

# Data Sci Discover Project

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## 1 Links

- [Research Proposal](#)
- [Paper](#)
- [Preliminary Implementation](#)
- [Implement Random Surfer on Sparse Matrix](#)
- [Implement Power Walk on Sparse Matrix](#)

## 2 Proposal

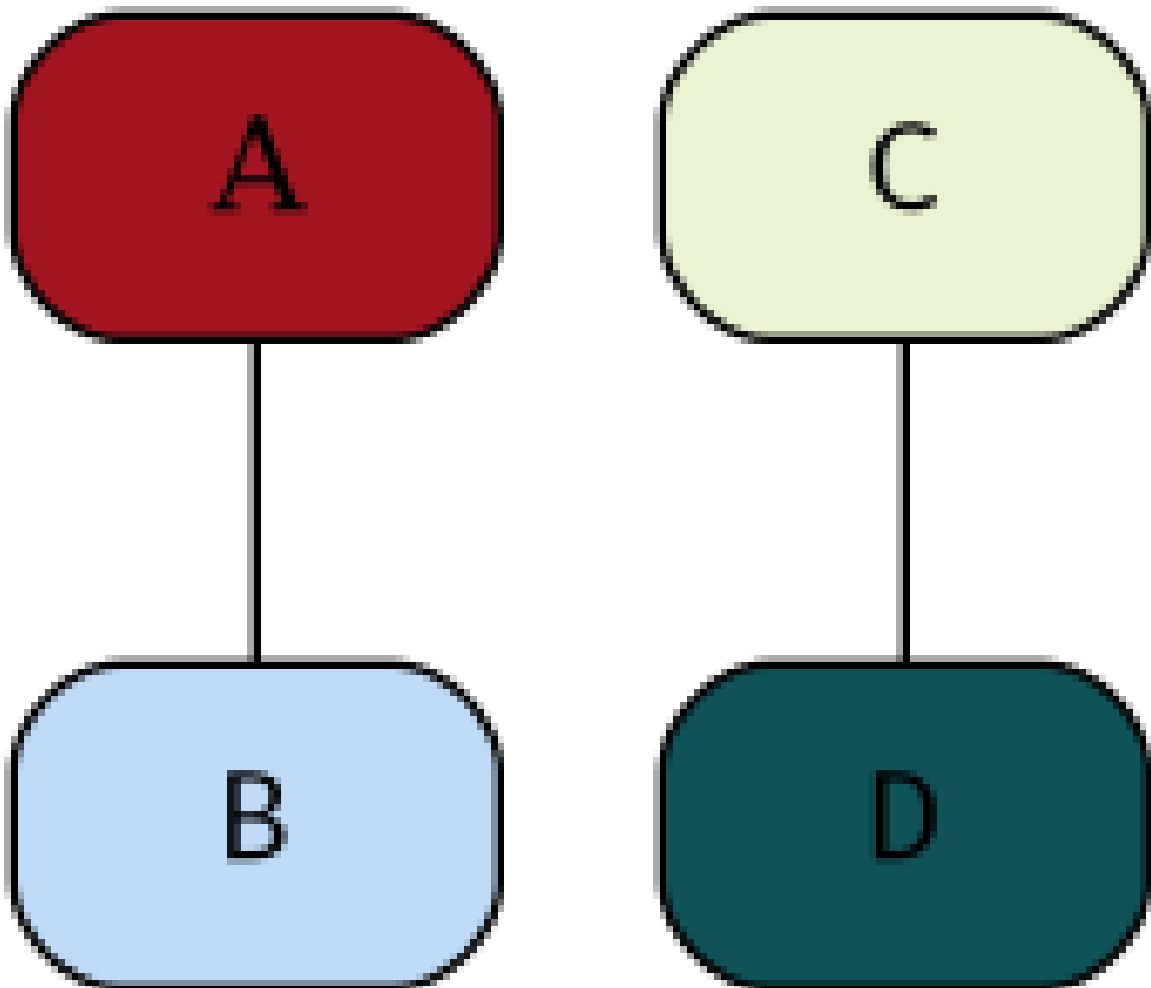
### 2.1 Question

*Can we determine the second eigenvalue from the method parameters? For PageRank, the second eigenvalue is equal to the smoothing parameter  $\alpha$*

Yes. An open question for the Power Walk method is, can we determine the second eigenvalue from the method parameters? For PageRank, the second eigenvalue is equal to the smoothing parameter  $\alpha$ . The second eigenvalue determines how long the algorithm takes to converge and how stable the solution is. To begin, implement the method for computing PageRank and then the Power Walk. It can all be done using sparse matrices, so it only requires a fraction of the memory and is each iteration is quick.

### 2.2 Working

Take the exemplar Graph from Figure 1:



$$\Gamma = I - nD_B^{-1} \quad (1)$$

$$(2)$$

Where we have the following:

$$\beta = 10 \quad (3)$$

$$B = \beta^A \quad (4)$$

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (5)$$

$$\Rightarrow B = \begin{bmatrix} 10 & 1 & 1 & 1 \\ 1 & 10 & 1 & 1 \\ 1 & 1 & 10 & 1 \\ 1 & 1 & 1 & 10 \end{bmatrix} \quad (6)$$

$$D_B \text{ is a diagonal matrix of the column sums:} \quad (7)$$

$$D = \begin{bmatrix} 13 & 0 & 0 & 0 \\ 0 & 13 & 0 & 0 \\ 0 & 0 & 13 & 0 \\ 0 & 0 & 0 & 13 \end{bmatrix} \quad (8)$$

$$\text{Hence the Inverse is:} \quad (9)$$

$$D_B^{-1} = \frac{I}{13} \quad (10)$$

$$\text{Putting it all together:} \quad (11)$$

$$\Gamma = I - nD_B^{-1} \quad (12)$$

$$= I - \frac{4 \cdot I}{13} \quad (13)$$

$$= \frac{9}{13} \cdot I \quad (14)$$

$$= \begin{bmatrix} \frac{9}{13} & 0 & 0 & 0 \\ 0 & \frac{9}{13} & 0 & 0 \\ 0 & 0 & \frac{9}{13} & 0 \\ 0 & 0 & 0 & \frac{9}{13} \end{bmatrix} \quad (15)$$

$$\approx \begin{bmatrix} 0.6923 & 0 & 0 & 0 \\ 0 & 0.6923 & 0 & 0 \\ 0 & 0 & 0.6923 & 0 \\ 0 & 0 & 0 & 0.6923 \end{bmatrix} \quad (16)$$

### 3 Working

```
if (require("pacman")) {
  library(pacman)
}else{
  install.packages("pacman")
}
```

```
library(pacman)
}
```

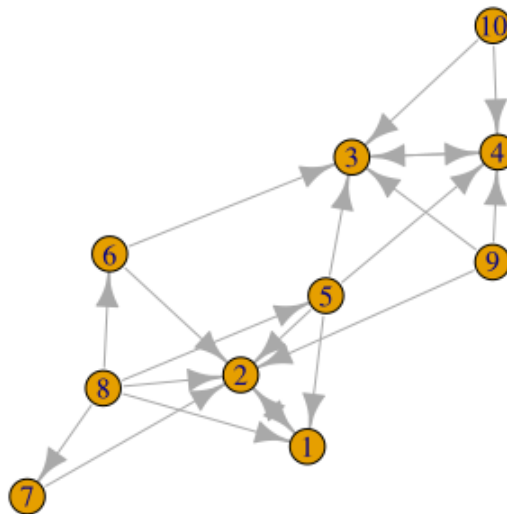
```
pacman::p_load(tidyverse, Matrix, igraph, plotly, mise, docstring)
```

## 3.1 Implementing Page Rank Method on a small graph

### 3.1.1 Example Graph

Consider the following Graph taken from the paper:

```
g1 <- igraph::graph.formula(1++2, 1+-8, 1+-5, 2+-5, 2+-7, 2+-8, 2+-6, 2+-9,
  3++4, 3+-5, 3+-6, 3+-9, 3+-10, 4+-9, 4+-10, 4+-5, 5+-8, 6+-8, 7+-8)
plot(g1)
```



1. Adjacency Matrix The adjacency Matrix is given by:

```
A <- igraph::get.adjacency(g1, names = TRUE, sparse = FALSE) %>%
  as.matrix()

## Adjust the Order
```

```
| (A <- A[order(as.integer(row.names(A))), order(as.integer(colnames(A)))])
```

```
##      1 2 3 4 5 6 7 8 9 10
## 1    0 1 0 0 0 0 0 0 0 0
## 2    1 0 0 0 0 0 0 0 0 0
## 3    0 0 0 1 0 0 0 0 0 0
## 4    0 0 1 0 0 0 0 0 0 0
## 5    1 1 1 1 0 0 0 0 0 0
## 6    0 1 1 0 0 0 0 0 0 0
## 7    0 1 0 0 0 0 0 0 0 0
## 8    1 1 0 0 1 1 1 0 0 0
## 9    0 1 1 1 0 0 0 0 0 0
## 10   0 0 1 1 0 0 0 0 0 0
```

2. State Distribution The state distribution is the transpose of the adjacency matrix:

```
| (p0 <- t(A))
```

```
##      1 2 3 4 5 6 7 8 9 10
## 1    0 1 0 0 1 0 0 1 0 0
## 2    1 0 0 0 1 1 1 1 1 0
## 3    0 0 0 1 1 1 0 0 1 1
## 4    0 0 1 0 1 0 0 0 1 1
## 5    0 0 0 0 0 0 0 0 1 0
## 6    0 0 0 0 0 0 0 0 1 0
## 7    0 0 0 0 0 0 0 0 1 0
## 8    0 0 0 0 0 0 0 0 0 0
## 9    0 0 0 0 0 0 0 0 0 0
## 10   0 0 0 0 0 0 0 0 0 0
```

3. Probability Transition Matrix The probability transition matrix is such that each column of the initial state distribution (i.e. the transposed adjacency matrix) is scaled to 1.

```
| p0 %*% diag(1/colSums(p0))
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8]      [,9] [,10]
## 1      0      1      0      0 0.25  0.0      0  0.2 0.0000000  0.0
## 2      1      0      0      0 0.25  0.5      1  0.2 0.3333333  0.0
## 3      0      0      0      1 0.25  0.5      0  0.0 0.3333333  0.5
## 4      0      0      1      0 0.25  0.0      0  0.0 0.3333333  0.5
## 5      0      0      0      0 0.00  0.0      0  0.2 0.0000000  0.0
## 6      0      0      0      0 0.00  0.0      0  0.2 0.0000000  0.0
## 7      0      0      0      0 0.00  0.0      0  0.2 0.0000000  0.0
## 8      0      0      0      0 0.00  0.0      0  0.0 0.0000000  0.0
## 9      0      0      0      0 0.00  0.0      0  0.0 0.0000000  0.0
## 10     0      0      0      0 0.00  0.0      0  0.0 0.0000000  0.0
```

(a) Create a Function

```
adj_to_probTrans <- function(adjMat) {
  t(adjMat) %*% diag(1/colSums(t(adjMat)))
}

(T <- adj_to_probTrans(A)) %>% round(2)
```

##		[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]
## 1		0	1	0	0	0.25	0.0	0	0.2	0.00	0.0
## 2		1	0	0	0	0.25	0.5	1	0.2	0.33	0.0
## 3		0	0	0	1	0.25	0.5	0	0.0	0.33	0.5
## 4		0	0	1	0	0.25	0.0	0	0.0	0.33	0.5
## 5		0	0	0	0	0.00	0.0	0	0.2	0.00	0.0
## 6		0	0	0	0	0.00	0.0	0	0.2	0.00	0.0
## 7		0	0	0	0	0.00	0.0	0	0.2	0.00	0.0
## 8		0	0	0	0	0.00	0.0	0	0.0	0.00	0.0
## 9		0	0	0	0	0.00	0.0	0	0.0	0.00	0.0
## 10		0	0	0	0	0.00	0.0	0	0.0	0.00	0.0

### 3.1.2 Page Rank Random Surfer

The random surfer page rank method modifies the probability transition matrix  $T$  so that the method works also for non-ergodic graphs by introducing the possibility of a random jump, we'll call the surfer transition matrix  $S$ :

$$S = \lambda T + (1 - \lambda) B : \quad (17)$$

$$(18)$$

$$B = \begin{bmatrix} \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \\ \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \end{bmatrix} \quad (19)$$

$$N = ||V|| \quad (20)$$

$$\lambda \in [0, 1] \quad (21)$$

```
B <- matrix(rep(1/nrow(T), length.out = nrow(T)**2), nrow = nrow(T))
l <- 0.8123456789

S <- l*T+(1-l)*B
```

1. Eigen Value Method The eigenvector corresponding to the the eigenvalue of 1 will be the stationary point:

```
eigen(S, symmetric = FALSE)

eigen() decomposition
$values
```

```
[1] 1.000000e+00 -8.123457e-01 -8.123457e-01 8.123457e-01 -3.407464e-09 3.407464e-09
[7] 6.878591e-17 -4.393838e-17 -1.126771e-18 -1.292735e-32
```

\$vectors

```
      [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
[1,] 0.48726141 -7.071005e-01 1.590774e-03 5.000000e-01 6.735753e-01 -6.735753e-01
[2,] 0.52676629 7.071005e-01 -1.590774e-03 5.000000e-01 9.622504e-02 -9.622505e-02
[3,] 0.49149620 -2.975837e-03 7.071050e-01 -5.000000e-01 9.622504e-02 -9.622505e-02
[4,] 0.48044122 2.975837e-03 -7.071050e-01 -5.000000e-01 2.886751e-01 -2.886751e-01
[5,] 0.04932738 1.463673e-18 -5.541166e-17 2.124631e-17 -3.849002e-01 3.849002e-01
[6,] 0.04932738 1.463673e-18 5.541166e-17 2.124631e-17 -3.849002e-01 3.849002e-01
[7,] 0.04932738 1.463673e-18 -2.077937e-17 2.124631e-17 -3.849002e-01 3.849002e-01
[8,] 0.04243328 -6.484884e-18 -1.103904e-17 6.319692e-17 8.072508e-09 8.072508e-09
[9,] 0.04243328 6.952446e-18 -9.740331e-18 6.005334e-17 8.072508e-09 8.072509e-09
[10,] 0.04243328 6.952446e-18 -9.740331e-18 6.005334e-17 8.072508e-09 8.072509e-09
      [,7]      [,8]      [,9]     [,10]
[1,] -3.963430e-01 3.962600e-01 1.828019e-01 -1.752367e-01
[2,] -1.291621e-01 2.027302e-01 2.199538e-01 -2.197680e-01
[3,] -3.955284e-01 3.894308e-02 2.223048e-01 -2.248876e-01
[4,] -4.215353e-01 1.043870e-01 2.747562e-01 -2.777266e-01
[5,] 5.166485e-01 -8.109210e-01 -8.798152e-01 8.790721e-01
[6,] 5.201366e-02 -1.308878e-01 -1.049028e-01 1.056778e-01
[7,] 1.346275e-01 -1.936007e-01 9.054366e-02 -9.554811e-02
[8,] 2.547528e-16 -1.352936e-16 -1.025353e-16 1.072771e-16
[9,] 3.196396e-01 1.965446e-01 -2.821213e-03 -5.466313e-03
[10,] 3.196396e-01 1.965446e-01 -2.821213e-03 1.388344e-02
```

So in this case the a stationary point is  $\langle -0.49, -0.53, -0.49, -0.48, -0.05, -0.05, -0.05, -0.04, -0.04, -0.04 \rangle$  which can be verified:

$$1\vec{p} = S\vec{p}$$

```
| (p      <- eigen(S)$values[1] * eigen(S)$vectors[,1])

## [1] -0.48531271 -0.52732002 -0.49152601 -0.47977477 -0.05288058 -0.05288058
## [7] -0.05288058 -0.04558671 -0.04558671 -0.04558671
```

```
| (p_new <- S %*% p)

##      [,1]
## 1 -0.48531271
## 2 -0.52732002
## 3 -0.49152601
## 4 -0.47977477
```

```
## 5 -0.05288058
## 6 -0.05288058
## 7 -0.05288058
## 8 -0.04558671
## 9 -0.04558671
## 10 -0.04558671
```

However this vector does not sum to 1 so the scale should be adjusted (for probabilities the vector should sum to 1):

```
| (p_new <- p_new/sum(p_new))
```

```
##      [,1]
## 1 0.2129185
## 2 0.2313481
## 3 0.2156444
## 4 0.2104889
## 5 0.0232000
## 6 0.0232000
## 7 0.0232000
## 8 0.0200000
## 9 0.0200000
## 10 0.0200000
```

2. Power Value Method Using the power method should give the same result, which it indeed does, but for the scale:

```
| p_new <- p_new *123456789
| while (sum(round(p, 9) != round(p_new, 9))) {
|   (p <- p_new)
|   (p_new <- S %*% p)
| }
| p_new
```

```
##      [,1]
## 1 26286237
## 2 28561500
## 3 26622771
## 4 25986282
## 5 2864198
## 6 2864198
## 7 2864198
## 8 2469136
## 9 2469136
## 10 2469136
```



```
| p
```

```
##      [,1]
## 1 26286237
## 2 28561500
## 3 26622771
## 4 25986282
## 5  2864198
## 6  2864198
## 7  2864198
## 8  2469136
## 9  2469136
## 10 2469136
```

This answer is however identical in direction, if it scaled to 1 the same value will be returned:

```
| (p_new <- p_new/sum(p_new))
```

```
##      [,1]
## 1 0.2129185
## 2 0.2313481
## 3 0.2156444
## 4 0.2104889
## 5 0.0232000
## 6 0.0232000
## 7 0.0232000
## 8 0.0200000
## 9 0.0200000
## 10 0.0200000
```

3. Scaling However if the initial state sums to 1, then the scale of the stationary vector will also sum to 1.

```
| p <- c(1, 0, 0, 0, 0, 0, 0, 0, 0, 0)
| p_new <- S %*% p
|
| while (sum(round(p, 9) != round(p_new, 9))) {
|   (p <- p_new)
|   (p_new <- S %*% p)
| }
|
| cbind(p_new, p)
```

```
##      [,1]      [,2]
## 1 0.2129185 0.2129185
## 2 0.2313481 0.2313481
## 3 0.2156444 0.2156444
```

```
## 4  0.2104889 0.2104889
## 5  0.0232000 0.0232000
## 6  0.0232000 0.0232000
## 7  0.0232000 0.0232000
## 8  0.0200000 0.0200000
## 9  0.0200000 0.0200000
## 10 0.0200000 0.0200000
```

## 3.2 Implementing Page Rank on a much Larger Graph

### 3.2.1 Creating the Probability Transition Matrix

Implementing the page rank method on a larger graph requires the use of more efficient form of matrix storage.

An adjacency matrix (atleast in the context of graphs relating to webpages and social networks) will contain elements that are mostly zero because the number of edges leaving any vertex will tend to be significantly less than the total number of vertices.

A matrix exhibiting this property is known as a sparse matrix CITE

The properties of a sparse matrix can be implemented in order to improve performance, one such method to acheive this is *Compressed Sparse Row* (CSR) storage, which involves creating a seperate array of values and corresponding indices. CITE

This is implemented by the Matrix package in **R**. CITE

An sparse matrix can be created using the following syntax, which will return a matrix of the class dgCMatrix:

```
library(Matrix)
## Create Example Matrix
n <- 20
m <- 10^6
i <- sample(1:m, size = n); j <- sample(1:m, size = n); x <- rpois(n, lambda = 90)
A <- sparseMatrix(i, j, x = x, dims = c(m, m))

summary(A)
```

```
1000000 x 1000000 sparse Matrix of class "dgCMatrix", with 20 entries
```

	i	j	x
1	803589	66922	118
2	61426	83355	97
3	401058	103999	71
4	610432	206922	84
5	542888	217196	69
6	821769	291405	79
7	187782	364814	74
8	152229	451810	104
9	614645	462031	82
10	776459	566334	91
11	288279	630438	97
12	233553	631441	84
13	139900	649740	83
14	381442	681415	87
15	578270	755635	99

```

16 175521 775788 98
17 57981 809115 89
18 821120 809688 103
19 541818 976802 78
20 595348 993420 85

```

As before in section 3, the probability transition matrix can be found by:

1. Transposing the adjacency matrix, then
2. Scaling the columns to one

To implement this for a sparseMatrix of the class dgCMatrix, the same technique of multiplying by a diagonalised matrix may be implemented, however to create this new matrix, a new sparseMatrix will need to be created using the properties of the original matrix, this can be done like so:

```

sparse_diag <- function(mat) {
  #' Diagonal Factors of Sparse Matrix
  #'
  #' Return a Diagonal Matrix of the 1 / colsum() such that
  #' matrix multiplication with this matrix would have all column sums
  #' sum to 1
  #'
  #' This should take the transpose of an adjacency matrix in and the output
  #' can be multiplied by the original matrix to scale it to 1.
  #' i
  ## Get the Dimensions
  n <- nrow(mat)

  ## Make a Diagonal Matrix of Column Sums
  D <- sparseMatrix(i = 1:n, j = 1:n, x = colSums(mat), dims = c(n,n))

  ## Throw away explicit Zeroes
  D <- drop0(D)

  ## Inverse the Values
  D@x <- 1/D@x

  ## Return the Diagonal Matrix
  return(D)
}
D <- sparse_diag(t(A))
summary(D)

```

1000000 x 1000000 sparse Matrix of class "dgCMatrix", with 20 entries

	i	j	x
1	57981	57981	0.011235955
2	61426	61426	0.010309278
3	139900	139900	0.012048193
4	152229	152229	0.009615385
5	175521	175521	0.010204082
6	187782	187782	0.013513514

```

7  233553 233553 0.011904762
8  288279 288279 0.010309278
9  381442 381442 0.011494253
10 401058 401058 0.014084507
11 541818 541818 0.012820513
12 542888 542888 0.014492754
13 578270 578270 0.010101010
14 595348 595348 0.011764706
15 610432 610432 0.011904762
16 614645 614645 0.012195122
17 776459 776459 0.010989011
18 803589 803589 0.008474576
19 821120 821120 0.009708738
20 821769 821769 0.012658228

```

and hence the probability transition matrix may be implemented by performing matrix multiplication accordingly:

```
| summary(t(A) %*% D)
```

```
1000000 x 1000000 sparse Matrix of class "dgCMatrix", with 20 entries
```

```

      i      j x
1  809115  57981 1
2   83355  61426 1
3  649740 139900 1
4  451810 152229 1
5  775788 175521 1
6  364814 187782 1
7  631441 233553 1
8  630438 288279 1
9  681415 381442 1
10 103999 401058 1
11 976802 541818 1
12 217196 542888 1
13 755635 578270 1
14 993420 595348 1
15 206922 610432 1
16 462031 614645 1
17 566334 776459 1
18  66922 803589 1
19 809688 821120 1
20 291405 821769 1

```

### 3.2.2 Solving the Random Surfer via the Power Method

Solving the eigenvalues for such a large matrix will not be feasible, instead the power method will need to be used to find the stationary point.

However, creating a matrix of background probabilities (denoted by  $B$  in section 3.1.2) will not be feasible, it would simply be too large, instead some algebra can be used to reduce  $B$  from a matrix into a vector containing only  $\frac{1-\alpha}{N}$ .

The power method is given by:

$$\vec{p} = \mathbf{S}\vec{p} \quad (22)$$

where:

$$S = \alpha \mathbf{T} + (1 - \alpha) \mathbf{B} \quad (23)$$

$$\vec{p} = (\alpha \mathbf{T} + (1 - \alpha) \mathbf{B}) \vec{p} \quad (24)$$

$$= \alpha \mathbf{T} \vec{p} + (1 - \alpha) \mathbf{B} \vec{p} \quad (25)$$

Let  $\mathbf{F} = \mathbf{B}\vec{p}$ , consider the value of  $\mathbf{F}$  :

$$\mathbf{F} = \begin{bmatrix} \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \\ \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \end{bmatrix} \begin{bmatrix} \vec{p}_1 \\ \vec{p}_2 \\ \vdots \\ \vec{p}_m \end{bmatrix} \quad (26)$$

$$= \begin{bmatrix} (\sum_{i=0}^m [p_i]) \times \frac{1}{N} \\ (\sum_{i=0}^m [p_i]) \times \frac{1}{N} \\ \vdots \\ (\sum_{i=0}^m [p_i]) \times \frac{1}{N} \end{bmatrix} \quad (27)$$

Probabilities sum to 1 and hence: (28)

$$= \begin{bmatrix} \frac{1}{N} \\ \frac{1}{N} \\ \frac{1}{N} \\ \frac{1}{N} \\ \vdots \\ \frac{1}{N} \end{bmatrix} \quad (29)$$

So instead the power method can be implemented by performing an algorithm to the effect of:

```
## Find Stationary point of random surfer
N    <- nrow(A)
alpha <- 0.8
F    <- rep((1-alpha)/N, nrow(A)) ## A nx1 vector of (1-alpha)/N

## Solve using the power method
p    <- rep(0, length.out = ncol(T)); p[1] <- 1
p_new <- alpha*T %*% p + F

## use a Counter to debug
i <- 0
while (sum(round(p, 9) != round(p_new, 9))) {
  p    <- p_new
  p_new <- alpha*T %*% p + F
  (i <- i+1) %>% print()
}

p %>% head() %>% print()
```

## 4 Notes

### Eigenvector Centrality PageRank

- The probability of landing on a vertex in a random walk by adding a small random probability to each vertex.

### Irreducible Ergodic

- All Vertices can be reached from any other vertex

## 4.1 Page Rank Methods

These assess node centrality by performing a random walk across the graph and recording the frequencies of landing on a given vertex.

If each vertex is connected the graph is said to be ergodic and there is a closed solution for the limit values of the frequencies given this random walk:

- The eigenvalue equal to 1
- If the graph is not directed  $\vec{p}$  is a vector of length  $n$ :
  - $n$  is the number of nodes in the graph  $G$
  - $\vec{p}_i = \frac{\deg(v_i)}{\text{vol}(G)}$ 
    - \*  $\text{vol}(G) = \sum_{i=1}^n [\text{indeg}(v)] = \sum_{i=1}^n [\text{outdeg}(v)] = \sum_{i=1}^n [\deg(v)]$

For large matrices calculating the eigenvalues will be expensive and so instead the power method is used, which is essentially looping over until the vector converges to a solution.

$$\vec{p} = T\vec{p} \quad (30)$$

where:

**A** Is the adjacency Matrix, an element is 1 if movement from the row vertex to the column vertex is permitted.

- The matrix may be weighted in some way, for example 5 edges between vertices may be such that a 5 is used in the matrix not a 1
- An undirected graph will be such that  $\mathbf{A} = \mathbf{A}^T$

**T** Is the transition probability matrix, an element in the matrix describes the probability of moving from the column-vertex to the row-vertex

- The transition matrix is intended to be such that for a given state distribution  $\vec{p}$ , the next iteration of a random walk will be  $T\vec{p}$
- Observe also that  $T = \frac{1}{\text{colsums}(\mathbf{A})} \mathbf{A}^T$ 
  - i.e. the transpose of the adjacency matrix with each column scaled to 1.

### 4.1.1 Random Surfer

If a graph is non-ergodic, then a random walk isn't as easy to implement because in essence there are multiple graphs, to address this, some value  $\lambda$  is introduced which represents the probability of moving from one vertex to any other vertex. Essentially the difference here is

### 4.1.2 Power Walk Method

$$\mathbf{T} = \mathbf{B}\mathbf{D}_B^{-1} \quad (31)$$

where:

- $\mathbf{B} = \beta^{\mathbf{A}}$ 
  - $x\beta^1$  probability of following an edge of weight 1
  - $x\beta^0$  probability of following an edge of weight 0
  - $x\beta^{-1}$  probability of following an edge of weight -
- $D_B = \text{colsums}(\mathbf{B})$

$\mathbf{A}$  The Adjacency Matrix

## 4.2 Simplifying Power Walk to be solved with Sparse Matrices

The Random Surfer model is:

$$\mathbf{S} = \alpha\mathbf{T} + \mathbf{F}$$

where:

- $\mathbf{T}$ 
  - is an  $i \times j$  matrix that describes the probability of travelling from vertex  $j$  to  $i$ 
    - \* This is transpose from the way that `igraph` produces an adjacency matrix.
- $\mathbf{F} = \begin{bmatrix} \frac{1}{n} \\ \frac{1}{n} \\ \vdots \\ \frac{1}{n} \end{bmatrix}$

Interpreting the transition probability matrix in this way is such that  $\mathbf{T} = \mathbf{A}\mathbf{D}_A^{-1}$  under the following conditions:

- No column of  $\mathbf{A}$  sums to zero
  - If this does happen the question arises how to deal with  $\mathbf{D}_A^{-1}$ 
    - \* I've been doing  $D'_{\mathbf{A},i,j} := \text{diag}\left(\frac{1}{\text{colsums}(\mathbf{A})}\right)$  and then replacing any 0 on the diagonal with 1.
  - What is done in the paper is to make another matrix  $\mathbf{Z}$  that is filled with 0, if a column sum of  $\mathbf{A}$  adds to zero then that column in  $\mathbf{Z}$  becomes  $\frac{1}{n}$ 
    - \* This has the effect of making each row identical
    - \* The probability of going from an orphaned vertex to any other vertex would hence be  $\frac{1}{n}$
    - \* The idea with this method is then to use  $D_{(\mathbf{A}+\mathbf{Z})}^{-1}$  this will be consistent with the *Random Surfer* the method using  $\mathbf{F}$  in ]

where each row is identical that is a 0

The way to deal with the *Power Walk* is more or less the same.  
observe that:

$$\mathbf{B} = \beta^{\mathbf{A}} \wedge \mathbf{A}_{i,j} \in \mathbb{R} \implies |\mathbf{B}_{i,j}| > 0 \quad \forall i, j > n \in \mathbb{Z}^+$$

Be mindful that the use of exponentiation in ] is not an element wise exponentiation and not an actual matrix exponential (which would be defined by using power series and logs but is defined)

So if I have:

- $\mathbf{O}_{i,j} := 0, \quad \forall i, j \leq n \in \mathbb{Z}^+$
- $\vec{p}_i$  as the state distribution, being a vector of length  $n$

Then It can be shown (see (48)):

$$\mathbf{O}\mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i = \text{repeat}(\vec{p} \bullet \delta^{\vec{T}}, n)$$

where:

- $\delta_i^{\vec{T}} = \frac{1}{\text{colsums}(\mathbf{B})}$   
– A vector...( $n \times 1$  matrix)

$\vec{1}$  is a vector containing all 1's

- A vector...( $n \times 1$  matrix)

$\delta^{\vec{T}}$  refers to the transpoxe of ( $1 \times n$  matrix)

$\delta^{\vec{T}}\vec{p}_i$  is some number (because it's a dot product)

This means we can do:

$$\overrightarrow{p_{i+1}} = \mathbf{T}_{\text{pw}} \vec{p}_i \tag{32}$$

$$= \mathbf{B}\mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i \tag{33}$$

$$= (\mathbf{B} - \mathbf{O} + \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i \tag{34}$$

$$= \left( (\mathbf{B} - \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1} + \mathbf{O}\mathbf{D}_{\mathbf{B}}^{-1} \right) \vec{p}_i \tag{35}$$

$$= (\mathbf{B} - \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i + \mathbf{O}\mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i \tag{36}$$

$$= (\mathbf{B} - \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i + \vec{1}(\delta^{\vec{T}}\vec{p}_i) \tag{37}$$

$$= (\mathbf{B} - \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i + \text{rep}(\delta^{\vec{T}}\vec{p}_i) \tag{38}$$

where:

Let  $(\mathbf{B} - \mathbf{O}) = \mathbf{B}_{\mathbf{O}}$ :

$$\overrightarrow{p_{i+1}} = \mathbf{B}_{\mathbf{O}}\mathbf{D}_{\mathbf{B}}^{-1}\vec{p}_i + \text{rep}(\delta^{\vec{T}}\vec{p}_i)$$

Now solve  $\mathbf{D}_{\mathbf{B}}^{-1}$  in terms of  $\mathbf{B}_{\mathbf{O}}$  :

$$\mathbf{B}_{\mathbf{O}} = (\mathbf{B} - \mathbf{O}) \tag{39}$$

$$\mathbf{B} = \mathbf{B}_{\mathbf{O}} + \mathbf{O} \tag{40}$$



If we have  $\delta_{\mathbf{B}}$  as the column sums of  $\mathbf{B}$ :

$$\delta_{\mathbf{B}}^{-1} = \vec{1}\mathbf{B} \quad (41)$$

$$= \vec{1}(\mathbf{B}_0 + \mathbf{O}) \quad (42)$$

$$= \vec{1}\mathbf{B}_0 + \vec{1}\mathbf{O} \quad (43)$$

$$= \vec{1}\mathbf{B}_0 + \langle n, n, n, \dots n \rangle \quad (44)$$

$$= \vec{1}\mathbf{B}_0 + \vec{1}n \quad (45)$$

$$\delta_{\mathbf{B}} = 1/(\text{colSums}(\mathbf{B}_0) + n) \quad (46)$$

Then if we have  $D_B = \text{diag}(\delta_B)$ :

$$\begin{aligned} D_B^{-1} &= \text{diag}(\delta_{\mathbf{B}}^{-1}) \\ &= \text{diag}(\text{ColSums}(\mathbf{B}_0) + n)^{-1} \end{aligned}$$

And so the the power method can be implemented using sparse matrices:

$$p_{i+1}^{\vec{}} = \mathbf{B}_0 \text{ diag}(\vec{1}\mathbf{B}_0 + \vec{1}n) \vec{p}_i + \vec{1}\delta^{\vec{T}}\vec{p}_i \quad (47)$$

in terms of  $\mathbf{R}$ :

```
p_new <- B0 %*% diag(colSums(B)+n) %*% p + rep(t() %*% p, n)

# It would also be possible to sum the element-wise product
(t() %*% p) == sum( * p)

# Because R treats vectors the same as a nX1 matrix we could also
# perform the dot product of the two vectors, meaning the following
# would be true in R but not generally

(t() %*% p) == ( %*% p)
```

#### 4.2.1 Solving the Background Probability

In this case a vertical single column matrix will represent a vector and  $\otimes$  will represent the outer product (i.e. the *Kronecker Product*):

Define  $\vec{\delta}$  as the column sums of

$$\begin{aligned} \vec{\delta} &= \text{colsum}(\mathbf{B})^{-1} \\ &= \frac{1}{\vec{1}^T \mathbf{B}} \end{aligned}$$

Then we have:

$$\begin{aligned}
\mathbf{OD}_{\mathbf{B}}^{-1} \vec{p}_i &= \begin{pmatrix} 1 & 1 & 1 & \dots \\ 1 & 1 & 1 & \dots \\ 1 & 1 & 1 & \dots \\ \vdots & & & \ddots \end{pmatrix} \begin{pmatrix} \frac{1}{\delta_1} & 0 & 0 & \dots \\ 0 & \frac{1}{\delta_2} & 0 & \dots \\ 0 & 0 & \frac{1}{\delta_{13}} & \dots \\ \vdots & & & \ddots \end{pmatrix} \begin{pmatrix} p_{i,1} \\ p_{i,2} \\ p_{i,3} \\ \vdots \end{pmatrix} \\
&= \begin{pmatrix} \frac{p_{i,1}}{\delta_1} + \frac{p_{i,2}}{\delta_2} + \frac{p_{i,3}}{\delta_3} & \dots \\ \frac{p_{i,1}}{\delta_1} + \frac{p_{i,2}}{\delta_2} + \frac{p_{i,3}}{\delta_3} & \dots \\ \frac{p_{i,1}}{\delta_1} + \frac{p_{i,2}}{\delta_2} + \frac{p_{i,3}}{\delta_3} & \dots \\ \vdots & \ddots \end{pmatrix} \\
&= \begin{pmatrix} \sum_{k=1}^n [p_{i,k} \delta_i] \\ \sum_{k=1}^n [p_{i,k} \delta_i] \\ \sum_{k=1}^n [p_{i,k} \delta_i] \\ \vdots \end{pmatrix} \\
&= \begin{pmatrix} \vec{\delta}^T \vec{p}_i \\ \vec{\delta}^T \vec{p}_i \\ \vec{\delta}^T \vec{p}_i \\ \vdots \end{pmatrix} \\
&= \vec{\delta}^T \vec{p}_i \begin{pmatrix} 1 \\ 1 \\ 1 \\ \vdots \end{pmatrix} \\
&= (\vec{\delta}^T \vec{p}_i) \vec{1} \\
&= \text{repeat}(\vec{\delta}^T \vec{p}_i, n)
\end{aligned}$$

Observe also that If we let  $\vec{\delta}$  and  $p_i$  be 1 dimensional vectors, this can also be expressed as a dot product:

Matrices	Vectors
$\vec{\delta}^T \vec{p}_i$	$\vec{\delta}^T \vec{p}_i$

## 4.3 Implementing the Power Walk

Load necessary packages etc:

```

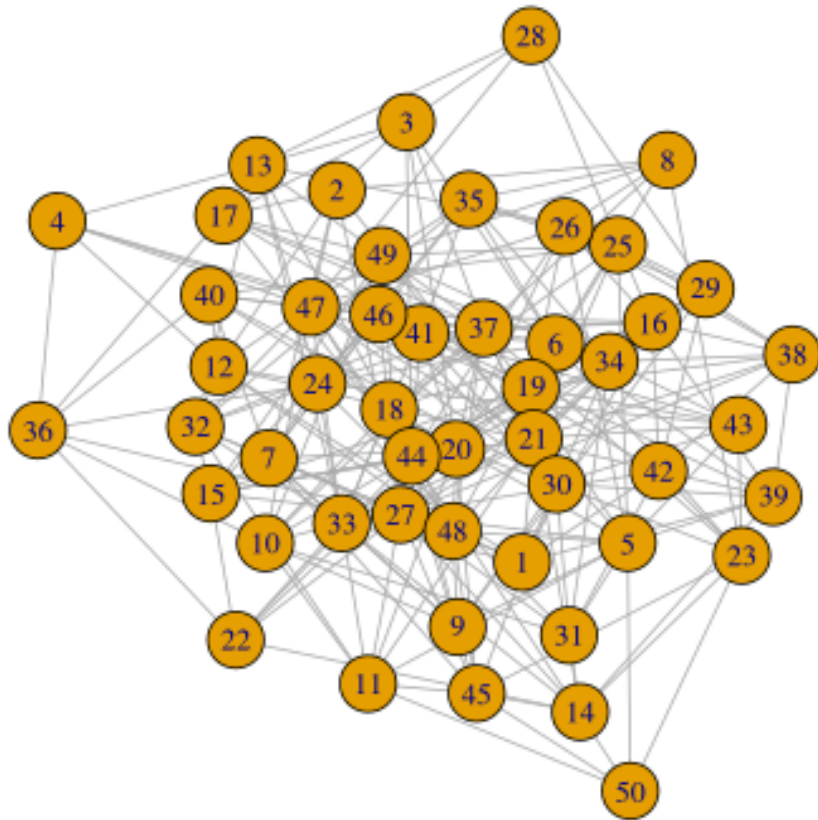
if (require("pacman")) {
  library(pacman)
}else{
  install.packages("pacman")
  library(pacman)
}
pacman::p_load(Matrix, igraph, plotly, mise, docstring, expm)

```

TRUE  
TRUE  
TRUE  
TRUE  
TRUE  
TRUE

Create an example Matrix:

```
g1 <- igraph::erdos.renyi.game(n = 50, 0.2)  
A <- igraph::get.adjacency(g1) # Row to column  
plot(g1)
```



#### 4.3.1 Using the Power Walk

1. Inspect the newly created matrix and create constants

```

beta <- 0.843234
  <- beta
n <- nrow(A)

str(A)

```

```

Formal class 'dgCMatrix' [package "Matrix"] with 6 slots
..@ i      : int [1:504] 11 15 20 29 31 32 38 41 47 2 ...
..@ p      : int [1:51] 0 9 17 25 31 44 55 66 73 81 ...
..@ Dim     : int [1:2] 50 50
..@ Dimnames:List of 2
.. ..$ : NULL
.. ..$ : NULL
..@ x      : num [1:504] 1 1 1 1 1 1 1 1 1 1 ...
..@ factors : list()

```

## 2. Create a Diagonalised Scaling Matrix

```

sparse_diag <- function(mat) {
  #' Diagonal Factors of Sparse Matrix
  #'
  #' Return a Diagonal Matrix containing either 1 / colsum() or 0 such that
  #' matrix multiplication with this matrix would have all columns
  #' sum to 1
  #'
  #' This should take the transpose of an adjacency matrix in and the output
  #' can be multiplied by the original matrix to scale it to 1.
  #' i
  # mat <- A
  ## Get the Dimensions
  n <- nrow(mat)

  ## Make a Diagonal Matrix of Column Sums
  D <- sparseMatrix(i = 1:n, j = 1:n, x = colSums(mat), dims = c(n,n))

  ## Throw away explicit Zeroes
  D <- drop0(D)

  ## Inverse the Values
  D@x <- 1/D@x

  ## Return the Diagonal Matrix
  return(D)
}

```

## 3. Weight the Edges Make the edges weighted with some real value

```

weight_adjMat <- function(adjMat) {
  #' Weight Adjacency Matrix
  #'
  #' Randomly weights an adjacency matrix so that terms
  #' are Real (as opposed to natural) values.

```

```

    A@x*rnorm(length(A@x), 0, 0.1)
  }

```

#### 4. Create a Probability Transition Matrix

```

adj_to_probTrans <- function(wadjmat, beta) {
  #' Adjacency to Probability Transition Matrix
  #'
  #' Returns a probability transition matrix from an input adjacency matrix
  #'
  #' Transposes an input matrix and then scales each column to sum to 1.
  #' Implemented with the Matrix dgCMatrix class in mind however also
  #' has logic to deal with a base matrix.
  #'
  #' @param wadjmat A weighted adjacency matrix, ideally of the class
  #'   dgCMatrix
  #' or atleast of the class matrix.
  #' @param beta The probability of following an edge

  wadjmat <- t(wadjmat) # transpose Assuming row->column (like igraph)
  # wadjmat <- A; beta <- 0.8

  if ("dgCMatrix" %in% class(wadjmat)) {

    #   B   <- sparseMatrix(i = summary(wadjmat)$i, j = summary(wadjmat)$j, x
    # = beta^wadjmat@x) # element wise exponentiation
    # Don't do this ^^ because it comes out with clipped off dimensions
    B   <- wadjmat
    B@x <- beta^wadjmat@x # Element Wise exponentiation
    D_in <- sparse_diag(B)
    T = B %*% D_in
    return(T)

  } else if ("matrix" %in% class(wadjmat)) {
    print("WARNING: expected dgCMatrix but matrix detected")
    print("Attempting to proceed anyway")
    for (i in ncol(wadjmat)) {
      # wadjmat[, i] <- wadjmat[, i] / sum(wadjmat[, i])
    }
    B   <- wadjmat
    B   <- beta^wadjmat # Element Wise exponentiation
    D_in <- sparse_diag(B)
    T = B %*% D_in
    return(as.matrix(T))
  }
  return(wadjmat)
} else {
  print("ERROR: Require sparse wadjmatrix of class dgCWadjmatrix to")
}
}

class(A)
(T <- adj_to_probTrans(A, beta = 0.843234)) %>% summary %>% head()

```

[1] "dgCMatrix"

```

attr("package")
[1] "Matrix"
50 x 50 sparse Matrix of class "dgCMatrix", with 504 entries
  i j      x
1 12 1 0.1111111
2 16 1 0.1111111
3 21 1 0.1111111
4 30 1 0.1111111
5 32 1 0.1111111
6 33 1 0.1111111

```

#### 5. Implement the Power Method to find the Stationary Point

```

## ** Power Method
p <- rep(0, nrow(T))
p[1] <- 1
p_new <- rep(0, nrow(T))
p_new[2] <- 1

while (sum(round(p, 9) != round(p_new, 9))) {
  p <- p_new
  p_new <- T %*% p
}

print(paste("The stationary point is"))
p %>% head()

```

```

[1] "The stationary point is"
6 x 1 Matrix of class "dgeMatrix"
[,1]
[1,] 0.01785714
[2,] 0.01587302
[3,] 0.01587302
[4,] 0.01190476
[5,] 0.02579365
[6,] 0.02182540

```

#### 4.3.2 Using Sparse Matrices

##### 1. Theory if I have:

- $\mathbf{O}_{i,j} := 0, \quad \forall i, j \leq n \in \mathbb{Z}^+$
- $\vec{p}_i$  as the state distribution, being a vector of length  $n$

Then it can be shown (see (48)):

$$\mathbf{OD}_B^{-1} \vec{p}_i = \text{repeat}(\vec{p} \bullet \vec{\delta}^T, n)$$

where:

- $\vec{\delta}_i = \frac{1}{\text{colsums}(\mathbf{B})}$

This means we can do:

$$\begin{aligned}
\overrightarrow{p_{i+1}} &= \mathbf{B} \mathbf{D}_{\mathbf{B}}^{-1} \overrightarrow{p_i} \\
&= (\mathbf{B} - \mathbf{O} + \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1} \overrightarrow{p_i} \\
&= \left( (\mathbf{B} - \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1} + \mathbf{O} \mathbf{D}_{\mathbf{B}}^{-1} \right) \overrightarrow{p_i} \\
&= (\mathbf{B} - \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1} \overrightarrow{p_i} + \mathbf{O} \mathbf{D}_{\mathbf{B}}^{-1} \overrightarrow{p_i} \\
&= (\mathbf{B} - \mathbf{O}) \mathbf{D}_{\mathbf{B}}^{-1} \overrightarrow{p_i} + \text{rep}(\overrightarrow{\delta} \overrightarrow{p_i})
\end{aligned}$$

Let  $(B - O) = \Xi$ , then:

$$\overrightarrow{p_{i+1}} = \Xi \mathbf{D}_{\mathbf{B}}^{-1} \overrightarrow{p_i} + \text{rep}(\overrightarrow{\delta} \overrightarrow{p_i})$$

Now solve  $D_B^{-1}$  in terms of  $\Xi$  :

$$\begin{aligned}
\Xi &= (B - O) \\
&= \Xi + O \\
\Rightarrow \delta_B^{-1} &= \vec{1} B \\
&= \vec{1} (\Xi + ) \\
&= \vec{1} \Xi + \vec{1} \\
&= \vec{1} \Xi + \langle n, n, n \dots n \rangle \\
D_B^{-1} &= \frac{1}{\delta^{-1} + \langle n, n, n, \dots, n \rangle} \\
&= \text{colSum}(\delta_B) + \mathbf{n}
\end{aligned}$$

And so the the power method can be implemented using sparse matrices.

(a) Solving the Background Probability Define  $\vec{\delta}$  as the column sums of

$$\begin{aligned}
\vec{\delta} &= \text{colsum}(\mathbf{B})^{-1} \\
&= \frac{1}{\vec{1}^T \mathbf{B}}
\end{aligned}$$

$$\begin{aligned}
\mathbf{OD}_B^{-1} \vec{p}_i &= \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 & \dots \\ 1 & 1 & 1 \\ \vdots & & \ddots \end{pmatrix} \begin{pmatrix} \delta_1 & 0 & 0 \\ 0 & \delta_2 & 0 & \dots \\ 0 & 0 & \delta_3 \\ 0 & \vdots & 0 & \ddots \end{pmatrix} \begin{pmatrix} p_1 \\ p_2 \\ p_3 \\ \vdots \end{pmatrix} \\
&= \begin{pmatrix} \frac{p_1}{\delta_1} + \frac{p_2}{\delta_2} + \frac{p_3}{\delta_3} \\ \frac{p_1}{\delta_1} + \frac{p_2}{\delta_2} + \frac{p_3}{\delta_3} & \dots \\ \frac{p_1}{\delta_1} + \frac{p_2}{\delta_2} + \frac{p_3}{\delta_3} \\ \vdots & \ddots \end{pmatrix} \\
&= \begin{pmatrix} \sum_{i=1}^n [p_i \delta_i] \\ \sum_{i=1}^n [p_i \delta_i] \\ \sum_{i=1}^n [p_i \delta_i] \\ \vdots \end{pmatrix} \\
&= \begin{pmatrix} \vec{\delta^T} \bullet \vec{p} \\ \vec{\delta^T} \bullet \vec{p} \\ \vec{\delta^T} \bullet \vec{p} \\ \vdots \end{pmatrix} \\
&= \text{repeat}(\vec{p} \bullet \vec{\delta^T}, n)
\end{aligned} \tag{48}$$

2. Set the value for B

```
| B <- A
| B@x <- ^ (A@x) -1
```

3. Create the Scaling Matrix The Transition probability matrix must sum to 1 so use the scaling matrix reduce the column sums.

```
| B <- 1/colSums(B)
| Bt <- t (B)
| DB <- diag (B)
```

4. Create the Trans Prob Mat

```
| T <- B %*% DB
```

5. Implement the Power Walk

(a) Set the Starting Values

```
| p_new <- rep(1/n, n) # Uniform
| p <- rep(0, n) # Zero
| <- 10^(-6)
```



(b) Implement the loop

```
while (sum(abs(p_new - p)) > ) {  
  (p <- as.vector(p_new)) # P should remain a vector  
  sum(p <- as.vector(p_new)) # P should remain a vector  
  p_new <- T %*% p + rep (Bt %*% p, n)  
}
```

```
Error in while (sum(abs(p_new - p))  
) { :  
  missing value where TRUE/FALSE needed
```

This error results because the  $\vec{p}_i \rightarrow \infty$

(c) Print the Stationary value

```
| p %>% head()
```

```
[1] -Inf -Inf -Inf -Inf -Inf -Inf
```

## 4.4 Debugging the Power Walk

2020-sep-13@22:39 These were the notes I took when trying to explain to Laurence the mistake I made

### 4.4.1 Setup

1. Load Packages

```
if (require("pacman")) {  
  library(pacman)  
}else{  
  install.packages("pacman")  
  library(pacman)  
}  
pacman::p_load(Matrix, igraph, plotly, mise, docstring, expm)  
mise()
```

Loading required package: pacman

2. Define function to create DiagonalsSparse Diagonal Function This doesn't matter for the power walk, real exponents will always give non-zero values anyway

```
sparse_diag <- function(mat) {  
  #' Diagonal Factors of Sparse Matrix  
  #'  
  #' Return a Diagonal Matrix containing either 1 / colsum() or 0 such that  
  #' matrix multiplication with this matrix would have all columns  
  #' sum to 1  
}
```

```

#'
#' This should take the transpose of an adjacency matrix in and the output
#' can be multiplied by the original matrix to scale it to 1.
#' i
# mat <- A
## Get the Dimensions
n <- nrow(mat)

## Make a Diagonal Matrix of Column Sums
  ## If a column sums to zero the diag can be zero iff the
  adjacency_matrix>=0
D <- sparseMatrix(i = 1:n, j = 1:n, x = colSums(mat), dims = c(n,n))

## Throw away explicit Zeroes
D <- drop0(D)

## Inverse the Values
D@x <- 1/D@x

## Return the Diagonal Matrix
return(D)
}

```

### 3. Make an Example Graph

```

g1 <- igraph::erdos.renyi.game(n = 20, 0.2)
A <- igraph::get.adjacency(g1) # Row to column

beta = 0.843234
= beta

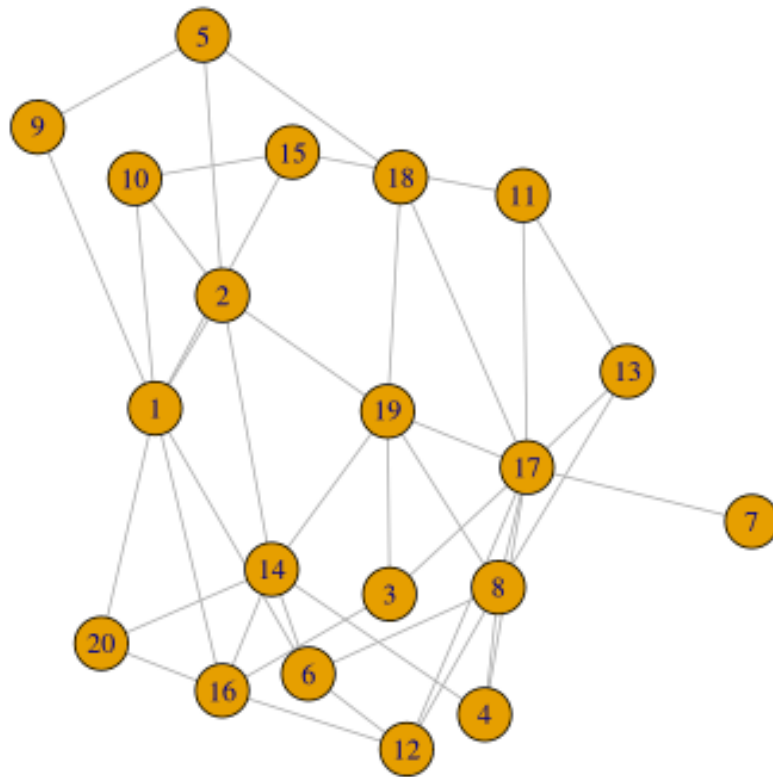
```

### 4. Plot

```

plot(g1)

```



#### 4.4.2 Power Walk

##### 1. Define B

```

B      <- A
B@x    <- ~(A@x)
B      <- A
B      <- ~A

Bo     <- A

# These two approaches are equivalent
Bo@x   <- ~(A@x) -1 # This in theory would be faster
# Bo    <- ~(A) -1
# Bo    <- drop0(Bo)

n <- nrow(A)

```

```
| print(B)
```

```
20 x 20 Matrix of class "dgeMatrix"
```

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]
[1,]	1.000000	0.843234	1.000000	1.000000	1.000000	0.843234	1.000000	1.000000
[2,]	0.843234	1.000000	1.000000	1.000000	0.843234	1.000000	1.000000	1.000000
[3,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[4,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234
[5,]	1.000000	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[6,]	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234
[7,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[8,]	1.000000	1.000000	1.000000	0.843234	1.000000	0.843234	1.000000	1.000000
[9,]	0.843234	1.000000	1.000000	1.000000	0.843234	1.000000	1.000000	1.000000
[10,]	0.843234	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[11,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[12,]	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234	1.000000	0.843234
[13,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234
[14,]	1.000000	0.843234	1.000000	0.843234	1.000000	0.843234	1.000000	1.000000
[15,]	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[16,]	0.843234	1.000000	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000
[17,]	1.000000	1.000000	0.843234	0.843234	1.000000	1.000000	0.843234	0.843234
[18,]	1.000000	1.000000	1.000000	1.000000	0.843234	1.000000	1.000000	1.000000
[19,]	1.000000	0.843234	0.843234	1.000000	1.000000	1.000000	1.000000	0.843234
[20,]	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
	[,9]	[,10]	[,11]	[,12]	[,13]	[,14]	[,15]	[,16]
[1,]	0.843234	0.843234	1.000000	1.000000	1.000000	1.000000	0.843234	0.843234
[2,]	1.000000	0.843234	1.000000	1.000000	1.000000	0.843234	1.000000	1.000000
[3,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234
[4,]	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234	1.000000	1.000000
[5,]	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[6,]	1.000000	1.000000	1.000000	0.843234	1.000000	0.843234	1.000000	1.000000
[7,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[8,]	1.000000	1.000000	1.000000	0.843234	0.843234	1.000000	1.000000	1.000000
[9,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[10,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234	1.000000
[11,]	1.000000	1.000000	1.000000	1.000000	0.843234	1.000000	0.843234	1.000000
[12,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234
[13,]	1.000000	1.000000	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000
[14,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234
[15,]	1.000000	0.843234	0.843234	1.000000	1.000000	1.000000	1.000000	1.000000
[16,]	1.000000	1.000000	1.000000	0.843234	1.000000	0.843234	1.000000	1.000000
[17,]	1.000000	1.000000	0.843234	0.843234	0.843234	1.000000	1.000000	1.000000
[18,]	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
[19,]	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234	1.000000	1.000000
[20,]	1.000000	1.000000	1.000000	1.000000	1.000000	0.843234	1.000000	0.843234
	[,17]	[,18]	[,19]	[,20]				
[1,]	1.000000	1.000000	1.000000	0.843234				
[2,]	1.000000	1.000000	0.843234	1.000000				
[3,]	0.843234	1.000000	0.843234	1.000000				

```

[4,] 0.843234 1.000000 1.000000 1.000000
[5,] 1.000000 0.843234 1.000000 1.000000
[6,] 1.000000 1.000000 1.000000 1.000000
[7,] 0.843234 1.000000 1.000000 1.000000
[8,] 0.843234 1.000000 0.843234 1.000000
[9,] 1.000000 1.000000 1.000000 1.000000
[10,] 1.000000 1.000000 1.000000 1.000000
[11,] 0.843234 1.000000 1.000000 1.000000
[12,] 0.843234 1.000000 1.000000 1.000000
[13,] 0.843234 1.000000 1.000000 1.000000
[14,] 1.000000 1.000000 0.843234 0.843234
[15,] 1.000000 1.000000 1.000000 1.000000
[16,] 1.000000 1.000000 1.000000 0.843234
[17,] 1.000000 0.843234 0.843234 1.000000
[18,] 0.843234 1.000000 0.843234 1.000000
[19,] 0.843234 0.843234 1.000000 1.000000
[20,] 1.000000 1.000000 1.000000 1.000000

```

```
| print(Bo)
```

20 x 20 sparse Matrix of class "dgCMatrix"

```

[1,] . -0.156766 . . . -0.156766 .
[2,] -0.156766 . . . -0.156766 . .
[3,] . . . . . . .
[4,] . . . . . . .
[5,] . -0.156766 . . . . .
[6,] -0.156766 . . . . . .
[7,] . . . . . . .
[8,] . . . -0.156766 . -0.156766 .
[9,] -0.156766 . . . -0.156766 . .
[10,] -0.156766 -0.156766 . . . . .
[11,] . . . . . . .
[12,] . . . . . -0.156766 .
[13,] . . . . . . .
[14,] . -0.156766 . -0.156766 . -0.156766 .
[15,] -0.156766 . . . . . .
[16,] -0.156766 . -0.156766 . . . .
[17,] . . -0.156766 -0.156766 . . -0.156766
[18,] . . . . -0.156766 . .
[19,] . -0.156766 -0.156766 . . . .
[20,] -0.156766 . . . . . .

[1,] . -0.156766 -0.156766 . . .
[2,] . . -0.156766 . . . -0.156766
[3,] . . . . . . .
[4,] -0.156766 . . . . . -0.156766
[5,] . -0.156766 . . . . .

```

```

[6,] -0.156766 . . . -0.156766 . -0.156766
[7,] . . . . . . .
[8,] . . . . -0.156766 -0.156766 .
[9,] . . . . . . .
[10,] . . . . . . .
[11,] . . . . . -0.156766 .
[12,] -0.156766 . . . . . .
[13,] -0.156766 . . -0.156766 . . .
[14,] . . . . . . .
[15,] . . -0.156766 -0.156766 . . .
[16,] . . . . -0.156766 . -0.156766
[17,] -0.156766 . . -0.156766 -0.156766 -0.156766 .
[18,] . . . . . . .
[19,] -0.156766 . . . . . -0.156766
[20,] . . . . . . -0.156766

```

```

[1,] -0.156766 -0.156766 . . . -0.156766
[2,] . . . . -0.156766 .
[3,] . -0.156766 -0.156766 . -0.156766 .
[4,] . . -0.156766 . . .
[5,] . . . -0.156766 . .
[6,] . . . . . .
[7,] . . -0.156766 . . .
[8,] . . -0.156766 . -0.156766 .
[9,] . . . . . .
[10,] -0.156766 . . . . .
[11,] -0.156766 . -0.156766 . . .
[12,] . -0.156766 -0.156766 . . .
[13,] . . -0.156766 . . .
[14,] . -0.156766 . . -0.156766 -0.156766
[15,] . . . . . .
[16,] . . . . . -0.156766
[17,] . . . -0.156766 -0.156766 .
[18,] . . -0.156766 . -0.156766 .
[19,] . . -0.156766 -0.156766 . .
[20,] . -0.156766 . . . .

```

```

(B <- 1/(colSums(Bo)+n))

```

```

[1] 0.05290267 0.05203951 0.05120406 0.05120406 0.05120406 0.05161840
[7] 0.05039501 0.05246754 0.05079631 0.05120406 0.05120406 0.05161840
[13] 0.05120406 0.05246754 0.05120406 0.05203951 0.05379495 0.05120406
[19] 0.05246754 0.05120406

```

```

(B <- 1/(colSums(B)))

```

```

[1] 0.05290267 0.05203951 0.05120406 0.05120406 0.05120406 0.05161840
[7] 0.05039501 0.05246754 0.05079631 0.05120406 0.05120406 0.05161840
[13] 0.05120406 0.05246754 0.05120406 0.05203951 0.05379495 0.05120406
[19] 0.05246754 0.05120406

```

```

DB <- diag(B)
## ** Create the Transition Probability Matrix
## Create the Trans Prob Mat using Power Walk
T <- Bo %*% DB

## ** Implement the Power Walk
## *** Set Initial Values
p_new <- rep(1/n, n) # Uniform
p <- rep(0, n) # Zero
      <- 10^(-6)
## *** Implement the Loop

while (sum(abs(p_new - p)) > ) {
  (p <- as.vector(p_new)) # P should remain a vector
  sum(p <- as.vector(p_new)) # P should remain a vector
  p_new <- T %*% p + rep(t(B) %*% p, n)
}
## ** Report the Values
print(paste("The stationary point is"))
print(p)

```

```

[1] "The stationary point is"
[1] 0.04882572 0.04963556 0.05044542 0.05044541 0.05044543 0.05004049
[7] 0.05125527 0.04923064 0.05085035 0.05044543 0.05044542 0.05004049
[13] 0.05044542 0.04923064 0.05044543 0.04963557 0.04801586 0.05044542
[19] 0.04923063 0.05044542

```