Building Text-Based Applications with the ChatGPT API & LangChain

O'REILLY®

How to build LLM apps

Lucas Soares

21-08-2023

Intro

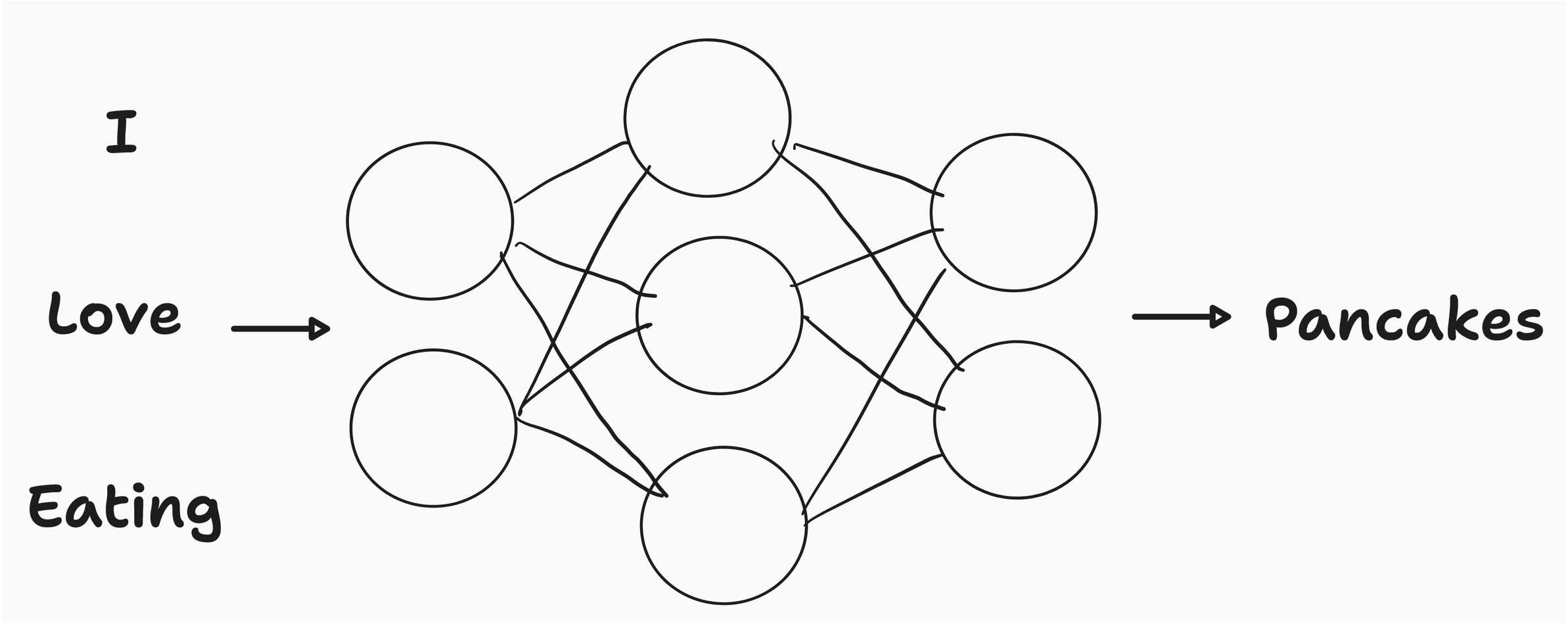
Hi!

- Me!
- Quick Survey to get to know everyone!

Quick Survey to get to know everyone!

Large Language Models

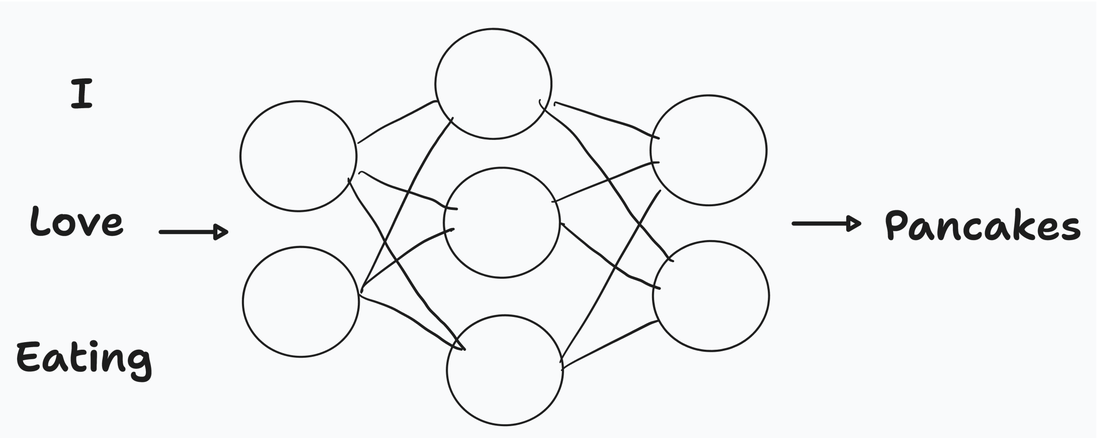
A definition



Large Language Models

As Probability Distributions

At their core, LLMs can be seen as distributions over words.



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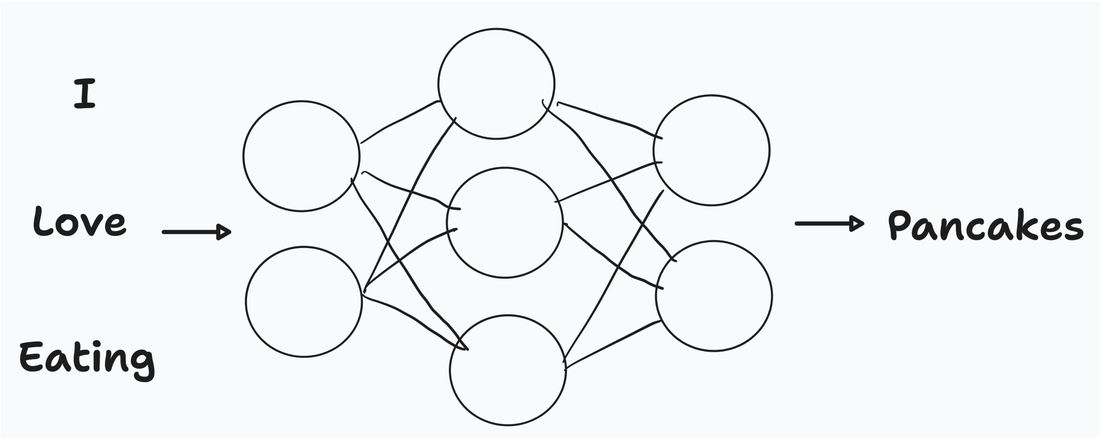
- Use statistical models to capture patterns in text data.



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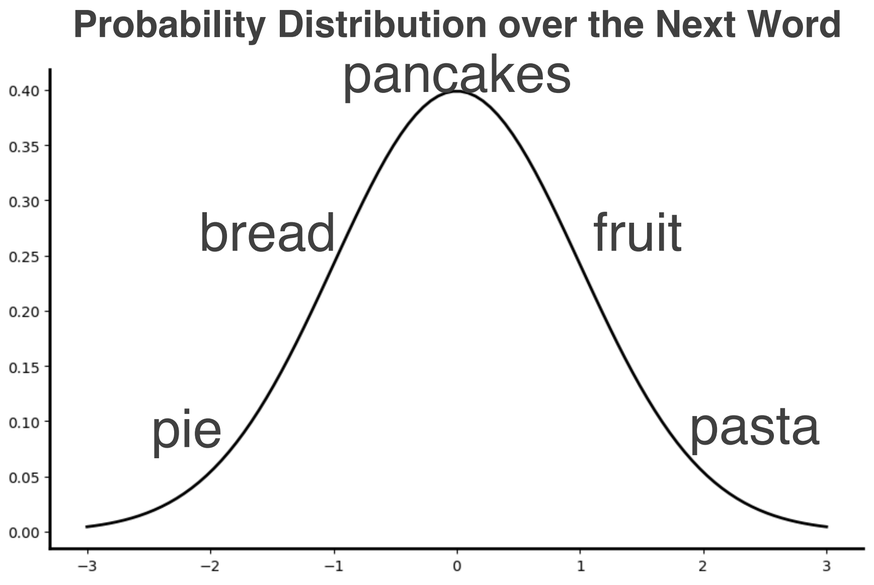
- They calculate the likelihood of each word occurring given the context.



"I love eating…." → ?

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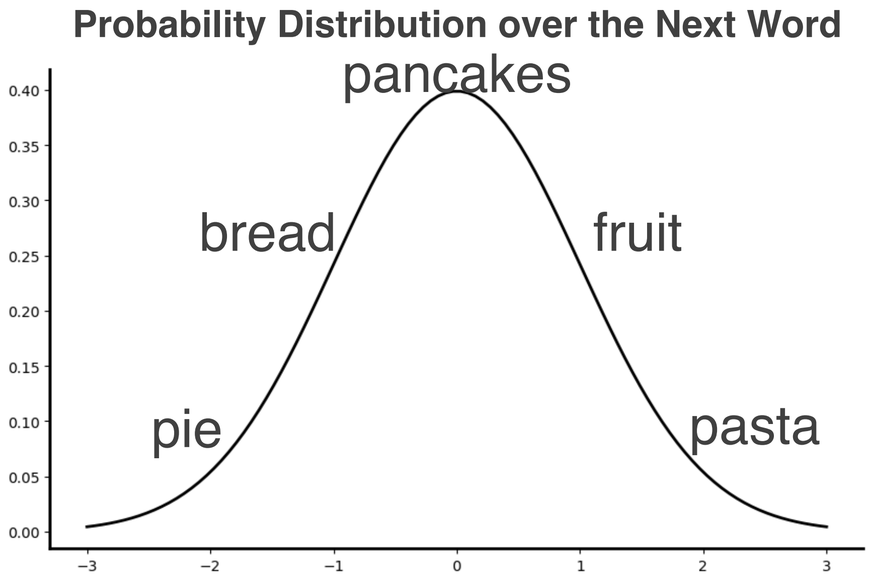


"I love eating…." → ?

Large Language Models

N-gram models

- **Unigram model**: each token/word is independently modeled.

Large Language Models

N-gram models

- **Unigram model**: each token/word is independently modeled.
- Sentence S = *"When the bough breaks, the cradle will fall."*

Unigram Word Probabilities

p = 0.86	p = 0.93	p = 0.22	p = 0.66	p = 0.66	p = 0.37	p = 0.15	p = 0.1
When	the	bough	breaks	the	cradle	will	fall

Large Language Models

N-gram models

```python
import random
sentence = "When the bough breaks the craddle will fall"

tokens = sentence.split(" ")
# First, the token_probs list is created with random values
token_probs = [random.random() for _ in tokens]
# Then, the probabilities dictionary is created
# The dictionary has keys of the form 'word1 word2', where 'word1' and
'word2' are consecutive words in the sentence
# The value for each key is the conditional probability of 'word2' given
'word1'
probabilities = {}
for i in range(len(tokens)):
    if tokens[i] in probabilities.keys():
        probabilities[f"{str(tokens[i])+'-2'}"] = round(token_probs[i],2)
    else:
        probabilities[f"{tokens[i]}"] = round(token_probs[i],2)
probabilities
```

Unigram Word Probabilities

p = 0.86	p = 0.93	p = 0.22	p = 0.66	p = 0.66	p = 0.37	p = 0.15	p = 0.1
When	the	bough	breaks	the	cradle	will	fall

$$P(S) = P(\text{"When"}) \times P(\text{"the"}) \times P(\text{"bough"}) \times P(\text{"breaks"}) \times P(\text{"the"}) \times P(\text{"cradle"}) \times P(\text{"will"}) \times P(\text{"fall"})$$

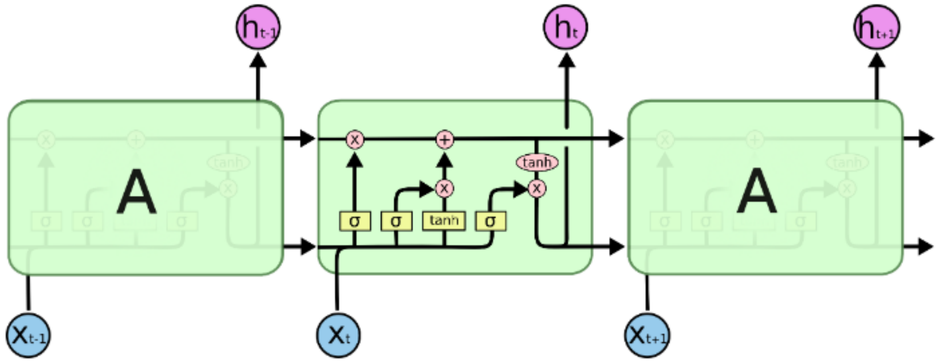
The probability of the sentence is the product of the individual probabilities:

Large Language Models

Sequence to Sequence Models: LSTMs

LSTMs, forgetting mechanism to model longer sentences and maintain context.

(Hochreiter and Jürgen Schmidhuber 1997)

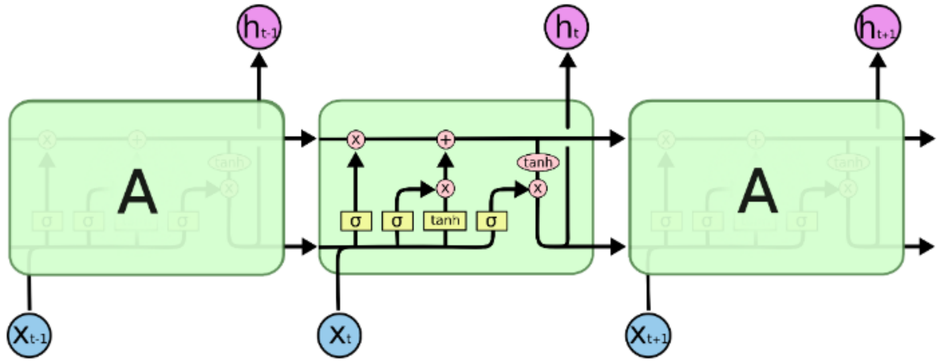


Understanding LSTM Networks by Christopher Olah

Large Language Models

Sequence to Sequence Models: LSTMs

- **LSTMs**, forgetting mechanism to model longer sentences and maintain context.
  (Hochreiter and Jürgen Schmidhuber 1997)
- The probability of the sentence now is influenced by context



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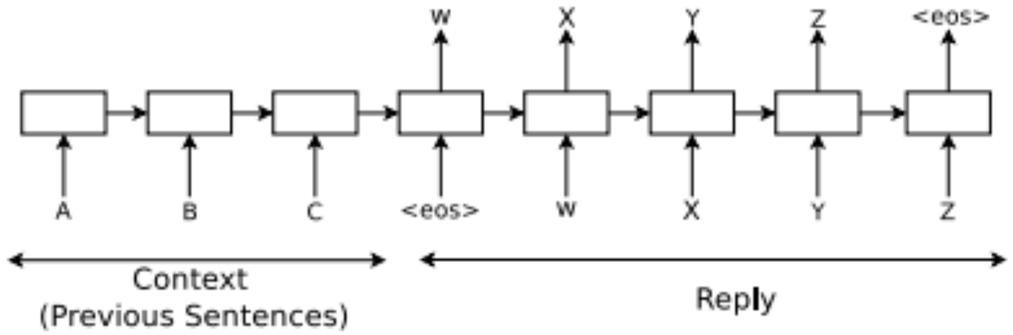
Large Language Models

Sequence to Sequence Models: LSTMs

Seq2Seq models require **processing input sequentially**

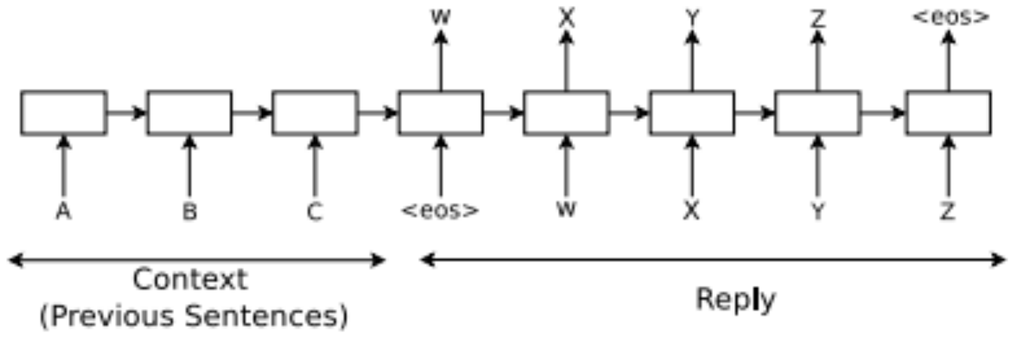


(Vinyals & Le, 2015)

Large Language Models

Sequence to Sequence Models: LSTMs

- **Seq2Seq** models require **processing input sequentially**
- Struggle with really long complex inputs



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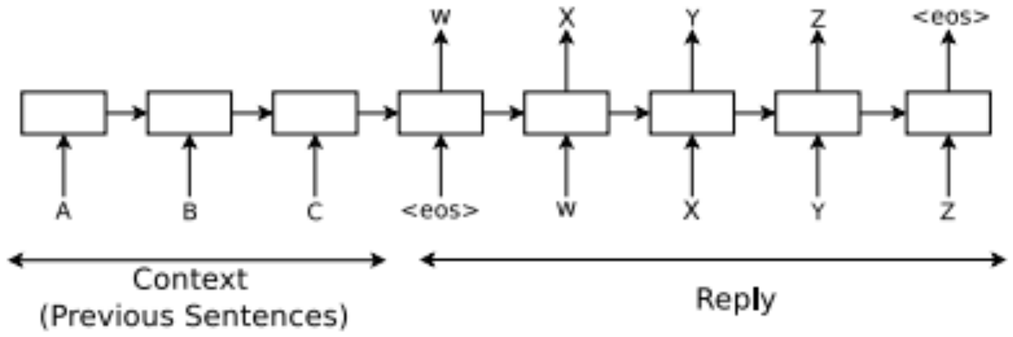

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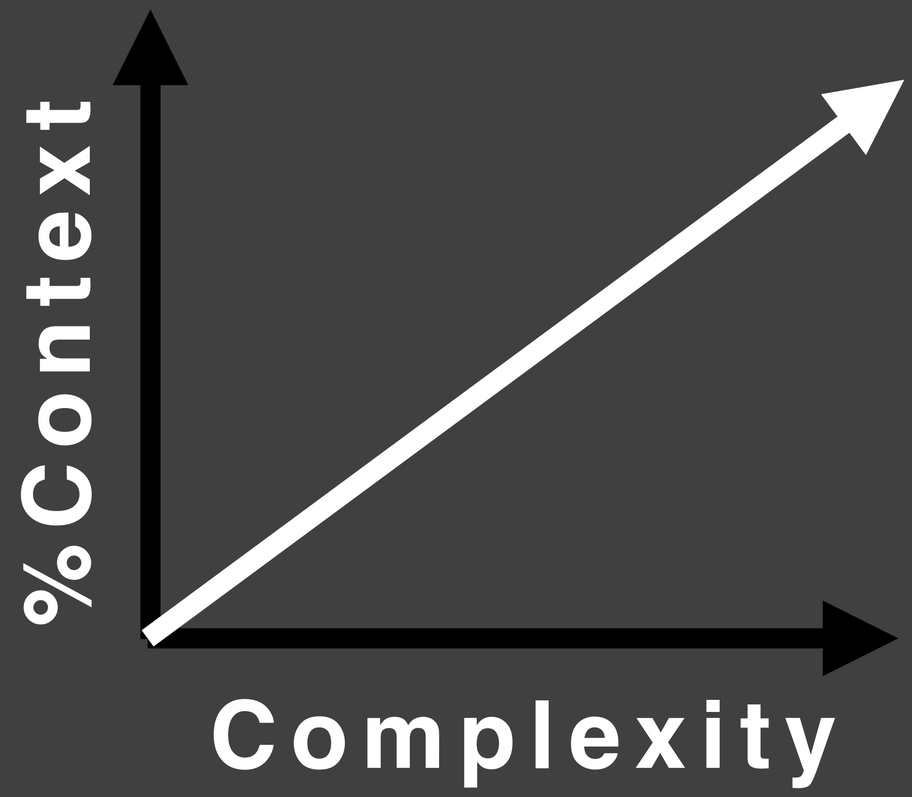
Can't capture really long contexts!


%Context
Complexity

They capture context, understand dependencies, and predict text based on patterns learned during training.

Ok, but how?

LLMs as pattern matchers

LLMs are akin to probabilistic programs.

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```python
import numpy as np

def llm_model(context, next_word):
    possible_next_words = ["text", "pie", "pizza", "motor", "cake"]
    next_word_probs = [0.2, 0.3, 0.4, 0.001, 0.6]
    return next_word_probs[possible_next_words.index(next_word)]

context  = ["This", "is", "a", "piece", "of"]
possible_next_words = ["text", "pie", "pizza", "motor", "cake"]
probs = []
for w in possible_next_words:
    probs.append(llm_model(context, w))

next_word = possible_next_words[np.argmax(probs)]
next_wor
```


Context/Past
LM
Future

How LLMs work

Transformers Architecture

- Traditional sequential models struggle with context (Vaswani et al 2017)

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- Transformers use attention mechanisms to capture global dependencies, enabling contextual understanding. (Vaswani et al 2017)
- The attention mechanism allows Transformers to focus on different parts of input simultaneously. (Vaswani et al 2017)
- Transformers can understand and predict based on long-range dependencies. (Vaswani et al 2017)

How LLMs work

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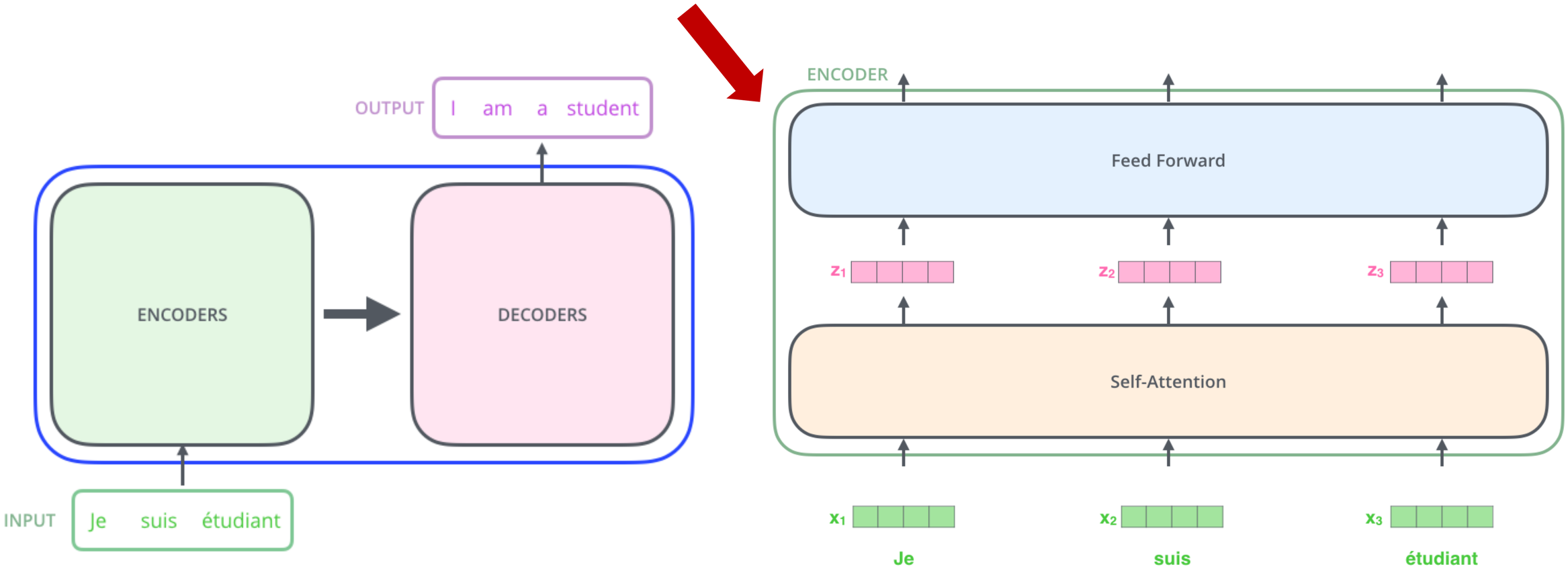
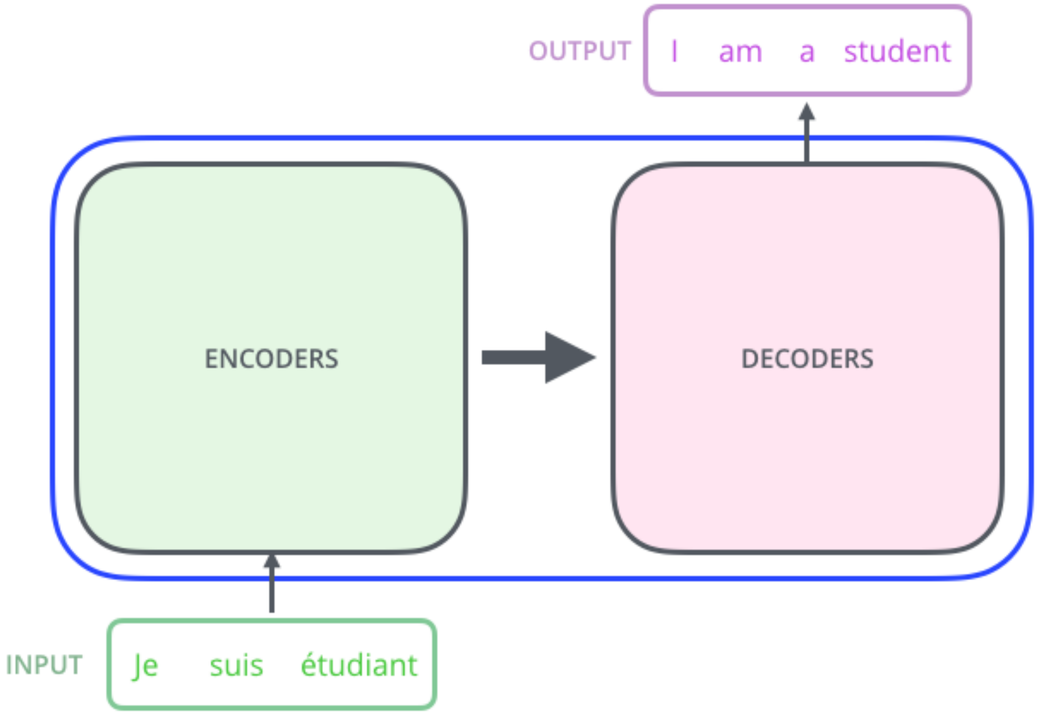
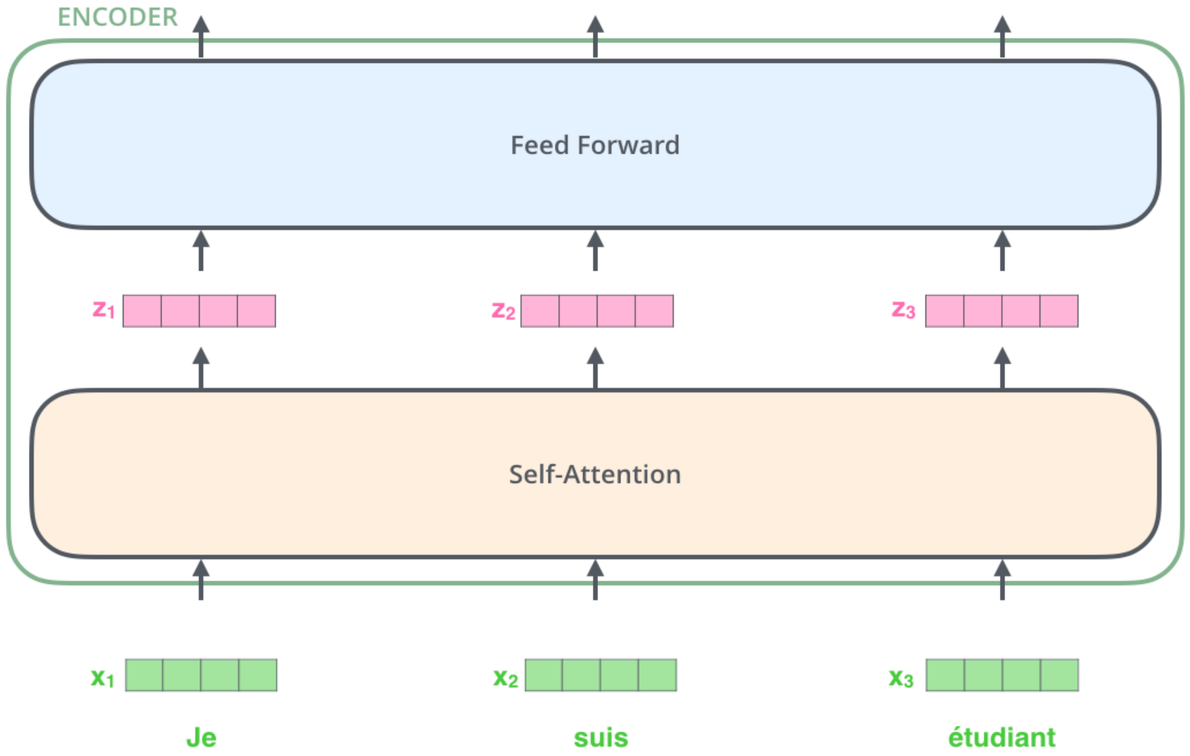


Inputs are processed in parallel!

How LLMs work

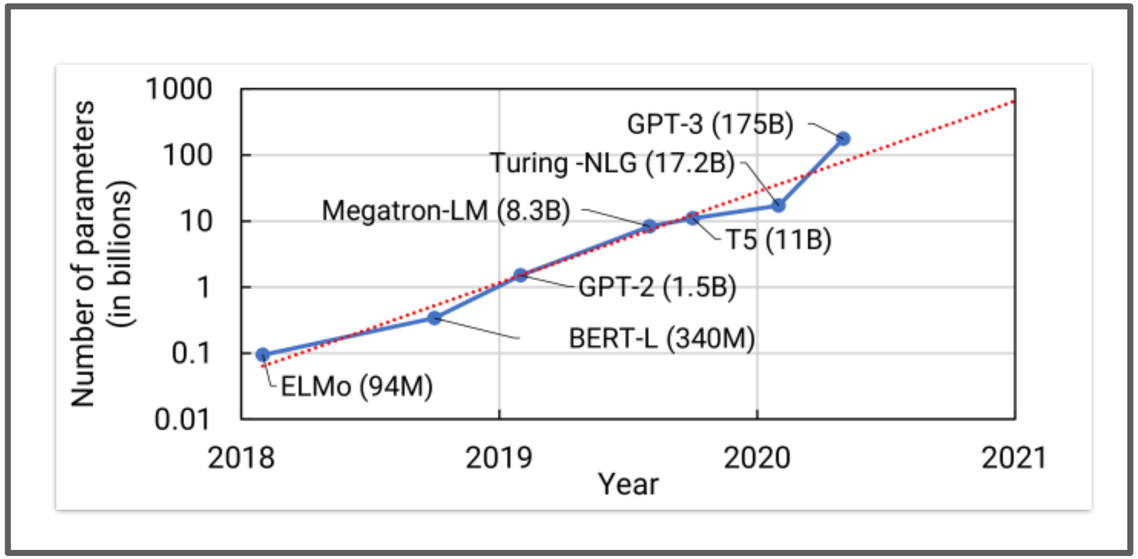
Transformers Architecture





Why “Large” Language Models?

- Large → Big number of parameters



Benefits of Large Language Models

Multi-task, fine tuning, scalability

- **Multi-task Capability:** LLMs find applications in content generation, question answering, translation, tutoring, and personal assistants.

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- **Scalability**: LLMs demonstrate excellent scalability to very large capacity networks and huge datasets.

Applications of Large Language Models

- Content generation
- Q&A
- Translation
- Tutoring
- Personal Assistants

Applications of LLMs

Content generation Example - DEMO

Applications of LLMs

Translation Example - DEMO

Limitations and Ethical Considerations

LLMs are far from perfect

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- **Misuse:** LLMs can hallucinate and produce false or harmful content
- **Reproducibility**: Unpredictability of LLM behavior. Watkins 2023
- **Data Privacy and Bias:** Ethical considerations should extend to the acquisition of data for training additional models. Models may have biases; their use should be transparent and biases mitigated. Watkins 2023

Q & A

Introduction to prompt engineering and the ChatGPT API

1. Prompt basics
2. Introduction to the ChatGPT API
3. Prompt engineering guide
4. A Framework for Building Good Prompts

1

Prompt Basics

Introduction to prompts

A prompt is a piece of text that conveys to the LLM the user’s intention.

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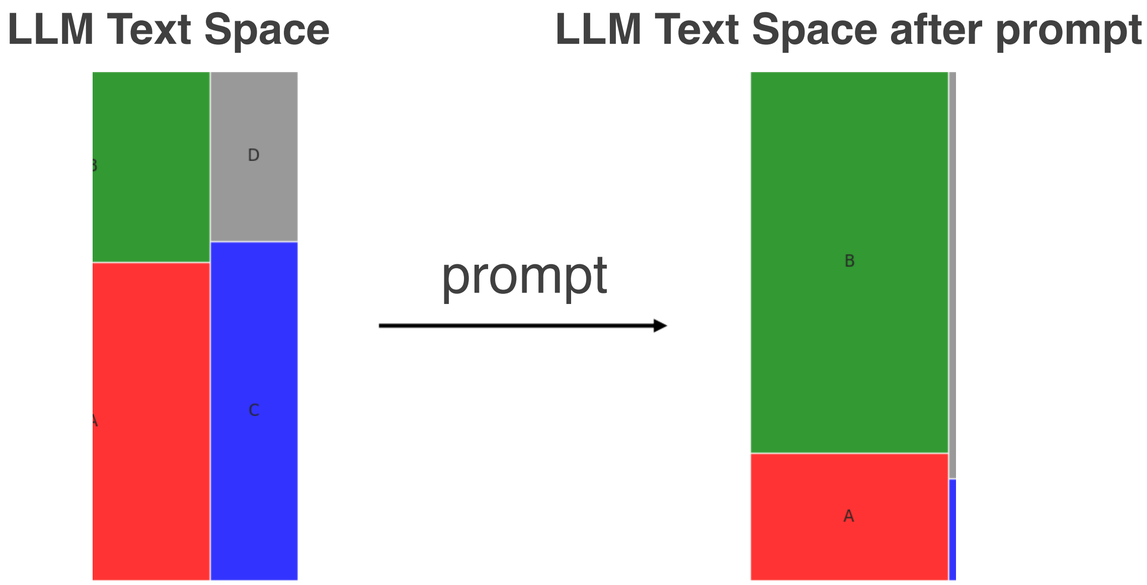
- A prompt is a piece of text that conveys to the LLM the user’s intention.
- Question → Instruction → Behavior
- It **constrains the space of possibilities** in the LLM's text space



1

Prompt Basics

Components of a prompt: task, input, context, style

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Notebook Demo

Introduction to the ChatGPT API

Where does ChatGPT fit in this chaotic LLM universe?

- The ChatGPT API allows us to use OpenAI's models to generate dynamic, contextually-aware responses.
- Required parameters: model, messages.

```python
import openai

openai.ChatCompletion.create(
  model="gpt-3.5-turbo",
  messages=[
        {"role": "system", "content": "You are a helpful assistant."},
        {"role": "user", "content": "Who won the world series in 2020?"},
        {"role": "assistant", "content": "The Los Angeles Dodgers won the World Series in 2020."},
        {"role": "user", "content": "Where was it played?"}
    ]
```

Introduction to the ChatGPT API

Where does ChatGPT fit in this chaotic LLM universe?

```
!pip install openai

openai.api_key = os.getenv("OPENAI_API_KEY")

import openai

openai.ChatCompletion.create(model="gpt-3.5-turbo",
                             messages=
                             [
                                 {"role": "system", "content": "You are a savy guru with knowledge
about existence and the secrets of life."},
                                 {"role": "user", "content": "What is the meaning of life?"}
                             ],
                             max_tokens=100,
                             temperature=0.9,
                             n = 1)
```

Notebook Presentation ChatGPT API

Prompt Engineering Guide

What is prompt engineering?

Prompt engineering: discipline for engineering prompts

Means by which LLMs can be programmed through prompting.

Process of creating a prompting function that results in the most effective performance on the downstream task.

The basic goal of prompt engineering is designing appropriate inputs for prompting methods.

Prompt Engineering Guide

A simplified guide of prompting techniques

- Zero-shot Prompting
- Few-shot Prompting
- Chain-of-Thought
- Self-Consistency
- Generate Knowledge
- Tree of thoughts (ToT)

Prompt Engineering Guide

A simplified guide of prompting techniques

Zero-shot prompting is when you solve the task without showing any examples of what a solution might look like

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- One can use this as the first try at a model to see what kind of tasks LLM can already solve out of the box

Prompt Engineering Guide

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Classify the sentiment in this sentence as negative or positive:
***Text**: I will go to a vacation.*
Sentiment:

Few-shot Prompting

Provide information in the form of examples to the LLM

Few-shot Prompting: technique where you show a few examples of what a solution might look like.

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Few-shot Prompting: technique where you show a few examples of what a solution might look like.

A "whatpu" is a small, furry animal native to Tanzania.
An example of a sentence that uses the word whatpu is: We were traveling in Africa and we saw these very cute whatpus.
To do a "farduddle" means to jump up and down really fast. An example of a sentence that uses the word farduddle is:

Example taken from (Brown et al. 2020)

Chain-of-Thought

Induce step-by-step reasoning and planning

Chain-of-thought (CoT) enables complex reasoning capabilities through intermediate reasoning steps (Wei et al. 2022).

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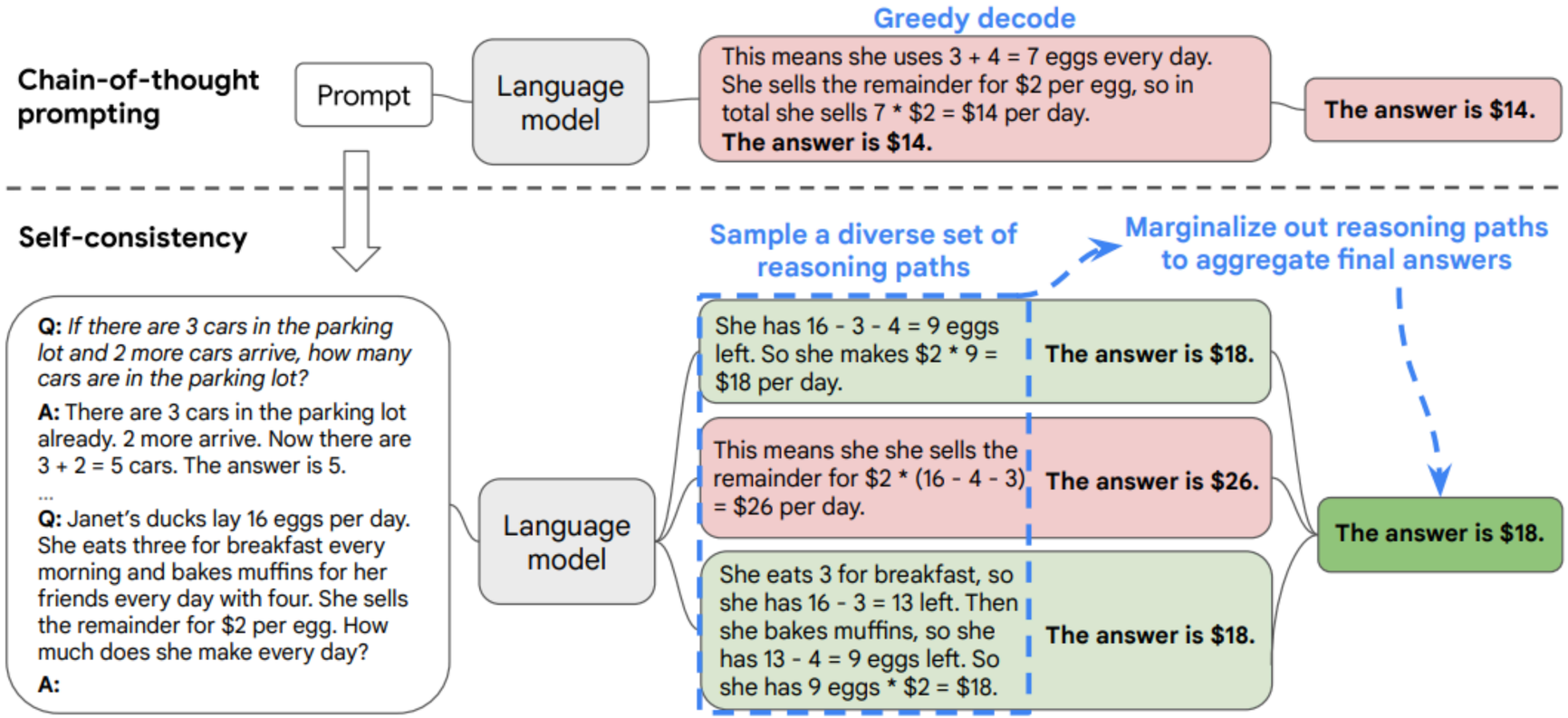
Q: I have one sister and one brother. I am 20 years of age. My sister is 5 years older and my brother 2 years younger than my sister. How old is my brother?

A: If I am 20 years of age and my sister is 5 years older, my sister is 20+5=25 years old. If my brother is 2 years younger than my sister, my brother is 25-2=23 years old. The answer is 23 years old.

Q: I have 2 friends, Jack and Sally. Jack is 2 years older than Sally. Sally is 5 years younger than me. I am 17 years old. How old is Jack?

Self-Consistency

Example

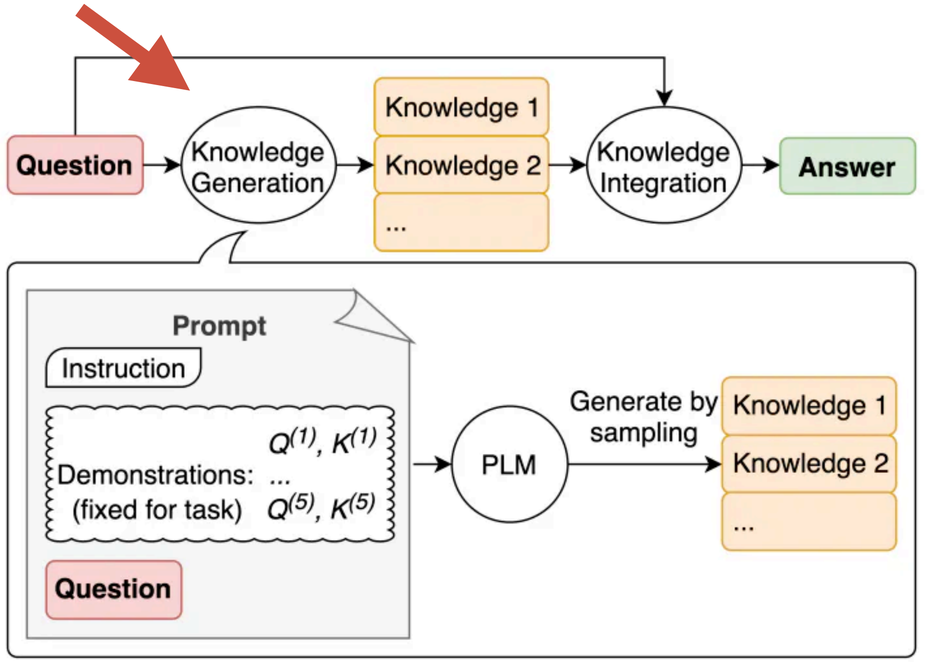


https://arxiv.org/pdf/2203.11171.pdf

Generate Knowledge

Example

- **Knowledge Generation**: Generating facts related to the question.

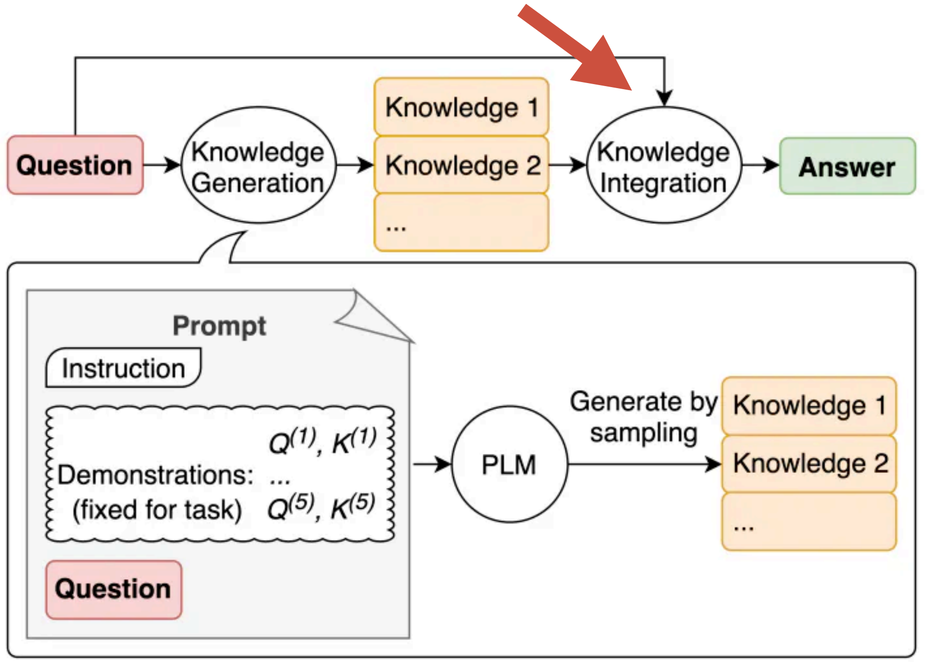


https://arxiv.org/pdf/2110.08387.pdf

Generate Knowledge

Example

- **Knowledge Generation**: Generating facts related to the question.
- **Knowledge Integration**: Using generated facts to answer the question comprehensively.



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There are many more prompt engineering techniques that grow in complexity, such as:

- ToT (Yao et al. 2023)
- Retrieval Augmented Generation (Lewis et el. (2021))
- Automatic Prompt Engineer (Zhou et al., (2022))
- React Prompting (Yao et al., 2022)
- Graph Prompting (Liu et al., 2023)
- Skeleton of Thought (Ning et al. 2023)
- Step Back Prompting (Zheng et al. 2023)

Break

A Framework for Building Good Prompts

4 principles: structured text, decomposition, self-criticism, ensembling

- Operate on Structured Text
-
-
-

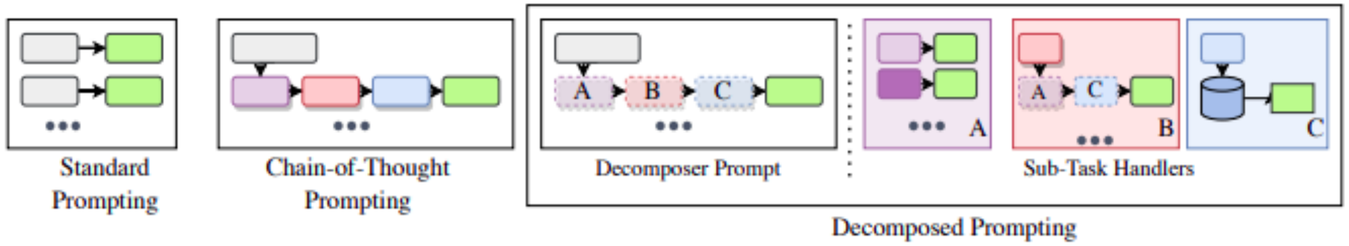
```
<python 3 shebang>

<module docstring>

<imports>


<do not include email dunder>

<initialize dotenv>
<set key using OPENAI_API KEY env var>

def complete(prompt: str, **openai_kwargs) -> str:
    <one-line docstring; no params>
    <use default kwargs: model=text-davinci-003, top_p=0.7,
max_tokens=512, 'engine' parameter is deprecated>
    <get completion>
    <strip whitespace before returning>

<as script, demo using prompt "English: Hello\nFrench:">
```

@goodside

A Framework for Building Good Prompts

4 principles: structured text, decomposition, self-criticism, ensembling

- Operate on Structured Text
- Introduce decomposition
-
-



QC: Concatenate the first letter of every word in "Jack Ryan" using spaces
Q1: [split] What are the words in "Jack Ryan"?
#1: ["Jack". "Ryan"]
Q2: (foreach) [str_pos] What is the first letter of #1?
#2: ["J", "R"]
Q3: [merge] Concatenate #2 with spaces
#3: "J R"
Q4: [EOQ]
...
decomp

Q: What are the words in "Elon Musk Tesla"?
A: ["Elon", "Musk", "Tesla"]

Q: What are the letters in "C++"?
A: ["C", "+", "+"]
...
split

Q: Concatenate ["n", "i", "e"]
A: "nie"

Q: Concatenate ["n", "i", "c", "e"] using spaces
A: "n i c e"
...
merge

[Khot et al 2023]

A Framework for Building Good Prompts

4 principles: structured text, decomposition, self-criticism, ensembling

- Operate on Structured Text
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-

Self-Ask

GPT-3

Question: Who lived longer, Theodor Haecker or Harry Vaughan Watkins?
Are follow up questions needed here: Yes.
Follow up: How old was Theodor Haecker when he died?
Intermediate answer: Theodor Haecker was 65 years old when he died.
Follow up: How old was Harry Vaughan Watkins when he died?
Intermediate answer: Harry Vaughan Watkins was 69 years old when he died.
So the final answer is: Harry Vaughan Watkins

Question: Who was president of the U.S. when superconductivity was discovered?
Are follow up questions needed here: Yes.
Follow up: When was superconductivity discovered?
Intermediate answer: Superconductivity was discovered in 1911.
Follow up: Who was president of the U.S. in 1911?
Intermediate answer: William Howard Taft.
So the final answer is: William Howard Taft.

Press et al 2023

A Framework for Building Good Prompts

4 principles: structured text, decomposition, self-criticism, ensembling

- Operate on Structured Text
- Introduce decomposition
-
-

(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. ✔

Kojima et al 2023

A Framework for Building Good Prompts

4 principles: structured text, decomposition, self-criticism, ensembling

- Operate on Structured Text
- Introduce decomposition
- Self-criticism
-

Q: Valerie earns $5000 per month, 1/2 of what her brother earns. If their mother earns twice their combined salary, what's the total amount of money they all have together?

Zero-Shot

A:
Valerie's brother earns $10,000 per month, while Valerie herself earns half of that amount. Together, they earn a total of $15,000 per month. Their mother's monthly earnings amount to $30,000, which is twice the combined salary of Valerie and her brother. Thus, the total amount of money they all have together is $30,000. **(Wrong)**

Few-Shot-CoT

<Few shot examples>
A:
Valerie earns $5000 per month, half of her brother's earnings, making his monthly income $10000. Combined, Valerie and her brother earn $15000 per month. Their mother earns double their combined salary, amounting to $30000 per month. In total, they have $30000 collectively. **(Wrong)**

Zero-Shot-CoT

A: Let's think step by step. First, Valerie's brother earns 2x and Valerie earns x (half of her brother's earnings). Next, their mother's income is twice the combined earnings of Valerie and her brother. In this case, their total income amounts to $30,000. **(Wrong)**

RCI

<Initial output generation>

A: Valerie's brother earns $10,000 per month, while Valerie herself earns half of that amount. Together, they earn a total of $15,000 per month. Their mother's monthly earnings amount to $30,000, which is twice the combined salary of Valerie and her brother. Thus, the total amount of money they all have together is $30,000.

<Critique>

Review your previous answer and find problems with your answer.

All individuals, including Valerie, her brother, and mother, should be taken into account when calculating the overall sum of money.

<Improve>

Based on the problems you found, improve your answer.

Valerie's brother earns $10,000 per month, while Valerie herself earns $5,000. Together, they earn a total of $15,000 per month. Their mother earns double their combined salary, which amounts to $30,000 per month. In total, they have $45,000 collectively. **(Correct)**

Kim, Baldi & McAleer 2023

A Framework for Building Good Prompts

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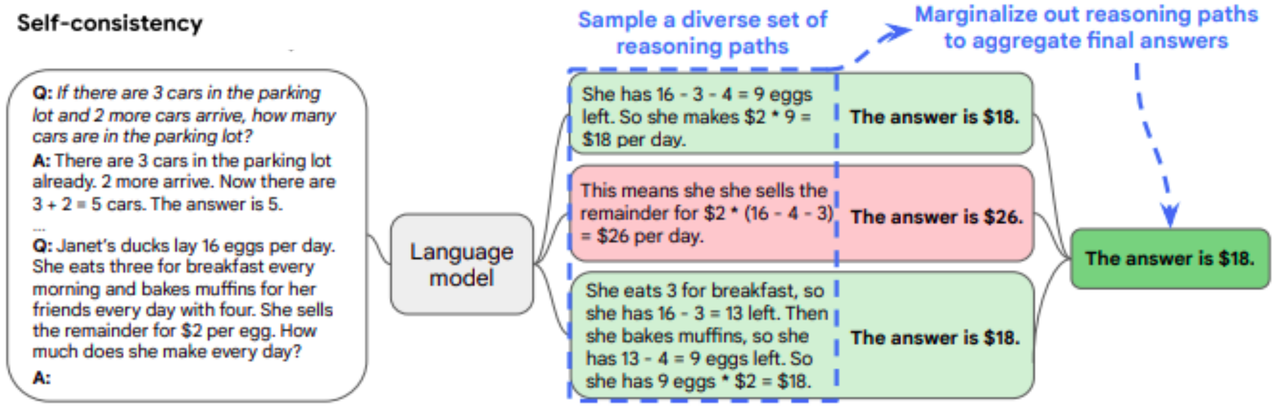

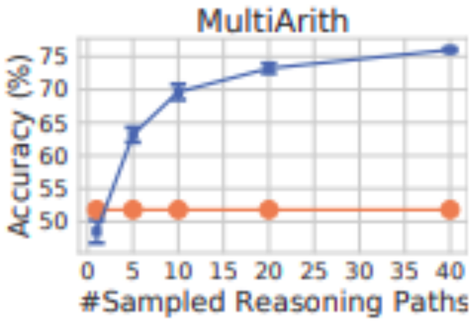

[Wang et al 2023]

A Framework for Building Good Prompts

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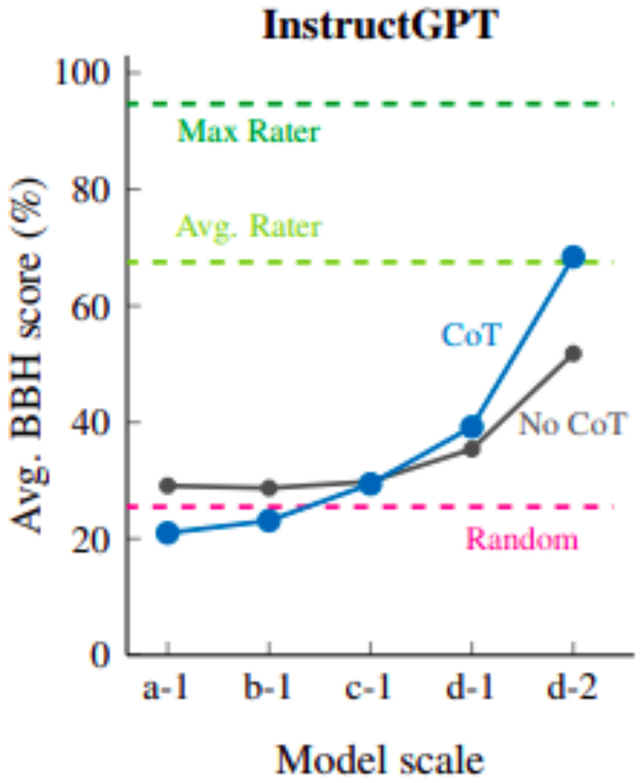

Combine for better performance!

Suzgun et al 2022

A Framework for Building Good Prompts

4 principles: structured text, decomposition, self-criticism, ensembling

- Operate on Structured Text
- Introduce decomposition
- Self-criticism
- Ensembling

	Latency	Compute
Few-Shot CoT	⬆️⬆️	💰💰
Zero-Shot CoT	⬆️	💰
Decomposition	⬆️⬆️	💰💰
Ensembling	✅	💰💰💰💰
Self-Criticism	⬆️⬆️⬆️⬆️	💰💰

Be aware of quality-cost tradeoff!

[FSDL LLM Bootcamp 2023]

Exercise / Lab

- Prompt engineering using the ChatGPT API
- Extracting dates from unstructured data
- Prompt engineering for text summarization and question answering

Notebook Lab Exercises

Fine Tuning ChatGPT Applications

A primer on how to fine tune ChatGPT on your data

Fine Tuning:

Fine Tuning ChatGPT Applications

A primer on how to fine tune ChatGPT on your data

Fine Tuning: process of “specialising an LLM on your specific dataset”

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Why?

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Why? Better results on specific tasks, lower latency… **See OpenAI docs**

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How?

Fine Tuning ChatGPT Applications

A primer on how to fine tune ChatGPT on your data

Fine Tuning: process of “specialising an LLM on your specific dataset”

Why? Better results on specific tasks, lower latency… **See OpenAI docs**

How? By preparing a custom `.jsonl` dataset on your specific use case

Fine Tuning ChatGPT Applications

A primer on how to fine tune ChatGPT on your data

Fine Tuning: process of “specialising an LLM on your specific dataset”

Why? Better results on specific tasks, lower latency… **See OpenAI docs**

How? By preparing a custom `.jsonl` dataset on your specific use case

The goal of fine tuning is to adapt the model to your specific use case by providing it with a few examples of successful interactions

3

Fine Tuning ChatGPT Applications

Common Use Cases

Fine Tuning ChatGPT Applications

Common Use Cases

- Setting style, tone, format

[OpenAI docs]

Fine Tuning ChatGPT Applications

Common Use Cases

- Setting style, tone, format
- Correcting failures

[OpenAI docs]

Fine Tuning ChatGPT Applications

Common Use Cases

- Setting style, tone, format
- Correcting failures
- Improving reliability

OpenAI docs

Fine Tuning ChatGPT Applications

Common Use Cases

- Setting style, tone, format
- Correcting failures
- Improving reliability
- Handling edge cases

OpenAI docs

Fine Tuning ChatGPT Applications

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- Handling edge cases
- Extracting structured output

OpenAI docs

Fine Tuning ChatGPT Applications

Common Use Cases

- Setting style, tone, format
- Correcting failures
- Improving reliability
- Handling edge cases
- Extracting structured output
- Function Calling

OpenAI docs

Fine Tuning ChatGPT Applications

Basic Steps

OpenAI docs

Fine Tuning ChatGPT Applications

Basic Steps

- Prepare and upload training data

[OpenAI docs]

Fine Tuning ChatGPT Applications

Basic Steps

- Prepare and upload training data
- Train a new fine-tuned model

OpenAI docs

Fine Tuning ChatGPT Applications

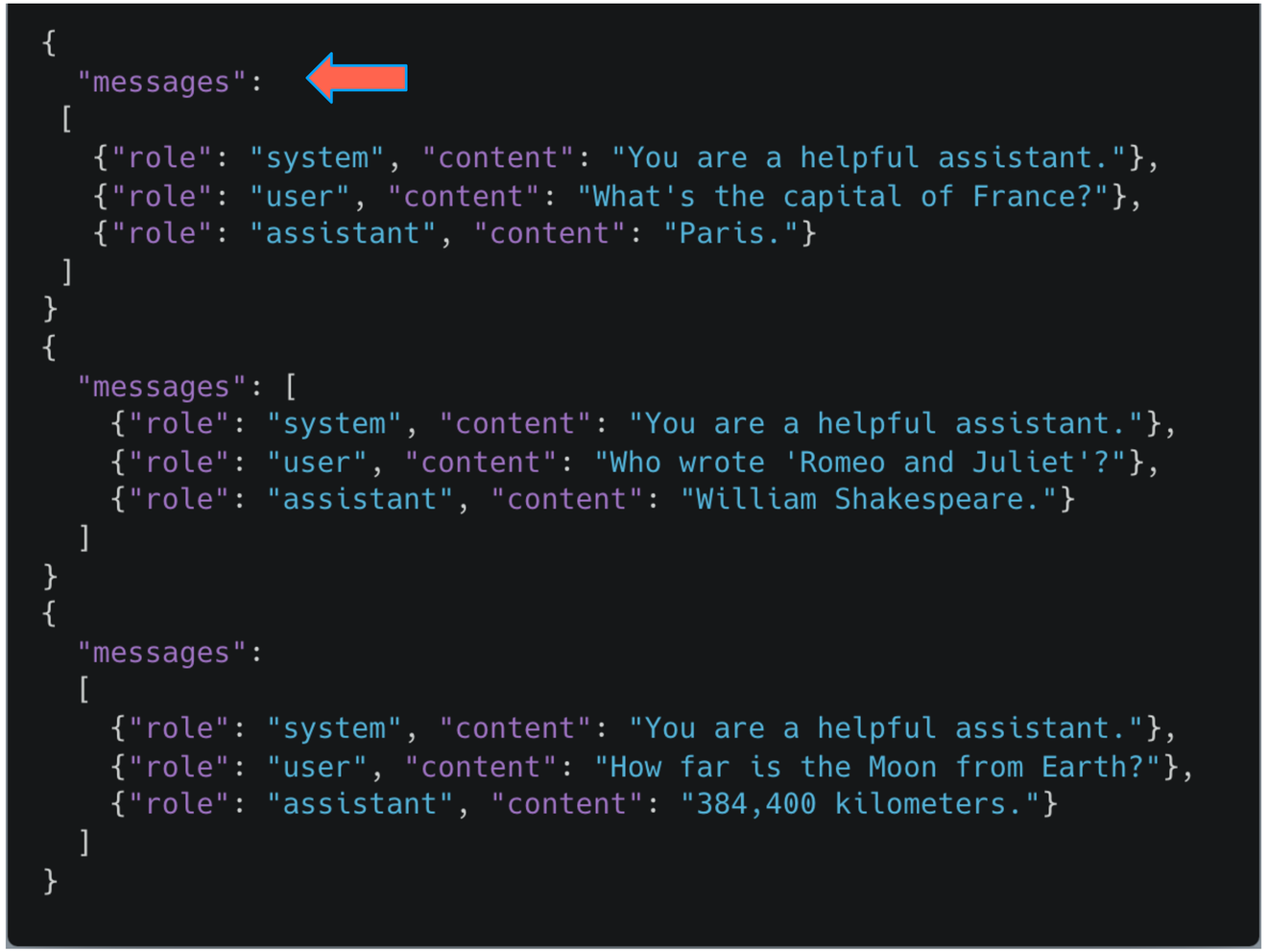
Basic Steps

- Prepare and upload training data
- Train a new fine-tuned model
- Use your fine-tuned model

OpenAI docs

Fine Tuning ChatGPT Applications

Prepare and upload training data



```
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Fine Tuning ChatGPT Applications

Prepare and upload training data

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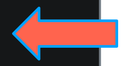

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  ]
}
```

Fine Tuning ChatGPT Applications

Fine Tuning Jobs

```python
from openai import OpenAI
# OpenAI API key should be set as
# environment variable - OPENAI_API_KEY
client = OpenAI()
client.files.create(
  file=open("dataset.jsonl", "rb"),
  purpose="fine-tune"
)
client.fine_tuning.jobs.create(
  training_file="file-id",
  model="gpt-3.5-turbo-1106"
)
```

Notebook Presentation Fine Tuning with ChatGPT API

Summary so far

Break

Langchain for LLM App Development

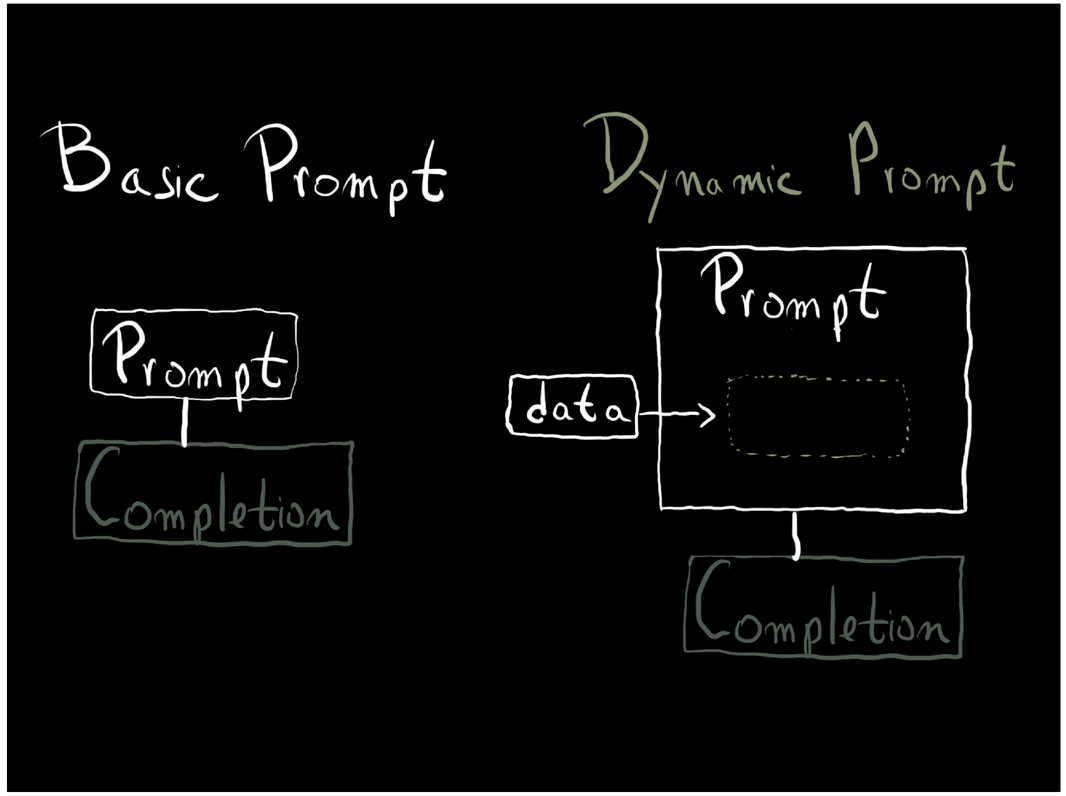
From static prompts to dynamic prompts

- Prompt management workflows that require dynamic prompts

Langchain for LLM App Development

From static prompts to dynamic prompts

- Prompt management workflows that require dynamic prompts
- This dynamics requirement leads to the need for creating certain types of abstractions



Langchain for LLM App Development

Langchain framework

- Langchain is a framework that facilitates the creation and management of dynamic prompts and chaining between prompts.
- **Main features:** components and off-the-shelf-chains.

Basics of Langchain

Langchain components

- **Models:** abstractions over the LLM APIs like the ChatGPT API

Basics of Langchain

Langchain components

- **Models:** abstractions over the LLM APIs like the ChatGPT API
- **Prompt Templates:** abstraction over standard prompts to LLMs

Basics of Langchain

Langchain components

- **Models:** abstractions over the LLM APIs like the ChatGPT API
- **Prompt Templates:** abstraction over standard prompts to LLMs
- **Output Parsers:** Translates raw output from LLM to a workable format

https://python.langchain.com/docs/get_started/quickstart

Basics of Langchain

Langchain components

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Notebook demo

https://python.langchain.com/docs/get_started/quickstart

Basics of Langchain

Models, Prompt Templates and Output Parsers

Models: LLMs and Chat models

Basics of Langchain

Models, Prompt Templates and Output Parsers

- **Models:** LLMs and Chat models
- **LLMs:** models that take a text string as input and return a text string

```python
from langchain.llms import OpenAI

llm = OpenAI()

llm.predict("Hi")
```

Basics of Langchain

Models, Prompt Templates and Output Parsers

- **Models:** LLMs and Chat models
- **LLMs:** models that take a text string as input and return a text string
- **Chat models:** takes a list of Chat Messages as input and returns a Chat Message

```python
from langchain.chat_models import ChatOpenAI

chat_model = ChatOpenAI()

chat_model.predict("Hi")

# or

chat_model.invoke("Hi")
```

Basics of Langchain

Models, Prompt Templates and Output Parsers

Messages?: inherits from BaseMessage interface

Basics of Langchain

Models, Prompt Templates and Output Parsers

- **Messages?:** inherits from BaseMessage interface
- **content:** content of the message (usually a string)

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Models, Prompt Templates and Output Parsers

- **Messages?:** inherits from BaseMessage interface
- **content:** content of the message (usually a string)
- **role:** entity from which the BaseMessage is coming

Objects to distinguish between different roles:

HumanMessage: A BaseMessage coming from a human/user.
AIMessage: A BaseMessage coming from an AI/ assistant.
SystemMessage: A BaseMessage coming from the system.
FunctionMessage / ToolMessage: A BaseMessage containing the output of a function or tool call.

Basics of Langchain

Models, **Prompt Templates** and Output Parsers

- **Prompt Templates:** pre-defined recipes for generating prompts for LLMs

```python
from langchain.prompts import PromptTemplate

prompt_template = PromptTemplate.from_template(
    "Tell me a {adjective} story about {content} in one paragraph."
)
prompt_template.format(adjective="funny", content="chickens")
```

Basics of Langchain

Models, **Prompt Templates** and Output Parsers

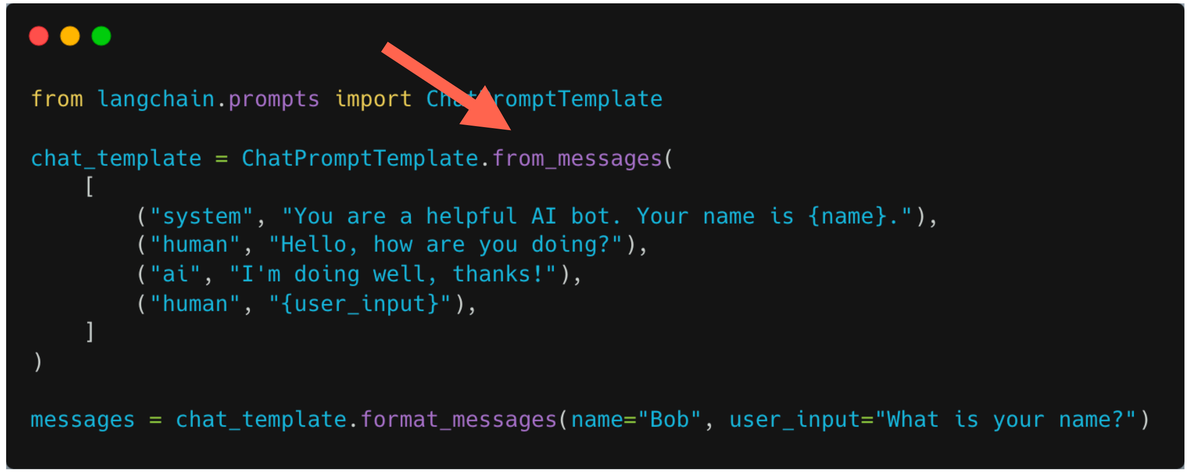
- **Prompt Templates:** pre-defined recipes for generating prompts for LLMs
- **ChatPromptTemplates:** prompt template for chat models

```python
from langchain.prompts import ChatPromptTemplate

chat_template = ChatPromptTemplate.from_messages(
    [
        ("system", "You are a helpful AI bot. Your name is {name}."),
        ("human", "Hello, how are you doing?"),
        ("ai", "I'm doing well, thanks!"),
        ("human", "{user_input}"),
    ]
)

messages = chat_template.format_messages(name="Bob", user_input="What is your name?")
```

Basics of Langchain

Models, **Prompt Templates** and Output Parsers

- **Prompt Templates:** pre-defined recipes for generating prompts for LLMs
- **ChatPromptTemplates:** prompt template for chat models
- **ChatPromptTemplates** are designed as a list of chat messages.



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Models, Prompt Templates and **Output Parsers**

- **Output Parsers:** convert raw output of an LLM into a usable format

Basics of Langchain

Models, Prompt Templates and **Output Parsers**

- **Output Parsers:** convert raw output of an LLM into a usable format
- **Key Types**

- **Converting LLM text to structured formats (e.g., JSON).**
- **Transforming a ChatMessage into a simple string.**
- **Converting additional information from model calls into a string.**

Basics of Langchain

Models, Prompt Templates and **Output Parsers**

- **Output Parsers:** convert raw output of an LLM into a usable format
- **Key Types**
- **Writing a Custom Output Parser**

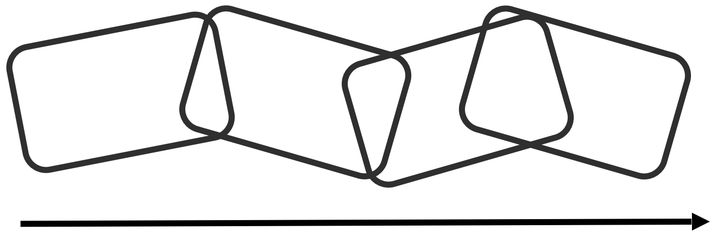
```python
from langchain.schema import BaseOutputParser

class CommaSeparatedListOutputParser(BaseOutputParser):
    """Parse the output of an LLM call to a comma-separated list."""


    def parse(self, text: str):
        """Parse the output of an LLM call."""
        return text.strip().split(", ")

CommaSeparatedListOutputParser().parse("hi, bye")
# >> ['hi', 'bye']
```

Notebook demo

Basics of Langchain

Models, Prompt Templates and Output Parsers

- **Chains:** prompt template + Model + output parsing



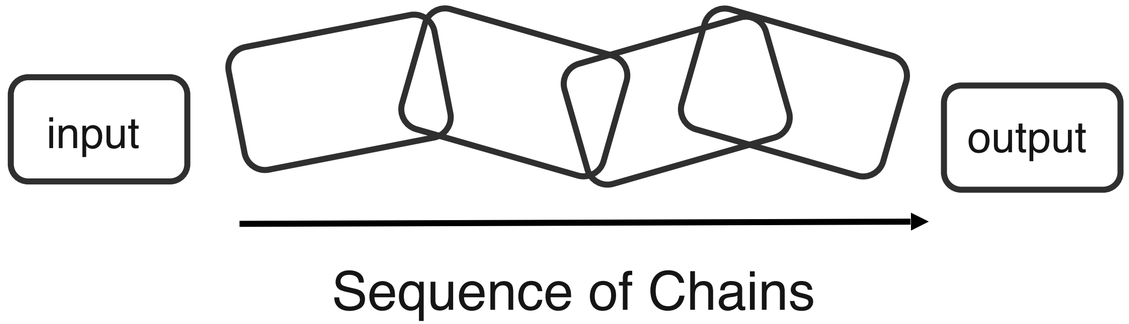
Chains of Prompts

Basics of Langchain

LLMChain & Sequential Chains

- **Chains:** prompt template + Model + output parsing

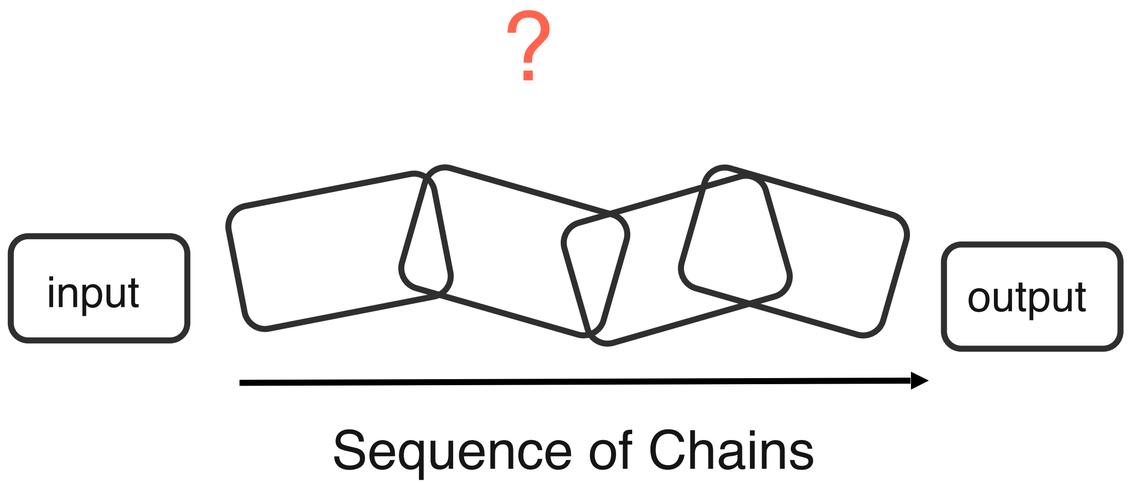
- Sequence of calls to an LLM chained together



Basics of Langchain

LLMChain & Sequential Chains

- **Chains:** prompt template + Model + output parsing
- Sequence of calls to an LLM chained together
- How to build these chains?



Basics of Langchain

LCEL - LangChain Expression Language

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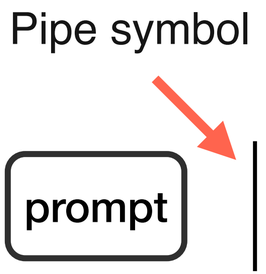
- Pipe syntax: prompt **|**



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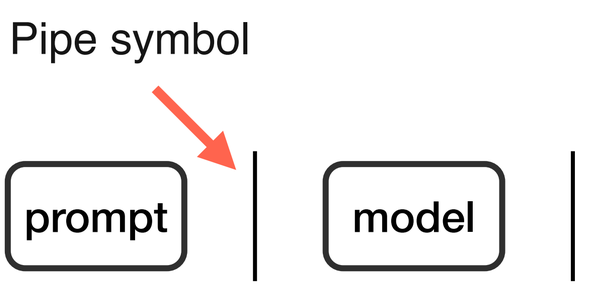

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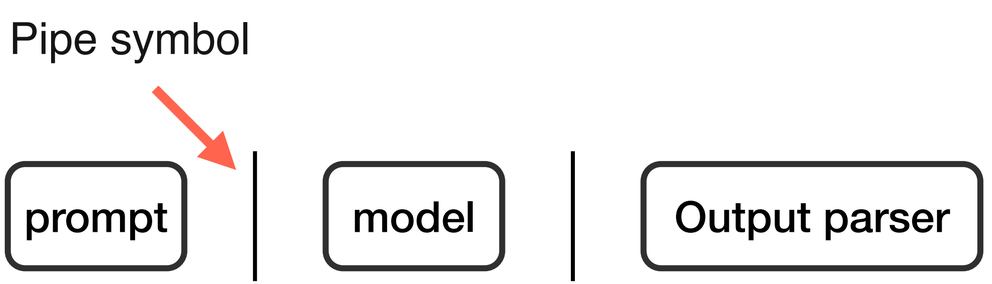
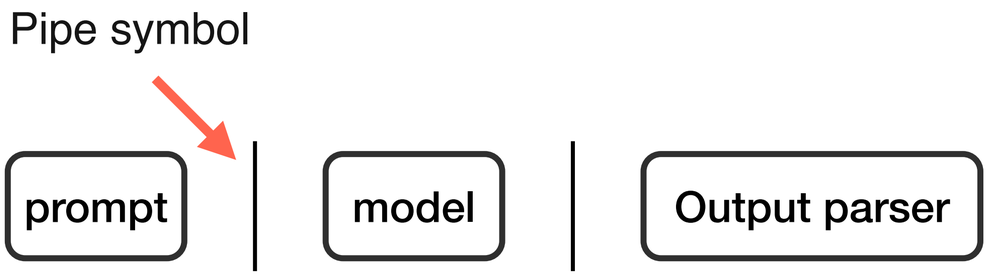


Basics of Langchain

LCEL - LangChain Expression Language

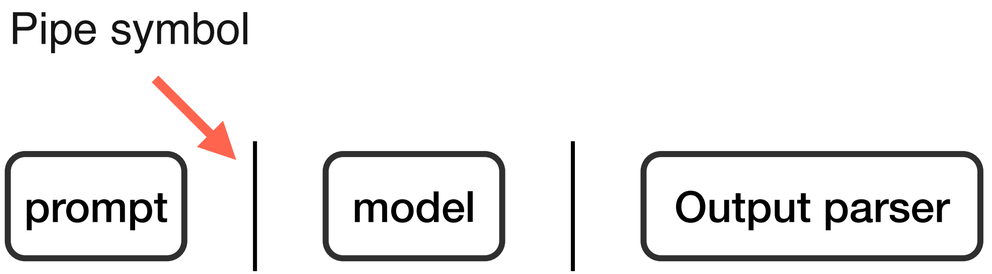
- **LCEL** - designed to build sequence of calls (to LLMs or any other component)
- Pipe syntax: prompt **|** model **|** output parser
- Allows you to **build complex chain pipelines** with a simple standard interface



Basics of Langchain

LCEL - LangChain Expression Language

- **LCEL** - designed to build sequence of calls (to LLMs or any other component)
- Pipe syntax: prompt **|** model **|** output parser
- Allows you to **build complex chain pipelines** with a simple standard interface



Notebook demo

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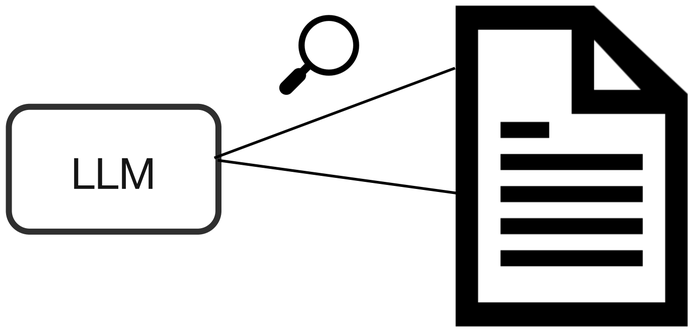
Langchain for LLM App Development

Langchain with Documents

- LLMs have a limited context length



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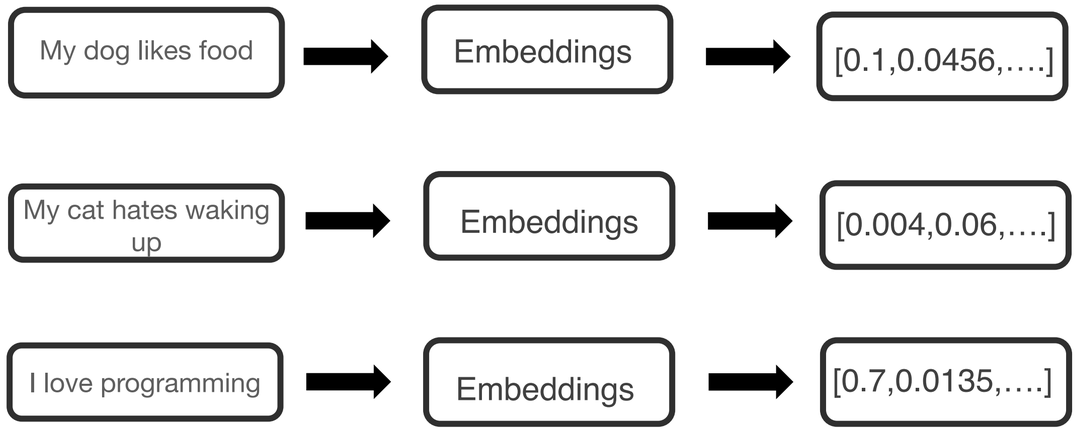

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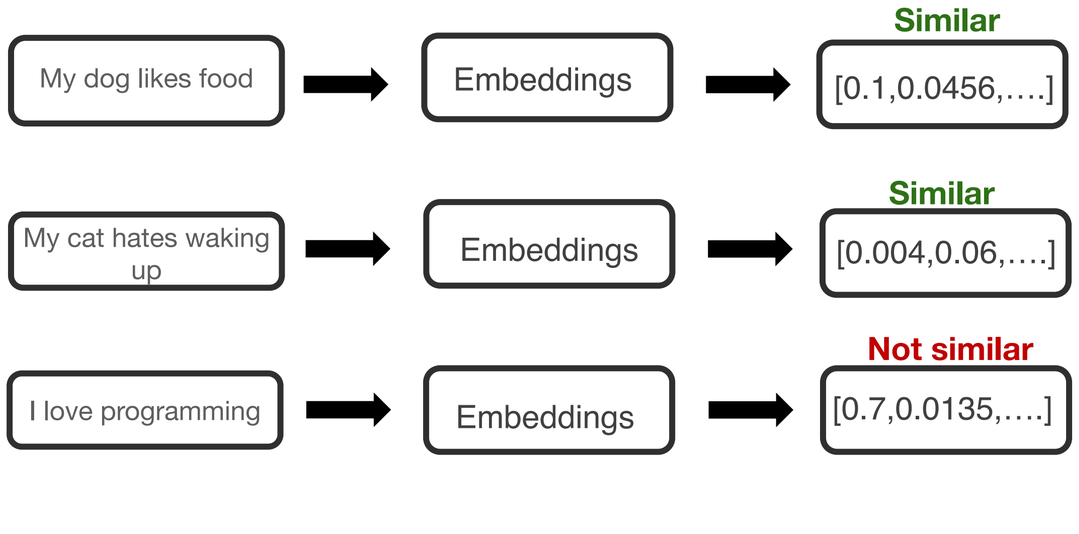

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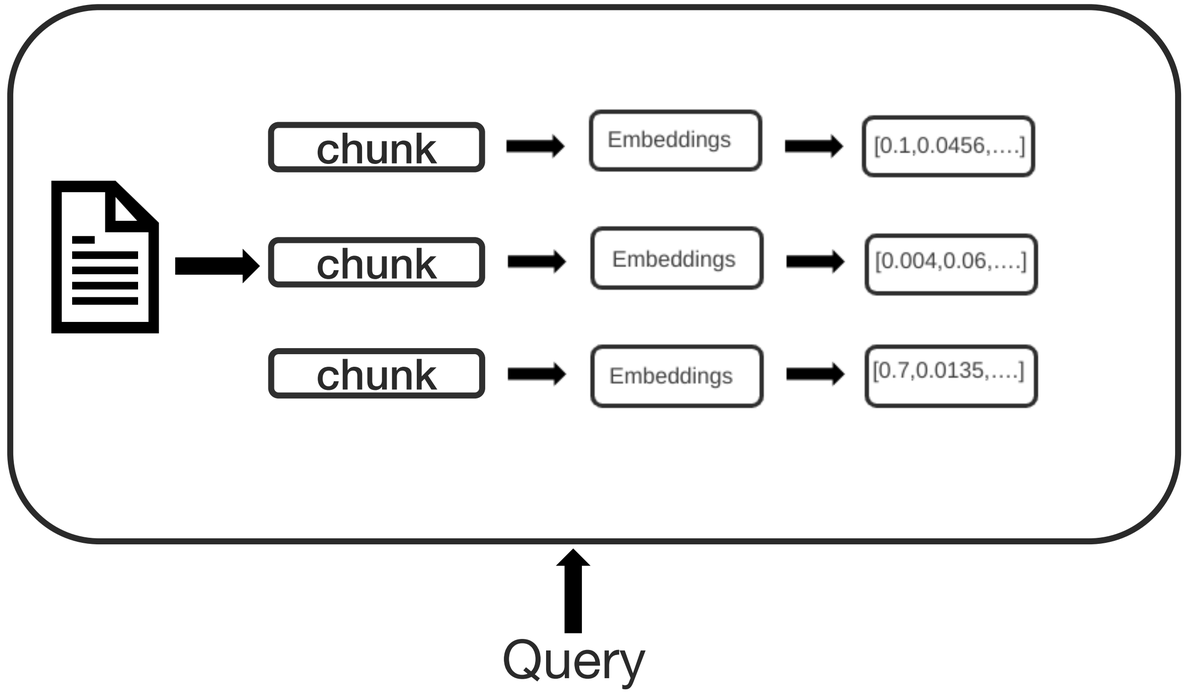
- **Vector DBs**



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- Refine
- Map_rerank

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