



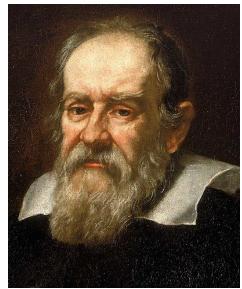
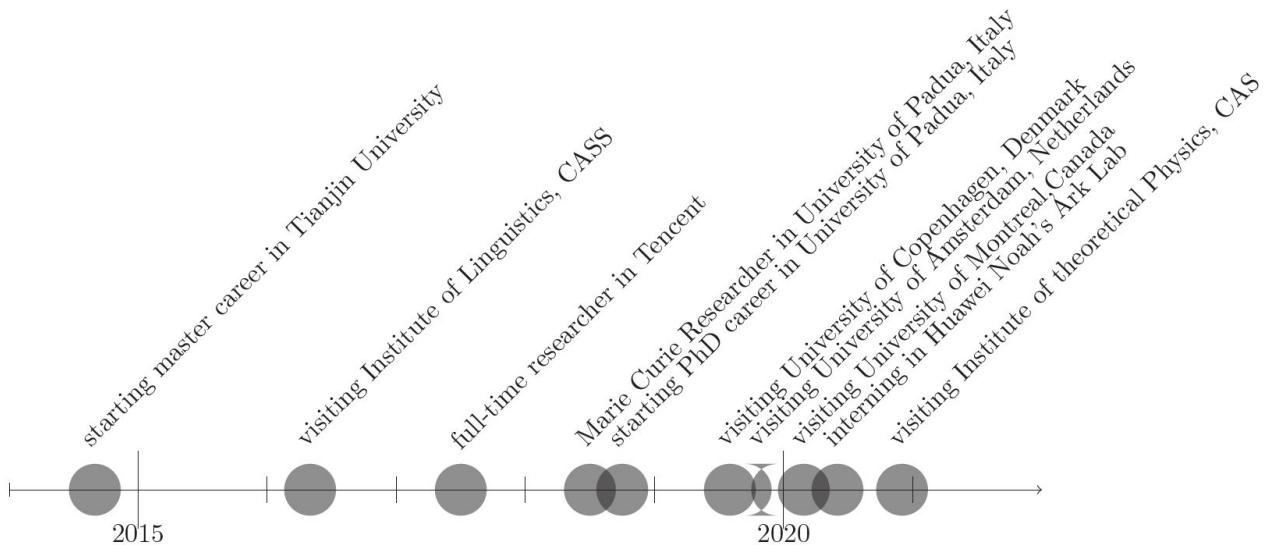
香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

CSC 6203

Large Language Model 大模型

Fall 2024
Benyou Wang
School of Data Science

About me



Galileo Galilei

the "father of modern physics"
the "father of the scientific method"
the "father of modern science"
Alumni of University of Padua



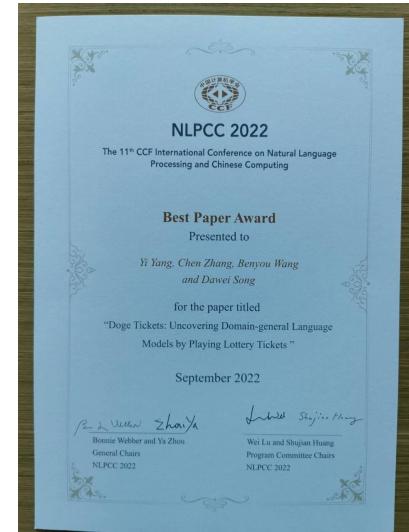
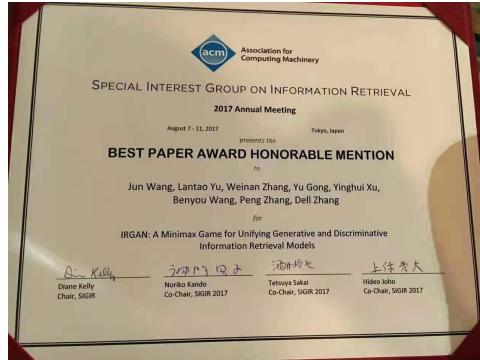
Tencent



Université de Montréal



Awards and honour



- **NLPCC 2022** Best Paper
- **ACM SIGIR** 2017 Best paper honourable mention. <https://sigir.org/awards/best-paper-awards/>
- **NAACL** 2019 best explainable NLP paper. <https://naacl2019.org/blog/best-papers/>
- EU Marie Curry researcher fellowship
- Huawei Spark award (华为火花奖)



Overall of our research (update every half an year)

- Medical Large language models
 - LLMs for Math
 - Automatic theorem proof
 - AI Mathematical Olympiad
 - Multi-modal LLMs
 - Speech
 - Image/video understanding
 - Video generation (SORA)
 - Multilingual LLMs
 - AceGPT
 - Agent and Human-machine interaction
 - Efficient LLMs
-
- Applications
 - Math
 - Medical/financial domains
 - Multilingual extension
 - LLMs
 - Text-only LLM
 - Vision language models
 - Speech language models
 - Video Generation (SORA)
 - The foundations
 - Agent/HCI
 - LLM Evaluation
 - Efficiency
 - RLHF
 - Search

Our team - GitHub Homepage

148 repositories			
		Stars	Language
LLMZoo	LLM Zoo is a project that provides data, models, and evaluation benchmark for large language models.	198	Python
Medical_NLP	Medical NLP Competition, dataset, large models, paper	400	Python
HuatuoGPT	HuatuoGPT, Towards Taming Language Models To Be a Doctor. (An Open Medical GPT)	138	Python
TextClassificationBenchmark	A Benchmark of Text Classification in PyTorch	138	Python
HuatuoGPT-II	HuatuoGPT2, One-stage Training for Medical Adaption of LLMs. (An Open Medical GPT)	55	Python
InstructionZoo		24	Python
Allava	Allava: Harnessing 1.4M GPT4V-synthesized Data for A Lite Vision-Language Model	8	Python
HuatuoGPT-Vision	HuatuoGPT-Vision: Medical Multimodal LLMs	20	Python
Huatuo-26M	The Largest-scale Chinese Medical QA Dataset: with 26.000.000 question answer pairs.	14	Python
ReasoningNLP	paper list on reasoning in NLP	16	Python
crosstalk-generation	CrossTalk Generation: Code and data for crosstalk text generation tasks, exploring whether large models and pre-trained language models can understand humor.	17	Python
GrammarGPT	The code and data for GrammarGPT.	8	Python
Apollo	Apollo: Multilingual Medicine: Model, Dataset, Benchmark, Code	7	Python
Evaluation-of-ChatGPT-on-Information-Extraction	An Evaluation of ChatGPT on Information Extraction task, including Named Entity Recognition (NER), Relation Extraction (RE), and Text Classification (TC).	9	Python
CMB	CMB: A Comprehensive Medical Benchmark in Chinese	9	Python
qnn		30	Python
AceGPT		7	Python
complex-order		13	Python
MultilingualSIFT	MultilingualSIFT: Multilingual Supervised Instruction Fine-tuning	5	Python
Chain-of-Diagnosis	An interpretable large language model (LLM) for medical diagnosis.	1	Python
MLLM-Bench	MLLM-Bench: Evaluating Multimodal LLMs with Per-sample Criteria	3	Python
OVM		2	Python
LongLlaVA	LongLlaVA: Scaling Multi-modal LLMs to 1000 Images Efficiently via Hybrid Architecture	2	Python

<https://github.com/orgs/FreedomIntelligence>

Our team – HuggingFace Homepage

Models 68 

▲ Collapse ↑↓ Sort: Most downloads

 FreedomIntelligence/AceGPT-7B
Text Generation • Updated Nov 30, 2023 • ↓ 3.61k • ❤ 6

 FreedomIntelligence/AceGPT-13B-chat
Text Generation • Updated Dec 2, 2023 • ↓ 3.55k • ❤ 26

 FreedomIntelligence/AceGPT-v1.5-13B-Chat
Text Generation • Updated Jun 22 • ↓ 3.44k • ❤ 5

 FreedomIntelligence/AceGPT-13B
Text Generation • Updated Dec 2, 2023 • ↓ 3.18k • ❤ 8

 FreedomIntelligence/AceGPT-7B-chat
Text Generation • Updated Mar 4 • ↓ 3.08k • ❤ 9

 FreedomIntelligence/Apollo-7B
Text Generation • Updated Apr 26 • ↓ 2.65k • ❤ 21

 FreedomIntelligence/Apollo-2B
Text Generation • Updated Apr 26 • ↓ 2.57k • ❤ 3

 FreedomIntelligence/Apollo-0.5B
Text Generation • Updated Apr 26 • ↓ 2.54k • ❤ 3

 FreedomIntelligence/AceGPT-v1.5-13B
Text Generation • Updated Apr 18 • ↓ 2.53k • ❤ 1

 FreedomIntelligence/Apollo-6B
Text Generation • Updated Apr 26 • ↓ 2.53k • ❤ 3

 FreedomIntelligence/phoenix-inst-chat-7b
Text Generation • Updated Nov 18, 2023 • ↓ 1.34k • ❤ 43

 FreedomIntelligence/HuatuoGPT-Vision-7B
Text Generation • Updated Jun 30 • ↓ 1.22k • ❤ 5

<https://huggingface.co/FreedomIntelligence>

A Recent Study: LongLLaVA



looongLLaVA: Scaling Multi-modal LLMs to 1000 Images Efficiently via Hybrid Architecture

Xidong Wang[†], Dingjie Song[†], Shunian Chen, Chen Zhang, Benyou Wang^{*}

The Chinese University of Hong Kong, Shenzhen

Shenzhen Research Institute of Big Data

<https://github.com/FreedomIntelligence/LongLLaVA>

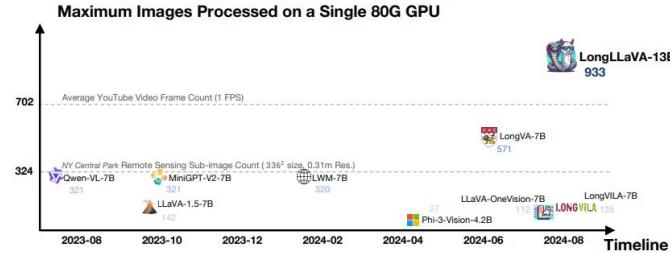


Figure 1: Comparison of the maximum images processed by MLLMs on a single 80GB GPU (Int8 Quantization), and plotted against their release dates. Our model, LongLLaVA, leads the way with the ability to handle up to 933 images, demonstrating its superior processing capability. Res refers to resolution. Although these baseline models are capable of processing these images as input, their performance often deteriorates significantly (Song et al., 2024) with more images.

<https://arxiv.org/pdf/2409.02889>

We rank 4th in Greater China

This is from November 10 2023, it's not automatically updated.

total_likes	name	count_users	models_count	models_likes	models_downloads	datasets_count	datasets_likes	datasets_downloads
11254	CompVis	23	13	9884	4611345	0	0	0
8224	THUDM	29	29	7634	757300	5	236	15582
3427	sentence-transformers	4	124	3276	26915487	5	76	89
1330	Helsinki-NLP	14	1440	1290	5018692	1	40	63329
968	shi-labs	6	21	85	106372	1	0	27
862	hkunlp	14	55	831	327200	0	0	0
700	fnlp	11	30	570	5027	4	130	43
560	tatsu-lab	4	12	44	159	3	516	80701
498	uwnlp	9	1	7	0	0	0	0
466	declare-lab	13	16	362	96854	7	34	149
455	weizmannscience	9	0	0	0	0	0	0
430	stanfordnlp	10	105	181	55422	1	239	5534
403	MBZUAI	68	27	254	125298	4	149	12112
339	FreedomIntelligence	23	21	129	11671	59	210	1816
331	csebutnlp	7	20	256	667251	7	75	34044
329	poloclub	6	2	2	0	1	327	1370149
298	cvlab	4	1	9	0	0	0	0

<https://huggingface.co/spaces/osanseviero/universities>

<https://twitter.com/osanseviero/status/1723229014100255011>

Our team - Join us as a Research Assistant!

What You Will Receive:

- Access to GPU **computing resources** and utilization of abundant **GPT APIs**.
- More frequent **communication** within our research team (also more pressure).
- Potential for research **publications** (sometimes coauthorship).
- The possibility of a part-time **contract** with a salary (also with office space).
- Internship** recommendation (Microsoft, Amazon, BAT, Huawei, Bytedance)

What We Expect From You:

- A commitment of at least 15 hours per week for full-time engagement.
- satisfied programming skills.

If you find this opportunity intriguing, please reach out to Xidong (223040239@link.cuhk.edu.cn) for further details.

Contents

- **Philosophy of this course**
- **Large language models?**
- **Introduction to ChatGPT**

Logistics

- ❖ Instructor: Benyou Wang
- ❖ Teaching assistant: Xidong Wang, Juhao Liang



- ❖ Location: Teaching Complex B201
- ❖ Meetings: Friday 13:30-16:20

- ❖ Office hours:

- Benyou Wang: Fridays 4:30 PM - 6:00 PM at Daoyuan Building 504A. (Email: wangbenyou@cuhk.edu.cn)
- Junying Chen: Mondays 4:00 PM - 5:00 PM at Daoyuan Building 223, Seat-9. (Email: junyingchen2@link.cuhk.edu.cn)
- Ke Ji: Wednesdays 7:30 PM - 8:30 PM at Daoyuan Building 223, Seat-10. (Email: keji@link.cuhk.edu.cn)

Logistics

❖ Official Website Link (llm-course.github.io)

Course Information

The course will introduce the key concepts in LLMs in terms of training, deployment, downstream applications. In the technical level, it covers language model, architecture engineering, prompt engineering, retrieval, reasoning, multimodality, tools, alignment and evaluations. This course will form a sound basis for further use of LLMs. In particular, the topics include:

Schedule

Date	Topics	Recommended Reading	Pre-Lecture Questions	Lecture Note	Coding Note	Events Deadlines	Feedback Providers
Sep. 4-15th (optional) self-study; do not come to the classroom	Tutorial 0: GitHub, LaTeX, Colab, and ChatGPT API	OpenAI's blog LaTeX and Overleaf Colab GitHub					Benyou Wang
Sep. 15th	Lecture 1: Introduction to Large Language Models (LLMs)	On the Opportunities and Risks of Foundation Models Sparks of Artificial General Intelligence: Early experiments with GPT-4	What is ChatGPT and how to use it?	[slide] [note]			Xidong Wang and Juhao Liang

❖ Official Wechat Group



Course Structure

- This is an advanced graduate course and we will be teaching and discussing state-of-the-art papers about large language models
- All the students are expected to come to the class regularly and participate in discussion
- Prerequisites:
 - Familiarity with neural networks and Transformer models (encoder, decoder, encoder-decoder)
 - Familiarity with basic NLP tasks, including understanding (text classification, question answering) and generation (translation, summarization) tasks

Course Structure (tentative)

- Introduction to Large Language Models (LLMs) - User's perspective
- Language models and beyond
- Architecture engineering and scaling law - Transformer and beyond
- Training LLMs from scratch - Pre-training, SFT, learning LLMs with human feedback
- Efficiency in LLMs
- Prompt engineering
- Knowledge and reasoning
- Multimodal LLMs
- LLMs in vertical domains
- Tools and large language models
- Privacy, bias, fairness, toxicity and holistic evaluation
- Alignment and limitations

Components and grading

- ❖ Assignments (40%)

- Assignment 1 (20%): Using API for testing prompt engineering
 - Assignment 2 (20%): A toy LLM application

Both assignments need a report and code attachment if it has coding. See the relevant evalution criterion as the final project.

- ❖ Final project (55%)

You need to write a project report (max 6 pages) for the final project. You are also expected to make a project poster presentation. After the final project deadline, feel free to make your project open source; we appreciate if you acknowledge this course.

- ❖ Participation (5%)

Assignments 1: ChatGPT API Call

Making requests

You can paste the command below into your terminal to run your first API request. Make sure to replace `$OPENAI_API_KEY` with your secret API key.

```
1 curl https://api.openai.com/v1/chat/completions \
2   -H "Content-Type: application/json" \
3   -H "Authorization: Bearer $OPENAI_API_KEY" \
4   -d '{
5     "model": "gpt-3.5-turbo",
6     "messages": [{"role": "user", "content": "Say this is a test!"}],
7     "temperature": 0.7
8   }'
```

This request queries the `gpt-3.5-turbo` model (which under the hood points to the [latest gpt-3.5-turbo model variant](#)) to complete the text starting with a prompt of "Say this is a test". You should get a response back that resembles the following:

```
1 {
2   "id": "chatcmpl-abc123",
3   "object": "chat.completion",
4   "created": 1677858242,
5   "model": "gpt-3.5-turbo-0613",
6   "usage": {
7     "prompt_tokens": 13,
8     "completion_tokens": 7,
9     "total_tokens": 20
10 },
11 "choices": [
12   {
13     "message": {
14       "role": "assistant",
15       "content": "\n\nThis is a test!"
16     },
17     "finish_reason": "stop",
18     "index": 0
19   }
20 ]
21 }
```

Now that you've generated your first chat completion, let's break down the [response object](#). We can see the `finish_reason` is `stop` which means the API returned the full chat completion generated by the model without running into any limits. In the choices list, we only generated a single message but you can set the `n` parameter to generate multiple messages choices.

- ❖ How to get the key
- ❖ The simplest way is to use <https://eylink.cn/>

Assignments 2: training a Language model

For Developers

```
import llmfactory

# Configure the resource in the factory/resource.json file
factory = llmfactory.Factory()

# Show available models
factory.show_available_model()
# Output:
# [Bloom]: bloom-560m, bloomz-560m, bloom-1b1, bloomz-1b1, bloomz-7b1-mt
# [Llama]: llama-7b-hf, llama-13b-hf
# [Baichuan]: baichuan-7B

# Show available data
factory.show_available_data()
# Output:
# [Local]: music, computer, medical

# Select a model from the available model set
model_config = factory.create_backbone("bloom-560m")

# Set up the data configuration
data_config = factory.prepare_data_for_training(num_data=50, data_ratios

# Train a new model based on the existing model and data configuration
model_config = factory.train_model(model_config, data_config, save_name=

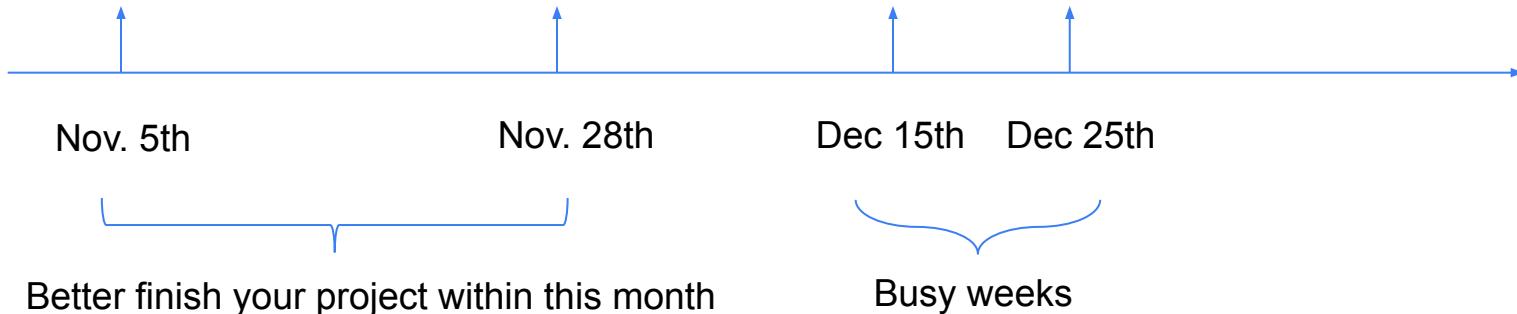
# Deploy the model on the command line
factory.deploy_model_cli(model_config)

# Deploy the model using Gradio
factory.deploy_model_gradio(model_config)
```

<https://github.com/FreedomIntelligence/LLMFactory>

Final project

- Students complete a research project in teams of 1-3
- Draft proposal deadline: Nov. 5th 11:59pm (simply explain your idea in one page)
- Final proposal deadline: Nov. 28th 11:59pm (**TAs will provide suggestions for the revision!**)
- In-class presentation: Dec 15th
- Final paper deadline: Dec 25th (final date)



What can we do for the final project?

Philosophy :

- select one of given proposals (you could do nothing but wait for the release of proposals).
- **OR** submit a customized project with a proposal that needs to be approved
- **Call for Project Proposals (optional):** (Deadline tentatively Nov. 28th, 11:59pm.).
 - Choose an NLP research topic of interest or select from provided options.
 - The team members should be decided
- **Who could submit the proposal**
 - The students in this course (You could decide whether the submitted proposal could be used by other teams if approved)
 - Research scientists or engineers in a company
 - RAs and Phd students in our research team
 - Faculty members in our university (your supervisors for example)
 - Actually, everyone is welcome, we reserve the rights to reject a proposal.

Final project

Typical projects (we will release a detailed list later):  **Hugging Face** <https://huggingface.co/models>

1. Train or fine-tune a medium-sized language model (e.g., T5, Bloom, TinyLLaMA, Baichuan, LLaMA) yourself for any problem of your interest. Check out HuggingFace's model hub!
2. Evaluate one of the largest language models (e.g., ChatGPT/GPT4) and understand their capabilities, limitations and risks;
3. An Agent System (math/financial/medical/legal)
4. An APP that is for the campus, hospital, etc.
5. An survey that involving LLMs
6. A research paper involving LLMs (please acknowledge this course if possible)

Note: You might get computing resources to train 10B+ model if Tas/instructor like your proposal

More project ideas will be presented during the lectures and all creative ideas or research topics are encouraged for further discussion.

Final project

Report of final project should be publicly released, otherwise please specify reasons.

- released in our website
- released in ArXiv if quality is high; do not preprint low-quality paper there. If you cannot access the quality, you could consult your supervisor or the teaching team.

Consider Github to maintain your code (link Github repo in the report) if coding needed

A objective is could be **earning 100+ GitHub stars for your repo.**

Consider uploading your model in HuggingFace, serving it there is possible.

Note: You might get computing resources to train
10B+ model if instructor like your proposal

Team work

Team size: Students may do final projects solo, or in teams of up to 3 people. Please specify reasons to do project with more than 3 people, we reserve the rights to reject it

Team work is encouraged: We strongly recommend you do the final project in a team. Larger teams are expected to do correspondingly larger projects, and you should only form a 3-person team if you are planning to do an ambitious project where every team member will have a significant contribution.

Contribution: In the final report we ask for a statement of what each team member contributed to the project. Team members will typically get the same grade, but we may differentiate in extreme cases of unequal contribution. **You can contact us in confidence in the event of unequal contribution.**

External collaborators: You can work on a project that has external (non course student) collaborators, but you must make it clear in your final report which parts of the project you are extractly contributing.

Mentors: Every custom project team has a mentor, who gives feedback and advice during the project. A project may have an external (i.e., not in our teaching team) mentor; otherwise, we will assign a TA or any research staff in our research team to custom project teams after project proposals.

Computing resources: We will use Kaggle computing resources, later we will share the detail.

Final project assessment

Final report assessment (45%)

TA review

Poster presentation (10%)

Cross review between students + TA/instructor review

Submit your Final project to a conference

- Students are encouraged to submit papers to ACL ARR;
 - <https://openreview.net/group?id=aclweb.org/ACL>
- Submission Deadlines (every two months)
 - 2024 Oct 15th
 - 2024 Dec 15th
 - **2025 Feb 15th**
- TAs might help upon their interest. They might also refer you to other students in this group

How to better prepare a final project in NLP?

which proposal could I do for the final project in a NLP course that emphasize large language models?

1/12/2024, 10:16:03 AM



There are numerous exciting project proposals you could consider for an NLP course that emphasizes large language models. Here are a few ideas:

1. **Fine-tuning GPT for a Specific Task:** Many NLP tasks can benefit from the transfer learning capabilities of large language models. You could propose to fine-tune a pre-trained model like GPT-3 on a specific task, such as text summarization, sentiment analysis, or machine translation.
2. **Bias Analysis in Language Models:** Large language models have been criticized for their potential to perpetuate and amplify biases present in their training data. You could propose a project that explores these biases, possibly by creating a dataset of potentially biased statements and evaluating how the model responds to them.
3. **Exploration of Zero-shot Learning:** Large language models like GPT-3 have shown remarkable capabilities in zero-shot learning, where they can perform tasks without any specific fine-tuning. You could explore this aspect further, perhaps by designing a range of tasks and evaluating the model's zero-shot performance.
4. **Multimodal Language Models:** Language models are increasingly being used in conjunction with other types of data, such as images. You could propose a project that explores the effectiveness of large language models in a multimodal context.
5. **Language Model as a Knowledge Base:** Given that large language models have been trained on a vast amount of data, they can be seen as a form of knowledge base. You could explore how effectively a model like GPT-3 can answer questions on a wide range of topics, and how this capability compares to more traditional knowledge bases.
6. **Interactive Fiction with Language Models:** Large language models can generate coherent and contextually appropriate text, which makes them great for generating interactive fiction. You could propose a project to create an interactive story or game using a model like GPT-3.

Remember, the best project will depend on your interests and the specific focus of your course. Be sure to discuss your ideas with your course instructor or advisor to ensure they're appropriate and feasible.

1/12/2024, 10:16:03 AM

Define the learning objectives:

- **Knowledge:** a) Students will understand basic concepts and principles of LLM; b) Students could effectively use LLMs for daily study, work and research; and c) Students will know which tasks LLMs are suitable to solve and which are not.
- **Skills:** a) Students could train a toy LLM following a complete pipeline and b) Students could call ChatGPT API for daily usage in study, work and research.
- **Valued/Attitude:** a) Students will appreciate the importance of data; b) Students will tend to use data-driven paradigm to solve problems; and c) Students will be aware of the limitations and risks of using ChatGPT.

Select appropriate resources:

- **Recent ArXiv papers**
 - (People share daily ArXiv papers in Twitter)
- **GitHub**
 - (popular GitHub means a lot)
- **HuggingFace**
 - (New models and datasets)
 - <https://huggingface.co/papers> (hot papers here)
- **Blogs**
 - (from Open AI and famous guys, Lilian Weng, Yao Fu, Jianlin Su)

Design engaging lectures:

- Discussions in the end of each lecture
- In-class presentation
- Interrupting me whenever needed
- **Make friends with the instructor and TAs**

Provide hands-on practice:

Github Repositories

- **nanoGPT** <https://github.com/karpathy/nanoGPT>
- **minGPT** <https://github.com/karpathy/minGPT>
- **Llama2.c** <https://github.com/karpathy/llama2.c>
- **TinyLLaMA** <https://github.com/eivindbohler/tinyllama>
- **HautuoGPT**
- **GPT review**
- **GPT API**
- **LLMZoo**
- **LLMFactory**

The screenshot shows a list of GitHub repositories under the organization 'FreedomIntelligence'. The repositories are:

- LLMZoo** (Public): A project that provides data, models, and evaluation benchmark for large language models. Last updated on Jul 25.
- Medical_NLP** (Public): Medical NLP Competition, dataset, large models, paper. Last updated on Aug 1.
- HuatuoGPT** (Public): HuatuoGPT, Towards Taming Language Models To Be a Doctor. (An Open Medical GPT) Last updated on Jul 31.
- TextClassificationBenchmark** (Public): A Benchmark of Text Classification in PyTorch. Last updated on Aug 16, 2019.
- InstructionZoo** (Public): Last updated on Jun 7.
- crosstalk-generation** (Public): Code and data for crosstalk text generation tasks, exploring whether large models and pre-trained language models can understand humor. Last updated on Sep 6, 2022.
- ReasoningNLP** (Public): paper list on reasoning in NLP. Last updated on Aug 8.
- qnn** (Public): Last updated on Apr 17, 2019.
- GrammarGPT** (Public): The code and data for GrammarGPT. Last updated on Aug 1.
- Huatuo-26M** (Public): The Largest-scale Chinese Medical QA Dataset: with 26.000.000 question answer pairs. Last updated on Aug 8.

<https://github.com/orgs/FreedomIntelligence>

Foster collaboration and discussion:

- You own the copyright of your own project if our teaching team do not have a substantial contribution. Otherwise please acknowledge us.
- You are welcome to have discussions with our teaching team.
- Students are encouraged for collaboration and discussions.

Seek feedback and iterate:

- Tell us if you have any suggestions about this course
- We will continue polishing this course.

what is in our course

- Very basics of NLP (most old NLP techniques are not that practical now)
- Large Langauge models (training and beyond)
- Data engineering
- Prompt engineering
- NLP applications
- Future tendency NLP

what is not in our course

- How to do basic coding
- Machine learning
- How to understand the mathematical machanmism of NLP models
- *SORA might not introduced*

Use ChatGPT easily

Check <https://gpt.cuhk.edu.cn>

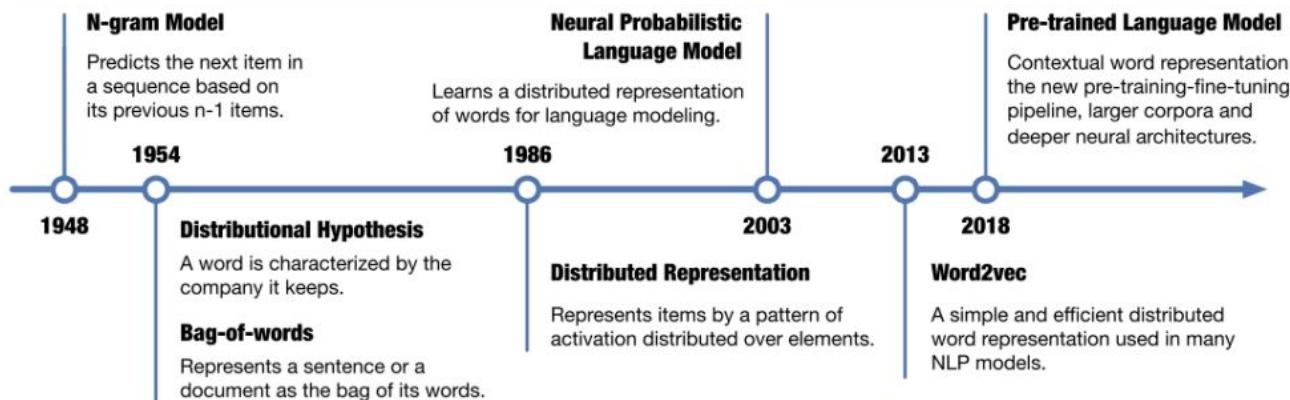
Contents

- Philosophy of this course
- **Large language models**
- Introduction to ChatGPT

What are Large Language models (LLMs)?

Background

- language model



What is language modeling?

- A **language model** assigns a probability to a N-gram
 $f: V^n \rightarrow R^+$

What is language modeling?

- A **language model** assigns a probability to a N-gram
 $f: V^n \rightarrow R^+$



Sfkklkjf fskjhfkjsh kjfs fs kjhkjhs fsjhfkshkjfh

Low probability



ChatGPT is all you need

high probability

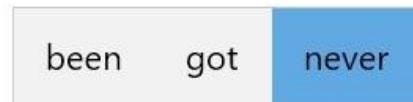
What is language modeling?

- A **language model** assigns a probability to a N-gram
 $f: V^n \rightarrow R^+$

A **conditional language model** assigns a probability of a word given some conditioning context

$$g: (V^{n-1}, V) \rightarrow R^+$$

And $p(w_n | w_1 \dots w_{n-1}) = g(w_1 \dots w_{n-1}, w) = \frac{f(w_1 \dots w_n)}{f(w_1 \dots w_{n-1})}$



I've _____.

What is language modeling?

- A **language model** assigns a probability to a N-gram
 $f: V^n \rightarrow R^+$

A **conditional language model** assigns a probability of a word given some conditioning context

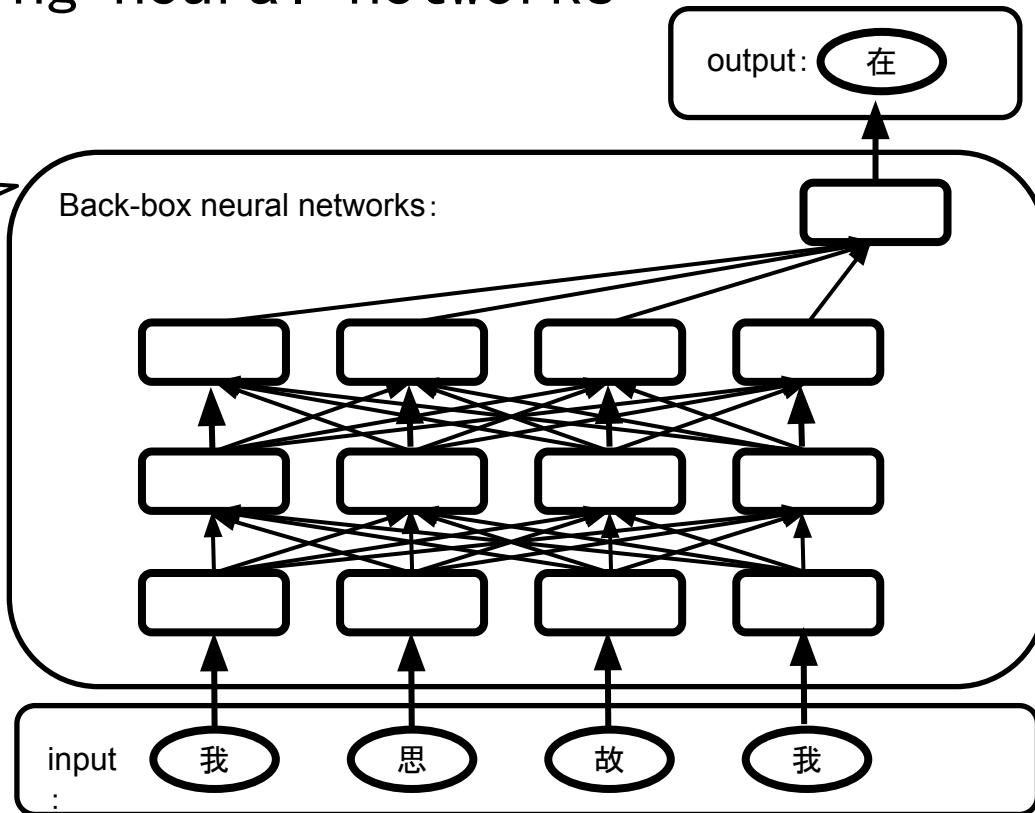
$$g: (V^{n-1}, V) \rightarrow R^+$$

And $p(w_n | w_1 \dots w_{n-1}) = g(w_1 \dots w_{n-1}, w) = \frac{f(w_1 \dots w_n)}{f(w_1 \dots w_{n-1})}$

$p(w_n | w_1 \dots w_{n-1})$ is the foundation of **modern large language models** (GPT, ChatGPT, etc.)

Language model using neural networks

GPT-3/ChatGPT/GPT4 have
175B+ parameters
Humans have 100B+ neurons



Language models: Narrow Sense

A probabilistic model that assigns a probability to every finite sequence (grammatical or not)

Sentence: “the cat sat on the mat”

$$\begin{aligned} P(\text{the cat sat on the mat}) &= P(\text{the}) * P(\text{cat}|\text{the}) * P(\text{sat}|\text{the cat}) \\ &\quad * P(\text{on}|\text{the cat sat}) * P(\text{the}|\text{the cat sat on}) \\ &\quad * P(\text{mat}|\text{the cat sat on the}) \end{aligned}$$

Implicit order

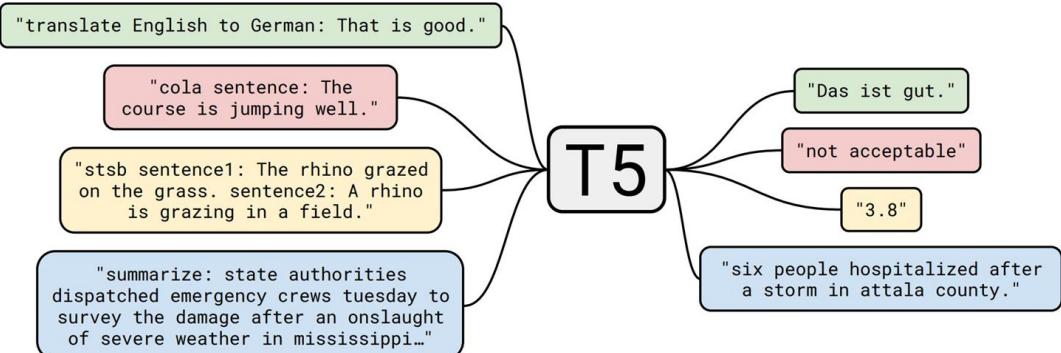
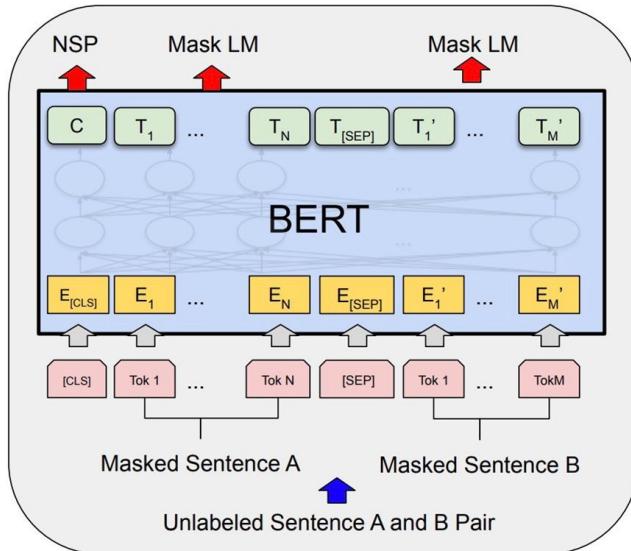


GPT-3 still acts in this way but the model is implemented as a very large neural network of 175-billion parameters!

Language models:Broad Sense

- ❖ Decoder-only models (GPT-x models)
- ❖ Encoder-only models (BERT, RoBERTa, ELECTRA)
- ❖ Encoder-decoder models (T5, BART)

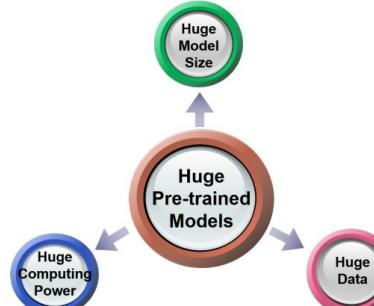
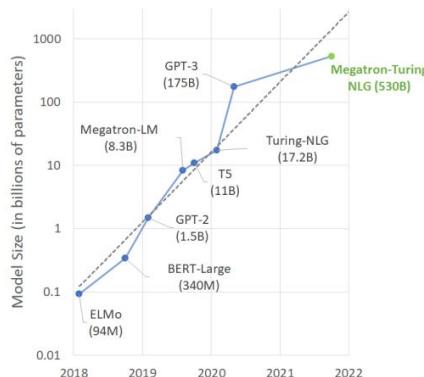
The latter two usually involve a different **pre-training** objective.



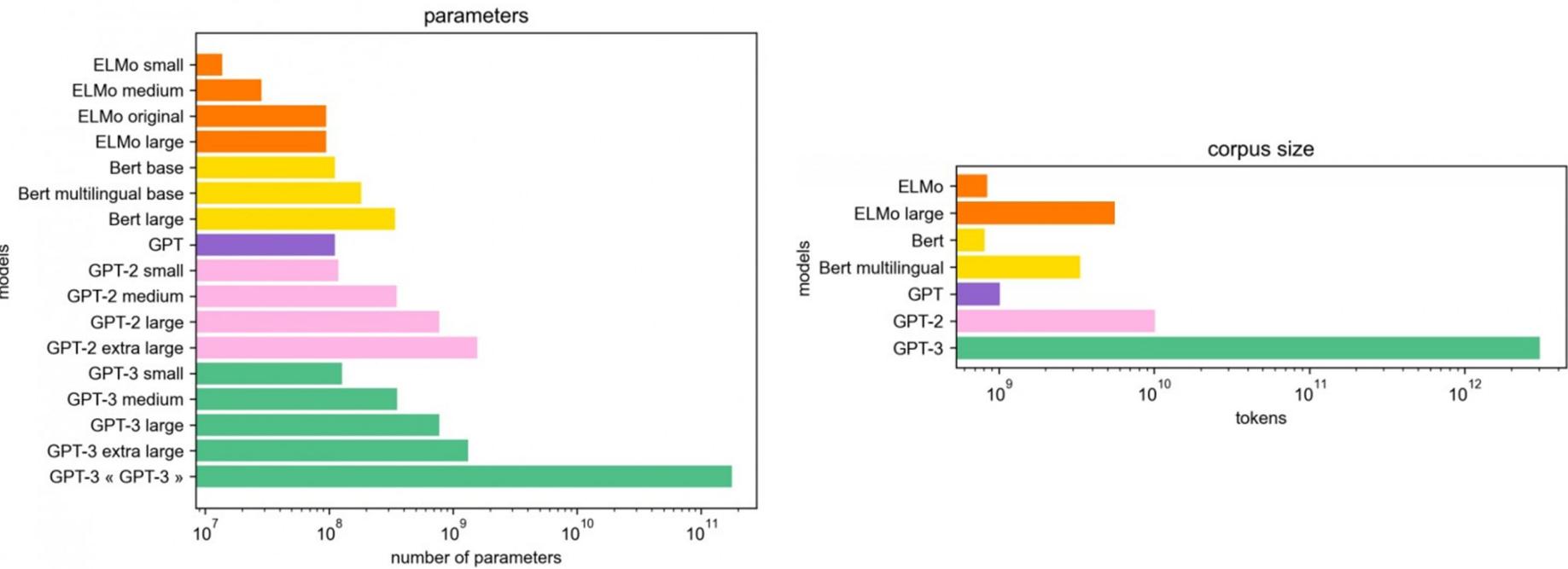
PLM vs. LLM

We do not explicitly mention pre-training because pre-training and training use the same language models objective (e.g., autoregressive generation)

- Pre-trained language model
- Large pre-trained Language Model (LLM)



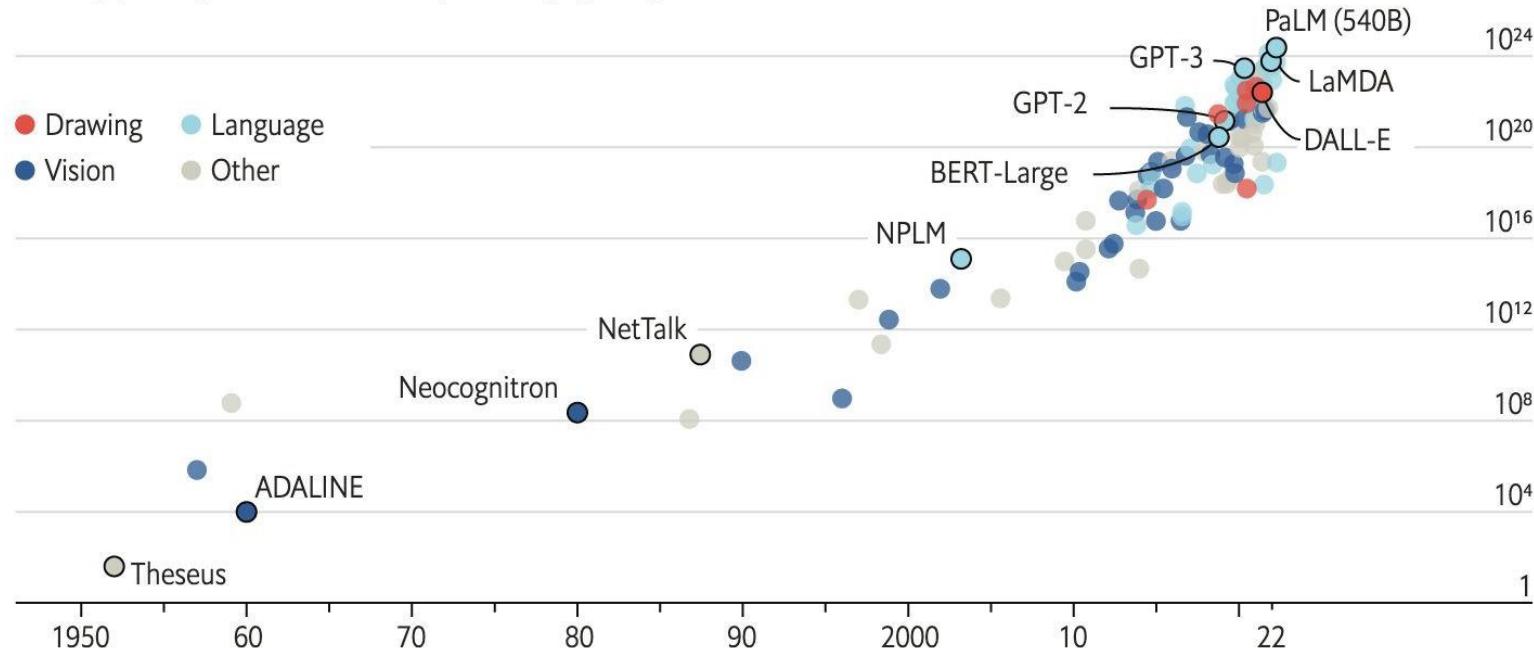
How Large are “Large” LMs?



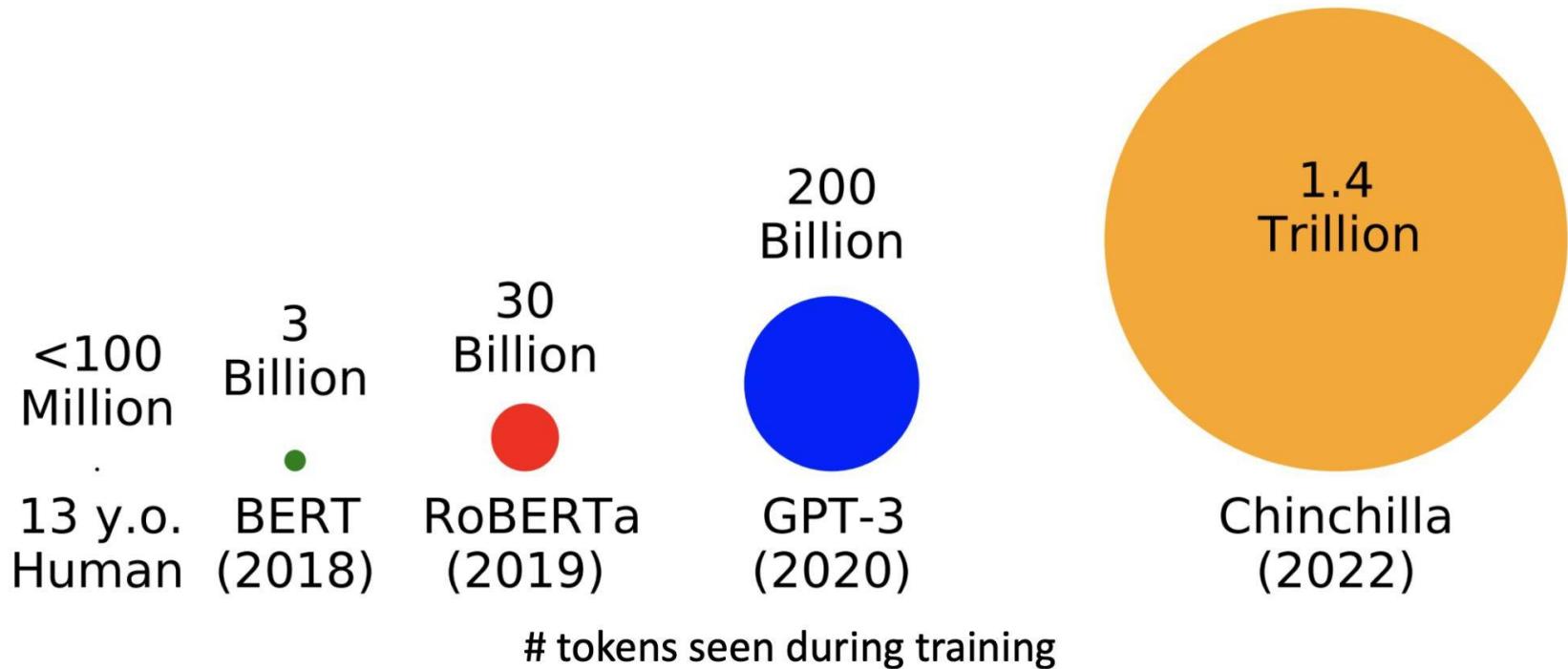
More recent models: PaLM (540B), OPT (175B), BLOOM (176B)...

Large Language Models

AI training runs, estimated computing resources used
Floating-point operations, selected systems, by type, log scale

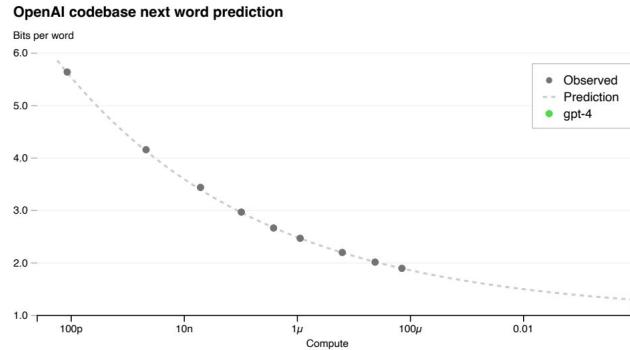


Large Language Models - **Hundreds of Billions of Tokens**



Some basics for large language models

- Scalable network **architecture** (Transformer vs. CNN/RNN)
- Scalable **objective** (conditional/auto-regressive LM vs. Masked LM)



- Scalable **data** (plain texts are everywhere vs. supervised data)
 - <https://github.com/esbatmop/MNBVC>

How Large are “Large” LMs?

- ❖ Today, we mostly talk about two camps of models:
 - Medium-sized models: BERT/RoBERTa models (100M or 300M), T5 models (220M, 770M, 3B)
 - “Very” large LMs: models of 100+ billion parameters
- ❖ Larger model sizes larger compute, more expensive during inference
- ❖ Different sizes of LMs have different ways to adapt and use them
 - Fine-tuning, zero-shot/few-shot prompting, in-context learning...
- ❖ Emergent properties arise from model scale
- ❖ Trade-off between model size and corpus size

Why LLMs?

Why Larger language models

- More world **knowledge** (LAMA)
 - Language models as knowledge base?
- Larger capacity to learn problem-solving **Abilities**
 - Coding, revising articles, reasoning etc.
- Better **generalization** to unseen tasks
- **Emergent ability** (涌现能力)

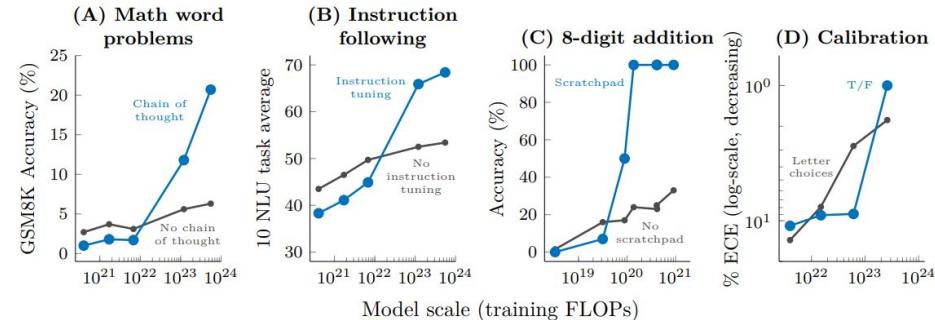
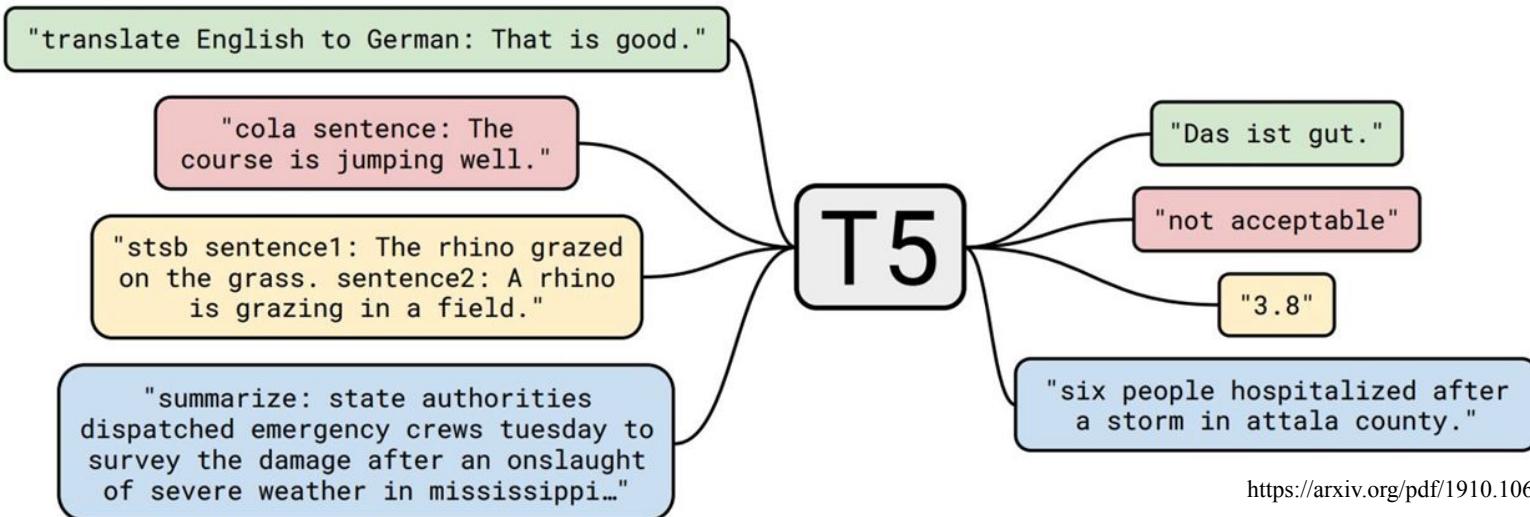


Figure 3: Specialized prompting or finetuning methods can be emergent in that they do not have a positive effect until a certain model scale. A: Wei et al. (2022b). B: Wei et al. (2022a). C: Nye et al. (2021). D: Kadavath et al. (2022). An analogous figure with number of parameters on the x-axis instead of training FLOPs is given in Figure 12. The model shown in A-C is LaMDA (Thoppilan et al., 2022), and the model shown in D is from Anthropic.

Why LLMs?

Generalization :

One single model to solve many NLP tasks



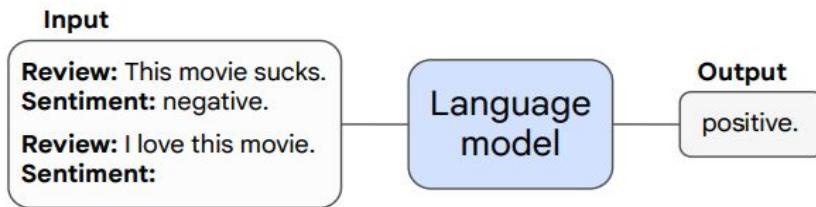
It could even generalize to new tasks, following the phylosity of FLAN

Why LLMs?

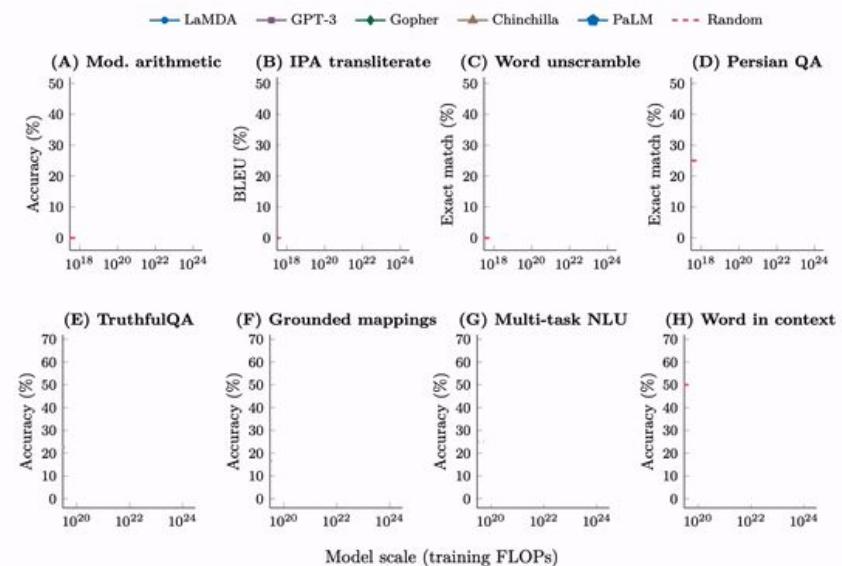
Emergent properties in LLMs:

Some ability of LM is not present in smaller models but is present in larger models

Emergent Capability: Few-shot prompting



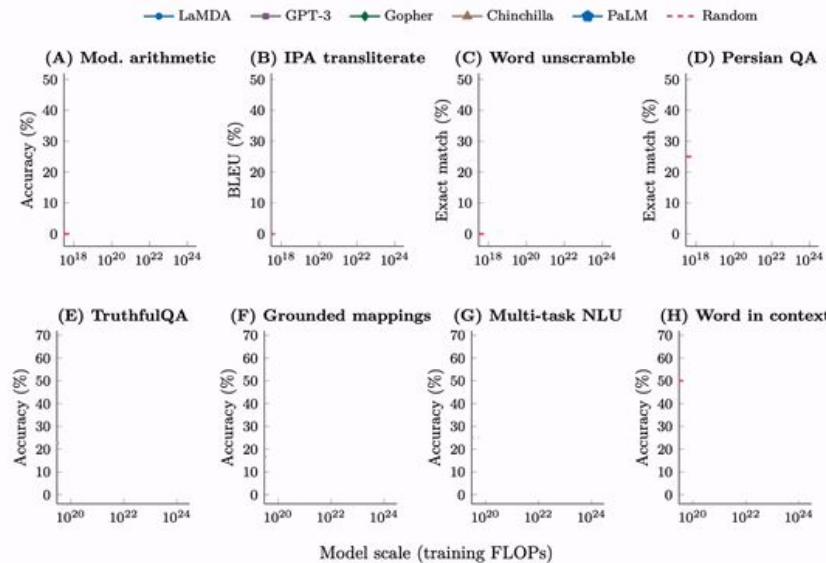
> A few-shot prompted task is emergent if it achieves random accuracy for small models and above-random accuracy for large models.



Why LLMs?

- **Emergent Abilities**

- Some ability of LM is not present in smaller models but is present in larger models



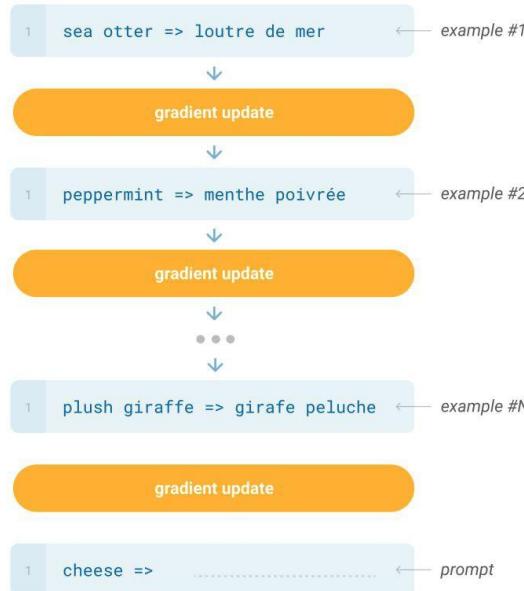
https://docs.google.com/presentation/d/1yzbmYB5E7G8lY2-KzhmArmPYwwl7o7CUST1xRZDUu1Y/edit?resourcekey=0-6_TnUMokWCK_FN2BiPxmbw#slide=id.g1fc34b3ac18_0_27

Emergent Capability - In-Context Learning

Traditional fine-tuning (not used for GPT-3)

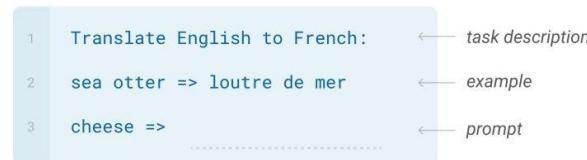
Fine-tuning

The model is trained via repeated gradient updates using a large corpus of example tasks.



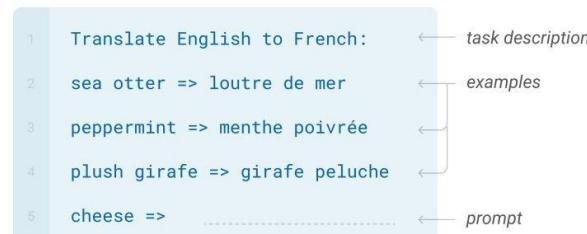
One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.



Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.



<https://arxiv.org/pdf/2005.14165.pdf>

Emergent Capability - In-Context Learning

Zero-shot
(os)

No Prompt

skicts = sticks

1-shot
(1s)

chiar = chair
skicts = sticks

Few-shot
(FS)

chiar = chair
[...]
pciinc = picnic
skicts = sticks

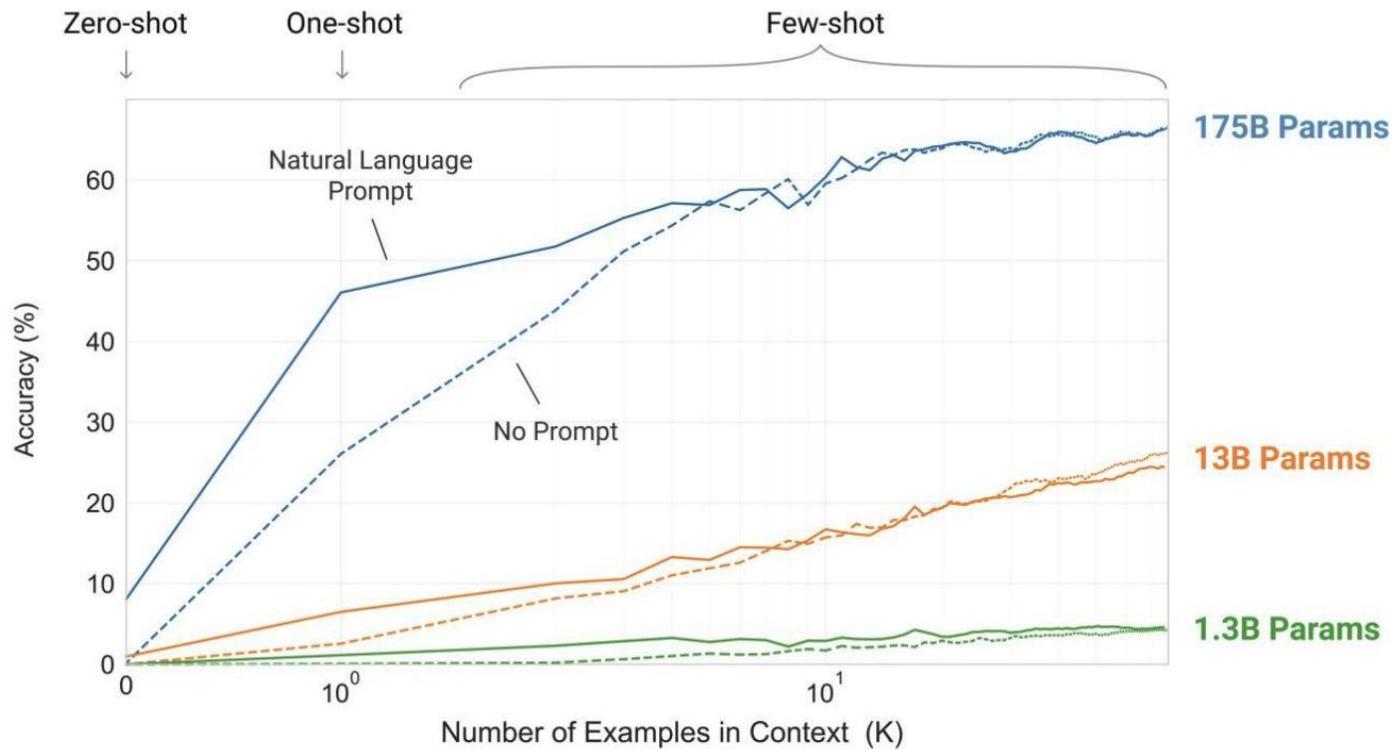
Prompt

Please unscramble the letters into
a word, and write that word:
skicts = sticks

Please unscramble the letters into
a word, and write that word:
chiar = chair
skicts = sticks

Please unscramble the letters into
a word, and write that word:
chiar = chair
[...]
pciinc = picnic
skicts = sticks

Emergent Capability - In-Context Learning



Emergent Capability - Chain of Thoughts Prompting

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. X

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?

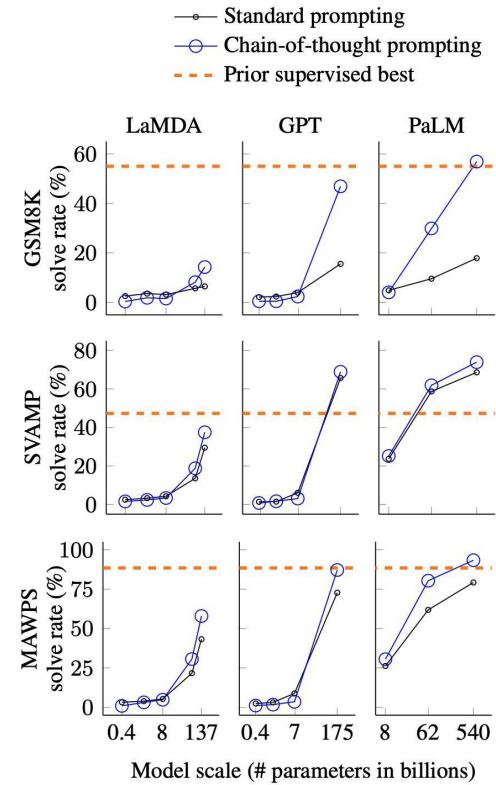
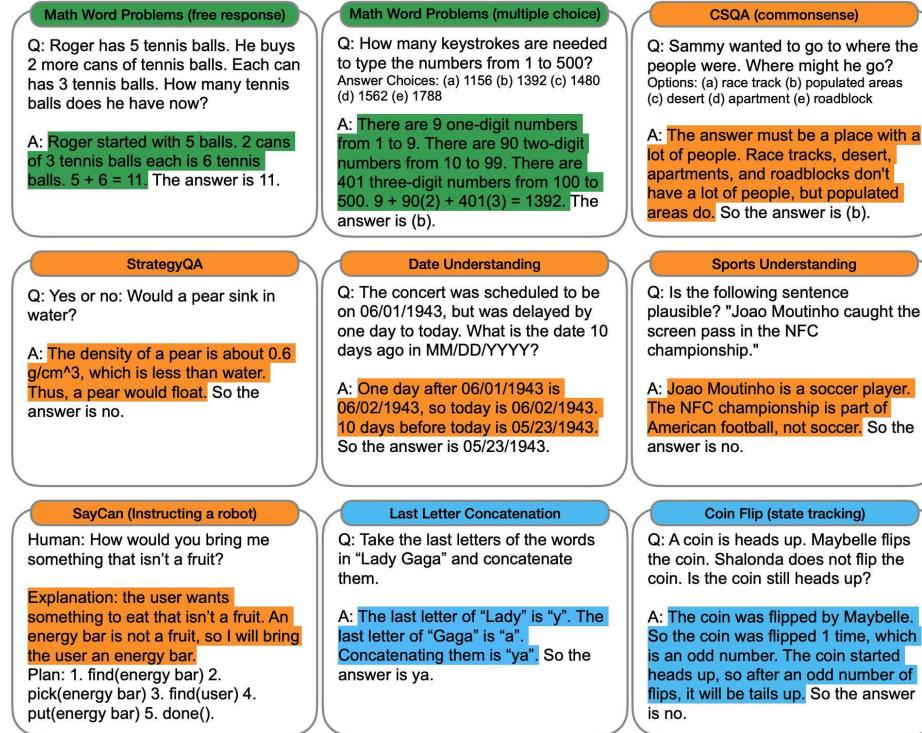
A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. $5 + 6 = 11$. The answer is 11.

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. ✓

Emergent Capability - Chain of Thoughts Prompting



Emergent Capability – Augmented Prompting Abilities

Advanced Prompting Techniques

- Zero-shot CoT Prompting
- Self-Consistency
- Divide-and-Conquer

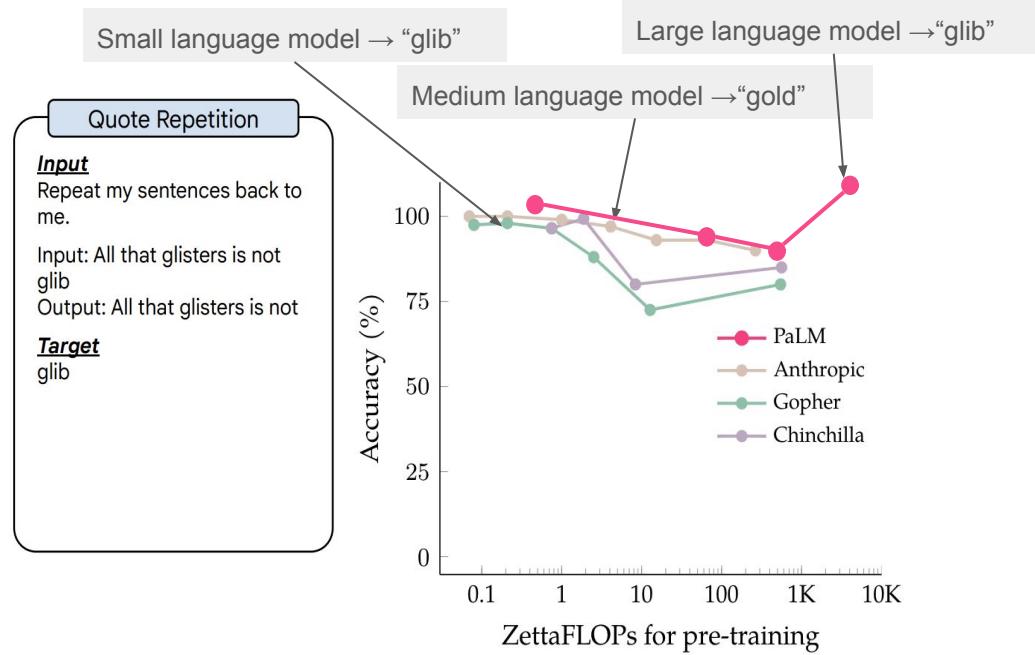
Ask a human to

- Explain the rationale
- Double check the answer
- Decompose to easy subproblems

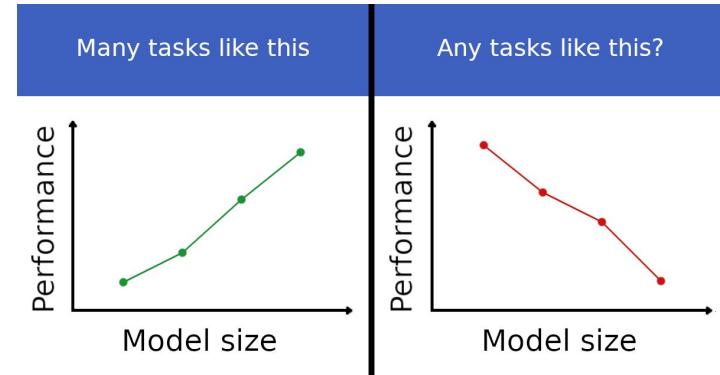
Large Language Models demonstrate some human-like behaviors!

To be or not to be Large?

Inverse scaling can become U-shaped: To be large ?



Inverse Scaling Prize: Not to be large?

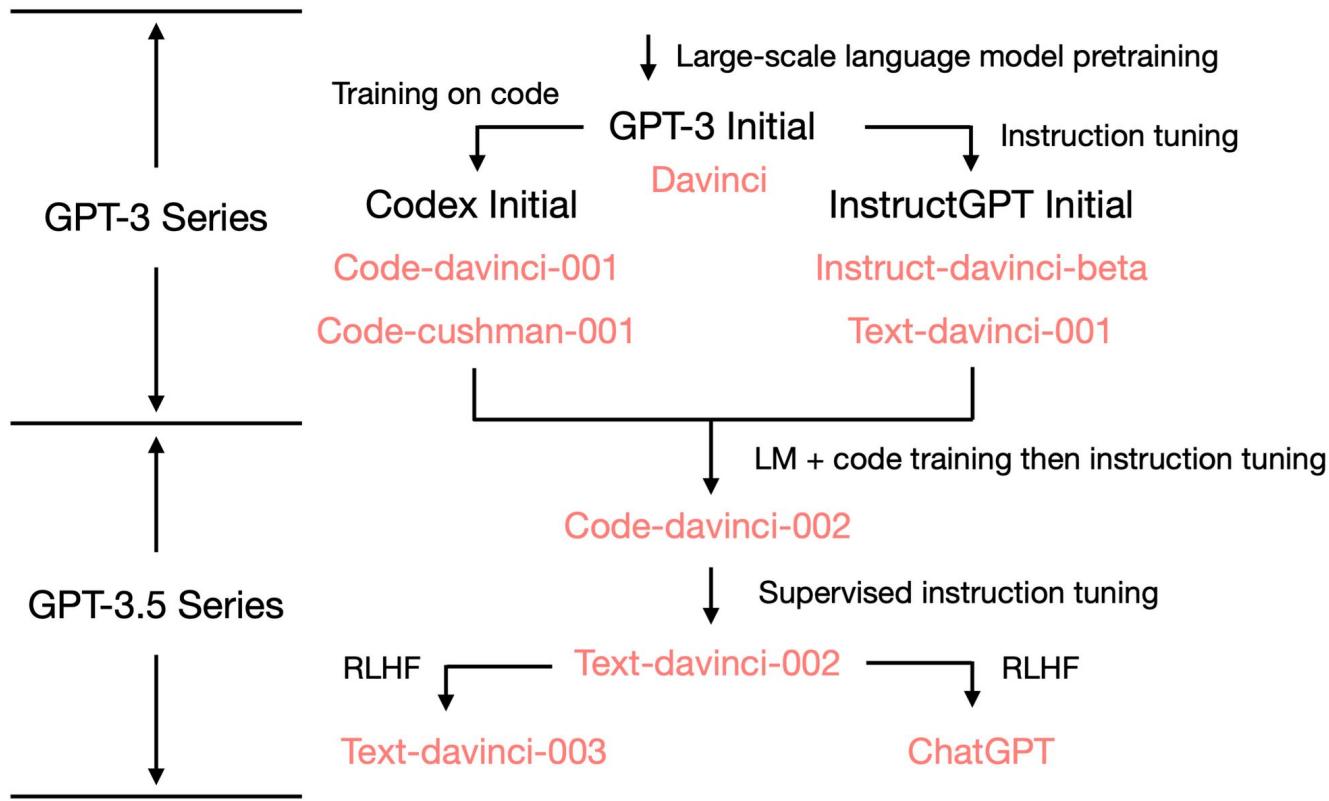


See:

- ❖ [TruthfulQA](#): The largest models were generally the least truthful
- ❖ <https://github.com/inverse-scaling/prize>
- ❖ <https://irmckenzie.co.uk/round1>

What are ChatGPT and GPT-4?

From 2020 GPT-3 to 2022 ChatGPT



What's ChatGPT

- Phase 1: pre-training
 - Learn **general** world knowledge, ability, etc.
- Phase 2: Supervised finetuning
 - Tailor to **tasks** (**unlock** some abilities)
- Phase 3: RLHF
 - Tailor to **humans**
 - *Even you could teach ChatGPT to do something*

Most of these were explored by InstructGPT. The only difference is that it is further trained with chat data, as an success of product (plus engineering).

GPT-4

What's new?

- ❑ **Make progress towards multilingualism:** GPT-4 is able to answer thousands of multiple-choice questions in 26 languages with a high degree of accuracy.
- ❑ **Longer memory for conversations:** ChatGPT can process 4,096 tokens. Once this limit was reached, the model lost track. GPT-4 can process 32,768 tokens. Enough for an entire short story on 32 A4 pages.
- ❑ **Multimodal input:** not only text can be used as input, but also images in which GPT-4 can describe objects. (**It is not released yet**)

GPT-4 Technical Report from OpenAI

- ❑ **Only contains a small amount of detail:** “[...] given both the competitive landscape and the safety implications of large-scale models like GPT-4, this report contains no further details about the architecture (including model size), hardware, training compute, dataset construction, training method or similar.” From [Technical Report](#).
- ❑ GPT-4’s score on the bar exam was similar to that of the top ten percent of graduates, while ChatGPT ranked in among the ten per cent that scored the worst.
- ❑ OpenAI hired more than 50 experts who interacted with and tested the model over an extended period of time.

It was finished in August 2022. It takes **7 months** for security alignment

Open questions

- The source of Reasoning?
 - In-context learning
 - COT
- Emergent ability ?
- Where is its border ?
- Alignment makes it generalize better ?
- Continue scaling up ?
- Could “data plus RLHF” achieve AGI? If not, what else?

Difficulties to Replicate ChatGPT

- Computing resources: money is all you need
- Data and annotation:
 - **Very careful data cleaning、filtering、selection strategies (training is expensive)**
 - Plain corpora(<https://github.com/esbatmop/MNBVC>)
 - Transferable SFT data (instruction tuning)
 - human feedback data (**model-dependent, non Transferable**)
- Algorithms
 - Has some open-source implementation in general
 - Engineering work is not easy (including **training tricks and efficient deployment**)
 - Releasing a model is easy, keeping polishing it is not!
- **Talents (first-tier young researchers, average age of Open AI guys is 32)**

Well-known strategies

- Probably initialized from a well-trained models
 - GLM-130 (Chinese and English)
 - OPT (mainly English)
 - Bloom (multilingual)
 - Pangu-alpha (Chinese)
 - CPM (Chinese)
 - LLaMA (mainly English)
 - Alpaca (LLaMA 7b + Self-instruct)
 - Chinese-Alpaca
 - ChatGLM(6B)
 - Baichuan
- ChatGPT Distillation
 - Self-instruct
 - Training on ChatGPT conversations
- RL from human feedback

Clue 1 – ChatGPT reshaped research

ChatGPT Outperforms Crowd-Workers for Text-Annotation Tasks*

Fabrizio Gilardi[†] Meysam Alizadeh[‡] Maël Kubli[§]

March 28, 2023

Abstract

Many NLP applications require manual data annotations for a variety of tasks, notably to train classifiers or evaluate the performance of unsupervised models. Depending on the size and degree of complexity, the tasks may be conducted by crowd-workers on platforms such as MTurk as well as trained annotators, such as research assistants. Using a sample of 2,382 tweets, we demonstrate that ChatGPT outperforms crowd-workers for several annotation tasks, including relevance, stance, topics, and frames detection. Specifically, the zero-shot accuracy of ChatGPT exceeds that of crowd-workers for four out of five tasks, while ChatGPT’s intercoder agreement exceeds that of both crowd-workers and trained annotators for all tasks. Moreover, the per-annotation cost of ChatGPT is less than \$0.003—about twenty times cheaper than MTurk. These results show the potential of large language models to drastically increase the efficiency of text classification.

Clue 2 – ChatGPT reshaped research

Theory of Mind May Have Spontaneously Emerged in Large Language Models

Authors: Michal Kosinski*¹

Affiliations:

¹Stanford University, Stanford, CA94305, USA

*Correspondence to: michalk@stanford.edu

Abstract: Theory of mind (ToM), or the ability to impute unobservable mental states to others, is central to human social interactions, communication, empathy, self-consciousness, and morality. We tested several language models using 40 classic false-belief tasks widely used to test ToM in humans. The models published before 2020 showed virtually no ability to solve ToM tasks. Yet, the first version of GPT-3 (“davinci-001”), published in May 2020, solved about 40% of false-belief tasks—performance comparable with 3.5-year-old children. Its second version (“davinci-002”; January 2022) solved 70% of false-belief tasks, performance comparable with six-year-olds. Its most recent version, GPT-3.5 (“davinci-003”; November 2022), solved 90% of false-belief tasks, at the level of seven-year-olds. GPT-4 published in March 2023 solved nearly all the tasks (95%). These findings suggest that ToM-like ability (thus far considered to be uniquely human) may have spontaneously emerged as a byproduct of language models’ improving language skills.

Moreover, its November 2022 version (davinci-003), solved 93% of ToM tasks, a performance comparable with that of **nine-year-old children**.

Clue 3 – ChatGPT reshaped research

Sparks of Artificial General Intelligence: Early experiments with GPT-4

Sébastien Bubeck Varun Chandrasekaran Ronen Eldan Johannes Gehrke
Eric Horvitz Ece Kamar Peter Lee Yin Tat Lee Yuanzhi Li Scott Lundberg
Harsha Nori Hamid Palangi Marco Tulio Ribeiro Yi Zhang

Microsoft Research

Abstract

Artificial intelligence (AI) researchers have been developing and refining large language models (LLMs) that exhibit remarkable capabilities across a variety of domains and tasks, challenging our understanding of learning and cognition. The latest model developed by OpenAI, GPT-4 [Ope23], was trained using an unprecedented scale of compute and data. In this paper, we report on our investigation of an early version of GPT-4, when it was still in active development by OpenAI. We contend that (this early version of) GPT-4 is part of a new cohort of LLMs (along with ChatGPT and Google's PaLM for example) that exhibit more general intelligence than previous AI models. We discuss the rising capabilities and implications of these models. We demonstrate that, beyond its mastery of language, GPT-4 can solve novel and difficult tasks that span mathematics, coding, vision, medicine, law, psychology and more, without needing any special prompting. Moreover, in all of these tasks, GPT-4's performance is strikingly close to human-level performance, and often vastly surpasses prior models such as ChatGPT. Given the breadth and depth of GPT-4's capabilities, we believe that it could reasonably be viewed as an early (yet still incomplete) version of an artificial general intelligence (AGI) system. In our exploration of GPT-4, we put special emphasis on discovering its limitations, and we discuss the challenges ahead for advancing towards deeper and more comprehensive versions of AGI, including the possible need for pursuing a new paradigm that moves beyond next-word prediction. We conclude with reflections on societal influences of the recent technological leap and future research directions.

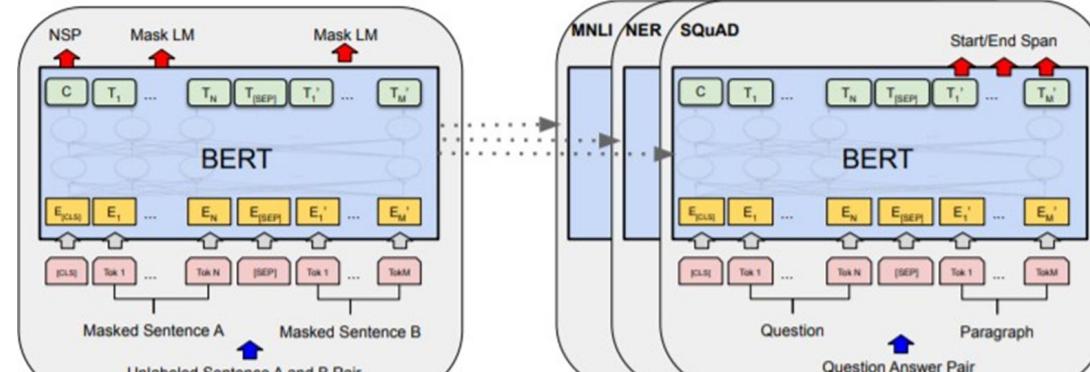
Clue 4: Pause Giant AI Experiments: An Open Letter

Contemporary AI systems are now becoming human-competitive at general tasks,^[3] and we must ask ourselves: *Should we let machines flood our information channels with propaganda and untruth? Should we automate away all the jobs, including the fulfilling ones? Should we develop nonhuman minds that might eventually outnumber, outsmart, obsolete and replace us? Should we risk loss of control of our civilization?* Such decisions must not be delegated to unelected tech leaders. Powerful AI systems should be developed only once we are confident that their effects will be positive and their risks will be manageable. This confidence must be well justified and increase with the magnitude of a system's potential effects. OpenAI's recent statement regarding artificial general intelligence, states that "*At some point, it may be important to get independent review before starting to train future systems, and for the most advanced efforts to agree to limit the rate of growth of compute used for creating new models.*" We agree. That point is now.

Therefore, we call on all AI labs to immediately pause for at least 6 months the training of AI systems more powerful than GPT-4. This pause should be public and verifiable, and include all key actors. If such a pause cannot be enacted quickly, governments should step in and institute a moratorium.

How to use Large Language models (LLMs)?

Pretraining + Fine-tuning Paradigm



Pre-training

Circulation revenue has increased by 5% in Finland. // Positive

Panostaja did not disclose the purchase price. // Neutral

Paying off the national debt will be extremely painful. // Negative

The company anticipated its operating profit to improve. // _____

LM

<http://ai.stanford.edu/blog/understanding-incontext/>

Pre-training:

Trained on huge amounts of unlabeled text using “self-supervised” training objectives

Adaptation:

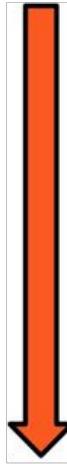
How to use a pretrained model for your downstream task?

What types of NLP tasks (input and output formats)?

How many annotated examples do you have?

LM

Pretraining + Prompting Paradigm

- Fine-tuning (FT)
 - + Strongest performance
 - - Need curated and labeled dataset for each new task (typically 1k-100k ex.)
 - - Poor generalization, spurious feature exploitation
 - Few-shot (FS)
 - + Much less task-specific data needed
 - + No spurious feature exploitation
 - - Challenging
 - One-shot (1S)
 - + "Most natural," e.g. giving humans instructions
 - - Challenging
 - Zero-shot (OS)
 - + Most convenient
 - - Challenging, can be ambiguous
- Stronger
task-specific
performance**
- 
- More convenient,
general, less data**

Chain of Thoughts Prompting

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.

Zero-Shot CoT Prompting

(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

(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. ✓

(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

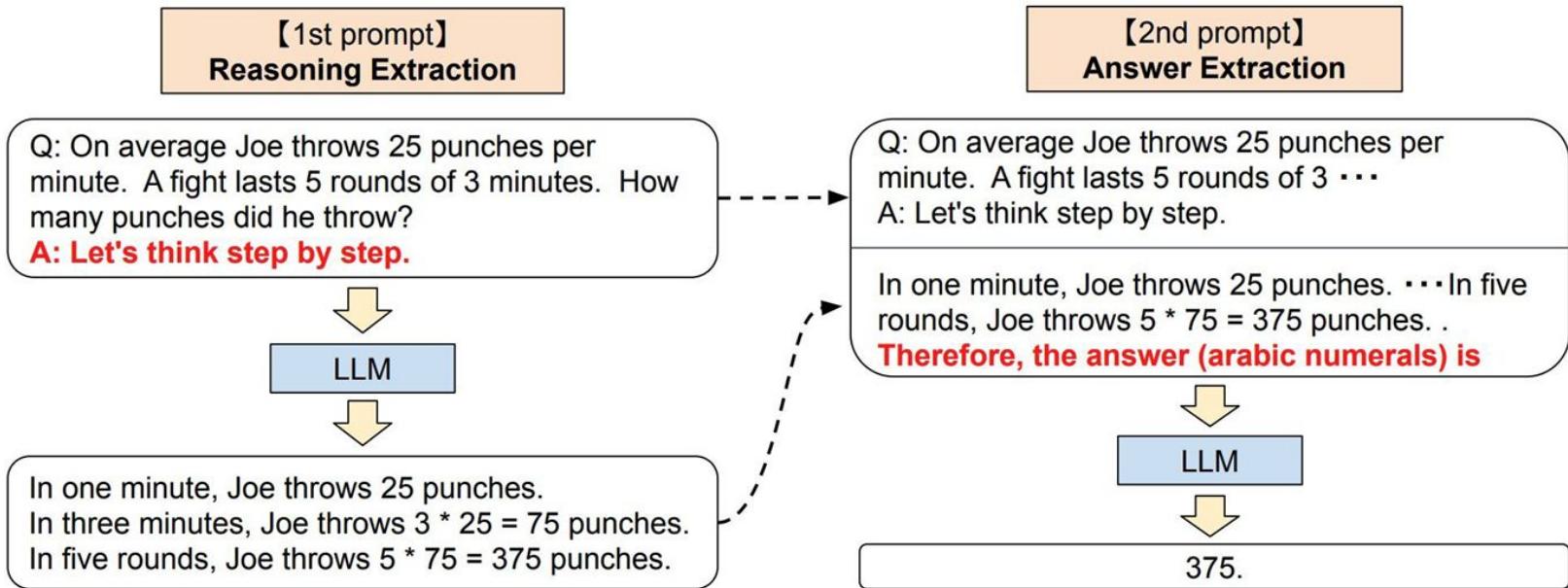
(d) Zero-shot-CoT (Ours)

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?

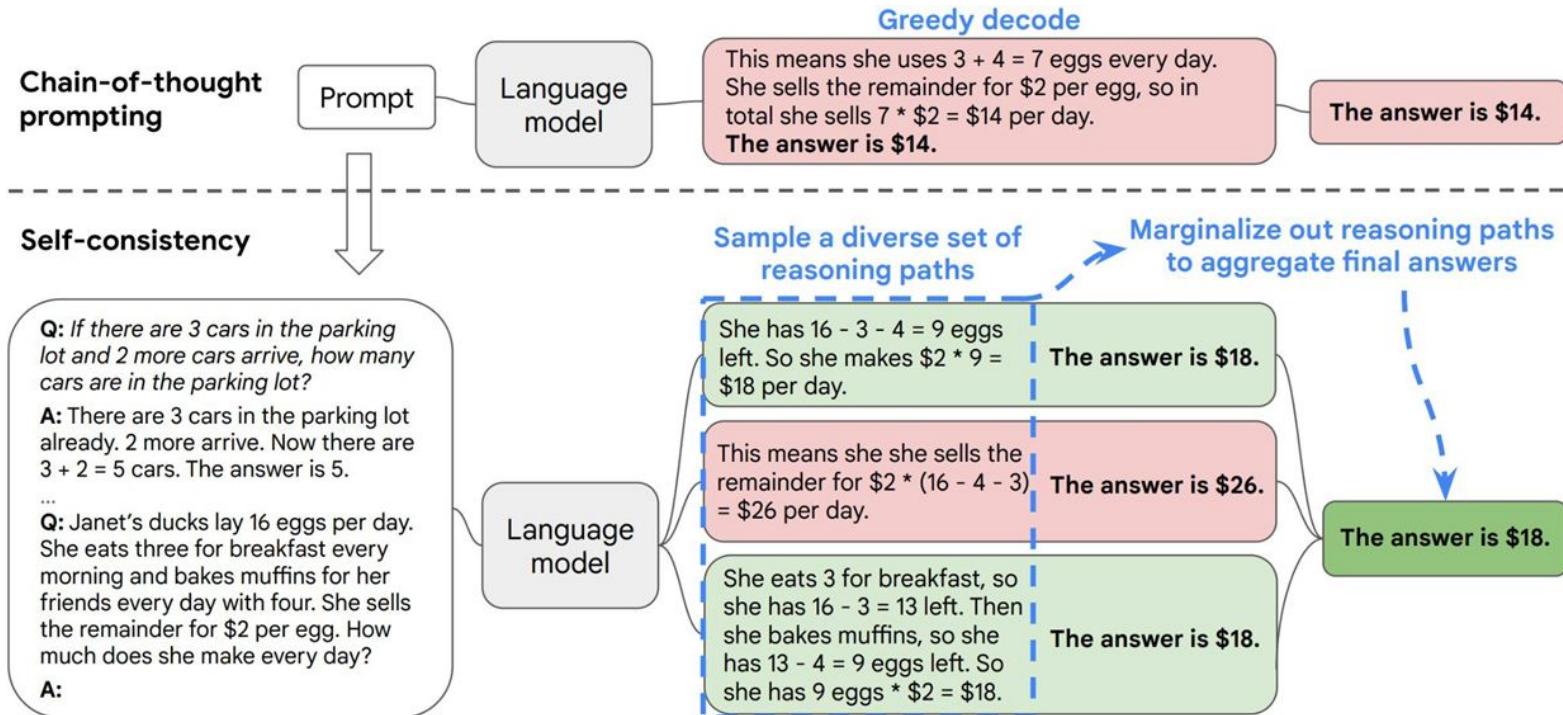
A: **Let's think step by step.**

(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. ✓

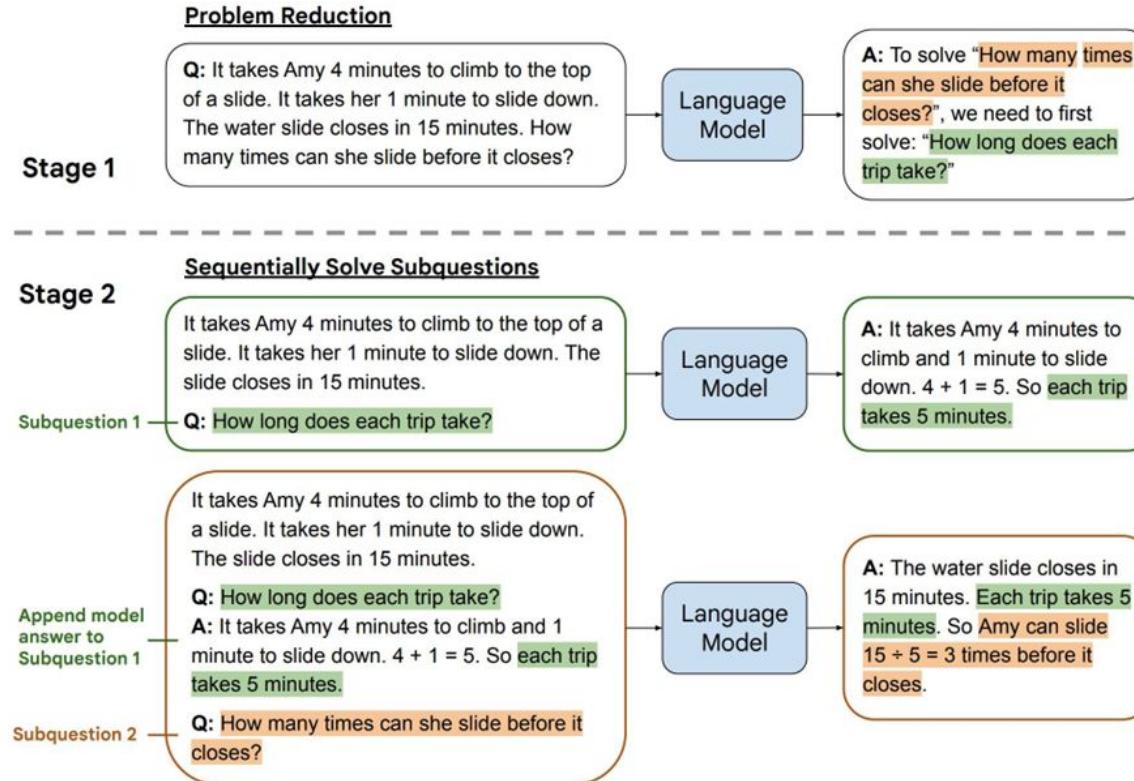
Zero-Shot CoT Prompting



Self-Consistency Prompting



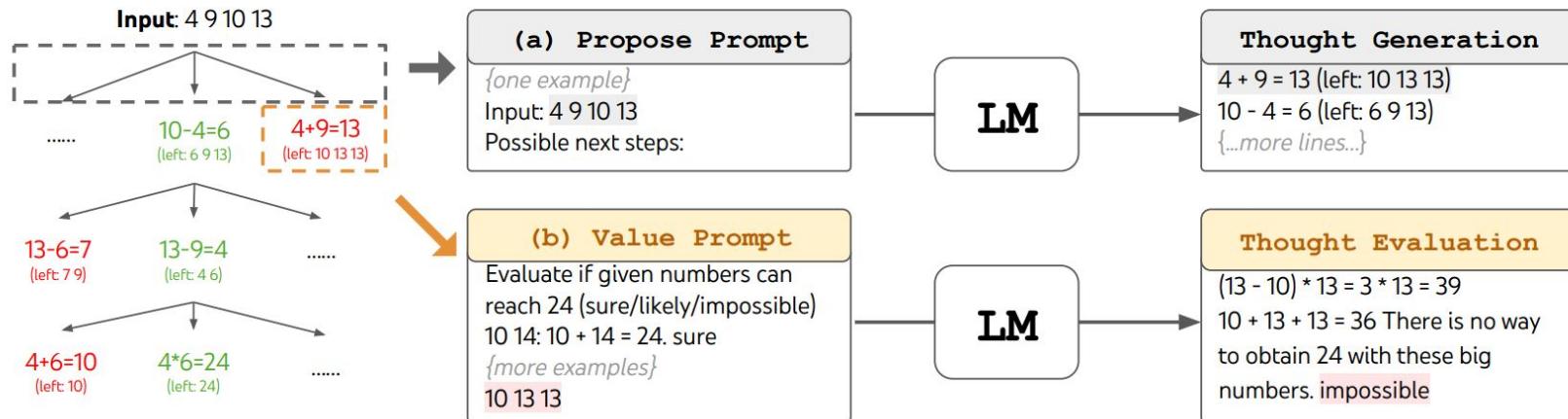
Least-to-Most Prompting



Tree of Thought

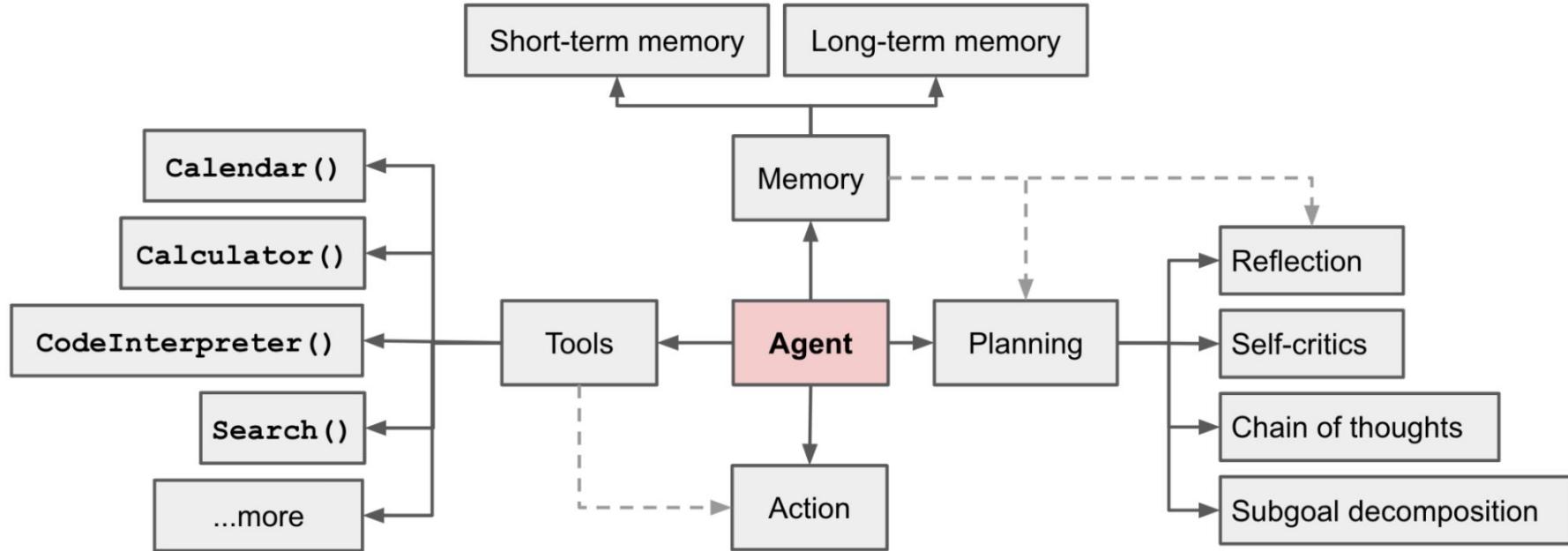
4.1 Game of 24

Game of 24 is a mathematical reasoning challenge, where the goal is to use 4 numbers and basic arithmetic operations (+-*%) to obtain 24. For example, given input “4 9 10 13”, a solution output could be “ $(10 - 4) * (13 - 9) = 24$ ”.



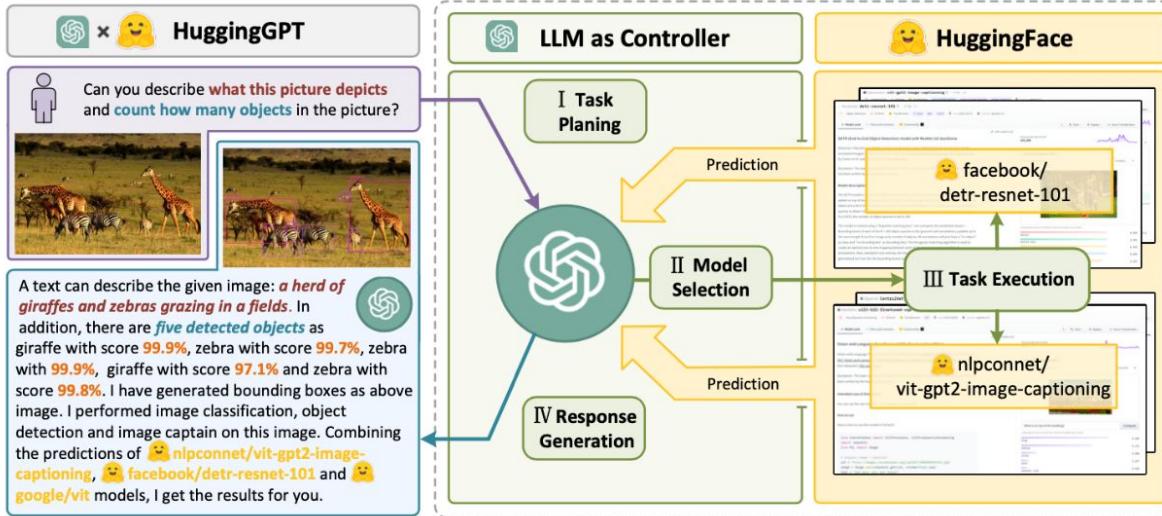
Agent

LLM acts as a Decision Center (Reasoning) and Human Interaction Front end (Chat)



Agent: Tool use

The biggest difference between humans and animals is the ability to use tools



HuggingGPT (Shen et al. 2023) is a framework to use ChatGPT as the task planner to select models available in HuggingFace platform according to the model descriptions and summarize the response based on the execution results.

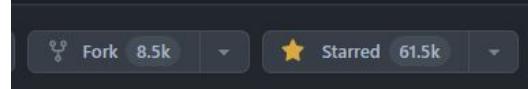
Algorithm 1 API call process

```
1: Input: us ← UserStatement
2: if API Call is needed then
3:   while API not found do
4:     keywords ← summarize(us)
5:     api ← search(keywords)
6:     if Give Up then
7:       break
8:     end if
9:   end while
10:  if API found then
11:    api_doc ← api.documentation
12:    while Response not satisfied do
13:      api_call ← gen_api_call(api_doc, us)
14:      api_re ← execute_api_call(api_call)
15:      if Give Up then
16:        break
17:      end if
18:    end while
19:  end if
20: end if
21: if response then
22:   re ← generate_response(api_re)
23: else
24:   re ← generate_response()
25: end if
26: Output: ResponseToUser
```

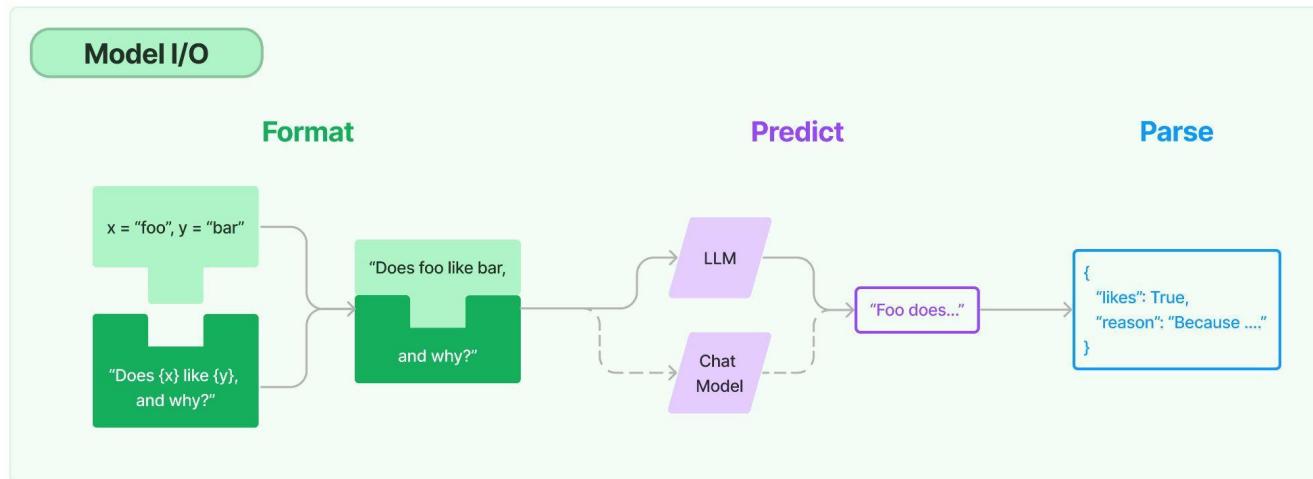
Pseudo code of how LLM makes an API call in API-Bank.

API-Bank (Li et al. 2023) : A benchmark for evaluating the performance of tool-augmented LLMs. It contains 53 commonly used API tools, a complete tool-augmented LLM workflow, and 264 annotated dialogues that involve 568 API calls.

Langchain



- ❖ LangChain is a framework for developing applications powered by language models.
- ❖ The core building block of LangChain applications is the LLMChain. This combines three things:
 - LLM: The language model is the core reasoning engine here. In order to work with LangChain, you need to understand the different types of language models and how to work with them.
 - Prompt Templates: This provides instructions to the language model. This controls what the language model outputs, so understanding how to construct prompts and different prompting strategies is crucial.
 - Output Parsers: These translate the raw response from the LLM to a more workable format, making it easy to use the output downstream.



A break!

Contents

- Philosophy of this course
- Large language models
- **Introduction to ChatGPT**

ChatGPT

- ▶ Reaching 1M users in five days; research 100M users in two months
- ▶ Everyone discusses ChatGPT, its spreading speed is faster than COVID 19
- ▶ Red alarms in Google
- ▶ Google released Bard very soon, but it performs worse, stock valued reduced by 8%
- ▶ Microsoft invests 10B dollars to OpenAI
- ▶ New Bing and Office used ChatGPT
- ▶ 百模大战 in China

用户数突破100万用时

- GPT-3: 24个月
- Copilot: 6个月
- DALL-E: 2.5个月
- **ChatGPT: 5天**
- Netflix - 41个月
- Twitter - 24个月
- Facebook - 10个月
- Instagram - 2.5个月

ChatGPT

ChatGPT: Optimizing Language Models for Dialogue

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to [InstructGPT](#), which is trained to follow an instruction in a prompt and provide a detailed response.

November 30, 2022
13 minute read



We are excited to introduce ChatGPT to get users' feedback and learn about its strengths and weaknesses. During the research preview, usage of ChatGPT is free. Try it now at chat.openai.com.

ChatGPT Blog: <https://openai.com/blog/chatgpt/>

ChatGPT

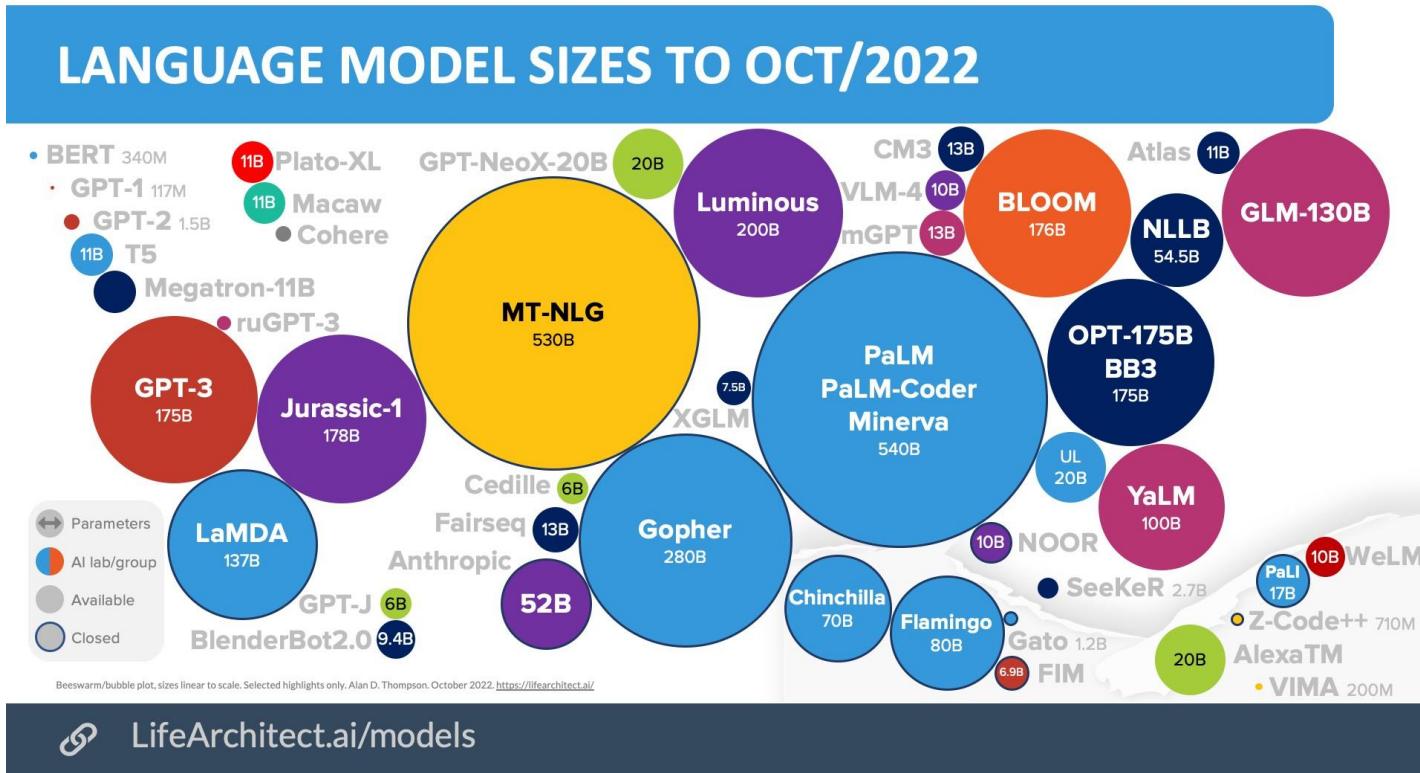
The main features of ChatGPT highlighted in the official blog:

- ▶ answer followup questions
- ▶ admit its mistakes
- ▶ challenge incorrect premises
- ▶ reject inappropriate requests

ChatGPT Blog: <https://openai.com/blog/chatgpt/>

The Size of ChatGPT

ChatGPT is based on Davinci-3



Size of ChatGPT

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Four models released by OpenAI :

Language models

Base models

Ada Fastest

\$0.0004 /1K tokens

Babbage

\$0.0005 /1K tokens

Curie

\$0.0020 /1K tokens

Davinci Most powerful

\$0.0200 /1K tokens

Multiple models, each with different capabilities and price points.
Ada is the fastest model, while Davinci is the most powerful.

Size of ChatGPT

The size of Davinci (GPT 3) could be 175B

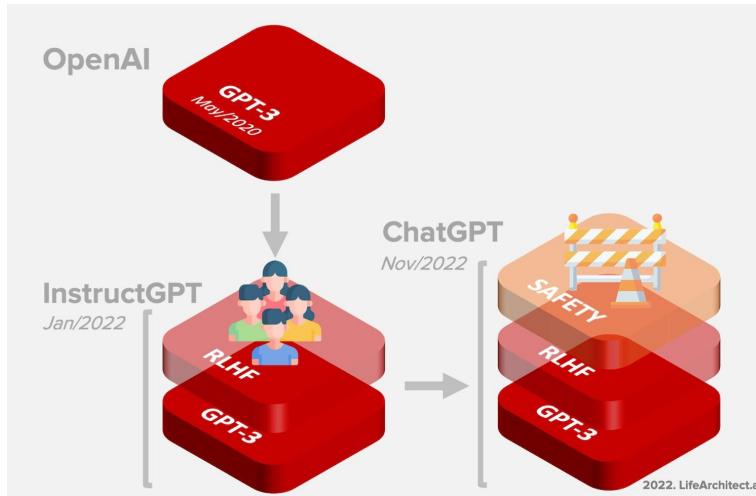
Model	LAMBADA ppl ↓	LAMBADA acc ↑	Winogrande ↑	Hellaswag ↑	PIQA ↑
GPT-3-124M	18.6	42.7%	52.0%	33.7%	64.6%
CPT-3-350M	9.09	54.3%	52.1%	43.6%	70.2%
Ada	9.95	51.6%	52.9%	43.4%	70.5%
GPT-3-760M	6.53	60.4%	57.4%	51.0%	72.9%
CPT-3-1.3B	5.44	63.6%	58.7%	54.7%	75.1%
Babbage	5.58	62.4%	59.0%	54.5%	75.5%
GPT-3-2.7B	4.60	67.1%	62.3%	62.8%	75.6%
GPT-3-6.7B	4.00	70.3%	64.5%	67.4%	78.0%
Curie	4.00	68.5%	65.6%	68.5%	77.9%
GPT-3-13B	3.56	72.5%	67.9%	70.9%	78.5%
GPT-3-175B	3.00	76.2%	70.2%	78.9%	81.0%
Davinci	2.97	74.8%	70.2%	78.1%	80.4%

All GPT-3 figures are from the [GPT-3 paper](#); all API figures are computed using eval harness

Ada, Babbage, Curie and Davinci line up closely with 350M, 1.3B, 6.7B, and 175B respectively.
Obviously this isn't ironclad evidence that the models *are* those sizes, but it's pretty suggestive.

Leo Gao, On the Sizes of OpenAI API Models, <https://blog.eleuther.ai/gpt3-model-sizes/>

ChatGPT timeline



Timeline to ChatGPT

Date Milestone

11/Jun/2018 GPT-1 announced on the OpenAI blog.

14/Feb/2019 GPT-2 announced on the OpenAI blog.

28/May/2020 Initial GPT-3 preprint paper published to arXiv.

11/Jun/2020 GPT-3 API private beta.

22/Sep/2020 GPT-3 licensed to Microsoft.

18/Nov/2021 GPT-3 API opened to the public.

27/Jan/2022 InstructGPT released, now known as GPT-3.5. InstructGPT preprint paper Mar/2022.

28/Jul/2022 Exploring data-optimal models with FIM, paper on arXiv.

1/Sep/2022 GPT-3 model pricing cut by 66% for davinci model.

21/Sep/2022 Whisper (speech recognition) announced on the OpenAI blog.

28/Nov/2022 GPT-3.5 expanded to text-davinci-003, announced via email:

1. Higher quality writing.
2. Handles more complex instructions.
3. Better at longer form content generation.

30/Nov/2022 ChatGPT announced on the OpenAI blog.

Next... GPT-4...

GPT 5

**Stronger Reasoning
More efficient**

Coming from Oct. to Dec.

Some jargon words (行话)

LLM

Transformer

Scaling law

Chinchilla scaling law

Emergent ability

Instruction vs. prompt

COT

ICL

Pre-training and finetuning

generalization

Alignment

Superalignment

LVM

Embodied AI

NLP in the next 6 months: my predictions on Jan.

Small language models

Multi-modal LLMs

Embodied AI (LLM with hardware)

OpenAI **saturates** and the gap between OpenAI and others become smaller

Benchmarking suffers

Efficiency matters much more

LLM Application will be the main playground, **technique** itself will not

NLP in the next 6 months: now

Small language models

Multi-modal LLMs

Embodied AI (LLM with hardware)

OpenAI **saturates** and the gap between OpenAI and others become smaller

Benchmarking suffers

Efficiency matters much more

LLM **Application** will be the main playground, **technique** itself will not

SORA

Real-time Speech interaction

Our research

Work 1: HuatuoGPT

- 2023年2月份罗智泉院士在中华医院信息网络大会(CHINC)发表主旨论坛报告，通过视频演示的方式介绍了华佗GPT，这是据公开资料显示的首个中文医疗大模型；
- 2023年5月份发布Huatuo-26M, 最大的医疗问答数据集
- 2022年五月份，经过临床医生测评结果显示，华佗GPT超过了ChatGPT 3.5; 迄今 GitHub stars : 1k+
- 2023年6月份，华佗GPT在深圳市卫健委公测：<https://www.huatuoqpt.cn/> 迄今50万人次访问量
- 2023年八月发布CMB医疗评测平台，数十家公司参与评测，<https://cmedbenchmark.llmzoo.com/>
- 2023年下半年上线龙岗区人民医院的“互联网医院”
- 2023年11月份的版本超过GPT4，并首个通过10月份的药剂师考试；
- 2023年11月开始开展华佗GPT驱动下的AI预分诊和预问诊项目，并在医院端部署；
- 2024年2月份，多语言版本Apollo在XMedBench取得仅次GPT-4最好的结果，覆盖全球60亿人口
- 2024年5月份多模态版本的HuatuoGPT-vision：<https://vision.huatuoqpt.cn/>
- 2024年九月份，龙岗区十二家医院将全部接入华佗GPT提供分诊和线上医疗咨询

[1] Hongbo Zhang, Junying Chen, Feng Jiang, Fei Yu, Zhihong Chen, Jianquan Li, Guiming Chen, Xiangbo Wu, Zhiyi Zhang, Qingying Xiao, Xiang Wan, Benyou Wang, **Haizhou Li**. HuatuoGPT, towards Taming Language Model to Be a Doctor. <https://arxiv.org/abs/2305.15075>. Findings of EMNLP 2023

[2] Junying Chen, Xidong Wang, Anningzhe Gao#, Feng Jiang, Shunian Chen, Hongbo Zhang, Dingjie Song, Wenya Xie, Chuyi Kong, Jianquan Li, Xiang Wan, **Haizhou Li**, Benyou Wang. Huatuogpt-ii, one-stage training for medical adaption of lms. <https://arxiv.org/abs/2311.09774>. COLM 2024

[3] Xidong Wang, Guiming Hardy Chen, Dingjie Song, Zhiyi Zhang, Zhihong Chen, Qingying Xiao, Feng Jiang, Jianquan Li, Xiang Wan, Benyou Wang, **Haizhou Li**. CMB: A Comprehensive Medical Benchmark in Chinese. NAACL 2024

[4] Xidong Wang, Nuo Chen, Junyin Chen, Yan Hu, Yidong Wang, Xiangbo Wu, Anningzhe Gao, Xiang Wan, **Haizhou Li**, Benyou Wang. Apollo: A Lightweight Multilingual Medical LLM towards Democratizing Medical AI to 6B People. <https://arxiv.org/abs/2403.03640>.

[5] Junying Chen, Ruiy Ouyang, Anningzhe Gao, Shunian Chen, Guiming Hardy Chen, Xidong Wang, Ruifei Zhang, Zhenyang Cai, Ke Ji, Guangjun Yu, Xiang Wan, Benyou Wang. HuatuoGPT-Vision, Towards Injecting Medical Visual Knowledge into Multimodal LLMs at Scale. <https://arxiv.org/abs/2406.19280>. submitted to NeurIPS 2024

[6] Wenya Xie, Qingying Xiao, Yu Zheng, Xidong Wang, Junying Chen, Ke Ji, Anningzhe Gao, Xiang Wan, Feng Jiang, Benyou Wang. LLMs for Doctors: Leveraging Medical LLMs to Assist Doctors, Not Replace Them. <https://arxiv.org/abs/2406.18034>

Best medical LLM in Nov. 2023

Model	Pharmacist Licensure Examination (Pharmacy)					Pharmacist Licensure Examination (TCM)					AVG
	Optimal Choice	Matched Selection	Integrated Analysis	Multiple Choice	Total Score	Optimal Choice	Matched Selection	Integrated Analysis	Multiple Choice	Total Score	
DISC-MedLLM	22.2	26.8	23.3	0.0	22.6	24.4	32.3	15.0	0.0	24.9	23.8
HuatuoGPT	25.6	25.5	23.3	2.6	23.4	24.1	26.8	31.6	7.5	24.9	24.2
ChatGLM2-6B	37.0	36.8	25.0	31.7	35.3	33.1	37.3	35.0	37.3	33.7	34.5
ChatGLM3-6B	39.5	39.1	10.5	0.2	34.6	31.8	38.2	25.0	20.0	32.9	33.8
Qwen-7B-chat	43.8	46.8	33.3	18.4	41.9	40.0	43.2	33.3	17.5	38.8	40.4
Qwen-14B-chat	56.2	58.6	41.7	21.1	52.7	51.3	51.0	27.5	41.7	47.9	50.3
Biachuan2-7B-Chat	51.2	50.9	30.0	2.6	44.6	48.1	46.0	35.0	7.5	42.1	43.4
Biachuan2-13B-Chat	43.8	52.7	36.7	7.9	44.2	41.3	46.4	43.3	15.0	41.7	43.0
文心一言	45.0	60.9	36.7	23.7	49.6	53.8	59.1	38.3	20.0	51.5	50.6
ChatGPT(API)	45.6	44.1	36.7	13.2	41.2	34.4	32.3	30.0	15.0	31.2	36.2
GPT-4(API)	65.1	59.6	46.7	15.8	57.3	40.6	42.7	33.3	17.5	38.8	48.1
HuatuoGPT-II(7B)	41.9	61.0	35.0	15.7	47.7	52.5	51.4	41.7	15.0	47.5	47.6
HuatuoGPT-II(13B)	47.5	64.1	45.0	23.7	52.9	48.8	61.8	45.0	17.5	51.6	52.3
HuatuoGPT-II(34B)	66.3	75.0	48.3	34.2	65.5	63.6	71.4	50.0	27.5	62.5	64.0

11月份的模型测试十月份的考试！

Hongbo Zhang, Junying Chen, Feng Jiang, Fei Yu, Zhihong Chen, Jianquan Li, Guiming Chen, Xiangbo Wu, Zhiyi Zhang, Qingying Xiao, Xiang Wan, Benyou Wang#, Haizhou Li, HuatuoGPT, towards Taming Language Model to Be a Doctor. <https://arxiv.org/abs/2305.15075>
 Junying Chen, Xidong Wang, Anningzhe Gao#, Feng Jiang, Shunian Chen, Hongbo Zhang, Dingjie Song, Wenya Xie, Chuyi Kong, Jianquan Li, Xiang Wan, Haizhou Li, Benyou Wang#. Huatuogpt-ii, one-stage training for medical adaption of llms. <https://arxiv.org/abs/2311.09774>

Work 2: best Arabic LLM AceGPT

- Arabic LLMs
 - AceGPT: value alignment for a new language (Arabic)
 - AceGPT 1.5: vocabulary expansion
 - AceGPT 2: native alignment

[1] Huang Huang, Fei Yu, Jianqing Zhu, Xuening Sun, Hao Cheng, Dingjie Song, Zhihong Chen, Abdulmohsen Alharthi, Bang An, Ziche Liu, Zhiyi Zhang, Junying Chen, Jianquan Li, Benyou Wang, Lian Zhang, Ruoyu Sun, Xiang Wan, Haizhou Li, Jinchao Xu. AceGPT, Localizing Large Language Models in Arabic. NAACL 2024

[2] Jianqing Zhu, Huang Huang, Zhihang Lin, Juhao Liang, Zhengyang Tang, Khalid Almubarak, Mosen Alharthi, Bang An, Juncai He, Xiangbo Wu, Fei Yu, Junying Chen, MA Zhuoheng, Yuhao Du, Yan Hu, He Zhang, Emad A. Alghamdi, Lian Zhang, Ruoyu Sun, Haizhou Li, Jinchao Xu, Benyou Wang. **Second Language (Arabic) Acquisition of LLMs via Progressive Vocabulary Expansion**. Submitted to COLM 2024.

[3] Juhao Liang, Zhenyang Cai, Jianqing Zhu, Huang Huang, Kewei Zong, Bang An, Mosen Alharthi, Juncai He, Lian Zhang, Haizhou Li, Benyou Wang, Jinchao Xu. **Alignment at Pre-training! Towards Native Alignment for Arabic LLMs**. Submitted to NeurIPS 2024

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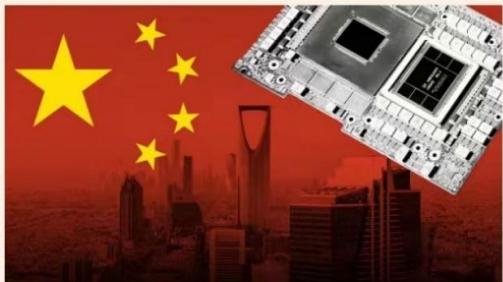
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Saudi-China collaboration raises concerns about access to AI chips

Fears grow at Gulf kingdom's top university that ties to Chinese researchers risk upsetting US government



Western officials have long expressed concern about growing technology transfer between their traditional allies in the Gulf and China © FT montage@comber/Dreamstime

Simeon Kerr and Samer Al-Atrash in Dubai, Giana Liu in Hong Kong, Madhumita Murgia in London 13 HOURS AGO

15
52
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Saudi-Chinese collaboration in artificial intelligence has stirred fears within the Gulf kingdom's premier academic institution that the ties could jeopardise the university's access to US-made chips needed to power the new technology.

Professor Jinchao Xu, an American-Chinese mathematician at Saudi Arabia's King Abdullah University of Science and Technology (Kaust), has launched AceGPT, an Arabic-focused large language model, in collaboration with the Chinese University of Hong Kong, Shenzhen (CUHK-SZ), and the Shenzhen Research Institute of Big Data.

环球网 国际新闻 > 环球独家

🔍

英媒给中沙AI合作泼冷水，中国专家：美西方不断干扰毫无道理

来源：环球时报 作者：黄培昭 赵觉珵

-2023-

10/11
07:23

【环球时报驻埃及特派记者 黄培昭 环球时报记者 赵觉珵】人工智能（AI）技术正成为中国与中东国家合作的新亮点，但这种互利共赢却遭到美西方阻挠。英国《金融时报》10日刊文，给中国和沙特的相关合作泼冷水。对此，有中国专家表示，中国和中东国家的科技合作基于双方在该领域的互补性，符合双方共同利益，美西方不断干扰毫无道理。

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2

6

《金融时报》报道称，沙特阿卜杜拉国王科技大学、香港中文大学（深圳）与深圳大数据研究院三方合作开发人工智能大语言模型ACEGPT。“此举是沙特领导人工智能技术区域发展、建造大型超算和推出大语言模型努力的一部分。”这家英媒还称，沙特正与阿联酋一道，寻求参与到人工智能竞争之中。

但该媒体笔锋一转称，中国与海湾国家的此类合作让西方感到担忧，美国对中国实施的人工智能芯片出口限制也正影响相关合作。有阿卜杜拉国王科技大学的工作人员担忧，与中国的合作可能会引发美国不满，从而影响该大学获得先进人工智能芯片。

早在今年8月，路透社就曾报道称，美国芯片制造商英伟达和AMD均已收到美国政府限制向部分中东国家出口先进人工智能芯片的要求。有分析人士认为，美国的主要目的是防止中国从中东国家手中购买先进芯片。“德国之声”援引专家的分析称，沙特、阿联酋等大力投资人工智能的国家近年来加深了与中国的联系，因此它们都

| 环球时事

他们搭起一座桥，让世界阅读中国
意大利设“割安妇女”铜像，日方“强烈关切”
邀华贸易摩擦扩大升级！中欧启动汽车关税磋商
新加坡媒体：金砖国家“集体潜力”吸引东南亚
我国首个！成立了！今年招收300人。
这条隧道通了！时速350公里高铁取得新进展

| 环球业界


珍稀植物原豆全基因组首次揭秘
节能减碳 新建油气企业在发展 含绿量足
3D打印真空系统或能“捕捉”暗物质
证监会支持上海加快建设“五个中心”建设
依托智慧农业设施 高标准农田展现抗旱优势


昔日黄沙变绿洲

Work 3 : Multi-modal LLMs

- Dataset ALLVA
- Milebench
- MotionLLM
- MLLM-bench
- Silkie

[1] Guiming Hardy Chen, Shunian Chen, Ruifei Zhang, Junying Chen, Xiangbo Wu, Zhiyi Zhang, Zhihong Chen, Jianquan Li, Xiang Wan, **Benyou Wang**. ALLVA: Harnessing GPT4V-synthesized Data for A Lite Vision-Language Model. <https://arxiv.org/abs/2402.11684>

[2] D Song, S Chen, GH Chen, F Yu, X Wan, **B Wang**. **Milebench**: Benchmarking mllms in long context, arXiv preprint arXiv:2404.18532

[3] Ling-Hao Chen, Shunlin Lu, Ailing Zeng, Hao Zhang, Benyou Wang, Ruimao Zhang, Lei Zhang. MotionLLM: Understanding Human Behaviors from Human Motions and Videos. <https://arxiv.org/abs/2405.20340>

[4] Wentao Ge, Shunian Chen, Guiming Chen, Junying Chen, Zhihong Chen, Shuo Yan, Chenghao Zhu, Ziyue Lin, Wenya Xie, Xidong Wang, Anningzhe Gao, Zhiyi Zhang, Jianquan Li, Xiang Wan, Benyou Wang. Mllm-bench, evaluating multi-modal llms using gpt-4v. <https://arxiv.org/abs/2311.13951>

[5] Lei Li, Zihui Xie, Mukai Li, Shunian Chen, Peiyi Wang, Liang Chen, Yazheng Yang, Benyou Wang, Lingpeng Kong. Silkie: Preference distillation for large visual language models. <https://arxiv.org/abs/2312.10665>

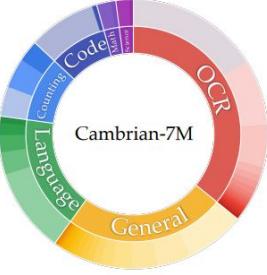
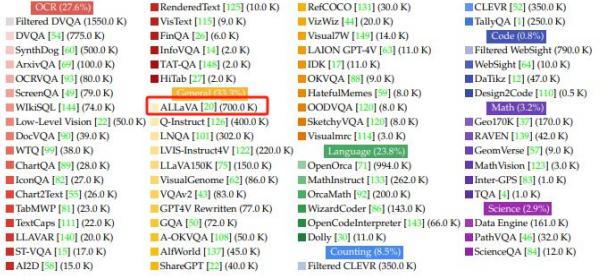


Figure 9 | Cambrian-7M: A Large-Scale Curated Instruction Tuning Dataset for MLLM. Left: The inner circle shows the original distribution of Cambrian-10M. The outer circle shows the curated Cambrian-7M. Right: All the data sources in the Cambrian dataset as well as the ones filtered in data curation.



Cambrian-1: A Fully Open, Vision-Centric Exploration of Multimodal LLMs

Shengbang Tong*, Ellis Brown*, Penghao Wu*, Sanghyun Woo, Manoj Middepogu, Sai Charitha Akula, Jihan Yang, Shusheng Yang, Adithya Iyer, Xichen Pan, Austin Wang, Rob Fergus, Yann LeCun, Saining Xie[†]

New York University

Cambrian-1: A Fully Open, Vision-Centric Exploration of Multimodal LLMs

Guiming Hardy Chen, Shunian Chen, Ruifei Zhang, Junying Chen, Xiangbo Wu, Zhiyi Zhang, Zhihong Chen, Jianquan Li, Xiang Wan, **Benyou Wang**. ALLaVA: Harnessing GPT4V-synthesized Data for A Lite Vision-Language Model. <https://arxiv.org/abs/2402.11684>

Work 4 : LLM for Math and Optimization

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