暨南大学本科实验报告专用纸

课程名称		数值计算实验					成约	责评定	?			
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实验时间	2023	年	12 月	1	日上	午 1	0:30	\sim $$	12:10			

I. Problem

- 1. Implement a simple web crawler;
- 2. Acquire the google matrix of the first 500 web pages from the main webpage of any university via the above web crawler, and give their adjacency matrix;
- 3. Implement the Power Method;
- 4. Compute the dominant eigenvector of the google matrix;
- 5. List the top 20 web pages.

II. Algorithm Summary

1. PageRank Algorithm

The PageRank algorithm, devised by Larry Page and Sergey Brin, co-founders of Google, is a method used to determine the importance of a webpage based on its relevance and connectivity within the web. It serves as a fundamental algorithm for Google's search engine, aiding in the sorting and ranking of webpages.

Key concepts of the PageRank algorithm include:

- 1. Link Graph: The internet is visualized as a vast graph where webpages are represented as nodes, and hyperlinks between them form directed edges.
- 2. Importance Transmission: PageRank measures the importance of a webpage by evaluating both the quantity and quality of incoming links. A webpage is considered more important if it is linked by other pages, especially those of high importance.
- 3. Markov Process: PageRank employs the concept of a Markov chain to model the transition between webpages. Webpages are treated as states, and the hyperlinks between them represent the probabilities of transitioning between states.
- 4. Iterative Calculation: The algorithm uses iterative methods to compute the weight (importance) of each webpage. Initially, all webpages are assigned equal weight, and through multiple iterations based on linking relationships, the weight of each webpage is updated until convergence.

5. Stability and Convergence: PageRank continues its iterative calculations to update webpage weights until they reach a stable state where further iterations do not significantly change the weights.

In short, the algorithm is implemented based on Markov process and power iteration method. Let's look at the following example flow:

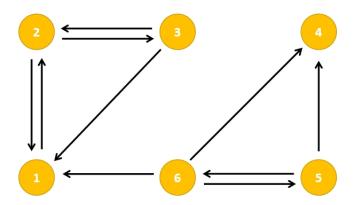


Figure 1: Page links diagram

This is a directed graph where outgoing links from a website refer to other pages. In this case, Site 1 refers to both Site 2 and Site 3. In computer science, directed graphs are commonly represented using an adjacency matrix **A**. For instance:

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

Now, The adjacency matrix A, we set $A_{ij}=1$ which indicates that Site i refers to Site j, while $A_{ij}=0$ signifies no reference. This representation helps depict the directed connections within the graph of web pages.

Typically, web pages are assigned priorities, and displaying high-priority pages at the top aims to facilitate easier access for users. However, determining the importance of these pages poses a challenge. We primarily rely on the relevance between web pages as a guide. If a webpage is linked to by many other pages, it implies higher importance. Similarly, pages referenced by high-priority pages might also carry significance. Common intuition suggests that users tend to spend more time on pages perceived as highly important.

Suppose there's a student named \mathbf{Hyq} currently browsing the internet. \mathbf{Hyq} has two choices while surfing:

- 1. Moving to a Random Site: **Hyq** might decide to move to a random site across the internet with a probability denoted as α .
- 2. Clicking a Link on the Current Page: Alternatively, **Hyq** may choose to click on a link present on the current page they're visiting with a probability of (1α) .

It's assumed that the probability of **Hyq** clicking on a link on any given site is equal, and there exist 'n' total websites available. Consequently, the probability of **Hyq** transitioning from Site i to Site j can be expressed as:

$$p_{ji} = \begin{cases} \frac{\alpha}{n} + (1 - \alpha) * \frac{A_{ji}}{\sum_{k=1}^{n} A_{ki}}, & \text{other} \\ \frac{1}{n}, & \sum_{k=1}^{n} A_{ki} = 0 \end{cases}$$

 p_{ji} means Rosen goes from site i to j .

By this time, let's transform our adjacency matrix **A** into a "surfing" matrix **M**:

$$\mathbf{M} = \begin{bmatrix} \frac{a}{6} & \frac{a}{6} + \frac{(1-a)}{2} & \frac{a}{6} + \frac{(1-a)}{2} & \frac{1}{6} & \frac{a}{6} & \frac{a}{6} + \frac{(1-a)}{3} \\ \frac{a}{6} + (1-a) & \frac{a}{6} & \frac{a}{6} + \frac{(1-a)}{2} & \frac{1}{6} & \frac{a}{6} & \frac{a}{6} \\ \frac{a}{6} & \frac{a}{6} + \frac{(1-a)}{2} & \frac{a}{6} & \frac{1}{6} & \frac{a}{6} & \frac{a}{6} \\ \frac{a}{6} & \frac{a}{6} & \frac{a}{6} & \frac{1}{6} & \frac{a}{6} + \frac{(1-a)}{2} & \frac{a}{6} + \frac{(1-a)}{3} \\ \frac{a}{6} & \frac{a}{6} & \frac{a}{6} & \frac{1}{6} & \frac{a}{6} + \frac{(1-a)}{2} & \frac{a}{6} + \frac{(1-a)}{3} \\ \frac{a}{6} & \frac{a}{6} & \frac{a}{6} & \frac{1}{6} & \frac{a}{6} + \frac{(1-a)}{2} & \frac{a}{6} \end{bmatrix}$$

The **M** refers to the "Google matrix/Stochastic Matrix/Markov Matrix." An interesting fact to note is that all elements of the matrix are positive, and the sum of each column of the matrix equals 1. In other words, there exists a left eigenvector $\mathbf{v} = (1, 1, \dots, 1)$:

$$\mathbf{v}\mathbf{M} = \mathbf{v}$$

That means the matrix M has an eigenvalue of 1. As per the Gershgorin circle theorem, it's established that the eigenvalues of M cannot exceed 1. Given the positivity of M, according to the Perron-Frobenius theorem, it follows that the absolute values of all eigenvalues of the matrix are less than 1, excluding the aforementioned eigenvalue of 1.

Now, when we say matrix \mathbf{M} possesses a steady-state distribution, what does it signify? Let's assume a vector \mathbf{p} , and $\mathbf{p_i}$, represents the number of people staying on page i. Assuming:

$$\mathbf{P} = (100, 0, 0, ..., 0)$$

This implies that initially, there were 100 people staying on page 1. After a considerable duration, we're interested in determining the number of people currently staying on the various web pages:

$$\mathbf{P_{now}} = \lim_{n \to \infty} \mathbf{G}^n \mathbf{P}$$

You'll be amazed to observe the convergence of the matrix power P_{now} ! This incredible outcome is due to the fact that 1 is the largest absolute eigenvalue of M! Take a look at this:

Assume $c_1, c_2 \neq 0$ and v_i is eigenvector of **M**

And
$$|\lambda_1| > |\lambda_2| \ge |\lambda_3| \ge \cdots \ge |\lambda_n|$$

$$\mathbf{P} = c_1 v_1 + \cdots + c_n v_n$$

$$\mathbf{P_k} = \mathbf{M}^k \mathbf{P} = c_1 \lambda_1^k v_1 + \cdots + c_n \lambda_n^k v_n$$

$$\frac{\mathbf{P_k}}{\lambda_1^k} = c_1 v_1 + c_2 \left(\frac{\lambda_2}{\lambda_1}\right)^k v_2 + \cdots + c_n \left(\frac{\lambda_n}{\lambda_1}\right)^k v_n$$

$$\lim k \to \infty, \left(\frac{\lambda_j}{\lambda_1}\right)^k \to 0$$

That's precisely why P_{now} will converge! It will gradually converge towards the eigenvector of the greatest absolute eigenvalue of M, eventually reaching a multiple of that eigenvalue. This process is referred to as the power iteration method.

By sorting the vector \mathbf{P}_{now} from largest to smallest, we've successfully obtained the ranking of pages! We've accomplished it gracefully.

III. Experimental procedures

Step1: Define the Web_Crawler class to implement the method of crawling pages and building an adjacency matrix between pages.

Step2: Start crawling pages from "https://www.jnu.edu.cn" and continue crawling until 500 web pages have been crawled.

Step3: Draw the adjacency matrix of these pages and convert the matrix to a google matrix.

Step4: Implement the Power Iteration Method and calculate the dominant eigenvector of the google matrix.

Step5: List the top 20 web pages with the highest rank value.

IV. Result Analysis

First we crawled 500 web pages:

```
| C. Wintinowally private are of Nicklesfor tow Naccessity (Nicklesfor tow Naccessity (Nicklesfor Naccessity (Nick
```

Figure 2: Crawling websites

```
| Caraling Page 40 | Miles | Alles | A
```

Figure 3: Crawling websites(cont.)

Based on the link relationships between these 500 pages, an adjacency matrix diagram can be constructed as follows:

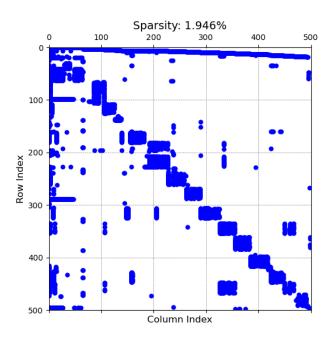


Figure 4: Sparsity matrix of these 500 pages

According to the PageRank algorithm, we get the top 20 web pages with the highest rank values:

```
TOP 1: 暨南大学田书馆
URL: https://ltb.inu.edu.cn
Rank Value: 0.836824973012285524
TDP 2: 暨南大学将長高等店-国家"双一流"建设高校
URL: https://www.inu.edu.cn
Rank Value: 0.83621698036059209
TDP 3: 暨南大学田书馆
URL: https://ltb.inu.edu.cn/department/index/11
Rank Value: 0.80248492226913659
TDP 4: 图书馆核不暨南大学田书馆
URL: https://ltb.inu.edu.cn/department/index/17
Rank Value: 0.8020536869120696315
TDP 5: 暨南大学田书馆
URL: https://lub.inu.edu.cn/2020/1124/c10374a565499/page.htm
Rank Value: 0.8020538873219076459
TDP 6: Mynet校园网用户自助服务平台
URL: https://mynet.inu.edu.cn/app/forgetPassword.html
Rank Value: 0.802033873219076459
TDP 7: 暨南大学田书馆
URL: https://ltb.inu.edu.cn/department/index/36
Rank Value: 0.81763508439933019
TDP 8: 暨南大学田书馆
URL: https://ltb.inu.edu.cn/department/index/22
Rank Value: 0.8170647285259862395
TDP 9: 暨南大学田书馆
URL: https://lib.inu.edu.cn/department/index/37
Rank Value: 0.8170647285259862395
TDP 9: 暨南大学田书馆
URL: https://lib.inu.edu.cn/department/index/37
Rank Value: 0.81685197034276468
TDP 10: 校地合作
URL: https://lb.inu.edu.cn/department/index/37
Rank Value: 0.8089215398454833808
```

Figure 5: Top 20 web pages(1-10)

```
TOP 11: 其他
URL: https://kjc.inu.edu.cn/33611/list.htm
Rank Value: 0.098737289959345666
TOP 12: 统一身价认证平台
URL: https://siteadmin.jnu.edu.cn
Rank Value: 0.088130817280861949
TOP 13: 创新平台科
URL: https://kjc.inu.edu.cn/33215/list.htm
Rank Value: 0.097815244223543832
TOP 14: JiNan University Undergraduate Admission
URL: https://sdaission.jnu.edu.cn
Rank Value: 0.09740225664963853
TOP 15: 首页 - 暨南大学新闻网
URL: https://sdaission.jnu.edu.cn
Rank Value: 0.087602933214455526
TOP 16: 机构简介
URL: https://sic.inu.edu.cn/33285/list.htm
Rank Value: 0.0973797373732383741568
TOP 17: 支部建设
URL: https://skc.inu.edu.cn/9317/list.htm
Rank Value: 0.097305802612076512
TOP 19: 国南沙项目
URL: https://skc.inu.edu.cn/9346/list.htm
Rank Value: 0.097305802612076512
TOP 19: 国南设
URL: https://skc.inu.edu.cn/9355/list.htm
Rank Value: 0.097305802612076512
TOP 19: 国南设
URL: https://skc.inu.edu.cn/9355/list.htm
Rank Value: 0.097305802612076512
TOP 19: 国南设
URL: https://skc.inu.edu.cn/9355/list.htm
Rank Value: 0.097305802612076512
TOP 20: 教学科研 - 暨南大学新闻网
URL: https://skc.inu.edu.cn/col9.html
Rank Value: 0.09731818069266735
```

Figure 6: Top 20 web pages (11-20)

Finally, we can plot the website rank value distribution:

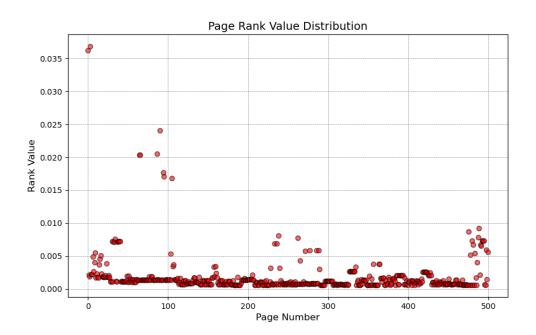


Figure 7: Rank value distribution

V. Experimental Summary

In this lab, we extracted data from 500 distinct web pages linked to Jinan University's official site, "https://www.jnu.edu.cn", forming an adjacency matrix $\bf A$. Utilizing $\bf A$, we constructed the Google matrix $\bf G$ and employed the power iteration algorithm to determine the relative importance and rankings of these sites.

It's important to note that for the adjacency matrix **A**, we ensured the sum of each column equals 1, contrary to the row sum. Additionally, we imposed a limit on the number of relative URLs per page to a maximum of 20. This was particularly relevant for pages like "https://www.jnu.edu.cn" to prevent overrepresentation of nodes from the same website's sub-pages. Moreover, we encountered numerous URLs referring to the same site (for instance, "http://www.jnu.edu.cn", "https://www.jnu.edu.cn", and "https://www.jnu.edu.cn/"). To address this, we focused exclusively on URLs starting with 'https' and eliminated any trailing '/' to avoid redundancy.

VI. Appendix: Source Code

In this experiment, the code implementation part uses Python and a series of related third-party libraries, including: **numpy**, **matplotlib**, **requests** and **beautifulsoup4**.

1. web_crawler.py

```
1
   from requests import get, head
   from bs4 import BeautifulSoup
3
   from random import sample
   from urllib.parse import urljoin
   # Constants for crawler configuration
7
   MAX\_SITES = 500
   MAX_RELATIVE_LINKS = 20
8
9
10
11
   class Web_Crawler:
12
       HEADERS = {
13
            'user-agent': 'Mozilla/5.0u(Macintosh; | InteluMacuOSuXu10_14_5) |
                AppleWebKit/537.36_(KHTML,_like_Gecko)_Chrome/87.0.4280.88_Safari
14
15
16
       def __init__(self, base_url, verbose=False):
17
            self.to_crawl = [base_url]
18
            self.site_count = 1
19
            self.crawled = set()
20
            self.unreachable = set()
21
            self.link_graph = {}
22
            self.verbose = verbose
23
24
       def extract_links(self, url):
25
            try:
26
                response = head(url)
27
                if 'text/html' not in response.headers.get('Content-Type', ''):
28
                    raise ValueError("No-HTML_content")
29
                response = get(url, headers=self.HEADERS, timeout=10)
30
            except:
31
                self.crawled.remove(url)
32
                self.unreachable.add(url)
33
                self.site_count = self.site_count - 1
34
                return -1
35
36
            response.encoding = 'utf-8'
37
            soup = BeautifulSoup(response.text, 'lxml')
38
39
            # Collect and normalize links
            links = [link['href'] for link in soup.find_all('a', href=True)]
40
41
            links = self._normalize_links(url, links)
42
43
            for link in links:
44
                if link not in self.to_crawl and \
45
                        link not in self.crawled and \
46
                        link not in self.unreachable and \
47
                        self.site_count < MAX_SITES:</pre>
48
                    self.to_crawl.append(link)
49
                    self.site_count += 1
```

```
50
51
            self.link_graph[url] = links
            response.close()
52
53
            return response.status_code
54
55
        def _normalize_links(self, base_url, links):
56
            relative = [link for link in links if link.startswith('/')]
57
            absolute = [link for link in links if link.startswith('https')]
            relative = sample(relative, min(len(relative), MAX_RELATIVE_LINKS))
58
59
            links = [link.rstrip('/') for link in absolute + [urljoin(base_url,
                rel) for rel in relative]]
60
            return links
61
62
        def run(self):
63
            index = 1
64
            while self.to_crawl:
65
                 current_url = self.to_crawl.pop(0)
66
                 self.crawled.add(current_url)
67
                 status = self.extract_links(current_url)
68
                 if self.verbose:
                     print('Crawling_Page', index, ':', current_url, ', Status:',
69
70
                           'No-HTML content' if status == -1 else status)
71
                     index += 1
72
            if self.verbose:
                 print('Crawling_completed._Total_sites:', self.site_count)
73
74
                 print('keys:', len(self.link_graph.keys()))
75
76
        def get_adjacent_matrix(self):
77
            keys = tuple(self.link_graph.keys())
78
79
            for key in keys:
80
                 for site in self.link_graph[key]:
81
                     if site not in keys or site == key:
82
                         self.link_graph[key] = [x for x in self.link_graph[key]
                             if x != site]
83
84
            matrix = [[0] * self.site_count for _ in range(self.site_count)]
85
86
            for site, links in self.link_graph.items():
87
                 site_index = keys.index(site)
                 for link in links:
88
89
                     link_index = keys.index(link)
                     matrix[site_index][link_index] = 1
90
91
92
            return matrix
93
94
95
    def get_page_title(url):
96
        try:
97
            response = get(url, headers=Web_Crawler.HEADERS)
            response.encoding = 'utf-8'
98
99
            soup = BeautifulSoup(response.text, 'lxml')
100
            title = soup.find('title').text
101
        finally:
102
            response.close()
103
        return title
```

2. algorithm.py

```
import numpy as np
3
4
   def power_iteration(matrix):
5
       num_nodes = matrix.shape[0]
6
       # Initialize vector: [1, 0, 0, ..., 0]
       rank_vector = np.zeros(num_nodes)
7
       rank_vector[0] = 1
8
9
       while True:
10
            new_rank_vector = np.dot(matrix, rank_vector)
11
            change = np.linalg.norm(new_rank_vector - rank_vector)
12
            # Convergence check (threshold set arbitrarily)
13
            if change < 1e-20:
14
                break
15
            else:
16
                rank_vector = new_rank_vector
17
18
       return new_rank_vector
19
20
21
   def convert_to_google_matrix(adj_matrix, num_sites, alpha):
22
       for row in range(num_sites):
23
            row_sum = sum(adj_matrix[row])
24
            if row_sum == 0:
25
                for col in range(num_sites):
26
                    adj_matrix[row][col] = 1 / num_sites
27
            else:
28
                for col in range(num_sites):
29
                    random_surf = alpha * (1 / num_sites)
30
                    outlink_surf = (1 - alpha) * (adj_matrix[row][col] / row_sum)
31
                    adj_matrix[row][col] = random_surf + outlink_surf
       return adj_matrix
```

3. utils.py

```
import matplotlib.pyplot as plt
   import numpy as np
3 from json import dump, load
5
   # Constants
  DATA_FILE = 'crawled_data.json'
6
   ALPHA = 0.15
   NUM_TOP_PAGES = 20
8
9
10
11
   def save_crawl_data(crawler, filename):
12
       data = {
13
            'adjacent_matrix': crawler.get_adjacent_matrix(),
14
            'directed_graph': crawler.link_graph,
15
            'num_site': crawler.site_count
16
       with open(filename, 'w', encoding='utf-8') as file:
17
18
            dump(data, file, ensure_ascii=False, indent=4)
19
20
   def load_data(filename):
21
22
       with open(filename, 'r') as file:
23
            return load(file)
24
25
26
   def plot_sparsity(matrix):
27
       size = len(matrix)
       plt.figure(figsize=(10, 6)) # Set a larger figure size
28
       plt.spy(matrix, markersize=5, marker='o', color='blue') # Increase
29
           marker size and change color
30
       plt.xlim([0, size])
31
       plt.ylim([size, 0])
32
33
       # Calculate sparsity
34
       non_zero_count = np.count_nonzero(matrix)
35
       sparsity_percentage = (non_zero_count / (size ** 2)) * 100
36
       plt.title(f'Sparsity: [sparsity_percentage:.3f}%', fontsize=14)
37
       plt.xlabel('Column_Index', fontsize=12)
38
       plt.ylabel('Row_Index', fontsize=12)
39
       plt.grid(color='gray', linestyle='--', linewidth=0.5)
40
       plt.show()
41
42
   def plot_rank_distribution(rank_values):
43
44
       plt.figure(figsize=(10, 6)) # Set a larger figure size
45
       plt.scatter(range(len(rank_values)), rank_values, color='red', alpha=0.6,
46
                    edgecolor='black') # Adjust color, transparency, and edge
       \verb|plt.title('Page_{\sqcup}Rank_{\sqcup}Value_{\sqcup}Distribution', fontsize=14)|\\
47
       plt.xlabel('Page_Number', fontsize=12)
48
       plt.ylabel('Rank_Value', fontsize=12)
49
50
       plt.grid(True, color='gray', linestyle='--', linewidth=0.5)
       plt.show()
```

4. main.py

```
1 from web_crawler import Web_Crawler, get_page_title
```

```
2 | from algorithm import power_iteration, convert_to_google_matrix
3 | from utils import *
4 from os.path import exists
5 from datetime import datetime
   import numpy as np
7
8
9
   def crawl_website(base_url, verbose=True):
10
        crawler = Web_Crawler(base_url=base_url, verbose=verbose)
11
        start_time = datetime.now()
12
        crawler.run()
13
        end_time = datetime.now()
14
        print('Crawling_time_used:', (end_time - start_time).total_seconds(), '
            seconds')
15
        return crawler
16
17
18
   def display_top_pages(page_rank, num_pages):
19
        for i, (url, rank) in enumerate(page_rank[:num_pages]):
20
            title = get_page_title(url)
21
            print(f'TOP_{\sqcup}\{i_{\sqcup}+_{\sqcup}1\}:_{\sqcup}\{title\}\setminus nURL:_{\sqcup}\{url\}\setminus nRank_{\sqcup}Value:_{\sqcup}\{rank\}')
22
23
24
   def main():
        # Crawl and save data if not already done
        if not exists(DATA_FILE):
26
27
            crawler = crawl_website('https://www.jnu.edu.cn')
28
            save_crawl_data(crawler, DATA_FILE)
29
30
        # Load data from file
31
        data = load_data(DATA_FILE)
32
33
        # Plotting and processing
34
        plot_sparsity(data['adjacent_matrix'])
35
        google_matrix = convert_to_google_matrix(np.array(data['adjacent_matrix'
            ], dtype=float), data['num_site'], ALPHA)
36
37
        # Power iteration
38
        rank_values = power_iteration(google_matrix.transpose())
39
        plot_rank_distribution(rank_values)
40
41
        # Ranking and displaying top pages
42
        ranked_pages = [(key, rank_values[i]) for i, key in enumerate(data['
            directed_graph'].keys())]
43
        page_rank = sorted(ranked_pages, key=lambda x: x[1], reverse=True)
44
        display_top_pages(page_rank, NUM_TOP_PAGES)
45
46
47
   if __name__ == "__main__":
48
        main()
```