On Browsing Behavior-based Traffic Model of Mobile Internet

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***Abstract*—With the rapid rising of the number of cellular phone users, accessing the Internet via handset devices is becoming a standard configuration in terms of network activities and people's daily life, resulting in an ever-increasing usage of the Mobile Internet. Yet, there were little knowing about how users' behavior on Mobile Internet is. Considering most Mobile Internet users satisfy browsing, the browsing traffic is focused in this paper. Through studying on users' browsing behavior on Mobile Internet with an extended On-Off model to understand generation mechanism of browsing traffic, this paper proposed a browsing traffic model in which such results as self-similarity of traffic volume and following Pareto and Weibull distribution of File Size, View Time and WAP Gateway Response Time were found out by investigating real data sets. This paper launches a primary research on traffic model for Mobile Internet browsing behavior.**

Keywords-Mobile Internet;User behavior;Browsing Traffic Model;K-S test

I. INTRODUCTION

Mobile Internet has become a profitable and promising business. According to CNNIC's (China Network Information Center) report [1], there were about 35,558 netizens investigated had Mobile Internet surfing experience with mobile phone in 2011, while 11,760 in 2008 which have increased about 3 times in these years. The report also shows that 62.1% and 60.9% Mobile Internet netizens habitually use news and search service [1], respectively, which means that browsing traffic is the main stream of Mobile Internet traffic now in China.

However, there were few studies on user behaviors on Mobile Internet while such throne market. Some previous researches [2] [3] [4] [5] focused on WAP-based (Wireless Application Protocol) mobile network behaviors. The model of the WAP traffic generated by requesting web pages that reply with Wireless Makeup Language (WML) files in General Packet Radio Service (GPRS) network was studied. Varga et al. [2] provided a traffic model based on long-term, live measurements, and observations to estimate the user behavior and the workload in GPRS network. Irene C. Y. Ma et al. [3] constructed a model of WAP traffic based on a number of user scenarios to study the characteristics of the WAP traffic. Toshihiko Yamakami [4,5] studied user behaviors on mobile Internet in Japan. By examining the long-term mobile Internet user transaction logs, he analyzed the long-term usage pattern to study the notion of user "age" (the length of user experience [4]) and explored regularity measures to track user behaviors based on an ad-hoc assumption that the user loyalty relates to the web visit regularity [5]. In some newest research on Mobile Internet traffic, Lymberopoulos et al. [20] proposed to use a machine learning approach based on stochastic gradient boosting techniques to efficiently model the signature of Mobile Internet users whose web access traces were analyzed. Chuan Xu et al. proposed a new method of measuring the similarity of daily clicks distribution by Pearson Correlated Coefficient and introduced various means to describe the heterogeneity of clicks distribution both in users and in websites [21]. Some interesting results (like users' obeying 20/80 rule) were found in [20][21].

Being a basic theoretical issue, the research of traffic model is valuable for WAP/Web site owners and network operators and also useful in study on future network. Most users of Mobile Internet, as page browsers, are satisfied with viewing page such as news and search. Thus, browsing traffic (or HTTP traffic) is the dominating traffic of Mobile Internet. This paper aims to build a traffic model of page browsing for describing the browsing traffic behaviors on Mobile Internet. The contributions of this paper are summarized as follows:

- An extended On-Off model is used to help understanding the mechanism of traffic generation of page browsing behavior on Mobile Internet. Traffic Volume, File Size, View Time and WAP Gateway Response Time were determined to describe the traffic model of page browsing behaviors.
- We analyzed the parameters of model through a real data set from methods such as Hurst coefficient [12] and K-S test [2].

This paper is organized as follow: We constructed a browsing traffic model in Section II. In Section III, data sets obtained in two years is presented. With these data sets, we worked out the analysis of the browsing traffic model by Hurst coefficient and K-S test with data we contained in Section IV. Finally, this paper is concluded in Section V.

II. MODEL CONSTRUCTION

A. *Communication Mode*

In user's browsing behavior on Mobile Internet, there are three kinds of communication entries involved. They are user, gateway and WAP/Web server as shown in Figure 1. On the Mobile Internet, the requests of users have to be transpond by the gateway before arriving servers. The same thing happens to the responses from server. Users' browsing pages of WAP site or Web site cause their sending two kinds of requests to servers: WAP browsing refers to the browsing demands for the hypertext pages that respond with the WML language following the WAP suite. Web browsing refers to the browsing demands for the PC-based pages to Web servers but through mobile terminals. Yet either the requests of WAP browsing or Web browsing should get through gateway on Mobile Internet. Thus, the traffic of Mobile Internet has to go through the gateway [2].

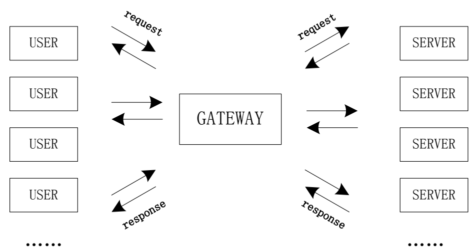

Fig. 1. Communication Mode.

Being in such a special network structure, the traffic behaviors on Mobile Internet are different from that of PC-based Internet.

B. Extended On-Off Model

The On-Off model is introduced in many researches of network traffic [6] [7] [19]. In analyzing the user traffic behaviors, each user is recognized as an On-Off source in which On-State represents traffic generating process and Off-State represents silent period.

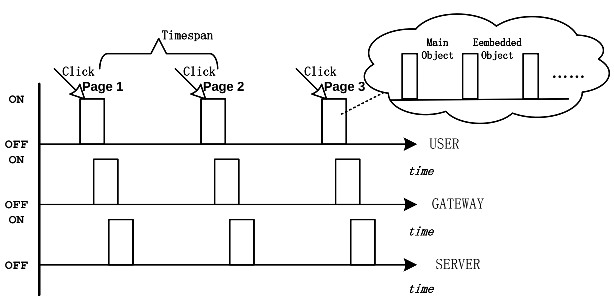

Fig. 2. The Extended On-Off Model.

To explain how the page browsing traffic is generated on Mobile Internet, we extend the On-Off model by adding details from the WAP gateway and WAP/Web server as shown in Figure 2. When a user launches a session, the WAP gateway and WAP/Web server should be ready for serving. It is explicit that user's behavior still can be recognized as two states, On-State for requesting hypertext page started by clicking which generates traffic and Off-State for reading. Consequently, WAP gateway and WAP/Web server would be on On-State for handling requests and sending responses back and Off-State for waiting for serving.

C. Browsing Traffic Model

As stated in previous section, the mechanism of traffic generation of page browsing for the traffic situation depends on the way users switch between On-State and Off-State and network structure. To study browsing traffic we need to answer such questions like how often the user clicks pages, how the pages traffic volume is and how the delay of Mobile Internet network is. Thus we consider 4 factors influencing page browsing traffic which are

- Traffic Volume (TV);
- File Size (FS), including main object size (MS) and embedded object size (ES);
- Viewing Time (VT);
- WAP Gateway Response Time (GRT).

Traffic Volume can directly descript the traffic situation. File Size indicates the traffic volume generated by browsing the traffic of which is also the main traffic of the network. Viewing Time denotes the user reading and clicking frequency. Moreover, WAP Gateway Response Time show how the WAP gateway affects browsing time consumption which is the very procedure delaying the traffic transmission.

With these 4 factors, we primarily establish the browsing traffic model on Mobile Internet. In the rest of this paper, we investigated this model by real data sets.

III. DATA SETS

The dataset in this paper is obtained from the log files of a WAP gateway which belongs to China Telecom. These WAP gateway logs record all the information of Mobile Internet users' online activities for one week from Apr. 5, 2010 to Apr. 11, 2010, and the other week from Apr. 4, 2011 to Apr. 10, 2011. Each record in the log files contains request and response information including Time, Destination Domain, URL, Client IP Address, User Agent, etc.

A basic statistics of these data sets is shown in table, as appendix. The change proportion of WAP traffic and Web traffic can roughly label the change of mobile terminal performance for users tend to abandon WAP page with high-performance terminal which also reflects the change of user behavior pattern.

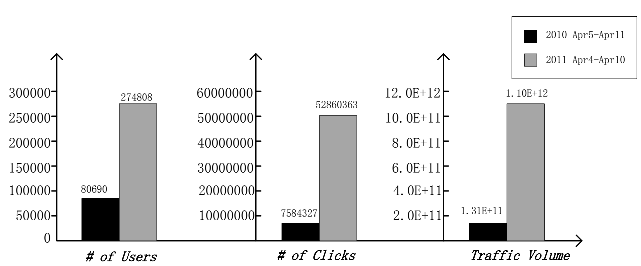

Fig. 3. Data Items Comparison

Here, base on the data obtained, we would like to study data characteristics by statistically analyzing. As shown in Figure 3, we worked out the total number of users, clicks and total flow traffic of the data of the two weeks which have increased about 4 to 8 times in these two years. We can infer that the WAP gateway burdens a higher workload at 2011 comparing 2010, indicating the exploding growing of Mobile Internet.

With the overview of our data sets shown above, we can get an outline about the development of Mobile Internet. However further study is still necessary for practical purposes.

IV. ANALYSIS OF MODEL

A. Traffic Volume

Traffic Volume (TV) is an indicator to simply describe traffic situation of network. Self-similarity is an important characteristic of Traffic Volume as mentioned in [7]. Thus at the beginning, we analyze the elementary daily Mobile Internet traffic pattern to find the law of user behavior by investigating self-similarity of Traffic Volume. However, the traffic analyzed is from macroscopic view, the analysis bases on statistic.

Here are the traffic distributions on statistic for a week in Figure 4. The daily Mobile Internet service condition could easily show the daily user behavior as users browse in day-time and sleep at night. The traffic is high in the daytime because people are active while the traffic stays low after about two hours in the early morning because most of people fall asleep. The relations between traffic of different days are not clear. Yet, we can think over the self-similarity of the Traffic Volume.

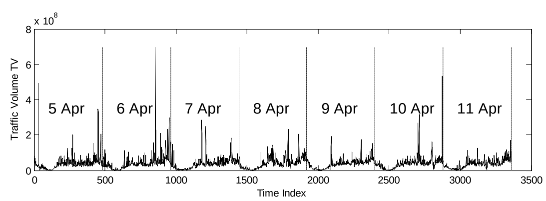

Fig. 4. Traffic Distributions for a Week.

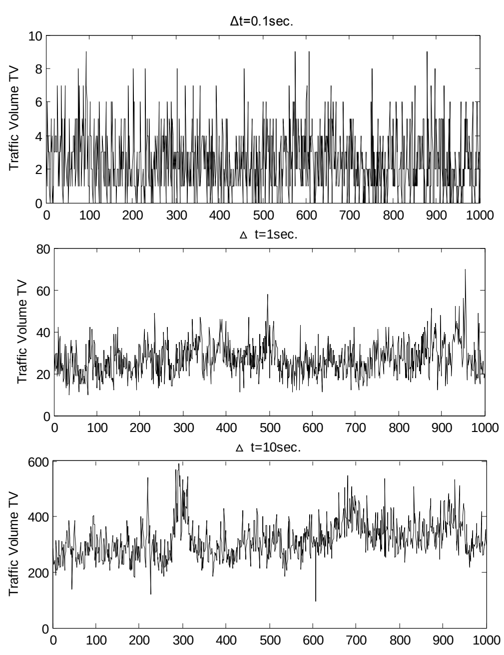

Fig. 5. Sample Aggregation Plot for Mobile Internet Traffic

The self-similarity of network traffic has been proven in many studies [8][9]. The studies on WAP traffic, for the most part, base on simulated WAP traffic or small data set of real trace which only comprise of pure WAP traffic [10][11]. The paper give a self-similarity study based on the data from a large scale data set of real trace of mobile Internet, which not only contains the WAP traffic but also the traffic generated by the connecting between the mobile terminals and Internet.

Mobile Internet traffic was aggregated into various time frames to roughly be observed self-similarity. For 27 consecutive hours of monitored mobile Internet from April 2010 trace, Figure 5 shows a sequence of simple plots of requests which counts for 3 different time frames, each subsequent plot is included in the previous one by increasing the time resolution by a factor of 10 on a random subinterval.

Intuitively, the curves of days in Figure 5 are 'similar' to one anther. To prove the self-similarity of daily mobile Internet traffic, R/S algorithm is used to calculate the Hurst coefficient of daily traffic.

Let $X=\{X_1, X_2, X_3, ..., X_L\}$ be a time series with length *L*, where the length of each series =10 sec. in the calculation. *X* is partitioned to be *d* subsequences with length *n* obviously, if the value *n* is definite, there would be $L=d\times n$. The R/S algorithm computes the Hurst coefficient according to [12].

Table I. Hurst Coefficient Distribution for the Week of 2010.

Date	*Num. of time series*	*Scale of partition*	*Num. of fit points*	*Hurst*
5 Apr.	7801	2~3900	2603	0.7984
6 Apr.	7788	2~3894	2598	0.8063
7 Apr.	7805	3~3902	1954	0.7968
8 Apr.	7797	3~3898	1952	0.8114
9 Apr.	7804	3~3902	1954	0.8200
10 Apr.	7748	2~3874	2585	0.7992
11 Apr.	7759	2~3879	2589	0.8038
5-11 Apr	54498	3~27249	13631	0.8169

Hurst found that many time series could be well represented by the relation $(R/S)_n \sim cn^H$, taking the logarithm of both side: $\log(R/S)_n = \log c + H\log n$, where *c* is a constant. The data fitting method is used after plotting $\log(R/S)_n$ versus $\log n$. The degree of self-similarity is given by *H*, which is the slope of line of fit above.

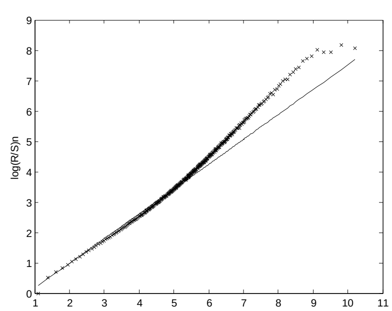

Fig. 6.The Result of R/S for a Week

In this experiment, Mobile Internet traffic was collected consecutively for a week, and the time series was partitioned according to 10 sec. We separately give the results under two different time scales, days and weeks, shown in the table I and the result of R/S for a week is shown in Figure 6.

The parameters of Hurst in Table I are all around 0.8, where a value above 0.5 indicates self-similarity. This compares to the Hurst parameters in the range between 0.76 and 0.83 exhibited by the actual traces captured from web browsing activity [13]. We believe that Mobile Internet in China now being in the preliminary stage, its properties on traffic and some other aspects may be similar with that of PC-based Internet traffic in the early stage.

B. *File Size*

Though the study on TV above provides the outline of the traffic model, we still need some more details about it. Through the On-Off model, we can understand how a page is generated. Main object, the response to user's clicking, constitutes the page associating with embedded object. As embedded object is requested by browser acting differently from user's clicking, it is necessary to study their traffic pattern respectively. File Size which refers to the size of page objects (such as html, flv and gif) from server is the source of browsing traffic. The investigation to MS and ES can clarify the detail of page browsing behavior.

We can easily obtain File Size by extracting information of DOWNLINK_CONTENT_LENGTH domain of each record in the data set. We distinguish main object record with embedded object record by the analysis of URL domain and Content_Type domain which are recording the URL (Uniform Resource Locator) and type of resource (text, img et) of the object. The two kinds of objects and the results are shown in the Figure 7.

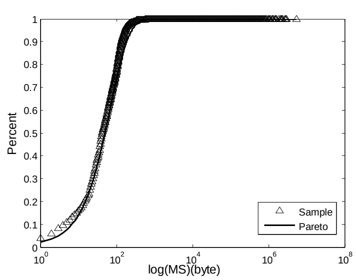

Fig. 7 (a) CDF of MS.

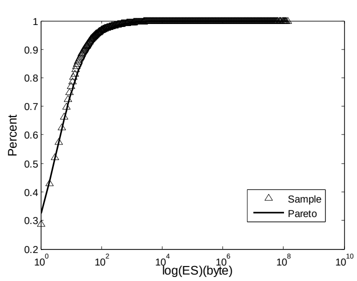

Fig. 7 (b). CDF of ES

Fig. 7. CDF of FS.

Having obtained the CDFs (Cumulative Distribution Function) of File Size, we perform the K-S test on them whose results are also shown in Figure 7 and Table II. In our testing, the samples of our data set follow the Pareto distribution. In Figure 7, we can find that the curves of empirical data fit theoretical curves perfectly. The result comes as the same as [14]. In Table II, the parameters of the fitting Pareto curves are shown.

Table II. K-S test to FS

	Parameter of Fitted Distr.	*Dn*				
	Pareto	*Pareto*	*Norm.*	*Exp.*	*Weibull*	*Loglgst.*
MS	k=0.13 λ =70	0.0353	0.4487	0.1813	0.5524	1
ES	k=1.21 λ =3	0.0747	0.6427	0.1534	0.8663	1

In Figure 7(a), the curve rises directly at about [80,120] which means most MS ranges between 80 to 120 byte. As the main object often carries the information the users going to read, we deem the trend of MS reflects the fact that one page usually provides few information for user on Mobile Internet. This is a normal phenomenon for the small screen of the terminal and specially arrangement of the WAP/Web site owners. The same trend also happens in Figure 7(b) plotting the curve of ES CDF. The ES concentrate on the range between 50 bytes to 200 bytes. It actually can be easily inferred by considering the simplicity of browser and the low capability of terminal. Thus, we believe the Pareto distribution is appropriate for describing the File Size.

C. *Viewing Time*

The Viewing Time (VT) denotes the timespan that a user browses a web page. The exact Viewing Time actually is difficult to count because we cannot trace the time that the user finishes receiving the web page, so the error is transmission time. However, the transmission time exists in every user click and is transitory compared to the whole VT. We roughly consider the timespan between two user requests in a session to be the view time on mobile Internet. Now, the problem is how to determine each user session (it refers to the course from spanning users' opening to closing browser software.) because the timespans between each user session are contained in the timespans between two user requests.

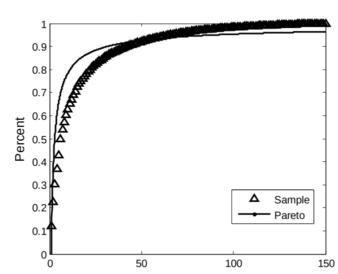

Fig. 8. CDF of VT.

The user session could be determined exactly by Client IP which is randomly assigned. We found Mobile Internet system randomly assigned Client IP when user logged on Mobile Internet, thus through tracing user log we could easily abandon the timespans between user sessions. However, when the user left idle for a long time (idle time) for some reasons, this timespan was still considered as VT. In PC-based Internet, 79 percent of our test users always scanned any new page they came across; only 16 percent read word-by-word [15], and our trace showed that 97.9% users' VT last within 150 seconds. Thus, VT on Mobile Internet could not be long. So, we give a threshold 150 seconds to determine the idle time, which means that VT lasts within 150 seconds while idle time last longer than it. According to the statistic, VT less than 10 seconds account for 62.85% of all VT of users; viewing time between 10 and 20 seconds is responsible for 17.97%. The CDF of VT is plotted in Figure 8.

In [16] and [17], VT follows Pareto distribution. The sample from our data set, through K-S test mentioned above, is proved to have no best fitted distribution, but the largest vertical distance of Pareto distribution in Figure 8 indeed turn out to be the minimum. It is obviously in Figure 8 that the curve of our sample rises relatively slower than the Pareto distribution. On the average Web page, users have time to read at most 28% of the words during an average visit; 20% is more likely [18]. Comparing to PC-based Internet, the reading habit of user on Mobile Internet is similar. However, because the size of screen for each mobile terminal is much smaller than ordinary computer screen, information delivered from mobile terminals is so limited that users are more willing to read word by word, and taking transmission time into consideration, the VT of mobile Internet users is relative longer than PC-based Internet, which is the reason why the curve of our sample rises slower than Pareto distribution. However, the details of how mobile Internet user read is still not clear, which will be our next work. We believe there is a certain reading habit rule for each user.

D. Gateway Response Time

Because of particular communication structure, the total response time of Mobile Internet is relatively longer than PC-based Internet for one request process. Firstly, the WAP Gateway Response Time (GRT) accounts for a significant part while there is no such period in PC-based Internet. Secondly, computing the Mobile Internet response time for one request need take many environmental factors such as weather conditions, geographic location into consideration. In this part, we observed the response time of the two main elements on Mobile Internet and explored their relations. At the same time, the Viewing Time from Mobile Internet will be made comparison with it on the PC-based Internet.

We observed the GRT for consecutive 168 hours and were looking forward to find its evolution with time. For better observation, the GRT for 168 hours was analyzed by dividing all the response time into several time ranges, and we explored how the different requests distribute in various time ranges, which is shown in Table III.

After exploring the response time in detail, we give a macroscopical description on GRT distribution shown in Figure 9. It could be predicted from Table III, which exhibits most of requests were processed in a certain time range.

Table III. GRT to Different Objects

Time ranges (millisec.)	*Num. of main object*	*Num. of embedded object*	*percentage*
Above 5000	4624	134	2.9%
500~5000	208	38	18.3%
300~500	249	14	5.6%
100~300	7606	226	3.0%
50~100	8488	140	1.6%
30~50	39694	100	0.3%
20~30	101889	318	0.3%
10~20	969056	52111	5.4%
5~10	6290582	2517246	40.0%
0~5	9894219	5515933	55.7%

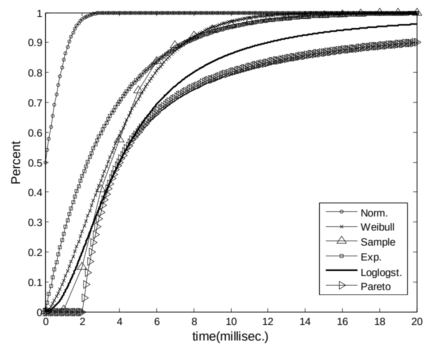

Fig. 10. K-S test to GRT.

Table IV. K-S test to GRT

	Mean	*Std. Dev.*	*Fitted Distr.*	*Parameter*	*α*
Response time	6.343	95.241	\	\	0.05
Normal response time	4.672	2.675	Weibull Distr.	λ =3 k=2	0.05
	Dn				
	Exp Distr.	*Norm. Distr.*	*Weibull Distr.*	*Loglgst Distr.*	*Pareto Distr.*
Response time	8.139	149335	7.003	26.587	3760
Normal response time	1.387	3.849	1.242	4.611	643

In Table IV, the K-S test was applied to measure the data set of the response time and no distribution was shown to be well fitted. The reason, through analysis, is that most of the requests were processed within the "normal" response time while few of requests for some reasons exceeded. Therefore, it is obvious to notice from Figure 10 that the curve is steep at beginning. The normal response time mentioned above refers to the response time within 20 milliseconds. We found that the normal response time well fitted the Weibull distribution through K-S test with $c(\alpha)$=1.358 and significance level of α=0.05, which is shown in table 5 and Figure 10 demonstrate the CDF of aggregated normal response time. By visual inspection, we can find that the

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CDF curve of Weibull distribution most closes to that of the sample.

In [2], non-rejects of K-S test occur rarely because the large size of data sets generated by some underlying mechanisms cannot be easily modeled. In our experiment, frankly speaking we didn't make clear of detailed mechanism in WAP gateway but depicted the data set from statistic. We found that the goodness of fitness for a certain function distribution changed with its parameters when applying the K-S test to the data set. So the fitted distribution we give maybe not the best one, but we want to do is to give an appropriate and exact description to our samples and elaborate its properties.

V. CONCLUSION

Considering the different network structures between Mobile Internet and PC-based Internet, we utilized the On-Off model extended to understand how the user's behavior of browsing page influents traffic situation of Mobile Internet. Based on that, we built up a model for the user's page browsing behaviors on Mobile Internet.

We performed an analysis of the traffic model by methods such as Hurst coefficient and K-S test with the data sets collected at the same period in 2010 and 2011 which also indicate a development of Mobile Internet in these two years. It was found that Traffic Volume was with the property of self-similarity; File Size followed Pareto distribution; Gateway Response Time followed Weibull distribution; yet the property of Viewing Time was hard to determine. These results are significantly valuable in assisting network operators to further optimize Mobile Internet network settings.

However the further works is still necessary. In the future, we will study the browsing traffic model established in the paper more deeply. We could try to find out the relation between the parameters of this model. This will help us get a better understanding of traffic situation of Mobile Internet.

ACKNOWLEDGMENT

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APPENDIX

Table. Basic Statistics of Data Sets.

Date	***Number of Records***	***WAP Requests***	***WEB Requests***	***WAP Traffic Volume(GB)***	***WAP Percent***	***WEB Traffic Volume(GB)***	***WEB Percent***
2010-4-5	2275407	806752	382918	5.96	31.49%	12.98	68.51%
2010-4-6	2487533	840858	471434	6.09	30.52%	13.87	69.48%
2010-4-7	2594647	888792	560126	6.29	34.04%	12.19	65.96%
2010-4-8	2534699	846169	567362	6.37	34.14%	12.29	65.86%
2010-4-9	2578779	865051	467761	6.59	37.05%	11.19	62.95%
2010-4-10	2427638	838695	409063	6.21	31.61%	13.45	68.39%
2010-4-11	2417913	876233	408261	6.27	36.05%	11.89	63.95%
2011-4-4	17321932	5371434	11950498	37.54	23.66%	121.14	76.34%
2011-4-5	16040697	4917835	11122862	34.03	24.02%	107.67	75.98%
2011-4-6	16694404	5017418	11676986	33.33	21.76%	119.89	78.24%
2011-4-7	17838468	5435136	12403332	37.78	22.62%	129.27	77.38%
2011-4-8	17591404	5330330	12261074	36.72	22.16%	129.03	77.84%
2011-4-9	16991844	5147989	11843855	35.28	21.82%	126.45	78.18%
2011-4-10	16450519	4933624	11516895	33.59	22.13%	118.21	77.87%
The Week in 2010	17316616	5962550	3266925	43.79	33.46%	87.08	66.54%
The Week in 2011	118929268	36153766	82775502	248.3	22.57%	851.68	77.43%

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