

Multimedia Technology

Lecture 4: Miscellaneous Techniques in IR

Lecturer: *Dr. Wan-Lei Zhao*

Autumn Semester 2024

Outline

- 1 PageRank and HITS
- 2 Crawler
- 3 Evaluation on IR performance
- 4 Chat-GPT
- 5 Retrieval-Augmented Generation

Pagerank: the motivation (1)

- Retrieval results returned by basic IR system usually are not satisfactory
- There are many reasons behind this
 - ① It is actually a very tough issue
 - ② Nearly all IR systems face the scalability issue
 - ③ Users are not able to express what they want by keywords only
 - ④ The same keyword for different people means different thing, e.g. “apple”
- It requires natural language understanding: **artificial intelligence**
- Hundreds of reranking approaches have proposed to optimize the search results
 - Share the story about SIGIR

Pagerank: the motivation (2)

- Keywords are very few
- Too many pages share similar similarity score

Google wanlei zhao

Web Images Videos News Maps More Search tools

About 19,200 results (0.35 seconds)

Wan-Lei Zhao - Google Scholar Citations
scholar.google.com/hk/citations?user=EChpPEAAAAJ&hl=en
 Xiamen University, Fujian, China - xmu.edu.cn
 Near-duplicate keyframe identification with interest point matching and pattern learning. WL Zhao, CW Ngo, HK Tan, X Wu. Multimedia, IEEE Transactions on 9 ...

Wanlei Zhao's homepage at Xiamen University
pami.xmu.edu.cn/~wzhaol/
 Oct 1, 2014 - Dr. Wan-Lei Zhao, PAMI research Lab, Computer Science Department, Faculty of Information Science and Technology, Xiamen University.

dblp: Wanlei Zhao
dblp.uni-trier.de Home Persons
 May 9, 2015 - List of computer science publications by Wanlei Zhao.

dblp: Wan-Lei Zhao
dblp.uni-trier.de Home Persons
 Feb 27, 2015 - Compiled list of computer science publications by Wan-Lei Zhao.

[PDF] LARGE-SCALE NEAR-DUPLICATE WEB VIDEO ... - VIR...
vireo.cs.cityu.edu.hk/papers/kme09-wanlei.pdf
 by WL Zhao - Cited by 18 - Related articles
 LARGE-SCALE NEAR-DUPLICATE WEB VIDEO SEARCH: CHALLENGE AND OPPORTUNITY. Wan-Lei Zhao, Song Tan and Chong-Wah Ngo. Department of ...

lip-vireo - Google Code
code.google.com/p/lip-vireo/
 Written by Wan-lei Zhao, 10/10/2010. B. Important notice. If user wants to try Flip ...
 written by Wan-lei Zhao, 27/11/2011. Terms - Privacy - Project Hosting Help.

Wanlei Zhao - GForge
<https://gforge.inria.fr/users/wanlei/>
 Jul 3, 2012 - Login Name: wanlei, Real Name: Dr. Wanlei Zhao, Email Address: wzhaol@nosppam@xmu.edu.cn, Xiamen University, Xiamen Fujian, China.

Page hyper-links

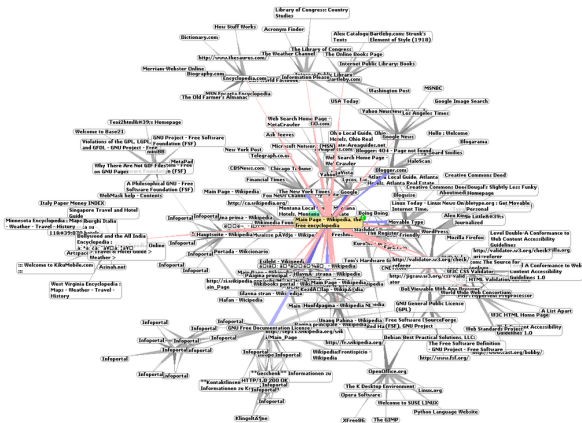
- We are now going to consider
- how hyper-links help to improve the search quality

```
1 <html>
2 <head>page head</head>
3 <body>
4 <p>HTML tutorials are available</p>
5 <a href="http://www.w3schools.com">hyper-link1</a>
6 <p>WWW standards are available</p>
7 <a href="http://www.w3.org">hyper-link2</a>
8 </body>
9 </html>
```

Pagerank: explained (1)

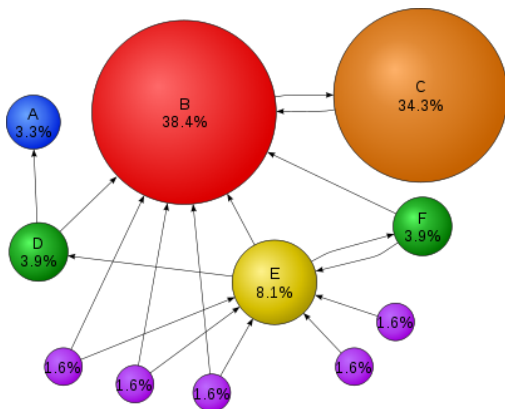
- Pagerank is one of the most successful reranking approaches
- It is a re-ranking approach
- It happens when we have the retrieval results
- Basic idea: make use of the hyperlinks between webpages
 - Pages being linked (pointed to) to by other pages should be important and ranked higher
- Start-up technology for Google

Pagerank: explained (2)



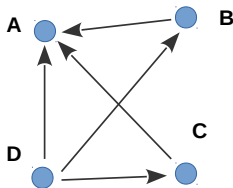
- We are connected by Internet
- Webpages are connected by hyperlinks

Pagerank: explained (3)



- Higher weights (pagerank) are assigned to the pages that have many in-ward links
- Notice that out-ward links will not impact your own ranking

Pagerank: build the model

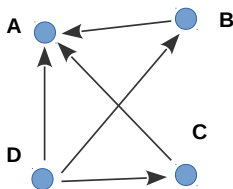


- Given 4 webpages, and the hyperlinks between them
- Calculate pagerank for each of them as following, $PR(.)$ for all the pages are initialized to **0.25**

$$PR(A) = \frac{PR(B)}{L(B)} + \frac{PR(C)}{L(C)} + \frac{PR(D)}{L(D)}, \quad (1)$$

where $PR(.)$ is the current pagerank,
 $L(.)$ is num. of out-ward links

Pagerank: build the model



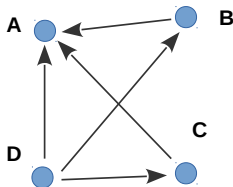
$$PR(A) = \frac{0.25}{1} + \frac{0.25}{1} + \frac{0.25}{3},$$

$$PR(B) = \frac{0.25}{3},$$

$$PR(C) = \frac{0.25}{3},$$

$$PR(D) = 0$$

Pagerank: the damping factor



- Given N is the num. of webpages, d is the damping factor,

$$PR(A) = \left(\frac{0.25}{1} + \frac{0.25}{1} + \frac{0.25}{3} \right) \cdot d + \frac{1-d}{N},$$

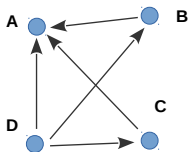
$$PR(B) = \frac{0.25}{3} \cdot d + \frac{1-d}{N},$$

$$PR(C) = \frac{0.25}{3} \cdot d + \frac{1-d}{N},$$

$$PR(D) = 0 \cdot d + \frac{1-d}{N}$$

Pagerank: the procedure

- 1 Produce Adjacent matrix by collecting all the webpage links
- 2 Initialize PR(.) to c
- 3 Do
- 4 Calculate PR(.) for each webpage
- 5 Update PR(.) for each webpage
- 6 Until convergence



$$M = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$

Pagerank: tricks to promote your webpage

- Share the story about Google
 - What Google means
 - Pagerank is born in the right season
 - Turning point of Google
 - Do we need to **reinvent the wheel**?
- Ask some webpage (has higher pagerank) to link to your webpage
 - Pagerank can be found by install firefox Toolbar or from pagerank website
 - Google robot will ignore hyperlink shares the same color as the background
- Register to Google Webtool
 - Once Google robot visits your site
 - Try to search and click-in your website with Google from different places

Outline

- 1 PageRank and HITS
- 2 Crawler**
- 3 Evaluation on IR performance
- 4 Chat-GPT
- 5 Retrieval-Augmented Generation

Recap

- We are able to retrieve documents on inverted files
 - Structure of inverted files
 - Static and dynamic inverted files
- We are able to evaluate the performance of IR system
 - Recall, Precision and F-measure
 - mean Average Precision

Puzzle: distributed and centralized Internet

- Internet is the biggest distributed system in the world
 - No central coordinator for information or computing resources
 - Machines, resources, societies are loosely connected
 - The major interface is web browser



- Search engine comes to play a unique role
- Ironically, it is somehow a central coordinator
- Without search engine, we are in dark
- Search engine is the de-facto interface to *WWW*, however not to everything

Web crawler: the information collector

- In June 1993, Matthew Gray from MIT wrote a perl script
- It is able to collect URLs, and keeps tracking on them
- It is also able to identify new websites



- It is the first web robot but not the first search engine
- The idea inspired many programmers to follow-up, leads to the birth of search engine
- Note that only 130 websites in the world in June 1993

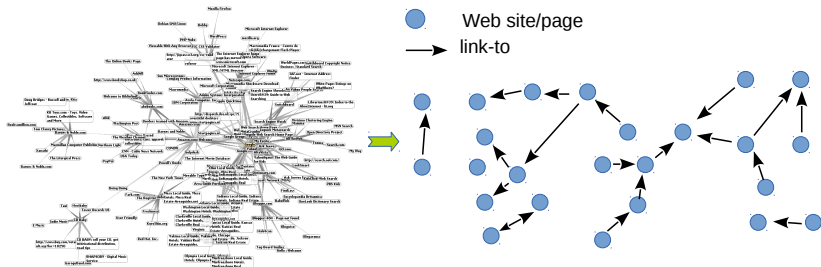
Web crawler: the general steps

- Other names: web robot and web spider
- Feed web robot with several URL seeds, the robot crawls websites into a database for archiving
- General steps:

Crawling (seed pages S)

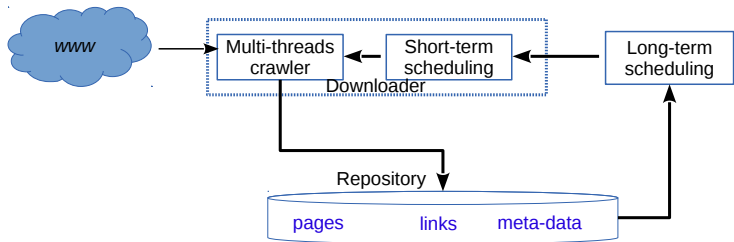
- (1) URLQueue $\leftarrow S$
- (2) **do** {
- (3) $p \leftarrow \text{Select-URL}(\text{URLQueue})$
- (4) content $\leftarrow \text{Download}(p)$
- (5) (text, links, structure, ...) $\leftarrow \text{Parse}(\text{content})$
- (6) URLQueue $\leftarrow \text{Add-new-links}(\text{URLQueue}, \text{links})$
- (7) } **until** (terminate condition)

Web crawler: the model



- It is a graph transverse problem
- Theoretically speaking, all nodes (pages) must be visited
- Either depth first or width first is fine
- The links between sites will be captivated later for ranking

Web crawler: the framework



- Crawling is a time consuming task

Web crawler: duties

- 1 Parsing DNS
 - DNS maintains the map between URL and IP
 - Frequent interaction with DNS causes overload
 - Caching DNS record is necessary
- 2 Normalize URL
 - Same site might be written in different way
 - “yahoo.com.cn” and “yahoo.cn”
- 3 Parsing web pages
 - HTML mark-ups have no semantic meaning
 - However, they indicate the structure of the page
- 4 Exceptions handling: soft **404 Error** page
- 5 Handling duplicate pages, partial duplicate rate: 29%; full duplicate rate: 22%

Web crawler scheduling: an example

- Example of 'sitemap.xml'

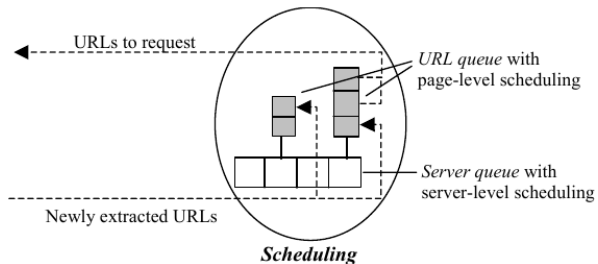
```
▼<urlset xmlns="http://www.sitemaps.org/schemas/sitemap/0.9">
  ▼<url>
    <loc>http://cmmlab.xmu.edu.cn</loc>
    <lastmod>202-09-22</lastmod>
  </url>
  ▼<url>
    <loc>http://cmmlab.xmu.edu.cn/wlzhao.htm</loc>
    <lastmod>202-09-22</lastmod>
  </url>
  ▼<url>
    <loc>http://cmmlab.xmu.edu.cn/wlzhao_cn.htm</loc>
    <lastmod>202-09-22</lastmod>
  </url>
  ▼<url>
    <loc>http://cmmlab.xmu.edu.cn/resc.html</loc>
    <lastmod>202-09-22</lastmod>
  </url>
  ▼<url>
    <loc>http://cmmlab.xmu.edu.cn/research.html</loc>
    <lastmod>202-09-22</lastmod>
  </url>
  ▼<url>
    <loc>http://cmmlab.xmu.edu.cn/pub.html</loc>
    <lastmod>202-09-22</lastmod>
  </url>
  ▼<url>
    <loc>http://cmmlab.xmu.edu.cn/members.html</loc>
    <lastmod>202-09-22</lastmod>
  </url>
</urlset>
```

Web crawler: scheduling strategies (1)

- 1 Intuitively, hottest sites should be crawled frequently
 - For example, sohu.com should be crawled in every 30 minutes
- 2 Depth-first? or breadth-first?
- 3 Page quality should be considered
 - Allocate more computing resources to these high quality pages
 - These pages are more meaningful to users too

Web crawler: scheduling strategies (2)

1 An exemplar framework



- Scheduling takes place on two levels: server and URLs
- Server queue and URL queue have been built

Web crawler: scheduling strategies (3)

- Three typical strategies
- ① Breadth-first scheduling
 - First-in-first-out principle
- ② Performance based scheduling

$$R(s, i) = \frac{P(s, i)}{T(s, i)} \quad (2)$$

where $P(s, i)$ is the numb. of pages from i th server
 $T(s, i)$ is the time to download them

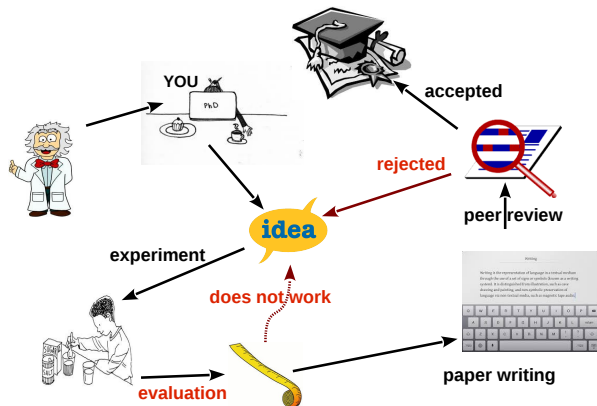
- ③ Quality based scheduling
 - prioritize high quality pages

Outline

- 1 PageRank and HITS
- 2 Crawler
- 3 Evaluation on IR performance**
- 4 Chat-GPT
- 5 Retrieval-Augmented Generation

How the “research game” is played

- Loop for experiment-driven research
- Evaluation on a certain benchmark plays key role in the loop



Recall, precision and F-measure

- True Positive (TP): the number of relevant documents retrieved
- False Negative (FN): the number of relevant documents missed
- False Positive (FP): the number of irrelevant documents retrieved
- True Negative (TN): the number of irrelevant documents not retrieved
- Given the documents we consider (top-K), and relevant document R

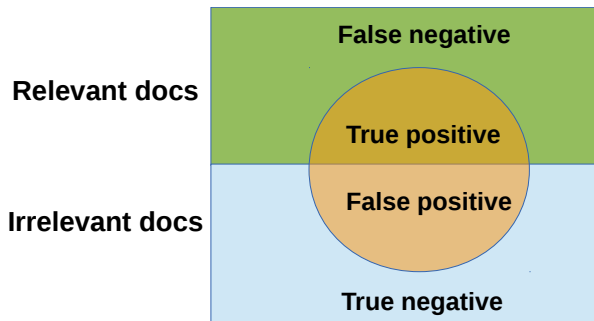
$$Recall = \frac{TP}{R} \quad (3)$$

$$Precision = \frac{TP}{K} \quad (4)$$

- F-measure is further defined as

$$F\text{-measure} = \frac{2 \cdot Recall \cdot Precision}{Recall + Precision} \quad (5)$$

Recall and precision illustration

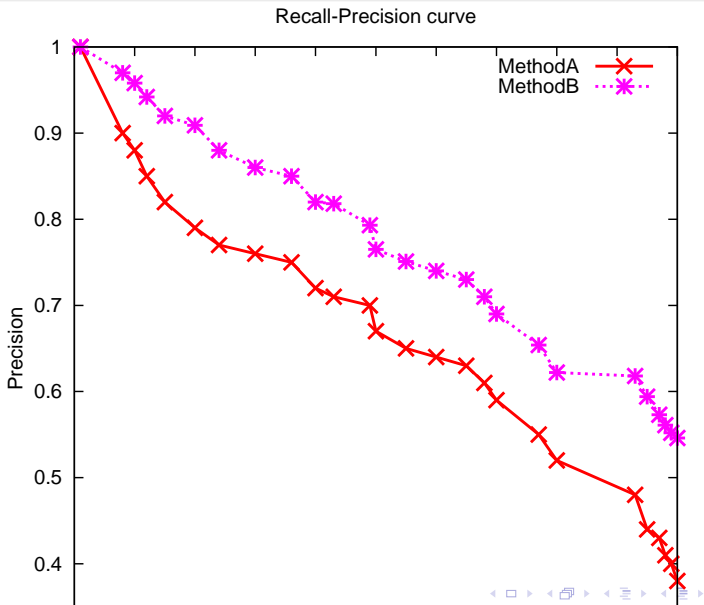


$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}}$$

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}}$$

- In classification task, the definition for 'Precision' changes

Curve of Recall V.S. precision



Average Precision

- Rankings of relevant docs are explicitly considered
- In practice, users are more sensitive to precision
- In-born advantage for a search engine:
users have no knowledge about recall
- Average Precision is such a measure fits in
- Average Precision (AP) is defined as

$$AP(i) = \frac{\sum_1^i(1)}{i} \quad (6)$$

- mean Average Precision (mAP) is defined as

$$mAP = \frac{\sum_{i=1}^K AP(i)}{K} \quad (7)$$

Exercise

- Given total num. of relevant docs is 10

Top	Relevancy
1	1
2	0
3	1
4	0
5	0
6	0
7	1
8	1
9	0

- See Recall=?, Precision=? and mAP=?

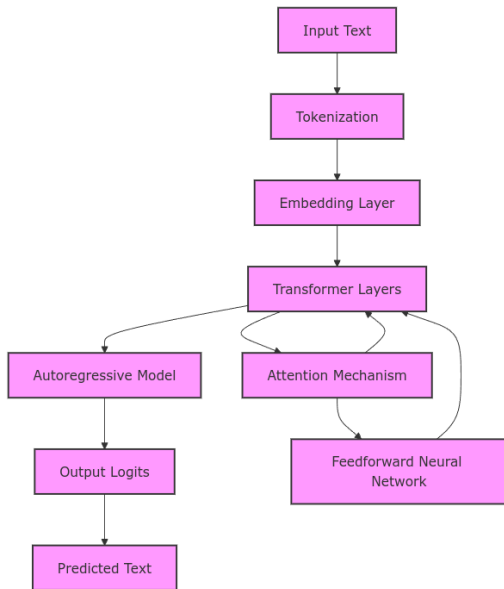
Outline

- 1 PageRank and HITS
- 2 Crawler
- 3 Evaluation on IR performance
- 4 Chat-GPT**
- 5 Retrieval-Augmented Generation

What is ChatGPT?

- ChatGPT is a conversational AI developed by OpenAI
- Based on the GPT (Generative Pre-trained Transformer) architecture
- Trained to understand and generate human-like text

Framework of ChatGPT



Key Features

- Natural Language Understanding
- Contextual Awareness
- Versatile Applications (eg, support, content creation)

How Does it Work?

- Utilizes deep learning techniques
 - Transformer and Reinforce learning
- Processes input text and generates responses

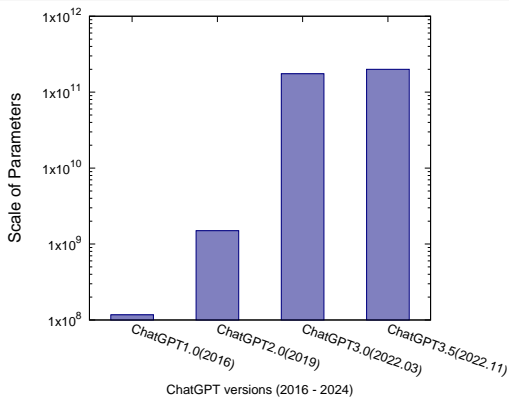
Jonh and his girl-friend are going to go to cinema to watch a movie.

- Learns from a diverse range of internet text
 - 1 Books
 - 2 Websites
 - 3 Wikipedia
 - 4 Research Papers
 - 5 Forums and Community Discussions

Applications

- Customer support automation
- Content generation and editing
- Personal assistants and chatbots

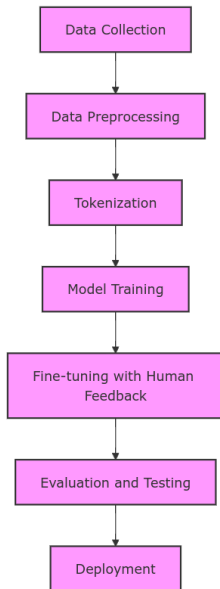
Challenges and Limitations



- May produce incorrect or nonsensical answers
- Sensitivity to input phrasing
- Ethical considerations and biases in AI
- The model of ChatGPT 3.5 takes at least 800G memory

Overview of GPT Training

- ChatGPT is based on the GPT architecture
- Trained using large corpora of text from the internet
- Focuses on predicting the next word in a sentence



Data Collection

- Utilizes diverse sources (books, articles, websites)
- Aims to cover a wide range of topics and language styles
- Ensures a broad understanding of human language

Preprocessing the Data

- Data is cleaned to remove low-quality content
- Tokenization: breaking text into manageable pieces (tokens)
- Transformation into a numerical format suitable for the model

Training Procedure

- Uses a technique called unsupervised learning
- Model is trained on predicting the next token based on context
Jonh and his girl-friend are going to go to cinema to watch a movie.
- Backpropagation algorithm optimizes model weights

Fine-tuning

- Model further refined on specific datasets for accuracy
- Involves supervised learning with human feedback
- Enhances performance on conversational tasks and context

ChatGPT vs. Conventional IR

- 1 ChatGPT compress/encode the huge amount of knowledge into a model
- 2 Conventional IR index the information
- 3 Conventional IR index can be easily updated
- 4 Conventional IR index provide both the information and its source
- 5 Conventional IR index is cheaper

Outline

- 1 PageRank and HITS
- 2 Crawler
- 3 Evaluation on IR performance
- 4 Chat-GPT
- 5 Retrieval-Augmented Generation

What is Retrieval-Augmented Generation?

- Most of the deep-models are not online model
- A hybrid approach combining retrieval and generation
- Enhances the capabilities of generative models
- Utilizes external knowledge sources to improve responses

How RAG Works

- Retrieves relevant documents based on user input
- Generates responses using both retrieved information and model knowledge
- Combines strengths of retrieval-based and generative methods

Key Components

- **Retrieval Component:** Searches for relevant documents
- **Generative Component:** Produces coherent and contextually relevant text
- **Integration Layer:** Merges information from both components

Benefits of RAG

- Access to up-to-date and specialized knowledge
- Improved accuracy and contextual relevance in responses
- Reduces the risk of generating incorrect information

Applications of RAG

- Question answering systems
- Conversational agents and chatbots
- Content generation and summarization tasks

Challenges and Considerations

- Dependence on the quality of retrieved documents
- Potential for biases in both retrieval and generation
- Need for efficient retrieval mechanisms

Q & A

Thanks for your attention!