Applied Machine Learning for Business Analytics

Lecture 9: LLM

Lecturer: Zhao Rui

Agenda

1. Intro to LLM
2. BERT
3. GPT
4. Scaling Law
5. From GPT to ChatGPT

1. Intro to LLM

TABLE I: High-level Overview of Popular Language Models

Type	Model Name	#Parameters	Release	Base Models	Open Source	#Tokens	Training dataset
Encoder-Only	BERT	110M, 340M	2018	-	✓	137B	BooksCorpus, English Wikipedia
	RoBERTa	355M	2019	-	✓	2.2T	BooksCorpus, English Wikipedia, CC-NEWS, STORIES (a subset of Common Crawl), Reddit
	ALBERT	12M, 18M, 60M, 235M	2019	-	✓	137B	BooksCorpus, English Wikipedia
	DeBERTa	-	2020	-	✓	-	BooksCorpus, English Wikipedia, STORIES, Reddit content
	XLNet	110M, 340M	2019	-	✓	32.89B	BooksCorpus, English Wikipedia, Giga5, Common Crawl, ClueWeb 2012-B
Decoder-only	GPT-1	120M	2018	-	✓	1.3B	BooksCorpus
	GPT-2	1.5B	2019	-	✓	10B	Reddit outbound
Encoder-Decoder	T5 (Base)	223M	2019	-	✓	156B	Common Crawl
	MT5 (Base)	300M	2020	-	✓	-	New Common Crawl-based dataset in 101 languages (m Common Crawl)
	BART (Base)	139M	2019	-	✓	-	Corrupting text
GPT Family	GPT-3	125M, 350M, 760M, 1.3B, 2.7B, 6.7B, 13B, 175B	2020		×	300B	Common Crawl (filtered), WebText2, Books1, Books2, Wikipedia
	CODEX	12B	2021	GPT	✓	-	Public GitHub software repositories
	WebGPT	760M, 13B, 175B	2021	GPT-3	×	-	ELI5
	GPT-4	1.76T	2023	-	×	13T	-
LLaMA Family	LLaMA1	7B, 13B, 33B, 65B	2023	-	✓	1T, 1.4T	Online sources
	LLaMA2	7B, 13B, 34B, 70B	2023	-	✓	2T	Online sources
	Alpaca	7B	2023	LLaMA1	✓	-	GPT-3.5
	Vicuna-13B	13B	2023	LLaMA1	✓	-	GPT-3.5
	Koala	13B	2023	LLaMA	✓	-	Dialogue data
	Mistral-7B	7.3B	2023		✓	-	-
	Code Llama	34	2023	LLaMA2	✓	500B	Publicly available code
	LongLLaMA	3B, 7B	2023	OpenLLaMA	✓	1T	-
	LLaMA-Pro-8B	8.3B	2024	LLaMA2-7B	✓	80B	Code and math corpora
	TinyLlama-1.1B	1.1B	2024	LLaMA1.1B	✓	3T	SlimPajama, Starcoderdata
PaLM Family	PaLM	8B, 62B, 540B	2022	-	×	780B	Web documents, books, Wikipedia, conversations, GitHub code
	U-PaLM	8B, 62B, 540B	2022	-	×	1.3B	Web documents, books, Wikipedia, conversations, GitHub code
	PaLM-2	340B	2023	-	✓	3.6T	Web documents, books, code, mathematics, conversational data
	Med-PaLM	540B	2022	PaLM	×	780B	HealthSearchQA, MedicationQA, LiveQA
	Med-PaLM 2	-	2023	PaLM 2	×	-	MedQA, MedMCQA, HealthSearchQA, LiveQA, MedicationQA
Other Popular LLMs	FLAN	137B	2021	LaMDA-PT	✓	-	Web documents, code, dialog data, Wikipedia
	Gopher	280B	2021	-	×	300B	MassiveText
	ERNIE 4.0	10B	2023	-	×	4TB	Chinese text
	Retro	7.5B	2021	-	×	600B	MassiveText
	LaMDA	137B	2022	-	×	168B	public dialog data and web documents
	ChinChilla	70B	2022	-	×	1.4T	MassiveText
	Galactia-120B	120B	2022	-		450B	
	CodeGen	16.1B	2022	-	✓	-	THE PILE, BIGQUERY, BIGPYTHON
	BLOOM	176B	2022	-	✓	366B	ROOTS
	Zephyr	7.24B	2023	Mistral-7B	✓	800B	Synthetic data
	Grok-0	33B	2023	-	×	-	Online source
	ORCA-2	13B	2023	LLaMA2	-	2001B	-
	StartCoder	15.5B	2023	-	✓	35B	GitHub
	MPT	7B	2023	-	✓	1T	RedPajama, m Common Crawl, S2ORC, Common Crawl
	Mixtral-8x7B	46.7B	2023	-	✓	-	Instruction dataset
	Falcon 180B	180B	2023	-	✓	3.5T	RefinedWeb
	Gemini	1.8B, 3.25B	2023		✓	-	Web documents, books, and code, image data, audio data, video data
	DeepSeek-Coder	1.3B, 6.7B, 33B	2024	-	✓	2T	GitHub's Markdown and StackExchange
	DocLLM	1B,7B	2024	-	×	2T	IIT-CDIP Test Collection 1.0, DocBank

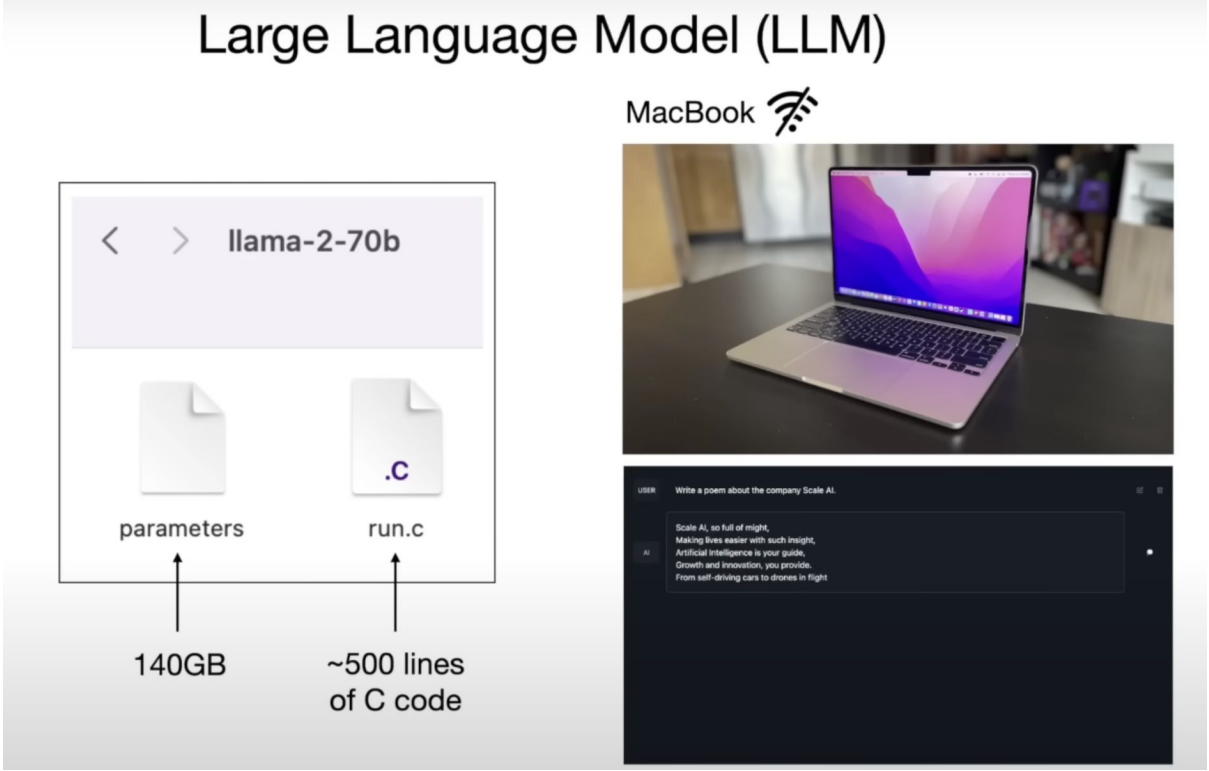
Source: https://arxiv.org/pdf/2402.06196.pdf

What is LLM

Large language models (LLMs) mainly refer to ransformer-based neural language models [1] that contain ens to hundreds of billions of parameters, which are pre-rained on massive text data, such as PaLM [31], LLaMA 32], and GPT-4 [33], as summarized in Table III. Compared

Source: https://arxiv.org/pdf/2402.06196.pdf

What is LLM



LLM Inference

Source:
https://www.youtube.com/watch?v=zjkBMFhNj_g

LLM is compressing the Internet

Google DeepMind

Language Modeling Is Compression

Grégoire Delétang[*1], Anian Ruoss[*1], Paul-Ambroise Duquenne[2], Elliot Catt[1], Tim Genewein[1], Christopher Mattern[1], Jordi Grau-Moya[1], Li Kevin Wenliang[1], Matthew Aitchison[1], Laurent Orseau[1], Marcus Hutter[1] and Joel Veness[1]
[*]Equal contributions, [1]Google DeepMind, [2]Meta AI & Inria

Internet data
~45TB of text

1024 A100 GPUs, 34 days
$5Mdata

GPT3 ~175B

LLM's Evolution Process

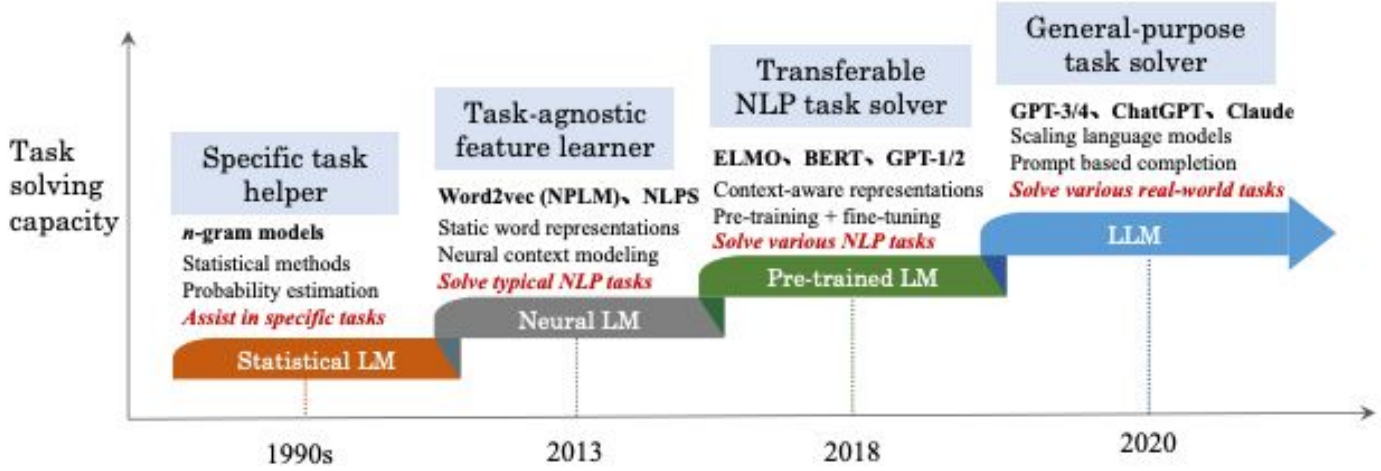
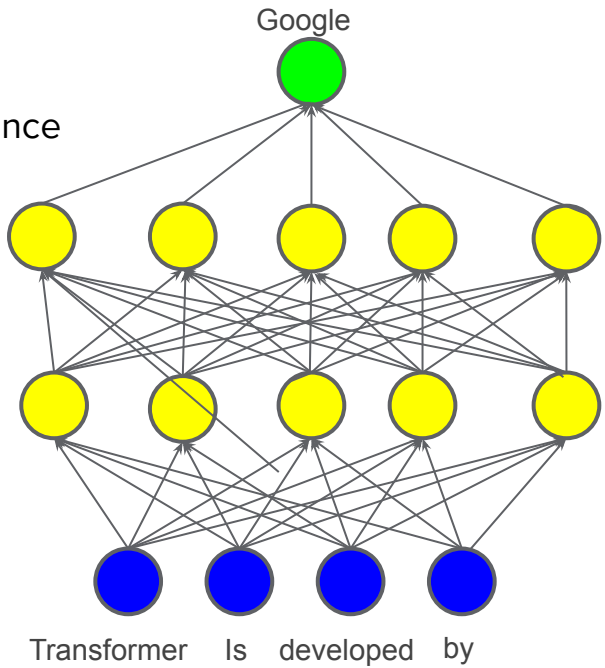


Fig. 2: An evolution process of the four generations of language models (LM) from the perspective of task solving capacity. Note that the time period for each stage may not be very accurate, and we set the time mainly according to the publish date of the most representative studies at each stage. For neural language models, we abbreviate the paper titles of two representative studies to name the two approaches: NPLM [1] (*"A neural probabilistic language model"*) and NLPS [2] (*"Natural language processing (almost) from scratch"*). Due to the space limitation, we don't list all representative studies in this figure.

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

LLM Pretraining

- LLM
  - Pre-trained by **large-scale** unannotated corpus
- Training target: token prediction
  - For GPT/decoder: next token prediction in sequence
  - For BERT/encoder: in-context token prediction



Word prediction is absorbing knowledge

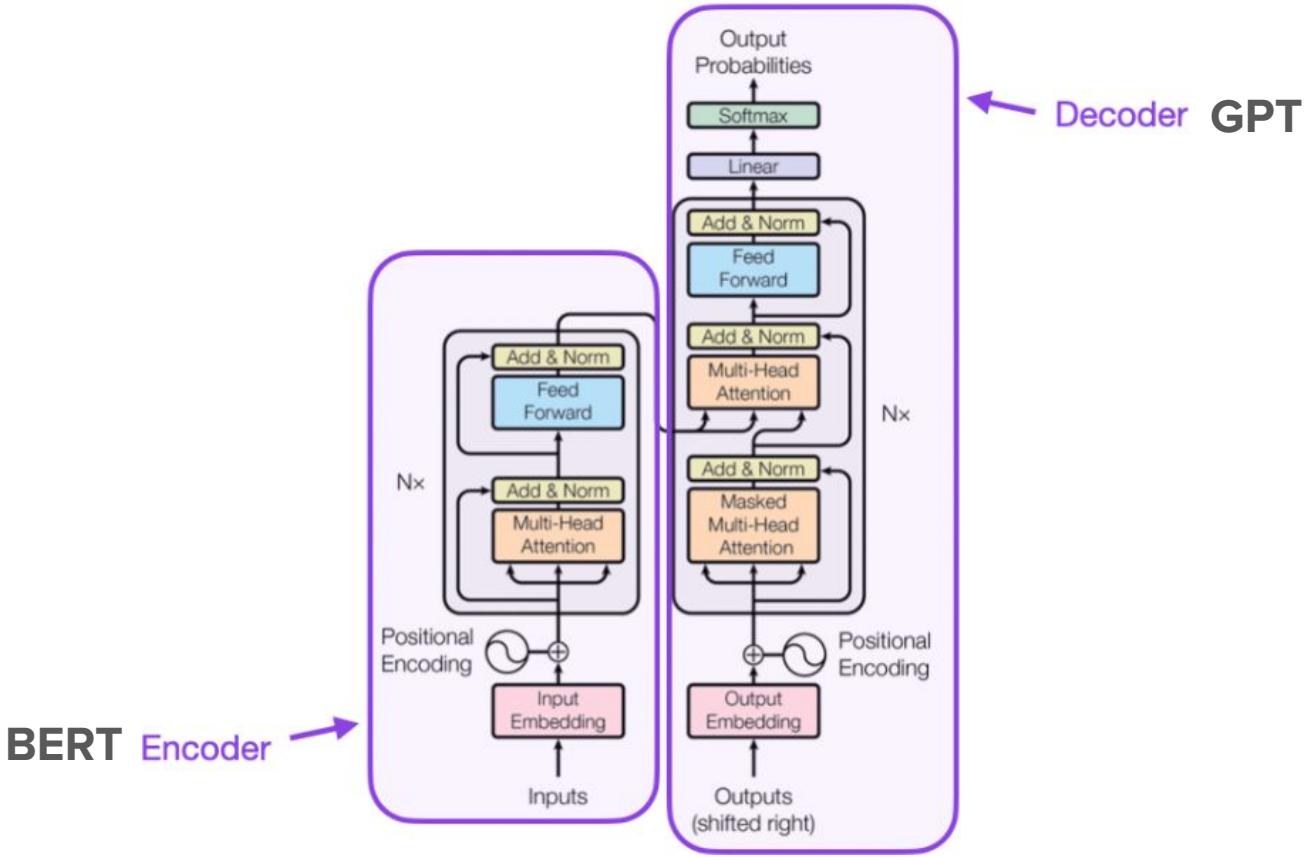
"Transformer architecture" redirects here. For the design of electrical transformers, see Transformer.

A **transformer** is a deep learning architecture based on the multi-head attention mechanism.[1] It is notable for not containing any recurrent units, and thus requires less training time than previous recurrent neural architectures, such as long short-term memory (LSTM),[2] and its later variation has been prevalently adopted for training large language models on large (language) datasets, such as the Wikipedia corpus and Common Crawl.[3] Input text is split into n-grams encoded as tokens and each token is converted into a vector via looking up from a word embedding table. At each layer, each token is then contextualized within the scope of the context window with other (unmasked) tokens via a parallel multi-head attention mechanism allowing the signal for key tokens to be amplified and less important tokens to be diminished. Though the transformer paper was published in 2017, the softmax-based attention mechanism was proposed in 2014 for machine translation,[4][5] and the Fast Weight Controller, similar to a transformer, was proposed in 1992.[6][7][8]

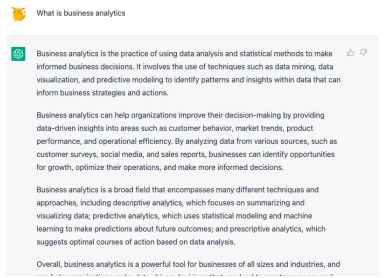
This architecture is now used not only in natural language processing and computer vision,[9] but also in audio[10] and multi-modal processing. It has also led to the development of pre-trained systems, such as generative pre-trained transformers (GPTs)[11] and BERT[12] (Bidirectional Encoder Representations from Transformers).

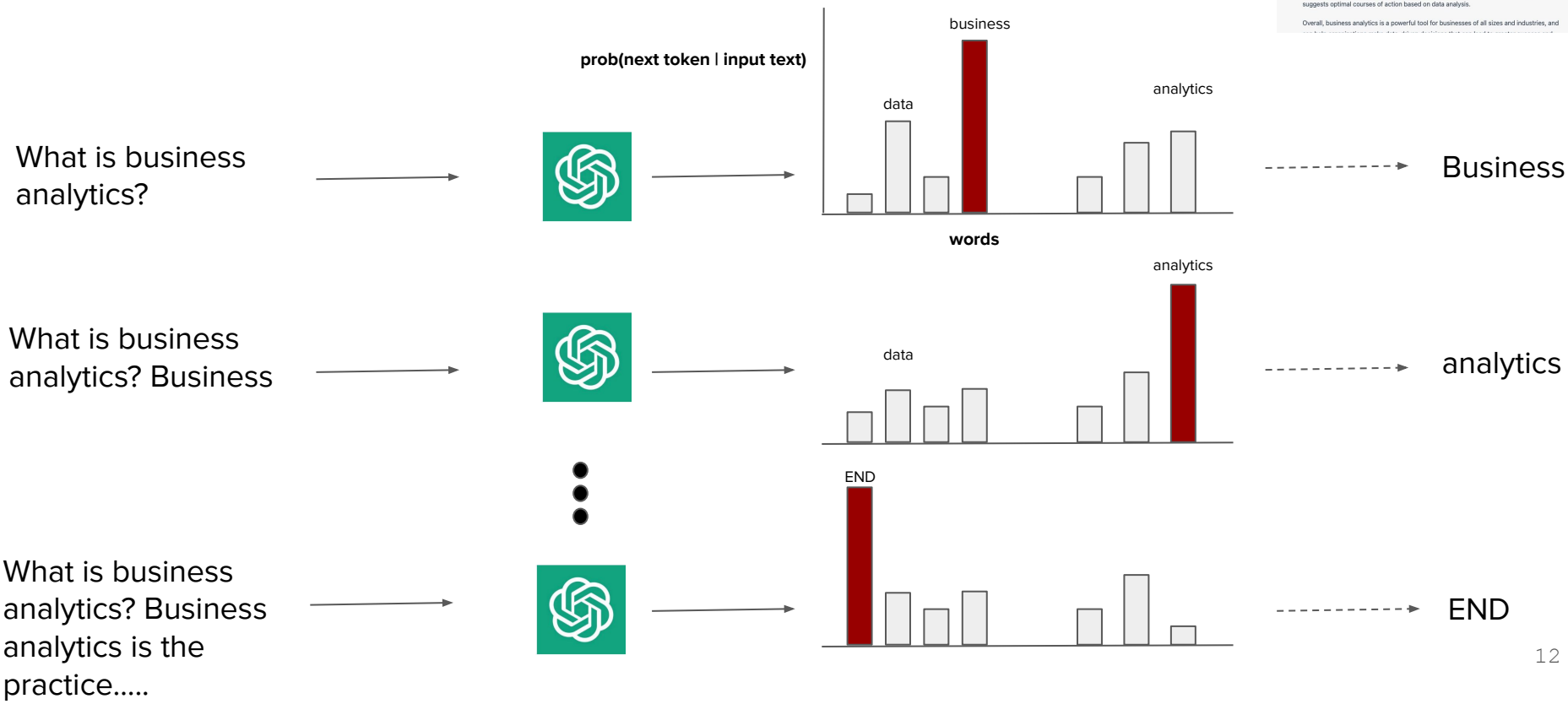
https://ig.ft.com/generative-ai/#:~:text=A%20key%20concept%20of%20the,important%20to%20understanding%20its%20meaning.

Transformer is the backbone of LLMs



How does it work



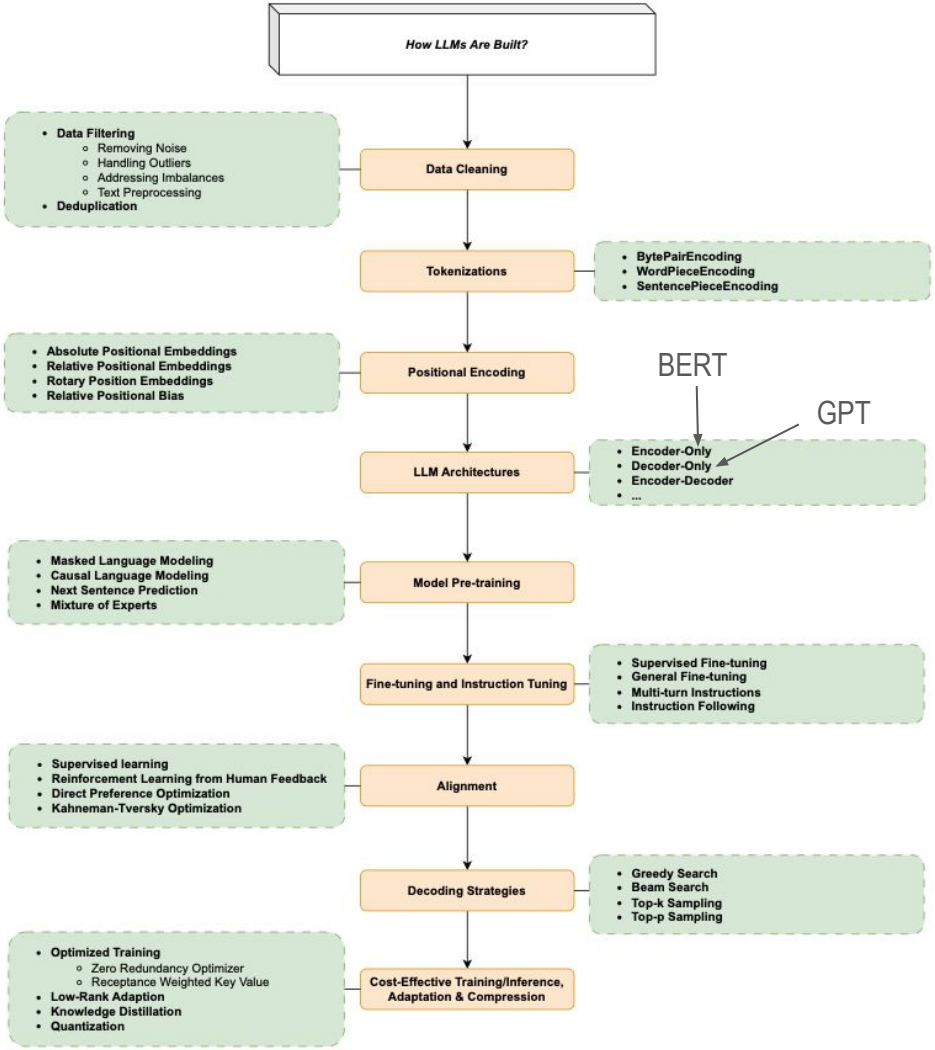


How does it work

- After pre-training, LLM is kind of knowledge database, but it is a total blackbox
  - Billions of parameters with nonlinear mapping
    - We can measure that this works
    - But we do not understand the full details that how those parameters collaborate to predict the next token
  - Sometimes, the performance is a bit strange and imperfect
    - Hallucination
    - Reversal Curse
    - Etc

Figure 1: **Inconsistent knowledge in GPT-4.** GPT-4 correctly gives the name of Tom Cruise's mother (left). Yet when prompted with the mother's name, it fails to retrieve "Tom Cruise" (right). We hypothesize this ordering effect is due to the Reversal Curse. Models trained on "*A* is *B*" (e.g. "Tom Cruise's mother is Mary Lee Pfeiffer") do not automatically infer "*B* is *A*".

source : https://arxiv.org/pdf/2309.12288.pdf

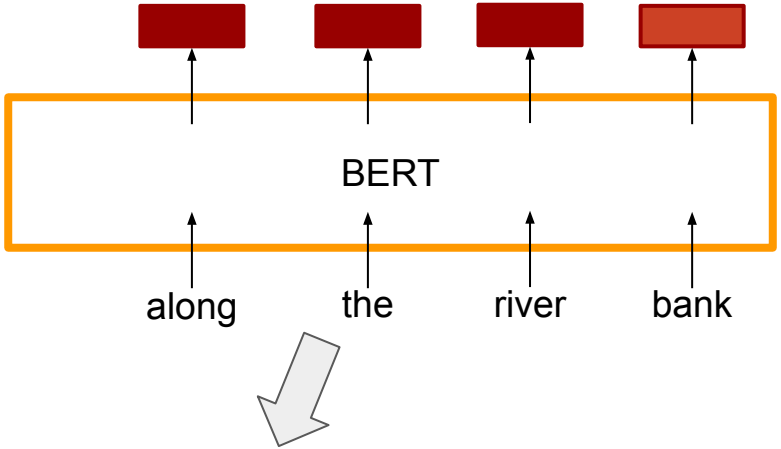


Source: https://arxiv.org/pdf/2402.06196.pdf

2. BERT

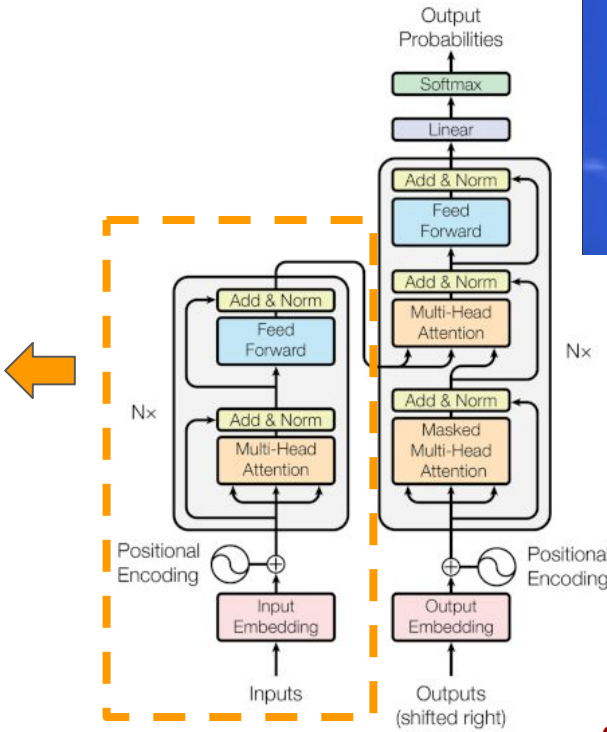
What is BERT

- **B**idirectional **E**ncoder **R**epresentations from **T**ransformers (**BERT**)
- BERT: Encoder of Transformer,



Given a sequence of words, generate a sequence of vectors and then can be used for various NLP tasks

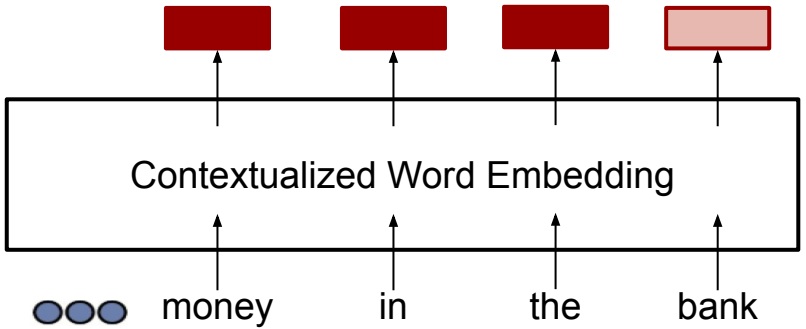
Transformer

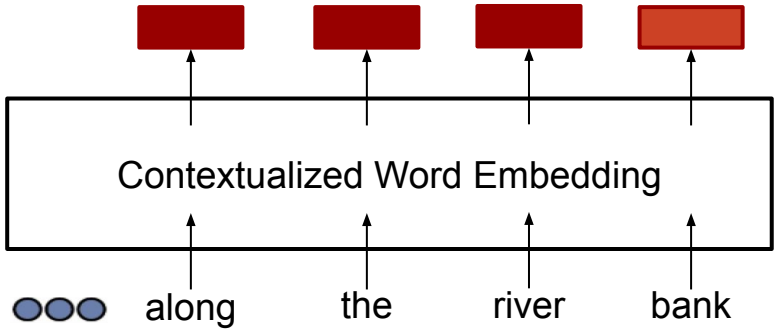


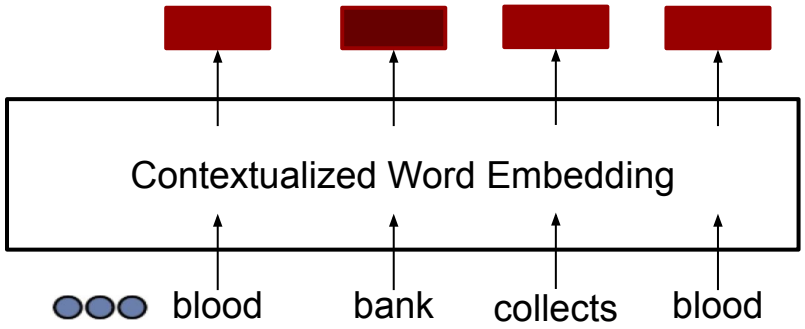
Solve Seq2Seq Task

Contextualized Word Embeddings

Encoded Embeddings





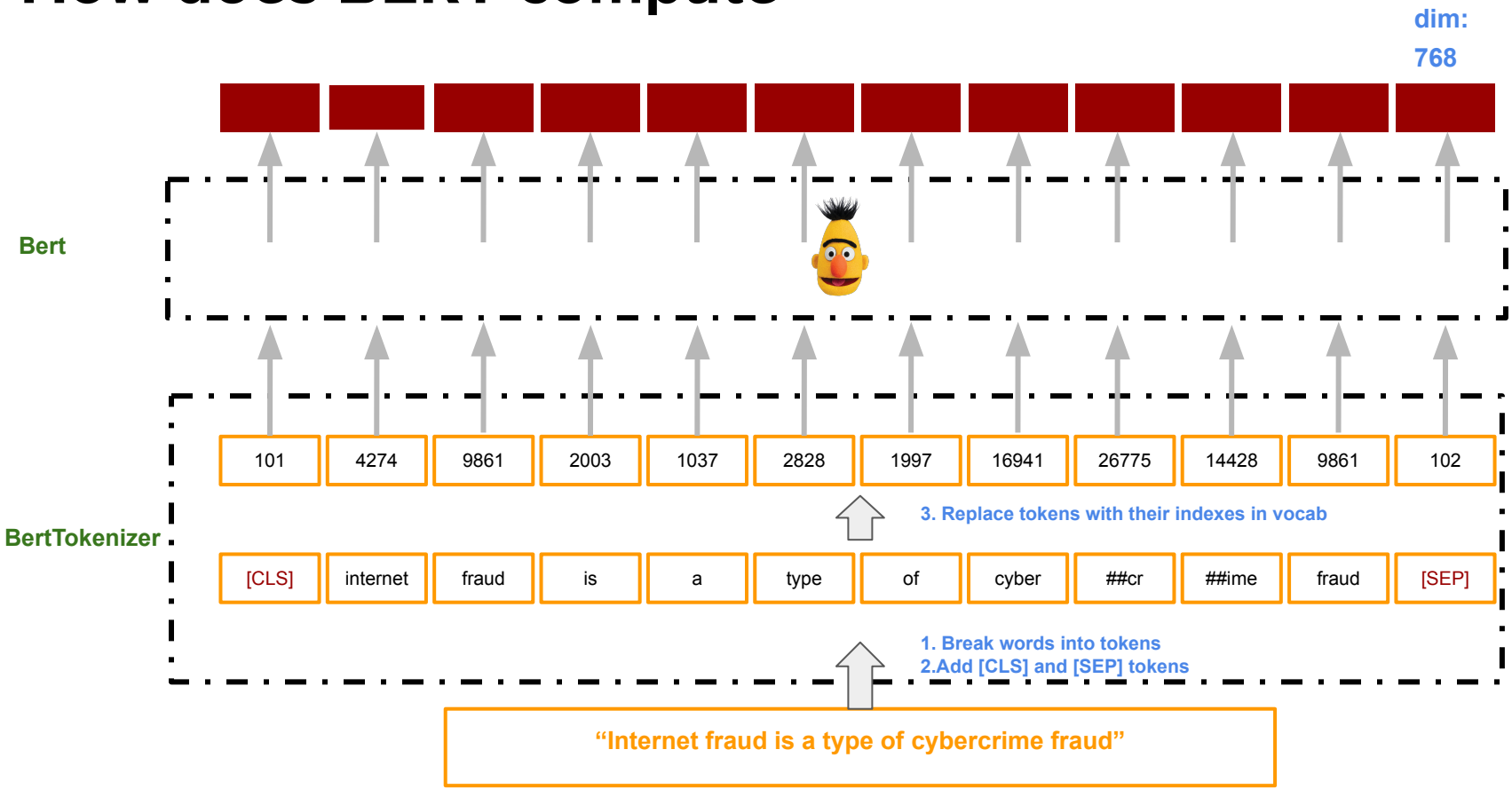


Different Contexts,
Different Encoded Embeddings for bank.

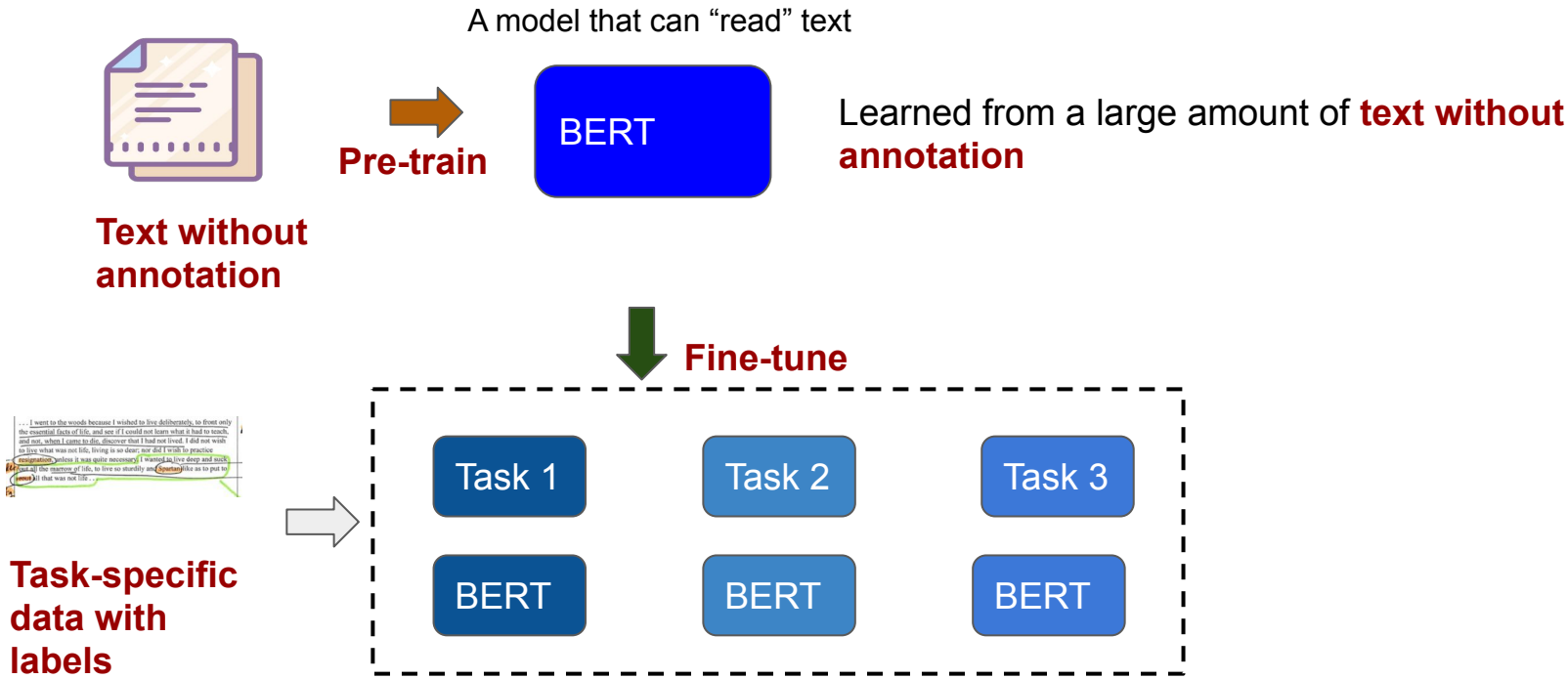
Embeddings generated from BERT

Cos-similarities among vectors of “apple” in different context

How does BERT compute



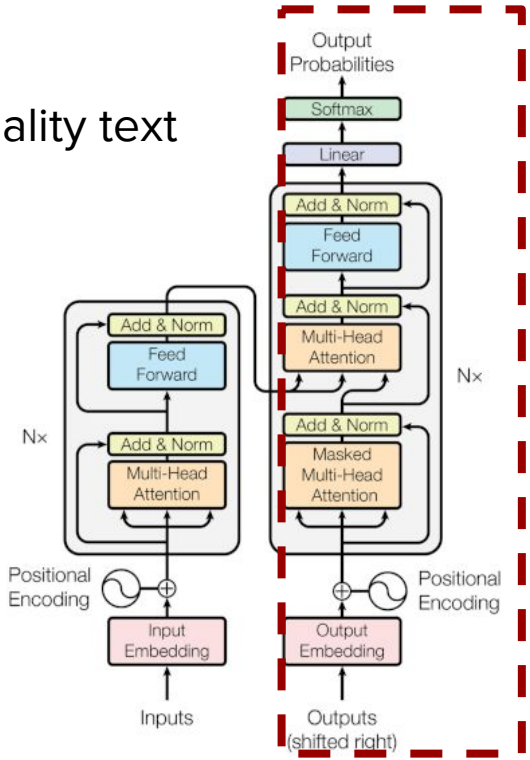
How to train BERT



3. GPT

What is GPT

- **G**enerative **P**re-trained **T**ransformer
  - GPT: Decoder only of Transformer
  - Goal: Learn how to generate high-quality text



Decoder Language Model

GPT1

Improving Language Understanding by Generative Pre-Training

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Abstract

Natural language understanding comprises a wide range of diverse tasks such as textual entailment, question answering, semantic similarity assessment, and document classification. Although large unlabeled text corpora are abundant, labeled data for learning these specific tasks is scarce, making it challenging for discriminatively trained models to perform adequately. We demonstrate that large gains on these tasks can be realized by *generative pre-training* of a language model on a diverse corpus of unlabeled text, followed by *discriminative fine-tuning* on each specific task. In contrast to previous approaches, we make use of task-aware input transformations during fine-tuning to achieve effective transfer while requiring minimal changes to the model architecture. We demonstrate the effectiveness of our approach on a wide range of benchmarks for natural language understanding. Our general task-agnostic model outperforms discriminatively trained models that use architectures specifically crafted for each task, significantly improving upon the state of the art in 9 out of the 12 tasks studied. For instance, we achieve absolute improvements of 8.9% on commonsense reasoning (Stories Cloze Test), 5.7% on question answering (RACE), and 1.5% on textual entailment (MultiNLI).

GPT1 laid the groundwork with a decoder-only architecture to show the potential of LLM.

GPT1 Training

1. Unsupervised Pre-training: next token prediction
2. Fine Tuning: A fully connected layer would be used for label prediction. And it is task-specific

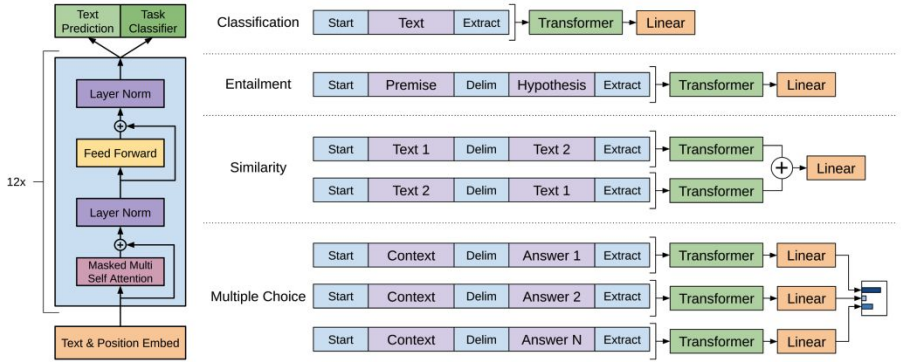


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

Source:
https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/language-unsupervised/language_understanding_paper.pdf

GPT2

Language Models are Unsupervised Multitask Learners

Alec Radford [*1] Jeffrey Wu [*1] Rewon Child [1] David Luan [1] Dario Amodei [**1] Ilya Sutskever [**1]

Abstract

Natural language processing tasks, such as question answering, machine translation, reading comprehension, and summarization, are typically approached with supervised learning on task-specific datasets. We demonstrate that language models begin to learn these tasks without any explicit supervision when trained on a new dataset of millions of webpages called WebText. When conditioned on a document plus questions, the answers generated by the language model reach 55 F1 on the CoQA dataset - matching or exceeding the performance of 3 out of 4 baseline systems without using the 127,000+ training examples. The capacity of the language model is essential to the success of zero-shot task transfer and increasing it improves performance in a log-linear fashion across tasks. Our largest model, GPT-2, is a 1.5B parameter Transformer that achieves state of the art results on 7 out of 8 tested language modeling datasets in a zero-shot setting but still underfits WebText. Samples from the model reflect these improvements and contain coherent paragraphs of text. These findings suggest a promising path towards building language processing systems which learn to perform tasks from their naturally occurring demonstrations.

competent generalists. We would like to move towards more general systems which can perform many tasks – eventually without the need to manually create and label a training dataset for each one.

The dominant approach to creating ML systems is to collect a dataset of training examples demonstrating correct behavior for a desired task, train a system to imitate these behaviors, and then test its performance on independent and identically distributed (IID) held-out examples. This has served well to make progress on narrow experts. But the often erratic behavior of captioning models (Lake et al., 2017), reading comprehension systems (Jia & Liang, 2017), and image classifiers (Alcorn et al., 2018) on the diversity and variety of possible inputs highlights some of the shortcomings of this approach.

Our suspicion is that the prevalence of single task training on single domain datasets is a major contributor to the lack of generalization observed in current systems. Progress towards robust systems with current architectures is likely to require training and measuring performance on a wide range of domains and tasks. Recently, several benchmarks have been proposed such as GLUE (Wang et al., 2018) and decaNLP (McCann et al., 2018) to begin studying this.

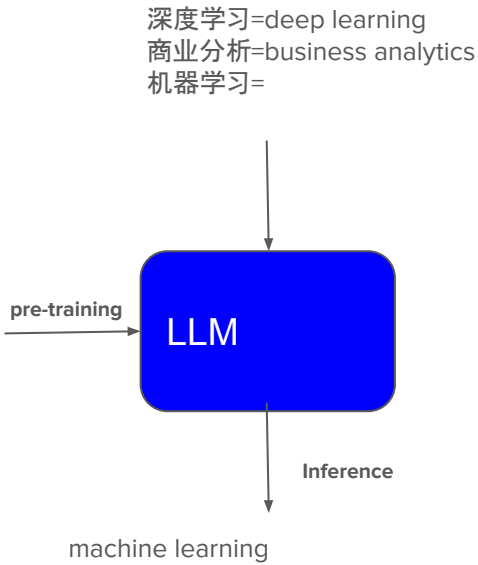
Multitask learning (Caruana, 1997) is a promising framework for improving general performance. However, multitask training in NLP is still nascent. Recent work reports modest performance improvements (Yogatama et al.,

1. GPT2 is trying to build a general language model that could do multi-task learning while training
2. Compared to GPT1, there is no change in architecture. GPT2 has more parameters and a much bigger training dataset
3. No fine-tuning

GPT2

”I’m not the cleverest man in the world, but like they say in French: **Je ne suis pas un imbecile [I’m not a fool].**
In a now-deleted post from Aug. 16, Soheil Eid, Tory candidate in the riding of Joliette, wrote in French: ”**Mentez mentez, il en restera toujours quelque chose**,” which translates as, ”**Lie lie and something will always remain.**”
“I hate the word ‘**perfume**,”’ Burr says. ‘It’s somewhat better in French: ‘**parfum**.’
If listened carefully at 29:55, a conversation can be heard between two guys in French: “**-Comment on fait pour aller de l’autre coté? -Quel autre coté?**”, which means “**- How do you get to the other side? - What side?**”.
If this sounds like a bit of a stretch, consider this question in French: **As-tu aller au cinéma?**, or **Did you go to the movies?**, which literally translates as Have-you to go to movies/theater?
“**Brevet Sans Garantie Du Gouvernement**”, translated to English: “**Patented without government warranty**”.

Table 1. Examples of naturally occurring demonstrations of English to French and French to English translation found throughout the WebText training set.



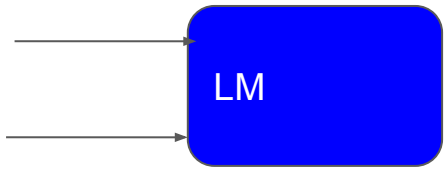
A context of example pairs of chinese text=english is provided to help the LLM infer this is the machine translation task.

Downstream NLP tasks can all be formulated as LM

- Language model is doing next token prediction
  - E.g., based on the previous tokens: I love this -> movie
- Downstream NLP tasks:
  - Sentiment analysis: given a sentence, **generate** sentiment label
    - I love this movie -> positive
  - Machine translation: given a source sentence, **generate** a target sentence
    - 深度学习 -> deep learning
- How LM differentiate those NLP tasks?
  - Provide in-context information (prompt)

深度学习 Translate it into english:

I love this movie. Label it sentiment



GPT3

Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam Girish Sastry

Amanda Askell Sandhini Agarwal Ariel Herbert-Voss Gretchen Krueger Tom Henighan

Rewon Child Aditya Ramesh Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

OpenAI

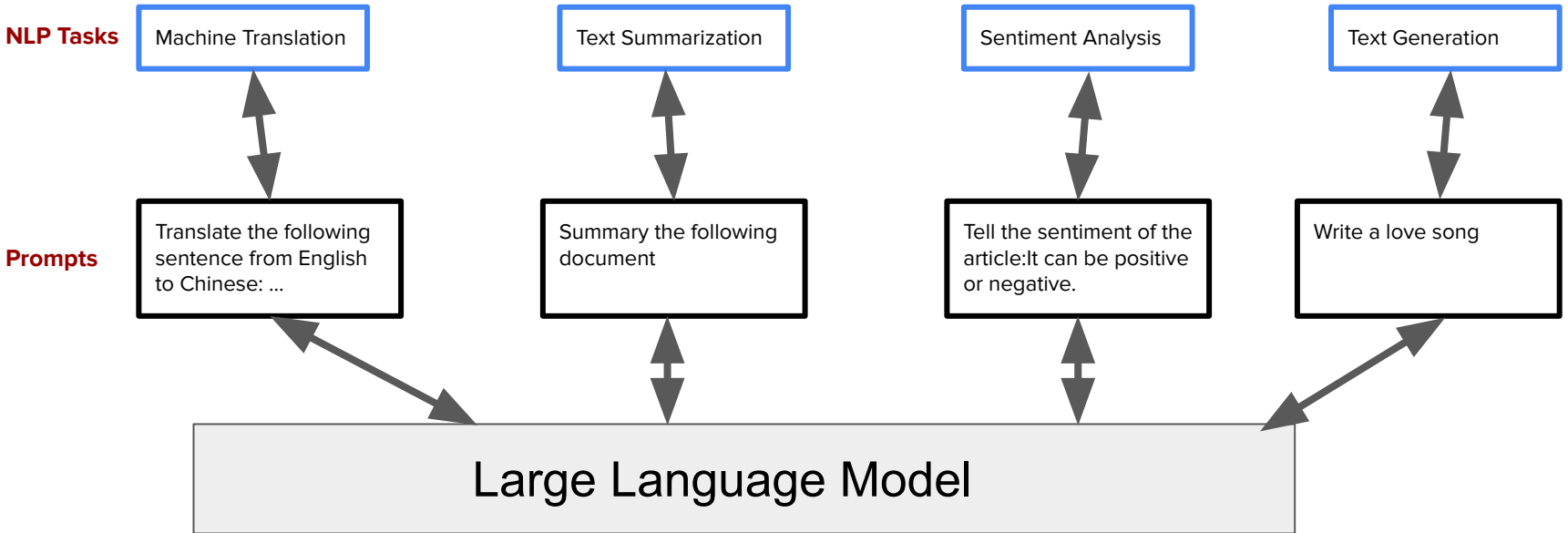
Abstract

Recent work has demonstrated substantial gains on many NLP tasks and benchmarks by pre-training on a large corpus of text followed by fine-tuning on a specific task. While typically task-agnostic in architecture, this method still requires task-specific fine-tuning datasets of thousands or tens of thousands of examples. By contrast, humans can generally perform a new language task from only a few examples or from simple instructions – something which current NLP systems still largely struggle to do. Here we show that scaling up language models greatly improves task-agnostic, few-shot performance, sometimes even reaching competitiveness with prior state-of-the-art fine-tuning approaches. Specifically, we train GPT-3, an autoregressive language model with 175 billion parameters, 10x more than any previous non-sparse language model, and test its performance in the few-shot setting. For all tasks, GPT-3 is applied without any gradient updates or fine-tuning, with tasks and few-shot demonstrations specified purely via text interaction with the model. GPT-3 achieves strong performance on many NLP datasets, including translation, question-answering, and cloze tasks, as well as several tasks that require on-the-fly reasoning or domain adaptation, such as unscrambling words, using a novel word in a sentence, or performing 3-digit arithmetic. At the same time, we also identify some datasets where GPT-3's few-shot learning still struggles, as well as some datasets where GPT-3 faces methodological issues related to training on large web corpora. Finally, we find that GPT-3 can generate samples of news articles which human evaluators have difficulty distinguishing from articles written by humans. We discuss broader societal impacts of this finding and of GPT-3 in general.

1. Compared to GPT2, more parameters and bigger training dataset are used in GPT3. And the generalization capability is named as in-context learning.
2. GPT2 has constraints in handling certain specific tasks while GPT3 show groundbreaking abilities. So it has paved the way for even bigger and more complex models

In-context Learning

In-context learning: using the text input of a pre-trained language model as a form of task specification: the model is conditioned on a natural language instruction and/or a few demonstrations of the task and is then expected to complete further instances of the task simply by predicting what comes next.



GPT3: Prompting

- Zero-shot Prompting
  - No examples are given in prompt
  - “Please answer, 3+2=?”
- One-shot Prompting
  - One example is given
  - “1+7=8, please answer, 3+2=?”
- Few-shot Prompting
  - A few shot examples of tasks are provided
  - “1+1=2,1+7=8, please answer, 3+2=?”

GPT3: Performances of Prompting

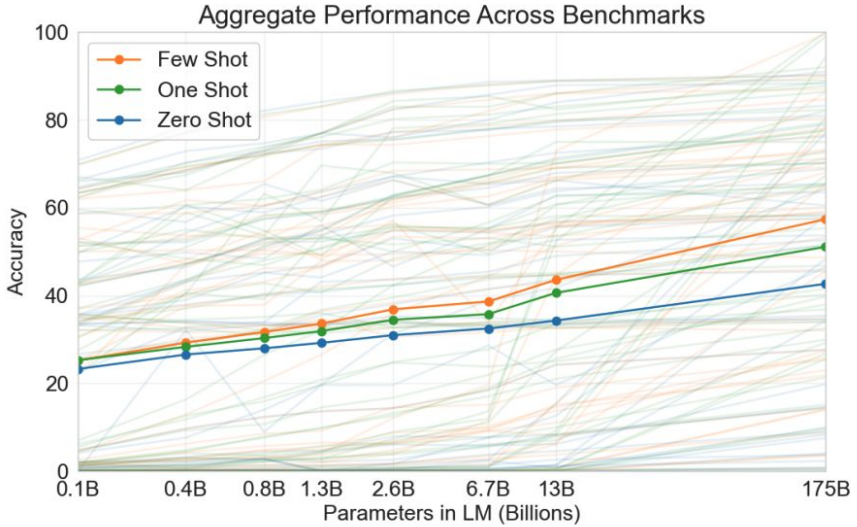


Figure 1.3: Aggregate performance for all 42 accuracy-denominated benchmarks While zero-shot performance improves steadily with model size, few-shot performance increases more rapidly, demonstrating that larger models are more proficient at in-context learning. See Figure 3.8 for a more detailed analysis on SuperGLUE, a standard NLP benchmark suite.

Source: https://arxiv.org/pdf/2005.14165.pdf

BERT vs GPT

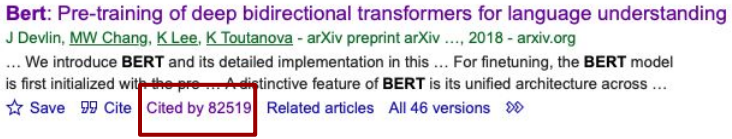
BERT

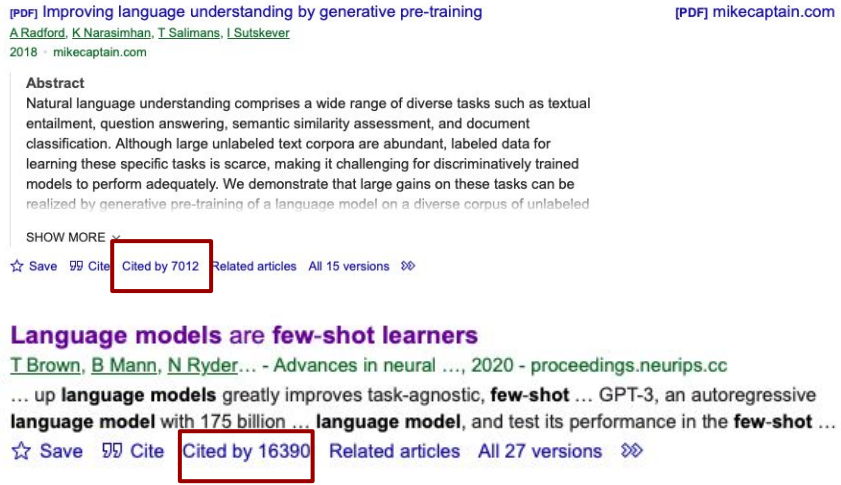
- Architecture:
  - Transformer Encoder block
  - Less training parameters (a few hundred M)
- Model learning:
  - Two objectives: masked language model (cbow) and next sentence prediction
  - Bi-directional
  - Less training data
- Applications:
  - Traditional NLP Tasks: summarization, classification, representation learning, information retrieval

GPT

- Architecture:
  - Transformer Decoder block
  - More training parameters (a few hundred B)
- Model learning:
  - Generative, next word prediction
  - Uni-directional (left to right)
  - More training data
- Applications:
  - Natural language generation, Q/A, chatbot

BERT vs GPT: BERT was winning





At beginning, BERT got more adoption from NLP community compared to GPT and GPT2 (82k citation vs 23k citation)

BERT vs GPT: Different Mindsets

BERT

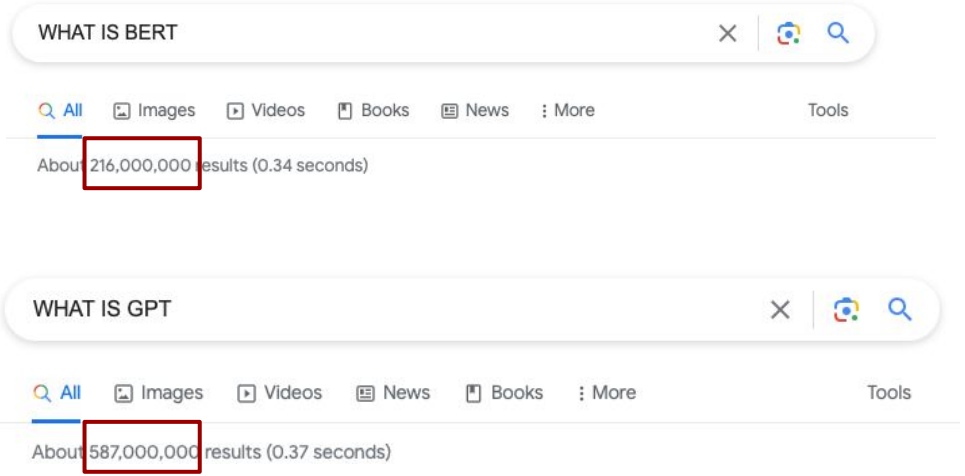
- Understand the language first before generating a response
- An encoder to learn the representation is the backbone
- Fine tune for specific tasks

GPT

- Mainly focus on predicting the next token
- The decoder to predict the next token
- One shot or few-shot prompting without fine-tuning
- Scaling up parameters

BERT vs GPT: GPT method is the SOTA now

- With the popularity of ChatGPT, GPT method is winning now
  - We understand others by the response
  - Representations or encodings does not matter, we can rely on outputs for any specific tasks
  - Closer to the idea of General AI (only one model)



4. Scaling laws

What is “Large” in LLM

- The scale of LLM is defined in three aspects:
  - Model size
  - Dataset size
  - Amount of computing power for training

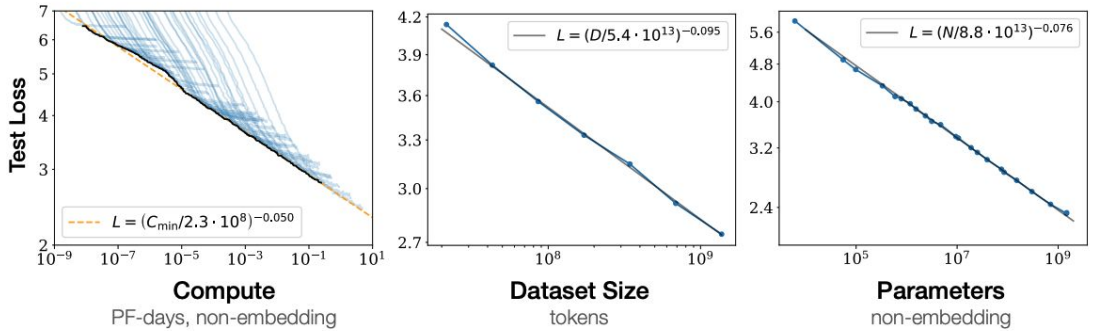
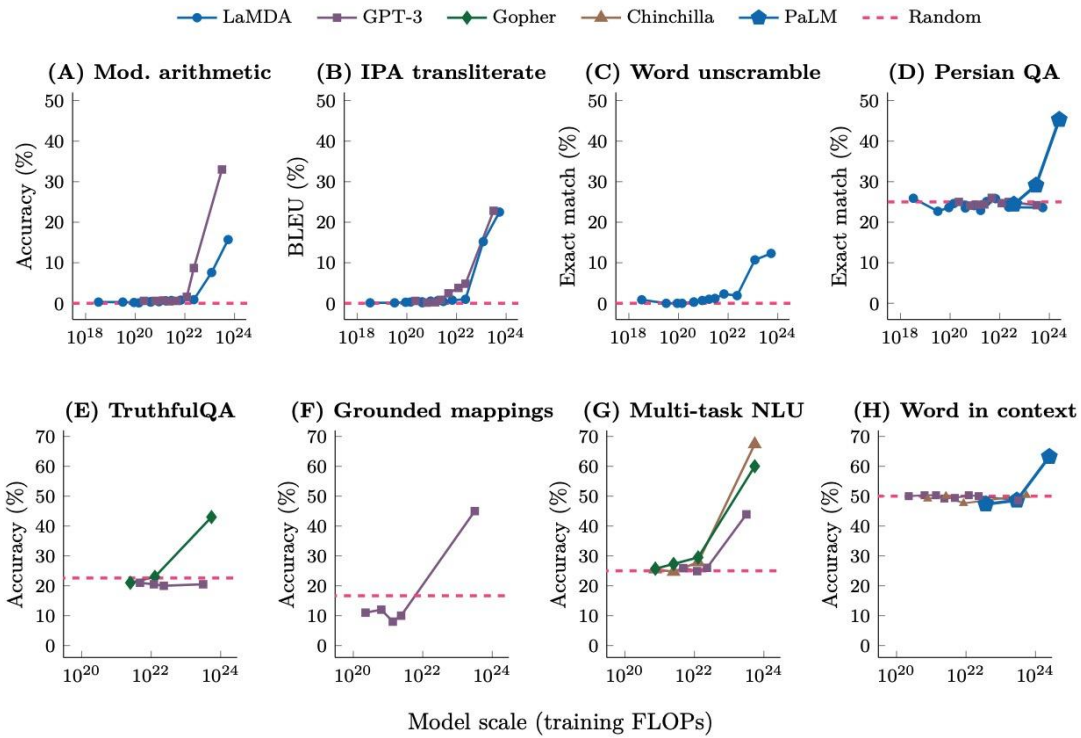


Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

Source: https://arxiv.org/pdf/2001.08361.pdf

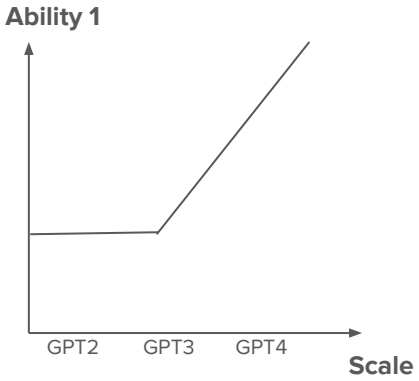
Emergent abilities of large language models

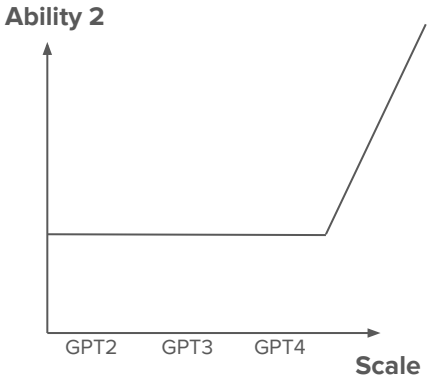
Emergence is when quantitative changes in a system result in qualitative changes in behavior



Source: https://arxiv.org/abs/2206.07682

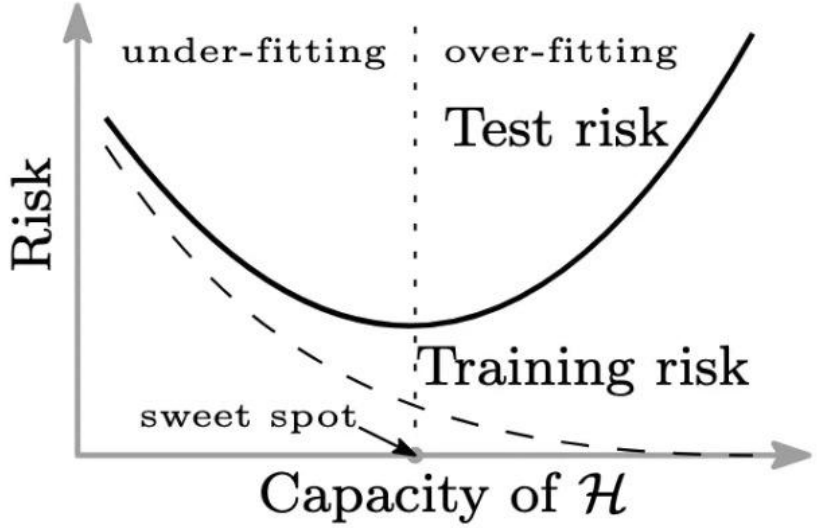
Simplified View of Emergent Abilities





Therefore, some researchers think even some abilities do not work with the current LLMs, we should think once larger models are available, many problems can be solved.

Conventional Machine Learning



Larger models are worse.

A model with zero training error is overfitting to the training data and will usually generalize poorly.

Double Descent

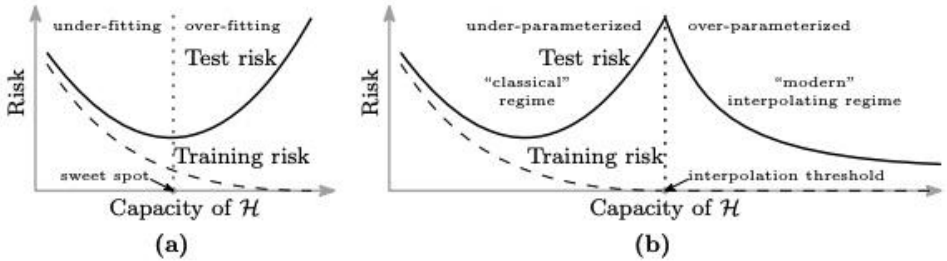


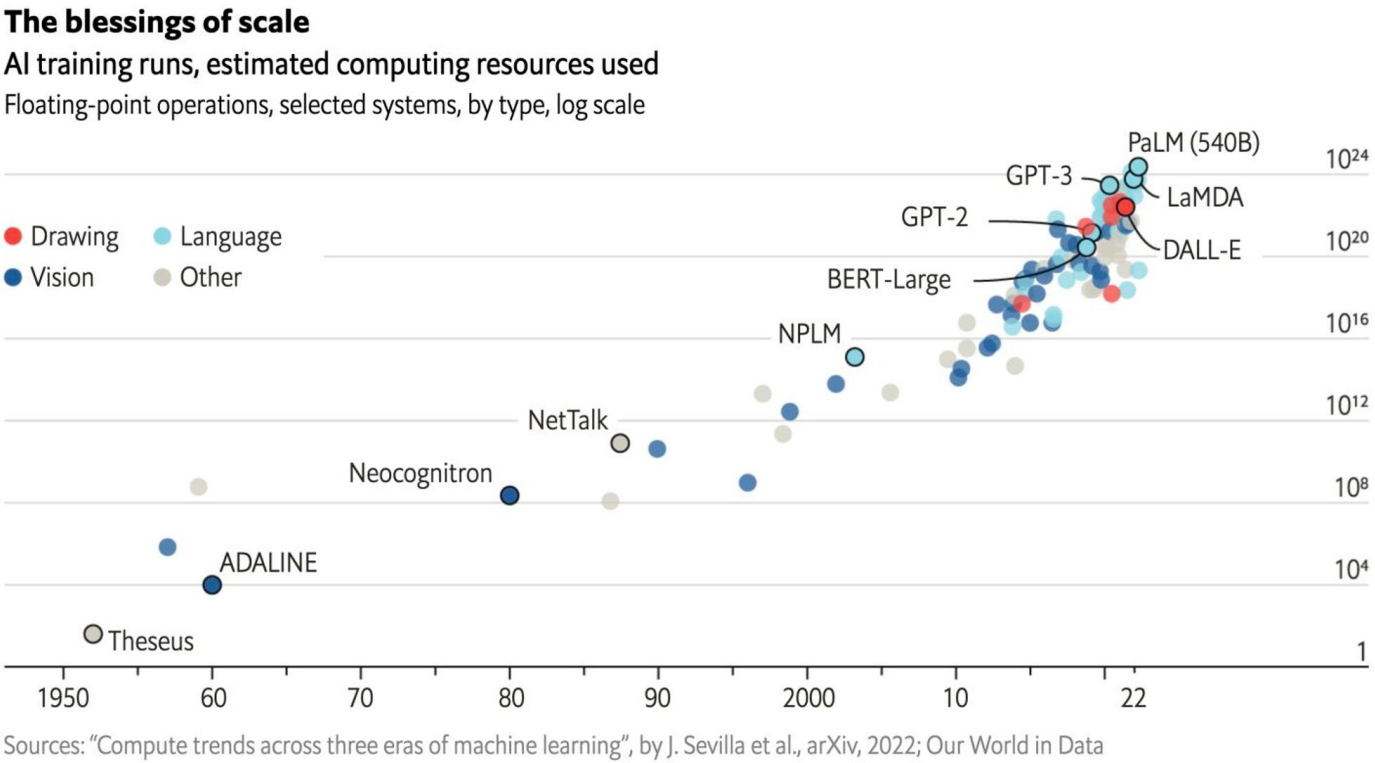
Figure 1: **Curves for training risk (dashed line) and test risk (solid line).** **(a)** The classical *U-shaped risk curve* arising from the bias-variance trade-off. **(b)** The *double descent risk curve*, which incorporates the U-shaped risk curve (i.e., the "classical" regime) together with the observed behavior from using high capacity function classes (i.e., the "modern" interpolating regime), separated by the interpolation threshold. The predictors to the right of the interpolation threshold have zero training risk.

Source: https://arxiv.org/pdf/1812.11118.pdf

When the model size is beyond a certain threshold i.e. interpolation threshold, the test error would be in downward trend

The threshold $\approx$ The number of class times the number of training examples

Pre-training



The Scale of GPTs and BERT

Model Version	*Architecture*	*Parameter count*	*Training data*
Bert-base	12-level, 12-headed Transformer encoder	0.11 billion	Toronto BookCorpus and English Wikipedia (3,200 million words)
Bert-Large	24-level, 16-headed Transformer encoder	0.34 billion	Toronto BookCorpus and English Wikipedia (3,200 million words)
GPT1	12-level, 12 headed Transformer decoder, followed by linear-softmax	0.12 billion	BookCorpus, 4.5 GB of text
GPT2	GPT-1, but with modified normalization	1.5 billion	WebText: 40 GB of text, 8 million documents
GPT3	GPT-2 but with modification to allow larger scaling	175 billion	570 GB plaintext, 0.4 trillion tokens

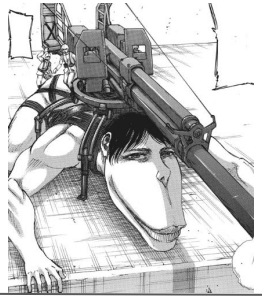
* The estimated model size of GPT4 is around 175B to 280B.

What is the scale of 175b

GPT-1
BERT-Base

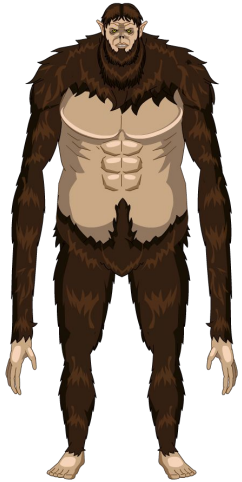
Levi 兵長 1.6m

BERT-Large



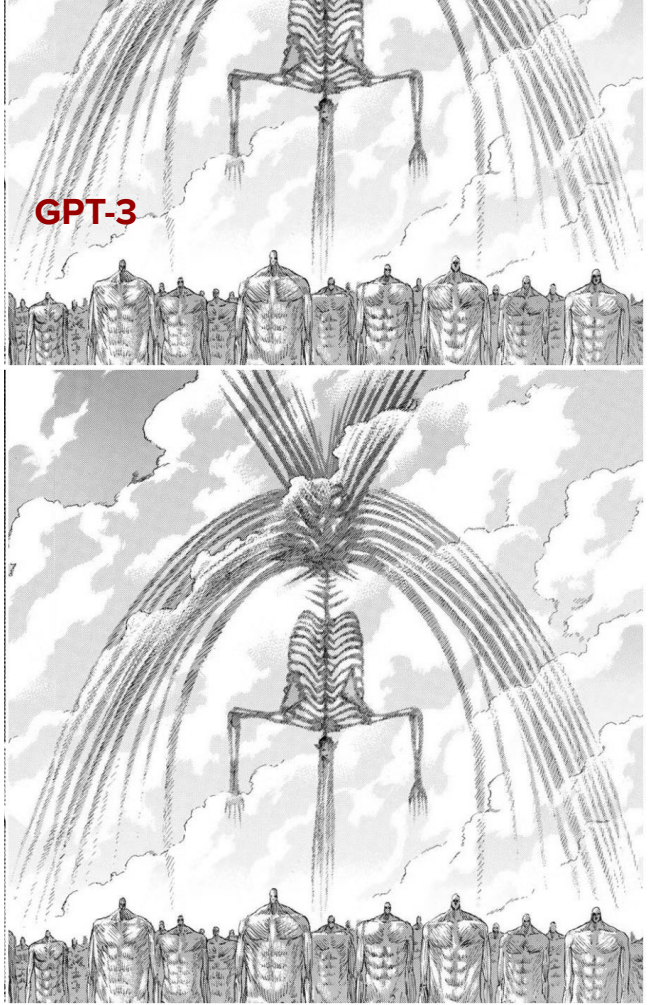
Cart Titan 車力の巨人 4m

GPT-2



Beast Titan 獣の巨人 17m

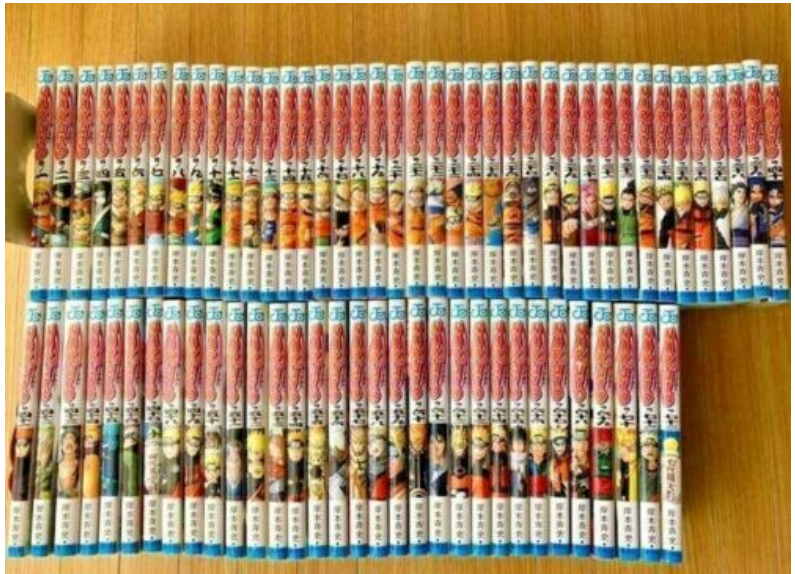
GPT-3



Two Stacked Eren Founding Titan 始祖の巨人 2*1000m

What is the scale 570GB

Read Naruto **270K** times



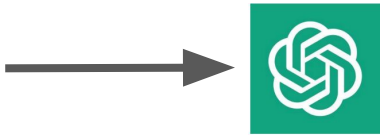
Only lines/text are counted.

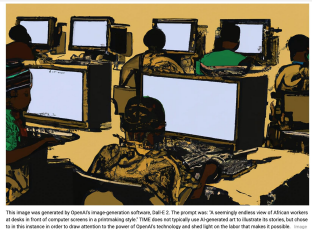
5. From GPT3 to ChatGPT: Finetuning + Alignment

How to train ChatGPT

Pre-training
GPT GPT2 GPT3

Fine-tuning + Alignment
InstructGPT/ChatGPT





https://time.com/6247678/openai-chatgpt-kenya-workers/

Unannotated data

Human labelled data

GPT3 is already powerful

- GPT3 can do everything that Chatgpt can do
  - https://pub.towardsai.net/crazy-gpt-3-use-cases-232c22142044
- Why not achieve the hype as ChatGPT?
  - It is a language model that is learned from all text across the open internet
  - GPT3 is a genius but do not know our humans' preference

GPT3's problem

What is the purpose of the list C in the code below?

```
def binomial_coefficient(n, r):
    C = [0 for i in range(r + 1)];
    C[0] = 1;
    for i in range(1, n + 1):
        j = min(i, r);
        while j > 0:
            C[j] += C[j - 1];
            j -= 1;
    return C[r]
```

The list C in this code is used to store the values of the binomial coefficient as the function iterates through the values of n and r. It is used to calculate the value of the binomial coefficient for a given value of n and r, and stores the result in the final return value of the function.

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source: https://arxiv.org/pdf/2203.02155.pdf

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A. to store the value of C[0]
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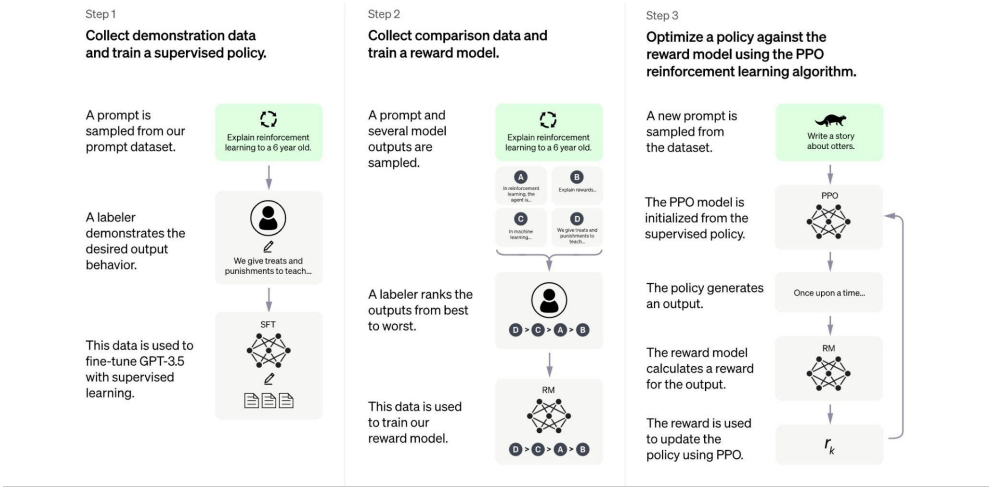
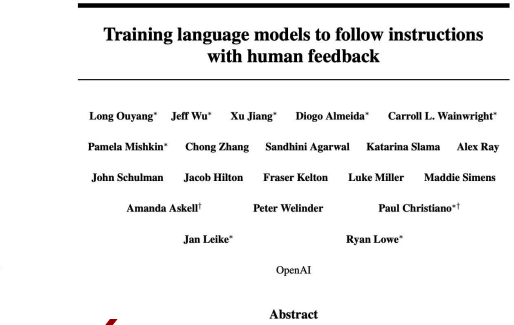
source: https://arxiv.org/pdf/2203.02155.pdf

How to inject human preference

- This is how ChatGPT is different from GPT3.
- Reinforcement Learning from Human Feeback (RLHF):





Training language models to follow instructions with human feedback

Long Ouyang* Jeff Wu* Xu Jiang* Diogo Almeida* Carroll L. Wainwright*
Pamela Mishkin* Chong Zhang Sandhini Agarwal Katarina Slama Alex Ray
John Schulman Jacob Hilton Fraser Kelton Luke Miller Maddie Simens
Amanda Askell† Peter Welinder Paul Christiano*†
Jan Leike* Ryan Lowe*
OpenAI

Abstract

Methods

We trained this model using Reinforcement Learning from Human Feedback (RLHF), using the same methods as InstructGPT, but with slight differences in the data collection setup. We trained an initial model using supervised fine-tuning: human AI trainers provided conversations in which they played both sides—the user and an AI assistant. We gave the trainers access to model-written suggestions to help them compose their responses. We mixed this new dialogue dataset with the InstructGPT dataset, which we transformed into a dialogue format.

source: https://openai.com/blog/chatgpt

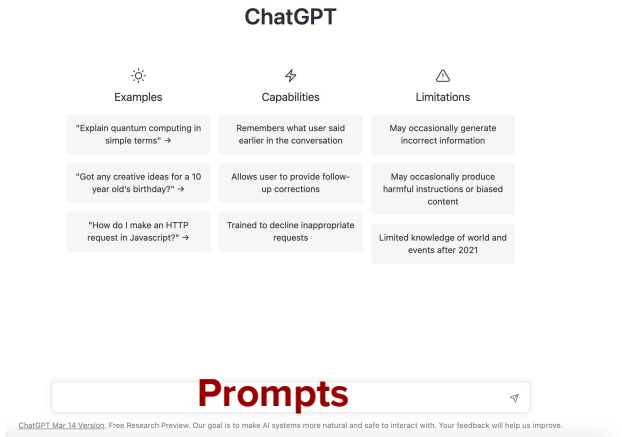
ChatGPT should be quite close to InstructGPT in terms of implementation

ChatGPT: Finetuning + Alignment

- It is not fully disclosed
- GPT3.5 +
  - SFT
  - RLHF
- Data quality and data collection is one key factor
  - From GPT3, Open AI has a framework to upweight high quality training text, and filter low quality ones
- Rumor:
  - About 10 times spend on human annotation budget
  - Improved version of RLHF

In the following, we will focus on InstructGPT

Start with Prompts



- Prompts: query sent to GPT models
- Prompts are generated in the following ways:
  - Plain: ask the labelers to come up with an arbitrary task
  - Few-shot: ask the labelers to come up with an instruction
    - Like any coding/programming related questions
  - User-based: collected use-cases from OpenAI API users. And labelers are asked to come up with related prompts

Try to increase the diversity and coverage of all prompts

Step 1: Supervised fine-tuning (InstructGPT)

- Prepare SFT dataset
  - It only has 13K training prompts with labeler demonstration
  - The ground-truth responses are provided directly
- Fine-tune the GPT model using the SFT dataset
  - Training target is the same as the pre-training: next word prediction

It is too **expensive** to prepare the prompts and answer pair in the above way. Sometime, it is even not possible. Think about some prompts such as “write a song for my best friend who is having the kaggle competition”

Step 1: Supervised fine-tuning (InstructGPT)

- SFT dataset
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It is too **expensive** to prepare prompts in the above way. Sometime, it is even not possible. Think about some prompts such as “write a song for my best friend who is having the kaggle competition”

We can not write songs but we can pick a better song.

Do you prefer MCQ or SAQ?

It is often much easier to compare Answers instead of writing Answers.

Step 2: Reward model (InstructGPT)

- Prepare RM dataset (33k prompts)
  - Given prompts and multiple model outputs, labelers are asked to give ranking
- Train a Reward model
  - Take a prompt and a response, and output a scalar reward
  - Loss function for the reward model:

$$\text{loss}(\theta) = -\frac{1}{\binom{K}{2}} E_{(x,y_w,y_l)\sim D}\left[\log\left(\sigma\left(r_\theta(x,y_w) - r_\theta(x,y_l)\right)\right)\right] \quad (1)$$

where $r_\theta(x, y)$ is the scalar output of the reward model for prompt x and completion y with parameters θ, y_w is the preferred completion out of the pair of y_w and y_l, and D is the dataset of human comparisons.

What is the purpose of the list C in the code below?

```
def binomial_coefficient(n, r):
    C = [0 for i in range(r + 1)];
    C[0] = 1;
    for i in range(1, n + 1):
        j = min(i, r);
        while j > 0:
            C[j] += C[j - 1];
            j -= 1;
    return C[r]
```

The list C in this code is used to store the values of the binomial coefficient as the function iterates through the values of n and r. It is used to calculate the value of the binomial coefficient for a given value of n and r, and stores the result in the final return value of the function.

A. to store the value of C[0]
B. to store the value of C[1]
C. to store the value of C[i]
D. to store the value of C[i - 1]

Step 3: Reinforcement learning (InstructGPT)

- Prepare PPO dataset (31k prompts)
  - Selected prompts and RM model from Step 2
- Fine-tune SFT model using PPO algorithm (one of Reinforcement Learning algorithms)
  - The environment here is: prompt is randomly presented and the SFT model is expected to generate a prompt
  - Given the prompt and response, RM model will output a reward value
  - SFT model is trained to achieve a higher reward value

From these three steps, we kind of enforce GPT model to learn our humans' preference

How good is RLHF

1.3B RLHF outperform 175B GPT3 on human preferences

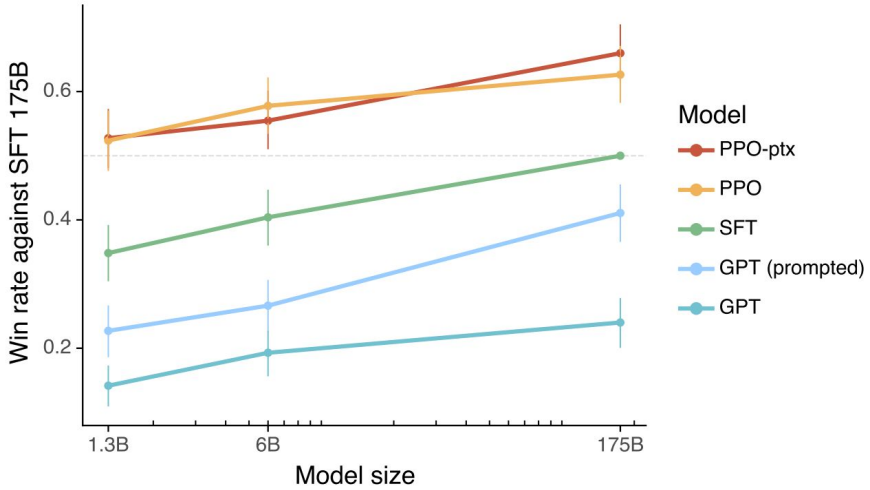


Figure 1: Human evaluations of various models on the API prompt distribution, evaluated by how often outputs from each model were preferred to those from the 175B SFT model. Our InstructGPT models (PPO-ptx) as well as its variant trained without pretraining mix (PPO) significantly outperform the GPT-3 baselines (GPT, GPT prompted); outputs from our 1.3B PPO-ptx model are preferred to those from the 175B GPT-3. Error bars throughout the paper are 95% confidence intervals.

Source :https://proceedings.neurips.cc/paper_files/paper/2022/file/b1efde53be364a73914f58805a001731-Paper-Conference.pdf

Wrap it up

- How to train your ChatGPT
  - Stage 1: Pretraining
    - Download large scale text data (~10TB)
    - Get a cluster of 6k GPUs
    - Compress the text into the 100 billion parameters and its associated neural network (~$2M and ~12days)
    - Obtain the foundation/base model
  - Stage 2: Finetuning + Alignment
    - Write labeling instructions
    - Hire ppls, collect 100K high quality prompt responses, and comparisons
    - Finetune the base model on this data
    - Obtain assistant/chatbot model
    - Run a lot of evaluations
    - Deploy, Monitor, Collect misbehaviors

Next Class: LLMs and its production

Appendix: How to train BERT

How to train BERT

Pre-training then connect with a downstream fully-connected layers for fine-tuning

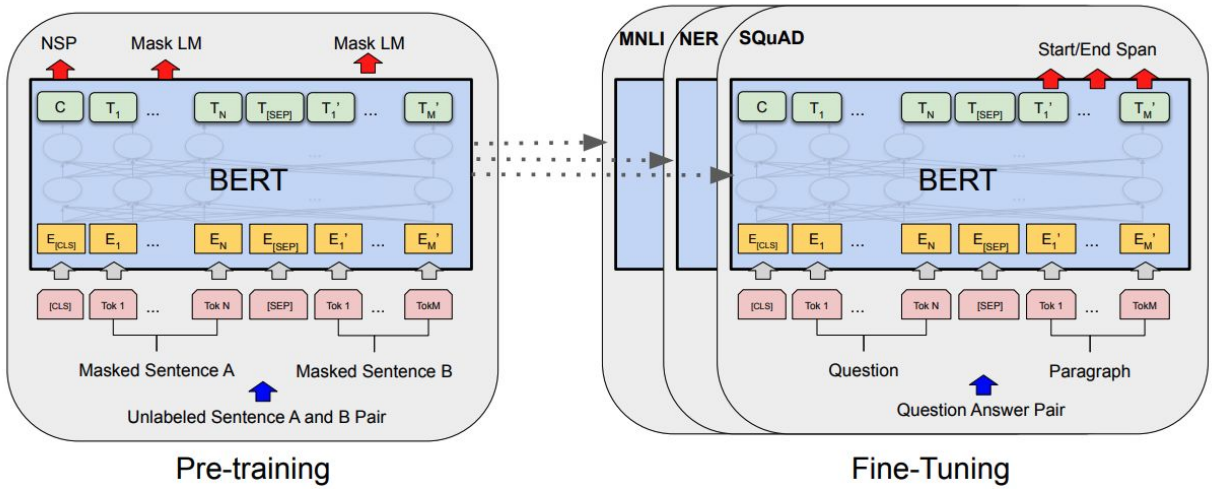
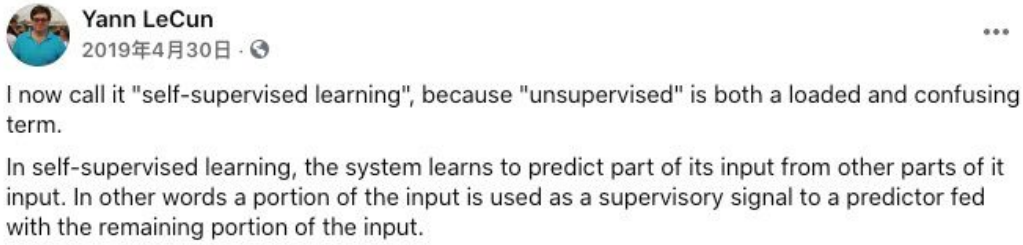


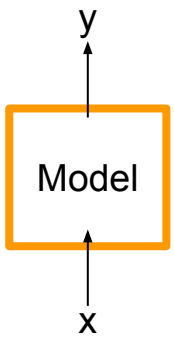
Figure 1: Overall pre-training and fine-tuning procedures for BERT. Apart from output layers, the same architectures are used in both pre-training and fine-tuning. The same pre-trained model parameters are used to initialize models for different down-stream tasks. During fine-tuning, all parameters are fine-tuned. [CLS] is a special symbol added in front of every input example, and [SEP] is a special separator token (e.g. separating questions/answers).

source: https://arxiv.org/pdf/1810.04805.pdf

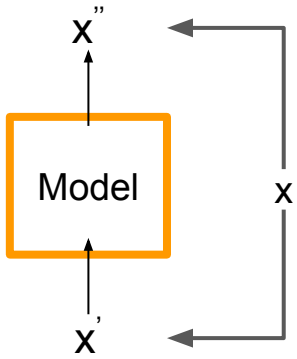
How to Pre-Train

The answer is **self-supervised learning**.





Supervised



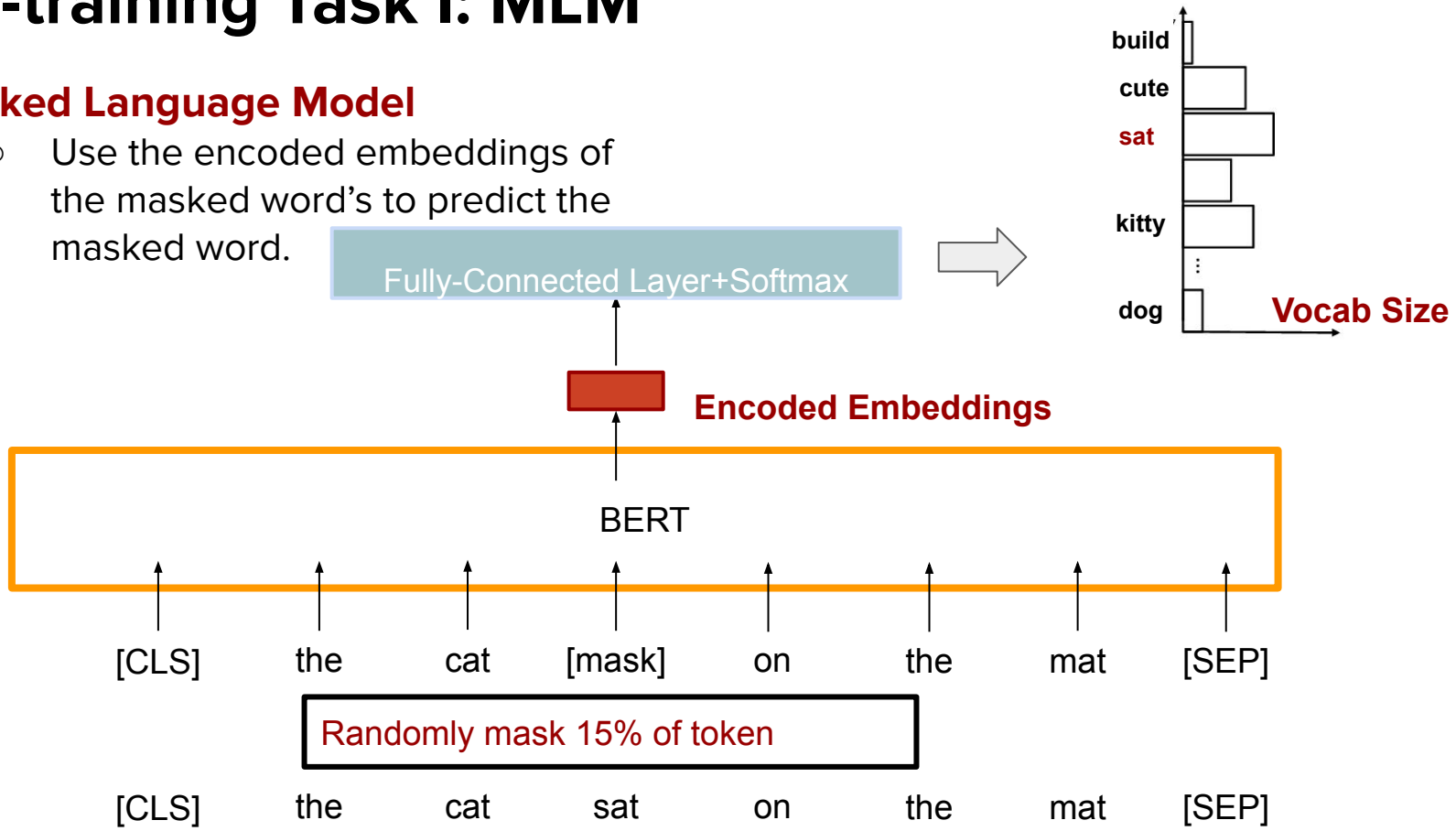
Generated by Rules

Automatically generate some kind of supervisory tasks

Self-Supervised

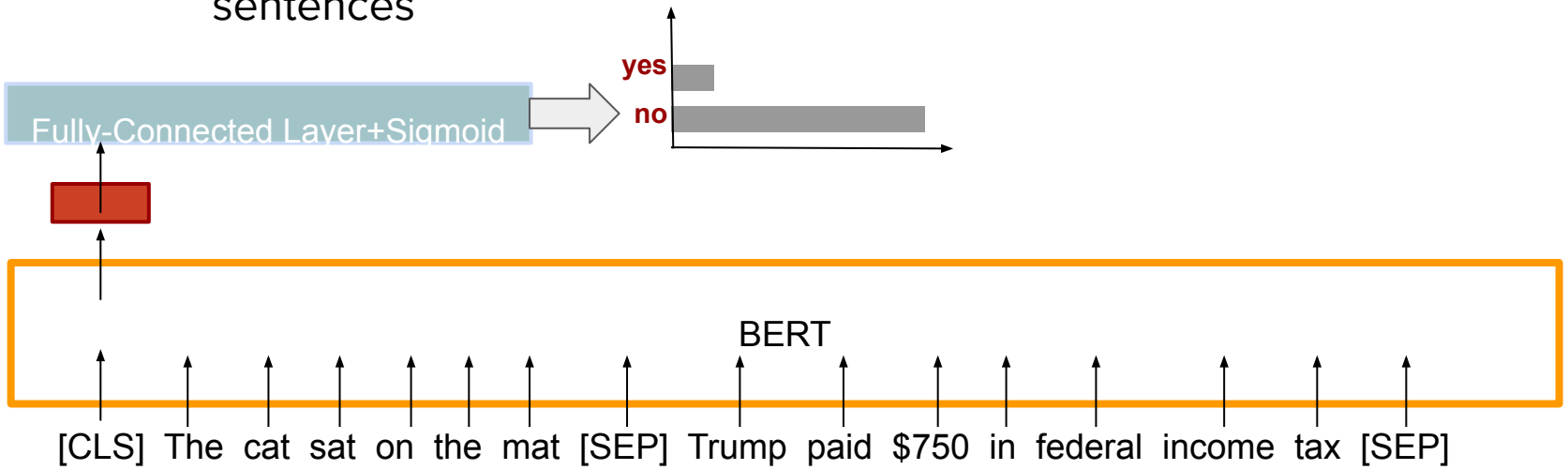
Pre-training Task I: MLM

- **Masked Language Model**
  - Use the encoded embeddings of the masked word's to predict the masked word.

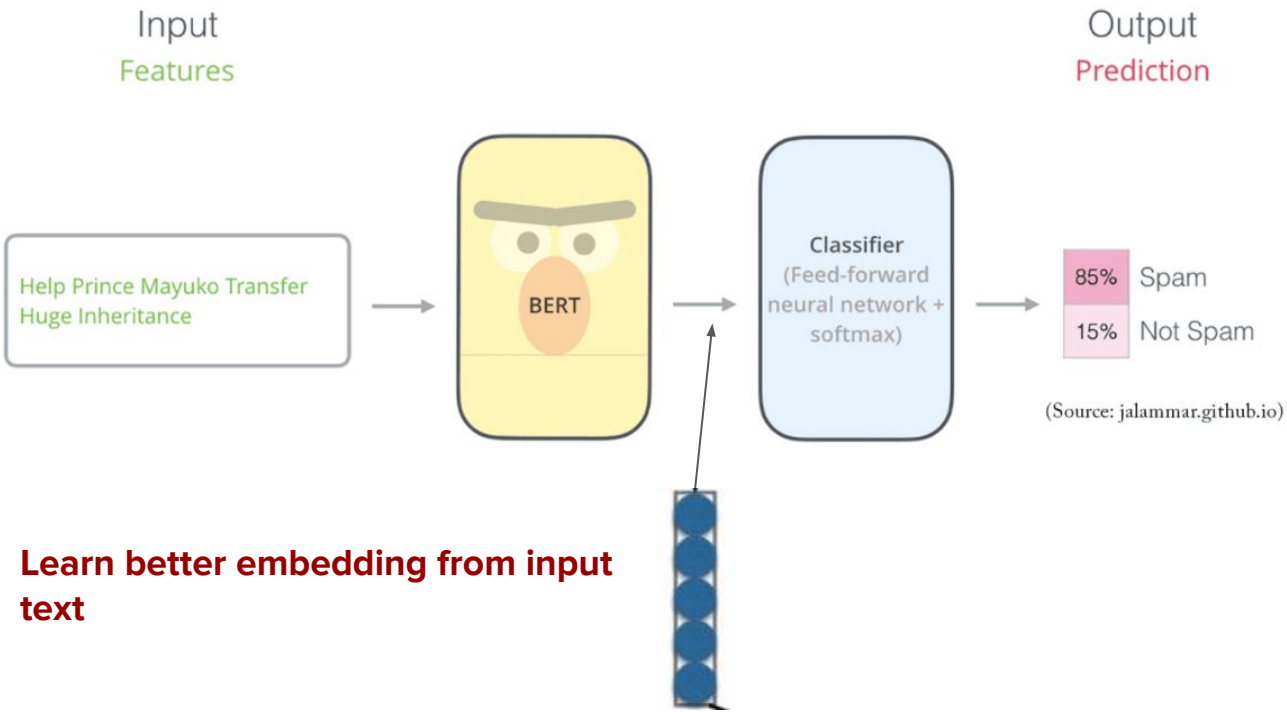


Pre-training Task II: NSP

- **Next sentence prediction**
  - Given two sentences A and B, is B likely to be the sentence followed by A?
  - Make bert good at handling relationships between multiple sentences



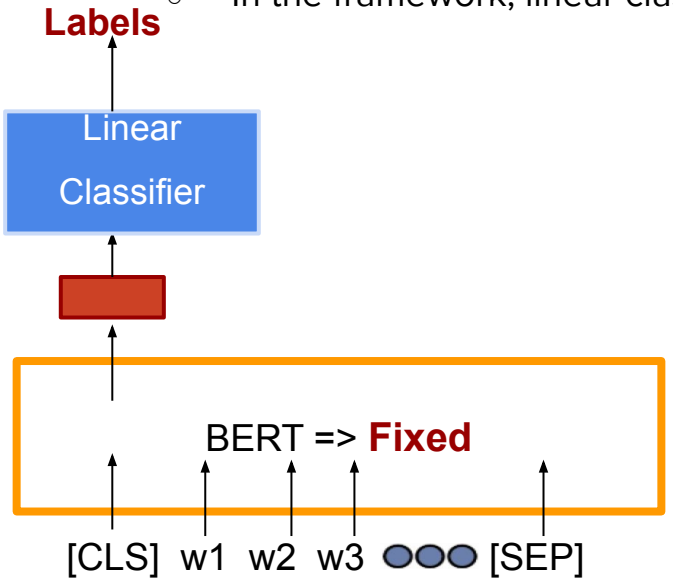
Bert + Fine-tuning

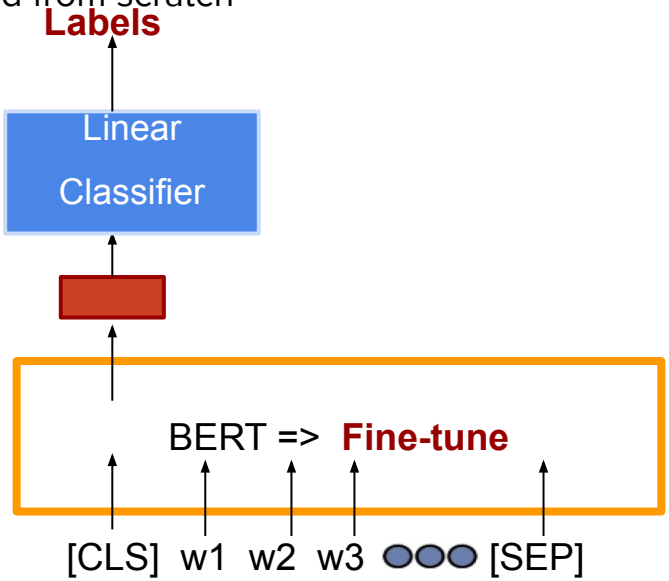


Learn better embedding from input text

How to use BERT - Sequence classification

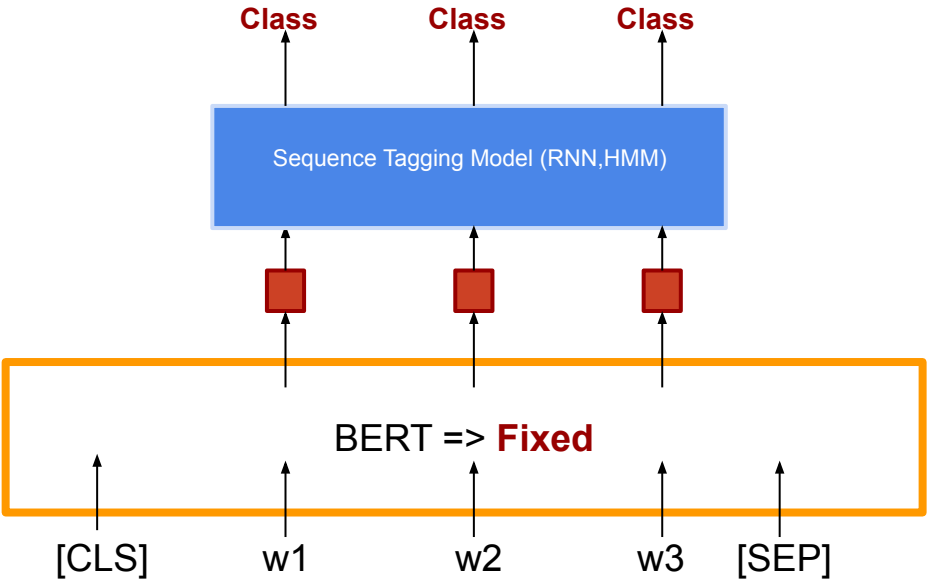
- **Input: Single Sentence Output: Class**
  - Sentiment Analysis
  - Document Classification
  - In the framework, linear classifier should be trained from scratch

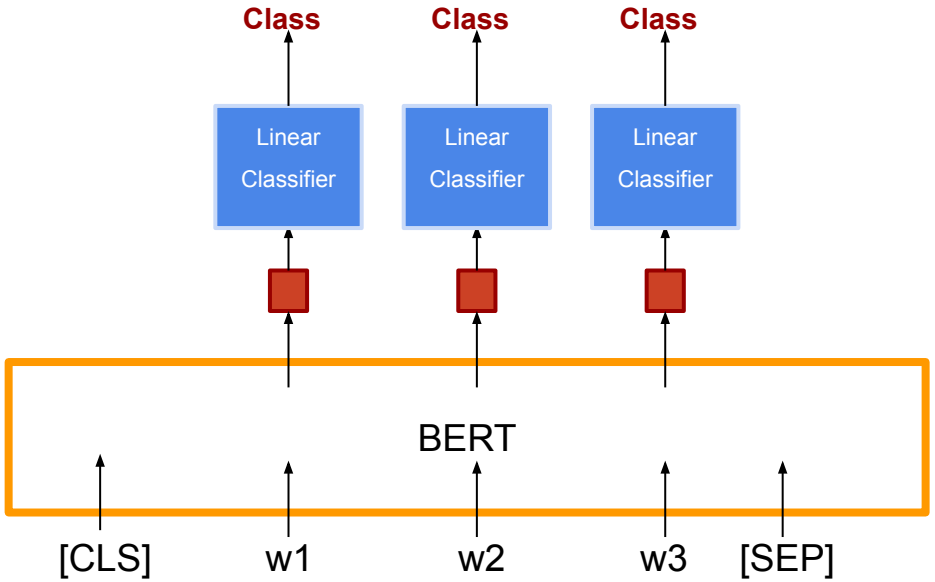




How to use BERT - Sequential Tagging

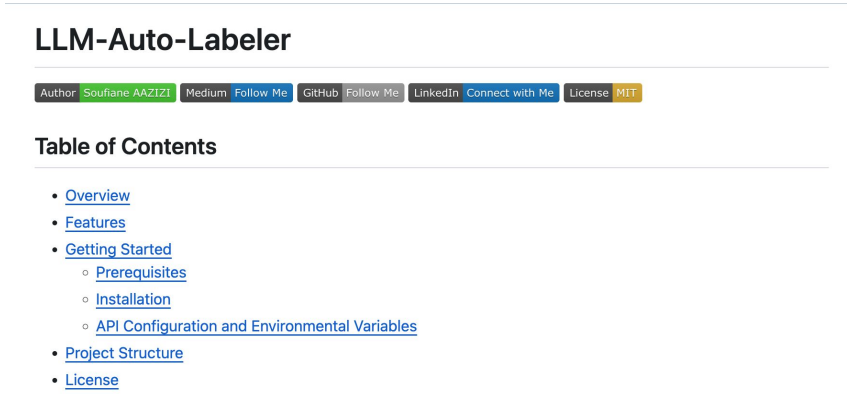
- **Input: Single Sentence Output: Class**
  - NER, POS Tagging





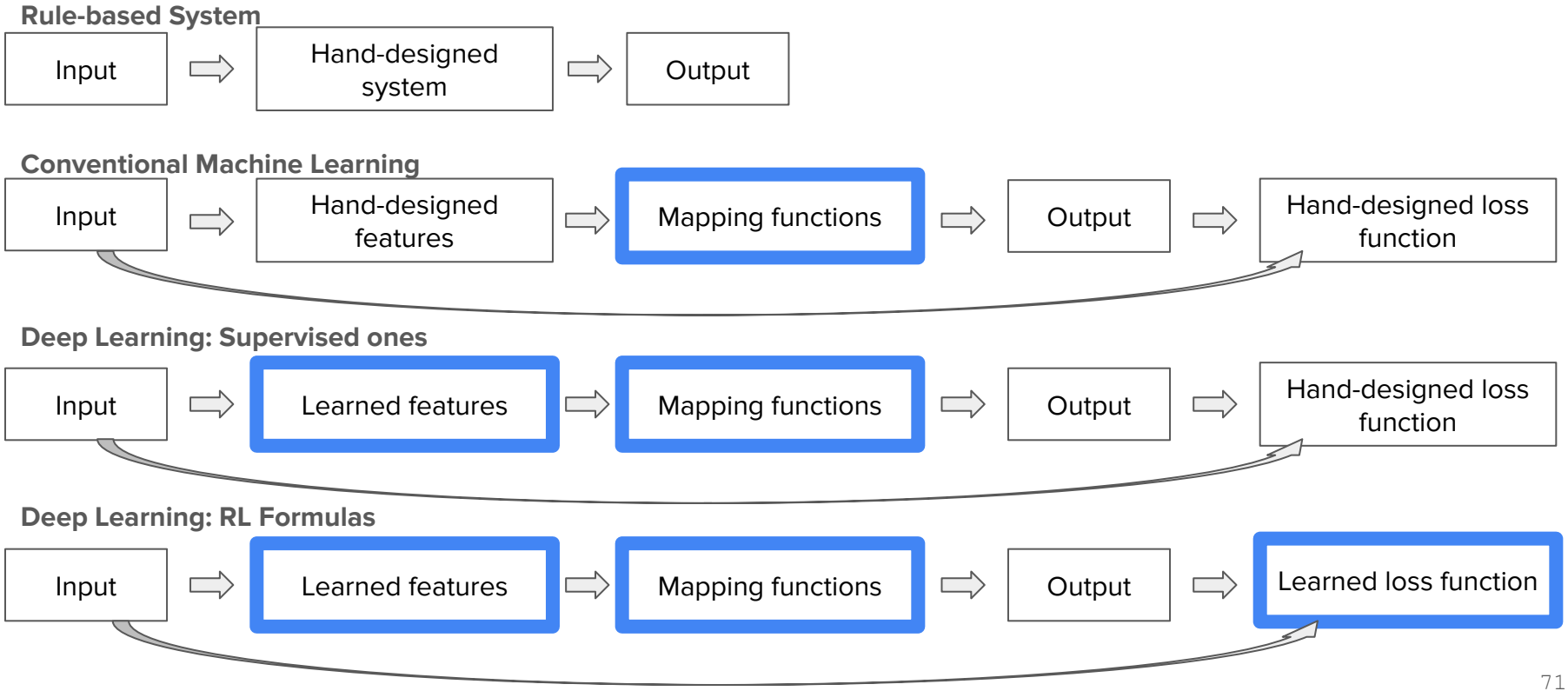
New Paradigm for Labeling

- With LLM, labeling is becoming a human-machine collaboration
- LLMs can reference and follow the labeling instructions just as humans can
  - LLMs can create drafts, for humans to slice together into a final label
  - LLMs can review and critique labels based on the instructions



Source: https://github.com/aazizisoufiane/llm-auto-labeler

RLHF makes loss function learnable



LLM Leaderboard from “Chatbot Arena”

Leaderboard

| Vote | Blog | GitHub | Paper | Dataset | Twitter | Discord |

🏆 This leaderboard is based on the following three benchmarks.

- Chatbot Arena - a crowdsourced, randomized battle platform. We use 130K+ user votes to compute Elo ratings.
- MT-Bench - a set of challenging multi-turn questions. We use GPT-4 to grade the model responses.
- MMLU (5-shot) - a test to measure a model's multitask accuracy on 57 tasks.

💻 Code: The Arena Elo ratings are computed by this notebook. The MT-bench scores (single-answer grading on a scale of 10) are computed by fastchat.llm_judge. The MMLU scores are mostly computed by InstructEval. Higher values are better for all benchmarks. Empty cells mean not available. Last updated: Dec 20, 2023.

Model	⭐ Arena Elo rating	📈 MT-bench (score)	MMLU	License
GPT-4-Turbo	1243	9.32		Proprietary
GPT-4-0314	1192	8.96	86.4	Proprietary
GPT-4-0613	1158	9.18		Proprietary
Claude-1	1149	7.9	77	Proprietary
Claude-2.0	1131	8.06	78.5	Proprietary
Mixtral-8x7b-Instruct-v0.1	1121	8.3	70.6	Apache 2.0
Claude-2.1	1117	8.18		Proprietary
GPT-3.5-Turbo-0613	1117	8.39		Proprietary
Gemini Pro	1111		71.8	Proprietary
Claude-Instant-1	1110	7.85	73.4	Proprietary
Tulu-2-DPO-70B	1110	7.89		AI2 ImpACT Low-risk

Snapshot @ 2024-Jan-01

Next Class: LLM and its production