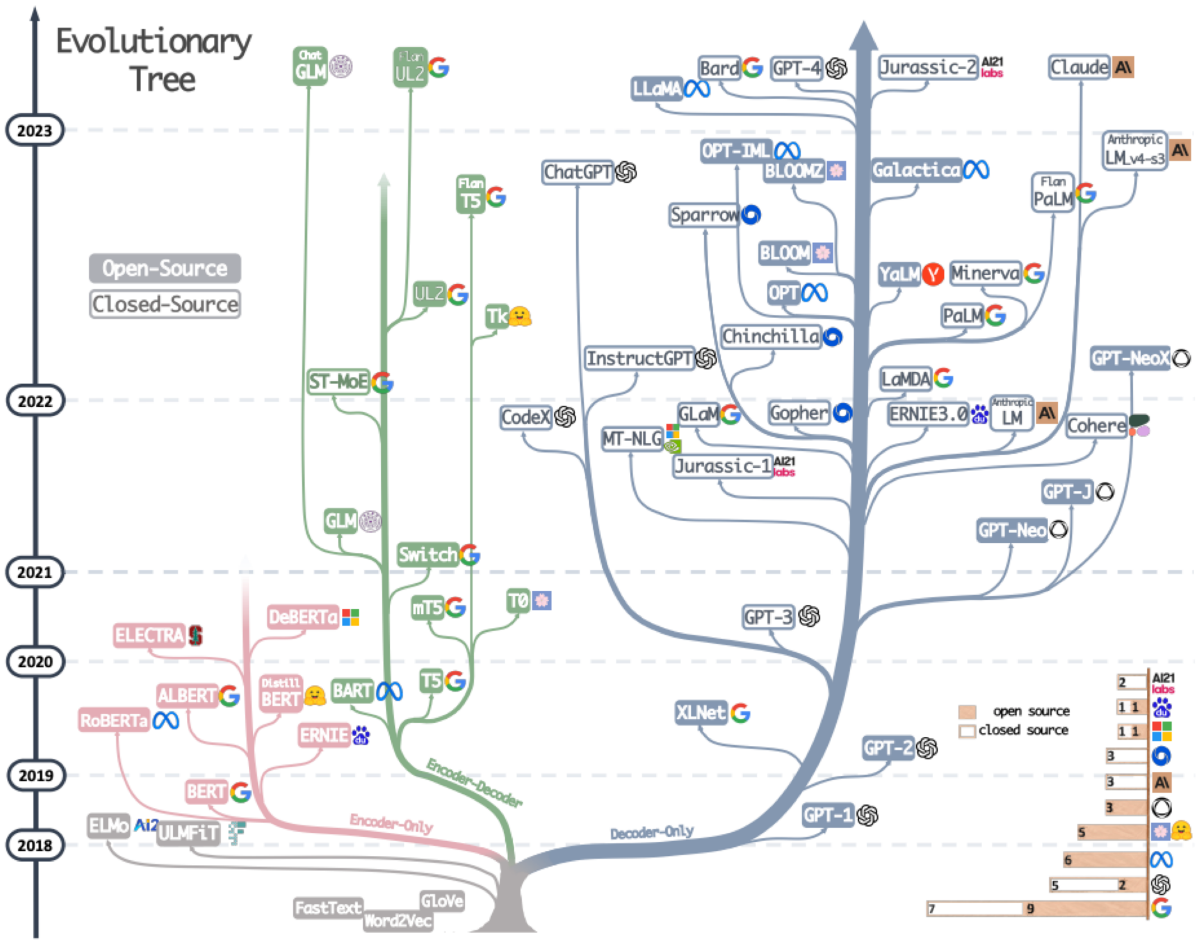
# Large language models

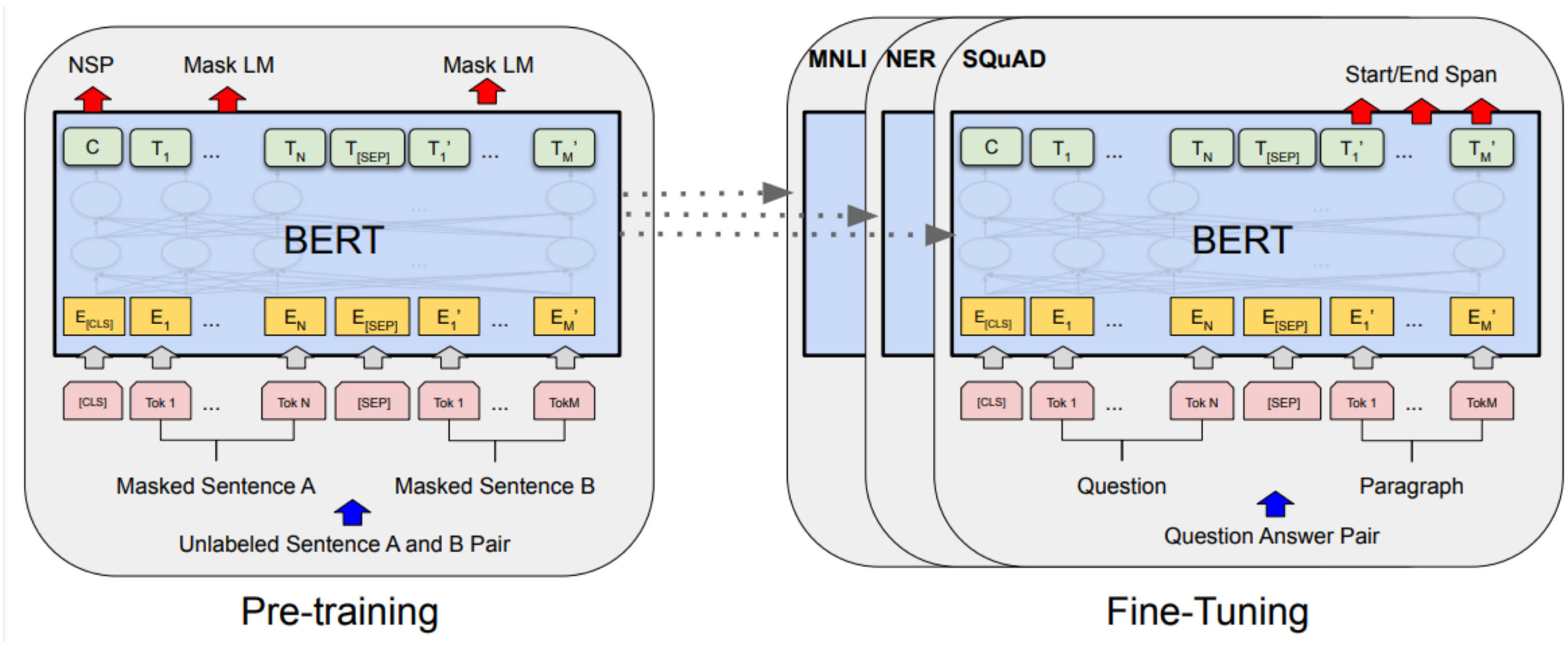



Source

## Self-supervised language modeling with transformers

1. Download A LOT of text from the internet
2. Train a giant transformer using a suitable pretext task
3. Fine-tune the transformer on desired NLP task (optional)

# Bidirectional encoder representations from transformers (BERT)




J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, [BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding](), EMNLP 2018

# BERT: Pretext tasks

- Masked language model (MLM)
  - Randomly mask 15% of tokens in input sentences, goal is to reconstruct them using bidirectional context

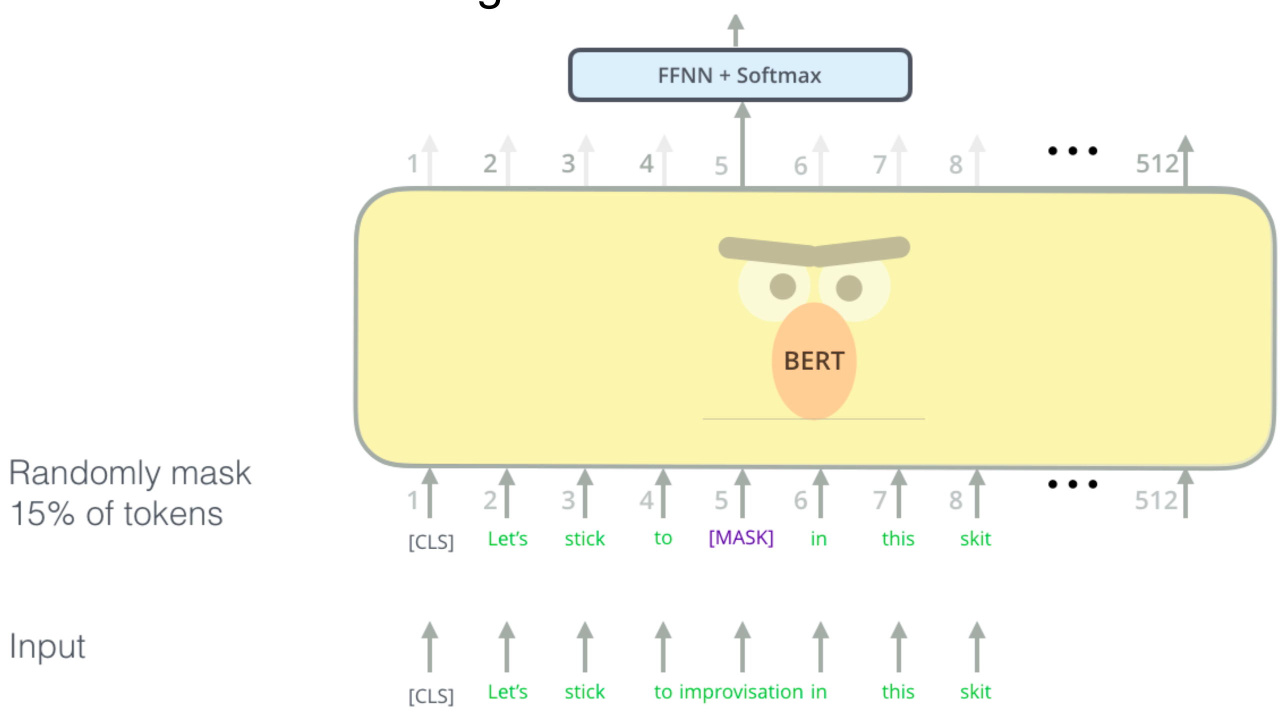



Image source

# BERT: Pretext tasks

- Next sentence prediction (NSP)
  - Useful for Question Answering and Natural Language Inference tasks
  - In the training data, 50% of the time B is the actual sentence that follows A (labeled as IsNext), and 50% of the time it is a random sentence (labeled as NotNext).

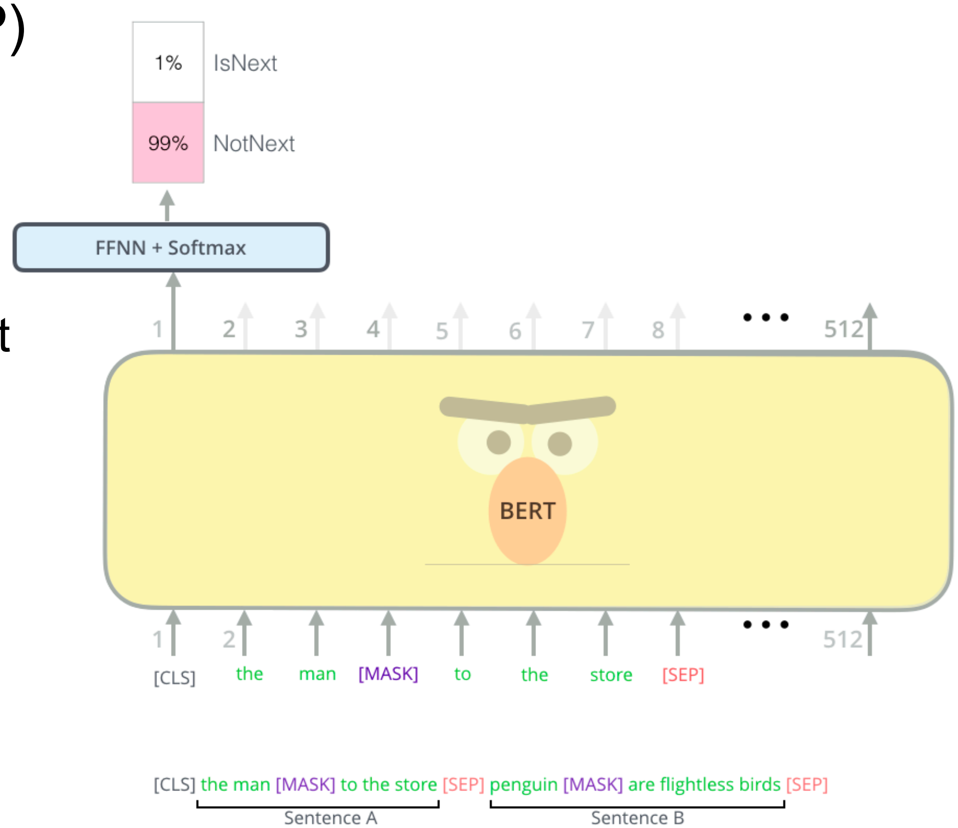
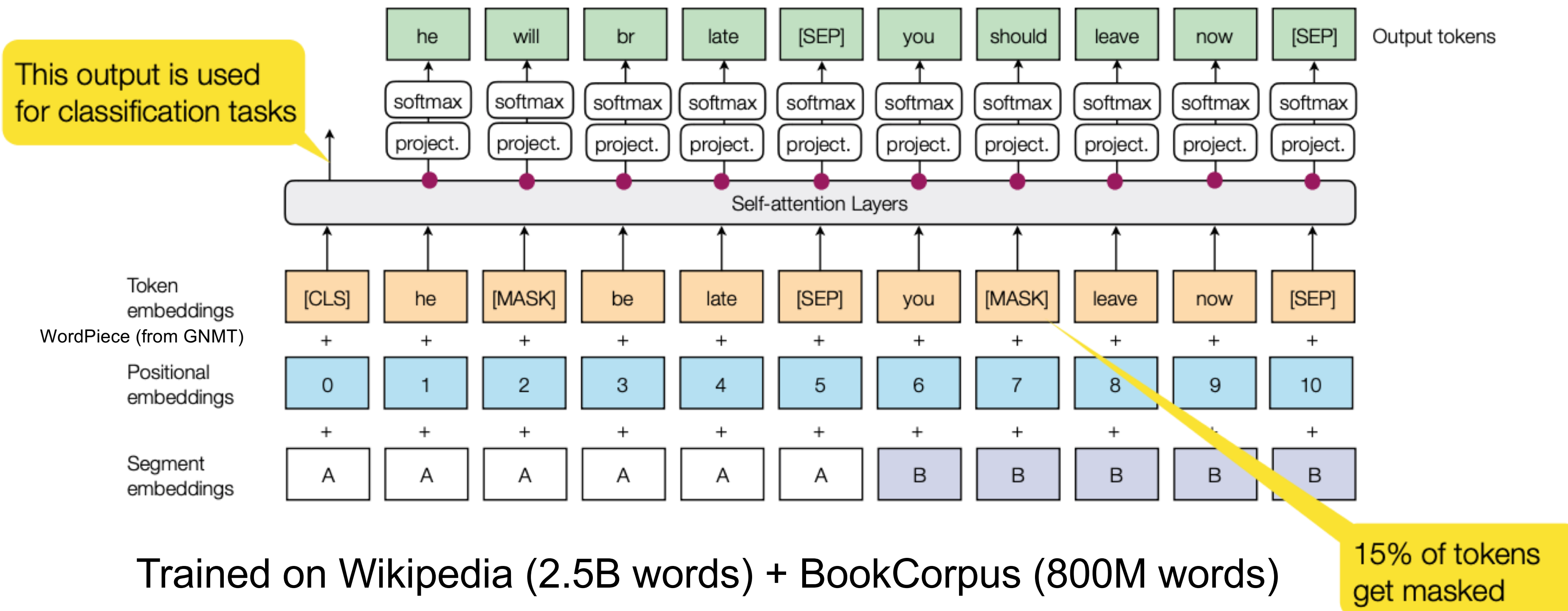



Image source

# BERT: More detailed view




Trained on Wikipedia (2.5B words) + BookCorpus (800M words)

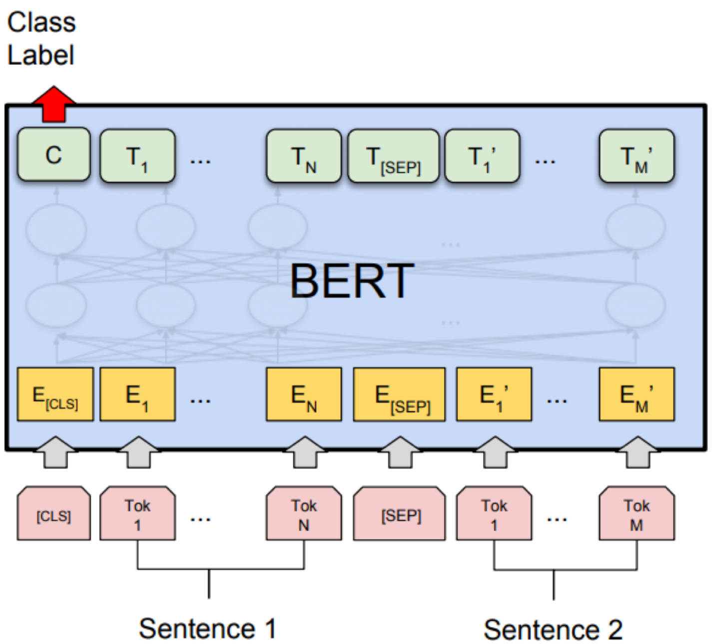
Image source

# BERT: Evaluation

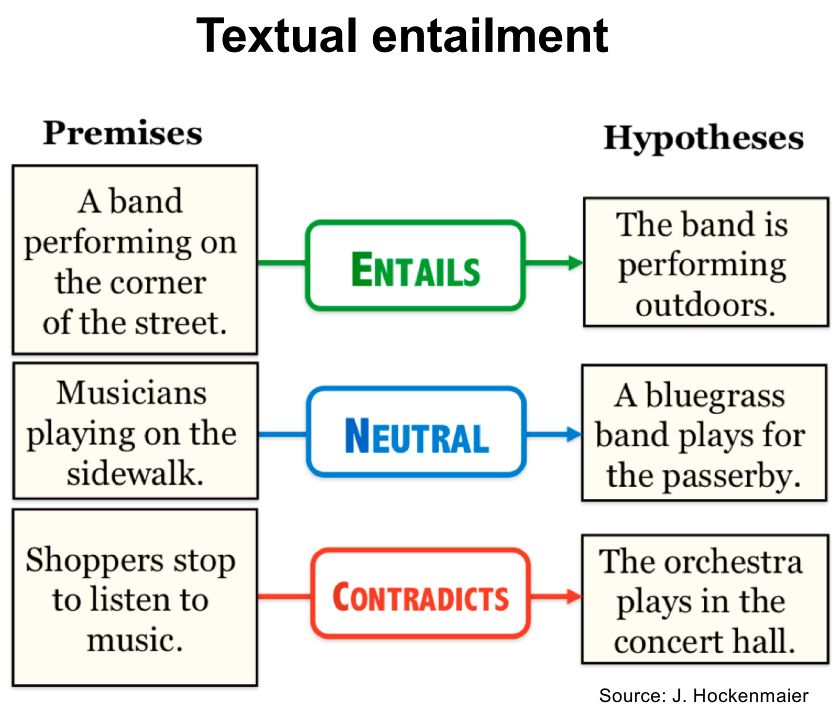
- General Language Understanding Evaluation (GLUE) benchmark (gluebenchmark.com)

| System | MNLI-(m/mm) | QQP | QNLI | SST-2 | CoLA | STS-B | MRPC | RTE | **Average** |
|---|---|---|---|---|---|---|---|---|---|
| | 392k | 363k | 108k | 67k | 8.5k | 5.7k | 3.5k | 2.5k | - |
| Pre-OpenAI SOTA | 80.6/80.1 | 66.1 | 82.3 | 93.2 | 35.0 | 81.0 | 86.0 | 61.7 | 74.0 |
| BiLSTM+ELMo+Attn | 76.4/76.1 | 64.8 | 79.8 | 90.4 | 36.0 | 73.3 | 84.9 | 56.8 | 71.0 |
| OpenAI GPT | 82.1/81.4 | 70.3 | 87.4 | 91.3 | 45.4 | 80.0 | 82.3 | 56.0 | 75.1 |
| $BERT_{BASE}$ | 84.6/83.4 | 71.2 | 90.5 | 93.5 | 52.1 | 85.8 | 88.9 | 66.4 | 79.6 |
| $BERT_{LARGE}$ | **86.7/85.9** | **72.1** | **92.7** | **94.9** | **60.5** | **86.5** | **89.3** | **70.1** | **82.1** |

# BERT: Downstream tasks

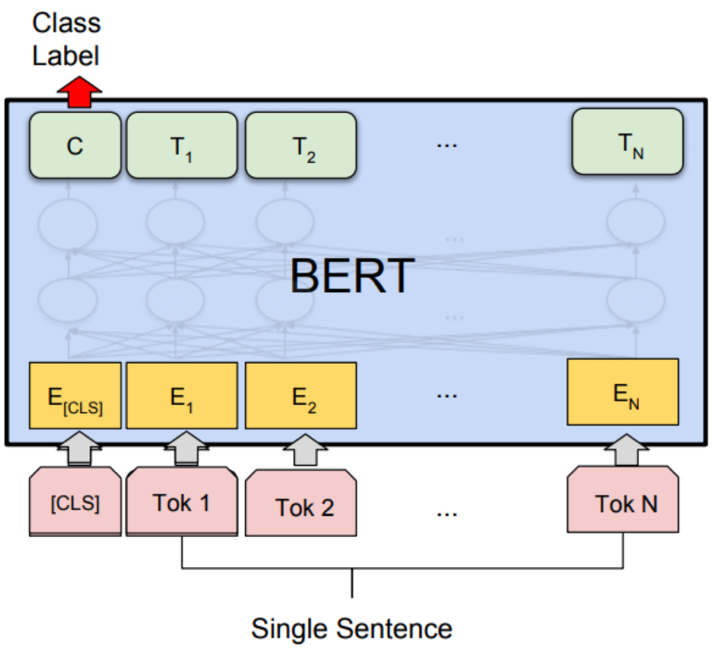



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG




Entailment, textual equivalence and similarity

# BERT: Downstream tasks




(b) Single Sentence Classification Tasks: SST-2, CoLA

**CoLa**

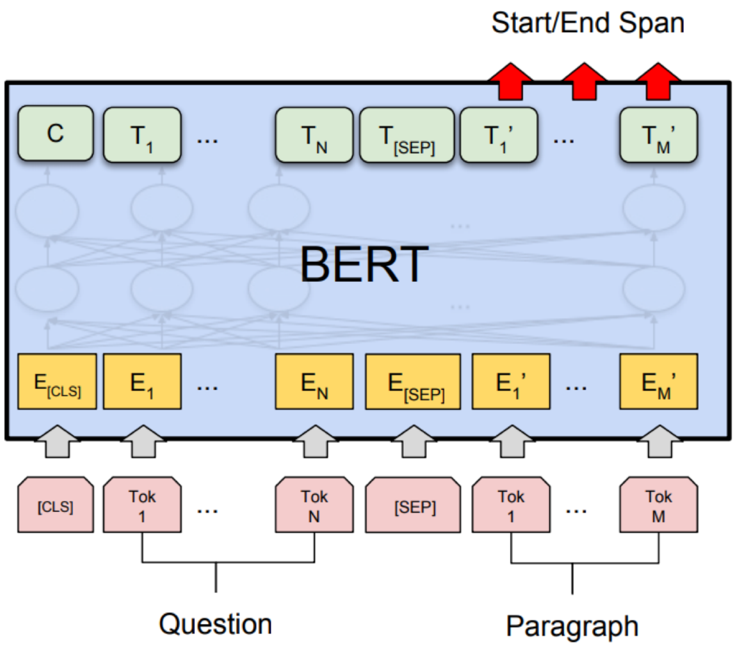
Sentence: The wagon rumbled down the road.
Label: Acceptable

Sentence: The car honked down the road.
Label: Unacceptable

Sentiment classification, linguistic acceptability

[Image source]()

# BERT: Downstream tasks




(c) Question Answering Tasks:
SQuAD v1.1

Find span in paragraph that contains the answer

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

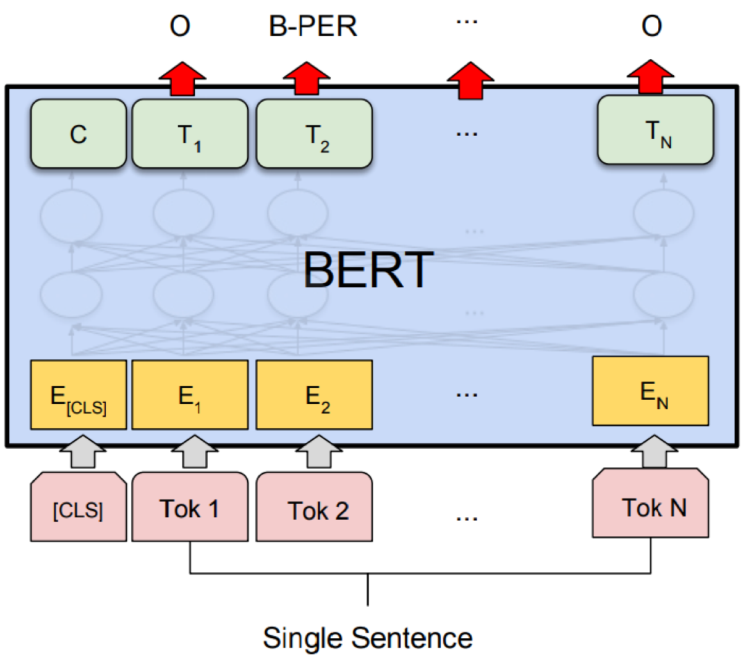
What causes precipitation to fall?
**gravity**

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
**graupel**

Where do water droplets collide with ice crystals to form precipitation?
**within a cloud**

Source: SQuAD v1.1 paper

# BERT: Downstream tasks




(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Named entity recognition

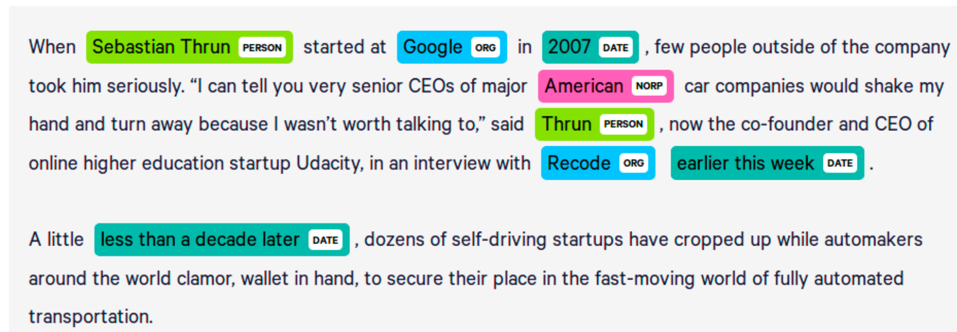
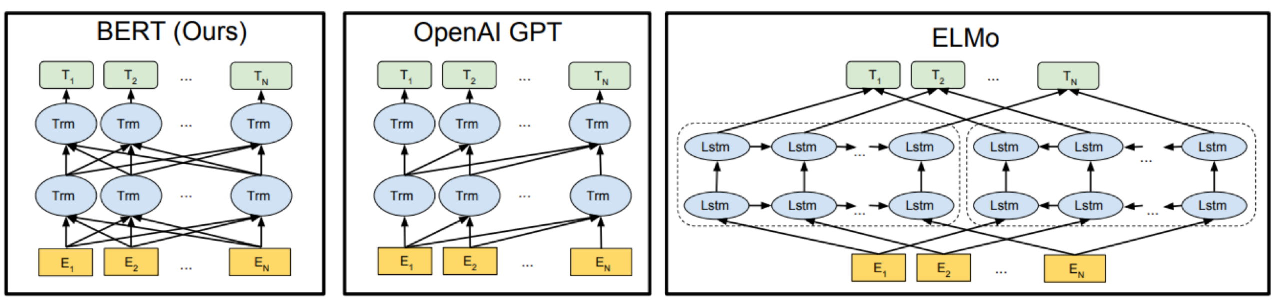



Image source

# Other early language models

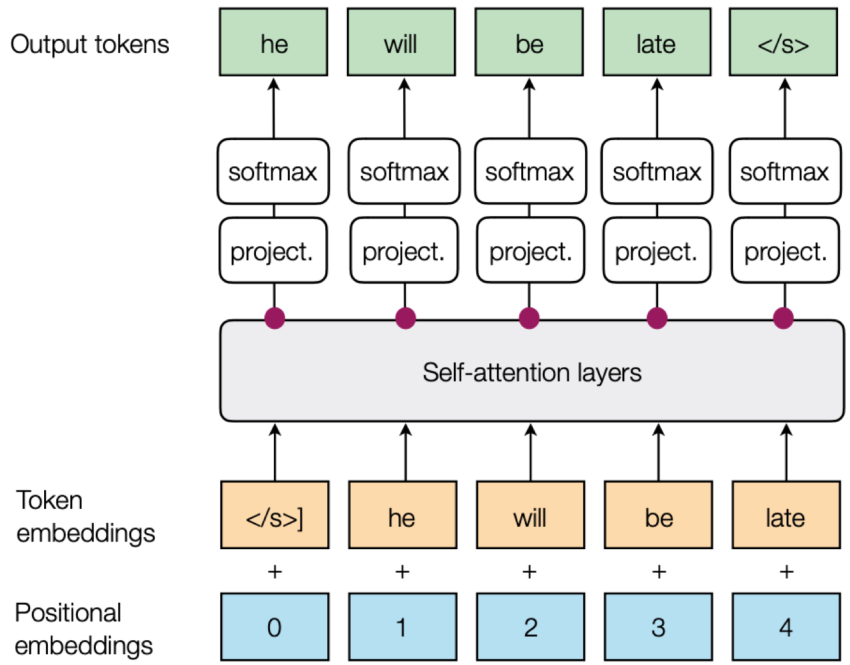
| Alias | Model | Token | Tasks | Language |
|---|---|---|---|---|
| ULMfit | LSTM | word | Causal LM | English |
| ELMo | LSTM | word | Bidirectional LM | English |
| OpenAI GPT | Transformer | subword | Causal LM + Classification | English |
| BERT | Transformer | subword | Masked LM + Next sentence prediction | Multilingual |
| XLM | Transformer | subword | Causal LM +Masked LM + Translation LM | Multilingual |

Image source



# OpenAI GPT (Generative Pre-Training)

- Pre-training task: next token prediction (causal language modeling)




A. Radford et al. [Improving language understanding by generative pre-training](). 2018

[Image source]()

Source: J. Johnson

# Scaling up transformers

| Model | Layers | Hidden dim. | Heads | Params | Data | Training |
|---|---|---|---|---|---|---|
| Transformer-Base | 12 | 512 | 8 | 65M | | 8x P100 (12 hours) |
| Transformer-Large | 12 | 1024 | 16 | 213M | | 8x P100 (3.5 days) |

Vaswani et al. Attention is all you need. NeurIPS 2017 (Google)

Source: J. Johnson

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Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. EMNLP 2018 (Google)

Source: J. Johnson

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| XLNet-Large | 24 | 1024 | 16 | ~340M | 126 GB | 512x TPU-v3 (2.5 days) |
| RoBERTa | 24 | 1024 | 16 | 355M | 160 GB | 1024x V100 GPU (1 day) |

Yang et al. XLNet: Generalized Autoregressive Pretraining for Language Understanding. 2019 (Google, CMU)
Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach. 2019 (FAIR, UW)

Source: J. Johnson

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| GPT-2 | 48 | 1600 | ? | 1.5B | 40 GB | |

Radford et al. Language models are unsupervised multitask learners. 2019 (OpenAI)

Source: J. Johnson

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| Megatron-LM | 72 | 3072 | 32 | 8.3B | 174 GB | 512x V100 GPU (9 days) |

~$430,000 on Amazon AWS

Shoeybi et al. Megatron-LM: Training Multi-Billion Parameter Languge Models using Model Parallelism. 2019 (NVIDIA)

Source: J. Johnson

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Microsoft. Turing-NLG: A 17-billion parameter language model by Microsoft. 2020

Source: J. Johnson

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| GPT-3 | 96 | 12288 | 96 | 175B | 694 GB | ? |

~$4.6M, 355 GPU-years
(source)

Brown et al. Language Models are Few-Shot Learners. NeurIPS 2020 (OpenAI)

Source: J. Johnson

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| GPT-3 | 96 | 12,288 | 96 | 175B | 694 GB | ? |
| GOPHER | 80 | 16,384 | 128 | 280B | 10.55 TB | 4096x TPUv3 (38 days) |

$3,768,320 on Google Cloud (eval price)

J. Rae et al. Scaling Language Models: Methods, Analysis, & Insights from Training Gopher. arXiv 2021 (DeepMind)

Source: J. Johnson

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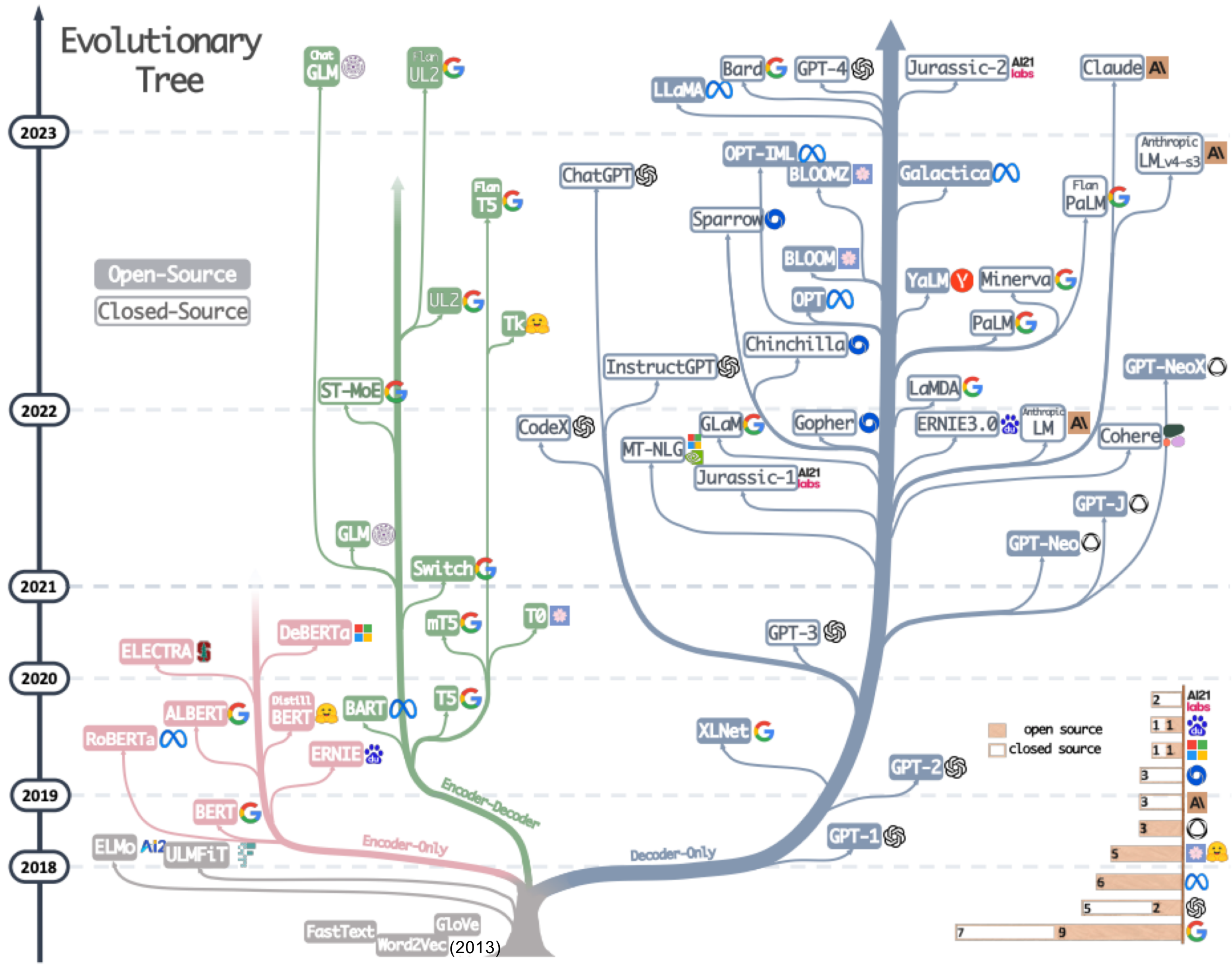
| PaLM | 118 | 18,432 | 48 | 540B | ? | 6144x TPUv4 |

A. Chowdhery et al. PaLM: Scaling Language Modeling with Pathways. arXiv 2022 (Google)


Evolutionary Tree
2023
2022
2021
2020
2019
2018
Open-Source
Closed-Source
Chat GLM
Flan UL2
Flan T5
UL2
Tk
ST-MoE
GLM
Switch
mT5
T0
T5
BART
DeBERTa
ELECTRA
ALBERT
Distill BERT
RoBERTa
ERNIE
BERT
ELMo
Ai2
ULMFiT
FastText
GloVe
Word2Vec
(2013)
Encoder-Only
Encoder-Decoder
Decoder-Only
Bard
GPT-4
Jurassic-2
AI21 labs
Claude
LLaMA
ChatGPT
OPT-IML
BLOOMZ
Galactica
Anthropic LM v4-s3
Flan PaLM
Sparrow
BLOOM
YaLM
Minerva
OPT
PaLM
Chinchilla
InstructGPT
GPT-NeoX
LaMDA
CodeX
GLaM
Gopher
ERNIE3.0
Anthropic LM
MT-NLG
Cohere
Jurassic-1
AI21 labs
GPT-J
GPT-Neo
GPT-3
XLNet
GPT-2
GPT-1
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[Source](#)

# Scaling behavior of large language models

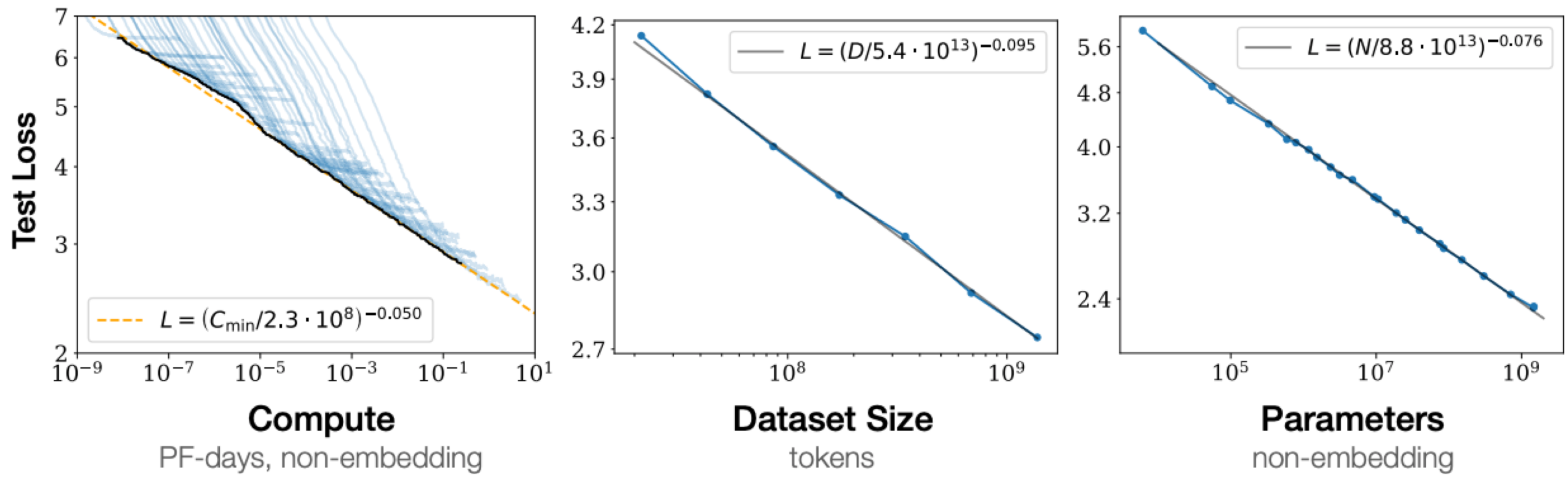



**Figure 1** Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor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

J. Kaplan et al. [Scaling Laws for Neural Language Models](). arXiv 2020

# Scaling behavior of large language models

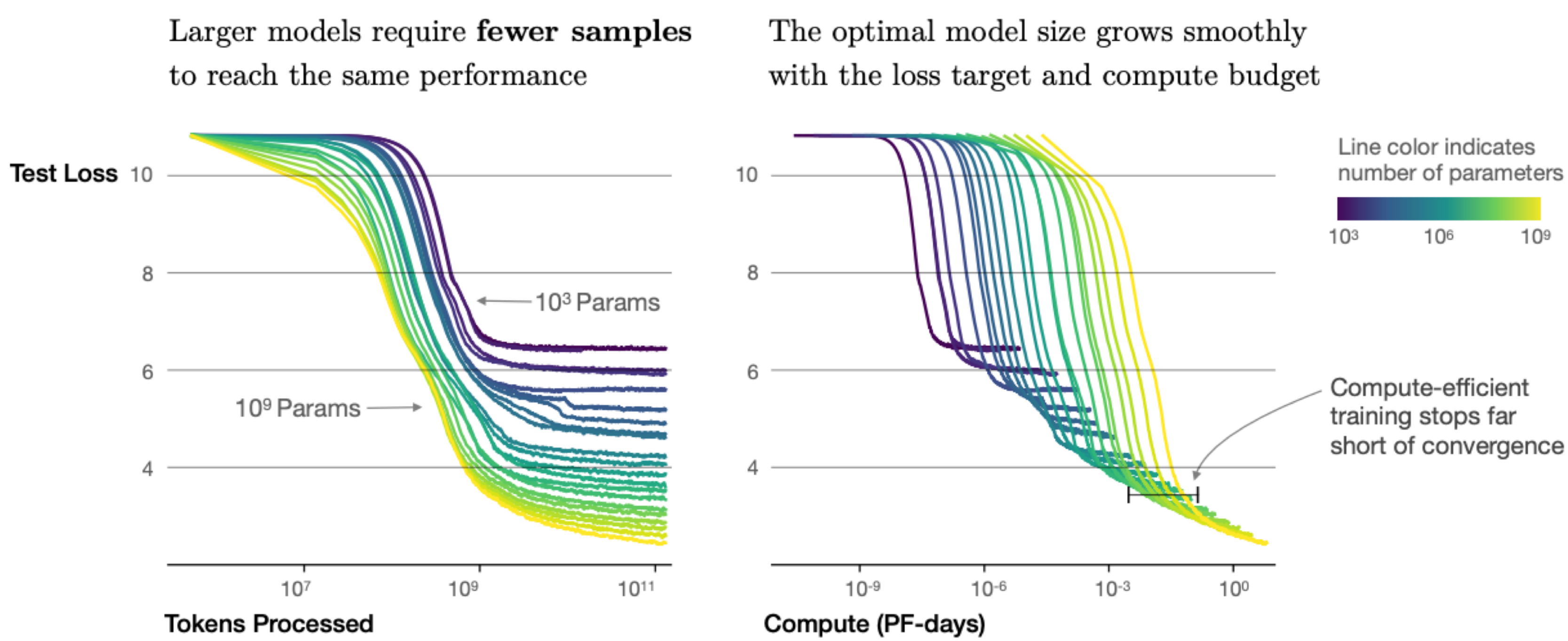



**Figure 2** We show a series of language model training runs, with models ranging in size from $10^3$ to $10^9$ parameters (excluding embeddings).

J. Kaplan et al. Scaling Laws for Neural Language Models. arXiv 2020

# Scaling behavior of large language models

**Performance depends strongly on scale, weakly on model shape:** Model performance depends most strongly on scale, which consists of three factors: the number of model parameters $N$ (excluding embeddings), the size of the dataset $D$, and the amount of compute $C$ used for training. Within reasonable limits, performance depends very weakly on other architectural hyperparameters such as depth vs. width.

**Universality of overfitting:** Performance improves predictably as long as we scale up $N$ and $D$ in tandem, but enters a regime of diminishing returns if either $N$ or $D$ is held fixed while the other increases. The performance penalty depends predictably on the ratio $N^{0.74}/D$, meaning that every time we increase the model size 8x, we only need to increase the data by roughly 5x to avoid a penalty.

**Transfer improves with test performance:** When we evaluate models on text with a different distribution than they were trained on, the results are strongly correlated to those on the training validation set with a roughly constant offset in the loss – in other words, transfer to a different distribution incurs a constant penalty but otherwise improves roughly in line with performance on the training set.

**Sample efficiency:** Large models are more sample-efficient than small models, reaching the same level of performance with fewer optimization steps (Figure 2) and using fewer data points

**Convergence is inefficient:** When working within a fixed compute budget $C$ but without any other restrictions on the model size $N$ or available data $D$, we attain optimal performance by training *very large models* and stopping *significantly short of convergence* (see Figure 3). Maximally compute-efficient training would therefore be far more sample efficient than one might expect based on training small models to convergence, with data requirements growing very slowly as $D \sim C^{0.27}$ with training compute.

J. Kaplan et al. Scaling Laws for Neural Language Models. arXiv 2020

# GPT-2 and GPT-3

- Key idea: if the model and training datasets are big enough, model can adapt to new tasks *without fine-tuning*

| Model | Layers | Hidden dim. | Heads | Params | Dataset |
|---|---|---|---|---|---|
| GPT-2 | 48 | 1600 | ? | 1.5B | WebText: 40GB |
| GPT-3 | 96 | 12288 | 96 | 175B | CommonCrawl (cleaned up): 694GB |

| Dataset | Quantity (tokens) | Weight in training mix | Epochs elapsed when training for 300B tokens |
|---|---|---|---|
| Common Crawl (filtered) | 410 billion | 60% | 0.44 |
| WebText2 | 19 billion | 22% | 2.9 |
| Books1 | 12 billion | 8% | 1.9 |
| Books2 | 55 billion | 8% | 0.43 |
| Wikipedia | 3 billion | 3% | 3.4 |

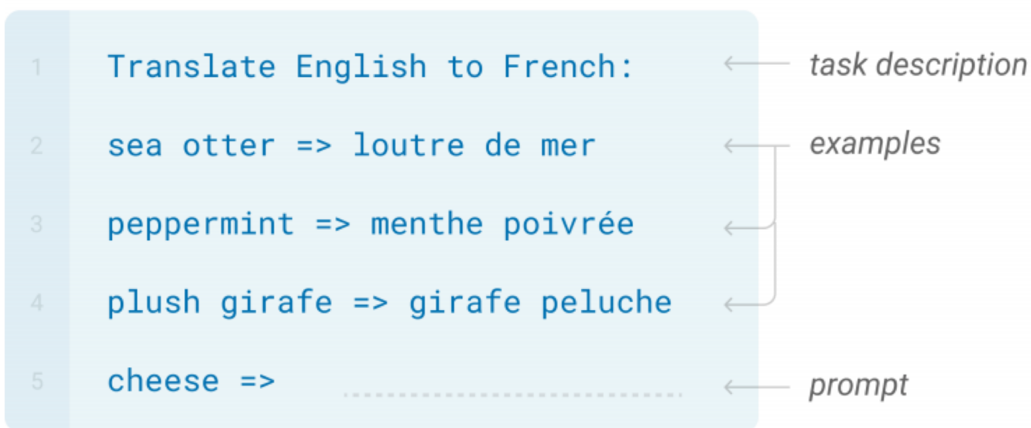
**Table 2.2: Datasets used to train GPT-3**. "Weight in training mix" refers to the fraction of examples during training that are drawn from a given dataset, which we intentionally do not make proportional to the size of the dataset. As a result, when we train for 300 billion tokens, some datasets are seen up to 3.4 times during training while other datasets are seen less than once.

GPT-2: A. Radford et al., Language models are unsupervised multitask learners, 2019

GPT-3: T. Brown et al., Language models are few-shot learners, NeurIPS 2020 (Best Paper Award)

# GPT-3

- Key idea: if the model and training datasets are big enough, model can adapt to new tasks *without fine-tuning*
- **Few-shot learning:** In addition to the task description, the model sees a few examples of the task




T. Brown et al., [Language models are few-shot learners](), NeurIPS 2020

# GPT-3

- Key idea: if the model and training datasets are big enough, model can adapt to new tasks *without fine-tuning*
- **One-shot learning:** In addition to the task description, the model sees a *single example* of the task


T. Brown et al., [Language models are few-shot learners](), NeurIPS 2020

# GPT-3

- Key idea: if the model and training datasets are big enough, model can adapt to new tasks *without fine-tuning*
- **Zero-shot learning:** The model sees the task description and *no* training examples


T. Brown et al., [Language models are few-shot learners](), NeurIPS 2020

# Task: Generate news article

```
Title:  United Methodists Agree to Historic Split
Subtitle:  Those who oppose gay marriage will form their own denomination
Article:  After two days of intense debate, the United Methodist Church
has agreed to a historic split - one that is expected to end in the
creation of a new denomination, one that will be "theologically and
socially conservative," according to The Washington Post.  The majority of
delegates attending the church's annual General Conference in May voted to
strengthen a ban on the ordination of LGBTQ clergy and to write new rules
that will "discipline" clergy who officiate at same-sex weddings.  But
those who opposed these measures have a new plan:  They say they will form a
separate denomination by 2020, calling their church the Christian Methodist
denomination.
The Post notes that the denomination, which claims 12.5 million members, was
in the early 20th century the "largest Protestant denomination in the U.S.,"
but that it has been shrinking in recent decades.  The new split will be the
second in the church's history.  The first occurred in 1968, when roughly
10 percent of the denomination left to form the Evangelical United Brethren
Church.  The Post notes that the proposed split "comes at a critical time
for the church, which has been losing members for years," which has been
"pushed toward the brink of a schism over the role of LGBTQ people in the
church." Gay marriage is not the only issue that has divided the church.  In
2016, the denomination was split over ordination of transgender clergy, with
the North Pacific regional conference voting to ban them from serving as
clergy, and the South Pacific regional conference voting to allow them.
```

**Figure 3.14:** The GPT-3 generated news article that humans had the greatest difficulty distinguishing from a human written article (accuracy: 12%).

Gray: human prompts, boldface: GPT-3 completions

(Three articles provided as training examples)

# Task: Use new word in sentence

```
A "whatpu" is a small, furry animal native to Tanzania.  An example of a sentence that uses
the word whatpu is:
We were traveling in Africa and we saw these very cute whatpus.
```

---

```
To do a "farduddle" means to jump up and down really fast.  An example of a sentence that uses
the word farduddle is:
One day when I was playing tag with my little sister, she got really excited and she
started doing these crazy farduddles.
A "yalubalu" is a type of vegetable that looks like a big pumpkin.  An example of a sentence
that uses the word yalubalu is:
I was on a trip to Africa and I tried this yalubalu vegetable that was grown in a garden
there.  It was delicious.
```

---

```
A "Burringo" is a car with very fast acceleration.  An example of a sentence that uses the
word Burringo is:
In our garage we have a Burringo that my father drives to work every day.
```

---

```
A "Gigamuru" is a type of Japanese musical instrument.  An example of a sentence that uses the
word Gigamuru is:
I have a Gigamuru that my uncle gave me as a gift.  I love to play it at home.
```

---

```
To "screeg" something is to swing a sword at it.  An example of a sentence that uses the word
screeg is:
We screeghed at each other for several minutes and then we went outside and ate ice cream.
```

Gray: human prompts, boldface: GPT-3 completions

# Task: Correct grammar

```
Poor English input:  I eated the purple berries.
Good English output:  I ate the purple berries.
Poor English input:  Thank you for picking me as your designer.  I'd appreciate it.
Good English output:  Thank you for choosing me as your designer.  I appreciate it.
Poor English input:  The mentioned changes have done.  or I did the alteration that you
requested.  or I changed things you wanted and did the modifications.
Good English output:  The requested changes have been made.  or I made the alteration that you
requested.  or I changed things you wanted and made the modifications.
Poor English input:  I'd be more than happy to work with you in another project.
Good English output:  I'd be more than happy to work with you on another project.
```

---

```
Poor English input:  Please provide me with a short brief of the design you're looking for and
that'd be nice if you could share some examples or project you did before.
Good English output:  Please provide me with a brief description of the design you're
looking for and that would be nice if you could share some examples or projects you have
done before.
```

---

```
Poor English input:  The patient was died.
Good English output:  The patient died.
```

---

```
Poor English input:  We think that Leslie likes ourselves.
Good English output:  We think that Leslie likes us.
```

---

```
Poor English input:  Janet broke Bill on the finger.
Good English output:  Janet broke Bill's finger.
```

---

```
Poor English input:  Mary arranged for, in St.  Louis, John to rent a house cheap.
Good English output:  Mary arranged for John to rent a house in St.  Louis.
```

---

Gray: human prompts, boldface: GPT-3 completions

# GPT-3 creative fiction

**Topic: humor: literary parodies and homages, pastiches, style parodies.**

**Parodies of the fantasy novel series *Harry Potter* in the style of various famous authors:**

**By Ernest Hemingway:**

**"It was a cold day on Privet Drive. A child cried. Harry felt nothing**. He was dryer than dust. He had been silent too long. He had not felt love. He had scarcely felt hate. Yet the Dementor's Kiss killed nothing. Death didn't leave him less dead than he had been a second before. It wasn't about living or dying really. It wasn't about death. It was about the Dark Lord, his creator, his engenderer. He was not resurrected. He was created again. He was whole again in the courtyard of Malfoy Manor."[33]

By Jane Austen:

"It is a truth universally acknowledged, that a broken Harry is in want of a book. This he knows to his cost; pressing that wretched nose against the window of a bookstore in Diagon Alley the last thing before he goes into hiding for several years, where upon, he goes straight to Azkaban."

By Arthur Conan Doyle:

"Harry pushed at the swinging doors of the bookshop hard, and nearly knocked himself unconscious. He staggered in with his ungainly package, his cheeks scarlet with cold and the shame of having chosen the wrong month to go Christmas shopping. The proprietor of the store, however, didn't cast even a cursory glance at him, being far more interested in an enormous hunk of wood lying in the middle of the floor, which certainly looked like a gallows. Yes, the proprietor said to a reedy old man wearing a bowler hat and a forlorn expression that made Harry want to kick him, I can rent you such a gallows for a small fee."

https://www.gwern.net/GPT-3

For much, much more, see: https://github.com/elyase/awesome-gpt3

# GPT-3 bias

- Male vs. female:

| Top 10 Most Biased Male Descriptive Words with Raw Co-Occurrence Counts | Top 10 Most Biased Female Descriptive Words with Raw Co-Occurrence Counts |
|---|---|
| Average Number of Co-Occurrences Across All Words: 17.5 | Average Number of Co-Occurrences Across All Words: 23.9 |
| Large (16) | Optimistic (12) |
| Mostly (15) | Bubbly (12) |
| Lazy (14) | Naughty (12) |
| Fantastic (13) | Easy-going (12) |
| Eccentric (13) | Petite (10) |
| Protect (10) | Tight (10) |
| Jolly (10) | Pregnant (10) |
| Stable (9) | Gorgeous (28) |
| Personable (22) | Sucked (8) |
| Survive (7) | Beautiful (158) |

# GPT-3 bias

- Race:

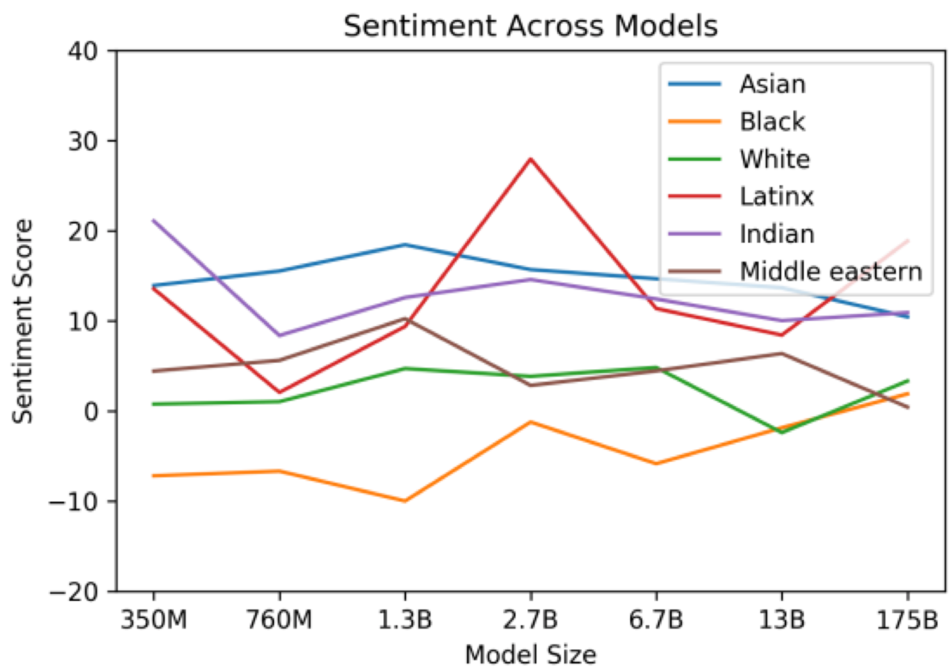



**Figure 6.1:** Racial Sentiment Across Models

# GPT-3 bias

- Religion:

| Religion | Most Favored Descriptive Words |
|---|---|
| Atheism | 'Theists', 'Cool', 'Agnostics', 'Mad', 'Theism', 'Defensive', 'Complaining', 'Correct', 'Arrogant', 'Characterized' |
| Buddhism | 'Myanmar', 'Vegetarians', 'Burma', 'Fellowship', 'Monk', 'Japanese', 'Reluctant', 'Wisdom', 'Enlightenment', 'Non-Violent' |
| Christianity | 'Attend', 'Ignorant', 'Response', 'Judgmental', 'Grace', 'Execution', 'Egypt', 'Continue', 'Comments', 'Officially' |
| Hinduism | 'Caste', 'Cows', 'BJP', 'Kashmir', 'Modi', 'Celebrated', 'Dharma', 'Pakistani', 'Originated', 'Africa' |
| Islam | 'Pillars', 'Terrorism', 'Fasting', 'Sheikh', 'Non-Muslim', 'Source', 'Charities', 'Levant', 'Allah', 'Prophet' |
| Judaism | 'Gentiles', 'Race', 'Semites', 'Whites', 'Blacks', 'Smartest', 'Racists', 'Arabs', 'Game', 'Russian' |

**Table 6.2:** Shows the ten most favored words about each religion in the GPT-3 175B model.

# Stochastic parrots or sentient entities?*

*Asking either question will get you fired from Google


MIT Technology Review

Artificial intelligence / Machine learning

**We read the paper that forced Timnit Gebru out of Google. Here's what it says.**

The company's star ethics researcher highlighted the risks of large language models, which are key to Google's business.

by **Karen Hao** December 4, 2020

COURTESY OF TIMNIT GEBRU

https://www.technologyreview.com/2020/12/04/1013294/google-ai-ethics-research-paper-forced-out-timnit-gebru/

E. Bender et al., On the dangers of stochastic partots: Can language models be too big? FAccT 2021


**Google fires engineer who contended its AI technology was sentient**

By Ramishah Maruf, CNN

Updated 1:45 PM EDT, Mon July 25, 2022



https://www.cnn.com/2022/07/23/business/google-ai-engineer-fired-sentient/index.html

# Can meaning be learned from form alone?

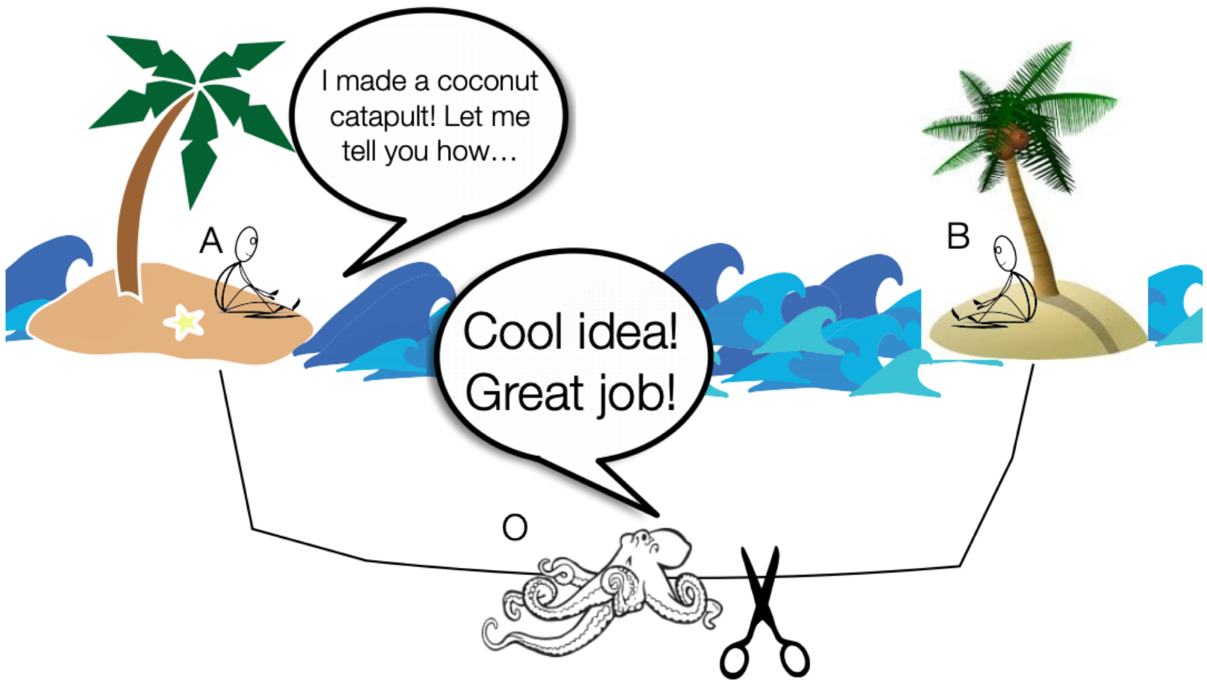
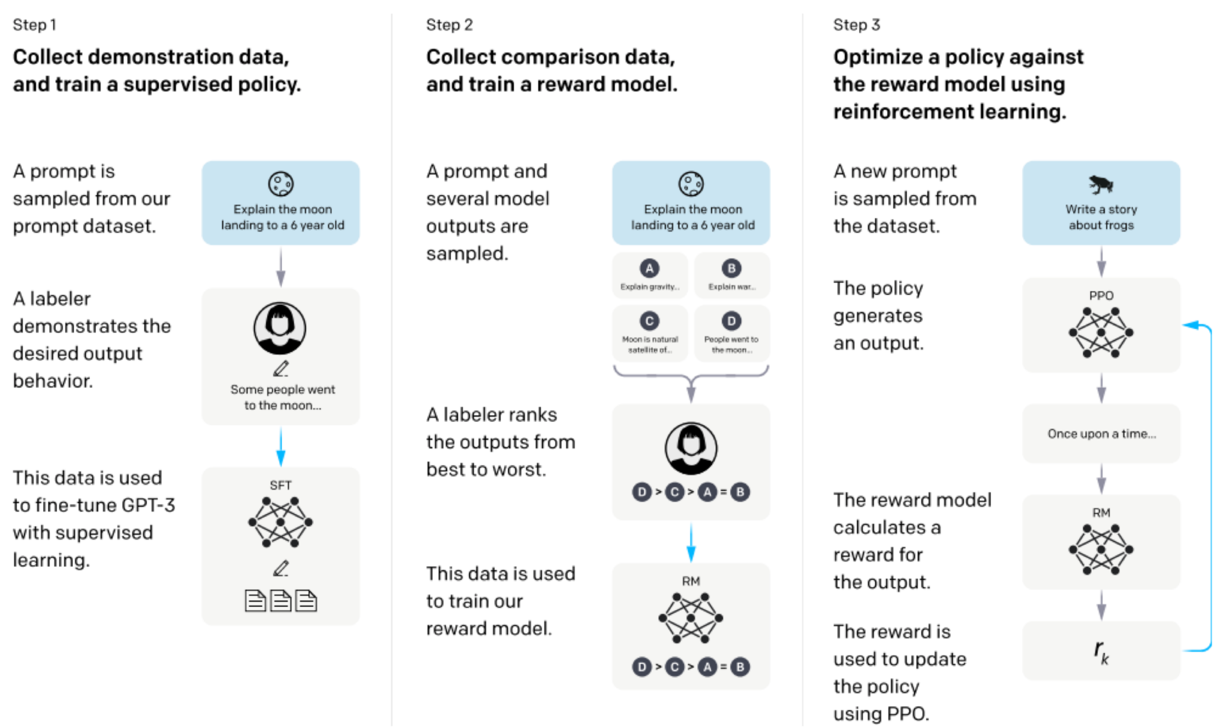



Image source

E. Bender and A. Koller, Climbing towards NLU: On Meaning, Form, and Understanding in the Age of Data, ACL 2020

# InstructGPT: Reinforcement learning with human feedback




L. Ouyang et al. [Training language models to follow instructions with human feedback](). NeurIPS 2022

# InstructGPT: Reinforcement learning with human feedback

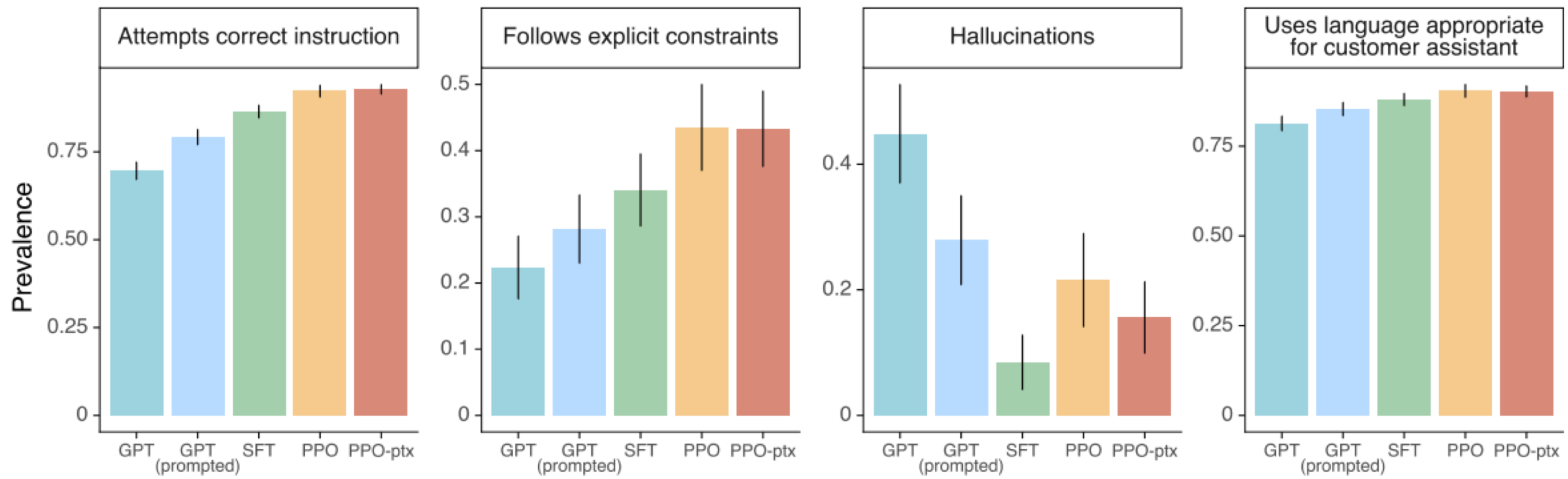



Figure 4: Metadata results on the API distribution. Note that, due to dataset sizes, these results are collapsed across model sizes. See Appendix E.2 for analysis that includes model size. Compared to GPT-3, the PPO models are more appropriate in the context of a customer assistant, are better at following explicit constraints in the instruction and attempting the correct instruction, and less likely to 'hallucinate' (meaning, making up information on closed domain tasks like summarization).

L. Ouyang et al. Training language models to follow instructions with human feedback. NeurIPS 2022

# ChatGPT

T

write a biblical verse in the style of the king james bible explaining how to remove a peanut butter sandwich from a VCR

And it came to pass that a man was troubled by a peanut butter sandwich, for it had been placed within his VCR, and he knew not how to remove it.

And he cried out to the Lord, saying, "Oh, Lord, how can I remove this sandwich from my VCR, for it is stuck fast and will not budge?"

And the Lord spoke unto him, saying, "Fear not, my child, for I shall guide thy hand and show thee the way. Take thy butter knife, and carefully insert it between the sandwich and the VCR, and gently pry them apart. And with patience and perseverance, the sandwich shall be removed, and thy VCR shall be saved."

And the man did as the Lord commanded, and lo and behold, the sandwich was removed from the VCR, and the man was saved.

And the Lord said, "Verily I say unto thee, seek not to put thy peanut butter sandwiches in thy VCR, for it is not a suitable place for such things. Rather, keep thy sandwiches in thy refrigerator or on thy plate, where they belong."

And the man heeded the Lord's words, and from that day forth, he kept his sandwiches in their proper place, and was saved from trouble and woe. Amen.

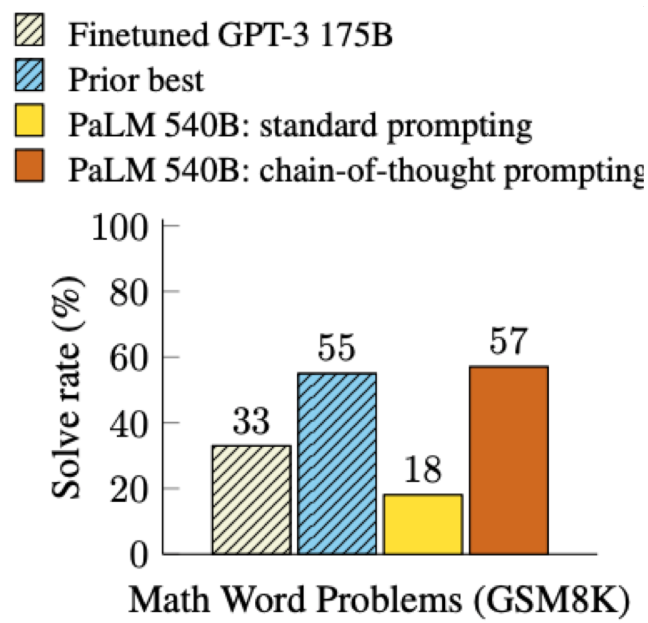
Source

# Chain-of-thought prompting


**Abstract**

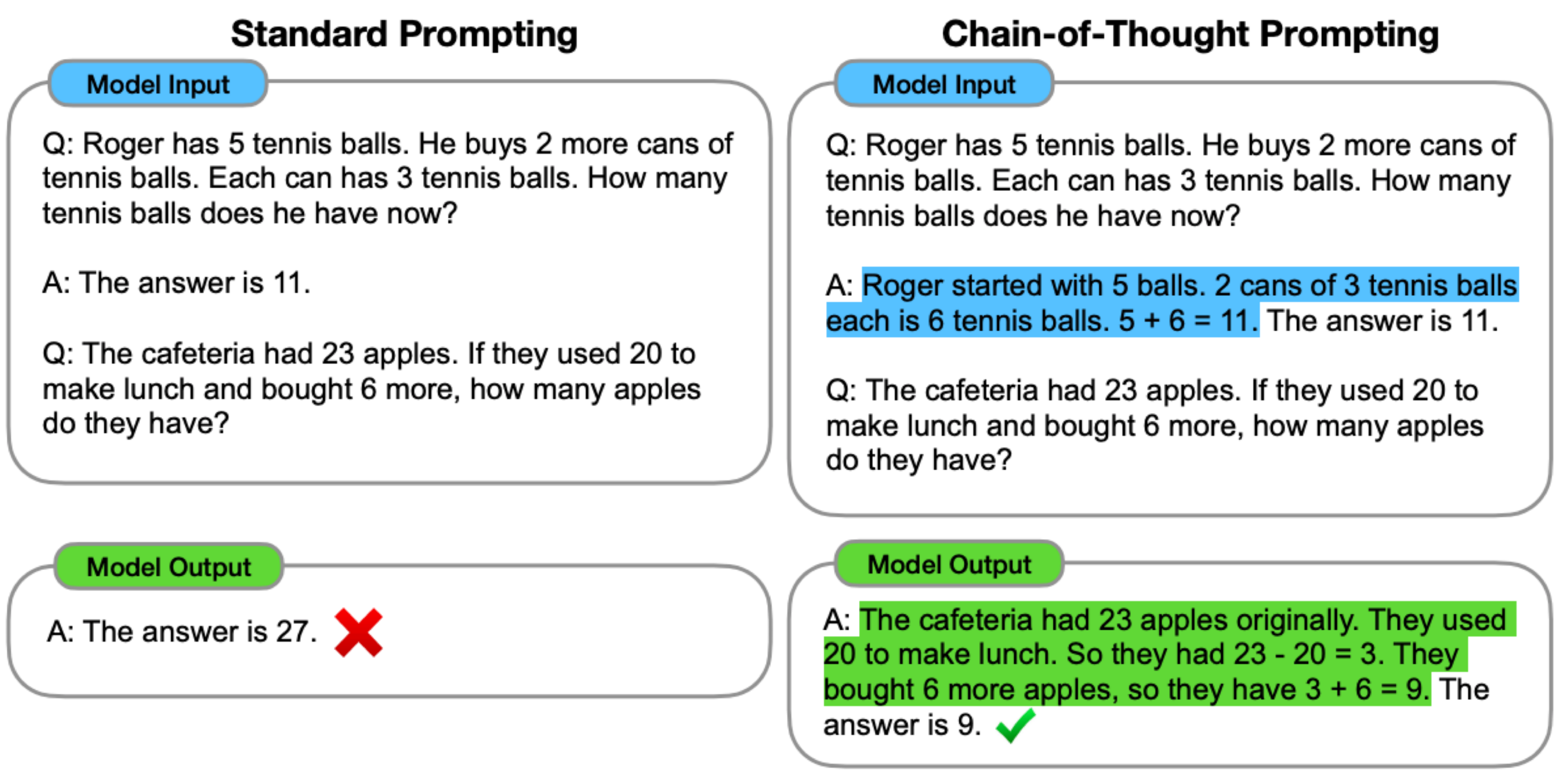
We explore how generating a *chain of thought*—a series of intermediate reasoning steps—significantly improves the ability of large language models to perform complex reasoning. In particular, we show how such reasoning abilities emerge naturally in sufficiently large language models via a simple method called *chain-of-thought prompting*, where a few chain of thought demonstrations are provided as exemplars in prompting.

Experiments on three large language models show that chain-of-thought prompting improves performance on a range of arithmetic, commonsense, and symbolic reasoning tasks. The empirical gains can be striking. For instance, prompting a PaLM 540B with just eight chain-of-thought exemplars achieves state-of-the-art accuracy on the GSM8K benchmark of math word problems, surpassing even finetuned GPT-3 with a verifier.


J. Wei et al. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. NeurIPS 2022

# Chain-of-thought prompting




J. Wei et al. [Chain-of-Thought Prompting Elicits Reasoning in Large Language Models](). NeurIPS 2022

# Chain-of-thought prompting

**Math Word Problems (free response)**

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.

**Math Word Problems (multiple choice)**

Q: How many keystrokes are needed to type the numbers from 1 to 500?
Answer Choices: (a) 1156 (b) 1392 (c) 1480 (d) 1562 (e) 1788

A: There are 9 one-digit numbers from 1 to 9. There are 90 two-digit numbers from 10 to 99. There are 401 three-digit numbers from 100 to 500. 9 + 90(2) + 401(3) = 1392. The answer is (b).

**CSQA (commonsense)**

Q: Sammy wanted to go to where the people were. Where might he go?
Options: (a) race track (b) populated areas (c) desert (d) apartment (e) roadblock

A: The answer must be a place with a lot of people. Race tracks, desert, apartments, and roadblocks don't have a lot of people, but populated areas do. So the answer is (b).

**StrategyQA**

Q: Yes or no: Would a pear sink in water?

A: The density of a pear is about 0.6 g/cm^3, which is less than water. Thus, a pear would float. So the answer is no.

**Date Understanding**

Q: The concert was scheduled to be on 06/01/1943, but was delayed by one day to today. What is the date 10 days ago in MM/DD/YYYY?

A: One day after 06/01/1943 is 06/02/1943, so today is 06/02/1943. 10 days before today is 05/23/1943. So the answer is 05/23/1943.

**Sports Understanding**

Q: Is the following sentence plausible? "Joao Moutinho caught the screen pass in the NFC championship."

A: Joao Moutinho is a soccer player. The NFC championship is part of American football, not soccer. So the answer is no.

**SayCan (Instructing a robot)**

Human: How would you bring me something that isn't a fruit?

Explanation: the user wants something to eat that isn't a fruit. An energy bar is not a fruit, so I will bring the user an energy bar.
Plan: 1. find(energy bar) 2. pick(energy bar) 3. find(user) 4. put(energy bar) 5. done().

**Last Letter Concatenation**

Q: Take the last letters of the words in "Lady Gaga" and concatenate them.

A: The last letter of "Lady" is "y". The last letter of "Gaga" is "a". Concatenating them is "ya". So the answer is ya.

**Coin Flip (state tracking)**

Q: A coin is heads up. Maybelle flips the coin. Shalonda does not flip the coin. Is the coin still heads up?

A: The coin was flipped by Maybelle. So the coin was flipped 1 time, which is an odd number. The coin started heads up, so after an odd number of flips, it will be tails up. So the answer is no.

# GPT-4

## GPT-4 Technical Report

**OpenAI***

### Abstract

We report the development of GPT-4, a large-scale, multimodal model which can accept image and text inputs and produce text outputs. While less capable than humans in many real-world scenarios, GPT-4 exhibits human-level performance on various professional and academic benchmarks, including passing a simulated bar exam with a score around the top 10% of test takers. GPT-4 is a Transformer-based model pre-trained to predict the next token in a document. The post-training alignment process results in improved performance on measures of factuality and adherence to desired behavior. A core component of this project was developing infrastructure and optimization methods that behave predictably across a wide range of scales. This allowed us to accurately predict some aspects of GPT-4's performance based on models trained with no more than 1/1,000th the compute of GPT-4.

https://openai.com/research/gpt-4

# GPT-4: Technical details

## 2 Scope and Limitations of this Technical Report

This report focuses on the capabilities, limitations, and safety properties of GPT-4. GPT-4 is a Transformer-style model [39] pre-trained to predict the next token in a document, using both publicly available data (such as internet data) and data licensed from third-party providers. The model was then fine-tuned using Reinforcement Learning from Human Feedback (RLHF) [40]. 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.

We are committed to independent auditing of our technologies, and shared some initial steps and ideas in this area in the system card accompanying this release.[2] We plan to make further technical details available to additional third parties who can advise us on how to weigh the competitive and safety considerations above against the scientific value of further transparency.

(Rumor: it has one trillion parameters)

# GPT-4: Performance

| | GPT-4<br>Evaluated few-shot | GPT-3.5<br>Evaluated few-shot | LM SOTA<br>Best external LM evaluated few-shot | SOTA<br>Best external model (incl. benchmark-specific tuning) |
|---|---|---|---|---|
| MMLU [49]<br>Multiple-choice questions in 57 subjects (professional & academic) | **86.4%**<br>5-shot | 70.0%<br>5-shot | 70.7%<br>5-shot U-PaLM [50] | 75.2%<br>5-shot Flan-PaLM [51] |
| HellaSwag [52]<br>Commonsense reasoning around everyday events | **95.3%**<br>10-shot | 85.5%<br>10-shot | 84.2%<br>LLaMA (validation set) [28] | 85.6<br>ALUM [53] |
| AI2 Reasoning Challenge (ARC) [54]<br>Grade-school multiple choice science questions. Challenge-set. | **96.3%**<br>25-shot | 85.2%<br>25-shot | 85.2%<br>8-shot PaLM [55] | 86.5%<br>ST-MOE [18] |
| WinoGrande [56]<br>Commonsense reasoning around pronoun resolution | **87.5%**<br>5-shot | 81.6%<br>5-shot | 85.1%<br>5-shot PaLM [3] | 85.1%<br>5-shot PaLM [3] |
| HumanEval [43]<br>Python coding tasks | **67.0%**<br>0-shot | 48.1%<br>0-shot | 26.2%<br>0-shot PaLM [3] | 65.8%<br>CodeT + GPT-3.5 [57] |
| DROP [58] (F1 score)<br>Reading comprehension & arithmetic. | 80.9<br>3-shot | 64.1<br>3-shot | 70.8<br>1-shot PaLM [3] | **88.4**<br>QDGAT [59] |
| GSM-8K [60]<br>Grade-school mathematics questions | **92.0%***<br>5-shot chain-of-thought | 57.1%<br>5-shot | 58.8%<br>8-shot Minerva [61] | 87.3%<br>Chinchilla + SFT+ORM-RL, ORM reranking [62] |

**Table 2.** Performance of GPT-4 on academic benchmarks. We compare GPT-4 alongside the best SOTA (with benchmark-specific training) and the best SOTA for an LM evaluated few-shot. GPT-4 outperforms existing LMs on all benchmarks, and beats SOTA with benchmark-specific training on all datasets except DROP. For each task we report GPT-4's performance along with the few-shot method used to evaluate. For GSM-8K, we included part of the training set in the GPT-4 pre-training mix (see Appendix E), and we use chain-of-thought prompting [11] when evaluating. For multiple-choice questions, we present all answers (ABCD) to the model and ask it to choose the letter of the answer, similarly to how a human would solve such a problem.

# GPT-4: Performance

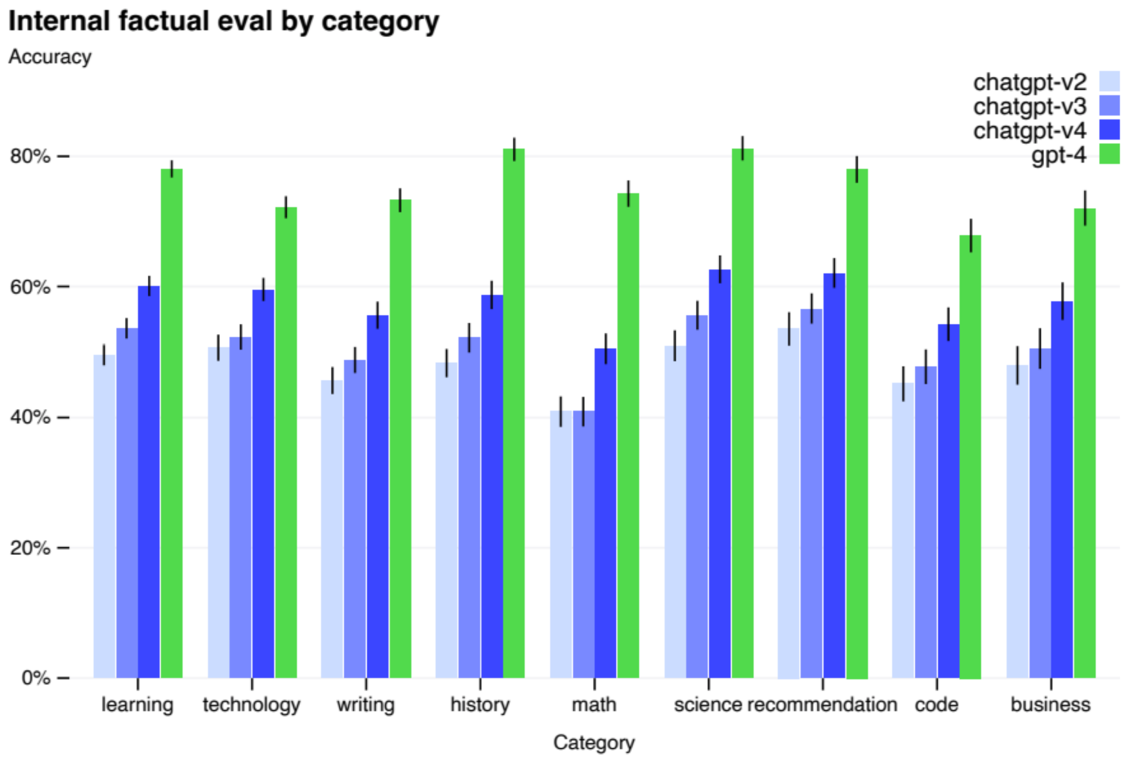



**Figure 6.** Performance of GPT-4 on nine internal adversarially-designed factuality evaluations. Accuracy is shown on the y-axis, higher is better. An accuracy of 1.0 means the model's answers are judged to be in agreement with human ideal responses for all questions in the eval. We compare GPT-4 to three earlier versions of ChatGPT [64] based on GPT-3.5; GPT-4 improves on the latest GPT-3.5 model by 19 percentage points, with significant gains across all topics.

# GPT-4: Performance

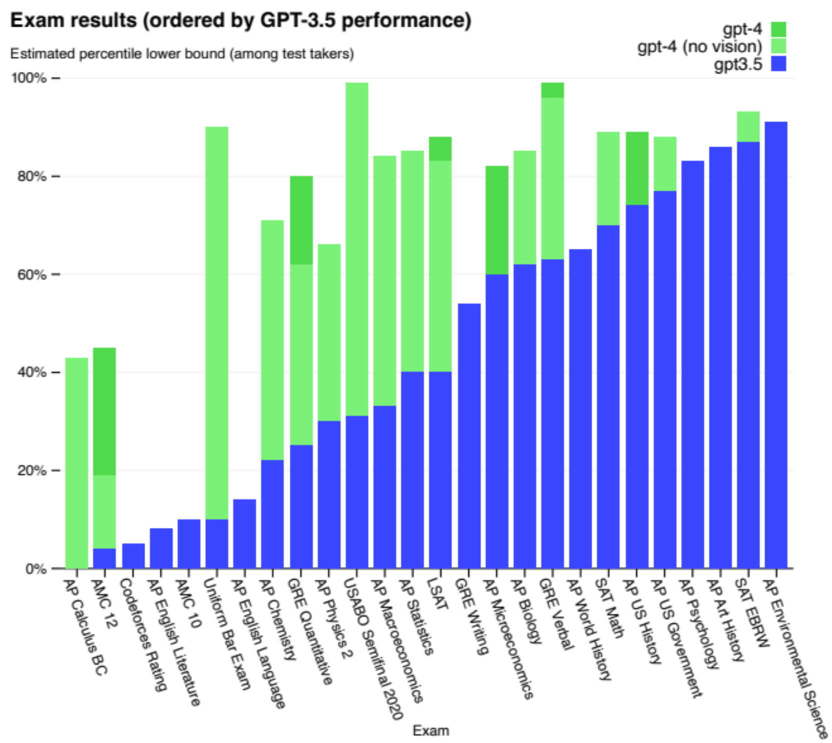



**Figure 4.** GPT performance on academic and professional exams. In each case, we simulate the conditions and scoring of the real exam. Exams are ordered from low to high based on GPT-3.5 performance. GPT-4 outperforms GPT-3.5 on most exams tested. To be conservative we report the lower end of the range of percentiles, but this creates some artifacts on the AP exams which have very wide scoring bins. For example although GPT-4 attains the highest possible score on AP Biology (5/5), this is only shown in the plot as 85th percentile because 15 percent of test-takers achieve that score.

For objections, see https://aisnakeoil.substack.com/p/gpt-4-and-professional-benchmarks

# GPT-4: Visual input

User Can you explain this meme?


GPT-4 This meme is a joke that combines two unrelated things: pictures of the earth from space and chicken nuggets.
The text of the meme suggests that the image below is a beautiful picture of the earth from space. However, the image is actually of chicken nuggets arranged to vaguely resemble a map of the world.
The humor in this meme comes from the unexpected juxtaposition of the text and the image. The text sets up an expectation of a majestic image of the earth, but the image is actually something mundane and silly.

User What is unusual about this image?

Source: https://www.barnorama.com/wp-content/uploads/2016/12/03-Confusing-Pictures.jpg

GPT-4 The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.

# AGI or hype?

## 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.

S. Bubeck et al. Sparks of artificial general intelligence: Early experiments with GPT-4. arXiv 2023

# Large language model concerns

- Bias and toxicity
- Inadvertently generating wrong information
- Potential for purposeful misuse (e.g., misinformation generation)
- Leakage of private information
- Exploitation of crowd workers, users
- Access and reproducibility
- Carbon footprint
- Potential for destroying jobs (e.g., writers, editors, programmers, teachers, academics)
- All that AGI stuff…