

An Effective User Profiling Data Structure for Dynamic License

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Abstract

In this work, we defined and constructed an effective user profiling data structure for the dynamic license of digital contents. The user profiling data structure can be deduced from the analysis on existing digital music license purchase pattern included in the user profiling data. It is designed to trace the user's license purchase pattern and can be used to analyze and trace the user's license access pattern with the history based aged-MRU algorithm. Since dynamic license has more complicate features on describing license actions and relations with other persons than static license, the user profiling data structure also should have more member items in metadata. By comparing the difference of static license features with dynamic license features, we can validate the user profiling data structure for dynamic license and can get the effectiveness of the data structure on license purchase prediction of the dynamic license as like the static license. In order to construct the user profiling data structure for the dynamic license, several metadata items should be added to the user profiling data structure for the static license. In this work, we proposed a kind of simple user profiling data structure for dynamic license and evaluated its effectiveness of the next user license purchase prediction with the aged-MRU algorithm. The evaluation results show that the proposed user profiling data structure for the dynamic license can present the related metadata to the license purchase and can predict the next license purchase activity in dynamic license environment.

Keywords: Dynamic License, License Purchase Prediction, Profiling Data Structure, User Profiling

1. Introduction

All digital contents constructed with the digital technology have unique identifiers. If a user wants to use any kind of digital content, a license along with the contents has to be purchased through legal way with or without payment^{1,2}. The license could be assigned to the specific content by its first owner or digital license management system. Since there is a various ways of license purchase, a user's the license purchase pattern also depends on what the user wants on the contents. The user's license purchase history can show the license purchase patterns or activities of the user, and we can easily extract it from the user profiling data³.

A user profiling data is a kind of a canonical log data and has all metadata writes and updates on the specified digital contents such as accesses, changes and actions for all users^{4,5}. If we want to access the user profiling data, we can analyze the license purchase pattern and can predict future license purchase activity of a specific user. We also can trace the license purchase history of the specific digital contents through the metadata analysis with user profiling data. In this work, we constructed a data structure that can present the license related metadata for the dynamic license. The metadata can be applied to analysis and prediction of the user license purchase or transfer pattern through the existing user profiling data for the static license.

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This paper is organized as follows; Chapter 2 introduces the difference between the static license and the dynamic license of digital content and explains the need for the user profiling data for the dynamic license. Chapter 3 shows the user profiling data structure with metadata for the dynamic license in programming language. Chapter 4 shows the evaluation of the user profiling data structure for the dynamic license including evaluation algorithm and results.

2. User Profiling Data

2.1 User Profiling Data for Static License

In case of the digital contents, a user profiling data has three sorts of metadata: user’s personal information, contents usage history information and license purchase information. In Table 1, metadata types contain various information related to the specified contents. The license related information has many general data about the kinds of the access rights, counts, access pattern and periods covered by the license. In general, a license shows the owner’s right and activation data such as number, period and so on. If one purchases a license for a digital content, the license should be dedicated to the owner and cannot be re-sold or transferred to another person. We can call such type of license as a static license. Almost of the existing digital contents such as music, video, TV program, movie, literature has been licensed as a type of static license. Therefore, if a license owner once purchases a digital content license, only the owner can use the contents according to the license contract along with the terms and conditions^{6,7}.

According to the expansion of the digital contents and users, there are many types and cases of the utilization of the licensed contents such as cut-and-paste, contents copy, content re-construction or adoption. Therefore, lots of licensed digital contents have been faced to many license conflict cases and should be solved to manage the

Table 1. License related metadata

Metadata types	Contents
License items	Number of purchase Period of purchase - Time & data of purchases
Item types	Download/streaming/complex Single/ multiple Period (1 month, 3 months, six months) Membership/one-time

license in an easy way. In order to overcome the problems of the static license, the dynamic license could be a nice solution in license transferring, sharing or modifying among the digital contents users.

2.2 Dynamic License History

In case of the dynamic license, there are lots of right and access relations among the contents and licenses. Figure 1 shows that more than one user over a contents has a sort of complication in their license and access right among the users^{8,9}. Since the dynamic license has to be focused on not the usage of the contents itself but the license usage, transfer history and ownership history of the contents. In order to verify the license change history of a specific content, we have to check and trace the transition and transfer route of the license on a contents and have to manage the license history with some kind of management methodology. User profiling data that describes on the license could be good information to save the usage and management history on the dynamic license.

For example, we can focus on the case of Alice in Figure 1. Alice is owner and consumer of the content. Alice also can share the licensed content with related persons such as Alice’s family, friends or others. The related persons could have/share the all or part of the license for access such as edit, preserve or distribute the content. This content license relation could make lots of complications in describing the license relation for a dynamic license. So, we have to make a kind of simple user profiling data structure for dynamic license to describe the dynamic license in an easy way.

3. User Profiling Data Structure

3.1 Profiling for Dynamic License

In a user profiling data, license purchase related metadata has information only about what kind of the license itself because the existing digital contents have been purchased in the form of the contents-dependent license. But in case of the dynamic license, it has to trace and manage the history of the license along with the transfer or the ownership change of the contents since the license should be tagged on the contents. Therefore, we need some kinds of additional data structure for history management of the dynamic licensed contents. Table 2 show the additional data items of the user profiling data structure for dynamic license vs. static license management such as history tracing.


```

typedef Static_Licensed_User { // Alice for Static License
    Byte User_Code; // code of owner from license site
    String User_Name;
    struct License_Context { // Context & history for the license itself
        Byte License_Domain // Audio(music), Video, Movie, TV program, Literature...
        Byte License_Code // Code number of license
        date Start_Date, End_Data;
        time Start_Time, End_Time;
        String Purchase_Site;
        Byte License_Service_Type; // code of streaming, download, complex
        Byte License_Activation_Type; // periodic, short term, 3-month...
        Byte License_Multiple; // single or multiple
    } Context[Max_History];
}
    
```

(a)

```

typedef Dynamic_Licensed_User { // Alice for Dynamic License
    struct User_Info {
        Byte User_Code; // code of owner from license site
        String User_Name;
    } Owner;
    struct License_Context { // Context & history for the license itself
        Byte License_Domain // Audio(music), Video, Movie, TV program, Literature...
        Byte License_Code // Code number of license
        date Start_Date, End_Data;
        time Start_Time, End_Time;
        String Purchase_Site;
        Byte License_Service_Type; // code of streaming, download, complex
        Byte License_Activation_Type; // periodic, short term, 3-month...
        Byte License_Multiple; // remained number of licenses
        // new feature for dynamic license
        struct User_Info Previous_Owner, // previous owner
            Original_Owner; // Original owner of this license
        Byte Initial_Licenses; //
        Byte Transter_Count; // number of transfer
        struct License_Service { // context for dynamic license users
            Byte Owner // same as User code
            Byte Service // Streaming, rental or others among the license types
            Byte Domain // has family, friend
            Byte Part_of_Service // Play, copy, move ...
            Byte Used_License; // used licenses in service
        } Owner, Group[MAX_Group], Others[MAX_Others];
        //
    } Context[Max_History];
}
    
```

(b)

Figure 2. (a) A part of user profiling data structure for static license. (b) A part of user profiling data structure for dynamic license.

4. Conformance Analysis and Results

4.1 Analysis Concept

To analyze the conformance of the dynamic license data structure, we should predict user's next license purchase action through tracking one's license purchase history. A user's next license purchase prediction can be conducted from the user profiling data with license purchase history by using the aged-MRU algorithm¹⁰. The gap between purchase prediction and real purchase could show the conformance the dynamic license data structure for describing dynamics of the user's license activities. If the gap between the purchase prediction and real purchase increases, the dynamic license data structure has lower conformance for describing dynamics of the user's license activity.

The aged-MRU algorithm could be a kind of easy history tracking analysis algorithm based on the user profiling data. It is a very simple algorithm that can increase the priority of recently used user license through the total history of the user's license purchase or other related activities. The license related metadata in user profiling data includes these activities. Therefore, we need lots of user profiling data generated from the real users in public licensed material such as music, literature, movie and something else to apply the aged-MU algorithm with metadata.

4.2 Test Environment

In this work, we had collected the user profiling data and extracted the metadata on license purchase history on Melon music license service site. The Melon is the largest online music distributor provided by Loen Entertainment Co. in Korea. It has occupied over 72% of online music listener and downloader in Korea and provides over 3.2 million of music for 24 million users at 2014. Table 3 shows the user percentile of the streaming and download music license service on Melon. From the Melon user profiling data, we investigated the skew of user license services. Although the Melon users could only be representative user constrained in the digital music area, other digital contents also could be almost the same characteristics in their license purchase tendency¹⁰.

In this work, we chose 143 user samples currently using the Melon services among the students in university

since Melon does not open their license database in detail. But we can get the user's license metadata details by posing questions to students one by one slightly closed to the results of Table 3. Therefore, we applied the aged-MRU algorithm to get the user's next license purchase prediction with the metadata details includes cross purchases and transfers among the owner, group and others. The history information and the license transfer relation between owner and group member or among the others had gathered through poll questions modified from static license metadata information.

4.3 Results and Analysis

Predictions with the static license and the dynamic license show the percentage of the same license purchase on the specific license type. Table 4 shows the next license purchase predictions on the cases of the static license and the dynamic license along with the next license type. It shows that in dynamic license environment, users tend to purchase other types of license compare to the static license case. Since the dynamic license environment can provide more chance to get some licensed content than static license environment, the comparison results show the fact that user need not persist the previous license type anymore.

Table 5 shows the term-based license purchase prediction. It shows that long-term users and short term users are not crossed or changed among the license types in the static license environment but changed large part of users

Table 3. User license type percentiles in Melon (2014)

License types	Shot-term (30days)	Long-term (3-month or over)	Periodic
Streaming only	3.3 %	18.3 %	11.3 %
Download only	2.6 %	3.9 %	8.2 %
Streaming + download	6.2 %	31.6 %	14.6 %

Table 4. Comparison results for the next license cases

Next license type	Prediction with static license	Prediction with dynamicLicense
Streaming	89.1	63.2
Download	88.7	45.9
Complex	97.3	74.3

Table 5. Comparison results for license term type

Periodic license type	Prediction with static license	Prediction with dynamic license
1-month	87.6	78.2
3-months	86.4	65.1
Six months or more	56.4	57.0

in the dynamic license environment. Under the dynamic license environment, users can get lots of licensed contents from the group or other owner and long-term license cannot be attractive to users. The comparison results also show the fact that the more license period increases, the less next license prediction in dynamic license environment. Since the user's tendency on license must be changed under the dynamic license environment unlike the static license environment, the digital content license producers or creators should think over the dynamic license environment of their content marketplace.

5. Conclusions

In this work, we constructed the user profiling data structure for the dynamic license and evaluated its effectiveness. It can be capable to trace, analyze and predict the user's license purchases through the existing static license utilization pattern analysis. In case of dynamic licensed digital contents, it is hard to trace the license transfer or ownership change history with the existing static licensed user profiling data. The proposed user profiling data structure can be effectively used to trace and analyze the dynamic license activities as well as existing static license. Therefore, it is very useful to the new license marketplace environment that can trade or transfer the dynamic licenses among the digital content users.

As like many online recommendation systems that provide some suggestion for users, the next license purchase prediction can be used as an effective recommendation. When users have to decide to purchase the new license, they can choose what license they have to purchase more easily. The dynamic license would become the most popular type of digital content license in movie or music license marketplace. Therefore, the dynamic license purchase recommendation also takes a large part

of multimedia information service on licensed digital contents.

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7. References

1. Maggs PB. The balance of copyright in the United States of America. *The American Journal of Comparative Law*. 2010; 58:369–76.
2. Mahdavi I, Cho N, Shirazi B, Sahebjamnia N. Designing evolving user profile in e-CRM with dynamic clustering of Web documents. *Data and Knowledge Engineering*. 2008 May; 65(2):355–72.
3. Maleszka M, Mianowska B, Nguyen NT. A method for collaborative recommendation using knowledge integration and hierarchical structure of user profile. *Knowledge-based Systems*. 2013 Jul; 47:1–3.
4. Han L, Chen G, Li M. A method for the acquisition of ontology-based user profile. *Advances in Engineering Software*. 2013 Nov; 65:132–7.
5. Kritikou Y, Demestichas P, Adamopoulou E, Demestichas K, Theologou M, Paradia M. User Profile Modeling in the context of web-based learning management systems. *Journal of Network and Computer Applications*. 2008 Nov; 31(4):603–27.
6. Hawalah A, Fasli M. Utilizing contextual ontological user profiles for personalized recommendations. *Expert Systems with Applications*. 2014 Aug; 41(10):4777–97.
7. Pierre S, Kacan C, Probst W. An agent-based approach for integrating user profile into a knowledge management process. *Knowledge-Based Systems*. 2000 Oct; 13(5):307–14.
8. Chen PM, Kuo FC. An information retrieval System based on a user profile. *The Journal of Systems and Software*. 2000 Sep; 54(1):3–8.
9. Kim JH, Lee HJ. Extraction of user profile based on workflow and information flow. *Expert Systems with Applications*. 2012 Apr; 39(5):5478–87.
10. Chang Y, Shin PS, Kim JM, Lee JC, Jung JJ. An analysis of music license purchase tendency based on the user profiling. *The Journal of Macro Trend in Applied Science*. 2015; 3(1).