

Snorkel

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Data development for GenAI: A systems-level view



Chris Glaze

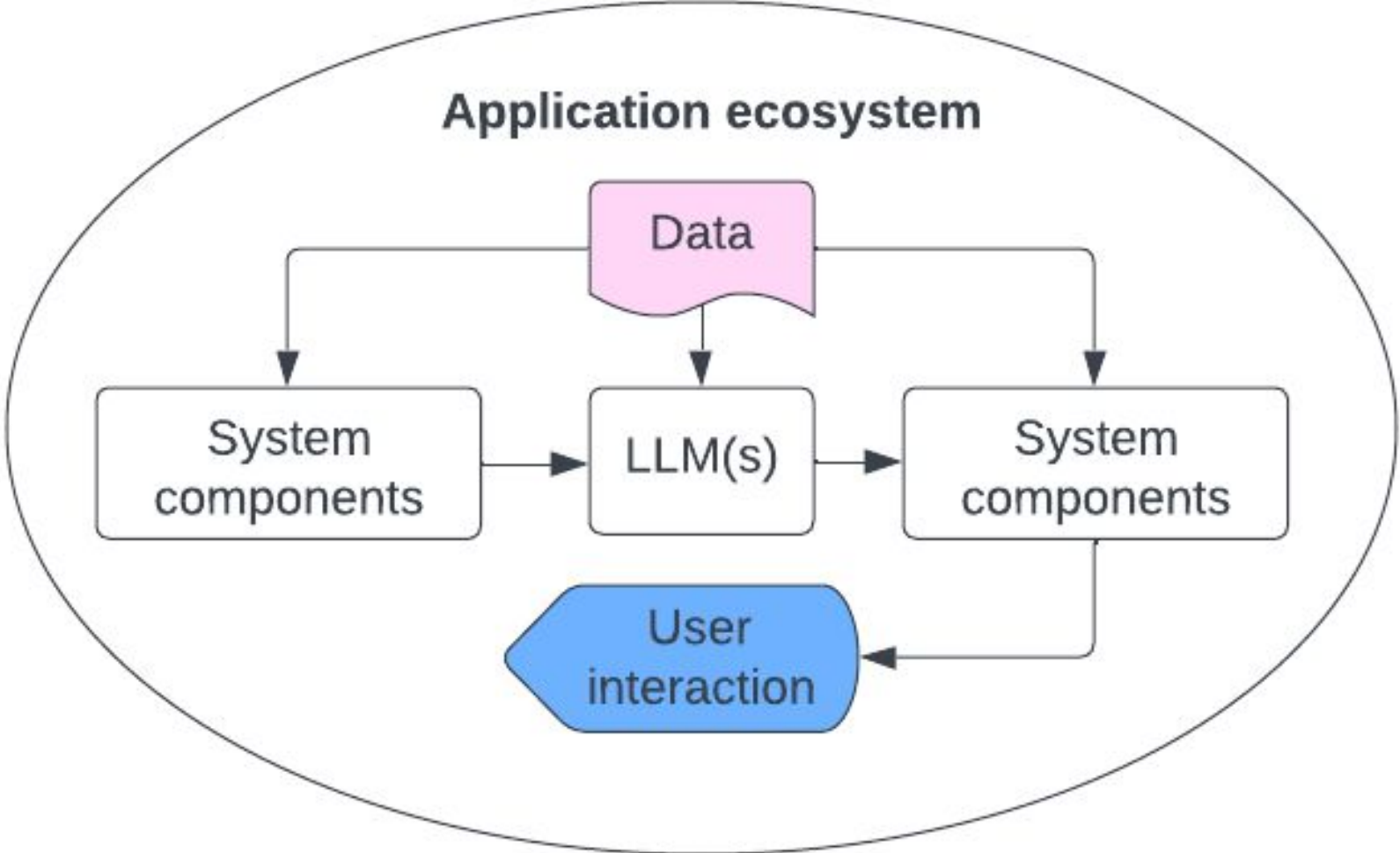
Staff Research Scientist

Summary

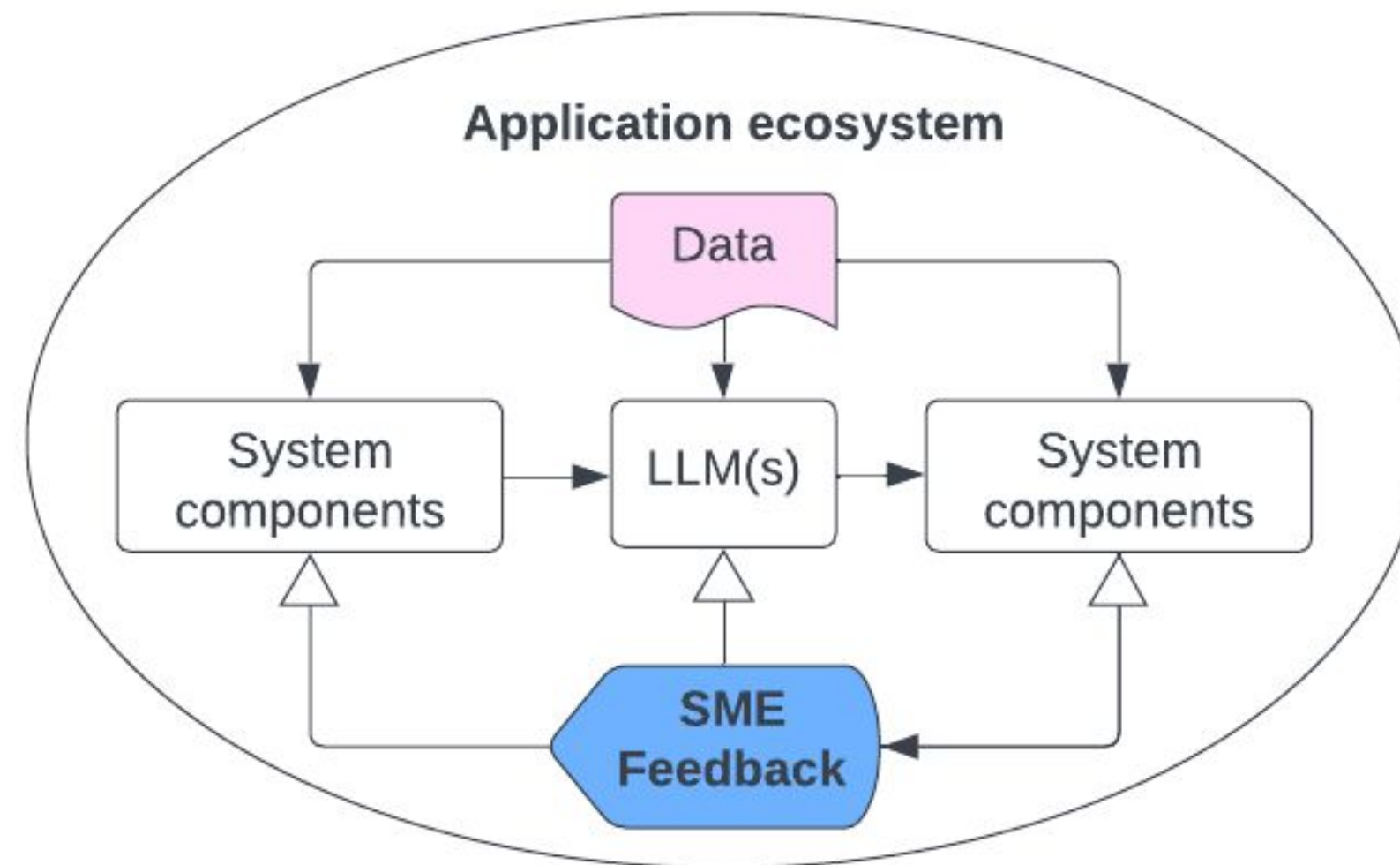
- **For large language models (LLMs) in targeted business use cases:**
 - ◆ **Accuracy depends on the larger ecosystem in which they live**
 - ◆ **All system components benefit from fine-tuning with subject-matter expert (SME) feedback**

- **Snorkel is developing methods that efficiently incorporate SMEs in these development loops**
 - ◆ **Case Study: retrieval-augmented generation (RAG) for a top global bank, 54 point increase in question-answering accuracy in 3 weeks**

Large language models do not exist in vacuums



Many components require fine-tuning



But subject-matter expert feedback has a scalability problem.

Keeping subject-matter experts in the loop

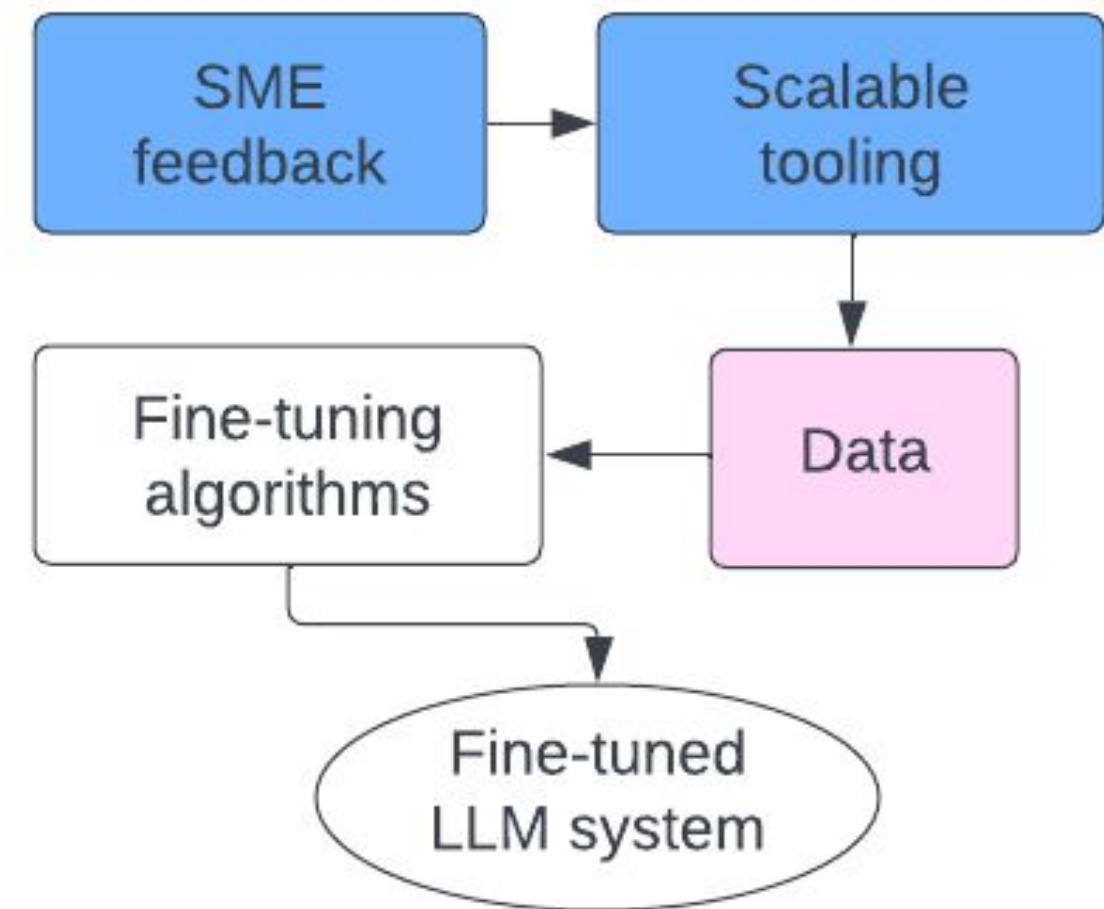
Snorkel thesis:

Data development is key.

Only subject-matter experts know what good looks like.

Snorkel approach:

- Keep subject-matter experts in the loop.
- Maximize value of their time with scalable methods to develop data.



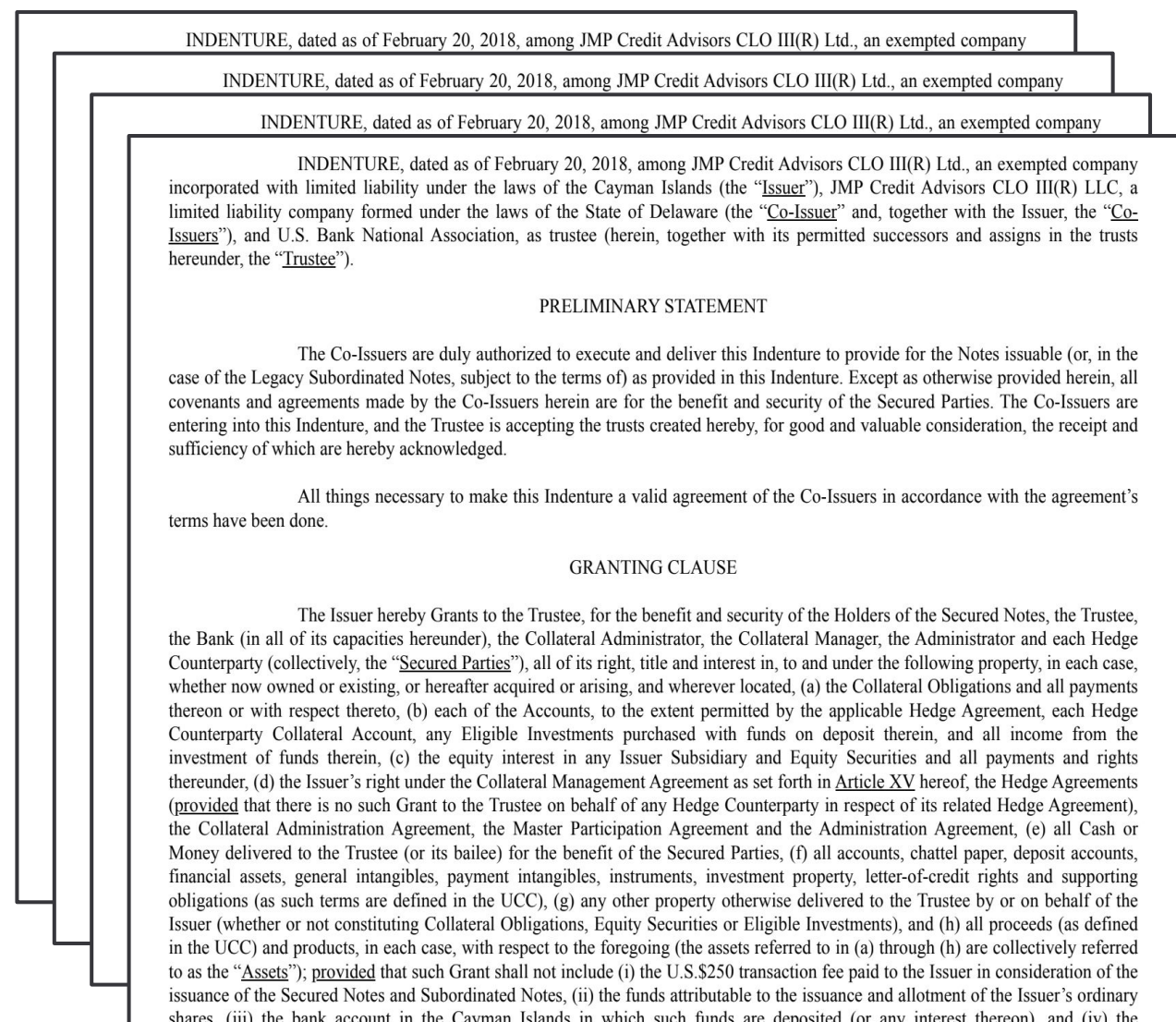
Case Study: Retrieval-augmented generation (RAG) for a top global bank

We fine-tuned portions of an LLM-based question-answering system using programmatically data development techniques, over a 3 week period:

	Baseline LLM (GPT-4) + vector retrieval	Fine-tuned LLM Q&A system	<i>Improvement</i>
Accuracy	25%	79%	<i>+54 pts.</i>

Case Study: Retrieval-augmented generation (RAG) for a top global bank

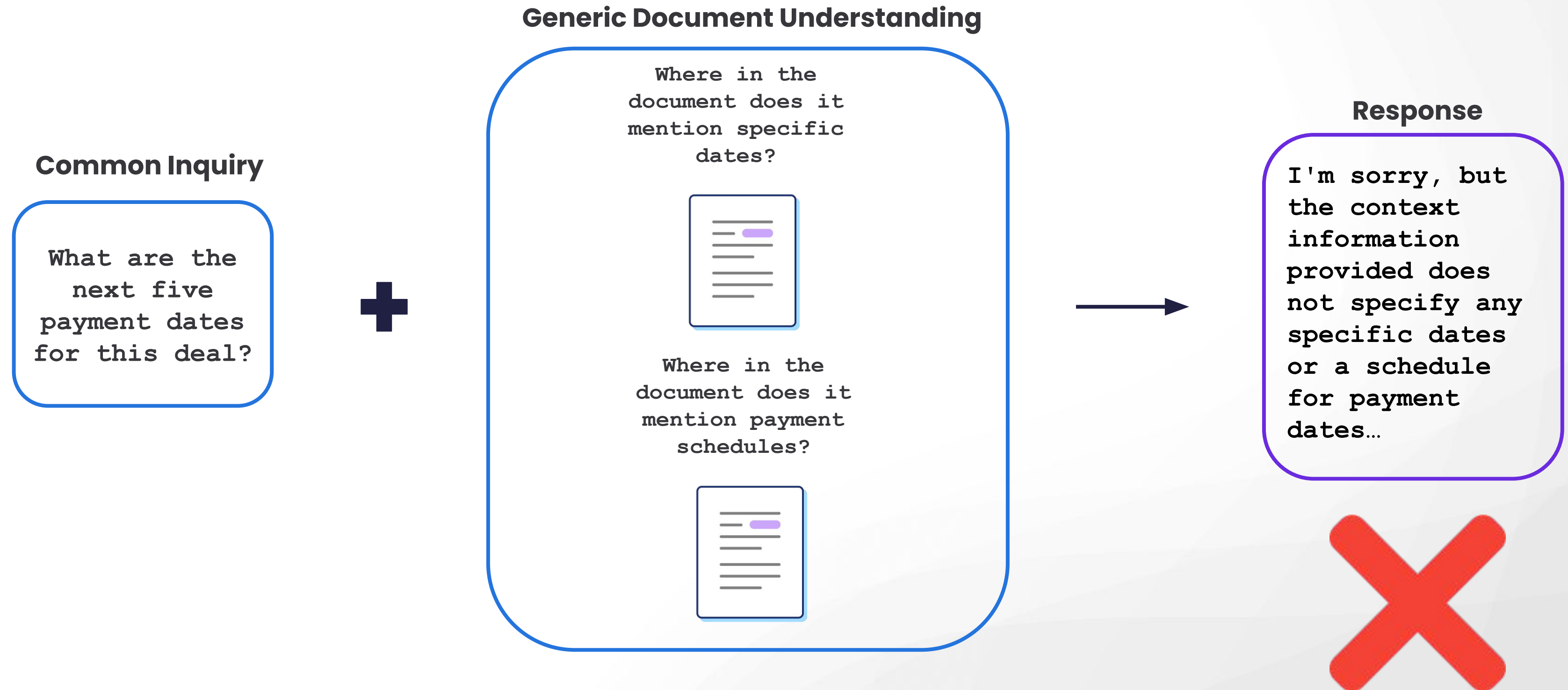
Unstructured Financial Documents



Document characteristics

- **Domain Specific:** Content is specific toniche financial products
- **Dense Documents:** Each document ranges from 200-500+ pages long
- **Subject Matter Expertise:** Bank experts are required to comprehend content and produce accurate results
- **Complex business logic:** to extract relevant information from various parts of the document

Example: Out-of-the-box RAG Performance



Example: Fine-tuned Performance

Contextual Financial Document Understanding

Common Inquiry

What are the next five payment dates for this deal?



What is the jurisdiction and business days?



Page 18

What's the payment schedule?



Page 70

When is the first payment date?



Page 144

What is today's date?



External info



Domain Knowledge

Most recent payment + six business weeks.

Repeat five times **OR** until payment is complete



Response

Payment dates for this deal are on a quarterly basis

...

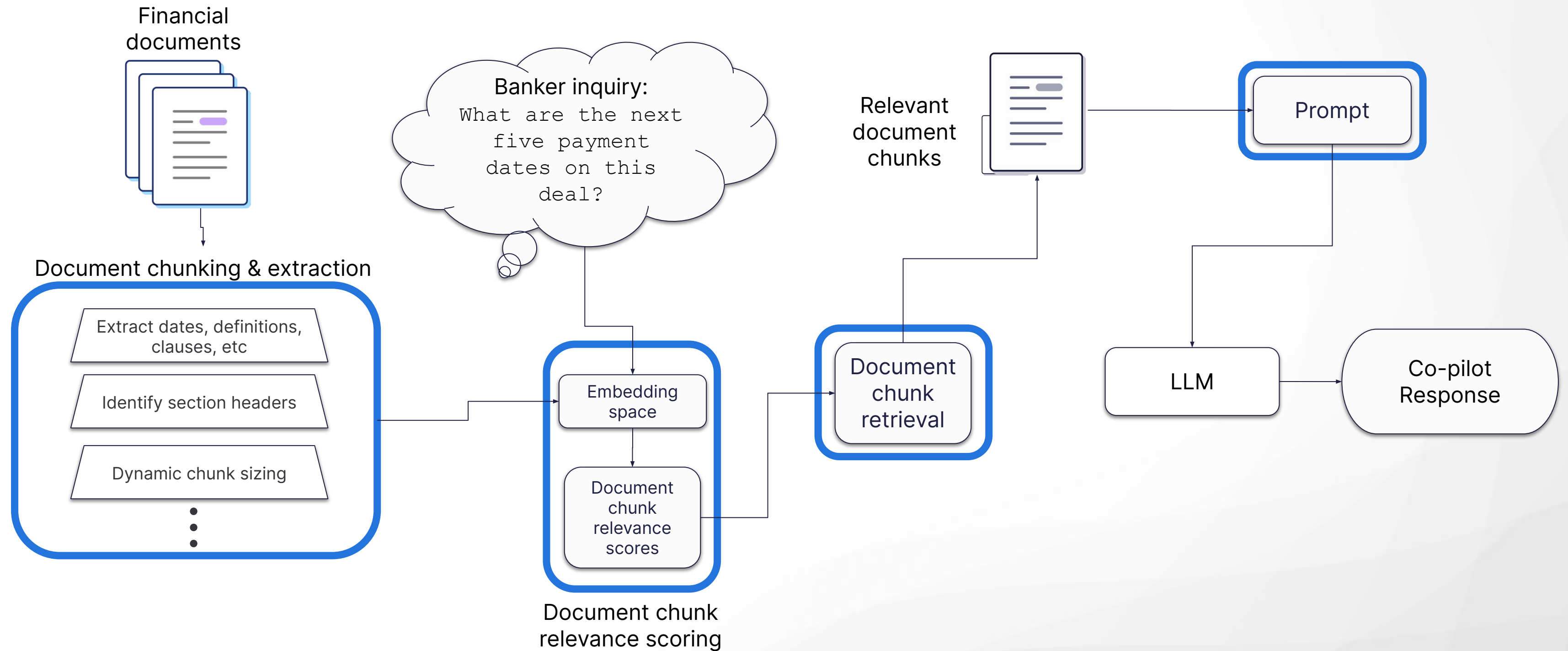
The next five payment dates would be:

- January 15, 2024
- April 16, 2024

...

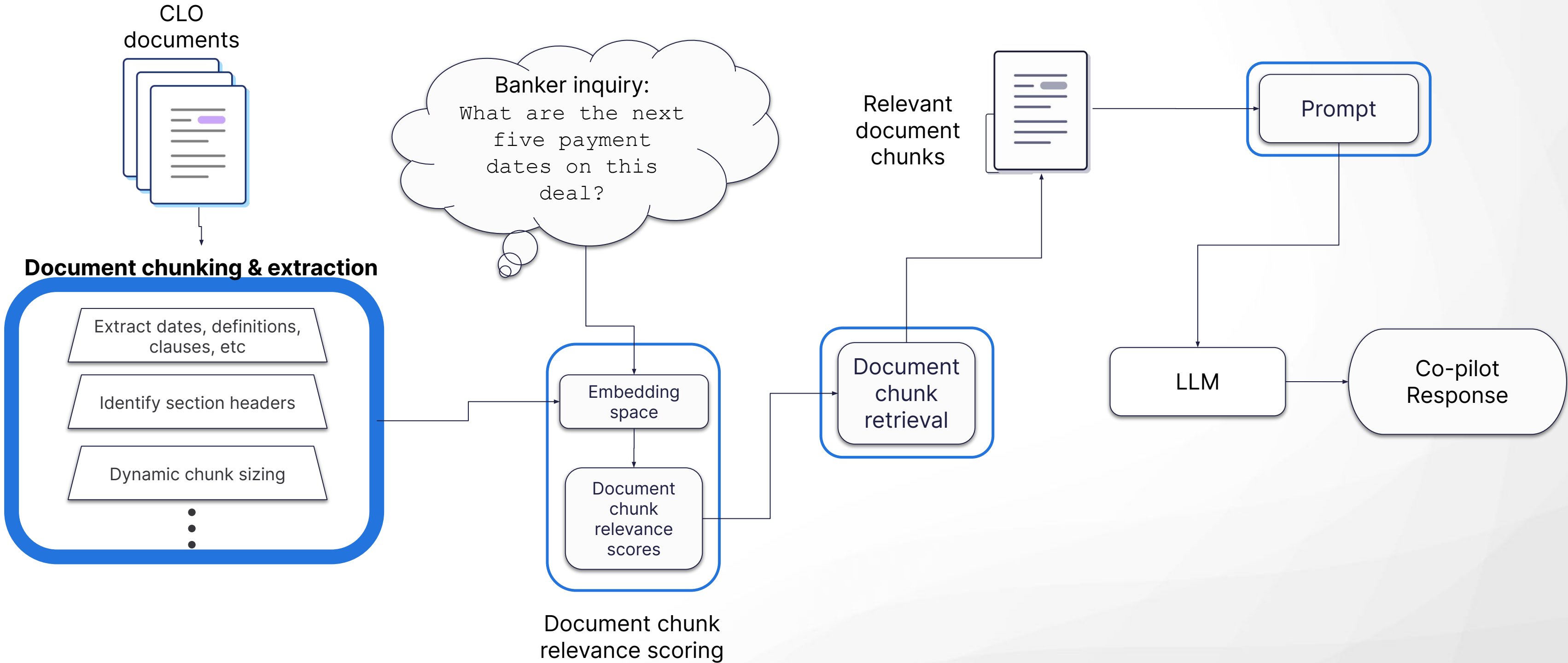


How Snorkel Did It



*Fine tuned all components with subject-matter expert input →
programmatically annotations*

Document chunking, tagging, & extraction



Document tagging & extraction

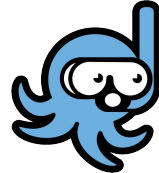


Challenge: Q&A system struggled with key entities like dates, entities, definitions

Solution: Use Snorkel Flow to rapidly label structured entities

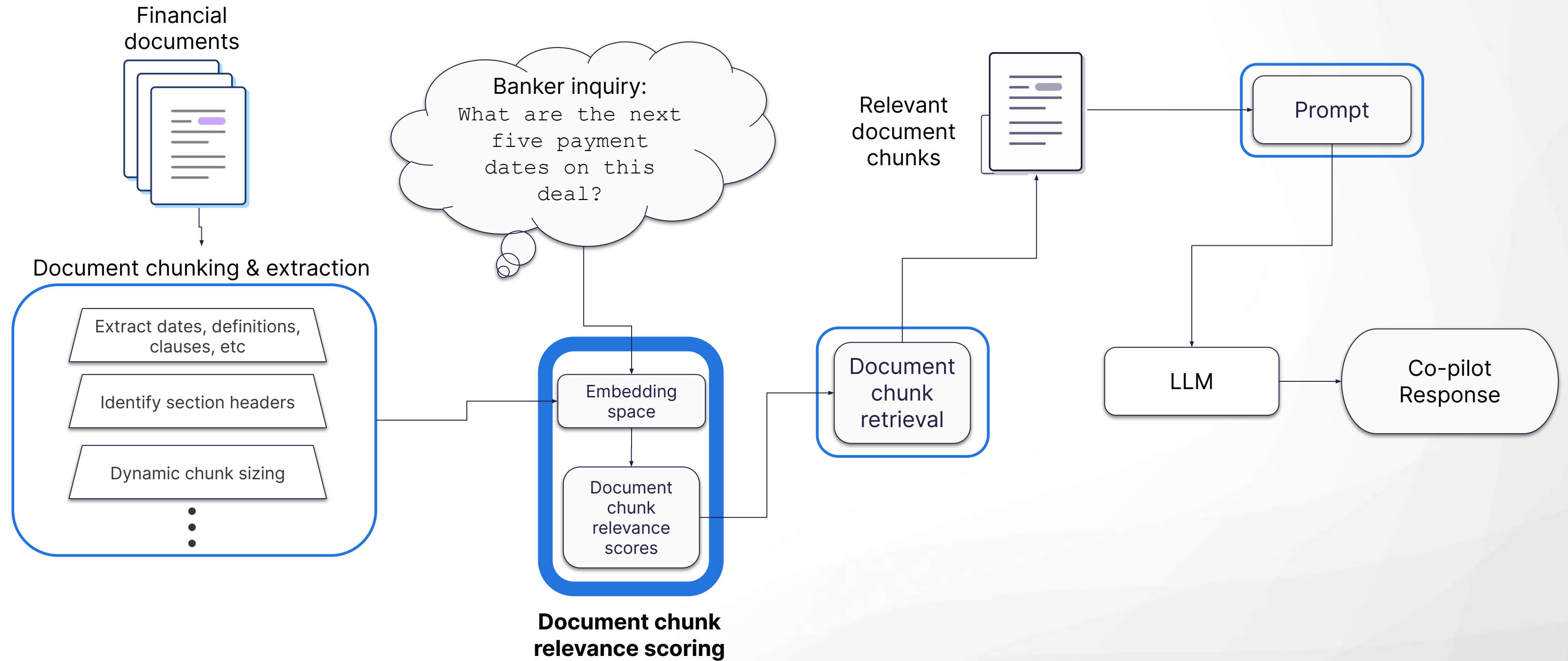
Challenge: Q&A system struggled to parse key sections, lumping them together

Solution: Use Snorkel Flow to parse section headers, tables, etc.

	Time to build training data & ML Model	SF Generated Labels	Model Accuracy
Date Model	4 hours	141,000 spans	99 F1
Definitions Model	4 hours	43,100 spans	93 F1

Subject-matter expert manually annotated relevant sections and gave us logic for those annotations → retrieval of key information

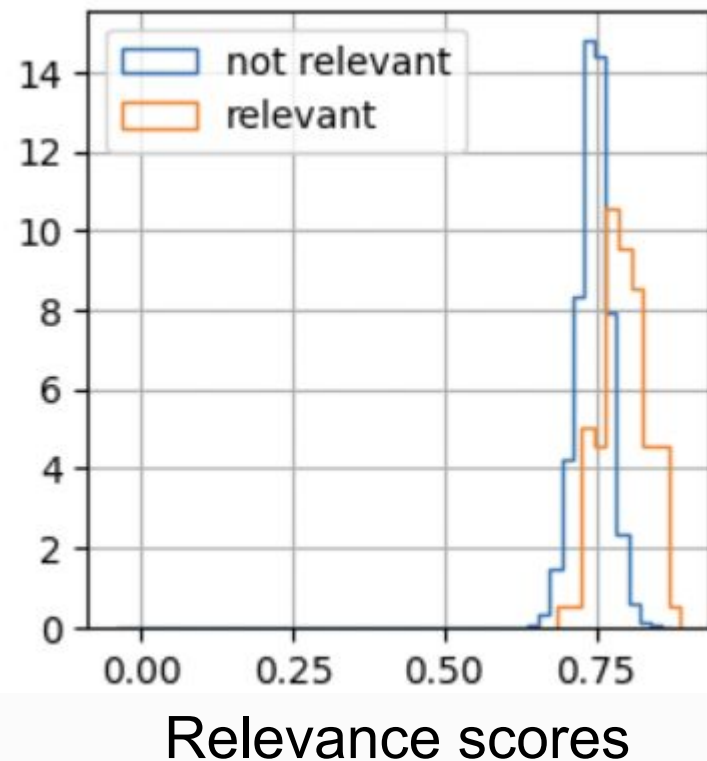
Fine-tuning the relevance scoring model



Fine-tuning the relevance scoring model

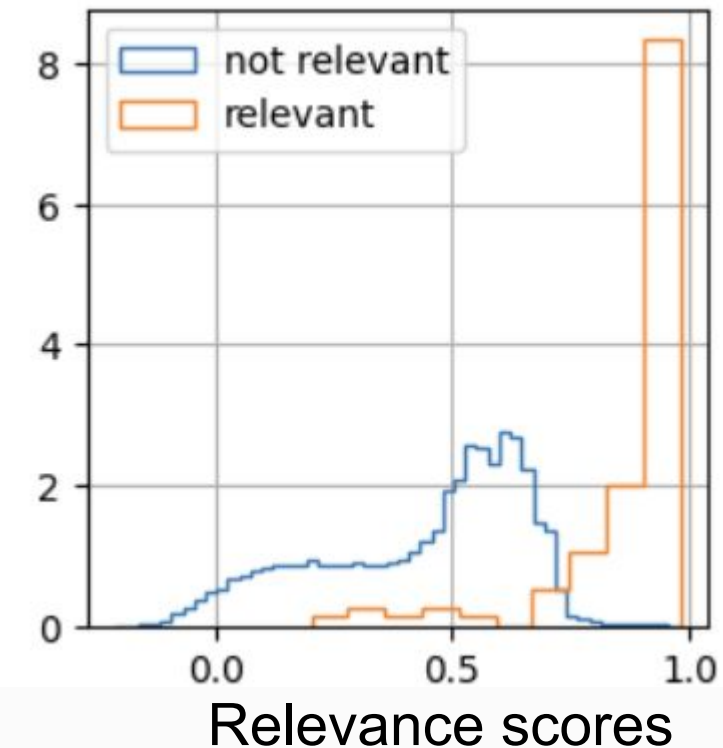
Baseline pipeline

- Pages and chunks ranked with Ada embedding



Fine tuned pipeline

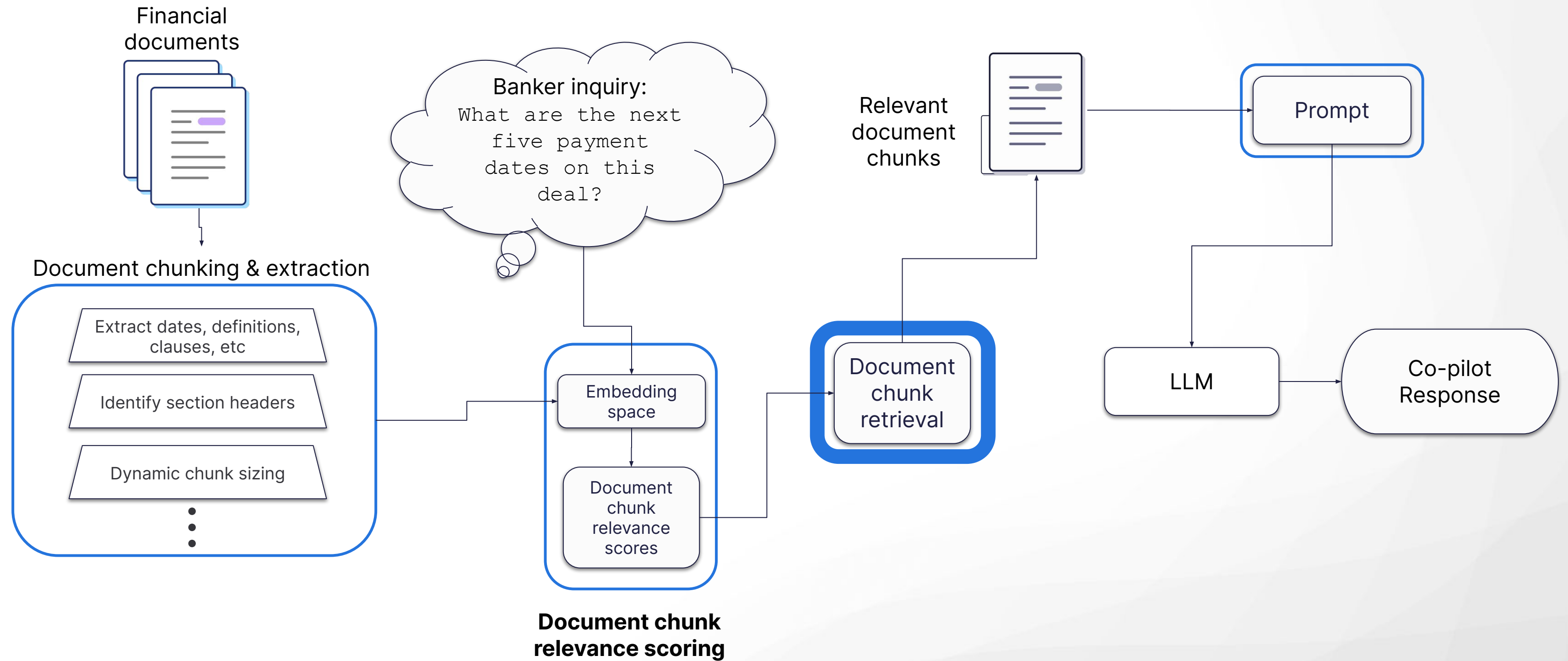
- Pages and chunks ranked with BGE embedding
- Embedding fine tuned with programmatic data



Challenge: Default embedding lumped together relevant and irrelevant chunks

Solution: Fine-tune embeddings to distinguished relevant and irrelevant chunks
Subject-matter expert annotations and logic used for training set

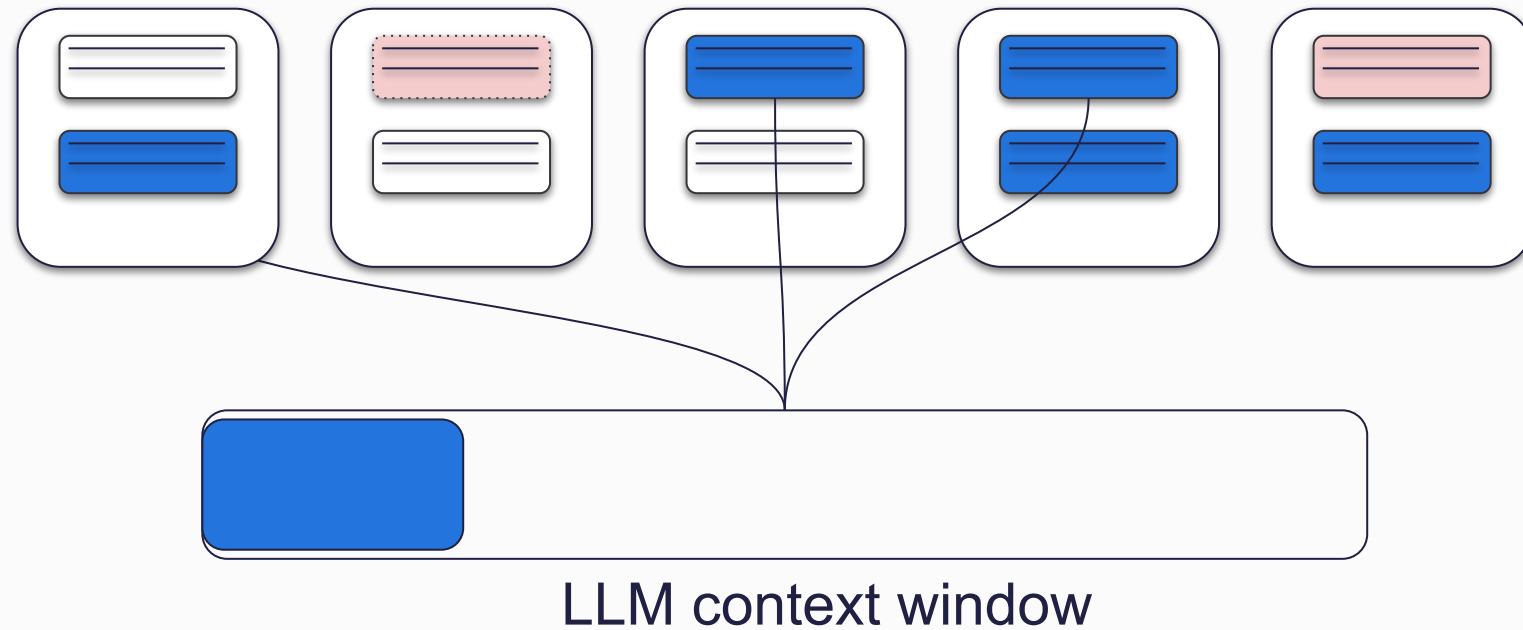
Fine-tuning the chunk retrieval algorithm



Fine-tuning the chunk retrieval algorithm

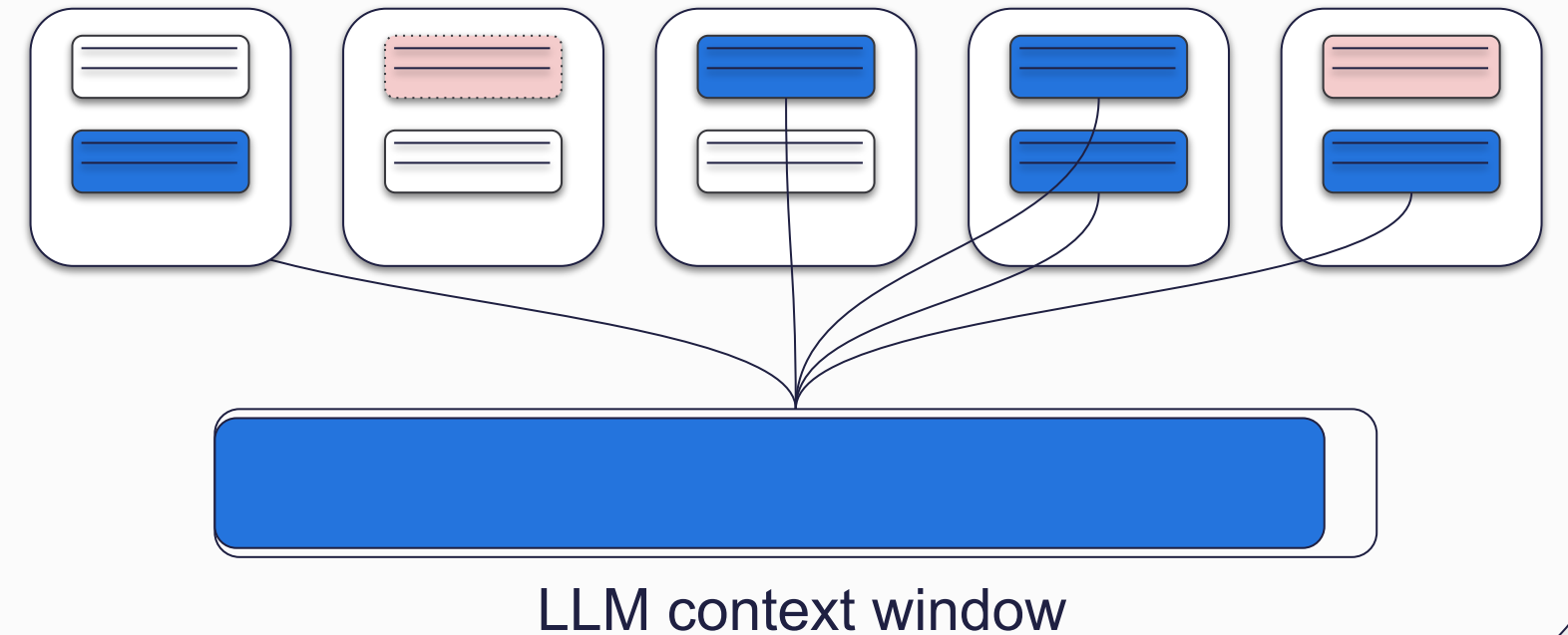
Baseline retrieval

- Fixed number (3) for every question based on ranking by relevance scores



Fine-tuned retrieval

- Number of chunks adaptive, based on relevance scores and context window size



 Low scoring chunks

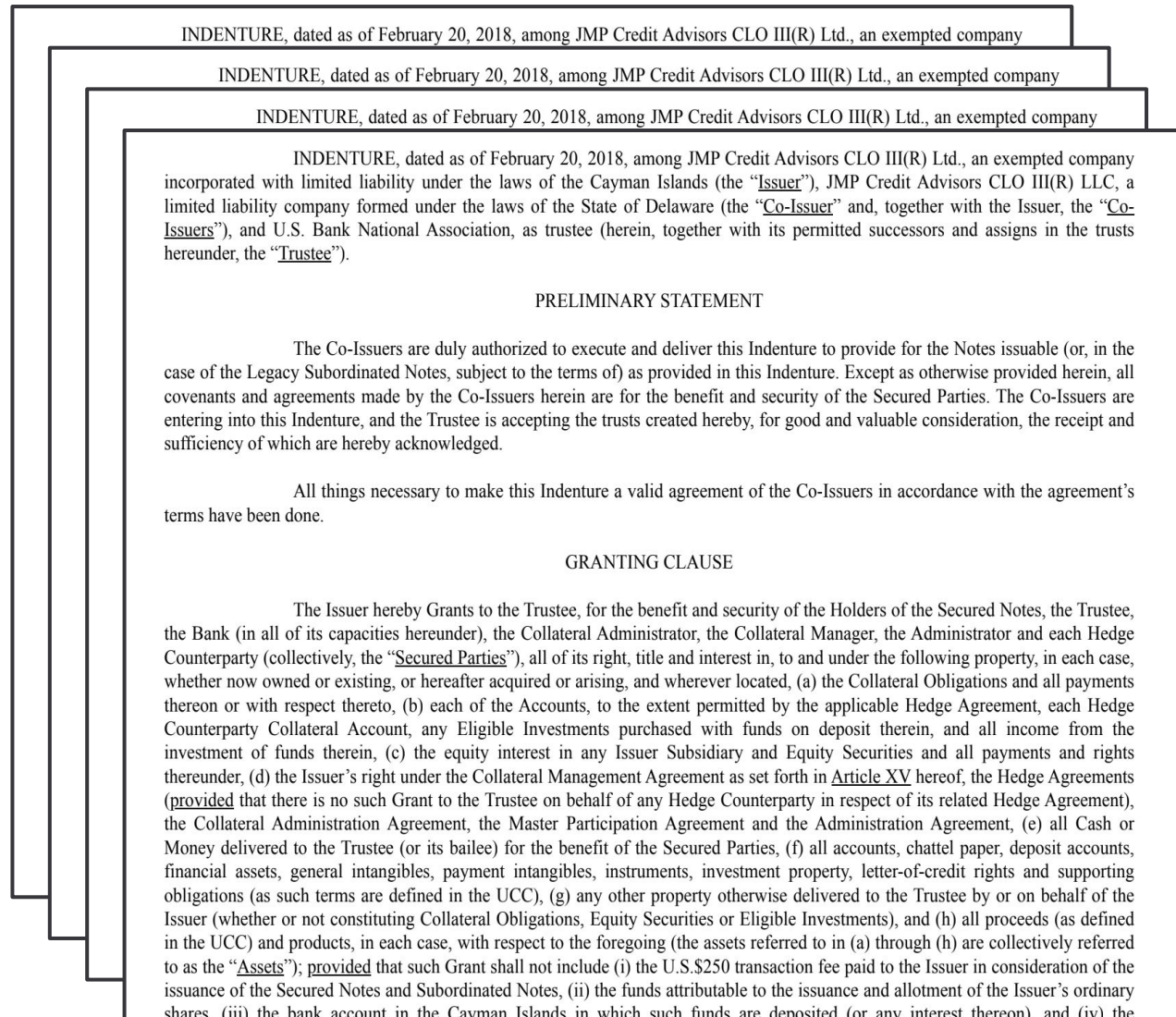
 High scoring chunks

Challenge: Multiple, disparate document sections can be relevant to a given question

Solution: Allow for varying number of retrieved chunks based on relevance scores
Subject-matter expert annotations and logic used for training set

Results: 54 point increase in answer accuracy

Unstructured Financial Documents



25% Accurate

With out-of-the-box LLM + RAG

Failed to answer hardest questions



79% Accurate

With fine-tuning + other data development

Subject-matter expert

<10 hours



in 3 weeks

Ablation studies: ½ of increase came from fine tuning the embeddings, ½ from fine tuning other components

Summary

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 - ◆ **Case Study: RAG for a top global bank, 54 point increase in QA accuracy in 3 weeks**

Thank you!

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