

Leveraging Generative Al for Granular Credit Data Utilization: A Multi-Agent Approach

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18-20 February 2025

Prepared for the 4th IFC workshop on "Data science in central banking", Rome, Italy



Regulatory Data Transformation (RDT)

A transformative redesign from static Data Management System to granular-level regulatory reporting standard for <u>credit data</u>



Rich dataset with 1000+ fields and over 25 million loan accounts per month, including credit lines, interest rate plan, and outstanding amount



Multi-faceted data architecture with specialized cubes for diverse and thorough credit data analysis



Enable insights for analyst and examiners across many domains from bank supervision to monetary policies



Complex data requires knowledge and advanced data analytical skills



Challenges with RDT Utilization



Problem translation

Users may not be able to translate business questions into data queries



Data understanding

RDT's data is complex

- Numerous data fields
- Structured into multiple "cubes" for different usages



Coding skills

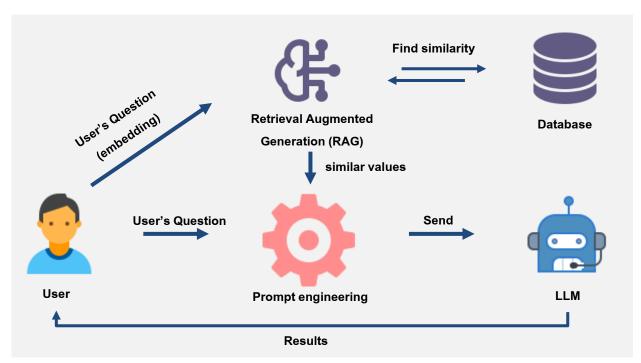
Require SQL / python knowledge to wrangle granular data effectively

 Most analysts and examiners are not proficient in coding

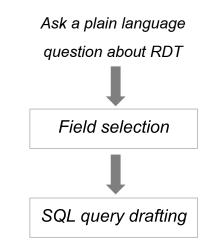


Generative AI as RDT assisting agents

- Large Language Model (LLM) can be utilized as a copilot for answering users' questions.
- Retreival-augmented Generation (RAG) is used to provide internal knowledges such as metadata to GenAl.
- Prompt Engineering instructs GenAl to produce SQL code based on questions and retrieved metadata.



standard single-agent GenAl with RAG workflow



```
SQL

SELECT
customers.name,
SUM(loans.amount) AS total_loan_amount

FROM customers
INNER JOIN loans ON customers.customer_id = loans.customer_id

GROUP BY customers.name

ORDER BY total_loan_amount DESC
LIMIT 3;
```



Challenges with GenAl workflow for RDT

Challenges

Impacts

Complex operation

Single LLM "agent" might struggle with multiple instructions for more complex tasks

Limit potentials for RDT utilization to basic querying

Context size

Retrieving metadata from all tables in RDT may exceed the context size of LLM

Unable to handle complex query that requires multiple tables or scale to larger data sources

Mixing LLMs

Cannot mix different models for different tasks to optimize cost

Consume more resources with running single large model for all tasks



Multi-agent framework

Single-agent Framework

A large agent capable of executing diverse tasks comprehensively.



Analyst

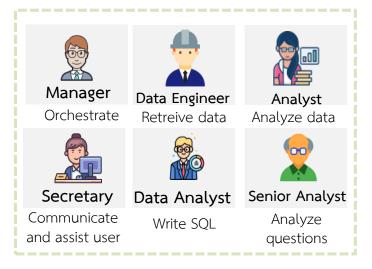
Data analytics tasks

- Analyze questions
- Retrieve data
- Select fields
- Write SQL

Framework	Pros	Cons
Single-agent	 Easier to manage Lower complexity to develop Consume less resource 	 Limit expertise for complex tasks Limit on context size Less flexibility No steps provided to users
Multi-agent	 Able to deal with more complex tasks Less limitation on context size Assign different task to agents with specialities Users can see broken-down steps 	 More complexity Consome more resource

Multi-agent Framework

A multi-agent approach decomposes the task into subtasks to be executed by different agents.





RDT Copilot: Modules





Translate user's problem into tangible statements and identify relevant data sources

Q: What should be the minimum payment rate for credit card debt repayment?

Brainstormer:

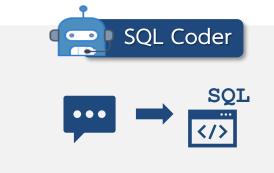
Find relationship between <code>credit_card_type</code>,

<code>first_payment_amount</code> and <code>total_interest_and_fee_rate</code>

to evaluate relationship between risks and payment.

Metadata Copilot

Search for the best data cube and fields required to answer users' questions



Assist users by converting natural language questions in to SQL query

Q: How many debtors have joined the debt restructuring program this year?

Metadata Copilot:

Field	Description
entity_id	ld for debtors
debt_restructuring_date	Date of debt restructuring

SQL Copilot:

SELECT

COUNT(distinct entity_id) AS number_of_debtors

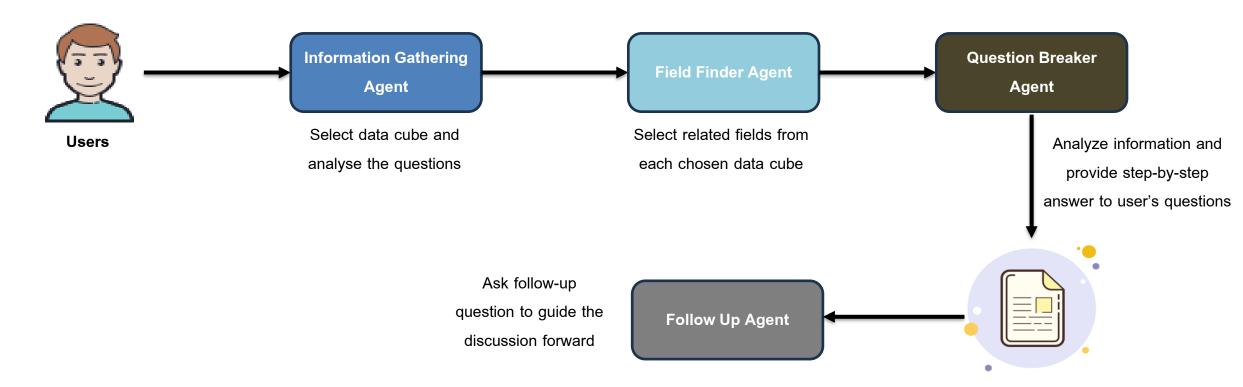
FROM CUBE 1

WHERE debt_restructuring_date > '2024-01-01'

...



Brainstormer

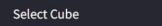


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New Chat

Task:

- RDT Brainstorming
- RDT Copilot Metadata
- RDT Copilot SQL Coder



Chat History

Report / Feedback

Change Password

Logout (nontawic)

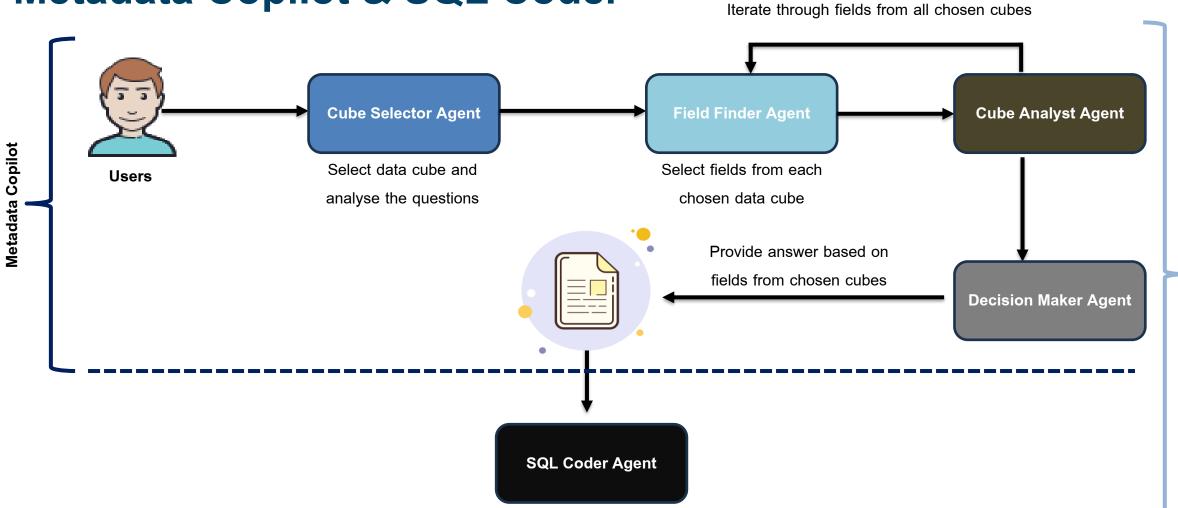
Hi Nontawit Cheewaruangroj! I am BotGPT, ready to provide assistance.

Input Question: I want to determine appropriate criterias for debt restructuring program.

Kindly input your query or command for prompt assistance...



Metadata Copilot & SQL Coder



with SQL Coder



New Chat

Task:

RDT Brainstorming

RDT Copilot - Metadata

RDT Copilot - SQL Coder



Chat History

Report / Feedback

Change Password

V

Logout (nontawic)



Hi Nontawit Cheewaruangroj! I am BotGPT, ready to provide assistance.

Input Question: Please find the "% MoM growth" of the total outstanding balance before deducting unearned revenue for OD loan, categorized by financial institutions and segmented by months.





Evaluation



Experiment: Compare the performance of each module against the *single-agent* versions.

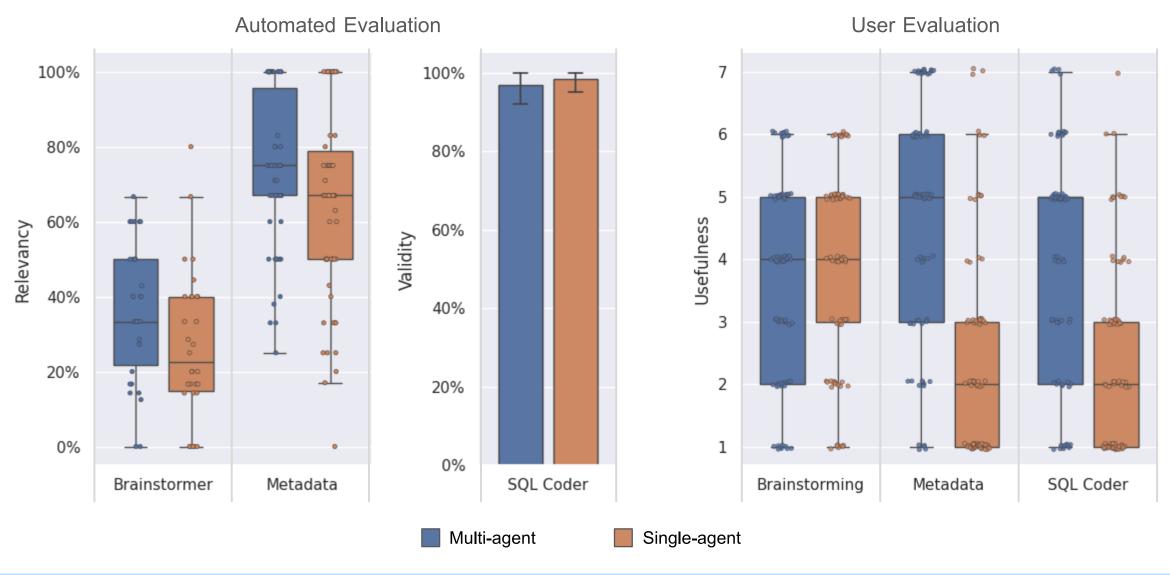


Metrics:

Module	Automated evaluation	Human evaluation
Brainstormer	Relevancy (Recall of expected fields required for business problem solving)	Usefulness (How useful the output for answering
Metadata Copilot	pilot Relevancy (Recall of expected fields required for querying data)	the question) - Likert scale of 1 to 7 - Evaluated by BOT's examiners & analysts
SQL Coder	Validity (Whether the generated SQL syntax is valid, i.e., executable)	



Results from evaluation



^{*} For automated evaluation, Brainstormer is evaluated with 30 qualitative questions. Metadata Copilot and SQL coder are evaluated with 62 quantitative questions.

^{**} For user evaluations, each module is evaluated with 10 questions by 8 analysts / examiners.



Discussion

Automated evaluation

- RDT Copilots can perform objective tasks, such as retrieving fields and writing SQL, very well.
- Multi-agent framework show good improvements in retrieving correct fields. For SQL generation, single-agent framework is already good.

User evaluation

- Users find multi-agent Metadata Copilot and SQL coder useful for answering quantitative questions.
- However, users do not find Brainstormer particularly useful for qualitative questions. Multi-agents framework does not show improvements over single-agent framework.
- Users also show different preferences towards writing styles of Brainstormer versions. Results are varied for different questions for all modules.



Conclusion

GenAl Tools can be useful in helping RDT data utilization.

RDT Copilots can help analysts and examiners find and retrieve required data.

Multi-agent framework can be applied to enhance RDT Copilots:

- Help address issues of limited context length for multiple tables data.
- Improve performance over single-agent approach for some tasks, especially in more objective tasks that require large contexts.
- Can be adopted for variety of tasks, both objective (coding) and subjective (brainstorming).



Challenges and Next Steps



Challenges

- Incomplete metadata. Internal jargons.
- Some domain knowledge not in documents or LLM knowledge.
- Difficult to get users engagement in designing and adoption.
- Difficult to experiment with different LLMs due to compliance & security concerns.

C Further Work

- Improve data dictionary. Enhance prompt to incorporate more domain knowledge.
- Brainstormer needs a revision to produce more useful outputs.
- Explore LLMs with improved reasoning capabilities such as OpenAl o1 model.
- Incorporate ability to directly process data, e.g., plotting graph.
- Explore multi-agent solutions for problems such as KM chatbots, supervision assistant agents.



