

DeepSeek-V3 Technical Report

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Abstract

We present DeepSeek-V3, a strong Mixture-of-Experts (MoE) language model with 671B total parameters with 37B activated for each token. To achieve efficient inference and cost-effective training, DeepSeek-V3 adopts Multi-head Latent Attention (MLA) and DeepSeekMoE architectures, which were thoroughly validated in DeepSeek-V2. Furthermore, DeepSeek-V3 pioneers an auxiliary-loss-free strategy for load balancing and sets a multi-token prediction training objective for stronger performance. We pre-train DeepSeek-V3 on 14.8 trillion diverse and high-quality tokens, followed by Supervised Fine-Tuning and Reinforcement Learning stages to fully harness its capabilities. Comprehensive evaluations reveal that DeepSeek-V3 outperforms other open-source models and achieves performance comparable to leading closed-source models. Despite its excellent performance, DeepSeek-V3 requires only 2.788M H800 GPU hours for its full training. In addition, its training process is remarkably stable. Throughout the entire training process, we did not experience any irrecoverable loss spikes or perform any rollbacks. The model checkpoints are available at <https://github.com/deepseek-ai/DeepSeek-V3>.

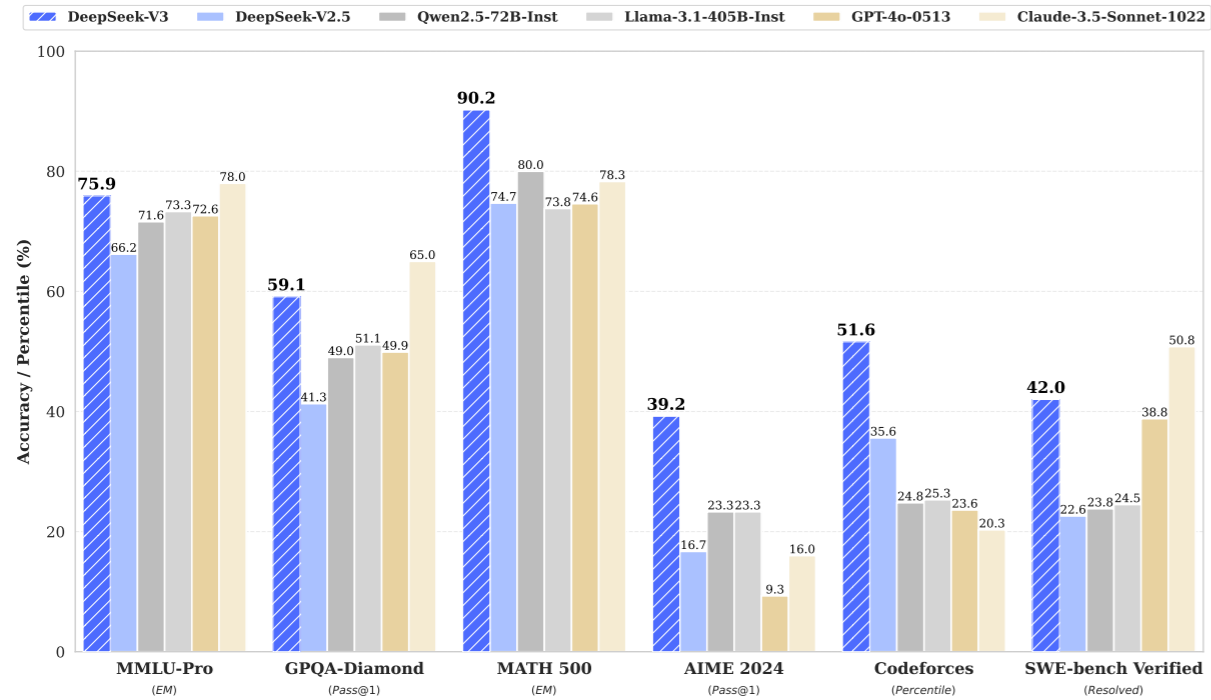


Figure 1 | Benchmark performance of DeepSeek-V3 and its counterparts.

DeepSeek-V3 技术报告

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摘要

我们介绍了 DeepSeek-V3, 一个强大的专家混合模型 (MoE) 语言模型, 拥有 671B 总参数量, 每个 token 激活 37B 参数。为了实现高效的推理和成本效益的训练, DeepSeek-V3 采用了多头潜在注意力 (MLA) 和 DeepSeekMoE 架构, 这些架构在 DeepSeek-V2 中经过了彻底的验证。此外, DeepSeek-V3 创新性地采用无辅助损失策略进行负载均衡, 并设定了多标记预测训练目标以实现更强的性能。我们在 14.8 万亿个多样且高质量的 token 上预训练 DeepSeek-V3, 随后进行监督微调 and 强化学习阶段, 以充分发挥其能力。全面的评估表明, DeepSeek-V3 优于其他开源模型, 并实现了与领先闭源模型相当的性能。尽管性能优异, DeepSeek-V3 的完整训练仅需 2.788M H800 GPU 小时。此外, 其训练过程非常稳定。在整个训练过程中, 我们没有遇到任何不可恢复的损失峰值, 也没有进行任何回滚。模型检查点可在 <https://github.com/deepseek-ai/DeepSeek-V3> 处获取。

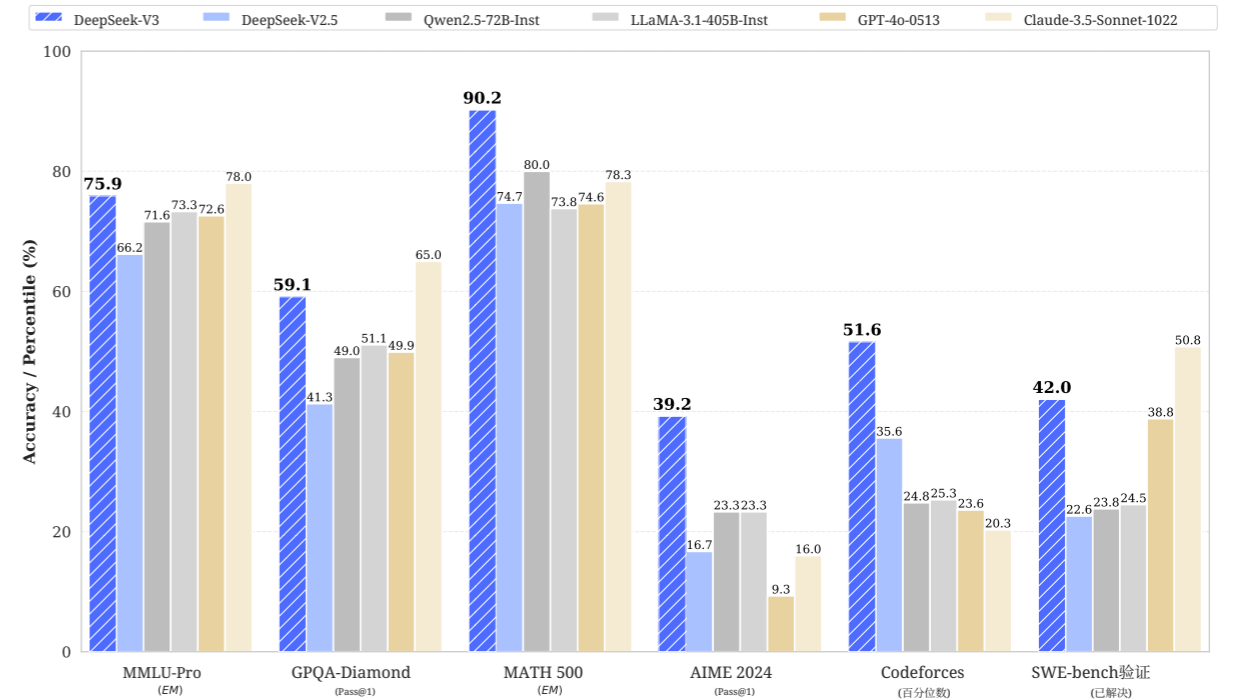


图 1 | DeepSeek-V3 及其对应模型的基准性能。

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1. Introduction

In recent years, Large Language Models (LLMs) have been undergoing rapid iteration and evolution (Anthropic, 2024; Google, 2024; OpenAI, 2024a), progressively diminishing the gap towards Artificial General Intelligence (AGI). Beyond closed-source models, open-source models, including DeepSeek series (DeepSeek-AI, 2024a,b,c; Guo et al., 2024), LLaMA series (AI@Meta, 2024a,b; Touvron et al., 2023a,b), Qwen series (Qwen, 2023, 2024a,b), and Mistral series (Jiang et al., 2023; Mistral, 2024), are also making significant strides, endeavoring to close the gap with their closed-source counterparts. To further push the boundaries of open-source model capabilities, we scale up our models and introduce DeepSeek-V3, a large Mixture-of-Experts (MoE) model with 671B parameters, of which 37B are activated for each token.

With a forward-looking perspective, we consistently strive for strong model performance and economical costs. Therefore, in terms of architecture, DeepSeek-V3 still adopts Multi-head Latent Attention (MLA) (DeepSeek-AI, 2024c) for efficient inference and DeepSeekMoE (Dai et al., 2024) for cost-effective training. These two architectures have been validated in DeepSeek-V2 (DeepSeek-AI, 2024c), demonstrating their capability to maintain robust model performance while achieving efficient training and inference. Beyond the basic architecture, we implement two additional strategies to further enhance the model capabilities. Firstly, DeepSeek-V3 pioneers an auxiliary-loss-free strategy (Wang et al., 2024a) for load balancing, with the aim of minimizing the adverse impact on model performance that arises from the effort to encourage load balancing. Secondly, DeepSeek-V3 employs a multi-token prediction training objective, which we have observed to enhance the overall performance on evaluation benchmarks.

In order to achieve efficient training, we support the FP8 mixed precision training and implement comprehensive optimizations for the training framework. Low-precision training has emerged as a promising solution for efficient training (Dettmers et al., 2022; Kalamkar et al., 2019; Narang et al., 2017; Peng et al., 2023b), its evolution being closely tied to advancements in hardware capabilities (Luo et al., 2024; Micikevicius et al., 2022; Rouhani et al., 2023a). In this work, we introduce an FP8 mixed precision training framework and, for the first time, validate its effectiveness on an extremely large-scale model. Through the support for FP8 computation and storage, we achieve both accelerated training and reduced GPU memory usage. As for the training framework, we design the DualPipe algorithm for efficient pipeline parallelism, which has fewer pipeline bubbles and hides most of the communication during training through computation-communication overlap. This overlap ensures that, as the model further scales up, as long as we maintain a constant computation-to-communication ratio, we can still employ fine-grained experts across nodes while achieving a near-zero all-to-all communication overhead. In addition, we also develop efficient cross-node all-to-all communication kernels to fully utilize InfiniBand (IB) and NVLink bandwidths. Furthermore, we meticulously optimize the memory footprint, making it possible to train DeepSeek-V3 without using costly tensor parallelism. Combining these efforts, we achieve high training efficiency.

During pre-training, we train DeepSeek-V3 on 14.8T high-quality and diverse tokens. The pre-training process is remarkably stable. Throughout the entire training process, we did not encounter any irrecoverable loss spikes or have to roll back. Next, we conduct a two-stage context length extension for DeepSeek-V3. In the first stage, the maximum context length is extended to 32K, and in the second stage, it is further extended to 128K. Following this, we conduct post-training, including Supervised Fine-Tuning (SFT) and Reinforcement Learning (RL) on the base model of DeepSeek-V3, to align it with human preferences and further unlock its potential. During the post-training stage, we distill the reasoning capability from the DeepSeek-R1 series of models, and meanwhile carefully maintain the balance between model accuracy

1. 简介

近年来，大语言模型（LLMs）正经历着快速迭代与演进（Anthropic, 2024; Google, 2024; OpenAI, 2024a），逐步缩小与通用人工智能（AGI）的差距。除了闭源模型，开源模型，包括 DeepSeek 系列（DeepSeek-AI, 2024a,b,c; Guo 等人, 2024）、LLaMA 系列（AI@Meta, 2024a,b; Touvron 等人, 2023a,b）、Qwen 系列（Qwen, 2023, 2024a,b）和 Mistral 系列（Jiang 等人, 2023; Mistral, 2024），也在取得显著进展，努力缩小与它们的闭源对应模型的差距。为了进一步拓展开源模型的能力边界，我们扩展了我们的模型，并推出了 DeepSeek-V3，这是一个拥有 671B 参数的大规模专家混合模型（MoE），其中每个 token 有 37B 参数被激活。

以前瞻性的视角，我们始终致力于实现强大的模型性能和经济的成本。因此，在架构方面，DeepSeek-V3 仍然采用多头潜在注意力（MLA）（DeepSeek-AI, 2024c）以实现高效的推理，并采用 DeepSeekMoE（Dai 等人, 2024）以实现经济的训练。这两种架构已在 DeepSeek-V2（DeepSeek-AI, 2024c）中得到验证，证明它们能够在实现高效的训练和推理的同时保持强大的模型性能。除了基本架构之外，我们实施了两种额外的策略以进一步增强模型能力。首先，DeepSeek-V3 推出无辅助损失策略（Wang 等人, 2024a）以实现负载均衡，旨在最大限度地减少因鼓励负载均衡而产生的对模型性能的不利影响。其次，DeepSeek-V3 采用多标记预测训练目标，我们观察到这能够提升模型在评估基准上的整体性能。

为了实现高效的训练，我们支持 FP8 混合精度训练，并为训练框架实现了全面的优化。低精度训练已成为高效训练的有前景的解决方案（Dettmers 等人, 2022; Kalamkar 等人, 2019; Narang 等人, 2017; 彭等人, 2023b），其发展紧密与硬件能力的进步相关（Luo 等人, 2024; Micikevicius 等人, 2022; Rouhani 等人, 2023a）。在这项工作中，我们引入了一个 FP8 混合精度训练框架，并首次在极大规模模型上验证了其有效性。通过支持 FP8 计算和存储，我们实现了加速训练和减少 GPU 内存使用。对于训练框架，我们设计了 DualPipe 算法以实现高效的流水线并行，该算法具有更少的流水线气泡，并通过计算通信重叠在训练过程中隐藏了大部分通信。这种重叠确保，随着模型进一步扩展，只要我们保持计算与通信的比率恒定，我们仍然可以在节点间使用细粒度专家，同时实现近零的全对全通信开销。此外，我们还开发了高效的跨节点全对全通信内核，以充分利用 InfiniBand（IB）和 NVLink 带宽。此外，我们还细致地优化了内存占用，使得无需使用昂贵的张量并行即可训练 DeepSeek-V3。结合这些努力，我们实现了高训练效率。

在预训练阶段，我们在 14.8T 高质量和多样化的 token 上训练 DeepSeek-V3。预训练过程非常稳定。在整个训练过程中，我们没有遇到任何不可恢复的损失峰值，也不需要回滚。接下来，我们对 DeepSeek-V3 进行两阶段上下文长度扩展。第一阶段将最大上下文长度扩展到 32K，第二阶段进一步扩展到 128K。随后，我们进行后训练，包括对 DeepSeek-V3 基础模型进行监督微调（SFT）和强化学习（RL），以使其符合人类偏好并进一步释放其潜力。在后训练阶段，我们从 DeepSeek-R1 系列模型中蒸馏推理能力，同时小心地保持模型准确率和生成长度之间的平衡。

Training Costs	Pre-Training	Context Extension	Post-Training	Total
in H800 GPU Hours	2664K	119K	5K	2788K
in USD	\$5.328M	\$0.238M	\$0.01M	\$5.576M

Table 1 | Training costs of DeepSeek-V3, assuming the rental price of H800 is \$2 per GPU hour.

and generation length.

We evaluate DeepSeek-V3 on a comprehensive array of benchmarks. Despite its economical training costs, comprehensive evaluations reveal that DeepSeek-V3-Base has emerged as the strongest open-source base model currently available, especially in code and math. Its chat version also outperforms other open-source models and achieves performance comparable to leading closed-source models, including GPT-4o and Claude-3.5-Sonnet, on a series of standard and open-ended benchmarks.

Lastly, we emphasize again the economical training costs of DeepSeek-V3, summarized in Table 1, achieved through our optimized co-design of algorithms, frameworks, and hardware. During the pre-training stage, training DeepSeek-V3 on each trillion tokens requires only 180K H800 GPU hours, i.e., 3.7 days on our cluster with 2048 H800 GPUs. Consequently, our pre-training stage is completed in less than two months and costs 2664K GPU hours. Combined with 119K GPU hours for the context length extension and 5K GPU hours for post-training, DeepSeek-V3 costs only 2.788M GPU hours for its full training. Assuming the rental price of the H800 GPU is \$2 per GPU hour, our total training costs amount to only \$5.576M. Note that the aforementioned costs include only the official training of DeepSeek-V3, excluding the costs associated with prior research and ablation experiments on architectures, algorithms, or data.

Our main contribution includes:

Architecture: Innovative Load Balancing Strategy and Training Objective

- On top of the efficient architecture of DeepSeek-V2, we pioneer an auxiliary-loss-free strategy for load balancing, which minimizes the performance degradation that arises from encouraging load balancing.
- We investigate a Multi-Token Prediction (MTP) objective and prove it beneficial to model performance. It can also be used for speculative decoding for inference acceleration.

Pre-Training: Towards Ultimate Training Efficiency

- We design an FP8 mixed precision training framework and, for the first time, validate the feasibility and effectiveness of FP8 training on an extremely large-scale model.
- Through the co-design of algorithms, frameworks, and hardware, we overcome the communication bottleneck in cross-node MoE training, achieving near-full computation-communication overlap. This significantly enhances our training efficiency and reduces the training costs, enabling us to further scale up the model size without additional overhead.
- At an economical cost of only 2.664M H800 GPU hours, we complete the pre-training of DeepSeek-V3 on 14.8T tokens, producing the currently strongest open-source base model. The subsequent training stages after pre-training require only 0.1M GPU hours.

Post-Training: Knowledge Distillation from DeepSeek-R1

- We introduce an innovative methodology to distill reasoning capabilities from the long-Chain-of-Thought (CoT) model, specifically from one of the DeepSeek R1 series models, into standard LLMs, particularly DeepSeek-V3. Our pipeline elegantly incorporates the

训练成本	预训练	上下文扩展	后训练	总计
H800 GPU 小时	2664K	119K	5K	2788K
美元	5328万美元	238万美元	1万美元	\$5.576M

表 1 | DeepSeek-V3的训练成本，假设H800的租赁价格为每GPU小时\$2

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和生成长度。

我们在一系列综合基准测试上评估了DeepSeek-V3。尽管其训练成本经济，但全面评估表明，DeepSeek-V3-Base是目前最强的开源基础模型，尤其是在代码和数学方面。其聊天版本也优于其他开源模型，并在一系列标准和开放式基准测试上实现了与领先的闭源模型（包括GPT-4o和Claude-3.5-Sonnet）相当的性能。

最后，我们再次强调DeepSeek-V3的经济型训练成本，如表1所示，这是通过我们优化的算法、框架和硬件协同设计实现的。在预训练阶段，每个万亿token的训练DeepSeek-V3仅需180K H800 GPU小时，即在我们拥有2048个H800 GPU的集群上需要3.7天。因此，我们的预训练阶段在不到两个月内完成，成本为2664K GPU小时。加上119K GPU小时用于上下文长度扩展和5K GPU小时用于后训练，DeepSeek-V3的完整训练成本仅为2.788M GPU小时。假设H800 GPU的租赁价格为每GPU小时\$2，我们的总训练成本仅为\$5.576M。请注意，上述成本仅包括DeepSeek-V3的官方训练，不包括先前在架构、算法或数据上的研究和消融实验的成本。

我们的主要贡献包括：

架构：创新的负载均衡策略和训练目标

- 在DeepSeek-V2的高效架构之上，我们开创了一种无辅助损失策略的负载均衡方法，这最小化了因鼓励负载均衡而导致的性能下降。
- 我们研究了一种多标记预测（MTP）目标，并证明其对模型性能有益。它也可用于推测解码以加速推理。

预训练：迈向终极训练效率

- 我们设计了一个FP8混合精度训练框架，首次验证了在极大规模模型上进行FP8训练的可行性和有效性。
- 通过算法、框架和硬件的协同设计，我们克服了跨节点MoE训练中的通信瓶颈，实现了接近完全的计算-通信重叠。这显著提升了我们的训练效率，降低了训练成本，使我们能够在不增加额外开销的情况下进一步扩大模型规模。
- 仅以2.664M H800 GPU小时的经济成本，我们在14.8T tokens上完成了DeepSeek-V3的预训练，生成了目前最强的开源基模型。预训练后的后续训练阶段仅需0.1M GPU小时。

后训练：从DeepSeek-R1进行知识蒸馏

- 我们介绍了一种创新的方法，将长思维链（CoT）模型的推理能力从DeepSeek R1系列模型之一蒸馏到标准大语言模型中，特别是DeepSeek-V3。我们的流程优雅地结合了

verification and reflection patterns of R1 into DeepSeek-V3 and notably improves its reasoning performance. Meanwhile, we also maintain control over the output style and length of DeepSeek-V3.

Summary of Core Evaluation Results

- **Knowledge:** (1) On educational benchmarks such as MMLU, MMLU-Pro, and GPQA, DeepSeek-V3 outperforms all other open-source models, achieving 88.5 on MMLU, 75.9 on MMLU-Pro, and 59.1 on GPQA. Its performance is comparable to leading closed-source models like GPT-4o and Claude-Sonnet-3.5, narrowing the gap between open-source and closed-source models in this domain. (2) For factuality benchmarks, DeepSeek-V3 demonstrates superior performance among open-source models on both SimpleQA and Chinese SimpleQA. While it trails behind GPT-4o and Claude-Sonnet-3.5 in English factual knowledge (SimpleQA), it surpasses these models in Chinese factual knowledge (Chinese SimpleQA), highlighting its strength in Chinese factual knowledge.
- **Code, Math, and Reasoning:** (1) DeepSeek-V3 achieves state-of-the-art performance on math-related benchmarks among all non-long-CoT open-source and closed-source models. Notably, it even outperforms o1-preview on specific benchmarks, such as MATH-500, demonstrating its robust mathematical reasoning capabilities. (2) On coding-related tasks, DeepSeek-V3 emerges as the top-performing model for coding competition benchmarks, such as LiveCodeBench, solidifying its position as the leading model in this domain. For engineering-related tasks, while DeepSeek-V3 performs slightly below Claude-Sonnet-3.5, it still outpaces all other models by a significant margin, demonstrating its competitiveness across diverse technical benchmarks.

In the remainder of this paper, we first present a detailed exposition of our DeepSeek-V3 model architecture (Section 2). Subsequently, we introduce our infrastructures, encompassing our compute clusters, the training framework, the support for FP8 training, the inference deployment strategy, and our suggestions on future hardware design. Next, we describe our pre-training process, including the construction of training data, hyper-parameter settings, long-context extension techniques, the associated evaluations, as well as some discussions (Section 4). Thereafter, we discuss our efforts on post-training, which include Supervised Fine-Tuning (SFT), Reinforcement Learning (RL), the corresponding evaluations, and discussions (Section 5). Lastly, we conclude this work, discuss existing limitations of DeepSeek-V3, and propose potential directions for future research (Section 6).

2. Architecture

We first introduce the basic architecture of DeepSeek-V3, featured by Multi-head Latent Attention (MLA) (DeepSeek-AI, 2024c) for efficient inference and DeepSeekMoE (Dai et al., 2024) for economical training. Then, we present a Multi-Token Prediction (MTP) training objective, which we have observed to enhance the overall performance on evaluation benchmarks. For other minor details not explicitly mentioned, DeepSeek-V3 adheres to the settings of DeepSeek-V2 (DeepSeek-AI, 2024c).

2.1. Basic Architecture

The basic architecture of DeepSeek-V3 is still within the Transformer (Vaswani et al., 2017) framework. For efficient inference and economical training, DeepSeek-V3 also adopts MLA and DeepSeekMoE, which have been thoroughly validated by DeepSeek-V2. Compared with DeepSeek-V2, an exception is that we additionally introduce an auxiliary-loss-free load balancing

验证和反思 R1 的模式到 DeepSeek-V3 中, 并显著提高了其推理性能。同时, 我们也控制着 DeepSeek-V3 的输出风格和长度。

核心评估结果摘要

- **知识:** (1) 在MMLU、MMLU-Pro和GPQA等教育基准测试中, DeepSeek-V3的表现优于所有其他开源模型, 在MMLU上达到88.5分, 在MMLU-Pro上达到75.9分, 在GPQA上达到59.1分。其表现与领先的闭源模型GPT-4o和Claude-Sonnet-3.5相当, 缩小了该领域开源模型与闭源模型之间的差距。(2) 在事实性基准测试中, DeepSeek-V3在SimpleQA和中文SimpleQA上表现优于其他开源模型。虽然它在英语事实性知识 (SimpleQA) 方面落后于GPT-4o和Claude-Sonnet-3.5, 但在中文事实性知识 (中文SimpleQA) 方面超越这些模型, 突显了其在中文事实性知识方面的优势。
- **代码、数学和推理:** (1) 在所有非长CoT开源和闭源模型中, DeepSeek-V3在数学相关基准测试中达到最先进水平。值得注意的是, 它在特定基准测试 (如MATH-500) 上甚至优于o1-preview, 展示了其强大的数学推理能力。(2) 在编程相关任务中, DeepSeek-V3成为编码竞赛基准测试中的表现最佳模型, 巩固了其在该领域的领先地位。对于工程相关任务, 虽然DeepSeek-V3的表现略低于Claude-Sonnet-3.5, 但仍显著优于其他所有模型, 展示了其在多样化技术基准测试中的竞争力。

本文余下部分, 我们首先详细介绍我们的 DeepSeek-V3 模型架构 (第 2 节)。随后, 我们介绍我们的基础设施, 包括计算集群、训练框架、FP8 训练支持、推理部署策略以及我们对未来硬件设计的建议。接下来, 我们描述我们的预训练过程, 包括训练数据构建、超参数设置、长上下文扩展技术、相关评估以及一些讨论 (第 4 节)。此后, 我们讨论我们的后训练工作, 包括监督微调 (SFT)、强化学习 (RL)、相应的评估和讨论 (第 5 节)。最后, 我们总结这项工作, 讨论 DeepSeek-V3 现有的局限性, 并提出未来研究的潜在方向 (第 6 节)。

2. 架构

我们首先介绍 DeepSeek-V3 的基本架构, 其特点是采用多头潜在注意力 (MLA) (DeepSeek-AI, 2024c) 以实现高效推理, 以及 DeepSeekMoE (Dai 等人, 2024) 以实现经济高效的训练。然后, 我们介绍多标记预测 (MTP) 训练目标, 我们观察到该目标提升了评估基准上的整体性能。对于其他未明确提及的细节, DeepSeek-V3 遵循 DeepSeek-V2 的设置 (DeepSeek-AI, 2024c)。

2.1. 基本架构

DeepSeek-V3 的基本架构仍然基于 Transformer (Vaswani 等人, 2017) 框架。为了实现高效的推理和经济的训练, DeepSeek-V3 也采用了 MLA 和 DeepSeekMoE, 这些技术已经在 DeepSeek-V2 中得到了充分验证。与 DeepSeek-V2 相比, 一个例外是我们额外引入了一种无辅助损失的负载均衡策略 (Wang 等人, 2024a), 用于缓解 DeepSeekMoE 在确保负载均衡时导致的性能下降。图 2 展示了 DeepSeek-V3 的基本架构, 在本节中我们将简要回顾 MLA 和 DeepSeekMoE 的细节。

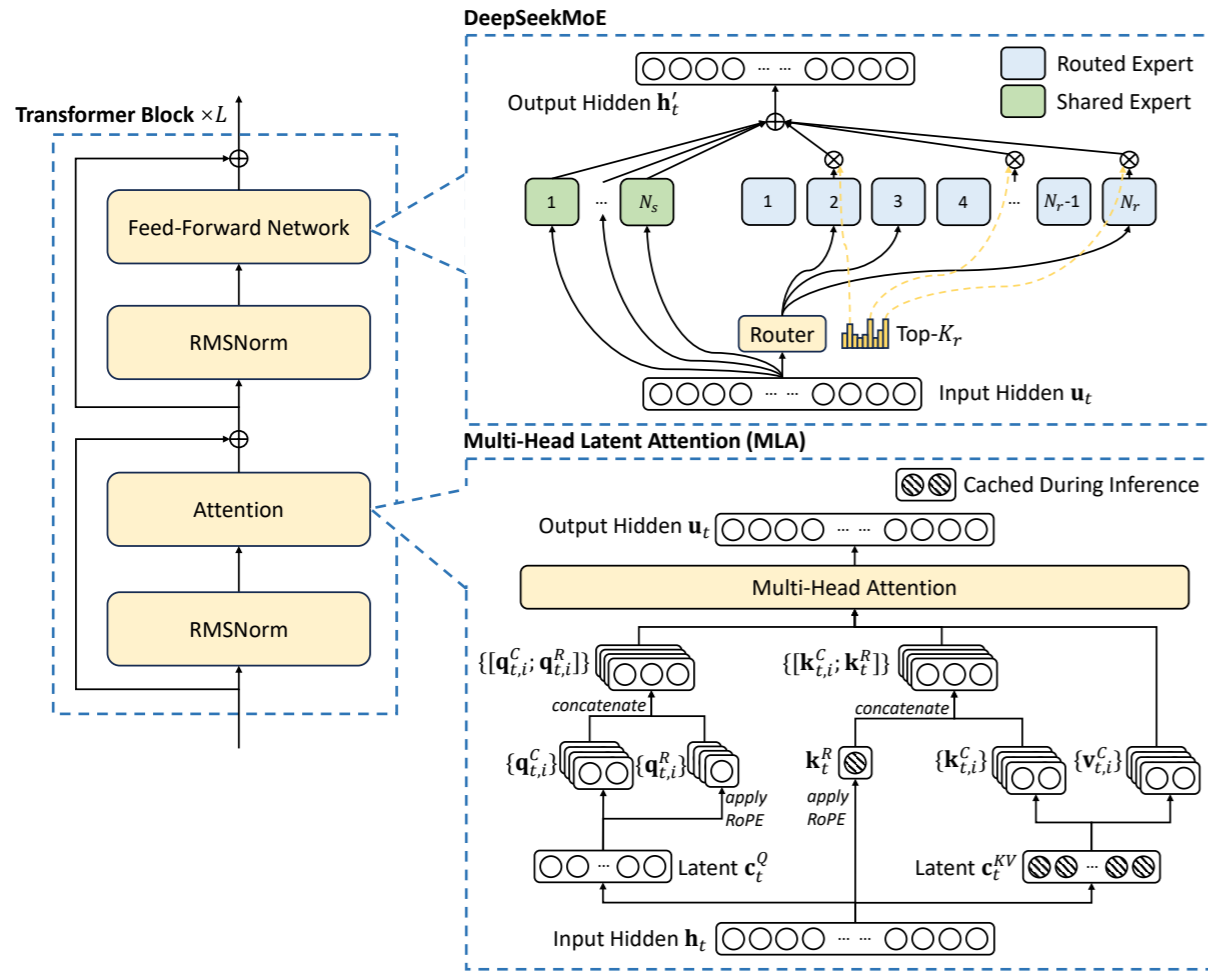


Figure 2 | Illustration of the basic architecture of DeepSeek-V3. Following DeepSeek-V2, we adopt MLA and DeepSeekMoE for efficient inference and economical training.

strategy (Wang et al., 2024a) for DeepSeekMoE to mitigate the performance degradation induced by the effort to ensure load balance. Figure 2 illustrates the basic architecture of DeepSeek-V3, and we will briefly review the details of MLA and DeepSeekMoE in this section.

2.1.1. Multi-Head Latent Attention

For attention, DeepSeek-V3 adopts the MLA architecture. Let d denote the embedding dimension, n_h denote the number of attention heads, d_h denote the dimension per head, and $\mathbf{h}_t \in \mathbb{R}^d$ denote the attention input for the t -th token at a given attention layer. The core of MLA is the low-rank joint compression for attention keys and values to reduce Key-Value (KV) cache during inference:

$$\mathbf{c}_t^{KV} = W^{DKV} \mathbf{h}_t, \quad (1)$$

$$[\mathbf{k}_{t,1}^C; \mathbf{k}_{t,2}^C; \dots; \mathbf{k}_{t,n_h}^C] = \mathbf{k}_t^C = W^{UK} \mathbf{c}_t^{KV}, \quad (2)$$

$$\mathbf{k}_t^R = \text{RoPE}(W^{KR} \mathbf{h}_t), \quad (3)$$

$$\mathbf{k}_{t,i} = [\mathbf{k}_{t,i}^C; \mathbf{k}_t^R], \quad (4)$$

$$[\mathbf{v}_{t,1}^C; \mathbf{v}_{t,2}^C; \dots; \mathbf{v}_{t,n_h}^C] = \mathbf{v}_t^C = W^{UV} \mathbf{c}_t^{KV}, \quad (5)$$

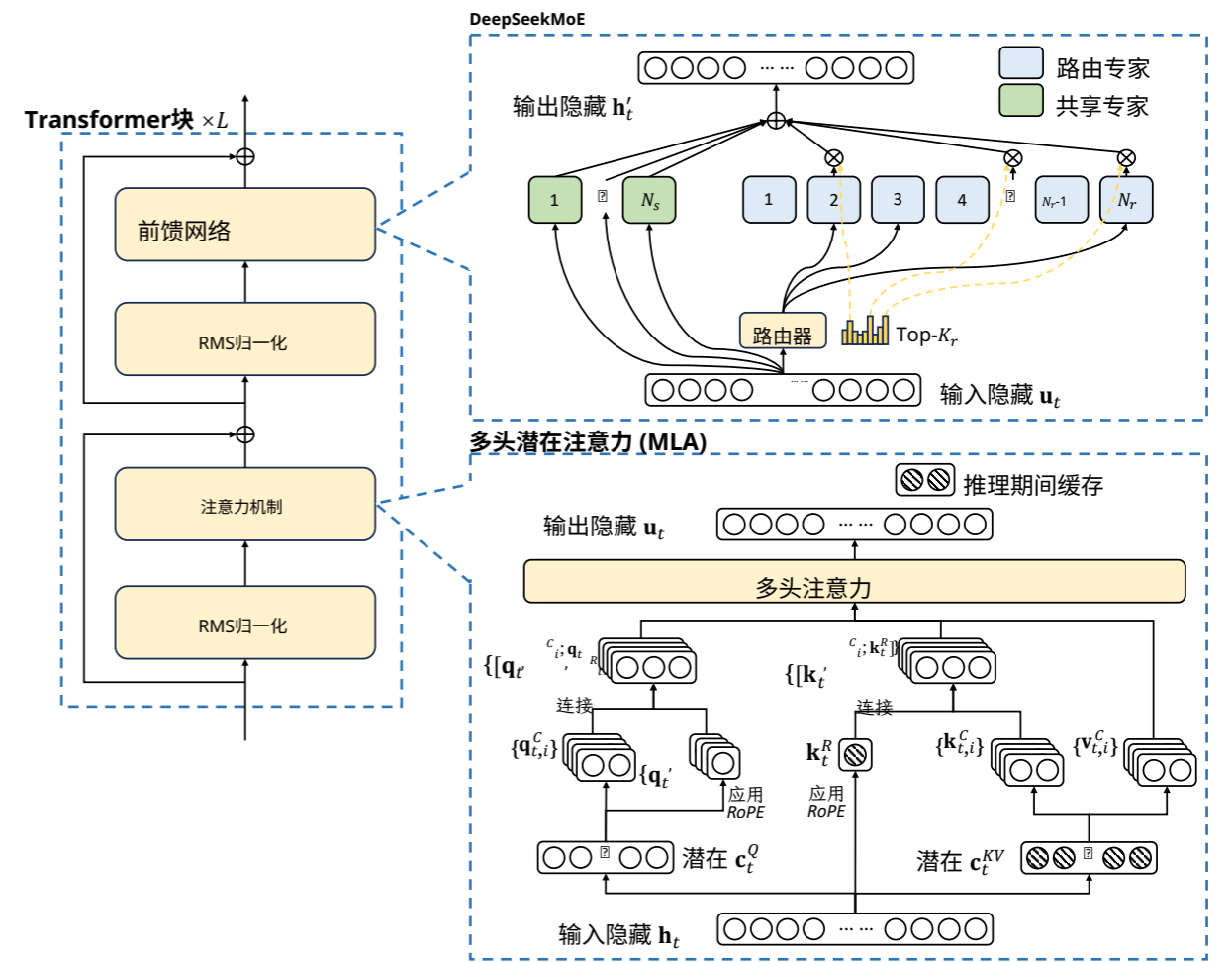


图 2 | DeepSeek-V3基本架构示意图。遵循DeepSeek-V2，我们采用MLA和DeepSeekMoE以实现高效推理和经济性训练。

DeepSeek-V3的基本架构仍然基于 Transformer (Vaswani 等人, 2017) 框架。为了实现高效的推理和经济的训练，DeepSeek-V3 也采用了 MLA 和 DeepSeekMoE，这些技术已经在 DeepSeek-V2 中得到了充分验证。与 DeepSeek-V2 相比，一个例外是我们额外引入了一种无辅助损失的负载均衡策略 (Wang 等人, 2024a)，用于缓解 DeepSeekMoE 在确保负载均衡时导致的性能下降。图 2 展示了 DeepSeek-V3 的基本架构，在本节中我们将简要回顾 MLA 和 DeepSeekMoE 的细节。

2.1.1. 多头潜在注意力

对于注意力机制，DeepSeek-V3 采用了多头潜在注意力 (MLA) 架构。令 d 表示嵌入维度， n_h 表示注意力头的数量， d_h 表示每个头的维度，以及 $\mathbf{h}_t \in \mathbb{R}^d$ 表示在给定注意力层中第 t 个 token 的注意力输入。MLA 的核心是对注意力键和值进行低秩联合压缩，以减少推理过程中的键值 (KV) 缓存：

$$\mathbf{c}_t^{KV} = W^{DKV} \mathbf{h}_t, \quad (1)$$

$$[\mathbf{k}_{t,1}^C; \mathbf{k}_{t,2}^C; \dots; \mathbf{k}_{t,n_h}^C] = \mathbf{k}_t^C = W^{UK} \mathbf{c}_t^{KV}, \quad (2)$$

$$\mathbf{k}_t^R = \text{RoPE}(W^{KR} \mathbf{h}_t), \quad (3)$$

$$\mathbf{k}_{t,i} = [\mathbf{k}_{t,i}^C; \mathbf{k}_t^R], \quad (4)$$

$$[\mathbf{v}_{t,1}^C; \mathbf{v}_{t,2}^C; \dots; \mathbf{v}_{t,n_h}^C] = \mathbf{v}_t^C = W^{UV} \mathbf{c}_t^{KV}, \quad (5)$$

where $\mathbf{c}_t^{KV} \in \mathbb{R}^{d_c}$ is the compressed latent vector for keys and values; $d_c (\ll d_h n_h)$ indicates the KV compression dimension; $W^{DKV} \in \mathbb{R}^{d_c \times d}$ denotes the down-projection matrix; $W^{UK}, W^{UV} \in \mathbb{R}^{d_h n_h \times d_c}$ are the up-projection matrices for keys and values, respectively; $W^{KR} \in \mathbb{R}^{d_h \times d}$ is the matrix used to produce the decoupled key that carries Rotary Positional Embedding (RoPE) (Su et al., 2024); $\text{RoPE}(\cdot)$ denotes the operation that applies RoPE matrices; and $[\cdot; \cdot]$ denotes concatenation. Note that for MLA, only the blue-boxed vectors (i.e., \mathbf{c}_t^{KV} and \mathbf{k}_t^R) need to be cached during generation, which results in significantly reduced KV cache while maintaining performance comparable to standard Multi-Head Attention (MHA) (Vaswani et al., 2017).

For the attention queries, we also perform a low-rank compression, which can reduce the activation memory during training:

$$\mathbf{c}_t^Q = W^{DQ} \mathbf{h}_t, \quad (6)$$

$$[\mathbf{q}_{t,1}^C; \mathbf{q}_{t,2}^C; \dots; \mathbf{q}_{t,n_h}^C] = \mathbf{q}_t^C = W^{UQ} \mathbf{c}_t^Q, \quad (7)$$

$$[\mathbf{q}_{t,1}^R; \mathbf{q}_{t,2}^R; \dots; \mathbf{q}_{t,n_h}^R] = \mathbf{q}_t^R = \text{RoPE}(W^{QR} \mathbf{c}_t^Q), \quad (8)$$

$$\mathbf{q}_{t,i} = [\mathbf{q}_{t,i}^C; \mathbf{q}_{t,i}^R], \quad (9)$$

where $\mathbf{c}_t^Q \in \mathbb{R}^{d'_c}$ is the compressed latent vector for queries; $d'_c (\ll d_h n_h)$ denotes the query compression dimension; $W^{DQ} \in \mathbb{R}^{d'_c \times d}$, $W^{UQ} \in \mathbb{R}^{d_h n_h \times d'_c}$ are the down-projection and up-projection matrices for queries, respectively; and $W^{QR} \in \mathbb{R}^{d_h \times d'_c}$ is the matrix to produce the decoupled queries that carry RoPE.

Ultimately, the attention queries ($\mathbf{q}_{t,i}$), keys ($\mathbf{k}_{j,i}$), and values ($\mathbf{v}_{j,i}^C$) are combined to yield the final attention output \mathbf{u}_t :

$$\mathbf{o}_{t,i} = \sum_{j=1}^t \text{Softmax}_j \left(\frac{\mathbf{q}_{t,i}^T \mathbf{k}_{j,i}}{\sqrt{d_h + d_h^R}} \right) \mathbf{v}_{j,i}^C, \quad (10)$$

$$\mathbf{u}_t = W^O [\mathbf{o}_{t,1}; \mathbf{o}_{t,2}; \dots; \mathbf{o}_{t,n_h}], \quad (11)$$

where $W^O \in \mathbb{R}^{d \times d_h n_h}$ denotes the output projection matrix.

2.1.2. DeepSeekMoE with Auxiliary-Loss-Free Load Balancing

Basic Architecture of DeepSeekMoE. For Feed-Forward Networks (FFNs), DeepSeek-V3 employs the DeepSeekMoE architecture (Dai et al., 2024). Compared with traditional MoE architectures like GShard (Lepikhin et al., 2021), DeepSeekMoE uses finer-grained experts and isolates some experts as shared ones. Let \mathbf{u}_t denote the FFN input of the t -th token, we compute the FFN output \mathbf{h}'_t as follows:

$$\mathbf{h}'_t = \mathbf{u}_t + \sum_{i=1}^{N_s} \text{FFN}_i^{(s)}(\mathbf{u}_t) + \sum_{i=1}^{N_r} g_{i,t} \text{FFN}_i^{(r)}(\mathbf{u}_t), \quad (12)$$

$$g_{i,t} = \frac{g'_{i,t}}{\sum_{j=1}^{N_r} g'_{j,t}}, \quad (13)$$

$$g'_{i,t} = \begin{cases} s_{i,t}, & s_{i,t} \in \text{Topk}(\{s_{j,t} | 1 \leq j \leq N_r\}, K_r), \\ 0, & \text{otherwise}, \end{cases} \quad (14)$$

$$s_{i,t} = \text{Sigmoid}(\mathbf{u}_t^T \mathbf{e}_i), \quad (15)$$

其中 $\mathbf{c}_t^{KV} \in \mathbb{R}^{d_c}$ 是键和值的压缩潜在向量； $d_c (\ll d_h n_h)$ 表示 KV 压缩维度； $W^{DKV} \in \mathbb{R}^{d_c \times d}$ 表示下投影矩阵； $W^{UK}, W^{UV} \in \mathbb{R}^{d_h n_h \times d_c}$ 分别是键和值的上投影矩阵； $W^{KR} \in \mathbb{R}^{d_h \times d}$ 是用于生成携带旋转位置嵌入 (RoPE) 的解耦键的矩阵 (Su 等人, 2024)； $\text{RoPE}(\cdot)$ 表示应用 RoPE 矩阵的操作；以及 $[\cdot; \cdot]$ 表示连接。请注意，对于 MLA，在生成过程中只需要缓存蓝色框内的向量（即 \mathbf{c}_t^{KV} 和 \mathbf{k}_t^R ），这显著减少了 KV 缓存，同时性能与标准多头注意力 (MHA) (Vaswani 等人, 2017) 相当。

对于注意力查询，我们还执行低秩压缩，这可以减少训练期间的激活内存：

$$\mathbf{c}_t^Q = W^{DQ} \mathbf{h}_t, \quad (6)$$

$$[\mathbf{q}_{t,1}^C; \mathbf{q}_{t,2}^C; \dots; \mathbf{q}_{t,n_h}^C] = \mathbf{q}_t^C = W^{UQ} \mathbf{c}_t^Q, \quad (7)$$

$$[\mathbf{q}_{t,1}^R; \mathbf{q}_{t,2}^R; \dots; \mathbf{q}_{t,n_h}^R] = \mathbf{q}_t^R = \text{RoPE}(W^{QR} \mathbf{c}_t^Q), \quad (8)$$

$$\mathbf{q}_{t,i} = [\mathbf{q}_{t,i}^C; \mathbf{q}_{t,i}^R], \quad (9)$$

其中 $\mathbf{c}_t^Q \in \mathbb{R}^{d'_c}$ 是查询的压缩隐向量； $d'_c (\ll d_h n_h)$ 表示查询压缩维度； $W^{DQ} \in \mathbb{R}^{d'_c \times d}$, $W^{UQ} \in \mathbb{R}^{d_h n_h \times d'_c}$ 分别是查询的下投影和上投影矩阵；而 $W^{QR} \in \mathbb{R}^{d_h \times d'_c}$ 是用于生成携带 RoPE 的解耦查询的矩阵。

最终，注意力查询 ($\mathbf{q}_{t,i}$)、键 ($\mathbf{k}_{j,i}$) 和值 ($\mathbf{v}_{j,i}^C$) 被组合以产生最终的注意力输出 \mathbf{u}_t ：

$$\mathbf{o}_{t,i} = \sum_{j=1}^t \text{Softmax}_j \left(\frac{\mathbf{q}_{t,i}^T \mathbf{k}_{j,i}}{\sqrt{d_h + d_h^R}} \right) \mathbf{v}_{j,i}^C, \quad (10)$$

$$\mathbf{u}_t = W^O [\mathbf{o}_{t,1}; \mathbf{o}_{t,2}; \dots; \mathbf{o}_{t,n_h}], \quad (11)$$

其中 $W^O \in \mathbb{R}^{d \times d_h n_h}$ 表示输出投影矩阵。

2.1.2. DeepSeekMoE 带有辅助损失无负载均衡

DeepSeekMoE的基本架构。 对于前馈网络 (FFNs)，DeepSeek-V3采用了DeepSeek MoE架构 (Dai等人, 2024)。与传统的MoE架构 (如GShard (Lepikhin等人, 2021)) 相比，DeepSeekMoE使用更细粒度的专家，并将一些专家隔离为共享专家。令 $\langle \mathbf{u} \rangle_t$ 表示第 t 个token的前馈网络输入，我们按如下方式计算前馈网络输出 $\langle \mathbf{u} \rangle_t$ ：

$$\mathbf{h}'_t = \mathbf{u}_t + \sum_{i=1}^{N_s} \text{FFN}_i^{(s)}(\mathbf{u}_t) + \sum_{i=1}^{N_r} g_{i,t} \text{FFN}_i^{(r)}(\mathbf{u}_t), \quad (12)$$

$$g_{i,t} = \frac{g'_{i,t}}{\sum_{j=1}^{N_r} g'_{j,t}}, \quad (13)$$

$$g'_{i,t} = \begin{cases} s_{i,t}, & s_{i,t} \in \text{Topk}(\{s_{j,t} | 1 \leq j \leq N_r\}, K_r), \\ 0, & \text{otherwise}, \end{cases} \quad (14)$$

$$s_{i,t} = \text{Sigmoid}(\mathbf{u}_t^T \mathbf{e}_i), \quad (15)$$

where N_s and N_r denote the numbers of shared experts and routed experts, respectively; $\text{FFN}_i^{(s)}(\cdot)$ and $\text{FFN}_i^{(r)}(\cdot)$ denote the i -th shared expert and the i -th routed expert, respectively; K_r denotes the number of activated routed experts; $g_{i,t}$ is the gating value for the i -th expert; $s_{i,t}$ is the token-to-expert affinity; \mathbf{e}_i is the centroid vector of the i -th routed expert; and $\text{Topk}(\cdot, K)$ denotes the set comprising K highest scores among the affinity scores calculated for the t -th token and all routed experts. Slightly different from DeepSeek-V2, DeepSeek-V3 uses the sigmoid function to compute the affinity scores, and applies a normalization among all selected affinity scores to produce the gating values.

Auxiliary-Loss-Free Load Balancing. For MoE models, an unbalanced expert load will lead to routing collapse (Shazeer et al., 2017) and diminish computational efficiency in scenarios with expert parallelism. Conventional solutions usually rely on the auxiliary loss (Fedus et al., 2021; Lepikhin et al., 2021) to avoid unbalanced load. However, too large an auxiliary loss will impair the model performance (Wang et al., 2024a). To achieve a better trade-off between load balance and model performance, we pioneer an auxiliary-loss-free load balancing strategy (Wang et al., 2024a) to ensure load balance. To be specific, we introduce a bias term b_i for each expert and add it to the corresponding affinity scores $s_{i,t}$ to determine the top- K routing:

$$g'_{i,t} = \begin{cases} s_{i,t}, & s_{i,t} + b_i \in \text{Topk}(\{s_{j,t} + b_j | 1 \leq j \leq N_r\}, K_r), \\ 0, & \text{otherwise.} \end{cases} \quad (16)$$

Note that the bias term is only used for routing. The gating value, which will be multiplied with the FFN output, is still derived from the original affinity score $s_{i,t}$. During training, we keep monitoring the expert load on the whole batch of each training step. At the end of each step, we will decrease the bias term by γ if its corresponding expert is overloaded, and increase it by γ if its corresponding expert is underloaded, where γ is a hyper-parameter called bias update speed. Through the dynamic adjustment, DeepSeek-V3 keeps balanced expert load during training, and achieves better performance than models that encourage load balance through pure auxiliary losses.

Complementary Sequence-Wise Auxiliary Loss. Although DeepSeek-V3 mainly relies on the auxiliary-loss-free strategy for load balance, to prevent extreme imbalance within any single sequence, we also employ a complementary sequence-wise balance loss:

$$\mathcal{L}_{\text{Bal}} = \alpha \sum_{i=1}^{N_r} f_i P_i, \quad (17)$$

$$f_i = \frac{N_r}{K_r T} \sum_{t=1}^T \mathbb{1}(s_{i,t} \in \text{Topk}(\{s_{j,t} | 1 \leq j \leq N_r\}, K_r)), \quad (18)$$

$$s'_{i,t} = \frac{s_{i,t}}{\sum_{j=1}^{N_r} s_{j,t}}, \quad (19)$$

$$P_i = \frac{1}{T} \sum_{t=1}^T s'_{i,t}, \quad (20)$$

where the balance factor α is a hyper-parameter, which will be assigned an extremely small value for DeepSeek-V3; $\mathbb{1}(\cdot)$ denotes the indicator function; and T denotes the number of tokens in a sequence. The sequence-wise balance loss encourages the expert load on each sequence to be balanced.

其中 N_s 和 N_r 分别表示共享专家的数量和路由专家的数量; $\text{FFN}_i^{(s)}(\cdot)$ 和 $\text{FFN}_i^{(r)}(\cdot)$ 分别表示第 i 个共享专家和第 i 个路由专家; K_r 表示激活的路由专家的数量; $g_{i,t}$ 是第 i 个专家的门控值; $s_{i,t}$ 是 token 到专家的亲和度; $\langle \mathbf{u} \rangle_i$ 是第 i 个路由专家的质心向量; $\text{Topk}(\cdot, K)$ 表示由第 t 个 token 和所有路由专家计算出的亲和度分数中前 K 高的分数组成的集合。与 DeepSeek-V2 略有不同, DeepSeek-V3 使用 Sigmoid 函数计算亲和度分数, 并在所有选定的亲和度分数之间进行归一化以生成门控值。

无辅助损失负载均衡。 对于 MoE 模型, 专家负载不平衡会导致路由崩溃 (Shazeer 等人, 2017 年) 并降低专家并行场景中的计算效率。传统解决方案通常依赖辅助损失 (Fedus 等人, 2021 年; Lepikhin 等人, 2021 年) 来避免负载不平衡。然而, 过大的辅助损失会损害模型性能 (Wang 等人, 2024a)。为了在负载均衡和模型性能之间实现更好的权衡, 我们开创了一种无辅助损失的负载均衡策略 (Wang 等人, 2024a) 来确保负载均衡。具体来说, 我们为每个专家引入一个偏差项 b_i , 并将其添加到相应的亲和度分数 $s_{i,t}$ 中, 以确定前 K 路由:

$$g'_{i,t} = \begin{cases} s_{i,t}, & s_{i,t} + b_i \in \text{Topk}(\{s_{j,t} + b_j | 1 \leq j \leq N_r\}, K_r), \\ 0, & \text{otherwise.} \end{cases} \quad (16)$$

请注意, 偏差项仅用于路由。门控值 (将与 FFN 输出相乘) 仍然来自原始亲和度分数 $s_{i,t}$ 。在训练期间, 我们持续监控每个训练步骤中整个批次上的专家负载。每步结束时, 如果其对应专家过载, 我们将偏差项减少 γ ; 如果其对应专家负载不足, 则增加 γ , 其中 γ 是一个称为偏差更新速度的超参数。通过动态调整, DeepSeek-V3 在训练期间保持平衡的专家负载, 并比那些通过纯辅助损失鼓励负载均衡的模型实现了更好的性能。

互补序列辅助损失。 尽管 DeepSeek-V3 主要依赖无辅助损失策略进行负载均衡, 但为了防止任何单个序列内出现极端不平衡, 我们还采用了一种互补序列平衡损失:

$$\mathcal{L}_{\text{Bal}} = \alpha \sum_{i=1}^{N_r} f_i P_i, \quad (17)$$

$$f_i = \frac{N_r}{K_r T} \sum_{t=1}^T \mathbb{1}(s_{i,t} \in \text{Topk}(\{s_{j,t} | 1 \leq j \leq N_r\}, K_r)), \quad (18)$$

$$s'_{i,t} = \frac{s_{i,t}}{\sum_{j=1}^{N_r} s_{j,t}}, \quad (19)$$

$$P_i = \frac{1}{T} \sum_{t=1}^T s'_{i,t}, \quad (20)$$

在 DeepSeek-V3 中, 平衡因子 α 是一个超参数, 将被分配一个极小的值; $\mathbb{1}(\cdot)$ 表示指示函数; 而 T 表示序列中的 token 数量。序列平衡损失鼓励每个序列上的专家负载保持平衡。

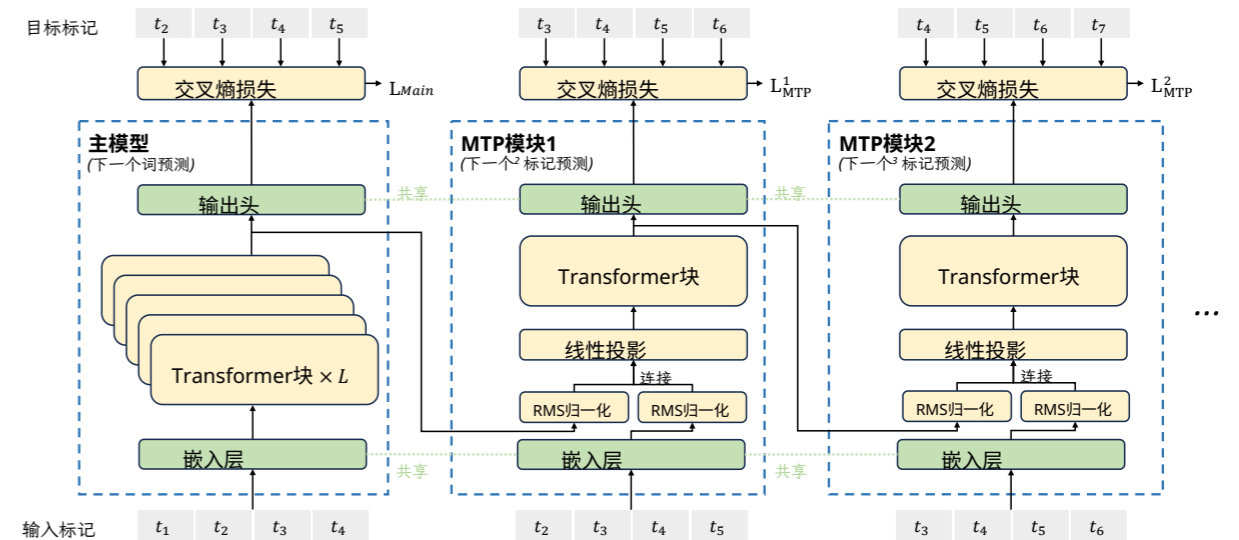
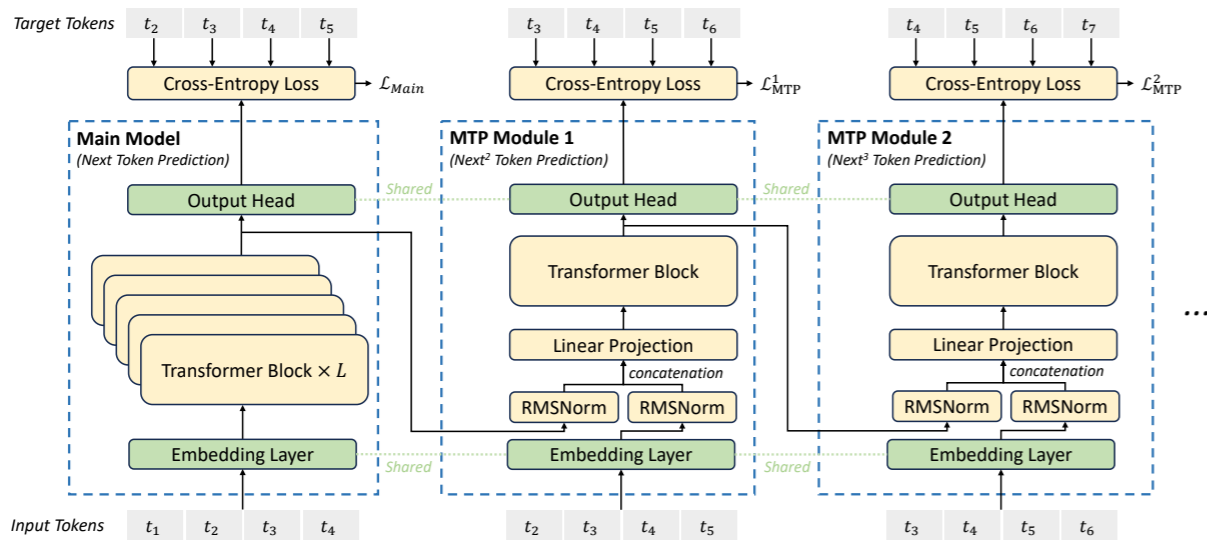


Figure 3 | Illustration of our Multi-Token Prediction (MTP) implementation. We keep the complete causal chain for the prediction of each token at each depth.

图 3 | 我们的多标记预测 (MTP) 实现的插图。我们在每个深度为每个标记的预测保留完整的因果链。

Node-Limited Routing. Like the device-limited routing used by DeepSeek-V2, DeepSeek-V3 also uses a restricted routing mechanism to limit communication costs during training. In short, we ensure that each token will be sent to at most M nodes, which are selected according to the sum of the highest $\frac{K_r}{M}$ affinity scores of the experts distributed on each node. Under this constraint, our MoE training framework can nearly achieve full computation-communication overlap.

节点限制路由。 与 DeepSeek-V2 使用的设备限制路由类似，DeepSeek-V3 也使用一种受限路由机制来限制训练过程中的通信成本。简而言之，我们确保每个 token 只会被发送到最多 M 个节点，这些节点是根据每个节点上分布的专家的最高 $\frac{K_r}{M}$ 亲和度分数之和来选择的。在此约束下，我们的 MoE 训练框架几乎可以实现完全的计算通信重叠。

No Token-Dropping. Due to the effective load balancing strategy, DeepSeek-V3 keeps a good load balance during its full training. Therefore, DeepSeek-V3 does not drop any tokens during training. In addition, we also implement specific deployment strategies to ensure inference load balance, so DeepSeek-V3 also does not drop tokens during inference.

不丢弃标记。 由于有效的负载均衡策略，DeepSeek-V3 在整个训练过程中保持良好的负载均衡。因此，DeepSeek-V3 在训练过程中不丢弃任何标记。此外，我们还实施了特定的部署策略以确保推理负载均衡，因此 DeepSeek-V3 在推理过程中也不丢弃标记。

2.2. Multi-Token Prediction

2.2. 多标记预测

Inspired by Gloeckle et al. (2024), we investigate and set a Multi-Token Prediction (MTP) objective for DeepSeek-V3, which extends the prediction scope to multiple future tokens at each position. On the one hand, an MTP objective densifies the training signals and may improve data efficiency. On the other hand, MTP may enable the model to pre-plan its representations for better prediction of future tokens. Figure 3 illustrates our implementation of MTP. Different from Gloeckle et al. (2024), which parallelly predicts D additional tokens using independent output heads, we sequentially predict additional tokens and keep the complete causal chain at each prediction depth. We introduce the details of our MTP implementation in this section.

受Gloeckle等人(2024)的启发，我们研究了为DeepSeek-V3设置多标记预测(MTP)目标，该目标将预测范围扩展到每个位置的多个未来标记。一方面，MTP目标使训练信号更加密集，并可能提高数据效率。另一方面，MTP可能使模型能够预先规划其表示，从而更好地预测未来标记。图3说明了我们的MTP实现。与Gloeckle等人(2024)并行地使用独立的输出头预测 D 额外标记不同，我们顺序地预测额外标记，并在每个预测深度保持完整的因果链。我们在本节中介绍了我们的MTP实现的细节。

MTP Modules. To be specific, our MTP implementation uses D sequential modules to predict D additional tokens. The k -th MTP module consists of a shared embedding layer $\text{Emb}(\cdot)$, a shared output head $\text{OutHead}(\cdot)$, a Transformer block $\text{TRM}_k(\cdot)$, and a projection matrix $M_k \in \mathbb{R}^{d \times 2d}$. For the i -th input token t_i , at the k -th prediction depth, we first combine the representation of the i -th token at the $(k-1)$ -th depth $\mathbf{h}_i^{k-1} \in \mathbb{R}^d$ and the embedding of the $(i+k)$ -th token $\text{Emb}(t_{i+k}) \in \mathbb{R}^d$

MTP模块。 具体来说，我们的MTP实现使用 D 序列模块来预测 D 额外标记。第 k -个MTP模块由一个共享的嵌入层 $\text{Emb}(\cdot)$ 、一个共享的输出头 $\text{OutHead}(\cdot)$ 、一个Transformer块 $\text{TRM}_k(\cdot)$ 和一个投影矩阵 $M_k \in \mathbb{R}^{d \times 2d}$ 组成。对于第 i -个输入标记 t_i ，在第 k -个预测深度，我们首先将第 i -个标记在第 $(k-1)$ -个深度的表示 $\mathbf{h}_i^{k-1} \in \mathbb{R}^d$ 与第 $(i+k)$ -个标记 $\text{Emb}(t_{i+k}) \in \mathbb{R}^d$ 的嵌入结合起来

with the linear projection:

$$\mathbf{h}_i'^k = M_k[\text{RMSNorm}(\mathbf{h}_i^{k-1}); \text{RMSNorm}(\text{Emb}(t_{i+k}))], \quad (21)$$

where $[\cdot; \cdot]$ denotes concatenation. Especially, when $k = 1$, \mathbf{h}_i^{k-1} refers to the representation given by the main model. Note that for each MTP module, its embedding layer is shared with the main model. The combined $\mathbf{h}_i'^k$ serves as the input of the Transformer block at the k -th depth to produce the output representation at the current depth \mathbf{h}_i^k :

$$\mathbf{h}_{1:T-k}^k = \text{TRM}_k(\mathbf{h}_{1:T-k}'^k), \quad (22)$$

where T represents the input sequence length and $i:j$ denotes the slicing operation (inclusive of both the left and right boundaries). Finally, taking \mathbf{h}_i^k as the input, the shared output head will compute the probability distribution for the k -th additional prediction token $p_{i+k}^k \in \mathbb{R}^V$, where V is the vocabulary size:

$$p_{i+k}^k = \text{OutHead}(\mathbf{h}_i^k). \quad (23)$$

The output head $\text{OutHead}(\cdot)$ linearly maps the representation to logits and subsequently applies the $\text{Softmax}(\cdot)$ function to compute the prediction probabilities of the k -th additional token. Also, for each MTP module, its output head is shared with the main model. Our principle of maintaining the causal chain of predictions is similar to that of EAGLE (Li et al., 2024b), but its primary objective is speculative decoding (Leviathan et al., 2023; Xia et al., 2023), whereas we utilize MTP to improve training.

MTP Training Objective. For each prediction depth, we compute a cross-entropy loss $\mathcal{L}_{\text{MTP}}^k$:

$$\mathcal{L}_{\text{MTP}}^k = \text{CrossEntropy}(P_{2+k:T+1}^k, t_{2+k:T+1}) = -\frac{1}{T} \sum_{i=2+k}^{T+1} \log P_i^k[t_i], \quad (24)$$

where T denotes the input sequence length, t_i denotes the ground-truth token at the i -th position, and $P_i^k[t_i]$ denotes the corresponding prediction probability of t_i , given by the k -th MTP module. Finally, we compute the average of the MTP losses across all depths and multiply it by a weighting factor λ to obtain the overall MTP loss \mathcal{L}_{MTP} , which serves as an additional training objective for DeepSeek-V3:

$$\mathcal{L}_{\text{MTP}} = \frac{\lambda}{D} \sum_{k=1}^D \mathcal{L}_{\text{MTP}}^k. \quad (25)$$

MTP in Inference. Our MTP strategy mainly aims to improve the performance of the main model, so during inference, we can directly discard the MTP modules and the main model can function independently and normally. Additionally, we can also repurpose these MTP modules for speculative decoding to further improve the generation latency.

3. Infrastructures

3.1. Compute Clusters

DeepSeek-V3 is trained on a cluster equipped with 2048 NVIDIA H800 GPUs. Each node in the H800 cluster contains 8 GPUs connected by NVLink and NVSwitch within nodes. Across different nodes, InfiniBand (IB) interconnects are utilized to facilitate communications.

进行线性投影:

$$\mathbf{h}_i'^k = M_k[\text{RMSNorm}(\mathbf{h}_i^{k-1}); \text{RMSNorm}(\text{Emb}(t_{i+k}))], \quad (21)$$

$[\cdot; \cdot]$ 表示连接。特别是, 当 $k = 1$ 时, \mathbf{h}_i^{k-1} 指由主模型给出的表示。请注意, 对于每个MTP模块, 其嵌入层与主模型共享。组合的 $\mathbf{h}_i'^k$ 作为第 k 层的Transformer块的输入, 以产生当前深度的输出表示 \mathbf{h}_i^k :

$$\mathbf{h}_{1:T-k}^k = \text{TRM}_k(\mathbf{h}_{1:T-k}'^k), \quad (22)$$

其中 T 表示输入序列长度, $i:j$ 表示切片操作 (包含左右边界)。最后, 以 \mathbf{h}_i^k 为输入, 共享的输出头将计算第 k 个附加预测标记 $p_{i+k}^k \in \mathbb{R}^V$ 的概率分布, 其中 V 是词汇量:

$$p_{i+k}^k = \text{OutHead}(\mathbf{h}_i^k). \quad (23)$$

输出头 $\text{OutHead}(\cdot)$ 将表示线性映射为logits, 并随后应用 $\text{Softmax}(\cdot)$ 函数来计算第 k 个附加标记的预测概率。此外, 对于每个MTP模块, 其输出头与主模型共享。我们保持预测因果链的原则与EAGLE (Li等人, 2024b) 相似, 但其主要目标是推测解码 (Leviathan等人, 2023; Xia等人, 2023), 而我们利用MTP来改进训练。

MTP训练目标。 对于每个预测深度, 我们计算交叉熵损失 $\mathcal{L}_{\text{MTP}}^k$:

$$\mathcal{L}_{\text{MTP}}^k = \text{CrossEntropy}(P_{2+k:T+1}^k, t_{2+k:T+1}) = -\frac{1}{T} \sum_{i=2+k}^{T+1} \log P_i^k[t_i], \quad (24)$$

其中 T 表示输入序列长度, t_i 表示第 i 个位置的真实标记, $P_i^k[t_i]$ 表示由第 k 个MTP模块给出的 t_i 对应的预测概率。最后, 我们计算所有深度的MTP损失的均值, 并将其乘以权重因子 λ , 得到整体MTP损失 \mathcal{L}_{MTP} , 该损失作为DeepSeek-V3的附加训练目标:

$$\mathcal{L}_{\text{MTP}} = \frac{\lambda}{D} \sum_{k=1}^D \mathcal{L}_{\text{MTP}}^k. \quad (25)$$

MTP推理。 我们的MTP策略主要旨在提高主模型的性能, 因此在推理期间, 我们可以直接丢弃MTP模块, 主模型可以独立且正常运行。此外, 我们还可以将这些MTP模块用于推测解码, 以进一步提高生成延迟。

3. 基础设施

3.1. 计算集群

DeepSeek-V3 在一个配备了 2048 块 NVIDIA H800 GPU 的集群上进行训练。H800 集群中的每个节点包含 8 块 GPU, 这些 GPU 通过 NVLink 和节点内的 NVSwitch 连接。在不同的节点之间, 则利用 InfiniBand (IB) 互连来促进通信。

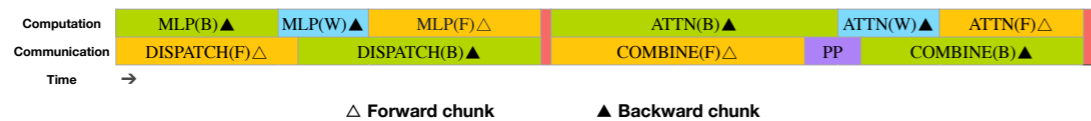


Figure 4 | Overlapping strategy for a pair of individual forward and backward chunks (the boundaries of the transformer blocks are not aligned). Orange denotes forward, green denotes "backward for input", blue denotes "backward for weights", purple denotes PP communication, and red denotes barriers. Both all-to-all and PP communication can be fully hidden.

3.2. Training Framework

The training of DeepSeek-V3 is supported by the HAI-LLM framework, an efficient and lightweight training framework crafted by our engineers from the ground up. On the whole, DeepSeek-V3 applies 16-way Pipeline Parallelism (PP) (Qi et al., 2023a), 64-way Expert Parallelism (EP) (Lepikhin et al., 2021) spanning 8 nodes, and ZeRO-1 Data Parallelism (DP) (Rajbhandari et al., 2020).

In order to facilitate efficient training of DeepSeek-V3, we implement meticulous engineering optimizations. Firstly, we design the DualPipe algorithm for efficient pipeline parallelism. Compared with existing PP methods, DualPipe has fewer pipeline bubbles. More importantly, it overlaps the computation and communication phases across forward and backward processes, thereby addressing the challenge of heavy communication overhead introduced by cross-node expert parallelism. Secondly, we develop efficient cross-node all-to-all communication kernels to fully utilize IB and NVLink bandwidths and conserve Streaming Multiprocessors (SMs) dedicated to communication. Finally, we meticulously optimize the memory footprint during training, thereby enabling us to train DeepSeek-V3 without using costly Tensor Parallelism (TP).

3.2.1. DualPipe and Computation-Communication Overlap

For DeepSeek-V3, the communication overhead introduced by cross-node expert parallelism results in an inefficient computation-to-communication ratio of approximately 1:1. To tackle this challenge, we design an innovative pipeline parallelism algorithm called DualPipe, which not only accelerates model training by effectively overlapping forward and backward computation-communication phases, but also reduces the pipeline bubbles.

The key idea of DualPipe is to overlap the computation and communication within a pair of individual forward and backward chunks. To be specific, we divide each chunk into four components: attention, all-to-all dispatch, MLP, and all-to-all combine. Specially, for a backward chunk, both attention and MLP are further split into two parts, backward for input and backward for weights, like in ZeroBubble (Qi et al., 2023b). In addition, we have a PP communication component. As illustrated in Figure 4, for a pair of forward and backward chunks, we rearrange these components and manually adjust the ratio of GPU SMs dedicated to communication versus computation. In this overlapping strategy, we can ensure that both all-to-all and PP communication can be fully hidden during execution. Given the efficient overlapping strategy, the full DualPipe scheduling is illustrated in Figure 5. It employs a bidirectional pipeline scheduling, which feeds micro-batches from both ends of the pipeline simultaneously and a significant portion of communications can be fully overlapped. This overlap also ensures that, as the model further scales up, as long as we maintain a constant computation-to-communication ratio, we can still employ fine-grained experts across nodes while achieving a near-zero all-to-all communication overhead.

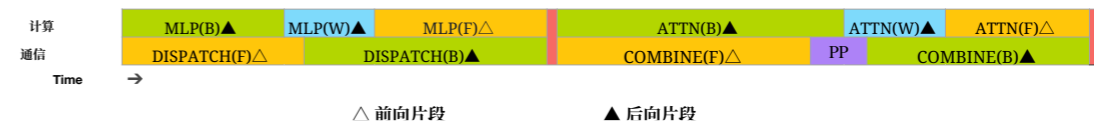


图 4 | 一对多前向和后向片段的重叠策略 (Transformer块的边界未对齐)。橙色表示前向, 绿色表示“输入后向”, 蓝色表示“权重后向”, 紫色表示PP通信, 红色表示屏障。全对全和PP通信都可以完全隐藏。

3.2. 训练框架

DeepSeek-V3 的训练得到了 HAI-LLM 框架的支持, 这是一个由我们工程师从零开始精心打造的、高效且轻量级的训练框架。总体而言, DeepSeek-V3 应用 16 路流水线并行 (PP)(Qi et al., 2023a)、64 路专家并行 (EP) (Lepikhin et al., 2021), 跨越 8 个节点, 以及 ZeRO-1 数据并行 (DP) (Rajbhandari et al., 2020)。

为了促进DeepSeek-V3的高效训练, 我们实施了细致的工程优化。首先, 我们设计了DualPipe算法以实现高效的流水线并行。与现有的PP方法相比, DualPipe的流水线气泡更少。更重要的是, 它在前向和后向过程中重叠计算和通信阶段, 从而解决了跨节点专家并行引入的通信开销过大的挑战。其次, 我们开发了高效的多节点全对全通信内核, 以充分利用IB和NVLink带宽并节省用于通信的流式多处理器 (SM)。最后, 我们细致地优化了训练期间的内存占用, 从而使我们能够不使用昂贵的张量并行 (TP) 的情况下训练DeepSeek-V3。

3.2.1. DualPipe 和 计算通信重叠

对于 DeepSeek-V3, 跨节点专家并行引入的通信开销导致计算与通信比率约为 1:1, 效率低下。为应对这一挑战, 我们设计了一种名为 DualPipe 的创新流水线并行算法, 该算法不仅通过有效重叠前向和后向计算通信阶段加速模型训练, 还减少了流水线气泡。

DualPipe 的关键思想是在一对独立的正向和反向块中重叠计算和通信。具体来说, 我们将每个块分为四个组件: attention、all-to-all dispatch、MLP 和 all-to-all combine。特别地, 对于反向块, attention 和 MLP 都进一步分为两个部分, backward for input 和 backward for weights, 就像 ZeroBubble (Qi 等人, 2023b) 中那样。此外, 我们还有一个 PP communication 组件。如图 4 所示, 对于一对正向和反向块, 我们重新排列这些组件, 并手动调整用于通信和计算的 GPU SM 的比例。在这种重叠策略中, 我们可以确保在执行期间所有对全和 PP 通信都可以完全隐藏。鉴于高效的 overlap 策略, 完整的 DualPipe 调度如图 5 所示。它采用双向管道调度, 同时从管道的两端为微批次供能, 并且大部分通信可以完全重叠。这种重叠还确保了, 随着模型进一步扩展, 只要我们保持计算与通信的恒定比例, 我们仍然可以在节点上采用细粒度专家, 同时实现近零的所有对全通信开销。



Figure 5 | Example DualPipe scheduling for 8 PP ranks and 20 micro-batches in two directions. The micro-batches in the reverse direction are symmetric to those in the forward direction, so we omit their batch ID for illustration simplicity. Two cells enclosed by a shared black border have mutually overlapped computation and communication.

Method	Bubble	Parameter	Activation
1F1B	$(PP - 1)(F + B)$	$1\times$	PP
ZB1P	$(PP - 1)(F + B - 2W)$	$1\times$	PP
DualPipe (Ours)	$(\frac{PP}{2} - 1)(F+B + B - 3W)$	$2\times$	$PP + 1$

Table 2 | Comparison of pipeline bubbles and memory usage across different pipeline parallel methods. F denotes the execution time of a forward chunk, B denotes the execution time of a full backward chunk, W denotes the execution time of a "backward for weights" chunk, and $F\&B$ denotes the execution time of two mutually overlapped forward and backward chunks.

In addition, even in more general scenarios without a heavy communication burden, DualPipe still exhibits efficiency advantages. In Table 2, we summarize the pipeline bubbles and memory usage across different PP methods. As shown in the table, compared with ZB1P (Qi et al., 2023b) and 1F1B (Harlap et al., 2018), DualPipe significantly reduces the pipeline bubbles while only increasing the peak activation memory by $\frac{1}{PP}$ times. Although DualPipe requires keeping two copies of the model parameters, this does not significantly increase the memory consumption since we use a large EP size during training. Compared with Chimera (Li and Hoefler, 2021), DualPipe only requires that the pipeline stages and micro-batches be divisible by 2, without requiring micro-batches to be divisible by pipeline stages. In addition, for DualPipe, neither the bubbles nor activation memory will increase as the number of micro-batches grows.

3.2.2. Efficient Implementation of Cross-Node All-to-All Communication

In order to ensure sufficient computational performance for DualPipe, we customize efficient cross-node all-to-all communication kernels (including dispatching and combining) to conserve the number of SMs dedicated to communication. The implementation of the kernels is co-designed with the MoE gating algorithm and the network topology of our cluster. To be specific, in our cluster, cross-node GPUs are fully interconnected with IB, and intra-node communications are handled via NVLink. NVLink offers a bandwidth of 160 GB/s, roughly 3.2 times that of IB (50 GB/s). To effectively leverage the different bandwidths of IB and NVLink, we limit each token to be dispatched to at most 4 nodes, thereby reducing IB traffic. For each token, when its routing decision is made, it will first be transmitted via IB to the GPUs with the same in-node index on its target nodes. Once it reaches the target nodes, we will endeavor to ensure that it is instantaneously forwarded via NVLink to specific GPUs that host their target experts, without being blocked by subsequently arriving tokens. In this way, communications via IB and NVLink are fully overlapped, and each token can efficiently select an average of 3.2 experts per node without incurring additional overhead from NVLink. This implies that, although DeepSeek-V3



图 5 | 示例DualPipe调度，针对8个PP等级和两个方向中的20个微批次。反向方向的微批次与正向方向的微批次对称，因此为简洁起见，我们省略了它们的批次ID。两个由共享黑色边框包围的单元具有相互重叠的计算和通信。

方法	气泡	参数	激活
1F1B	$(PP - 1)(F + B)$	$1\times$	PP
ZB1P	$(PP - 1)(F + B - 2W)$	$1\times$	PP
DualPipe (我们的)	$(\frac{PP}{2} - 1)(F+B + B - 3W)$	$2\times$	$PP + 1$

表 2 | 不同管道并行方法的管道气泡和内存使用比较。 F 表示正向块的执行时间， B 表示完整反向块的执行时间， W 表示“反向用于权重”块的执行时间， $F\&B$ 表示两个相互重叠的正向和反向块的执行时间。

此外，即使在通信负担更普遍的场景中，DualPipe 仍然展现出效率优势。在表 2 中，我们总结了不同 PP 方法下的流水线气泡和内存使用情况。如表所示，与 ZB1P (Qi 等人, 2023b) 和 1F1B (Harlap 等人, 2018) 相比，DualPipe 显著减少了流水线气泡，同时仅将峰值激活内存增加了 $\frac{1}{PP}$ 倍。尽管 DualPipe 需要保留模型参数的两个副本，但由于我们在训练期间使用了较大的 EP 大小，这并不会显著增加内存消耗。与 Chimera (Li 和 Hoefler, 2021) 相比，DualPipe 仅要求流水线阶段和微批次能被 2 整除，而无需微批次能被流水线阶段整除。此外，对于 DualPipe，随着微批次数量的增加，气泡和激活内存都不会增加。

3.2.2. 跨节点全对全通信的高效实现

为了确保 DualPipe 具备足够的计算性能，我们定制了高效的跨节点全对全通信内核（包括调度和合并），以节省用于通信的 SM 数量。这些内核的实现与 MoE 门控算法和集群的网络拓扑协同设计。具体来说，在我们的集群中，跨节点 GPU 通过 IB 完全互联，而节点内通信则通过 NVLink 处理。NVLink 提供 160 GB/s 的带宽，大约是 IB (50 GB/s) 的 3.2 倍。为了有效利用 IB 和 NVLink 的不同带宽，我们将每个 token 限制最多调度到 4 个节点，从而减少 IB 流量。对于每个 token，当其路由决策做出时，会首先通过 IB 传输到目标节点上具有相同节点内索引的 GPU。一旦到达目标节点，我们将尽力确保它通过 NVLink 立即转发到承载其目标专家的特定 GPU，而不会被后续到达的 token 阻塞。通过这种方式，IB 和 NVLink 的通信完全重叠，每个 token 可以高效地选择每个节点平均 3.2 个专家，而不会产生额外的 NVLink 开销。这意味着，尽管 DeepSeek-V3 实际上只选择 8 个路由专家，但它可以将这个数量扩展到最多 13 个专家 (4 个节点 {v1}.2 个专家/节点)，同时保持相同的通信成本。总体而言，在这种通信策略下，只需要 20 个 SM 就足以完全利用 IB 和 NVLink 的带宽。

selects only 8 routed experts in practice, it can scale up this number to a maximum of 13 experts (4 nodes \times 3.2 experts/node) while preserving the same communication cost. Overall, under such a communication strategy, only 20 SMs are sufficient to fully utilize the bandwidths of IB and NVLink.

In detail, we employ the warp specialization technique (Bauer et al., 2014) and partition 20 SMs into 10 communication channels. During the dispatching process, (1) IB sending, (2) IB-to-NVLink forwarding, and (3) NVLink receiving are handled by respective warps. The number of warps allocated to each communication task is dynamically adjusted according to the actual workload across all SMs. Similarly, during the combining process, (1) NVLink sending, (2) NVLink-to-IB forwarding and accumulation, and (3) IB receiving and accumulation are also handled by dynamically adjusted warps. In addition, both dispatching and combining kernels overlap with the computation stream, so we also consider their impact on other SM computation kernels. Specifically, we employ customized PTX (Parallel Thread Execution) instructions and auto-tune the communication chunk size, which significantly reduces the use of the L2 cache and the interference to other SMs.

3.2.3. Extremely Memory Saving with Minimal Overhead

In order to reduce the memory footprint during training, we employ the following techniques.

Recomputation of RMSNorm and MLA Up-Projection. We recompute all RMSNorm operations and MLA up-projections during back-propagation, thereby eliminating the need to persistently store their output activations. With a minor overhead, this strategy significantly reduces memory requirements for storing activations.

Exponential Moving Average in CPU. During training, we preserve the Exponential Moving Average (EMA) of the model parameters for early estimation of the model performance after learning rate decay. The EMA parameters are stored in CPU memory and are updated asynchronously after each training step. This method allows us to maintain EMA parameters without incurring additional memory or time overhead.

Shared Embedding and Output Head for Multi-Token Prediction. With the DualPipe strategy, we deploy the shallowest layers (including the embedding layer) and deepest layers (including the output head) of the model on the same PP rank. This arrangement enables the physical sharing of parameters and gradients, of the shared embedding and output head, between the MTP module and the main model. This physical sharing mechanism further enhances our memory efficiency.

3.3. FP8 Training

Inspired by recent advances in low-precision training (Dettmers et al., 2022; Noune et al., 2022; Peng et al., 2023b), we propose a fine-grained mixed precision framework utilizing the FP8 data format for training DeepSeek-V3. While low-precision training holds great promise, it is often limited by the presence of outliers in activations, weights, and gradients (Fishman et al., 2024; He et al.; Sun et al., 2024). Although significant progress has been made in inference quantization (Frantar et al., 2022; Xiao et al., 2023), there are relatively few studies demonstrating successful application of low-precision techniques in large-scale language model

选择 8 个路由专家，但它可以将这个数量扩展到最多 13 个专家（4 个节点 \times 3.2 个专家/节点），同时保持相同的通信成本。总体而言，在这种通信策略下，只需要 20 个 SM 就足以完全利用 IB 和 NVLink 的带宽。

具体来说，我们采用warp特殊化技术（Bauer等人，2014年）将20个SM分区为10个通信通道。在调度过程中，(1) IB发送、(2) IB至NVLink转发以及(3) NVLink接收均由各自的warp处理。分配给每个通信任务的warp数量会根据所有SM的实际工作负载动态调整。类似地，在合并过程中，(1) NVLink发送、(2) NVLink至IB转发与累加以及(3) IB接收与累加也由动态调整的warp处理。此外，调度和合并内核与计算流重叠，因此我们也考虑它们对其他SM计算内核的影响。具体而言，我们采用定制的PTX（并行线程执行）指令并自动调整通信块大小，这显著减少了L2缓存的利用率以及对其他SM的干扰。

3.2.3. 极致内存节省与最小开销

为了 为减少训练过程中的内存占用，我们采用以下技术 s.

RMS归一化和多头潜在注意力向上投影的重新计算。 我们在反向传播期间重新计算所有RMS归一化操作和多头潜在注意力向上投影，从而消除了持续存储其输出激活的需求。以轻微的开销，这种策略显著降低了存储激活所需的内存需求。

CPU中的指数移动平均。 在训练过程中，我们保留模型的参数指数移动平均（EMA），以便在学习率衰减后对模型性能进行早期估计。EMA参数存储在CPU内存中，并在每次训练步骤后异步更新。这种方法使我们能够在不产生额外内存或时间开销的情况下维护EMA参数。

用于多标记预测的共享嵌入层和输出头。 通过DualPipe策略，我们将模型的浅层（包括嵌入层）和深层（包括输出头）部署在同一个PP rank上。这种安排使得共享嵌入层和输出头之间的参数和梯度能够进行物理共享，MTP模块和主模型之间能够共享这些物理共享的参数和梯度。这种物理共享机制进一步提高了我们的内存效率。

3.3. FP8训练

受近期低精度训练进展的启发（Dettmers等人，2022；Noune等人，2022；彭等人，2023b），我们提出了一种利用FP8数据格式进行DeepSeek-V3训练的细粒度混合精度框架。虽然低精度训练具有巨大潜力，但在激活值、权重和梯度中存在异常值时往往受到限制（Fishman等人，2024；He等人；Sun等人，2024）。尽管推理量化已取得显著进展（Frantar等人，2022；Xiao等人，2023），但展示低精度技术在大型语言模型中成功应用的研究相对较少

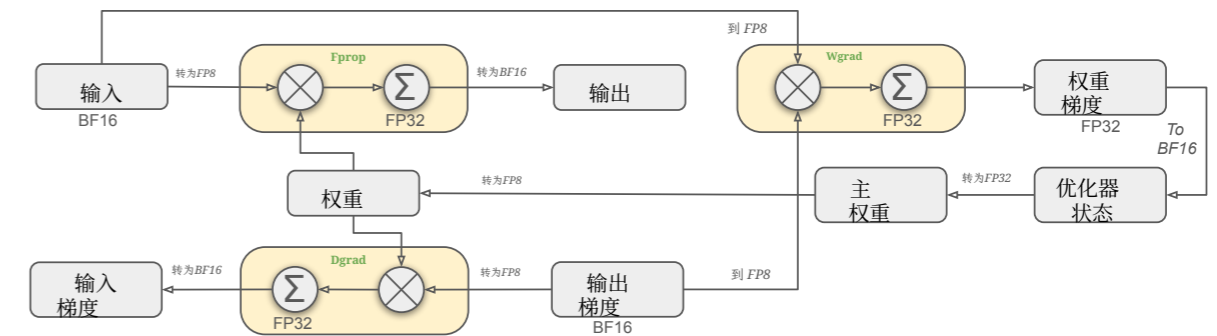
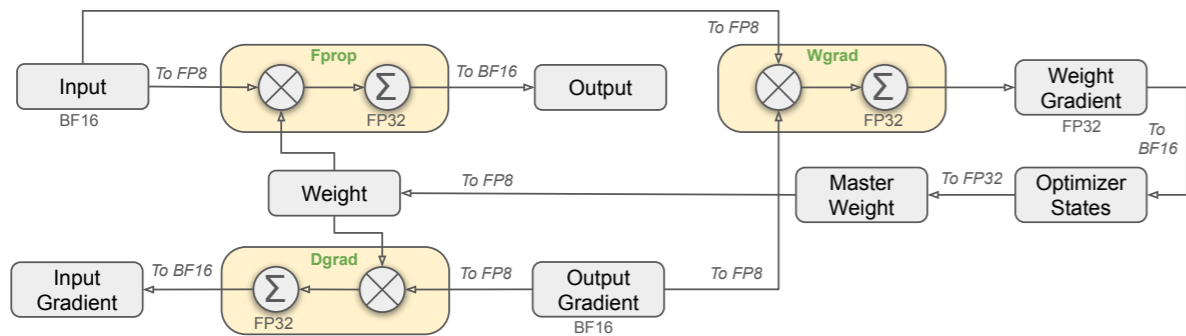


Figure 6 | The overall mixed precision framework with FP8 data format. For clarification, only the Linear operator is illustrated.

图 6 | 整体混合精度框架，采用FP8数据格式。为清晰起见，仅绘制了 Linear 算子。

pre-training (Fishman et al., 2024). To address this challenge and effectively extend the dynamic range of the FP8 format, we introduce a fine-grained quantization strategy: tile-wise grouping with $1 \times N_c$ elements or block-wise grouping with $N_c \times N_c$ elements. The associated dequantization overhead is largely mitigated under our increased-precision accumulation process, a critical aspect for achieving accurate FP8 General Matrix Multiplication (GEMM). Moreover, to further reduce memory and communication overhead in MoE training, we cache and dispatch activations in FP8, while storing low-precision optimizer states in BF16. We validate the proposed FP8 mixed precision framework on two model scales similar to DeepSeek-V2-Lite and DeepSeek-V2, training for approximately 1 trillion tokens (see more details in Appendix B.1). Notably, compared with the BF16 baseline, the relative loss error of our FP8-training model remains consistently below 0.25%, a level well within the acceptable range of training randomness.

预训练 (Fishman 等人, 2024年)。为应对这一挑战并有效扩展FP8格式的动态范围, 我们引入了一种细粒度量策略: 以 $1 \times N_c$ 个元素为单位的分块分组或以 $N_c \times N_c$ 个元素为单位的区域分组。相关的解量化开销在我们的高精度累积过程中得到大幅缓解, 这是实现精确FP8通用矩阵乘法 (GEMM) 的关键。此外, 为进一步降低MoE训练中的内存和通信开销, 我们在FP8中缓存和调度激活值, 同时将低精度优化器状态存储在BF16中。我们在两个与DeepSeek-V2-Lite和DeepSeek-V2相似的模型规模上验证了所提出的FP8混合精度框架, 训练约1万亿个token (更多细节见附录B.1)。值得注意的是, 与BF16基线相比, 我们FP8训练模型的相对损失误差始终保持在0.25%以下, 这一水平完全在训练随机性的可接受范围内。

3.3.1. Mixed Precision Framework

3.3.1. 混合精度框架

Building upon widely adopted techniques in low-precision training (Kalamkar et al., 2019; Narang et al., 2017), we propose a mixed precision framework for FP8 training. In this framework, most compute-density operations are conducted in FP8, while a few key operations are strategically maintained in their original data formats to balance training efficiency and numerical stability. The overall framework is illustrated in Figure 6.

基于在低精度训练中广泛采用的成熟技术 (Kalamkar 等人, 2019年; Narang 等人, 2017年), 我们提出了一种用于FP8训练的混合精度框架。在该框架中, 大部分计算密集型操作在FP8中执行, 而少数关键操作则策略性地保留其原始数据格式, 以平衡训练效率和数值稳定性。整体框架如图6所示。

Firstly, in order to accelerate model training, the majority of core computation kernels, i.e., GEMM operations, are implemented in FP8 precision. These GEMM operations accept FP8 tensors as inputs and produce outputs in BF16 or FP32. As depicted in Figure 6, all three GEMMs associated with the Linear operator, namely Fprop (forward pass), Dgrad (activation backward pass), and Wgrad (weight backward pass), are executed in FP8. This design theoretically doubles the computational speed compared with the original BF16 method. Additionally, the FP8 Wgrad GEMM allows activations to be stored in FP8 for use in the backward pass. This significantly reduces memory consumption.

首先, 为了加速模型训练, 大部分核心计算内核, 即GEMM操作, 均以FP8精度实现。这些GEMM操作接受FP8张量作为输入, 并产生BF16或FP32格式的输出。如图6所示, 与 Linear 操作相关的三个GEMM, 即 Fprop (前向传递)、Dgrad (激活反向传递) 和 Wgrad (权重反向传递), 均以FP8执行。理论上, 与原始BF16方法相比, 这种设计将计算速度翻倍。此外, FP8 WgradGEMM允许激活值以FP8格式存储, 用于反向传递。这显著降低了内存消耗。

Despite the efficiency advantage of the FP8 format, certain operators still require a higher precision due to their sensitivity to low-precision computations. Besides, some low-cost operators can also utilize a higher precision with a negligible overhead to the overall training cost. For this reason, after careful investigations, we maintain the original precision (e.g., BF16 or FP32) for the following components: the embedding module, the output head, MoE gating modules, normalization operators, and attention operators. These targeted retentions of high precision ensure stable training dynamics for DeepSeek-V3. To further guarantee numerical stability, we store the master weights, weight gradients, and optimizer states in higher precision. While

尽管FP8格式具有效率优势, 但某些算子仍需更高精度, 因为它们对低精度计算较为敏感。此外, 一些低成本算子也可以通过略微增加整体训练成本来利用更高精度。为此, 在经过仔细研究后, 我们为以下组件保留了原始精度 (例如BF16或FP32): 嵌入模块、输出头、MoE门控模块、归一化算子和注意力算子。这些针对性的高精度保留确保了DeepSeek-V3的稳定训练动态。为了进一步保证数值稳定性, 我们将主权重、权重梯度和优化器状态存储在更高精度中。虽然

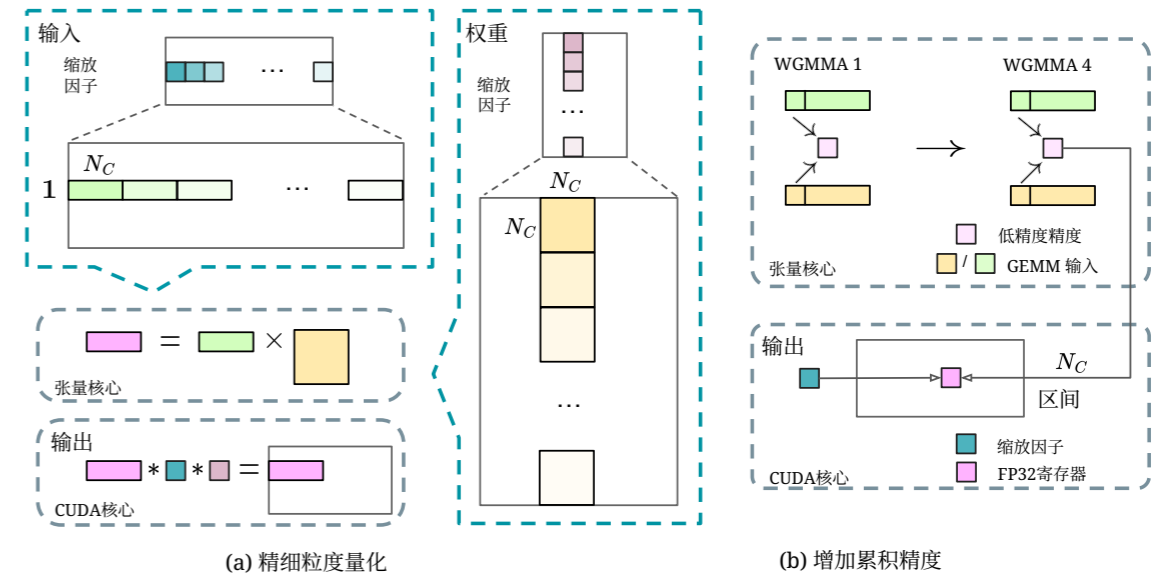
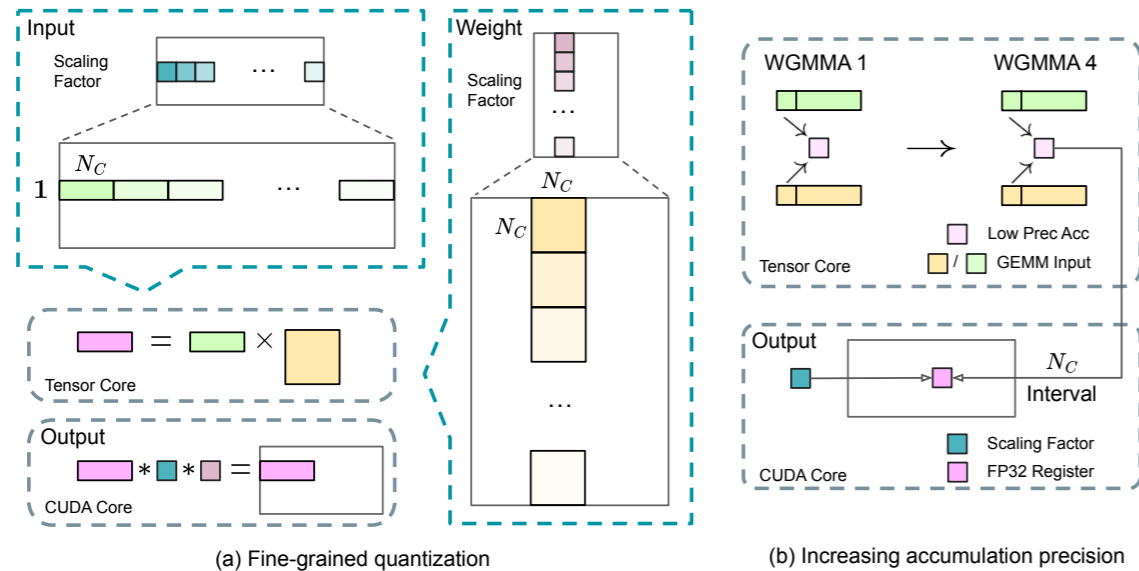


Figure 7 | (a) We propose a fine-grained quantization method to mitigate quantization errors caused by feature outliers; for illustration simplicity, only Fprop is illustrated. (b) In conjunction with our quantization strategy, we improve the FP8 GEMM precision by promoting to CUDA Cores at an interval of $N_C = 128$ elements MMA for the high-precision accumulation.

图 7 | (a) 我们提出了一种精细粒度量化方法，以减轻由特征异常值引起的量化误差；为简单起见，仅说明了 Fprop。(b) 与我们的量化策略相结合，我们通过将高精度累积的 $N_C = 128$ 个元素 MMA 提升到 CUDA 核心，从而提高了 FP8 GEMM 的精度，其间隔为 $N_C = 128$ 元素。

these high-precision components incur some memory overheads, their impact can be minimized through efficient sharding across multiple DP ranks in our distributed training system.

这些高精度组件会带来一些内存开销，但它们的影响可以通过在我们的分布式训练系统中在多个 DP 秩之间进行高效分片来最小化。

3.3.2. Improved Precision from Quantization and Multiplication

3.3.2. 量化与乘法带来的精度提升

Based on our mixed precision FP8 framework, we introduce several strategies to enhance low-precision training accuracy, focusing on both the quantization method and the multiplication process.

基于我们的混合精度 FP8 框架，我们引入了几种策略来提高低精度训练的准确性，重点关注量化方法和乘法过程。

Fine-Grained Quantization. In low-precision training frameworks, overflows and underflows are common challenges due to the limited dynamic range of the FP8 format, which is constrained by its reduced exponent bits. As a standard practice, the input distribution is aligned to the representable range of the FP8 format by scaling the maximum absolute value of the input tensor to the maximum representable value of FP8 (Narang et al., 2017). This method makes low-precision training highly sensitive to activation outliers, which can heavily degrade quantization accuracy. To solve this, we propose a fine-grained quantization method that applies scaling at a more granular level. As illustrated in Figure 7 (a), (1) for activations, we group and scale elements on a 1×128 tile basis (i.e., per token per 128 channels); and (2) for weights, we group and scale elements on a 128×128 block basis (i.e., per 128 input channels per 128 output channels). This approach ensures that the quantization process can better accommodate outliers by adapting the scale according to smaller groups of elements. In Appendix B.2, we further discuss the training instability when we group and scale activations on a block basis in the same way as weights quantization.

细粒度量化。 在低精度训练框架中，由于 FP8 格式的动态范围有限且指数位被缩减，溢出和下溢是常见的挑战。作为一种标准做法，通过将输入张量的最大绝对值缩放到 FP8 的最大表示值来对齐输入分布到 FP8 的表示范围内 (Narang 等人, 2017 年)。这种方法使低精度训练对激活异常值高度敏感，这会严重降低量化精度。为了解决这个问题，我们提出了一种细粒度量化方法，该方法在更细粒度的级别应用缩放。如图 7 (a) 所示，(1) 对于激活值，我们在 1×128 块的基础上分组和缩放元素（即每个 token 每 128 个通道）；(2) 对于权重，我们在 128×128 块的基础上分组和缩放元素（即每 128 个输入通道每 128 个输出通道）。这种方法确保量化过程可以通过根据较小元素的组别调整缩放来更好地适应异常值。在附录 B.2 中，我们进一步讨论了当我们以与权重量化相同的方式在块级别对激活值进行分组和缩放时出现的训练不稳定性。

One key modification in our method is the introduction of per-group scaling factors along the inner dimension of GEMM operations. This functionality is not directly supported in the standard FP8 GEMM. However, combined with our precise FP32 accumulation strategy, it can

我们方法中的一个关键修改是在 GEMM 操作的内维引入按组的缩放因子。这项功能在标准的 FP8 GEMM 中并不直接支持。然而，结合我们精确的 FP32 累加策略，它可以

be efficiently implemented.

Notably, our fine-grained quantization strategy is highly consistent with the idea of microscaling formats (Rouhani et al., 2023b), while the Tensor Cores of NVIDIA next-generation GPUs (Blackwell series) have announced the support for microscaling formats with smaller quantization granularity (NVIDIA, 2024a). We hope our design can serve as a reference for future work to keep pace with the latest GPU architectures.

Increasing Accumulation Precision. Low-precision GEMM operations often suffer from underflow issues, and their accuracy largely depends on high-precision accumulation, which is commonly performed in an FP32 precision (Kalamkar et al., 2019; Narang et al., 2017). However, we observe that the accumulation precision of FP8 GEMM on NVIDIA H800 GPUs is limited to retaining around 14 bits, which is significantly lower than FP32 accumulation precision. This problem will become more pronounced when the inner dimension K is large (Wortsman et al., 2023), a typical scenario in large-scale model training where the batch size and model width are increased. Taking GEMM operations of two random matrices with $K = 4096$ for example, in our preliminary test, the limited accumulation precision in Tensor Cores results in a maximum relative error of nearly 2%. Despite these problems, the limited accumulation precision is still the default option in a few FP8 frameworks (NVIDIA, 2024b), severely constraining the training accuracy.

In order to address this issue, we adopt the strategy of promotion to CUDA Cores for higher precision (Thakkar et al., 2023). The process is illustrated in Figure 7 (b). To be specific, during MMA (Matrix Multiply-Accumulate) execution on Tensor Cores, intermediate results are accumulated using the limited bit width. Once an interval of N_C is reached, these partial results will be copied to FP32 registers on CUDA Cores, where full-precision FP32 accumulation is performed. As mentioned before, our fine-grained quantization applies per-group scaling factors along the inner dimension K . These scaling factors can be efficiently multiplied on the CUDA Cores as the dequantization process with minimal additional computational cost.

It is worth noting that this modification reduces the WGMMA (Warpgroup-level Matrix Multiply-Accumulate) instruction issue rate for a single warpgroup. However, on the H800 architecture, it is typical for two WGMMA to persist concurrently: while one warpgroup performs the promotion operation, the other is able to execute the MMA operation. This design enables overlapping of the two operations, maintaining high utilization of Tensor Cores. Based on our experiments, setting $N_C = 128$ elements, equivalent to 4 WGMMA, represents the minimal accumulation interval that can significantly improve precision without introducing substantial overhead.

Mantissa over Exponents. In contrast to the hybrid FP8 format adopted by prior work (NVIDIA, 2024b; Peng et al., 2023b; Sun et al., 2019b), which uses E4M3 (4-bit exponent and 3-bit mantissa) in Fprop and E5M2 (5-bit exponent and 2-bit mantissa) in Dgrad and Wgrad, we adopt the E4M3 format on all tensors for higher precision. We attribute the feasibility of this approach to our fine-grained quantization strategy, i.e., tile and block-wise scaling. By operating on smaller element groups, our methodology effectively shares exponent bits among these grouped elements, mitigating the impact of the limited dynamic range.

Online Quantization. Delayed quantization is employed in tensor-wise quantization frameworks (NVIDIA, 2024b; Peng et al., 2023b), which maintains a history of the maximum absolute

被高效地实现。

值得注意的是，我们的细粒度量化策略与微缩格式 (Rouhani等人, 2023b) 的思想高度一致，而NVIDIA下一代GPU (Blackwell系列) 的张量核心已宣布支持具有更小量化粒度的微缩格式 (NVIDIA, 2024a)。我们希望我们的设计能为未来工作提供一个参考，以跟上最新的GPU架构。

提高累积精度。 低精度 GEMM 操作常受下溢问题困扰，其精度很大程度上取决于高精度累积，这通常以 FP32 精度 (Kalamkar 等人, 2019; Narang 等人, 2017) 执行。然而，我们观察到 NVIDIA H800 GPU 上的 FP8 GEMM 累积精度仅限于保留约 14 位，这远低于 FP32 累积精度。当内维度 K 较大时 (Wortsman 等人, 2023)，这个问题会更加明显，这在大型模型训练中很常见，其中批处理大小和模型宽度都会增加。以两个随机矩阵的 GEMM 操作为例， $K = 4096$ ，在我们的初步测试中，张量核心中的有限累积精度导致最大相对误差接近 2%。尽管存在这些问题，但在少数 FP8 框架 (NVIDIA, 2024b) 中，有限的累积精度仍然是默认选项，严重限制了训练精度。

为解决此问题，我们采用将计算提升至 CUDA 核心来提高精度 (Thakkar 等人, 2023)。该过程如图 7 (b) 所示。具体而言，在张量核心上执行 MMA (矩阵乘累加) 操作时，中间结果会使用有限的位宽进行累加。一旦达到 N_C 个区间的长度，这些部分结果将被复制到 CUDA 核心的 FP32 寄存器上，在那里执行全精度的 FP32 累加。如前所述，我们的细粒度量化沿内维 K 应用分组缩放因子。这些缩放因子可以在 CUDA 核心上高效地进行乘法运算，作为解量化过程，且附加的计算开销极小。

值得注意的是，此修改会降低单个 warpgroup 的 WGMMA (Warpgroup 级别矩阵乘累加) 指令发射率。然而，在 H800 架构中，通常会有两个 WGMMA 同时存在：当一个 warpgroup 执行提升操作时，另一个能够执行 MMA 操作。这种设计使两种操作能够重叠执行，从而保持张量核心的高利用率。根据我们的实验，设置 $N_C = 128$ 个元素，相当于 4 个 WGMMA，代表了能够显著提高精度且不会引入过多开销的最小累加区间。

尾数位超过指数位。 与先前工作 (NVIDIA, 2024b; 彭等人, 2023b; 孙等人, 2019b) 采用的混合 FP8 格式不同，该格式在 Fprop 和 E5M2 中使用 E4M3 (4位指数和3位尾数位)，在 Dgrad 和 Wgrad 中使用 E5M2 (5位指数和2位尾数位)，我们采用 E4M3 格式对所有张量进行更高精度的处理。我们将此方法的可行性归因于我们的细粒度量化策略，即块和区块的缩放。通过操作更小的元素组，我们的方法有效地在这些分组元素之间共享指数位，减轻了动态范围受限的影响。

在线量化。 延迟量化被应用于张量量化框架 (NVIDIA, 2024b; 彭等人, 2023b)，该框架维护先前迭代中最大绝对值的历史记录以推断当前值。为确保精确的缩放因子并简化框架，我们为每个激活块或权重块在线计算最大绝对值。基于此，我们推导出缩放因子，然后将激活值或权重在线量化为 FP8 格式。

values across prior iterations to infer the current value. In order to ensure accurate scales and simplify the framework, we calculate the maximum absolute value online for each 1×128 activation tile or 128×128 weight block. Based on it, we derive the scaling factor and then quantize the activation or weight online into the FP8 format.

3.3.3. Low-Precision Storage and Communication

In conjunction with our FP8 training framework, we further reduce the memory consumption and communication overhead by compressing cached activations and optimizer states into lower-precision formats.

Low-Precision Optimizer States. We adopt the BF16 data format instead of FP32 to track the first and second moments in the AdamW (Loshchilov and Hutter, 2017) optimizer, without incurring observable performance degradation. However, the master weights (stored by the optimizer) and gradients (used for batch size accumulation) are still retained in FP32 to ensure numerical stability throughout training.

Low-Precision Activation. As illustrated in Figure 6, the Wgrad operation is performed in FP8. To reduce the memory consumption, it is a natural choice to cache activations in FP8 format for the backward pass of the Linear operator. However, special considerations are taken on several operators for low-cost high-precision training:

(1) Inputs of the Linear after the attention operator. These activations are also used in the backward pass of the attention operator, which makes it sensitive to precision. We adopt a customized E5M6 data format exclusively for these activations. Additionally, these activations will be converted from an 1×128 quantization tile to an 128×1 tile in the backward pass. To avoid introducing extra quantization error, all the scaling factors are round scaled, i.e., integral power of 2.

(2) Inputs of the SwiGLU operator in MoE. To further reduce the memory cost, we cache the inputs of the SwiGLU operator and recompute its output in the backward pass. These activations are also stored in FP8 with our fine-grained quantization method, striking a balance between memory efficiency and computational accuracy.

Low-Precision Communication. Communication bandwidth is a critical bottleneck in the training of MoE models. To alleviate this challenge, we quantize the activation before MoE up-projections into FP8 and then apply dispatch components, which is compatible with FP8 Fprop in MoE up-projections. Like the inputs of the Linear after the attention operator, scaling factors for this activation are integral power of 2. A similar strategy is applied to the activation gradient before MoE down-projections. For both the forward and backward combine components, we retain them in BF16 to preserve training precision in critical parts of the training pipeline.

3.4. Inference and Deployment

We deploy DeepSeek-V3 on the H800 cluster, where GPUs within each node are interconnected using NVLink, and all GPUs across the cluster are fully interconnected via IB. To simultaneously ensure both the Service-Level Objective (SLO) for online services and high throughput, we employ the following deployment strategy that separates the *prefilling* and *decoding* stages.

在延迟量化中，我们计算每个 1×128 激活块或 128×128 权重块的最大绝对值，以推断当前值。为了确保精确的缩放因子并简化框架，我们在线计算每个 1×128 激活块或 128×128 权重块的最大绝对值。基于此，我们推导出缩放因子，然后将激活值或权重在线量化为FP8格式。

3.3.3. 低精度存储与通信

结合我们的FP8训练框架，我们通过将缓存的激活值和优化器状态压缩为低精度格式，进一步降低了内存消耗和通信开销。

低精度优化器状态。 我们采用BF16数据格式代替FP32来追踪AdamW (Loshchilov和Hutter, 2017) 优化器中的第一和第二矩，而不会导致可观察的性能下降。然而，主权重（由优化器存储）和梯度（用于批量大小累积）仍然保留在FP32中，以确保整个训练过程中的数值稳定性。

低精度激活。 如图6所示，Wgrad操作在FP8中执行。为了减少内存消耗，将Linear算子的反向传播中的激活值缓存为FP8格式是一种自然的选择。然而，对于低成本的精度训练，对几个算子进行了特殊考虑：

(1) 注意力算子后的 Linear 输入。 这些激活值也用于注意力算子的反向传播，这使得它对精度敏感。我们为这些激活值采用了一种定制的 E5M6 数据格式。此外，这些激活值在反向传播中将从 1×128 量化瓦片转换为 128×1 瓦片。为了避免引入额外的量化误差，所有缩放因子都进行了舍入缩放，即2的整数次幂。

(2) MoE 中 SwiGLU 算子的输入。 为了进一步降低内存成本，我们缓存 SwiGLU 算子的输入，并在反向传播中重新计算其输出。这些激活值也使用我们的细粒度量化方法以 FP8 格式存储，在内存效率和计算精度之间取得了平衡。

低精度通信。 通信带宽是 MoE 模型训练中的关键瓶颈。为了缓解这一挑战，我们在 MoE 上采样前将激活量化为 FP8，然后应用 dispatch 组件，该组件与 MoE 上采样中的 FP8 Fprop 兼容。类似于注意力算子后的 Linear 输入，此激活的缩放因子是 2 的整数幂。类似的策略也应用于 MoE 下采样前的激活梯度。对于前向和后向 combine 组件，我们保留它们在 BF16 中以及在训练管道的关键部分保留训练精度。

3.4. 推理与部署

我们在 H800 集群上部署 DeepSeek-V3，其中每个节点的 GPU 通过 NVLink 互连，而集群内所有 GPU 则通过 IB 完全互连。为了同时确保在线服务的等级目标 (SLO) 和高吞吐量，我们采用以下部署策略，将预填充和解码阶段分开处理。

3.4.1. Prefilling

The minimum deployment unit of the prefilling stage consists of 4 nodes with 32 GPUs. The attention part employs 4-way Tensor Parallelism (TP4) with Sequence Parallelism (SP), combined with 8-way Data Parallelism (DP8). Its small TP size of 4 limits the overhead of TP communication. For the MoE part, we use 32-way Expert Parallelism (EP32), which ensures that each expert processes a sufficiently large batch size, thereby enhancing computational efficiency. For the MoE all-to-all communication, we use the same method as in training: first transferring tokens across nodes via IB, and then forwarding among the intra-node GPUs via NVLink. In particular, we use 1-way Tensor Parallelism for the dense MLPs in shallow layers to save TP communication.

To achieve load balancing among different experts in the MoE part, we need to ensure that each GPU processes approximately the same number of tokens. To this end, we introduce a deployment strategy of *redundant experts*, which duplicates high-load experts and deploys them redundantly. The high-load experts are detected based on statistics collected during the online deployment and are adjusted periodically (e.g., every 10 minutes). After determining the set of redundant experts, we carefully rearrange experts among GPUs within a node based on the observed loads, striving to balance the load across GPUs as much as possible without increasing the cross-node all-to-all communication overhead. For the deployment of DeepSeek-V3, we set 32 redundant experts for the prefilling stage. For each GPU, besides the original 8 experts it hosts, it will also host one additional redundant expert.

Furthermore, in the prefilling stage, to improve the throughput and hide the overhead of all-to-all and TP communication, we simultaneously process two micro-batches with similar computational workloads, overlapping the attention and MoE of one micro-batch with the dispatch and combine of another.

Finally, we are exploring a *dynamic redundancy* strategy for experts, where each GPU hosts more experts (e.g., 16 experts), but only 9 will be activated during each inference step. Before the all-to-all operation at each layer begins, we compute the globally optimal routing scheme on the fly. Given the substantial computation involved in the prefilling stage, the overhead of computing this routing scheme is almost negligible.

3.4.2. Decoding

During decoding, we treat the shared expert as a routed one. From this perspective, each token will select 9 experts during routing, where the shared expert is regarded as a heavy-load one that will always be selected. The minimum deployment unit of the decoding stage consists of 40 nodes with 320 GPUs. The attention part employs TP4 with SP, combined with DP80, while the MoE part uses EP320. For the MoE part, each GPU hosts only one expert, and 64 GPUs are responsible for hosting redundant experts and shared experts. All-to-all communication of the dispatch and combine parts is performed via direct point-to-point transfers over IB to achieve low latency. Additionally, we leverage the IBGDA (NVIDIA, 2022) technology to further minimize latency and enhance communication efficiency.

Similar to prefilling, we periodically determine the set of redundant experts in a certain interval, based on the statistical expert load from our online service. However, we do not need to rearrange experts since each GPU only hosts one expert. We are also exploring the *dynamic redundancy* strategy for decoding. However, this requires more careful optimization of the algorithm that computes the globally optimal routing scheme and the fusion with the dispatch kernel to reduce overhead.

3.4.1. 预填充

预填充阶段的最小部署单元由 4 个节点和 32 个 GPU 组成。attention 部分采用 4 路张量并行 (TP4) 与序列并行 (SP) 相结合的 8 路数据并行 (DP8)。其较小的 TP 大小为 4, 限制了 TP 通信的开销。对于 MoE 部分, 我们使用 32 路专家并行 (EP32), 这确保每个专家处理足够大的批次大小, 从而提高计算效率。对于 MoE 全对全通信, 我们使用与训练相同的方法: 首先通过 IB 在节点间传输 token, 然后在节点内 GPU 之间通过 NVLink 进行转发。特别是, 我们为浅层中的密集 MLP 使用 1 路张量并行, 以节省 TP 通信。

为了在 MoE 部分的各个专家之间实现负载均衡, 我们需要确保每个 GPU 处理的 token 数量大致相同。为此, 我们引入了冗余专家的部署策略, 该策略会复制高负载专家并将其冗余部署。高负载专家是根据在线部署期间收集的统计数据检测到的, 并会定期调整 (例如, 每 10 分钟调整一次)。在确定冗余专家集合后, 我们会根据观察到的负载, 在节点内的各个 GPU 之间重新分配专家, 力求在不增加跨节点全对全通信开销的情况下, 尽可能平衡 GPU 之间的负载。对于 DeepSeek-V3 的部署, 我们在预填充阶段设置了 32 个冗余专家。对于每个 GPU, 除了它原本承载的 8 个专家外, 它还会额外承载一个冗余专家。

此外, 在预填充阶段, 为了提高吞吐量并隐藏全对全和 TP 通信的开销, 我们同时处理两个计算负载相似的微批次, 将一个微批次的 attention 和 MoE 与另一个微批次的 dispatch 和 combine 重叠处理。

最后, 我们正在探索一种针对专家的动态冗余策略, 其中每个 GPU 承载更多专家 (例如, 16 个专家), 但在每次推理步骤中仅激活 9 个。在每一层的全连接操作开始之前, 我们会动态计算全局最优路由方案。鉴于预填充阶段涉及大量计算, 计算此路由方案的开销几乎可以忽略不计。

3.4.2. 解码

解码过程中, 我们将共享专家视为一个路由专家。从这个角度来看, 每个 token 在路由过程中将选择 9 个专家, 其中共享专家被视为一个高负载专家, 总是会被选中。解码阶段的最小部署单元由 40 个节点和 320 个 GPU 组成。attention 部分采用 TP4 与 SP 结合 DP80, 而 MoE 部分使用 EP320。对于 MoE 部分, 每个 GPU 只托管一个专家, 而 64 个 GPU 负责托管冗余专家和共享专家。dispatch 和 combine 部分的全对全通信通过 IB 直接点对点传输来实现低延迟。此外, 我们利用 IBGDA (NVIDIA, 2022) 技术进一步降低延迟并提高通信效率。

与预填充类似, 我们定期在一个区间内根据在线服务的统计专家负载确定冗余专家的集合。然而, 我们无需重新排列专家, 因为每个 GPU 仅托管一个专家。我们还在探索用于解码的动态冗余策略。但是, 这需要更仔细地优化计算全局最优路由方案和与 dispatch 内核融合的算法, 以减少开销。

Additionally, to enhance throughput and hide the overhead of all-to-all communication, we are also exploring processing two micro-batches with similar computational workloads simultaneously in the decoding stage. Unlike prefilling, `attention` consumes a larger portion of time in the decoding stage. Therefore, we overlap the `attention` of one micro-batch with the `dispatch+MoE+combine` of another. In the decoding stage, the batch size per expert is relatively small (usually within 256 tokens), and the bottleneck is memory access rather than computation. Since the MoE part only needs to load the parameters of one expert, the memory access overhead is minimal, so using fewer SMs will not significantly affect the overall performance. Therefore, to avoid impacting the computation speed of the `attention` part, we can allocate only a small portion of SMs to `dispatch+MoE+combine`.

3.5. Suggestions on Hardware Design

Based on our implementation of the all-to-all communication and FP8 training scheme, we propose the following suggestions on chip design to AI hardware vendors.

3.5.1. Communication Hardware

In DeepSeek-V3, we implement the overlap between computation and communication to hide the communication latency during computation. This significantly reduces the dependency on communication bandwidth compared to serial computation and communication. However, the current communication implementation relies on expensive SMs (e.g., we allocate 20 out of the 132 SMs available in the H800 GPU for this purpose), which will limit the computational throughput. Moreover, using SMs for communication results in significant inefficiencies, as tensor cores remain entirely under-utilized.

Currently, the SMs primarily perform the following tasks for all-to-all communication:

- **Forwarding data** between the IB (InfiniBand) and NVLink domain while aggregating IB traffic destined for multiple GPUs within the same node from a single GPU.
- **Transporting data** between RDMA buffers (registered GPU memory regions) and input/output buffers.
- **Executing reduce operations** for all-to-all combine.
- **Managing fine-grained memory layout** during chunked data transferring to multiple experts across the IB and NVLink domain.

We aspire to see future vendors developing hardware that offloads these communication tasks from the valuable computation unit SM, serving as a GPU co-processor or a network co-processor like NVIDIA SHARP Graham et al. (2016). Furthermore, to reduce application programming complexity, we aim for this hardware to unify the IB (scale-out) and NVLink (scale-up) networks from the perspective of the computation units. With this unified interface, computation units can easily accomplish operations such as `read`, `write`, `multicast`, and `reduce` across the entire IB-NVLink-unified domain via submitting communication requests based on simple primitives.

3.5.2. Compute Hardware

Higher FP8 GEMM Accumulation Precision in Tensor Cores. In the current Tensor Core implementation of the NVIDIA Hopper architecture, FP8 GEMM suffers from limited accumulation precision. After aligning 32 mantissa products by right-shifting based on the maximum exponent, the Tensor Core only uses the highest 14 bits of each mantissa product for addition,

此外, 为了提高吞吐量并隐藏所有对全通信的开销, 我们还在解码阶段探索同时处理计算负载相似的两个微批次。与预填充不同, `attention` 在解码阶段消耗了更多时间。因此, 我们将一个微批次的 `attention` 与另一个的 `dispatch+MoE+combine` 重叠。在解码阶段, 每个专家的批次大小相对较小 (通常在256个token以内), 瓶颈是内存访问而不是计算。由于 MoE 部分只需加载一个专家的参数, 内存访问开销很小, 因此使用较少的SM不会显著影响整体性能。因此, 为了避免影响 `attention` 部分的计算速度, 我们可以仅将一小部分SM分配给 `dispatch+MoE+combine`。

3.5. 硬件设计建议

基于我们对全对全通信和FP8训练方案的实施, 我们向AI硬件供应商提出以下芯片设计建议。

3.5.1. 通信硬件

在DeepSeek-V3中, 我们实现了计算与通信的重叠, 以隐藏计算过程中的通信延迟。这显著降低了与串行计算和通信相比对通信带宽的依赖。然而, 当前的通信实现依赖于昂贵的SM (例如, 我们为这个目的分配了H800 GPU中可用的132个SM中的20个), 这将限制计算吞吐量。此外, 使用SM进行通信会导致显著的低效率, 因为张量核心完全未被充分利用。

目前, SM主要执行以下任务以支持全对全通信:

- **在InfiniBand (IB) 和NVLink域之间转发数据**, 同时从单个GPU聚合 destined for multiple GPUs within the same node 的IB流量。
- **在 RDMA 缓冲区 (注册的 GPU 内存区域) 和输入/输出缓冲区之间传输数据。**
- **执行 reduce 操作** 为 all-to-all combine。
- **在 分块数据传输到 IB 和 NVLink 域的多个专家期间管理细粒度内存布局。**

我们期望未来的供应商开发能够从宝贵的计算单元 SM 卸载这些通信任务的硬件, 作为 GPU 协处理器或像 NVIDIA SHARP Graham 等人 (2016) 那样的网络协处理器。此外, 为了降低应用程序编程复杂性, 我们希望该硬件能够从计算单元的角度统一 IB (扩展型) 和 NVLink (扩展型) 网络。通过这个统一接口, 计算单元可以通过基于简单原语提交通信请求, 在整个 IB-NVLink-统一域内轻松完成 `read`, `write`, `multicast` 和 `reduce` 等操作。

3.5.2. 计算硬件

在NVIDIA Hopper架构的张量核心当前实现中, FP8 GEMM存在积累精度有限的问题。在基于最大指数通过右移对32个尾数乘积进行对齐后, 张量核心仅使用每个尾数乘积的最高14位进行加法运算,

and truncates bits exceeding this range. The accumulation of addition results into registers also employs 14-bit precision. Our implementation partially mitigates the limitation by accumulating the addition results of 128 FP8×FP8 multiplications into registers with FP32 precision in the CUDA core. Although helpful in achieving successful FP8 training, it is merely a compromise due to the Hopper architecture’s hardware deficiency in FP8 GEMM accumulation precision. Future chips need to adopt higher precision.

Support for Tile- and Block-Wise Quantization. Current GPUs only support per-tensor quantization, lacking the native support for fine-grained quantization like our tile- and block-wise quantization. In the current implementation, when the N_C interval is reached, the partial results will be copied from Tensor Cores to CUDA cores, multiplied by the scaling factors, and added to FP32 registers on CUDA cores. Although the dequantization overhead is significantly mitigated combined with our precise FP32 accumulation strategy, the frequent data movements between Tensor Cores and CUDA cores still limit the computational efficiency. Therefore, we recommend future chips to support fine-grained quantization by enabling Tensor Cores to receive scaling factors and implement MMA with group scaling. In this way, the whole partial sum accumulation and dequantization can be completed directly inside Tensor Cores until the final result is produced, avoiding frequent data movements.

Support for Online Quantization. The current implementations struggle to effectively support online quantization, despite its effectiveness demonstrated in our research. In the existing process, we need to read 128 BF16 activation values (the output of the previous computation) from HBM (High Bandwidth Memory) for quantization, and the quantized FP8 values are then written back to HBM, only to be read again for MMA. To address this inefficiency, we recommend that future chips integrate FP8 cast and TMA (Tensor Memory Accelerator) access into a single fused operation, so quantization can be completed during the transfer of activations from global memory to shared memory, avoiding frequent memory reads and writes. We also recommend supporting a warp-level cast instruction for speedup, which further facilitates the better fusion of layer normalization and FP8 cast. Alternatively, a near-memory computing approach can be adopted, where compute logic is placed near the HBM. In this case, BF16 elements can be cast to FP8 directly as they are read from HBM into the GPU, reducing off-chip memory access by roughly 50%.

Support for Transposed GEMM Operations. The current architecture makes it cumbersome to fuse matrix transposition with GEMM operations. In our workflow, activations during the forward pass are quantized into 1x128 FP8 tiles and stored. During the backward pass, the matrix needs to be read out, dequantized, transposed, re-quantized into 128x1 tiles, and stored in HBM. To reduce memory operations, we recommend future chips to enable direct transposed reads of matrices from shared memory before MMA operation, for those precisions required in both training and inference. Combined with the fusion of FP8 format conversion and TMA access, this enhancement will significantly streamline the quantization workflow.

4. Pre-Training

4.1. Data Construction

Compared with DeepSeek-V2, we optimize the pre-training corpus by enhancing the ratio of mathematical and programming samples, while expanding multilingual coverage beyond

并截断超出此范围的部分。将加法结果累积到寄存器中也采用了14位精度。我们的实现通过将128个FP8×FP8乘法的结果以FP32精度累积到CUDA核心的寄存器中来部分缓解这一限制。虽然这有助于实现成功的FP8训练，但由于Hopper架构在FP8 GEMM累积精度方面的硬件缺陷，这只是一个妥协。未来的芯片需要采用更高的精度。

支持块级和区域级量化。当前的GPU仅支持逐张量量化，缺乏对细粒度量化的原生支持，例如我们的块级和区域级量化。在当前实现中，当 N_C 区间被达到时，部分结果将从张量核心复制到 CUDA 核心，乘以缩放因子，并加到 CUDA 核心的 FP32 寄存器上。尽管与我们的精确 FP32 累加策略相结合，量化反量化开销已显著降低，但张量核心和 CUDA 核心之间频繁的数据移动仍然限制了计算效率。因此，我们建议未来的芯片通过使能张量核心接收缩放因子并实现带组缩放的 MMA 来支持细粒度量化。这样，整个部分和累加以及量化反量化可以直接在张量核心内完成，直到最终结果产生，避免频繁的数据移动。

支持在线量化。当前实现难以有效支持在线量化，尽管我们在研究中证明了其有效性。在现有流程中，我们需要从 HBM（高带宽内存）读取 128 个 BF16 激活值（先前计算的结果）进行量化，然后将量化的 FP8 值写回 HBM，之后再次读取以用于 MMA。为解决这种低效问题，我们建议未来芯片将 FP8 转换和 TMA（张量内存加速器）访问整合为单个融合操作，以便在激活从全局内存传输到共享内存的过程中完成量化，避免频繁的内存读写。我们还建议支持用于加速的 warp 级转换指令，这进一步促进了层归一化和 FP8 转换的更好融合。或者，可以采用近内存计算方法，将计算逻辑放置在靠近 HBM 的位置。在这种情况下，BF16 元素可以在从 HBM 读取到 GPU 时直接转换为 FP8，减少片外内存访问约 50%。

支持转置GEMM运算。当前架构使得矩阵转置与GEMM运算的融合变得复杂。在我们的工作流程中，前向传递期间的激活值被量化为 1x128 FP8块并存储。在反向传递期间，矩阵需要被读取出来，去量化，转置，重新量化为 128x1 块，并存储在HBM中。为了减少内存操作，我们建议未来的芯片在MMA操作之前，对那些在训练和推理中都需要使用的精度，支持从共享内存直接读取转置矩阵，结合FP8格式转换和TMA访问的融合，这项增强将显著简化量化工作流程。

4. 预训练

4.1. 数据构建

与 DeepSeek-V2 相比，我们通过提升数学和编程样本的比例，优化了预训练语料库，同时将多语言覆盖范围扩展至英语和中文之外。

English and Chinese. Also, our data processing pipeline is refined to minimize redundancy while maintaining corpus diversity. Inspired by Ding et al. (2024), we implement the document packing method for data integrity but do not incorporate cross-sample attention masking during training. Finally, the training corpus for DeepSeek-V3 consists of 14.8T high-quality and diverse tokens in our tokenizer.

In the training process of DeepSeekCoder-V2 (DeepSeek-AI, 2024a), we observe that the Fill-in-Middle (FIM) strategy does not compromise the next-token prediction capability while enabling the model to accurately predict middle text based on contextual cues. In alignment with DeepSeekCoder-V2, we also incorporate the FIM strategy in the pre-training of DeepSeek-V3. To be specific, we employ the Prefix-Suffix-Middle (PSM) framework to structure data as follows:

$$\langle |f_{im_begin}| \rangle f_{pre} \langle |f_{im_hole}| \rangle f_{suf} \langle |f_{im_end}| \rangle f_{middle} \langle |eos_token| \rangle.$$

This structure is applied at the document level as a part of the pre-packing process. The FIM strategy is applied at a rate of 0.1, consistent with the PSM framework.

The tokenizer for DeepSeek-V3 employs Byte-level BPE (Shibata et al., 1999) with an extended vocabulary of 128K tokens. The pretokenizer and training data for our tokenizer are modified to optimize multilingual compression efficiency. In addition, compared with DeepSeek-V2, the new pretokenizer introduces tokens that combine punctuations and line breaks. However, this trick may introduce the token boundary bias (Lundberg, 2023) when the model processes multi-line prompts without terminal line breaks, particularly for few-shot evaluation prompts. To address this issue, we randomly split a certain proportion of such combined tokens during training, which exposes the model to a wider array of special cases and mitigates this bias.

4.2. Hyper-Parameters

Model Hyper-Parameters. We set the number of Transformer layers to 61 and the hidden dimension to 7168. All learnable parameters are randomly initialized with a standard deviation of 0.006. In MLA, we set the number of attention heads n_h to 128 and the per-head dimension d_h to 128. The KV compression dimension d_c is set to 512, and the query compression dimension d'_c is set to 1536. For the decoupled queries and key, we set the per-head dimension d_h^R to 64. We substitute all FFNs except for the first three layers with MoE layers. Each MoE layer consists of 1 shared expert and 256 routed experts, where the intermediate hidden dimension of each expert is 2048. Among the routed experts, 8 experts will be activated for each token, and each token will be ensured to be sent to at most 4 nodes. The multi-token prediction depth D is set to 1, i.e., besides the exact next token, each token will predict one additional token. As DeepSeek-V2, DeepSeek-V3 also employs additional RMSNorm layers after the compressed latent vectors, and multiplies additional scaling factors at the width bottlenecks. Under this configuration, DeepSeek-V3 comprises 671B total parameters, of which 37B are activated for each token.

Training Hyper-Parameters. We employ the AdamW optimizer (Loshchilov and Hutter, 2017) with hyper-parameters set to $\beta_1 = 0.9$, $\beta_2 = 0.95$, and $weight_decay = 0.1$. We set the maximum sequence length to 4K during pre-training, and pre-train DeepSeek-V3 on 14.8T tokens. As for the learning rate scheduling, we first linearly increase it from 0 to 2.2×10^{-4} during the first 2K steps. Then, we keep a constant learning rate of 2.2×10^{-4} until the model consumes 10T training tokens. Subsequently, we gradually decay the learning rate to 2.2×10^{-5} in 4.3T tokens, following a cosine decay curve. During the training of the final 500B tokens, we keep a constant learning rate of 2.2×10^{-5} in the first 333B tokens, and switch to another constant learning rate

此外，我们的数据处理流程经过优化，以减少冗余并保持语料库多样性。受 Ding 等人 (2024) 的启发，我们实现了文档打包方法以确保数据完整性，但在训练过程中未采用跨样本注意力掩码。最后，DeepSeek-V3 的训练语料库包含我们分词器中的 14.8T 高质量和多样化的 token。

在 DeepSeekCoder-V2 (DeepSeek-AI, 2024a) 的训练过程中，我们观察到 Fill-in-Middle (FIM) 策略在启用模型根据上下文线索准确预测中间文本的同时，并未损害其下一词预测能力。与 DeepSeekCoder-V2 保持一致，我们在 DeepSeek-V3 的预训练中也采用了 FIM 策略。具体来说，我们采用 Prefix-Suffix-Middle (PSM) 框架来构建数据，结构如下：

$$\langle |f_{im_begin}| \rangle f_{pre} \langle |f_{im_hole}| \rangle f_{suf} \langle |f_{im_end}| \rangle f_{middle} \langle |eos_token| \rangle.$$

该结构在文档级别作为预打包过程的一部分被应用。FIM 策略的应用率为 0.1，与 PSM 框架保持一致。

DeepSeek-V3 的分词器采用字节级 BPE (Shibata 等人, 1999) 并扩展了包含 128K 个词元的词汇表。我们的分词器的预分词器和训练数据被修改以优化多语言压缩效率。此外，与 DeepSeek-V2 相比，新的预分词器引入了结合标点和换行符的词元。然而，当模型处理没有终止换行符的多行提示时，这种技巧可能会引入词边界偏差 (Lundberg, 2023)，尤其是在少样本评估提示中。为解决此问题，我们在训练期间随机拆分了一定比例的此类组合词元，这使模型接触了更广泛的各种特殊情况，从而减轻了这种偏差。

4.2. 超参数

模型超参数。 我们将 Transformer 层数设置为 61，隐藏维度设置为 7168。所有可学习参数均使用标准差为 0.006 的随机初始化。在 MLA 中，我们将注意力头数 n_h 设置为 128，每个头的维度 d_h 设置为 128。KV 压缩维度 d_c 设置为 512，查询压缩维度 d'_c 设置为 1536。对于解耦查询和键，我们将每个头的维度 d_h^R 设置为 64。我们将除前三个层以外的所有 FFN 替换为 MoE 层。每个 MoE 层由 1 个共享专家和 256 个路由专家组成，其中每个专家的中间隐藏维度为 2048。在路由专家中，每个 token 将激活 8 个专家，并且每个 token 将确保最多被发送到 4 个节点。多标记预测深度 D 设置为 1，即除了精确的下一个 token，每个 token 还将预测一个额外的 token。与 DeepSeek-V2 一样，DeepSeek-V3 在压缩后的潜在向量之后也采用了额外的 RMSNorm 层，并在宽度瓶颈处乘以额外的缩放因子。在此配置下，DeepSeek-V3 共包含 671B 个总参数，其中每个 token 激活 37B 个参数。

训练超参数。 我们采用 AdamW 优化器 (Loshchilov 和 Hutter, 2017)，其超参数设置为 $\beta_1 = 0.9$, $\beta_2 = 0.95$ ，以及权重衰减 $_ = 0.1$ 。我们在预训练期间将最大序列长度设置为 4K，并在 14.8T 令牌上预训练 DeepSeek-V3。关于学习率调度，我们首先在最初的 2K 步内将其从 0 线性增加到 2.2×10^{-4} 。然后，我们保持 2.2×10^{-4} 的恒定学习率，直到模型消耗 10T 训练令牌。随后，我们逐渐将学习率衰减到 2.2×10^{-5} ，在 4.3T 令牌内遵循余弦衰减曲线。在训练最后 500B 令牌期间，我们在最初的 333B 令牌内保持 2.2×10^{-5} 的恒定学习率，然后在剩余的 167B 令牌内切换到另一个恒定学习率

of 7.3×10^{-6} in the remaining 167B tokens. The gradient clipping norm is set to 1.0. We employ a batch size scheduling strategy, where the batch size is gradually increased from 3072 to 15360 in the training of the first 469B tokens, and then keeps 15360 in the remaining training. We leverage pipeline parallelism to deploy different layers of a model on different GPUs, and for each layer, the routed experts will be uniformly deployed on 64 GPUs belonging to 8 nodes. As for the node-limited routing, each token will be sent to at most 4 nodes (i.e., $M = 4$). For auxiliary-loss-free load balancing, we set the bias update speed γ to 0.001 for the first 14.3T tokens, and to 0.0 for the remaining 500B tokens. For the balance loss, we set α to 0.0001, just to avoid extreme imbalance within any single sequence. The MTP loss weight λ is set to 0.3 for the first 10T tokens, and to 0.1 for the remaining 4.8T tokens.

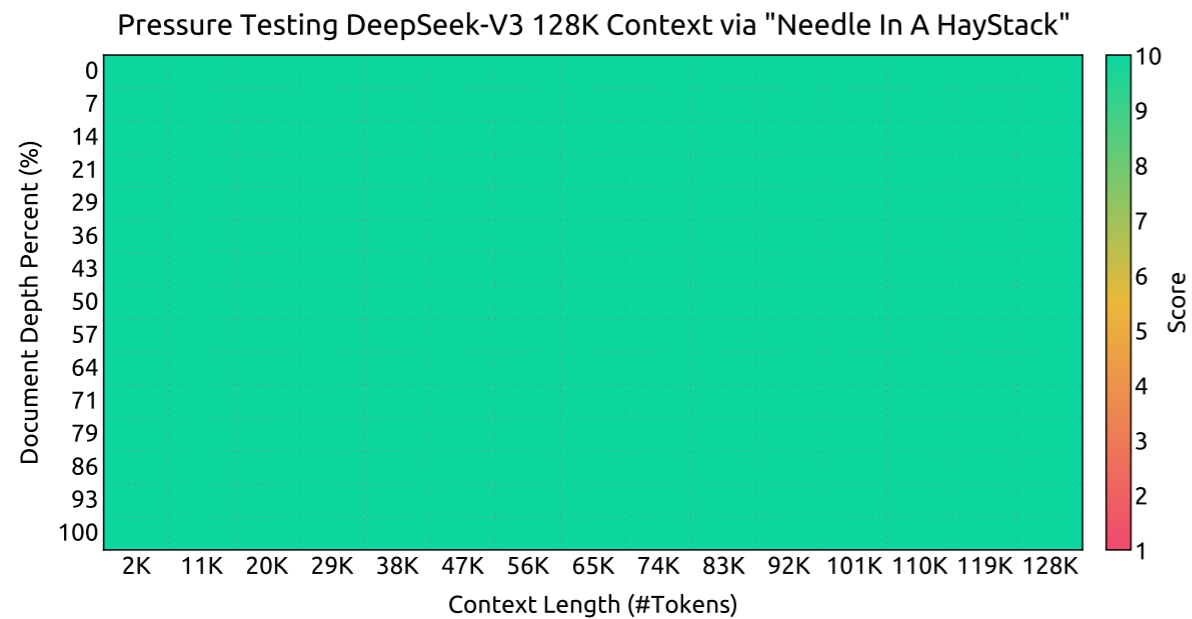


Figure 8 | Evaluation results on the "Needle In A Haystack" (NIAH) tests. DeepSeek-V3 performs well across all context window lengths up to 128K.

4.3. Long Context Extension

We adopt a similar approach to DeepSeek-V2 (DeepSeek-AI, 2024c) to enable long context capabilities in DeepSeek-V3. After the pre-training stage, we apply YaRN (Peng et al., 2023a) for context extension and perform two additional training phases, each comprising 1000 steps, to progressively expand the context window from 4K to 32K and then to 128K. The YaRN configuration is consistent with that used in DeepSeek-V2, being applied exclusively to the decoupled shared key \mathbf{k}_t^R . The hyper-parameters remain identical across both phases, with the scale $s = 40$, $\alpha = 1$, $\beta = 32$, and the scaling factor $\sqrt{t} = 0.1 \ln s + 1$. In the first phase, the sequence length is set to 32K, and the batch size is 1920. During the second phase, the sequence length is increased to 128K, and the batch size is reduced to 480. The learning rate for both phases is set to 7.3×10^{-6} , matching the final learning rate from the pre-training stage.

Through this two-phase extension training, DeepSeek-V3 is capable of handling inputs up to 128K in length while maintaining strong performance. Figure 8 illustrates that DeepSeek-V3, following supervised fine-tuning, achieves notable performance on the "Needle In A Haystack" (NIAH) test, demonstrating consistent robustness across context window lengths up to 128K.

7.3×10^{-6} 。梯度裁剪范数设置为 1.0。我们采用批量大小调度策略，其中批量大小在训练最初的 469B 令牌期间从 3072 逐渐增加到 15360，然后在剩余训练中保持 15360。我们利用流水线并行性将模型的层部署在不同的 GPU 上，并且对于每一层，路由专家将被均匀部署在属于 8 个节点的 64 个 GPU 上。关于节点限制路由，每个令牌最多将被发送到最多 4 个节点（即 $M = 4$ ）。对于无辅助损失的负载均衡，我们将偏差更新速度 γ 在最初的 14.3T 令牌设置为 0.001，在剩余的 500B 令牌设置为 0.0。对于平衡损失，我们将 α 设置为 0.0001，以避免任何单个序列内的极端不平衡。MTP 损失权重 λ 在最初的 10T 令牌设置为 0.3，在剩余的 4.8T 令牌设置为 0.1。

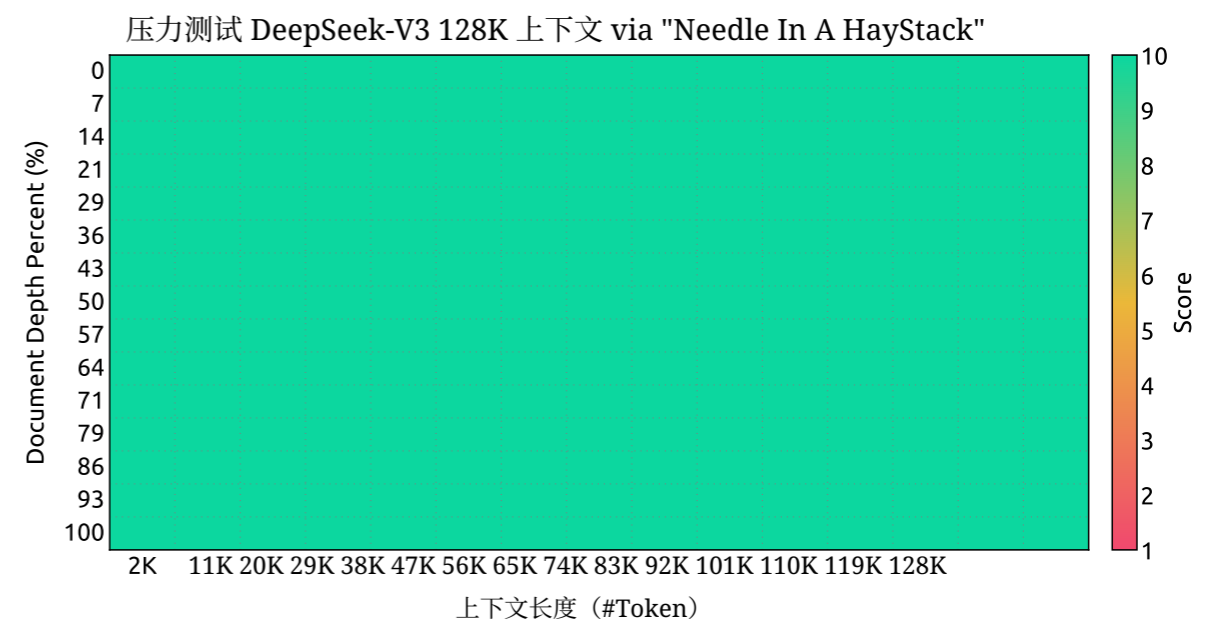


图 8 | 在 "Needle In A HayStack" (NIAH) 测试上的评估结果。DeepSeek-V3 在所有上下文窗口长度至 128K 的测试中都表现良好。

4.3. 长上下文扩展

我们采用与 DeepSeek-V2 (DeepSeek-AI, 2024c) 类似的方法，为 DeepSeek-V3 实现长上下文能力。在预训练阶段后，我们应用 YaRN (彭等人, 2023a) 进行上下文扩展，并执行两个额外的训练阶段，每个阶段包含 1000 步，逐步将上下文窗口从 4K 扩展到 32K，然后扩展到 128K。YaRN 的配置与 DeepSeek-V2 中使用的配置一致，仅应用于解耦共享键 \mathbf{k}_t^R 。两个阶段的超参数保持相同，包括缩放 $s = 40$, $\alpha = 1$, $\beta = 32$ 和缩放因子 $\sqrt{t} = 0.1 \ln s + 1$ 。在第一阶段，序列长度设置为 32K，批大小为 1920。在第二阶段，序列长度增加到 128K，批大小减少到 480。两个阶段的学习率设置为 7.3×10^{-6} ，与预训练阶段最终的学习率匹配。

通过这个两阶段扩展训练，DeepSeek-V3 能够处理长达 128K 的输入，同时保持优异性能。图 8 展示了 DeepSeek-V3 在经过监督微调后，在 "Needle In A Haystack" (NIAH) 测试中取得了显著性能，并在上下文窗口长度高达 128K 的范围内表现出一致的鲁棒性。

4.4. Evaluations

4.4.1. Evaluation Benchmarks

The base model of DeepSeek-V3 is pretrained on a multilingual corpus with English and Chinese constituting the majority, so we evaluate its performance on a series of benchmarks primarily in English and Chinese, as well as on a multilingual benchmark. Our evaluation is based on our internal evaluation framework integrated in our HAI-LLM framework. Considered benchmarks are categorized and listed as follows, where underlined benchmarks are in Chinese and double-underlined benchmarks are multilingual ones:

Multi-subject multiple-choice datasets include MMLU (Hendrycks et al., 2020), MMLU-Redux (Gema et al., 2024), MMLU-Pro (Wang et al., 2024b), MMMLU (OpenAI, 2024b), C-Eval (Huang et al., 2023), and CMMLU (Li et al., 2023).

Language understanding and reasoning datasets include HellaSwag (Zellers et al., 2019), PIQA (Bisk et al., 2020), ARC (Clark et al., 2018), and BigBench Hard (BBH) (Suzgun et al., 2022).

Closed-book question answering datasets include TriviaQA (Joshi et al., 2017) and NaturalQuestions (Kwiatkowski et al., 2019).

Reading comprehension datasets include RACE Lai et al. (2017), DROP (Dua et al., 2019), C3 (Sun et al., 2019a), and CMRC (Cui et al., 2019).

Reference disambiguation datasets include CLUEWSC (Xu et al., 2020) and WinoGrande Sakaguchi et al. (2019).

Language modeling datasets include Pile (Gao et al., 2020).

Chinese understanding and culture datasets include CCPM (Li et al., 2021).

Math datasets include GSM8K (Cobbe et al., 2021), MATH (Hendrycks et al., 2021), MGSM (Shi et al., 2023), and CMath (Wei et al., 2023).

Code datasets include HumanEval (Chen et al., 2021), LiveCodeBench-Base (0801-1101) (Jain et al., 2024), MBPP (Austin et al., 2021), and CRUXEval (Gu et al., 2024).

Standardized exams include AGIEval (Zhong et al., 2023). Note that AGIEval includes both English and Chinese subsets.

Following our previous work (DeepSeek-AI, 2024b,c), we adopt perplexity-based evaluation for datasets including HellaSwag, PIQA, WinoGrande, RACE-Middle, RACE-High, MMLU, MMLU-Redux, MMLU-Pro, MMMLU, ARC-Easy, ARC-Challenge, C-Eval, CMMLU, C3, and CCPM, and adopt generation-based evaluation for TriviaQA, NaturalQuestions, DROP, MATH, GSM8K, MGSM, HumanEval, MBPP, LiveCodeBench-Base, CRUXEval, BBH, AGIEval, CLUEWSC, CMRC, and CMath. In addition, we perform language-modeling-based evaluation for Pile-test and use Bits-Per-Byte (BPB) as the metric to guarantee fair comparison among models using different tokenizers.

4.4.2. Evaluation Results

In Table 3, we compare the base model of DeepSeek-V3 with the state-of-the-art open-source base models, including DeepSeek-V2-Base (DeepSeek-AI, 2024c) (our previous release), Qwen2.5 72B Base (Qwen, 2024b), and LLaMA-3.1 405B Base (AI@Meta, 2024b). We evaluate all these models with our internal evaluation framework, and ensure that they share the same evaluation setting. Note that due to the changes in our evaluation framework over the past months, the performance

4.4. 评估

4.4.1. 评估基准

DeepSeek-V3 的基础模型在包含英语和中文的多语言语料库上进行了预训练，因此我们在一系列主要使用英语和中文的基准测试，以及多语言基准测试上评估其性能。我们的评估基于集成在我们 HAI-LLM 框架中的内部评估框架。考虑的基准测试按类别分类并列出如下，其中下划线表示中文基准测试，双下划线表示多语言基准测试：

多学科多项选择题数据集包括 MMLU (Hendrycks 等人, 2020年)、MMLU-Redux (Gema 等人, 2024年)、MMLU-Pro (Wang 等人, 2024b)、MMMLU (OpenAI, 2024b)、C-Eval (Huang 等人, 2023年) 和 CMMLU(Li 等人, 2023年)。

语言理解和推理数据集包括 HellaSwag (Zellers 等人, 2019年)、PIQA (Bisk 等人, 2020年)、ARC (Clark 等人, 2018年) 和 BigBench Hard (BBH) (Suzgun 等人, 2022年)。

闭卷问答数据集包括 TriviaQA (Joshi 等人, 2017年) 和 NaturalQuestions (Kwiatkowski 等人, 2019年)。

阅读理解数据集包括 RACE Lai 等人(2017), DROP (Dua 等人, 2019), C3 (Sun 等人, 2019a), 以及 CMRC (Cui 等人, 2019)。

参考消歧数据集包括 CLUEWSC (Xu 等人, 2020) 和 WinoGrande Sakaguchi 等人 (2019)。

语言建模数据集包括 Pile (Gao 等人, 2020)。

中文理解与文化数据集包括 CCPM (Li 等人, 2021)。

数学数据集包括 GSM8K (Cobbe 等人, 2021), MATH (Hendrycks 等人, 2021), MGSM (Shi 等人, 2023), 以及 CMath (Wei 等人, 2023)。

代码数据集包括 HumanEval (Chen 等人,2021), LiveCodeBench-Base (0801-1101) (Jain 等人, 2024), MBPP (Austin 等人, 2021), 以及 CRUXEval (Gu 等人, 2024)。

标准化考试包括 AGIEval (Zhong 等人, 2023)。请注意, AGIEval 包含英语和中文子集。

基于我们之前的工作 (DeepSeek-AI, 2024b,c), 我们采用困惑度评估方法对 HellaSwag、PIQA、WinoGrande、RACE-Middle、RACE-High、MMLU、MMLU-Redux、MMLU-Pro、MMMLU、ARC-Easy、ARC-Challenge、C-Eval、CMMLU、C3 和 CCPM 等数据集进行评估, 并采用生成式评估方法对 TriviaQA、NaturalQuestions、DROP、MATH、GSM8K、MGSM、HumanEval、MBPP、LiveCodeBench-Base、CRUXEval、BBH、AGIEval、CLUEWSC、CMRC 和 CMath 进行评估。此外, 我们对 Pile-test 进行基于语言模型的评估, 并使用比特每字节 (BPB) 作为指标, 以确保使用不同分词器的模型之间具有公平的比较。

4.4.2. 评估结果

在表3中, 我们将DeepSeek-V3的基础模型与当前最先进的开源基础模型进行比较, 包括DeepSeek-V2-Base (DeepSeek-AI, 2024c) (我们之前的发布版本)、Qwen2.5 72B Base (Qwen, 2024b) 和LLaMA-3.1 405B Base (AI@Meta, 2024b)。我们使用内部评估框架评估所有这些模型, 并确保它们共享相同的评估设置。请注意, 由于我们评估框架在过去几个月中的变化, DeepSeek-V2-Base的性能与我们的先前报告结果略有不同。总体而言, DeepSeek-V3-Base全面优于DeepSeek-V2-Base和Qwen2.5 72B Base, 并在大多数基准测试中超越了LLaMA-3.1 405B Base, 基本上成为最强的开源模型。

Benchmark (Metric)	# Shots	DeepSeek-V2 Base	Qwen2.5 72B Base	LLaMA-3.1 405B Base	DeepSeek-V3 Base	
Architecture	-	MoE	Dense	Dense	MoE	
# Activated Params	-	21B	72B	405B	37B	
# Total Params	-	236B	72B	405B	671B	
English	Pile-test (BPB)	-	0.606	0.638	0.542	0.548
	BBH (EM)	3-shot	78.8	79.8	82.9	87.5
	MMLU (EM)	5-shot	78.4	85.0	84.4	87.1
	MMLU-Redux (EM)	5-shot	75.6	83.2	81.3	86.2
	MMLU-Pro (EM)	5-shot	51.4	58.3	52.8	64.4
	DROP (F1)	3-shot	80.4	80.6	86.0	89.0
	ARC-Easy (EM)	25-shot	97.6	98.4	98.4	98.9
	ARC-Challenge (EM)	25-shot	92.2	94.5	95.3	95.3
	HellaSwag (EM)	10-shot	87.1	84.8	89.2	88.9
	PIQA (EM)	0-shot	83.9	82.6	85.9	84.7
	WinoGrande (EM)	5-shot	86.3	82.3	85.2	84.9
	RACE-Middle (EM)	5-shot	73.1	68.1	74.2	67.1
	RACE-High (EM)	5-shot	52.6	50.3	56.8	51.3
	TriviaQA (EM)	5-shot	80.0	71.9	82.7	82.9
	NaturalQuestions (EM)	5-shot	38.6	33.2	41.5	40.0
	AGIEval (EM)	0-shot	57.5	75.8	60.6	79.6
	Code	HumanEval (Pass@1)	0-shot	43.3	53.0	54.9
MBPP (Pass@1)		3-shot	65.0	72.6	68.4	75.4
LiveCodeBench-Base (Pass@1)		3-shot	11.6	12.9	15.5	19.4
CRUXEval-I (EM)		2-shot	52.5	59.1	58.5	67.3
CRUXEval-O (EM)		2-shot	49.8	59.9	59.9	69.8
Math	GSM8K (EM)	8-shot	81.6	88.3	83.5	89.3
	MATH (EM)	4-shot	43.4	54.4	49.0	61.6
	M GSM (EM)	8-shot	63.6	76.2	69.9	79.8
	CMath (EM)	3-shot	78.7	84.5	77.3	90.7
Chinese	CLUEWSC (EM)	5-shot	82.0	82.5	83.0	82.7
	C-Eval (EM)	5-shot	81.4	89.2	72.5	90.1
	CMMLU (EM)	5-shot	84.0	89.5	73.7	88.8
	CMRC (EM)	1-shot	77.4	75.8	76.0	76.3
	C3 (EM)	0-shot	77.4	76.7	79.7	78.6
	CCPM (EM)	0-shot	93.0	88.5	78.6	92.0
Multilingual	MMMLU-non-English (EM)	5-shot	64.0	74.8	73.8	79.4

Table 3 | Comparison among DeepSeek-V3-Base and other representative open-source base models. All models are evaluated in our internal framework and share the same evaluation setting. Scores with a gap not exceeding 0.3 are considered to be at the same level. DeepSeek-V3-Base achieves the best performance on most benchmarks, especially on math and code tasks.

of DeepSeek-V2-Base exhibits a slight difference from our previously reported results. Overall, DeepSeek-V3-Base comprehensively outperforms DeepSeek-V2-Base and Qwen2.5 72B Base, and surpasses LLaMA-3.1 405B Base in the majority of benchmarks, essentially becoming the strongest open-source model.

From a more detailed perspective, we compare DeepSeek-V3-Base with the other open-source base models individually. (1) Compared with DeepSeek-V2-Base, due to the improvements in our model architecture, the scale-up of the model size and training tokens, and the enhancement of data quality, DeepSeek-V3-Base achieves significantly better performance as expected. (2) Compared with Qwen2.5 72B Base, the state-of-the-art Chinese open-source model, with only half of the activated parameters, DeepSeek-V3-Base also demonstrates remarkable advantages,

基准 (指标)	# 射击次数	DeepSeek-V2 Base	Qwen2.5 72B 基础版	LLaMA-3.1 405B 基础版	DeepSeek-V3 Base	
架构	-	MoE	密集	密集	MoE	
# 激活参数	-	21B	72B	405B	37B	
# 总参数	-	236B	72B	405B	671B	
英语	Pile测试 (BPB)	-	0.606	0.638	0.542	0.548
	BBH (EM)	3-shot	78.8	79.8	82.9	87.5
	MMLU (EM)	5-shot	78.4	85.0	84.4	87.1
	MMLU-Redux (EM)	5-shot	75.6	83.2	81.3	86.2
	MMLU-Pro (EM)	5-shot	51.4	58.3	52.8	64.4
	DROP (F1)	3-shot	80.4	80.6	86.0	89.0
	ARC-Easy (EM)	25-shot	97.6	98.4	98.4	98.9
	ARC-Challenge (EM)	25-shot	92.2	94.5	95.3	95.3
	HellaSwag (EM)	10-shot	87.1	84.8	89.2	88.9
	PIQA (EM)	0-shot	83.9	82.6	85.9	84.7
	WinoGrande (EM)	5-shot	86.3	82.3	85.2	84.9
	RACE-Middle (EM)	5-shot	73.1	68.1	74.2	67.1
	RACE-High (EM)	5-shot	52.6	50.3	56.8	51.3
	TriviaQA (EM)	5-shot	80.0	71.9	82.7	82.9
	NaturalQuestions (EM)	5-shot	38.6	33.2	41.5	40.0
	AGIEval (EM)	0-shot	57.5	75.8	60.6	79.6
	Code	HumanEval (Pass@1)	0-shot	43.3	53.0	54.9
MBPP (Pass@1)		3-shot	65.0	72.6	68.4	75.4
LiveCodeBench-Base (Pass@1)		3-shot	11.6	12.9	15.5	19.4
CRUXEval-I (EM)		2-shot	52.5	59.1	58.5	67.3
CRUXEval-O (EM)		2-shot	49.8	59.9	59.9	69.8
Math	GSM8K (EM)	8-shot	81.6	88.3	83.5	89.3
	数学 (EM)	4-shot	43.4	54.4	49.0	61.6
	M GSM (EM)	8-shot	63.6	76.2	69.9	79.8
	CMath (EM)	3-shot	78.7	84.5	77.3	90.7
中文	CLUEWSC (EM)	5-shot	82.0	82.5	83.0	82.7
	C-Eval (EM)	5-shot	81.4	89.2	72.5	90.1
	CMMLU (EM)	5-shot	84.0	89.5	73.7	88.8
	CMRC (EM)	1-shot	77.4	75.8	76.0	76.3
	C3 (EM)	0-shot	77.4	76.7	79.7	78.6
	CCPM (EM)	0-shot	93.0	88.5	78.6	92.0
多语言	MMMLU非英语 (EM)	5-shot	64.0	74.8	73.8	79.4

表 3 | DeepSeek-V3-Base与其他代表性开源基础模型的对比。所有模型均在我们的内部框架中进行评估，并共享相同的评估设置。分数差距不超过0.3的被视为处于同一水平。DeepSeek-V3-Base在大多数基准测试中表现最佳，尤其是在数学和代码任务上。

DeepSeek-V2-Base的性能与我们的先前报告结果略有不同。总体而言，DeepSeek-V3-Base全面优于DeepSeek-V2-Base和Qwen2.5 72B Base，并在大多数基准测试中超越了LLaMA-3.1 405B Base，基本上成为最强的开源模型。

从更详细的角度来看，我们逐个将 DeepSeek-V3-Base 与其他开源基础模型进行比较。(1) 与 DeepSeek-V2-Base 相比，由于我们模型架构的改进、模型规模和训练令牌的扩大以及数据质量的提升，DeepSeek-V3-Base 如预期般实现了显著更好的性能。(2) 与 Qwen2.5 72B Base 相比，作为目前最先进的中文开源模型，DeepSeek-V3-Base 仅使用一半的激活参数，也展现了卓越的优势，

especially on English, multilingual, code, and math benchmarks. As for Chinese benchmarks, except for CMMLU, a Chinese multi-subject multiple-choice task, DeepSeek-V3-Base also shows better performance than Qwen2.5 72B. (3) Compared with LLaMA-3.1 405B Base, the largest open-source model with 11 times the activated parameters, DeepSeek-V3-Base also exhibits much better performance on multilingual, code, and math benchmarks. As for English and Chinese language benchmarks, DeepSeek-V3-Base shows competitive or better performance, and is especially good on BBH, MMLU-series, DROP, C-Eval, CMMLU, and CCPM.

Due to our efficient architectures and comprehensive engineering optimizations, DeepSeek-V3 achieves extremely high training efficiency. Under our training framework and infrastructures, training DeepSeek-V3 on each trillion tokens requires only 180K H800 GPU hours, which is much cheaper than training 72B or 405B dense models.

Benchmark (Metric)	# Shots	Small MoE Baseline	Small MoE w/ MTP	Large MoE Baseline	Large MoE w/ MTP
# Activated Params (Inference)	-	2.4B	2.4B	20.9B	20.9B
# Total Params (Inference)	-	15.7B	15.7B	228.7B	228.7B
# Training Tokens	-	1.33T	1.33T	540B	540B
Pile-test (BFB)	-	0.729	0.729	0.658	0.657
BBH (EM)	3-shot	39.0	41.4	70.0	70.7
MMLU (EM)	5-shot	50.0	53.3	67.5	66.6
DROP (F1)	1-shot	39.2	41.3	68.5	70.6
TriviaQA (EM)	5-shot	56.9	57.7	67.0	67.3
NaturalQuestions (EM)	5-shot	22.7	22.3	27.2	28.5
HumanEval (Pass@1)	0-shot	20.7	26.8	44.5	53.7
MBPP (Pass@1)	3-shot	35.8	36.8	61.6	62.2
GSM8K (EM)	8-shot	25.4	31.4	72.3	74.0
MATH (EM)	4-shot	10.7	12.6	38.6	39.8

Table 4 | Ablation results for the MTP strategy. The MTP strategy consistently enhances the model performance on most of the evaluation benchmarks.

4.5. Discussion

4.5.1. Ablation Studies for Multi-Token Prediction

In Table 4, we show the ablation results for the MTP strategy. To be specific, we validate the MTP strategy on top of two baseline models across different scales. At the small scale, we train a baseline MoE model comprising 15.7B total parameters on 1.33T tokens. At the large scale, we train a baseline MoE model comprising 228.7B total parameters on 540B tokens. On top of them, keeping the training data and the other architectures the same, we append a 1-depth MTP module onto them and train two models with the MTP strategy for comparison. Note that during inference, we directly discard the MTP module, so the inference costs of the compared models are exactly the same. From the table, we can observe that the MTP strategy consistently enhances the model performance on most of the evaluation benchmarks.

4.5.2. Ablation Studies for the Auxiliary-Loss-Free Balancing Strategy

In Table 5, we show the ablation results for the auxiliary-loss-free balancing strategy. We validate this strategy on top of two baseline models across different scales. At the small scale, we train a baseline MoE model comprising 15.7B total parameters on 1.33T tokens. At the large scale, we train a baseline MoE model comprising 228.7B total parameters on 578B tokens.

尤其是在英语、多语言、代码和数学基准测试上。至于中文基准测试，除了 CMMLU（一个中文多科目选择题任务）之外，DeepSeek-V3-Base 的性能也优于 Qwen2.5 72B。(3) 与 LLaMA-3.1 405B Base 相比，作为拥有 11 倍激活参数的最大开源模型，DeepSeek-V3-Base 在多语言、代码和数学基准测试上也表现出远超的性能。至于英语和中文语言基准测试，DeepSeek-V3-Base 展现出具有竞争力的或更好的性能，尤其是在 BBH、MMLU 系列、DROP、C-Eval、CMMLU 和 CCPM 上。

由于我们高效的架构和全面的工程优化，DeepSeek-V3 实现了极高的训练效率。在我们的训练框架和基础设施下，每个万亿token的训练DeepSeek-V3仅需180K H800 GPU小时，这比训练72B或405B密集模型要便宜得多。

基准 (指标)	# 射击次数	小MoE 基线	小MoE 带MTP	大MoE 基线	大型MoE 带MTP
# 激活参数 (Inference)	-	2.4B	2.4B	20.9B	20.9B
# 总参数 (Inference)	-	15.7B	15.7B	228.7B	228.7B
# 训练令牌	-	1.33T	1.33T	540B	540B
Pile测试 (BFB)	-	0.729	0.729	0.658	0.657
BBH (EM)	3-shot	39.0	41.4	70.0	70.7
MMLU (EM)	5-shot	50.0	53.3	67.5	66.6
DROP (F1)	1-shot	39.2	41.3	68.5	70.6
TriviaQA (EM)	5-shot	56.9	57.7	67.0	67.3
NaturalQuestions (EM)	5-shot	22.7	22.3	27.2	28.5
HumanEval (Pass@1)	0-shot	20.7	26.8	44.5	53.7
MBPP (Pass@1)	3-shot	35.8	36.8	61.6	62.2
GSM8K (EM)	8-shot	25.4	31.4	72.3	74.0
数学 (EM)	4-shot	10.7	12.6	38.6	39.8

表 4 | Ablation结果，用于MTP策略。MTP策略在大多数评估基准上始终提升了模型性能。

4.5. 讨论

4.5.1. 多标记预测的消融研究

在表4中，我们展示了MTP策略的消融结果。具体来说，我们在不同规模上基于两个基线模型验证了MTP策略。在小规模上，我们在1.33T tokens上训练了一个包含15.7B总参数的基线MoE模型。在大规模上，我们在540B tokens上训练了一个包含228.7B总参数的基线MoE模型。在它们之上，保持训练数据和其它架构相同，我们向它们附加了一个1深度的MTP模块，并使用MTP策略训练两个模型进行比较。请注意，在推理时，我们直接丢弃了MTP模块，因此比较模型的推理成本完全相同。从表格中，我们可以观察到MTP策略在大多数评估基准上始终提升了模型性能。

4.5.2. 辅助损失无平衡策略的消融研究

在表5中，我们展示了无辅助损失平衡策略的消融结果。我们在不同规模上基于两个基线模型验证该策略。在小规模上，我们在1.33T个token上训练了一个包含15.7B总参数的基线MoE模型。在大规模上，我们在578B个token上训练了一个包含228.7B总参数的基线MoE模型。

Benchmark (Metric)	# Shots	Small MoE		Large MoE	
		Aux-Loss-Based	Aux-Loss-Free	Aux-Loss-Based	Aux-Loss-Free
# Activated Params	-	2.4B	2.4B	20.9B	20.9B
# Total Params	-	15.7B	15.7B	228.7B	228.7B
# Training Tokens	-	1.33T	1.33T	578B	578B
Pile-test (BPB)	-	0.727	0.724	0.656	0.652
BBH (EM)	3-shot	37.3	39.3	66.7	67.9
MMLU (EM)	5-shot	51.0	51.8	68.3	67.2
DROP (F1)	1-shot	38.1	39.0	67.1	67.1
TriviaQA (EM)	5-shot	58.3	58.5	66.7	67.7
NaturalQuestions (EM)	5-shot	23.2	23.4	27.1	28.1
HumanEval (Pass@1)	0-shot	22.0	22.6	40.2	46.3
MBPP (Pass@1)	3-shot	36.6	35.8	59.2	61.2
GSM8K (EM)	8-shot	27.1	29.6	70.7	74.5
MATH (EM)	4-shot	10.9	11.1	37.2	39.6

Table 5 | Ablation results for the auxiliary-loss-free balancing strategy. Compared with the purely auxiliary-loss-based method, the auxiliary-loss-free strategy consistently achieves better model performance on most of the evaluation benchmarks.

Both of the baseline models purely use auxiliary losses to encourage load balance, and use the sigmoid gating function with top-K affinity normalization. Their hyper-parameters to control the strength of auxiliary losses are the same as DeepSeek-V2-Lite and DeepSeek-V2, respectively. On top of these two baseline models, keeping the training data and the other architectures the same, we remove all auxiliary losses and introduce the auxiliary-loss-free balancing strategy for comparison. From the table, we can observe that the auxiliary-loss-free strategy consistently achieves better model performance on most of the evaluation benchmarks.

4.5.3. Batch-Wise Load Balance VS. Sequence-Wise Load Balance

The key distinction between auxiliary-loss-free balancing and sequence-wise auxiliary loss lies in their balancing scope: batch-wise versus sequence-wise. Compared with the sequence-wise auxiliary loss, batch-wise balancing imposes a more flexible constraint, as it does not enforce in-domain balance on each sequence. This flexibility allows experts to better specialize in different domains. To validate this, we record and analyze the expert load of a 16B auxiliary-loss-based baseline and a 16B auxiliary-loss-free model on different domains in the Pile test set. As illustrated in Figure 9, we observe that the auxiliary-loss-free model demonstrates greater expert specialization patterns as expected.

To further investigate the correlation between this flexibility and the advantage in model performance, we additionally design and validate a batch-wise auxiliary loss that encourages load balance on each training batch instead of on each sequence. The experimental results show that, when achieving a similar level of batch-wise load balance, the batch-wise auxiliary loss can also achieve similar model performance to the auxiliary-loss-free method. To be specific, in our experiments with 1B MoE models, the validation losses are: 2.258 (using a sequence-wise auxiliary loss), 2.253 (using the auxiliary-loss-free method), and 2.253 (using a batch-wise auxiliary loss). We also observe similar results on 3B MoE models: the model using a sequence-wise auxiliary loss achieves a validation loss of 2.085, and the models using the auxiliary-loss-free method or a batch-wise auxiliary loss achieve the same validation loss of 2.080.

In addition, although the batch-wise load balancing methods show consistent performance advantages, they also face two potential challenges in efficiency: (1) load imbalance within

基准 (指标)	# 射击次数	小型 MoE	小型 MoE	大型 MoE	大型 MoE
		基于辅助损失	无辅助损失	基于辅助损失	无辅助损失
# 激活参数	-	2.4B	2.4B	20.9B	20.9B
# 总参数	-	15.7B	15.7B	228.7B	228.7B
# 训练令牌	-	1.33T	1.33T	578B	578B
Pile测试 (BPB)	-	0.727	0.724	0.656	0.652
BBH (EM)	3-shot	37.3	39.3	66.7	67.9
MMLU (EM)	5-shot	51.0	51.8	68.3	67.2
DROP (F1)	1-shot	38.1	39.0	67.1	67.1
TriviaQA (EM)	5-shot	58.3	58.5	66.7	67.7
NaturalQuestions (EM)	5-shot	23.2	23.4	27.1	28.1
HumanEval (Pass@1)	0-shot	22.0	22.6	40.2	46.3
MBPP (Pass@1)	3-shot	36.6	35.8	59.2	61.2
GSM8K (EM)	8-shot	27.1	29.6	70.7	74.5
数学 (EM)	4-shot	10.9	11.1	37.2	39.6

表 5 | 无辅助损失策略的消融结果。与纯辅助损失方法相比，无辅助损失策略在大多数评估基准上始终能实现更好的模型性能。

这两个基线模型纯粹使用辅助损失来鼓励负载均衡，并使用带有top-K亲和度归一化的Sigmoid门控函数。它们分别控制辅助损失强度的超参数与DeepSeek-V2-Lite和DeepSeek-V2相同。在这些两个基线模型上，保持训练数据和其它架构不变，我们移除所有辅助损失并引入无辅助损失平衡策略进行比较。从表格中，我们可以观察到无辅助损失策略在大多数评估基准上始终实现了更好的模型性能。

4.5.3. 批次式负载均衡 VS. 序列式负载均衡

辅助损失无关平衡与序列辅助损失的关键区别在于它们的平衡范围：批处理式与序列式。与序列辅助损失相比，批处理式平衡施加了更灵活的约束，因为它不会强制要求每个序列在领域内平衡。这种灵活性使专家能更好地专业化于不同领域。为了验证这一点，我们记录并分析了16B辅助损失基线和16B辅助损失无关模型在Pile测试集不同领域上的专家负载。如图9所示，我们观察到辅助损失无关模型如预期所示表现出更强的专家专业化模式。

为了进一步研究这种灵活性与模型性能优势之间的相关性，我们额外设计并验证了一种批处理式辅助损失，它鼓励在每个训练批次上而不是每个序列上实现负载均衡。实验结果表明，在实现相似的批处理式负载平衡水平时，批处理式辅助损失也能达到与辅助损失无关方法相似的模型性能。具体来说，在我们的1B MoE模型实验中，验证损失分别为：2.258（使用序列辅助损失）、2.253（使用辅助损失无关方法）和2.253（使用批处理式辅助损失）。我们还观察到3B MoE模型上的相似结果：使用序列辅助损失的模型验证损失为2.085，而使用辅助损失无关方法或批处理式辅助损失的模型则达到相同的验证损失2.080。

此外，尽管批量式负载均衡方法表现出一致的性能优势，但它们在效率方面也面临两个潜在挑战：(1) 负载不平衡

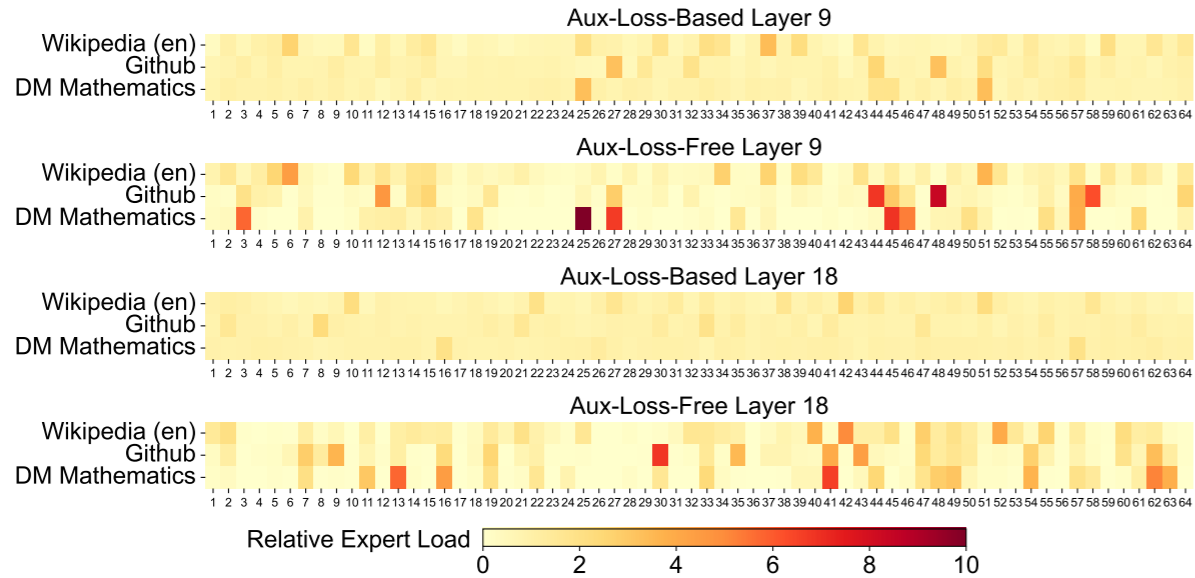


Figure 9 | Expert load of auxiliary-loss-free and auxiliary-loss-based models on three domains in the Pile test set. The auxiliary-loss-free model shows greater expert specialization patterns than the auxiliary-loss-based one. The relative expert load denotes the ratio between the actual expert load and the theoretically balanced expert load. Due to space constraints, we only present the results of two layers as an example, with the results of all layers provided in Appendix C.

certain sequences or small batches, and (2) domain-shift-induced load imbalance during inference. The first challenge is naturally addressed by our training framework that uses large-scale expert parallelism and data parallelism, which guarantees a large size of each micro-batch. For the second challenge, we also design and implement an efficient inference framework with redundant expert deployment, as described in Section 3.4, to overcome it.

5. Post-Training

5.1. Supervised Fine-Tuning

We curate our instruction-tuning datasets to include 1.5M instances spanning multiple domains, with each domain employing distinct data creation methods tailored to its specific requirements.

Reasoning Data. For reasoning-related datasets, including those focused on mathematics, code competition problems, and logic puzzles, we generate the data by leveraging an internal DeepSeek-R1 model. Specifically, while the R1-generated data demonstrates strong accuracy, it suffers from issues such as overthinking, poor formatting, and excessive length. Our objective is to balance the high accuracy of R1-generated reasoning data and the clarity and conciseness of regularly formatted reasoning data.

To establish our methodology, we begin by developing an expert model tailored to a specific domain, such as code, mathematics, or general reasoning, using a combined Supervised Fine-Tuning (SFT) and Reinforcement Learning (RL) training pipeline. This expert model serves as a data generator for the final model. The training process involves generating two distinct types of SFT samples for each instance: the first couples the problem with its original response in the format of <problem, original response>, while the second incorporates a system prompt

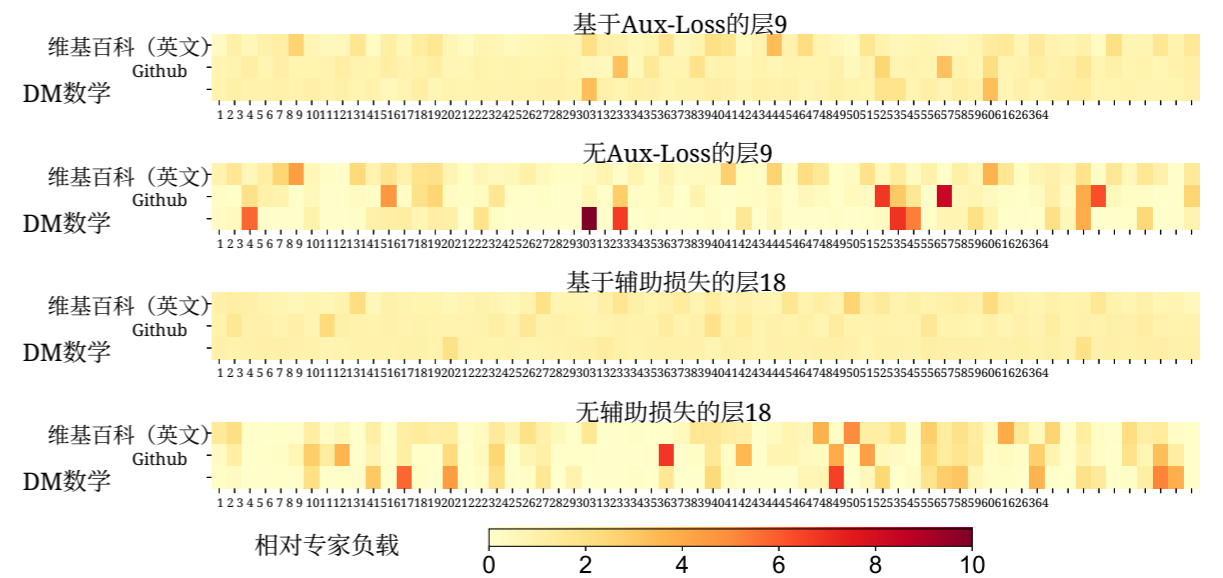


图9 | 在Pile测试集上，无辅助损失层和基于辅助损失的模型在三个领域的专家负载。无辅助损失层的模型显示出比基于辅助损失的模型更明显的专家专业化模式。相对专家负载表示实际专家负载与理论上平衡的专家负载之间的比率。由于篇幅限制，我们仅以两层的结果为例，所有层的结果在附录C中提供。

此外，尽管批处理负载均衡方法表现出一致的性能优势，但在效率方面也面临两个潜在挑战：(1) 某些序列或小批次的负载不平衡，以及(2) 推理过程中的领域偏移引起的负载不平衡。第一个挑战自然地由我们使用的训练框架解决，该框架采用大规模专家并行和数据并行，确保每个微批次的大小足够大。对于第二个挑战，我们还设计并实现了一个具有冗余专家部署的高效推理框架，如第3.4节所述，以克服这一问题。

5. 后训练

5.1. 监督微调

我们精心策划的指令微调数据集包含 1.5M 个跨多个领域的实例，每个领域采用针对其特定需求定制的数据创建方法。

推理数据。 对于推理相关数据集，包括专注于数学、代码竞赛问题和逻辑谜题的数据集，我们通过利用内部 DeepSeek-R1 模型生成数据。具体而言，虽然 R1 生成的数据准确性很高，但它存在过度思考、格式不佳和长度过长等问题。我们的目标是平衡 R1 生成的推理数据的高准确性与常规格式推理数据的清晰度和简洁性。

为建立我们的方法论，我们首先开发一个针对特定领域的专家模型，例如代码、数学或通用推理，使用结合了监督微调 (SFT) 和强化学习 (RL) 的训练流程。该专家模型作为最终模型的数据生成器。训练过程涉及为每个实例生成两种不同类型的 SFT 样本：第一种将问题与其原始响应以 <问题, 原始响应> 的格式配对，第二种则包含系统提示

alongside the problem and the R1 response in the format of <system prompt, problem, R1 response>.

The system prompt is meticulously designed to include instructions that guide the model toward producing responses enriched with mechanisms for reflection and verification. During the RL phase, the model leverages high-temperature sampling to generate responses that integrate patterns from both the R1-generated and original data, even in the absence of explicit system prompts. After hundreds of RL steps, the intermediate RL model learns to incorporate R1 patterns, thereby enhancing overall performance strategically.

Upon completing the RL training phase, we implement rejection sampling to curate high-quality SFT data for the final model, where the expert models are used as data generation sources. This method ensures that the final training data retains the strengths of DeepSeek-R1 while producing responses that are concise and effective.

Non-Reasoning Data. For non-reasoning data, such as creative writing, role-play, and simple question answering, we utilize DeepSeek-V2.5 to generate responses and enlist human annotators to verify the accuracy and correctness of the data.

SFT Settings. We fine-tune DeepSeek-V3-Base for two epochs using the SFT dataset, using the cosine decay learning rate scheduling that starts at 5×10^{-6} and gradually decreases to 1×10^{-6} . During training, each single sequence is packed from multiple samples. However, we adopt a sample masking strategy to ensure that these examples remain isolated and mutually invisible.

5.2. Reinforcement Learning

5.2.1. Reward Model

We employ a rule-based Reward Model (RM) and a model-based RM in our RL process.

Rule-Based RM. For questions that can be validated using specific rules, we adopt a rule-based reward system to determine the feedback. For instance, certain math problems have deterministic results, and we require the model to provide the final answer within a designated format (e.g., in a box), allowing us to apply rules to verify the correctness. Similarly, for LeetCode problems, we can utilize a compiler to generate feedback based on test cases. By leveraging rule-based validation wherever possible, we ensure a higher level of reliability, as this approach is resistant to manipulation or exploitation.

Model-Based RM. For questions with free-form ground-truth answers, we rely on the reward model to determine whether the response matches the expected ground-truth. Conversely, for questions without a definitive ground-truth, such as those involving creative writing, the reward model is tasked with providing feedback based on the question and the corresponding answer as inputs. The reward model is trained from the DeepSeek-V3 SFT checkpoints. To enhance its reliability, we construct preference data that not only provides the final reward but also includes the chain-of-thought leading to the reward. This approach helps mitigate the risk of reward hacking in specific tasks.

, 以及问题与R1响应以 <系统提示, 问题, R1响应>的格式结合。

系统提示被精心设计, 包含指导模型生成包含反思和验证机制的响应的指令。在强化学习阶段, 模型利用高温采样生成包含 R1 生成的和原始数据模式的响应, 即使在缺乏明确系统提示的情况下也是如此。经过数百次强化学习步骤后, 中间强化学习模型学会结合 R1 模式, 从而战略性地提升整体性能。

完成强化学习训练阶段后, 我们采用拒绝采样来筛选高质量的SFT数据, 用于最终模型, 其中专家模型被用作数据生成源。这种方法确保了最终训练数据保留了DeepSeek-R1的优势, 同时生成的回复简洁有效。

非推理数据。 对于非推理数据, 例如创意写作、角色扮演和简单问答, 我们利用 DeepSeek-V2.5 生成回复, 并聘请人工标注员来验证数据的准确性和正确性。

SFT设置。 我们使用SFT数据集对DeepSeek-V3-Base进行两个epoch的微调, 采用余弦衰减学习率调度, 初始值为 5×10^{-6} , 并逐渐衰减至 1×10^{-6} 。在训练过程中, 每个单序列由多个样本打包而成。然而, 我们采用样本掩码策略, 以确保这些示例保持隔离且相互不可见。

5.2. 强化学习

5.2.1. 奖励模型

We 在我们的强化学习过程中采用基于规则的奖励模型 (RM) 和基于模型的RM

基于规则的奖励模型。 对于可以使用特定规则进行验证的问题, 我们采用基于规则的奖励系统来确定反馈。例如, 某些数学问题具有确定性结果, 我们要求模型以指定的格式 (例如, 在括号内) 提供最终答案, 从而允许我们应用规则来验证正确性。类似地, 对于LeetCode问题, 我们可以利用编译器根据测试用例生成反馈。通过尽可能利用基于规则的验证, 我们确保了更高的可靠性, 因为这种方法对操纵或利用具有抵抗力。

基于模型的奖励模型。 对于具有自由形式ground-truth答案的问题, 我们依赖奖励模型来判断响应是否与预期的ground-truth匹配。相反, 对于没有明确ground-truth的问题, 例如涉及创意写作的问题, 奖励模型需要根据问题和相应的答案作为输入来提供反馈。奖励模型是从 DeepSeek-V3 SFT检查点训练的。为了提高其可靠性, 我们构建了偏好数据, 这些数据不仅提供最终奖励, 还包括导致奖励的思维链。这种方法有助于降低特定任务中奖励攻击的风险。

5.2.2. Group Relative Policy Optimization

Similar to DeepSeek-V2 (DeepSeek-AI, 2024c), we adopt Group Relative Policy Optimization (GRPO) (Shao et al., 2024), which foregoes the critic model that is typically with the same size as the policy model, and estimates the baseline from group scores instead. Specifically, for each question q , GRPO samples a group of outputs $\{o_1, o_2, \dots, o_G\}$ from the old policy model $\pi_{\theta_{old}}$ and then optimizes the policy model π_{θ} by maximizing the following objective:

$$\mathcal{J}_{GRPO}(\theta) = \mathbb{E}[q \sim P(Q), \{o_i\}_{i=1}^G \sim \pi_{\theta_{old}}(O|q)] \frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{old}}(o_i|q)} A_i, \text{clip} \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{old}}(o_i|q)}, 1 - \varepsilon, 1 + \varepsilon \right) A_i \right) - \beta \mathbb{D}_{KL}(\pi_{\theta} || \pi_{ref}) \right), \quad (26)$$

$$\mathbb{D}_{KL}(\pi_{\theta} || \pi_{ref}) = \frac{\pi_{ref}(o_i|q)}{\pi_{\theta}(o_i|q)} - \log \frac{\pi_{ref}(o_i|q)}{\pi_{\theta}(o_i|q)} - 1, \quad (27)$$

where ε and β are hyper-parameters; π_{ref} is the reference model; and A_i is the advantage, derived from the rewards $\{r_1, r_2, \dots, r_G\}$ corresponding to the outputs within each group:

$$A_i = \frac{r_i - \text{mean}(\{r_1, r_2, \dots, r_G\})}{\text{std}(\{r_1, r_2, \dots, r_G\})}. \quad (28)$$

We incorporate prompts from diverse domains, such as coding, math, writing, role-playing, and question answering, during the RL process. This approach not only aligns the model more closely with human preferences but also enhances performance on benchmarks, especially in scenarios where available SFT data are limited.

5.3. Evaluations

5.3.1. Evaluation Settings

Evaluation Benchmarks. Apart from the benchmark we used for base model testing, we further evaluate instructed models on IFEval (Zhou et al., 2023), FRAMES (Krishna et al., 2024), LongBench v2 (Bai et al., 2024), GPQA (Rein et al., 2023), SimpleQA (OpenAI, 2024c), C-SimpleQA (He et al., 2024), SWE-Bench Verified (OpenAI, 2024d), Aider¹, LiveCodeBench (Jain et al., 2024) (questions from August 2024 to November 2024), Codeforces², Chinese National High School Mathematics Olympiad (CNMO 2024)³, and American Invitational Mathematics Examination 2024 (AIME 2024) (MAA, 2024).

Compared Baselines. We conduct comprehensive evaluations of our chat model against several strong baselines, including DeepSeek-V2-0506, DeepSeek-V2.5-0905, Qwen2.5 72B Instruct, LLaMA-3.1 405B Instruct, Claude-Sonnet-3.5-1022, and GPT-4o-0513. For the DeepSeek-V2 model series, we select the most representative variants for comparison. For closed-source models, evaluations are performed through their respective APIs.

Detailed Evaluation Configurations. For standard benchmarks including MMLU, DROP, GPQA, and SimpleQA, we adopt the evaluation prompts from the simple-evals framework⁴.

¹<https://aider.chat>

²<https://codeforces.com>

³<https://www.cms.org.cn/Home/comp/comp/cid/12.html>

⁴<https://github.com/openai/simple-evals>

5.2.2. 组相对策略优化

类似于DeepSeek-V2 (DeepSeek-AI, 2024c), 我们采用组相对策略优化 (GRPO) (Shao 等人, 2024), 它放弃了通常与策略模型大小相同的评价者模型, 并从组分数中估计基线。具体来说, 对于每个问题 q , GRPO从旧策略模型 $\pi_{\theta_{old}}$ 中采样一组输出 $\{o_1, o_2, \dots, o_G\}$, 然后通过最大化以下目标来优化策略模型 π_{θ} :

$$\mathcal{J}_{GRPO}(\theta) = \mathbb{E}[q \sim P(Q), \{o_i\}_{i=1}^G \sim \pi_{\theta_{old}}(O|q)] \frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{old}}(o_i|q)} A_i, \text{clip} \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{old}}(o_i|q)}, 1 - \varepsilon, 1 + \varepsilon \right) A_i \right) - \beta \mathbb{D}_{KL}(\pi_{\theta} || \pi_{ref}) \right), \quad (26)$$

$$\mathbb{D}_{KL}(\pi_{\theta} || \pi_{ref}) = \frac{\pi_{ref}(o_i|q)}{\pi_{\theta}(o_i|q)} - \log \frac{\pi_{ref}(o_i|q)}{\pi_{\theta}(o_i|q)} - 1, \quad (27)$$

其中 ε 和 β 是超参数; π_{ref} 是参考模型; 而 A_i 是优势, 源自于每个组内对应输出的奖励 $\{r_1, r_2, \dots, r_G\}$:

$$A_i = \frac{r_i - \text{mean}(\{r_1, r_2, \dots, r_G\})}{\text{std}(\{r_1, r_2, \dots, r_G\})}. \quad (28)$$

我们在强化学习过程中整合了来自不同领域的提示, 如编码、数学、写作、角色扮演和问答。这种方法不仅使模型更紧密地符合人类偏好, 还提升了基准测试的性能, 尤其是在可用 SFT数据有限的情况下。

5.3. 评估

5.3.1. 评估设置

评估基准。除了用于基础模型测试的基准外, 我们还使用IFEval (Zhou等人, 2023)、FRAMES (Krishna等人, 2024)、LongBench v2 (Bai等人, 2024)、GPQA (Rein等人, 2023)、SimpleQA (OpenAI, 2024c)、C-SimpleQA (He等人, 2024)、SWE-Bench验证 (OpenAI, 2024d)、Aider 1、LiveCodeBench (Jain等人, 2024) (问题来自2024年8月至11月)、Codeforces 2、中国高中生数学奥林匹克 (CNMO 2024)³, 以及美国邀请数学考试2024 (AIME 2024) (MAA, 2024)。

与基准模型对比。我们对我们的聊天模型与多个强基准进行了全面评估, 包括 DeepSeek-V2-0506、DeepSeek-V2.5-0905、Qwen2.5 72B Instruct、LLaMA-3.1 405B Instruct、Claude-Sonnet-3.5-1022 和 GPT-4o-0513。对于 DeepSeek-V2 模型系列, 我们选择了最具代表性的变体进行比较。对于闭源模型, 评估通过其各自的 API 进行。

详细评估配置。对于包括 MMLU、DROP、GPQA 和 SimpleQA 在内的标准基准, 我们采用来自 simple-evals 框架⁴的评估提示。

¹<https://aider.chat>

²<https://codeforces.com>

³<https://www.cms.org.cn/Home/comp/comp/cid/12.html>

⁴<https://github.com/openai/simple-evals>

We utilize the Zero-Eval prompt format (Lin, 2024) for MMLU-Redux in a zero-shot setting. For other datasets, we follow their original evaluation protocols with default prompts as provided by the dataset creators. For code and math benchmarks, the HumanEval-Mul dataset includes 8 mainstream programming languages (Python, Java, Cpp, C#, JavaScript, TypeScript, PHP, and Bash) in total. We use CoT and non-CoT methods to evaluate model performance on LiveCodeBench, where the data are collected from August 2024 to November 2024. The Codeforces dataset is measured using the percentage of competitors. SWE-Bench verified is evaluated using the agentless framework (Xia et al., 2024). We use the “diff” format to evaluate the Aider-related benchmarks. For mathematical assessments, AIME and CNMO 2024 are evaluated with a temperature of 0.7, and the results are averaged over 16 runs, while MATH-500 employs greedy decoding. We allow all models to output a maximum of 8192 tokens for each benchmark.

Benchmark (Metric)	DeepSeek V2-0506	DeepSeek V2.5-0905	Qwen2.5 72B-Inst.	LLaMA-3.1 405B-Inst.	Claude-3.5- Sonnet-1022	GPT-4o 0513	DeepSeek V3	
Architecture	MoE	MoE	Dense	Dense	-	-	MoE	
# Activated Params	21B	21B	72B	405B	-	-	37B	
# Total Params	236B	236B	72B	405B	-	-	671B	
English	MMLU (EM)	78.2	80.6	85.3	88.6	88.3	87.2	88.5
	MMLU-Redux (EM)	77.9	80.3	85.6	86.2	88.9	88.0	89.1
	MMLU-Pro (EM)	58.5	66.2	71.6	73.3	78.0	72.6	75.9
	DROP (3-shot F1)	83.0	87.8	76.7	88.7	88.3	83.7	91.6
	IF-Eval (Prompt Strict)	57.7	80.6	84.1	86.0	86.5	84.3	86.1
	GPQA-Diamond (Pass@1)	35.3	41.3	49.0	51.1	65.0	49.9	59.1
	SimpleQA (Correct)	9.0	10.2	9.1	17.1	28.4	38.2	24.9
	FRAMES (Acc.)	66.9	65.4	69.8	70.0	72.5	80.5	73.3
	LongBench v2 (Acc.)	31.6	35.4	39.4	36.1	41.0	48.1	48.7
	Code	HumanEval-Mul (Pass@1)	69.3	77.4	77.3	77.2	81.7	80.5
LiveCodeBench (Pass@1-COT)		18.8	29.2	31.1	28.4	36.3	33.4	40.5
LiveCodeBench (Pass@1)		20.3	28.4	28.7	30.1	32.8	34.2	37.6
Codeforces (Percentile)		17.5	35.6	24.8	25.3	20.3	23.6	51.6
SWE Verified (Resolved)		-	22.6	23.8	24.5	50.8	38.8	42.0
Aider-Edit (Acc.)		60.3	71.6	65.4	63.9	84.2	72.9	79.7
Aider-Polyglot (Acc.)		-	18.2	7.6	5.8	45.3	16.0	49.6
Math		AIME 2024 (Pass@1)	4.6	16.7	23.3	23.3	16.0	9.3
	MATH-500 (EM)	56.3	74.7	80.0	73.8	78.3	74.6	90.2
	CNMO 2024 (Pass@1)	2.8	10.8	15.9	6.8	13.1	10.8	43.2
Chinese	CLUEWSC (EM)	89.9	90.4	91.4	84.7	85.4	87.9	90.9
	C-Eval (EM)	78.6	79.5	86.1	61.5	76.7	76.0	86.5
	C-SimpleQA (Correct)	48.5	54.1	48.4	50.4	51.3	59.3	64.8

Table 6 | Comparison between DeepSeek-V3 and other representative chat models. All models are evaluated in a configuration that limits the output length to 8K. Benchmarks containing fewer than 1000 samples are tested multiple times using varying temperature settings to derive robust final results. DeepSeek-V3 stands as the best-performing open-source model, and also exhibits competitive performance against frontier closed-source models.

5.3.2. Standard Evaluation

Table 6 presents the evaluation results, showcasing that DeepSeek-V3 stands as the best-performing open-source model. Additionally, it is competitive against frontier closed-source models like GPT-4o and Claude-3.5-Sonnet.

我们在零样本设置下，为 MMLU-Redux 使用 Zero-Eval 提示格式 (Lin, 2024)。对于其他数据集，我们遵循其原始评估协议，并使用数据集创建者提供的默认提示。对于代码和数学基准，HumanEval-Mul 数据集总共包含 8 种主流编程语言 (Python、Java、Cpp、C#、JavaScript、TypeScript、PHP 和 Bash)。我们使用 CoT 和非 CoT 方法评估模型在 LiveCodeBench 上的性能，数据收集时间从 2024 年 8 月到 2024 年 11 月。Codeforces 数据集使用竞争者的百分比进行衡量。SWE-Bench 验证使用无代理框架 (Xia 等人, 2024) 进行评估。我们使用“diff”格式评估与 Aider 相关的基准。对于数学评估，AIME 和 CNMO 2024 使用 0.7 的温度进行评估，结果在 16 次运行中取平均，而 MATH-500 采用贪婪解码。我们允许所有模型为每个基准输出最多 8192 个 token。

基准 (指标)	DeepSeek V2-0506	DeepSeek V2.5-0905	Qwen2.5 72B-Inst.	LLaMA-3.1 405B-Inst.	Claude-3.5- Sonnet-1022	GPT-4o 0513	DeepSeek V3	
架构	MoE	MoE	密集	密集	-	-	MoE	
# 激活参数	21B	21B	72B	405B	-	-	37B	
# 总参数	236B	236B	72B	405B	-	-	671B	
英语	MMLU (EM)	78.2	80.6	85.3	88.6	88.3	87.2	88.5
	MMLU-Redux (EM)	77.9	80.3	85.6	86.2	88.9	88.0	89.1
	MMLU-Pro (EM)	58.5	66.2	71.6	73.3	78.0	72.6	75.9
	DROP (3-shot F1)	83.0	87.8	76.7	88.7	88.3	83.7	91.6
	IF-Eval (Prompt 严格)	57.7	80.6	84.1	86.0	86.5	84.3	86.1
	GPQA-Diamond (Pass@1)	35.3	41.3	49.0	51.1	65.0	49.9	59.1
	SimpleQA (正确)	9.0	10.2	9.1	17.1	28.4	38.2	24.9
	FRAMES (准确率)	66.9	65.4	69.8	70.0	72.5	80.5	73.3
	LongBench v2 (Acc.)	31.6	35.4	39.4	36.1	41.0	48.1	48.7
	Code	HumanEval-Mul (Pass@1)	69.3	77.4	77.3	77.2	81.7	80.5
LiveCodeBench (Top1 准确率-Chain-of-Thought)		18.8	29.2	31.1	28.4	36.3	33.4	40.5
LiveCodeBench (Pass@1)		20.3	28.4	28.7	30.1	32.8	34.2	37.6
Codeforces (百分位数)		17.5	35.6	24.8	25.3	20.3	23.6	51.6
SWE 验证 (已解决)		-	22.6	23.8	24.5	50.8	38.8	42.0
Aider-Edit (准确率)		60.3	71.6	65.4	63.9	84.2	72.9	79.7
Aider-Polyglot (准确率)		-	18.2	7.6	5.8	45.3	16.0	49.6
Math		AIME 2024 (Pass@1)	4.6	16.7	23.3	23.3	16.0	9.3
	MATH-500 (数学)	56.3	74.7	80.0	73.8	78.3	74.6	90.2
	CNMO 2024 (Pass@1)	2.8	10.8	15.9	6.8	13.1	10.8	43.2
中文	CLUEWSC (EM)	89.9	90.4	91.4	84.7	85.4	87.9	90.9
	C-Eval (EM)	78.6	79.5	86.1	61.5	76.7	76.0	86.5
	C-SimpleQA (正确)	48.5	54.1	48.4	50.4	51.3	59.3	64.8

表 6 | DeepSeek-V3 与其他代表性聊天模型的对比。所有模型均在输出长度限制为 8K 的配置下进行评估。包含少于 1000 个样本的基准测试使用不同的温度设置进行多次测试，以得出稳健的最终结果。DeepSeek-V3 是表现最佳的开源模型，同时在性能上也与前沿闭源模型具有竞争力。

5.3.2. 标准评估

表6展示了评估结果，表明DeepSeek-V3是表现最佳的开放源模型。此外，它在与前沿闭源模型如GPT-4o和Claude-3.5-Sonnet的竞争中同样具有竞争力。

English Benchmarks. MMLU is a widely recognized benchmark designed to assess the performance of large language models, across diverse knowledge domains and tasks. DeepSeek-V3 demonstrates competitive performance, standing on par with top-tier models such as LLaMA-3.1-405B, GPT-4o, and Claude-Sonnet 3.5, while significantly outperforming Qwen2.5 72B. Moreover, DeepSeek-V3 excels in MMLU-Pro, a more challenging educational knowledge benchmark, where it closely trails Claude-Sonnet 3.5. On MMLU-Redux, a refined version of MMLU with corrected labels, DeepSeek-V3 surpasses its peers. In addition, on GPQA-Diamond, a PhD-level evaluation testbed, DeepSeek-V3 achieves remarkable results, ranking just behind Claude 3.5 Sonnet and outperforming all other competitors by a substantial margin.

In long-context understanding benchmarks such as DROP, LongBench v2, and FRAMES, DeepSeek-V3 continues to demonstrate its position as a top-tier model. It achieves an impressive 91.6 F1 score in the 3-shot setting on DROP, outperforming all other models in this category. On FRAMES, a benchmark requiring question-answering over 100k token contexts, DeepSeek-V3 closely trails GPT-4o while outperforming all other models by a significant margin. This demonstrates the strong capability of DeepSeek-V3 in handling extremely long-context tasks. The long-context capability of DeepSeek-V3 is further validated by its best-in-class performance on LongBench v2, a dataset that was released just a few weeks before the launch of DeepSeek V3. On the factual knowledge benchmark, SimpleQA, DeepSeek-V3 falls behind GPT-4o and Claude-Sonnet, primarily due to its design focus and resource allocation. DeepSeek-V3 assigns more training tokens to learn Chinese knowledge, leading to exceptional performance on the C-SimpleQA. On the instruction-following benchmark, DeepSeek-V3 significantly outperforms its predecessor, DeepSeek-V2-series, highlighting its improved ability to understand and adhere to user-defined format constraints.

Code and Math Benchmarks. Coding is a challenging and practical task for LLMs, encompassing engineering-focused tasks like SWE-Bench-Verified and Aider, as well as algorithmic tasks such as HumanEval and LiveCodeBench. In engineering tasks, DeepSeek-V3 trails behind Claude-Sonnet-3.5-1022 but significantly outperforms open-source models. The open-source DeepSeek-V3 is expected to foster advancements in coding-related engineering tasks. By providing access to its robust capabilities, DeepSeek-V3 can drive innovation and improvement in areas such as software engineering and algorithm development, empowering developers and researchers to push the boundaries of what open-source models can achieve in coding tasks. In algorithmic tasks, DeepSeek-V3 demonstrates superior performance, outperforming all baselines on benchmarks like HumanEval-Mul and LiveCodeBench. This success can be attributed to its advanced knowledge distillation technique, which effectively enhances its code generation and problem-solving capabilities in algorithm-focused tasks.

On math benchmarks, DeepSeek-V3 demonstrates exceptional performance, significantly surpassing baselines and setting a new state-of-the-art for non-o1-like models. Specifically, on AIME, MATH-500, and CNMO 2024, DeepSeek-V3 outperforms the second-best model, Qwen2.5 72B, by approximately 10% in absolute scores, which is a substantial margin for such challenging benchmarks. This remarkable capability highlights the effectiveness of the distillation technique from DeepSeek-R1, which has been proven highly beneficial for non-o1-like models.

Chinese Benchmarks. Qwen and DeepSeek are two representative model series with robust support for both Chinese and English. On the factual benchmark Chinese SimpleQA, DeepSeek-V3 surpasses Qwen2.5-72B by 16.4 points, despite Qwen2.5 being trained on a larger corpus comprising 18T tokens, which are 20% more than the 14.8T tokens that DeepSeek-V3 is

英语基准测试。 MMLU是一个广泛认可的基准测试，旨在评估大语言模型在多个知识领域和任务中的表现。DeepSeek-V3表现出具有竞争力的性能，与顶级模型如LLaMA-3.1-405B、GPT-4o和Claude-Sonnet 3.5相当，而显著优于Qwen2.5 72B。此外，在更具挑战性的教育知识基准MMLU-Pro中，DeepSeek-V3紧随Claude-Sonnet 3.5之后。在MMLU-Redux（MMLU的提炼版本，标签已修正）中，DeepSeek-V3超越了其竞争对手。此外，在博士级别的评估测试平台GPQA-Diamond上，DeepSeek-V3取得了卓越的成果，仅次于Claude 3.5 Sonnet，并大幅领先所有其他竞争对手。

在DROP、LongBench v2和FRAMES等长上下文理解基准测试中，DeepSeek-V3持续展现出其顶级模型的地位。在DROP的3-shot设置下，它取得了令人印象深刻的91.6 F1分数，超越该类别中的所有其他模型。在FRAMES上，这是一个需要处理超过10万令牌上下文的问题回答基准测试，DeepSeek-V3虽然紧随GPT-4o之后，但仍显著优于其他所有模型。这证明了DeepSeek-V3在处理极长上下文任务方面的强大能力。DeepSeek-V3的长上下文能力还通过其在LongBench v2上的最佳表现得到进一步验证，该数据集是在DeepSeek V3发布前几周发布的。在事实性知识基准测试SimpleQA上，DeepSeek-V3落后于GPT-4o和Claude-Sonnet，这主要由于其设计重点和资源分配。DeepSeek-V3将更多训练令牌分配给学习中文知识，因此在C-SimpleQA上表现优异。在指令遵循基准测试中，DeepSeek-V3显著优于其前身DeepSeek-V2-series，突显了其理解和遵循用户定义格式约束能力的提升。

代码和数学基准。 编程是大语言模型面临的具有挑战性和实践性的任务，包含以工程为导向的任务（如SWE-Bench-Verified和Aider）以及算法任务（如HumanEval和LiveCodeBench）。在工程任务中，DeepSeek-V3落后于Claude-Sonnet-3.5-1022，但显著优于开源模型。开源的DeepSeek-V3有望促进与编程相关的工程任务的进步。通过提供其强大的功能，DeepSeek-V3可以推动软件工程和算法开发等领域的创新和改进，赋能开发者和研究人员，推动开源模型在编程任务中达到新的高度。在算法任务中，DeepSeek-V3表现出卓越的性能，在HumanEval-Mul和LiveCodeBench等基准测试中超越了所有基线模型。这一成功归功于其先进的知识蒸馏技术，该技术有效地增强了其在算法导向任务中的代码生成和问题解决能力。

在数学基准测试中，DeepSeek-V3表现出卓越的性能，显著超越基线，为非 o1 类模型设定了新的 SOTA 水平。具体来说，在 AIME、MATH-500 和 CNMO 2024 上，DeepSeek-V3 在绝对分数上比第二好的模型 Qwen2.5 72B 高出约 10%，对于这样具有挑战性的基准测试来说，这是一个相当大的差距。这种卓越的能力突显了 DeepSeek-R1 提取技术的有效性，该技术已被证明对非 o1 类模型非常有益。

中文评测基准。 Qwen 和 DeepSeek 是两款具有强大中英文支持代表性的模型系列。在事实性评测基准中文SimpleQA上，DeepSeek-V3 超过 Qwen2.5-72B 16.4 分，尽管 Qwen2.5 训练在包含 18T tokens 的大规模语料库上，比 DeepSeek-V3 使用的 14.8T tokens 多了 20%，

Model	Arena-Hard	AlpacaEval 2.0
DeepSeek-V2.5-0905	76.2	50.5
Qwen2.5-72B-Instruct	81.2	49.1
LLaMA-3.1 405B	69.3	40.5
GPT-4o-0513	80.4	51.1
Claude-Sonnet-3.5-1022	85.2	52.0
DeepSeek-V3	85.5	70.0

Table 7 | English open-ended conversation evaluations. For AlpacaEval 2.0, we use the length-controlled win rate as the metric.

pre-trained on.

On C-Eval, a representative benchmark for Chinese educational knowledge evaluation, and CLUEWSC (Chinese Winograd Schema Challenge), DeepSeek-V3 and Qwen2.5-72B exhibit similar performance levels, indicating that both models are well-optimized for challenging Chinese-language reasoning and educational tasks.

5.3.3. Open-Ended Evaluation

In addition to standard benchmarks, we also evaluate our models on open-ended generation tasks using LLMs as judges, with the results shown in Table 7. Specifically, we adhere to the original configurations of AlpacaEval 2.0 (Dubois et al., 2024) and Arena-Hard (Li et al., 2024a), which leverage GPT-4-Turbo-1106 as judges for pairwise comparisons. On Arena-Hard, DeepSeek-V3 achieves an impressive win rate of over 86% against the baseline GPT-4-0314, performing on par with top-tier models like Claude-Sonnet-3.5-1022. This underscores the robust capabilities of DeepSeek-V3, especially in dealing with complex prompts, including coding and debugging tasks. Furthermore, DeepSeek-V3 achieves a groundbreaking milestone as the first open-source model to surpass 85% on the Arena-Hard benchmark. This achievement significantly bridges the performance gap between open-source and closed-source models, setting a new standard for what open-source models can accomplish in challenging domains.

Similarly, DeepSeek-V3 showcases exceptional performance on AlpacaEval 2.0, outperforming both closed-source and open-source models. This demonstrates its outstanding proficiency in writing tasks and handling straightforward question-answering scenarios. Notably, it surpasses DeepSeek-V2.5-0905 by a significant margin of 20%, highlighting substantial improvements in tackling simple tasks and showcasing the effectiveness of its advancements.

5.3.4. DeepSeek-V3 as a Generative Reward Model

We compare the judgment ability of DeepSeek-V3 with state-of-the-art models, namely GPT-4o and Claude-3.5. Table 8 presents the performance of these models in RewardBench (Lambert et al., 2024). DeepSeek-V3 achieves performance on par with the best versions of GPT-4o-0806 and Claude-3.5-Sonnet-1022, while surpassing other versions. Additionally, the judgment ability of DeepSeek-V3 can also be enhanced by the voting technique. Therefore, we employ DeepSeek-V3 along with voting to offer self-feedback on open-ended questions, thereby improving the effectiveness and robustness of the alignment process.

模型	Arena-Hard	AlpacaEval 2.0
DeepSeek-V2.5-0905	76.2	50.5
Qwen2.5-72B-Instruct	81.2	49.1
LLaMA-3.1 405B	69.3	40.5
GPT-4o-0513	80.4	51.1
Claude-Sonnet-3.5-1022	85.2	52.0
DeepSeek-V3	85.5	70.0

表 7 | 英语开放式对话评估。对于 AlpacaEval 2.0, 我们使用长度控制的胜率作为指标。

预训练于。

在 C-Eval (中文教育知识评测代表性基准) 和 CLUEWSC (中文Winograd Schema Challenge) 上, DeepSeek-V3 和 Qwen2.5-72B 表现相似, 表明两款模型都针对具有挑战性的中文推理和教育任务进行了优化。

5.3.3. 开放式评估

除了标准基准测试外, 我们还使用大语言模型作为评判者, 在开放式生成任务上评估我们的模型, 结果如表7所示。具体而言, 我们遵循AlpacaEval 2.0 (Dubois等人, 2024年) 和 Arena-Hard (李等人, 2024a) 的原有配置, 后者利用GPT-4-Turbo-1106作为评判者进行成对比较。在Arena-Hard上, DeepSeek-V3以超过86%的胜率击败基线GPT-4-0314, 表现与 Claude-Sonnet-3.5-1022等顶级模型相当。这突显了DeepSeek-V3的强大能力, 尤其是在处理复杂提示方面, 包括编码和调试任务。此外, DeepSeek-V3成为首个在Arena-Hard基准上超过85%的开源模型, 实现了突破性里程碑。这一成就显著缩小了开源模型与闭源模型之间的性能差距, 为开源模型在挑战性领域能取得的成绩树立了新标准。

同样地, DeepSeek-V3 在 AlpacaEval 2.0 上展现出卓越的性能, 超越了闭源模型和开源模型。这表明其在写作任务和处理简单的问答场景方面具有出色的能力。值得注意的是, 它比 DeepSeek-V2.5-0905 高出 20% 的显著差距, 突显了其在处理简单任务方面的巨大改进, 并展示了其进步的有效性。

5.3.4. DeepSeek-V3 作为生成式奖励模型

我们将 DeepSeek-V3 的判断能力与当前顶尖模型 (即 GPT-4o 和 Claude-3.5) 进行比较。表 8 展示了这些模型在 RewardBench (Lambert 等人, 2024) 中的表现。DeepSeek-V3 的性能与 GPT-4o-0806 和 Claude-3.5-Sonnet-1022 的最佳版本相当, 同时超越了其他版本。此外, DeepSeek-V3 的判断能力还可以通过投票技术来增强。因此, 我们采用 DeepSeek-V3 并结合投票技术, 对开放式问题进行自反馈, 从而提高对齐过程的有效性和鲁棒性。

Model	Chat	Chat-Hard	Safety	Reasoning	Average
GPT-4o-0513	96.6	70.4	86.7	84.9	84.7
GPT-4o-0806	96.1	76.1	88.1	86.6	86.7
GPT-4o-1120	95.8	71.3	86.2	85.2	84.6
Claude-3.5-sonnet-0620	96.4	74.0	81.6	84.7	84.2
Claude-3.5-sonnet-1022	96.4	79.7	91.1	87.6	88.7
DeepSeek-V3	96.9	79.8	87.0	84.3	87.0
DeepSeek-V3 (maj@6)	96.9	82.6	89.5	89.2	89.6

Table 8 | Performances of GPT-4o, Claude-3.5-sonnet and DeepSeek-V3 on RewardBench.

Model	LiveCodeBench-CoT		MATH-500	
	Pass@1	Length	Pass@1	Length
DeepSeek-V2.5 Baseline	31.1	718	74.6	769
DeepSeek-V2.5 +R1 Distill	37.4	783	83.2	1510

Table 9 | The contribution of distillation from DeepSeek-R1. The evaluation settings of LiveCodeBench and MATH-500 are the same as in Table 6.

5.4. Discussion

5.4.1. Distillation from DeepSeek-R1

We ablate the contribution of distillation from DeepSeek-R1 based on DeepSeek-V2.5. The baseline is trained on short CoT data, whereas its competitor uses data generated by the expert checkpoints described above.

Table 9 demonstrates the effectiveness of the distillation data, showing significant improvements in both LiveCodeBench and MATH-500 benchmarks. Our experiments reveal an interesting trade-off: the distillation leads to better performance but also substantially increases the average response length. To maintain a balance between model accuracy and computational efficiency, we carefully selected optimal settings for DeepSeek-V3 in distillation.

Our research suggests that knowledge distillation from reasoning models presents a promising direction for post-training optimization. While our current work focuses on distilling data from mathematics and coding domains, this approach shows potential for broader applications across various task domains. The effectiveness demonstrated in these specific areas indicates that long-CoT distillation could be valuable for enhancing model performance in other cognitive tasks requiring complex reasoning. Further exploration of this approach across different domains remains an important direction for future research.

5.4.2. Self-Rewarding

Rewards play a pivotal role in RL, steering the optimization process. In domains where verification through external tools is straightforward, such as some coding or mathematics scenarios, RL demonstrates exceptional efficacy. However, in more general scenarios, constructing a feedback mechanism through hard coding is impractical. During the development of DeepSeek-V3, for these broader contexts, we employ the constitutional AI approach (Bai et al., 2022), leveraging the voting evaluation results of DeepSeek-V3 itself as a feedback source. This method has

模型	Chat	Chat-Hard	安全	推理	平均
GPT-4o-0513	96.6	70.4	86.7	84.9	84.7
GPT-4o-0806	96.1	76.1	88.1	86.6	86.7
GPT-4o-1120	95.8	71.3	86.2	85.2	84.6
Claude-3.5-sonnet-0620	96.4	74.0	81.6	84.7	84.2
Claude-3.5-sonnet-1022	96.4	79.7	91.1	87.6	88.7
DeepSeek-V3	96.9	79.8	87.0	84.3	87.0
DeepSeek-V3 (maj@6)	96.9	82.6	89.5	89.2	89.6

Table 8 | GPT-4o、Claude-3.5-Sonnet 和 DeepSeek-V3 在 RewardBenc 上的表现 h.

模型	LiveCodeBench-CoT		MATH-500	
	Pass@1	长度	Pass@1	长度
DeepSeek-V2.5 基线	31.1	718	74.6	769
DeepSeek-V.5 +R1 演绎	37.4	783	83.2	1510

表 9 | DeepSeek-R1 演绎的贡献。Live-CodeBench 和 MATH-500 的评估设置与表 6 相同。

5.4. 讨论

5.4.1. DeepSeek-R1 演绎

我们基于 DeepSeek-V2.5，消融了 DeepSeek-R1 中蒸馏的贡献。基线模型在短 CoT 数据上训练，而其竞争对手则使用上述专家检查点生成数据。

表9展示了蒸馏数据的有效性，显示了在LiveCodeBench和MATH-500基准测试中的显著改进。我们的实验揭示了一个有趣的成本效益权衡：蒸馏带来了更好的性能，但也显著增加了平均响应长度。为了在模型准确率和计算效率之间保持平衡，我们仔细为DeepSeek-V3选择了蒸馏的最佳设置。

我们的研究表明，从推理模型中进行知识蒸馏为后训练优化提供了一个有前景的方向。虽然我们当前的工作专注于从数学和编码领域蒸馏数据，但这种方法显示出在更广泛的领域应用的可能性。在这些特定领域展示的有效性表明，长CoT蒸馏可能对增强需要复杂推理的其他认知任务中的模型性能具有重要价值。未来研究的一个重要方向是在不同领域进一步探索这种方法。

5.4.2. 自我奖励

奖励在强化学习中扮演着关键角色，引导优化过程。在外部工具验证简便的领域，如某些编码或数学场景，强化学习展现出卓越的效能。然而，在更通用的场景中，通过硬编码构建反馈机制是不切实际的。在DeepSeek-V3的开发过程中，针对这些更广泛的上下文，我们采用了宪法AI方法（Bai等人，2022年），利用DeepSeek-V3自身的投票评估结果作为反馈来源。这种方法已

produced notable alignment effects, significantly enhancing the performance of DeepSeek-V3 in subjective evaluations. By integrating additional constitutional inputs, DeepSeek-V3 can optimize towards the constitutional direction. We believe that this paradigm, which combines supplementary information with LLMs as a feedback source, is of paramount importance. The LLM serves as a versatile processor capable of transforming unstructured information from diverse scenarios into rewards, ultimately facilitating the self-improvement of LLMs. Beyond self-rewarding, we are also dedicated to uncovering other general and scalable rewarding methods to consistently advance the model capabilities in general scenarios.

5.4.3. Multi-Token Prediction Evaluation

Instead of predicting just the next single token, DeepSeek-V3 predicts the next 2 tokens through the MTP technique. Combined with the framework of speculative decoding (Leviathan et al., 2023; Xia et al., 2023), it can significantly accelerate the decoding speed of the model. A natural question arises concerning the acceptance rate of the additionally predicted token. Based on our evaluation, the acceptance rate of the second token prediction ranges between 85% and 90% across various generation topics, demonstrating consistent reliability. This high acceptance rate enables DeepSeek-V3 to achieve a significantly improved decoding speed, delivering 1.8 times TPS (Tokens Per Second).

6. Conclusion, Limitations, and Future Directions

In this paper, we introduce DeepSeek-V3, a large MoE language model with 671B total parameters and 37B activated parameters, trained on 14.8T tokens. In addition to the MLA and DeepSeekMoE architectures, it also pioneers an auxiliary-loss-free strategy for load balancing and sets a multi-token prediction training objective for stronger performance. The training of DeepSeek-V3 is cost-effective due to the support of FP8 training and meticulous engineering optimizations. The post-training also makes a success in distilling the reasoning capability from the DeepSeek-R1 series of models. Comprehensive evaluations demonstrate that DeepSeek-V3 has emerged as the strongest open-source model currently available, and achieves performance comparable to leading closed-source models like GPT-4o and Claude-3.5-Sonnet. Despite its strong performance, it also maintains economical training costs. It requires only 2.788M H800 GPU hours for its full training, including pre-training, context length extension, and post-training.

While acknowledging its strong performance and cost-effectiveness, we also recognize that DeepSeek-V3 has some limitations, especially on the deployment. Firstly, to ensure efficient inference, the recommended deployment unit for DeepSeek-V3 is relatively large, which might pose a burden for small-sized teams. Secondly, although our deployment strategy for DeepSeek-V3 has achieved an end-to-end generation speed of more than two times that of DeepSeek-V2, there still remains potential for further enhancement. Fortunately, these limitations are expected to be naturally addressed with the development of more advanced hardware.

DeepSeek consistently adheres to the route of open-source models with longtermism, aiming to steadily approach the ultimate goal of AGI (Artificial General Intelligence). In the future, we plan to strategically invest in research across the following directions.

- We will consistently study and refine our model architectures, aiming to further improve both the training and inference efficiency, striving to approach efficient support for infinite context length. Additionally, we will try to break through the architectural limitations of Transformer, thereby pushing the boundaries of its modeling capabilities.

产生了显著的对齐效果，显著提升了DeepSeek-V3在主观评估中的表现。通过整合额外的宪法输入，DeepSeek-V3可以优化向宪法方向。我们相信，这种将补充信息与大语言模型结合作为反馈来源的范式至关重要。大语言模型作为多功能处理器，能够将来自不同场景的非结构化信息转化为奖励，最终促进大语言模型的自改进。除了自我奖励外，我们还在致力于发现其他通用且可扩展的奖励方法，以持续提升模型在通用场景中的能力。

5.4.3. 多标记预测评估

DeepSeek-V3 不再仅预测下一个单个标记，而是通过 MTP 技术预测接下来的 2 个标记。结合推测解码框架 (Leviathan 等人, 2023; Xia 等人, 2023)，它可以显著加速模型的解码速度。一个自然的问题是额外预测标记的接受率。根据我们的评估，在各个生成主题中，第二个标记预测的接受率介于 85% 到 90% 之间，显示出持续可靠性。这种高接受率使 DeepSeek-V3 能够显著提高解码速度，实现 1.8 倍 TPS (每秒令牌数)。

6. 结论、局限性与未来方向

在本文中，我们介绍了 DeepSeek-V3，一个拥有 671B 总参数量和 37B 激活参数的大型 MoE 语言模型，训练数据量为 14.8T 标记。除了 MLA 和 DeepSeekMoE 架构外，它还开创了一种用于负载均衡的无辅助损失策略，并设定了多标记预测训练目标以实现更强性能。由于支持 FP8 训练和细致的工程优化，DeepSeek-V3 的训练具有成本效益。后训练也成功地将推理能力从 DeepSeek-R1 系列模型中蒸馏出来。综合评估表明，DeepSeek-V3 已成为当前最强的开源模型，其性能与 GPT-4o 和 Claude-3.5-Sonnet 等领先的闭源模型相当。尽管性能强大，它仍保持了经济的训练成本。其完整训练（包括预训练、上下文长度扩展和后训练）仅需 2.788M H800 GPU 小时。

在承认其性能强大且成本效益高的同时，我们也认识到 DeepSeek-V3 存在一些局限性，尤其是在部署方面。首先，为确保高效推理，DeepSeek-V3 推荐的部署单元相对较大，这可能给小型团队带来负担。其次，尽管我们的 DeepSeek-V3 部署策略已实现比 DeepSeek-V2 高两倍以上端到端生成速度，但仍存在进一步优化的潜力。幸运的是，随着更先进硬件的发展，这些局限性预计将自然而然地得到解决。

DeepSeek 始终坚持长期主义的开源模型路线，旨在稳步接近通用人工智能 (AGI) 的最终目标。未来，我们计划在以下方向进行战略性投资。

- 我们将持续研究和优化我们的模型架构，旨在进一步提高训练和推理效率，力求实现对无限上下文长度的有效支持。此外，我们将尝试突破Transformer的架构限制，从而推动其建模能力的边界。

- We will continuously iterate on the quantity and quality of our training data, and explore the incorporation of additional training signal sources, aiming to drive data scaling across a more comprehensive range of dimensions.
- We will consistently explore and iterate on the deep thinking capabilities of our models, aiming to enhance their intelligence and problem-solving abilities by expanding their reasoning length and depth.
- We will explore more comprehensive and multi-dimensional model evaluation methods to prevent the tendency towards optimizing a fixed set of benchmarks during research, which may create a misleading impression of the model capabilities and affect our foundational assessment.

- 我们将持续迭代训练数据的质量和数量，并探索整合额外的训练信号源，旨在推动数据扩展到更广泛的维度范围。
- 我们将持续探索和迭代模型的深度思考能力，通过扩展其推理长度和深度来提升其智能和问题解决能力。
- 我们将探索更全面、多维度的模型评估方法，以防止在研究过程中倾向于优化一个固定的基准集，这可能造成对模型能力的误导印象，并影响我们的基础评估。

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Appendix

A. Contributions and Acknowledgments

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附录

A. 贡献与致谢

研究与工程

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在每个角色中，作者按姓氏首字母列出。带*标记的姓名表示已离开我们团队的成员。

B. Ablation Studies for Low-Precision Training

B. 低精度训练的消融研究

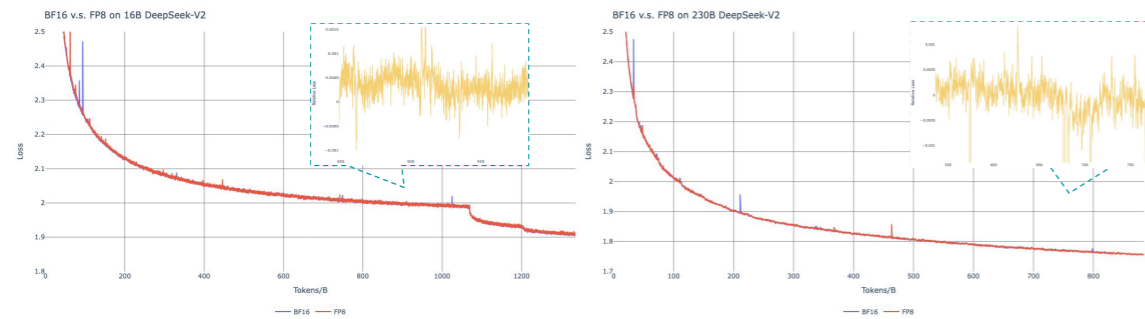


Figure 10 | Loss curves comparison between BF16 and FP8 training. Results are smoothed by Exponential Moving Average (EMA) with a coefficient of 0.9.

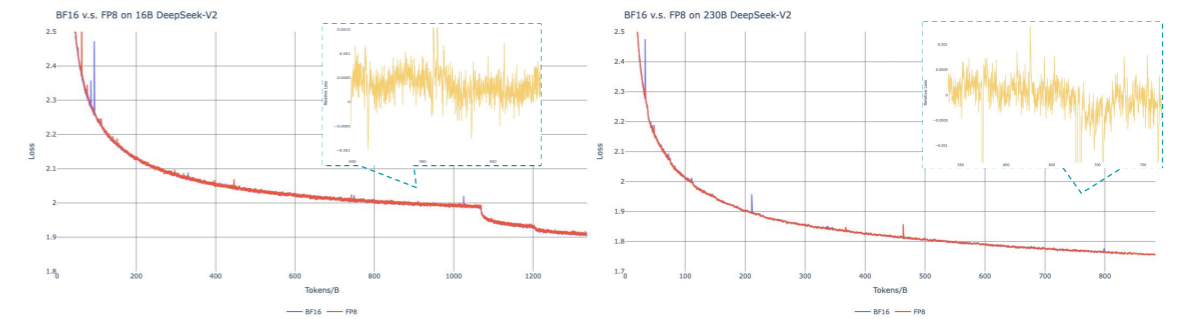


图 10 | BF16和FP8训练的损失曲线对比。结果由系数为0.9的指数移动平均（EMA）平滑。

B.1. FP8 v.s. BF16 Training

B.1. FP8与BF16训练

We validate our FP8 mixed precision framework with a comparison to BF16 training on top of two baseline models across different scales. At the small scale, we train a baseline MoE model comprising approximately 16B total parameters on 1.33T tokens. At the large scale, we train a baseline MoE model comprising approximately 230B total parameters on around 0.9T tokens. We show the training curves in Figure 10 and demonstrate that the relative error remains below 0.25% with our high-precision accumulation and fine-grained quantization strategies.

我们通过对不同规模上对两个基线模型的BF16训练进行比较，验证了我们的FP8混合精度框架。在小规模上，我们在1.33T token上训练一个包含约16B总参数的基线MoE模型。在大规模上，我们在约0.9T token上训练一个包含约230B总参数的基线MoE模型。我们在图10中展示了训练曲线，并证明在采用高精度累积和细粒度量化策略的情况下，相对误差始终保持在0.25%以下。

B.2. Discussion About Block-Wise Quantization

B.2. 关于分块量化的讨论

Although our tile-wise fine-grained quantization effectively mitigates the error introduced by feature outliers, it requires different groupings for activation quantization, i.e., 1×128 in forward pass and 128×1 for backward pass. A similar process is also required for the activation gradient. A straightforward strategy is to apply block-wise quantization per 128×128 elements like the way we quantize the model weights. In this way, only transposition is required for backward. Therefore, we conduct an experiment where all tensors associated with Dgrad are quantized on a block-wise basis. The results reveal that the Dgrad operation which computes the activation gradients and back-propagates to shallow layers in a chain-like manner, is highly sensitive to precision. Specifically, block-wise quantization of activation gradients leads to

尽管我们的逐瓦片细粒度量化有效地减轻了特征异常值引入的错误，但它需要不同的激活量化分组，即在正向传递中使用 1×128 ，在反向传递中使用 128×1 。激活梯度也需要类似的过程。一种直接策略是像我们量化模型权重的方式一样，对每个 128×128 元素进行块状量化。这样，反向传递只需要进行转置。因此，我们进行了一项实验，对与 Dgrad 相关的所有张量进行块状量化。结果表明，计算激活梯度并以链式方式反向传播到浅层层的 Dgrad 操作对精度高度敏感。具体来说，激活梯度的块状量化会导致

model divergence on an MoE model comprising approximately 16B total parameters, trained for around 300B tokens. We hypothesize that this sensitivity arises because activation gradients are highly imbalanced among tokens, resulting in token-correlated outliers (Xi et al., 2023). These outliers cannot be effectively managed by a block-wise quantization approach.

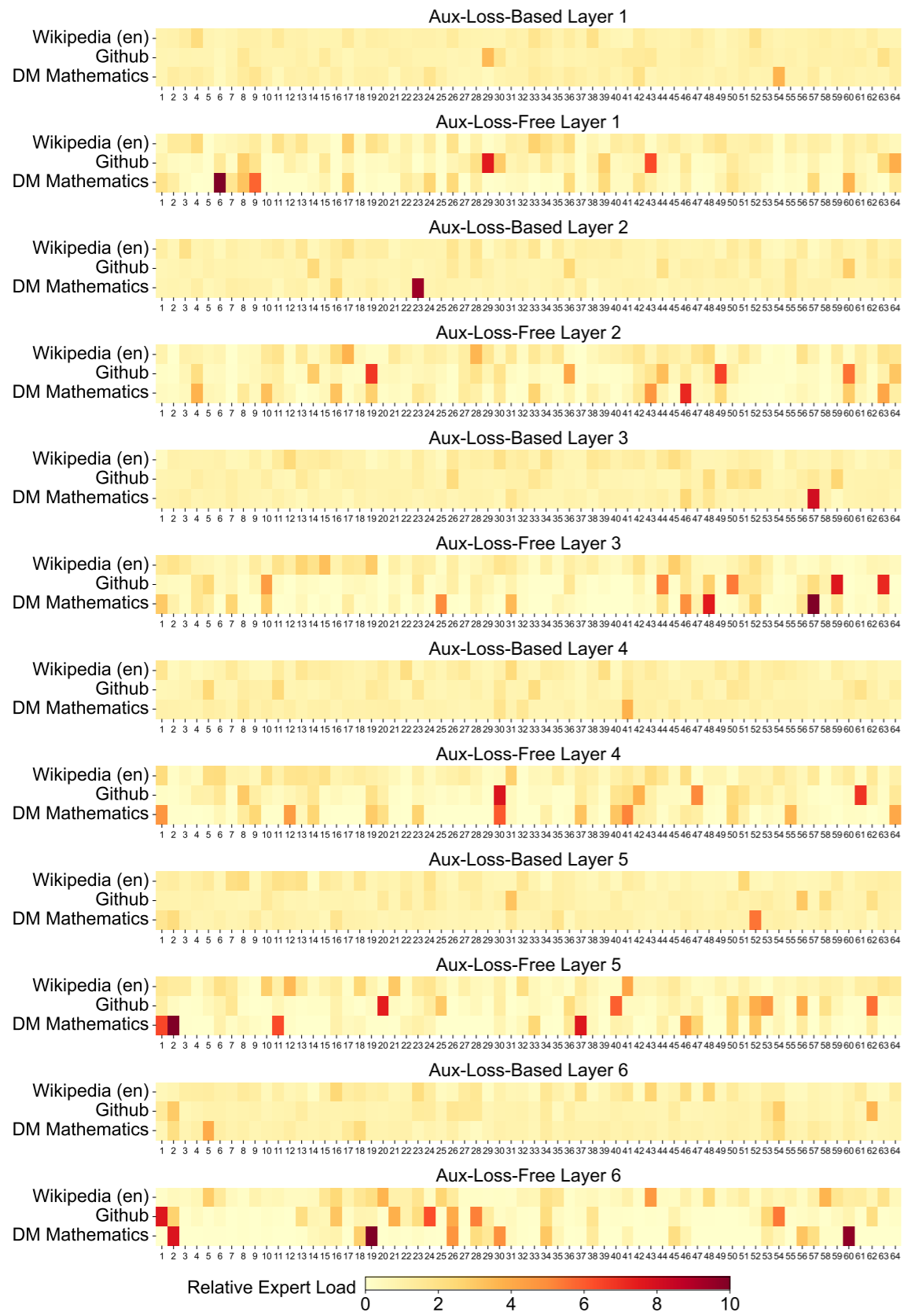
C. Expert Specialization Patterns of the 16B Aux-Loss-Based and Aux-Loss-Free Models

We record the expert load of the 16B auxiliary-loss-based baseline and the auxiliary-loss-free model on the Pile test set. The auxiliary-loss-free model tends to have greater expert specialization across all layers, as demonstrated in Figure 10.

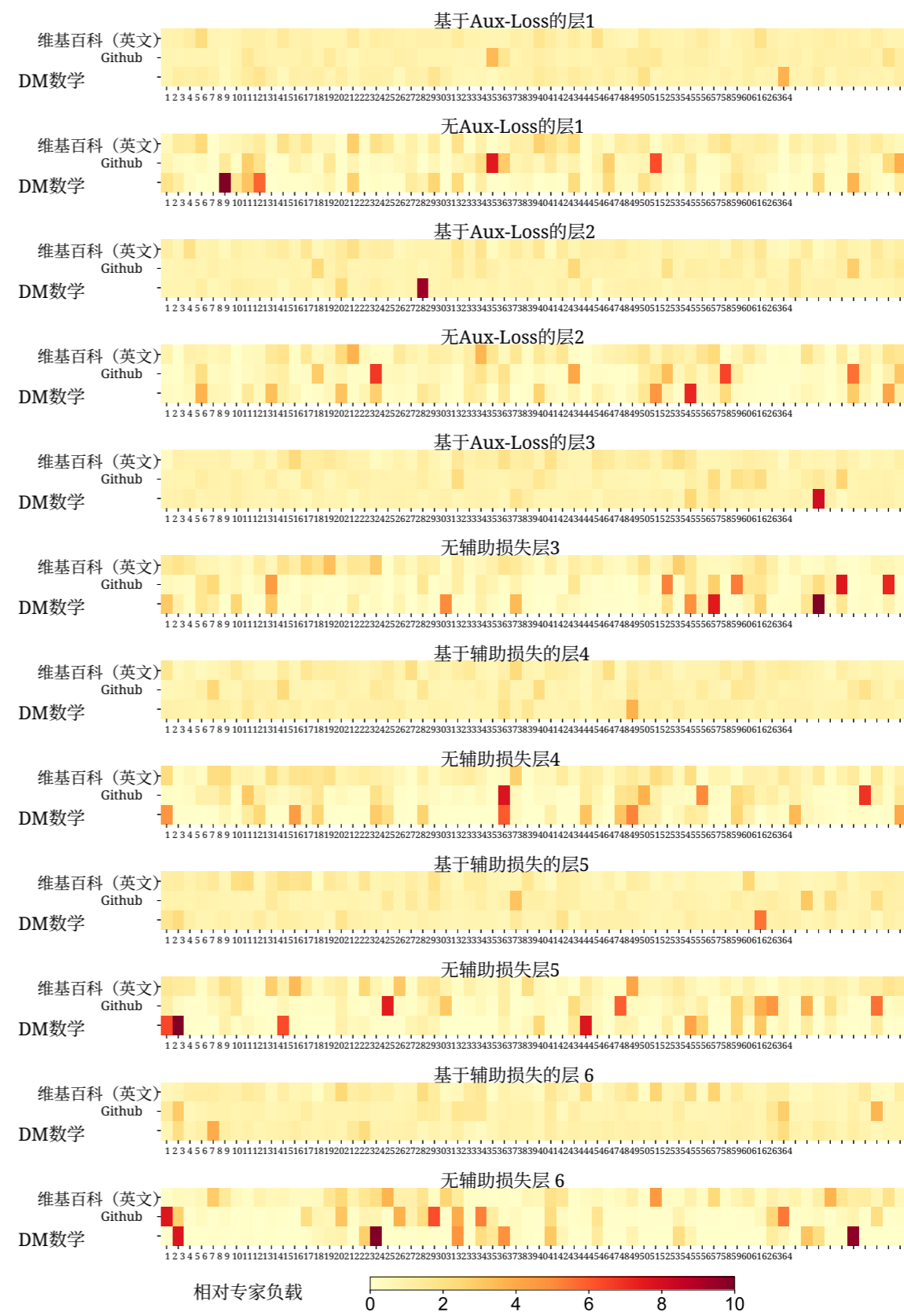
MoE 模型上的模型发散，该模型包含大约 16B 个总参数，训练了大约 300B 个 token。我们假设这种敏感性产生的原因是激活梯度在 token 之间存在高度不平衡，导致 token 相关的异常值 (Xi 等人, 2023)。这些异常值无法通过块状量化方法进行有效管理。

C. 16B 辅助损失模型与无辅助损失模型的专家专业化模式

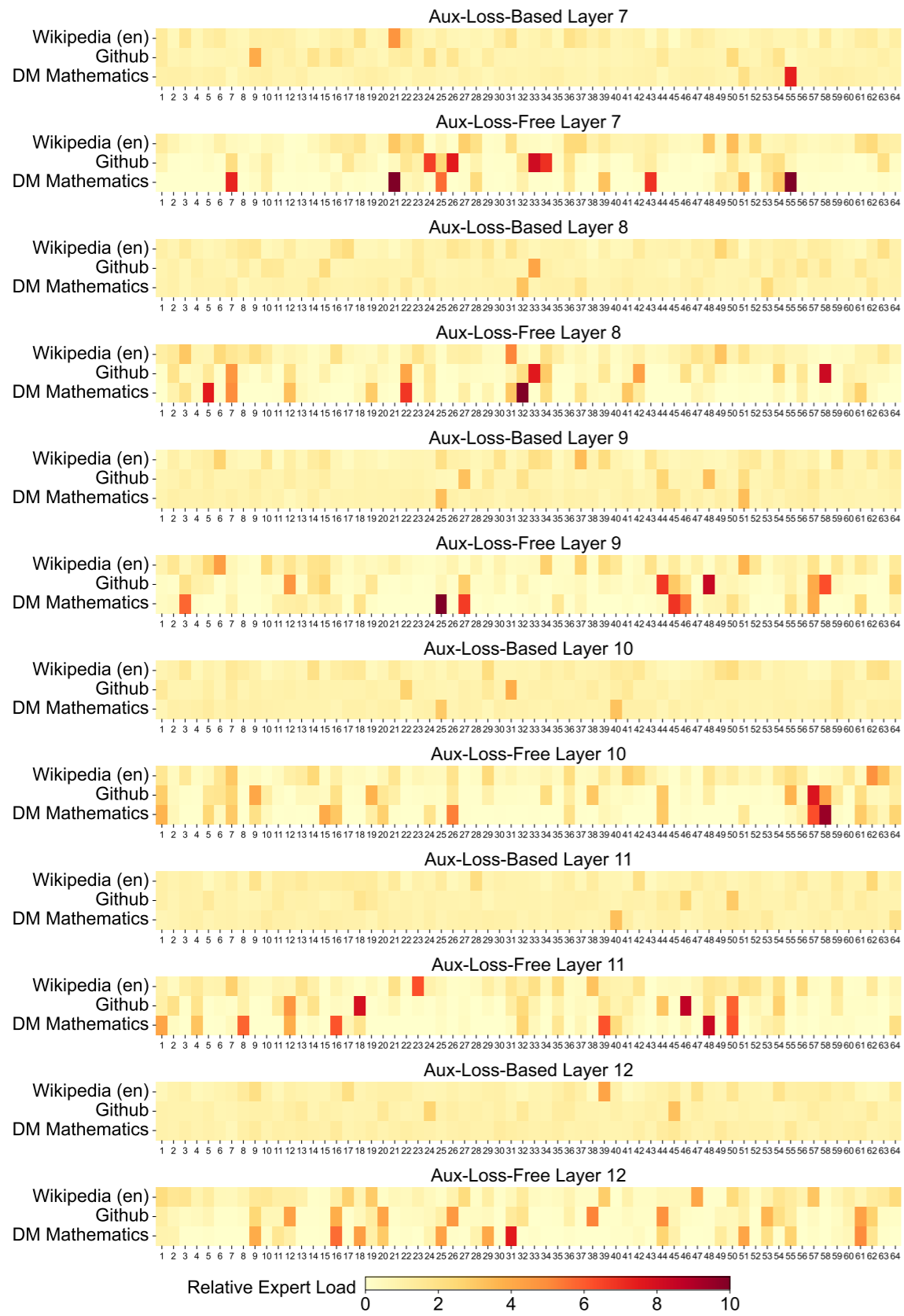
我们在 Pile 测试集上记录了 16B 辅助损失基线模型和无辅助损失模型的专家负载。无辅助损失模型在所有层都倾向于具有更高的专家专业化程度，如图 10 所示。



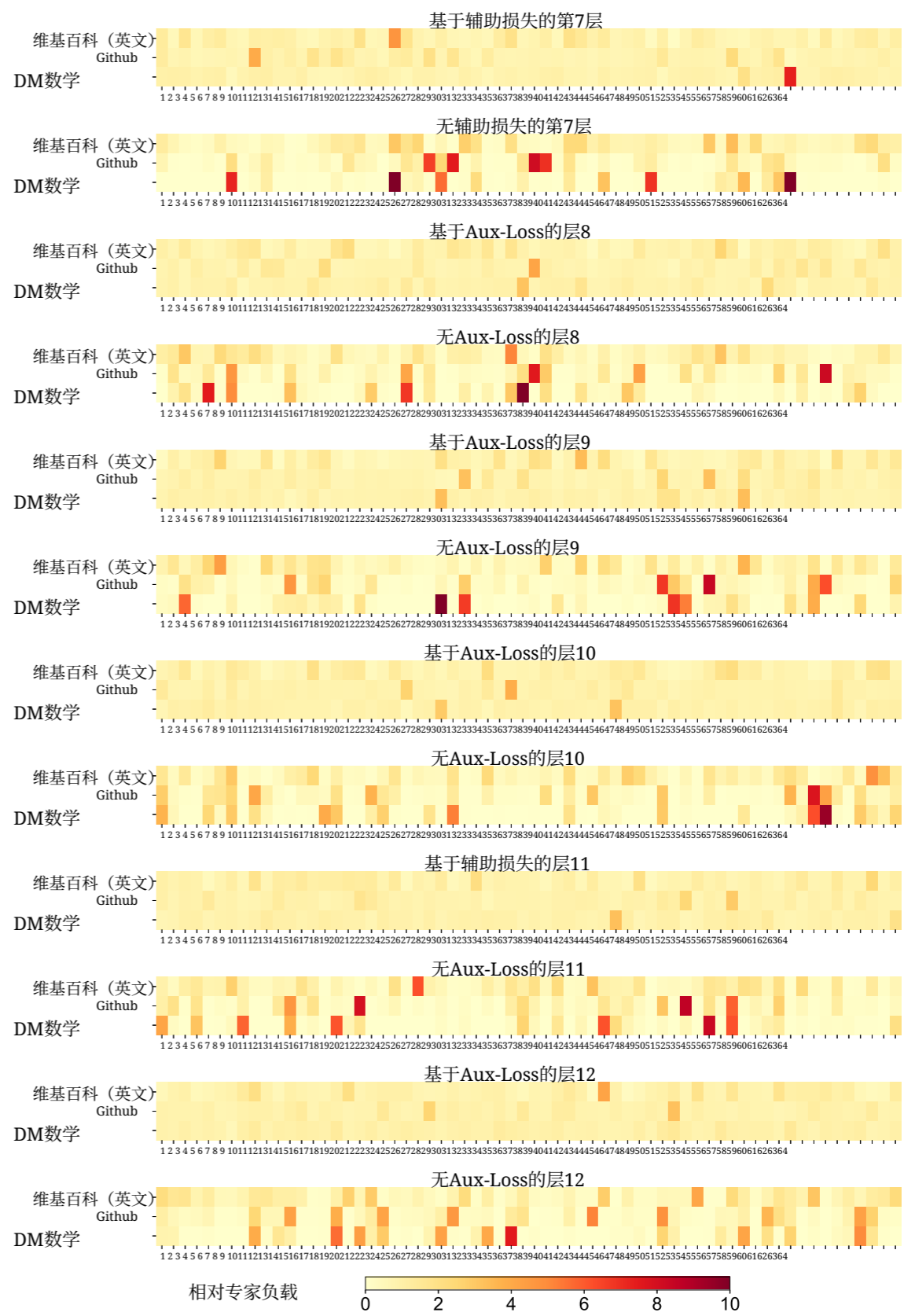
(a) Layers 1-7



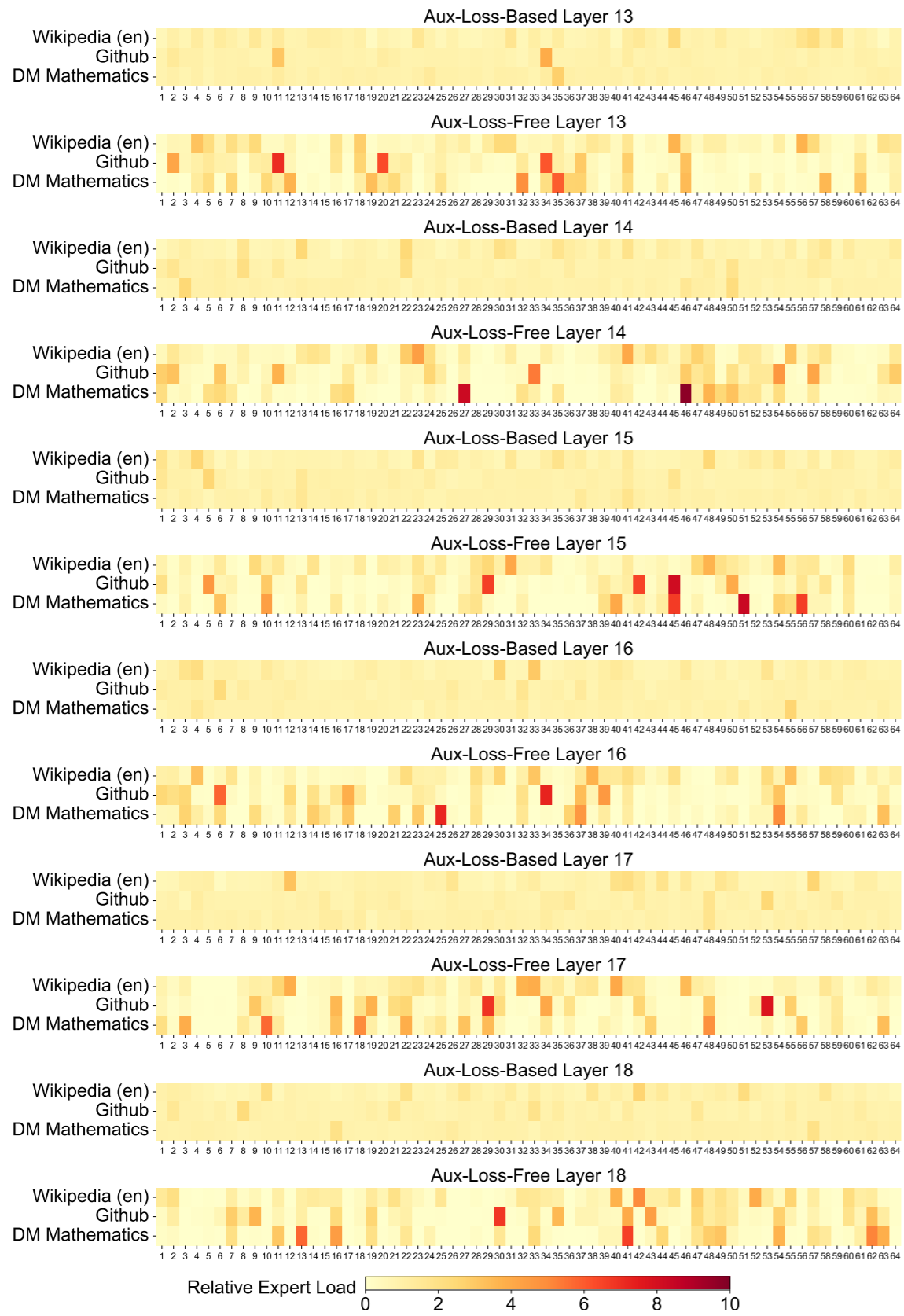
(a) 层级 1-7



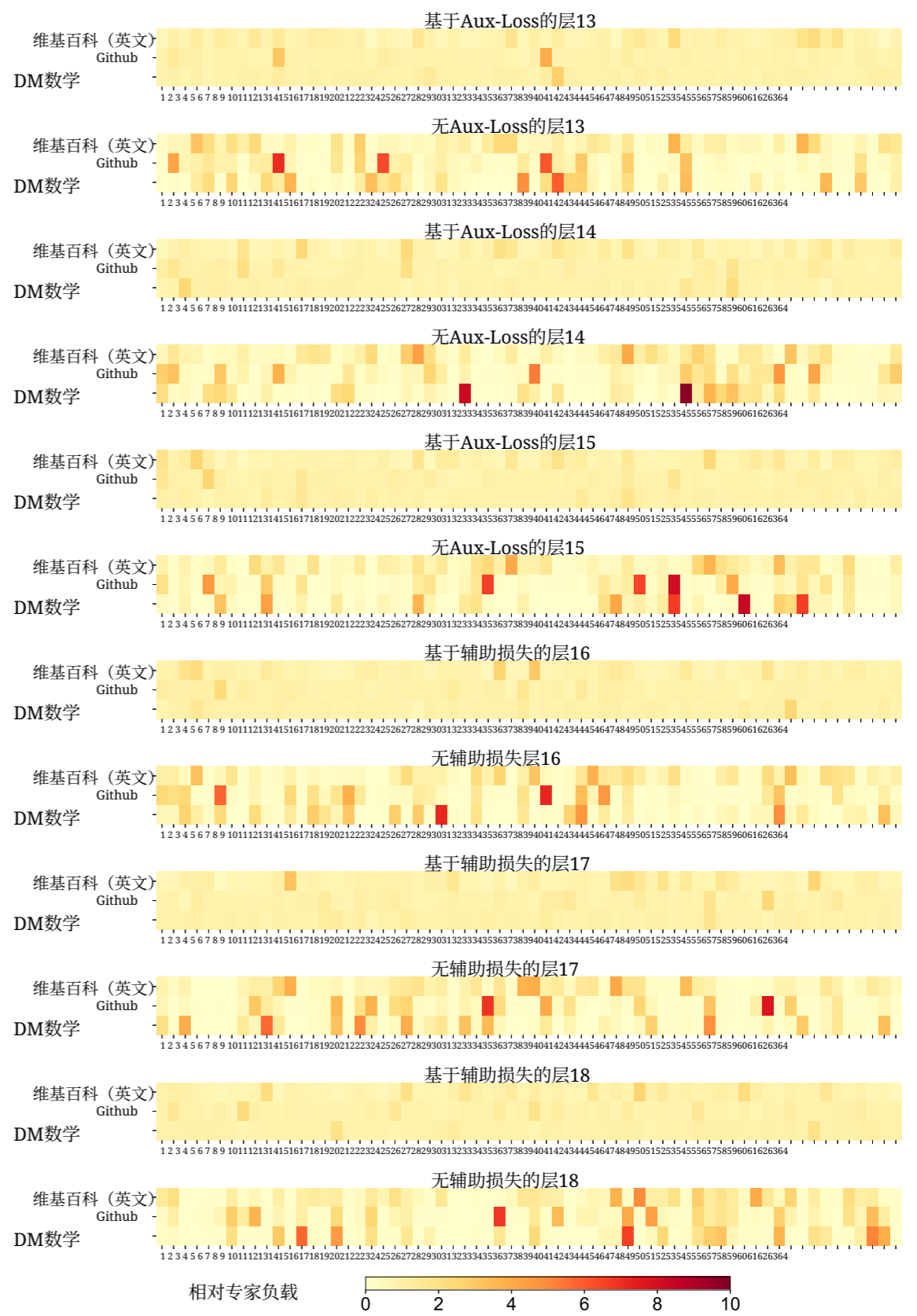
(b) Layers 7-13



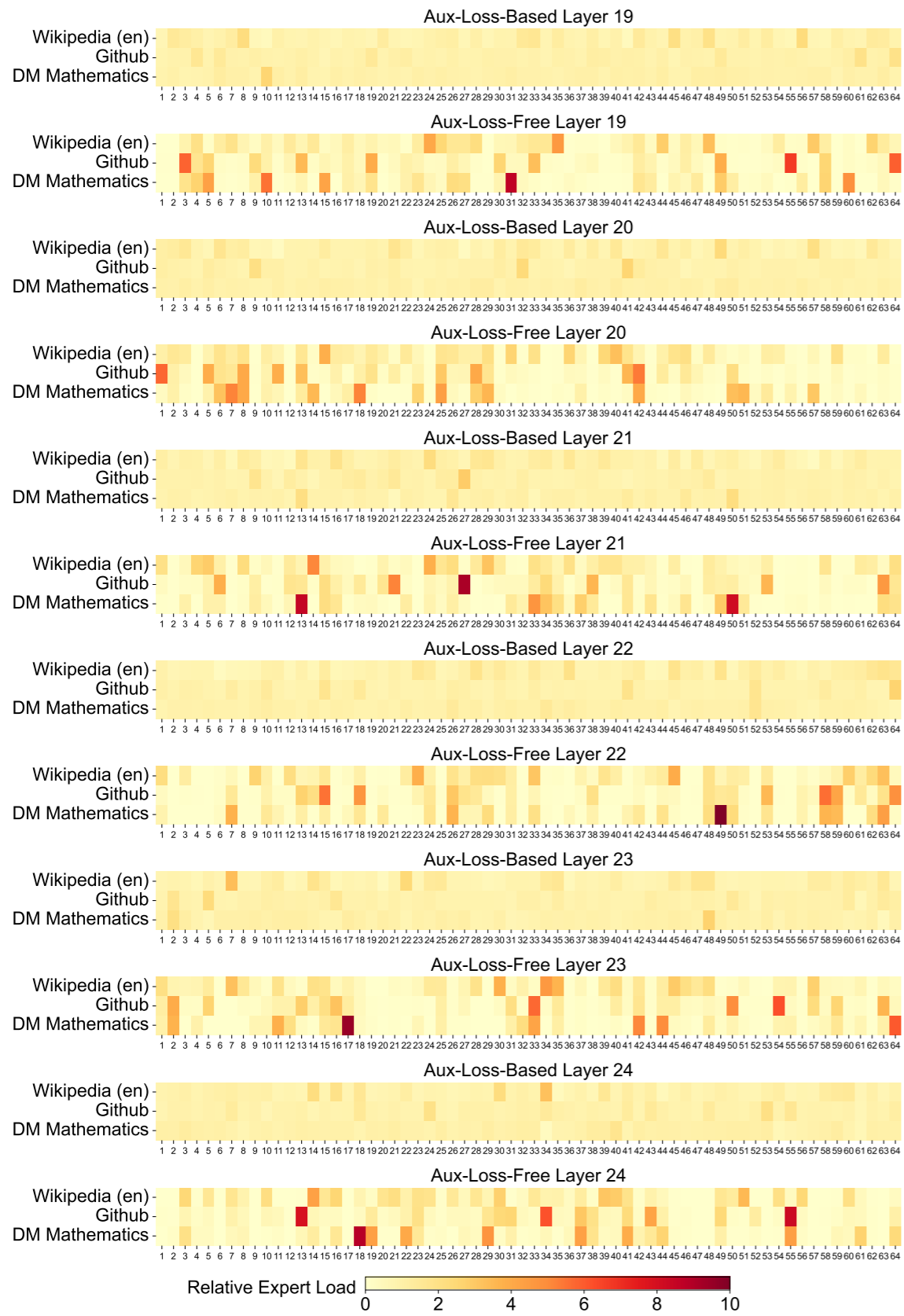
(b) 层7-13



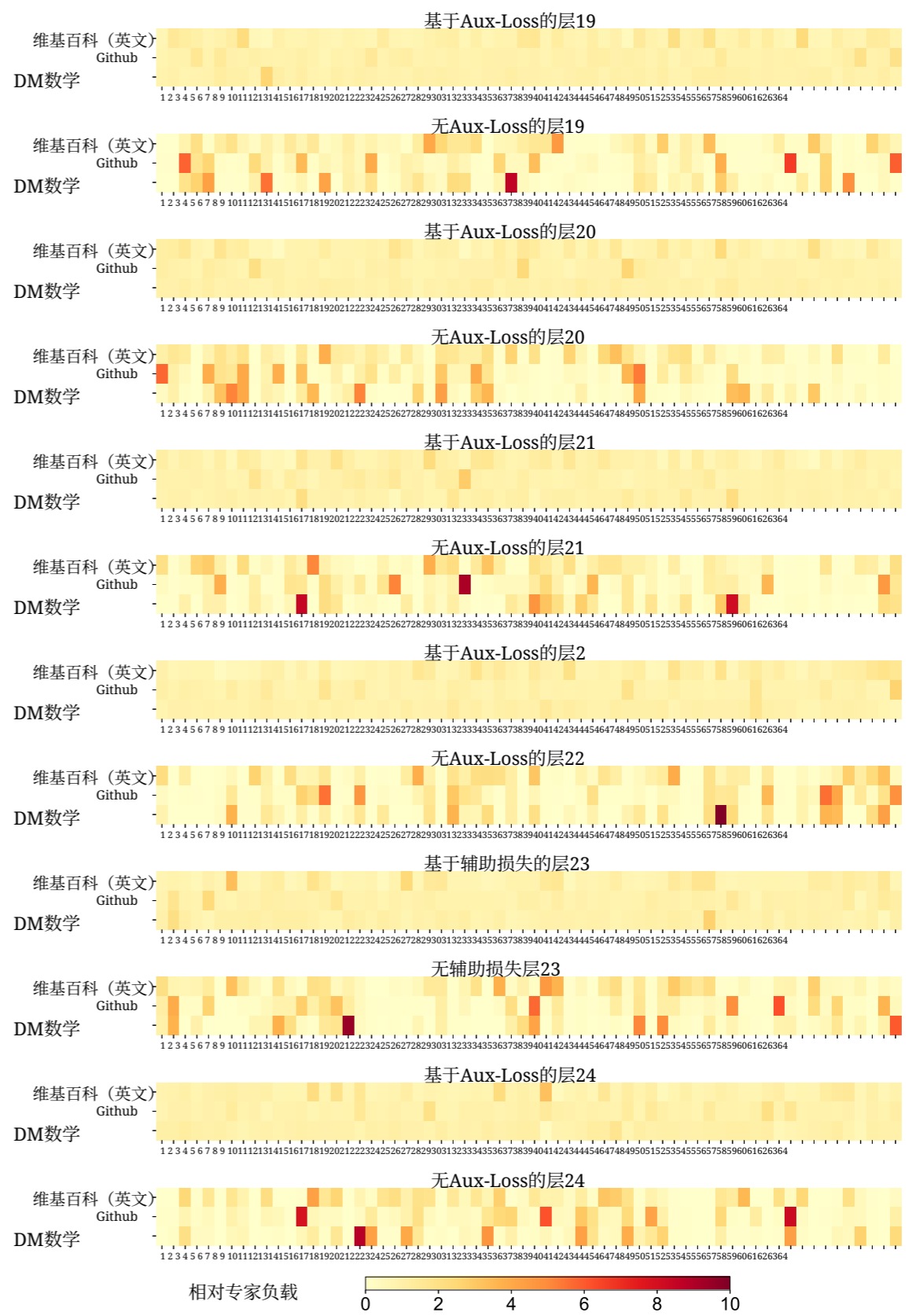
(c) Layers 13-19



(c) 层级 13-19



(d) Layers 19-25



(d) 层19-25

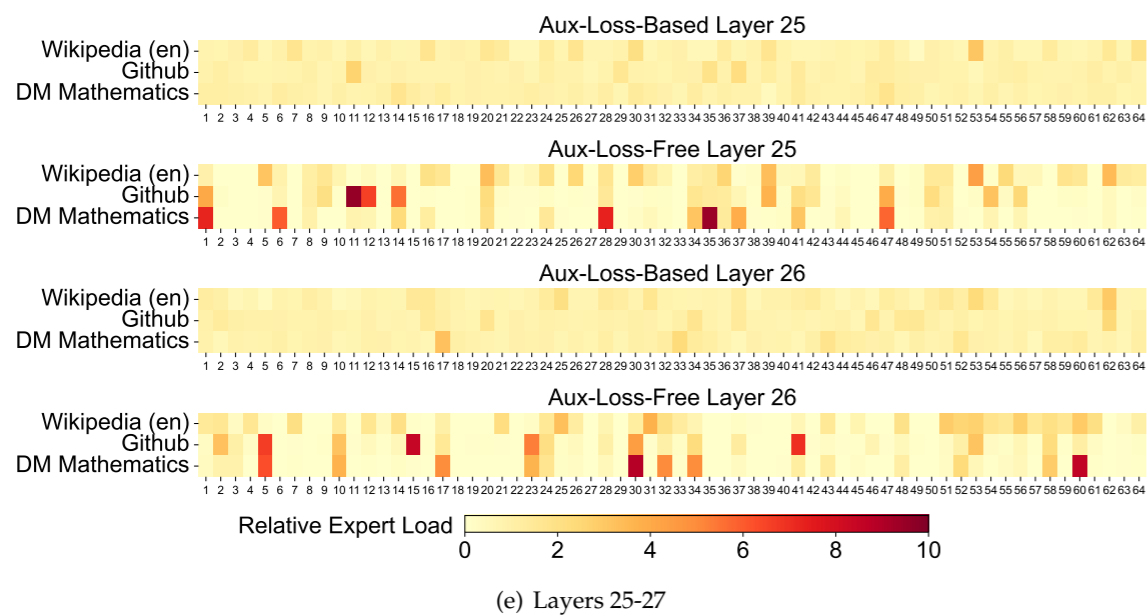


Figure 10 | Expert load of auxiliary-loss-free and auxiliary-loss-based models on three domains in the Pile test set. The auxiliary-loss-free model shows greater expert specialization patterns than the auxiliary-loss-based one. The relative expert load denotes the ratio between the actual expert load and the theoretically balanced expert load.

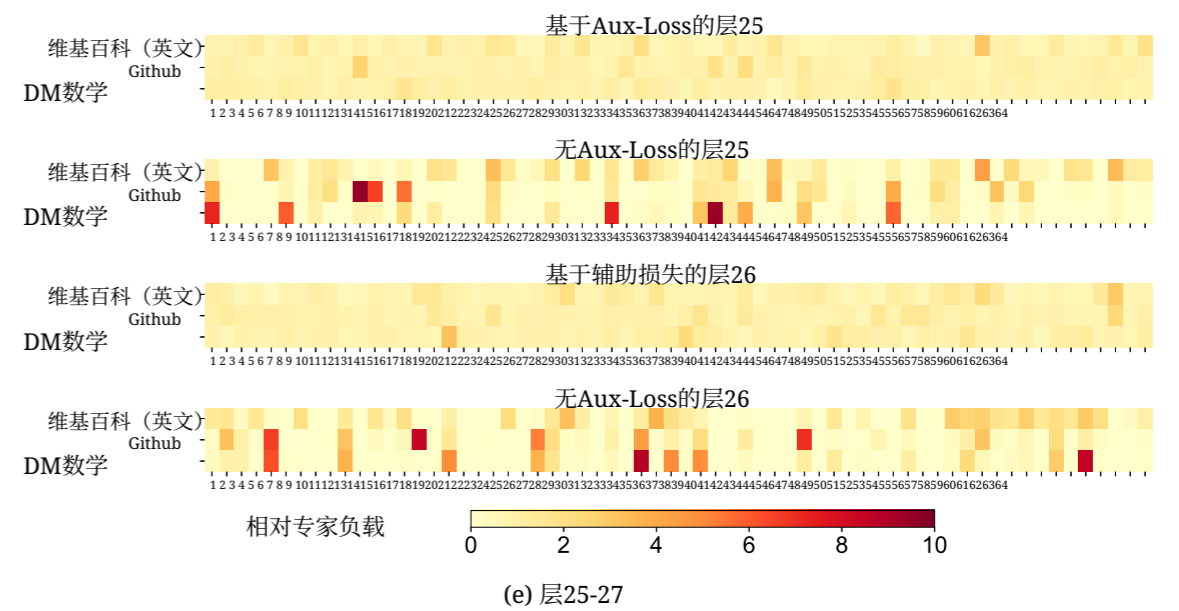


图 10 |：在Pile测试集上，无辅助损失层和辅助损失层模型的专家负载。无辅助损失层模型比辅助损失层模型表现出更明显的专家专业化模式。相对专家负载表示实际专家负载与理论上平衡的专家负载之间的比率。