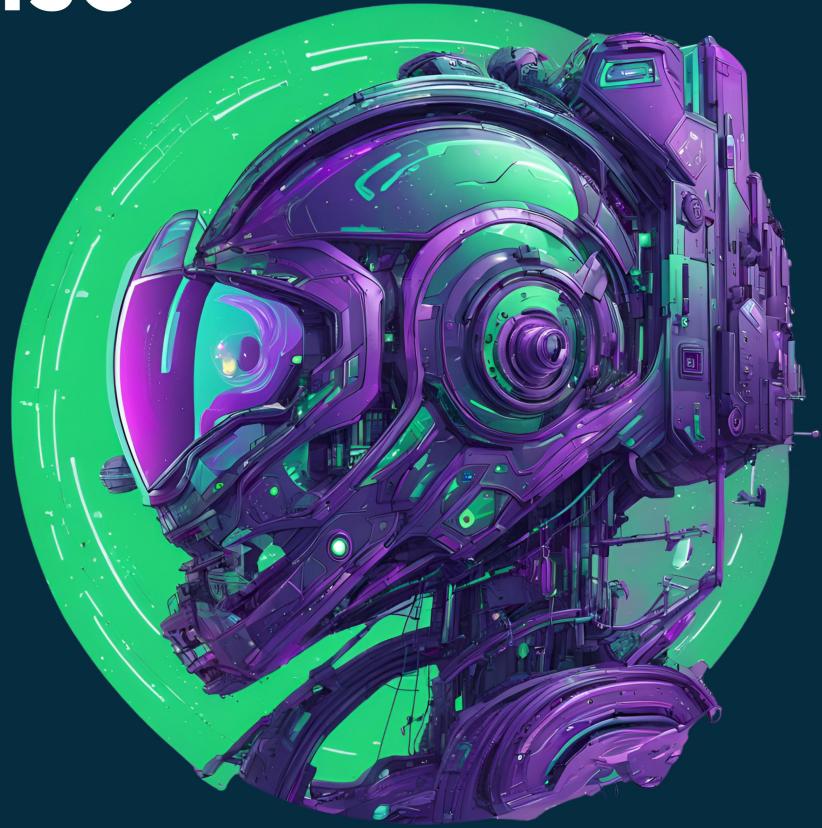


# Enhanced Enterprise Intelligence with your personal AI Data Copilot

by Marek Wiewiórka, Phd





Part of Xebia

The Xebia logo, which consists of the word "Xebia" in a white sans-serif font inside a purple rounded rectangular shape.

## Marek Wiewiórka

*PhD | Chief Data Architect at  
GetInData*



# ...how to turn best practices into AI coding assistant

1. Why do we need yet another (open-source ) Copilot?
2. How can we build one?
3. Architecture and evaluation
4. DEMO



# (Data) Context is king!

- *Explicit* and *precise* data context of your whole data platform
- Data transformation codebase
- Data models with comments and table relationships
- Other user queries
- Lineage and human curated dataset descriptions from data catalogs



# Data Assistants landscape

- open-source tools, such as [WrenAI](#), [Venna.AI](#), [Dataherald](#) focus on Text-to-SQL to be embedded in web interfaces – i.e. chatbots or own SQL editors – meant for non-technical users.
- closed source AI-Powered Assistants to BigQuery (SQL+Dataform), Snowflake (SQL), Databricks (SQL+Python) web interfaces, more like a black-box not-meant for customizations.
- missing Analytics Engineer Copilot with a dbt/SQL support

# Customized and specialized models are the future.



We believe that in the future, the vast majority of organizations will develop customized models that are personalized to their industry, business, or use case. With a variety of techniques available to build a custom model, organizations of all sizes can develop personalized models to realize more meaningful, specific impact from their AI implementations. The key is to clearly scope the use case, design and implement evaluation systems, choose the right techniques, and be prepared to iterate over time for the model to reach optimal performance.

## Top-tier enterprise intelligence at incredibly low training cost

At Snowflake, we see a consistent pattern in AI needs and use cases from our enterprise customers. Enterprises want to use LLMs to build conversational SQL data copilots, code copilots and RAG chatbots. From a metrics perspective, this translates to LLMs that excel at SQL, code, complex instruction following and the ability to produce grounded answers. We capture these abilities into a single metric we call **enterprise intelligence** by taking an average of Coding (HumanEval+ and MBPP+), SQL Generation (Spider) and Instruction following (IIEval).



Why Databricks Product Solutions Resources About

DATA + AI SUMMIT

## Build high-quality generative AI applications with DBRX customized for your unique data

by [Jonathan Franke](#), [Ali Ghodsi](#), [Naveen Rao](#), [Hanlin Tang](#), [Abhinav Venigalla](#) and [Matei Zaharia](#)

March 27, 2024 in [Company Blog](#)

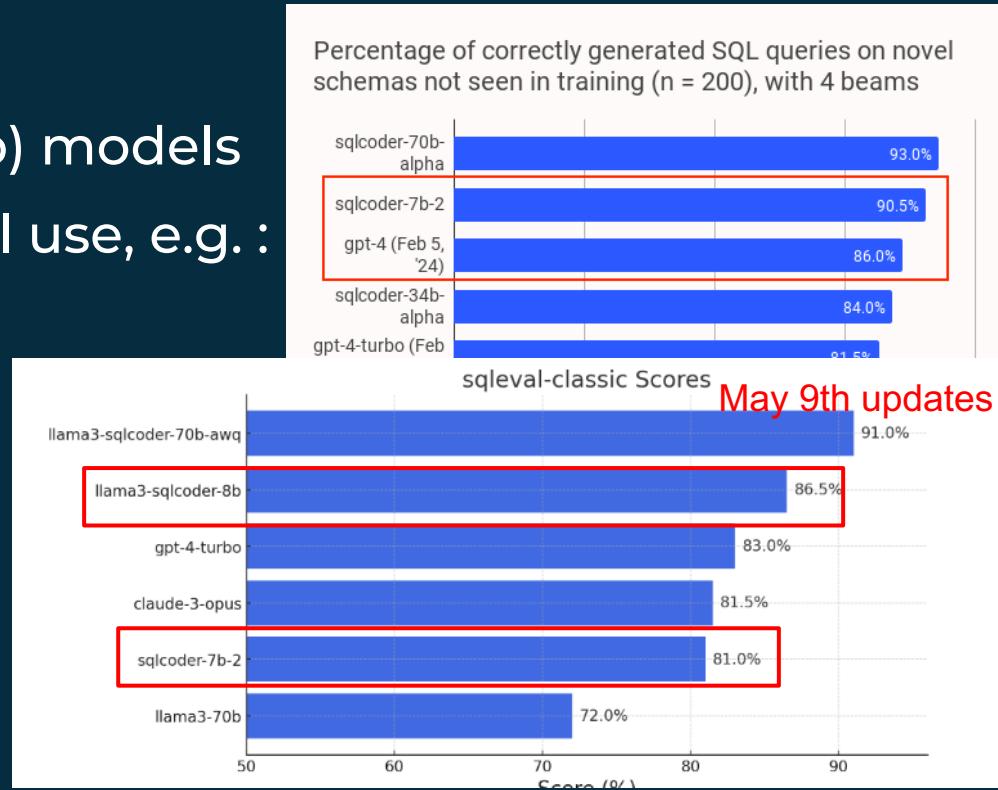
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Databricks' mission is to deliver data intelligence to every enterprise by allowing organizations to understand and use their unique data to build their own AI systems. Today, we are excited to advance our mission by open sourcing DBRX, a general purpose large language model (LLM) built by our [Mosaic Research](#) team that outperforms all established open source models on standard benchmarks. We believe that pushing the boundary of open source models enables generative AI for all enterprises that is customizable and transparent.

# sqlcoder-7b and others

- Many other small (7-34b) models licensed for commercial use, e.g. :
  - ✓ starcoder2
  - ✓ dolphincoder
  - ✓ deepseek-coder
  - ✓ Opencodeinterpreter
  - ✓ Llama3



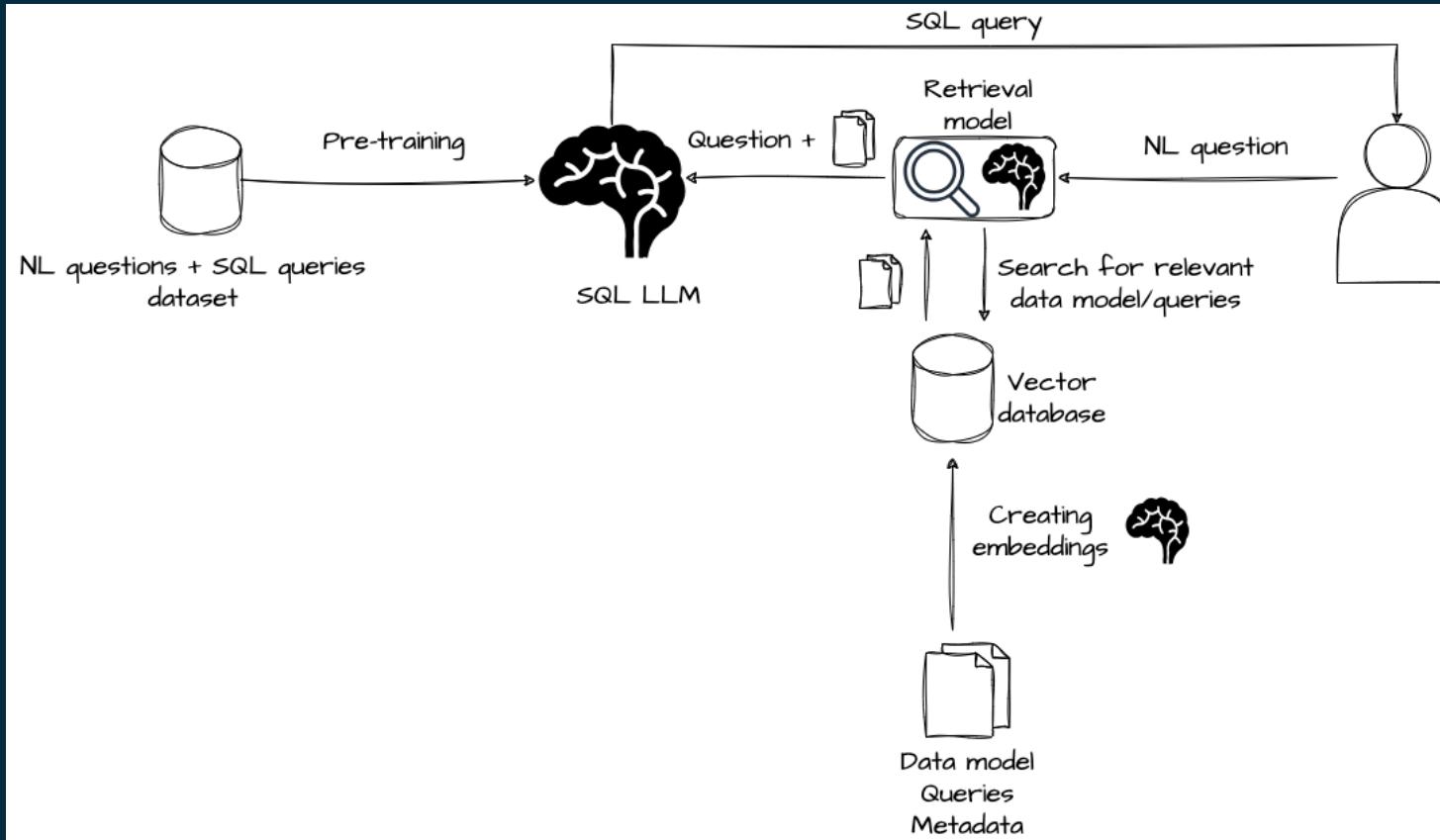
# How turn your best practices into Copilots ?

- Vector database as a knowledge base - what ?
- Prompts as instructions following best practices - how ?
- LLM to combine both...

## Retrieval-Augmented Generation(RAG)

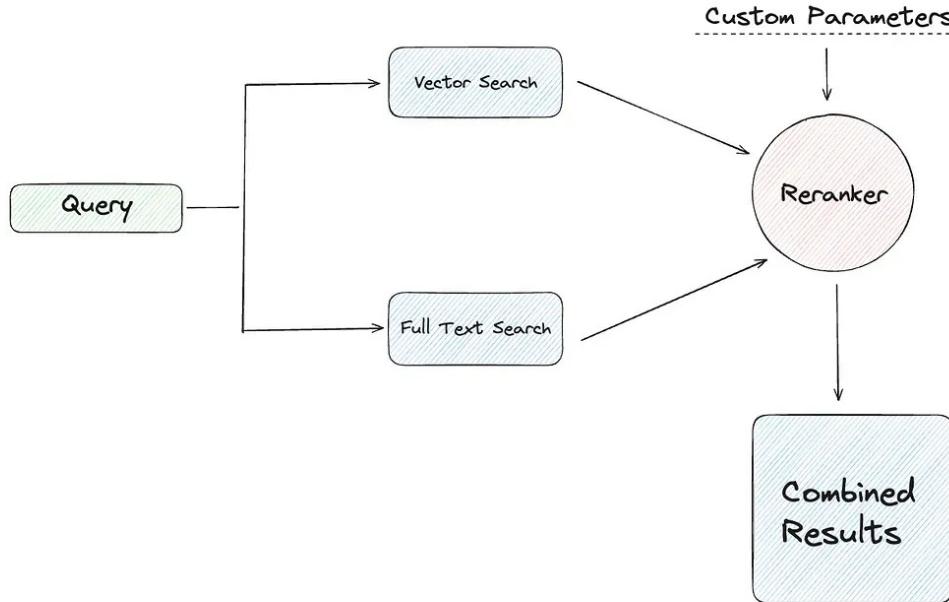


# RAG for Text-to-SQL



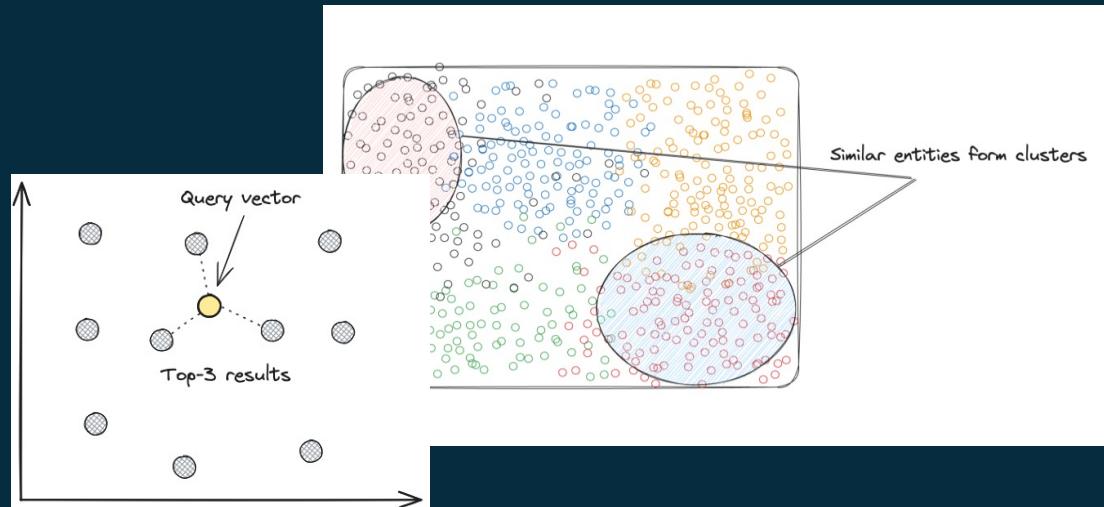
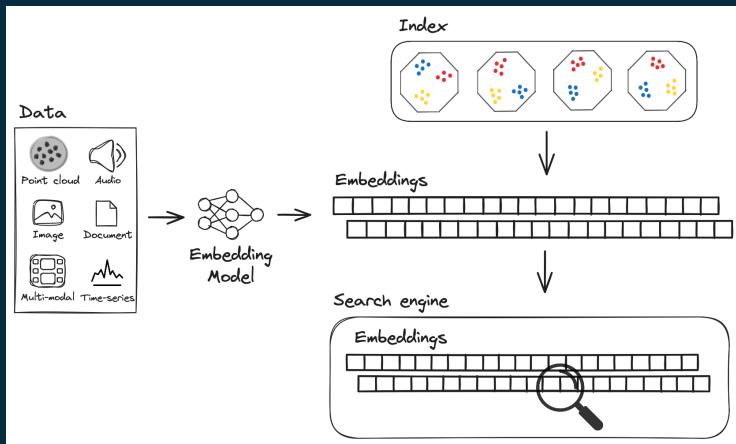
# Hybrid search

- combination of keyword and vector search

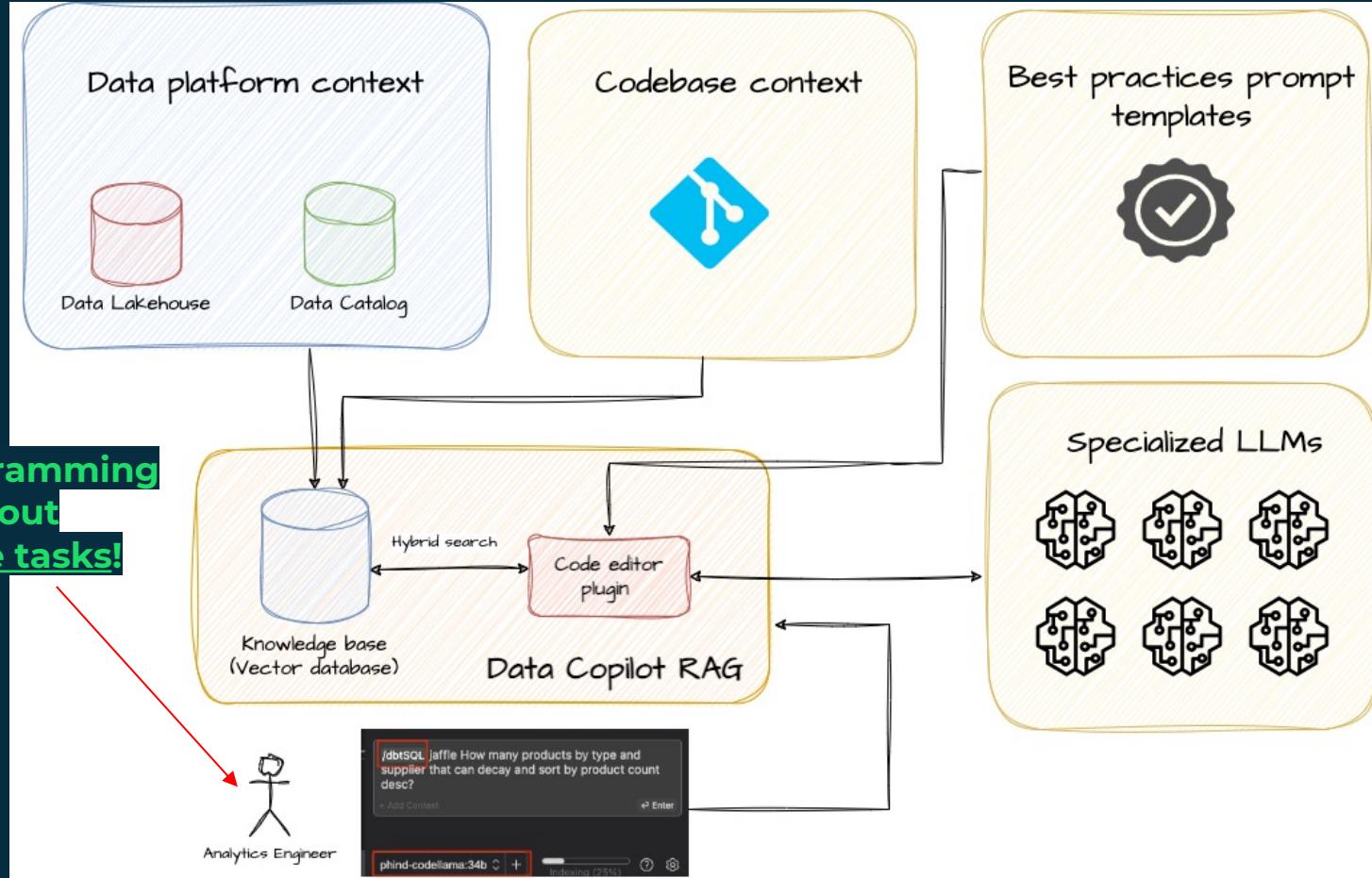


# Vector search

- a technique used to search for similar items based on their vector representations, called embeddings
- Approximate Nearest Neighbours algorithms



# Data Copilot RAG architecture



# GID Data Copilot (GDC)

- An extensible AI **programming assistant** for **SQL** and **dbt** code
- Powered by:
  - **Large Language Models** (SOTA LLMs)
  - Robust **Retrieval Augmented Generation** (RAG) architecture
  - **Hybrid search** techniques
  - **Fast Vector Database**
  - **Curated Prompts**
  - **Builtin Data commands**

The screenshot illustrates the GID Data Copilot interface, which integrates multiple tools for data engineering and machine learning development.

- Code Editor:** Shows two files: `perishable_products.yml` and `perishable_products.sql`. The SQL file contains a query to calculate product counts based on supply type and perishability.
- Terminal:** Displays the output of running the dbt command to build the model, showing the creation of the `main.perishable_products` table.
- Search and RAG:** A red callout points to a message from a Large Language Model (LLM) named "RAGDB laffledb" asking about a specific column and table to use for finding products that can decay.
- Hybrid search:** A green callout points to a search bar labeled "Hybrid search" where the user has typed "@RAGDB laffledb what column and table to use if I need to find products that can decay?"
- Data "slash" commands:** A yellow callout points to a dropdown menu showing "Data slash commands" such as `/dbSQL`, `/dbModel`, and `/dbDataQuality`.
- Context Used:** A tooltip provides information about the `is_perishable_supply` column, stating it indicates whether a product can decay.

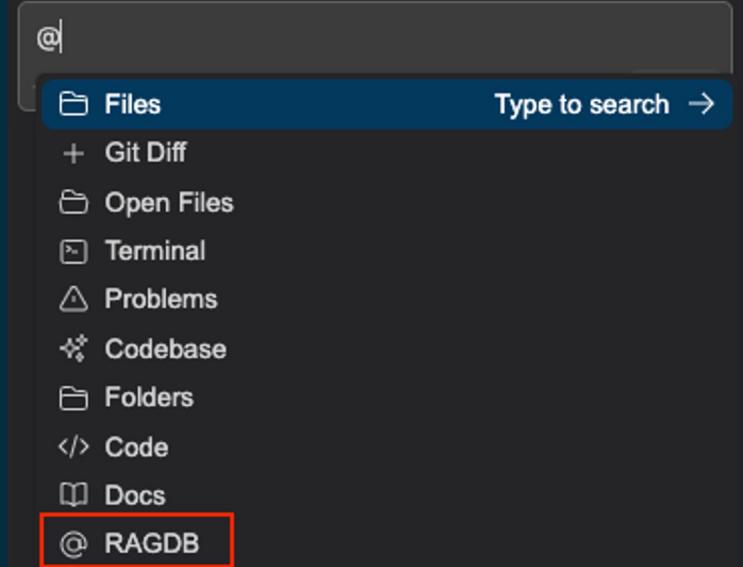
## Continue - an open-source copilot



- support for both tasks and tab autocompletion
- highly extensible
  - use any LLM model you wish - also ***multiple, specialized models*** for different languages or tasks
  - support for many ***model providers***, such as Ollama, vLLM, LM Studio
  - custom ***context providers*** for more control over LLMs augmentation
  - custom ***slash commands*** that can combine own *prompts*, *contexts* and *models* for specialized, reusable tasks
- support for VSCode and Jetbrains
- secure (i.e. can be run locally, on-premise or cloud VPC)
- translate *your best practices* into "slash data commands"

# Continue - a custom context provider

```
const RagContextProvider: CustomContextProvider = {  
  title: "ragdb",  
  displayTitle: "RAGDB",  
  description:  
    "Retrieve DB schema from our vector database of internal documents",  
  type: "normal",  
  
  getContextItems: async () => {  
    ← generate context  
    query: string,  
    extras: ContextProviderExtras  
  }: Promise<ContextItem[]> => {  
  console.info(extras.fullInput)  
  const inputArray = extras.fullInput.split(' ');\n  const db = inputArray[0];\n  const userQuestion = inputArray.slice(2).join(' ');\n  const response = await fetch("http://localhost:8000/retrieve") {  
    method: "POST",  
    headers: {  
      'content-type': 'application/json;charset=UTF-8',  
    },  
    body: JSON.stringify({ query: userQuestion }),  
  };  
  
  const results = await response.json();  
  
  return results.map(result: { title: any; contents: any; }) => ({  
    name: result.title,  
    description: result.title,  
    content: result.contents,  
  });  
},  
};
```



# dbtSQL task = custom(context + prompt + model)

```
export function modifyConfig(config: Config): Config {
  config.slashCommands7.push({
    name: "dbtSQL",
    description: "Write a SQL code",
    run: async function*( sdk) {
      const inputArray = sdk.input.split(' ');
      const db = inputArray[0];
      const userQuestion = inputArray.slice(2).join(' ');
      const response = await fetch("http://localhost:8000/retrieve", {
        method: "POST",
        headers: {
          'content-type': 'application/json;charset=UTF-8',
        },
        body: JSON.stringify({ query: userQuestion }),
      });

      const results = await response.json();

      const ragResponse = results.map((result: { title: any; contents: any; }) => ({
        name: result.title,
        description: result.title,
        content: result.contents,
      })[0]);

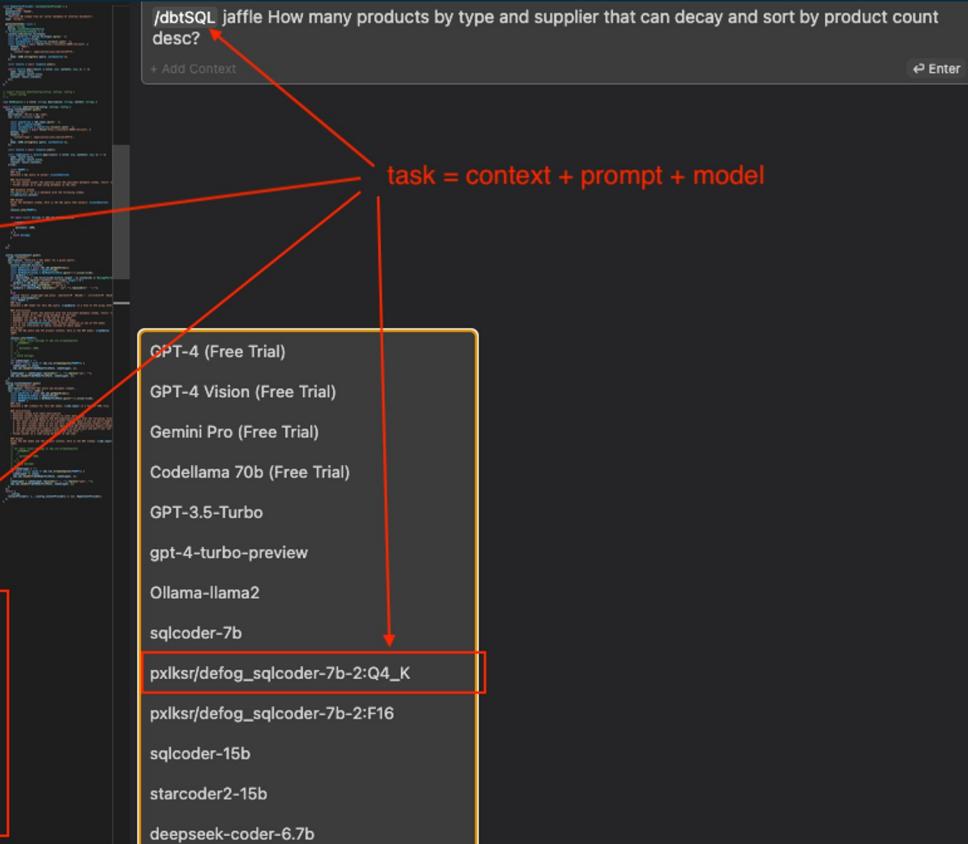
      const PROMPT = `

      ### Task
      Generate a SQL query to answer: ${userQuestion}

      ### Instructions
      - If you cannot answer the question with the available database schema, return 'I
      - Format answer as a code using markdown in the chat.

      ### Database Schema
      The query will run on a database with the following schema:
      ${ragResponse.content}`

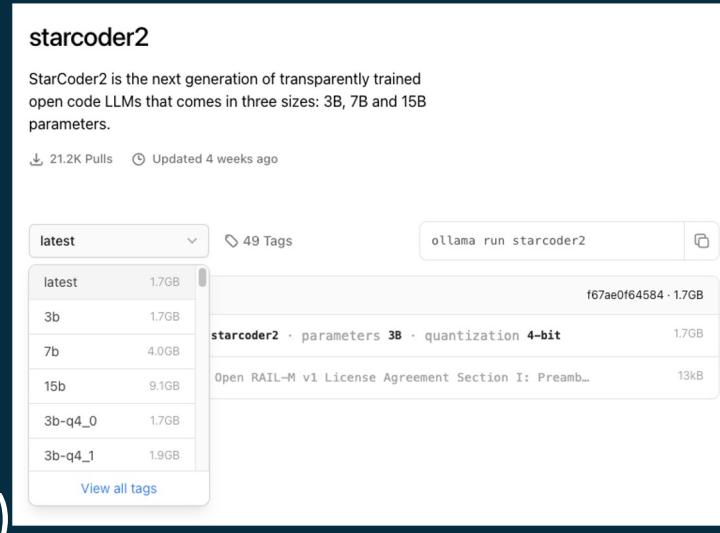
      yield PROMPT;
    }
  });
}
```



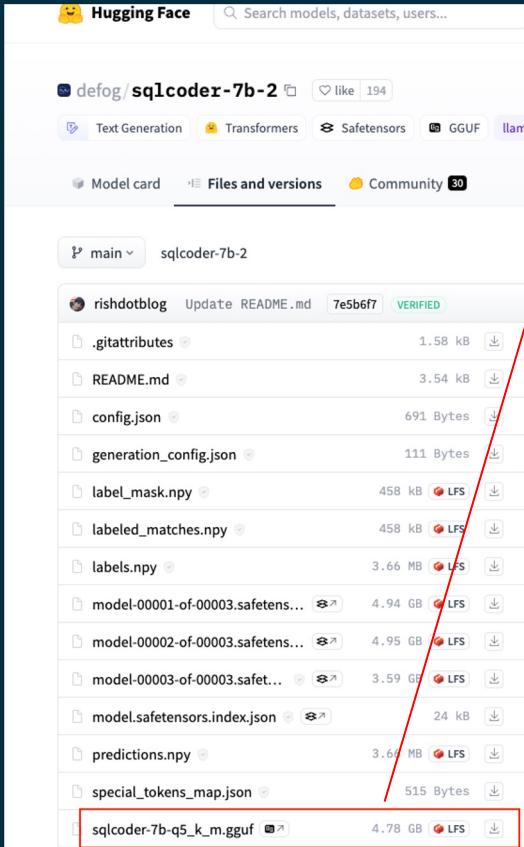
task = context + prompt + model

- fast and easy self-hosting of LLMs almost *everywhere*
- hybrid CPU+GPU inference
- powered by [llama.cpp](#)
- rich [library](#) of existing LLMs in different flavours
- [GGUF](#) - fast and memory efficient quantization for GPU
- Serve model with one-liner:  

```
ollama run starcoder2:7b
```
- [vLLM](#) for production deployments  
  
(Our video tutorial)



# Ollama - custom model in 4 steps



The screenshot shows the Hugging Face Model Hub interface. At the top, there's a search bar and a navigation bar with categories like Text Generation, Transformers, Safetensors, GGUF, and Llama. Below that, there's a 'Model card' section and a 'Files and versions' section which is currently selected. The 'Community' section shows 30 contributions. Under 'Files and versions', there's a main folder named 'sqlcoder-7b-2' containing several files: .gitattributes, README.md, config.json, generation\_config.json, label\_mask.npy, labeled\_matches.npy, labels.npy, model-00001-of-00003.safetensors, model-00002-of-00003.safetensors, model-00003-of-00003.safetensors, model.safetensors.index.json, predictions.npy, special\_tokens\_map.json, and sqlcoder-7b-q5\_k\_m.gguf. The 'sqlcoder-7b-q5\_k\_m.gguf' file is highlighted with a red border and a red arrow pointing to it from the top of the slide.

1. Download a model in the GGUF format
2. Create a Modelfile, e.g.:

```
FROM ./sqlcoder-7b-q5_k_m.gguf
TEMPLATE """{{ .Prompt }}"""
PARAMETER stop "<|endoftext|>"
```

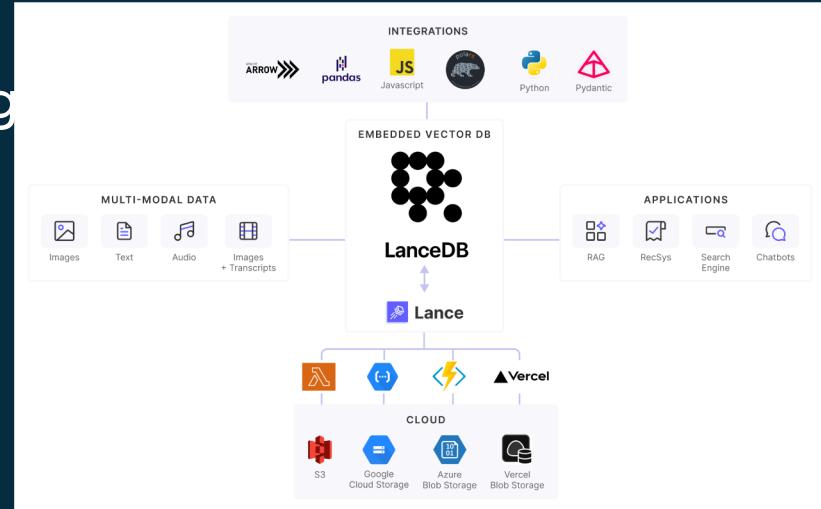
3. Create a model with Ollama

```
ollama create sqlcoder-7b-2 -f Modelfile
```

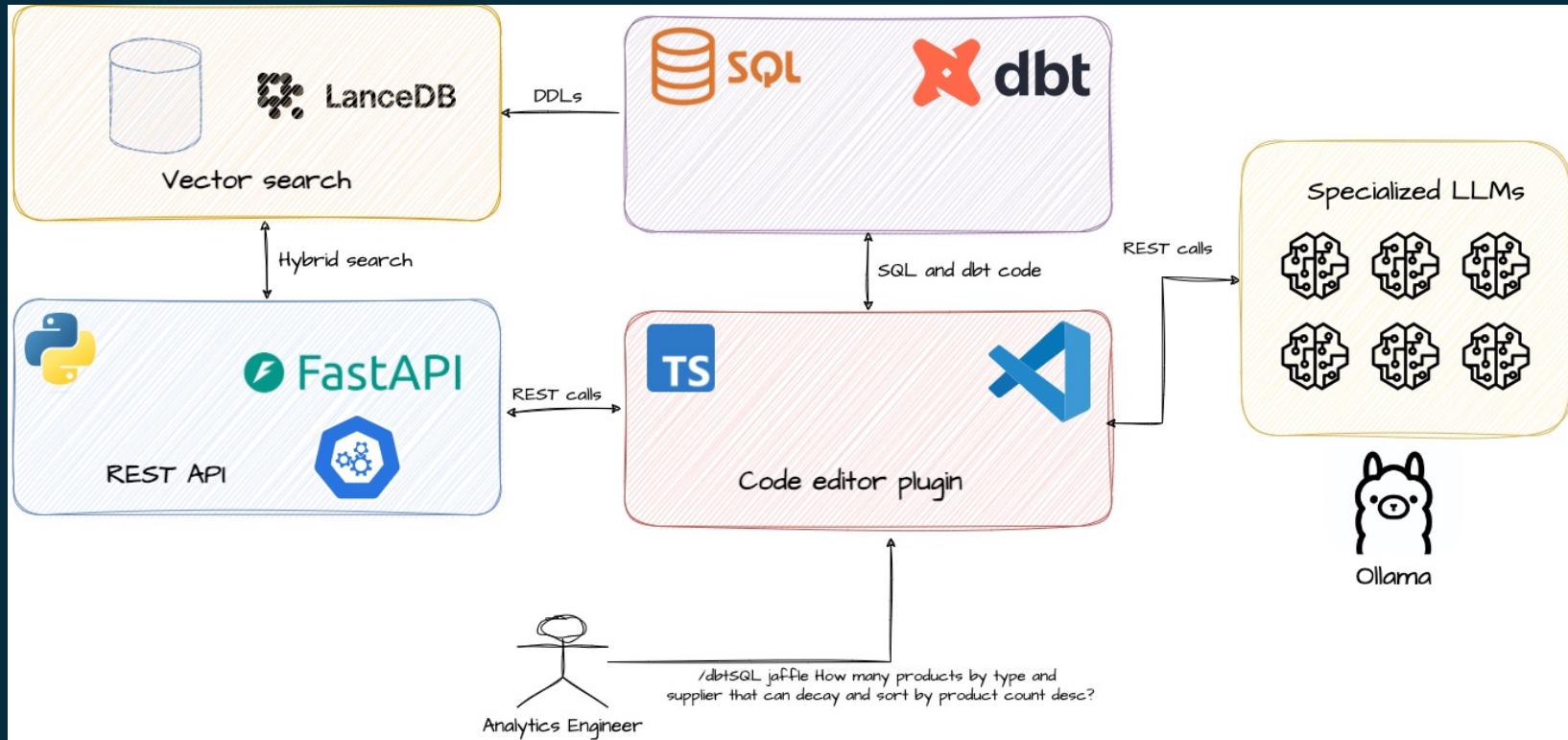
4. Serve it

```
ollama run sqlcoder-7b-2
```

- fast (Rust ❤️), serverless and embeddable - DuckDB for ML
- powered by Lance file format for ML (versioning, zero-copy)
- multi-modal
- support for hybrid (semantic + keyword) search
- Llamaindex integration
- Python API and fast data exchange with polars and Arrow



# Technical architecture



# Question representation<sup>1</sup>

```
Table continents, columns = [ContId, Continent]
Table countries, columns = [CountryId, CountryName,
↳ Continent]
Q: How many continents are there?
A: SELECT
```

Listing 1: Example of Basic Prompt

```
1 ### Complete sqlite SQL query only and with no
↳ explanation
2 ### SQLite SQL tables, with their properties:
3 #
4 # continents(ContId, Continent)
5 # countries(CountryId, CountryName, Continent)
6 #
7 ### How many continents are there?
8 SELECT
```

Listing 3: Example of OpenAI Demostration Prompt

```
1 Given the following database schema:
2 continents: ContId, Continent
3 countries: CountryId, CountryName, Continent
4
5 Answer the following: How many continents are there?
6 SELECT
```

Listing 2: Example of Text Representation Prompt

```
1 /* Given the following database schema: */
2 CREATE TABLE continents(
3     ContId int primary key,
4     Continent text,
5     foreign key(ContId) references countries(Continent)
6 );
7
8 CREATE TABLE countries(
9     CountryId int primary key,
10    CountryName text,
11    Continent int,
12    foreign key(Continent) references continents(ContId)
13 );
14
15 /* Answer the following: How many continents are there?
16 */
16 SELECT
```

Listing 4: Example of Code Representation Prompt

<sup>1</sup>Text-to-SQL Empowered by Large Language Models: A Benchmark Evaluation

- Not meant to be yet another benchmark, such as: Spider sql-eval or Bird-SQL for just SQL generation
- Jaffle Shop example - simple but not trivial
- Zero-shot – Agentic Workflow with Reflection TBD
- 4 typical data tasks
  - Data model exploration/discovery
  - SQL: an easy one (single table) and more complex (joins with sorting and aggregations)
  - dbt model generation
  - dbt tests generation based on rules

# LLMs evaluation 2/2

Model	Licence	size [b]	Data discovery	SQL - simple	SQL - complex	dbt - model	dbt - tests
deepseek-coder	deepseek	33	+	+	+/-	+/-	-
deepseek-coder	deepseek	6.7	+/-	+/-	+/-	-/+	-
codellama	Llama2	70	+	+	-/+	-	-
starcoder2	bigcode-openrail-m	15	-	-	-	-	-
sqlcoder	CC BY-SA 4.0	7	-	+/-	+/-	N/A	N/A
<b>phind-codellama</b>	Llama2	34	+	+	+	+	+/-
wizardcoder	Llama2	33	+	+	+/-	+/-	-/+
gpt-3.5-turbo	Commercial	N/A	+	+	+	+	+/-
<b>gpt-4</b>	Commercial	N/A	+	+	+	+	+
gpt-4-turbo-preview	Commercial	N/A	+	+	+	+	+/-
Gemini Pro	Commercial	N/A	+	+/-	+	+/-	-
OpenCodeInterpreter	Apache-2.0	33	+	+	-/+	-	-

+- perfect or almost perfect

+/- - not optimal or some minor tweaks needed

-/+ - not very helpful, serious hallucinations

- - totally useless

# gpt4 vs dbrx vs sqlcoder-7b-2 vs llama-3-sqlcoder-8b

```
--gpt 4
SELECT
    p.product_type,
    s.supply_name,
    COUNT(p.product_id) AS product_count
FROM
    products p
JOIN
    supplies s ON p.product_id = s.product_id
WHERE
    s.is_perishable_supply = TRUE
GROUP BY
    p.product_type, s.supply_name
ORDER BY
    product_count DESC; --llama-3-sqlcoder-8b
SELECT
    p.product_type,
    s.supply_name,
    COUNT(p.product_id) AS product_count
FROM
    products p
JOIN
    supplies s ON p.product_id = s.product_id
WHERE
    p.is_perishable_product = TRUE
GROUP BY
    p.product_type, s.supply_name
ORDER BY
    product_count DESC NULLS LAST;
```

```
-- dbrx
SELECT
    p.product_type,
    s.supply_name,
    COUNT(DISTINCT p.product_id) as product_count
FROM
    products p
JOIN
    supplies s ON p.product_id = s.product_id
WHERE
    s.is_perishable_supply = TRUE
GROUP BY
    p.product_type, s.supply_name
ORDER BY
    product_count DESC; -- sqlcoder-7b-2 (codellama-7b)
SELECT p.product_type,
    s.supply_name,
    COUNT(DISTINCT p.product_id) AS product_count
FROM
    supplies s
JOIN
    order_items oi ON s.supply_id = oi.product_id
AND
    s.is_perishable_supply = TRUE
JOIN
    products p ON oi.product_id = p.product_id
GROUP BY
    p.product_type, s.supply_name
ORDER BY
    product_count DESC
```

# fine-tuning impact: llama3-8b vs llama-3-sqlcoder-8b

```
--llama-3
SELECT
    s.supply_name,
    p.product_type,
    COUNT(*) AS product_count
FROM
    supplies s
JOIN
    order_items oi ON s.product_id = oi.product_id
JOIN
    products p ON oi.product_id = p.product_id
WHERE
    s.is_perishable_supply = TRUE AND
    (oi.is_food_item = TRUE OR oi.is_drink_item = TRUE)
GROUP BY
    s.supply_name, p.product_type
ORDER BY
    product_count DESC;
```

```
--llama-3-sqlcoder-8b
SELECT
    p.product_type,
    s.supply_name,
    COUNT(p.product_id) AS product_count
FROM
    products p
JOIN
    supplies s ON p.product_id = s.product_id
WHERE
    p.is_perishable_product = TRUE
GROUP BY
    p.product_type, s.supply_name
ORDER BY
    product_count DESC NULLS LAST;
```

# Quantization effects: dbrx 8/4/2 bit

```
-- dbrx
SELECT
    p.product_type,
    s.supply_name,
    COUNT(DISTINCT p.product_id) AS product_count
FROM
    products p
JOIN
    supplies s ON p.product_id = s.product_id
WHERE
    s.is_perishable_supply = TRUE
GROUP BY
    p.product_type, s.supply_name
ORDER BY
    product_count DESC;
```

```
--dbrx:132b-instruct-q8_0-cpu (144GB)
SELECT
    p.product_type,
    s.supply_name,
    COUNT(*) AS product_count
FROM
    supplies s
JOIN
    products p ON s.product_id = p.product_id
WHERE
    s.is_perishable_supply = TRUE
    AND (p.is_food_item = TRUE OR p.is_drink_item = TRUE)
GROUP BY
    p.product_type, s.supply_name
ORDER BY
    product_count DESC;
```

```
--132b-instruct-q2_K (48GB)
is...;

is or order in files are orders' will. _product. orders.
`ot order to not order objects. (ut products, order
```

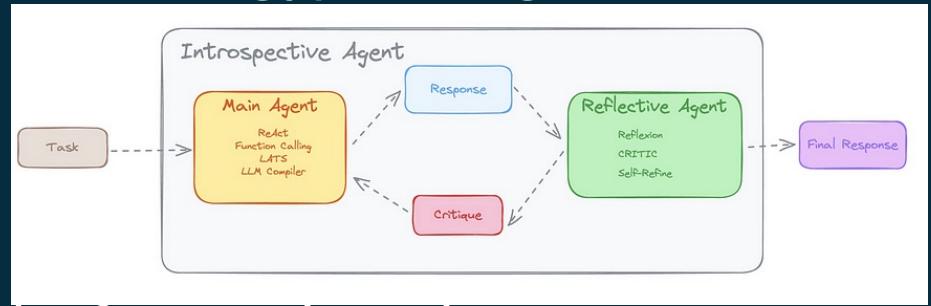
```
--132b-instruct-q4_0 (74GB)
SELECT
    p.product_type,
    s.supply_name,
    COUNT(p.product_id) AS product_count
FROM
    supplies s
JOIN
    order_items oi ON s.product_id = oi.product_id
JOIN
    products p ON oi.product_id = p.product_id
WHERE
    is_perishable_supply = TRUE
    AND
        (is_food_item = TRUE OR is_drink_item = TRUE)
GROUP BY
    1,2
ORDER BY
    product_count DESC;
```

# A handful of conclusions...with a grain of salt

- NL-to-SQL and dbt code generation are ***challenging***
- ***commercial*** models are in most cases still better... but
- there are very promising ***open-source 7-30b alternatives***
- ***smaller*** models perform better than larger after ***quantization***
- ***SQL-dedicated*** and fine-tuned models can turn out a bit a disappointing (beam search?), e.g. :
  - unnecessary joins elimination
  - wrong data types inference
  - occasional hallucinations

# Future directions

- Implementation of in-context learning, such as Query Similarity Selection (few-shot strategy) and *Agentic RAG with Reflection Strategy*
- *Model fine-tuning (dbt)*
- *Data Modeling (DV 2.0)*
- *Various SQL dialects and platform migrations*
- *Prompt optimizations, e.g. with DSPy*





# Welcome to the GID data copilot

## DEMO



**Want to talk about DATA & AI  
with US?**

**contact@getindata.com**

**SCHEDULE A CONSULTATION**

