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Toward user-classified P2P IPTV systems: a persona-based approach

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***Abstract*—Peer-to-Peer (P2P) approaches are a promising choice for media streaming in order to reach a global audience and to ease the deployment of such services. However, since P2P systems are in fact networks of users where the latter directly control the peers, user behavior is critical to the performance of these systems. Current literature propose global behavior models which do not help greatly to design adaptive control mechanism at peer level. In this paper, we propose a classification mechanism that associates a video streaming user to a behavioral class. This classification can help in building user-aware systems optimized for an improved streaming quality. We validate our model through simulations over a thousand users on a hundred-day period. We also present a proof-of-concept application of our classifier for the design of churn-resilient topologies that can be used by service providers or network operators in P2P IPTV applications.**

I. Introduction

Video streaming over a P2P architecture has attracted great attention both from the academia and industry [1]. P2P approach allows end-hosts, called peers, to self-organize into a network. Peers share their resources such as computing power and upload bandwidth in order to cache and relay the video content to other peers in the network. However, these systems suffer from performance issues such as delays and stream disruption. Since peers depend upon each other to receive the video stream, the behavior of a peer has a direct impact over the performance of the network. For example, a sudden departure of a peer can disrupt the stream to its neighbor peers. Consequently, integrating the user behavior into service control mechanisms (e.g., topology maintenance) of future P2P-based IPTV services is crucial to be able to deal with QoS guaranties.

To this end, numerous large-scale measurements have been carried out to understand user behavior. However, these measurements only observe the global behavior at the system scale due to difficulties in identifying individual users. Such a model represents an average behavior which can be far from the behavior of an individual [2]. As a consequence, any control system, based on the user behavior will take inaccurate decisions or need a long time to learn online the user habits. For example, in a previous work [3] we have proposed a QoS control system based on a user model that require on average 33 days to work properly which is not acceptable in case of an operated service with QoS assurance. Being able to classify users according to their service usage could thus help user-based control system to take more accurate decisions with a shorter learning time. This is why, we propose a Bayesian classifier which associates a P2P video streaming user to a predefined behavior class. The classifier encodes the dependency relationships among peers established in the measurement studies. We evaluate our model through simulations over a thousand users who join and leave the system during a hundred days period. We also present our first validation results, forming a basic proof-of-concept for this classifier by showing its ability to build and maintain stable topologies for P2P IPTV applications. Our simulation results show that the stream disruption incurred by peers' dynamics is significantly reduced.

The remainder of the paper is organized as follows: Section II presents the work related to user behavior modeling and learning. In section III, we discuss major criteria to identify user classes and present our Bayesian network. In section IV, we use several behavior classes to train the classifier and propose some solutions to enhance its accuracy. Section V presents a proof-of-concept of our classifier through an application that builds churn-resilient topologies. Finally, section VI draws conclusions and gives future directions.

II. Related work

For the last few years a number of large-scale measurement campaigns have been carried out over video streaming applications [4], [5], [6], [7]. All of them agree over the fact that the user population follows diurnal patterns during a week. Concerning the users' arrival models, exponential distribution [5] and Poisson distribution [4] are more often observed. In addition, lognormal distribution [7], [4] or exponential distribution [6] fit well with the session durations. It is clear that these works focus only on global models of users, while individual behaviors can be far from the average one due to users' preferences and interests [2].

Some other works focus on the identification of behavior criteria and its prediction. Tang *et al.* [7] propose a neighbor selection strategy that prefers the long-lived peers over the others. A similar method has been used to identify stable peers for putting them in the backbone of the topology [8]. Nevertheless, these approaches tend to consider all peers that have recently joined the system as unstable, which is not always the case. Liu *et al.* [9] observe the impact of streaming quality over the stability and upload bandwidth contribution of peers. They observe that streaming quality has a positive

correlation with these two metrics and they propose models for their estimation. However, these models do not consider all the impacting factors and remain global.

Nevertheless, Horovitz and Dolev [10] propose an individual model which learns the load in uplink of source peers through Support Vector Machine (SVM). Client peers are then informed to replace their source. A limitation of this model is that it does not consider any external impacting factor of upload contribution. In our previous work, [3], we have proposed a Bayesian network model that learns the behavior of individual peers through encoding the dependency relationships identified in the measurement studies. Such a proposal forms the ground of an autonomous topology management framework able to deal with disruption in video streams provisioning [11]. However, the evaluation of this work has exhibited that our model takes long to learn the behavior of a user and during that period, it cannot produce accurate results, thus motivating the need for a way to classify it.

III. Users classification

A. A Bayesian network classifier

The principal criterion of user identification is the time duration for which he/she watches a channel under certain conditions. We term this time period as **session duration** of a user.To find all the related variables of the session duration we extensively analyzed the existing literature. As a result, four metrics were found that influence the session duration:

– **Streaming quality:** A positive correlation between the session duration and initial streaming quality received by a user has been observed [9]. Indeed, a user who receives initially a high buffer size shows a tendency to stay connected for a longer period as compared to a user with a low initial buffer because this latter experiences more disruption at the beginning.

– **Popularity:** Popularity of a channel or a program is measured from the online population watching that channel or program. Users watch popular programs for longer periods than unpopular ones [9], [12].

– **Content type :** Cha *et al.* [5] observe shorter session durations for news and music channels as compared to documentaries and kids channels. From their work, three kinds of user behavior can be identified which lead to different behaviors. They are fiction- (films, series), reality- (news, music) and sports-loving users.

– **Time-of-day:** Time-of-day impacts both session duration and popularity. Liu *et al.* [9] observe that session duration of a user is strongly correlated with time-of-day. Moreover, during noon and early night, popularity is higher than on other parts of the day [13].

Therefore, we can classify the behavior of a user through its session duration, given the values of all these metrics. For that purpose, we use a Bayesian network since such a model encodes naturally causal relationships. This network is shown in Figure 1. It consists of six nodes where dependencies are depicted through a directed edge: one node for the session duration, four for the above-mentioned metrics and one for the user class.

All variables in this network are chosen to be discrete in order to reduce the complexity of our model. Therefore, we discretize time-of-day into 24 states, having one state for each hour. The content type is discretized into 3 states namely, fiction, reality and sports. Popularity and streaming quality are discretized into 5 states each where each state represents a ratio of the maximum value of the given variable in the available trace. Session duration is discretized into 100 states at a granularity of one minute. Finally, user class variable is assigned with 6 states, each of them representing a different behavior class.

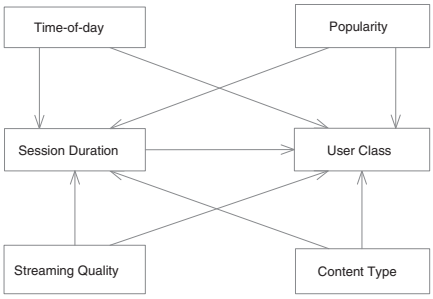


Fig. 1. User classifier

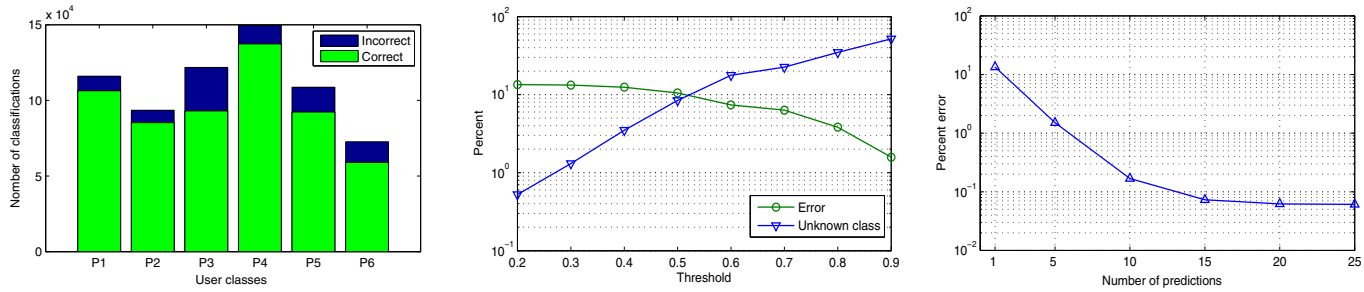
B. Preliminary evaluation

Since our classifier is aimed at the classification of individual users, we assign a dedicated classifier to each peer. We use synthetic traces for evaluation of our model because real traces of individual users are not available due to the difficulty in tracking a user over different sessions. The synthetic traces model [14] is able to generate traces for six different kinds of fictional behaviors called personas. The global behavior represented by these traces is near to the real ones, especially in terms of distribution of session durations and one day population of generated traces. To validate our model, we perform simulations with Matlab and Bayes Net Toolbox. We simulate a community of 1000 users who join and leave the system during a 100 days period where the content type changes uniformly after each 2 hours time. Such number of users allows a supervised learning (related to the conditional probabilities tables) over the traces of first 60-days period through a maximum likelihood learning algorithm. Let us remark that increasing the number of users to fit with real networks reduces this step duration. From 61st day onward, the user class variable is hidden. Each time a user joins the system, the classifier estimates its class as the one with the highest probability given the other variables through a junction tree algorithm.

We present the correct and incorrect classifications for each persona in Figure 2.a. It is noticeable that the classification error varies from 8.34% to 23.6% for different personas. It means that some of the user groups are more similar to each other, which lead to higher errors in the classification. Indeed, for about half of the personas the error is over 15%, which requires further improvement.

IV. Improving the classifier

We propose to improve these classifications further by using two methods. The first method involves the probability of the classification which is readily estimated by the classifier.



(a) (b) (c)

Fig. 2. (a) Classification of different personas; (b) Mean error evolution over different thresholds; (c) Mean error evolution over different history sizes

This probability can be used as a measure of confidence over the classification. The second method considers a history of all classifications of a single user.

A. Unknown class

This method can only be used in situations where the classification of each user is not necessarily required but only a subset of peers is needed. For example, only few peers are needed to build a backbone of super peers which can be distilled through this approach. All the unclassified users belong to an unknown class. Such peers cannot help in decision making. In this approach, we set a probability threshold and if the probability with which a user is classified, is less than this threshold, that user is considered as a member of the unknown class. We choose different thresholds and depict the obtained results in Figure 2.b. Obviously, an increase in the value of the threshold increases the number of users classified as an unknown persona. On the other hand, the mean classification error is significantly reduced from 13.42% to 1.57% for a probability threshold of 0.9. However, the number of unclassified users reaches to 51.86%, meaning that we can distinguish around half of the peers with a high accuracy.

B. Consideration of classification history

The second method is based on the history of previous classifications. It does not involve an unknown class and hence each user is classified. In this method, a given set of the most recent classifications for a user U_i is considered and the probability that U_i belongs to class C_j is given by (1), where $|O|$ is the number of considered classifications and α_j is the number of classifications resulted in $U_i \in C_j$.

$$f(\phi_j) = \frac{\alpha_j + 1}{|O| + 6} \tag{1}$$

We evaluate the impact of the history size on the accuracy of estimated classes. As depicted in Figure 2.c, the error decreases abruptly from 13.42% to less than 2% by considering five classifications. Afterwards it shows a slight decrease reaching to 0.06% at a history size of 20 classification. This is a negligible error in the given context. Overall, these results show a good accuracy of the classifier. However, its application to concrete scenarios needs to be considered to evaluate its performance.

V. Proof-of-concept

The construction of stable P2P topologies for IPTV services is one of the applications of our classifier. We are interested in a tree topology since this topology is efficient in terms of timely delivery of content as compared to mesh topologies. However, trees are churn-sensitive: the departure of a peer disrupts the stream to its descendent ones. Therefore, constructing stable trees can improve the performance. To evaluate such an application, we consider the scenario of an operated P2P-TV service in which the provider allows the service join through a public boostrap node that will act as the root of a tree topology. A total of 1000 users join and leave the network dynamically during a period of 100 days. Each user is associated to one of the six classes as mentioned earlier. A user receives the content through joining the tree. The number of child peers for a node varies between 1 and 5. Then we consider three cases: (1) peers are placed in the tree randomly without taking their stability into account; (2) the class of a user is predicted and is used for estimating the current session duration, then the peers are placed in the tree in such a way that more stable peers occupy positions near to the root while unstable peers are put at the leaf nodes. The process is carried out periodically after each 5 minutes duration. We call this kind of topology a controlled one; (3) we also consider an ideal case in which all the predictions are correct and the stabilization is performed as in the second case.

The algorithm we used assumes that each peer is identified through a distinct identifier. Each peer uses a Bayesian network to estimate its user class and then its current session duration knowing all other variables. Time-of-day and streaming quality are measured directly on the peer, the popularity is measured by the instantaneous population in the network through a decentralized aggregation protocol [15] and the content type is broadcast by the service operator through a signaling protocol. After each 5 minutes duration, the peer updates its estimation and publishes it to the root node owned by the service provider. Given all the estimations about all peers in the network, the service provider computes a new tree structure as the more stable peers occupy positions near to the root while unstable peers are put at the leaf nodes. This new structure is then broadcast through the current tree, and the peers reorganize themselves by updating their neighborhood.

To compare these approaches, we are interested in the number of peers interrupted due to the departures during a given unit of time. Figure 3.a represents the disruption rate during

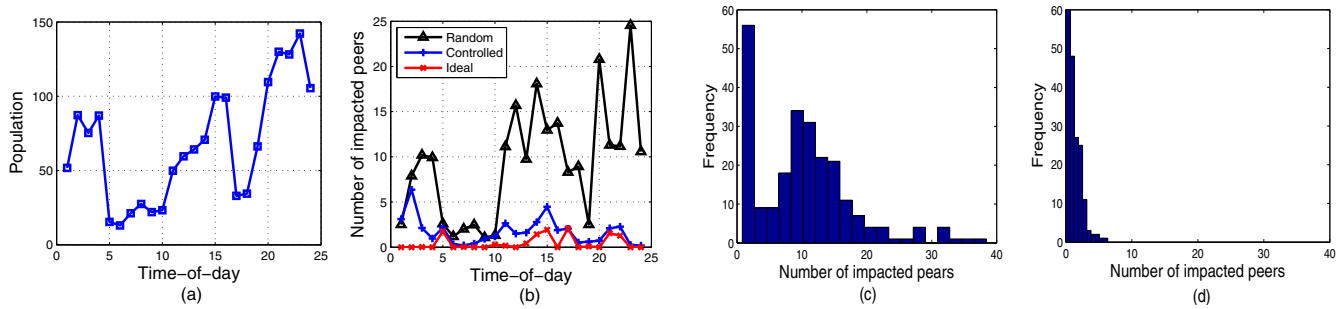


Fig. 3. Results : (a) Online users; (b) Network perturbation; (c) Frequency distribution of perturbation in random topology; (d) Over controlled topology

24 hours since the peers behavior is cyclic on this period. The evolution in total population during the same period is depicted in Figure 3.b. In case of random topology the average perturbation rate is 10.23 nodes per minute while it is 1.03 nodes per minute in case of controlled topology. We also notice that the controlled approach produces comparable results to the ideal case. Moreover, the variation in the perturbation rate remains low in the controlled case. Then, Figures 3.c and 3.d show the frequency of the number of peers impacted due to one departure. It is noticeable that the random topology (figure 3.c) presents important variations by contrast with the controlled topology (figure 3.d) that clearly shows that most of departures occur at leaves of the tree in the latter case. In view of these preliminary results, our controlled topology brings a significant improvement to the system.

VI. Conclusion and Future Work

The behavior of users becomes important in P2P streaming systems since peers are controlled by users. However, designing systems able to control and manage this kind of service according to the behavior of users is a complex operation since all users exhibit different behaviors that need first to be learned before being able to infer over it. To simplify this issue, in this paper, we proposed a Bayesian classifier that associates each user to a behavior class. We instantiated this classifier over six defined classes of users. We also proposed two methods to improve its accuracy. Simulation results showed that the classifier provides satisfactory results. To illustrate one of the applications of our classifier, we simulated a video distribution tree. This tree is controlled through periodically promoting stable nodes to higher levels of the tree while unstable nodes are pushed towards the outskirts. This approach minimizes significantly the impact of user departures.

This work needs to be further extended. Firstly, the classification method can be improved by combining the threshold-based and history-based methods. We only evaluated the potential gain through utilization of classifications to construct stable topologies. This application need to be evaluated in terms of the performance and cost through concrete experiments. To this end, we are currently planning large-scale experiments on real P2P clients through the PlanetLab network. Then, we plan to convert our stabilization algorithm into a distributed one, allowing peers to self-organize in a decentralized way: (1) each peer uses a Bayesian network to estimate its user class and those of its neighbors; (2) the peers self-organize locally by making neighbors according to their behaviors. Finally, confronting our classifier to real session traces would be necessary to actually validate numerical parameters of the classes we proposed. This work would obviously lead to adjustments related to our basic user archetypes, although realistic, they are not concrete behaviors.

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