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Independent Research Project
Final Report

Current Content Discovery for Module Teaching

by

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Abstract

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1   Introduction

1.1   Problem background

Since the emergence of the first Business schools in the late 19th century [45, 38], several distinct pedagogical teaching strategies have been applied. First institutionalized at Harvard Business School [18, 6] in the early 20th century, a method about teaching students with real world business cases (will be called *case method* in the rest of the thesis) has been found more effective and engaging [47, 4, 27] than many traditional, for example, big lecture based, teaching methods. The case method is valued as a form of *active learning* methods for students, for its ability to expose students to complex, context-specific problems that lack clear-cut solutions. As such, it has found wide adoption across the world [46, 12].

However, despite its aforementioned adoption and performance in business school teaching, the case method faces a significant constraint: the availability and collection of timely and relevant case material [41, 32]. In particular, Christensen has identified in his classical article that instructors would have to conduct "extensive preparation" [9] for case method. Another factor contributing to this constraint of case method is the ever-evolving business world and the necessity of the latest information: Clark argues that, because learned skill will lose value quickly in five years, it is critical for students to be up to date to remain relevant in the business world [10]; McFarlane emphasises the importance of updated cases, as otherwise students could be disengaged or discouraged [28].

1.2   Past advancements in information retrieval

During the past two centuries, a number of key developments have profoundly expanded an individual's capacity to retrieve information about the world. In the early 19th century, the transmission of information was still traditional — carried by person on paper or simply remembered. This fundamentally limited both the speed and geographic reach of information retrieval. The invention of telegraph in the 1840s by Morse, Cornell, and Henry [39, 26], notably with Morse's first telegraph message, "*What hath God wrought?*" in 1844 [30], marked a paradigm shift by enabling very fast transmission of encoded information over relatively short distances (w.r.t. the earth) via wired networks. This technological innovation was considerably improved by the invention of the telephone by Bell in 1876 [49, 14], enabling communication directly by human voice, instead of encoded Morse code.

Wired communication is critically constrianed by geographical features on where the wires were laid. Around the late 19th century, Marconi's experiments with wireless telegraphy [13] and the first successful transatlantic signal in 1901 [3] introduced electromagnetic wave-based wireless communication, eventually accumulating into the world's first voice broadcast by radio in 1906 [44]. These milestones collectively redefined the temporal and spatial boundaries of information access.

The next many decades have seen people improving on the serious limitations of wireless communication: signal strength, interferences and attenuation, carrying capacity, and even deliberate sabotage during war times [17, 50, 1]. Theoretically, Hartley observed a logritham pattern of information capacity [19] and then Shannon expanded on it to first define *bits* and *entropy*, giving a formal mathematical theory of information [42] in 1948. Meanwhile, engineers

were experimenting with alternative modulation techniques, notably frequency modulation (FM), and the concepts were formalized in the 1930s [20].

As the theoretical understanding of information progressed, people began to have the idea of *searching* for information based on content and by relevance, instead of by unique identifier [36]. Actually, the term *information retrieval* was not invented until Mooers coined it in 1950 [29]. Since then, information retrieval systems have quickly evolved, and went through four phases before 2000: "(1) manual and mechanical devices; (2) offline computing; (3) online computing, vendor access; (4) distributed, networked, and mass computing." [16], with the last three substantially contributed to by the invention of the Internet [25], and consequently the emergence of search engines in the 1990s [40, 31]. For the next two decades, search engines greatly expanded in speed and coverage and has been significantly impacting the society's information for at least a decade [8, 22]. Nevertheless, one would need to carefully craft search engine prompts into clearly and precise list of words or a short sentence, often necessitating the use of advanced search features, such as boolean query (i.e. use logical connections like AND, OR) to achieve desired performance [2, 33].

LLMs have undoubtedly entered and transformed many areas, including daily life, business and the industry, and research [11]. One strong appeal of LLMs is that they could process user's natural language input and generate natural language output in return with remarkable resemblence to what a human would say [52, 24]. However, because of the inherent limit of neural networks, some argue that they could not formally reason about what they output [37, 23, 35]. Indeed, hallucination [21, 34] and other forms of distortion of facts, is a big problem of LLMs. On the other hand, although search engines rely on determinstic algorithms that give precise reference to searched result, they could not compare with LLMs' ability to process search prompts and summarize results.

Therefore, various attempts have been made to integrate LLMs with search engines [51, 43, 48]. Specifically, Xiong et al. proposes to categorize them into "LLM4Search" and "Search4LLM", where "A4B" means using A to improve B [51]. Here is where my thesis will build upon. Now, with the help with LLMs that can easily process frivolous natural language input, I plan to integrate them together to boost information retrieval further, especially in the area of business school teaching content discovery.

To summarize the above overview of the history,

- Information retrieval had been a manual, incomplete, and slow process for many centuries.

- Technical inventions and theoretical advancements in the 19th and 20th centuries improved on all of the aspects, greatly increasing the reach and speed of the spread of information.

- The invention of digital computers had transformed the manual labor of searching for and filtering information into a semi-automatic manner. Additionally, the Internet has connected the previously separated information storages around the world.

- Still, current search engines operate semi-automatically, requiring careful craft of search prompts. On the other hand, LLMs allow for frivolous prompts but often hallucinates.

1.3 Goals

In this project, I will attempt to improve the current state of information retrieval (mostly limited to business teach related information) further by designing and developing a software system. More precisely, these are the goals:

1. By combining LLMs and search engines, compensate each other's weakeness in information retrieval.

   (a) The system shall improve search engines on prompt engineering to the extent that a user would only need to give a rough and vague natural language description of the target information to the system.

   (b) The system shall improve LLMs on result credibility and interpretibility. If pure LLMs lack the two properties, then combination with deterministic and well-designed ranking and searching algorithms in search engines will compensate for that.

2. Enhance the automation of the current general public information retrieval tools, e.g., Google search, ChatGPT, to the extent that a user would only need to occasionally configure the system, instead of giving search prompts each time.

3. Specially tailor the system to business teaching related information, aiming to gather information from authentic and reliable sources.

4. The system shall support up-to-date information retrieval. More precisely, the system shall support the user to specify a time range of information, and the user is allowed to set the end of the range to the current time.

5. The system could support user feedback and learning from it to provide information more close to one's need.

1.3.1 Not included in the goals

On the other hand, these possible targets are beyond the scope of my project:

1. Providing a method to rank business information. This is rather subjective and I believe is better left for the user to judge.

2. Enforcing strict security measures. Because the use group of the system is limited to business school teaching teams, enforcing output security or censorship of harmful or adult content is not a goal.

2 Methods

2.1 Architecture

Based on the goals, the system is designed to be a chain of tools invoking each other.

What directs the system is the user's configuration, which is expected to include

1. A time range of information to retrieve.

2. A natural language description of the types of information to retrieve.

3. How the retrieved information is sent to the user.

4. A frequency of running the tool.

Based on the configured running frequency, the tool runs, which

1. Use LLMs to translate the configured description and generate a list of search engine prompts.

2. The prompts are fed to search engines, with the configured time constraint.

3. The search results are gathered and processed. How the information is processed and filtered may rely on other AI systems like a rule-based expert system.

4. The processed results may be summarized by LLMs.

5. The results are sent to the users via the configured ways.

6. Optionally, the user gives feedback to the results. The tool can thus improve on the search engine prompts, the information processing, and LLM parameters, based on the feedback. The improvement algorithm may use something like recommendation algorithms. Then, the tool can iterate on the user's configuration automatically.

Figure 1 demonstrates my architecture design and the workflow of the system.
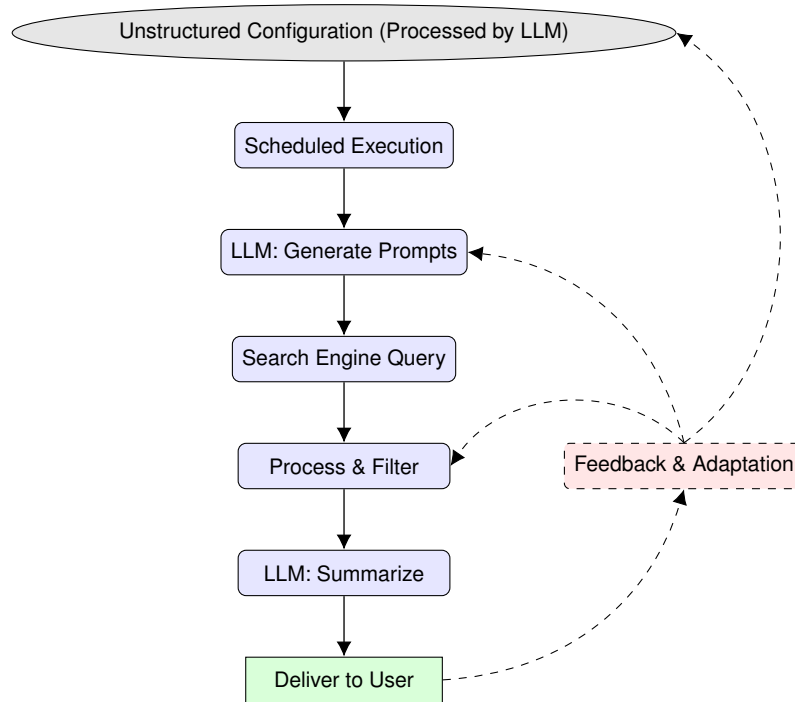

Figure 1: Architecture and operational flow of the software system

What directs the system is the user's configuration, which is expected to include a time range of information to retrieve, a natural language description of the types of information to retrieve, how the retrieved information is sent to the user, and a frequency of running the tool.

2.2 Implementation plan

In this section, I give the plan of my implementation. It is for the project plan and only has specific directions, not concrete programming language, tool, or frameworks, as they will subject to tests and changes during the project. In the thesis, I will replace them with details.

2.2.1 Configuration format

LLMs have demonstrated unprecedented ability to process unstructured data [7, 5]. Thus, it is desirable for the system to accept unstructured configuration from the user. The user may give a natural language description of the wanted information, give some examples, e.g., URLs, or simply feed the LLM the teaching slides and videos from previous classes.

Nevertheless, there are a few configurations that must be formatted.

1. A range of time for the information retrieved.

2. (Optional) A list of sources (e.g. websites) to always include or exclude.

3. The destination of the collected information (e.g. email addresses of teaching staff).

Of course, LLMs can still try to infer them from the given unstructured data, but they must be presented to the user for her to decide and correct, because these configurations are strict and a little error will have great effects.

Another important output from unstructured configuration is the search prompts or insturctions generated by the LLMs. As this output direct controls the information retrieved. LLMs for this task will be specifically tuned to ensure

- Diversity of results.

- A specific distribution of results. E.g., a more authentic website will contribute relatively more information.

2.2.2   Scheduled Execution

Based on the configured running frequency, the system will run every once a while automatically. The scheduling component must handle different frequencies (daily, weekly, monthly) and manage execution timing to avoid overwhelming external APIs or generating excessive costs. This involves implementing a robust scheduling system that can handle failures, retries, and load balancing across multiple users.

2.2.3   Multi-Source Search Integration

One problem of search engine APIs is that they have ungenerous search limits [15], allowing about 1000 queries per month, which is not enough for frequent testing and prototyping.

As a result, I plan to use some other self-developed system in parallel with search engines, which do only a small amount of tasks that truly require whole Internet searching. The majority of the searching will be handled by scraping a limited sets of websites, most likely.

2.2.4   Content Processing and Filtering

Search results will be gathered and processed through a multi-stage filtering system. This involves content deduplication, relevance scoring, source credibility assessment, and quality filtering. The processing pipeline will need to handle various content formats including articles, reports, videos, and social media posts.

The filtering system will combine rule-based approaches (such as keyword matching and source whitelisting) with machine learning techniques for relevance scoring and content classification. Natural language processing techniques will be employed to extract key information and assess content quality. The system will also need to handle different languages and cultural contexts in business information.

2.2.5   LLM-Based Summarization

Processed results will be summarized using LLMs with business-focused prompting strategies. The summarization component must balance comprehensiveness with conciseness, ensuring that key business insights are preserved while making information digestible for educators. This involves developing prompting strategies that can identify the most relevant information for case method teaching and present it in a structured format.

The summarization process may involve extractive techniques (selecting key sentences from original content) and abstractive techniques (generating new summaries). Different summarization styles may be needed for different types of content and user preferences.

2.2.6 Delivery and User Interface

Results shall be sent to users via configured methods, which may include email summaries, web dashboards, or integration with existing educational platforms. The delivery component shall handle different user preferences and ensure information is presented in a format suitable for educational use.

2.2.7 Feedback and Adaptation System

The system shall collect user feedback on result quality and relevance, using this information to improve future searches. This involves designing feedback mechanisms that capture both explicit user ratings and implicit behavioral signals. Possible algorithms include recommendation algorithms and other machine learning models.

2.3 Technical Considerations

The system will be a high-level program, which calls for simply programming languages like Python. On the other hand, the system may have specific performance requirements, especially for LLMs and other machine learning algorithms. The likely result is a combination of different programming languages and technical frameworks.

2.4 Evaluation and Validation

System effectiveness will be evaluated through multiple metrics including information retrieval precision and recall, user satisfaction surveys, time savings measurements, and comparison with manual search processes. Evaluation will involve collaboration with business educators to assess the practical utility of discovered content for case method teaching.

The system will be tested with different types of business information requests and across different time periods to ensure robust performance. A/B testing may be employed to compare different algorithmic approaches and user interface designs.

3 Results

4 Discussion

5 Conclusion

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