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Independent Research Project
Final Report

Current Content Discovery for Business Module Teaching

by

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AI Acknowledgement Statement

I have used two LLM tools to help with programming, each of which has individual use cases:

1. ChatGPT 4 and 5 (5 was released during the project, and OpenAI forced the switch. I did not intentionally switch to it for any reason.) **Publisher**: OpenAI. **URL**: `https://chatgpt.com/`. **Usage**: *Help me diagonose errors like C++ compilation or linkage errors; suggest libraries alternatives when one didn't work; help me learn to use a third-party library or Python module fast.*

2. Claude AI. **Publisher**: Anthropic. **URL**: `https://claude.ai/`. **Usage**: *Help me generate very (logically) simple code that would be tedious to write to hand. Three cases in my project: 1. tedious GUI elements creation (not all GUI elements; some special UI elements are manually written) 2. tedious logging (I adjusted the logging sentences). 3. tedious unit test cases (not all cases. Some cases are special and I manually wrote them). I also review and adjust generated code.*

I confirm that all submitted works are my own, despite the assistance from those LLM tools.

Abstract

Business school teaching using the well-known case method requires a substantial amount of information about latest business events to keep the course relevant. Digital technologies like web search engines and LLMs can offer substantial assistance to this process. However, several challenges remain: 1) search engines struggle to process unstructured search queries. 2) while LLMs excel in understanding unstructured input, they have problems in ensure the accuracy and timelyness of retrieved information. 3) these tools still require manual invocation. In this project, I aim to address these challenges by a software system that compensates search engines and LLMs with each other, while also supporting automatic execution of the whole process and the delivery of the results to users, requiring minimal user configuration.

Keywords: information retrieval, LLM, search engines, case method, Business school

1 Introduction

1.1 Project background

Since the emergence of the first Business schools in the late 19th century [68, 60], several distinct pedagogical teaching strategies have been invented. First institutionalized at Harvard Business School [25, 9] 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 [73, 7, 37] than many traditional, for example, big lecture based, teaching methods. Thus, it obtained wide adoption across the world [71, 14].

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 [64, 50]. In particular, Christensen identifies in his classical article that instructors have to conduct "extensive preparation" [10] for it. Another reason is the ever-evolving business world and the necessity of the latest information: Clark argues that learned skill will lose value quickly in five years, and then it is critical for students to be up to date to remain relevant in the business world [11]; McFarlane emphasises the importance of updated cases, as otherwise students could be disengaged or discouraged [39].

1.2 Past advancements in information retrieval

The thesis summarizes the challenges in information retrieval into two general problems:

1.2.1 Problem (1): collect/gather information

During the past two centuries, several key developments have profoundly expanded one's capacity to gather information about the world. In the early 19th century, the transmission of information was still traditional — carried by person on paper or simply remembered. The invention of telegraph in the 1840s by Morse et al. [62, 35], notably with Morse's first telegraph message, "*What hath God wrought?*" in 1844 [42], marked a paradigm shift. This technological innovation was considerably improved by Bell's telephone in 1876 [75, 17], enabling communication directly by human voice, instead of encoded Morse code.

Wired communication is critically constrained by geographical features (where the wires were laid). Around the late 19th century, Marconi's experiments with wireless telegraphy [15] and the first successful transatlantic signal in 1901 [6] introduced wireless communication, eventually accumulating into the world's first voice broadcast by radio in 1906 [67]. These milestones collectively redefined the temporal and spatial boundaries of information gathering.

Parallel to improving the weaknesses of wireless communication [24, 77, 1], reseachers also worked on a theory of information. Hartley observed a logritham pattern of information capacity [26] and then Shannon expanded on it to first define *bits* and *entropy*, giving a formal mathematical theory of information [65] in 1948. Meanwhile, engineers were experimenting with alternative modulation techniques, notably frequency modulation (FM), and the concepts were formalized in the 1930s [27].

1.2.2 Problem (2): identify/find desired information from collection

Although solutions to problem (1) had enormously improved during these times, substantial progress in problem (2) would have to wait until digital computers were invented in the 1940s [76], which were made to repeat tedious operations fast. Actually, the term *information retrieval (IR)* was not there until Mooers coined it in 1950 [41]. The nature of information reveals two subproblems of problem (2): (2.1) how to process (extract useful information from) potentially unstructured data. (2.2) how to related human queries to the content a user actually wants.

According to Griffiths and King, early IR systems (in the USA) were mainly transferring human computing activity (bookkeeping in a library or database) into digital forms, by various sorting, indexing, and searching algorithms [21]. The form slowly went from "offline, batch" computing to "online, real-time" computing, and finally became "distributed, networked, and mass computing",

thanks to the Internet and various of its applications [21, 33]. Then commercial search engines emerged in the 1990s, opearting on the scale of the whole Internet [63, 45].

The aforementioned sorting, searching, and indexing algorithms were partial solutions to problem (2.1) and (2.2), with fundamental designs like inverted index [61, chap. 2], [81, sect. 2], boolean search [61, chap. 1], and various clever ideas such as spelling correction (stemming) [61, chap. 3.3], positional indexing [81, sect. 3]. Because the database can be extremely large, specific index construction [61, chap. 4], [81, sect. 5] compression [61, chap. 5] algorithms have appeared. Also, people saw ample opportunity to explore distributed computing, with the most notable model probably being MapReduce [12].

Nevertheless, these inventions were still mostly doing textual processing, and machines struggled to "understand" information. Thus, advanced and complex search queries are often needed to achieve desired performance [2, 53]. The research on making computers understand natural language (NLP), images and visuals (computer vision), etc. were consequently and gradually being integrated into search engines, since 2000, notably with Google's Panda, Penguin, and Hummingbird algorithms that aim to understand web content better to rank them in searches [49].

One major breakthrough in NLP is Vaswani et al.'s transformer [72]. Building upon it, OpenAI created generative pre-trained transformers (GPTs) trained on massive amount of data [52], which, after a few iterations, evolved into a chatbot facing the general public, ChatGPT, and it was perhaps then when LLMs started to recieve massive amount of public attention. Here, LLM stands for large language model, language models that are *large* in trained data and parameters.

Although public attention is not the same as academic importance, LLMs have undoubtedly entered and transformed many areas, including daily life, business and the industry, and research [13]. One strong appeal of LLMs is that they could process unstructured natural language input and generate natural language output in return with remarkable resemblence to what a human would say [79, 32]. However, because of the inherent limit of neural networks, some raise concerns about their formal reasoning capabilities [59, 31, 58]. Indeed, hallucination [28, 55] and other forms of distortion of facts, is a big problem of LLMs.

Despite the drawbacks of LLMs, they are currently the most successful tool in NLP, and naturally various attempts have been made to integrate LLMs with search engines [78, 66, 74]. Specifically, Xiong et al. proposes to categorize them into "LLM4Search" and "Search4LLM", where "A4B" means using A to improve B [78]. 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 an individual's information retrieval further, especially in the area of business school teaching content discovery.

1.3 Contemporary related work

1.3.1 Retrieval augmented generation

During training, LLMs turn training data into their parameters (also parametric-memory). Its immutability after training is a weakness for information/knowledge based tasks, as information cannot be easily added without retraining. RAG is a general approach to fine-tune a trained model with non-parametric memory [34].

RAG was designed to enrich a trained LLM with a pre-trained retriever. Addressing hallucination is its major concern. Because the retriever also needs to be pre-trained, it cannot inherently solve the outdated training data problem. In fact, their work's retriever, also a neural network,

was trained on a 2018 Wikipedia dump [34, Section 3]. These are the major differences from my work.

1.3.2 Other hybrid methods

Beside RAG, numerous studies were conducted to augment pre-trained LLMs with external knowledge [23, 29, 8, 80, 43]. Some worked on the retriever, some on how information is integrated into the LLM, and some on both. Unlike my work, they focus on question-answering tasks, and none of them had getting the latest information as a requirement.

Among them, Nakano et al.'s WebGPT is perhaps the closest to my work: their retriever is a text-based web-browser [43]. Nevertheless, WebGPT was designed to answer long-form questions, trained primarily to answer questions from a specific dataset. Moreover, it used human feedback to improve quality. These are the differences from my work.

1.3.3 Search engine centric

As the aforementioned studies work on improving LLMs, various works are also committed to improve search engines. Some of them rewrite and improve search queries with LLMs [40, 3]; some turn to assist ranking of search results [69, 69]. My work has both elements: in my project LLM will both be used on search queries and on search result synthesis.

Furthermore, LLMs can potentially help document indexing with their excellent NLP abilities in term extraction [38, 18] and document filtering [57], although the first two cited work do not primarily consider search engine applications.

1.4 Goals

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

   (a) The system shall improve search engines so 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 reliability and accuracy. If pure LLMs lack the two properties, then combination with deterministic search engines, using deterministic and accurate algorithms.

2. Enhance the automation of the current general public information retrieval tools, e.g., Google search, ChatGPT, so that user would only need to occasionally configure the system for it to schedule running automatically.

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. It should support restricting the date range of results.

5. (Optional) The system could support user feedback and learning from it.

1.4.1 Not in the goals

1. Providing a method to rank business information. That is rather subjective.

2. Design, build, and train a LLM. That is too much work for the time.

2 Methods

2.1 Design philosophy

The core of this project is a big software system designed to achieve the goals. Considering the scale and complexity of the software system, its development will greatly benefit from a clear design philosophy.

The design philosophy is a set of the following philosophical approaches to develop the system. Approaches 1–3 are from MIT Software Construction [19]. Approach 4 is part of the Unix philosophy [30].

1. *Correct today and in the unknown future*: By developing the system using design concepts like abstract datatypes [36], immutability, and software testing, its current correctness is defended; by defensive programming (type safety, robust checks, etc.), its correctness is defended from my future mistakes and stupidity.

2. *Easy to understand*: Via thorough documentation, static type hints, and again immutability, the code can communicate well with the future me who may need to fix bugs or extend the system.

3. *Ready for change*: The system should be designed to make extensions easy; it would not be ideal to discard and rewrite a lot of code for extensions.

4. *Do one thing and do it well*: The system is composed of a collection of programs, each of which is designed to do one particular job, and all of which are designed to work together.

2.2 Architecture

As clarified previously, the system is a collection of programs working together. What threads them together is a pipeline, taking the user's configuration as input to produce current information about the business topics mentioned in the configuration as output. The workflow of the pipeline is:

1. LLMs generate a list of search engine prompts based on the business topics in the configuration.

2. The prompts are fed to search engines.

3. The search results are gathered and filtered. In particular, filter by date.

4. The processed results are synthesized by LLMs.

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

6. Optionally, the user gives feedback to the results.

The pipeline needs to retrieve current information from somewhere. Thus, another big module of the system is a minimal web search engine that can index business news websites for latest news. The purpose of this self-made search engine is to provide explicit control of the indexed contents and to avoid commerical limitations on the usage. See section 2.2.1 for the complete discussion. Still, third-party search engines are also used to improve result coverage.

Surrounding the pipeline and the search engine are the supporting programs which handle automation, output delivery, and user-friendly (GUI) configuration management. Table 1 lists all programs in the system and their functionality. They are not full paths, to not overflow the table. The C++ programs can be found in `src/CMakeLists.txt`; the Python scripts can be found in `src/`.

indexer, searcher, updater	Build a search engine database from scratch, search a database, and update a database by adding new entries from RSS and removing old ones, respectively.
rm_doc, upd_doc	Tools intended for the developer (me) to fine-tune the database by removing and updating specific documents in it, respectively.
llm_pipeline.py	The main pipeline program.
config_gui.py	A user friendly GUI program to configure the system.
search_combined.py	Obtains the search result from my custom search engine as well as Google, filters them, and combines them.
setup_schedules.py	Schedule automatic executions for various programs in the system to make the system automatic.
tests/*	Unit tests
misc/*, doc_dist	Miscellaneous programs for analyzing the system in the results section.

Table 1: All programs in the software system

Figure 1 demonstrates my architecture design and the workflow of the system, where blue boxes form the pipeline, the yellow boxes are the other supporting programs, and the red box with the dashed lines are optional.
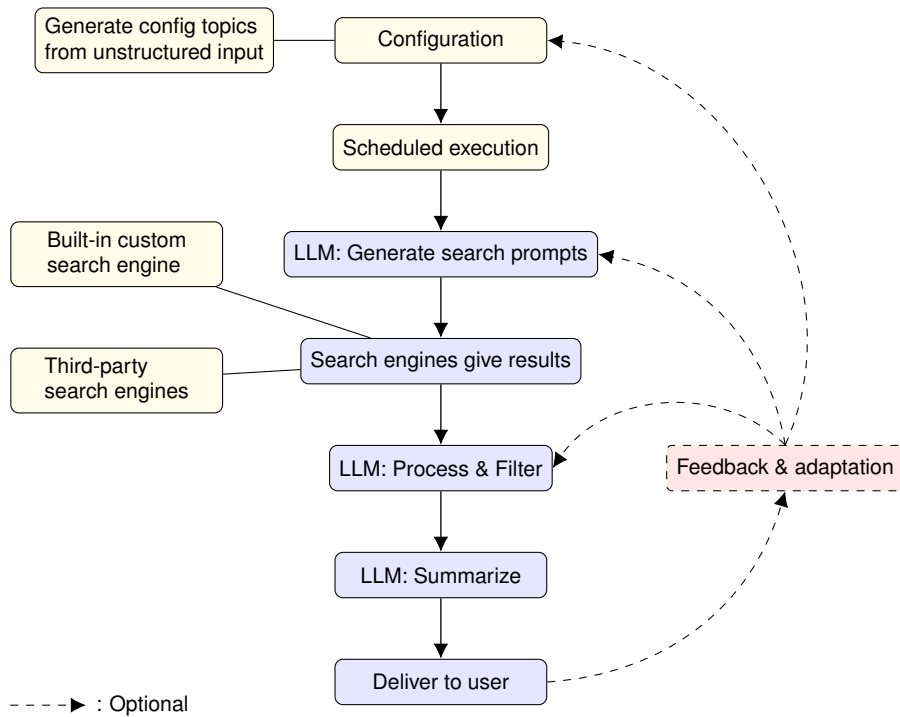

Figure 1: Architecture and operational flow of the software system

2.2.1 Search engines

The easiest way to integrate a web search engine is to use a commerical search API, building upon the large database the commerical company provides. However, this suffer from a few serious problems.

1. The free-tier APIs often have various ungenerous limits, e.g., number of queries, number of results returned, and filtering of search results. For instance, see Google's [20].

2. The mechanism of the search engines is proprietory; I cannot control what they give. This is a big problem, because my goal is not about retrieving general information but specific information of business teaching value.

Therefore, I plan to use my custom minimal search engine alongside commerical search APIs. The custom search engine will address the two problems with unlimited usage and specific information retrieval. To achieve the latter, I configure the search engine to *only* index business news websites. Clearly, I will not have the resource to index most of the Internet and store them, and this coverage weakness will be compensated by the use of commercial search APIs.

2.3 Implementation detail

Following the design philosophy and architecture, here are the details of the implementation.

2.3.1 Configuration format

Most of the configuration have to be exact, e.g.,

1. Scheduled time of the executions.

2. A list of email addresses to deliver the results to.

3. System prompts.

The business topics in the configuration are used as input to the system. Here, LLMs will be used to extract them from unstructured data, including both user natural language input and images input[1].

2.3.2 LLM invocation

Considering the heavy use of LLMs and the strict limitation of commercial LLM APIs [48, 4], the project will use local LLMs powered by Ollama [46].

Ollama provides two main modes to communicate with LLM, `generate` and `chat`; both access the Ollama local server at `localhost:11434` via HTTP POST. Because the system is not interactive, only the `generate` method is used.

Apparently, the system prompts are essential to our tasks. There is generally no fixed algorithm to derive the best prompts given to LLMs, as the results not only depend on many aspects including how the input is given, but also probably are not deterministic, given that probalisitic processes are widely used in deep neural networks and complex machine learning models. Thus, the only way to obtain desirable prompts is to manually craft the prompts and test them.

Initially, each stage invoking LLMs was one-shot (using only one invocation of the LLM). Later tests revealed that this approach was extremely hard to tune for all situations. Therefore, I turned to have a multi-stage invocation for each step, enabling the LLM to focus on one specific task at one time.

The manual tests are done in two ways. The straight-forward way is to directly change the prompts in my system, which is easy, thanks to the fact that I put them in configuration. Still, this requires running a large part of the system and is inefficient. Another approach involves

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[1]For all the configuration entries, see `config.py`.

OpenWebUI [5], a GUI tool that allows me to interact directly with the LLM models via a web UI. Note that the models there are in `chat` mode instead of `generate` mode. Nevertheless, practice proved that prompts good in chat mode is still useful in the generate mode.

The LLM models are selected prioritizing usability on personal computers. Thus, the maximum number of parameters is limited. Among all the models Ollama offers [47], I chose `llama3.1:8b` for its competitive ability on text generation and summarization, proven by several academic studies and benchmarks [56, 54, 70]. Unfortunately, llama3.1:8b is text-only. When the user uses images to generate business topics, as mentioned earlier, another model fine-tuned with llama3 instructs, `llava-llama3`, is used.

2.3.3 Search engines

My custom search engine is implemented in C++ with `libcurl` for url handling, `lexbor` for HTML parsing, and `xapian` for database building and searching. Also, `pugixml`, `boost.url`, `boost.test`, and `amosnier/sha2` are used as support libraries. Finally, Python is linked to call Python functions inside C++.

The custom search engine's algorithm is similar to the mainstream ones: Starting from initial urls, scrap each. And for every url found in each, scrap them too. More precisely, the indexing of a webpage and the recursion into its urls included are controlled by four predicate filters. Two are on URLs and two are on the webpages. A webpage is indexed if both URL & webpage index predicates return true; each of its url is considered further if both URL & webpage recurse predicates return true. I separate the URL & webpage predicates because I can then delay scraping of a webpage only after its URL passes the conditions.

When search prompts generated by LLMs are given, they will be fed to both my custom search engine and Google's programmable search engine, with their results combined and filtered.

2.3.4 Task Schedulling

The scheduled tasks are installed on the target operating system via cron, a task scheduler on Unix-like systems. Before the tasks are actually installed, the installer script will check if two jobs execute at the same time and abort the installation if they do, to avoid parallel access to the custom search engine database.

2.3.5 Report delivery

The results, finally summarized as a report, is sent to the users automatically via email. Because the code is visible in the repository along with the login credentials, I registered a burner Google account for email delivery. The configuration records a list of destination email addresses, to each of which the final results of running the pipeline will be sent from the burner account. The protocol is SMTP + TLS to ensure that the email content is confidential.

3   Results

This section demonstrates the completed system. Next, using the same inputs, information retrieved by mainstream LLMs & search engines are also displayed for comparsion.

As a Business School teacher, Sean O'Grady provides me with a list (LIST 1) of topics from his modules which will be used as inputs for demonstrating results.

1. Vertical integration

2. Diversification

3. Competitive advantage

4. Foreign direct investment

3.1 Completed system

3.1.1 Configuration GUI

The GUI used for end-users to configure the pipeline is implemented in Tkinter [51], a Python GUI interface. By the principles in section 2.1, the configuration is divided into different separate `ConfigSection`s, each of which is managed by a GUI class inheriting from base class `Config SectionFrame`[2].

Figure 2 is a screenshot of the GUI.

Figure 2: Configuration GUI

3.1.2 Custom search engine

Recall that the main goal of developing this custom search engine is to restrict information sources by explicit control over it. Figure 3 displays[3] the host distribution of all the indexed data on my personal computer, as of 7 August. Unfortunately, because of the volatility of the Internet content, the exact data is probably not reproducible. Arguably, all domains from the database are reputable Business news publishers.

Since it is entirely local, its response times are anticipated to be much shorter than web-based search engines. Nielsen claims that having a ≤ 0.1 second response time makes users experience instantaneous interaction [44, Chapter 5], a standard I expect it to achieve.

To verify this anticipation, a performance profiling is conducted using around 100 search queries generated by LLM for representativeness. Figure 4 contains[4] the result; all except one of average response times are below 0.1 second.

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[2]The source is in `config_gui.py`.

[3]Produced by `src/misc/doc_dist_pie.py` and `src/search/tools/doc_dist.cpp`

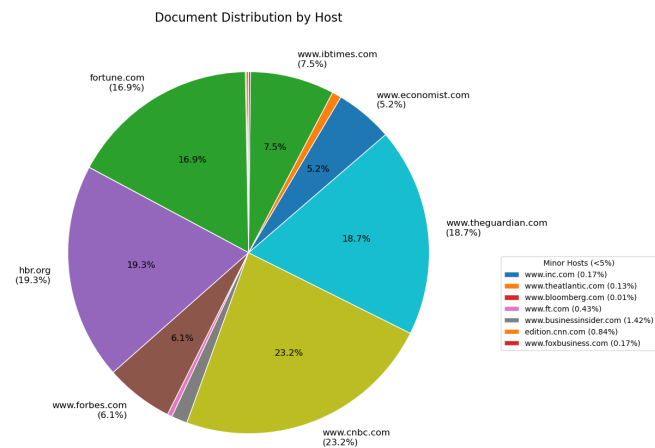[4]Produced by `src/misc/search_eng_profiling.py`.
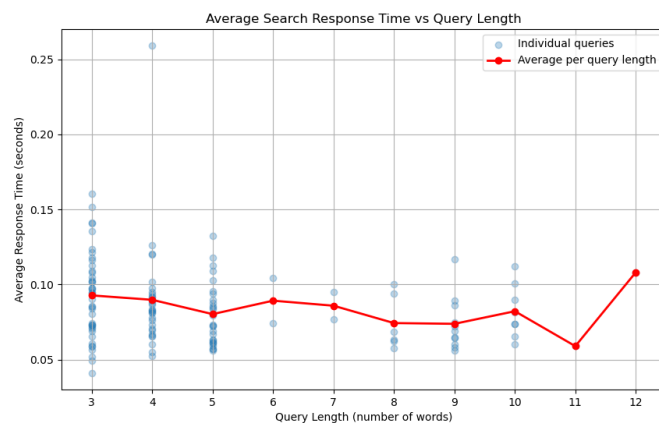
Figure 3: Indexed document host distribution

Figure 4: Average response time vs. query length

3.1.3 LLM invocation

LLMs are invoked with two main purposes in the project, search query generation from business topics, and filtering + synthesis of search results.

Table 2 lists the results of search query generation, using inputs from LIST 1. They are collected from the output of `llm_pipeline.py`. The results demonstrate very high relevance to the topic, although one of them cites an old year (... trends 2024 examples). A search query is judged as relevant, if it contains the exact phrase or synonyms, or express the same meaning as the topic.

Topic	Search Queries	Relevance
Competitive advantage	innovation strategies for business competitiveness intrapreneurship best practices for sustainable growth tech firms leveraging digital innovation to gain market edge sustainable competitive advantage through emerging technologies examples Amazon supply chain innovation Walmart logistics strategies	1, 2, 3, 4 (4/6)
Vertical integration	vertical integration advantages and disadvantages pros and cons of integrating supply chain vertically Vertical integration success stories Failed vertical integration examples in manufacturing industry	1, 2, 3, 4 (4/4)
Diversification strategies	Diversification strategies mergers acquisitions recent news M&A diversification trends 2024 examples geographical expansion impact on company performance case studies expansion into new markets and its effects on corporate success stories Product line diversification vs market expansion best practices	1, 2, 3, 4, 5 (5/5)
Foreign direct investment	Effects of foreign direct investment on local job market and labor laws in India and China Foreign investment impact on domestic employment and labor regulations worldwide Foreign direct investment emerging market economic growth Economic development in emerging markets foreign investment impact	1, 2, 3, 4 (4/4)

Table 2: Relevance of generated queries

The results of search summarization are even harder to qualify objectively. An objective merit is that the LLMs can sometimes uncover surprising angles, while an objective shortcoming is that the summarization quality sometimes cannot meet expectation. One novalty in the summarization, only discovered in late stage after several testing, is to make LLM output individually for each search result a relevance number, which is used for filtering and reranking, instead of giving all results to the LLM, in which case the LLM often distort the search results.

3.1.4 Walkthrough

The full system starts with the user's configuring the system: business topics, system prompts, automatic scheduelling, the accounts (sender email, destination email, and Google search API key). All of them are configured on the GUI.

After the configuration, a setup script needs to be run to install the schedualling tasks on the operating system. The user should also run the indexer to initialize the custom search engine database. Then, at scheduled times, the LLM pipeline and database updater will run.

The LLM pipeline starts by reading the business topics, then

1. Invoke LLM to divide each topic into a diverse range of subtopics.

2. Invoke LLM to generate search queries for each subtopic.

3. Invoke both the custom search engine and Google's to produce search results and combine them.

4. Invoke LLM to filter and rerank the search results.

5. Invoke LLM to summarize all of them to a final report.

6. Send the final report to the configured destination email addresses.

The result includes both a final report and a directory of intermediate results (e.g. search queries generated and raw search results), and thus cannot be included in this word-count-limited thesis. Moreover, the use of LLM makes them non-deterministic. The reader can instead run the pipeline herself to examine output.

The database updater pulls the latest business news from the RSS feeds of reputable Business sites, and then also removes the oldest documents from the database, if the total number of documents exceeds a limit.

The user is free to reconfigure the system, and the changes will be reflected the next time tasks are run.

3.2 Results from mainstream tools

I feed the same input to mainstream tools. Later in the Discussion section, I will compare them with my system.

3.2.1 ChatGPT

When given the exact four topics used to produce Table 2 and asked to summarize current business news about them, GPT-4.1-mini produced remarkable result[5]. For each topic, it summarizes three recent examples that are all relevant. However, from the sources it cites, a few issues can be identified:

1. Some of the search results of ChatGPT did not originate from reputable Business news publishers, including sources from "The Motley Fool" and "AInvest".

2. ChatGPT failed to find only sources from 2025, despite the presence of "current" in the prompt.

3.2.2 Google

The four topics are each separatedly given to the Google search engine, using the phrase "Current business news about [topic]"[6]. Note that the results are purely identified by the URIs with the search queries embedded in. As Google continues to update its service, there is no guarantee that the observed results will remain the same.

Compared with ChatGPT, Google performed worse for all four topics. Each results page contains some websites that describes/elaborates on the topic itself or websites that act as a collection of articles on the topic, instead of Business news about it.

However, sometimes the AI Overview would trigger for the search results, but that shares the same problems of ChatGPT. Worse than ChatGPT, Google's version will also include webpages that are not news articles at all. Figure 5 displays Google's top results with and without its AI Overview.

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[5]link `https://chatgpt.com/share/689a428d-f01c-8011-a115-57b4ca19a278`
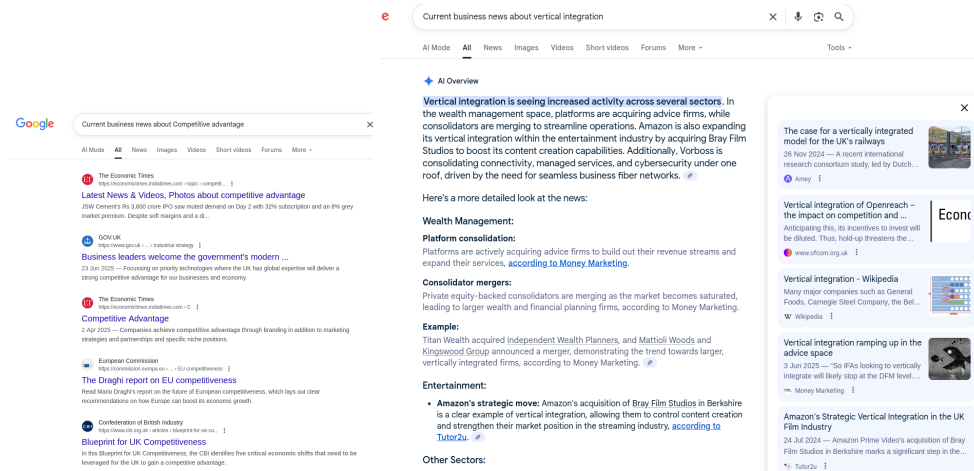[6]Results as clickable links: 1, 2, 3, 4.

Figure 5: Google results on the topics

4 Discussion

4.1 Analysis of results

4.1.1 Alignment with design

The system conforms to my design philosophy and methodology strictly, except in a few places.

Carefully designed OOP class hirerachy and interfaces are used in both C++ programs and Python scripts; interfaces of classes are chosen to make them highly cohesive and loosely coupled. In C++, `const` is widely applied to ensure immutability of data classes after construction. Comments cover all functions, except for trivial ones whose name gives its meaning. Unit testing were conducted for important features, because time constraints prevented me to test all features. These together adhere to design philosophies 1–3.

Executables are separated to mostly doing one thing, often taking another's output as input. This adheres to design philosophy 4.

Except for the optional feature of accepting user feedback and self-improving, all features mentioned in methodology are implemented.

4.1.2 Fulfilment of goals

Goal 1(a) is fulfilled, since the user only needs to give unstructured text/images as input. One limitation of the system, however, is the lack of support for other different file types, like lecture notes in PDF.

Goal 1(b) is fulfilled, by having a custom search engine only indexing reputable Business news websites, and having both it and Google search only results in specific date ranges. Both of the measures are deterministic, providing reliability and accuracy to the system. Conversely, site-limiting indexing inherently is inflexible and lack coverage of good information from less reputable sources. A fixed range of dates also excludes the possibility to include old discussions of concurrent events that spans a long time.

Goal 2 is fulfilled by the pipeline, which can be schedulled for execution, once the user configured the system. Still, the automation can be further improved by having a LLM generate all the configuration, with only a natural language description from the user. Alternatively, I could

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exchange some automation for more accuracy of the system, by having the pipeline interrupt the user in the middle, asking her to select from the generated subtopics/search queries.

Goal 3 is fulfilled by indexing only specific websites in the custom search engine, too. Beside the inflexibility and coverage problem mentioned earlier, the metric of reputability is inherently subjective. In this project, I took advice from Sean O'Grady and consorted rankings of Business news websites [22, 16].

Goal 4 is fulfilled by using LLM only on real data from the search engines. However, this cannot stop LLMs from hallucinating when generating search queries or summarizing them.

The optional Goal 5 is not fulfilled.

4.2   Comparsion with mainstream tools

Against ChatGPT, my system successfully eliminated search results from non-reputable sites. However, my system produced a few irrelavant search queries and could not compete with ChatGPT in summary quality.

Versus Google, my system retrieved more reputable and current information, but lacked in breadth. When Google's AI overview was triggered, its summary quality also appeared to be superior.

Compared with the surveyed studies combining search engine of LLMs which have a focus (either LLM4Search or Search4LLM) [78], my system is a more neutral combination with a more general framework for information retrieval. Orthognoal to their work aiming to address specific weakness of one of the two, my work aims primarily to solve the specific information retrieval problem.

4.3   Examination by a real user

Sean O'Grady, business school teacher, will be a real user of the project. He examined carefully the result for the first item in LIST 1, and informed me that 4 out of the 5 results would be useful to him and help him to enhance the modules they are working on.

4.4   Challenges and future plans

The biggest engineering challenge overcome was implementing the custom search engine. The indexing algorithm is simple, but a search engine spans many different areas of computer science, networking, concurrency, program design, database, algorithms. Many third-party libraries had to be picked and used. Moreover, information retrieval on the current Internet is messy. One particular problem was to handle different URL formats used by different publishers.

The most significant optimization challenge was to fine-tune my pipeline and LLMs. Tuning the prompts is complicated; changing a prompt to solve a current problem may trigger another problem. The multi-stage design was consequently implemented to ensure the LLM focuses on one problem at a time.

The system is significantly limited by the time-span of the project and my resources. Particularly, I had no fund to purchase commercial LLM APIs and could only rely on much less powerful local LLMs, constrained by local computing resources. Additionally, the indexing database of my custom search engine has to be built from scratch. Conversely, the minimal nature of my system enables it to become a free personal solution running locally on PCs.

Most of the system's capabilities could be enhanced with more resources. Nevertheless, there are a few design limitations to improve next:

1. Currently, the LLMs and search engines are loosely coupled (design philosophy 4). But in some cases integrating them more deeply (e.g. at the LLM model level) could be beneficial.

2. Some parts are hard-coded to work for Business topics, damaging its potential to extend for general topics.

3. The system is not designed to integrate with teaching platforms.

4. The system is not designed to be cross-platform.

5   Conclusion

I successfully designed a pipeline and developed a corresponding system that combines LLMs with search engines to supply current content in business school teaching. The system complements each individual tool substantially with another, by limiting indexed websites, deterministic search results, and multi-stage LLM invocation. Moreover, the system achieves more automation than mainstream similar tools.

The methods worked considerably well in fulfilling my project goals. Additionally, examination by a real user also proved its usefulness. However, the system faces significant challenges to become a mature tool for general public usage. While many of them could be mitigated by more resources, such as purchasing a (more powerful) LLM API, or devoting more time to make it cross-platform, the system's design choices exhibit some inflexibility, leaning towards Business topics.

Although my system contributes as an engineering solution and an innovative framework to integrate search engine and LLMs, it is not a theoretical improvement of them; intrinsic problems like hallucination of LLMs and non-semantical understanding of queries of search engines are still present. Future work could also improve the two inherently and replace them in the framework.

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