

Interacting with structured and unstructured scouting reports.

## Agenda

- 01. Data source
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- 03. Retreival Augmented Q/A Pipeline
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## Data Source

- Data for this project was downloaded from the GitHub page of "Trouble with the Curve", which is a CMU research paper focusing on ~10000 scouting reports till 2019.
- Data overview :

	#	Column	Non-Null Count	Dtype 
ı	0	name	9175 non-null	object
	1	key_mlbam	9175 non-null	object
	2	key_fangraphs	9175 non-null	object
	3	age	9175 non-null	float64
	4	year	9175 non-null	int64
	5	<pre>primary_position</pre>	9175 non-null	object
	6	eta	9175 non-null	int64
	7	report	9175 non-null	object
	8	Arm	9175 non-null	int64
	9	Changeup	9175 non-null	int64
	10	Control	9175 non-null	int64
	11	Curveball	9175 non-null	int64
	12	Cutter	9175 non-null	int64
	13	Fastball	9175 non-null	int64
	14	Field	9175 non-null	int64
	15	Hit	9175 non-null	int64
	16	Power	9175 non-null	int64
	17	Run	9175 non-null	int64
	18	Slider	9175 non-null	int64
	19	Splitter	9175 non-null	int64
	20	source	9175 non-null	object
	21	birthdate	9175 non-null	object
	22	mlb_played_first	9175 non-null	int64
	23	debut_age	9175 non-null	float64
	24	label	9175 non-null	int64
	25	text	9175 non-null	object

- Size: 9,175 scouting reports covering amateur draft, international, & MiLB prospects.
- Scope: Seasons 2013-2019 ( year ).
- Two Information Layers: "report" scout report and "text" fallback article.
- Pitcher-related columns: "Fastball"," Slider", "Changeup", "Control", etc.
- Hitter-related columns: "Hit", "Power, Run", "Field", "Arm".
- Player Metadata "Name", "primary\_position"

#### Data Preprocessing, Chunking and Embedding Strategy

- 1 Row → Rich Text Blob merge narrative report with inline tool grades (e.g., "Fastball 60 Slider 55") so numeric traits become searchable by the embedding model.
- Smart Split Rule only rows > 1600 chars get chunked; RecursiveCharacter splitter makes ~400-token segments with 50-token overlap to preserve sentence context.
- High-Recall Embeddings OpenAI text-embedding-3-large (3 072-dim) encodes each chunk; numbers + prose live in the same vector space.
- Metadata Attached, Not Embedded name, year, pos, eta, source stored as Pinecone metadata for fast filter queries (e.g., pos = "LHP", year = 2018).
- Pinecone Vector Store ~9 k rows  $\rightarrow$  ~9 k chunks  $\rightarrow$  upserted to a 3 072-dim cosine index; query retrieves k nearest chunks, then GPT-40 answers with strictly grounded context.

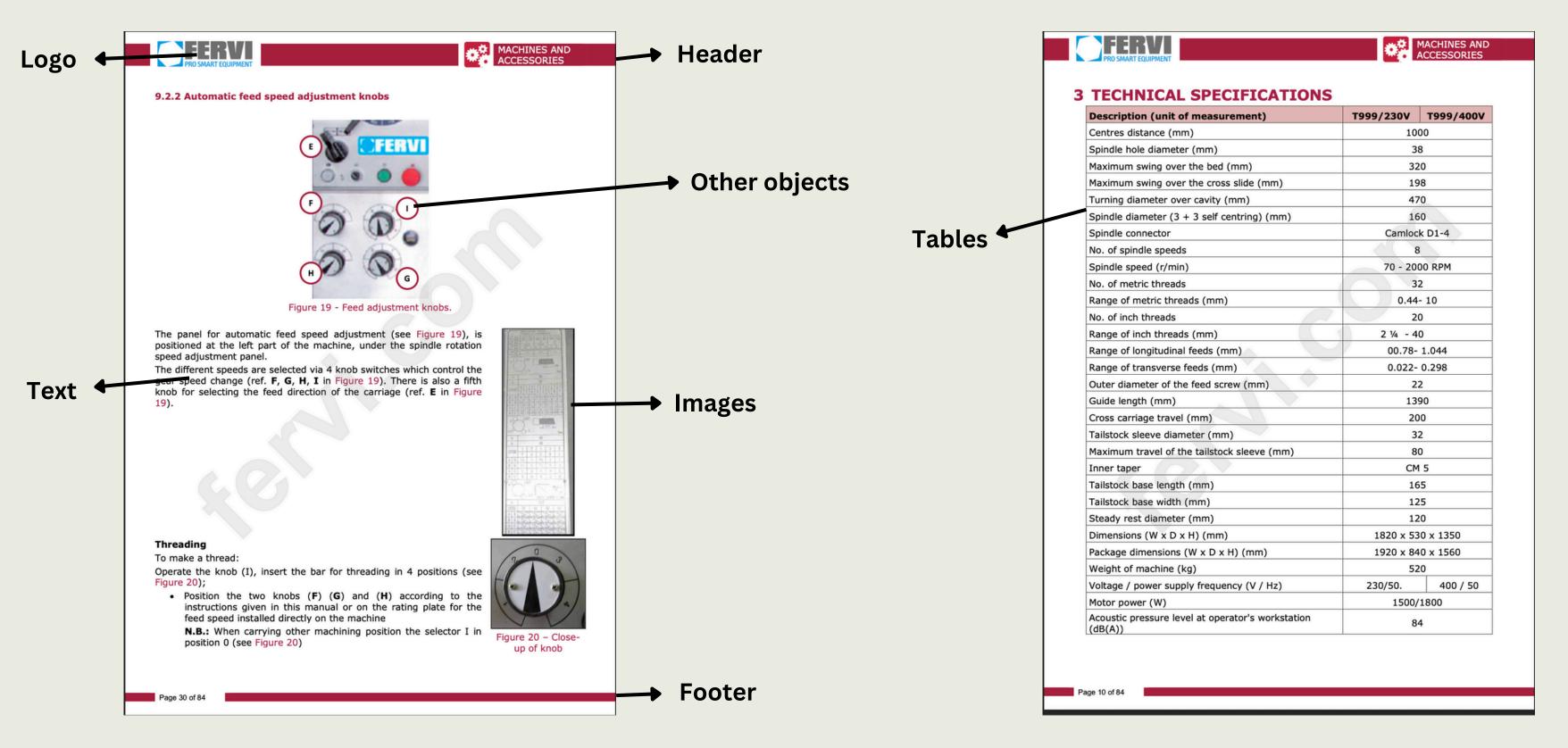
# Retreival Augmented Q/A Pipeline

- User Question: Free-form query ("Which left-handed 2018 arms show plus command + CH  $\geq$  50?")
- Metadata Filter (optional): pos = "LHP", year = 2018 applied inside Pinecone  $\rightarrow$  trims search space.
- Vector Search (Pinecone, k = 4): Cosine similarity on 3 072-dim embeddings → returns top-k chunk IDs
  + scores.
- Context Builder: Concatenate retrieved chunks with --- dividers  $\rightarrow$  ~2-4 × 400 tokens
- System prompt enforces: "Use context only, obey numeric cut-offs, no hallucination."
- **GPT-40 Answer**: LLM reasons over context  $\rightarrow$  returns concise list; code then prints the ranked source

Preview

**Typical latency**: ~2.3 s end-to-end • Cost:  $\approx$  \$0.0006 per query **Grounding gap closed**: answer always traceable to cited scouting-report snippets

## Unstructured Data for RAG



Solution: Multimodal RAG!

### Dealing with Unstructured Scouting Reports

- **Unified Loader**: *PyPDFLoader* pulls every page → one Document per page with page # metadata.
- Text Handling pdfminer-based extraction keeps paragraph order and heading levels.
  RecursiveCharacterTextSplitter respects "##/###" headers → ~400-token, 50-overlap chunks so sentences stay whole.
- Images & Diagrams: Non-text objects skipped during parse (no OCR needed for scouting PDFs).
  Figure captions are kept as plain text → preserved scouting notes on arm slots or biomechanics photos.
- **Tables**: In-line grade tables (e.g., "Fastball | 60") flatten to ASCII rows; regex converts to "Fastball 60" strings so embeddings capture numeric meaning. Column borders & shading stripped to avoid token waste.
- **Noise Cleanup**: Footers like "Page 12 of 25" and watermark text removed via regex, set configuration for logos (example: DIAGRAM\_THRESHOLD = 0.60, LOGO\_THRESHOLD = 0.10)
- Unicode tidy: curly quotes → straight, em-dashes → "-", ligatures split.
- **Rich Metadata Tags**: {"source\_type": "pdf", "file": "2024-draft-catchers.pdf", "page":17} attached to every chunk for precise citation & filters.

## Future Scope

• All-in-one Lakehouse stack – store our scouting-report vectors in Mosaic AI Vector Search, orchestrate the workflow in a Databricks notebook or job, and call GPT-40 through a model serving endpoint.

• Agent Framework + LangChain – Databricks' new Agent Framework lets us wrap each step (retrieve → reason → write) as tool-calling agents; LangChain integrations come pre-wired.

• Model Context Protocol (MCP) – Databricks hosts an MCP server that auto-registers our vector search and SQL helper functions as tools; any compliant agent can discover and invoke them without custom glue code.