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Excavating Evidence since Temporal Performance of Network Convention

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Abstract— Web mining has been explored to a vast degree and diverse systems have been proposed for a assortment of applications that join Web Search, Web Classification, Web Personalization, Versatile Web Locales etc. Mining Web structure Data has resulted in assortment of hyper join based algorithms to rank results of a query. Similarly, Web use Data has been utilized to distinguish user-sessions and group them for better forecast of client route patterns. Most relook on Web mining has so far been from a "data-centric" point of view. In this venture we examine the temporal measurement of the Web use data. We study in specific the conduct of Web use Data over a period of time and group pages that follow comparable access patterns. Such kind of examination could be valuable for target marketing based on time or for web services optimization. In the second part of the project, we characterize a new measure called "Page Popularity" that counts the number of hits to Web pages amid a certain time period and giving more weight to the pages that have been accessed frequently amid a "recent" period of time. This kind of examination helps in distinguishing emerging "popular" themes and brings down the bias on any subject that is "obsolete" yet has been accessed a part amid an prior period of time.

Keywords— Web mining, Web Content, Web Structure, Web Services, Web Clustering

I. INTRODUCTION

Web Mining, characterized as the application of Data mining systems to separate Data from the World Wide Web, has been classified into three sub-fields: Web Content Mining, Web Structure Mining and Web Use Mining based on the kind of the Data available. This kind of classification is represented in Figure 1. While the Web Content provides the genuine textual and other multimedia information, the Web Structure reflects the association of the Web reports and therefore helping in determining their relative importance. Web Structure has been exploited to separate Data about the quality of Web pages in the Web. Traditionally, Data given by Web content joined with the Web Structure has been utilized in the context of look and positioning pages returned by a look result for a query. The stability of the Web structure led to the more relook related to Hyper join Examination and the field gained more recognition with the advent of Google. Desikan et al give an extensive review on Hyper join Examination is provided. Auxiliary Data has too been utilized for 'utilized crawling' – deciding the pages that need to be slithered first. The Web content and structure Data have been successfully joined to classify Web pages concurring to different themes or to distinguish the themes that a page is known for. The Web structure Data has too been connected to distinguish group of Web pages that share a certain set ideas, called Web Communities. Thus, most of the initial relook on Web Mining was utilized on Web content and later Web Structure.

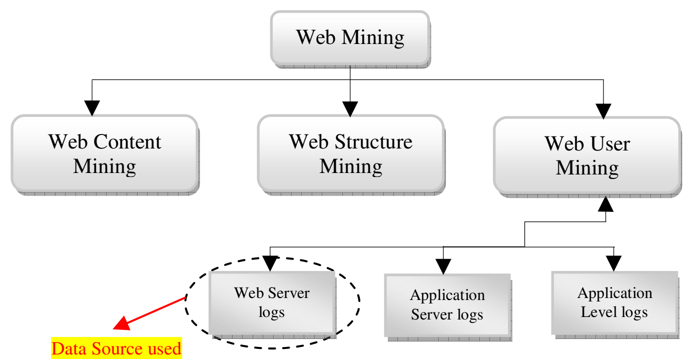

Figure 1: Web Mining Taxonomy

The third kind of Web data, Web Use uncovers the clients surfing designs that has been of interest for an assortment of applications. The Web has been widely utilized for diverse sorts of personal, business and professional applications that depend on client interactivities in the Web. This has increased the need for understanding the clients' interests and his browsing behavior. The Web Use Data has therefore received much attention in the later times to study human behavior. Srivastava et al give a review on Web Use Mining, distinguishing the diverse sorts of Web Use data, their sources and too give a taxonomy for the major application areas in Web Use Mining. At a high level, Web Use Mining can be divided into three categories depending on the kind of data:

- ***Web Server Data:*** They correspond to the client logs that are gathered at Web server. They contain

Data about the IP address from which the demand was made, the time of request, the URIs of the requested and referral reports and the type pf operators that sent the request.

- ***Application Server data:*** The Data that is generated by dynamically by the different application servers such as the.asp and .jsp files that allow certain applications to be built on top of them and collect the Data that results due to certain client activities on the application.

- Application Level Data: The Data that is given by the client for an application, such as demographic data. These sorts of Data can be logged for each client or occasion and can be later utilized to derive valuable information.

Web mining relook has therefore utilized more recently on Web Structure and Web Usage. In this venture we center on another imperative measurement of Web Mining as identified by - the Temporal Development of the Web. The Web is changing fast over time and so is the client's cooperation in the Web recommending the need to study and create models for the developing Web Content, Web Structure and Web Usage.

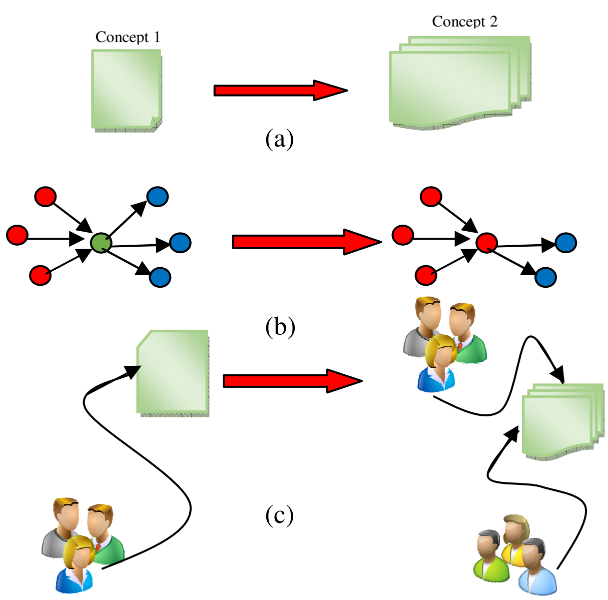

Figure 2: Temporal Development of a single Web Report
a) Change in the Web Content of a report over time.
b) Change in the Web Structure i.e. number of in joins and out links; of a report over time.
c) Change in Web Use of the report over time.

The need to study the Temporal Development of the Web, understand the change in the client conduct and cooperation in the World Wide Web has motivated us to dissect the Web Use data. We use the client logs acquired from the Web server to study the Development of the use of Web reports over time. We perform two sorts of analysis:

Temporal Concepts: We first group Web pages that have comparable access designs over a period of time and look at Web pages that have comparable access designs amid the time period and see how they are related and if they represent any idea or related thoughts or any other valuable information.

Page Popularity: We characterize a measure for the "popularity" of a page proportional to the number of hits to the page amid the time period with more weight to the "recent" history.

We finally compare the results of this measure compares to the some of the other popular existing measures to rank Web pages. The experimental results reflect noticeable difference in the rankings. While the use based positioning metrics, support up the positions of the pages that are utilized as restricted to the unadulterated Hyper join based measurements that rank pages that are utilized rarely high. In particular, we notice that the Page Fame positions the pages that have been utilized more recently high and brings down the rank of the pages that have been utilized prior yet have had exceptionally low access amid the later period.

The rest of the report is organized as follows: In Territory 2 we talk about the related work in this territory and in the following section, we examine the approach followed by us. Territory 4 discusses the tests performed and the results. In Territory 5 we dissect the results and finally in Territory 6, we conclude and give future directions.

II. RELATED WORK

In our approach, we take into account unadulterated Web use Data to separate the Temporal conduct designs of Web pages. Web use Data has been a major source of Data and has been studied extensively amid the later times. Understanding client profiles and client route designs for better versatile web locales and anticipating client access designs has been of huge interest to the relook and the business community. Cooley et al in and examine systems to pre-process the client log Data and to separate web page references into those made for navigational purposes and those made for content purposes. Client route designs have evoked much interest and have been studied by different other researchers. Srivastava et al examine the systems to pre-process the use and content data, discover designs from them and filter out the non-relevant and fascinating designs discovered. Too serve as great surveys for web use mining.

As examined prior use insights has been connected to Hyper join structure for better join forecast in field of versatile web sites. The idea of versatile web locales was proposed by Pekrowitz and Etzioni. Pirolli and Pitkow examine about anticipating user-browsing conduct based on past surfing ways utilizing Markov models. In Ramesh Sarukkai has examined about join forecast and path examination for better client navigations. He proposes a Markov chain model to anticipate the client access design based on the client access logs previously collected. Zhu et al. extend this by introducing the maximal forward reference to eliminate the impact of backward references by the user. They too anticipate client conduct inside the 'n' future steps, utilizing a N-Step Markov chain as restricted to the one step approach by Sarukkai. Data foraging theory thoughts have too been utilized recently by Chi et al to join client conduct into the existing content and join structure. They have displayed client needs and client activities utilizing the notion of Data Scent as depicted earlier.

Cadez et al in group clients with comparable route ways in the same site. They create a visualization methodology to display ways for the clients inside each cluster. They use first request Markov models for clustering, to take into account the request in which the client requests the page.

Huang et al in present a "Cube-Model" to represent Web access sessions for Data mining. They use K-modes calculation to group sessions depicted as sequence of page URL Ids.

On the other hand, in the territory of Web structure mining there has been a part of relook on positioning of Web pages utilizing Hyper join analysis. There have been diverse Hyper join based systems that have been proposed. Page Rank is a metric for positioning hypertext reports that determines the quality of these documents. Page et al. developed this metric for the popular look engine, Google. The key thought is that a page has high rank if it is pointed to by many highly positioned pages. So the rank of a page depends upon the positions of the pages indicating to it. This process is done iteratively till the rank of all the pages is determined. The rank of a page p can therefore be written as:

$$PR(p) = d/n + (1-d) \cdot \sum_{(q,p) \in G} PR(q) / OutDegree(q)$$

Here, n is the number of nodes in the diagram and *OutDegree(q)* is the number of Hyper join s on page q. Intuitively, the approach can be seen as a stochastic examination of a irregular walk on the Web graph. The first term in the right hand side of the equation relates to the likelihood that a irregular Web surfer arrives at a page p out of nowhere, i.e. (s)he could arrive at the page by writing the URL or from a bookmark, or might have a specific page as his/her homepage. d would then be the likelihood that a irregular surfer picks a URL straightforwardly – i.e. writing it, utilizing the bookmark list, or by default – rather than crossing a join. Finally, 1/n relates to the uniform likelihood that a individual picks the page p from the complete set of n pages on the Web. The second term in the right hand side of the equation relates to element contributed by arriving at a page by crossing a link. 1- d is the likelihood that a individual arrives at the page p by crossing a link. The summation relates to the sum of the rank contributions made by all the pages that point to the page p. The rank contribution is the Page Rank of the page multiplied by the likelihood that a specific join on the page is traversed. So for any page q indicating to page p, the likelihood that the join indicating to page p is navigated would be 1/*OutDegree(q)*, assuming all joins on the page is chosen with uniform probability.

The other popular metric is Hubs and Authorities. They can be seen as 'fans' and 'centers' in a bipartite core of a Web graph. The hub and power scores processed for each Web page indicate the degree to which the Web page serves as a "hub" indicating to great "authority" pages or as an "authority" on a subject pointed to by great hubs. The hub and power scores for a page are not based on a equation for a single page, yet are processed for a set of pages related to a subject utilizing an iterative procedure called HITS calculation.

More recently, Oztekin et al , proposed Use Mindful PageRank. They modified the fundamental PageRank metric to join use information. In their fundamental approach allocated weights to the joins based on the number of traversals on the link, and therefore modifying the likelihood that a client traverses a specific join in the fundamental PageRank from $1/OutDegree(q)$ to $W_l/OutTraversed(q)$, where W_l is the number of traversals on the join l and *OutTraversed(q)* is the absolute number of traversals of all joins from the page *q*. And too the likelihood to arrive at a page straightforwardly is processed utilizing the use statistics. The final equation for Use Mindful PageRank is:

$$UPR(p) = \alpha \cdot \left(d/N + (1-d) \cdot \sum_{(q \to p) \in G} UPR(q) / OutDegree(q) \right) + (1-\alpha) \cdot \left(d \cdot W_{nl} + (1-d) \cdot \sum_{(q \to p) \in G} UPR(q) \Big/ \frac{W_l}{OutTraversed(q)} \right)$$

where α is the emphasis element that decides the weight to be given to the structure versus the use Data.

III. OUR APPROACH

Our goal is to group pages that have comparable use designs over time and study them. The motivation behind the venture was to study how the Data on the Web changes over time and how to model such a change in the information. As time changes, the content, structure and use of a Web page changes. These changes can be displayed both a single page level or for a collection of pages. Looking from a point of view of a single page, the idea that a Web page represents might change or evolve with regard to the time. Also, the fundamental structure of a page might change, i.e. the number of in joins and the number of out joins might change. Since most auxiliary mining work considers that "if a page is pointed to by some other page, them it endorses the view of that page". So as the number of incoming joins changes, the subject that the page represents might change with period of time. Similarly the change in the number of out joins might reflect the change in the relevance of the page with regard to a certain topic. The use Data is too influenced by the content and auxiliary change in a Web page. The use Data brings in Data about the subject the page is "popular" for. And this "popularity" might or might not be necessarily be reflected by the change in the content of the page or the pages indicating to it. A page's Fame might or might not be influenced by the change in its indegree or outdegree.

This motivates the need to study the change in the conduct of the Web over a period of time. This thought is not entirely new, the changes to the Web are being recorded by the pioneering Web Document venture. Large organizations generally Document (at minimum portions of) use Data from there Web sites. With these sources of Data available, there is a large scope of relook to create systems for analyzing of how the Web evolves over time. In our venture we center on trying to separate Data from the Web use Data inn general and Data from Web Server logs to be more specific.

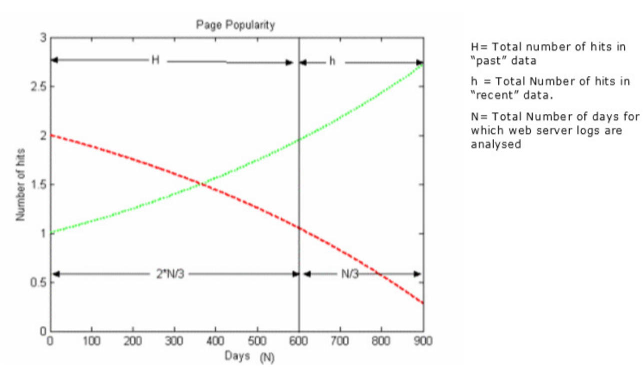

Figure 3: Concept of Page Popularity

We first try to group pages based on the absolute number of hits per day for each Web page. This would group pages that have comparable access designs amid the given time period. This might reflect pages that are related in some manner, due to which their access designs have been similar. This kind of examination will too help in distinguishing pages that were "popular" amid a certain frame of time.

The next thing we bring up in this venture is a measure called "Page Popularity" to determine the "popularity" of the page in the time period for which we analyzed the data.. In this measure we take into give more weight to the "later history" than the past, so as to enable upcoming themes to be positioned better than old topics. Though this kind of a thing could be done by just considering a "recent" time period of Data that would result in misfortune of Data of the old data. So it would be better to consider the use Data for a longer duration and then weigh the "later history" more so that there is no misfortune of information. Considering the old Data would be important, especially when doing structure mining, as the web pages are slithered from time to time. So it would be a great thought to store the previous Data from the Web diagram that existed prior and too make use the new diagram to mine information. This kind of auxiliary Data can be acquired for the Web Document Venture site.

We now present the fundamental thought of "Page Popularity" as appeared in Figure 3. The thought is though the Web page that has the access design "red" might have absolute number of hits high, the Web page represented by "green" bend has an increasing use and so might represent a newer subject or something that is gaining "popularity" as restricted to the Web page that is represented by the "red" curve" which is no longer utilized that much. The equation we propose is exceptionally naïve at this stage, though it captures the fundamental thought behind the approach. The Page Fame is characterized as:

$$PagePopularity = K * {(H + \alpha \cdot h)} / {(H + h)}$$

Where K is some constant and H is the absolute number of hits for a Web page in the time period considered "past" and 'h' is the number of hits for the same web page in the "recent" period. α is some parameter that is utilized to give weight to "later history". α can be varied depending on the significance of the "recent" data. In our genuine implementation, we took the normal number of hits amid the "past" time period and the "average" number of hits in the "recent" time period. Normal was considered as it would neutralize the impact of any sudden spikes or drops in use per day. If we weigh concurring to some other scale like linear, such sudden changes might drastically support or bring down the rank of a page. We considered the first two-thirds of the time as “past” history and last one-third as “later history”. There was no specific reason to choose so, yet it appeared a reasonable estimate. We then weighed the hits in the “recent” history twice as that of the hits in the “past history”. So in the usage the equation boils down to:

$$PagePopularity = \frac{1}{3} \cdot \frac{H}{\left(2N/_{3}\right)} + \frac{2}{3} * \frac{h}{N/_{3}} = \left(\frac{1}{2N}\right) * \frac{(H + 4 \cdot h)}{H + h}$$

IV. DATA PRE-PROCESSING

One of the fundamental issues in Web use mining is Data pre-processing. Web use Data consists of all sorts of access to web pages. The general format of a Web server log Data looks is appeared in Figure 4.

IP Address	Rfc931	Authuser	Date and time of request	request	Status	Bytes	Referrer	User agent
109.203.110.101	-	-	2011-12-28 00:00:36	GET / - 80 - 61.135.249.32 HTTP/1.1	200	3014	http://thanjavurcity.com	Mozilla/4.0+(compatible;+MSIE+7.0;

IP address: IP address of the remote host
Rfc931: the remote login name of the user
Authuser: the username as which the user has authenticated himself.
Data: date and time of the request
Request: the request line exactly as it came from the client
Status: the http- response code returned to the client
Bytes: the number of bytes transferred
Referrer: the url client was on before requesting your url

Figure 4: Extended Common Log Format (ECLF) of Web Server log

For our experiment, we considered just Web pages with.html extension. We too eliminated “robots” by considering web pages that did not have “Mozilla” string in the user-operators field. In spite of this we noticed some robots like “inktomi” utilized “Mozilla” in the client agent, which we noticed and so uprooted all Data that had “slurp/cat” string the client operator’s field. This took care of eliminating most robots and undesirable data. We too pruned Data for which the absolute number of hits was exceptionally “low” i.e. lower than the at minimum the number of days in the “later period”. This was just to take into account a web page that was begun to use in the “recent” time period and is gradually picking up and so the number of accesses it might have will be low compared to other pages and so if it is a new page it should not be neglected.

The Data considered was from April through June. We didn’t have use Data after June, and for Data before April, the CS site had been restructured, so that could mess up the kind of use Data required for our experiment. The Data we utilized however was great for natural purposes as it contained Data in end of Spring Semester and then the period between Spring and summer term where the classes had not begun full-fledged. So this would give us fascinating result as the class web page access would change significantly after the end of a term. So the bunching of web page designs for at minimum certain pages should be similar. Else in general it is troublesome to find patterns, as most web pages are accessed exceptionally randomly.

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V. RESULTS

5.1 Clustering

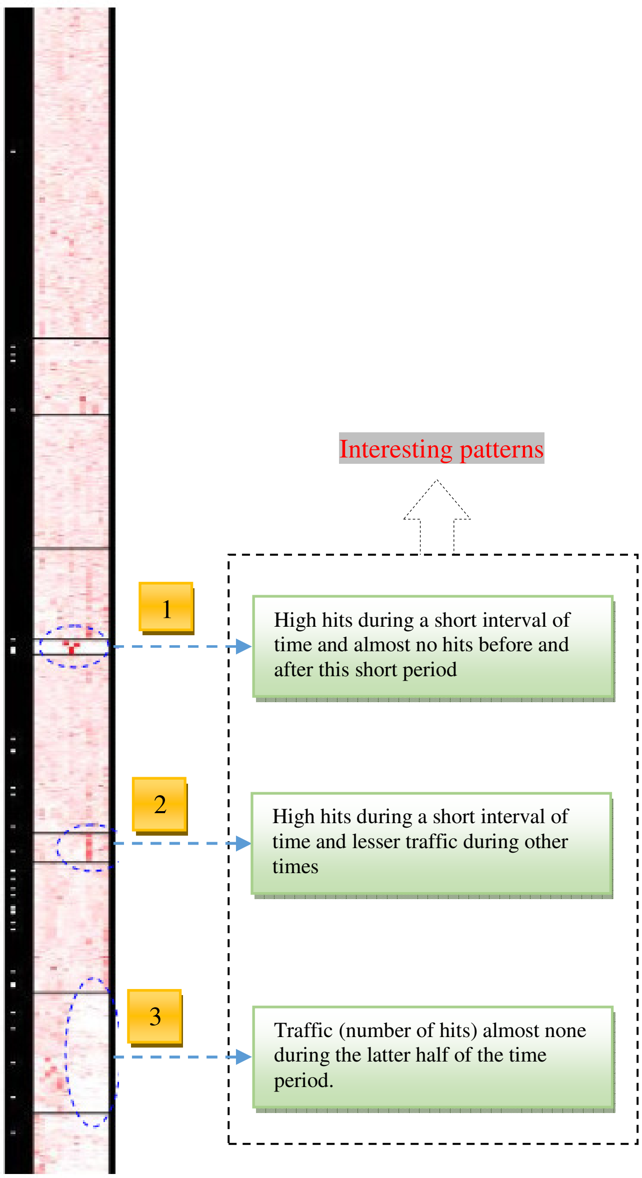

Figure 5: Clustering of Web pages based on number of hits per day

The bunching of the Web pages was done utilizing the tool CLUTO. The number of bunches specified was 10. We tried with different number of bunches and of them 10 revealed a decent bunching of pages from the dendogram produced and as appeared in Figure 5

Three fascinating designs were found. The kind of Web pages that belong to these bunches is appeared in Figure 6. The first group belongs to the set of pages that were accessed a part amid a exceptionally short period of time. Most of them are some kind of wedding photos that were accessed a lot, recommending some kind of a "wedding" occasion that took place amid that time. The group of pages is again related to some talk slides of The Twin Cities programming process change network (Twin-SPIN), that is a regional association established in January of 1996 as a forum for the free and open exchange of programming process change experiences and ideas. They appeared to have a talk amid that period and thus the access to the slides. The third group was the most interesting. It had mostly class web pages and some pages related to "Data Mining" slides. These set of pages had high access amid the first period of time, possibly the spring term and then their access died out. So it appeared the "Data Mining" web page was accessed, since someone was doing some work related to "Data mining" amid that semester, though no "Data Mining" course was as such not offered.

Figure 6: Web pages that belong to the "interesting" clusters

5.2 Page Fame

Our next set of results was with regard to the Page Fame measure. We positioned the web pages in accordance with the Page Rank, Page Popularity, and Absolute Number of hits and Use Mindful PageRank. The results are appeared in the following figures:

Eg. These web pages do not figure in usage based rankings

Page Ranks Results

1. 0.00075915	http://thanjavurcity.com/SHOPPING%20MALL.aspx
2. 0.00015225	http://thanjavurcity.com/Ice%20Cream%20Parlors.aspx
3. 0.00008505	http://thanjavurcity.com/interiorsandexteriors.aspx
4. 0.00005565	http://thanjavurcity.com/offices.aspx
5. 0.00005355	http://thanjavurcity.com/Textiles.aspx
6. 0.0000525	http://thanjavurcity.com/buildingmaterial.aspx
7. 0.0000525	**http://thanjavurcity.com/gym.aspx**
8. 0.0000483	**http://thanjavurcity.com/mobiles.aspx**
9. 0.0000462	**http://thanjavurcity.com/bookshops.aspx**
10. 0.0000441	http://thanjavurcity.com/plant%20nursery.aspx
11. 0.0000441	http://thanjavurcity.com/petshop.aspx
12. 0.000004095	http://thanjavurcity.com/orphanage.aspx
13. 0.00003885	http://thanjavurcity.com/beautyparlor.aspx
14. 0.00003885	http://thanjavurcity.com/Theaters.aspx
15. 0.0000357	http://thanjavurcity.com/Actorgallery.aspx
16. 0.000042	http://thanjavurcity.com/tamilmovietrailer.aspx

Figure 7: Ranking Results from PageRank

Eg. Ranked 29th if we count pure hits

Page Papularity Results

1. 0.013207898	http://thanjavurcity.com/Actorgallery.aspx
2. 0.013083809	http://thanjavurcity.com/beautyparlor.aspx
3. 0.011157657	http://thanjavurcity.com/petshop.aspx
4. 0.011157657	**http://thanjavurcity.com/bookshops.aspx**
5. 0.002175506	http://thanjavurcity.com/Textiles.aspx
6. 0.002014268	http://thanjavurcity.com/interiorsandexteriors.aspx
7. 0.001851108	http://thanjavurcity.com/SHOPPING%20MALL.aspx
8. 0.001851087	**http://thanjavurcity.com/mobiles.aspx**
9. 0.001755096	http://thanjavurcity.com/tamilmovietrailer.aspx
10. 0.001713894	http://thanjavurcity.com/Theaters.aspx
11. 0.001628529	http://thanjavurcity.com/orphanage.aspx
12. 0.001295007	http://thanjavurcity.com/plant%20nursery.aspx
13. 0.00109808	http://thanjavurcity.com/buildingmaterial.aspx
14. 0.001098059	http://thanjavurcity.com/offices.aspx
15. 0.001018059	**http://thanjavurcity.com/gym.aspx**
16. 0.00800457	http://thanjavurcity.com/Ice%20Cream%20Parlors.aspx

Figure 8: Page Popularity based rankings

Total Hits based Rankings

1. 0.00003885	http://thanjavurcity.com/Theaters.aspx
2. 0.0000441	http://thanjavurcity.com/plant%20nursery.aspx
3. 0.0000525	http://thanjavurcity.com/buildingmaterial.aspx
4. 0.00015225	http://thanjavurcity.com/Ice%20Cream%20Parlors.asp
5. 0.000042	http://thanjavurcity.com/tamilmovietrailer.aspx
6. 0.000004095	http://thanjavurcity.com/orphanage.aspx
7. 0.0000483	**http://thanjavurcity.com/mobiles.aspx**
8. 0.00005565	http://thanjavurcity.com/offices.aspx
9. 0.00075915	http://thanjavurcity.com/SHOPPING%20MALL.aspx
10. 0.0000357	http://thanjavurcity.com/Actorgallery.aspx
11. 0.0000525	**http://thanjavurcity.com/gym.aspx**
12. 0.0000441	http://thanjavurcity.com/petshop.aspx
13. 0.00008505	http://thanjavurcity.com/interiorsandexteriors.aspx
14. 0.00003885	http://thanjavurcity.com/beautyparlor.aspx
15. 0.0000462	http://thanjavurcity.com/bookshops.aspx
16. 0.00005355	http://thanjavurcity.com/Textiles.aspx

Figure 9: Total Hits based ranking

Low-Ranked because course web-pages were not accessed in the month of June, which was considered recent and hence more weight given to pages accessed during that period

Usage Aware PageRank

1. 0.00075915	http://thanjavurcity.com/interiorsandexteriors.aspx
2. 0.00015225	**http://thanjavurcity.com/mobiles.aspx**
	(72acc. To page popularity)
3. 0.00008505	http://thanjavurcity.com/Theaters.aspx
4. 0.00005565	http://thanjavurcity.com/tamilmovietrailer.aspx
5. 0.00005355	**http://thanjavurcity.com/gym.aspx**
	(37acc. To page popularity)
6. 0.0000525	http://thanjavurcity.com/plant%20nursery.aspx
7. 0.0000525	http://thanjavurcity.com/Textiles.aspx
8. 0.0000483	http://thanjavurcity.com/offices.aspx
9. 0.0000462	http://thanjavurcity.com/buildingmaterial.aspx
10. 0.0000441	http://thanjavurcity.com/beautyparlor.aspx
11. 0.0000441	http://thanjavurcity.com/Ice%20Cream%20Parlors.aspx
12. 0.000004095	http://thanjavurcity.com/petshop.aspx
13. 0.00003885	**http://thanjavurcity.com/bookshops.aspx**
	(3acc. To page popularity)
14. 0.00003885	http://thanjavurcity.com/orphanage.aspx
15. 0.0000357	http://thanjavurcity.com/beautyparlor.aspx
16. 0.000042	http://thanjavurcity.com/SHOPPING%20MALL.aspx

Figure 10: Usage Aware PageRank

The results from the diverse positioning measures uncovers that since PageRank gives more significance to structure and does not join use statistics, it positions pages that are well connected high, though they are never used. For example, it positioned all the "cisco" and "jave-help" pages really high as they were structurally well-connected. Simple count of absolute hits is not exceptionally valuable as the number of hits could be accumulating for a assortment of reasons and pages that are utilized since a long time will tend to get a higher rank. Although simply counting the hits uncovers to some degree what the client actually finds useful. Use Mindful PageRank makes use of both the use insights and the join structure and in all gives a balanced result in terms of the both the use and Join structure. As it can been the CS home page is positioned high in Use Mindful PageRank and is positioned below '100' utilizing PageRank. It can be noticed that two of the pages in UPR are course web pages that are connected from the home pages of the professors and have been accessed a lot. So the rank of these pages has been boosted up. Yet "Page Popularity" on the other hand gives more weight to the "later history" and since these course web-pages were not accessed amid the month of June after the semester ended, their rankings were brought down. Therefore by weighing the "recent" history more we can support the positions of the pages that are more "popular" or huge for that time period.

VI. Conclusions and Future Directions

Bunching web page access designs over time might help in distinguishing a "concept" that is "popular" amid a time period. PagePositions tend to give more significance to structure alone, thus pages that are heavily connected might be positioned higher though not used. Thus the significance is given to the individual who creates the Web page. Use Mindful Pagerank combines use insights with join Data giving significance to both the creator and the genuine client of a web page. Page Fame gives more weight to 'recent' history and helps in positioning "obsolete" items lower and boosting up the themes that are more "popular" amid that time period.

Certainly, more tests run over longer time-period data. Too there needs to be a refinement of "recent" history definition in terms of the time period that is considered later and the weight to be given to "recent" history. Another valuable thing would be to apply time-based use weights to join traversals and re-compute use Mindful page rank. In general it would be great to come up with time based measurements that would help in positioning Web pages or any Web based properties relevant to the time period. For example,

$$Metric(t+\Delta t)=\alpha\cdot Metric(t)+(1-\alpha)\cdot Metric(\Delta t)$$

where Δt would be the "recent" time period and α is the weight allocated to the Data gathered from the "past". This kind of examination would too help us not lose Data about the Data that changed amid a period of time.

Therefore the study the conduct of change in the web content, web assembly and web use over time and their effects on each other would help us understand the way Web is developing and the necessary steps that can be taken to make it a better source of evidence.

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