



Adaptation of LLMs

<https://adapt-llm.github.io/>



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Minimal LLM Basics

Prerequisites



Training ML Models

- **Learning algorithms related:**
 - SGD, Learning rate, AdamW, Batch size
- **Model architecture related:**
 - Cross and Self Attentions
 - Encoder-Decoder
 - Transformers

Basic LLM concepts

- Transformer decoder
- Next token prediction
- Tokenization, sequence/context length
- In-context learning:
 - Zero- and few-shot learning

This Tutorial

Goals

Build Foundational understanding for LLM Adaptation

- Evaluation methods
- Key concepts of LLM adaptation
- Key techniques for LLM adaptation
 - Data perspective
 - Model perspective
- Key trends

Table of contents

Introduction and Motivation ~ 40min

Evaluation and Benchmark ~20min

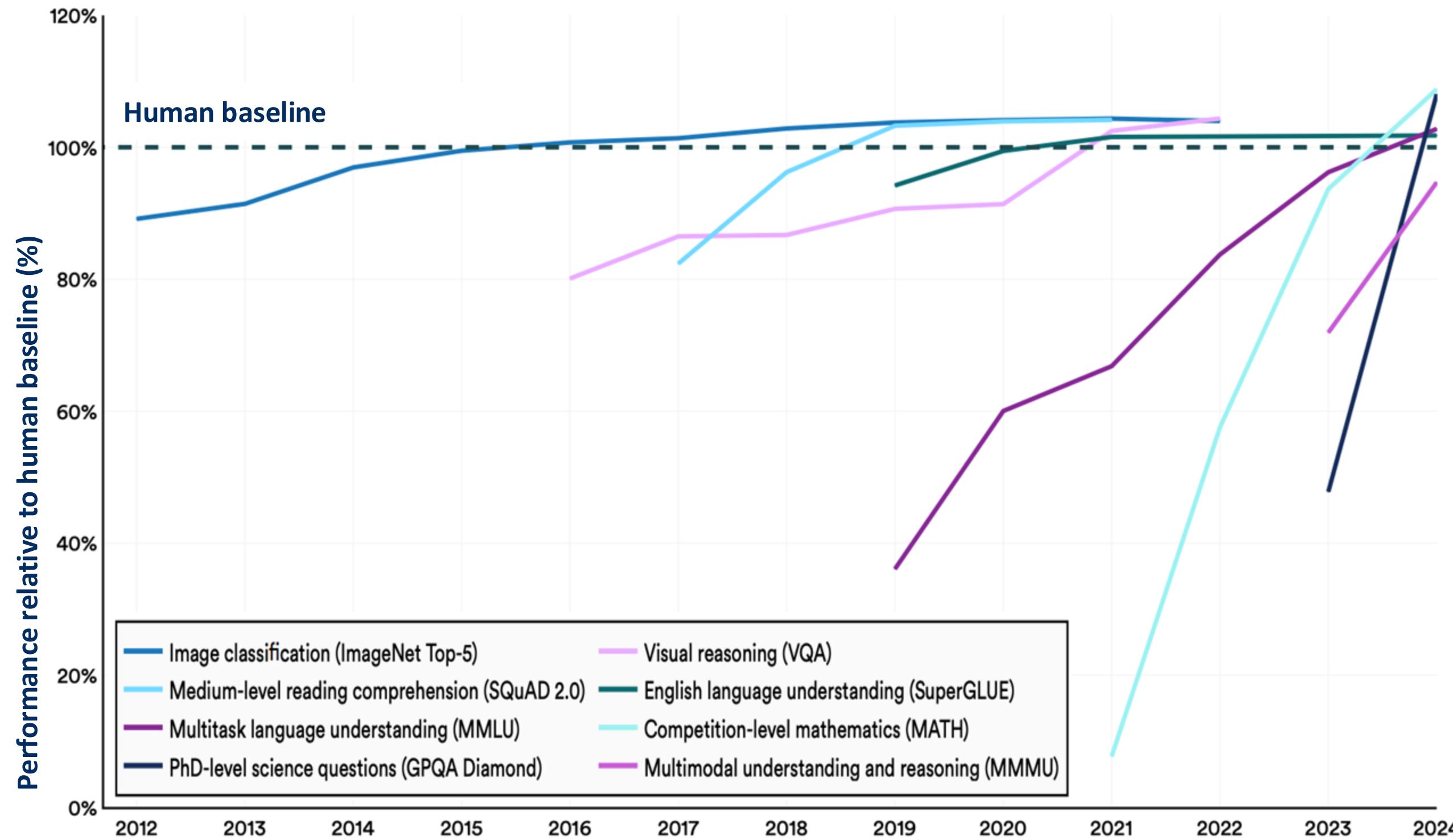
Parametric Knowledge Adaptation ~ 60min

Semi-Parametric Knowledge Adaptation ~ 30min

Summary, Discussion, QAs ~ 30min



LLM vs. human performance



$$M_{adapt} = F_{adapt}(M_{base})$$

Adapted LLM

Base LLM

Adaptation Method



Why We *Still* Need *Adaptation*

Domain

SaulLM-54B & SaulLM-141B: Scaling Up Domain Adaptation for the Legal Domain

Pierre Colombo^{equall} Telmo Pires^{equall} Malik Boudiaf^{equall} Rui Melo^{equall}
Equall Equall Equall Equall

BioMedLM: A 2.7B Parameter Language Model Trained On Biomedical Text

Elliot Bolton^{1†}, Abhinav Venigalla², Michihiro Yasunaga¹, David Hall¹, Betty Xiong¹,
Tony Lee¹, Roxana Daneshjou¹, Jonathan Frankle²,

Demystifying Domain-adaptive Post-training for Financial LLMs

Zixuan Ke, Yifei Ming, Xuan-Phi Nguyen, Caiming Xiong and Shafiq Joty
Salesforce AI Research

{zixuan.ke,yifei.ming,xnguyen,cxióng,sjoty}@salesforce.com

Project Page: <https://github.com/SalesforceAIResearch/FinDAP>

Datasets: <https://huggingface.co/datasets/Salesforce/FinEval>

Task

SFR-RAG: Towards Contextually Faithful LLMs

Foundational Autoraters: Taming Large Language Models for Better Automatic Evaluation

🔥 PROMETHEUS: INDUCING FINE-GRAINED EVALUATION CAPABILITY IN LANGUAGE MODELS

Seungone Kim^{1,2*†} Jamin Shin^{2,3*†} Yejin Cho^{1*†} Joel Jang⁴ Shayne Longpre⁵
Hwaran Lee^{2,3} Sangdoo Yun^{2,3} Seongjin Shin³ Sungdong Kim^{1,2,3}
James Thorne¹ Minjoon Seo^{1†}

¹KAIST AI ²NAVER AI Lab ³NAVER Cloud ⁴University of Washington ⁵MIT

Adaptation → Performance↑



Domain/Language

Code Llama: Open Foundation Models for Code

Baptiste Rozière[†], Jonas Gehring[†], Fabian Gloeckle^{†,*}, Sten Sootla[†], Itai Gat, Xiaoqing Ellen Tan, Yossi Adi[◦], Jingyu Liu, Romain Sauvestre, Tal Remez, Jérémie Rapin, Artyom Kozhevnikov, Ivan Evtimov, Joanna Bitton, Manish Bhatt, Cristian Canton Ferrer, Aaron Grattafiori, Wenhan Xiong, Alexandre Défossez, Jade Copet, Faisal Azhar, Hugo Touvron, Louis Martin, Nicolas Usunier, Thomas Scialom, Gabriel Synnaeve[†]

Meta AI

CHIMED-GPT: A Chinese Medical Large Language Model with Full Training Regime and Better Alignment to Human Preferences

Yuanhe Tian^{◆◆*}, Ruyi Gan^{◆◆*}, Yan Song^{◆†}, Jiaxing Zhang[◆], Yongdong Zhang[◆]

ALLaM: Large Language Models for Arabic and English



Task

How to Train Long-Context Language Models (Effectively)

Tianyu Gao* Alexander Wettig* Howard Yen Danqi Chen
Princeton Language and Intelligence, Princeton University
{tianyug,awettig,hyen,danqic}@cs.princeton.edu

DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning

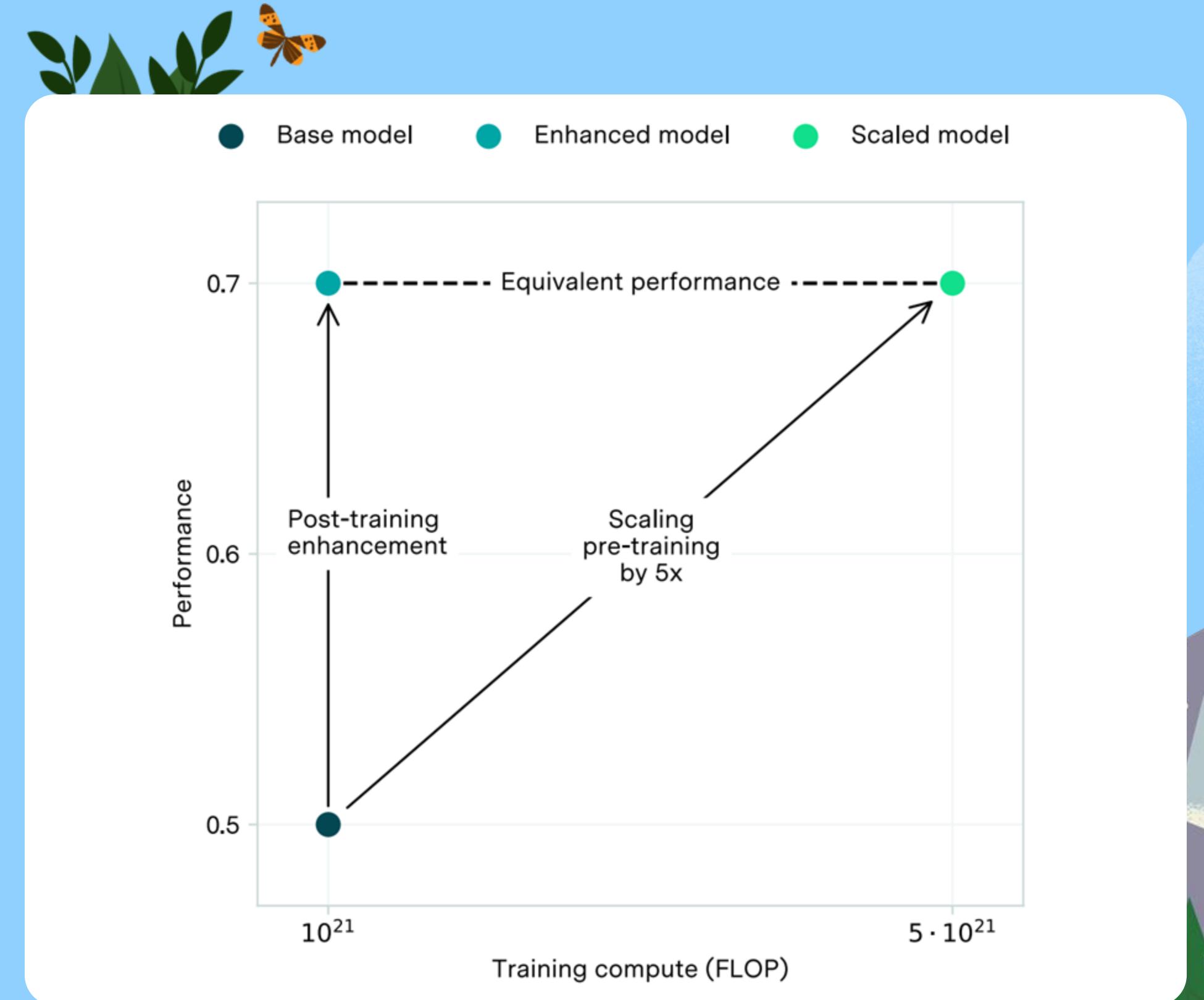
DeepSeek-AI

research@deepseek.com

Toolformer: Language Models Can Teach Themselves to Use Tools

Timo Schick Jane Dwivedi-Yu Roberto Dessì[†] Roberta Raileanu
Maria Lomeli Luke Zettlemoyer Nicola Cancedda Thomas Scialom
Meta AI Research [†]Universitat Pompeu Fabra

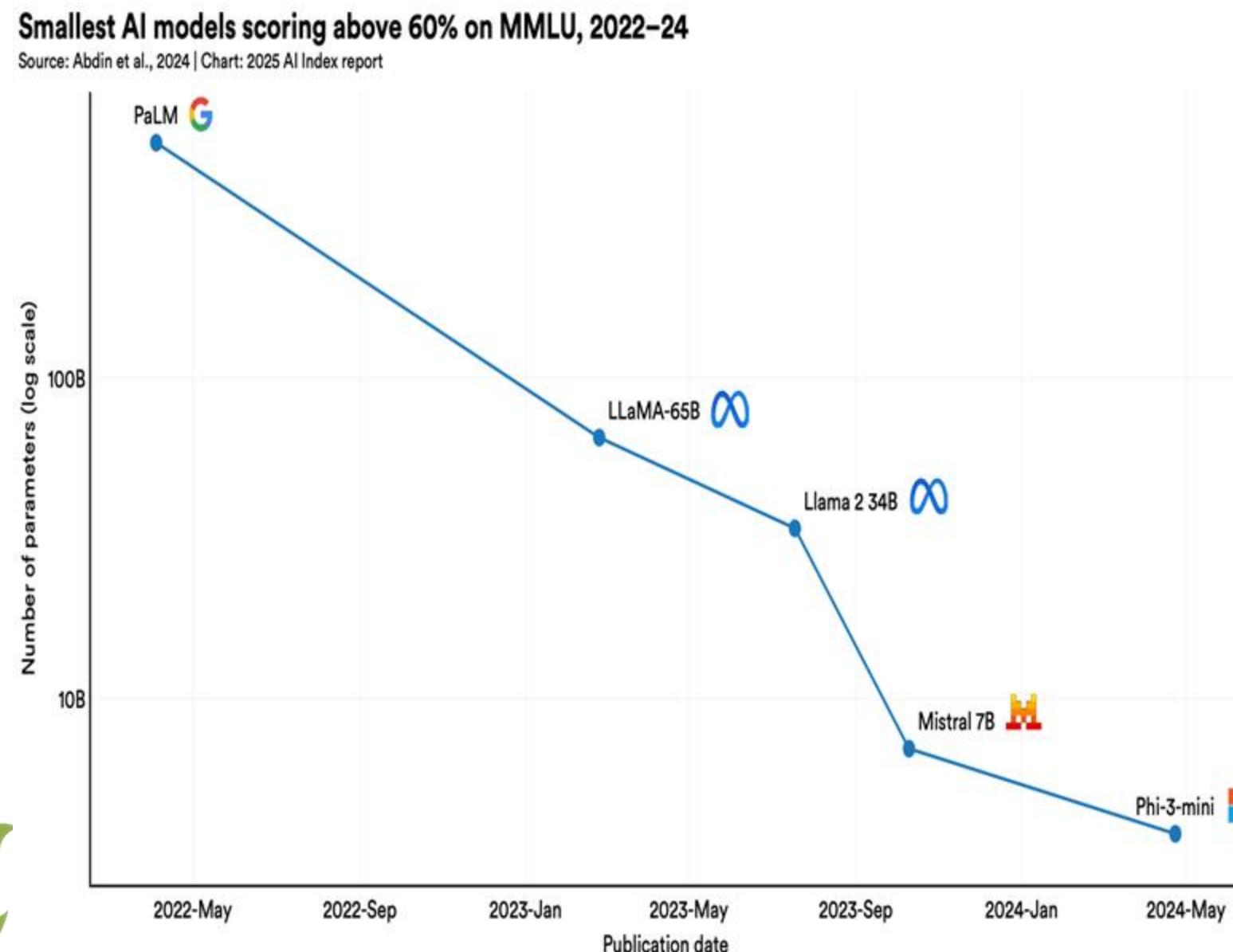
Adaptation →
Performance ↑
Cost ↓



Training is Becoming Increasingly Affordable



Size↓



Cost↓

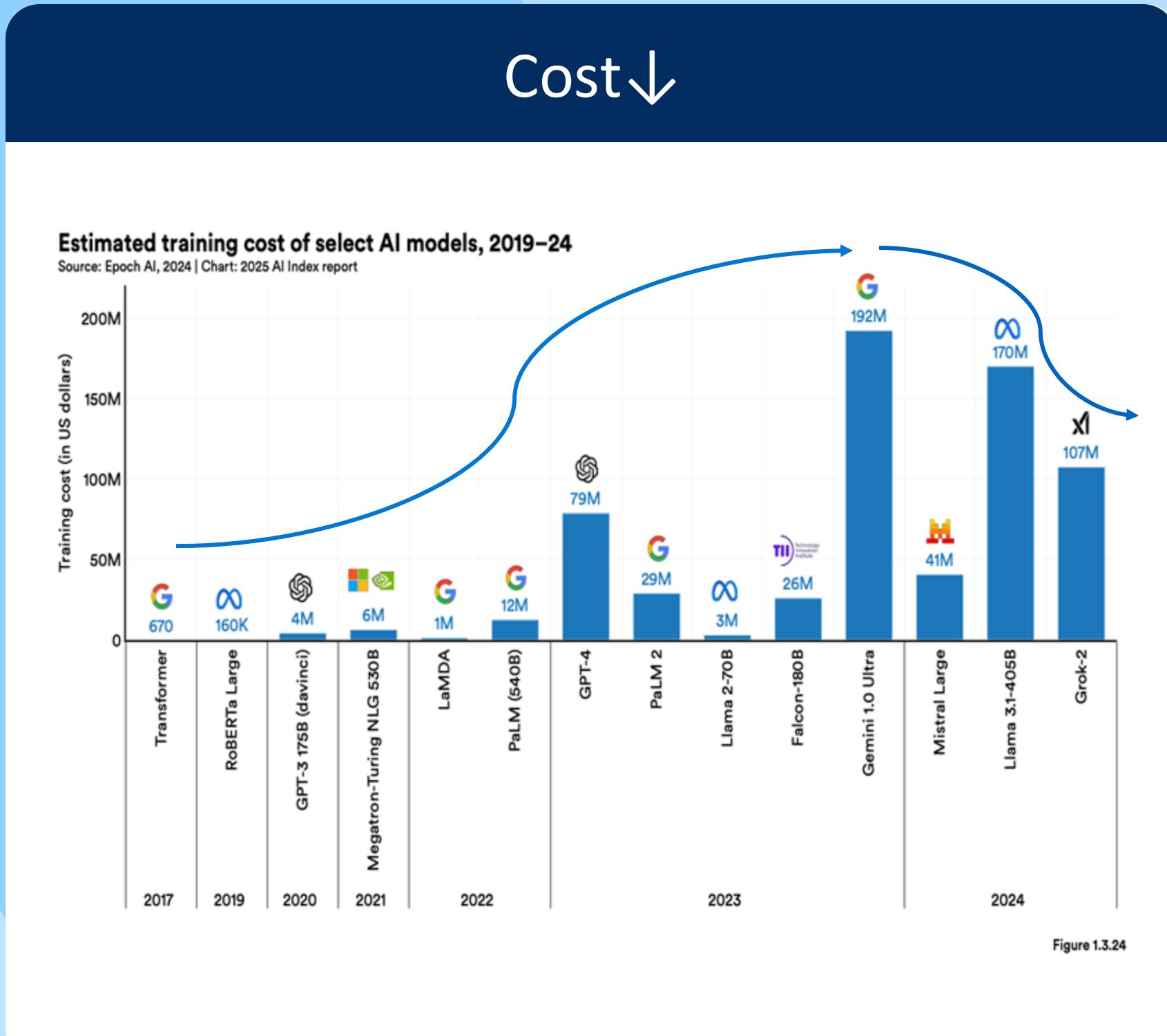
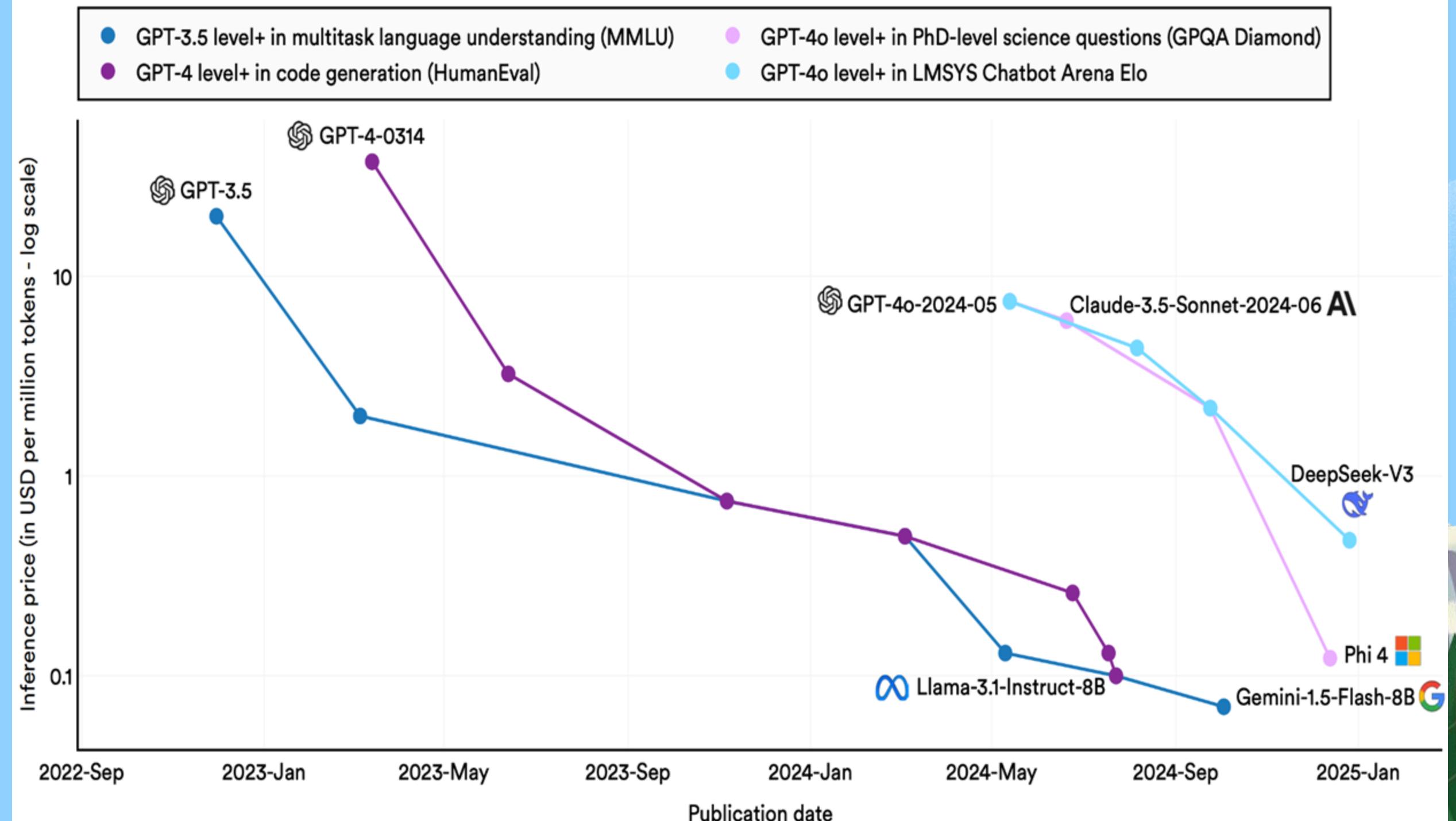


Figure 1.3.24

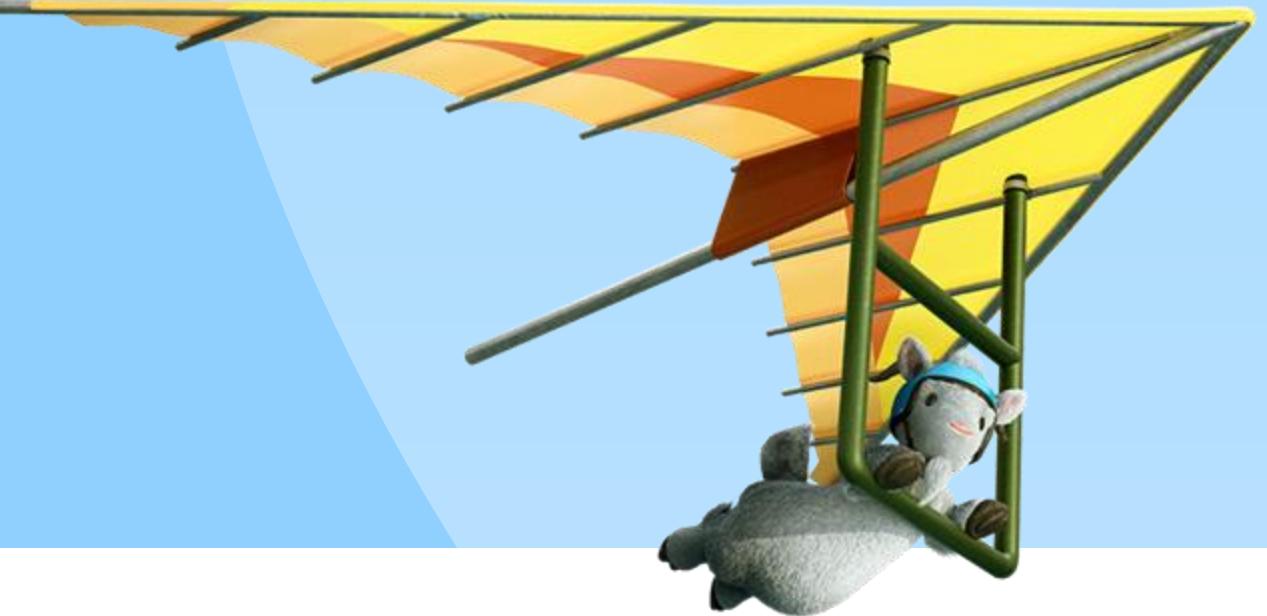
Lower cost- to-serve
for small domain or
task specific models

Inference price across select benchmarks, 2022–24

Source: Epoch AI, 2025; Artificial Analysis, 2025 | Chart: 2025 AI Index report



Adaptation in the Era of Experience



Our World is changing — LLMs must adapt accordingly

- Long-tail domains/tasks
- Emerging domains/tasks

To go beyond human data, LLMs need to adapt through their own experience

- Self-discover own knowledge + adaptation

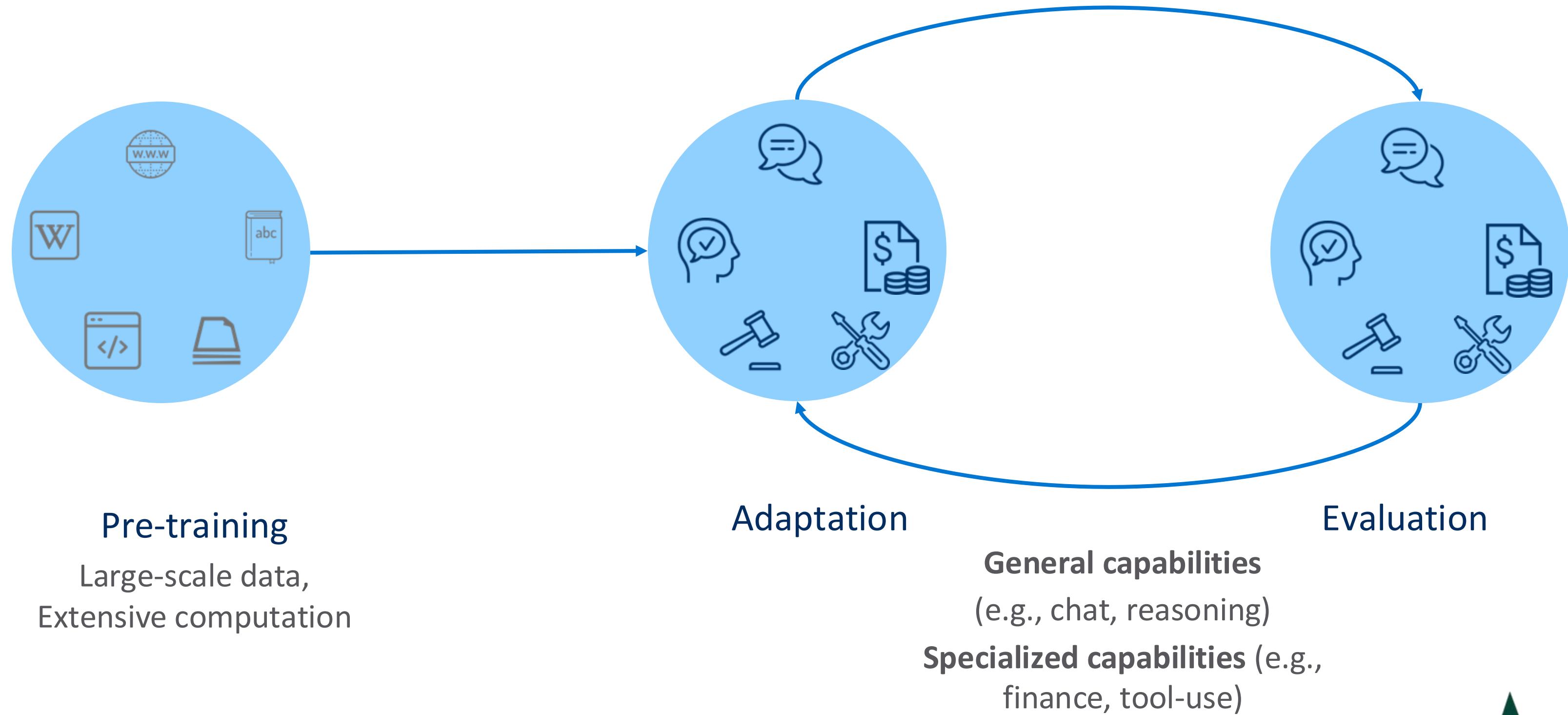


My personal bet is we're going to see a mixture of general models and specialist models that are much more focused

Dan Klein, professor at UC Berkeley (Mar, 2025)

Key Concepts in Adaptation

LLM Workflow



Adaptation – Regimes



In-context Learning

Single LLM, zero-shot,
few-shot, **No**
parameters updated

Learning to Adapt

Update the LLM parameters to adapt
LLM to specific
task/domain/environment

Main focus of this tutorial

Inference Scaling

Multiple LLM calls, **No**
parameters updated

Adaptation – Paradigms



Parametric Knowledge

Update LLM parameters, without interacting with external environment (e.g., domain- and task-specific LLMs)

Semi-Parametric Knowledge

Update LLM parameters to interact with external environment (e.g., RAG)

This represents the shift from standalone LLMs → **agents**

Adaptation – A Comparison



Pre-training

Learn the foundation knowledge, but the raw pre-trained LLMs are **neither** safe **nor** robust for public use and interactions (thus “alignment/adaptation” is required)

Post-training

Convention:
Adaptation = Adapt model from source to target distribution

LLM Era:
Adaptation \approx Post-training

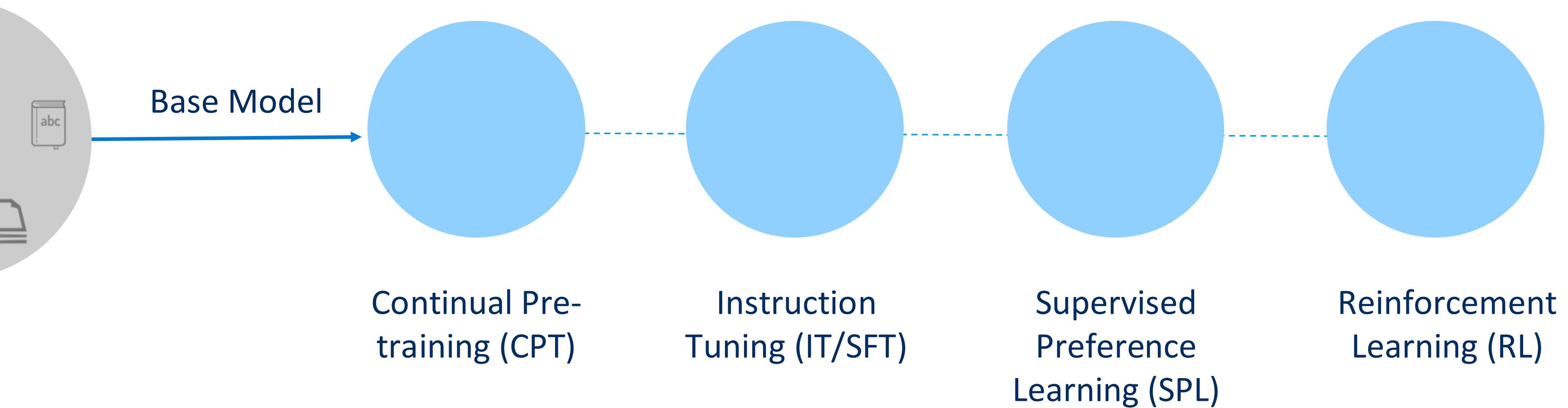
Continual Learning

Convention: Learning a sequence of disjoint tasks;
Main focus: prevent forgetting

Side focus: encourage transfer

LLM era: Tasks not disjoint;
Main focus: encourage transfer + prevent forgetting

Adaptation – Four Most Popular Methods



Adaptation – Four Most Popular Methods



```
<|begin_of_text|>  
SEC Finalizes ARS Settlement  
to Provide $7 Billion in  
Liquidity to Wachovia  
Investors...  
<|end_of_text|>
```

Continual Pre-training

Inject or emphasize target knowledge (e.g., domain knowledge)

```
<|system|>  
You are a helpful assistant  
<|end|>  
<|user|>  
How many helicopters can you eat?  
<|end|>  
<|assistant|>  
{Answer goes here}
```

Instruction Tuning

Formatting and instruction following

```
<|prompt|>what are the minimum  
lease payments in 2022  
<|end|>  
<|rejected|>  
$17,188 / $34,356 * 100  
= 49.98%.  
<|end|>  
<|chosen|>  
$17,188 / $34,356 * 100  
= 49.99%.  
<|end|>
```

Sup. Preference Learning

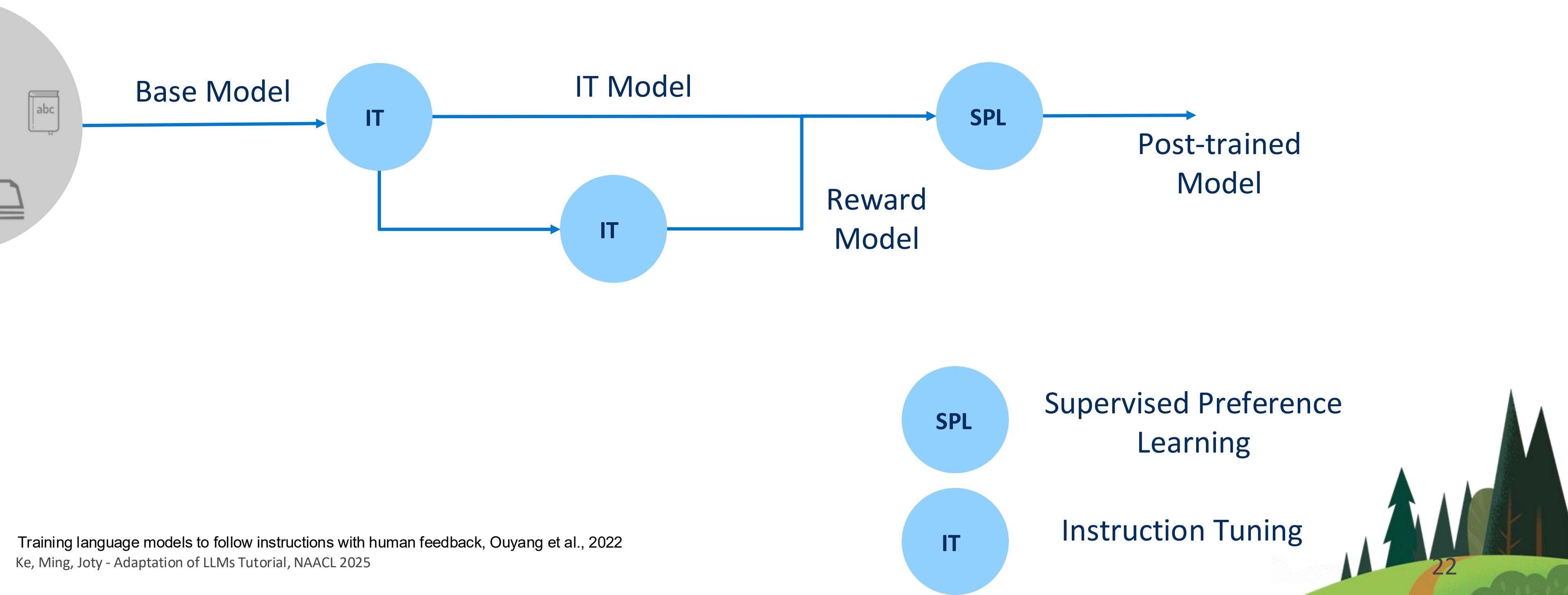
Align to human or AI preferences

```
<|prompt|>  
I'm not sure if it's the right  
to do and could use some  
outside opinions.  
TL;DR:  
<|end|>
```

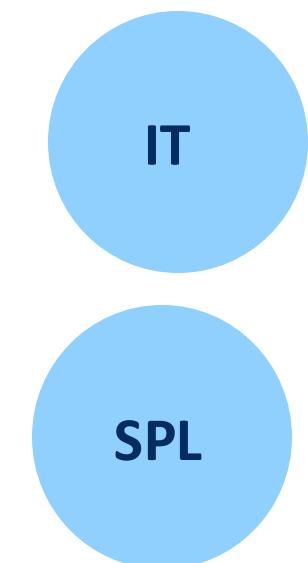
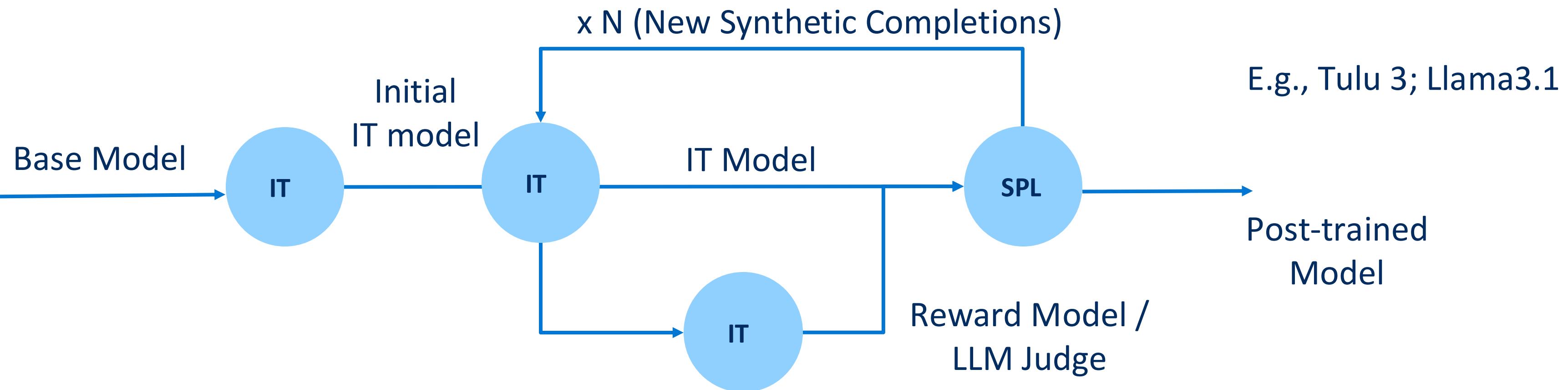
Reinforcement Learning

Boost performance on complicated (and verifiable) tasks (e.g., reasoning)

Adaptation – Example Training Workflow



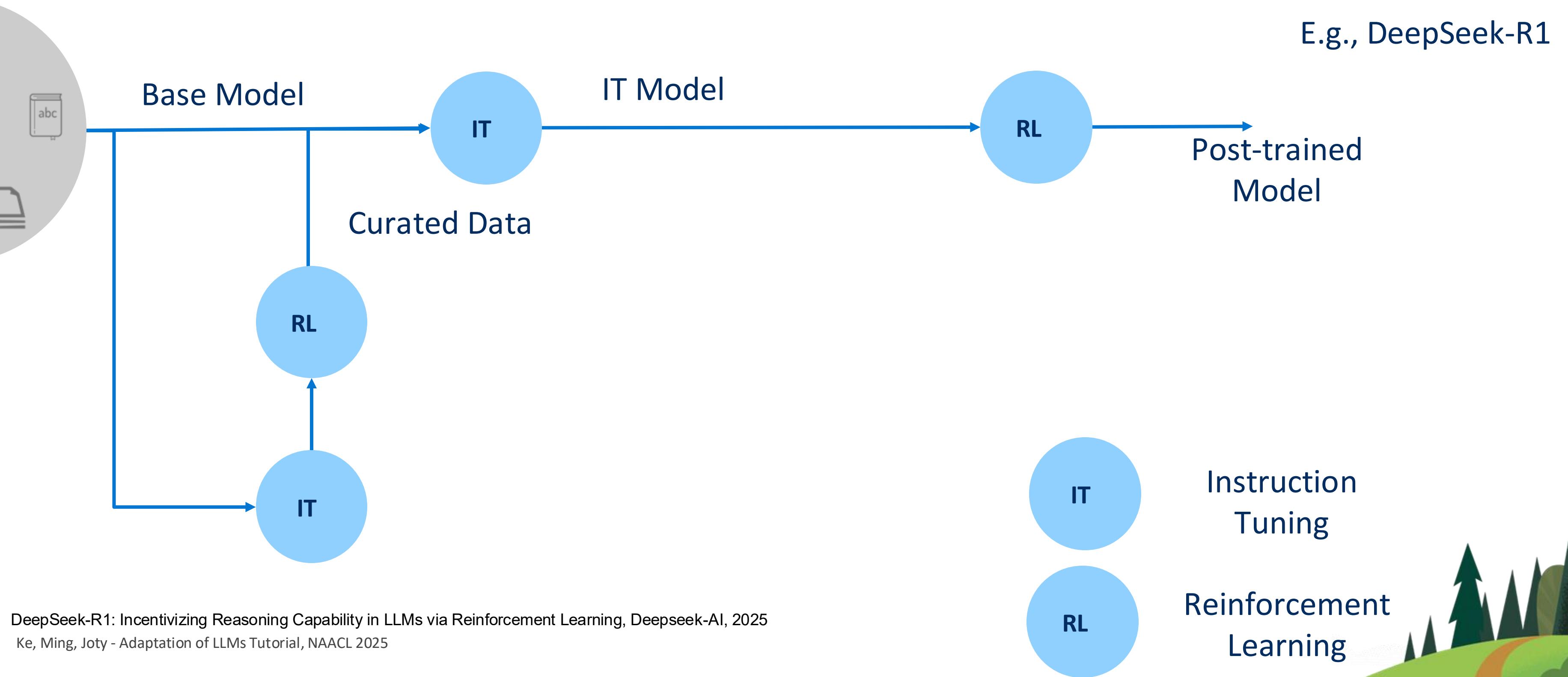
Adaptation – Example Training Workflow



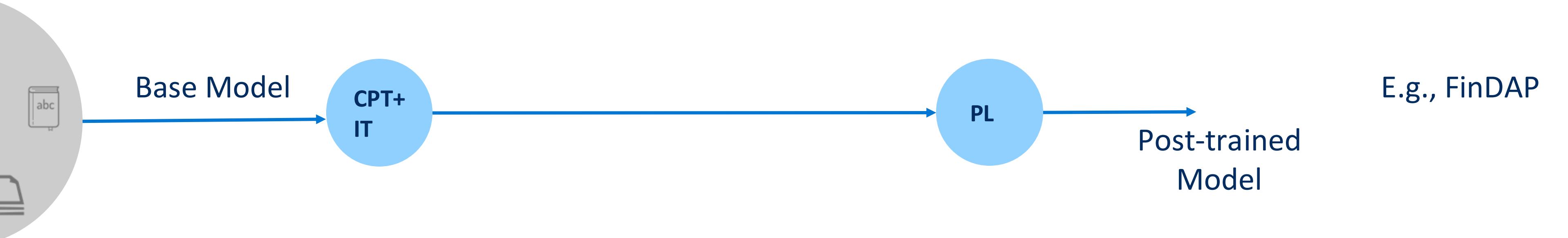
Instruction
Tuning

Supervised Preference
Learning

Adaptation – Example Training Workflow



Adaptation – Example Training Workflow



CPT Continual Pre-training

IT
Instruction Tuning

SPL
Supervised Preference Learning

Adaptation – Example Training Workflow



..... We should expect more to come



Research Questions in LLM Adaptation

Data Perspective

Seed Data: What gives a good data mixture and how to obtain high-quality data? (often limited in amount)

Data Recipe: Given the limited amount of seed data, how to synthesize or construct high-quality data?

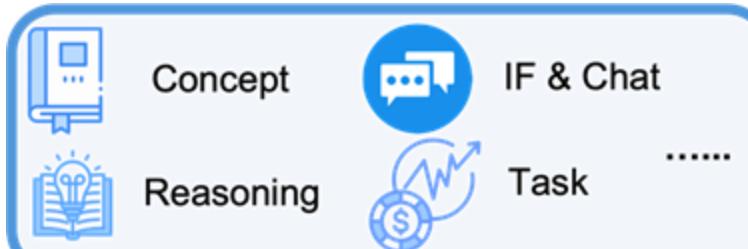
Model Perspective

Methods: What are the basic methods and their variants of LLM adaptation?

Training Workflow: What is the effective workflow to connect those basic methods?

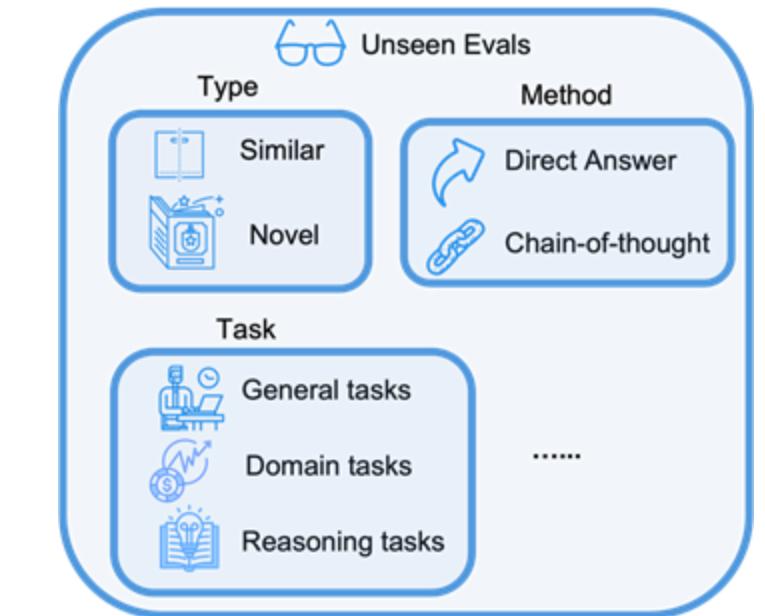


Adaptation – Four Considerations



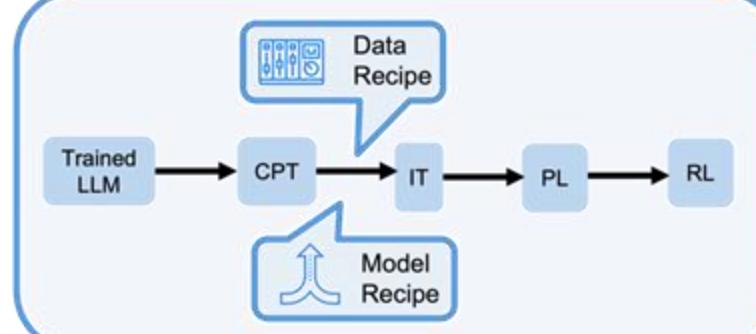
Core Capabilities

What capabilities do you actually care about?



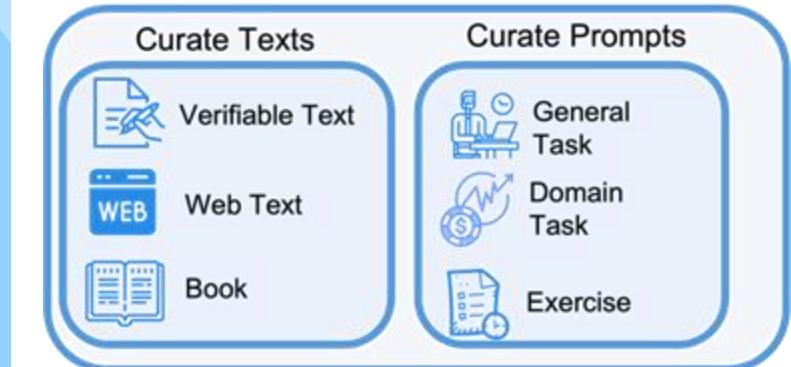
Evaluation

How do you measure the progress toward targeted capabilities?



Training Recipe

How do you construct useful data from your seed data and what is your model recipe?



Seed Data

What seed data should be used to implement your training recipe?