Analysis of User Access Behavior in Distance Education Website

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Abstract: Based on the acquisition of a distance education website user access behavior data, the paper analyzed two diversion indicators, PV and UV, and several sticky indicators that reflect video on demand and live streaming browsing. By the data analysis, the paper found the change regulation of the PV, the hot time of the user access, the reason why user access evaluation results are optimal. The results shown that the website may focus on pushing some video resources during periods of high user access, and promptly give push tips.

1. Introduction

Over the years, user behavior analyses have evolved considerably. Because the user can show a variety of types of browsing behavior in the browsing process, so the relationship among the different type of user browsing behavior analysis can provide more sufficient and detailed clues to solve the actual user interest, access habit and learning effect in the page[1]. As an important research method, user online behavior analysis is widely used. Data analysis is actually a process of logical construction among different data with statistical meaning.

In this paper, based on the acquisition of a distance education website user access behavior data, according to diversion indicators including the page view and study duration, clicks, viewing integrity, timely attention and video type preferences data analysis and mining are carried out in-depth. User behavior patterns of distance education website are found behind the data. The patterns include the influencing factors of the page view, the time of the user access to the website, the relationship between learning effect and study duration, the degree of user's interest in the video site, and the preference for different video types.

2. Diversion Indicators Analysis

Network user behavior refers to the law of user in the use of cyber source[2].This rule is usually obtained according to records, statistics and analysis based on the use of cyber source of user data. The diversion indicators included PV (page view), UV (unique visitor), VV (visit view), access times, and number of new visitors, new visitor ratio, IP and so on. This section focuses on visual analysis of PV trends, VV, and access time.

2.1. PV Analysis

A page view (PV) is a request to load a single HTML file (web page) of an Internet site [3]. On the World Wide Web, a page request would result from a web surfer clicking on a link on another "page" pointing to the page in question. A page view has long been a measure of user activity on a website. Page views may be counted as part of web analytics. For the owner of the site, this information can be useful to see if any change in the "page" (such as the information or the way it is presented) results in more visits. [4]

2.1.1. Data Preparation

This paper intercepts the daily browsing information of a distance education website in a given period of time (2017/05/15-2017/05/28) by random sampling. Statistics were conducted in a week cycle, and the data were divided into two groups last week and this week, as shown in table 1.

Table 1 Daily PV data.

	2017/5/15-2017/05/21 (Times)	2017/05/22 - 2017/05/28 (Times)	Compared With Same Day Last Week	Compared With Yesterday
MON	5080	7202	41.8%	
TUE	5436	6833	25.7%	-5.1%
WED	5891	6764	14.8%	-1.0%
THU	5971	5506	-7.8%	-18.6%
FRU	5203	5196	-0.1%	-5.6%
SAT	3525	4824	36.9%	-7.2%
SUN	1470	1173	-20.2%	-75.7%

2.1.2. Data Visualization Analysis

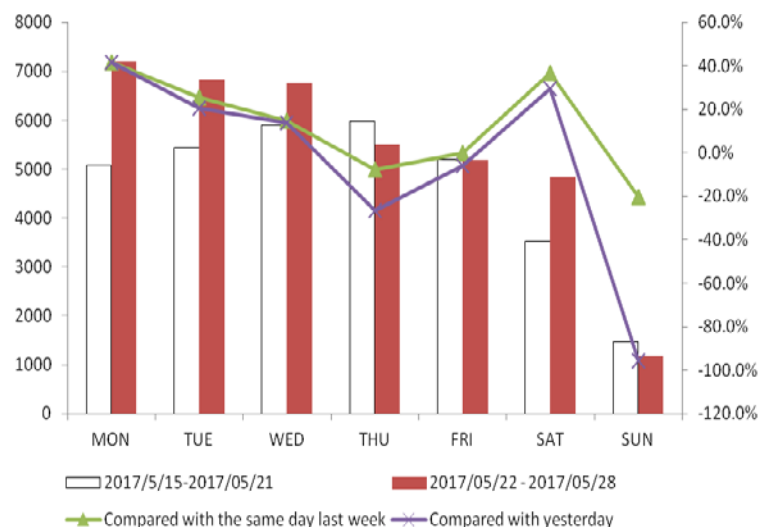PV trend analysis is shown in figure 1.

Figure 1 PV trend analysis.

From Monday to Wednesday, daily PV was slightly different, with growth compared with the same day last week, especially a growth of 41.8% on Monday. Visits decreased significantly on Saturday and Sunday, compared with Sunday's minimum of -75.7%. Data changes indicate that users of distance education websites are more concentrated in the first half of the week, and that users are learning in a normal state in the sampling cycle.

2.2. UV Analysis

When tracking the amount of traffic on a Web site, it refers to a person who visits a Web site more than once within a specified period of time. Different from a site's hits or page views which are measured by the number of files that are requested from a site -- unique visitors are measured according to their unique IP addresses, which are like online fingerprints, and unique visitors are counted only once no matter how many times they visit the site. [5]

If visitors don't reopen and refresh the web page of the site, or if the visitor closes the browser for more than 30 minutes, the number of visits increases by 1 when the visitor visits the site next time. On the other hand, re access within half an hour is considered the same visit. All of the above visitors shall be judged by Cookie.

2.2.1. Data Preparation

In this paper, the daily UV of the week is calculated according to the period of division, every two hours for a period of time, as shown in table 2.

Table 2   UV for each time period.

	MON	TUE	WED	THU	FRI	SAT	SUN	WEEK
22:00-23:59	10	79	102	66	3	22	45	327
20:00-21:59	77	93	53	43	94	81	44	485
18:00-19:59	30	25	67	116	81	8	86	413
16:00-17:59	133	158	136	74	73	114	12	700
14:00-15:59	127	153	139	146	202	177	100	1044
12:00-13:59	146	139	145	51	30	49	92	652
10:00-11:59	132	245	248	214	217	228	14	1298
8:00-9:59	420	338	318	297	382	231	108	2094
6:00-7:59	107	113	120	97	85	78	5	605
4:00- 5:59	43	40	1	86	100	24	98	392
2:00-3:59	55	31	86	86	14	59	85	416
0:00-1:59	92	75	4	2	66	88	69	396

2.2.2. Data Visualization Analysis

The UV trend chart shows the UV per unit time period from Monday to Sunday, as well as the total UV during the whole week, as shown in figure 2.

According to figure 2, the curve is basically the same in distance education website from Monday to Sunday and the whole week. The number of users who visit the website in 0-6 and 18-24 is very few. The number of visits has slow increased in 6-8, 10-14 and 16-18. Users are mainly forced in 8-10 and 14-16 of the two time periods, and the peak value of 8-10. The amount of UV is consistent with the work time. This reflects that distance education site users are basically learning during working hours.
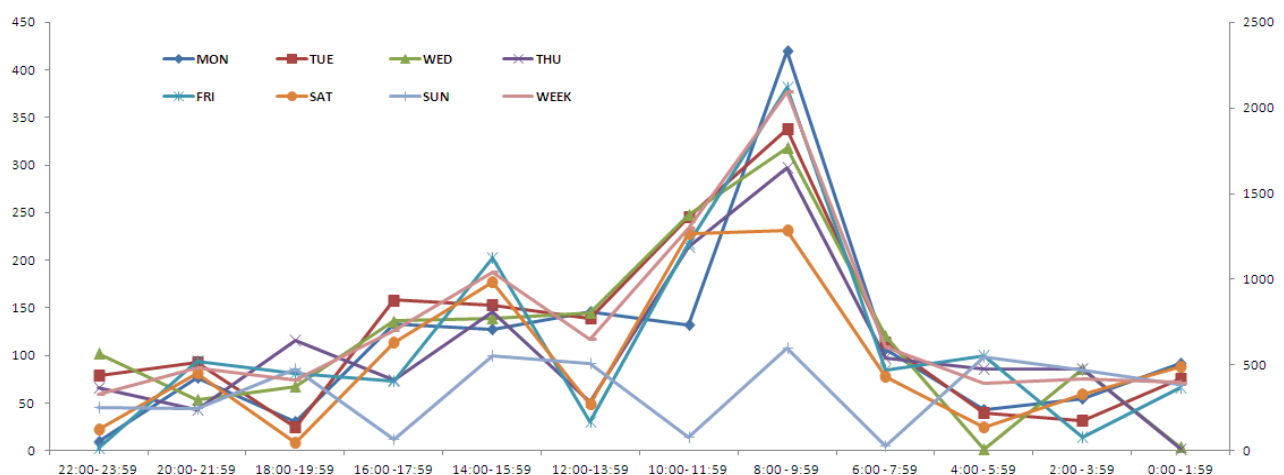

Figure 2 UV trend analysis.

2.3. Result

From Figure 1, the distance education website is in a normal developing state. From Figure 3, the distance education web site visitors are basically stable. Subject to the nature of the distance education website itself, visitors are mainly accessed during working hours. PV and UV are an overview of the web site. It is not reasonable to measure the success or failure of a website solely by PV and UV; just they are only a simple reflection of quantity change.

3. Sticky Indicators Analysis

The stickiness index of distance education website can be judged by the use of video on demand (VOD) and live streaming, such as, study duration, clicks, viewing integrity, and timely attention and so on.

3.1. VOD and Live Streaming Indicators Analysis

VOD is composed of nine parts, including number of videos viewed, clicks, and time per viewer, enrolment rate, scoring numbers and others, for details see Tables 3.Live streaming is composed of three parts. The higher the score, the more users realizes the development goal of the distance education website.

Table 3   User stickiness evaluation index.

First level	Second level	Weight	Criteria	Grade	First level	Second level	Weight	Criteria	Grade
Video on Demand (VOD)	Number of videos viewed	0.0996	≤800 801～1200 1201～1600 1601～2000 ≥2001	1 2 3 4 5	Video on Demand (VOD)	Message（Piece）	0.0426	≤5 6～14 15～23 24～32 ≥33	1 2 3 4 5
	Clicks（Times）	0.0925	≤3000 3001～12000 12001～21000 21001～30000 ≥30001	1 2 3 4 5		Viewing Integrity（%）	0.0823	50～60% 61～70% 71～80% 81～90% 91～100%	1 2 3 4 5
	Time Per Viewer（Hour）	0.1397	≤2000 2001～7000 7001～12000 12001～17000 ≥17001	1 2 3 4 5		Timely Attention（Day）	0.058	29～40 22～28 15～21 8～14 1～7	1 2 3 4 5
	Enrollment Rate（%）	0.0573	≤20% 21%～40% 41%～60% 61%～80% ≥81%	1 2 3 4 5	Live Streaming	Clicks（Times）	0.0979	≤3500 3501～4000 4001～4500 4501～5000 ≥5001	1 2 3 4 5
	Scoring Numbers（Times）	0.0584	≤10 11～40 41～70 71～100 ≥101	1 2 3 4 5		Time Per Viewer（Hour）	0.1455	≤2400 2401～3100 3101～3800 3801～4500 ≥4501	1 2 3 4 5
	Score	0.0715	1 Star =1 Points	1 2 3 4 5		Enrolment Rate（%）	0.0573	≤20% 21%～40% 41%～60% 61%～80% ≥81%	1 2 3 4 5

3.1.1. Data Preparation

According to the video modules provided by the website, the collected data is integrated. Furthermore, partial data can be automatically obtained from the distance education decision support system, based on the scoring criteria in table 3. The weight is obtained according to Delphi method.

3.1.2. Data Visualization Analysis

In this section, the video learning data of distance education website users in 2016 is selected as the reference group, and compared with the same period in 2015.

Table 4   All user evaluation Result

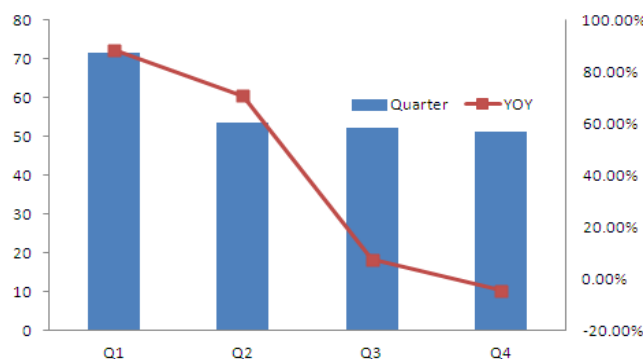|	Q1	Q2	Q3	Q4
Quarter(2016)	71.6	53.6	52.4	51.2
YOY	88.42%	70.70%	7.38%	-4.48%

Figure 3 All users evaluation Trend Analysis.

According to figure 3, besides the first quarter of distance education, the other 3 quarters of User stickiness evaluation are not very high, just over 50 points, and showed a slow decline trend in 2016. However, according to year-on-year data show that the user viscosity in 2016 has greatly improved than in 2015. Since the third quarter of 2016, the year-on-year difference has been smaller, indicating that the user viscosity has improved rapidly since the third quarter of 2015 until the third quarter of 2016, peaking in the first quarter of 2016. Compared to the fourth quarter of 2016 and the fourth quarter of 2015, user viscosity was negative. The user viscosity is lower than the same period last year.

3.2. Result

We want to know how users have traversed pages (page path flow), what are their interest areas (page sections), what links they click etc. Why is the user evaluation result optimal in the first quarter of 2016? The reason is that a number of new video resources have been uploaded at the end of 2015.These videos are basically micro video, animation, piece of information science by the users love.

4. Conclusion

Using data analysis to drive website optimization is one of the most scientific decision-making methods. The purpose of online user behavior analysis is to predict learning outcomes and to intervene in order to better improve the learning effectiveness of distance education websites. The analysis of learning aims to provide users with input skills evaluation, but the technology is not absolutely reliable, any technology there will be errors, so learning report to make a comprehensive judgment requires a combination of knowledge and theory. According to the results of the analysis, combined with users like to begin study activities in workday 8-10 and 14-16, especially Monday to Wednesday, the website may focus on pushing some video resources, and promptly give push tips. More importantly, the content and quality of the website need be optimized according to the video content and type that most users like, and other indicators that reflect stickiness. Only by relying on high-quality and rich content, the websites can stimulate users' interest in browsing and attract and retain more users.

Acknowledgements

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