of such information to the recommenders can be illustrated by considering the information from the Interval between accesses over time, as defined in Table 2. Users with a smaller interval between accesses may impose a stronger requirement of diversity for their recommendation list, since consuming very similar items in a short period of time may annoy the users.

The major metrics defined for this step are described in Table 2. As mentioned, the proposed set of metrics can be expanded to capture other relevant information to the recommenders. For example, metrics based on access log, which determine the user navigation paths in the system, or access time, among others, represent potentially relevant information.

3.3 Users Profile Analysis

Finally, our methodology focuses on understanding the behavior of users in the system regarding the consumed object, defined as the user profile. In fact, this step represents a quantitative analysis about the users behavior. Such analysis is based on two main dimensions: the diversity of items consumed by each user as well as the temporization of their actions. We mean by temporization the measurements of the time intervals between the actions of a user on the system in order to understand recurrent behavioral patterns over time. The understanding of this profile is essential to guide the recommendation in an individualized strategy. For example, knowing that users, or even a specific user, have an average diversity in consumption of X distinct items per week suggests that the recommender should not provide more than X distinct items per week to each user.

Table 3: Metrics for Diversity Analysis (DA) of Consumption.

Metric	**Description**
Diversity Distribution (**DA-1**)	For each user, we determine the number of distinct items consumed throughout his lifetime in the system. Such information describe the consumption profiles of the users regarding the items diversification.
Average diversity per lifetime (**DA-2**)	For each user "age" in the system, measured through the temporal unit of analysis, we verify how many distinct items on average the users consume. Thus we can identify the trend of diversification of the users consumption profiles during their lifetime.
Items Diversity in an ordered set of size N (**DA-3**)	For each moment X of analysis, we measure the percentage of overlap between the N most relevant items for a user u_i at the moment X and the N most relevant items for u_i at each distinct moment Y after X.
Relevance Variability of the Items (**DA-4**)	It determines the mean value of relevance of the items consumed by each user at each distinct moment.

It is important to point out that the definition of some mentioned metrics, both for the Diversity of Consumption Analysis and for the Actions Temporization, uses an ordered set of items for each user, that is based on a relevance measure. We can define the relative relevance of the items considering different aspects, such as consumption frequency, similarity between items, transition probability in a "navigation" network between items, among others. Thus, most relevant items are in top positions in the set, while less important ones are maintained in the last positions. Moreover, the proposed analysis can be performed by considering different temporal granularities (e.g., weeks, months, semesters, among others) as well as different sizes of item sets. At this way, it is possible to define a broader evaluation, able to contrast the evolutionary behavior of users in different temporal granularities, as well for distinct sizes of item sets.

Next, we define the main metrics used for both dimensions of the Users Profile Analysis:

- Diversity of Consumption: it aims to evaluate how users behave in terms of diversity of consumed objects. Moreover, variations of this diversity over time, as well as its evolutionary trend is the research focus in this step of the analysis. The proposed metrics for this analysis are presented in Table 3.
- Actions Temporization: it aims to understand recurrent behavioral patterns over time, such as the time period in which users consume the items and the time required for an item no longer be consumed or be re-consumed. The proposed metrics for this analysis are presented in Table 4.

In the following section we apply the metrics described in this section on data derived from the *Last.Fm*, bringing up the opportunity to further discuss the main concepts related to each of them. Moreover, we present the conclusions that can be obtained by applying our methodology, as well as several kinds of useful information that can be exploited by RSs. Finally, we discuss how such information can help to identify the most promising RSs techniques for domains with distinct characteristics.

4 CASE STUDY

4.1 Database Description

In order to set the context, we present the dataset used in our analysis. We use a dataset from *Last.Fm* system[1], which is an UK-based Internet radio and music community website, founded in 2002. At the moment of the data acquisition, it claimed over 30 million active users. It is also estimated that *Last.Fm* had more than 27 million different tracks and 12 million distinct artists in its database[2]. As *Last.Fm* represents one of the biggest musical community in the world, and since all the data is readily available on the WEB, it is a good data source for music recommender systems.

Our analysis was performed on a sample of data from *Last.Fm*. These data were collected through an API provided by *Last.Fm*[3]. This API allows us to obtain information related to several data entities such as artists, albums, tracks, users, among others. We consider as relevant to our analysis only information related to users and tracks. Such information was collected for a set of 146,973 distinct users and 1,515,258 distinct tracks in the time interval from 02/12/2005 to 04/26/2009.

[1] Available at http://www.last.Fm/.

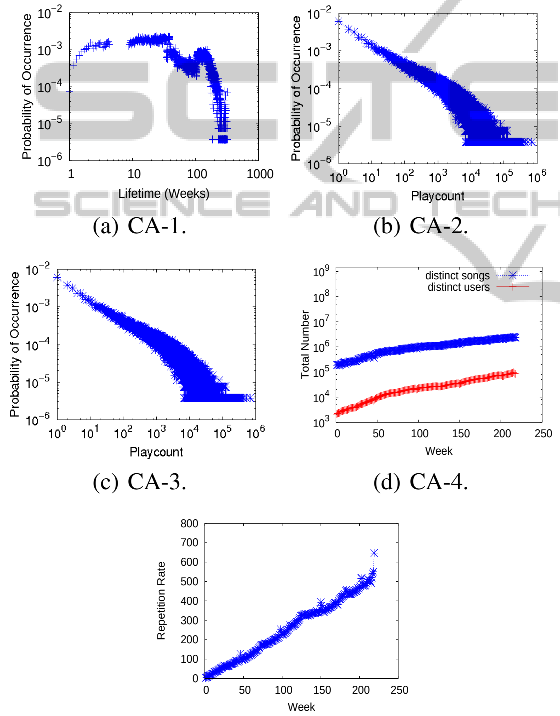
[2] These information were retrieved from the *Last.Fm Radio Announcement*, on 03/25/2009, available at http://blog.last.fm/2009/03/24/lastfm-radio-announcement.

[3] http://www.last.fm/api.

Table 4: Metrics for Temporization Analysis (TA) of Actions.

Metric	**Description**
Distribution of Stability Period (**TA-1**)	It determines the continuous period of time that items remain as the most relevant to each user. A distribution of these values shows if, in general, items remain relevant for a long period in a domain.
Probability of Re-execution (**TA-2**)	It determines the probability of an item more relevant in the moment X be consumed at least once in every moment Y after X. This measure is related with the possibility of an item to be relevant again in future, given that it is relevant in the present.
Saturation Time (**TA-3**)	It determines the average time required for an item no longer be consumed, from the moment it was first consumed by each user.
Probability of Return (**TA-4**)	It determines the probability of an item that has been relevant for a user in the past, but is no longer consumed by him, come back to be consumed again.

4.2 System Context Analysis



(a) CA-1. (b) CA-2. (c) CA-3. (d) CA-4. (e) CA-5.

Figure 1: Context Analysis Metrics.

The plots in Figure 1 present the metrics described for the Context Analysis in the previous section. We start our analysis by the distribution of the users lifetime in the system, shown in Figure 1 *(a)*. We can see that most collected users have between 10 and 50 weeks of lifetime in the system. Very short periods (less than 5 weeks) or very long ones (over 150 weeks) have a very low probability of occurrence. This shows that although users explore the system for some period, *Last.Fm* is not able to keep them assiduous for a long time.

In Figure 1 *(b)* we present the distribution of total number of songs listened to by the users. We observe that the probability of users listen to few songs in the system is very high. Furthermore, it is important to realize that this distribution follows a power law, emphasizing the huge difference of probabilities between listening to few songs and many songs. Thus, in addition to remain for a short period of time in the system, users tend to consume few items, stressing the *Cold Start* problem for recommendation in the *Last.Fm* (Schein et al., 2002).

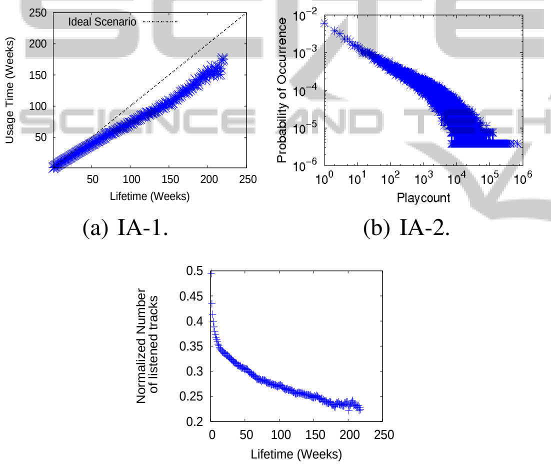
Our next analysis concerns to the distribution of song popularity in the system, as shown in Figure 1 *(c)*. Most of the tracks in our dataset have been listened to by less than 100 distinct users, and only a very restricted number of them have been listened to by many users. Thus, *Last.Fm* represents a scenario in which very few items manage to become popular. Consequently, simple recommendations strategies based on popularity would not be appropriate for most of the items.

The graphic in Figure 1 *(d)* presents the number of distinct users and items that arise in the system at each moment. Since we do not have the whole set of users and tracks that appear in the *Last.Fm* globally, this plot, in fact, exhibit the set of new users that appear in our dataset at each week and the number of distinct songs that were listened to by at least one user from this set at each week. As we can see, there is a significant increase of unique users present in the system each week, and also an increase of distinct musics. Such growth in the number of users and tracks is slightly rising, generating an increasing sparsity of information for RSs, which, to be effective, must be skilled in dealing with this problem.

Finally, we analyze the repetition rate in the consumption, as presented in Figure 1 *(e)*. We note that *Last.Fm* not only constitutes an environment with high repetition rate, but also by a growing trend in that rate. That is, despite the amount of distinct tracks increases over time, users tend to listen to more often the same tracks over time. This observation has two important implications for recommenders. The first one is that items already consumed by the users could be recommended again for several times. The second implication is that the recommenders should be robust to the super specialization problem, avoiding the recommendations to be always anchored in the items already known by the users.

In summary, the context analysis suggests that *Last.Fm* represents a challenging scenario to recommenders, since, despite the huge diversity of users and items, the usage history for most users is small, concentrated in few items, and is characterized by a high repetition rate in consumption. Further, simple popularity-based strategies for recommendation seems to be not effective in this scenario.

4.3 Interaction Analysis



(a) IA-1. (b) IA-2.

(c) IA-3.

Figure 2: Interaction Analysis Metrics.

We start the interaction analysis in the *Last.Fm* observing the Figure 2 *(a)*, which shows the Usage Time per Lifetime for all users. Both metrics are calculated considering the number of distinct weeks. The curve called “Ideal Scenario” represents the scenario in which the usage time is equal to the lifetime, that is, the users listen to songs in the system every week during their lifetime. It is interesting to note that over time users tend to use less frequently the system. In the *Last.Fm*, as users “grow old” in the system, the usage time tends to move away from the lifetime. In this case, more decisive recommendation strategies are necessary in order to keep users in the system.

Our next analysis concerns about the average interval between system accesses. Figure 2 *(b)* presents the *Complementary Cumulative Distribution Function* (CCDF) for these interval. Actually, as we do not have the access log for the *Last.Fm*, we measure the interval between consecutive listenings for each user. We can observe that only 0.1% of the users have an interval greater than 10 weeks, that is, the vast majority of users have a small average interval between listenings. Moreover, as the time interval increases, the percentage of users decreases, following two distinct linear regimes: at first, until about the tenth week, the decay is sharp, from this point the decay becomes smoother. This result, associated to that presented in Figure 1 *(a)*, shows that in *Last.Fm* new users use the system frequently, but tend to abandon it quickly instead of gradually reducing their system usage. This information is important for recommenders, which can prioritize users with an interval between listenings that is slightly more than 1 week, since they will potentially abandon the system.

Figure 2 *(c)* shows the average number of songs listened to by users over time. This average was calculated using the values normalized by the maximum number of songs listened to by each user in a single week. As we can note, there is a noticeable decay in the number of songs listened to over time. In general, users tend to use the system less frequently. Again, RSs may be relevant tools to reduce this decay in the usage frequency.

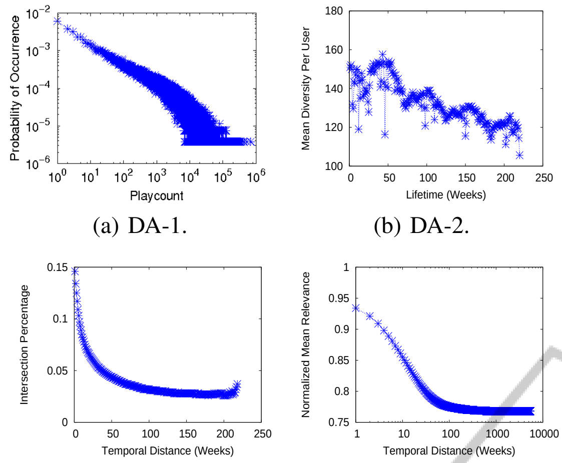
From the analysis of this step we can better discern the interaction between the users and the *Last.Fm*, characterizing the latter as a system primarily composed by activities performed by new users, which present a downward consumption trend. Such behavior may be related to some type of system limitation, such as poor quality recommendations or lack of some features in the system. Some of the metrics defined in Section 3 could not be evaluated because we do not have information about access in our data.

4.4 Users Profile Analysis

As described in Section 3, we divide our user profile analysis into two steps: Diversity Analysis and Temporization Analysis. The following subsections describe the main results found at each step. The understanding of this profile, along with the understanding of the environment and the user interactions, previously obtained, comprises a set of extremely rich and useful information for RSs.

4.4.1 Consumption Diversity

In Figure 3 *(a)* we present the diversity distribution of items consumed by the users. We observe that the vast majority of users (more than 90%) listen to up to 200 distinct songs, while few users have a very high diversity of songs (i.e., above 5,000). This shows that users in *Last.Fm* have a consume behavior focused on



(a) DA-1. (b) DA-2. (c) DA-3. (d) DA-4.

Figure 3: Diversity Analysis Metrics.

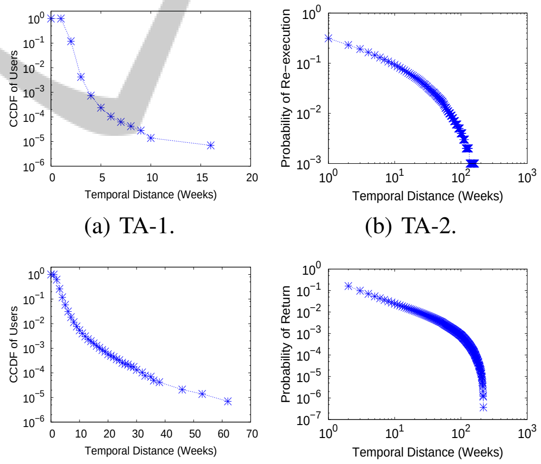
a small number of distinct items. Thus, it is possible to draw distinct consumer profiles based on how diverse are their consumption historic, and RSs can provide recommendations with diversity levels according to each consumer profile.

In addition, Figure 3 *(b)* presents the mean diversity of consumed items per user over time. We observed that users listen to, on average, 150 distinct songs in their first weeks of life. However, as the users "grow older" in the system, the diversity of consumed items reduces significantly. This information may be relevant to RSs, since it informs to them, at each moment, the limit of items diversity to be recommended.

We also analyzed the intersection between the most relevant items consumed by users at distinct moments over time, as shown in Figure 3 *(c)*. In this case, we defined as relevance metric the frequency with which each distinct track was listened to by each user in each single week. After, we select for analysis only the 100 most relevant tracks for each user in each week. At the end, we calculate the intersection percentage between each week X and all other further weeks Y, and define a mean intersection percentage per temporal distance between X and Y. We observe that the percentage of intersection is very low even between adjacent weeks (i.e., less than 15%). Moreover, this intersection quickly decreases over time, obeying a power law and achieving a value close to zero in 54 weeks. That is, within one year, the users habit changes almost completely. At this way, we can guide the recommenders about the percentage of music currently consumed by each user that should be changed at each different time interval (e.g., every week, month or semester).

Finally, we show in Figure 3 *(d)* the analysis of relevance variability of the consumed items over time. Again, we defined the relevance metric as the frequency with which each song was listened to at each distinct week. The frequency of each pair user/song was normalized by the highest frequency with which the user listened to, in a single week, the song. Starting from the first time a user listened to each song, we calculated the average relevance of all songs at each subsequent moments. Finally, we defined an average value of relevance for all pairs of user/music observed in each of these subsequent moments. We observe that the average song relevance tends to be high at moments close to when they were listened to for the first time. In the later moments, this relevance decreases sharply, stabilizing at very low values. This shows that a song remains interesting to the users only for a short period of time, close to the first moment it was listened to. Since *Last.Fm* is an environment with a high consumption repetition, this relevance decay suggests that repeated recommendations are more prone to succeed at moments near to the first time that each song was listened to.

4.4.2 Actions Temporization



(a) TA-1. (b) TA-2. (c) TA-3. (d) TA-4.

Figure 4: Actions Temporization Metrics.

First, we evaluate the distribution of stability periods in the *Last.Fm*, Figure 4 *(a)*. For this analysis we considered only the five most relevant songs (i.e., favorite songs) to each user at each distinct moment over time. Further, we defined temporal distances for each song considering the first time that it becomes favorite for a user. For instance, the temporal distance zero refers to the first moment in which a song figures between the 5 favorite songs for a user. We can observe that, on average, almost all songs figure as the 5 most relevant ones for a user about two consecutive weeks. However, in the third week (i.e., temporal distance 2) only 2.5% of the songs remains among the favorites. This clearly shows that the users preference remains stable for a short period, generating a certain dynamics in the set of favorite songs that should be captured by RSs.

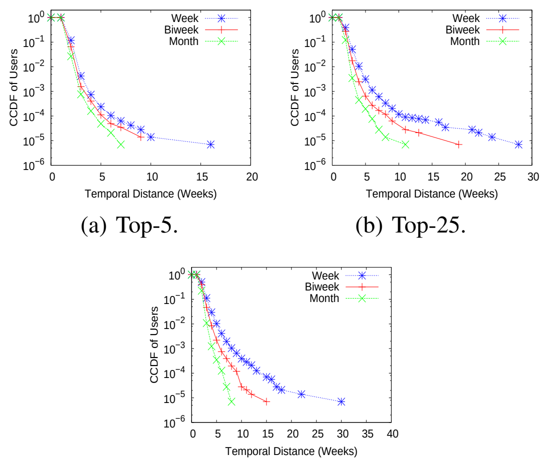
Our next evaluation is about the probability of re-execution of the favorite songs. Thus, we present in Figure 4 *(b)* the average probability of a favorite song be listened to at each temporal distance starting from the week in which it became favorite. We observed that only a third of the songs that have become the favorite are listened to again in the next week. Moreover, only 23% of them are listened to again after two weeks. This decay follows a power law until the hundredth week. These observations suggest that recommending favorite songs after a few weeks would not be a good strategy, since the users might be "saturated" quickly. Another interesting point is that, from the hundredth week, the probability of a user listen to their favorite songs is almost zero, which shows that older songs may become "forgotten" by the users.

In Figure 4 *(c)* we show the results for the saturation time analysis. For this analysis we measured how long, on average, a user can continually listen to songs that have been, at some point, between the 5 favorites. We can observe that the probability of any music been listened to by two (98%) or three (62%) consecutive weeks, after to become one of the five favorites is much higher than during more than four weeks (6% only). This shows that, in general, users are interested in listening to a song for a short period of time, presenting subsequently a significantly lower interest for these songs.

We also evaluate the average probability of return for the favorite songs of each user. For such analysis, we evaluate the probability of the weekly most relevant song *X* of each user to figure between his 100 favorite songs at each distinct week after the first time *X* has no longer been listened, defined as the temporal distance zero. Figure 4 *(d)* presents the distribution of the average probability of return for all favorite songs at each moment. We note that just over 15% of these songs are listened to a week after the first week they are not observed between the 100 most relevant songs. The probabilities present a descendant behavior that also follows a power law for temporal distances up to approximately 150 weeks. This shows that, in fact, over time the songs become "forgotten". Therefore, we have two important implications for RSs. The first one is that once the user stops listening to a favorite song, it will hardly return to listen to it in the near future. The second implication is that in a distant future such songs could be a good way to diversify the recommendation to users.

The analysis of this step allows us to define *Last.Fm* users as presenting a not very diversified consumption, besides defining a very dynamic behavior, quickly varying the set of favorite songs. In addition, each song is most often consumed at moments close to the first time users listened to them. We also note that such users listen to the same song during a short and continuous period of time, and once they stop listening to it, they will hardly listen to it again.

Finally, it is important to note that several of the metrics analyzed in this section may be reevaluated varying both temporal granularities and distinct sizes of ordered sets. Thus, it is possible to contrast the evolutionary behavior considering different perspectives of analysis. In the plots of Figure 5, for example, we present an analysis of the distribution of stability period for various temporal granularities, aggregated by different sizes of ordered sets. An interesting aspect to note is that as we increase the temporal granularity, the decay of probabilities is more pronounced, showing that in longer periods of time there is a larger diversity of items consumed by users. We also note that, as we increase the size of the analyzed set, the differences of probabilities between major and minor temporal granularities tend to be higher. This shows that larger sets of favorite items are more stable at lower temporal granularities. Thus, it would be possible to define distinct recommendation strategies by combining the user behavior in distinct temporal granularities, as well as the sizes of ordered sets, in order to provide more precise recommendations.



(a) Top-5. (b) Top-25.

(c) Top-50.

Figure 5: Analysis of AT-1 Metric for distinct Top-N.

In general, the information from each step of our methodology can assist in choosing the most appropriate recommendations techniques for each scenario. For *Last.Fm*, for example, we observed that the *Cold*

Start issue is more prominent than the problem of sparsity. Therefore, techniques such as those proposed in (Schein et al., 2002) are preferable. Moreover, we note that a model based only on the top-*N* musics listened to by a user may be more promising than to consider all the musics he listened to in a given period, since the musics diversity is low and there is a high repetition rate in the system. Considering the challenge of temporal evolution, we found that smaller temporal granularities are better both to model user behavior and to update the “knowledge” of the RSs, since users in the *Last.Fm* are highly dynamic, changing the set of favorite songs quickly. Finally, it’s worth to note that, in this domain, the diversification of the recommendation is an issue bigger than the accuracy, since users often consume items that they already know. Thus, techniques to diversify recommendation like those presented in (Zhang and Hurley, 2008) are particularly relevant to *Last.Fm*.

A point to be highlighted is the need to validate these observations and conclusions. For this purpose, we adopted as validation strategy the implementation of a new RS method, which incorporates many of the observations raised up, and the subsequent contrast of results between the proposed technique and traditional ones. This strategy is currently in development and its application on the *Last.fm* represents our next step.

5 CONCLUSIONS AND FUTURE WORKS

In this work, we present a methodology for evolutionary characterization of users and applications in order to provide subsidies for the proposal of new recommendation techniques, as well as for proper changes in traditional techniques. Despite the relevance of the temporal evolution over the recommendation, we did not find studies that aim to understand and characterize such evolution. In turn, our methodology is useful for assessing practical issues about RSs, usually disregarded in the literature.

In order to verify the applicability of our methodology, we evaluate as a case study the music system *Last.Fm*. Measurements of a not closed set of characteristics pertinent to recommendation domains allowed us to better understand the *Last.Fm*. This is an environment with a wide diversity of items, as well as a growing number of users and new items over time. However, *Last.Fm* fails to keep its users for a long time, becoming anchored by new users, who present a low and declining system usage rate. These findings allow us to identify a series of challenges for recommender systems, such as increasing sparsity of the domain, little information about the users, and the *Cold Start* problem.

The relevance of this type of observation goes beyond the understanding of the environment. It allows us to better identify which recommendation techniques would be more appropriate for each type of environment, and better adjust RSs in order to provide better recommendations. For instance, for *Last.FM* we verified that specific techniques that address the problems of *Cold Start* and low diversity in recommendations are more relevant.

As future work, we aim, at first, to validate our conclusions. For such, we are implementing a new RS method, which incorporates several of the observations raised up, that will be applied to the *Last.fm*. Results of this new technique will be contrasted with traditional ones, in order to verify the relevance of these new information. Later, we aim to analyze other metrics, as well as to apply our methodology in other recommendation scenarios. .

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