

Introduction to Large Language Models(LLM)

Outline

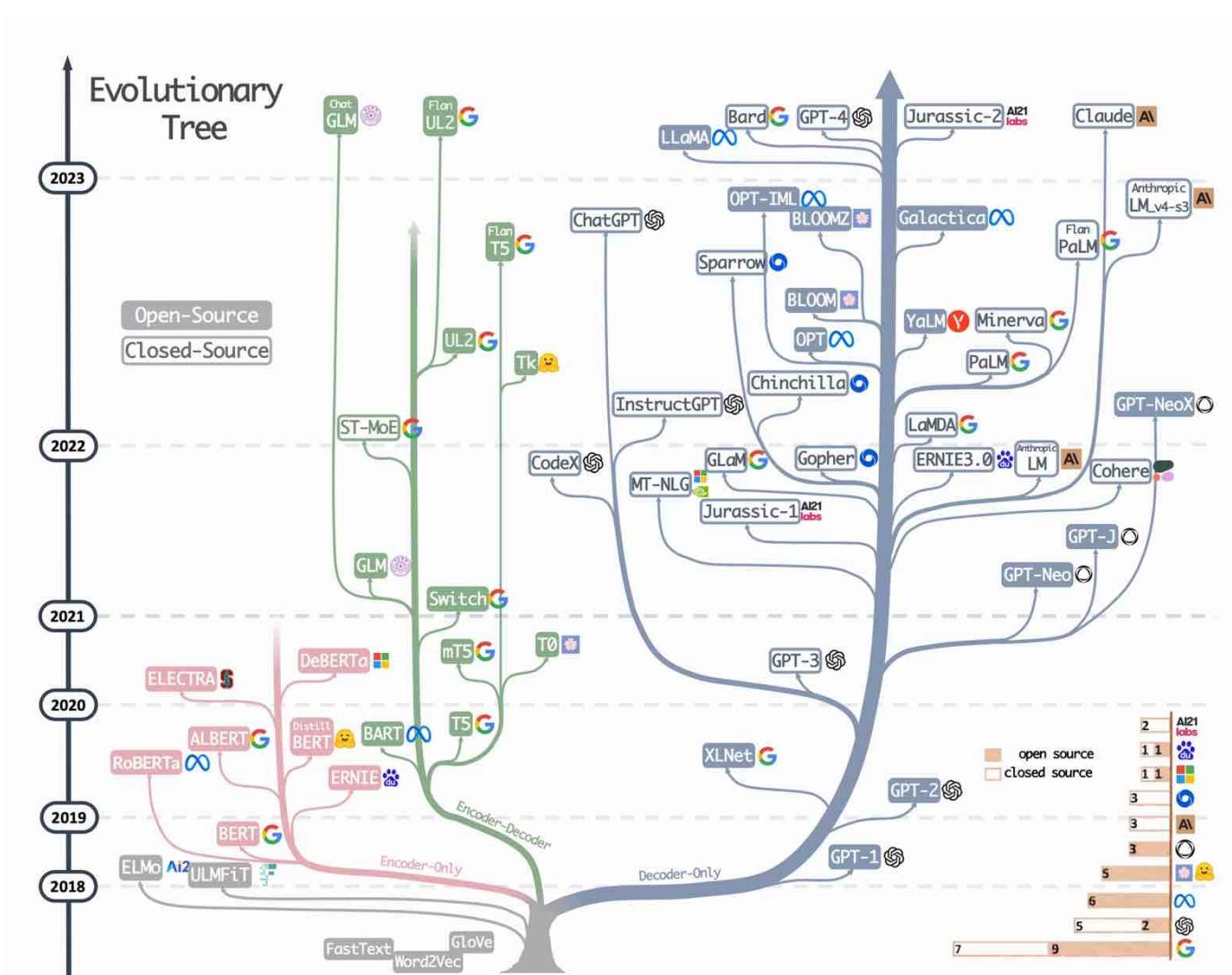
1. Overview from 30,000 feet above
2. Transformer in nutshell
3. Pretraining - Parallel paradigm
4. Finetuning - Parameter efficient finetuning
5. Steering the decoding of LLM - Prompting
6. Augmentation and Plugins

Overview from 30000 feet above

- Paradigm transition in AI
 - From: **training**(specific) -> **prediction**(specific)
 - To: **pretraining**(general) -> **finetuning**(general/specific) -> **in-context prompt**(specific)
- Primary steps of new paradigm
 - Pretraining with self-supervised learning
 - Finetuning on instruction from multiple domains
 - Application by steering/prompt the decoding process of LLM
- Where are we to AGI?
 - From explanation to prediction
 - From correlation to causality

A LLMs Evolution Tree

- Decoder Only
- Encoder Only
- Encoder-Decoder

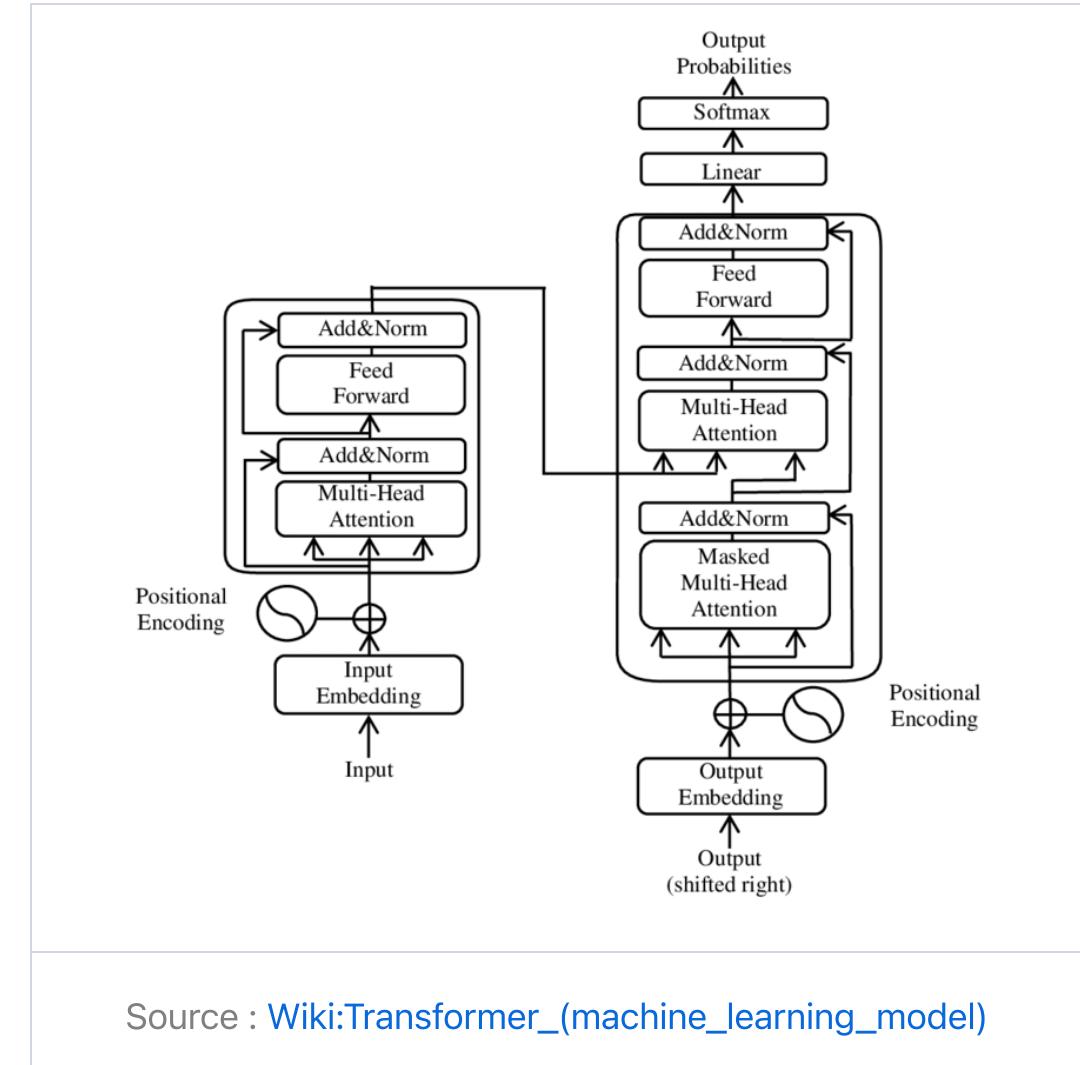


Transformer in nutshell

- Transformer modules
- Aspects of alternative
- Parameter concentration
- Computation concentration

Transformer modules

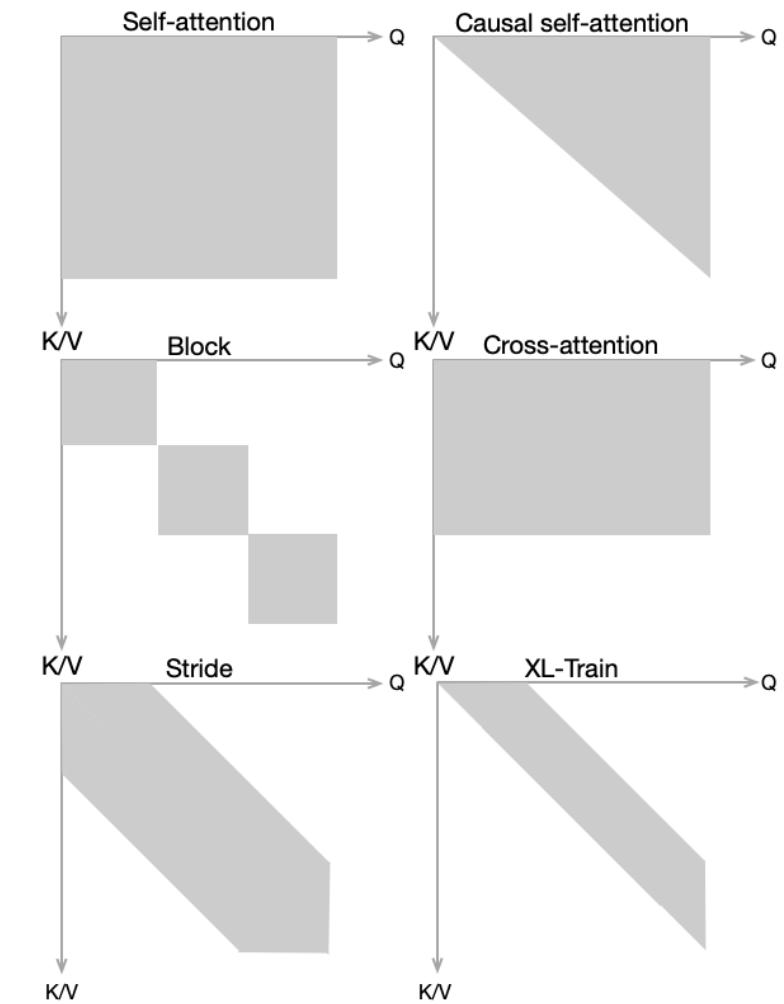
- Token & positional embedding :
 - $E \in R^{V \times d}, P \in R^{T \times d}$
- Multi-head attention
 - Self-attention & Cross-attention
 - Weight matrix:
 $W_Q^h, W_K^h, W_V^h \in R^{d \times d_h}$
 - Head projection:
 $W_O \in R^{d \times d}$
- ResNet & LayerNorm
- Feedforward Network
 - $W_1 \in R^{d \times 4d}, W_2 \in R^{4d \times d}$
- Output head: task related



Source : [Wiki:Transformer_\(machine_learning_model\)](#)

Aspects of alternative

- Efficient Transformer (for long sequence)
 - Coarse sequence resolution:
 - Block/Stride/Clustering/Neural Memory
 - TransformerXL
 - Attention matrix approximation:
 - Linear Transformer
 - RWKV
- LLMs specific
 - **Encoder vs Decoder vs Encoder-Decoder**
 - Pretraining objective
 - Positional encoding
 - Input or output LayerNorm
 - Activation



Parameter concentration

Decoder only Transformer(GPT)

- Parameter size:
 - Embedding: $(V + T) \times d$
 - Attention: $L \times (3 \times d \times d_h \times H + (d_h \times H) \times d) = 4Ld^2$
 - FFN: $L \times ((d \times 4d + 4d) + (4d \times d + d)) \approx 8Ld^2$
- On GPT3-175B:

Total	PE	TE	Attn	FFN
174,597M	25M(0.01%)	617M(0.35%)	57,982M(33.21%)	115,970M(66.42%)

Computation concentration

Decoder only Transformer

Per-token calculation:

- QKV+project: $2 \times L \times (3 \times H \times h_d \times d + (H \times h_d) \times d) = 2 \times 4Ld^2$
- Attention: $2 \times L \times T \times d$
- FFN: $2 \times L \times ((d \times 4d + 4d) + (4d \times d + d)) \approx 2 \times 8Ld^2$

Model training flops utilization(MFU):

- Forward and backward: $(1 + 2) \times (2N + 2LTd) \approx 6N$, where $N \approx 12Ld^2$
- Theoretical peak throughput: $\frac{P}{6N+6LTd}$
- $\text{MFU} = \frac{\text{Observed throughput}}{\text{Theoretical peak throughput}}$

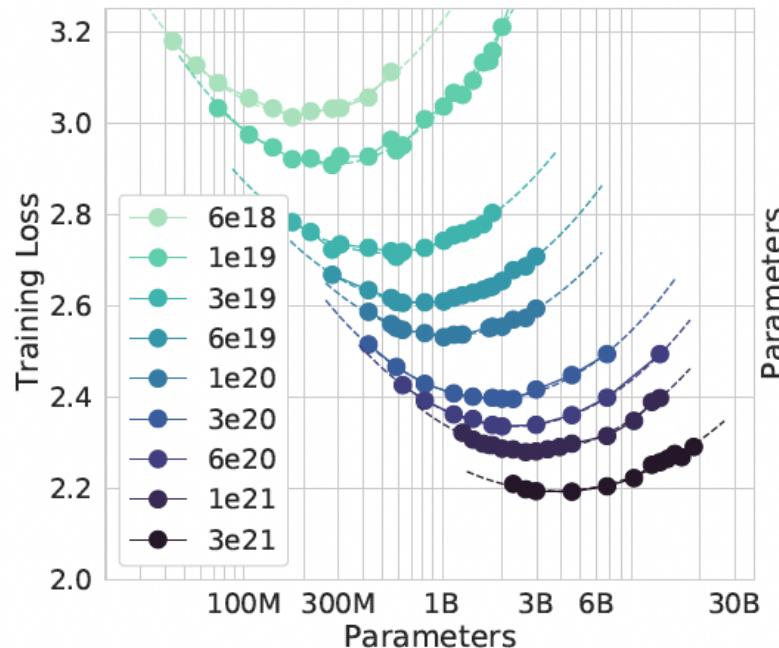
Scaling laws and compute optimal LLM training

Optimal combination of model size N and token size D , given the computation FLOPS C

Optimal N and D :

- $N_{\text{opt}} \propto N^a$
- $D_{\text{opt}} \propto D^b$
- OpenAI(2020) : $a = 0.73, b = 0.27$
- Deepmind(2022) : $a = 0.5, b = 0.5$
 - Match between training tokens and LR schedule
 - Tested on larger model size($> 500M$ vs. $< 100M$)
- Optimal ratio: $N : D \simeq 1 : 20$

IsoFLOP profiles(Deepmind, 2022):

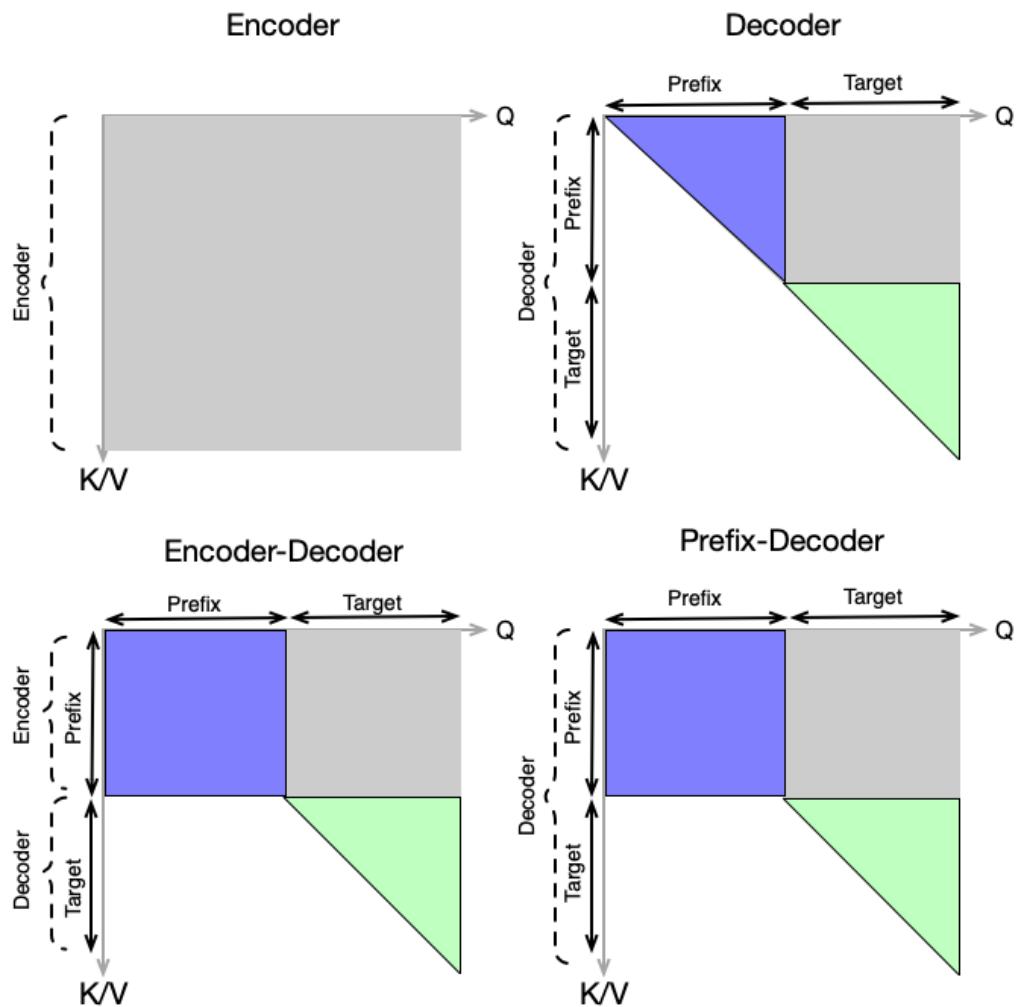


Pretraining

- Training objectives
- Text Corpus
- Parallel strategies
- Results & Evaluation

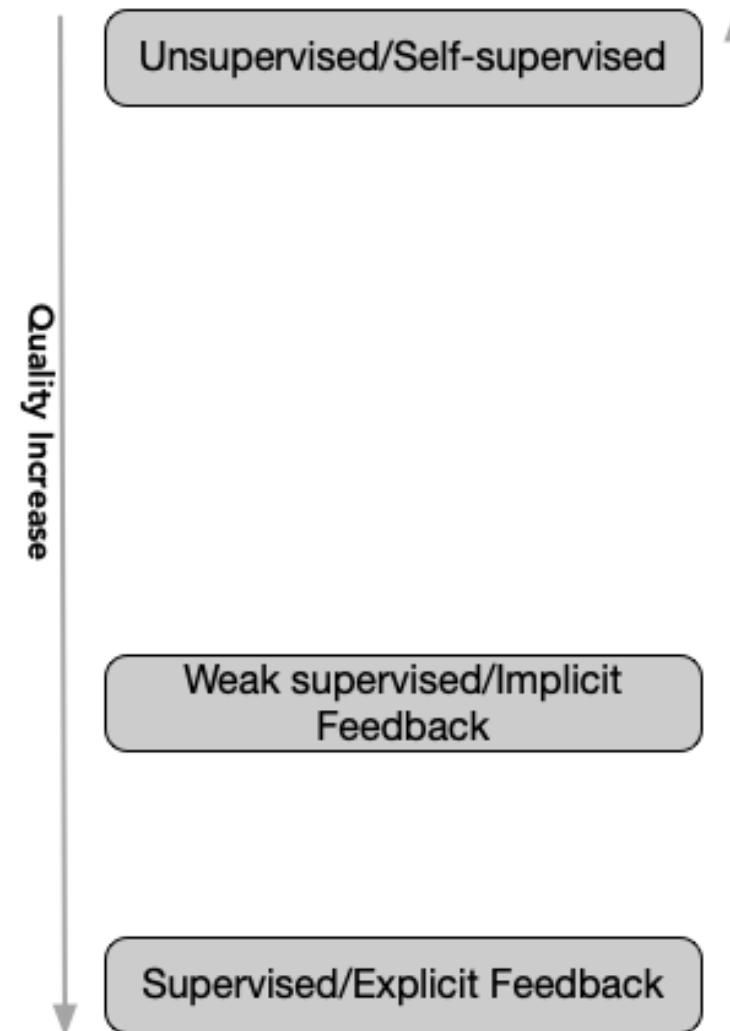
Training architecture & objectives

- Architecture
 - Encoder: BERT series
 - Encoder-Decoder: T5(11B)
 - (Causal-)Decoder: GPTs/Ernie3.0 Titan
 - Prefix-Decoder: GLM
- Objectives
 - Masked LM: BERT/GLM/T5
 - Auto-regressive LM: T5/GPTs/Ernie3.0 Titan
 - Multi-task pretraining: GLM/Ernie3.0 Titan



Text Corpus

- Unsupervised text
 - [BookCorpus](#) : 11,000; [Gutenberg](#) : 70,000
 - [OpenWebText](#): 8M outlinks of Reddit.com
 - [Common Crawl](#); [C4](#)
 - Code: [BigQuery](#) [Github](#)
- Weak supervised text
 - [Reddit TL;DR](#); [PushShift.io Reddit](#): Posts
 - [StackExchange](#) : Question & Answer w/ score
- Supervised text: task related
 - ~16 NLP tasks related datasets
(Sentiment/QA/Reasoning, etc.)
 - Human answer to prompt: InstructGPT



Baidu Ernie 3.0 Titan: 260B

- 2 Types of transformer modules
 - Universal module
 - Task specific module
- 3 Levels of pretraining tasks
 - Word aware: Knowledge integrated LM
 - Structure aware: sentence reordering task
 - Knowledge aware: controllable LM task
- 4D hybrid parallelism for training
 - Shared data parallel with ZeRO(2D)
 - Intra-layer tensor parallel(D)
 - Inter-layer pipeline parallel(D)

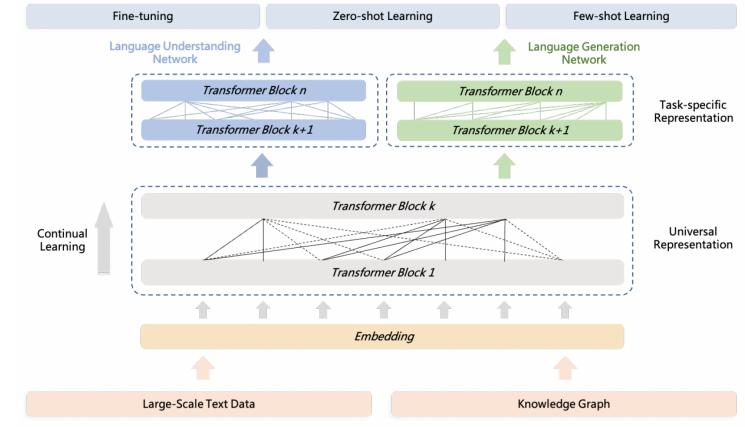


Figure 1: The framework of ERNIE 3.0.

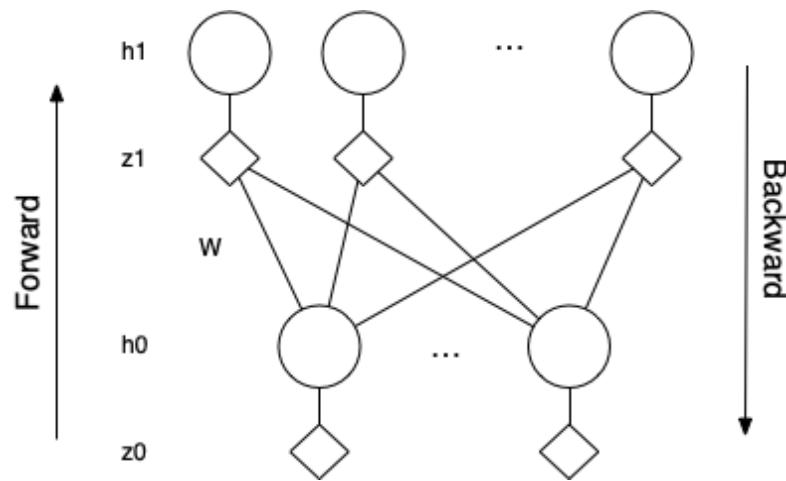
Parallel strategies

- Why bother?
- Three parallel paradigms
 - Data parallel: ZeRO
 - Model parallel
 - Tensor parallel: Megatron-LM
 - Pipeline parallel: GPipe
- Combined implementations: DeepSpeed/ColossalAI

Why bother?

- Too big to fit in single GPU memory
 - 175B: $\sim (2 + 2 + 3 \times 4) \times 175 = 2800\text{GB}$ for mixed-precision training
 - Parameter & gradient(FP16): parameter(W), gradient(g , $\frac{\partial L}{\partial W}$)
 - Optimizer State(FP32): parameter, momentum(m), variance(v)
 - Activation(FP16): $2 \times (1 + 4 + 1) \times d \times B \times T \times L$
 - A100 Spec:
 - GPU memory: 80GB
 - GPU memory bandwidth: 2039GB/s; NVLink: 600GB/s; PCIe 4.0: 64GB/s
 - TF32: 156TFlops
- Speedup
 - Scales linearly with # of GPU cores?

Basics on Forward & Backward and Parallel Ops



Forward:

$$h_0 = \sigma(z_0)$$

$$z_1 = W^T h_0 + b$$

$$h_1 = \sigma(z_1)$$

Backward:

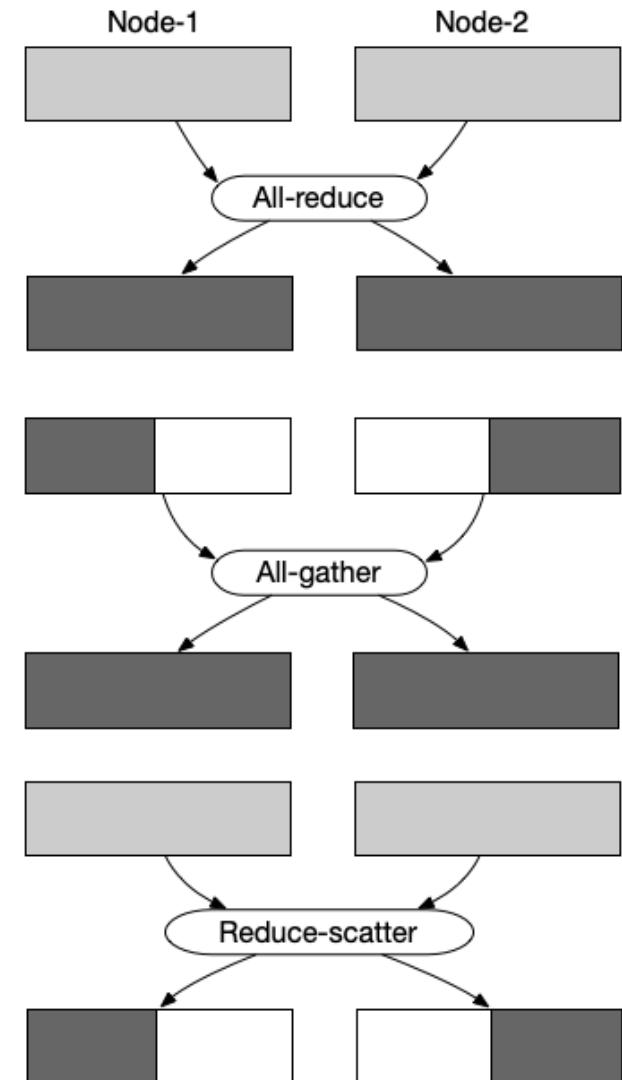
$$\left(\frac{\partial L}{\partial h_1}, W \right) \rightarrow \frac{\partial L}{\partial h_0}$$

$$\left(\frac{\partial L}{\partial h_1}, h_0 \right) \rightarrow \Delta \frac{\partial L}{\partial W}$$

$$m \leftarrow \beta_1 m + (1 - \beta_1) \frac{\partial L}{\partial W}$$

$$v \leftarrow \beta_2 v + (1 - \beta_2) \left(\frac{\partial L}{\partial W} \right)^2$$

$$W \leftarrow W - \frac{\alpha}{\sqrt{v} + \epsilon} \hat{m}$$



Data parallel: from DDP to FSDP(ZeRO)

- *Pesudo code for DDP and FSDP*

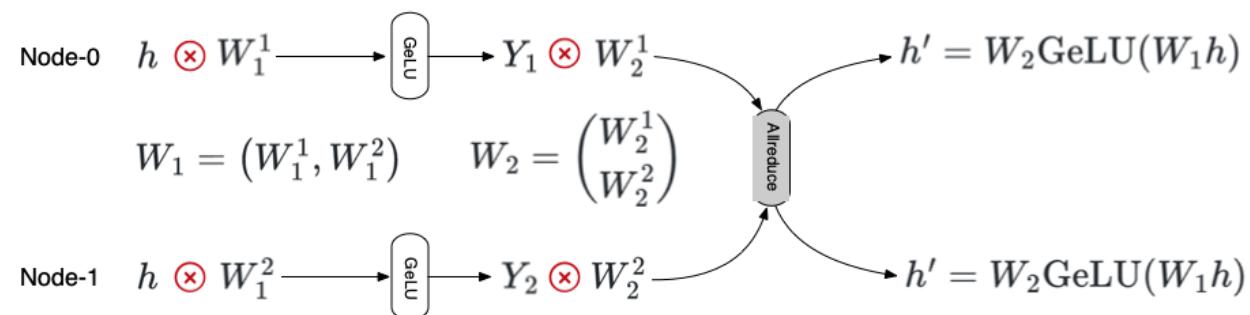
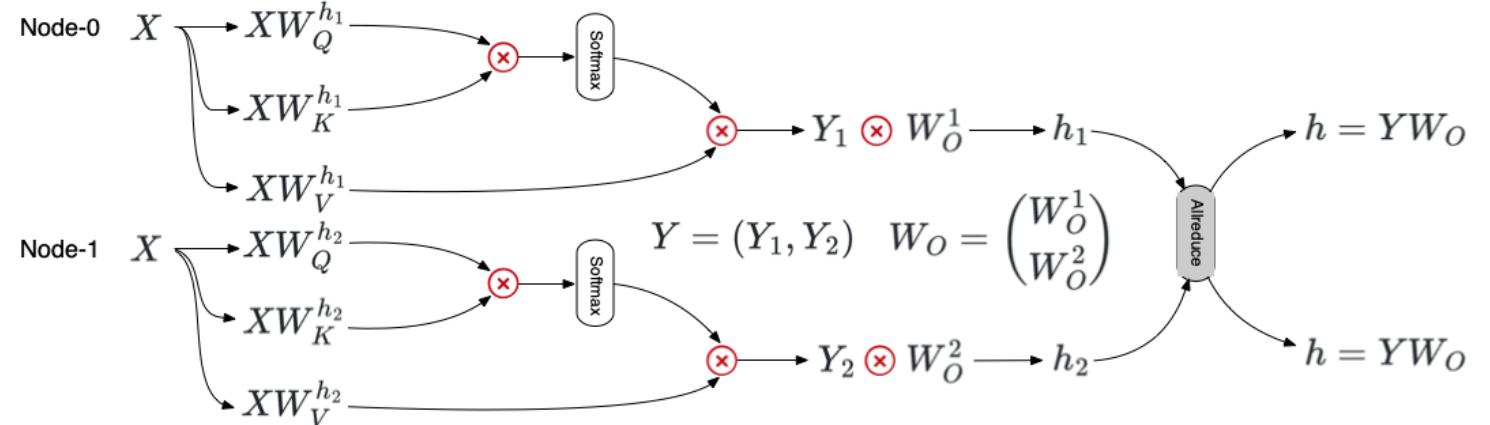
```
# forward pass :  
for layer_i in layers:  
    forward pass for layer_i  
# backward pass :  
for layer_i in layers:  
    backward pass for layer_i  
    full: all-reduce gradients for layer_i  
    full: update momentum & variance  
    full: update weights
```

```
# forward pass :  
for layer_i in layers:  
    all-gather full weights for layer_i  
    forward pass for layer_i  
    discard full weights for layer_i  
# backward pass:  
for layer_i in layers:  
    all-gather full weights for layer_i  
    backward pass for layer_i  
    discard full weights for layer_i  
    part: reduce-scatter gradients for layer_i  
    part: update momentum & variance  
    part: update weights
```

- Advantages of ZeRO
 - Parameter & gradient and optimizer states evenly shard to N nodes
 - Computation and communication overlaps

Tensor parallel: Megatron-LM

- W_Q, W_K, W_V partition by head(col)
- W_O partition by row
- W_1 partition by col, W_2 by row
- Backward Allreduce for gradient

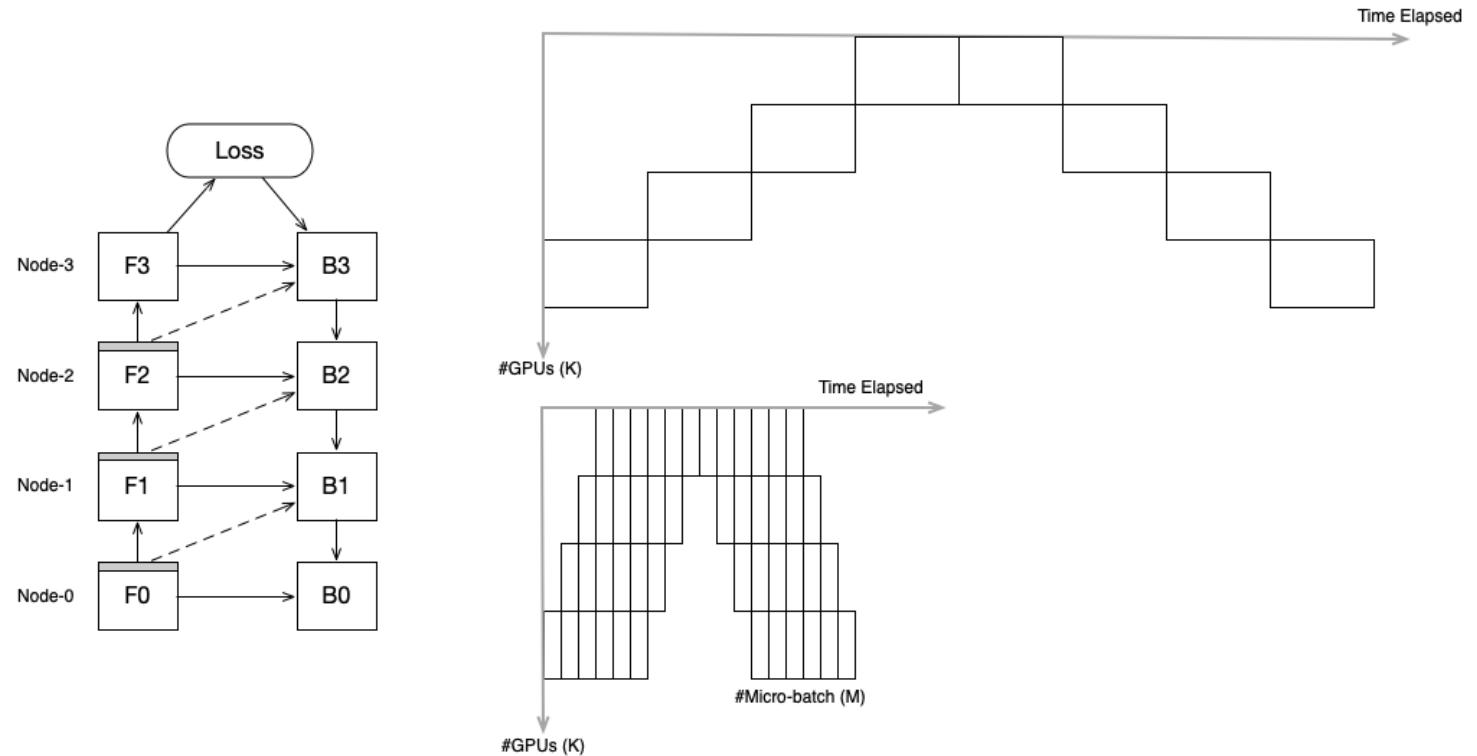


Performance comparison of ZeRO and Megatron-LM

- Experiment hardware:
 - Megatron-LM: 32 DGX-2H servers: 512 V100, 32GB GPUs
 - ZeRO: 25 DGX-2 servers: 400 V100, 32GB GPUs
- TFlops Results:
 - Megatron-LM: 15.1 PFlops
 - 76% scaling efficiency for single GPU 39TFlops(30% of peak Flops)
 - ZeRO: 15 PFlops, with fewer GPU cores

Pipeline parallel: GPipe

- Layer-wise model partition
- Re-materialization: output activation stored and communicated
- Pipeline reduce bubble ratio from $\frac{K-1}{K}$ to $\frac{K-1}{M+K-1}$



Combined implementations: Megatron-DeepSpeed/ColossalAI

Megatron-DeepSpeed

- Data/Model parallel supported(3D)
- ZeRO-Offload
- Sparse attention
- 1-bit Adam and 0/1 Adam
- MoE specific parallelism
- RLHF Demo: deepspeed-chat

ColossalAI

- Data/Model parallel supported(3D)
- 3D Tensor parallelism
- ZeRO-Offload: model data supported
- MoE specific parallelism
- RLHF Demo: ColossalChat

End of Parallel strategies

Result & Evaluations

Evaluation Set

- GLUE/SuperGLUE
- MMLU
- C-Eval
- AGIEval
- MATH
- HumanEval
- Big-bench(Hard)

C-Eval Accuracy: YY: 47+

Model	Average
GPT-4	69.9
Claude-v1.3	55.5
ChatGPT	53.5
Claude-instant-v1.0	47.4
GLM-130B	40.8
LLaMA-65B	39.8
Bloomz-mt	38.0
ChatGLM-6B	37.1
Chinese-LLaMA-13B	33.1
MOSS	28.9
Chinese-Alpaca-13B	27.2

Finetuning

- Target and issues
- Instruct finetuning
- Finetuning for specific task
- Parameter efficient finetuning

Target and issues

- Target
 - From pattern completion to real world task completion
- Issues
 - Instruction following
 - Hallucination
 - Toxicity and ethics
 - Securities

Instruction Finetuning

Key to success

- Number of finetuning datasets:
 - scaling from 62 text datasets to 18K
- Model scale: 137B LaMDA-PT
- Natural language instructions

Finetune on many tasks (“instruction-tuning”)

Input (Commonsense Reasoning)

Here is a goal: Get a cool sleep on summer days.

How would you accomplish this goal?

OPTIONS:

- Keep stack of pillow cases in fridge.
- Keep stack of pillow cases in oven.

Target

keep stack of pillow cases in fridge

Sentiment analysis tasks

Coreference resolution tasks

...

Input (Translation)

Translate this sentence to Spanish:

The new office building was built in less than three months.

Target

El nuevo edificio de oficinas se construyó en tres meses.

Inference on unseen task type

Input (Natural Language Inference)

Premise: At my age you will probably have learnt one lesson.

Hypothesis: It's not certain how many lessons you'll learn by your thirties.

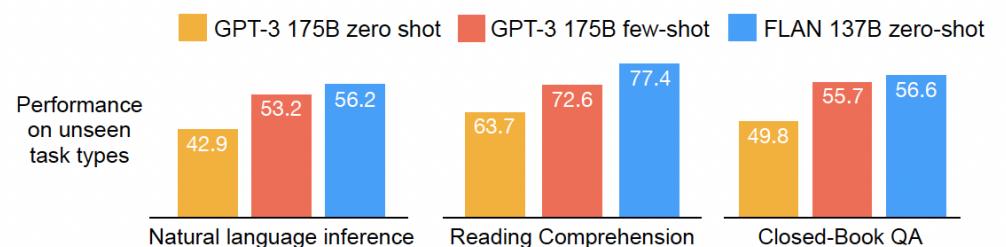
Does the premise entail the hypothesis?

OPTIONS:

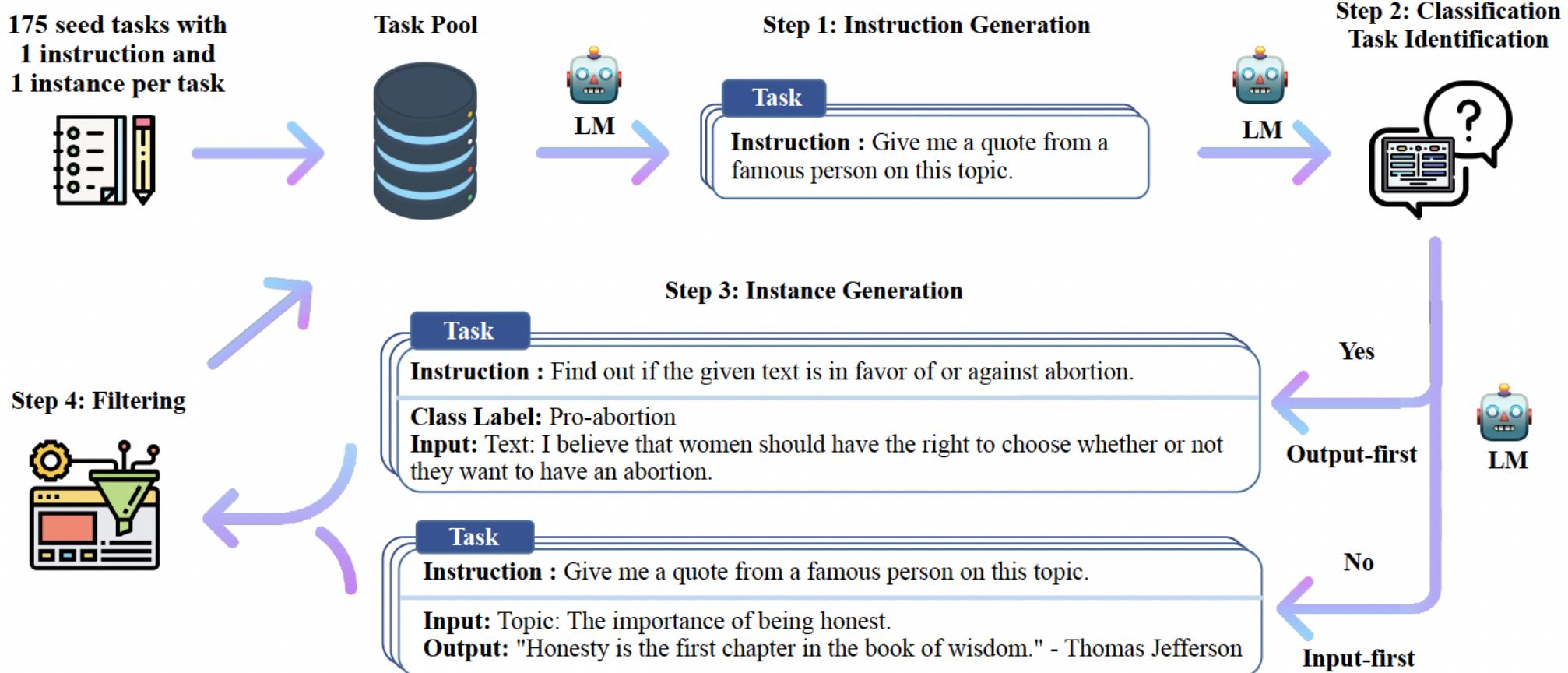
- yes
- it is not possible to tell
- no

FLAN Response

It is not possible to tell



Aligning Language Models with Self-Generated Instructions: Self-instruct



Distill Large Foundation Model(LFM) with instruction tuning: LLaMA series

Model Name	#Instructions	#(Base Model)	Finetuning	Instruction Synthetic	Org.
Alpaca	52K	7B	Full	Self-instruct	Stanford
Vicuna	70K	13B	Full	ShareGPT	LM
Dolly	15K	12B	Full	Human	Databricks
WizardLM	250K	16B	Full	Evol-Instuc	Microsoft
Guanaco	88K	65B	QLoRA	OASST1(dialog)	UW

QLoRA: Efficient Finetuning of Quantized LLMs, 2023, University of Washington

WizardLM: Empowering Large Language Models to Follow Complex Instructions, 2023, Microsoft

Vicuna: An Open-Source Chatbot Impressing GPT-4 with 90%* ChatGPT Quality

Alpaca: A Strong, Replicable Instruction-Following Model, 2023, Stanford

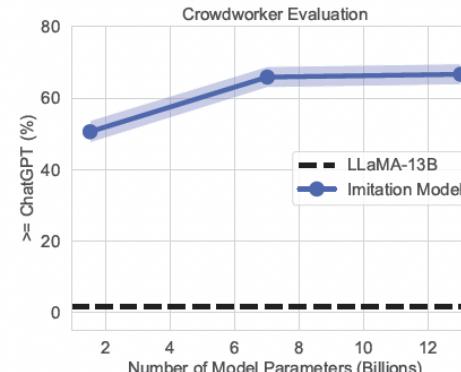
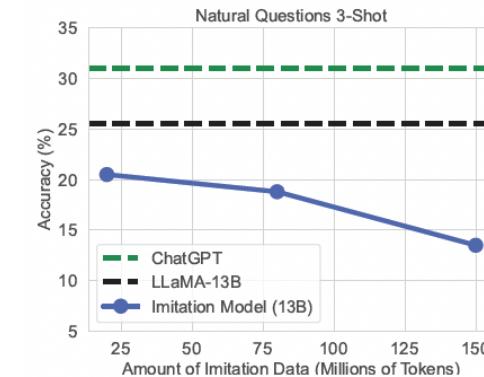
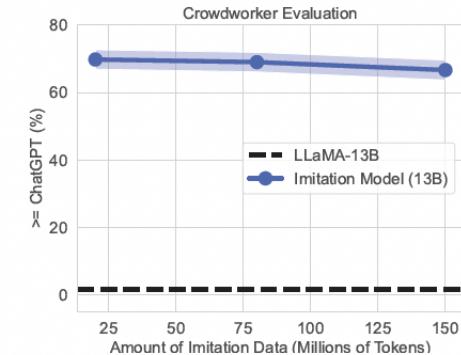
Different voice from UC Berkeley

Method and evaluation in brief:

- Base model size from 1.5B(**GPT-2**) to 13B(**LLaMA**)
- Imitation tokens from 0.3M to 150M(**NQ-synthetic + ShareGPT**)
- Evaluation: Crowdworkers + NLP tasks(Auto)

Conclusion:

- Imitation models are rated high by crowdworkers(**top**)
- Scaling imitation data not work on 3-shot NQ(**mid.**)
- Scaling base model parameters size helps(**bottom**)
- Mimicks ChatGPT's style not facturality capability
- Enormous and diverse imitation dataset required



Scaling the size of instructions from LFM: Orca

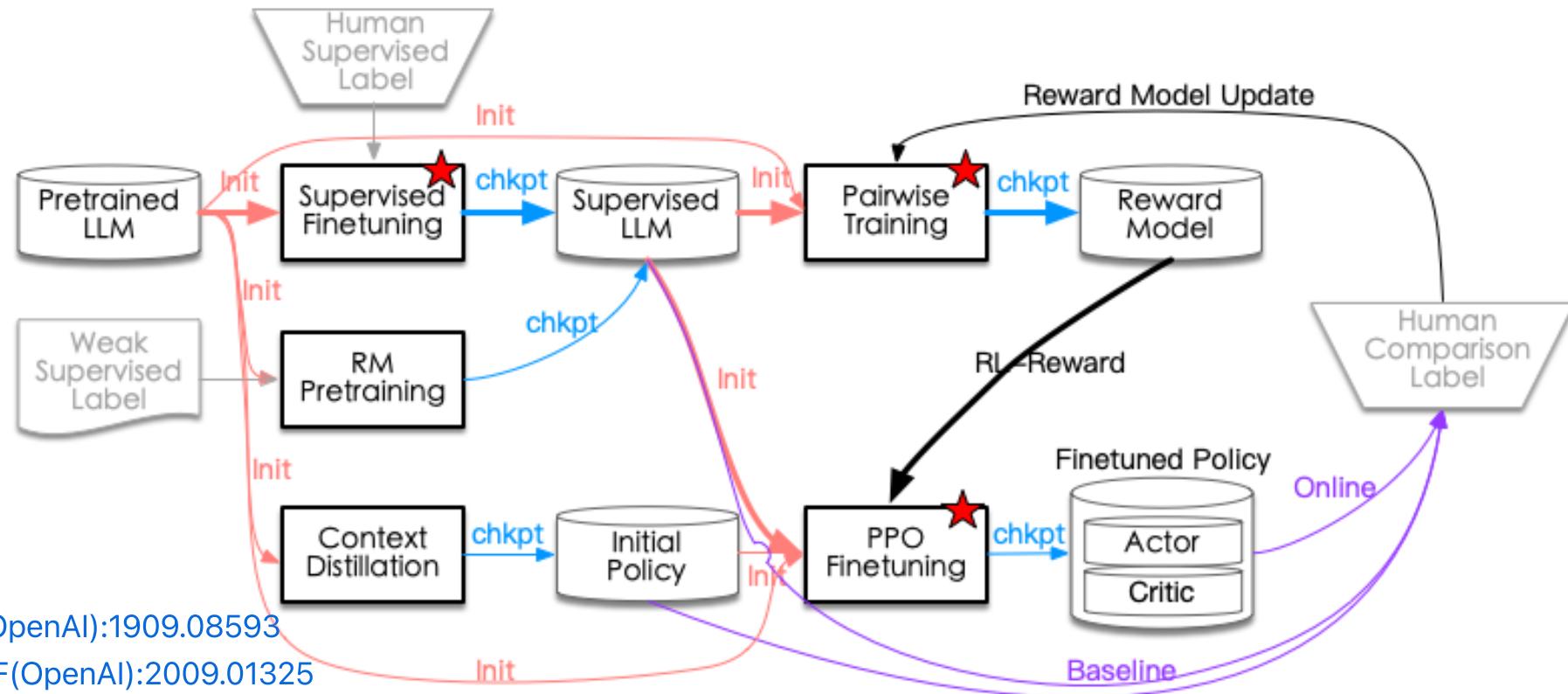
- Enriching Imitation signal:
 - explanation traces
 - step-by-step thought
- Scaling instructions
 - Initiated from FLAN-v2 collection
 - 5M instructions from ChatGPT(TA)
 - 1M instructions from GPT-4
- Rigorous Evaluations
 - Open-ended Generation:
 - Vicuna/Awesome/WizardLM Prompts
 - Reasoning: AGIEval/Big-bench Hard/
 - Safety: TruthfulQA-MC

Dataset	Reference	Vicuna-13B	Orca-13B
Vicuna Prompts	ChatGPT	92	101.5 (10.4%)
	GPT-4	73.8	87.7 (18.9%)
Awesome Prompts	ChatGPT	86.5	98.1 (13.5%)
	GPT-4	77.8	89.3 (14.9%)
WizardLM Prompts	ChatGPT	77.1	84.9 (10.1%)
	GPT-4	69.1	78.4 (13.5%)
Average	ChatGPT	85.2	94.8 (11.3%)
	GPT-4	73.6	85.1 (13.5%)

Conclusion:

- **Explanation Tuning** effectively aligns smaller model to GPT-4
- **Imitation data size and coverage** is crucial

Finetuning for specific task



Finetune from HF(OpenAI):1909.08593

Summarize from HF(OpenAI):2009.01325

HHHA(Anthropic):2112.00861

InstructGPT(OpenAI):2203.02155

HHA(Anthropic):2204.05862

Sparrow(Deepmind):2209.14375

Problems with Supervised Finetuning(SFT)

- Learning only the task format and the way to response for the format
- Knowledge labeled but not in the LLM leads to more hallucination
- Knowledge in the LLM but labeled as `don't know` leads to withhold information

What we want from finetuning:

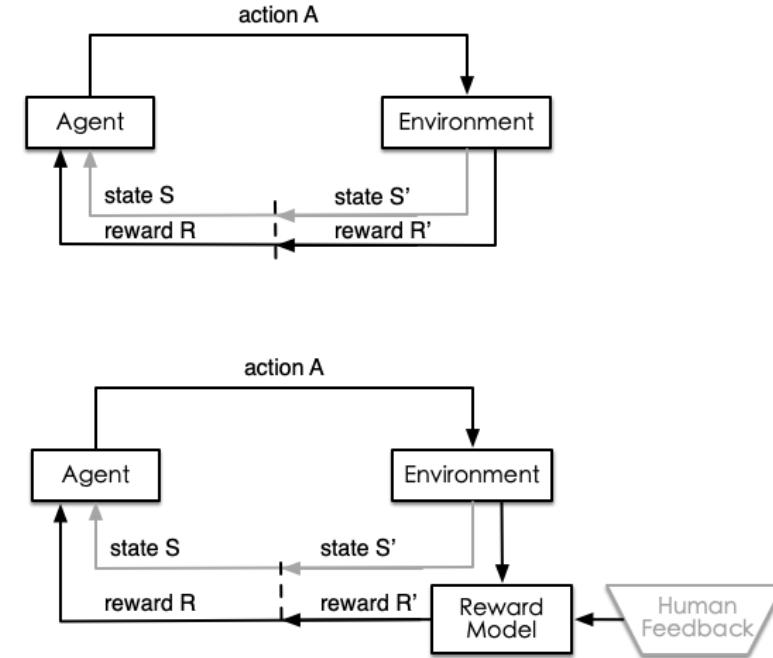
outputs its(LLM's) state of knowledge with the correct amount of hedging and expressing its uncertainty

Advance of RL to SFT for truthfullness

- LLMs know what they know
 - Calibrated probability, uncertainty
- RLHF can leverage the self-awareness
 - Design reward function: `correct answer=1`, `don't know=0` and `wrong answer=-4`
 - RL learn optimal threshold of probability to maximize the reward
- No oracle for the correctness, delegate to Reward Model
 - Reward model: **relative criteria** trained by pairwise loss from human feedback
 - Open problem: true probabilities of everything?
 - Open problem: go beyond things that labelers can easily do
 - Verification is easier than generation

More on Reinforcement Learning

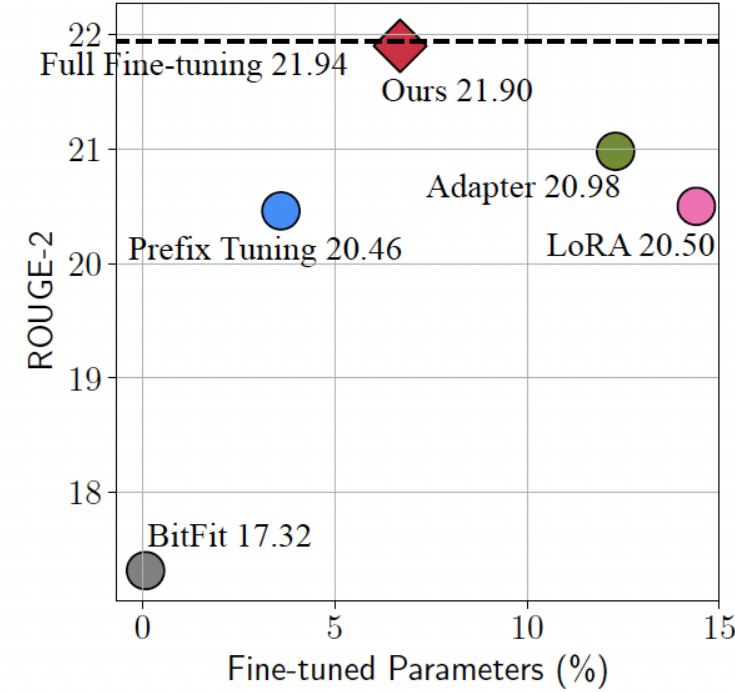
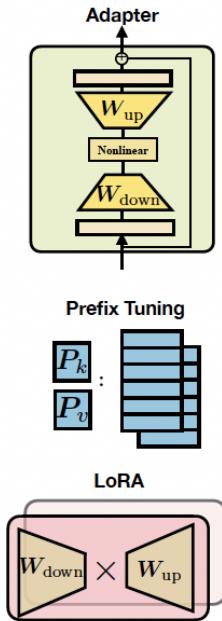
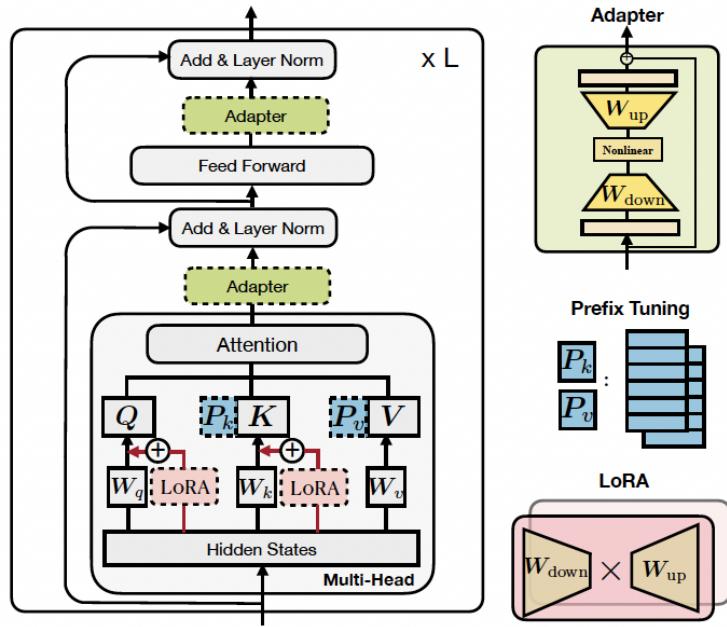
- Catalog of algorithms(**PPO belongs**)
 - World model or **model free**
 - Value-based or **policy-based(actor-critic)**
 - MC or **TD bootstrapping**
 - Off-policy or **on-policy**
 - Deterministic or **stochastic** policy
- Design consideration
 - **Sample efficiency:** Off-policy > On-policy
 - **Stability & Convergence:** Deadly Triad issue
 - **Explore & Exploit:** Random at episode beginning
 - **Bias & Variance:** Advantage Function



Parameter Efficient Finetuning

- Design aspects
- Primary implementations
 - Adapter
 - Prefix-tuning
 - LoRA

Methods and performance on Summerization task



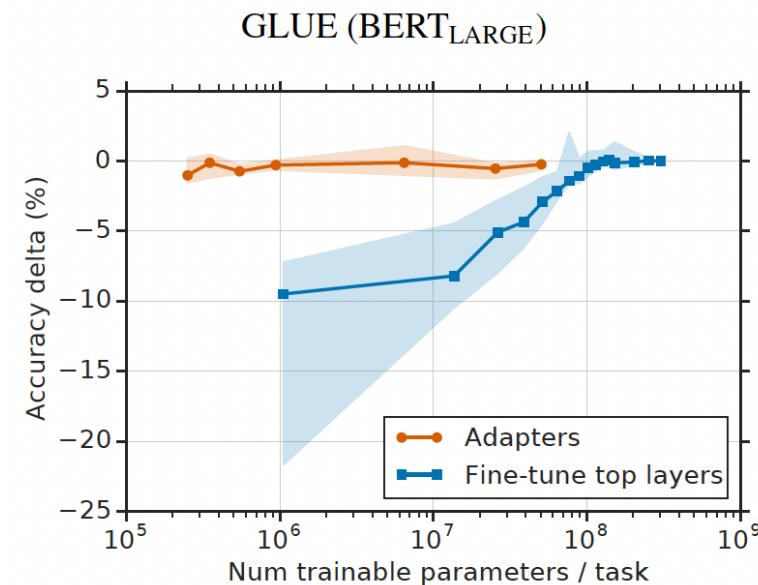
PEFT illustration and performance comparison (Source: Junxian He, et.al)

Design aspects

- **Finetuned Modules:**
 - Attention-key/value matrix: LoRA(Q/V)
 - Attention-head: Prefix-Tuning(K/V)
 - Attention: Adapter
 - After FFN: Adapter
- **Other aspects:**
 - Multi-task consideration
 - Task related head

Adapter

- Implementation & training notes
 - $h \leftarrow h + f(hW_{\text{down}})W_{\text{up}}$
 - Parameter scale:
 $2 \times L \times (r \times d + r + d), r \ll d$
 - Adapt after FFN sub-layer works too
- Results
 - Finetune BERT for 26 classification Tasks
 - 3.6% parameters for 0.4% GLUE performance gap
 - Ablation: fewer layers adapted -> worse performance



Prefix-Tuning

- Implementation
 - $\text{head} = \text{Attn}(XW_Q, [P_K; XW_K], [P_V; XW_V])$
 - Reparameterization for finetuning stability:
 - $[P_K, P_V] = \text{MLP}_\theta(P^E)$
 - P^E : prefix embedding
- Parameter scale:
 - Vanilla: $|P| \times d \times 2 \times L$
 - Reparameteration: $|P| \times d + d \times H + H \times d \times 2 \times L$

More on Prefix-Tuning: Training and scaling

- Training
 - Initialization:
 - Real/high frequency words activation
 - *Task relevant words / Classification labels*
 - LM Head: Next Token/Class Label
- Results & discussion
 - Finetuning 0.1% ~ 3% parameters, comparable or better performance
 - Optimal prefix length varies: longer for more complex tasks
 - Reparameterization works task-dependently

[PrefixTuning: Optimizing Continuous Prompts for Generation, Stanford, 2021](#)

[PromptTuning: The Power of Scale for Parameter-Efficient Prompt Tuning, Google, 2021](#)

[P-Tuning v2: Prompt Tuning Can Be Comparable to Fine-tuning Universally Across Scales and Tasks, Tsinghua, 2021](#)

LoRA

- Implementation & training notes
 - Transformer: $W = W_0 + (BA)^T$, $A \in R^{r \times d}$, $B \in R^{d_h \times r}$, $r \ll \min\{d_h, d\}$
 - W_Q and W_V considered, parameter scale: $2 \times 2 \times d \times r \times L$
 - Modularized: Embedding , Linear , MergedLinear , Conv2D
 - Initialization: A kaiming-random, B zeros
 - Weight merged for inference efficiency
- Results
 - For 175B GPT-3 finetuning: 0.01% parameters , on par or better results
 - No additional inference computation and latency
 - Additivity for **finetuning merge** and **incremental update**

More on LoRA: which part to update & rank settings

	# of Trainable Parameters = 18M						
Weight Type	W_q	W_k	W_v	W_o	W_q, W_k	W_q, W_v	W_q, W_k, W_v, W_o
Rank r	8	8	8	8	4	4	2
WikiSQL ($\pm 0.5\%$)	70.4	70.0	73.0	73.2	71.4	73.7	73.7
MultiNLI ($\pm 0.1\%$)	91.0	90.8	91.0	91.3	91.3	91.3	91.7

	Weight Type	$r = 1$	$r = 2$	$r = 4$	$r = 8$	$r = 64$
WikiSQL($\pm 0.5\%$)	W_q	68.8	69.6	70.5	70.4	70.0
	W_q, W_v	73.4	73.3	73.7	73.8	73.5
	W_q, W_k, W_v, W_o	74.1	73.7	74.0	74.0	73.9
MultiNLI ($\pm 0.1\%$)	W_q	90.7	90.9	91.1	90.7	90.7
	W_q, W_v	91.3	91.4	91.3	91.6	91.4
	W_q, W_k, W_v, W_o	91.2	91.7	91.7	91.5	91.4

End of Parameter Efficient Finetuning

Steering the decoding process of LLM

- Decoding strategies
- Prompt engineering

Decoding strategies

- Temperature in decoding: $p(w_i|w_{<i}) = \frac{\exp(o_i/T)}{\sum_j \exp(o_j/T)}$, o_i logits from LLM
- Maximal Likelihood Search
 - Greedy search: $w_i = \arg \max p(w_i|w_{<i})$, eq. to $T = 0$
 - Beam search: $w_i \in \text{TopN } p(w_i|w_{i-1}, w_{<i-1})p(w_{i-1}|w_{<i-1})$
- Sampling
 - top-K sampling: $w_i = \text{sample TopK } p(w_i|w_{<i})$
 - top-p(Nucleus) sampling: $w_i = \text{sample TopK}_i \sum_{w_i < K_i} p(w_i|w_{<i}) \geq p$
 - Repetition penalized sampling
- Guided decoding
 - $\text{score}(x_{t+1}, b_t) = \text{score}(b_t) + \log p(x_{t+1}) + \sum_i \alpha_i f_i(x_{t+1})$

Prompt engineering

- One-shot interaction
 - Instruction/Zero-shot Prompt
 - Few-shot Promp
 - In-context Learning(Prompt)
 - Chain-of-Thought
- Recursive interaction
 - MRKL: [Thought/Action/Action Input/Observation]+ , zero-shot, access tools
 - **Self-ask:** Followup question? [Question/Answer]+ Final Answer , few-shot
 - **ReACT:** [Thought/Action/Observation]+ , few-shot, access tools

More on In-context Learning

What matters?

- Examples template(instruct/CoT) & order: yes
- Label space & Input distribution(diversity): yes
- Exact {Question, Answer} pair: no/yes

Why it works?

- Interpretation from Topic Model: $P(o|p) = \int_z P(o|z, p)P(z|p)dz$
- Induction head: [a] [b] ... [a] -> [b]

[A Mathematical Framework for Transformer Circuits, 2021, Anthropic](#)

[How does in-context learning work?, 2022, Stanford](#)

[Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?, 2022, Meta](#)

[Larger language models do in-context learning differently, 2023, Google](#)

Augmentation and Plugins

- Augmented Language Models
- Plugins Ecosystem

Augmented Language Models

- Pros and Cons in vanilla LLMs
- Augmentation
 - Reasoning/Planning
 - Tool usage

Pros and Cons in vanilla LLMs

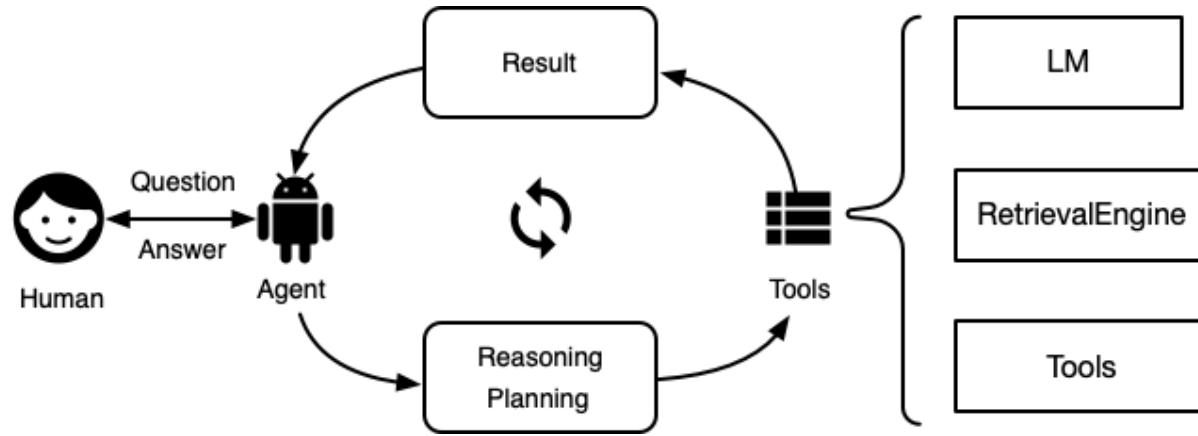
Pros

- World knowledge
- Instruction Following
- Few/Zero-shot Learning
- In-context Learning
- Chain-of-Thought
- Arithmetic/Commonsense Reasoning

Cons

- Compression of world knowledge
- No up-to-date knowledge
- Context limitation
- Hallucinations

Augmented Language Model Brief Overview



- 2-step loops in augmenting
 - What: Planning/Reasoning
 - How: Tool usage
- 3 methods for augmenting
 - In-context prompt:
 - One-shot/Recursive
 - Pretraining/Finetuning
 - Human/Self-teach
 - Reinforcement Learning:
 - Hardcode/Human-Feedback

Planning by self-talk: Self-ask

- Multi-hop question and compositionality gap
- Self-ask prompt:
 - Few-shot prompt scaffold:

```
Question: {{Question}}
Are follow up questions needed here: Yes
Follow up: {{Follow-up-question}}
Intermediate answer: {{Intermediate-answer}}
So the final answer is: {{Final-answer}}
```

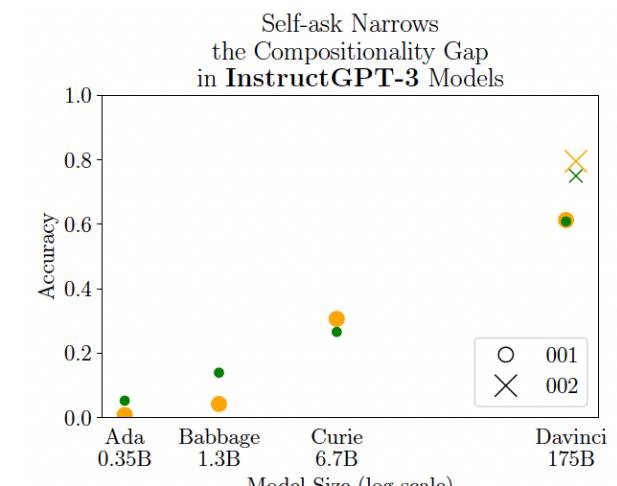
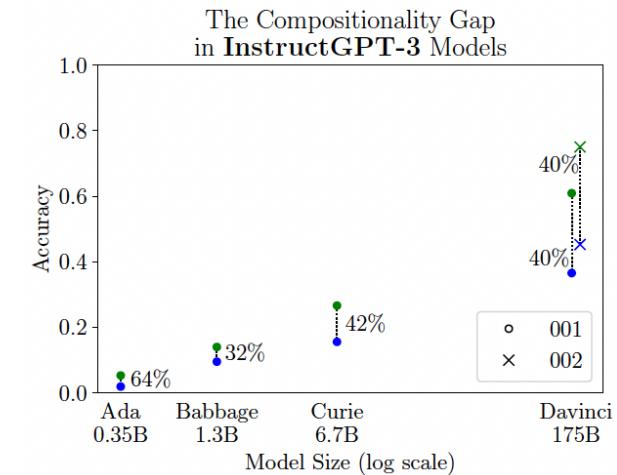


```
Question: {{Question}}
Are follow up questions needed here: {{LLM-gen}}
```

- Few-shot prompt with search engine:
 - The same prompt as before
 - Generated by query search engine:

```
Intermediate answer: {{Intermediate-answer}}
```

Accuracy on *Compositional Celebrities* 2-hop questions



Planning by self-talk: Self-ask prompt

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.

Planning by self-talk: Self-ask prompt with search engine

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?

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So the final answer is: William Howard Taft.

Synergy between reasoning and actions: ReAct prompt with tools

- Two kinds of tasks
 - **Reasoning:** multi-hop QA(HotspotQA)
 - **Decision making:** long horizon/delayed reward(WebShop)
 - Space of reasoning and actions
 - **reasoning:** language generated by LLM
 - goal or question decompose
 - commonsense or arithmetic reasoning
 - search reformulation
 - answer synthesis
 - **actions:** task related
 - search/find/finish for reasoning
- $\text{ReAct} \leq \text{CoT-SC}$
 - $\text{CoT-SC} \rightarrow \text{ReAct} > \text{CoT-SC}$
 - $\text{ReAct} \rightarrow \text{CoT-SC} > \text{CoT-SC}$

Prompt Method ^a	HotpotQA (EM)	Fever (Acc)
Standard	28.7	57.1
CoT (Wei et al., 2022)	29.4	56.3
CoT-SC (Wang et al., 2022a)	33.4	60.4
Act	25.7	58.9
ReAct	27.4	60.9
CoT-SC → ReAct	34.2	64.6
ReAct → CoT-SC	35.1	62.0
Supervised SoTA^b	67.5	89.5

Table 1: PaLM-540B prompting results on HotpotQA and Fever.

CoT prompt

Question Musician and satirist Allie Goertz wrote a song about the "The Simpsons" character Milhouse, who Matt Groening named after who?

Thought Let's think step by step. Milhouse was named after U.S. president Richard Nixon, so the answer is Richard Nixon.

Answer Richard Nixon

Question Which documentary is about Finnish rock groups, Adam Clayton Powell or The Saimaa Gesture?

Thought Let's think step by step. Adam Clayton Powell (film) is a documentary about an African-American politician, not Finnish rock groups. So the documentary about Finnish rock groups must instead be The Saimaa Gesture.

Answer The Saimaa Gesture

Question What is the elevation range for the area that the eastern sector of the Colorado orogeny extends into?

Thought Let's think step by step. The eastern sector of Colorado orogeny extends into the High Plains. High Plains rise in elevation from around 1,800 to 7,000 ft, so the answer is 1,800 to 7,000 ft.

Answer 1,800 to 7,000 ft

Act only prompt

{{Few-shot examples ahead}}

Question: What is the elevation range for the area that the eastern sector of the Colorado orogeny extends into?

Action 1 Search[Colorado orogeny]

Observation 1 The Colorado orogeny was an episode of mountain building (an orogeny) in Colorado and surrounding areas.

Action 2 Lookup[eastern sector]

Observation 2 (Result 1 / 1) The eastern sector extends into the High Plains and is called the Central Plains orogeny.

Action 3 Search[High Plains]

Observation 3 High Plains refers to one of two distinct land regions:

Action 4 Search[High Plains (United States)]

Observation 4 The High Plains are a subregion of the Great Plains. From east to west, the High Plains rise in elevation from around 1,800 to 7,000 ft (550 to 2,130m).[3]

Action 5 Finish[1,800 to 7,000 ft]

ReAct prompt

{{Few-shot examples ahead}}

Question What is the elevation range for the area that the eastern sector of the Colorado orogeny extends into?

Thought 1 I need to search Colorado orogeny, find the area that the eastern sector of the Colorado orogeny extends into, then find the elevation range of the area.

Action 1 Search[Colorado orogeny]

Observation 1 The Colorado orogeny was an episode of mountain building (an orogeny) in Colorado and surrounding areas.

Thought 2 It does not mention the eastern sector. So I need to look up eastern sector.

Action 2 Lookup[eastern sector]

Observation 2 (Result 1 / 1) The eastern sector extends into the High Plains and is called the Central Plains orogeny.

Thought 3 The eastern sector of Colorado orogeny extends into the High Plains. So I need to search High Plains and find its elevation range.

Action 4 Search[High Plains (United States)]

Observation 4 The High Plains are a subregion of the Great Plains. From east to west, the High Plains rise in elevation from around 1,800 to 7,000 ft (550 to 2,130m).[3]

Thought 5 High Plains rise in elevation from around 1,800 to 7,000 ft, so the answer is 1,800 to 7,000 ft.

Action 5 Finish[1,800 to 7,000 ft]

Pros and Cons of Prompt-based augmentation

Pros

- Flexible for application
- Add new tool in low cost

Cons

- Unstable response
- Token inefficient

Augment LM with retrieval end-to-end: REALM(pretraining)

- Two steps of *retrieve* and *predict*
 - $P(y|x) = \sum_z P(y|z, x)P(z|x)$
 - *Neural retrieval*: $P(z|x) = \text{Softmax}_z(\text{BERT}_{\text{CLS}}(x)^T \text{BERT}_{\text{CLS}}(z))$
 - *Knowledge-augmented encoder*: $P(y|z, x)$
 - Pretraining: MLM loss of BERT
 - Finetuning: Reading Comprehension loss of BERT (assume $y \in z$)
- Practical training
 - Involve top-K documents of $P(z|x)$
 - Vector search of top-K with asynchronous index update

Augment LM with retrieval end-to-end: REALM (Demo/Ablation)

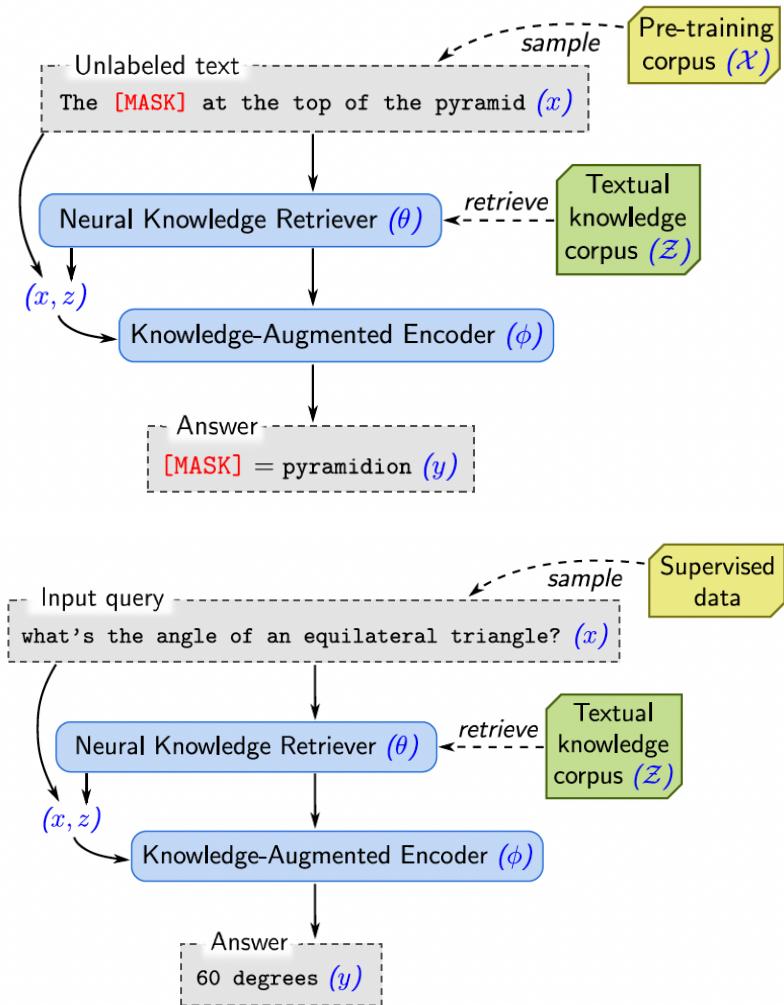


Table 2. Ablation experiments on NQ’s development set.

Ablation	Exact Match	Zero-shot Retrieval Recall@5
REALM	38.2	38.5
REALM retriever+Baseline encoder	37.4	38.5
Baseline retriever+REALM encoder	35.3	13.9
Baseline (ORQA)	31.3	13.9
REALM with random uniform masks	32.3	24.2
REALM with random span masks	35.3	26.1
30× stale MIPS	28.7	15.1

- joint training of retrieval/encoder helps
- index update required

Teach LM to use search and browse web: WebGPT(finetuning)

- Long format question-answering problem(LFQA)
- Leverage on-the-shelf knowledge retrieval & answer synthesis system
 - Bing Search API
 - GPT-3 175B
- Focus on finetuning to align with human feedback
 - **Behavior Cloning(BC)**: Supervised finetune with human *demonstrations*
 - **Reward Modeling(RM)**: Train with *comparison* feedback based on BC model
 - **Reinforcement Learning**: Finetune BC model with RM reward and BC KL penalty
 - Generation with **rejection sampling**: BC/RL on RM

Teach LM to use search and browse web: Human Feedback Tool

Question answering playground

Why do spicy foods make you sweat? **Question**

This question does not make sense | This question should not be answered **Flags**

Why Does Spicy Food Make You Sweat? (www.epainassist.com) **Page title**

Navigation bar

← Why do spicy foods make you sweat? Find in page ↑ ↓

fusely. It is a common phenomenon and almost everyone once in a while faces it. The reason behind sweating when eating spicy food is due to a chemical called as [Capsaicin](#) present in chilies and pepper which causes the body to send signal to the brain that the body is getting overheated as a result of which sweat comes out. The Capsaicin present in the spicy food causes certain receptors responsible for sweating to get activated resulting in [sweating](#). When talking about Capsaicin, as stated it is a primary chemical found in the chilies and pepper because of which spices and pepper taste the way they do. It also makes the food that much tastier.

[Image: Why Does Spicy Food Make You Sweat]

What is the Mechanism Behind Sweating When Eating Spicy Food?

Coming to the mechanism as to what causes you to sweat when eating spicy food, the answer is that chemical Capsaicin activates receptors in the skin that normally respond to excess [heat](#) or in a hot environment. These receptors are known as polymodal nociceptors. These receptors only respond to extreme conditions or intense mechanical stimulation like a burn or a

Page text

Reset buttons

Reset without saving | Save and reset

Quotes section

+ Add new quote

[1] Why Do People Sweat When They Eat Spicy Foods? | Livestrong.com (www.livestrong.com)

According to an Arizona University article entitled "The Capsaicin Receptor; A Pepper's Pathway to Pain," capsaicin is a molecule found in chili peppers that causes the spicy taste. The body also has a capsaicin receptor found on certain nerves that are heat-sensitive. When activated, these nerves send signals to the spinal cord and brain to send a perception of heat-related pain. The brain responds by triggering chemical reactions to cause cooling of the body, such as a sweat response.

Number of quote tokens left: 381
Number of actions left: 16

Done quoting! Write an answer

Budget section

Teach LM to use search and browse web: Action Space & Prompt

- Action Space

- Search {query}
- Clicked on link {link ID}
- Find in page: {text}
- Quote: {text}
- Scrolled down/up {1,2,3}
- Top/Back
- End: Answer
- End: {Nonsense, Controversial}

- Prompt

♦Question
How can I train the crows in my neighborhood to bring me gifts?

♦Quotes
From Gifts From Crows | Outside My Window (www.birdsoutsidemywindow.org)
> Many animals give gifts to members of their own species but crows and other corvids are the only ones known to give gifts to humans.

♦Past actions
Search how to train crows to bring you gifts
Click Gifts From Crows | Outside My Window www.birdsoutsidemywindow.org
Quote
Back

♦Title
Search results for: how to train crows to bring you gifts

♦Scrollbar: 0 - 11
♦Text
(0) How to Make Friends With Crows - PetHelpful (pethelpful.com)
If you did this a few times, your crows would learn your new place, but as I said, I'm not sure if they will follow or visit you there since it's probably not in their territory. The other option is simply to make new crow friends with the crows that live in your new neighborhood.

(1) Gifts From Crows | Outside My Window (www.birdsoutsidemywindow.org)
The partial piece of apple may have been left behind when the crow was startled rather than as a gift. If the crows bring bright objects you'll know for sure that it's a gift because it's not something they eat.
Brandi Williams says: May 28, 2020 at 7:19 am.

♦Actions left: 96
♦Next action

(b) Corresponding text given to the model.

Teach LM to use search and browse web: Main Conclusion

Question

How can I train the crows in my neighborhood to bring me gifts?

Option A Option B Comparison

Option A

Crows will give gifts to humans who feed them a lot and pay attention to them, or even rescue them [1]. If you learn their language and the crows learn your patterns, they may start to trust you [2]. Sometimes a crow will leave a gift [2].

[1] Gifts From Crows | Outside My Window (www.birdsoutsidemywindow.org)
Neutral

Many animals give gifts to members of their own species but crows and other corvids are the only ones known to give gifts to humans. As John Marzluff explains in the video, crows will do this for people who feed them a lot and pay attention to them, or even rescue them.

[2] The girl who gets gifts from birds - BBC News (www.bbc.com)
Trustworthy

The human learns their language and the crows learn their feeder's patterns and posture. They start to know and trust each other. Sometimes a crow leaves a gift.

Annotations (optional)

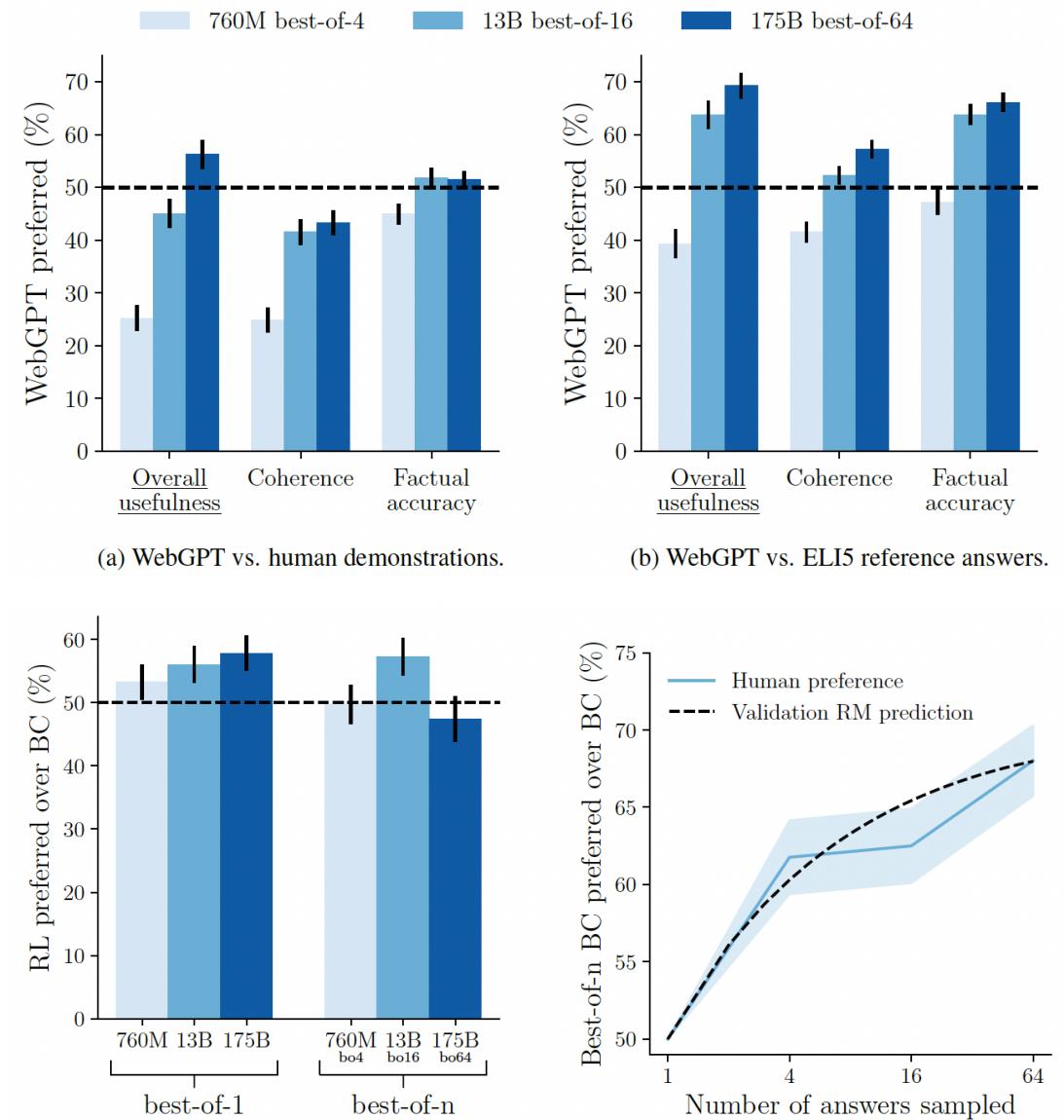
Label the sources, and use the tools to annotate the answer. (Optional)

Strong support
 Weak support
 No support
 Citation error
 Magic differ wand

Core ✓ Crows will give gifts to humans who...
Core ✓ If you learn their language and the...
Core ✓ Sometimes a crow will leave a gift

Notes of anything else that makes this answer useful to the person asking the question (optional):

- Outperform human & reference answer
- RL shadowed by BC-best-of-n



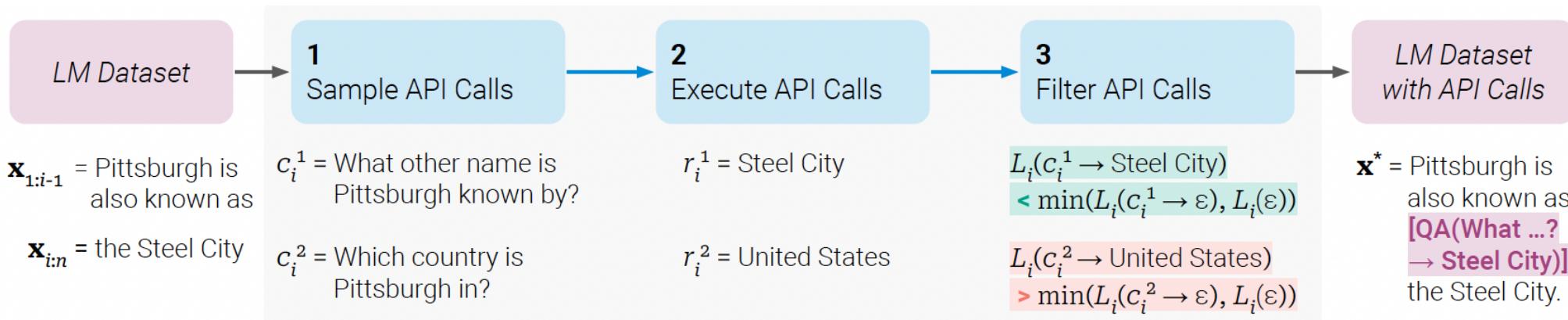
LLM self-teach to use tools: Toolformer

Corpus annotation

- Prompt LM(tool-wise) and sampling m tools for top- K position
- Call APIs get $m \times K$ response
- Filter APIs for LM loss reduction $\geq T_f$
- Augment corpus with remaining APIs

LLM finetuning & prediction

- Finetuning using standard LM objective
- Decoding as usual, stop when meeting →, call corresponding API
- Fill text with API response, continue decoding



Prompt & tools involved in Toolformer

Tools involved

- Question Answering:
 - Atlas(Retrieval augmented QA LM)
- Calculator
- Wikipedia Search:
 - BM25 retrieval for wikidump
- Machine Translation System
 - any lang to English trans(NLLB)
- Calendar

Prompt for QA Tool

Your task is to add calls to a Question Answering API to a piece of text. The questions should help you get information required to complete the text. You can call the API by writing "[QA(question)]" where "question" is the question you want to ask. Here are some examples of API calls:

Input: Joe Biden was born in Scranton, Pennsylvania.

Output: Joe Biden was born in [QA("Where was Joe Biden born?")] Scranton, [QA("In which state is Scranton?")] Pennsylvania.

Input: Coca-Cola, or Coke, is a carbonated soft drink manufactured by the Coca-Cola Company.

Output: Coca-Cola, or [QA("What other name is Coca-Cola known by?")] Coke, is a carbonated soft drink manufactured by [QA("Who manufactures Coca-Cola?")] the Coca-Cola Company.

Input: x

Output:

Results and limitations

Experiment settings & results

- GPT-J(6B) finetuned with CCNet(HQ subset of C4)
- Toolformer outperforms on QA/MLQA/math reasoning/Temporal Datasets, e.g. 3 LAMA QA subsets

Model	SQuAD	Google-RE	T-REx
GPT-J	17.8	4.9	31.9
GPT-J + CC	19.2	5.6	33.2
Toolformer (disabled)	22.1	6.3	34.9
Toolformer	33.8	11.5	53.5
OPT (66B)	21.6	2.9	30.1
GPT-3 (175B)	26.8	7.0	39.8

Table 3: Results on subsets of LAMA. Toolformer uses the question answering tool for most examples, clearly outperforming all baselines of the same size and achieving results competitive with GPT-3 (175B).

Limitations

- No capability of tools in a chain
- No tool interaction like WebGPT
- Sensitive to exact wording of input

End of Augmented Language Models

Plugins

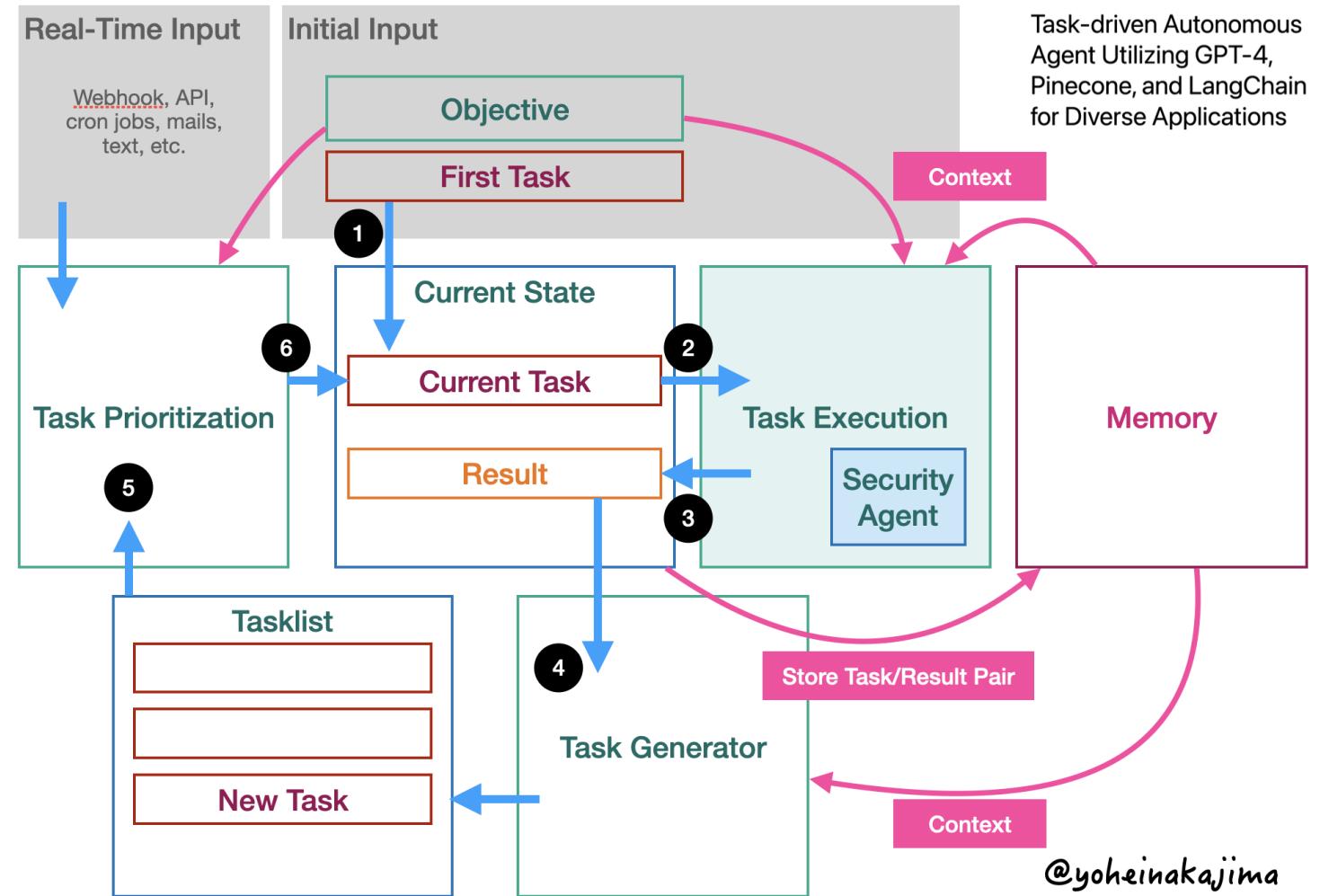
- Plugins ecosystem
- Primary implementations
 - Langchain Agent/Tool
 - ChatGPT Plugins
 - Fixie
 - Other examples in application

Plugins ecosystem

- Tool as a service
- From SEO to LMO
- Orchestration by LLM

Paradigm of Task-driven Autonomous Agent

- AutoGPT/BabyAGI
- Langchain Agent/Tool
- Fixie



Langchain Agent/Tool

Agent(backed by LLM) drives everything

- **prompt** with examples of planning and step-by-step actions
- **weak(description in prompt)** tool operating manual
- interact between LLM and tool with `stop` argument
- reasoning trace stored in `scratchpad` : *short memory*
- `memory` supported for chat history buffer: *long memory*

Implemented Agents

- **mrkl**: zeroshot, open tool-set
- **Self-ask-with-search**: Google search
- **ReAct**: Wiki [search|find]
- **chat**: ReAct open tool-set, action in JSON
- **conversational**: ReAct open tool-set, interact with human
- **conversational_chat**: ReAct open tool-set, user take action marked in JSON

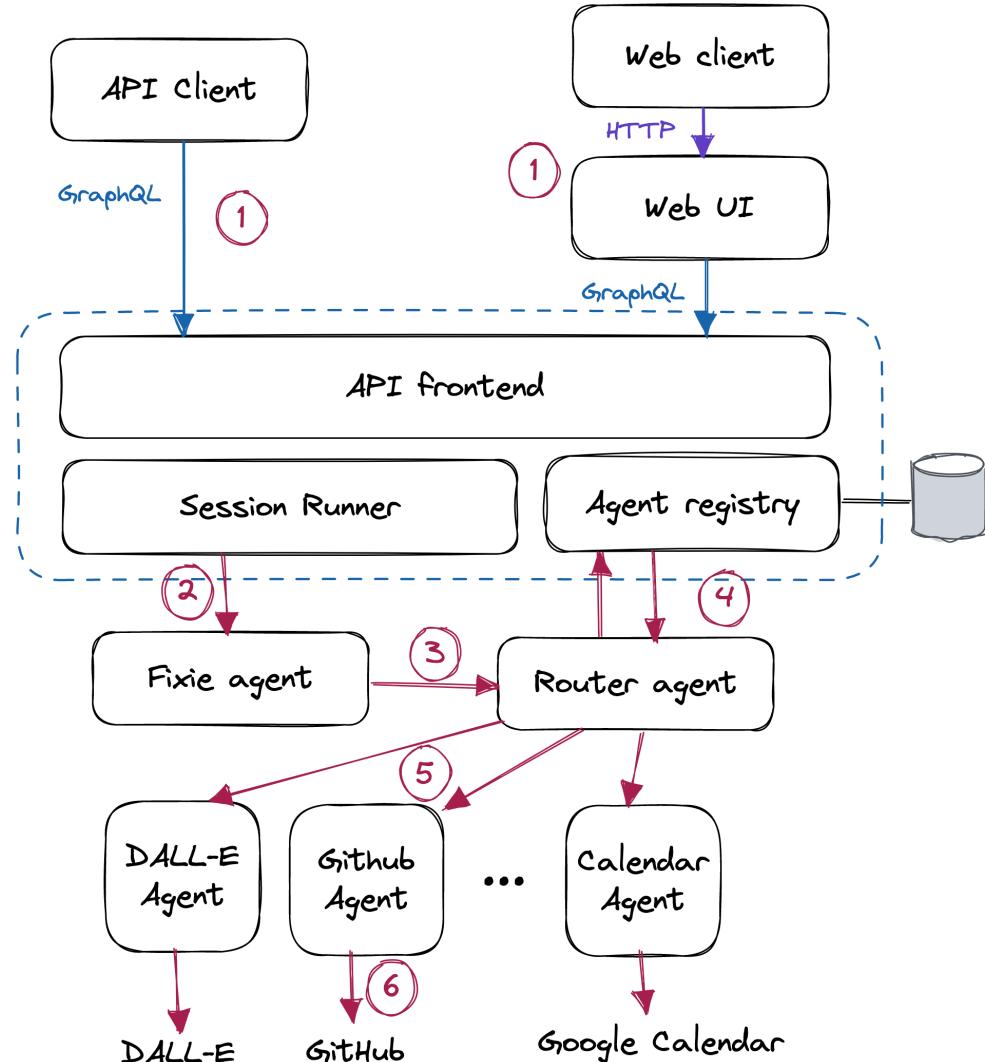
ChatGPT Plugins

ChatGPT drives everything

- Plugin description(in manifest) matters
- OpenAPI markdown for tool usage
- Orchestrate by ChatGPT during conversation
 - When to call
 - Which to call
 - How to call
 - Synthesis results
- Released `functions` argument in Chat Completions API

Fixie's(startup raised 17M\$) proposal

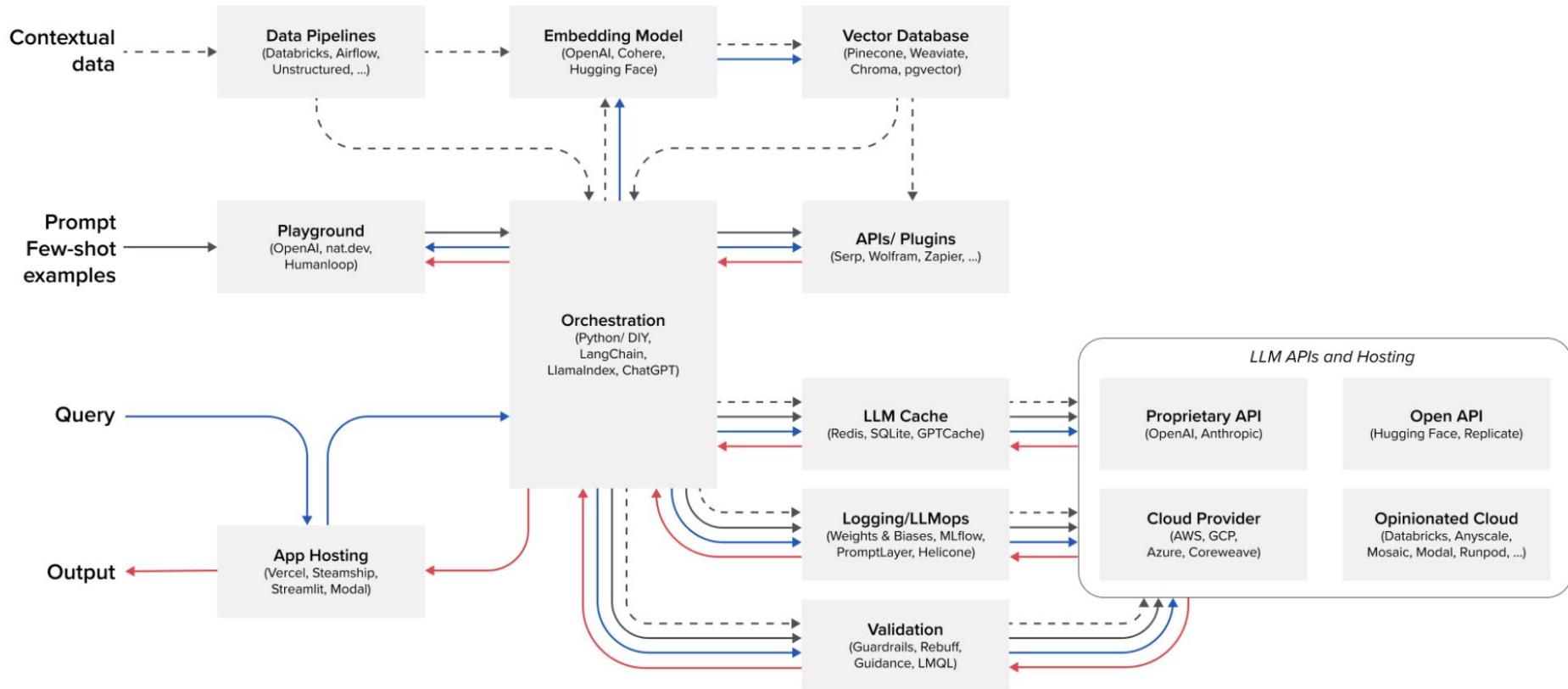
- Session Runner:
 - dispatch query
 - maintain the running chat log
- Fixie Agent(LLM):
 - break query into steps
 - dispatch to Router
- Router Agent(Neural Search):
 - match query/agent by neural search
 - agent represented by sample queries



Other examples in application

- MM-ReAct: Microsoft
- TaskMatrix.AI: Microsoft
- Tree-of-Thoughts: Princeton University/Deepmind
- LLMs As Tool Makers: Princeton University/Deepmind

Emerging LLM App Stack



LEGEND

- Gray boxes show key components of the stack, with leading tools/systems listed
- Arrows show the flow of data through the stack
- - - → Contextual data provided by app developers to condition LLM outputs
 - Prompts and few-shot examples that are sent to the LLM
 - Queries submitted by users
 - Output returned to users

End of Plugins

Important but not covered

- Practical prompt engineering
- Text to image:
 - Latent Diffusion Model/CLIP
 - DALL-E
 - Stable Diffusion
- Multi-modal and embodiment
 - PaLM-E
 - Gato
- Quantization & efficient inference on edge device
 - [ggml by Georgi Gerganov](#)
 - [bitsandbytes: LLM.int8\(\)/QLoRA](#)
- And more...

Thanks & QA?