GENERATIVE AI'S POTENTIAL FOR KNOWLEDGE MANAGEMENT

In the first part of our generative AI series, we explored how GenAI can industrialize the software delivery process. During our experiments, it became clear that the quality and detail of the input queries – the natural language requests associated with writing code, creating user requirements, testing and so on that we presented to the AI models – strongly affect the quality of the output generated. In this second article, we focus on the AI's potential to aggregate knowledge and generate reliable, detailed, and tailored responses to natural language queries.

EXPERIMENT OVERVIEW

To allow us to test these concepts, we chose to use a knowledge management system that captures information around the technology stack supporting a payments solution.

More specifically, the information in this knowledge management system is stored as a knowledge graph, a type of database which allows the source information to be captured in a highly structured manner. The more structured the source information, the more accurate and contextually correct the Al's responses will be.

Once the Al has been provided with contextual information around the architecture and technology stack of our Payments solution, we can make this knowledge highly consumable to a variety of types of end-users through two mechanisms:

 Automated, static content is provided through a web portal where detailed information about the system is sliced along business capabilities and tailored through different persona lenses (example: Data Architect vs. Test Analyst). Personas that we cater for include Developers, Quality Engineers, Business Analysts, Data Architects, as well as Security Analysts. Note that continuous updates of the content pages are automated through incorporating our solution on the DevOps pipeline.

 Dynamic content through a Chatbot experience where the end user can ask Al anything about the source code. These questions can include deep dives around how a particular capability works, or more complex ones such as shown in the examples in the table below.

It is important to highlight that our solution does not have a lock-in with a specific Large Language Model (LLM). Instead, it is designed to be flexible and modular, allowing for integration with multiple LLMs.

TOPIC	QUESTION
Knowledge transfer	Which microservices and API endpoints form part of the customer onboarding journey, and how do they interact as part of the onboarding workflow?
Impact analysis	A data element commonly used across services will change from numeric to alphanumeric. Which API endpoints across the entire services stack are impacted?
Consolidation	I am working on a strategy to deduplicate technology solutions in the bank. Show me how the technical solution for obtaining an account statement varies between retail and SME customer segments?
Design	Based on the current architecture that supports the instant payments business capability, where will I have to modify my existing technology stack to future-date the instant payment? Specify which data elements I would need to include on new or modified API endpoints.

MAGNITUDE OF THE TASK

For a complex banking application, such questions are not easy to answer, as the information would need to be pulled from many different source documents, and aggregated and analyzed to derive the correct response.

A typical banking app comprises hundreds of interconnected components. Answering our questions requires access to the technical specs for each of these components, ensuring that each of these specs is up-to-date, and then processing this

vast amount of information to formulate a response. This is an immense task that is as good as impossible for a human to complete.

Al can remove the burden of knowledge aggregation and dissemination, taking on the task of updating information in a knowledge system, and generating answers in response to natural language questions and requests.

HOW AI PERFORMED

As part of our experiment, we created a Python script to convert the entire instant payments app technical knowledge database from endless pages of raw code — which would be inefficient and expensive for the Al to work with — into a 'narrative', a set of natural language statements which provide semantic context for the Al.

We then tested the Al's ability to respond to our natural language questions and requests, using the narrative version of the database as its source material.

On the scale of one to five we adopted in the first part of this series, where 'five' represents Al outputs that can be fully

trusted and used without any human oversight or review, we saw a fundamental improvement – from 3 to 4.5 – in the quality of the Al's responses compared to the results we described in that previous article.

The results returned by GenAl in response to straight-forward questions or requests – for example, 'Which data element is most frequently used across all API endpoints, and what is its purpose?' or 'Can you create a component diagram of the solution that describes the input I provided?' – were 100 percent accurate. This is not surprising considering that data extraction and summarization are GenAl's key strengths.

Moreover, the AI was able to provide highly detailed answers to questions that have a greater degree of abstraction — for example, 'Where are potential performance bottlenecks in the code, why, and how can this be improved?'.

We were further impressed by the level of accuracy and detail in the Al's responses when asked to create the app design assets based on new requirements — for example, 'How can I put in a check that allows only specific countries in customer data, an what should the code look like?'

Finally, the Al provided valid responses to queries about the app architecture convergence, based on its assessment of

similarities between different parts of the app design – for example, 'Which two API endpoints are most alike in their response definitions, and why? Can they be converged to a single endpoint?'. Al models identified code duplication, system inefficiencies and opportunities for functionality consolidation.

In summary, Al enhances the chatbot's ability to generate coherent and contextually appropriate responses. It can provide summaries, detailed explanations, and even suggest follow-up questions to refine the results. It thus ensures that the chatbot not only finds information but also communicates it effectively, and this makes the solution accessible to users with varying levels of technical expertise.

CONCLUSION

The Al's responses based on structured and comprehensive contextual information were accurate, detailed and complete. Moreover, thanks to the ability to tailor the knowledge to different personas through our approach, we would feel confident in using GenAl for knowledge transfer, impact analysis, architecture consolidation and solution design related activities — the tasks that banking IT specialists wrestle with as part of day-to-day technology support.

Armed with quality source data which is highly structured (as in our example of using a knowledge graph), GenAl acts as a dynamic knowledge engine that can provide reliable answers to complex technology related questions, in seconds.

The use of GenAI to update, manipulate and disseminate information in a knowledge management system is not limited to our instant payments app use case. Any knowledge system where complex information can be effectively modelled will benefit from this approach. Examples include:

- Supporting fraud detection, risk assessment, and compliance by analyzing relationships between entities such as customers, transactions, accounts, and external data sources (e.g. market data, credit reference agencies, sanctions lists).
- Powering recommendation systems and suggesting products and services by analyzing the relationships between user needs and preferences and transaction data.

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