



UNIVERSITY OF ILLINOIS SPRINGFIELD

BIG DATA ANALYTICS (CSC 570 U) FINAL PROJECT SPRING 2016

"FINDING MOST INFLUENTIAL PAPERS BASED ON DBLP CITATION NETWORK"

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I. INTRODUCTION

The World Wide Web creates several challenges for retrieval of the data. It is substantial and diverse. Current assessments are that there are more than 150 million web sites with a multiplying life which is short than a year. Giving significant data to the users to meet their requirements is the essential objective of the website proprietors. In this manner, finding the substance of the Web and recovering the users interests and demands from their actions have become essentially important. Therefore Web Mining is utilized to classify the users and web pages by interpreting the users' conduct or actions, the information of the web pages and the order of the URLs that needs to be accessed in order. HITS and PageRank are the two page ranking algorithms that are mainly used in web structure mining.

II. PageRank Algorithm

In order to estimate the relative importance of Web pages, PageRank was developed at Stanford University by Larry page (cofounder of Google), a method for calculating a ranking for every web page taking into account the graph of the web. In other words, PageRank is nothing but a vote that is casted by all the other pages which are on the Web, to show how important a page is. A link to a page counts as a vote of support. Google utilizes this algorithm to order its search results in a way that imperative documents move up in the search results whereas moving the less critical pages down in its list. It has applications in ranking tweets in twitter, recommendation systems, suggesting friends over twitter, etc.

This algorithm states that **“If a page has some important incoming links to it, then its outgoing links to other pages also becomes important, thus it takes backlinks into account and propagates the ranking through the links.”** When some query is given, Google consolidates precomputed PageRank scores with content matching scores to obtain an overall ranking score for each web page in response to the given query.

A simplified version of PageRank is defined as follows:-

$$PR(u) = c \sum_{v \in B(u)} \frac{PR(v)}{N_v}$$

Where u represents a web page. $B(u)$ is the set of pages that point to u . $PR(u)$ and $PR(v)$ are rank scores of page u and v respectively. N_v denotes the number of outgoing links of page v . c is a factor used for normalization.



III. Weighted PageRank Algorithm

Wenpu Xing and Ali Ghorbani proposed an expansion to standard PageRank called Weighted PageRank (WPR). It presumes that more prominent the web pages are more linkages other website pages tend to have to them or are connected to by them. This algorithm allocates bigger rank values to more prominent pages rather than partitioning the rank value of a page uniformly among its outgoing linked pages. Each outlink page gets a value corresponding to its significance and this prominence is measured by its number of incoming and outgoing links. This significance is assigned in terms of weight values to the incoming and outgoing links which are represented as $W_{in}(v,u)$ and $W_{out}(v,u)$.

$W_{in}(v,u)$ is the weight of $link(v,u)$ that is estimated based on the number of inlinks of page u and the number of inlinks of all reference pages of page v .

$$W_{(v,u)}^{in} = \frac{I_u}{\sum_{p \in R(v)} I_p}$$

$W_{out}(v,u)$ is the weight of $link(v, u)$ that is estimated based on the number of outlinks of page u and the number of outlinks of all reference pages of page v .

$$W_{(v,u)}^{out} = \frac{O_u}{\sum_{p \in R(v)} O_p}$$

Considering the significance of pages, the original PageRank formula is altered as

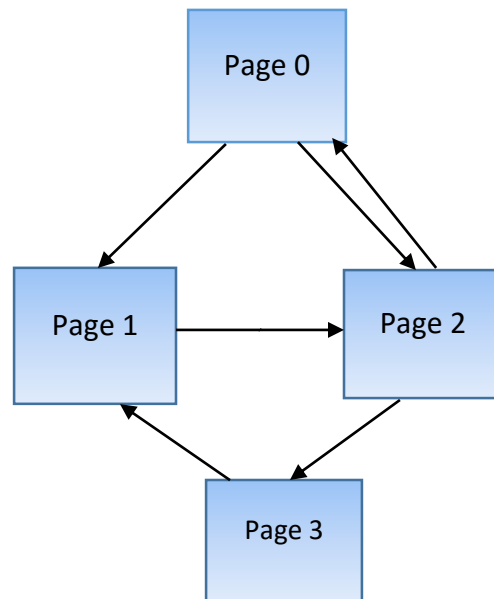
$$PR(u) = \frac{1-d}{N} + d \sum_{v \in in(u)} PR(v) \times W_{(v,u)}^{in} \times W_{(v,u)}^{out}$$

Where

- d : is a constant (typically set to 0.85)
- N : is the total number of nodes (In this case total number of papers in the citation network)
- $in(u)$: The set of all the nodes which link to node u



Consider a small example, suppose there is a network consisting of four papers i.e. Page 0, Page 1, Page 2 and Page 3, where Page 0 has references Page 1 and page 2, Page 1 has reference Page 2, Page 2 has reference Page 0 and Page 3, Page 3 has reference Page 1.



Step 1: We initialize $d=0.85$, $N=4$, $PR(\text{Page } 0)=1/4$, $PR(\text{Page } 1)=1/4$, $PR(\text{Page } 2)=1/4$, $PR(\text{Page } 3)=1/4$

Step 2: Calculate the number of inlinks and the number of outlinks for all of the above links:

Papers	inlinks	outlinks
Page 0	1	2
Page 1	2	1
Page 2	2	2
Page 3	1	1



Step 3: Calculating Win and Wout

Lets calculate for Page 1, Page 2

$$\text{Win}(\text{Page 1, Page 2}) = \frac{\text{\#inlinks}(\text{Page 2})}{\text{\#inlinks}(\text{Page 2})} = \frac{2}{2} = 1$$

$$\text{Wout}(\text{Page 1, Page 2}) = \frac{\text{\#outlinks}(\text{Page 2})}{\text{\#outlinks}(\text{Page 2})} = \frac{2}{2} = 1$$

Step 4: Now lets calculate PageRank i.e PR(Page1)

$$\text{PR}(\text{Page1}) = (1-d)/N + d * [\text{PR}(\text{Page 0}) * \text{Win}(\text{Page 0, Page 1}) * \text{Wout}(\text{Page 0, Page 1}) + \text{PR}(\text{Page 3}) * \text{Win}(\text{Page 3, Page 1}) * \text{Wout}(\text{Page 3, Page 1})]$$

And we can get the PageRank of Page 1 by substituting the values after all the calculations are performed.

IV. AIM:

Our aim in this project is to obtain the top rated papers from the list of papers in the given set of Publications. To implement this, Weighted PageRank algorithm is used.

V. METHODOLOGY:

In this problem, to calculate the page ranks of the paper and produce top 10 papers with highest page rank, we must have to extract the required data from the dataset in very first place. For the simplicity, we have divided this program in two steps. In first place, we have used Map-Reduce framework to extract the index, citations and title with two different Map-Reduce jobs.

Map-Reduce produces the output which we consider it as link.txt and title.txt. These files are used as input to the Hive program to calculate the inlinks, outlinks and weights of papers. Using these attributes, we calculate page rank of each paper. After the 10 iterations, the final page rank will be generated and we can get top 10 papers which are having highest page rank amongst all.

Here is the approach to the program.



Step-1: Map-Reduce algorithm

- In the first step, to distinguish between the required data and original data, we need to use DBLP input format. Include it as a Map-Reduce Job in the Driver class.
- As we are not going to use reducer, set number of reduce task to 0.
- Split the incoming string with the new line (`\n`).
- There might be inconsistency in the dataset. So to omit those records, we need to match the pattern starting with “#index” to get the index values.
- If it matches, then for the records after 5th column (i.e. citations), check for another pattern start with “#%” till the total citations are found for the particular index.
- If it matches, then emit the index and citations delimited by “\t”. (linkgraph)
- To emit the titles, again find the pattern which contains the text. If found, then emit the title corresponding to index delimited by “\t”. (titlegraph)
- Save the outputs as link.txt and title.txt.

Step-2: Hive algorithm

- Load the data from link.txt into the table linkgraph.
- Load the data from title.txt into the table titlegraph.
- Define total number of nodes in the citation graph and store it into the table nodes.
- Define scaling factor $(1-d)/N$ and store it into table scale_factor.
- Find the inlinks and outlinks for the papers.
- Then calculate the total number of inlinks and total number of outlinks for the paper.
- Using the existing values of inlinks, outlinks, total inlinks and total outlinks, compute in-weights and out_weights.
- Assign the initial rankings as the base to compute future ranks within the iterations.
- Using the page rank formula ($\text{scaling factor} + d * \text{summation of page ranks of inlinks} * W_{in} * W_{out}$) to calculate the new page rank.
- Update the page rank after every iteration and iterate it for 10 times.
- After all the iterations, find out the top 10 papers with title, number of citations and highest page ranks.
- Store the result as paper-rank.txt.



VI. RESULTS

Map-Reduce Output

HDFS:/user/hive/final_project/link.txt/part-m-00000 - Mozilla Firefox

bd-s106:50075/browseBlock.jsp?blockId=902475516466690363&blockSize=6160462&genstan

File: **/user/hive/final_project/link.txt/part-m-00000**

Goto:

[Go back to dir listing](#)
[Advanced view/download options](#)

[View Next chunk](#)

370	770472
370	832291
370	3006707
370	3006149
370	3006258
384	248799
384	1073239
384	1075533
384	1127700
386	770739
386	773466
386	832742
386	833078
386	951454
387	690
387	2022
387	2375
387	2487
387	3774
387	3006547
392	2355
392	832426
392	1117337
392	3003317
394	613063
394	613056

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HDFS:/user/hive/final_project/title.txt/part-m-00000 - Mozilla Firefox

bd-s206:50075/browseBlock.jsp?blockId=5212454480269864261&blockSize=34241430&genst

File: **/user/hive/final_project/title.txt/part-m-00000**

Goto:

[Go back to dir listing](#)
[Advanced view/download options](#)

[View Next chunk](#)

370	770472	Parallelizing Compilers.
370	832291	Parallelizing Compilers.
370	3006707	Parallelizing Compilers.
370	3006149	Parallelizing Compilers.
370	3006258	Parallelizing Compilers.
384	248799	Distributed and Multiprocessor Scheduling.
384	1073239	Distributed and Multiprocessor Scheduling.
384	1075533	Distributed and Multiprocessor Scheduling.
384	1127700	Distributed and Multiprocessor Scheduling.
386	770739	Logic Programming and Constraint Logic Programming.
386	773466	Logic Programming and Constraint Logic Programming.
386	832742	Logic Programming and Constraint Logic Programming.
386	833078	Logic Programming and Constraint Logic Programming.
386	951454	Logic Programming and Constraint Logic Programming.
387	690	Pattern Matching and Text Compression Algorithms.
387	2022	Pattern Matching and Text Compression Algorithms.
387	2375	Pattern Matching and Text Compression Algorithms.
387	2487	Pattern Matching and Text Compression Algorithms.
387	3774	Pattern Matching and Text Compression Algorithms.
387	3006547	Pattern Matching and Text Compression Algorithms.
392	2355	Virtual Memory.
392	832426	Virtual Memory.
392	1117337	Virtual Memory.
392	3003317	Virtual Memory.
394	613063	Distributed File Systems and Distributed Memory.
394	613056	Distributed File Systems and Distributed Memory.

[Download this file](#)



Hive Output

```
hive> select * from final_pagerank;
OK
Singularity Theory and Phantom Edges in Scale Space.      14      1.05240281017550
77E-4
A Method for Obtaining Digital Signatures and Public-Key Cryptosystems. 1724    6
.211774177579805E-5
Chunking in Soar: The Anatomy of a General Learning Mechanism. 75      5.860968
0669899826E-5
Explanation-Based Generalization: A Unifying View.      199      4.50354368634409
2E-5
Authenticating Edges Produced by Zero-Crossing Algorithms. 21      4.332521
461418009E-5
Graph-Based Algorithms for Boolean Function Manipulation. 1722    3.788872
249814678E-5
The Complexity of Theorem-Proving Procedures      658      2.8227001186504785E-5
Communicating Sequential Processes.      740      2.5653238255030796E-5
Segmentation and the Design of Multiprogrammed Computer Systems.      40      2
.4464957140453658E-5
Secure Communications Over Insecure Channels.      74      2.4340236981664805E-5
Time taken: 2.198 seconds, Fetched: 10 row(s)
hive>
```

VII. CONCLUSION:

- Page Rank algorithm measures the importance of a page by considering importance of the other pages.
- Weighted PageRank algorithm is the extension to the standard page rank which considers the inlinks and outlinks of a page and distribute the rank score based on the popularity/importance of a page.
- This algorithm is scalable and can be applied to any size of data. But the condition is it must be a linked network.
- In this problem, the top 10 papers with highest page rank are successfully computed.



VIII. REFERENCES:

[1] Lecture Notes, Stanford University,

<http://ilpubs.stanford.edu:8090/422/1/1999-66.pdf>

[2] Wenpu Xing and Ali Ghorbani,” Weighted PageRank Algorithm” Faculty of Computer Science University of New Brunswick Fredericton, NB, E3B 5A3, Canada

[3] Rashmi Rani and Vinod Jain “Weighted PageRank using the Rank Improvement” Department of Computer Science and Engineering, B.S. Anangpuria. Institute of Technology and Management, Faridabad, India

[4] NeelamDuhan, A. K. Sharma, Komal Kumar Bhatia, “Page Ranking Algorithms: A Survey”. In proceedings of the IEEE International Advanced Computing Conference (IACC), 2009.

[5] Book - Programming Hive, Dean Wampler, Edward Capriolo, Jason Rutherglen