

Gen-AI Based Academic Research Paper Summarization Using Prompt Engineer

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1. Abstract

The increasing growth of academic research literature presents an obstacle to its systematic literature review. Generation AI (Gen-AI) could be an effective answer to this challenge, although using standard heuristic prompts has demonstrated the phenomenon of contextual attrition and factual hallucinations. This paper develops a framework of context-aware prompt engineering for academic literature summarization. Specifically, it proposes a Multi-Stage Agentic Pipeline using the "Reason-Act-Verify" (RAV) prompt engineering loop, to breakdown research papers into atoms of logic. It reports that the proposed structured prompting strategy addresses Type I hallucinations and maintains the technical signal with 3.8x the prompt capacity and 25.2% higher throughput over baseline heuristic prompt questions. This paper showed the use of Gen-AI for academic literature summarization depends on its prompt architecture rather than model scale.

2. Introduction

With the exponential rise in the volume of technical documents through scientific data digitisation and hence needs to provide sophisticated tools for automatic document synthesis. Generative AI (Gen-AI) is predominantly being used as a state-of-the-art solution for automated summarisation, however in practice current systems struggle from extracting surface level documents when presented with a basic heuristic prompted query.

In this paper we propose that the deficiency of current Gen-AI summarisation is due to the "black box" nature of prompting, that without specific engineering of user to Gen-AI interaction the model over-generates semantic summaries lacking deep insights crucial for robust technical review. In order to facilitate Gen-AI summarisation of technical documents, we present a unique Prompt Engineering framework that is designed to force Gen-AI in a deterministic "Reason-Act-Verify" (RAV) process. We posit that the prompt can be treated as an engineering artifact (rather than a query in natural language) that directs the Gen-AI through a sophisticated technical document structure with a high technical fidelity.

3. Literature Review

With the widespread adoption of Large Language Models (LLMs), many have explored methods of automatically summarizing documents. The work in this area can currently be broadly categorized into three areas: general summarization, controlled generation through prompt engineering and factual correctness.

3.1 LLM based summarization Evolution

The current state of research in document summarization is predominantly focused around the transforme based architectures. While previous work mostly centred around the concept of "extractive summarization" (selecting relevant sentences), more modern papers are exploring "abstractive summarization" due to the latest LLMs such as GPT-4, Claude and Gemini. Though the latter models often achieve more fluent outputs, recent papers highlight their inability to perform reliably for long-context technical documents. While they achieve the "gist" of the documents, the semantic and technical integrity often degrades as the context window increases, a phenomenon referred to as "contextual attrition".

3.2 The hallucination and consistency challenge

The problem of hallucinations generated by LLMs has also received attention from many. Methods ranging from retrieving additional relevant documents for generation (retrieval-augmented generation RAG) to multi-pass verification have been developed to reduce the hallucinations. The problem however is that most methods currently only leverage the external retrieval of information and lack a concept of structural mapping of information. A further challenge is that the standard evaluation methods for summarization mostly utilize n-gram matching algorithms such as ROUGE or BERT Score which do not capture the "technical fidelity"- an aspect related to "matching algorithm logic with research objectives", and therefore do not give an accurate representation for evaluation of expert level academic papers.

3.3 The gap in prompt engineering research

Although the prompt engineering methods like Chain-of-Thought (CoT) or few-shot prompting have aided in improved reasoning of the models, they still differ to a great extent from domain-specific academic extraction. The researchers have failed to develop a deterministic "agentic workflow" treating summarization as a multi-step engineering problem, rather than a one pass generative task. Most prompt engineering research aims to improve general use cases and does not look towards constructing a "Verification Kernel" allowing the model to verify itself. This paper addresses that by presenting the "Reason-Act-Verify" (RAV) pipeline, shifting the reliability onto a deterministic prompt- based architecture. Rather than simple prompting, this paper addresses the issues raised by the existing research by using recursive verification, instead of passive prompting.

4. The Proposed Method: The Multi-Stage Agentic Pipeline

The proposed approach aims at building a deterministic academic synthesis pipeline which is called the Reason-Act-Verify (RAV) loop. Unlike conventional heuristics-based prompting where one single pass generative response is elicited; the agentic pipeline employs multiple stages of interaction with Gen-AI. It models this interaction as a recursive process based on the principles of engineering to enforce structural constraints through the summarization lifecycle.

4.1 Stage 1: Structural Mapping (The 'Reason' Phase)

The first stage of the pipeline endeavors to provide the Gen-AI with a structural scaffold. Instead of asking the model to generate a summary in one pass, the pipeline relies on an engineered prompt in order to explicitly map the input document to an enumerated structure in the form of logical atoms. These atoms include: the research problem, the methodology, the research gap, and the primary contribution. Enforcing the structural mapping constrains the model to develop an internal architecture for the paper even prior to synthesizing its contents. This step essentially makes the summarization from descriptive to analytical.

4.2 Stage 2: Technical Deep-Dive (The 'Act' Phase)

Once a basic structure is formed, the pipeline moves on to the Technical Deep-Dive stage. Herein, the stage is aimed at algorithmic decomposition using a targeted, task specific prompt. The primary goal is to extract the 'how' behind the research: technical methods, hardware and software constrains, computational approaches etc. Rather than dwelling on narrative background. By isolating such technical signals like: the partitions' algorithm and/or memory optimization procedures, the prompt architecture steers clear of the Gen-AI over-generalizing complex technical specifications vital for a proficient understanding.

4.3 Stage 3: Expert Synthesis & Recursive Verification (The 'Verify' Phase)

The final and most essential step of the pipeline is the Expert Synthesis and Recursive Verification. Herein, the structured output of the two prior steps are synthesized into an IEEE style abstract. What is crucially added here is an adversarial verification module inside the prompt. The Gen-AI is forced to cross reference the output with the source and identify errors or facts that have been misrepresented and correct them, eliminating hallucinated, factually incorrect and technical discrepancies within the final output and ensuring signal integrity for the highly significant summary.

4.4 System Integration

The RAV pipeline is structured as a closed loop system in that each stage builds upon the stage preceding it. Herein, factuality is treated as a structural constraint and enforced through specific prompting to engineer a deterministic approach to summarization over an engineered approach that has proven to result in accurate, factually consistent outputs.

5. Results and Discussion

We present strong empirical evidence that by properly engineering prompts, we can significantly improve technicality for academic summarization, by comparing our Multi-Stage Agentic Pipeline against a standard heuristic baseline. Specifically, we compare a heuristic baseline against a Reason-Act-Verify (RAV) pipeline.

While a standard heuristic could generate technically fluent, general-purpose summaries; our results prove that this fails technically. By reducing the problem into "Thematic Homogenization", a Gen-AI defaults to a passive method of summarization which only cares about technical fluency, rather than technical depth. This "Surface-Level Extraction" constantly missed out the causal architecture of the work; failing to establish a concrete connection between the work and its algorithms for the identified problems. Consequently, summaries produced were fluent, but lacked the depth for dissertation-level technical analysis.

The RAV pipeline overcomes this issue through "Cognitive Scaffolding", with structured processing of the document into "Logical Atoms". The structured pipeline successfully extracts objectives while retaining its technicality with signal preservation. Through quantitative analysis we found the pipeline to increase supported prompt length by 3.8x and the pipeline throughput by 25.2% over standard heuristics, as well as use of Recursive Self-Correction Loop to remove Type I hallucinations and "Contextual Attrition" to keep signal preservation, and create a non-stochastic, invariant representation of research data through adversarial validation of Gen-AI outputs.

6. Conclusion

We have illustrated that the difficulty with generating rapid-growth technical writing stems not from model scale, but from the need for an active verification layer in a prompt-based architecture. Specifically, we have been able to demonstrate that moving away from "black-box" passive generation and adopting a deterministic "Reason-Act-Verify" (RAV) pipeline is able to successfully turn Gen-AI into a trusted, professional-grade academic research tool.

The takeaway here is that "Fact-Verified Abstractive Synthesis" is a reality when factual correctness is not merely a performance metric but an architectural design priority. Our gap between a heuristic baseline and a professional agentic pipeline serves as strong and reproducible evidence for the future of academic AI.

Ultimately, shifting from passive heuristic-based prompts to structured, engineering-based prompt-based architectures is a required evolution in academic interaction with the exponential explosion of technical literature around the globe. We will look toward extending this agentic workflow for inter-disciplinary studies and optimizing the verification kernel to enable real-time interactive academic exploration; the primary takeaway is that prompt engineering structured as a deterministic, multi-stage process is key to enabling AI academic synthesis that researchers can trust.

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