On an Algorithm for Identifying Sessions from Web Logs

Claudia Elena Dinucă¹, Dumitru Ciobanu²

Abstract. The quality of decisions is based on the quality of processed data. So it is important that at the beginning of the data mining process to provide correct and quality data. The preprocessing data is a necessity for avoiding the failure of the data analysis. The idea that the data mining process can be done without human supervision has proved to be wrong. Even so, the humans are trying to automate as much as possible the process. From here are resulting many algorithms and techniques that are implemented using various programming language. In this work is presented an algorithm for identifying the sessions from a web logs file. It uses a value of 30 minutes to mark the end of a session and start another. We compute the average time for visiting the pages and using this we show that the presented algorithm produces errors in identifying sessions. We consider that the correct way to identify the session is to take into account the average time for visiting the pages.

Keywords: clickstream analysis; preprocessing data; sessions' identification.

JEL Classification: L86; C63; C88.

1. Introduction

World Wide Web or Web on short is the universal information space that can be accessed by companies, governments, universities, students, teachers, businessmen and some users. In this universal space trading and advertising activities are held. A Web site is a lot of interconnected web pages that are developed and maintained by a person or organization. Web mining and analyzing studies reveal useful information on the web. Web mining studies analyzes and reveals useful information from the Web (Cooley, Mobasher & Srivastava, 1997). Web mining is a term used for applying data mining techniques to Web access logs (Zaiane, 2000). Data mining is a non-trivial process of extracting previously unknown and potentially useful knowledge from large databases (Piatetsky-Shapiro, Fayyad, Smith & Uthurusamy, 1996).

¹ PhD Student, University of Craiova, Faculty of Economic and Business Administration, Romania, Address: A. I. Cuza, no. 13, Craiova, 200585, Romania, Tel: +4(251) 411317, Corresponding author: clauley4u@yahoo.com.

² PhD Student, University of Craiova, Faculty of Economic and Business Administration, Romania, Address: A. I. Cuza, no. 13, Craiova, 200585, Romania, Tel: +4(251) 411317, e-mail: ciobanubebedumitru@yahoo.com.

Web mining can be divided into three categories: Web content mining, Web structure mining and Web usage mining (Zaiane & Han, 1998). Web content mining is the process of extracting knowledge from documents and content description. Web structure mining is the process of obtaining knowledge from the organization of the Web and the links between Web pages.

Web usage mining analyzes information about website pages that were visited which are saved in the log files of Internet servers to discover the previously unknown and potentially interesting patterns useful in the future. Web usage mining is described as applying data mining techniques on Web access logs to optimize web site for users.

Click-stream means a sequence of Web pages viewed by a user; pages are displayed one by one on a row at a time. Analysis of clicks is the process of extracting knowledge from web logs. This analysis involves first the step of data preprocessing and then applying data mining techniques. Data preprocessing involves data extraction, cleaning and filtration followed by identification of their sessions.

2. Sessions Identification

Correct identification of sessions is an important step in preprocessing data from web logs. Some studies indicate a period of 30 minutes between pages viewed as sufficient to establish the end of a session and start another. However, this period may not be sufficient for certain types of websites, for example those which contains documents that the user reads. Also in this category may fall and commerce sites pages which are opinions about products. Should be taken into account that different people need time to cover the same amount of information, for example an elderly person can slowly follow the information presented on the website. Also in the case when a potential client who wants to better inform about a product may exceed this time and the analyst wrongly consider the session ended, longer time spent on the website in this case showing interest in the product and maybe the wish to purchase the product than to leave the website. More bad decisions in sessions' identification can significantly alter the results of applying data mining techniques. In an attempt to reduce errors in session identification, an improved algorithm is proposed to amend the classic algorithm. More bad decisions identification sessions can significantly alter the results of applying data mining techniques.

In an attempt to reduce errors in sessions identification we propose to amend the sessions identification algorithm.

Model description.

We consider IP the set of IP adresses of users = {IP1, IP2, ..., IPN}. PIPk is the set of user pages that were visited by the user identified through $IP_k IP$, PIPk ={PIPk1, PIPk2, ...} and TS_PIPki is the timestamp of PIPki page. We denote by ID_PIPki the sessions identifications numbers assigned to PIPki page and we note ID the set of all these identifications numbers.

The pseudo-code Algorithm

For each IP IP_k repeat If | PIP_k|=1 and ID_PIP_{k1}=max(ID)+1; Then ID_PIP_{k1}=max(ID)+1; I=1; While (I<| PIP_k |) repeat I=I+1; If TS_PIP_{ki}- TS_PIP_{ki-1}<1800 then ID_PIP_{ki}= ID_PIP_{ki-1}; Else ID_PIP_{ki}= ID_PIP_{ki-1}+1;

In the logs table from the database we create a column to keep the time that user spent on the page regardless of session. We select the pages for each IP ordered by timestamp of the IP we make the difference between timestams of consecutive pages. For the last page we attribute a great value for example 20,000 seconds. Now we can calculate in various ways an average time that user spent on a web page. We set a maximum time limit of 2 hours time for the visit allocated to a page visit and a minimum of 2 seconds. We eliminate records that are off limit and calculate the average time spent by an user on a page. Based on this average time we will decide if the page is part of the old session or it is the first page in a new one.

If the average time spent by users on that page is close to 30 minutes it is clear that the algorithm presented above will produce errors in identifying sessions.

3. Case Study

We used the logs database that can be free downloaded from NASA website by http://ita.ee.lbl.gov/html/contrib/NASA-HTTP.html. For clicking on the implementation we used Java programming language. We used the version Java jdk.1.6.0. It is used NetBeans IDE, version 6.9.1. We calculated how long an user could stay on a page. For this we proceeded as follows. First we selected all the distinct IDs. For each ID we selected the identifications codes for each visited pages and the timestamp. When we have found some pages accessed only one time we attribute a default value of 20000 seconds. When we have more viewed pages, we calculate the time as the difference between two consecutive timestamps and for the last page we would set the default value of 20000. After data preprocessing phase there have been obtained 47 583 for 508 separate pages and 12 805 distinct IDs.

From these 508 pages, 118 pages were visited only once or twice.

To calculate the average time spent on a page we have eliminated times greater than 19000 seconds and we grouped by the codes of pages.

In Fig. 1. we display the pages in descending order of average time spent on those pages by users. The fields displayed in Fig. 1. are cod page (COD_PAGINA), average time (MEDIE_TIMP) and the number of visits (NR_PAGINI) for the page identified by cod page. Thus for the 14 pages that the average time of visiting is more than 1500 seconds, the probability to assume wrongly a session end is very high. We will look more closely at page 207 that has the most visits and the average visitation time is 1608.80 seconds.

COD_PAGINA Page Size: 503 TotaRows: 361 Page: 1 of 1 I 409 3515.000 3 2 388 3402.6666 6 3 252 3077.5555 9 4 351 3011.1250 6 6 72 197.45899 76 6 72 197.4589 78 9 137 1949.1818 11 10 410 174.08666 15 11 500 171.7777 54 12 207 1666.6000 5 13 2017 1698.8012 96 14 65 1522.9302 43 15 146 1453.0000 4 16 346 1466.158 13 17 255 1445.9299 27 18 322 1430.111 9 19 378 1411.6533 11	4 gr 5 ha 6 or	ere timp_pag<19000 oup by cod_pagina ving count(cod_pagina)>2 der by 2 desc d pagna, avg(t ×								
1 404 3515 000 3 2 396 34026666 6 3 252 3077 555 9 5 140 2511 200 5 5 72 1897,8689 78 6 203 1944,8633 12 7 203 1944,8633 12 8 157 1877,0600 16 9 137 1894,8633 12 10 410 1750,8666 15 111 500 171,777 54 122 270 1666,8002 56 133 207 1666,8002 496 15 146 145,3000 4 16 346 152,9002 43 16 346 1456,1538 13 17 255 1445,9259 27 18 322 1430,111 9 19 378 1411,833 11										
2 396 3402.666 6 2252 3007.5555 9 4 351 3011.1250 8 5 72 197.6689 78 6 72 197.6689 78 9 157 197.0000 16 9 157 197.0000 16 10 410 1740.8666 15 11 500 171.7777 54 12 270 1666.6000 5 13 207 1606.8000 4 65 152.29302 43 155 146 1463.0000 4 16 346 1466.1538 13 155 146 1463.0000 4 16 346 1466.158 13 16 346 1465.158 13 16 325 1445.929 27 18 332 1430.111 9 19 378 141.1583	#	COD_PAGINA	MEDIE_TIMP	NR_PAGINI						
2 307 555 9 4 351 3011 259 8 5 140 2391 200 6 7 203 1994.0839 70 8 157 1974.0839 12 9 157 1974.0836 15 10 410 1780.5866 15 11 500 177.777 54 12 270 1666.500 5 13 2077 1008.012 966 146 145.3000 4 16 15 146 145.3000 4 16 346.000 12 12 17 255 146.529 27 18 322 1430.111 9 19 378 141.583 11	1	484	3515.0000	3						
351 3011.1250 8 140 2321.200 5 147 1997.8689 78 140 2321.300 5 141 72 1997.8689 78 141 157 1877.000 16 141 177 1879.000 16 152 200 1717.777 54 14 500 1717.7777 54 2 207 1666.600 5 3 2077 1608.8012 966 5 1146 1460.0000 4 6 366 152.2002 43 5 146 1460.0000 4 6 366 152.2002 43 6 366 152.2002 43 6 366 1456.153 13 7 255 14456.4559 27 8 322 1430.111 9 9 378 1411.653 11		398	3402.6666	6						
140 2391,200 5 72 1997,4033 5 11 157 1970,003 16 12 157 1970,003 16 13 101 1777,777 54 2 270 1666,6000 5 3 2077 1606,6000 4 6 346 1450,358 13 6 346 1450,359 27 8 3322 1440,1111 9 9 378 1415,633 11	1	252	3077.5555	9						
72 1997.869 78 2000 1994.6839 12 1157 1874.0000 16 1157 1874.000 16 11 11 11 0 410 170.000 16 1 500 1717.777 54 2 270 1666.600 5 3 2077 1608.8012 996 4 65 152.202 43 5 146 1450.133 13 6 346 1456.153 13 7 255 1445.6359 27 8 322 1430.111 9 9 378 141.636 11		351	3011.1250	8						
200 1994.033 12 157 1670.000 16 137 1994.018 11 0 410 170.0566 15 1 5500 1717.777 54 2 2701 1666.6001 5 3 2077 1660.6002 49 6 346 1452.902 43 6 346 1450.153 13 7 2255 1446.5259 27 8 332 1430.111 9 9 378 1416.633 11		140	2391.2000	5						
1 157 187 000 16 1 137 1491,088 11 0 410 170,0866 15 1 500 1717,777 54 2 270 1666,600 5 3 207 1696,500 4 65 152,202 43 6 346 1465,000 4 7 255 1445,053 13 7 255 1445,055 27 8 322 1430,111 9 9 378 1411,653 11		72	1987.8589	78						
137 1949.188 11 0 410 170.066 15 1 500 1717.777 54 2 270 1666.060 5 3 2077 1608.012 966 5 146 1450.000 4 6 346 1450.138 13 7 225 1445.555 27 8 332 1430.111 9 9 378 141.03.111 91		203	1934.0833	12						
0 410 1760.866 15 1 500 1717.777 54 2 270 1666.600 5 3 207 1695.612 996 4 65 1522.902 43 5 146 1463.000 4 6 946 1466.153 13 7 255 1445.925 27 8 322 1430.111 9 9 378 1416.63 11		157	1877.0000	16						
1 500 1717.777 54 2 270 1686.600 5 3 207 1608.012 986 4 65 1522.930 43 5 146 1450.000 4 6 346 1450.138 13 7 225 1445.655 27 8 332 1430.111 9 9 378 1411.636 11		137	1849.1818	11						
2 270 1686.600 5 3 207 1608.600 966 4 65 1529.902 43 5 1166 1463.000 4 6 346 1465.000 4 7 255 1465.92 27 8 322 1430.111 9 9 378 1416.63 11	0	410	1760.8666	15						
3 207 1608.8012 996 4 65 1552.9002 43 5 146 1463.0000 4 6 346 1456.1530 4 7 2255 14456.4559 27 8 322 1430.1111 9 9 378 1411.6563 11	1	500	1717.7777	54						
4 65 1522,9302 43 5 146 1463,000 4 6 346 1456,153 13 7 255 1445,8259 27 8 322 1430,111 9 9 378 141,653 11	2	270	1686.6000	5						
5 146 1443.000 4 6 346 1456.1538 13 7 255 1445.8559 27 8 322 1430.1111 9 9 378 1411.653 11	3	207	1608.8012	966						
6 346 1456.1538 13 7 255 1445.9559 27 8 322 1430.1111 9 9 378 1411.4563 11		65	1522.9302	43						
7 255 1445.8289 27 8 322 1430.1111 9 9 378 1411.6583 11		146	1463.0000	4						
8 322 1430.1111 9 9 378 1411.6363 11			1456.1538							
9 378 1411.6363 11										
	8	322	1430.1111	9						
20 396 1406.6363 11										
1100.000 11	20	396	1406.6363	11						

Fig. 1.

From the 966 visits of page 207, 197 visits have visited time greater than 1800 seconds (Fig.2.) and can lead to errors in the sessions' identification.

2	from LOGURI1 where timp pag < 19	000					
3 4	and cod pagina=207	000					
5	order by 2 desc						
3	order by 2 desc						
sele	ect cod_pagina, timp_p ×						
	📰 🖩 🔳 🕱 I 🍣 K -	< > >	Page Size:	1000	Total Rows:	966	Pa
#	COD_PAGINA		TIMP_PAG				
190		207			1929		
191		207			1924		
192		207			1918		
193		207			1848		
194		207			1842		
195		207			1823		
196		207			1809		
197		207			1805		
198		207			1798		
199		207			1780		
200		207			1773		
201		207			1755		
202		207			1751		
203		207			1751		
204		207			1737		
205		207			1726		
206		207			1725		
207		207			1684		
208		207			1679		
209		207			1675		

Fig. 2.

Last observation justifies the proposal to replace the value of 1800 seconds (30 minutes) from the session' identification algorithm with another value that depends on the average time.

4. Conclusions

For a successful analysis of click-stream it requires the use as accurate data from web clicks. Sessions identification is an important step in data preprocessing whose poor performance may negatively influence the results. We note that the determination of the main visiting time of web pages from the websites requires, depending on the size of log files used for a certain period of time that is unprofitable to determine in real time. But calculating the mean can be offline and may be updated, depending on the level of accessing the website, daily, weekly or even less. Using a calculated time depending on average time for sessions' identification increases the accuracy of data used in the knowledge extraction process. It remains an open problem on a different calculation method of the time based on the mean time to have maximum effect when used to identify sessions.

5. References

Brendt B., Spiliopoulou M. (2000). Analysis of Navigation Behaviour in Web Sites Integrating Multiple Information Systems. VLDB, 9(1), 56-75.

Clark L., Ting I., Kimble C., Wrigth P., Kudenko D. (2006). Combining Ethnographic and Clickstream Data to Identify Strategies Information Research 11(2), paper 249.

Cooley R., Mobasher B., Srivastava J. (1997). Web mining: Information and Pattern Discovery on the World Wide Web. A survey paper. In: Proc. ICTAI-97.

Database with log file NASA Kennedy Space Center Log available online at http://ita.ee.lbl.gov/html/contrib/NASA-HTTP.html.

Hay B., Geert W., Koen V.(2005). *Discovering interesting navigations on a web site using SAM^I*, Springer-Verlag Berlin.

Kohavi R., Parekh R. (2003). Ten supplementary analysis to improve e-commerce web sites, Proceedings of the Fifth WEBKDD workshop.

Li T. R., Xu Y., Ruan D., Pan W. M. (2005). Sequential Pattern Mining. Springer-Verlag Berlin.

Liu B. (2006), Web Data Mining: Exploring Hyperlinks, Contents and Usage Data, Springer Berlin Heidelberg New York.

Mobasher B., Cooley R., Srivastava J. (1999), Creating Adaptive Web Sites trough usage based clustering of URLs, IEEE knowledge & Data Engg work shop (KDEX'99).

Piatetsky-Shapiro g., Fayyad U., Smith P., Uthurusamy R. (1996), Advances in Knowledge Discovery and Data Mining., AAAI/MIT Press.

Srivastava J., Cooley R., Deshpande M., Tan P.-N. (2000), Web usage mining: discovery and applications of usage patterns from web data, SIGKDD Explorations, 1(2), 12-23.

Zaiane O. (2000) Conference Tutorial Notes: Web Mining: Concepts, Practices and Research. In: Proc. SDBD-2000, 410-474.

Zaiane O., Han J. (1998), WebML: Querying the World Wide Web for resources and knowledge. In: Workshop on Web Information and Data Management WIDM98, Bethesda, 9-12.