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Department of Artificial Intelligence & Data Science

Aim: To implement Page Rank Algorithm

Objective: Develop a program to implement a page rank algorithm.

Theory:

PageRank (PR) is an algorithm used by Google Search to rank web pages in their search engine results. PageRank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. Page Rank Algorithm is designed to increase the effectiveness of search engines and improve their efficiency. It is a way of measuring the importance of website pages. Page rank is used to prioritize the pages returned from a traditional search engine using keyword searching. Page rank is calculated based on the number of pages that point to it. The value of the page rank is the probability will be between 0 and 1. A web page is a directed graph having two important components: nodes and connections. The pages are nodes and hyperlinks are the connections, the connection between two nodes. Page rank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important website are likely to receive more links from other websites. The page rank value of individual node in a graph depends on the page rank value of all the nodes which connect to it and those nodes are cyclically connected to the nodes whose ranking we want; we use converging iterative method for assigning values to page rank. In short page rank is a vote, by all the other pages on the web, about how important a page is. A link to a page count as a vote of support. If there is no link, there is no support.

We assume that page A has pages B.....N which point to it. Page rank of a page A is given as follows:

$$PR(A) = (1-\beta) + \beta \left(\frac{PR(B)}{cout(B)} + \frac{PR(C)}{cout(C)} + \dots + \frac{PR(N)}{cout(N)} \right)$$

Parameter β is a teleportation factor which can be set between 0 and 1. Cout(A) is defined as

the number of links going out of page A.

CODE:

```
import java.util.*;
import java.io.*;
public class PageRank {
    public int path[][] = new int[10][10];
    public double pagerank[] = new double[10];
    public void calc(double totalNodes) {
        double InitialPageRank;
        double OutgoingLinks = 0;
        double DampingFactor = 0.85;
        double TempPageRank[] = new double[10];
        int ExternalNodeNumber;
```



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```
int InternalNodeNumber;
int k = 1; // For Traversing
int ITERATION_STEP = 1;
InitialPageRank = 1 / totalNodes;
System.out.printf(" Total Number of Nodes : " + totalNodes + "\t Initial PageRank of All
Nodes : " + InitialPageRank + "\n");

// 0th ITERATION _ OR _ INITIALIZATION PHASE //

for (k = 1; k <= totalNodes; k++) {
    this.pagerank[k] = InitialPageRank;
}

System.out.printf("\n Initial PageRank Values , 0th Step \n");
for (k = 1; k <= totalNodes; k++) {
    System.out.printf(" Page Rank of " + k + " is :\t" + this.pagerank[k] + "\n");
}

while (ITERATION_STEP <= 2) // Iterations
{
    // Store the PageRank for All Nodes in Temporary Array
    for (k = 1; k <= totalNodes; k++) {
        TempPageRank[k] = this.pagerank[k];
        this.pagerank[k] = 0;
    }

    for (InternalNodeNumber = 1; InternalNodeNumber <= totalNodes;
InternalNodeNumber++) {
        for (ExternalNodeNumber=1;
ExternalNodeNumber <= totalNodes;
ExternalNodeNumber++) {
            if (this.path[ExternalNodeNumber][InternalNodeNumber] == 1) {
                k = 1;
                OutgoingLinks = 0; // Count the Number of Outgoing Links for each
ExternalNodeNumber
                while (k <= totalNodes) {
                    if (this.path[ExternalNodeNumber][k] == 1) {
                        OutgoingLinks = OutgoingLinks + 1; // Counter for Outgoing Links
                    }
                    k = k + 1;
                }
                // Calculate PageRank
                this.pagerank[InternalNodeNumber] += TempPageRank[ExternalNodeNumber] * (1
/ OutgoingLinks);
            }
        }
    }
}
```



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```
System.out.printf("\n After " + ITERATION_STEP + "th Step \n");

for (k = 1; k <= totalNodes; k++)
    System.out.printf(" Page Rank of " + k + " is :\t" + this.pagerank[k] + "\n");

ITERATION_STEP = ITERATION_STEP + 1;
}
// Add the Damping Factor to PageRank
for (k = 1; k <= totalNodes; k++) {
    this.pagerank[k] = (1 - DampingFactor) + DampingFactor * this.pagerank[k];
}

// Display PageRank
System.out.printf("\n Final Page Rank : \n");
for (k = 1; k <= totalNodes; k++) {
    System.out.printf(" Page Rank of " + k + " is :\t" + this.pagerank[k] + "\n");
}

}

public static void main(String args[]) {
    int nodes, i, j, cost;
    Scanner in = new Scanner(System.in);
    System.out.println("Enter the Number of WebPages \n");
    nodes = in.nextInt();
    PageRank p = new PageRank();
    System.out.println("Enter the Adjacency Matrix with 1->PATH & 0->NO PATH Between
two WebPages: \n");
    for (i = 1; i <= nodes; i++)
        for (j = 1; j <= nodes; j++) {
            p.path[i][j] = in.nextInt();
            if (j == i)
                p.path[i][j] = 0;
        }
    p.calc(nodes);
}
}
```

OUTPUT:



Enter the Number of WebPages

1

Enter the Adjacency Matrix with 1->PATH & 0->NO PATH Between two WebPages:

1234

Total Number of Nodes :1.0 Initial PageRank of All Nodes :1.0

Initial PageRank Values , 0th Step

Page Rank of 1 is : 1.0

After 1th Step

Page Rank of 1 is : 0.0

After 2th Step

Page Rank of 1 is : 0.0

Final Page Rank :

Page Rank of 1 is : 0.15000000000000002

=== Code Execution Successful ===

Conclusion:

What are the key parameters of the PageRank algorithm, and how do they affect the algorithm's performance?

The **PageRank algorithm** is a cornerstone of web search ranking, developed by Google to measure the **importance of web pages** based on the structure of hyperlinks. Its performance and output are influenced by several **key parameters**:

1. Damping Factor (d)

- **Definition:** Probability that a user will continue clicking links rather than jumping to a random page.
- **Typical Value:** 0.85 (common in practice)
- **Effect on Performance:**
 - Higher **d** → More emphasis on the link structure; pages with many inbound links get higher PageRank.
 - Lower **d** → More uniform distribution; random jumps are more significant.



- **Insight:** Balances between following links (structural importance) and teleportation (preventing rank sinks).

2. Convergence Threshold (ϵ)

- **Definition:** The small value used to determine when iterative calculations have converged.
- **Effect on Performance:**
 - Smaller $\epsilon \rightarrow$ More iterations, more precise results, but slower computation.
 - Larger $\epsilon \rightarrow$ Fewer iterations, faster computation, but less accuracy.

3. Initial PageRank Values

- **Definition:** The starting rank assigned to each page before iterations begin (often uniform, e.g., $1/N$).
- **Effect on Performance:**
 - Usually does not affect the final converged PageRank significantly.
 - May influence **number of iterations** needed for convergence.

4. Number of Iterations

- **Definition:** How many times the PageRank formula is applied.
- **Effect on Performance:**
 - More iterations \rightarrow closer to true PageRank values.
 - Stopping too early \rightarrow inaccurate ranking.

5. Graph Structure (Link Connectivity)

- While not a tunable parameter, the **topology of the web graph** affects how PageRank is distributed.
- Pages with **many high-quality inbound links** get higher ranks.
- Dangling nodes (pages with no outbound links) can affect convergence if not handled correctly.