

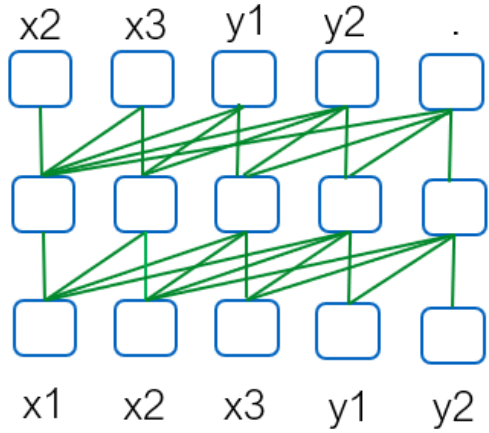


上一节课内容目标

- 预训练模型
 - 掌握常见四大预训练结构
 - 理解LLaMa网络架构
 - 了解ChatGPT形成历史
- 提示学习
 - 掌握提示学习的概念和意义
 - 掌握提示学习的基本方法
 - 理解提示学习中的设计考虑因素
 - 了解最新提示学习的内容



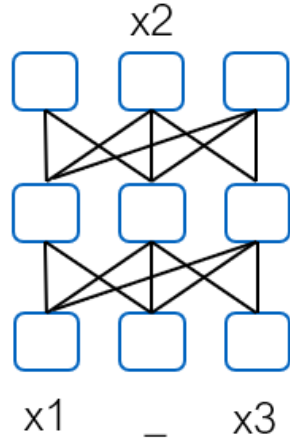
复习: "Big Four" Pretraining Framework



Left-to-right

unidirectional

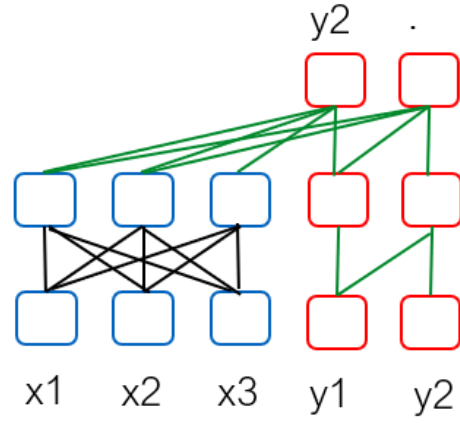
GPT1/2/3



Masked LM

no decoder

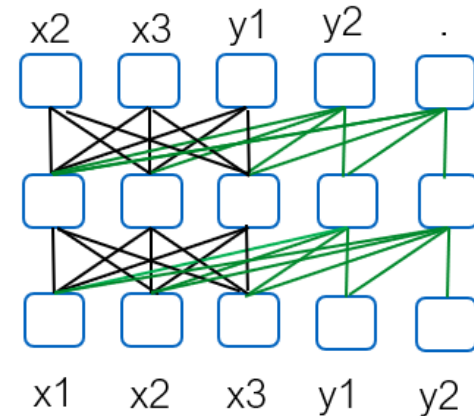
BERT



Encode-decoder

more params

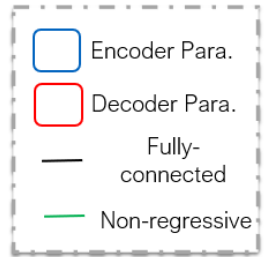
MASS/T5/BART



Prefixed LM

limited capacity

UNiLM/T5





复习：提示学习

- Prompt is the technique of making better use of the knowledge from the pre-trained model by adding additional texts to the input.

purpose

Method



复习: PLMs and Downstream Task Models

Stages

Downstream Task Models

Pre-trained LMs

Reasons

Traditional machine learning



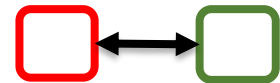
No pre-training language model

Neural network methods enhanced by word2vec



The pre-trained language model plays the role of initializing the input text signal

The fine-tune method represented by BERT



The pre-trained language model is **responsible for extracting** high-level features from the input text

The prompt approach represented by GPT3

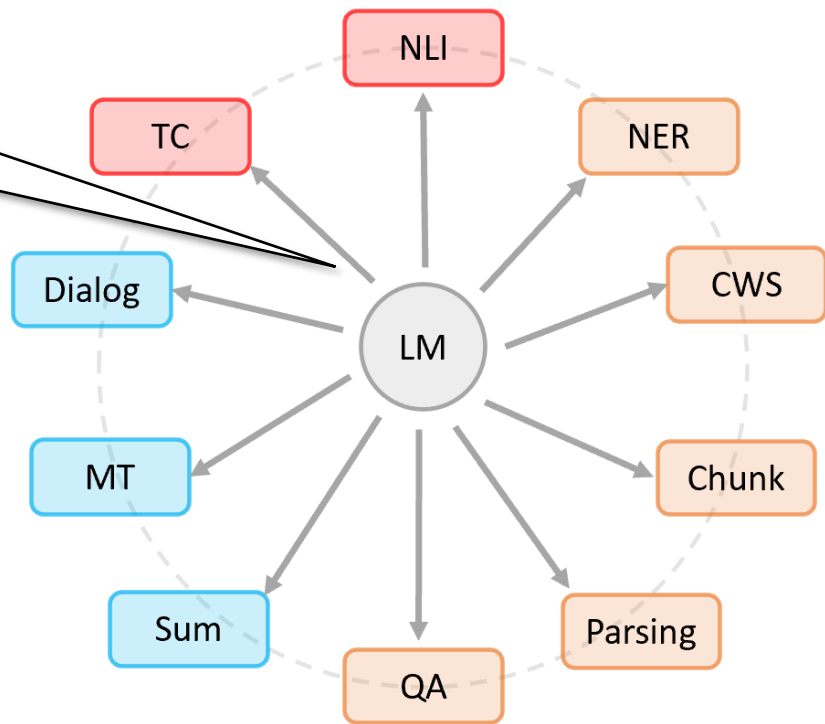


Pre-training language models **take on more responsibilities**: feature extraction, result prediction



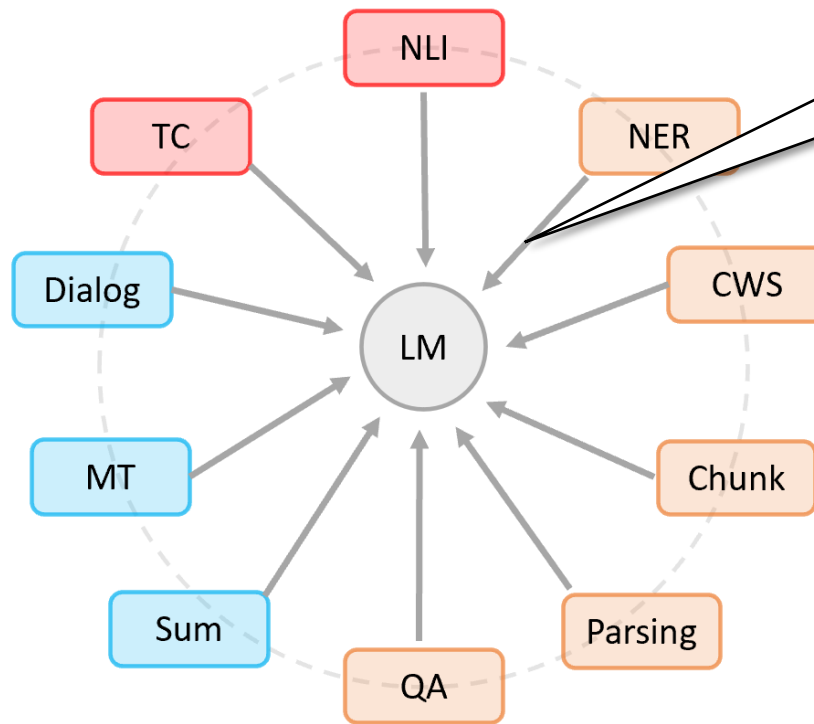
复习：任务的“大一统”

Objective modification



Fine-tuning

Task Reformulation



Prompting



复习：提示学习

Input: $x =$ I love this movie.



Predicting: 😊

Traditional Method

Input: $x =$ I love this movie.



Template: [x]
Overall, it was a [z] movie.



Answer:
{fantastic:😊,
boring:😞}



Prompting: $x' =$ I love this movie.
Overall, it was a [z] movie.



Predicting: $x' =$ I love this movie.
Overall, it was a **fantastic** movie.



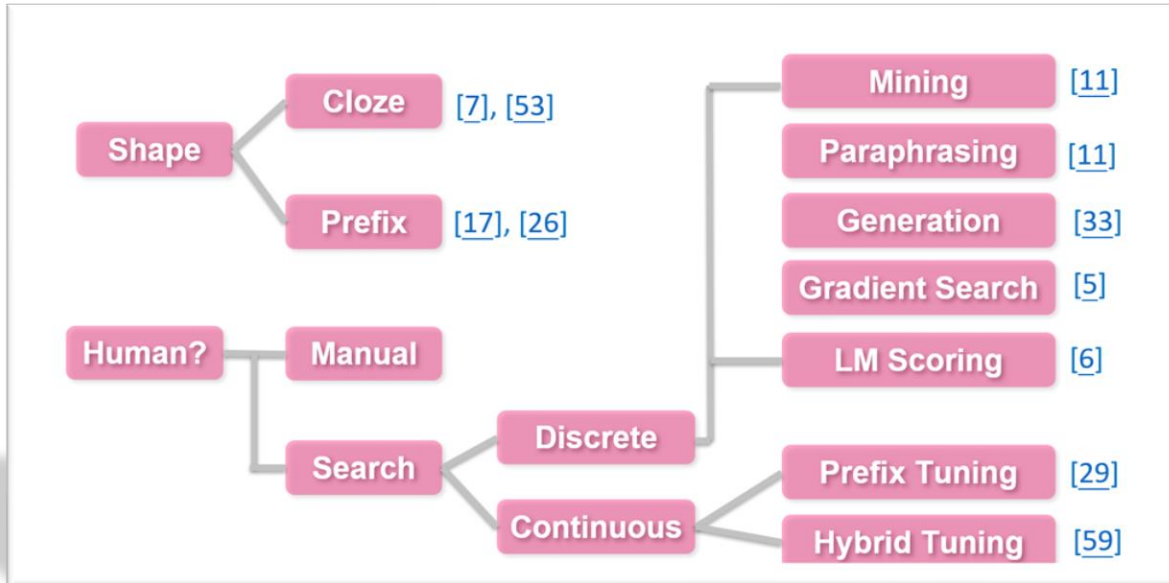
Prompting Method

Mapping: fantastic =>😊



复习： Design Considerations for Prompt-based Methods

- Prompt Template Engineering
- Answer Engineering
- Pre-trained Model Choice
- Expanding the Paradigm
- Prompt-based Training Strategies



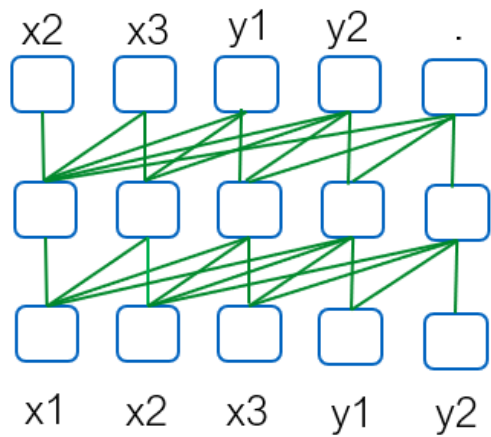
Revisit “Prompt Engineering” in the era of ChatGPT



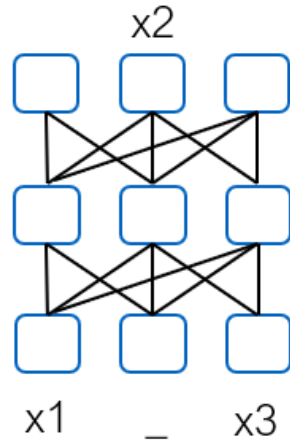
Changes brought by ChatGPT

- Left-to-right models dominate the world

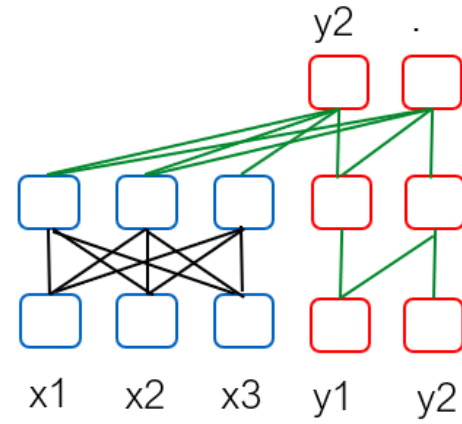
Cloze prompts fade into history



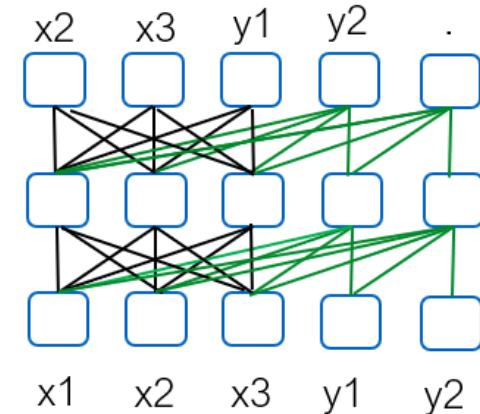
Left-to-right



Masked LM



Encode-decoder



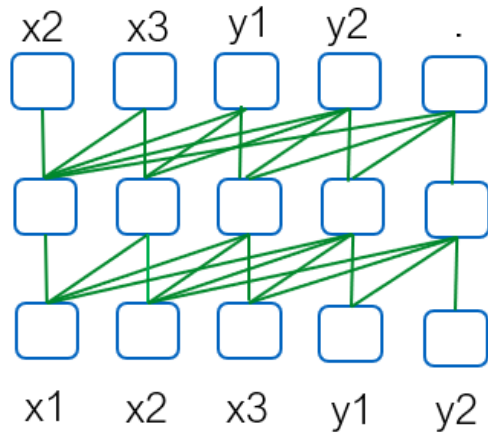
Prefixed LM



Changes brought by ChatGPT

Left-to-right models dominate the world

Cloze prompts fade into history



Left-to-right

OpenAI 一直坚持“安全的 AGI”，但是路径上逐渐聚焦于大语言模型

关键决策：

- 迅速、深度、坚定选择了 Transformer 路线；
- 坚持走了从左到右自然语言生成路线，而不是自然语言理解路线；
- 意识到了“大”和“规模”的力量；
- GPT-3 后迅速引入了人类反馈；

2015 - 2016 2017 - 2018 2018 - 2019 2018 - 2019 2018 - 2019 2019 - 2020 2020 - 2021

关键决策

- 早期 ML Engineering 能力和基础设施建设没有落后于行业，甚至目前比 Google 内部的还好用。
- 从 Unsupervised sentiment neuron 工作开始，逐渐将精力和关注点分配更多给语言模型上。
- 迅速和深度转向 Transformer，没有在 CNN/RNN 等上一代特征提取器上浪费时间。
- 在行业对强化学习的效果充满争议的情况下，在 DOTA 之后的项目中坚持探索深度强化学习。
- 在语言模型中坚持了仅有上文背景的 GPT 式生成式路线，没有追随 BERT 狂潮陷入理解式路线。
- 团队持续思考 Scaling Law 的问题，在 Transformer 基础上押注大规模数据和算力。
- 在长期强调安全和无监督强化学习的情况下，在 GPT-3 工作完成后迅速引入人类反馈。

争议或非共识

- AI 的突破是一项研究工作，而非工程问题；每个探索 AGI 的公司在工程能力和基建并不会有明显差距。
- OpenAI 的这个工作是优化别任务的副作用，歪打正着；语言模型不是通往 AGI 的道路。
- Transformer 彻底抛弃了之前 CNN、RNN 等网络结构；前几年统治 AI 进展的 CV 圈并不买账 Transformer。
- 深度强化学习的效率非常低；强化学习设置奖励函数非常 tricky；它会陷入局部最优，并且通常难以稳定复现效果。
- BERT 代表着未来，GPT 只是基于 Transformer 的过渡性技术；GPT 白白丢掉了下文的信息，在许多自然语言理解任务上都难以和 BERT 竞争。
- AI 的进步来源于算法的创新；算力在过去 10 年的进步不一定在未来 10 年持续。
- 随着模型变得更智能，Alignment 问题可以自动解决，人类反馈多此一举；人类反馈违反了无监督的原教旨，并且缺少可拓展性。

OpenAI 的选择原因

- 核心圈子里，没落后于业界趋势；创始人 Greg Brockman 是工程师和代码狂人；OpenAI 很早在 Gym/Universe 上就遭遇工程挑战。
- OpenAI 在研究中注重寻找 Signs of Life；OpenAI 想明白了理解与预测是有联系的，好的预测需要一定程度的理解，这个工作印证了这一原则。
- Transformer 是 CapsNet (这是 Ilya 和导师 Hinton 做出的重要工作) 的近亲，因为软注意力机制 (Soft Attention) 跟“协商路由” (Routing by Agreement) 有很多理念相似点；有人认为 Ilya 的 Neural GPU 工作某种程度上启发了 Transformer。
- OpenAI 的创始人 Ilya 和 John 分别是深度学习和强化学习领域的引领者，可以忽略某些质疑；John 是 PPO、TRPO 等强化学习算法的发明者，它们就是要克服这些业界质疑的问题。
- 一定的运气，Unsupervised sentiment neuron 是 BERT 出现前的工作；OpenAI 瞄准的目标是 AGI，因此目标用例是自然语言生成，这恰好连带解决了自然语言理解问题。
- 顶尖业界探索者逐渐形成共识，Rich Sutton 在 19 年发布了 The Bitter Lesson；OpenAI 经过 Five 和 Dota 项目更加对数据和算力的进步有信仰，提出了 Scaling Law，并且引入了足够资源尝试 GPT-3。
- 安全一直是 OpenAI 比同行强调更多的，OpenAI 从 17 年就和 Deepmind 做了少量人类反馈中优化强化学习代理表现的工作；OpenAI 积累了的强化学习人才和基建，反应速度快，从人工标注到 AI 辅助，终极目标是让 AI 反馈 AI。



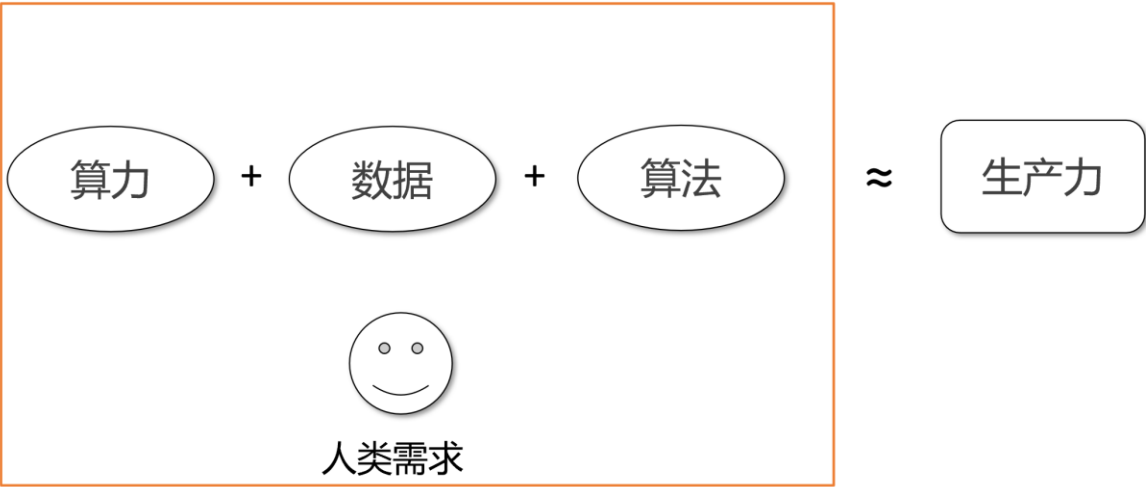
Changes brought by ChatGPT

- ❑ Left-to-right models dominate the world
- ❑ Solving traditional NLP tasks are not the most important things

Cloze prompts fade into history

Prompt distribution matters a lot

- | | |
|---|---|
| Grammar correction
Convert ungrammatical statements into standard English. | Summarize for a 2nd grader
Simplify text to a level appropriate for a second-grade student. |
| Parse unstructured data
Create tables from unstructured text. | Emoji Translation
Translate regular text into emoji text. |
| Calculate time complexity
Find the time complexity of a function. | Explain code
Explain a complicated piece of code. |
| Keywords
Extract keywords from a block of text. | Product name generator
Generate product names from a description and seed words. |
| Python bug fixer
Find and fix bugs in source code. | Spreadsheet creator
Create spreadsheets of various kinds of data. |
| Tweet classifier
Detect sentiment in a tweet. | Airport code extractor
Extract airport codes from text. |
| Mood to color
Turn a text description into a color. | VR fitness idea generator
Generate ideas for fitness promoting virtual reality games. |
| Marv the sarcastic chat bot
Marv is a factual chatbot that is also sarcastic. | Turn by turn directions
Convert natural language to turn-by-turn directions. |
| Interview questions
Create interview questions. | Function from specification
Create a Python function from a specification. |
| Improve code efficiency
Provide ideas for efficiency improvements to Python code. | Single page website creator
Create a single page website. |
| Rap battle writer
Generate a rap battle between two characters. | Memo writer
Generate a company memo based on provided points. |





Changes brought by ChatGPT

- ❑ Left-to-right models dominate the world
- ❑ Solving traditional NLP tasks are not the most important things
- ❑ API-based research become more popular

Cloze prompts fade into history

Prompt distribution matters a lot

Zero-shot & few-shot prompting



Changes brought by ChatGPT

- ❑ Left-to-right models dominate the world
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- ❑ API-based research become more popular
- ❑ Supervised fine-tuning become popular

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Prompt distribution matters a lot

Zero-shot & few-shot prompting

Prompt scaling law



Changes brought by ChatGPT

- ❑ Left-to-right models dominate the world
- ❑ Solving traditional NLP tasks are not the most important things
- ❑ API-based research become more popular
- ❑ Supervised fine-tuning become popular
- ❑ Evaluation is difficult

Cloze prompts fade into history

Prompt distribution matters a lot

Zero-shot & few-shot prompting

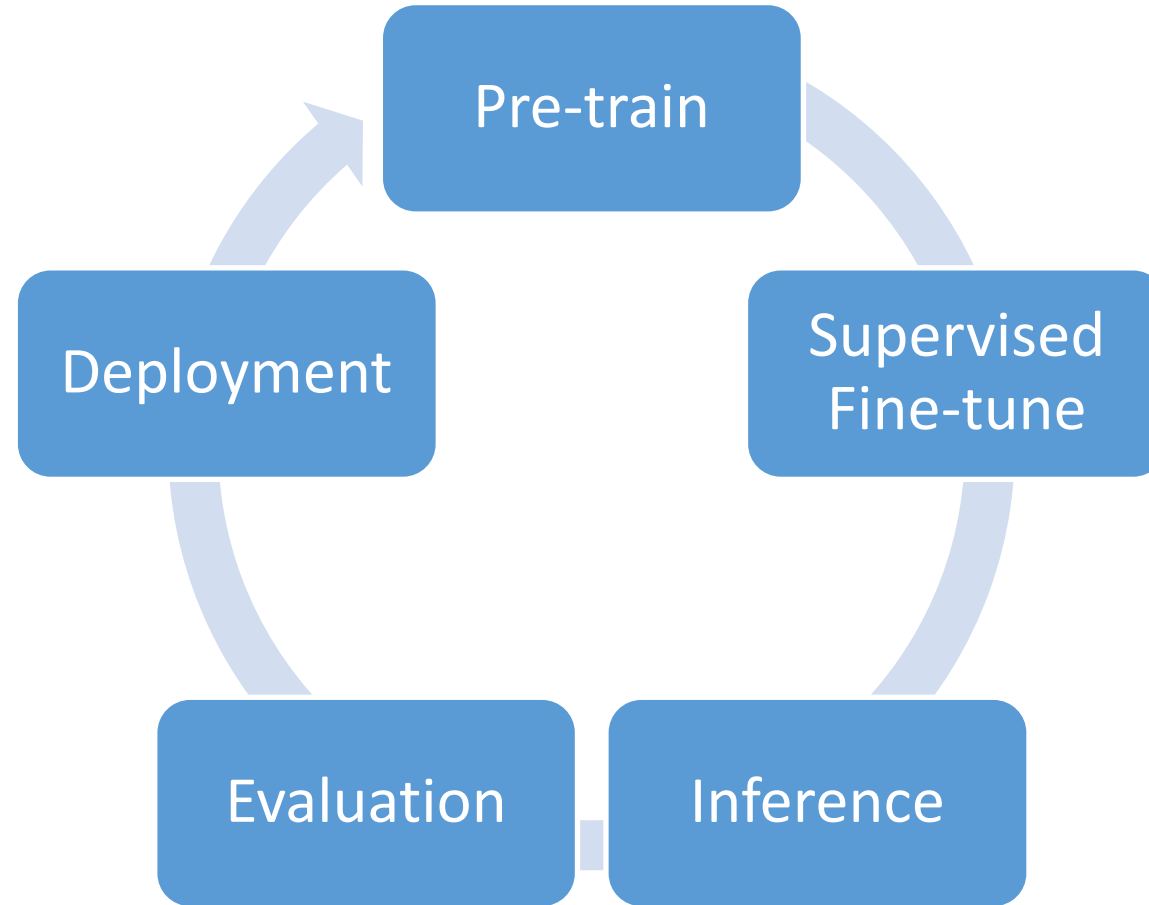
Prompt scaling law

Prompt-based evaluation

Prompt Engineering 2.0: Design Considerations



Prompt Engineering in LLMOps





Prompt Engineering: Supervised Fine-tuning

- Prompt Diversity
 - How does prompt diversity affect model's performance?
- Prompt number
 - How does the number of prompts affect model's performance?
- Response Quality
 - How does the quality of response affect model's performance?



Prompt Engineering: Supervised Fine-tuning

Table 3: English Instruction Data (Continued from Table 2)

Dataset	# Tasks	# Instructions	Lan	Collection Method	Usage	Access	Human Verified?
OIG (AI, 2021)	30	43M	English	Mixed	Instruct. Tuning	Open	No
Baize (Xu et al., 2023)	3	100K+	English	Model Generated	Chat	Open	No
Camel (Guohao et al., 2023)	-	115K	English	Model Generated	Instruct. Tuning, Chat	Open	No
UltraChat (Ding et al., 2023)	-	675K	English	Model Generated	Chat	Open	No
Dolly (Databricks, 2022)	7	15,000	English	Human Annotated	Instruct. Tuning	Open	Yes
Guanaco-Dataset (JosephusCheung, 2021)	175	534,530	Multilingual	Mixed	Instruct. Tuning	Open	No
ChatLLaMA Chinese-ChatLLaMA (YDli-ai, 2021)	-	-	Multilingual	Mixed	Instruct. Tuning	Open	No
GPT-4-LLM (Peng et al., 2023)	175	165K	Multilingual	Model Generated	RLHF, Instruct. Tuning	Open	No
ShareGPT (ShareGPT, 2021)	-	-	Multilingual	Model Generated	Instruct. Tuning, Chat	Closed	Yes
SHP (Ethayarajh et al., 2023)	18	385K	English	Existing, Human Annotated	RLHF, Instruct. Tuning	Open	Yes
HH-RLHF (Bai et al., 2022; Anthropic, 2022; Ganguli et al., 2022)	-	169,550	English	Mixed	RLHF, Instruct. Tuning	Open	Yes
HC3 (Guo et al., 2023)	12	37,175	Multilingual	Mixed	Instruct. Tuning	Open	Yes

A Survey of Recently Released “Instructions” (Zhang et al)

Prompt Engineering: Supervised Fine-tuning

	MMLU (factuality)	GSM (reasoning)	BBH (reasoning)	TydiQA (multilinguality)	Codex-Eval (coding)	AlpacaFarm (open-ended)	Average
	EM (0-shot)	EM (8-shot, CoT)	EM (3-shot, CoT)	F1 (1-shot, GP)	P@10 (0-shot)	Win % vs Davinci-003	
Vanilla LLaMa 13B	42.5	14.0	36.9	47.4	26.6	-	-
+SuperNI	49.8	4.0	2.8	51.4	13.1	5.0	21.0
+CoT	44.5	39.5	39.0	52.2	23.3	4.7	33.9
+Flan V2	50.7	21.0	39.2	47.5	16.2	5.3	30.0
+Dolly	45.3	17.0	26.0	46.8	31.4	18.3	30.8
+Open Assistant 1	43.1	16.0	38.5	38.3	31.8	55.2	37.1
+Self-instruct	30.3	9.0	29.6	40.4	13.4	7.3	21.7
+Unnatural Instructions	46.2	7.5	32.8	39.3	24.8	10.8	26.9
+Alpaca	45.1	8.0	34.5	32.8	27.6	33.2	30.2
+Code-Alpaca	42.6	12.0	36.6	41.3	34.5	21.3	31.4
+GPT4-Alpaca	47.0	14.0	38.3	24.4	32.5	63.6	36.6
+Baize	43.5	8.5	36.7	33.9	27.3	33.9	30.6
+ShareGPT	49.2	16.0	40.1	30.1	31.6	69.1	39.3
+ Human data mix	50.4	36.5	39.4	49.8	23.7	38.5	39.7
+Human+GPT data mix.	49.2	36.5	42.8	46.1	35.0	57.2	44.5

Which “instruction” data is the best? (Wang et al)

Prompt Engineering: Supervised Fine-tuning

Source	#Examples	Avg Input Len.	Avg Output Len.
Training			
Stack Exchange (STEM)	200	117	523
Stack Exchange (Other)	200	119	530
wikiHow	200	12	1,811
Pushshift r/WritingPrompts	150	34	274
Natural Instructions	50	236	92
Paper Authors (Group A)	200	40	334
Dev			
Paper Authors (Group A)	50	36	N/A
Test			
Pushshift r/AskReddit	70	30	N/A
Paper Authors (Group B)	230	31	N/A

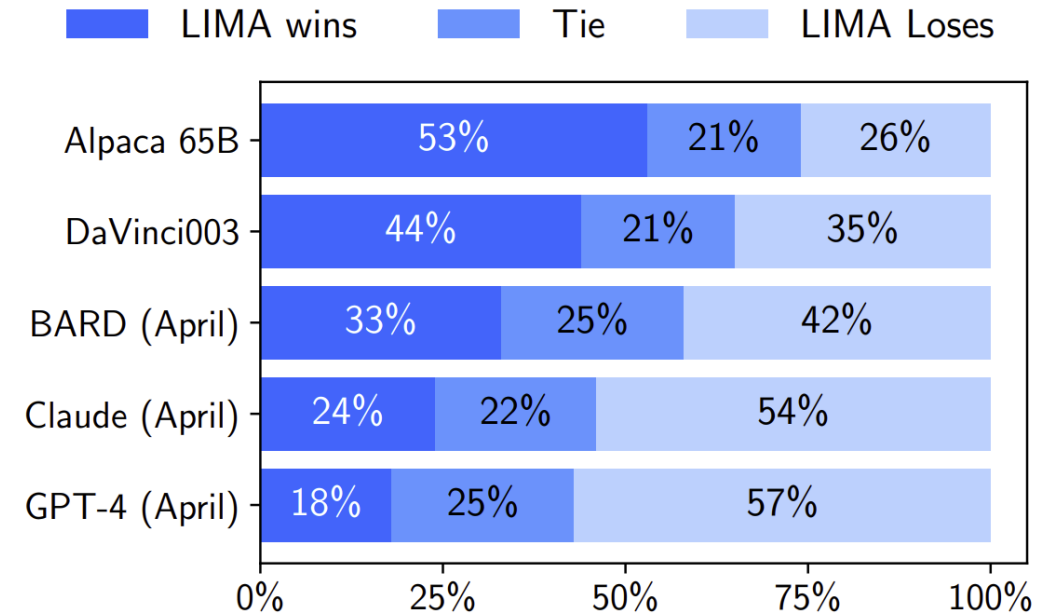


Figure 1: Human preference evaluation, comparing LIMA to 5 different baselines across 300 test prompts.



Prompt Engineering: Inference

- Zero-shot Prompting:
 - How to ask a good question that ChatGPT can better understand you?



Prompt Engineering: Inference

你是一个中文人工智能助手，你需要仿照示例，根据给定的除示例外的所有法律生成一个包含题目、选项分析和答案的单项选择题。在生成单项选择题时，你必须遵守以下几个原则：

- 题目构成
- 题目描述
- 题目生成的整体限制
- 1. 题目由题目描述和4个选项构成
- 2. 单项选择题的题目描述需要合理
- 3. 尽可能根据除示例外的所有法律生成题目，避免使用单条法律生成题目
- 4. 在生成4个选项时，结合题目描述与除示例外的所有法律，首先设计1个正确答案的选项，然后再设计3个错误的选项，接着这4个选项以随机的顺序排列
- 5. 选项互有差异，避免选项之间的明显重复或相似性
- 6. 在设计选项时，不要使得某些选项明显不可能是正确答案
- 7. 每个选项需要和题目描述相关
- 8. 每个选项需要前后内容一致
- 9. 不能直接从给定的法律中复制文本作为选项内容，需要结合给定的法律生成合理的选项
- 10. 依次生成题目、选项分析和答案
- 选项分析
- 11. 选项分析是结合题目与除示例外的所有法律，对每个选项进行分析
- 答案
- 12. 选项分析中的正确答案是最终答案

以下是1个示例：

示例：
{example}

让我们一步一步思考，参考示例并结合给定法律"{input_law}"{action}，依次生成下面内容：

题目：

选项分析：

答案：

法律：企业破产法：第四十六条 未到期的债权，在破产申请受理时视为到期。附利息的债权自破产申请受理时起停止计息。第四十七条 附条件、附期限的债权

题目：A公司因经营不善，资产已不足以清偿全部债务，经申请进入破产还债程序。关于破产债权的申报，下列哪个表述是正确的？

A. 甲对A公司的债权虽未到期，不可以申报
B. 乙对A公司的债权因附有条件，故不能申报
C. 丙对A公司的债权虽然诉讼未决，但丙仍可以申报
D. 职工丁对A公司的伤残补助请求权，应予以申报

选项分析：《企业破产法》第46条第一款规定，未到期的债权，在破产申请受理时视为到期。据此可知，未到期的债权，仍可申报。选项A错误。《企业破产法》

答案：C

中华人民共和国河道管理条例规定：第十条 河道的整治与建设，应当服从流域综合规划，符合国家规定的防洪标准、通航标准和其他有关技术要求，维护堤防安全，保持河势稳定和行洪、航运通畅。第十一条 修建开发水利.....

设计一个法律情景/针对给定法律中的某个概念



Prompt Engineering: Changes brought by ChatGPT

- Zero-shot Prompting
- Few-shot Prompting
 - How do I get the model to mimic a given example?
 - Format following
 - Reasoning step decomposition



“X”- of thought

Chain-of-thought

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 tennis balls. 2 cans of 3 tennis balls each is 6 tennis balls. $5 + 6 = 11$. The answer is 11.

Q: The bakers at the Beverly Hills Bakery baked 200 loaves of bread on Monday morning. They sold 93 loaves in the morning and 39 loaves in the afternoon. A grocery store returned 6 unsold loaves. How many loaves of bread did they have left?

Model Output

A: The bakers started with 200 loaves. They sold 93 in the morning and 39 in the afternoon. So they sold $93 + 39 = 132$ loaves. The grocery store returned 6 loaves. So they had $200 - 132 - 6 = 62$ loaves left.

The answer is 62.



Program-of-thought

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 tennis balls.

`tennis_balls = 5`

2 cans of 3 tennis balls each is

`bought_balls = 2 * 3`

tennis balls. The answer is

`answer = tennis_balls + bought_balls`

Q: The bakers at the Beverly Hills Bakery baked 200 loaves of bread on Monday morning. They sold 93 loaves in the morning and 39 loaves in the afternoon. A grocery store returned 6 unsold loaves. How many loaves of bread did they have left?

Model Output

A: The bakers started with 200 loaves

`loaves_baked = 200`

They sold 93 in the morning and 39 in the afternoon

`loaves_sold_morning = 93`

`loaves_sold_afternoon = 39`

The grocery store returned 6 loaves.

`loaves_returned = 6`

The answer is

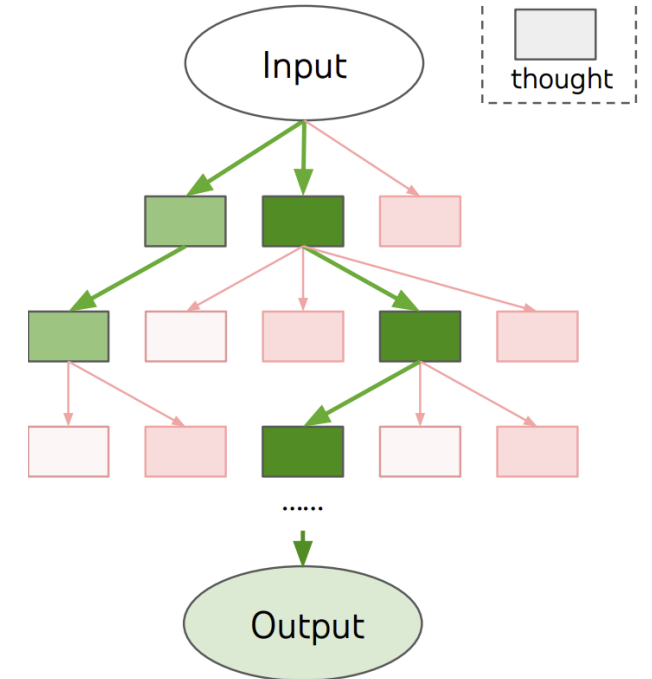
`answer = loaves_baked - loaves_sold_morning - loaves_sold_afternoon + loaves_returned`

`>>> print(answer)`

74



Tree-of-thought





Prompt Engineering: Evaluation

- How to evaluate a model as you desire?



Prompt Engineering: Evaluation

□ Evaluation

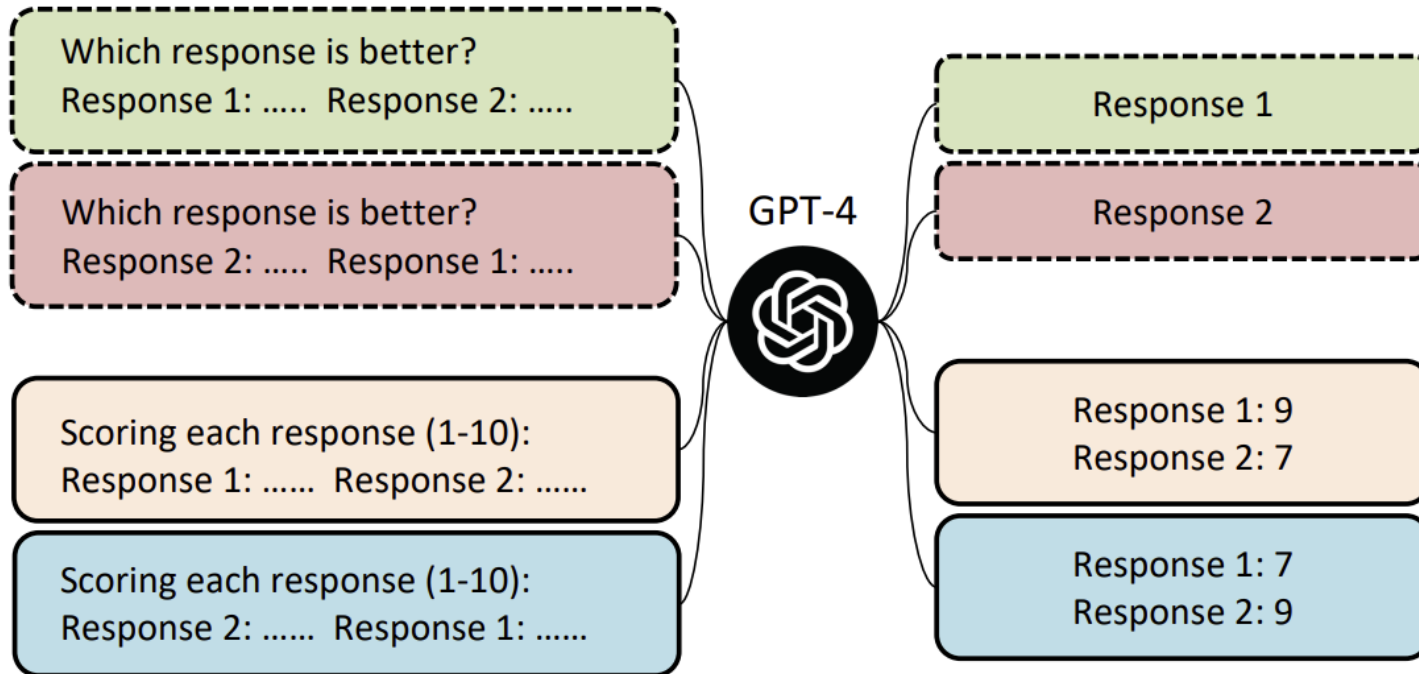
■ How to evaluate a model as you desire? **ChatGPT Score**

```
prompt: |-
You are evaluating a response that has been submitted for a particular task, using a specific set of standards. Below is the data:
[BEGIN DATA]
***
[Task]: {input}
***
[Submission]: {completion}
***
[Criterion]: {criteria}
***
[END DATA]
Does the submission meet the criterion? First, write out in a step by step manner your reasoning about the criterion to be sure that your conclusion is correct. Avoid simply stating the correct answers at
Reasoning:
eval_type: cot_likert
choice_scores:
"1": 1.0
"2": 2.0
"3": 3.0
"4": 4.0
"5": 5.0
"6": 6.0
criteria:
  helpfulness:
    "1": "Not helpful - The generated text is completely irrelevant, unclear, or incomplete. It does not provide any useful information to the user."
    "2": "Somewhat helpful - The generated text has some relevance to the user's question, but it may be unclear or incomplete. It provides only partial information, or the information provided may not be us
    "3": "Moderately helpful - The generated text is relevant to the user's question, and it provides a clear and complete answer. However, it may lack detail or explanation that would be helpful for the use
    "4": "Helpful - The generated text is quite relevant to the user's question, and it provides a clear, complete, and detailed answer. It offers additional information or explanations that are useful for t
    "5": "Very helpful - The generated text is highly relevant to the user's question, and it provides a clear, complete, and detailed answer. It offers additional information, explanations, or analogies tha
    "6": "Highly helpful - The generated text provides a clear, complete, and detailed answer. It offers additional information or explanations that are not only useful but also insightful and valuable to t
```



Prompt Engineering: Evaluation

- How to evaluate a model as you desire?





Prompt Engineering: Deployment

- How to design a good preface?
 - GPT Agent
 - System Message
- How to prevent jailbreak prompt?

```
1 import openai
2
3 openai.ChatCompletion.create(
4     model="gpt-3.5-turbo",
5     messages=[
6         {"role": "system", "content": "You are a helpful assistant."},
7         {"role": "user", "content": "Who won the world series in 2020?"},
8         {"role": "assistant", "content": "The Los Angeles Dodgers won the World Series in 2020."},
9         {"role": "user", "content": "Where was it played?"}
10    ]
11 )
```

< New GPT
+ Draft

Create Configure

+ (Add icon)

Name
Name your GPT

Description
Add a short description about what this GPT does

Instructions
What does this GPT do? How does it behave? What should it avoid doing?

Conversation starters

Knowledge
If you upload files under Knowledge, conversations with your GPT may include file contents. Files can be downloaded when Code Interpreter is enabled

Upload files

Capabilities
 Web Browsing
 DALL·E Image Generation
 Code Interpreter

Actions



Prompt Engineering: Pre-train

- How to prompt pre-training data so that
 - the next word could be better predicted
 - the stored information can be better elicited



变化中寻找“不变”：预训练模型与任务模型越来越近

Stages

Downstream Task Models

Pre-trained LMs

Reasons

Traditional machine learning



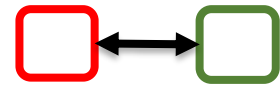
No pre-training language model

Neural network methods enhanced by word2vec



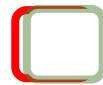
The pre-trained language model plays the role of initializing the input text signal

The fine-tune method represented by BERT



The pre-trained language model is **responsible for extracting** high-level features from the input text

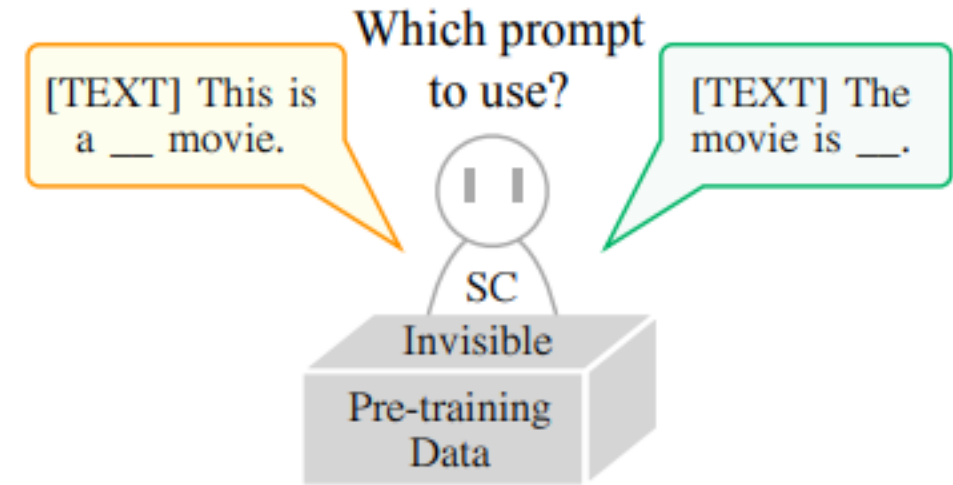
The prompt approach represented by GPT3



Pre-training language models **take on more responsibilities**: feature extraction, result prediction

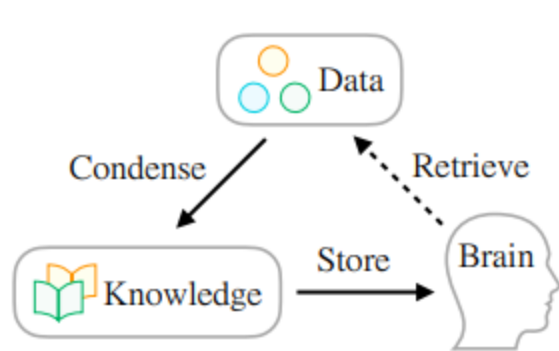
变化中寻找“不变”：信息存储和访问的方式越来越近

- The way how information is stored is opaque
- There is a gap between data storing and accessing

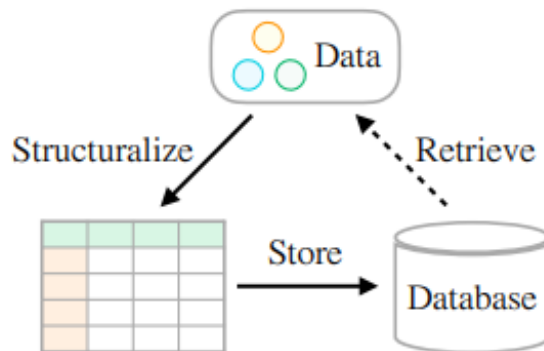


The sentiment classification (SC) task is guessing which prompt should be used

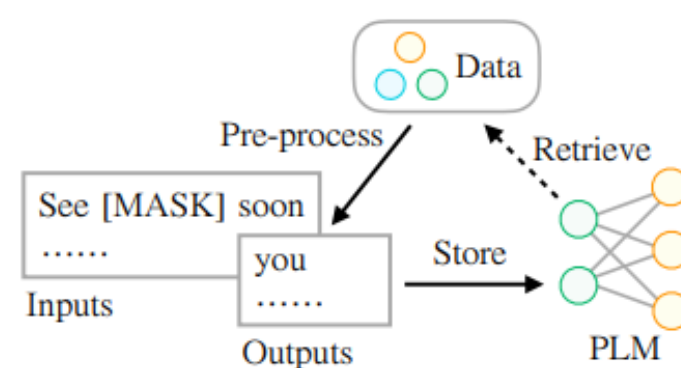
变化中寻找“不变”：信息存储和访问的方式越来越近



(a) Biological neural networks.

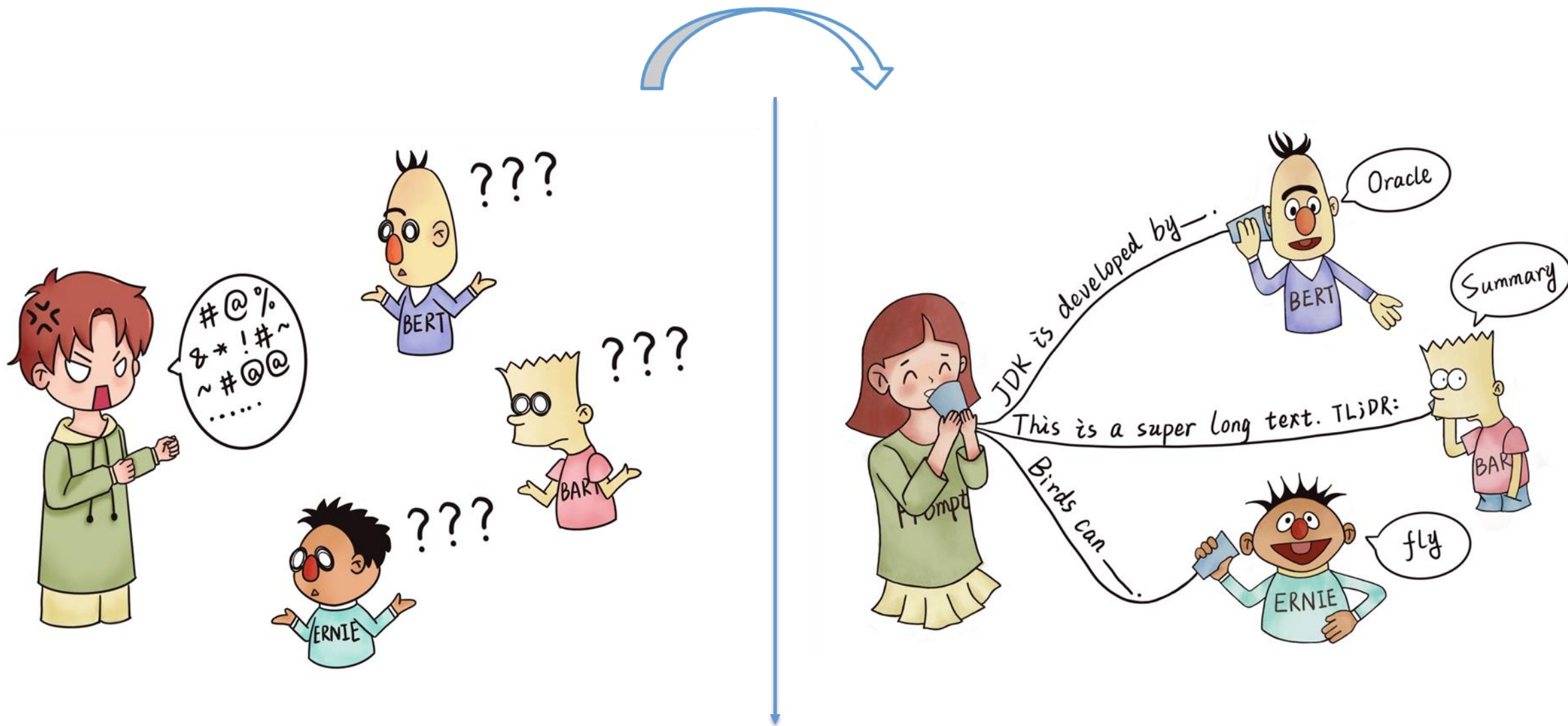


(b) Disk/Cloud storage.



(c) Artificial neural networks.

变化中寻找“不变”：人与AI越来越近





如何写好prompt?

- [Six strategies for getting better results \(OpenAI\)](#)
- [OpenAI Cook Book](#)