

Crawl data with requests and bs4

```
#get raw page markup with requests
```

```
resp = requests.get(url)
```

```
#parse raw to html with BeautifulSoup
```

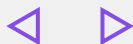
```
soup = BeautifulSoup(resp.content, "html.parser")
```

```
#select element with selector
```

```
links = soup.select(' a[href^="/"], a[href^="https://demo.org"] ')
```

```
for link in links:
```

```
    successor = link['href'] #value of href attribute
```



Analyze

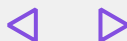
OutDegree and DeadEnd

OutDegree is the number of out-link from a page

DeadEnd is a page that has no out-link

Google '98 PageRank Algo

Introduce and how to implement the algorithm

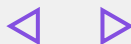


Calculate OutDegree and DeadEnd

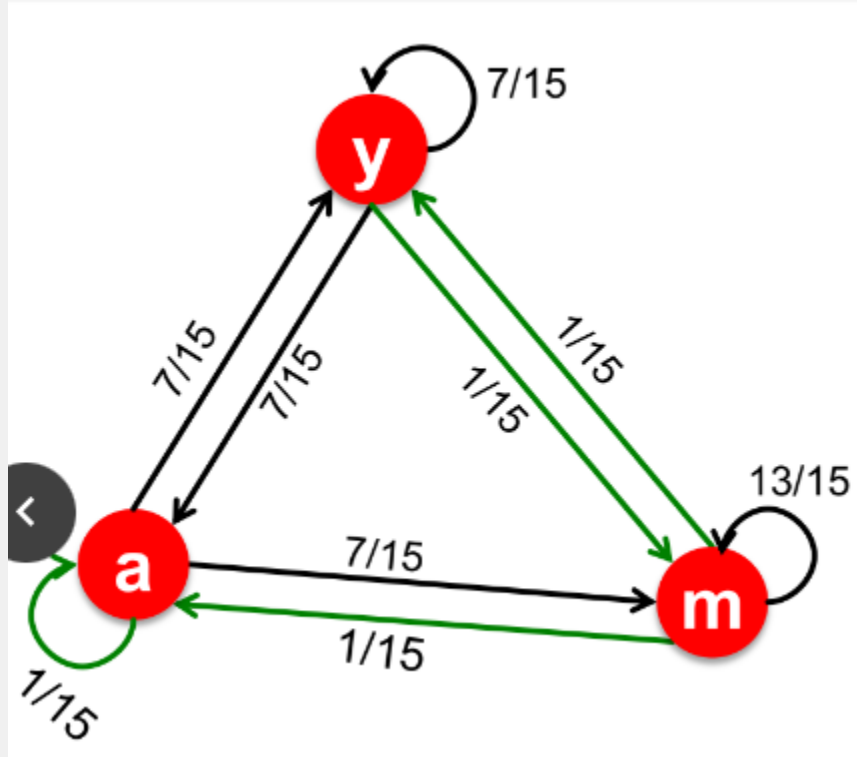


```
data = sqlc.sql("\n
SELECT pr.*, od.OutDegree, de.DeadEnds \n
FROM PageRank pr \n
INNER JOIN ( \n
    SELECT Page, COUNT(*) as OutDegree \n
    FROM PageRank GROUP BY Page\n
) od ON od.Page = pr.Page \n
INNER JOIN ( \n
    SELECT DISTINCT s.Successor, (CASE WHEN p.Page IS NULL THEN 1 ELSE 0 END) AS DeadEnds \n
    FROM PageRank s \n
    LEFT JOIN PageRank as p ON p.Page = s.Successor \n
) de ON de.Successor = pr.Successor \n
")

data.show()
```



Calculate OutDegree and DeadEnd



Page	Successor
y	y
y	m
y	a
a	a
a	y
a	m
m	m
m	y
m	a

Calculate OutDegree

Page	Successor
y	y
y	m
y	a
a	a
a	y
a	m
m	m
m	y
m	a

```
select Page, count(Successor) as  
OutDegree  
from df  
group by Page
```



Page	OutDegree
y	3
a	3
m	3

Check DeadEnd

Page	Successor
y	y
y	m
y	a
a	a
a	y
a	m
m	m
m	y
m	a

Ideas:

For each distinct element in Successor:
 if(element exists in Page):
 element is not deadend
 else:
 element is deadend

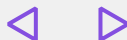
Google '98 PageRank Algo

What is PageRank

Simply pagerank is the likelihood (probability) that one user click on that page

Google '98 Algo

Introduce and how to implement the algorithm

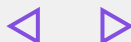


Introduce the algo

- We just rearranged the **PageRank equation**

$$\mathbf{r} = \beta \mathbf{M} \cdot \mathbf{r} + \left[\frac{1 - \beta}{N} \right]_N$$

- where $[(1-\beta)/N]_N$ is a vector with all N entries $(1-\beta)/N$
- \mathbf{M} is a **sparse matrix!** (with no dead-ends)
 - 10 links per node, approx $10N$ entries
- So in each iteration, we need to:
 - Compute $\mathbf{r}^{\text{new}} = \beta \mathbf{M} \cdot \mathbf{r}^{\text{old}}$
 - Add a constant value $(1-\beta)/N$ to each entry in \mathbf{r}^{new}
 - **Note if \mathbf{M} contains dead-ends then $\sum_j r_j^{\text{new}} < 1$ and we also have to renormalize \mathbf{r}^{new} so that it sums to 1**



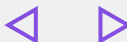
Introduce the algo

- **Input: Graph G and parameter β**
 - Directed graph G (can have **spider traps** and **dead ends**)
 - Parameter β
- **Output: PageRank vector r^{new}**

- **Set:** $r_j^{old} = \frac{1}{N}$
- **repeat until convergence:** $\sum_j |r_j^{new} - r_j^{old}| < \varepsilon$
 - $\forall j: r_j^{new} = \sum_{i \rightarrow j} \beta \frac{r_i^{old}}{d_i}$
 $r_j^{new} = 0$ if in-degree of j is 0
 - **Now re-insert the leaked PageRank:**
 $\forall j: r_j^{new} = r_j^{new} + \frac{1-S}{N}$ **where:** $S = \sum_j r_j^{new}$
 - $r^{old} = r^{new}$

If the graph has no dead-ends then the amount of leaked PageRank is $1-\beta$. But since we have dead-ends the amount of leaked PageRank may be larger. We have to explicitly account for it by computing S .

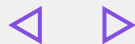
Jure Leskovec & Mina Ghashami, Stanford C246: Mining Massive Datasets



Implement

Convert data to a graph

Main functions



Create graph - adjacency matrix

Page	Succ
y	y
y	m
y	a
a	a
a	y
a	m
m	m
m	y
m	a

Dict =
{'y': 0,
'a': 1,
'm': 2}

Page	Succ
0	0
0	2
0	1
1	1
1	0
1	2
2	2
2	0
2	1

$M[p,s]=1$

$m[0,0]=1$

...
 $m[1,1]=1$

Col j Row i	0	1	2
0	1	1	1
1	1	1	1
2	1	1	1

Remember to transpose

Col i Row j	0	1	2
0	1	1	1
1	1	1	1
2	1	1	1

Main Functions

- Compute $r^{new} = \beta M \cdot r^{old}$
- Add a constant value $(1-\beta)/N$ to each entry in r^{new}
 - Note if M contains dead-ends then $\sum_j r_j^{new} < 1$ and we also have to renormalize r^{new} so that it sums to 1

Leaky PageRank

- Set: $r_j^{old} = \frac{1}{N}$
- repeat until convergence: $\sum_j |r_j^{new} - r_j^{old}| < \epsilon$
 - $\forall j: r_j^{new} = \sum_{i \rightarrow j} \beta \frac{r_i^{old}}{d_i}$
 $r_j^{new} = 0$ if in-degree of j is 0
 - Now re-insert the leaked PageRank:
 $\forall j: r_j^{new} = r_j^{new} + \frac{1-S}{N}$ where: $S = \sum_j r_j^{new}$
 - $r^{old} = r^{new}$

If the graph has no dead-ends then the amount of leaked PageRank is $1-\beta$. But since we have r

Find M

Col i Row j	0	1	2
0	1	1	1
1	1	1	1
2	1	1	1

3 values $\neq 0$

Col i Row j	0	1	2
0	$1/3$	$1/3$	$1/3$
1	$1/3$	$1/3$	$1/3$
2	$1/3$	$1/3$	$1/3$

Col i Row j	0	1	2
0	1	1	1
1	1	1	1
2	0	1	1

2 values $\neq 0$

Col i Row j	0	1	2
0	$1/2$	$1/3$	$1/3$
1	$1/2$	$1/3$	$1/3$
2	0	$1/3$	$1/3$

Find Matrix M

```
def findM(G, N):  
    tmp = [] # tmp == r_tmp_new_j  
    for col_i in range(N):  
  
        col = G[:, col_i]  
  
        if(np.sum(col) > 0): #no deadend  
            #divide r_i to number of out degree (number of values != 0)  
            out_dgs = (col > 0).sum() #total values != 0 in each col  
            tmp.append(col/out_dgs)  
        else: #deadend  
            tmp.append(np.array([0]*N))  
  
    return np.array(tmp).T #stochastic matrix with prob.
```

Main Functions

$$\mathbf{r} = \beta \mathbf{M} \cdot \mathbf{r} + \left[\frac{1 - \beta}{N} \right]_N$$

- Compute $\mathbf{r}^{new} = \beta \mathbf{M} \cdot \mathbf{r}^{old}$

- Add a constant value $(1-\beta)/N$ to each entry in \mathbf{r}^{new}

- Note if \mathbf{M} contains dead-ends then $\sum_j r_j^{new} < 1$ and we also have to renormalize \mathbf{r}^{new} so that it sums to 1

- Set: $r_j^{old} = \frac{1}{N}$

- repeat until convergence: $\sum_j |r_j^{new} - r_j^{old}| < \varepsilon$

- $\forall j: r_j^{new} = \sum_{i \rightarrow j} \beta \frac{r_i^{old}}{d_i}$
 $r_j^{new} = 0$ if in-degree of j is 0

- Now re-insert the leaked PageRank:

- $\forall j: r_j^{new} = r_j^{new} + \frac{1-S}{N}$ where: $S = \sum_j r_j^{new}$

- $\mathbf{r}^{old} = \mathbf{r}^{new}$

If the graph has no dead-ends then the amount of leaked PageRank is $1-\beta$. But since we have

PageRank Function

```
def gg_pagerank(G, b, N):  
    r_j_old = np.array([ 1/N ]*N).T  
    r_j_new = np.array([ 0 ]*N).T  
  
    thresh_hold = 10**-8  
  
    ### stochastic matrix with prob in gg algo  
    M = findM(G,N)*b  
  
    ### leaked  
    leaked = (1-b)/N  
  
    ### begin iteration  
    while np.sum((np.absolute(r_j_new - r_j_old))) >= thresh_hold:  
  
        ###update to exit while  
        r_j_old = r_j_new  
        r_j_new = M.dot(r_j_old) + leaked  
  
        ###normalized  
        if(np.sum(r_j_new.T) < 1):  
            tmp = [r_j_new.T[i]/np.sum(r_j_new.T) for i in range(N)]  
            r_j_new = np.array(tmp).T  
  
    return r_j_new
```

$[a, b, c] \rightarrow a + b + c \neq 1$

$[a/(a+b+c), b/(a+b+c), c/(a+b+c)]$
 $\rightarrow a/(a+b+c) + b/(a+b+c) + c/(a+b+c) = 1$

$[i/\text{sum}(\text{arr}) \text{ for } i \text{ in arr}]$



Thanks!

CREDITS: This presentation template was created by Slidesgo, including icons by Flaticon and infographics & images by Freepik