Vidyavardhini's College of Engineering and Technology

Department of Artificial Intelligence & Data Science

AY: 2025-26

Class:	**TE**	**Semester:**	**V**
Course Code:	**CSC504**	**Course Name:**	**Data Warehousing and Mining**

Name of Student:	**Shravani Sandeep Raut**
Roll No. :	**51**
Experiment No.:	**10**
Title of the Experiment:	**Implementation of page rank algorithm**
Date of Performance:	
Date of Submission:	

Evaluation

Performance Indicator	**Max. Marks**	**Marks Obtained**
Performance	5	
Understanding	5	
Journal work and timely submission	10	
Total	20	

Performance Indicator	**Exceed Expectations (EE)**	**Meet Expectations (ME)**	**Meet Expect Below Expectations (BE)**
Performance	4-5	2-3	1
Understanding	4-5	2-3	1
Journal work and timely submission	8-10	5-8	1-4

Checked by

Name of Faculty : Ms. Neha Raut

Signature :

Date:

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-β) +β ((PR(B)/cout(B))+ (PR(C)/cout(C))+-----+(PR(N)/cout(N)))

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.

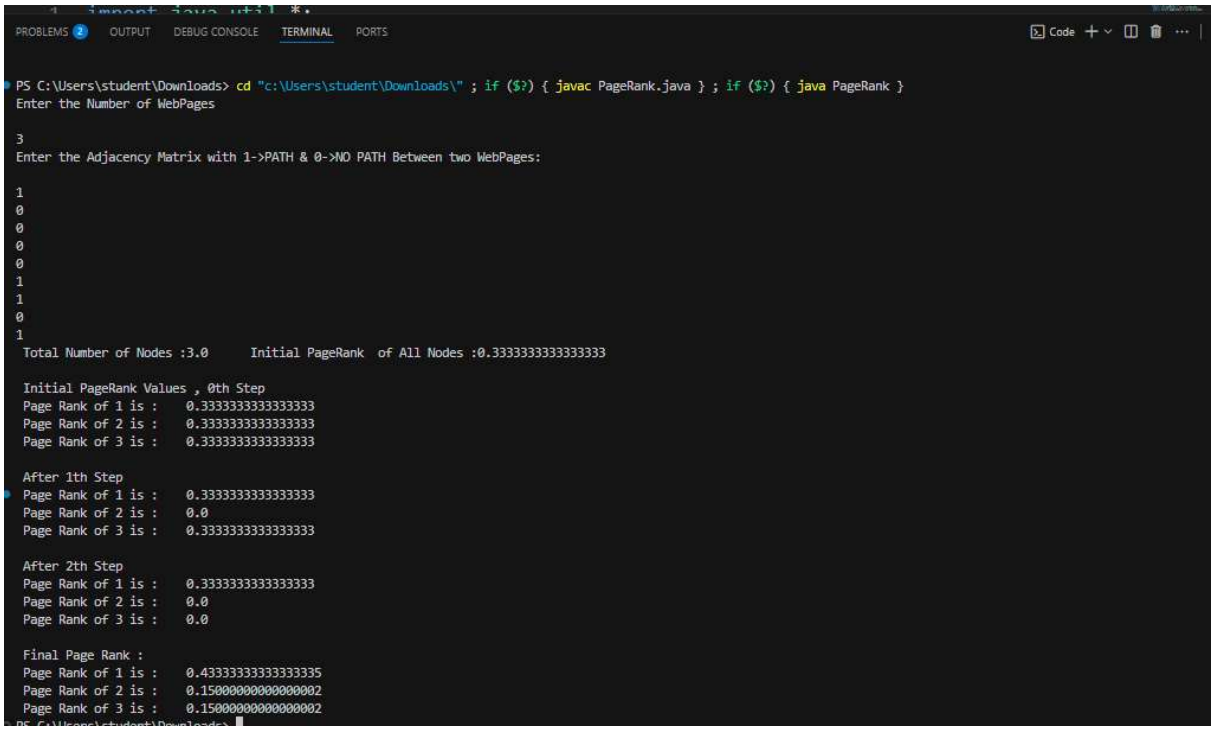
CODE:

```
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;
  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);
   }
  }
 }

 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:



Conclusion:

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

The key parameters of the PageRank algorithm include the damping factor, the number of iterations (or convergence threshold), the initialization of PageRank values, and the handling of dangling nodes. The damping factor, typically set around 0.85, controls the probability that a user will continue following links rather than jumping to a random page, balancing the influence between the link structure and random surfing; a higher damping factor places more emphasis on the link graph but can slow convergence, while a lower value spreads rank more evenly. The number of iterations or convergence criteria determine when the algorithm stops running; more iterations lead to more accurate rankings but increase computational cost. Initialization of PageRank values usually starts uniformly and has little effect on the final results, though it can affect how quickly the algorithm converges. Finally, dangling nodes—pages with no outgoing links—must be handled carefully to avoid rank leakage; typically, their rank is redistributed across all nodes to maintain stability and ensure proper convergence. Together, these parameters influence the accuracy, stability, and efficiency of the PageRank calculation.