

An application for clickstream analysis

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Abstract— In the Internet age there are stored enormous amounts of data daily. Nowadays, using data mining techniques to extract knowledge from web log files has become a necessity. The behavior of Internet users can be found in the log files stored on Internet servers. Web log analysis can improve business firms that are based on a Web site through learning user behavior and applying this knowledge to target them for example to pages that other users with similar behavior have visited. The extraction of useful information from these data has proved to be very useful for optimizing Web sites and promotional campaigns for marketing, etc. In this paper I will focus on finding associations as a data mining technique to extract potentially useful knowledge from web usage data. I implemented in Java programming language, using NetBeans IDE, a program for identification of pages' association from sessions. For exemplification, I used the log files from a commercial web site.

Keywords—Apriori algorithm, Association rules, Clickstream analysis, Sessions' identification, Web server logs, Web usage mining.

I. INTRODUCTION

WEB mining is an area that lately has gained a lot of interested. This is due essentially to the exponential growth of the World Wide Web and its anarchic architecture and also due to the increase of its importance over the people's life. A Web site is a lot of interconnected web pages that are developed and maintained by a person or organization. Web mining studies analyzes and reveals useful information from the Web [11]. Web mining deals with the data related to the Web, they may be the data actually present in Web pages or the data concerning the Web activities. The Web can be viewed as the largest unstructured data source available, although the data on the Web sites, which composed them, is structured. This presents a challenging task for effective design of and access to Web pages. Web mining is a term used for applying data mining techniques to Web access logs [12]. Data mining is a non-trivial process of extracting previously unknown and potentially useful knowledge from large databases [5].

Web mining is an area that lately has gained a lot of interested. This is due essentially to the exponential growth of the World Wide Web and its anarchic architecture and also due to the increase of its importance over the people's life. Scientists and engineers want to extract information from it, in order to better understand and to improve its features. They

applied data mining techniques on the web. Therefore, Web mining can be defined as the application of Data Mining techniques to the web related data.

Web mining can be divided into three categories: Web content mining, Web structure mining and Web usage mining [10]. 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.

Due to the immense volume of Internet usage and web browsing in recent years, log files generated by web servers contain enormous amounts of web usage data that is potentially valuable for understanding the behavior of website visitors.

This knowledge can be applied in various ways, such as enhancing the way that the web pages are interconnected or for increasing the sales of the commercial web sites.

II. DATA PREPROCESSING

Log files are created by web servers and filled with information about user requests on a particular Web site. They may contain information about: domains, sub domains and host names; resources requested by the user, time of request, protocol used, errors returned by the server, the page size for successful requests.

Because a successful analysis is based on accurate information and quality data, preprocessing plays an important role. Preparation of data requires between 60 and 90% of the time from data analysis and contributes to the success rate of 75-90% to the entire process of extracting knowledge [3].

For each IP or DNS we determine user sessions. The log files have entries like these:

```
95.175.194.33 - - [27/Jul/2011:07:23:04 -0500] "GET /css/preview_style.css HTTP/1.1" 200 2553 "http://www.nice-layouts.com/preview.php?p=34062" "Mozilla/5.0 (Windows;
```

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U; Windows NT 5.1; en-US; rv:1.9.2.3) Gecko/20100401
 Firefox/3.6.3 (.NET CLR 3.5.30729)"
 95.175.194.33 -- [27/Jul/2011:07:23:04 -0500] "GET
 /css/tabright.gif HTTP/1.1" 200 2095 "http://www.nice-
 layouts.com/css/preview_style.css" "Mozilla/5.0 (Windows;
 U; Windows NT 5.1; en-US; rv:1.9.2.3) Gecko/20100401
 Firefox/3.6.3 (.NET CLR 3.5.30729)"
 95.175.194.33 -- [27/Jul/2011:07:23:04 -0500] "GET
 /css/tableft.gif HTTP/1.1" 200 377 "http://www.nice-
 layouts.com/css/preview_style.css" "Mozilla/5.0 (Windows;
 U; Windows NT 5.1; en-US; rv:1.9.2.3) Gecko/20100401
 Firefox/3.6.3 (.NET CLR 3.5.30729)"
 95.175.194.33 -- [27/Jul/2011:07:23:05 -0500] "GET
 /secure/none.gif HTTP/1.1" 200 827 "https://www.nice-
 layouts.com/secure/custom_css.css" "Mozilla/5.0 (Windows;
 U; Windows NT 5.1; en-US; rv:1.9.2.3) Gecko/20100401
 Firefox/3.6.3 (.NET CLR 3.5.30729)"

As can be noticed above, each record in the file contain the IP, date and time, protocol, page views, error code, number of bytes transferred. The steps needed for data preprocessing were presented in detail in [1]. For sessions' identification in the first case was considered that a user can not be stationed on a page more than 30 minutes. This value is used in several previous studies, as can be seen in the work [2]. The current study intends to add an improvement in sessions' identification by determining an average time of page visiting the sites for the visit duration determined by analysis of web site visit duration, data which can be found in the log files of the site. Thus, for each visited page, is calculated the visit duration, which is determined by the difference between two consecutive timestamps for the same user, which is identified by IP. For records of pages with the highest timestamp among those visited by a user is assigned a predefined value of our choice to 20,000 seconds. I calculate the average visit time for a page by the average of all the times spent on that page. When calculating the average visiting time we don't take into consideration the pages with the time less than 2 seconds and largest than 20,000 seconds. Thus for our analysis I selected only those log records that contained a web page, eliminating the required load images and other files adjacent to it, this information being considered not important for analysis. I kept only pages that have status code of class 200, a successfully loaded page. Thus, we calculated how long a user stayed on a page as the difference between consecutive timestamps of visited pages for the same person, same IP. I calculated the average visiting time for a page as the media of time spent for different users on that page and used this mean to better identify sessions. I have removed pages of double sessions and I just kept for review sessions with more than 1 page views.

After preprocessing stage we obtained a file containing the user sessions. I implemented in Java the Apriori algorithm in order to obtain the association rules between the pages from the sessions. I applied this algorithm on the sessions obtained.

III. ASSOCIATIONS MINING

Items that occur often together can be associated to each other. These together occurring items form a **frequent itemset**. Conclusions based on the frequent itemsets form **association**

rules. For ex. {milk, cocoa powder} can bring a rule *cocoa powder* \rightarrow *milk*.

Consider we have database D consists of events T_1, T_2, \dots, T_m , that is $D = \{T_1, T_2, \dots, T_m\}$. Let there be an itemset X that is a subregion of event T_k , that is $X \subseteq T_k$.

The support can be defined as :

$$\text{sup}(X) = \frac{|\{T_k \in D \mid X \subseteq T_k\}|}{|D|}$$

this relation compares number of events containing itemset X to number of all events in database.

Any frequent item set (support is higher than the minimal support): I frequent, $\text{sup}(I) \geq \text{sup}_{\min}$.

Properties of the Support of an Item Set are:

- No superset of an infrequent item set can be frequent, the well known Apriori property.
- All subsets of a frequent item set are frequent.

Algoritmul Apriori

Apriori algorithm defined in 1994 by Agrawal and Srikant is the benchmark among unsupervised learning system based on association rules. Apriori algorithm is the first and most important efficient algorithm for discovering association rules.

The general scheme of the Apriori algorithm after Borgelt[8]:

- Determine the support of the one element item sets and discard the infrequent items.
- Form candidate item sets with two items (both items must be frequent), determine their support, and discard the infrequent item sets.
- Form candidate item sets with three items (all pairs must be frequent), determine their support, and discard the infrequent item sets.
- Continue by forming candidate item sets with four, five etc. items until no candidate item set is frequent.

It is based on two main steps: candidate generation and pruning. All frequent item set mining algorithms are based on these steps in some form.

Apriori uses a scroll in depth strategy to compute the support sets of elements and uses a function to generate candidates that uses circumscribed lower of support property.

If we consider the time for the selected elements, then we have a sequential association.

In the case of clickstream analysis we can apply both of them. So, we can determine association with pages, sequential association, associations rules and sequential rules in order to determine navigation paths models from the log files.

I implemented an application for applying data mining algorithms on log files in order to extract interesting knowledges from data.

IV. CASE STUDY

To implement the algorithm presented earlier and the entire models extraction application I used the Java programming language, the code is written using NetBeans IDE.

For implementation I created the NetBeans project ClickstreamAnalysis and it's componenets can be seen in the following image :

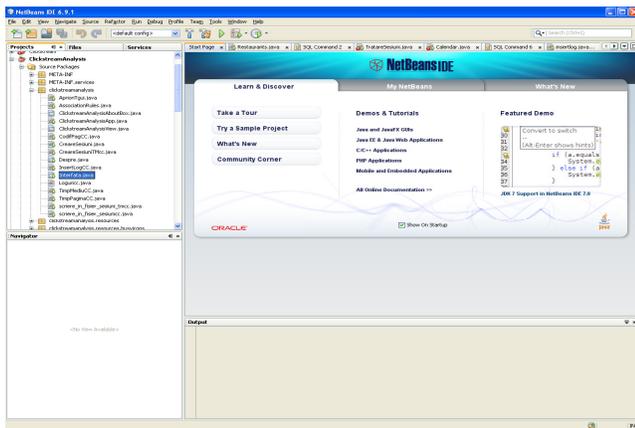


Fig. 1. The ClickstreamAnalysis project into NetBeans IDE

The application contains all the preprocessing steps needed to obtain the data in a form necessary for using it as input to algorithms. Using this developed application we can do the following operations. First we can read the data from web log file, clean the data and insert them in a database table in order to be able to perform the next preprocessing steps. Then we execute the following operations: the pages are codified, we calculate the average time for every page, we calculate the sessions with the method of in which we consider a user can't stay longer than 30 minutes on a page and then we also create the

sessions using the method proposed by us with the average time for each sessions.

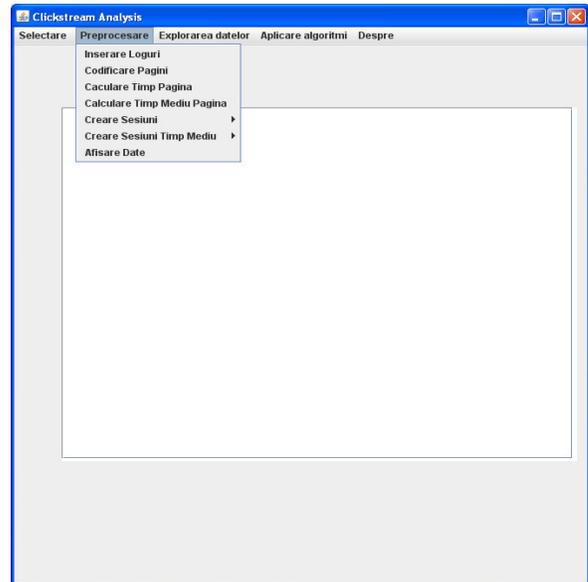


Fig. 2. The main window with the preprocess menu

After each preprocessing step the data can be seen in a window, as the one from figure 3, so the analyst is able to monitor and modify the data at each moment.

Id Solicitant	Data Ora	Metoda	Pagina	Protocol	Cod Eroare	Nr Bti	Timestamp	Cod Pagina	Id Sesiune Tm	Id Sesiune	Timp Pag	Timp Mediu Pag
66.249.72.228	27/Jul/2011:07:...	GET	/wordpress-the...	HTTP/1.1	200	21048	2273027	113	811	821	235	79
117.212.43.199	27/Jul/2011:07:...	GET	/flash-8-templa...	HTTP/1.1	200	21910	2273102	264	488	490	20000	16
67.195.113.239	27/Jul/2011:07:...	GET	/phpbb2-templa...	HTTP/1.0	200	21929	2273155	173	1239	1257	581	429
60.242.38.16	27/Jul/2011:07:...	GET	/wordpress-the...	HTTP/1.1	200	21067	2273249	106	260	261	20000	260
66.249.72.228	27/Jul/2011:07:...	GET	/flash-8-templa...	HTTP/1.1	200	21479	2273262	269	811	821	469	134
157.55.17.103	27/Jul/2011:07:...	GET	/flash-8-templa...	HTTP/1.1	200	21990	2273450	240	137	137	20000	1064
207.46.204.187	27/Jul/2011:07:...	GET	/wordpress-the...	HTTP/1.1	200	21179	2273479	193	1196	1214	20000	969
217.21.155.210	27/Jul/2011:07:...	GET	/css-web-templa...	HTTP/1.1	200	21905	2273680	481	499	501	20000	1896
66.249.72.228	27/Jul/2011:07:...	GET	/wordpress-the...	HTTP/1.1	200	21449	2273731	429	811	821	469	112
67.195.113.239	27/Jul/2011:07:...	GET	/php-nuke-templ...	HTTP/1.0	200	21979	2273736	68	1239	1257	829	3536
79.126.232.59	27/Jul/2011:07:...	GET	/css-web-templa...	HTTP/1.1	200	21231	2273759	352	106	106	20000	107
196.2.126.174	27/Jul/2011:07:...	GET	/jss-web-templa...	HTTP/1.1	200	21416	2274099	276	207	207	345160	140
66.249.72.228	27/Jul/2011:07:...	GET	/web-templates/...	HTTP/1.1	200	21937	2274200	100	811	821	1406	712
67.195.113.239	27/Jul/2011:07:...	GET	/full-site-templa...	HTTP/1.0	200	21179	2274565	389	1239	1257	389	2939
67.195.113.239	27/Jul/2011:07:...	GET	/icon-sets-templ...	HTTP/1.0	200	21943	2274954	443	1239	1257	1262	732
209.85.226.87	27/Jul/2011:07:...	GET	/flash-8-templa...	HTTP/1.1	200	21682	2275181	77	755	765	20000	1003
41.216.220.117	27/Jul/2011:08:...	GET	/joomla-templa...	HTTP/1.1	200	21602	2275212	436	1181	1199	20000	52
78.62.209.70	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21961	2275243	194	776	786	20000	772
66.249.72.228	27/Jul/2011:08:...	GET	/flash-8-templa...	HTTP/1.1	200	21483	2275606	402	811	821	1172	315
41.54.84.137	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21871	2275776	28	331	332	3048	1344
46.70.130.108	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21875	2275901	266	975	991	20000	427
67.195.113.239	27/Jul/2011:08:...	GET	/web-2-0-templa...	HTTP/1.0	200	21780	2276216	340	1239	1257	4947	2919
49.15.174.49	27/Jul/2011:08:...	GET	/jss-web-templa...	HTTP/1.1	200	21736	2276246	205	291	292	20000	333
65.52.110.47	27/Jul/2011:08:...	GET	/jss-web-templa...	HTTP/1.1	200	21835	2276307	72	486	488	20000	318
46.73.252.1	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.0	200	21573	2276416	309	639	650	20000	320
190.88.108.69	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21360	2276487	317	327	328	20000	1353
114.17.194.149	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21876	2276584	249	1217	1235	20000	890
118.97.15.21	27/Jul/2011:08:...	GET	/jquery-templates/	HTTP/1.1	200	21451	2276758	93	927	943	20000	463
66.249.72.228	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21360	2276778	317	812	821	703	1353
66.249.72.228	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21875	2277481	266	812	821	469	427
75.68.70.39	27/Jul/2011:08:...	GET	/wordpress-the...	HTTP/1.1	200	21875	2277527	266	1649	1699	20000	427
207.46.198.233	27/Jul/2011:08:...	GET	/joomla-templa...	HTTP/1.1	200	21928	2277530	384	1083	1100	20000	664

Fig. 3. The window for monitoring all the preprocessing steps.

The analyst can delete records of data that are considered irrelevant or outliers from the data. The form has the ability of refreshing the data.

So, in the interface I gave the opportunity for the user to choose the file with sessions. The content of the file must be in the following format :

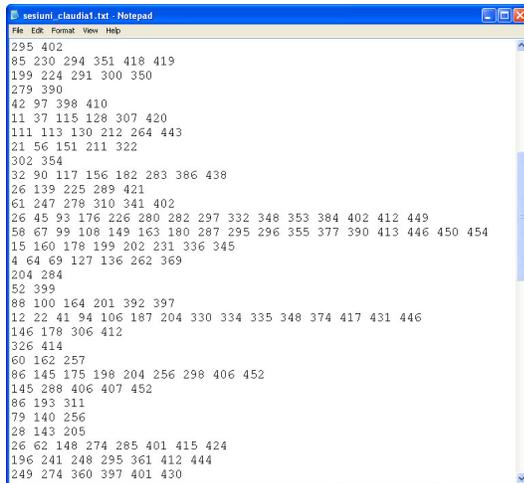


Fig.4.

As, it can be seen in the figure before, in the preprocessing stage, we codified the pages from the log files.

The user can also choose the minimum support threshold. After all these being set, we can run the algorithm.

After applying the Apriori algorithm we obtained some important associations between pages. For example, we obtained the result shown in Fig. 5.

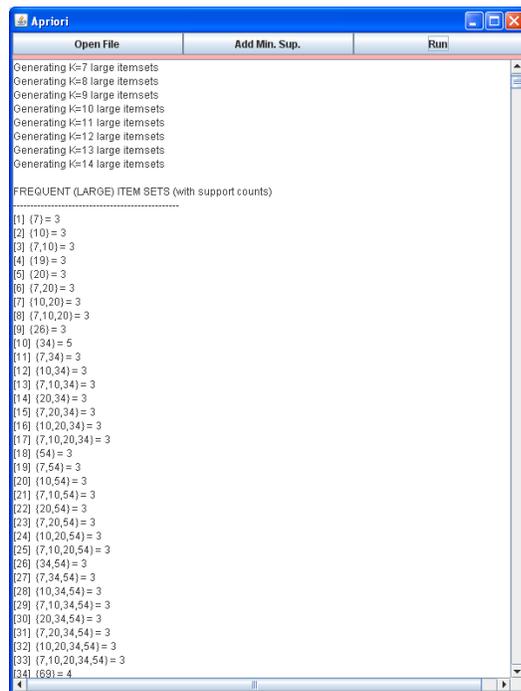


Fig. 5.

When we decrease the support, we obtain more association between pages.

Another way of obtaining association rules on pages from a web-site is by transforming this file with sessions that we obtained before in a matrix containing 0 and 1 and create an .arff file from all these pages, having as attributes the pages that can take values 0 or 1 and the relation defined between being the sessions, the data from the .arff are the values of the sessions.

The .arff file can be defined in a sparse or dense manner. After obtaining the .arff file, it can be applied to the Apriori algorithm from Weka, or any open source data mining tool that accepts this format.

Generating sets of pages frequently visited together is determined by going to the main window and choosing the application algorithms option AplicareAlgoritmi → FPGrowth. There is an option to generate steps of frequent pages accessed together with coded pages and with the exact name of the pages. FPGrowth algorithm is used to generate associations of pages frequently visited together [15].

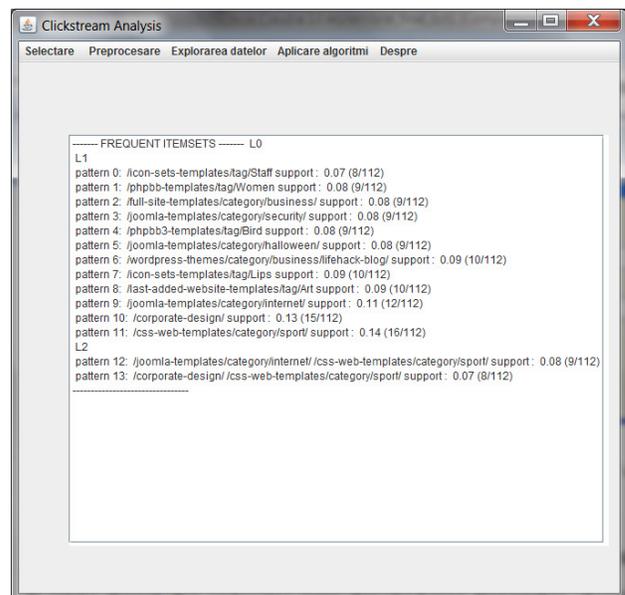


Fig. 6. Frequent itemsets presented in the main window of the application.

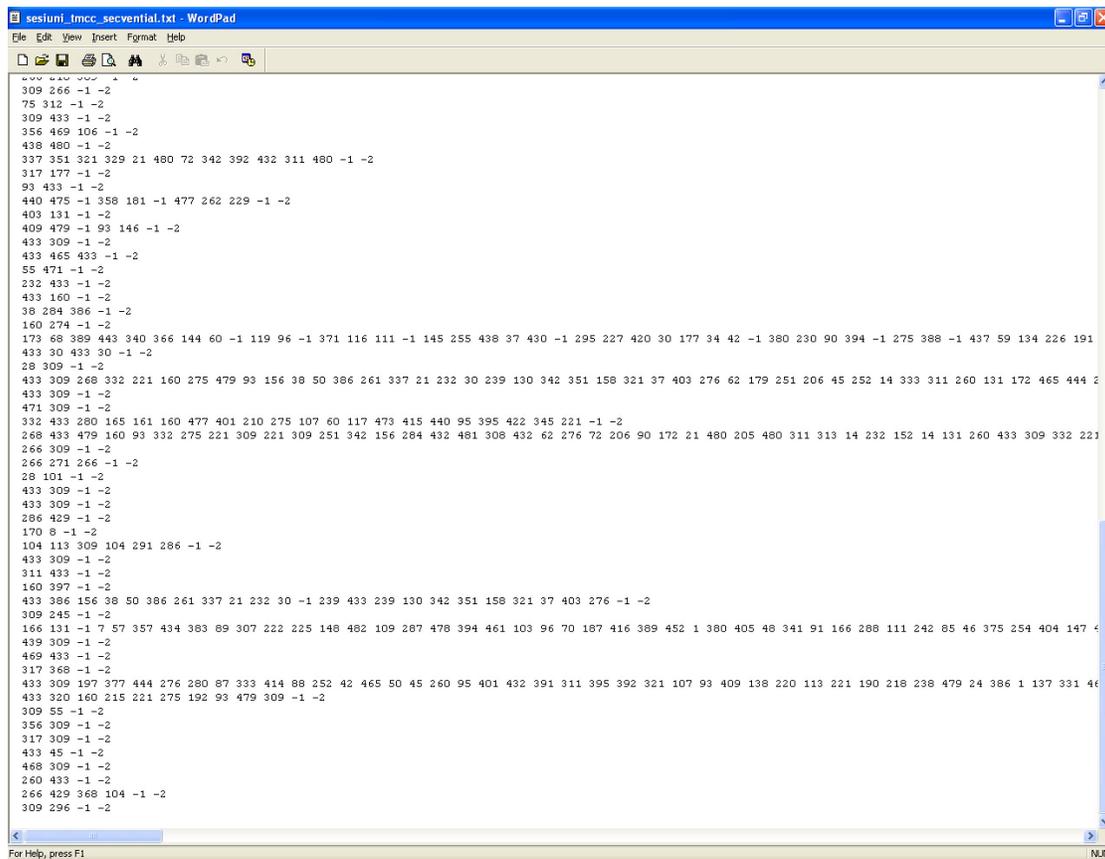
ID_SESIUNE	NrActiuniVizitare	DurataSesiunii	TimpPePagina
264	7	850	141.66666666666666
278	4	211	70.33333333333333
280	3	681	340.50000000000000
293	2	173	173.00000000000000
307	2	20	20.00000000000000
312	2	4	4.0000000000000000
314	4	352	117.33333333333333
316	2	173	173.00000000000000
322	3	140	70.00000000000000
324	3	1207	603.50000000000000
327	2	69	69.00000000000000
344	2	5149	5149.00000000000000
346	3	1	0.5000000000000000
358	3	612	306.00000000000000
364	3	61	30.5000000000000000
374	3	1754	877.00000000000000
378	2	107	107.00000000000000
381	2	428	428.00000000000000
383	3	1576	788.00000000000000
384	35	6689	196.7352941176
385	13	7033	586.08333333333333
390	3	0	0.0000000000000000

Fig 7. Exploratory data analysis

The menu **Data Exploration** contains Sessions' Information submenu which provides information about

resulted sessions such as session ID, number of visits in that session, session length, the average time per page in a session

as it is shown in the figure 4.

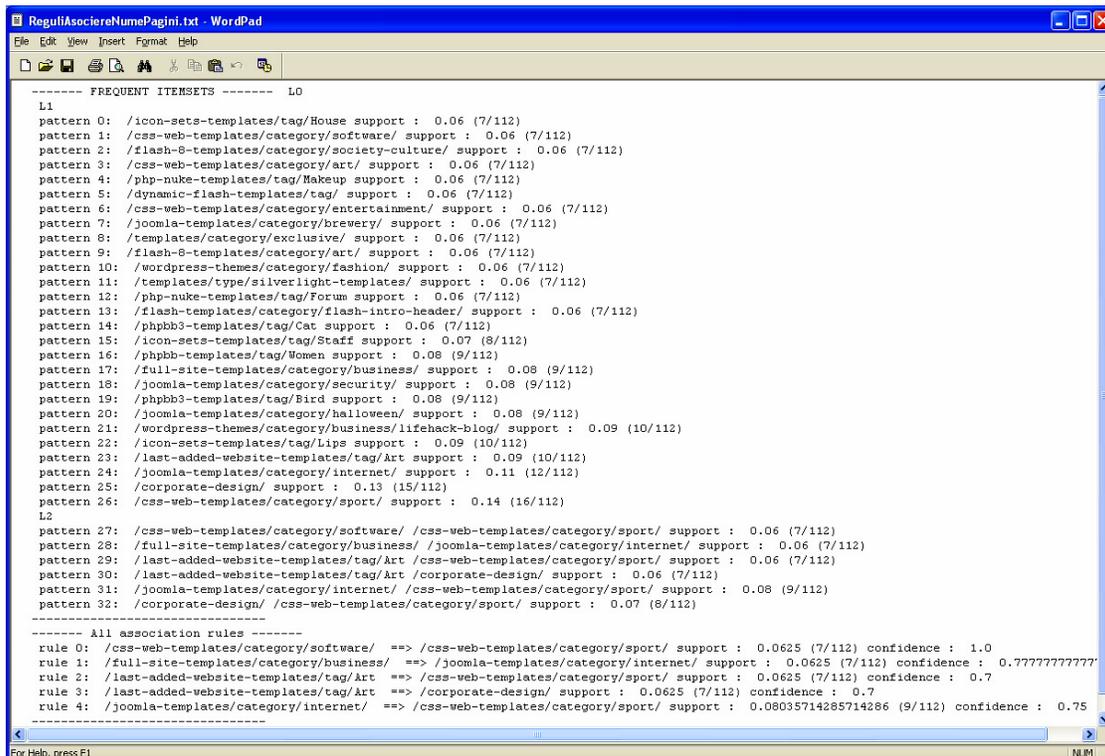


```

309 266 -1 -2
75 312 -1 -2
309 433 -1 -2
356 469 106 -1 -2
438 480 -1 -2
337 351 321 329 21 480 72 342 392 432 311 480 -1 -2
317 177 -1 -2
93 433 -1 -2
440 475 -1 358 181 -1 477 262 229 -1 -2
403 131 -1 -2
409 479 -1 93 146 -1 -2
433 309 -1 -2
433 465 433 -1 -2
55 471 -1 -2
232 433 -1 -2
433 160 -1 -2
38 284 386 -1 -2
160 274 -1 -2
173 68 389 443 340 366 144 60 -1 119 96 -1 371 116 111 -1 145 255 438 37 430 -1 295 227 420 30 177 34 42 -1 380 230 90 394 -1 275 388 -1 437 59 134 226 191
433 30 433 30 -1 -2
28 309 -1 -2
433 309 268 332 221 160 275 479 93 156 38 50 386 261 337 21 232 30 239 130 342 351 158 321 37 403 276 62 179 251 206 45 252 14 333 311 260 131 172 465 444 2
433 309 -1 -2
471 309 -1 -2
332 433 280 165 161 160 477 401 210 275 107 60 117 473 415 440 95 395 422 345 221 -1 -2
268 433 479 160 93 332 275 221 309 251 342 156 284 432 481 308 432 62 276 72 206 90 172 21 480 205 480 311 313 14 232 152 14 131 260 433 309 332 223
266 309 -1 -2
266 271 266 -1 -2
28 101 -1 -2
433 309 -1 -2
433 309 -1 -2
286 429 -1 -2
170 8 -1 -2
104 113 309 104 291 286 -1 -2
433 309 -1 -2
311 433 -1 -2
160 397 -1 -2
433 386 156 38 50 386 261 337 21 232 30 -1 239 433 239 130 342 351 158 321 37 403 276 -1 -2
309 245 -1 -2
166 131 -1 7 57 357 434 383 89 307 222 225 148 482 109 287 478 394 461 103 96 70 187 416 389 452 1 380 405 48 341 91 166 288 111 242 85 46 375 254 404 147 4
439 309 -1 -2
469 433 -1 -2
317 368 -1 -2
433 309 197 377 444 276 280 87 333 414 88 252 42 465 50 45 260 95 401 432 391 311 395 392 321 107 93 409 138 220 113 221 190 218 238 479 24 386 1 137 331 46
433 320 160 215 221 275 192 93 479 309 -1 -2
309 55 -1 -2
356 309 -1 -2
317 309 -1 -2
433 45 -1 -2
468 309 -1 -2
260 433 -1 -2
266 429 368 104 -1 -2
309 296 -1 -2

```

Fig. 8. The file with sequential sessions.



```

----- FREQUENT ITEMSETS ----- L0
L1
pattern 0: /icon-sets-templates/tag/House support : 0.06 (7/112)
pattern 1: /css-web-templates/category/software/ support : 0.06 (7/112)
pattern 2: /flash-8-templates/category/society-culture/ support : 0.06 (7/112)
pattern 3: /css-web-templates/category/art/ support : 0.06 (7/112)
pattern 4: /php-nuke-templates/tag/Makeup support : 0.06 (7/112)
pattern 5: /dynamic-flash-templates/tag/ support : 0.06 (7/112)
pattern 6: /css-web-templates/category/entertainment/ support : 0.06 (7/112)
pattern 7: /joomla-templates/category/brevary/ support : 0.06 (7/112)
pattern 8: /templates/category/exclusive/ support : 0.06 (7/112)
pattern 9: /flash-8-templates/category/art/ support : 0.06 (7/112)
pattern 10: /wordpress-themes/category/fashion/ support : 0.06 (7/112)
pattern 11: /templates/type/silverlight-templates/ support : 0.06 (7/112)
pattern 12: /php-nuke-templates/tag/Forum support : 0.06 (7/112)
pattern 13: /flash-templates/category/flash-intro-header/ support : 0.06 (7/112)
pattern 14: /phpbb3-templates/tag/Cat support : 0.06 (7/112)
pattern 15: /icon-sets-templates/tag/Staff support : 0.07 (8/112)
pattern 16: /phpbb-templates/tag/Women support : 0.08 (9/112)
pattern 17: /full-site-templates/category/business/ support : 0.08 (9/112)
pattern 18: /joomla-templates/category/security/ support : 0.08 (9/112)
pattern 19: /phpbb3-templates/tag/Bird support : 0.08 (9/112)
pattern 20: /joomla-templates/category/halloween/ support : 0.08 (9/112)
pattern 21: /wordpress-themes/category/business/lifehack-blog/ support : 0.09 (10/112)
pattern 22: /icon-sets-templates/tag/Lips support : 0.09 (10/112)
pattern 23: /last-added-website-templates/tag/Art support : 0.09 (10/112)
pattern 24: /joomla-templates/category/internet/ support : 0.11 (12/112)
pattern 25: /corporate-design/ support : 0.13 (15/112)
pattern 26: /css-web-templates/category/sport/ support : 0.14 (16/112)
L2
pattern 27: /css-web-templates/category/software/ /css-web-templates/category/sport/ support : 0.06 (7/112)
pattern 28: /full-site-templates/category/business/ /joomla-templates/category/internet/ support : 0.06 (7/112)
pattern 29: /last-added-website-templates/tag/Art /css-web-templates/category/sport/ support : 0.06 (7/112)
pattern 30: /last-added-website-templates/tag/Art /corporate-design/ support : 0.06 (7/112)
pattern 31: /joomla-templates/category/internet/ /css-web-templates/category/sport/ support : 0.08 (9/112)
pattern 32: /corporate-design/ /css-web-templates/category/sport/ support : 0.07 (8/112)
-----
----- All association rules -----
rule 0: /css-web-templates/category/software/ ==> /css-web-templates/category/sport/ support : 0.0625 (7/112) confidence : 1.0
rule 1: /full-site-templates/category/business/ ==> /joomla-templates/category/internet/ support : 0.0625 (7/112) confidence : 0.7777777777
rule 2: /last-added-website-templates/tag/Art ==> /css-web-templates/category/sport/ support : 0.0625 (7/112) confidence : 0.7
rule 3: /last-added-website-templates/tag/Art ==> /corporate-design/ support : 0.0625 (7/112) confidence : 0.7
rule 4: /joomla-templates/category/internet/ ==> /css-web-templates/category/sport/ support : 0.08035714285714286 (9/112) confidence : 0.75

```

Fig. 9. Frequent itemsets and association rules obtained from web pages

In order to determine frequent web pages accessed together I use FP-Growth algorithm, and then the algorithm for generation of association rules created by Agraval and Srikant,1994 [9] from these frequent pages.

In order to apply data mining methods and algorithms for data mining the sessions are saved in a file like the one from figure 1, the sessions containing the coded pages. For algorithms which determine frequent sequential pages we use for input a text file which contains the user sessions in a temporal order as in Fig. 8. Thus, the value -1 is used to separate sessions from the same IP and the value -2 is used to separate sessions from different IPs.

Sequence mining is the task of finding temporal patterns over a database of sequences, in this case a data base of click streams. Sequence mining is considered to be an extension of associations mining that only finds nontemporal patterns.

This technique can have a very important role in knowledge discovery in web log data, due to the (temporally) ordered nature of click-streams.

The type of patterns that results from the application of this technique, can have an example like this:

”If user visits page X, and then page Y, it will visit page Z with c% of chance”. The algorithms for sequence mining inherited much from the association mining algorithms, and many of them are extensions of the firsts, where the main difference is that in sequence mining inter-sequence patterns are searched, where in the association mining the patterns searched are intra-sequence patterns. For the determination of successive sets of frequently accessed together pages using PrefixSpan algorithm developed by Pei and others, 2004. Running the algorithm for generating frequent sets of sequential pages with minimum support 0.09 we obtain the results that can be seen below.

```

===== Algorithm - STATISTICS =====
Total time ~ 55 ms
Frequent sequences count: 20
-----FREQUENT SEQUENTIAL PATTERNS -----
L0
L1
pattern 1: (93 ) Sequence ID: 35 87 2 101 98 42 58 24 124 123 105 90 support: 0.09 (12/133)
pattern 2: (104 ) Sequence ID: 101 39 37 42 77 131 10 73 14 21 20 113 23 58 28 support: 0.11 (15/133)
pattern 3: (160 ) Sequence ID: 68 35 2 70 101 98 65 97 42 10 13 104 105 119 116 58 95 124 support: 0.14 (18/133)
pattern 4: (221 ) Sequence ID: 35 2 70 71 101 98 65 42 10 104 105 24 58 124 123 support: 0.11 (15/133)
pattern 5: (210 ) Sequence ID: 68 35 101 98 53 42 58 79 104 105 15 support: 0.08 (11/133)
pattern 6: (249 ) Sequence ID: 101 8 42 10 46 44 119 16 48 20 23 58 56 support: 0.1 (13/133)
pattern 7: (275 ) Sequence ID: 35 2 70 101 4 98 65 42 10 11 41 47 104 105 24 58 124 support: 0.13 (17/133)
pattern 8: (266 ) Sequence ID: 1 101 98 67 42 77 131 10 79 106 107 14 54 80 23 58 support: 0.12 (16/133)
pattern 9: (309 ) Sequence ID: 2 4 129 8 9 10 132 25 24 28 35 33 39 36 37 42 41 46 44 50 48 54 58 56 63 70 66 67 79 73 80 82 91 102 103 100 101 98 110 109 106 105 118 114 113 127 126 125 124
    
```

Data are implemented in the developed program. We run the algorithm for generating sequential rule by using the following path AplicareAlgoritmi → GenerareReguliSecventialeRuleGen.

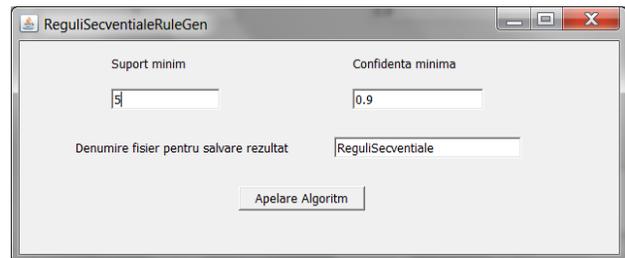


Fig. 10. Window used for algorithm call for generating sequential rules

After setting the minimum support, minimum confidence and the file name where you want to save the result file with the obtained rules we click on the button „Apelare Algoritmi”. For convenience these rules may be obtained with coded pages. Having a minimum support threshold and a minimum confidence, we determine sequential rules by using RuleGen algorithm [14]. First, this algorithm applies another algorithm to determine frequent sequential pages, in this case we use PrefixSpan, and then frequent pairs of models are combined to determine sequential rules from pages. In the following images it can be seen the sequential rules obtained from web pages with the coded pages in Fig. 11. and exact name of the pages in Fig. 12.

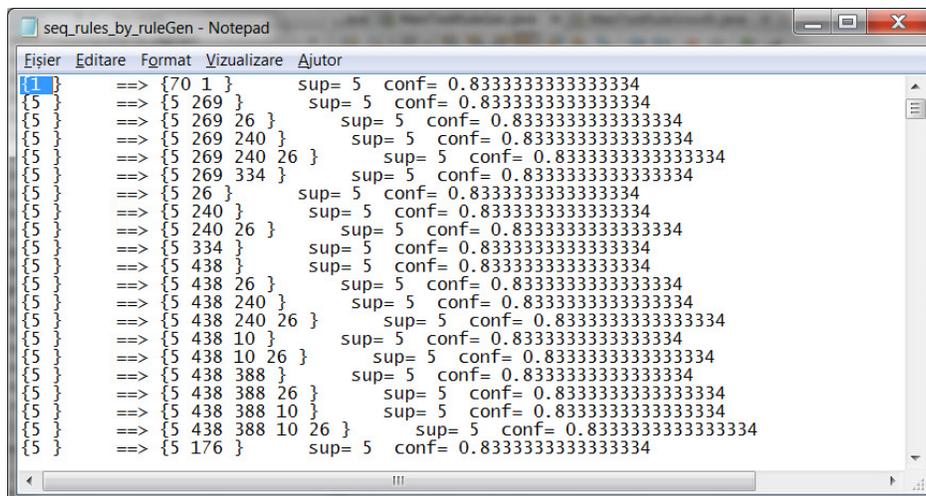


Fig. 11. Sequential rules obtained with the coded pages.

```

File Edit Format View Help
(/joomla-templates/category/music/ ) ==> (/joomla-templates/category/music/ ) sup= 8 conf= 0.6666666666666666
(/corporate-identity-templates/tag/Staff ) ==> (/corporate-identity-templates/tag/Staff /joomla-templates/category/beauty/ ) sup= 9 conf= 0.5
(/corporate-identity-templates/tag/Staff ) ==> (/full-site-templates/category/entertainment/ /corporate-identity-templates/tag/Staff ) sup= 11
conf= 0.6111111111111111
(/corporate-identity-templates/tag/Staff ) ==> (/full-site-templates/category/entertainment/ /corporate-identity-templates/tag/Staff
/joomla-templates/category/beauty/ ) sup= 9 conf= 0.5
(/joomla-templates/category/beauty/ ) ==> (/corporate-identity-templates/tag/Staff /joomla-templates/category/beauty/ ) sup= 9 conf=
0.5294117647058824
(/corporate-identity-templates/tag/Staff /joomla-templates/category/beauty/ ) ==> (/full-site-templates/category/entertainment/
/corporate-identity-templates/tag/Staff /joomla-templates/category/beauty/ ) sup= 9 conf= 1.0
(/live-chat ) ==> (/live-chat /joomla-templates/category/beauty/ ) sup= 9 conf= 0.6
(/live-chat ) ==> (/full-site-templates/category/entertainment/ /live-chat ) sup= 12 conf= 0.8
(/live-chat ) ==> (/full-site-templates/category/entertainment/ /live-chat /joomla-templates/category/beauty/ ) sup= 8 conf= 0.5333333333333333
(/joomla-templates/category/beauty/ ) ==> (/live-chat /joomla-templates/category/beauty/ ) sup= 9 conf= 0.5294117647058824
(/live-chat /joomla-templates/category/beauty/ ) ==> (/full-site-templates/category/entertainment/ /live-chat /joomla-templates/category/beauty/ )
sup= 8 conf= 0.8888888888888888
(/joomla-templates/category/beauty/ ) ==> (/joomla-templates/category/beauty/ /joomla-templates/category/music/ ) sup= 8 conf=
0.47058823529411764
(/joomla-templates/category/beauty/ ) ==> (/full-site-templates/category/entertainment/ /corporate-identity-templates/tag/Staff
/joomla-templates/category/beauty/ ) sup= 9 conf= 0.5294117647058824
(/joomla-templates/category/beauty/ ) ==> (/full-site-templates/category/entertainment/ /joomla-templates/category/beauty/ ) sup= 10 conf=
0.5882352941176471
(/joomla-templates/category/beauty/ ) ==> (/full-site-templates/category/entertainment/ /live-chat /joomla-templates/category/beauty/ ) sup= 8
conf= 0.47058823529411764
(/templates/category/exclusive/ ) ==> (/full-site-templates/category/entertainment/ /templates/category/exclusive/ ) sup= 19 conf=
0.37254901960784315
(/full-site-templates/category/entertainment/ ) ==> (/full-site-templates/category/entertainment/ /templates/category/exclusive/ ) sup= 19 conf=
0.41304347826086957
(/full-site-templates/category/entertainment/ ) ==> (/full-site-templates/category/entertainment/ /flash-intro-header/tag/Puppy ) sup= 8 conf=
0.17391304347826086
(/full-site-templates/category/entertainment/ ) ==> (/full-site-templates/category/entertainment/ /corporate-identity-templates/tag/Staff ) sup=
11 conf= 0.2391304347826087
(/full-site-templates/category/entertainment/ ) ==> (/full-site-templates/category/entertainment/ /corporate-identity-templates/tag/Staff
/joomla-templates/category/beauty/ ) sup= 9 conf= 0.1956521739130435
(/full-site-templates/category/entertainment/ ) ==> (/full-site-templates/category/entertainment/ /joomla-templates/category/beauty/ ) sup= 10
conf= 0.21739130434782608
(/full-site-templates/category/entertainment/ ) ==> (/full-site-templates/category/entertainment/ /live-chat ) sup= 12 conf= 0.2608695652173913
(/full-site-templates/category/entertainment/ ) ==> (/full-site-templates/category/entertainment/ /live-chat /joomla-templates/category/beauty/ )
sup= 8 conf= 0.17391304347826086
(/flash-intro-header/tag/Puppy ) ==> (/full-site-templates/category/entertainment/ /flash-intro-header/tag/Puppy ) sup= 8 conf=
0.6666666666666666
(/full-site-templates/category/entertainment/ /corporate-identity-templates/tag/Staff ) ==> (/full-site-templates/category/entertainment/
/corporate-identity-templates/tag/Staff /joomla-templates/category/beauty/ ) sup= 9 conf= 0.8181818181818182
(/full-site-templates/category/entertainment/ /joomla-templates/category/beauty/ ) ==> (/full-site-templates/category/entertainment/
/corporate-identity-templates/tag/Staff /joomla-templates/category/beauty/ ) sup= 9 conf= 0.9
(/full-site-templates/category/entertainment/ /joomla-templates/category/beauty/ ) ==> (/full-site-templates/category/entertainment/ /live-chat
/joomla-templates/category/beauty/ ) sup= 8 conf= 0.8
(/full-site-templates/category/entertainment/ /live-chat ) ==> (/full-site-templates/category/entertainment/ /live-chat
/joomla-templates/category/beauty/ ) sup= 8 conf= 0.6666666666666666

```

Fig. 12. Sequential rules from web pages with the exact name of pages.

V. CONCLUSIONS

Nowadays, the web is an important part of human life. The web is a very good place to do businesses. Today, large companies rethink their business using the Internet to improve business. Business carried on the Web offers the opportunity to potential customers or partners where our products and specific company can be found. To differentiate through the Internet economy, winning companies have realized that e-commerce transactions is more than just buying / selling, so the appropriate strategies are the key to improve competitive power. One effective technique used for this purpose is data mining. Data mining is the process of extracting interesting knowledge from data. Web mining is the use of data mining techniques to extract information from web data.

Web mining can be divided as was stated above in three categories: Web content mining, Web structure mining and Web usage mining. Data mining as applied to e-commerce is a breakthrough technology that can gather information in an automated fashion and build models used to predict customer purchasing decisions and navigation models with remarkable accuracy.

At the beginning I present the data preprocessing steps which has been performed on the log files from this commercial web site. Data preparation phase starts with data collection. Usually, the analyst does not participate in the process of data collection, so his goal is to select from existing

data those that best fit the analyse it wishes to perform. Variables and records used depend on what it is desired to obtain. The primary source used for web usage mining are logs files of the server. The data used to analyze web usage mining may come from two sources: the period of testing and web logs. The log files from the testing periods are rarely used because of the large time required and high cost. Web log files consist of information which track web users work in their interaction with web servers. Logs files can be located as follows: on the web server, a proxy server or client computers. Logs available on Web servers are most often used because they contain accurate and complete data on site usage.

Here I presented the method that I proposed for session identification by adding the medium time that a user can spend on a specific page as a threshold for session identification. Having the data preprocessing step done, we can then go to another important step in web mining, the one of effectively extracting useful information from all this data. Mining the associations from web site pages is an important task as it helps web site designers to improve the design of the site. It gives better satisfaction for the final user. By mining associations of web pages from web logs the web site designer can discover the bad web page association and can change the design.

This article presents different ways of solving this problem. I apply different algorithms for discovering navigation patterns from data log files.

The novelty brought by this work is represented by the Java application with a friendly graphical user interface, use the mean time to identify sessions and application of different data mining algorithms on Web logs for navigation patterns extraction.

Analyses aim is improving the site design and so leading to customer satisfaction and increasing the number of visits, visitors and therefore sales.

By it's architecture, the application provides a highly flexible environment and can be easily modified by its content, distributed and improved.

For the future I consider adding new modules to the applications developed in order to execute various data mining analysis.

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