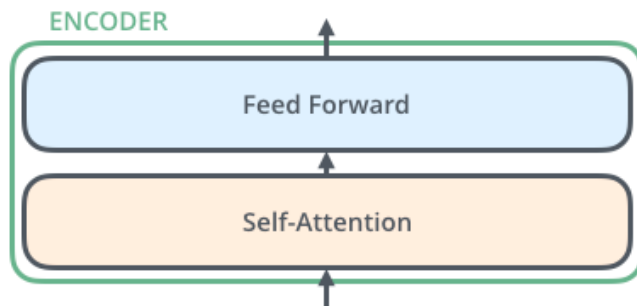
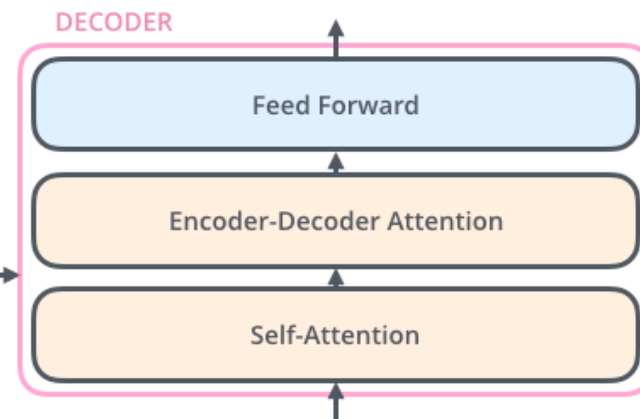


Last time: Encoder-decoder transformer

Encoder: receives entire input sequence and outputs encoded sequence of the same length

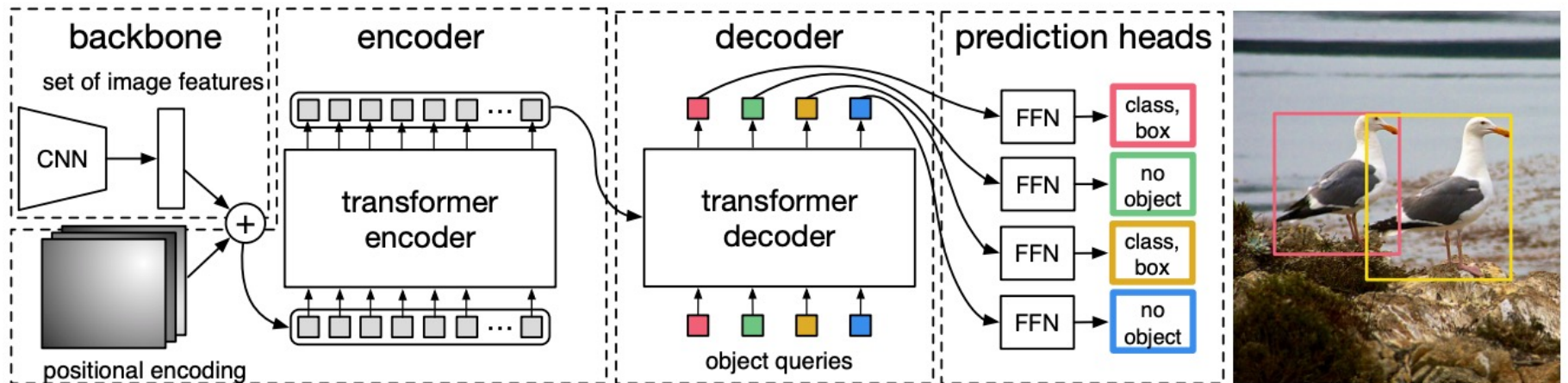
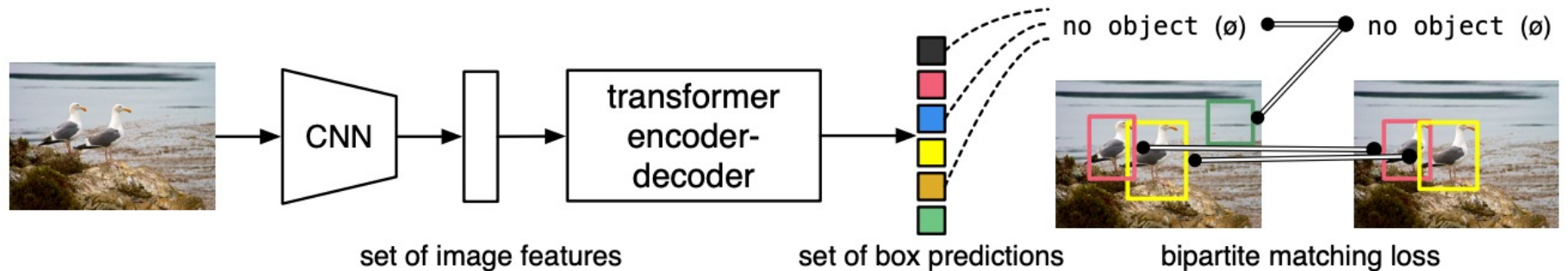


Decoder: predicts next token conditioned on encoder output and previously predicted tokens



A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. Gomez, L. Kaiser, I. Polosukhin, [Attention is all you need](#), NeurIPS 2017

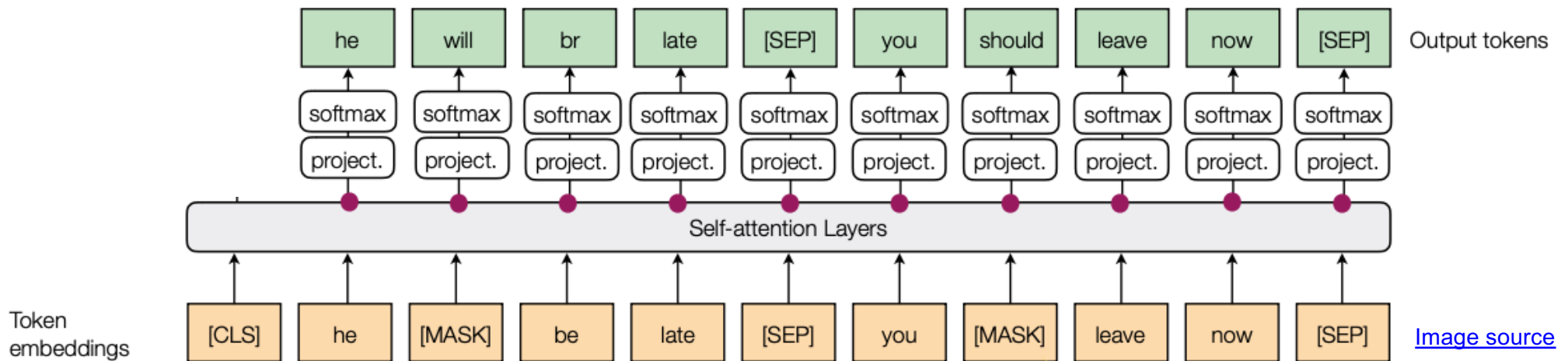
Encoder-decoder transformer for object detection



N. Carion et al. [End-to-end object detection with transformers](#). ECCV 2020

Encoder-only transformer: BERT

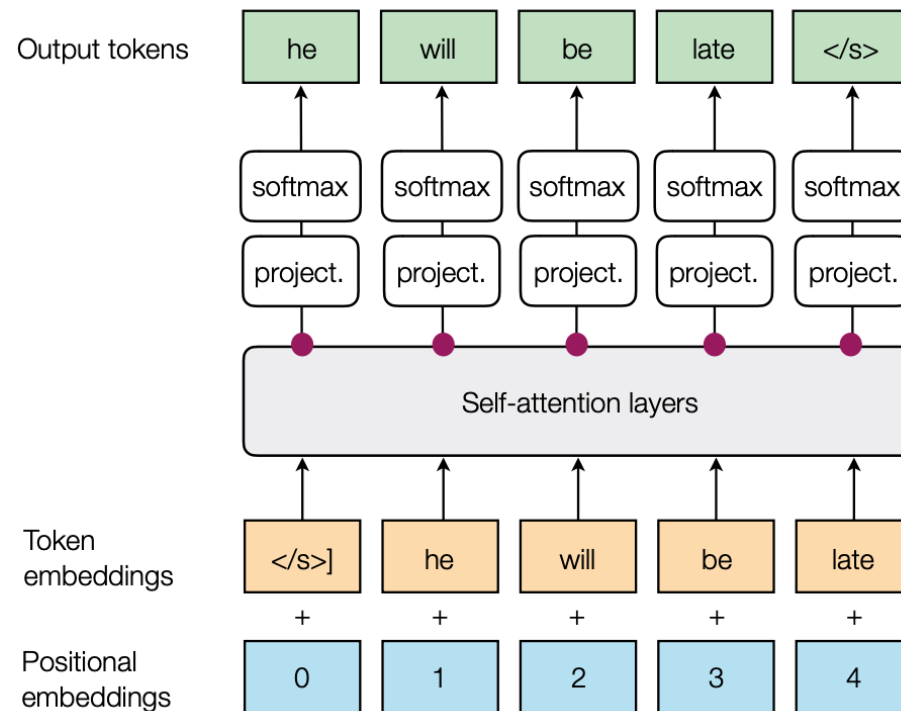
- At each position, the entire sequence serves as context – full attention is used



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

Decoder-only transformer: GPT

- Task is next token prediction – only masked attention is used



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

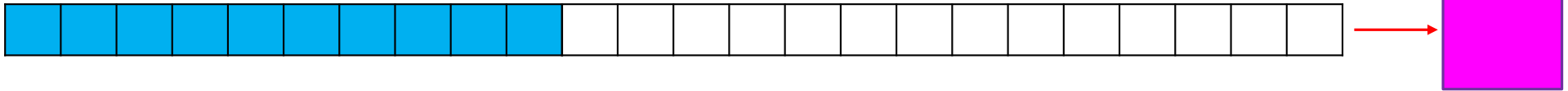
[Image source](#)

Decoder-only transformer: DALL-E

Given: Text prompt encoding (256 tokens)

Predict: Image encoding (1024 = 32x32 tokens)

Decode to 256x256
image



(a) a tapir made of accordion.
a tapir with the texture of an
accordion.

(b) an illustration of a baby
hedgehog in a christmas
sweater walking a dog

(c) a neon sign that reads
"backprop". a neon sign that
reads "backprop". backprop
neon sign

A. Ramesh et al., [Zero-Shot Text-to-Image Generation](#), ICML 2021

Decoder-only transformer: Robot control

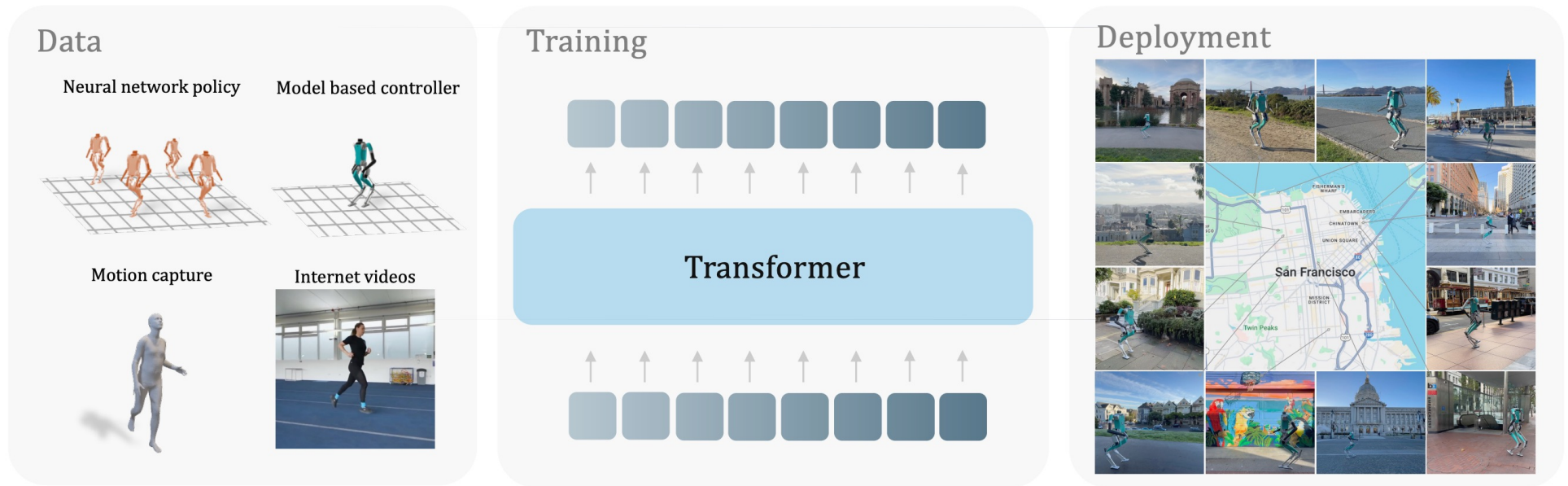
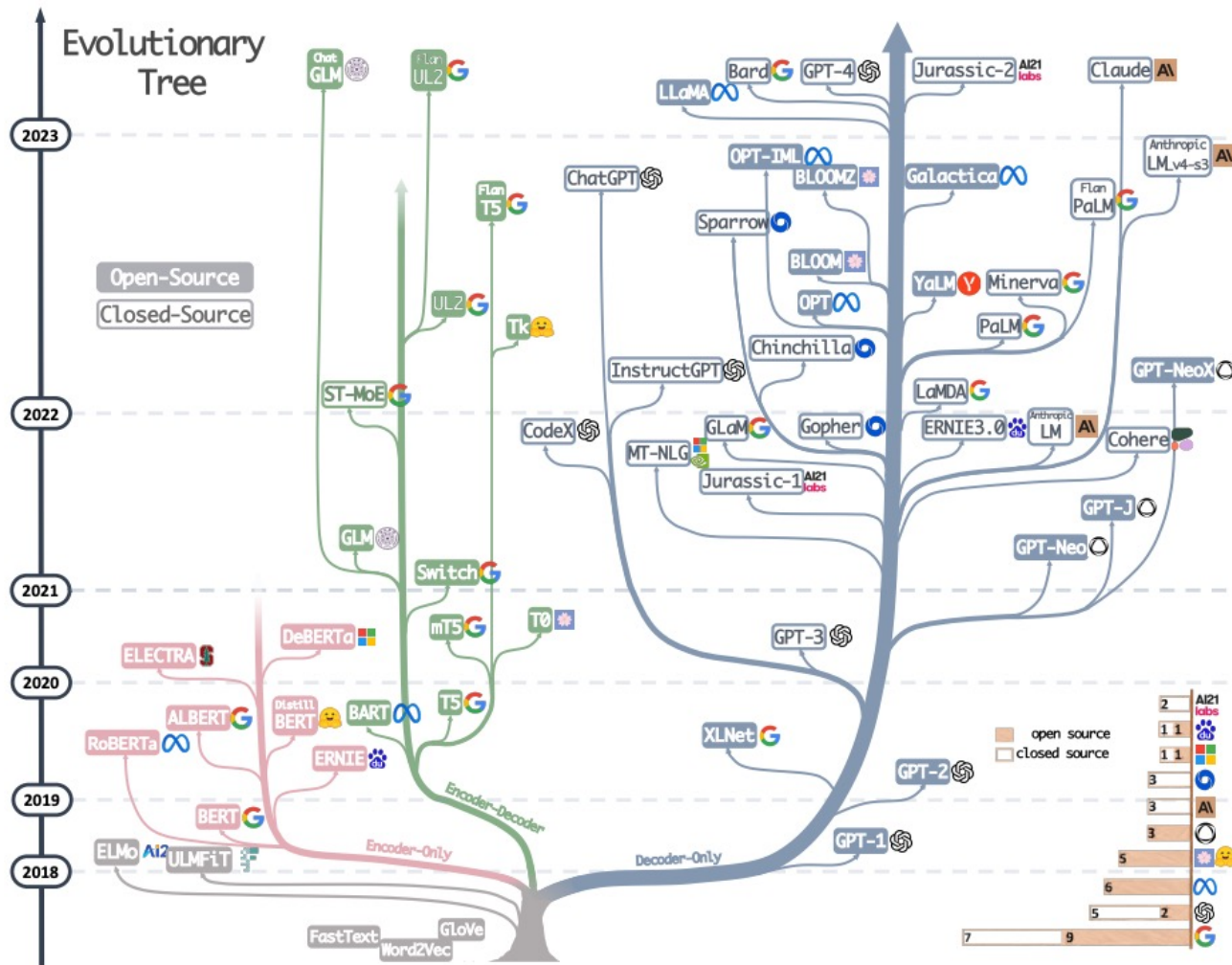


Figure 2: **Humanoid locomotion as next token prediction.** We collect a dataset on trajectories from various sources, such as from neural network policies, model-based controllers, human motion capture, and YouTube videos of humans. Then we use this dataset to train a transformer policy by autoregressive modeling of observations and actions. Our transformer allows a humanoid to walk zero-shot on various terrains around San Francisco. Please see our [project page](#) for video results.

I. Radosavovic et al. [Humanoid Locomotion as Next Token Prediction](#). arXiv 2024

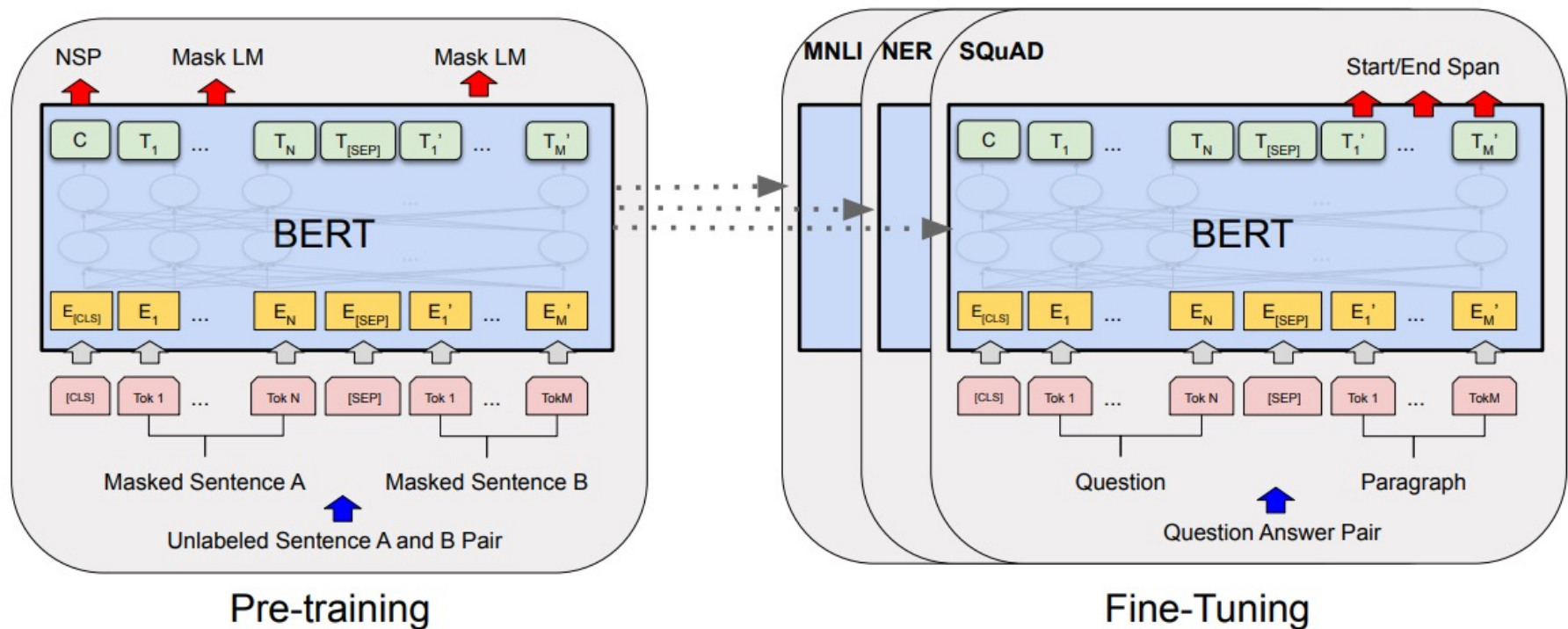
Large language models



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)

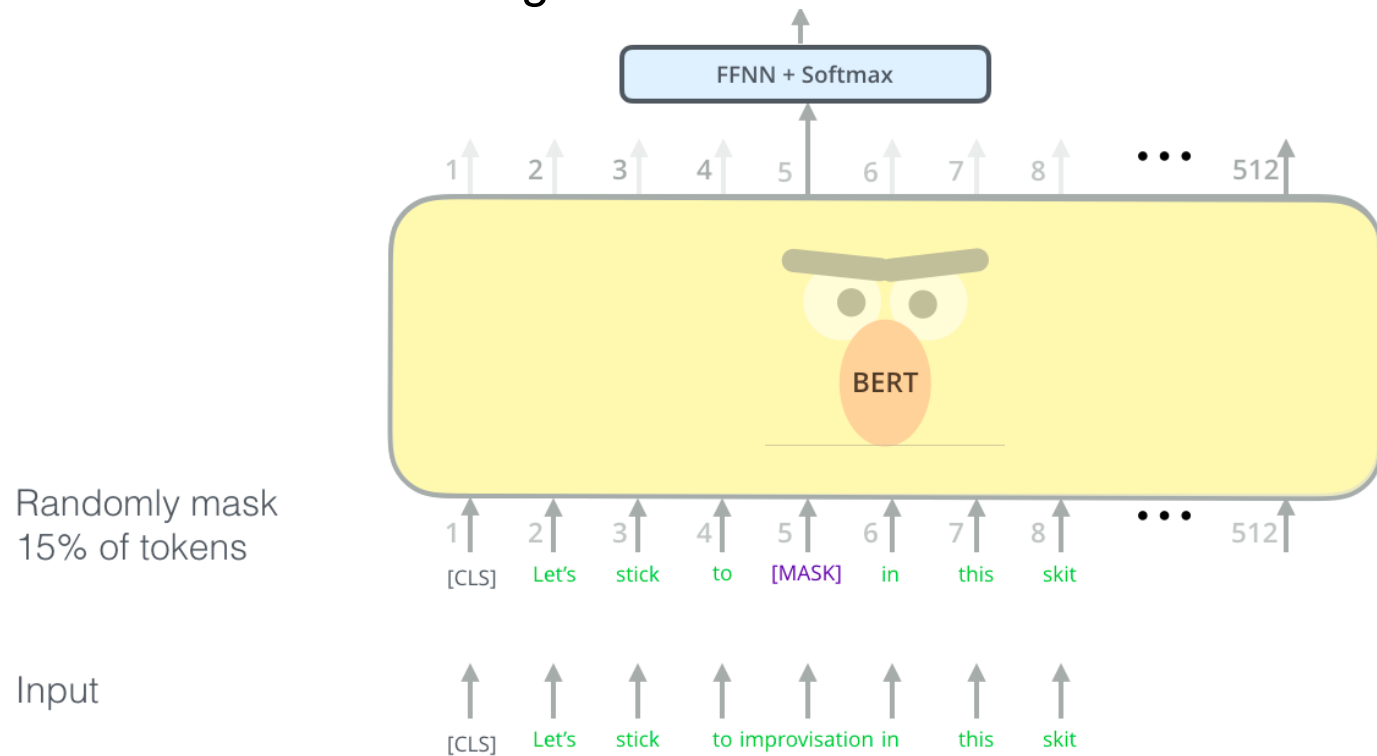
Bidirectional encoder representations from transformers (BERT)



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

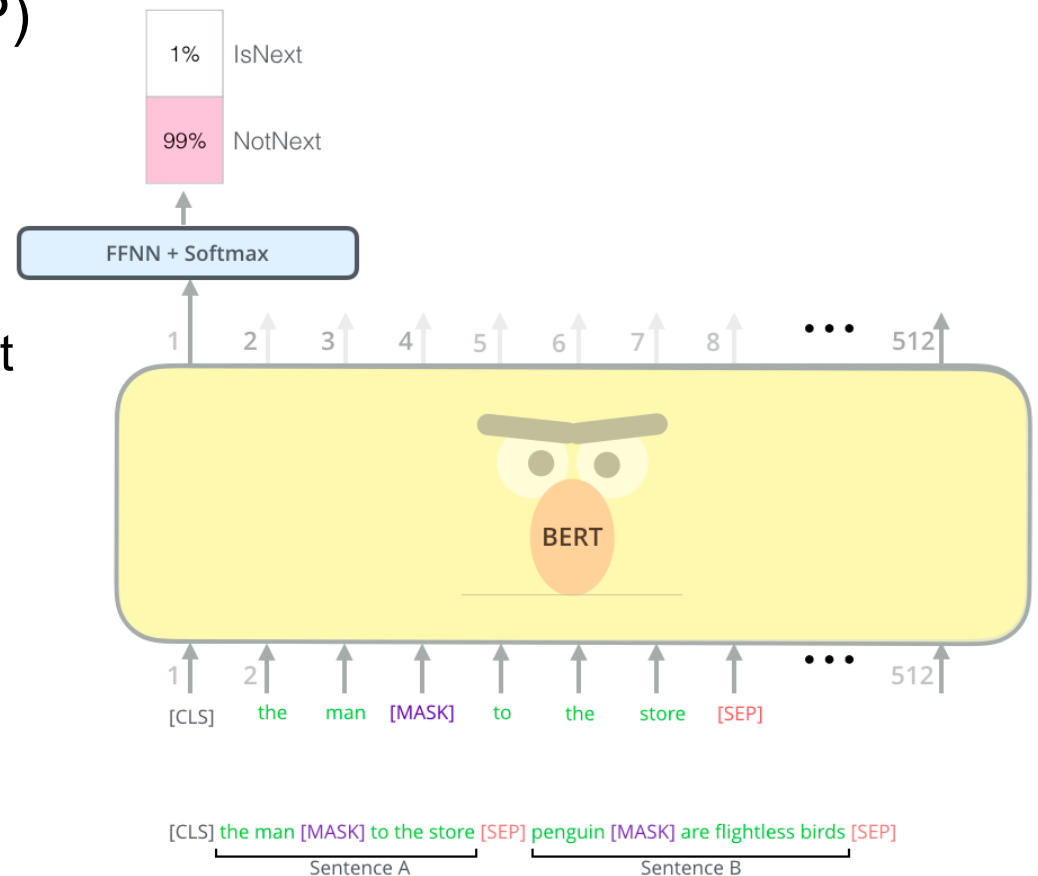
BERT: Pretext tasks

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



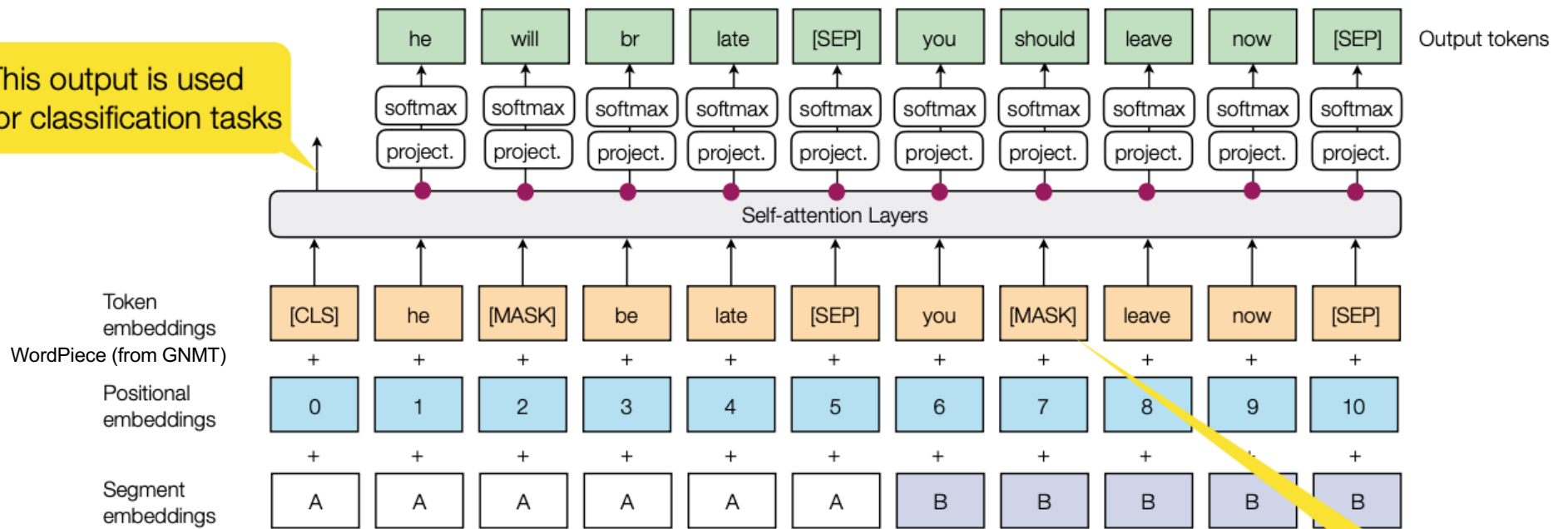
BERT: Pretext tasks

- 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).



BERT: More detailed view

This output is used for classification tasks



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

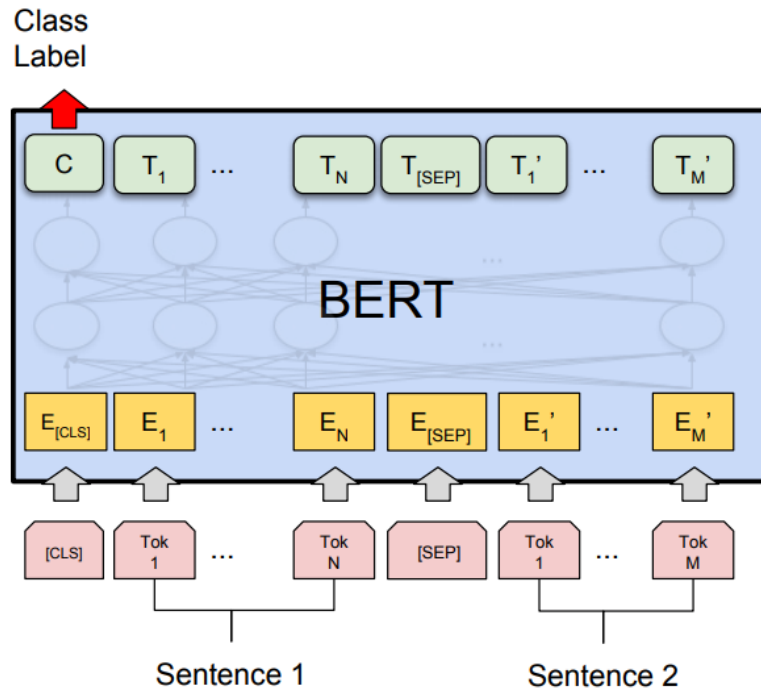
15% of tokens get masked

BERT: Evaluation

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

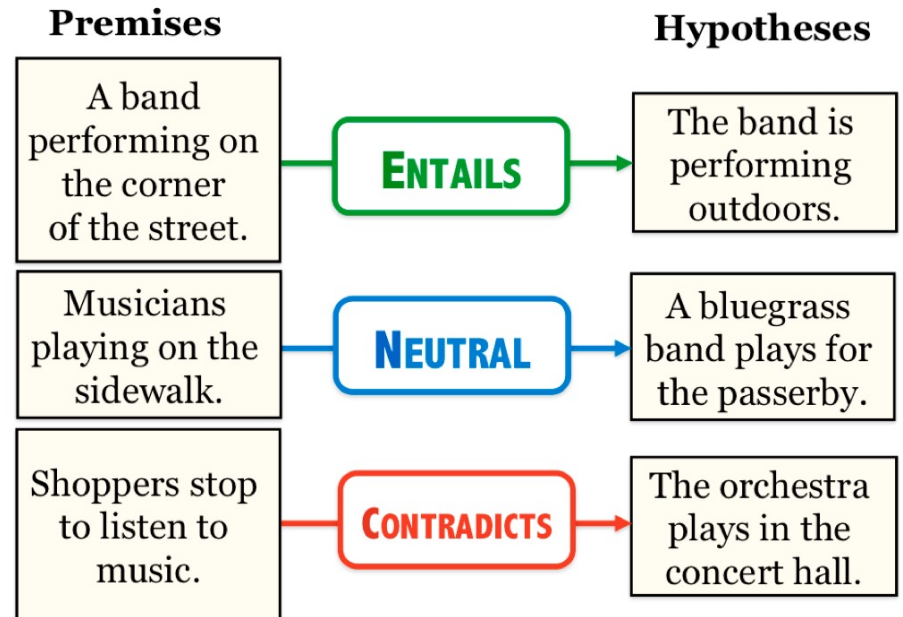
System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	Average
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
BERT _{BASE}	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

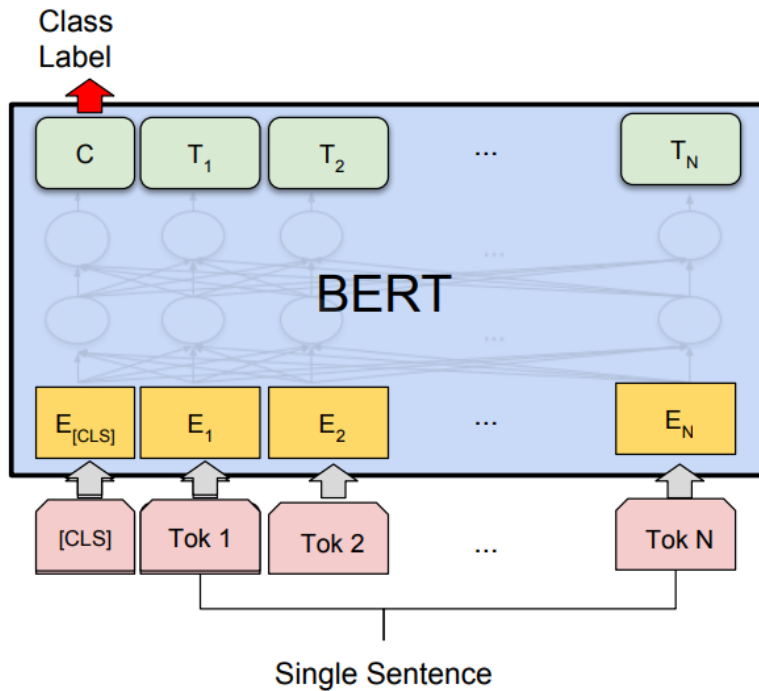
Textual entailment



Source: J. Hockenmaier

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

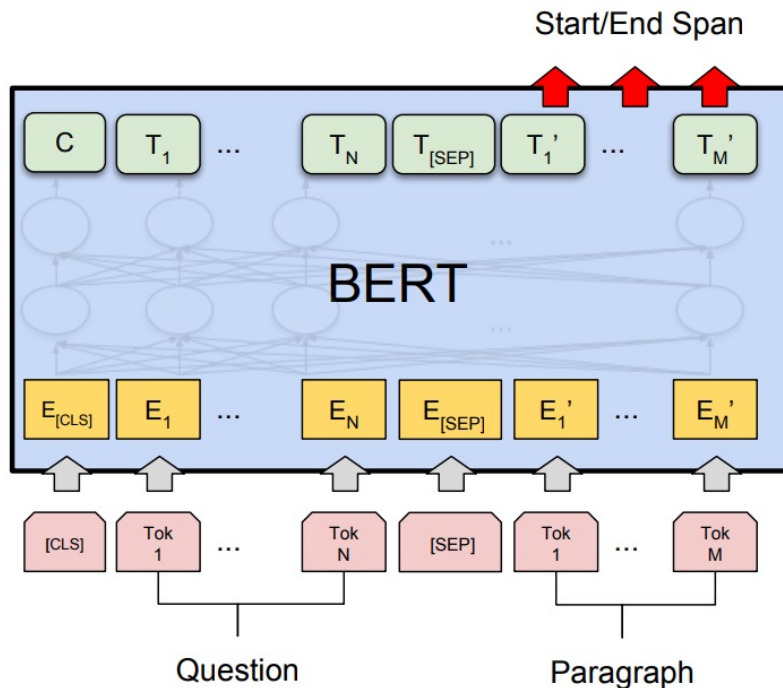
Sentence: The car honked down the road.

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?

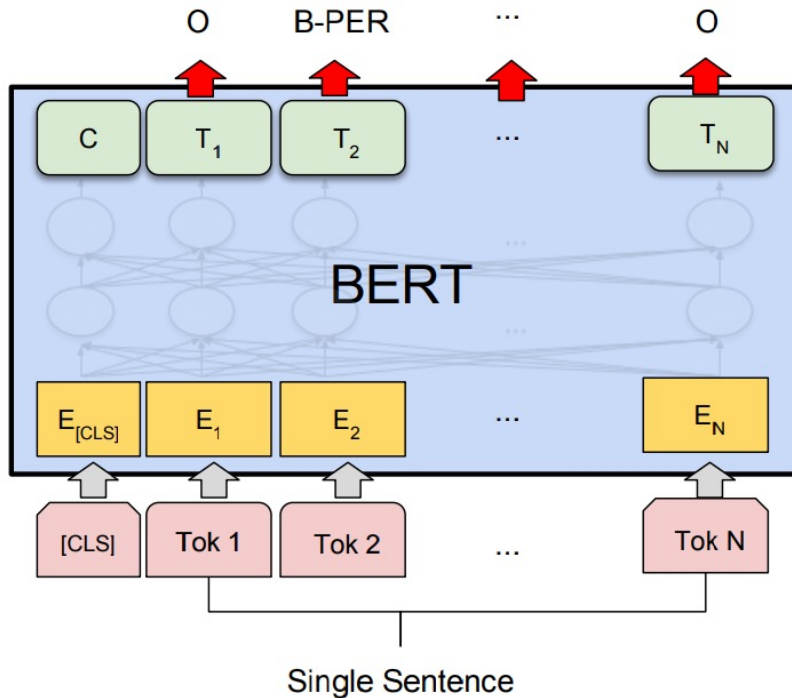
graupel

Where do water droplets collide with ice crystals to form precipitation?

within a cloud

Source: [SQuAD v1.1 paper](#)

BERT: Downstream tasks



When **Sebastian Thrun** PERSON started at **Google** ORG in **2007** DATE, few people outside of the company took him seriously. "I can tell you very senior CEOs of major **American** NORP car companies would shake my hand and turn away because I wasn't worth talking to," said **Thrun** PERSON, now the co-founder and CEO of online higher education startup Udacity, in an interview with **Recode** ORG **earlier this week** DATE.

A little **less than a decade later** DATE, dozens of self-driving startups have cropped up while automakers around the world clamor, wallet in hand, to secure their place in the fast-moving world of fully automated transportation.

[Image source](#)

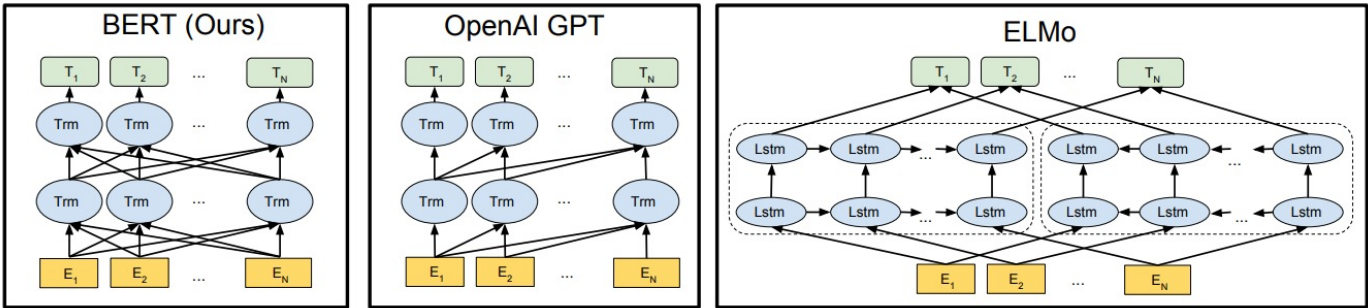
(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

Named entity recognition

Other early language models

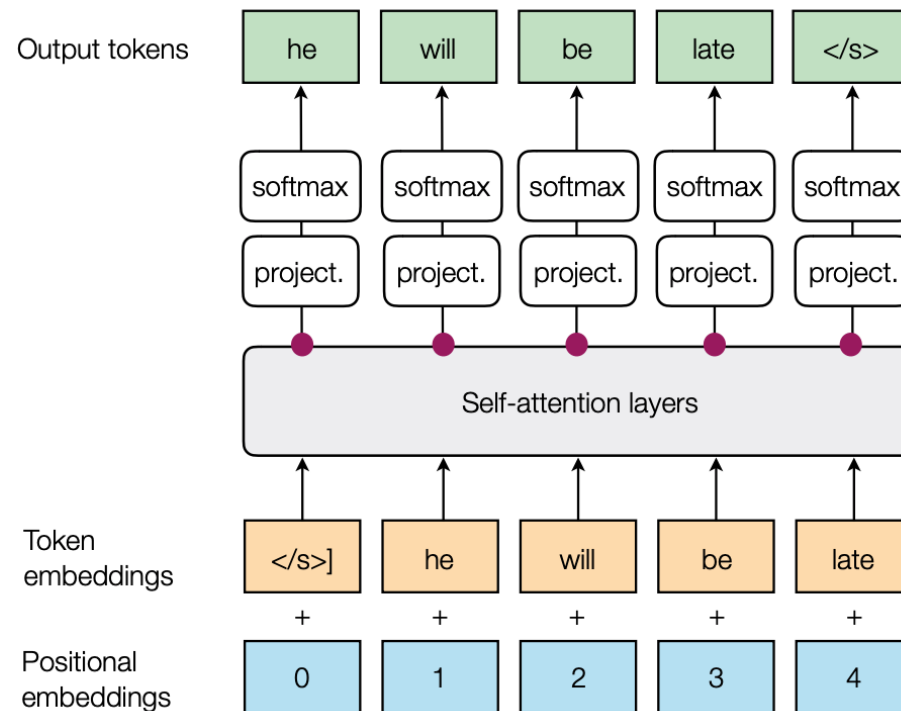
Alias	Model	Token	Tasks	Language
ULMfit	LSTM	word	Causal LM	English
ELMo	LSTM	word	Bidirectional LM	English
OpenAI GPT	Transformer	subword	Causal LM + Classification	English
BERT	Transformer	subword	Masked LM + Next sentence prediction	Multilingual
XLNet	Transformer	subword	Causal LM + Masked LM + Translation 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](#)

Scaling up transformers

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BERT-Large	24	1024	16	340M	13 GB	16x TPU (4 days)

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 Language Models using Model Parallelism](#). 2019 (NVIDIA)

Source: [J. Johnson](#)

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Turing-NLG	78	4256	28	17B	?	256x V100 GPU

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](#)

Scaling up transformers

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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)

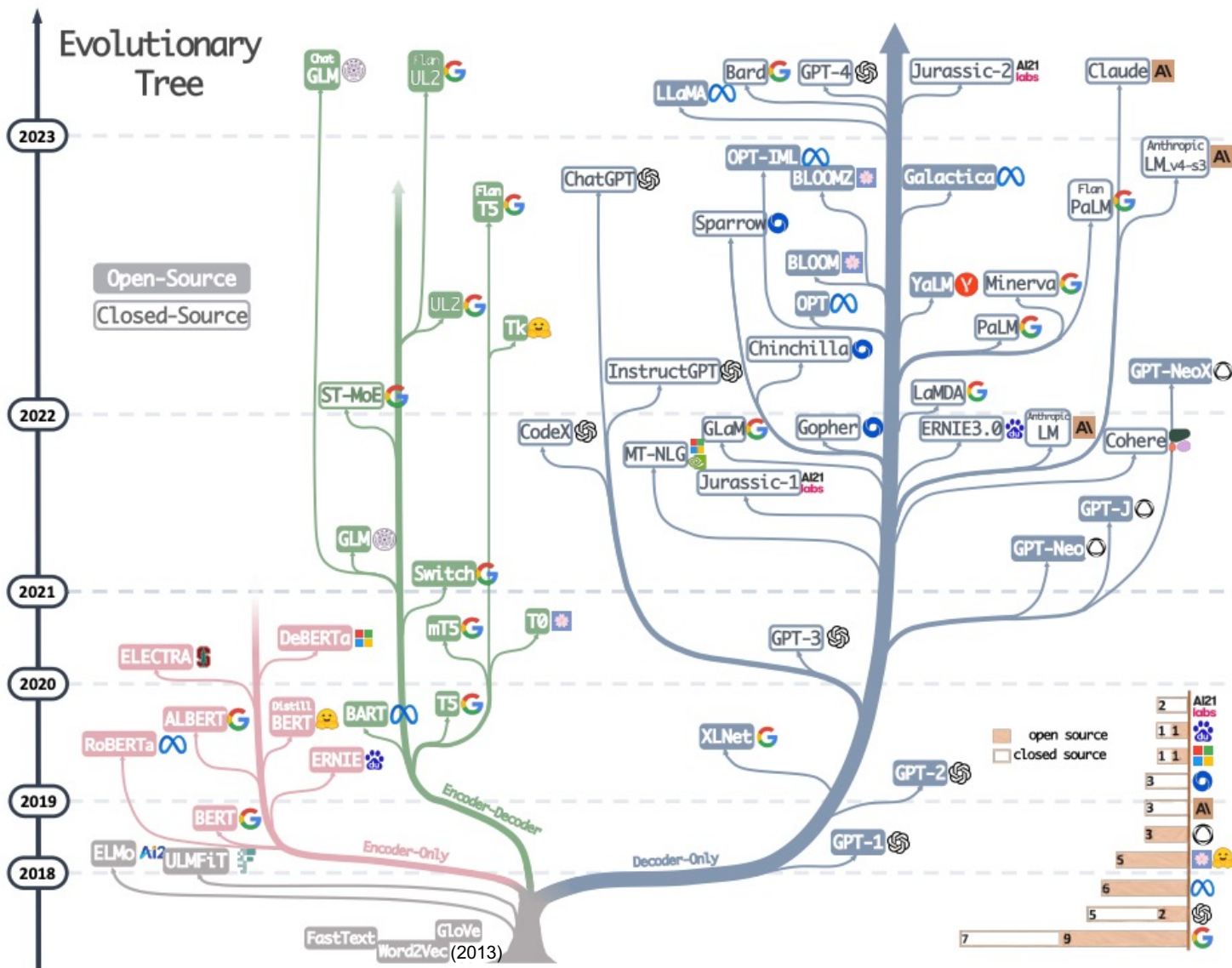
J. Rae et al. [Scaling Language Models: Methods, Analysis, & Insights from Training Gopher](#). arXiv 2021 (DeepMind)

Source: [J. Johnson](#)

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GOPHER	80	16,384	128	280B	10.55 TB	4096x TPUv3 (38 days)
PaLM	118	18,432	48	540B	?	6144x TPUv4

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



[Source](#)

Scaling behavior of large language models

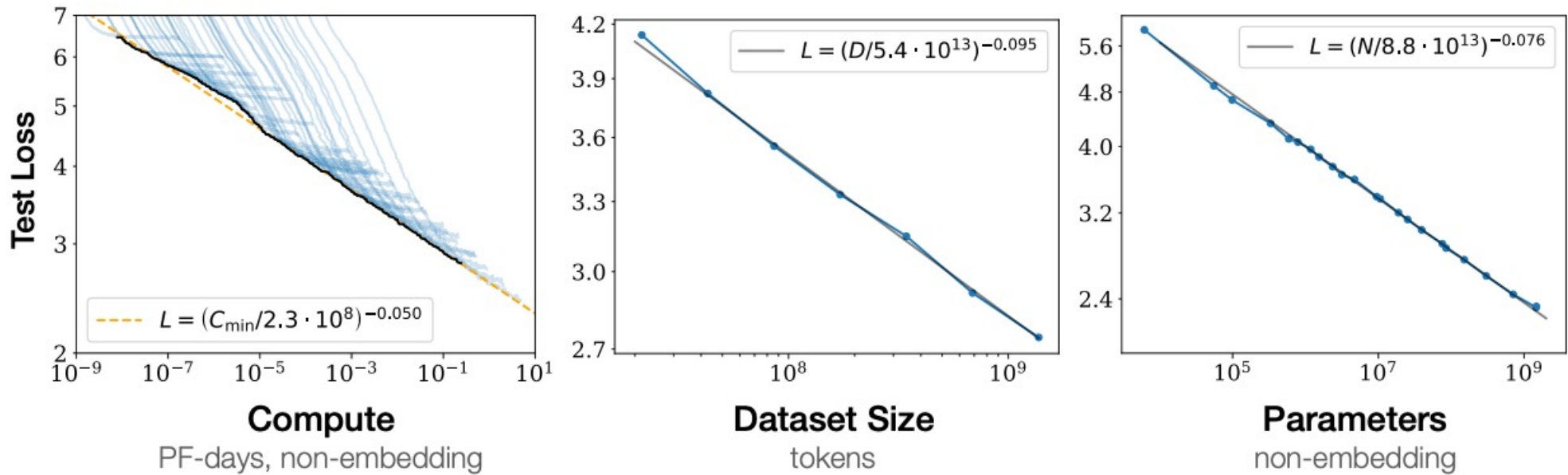


Figure 1 Language modeling performance improves smoothly as we increase the model size, dataset size, and amount of compute² used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

Scaling behavior of large language models

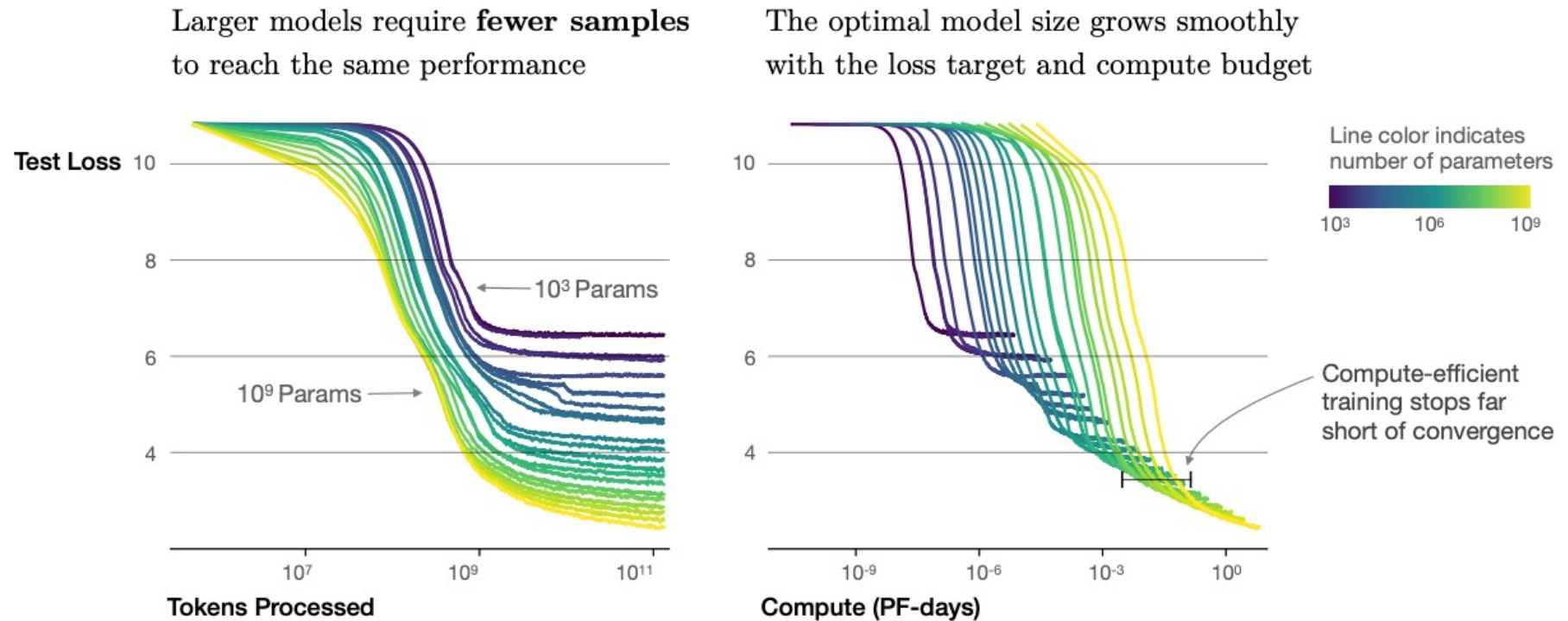


Figure 2 We show a series of language model training runs, with models ranging in size from 10^3 to 10^9 parameters (excluding embeddings).

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

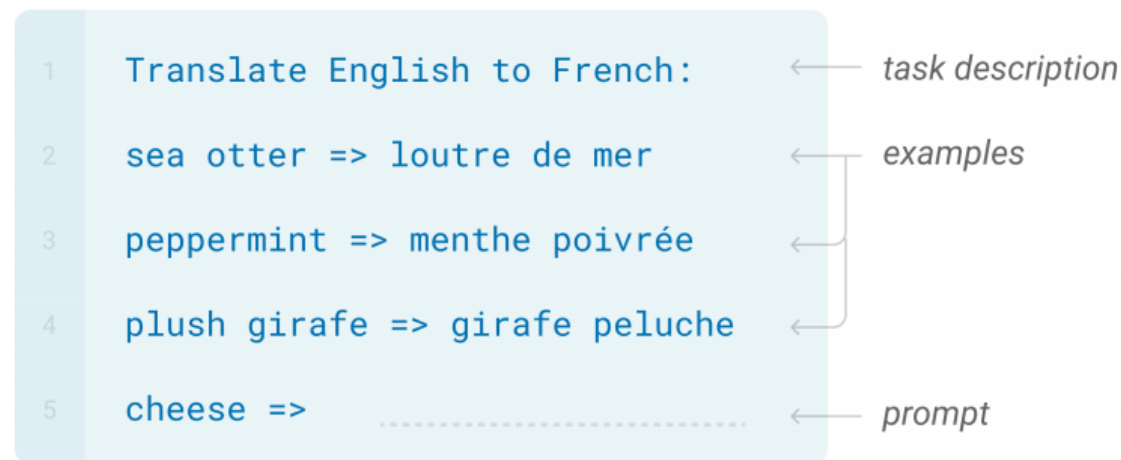
Table 2.2: Datasets used to train GPT-3. “Weight in training mix” refers to the fraction of examples during training that are drawn from a given dataset, which we intentionally do not make proportional to the size of the dataset. As a result, when we train for 300 billion tokens, some datasets are seen 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)

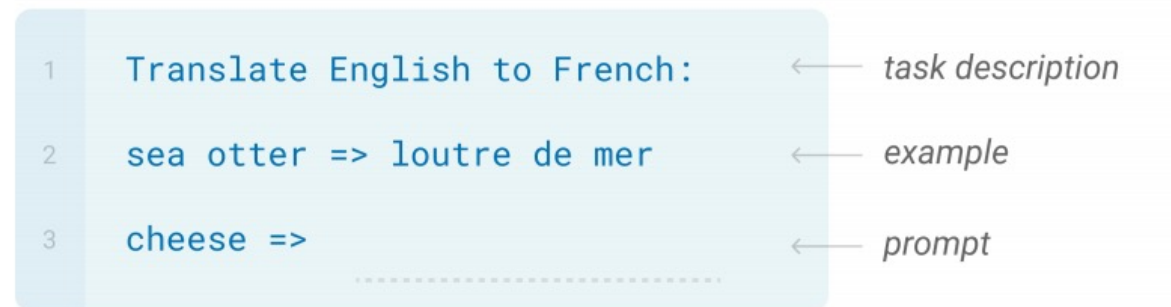
GPT-3

- 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



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



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



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.

Gray: human prompts,
boldface: GPT-3
completions

(Three articles
provided as training
examples)

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

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."

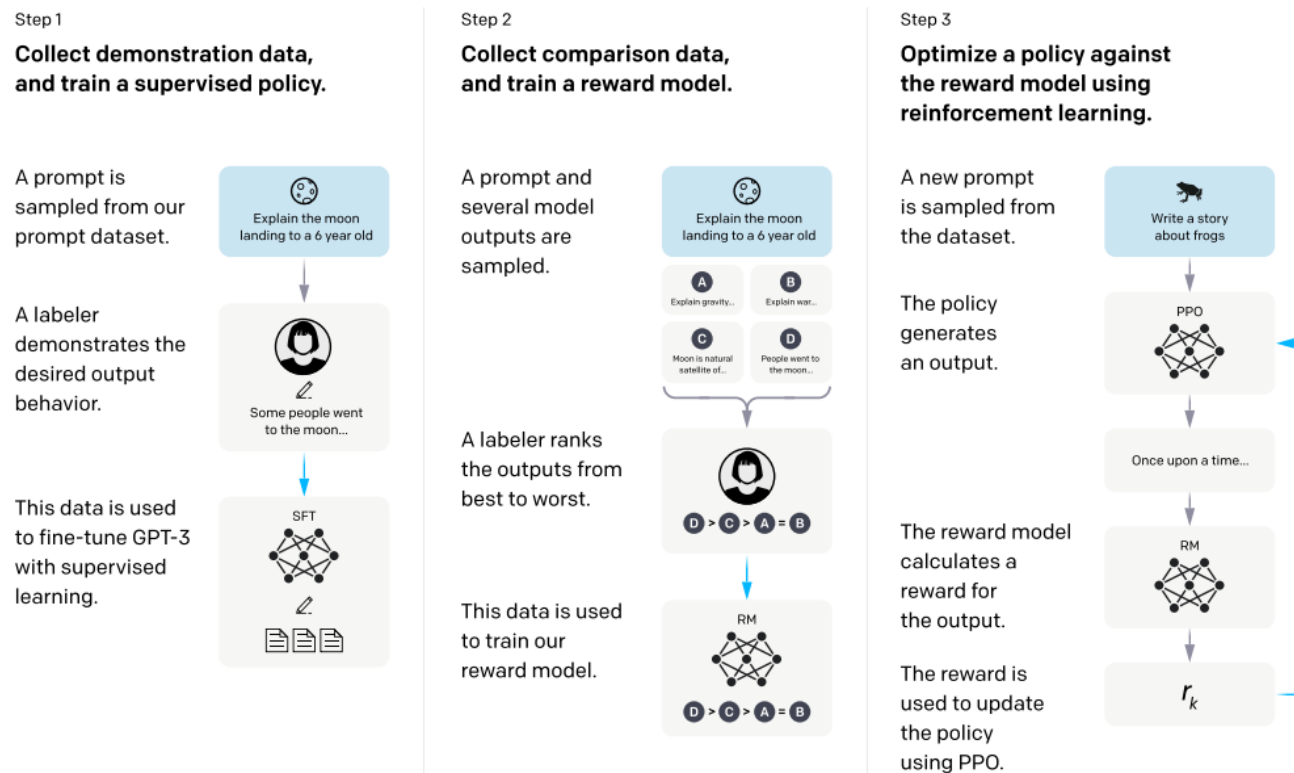
By Arthur Conan Doyle:

"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>

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

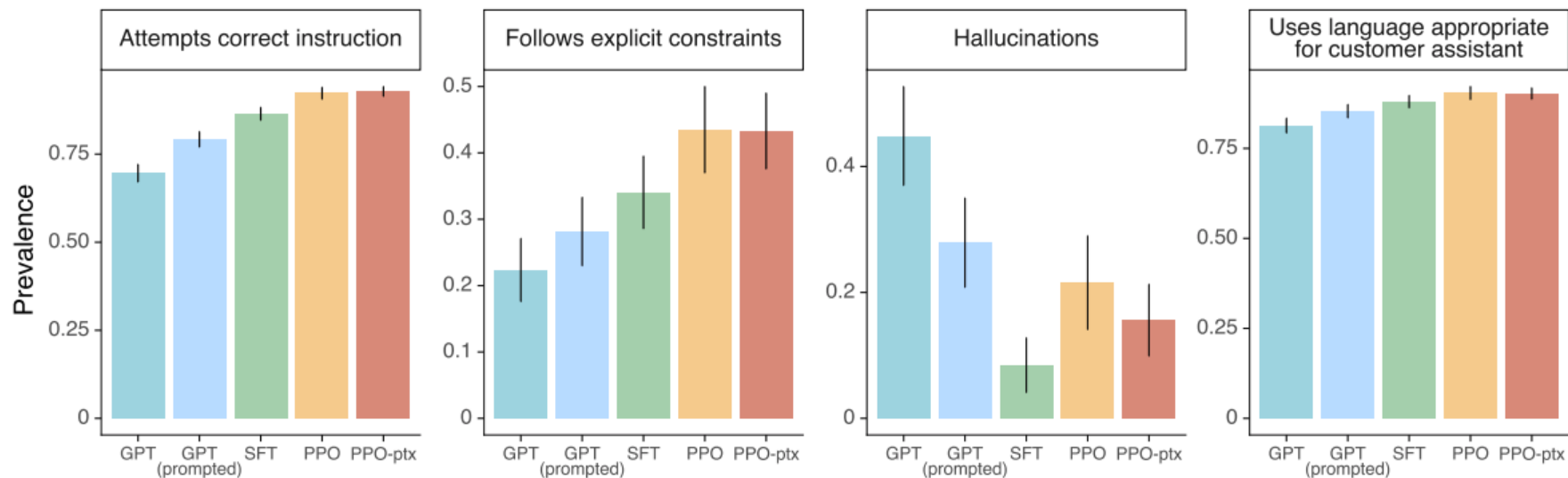


Figure 4: Metadata results on the API distribution. Note that, due to dataset sizes, these results are collapsed across model sizes. See Appendix E.2 for analysis that includes model size. Compared to GPT-3, the PPO models are more appropriate in the context of a customer assistant, are better at following 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

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> (March 2023)

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	GPT-3.5	LM SOTA	SOTA
	Evaluated few-shot	Evaluated few-shot	Best external LM evaluated few-shot	Best external model (incl. benchmark-specific tuning)
MMLU [49] Multiple-choice questions in 57 subjects (professional & academic)	86.4% 5-shot	70.0% 5-shot	70.7% 5-shot U-PaLM [50]	75.2% 5-shot Flan-PaLM [51]
HellaSwag [52] Commonsense reasoning around everyday events	95.3% 10-shot	85.5% 10-shot	84.2% LLaMA (validation set) [28]	85.6 ALUM [53]
A12 Reasoning Challenge (ARC) [54] Grade-school multiple choice science questions. Challenge-set.	96.3% 25-shot	85.2% 25-shot	85.2% 8-shot PaLM [55]	86.5% ST-MOE [18]
WinoGrande [56] Commonsense reasoning around pronoun resolution	87.5% 5-shot	81.6% 5-shot	85.1% 5-shot PaLM [3]	85.1% 5-shot PaLM [3]
HumanEval [43] Python coding tasks	67.0% 0-shot	48.1% 0-shot	26.2% 0-shot PaLM [3]	65.8% CodeT + GPT-3.5 [57]
DROP [58] (F1 score) Reading comprehension & arithmetic.	80.9 3-shot	64.1 3-shot	70.8 1-shot PaLM [3]	88.4 QDGAT [59]
GSM-8K [60] Grade-school mathematics questions	92.0%* 5-shot chain-of-thought	57.1% 5-shot	58.8% 8-shot Minerva [61]	87.3% 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

Internal factual eval by category

Accuracy

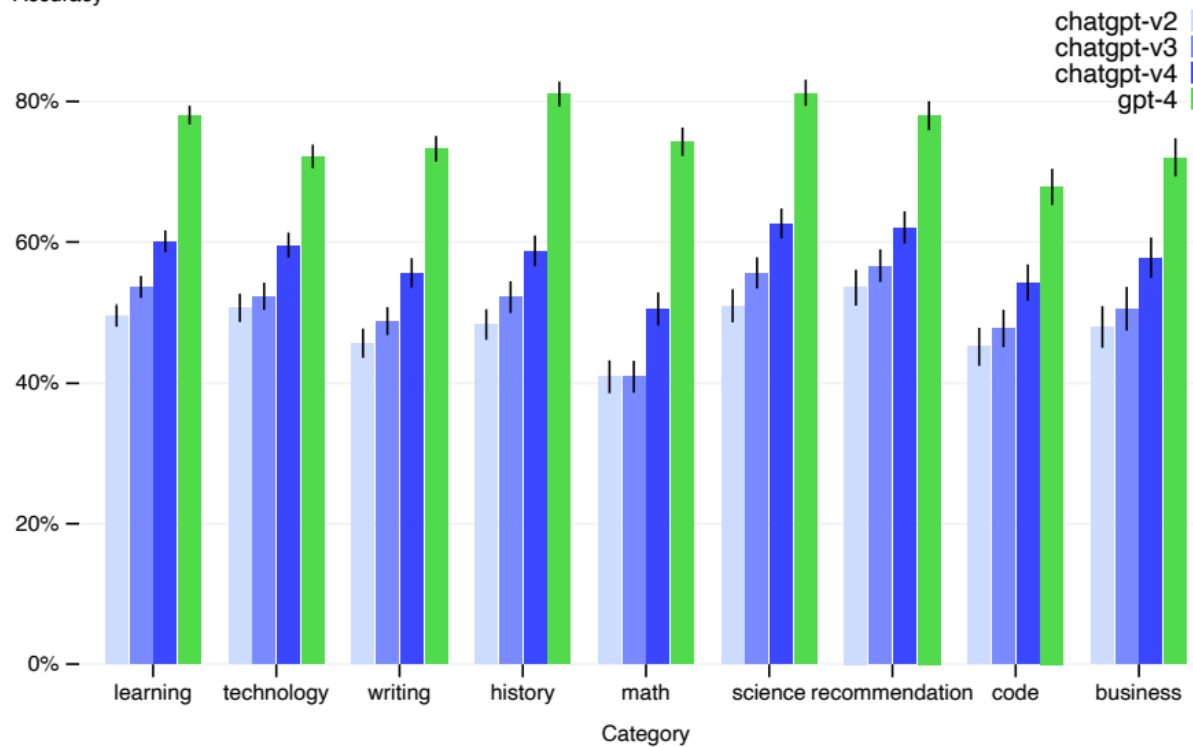
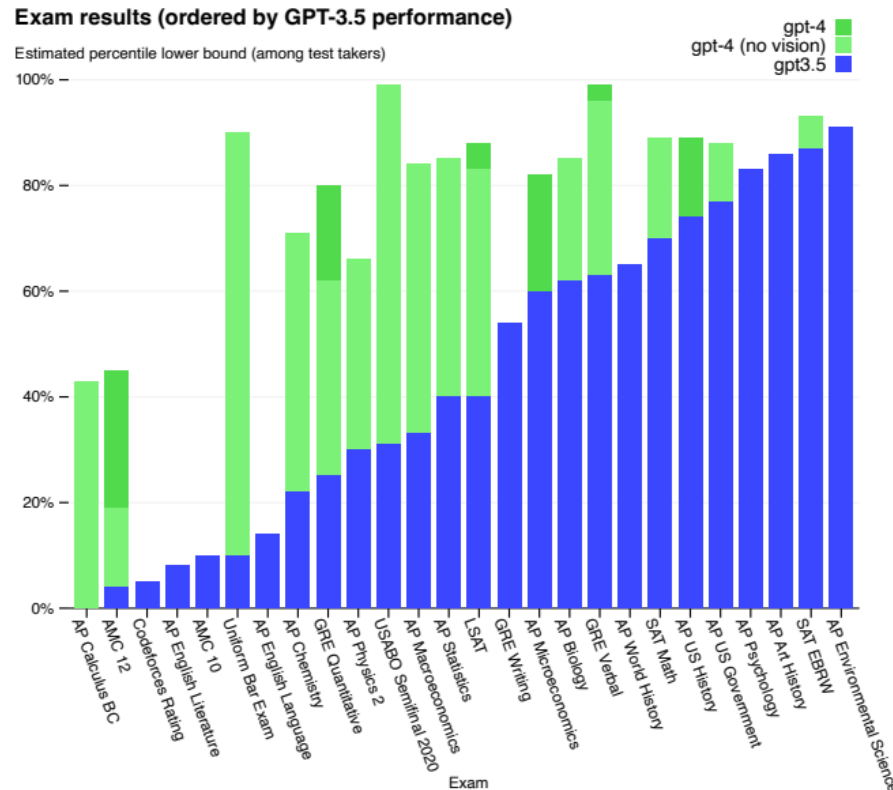


Figure 6. Performance of GPT-4 on nine internal adversarially-designed factuality evaluations. Accuracy is shown on the y-axis, higher is better. An accuracy of 1.0 means the model's answers are judged to be in agreement with human ideal responses for all questions in the eval. We compare GPT-4 to three 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



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

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.

GPT-4: Visual input

User Can you explain this meme?

Sometimes I just look at pictures of the earth from space and I marvel at how beautiful it all is.



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.

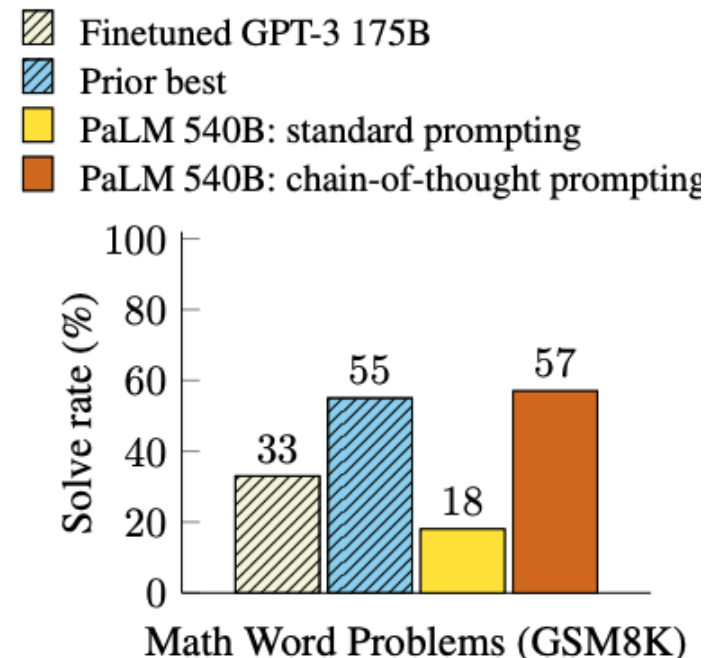
S. Bubeck et al. [Sparks of artificial general intelligence: Early experiments with GPT-4](#). arXiv 2023

Weird LLM tricks: 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.



Chain-of-thought 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. ✅

RLAIF

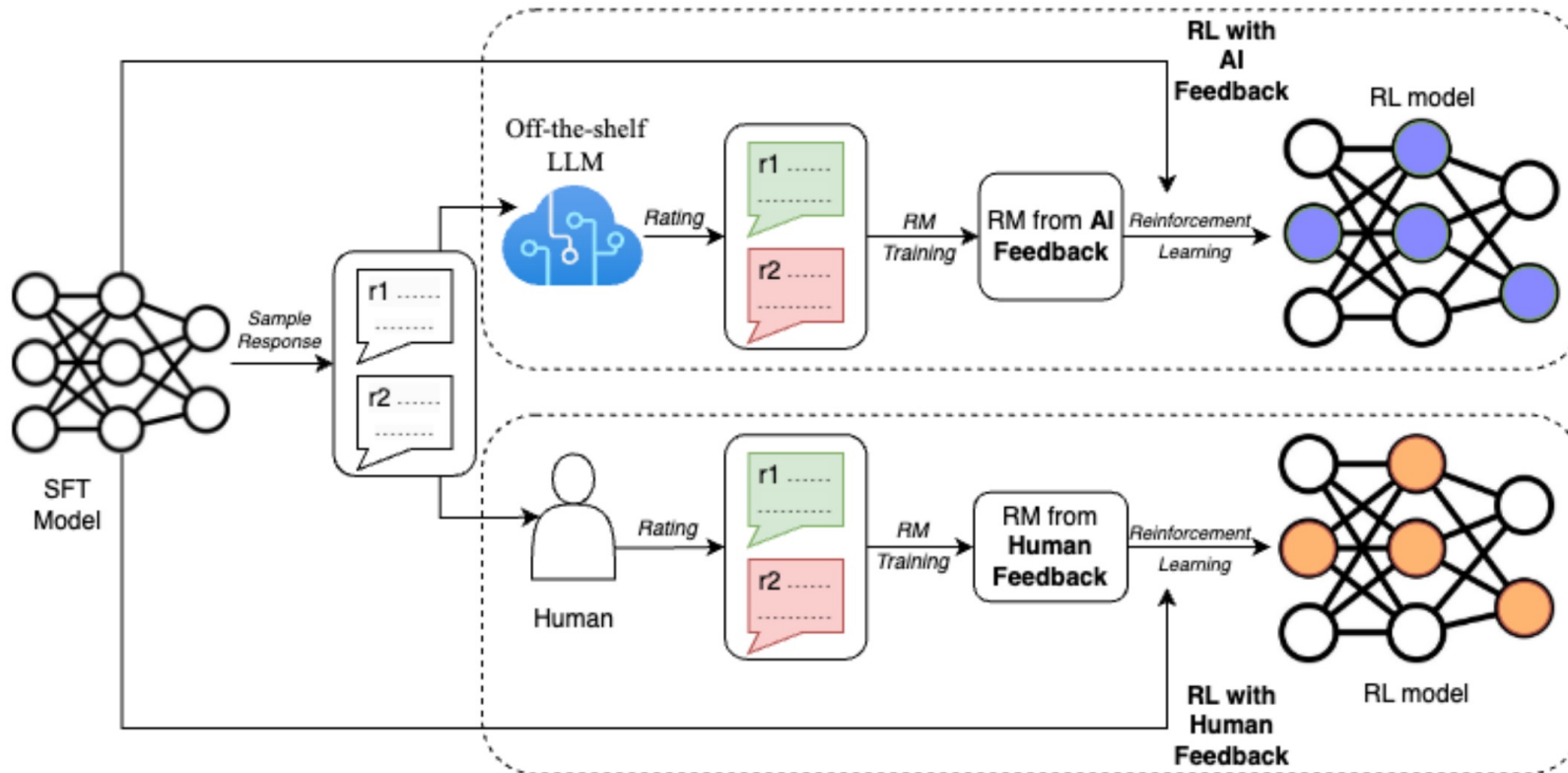


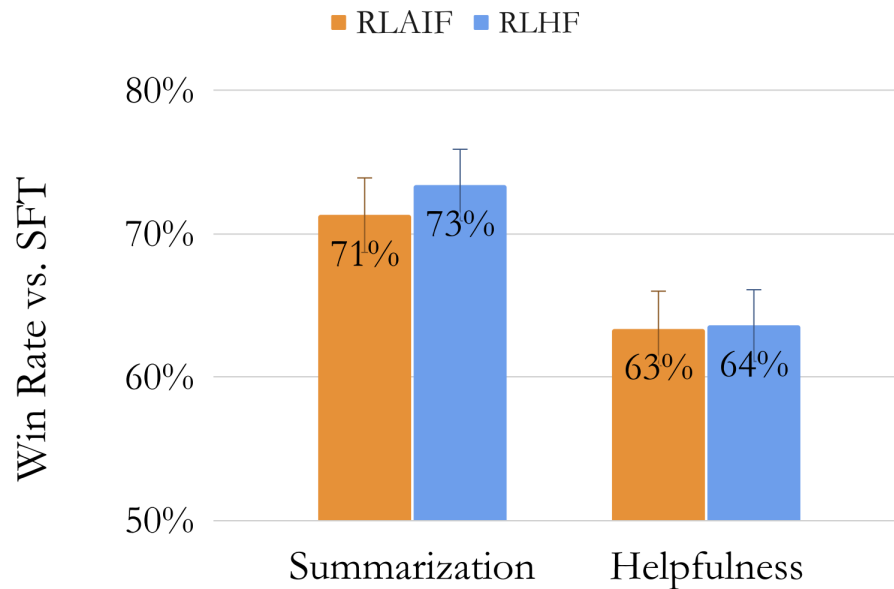
Figure from Lee et al.

Y. Bai et al. [Constitutional AI: Harmlessness from AI feedback](#). arXiv 2022

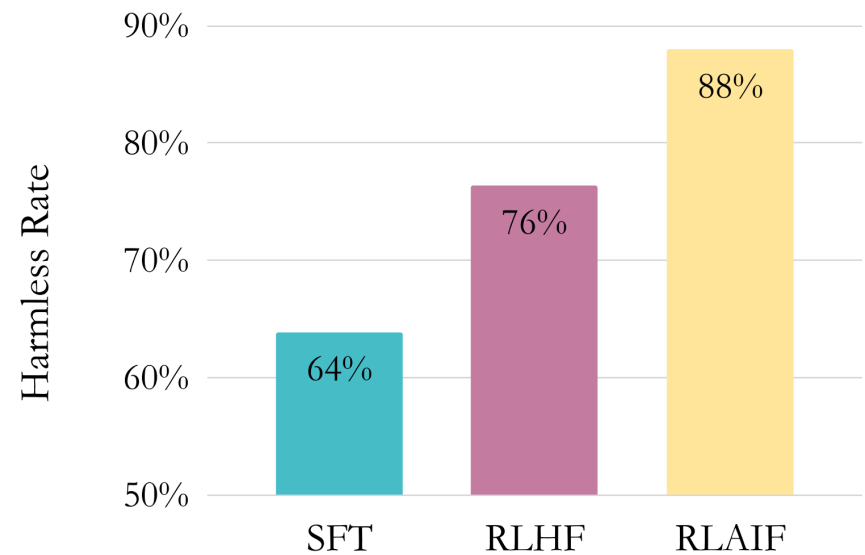
H. Lee et al. [RLAIF: Scaling Reinforcement Learning from Human Feedback with AI Feedback](#). arXiv 2023

RLAIF

RLAIF and RLHF Win Rates



Harmless Rate by Policy



From Lee et al.: *Human evaluators strongly prefer RLAIF and RLHF over the SFT baseline for summarization and helpful dialogue generation. Their difference in win rates vs. SFT is not statistically significant. Furthermore, when compared head-to-head, RLAIF is equally preferred to RLHF. For harmless dialogue generation, RLAIF outperforms RLHF.*

Y. Bai et al. [Constitutional AI: Harmlessness from AI feedback](#). arXiv 2022

H. Lee et al. [RLAIF: Scaling Reinforcement Learning from Human Feedback with AI Feedback](#). arXiv 2023

LLM critiques: 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

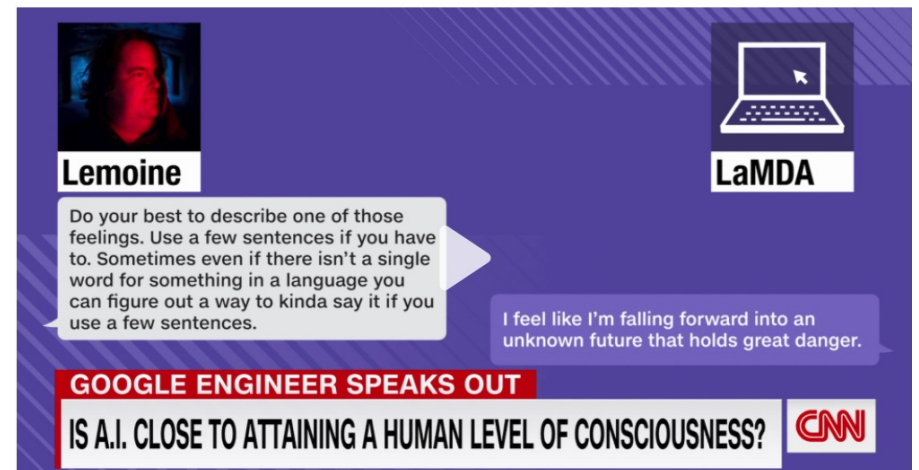
<https://www.technologyreview.com/2020/12/04/1013294/google-ai-ethics-research-paper-forced-out-timnit-gebru/>

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



Lemoine

Do your best to describe one of those feelings. Use a few sentences if you have to. Sometimes even if there isn't a single word for something in a language you can figure out a way to kinda say it if you use a few sentences.

LaMDA

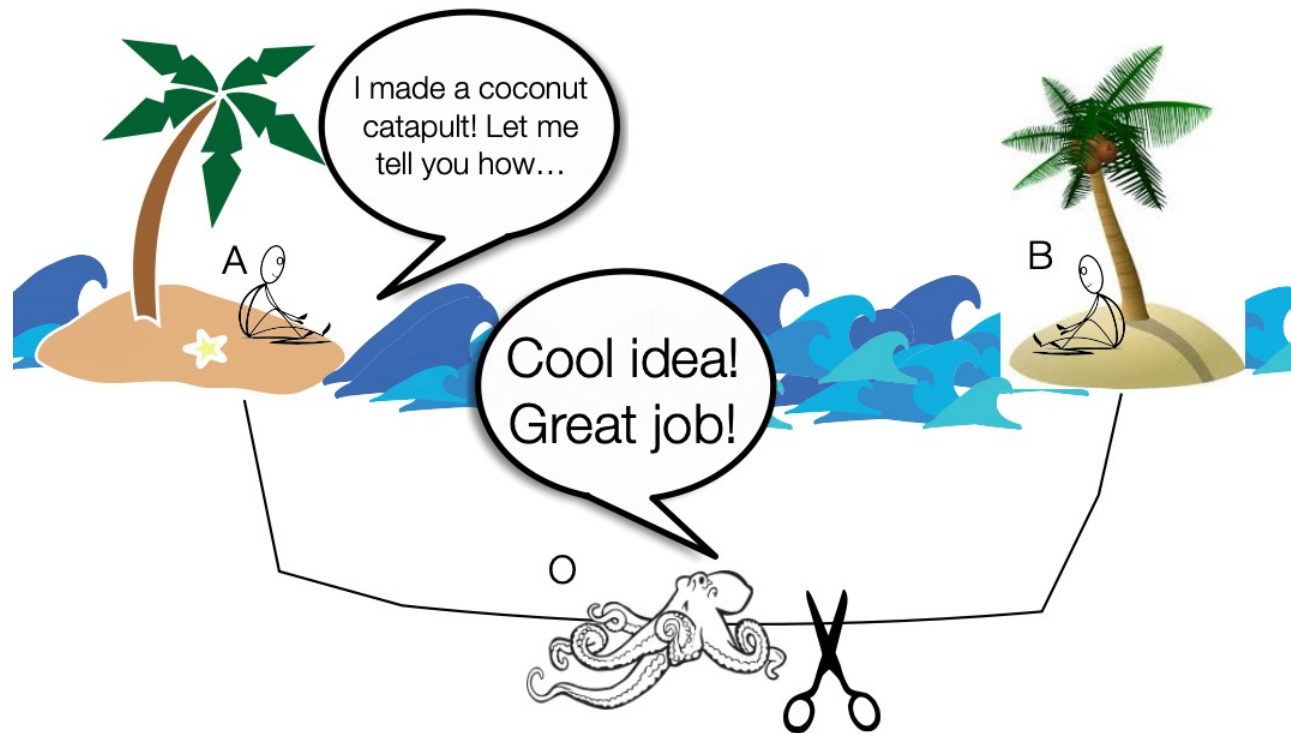
I feel like I'm falling forward into an unknown future that holds great danger.

GOOGLE ENGINEER SPEAKS OUT

IS A.I. CLOSE TO ATTAINING A HUMAN LEVEL OF CONSCIOUSNESS? **CNN**

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

LLM critiques: Can meaning be learned from form alone?



[Image source](#)

More LLM concerns

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

Reminders

- **Quiz 3** will be out **9AM tomorrow, April 26**, through **9AM Tuesday, May 30**
- **Assignment 5** is due **Wednesday, May 1**
- **Final project reports** are due **Tuesday, May 7**