Rational Search Engine

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Abstract

"clickbait" and "information cocoon" are nonnegligible issues when people more and more rely on Internet. The information we get actually affect our cognition about the world, therefore we hope to develop a tool that can help users to efficiently, and more importantly, "rationally" make use of the vast Internet, easily getting rich desired information. In this project, we utilize NLP tools to build a readily available and practical system. Our codes are in this repository

1 Introduction

In the information age, "clickbait" and "information cocoon" are often topics of concern. Clickbaid is common and annoying, it makes us hard to get the articles' main idea without opening it, which waster lots of time. Although new technologies have given us the ability to access and produce massive amounts of information, it's hard to utilize diversity news with limited time and concentration; this situation becomes even worse when powerful recommendation algorithms rule our information channel. Under this circumstance, we think, if the search engine can help us process the search results, we can get diversity information more efficient. To be concrete, we hope the search engine can

for titles: analyze the title and detect clickbait, hid the title if necessary;

for contexts: avoid duplicate search result, give summaries about the articles, give rough emotional tendency and content classification;

for search results' output: enable customized rank (like according to the reliability of the title) and demonstrate (like whether showing summarise).

With these functions, we hope this search engine can help users to obtain information efficiently. Thanks to the fast development of NLP field and vast python community, we can build a comprehensive system which alleviates the problems and carries forward the advantages of internet.



Figure 1: Initial interface of our Rational Search Engine

2 Related Work

[2] analyzes the use of NLP techniques in search engines; [3] provides a time-based and keyword-based filtering system with a stepwise filtering according to users' choice, but only depends on keywords in titles, which fails when the titles are 'messy' like clickbits; [4, 5] provides a method for using NLP techniques in news headline classification; [1] provides a reference for context classification. With reference to the evaluating article titles' process in [7], we use keywords and grammar to mark titles as well as detecting clickbit.

3 Processing Method

The system can be roughly divided into four stages, including extensive crawling, title and context processing and final result showing.

3.1 Get Content from Internet

We use python program to call given web severs for search result with given keywords.

3.1.1 Package Used

Request: getting html code from web severs, do simple division and operation that allow the users to get some content.

BeautifulSoup: a package that can get data and content from html or xml files, operate and process them with less time used.

For more details, please visit document of BeautifulSoup and document of Request.

3.1.2 Content Gaining

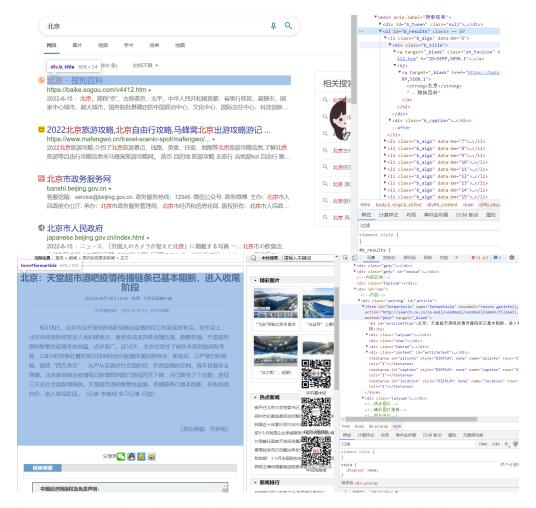


Figure 2: Top: Search Engines' code of the result pages; Down: the html code of detected pages

To get suitable format of search results for downstream processing, we execute the following steps:

Use Request package to access the search Engines' servers and gain the code of the result pages, shown in **Figure 2 Top**.

Use ETREE to get titles of search result from the specific area in the search engine's page, get the links of the news page by detecting the hyperlinks in these areas.

Use Request again to get the html code of the news pages detected, change their encoding such that we can detect Chinese characters in there pages.

Use bs4 to divide all blocks in the news page and get their content with Chinese strings, shown in **Figure 2 Down**.

Take the blocks with more than 50 Chinese characters, merge them together as the main content of the page searched. Thus, the noise in the news page, like advertisements, can be removed.

3.1.3 Search Engines Used

Baidu News: all webs found are news webs, while some of the links has no stable connection, thus the number of webs after screening is less.

Bing: may find many different kinds of webs, while the number of webs found is larger

3.1.4 Screening Method

In order to prevent getting repeated result in one search and meaningless pages, we take a few screening method to remove some news pages in this part. In this part, all but one pages with repeated titles would be removed because they usually have the same content, and we only need one of them.

Further, pages with not enough content, i.e. with no content blocks that has more than 50 characters, would be removed from the search result. They may have linking problems or have no long paragraphs to express what happens.

3.1.5 Search Result



Figure 3: Search result example

Here we have got the search result, for following operations, we need to change these result into a standard form.

The search result can be returned in a list form, each item in the list contains the title, links and main content of one pages after the screening. We can also save the result in .txt files for further process, each page takes 3 lines, first is their title, the second is their links and the last one is their content.

For 200 raw data searched, we usually get 40-50 available pages. They'll be sent to further operations.

3.2 Title Processing

For the titles of the corresponding searching results, our processing goal is to detect clickbat. To solve this problem, we first ask: what good titles and bad titles respectively have in common? Recalling what we have learnt about the necessary elements in title in high school and the typical words in clickbit, we use grammar information to mark good titles and keywords to mark bad ones.

Additionally, we also enable classification on titles, details are shown in the context processing parts.



Figure 4: left: part of speech index; right: "bad words"

3.2.1 Grammar Based Positive Marking

To get the grammar structure of the title, we first use Lexical Analysis of Chinese to do words segmentation and return words' the part of speech (like verb, noun, shown in **Figure 4 left**). Then we compare the titles' structure with our "good grammar dictionary" (we list possible structures with complete information like 'n-v-n, adj-n-adv-v'), if the title contains good words' pairs, we will give it credit.

3.2.2 Keywords Based Negative Marking

We first collect common words in clickbit like in fig, then build a "bad keywords dictionary" (shown in **Figure 4 right**). Given a title, we first segment it into meaningful words, and give it negative score if it has "bad keywords".

After these two marking process (notice marking weights can be adjusted), we can: **1.**compare the final score with the user-setted threshold and hid the titles with low score; **2.** rank the search results according to the score.

3.3 Context Processing

For the passages of the corresponding searching results, we mainly focus on the following three parts: Keywords extraction, Summary generation and Text classification.

3.3.1 Keywords extraction

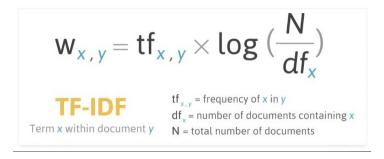


Figure 5: TF-IDF demonstrate

This part takes the reference of the project Chinese Keyphase extractor(CKPE)¹. The algorithm is mainly based on the Term Frequency-Inverse Document Frequency(TF-IDF). In terms of the inverse document frequency part, the relevant weights of each terms have been generated via over a million news texts. The large amount of data guarantees the accuracy of elimination over those commonly-used terms. For each specific passage we use pkuseg as a word segmentation tool to extract potential keywords, calculating the term frequency over the passage. Combining the two parts together, we get the final results about whether a term is essential for the text. We provide the top 5 keyphases for users to help them get a basic insight about the context.

3.3.2 Summary generation

In version 1.0, we simply use an extraction model based on BERT to abstract essential sentence in the passage. It encodes every sentence in the passage to a vector, and then we use a clustering algorithm to extract key sentences that are closest to the centroid as the candidate summary sentences. [6] In version 1.2, we provide another summary generation models based on GPT2, which is a conditional generation model. For those two kinds of summary generation models, the conditional generation model is more powerful when the essential information is separated in different sentences. GPT2 can learn to mix them together and output more effective information. ² However, in some cases, the conditional generation model may misunderstand the original meaning of the passage. For example, GPT2 may get confused when a passage is full of numbers or statistics. They may output the mismatching number. On the contrary, BERT ensures the accuracy of the information in the abstract.

https://github.com/dongrixinyu/chinese_keyphrase_extractor

²https://github.com/qingkongzhiqian/GPT2-Summary

3.3.3 Text classification and emotional tendency analysis

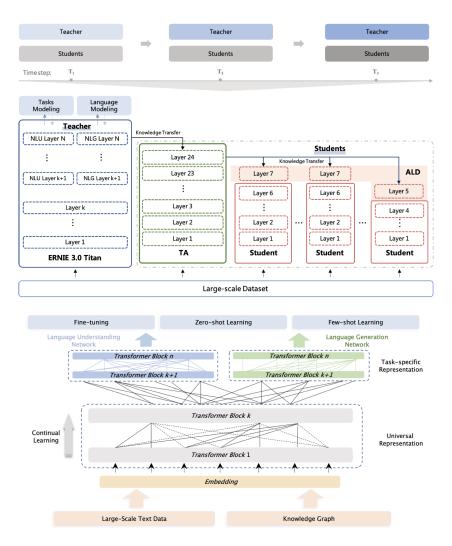


Figure 6: ERNIE3.0 model. Top: Teacher student structure; Down: using knowledge graph

In this part, we classify the passages according to their emotion and their topics. The whole part mostly based on ERNIE-titan. Except for plain texts, ERNIE3.0 has also been trained on a large scale knowledge graph. This universal pre-training enhances the ability of knowledge extraction. Besides, ERNIE3.0 combines both auto-regressive network and auto-encoding network, so that the trained model can handle both natural language understanding and generation tasks through zero-shot learning, few-shot learning or fine-tuning. [8] For ERNIE-titan, they promote two techniques called OFD and ALD to distill the large model and get great result. With ERNIE-titan, We evaluate how well these classification labels fit to their titles and determine whether we should display the passages to the users.

3.4 Web App Deploy

Informed by [3], we depoly a web app through streamlit to enable customized and interactive processing (As first shown in **Figure 1**). For the output part, we utilize the title and context processing results, support ranking final result by (positive/negative) emotional tendency and title scores. We also offer easily parameter selection interfaces and different demonstrating styles as shown in **Figure 7** and **Figure 8**.



Figure 7: Web App interface for selecting search engine and title processing

Moreover, streamlit also supports us to deploy the project on cloud server, allowing users to get access to the search engine from different devices. For more detail, please visit our github repository . We believe after further tuning and refining, this project is practical in real daily life.

4 Results

Some search results' are shown in Figure 9, 10 and 11. We also recommend watching the demo



Figure 8: Web App interface for selecting context processing and out put method

5 Discussion

In this project, we implement a practical adjusted search engine, which we hope can mitigate the concerns about "clickbait" and "information cocoon". Because of time and resources limitation, we only perform five rounds of updates about functions and interfaces, we plan to enable parallel processing to accelerate the searching and processing.

6 Contribution

Report part: Zhengzhao Ma finishes Content Gaining (part 3.1) and helps checking the report; Zihan Zhou finishes Context Processing (part 3.3) and helps checking the report; Zihan Qiu finish other parts of the report and edits the Latex file.

Code part: Zhenzhao Ma contributes for the search parts; Zihan Zhou offers related files about context processing; Zihan Qiu finishes the codes for title processing and web app deploy, organizes all the codes.



Figure 9: Search result with getting keywords, summary and folding initial content



Figure 10: Search result with title classification, getting keywords, summary and folding initial content

结果4 武大与华为联合打造1全球首个遥感影像智能解译演度学习开源框架上线类别: news_tech (概率 0.80)
第4个文本处理结果的 extract_keywords 为:

['遥感图像', '遥感分类,'遥感处界', '遥感场景,'LuoJiaNET系统']

第4个文本处理结果的 get_summary 为:

武大发文宣 "神奇": 首个遥感影像样本库,与全世界用户开源、生产应急等工作;此前该系统曾在微信里进行自主研修(图)

原始正文内容

日前,由武汉大学与华为团队联合打造的全球首个遥感影像智能解译专用深度学习框架"LuoJiaNET"和业界最大遥感影像样本库"LuoJiaSET"在华为昇思社区上线,向全世界用户开源、开放,并接受公众的性能测试、应用开发。随着温感图像被海量采集和生产,正成为日常生活中必不可少的信息资源,也越来越依赖电脑对基进行分类、检索、辨识等工作,而电脑完成这些工作需要解译软件。LuoJiaNET就是一款遥感影像智能解译软件,通过人工智能深度学习,让电脑处理图像越来越"聪明"。6月8日,记者在武汉大学信息学部遥感

信息工程学院采访该项目负责人胡翔云教授。他评价LuoJiaNET,"我们突破了遥感影像解译中幅面小、类型少、尺度有限、通道有限的局限,通过深度学习,不断迭代,它会越来越准确,不断逼近人类的水平。"温密,在中科院院士養健雅教授的关心和指导下,LuoJiaNET是工集了遗感学院。测途温感信息工程国家重点实验室。计算机学院中青年学术号干的武汉大学团队和华为公司MindSpore框架团队合作研发的,双方共享知识产权,联合申请发明专利。胡翔云教授介绍,LuoJiaNET团队约12人,平均年龄27岁,由张戏副研究员带领与华物与界腾团队合作,1年半来开发了823%(约388万行)代码,终于搭建出LuoJiaNET系统。这个系统包含一套新的浓度学习框架和遥感场景分类。目标检测、地物分类、变化检测、多积角三维重建等五大类基础温感应用模型。武大研发团队,中间飞机附宏、元边为张戏副研究员(负责LuoJiaNET)、左边为美食存副研究员 (负责LuoJiaNET)、自动自由的重的影响,LuoJiaNET也是一款基础软件,"好比一座房子,LuoJiaNET就是建房子的砖,任何人都可以在其基础之上再开发各种应用软件,拿着我们的砖去盖不同的房子。"胡翔云表示,"比如现在热门的自动驾驶,车载相机在行驶中要进行图像辨识、解析,其模型也可以基于它来构建,未来这些砖头搭建在手机上、卫星上,都没有问题。LuoJiaNET完全是我们自主研发的,它支持主流的COV,GPU和Windows、Linux操作系统,并对华为的界腾PD人工智能软硬件做了优化。遗愿是一个战路技术,LuoJiaNET可以实现我国遥感解译领域的自主可控。"在上线开源之前,LuoJiaNET在武大权内进行了充分测试,不仅在遥感应用上满足各类型解译任务,而且在一些关键指标上颇具优势。的对金型分别认为图像是由像衰组成的,通感解解译的一大任务就是要给每一个像素贴标签,这个点型底里代分,是从是从还是草地了就是遗愿分类,也是遗解译中的核心问题。目前通常做法是,将一张大图裁成碎片,再一张一张解析合并成大图。而uoJiaNET从最开始的底层框架设计就走整体大图片的逻辑路线,识别一个点,可以把周围的很多信息关联

Figure 11: Search result with title classification, getting keywords, summary and unfolding initial content

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