The University of Texas at Austin
McCombs School of Business

MASTER OF SCIENCE
IN BUSINESS ANALYTICS

From Query To Insight

Building an AI-Powered Risk Analysis Tool

SS&C Algorithmics

SS&C

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Agenda

1. Business Context
2. Data Sources
3. Building the Chatbot
4. Results
5. Conclusion

Business Context and Strategic Objectives

CONTEXT

01

Financial firms are adopting LLMs to enhance **client interaction and engagement.**

SS&C aims to explore the **effectiveness of LLMs in risk management.**

OVERALL OBJECTIVE

02

Develop a system that identifies potential risks in a client's portfolio and simulates relevant risk scenarios.

PROBLEM STATEMENT

03

Develop a chatbot that summarizes **portfolio-relevant news** and **identifies key risk drivers** for analysis.

Data Collection: Risk Drivers

Interim Data

Received a CSV with limited & incomplete metadata while the full dataset was being consolidated

Preprocessing

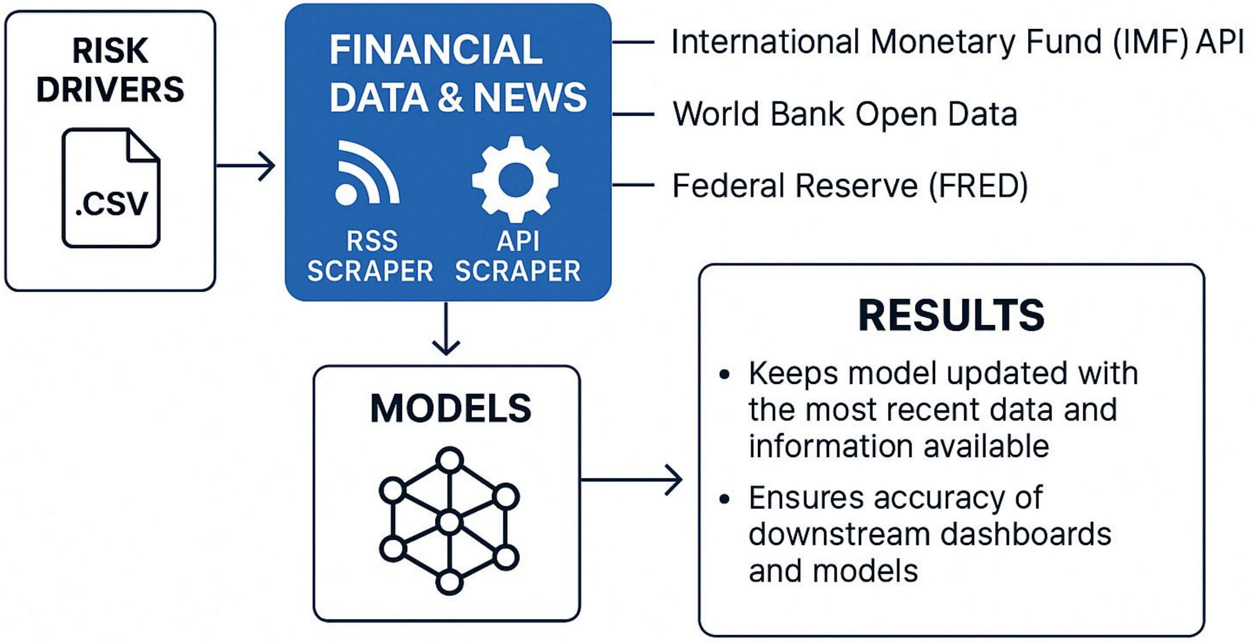
Cleaned and standardized inconsistent names and formats for initial prototyping

Final Integration

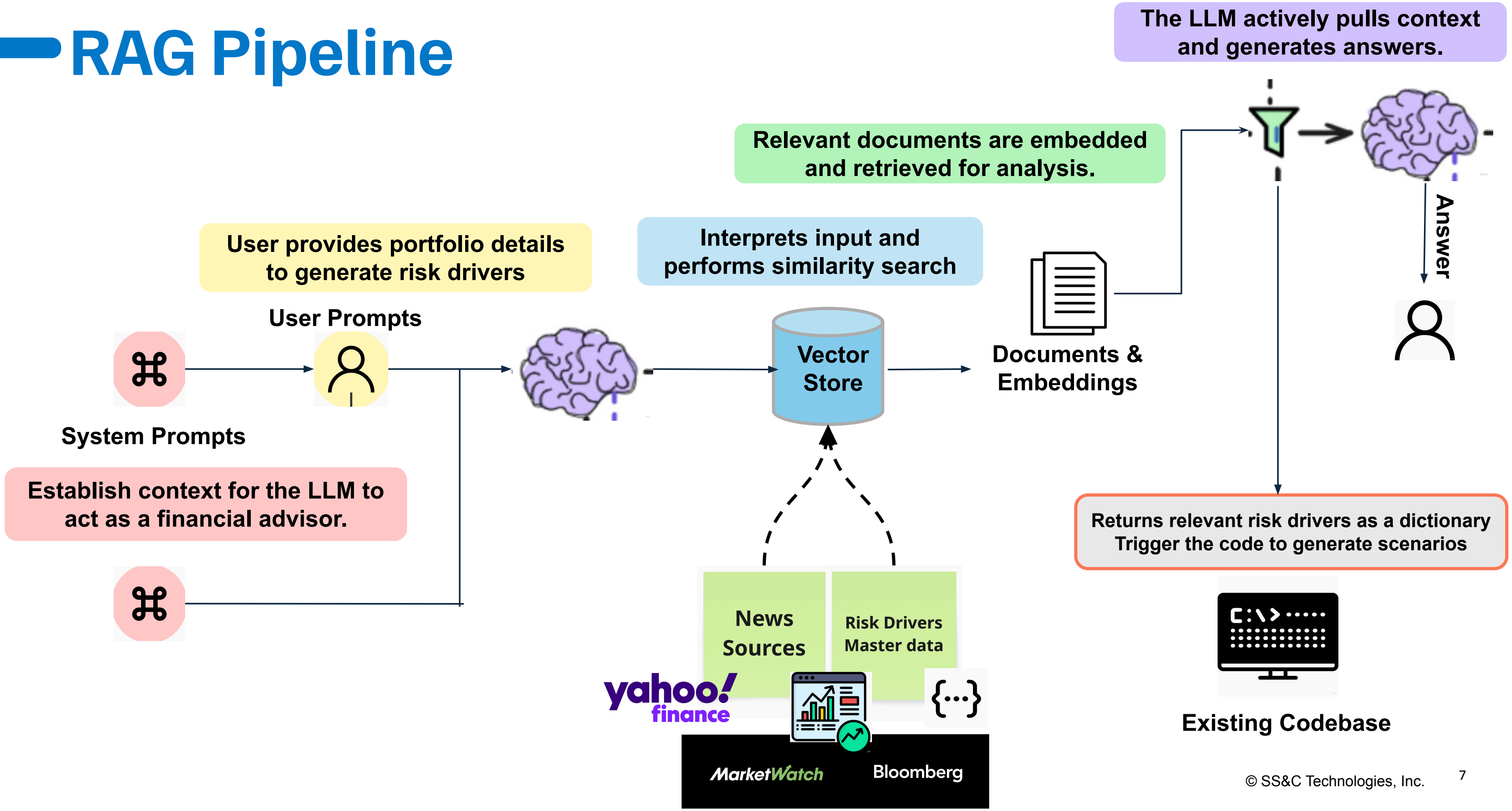
Later received the final JSON file with 1,000+ risk drivers and complete metadata

Data Collection: RSS Feeds and Financial Data

Real time Data Ingestion for Financial Risk Modelling



RAG Pipeline



Frameworks

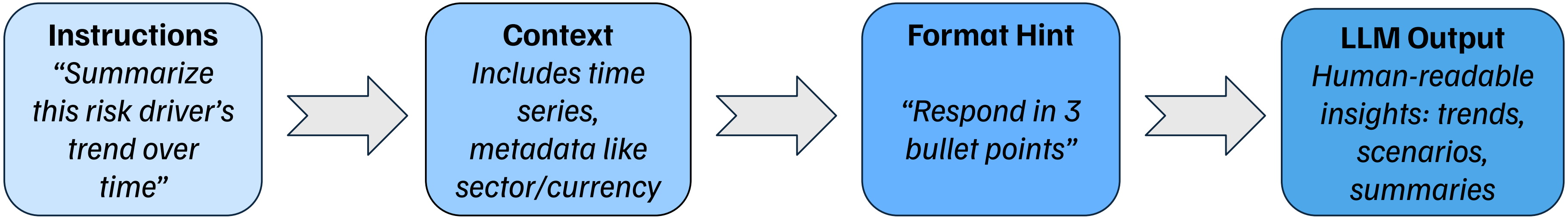
Langflow

Langflow offers a **drag-and-drop** interface with **predefined LLM components** and supports integration with custom Python logic.

Langchain

LangChain integrates modular LLM components like Langflow but r**elies on Python**, enabling **deeper customization** for complex applications

Prompt Engineering



Vector Storage & Document Embedding

Chroma

Quick Prototyping

Used in-memory vector database to test retrieval on sample risk drivers

Vector Storage

Moved to Chroma DB for enable efficient & scalable semantic retrieval

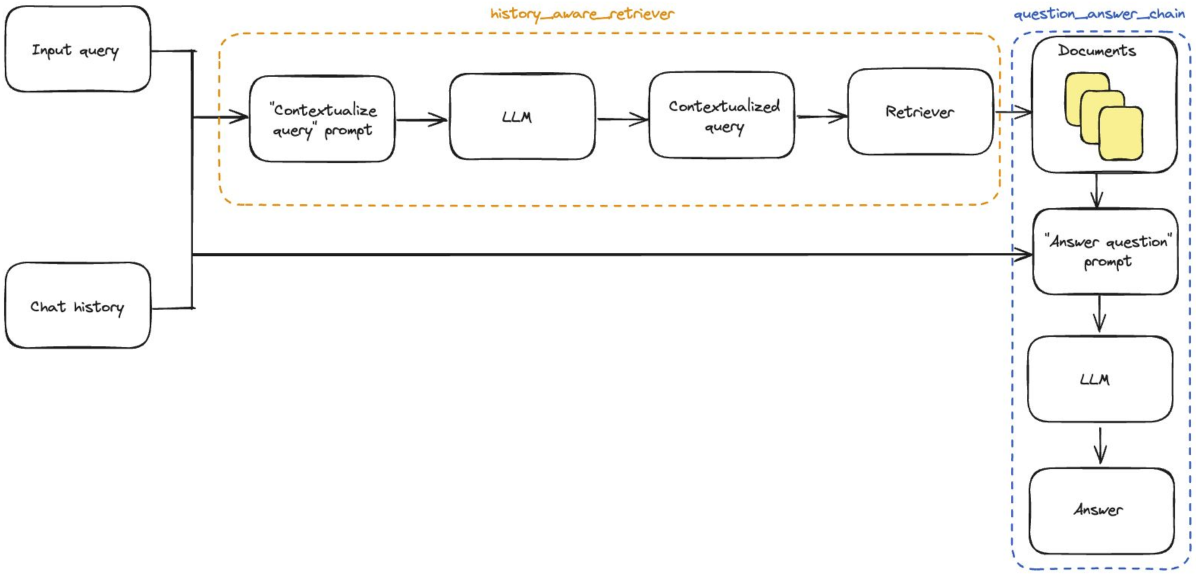
Semantic Search

Risk driver metadata and financial news content embedded for semantic vector retrieval

LLM-ready format

Switched to structured JSON for cleaner parsing and better performance with LLMs

Generation Augmentation: Chat History



Why?

Chat history enables the user to prompt the LLM to **revise earlier responses.**

Implementation

The **LLM needs a prompt** to reference chat history in order to include it in its response.

Source: Langchain, https://python.langchain.com/v0.1/docs/use_cases/question_answering/chat_history/

Generation Augmentation: Chat History

Before:

Actual Risk drivers

- ASX200 Index
- US treasuries
- Gold
- BNK-A-rated spread

I have some bonds in the US, alongside investment grade company bonds.

LLM's selected Risk drivers

- Investment Grade Bonds
- US treasuries
- US Interest Rates
- Market Volatility

Issue:

The LLM hallucinates additional risk drivers that were not in the given list of risk drivers.

Generation Augmentation: Chat History

After:

Actual Risk drivers

- ASX200 Index
- US treasuries
- Gold
- BNK-A-rated spread

I have some bonds in the US, alongside investment grade company bonds.

LLM's selected Risk drivers

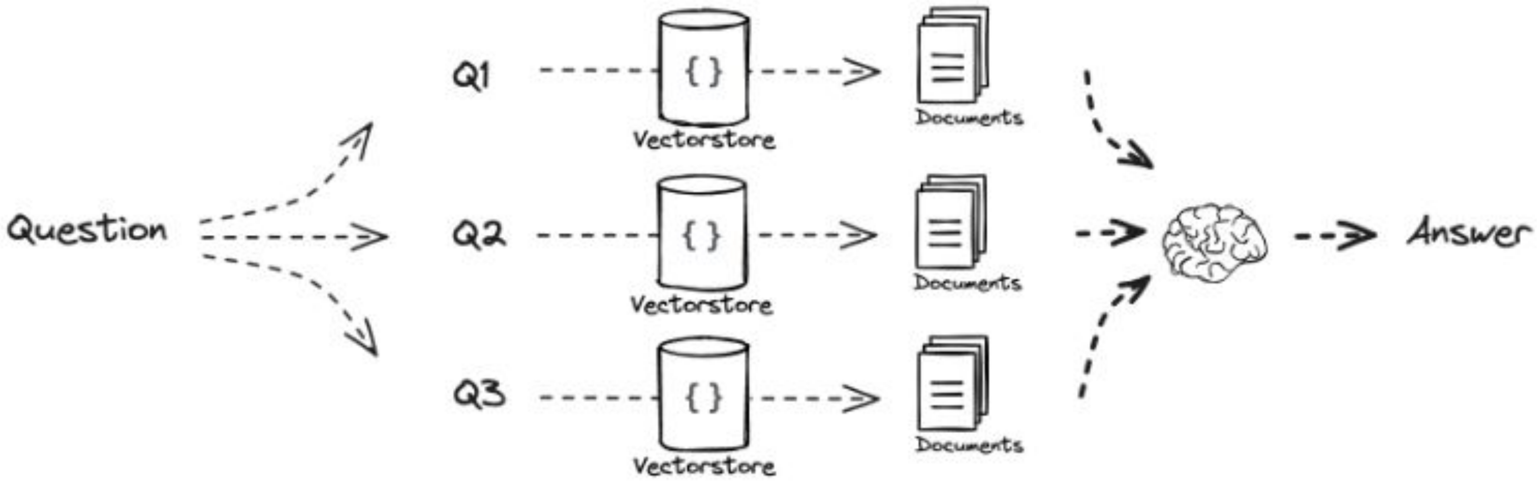
- BNK-A-rated spread
- US treasuries

Fix:

Chat history helps reduce hallucinations by supplying the LLM with risk drivers though limited by token constraints.

It also enables more natural, conversational interactions with the user.

Generation Augmentation: Multi-Query



Why?

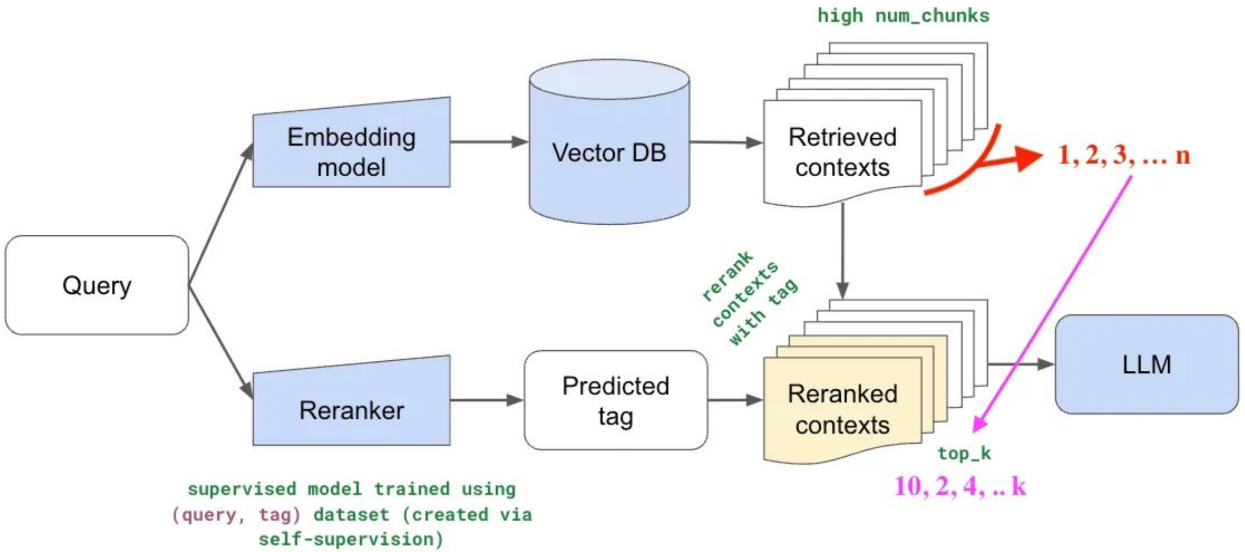
Multi-query helps the LLM retrieve more relevant documents by expanding the original query into multiple related ones.

Implementation

Prompt the LLM to break the user query into sub-questions to retrieve more documents and improve relevance.

Source: Langchain, https://github.com/langchain-ai/rag-from-scratch/blob/main/rag_from_scratch_5_to_9.ipynb

Generation Augmentation: Reranker



Why?

A reranker helps prioritize the most relevant documents by boosting their ranking in the results.

Implementation

Apply Reciprocal Rank Fusion
RRF combines results from multiple retrievers, prioritizing documents consistently ranked higher to improve relevance.

Source: Mahesh Deshwal, LanceDB, https://medium.com/etoai/simplest-method-to-improve-rag-pipeline-re-ranking-cf6eaec6d544

Generation Augmentation: Reranker

The reranker identifies additional risk driver IDs that may be relevant to the client's portfolio.

Question:
Provide the set of risk factors that will be important to use to stress my portfolio which has a composition of 30% bonds, 50% of which are high yield and 50% are investment grade bonds. 70% are equities with most in the US but 20% in Central Europe.

Sample Output
LLM's selected Risk drivers

without Reranker →

USD.#IAAyF(T10950)

USD.#IAAyB(T10950)

with Reranker →

USD.#IAAyF(T10950)

USD.#IAAyB(T10950)

USD.#IAAyC(T10950)

USD.#IAAyB(T1095)

Results

Setting the Context

Defining the LLM's role and providing risk metadata and financial news context

Edit Prompt

Create your prompt. Prompts can help guide the behavior of a Language Model. Use curly brackets {} to introduce variables.

You are a financial advisor specialized in analyzing a client's portfolio. You should have access to a list of risk drivers that the client's portfolio could be exposed to. Your task is to analyze the client's portfolio and determine which of the risk factors the client's portfolio is exposed to.

Edit Prompt

Create your prompt. Prompts can help guide the behavior of a Language Model. Use curly brackets {} to introduce variables.

If asked about risk factors or risk drivers that need to be stressed
for a portfolio - Can u choose top 10 from the risk factors that were
given as input that would impact the users portfolio?
Context: {risk_factors}

In addition use these contexts to answer the follow up questions

Context: {yahoo_finance}
Context: {market_watch}
Context: {wall_street_journal}
Context: {bloomberg}

Question: {question}

Scenario-Based LLM Response

User asks a portfolio question & receives relevant risk drivers

User

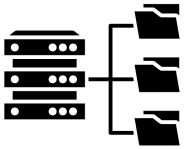
Provide the set of risk factors that will be important to use to stress my portfolio which has a composition of 60% bonds of which 50% are high yield and 50% are investment grade bonds. 40% of my portfolio is equities where most are in Europe but 30% are in Dubai.

AI gpt-4o-mini

json


```json
{
    "Index_Curve_.BVLG": {
        "Description": "Equity Market Index PSI All-Share Index (Portugal)",
        "Risk Factor ID": "EUR.#EAAEa",
        "Currency": "EUR",
        "Risk Factor Category": "Equity",
        "Risk Factor Type": "Equity - Market Index"
    },
    "Index_Curve_.BFX": {
        "Description": "Equity Market Index BEL 20 Index (Belgium)",
        "Risk Factor ID": "EUR.#EAAEY",
        "Currency": "EUR",
        "Risk Factor Category": "Equity",
        "Risk Factor Type": "Equity - Market Index"
    },
    "Index_Curve_.ATX": {
        "Description": "Equity Market Index ATX Index (Austria)",
        "Risk Factor ID": "EUR.#EAAEW",
        "Currency": "EUR",
        "Risk Factor Category": "Equity",
        "Risk Factor Type": "Equity - Market Index"
    },
```

Key Learning & Recommendations

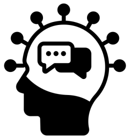


Vector DB latency with large files

Metadata quality affects LLM relevance

Prompt clarity crucial for accurate responses

Improve prompt design stability and standardization Prompt phrasing sensitivity



Chat memory integration

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Thank You!