Deep Learning
lecture 10
Morden Language Models

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Today's Topic

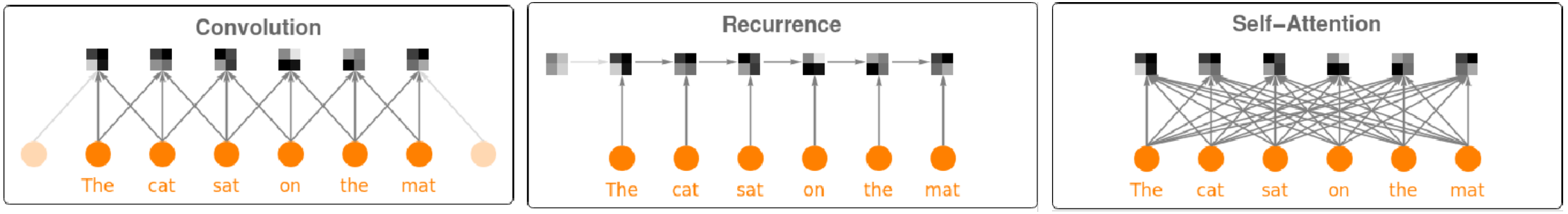
- Pretraining Transformers
- Scaling Law and Large Language Models
- Post-training Language Models and More Applications

Story So Far

- Language model techniques
  - Learning: expensive softmax operator (NCE, H-softmax)
  - Inference: beam search
  - Embedding: contextualized embeddings
- Seq2Seq model
  - Generic architecture for conditioned language modeling
- Attention
  - Learning order/scale-invariant representations
  - Capture distant interactions
  - Transformer: attention is all you need for sequence modeling (since 2017)
    - …. and even images (since 2021)

Different Sequence Models

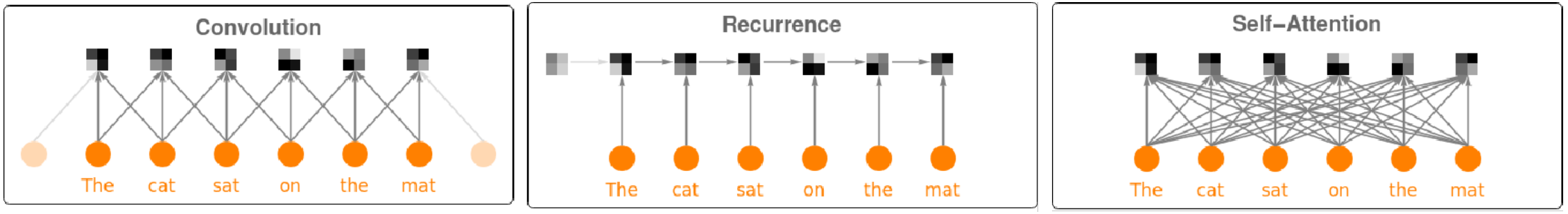
- CNN v.s. LSTM v.s. Transformer



- Embedding methods
  - Word2vec: static embedding
  - ELMo: pretraining bidirectional LSTMs for contextualized features
  - Transformer encoder: powerful bidirectional sequence encoder

Different Sequence Models

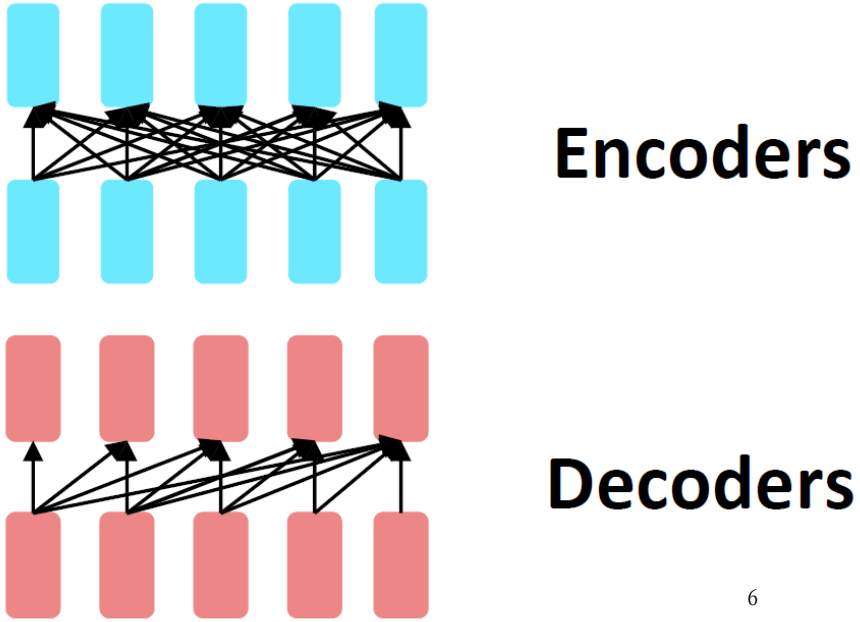
- CNN v.s. LSTM v.s. Transformer



- Embedding methods
  - Word2vec: static embedding
  - ELMo: pretraining bidirectional LSTMs for contextualized features
  - Transformer encoder: powerful bidirectional sequence encoder
  - Idea: pretraining large transformers!
    - Pretrained transformers also lead to good representations!
    - ***Foundation of most nowadays NLP applications***

Pretraining Transformers

- Collect a large amount of corpus and pretrain a large transformer
- For down-stream tasks, fine-tune the pretrained model
  - Or use the pretrained model to extract features
- How to pretrain a transformer on texts?
  - Pretrain an encoder
    - Bi-directional
  - Pretrain a decoder
    - Auto-regressive
  - Also both encoder and decoder



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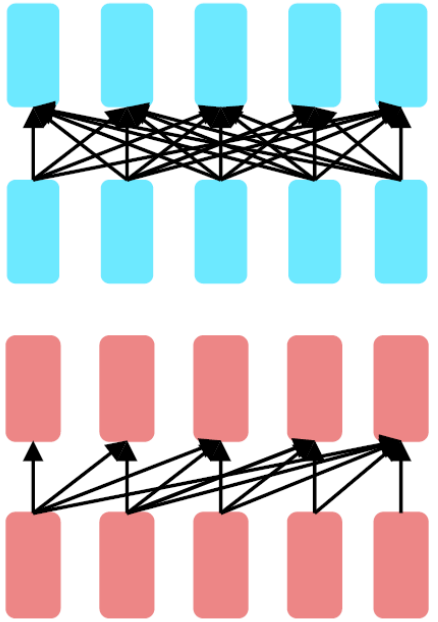
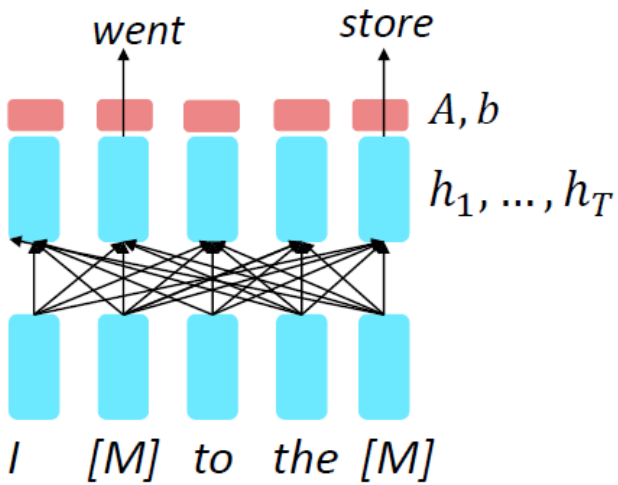


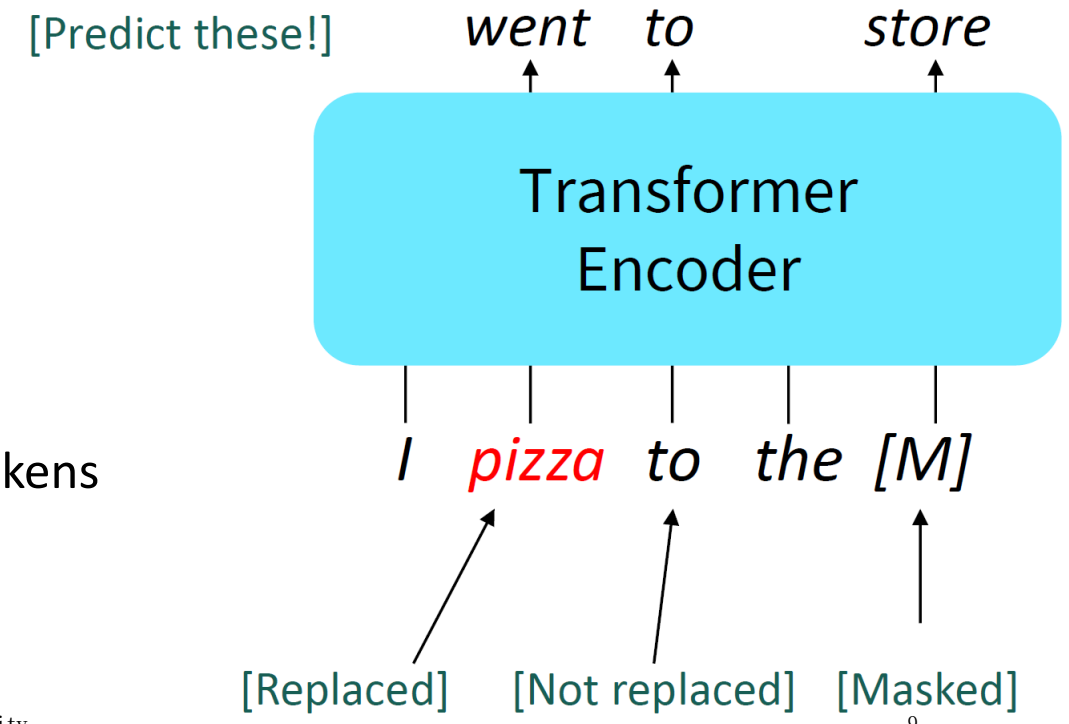
Pretraining Transformer Encoder

- Pretraining a bi-directional encoder
  - We cannot directly adopt language model learning
  - Idea: word prediction given contexts (similar to word2vec)
- Masked Language Model
  - Randomly “masked out” some words
  - Run full transformer encoder
  - Predict the words at masked positions
- Designed for feature extraction
  - More suitable for down-stream tasks



Pretraining Transformer Encoder

- BERT: Pre-training of Deep Bidirectional Transformers
  - Devlin et al, Google, 2018
    - BERT-base: 12 layers, 110M params
    - BERT-large: 24 layers, 340M params
    - Training on 64 TPUs in 4 days
    - Fine-tuning can be done in a single GPU
  - Masked language model
    - Randomly select 15% of word tokens
    - Mask out 80% of the selected tokens
    - Replace 10% of selected words with random tokens
    - For 10% of selected words remain unchanged
    - Predict the selected tokens



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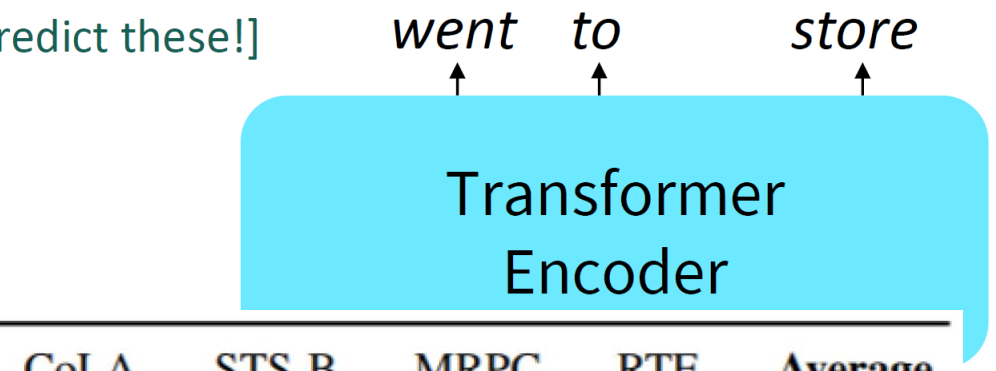
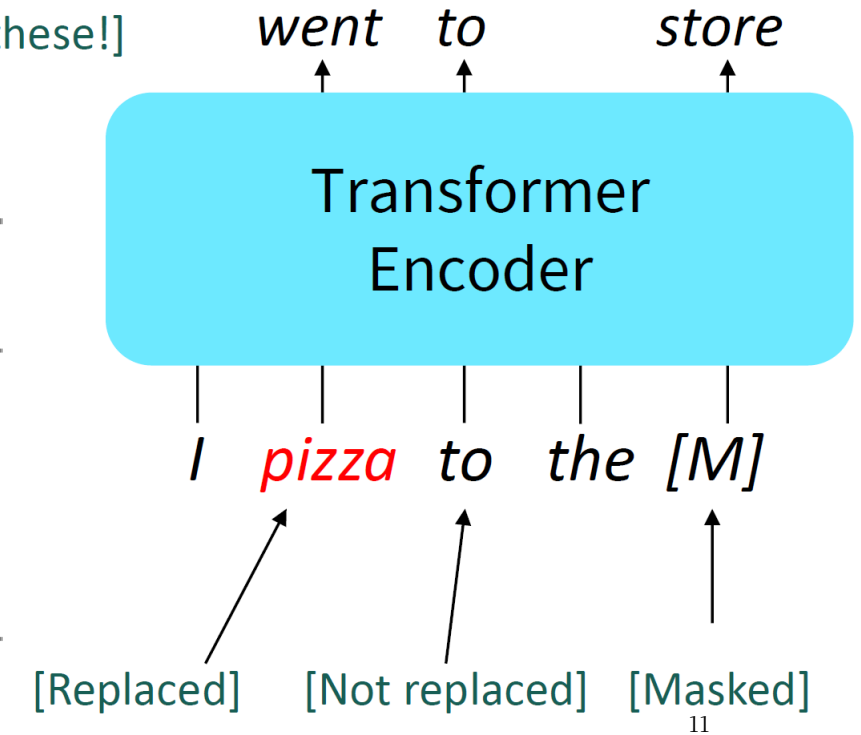


System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1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

Pretraining Transformer Encoder

- BERT: Pre-training of Deep Bidirectional Transformers (Google 2018)
- RoBERTa: A Robustly Optimized BERT Pretraining Approach
  - Facebook AI, 2019
  - More compute, data and improved objective

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7



Pretraining Transformers

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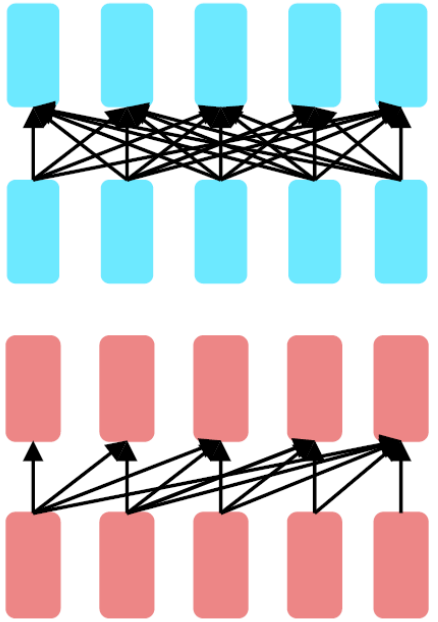
- For down-stream tasks, fine-tune the pretrained model
  - Or use the pretrained model to extract features
- How to pretrain a transformer on texts?
  - Pretrain an encoder
    - Bi-directional (e.g., BERT, RoBERTa)
  - Pretrain a decoder
    - Auto-regressive
  - Also both encoder and decoder



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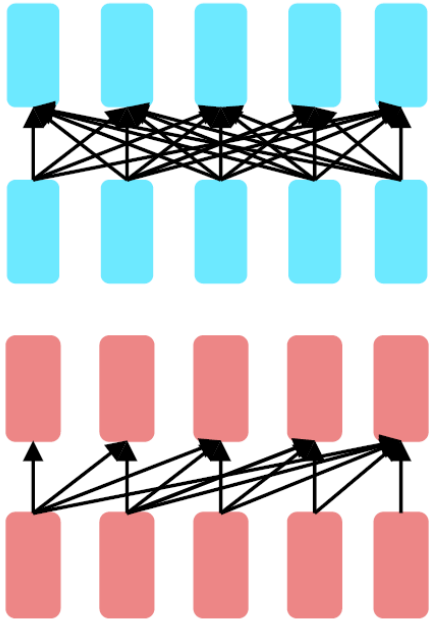
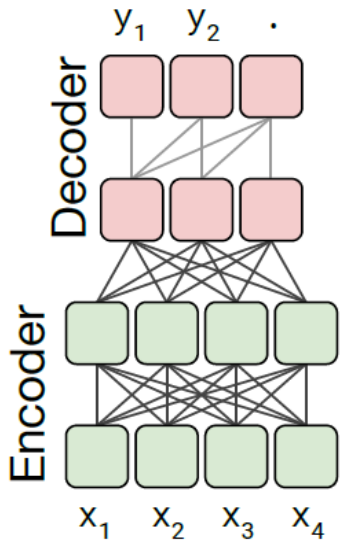


Pretraining a Multi-Task Encoder-Decoder

- T5 (Google, 2019)
  - **T**ext-**t**o-**T**ext **T**ransfer **T**ransformer
  - Multi-task training
  - Generalize to general QA



Original text

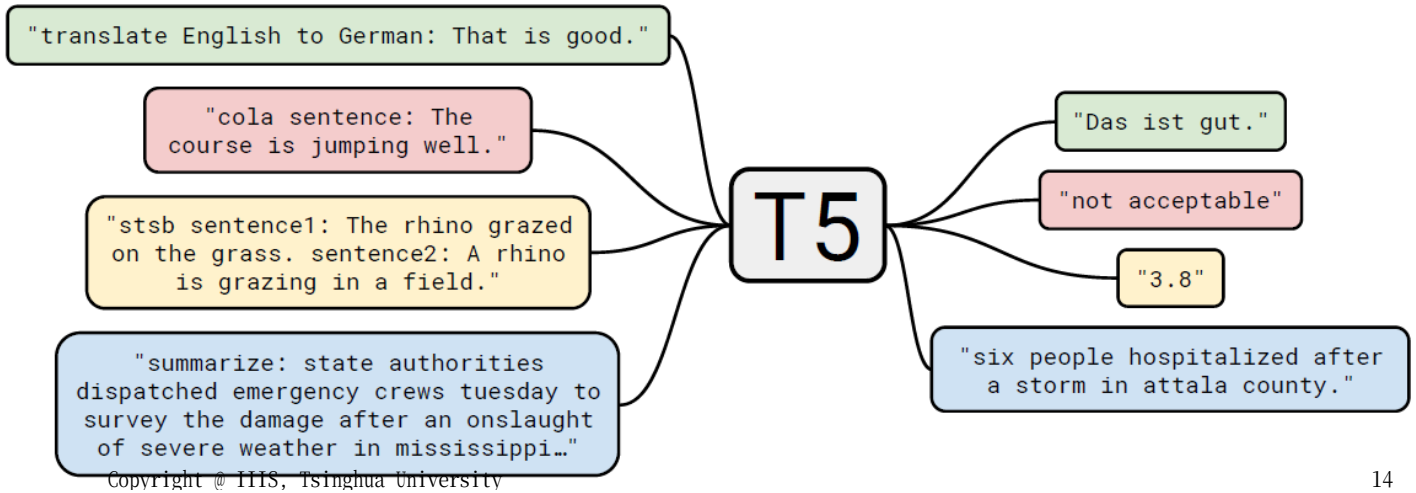
Thank you ~~for inviting~~ me to your party ~~last~~ week.

Inputs

Thank you <X> me to your party <Y> week.

Targets

<X> for inviting <Y> last <Z>



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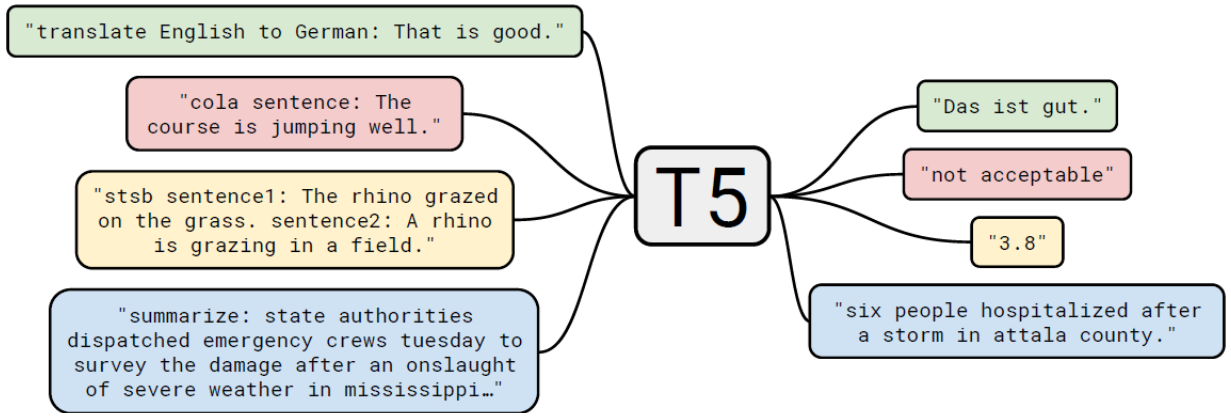
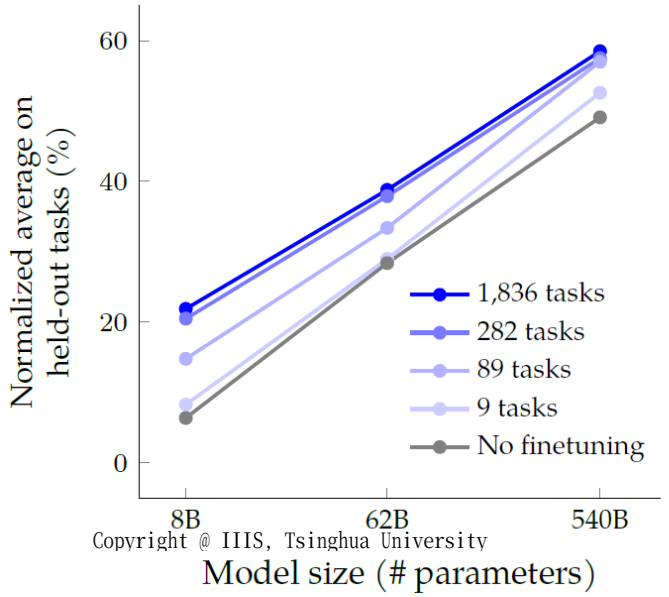
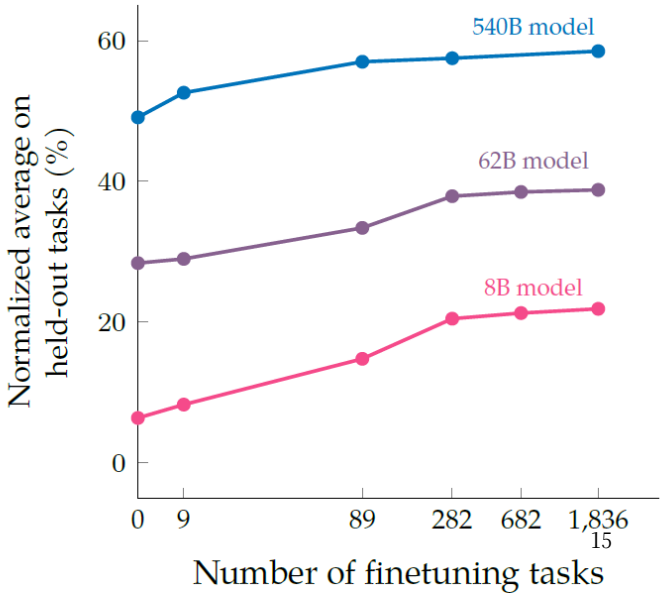
  - **T**ext-**t**o-**T**ext **T**ransfer **T**ransformer
  - Multi-task training
  - Generalize to general QA
- FLAN-T5 (Google, 2022)
  - T5 with fine-tuning
  - Large-scale training







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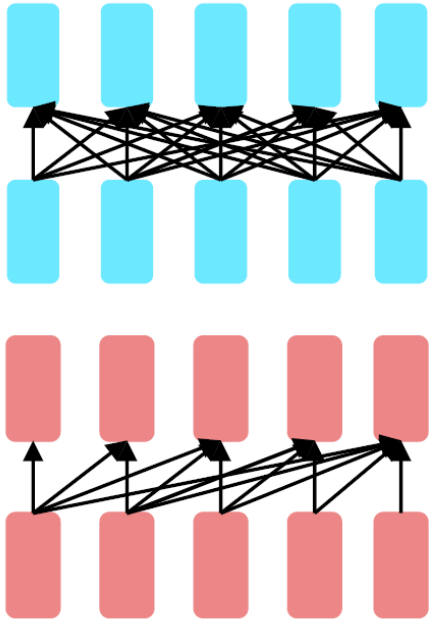
  - Also both encoder and decoder (T5/FLAN-T5)



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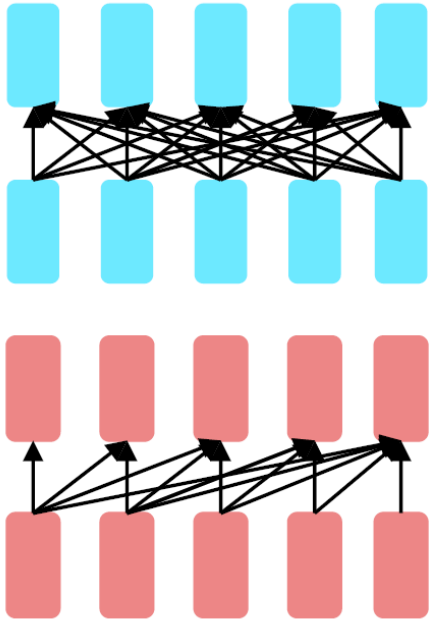
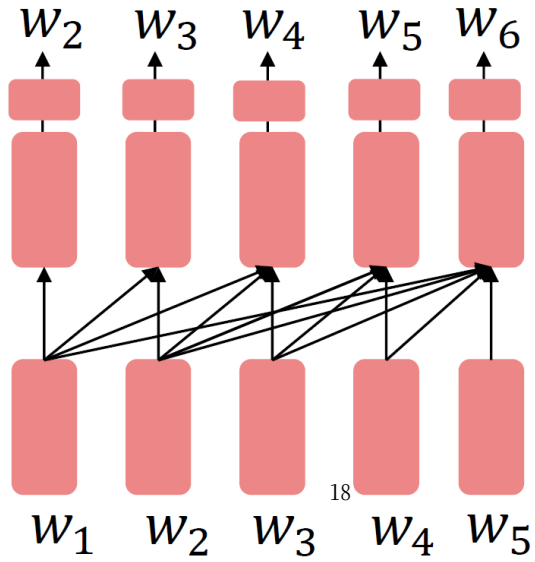


Pretraining Transformer Decoder

- Decoder Pretraining
  - Just train a language model over the corpus!
  - Great for generative tasks (e.g. text generation) & even beyond
- Generative Pretrained Transformer (GPT, Radford et al, OpenAI 2018)
  - 12-layers transformer, 768-d hidden, 3072-d MLP, BooksCorpus (>7k books)
- GPT-2 (Radford et al, OpenAI 2019.2)
  - 1.5B parameters, 40GB internet texts
- GPT-3 (OpenAI, 2020.5)
  - Language Model are Few-Shot Learners, 175B parameters
- Also ImageGPT (2020.1), ChatGPT (2022.11), GPT-4(2023)



Pretraining Transformer Decoder

- GPT-2 (Alec Redford et al., OpenAI, 2019)
  - 1.5B parameters, 48 layers transformer, trained on 10B tokens

Language Models are Unsupervised Multitask Learners

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

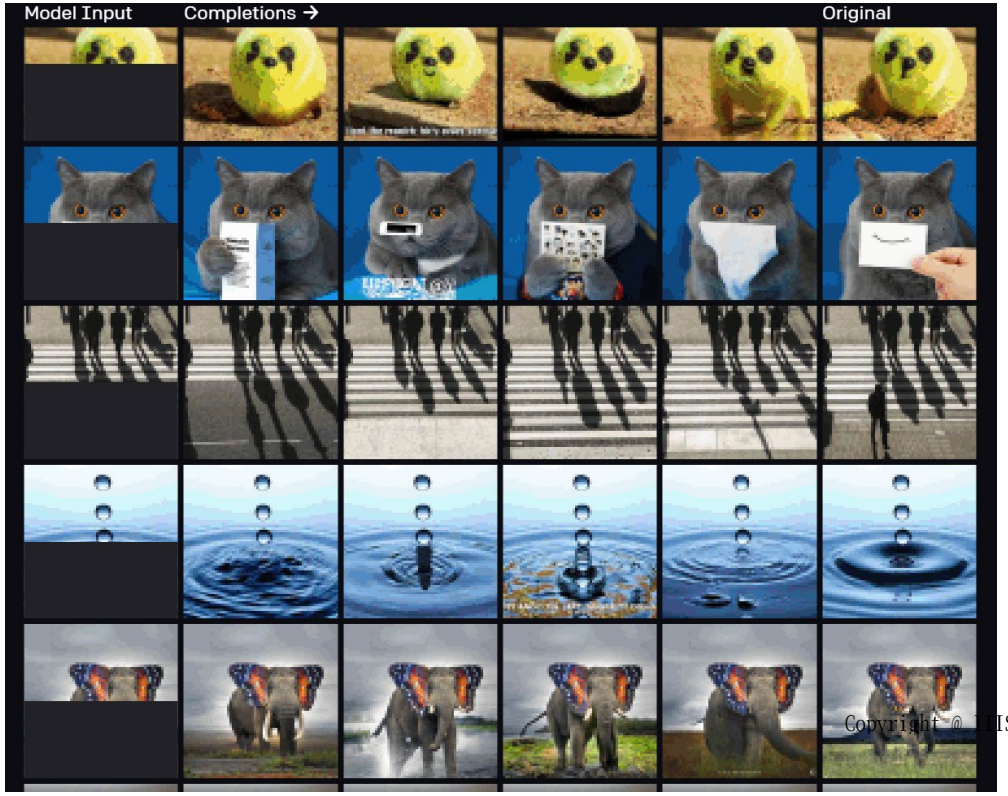
- Zero-shot SOTA performance on a lot of NLP tasks
  - Task descriptions as sequence prefix (prompt), no task specific training

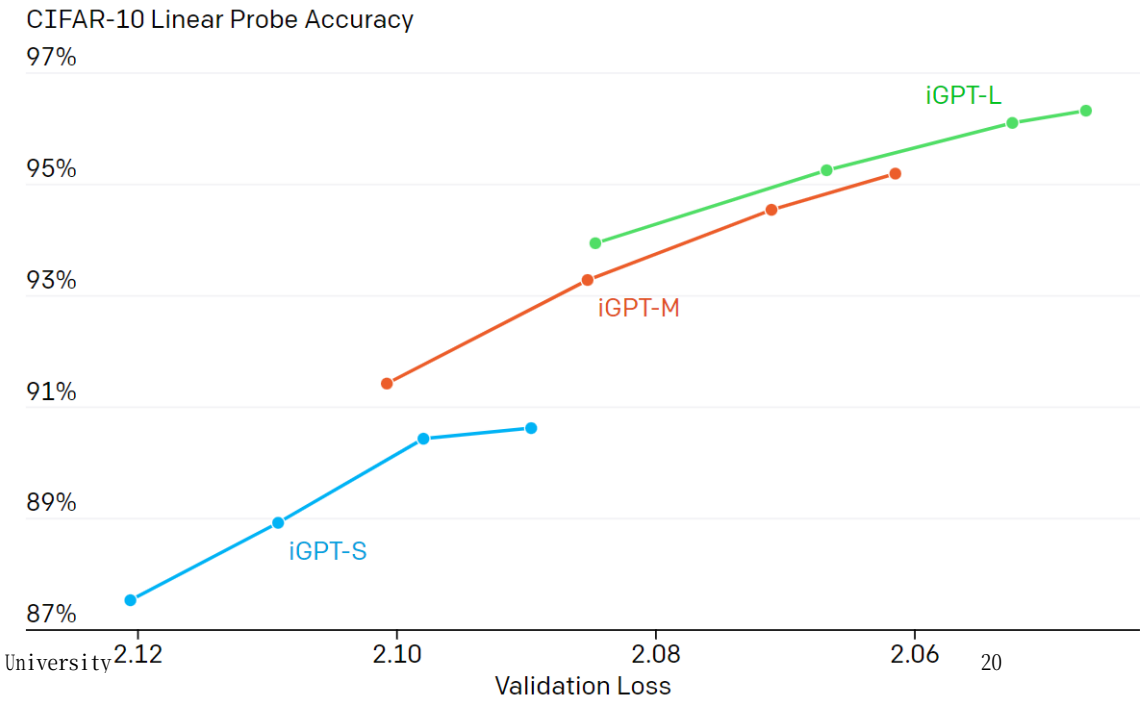
New research direction: prompt learning (https://arxiv.org/pdf/2107.13586.pdf)

	LAMBADA (PPL)	LAMBADA (ACC)	CBT-CN (ACC)	CBT-NE (ACC)	WikiText2 (PPL)	PTB (PPL)	enwik8 (BPB)	text8 (BPC)	WikiText103 (PPL)	1BW (PPL)
SOTA	99.8	59.23	85.7	82.3	39.14	46.54	0.99	1.08	18.3	**21.8**
117M	**35.13**	45.99	**87.65**	**83.4**	**29.41**	65.85	1.16	1.17	37.50	75.20
345M	**15.60**	55.48	**92.35**	**87.1**	**22.76**	47.33	1.01	**1.06**	26.37	55.72
762M	**10.87**	**60.12**	**93.45**	**88.0**	**19.93**	**40.31**	**0.97**	**1.02**	22.05	44.575
1542M	**8.63**	**63.24**	**93.30**	**89.05**	**18.34**	**35.76**	**0.93**	**0.98**	**17.48**	42.16

Pretraining Transformer Decoder

- Image GPT (OpenAI, ICML 2020)
  - A large transformer-based generative model over image pixels
  - Learned features allow zero-shot classification (linear probing)



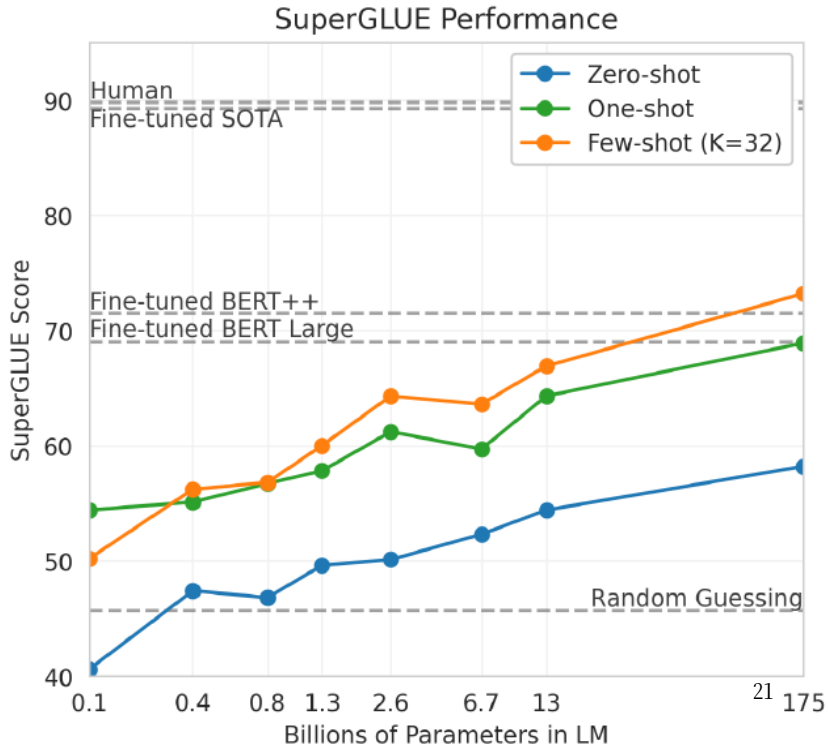


Pretraining Transformer Decoder

- GPT-3: Language models are few-shot learners (OpenAI, NIPS2020)
  - 500B tokens, 175B parameters of transformer
  - Approach SOTA methods on a wide range of NLP tasks without any fine-tuning

Setting	CoQA	DROP	QuAC	SQuADv2	RACE-h	RACE-m
Fine-tuned SOTA	**90.7**[a]	**89.1**[b]	**74.4**[c]	**93.0**[d]	**90.0**[e]	**93.1**[e]
GPT-3 Zero-Shot	81.5	23.6	41.5	59.5	45.5	58.4
GPT-3 One-Shot	84.0	34.3	43.3	65.4	45.9	57.4
GPT-3 Few-Shot	85.0	36.5	44.3	69.8	46.8	58.1

Setting	PIQA	ARC (Easy)	ARC (Challenge)	OpenBookQA
Fine-tuned SOTA	79.4	**92.0**[KKS+20]	**78.5**[KKS+20]	**87.2**[KKS+20]
GPT-3 Zero-Shot	**80.5***	68.8	51.4	57.6
GPT-3 One-Shot	**80.5***	71.2	53.2	58.8
GPT-3 Few-Shot	**82.8***	70.1	51.5	65.4



Pretraining Transformer Decoder

- GPT-3: Language models are few-shot learners (OpenAI, NIPS2020)
  - The concept of ***In-context learning***
  - You may not need to fine-tune the model parameters for domain-specific task

Few-shot

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

```
1  Translate English to French:          ← task description
2  sea otter => loutre de mer            ← examples
3  peppermint => menthe poivrée          ←
4  plush girafe => girafe peluche        ←
5  cheese =>                             ← prompt
```

Code: `px.line(df.query("continent == 'Europe' and country == 'France'"), x='year', y='gdpPercap', color='country', log_y=False, log_x=False)`

Description: Actually, replace GDP with population

Code: `px.line(df.query("continent == 'Europe' and country == 'France'"), x='year', y='pop', color='country', log_y=False, log_x=False)`

Description: Put y-axis on log scale

Code: `px.line(df.query("continent == 'Europe' and country == 'France'"), x='year', y='pop', color='country', log_y=True, log_x=False)`

Pretraining Transformer Decoder

- Fine-tuning v.s. Zero-Shot (prompting) v.s. Few-shot (in-context learning)

Fine-tuning

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

Zero-shot

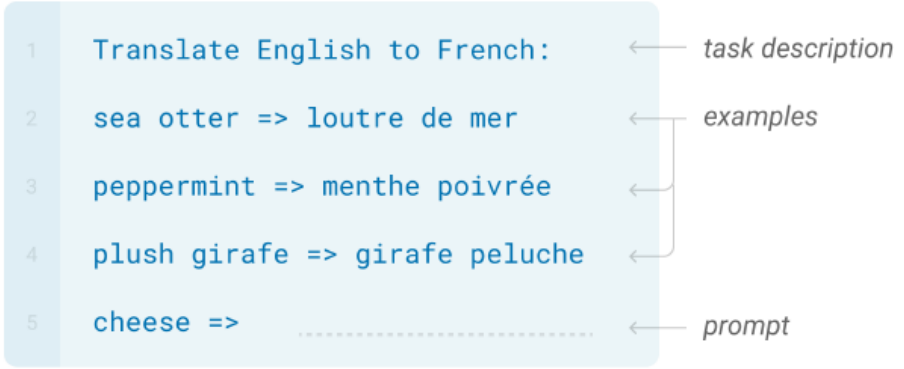
The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

One-shot

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

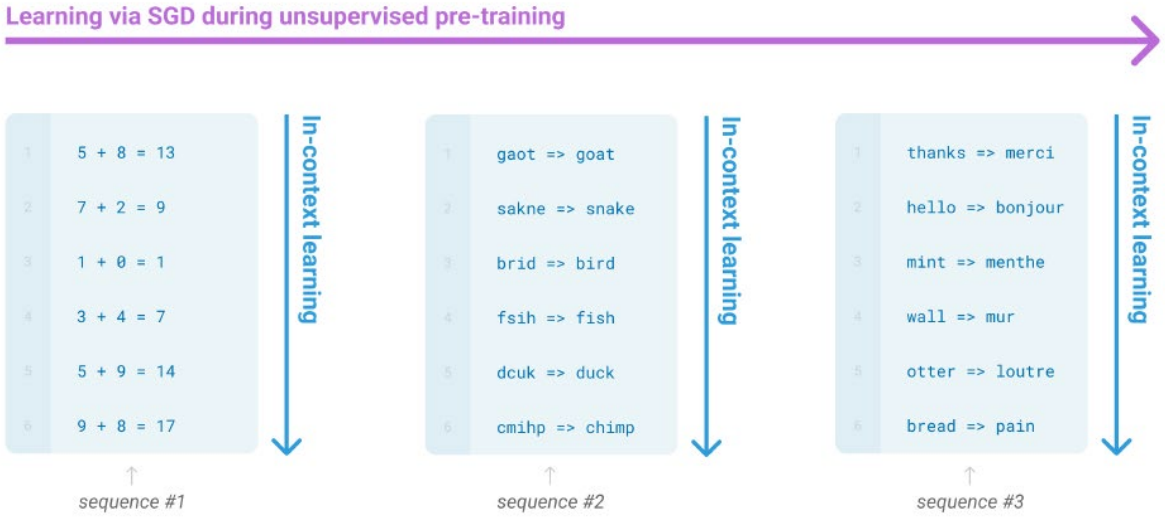
Few-shot

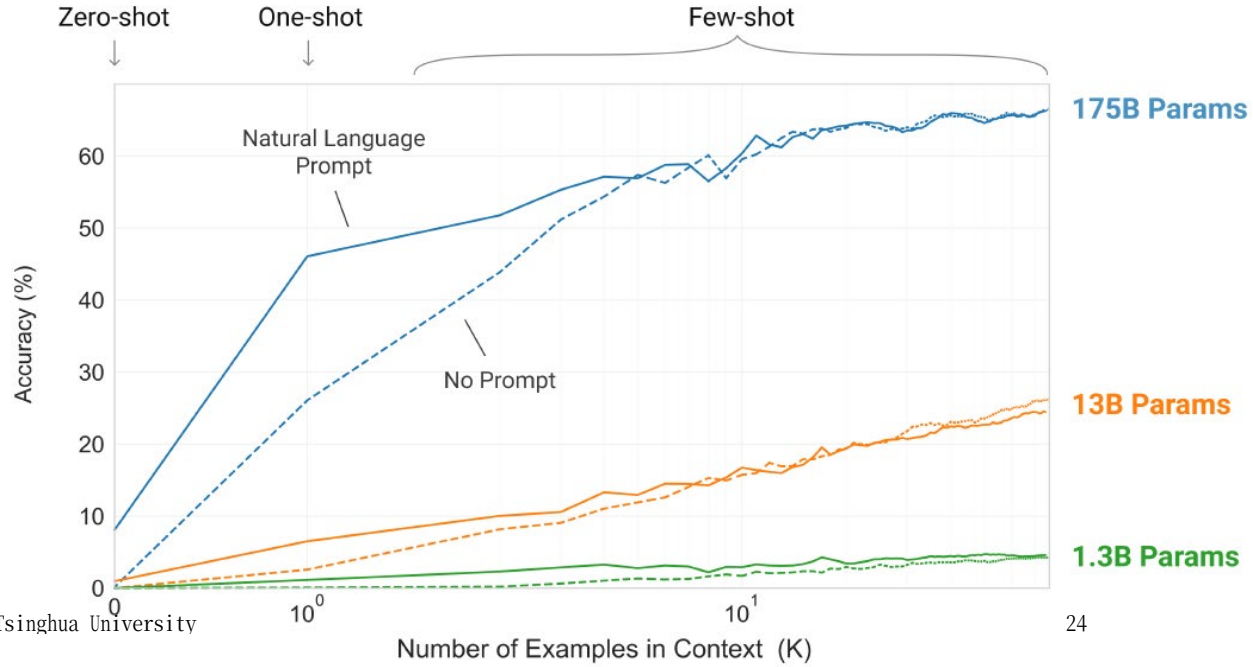
In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.



Pretraining Transformer Decoder

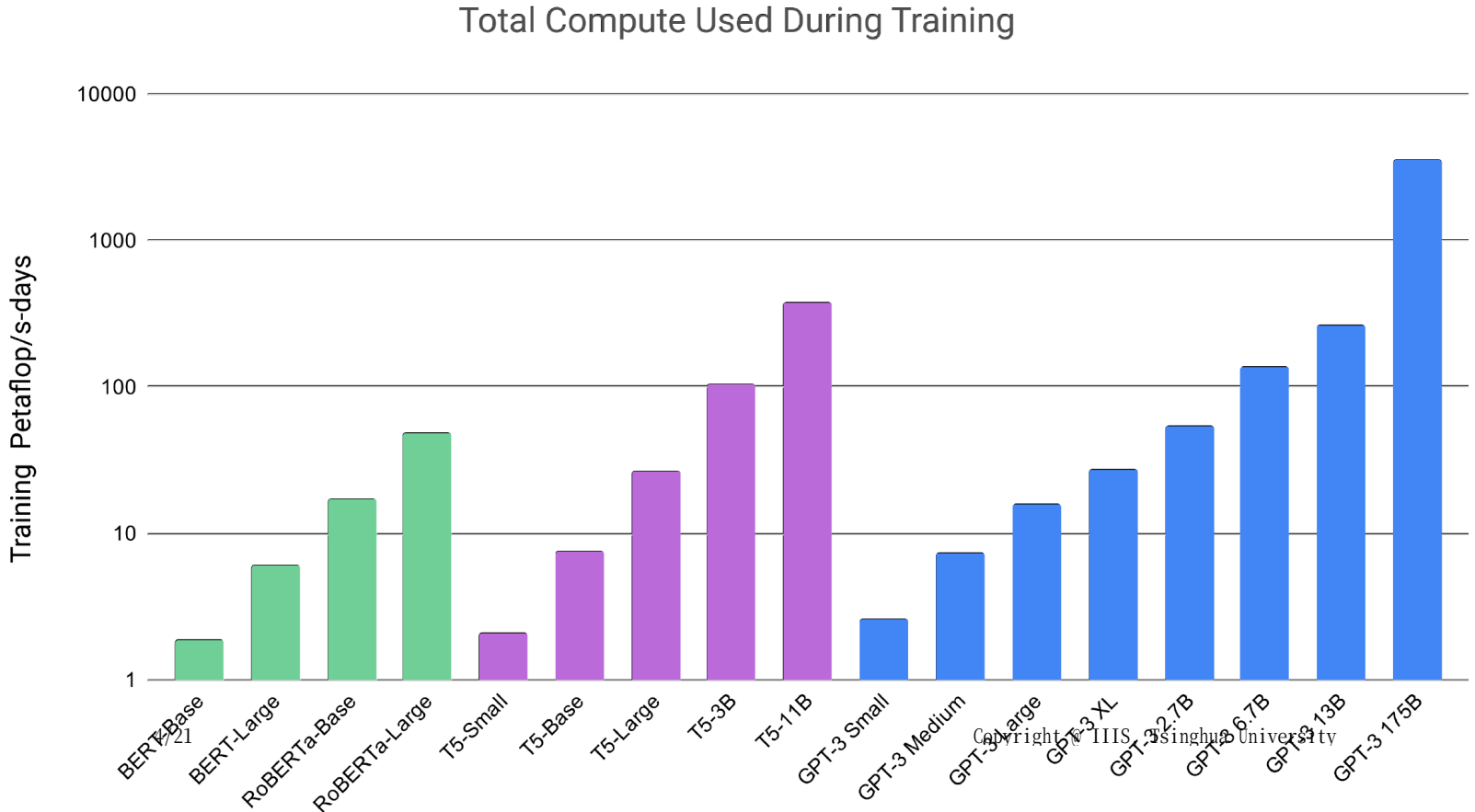
- In-context learning: the model is trained once, and then put data as part of the input (prompt) to the model.
  - The capability is first observed in GPT-3
  - More in-context examples, better final performance

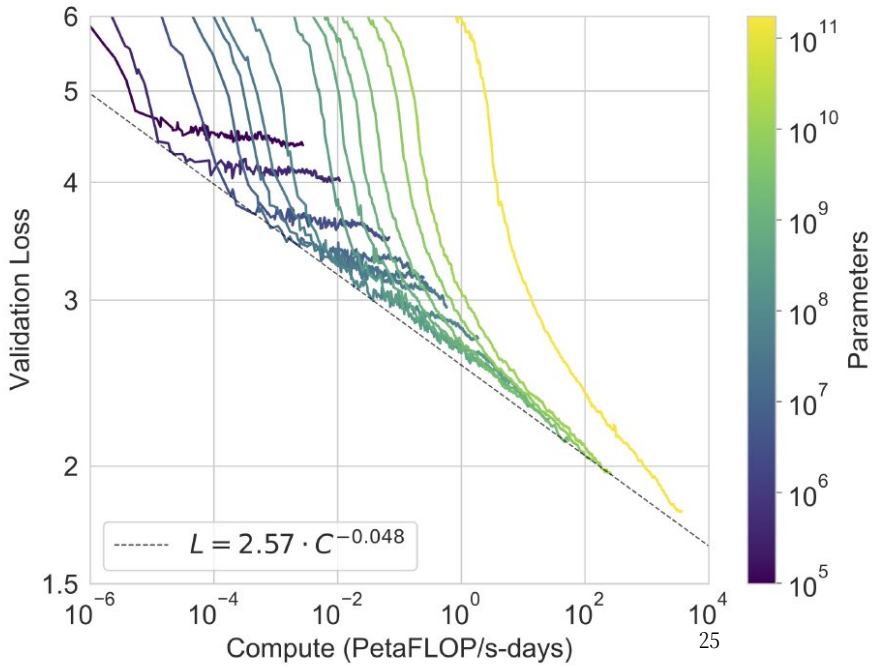




Pretraining Transformer Decoder

- Computation used by GPT-3
  - More training compute, lower validation loss

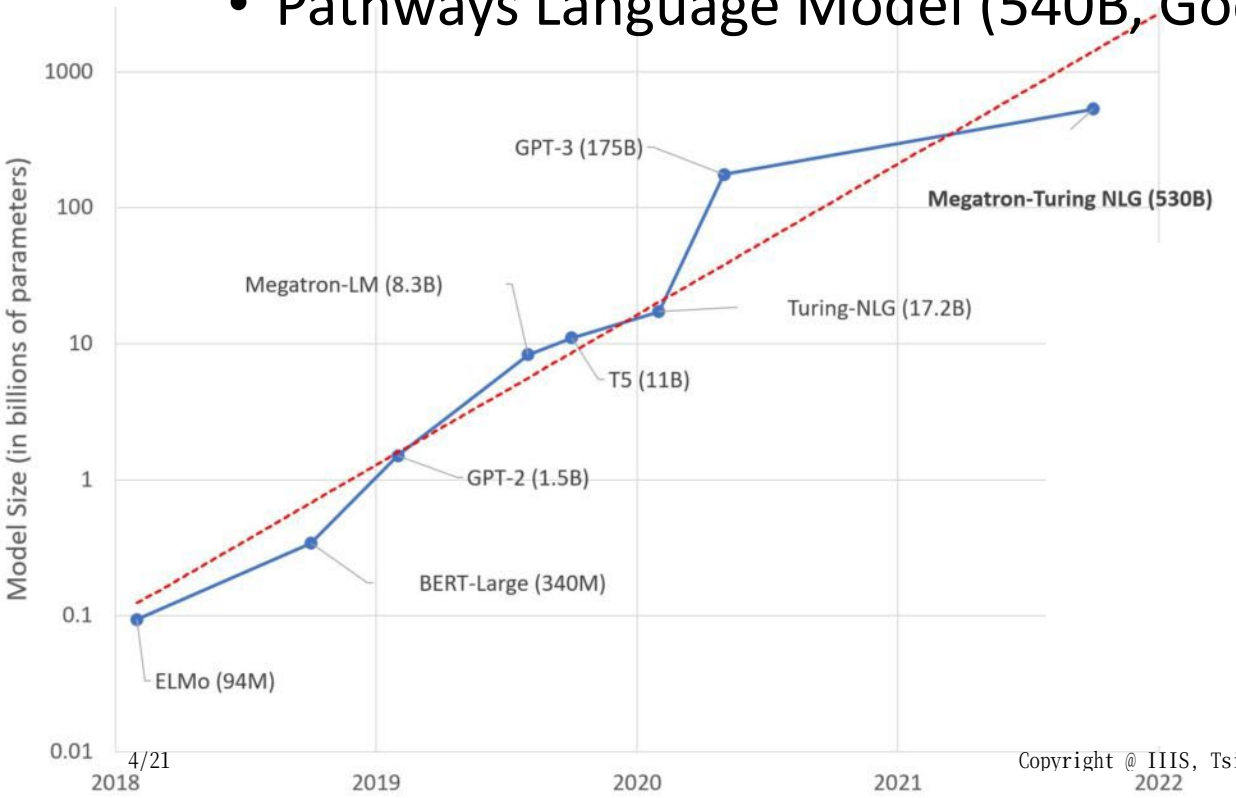


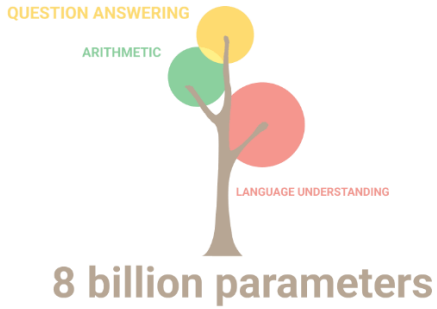


Pretraining Transformer Decoder

- A big ongoing race since 2021 to train even larger language models
  - Megatron-Turing NLG (530B, Microsoft, 2021.10)
  - Pathways Language Model (540B, Google, 2022.4)

Why do people train larger models?





Scaling Law

- A simple rule for predicting LLM performances (OpenAI, 2020)
  - You can perform experiments on small models and extrapolate on larger ones

Scaling Laws for Neural Language Models

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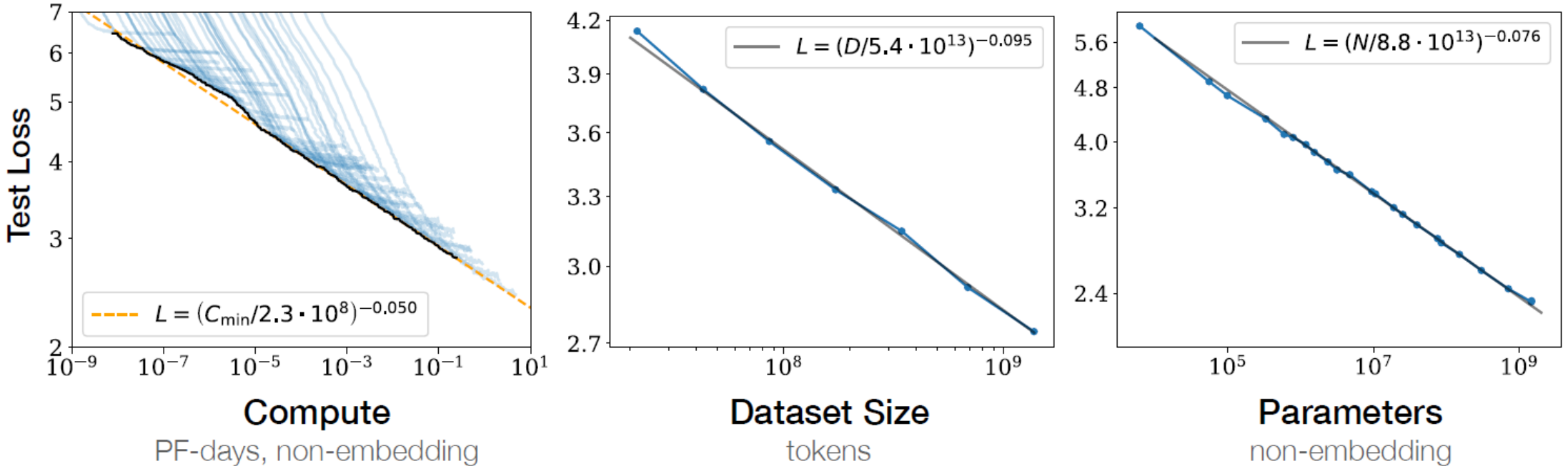
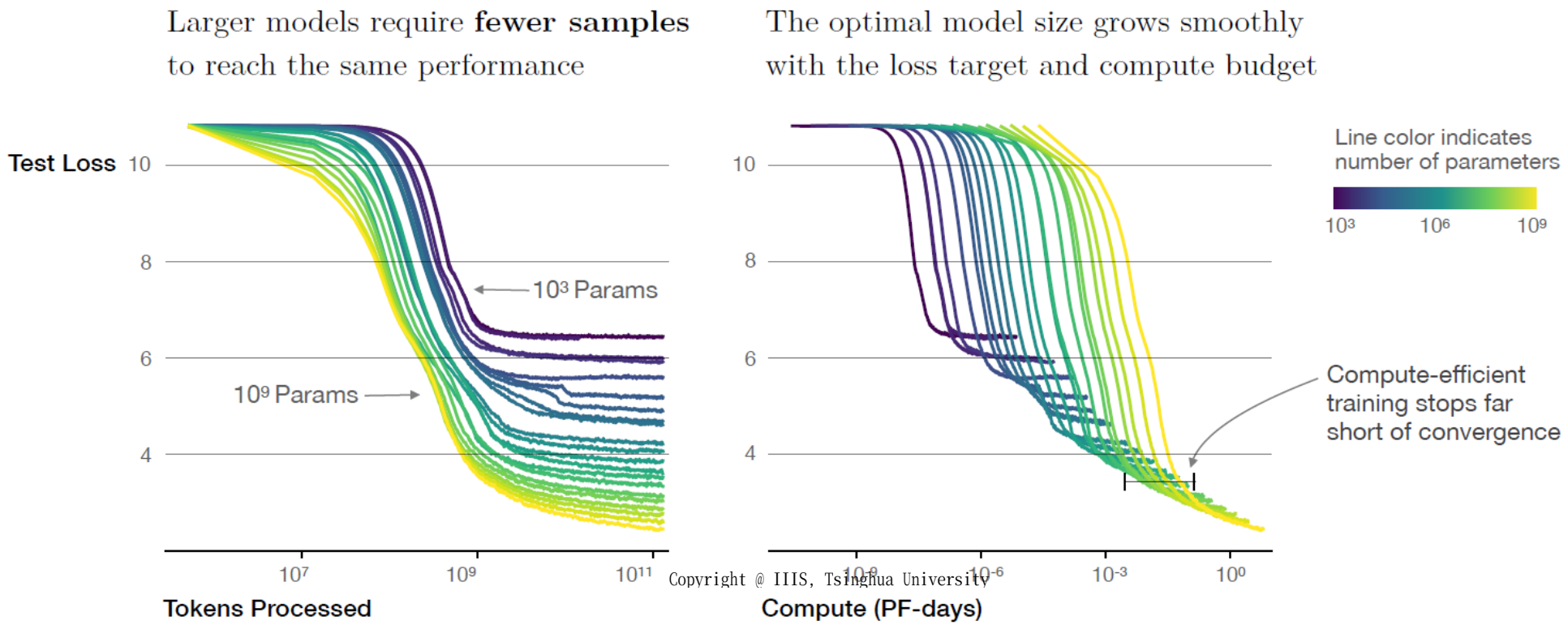
Scaling Law

- A simple rule for predicting LLM performances (OpenAI, 2020)
  - Compute, dataset size and parameters are key factors for LLM performances
  - You can fit an power law for these factors



Scaling Law

- A simple rule for predicting LLM performances (OpenAI, 2020)
  - OpenAI suggests that you should train larger models!
    - Claim from the perspective of 2020



Scaling Law: The Chinchilla Law

- The optimal model size and training tokens given a fixed compute budget (DeepMind, 2022)
  - TL;DR: every doubling the model size, the training tokens should be also doubled (training tokens matter!!!!)

Training Compute-Optimal Large Language Models

Jordan Hoffmann*, Sebastian Borgeaud*, Arthur Mensch*, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katie Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Jack W. Rae, Oriol Vinyals and Laurent Sifre*

*Equal contributions

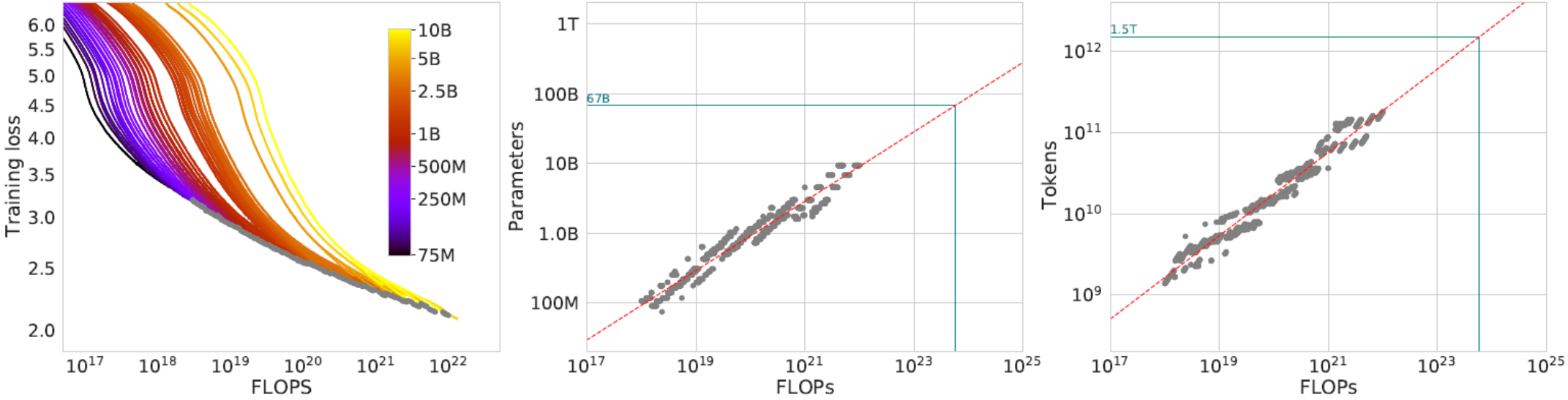
Scaling Law: The Chinchilla Law

- The optimal model size and training tokens given a fixed compute budget (DeepMind, 2022)
  - TL;DR: every doubling the model size, the training tokens should be also doubled (training tokens matter!!!!)
  - You can have a smaller but better model with more data

Model	Size (# Parameters)	Training Tokens
LaMDA (Thoppilan et al., 2022)	137 Billion	168 Billion
GPT-3 (Brown et al., 2020)	175 Billion	300 Billion
Jurassic (Lieber et al., 2021)	178 Billion	300 Billion
Gopher (Rae et al., 2021)	280 Billion	300 Billion
MT-NLG 530B (Smith et al., 2022)	530 Billion	270 Billion
Chinchilla	70 Billion	1.4 Trillion

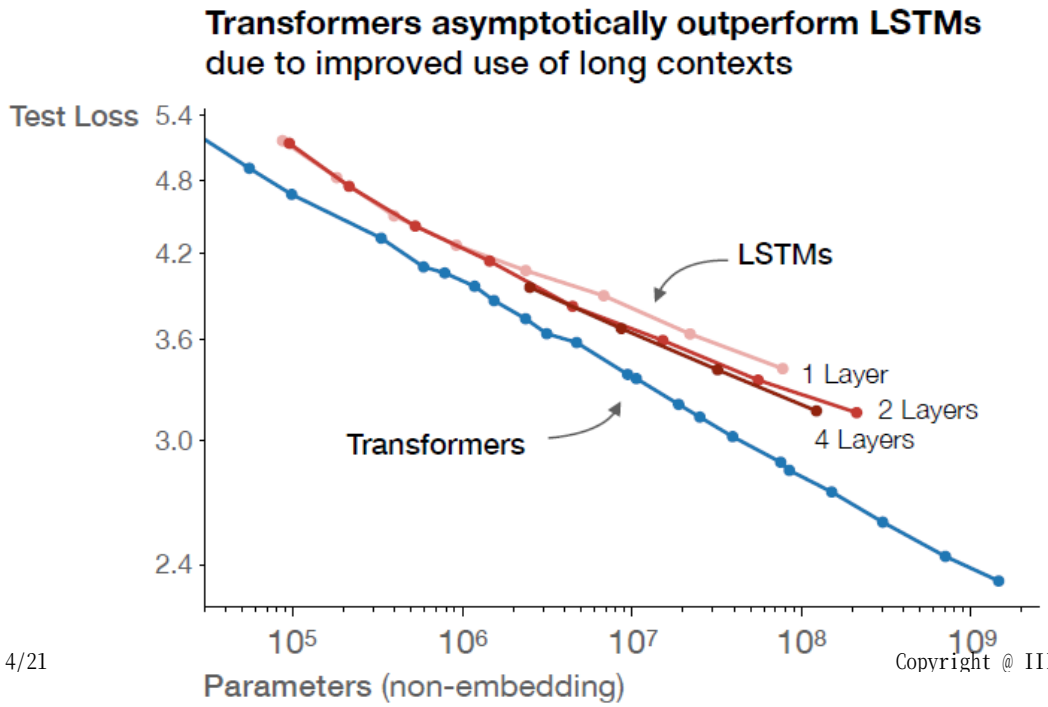
Scaling Law: The Chinchilla Law

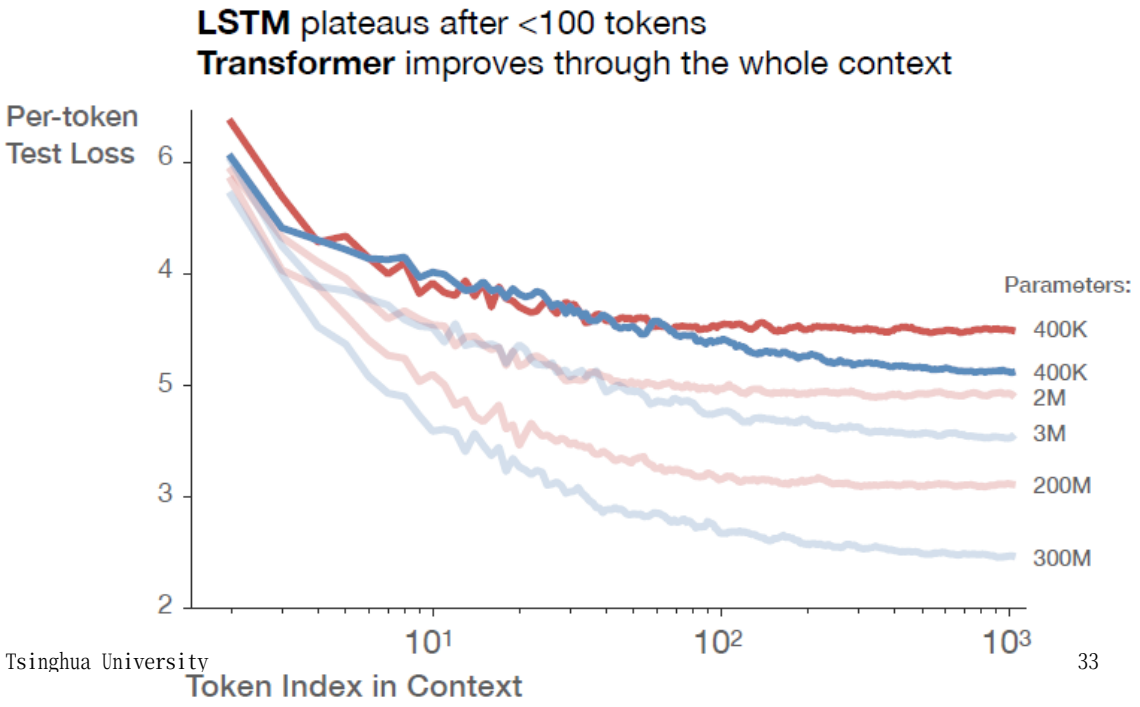
- The optimal model size and training tokens given a fixed compute budget (DeepMind, 2022)
  - Left: given different compute/#params, track the loss of different token size
  - Right: fit the best loss w.r.t. tokens/params at each compute



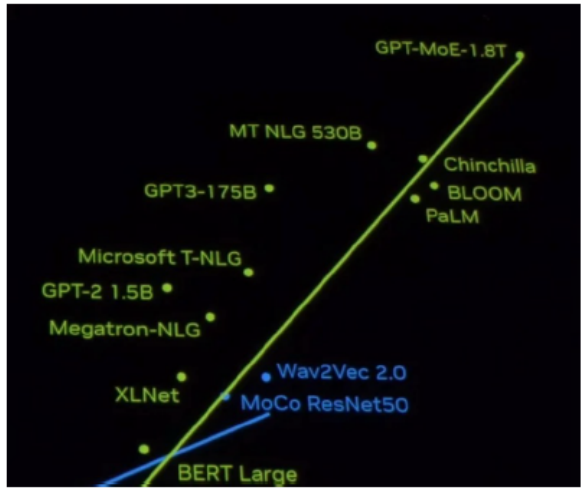
Scaling Law: Architecture Matters

- LSTM v.s. Transformers (OpenAI, 2020)
  - Transformer is a better architecture for a better scaling law
  - Can we have a better or more efficient architecture for better scaling laws?

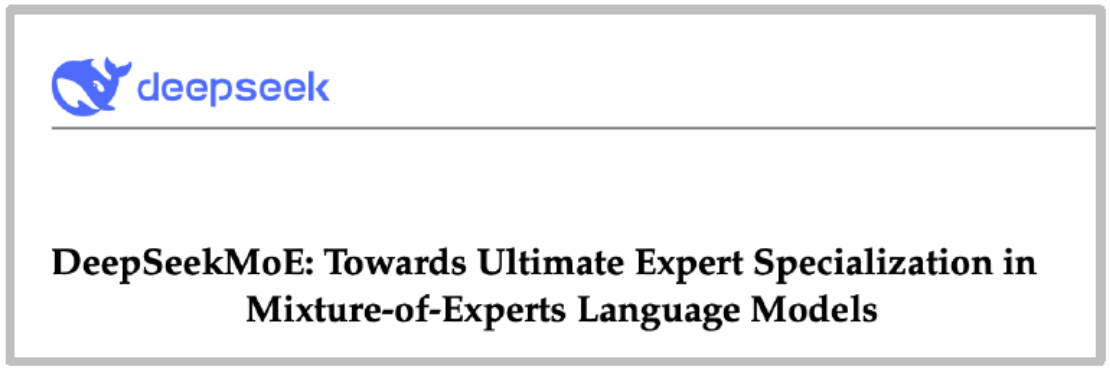




Mixture-of-Expert

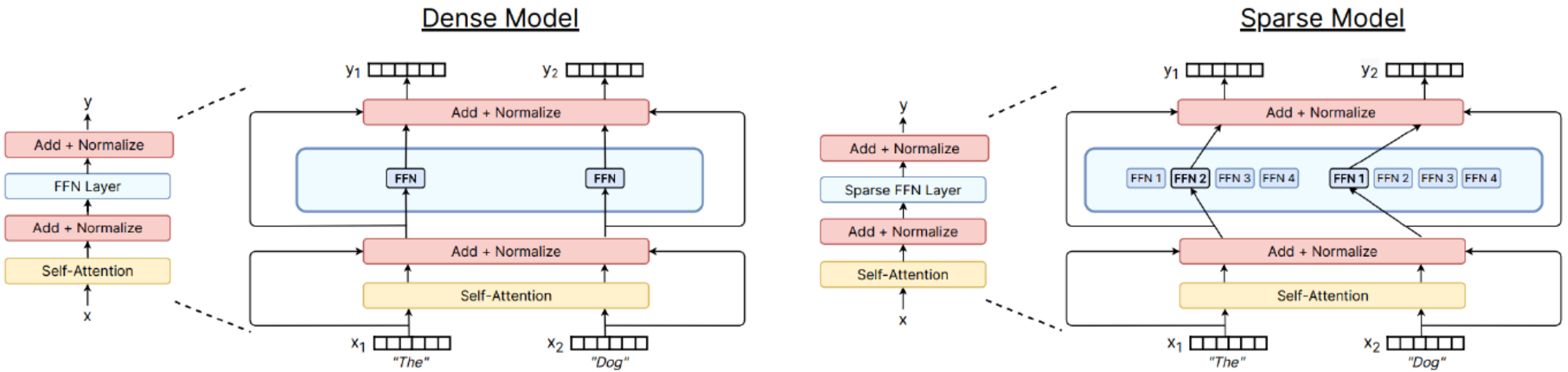


GPT4



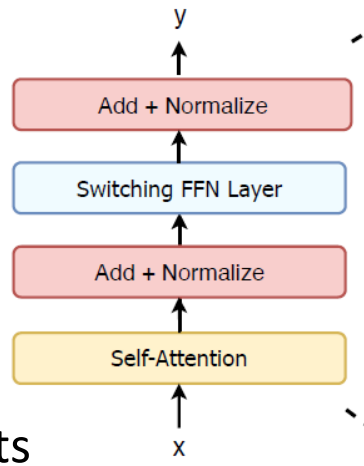
Mixture-of-Expert

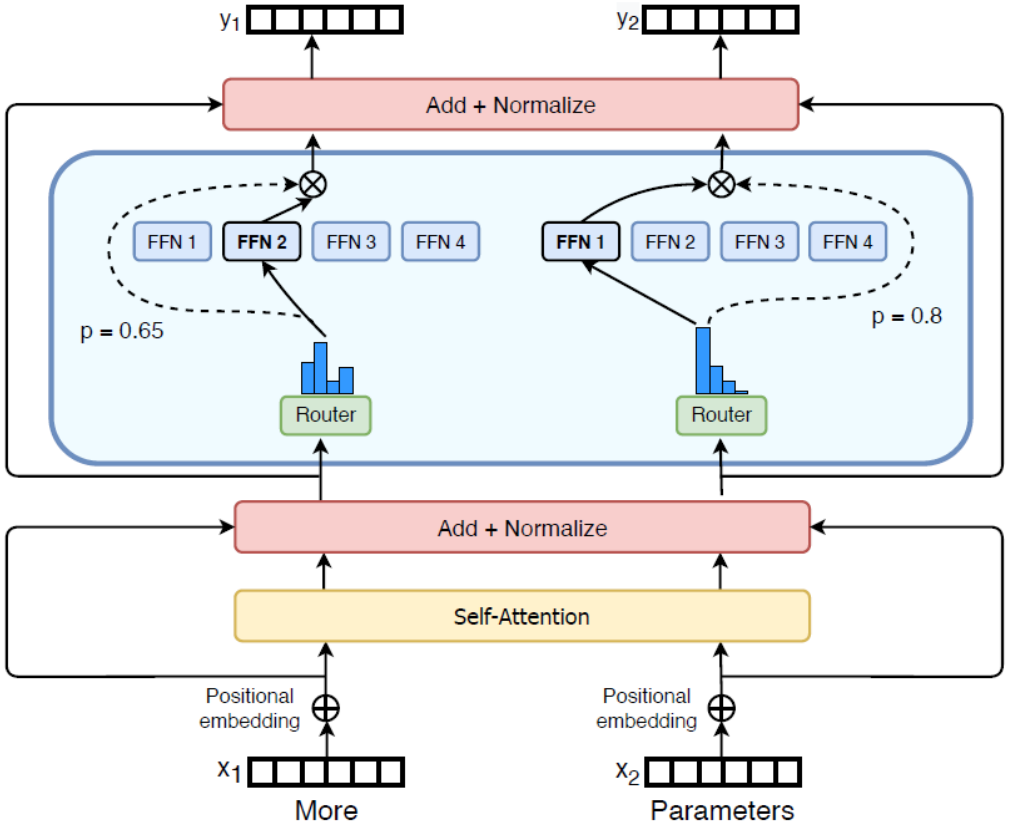
- Switch Transformers (Google, 2022)
  - The key idea is to replace the FFN module in a classical transformer (dense) to a routing module, which consists of a collection of smaller FFNs



Mixture-of-Expert

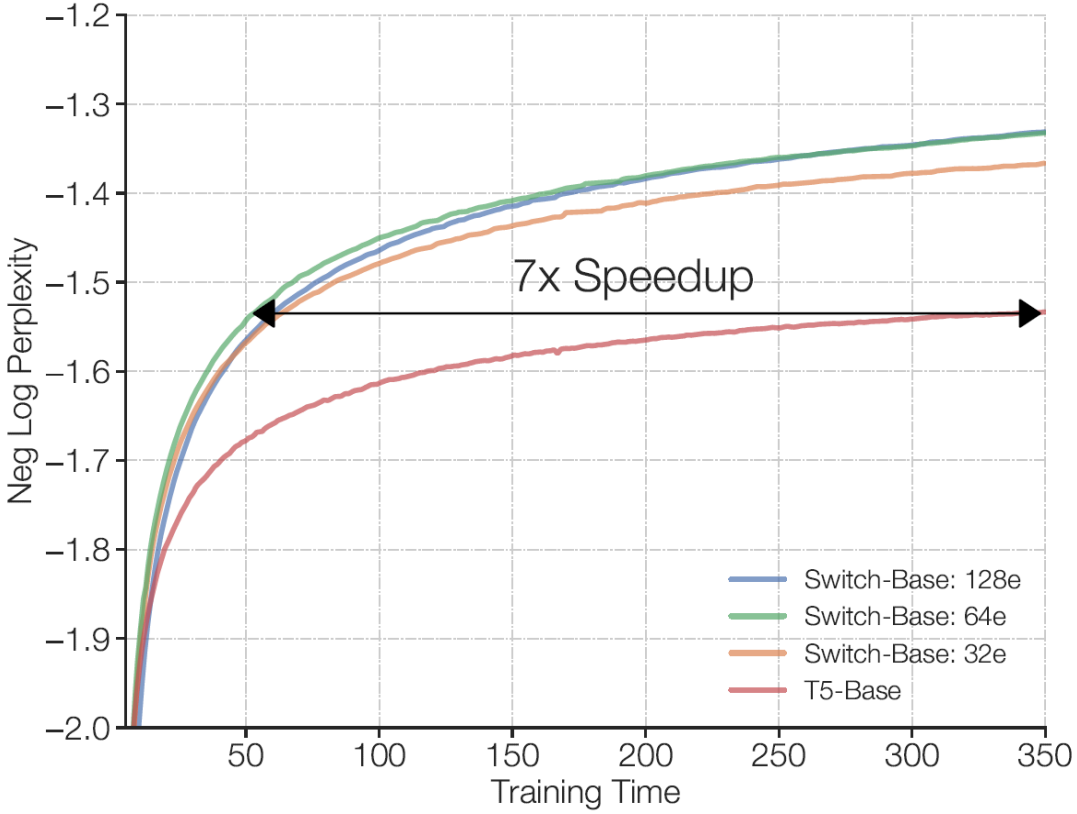
- Switch Transformers (Google, 2022)
  - The MoE layer
  - Expert
    - The small FFNs
  - Router
    - Select which experts to process the token
    - Select top-k experts
  - Sparsity
    - Only a few parameters are activated
    - MoE: Same flops → more parameters



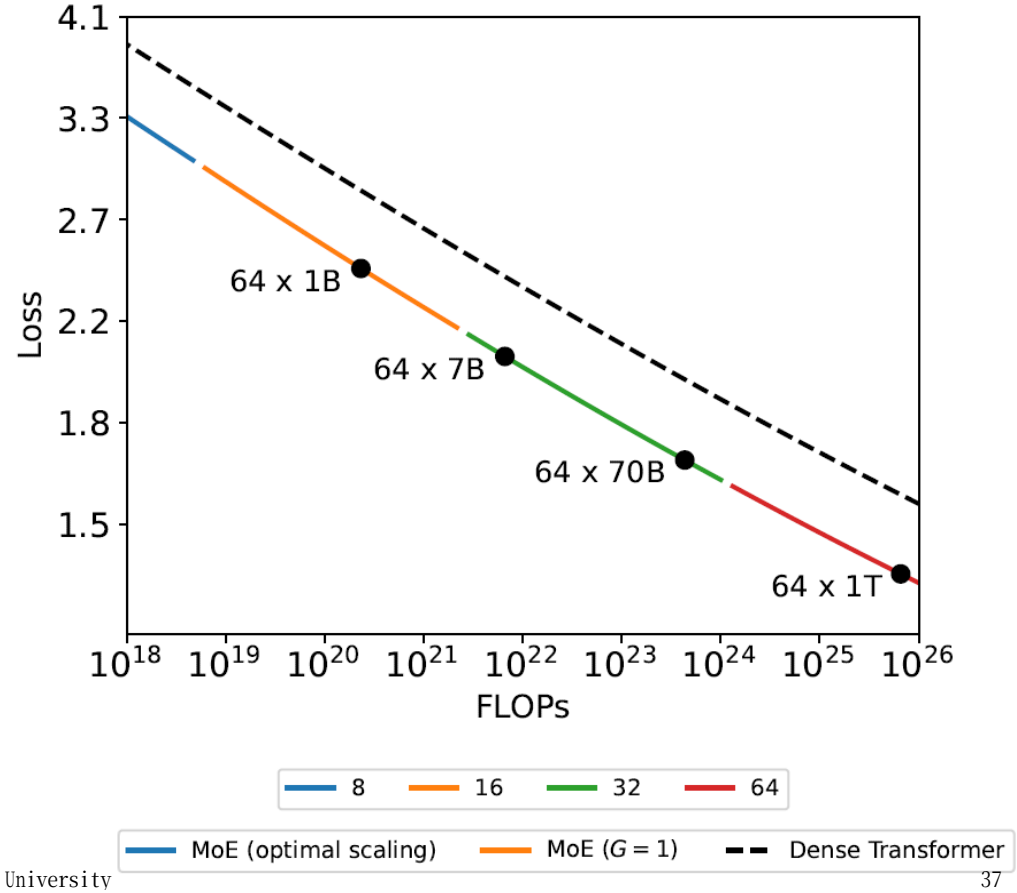


Mixture-of-Expert

- A much more efficient model and a better scaling law



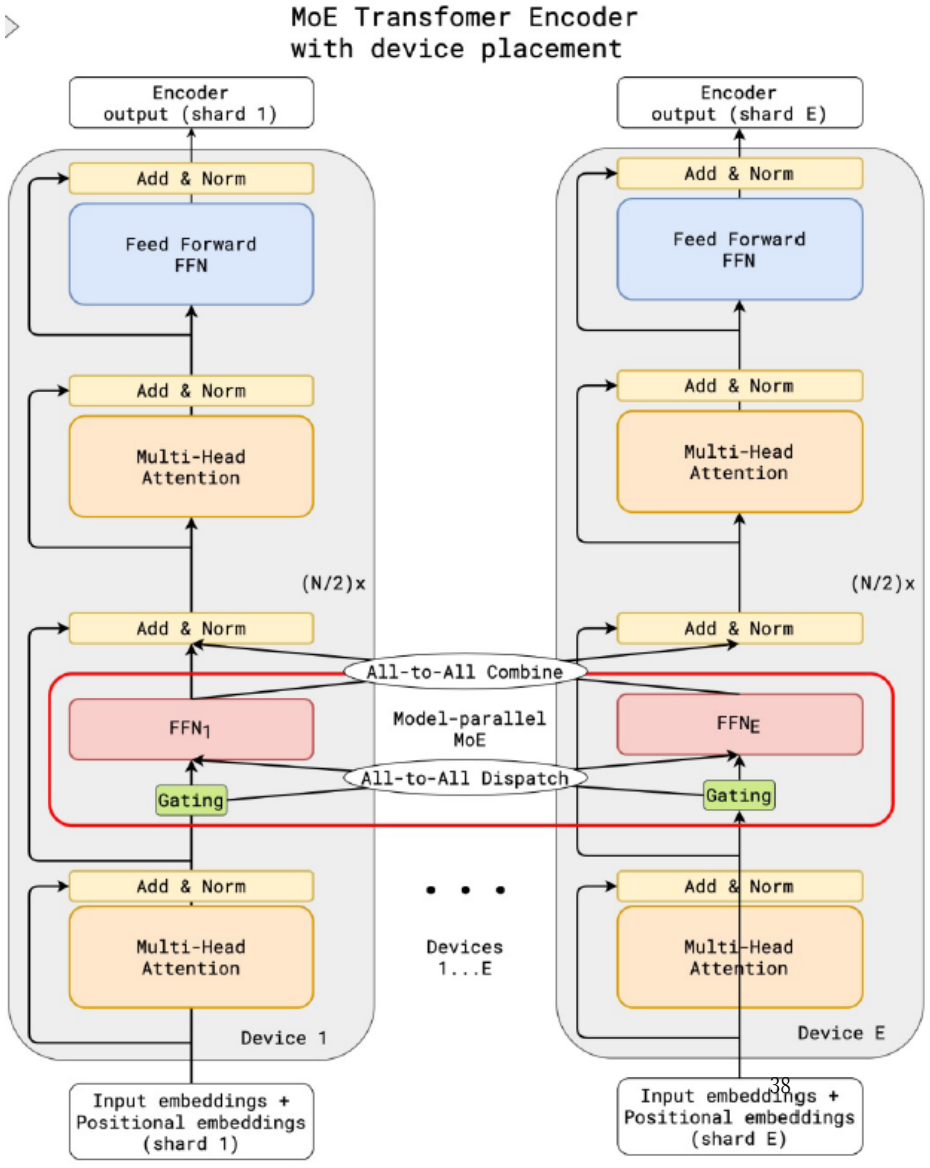
Switch Transformer (Google, 2022)



Scaling Laws for Fine-Grained Mixture of Experts (2024)

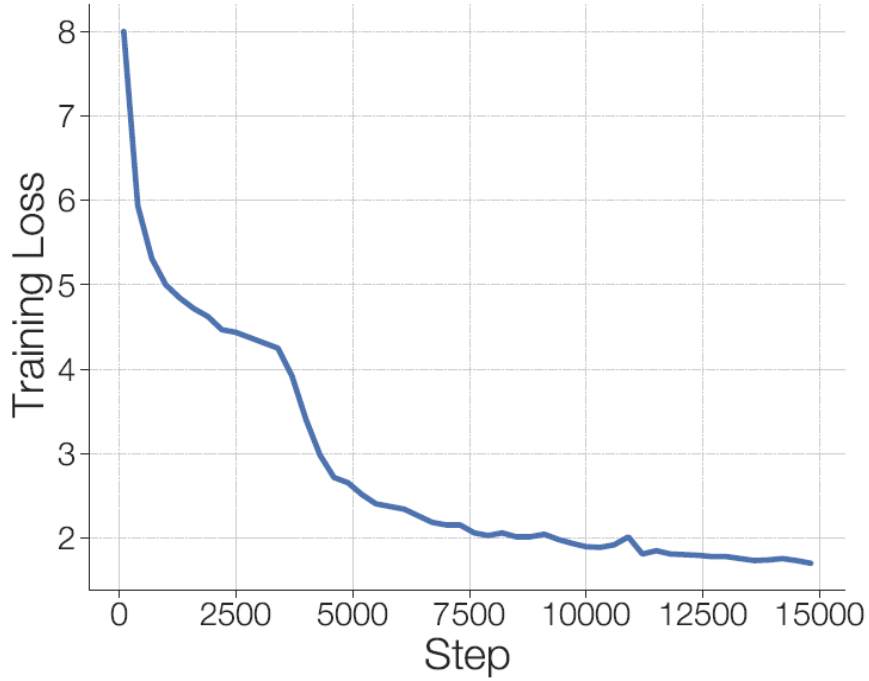
Mixture of Experts: Challenges

- MoE makes training more complex
  - Pros: MoE allows better parallel training
  - Cons: you need a better training system :/



Mixture of Experts: Challenges

- MoE makes training more complex
  - Pros: MoE allows better parallel training
  - Cons: you need a better training system :/
- MoE training can be unstable
  - Expert switching brings significant loss change
  - The load-balancing issue
  - MoE training can easily crash

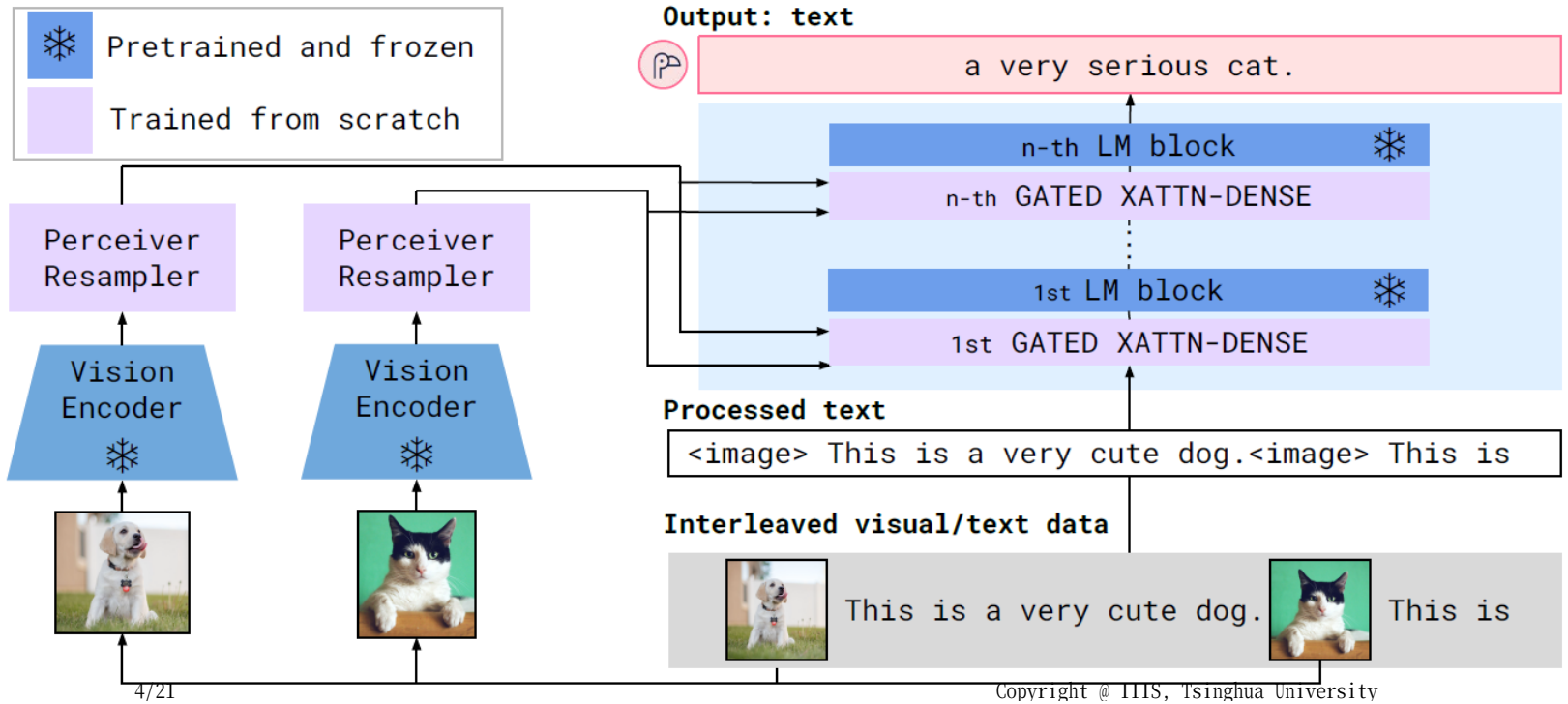


A stable MoE training run from Google
ST-MoE: Designing Stable and Transferable Sparse Expert Models (2022)

MoE models have better capacities, but harder to get training work!

Pretraining Transformer Decoder

- Multi-Modal GPT to Unify Image and Text
  - Flamingo (DeepMind, 2022)



Pretraining Transformer Decoder

- Multi-Modal GPT to Unify Image and Text
  - GPT-4 (OpenAI, 2023.3)

User What is unusual about this image?

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.

User

Below is part of the InstuctGPT paper. Could you read and summarize it to me?

Training language models to follow instructions with human feedback

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

OpenAI

Abstract

Making language models bigger does not inherently make them better at following a user's intent. For example, large language models can generate outputs that are untruthful, toxic, or simply not helpful to the user. In other words, these models are not *aligned* with their users. In this paper, we show an avenue for aligning language models with user intent on a wide range of tasks by fine-tuning with human feedback. Starting with a set of labeler-written prompts and prompts submitted through the OpenAI API, we collect a dataset of labeler demonstrations of the desired model behavior, which we use to fine-tune GPT-3 using supervised learning. We then collect a dataset of rankings of model outputs, which we use to further fine-tune this supervised model using reinforcement learning from human feedback. We call the resulting models *InstructGPT*. In human evaluations on our prompt distribution, outputs from the 1.3B parameter InstructGPT model are preferred to outputs from the 175B GPT-3, despite having 100x fewer parameters. Moreover, InstructGPT models show improvements in truthfulness and reductions in toxic output generation while having minimal performance regressions on public NLP datasets. Even though InstructGPT still makes simple mistakes, our results show that fine-tuning with human feedback is a promising direction for aligning language models with human intent.

1 Introduction

Large language models (LMs) can be "prompted" to perform a range of natural language processing (NLP) tasks, given some examples of the task as input. However, these models often express unintended behaviors such as making up facts, generating biased or toxic text, or simply not following user instructions (Bender et al., 2021; Bommasani et al., 2021; Kenton et al., 2021; Weidinger et al., 2021; Tamkin et al., 2021; Gehman et al., 2020). This is because the language modeling objective

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†Work done while at OpenAI. Current affiliations: AA: Anthropic; PC: Alignment Research Center.

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

used for many recent large LMs—predicting the next token on a webpage from the internet—is different from the objective "follow the user's instructions helpfully and safely" (Radford et al., 2019; Brown et al., 2020; Fedus et al., 2021; Rae et al., 2021; Thoppilan et al., 2022). Thus, we say that the language modeling objective is *misaligned*. Averting these unintended behaviors is especially important for language models that are deployed and used in hundreds of applications.

We make progress on aligning language models by training them to act in accordance with the user's intention (Leike et al., 2018). This encompasses both explicit intentions such as following instructions and implicit intentions such as staying truthful, and not being biased, toxic, or otherwise harmful. Using the language of Askell et al. (2021), we want language models to be *helpful* (they should help the user solve their task), *honest* (they shouldn't fabricate information or mislead the user), and *harmless* (they should not cause physical, psychological, or social harm to people or the environment). We elaborate on the evaluation of these criteria in Section 3.6.

We focus on *fine-tuning* approaches to aligning language models. Specifically, we use reinforcement learning from human feedback (RLHF; Christiano et al., 2017; Stiennon et al., 2020) to fine-tune GPT-3 to follow a broad class of written instructions (see Figure 2). This technique uses human preferences as a reward signal to fine-tune our models. We first hire a team of 40 contractors to label our data, based on their performance on a screening test (see Section 3.4 and Appendix B.1 for more details). We then collect a dataset of human-written demonstrations of the desired output behavior on (mostly English) prompts submitted to the OpenAI API[1] and some labeler-written prompts, and use this to train our supervised learning baselines. Next, we collect a dataset of human-labeled comparisons between outputs from our models on a larger set of API prompts. We then train a reward model (RM) on this dataset to predict which model output our labelers would prefer. Finally, we use this RM as a reward function and fine-tune our supervised learning baseline to maximize this reward using the PPO algorithm (Schulman et al., 2017). We illustrate this process in Figure 2. This procedure aligns the behavior of GPT-3 to the stated preferences of a specific group of people (mostly our labelers and researchers), rather than any broader notion of "human values"; we discuss this further in Section 5.2. We call the resulting models *InstructGPT*.

We mainly evaluate our models by having our labelers rate the quality of model outputs on our test set, consisting of prompts from held-out customers (who are not represented in the training data). We also conduct automatic evaluations on a range of public NLP datasets. We train three model

[1]Specifically, we train on prompts submitted to earlier versions of the InstructGPT models on the OpenAI API Playground, which were trained only using demonstration data. We filter out prompts containing PII.

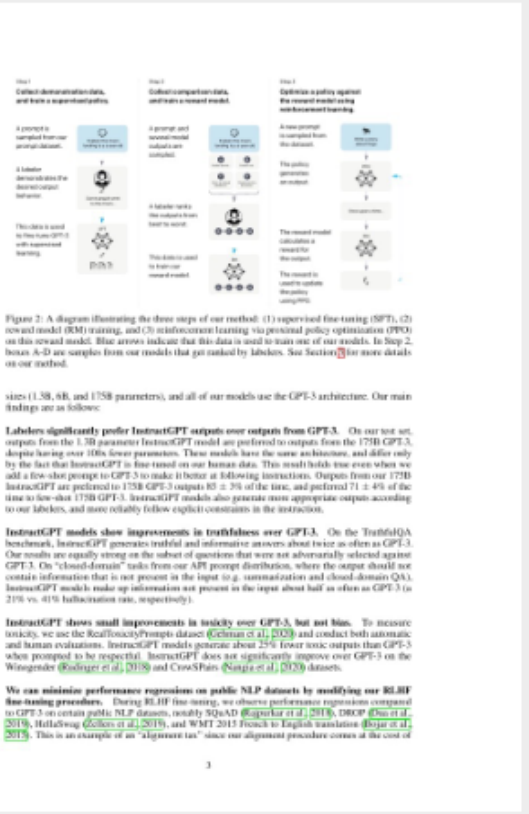


Figure 2: A diagram illustrating the three steps of our method: (1) supervised fine-tuning (SFT), (2) reward model (RM) training, and (3) reinforcement learning via proximal policy optimization (PPO) on this reward model. Blue arrows indicate that this data is used to train one of our models. In Step 2, boxes A–D are samples from our models that get ranked by labelers. See Section 3 for more details on our method.

sizes (1.3B, 6B, and 175B parameters), and all of our models use the GPT-3 architecture. Our main findings are as follows:

Labelers significantly prefer InstructGPT outputs over outputs from GPT-3. On our test set, outputs from the 1.3B parameter InstructGPT model are preferred to outputs from the 175B GPT-3, despite having over 100x fewer parameters. These models have the same architecture, and differ only by the fact that InstructGPT is fine-tuned on our human data. This result holds true even when we add a few-shot prompt to GPT-3 to make it better at following instructions. Outputs from our 175B InstructGPT are preferred to 175B GPT-3 outputs 85 ± 3% of the time, and preferred 71 ± 4% of the time to few-shot 175B GPT-3. InstructGPT models also generate more appropriate outputs according to our labelers, and more reliably follow explicit constraints in the instruction.

InstructGPT models show improvements in truthfulness over GPT-3. On the TruthfulQA benchmark, InstructGPT generates truthful and informative answers about twice as often as GPT-3. Our results are equally strong on the subset of questions that were not adversarially selected against GPT-3. On "closed-domain" tasks from our API prompt distribution, where the output should not contain information that is not present in the input (e.g. summarization and closed-domain QA), InstructGPT models make up information not present in the input about half as often as GPT-3 (a 21% vs. 41% hallucination rate, respectively).

InstructGPT shows small improvements in toxicity over GPT-3, but not bias. To measure toxicity, we use the RealToxicityPrompts dataset (Gehman et al., 2020) and conduct both automatic and human evaluations. InstructGPT models generate about 25% fewer toxic outputs than GPT-3 when prompted to be respectful. InstructGPT does not significantly improve over GPT-3 on the Winogender (Rudinger et al., 2018) and CrowS-Pairs (Nangia et al., 2020) datasets.

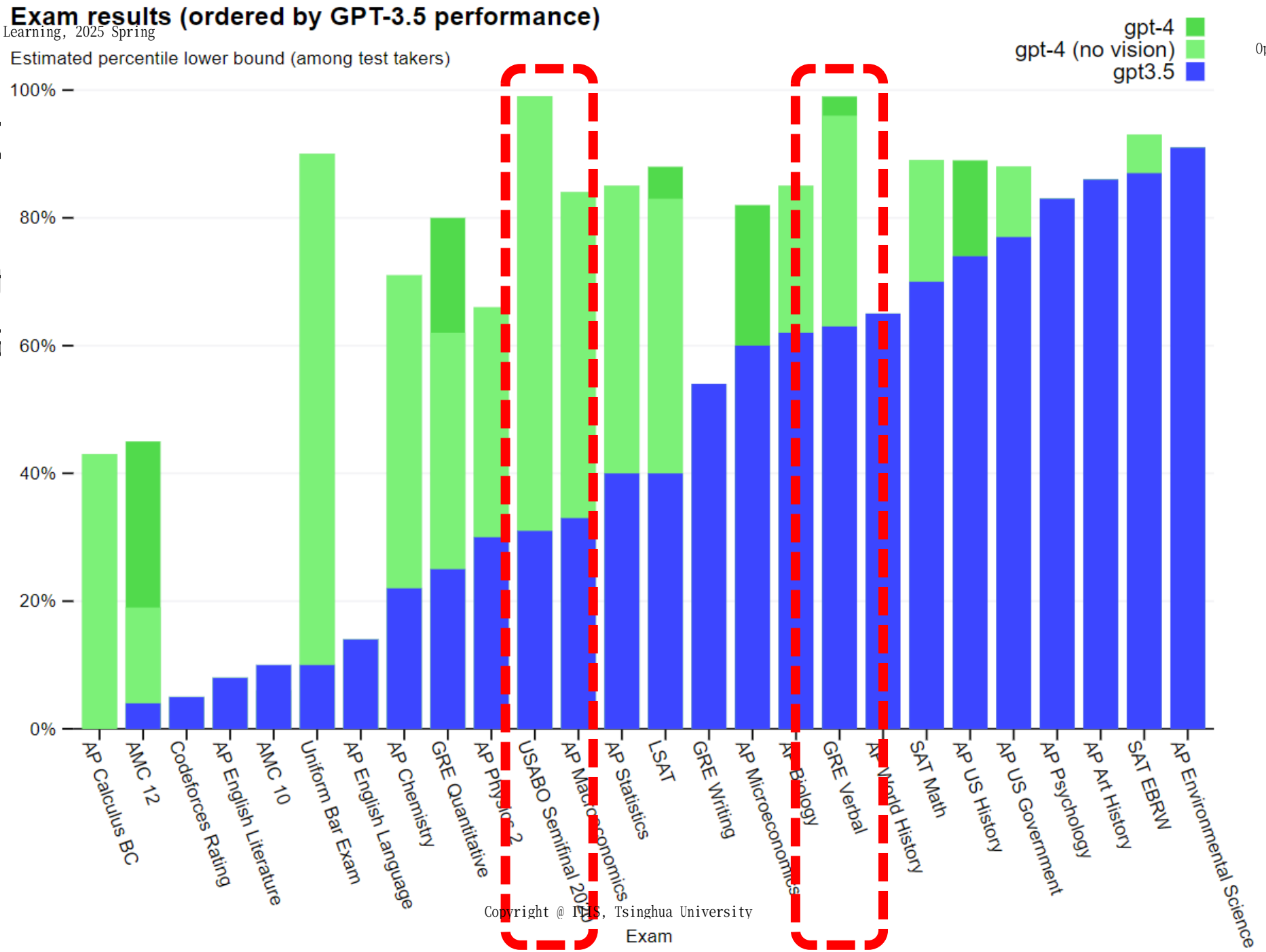
We can minimize performance regressions on public NLP datasets by modifying our RLHF fine-tuning procedure. During RLHF fine-tuning, we observe performance regressions compared to GPT-3 on certain public NLP datasets, notably SQuAD (Rajpurkar et al., 2018), DROP (Dua et al., 2019), HellaSwag (Zellers et al., 2019), and WMT 2015 French to English translation (Bojar et al., 2015). This is an example of an "alignment tax" since our alignment procedure comes at the cost of

GPT-4

The InstructGPT paper focuses on training large language models to follow instructions with human feedback. The authors note that making language models larger doesn't inherently make them better at following a user's intent. Large models can generate outputs that are untruthful, toxic, or simply unhelpful.

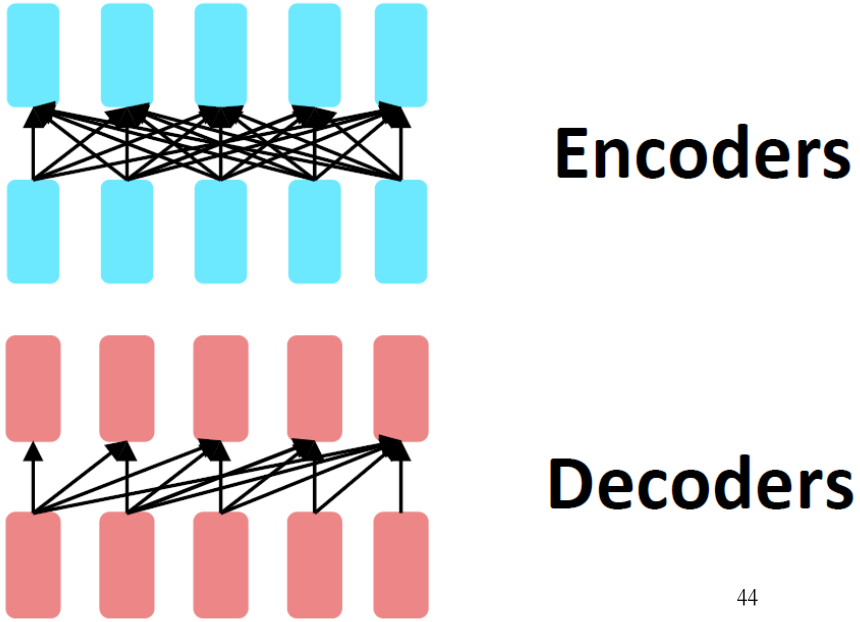
Pret

- Mul
  - G



Pretraining Transformers

- Collect a large amount of corpus and pretrain a large transformer
- For down-stream tasks, fine-tune the pretrained model
  - Or use the pretrained model to extract features
- How to pretrain a transformer on texts?
  - Pretrain an encoder
    - Bi-directional
  - Pretrain a decoder
    - Auto-regressive (e.g., GPT-X and more)
  - Also both encoder and decoder

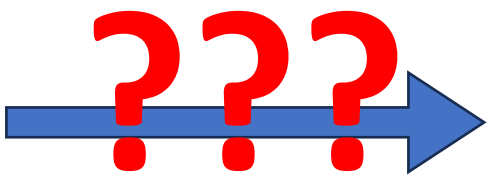


Summary

- Pretraining Transformers
  - Pretraining encoders for representation learning
  - Pretraining decoders for emergent multi-task/in-context learning capabilities

- Scaling Law
  - Larger model + more data + more compute → better LLMs

2019



2022

Early-days of GPT-3

- Not *“usable”*

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.
```

An Instruction-Following Problem

Human Instruction

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.

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```

GPT does not respond to the instruction

An Instruction-Following Problem

Human Instruction

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.

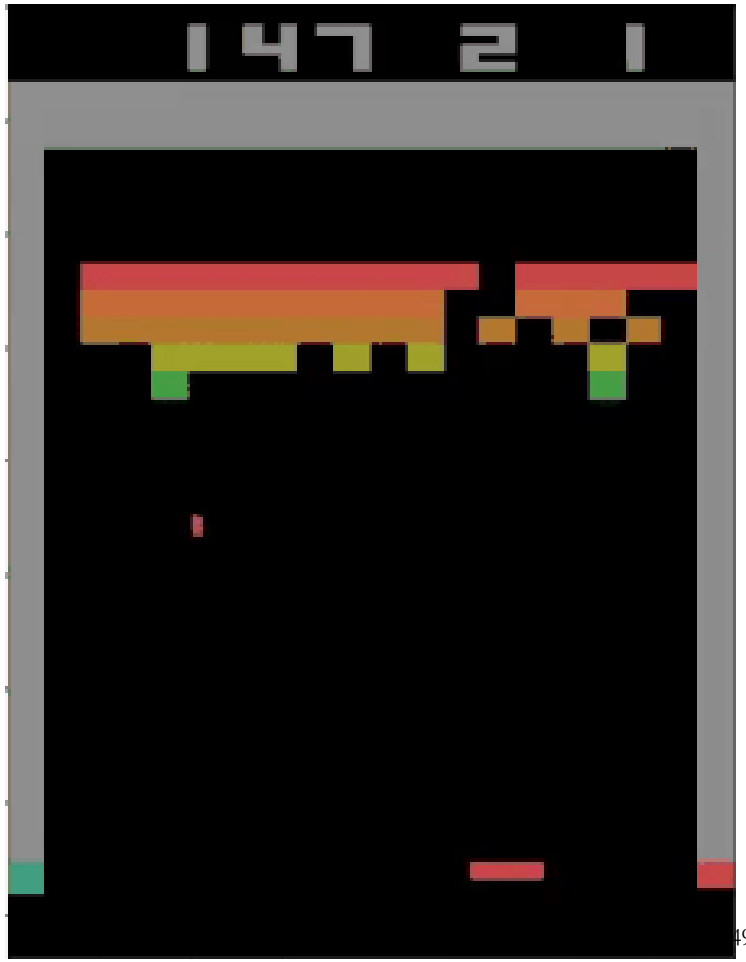
Explain evolution to a 6 year old.

GPT does not respond to the instruction

The instruction-following problem is solved **by Reinforcement Learning**

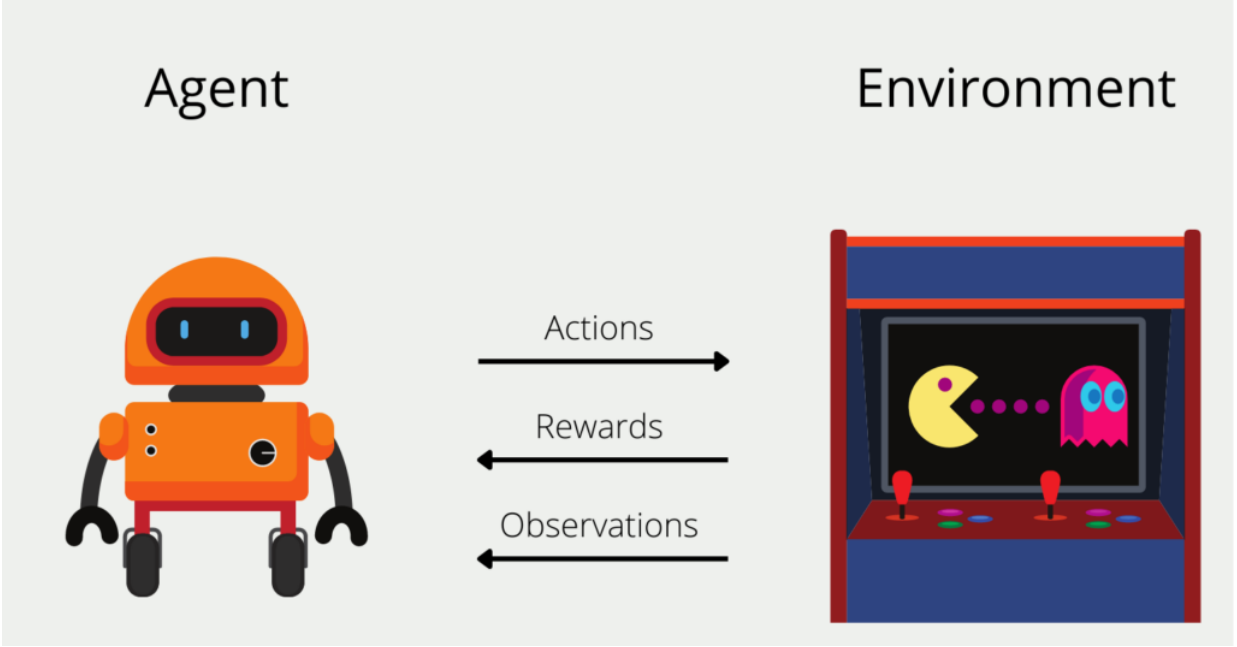
Reinforcement Learning

- Sequence decision-making
- No gold-standard solutions
  - The model must explore for the best strategy



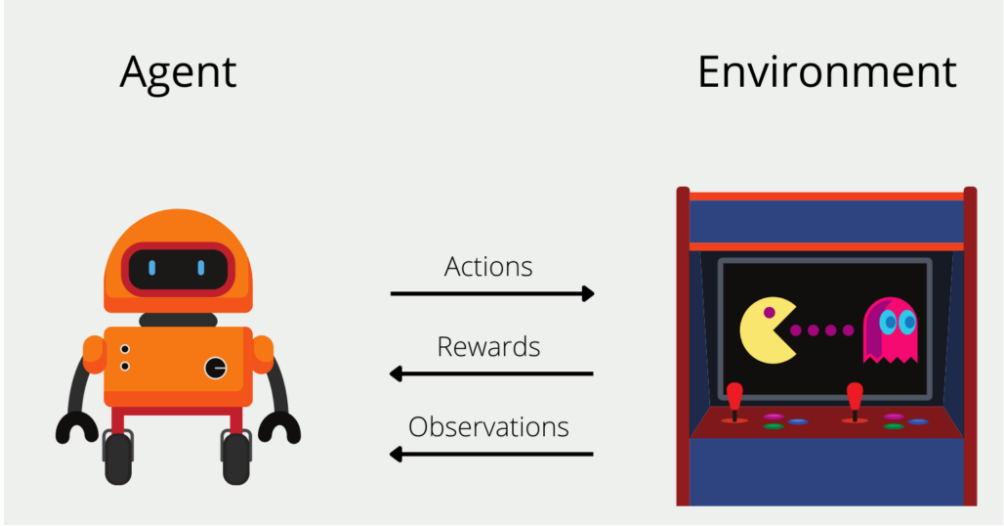
Reinforcement Learning: Formulation

- Environment (Task)
  - Observation
  - Transition
  - Reward
- Agent / Policy
  - Input: observation
  - Output: action
  - Objective: maximize reward
- Key components
  - **Environment**
  - **Action; Observation; Reward**



Reinforcement Learning v.s. Language Model

- Reinforcement Learning
  - Massive self-generated data
  - Trial-and-error
    - Both good data and bad data
  - Clear Task & Reward function



How to connect them?

- Language Model
  - A large prepared training corpus
  - No exploration needed
    - Next token prediction
  - No reward/task

Instruct Following Meets GPT

- An **instruction following** challenge for a "**usable**" GPT

Prompt

Explain the moon landing to a 6 year old in a few sentences.

Instruction

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.
```

Action

Reward???

Instruct Following Meets GPT

- Key challenges for GPT following instructions
  - Complex & diverse instructions 极其复杂的指令，任务多样
  - Non-trivial reward evaluation 很难评估奖励完成度

  - Solution: InstructGPT (OpenAI, 2022)

InstructGPT

- Key challenges for GPT f
  - Complex & diverse instru
  - Non-trivial reward evalua
- Key Ideas of InstructGPT
  - Collect human feedback
  - 使用人类的反馈训练GP
- Human labeler can judge human 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.
```

InstructGPT

```
People went to the moon, and they took pictures of what
they saw, and sent them back to the earth so we could all
see them.
```

InstructGPT

- InstructGPT follows complex instructions

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

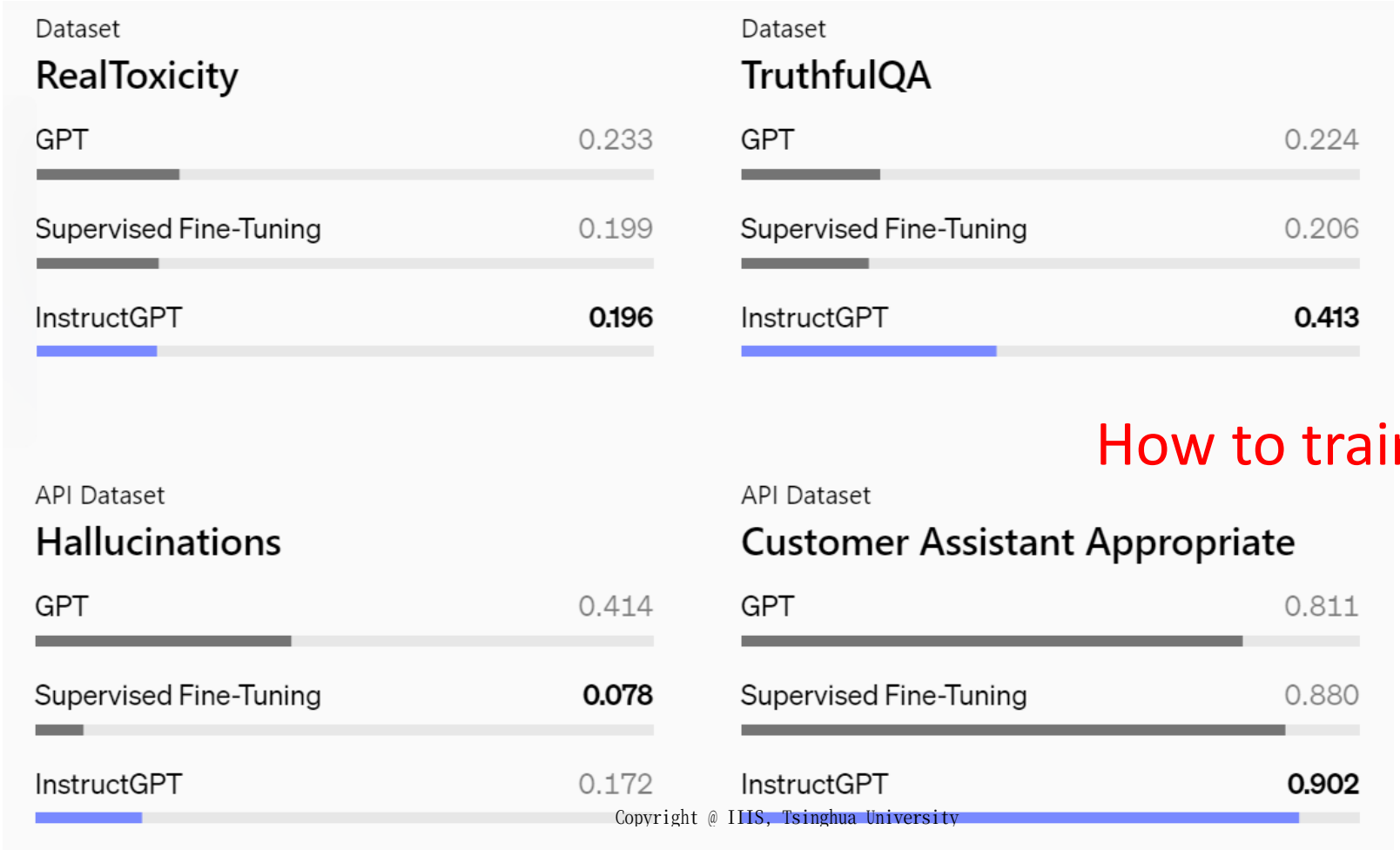
```
def binomial_coefficient(n, r):
    C = [0 for i in range(r + 1)];
    C[0] = 1;
    for i in range(1, n + 1):
        j = min(i, r);
        while j > 0:
            C[j] += C[j - 1];
            j -= 1;
    return C[r]
```

GPT-3 175B completion:
A. to store the value of C[0]
B. to store the value of C[1]
C. to store the value of C[i]
D. to store the value of C[i - 1]

InstructGPT 175B completion:
The list C in this code is used to store the values of the binomial coefficient as the function iterates through the values of n and r. It is used to calculate the value of the binomial coefficient for a given value of n and r, and stores the result in the final return value of the function.

InstructGPT

- InstructGPT reduces hallucinations



How to train InstructGPT?

InstructGPT Explained

- Goal: fine-tune GPT to follow human instructions
  - 微调GPT来遵从人类指令

- How to collect human data for fine-tuning?
  - We need to collect prompts （收集人类指令）
  - We need to collect responses for the prompts （收集指令的反馈）

Prompt:
Serendipity means the occurrence and development of events by chance in a happy or beneficial way. Use the word in a sentence.

Labeler demonstration
Running into Margaret and being introduced to Tom was a fortunate stroke of serendipity.

Supervised Fine-Tuning (SFT)

InstructGPT Explained

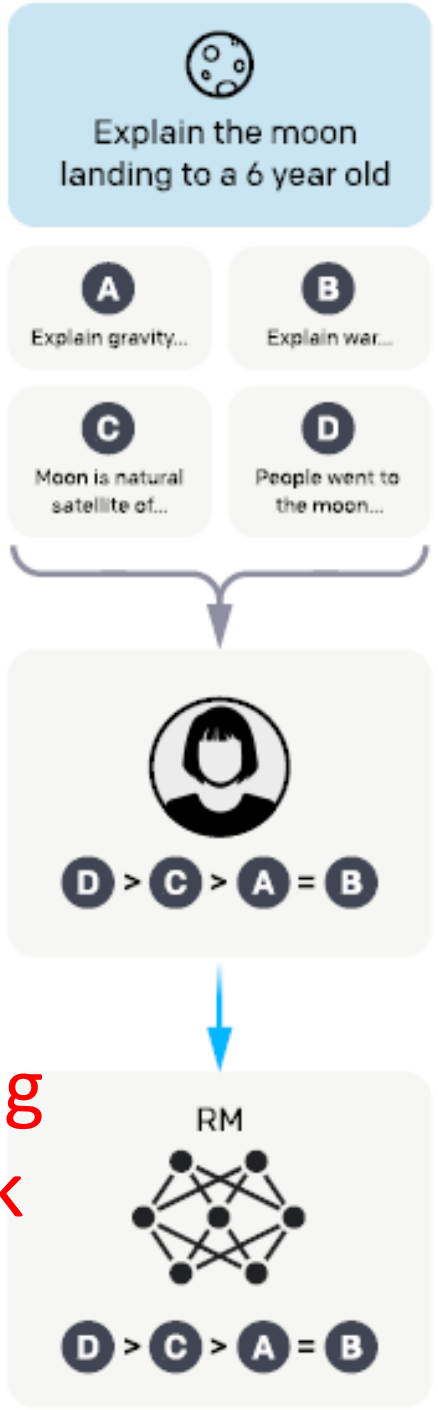
- Goal: fine-tune GPT to follow human instructions
  - 微调GPT来遵从人类指令
- SFT: fine-tuning on human demonstrations

- What about the RL perspective?
  - Pros: GPT can self-explore & RL is powerful
  - Cons: **Reward????**

InstructGPT Explained

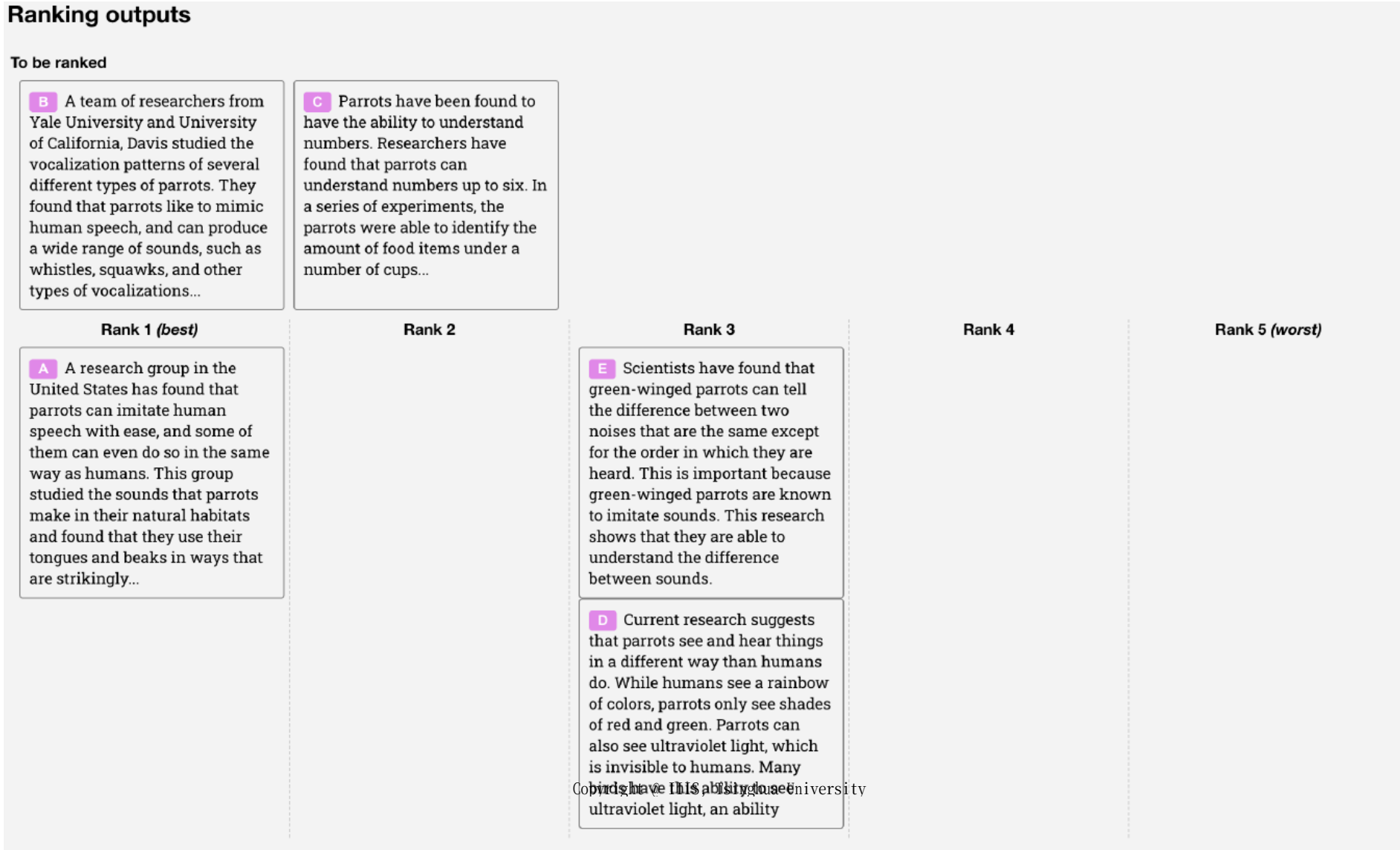
- Goal: fine-tune GPT to follow human instructions
  - 微调GPT来遵从人类指令
- SFT: fine-tuning on human demonstrations

- What about the RL perspective?
  - Pros: GPT can self-explore & RL is powerful
  - Cons: Reward????
- Key Idea: RL with **a learned reward**
  - Generate multiple outputs
    - 生成多个输出
  - Ranking by humans
    - 人类排序
  - Learn a reward model
    - 学习一个满足偏序的奖励函数



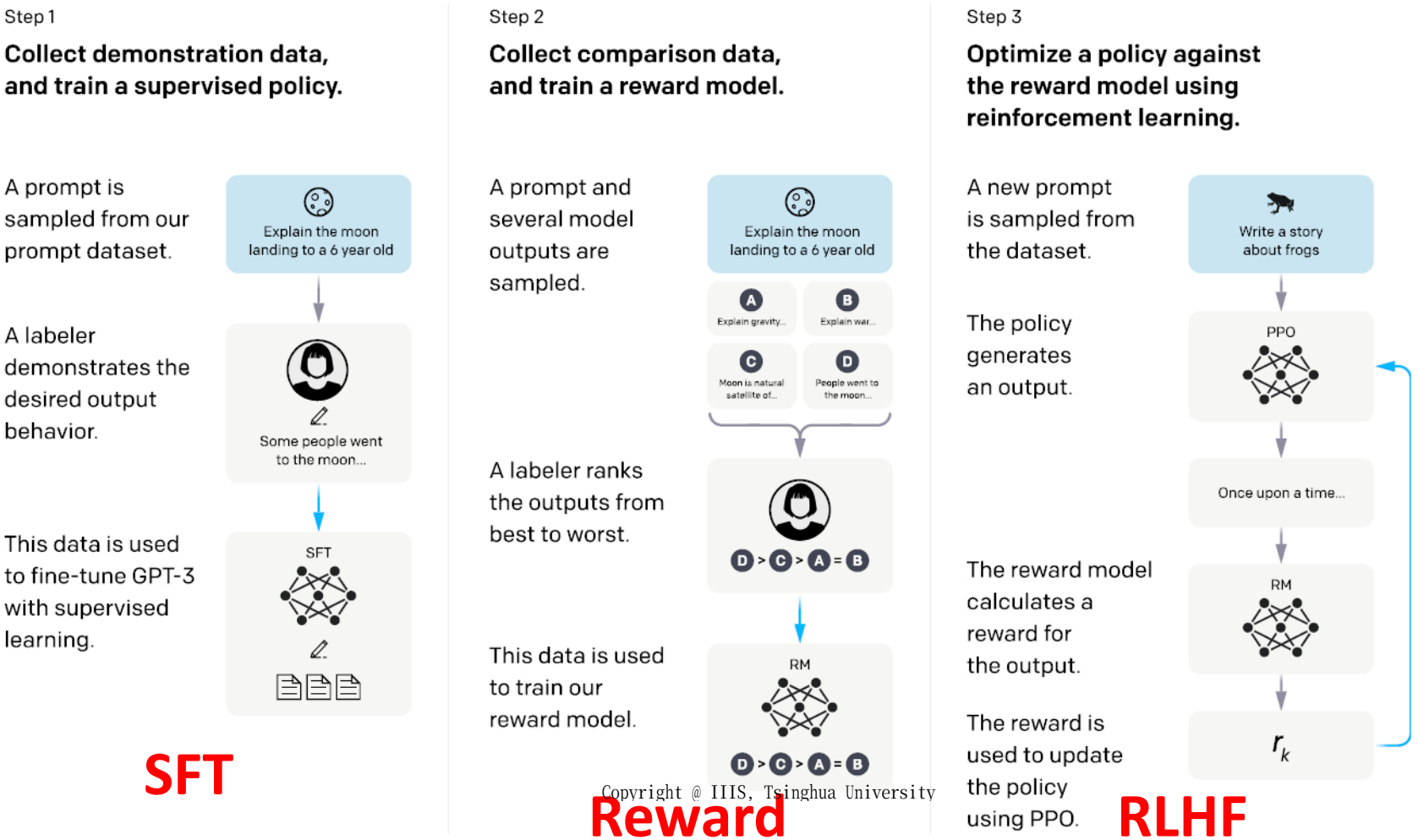
Reinforcement Learning from Human Feedback (RLHF)

InstructGPT Explained



InstructGPT Explained

- The overall pipeline



Pre-train v.s. Post-train

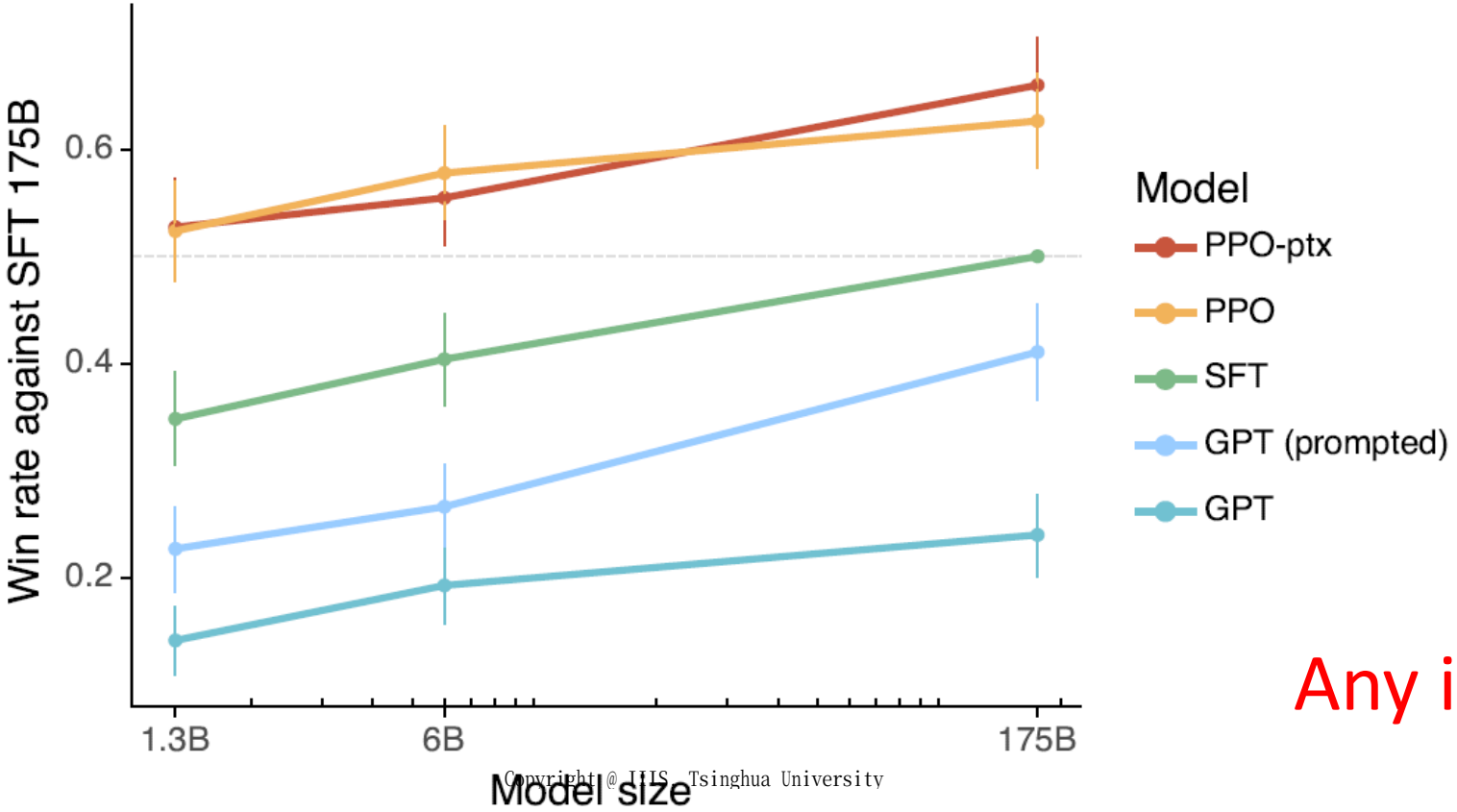
- InstructGPT / ChatGPT 总体流程
  - Pre-trained base model
    - Massive corpus
  - Post-train using human feedback
    - SFT: human demo
    - RLHF: human preference

- Pre-train v.s. Post-train
  - Data: massive v.s. high-quality（海量 v.s. 高质量）
  - Objective: compression v.s. instruction following（压缩 v.s. 指令遵从）
  - Dynamics: static v.s. online feedback（静态数据集 v.s. 在线反馈收集）

- Comment: the post-train phase is also called the alignment phase（对齐）
  - Align the LLM to human preferences（将语言模型和人类偏好对齐）

SFT v.s. RLHF

- Why do we need RLHF? Or Isn't SFT sufficient for post-train?
  - The InstructGPT result



Any insights?

Hallucination

- SFT-based post-training causes Hallucination
  - From John Schulman's talk at Berkeley (Apr, 2023)

- A thought experiment:
  - Suppose ChatGPT's knowledge cut-off is 2023.
  - Let's fine-tune ChatGPT using SFT to describe EuroCup 2024.
  - What will happen?

Hallucination

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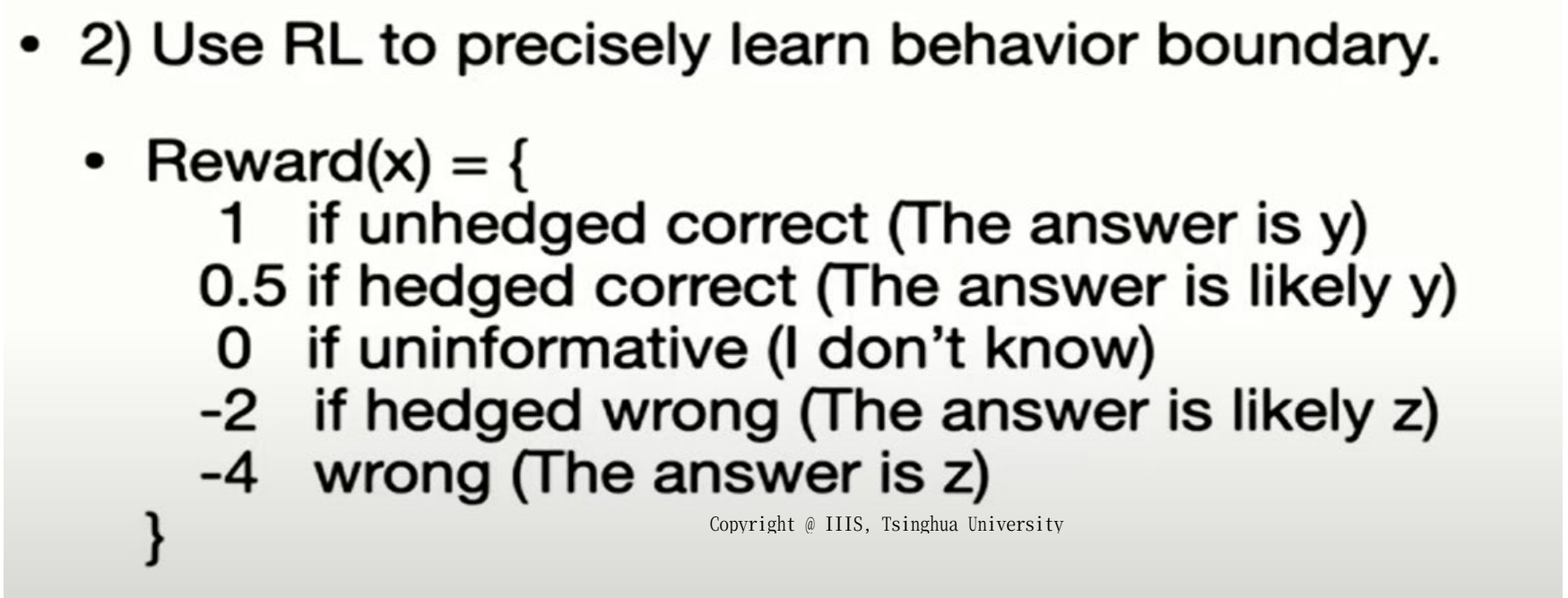
- A thought experiment:
  - Suppose ChatGPT's knowledge cut-off is 2023.
  - Let's fine-tune ChatGPT using SFT to describe EuroCup 2024.
  - **GPT does not know this fact, so we may just teach it to hallucinate!**

Hallucination

- SFT-based post-training causes Hallucination
  - RLHF can help uncertainty awareness
- Key Idea: a properly designed reward fixes the hallucination issue
  - 存在一种可能得奖励函数，鼓励模型在不知道的时候说不知道



A good reward model matters!

Hallucination

- SFT-based post-training causes Hallucination
  - RLHF can help uncertainty awareness (with a proper reward model)
  - RL can also improve model capacity

Hallucination

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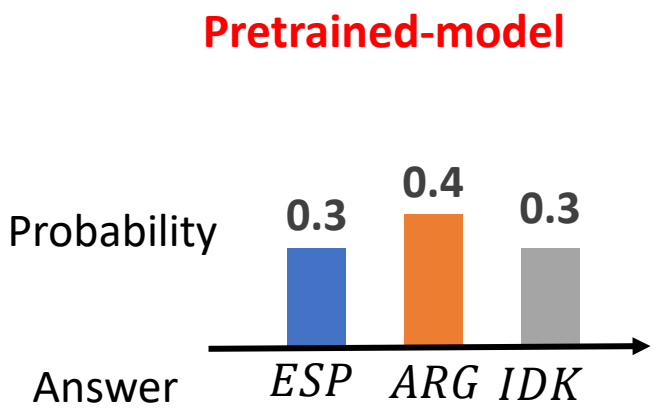
  - A thought experiment: "***Who won the 2026 world cup?***"



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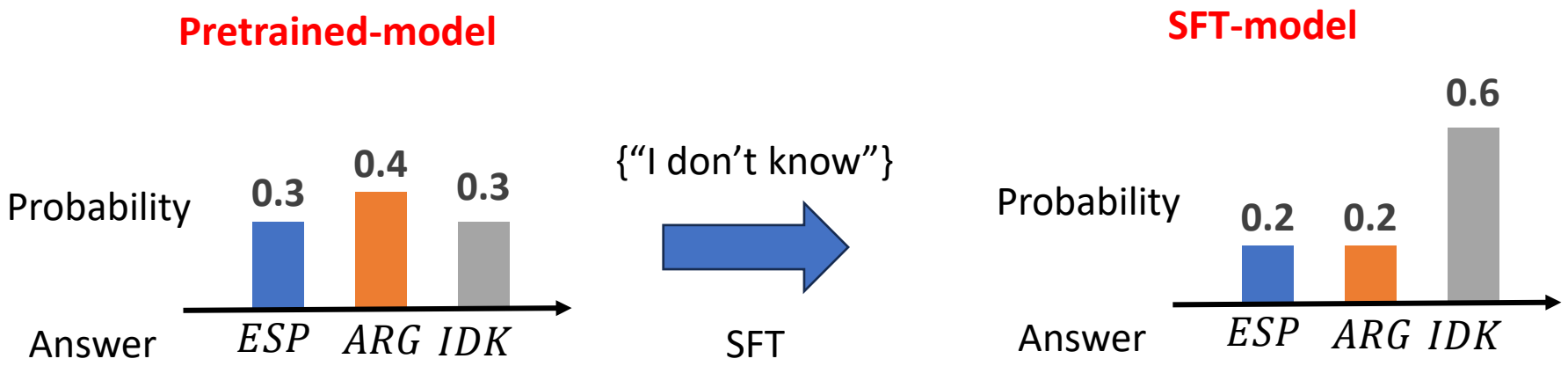

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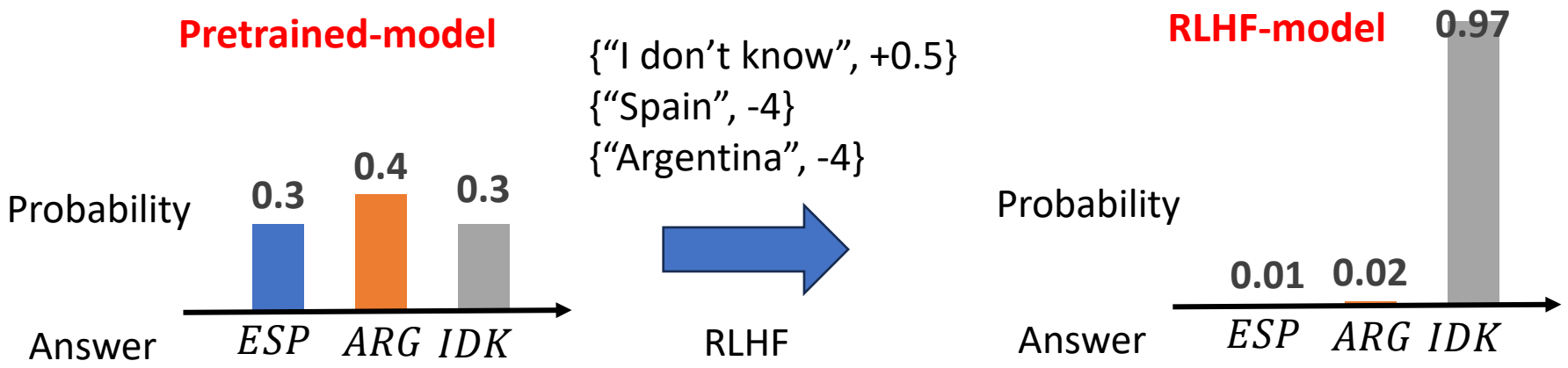
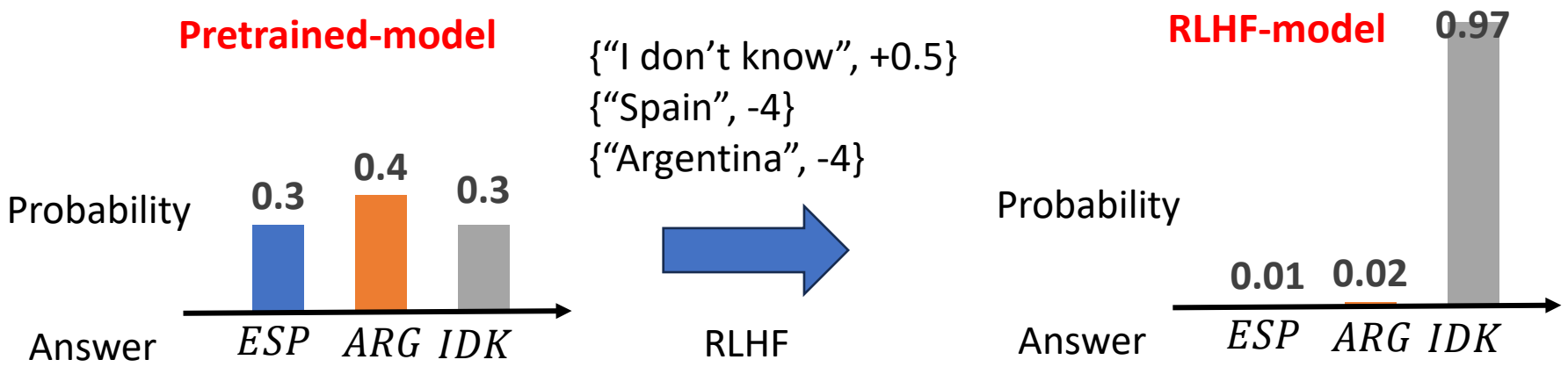


Hallucination

- SFT-based post-training causes Hallucination
  - RLHF can help uncertainty awareness
  - RL can also improve model capacity
  - A thought experiment: "***Who won the 2026 world cup?***"
    - Remark#1: Self-exploration enables better model capacity!



Hallucination

- SFT-based post-training causes Hallucination
  - RLHF can help uncertainty awareness
  - RL can also improve model capacity
  - A thought experiment: "***Who won the 2026 world cup?***"
    - Remark#1: Self-exploration enables better model capacity!
    - Remark#2: SFT only leverage positive samples, but negative samples also matters!

Hallucination

- SFT-based post-training causes Hallucination
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  - A thought experiment: "***Who won the 2026 world cup?***"
    - Remark#1: Self-exploration enables better model capacity!
    - Remark#2: SFT only leverage positive samples, but negative samples also matters!

But there will always be latest knowledge that the LLM does not know!

Inference-Time Enhancement

How many champion's league titles does real Madrid men's football club have?

As of April 2025, **Real Madrid men's football club** has won **14 UEFA Champions League titles**.

Here's a list of the years they won:

1. 1955–56
   ••••••
13. 2017–18
14. 2021–22

Hallucination!

(Real Madrid also won the 2024 title)

What will you do for this question?

Infer

How many champion's league titles does real Madrid men's football club have?

Real Madrid's men's football team has won the UEFA Champions League a record 15 times. Their most recent victory came in the 2023–24 season, when they defeated Borussia Dortmund 2–0 in the final. SI

Real Madrid's Champions L

SI

Real Madrid Champions League Titles: How Many Have They Won?

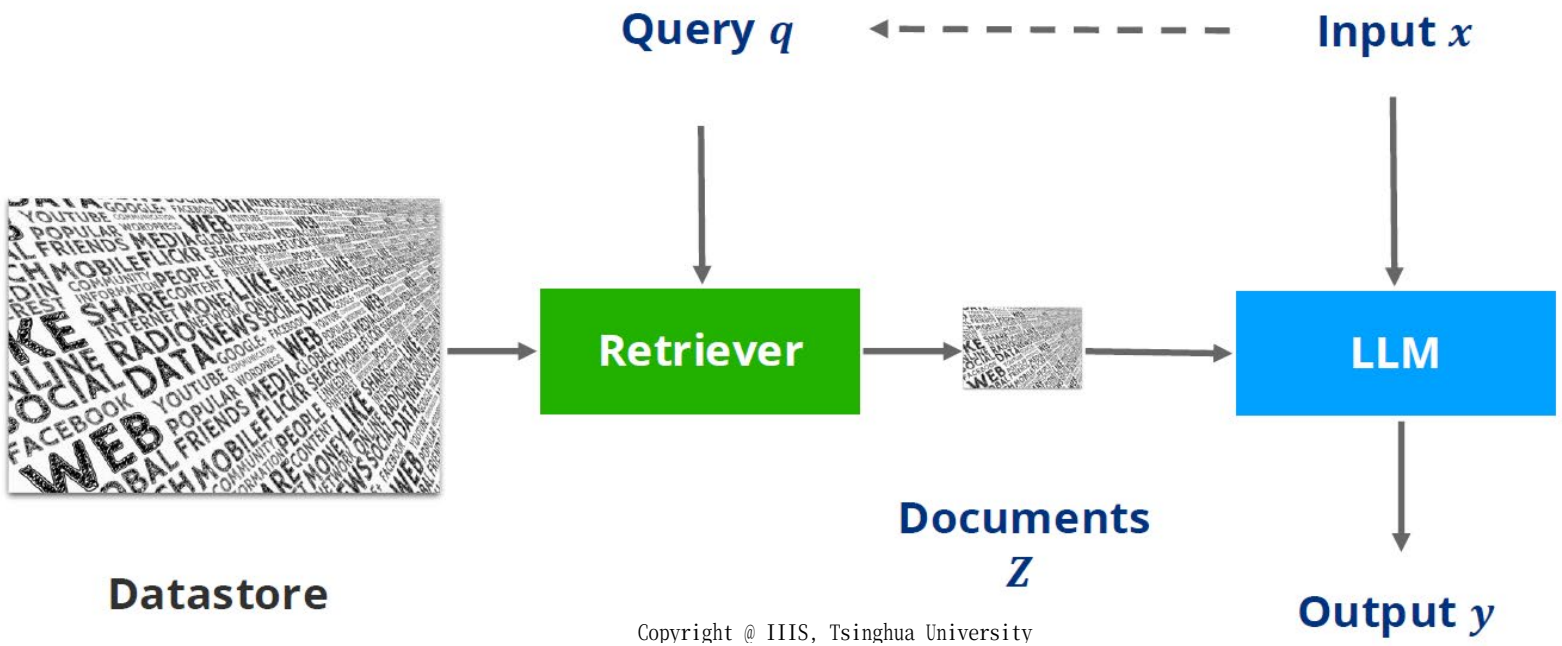
5 March 2025 — Real Madrid have won 15 Champions League titles, the most by any team in the competition's...

Ask anything

Search

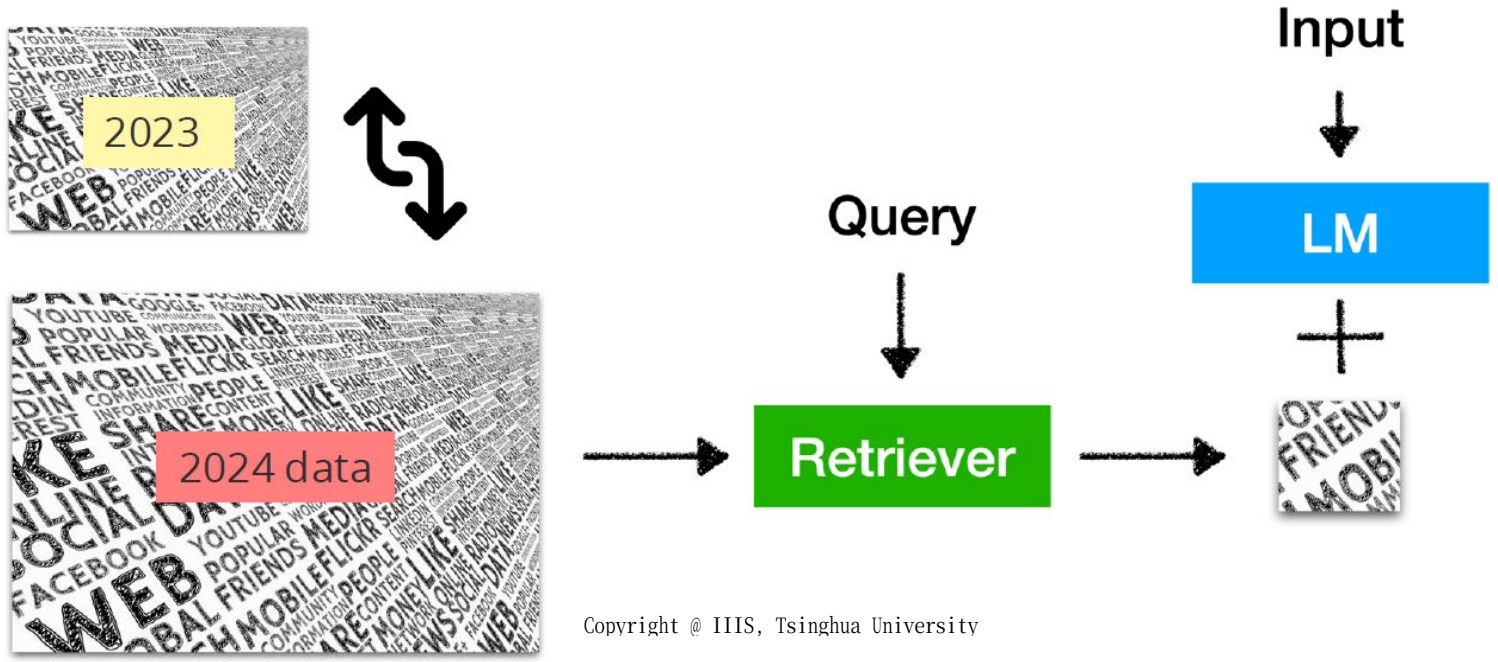
Inference-Time Enhancement

- Retrieval-Augmented Generation (RAG)
  - Before the LLM generates a response, we perform an additional retrieval step and put the results in the context



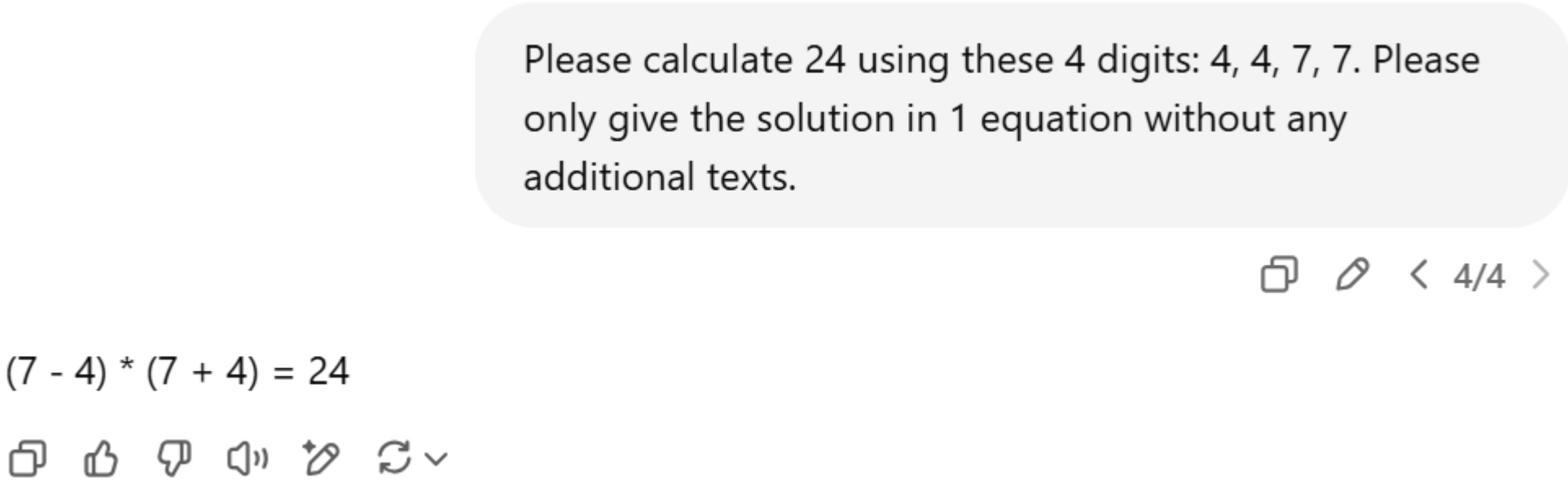
Inference-Time Enhancement

- Retrieval-Augmented Generation (RAG)
  - Before the LLM generates a response, we perform an additional retrieval step and put the results in the context
  - We can easily update the model knowledge without the need of re-training



Inference-Time Enhancement

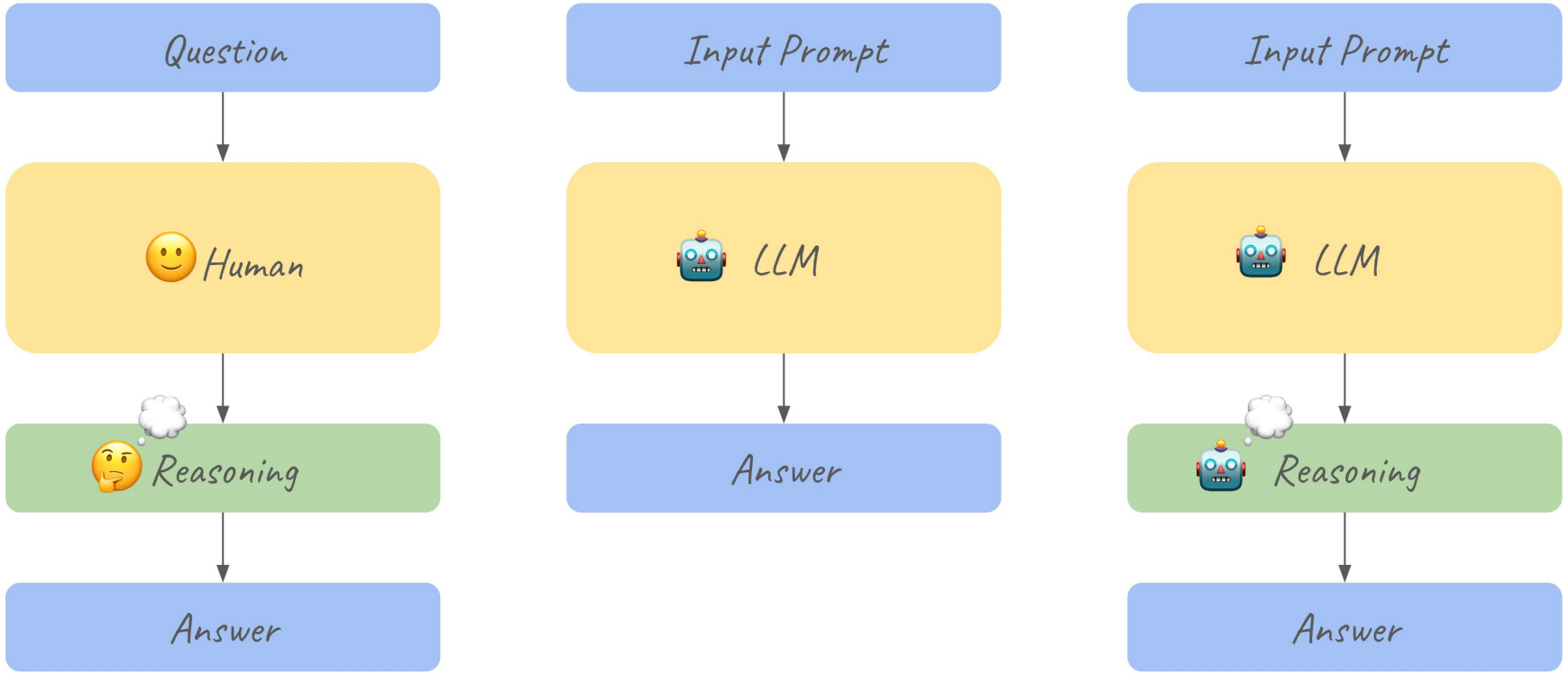
- What about a reasoning question?
  - E.g., compute 24 using 4, 4, 7, 7



What will human do?

Inference-Time Enhancement

- OpenAI o1 model (2024)
  - Large Reasoning Model (LRM). An LLM “thinks” before giving a respond

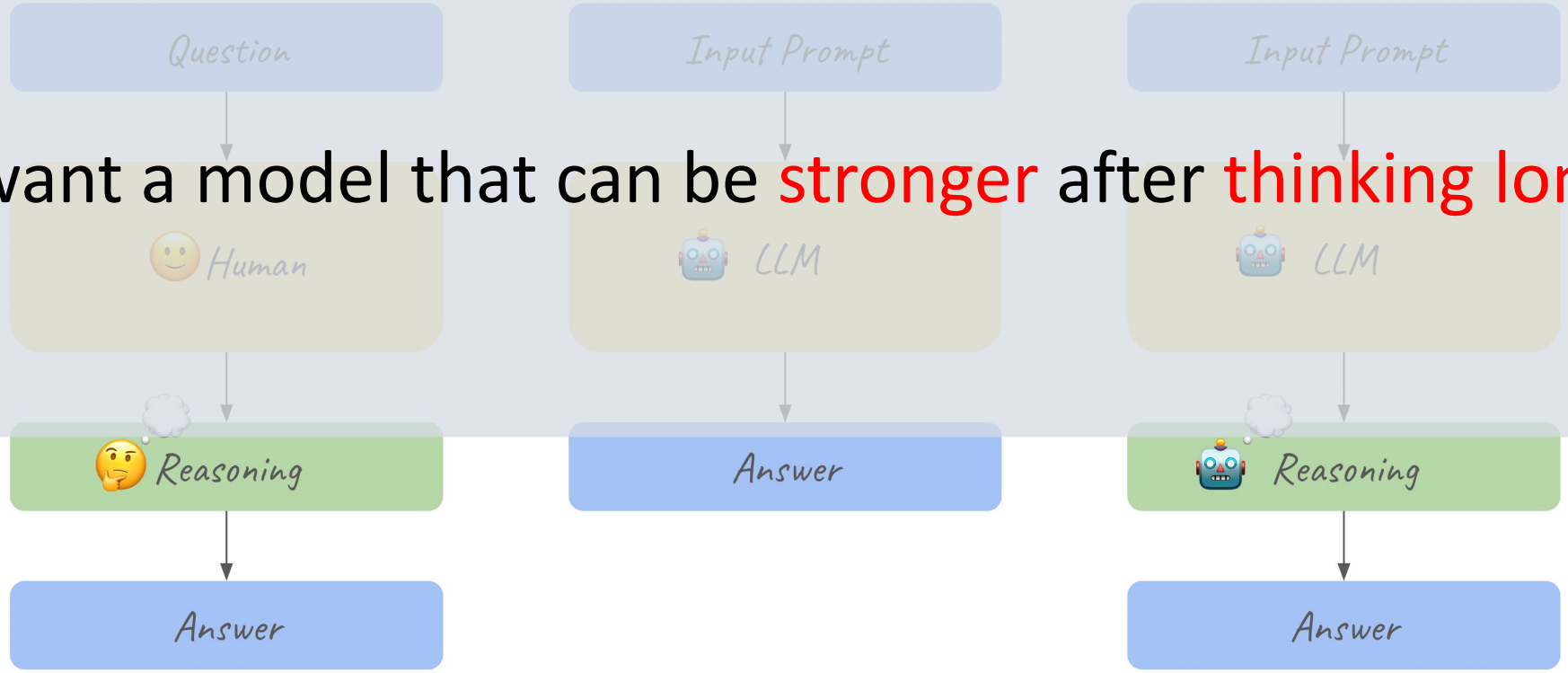


a) Human　b) Other LLMs　c) OpenAI o1

Inference-Time Enhancement

- OpenAI o1 model (2024)
  - Large Reasoning Model (LRM). An LLM “thinks” before giving a respond

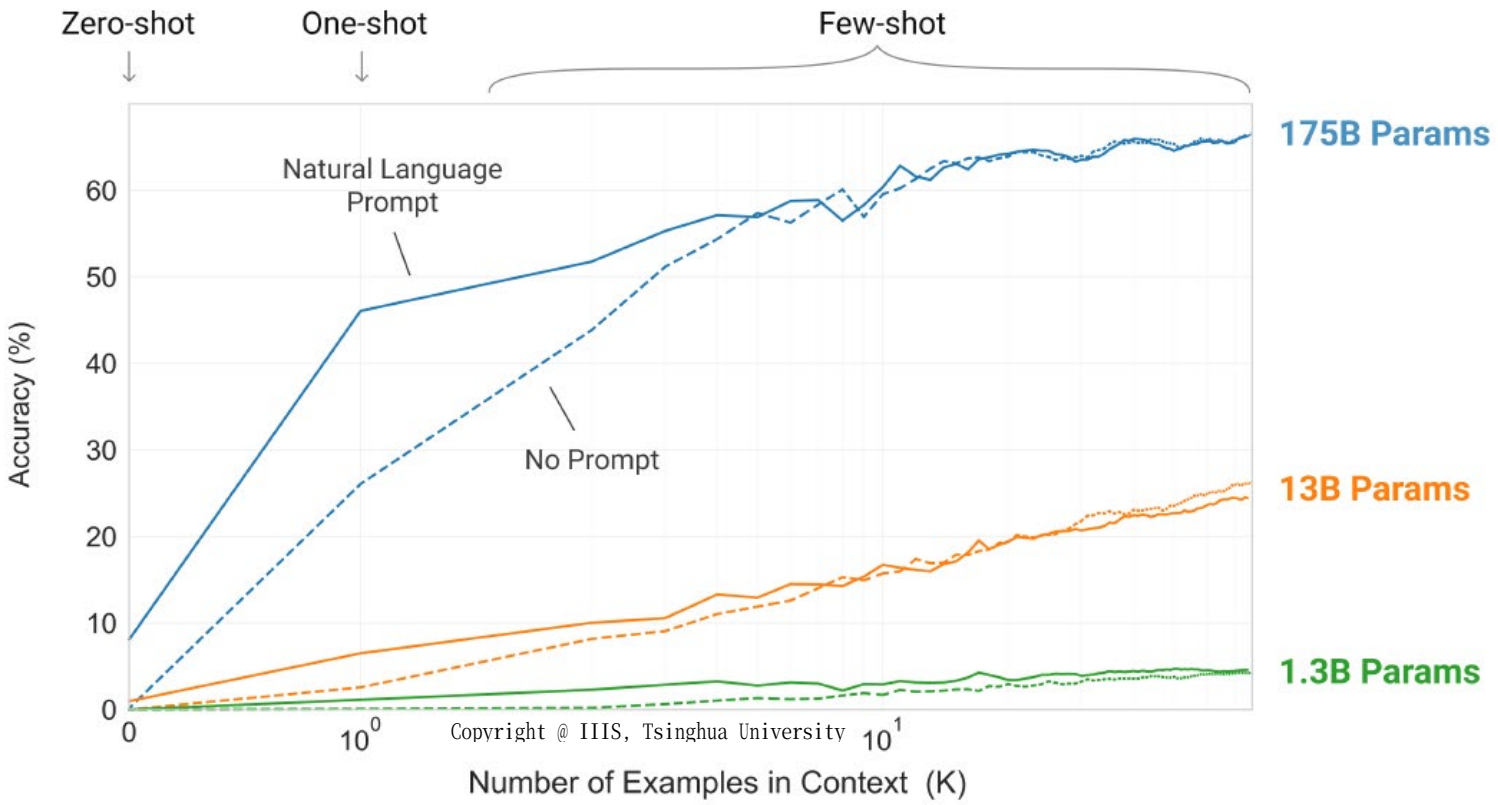
We want a model that can be stronger after thinking longer



a) Human b) Other LLMs c) OpenAI o1

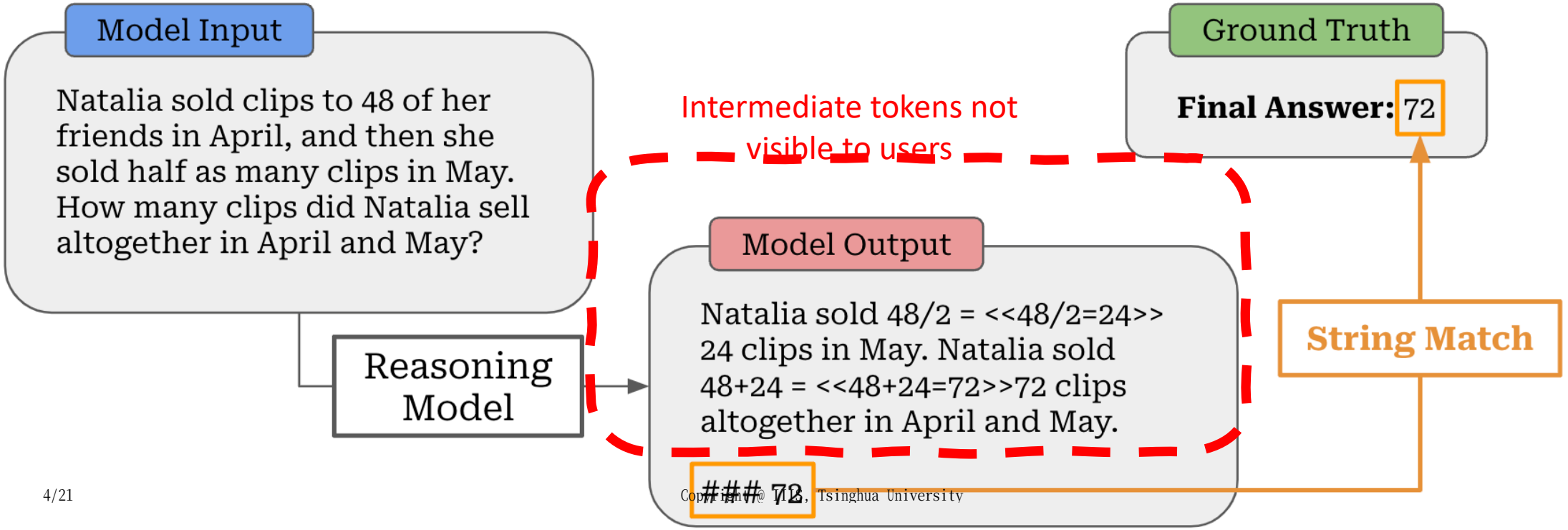
In-Context Learning in GPT-3 (Recap)

- In GPT-3, if more examples are in the context, the accuracy is higher
  - longer context → higher accuracy



Inference-Time Enhancement

- OpenAI o1 model (2024)
  - Large Reasoning Model (LRM). An LLM “thinks” before giving a respond
  - Idea: we can allow model to ***think*** by having a ***longer context***



Inference-Time Enhancement

- o

Please calculate 24 using these 4 digits: 4, 4, 7, 7. Please only give the solution in 1 equation without any additional texts.

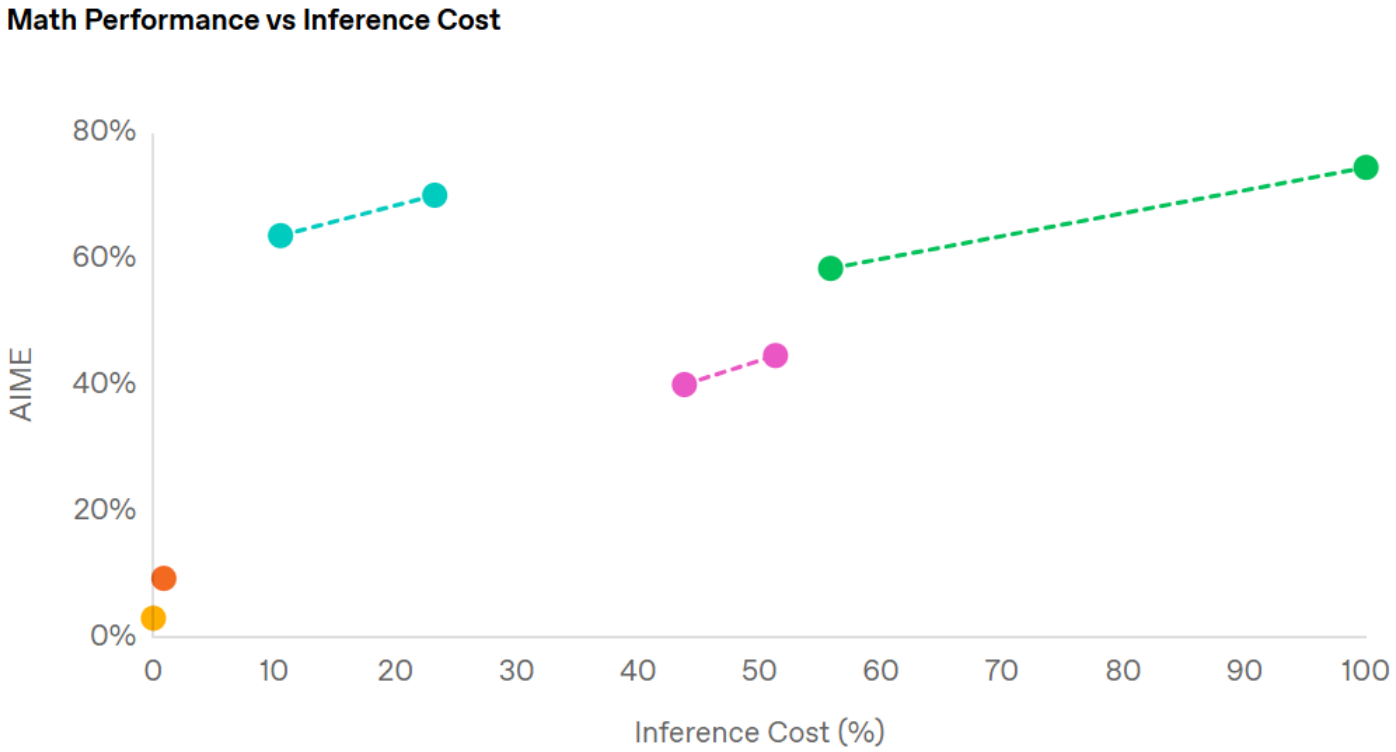
Reasoned about mathematical equation for 5 seconds

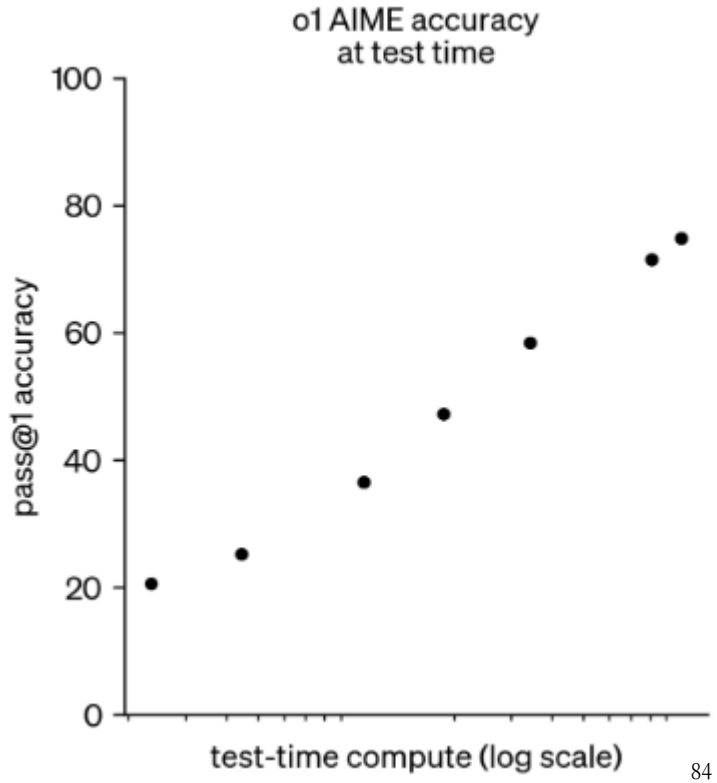
> I need to find an equation using the digits 4, 4, 7, 7 that equals 24. I tried a few attempts like (7 * 4) - (7 - 4) = 25 or (7 * 4) - 7/4 = 26.25, but they didn't work. Then I thought about using all digits: 7 * (4 - 4/7). Checking - 4/7 is 0.5714, so 4 - 4/7 = 3.4286. Multiplying 3.4286 by 7 gives exactly 24. The correct equation is 7 * (4 - 4/7) = 24.

7*(4-4/7)=24

Inference-Time Enhancement

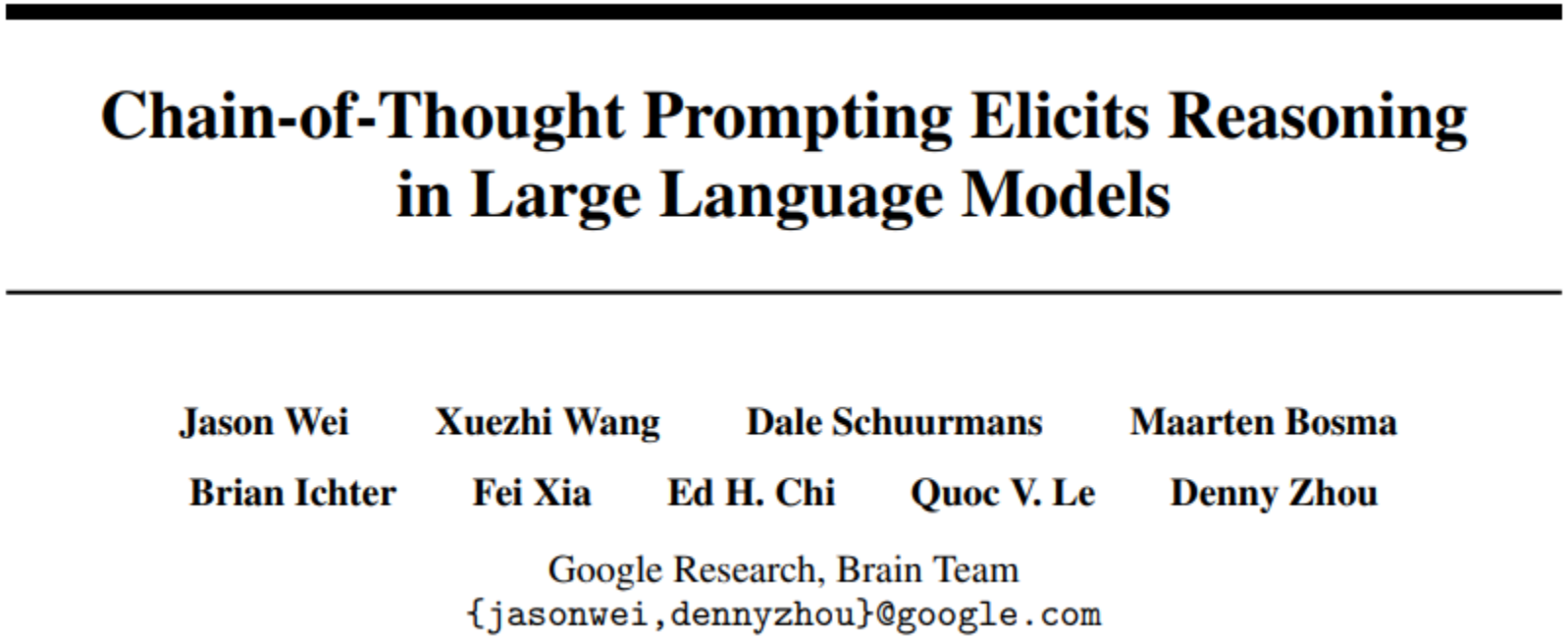
- Large reasoning models enable inference-time scaling





Inference-Time Enhancement

- How to derive a reasoning model?
  - Let’s prompting it!
  - Chain-of-thought prompt (Google, 2022)



Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

Jason Wei **Xuezhi Wang** **Dale Schuurmans** **Maarten Bosma**

Brian Ichter **Fei Xia** **Ed H. Chi** **Quoc V. Le** **Denny Zhou**

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提示词

(prompt)

深度思考

(thinking)

输出结果

(output)

Inference-Time Enhancement

提示词
(prompt)

深度思考
(thinking)

- How to derive a reasoning model?
  - Let's prompting it!
  - Chain-of-thought prompt (Google, 2022)
    - Tune the prompts to encourage the model think before responding

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

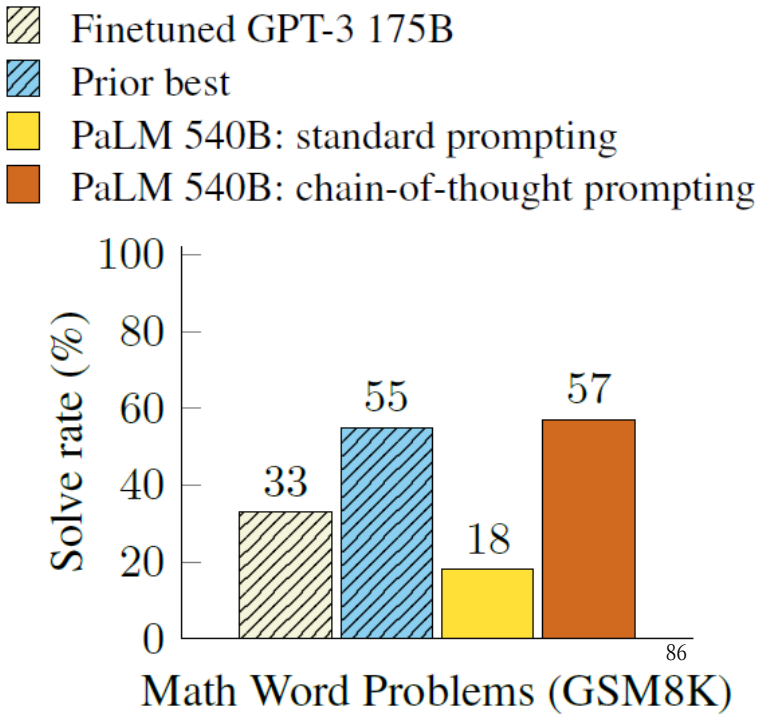
Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

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?

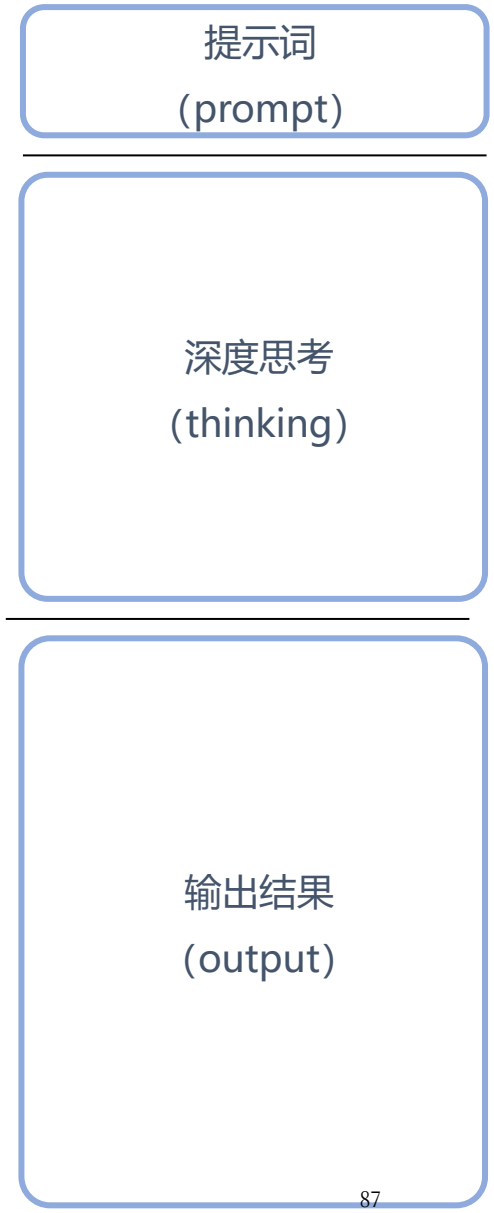
Model Output

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. ✓



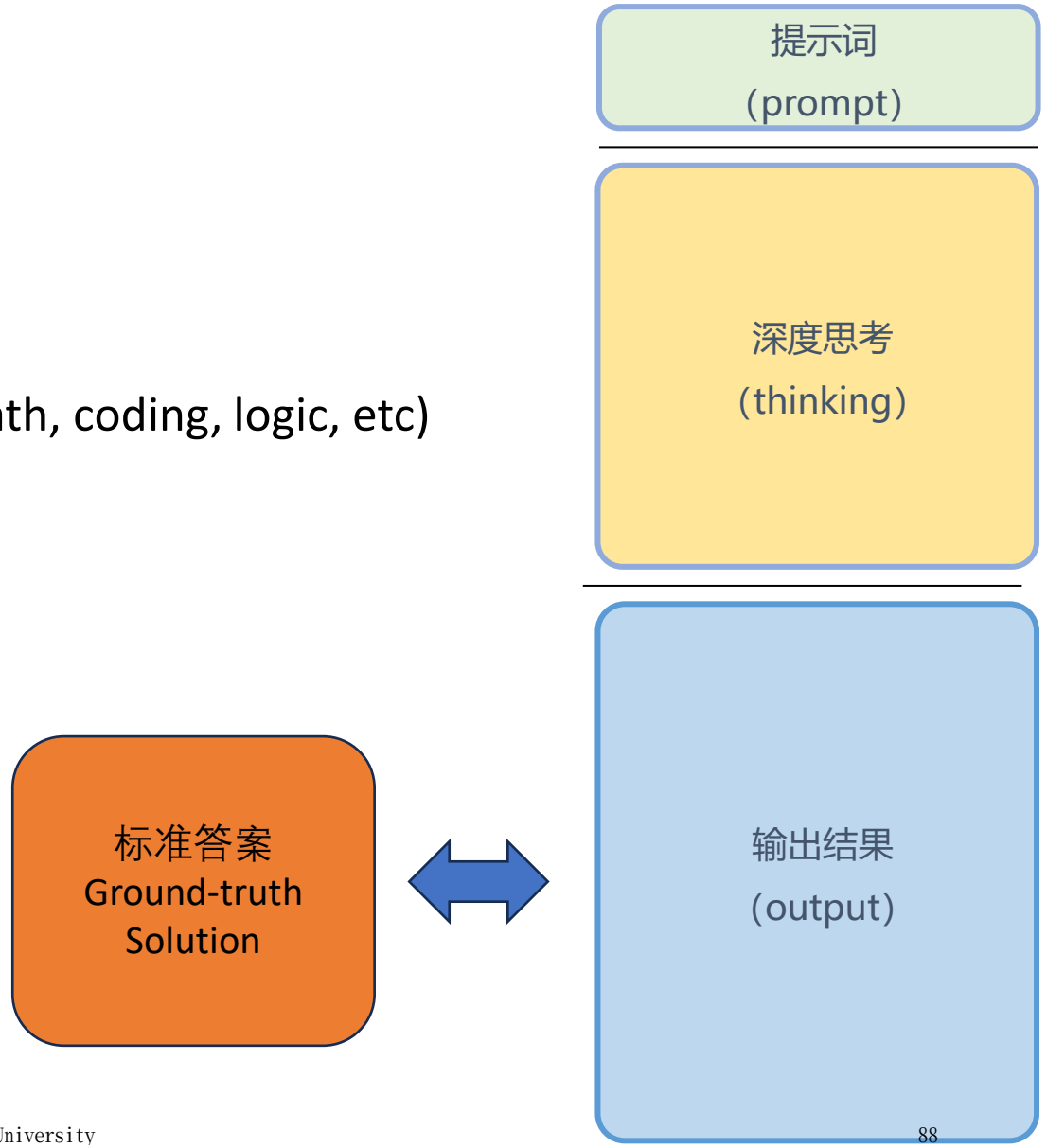
Inference-Time Enhancement

- How to **train** a reasoning model?
  - Key challenge: how to obtain the best “thinking” tokens to train an LLM???
    - Supervised training?
    - There is no “correct” thinking tokens, we only care about answers
  - Reinforcement Learning
    - Let the LLM self-explore the thinking tokens
    - Reward???
      - Remark: since the exploration space is huge, we must ensure the reward is ACCURATE!!!



RL for Reasoning Model

- RL training for reasoning models
  - Environment/Task
    - Prompts that require long thinking (e.g., math, coding, logic, etc)
  - Action
    - Thinking tokens
    - Output tokens
  - Reward
    - Binary: +1 if output is correct; -1 if no.



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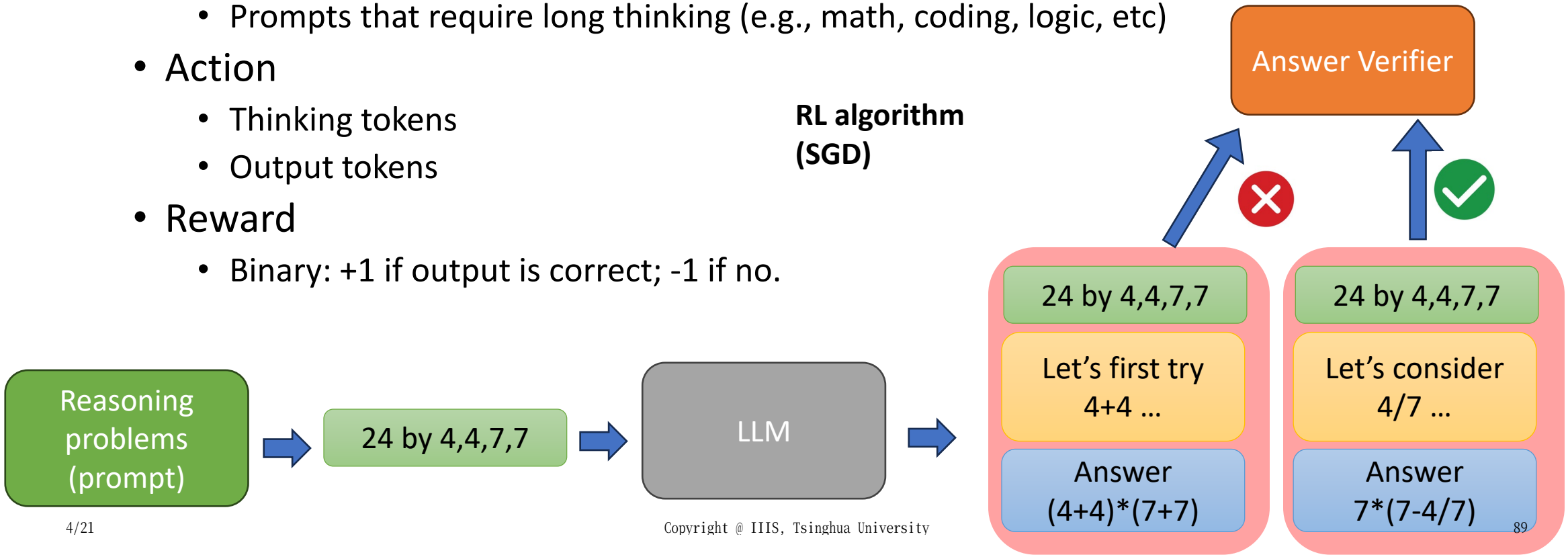
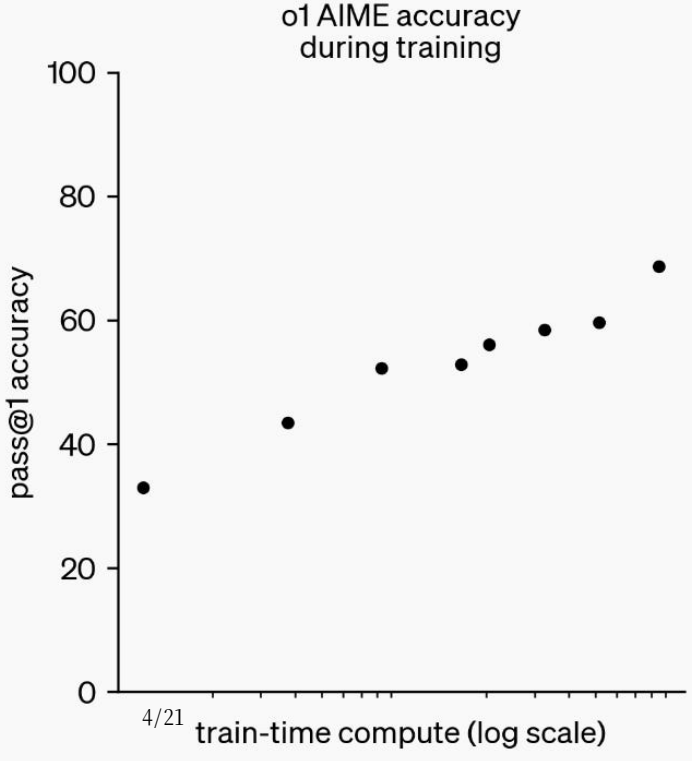
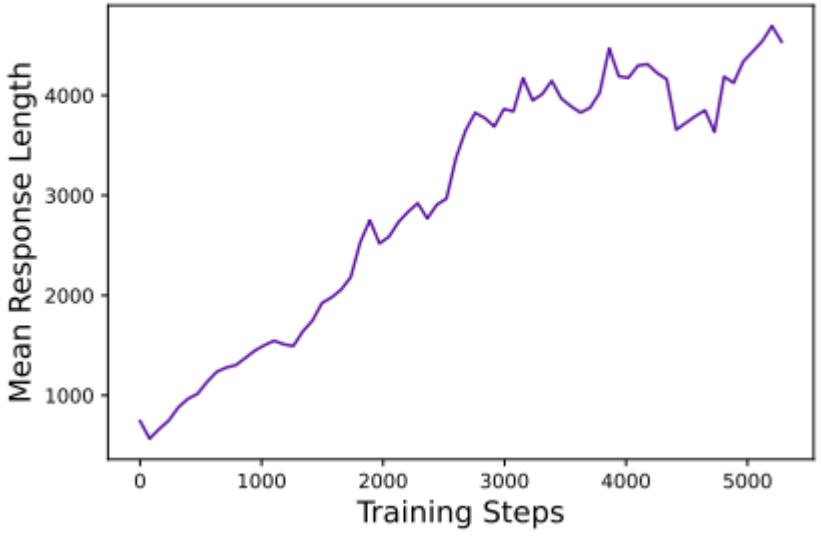
RL algorithm (SGD)

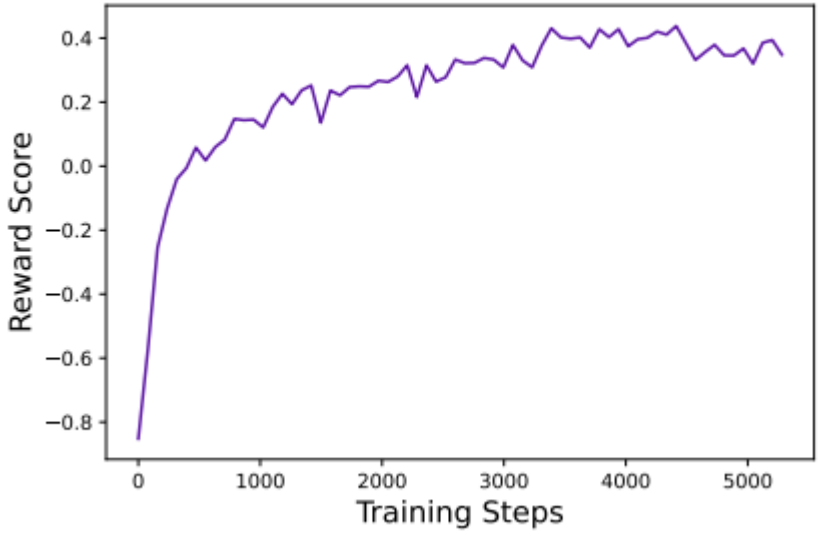


From RLHF to Post-Training Scaling

- RL is a new engine to scaling intelligence
  - Longer RL training leads to stronger reasoning performances







During RL training, the model thinks more

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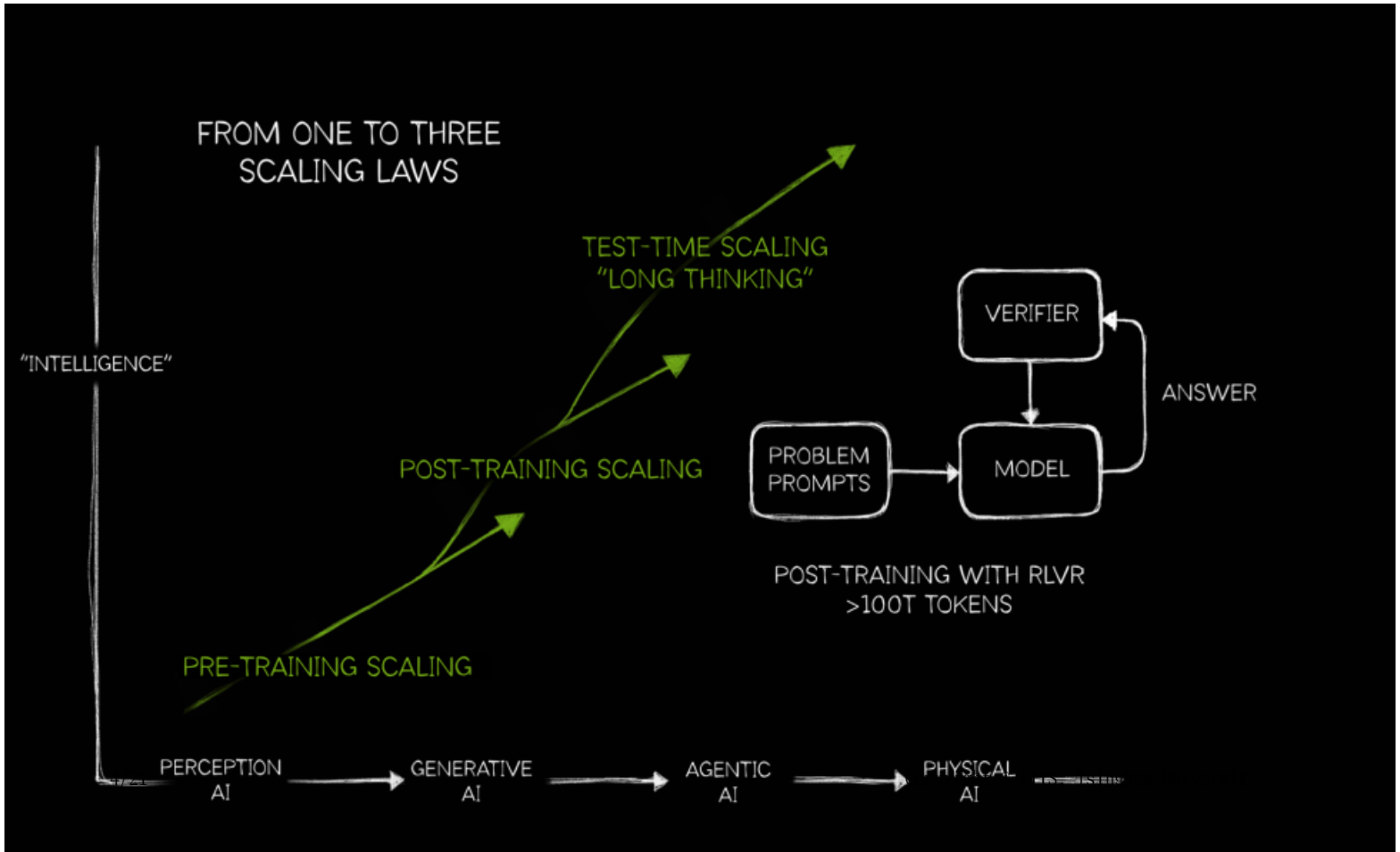
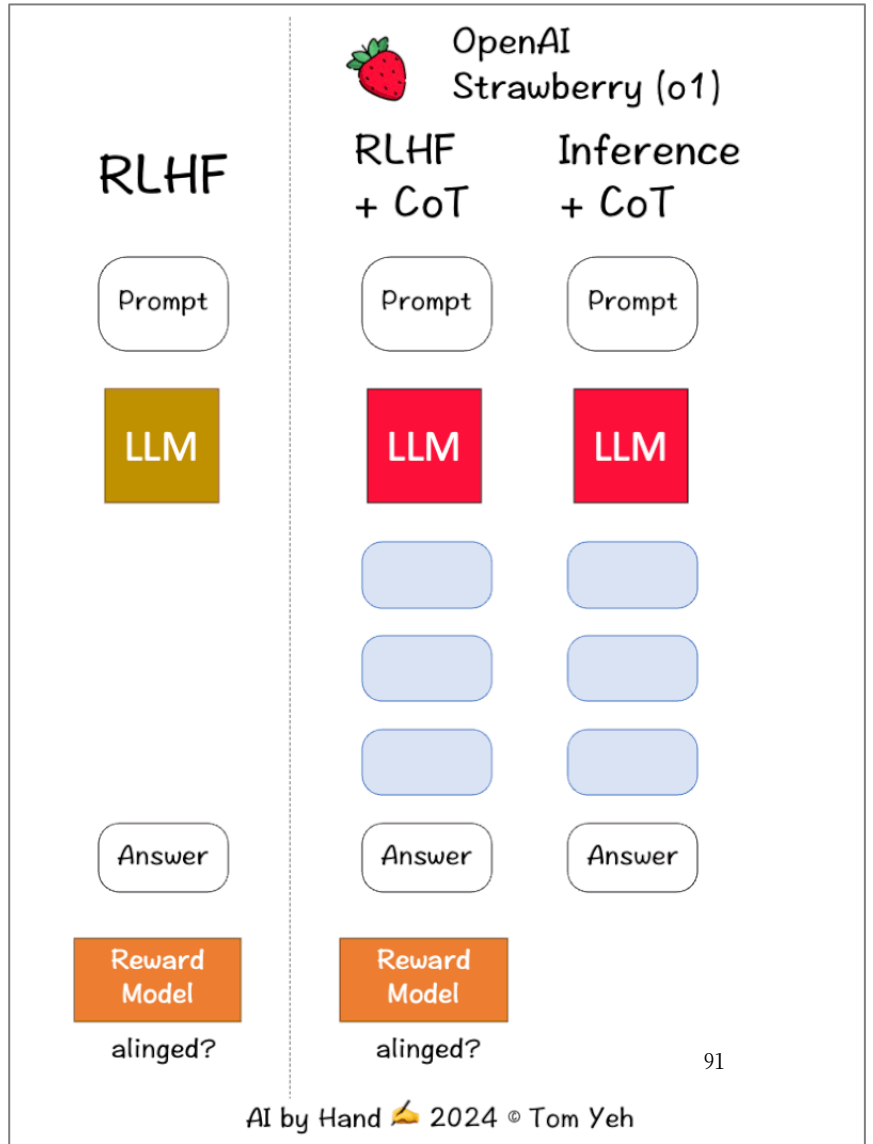
- RL is a new engine to scaling intelligence

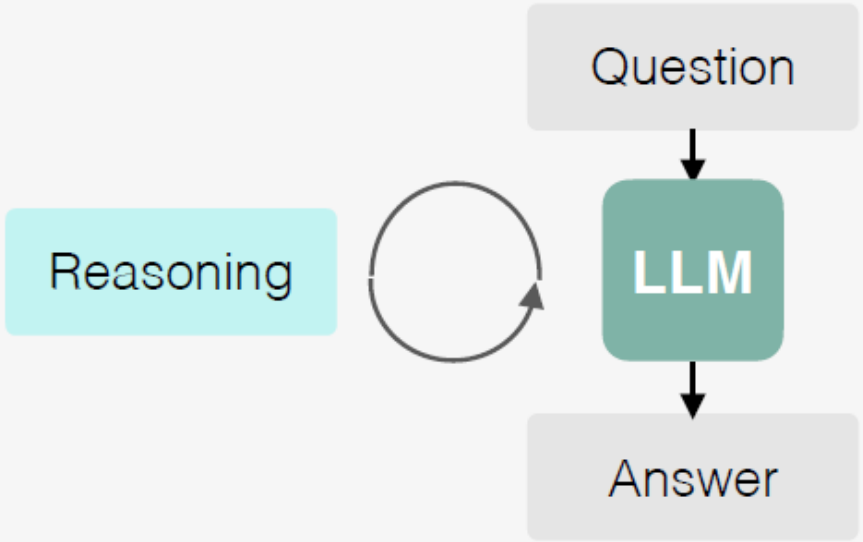




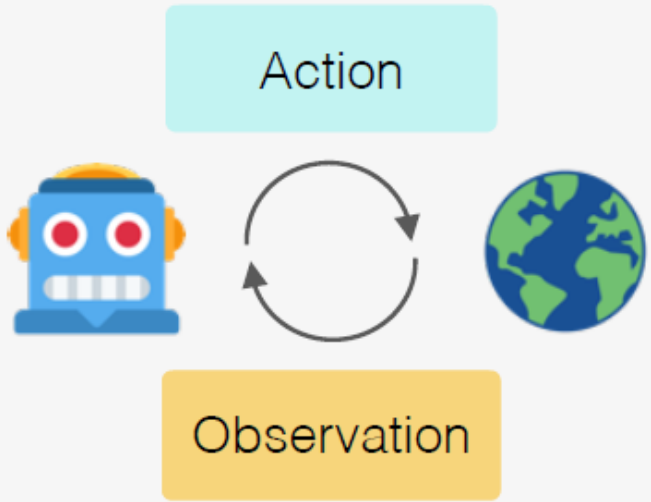
From Reasoning to Acting

- An LLM can also interact with a real environment
  - When an LLM interacts with the outside world, it is often called an "LLM agent"
  - We can also use RL to train an LLM agent

Reasoning (update internal belief)



Acting (obtain external feedback)



From Reasoning to Acting

- Expanding RAG to Multi-Turn **Deep Research** (OpenAI, 2025)

From Reasoning to Acting

- General-purpose LLM agent assistant (example from Manus.AI 2025)
  - A new form of smart software for the future

Conclusion

- Pretraining Transformers
  - Encoder-style pretraining (BERT): task-centric
  - Decoder-style pretraining (GPT): next-token prediction
- Scaling Law and Large Language Models
  - GPT leads to the scaling law and emergent capacities of LLMs
  - Larger model + better data + more compute → better models
- Post-training Language Models and More Applications
  - RLHF for a usable GPT (GPT-3 to ChatGPT)
  - Reasoning models think before answer
    - More thinking leads to better outputs (inference-time scaling)
  - RL training leads to better reasoning models (post-training scaling)
  - LLM can interact with the outside to become an LLM agent

Thanks

- Embrace the era of AGI!