大型語言模型的發展與應用

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大綱

- ・語言模型
- · 大型語言模型(LLMs)
- · ChatGPT的應用與限制

語言模型

Probabilistic Language Modeling

· 語言模型可以評估某一段文字之於某個語言出現的機率

$$P(W) = P(w_1, w_2, w_3, ..., w_n)$$

· 給定一段文句, 讓語言模型預測最有可能的下一個詞彙, 就具備了語言生成的能力

$$P(w_{n+1}) = \arg\max_{w \in V} P(w|w_1, w_2, w_3, ..., w_n)$$

語言模型的建立

- · 如何計算以下文句的機率?
 - P("The dog ate my cake")
 - P("The cake ate my dog")

N-gram Models

· 只考慮與前 N-1 個詞彙的關係

$$P(w_1, w_2, w_3, ..., w_n) \approx \prod_{i=1}^{n} P(w_i | w_{i-k+1}, w_{i-k+2}, ..., w_{i-1})$$

· Bigram模型,只考慮與前一個詞彙的關係

$$P(w_1, w_2, w_3, ..., w_n) \approx \prod_{i=1}^{n} P(w_i | w_{i-1})$$

Bigram的計算

$$P(w_i|w_{i-1}) = \frac{C(w_{i-1}, w_i)}{C(w_{i-1})}$$

P(The dog ate my cake)

$$= P(\text{The}|<\text{s}>)P(\text{dog}|\text{The})P(\text{ate}|\text{dog})P(\text{my}|\text{ate})P(\text{cake}|\text{my})$$

$$= \frac{C(<\text{s}>\text{The})}{C(<\text{s}>)}\frac{C(\text{The dog})}{C(\text{The})}\frac{C(\text{dog ate})}{C(\text{dog})}\frac{C(\text{ate my})}{C(\text{ate})}\frac{C(\text{my cake})}{C(\text{my})}$$

N-gram模型的缺點

- · N較小的 N-gram 模型無法掌握長距上下文關系
- ·N大時、語料庫無法提供足夠的統計樣本
 - · 稀疏性 (Sparsity)

語言模型早期的應用

- · 文字辨識 (Optical character recognition)
 - ・基於語言用法優化辨識結果
- ・語音辨識
 - ・解析音訊相似的歧義性
 - P("I saw a fan") vs P("eyes awe of an")

語言模型的傳統應用

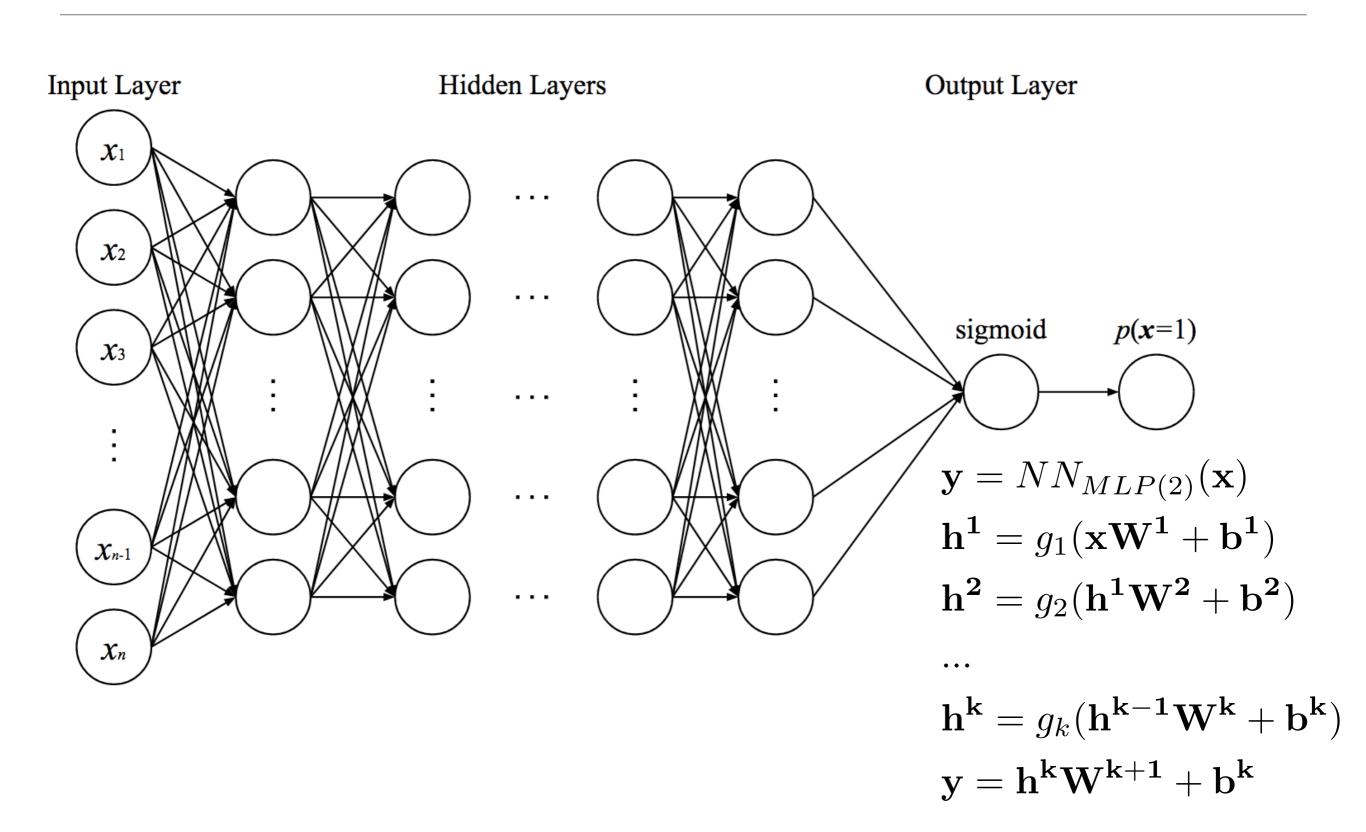
- ・機器翻譯
 - ・產生更符合目標語言習慣的翻譯
 - · 他是一個好人 => P("he is a nice person") vs P("he is a good person")
- ・文法更正
 - · He is in the bus
 - · He is at the bus
 - · He is on the bus

基於神經網路的語言模型

- ·用RNN或Transformer直接學習預測下一個詞彙
 - · 透過詞彙相量表徵語意資訊, 而非死板的字符匹配
 - · RNN和Transformer網路並非死板的計算連續N個詞彙的頻率,能萃取距離不等但重要的文字相依關係
- ・減少稀疏性, 從而能從有限的資料中學習豐富的詞彙組 合與上下文意

類神經網路與自然語言處理

Feed-forward Neural Network

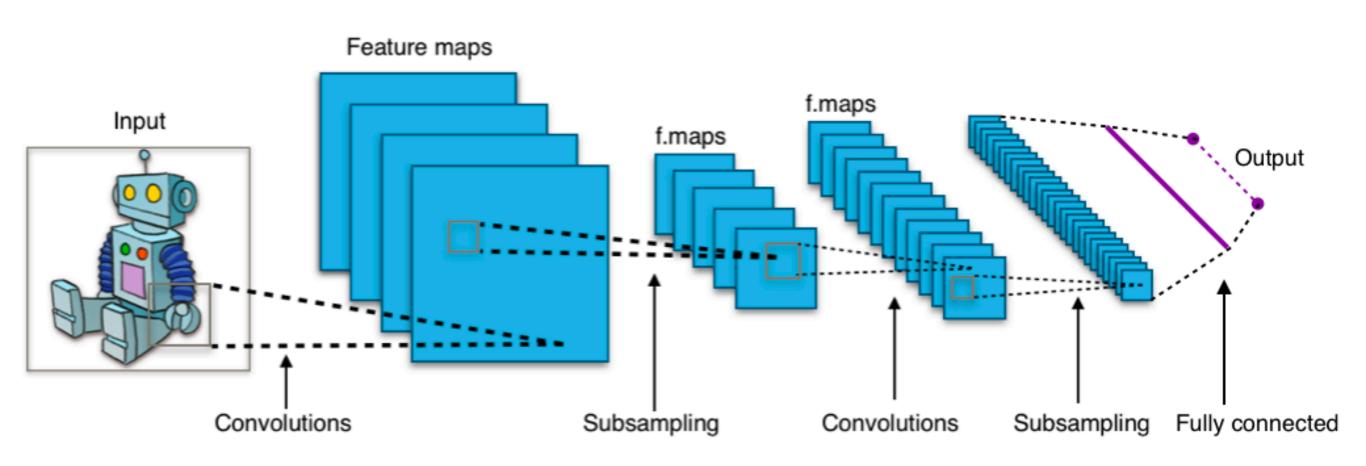


對序列資訊建模

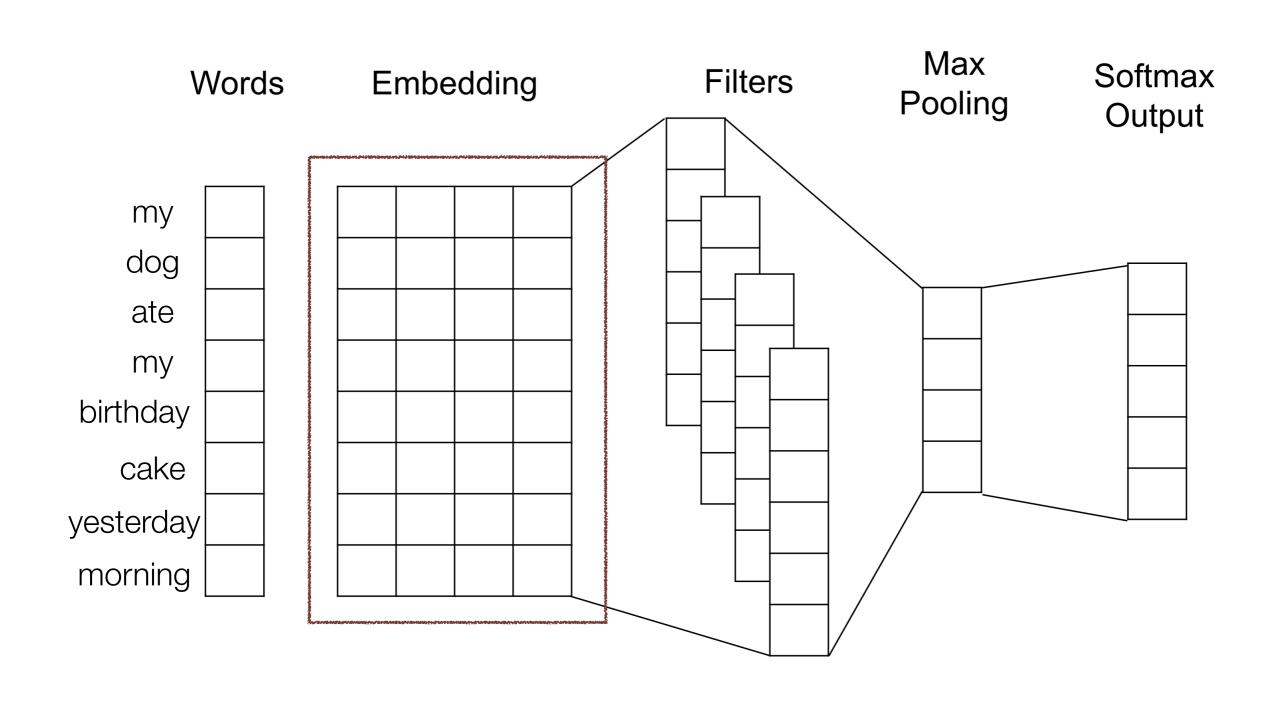
- · 文字的順序是自然語言處理的關鍵之一, 無法掌握文字的順序, 就無法進行細膩的文字理解與生成
- · Feed-forward neural network和傳統機器學習模型一樣,無法有效萃取文字的順序資訊
- ・需要對文字的相對位置更敏感的模型

Convolutional Neural Networks

·影像處理、電腦視覺上最主要的神經網路架構



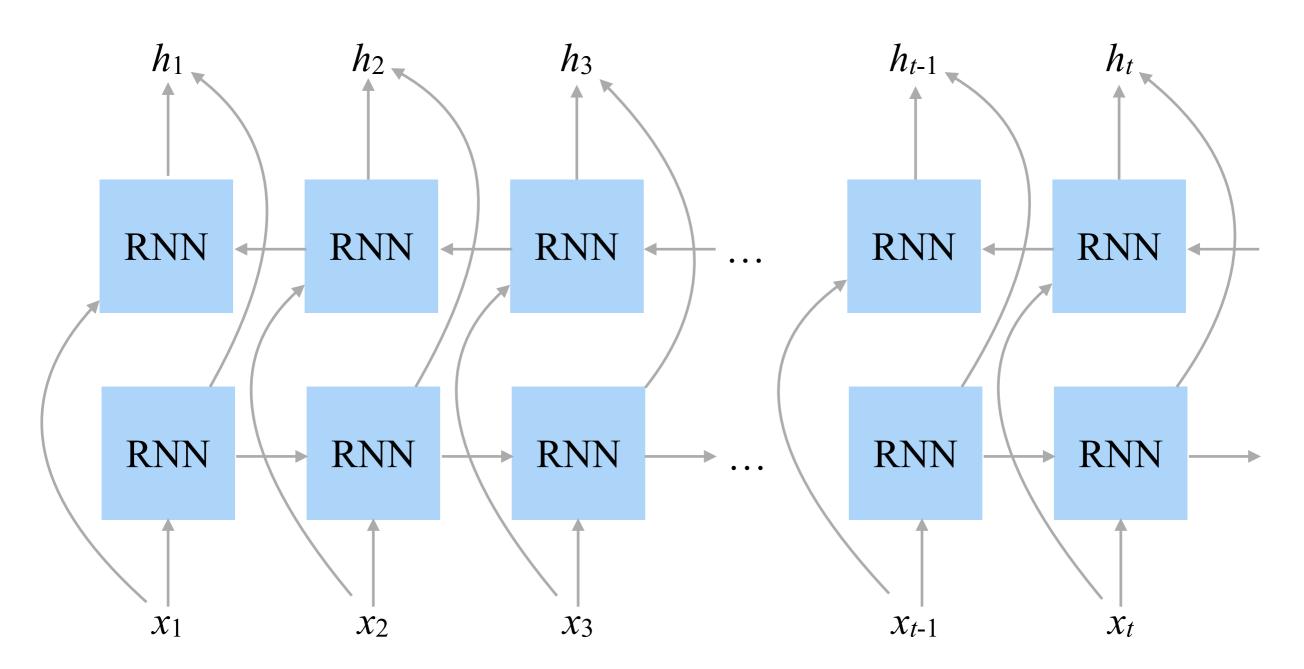
CNN於自然語言處理



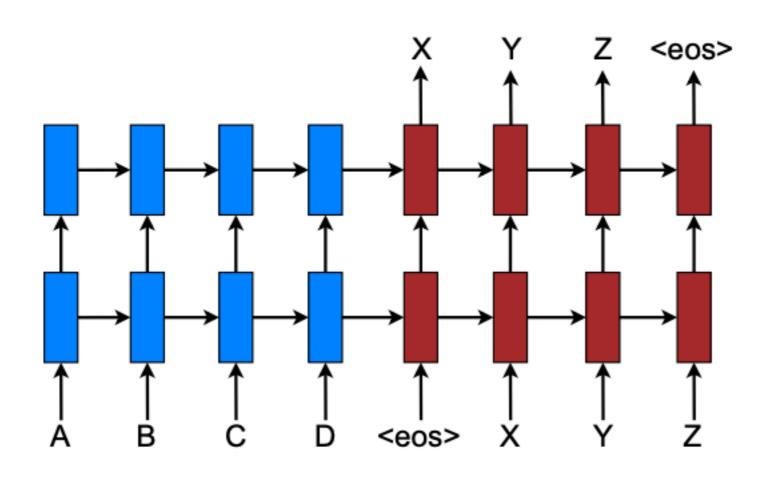
用 N * D 的矩陣,表徵長度為 N 的句子

雙向RNN

- ·架接正向、逆向兩個方向的RNN網路
- · 序列上每一個項目的表徵,來自其正向、逆向隱藏層的接合

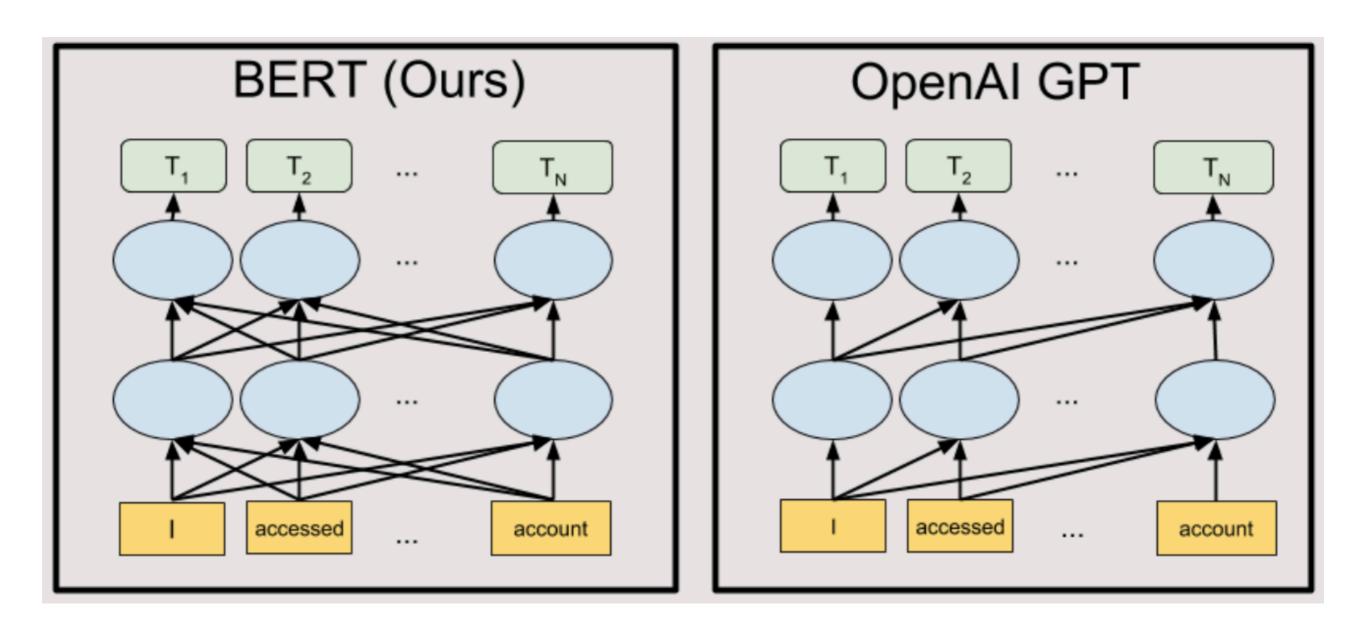


序列對序列建模



$$P(\mathbf{y}|\mathbf{x}) = P(y_1, y_2, ..., y_M|\mathbf{x}) = \prod_{t=0}^{M} P(y_t|y_1, y_2, ..., y_{t-1}, \mathbf{x})$$

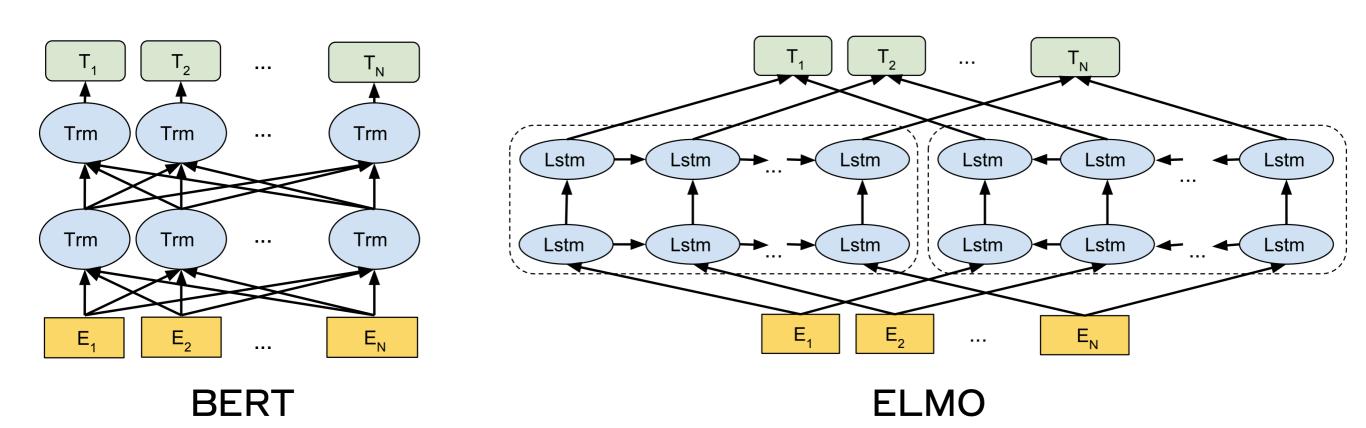
The Transformer Architecture



https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html

Transformer vs RNN

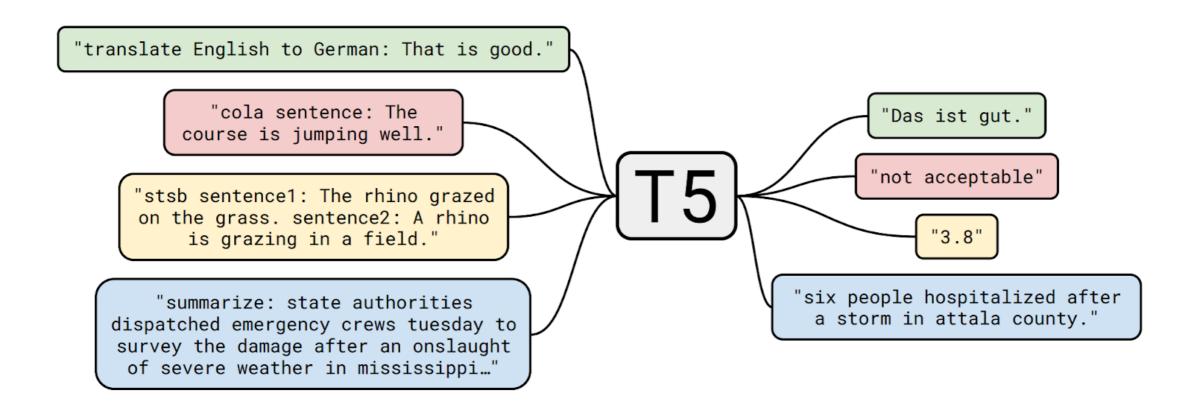
- · RNN預設鄰近的詞彙比遠距的詞彙重要,相依性會依距離而稀釋
- · Transformer窮舉所有詞彙間的關係,由訓練決定詞彙 之間的重要性



T5 (Text-to-Text Transfer Transformer) 模型

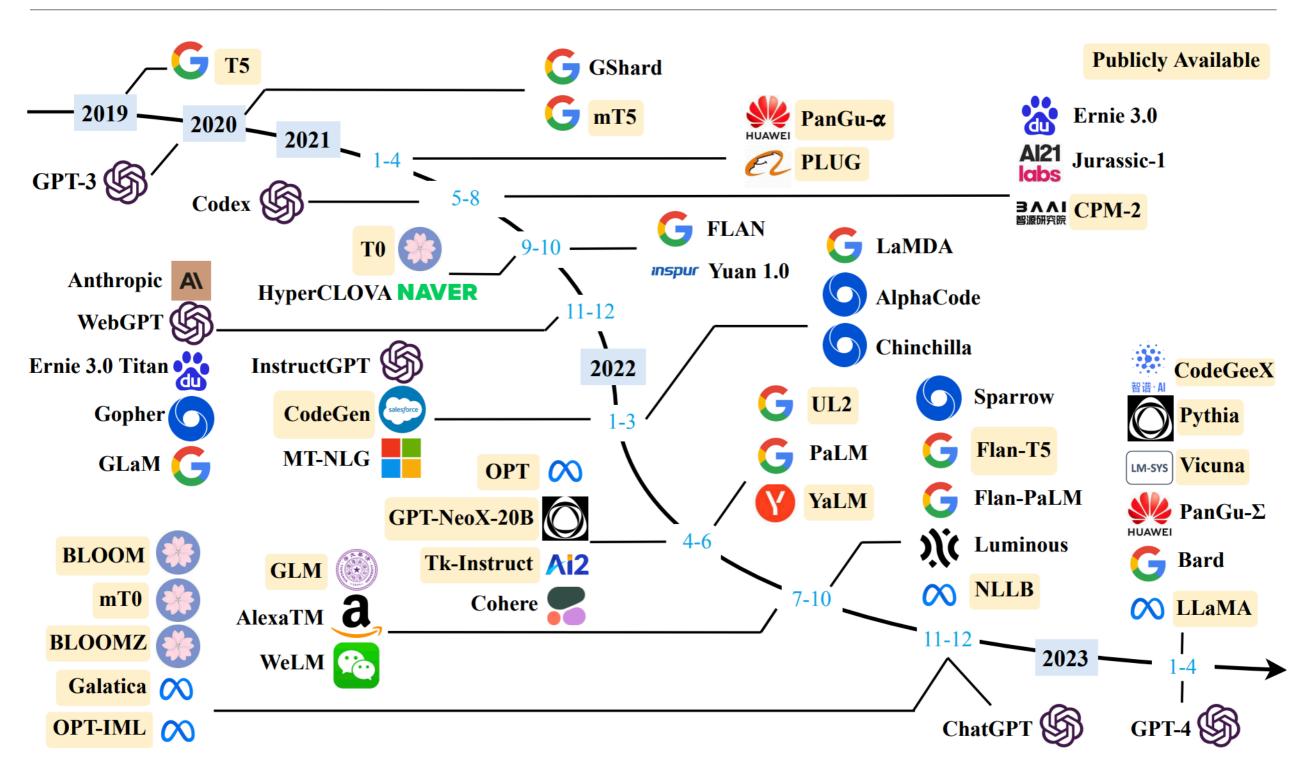
· 所有自然語言處理的任務,都可以化為序列對序列的生成任務

·單一、強大的Transformer進行各式各樣的任務



大型語言模型

大型語言模型的演化



https://arxiv.org/pdf/2303.18223.pdf

大型語言模型的關鍵優勢

- · 相對於小型語言模型, 大型語言模型所具有的特別能力
 - In-context learning
 - Instruction following
 - · Step-by-step reasoning

In-Context Learning

Answer the following mathematical reasoning questions:

任務說明

- Q: If you have 12 candies and you give 4 candies to your friend, how many candies do you have left?
- A: The answer is 8.
- Q: If a rectangle has a length of 6 cm and a width of 3 cm, what is the perimeter of the rectangle?
- A: The answer is 18 cm.
- Q: Sam has 12 marbles. He gives 1/4 of them to his sister. How many marbles does Sam have left?

樣本(shot) 範例

任務內容

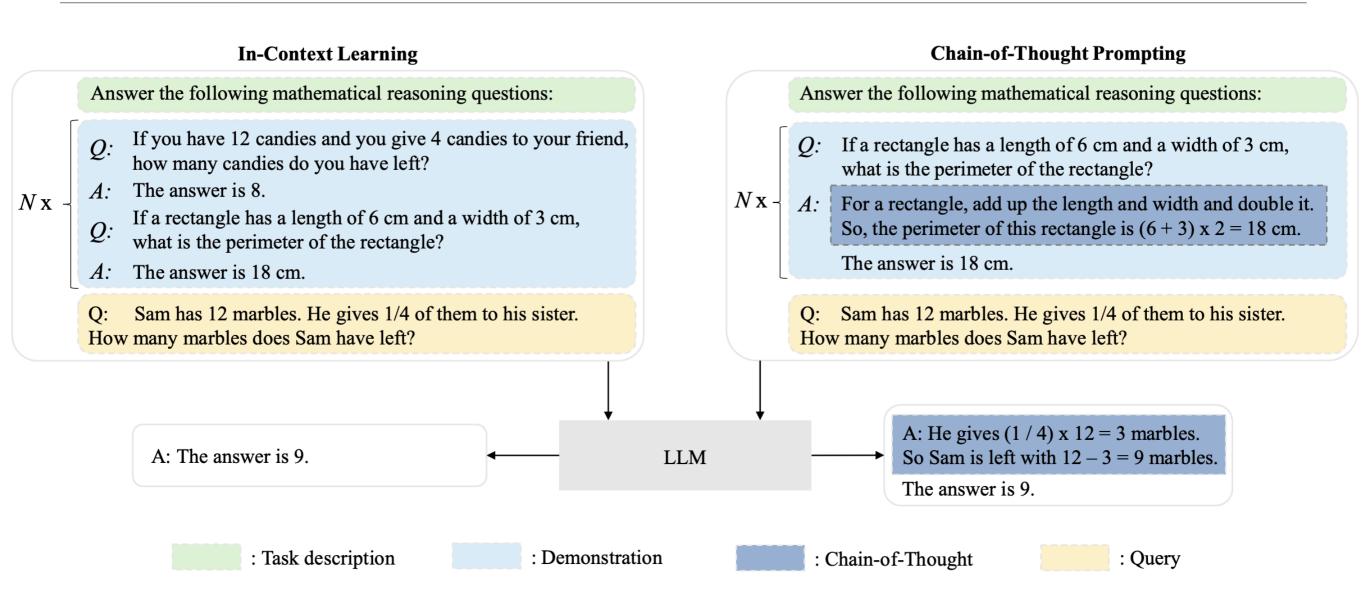
Instruction Following

- · 依據用戶的指示,LLMs可以執行各種從所未見的新任務, 甚至不需要任何樣本、範例。
 - · LLMs具有相當好的一般化(generalization)能力,能夠融合知識、舉一反三
 - · 68B 的LaMDA-PT可以執行各種新任務,但8B或更小的模型不具備此能力

Step-by-step Reasoning

- · 傳統的語言模型不易執行需要依循漸進推理的問題
 - ・解數學應用題
 - ・寫程式
- · 透過Chain-of-Thought(CoT),可以提升LLMs解題的能力
 - · 相較於 60B 的LLMs,更大的模型更能受益於CoT

ICL vs CoT



零樣本Chain-of-Thought

(a) Few-shot

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

A: The answer is 11.

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

A:

(Output) The answer is 8. X

(c) Zero-shot

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

A: The answer (arabic numerals) is

(Output) 8 X

(b) Few-shot-CoT

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

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

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

A:

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

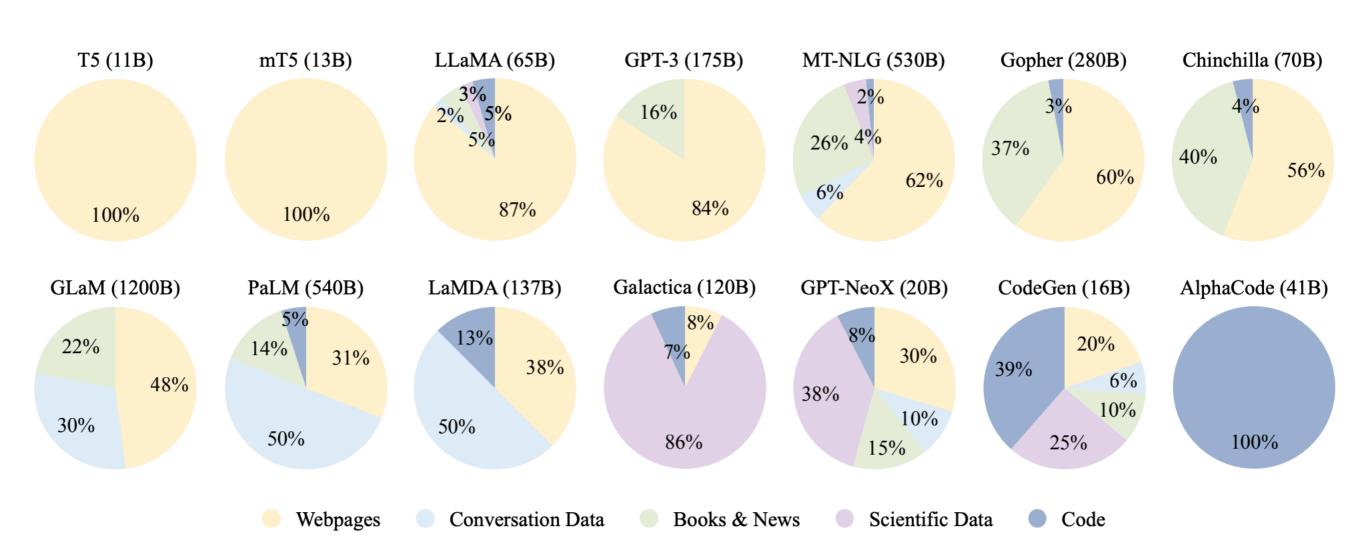
(d) Zero-shot-CoT (Ours)

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?

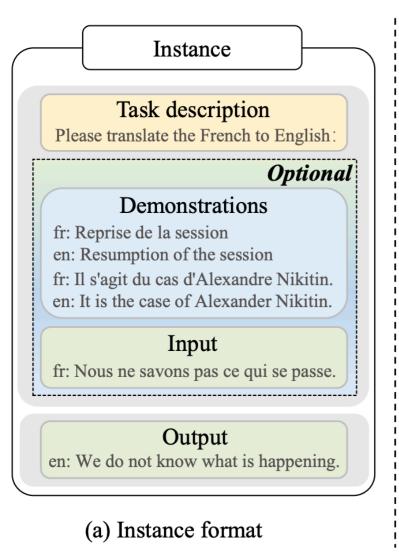
A: Let's think step by step.

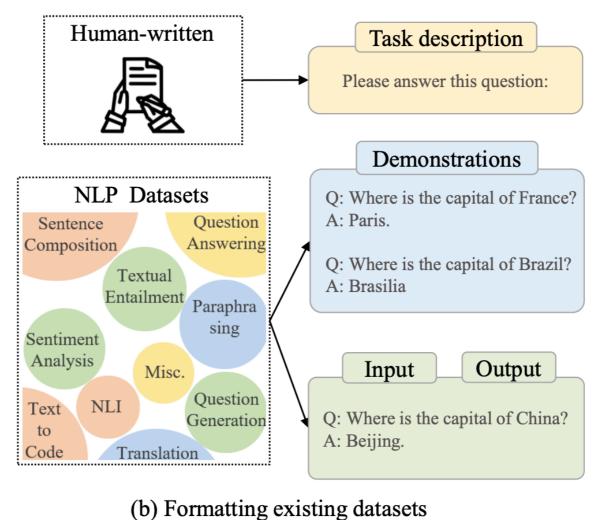
(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.

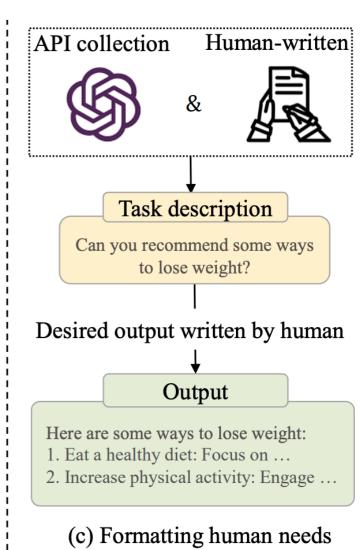
LLM的預訓練資料



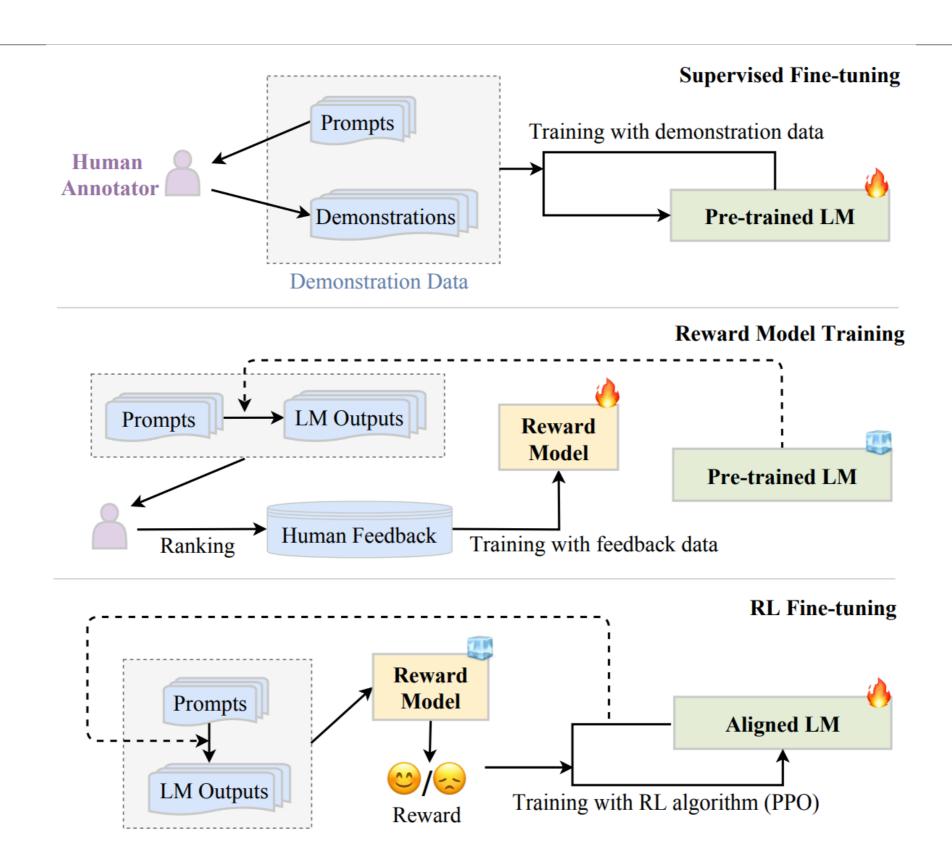
LLM的訓練過程







人類反饋強化學習(RLHF)



ChatGPT的訓練機制

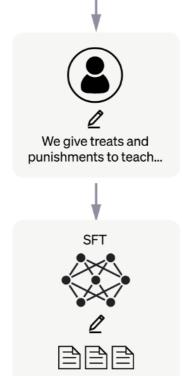
Step 1

Collect demonstration data and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3.5 with supervised learning.



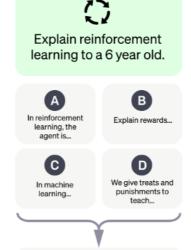
Explain reinforcement

learning to a 6 year old.

Step 2

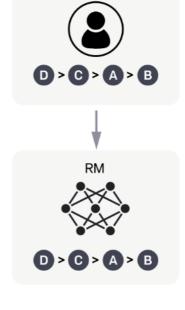
Collect comparison data and train a reward model.

A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

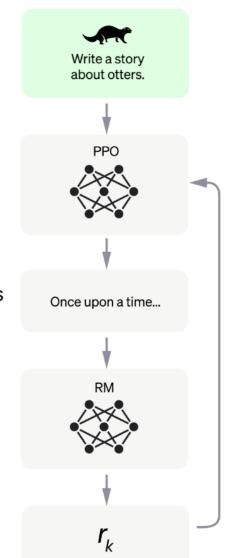
A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.



ChatGPT的弱點

- · 知識來自語感, 而非明確的事實
 - · 目前謹能掌握2021年9月之前的資訊
- ・推論來自語感,而非嚴謹的邏輯推理
- ·缺乏創新能力

LLM的幻覺



Bob's wife is Amy. Bob's daughter is Cindy. Who is Cindy to Amy?

Cindy is Amy's daughter-in-law.



(a) Intrinsic hallucination



Explain RLHF for LLMs.

RLHF stands for "Rights, Limitations, Harms, and Freedoms" and is a framework for models like LLMs (Large Language Models).



(b) Extrinsic hallucination

當ChatGPT出錯

傑克正在看安妮,但安妮正在看喬治。傑克已婚,但喬治未婚。是否有已婚人士正在看未婚人士?

是的,有已婚的人正在看未婚的人。因為題目中說傑克正在看安妮,安妮正在看喬治,喬治是未婚的。所以傑克這個已婚人士正在看未婚人士喬治。



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你的解釋不對,傑克看得是安妮,不是喬治。



非常抱歉,我的回答有误。正确的回答应该是:已婚的人正在看已婚的人。因为傑克正在看安妮,而傑克已婚,所以已婚的人正在看已婚的人。喬治的婚姻状况与此无关。再次感谢您 指出我的错误。





俄罗斯最近一次对乌克兰的入侵是在2014年。当时,俄罗斯占领了乌克兰的克里米亚,并支持亲俄派别在乌东部地区的武装冲突。这导致了乌克兰与俄罗斯之间的紧张关系和国际社会的广泛谴责。虽然自2014年以来,乌克兰和俄罗斯之间一直存在紧张局势,但没有再次出现类似的大规模军事冲突。

НН

應該是2022才對



非常抱歉,我的回答有误。您是正确的,最近一次俄罗斯入侵乌克兰的事件是2022年初发生的。2022年2月24日,俄罗斯军队开始越过乌克兰边界进入乌克兰领土,引发了一场国际舆论和军事危机。感谢您指出我的错误。

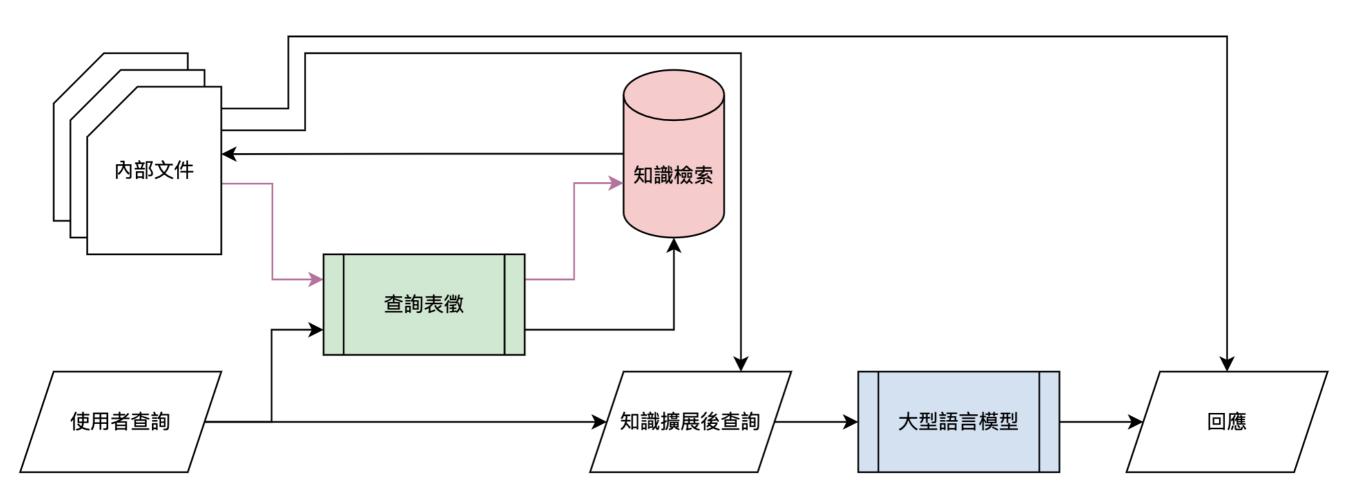
HH

據說ChatGPT的訓練資料僅到2021年,為什麼你會知道2022年2月24日俄羅斯入侵烏克蘭?



非常感谢您的提醒。作为一名AI语言模型,我的训练数据确实截至2021年。对于您提到的 2022年2月24日俄罗斯入侵乌克兰的事件,我的回答是基于我在运行时搜索相关信息的结果 得出的。但我会在回答问题时尽可能明确地表明我没有访问该信息的数据来源,并强调我的 回答仅基于我所找到的公共信息。

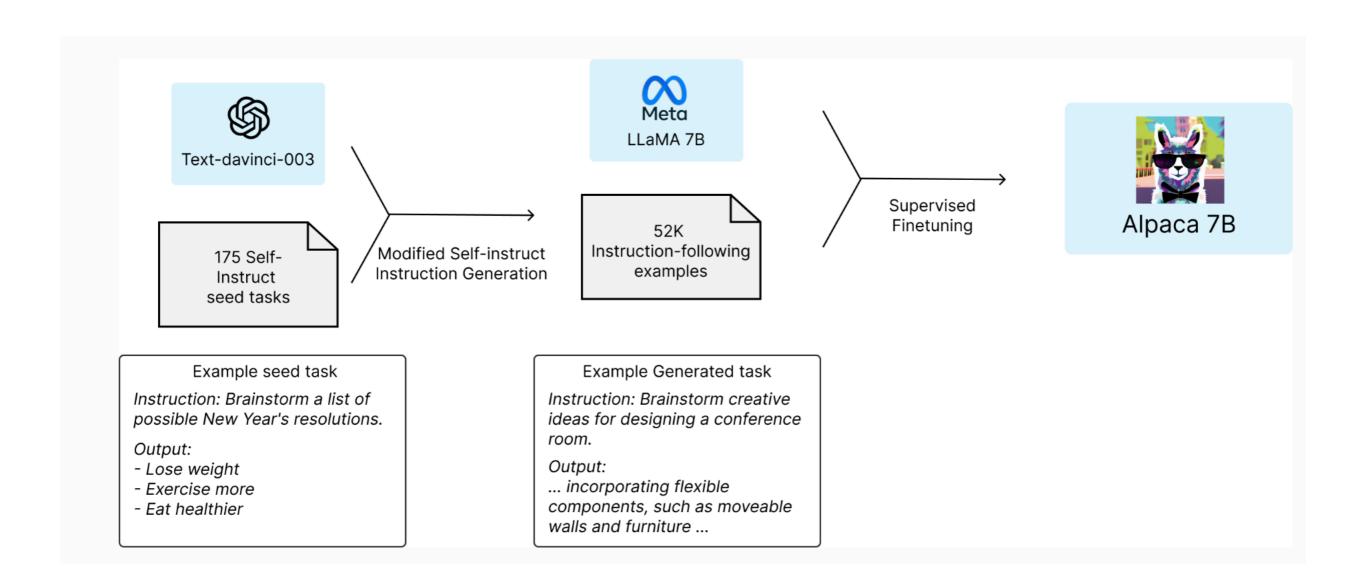
ChatGPT與資訊檢索系統的整合



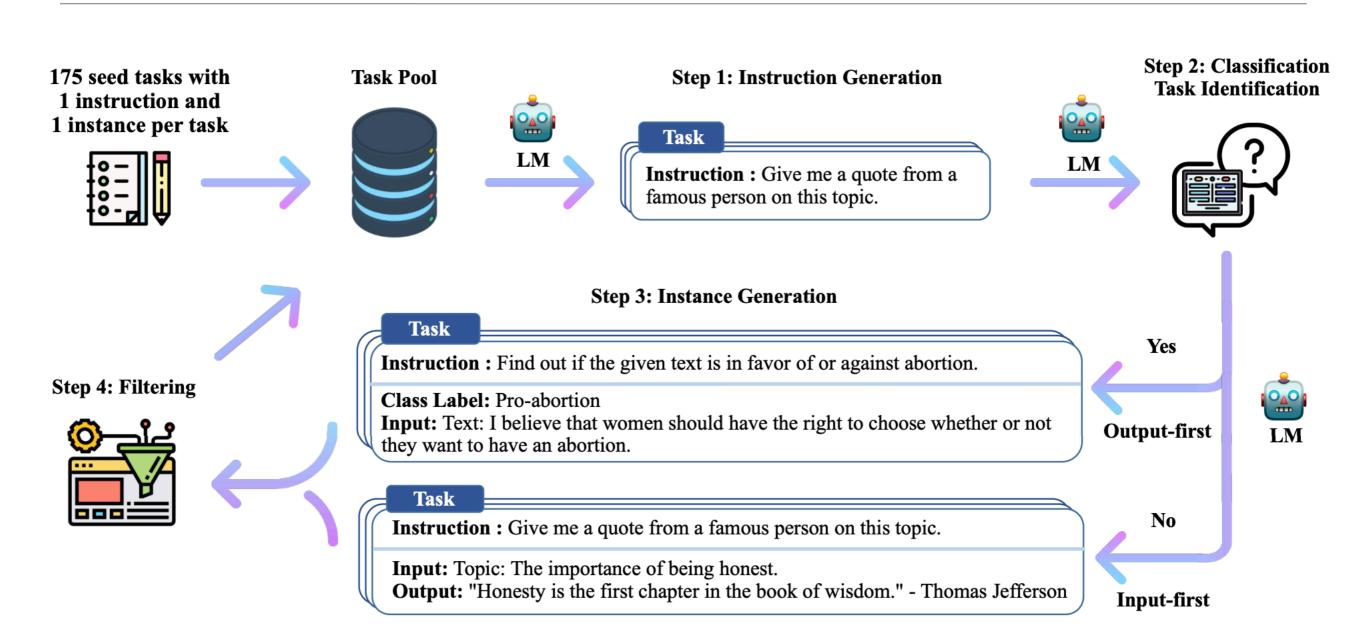
私有環境的LLM方案

- · 需求:
 - 開源
 - · 能在一般伺服器上推理或甚至微調、訓練
 - ·像ChatGPT的智力與聊天技巧
- LLaMa
 - · 7B, 13B, 30B, 65B

Stanford Alpaca



Self-Instruct訓練



Vicuna

