COLUMBIA+

Module 2

Programming an LLM

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LLM Programming Tools

LLMs come with support for programmers through platforms, APIs, and third party libraries

OpenAI API

Meta LLaMa 3

Google Gemini
Vertex API

What is an API?

An API allows you to:

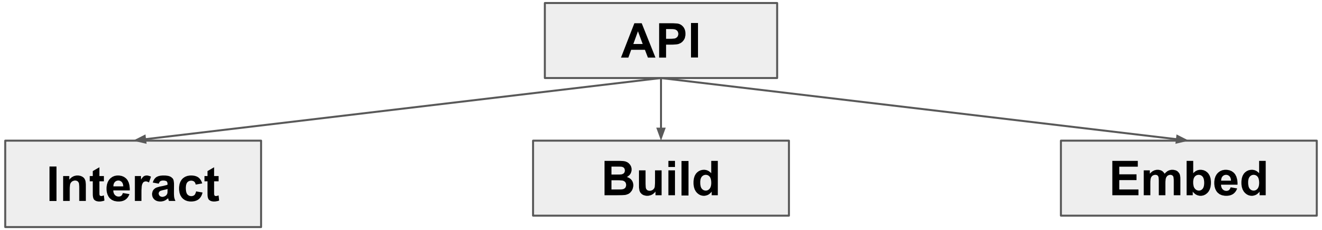
- ❏ Write complex threaded queries
- ❏ Extract relevant responses
- ❏ Build code
- ❏ Tailor an LLM to your specific domain
- ❏ Embed the LLM in your own applications

OpenAI API

The OpenAI API allows you to programmatically access various GPT models

OpenAI API Docs: https://platform.openai.com/docs/overview

OpenAI API



Interact with a GPT LLM in the same manner as ChatGPT but from inside a program

- Ask questions
- Chat with the model
- Analyze data (input data into the LLM)
- Get programming suggestions or fix code

Build a specialized version of the LLM for your own application or organization

Embed a GPT based chatbot in your own web or mobile application - seamless integration of the LLM into a broader application

OpenAI API: What You Need

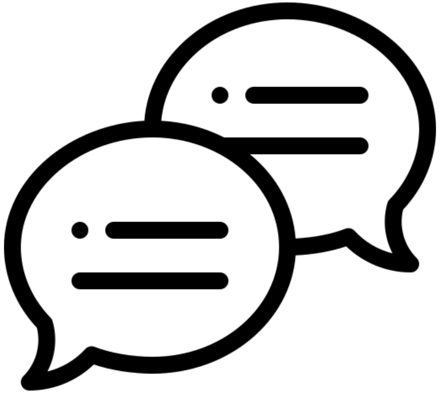
- An OpenAI account
  - https://platform.openai.com/signup
- Create a project
  - https://platform.openai.com/organization/projects
- Create a secret API key
  - https://platform.openai.com/api-keys
- Store the key in a safe place
  - The “Colab notebooks” folder on your Google Drive is probably the easiest
  - Don’t share it with anyone!

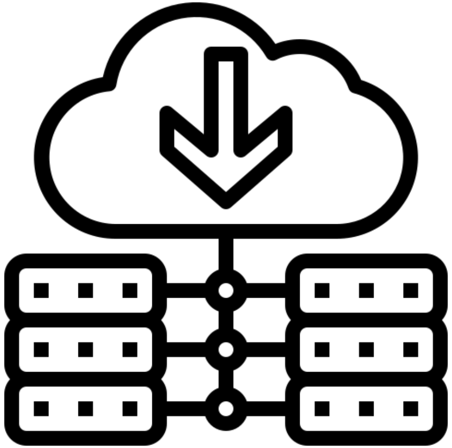
Summary

LLM Programming Tools
What is an API?
OpenAI API

OpenAI API: Using the Key

OpenAI API Notebook





Flight number: 42

Arrival time: 4:00 pm

Flight number: 42

Arrival time: 4:10pm

Examples of applications

- ❑ Customer service chatbots
- ❑ Discovering new proteins
- ❑ Symptom diagnosis
- ❑ Accessibility
- ❑ Learning history
- ❑ Document summarization
- ❑ Search engines
- ❑ Video editing
- ❑ Marketing campaigns
- ❑ Accounting

Building Custom LLMs

Human Agent vs LLM Agent - 1

A human agent

- Has some basic knowledge of the world (e.g., a college degree)
- Can converse in natural language
- Can answer general questions
- Can make deductive inferences
- But doesn’t know the internal business knowledge to answer business specific questions

An LLM agent

- Has been trained on large amounts of text data
- Can converse in natural language
- Can answer general questions
- Has some ability to make deductions as long as they have been trained on relevant information
- But doesn’t know the internal business knowledge to answer business specific questions

Human Agent vs LLM Agent - 2

- A human agent can add to knowledge

Human

By going back to school

- a graduate degree, professional certifications, etc.
- Usually requires a significant financial outlay

By being provided in-house training

- an onboarding program at an organization
- Trade subscriptions
- Usually a smaller cost

Human Agent vs LLM Agent - 3

- An LLM agent can add to knowledge

LLMs

By Being Retrained

Very expensive
(analogous to sending a human agent back to elementary school!)

Fine Tuning

- Adjusting model parameters using supervised learning
- **Expensive and time consuming** (analogous to sending a human agent to graduate school or to a professional certification program)

Retrieval Augmented Generation (RAG)

- Provide the model with specialized information and a mechanism to retrieve this information
- The model will use this specialized information and fall back to generalized knowledge if necessary
- Model parameters don’t change
- **Relatively inexpensive**

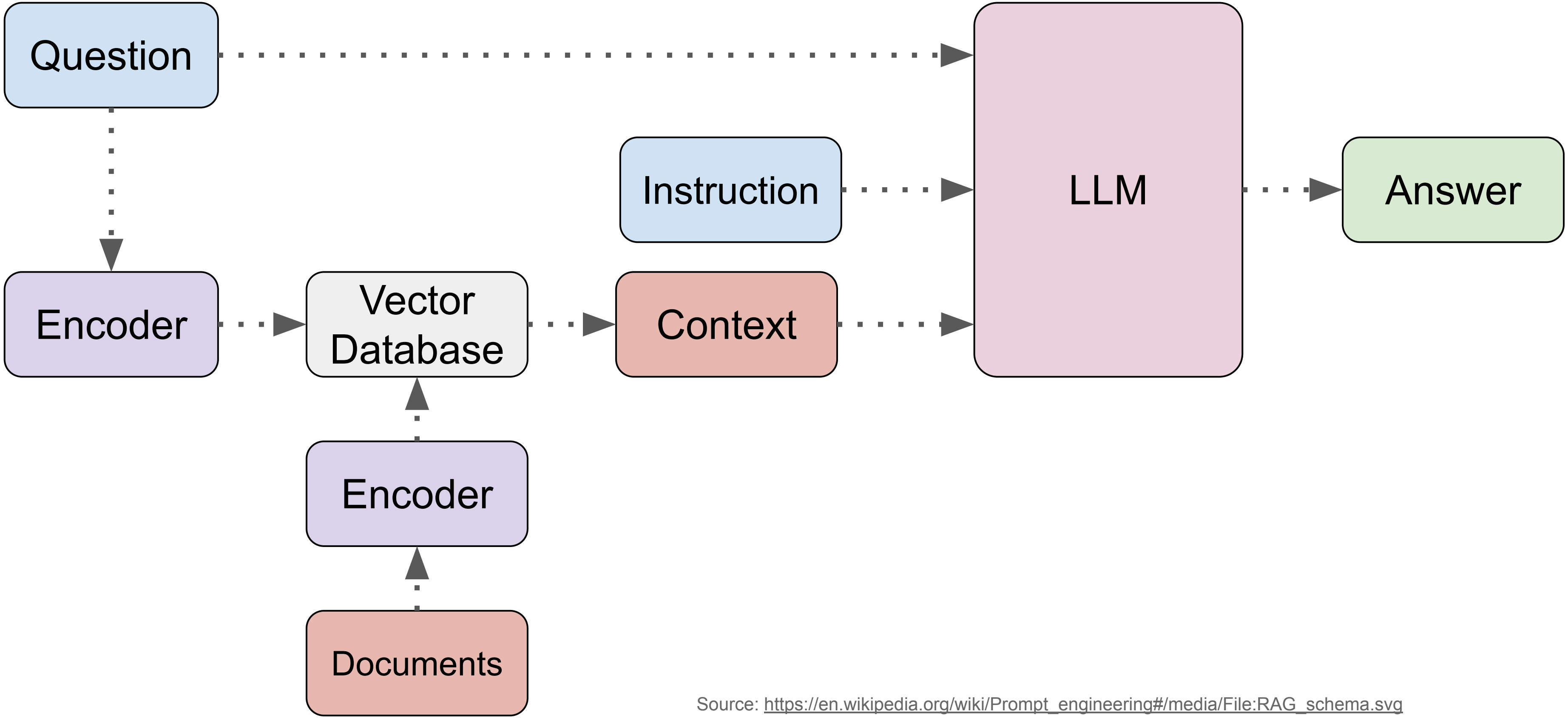
Retrieval-Augmented Generation - 1

- The LLM accesses information from an external (to its model) document repository
- It uses this document repository, as well as its trained model, to answer queries
- Roughly:
    - The documents are converted into chunks (short sequences of words)
    - The chunks are converted into embedded vectors
    - The query is converted into embedded vectors
    - The most similar document embedded vectors are chosen using a similarity algorithm
    - The LLM then uses its “language skills” to respond to the query

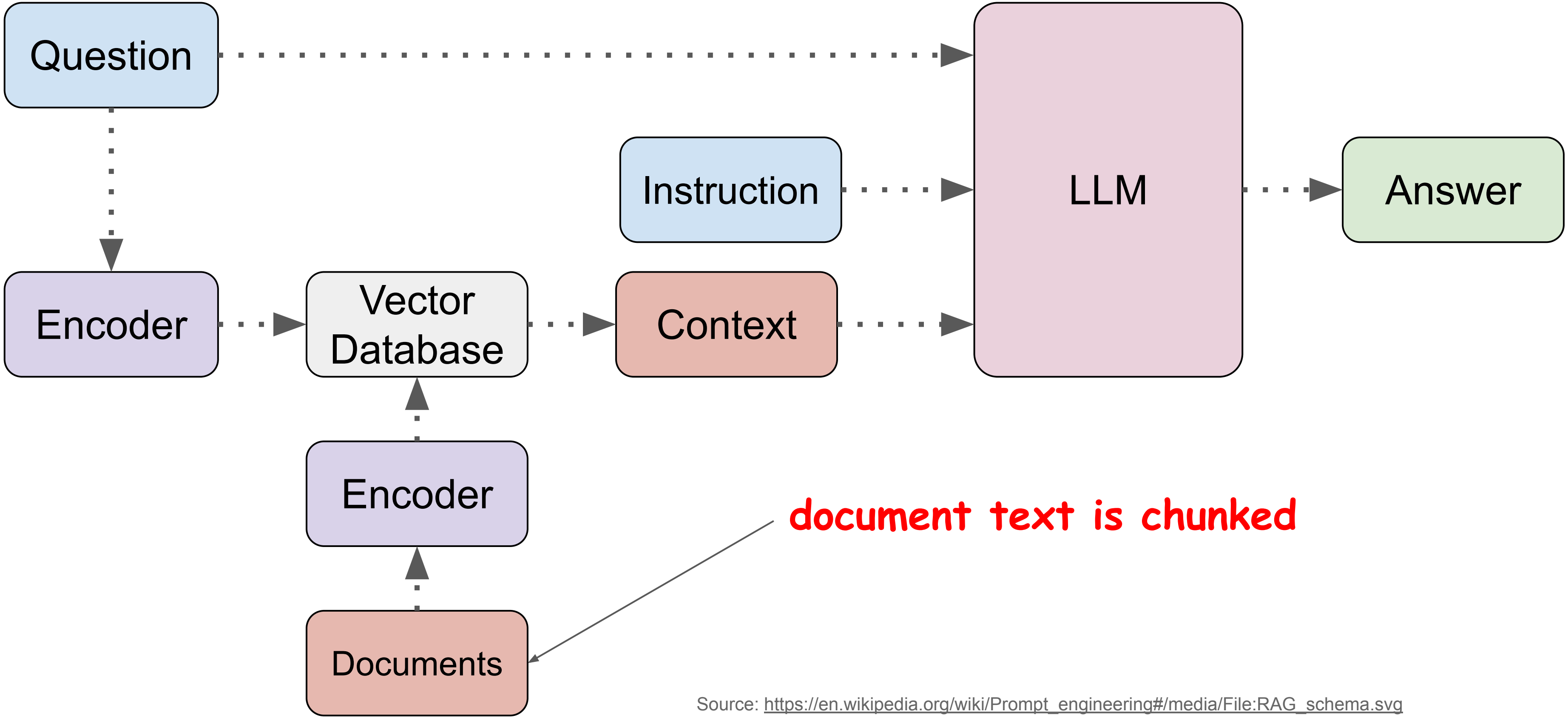
Embedding Chunked Vectors

- Since chunks are smaller groups of information
  - For example, 250 word chunks from a 10,000 word document
  - The likelihood of the “objects” in the chunks being related is high
  - Embedded vectors from these chunks will capture relationships better

Retrieval-Augmented Generation - 2



Retrieval-Augmented Generation - 3



Source: https://en.wikipedia.org/wiki/Prompt_engineering#/media/File:RAG_schema.svg
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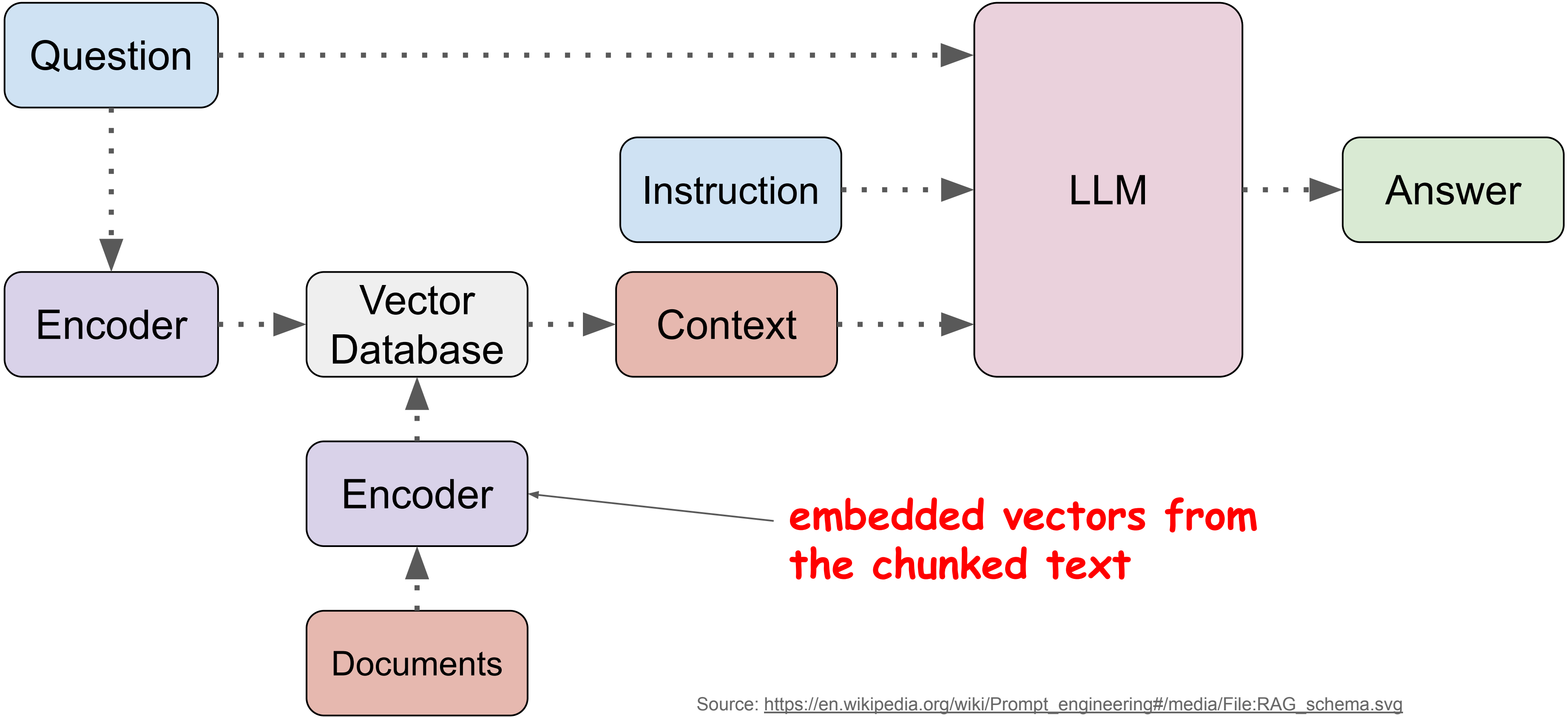
Chunking

- Text documents are large and contain a variety of information
    - A customer service agent may contain information on
        - How to return products
            - With different policies for different products
        - How to contact a human agent
        - Locations of retail stores
- Chunking increases the probability that related information is grouped

Retrieval-Augmented Generation - 4



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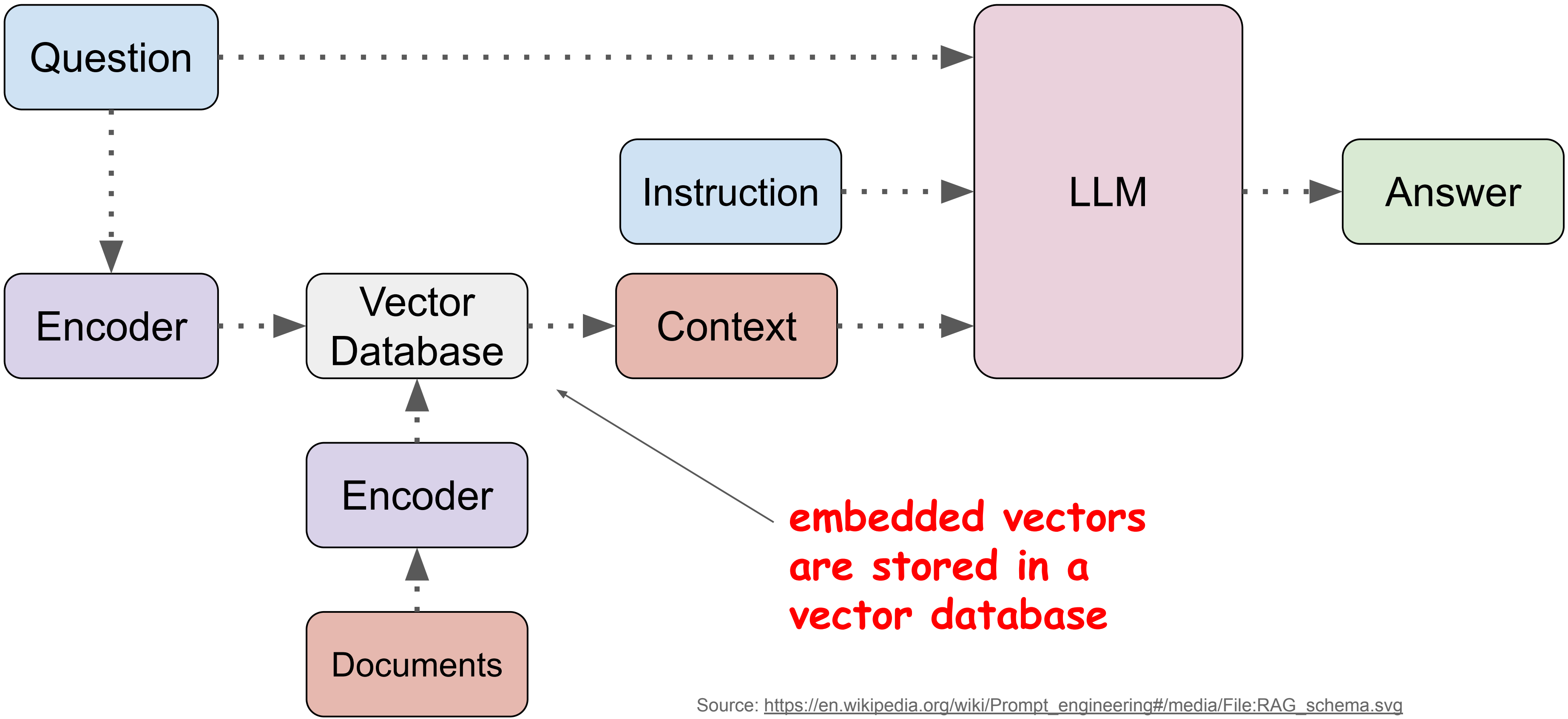
Retrieval-Augmented Generation - 5



Source: https://en.wikipedia.org/wiki/Prompt_engineering#/media/File:RAG_schema.svg

Vector Databases and Vector Search

- Indexed databases for storing vectors
- Given a vector as input, vector databases search for matching vectors using a similarity algorithm
  - Cosine similarity:
    - Calculates the cosine of the angle between two vectors
    - The smaller the angle, the closer the cosine is to 1, and the more similar the vectors
- The number of vectors is large and calculating the similarity between every pair of vectors is computationally expensive
  - The input prompt is converted into a large number of vectors
  - The document repository is converted into a large number of vectors
  - The product of the two is large

Embedding Vectors and Cosine Similarity Notebook

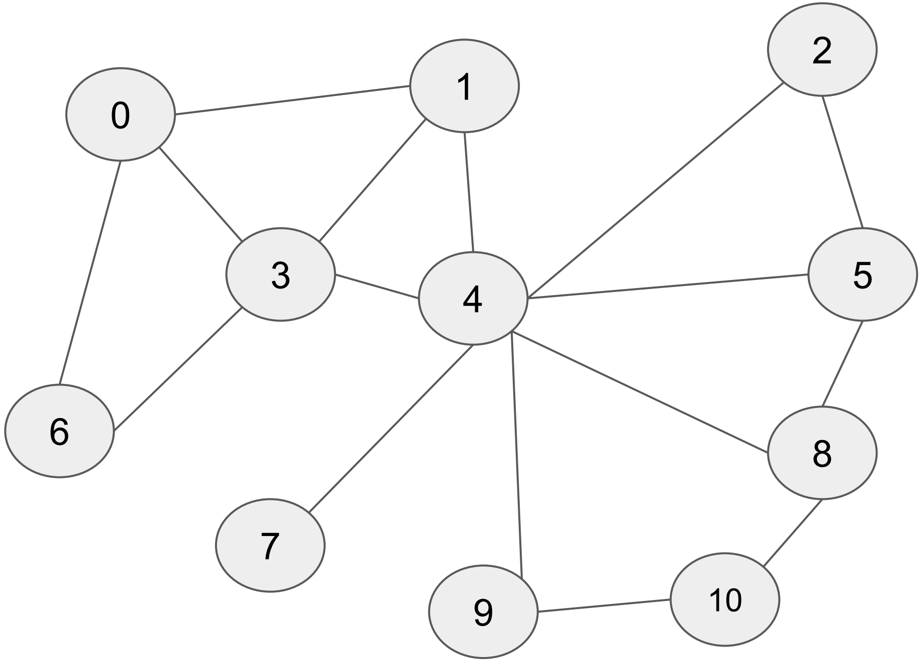
Vector Search: Retrieving Similar Vectors

Navigable Small Worlds (NSW) algorithm

- Store a pre-constructed similarity graph of document chunks
- Randomly pick a chunk and compute the similarity with the input vector
- Move to a neighbor of the chunk and recompute the similarity
- Stop when the similarity doesn’t get better
- Repeat and report the top-n similar chunks
- NSW algorithms rely on the “six degrees of separation” idea
    - The best similarity will be utmost some small n away from a random chunk

Navigable Small Worlds - 1

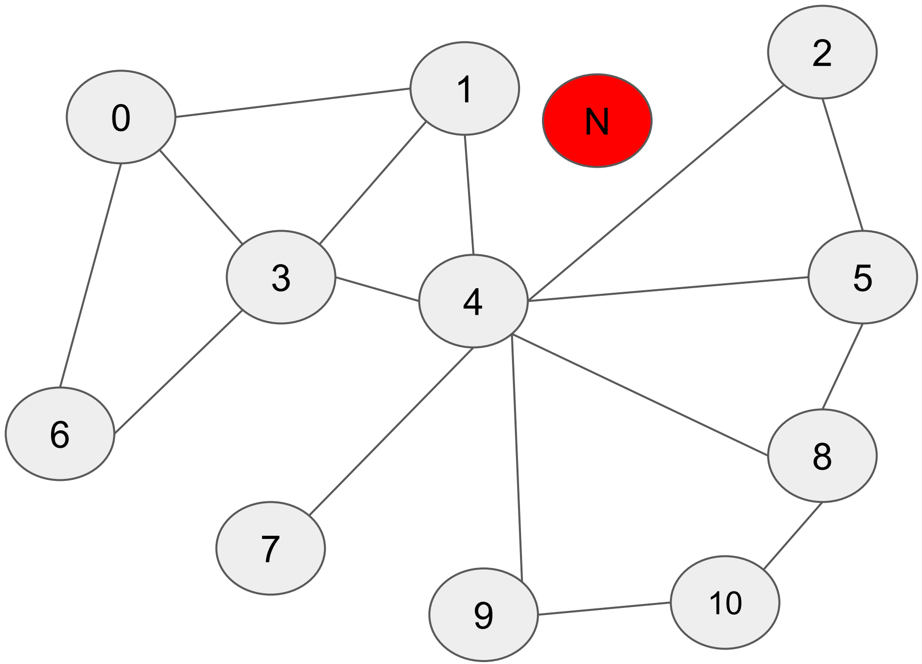
M=2



- Construct the base graph
- The parameter M specifies the number of connections a chunk makes to other chunks
- For a large number of chunks, the graph will be sparse
- The edge attribute is the inverse of cosine similarity

Navigable Small Worlds - 2

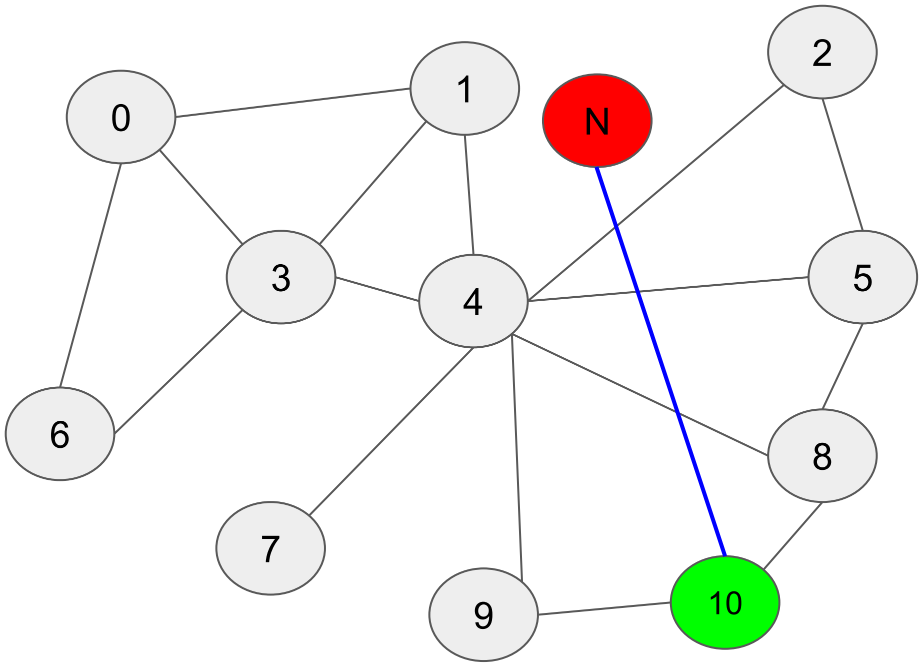
M=2



- A new chunk (from the LLM prompt) arrives
- And is inserted into the graph

Navigable Small Worlds - 3

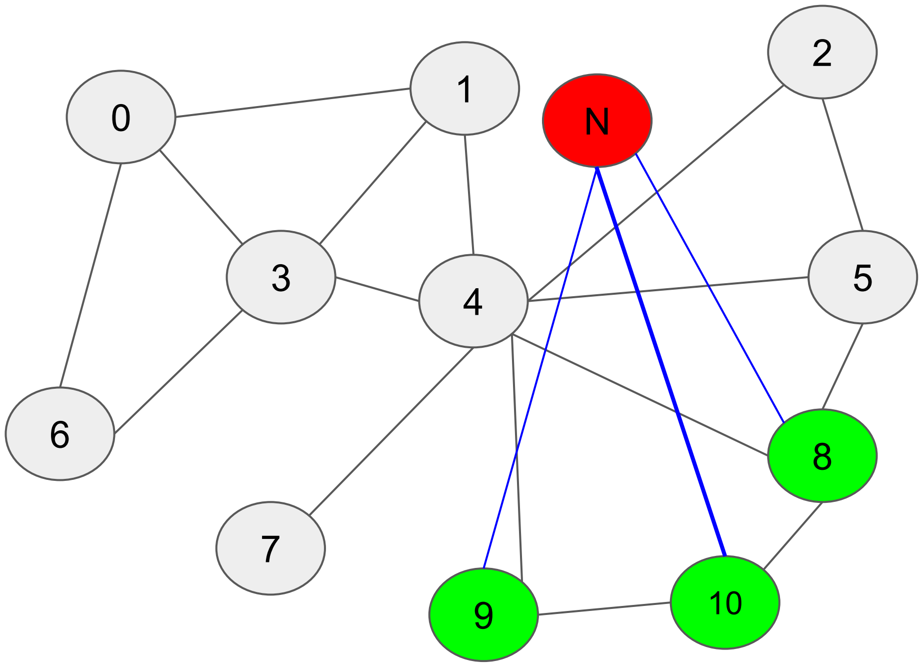
M=2



- Choose a random chunk (e.g., 10)
- And calculate the distance
    - add a new edge between 10 and N

Navigable Small Worlds - 4

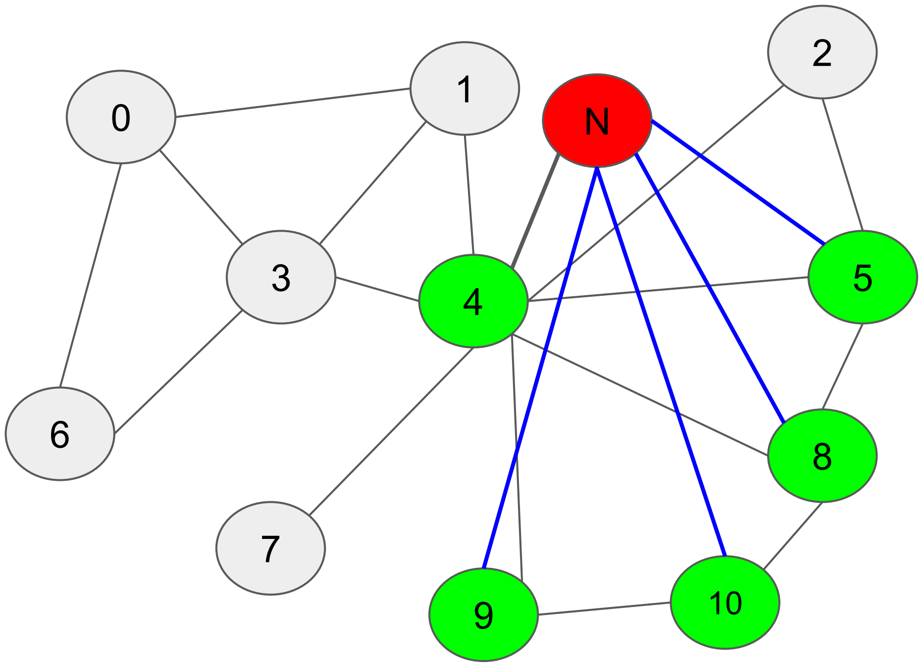
M=2



- Check distance (similarity) from two neighbors
- And calculate the distance
    - add new edges from 9 and 8 to N

Navigable Small Worlds - 5

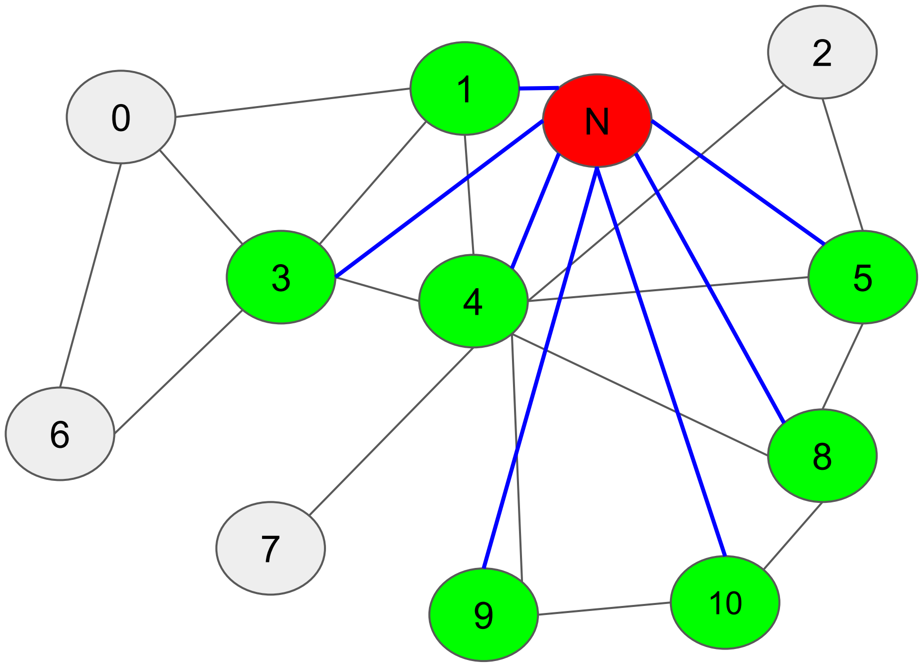
M=2



- 8 is closer
- Calculate distance from 4 and 5 to N

Navigable Small Worlds - 6

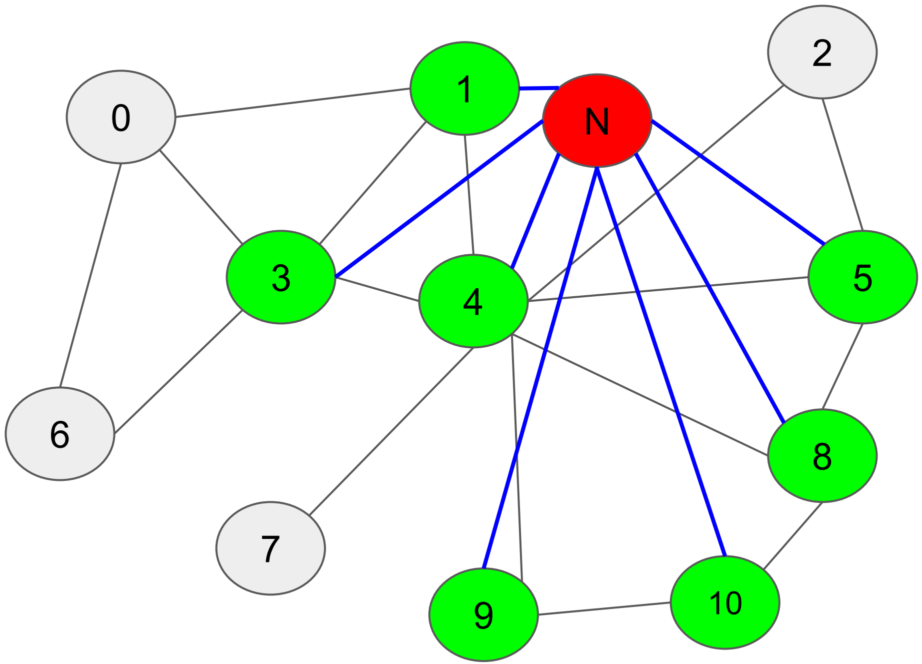
M=2



- 4 is closer
- Calculate distance from 1 and 3 to N

Navigable Small Worlds - 7

M=2

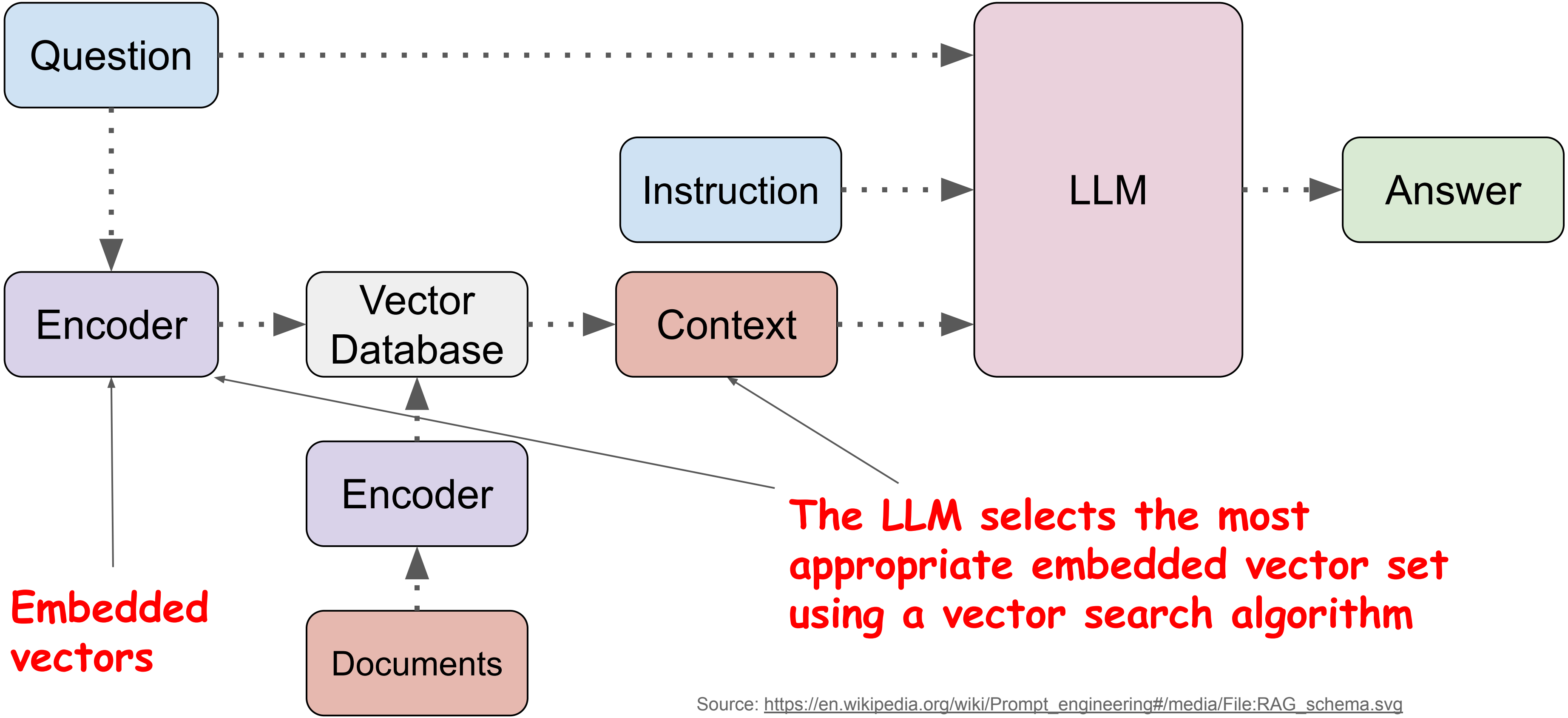


- 1 is closer
- Calculate distance from 0 and 3 to N
- Since neither 0 nor 3 is closer than 1, stop. 1 is the closest chunk

Vector Search: Retrieving Vectors

- Hierarchical Navigable Small Worlds (HNSW) algorithm
  - Adaptation of NSW but the pre-constructed graph is hierarchical with a small number of starting chunks with subsequent chunks arranged in a hierarchy
  - The algorithm picks a random chunk from the top level and then searches in that hierarchy
  - Using the NSW algorithm at each level
  - Facebook AI Search Similarity (FAISS) is a commonly used HNSW implementation and you will see it used later in this course
- Constructing the hierarchy and the base network is the hard part of HNSW
- We won't look at it in detail here but, if you're interested:
  - https://www.datastax.com/guides/hierarchical-navigable-small-worlds

Retrieval-Augmented Generation - 6



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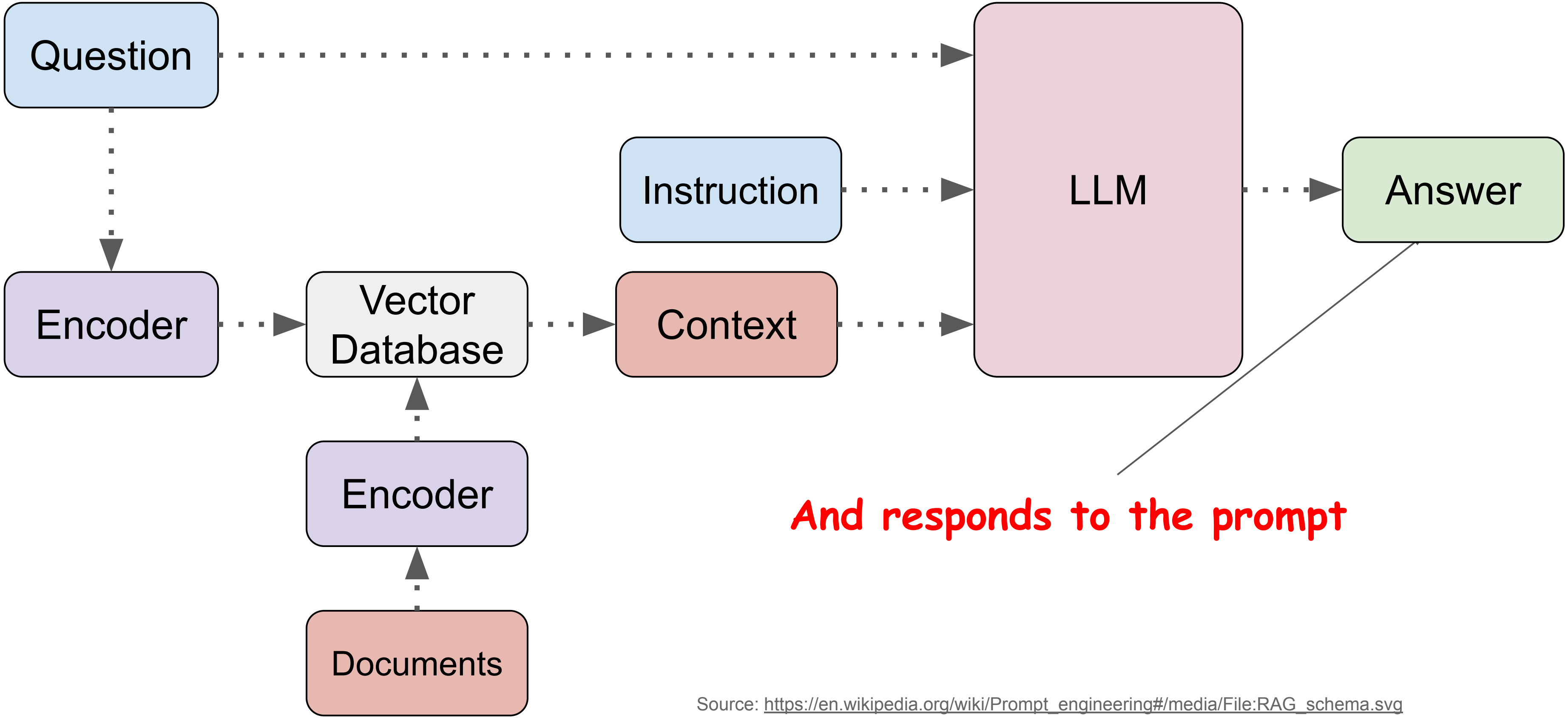
Retrieval-Augmented Generation - 7



And responds to the prompt

Source: https://en.wikipedia.org/wiki/Prompt_engineering#/media/File:RAG_schema.svg

RAG Example Notebook (Xilin)

Knowledge Graphs

- A knowledge graph is a data model that uses a graph to organize and represent domain knowledge in the form of entities and relationships
- Knowledge graphs have a formal semantics for
  - Storing knowledge (entities, relationships)
  - Retrieving knowledge (knowledge searching)

Knowledge Graph: Example

Fine Tuning an LLM

Fine Tuning an LLM

- When custom data is added to an LLM using RAG, the model itself is not updated
  - All the parameters stay the same
  - Vectors representing the new knowledge are computed and stored in a database
  - The LLM retrieves these vectors (i.e., the specific data chunks) and combines it with its model (the LLM network parameters) to figure out the output
  - The LLM itself is unchanged
- In fine tuning
  - The model is updated with new parameters
  - You get, in essence, a new LLM
- When fine tuning, you need to go through all the steps in the machine learning process

Fine Tuning: Broad Steps

- Gather data: The quality of the data is the most important input into a model. Data should be representative of the domain you are customizing on; should be sufficient in quantity
- Preprocessing and feature engineering
  - Clean the data
  - Create appropriate features
- Split into training/validation/testing sets: Fine tuning changes model parameters and you need to ensure that the model is learning “correctly”
- Fine tune the model
- Test the fine tuned model

Supervised Fine Tuning: Process

Supervised fine tuning

- The pre-trained LLM is given specific labeled examples
    - A prompt
        - *How can I return my LCD TV?*
    - A response
        - *To return your LED TV, ensure it is in its original packaging and includes all accessories. Returns are accepted within 30 days of purchase. A restocking fee of 15% may apply.*
- The prompt is used to generate a response
        - Example: A generic response on returns
- The generated response is compared with the labeled response
- Weights are adjusted to account for the error
- The process is repeated

Supervised Fine Tuning: Advantages and Disadvantages

- Advantages:
  - Lower processing and memory requirements than full retraining
  - Fall back to pre-trained model is more seamless (compared to RAG)
  - Adapts to the specific domain (like RAG)
- Disadvantages:
  - Model weights are changed and this may compromise the reliability of the LLM for non-domain questions
  - Overfitting: This is a big danger since the model weights are changed. General queries may still give a domain specific response even where they are not suitable
  - Data issues: Data has to be reconstituted in a prompt response format and this may not be practical
    - For example, many different forms of the LCD TV prompt need to prepared
    - And this has to be repeated for all possible prompt/response pairs

Instruction Tuning

- In instruction tuning, the pre-trained LLM is provided with an instruction and given a response
  - Instruction: Translate *I love you* into Italian
  - Response: te amo
- Typical use cases:
  - Language translation
  - Multiple choice tests
- Instruction fine tuning works like supervised fine tuning (the model is updated) but is used
  - when there is insufficient labeled data
  - When the response is well defined

Parameter Efficient Fine Tuning (PEFT)

- Supervised fine tuning and instruction fine tuning update the entire model
- Since an LLM is huge (trillions of parameters), these methods are relatively resource intensive
  - Though less intensive than a complete retraining!
- Parameter efficient fine tuning focuses on updating a small part (subset) of the model
  - Can work with less data (since the training is focused)
  - More efficient (since only a small subset of the model is being changed)
  - Less likely to be overfitted (since the LLM is largely unchanged)
  - However, not as reliable (since only a small subset of the LLM is retrained)
- PEFT is mostly used when
  - Resources are limited
  - Data availability is limited

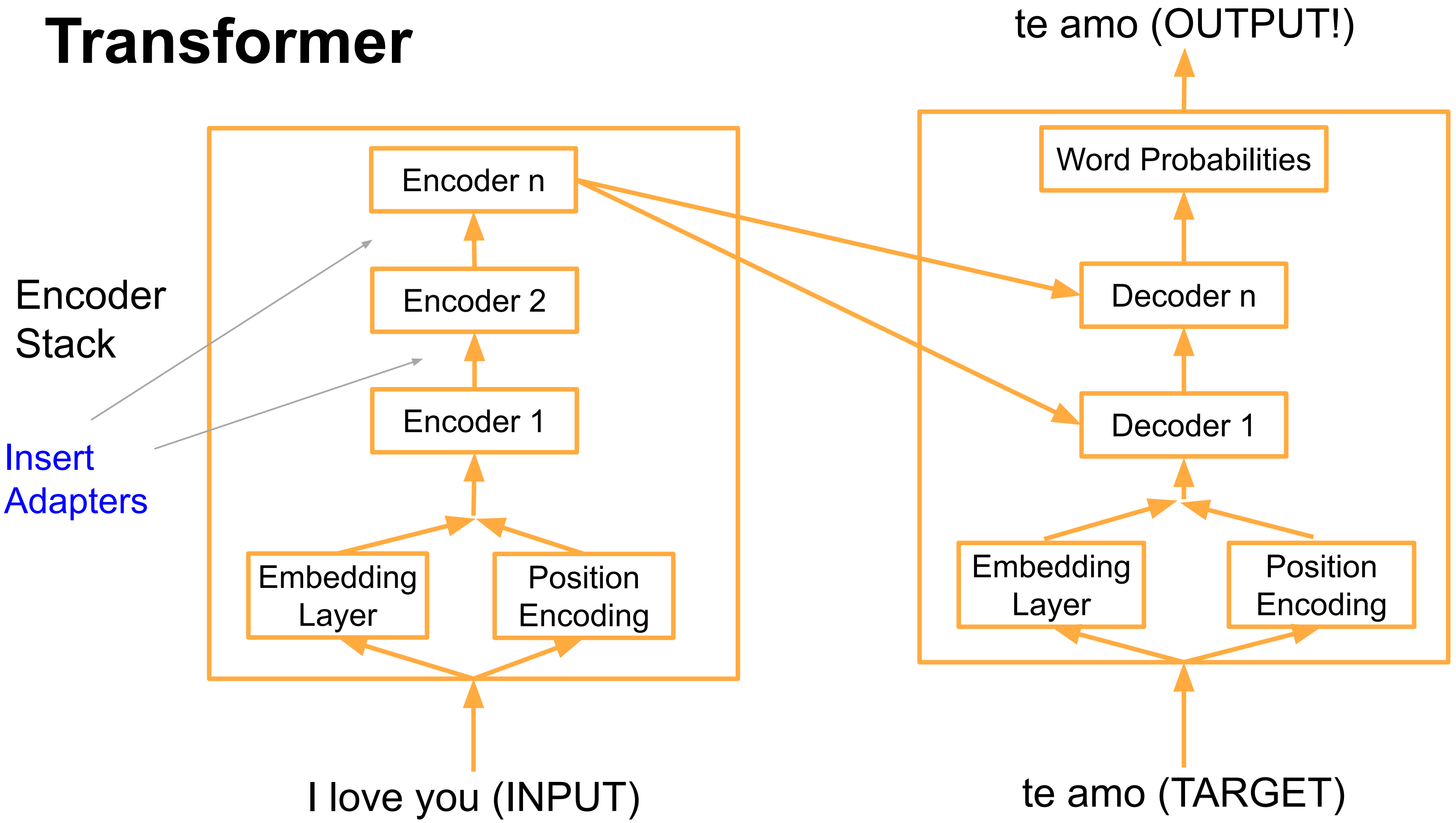
Types of Parameter Efficient Fine Tuning

- Adapters
- Low rank adaption (LORA) and Quantized Low Rank Adaption (QLORA)
- Infused Adapter by Inhibiting and Amplifying Inner Activations (IA3)
- Layer freezing
- Prefix tuning
- Prompt tuning

Adapters

- Adapters are new submodules that are inserted into the transformer architecture
- With each training case (labeled) only the weights in the adapter modules are updated
- The original pre-trained LLM weights are not changed
- Since the adapters are relatively small (few weights) the resources required are relatively low

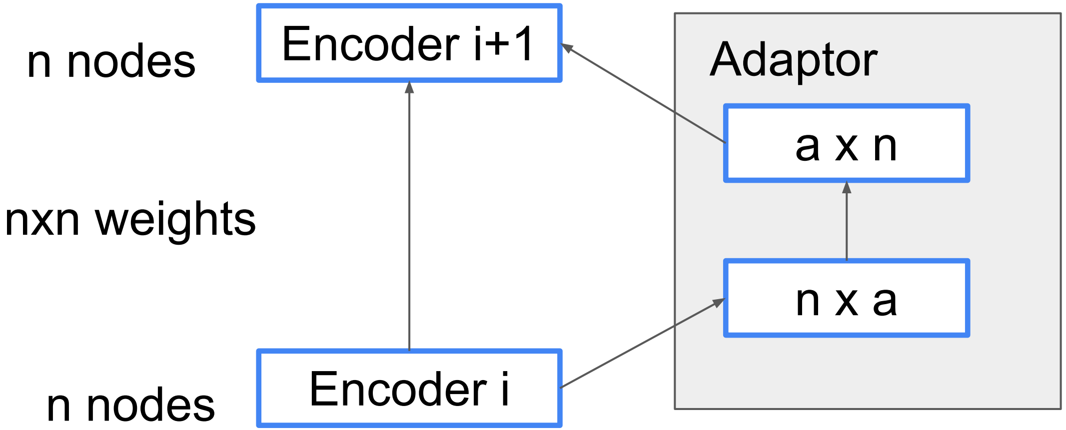
Transformer



LORA: Low Rank Adaptation

- In between any two layers of a transformer, there are n x n weights
- LORA keeps two smaller matrices
  - n x a and a x n, where a << n
- As each case is passed through the transformer
  - The change in weights is computed
  - A lower dimension approximation of this change is used to update the weights in the LORA adaptor
  - The original weights are unchanged
- The main advantage is the reduced memory and processing requirement
  - The LORA adaptor is many (many!) orders of magnitude smaller than the pre-trained LLM

LORA Adaptor



a << n

IA3

- IA3 is structurally similar to LORA
- But, the low rank vectors are directly learned rather than computed from the weight changes of the original model
- This makes IA3 faster and more memory efficient than LORA

Layer Freezing

- Roughly
  - The early layers in a model are more general
    - Language elements
    - General knowledge
  - Later layers are more specialized
    - Domain specific knowledge
    - Derived knowledge
    - How to knowledge (classify, summarize, translate, etc.)
- Layer freezing attempts to freeze early layers and update weights only in later layers when fine tuning a model
- Models can be trained to figure out which layers (or parameters) need to be updated (beyond the scope of our class!)

Prefix Tuning

- A vector is prepended to the model, before the input
- The purpose of the vector is to provide an operational context to the LLM
- For example:
  - A prefix vector may guide the model to produce a summary of the input
  - A prefix vector may guide the model to produce a translation of the input
  - A prefix vector may guide the model to set the context to Olympics
  - A prefix vector may guide the model to set the context to the presidential elections
- Advantages and disadvantages
  - Very memory efficient (a vector) and fast training (only the prefix vector is updated)
  - Limited use since it is setting a context rather than building new information into the LLM

Prompt Tuning

- The same prompt can be written in many different ways
  - How do I return my LCD TV
  - I bought an LCD TV from your store and now realize it is too big for the space and want to return it. What should I do?
- The above two examples ask the same question but in different ways
- In prompt tuning, a preprocessing layer that is trained with sample prompts is inserted between the input and the model
  - The preprocessing layer adds a set of embeddings to the prompt
  - These embeddings direct the prompt (sort of) toward a standard prompt
  - In the two examples above, both prompts will be directed toward the same question
- No new knowledge is added but the model can be guided toward a specific purpose

Fine Tuning Example

How to create an Open AI API Key

Screenshots or b-roll

https://whatsthebigdata.com/how-to-get-openai-api-key/