

# Hack the Future: A Gen AI Sprint Powered by Data

Data and AI Week



## Team details

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# Entry Submission Summary

Idea Title	Problem Statement 1: Optimizing Retail Inventory with Multi Agents
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Problem Statement	Problem Statement 1: Optimizing Retail Inventory with Multi Agents. The goal is to create a multi-agent AI system that can predict demand, ensure product availability, reduce inventory holding costs, and improve supply chain efficiency. Your solution should enable seamless collaboration among different agents to manage inventory proactively, avoid stockouts, and minimize the excess holding of inventory, thereby maximizing sales and improving operational efficiency.
Proposed Solution	Multi Agent Framework used to develop our Research Agent capable of all sorts of queries handeling and enabling all features to optimise retialInventory with Multi Agents

# Proposed Solution Overview

The solution is a comprehensive retail analytics system built using **LlamaIndex** and **Groq's** LLM models. It creates an AI-powered agent that can answer natural language queries about retail data by:

1. Processing multiple retail datasets (demand forecasting, inventory monitoring, pricing optimization)
2. Using specialized query engines for each dataset that convert natural language to executable Python code
3. Employing a multi-agent architecture with three ReAct agents working in parallel:
  - **Agent 1**: Primary query processor using Gemma 2-9B
  - **Agent 2**: Secondary processor using Qwen 2.5 Coder
  - **Agent 3**: Consensus builder that synthesizes results from the other agents

**The system presents results through an interactive Streamlit dashboard that shows both final answers and the reasoning process. This approach combines the strengths of different LLMs and allows transparent, step-by-step reasoning for data analysis.**

# Technologies Used

## LLMs:

- Gemma 2-9B-IT hosted on Groq's cloud model for general reasoning
- Qwen 2.5 Coder (32B) hosted on Groq's cloud for code generation and data analysis

## Frameworks & Libraries:

- LlamaIndex: For creating query engines and ReAct agents
- Pandas: For data manipulation and analysis
- Streamlit: For interactive web dashboard

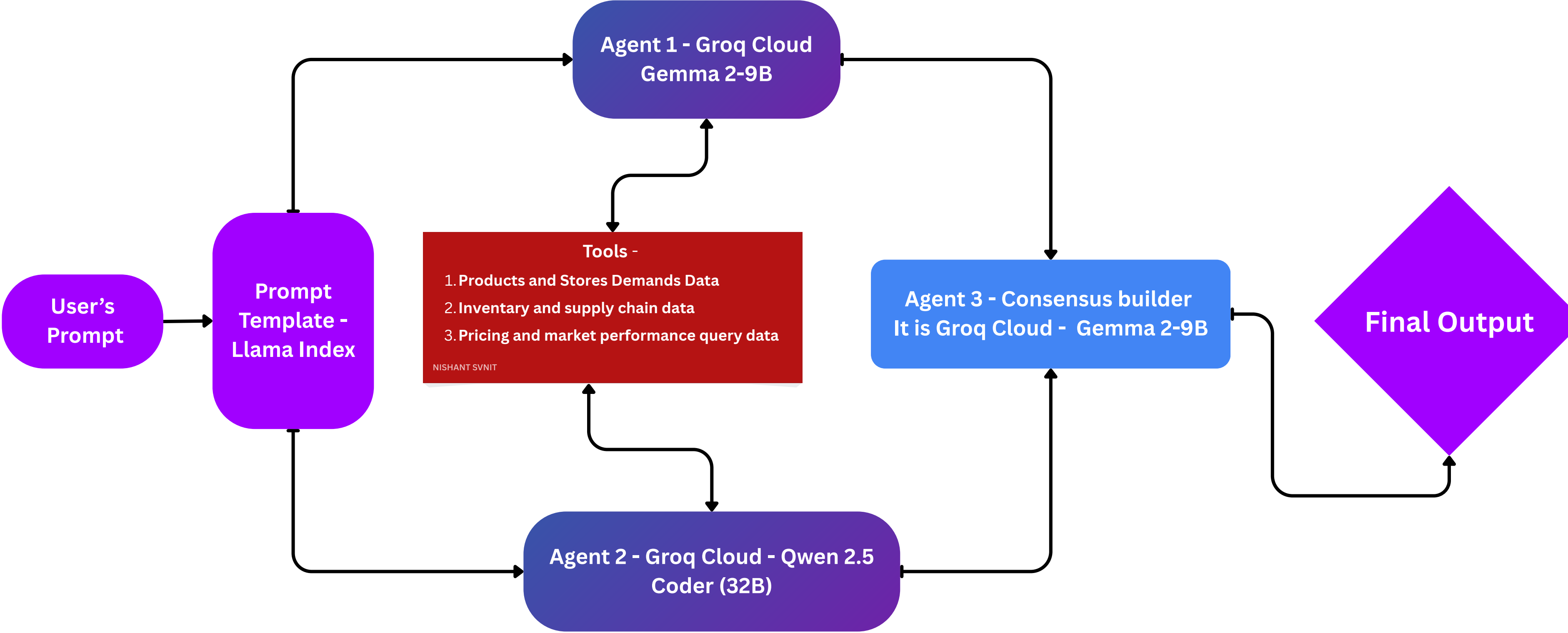
## Development Tools:

- Python: Core programming language
- Git: Implied for version control
- Custom prompt templates for enhancing LLM performance

## Approaches:

- ReAct framework: For reasoning and acting iteratively
- Chain of thought processing: Making agent reasoning transparent
- Parallelized agent architecture for better results

# Agents' interaction design





# Code structure

## The codebase follows a modular structure:

### Data Processing Layer:

CSV data loading via Pandas

Three separate datasets for different aspects of retail analytics

### Query Engine Layer:

Three PandasQueryEngine instances (one per dataset)

Custom prompt templates with detailed schema information

Instruction strings to guide code generation

### Agent Layer:

Three ReAct agents with different roles

Tool definitions connecting agents to query engines

Verbose output logging for transparency

### UI Layer:

Streamlit-based dashboard

Split panel design with chat interface and reasoning display

Custom styling with CSS

Expandable dataset previews

### Helper Functions:

format\_agent\_output(): For cleaning and formatting agent outputs

parse\_agent\_output(): For processing agent reasoning steps

Session state management for preserving conversation history

# Conclusion

This solution effectively addresses retail analytics challenges by combining the power of large language models with structured data analysis. The multi-agent architecture provides more robust and accurate answers by leveraging the strengths of different models and allowing them to compensate for each other's weaknesses.

The **system's key strengths are:**

**Accessibility:** Complex data analysis is accessible through natural language queries

**Transparency:** Users can see each step of the reasoning process

**Accuracy:** Multiple agents working in parallel improve result quality

**Versatility:** Can analyze patterns across sales, inventory, and pricing data

**Scalability:** Architecture supports adding new datasets and capabilities

By implementing this solution, retailers can make more informed decisions through natural language interaction with their data, removing technical barriers to insights and empowering business users to perform sophisticated data analysis without specialized training.

# References/Other details

- LlamaIndex Main Documentation: <https://docs.llamaindex.ai/>
- ReAct Agent Documentation: [https://docs.llamaindex.ai/en/latest/examples/agent/react\\_agent/](https://docs.llamaindex.ai/en/latest/examples/agent/react_agent/)
- PandasQueryEngine Guide: [https://docs.llamaindex.ai/en/latest/examples/query\\_engine/pandas\\_query\\_engine/](https://docs.llamaindex.ai/en/latest/examples/query_engine/pandas_query_engine/)
- Tools Framework Documentation: [https://docs.llamaindex.ai/en/latest/module\\_guides/querying/tools/tools\\_overview/](https://docs.llamaindex.ai/en/latest/module_guides/querying/tools/tools_overview/)
- Multi-Modal Agents Guide: [https://docs.llamaindex.ai/en/latest/examples/agent/multi\\_modal\\_rag/](https://docs.llamaindex.ai/en/latest/examples/agent/multi_modal_rag/)
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- Memory Module Documentation: [https://docs.llamaindex.ai/en/latest/module\\_guides/observability/memory/](https://docs.llamaindex.ai/en/latest/module_guides/observability/memory/)



Thank You