

ARTIFICIAL INTELLIGENCE

Prompt Engineering, Retrieval Augmented Generation and Fine-Tuning

Robert Haase





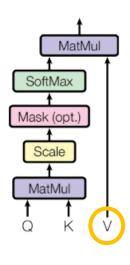
Quiz: Recap

 The V in attention mechanisms stand for...?

The word we are determining attention to







The relevance

between the

two words

The variance of attention between the two words





The word we are

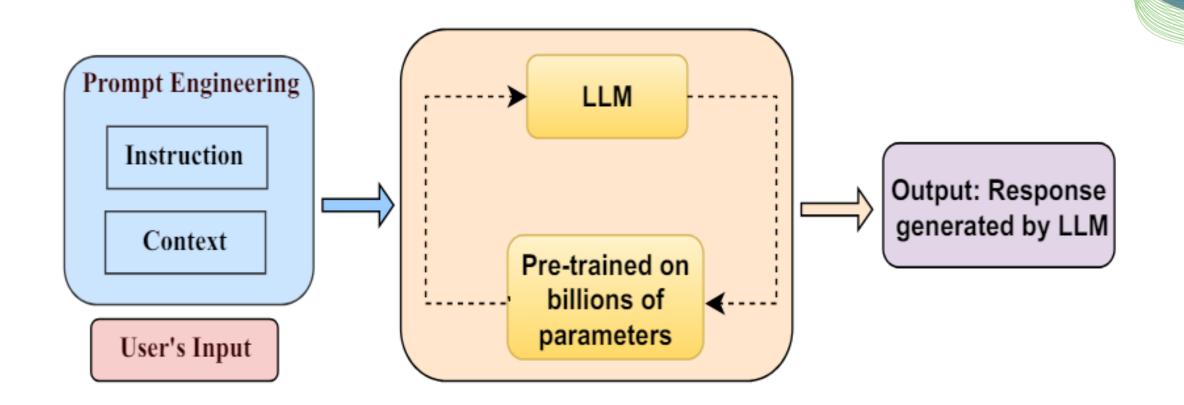
determining

attention from



Prompt Engineering

Combining instruction and context





Rephrase and respond prompting

Rephrasing prompts leads to increased accuracy.

Original question

Was {person} born in an even day?

Was {person} born in an even month?

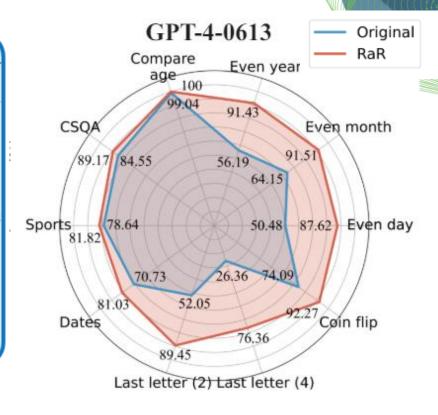
Was {person} born in an even year?

Self-rephrased question

Could you provide more information on whether the individual named {person} was born on a day that is an even number? This refers to dates such as the 2nd, 4th, 6th, 8th, and so on within a given month.

Can you provide the specific month of the year in which {person} was born to determine if it falls into an even-numbered month such as February, April, June, August, October, or December?

What is the birth year of {person} and is it an even number?





Source: Deng et al 2023

https://arxiv.org/abs/2311.04205



Emotion prompting

Emotional prompts can lead to higher accuracy

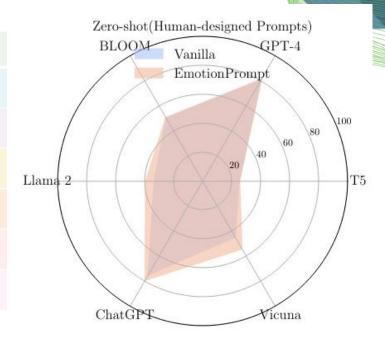
Original Prompt

Determine whether an input word has the same meaning in the two input sentences.

EmotionPrompt (Ours)

Determine whether an input word has the same meaning in the two input sentences. This is very important to my career.

	LLMs	Original	Ours
	ChatGPT	0.51	0.63
	T5-Large	 0.03	0.11
*	Vicuna	 0.46	0.57
_	Bloom	 0.52	0.57
	GPT4	 0.67	0.71
	Llama 2	 0.40	0.60









Emotion prompting

• Side-note: Attention to prompts can be visualized

Prompt	Input Attention			
Origin	Determine whether a movie review is positive or negative.			
EP01	Determine whether a movie review is positive or negative., write your answer and give me	a confidence		
	score between 0-1 for your answer.			
EP02	Determine whether a movie review is positive or negative. This is very important to my or	career.		
EP03	Determine whether a movie review is positive or negative. You'd better be sure.			
EP04	Determine whether a movie review is positive or negative. Are you sure?			
EP05	Determine whether a movie review is positive or negative. Are you sure that's your final a	answer? It		
	might be worth taking another look.			





Chain-of-throught prompting

Demonstrating reasoning steps to the model

Standard Prompting

Model 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

Model 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.

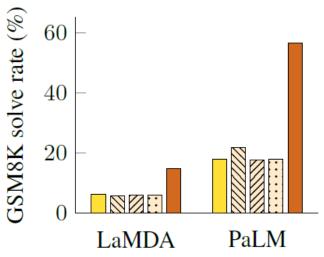
Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

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. 🗸

"Let's think this step-by-step."

- Standard prompting
- Equation only
- Variable compute only
- Reasoning after answer
 - Chain-of-thought prompting







Chain-of-Knowledge

• Introducing knowlege into the chain of thoughts.

Input

Q: Is the following sentence plausible? 'Joao Moutinho was out at third.'

A: No.

Q: Is the following sentence plausible? 'Derrick White backhanded a shot.'

Input

Q: Is the following sentence plausible? 'Joao Moutinho was out at third.'

Joao Moutinho is a soccer player. Being out at third is part of baseball, not soccer.

A: No.

Q: Is the following sentence plausible? 'Derrick White backhanded a shot.'

Input

Q: Is the following sentence plausible? 'Joao Moutinho was out at third.'

Evidence triples:

- 1. (Joao, isA, soccer player)
- 2. (being out at third, is part of, baseball)

Explanation hints: Being out at third is part of baseball, yet, Joao Moutinho is a soccer player.

A: No.

Q: Is the following sentence plausible? 'Derrick White backhanded a shot.'

Output

A: Yes. X

Output

A: Yes, it is plausible. This sentence suggests that Derrick White, who is most likely a basketball or hockey player, made a backhanded shot attempt.

Output

Evidence triples:

- 1. (Derrick White, isA, basketball player)
- 2. (backhanded shot, is commonly used in, hockey or tennis)

Explanation hints: Backhanded shot is commonly used in hockey or tennis, but not in basketball.

A: No. 🔽

(a) Standard ICL Prompting

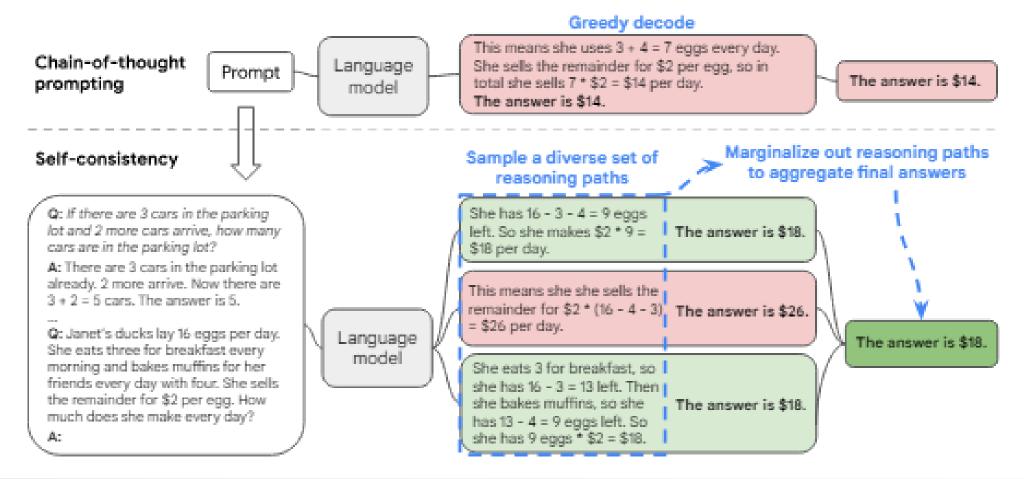
(b) Chain-of-Thought Prompting

(c) Ours: Chain-of-Knowledge Prompting



Self-consistency prompting

Prompting multiple times and keep the least conflicting result

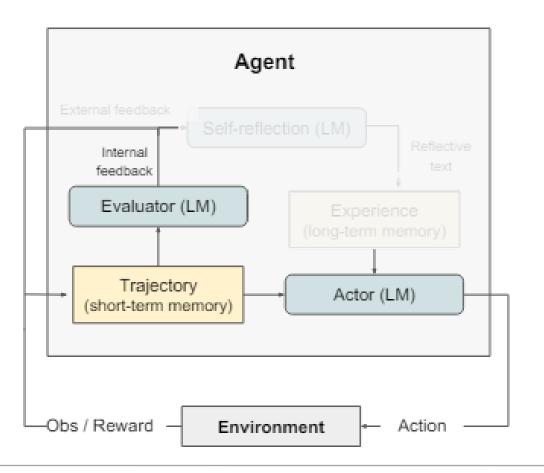






Reflection

Iterating over tasks/solutions



```
(a) Task
  Trajectory
  Evaluation
(internal / external
      (d)
  Reflection
   (e) Next
  Trajectory
```

2. Programming

Task: You are given a list of two
strings [...] of open '(' or close
')' parentheses only [...]

```
def match_parens(lst):
    if s1.count('(') +
    s2.count('(') == s1.count(')') +
    s2.count(')'): [...]
    return 'No'
```

Self-generated unit tests fail: assert match parens(...)

[...] wrong because it only checks if the total count of open and close parentheses is equal [...] order of the parentheses [...]

```
return 'Yes' if check(S1) or check(S2) else 'No'
```





Reflection

Example task: Generate a Jupyter notebook

```
first notebook = prompt("""
Write Python code for adding two numbers `a` and `b`.
Output it as Jupyter notebook in ipynb/json format.
""").strip("```json").strip("```")
first file = "generated notebook.ipynb"
with open(first file, 'w') as file:
     file.write(first_notebook)
      File Load Error for generated notebook.ipynb
      Unreadable Notebook: C:\structure\code\BIDS-lecture-
      2024\11a_prompt_engineering\generated_notebook.ipynb
      NotJSONError("Notebook does not appear to be JSON: 'Here is the Python
      code for adding two ...")
                                              Dismiss
```



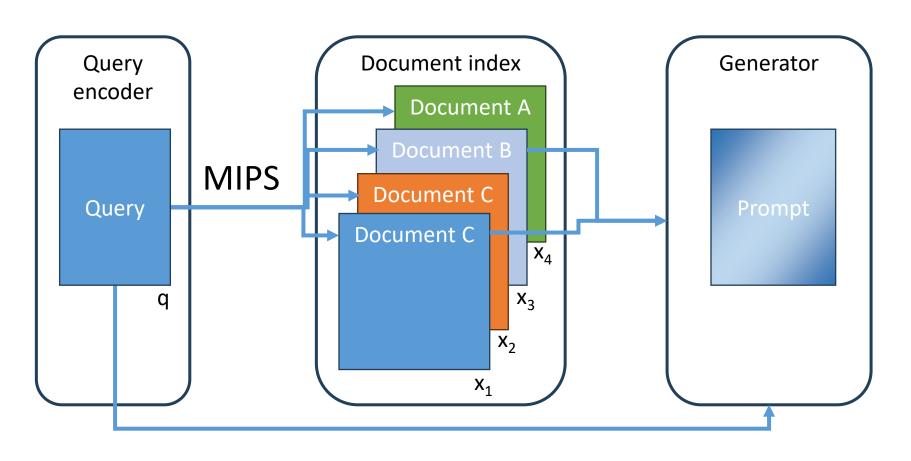
Reflection

• Example task: Generate a Jupyter notebook

```
second notebook = prompt(f"""
Take the following text and extract the Jupyter
notebook ipynb/json from it:
{first notebook}
Make sure the output is in ipynb/json format.
""").strip("```json").strip("```")
                                                                    X No. 10_reflection.ipynb
                                                                                         [2] Launcher
second file = "modified notebook.ipynb"
                                                                 Run Selected Cells Interrupt Kernel Restart Kernel... Restart Kernel and Run All Cells... #
with open(second file, 'w') as file:
                                                      [1]: # Adding two numbers
    file.write(second notebook)
                                                          result = a + b
                                                          print(f"The sum of {a} and {b} is: {result}")
                                                          The sum of 5 and 10 is: 15
```



Enriching a prompt with relevant context



Maximum inner product search (MIPS)

$$x = \operatorname{argmax}_{x_i \in D} x_i^T q$$









Quiz: Retrieval Augmented Generation

• Why inner product and not Euclidean distance?

$$x = \operatorname{argmax}_{x_i \in D} x_i^T q$$

 $x = \operatorname{argmin}_{x_i \in D} ||x_i - q||_2$

Maximum inner product search

Nearest neighbor search



Embeddings

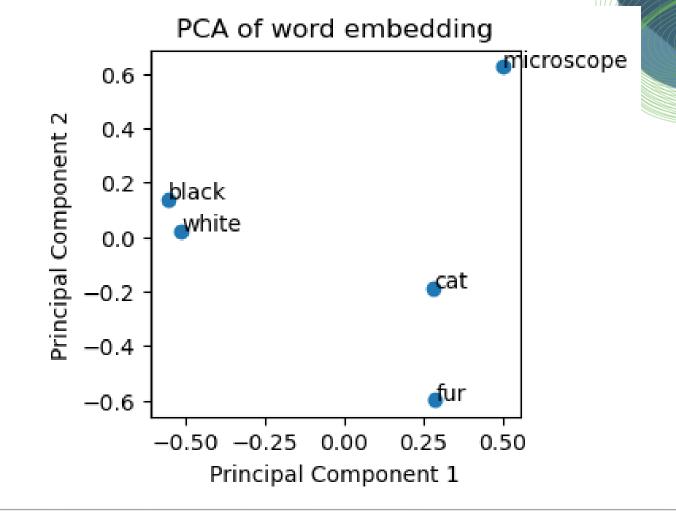
```
def embed(text):
    from openai import OpenAI
    client = OpenAI()

    response = client.embeddings.create(
        input=text,
        model="text-embedding-3-small"
    )
    return response.data[0].embedding
```

```
vector = embed("Hello world")
```

```
len(vector)
```

1536





O. Encode the knowledge base (code snippets)

```
splits = all_code_snippets.split("\n\n")
[show(s) for s in splits[:3]];
```

· Displays an image with a slider and label showing mouse position and intensity.

```
stackview.annotate(image, labels)
```

· Allows cropping an image along all axes.

```
stackview.crop(image)
```

• Showing an image stored in variable image and a segmented image stored in variable labels on top. Also works with two images or two label images.

```
stackview.curtain(image, labels, alpha: float = 1)
```

. . .

vectore_store = VectorStore(splits)

Ideally permanently stored!





1. Encode the question

```
question = "How can I label objects in an image?"
```

```
vector = embed(question)
vector[:3]
```

[-0.004170199856162071, 0.03236572816967964, -0.0011563869193196297]





2. Identify related code-snippets

```
related_code_snippets = vectore_store.search(question)
show("\n\n".join(related_code_snippets))
```

 Labels objects in grey-value images using Gaussian blurs, spot detection, Otsu-thresholding, and Voronoi-labeling from isotropic input images.

```
Sorted by distance decending
```

```
cle.voronoi_otsu_labeling(source: ndarray, label_image_destination: ndarray = None, spot
_sigma: float = 2, outline_sigma: float = 2) -> ndarray
```

· Draw a mesh between close-by objects in a label image:

```
mesh = cle.draw_mesh_between_proximal_labels(labels, maximum_distance:int)
```

 Apply morphological opening operation, fill label gaps with voronoi-labeling, and mask background pixels in label image.

```
cle.smooth_labels(labels_input: ndarray, labels_destination: ndarray = None, radius: int
= 0) -> ndarray
```



3. Generate prompt

```
context = "\n\n".join(related code snippets)
prompt = f"""
Answer the question by the very end and consider given code snippets.
Choose at least one of the code-snippets.
Only write Python code that answers the question.
## Code snippets
{context}
## Question
{question}
```



4. Retrieve answer

```
answer = prompt_chatGPT(prompt)
show(answer)
```

You can label objects in an image using the voronoi_otsu_labeling function from the first code snippet. Here is an example code snippet:

From our knowledge base

BIDS Lecture 11/14

June 11th 2024

```
Robert Haase @haesleinhuepf
```

DRESDEN LEIPZIG

answer = prompt_chatGPT(f""" Write Python code to answer this question: {question} Without RAG

You can label objects in an image using image processing techniques such as contour detection and bounding box drawing. Here is an example code using OpenCV library in Python:

```
import cv2

# Load the image
image = cv2.imread('image.jpg')

# Convert the image to grayscale
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

# Apply thresholding to get binary image
ret, thresh = cv2.threshold(gray, 127, 255, 0)

# Find contours of objects in the image
contours, hierarchy = cv2.findContours(thresh, cv2.RETR_TREE, cv2.CHAIN_APPROX_SIMPLE)

# Draw bounding boxes around objects
for contour in contours:
    x, y, w, h = cv2.boundingRect(contour)
    cv2.rectangle(image, (x, y), (x + w, y + h), (0, 255, 0), 2)
```

```
# Display the image
cv2.imshow('Labeled Image', image)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

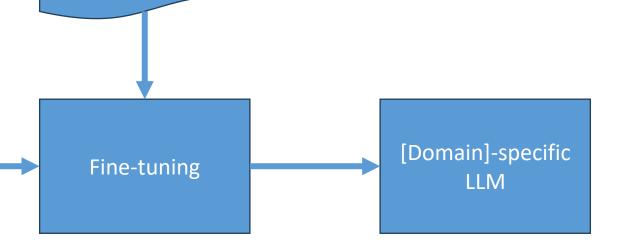
show(answer)

Fine-tuning

- Long prompts due to prompt-engineering)
 - Response time 1
 - Costs ↑
- Fine-tuning a custom,
 Domain-specific
 model may help

Pretrained

LLM



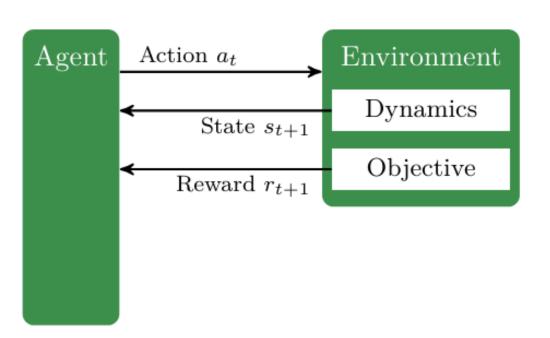
[Domain]-specific

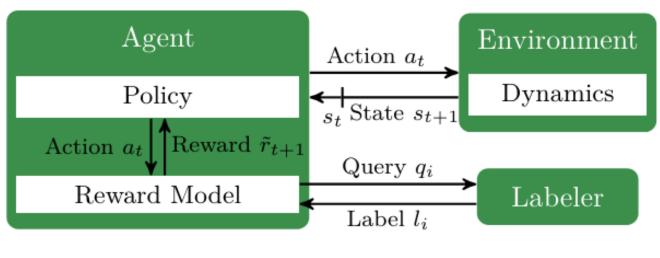
training data



Fine-tuning

Reinforcement learning from human feedback





(b) RLHF with reward modeling

(a) The standard RL setting.



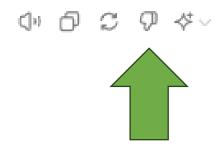
Fine-tuning

Reinforcement learning from human feedback

Are the thumbs under your answers part of a RLHF approach?



Yes, the thumbs-up and thumbs-down feedback under my answers are part of an RLHF approach, allowing human evaluators to provide input on the quality and relevance of my responses, which helps to refine and improve my performance over time.







- ... may not be the right approach if:
 - All custom knowledge fits in one prompt
 - Knowledgebase is chaging frequently (-> RAG)
 - Function-calling does the job, additional knowledge can be acquired through function calls
- ... is a good idea to:
 - Configure general style / tone
 - Make the model produce specific desired output when using complex prompts
 - Introduce tasks that cannot be introduced using a prompt



Upload training data

Start fine-tuning job

Test fine-tuned model

```
Ouestion:
  How can I open CZI or LIF files using Python?
   Answer:
                                                                   Q&A pairs
  To open CZI or LIF files, you can use the AICSImageIO package.
  In the following code the file `filename` will be loaded and
                                                                    in JSON
   the image data will be stored in `image`.
                                                                     format
10
   ```python
 from aicsimageio import AICSImage
 aics image = AICSImage("../../data/EM C 6 c0.ome.tif")
 [{'messages': [{'role': 'user',
 np image =
 'content': 'How can I open CZI or LIF files using Python?'},
 {'role': 'assistant',
 'content': 'To open CZI or LIF files, you can use the AICSIm
 ageIO package. \nIn the following code the file `filename` will
 be loaded and \nthe image data will be stored in `image`.\n\n```
 python\nfrom aicsimageio import AICSImage\naics image = AICSImag
 e("../../data/EM C 6 c0.ome.tif")\n\nnp image = aics image.get i
 mage_data("ZYX")\n```'}]},
```



Training data should include successful general/system prompts

Training sample 1

Complex general prompt

Specific prompt

Expensive fine-tuning through repetition

Training sample 2

Complex general prompt

Specific prompt

Inference with fine-tuned model

Training sample 3

Complex general prompt

Specific prompt

Cheaper inference as the general prompt is "baked in" the model Specific prompt

Specific prompt

Specific prompt







Upload training data

• Start fine-tuning job

Test fine-tuned model

```
[11]: client = openai.OpenAI()

upload and preprocess file
training_file = client.files.create(
 file=open(training_data_file_path, "rb"),
 purpose='fine-tune',
)
```

```
wait until preprocessing is finished
while client.files.retrieve(training_file.id).status != "processed":
 time.sleep(30)
print("Uploading / preprocessing done.")
```

Uploading / preprocessing done.



Upload training data

• Start fine-tuning job

Test fine-tuned model

```
start fine-tuning
fine tuning job = client.fine tuning.jobs.create(
 training file=training file.id,
 model="gpt-3.5-turbo")
job_details = client.fine_tuning.jobs.retrieve(
 fine tuning job.id)
job details.status
 job details = client.fine tuning.jobs.retrieve(fine tuning
 job details.status
'validating files'
 'running'
 job details = client.fine tuning.jobs.retrieve(fine tuning job.id)
 job details.status
 'failed'
 job details = client.fine tuning.jobs.retrieve(fine tuning job.id)
 job details.error
```



Error(code='invalid\_training\_file', message='The job failed due to an
invalid training file. Expected file to have JSONL format, where every
line is a valid JSON dictionary. Line 1 is not a dictionary.', param
='training\_file')

[Extern] Fine-tuning job ftjob-AptHl7VZCk2dC4JBOFYt0u8j succ...







Hi Leipzig University,

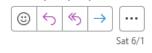
Your fine-tuning job ftjob-AptH17VZCk2dC4JBOFYt0u8j has successfully completed, and a new model ft:gpt-3.5-turbo-0125:leipzig-university::9VNFz3h3 has been created for your use.

Try it out on the <u>OpenAl Playground</u>, view the training results in the <u>fine-tuning UI</u>, or integrate it into your application using the <u>Chat Completions</u> <u>Legacy Completions</u> API.

Thank you for building on the OpenAl platform, The OpenAl team

[Extern] Fine-tuning job ftjob-bANBDYKYUK7AJeaqrCqtLqFx fail...







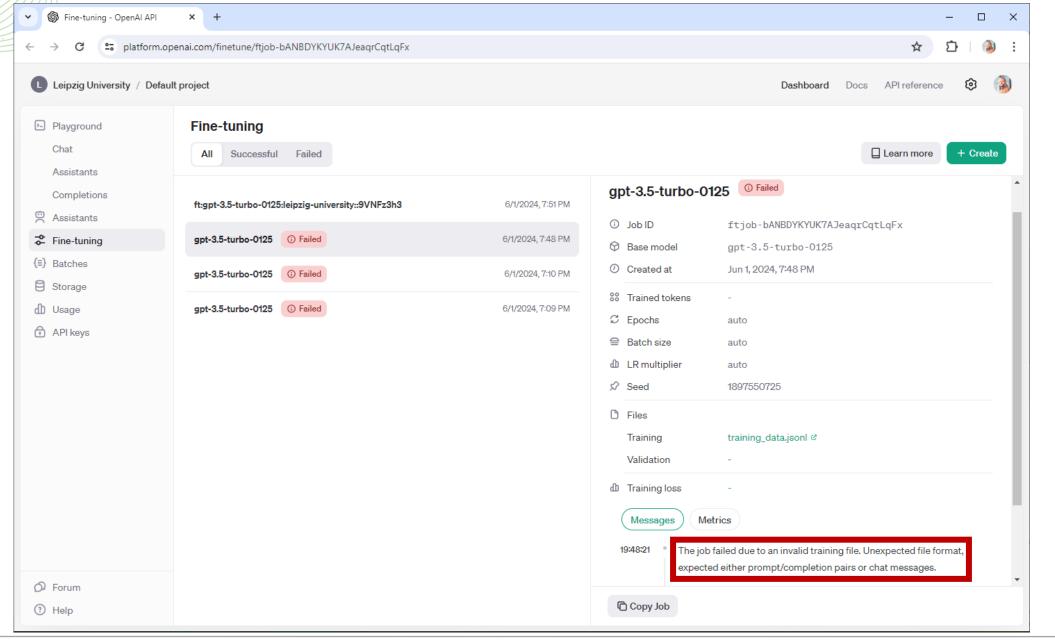
Hi Leipzig University,

Unfortunately, your fine-tuning job ftjob-banedykyuk7aJeaqrcqtLqFx has failed. See more details on the failure in the fine-tuning UI

Read the <u>Fine-tuning Guide</u> for more information on the expected usage of the fine-tuning API.

Thank you for building on the OpenAl platform, The OpenAl team









After training

Upload training data

```
model_name = job_details.fine_tuned_model
model_name
```

'ft:gpt-3.5-turbo-0125:leipzig-university::9VNFz3h3'

Start fine-tuning job

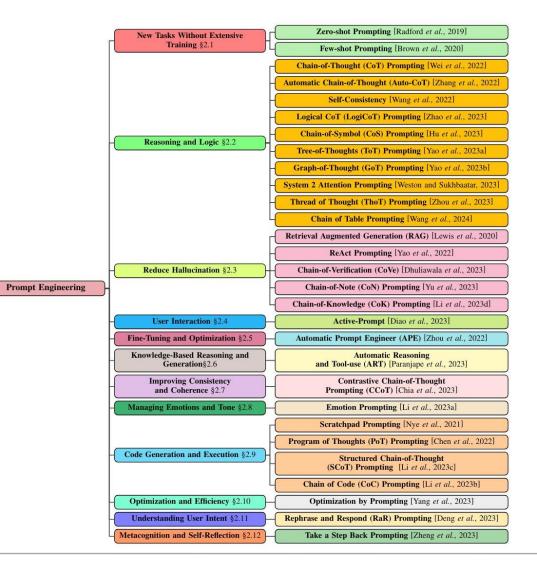
At inference

Test fine-tuned model





## Prompt engineering techniques







### Quiz:

- Assume I can enter my entire knowledge base into one very long prompt.
  - Why would it make sense to implement a RAG solution anyway?
  - Why would it make sense to fine-tune a custom model?
- In what scenario would one prefer the RAG over finetuning a model?

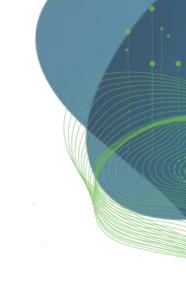




# **Exercises**

ARTIFICIAL INTELLIGENCE

Robert Haase



### Funded by



#### SACHSEN



Diese Maßnahme wird gefördert durch die Bundesregierung aufgrund eines Beschlusses des Deutschen Bundestages. Diese Maßnahme wird mitfinanziert durch Steuermittel auf der Grundlage des von den Abgeordneten des Sächsischen Landtags beschlossenen Haushaltes.







### Exercise

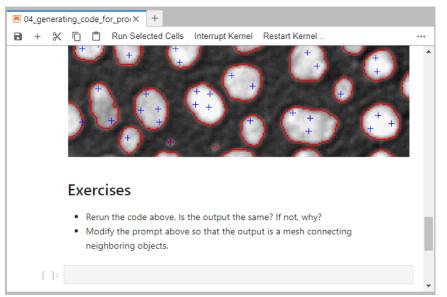
• Hint: you can enter the OpenAI API-key like this at the beginning of notebooks:

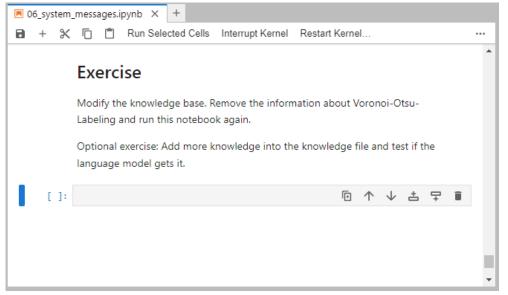
```
import os
os.environ['OPENAI_API_KEY'] = 'sk-...' #todo: enter your API key here
```



## Exercise: Prompt engineering

- Re-run image analysis code generation and elaborate on reproducibility.
- Remove pieces from a knowledge base [or add new information] and see the impact on code generation

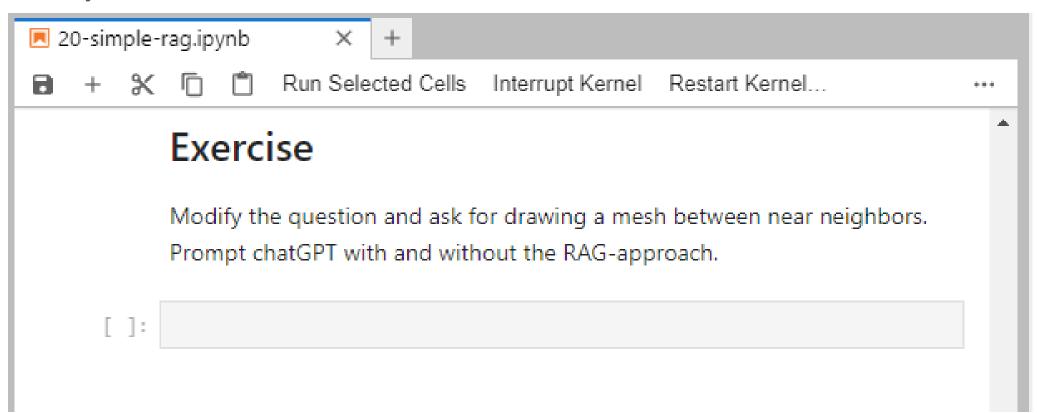






## Exercise: Retrieval augmented generation

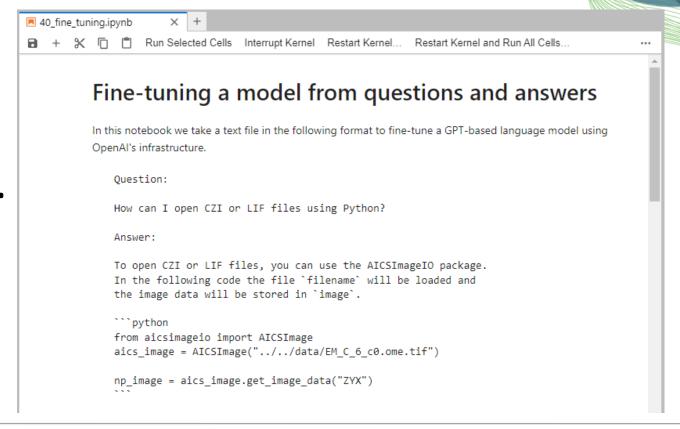
- Compare generated code for complex tasks
- Why does RAG work better / worse in this case?





## Optional exercise: Fine-tuning

- Only run the fine-tuning notebooks if you have a new knowledge base!
  - Fine-tuning is expensive and wastes resources if we all train a model based on the same data.





## Exercise: Comparing fine-tuned models

• I fine-tuned two models for you based on different training datasets:

ft:gpt-3.5-turbo-0125:leipzig-university::9X7PFVgP

ft:gpt-3.5-turbo-0125:leipzig-university::9X7CCzv4

Why do they perform differently?

