HOW YOU – YES, YOU! – CAN TRAIN AN LLM*

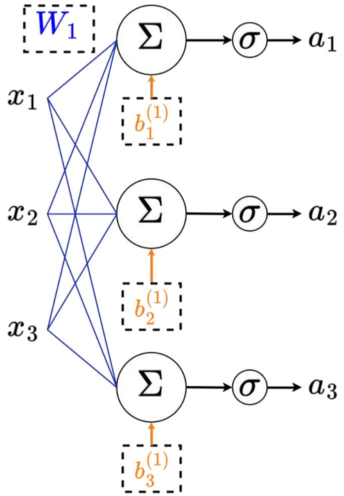
Sam Bowyer

*(SORT OF...)

What even is a neural network?

- Basic neural network layer

$$f(x; W, b) = \sigma(Wx + b)$$



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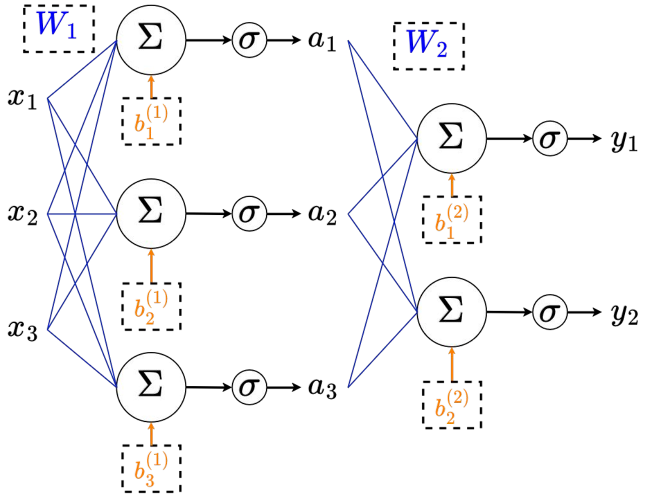

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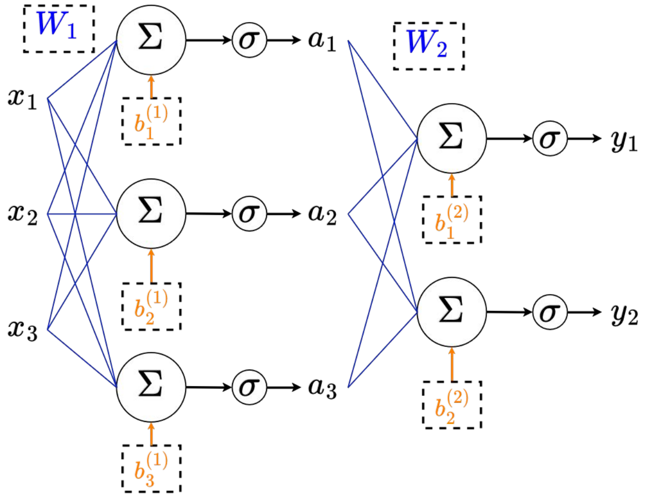

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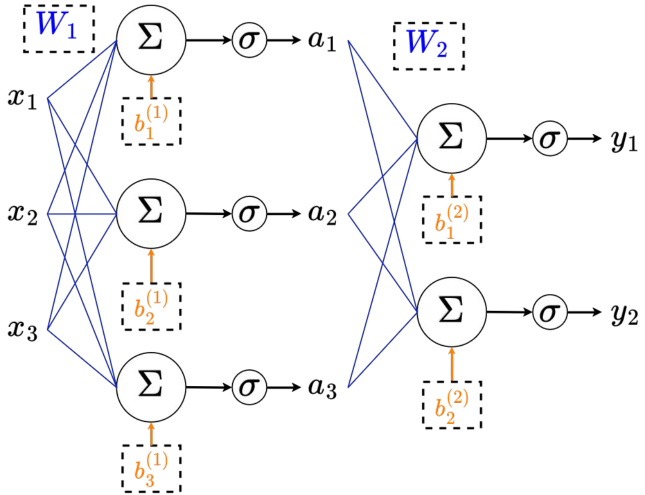

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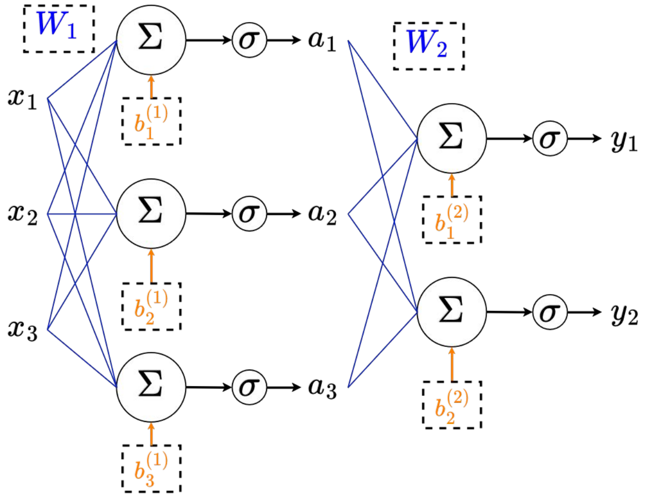

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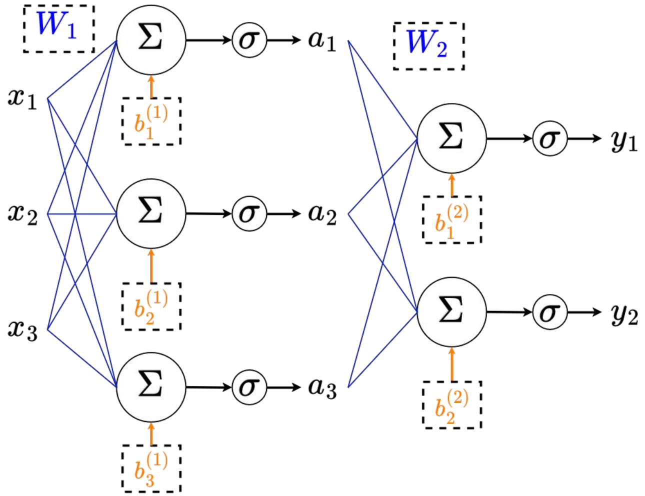

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- In an LLM: x - start of some text; y - the rest of the text

Large Language Models are LARGE

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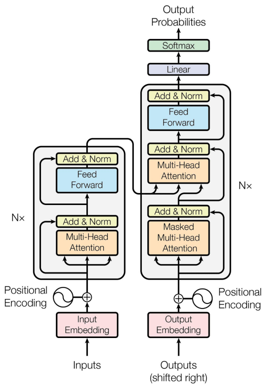
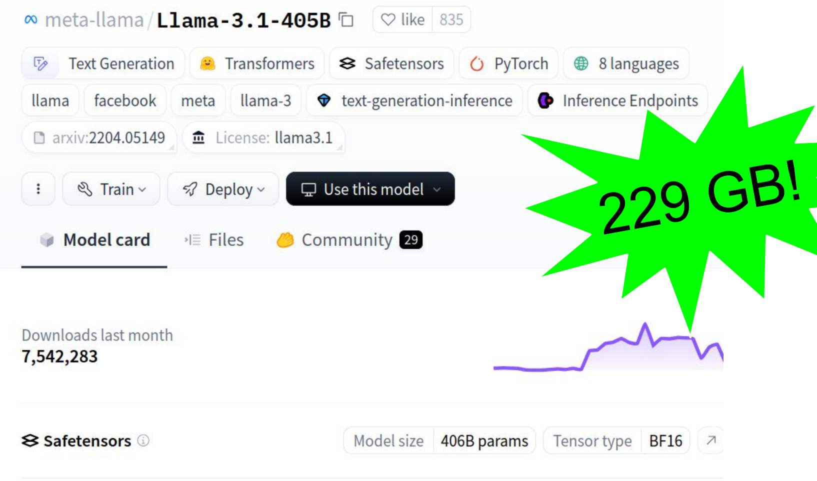


Attention Is All You Need.
Vaswani et al. (2017)



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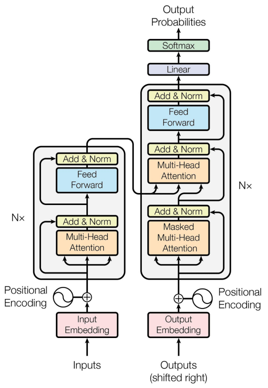

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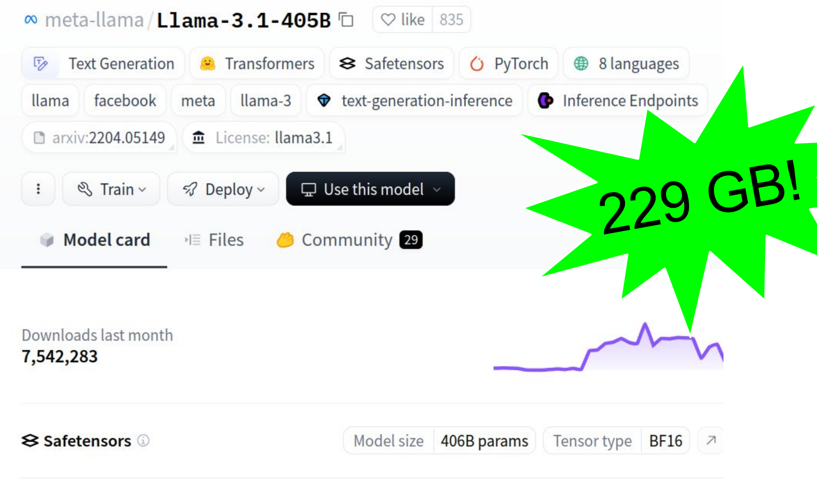

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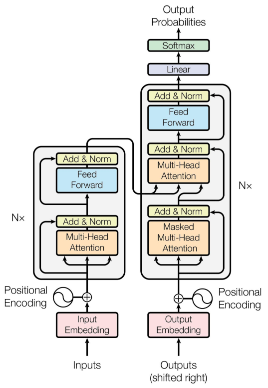

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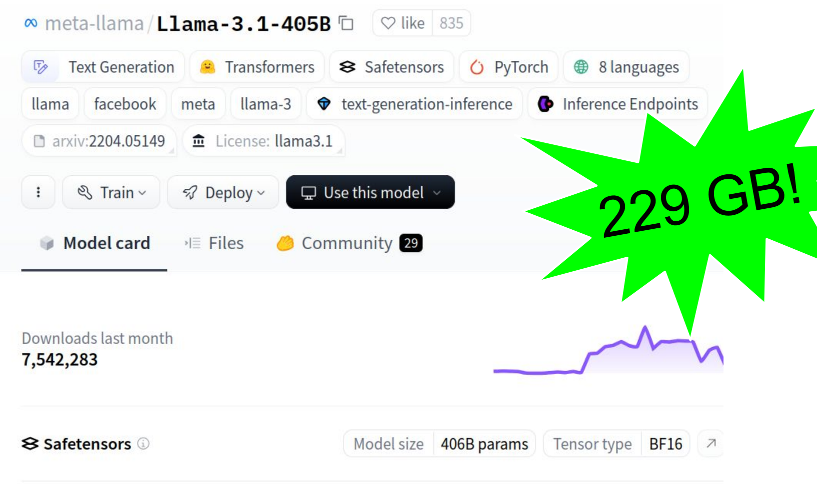

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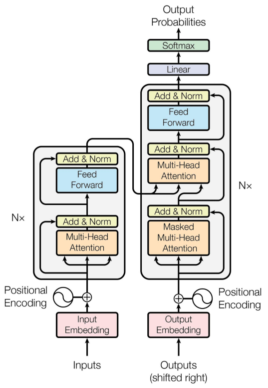

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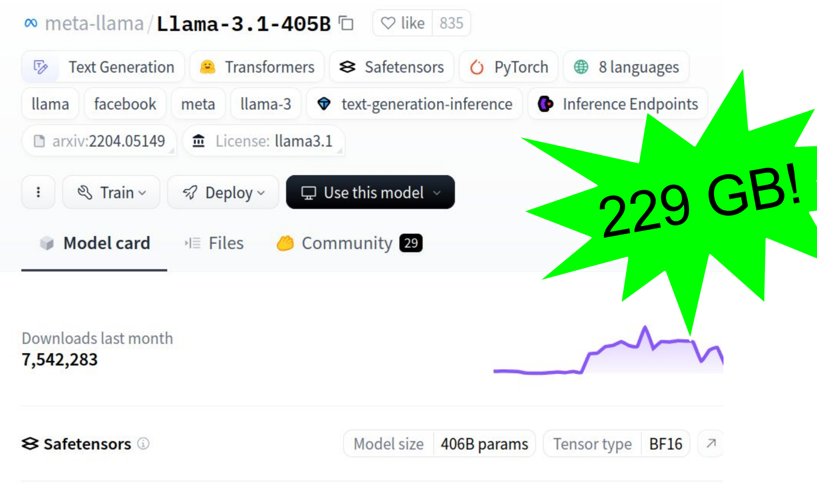

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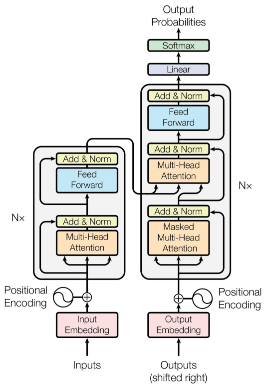

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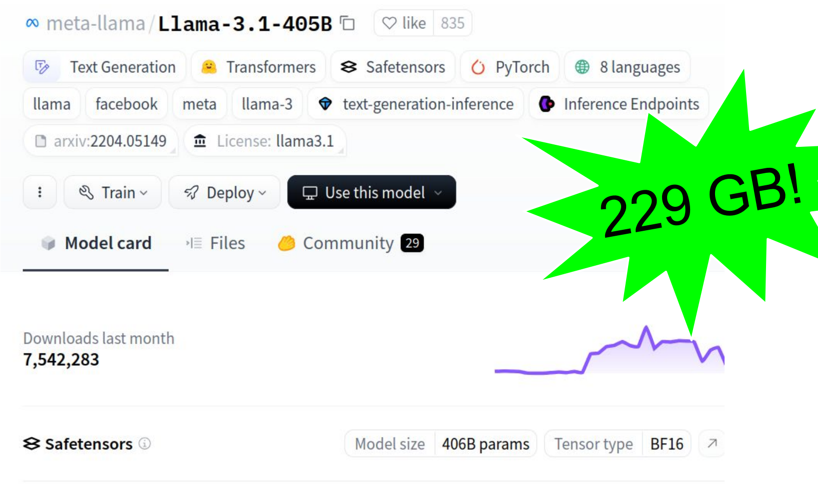

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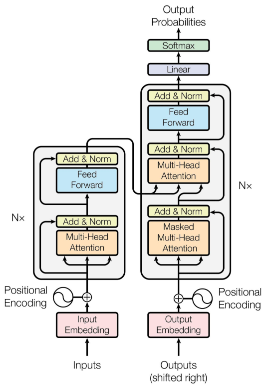

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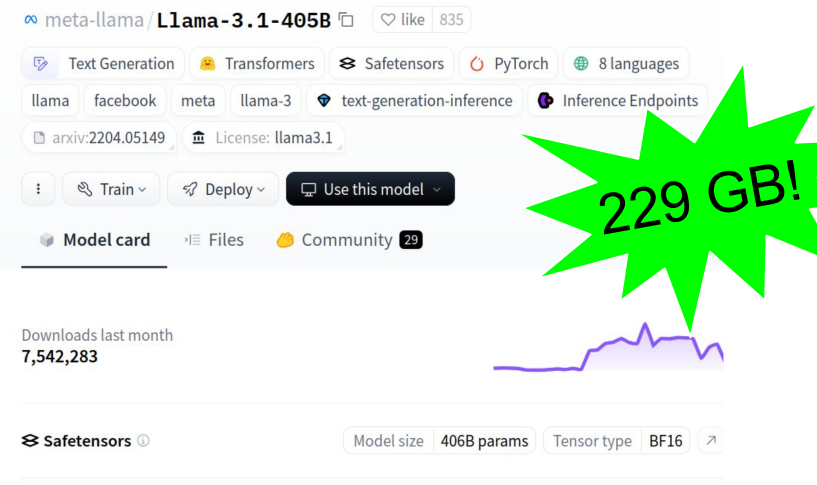

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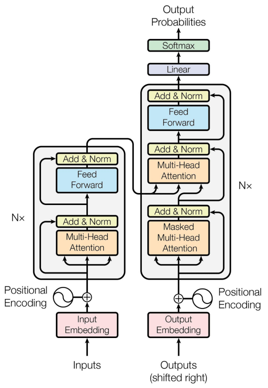

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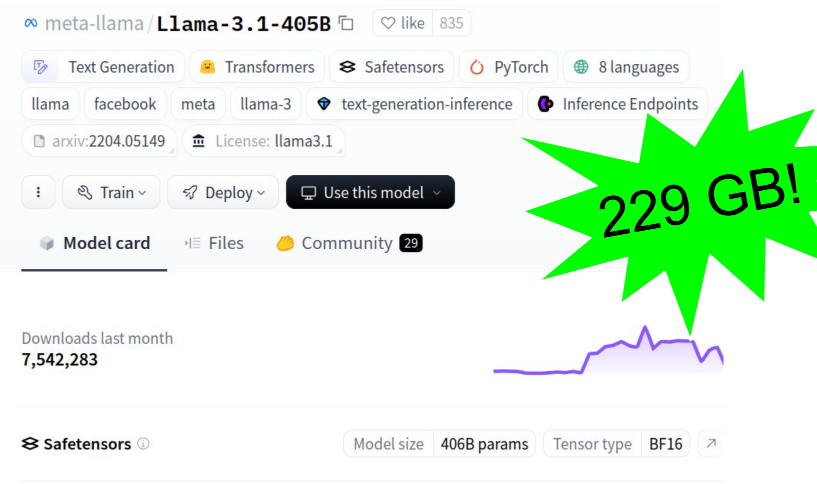

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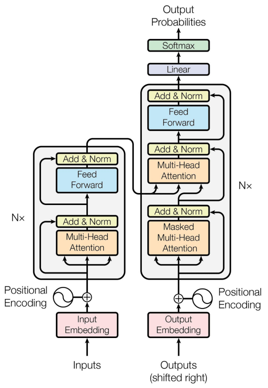

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  - Lots of time
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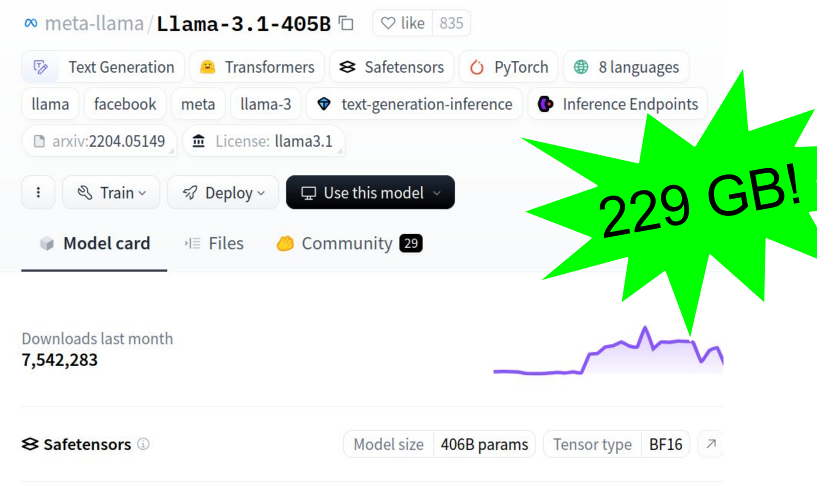

2021-11-28 1:50am ET [Stephen]: 12.27

Looks like 26 tried to immediately upload a checkpoint and failed its cp commands! Then it took another step, lowered its scalar, and tried uploading again! And again! The humanity! We're already at loss scale 0.25.

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ChatGPT

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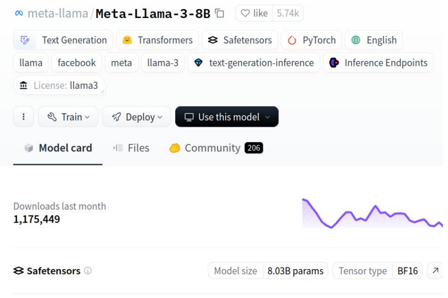
Meta AI

Hugging Face



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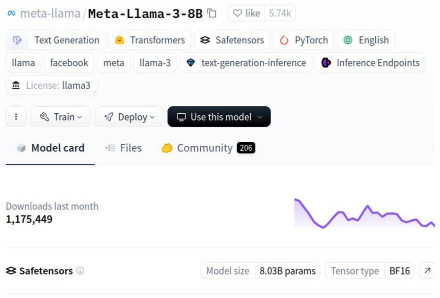

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- *Full Finetuning* $\theta^* = \arg\max_{\theta} p(\mathcal{Y}_{\mathrm{FT}} | \mathcal{X}_{\mathrm{FT}}; \theta)$
- *Partial Finetuning*: freeze some parameters $\theta_{\mathrm{frozen}} \subset \Theta$ and not others $\theta_{\mathrm{FT}} \subset \Theta$

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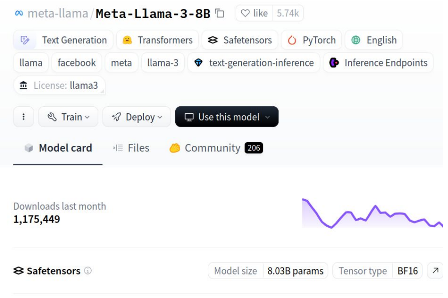

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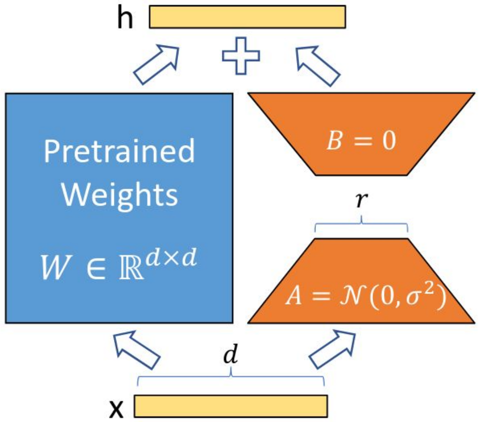

LoRA: Low-Rank Adaptation of Large Language Models. Hu et al. (2021)

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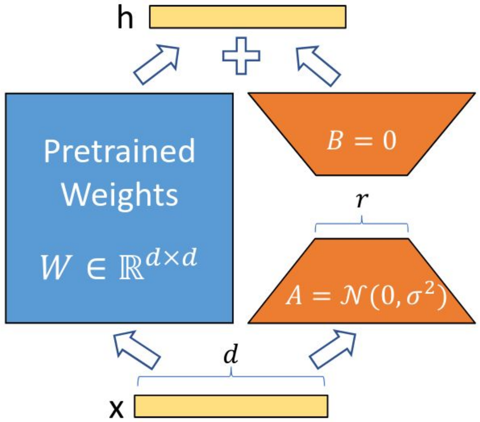
  – Only requires training $2dr$ parameters instead of d^2



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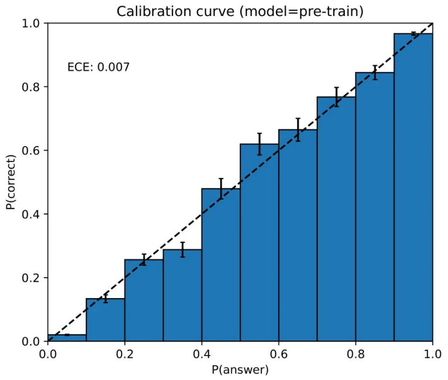

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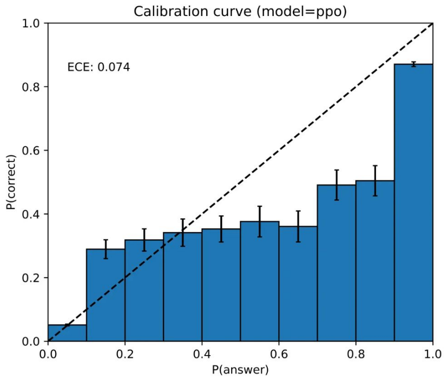

GPT-4 Technical Report. OpenAI (2023)

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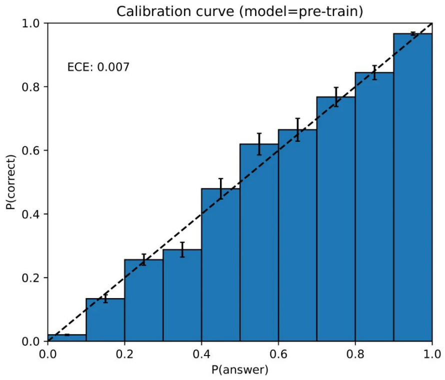

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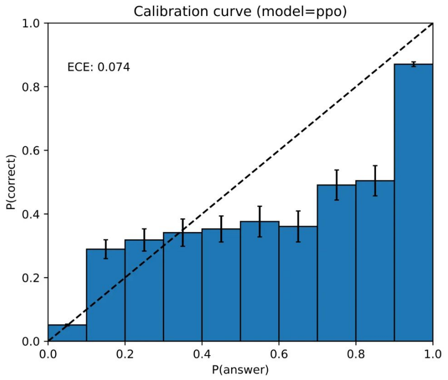

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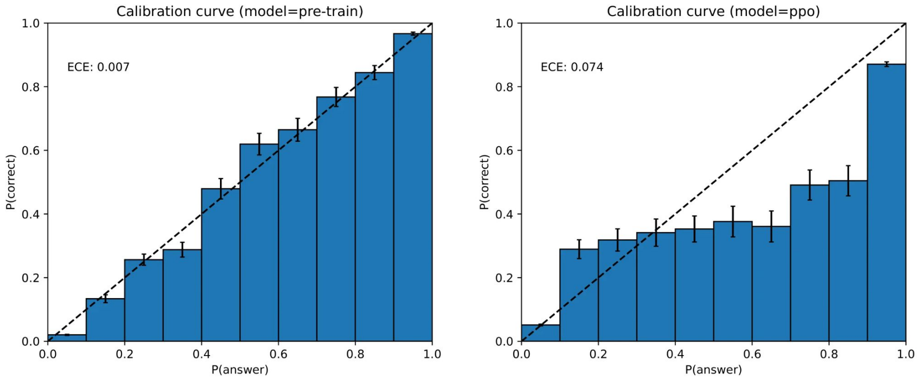
- Use knowledge of this distribution to correct the model's overconfidence

(Before finetuning) (After finetuning)



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