Characterizing Broadband User Behavior*

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ABSTRACT

This paper presents a characterization of broadband user behavior from a Internet service provider. Users are broken into two major categories: residential and Small-Office/Home-Office (SOHO). For each user category, the characterization is performed along four criteria: (i) session arrival process, (ii) session duration, (iii) number of bytes transferred within a session and (iv) user request patterns.

Our results show that both residential and SOHO session inter-arrival times are exponentially distributed. Whereas residential session arrival rates remain relatively high during the day, SOHO session arrival rates vary much more significantly during the day. On the other hand, a typical SOHO user session is longer and transfers a larger volume of data. Furthermore, our analysis uncovers two main groups of session request patterns within each user category. Sessions from the first group use traditional Internet services, such as www, e-mail and instant messengers, and sessions from the second, a smaller group, use typically file sharing applications (peer-to-peer). This second group remains for longer periods and transfers a large amount of data. Understanding these user behavior patterns is important to the development of more efficient applications for broadband users.

Categories and Subject Descriptors

C.4 [**Performance of Systems**]: Modeling techniques; C.4 [**Performance of Systems**]: Measurement techniques.

General Terms

Performance, Measurement.

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Keywords

Broadband Networks, Workload Characterization.

1. INTRODUCTION

Understanding the nature and characteristics of broadband user behavior is a crucial step to improve the quality of service offered to users in the next generation broadband environments. Broadband user behavior characterization can lead to a better understanding of the interaction between users and service providers. It can also help the design of systems with better QoS metrics, such as performance, availability, security and cost.

Broadband penetration keeps growing fast for users and households. However, studies of broadband user behavior are scarce in the literature, mainly because of the difficulty in obtaining actual logs from Internet Service Providers (ISPs). Most of the service providers on the Internet consider logs as very sensitive data. Existing studies, such as the one done by Pew Internet & American Life [2], concentrate on qualitative analysis based on surveys. The Pew report shows how on-line Americans' behavior changes with high speed connections at home. The study also shows that broadband services allow users to distinguish themselves from dial-up counterparts in the following ways: (i) broadband users engage in multiple Internet activities on a daily basis, (ii) high speed users become creators and managers of different types of on-line content and (iii) broadband users perform a large variety of queries for information. In spite of the Pew report, quantitative studies of broadband user behavior are still lacking.

This paper intends to fill this gap. To understand the broadband user behavior, we present a characterization from a broadband ISP, which classifies their users into two major categories: residential and Small-Office/Home-Office (SOHO). For each category, we identify user sessions, which are defined as the period that a user is connected to the broadband network. Basically, the behavior of users is defined as a function of the way users arrive at the ISP, how long they remain on-line, the number of bytes they transfer and what they do while connected, i.e., the request pattern. Thus, the characterization process is performed along four criteria: (i) session arrival process, (ii) session duration, (iii) number of bytes transferred within a session and (iv) user request pattern. The broadband user behavior characterization is based on logs collected on an authentication server and by Netflow [1] running in a border router. The data collecting architecture implemented in the ISP allows us to identify the services used by each user category.

In order to analyze the service request patterns, we use a state transition graph called Customer Behavior Model Graph (CBMG) [14] which is used to describe the behavior of groups of customers who exhibit similar navigational patterns. We then applied clustering algorithms to user session data (both residential and SOHO) to determine groups of users that exhibit similar behavior graphs. The main findings of the characterization process are:

- Both residential and SOHO session inter-arrival times are exponentially distributed during periods of stable arrival rates. Residential session arrival rates remain relatively high during the day, whereas SOHO session arrival rates vary much more significantly through the day.

- Residential user session durations can be accurately approximated by a Lognormal distribution. On the other hand, the duration of SOHO user sessions is better modeled with a combination of a Lognormal distribution for the body and a Pareto for the tail.

- For both residential and SOHO sessions, the numbers of incoming and outgoing bytes can be modeled with Lognormal distributions. Moreover, typical the ratio of the average number of incoming bytes to the average number of outgoing bytes per session falls in the 3 to 5 range.

- The use of a state transition graph (CBMG) uncovered six classes of significantly different patterns in the user behavior of both categories. For example, one class is dominated by HTTP requests. A second class has a lot of HTTP requests but include some requests to other services, such as P2P, Instant Messengers, etc. Another class is dominated by P2P requests, which lasts much longer than HTTP sessions.

The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 describes the data collection process and the characterization methodology. Section 4 analyzes the logs from a TV cable company that provides broadband services to its users and characterizes the user behavior, in terms of session statistics and clusters of graphs that exhibit the service request patterns. Finally, concluding remarks are offered in Section 5.

2. RELATED WORK

A number of workload and user behavior characterizations are available in the literature. Traditional web workloads, consisting mainly of requests to HTTP and image files, are analyzed in several previous studies, focused on either server-side [3, 5] or client-side workloads [6, 8].

More recent studies characterize the workloads of other types of applications like on-demand and live distribution of streaming media [7, 17] and peer-to-peer (P2P) services [10, 13, 15, 16], which are both becoming increasingly popular possibly due to the availability of broadband "last mile" connections [12]. Previous streaming media workload characterizations propose hierarchical models to capture the most relevant aspects of user behavior for the specific type of workload studied (live [17] versus on-demand [7]) and produce extensive characterizations of each component of the proposed models. Previous peer-to-peer workload studies analyze several aspects of the traffic generated by these applications such as object popularity, object size, bandwidth utilization and session durations [10, 11, 13, 15, 16].

These previous workload analyzes focus on a specific type of application. In contrast, our work looks into a client-side broadband workload including requests to a multitude of different applications. In that sense, the extensive characterization of a broadband ISP web proxy [4] is possibly the previous work that is most closely related to ours. However, that work focuses on the traffic generated by the analyzed broadband community, characterizing file types, sizes, popularity and frequency of requests to different services (HTTP, FTP, etc). In contrast, our focus is not only on the traffic generated by broadband users but, especially, on the patterns of user requests to different services that most accurately represent the typical behavior within a broadband session. In other words, we characterize not only traditionally analyzed aspects such as user session arrival process, duration and traffic volume but also the most commonly observed patterns of user requests to different services within the same session. Furthermore, we also compare our findings for two different categories of broadband users: residential and SOHO users.

3. CHARACTERIZATION METHODOLOGY

This section presents our characterization methodology and describes how it is applied to the ISP environment. The goal is to analyze the user activity while connected to the Internet, quantifying and qualifying the workload they generate.

Our characterization is based on four criteria: session arrival process, session duration, traffic volume, and user request pattern. The session arrival process and session duration provide temporal information about the workload associated with users, since we may estimate how frequently and for how long a user is connected. The traffic volume provides leverage on how the users are using their connection regarding a critical resource for any ISP: bandwidth. Finally, the user request pattern qualifies the nature of the services being requested by users and how they are distributed across the connection time.

We employ three sources of data in the proposed characterization: user authentication log, user database, and traffic log. The user authentication log is compatible with the RADIUS protocol (RFC 2865 and RFC 2866). It has an entry for each user session containing the following information: start date and time, duration, number of bytes transferred, and the dynamic IP assigned to the user. The user database is just a table that informs the user category, which may be residential or Small-Office/Home-Office (SOHO) in the ISP analyzed. The third log is collected using Netflow [1]. The traffic is divided into flows and each flow is characterized by a timestamp that indicates when the flow was recorded, source and destination IPs, protocols and ports, and the volume of bytes transferred. The traffic log, which generated the results presented in the next section, was collected at one of the three backbone routers of the ISP and corresponded to about 30% of the overall traffic. Since the user population is equally spread across the three routers, we believe that it does not affect the meaning of the results.

Before we start characterizing each criterion, we divide the data into two sets according to the user categories defining then two separate broadband workloads. Our *residential workload* consists of all sessions initiated by users categorized as such by the service provider. Similarly, the *SOHO workload* consists of all SOHO user sessions. We then characterize the four user behavior criteria for each workload, separately.

The session arrival, session duration and traffic volume criteria are characterized by using the authentication log. For the sake of characterization, we take into consideration only sessions that start and finish within the collection time interval. We characterize traffic volume separately depending on its direction: inbound and outbound. For each analyzed criterion, we determine statistical dis-

	Residential	*SOHO*
Period	12/23/03 - 01/21/04	12/23/03 - 01/21/04
Total # user sessions completed	256,239	61,112
Total # incoming bytes (GB)	11,422	4,135
Total # outgoing bytes (GB)	4,135	1,128
Mean (CV) # sessions completed per user	45 (0.76)	36 (0.74)
Mean (CV) # session duration (hours)	9.80 (5.00)	13.41 (4.29)
Mean (CV) # incoming bytes (MB)	46 (5.02)	70 (3.79)
Mean (CV) # outgoing bytes (MB)	20 (8.47)	18 (7.89)

Table 1: Summary of the Workloads (CV = Coefficient of Variation)

tribution, using least-square fit method and visual inspection, that best fits the measured data.

The user request pattern is characterized from traffic logs in terms of the services that are requested by the users within each of his / her sessions. A service is a request to an application or application class, such as HTTP, mail, and P2P, and is usually identified by one or more port numbers where its server answer requests to the service. We use and extend the IANA taxonomy[1] to match ports to services. The extension is necessary because there are some protocols/ports that are well-known, but not registered there, such as port 4662, which that is typically used by eDonkey. By using the resulting port-to-service translation table, we can transform each user session into a sequence of services.

We then calculate the Customer Behavior Model Graph (CBMG) [14] for each session. The CBMG is a state transition graph that has one node for each possible service and transitions between these services. A probability is assigned to a transition between two services representing the frequency at which the user requested the services consecutively in the session. The CBMG is a condensed and semantically rich representation of the user behavior since different types of users may be characterized by different CBMGs in terms of the transition probabilities. Representative session profiles are identified by clustering the session CBMGs. We employed k-means algorithm and chose the number of clusters based on the β_{CV} metric, as described in [14].

4. RESULT ANALYSIS

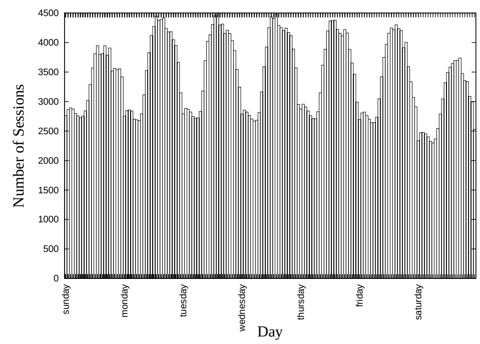
This section analyzes the characteristics of our broadband workloads. Section 4.1 provides an overview of the workloads. Session inter-arrival times, session duration and number of incoming and outgoing bytes transferred within each user session are analyzed in sections 4.2, 4.3 and 4.4, respectively. Section 4.5 presents the most commonly observed session profiles of user request patterns.

4.1 Workload Overview

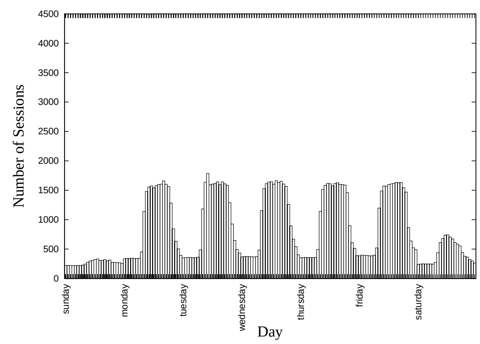
An overview of our residential and SOHO workloads is provided in Table 1. Our logs cover a period of 28 days (12/23/2003 to 01/21/2004), during which a total of over 310 thousand user sessions were completed. Over 80% of them are from residential users. Similarly, over 73% of all incoming bytes and over 78% of all outgoing bytes are from residential users.

Figures 1(a) and 1(b) show the number of simultaneous sessions active (open) during one week for both user categories, residential and SOHO, respectively. Figures 2(a) and 2(b) show the same measured over a single weekday (a Wednesday). Note that most SOHO sessions are active during typical and weekdays. On the other hand, there is a much longer number of residential sessions active during the night and over the weekend.

On average, a residential user completes 1.62 sessions per day



(a) Residential



(b) SOHO

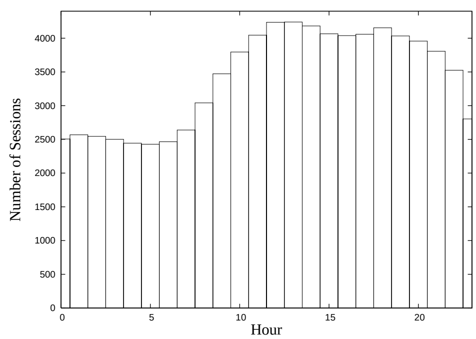
Figure 1: Number of Simultaneous Sessions Active (Typical Week)

and a SOHO user completes only 1.28 sessions per day. This indicates that residential users either close their sessions themselves or are interrupted by timeout (4 hours) more frequently, during a typical day. On average, a residential user session lasts approximately 9.8 hours, during which 46 MB of data are received and 19 MB of data are sent out. In contrast, typical SOHO user sessions last longer and receive much more data. On average, a SOHO user remains connected during approximately 13 hours, receives 70 MB of data and sends 18 MB of data. Finally, it is also interesting to note the high variability (i.e., high coefficient of variation) in the number of sessions as well as in the number of bytes transferred within residential and SOHO user sessions. This implies that there might be some heterogeneity among different user sessions within the same category (residential or SOHO).

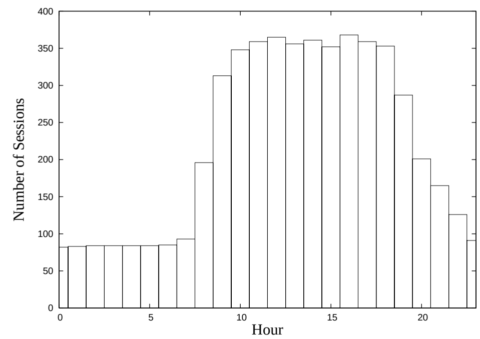
4.2 Session Arrival Process

This section characterizes the user session arrival process during periods of roughly stable session arrival rate in order to avoid spurious effects due to data aggregation. We carefully selected a large number of stable periods covering different times of the day and different days of the week, including weekends.

[1]Internet Assigned Numbers Authority (http://www.iana.org/assignments/port-numbers)

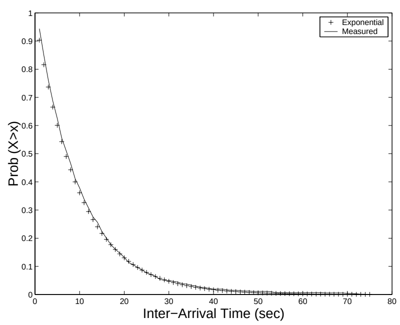


(a) Residential

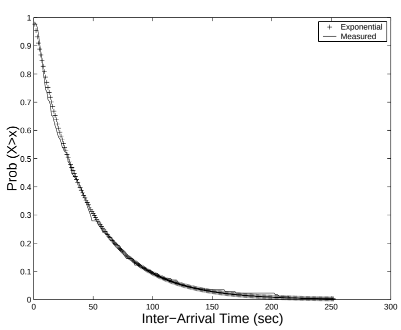


(b) SOHO

Figure 2: Number of Simultaneous Sessions Active (Weekday)

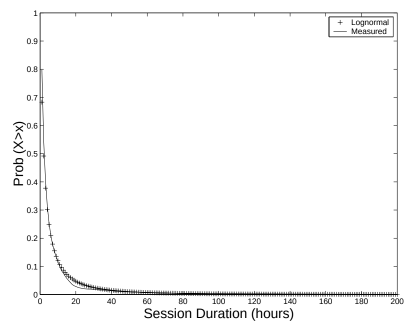


(a) Residential

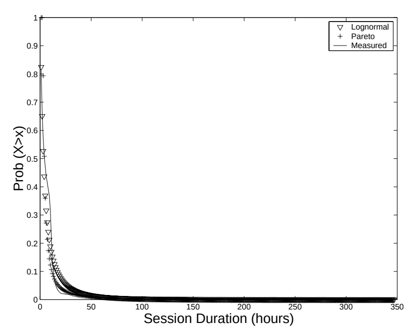


(b) SOHO

Figure 3: Distribution of Session Inter-Arrival Times (*seconds*)



(a) Residential



(b) SOHO

Figure 4: Distribution of Session Duration on a Typical Day (*hours*)

We found that the user session inter-arrival times are exponentially distributed for both residential and SOHO users, as illustrated in Figures 3(a) and 3(b), respectively, for typical periods of stable arrival rate in each workload. Table 2 summarizes our findings providing the ranges of mean and coefficient of variation (CV) of inter-arrival times as well as the range values of the λ parameter (session arrival rate) of the best-fitted exponential distribution, for all periods analyzed, in each workload. This result is consistent with those presented in [9, 17].

The tighter range of λ values for residential users shows that, although SOHO users usually initiate their sessions during working hours, residential sessions are initiated at relatively high rates (one each 4 to 10 seconds, on average), throughout the day. In other words, the traditional daily access pattern with peaks in the middle of the day and on weekdays, pointed out [9], is more pronounced among SOHO users.

4.3 Session Duration

The durations of residential and SOHO user sessions are characterized separately for different days to avoid data aggregation. For each of the two workloads we separately characterize the distribution of the durations of all sessions that are initiated on a given day, for a large number of days.

We found that the durations of residential user sessions can be accurately approximated, both at the body and at the tail of the measured data, by a Lognormal distribution, as illustrated in Figure 4(a) for a typical day, and consistent with results in [9, 17]. In contrast, the duration of SOHO user sessions are better modeled with a combination of a Lognormal distribution, for the body, and a Pareto distribution for the tail. As illustrated in Figure 4(b), the breaking point is around 12 hours. We speculate this behavior reflects two different classes of SOHO users: (1) users who remain connected

Workload	*Inter-Arrival Times* *Mean (sec)*	*CV*	*Exponential Parameter* λ
Residential	4.81 - 10.20	1.02 - 1.05	0.10 - 0.21
SOHO	4.63 - 42.19	0.98 - 0.99	0.02 - 0.22

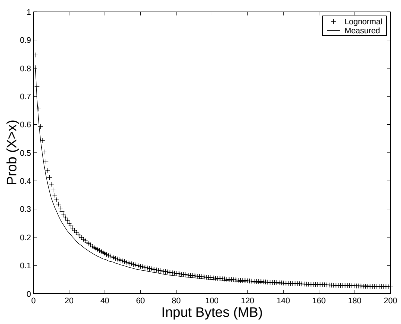
Exponential (PDF): $p_X(x) = \lambda e^{-\lambda x}$

Table 2: Summary of the Distribution of Inter-Arrival Times

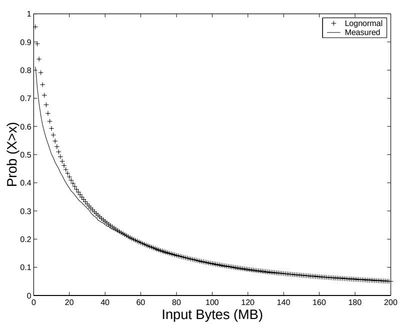
Workload	*Mean (hours)*	*CV*	*LogNormal Parameters*		*Pareto Parameters*	
			σ	μ	k	α
Residential	4.71 - 13.09	1.75 - 2.47	1.18 - 1.52	0.48 - 1.86	-	-
SOHO	6.95 - 19.21	1.53 - 1.62	0.92 - 1.45	1.04 - 2.30	1.82 - 7.18	1.28 - 1.95

Lognormal (PDF): $p_X(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\frac{-(ln(x)-\mu)^2}{2\sigma^2}}$ Pareto (PDF): $p_X(x) = \frac{\alpha k^{\alpha}}{x^{\alpha+1}}$, where $x \geq k$.

Table 3: Summary of the Distribution of Session Duration (*hours*)

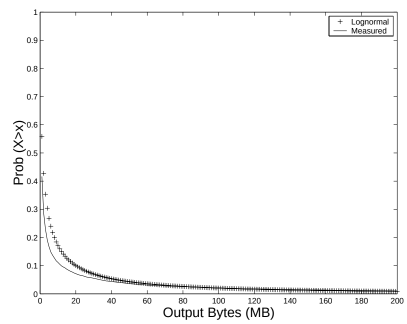


(a) Residential

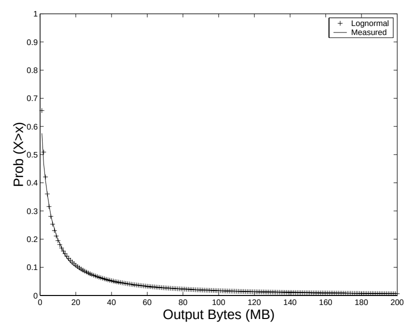


(b) SOHO

Figure 5: Distribution of the Number of Incoming Bytes per User Session (*MB*)



(a) Residential



(b) SOHO

Figure 6: Distribution of the Number of Outgoing Bytes per User Session (*MB*)

mostly while at work, and (2) users who either work longer journeys or remain connected even after leaving the workplace. Table 3 summarizes these results. Note that, on average, a residential user session lasts from 5 to 13 hours. In contrast, an average SOHO user session lasts longer, from 7 to 19 hours.

4.4 Inbound and Outbound Traffic

This section characterizes the total number of incoming and outgoing bytes, transferred within each user session. As in the previous section, the analysis is performed separately for different days.

We found that, for both residential or SOHO sessions, the number of incoming bytes and the number of outgoing bytes can be each well modeled with Lognormal distributions, as illustrated in Figures 5 and 6, respectively. These results confirm those presented in [4, 6, 9]. Table 4 presents a summary of our results. Compared to residential users, SOHO users typically receive and send larger amounts of data within each session, possibly due to the longer average session duration. Moreover, for each workload, the ratio of the average number of incoming bytes to the average number of outgoing bytes per session is not very high, falling, typically, in the 3 to 5 range. This may be due to the use of services which bulk transfers in both directions, such as peer-to-peer applications.

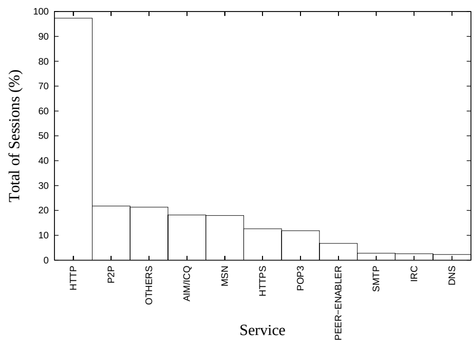
In conclusion, compared to SOHO users, residential users usually initiate a larger number of sessions throughout the day. Moreover, residential sessions are typically shorter and transfer fewer bytes, both downstream and upstream.

4.5 User Request Pattern

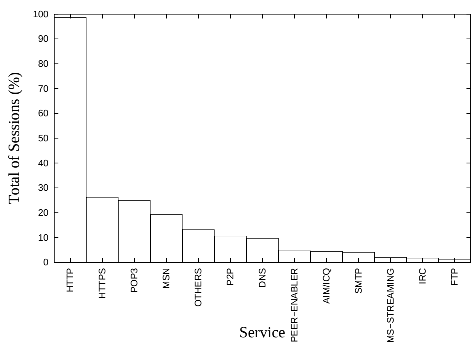
We now turn to the analysis of the most commonly observed user request patterns within a session in our two broadband workloads.

Workload	Metric	*Transferred Bytes*		*Lognormal Parameters*	
		Mean(MB)	*CV*	σ	*μ*
Residential	Incoming	28 - 44	3.95 - 4.63	1.62 - 1.83	1.76 - 2.46
SOHO	Incoming	47 - 80	3.31 - 3.40	1.47 - 1.70	2.39 - 3.27
Residential	Outgoing	10 - 16	6.82 - 8.27	1.84 - 2.09	0.31 - 1.09
SOHO	Outgoing	9 - 23	2.98 - 6.82	1.51 - 2.09	0.41 - 1.31

Table 4: Summary of the Distributions of Incoming and Outgoing Bytes per Session



(a) Residential



(b) SOHO

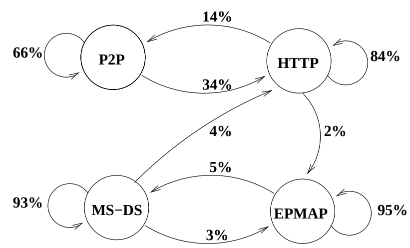
Figure 7: Service Popularity

Our analysis focuses on classes of the services (i.e., HTTP, POP3, P2P, etc) most commonly requested by the users. We first look into the popularity of different services in the SOHO and residential workloads. The popularity of a service is assessed in terms of the percentage of sessions that include at least one request addressed to a port number that identifies the service (e.g., 80 for HTTP).

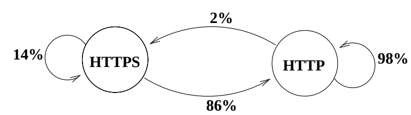
Figures 7(a) and 7(b) show the popularity of different services among residential and SOHO sessions. Although HTTP appears in over 95% of all sessions in both workloads, e-mail (POP3, SMTP) as well as interactive applications such as Instant Messenger and ICQ are also popular among both residential and SOHO users. We also point out the significant fraction of sessions that include requests to P2P services, such as Kazaa. In particular, around 23% of the residential sessions and 12% of the SOHO sessions have requests addressed to P2P services, showing the growth of these applications in broadband network presented in [11, 12]. Interestingly, applications that have higher bandwidth requirements such as streaming media are very modestly used by our users.

Given the inherently different nature of the services typically requested by users in our broadband workloads, we next characterize user sessions by the frequency of requests to each service and the frequency at which a user switches between different services, within the session. To do so, we represent the sequence of service requests within each session with a CBMG, as described in Section 3, and use standard clustering techniques to find the most representative per-session user request patterns.

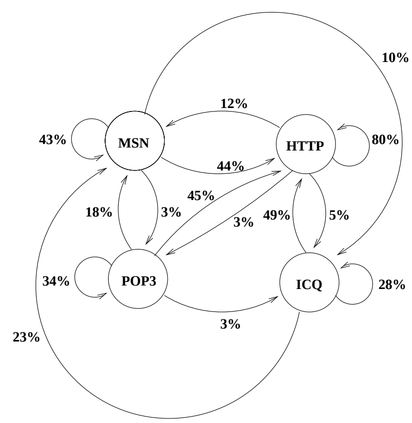
Our analysis uncovered six classes of significantly different request patterns in each workload, summarized in Tables 5 and 6 for residential and the SOHO workloads, respectively. Due to space constraints, we focus only on the classes that accounted for at least 3% of the sessions, omitting two unpopular residential classes and one unpopular SOHO class. Each class is defined by the frequency of requests to each service within a session (first row).



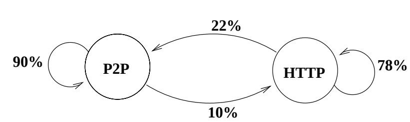
(a) Class 1



(b) Class 2



(c) Class 3

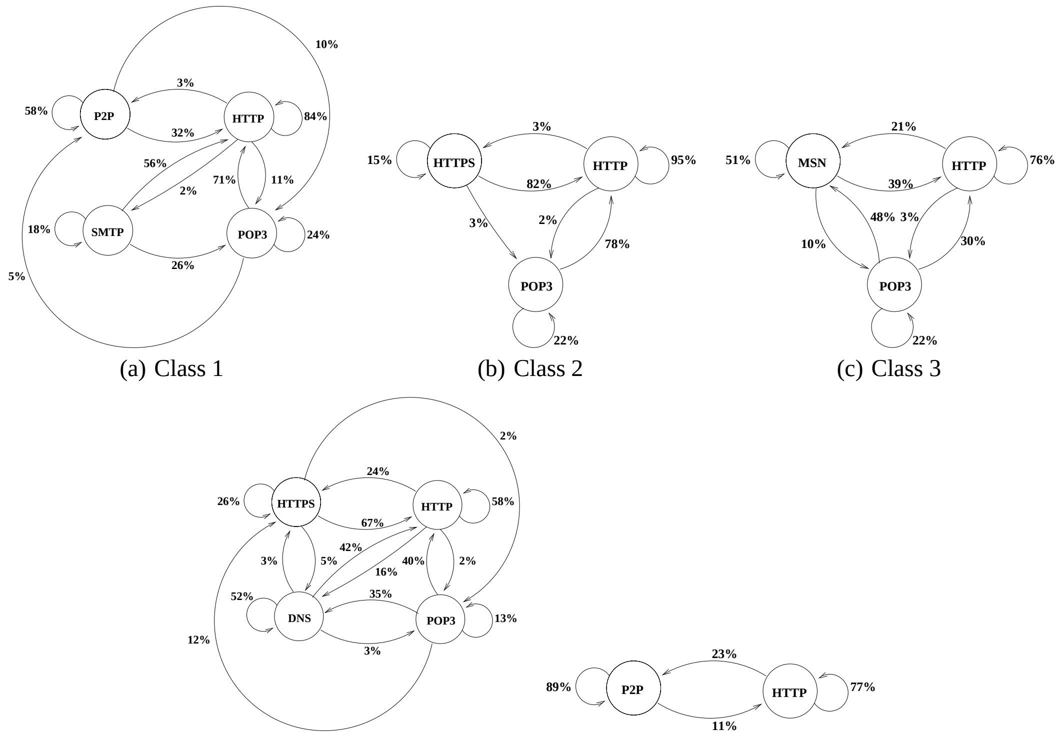


(d) Class 4

Figure 8: Main Classes of Request Patterns for Residential Sessions

	Class 1	*Class 2*	*Class 3*	*Class 4*
Services requested within session	HTTP(43%) P2P(24%) MS-DS(19%) EPMAP(14%)	HTTP(97%) HTTPS(3%)	HTTP(73%) MSN(18%) ICQ(6%) POP3(3%)	P2P(68%) HTTP(32%)
Total # sessions (%)	3,249 (4%)	51,606 (66%)	9,797 (13%)	10,640 (14%)
Total # incoming bytes (GB) (%)	214 (7%)	1,436 (47%)	361 (12%)	806 (26%)
Total # outgoing bytes (GB) (%)	75 (6.5%)	451.6(39%)	111 (10%)	405 (35%)
Mean (CV) duration (hours)	9.01 (2.16)	6.06 (2.61)	8.13 (2.48)	10.43 (2.24)
Mean (CV) incoming bytes (MB)	65.88 (3.76)	27.82 (5.09)	36.80 (4.37)	75.79 (3.69)
Mean (CV) outgoing bytes (MB)	23.14 (4.89)	8.75 (10.33)	11.29 (8.18)	38.06 (4.99)

Table 5: Summary of the Main Classes of Request Patterns for Residential Sessions



(a) Class 1 (b) Class 2 (c) Class 3

(d) Class 4 (e) Class 5

Figure 9: Main Classes of Request Patterns for SOHO Sessions

Within both residential and SOHO workloads, the session classes can be further grouped into two major super-classes. One super-class represents those sessions that are dominated by HTTP requests but also may include some requests to other services such as e-mail, Instant Messenger, ICQ and, generally speaking, P2P services. This category consists of classes 1, 2 and 3 in the residential workload, and classes 1, 2, 3 and 4 in the SOHO workload. Compared to sessions consisting mostly of HTTP requests (class 2 in both workloads), the use of e-mail and interactive chatting applications increase significantly the average session duration and the volume of traffic received and sent out. In other words, users remain connected for longer periods communicating with other people. Sessions that include some requests to P2P services (class 1 in both workloads) are even longer and transfer more data, as one might expect.

The second user session super-class is dominated by P2P requests (classes 4 in the residential workload and 5 in the SOHO workload). They last, on average, much longer than the HTTP-based sessions and transfer significantly larger volume of data.

We note the significantly lower coefficients of variation for the session duration and numbers of incoming and outgoing bytes, for each session class, compared to the variations observed in the aggregated SOHO and residential workloads, shown in Table 1.

Finally, Figures 8 and 9 show the CBMGs of the request pattern classes offered for residential and SOHO sessions, respectively. For instance, a class-3 residential user (Figure 8(c)), requesting a HTTP service, will switch to a POP3 service with probability 0.03, will switch to ICQ with probability 0.05, will start using Instant Messenger (MSN) with probability 0.12 and, finally, with probability 0.80, he / she will remain requesting HTTP service. Note that, in each class, for both residential and SOHO users, the self-loop transitions are very common. In other words, a user tends to use the same kind of service repeatedly.

5. CONCLUSIONS AND FUTURE WORK

Several studies have published regarding characterization of different Web services, such as HTTP, streaming media, and P2P. However, very few studies are available for Internet broadband services. This paper used a quantitative approach for characterizing the behavior of broadband users. The characterization relies on data collected at very specific points in a service provider. The sources of data are the authentication logs, the user database and traffic

	Class 1	*Class 2*	*Class 3*	*Class 4*	*Class 5*
Services requested within sessions	HTTP(77%) POP3(13%) P2P(6%) SMTP(4%)	HTTP(96%) HTTPS(3%) POP3(1%)	HTTP(60%) MSN(34%) POP3(4%)	HTTP(56%) DNS(22%) HTTPS(18%) POP3(4%)	P2P(64%) HTTP(36%)
Total # sessions (%)	1,644 (7%)	16,010 (67%)	2,458 (10%)	1,603 (7%)	1,572 (7%)
Total # incoming bytes (GB) (%)	162.8 (12%)	573.6 (44%)	199.3 (15%)	122.7 (9%)	235.7 (18%)
Total # outgoing bytes (GB) (%)	36.9 (11%)	134.2 (38%)	35.3 (10%)	39.1 (11%)	101.4 (29%)
Mean(CV) duration (hours)	12.23 (2.07)	7.89 (2.53)	11.99(1.50)	11.40 (3.51)	14.82 (1.98)
Mean(CV) incoming bytes (MB)	99.03 (2.60)	35.83 (3.60)	81.08 (2.70)	76.56 (3.26)	149.92 (2.58)
Mean(CV) outgoing bytes (MB)	22.44 (4.81)	8.38 (11.35)	14.37 (3.02)	24.37 (6.85)	64.5 (3.91)

Table 6: Summary of the Main Classes of Request Patterns for SOHO Sessions

logs. The characterization was done at the session level and the request level. The paper uses a state transition graph called Customer Behavior Model Graph (CBMG) [14], to describe groups of users who exhibit similar behavior in terms of request pattern. Some of the findings are: (i) both residential and SOHO session inter-arrival times are exponentially distributed, (ii) for residential and SOHO sessions, the number of incoming and outgoing bytes can be modeled with a Lognormal distribution, (iii) The use of a state transition graph (CBMG) uncovered six classes of significantly different patterns in the user behavior. The results presented in this paper are a first attempt to characterize the behavior of broadband users. We are in the process of refining the characterization of the CBMGs, to evaluate the behavior of other services such as games and operating system-oriented services. We are also working to create CBMGs that group classes of users, instead of classes of sessions, and the characterization of broadband daily pattern use.

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