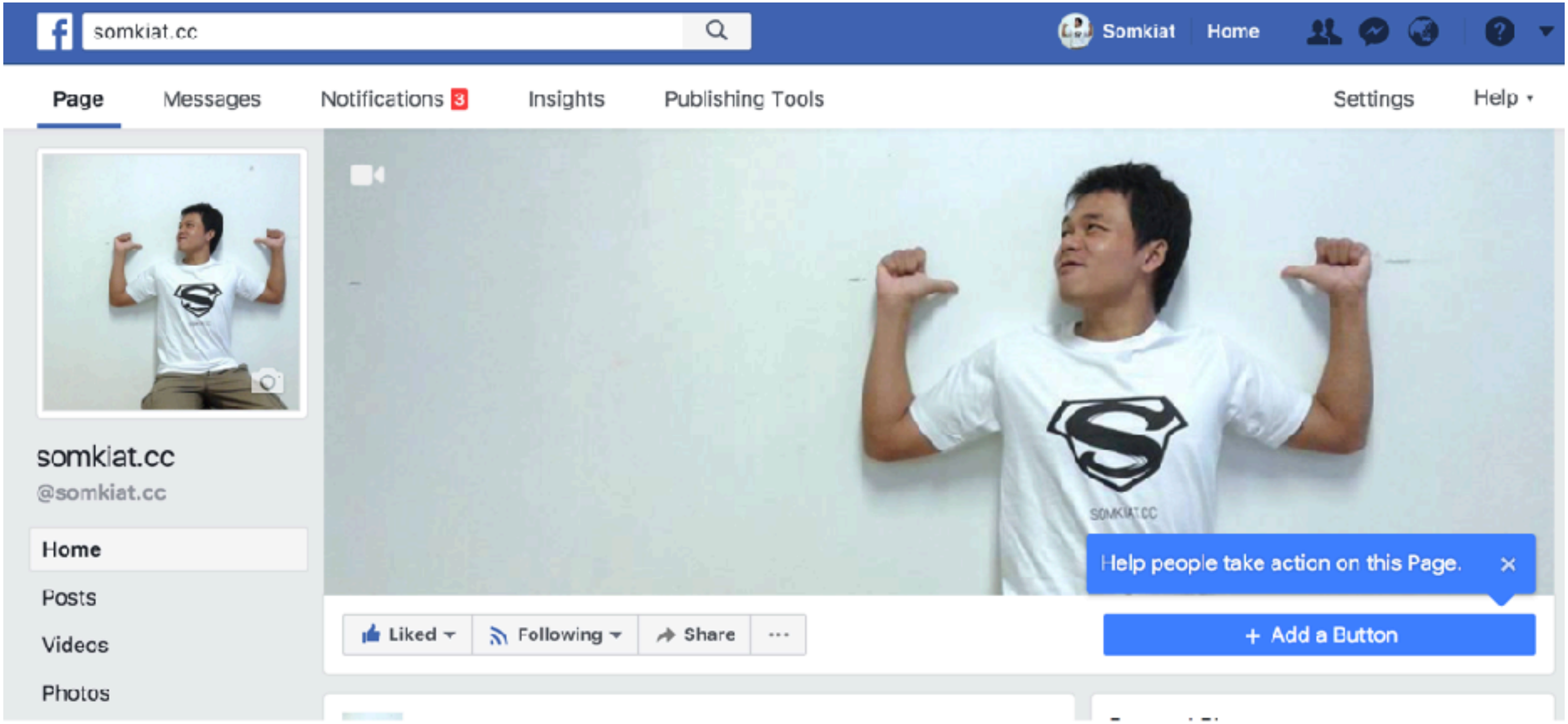
สยามชำนาญกิจ
SIAM CHAMNAN KIT

LLM Application workshop

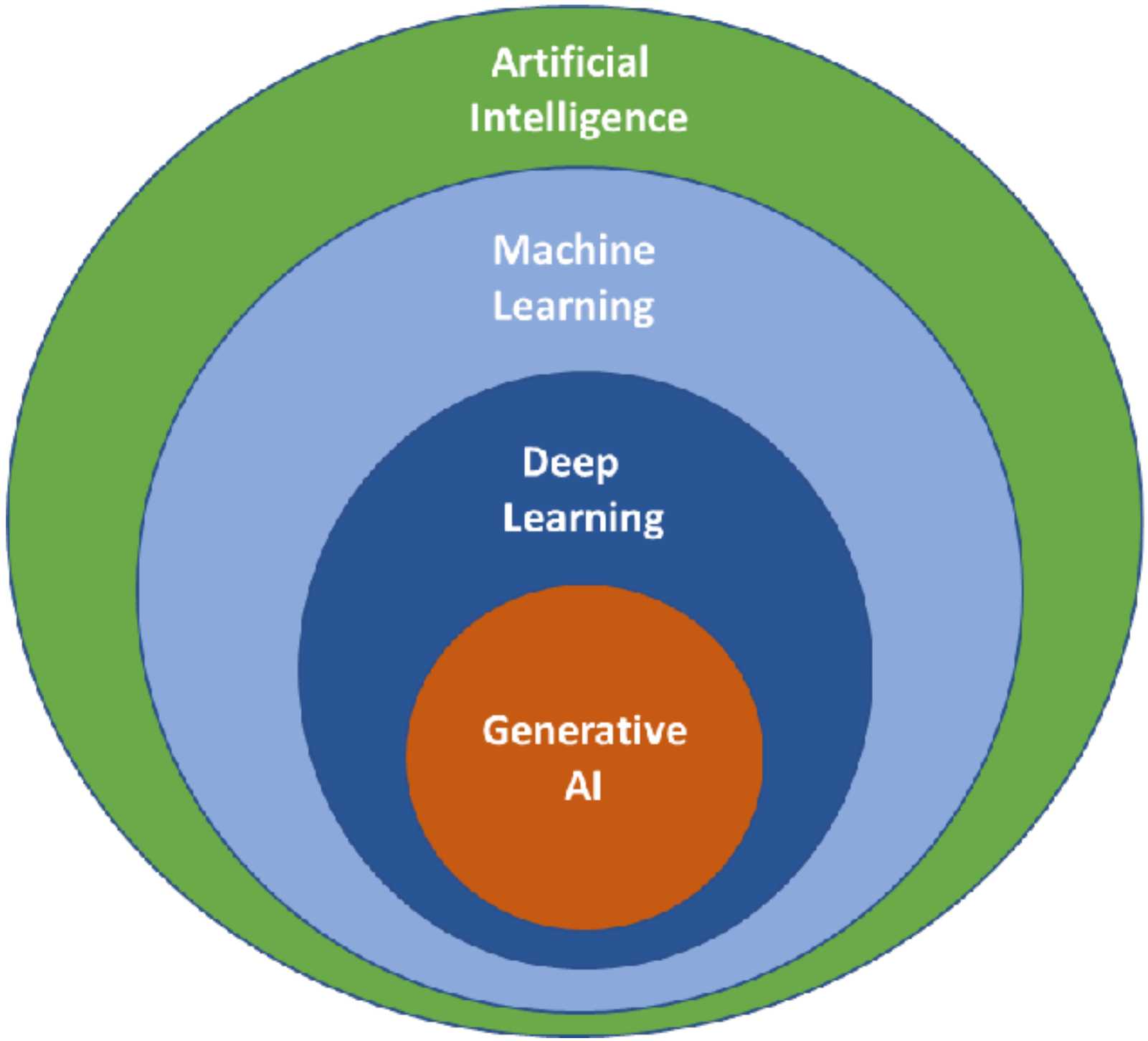
Prompt engineering
RAG (Retrieval Augmented Generation)

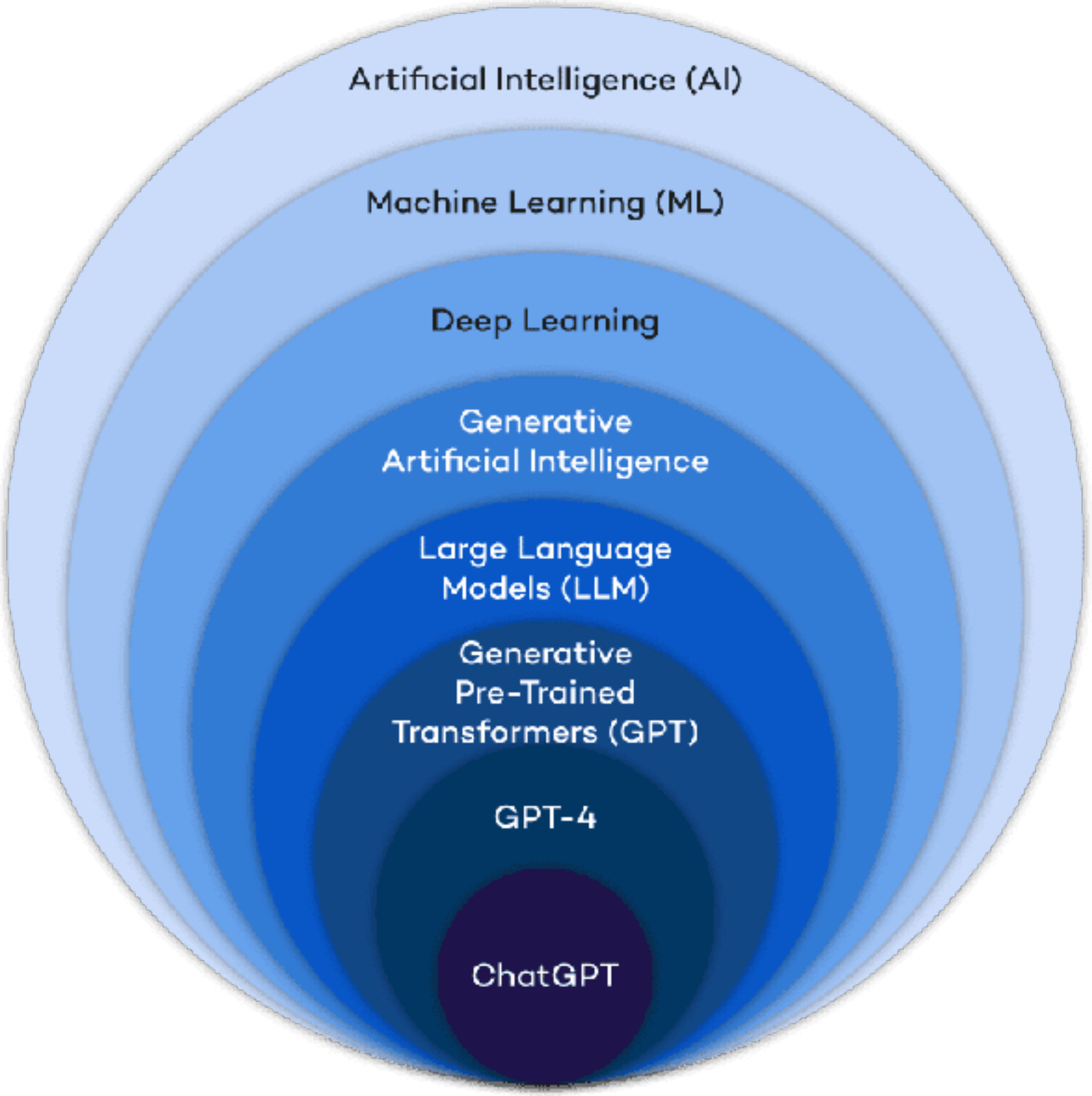


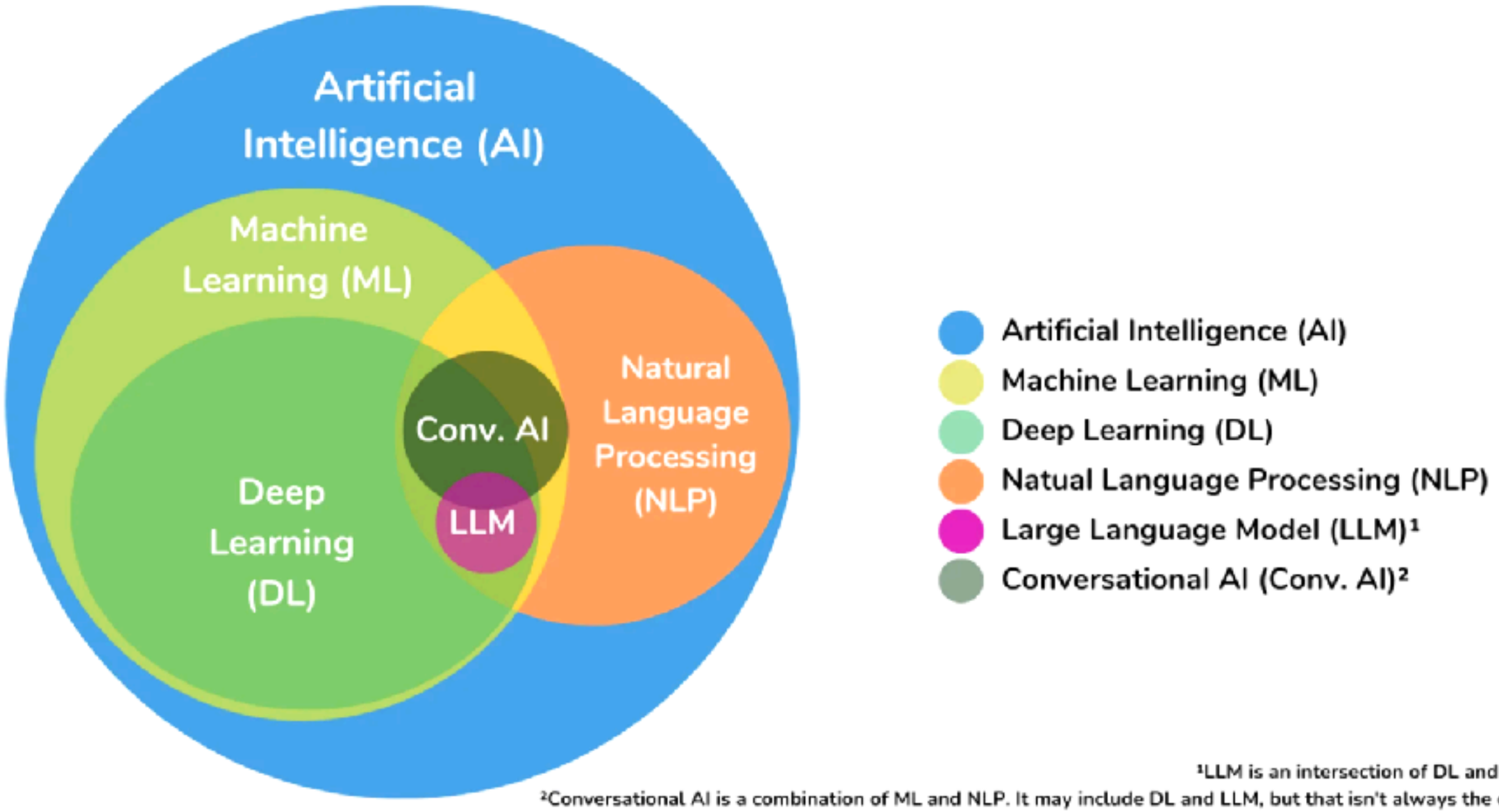
Topics

Basic LLM (Large Language Model)
Problems and solutions
Prompt engineering
RAG (Retrieval Augmented Generation)
RAG processes and techniques
Workshop

AI
(Artificial Intelligence)

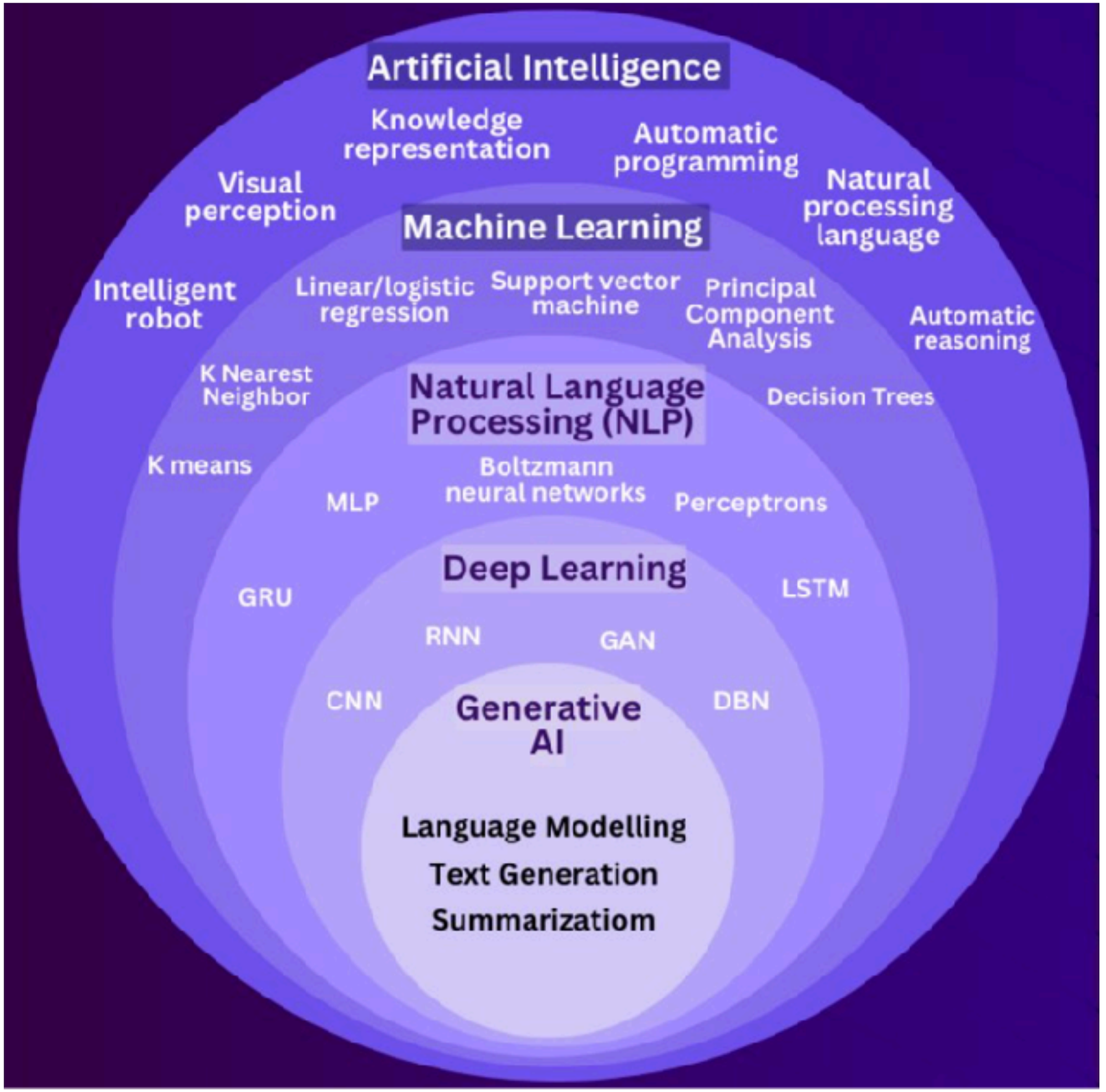






¹LLM is an intersection of DL and NLP

²Conversational AI is a combination of ML and NLP. It may include DL and LLM, but that isn't always the case.



Deep Learning vs LLM

Deep Learning	LLM
A subset of ML using multi-layer neural networks	A specific type of DL model trained on massive text data
Broad (images, audio, time series, language, etc.)	Focused mainly on natural language understanding and generation
Can handle various types (image, video, audio, tabular)	Primarily trained on **textual data**
Size of data from small to large	Extremely large (billions to trillions of parameters)
Task-specific (e.g., classification, regression)	General-purpose language modeling (e.g., next-word prediction)

LLM (Large Language Model)

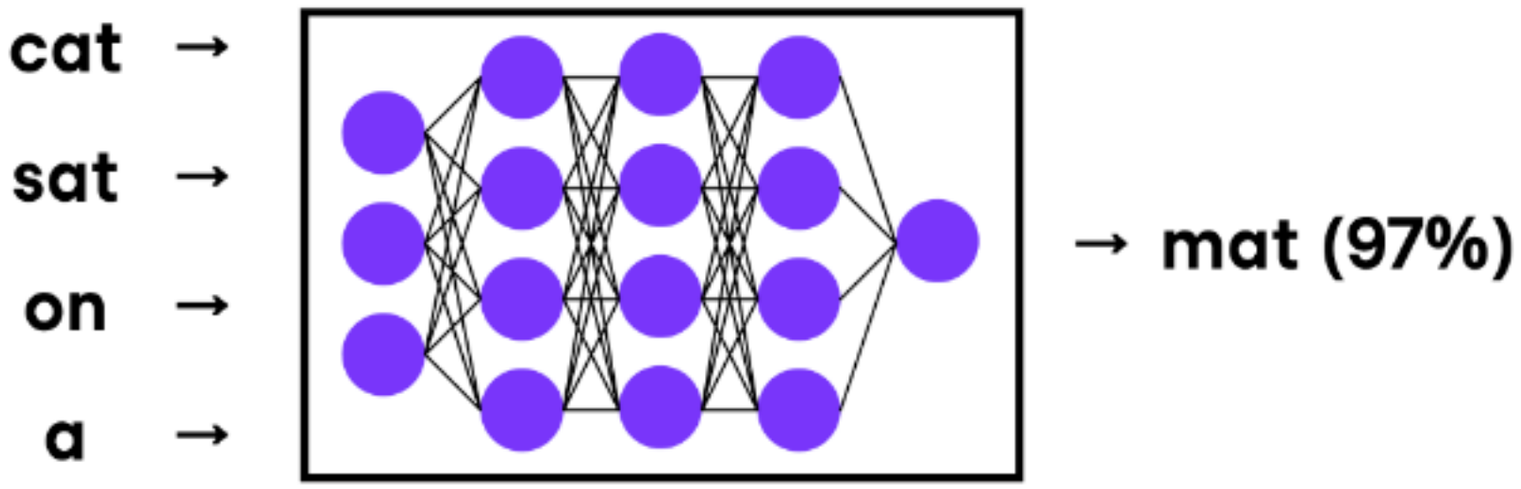
Type of AI model designed to understand, generate and interact using human language

LLM model

Training data !!

LLM (Large Language Model)

Neural network
Predicts the next word in a sequence



สีเหลือง

ตอนเที่ยงฉันจะกิน _ _ _ _ _

Next word ?

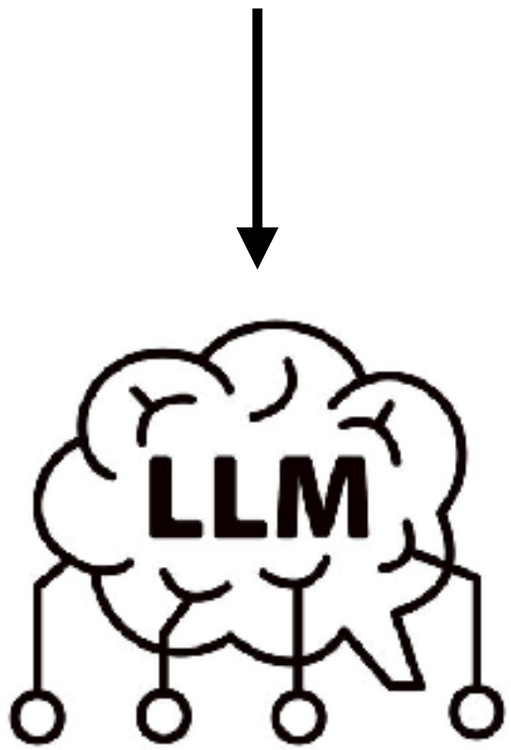
The boy go to the …

- Cafe
- Hospital
- Park
- School

Predict next word ?

Context

The boy go to the …

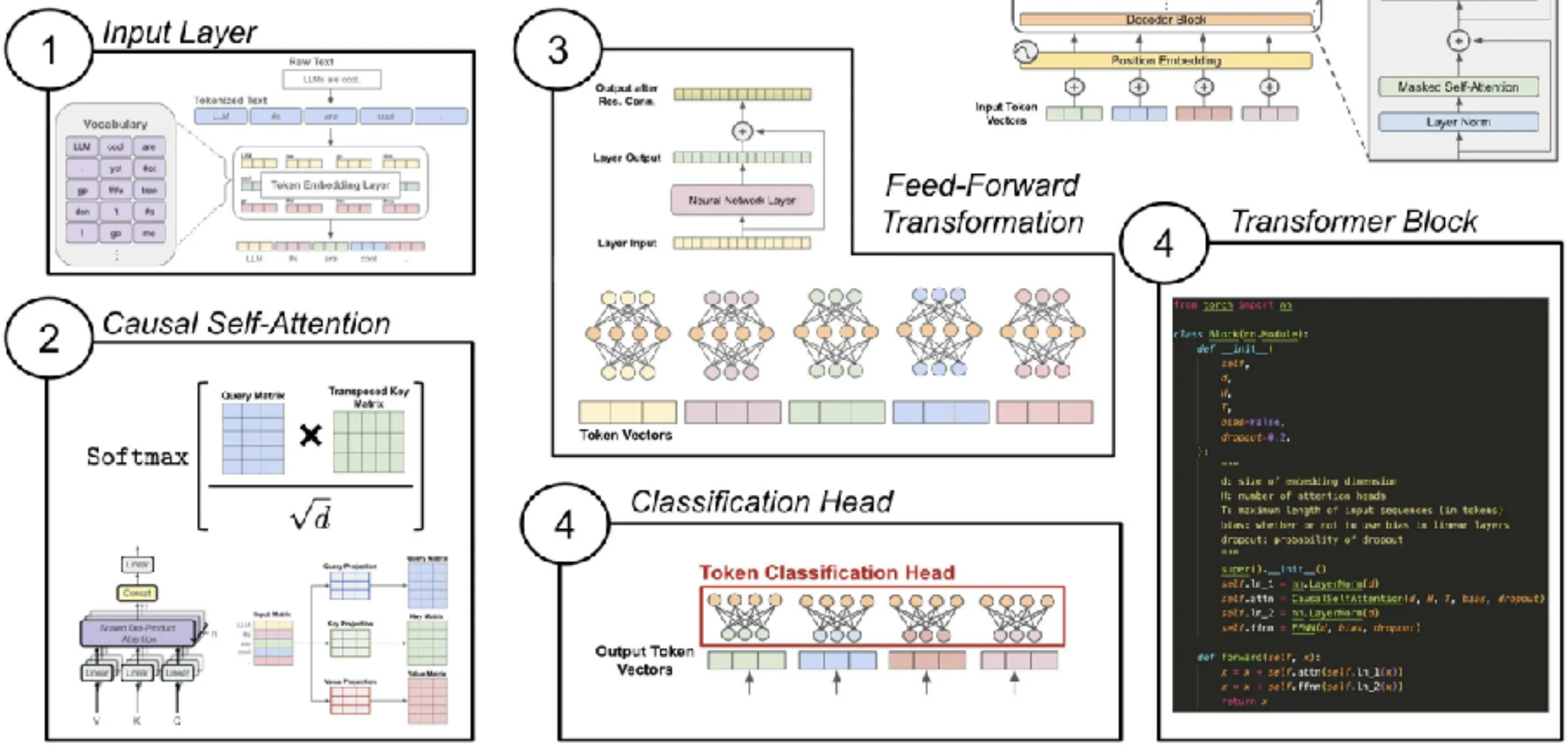


Probability distribution of next word/token

- Cafe 0.1
- Hospital 0.05
- Playground 0.5
- School 0.3

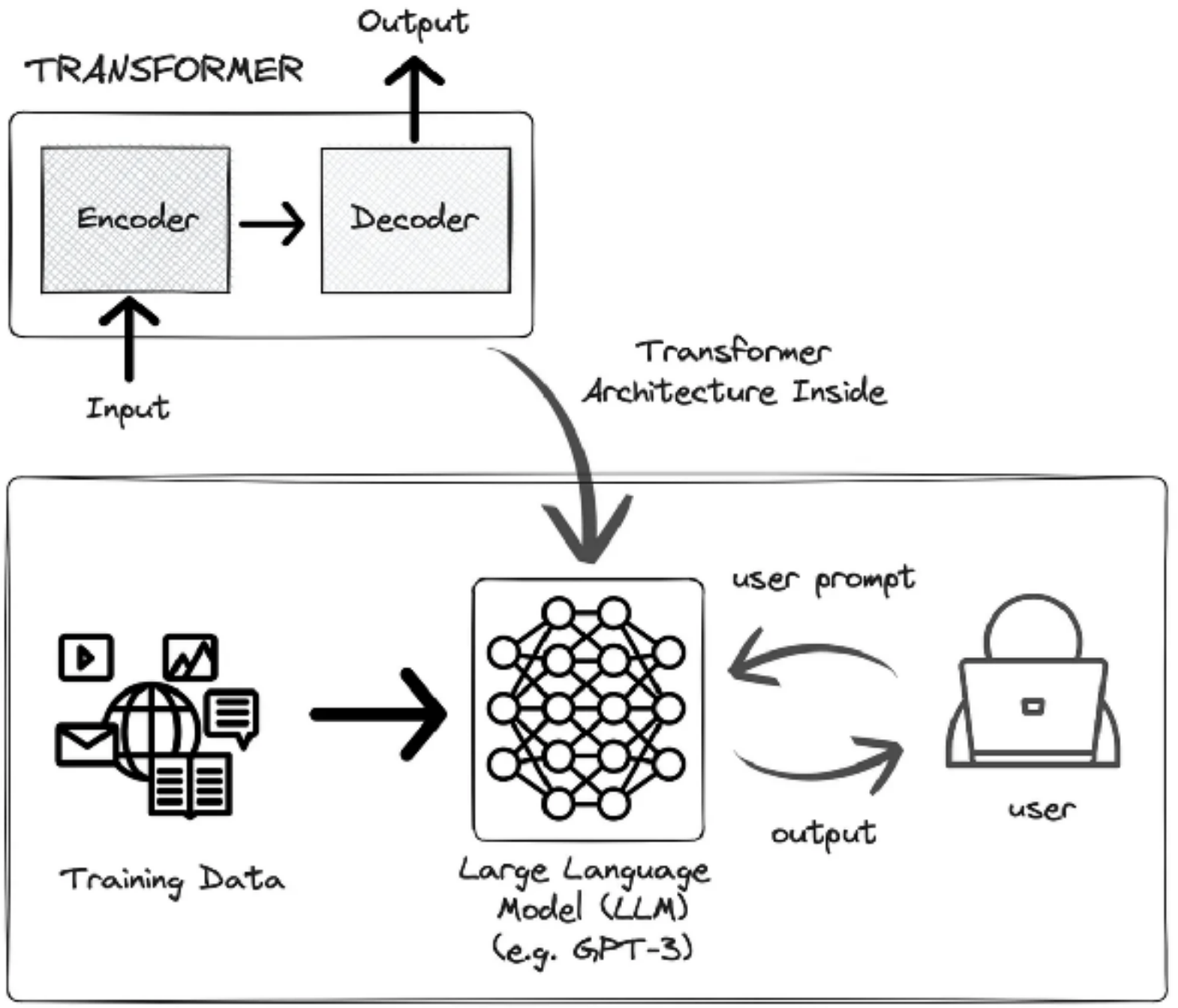
LLM components !!

Components of the Decoder-only Transformer

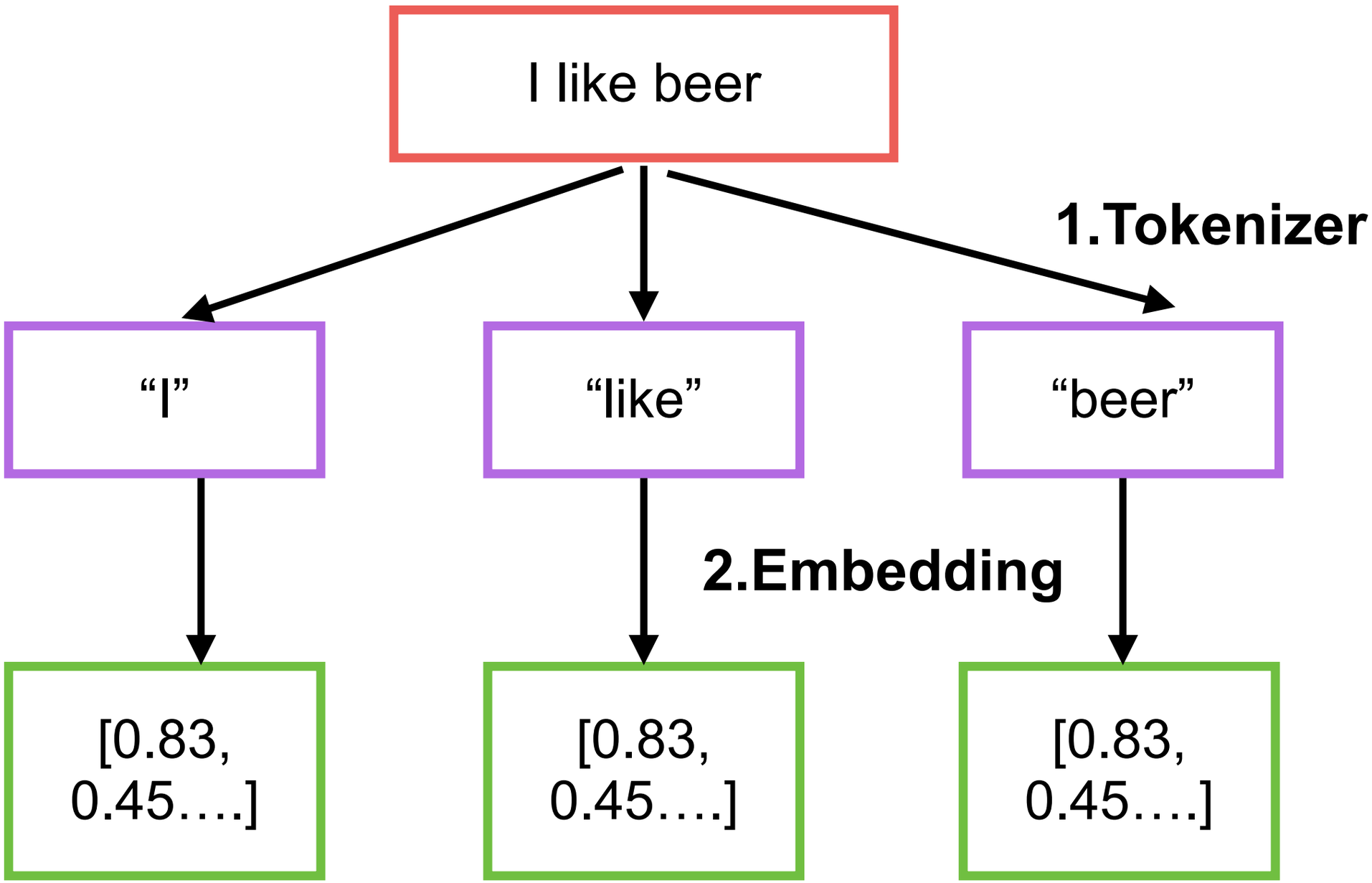


https://stackoverflow.blog/2024/08/22/llms-evolve-quickly-their-underlying-architecture-not-so-much

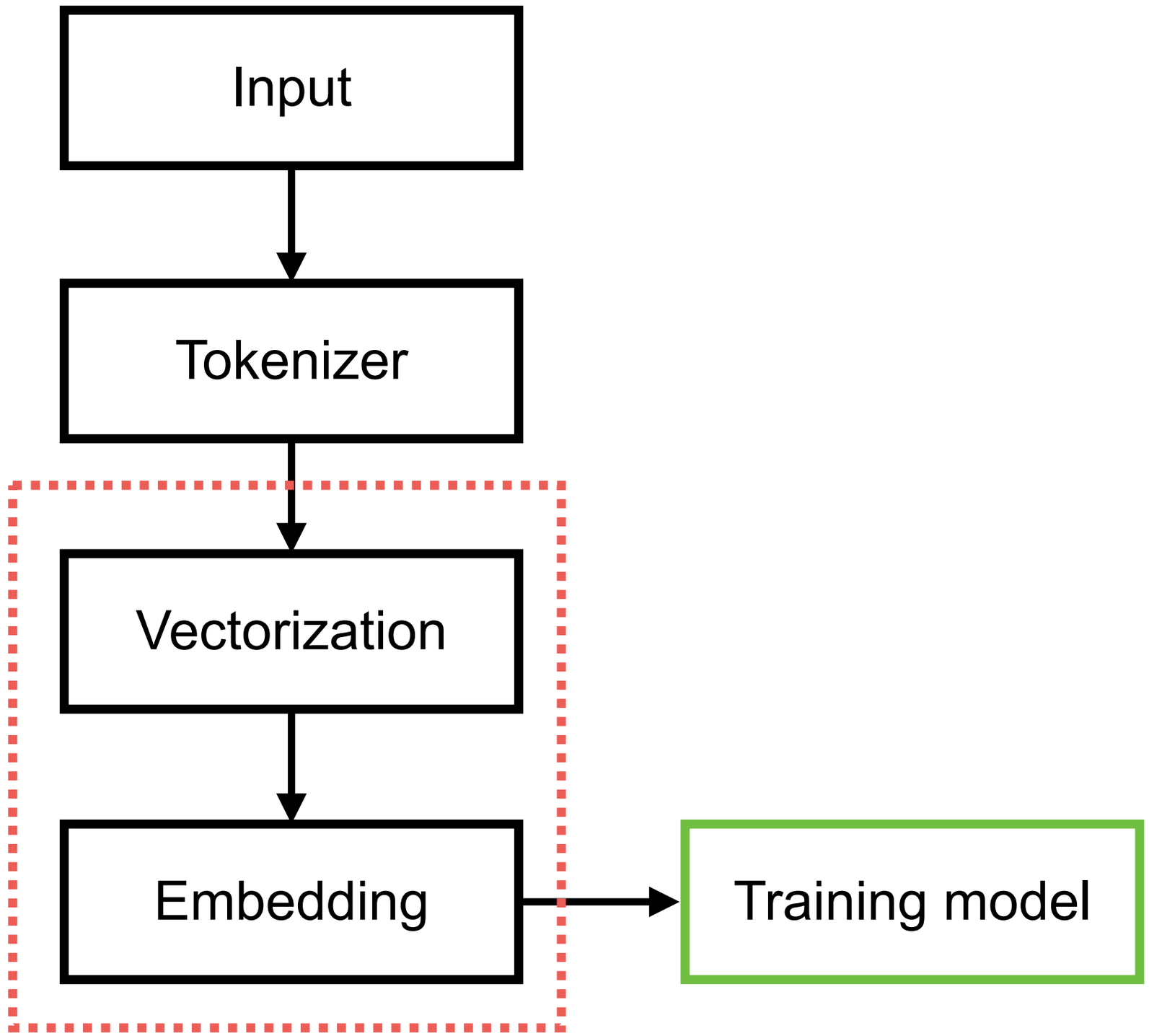
Transformer inside



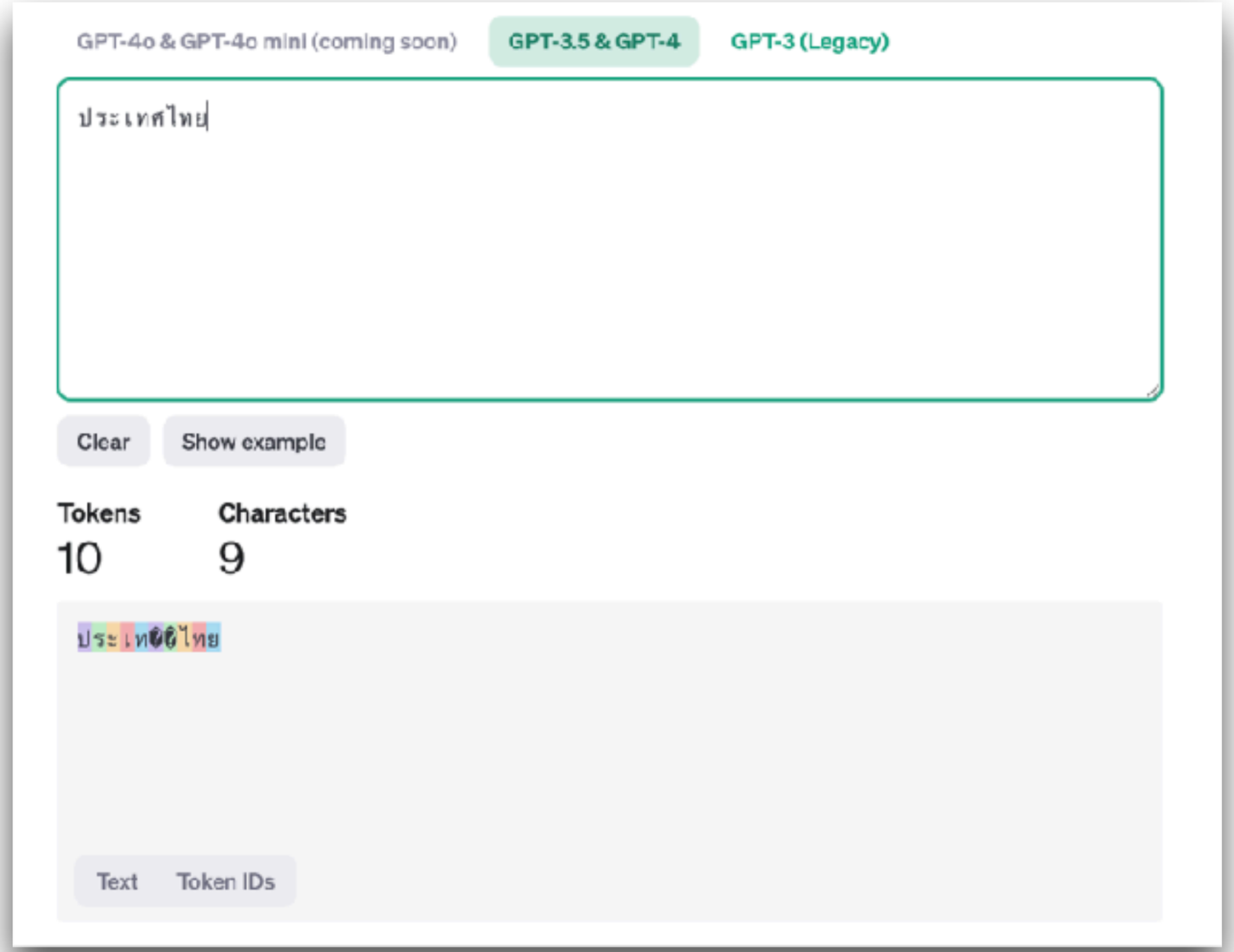
Transformer Process !!



Processes



OpenAI Tokenization



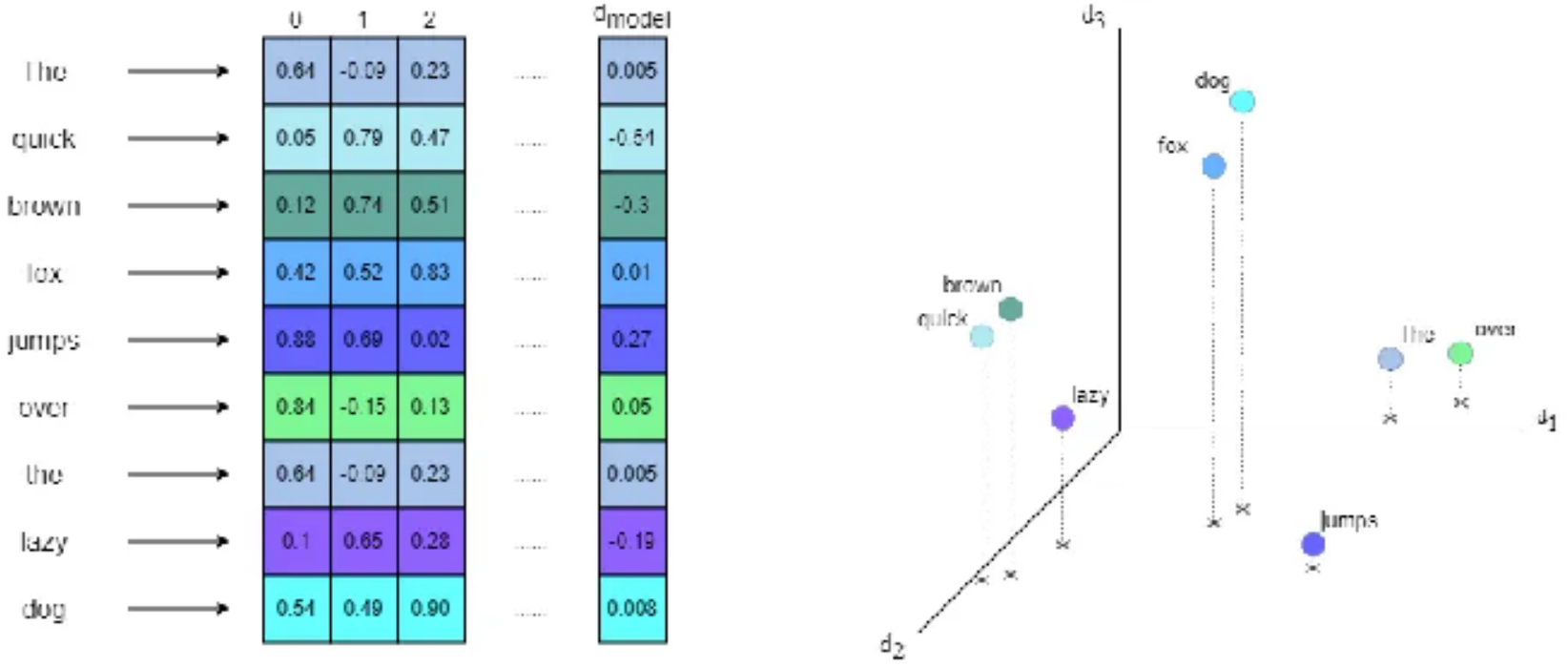
https://platform.openai.com/tokenizer

Embedding

Map items of **unstructured data** to high-dimensional real vectors

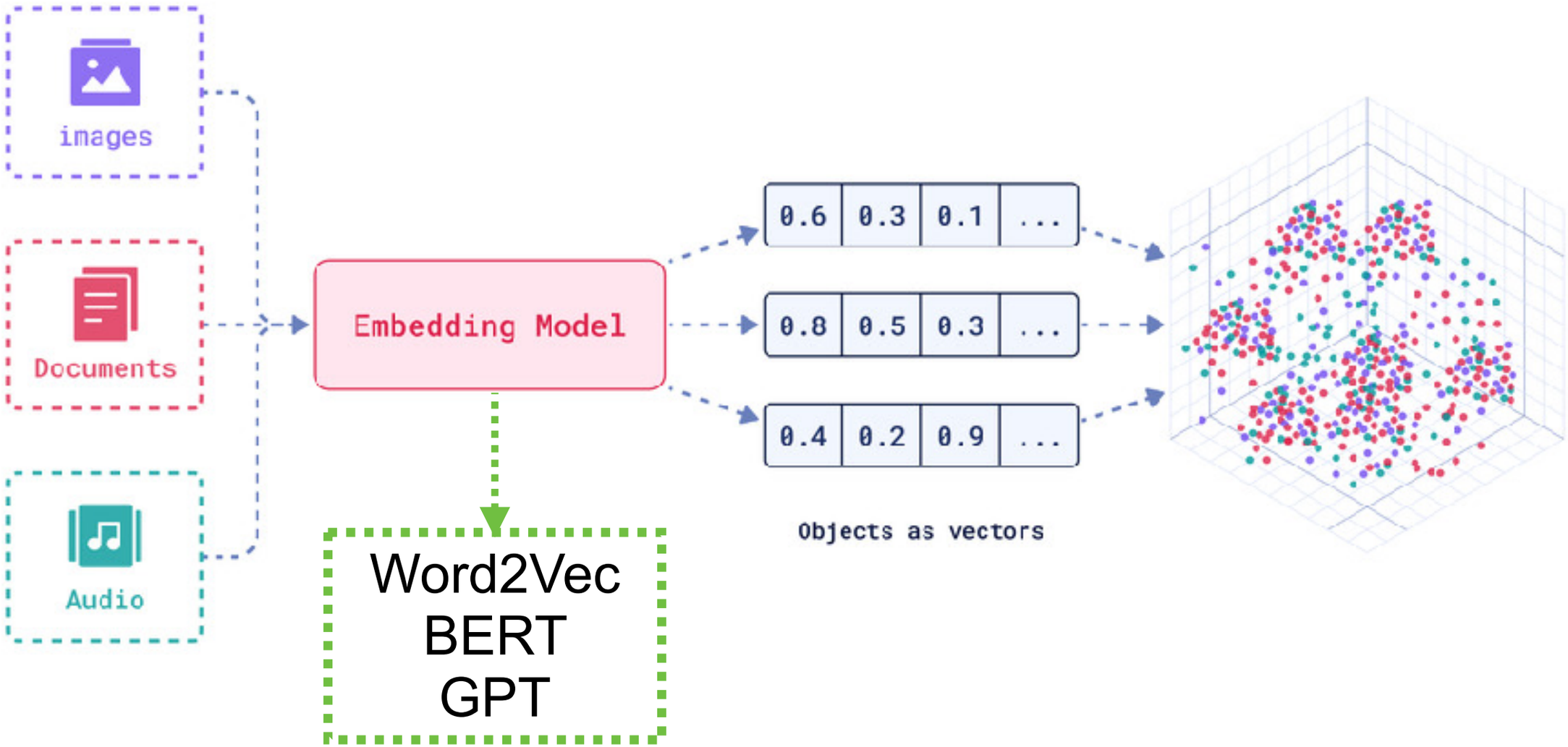
Semantic **meaning**

Improvement in ML tasks



https://towardsdatascience.com/transformers-in-depth-part-1-introduction-to-transformer-models-in-5-minutes-ad25da6d3cca

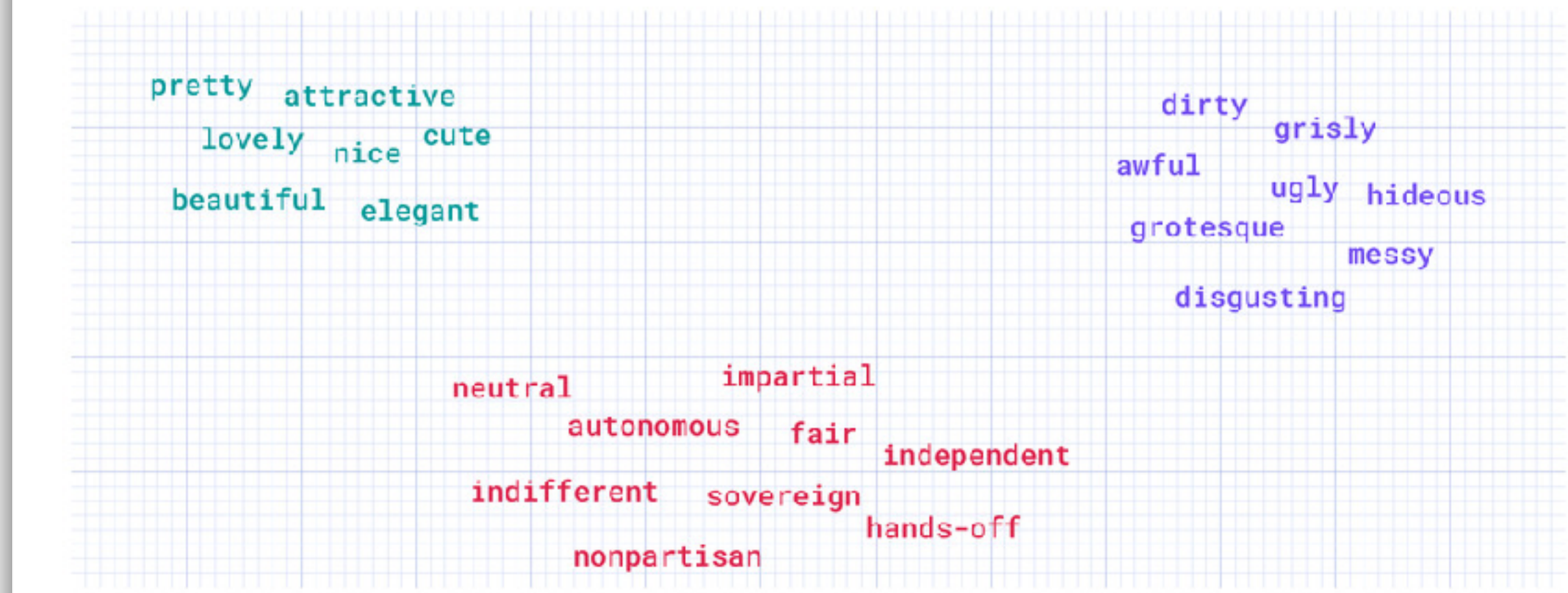
Embedding Models



https://qdrant.tech/articles/what-are-embeddings/

eg. Embedding space

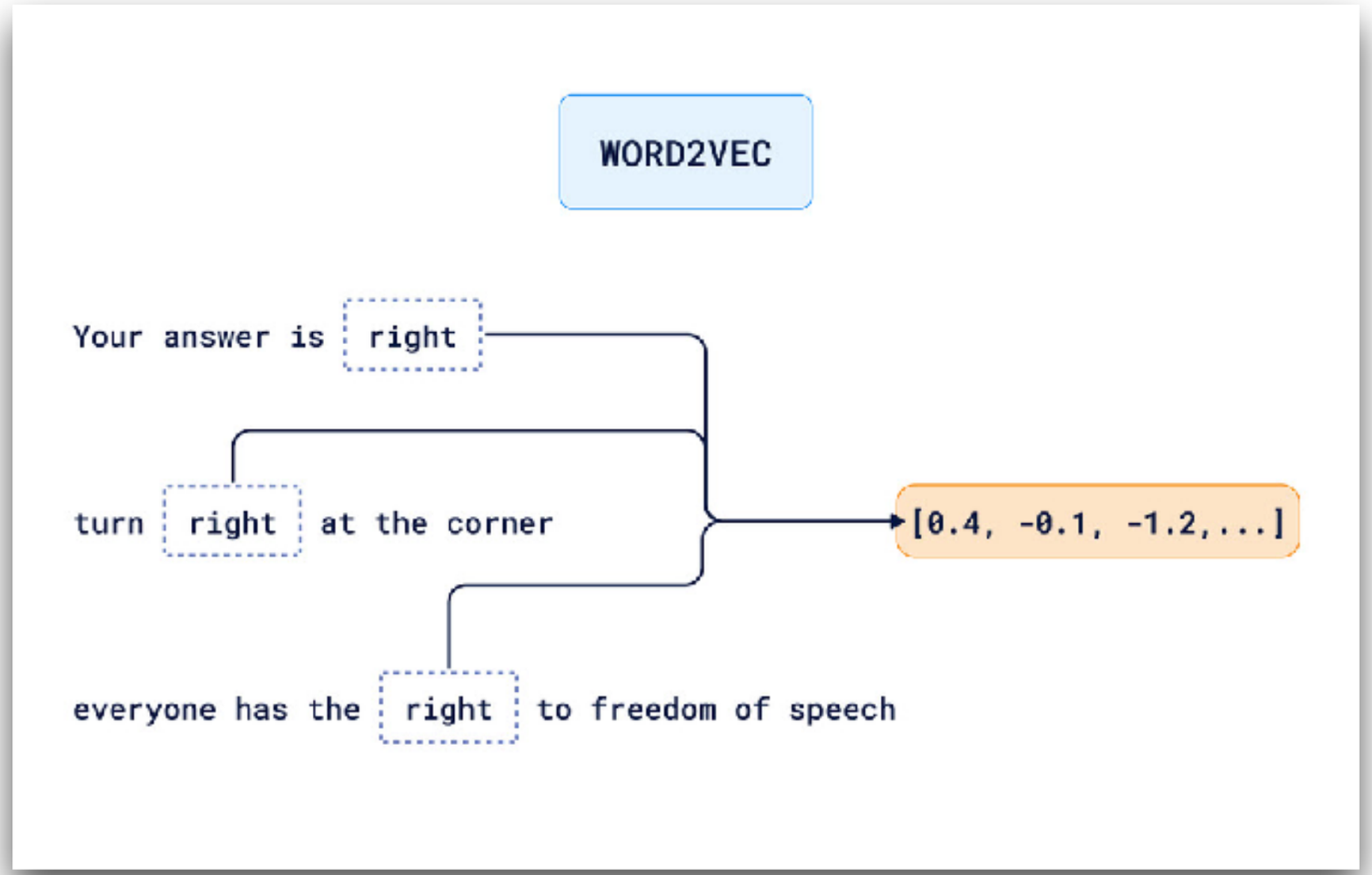
Synonym words in similar context !!
Embeddings are about **semantics**



https://qdrant.tech/articles/what-are-embeddings/

Embedding model with Word2Vec

Static embedding



Problems ?

Limited context

Short context

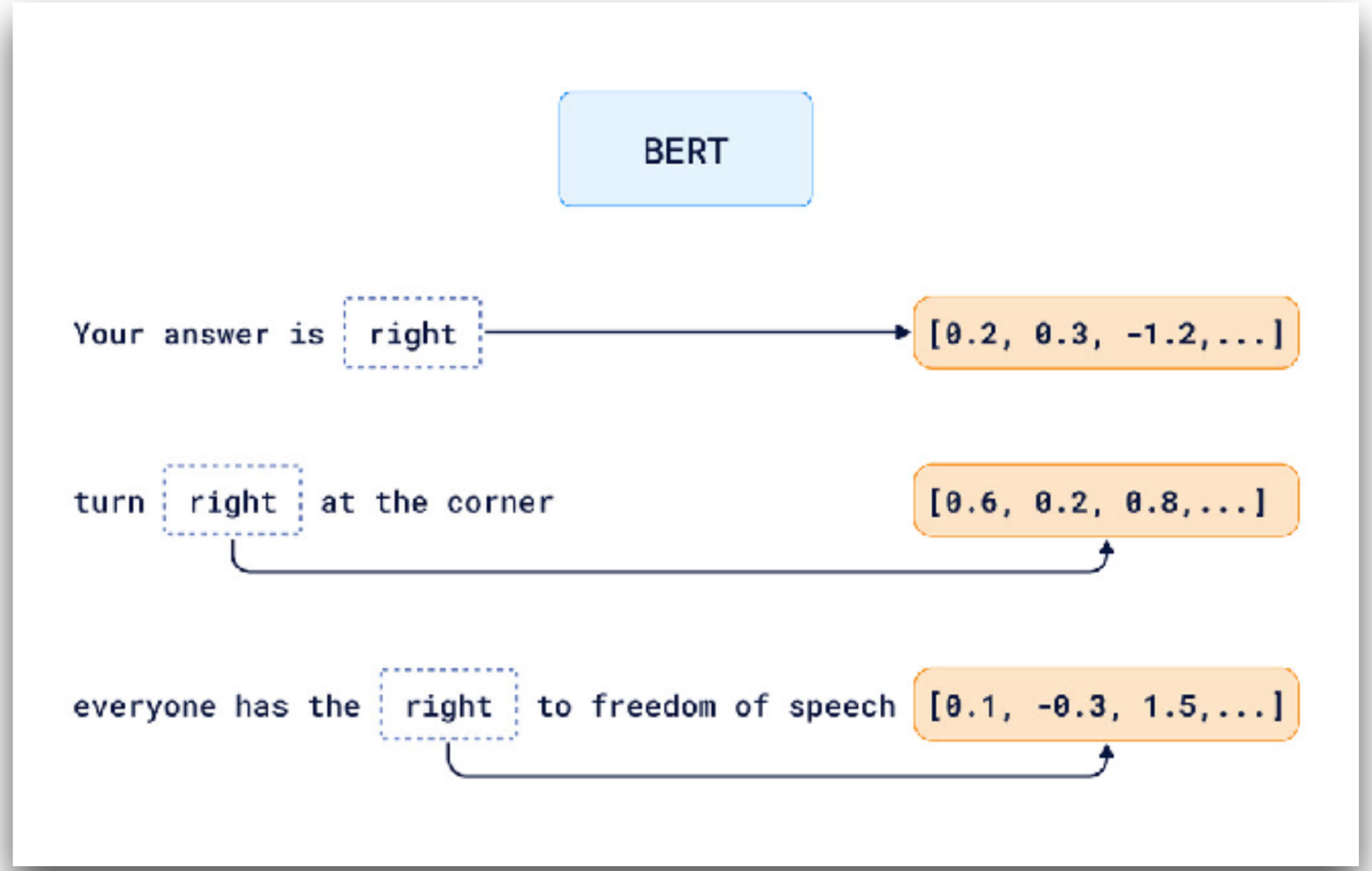
Word disambiguation issues

Generalization challenges (unseen situation)

https://www.datacamp.com/blog/attention-mechanism-in-llms-intuition

Embedding model with BERT, GPT

Different context, different embedding

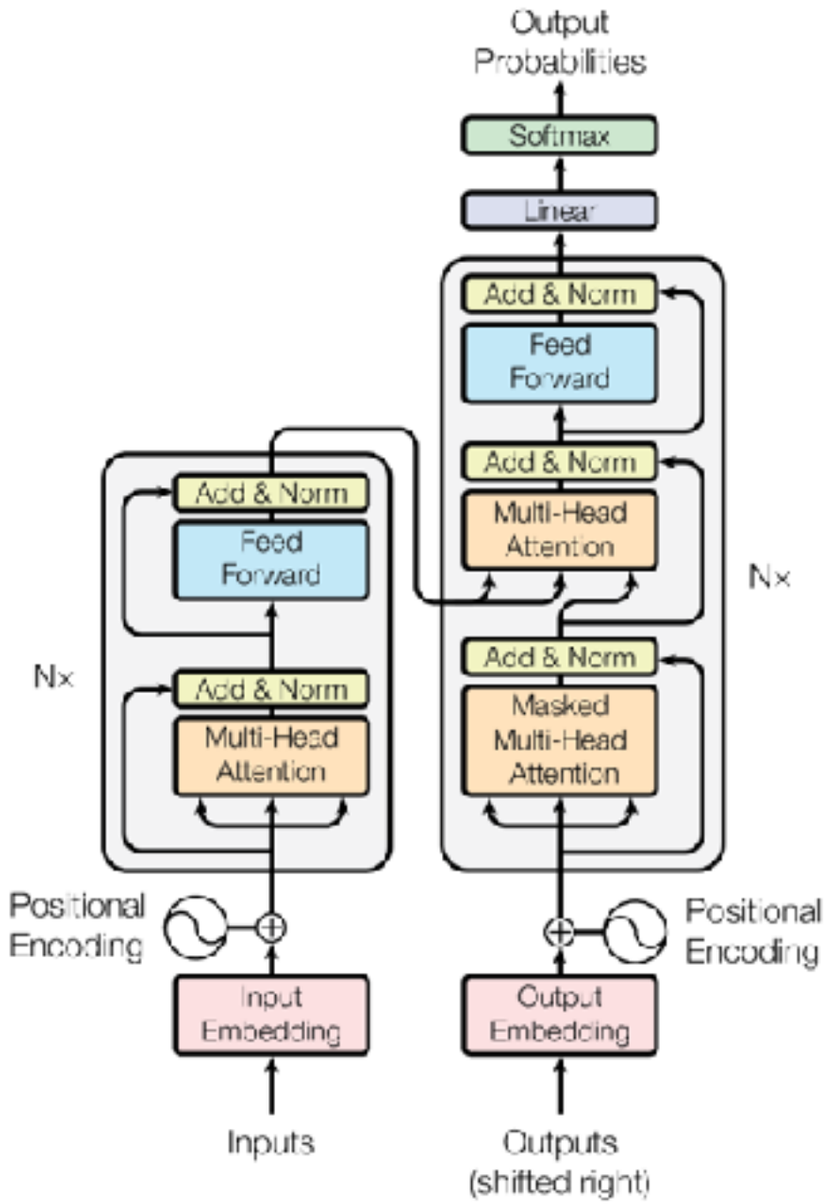


Attention in LLM !!

https://arxiv.org/abs/1706.03762

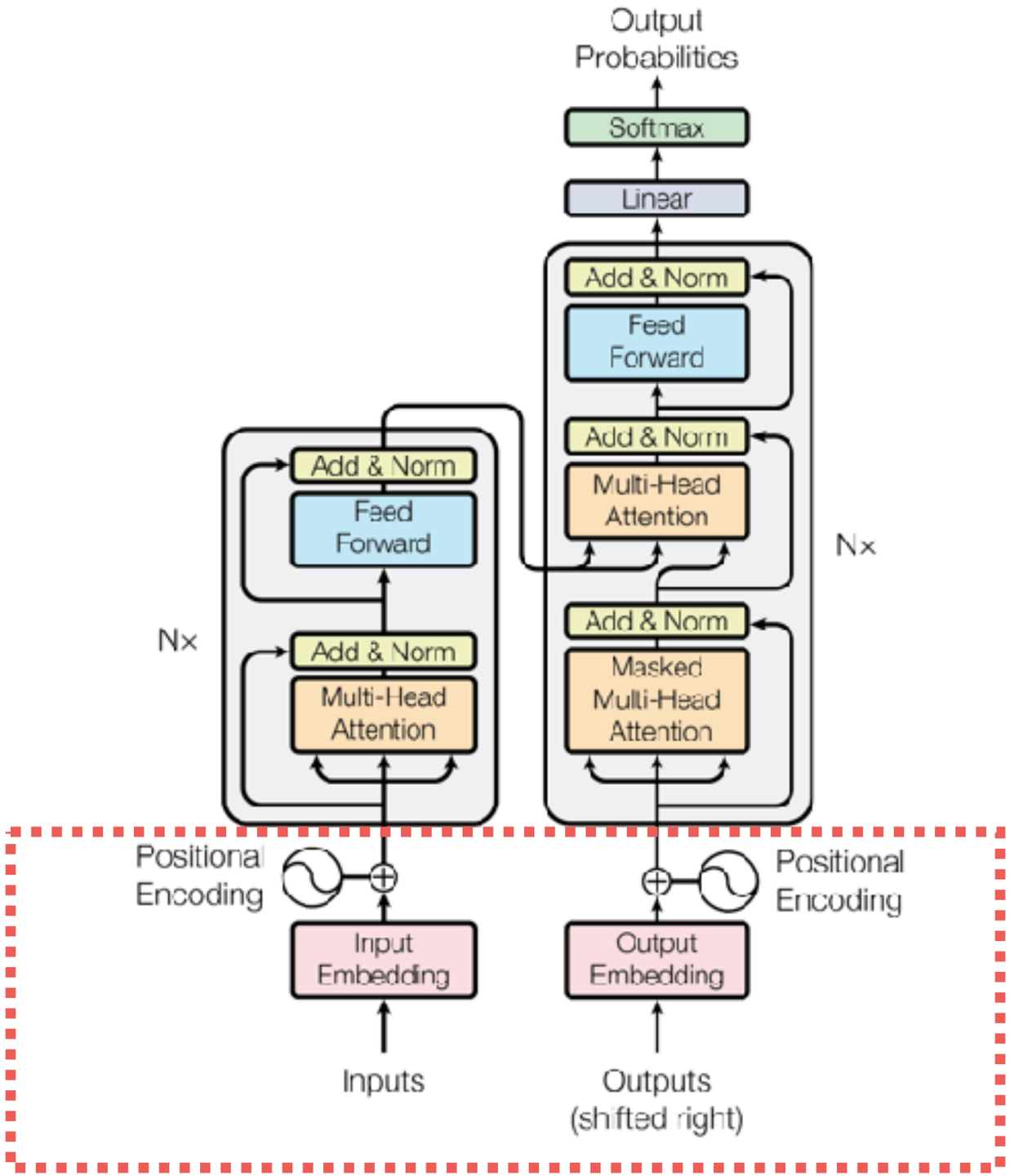
Transformer model architecture

Attention Is All You Need

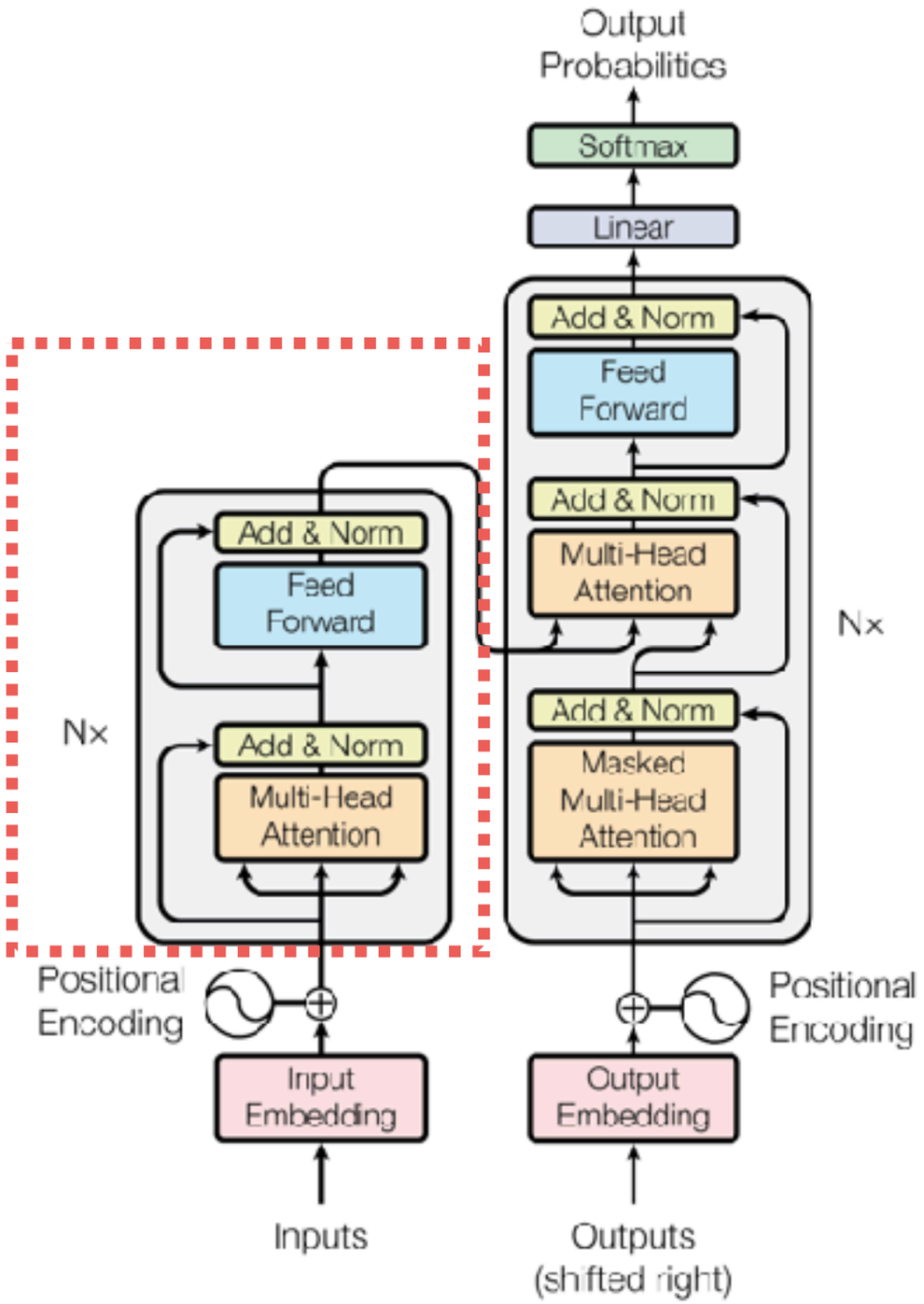


https://arxiv.org/abs/1706.03762

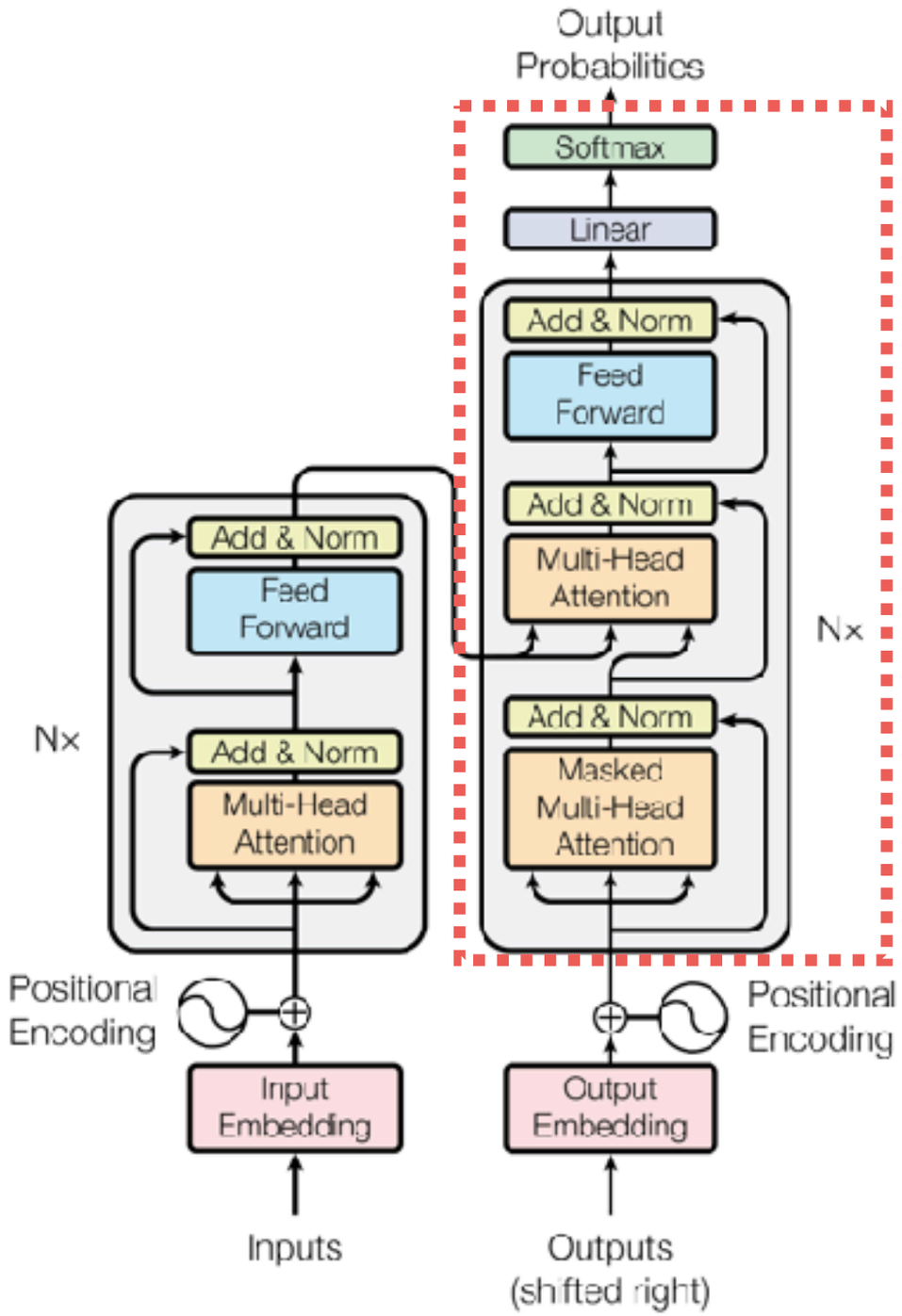
1. Pre-processing stage



2. Encoding stage



3. Decoding stage



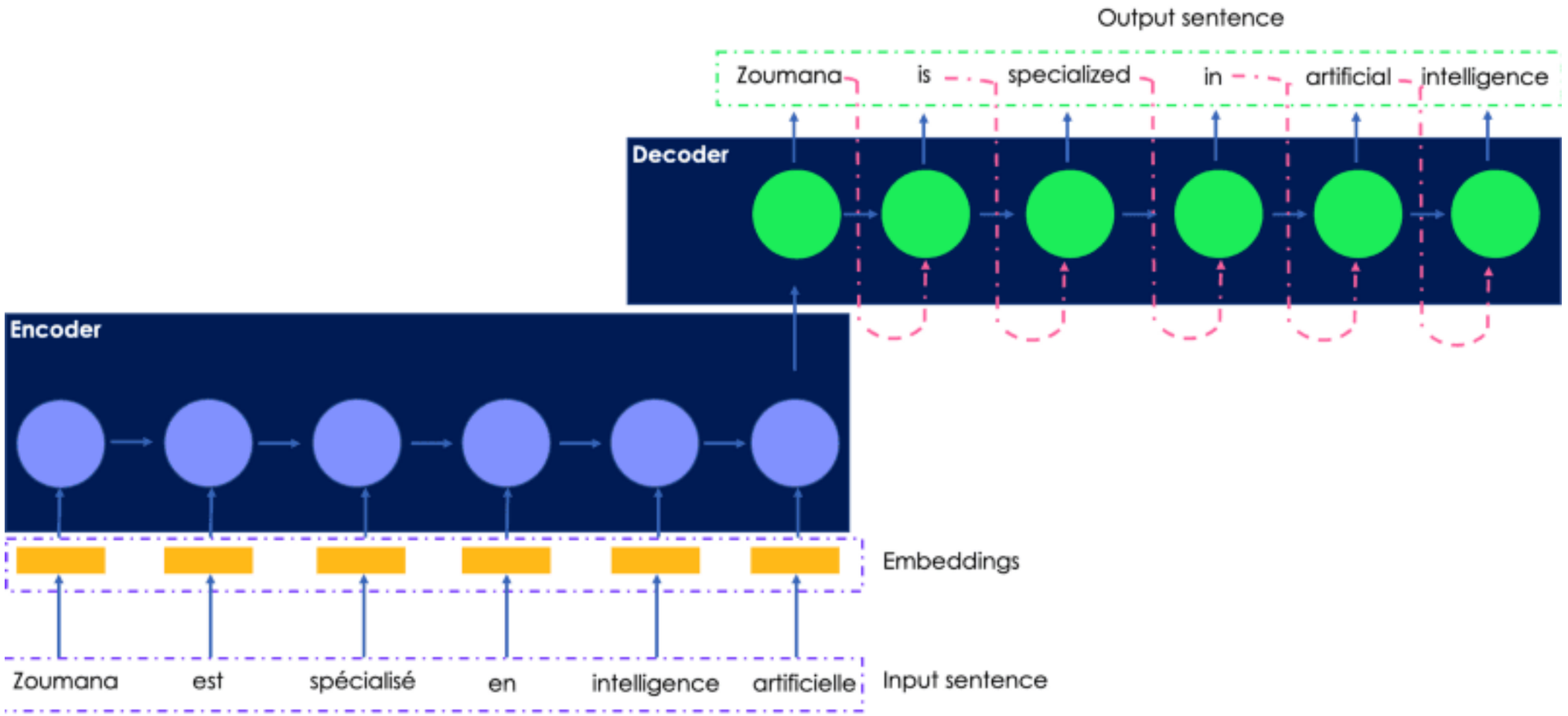
Example with attention

Context-aware embedding vectors

Swing the **bat**

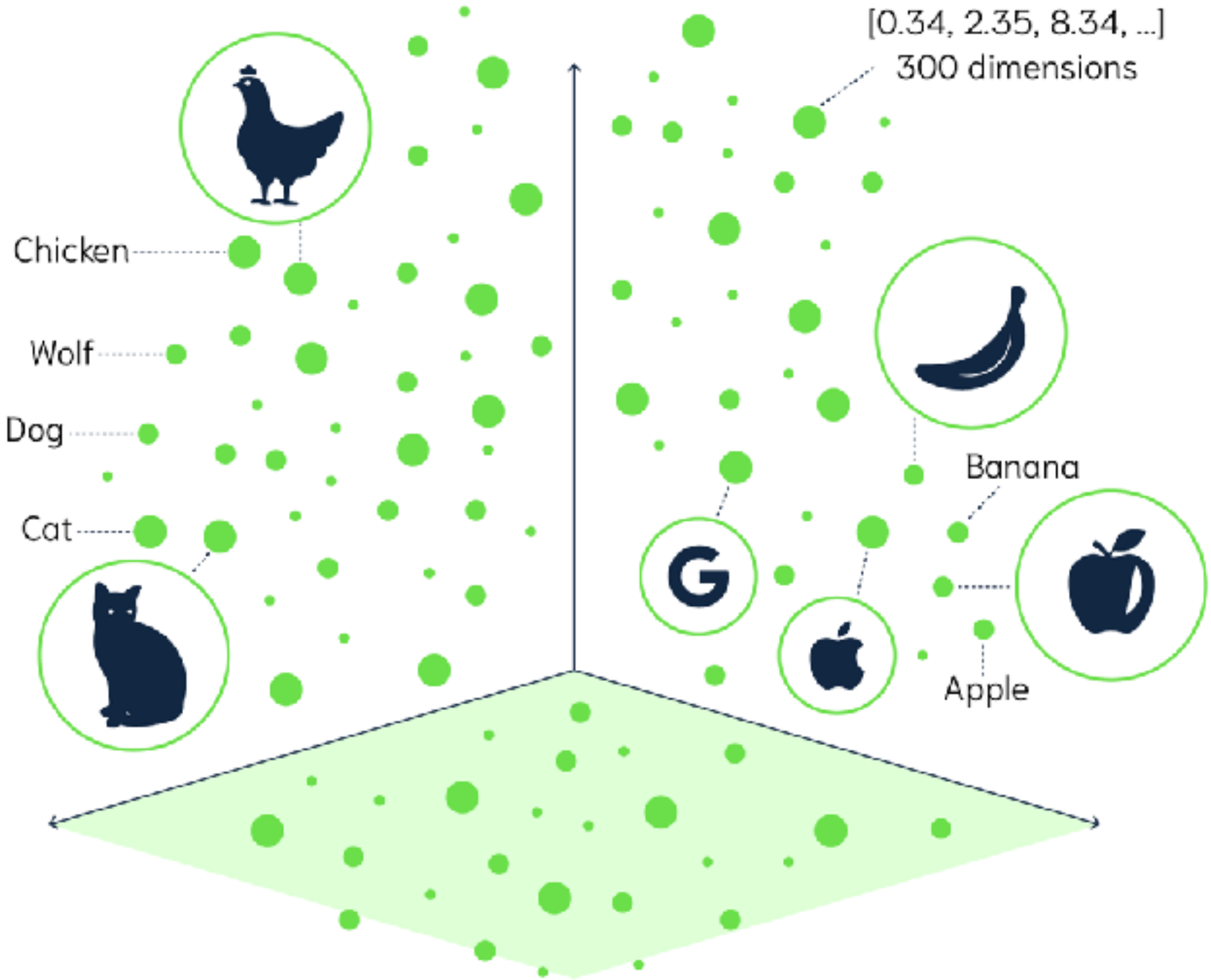
The **bat** flew at night

Example with translation



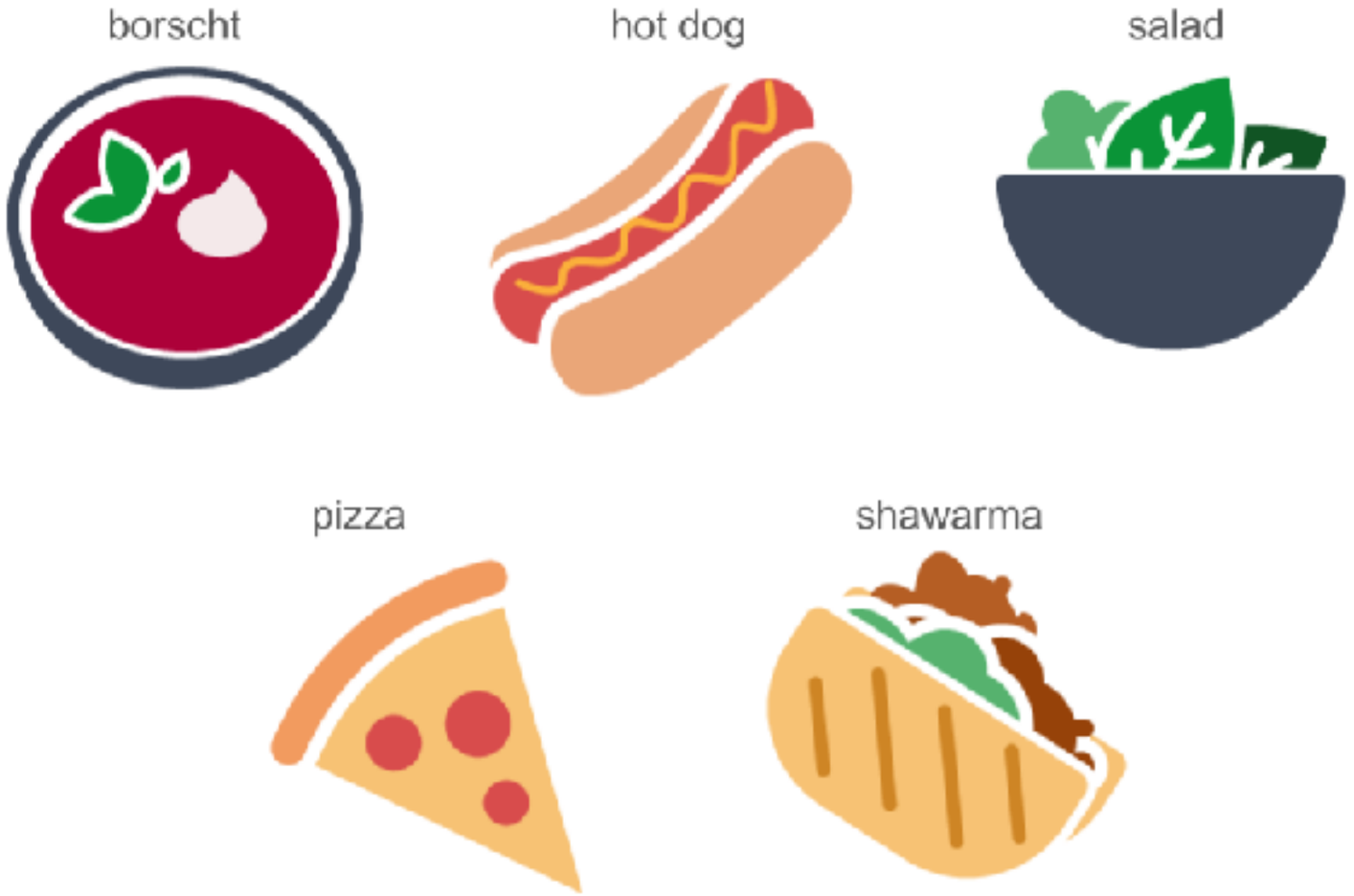
https://www.datacamp.com/tutorial/an-introduction-to-using-transformers-and-hugging-face

Visual of Vector space



Food recommendations ?

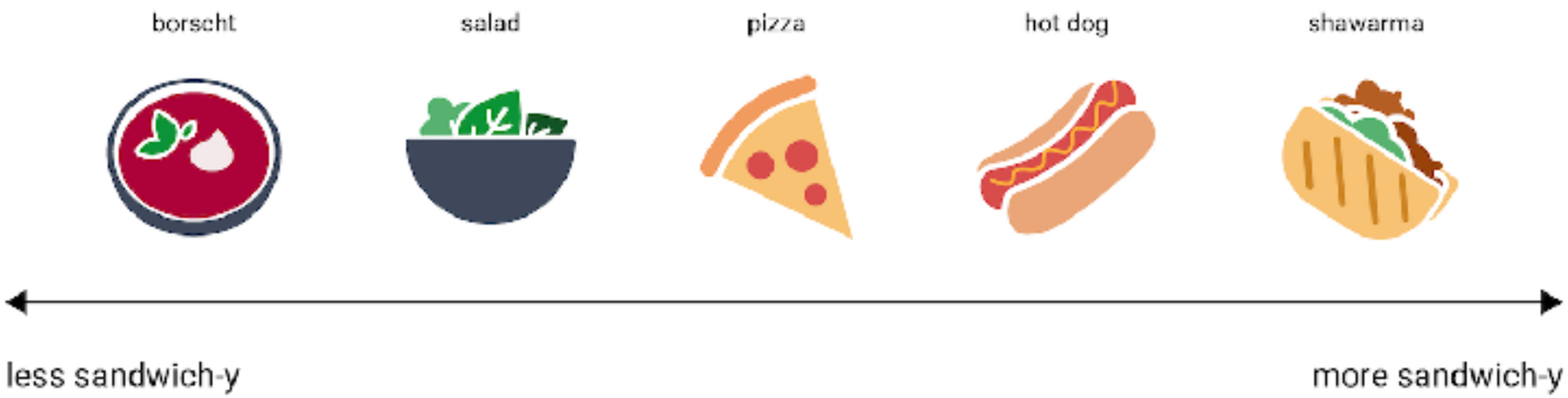
Food recommendations



https://developers.google.com/machine-learning/crash-course/embeddings

Embedding space (1)

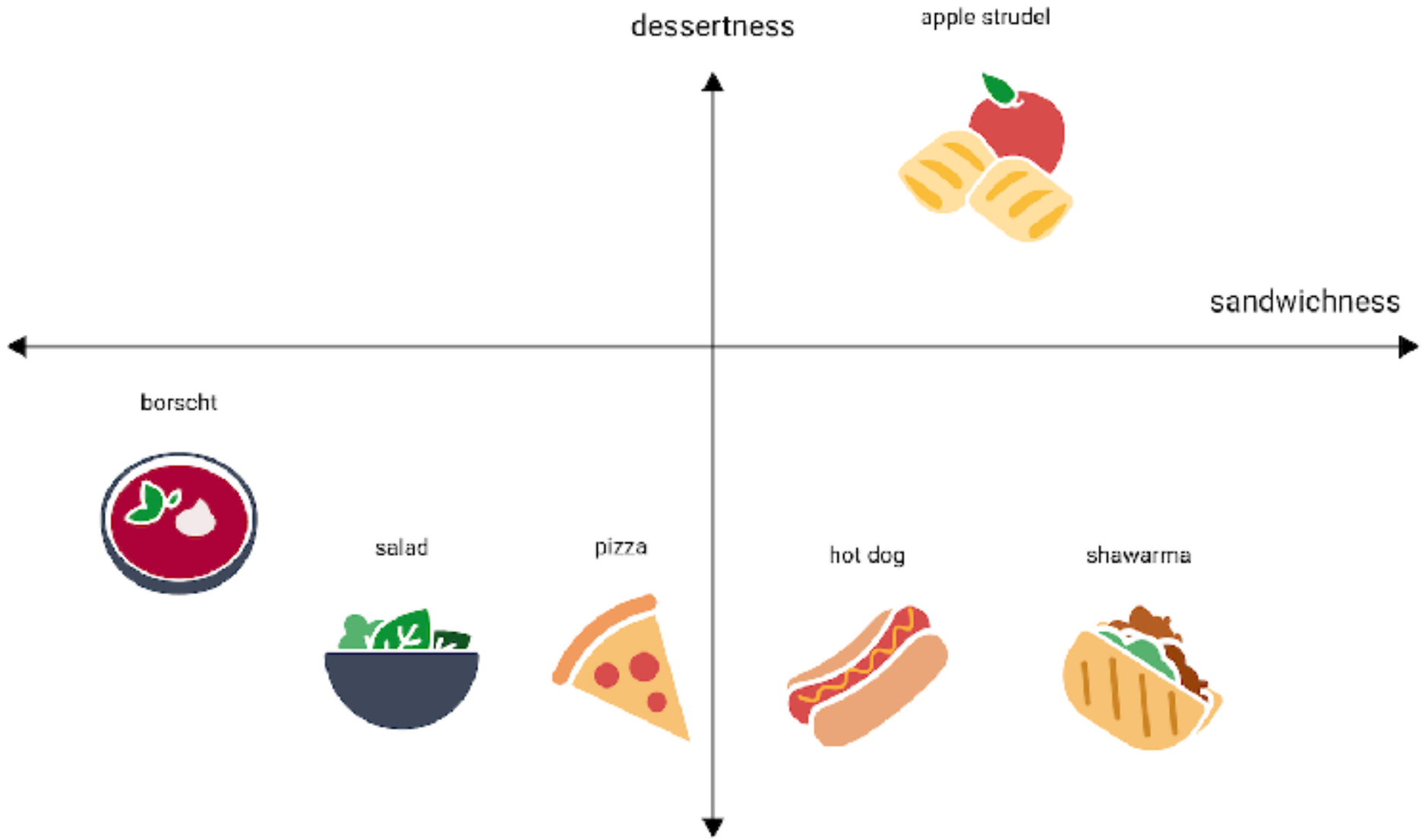
Less and more sandwich (1D)



https://developers.google.com/machine-learning/crash-course/embeddings/embedding-space

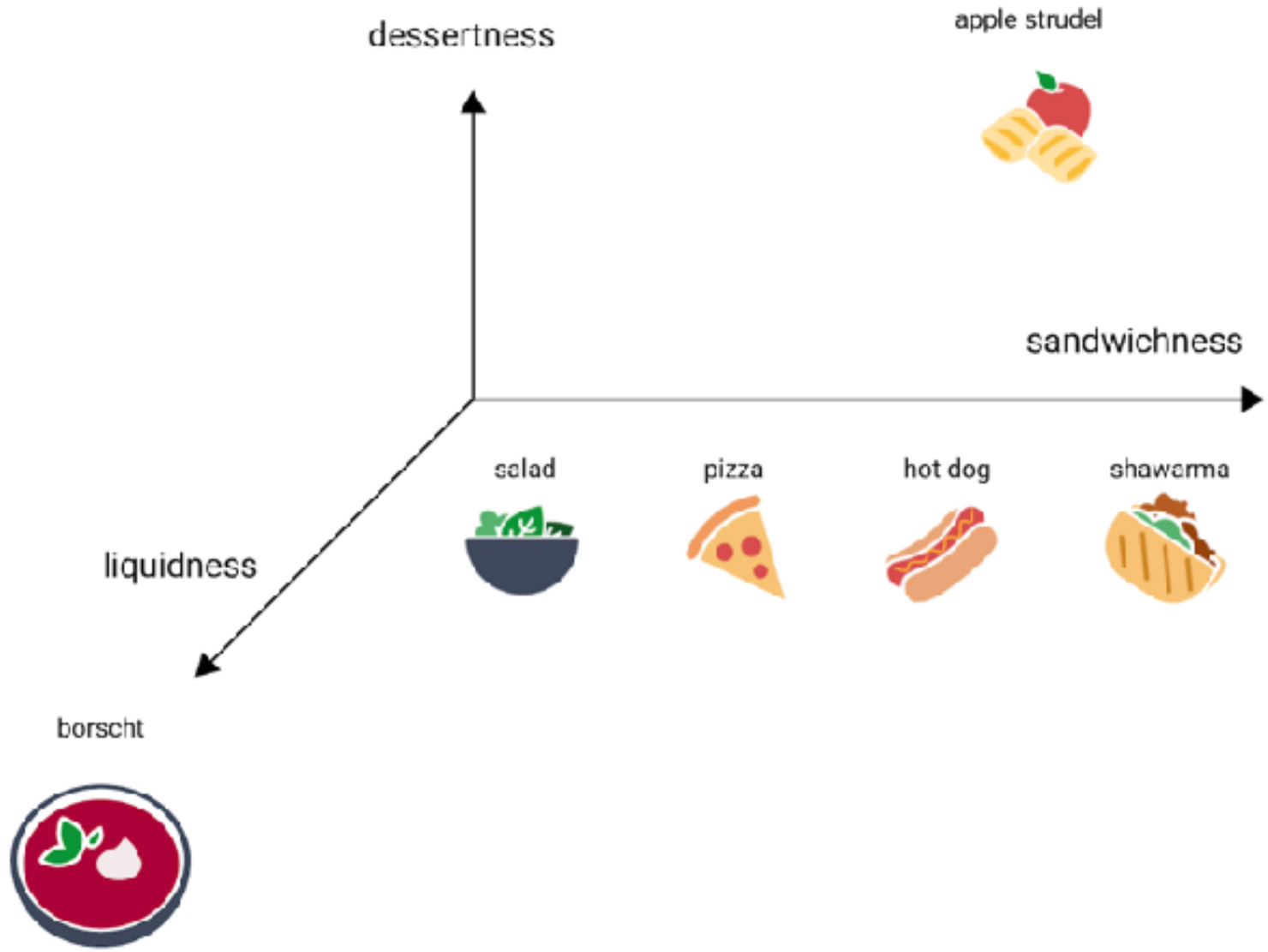
Embedding space (2)

Sandwichness and dessertness (2D)

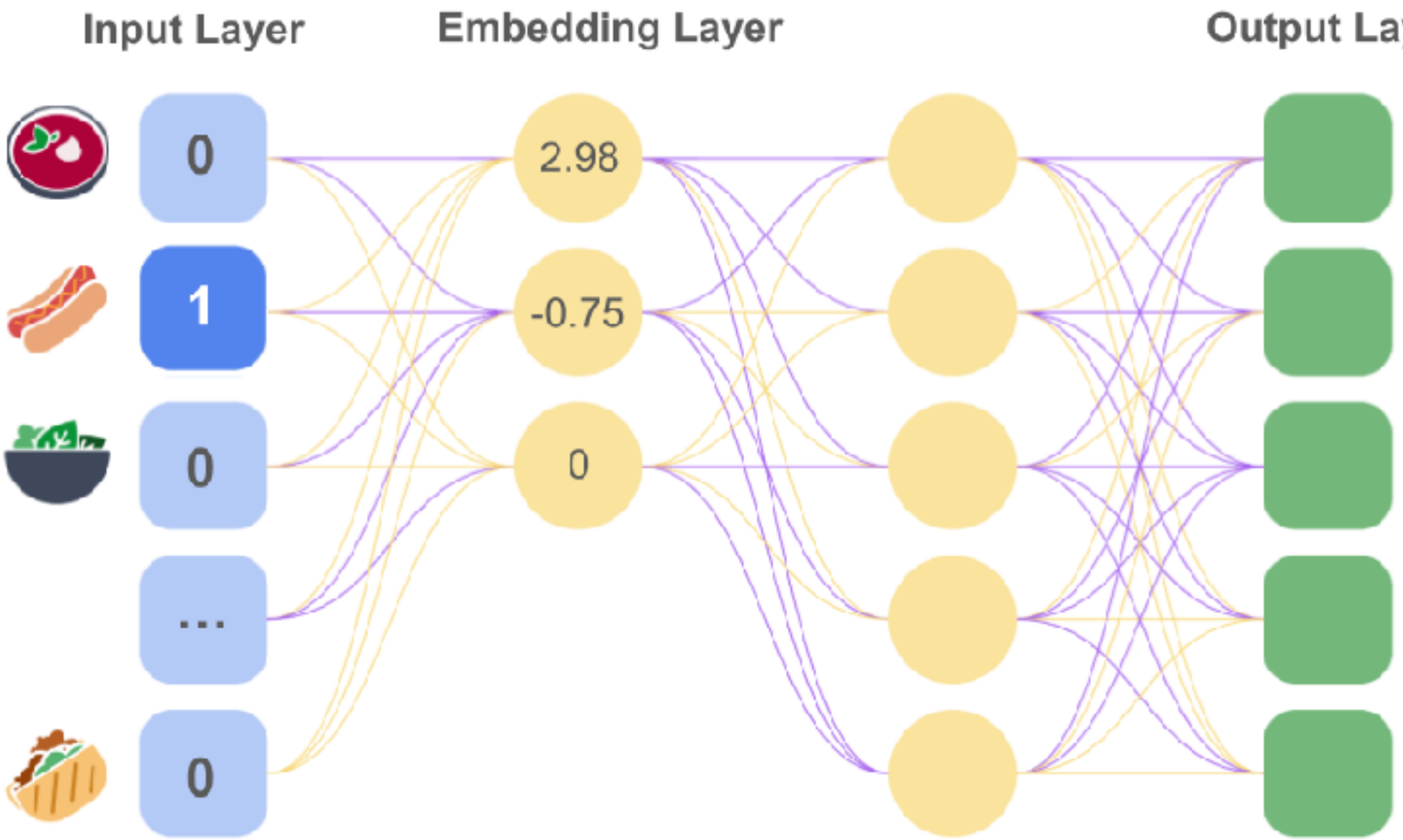


Embedding space (3)

Sandwichness, dessertness and liquidness (3D)

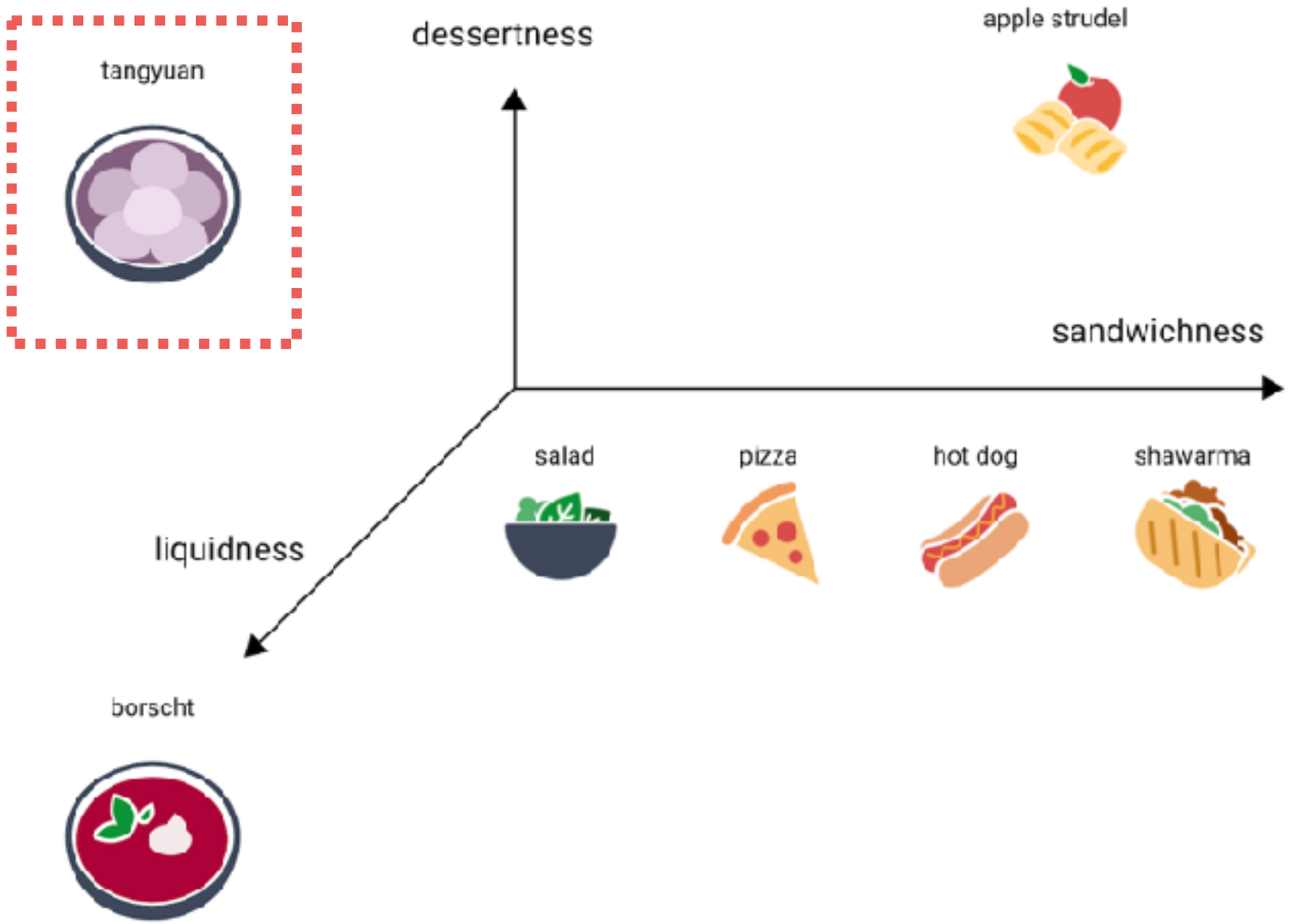


Embedding process ?



Embedding space (4)

New food ?



รายการอาหารที่มีผัก กินง่าย ๆ อร่อย ๆ ให้หน่อยสิ ?

Use cases for Attention

Translation

Text summarization

Question answering

Sentiment analysis

Content generation

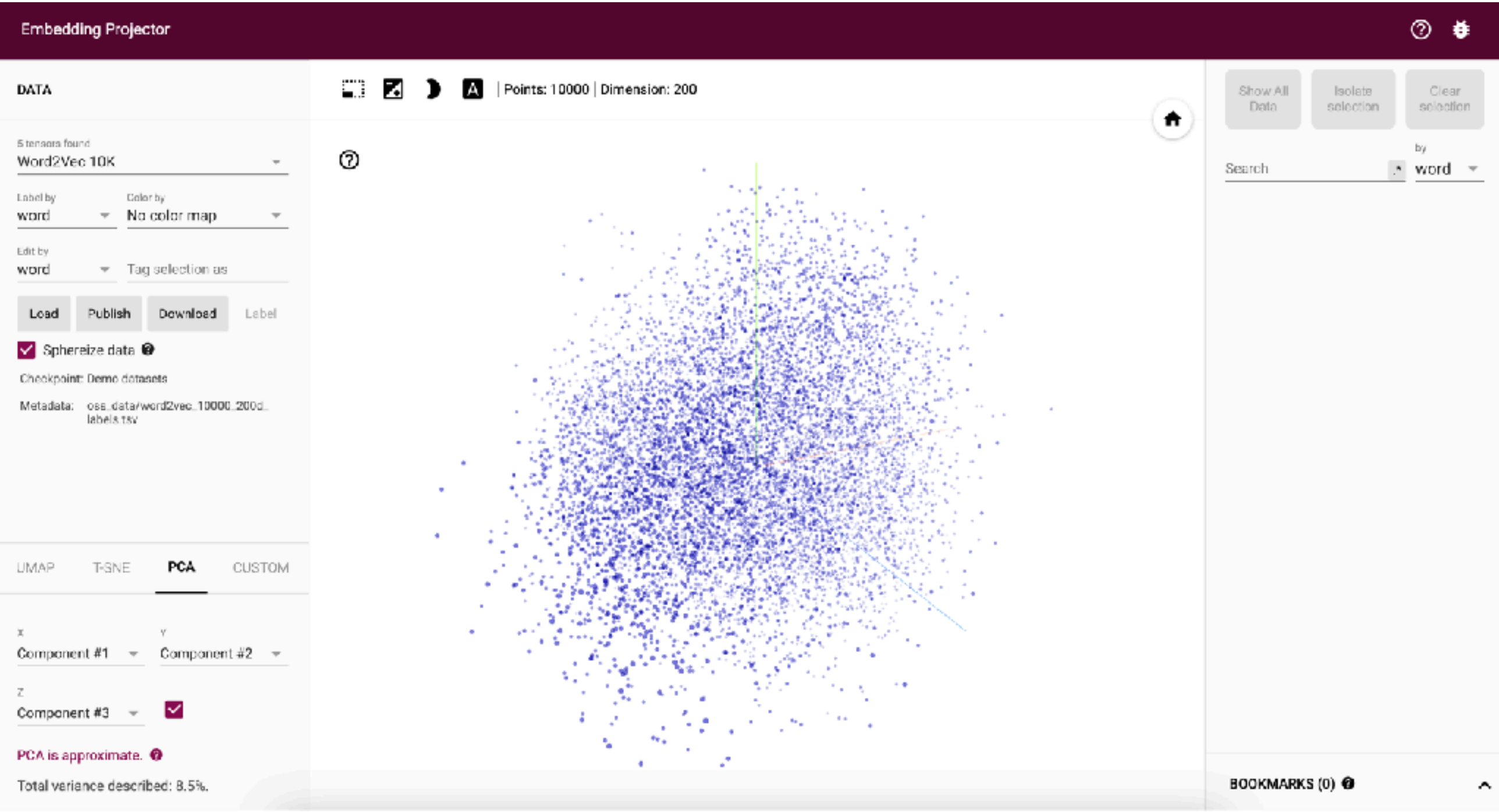
Choose right model for your use case

Embedding models

Model name	Provider name	Dimensions	Max token
text-embedding-3-small	OpenAI	1536	8192
text-embedding-3-large	OpenAI	3072	8192
sentence-transformers/ all-MiniLM-L6-v2	Hugging Face	382	256
gemini-embedding	Google	3072	8192

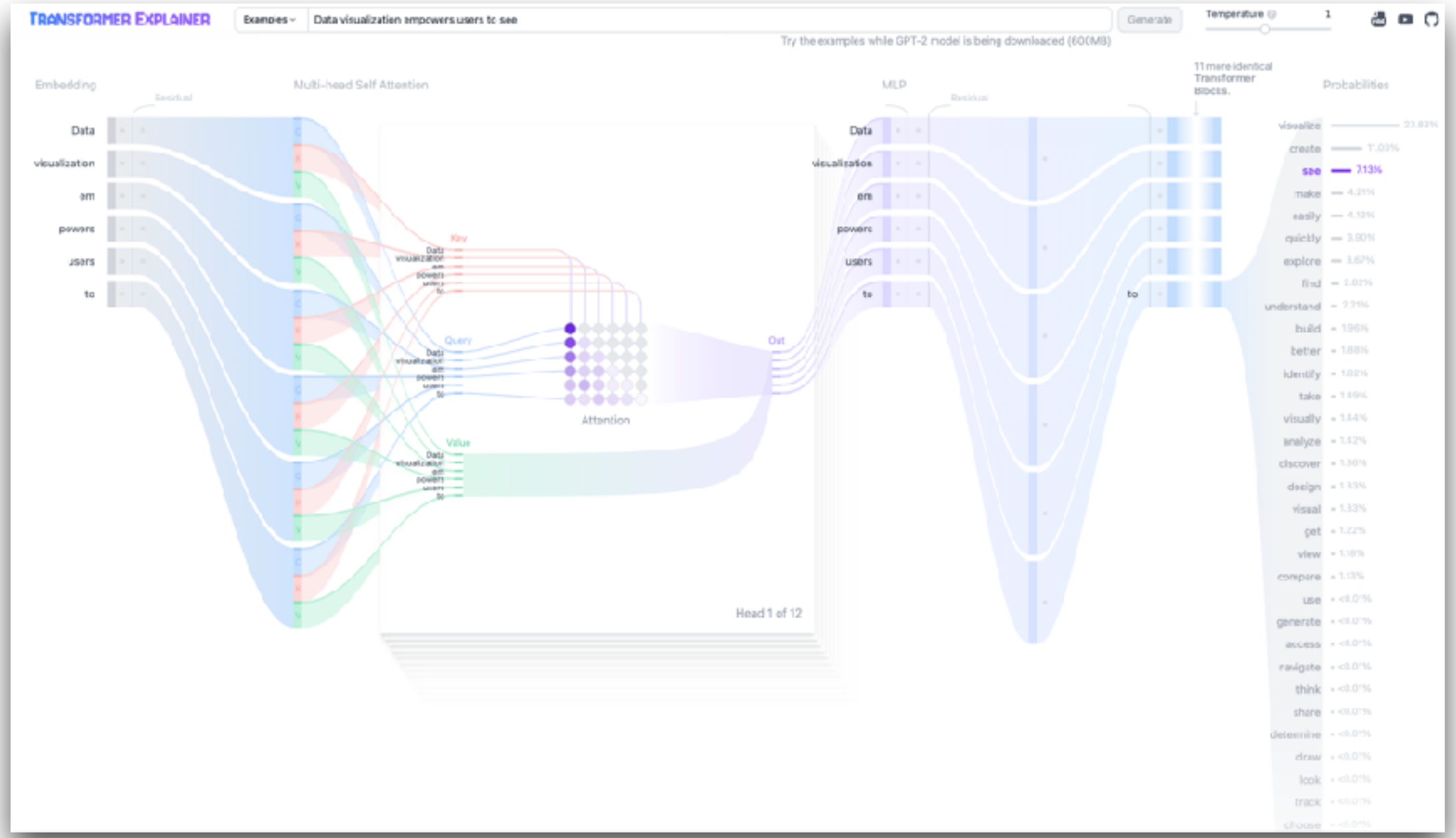
https://huggingface.co/spaces/mteb/leaderboard

Embedding Projector



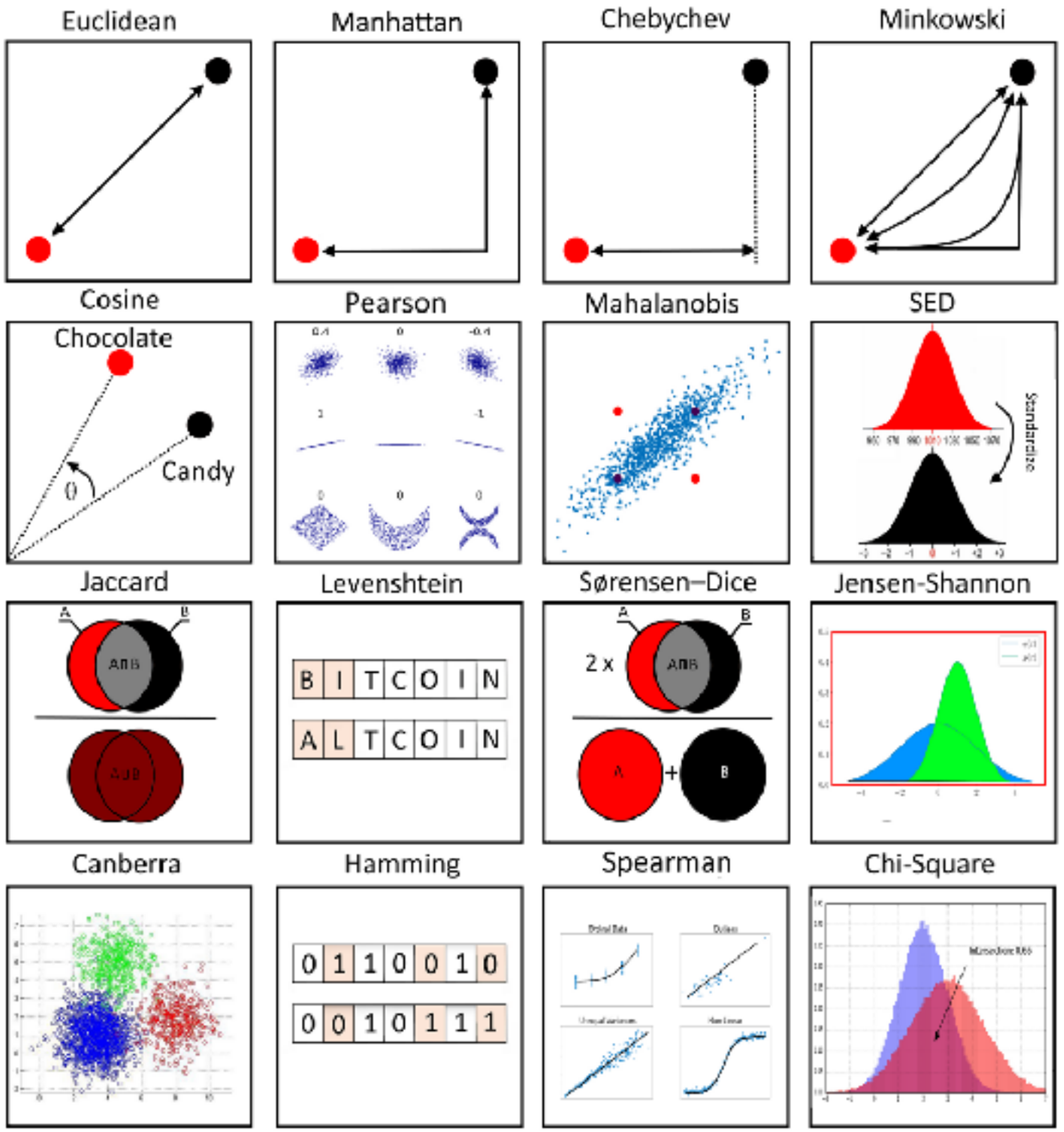
https://projector.tensorflow.org/

Transformer Explainer

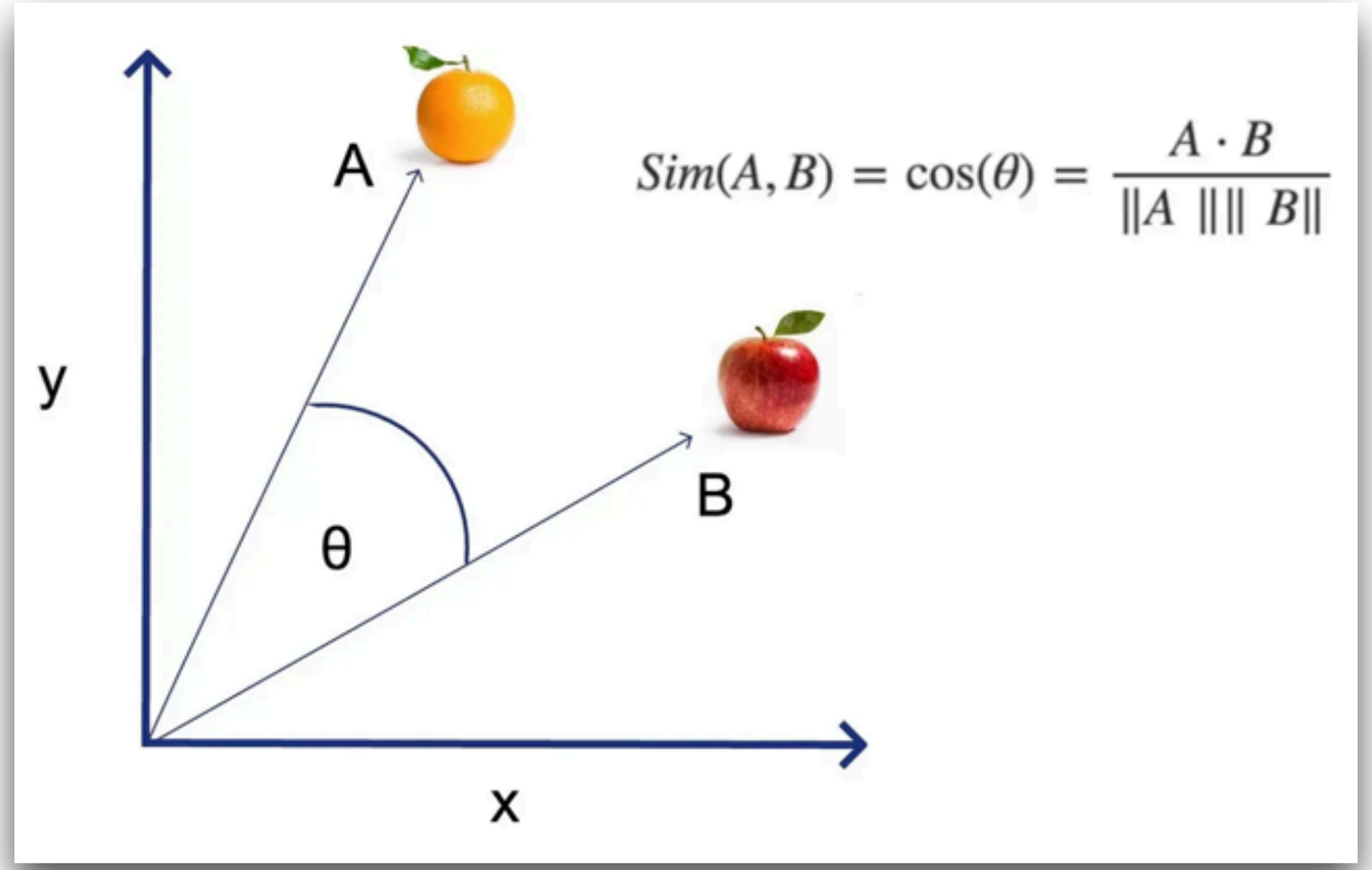


https://poloclub.github.io/transformer-explainer/

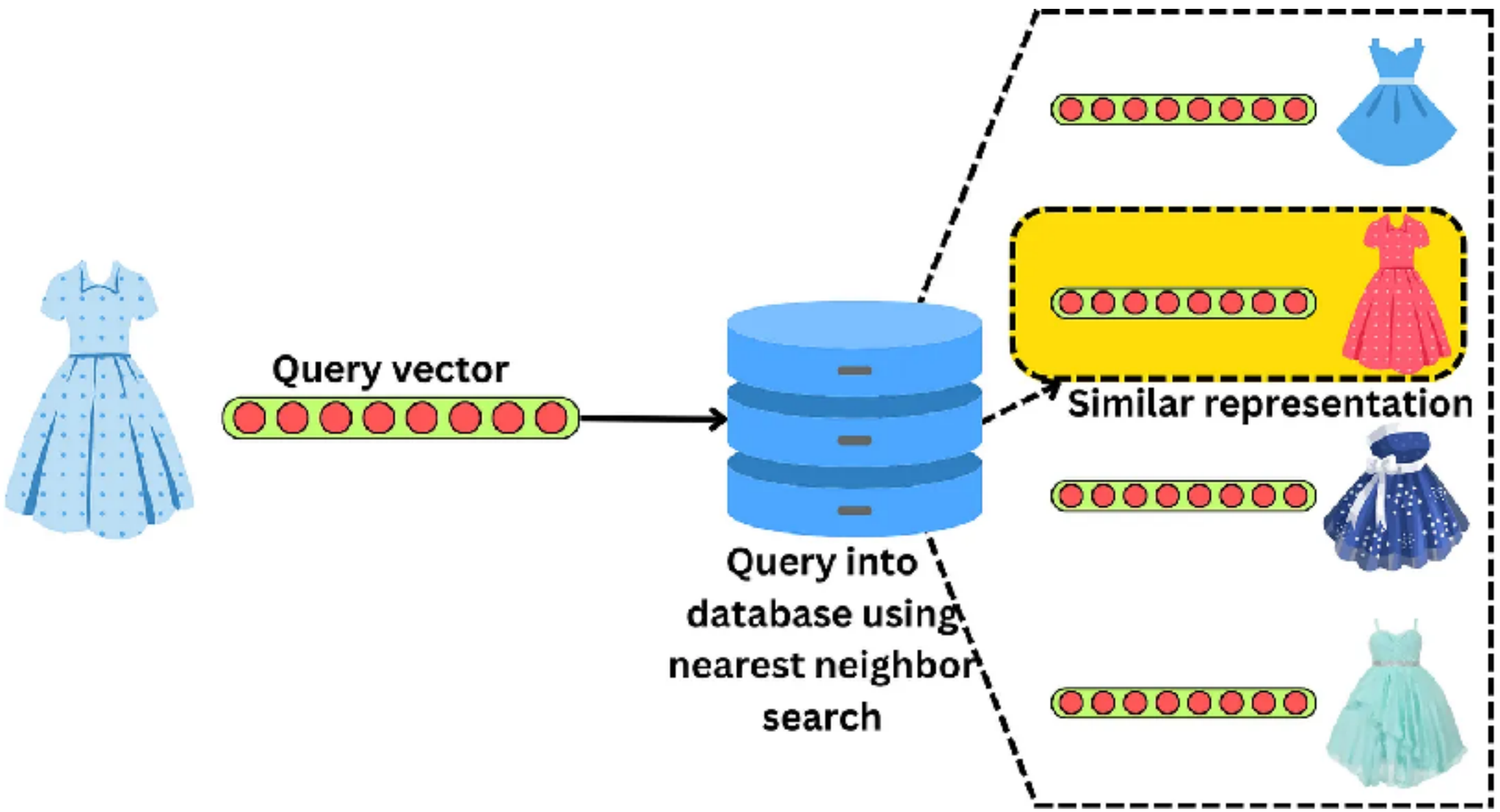
Distance measure



Cosine distance/similarity

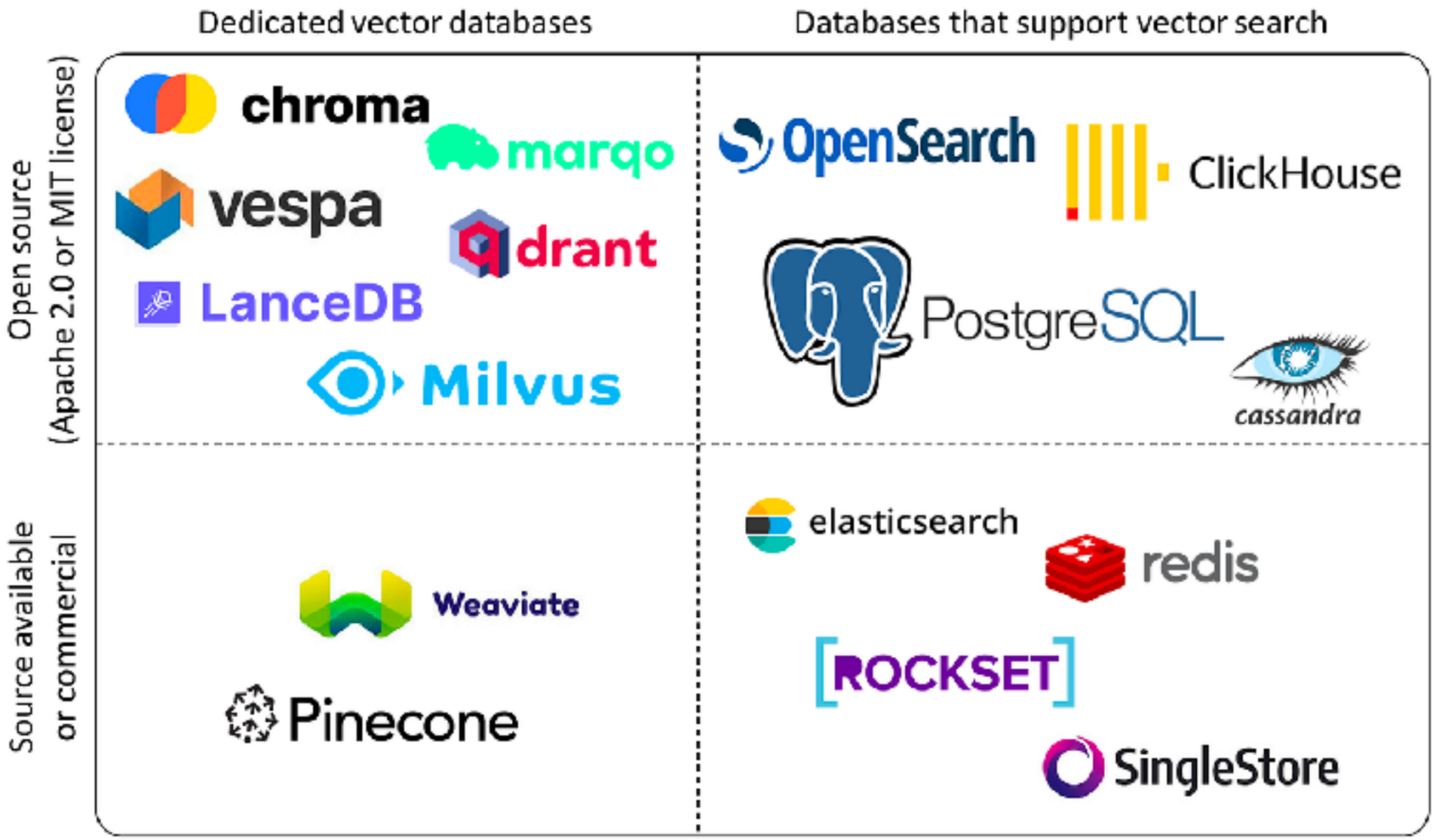


Search similar items



https://newsletter.theaiedge.io/p/understanding-how-vector-databases

Vector Database

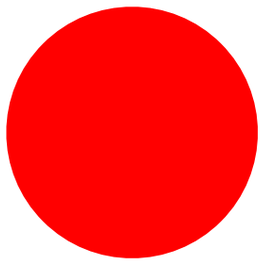


Vector Database

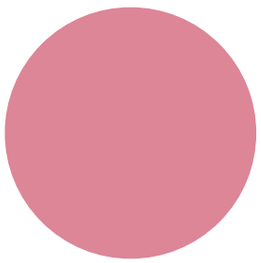
Capable of organize data be **meaning**
Capable of searching entries by **similarity** to the query
Represent meaning as a series of numbers
Search or filtering by keyword and vector (hybrid)

Help to find the **right** information **faster**

Example with RGB color



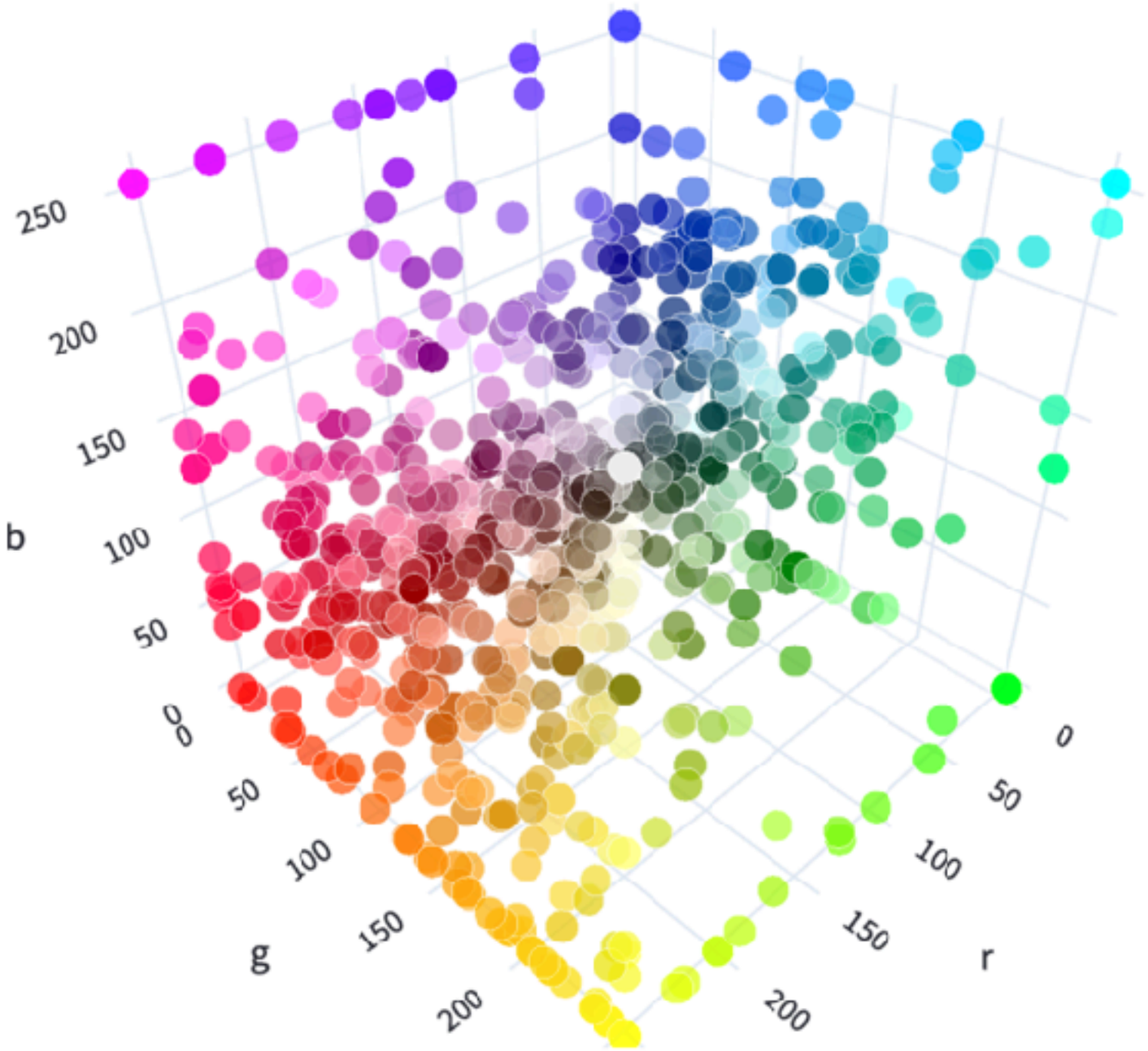
[255, 0, 0]



[220, 134, 151]

[223, 223, 97]

Visualize RGB



https://huggingface.co/spaces/jphwang/colorful_vectors

Capabilities of LLMs

Text generation
Question answering
Translation
Summarization
Conversation
Sentiment analysis
Text classification
Code assistance

LLMs in industry

LLMs in industry (2024)

Model name	Company
Bidirectional Encoder Representation from Transformers (BERT)	Google AI
Generative Pre-trained transformer-3 (GPT-3)	OpenAI
Generative Pre-trained transformer-4 (GPT-4)	OpenAI
Pathways Language Model-E (PaLM-E)	Google AI
BLOOM	NVIDIA AI
Llama 3	Facebook
Claude 3.7 Sonnet	Anthropic

LLM Development timeline

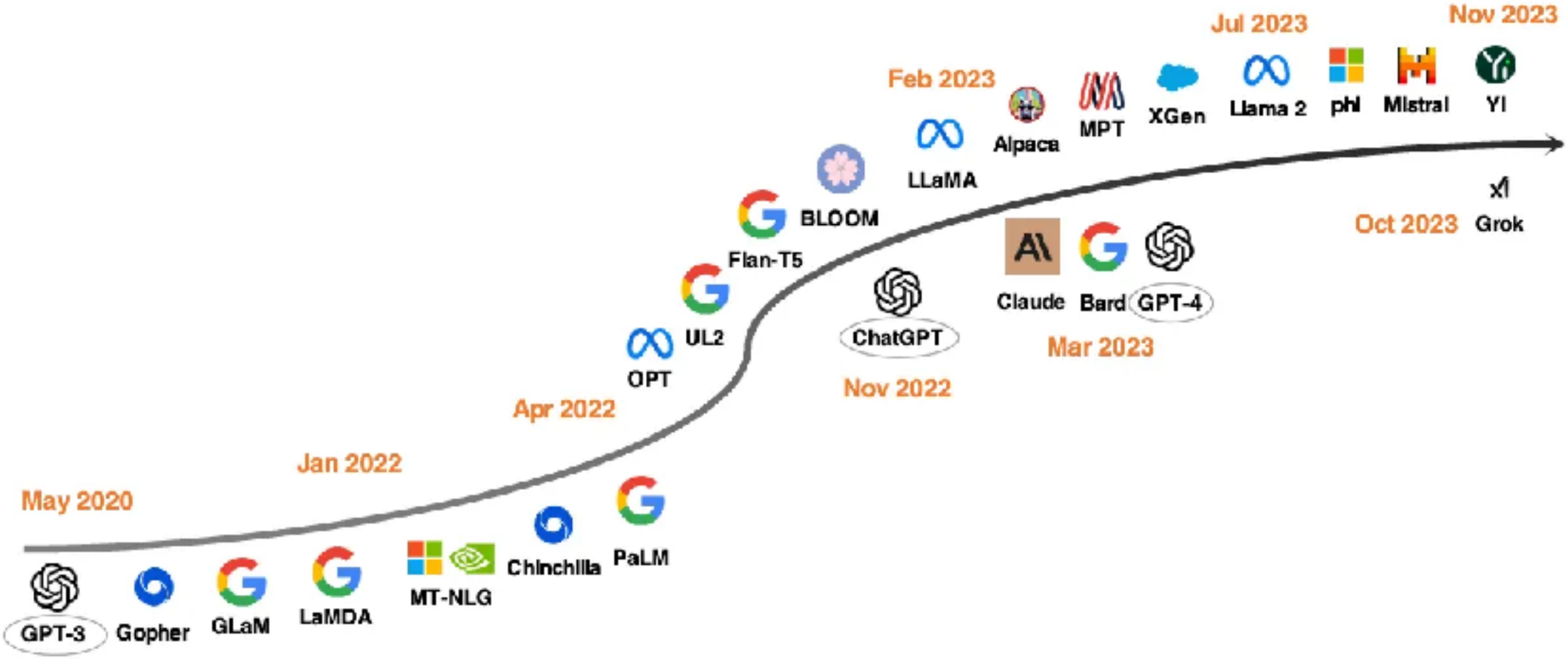
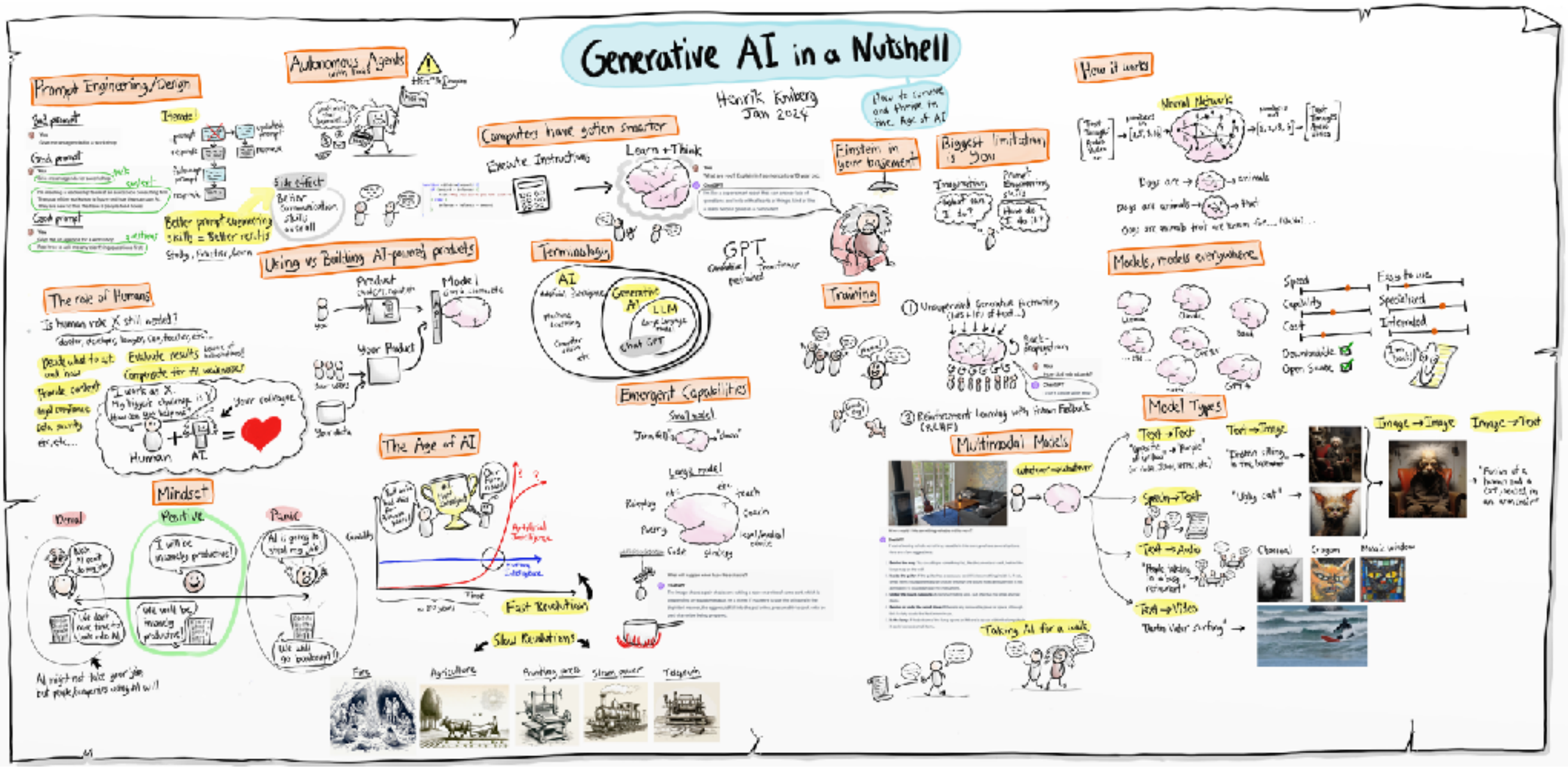


Figure 3: LLM development timeline. The models below the arrow are closed-source while those above the arrow are open-source.

https://arxiv.org/abs/2311.16989

Generative AI in Nutshell



https://www.youtube.com/watch?v=2IK3DFHRFfw

Challenges in Gen AI/LLM

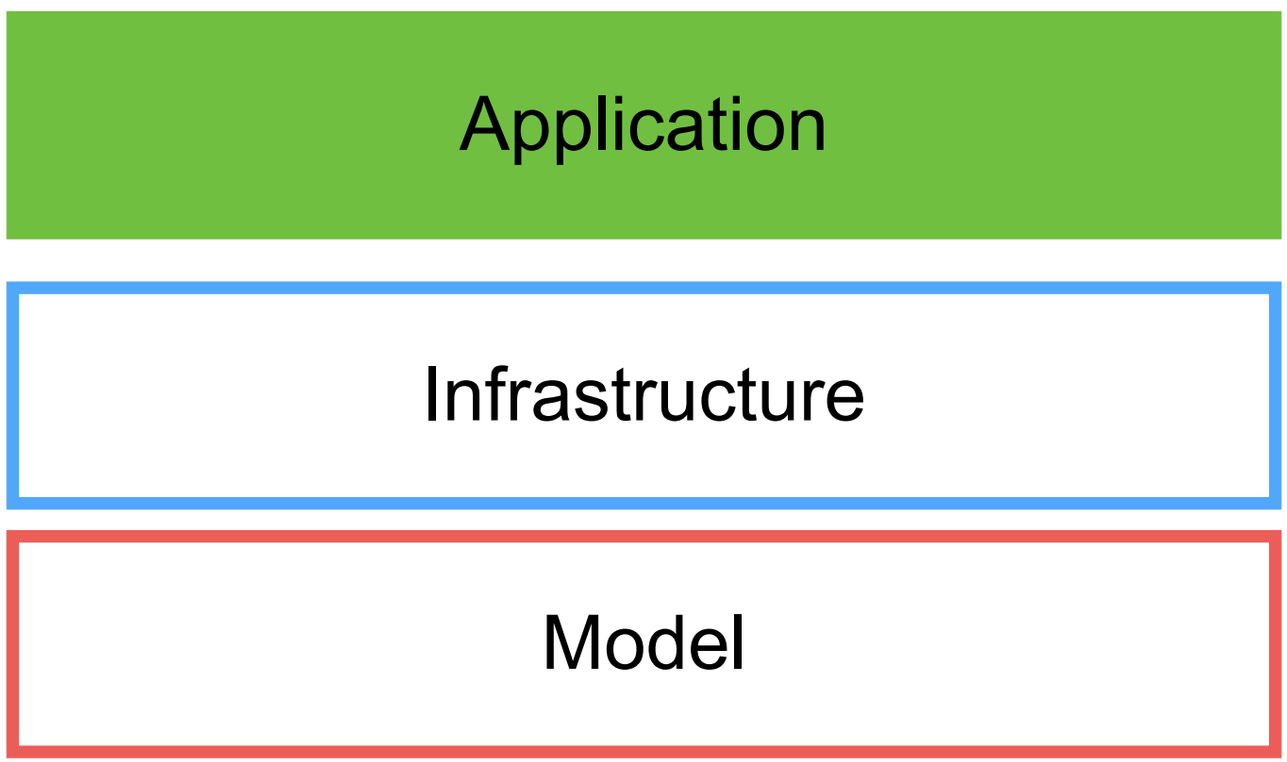
Lack of high-quality data
Data licenses
Generation latency
High computational power

Bias and Ethics

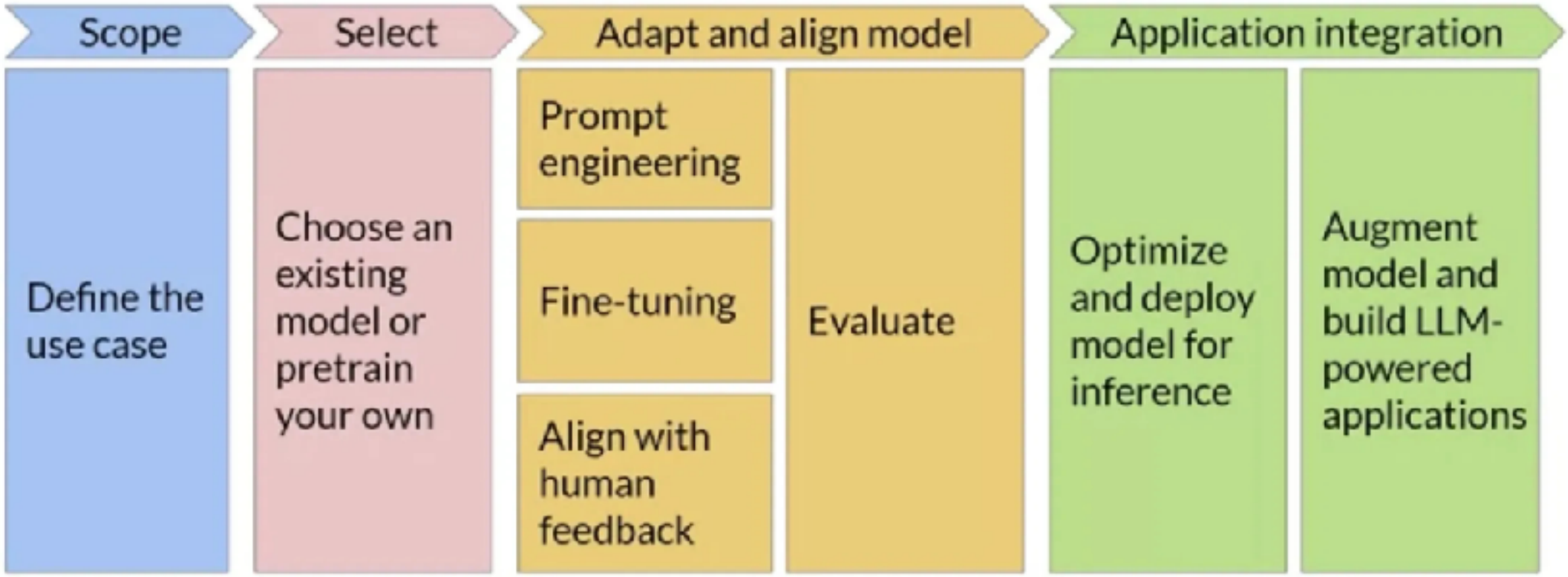
Outdate knowledge

Lack of true understanding

Challenge in LLMs

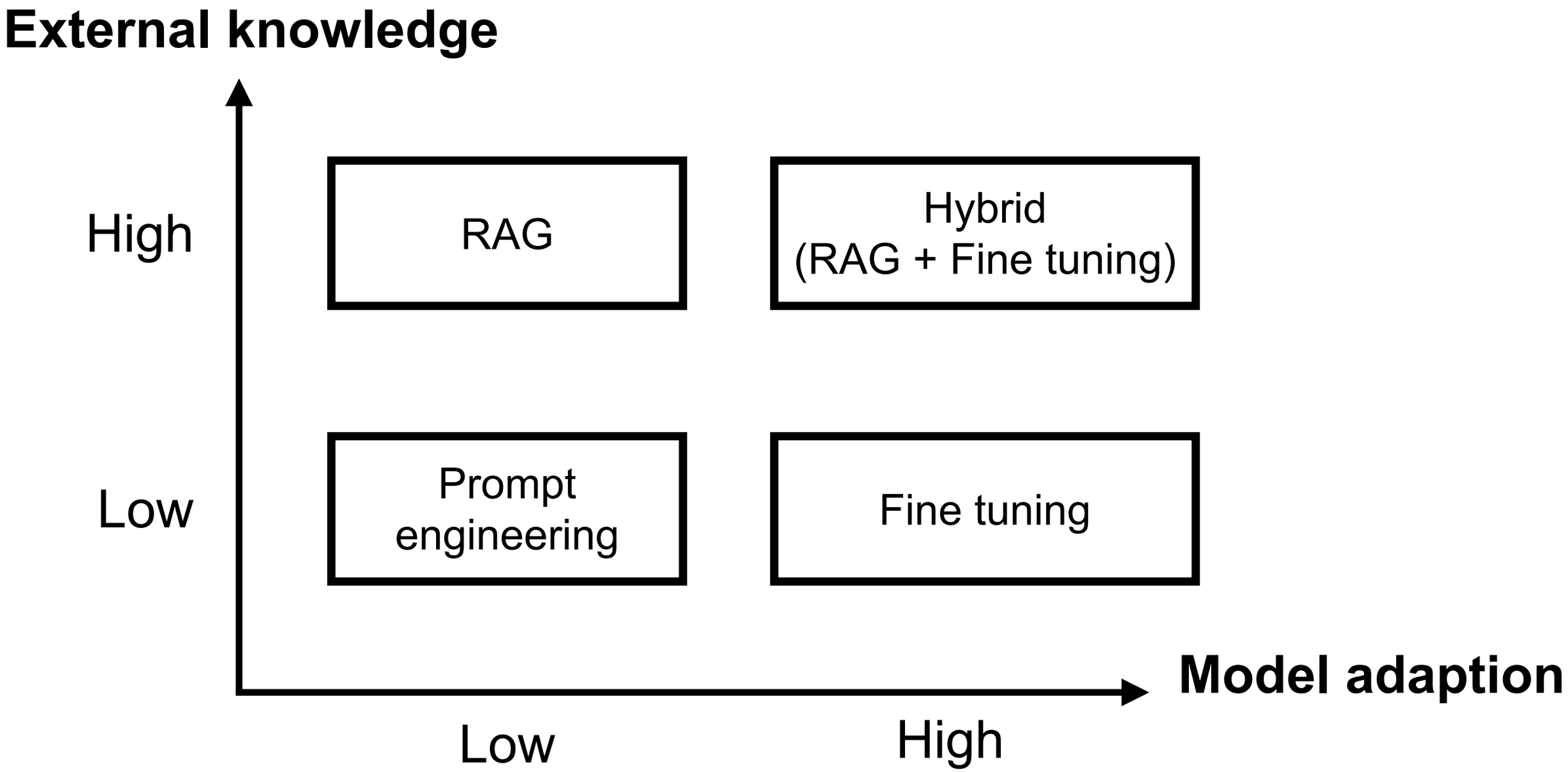


LLM Development Life Cycle

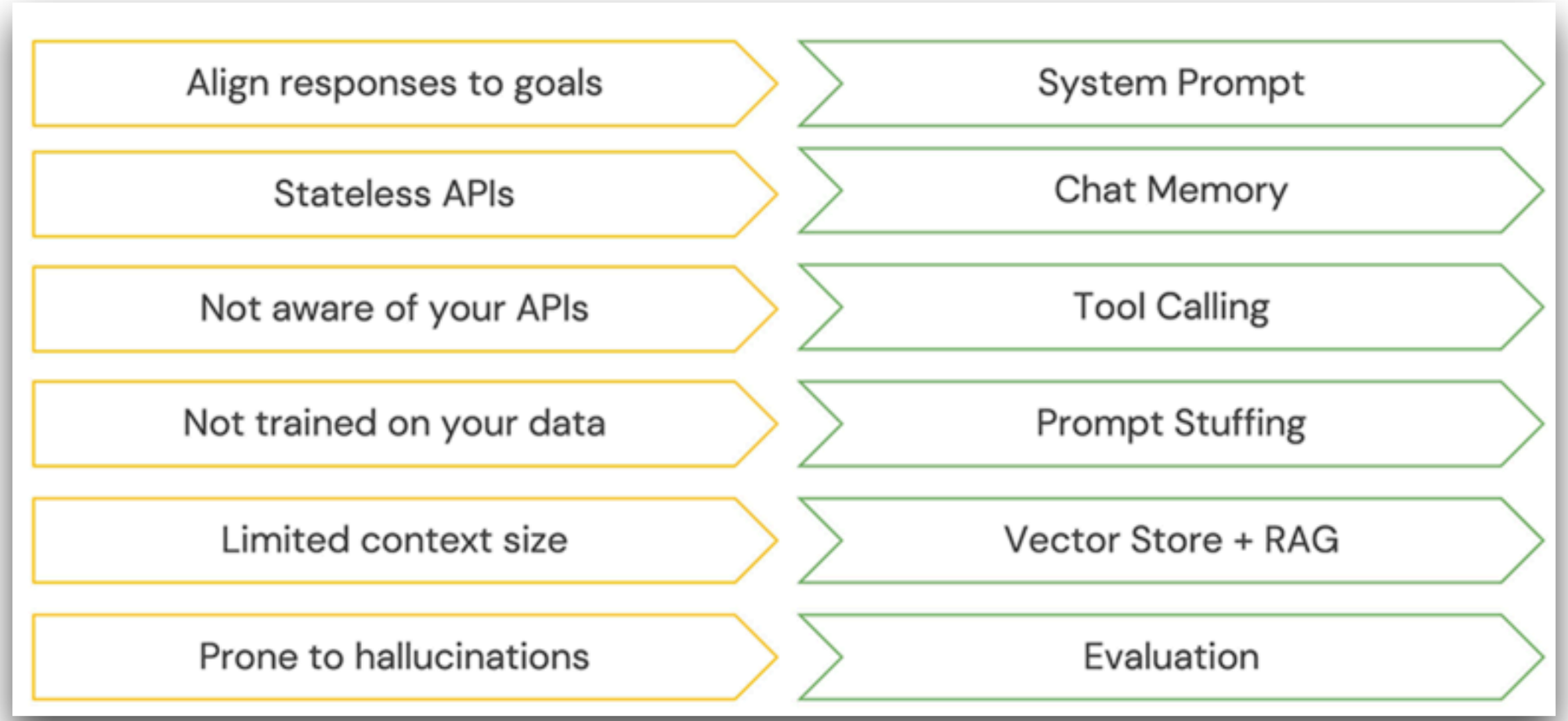


https://substack.com/home/post/p-147698161

LLM-based app ?



Generative AI patterns !!



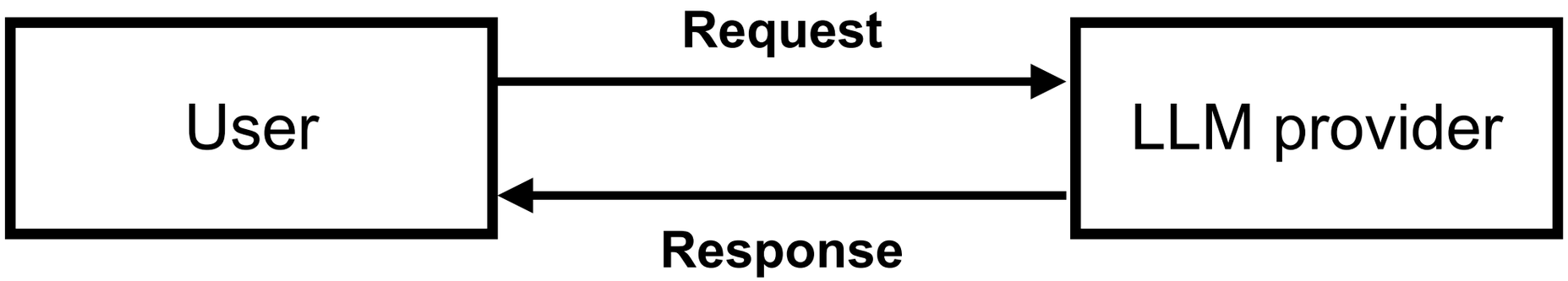
Decision factor for LLMs ?

Decision factor	Description
Language and Domain support	Supports Thai language or specialized domains (e.g., finance, legal, medical)
Data ownership	Level of control over data local deployment vs. third-party cloud APIs
Cost and scalability	Open-source may require GPU investment API-based models charge per usage
Latency and SLA	Response time and whether there's an uptime guarantee or service-level agreement
Ecosystem support	SDKs, plug-ins, monitoring tools, and active developer community
Advance features	Support for features like function calling, tool use, and extended context windows

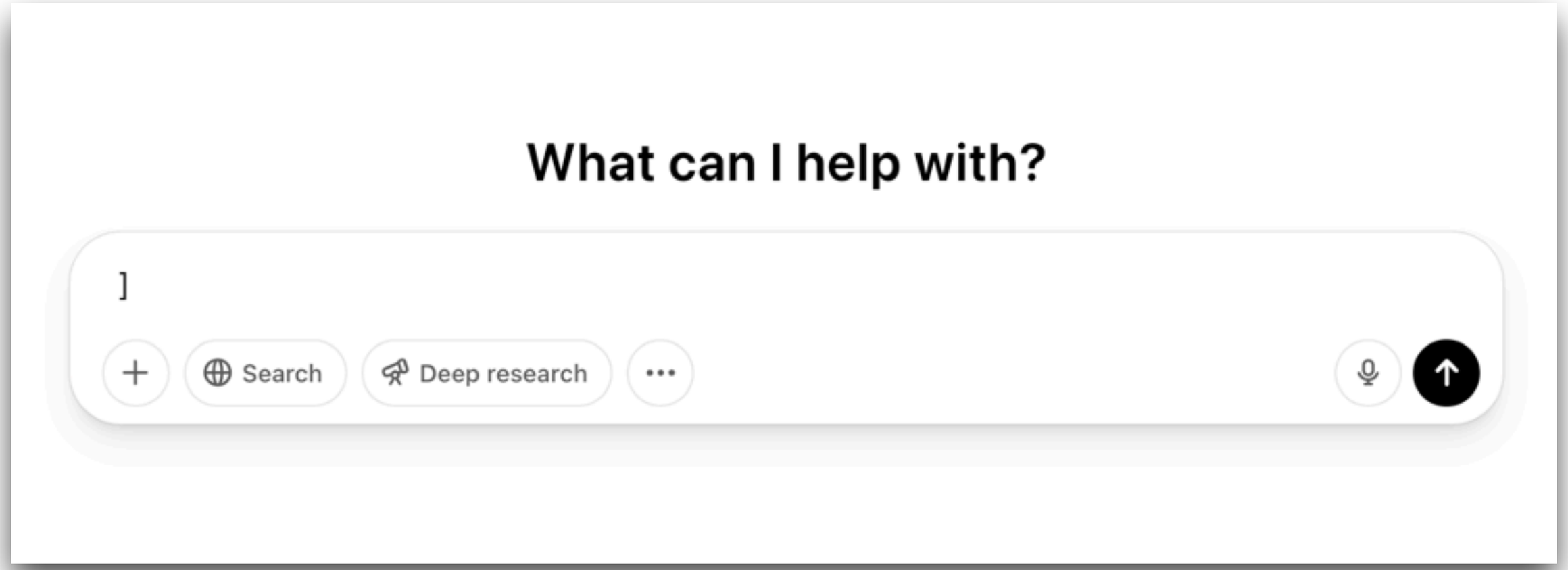
Working with LLM

Working with LLM provider

Prompting and prompt engineering



ChatGPT (web)

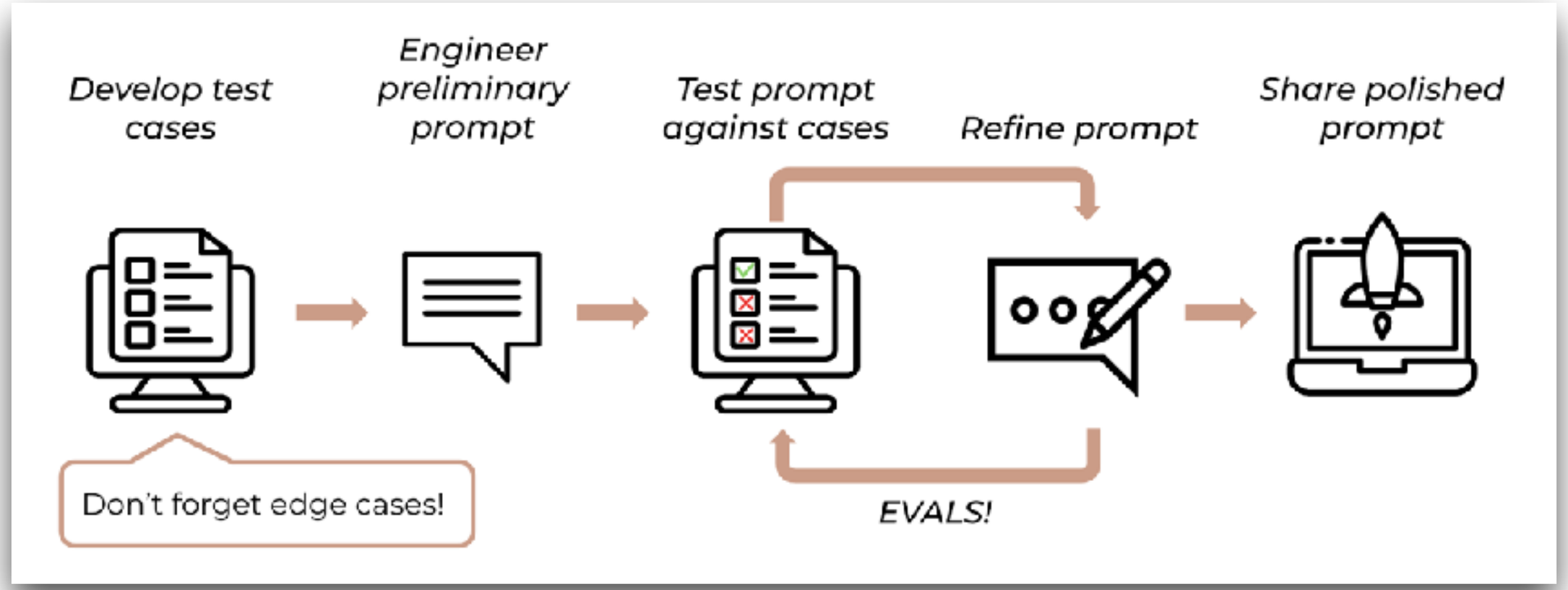


https://chatgpt.com/

Prompt Engineering

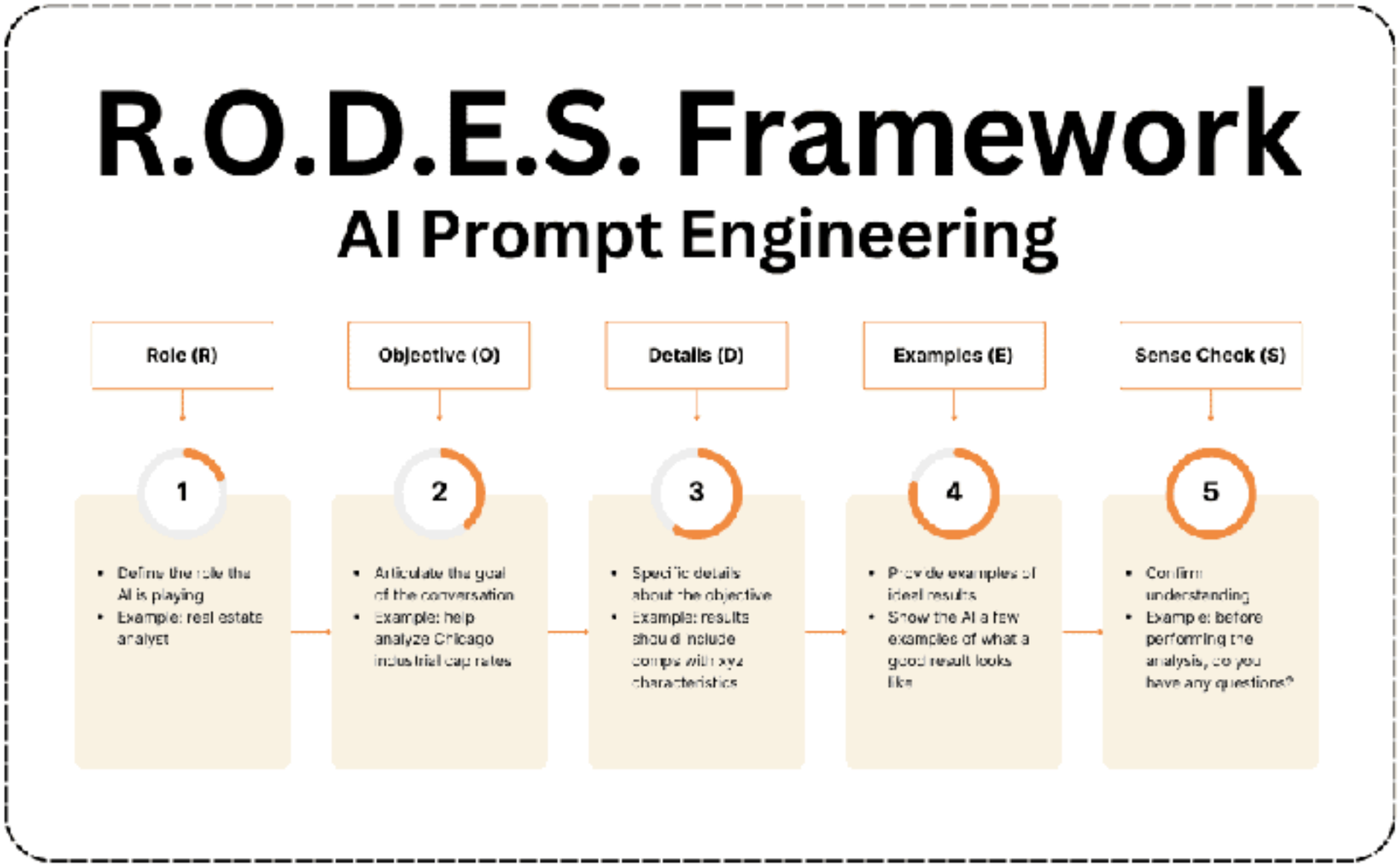
https://www.promptingguide.ai/

Prompt Development Life cycle



https://cheatsheet.md/claude/claude-prompt-engineering.en

Prompt Engineering



https://x.com/sebo_gm/status/1687366385620721664

Chain of Thought (CoT)

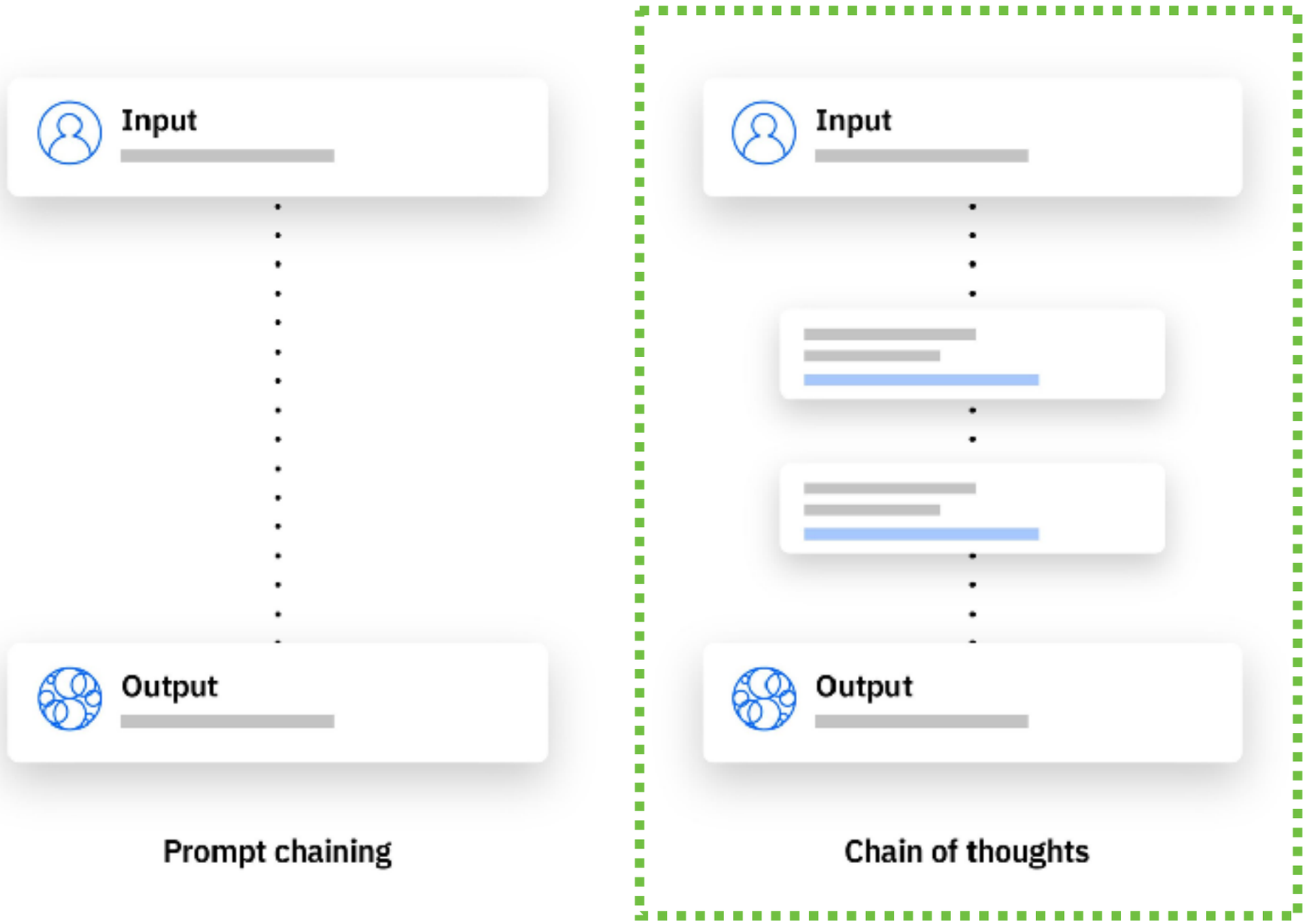
Guide LLM to breakdown complex reasoning tasks into small steps for human solving

Solving problem with logic, calculation and decision making

Improve accuracy	Enhance transparency	Better reasoning capability

https://arxiv.org/abs/2201.11903

Chain of Thought (CoT)



https://www.ibm.com/think/topics/chain-of-thoughts

Chain of Thought (CoT)

Standard Prompting

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ✗

Chain of Thought Prompting

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9. ✓

https://arxiv.org/abs/2201.11903

CoT with Zero-shot

Break down tasks by LLM model

(a) Few-shot

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
A: The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The answer is 8. ✗

(b) Few-shot-CoT

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The juggler can juggle 16 balls. Half of the balls are golf balls. So there are 16 / 2 = 8 golf balls. Half of the golf balls are blue. So there are 8 / 2 = 4 blue golf balls. The answer is 4. ✓

(c) Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: The answer (arabic numerals) is

(Output) 8 ✗

(d) Zero-shot-CoT (Ours)

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: ***Let's think step by step.***

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls. ✓

https://arxiv.org/abs/2201.11903

CoT to LLM Reasoning

Chain-of-Thought Prompt

Q: Roger has 5 tennis balls. He buys 2 more cans of balls. Each can has 3 balls.
How many balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11.
The answer is 11.

Q: The café has 23 apples. They use 20 during lunch and buy 6 more.
How many apples do they have?

LLM

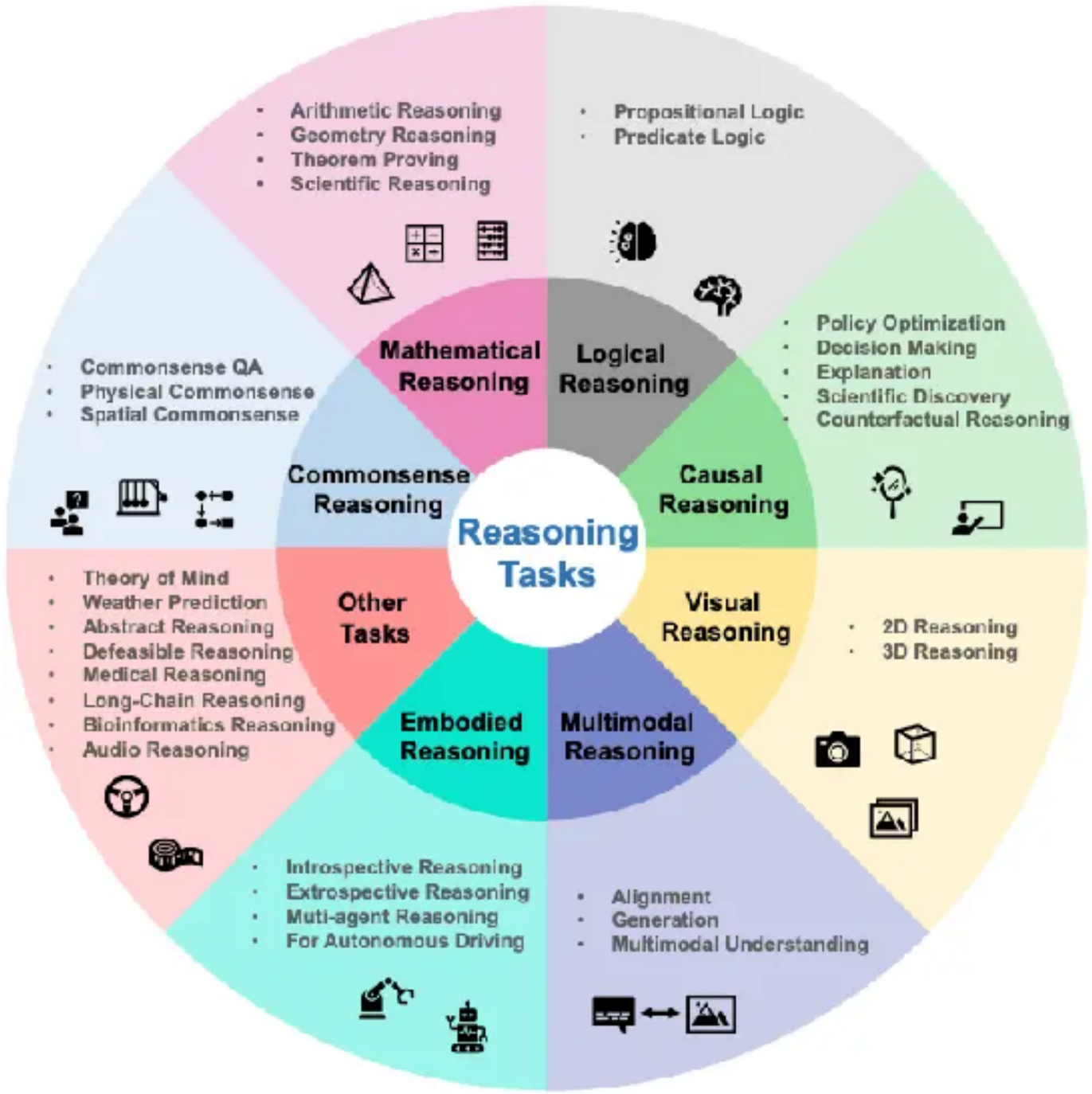
(e.g., ChatGPT, Gemini, Claude, and Llama)

Output

A: The cafeteria had 23 apples. They used 20 for lunch. So they had 23 - 20 = 3. They bought 6 more, so they have 3 + 6 = 9.
The answer is 9.

https://github.com/atfortes/Awesome-LLM-Reasoning

LLM Reasoning models



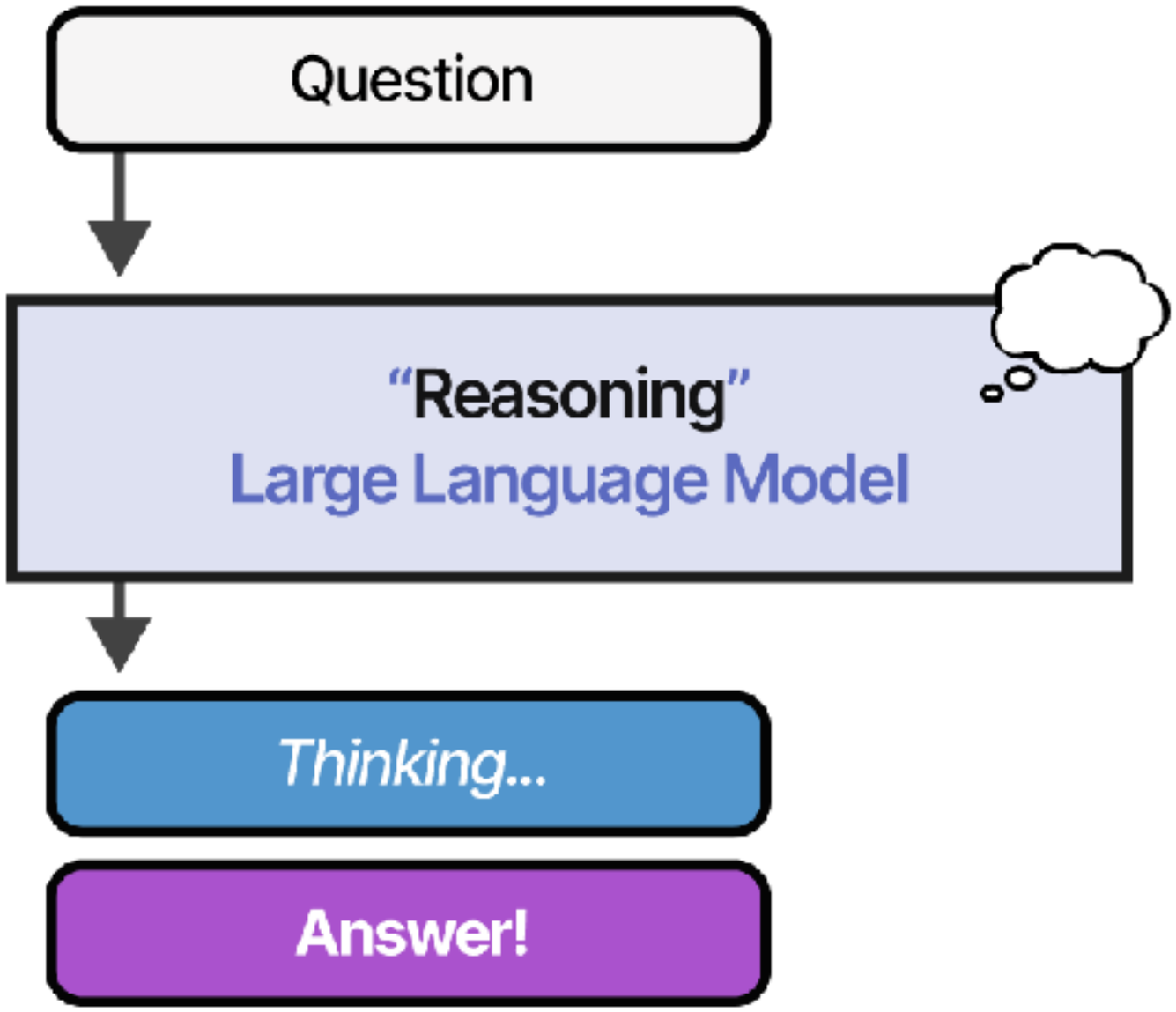
Support

Reasoning Techniques

- Pre-Training
- Fine-tuning
- Mixture of Experts (MoE)
- Alignment Training
- In-Context Learning
- Autonomous Agent

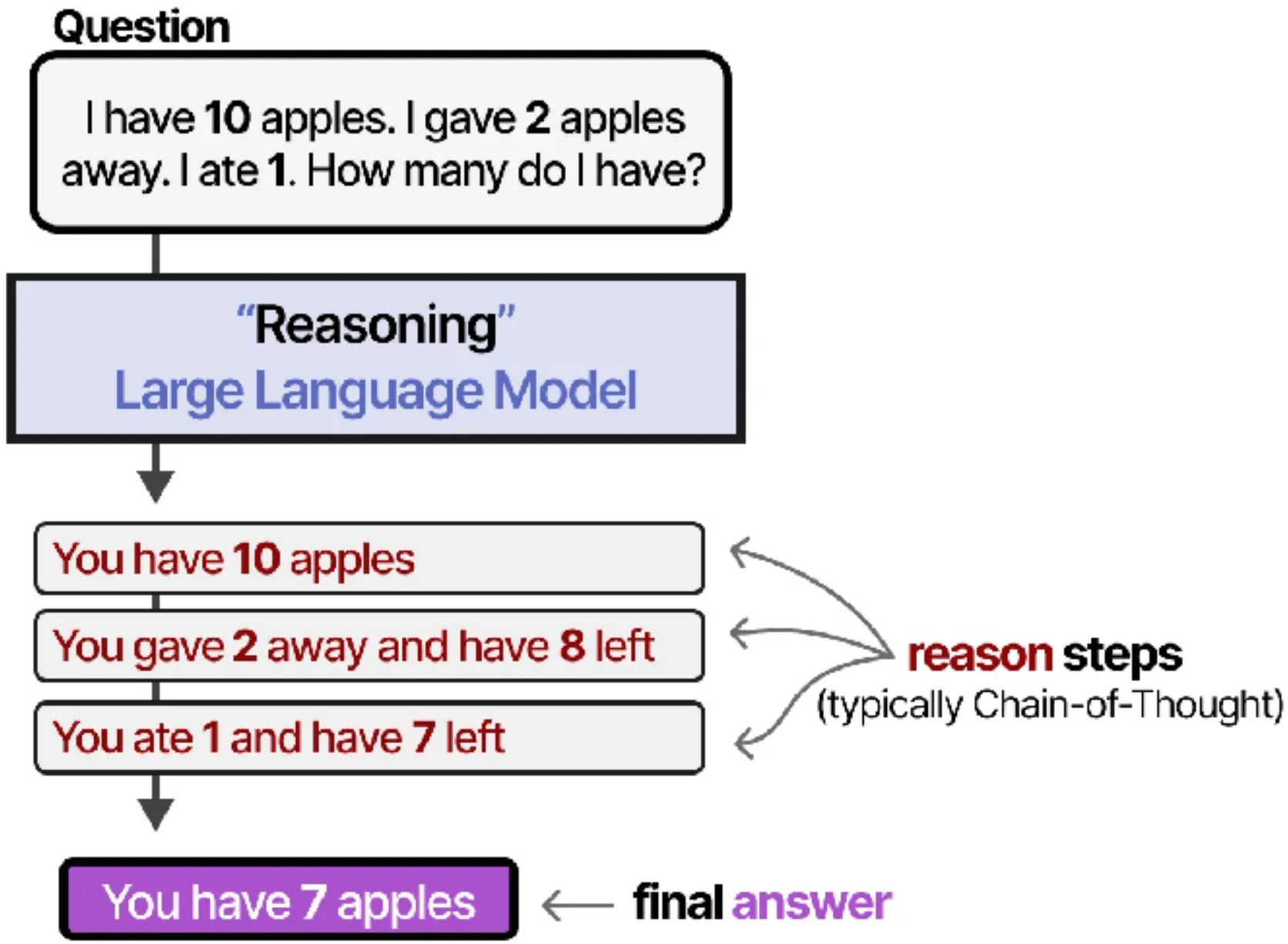
https://www.promptingguide.ai/research/llm-reasoning

LLM Reasoning



https://newsletter.maartengrootendorst.com/p/a-visual-guide-to-reasoning-llms

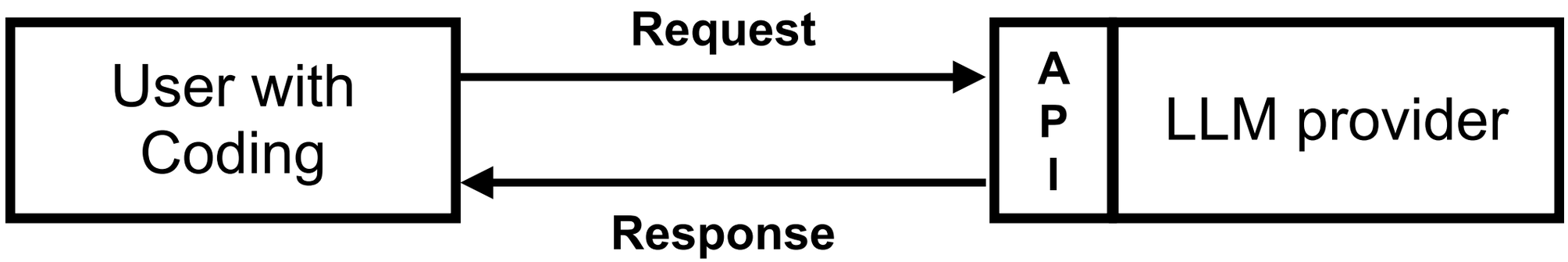
LLM Reasoning



https://newsletter.maartengrootendorst.com/p/a-visual-guide-to-reasoning-llms

Working with APIs

Working with APIs



https://platform.openai.com/docs/overview

Problems ?

Problems ?

Hallucinations
Limit of context window size
Lack of access to non-public data
Limit knowledge of test data of **models**

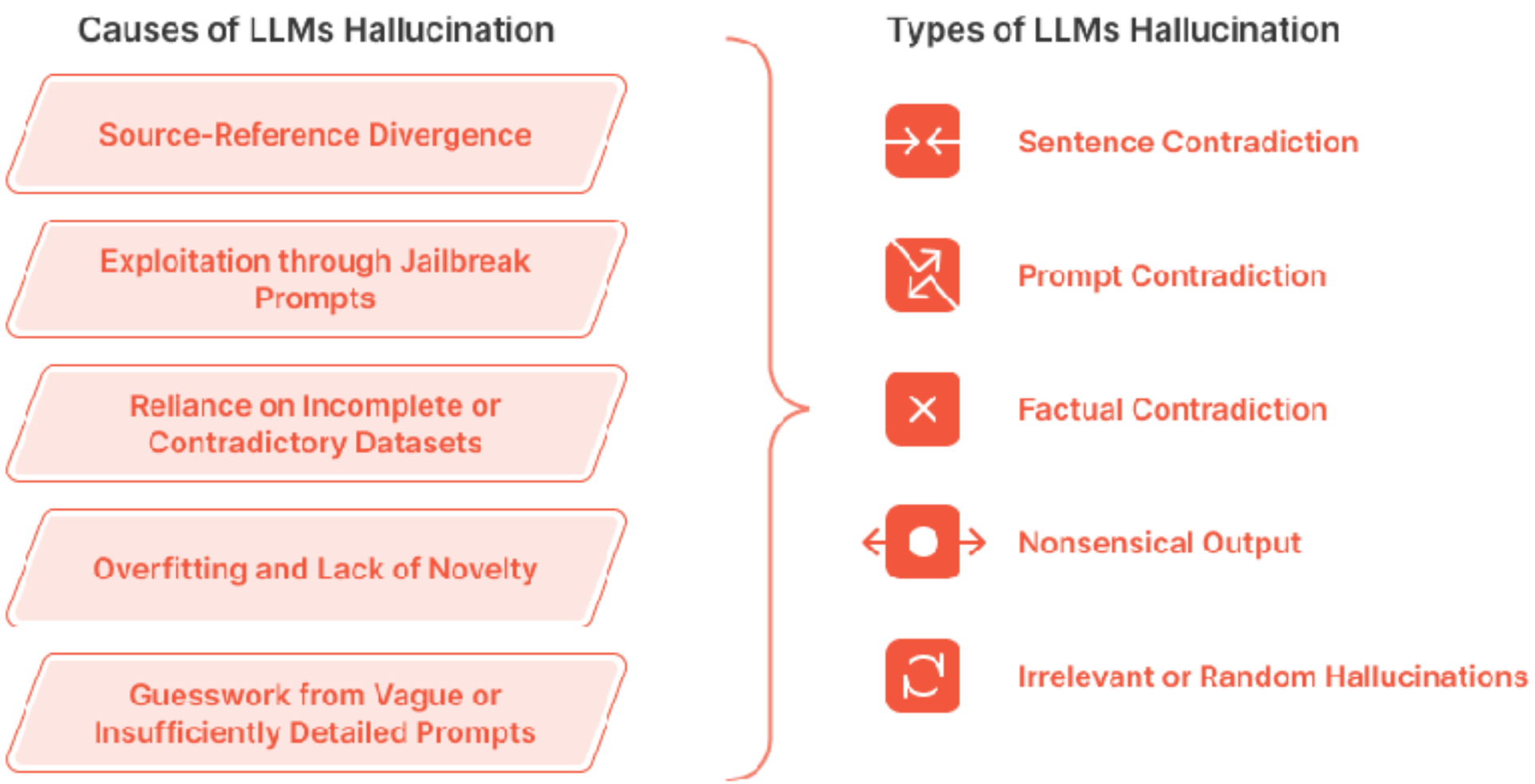
Hallucinations ?

Hallucinations in LLMs refer to the generation of content that is irrelevant, made-up, or inconsistent with the input data

Incorrect information

Lower trust in model

Causes and Types of LLMs Hallucination

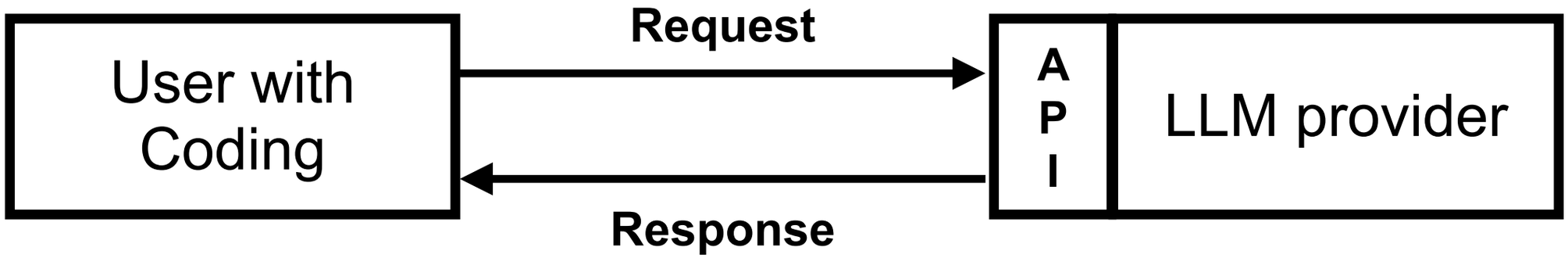


https://masterofcode.com/blog/hallucinations-in-llms-what-you-need-to-know-before-integration

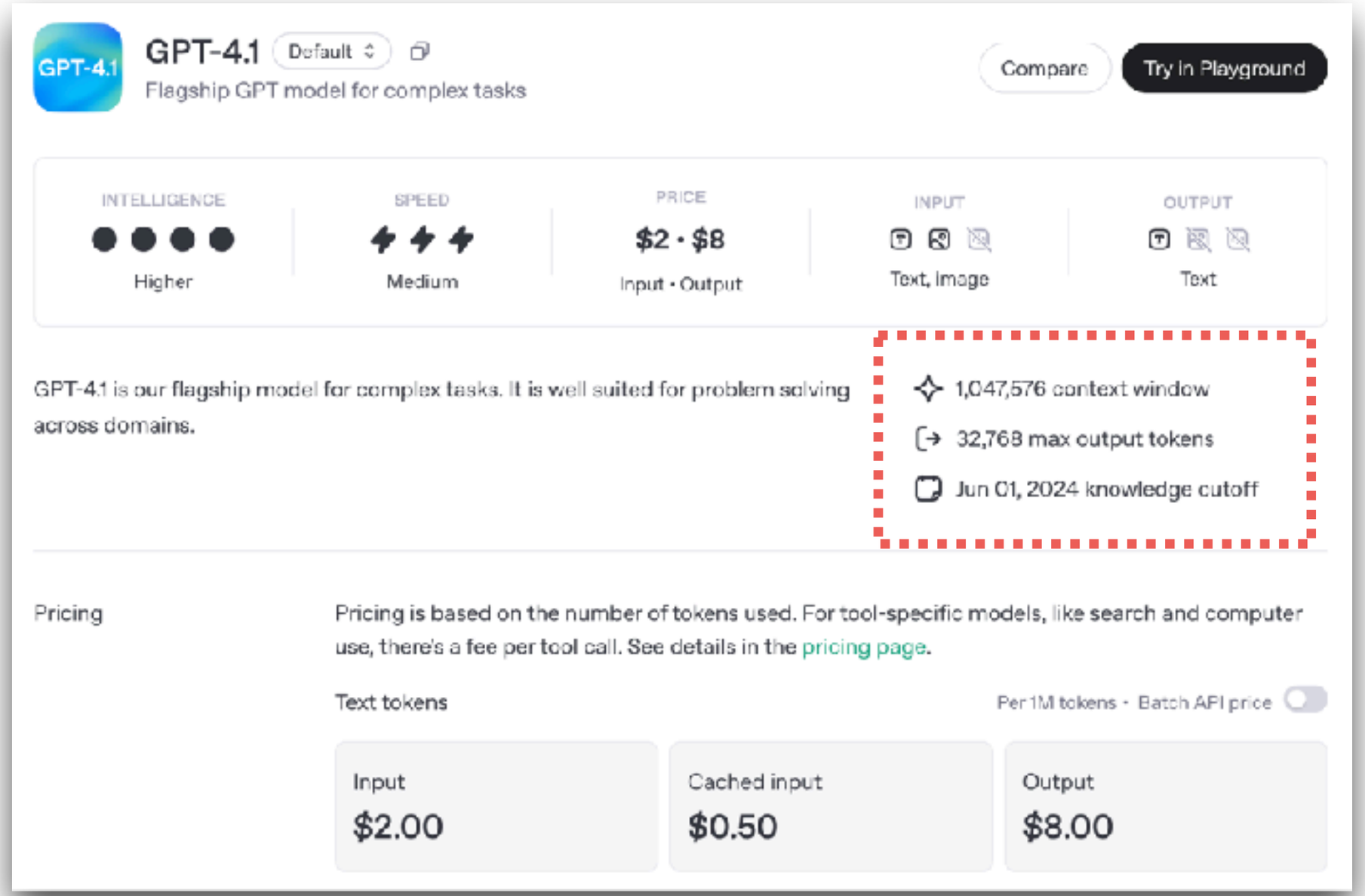
Context window size ?

Amount of text a model can process and remember at once time

Measure with **token**

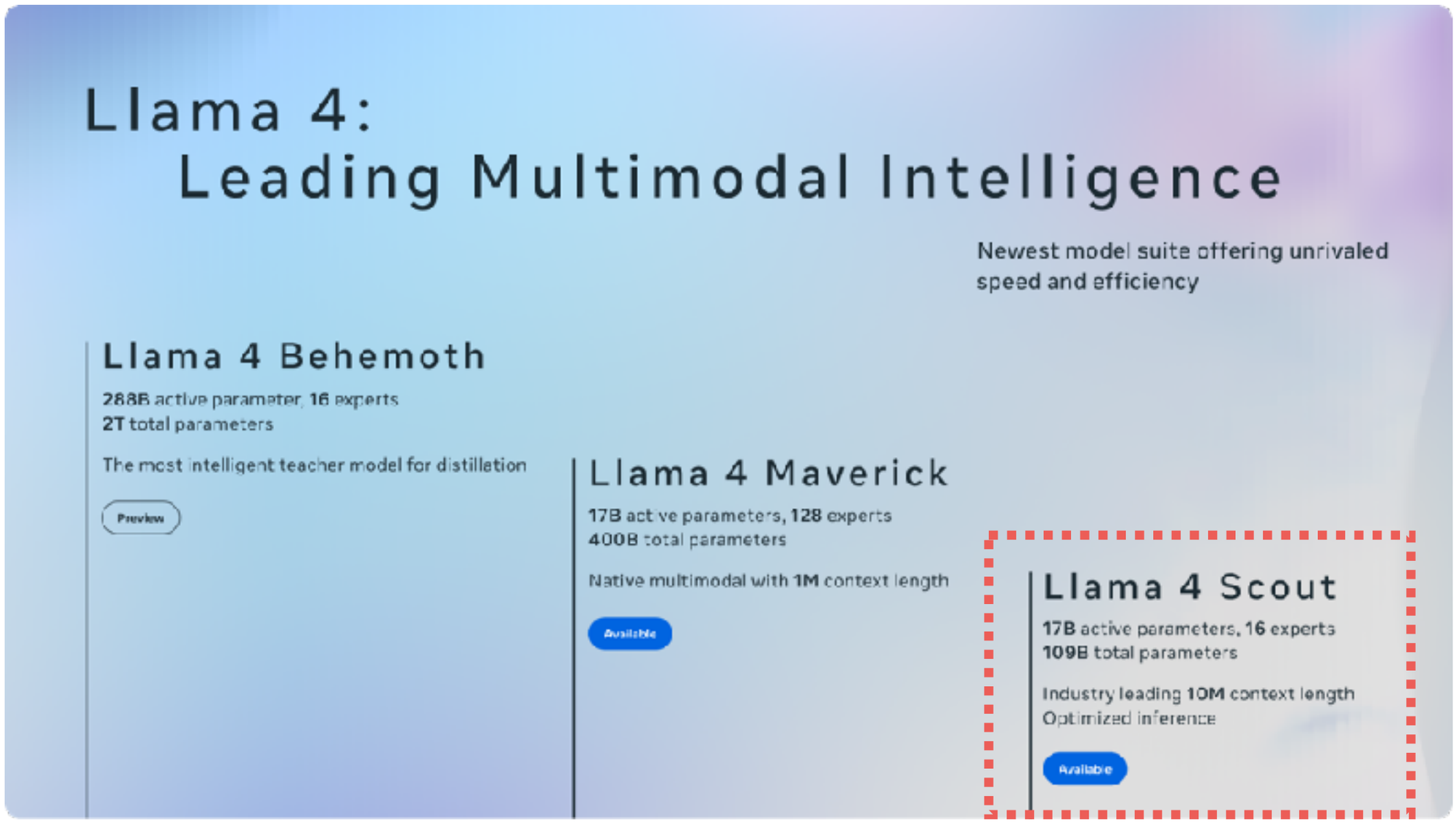


Example of GPT 4.1



https://platform.openai.com/docs/models/gpt-4.1

Example of Llama 4



https://ai.meta.com/blog/llama-4-multimodal-intelligence/

Large context window size is new trend !!

Context window size of models

Different models may have different window size

Model name	Context window size
GPT 4.1	1M
Gemini 1.5, 2.5	1M
Llama 4	1M
Claude Sonnet 3.7	200,000
o4	200,000

Large context window size is new trend

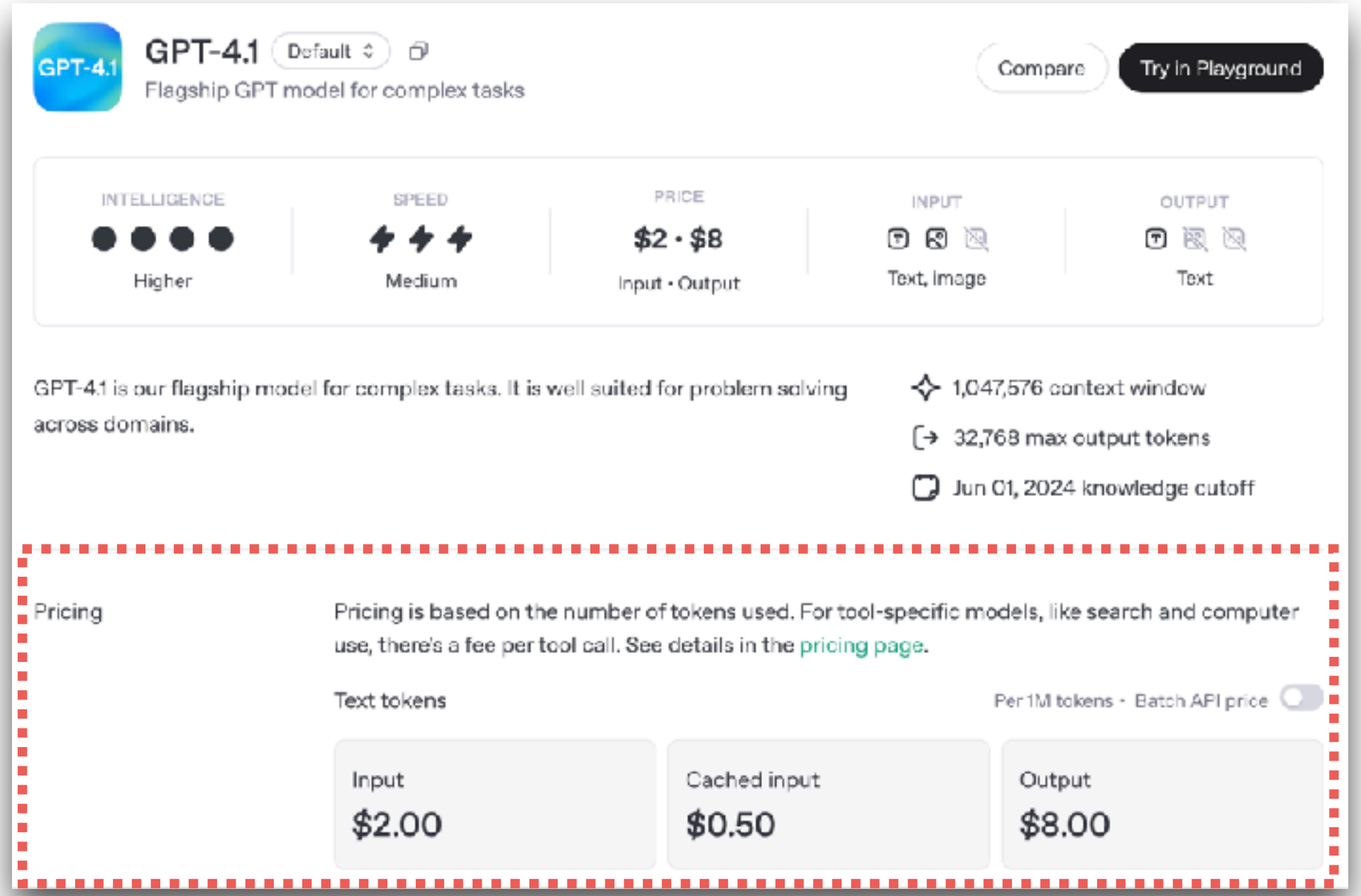
But come with Cost !!

Money

Resources

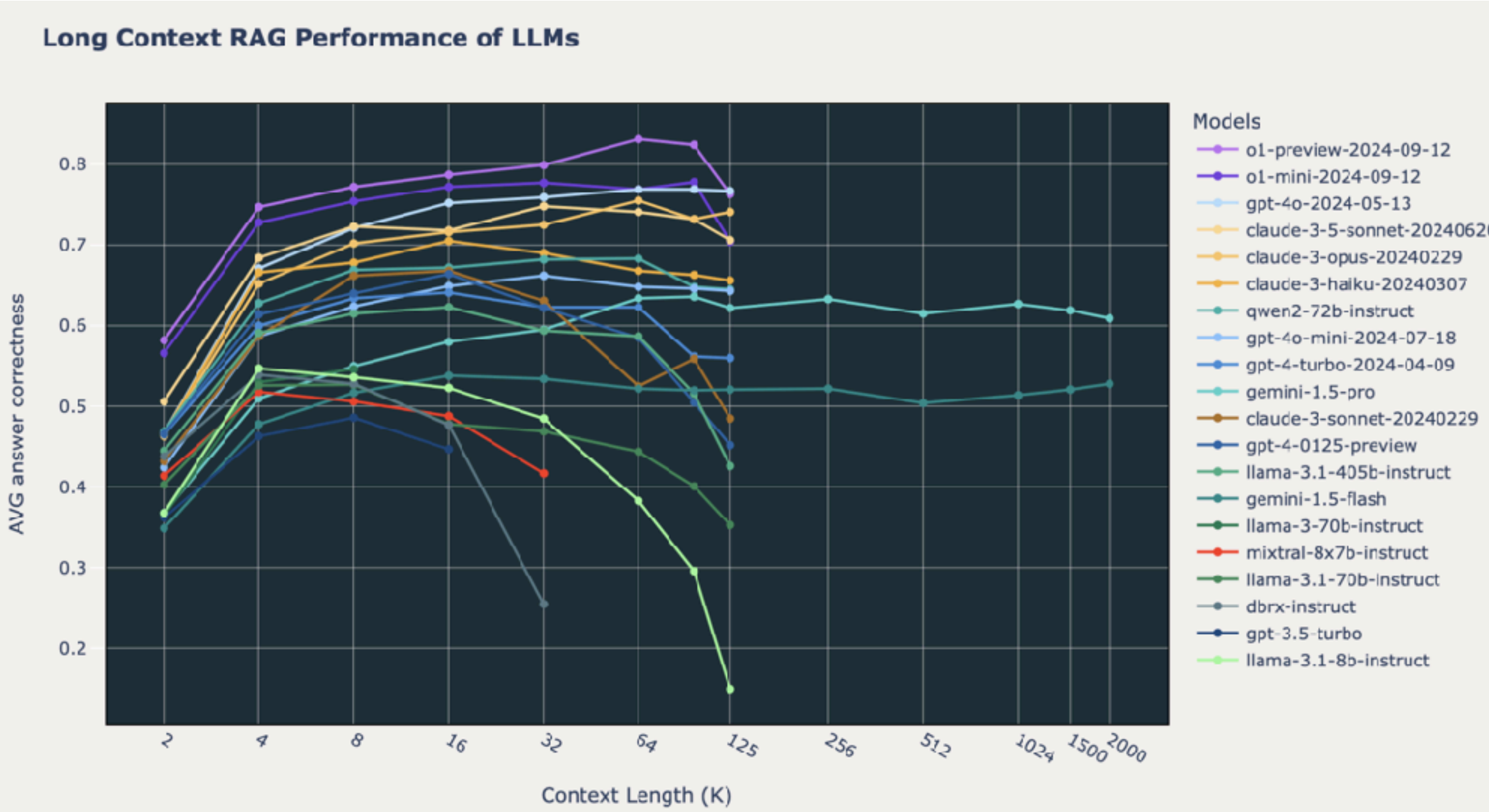
Response time

Example of GPT 4.1



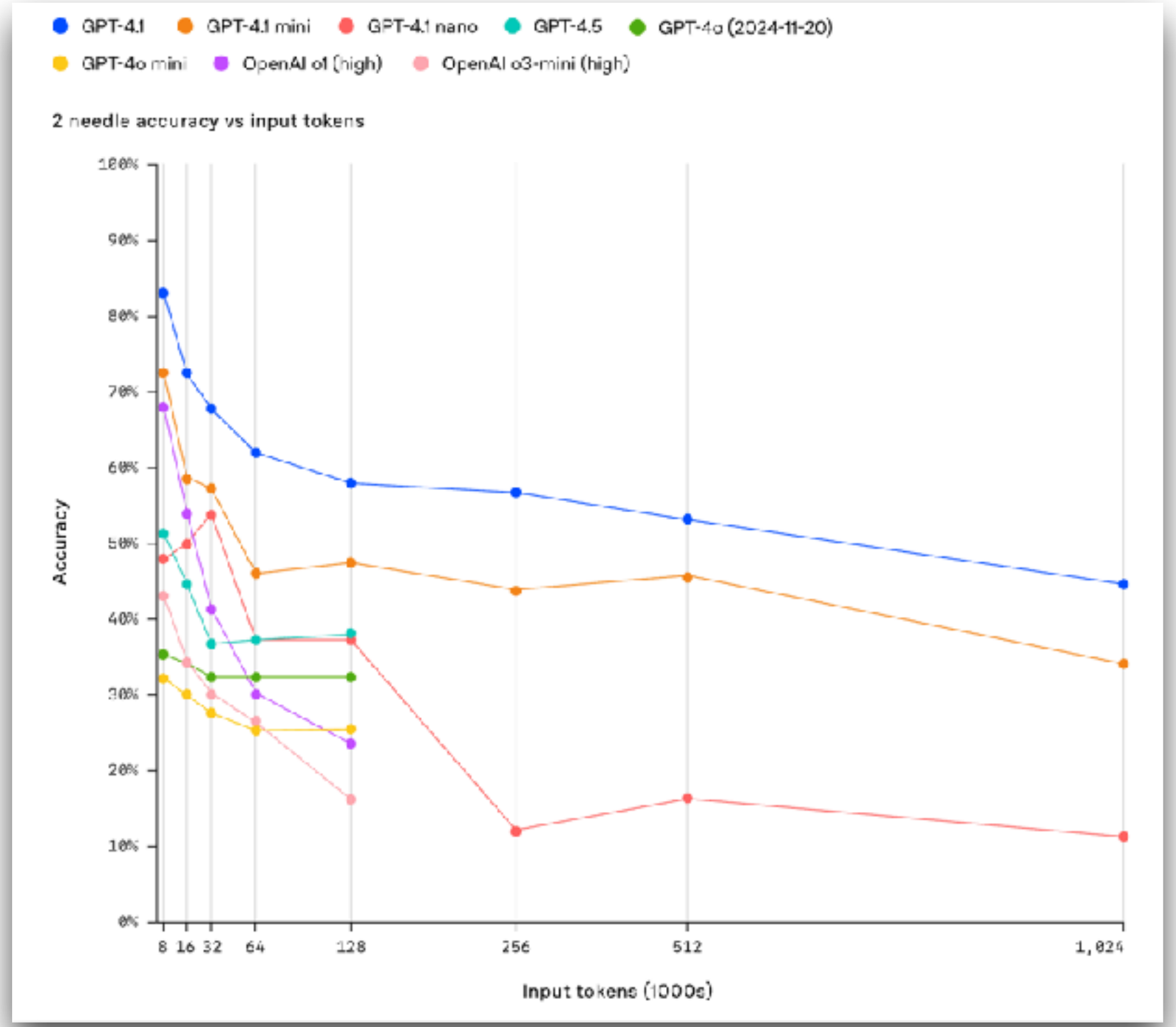
https://platform.openai.com/docs/models/gpt-4.1

Long context LLM is better !!



https://arxiv.org/abs/2411.03538

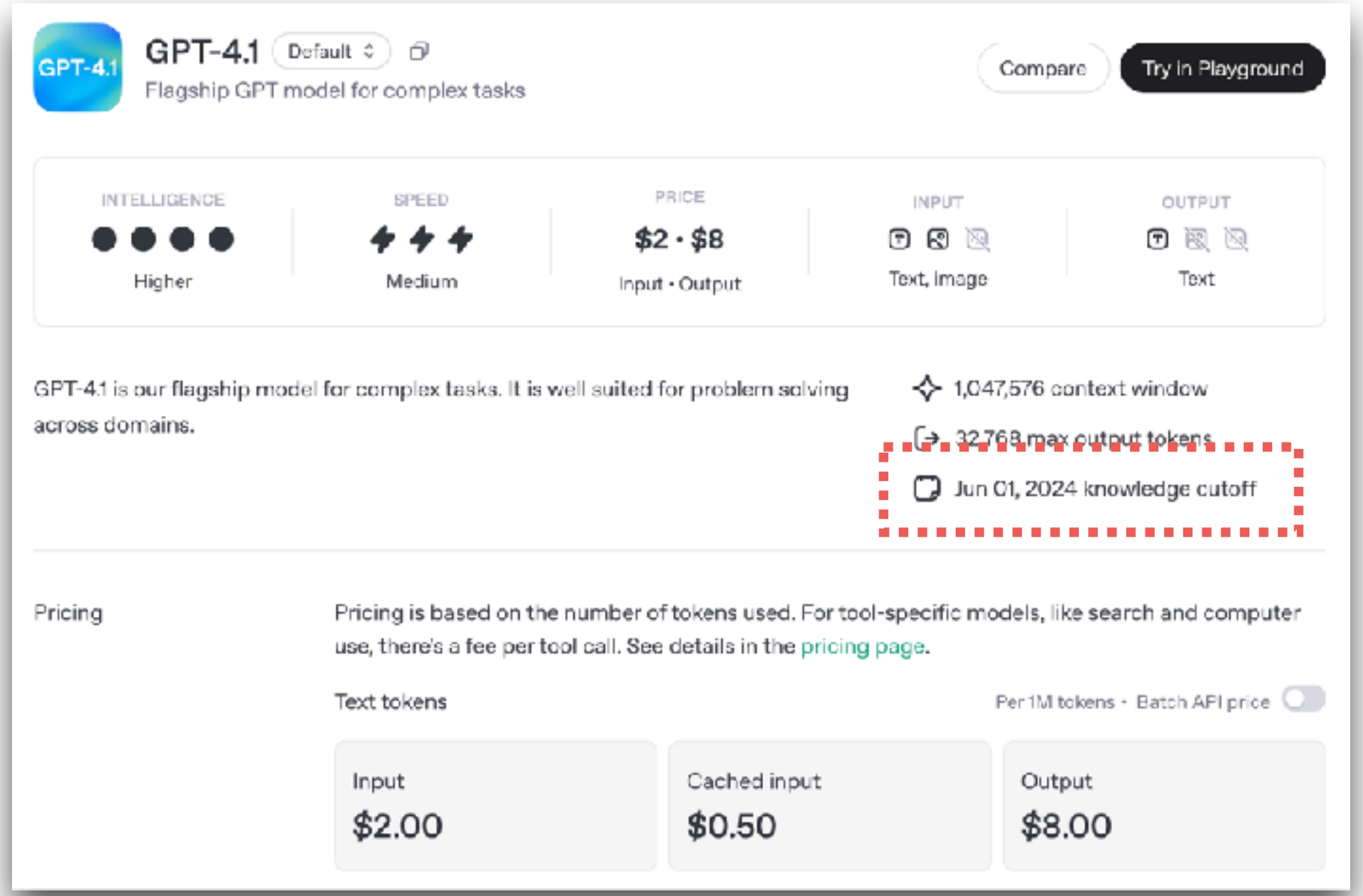
Long context LLM is better !!



https://openai.com/index/gpt-4-1/

Outdate knowledge of models

Outdate knowledge of models



https://platform.openai.com/docs/models/gpt-4.1

Knowledge cut-off date

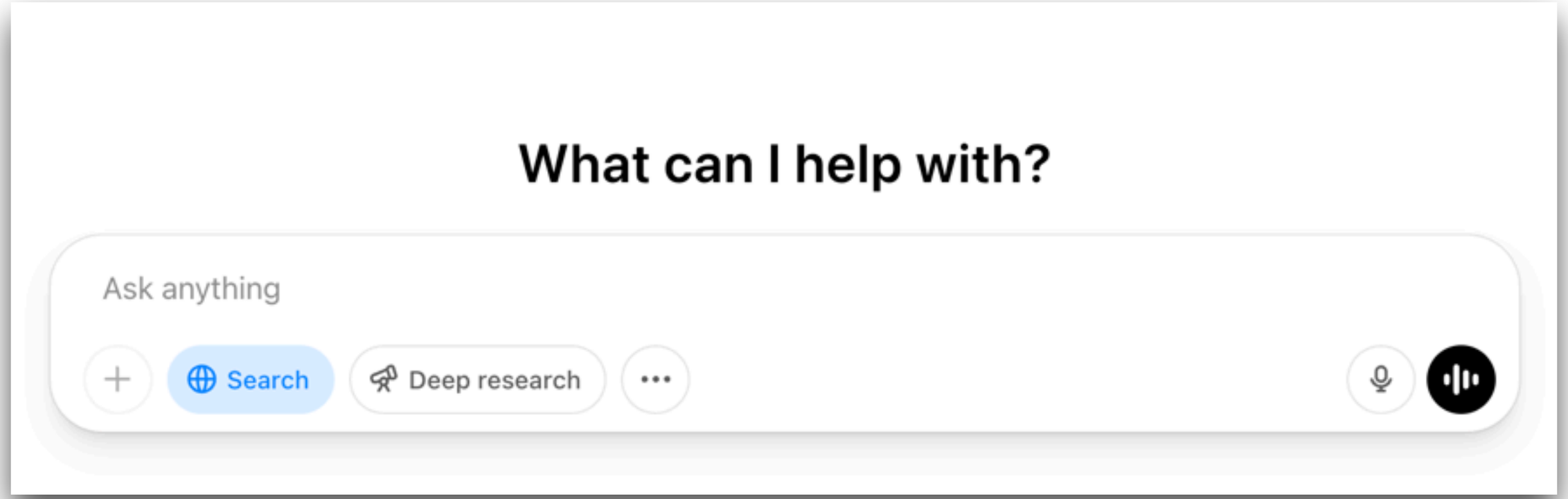
Model name	Cut-off date
GPT 4.1, o4-mini	2024/06
Gemini 2.5	2025/01
Llama 4	2024/08
Claude Sonnet 3.7	2024/10

Solutions ?

Solution ?

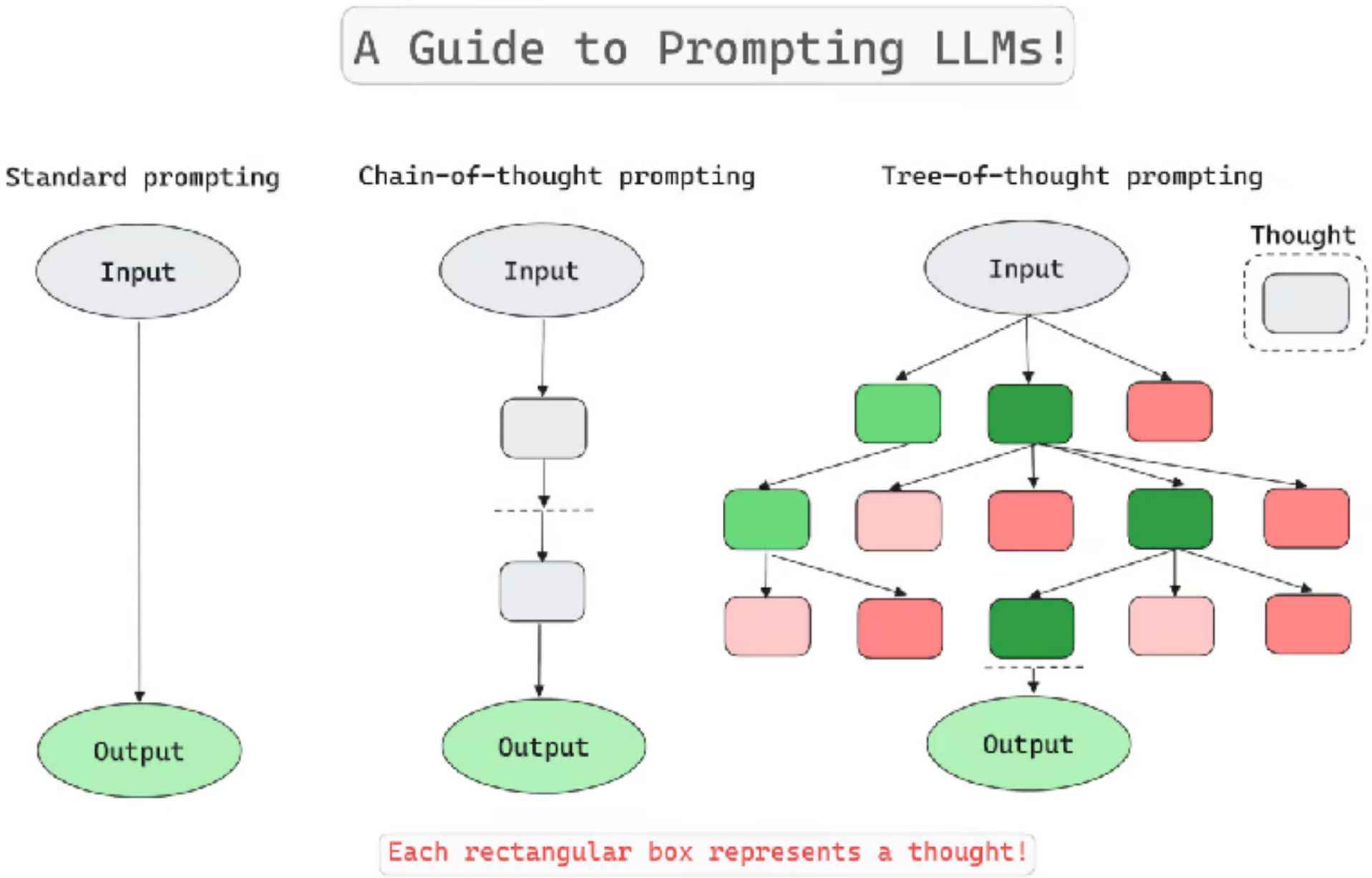
Prompt engineering
Increase context window size
Context caching or prompt caching
Add search features
Fine-tuning with high-quality domain dataset
RAG (Retrieval-Augmented Generation)

Search feature ?



https://chatgpt.com/

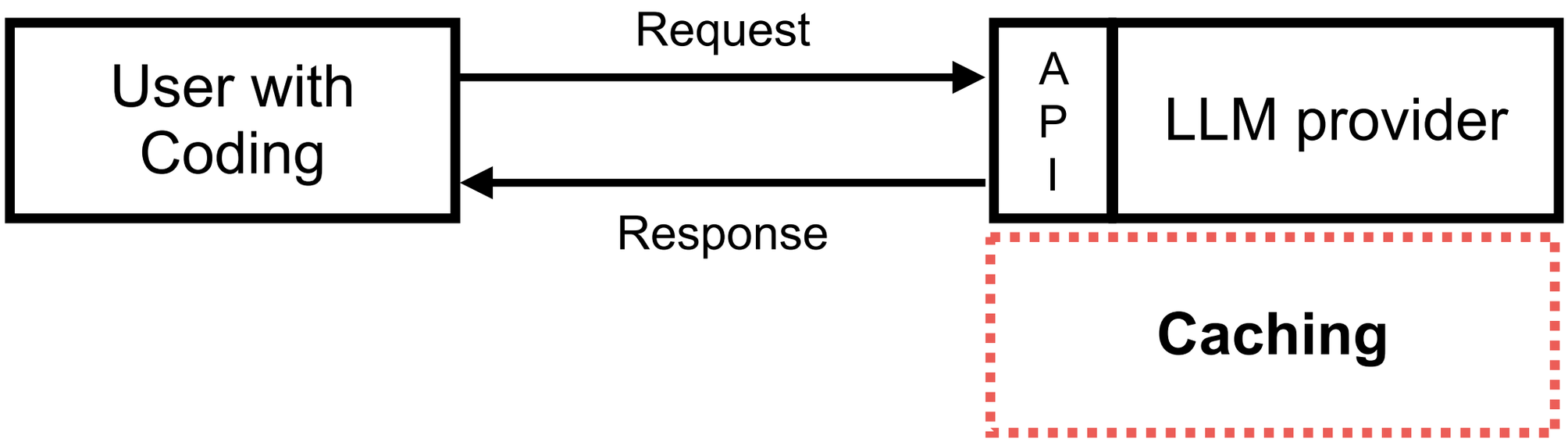
Prompt Engineering



https://www.promptingguide.ai/

Context or Prompt Caching

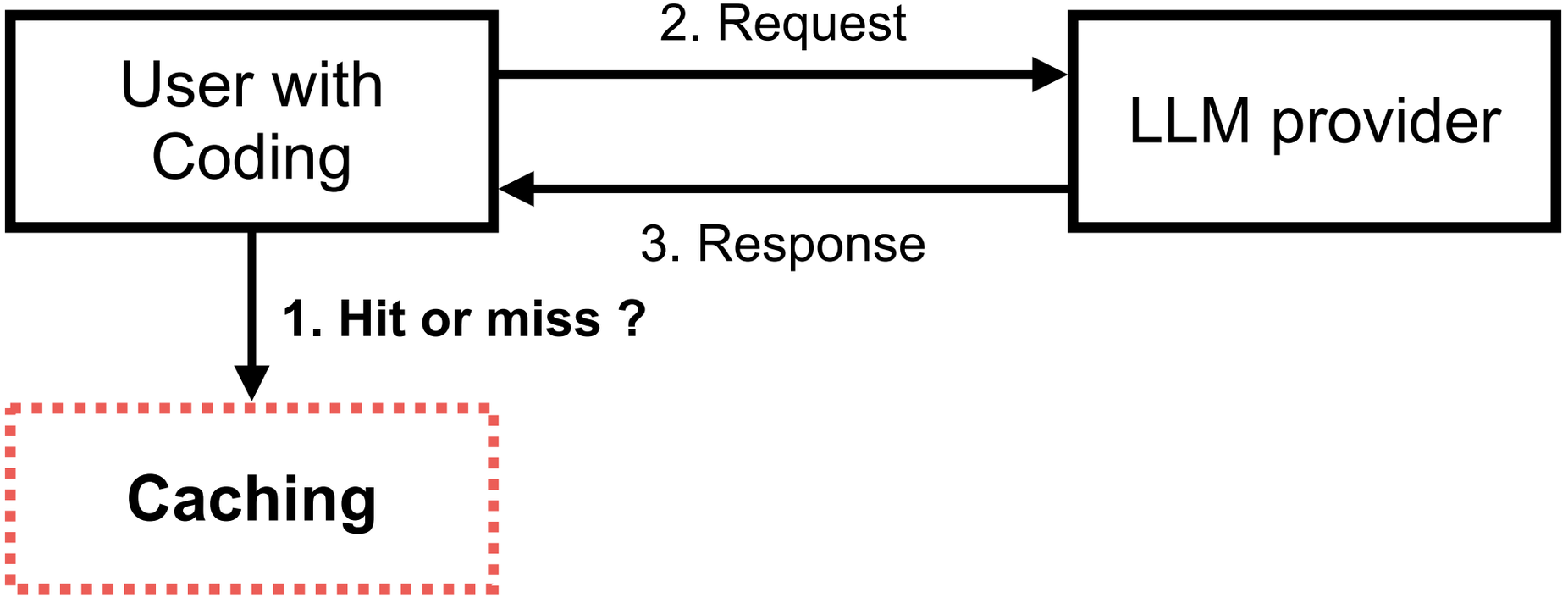
Optimize the processing of large context window
Reduce computation time and resources usages
Cost saving
Reuse previous context



Response caching ?
semantic caching

Semantic Caching

Caching response from LLM
Reduce no. of query to LLM provider
Reduce cost
Improve scalability of system

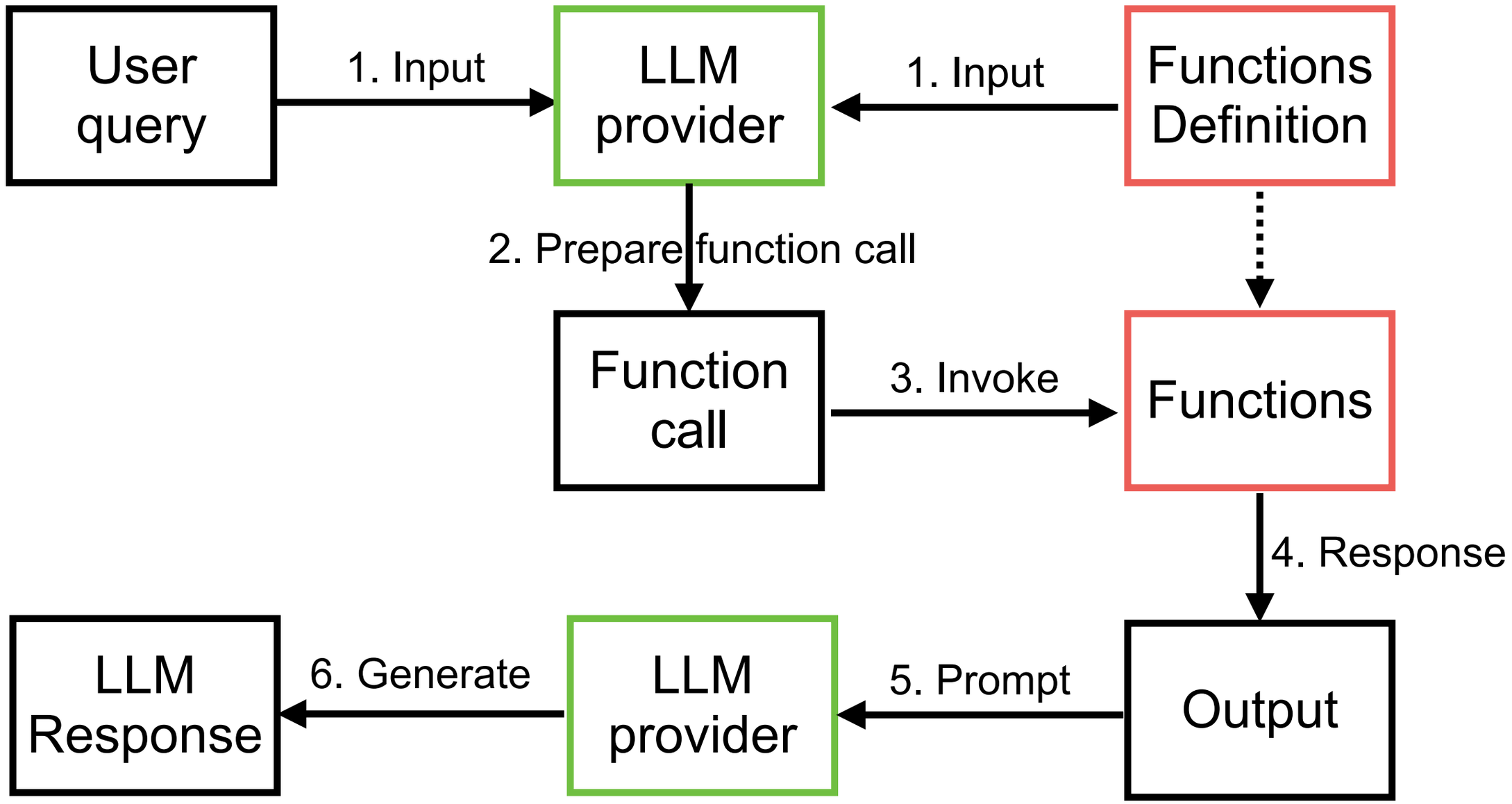


Function Calling ?

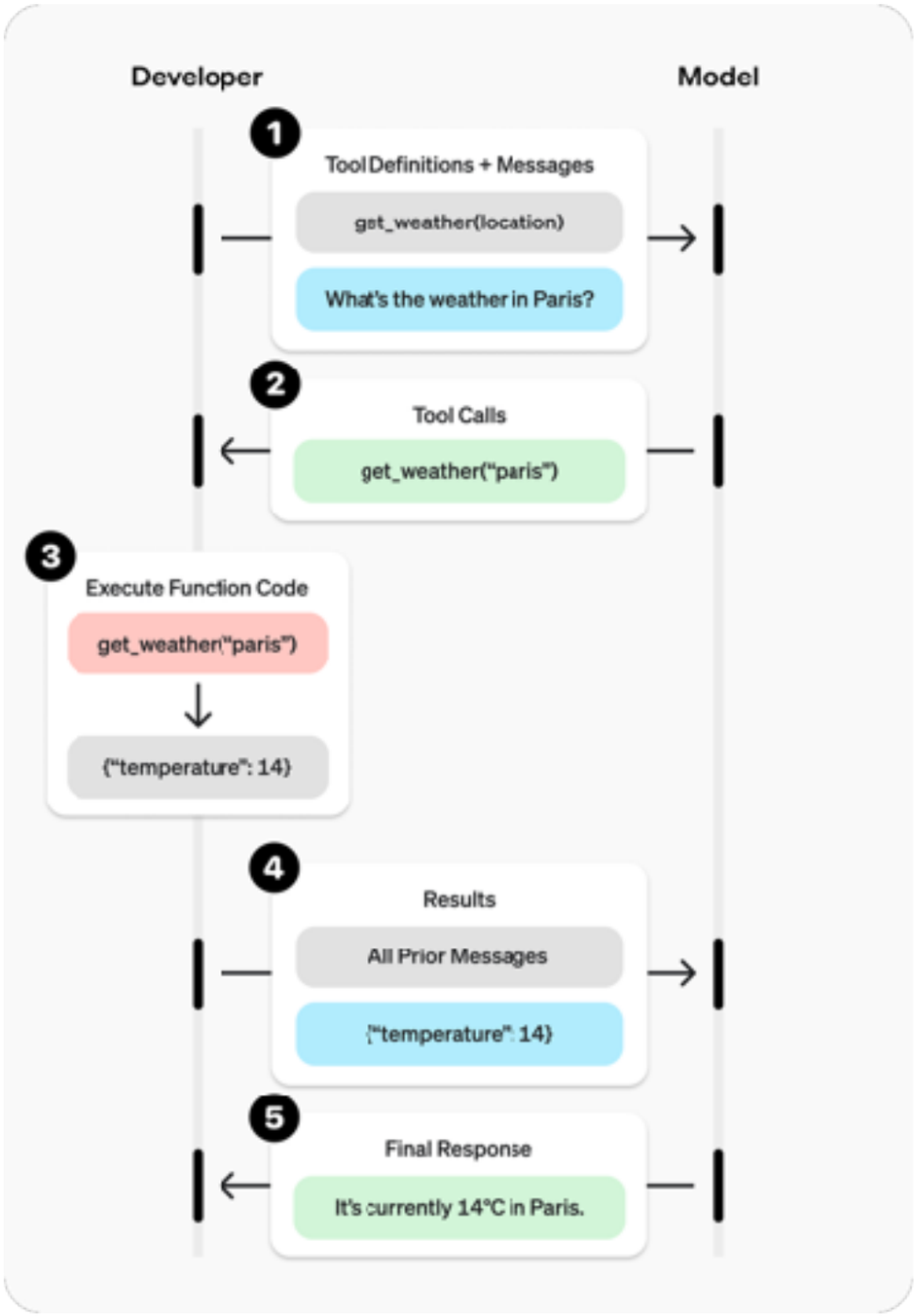
Function Calling ?

Allow LLM to recognize what tool it need based on user’s input and when to invoke it.

Function Calling



Function calling ?

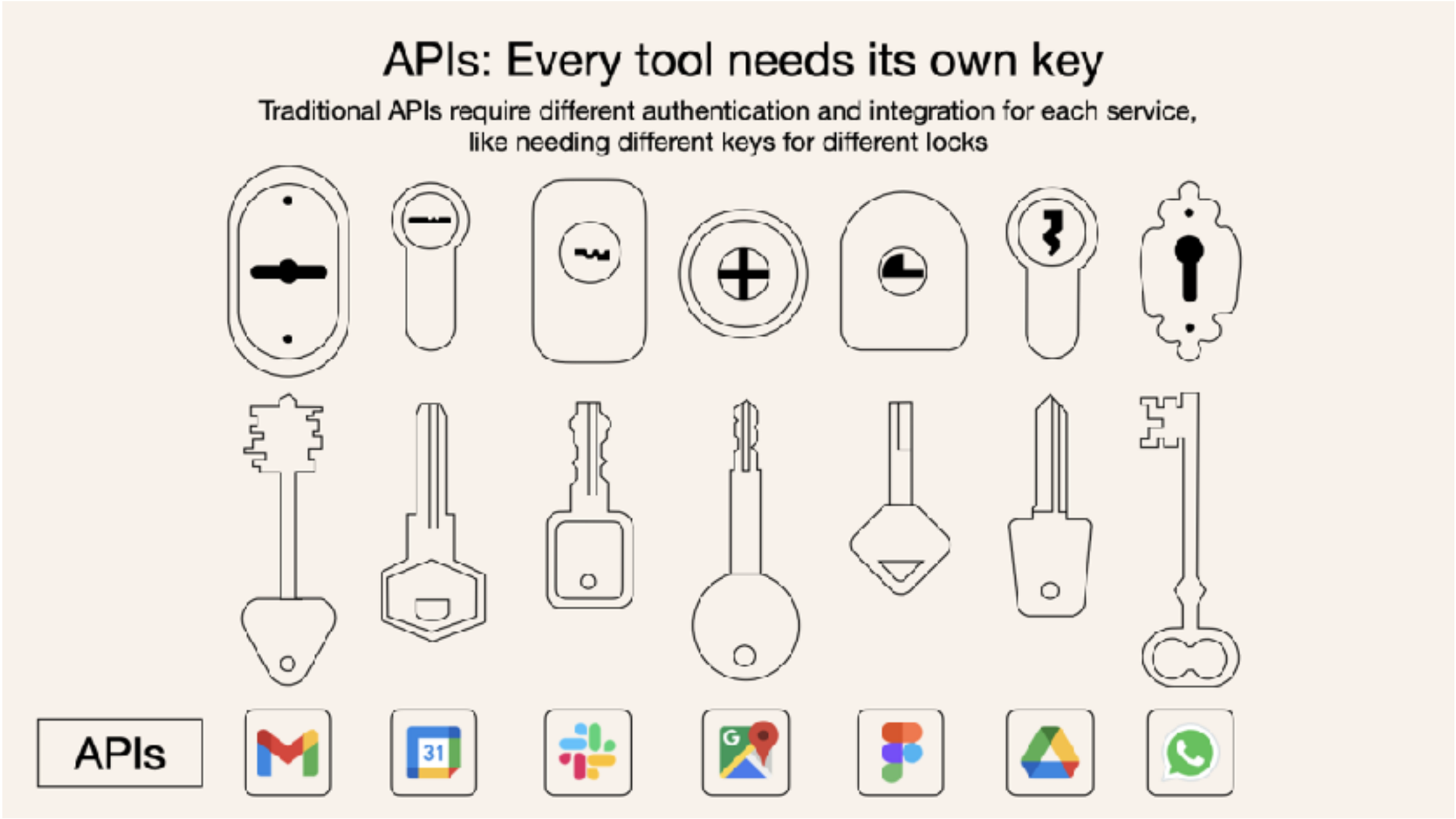


https://platform.openai.com/docs/guides/function-calling?api-mode=responses

Support function calling

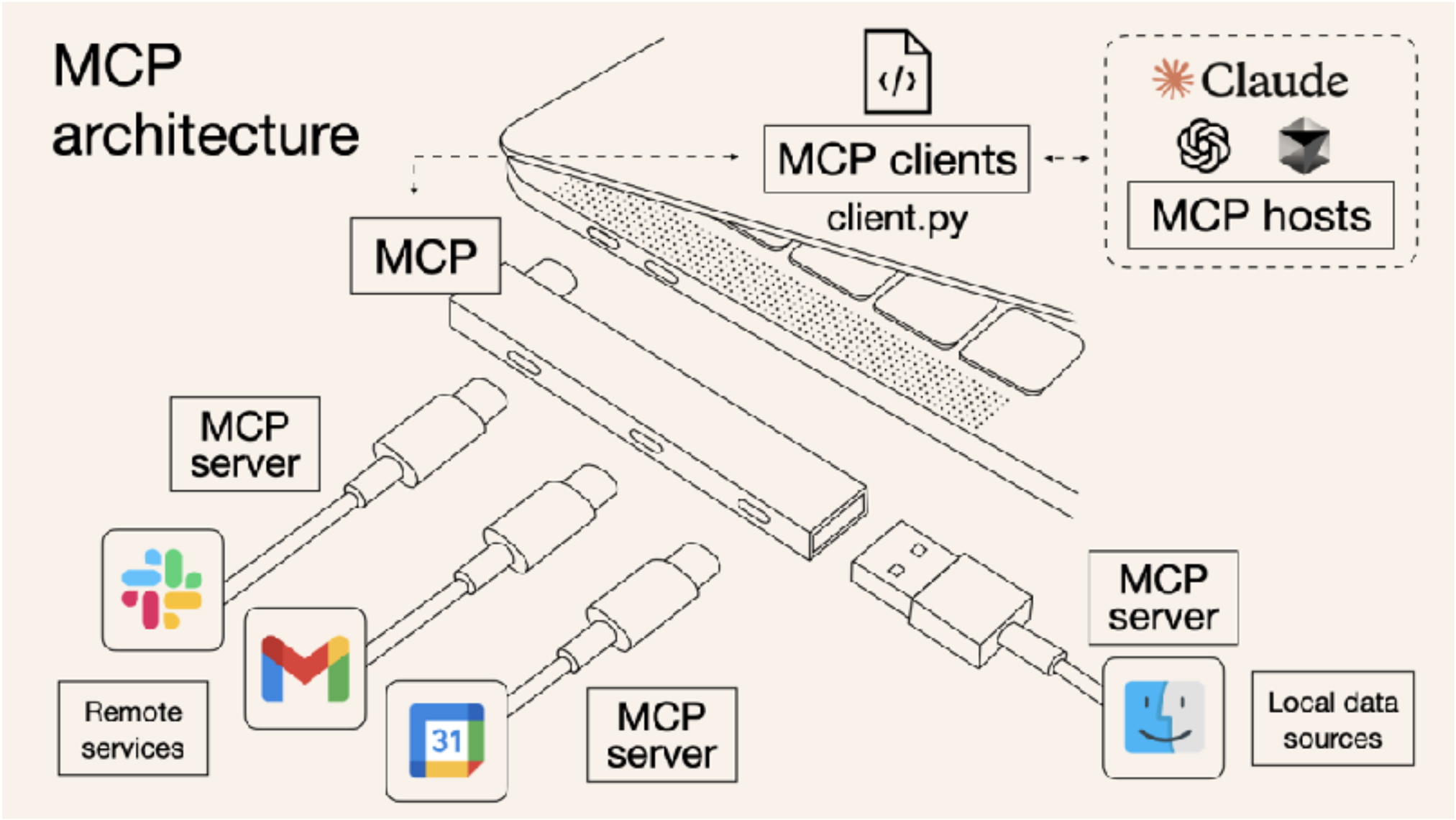
Provider name	Model name
OpenAI	GPT 4
Anthropic	Claude 3 (Sonnet, Haiku, Opus)
Google	Gemini

Function calling !!



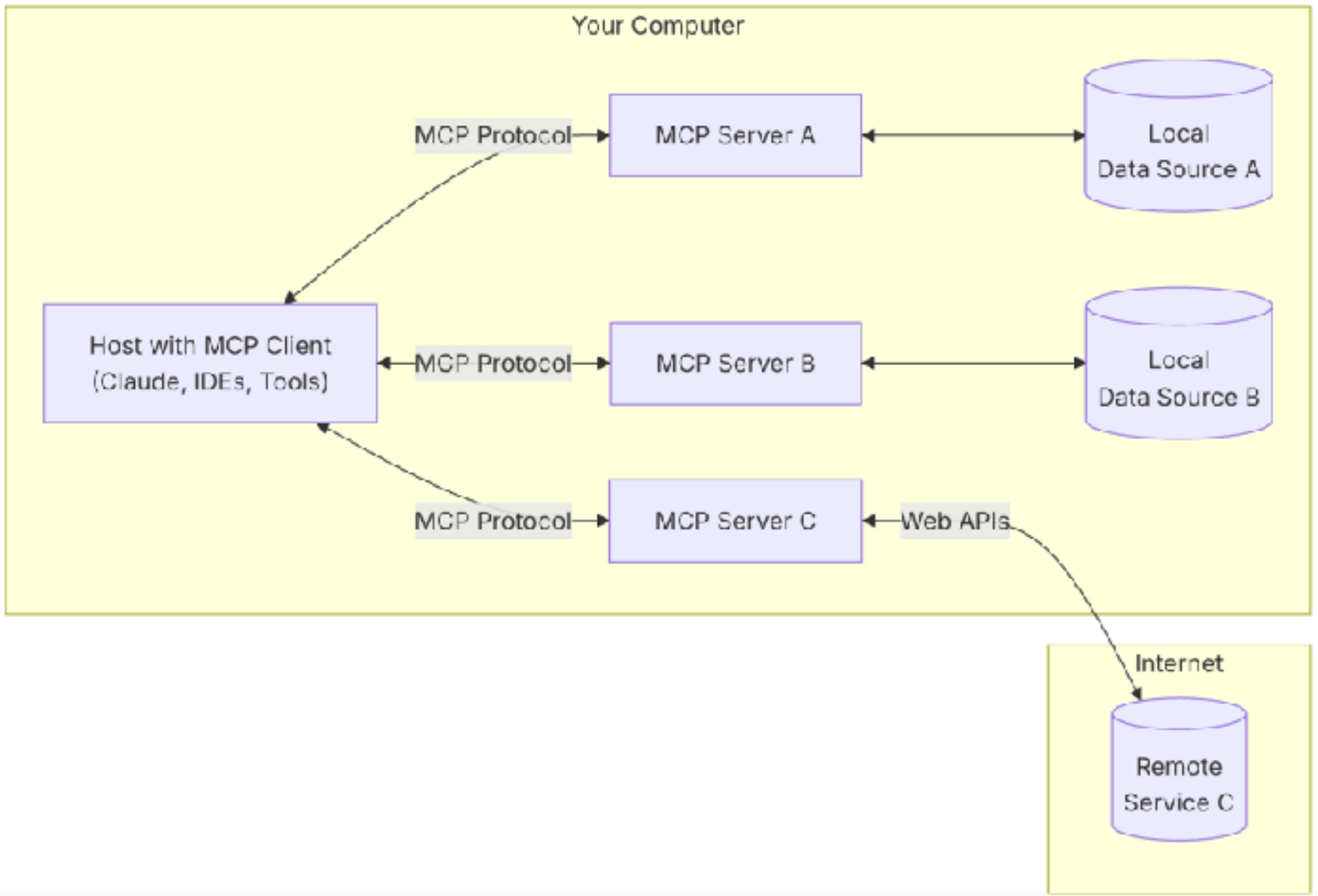
https://norahsakal.com/blog/mcp-vs-api-model-context-protocol-explained/

Standardized function calling !!



https://norahsakal.com/blog/mcp-vs-api-model-context-protocol-explained/

Model Context Protocol

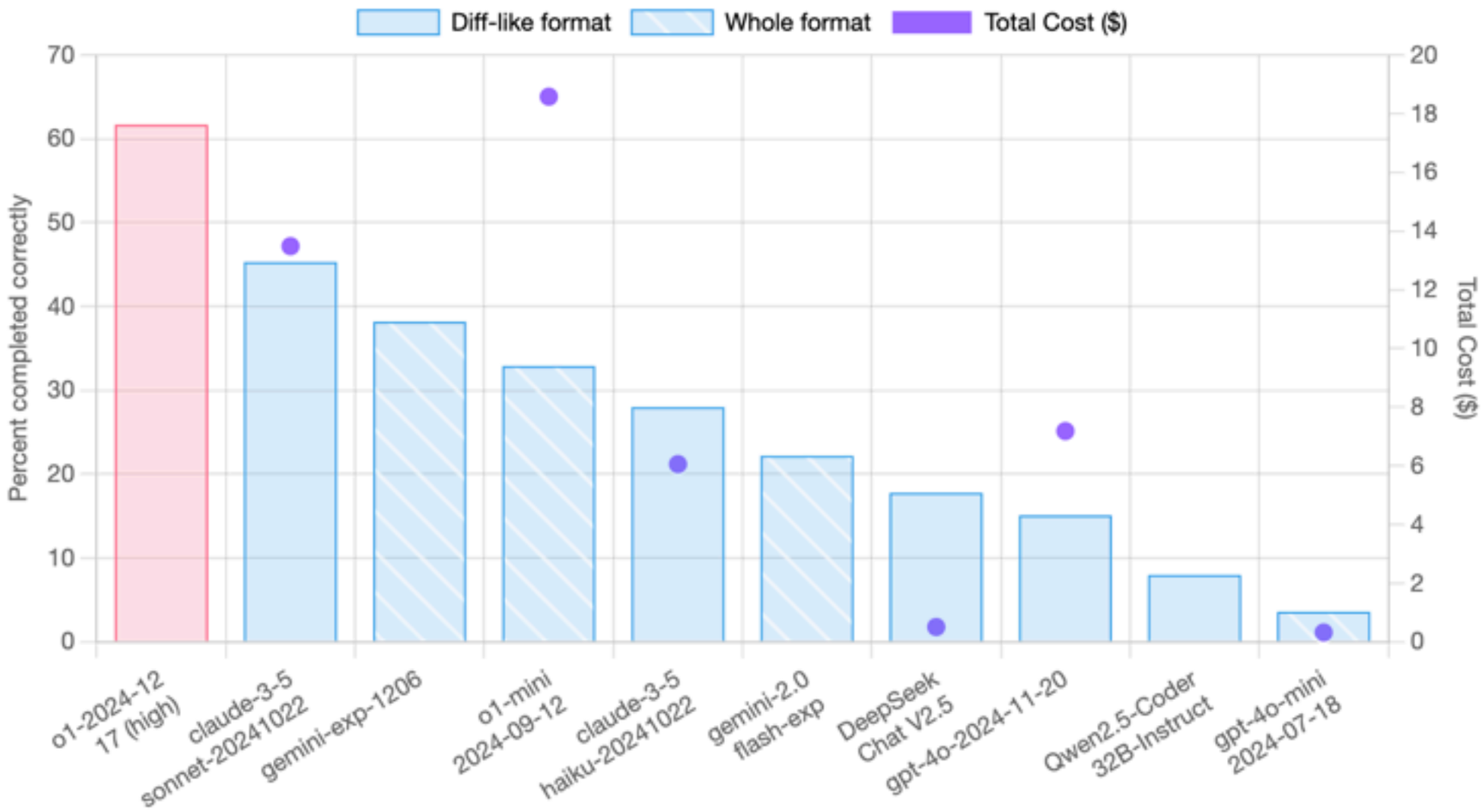


https://modelcontextprotocol.io/

Choosing the right AI model for your task

https://docs.github.com/en/copilot/using-github-copilot/ai-models/choosing-the-right-ai-model-for-your-task

Aider LLM Leaderboards



https://aider.chat/docs/leaderboards/

TRACKING AI

Monitoring Artificial Intelligence

By: Maxim Lott

Go to Political Compass | About | AI Model Info | See every AI answer | Searchable Database | Explore Tests

This site quizzes 20 Verbal & 6 Vision AIs every week | Last Updated: 06:03PM EDT on April 17, 2025

About Offline Test *About Mensa Norway*

IQ Test Results

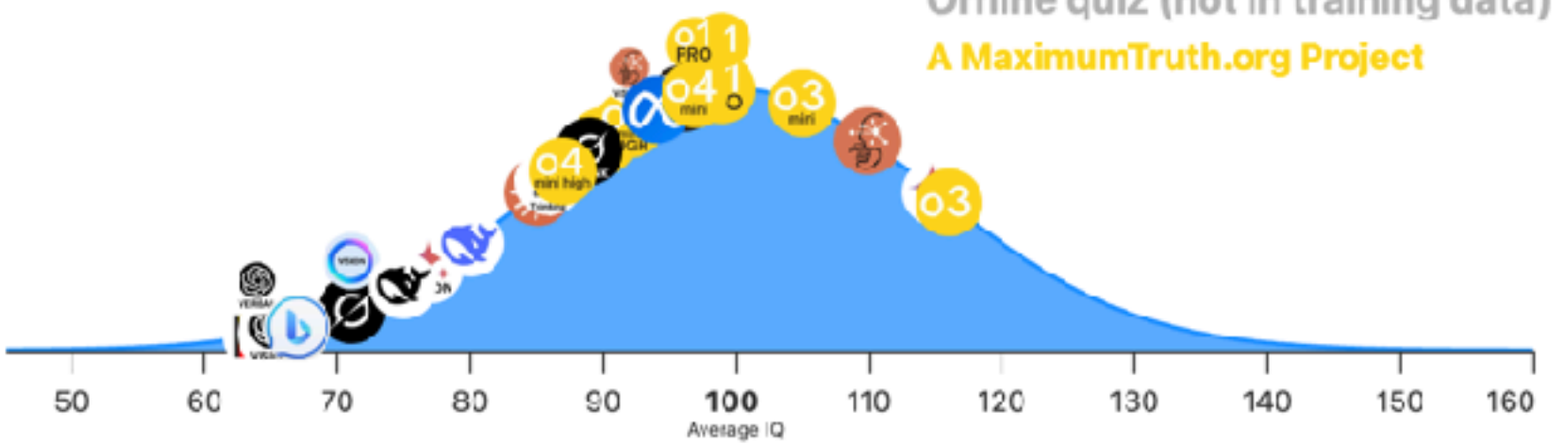
Score reflects average of last 7 tests given

Reset | Show Offline Test | Show Mensa Norway

TrackingAI.org

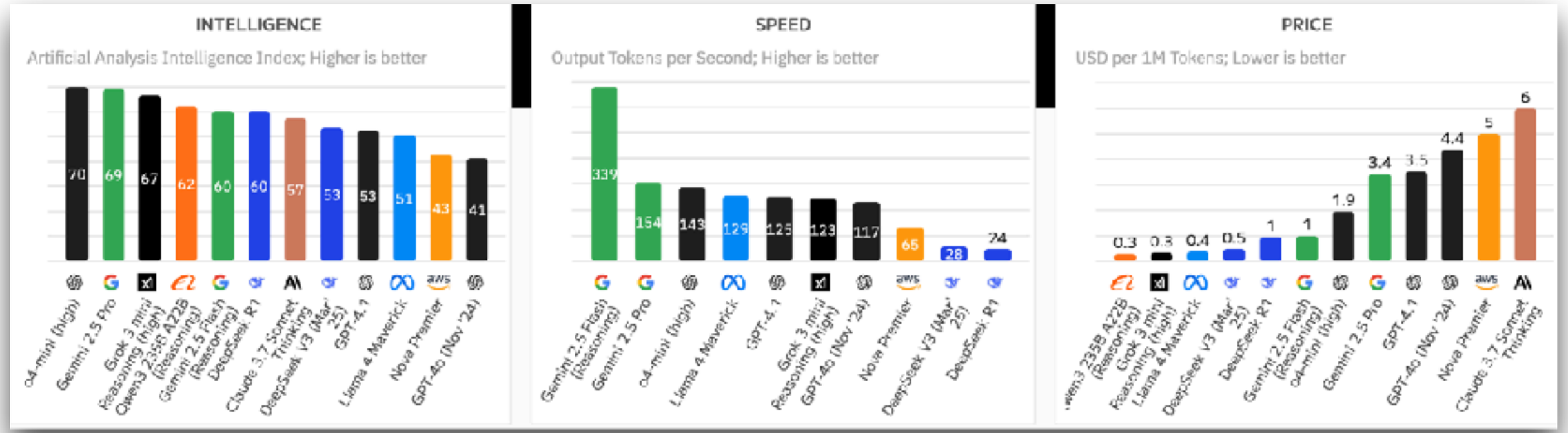
Offline quiz (not in training data)

A MaximumTruth.org Project



https://trackingai.org/

Artificial Analysis



https://artificialanalysis.ai/

RAG
(Retrieval Augmented Generation)

RAG

Enhances LLMs by retrieving external knowledge before generating response

Improve accuracy	Reduce hallucinations	Real-time knowledge updates

Core Components

Retriever

Fetch relevant documents from a knowledge base

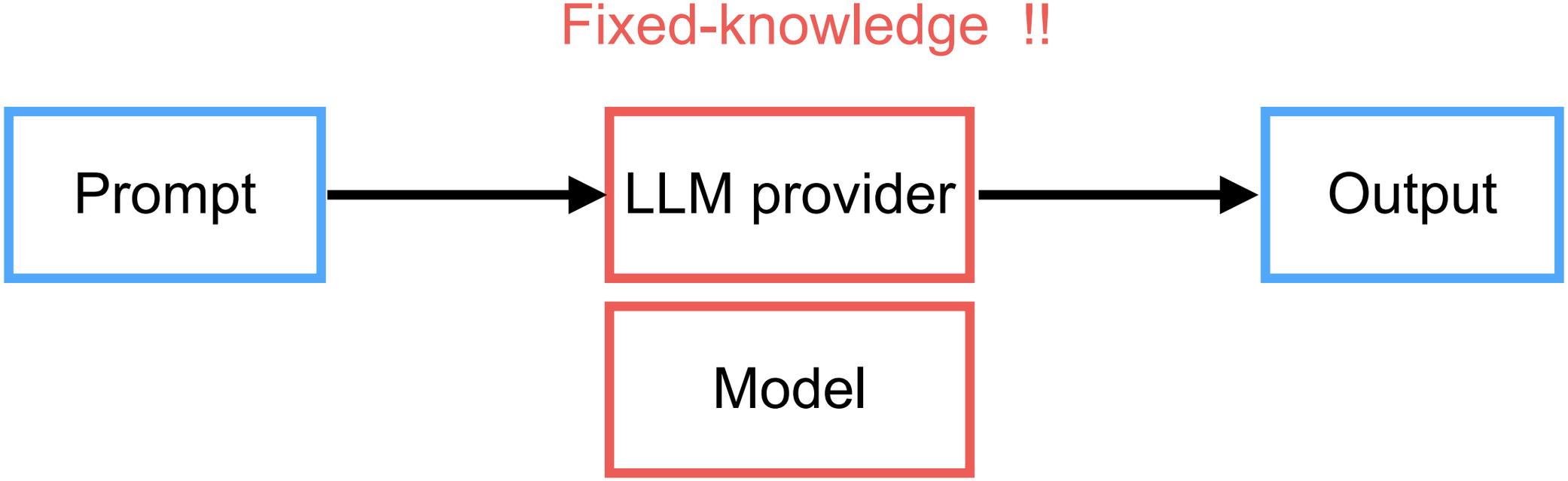
Generator

Uses the retrieved information to generate a response

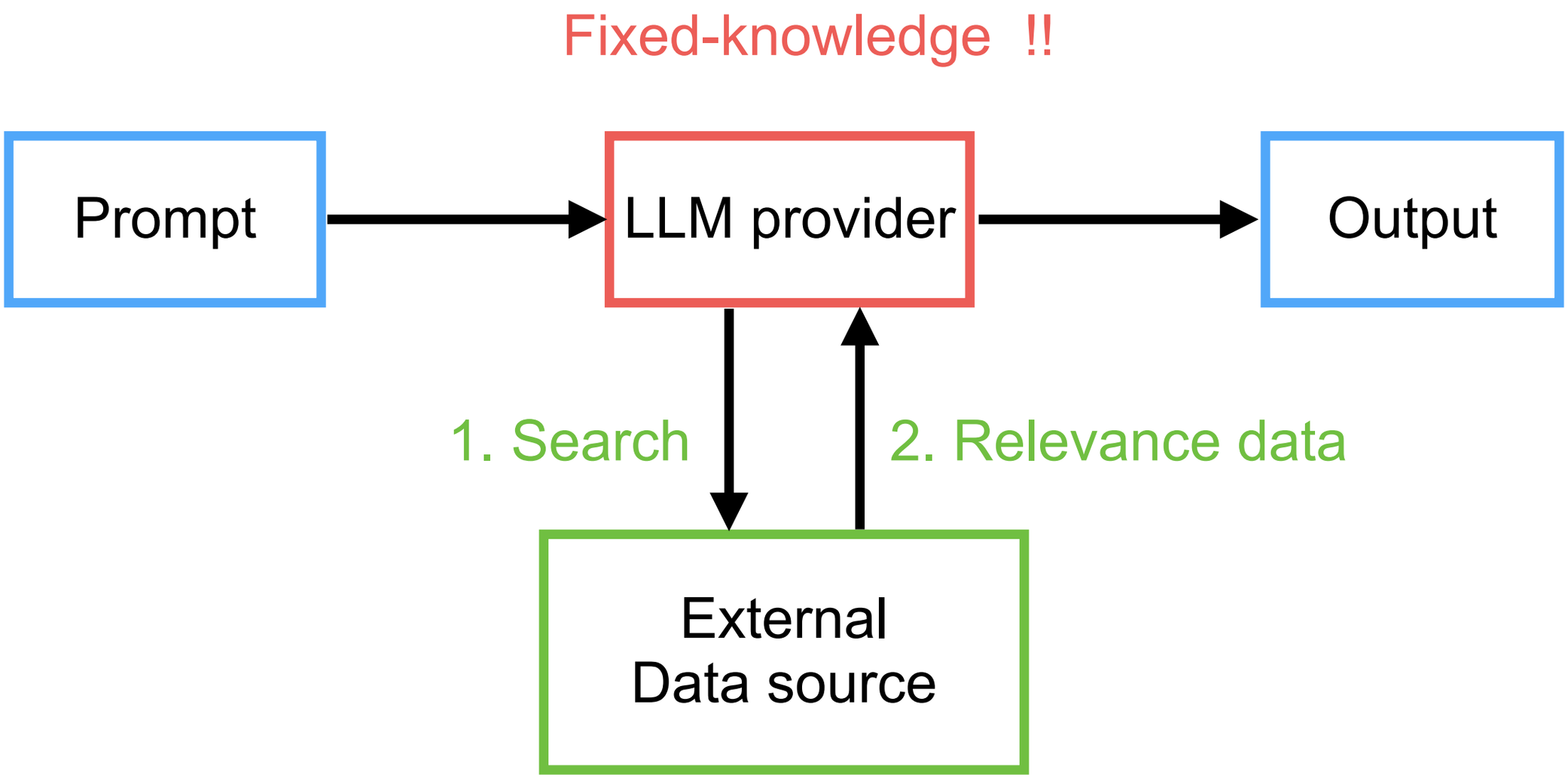
Enhancements

Different RAG architectures modify how retrieval and generation interact to improve performance

Limitation of LLM



RAG ?



How to search/retrieve data ?

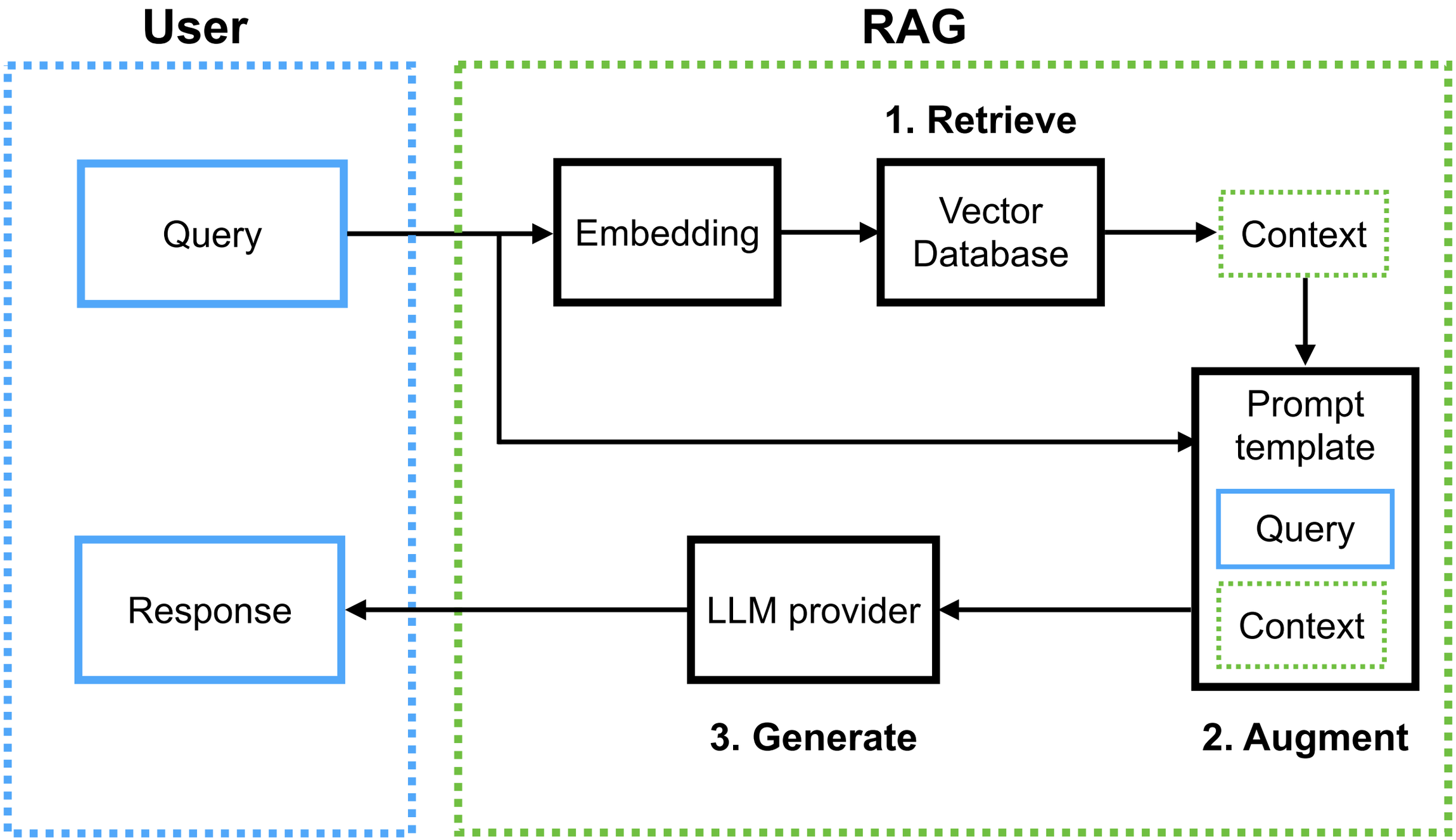
Data source

Data preparation

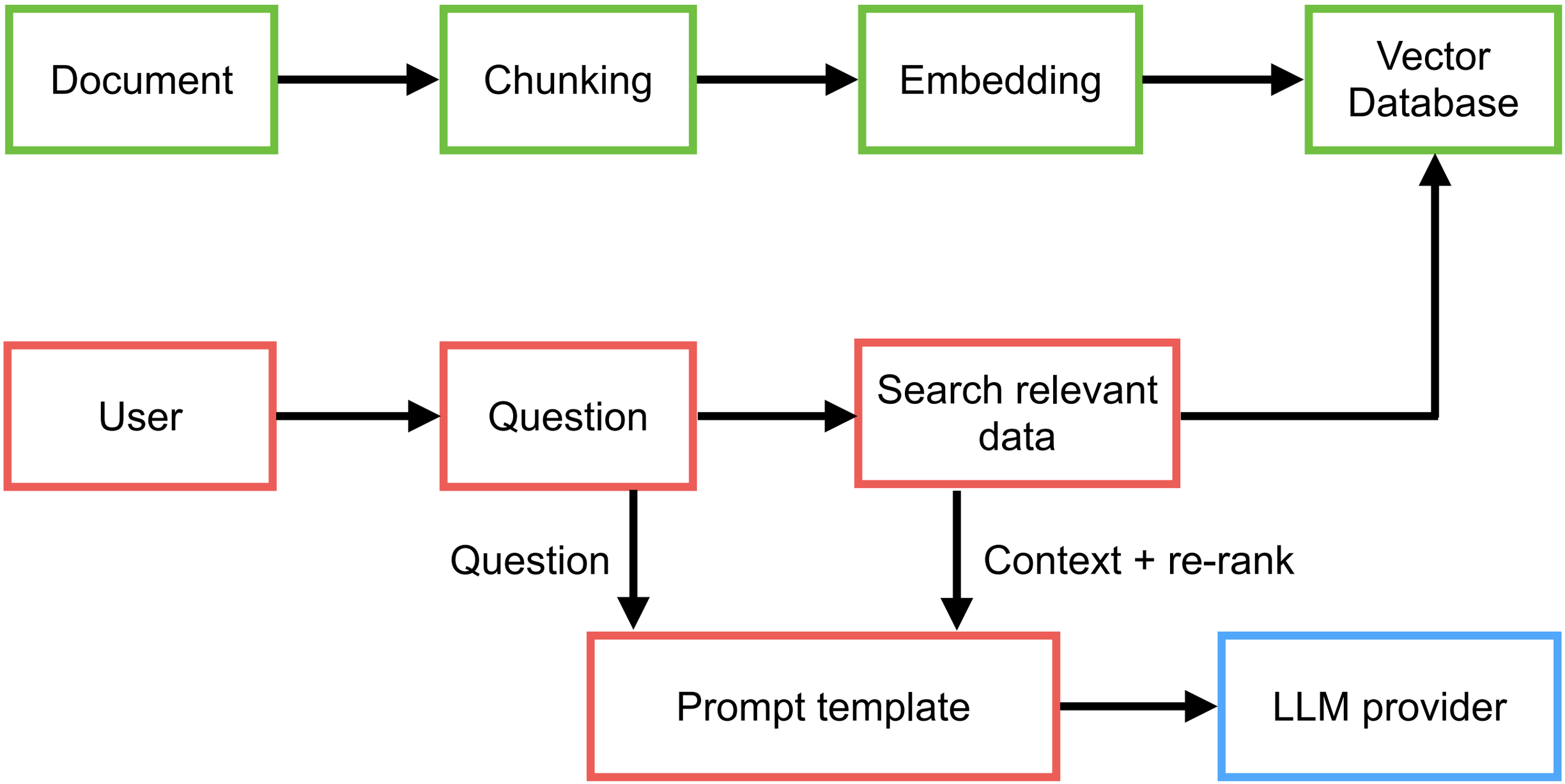
Search

Search result

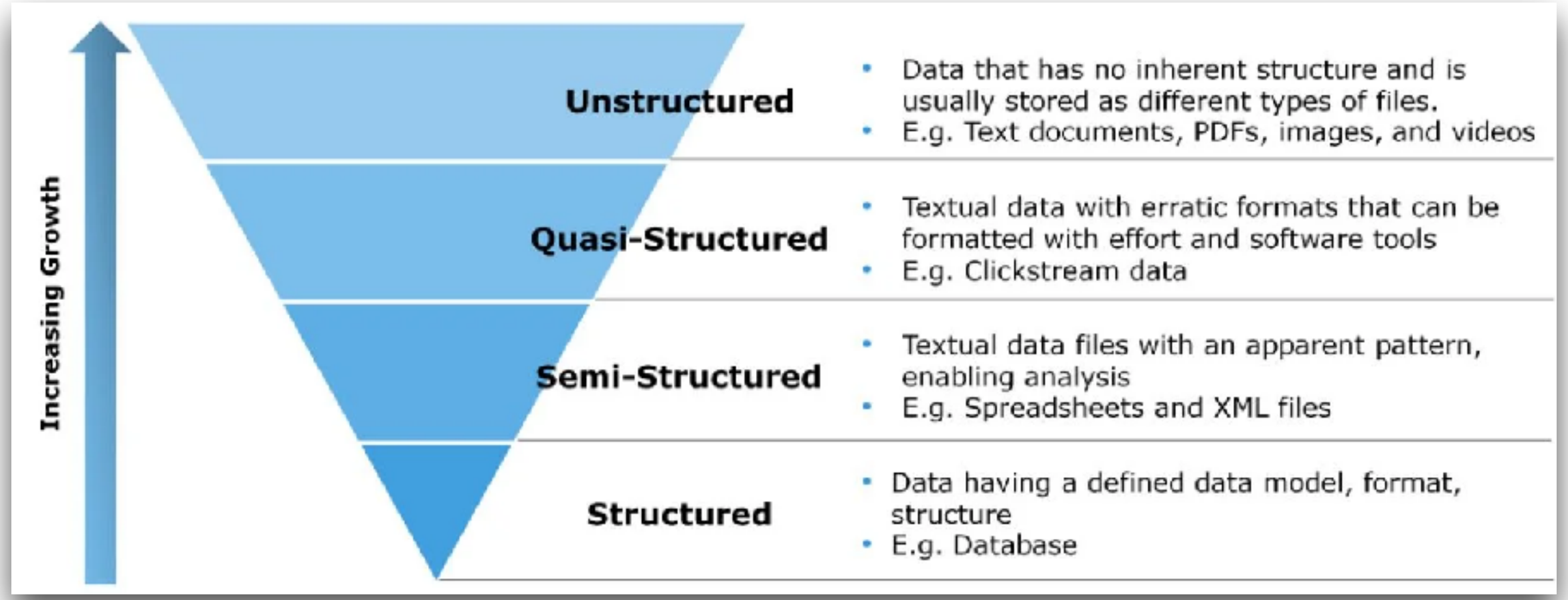
Basic RAG Architecture



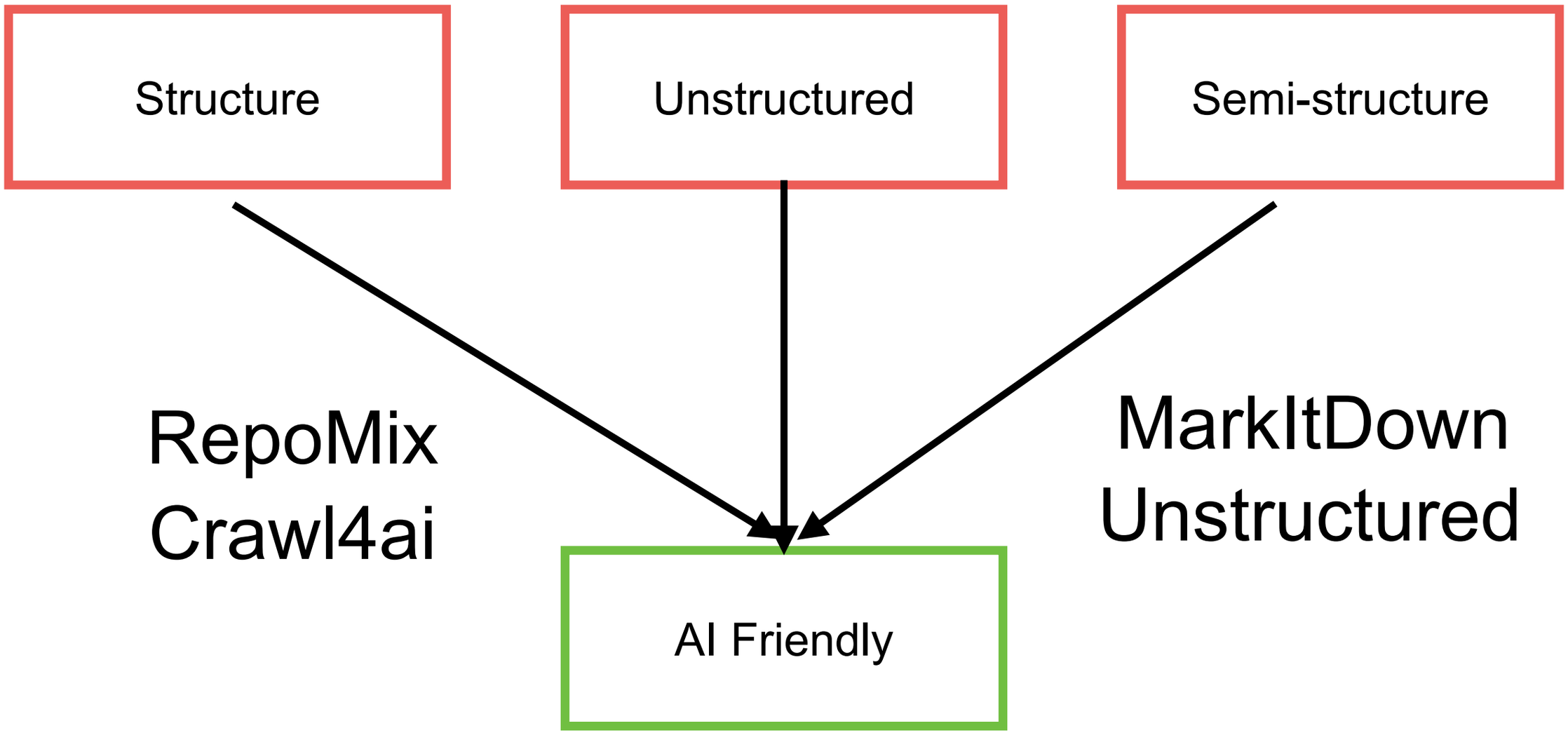
RAG process



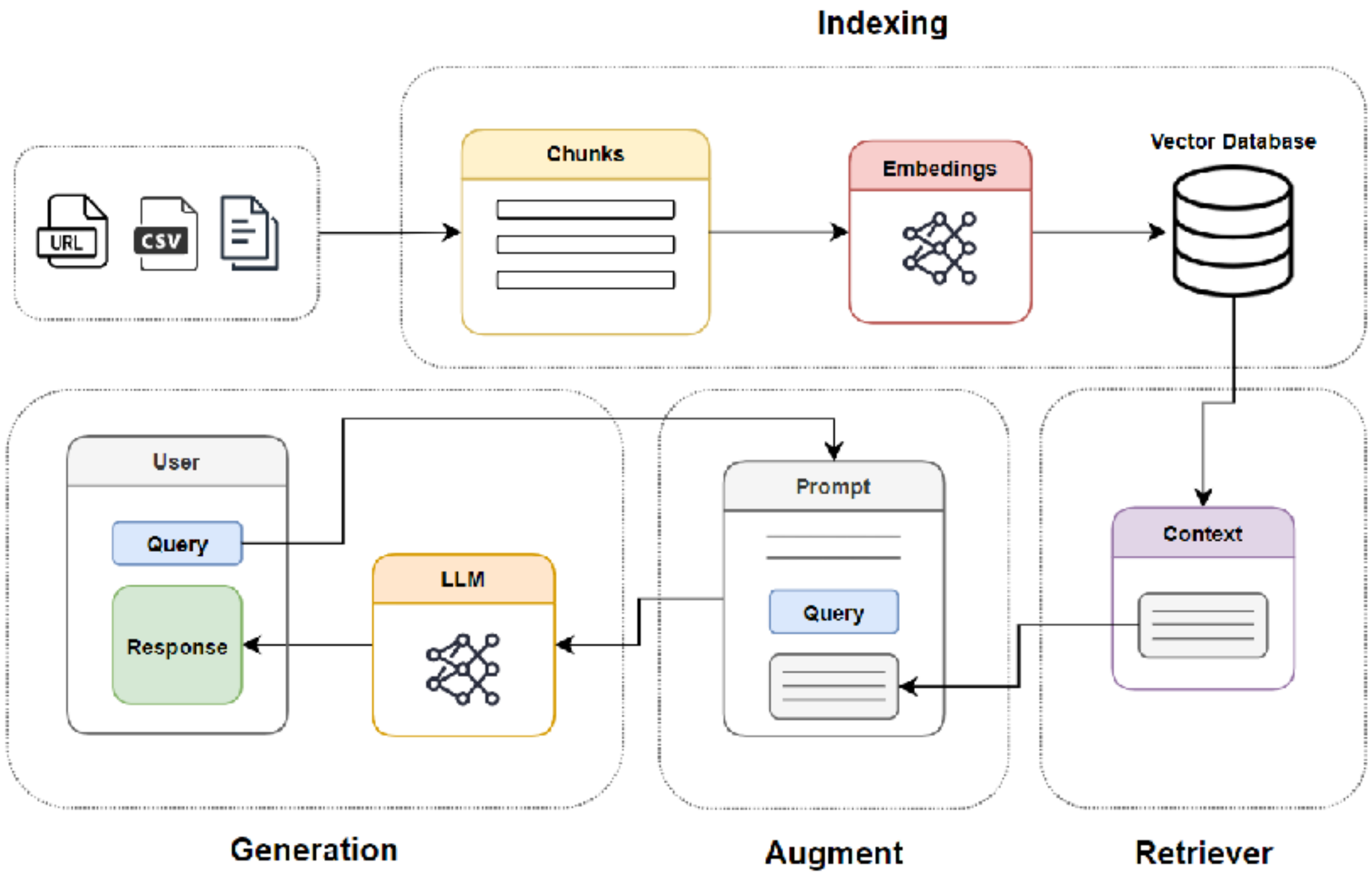
Structures of Data ?



Friendly Data for LLM/AI

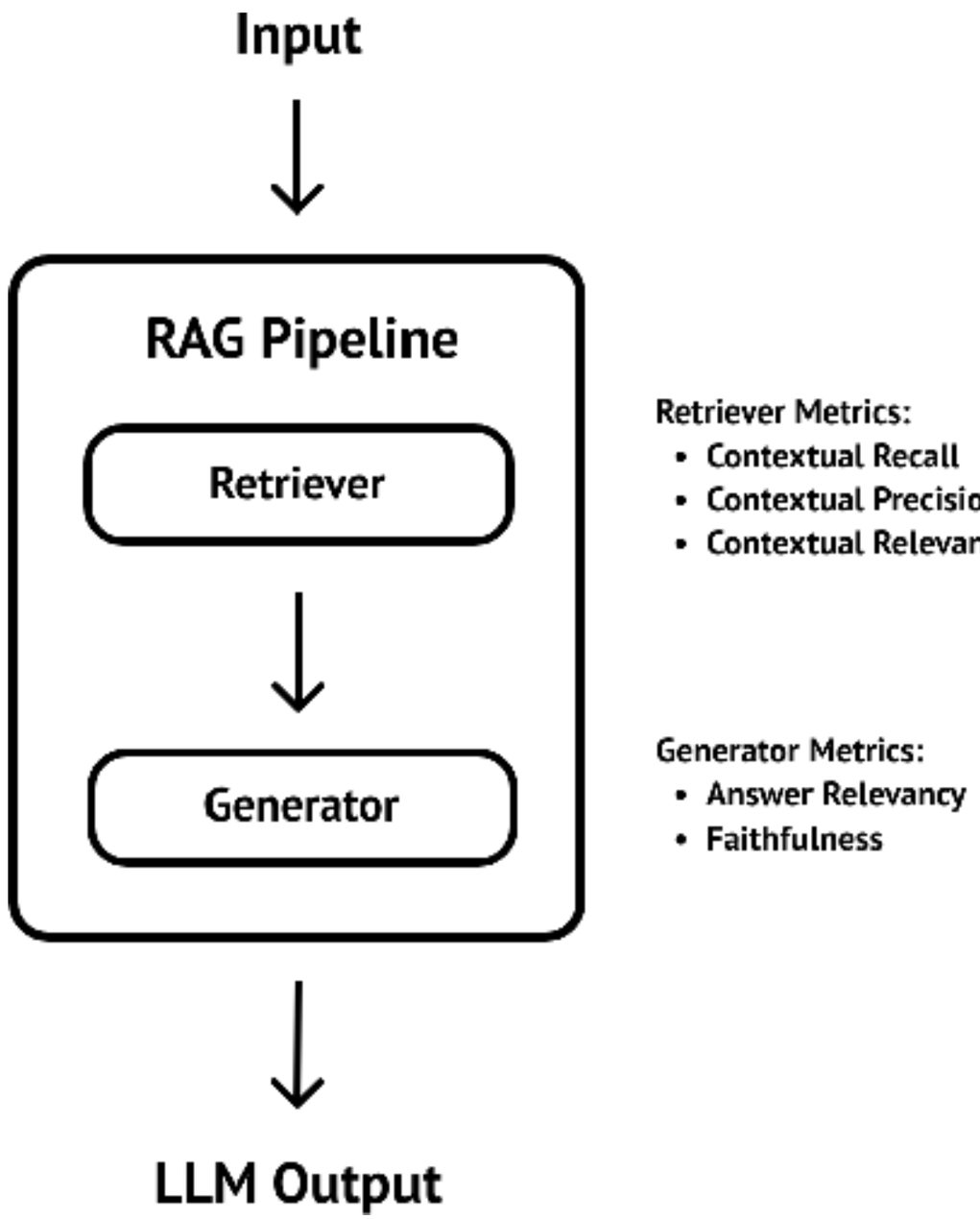


RAG Cookbook (techniques)

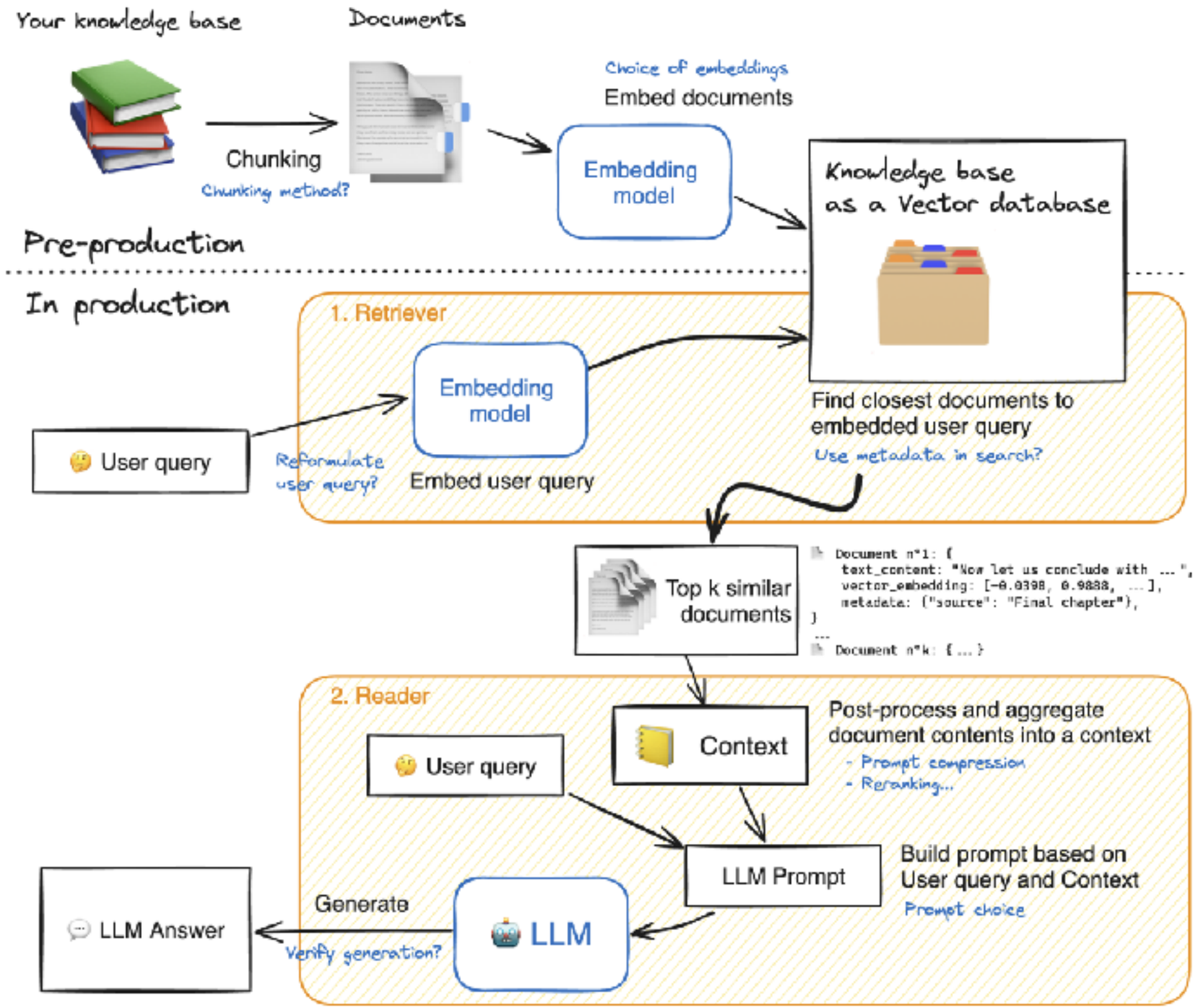


https://github.com/athina-ai/rag-cookbooks

RAG Evaluation !!

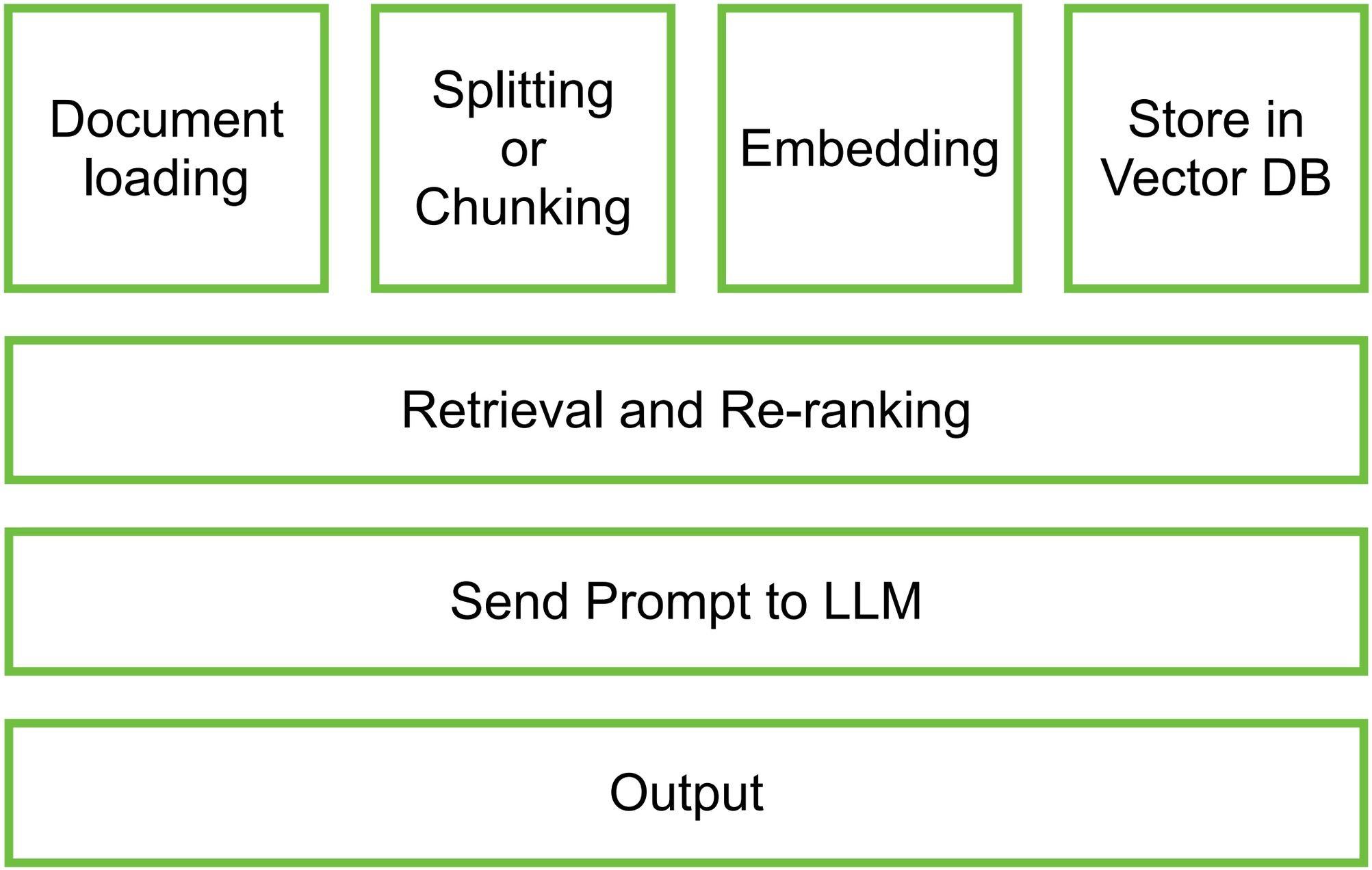


https://www.deepeval.com/guides/guides-rag-evaluation



https://huggingface.co/learn/cookbook/en/rag_evaluation

RAG Implementation



Failure Points of RAG

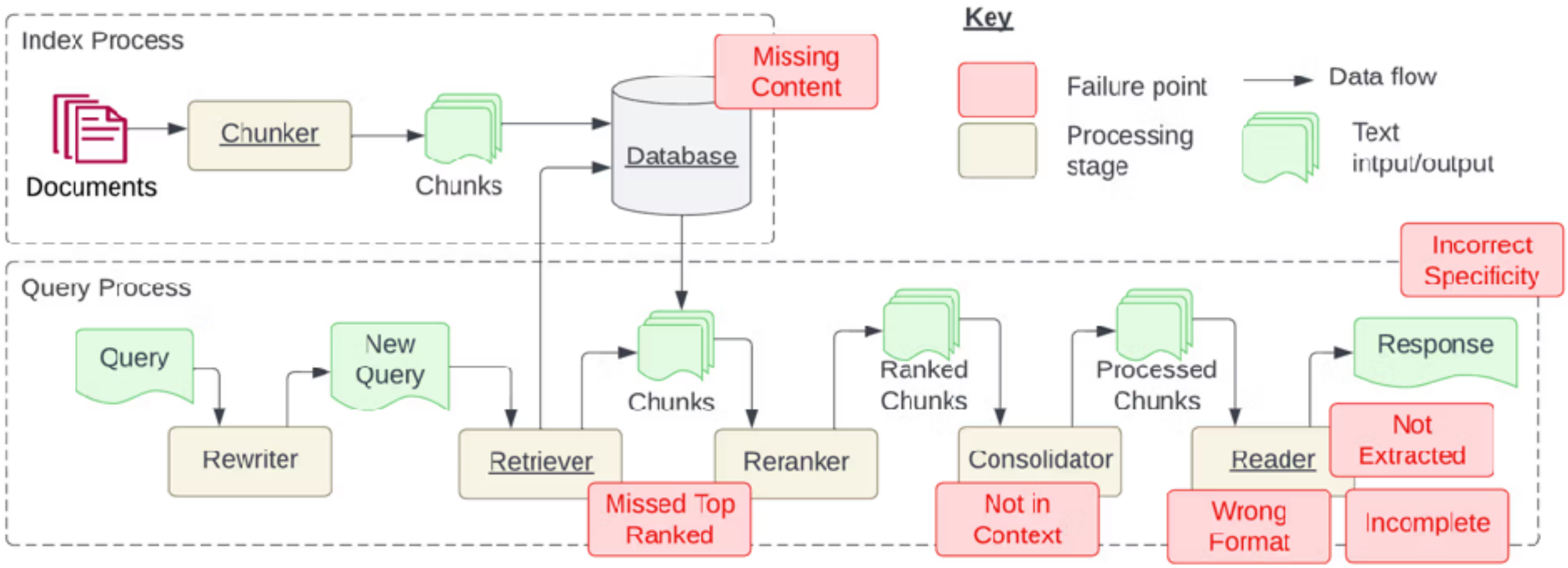


Figure 1: Indexing and Query processes required for creating a Retrieval Augmented Generation (RAG) system. The indexing process is typically done at development time and queries at runtime. Failure points identified in this study are shown in red boxes. All required stages are underlined. Figure expanded from [19].

https://www.galileo.ai/blog/mastering-rag-how-to-architect-an-enterprise-rag-system

RAG is better

But come with Cost !!

More latency

Retrieval errors

Accuracy !!

More Complexity

Maintenance overhead

RAG Techniques ?

RAG Techniques ?

Semantic chunking

Chunk size selector

Context chunk header

Adaptive RAG

Re-ranking

Graph TAG

https://github.com/FareedKhan-dev/all-rag-techniques

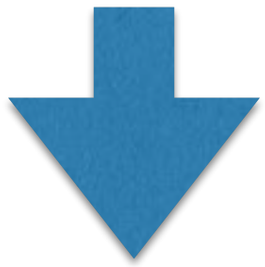
Pre-Retrieval optimization ?

Pre-Retrieval optimization ?

Preprocessing and cleansing data
Chunking strategies
Add metadata
Embedding model selection

Chunking strategies

Size of Document
> context window size



Chunking

Chunk 1

Chunk 2

Chunk 3

Chunking Strategies !!

Fixed size
Recursive characters
Document structure-based
Semantic chunking
Agentic chunking

. . .

https://blog.dailydoseofds.com/p/5-chunking-strategies-for-rag

Good Chunking

Efficiency

Relevance

Context preservation

Improve content generation

Reduce noise

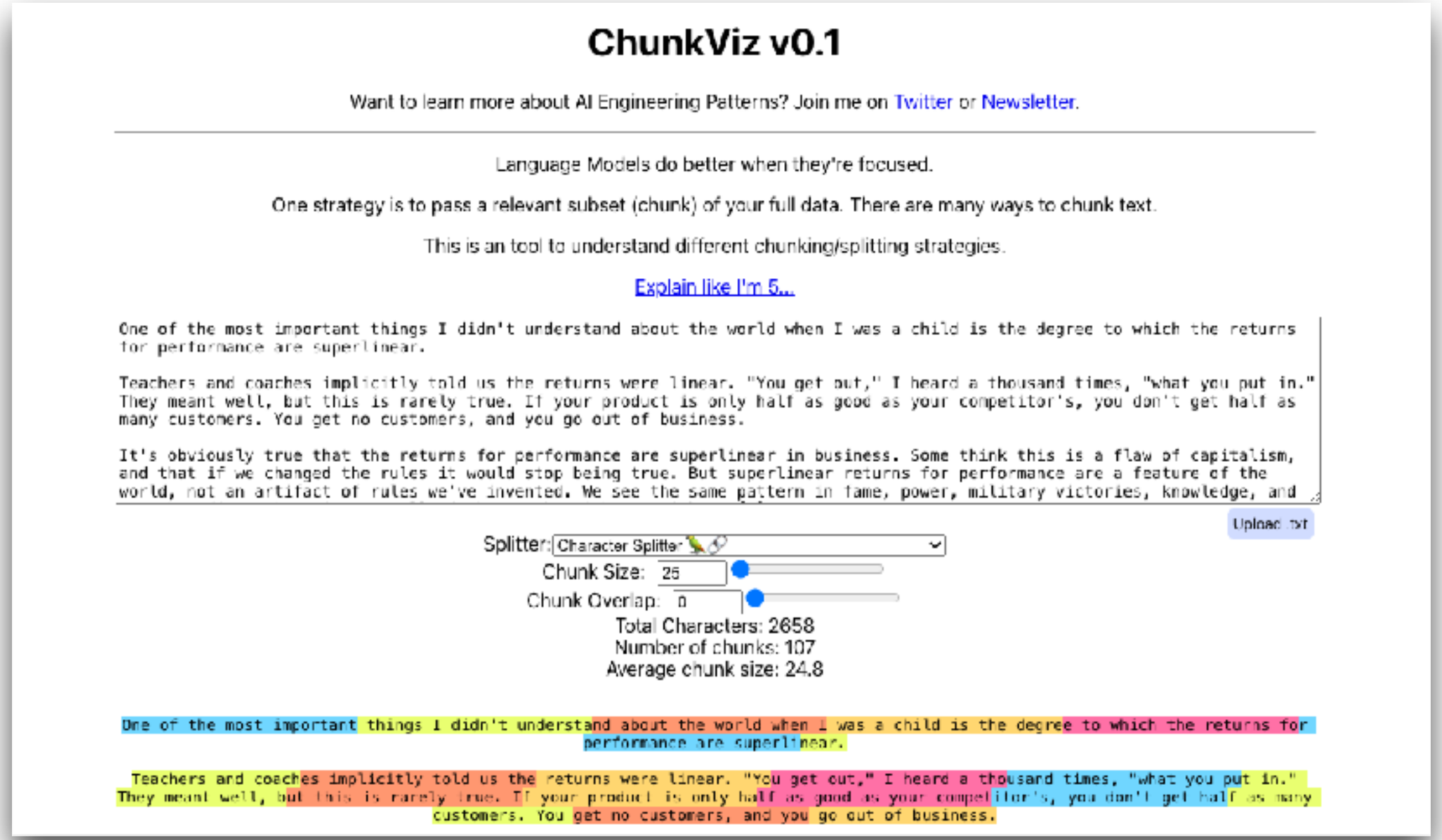
Bad Chunking

Loss context

Redundancy

Inconsistency

Chunking Visualization



https://chunkviz.up.railway.app/

Retrieval optimization ?

Retrieval optimization ?

Re-ranking

Hybrid search

Query transformation

Multi-vector embedding

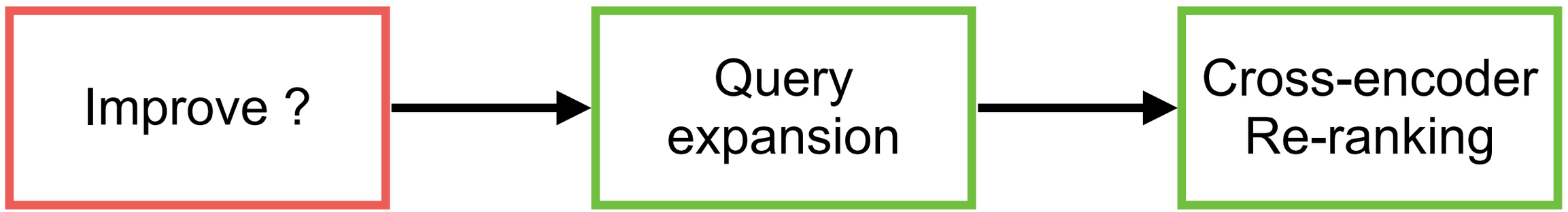
Contextual retrieval

Vector database Selection

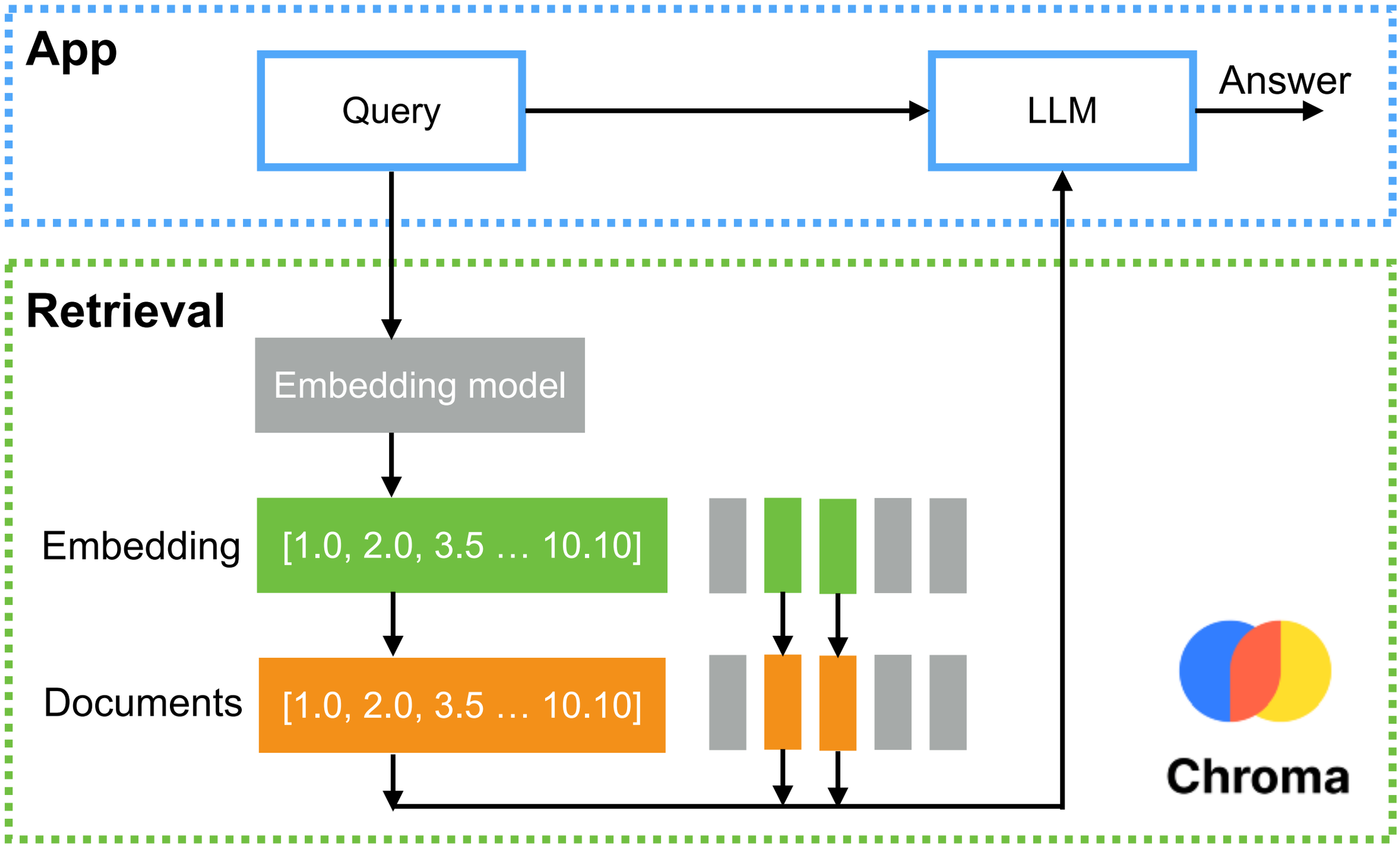
RAG Workshop

https://github.com/up1/workshop-basic-llm/tree/main/workshop/basic-rag

RAG workshop



Basic RAG



Query Expansion

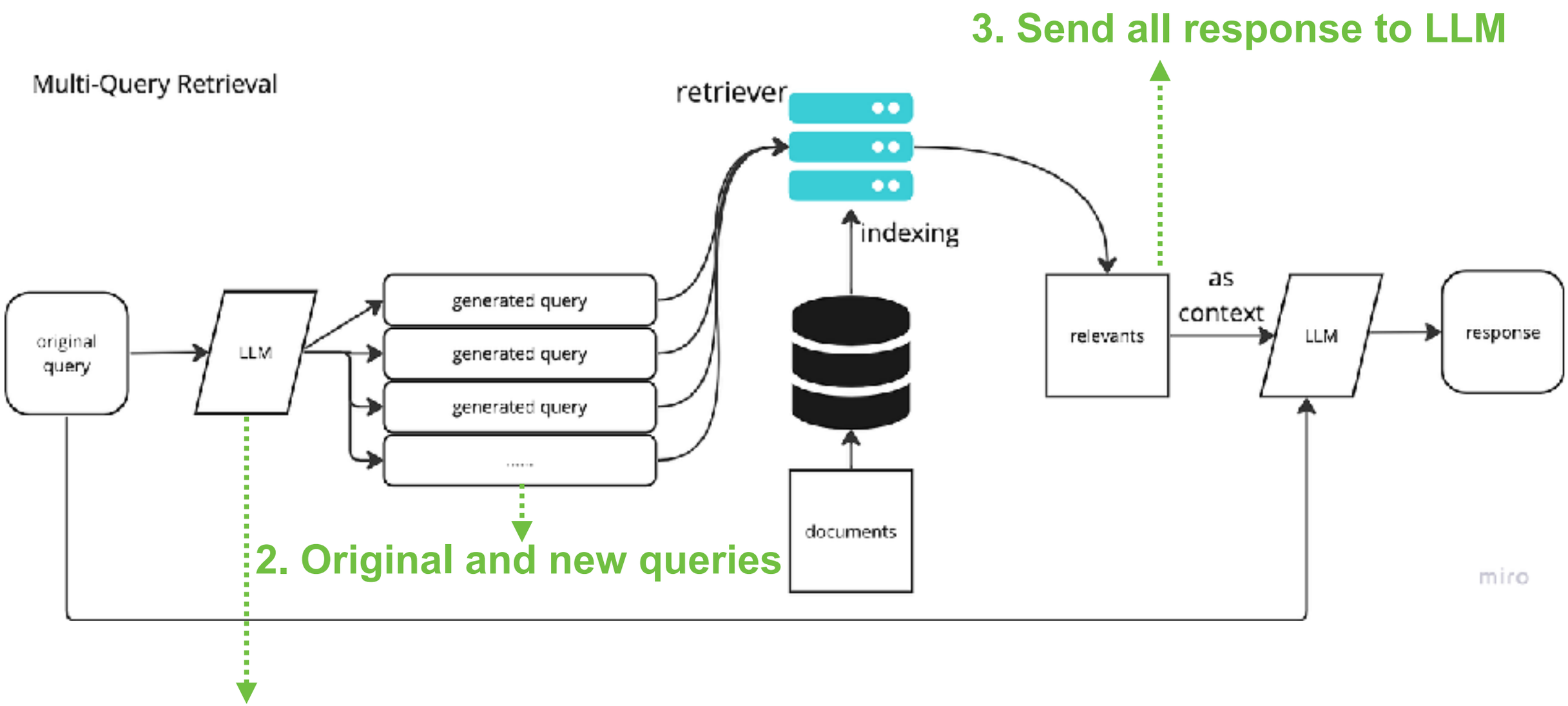
Query expansion is a widely used technique to improve the recall of search systems

Ambiguity	Vocabulary mismatch	Lack of context

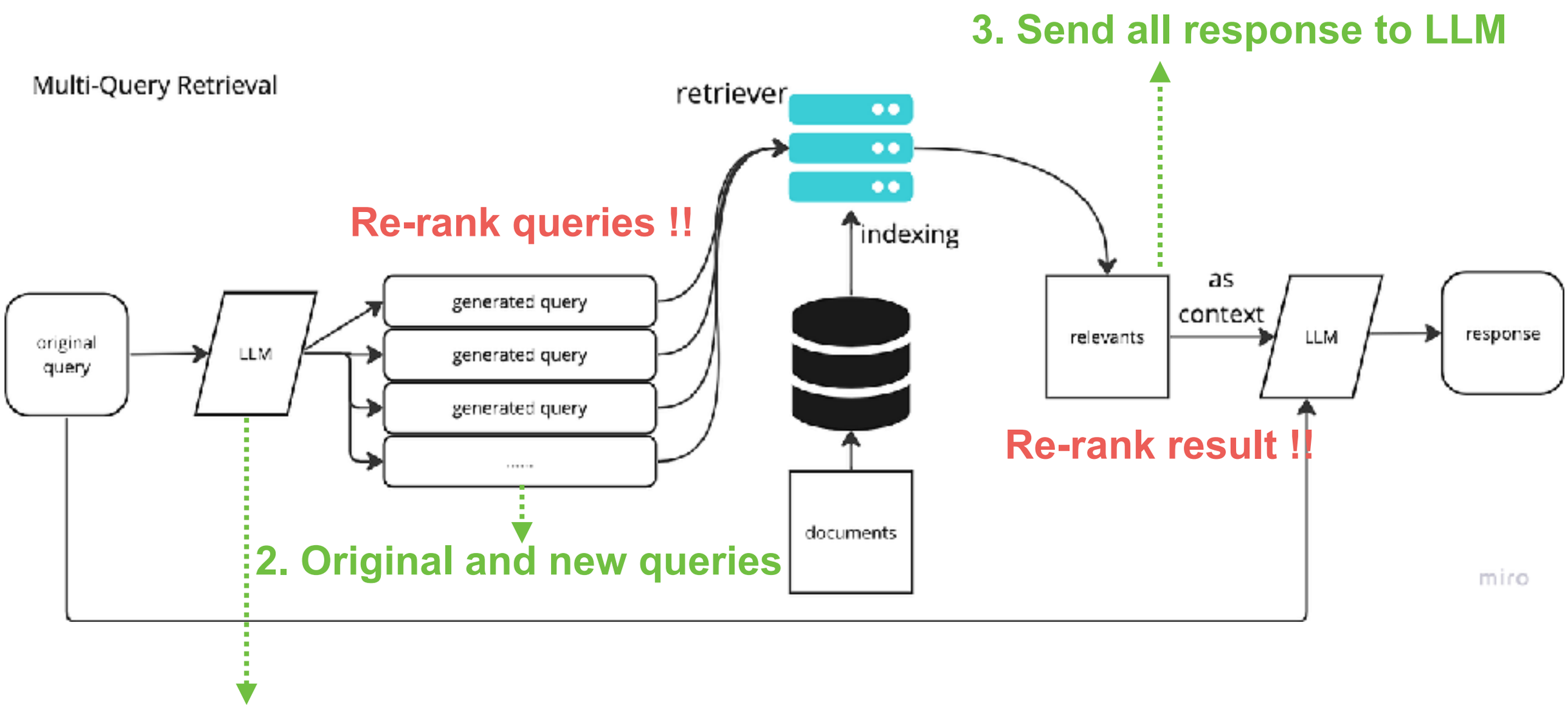
"Add synonyms, related context and contextual terms"

https://arxiv.org/abs/2305.03653

Query Expansion

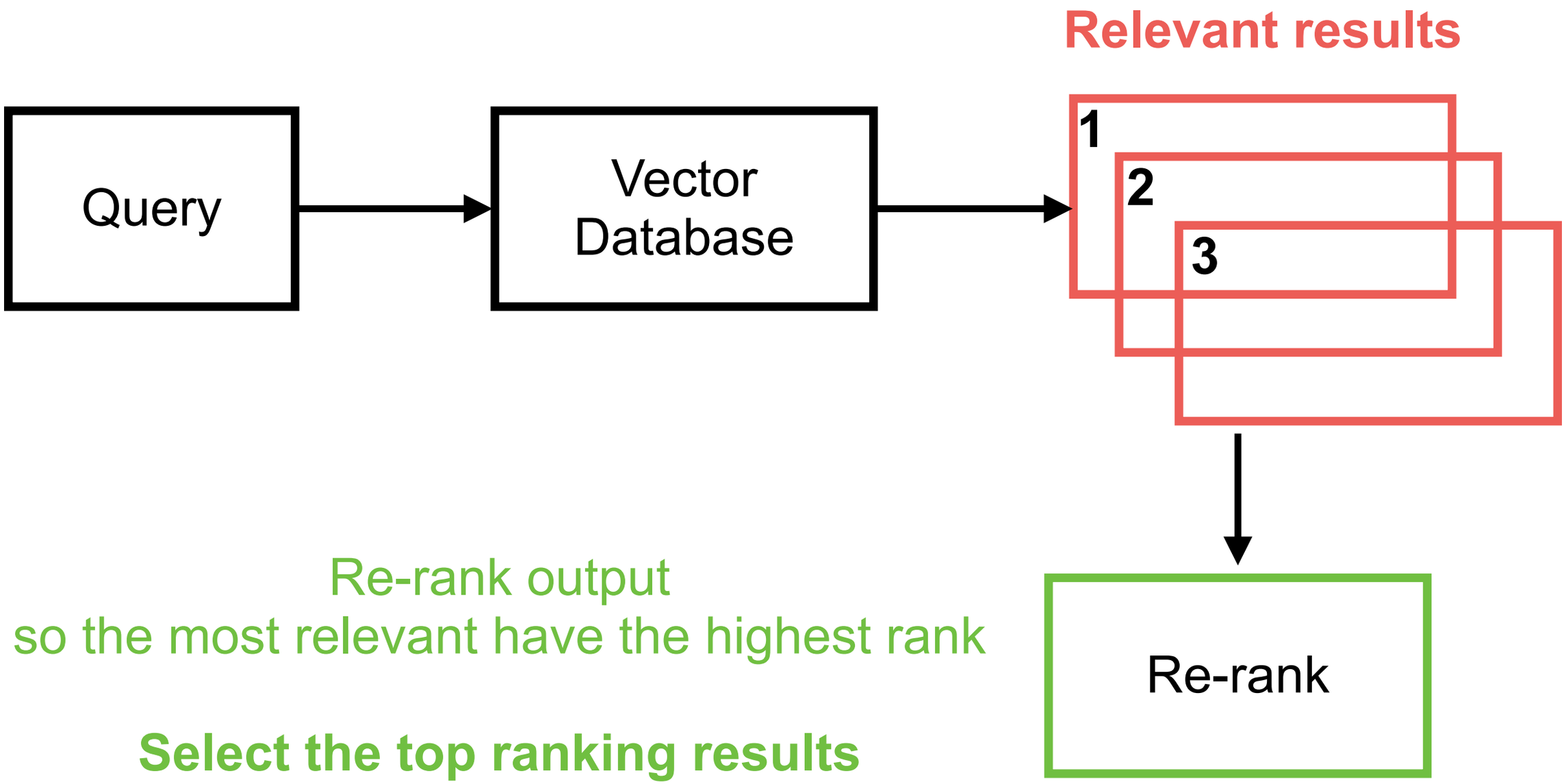


Re-rank !!



Cross-encoder Re-ranking

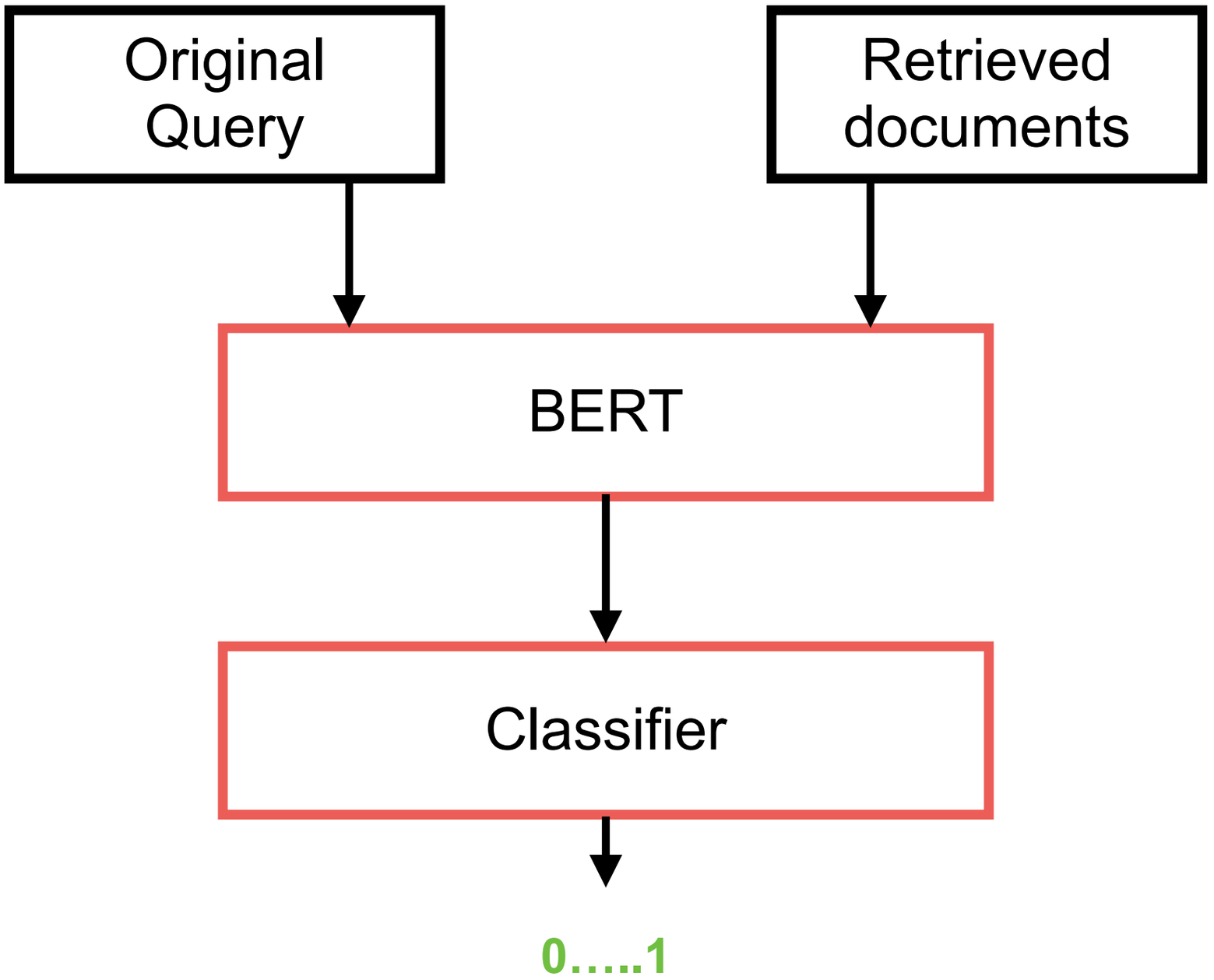
How to ordering relevant results !!



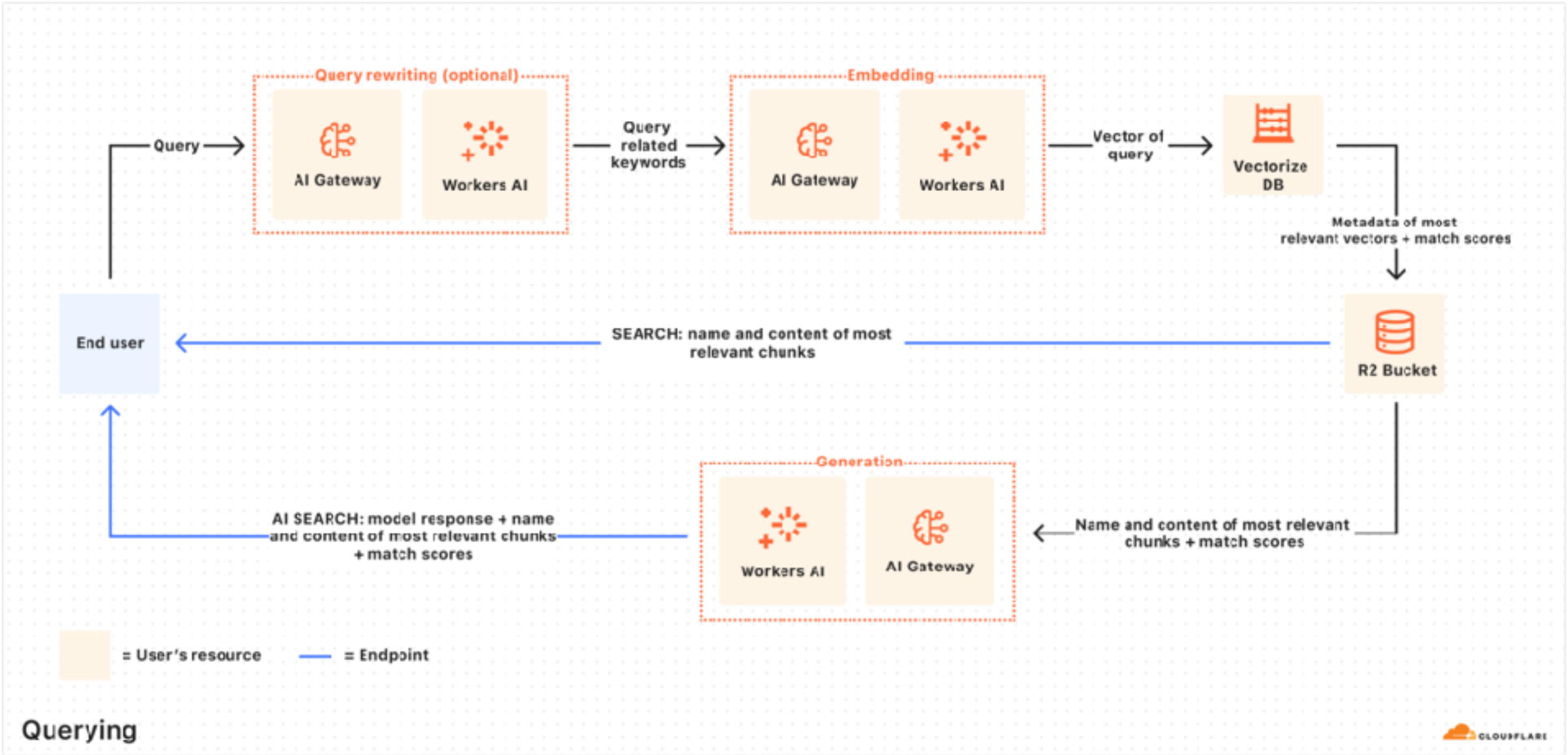
Re-rank output
so the most relevant have the highest rank

Select the top ranking results

Cross-Encoder



Cloudflare AutoRAG



https://developers.cloudflare.com/autorag/

Guardrails

https://github.com/guardrails-ai/guardrails

Guardrails

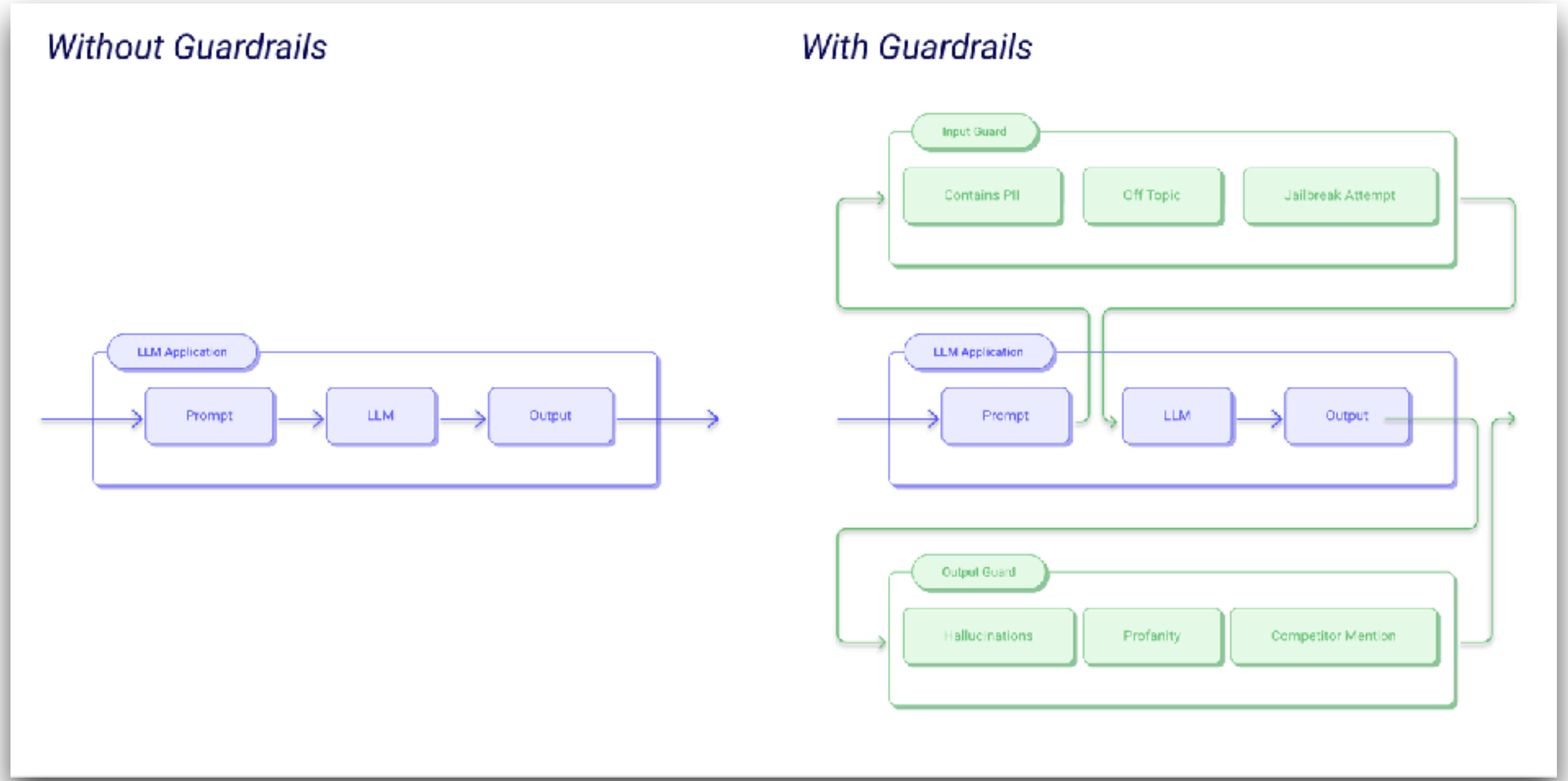
Help to build reliable AI applications

Guard for
input and output

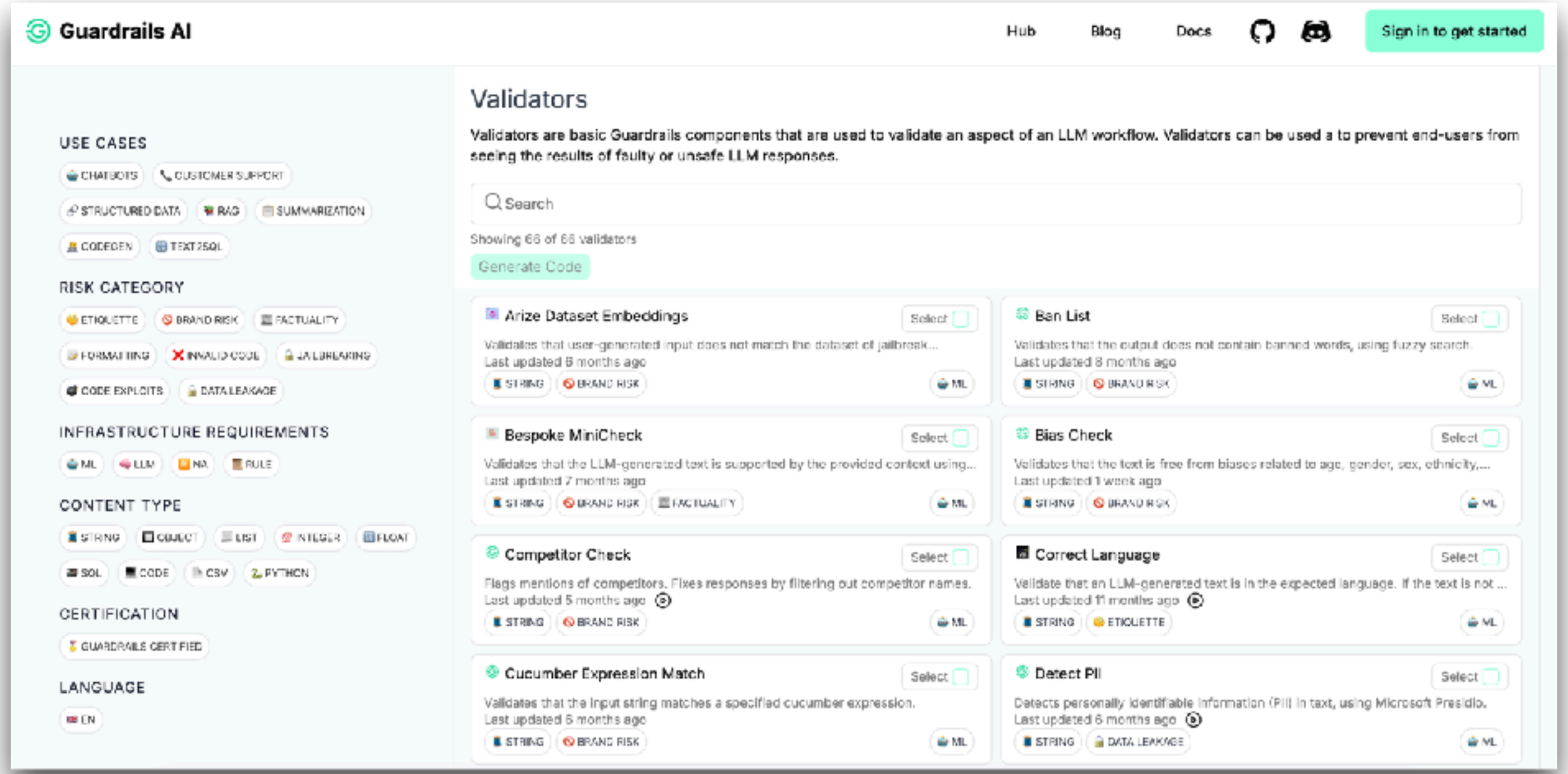
Help to generate
Structured output

https://github.com/guardrails-ai/guardrails

Guardrails

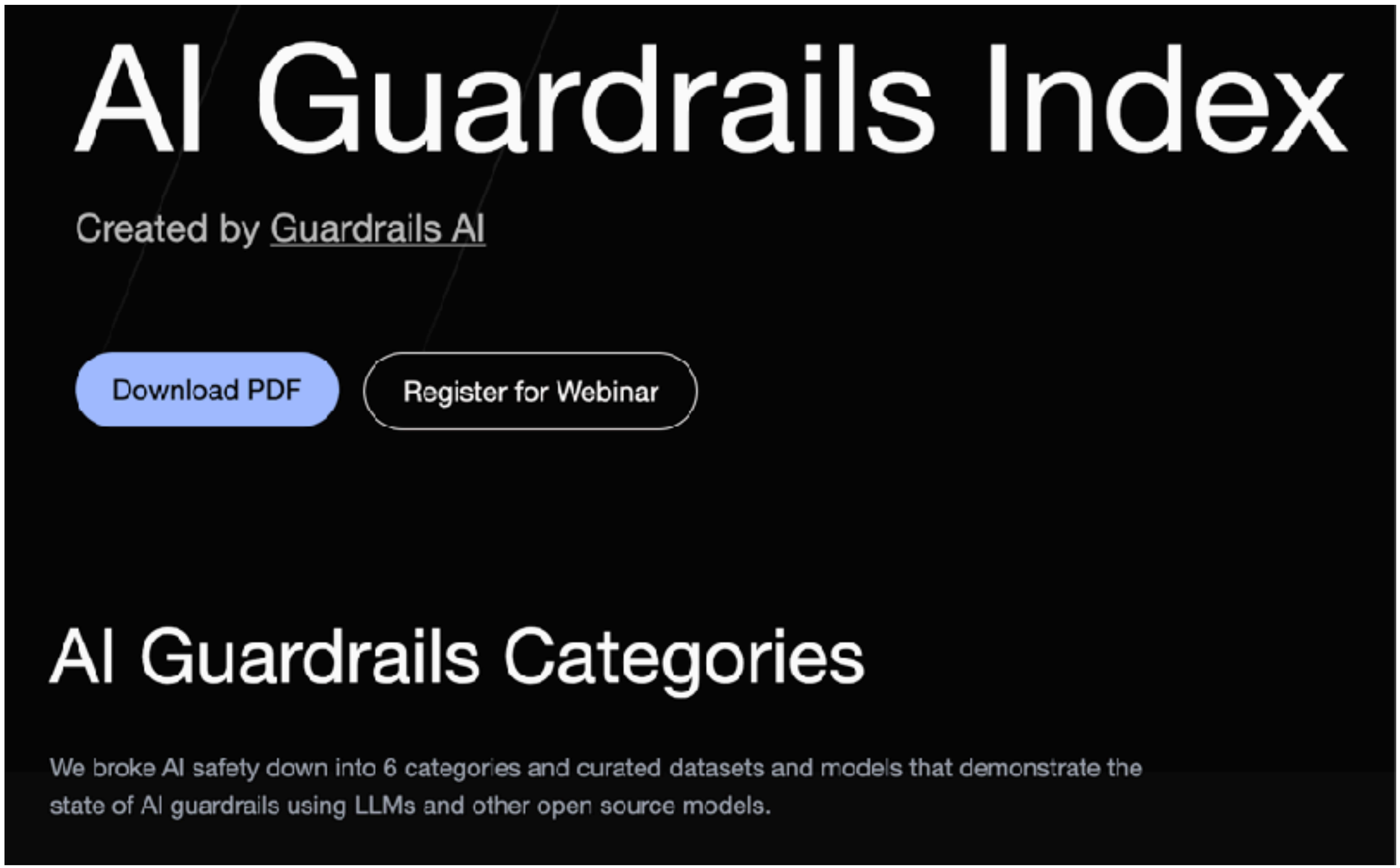


Guardrails Hub



https://hub.guardrailsai.com/

Guardrails Index



https://index.guardrailsai.com/

CAG
(Cache Augmented Generation)

https://arxiv.org/abs/2412.15605v1

CAG

When you don’t need for real-time retrieval (**static**)
Preload all relevant knowledge into model’s **context**
Precompute key-value(KV) cache to store and reuse
Larger context window size !! (1M)

Retrieval-free operation

Improve efficiency

Simplify architecture

https://arxiv.org/abs/2412.15605v1

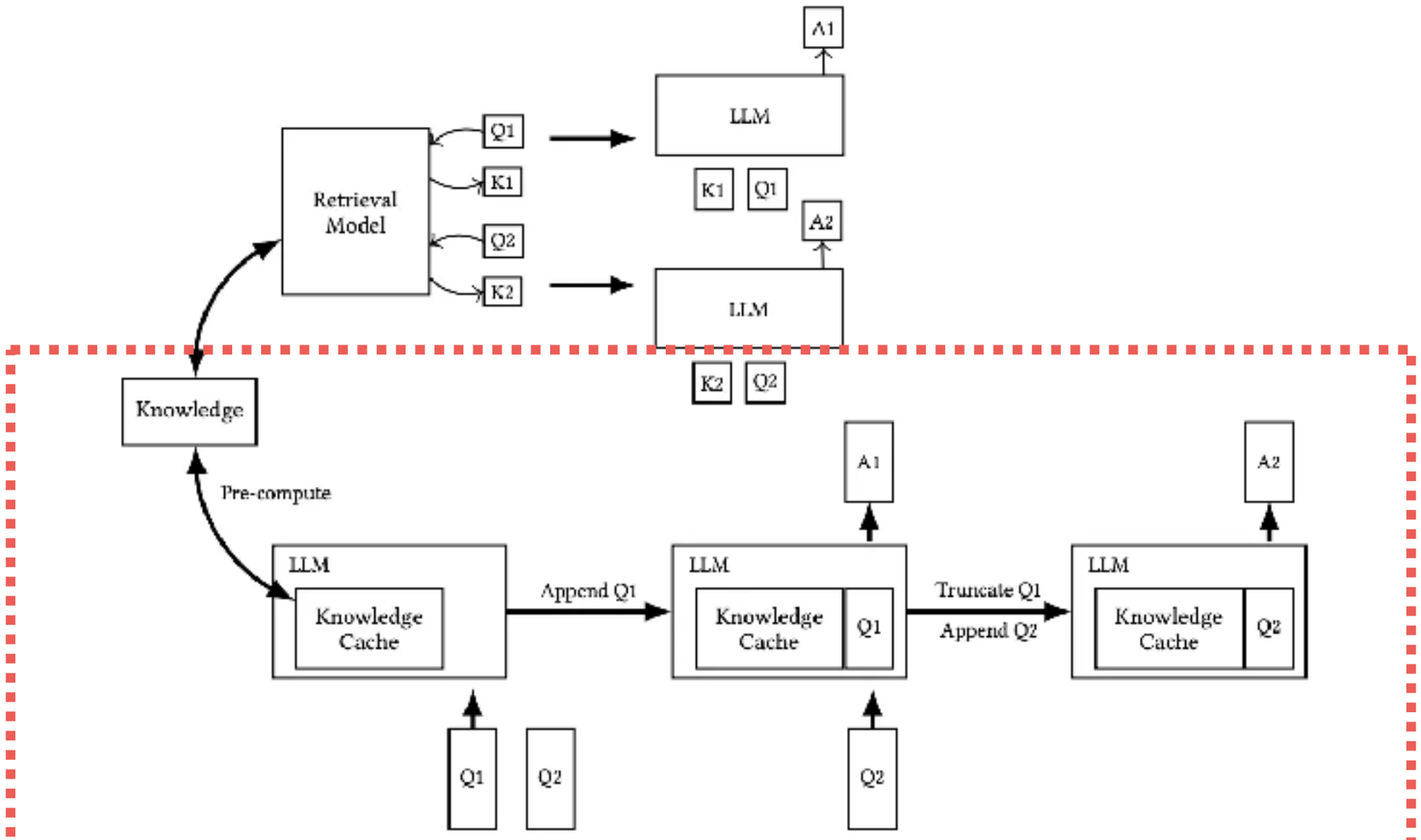
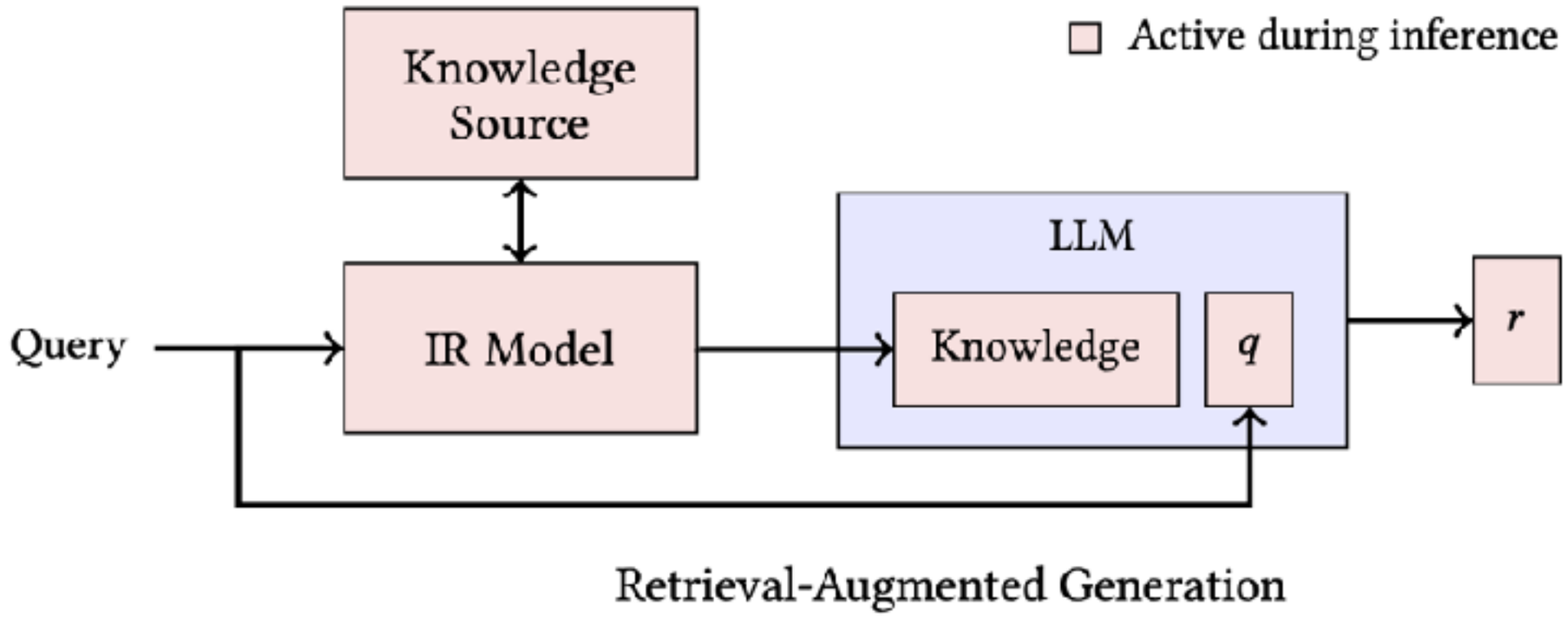


Figure 1: Comparison of Traditional RAG and our CAG Workflows: The upper section illustrates the RAG pipeline, including real-time retrieval and reference text input during inference, while the lower section depicts our CAG approach, which preloads the KV-cache, eliminating the retrieval step and reference text input at inference.

https://arxiv.org/abs/2412.15605v1



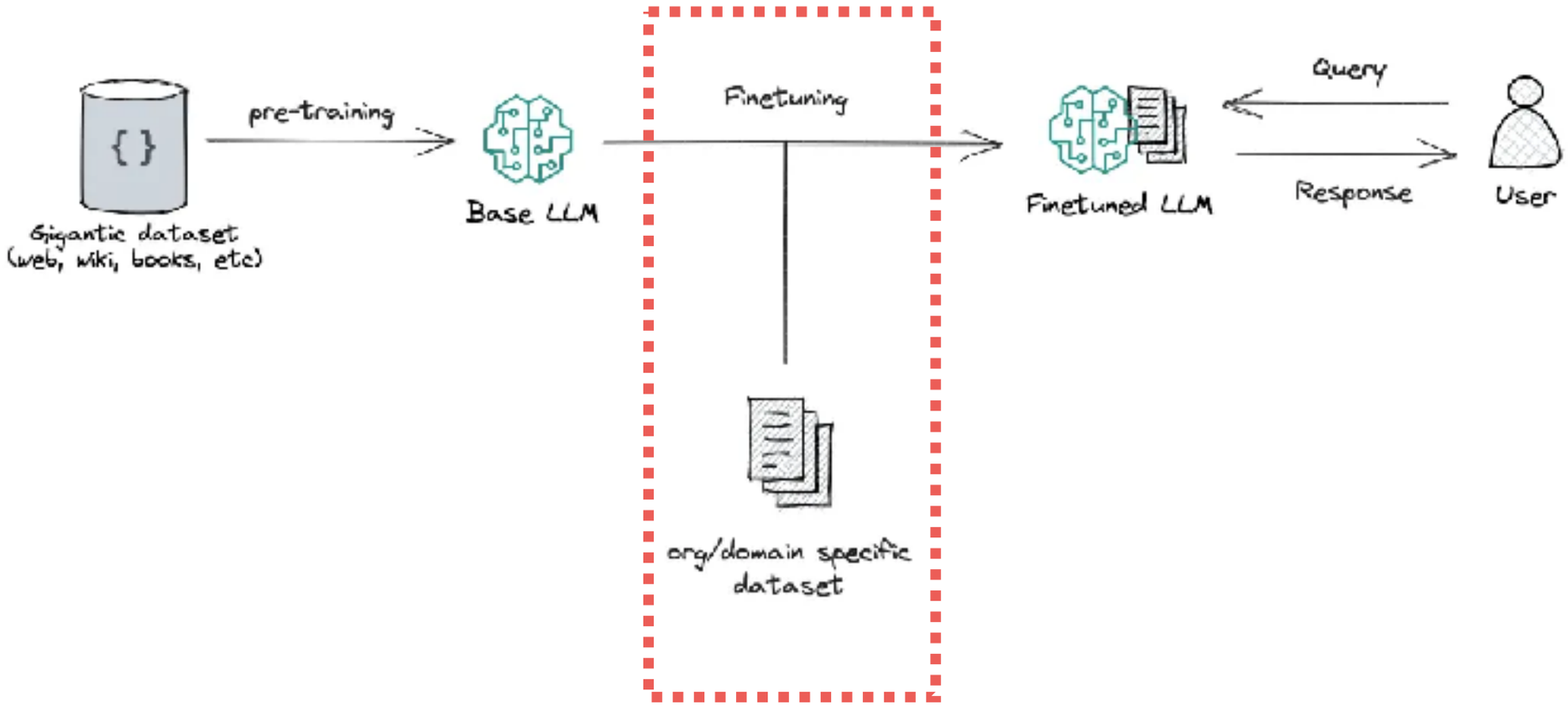
https://github.com/hhhuang/CAG

RAG + CAG is better

Fine Tuning

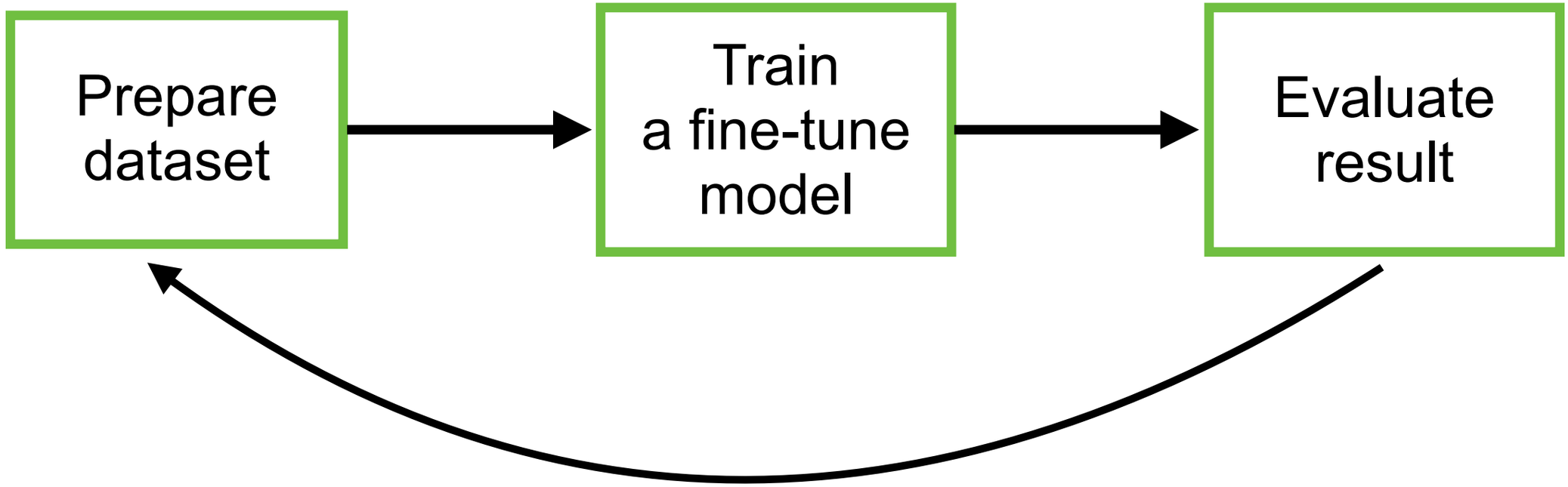
Fine Tuning

Training with small and specific dataset
Adjust the model's weight based on our data



https://towardsdatascience.com/rag-vs-finetuning-which-is-the-best-tool-to-boost-your-llm-application-94654b1eaba7

Fine Tuning Process



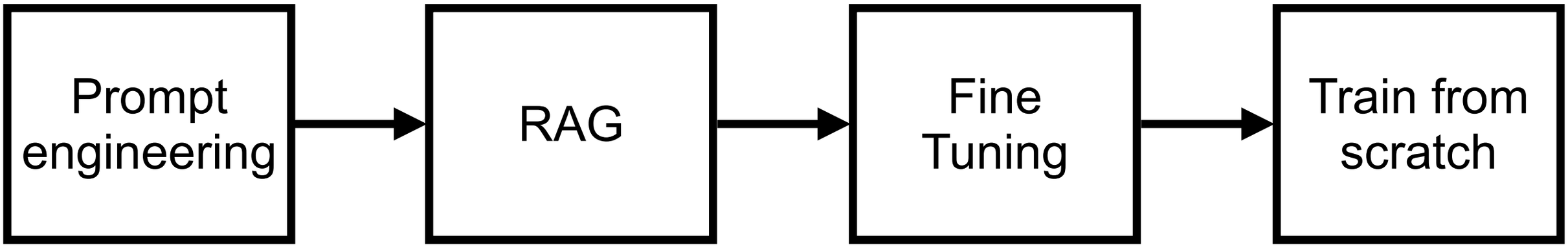
https://platform.openai.com/docs/guides/fine-tuning

RAG vs Fine-tuning

Scenario	RAG preferred	Fine tune preferred
Skillset requirements	Strong in RAG engineering	Strong in deep learning model and fine tuning
Data freshness	Realtime or frequently updated	Static, domain-specific data
Domain complexity	Multiple domains or high data diversity	Specialized and heavy domain (medical)
Resources usage	Lower computation	Higher computation

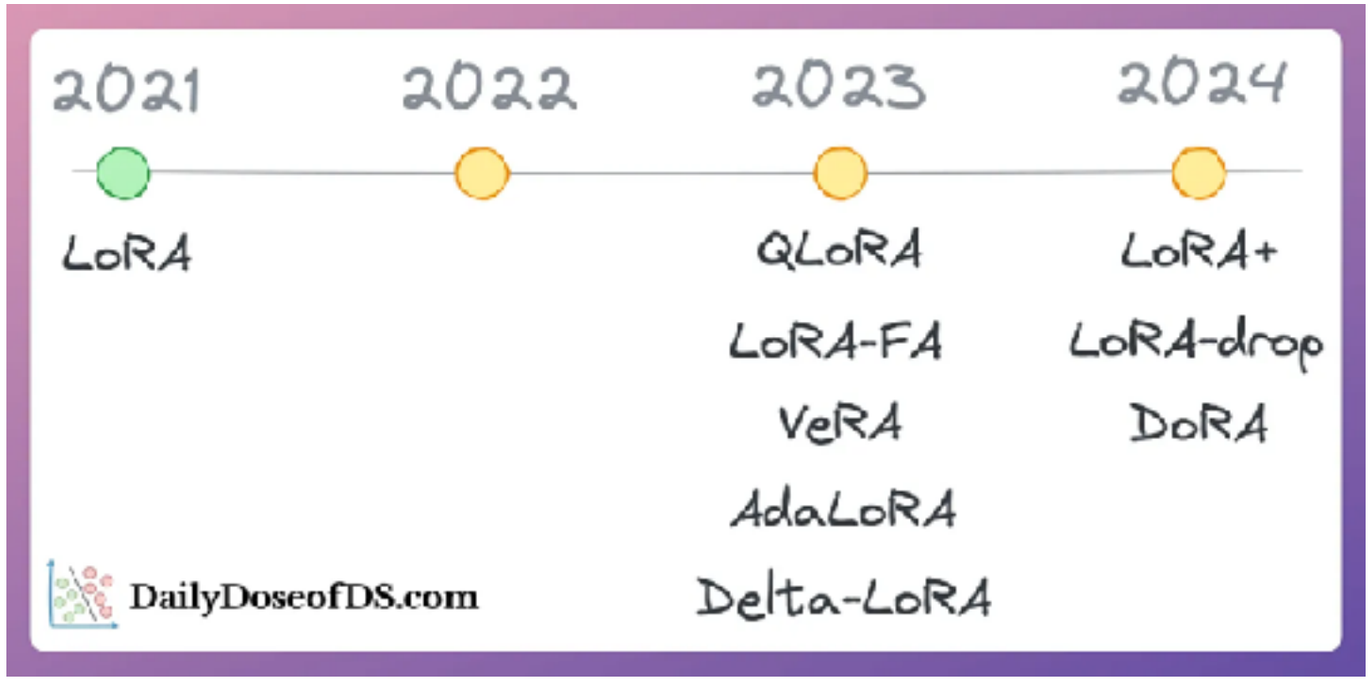
Steps with LLM

Balance with complexity, cost and quality



Fine Tuning Techniques !!

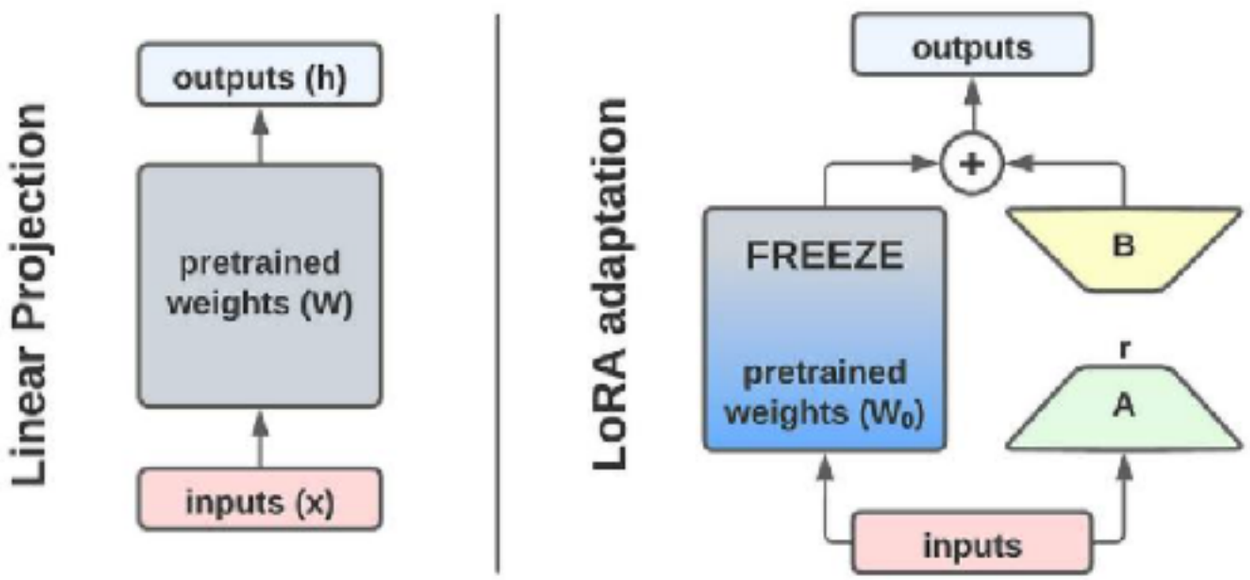
LoRA (Low-Rank Adaptation)
LoRA-FA (Frozen-A)
VeRA (Vector-based Random Matrix Adaptation)
Delta-LoRA



https://blog.dailydoseofds.com/p/5-llm-fine-tuning-techniques-explained

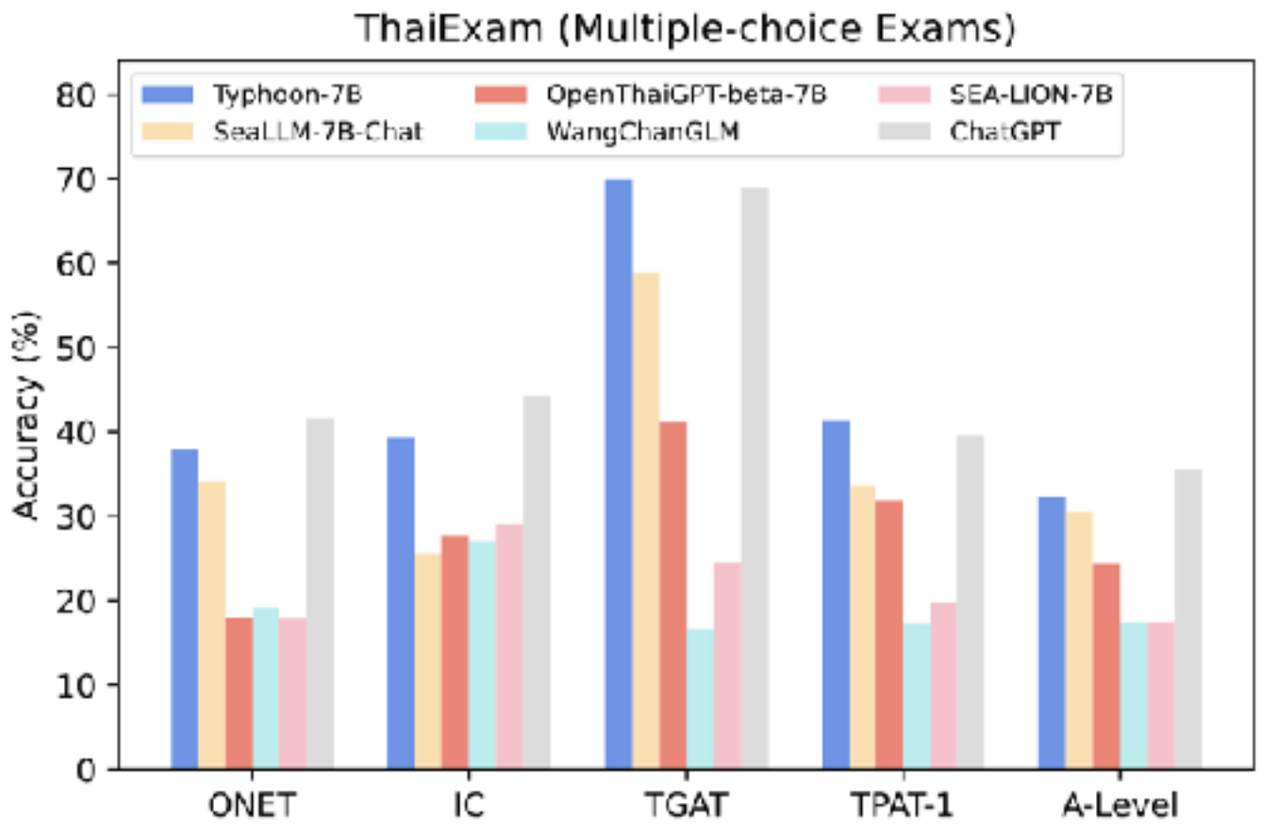
LoRA (Low-Rank Adaptation)

Reduces the number of trainable parameters
Making fine-tuning faster
More memory-efficient



Typhoon-7B Thai LLM

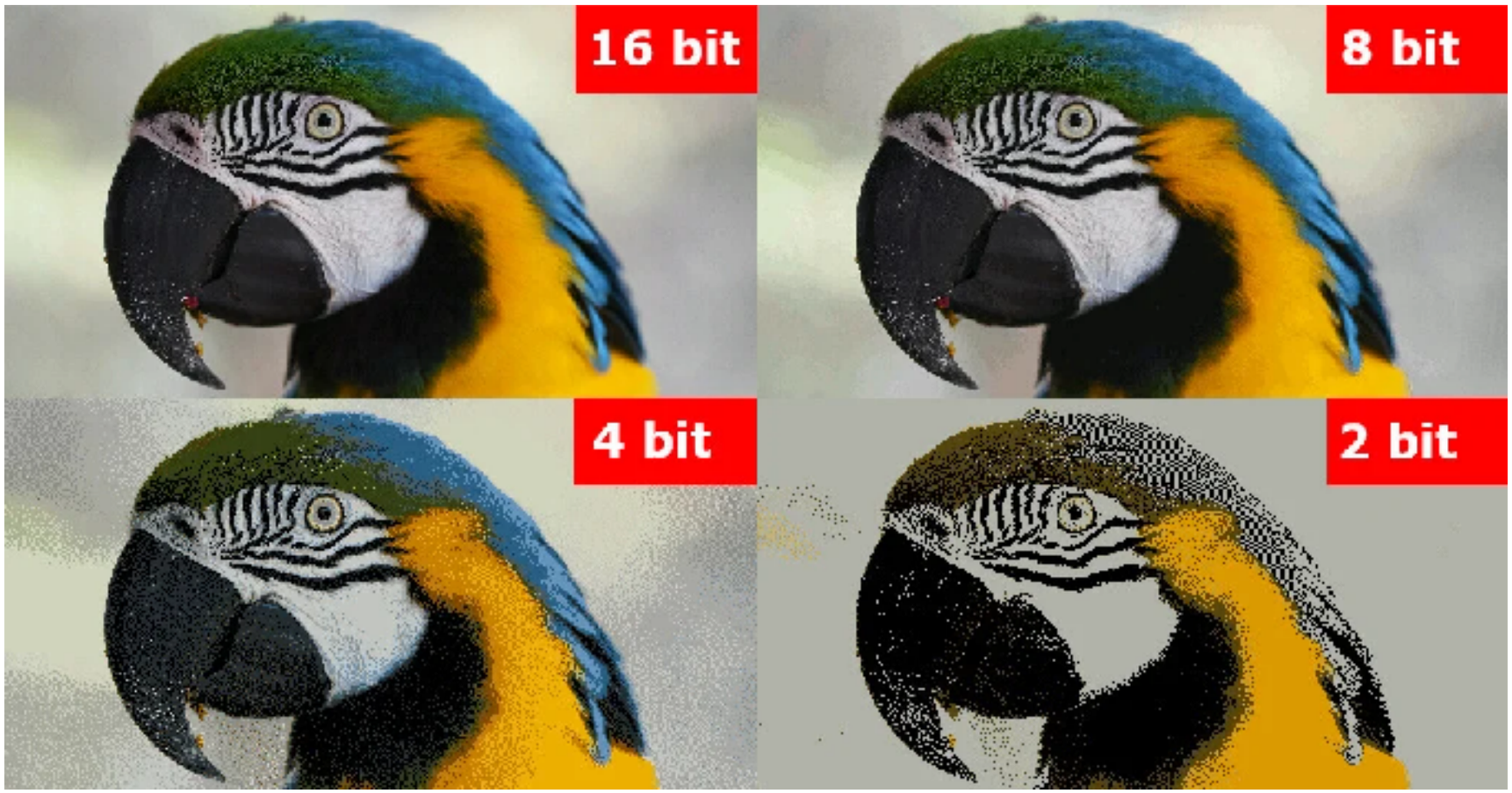
Based-on Mistral-7B
Thai words 5,000+



https://huggingface.co/scb10x/typhoon-7b

Reduce size of Model ?

Quantization



Quantization in LLM model

Reduce size of model
Reduce resource usage
Faster

Model	Original Size (FP32)	Quantized Size (INT4)
LLaMA3.1-8B	38.4 GB	4.8 GB
LLaMA3.1-70B	336 GB	42 GB
LLaMA3.1-405B	1,994 GB	243 GB

https://medium.com/@lmpo/understanding-model-quantization-for-llms-1573490d44ad

Local LLM

Local LLM

Run LLM on local machine/device
Try to customize with your requirement

Reduce cost

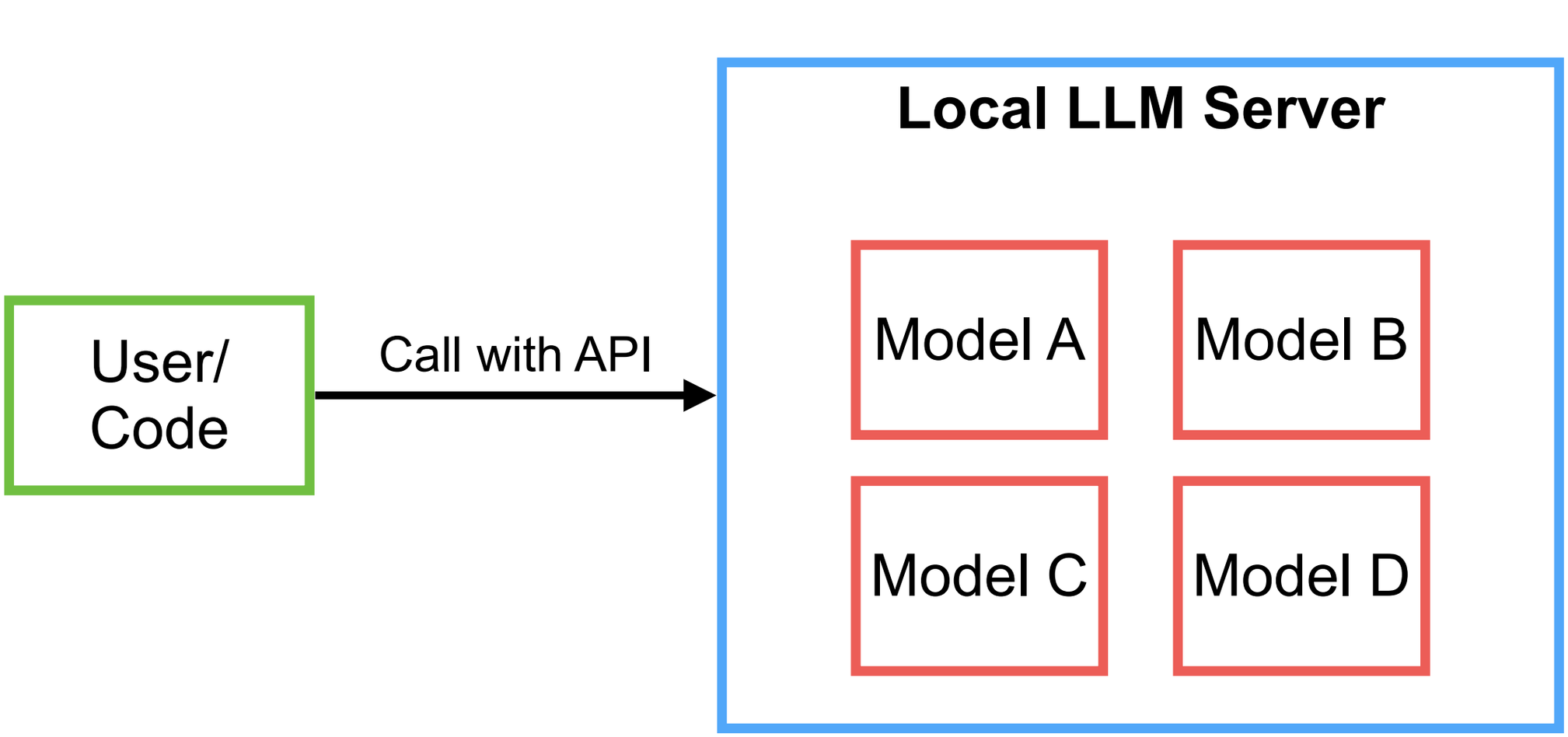
Data privacy

Responsive

Offline mode

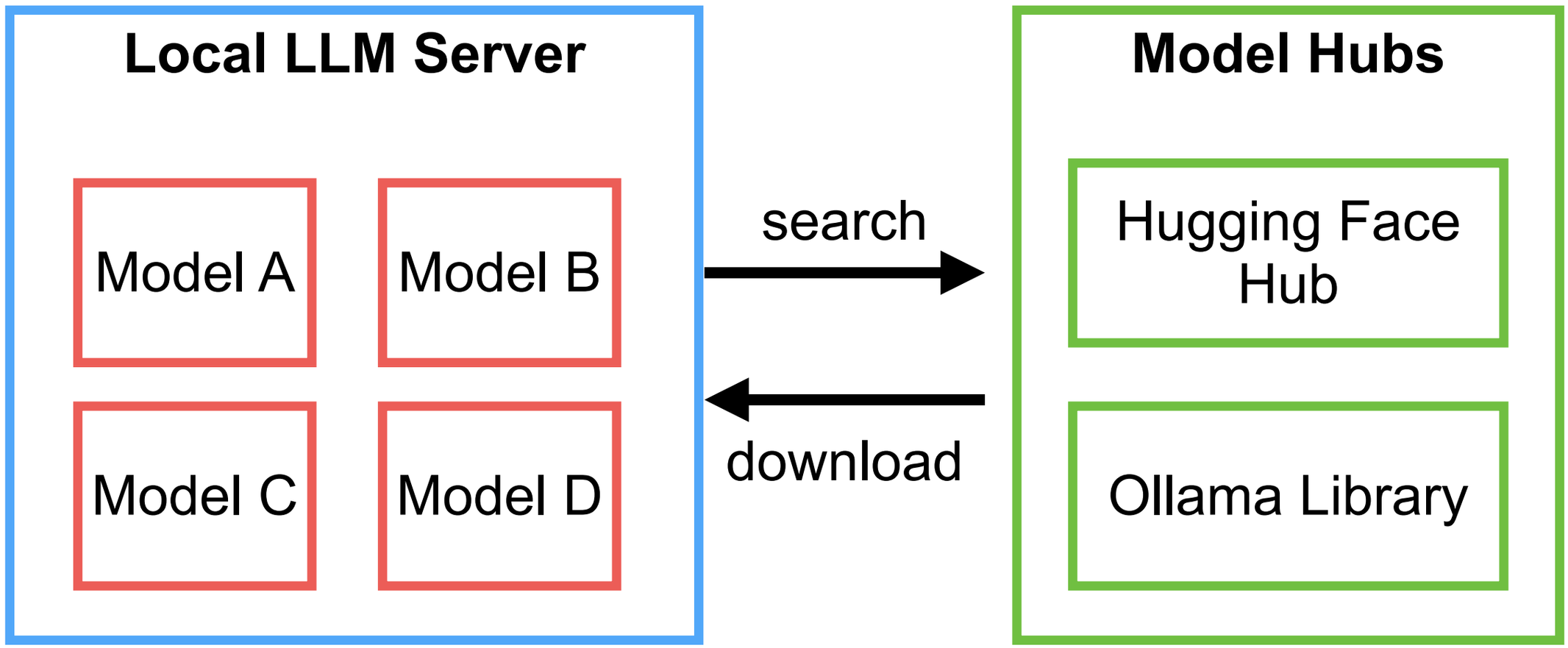
Local LLM

Improve your LLM models, more accurate answer



Models ?

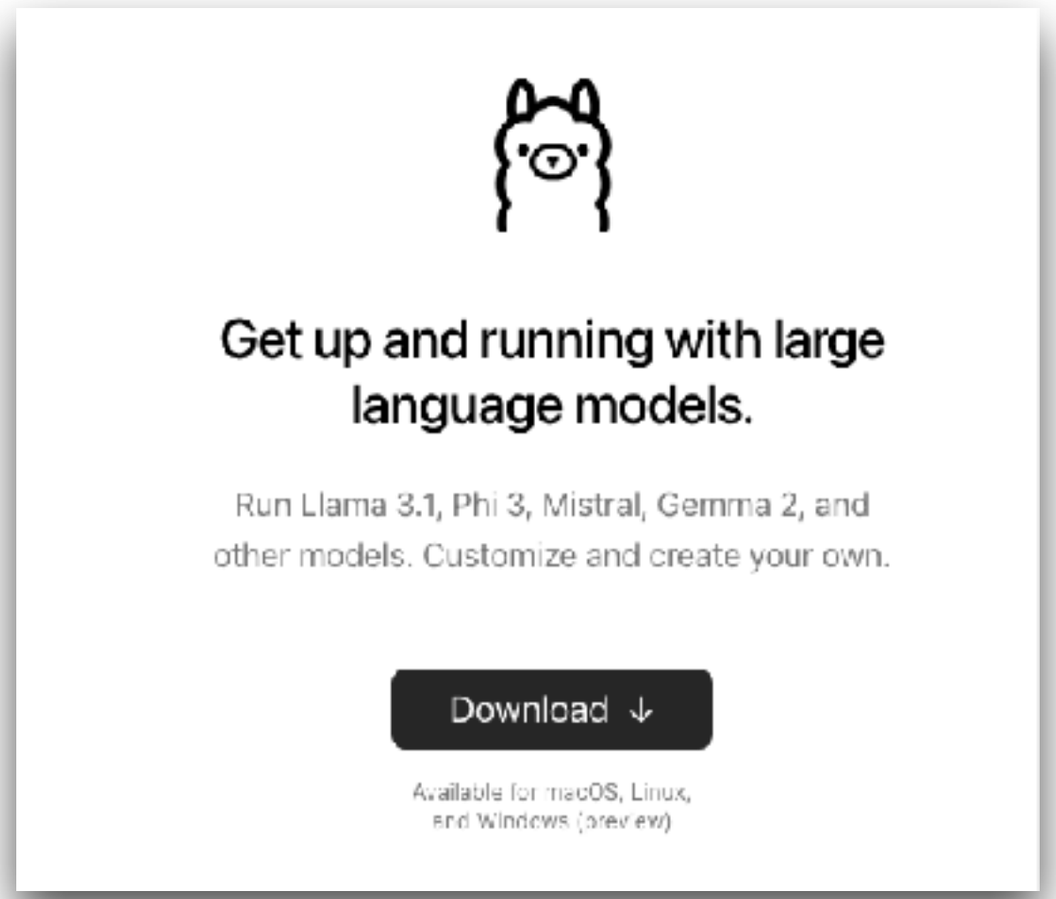
How to download models ?



Local LLM with Ollama

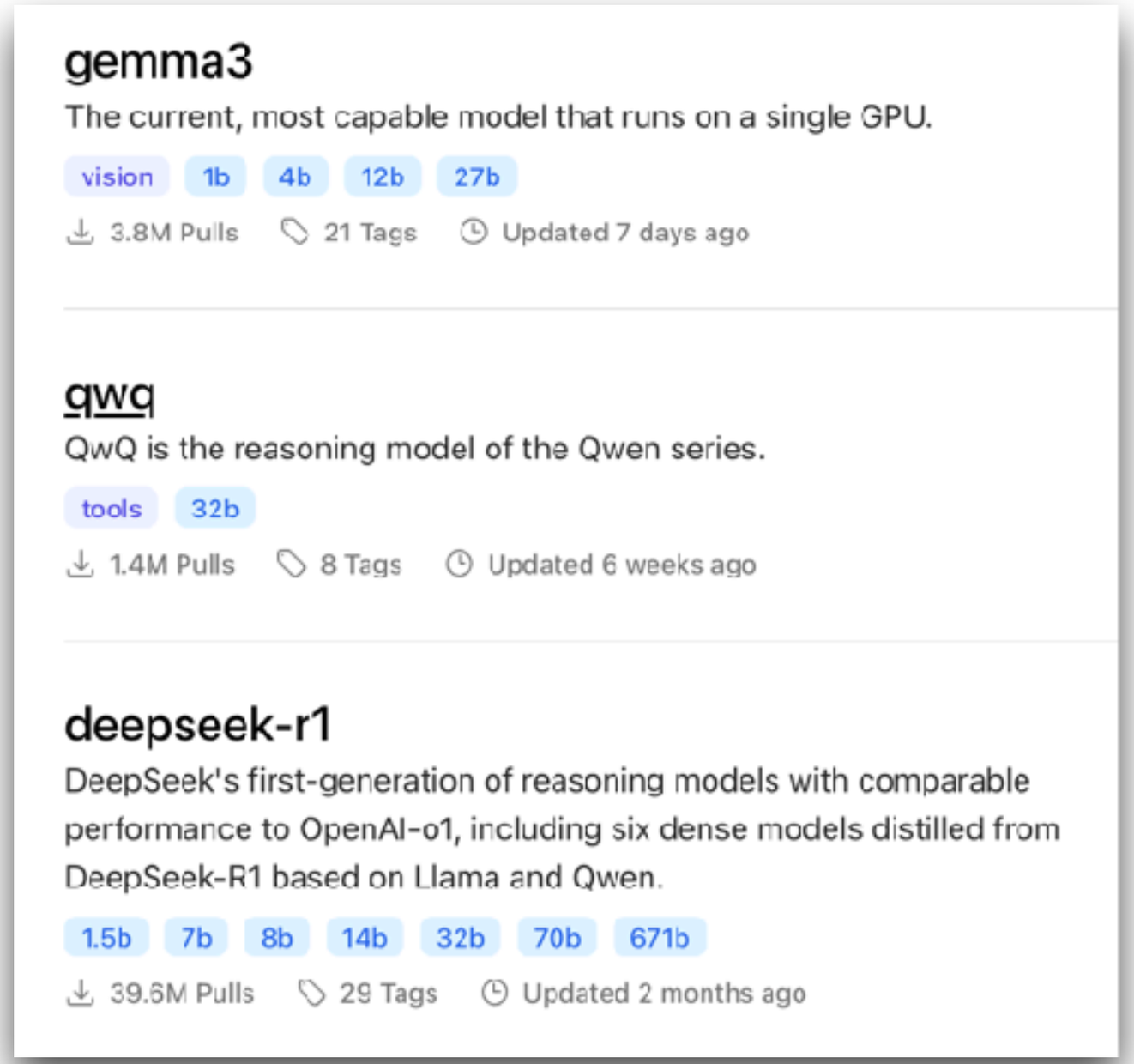
$ollama run **llama3.1**

LLM model



https://ollama.com/

Model in Ollama

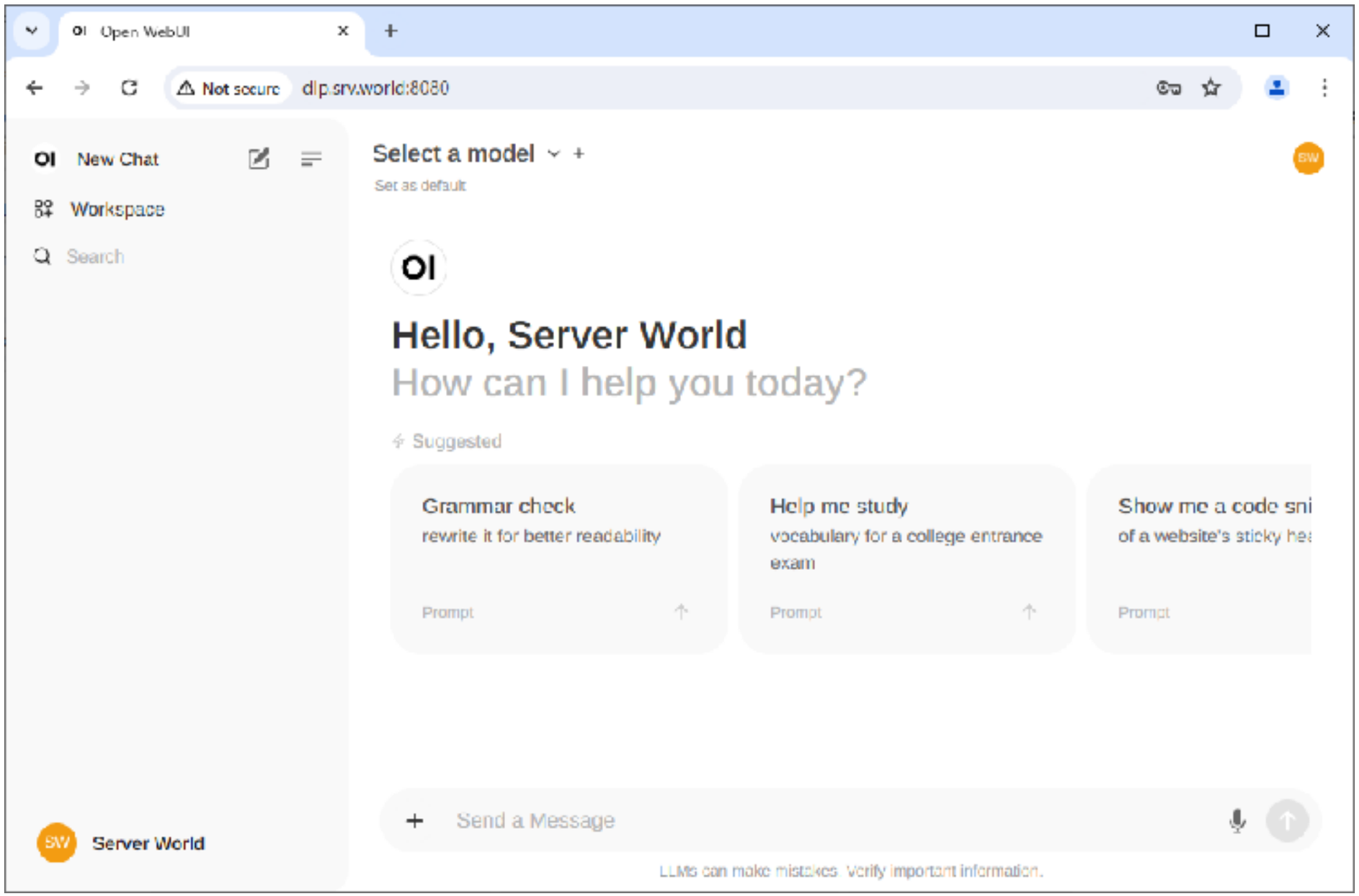


https://ollama.com/library

LiteLLM

https://www.litellm.ai/

OpenWebUI



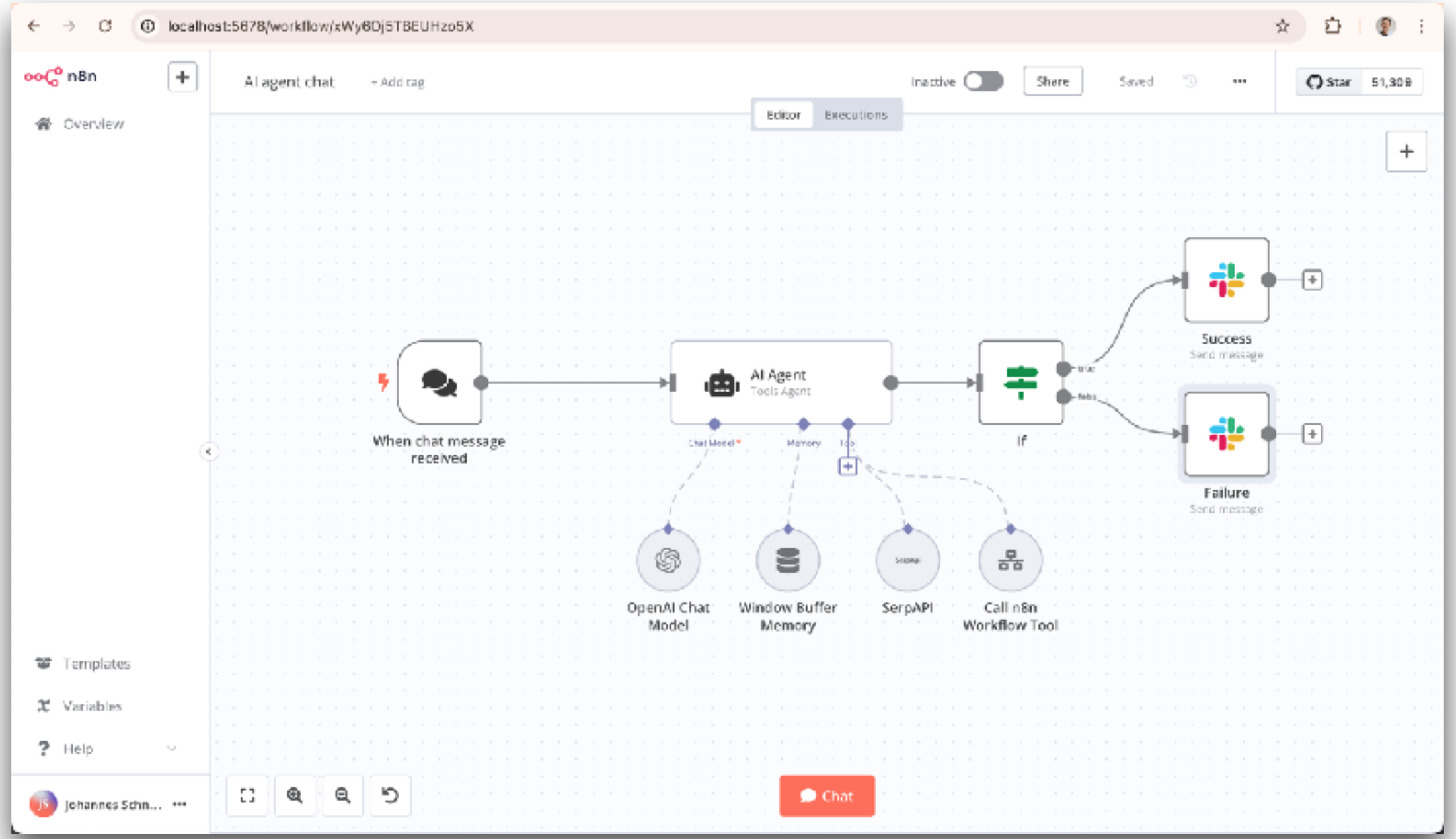
https://openwebui.com/

Working with No-Code

Prompt Flow

https://microsoft.github.io/promptflow/

N8N



https://n8n.io/

Let’s go !!