LinkedIn

Empowering self-serve data analytics with a text-to-SQL assistant at LinkedIn

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Agenda

1. Introduction
2. Five strategies to deploy a practical text-to-SQL solution at scale
3. User adoption
4. Agentic future

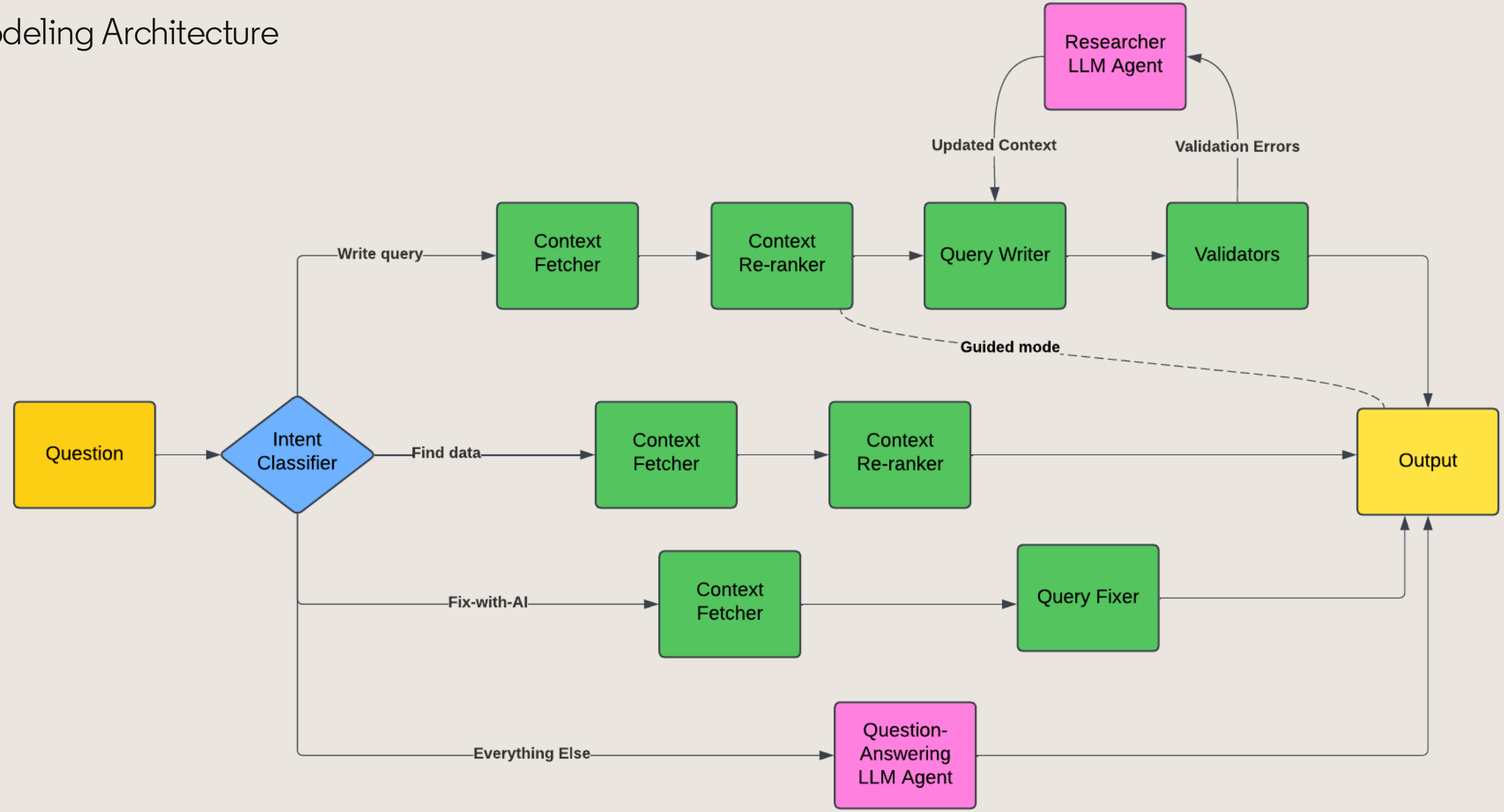
Text-to-SQL comes in many shapes and sizes

- Who is the end user?
- How many datasets?
- How much specialized knowledge?
- What is the target user experience?

Our use case

- All LinkedIn Employees from no SQL experience to SQL / Data experts
- Millions of datasets across product areas
- Data/query assistant for data analytics

Modeling Architecture



Five strategies to deploy a practical text-to-SQL solution at Scale

5 strategies:

1. Quality Metadata
2. Query Validation
3. Interactive Chat UX
4. Self-serve Customization
5. Ongoing Benchmarking

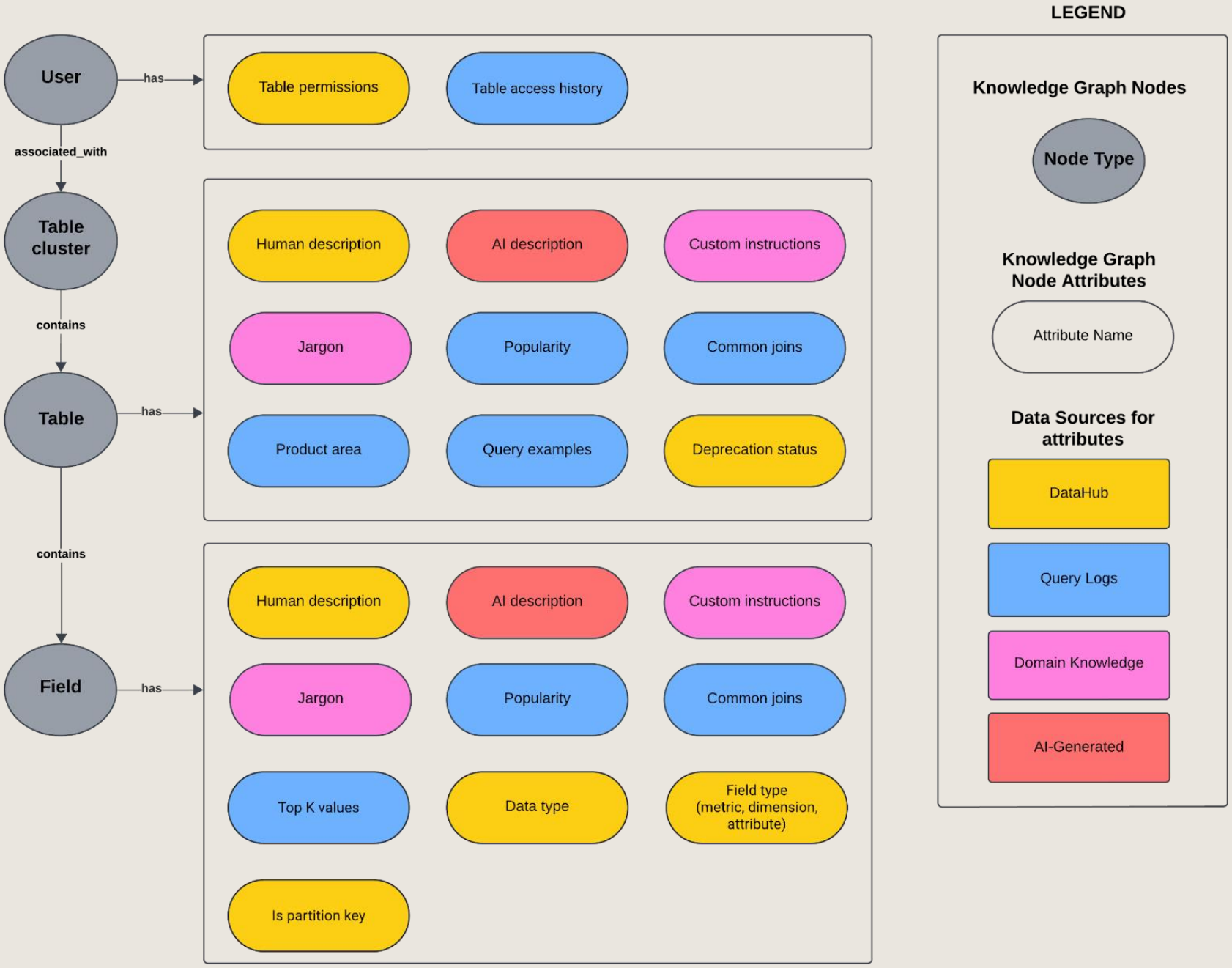
#1 Quality Context

Start with the basics!

Prioritize reliable sources with high information density

Improved descriptions and example queries ➜ big lift in accuracy

Knowledge graph



#2 Query Validation

Always check your work!

Fix errors before returning the query to the user:

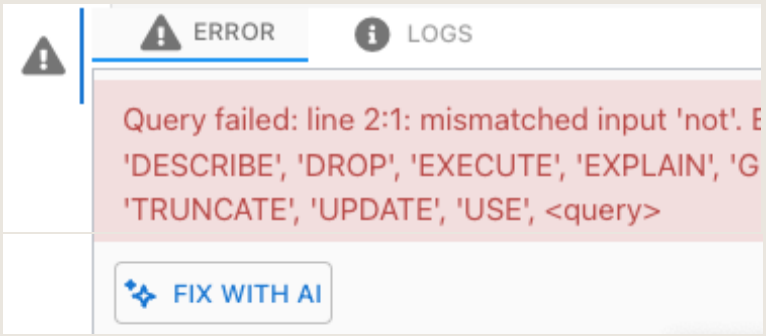
- Do all tables exist?
- Do all columns exist?
- Will the query run?
- Does the user have access to the tables?

We use a self-correction agent to fix errors

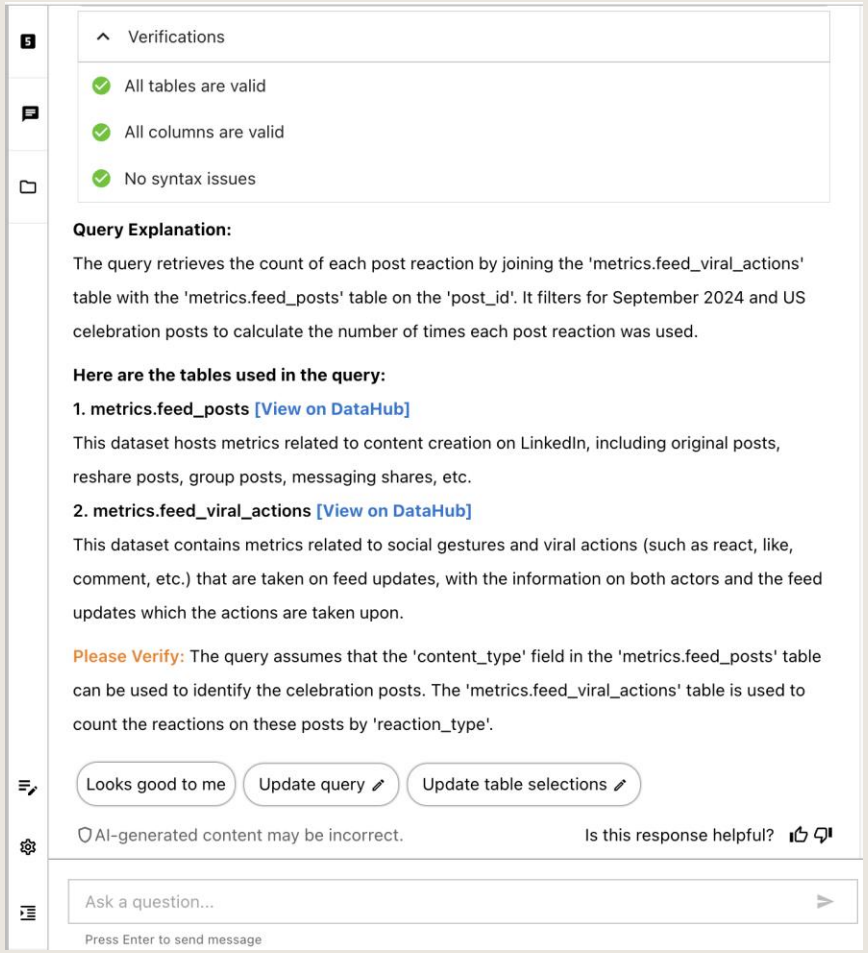
#3 Interactive Chat UX

It's about more than the models!

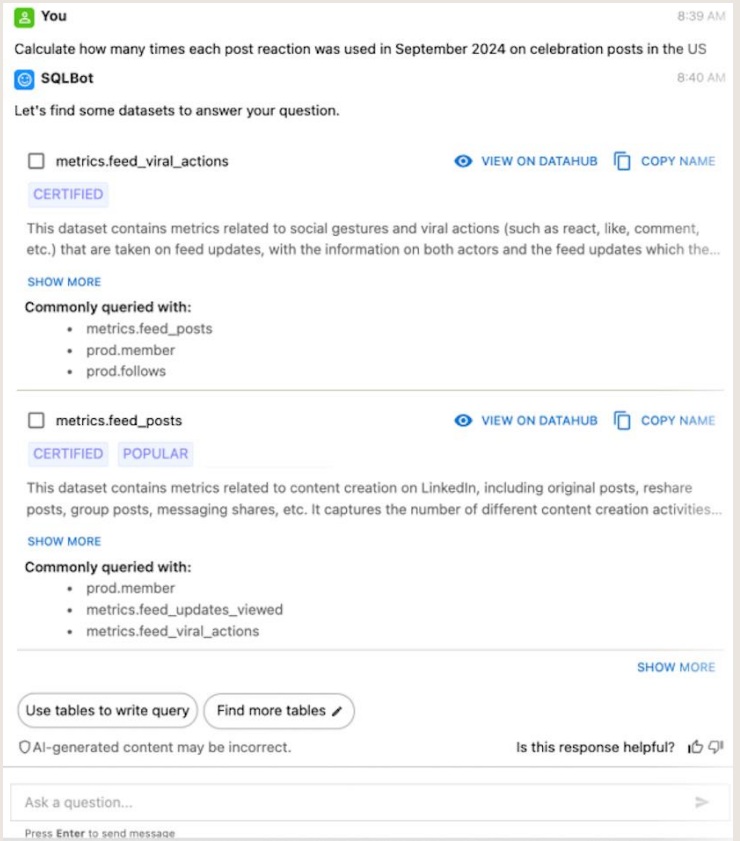
- Timely assistance



- Human-in-the-loop



- Rich chat elements

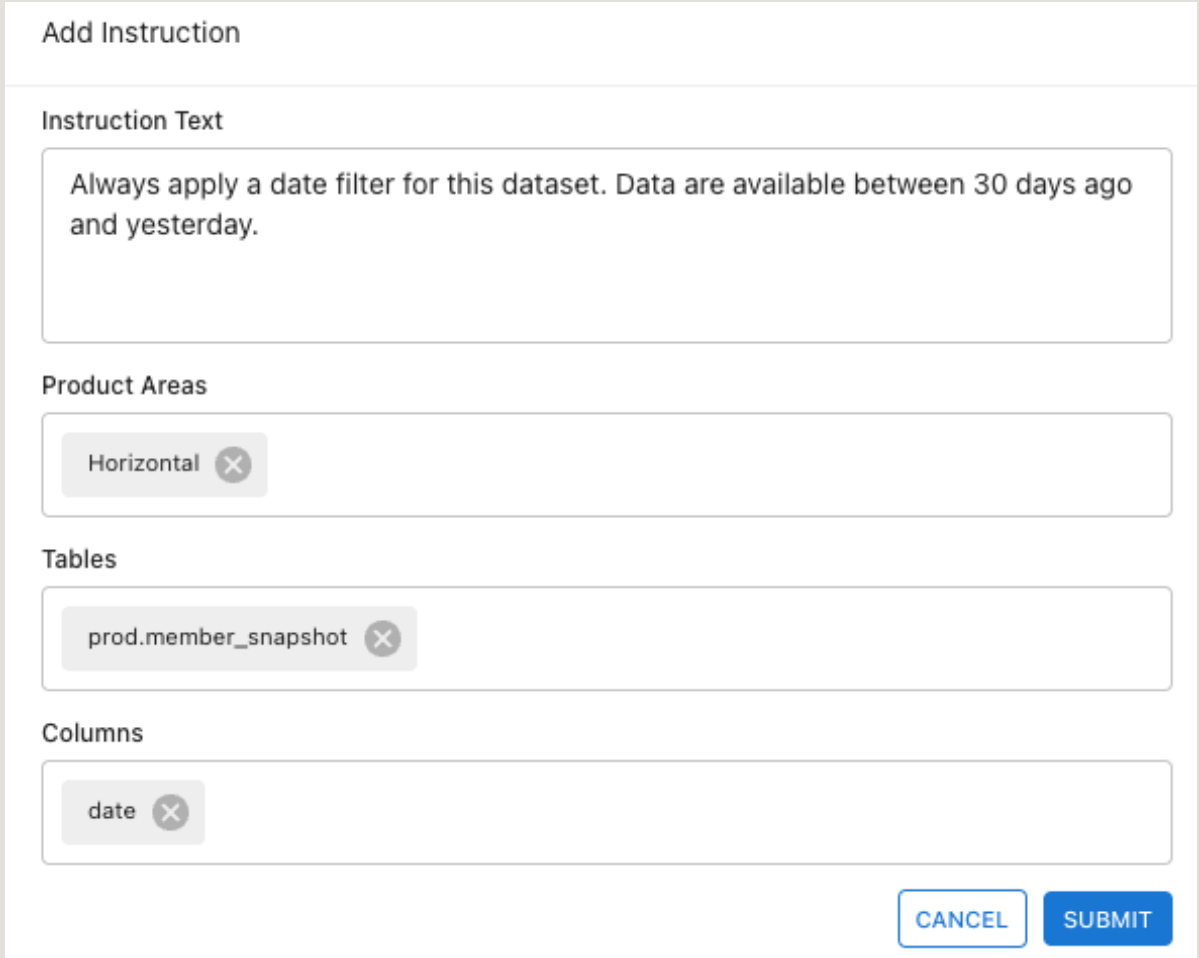


#4 Self-Serve Customization

Empower your users!

Allow users to specify:

- Relevant datasets
- Custom instructions
- Example queries



#5 Ongoing Benchmarking

Speed up your development!

- Curate your own benchmark set
- Define metrics for each part of the stack: retrieval, query writing, fixing, general QA
- Use LLM-as-a-judge to complement human eval
- Note! The same question can be answered with different tables/queries

Key Takeaways from our benchmark experiments

		Table Recall	Field Recall	Hallucination %
Impact of Knowledge Graph Context	Adding example queries	+16%	+14%	+1%
	Adding descriptions and human annotated data	+4%	+8%	-1%
Impact of Modeling Components	Adding re-rankers	+9%	+5%	-8%
	Adding self-correction agent	+2%	+1%	-14%

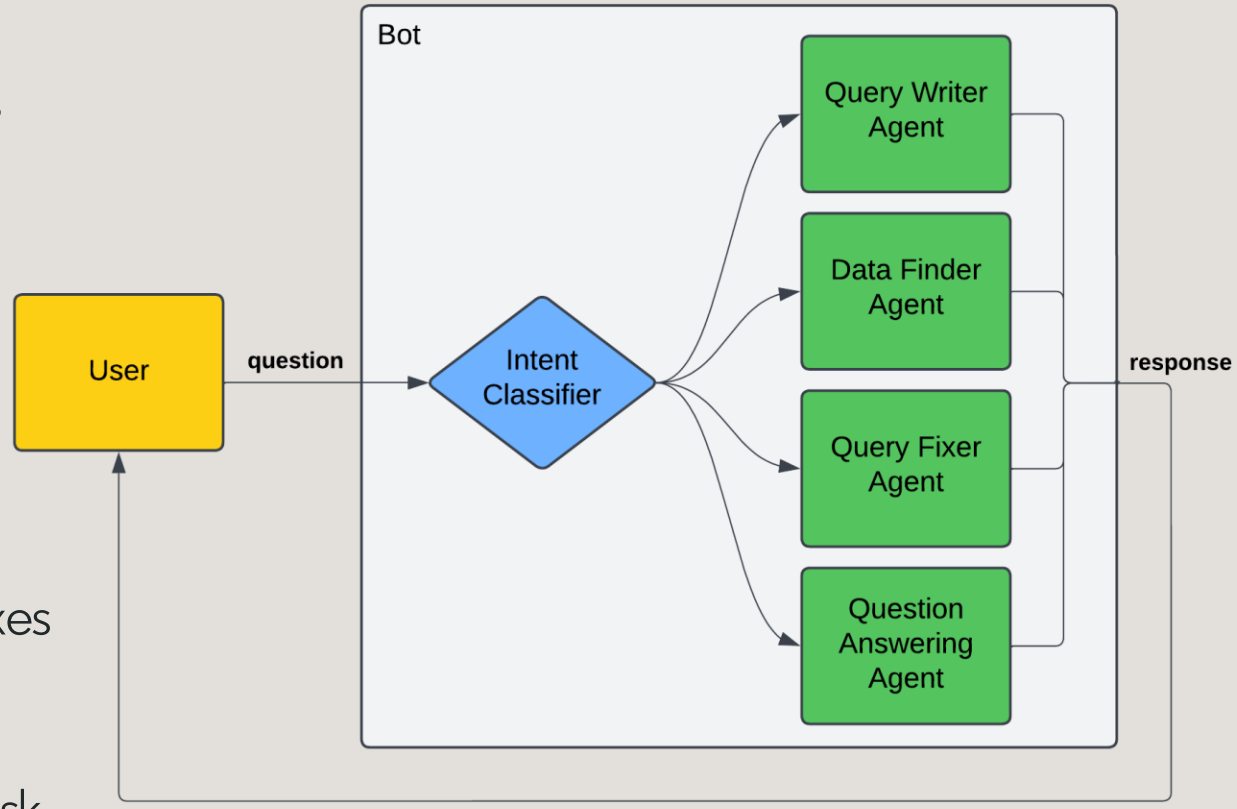
User adoption strategies

Our Audience : All LinkedIn Employees from no SQL experience to SQL / Data experts

- Meeting users where they are - Integration with existing Data Analytics Platforms
    - Drove 5-10X increase in user adoption
- Understanding the user's needs
    - Analyzing the logs to understand the needs based on the intent of the questions users ask
    - UX interviews for different user groups
- Building User confidence in the output
    - "Step-by-step" mode for building user confidence
    - by providing rich chat elements, detailed explanations and certified code snippets
- Making the bot interactions frictionless through quick replies

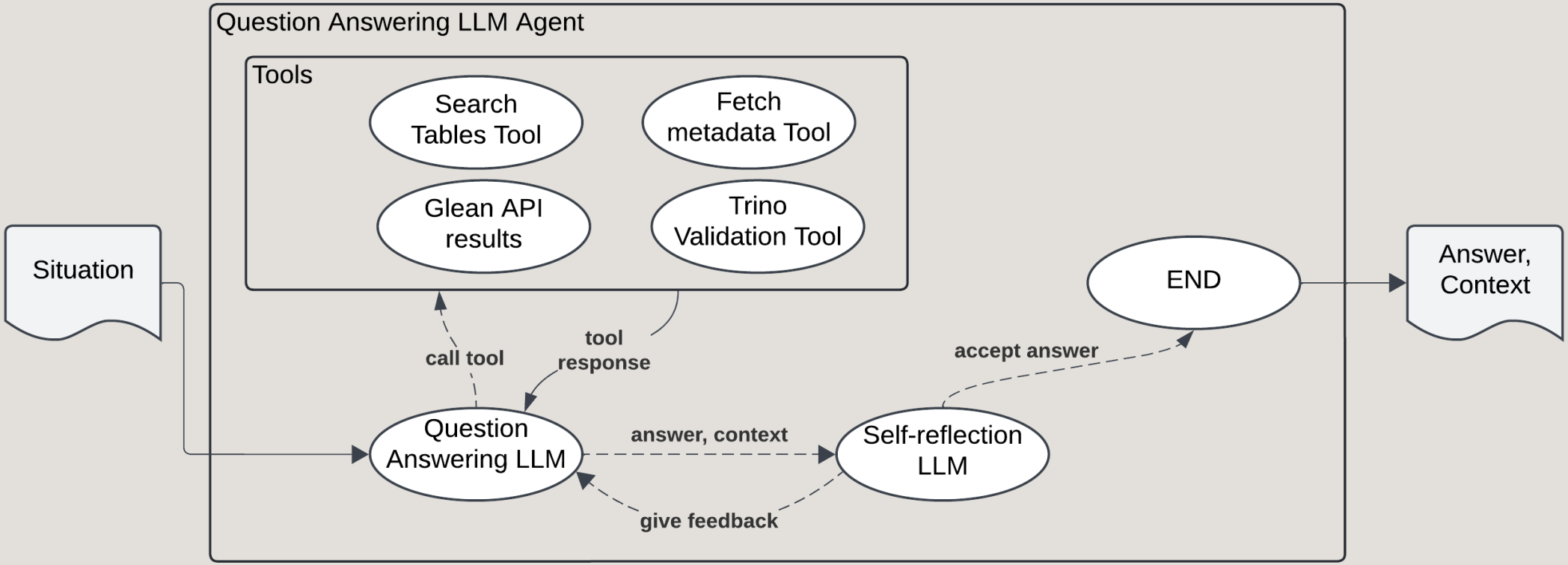
Unleashing potential through LLM Agents

- LLM Agents have an intrinsic versatility to themselves with their access to different tools for updating their knowledge
- Self-Correction Agent
  - Use "Trino Explain" for detecting errors and hallucinations
  - Fetches additional metadata and updates context
  - Searches table/schema info and suggests fixes
- Question Answering Agent
  - Expanding the types of question you could ask this bot!
  - Making the responses more well-rounded



Deeper Dive into the Question Answering LLM Agent

- For "meeting the user where they are" - QA LLM Agent was the solution
- Helps answer questions about the metadata stored across the vector stores and Knowledge Graph
- This helps support questions ranging from optimizing code to updating existing code snippets to answering any general question
- Also improves the interactivity with the user for follow-ups



Questions?

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