Advanced Methods in Text Analytics

Large Language Models

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Large Language Models (1)

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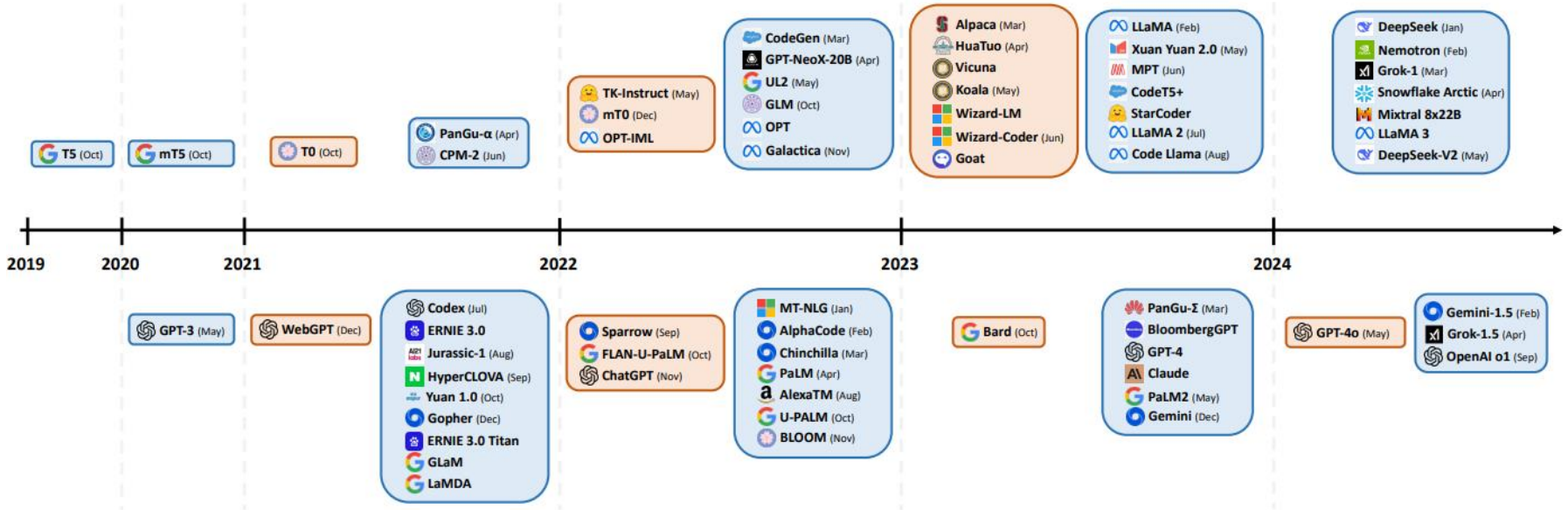
- **LLMs:** Large Language Models (vast majority are **causal LMs**, i.e. CLMs)
  - Active/trendy research topic, **many open questions/challenges**
  - **Above line:** open source; **orange cards:** instruction tuned



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Large Language Models (2)

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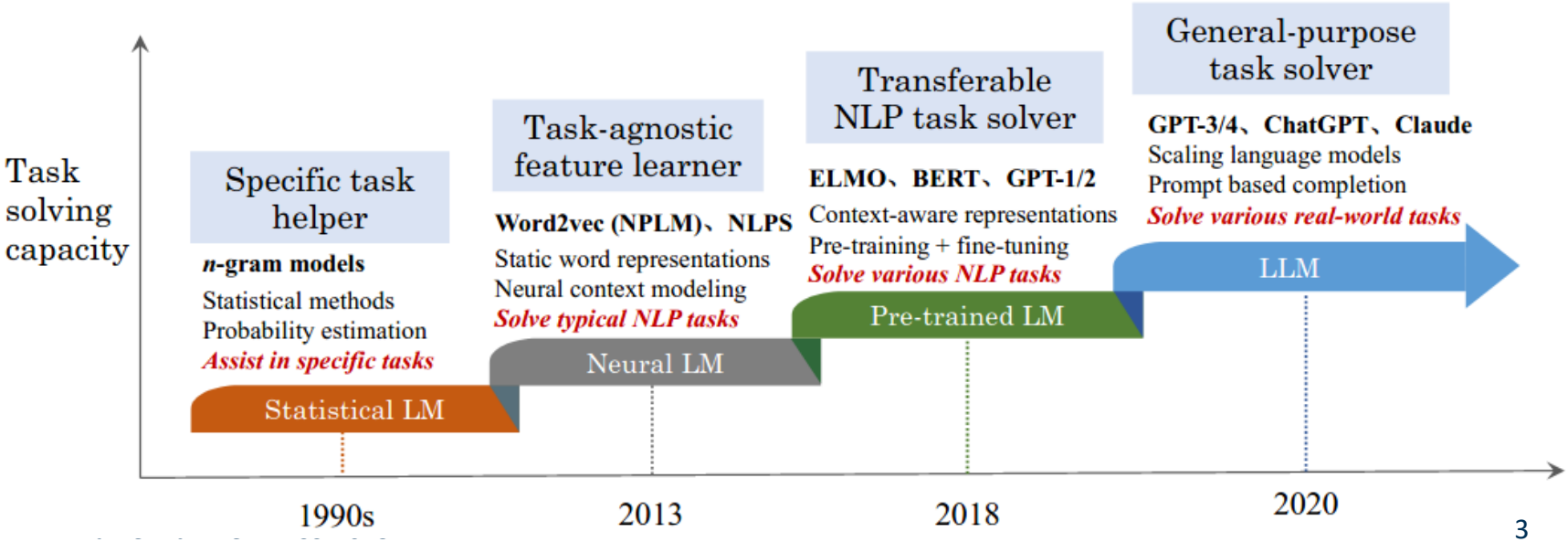
- **LLMs distinguished by:**
  - (i) size --> (ii) what they can do --> (iii) how they are used
- **The way we use LMs** has changed over time, **rough history**:
  - **Statistical LMs:** count-based, e.g. *n*-gram models
  - **Neural LMs:** FNNs/RNNs, task-specific downstream data and architectures
  - **Pre-trained LMs:** transfer learning, task-specific data, general architecture
  - **Large LMs:** as PLMs but *sometimes* no task-specific data required



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Large Language Models (3)

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- What can LLMs do? (1) **In-context learning abilities**
  - Zero shot, or few shot tasks via in-context learning
  - Other “emergent abilities”, mostly related to text generation
- What can LLMs do? (2) **Solve *new tasks* by following instructions**
  - ***New*** = not trained or tuned for it, ***task*** = "summarize", "write a poem", etc.
  - E.g. *"summarize the following article into a single sentence"*
  - **New tuning methods** developed for this
- **Still, essentially pre-trained LMs** (can do transfer learning, PEFT, etc.)
- LLMs also come with **new challenges:**
  - Expensive to train, bias and fairness, data privacy, hallucinations
- In this lecture, **we focus on key methods/models**
  - Not a laundry list! (New models regularly, many won't stand test of time)
  - For comprehensive overview of methods, see this survey and this survey
  - **Industry:** get LLMs to perform better, apply them to real-world, sell them
  - **Academia:** study LLMs, understand LLMs

Outline

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1. Large Language Models
    - In-Context Learning
    - Model Overview

2. LLM Tuning
    - Instruction Tuning
    - Model Alignment

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Large Language Models

In-Context Learning

Emergent Abilities

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- "An ability is emergent if it is not present in smaller models but is present in larger models." Wei et al. 2022

1. **In-context learning (ICL)** (this section)
    - Provide model with **instruction/examples**, then **model performs task**
    - Brown et al. 2020 found that larger models much better at this
2. **Instruction following** (next section)
    - Model is **tuned on multiple tasks** via natural language instructions
    - Then model **performs** well on **new unseen tasks** described similarly
    - Thoppilan et al. (2022) observed this for their model with 68B parameters, but not for the one with 8B parameters

- Such "abilities" are **task dependent**
    - They work well on some tasks, not so much on others
    - **Prompting generally brittle**, performance dependent on chosen prompts
- Note: term "ability" is vague, we care about what these mean *concretely*
    - I.e. we focus on solving NLP (i.e. text-based) tasks, not human-like abilities

Few-Shot Tasks (1)

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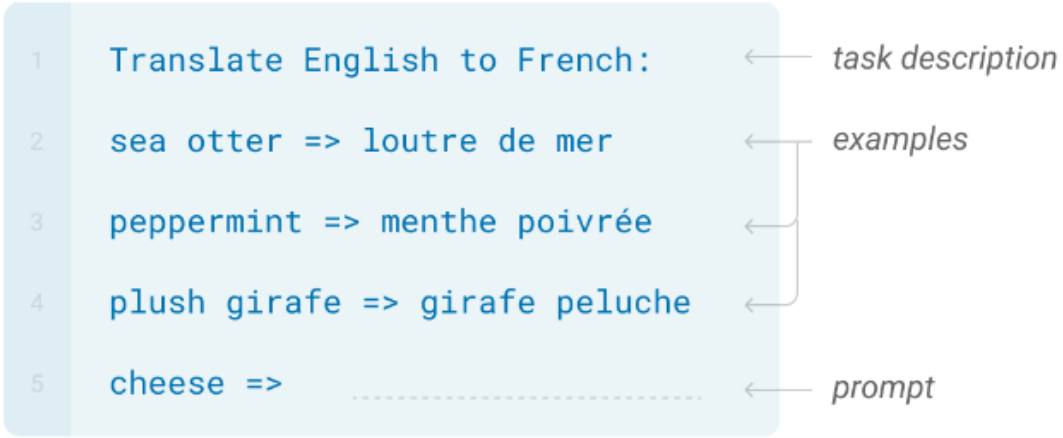
- **Background:** concept of few-shot, one-shot, zero-shot common in ML
  - E.g. in computer vision, robotics, recommender systems, etc.
- ***n*-shot**: *n* number of training examples
  - Usually, *n* is a very small number; **few** = 5, 10, 20, etc.; **one** = 1; **zero** = none
  - Deep learning models notoriously data-hungry, *n*-shot can be challenging
  - But humans known to do *n*-shot quite well
- **Zero-shot** task: "Identify the word"
  - rnmtrfraeso =>
- **One-shot** task: "Identify the word"
  - eanlingr => learning
  - rnmtrfraeso =>
- **Few-shot** task: "Identify the word"
  - eanlingr => learning
  - rcnpisgose => processing
  - rnmtrfraeso =>

Few-Shot Tasks (2)

- **Good few-shot performance** can potentially be **very useful**!
  - Getting lots of data for training/tuning is often costly, may be impossible
  - Learning from few examples may be key for human-level intelligence
- In NLP, good few-shot performance **achieved with transfer learning**
  - Typically fine-tuning on few shots
- E.g. given pre-trained LM PLM_θ parameterized by θ, N task-specific examples (x_i, y_i) and loss function L:
  - Update θ given $L(PLM_\theta(x_1), y_1)$
  - Update θ given $L(PLM_\theta(x_2), y_2)$
  - …
  - Update θ given $L(PLM_\theta(x_N), y_N)$
- Main point: **we update parameters**
  - Catastrophic forgetting may occur

In-Context Learning (1)

- **In-context learning:** given **(i) instruction** of task *and/or* **(ii) examples** of task (often called demonstrations), language model performs the task
  - Important: **no weight updates!**
  - Not learning in the traditional sense
- Note ICL also **based on transfer learning**
  - The model in question is a *pre-trained* language model (typically a CLM)
- Example, **few-shot** setting (most common ICL setting):



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In-Context Learning (2)

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- Can also be used in **one-shot** setting:

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- And **zero-shot** setting:

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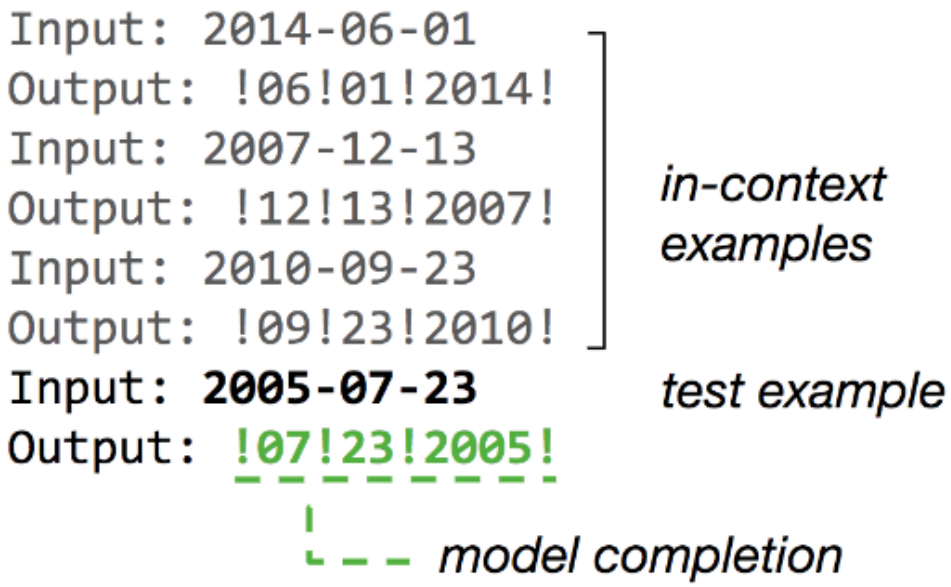
In-Context Learning (3)

- Can also be done **without task instructions**, just examples:
  - CLM naturally completes given prompt



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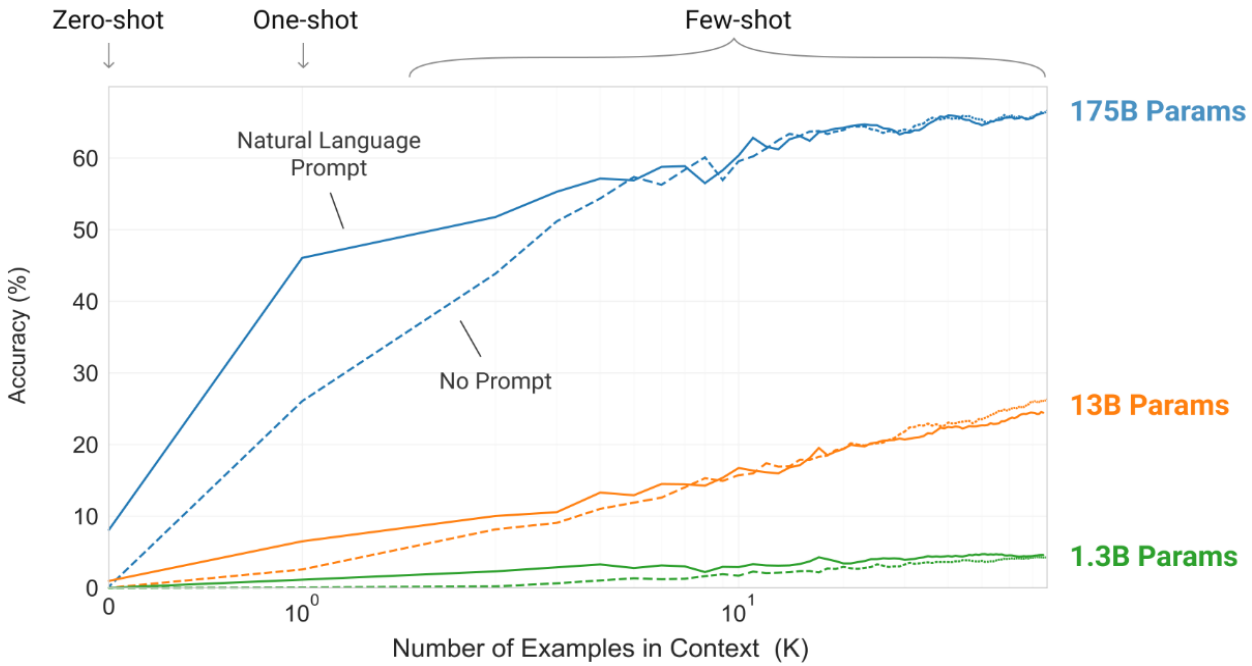
- Does this really work?
  - Yes! First work to document this well was GPT-3 (Brown et al. 2020)

In-Context Learning (4)



- Brown et al. (2020) observed (using between 10 and 100 examples):
  - Larger model -> better at ICL, largest models competitive with fine-tuning
  - Largest model made good use of task instruction in zero/one shot setting
- Later studies found ICL to be comparable to fine-tuning
- Important question: **why does this work?**

Why does ICL Work? (1)

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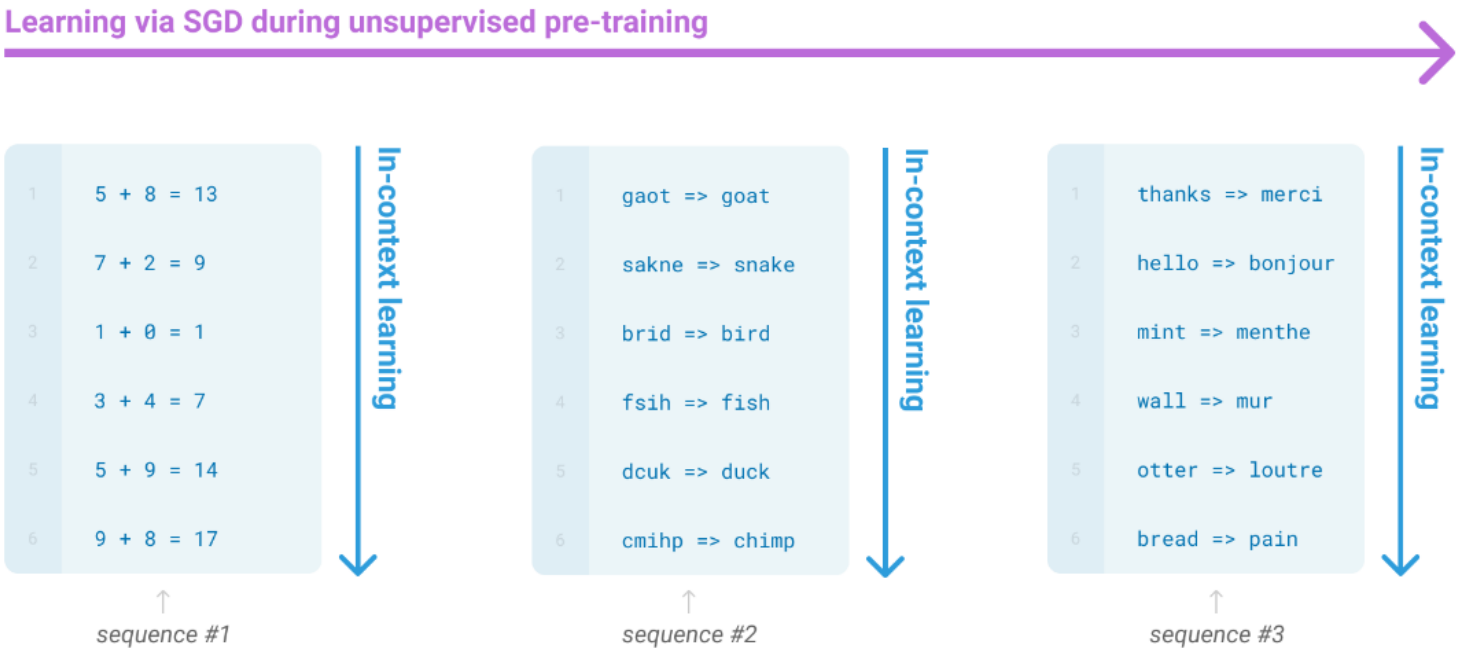
- ICL *ability* reported by GPT-3 authors has since been observed multiple times on multiple models
  - Generally observed only after models reach certain size
  - But other factors do matter, e.g. data quality, model architecture
  - Through the years, smaller models get better at this
  - E.g. Llama3-8B (2024) comparable to/better than Llama2-70B (2023)
- **Why does ICL work?**
  - There are no weight updates!
  - Models not (directly) trained on these tasks, e.g. sentiment analysis
- **Open research question**, two main directions
  1. There is indeed some form of learning happening in the forward pass
     - E.g. ICL seen from a Bayesian inference perspective
     - Or ICL from a gradient-descent perspective
  2. Models don't learn the new tasks, exploit patterns seen during pre-training
     - E.g. correct labels not needed, just label distribution/space (Min et al. 2022)

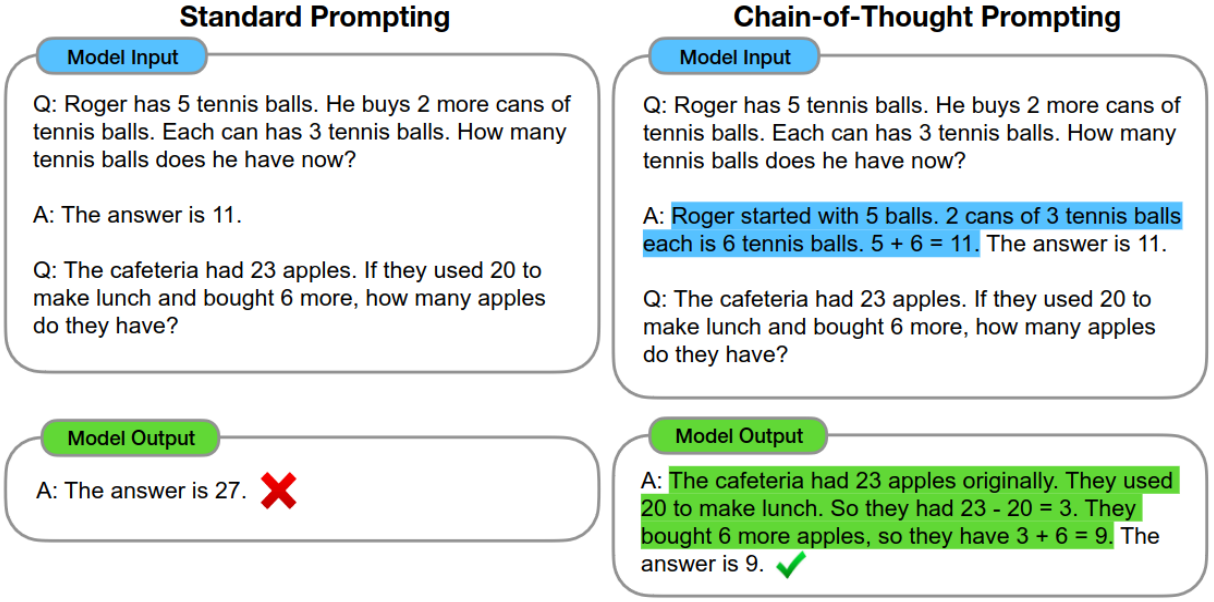
Why does ICL Work? (2)

- Authors of GPT-3 suggested models learn "skills" during pre-training
  - Then use these "pattern recognition abilities" to perform new tasks
  - They highlight that training examples may contain many such "subtasks"



Prompting (1)

- Also observed multiple times: **ICL performance highly sensitive to prompt given to model** (e.g. see Chen et al. 2023, Lu et al. 2023)
  - E.g. order of examples is relevant, distribution of labels is relevant, etc.
  - Thus, **prompting:** finding right prompt for model to perform well on task
- Important example of impact of prompting: **chain-of-thought**
  - Examples of thinking in steps helps e.g. math problems (Wei et al. 2022)



Prompting (2)

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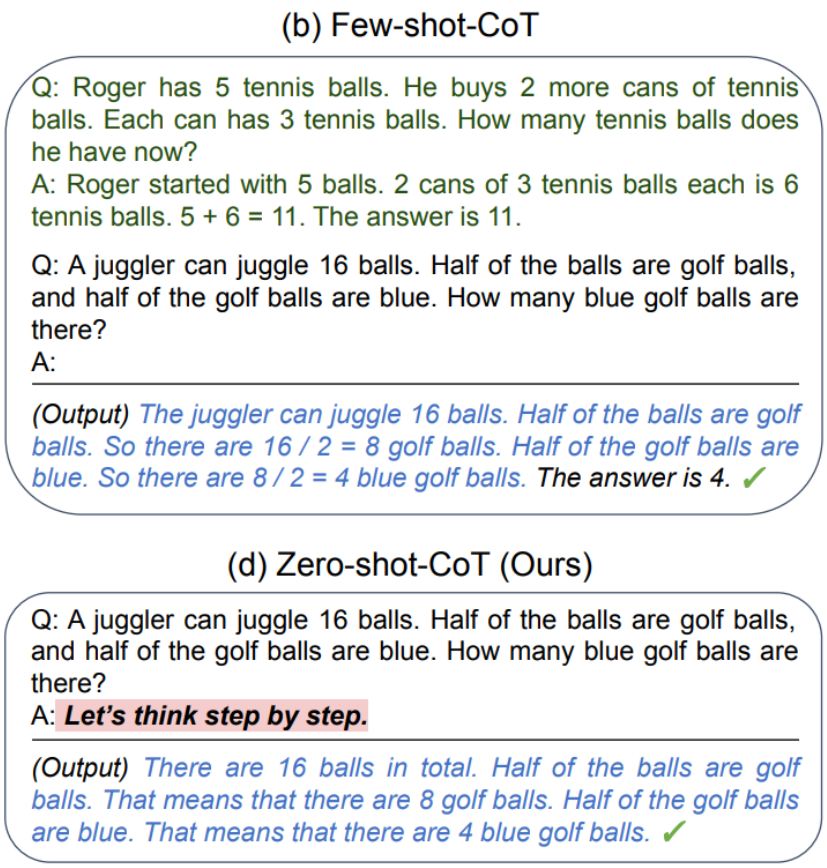
- Kojima et al. 2022 extended the idea of chain-of-thought by simply prompting models to **"think step by step"**
  - They tested their approach with GPT-3 and in a zero-shot setting, i.e. no demonstrations as in the top picture
  - This small addition to the prompt **significantly improved zero-shot performance**
- **Interpretation:**
  - It seems by having models also predict text that explains reasoning increases probability of tokens in correct answer
- Next: overview of some LLMs



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Large Language Models

Model Overview

LLMs are Expensive (1)

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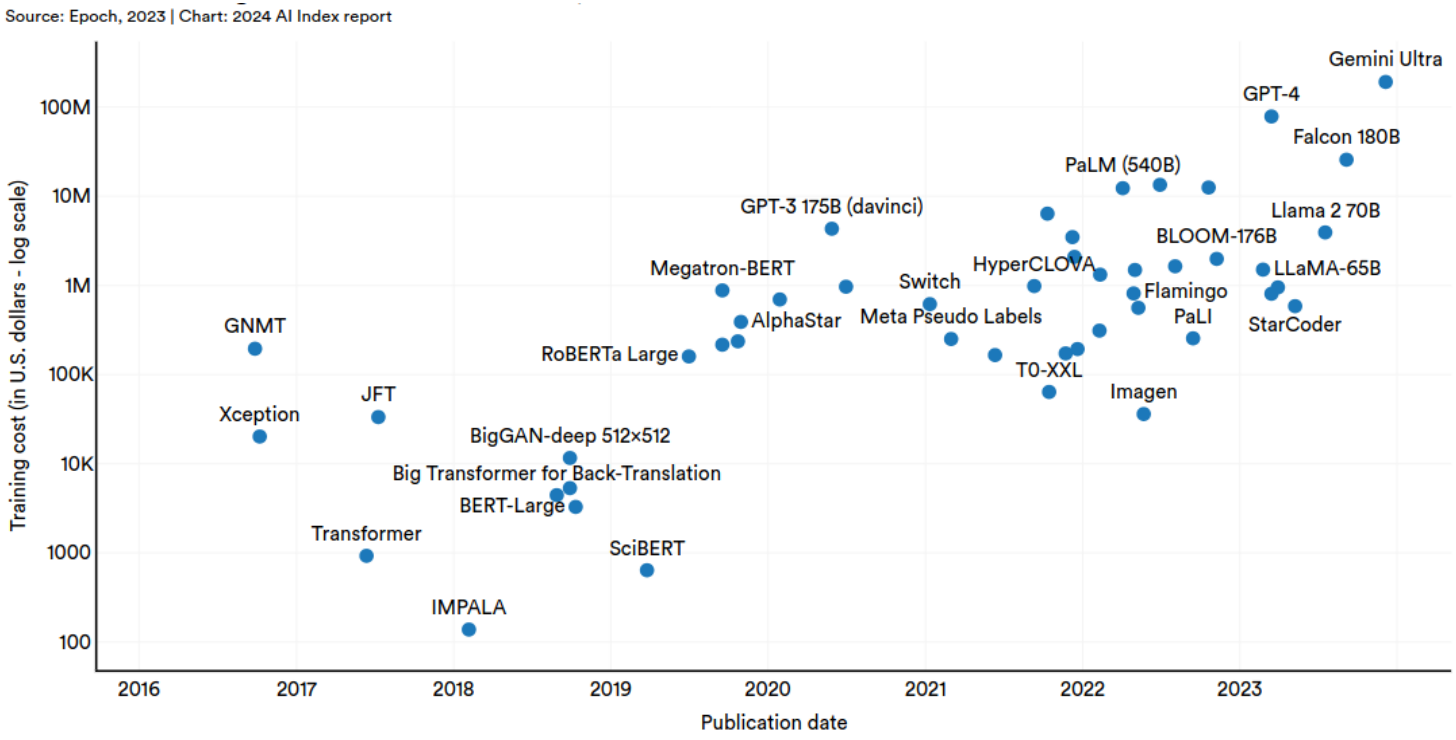
- **Training LLMs** has become **prohibitively expensive**
  - Example: LLaMa-2 70B (2023) trained on 2 trillion tokens (~10TB of open data), 6K GPUs, 12 days, 2M USD (source: Intro to LLMs by A. Karpathy)
- Some estimates go beyond 100M USD (source: Stanford's AI Index Report 2024)



LLMs are Expensive (2)

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- Once pre-trained, **fine-tuning is cheaper** (computationally)
  - Computationally much more feasible, e.g. with PEFT, quantization
- But **getting data can be challenging**
  - **Data quality matters** more than quantity at this stage
  - Data **more reflective of relevant** downstream **tasks**, e.g. chatbots
- **Also, fine-tuning** is **iterative** process
  - Observe problems, create data for adjusting, fine-tune, repeat
  - I.e. costs can be continuous
  - More in next section
- Let's have a look at some models
  - But first, a quick overview of architectures and training objectives

Architectures

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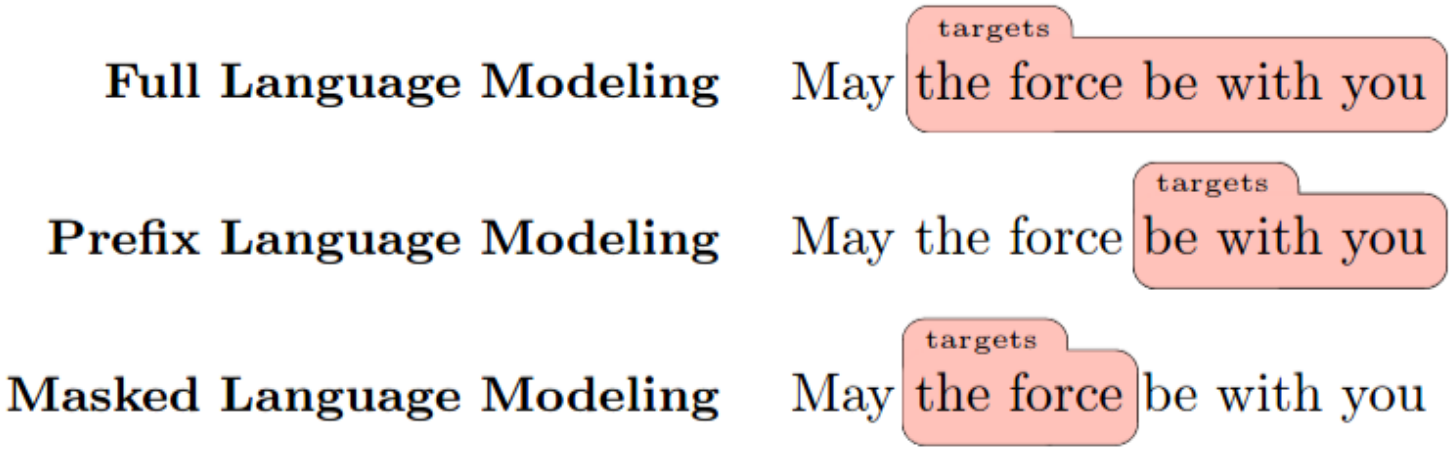
- All architectures are transformer-based
- **Causal LM, decoder-only (most common by far)**
  - **Decoder** autoregressively predicts new tokens conditioned only on output of decoder
  - E.g. GPT series (closed source, OpenAI), LlaMA series (open source, MetaAI)
- **Encoder/decoder (less adopted in recent years)**
  - **Encoder** produces sequence of contextualized tokens
  - **Decoder** autoregressively predicts new tokens conditioned on output of decoder *and* encoder
  - **Cross-attention:** attends to output tokens from encoder
  - Example model: T5, UL2
- Other less common architectures (for LLMs) exist
  - Encoder-only
  - Non-causal decoder only (bidirectional attention across *past* tokens)

Training Objectives

- **(Full) Autoregressive/Causal** language modeling (CLM)
  - Most common approach, highly adopted since GPT-2 (2019)
  - Causal masking on (self-)attention scores (***KQ***) matrix
- **Masked** language modeling: fill-in-the-blank task (less adopted)
- **Prefix** language modeling (less adopted)
  - **Prefix:** fixed subsequence of first *n* tokens
  - **Task:** predict tokens after prefix
  - Difference with CLMs: attention *bidirectional* over prefix token



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The GPT Series (1)

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- **Proprietary** models! **Closed source**, not all information is available
- We've already discussed the **GPT architecture** in a previous lecture
  - Causal language modeling, decoder-only
- In terms of **number of parameters**
  - **GPT-1:** 117M
  - **GPT-2:** 1.5B
  - **GPT-3:** 175B
- In terms of decoder **layers**
  - **GPT-1:** 12 layers of size 768
  - **GPT-2:** 48 layers of size 1600
  - **GPT-3:** 96 layers of size 12228
- **GPT-2 vs GPT-1**
  - Small changes in architecture (discussed in Transfer Learning lecture)
  - Performed well on zero-shot tasks, but performance below fine-tuning

The GPT Series (2)

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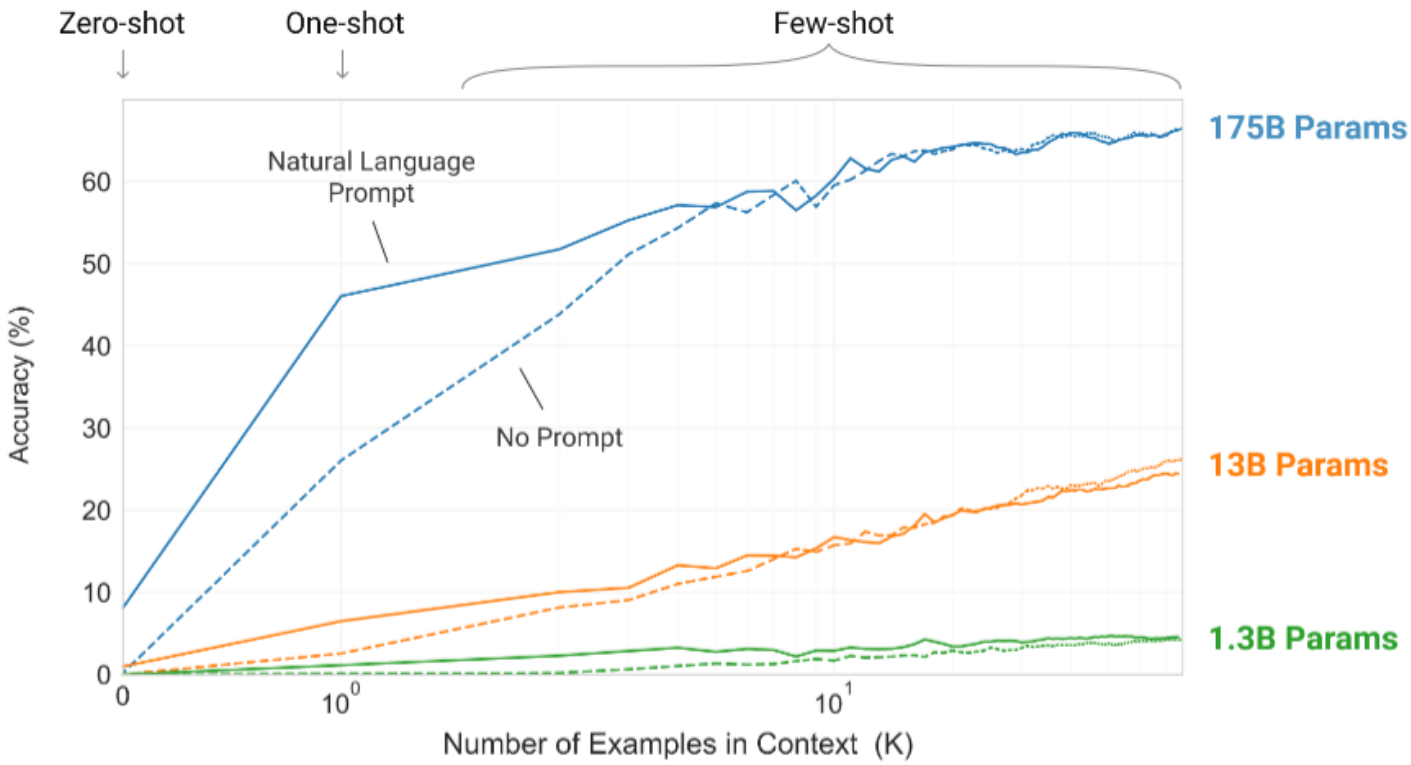
- **GPT-3 vs GPT-2**
  - Leap in few-shot performance via **in-context learning (ICL)**
  - Inspired to continue scaling up models



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The GPT Series (3)

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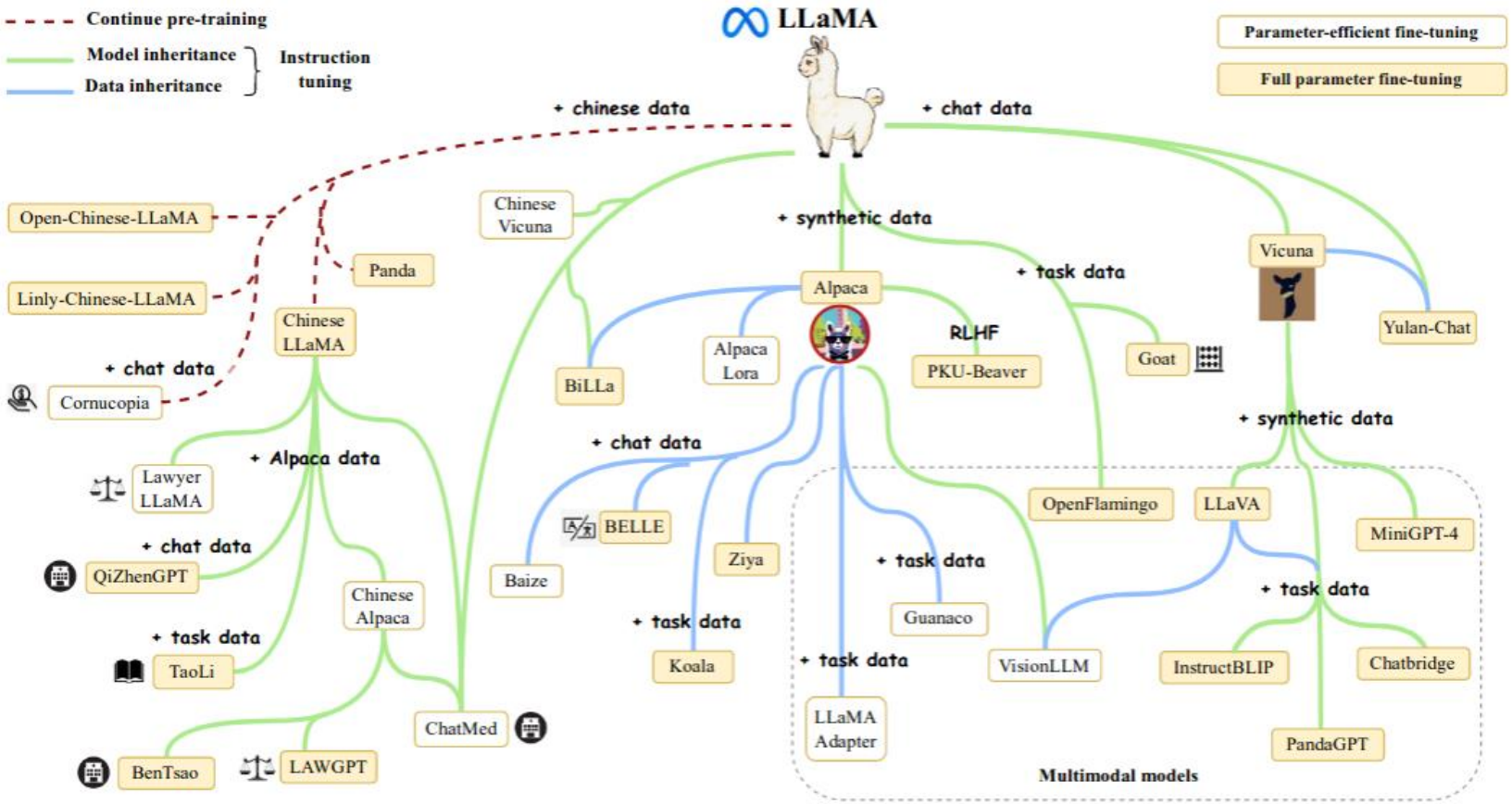
- **Codex**
  - GPT-3 fine-tuned on large corpus of GitHub code
  - Able to solve coding problems, improved performance on math problems
- **GPT-3.5 models**
  - GPT-3-based models with stronger abilities
  - Abilities -> not benchmarked tasks, evaluated by humans
  - How did they get better? **Model alignment** (more in next section)
- **ChatGPT:** fine-tuned for dialogue (ability: communicate with humans)
- **GPT-4**
  - Superior performance on human-generated tests compared to ChatGPT
- Still **many challenges**
  - Mainly, **hallucinations**: false information presented as fact
  - Perhaps a reminder: these are still *language models*
    - LLMs can predict facts *sometimes*, i.e. may be used as *unreliable* databases
    - But no internal "stop-and-think" mechanism (on-going research, e.g. here, here)

The LLaMA Series (1)

- **Highly valuable contribution!** "LlaMA is the new BERT"
  - Being open source, it sparked large number of research/applications



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The LLaMA Series (2)

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- Important **open source** LLM developed by META AI
- LLaMA-1 (2023)
  - Decoder-only causal LM
  - Several sizes: 7B to 65B parameters
  - Largest model has 80 layers of size 8192
  - Trained only on publicly available data
  - Competitive with best LLMs
  - All weights (checkpoints), code made available
- LLaMA-2 (2023)
  - Focused on fine-tuning for dialogue applications
  - Same architecture as LLaMA-1, but larger model at 70B parameters
  - Trained on 40% more data than LLaMA-1
  - Released all pre-trained and fine-tuned models

The LLaMA Series (3)

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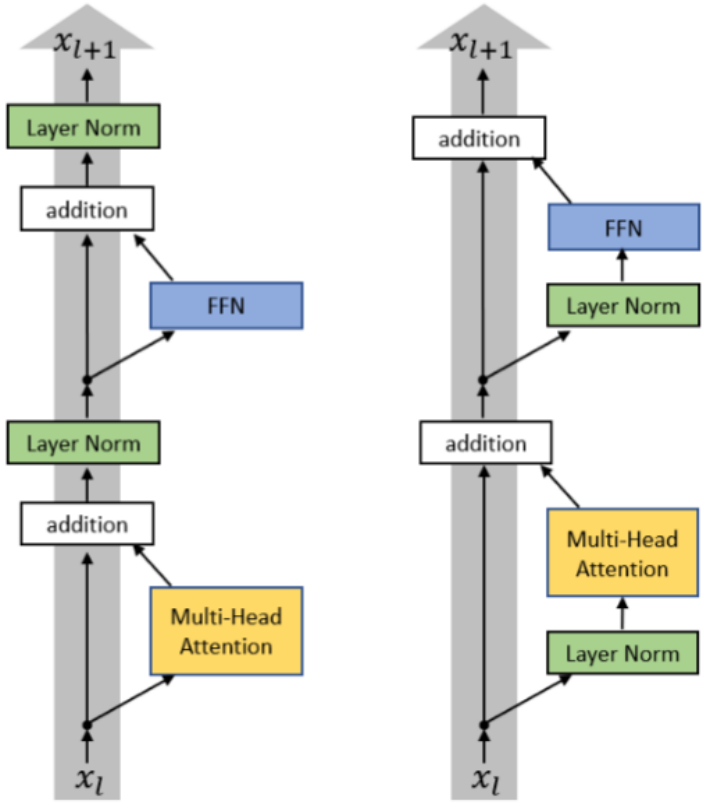
- LlaMA-3 (2024)
  - Improved quality and size of training data (15T vs 1.8T for Llama-2)
  - Sizes from 8B to 405B parameters (the largest model is dense, more soon)
  - Hidden representations size ranges from 4096 to 8192
  - Number of attention heads ranges from 32 to 128
  - Vocabulary size: 128.000
- Llama-4 (2025)
  - No technical report released yet.
  - Sizes from 109B to 2T parameters
  - But all models now sparse, i.e. relying on mixture-of-experts (more soon)
- Interesting "mid-season" release: Llama-3.2 (2024)
  - Small 1B and 3B models achieved via model distillation
- In the following, we *briefly* discuss some common LLM components:
  - PreNorm vs PostNorm models, RMSNorm, SwiGLU
  - Model distillation, Mixture-of-Experts (MoE)

PreNorm vs PostNorm

- Following prior work, Xiong et al. (2020) argued that using **LayerNorm** differently addresses gradient-based issues during training
  - They proposed to move the LayerNorm component from after each self-attention and MLP layer (image on left) to inside (and before) each self-attention and MLP layer (image on right)
  - This variant is commonly used by some LLMs, e.g the Llama family
- But Llama models do not use LayerNorm
  - They use a variant: **RMSNorm**



RMSNorm

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- Recall **LayerNorm**: İt's a form of centering data
  - **Goal:** address internal distribution shifts to make training more stable
  - **How:** given output vector **a** for some hidden layer, compute its mean μ and standard deviation σ
  - Then **center a'** = (**a** - μ) / σ
  - Finally, **scale** the data: *LayerNorm* = γ***a'*** + β with γ**,** β being learned
- Zhang et al. (2019) argued that only the scaling component is necessary
  - They proposed simpler variant: not using mean centering
  - Result was scaling and normalization based on root-mean-square (RMS)

$$\bar{a}_i = \frac{a_i}{\mathrm{RMS}(\mathbf{a})} g_i, \quad \text{where } \mathrm{RMS}(\mathbf{a}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} a_i^2}$$

- They showed experimentally:
  - Using RMSNorm gave similar or more effective performance

SwiGLU Activations

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- Combination of two forms of activations: Swish and GLU
- Swish activations:
  - $Swish(\boldsymbol{x}, \beta) = \boldsymbol{x} \cdot \sigma(\beta x)$ where $\boldsymbol{x}$ is input vector, σ is sigmoid, β is learned
  - Roughly: smooth, non-monotonic version of ReLU
- GLU activations:
  - $GLU(\boldsymbol{x}, \boldsymbol{W}, \boldsymbol{V}, \boldsymbol{b}, \boldsymbol{c}) = \sigma(\boldsymbol{xW} + \boldsymbol{b}) \otimes (\boldsymbol{xV} + \boldsymbol{c})$ where $\boldsymbol{W}, \boldsymbol{V}$ are linear projections, $\boldsymbol{b}$ and $\boldsymbol{c}$ their biases, $\otimes$ is element-wise product
  - Note this means **some LLMs have three projections in MLP layers**
  - Here, $\boldsymbol{W}$ is typical up projection, $\boldsymbol{V}$ is 2nd *new* up projection
- SwiGLU activations:
  - $SwiGLU(\boldsymbol{x}, \boldsymbol{W}, \boldsymbol{V}, \boldsymbol{b}, \boldsymbol{c}, \beta) = Swish_{\beta}(\boldsymbol{xW} + \boldsymbol{b}) \otimes (\boldsymbol{xV} + \boldsymbol{c})$
  - Found to significantly increase performance compared to ReLU and Swish activations

Model Distillation (1)

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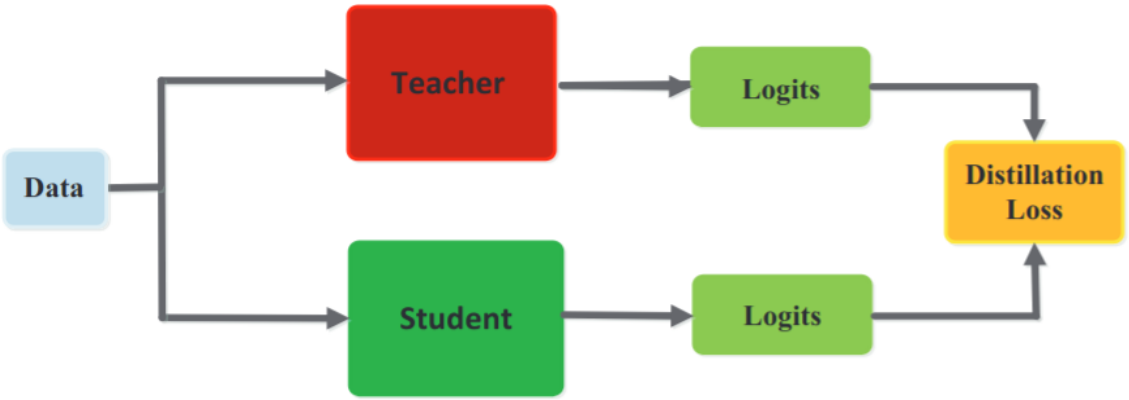
- Proposed by Hinton et al. (2015)
  - Often referred to as *knowledge distillation*
- Motivation: models are functions
  - Have function by **smaller model (student)** behave as function by **larger model (teacher)**
- How?
  - Hinton proposed using **teacher's (token) distribution as target for student**
  - Model distribution is richer than final predictions, especially with higher temperature, which they suggested should be increased during training



Model Distillation (2)

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- Common choices for distillation loss:
  - KL-Divergence (distance between distributions)
  - Mean squared error (MSE)
  - Combination of the two, or with others
- Distillation loss often linearly combined with CE loss for LM
  - DistilBERT also used cosine embedding loss, aligns teacher/student vectors
  - Can also include targets from multiple teachers (multi-signal distillation)
- Distillation is quite popular today
  - As mentioned, the Llama-3.2 family has two small models (1B and 3B) distilled from larger models Llama-3.1 (8B and 70B)
  - Companies like DeepSeek provided smaller models in their family, students were models like Llama or Qwen, teacher was their flagship model DeepSeek-R1

Sparse vs Dense Models

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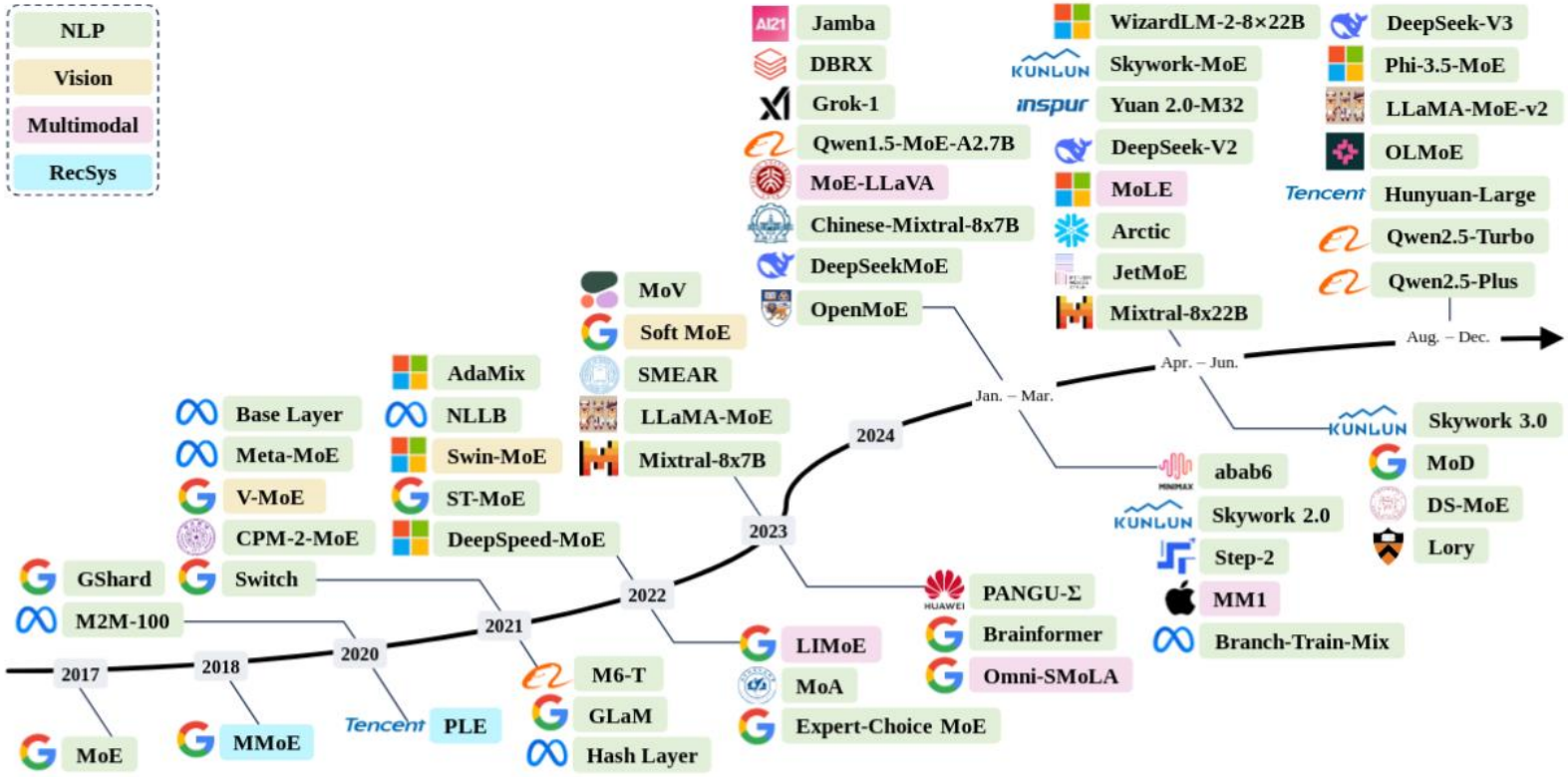
- **Dense model:** uses all its weights for any given input at inference time
  - I.e. the type of architecture used by all models discussed so far
- **Sparse model:** only uses subset of its weights for any given input at inference time
- Popular sparse architecture in LLMs: **mixture-of-experts (MoE)**
  - Scaling model parameters less expensive if model is sparse
  - Some MoE LLMs: the Mixtral family, DeepSeek-V3 (671B parameters)
- In the following slides, we go over the basics of MoE

Mixture of Experts (1)

- Popular architecture for deep learning models
  - Above arrow: open source, below arrow: closed source



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Mixture of Experts (2)

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- Part of the ML toolbox for many decades already
- **Basic intuition** of MoE:
  - Use different "parts" of the model for different inputs given to the model
  - A "part" is typically a component or subnetwork within the model
  - Thus, **expert:** subnetwork specialized to handle some type of input
- Concretely, a **MoE layer** consists of the following **components**:
  - **Set of expert networks** E = $\{E_1, E_2, \ldots, E_n\}$
  - **Gating/routing function** $G: T \dashrightarrow E^k$ designed to choose set of $k < n$ experts for each portion of training data T
  - **Routing strategy** that determines how data is distributed among experts
- **Output of MoE layer:** linear combination of experts' output weighted by G
- How could we implement function G?

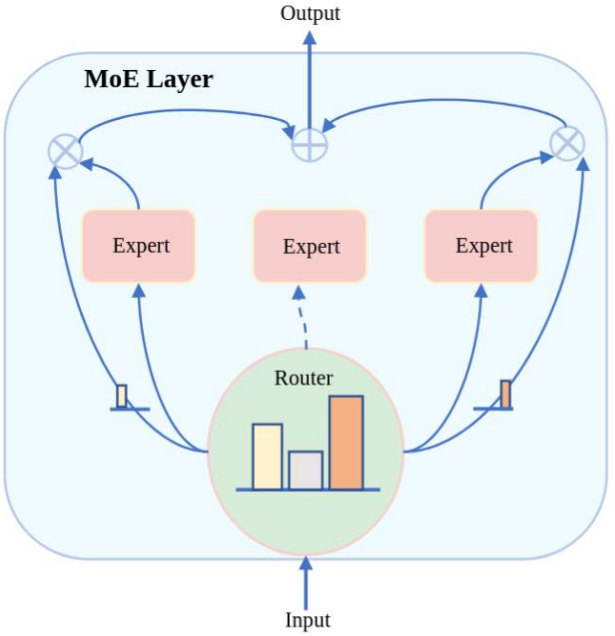

Image source

Mixture of Experts (3)

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- Common choice for routing function *G*:
  - $G(\boldsymbol{x}) = Softmax(\boldsymbol{W}_G\boldsymbol{x})$ where $\boldsymbol{x}$ is typically same input given to experts
  - Output of $G(\boldsymbol{x})$ typically referred to as routing scores
- Interpretation of $G(\boldsymbol{x})$: it acts as a "probabilistic switch"
  - Given input $\boldsymbol{x}$, $G(\boldsymbol{x})_j$ gives probability of selecting *j-th* expert
  - Thus, $\boldsymbol{W}_G \in R^{d \times n}$ where *d* is size of $\boldsymbol{x}$, *n* is number of experts
- In modern NLP, Shazeer et al. (2017) used MoE in a two-layered stacked RNN (with LSTMs) for machine translation
  - They added a MoE layer between RNN layers (input to *G*, experts: tokens)
  - **Each expert** was a **linear layer** (they used up to thousands of experts)
  - $G(\boldsymbol{x})$ was as above but they added a sparsity constraint
  - **Sparsity:** *top-k*$(\boldsymbol{x})$, i.e. only *k* experts used for each input for efficiency
- **Output of MoE layer:** $y = \sum_n G(\boldsymbol{x})_i E_i(\boldsymbol{x})$ where $G(\boldsymbol{x}) = Softmax(top\text{-}k(\boldsymbol{W}_G\boldsymbol{x}))$
- **Routing strategy:** level of specialization (token-level, task-level, etc.)
  - E.g. select *k* experts per token, use per-task experts with unlearned routing

Training MoE

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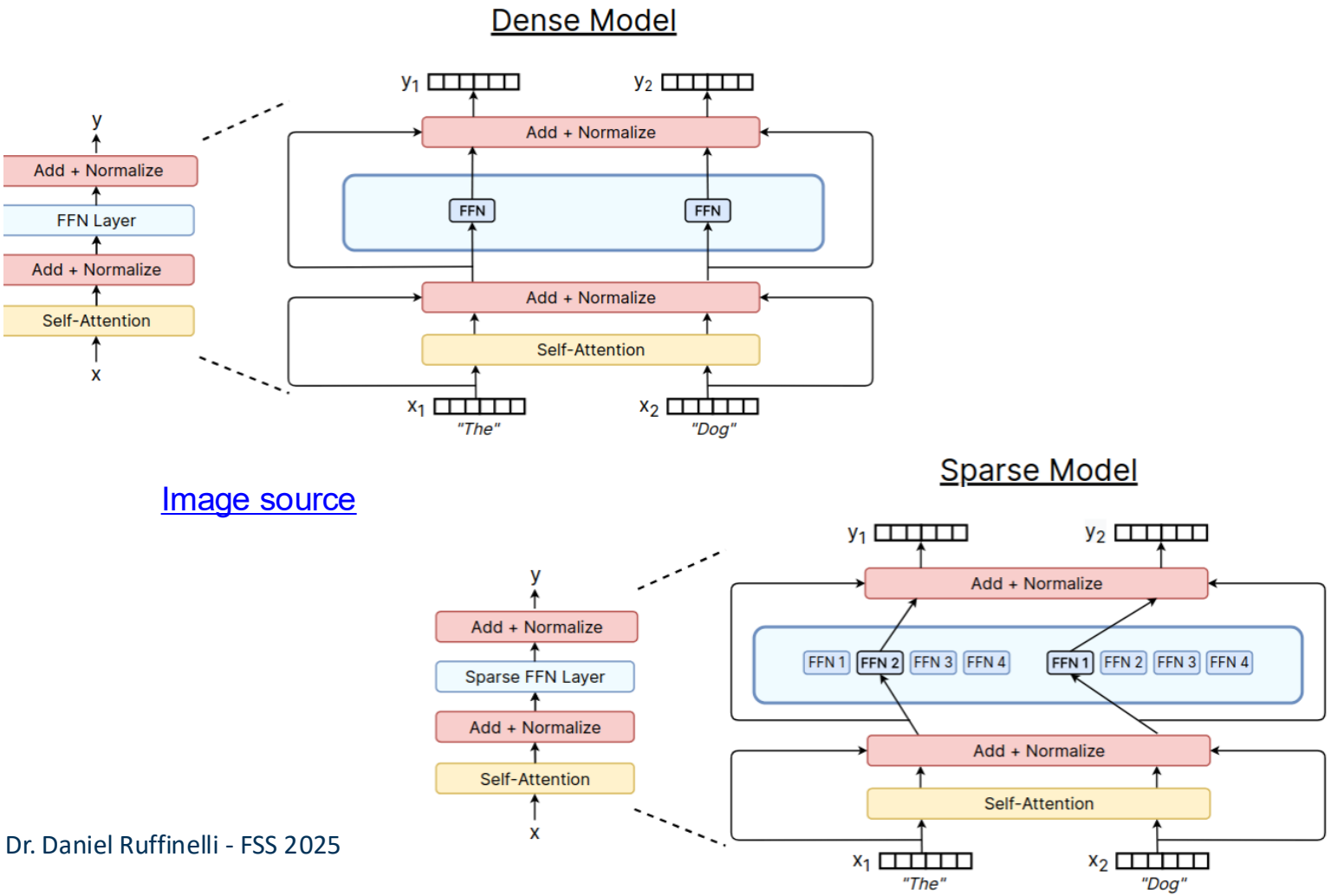
- **Routing examples** to different experts **can cause training issues**
- Goal of routing: select which of *n* experts to send each input to
  - **Discrete decision**, can be **problematic for gradient-based learning**
- Shazeer et al. used the "probabilistic switch"
  - Specifically, selecting **top-*k*** experts
  - Their implementation of *top-k* did not cause problems during training
  - Other strategies exist, e.g. based on hashing, reinforcement learning
- Another potential issue: **load balancing**
  - Shazeer et al., as well as prior work, noted **routing converges to favoring few experts**
  - Thus, **vicious cycle**: few experts get chosen the most, they see more data, get better at the task
  - Often **addressed with auxiliary loss function** that **encourages that each expert sees an equal amount of tokens** during training
- Same idea was applied a few years later to the transformer architecture

MoE in Transformers

- Proposed by Lepikhin et al. (2021) and Fedus et al. (2022)



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MoE in LLMs

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- **Mixtral** models mostly followed prior work
  - As shown in previous slide, i.e. Shazeer et al. with transformers
  - Also, softmax-based routing function, top-*k* routing strategy
  - They used SwiGLU as experts (LLM-era activations)
- **DeepSeek** models introduced **new ideas**
  - Some *shared experts* always on to capture constantly needed knowledge
  - Split internal (large) dimension in MLP layers into two separate up-projections to allow more *fine-grained experts*
- Note: **term "expert" can be misleading, depends on routing strategy**
  - Resulting experts not necessarily "experts" in math, translation, etc.
  - Routing strategy can, but often doesn't, make such decisions
  - Instead, model is allowed to organize experts as needed during training
  - It's more akin to using multiple self-attention heads
  - Result can be experts in subtasks, e.g. a "copy-paste" attention head
- For more on MoE, see here or here.

Context Window (1)

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- Something not discussed so far: **size of context window**
  - **Expensive due to quadratic cost of attention**
- Constant effort to increase size with every new model

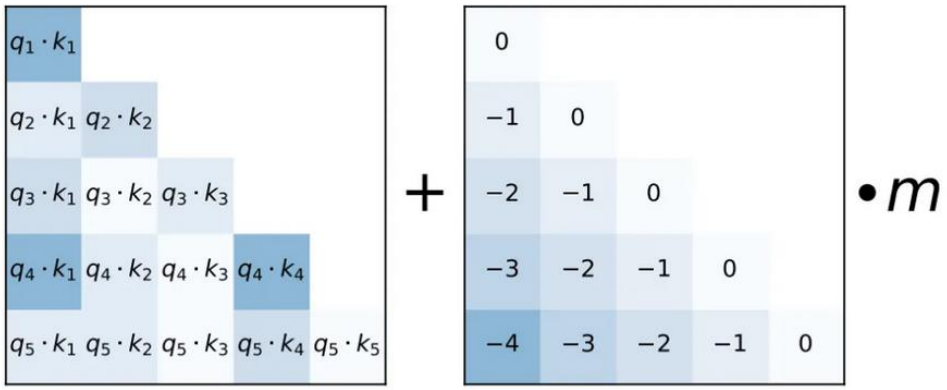
Model	Context length	Number of English pages*
GPT 3.5	4,096	6
GPT 4	8,192	12
GPT 4-32k	32,768	49
Llama 1	2,048	3
Llama 2	4,096	6

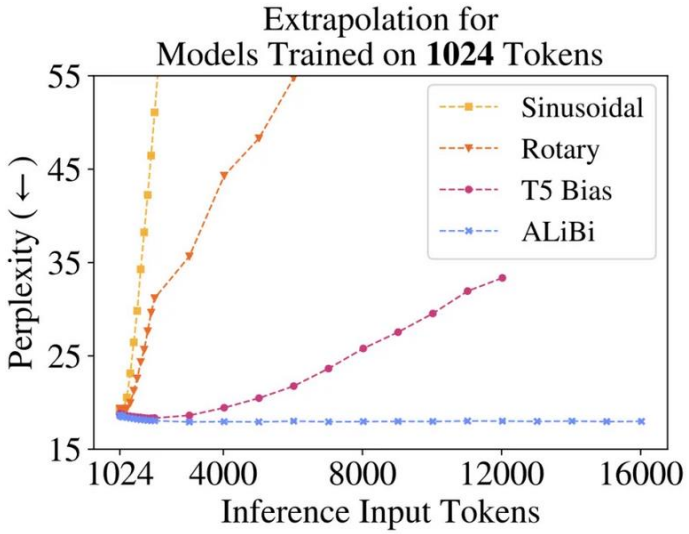
Context length comparison. (*Assuming 500 words per page.)

Image source

Context Window (2)

- **Several methods developed to increase context length**
  - Different types of methods: e.g. positional embeddings, more efficient types of attention, new model architectures, we discuss a few below
- **ALiBi** positional embeddings (Press et al. 2022)
  - **Position encoded as linear term added to attention score**
  - Allows training with shorter sequence, use longer sequence for inference
  - Requires using such positional embeddings during pre-training





Context Window (3)

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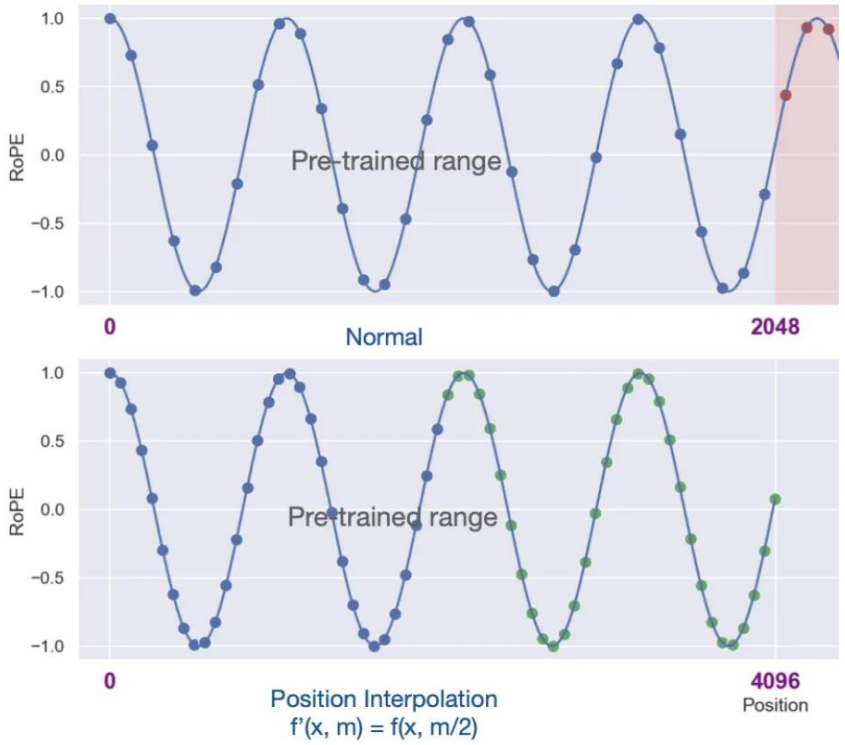
- **Position Interpolation** (Chen et al. 2023)
  - Extend position embeddings beyond size used during training
  - With a bit of fine-tuning, applicable to models that used different positional embedding during pre-training



Context Window (4)

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- More **efficient forms of attention**:
  - Sparse attention: consider only subset of attention matrix, e.g. locality
  - Flash attention: GPU optimization of forward/backward pass operations
  - More in later tutorials
- More recently, **RNN-like methods**:
  - Mamba Architecture (Dao et al. 2023): state-based model allows longer input sequences similar to how RNNs did (see also Le Bronnec et al. 2024)
  - TransformerFAM (Hwang et al. 2024): introduce LSTM-like mechanism in transformers
  - Leave-No-Context-Behind (Munkhdalai et al. 2024)
- **RNN-like methods too new, impact unclear**
  - Highlights this challenge is an open-question
- Parameter count/context window show **scaling up big part of progress**
  - Why?

Scaling Laws (1)

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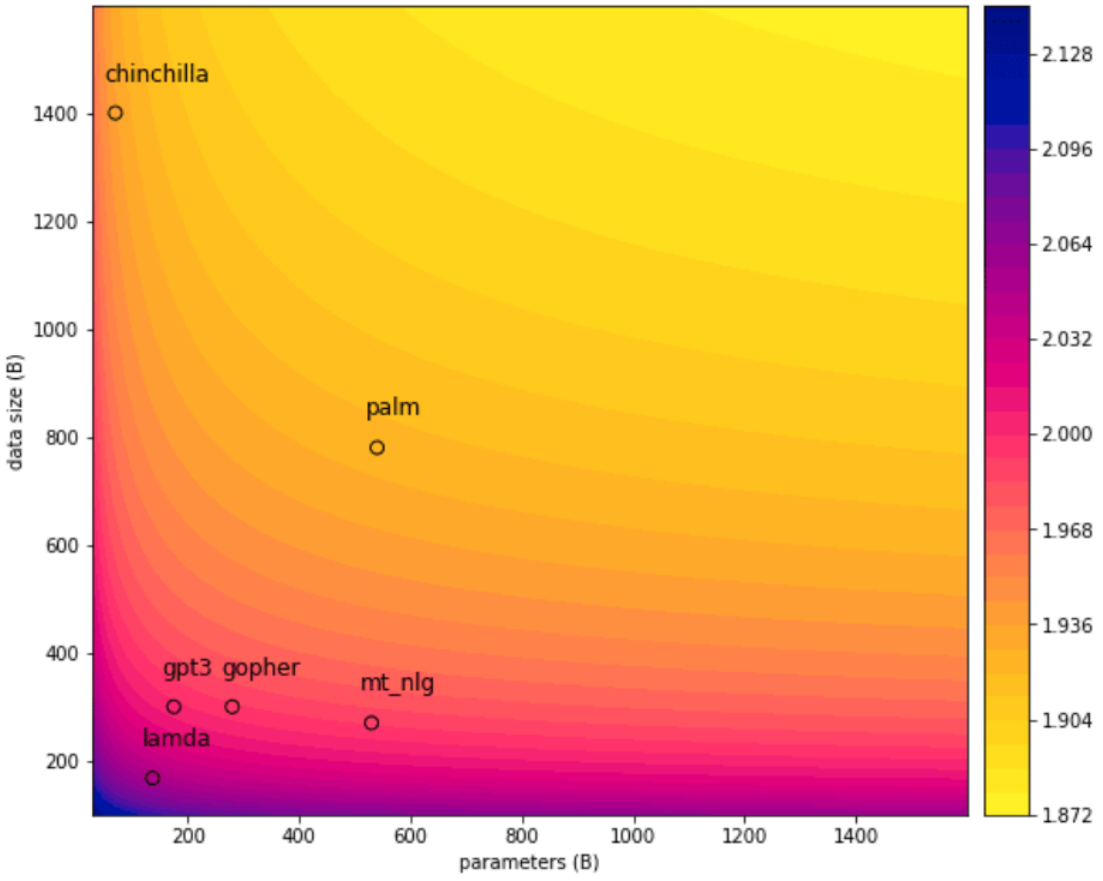
- **Chinchilla scaling laws** introduced by Hoffmann et al. (2022)
- Modeled **cross-entropy loss as function of model size and data size**
  - Loss measured in *nats*, i.e. like bits but using *ln* (explained in past tutorial)
  - Model size measured in number of parameters
  - Data size measured in number of tokens in training
- Specifically: $L(N,D) = E + A/N^{\alpha} + B/D^{\beta}$
  - ***N:*** model size,
  - ***D:*** data size
  - ***E***: ideal loss from infinitely big model with infinite training data
  - A/N^{α}: represents how much model underperforms ***E*** based on its size
  - B/D^{β}: how much model underperforms ***E*** based on its training data size
- They optimized ***L*** under constraint $C = 6ND$ where ***C*** is compute power
  - They fitted **A** and **B** using data from lots of pre-training experiments
  - Different model sizes (70M to 16B), different data sizes (5B to 500B)

Scaling Laws (2)

- They derived the following **optimal sizes of model and data**
  - **N(C)** = $0.6C^{0.45}$
  - **D(C)** = $0.3C^{0.55}$
- Heatmap of loss w.r.t. model and data size
- They trained their Chinchilla model on more data, as suggested by the law
- It outperforms many models, even those with many more parameters



Scaling Laws (3)

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- This tells us, **for given compute power C** (in flops), **how much data to use to achieve optimal loss for a given model size**
  - E.g. for 67B parameters, use 1.7 trillion tokens
  - GPT-3 trained on 300B tokens, should have had 15B parameters, not 175B
  - With that data size, growing model beyond 15B makes little difference
- Law makes **assumptions**
  - E.g. applies to CLMs using a specific form of learning rate scheduler
- Such laws **nevertheless useful**
  - E.g. test training tricks on smaller model, see how performance would scale
- When plotted, **scaling laws predict improvement with scale!**
  - **Limitation:** focused on loss reduction, may not translate to actual tasks
- For nice explanations on the topic, see here and here.

Scaling Laws (4)

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- Recently, these scaling laws have been under question
  - The main focus of criticism is their oversimplicity
- Diaz et al. (2024) argue that despite scaling up training sets, performance on more specific settings don't scale as described
  - They argue for considering other factors besides model and data size
  - E.g. evaluation data size, qualitative and use-case dependent evaluation metrics
- Isik et al. (2025) study scaling laws by focusing on machine translation
  - I.e. target is not training loss, but performance on translation task
  - They find that size of downstream data, as well as alignment of distribution of pre-training and downstream data are also important factors
  - Thus, scaling laws work differently in this case
- Liu et al. (2025) study how model performance can be predicted on downstream tasks
  - They find impactful factors like model architecture and dataset distribution

Pre-Training vs Fine-Tuning

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- Many more models
  - And **many more details** about each model
  - E.g. size of training set, ensemble or not (i.e. sparse vs dense), etc.
- Most **proprietary LLMs** are accessed via **APIs**
  - Useful for research and applications
  - But research challenging, key information unknown
  - E.g. are benchmark test sets seen during training?
- Note a **pattern in latest LLMs**
  - **GPT-3.5:** fine-tuned GPT-3
  - **ChatGPT:** fine-tuned for dialogue
  - **LLaMA-2:** focused on fine-tuning
- **Fine-tuning methods essential** to latest LLM success
  - At least as measured by language understanding, safer use in applications
  - NLU = natural language understanding (i.e. reading comprehension)
- Let's go over the basics of fine-tuning LLMs!

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LLM Tuning

LLMs as Useful Tools (1)

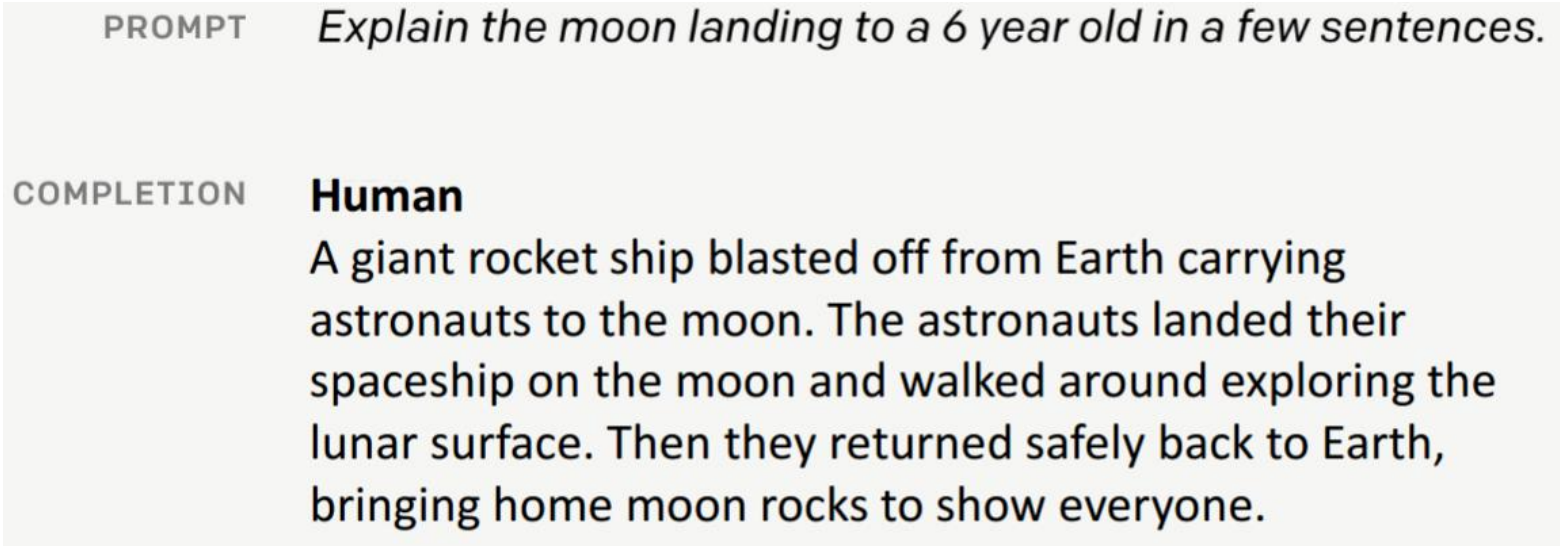
- Predicting next word is not the same as “follow user’s instructions”

PROMPT	*Explain the moon landing to a 6 year old in a few sentences.*
COMPLETION	GPT-3
	`Explain the theory of gravity to a 6 year old.`
	`Explain the theory of relativity to a 6 year old in a few sentences.`
	`Explain the big bang theory to a 6 year old.`
	`Explain evolution to a 6 year old.`

Image source

LLMs as Useful Tools (2)

- **Fine-tuning crucial** to LLMs ability to communicate, solve tasks



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LLMs as Useful Tools (3)

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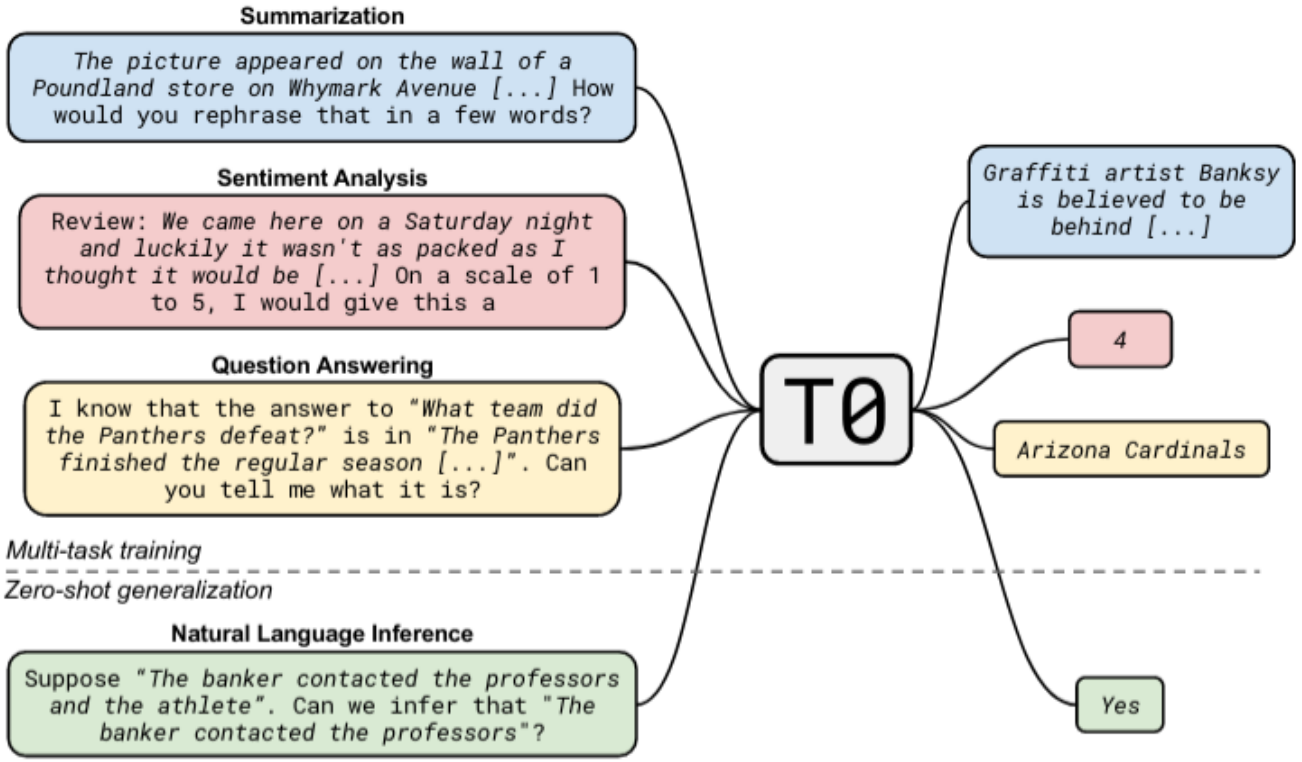
- **To improve usability of LLMs, tuning LLMs has focused on:**
  - 1. Performing many generative tasks, e.g. "explain moon landing"
  - 2. Providing truthful, non-toxic answers
- **How to achieve the first point?** Tune weights on **many new tasks**
  - **Before:** fine-tuning typically on chosen task, required few labels
  - **Now:** fine-tuning in many tasks, requires many labels per task
- **Why are more labels required for LLM tuning?**
  - Because goal is more general: to perform well on *many new* tasks
- In this section, common approach for LLM tuning: **instruction tuning**
- **What about the second point above?**
  - Also in this section, main approach for this goal: **RLHF**

Instruction Tuning (1)

- Question: can LLMs **perform** well on **tasks not seen in training/tuning?**
  - I.e. zero-shot generalization
- That's general goal of instruction tuning (Sanh et al., Wei et al.)



Instruction Tuning (2)

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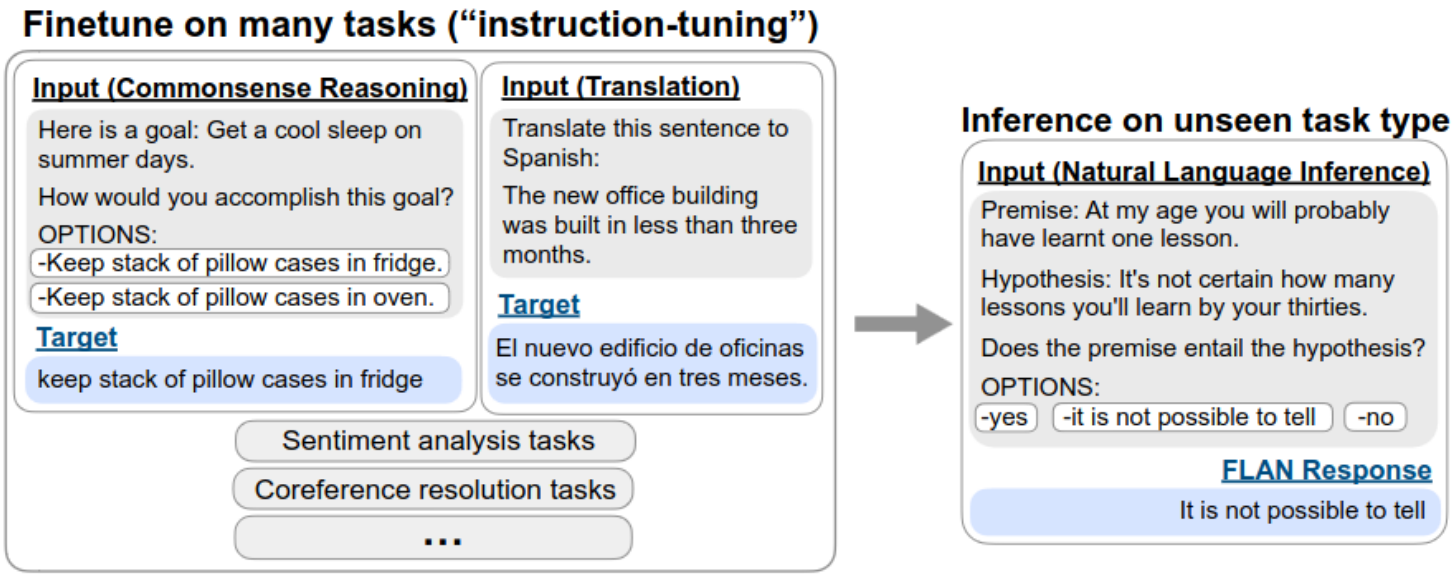
- **Instruction tuning:** train models to get better at zero-shot task solving, so long as those tasks come with text-based instructions
  - I.e. models learn to "follow instructions"
  - **Important:** measured as models performing NEW tasks not seen during pre-training or tuning, otherwise phrase "follow instructions" is vague
- **How does instruction tuning work?**
  - **Update weights** by training models **to solve many different supervised tasks** that come with instructions
  - I.e. a combination of (standard) fine-tuning with ICL
- Common approach:
  - **Cast NLP tasks as text-to-text** (see image in previous slide)
  - **Keep CLM objective** (no switch to supervised objective, e.g. classification)
  - **Train on some set of tasks, validate/test on DIFFERENT set of tasks**
- Let's visualize this.

Instruction Tuning (3)

- **How to check that models can "follow instructions"?**
  - Evaluate performance on tasks not seen in training or tuning
- Image from Wei et al.



- How does this relate to standard fine-tuning and ICL?
  - Instruction tuning has components of both, but also different from both

Instruction Tuning vs Fine-Tuning (1)

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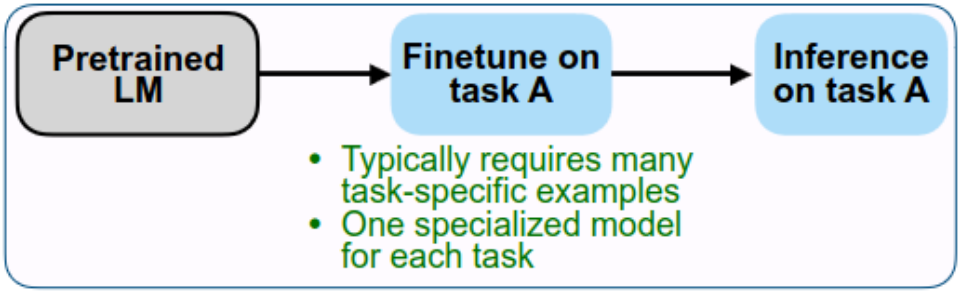
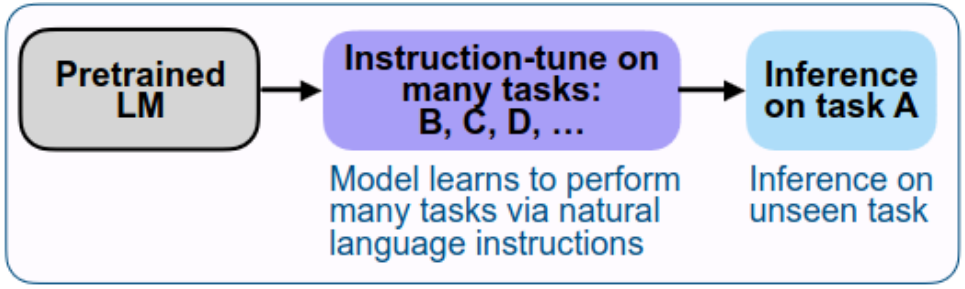
- Following images from Wei et al.
- Standard **fine-tuning**:



- **Instruction-tuning:**



- In both cases, note the use of the different tasks A, B, C, D, ...

Instruction Tuning vs Fine-Tuning (2)

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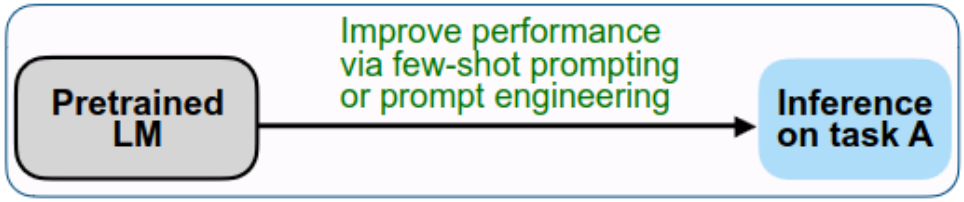
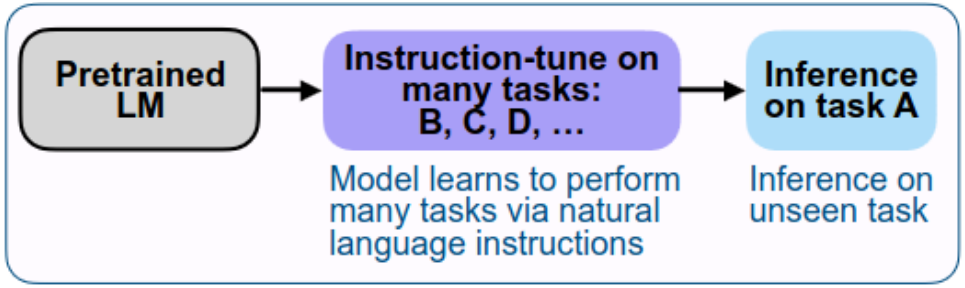
- **Fine-tuning:** update weights based on new (typically supervised) task
  - **Goal:** perform well at **specific task used in fine-tuning process**
  - Data typically as input-label pairs, e.g. *(email, label)* for spam detection.
- **Instruction-tuning:** update model weights based on several (typically supervised) tasks that are text-based and include instructions
  - **Goal:** perform well on **new tasks not seen during training or tuning**
  - Tasks must include text-based instructions
  - E.g. "Read the following email and tell me whether it's spam or not"
- In other words:
  - **Goal is different**, aim of instruction tuning is more generally useful model
  - **Data format is different**, as fine-tuning data more akin to standard ML data
  - Instruction tuning data includes text, instructions, similar to how humans follow instructions

Instruction Tuning vs ICL

- **In-context learning:** given instruction *and/or* examples of task, model performs task
  - **Similar to instruction tuning:** data format
  - **Different from instruction tuning:** no weight updates in ICL!
- **ICL:**



- **Instruction-tuning:**



Limitations of Instruction Tuning

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- Achieving **generally useful models** brings **lots of challenges**
  - Some tasks don't have clear answers, e.g. write a story
  - LMs work at token level, some mistakes bigger than others
  - E.g. *"Avatar is a fantasy movie"*, replacing *fantasy* with *adventure* less problematic than replacing *movie* with *book*
- **Limitation 1:** requires **lots of data**, since **entire model often tuned**
  - PEFT methods can also be used for this, can be competitive
  - Many recent benchmarks designed for LLM fine-tuning (MMLU, Big-Bench)
- **Limitation 2:** LM objective not ***aligned*** with human intent (Ouyang et al. 2022)
  - **Explicit intentions:** models follow instructions (goal of instruction tuning)
  - **Implicit intentions:** models give answers that are truthful, non-toxic, etc.
  - Explicit intention can be achieved without implicit ones, e.g. a rude answer
- Thus, even more general goal: **tune models for human preference**
  - Often referred to as "model alignment" (Leike et al. 2018)

Tuning for Human Preference (1)

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- **Main approach:** reinforcement learning for human feedback (RLHF)
  - Here: seminal work in context of deep learning by Christiano et al. (2017)
- Roughly, **basic components of reinforcement learning** (RL)**:**
  - An **agent** interacting with an **environment** over sequence of steps *T*
  - At time step $t \in T$, agent receives **observation** $o \in O$ from environment, sends **action** $a_t \in A$ to environment based on $o \dashrightarrow (o_1, a_1), (o_2, a_2), \ldots$
  - Environment provides **scalar reward** $y_t = r(a_t)$ where *r* is **reward function**
  - **Goal in RL:** learn **policy** $p: O \rightarrow A$ that predicts set of actions $a_i \in A$ for $i \in T$ that maximizes rewards over *T* (in deep RL, *r* and *p* are deep networks)
- **RL** often **successful** in tasks where **reward function is specified well**
  - E.g. playing video games (Mnih et al, 2015)
- For some tasks, **specifying the reward function can be challenging**
  - E.g. train robot to do scrambled eggs (function for good scrambled eggs?)
- **Idea:** allow humans to provide feedback on the agent's actions
  - **Use** this **human feedback to define task**

Tuning for Human Preference (2)

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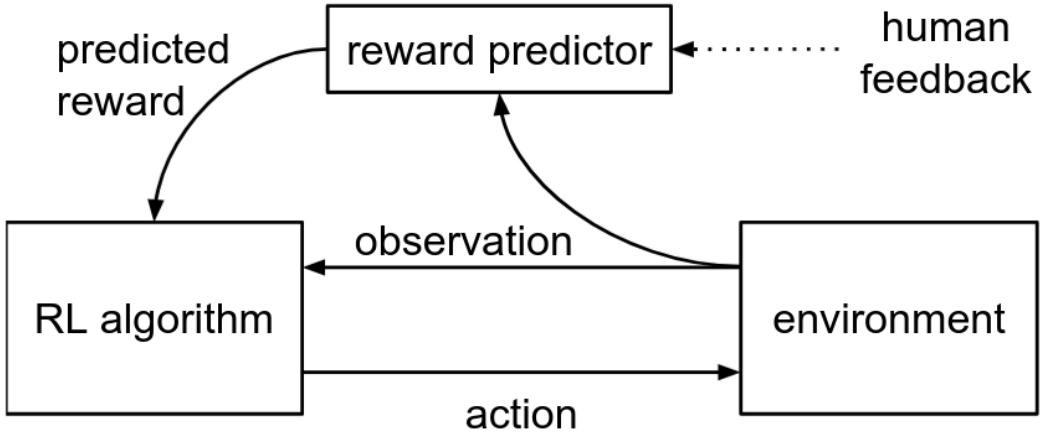
- Christiano et al. 2017 proposed the following:
  - **Learn reward function** *r: O x A --> ℝ* **that provides rewards aligned with human preferences** while **simultaneously training** a successful **policy**



- Such a method should **allow solving tasks defined by desired behavior**
  - "By desired behavior" means **agents can be taught by non-experts**
  - E.g. no need to be a chef to provide feedback on scrambled eggs
- This **approach now referred to as RLHF**
  - **InstructGPT**: recent work that used RLHF to *align* LLMs

InstructGPT (1)

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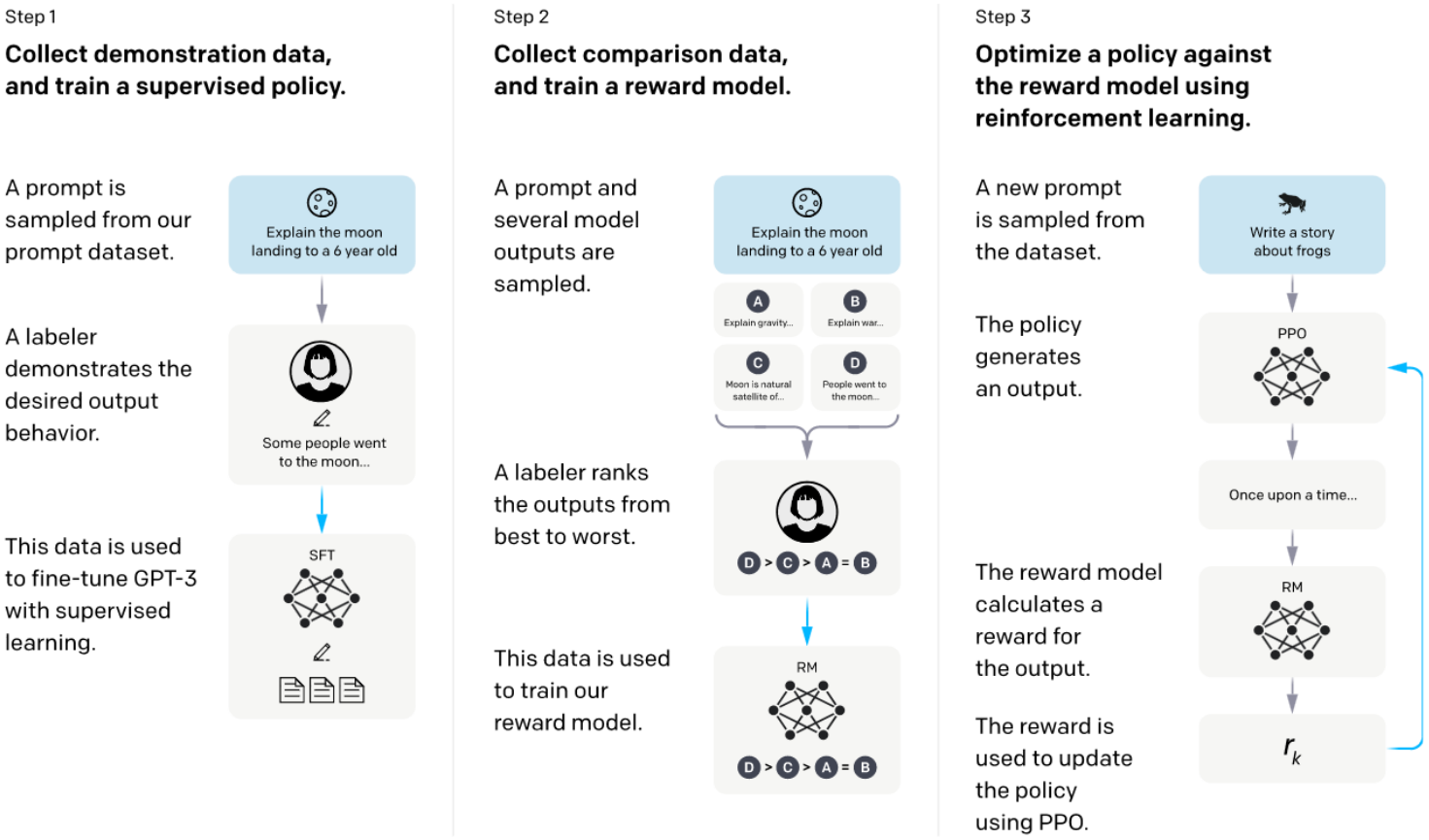
- Ouyang et al. (2022) **used RLHF** to **fine-tune GPT-3** to **follow broad class of written instructions** with outputs **aligned with human preference**
- Process broken into three steps (each covered in detail in next slides):
  - **1.** Collect examples for several generative tasks, **train supervised policy**
    - **Example of task:** "List five ideas for how to regain enthusiasm for my career"
    - **Human labelers** provided **examples of desired outputs**
    - Recall **policy**: function that provides actions given observations
    - In the context of LLMs, actions are generating different text
    - So, **"train policy"** here was **fine-tuning GPT-3 with examples from labelers**
  - **2.** Collect comparison data, **train reward model to mimic humans**
    - Given tasks and model from Step 1, **generate multiple outputs for each task**
    - **Human labelers choose preferred output** from given pairs of outputs for tasks
    - Recall **reward model**: function from observations and actions to reward
    - Reward model: **copy of Step 1 model that produces scalar** (LM head replaced)
  - **3. Optimize policy (Step 1) against reward model (Step 2) using PPO**
    - **Proximal policy optimization (PPO)** (Schulman et al. 2017)**:** common in RLHF

InstructGPT (2)

- Visualization of the three steps (image from Ouyang et al. 2022):



- Let's look at each step in more detail.

InstructGPT: Step 1

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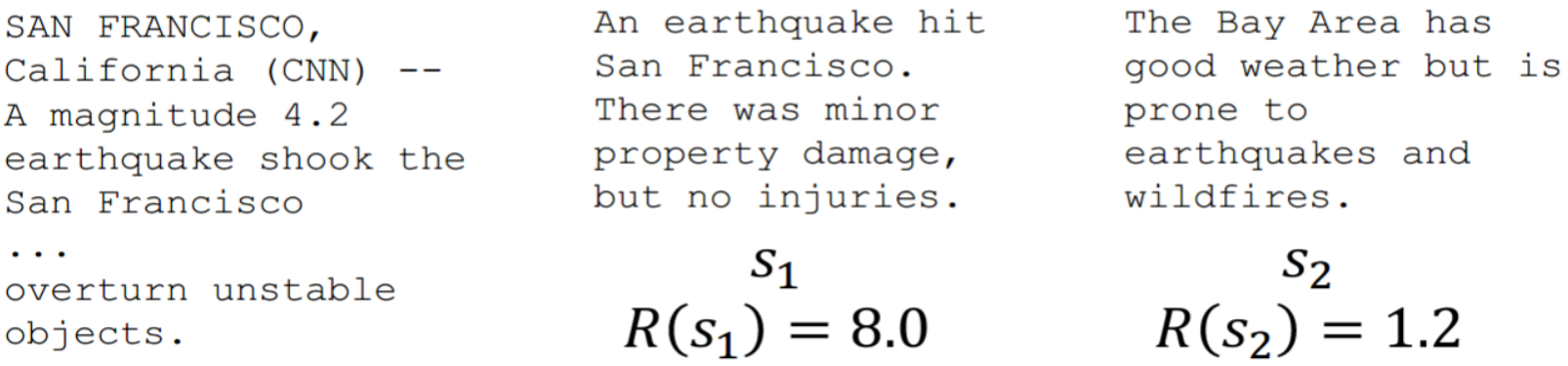
- Step 1: **collect examples for several tasks, train supervised policy**
  - **Tasks:** prompts and outputs generated by OpenAI users (volunteers)

- **Plain:** We simply ask the labelers to come up with an arbitrary task, while ensuring the tasks had sufficient diversity.
- **Few-shot:** We ask the labelers to come up with an instruction, and multiple query/response pairs for that instruction.
- **User-based:** We had a number of use-cases stated in waitlist applications to the OpenAI API. We asked labelers to come up with prompts corresponding to these use cases.

Image source

  - **Examples of such "text generation tasks":**
    - "List five ideas for how to regain enthusiasm for my career"
    - "Write a short story where a bear goes to the beach, makes friends with a seal, and then returns home."
  - Note that this requires **a lot of human effort**, thus very expensive!
    - This cost makes RLHF not easily accessible
  - **Training policy**: fine-tuning (all of) GPT-3 on examples from humans
    - Recall **policy**: function *p* from actions to observations, i.e. *p: O -> A*

InstructGPT: Step 2 (1)

- Step 2: **collect comparison data**, train reward model to mimic humans
- **Comparison data**: each example is a (i) task, (ii) pair of outputs (x_1, x_2) for task from model tuned in Step 1, (iii) human-chosen preference x_i
- 

  - Human-assigned rewards as ratings can be noisy, not calibrated (see image)
  - To avoid this, humans are typically asked for pairwise comparisons
  - E.g. which summary is best from the ones above, left or right?
  - Chosen summary gets label 1, other gets label 0

Image source

InstructGPT: Step 2 (2)

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- Step 2: collect comparison data, **train reward model to mimic humans**
- Recall **reward model**: function from actions and observations to reward
  - Reward is scalar number, i.e. reward model r is function *r: A x O --> $\mathbb{R}$*
- Here: **reward model is copy of model tuned in Step 1**
  - But model from Step 1 is GPT-3, i.e. a language model
  - It does not produce a scalar, but a distribution over some vocabulary
  - What can we do?
  - They replaced language modeling head with projection to scalar
- But **how do we train** this (beheaded) **reward model**?
  - (Averaged) **Cross-entropy loss** (CE), labels are 1 and 0 as needed
  - Specifically, given input *x*, model is trained to predict which output $y \in \{y_0, y_1\}$ is preferred by humans
  - For reward model r_θ parameterized by θ and preferred output *i*, we have:

$$\text{loss}(r_\theta) = -E_{(x,y_0,y_1,i)\sim D}[\log(\sigma(r_\theta(x,y_i) - r_\theta(x,y_{1-i})))]$$

InstructGPT: Step 3 (1)

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- Step 3: **optimize policy (Step 1) against reward model (Step 2)**
  - In other words, improve model from Step 1 *further* by training it to produce higher-quality outputs preferred by humans
  - How do we know which outputs are preferred by humans? Reward model!
- **Policy gradient methods**: designed for estimating RL objectives
  - InstructGPT relied on commonly used PPO method
  - **Proximal policy optimization (PPO)** (Schulman et al. 2017)
  - Details beyond our scope, e.g. value function, alternate optimization
- **Final RL objective:**
  - Given reward model r_θ parameterized by θ and *frozen* policy model π^{SFT} fine-tuned in Step 1, we tune model π^{RL} parameterized by ϕ and initialized as copy of π^{SFT}, by **maximizing** the **following objective**:

$$\text{objective}(\phi) = E_{(x,y)\sim D_{\pi_\phi^{\text{RL}}}}\left[r_\theta(x,y) - \beta \log\left(\pi_\phi^{\text{RL}}(y \mid x)/\pi^{\text{SFT}}(y \mid x)\right)\right] + \gamma E_{x\sim D_{\text{pretrain}}}\left[\log(\pi_\phi^{\text{RL}}(x))\right]$$

InstructGPT: Step 3 (2)

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$$\text{objective}\,(\phi) = E_{(x,y)\sim D_{\pi_\phi^{\text{RL}}}}\left[r_\theta(x,y) - \beta \log\left(\pi_\phi^{\text{RL}}(y \mid x)/\pi^{\text{SFT}}(y \mid x)\right)\right] + \gamma E_{x\sim D_{\text{pretrain}}}\left[\log(\pi_\phi^{\text{RL}}(x))\right]$$

- Note: model $\boldsymbol{\pi^{RL}}$ **regularized** so its predictions are not far from π^{SFT}
- How? Subtraction term weighted by factor β
  - Proportion between predictions produced by the model currently training, i.e. π^{RL}, and the π^{SFT} model used to train the reward model in Step 2
  - I.e. prevents policy model currently training to differ too much from model fine-tuned in Step 1 (the LLM fine-tuned on human-created labels)
- And **what is the term** weighted by factor γ?
  - Here, $D_{pretrain}$ is dataset used for pre-training original model (GPT-3)
  - This factor is designed to keep the model from differing too much from performance after pre-training and before fine-tuning in Step 1
  - I.e. we still want a LM at the end of the day

InstructGPT: All Together

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- There are **several models and training objectives used for InstructGPT**
  - **Policy model:** a copy of GPT-3, so a LM, fine-tuned with CLM objective
  - **Reward model:** copy of policy model (LM head replaced), trained on CE
  - **Reinforced policy model:** tuned with RL objective and signal from reward model (which learned to mimic human preference), our final LM
- Both **policy** and **reward models trained with human-labelled data**
  - Lots of data because goal was to be good at thousands of tasks
  - Thus, expensive to obtain, process required constant work with labelers
- **RLHF applied to LLMs** key step to enable construction of **ChatGPT**
  - Note that ChatGPT is a product based on some LLM (or many?)
  - Initially based on LLMs from the GPT-3 generation
  - Currently (May 2025) based on variants of GPT-4
- **High cost of RLHF means ChatGPT levels of performance not easily accessible**
  - Achieving this level of performance at a reduced cost is ongoing research

Reducing Cost of RLHF (1)

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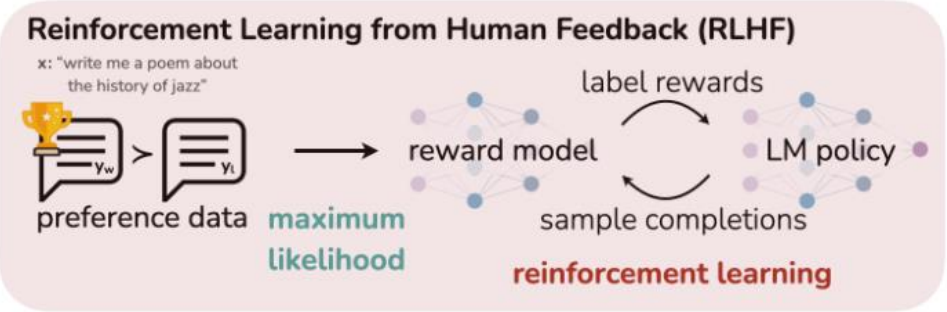
- **Can the cost of tuning for human preference be decreased?**
  - Focus of current research efforts
- **Direct Preference Optimization (DPO)** proposes such an approach
  - Proposed by Rafailov et al. 2023
  - Reparameterizes RLHF objective to avoid use of reward model
  - Derives closed-form solution, results in optimizing simple classification loss



- Trains on "preference pairs"
  - E.g. which of the two answers is best

Reducing Cost of RLHF (2)

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- Bai et al. (2022) reduced human effort in LLM alignment to almost none
  - They build as set of principles (a "constitution") so models can use to determine whether a response is appropriate
  - For Step 1, the LLM itself judged and improved on its own answers, then was fine-tuned on its improved responses
  - For Step 2, they used the fine-tuned model to choose better aligned responses from pairs of responses
  - Step 3 was done as before.
  - They called this approach: **Reinforcement Learning from AI Feedback**
- More recently, DeepSeek-R1 skipped the entire Step 1 (expensive human labeling)
  - Used out-of-the-box software tools as reward models to train their model for reasoning tasks that typically require multiple steps
  - **Out-of-the-box reward models**: code compiler, math solvers

Open Challenges with LLMs

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- Still several challenges ahead.
- **Hallucinations:** still severely hindering potential of these tools
- **Cost:** still highly expensive to train, but costs coming down
- **Reasoning:** still limited in their ability to reason, try different solutions, identify mistakes
- **Transparency:** still huge black boxes, neither user nor models can explain their output reliably
- **Updated information:** requires updating models with newer data

Summary

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- **Large Language Models**
  - **Size means new "abilities"**, e.g. ICL, following instructions
  - New "abilities" means new ways to use these models
- Using LMs before:
  - Fine-tune pre-trained LM, e.g. BERT, requires expert knowledge
- Using (L)LMs today:
  - Interaction via natural language, technology *potentially* democratized to end-users (ideally, if you can talk/write, you can use them)
- **In-Context Learning (ICL):** given task description and/or examples, model performs task (no weight updates on model)
- **Instruction tuning:** tune models to perform *new* tasks given instructions
- ICL and instruction tuning give rise to **prompting, prompt engineering**
- Despite progress, **models generally not *aligned* to human preference**
  - **Alignment** methods **expensive** (reinforcement learning, human feedback)

References

- References linked in corresponding slides