【论文导读】大语言模型综述（二）：大语言模型的背景的GPT系列的技术发展历程

Info

上篇

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**视频简介**
本系列为《A Survey of Large Language Model》的论文导读系列视频，本视频导读内容为论文的第二章的前半部分，即第二章Overview下的2.1 Background for LLMs。
本次介绍内容主要包括"尺度效应"(Scaling Law)、"涌现能力"(Emergent Abilities)和大语言模型的重要技术概念。
论文引用：W. X. Zhao et al., ‘A Survey of Large Language Models’. arXiv, Nov. 24, 2023. doi: 10.48550/arXiv.2303.18223.
拓展阅读：
Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., Gray, S., Radford, A., Wu, J., & Amodei, D. (2020). Scaling Laws for Neural Language Models. ArXiv. https://www.semanticscholar.org/paper/Scaling-Laws-for-Neural-Language-Models-Kaplan-McCandlish/e6c561d02500b2596a230b341a8eb8b921ca5bf2
Hoffmann, J., Borgeaud, S., Mensch, A., Buchatskaya, E., Cai, T., Rutherford, E., Casas, D. de L., Hendricks, L. A., Welbl, J., Clark, A., Hennigan, T., Noland, E., Millican, K., Driessche, G. van den, Damoc, B., Guy, A., Osindero, S., Simonyan, K., Elsen, E., … Sifre, L. (2022). Training Compute-Optimal Large Language Models (arXiv:2203.15556). arXiv. https://doi.org/10.48550/arXiv.2203.15556
OpenAI, Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., Avila, R., Babuschkin, I., Balaji, S., Balcom, V., Baltescu, P., Bao, H., Bavarian, M., Belgum, J., … Zoph, B. (2024). GPT-4 Technical Report (arXiv:2303.08774). arXiv. https://doi.org/10.48550/arXiv.2303.08774
Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C. L., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L., Simens, M., Askell, A., Welinder, P., Christiano, P., Leike, J., & Lowe, R. (2022). Training language models to follow instructions with human feedback (arXiv:2203.02155). arXiv. https://doi.org/10.48550/arXiv.2203.02155
Hendrycks, D., Burns, C., Basart, S., Zou, A., Mazeika, M., Song, D., & Steinhardt, J. (2021). Measuring Massive Multitask Language Understanding (arXiv:2009.03300). arXiv. https://doi.org/10.48550/arXiv.2009.03300
笔记注记：
黄色：名词组分
粉色：动词组分
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绿色：状语和修饰语组分
橙色：专有名词
紫色：扩展阅读链接
视频内容/字幕勘误：
无
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下篇

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**视频简介**
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本次介绍内容主要介绍了OpenAI基于GPT系列模型开发的技术探索历程和重要实践经验。
论文引用：W. X. Zhao et al., ‘A Survey of Large Language Models’. arXiv, Nov. 24, 2023. doi: 10.48550/arXiv.2303.18223.
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视频内容/字幕勘误：
无
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Further Reading

Scaling Law

“KM scaling law.” (Kaplan et al., 2020, page 4)

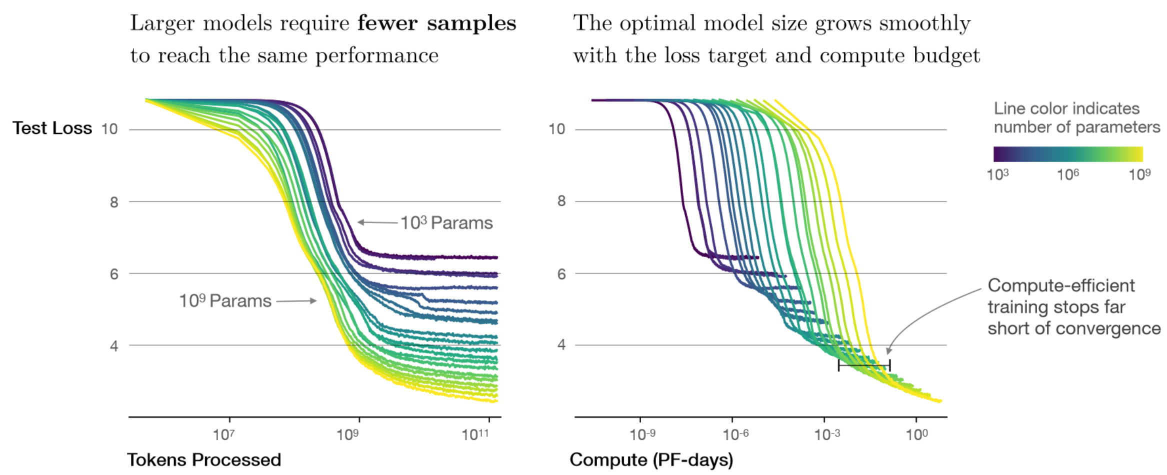

Figure 2 We show a series of language model training runs, with models ranging in size from 10^3 to 10^9 parameters (excluding embeddings).

“Chinchilla scaling law” (Hoffmann et al., 2022, page 8)

Table 2 | **Estimated parameter and data scaling with increased training compute.** The listed values are the exponents, a and b, on the relationship $N_{opt} \propto C^a$ and $D_{opt} \propto C^b$. Our analysis suggests a near equal scaling in parameters and data with increasing compute which is in clear contrast to previous work on the scaling of large models. The 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles are estimated via bootstrapping data (80% of the dataset is sampled 100 times) and are shown in parenthesis.

Approach	Coeff. a where $N_{opt} \propto C^a$	Coeff. b where $D_{opt} \propto C^b$
1. Minimum over training curves	$0.50\ (0.488, 0.502)$	$0.50\ (0.501, 0.512)$
2. IsoFLOP profiles	$0.49\ (0.462, 0.534)$	$0.51\ (0.483, 0.529)$
3. Parametric modelling of the loss	$0.46\ (0.454, 0.455)$	$0.54\ (0.542, 0.543)$
Kaplan et al. (2020)	0.73	0.27

> Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., Gray, S., Radford, A., Wu, J., & Amodei, D. (2020). Scaling Laws for Neural Language Models. *ArXiv*. https://www.semanticscholar.org/paper/Scaling-Laws-for-Neural-Language-Models-Kaplan-McCandlish/e6c561d02500b2596a230b341a8eb8b921ca5bf2
>
> Hoffmann, J., Borgeaud, S., Mensch, A., Buchatskaya, E., Cai, T., Rutherford, E., Casas, D. de L., Hendricks, L. A., Welbl, J., Clark, A., Hennigan, T., Noland, E., Millican, K., Driessche, G. van den, Damoc, B., Guy, A., Osindero, S., Simonyan, K., Elsen, E., … Sifre, L. (2022). *Training Compute-Optimal Large Language Models* (arXiv:2203.15556). arXiv. https://doi.org/10.48550/arXiv.2203.15556

Scaling Law in GPT-4

"GPT-4 (OpenAI et al., 2024, page 2) has reported that some capabilities (e.g., coding ability) can be accurately predicted via scaling law."

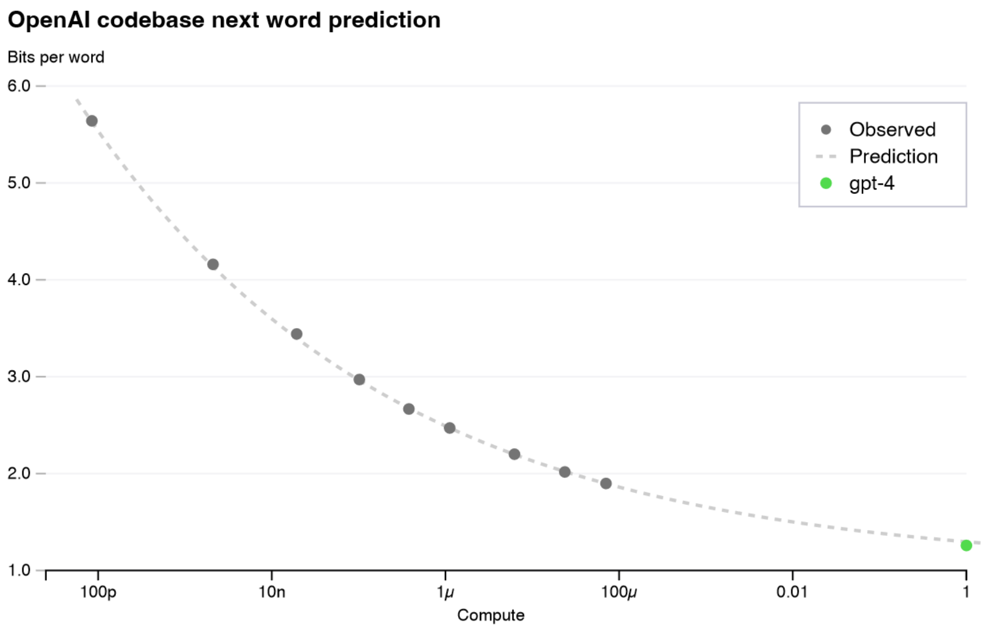

Figure 1. Performance of GPT-4 and smaller models. The metric is final loss on a dataset derived from our internal codebase. This is a convenient, large dataset of code tokens which is not contained in the training set. We chose to look at loss because it tends to be less noisy than other measures across different amounts of training compute. A power law fit to the smaller models (excluding GPT-4) is shown as the dotted line; this fit accurately predicts GPT-4's final loss. The x-axis is training compute normalized so that GPT-4 is 1.

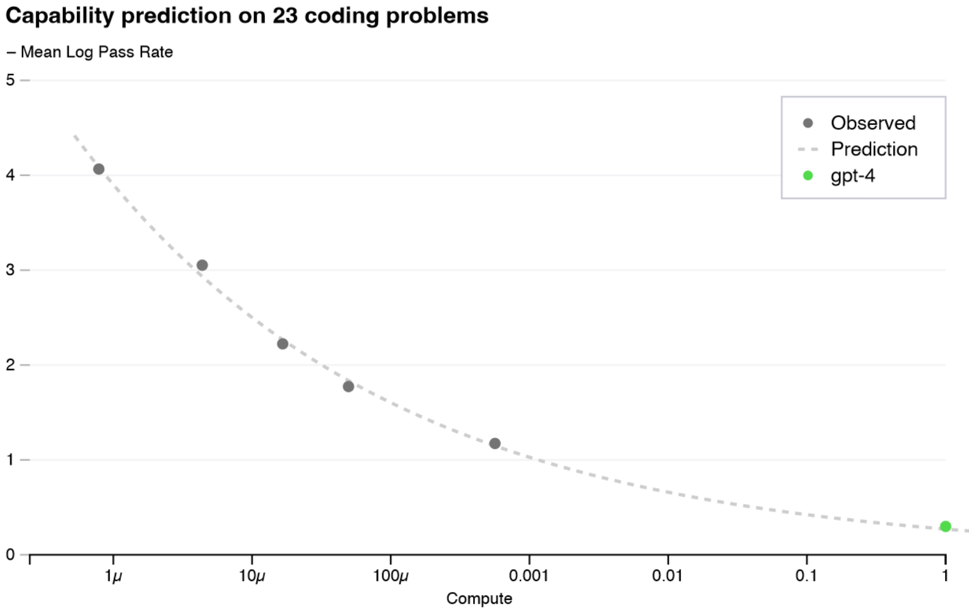

Figure 2. Performance of GPT-4 and smaller models. The metric is mean log pass rate on a subset of the HumanEval dataset. A power law fit to the smaller models (excluding GPT-4) is shown as the dotted line; this fit accurately predicts GPT-4's performance. The x-axis is training compute normalized so that GPT-4 is 1.

> OpenAI, Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., Avila, R., Babuschkin, I., Balaji, S., Balcom, V., Baltescu, P., Bao, H., Bavarian, M., Belgum, J., ... Zoph, B. (2024). *GPT-4 Technical Report* (arXiv:2303.08774). arXiv. https://doi.org/10.48550/arXiv.2303.08774

RLHF in InstructGPT

"reinforcement learning with human feedback" (Ouyang et al., 2022, page 3)

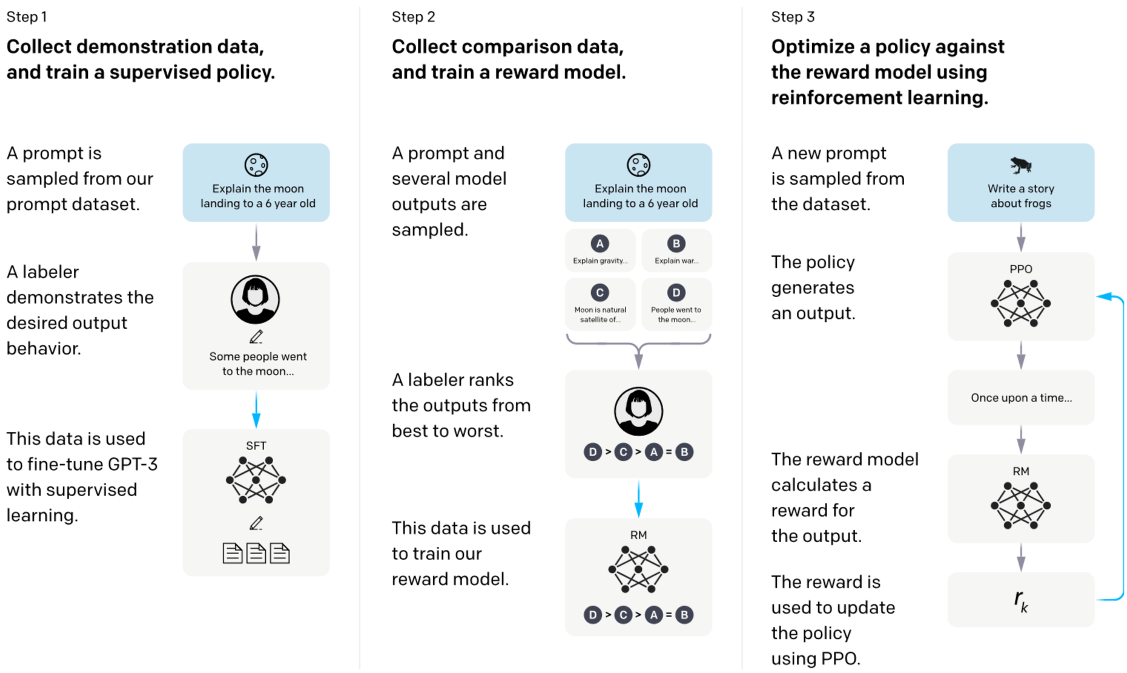

Figure 2: A diagram illustrating the three steps of our method: (1) supervised fine-tuning (SFT), (2) reward model (RM) training, and (3) reinforcement learning via proximal policy optimization (PPO) on this reward model. Blue arrows indicate that this data is used to train one of our models. In Step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

> Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C. L., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L., Simens, M., Askell, A., Welinder, P., Christiano, P., Leike, J., & Lowe, R. (2022). *Training language models to follow instructions with human feedback* (arXiv:2203.02155). arXiv. https://doi.org/10.48550/arXiv.2203.02155

Interview with OpenAI (former)Chief Scientist

"What the neural network learns is some representation of the process that produced the text. This text is actually a projection of the world...the more accurate you are in predicting the next word, the higher the fidelity, the more resolution you get in this process..."[1]

> 1. https://lifearchitect.ai/ilya/

"Language models are few-shot learners" from GPT-3

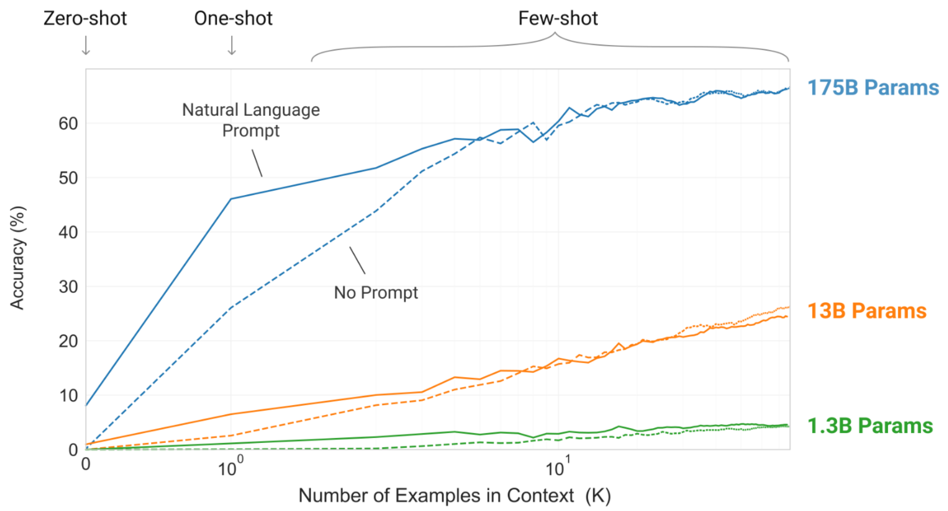

Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning curves" for large models demonstrate improved ability to learn a task from contextual information. We see qualitatively similar behavior across a wide range of tasks.

> Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., … Amodei, D. (2020). Language Models are Few-Shot Learners. *ArXiv*. https://www.semanticscholar.org/paper/Language-Models-are-Few-Shot-Learners-Brown-Mann/90abbc2cf38462b954ae1b772fac9532e2ccd8b0

OpenAI API & Model & Pricing

> https://openai.com/api/pricing/
>
> https://platform.openai.com/docs/models/

[Transforming AI | NVIDIA GTC 2024 Panel Hosted by Jensen Huang]