DeepSeek-V3 Technical Report

DeepSeek-AI

research@deepseek.com

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`.

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Abstract

我们介绍了 DeepSeek-V3，这是一个具有 6710 亿总参数的强混合专家（MoE）语言模型，每个 token 激活 370 亿参数。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 中得到了充分验证。此外，DeepSeek-V3 首次采用无辅助损失的负载平衡策略，并设置多 token 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，随后通过监督微调和强化学习阶段来充分发挥其能力。全面评估表明，DeepSeek-V3 在性能上优于其他开源模型，并且达到了与领先闭源模型相当的性能。尽管性能出色，DeepSeek-V3 的完整训练仅需 2.788 百万 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激增或进行任何回滚。模型检查点可在 `https://github.com/deepseek-ai/DeepSeek-V3` 获取。

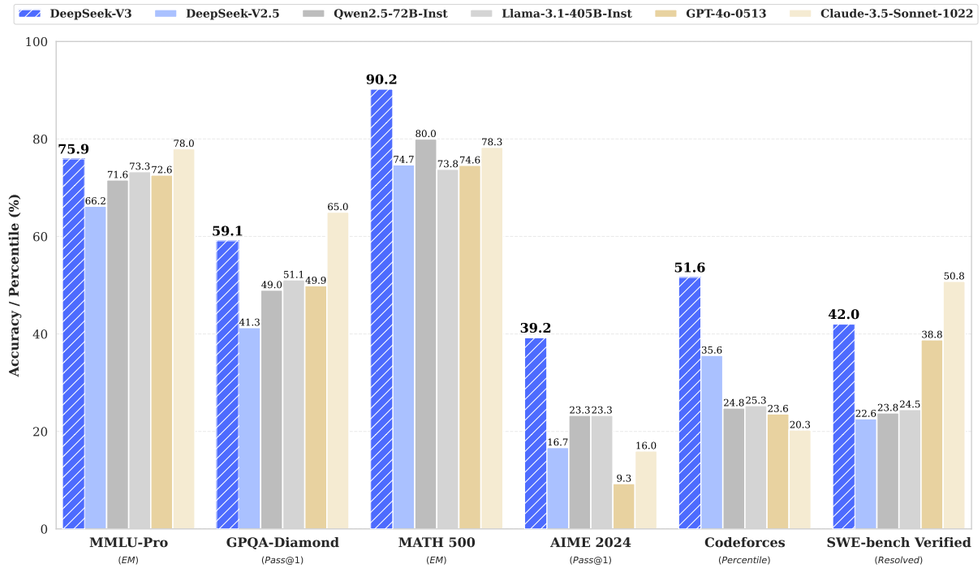


Figure 1 | Benchmark performance of DeepSeek-V3 and its counterparts.

Contents

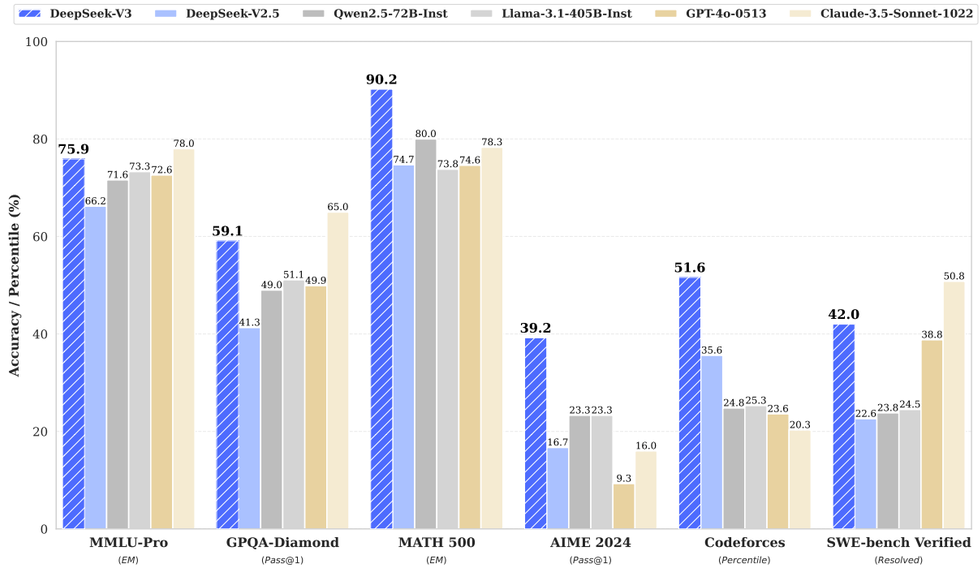


Figure 1 | DeepSeek-V3及其同类产品的基准性能。

Contents

4

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

1. Introduction

近年来，大型语言模型（LLMs）经历了快速的迭代和演变 (Anthropic, 2024; Google, 2024; OpenAI, 2024a)，逐步缩小了与通用人工智能（AGI）之间的差距。除了闭源模型外，包括DeepSeek系列 (DeepSeek-AI, 2024a,b,c; Guo et al., 2024)、LLaMA系列 (AI@Meta, 2024a,b; Touvron et al., 2023a,b)、Qwen系列 (Qwen, 2023, 2024a,b)和Mistral系列 (Jiang et al., 2023; Mistral, 2024)在内的开源模型也在取得显著进展，努力缩小与闭源模型之间的差距。为了进一步推动开源模型能力的边界，我们扩大了模型规模，并引入了DeepSeek-V3，这是一个拥有6710亿参数的大型专家混合（MoE）模型，每个token激活37亿参数。

从前瞻性角度来看，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，以及DeepSeekMoE (Dai et al., 2024)以实现成本效益的训练。这两种架构已在DeepSeek-V2 (DeepSeek-AI, 2024c)中得到验证，证明了它们在保持稳健模型性能的同时，能够实现高效训练和推理的能力。除了基本架构外，我们还实施了两种额外的策略以进一步增强模型能力。首先，DeepSeek-V3开创了一种无辅助损失的负载均衡策略 (Wang et al., 2024a)，旨在最小化鼓励负载均衡对模型性能的不利影响。其次，DeepSeek-V3采用多token预测训练目标，我们观察到这可以增强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，并对训练框架进行了全面优化。低精度训练已成为高效训练的一种有前途的解决方案 (Dettmers et al., 2022; Kalamkar et al., 2019; Narang et al., 2017; Peng et al., 2023b)，其发展与硬件能力的进步密切相关 (Luo et al., 2024; Micikevicius et al., 2022; Rouhani et al., 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并减少了GPU内存使用。至于训练框架，我们设计了DualPipe算法以实现高效的管道并行，该算法具有较少的管道气泡，并通过计算-通信重叠在训练过程中隐藏了大部分通信。这种重叠确保了，随着模型的进一步扩展，只要我们保持恒定的计算-通信比，我们仍然可以在节点间使用细粒度的专家，同时实现接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，我们精心优化了内存占用，使得在不使用昂贵的张量并行的情况下也能训练DeepSeek-V3。通过这些努力，我们实现了高训练效率。

在预训练过程中，我们在14.8万亿高质量和多样化的token上训练DeepSeek-V3。预训练过程非常稳定。在整个训练过程中，我们没有遇到任何无法恢复的损失峰值或需要回滚的情况。接下来，我们对DeepSeek-V3进行了两阶段的上下文长度扩展。在第一阶段，最大上下文长度扩展到32K，第二阶段进一步扩展到128K。随后，我们对DeepSeek-V3的基础模型进行了后训练，包括监督微调（SFT）和强化学习（RL），以使其与人类偏好对齐并进一步释放其潜力。在后训练阶段，我们从DeepSeek-R1系列模型中提取推理能力，同时仔细保持模型准确性和生成长度之间的平衡。

我们对DeepSeek-V3进行了全面的基准测试。尽管其训练成本经济，但全面评估显示，DeepSeek-

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.

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 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

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 | 假设H800的租用价格为每GPU小时2美元，DeepSeek-V3的训练成本。

V3-Base已成为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性基准上实现了与领先的闭源模型（如GPT-4o和Claude-3.5-Sonnet）相当的性能。

最后，我们再次强调 DeepSeek-V3 的经济训练成本，如表 1 所总结，这是通过我们对算法、框架和硬件的优化协同设计实现的。在预训练阶段，训练 DeepSeek-V3 每万亿个标记仅需 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的时间内完成，耗时 2664K GPU 小时。结合用于上下文长度扩展的 119K GPU 小时和用于后训练的 5K GPU 小时，DeepSeek-V3 的完整训练仅需 2.788M GPU 小时。假设 H800 GPU 的租赁价格为每 GPU 小时 2 美元，我们的总训练成本仅为 5576 万美元。请注意，上述成本仅包括 DeepSeek-V3 的正式训练，不包括与架构、算法或数据相关的前期研究和消融实验的成本。

我们的主要贡献包括：

架构:创新的负载平衡策略和训练目标

- 在DeepSeek-V2的高效架构基础上，我们开创了一种无辅助损失的负载均衡策略，该策略最小化了因鼓励负载均衡而产生的性能下降。
- 我们研究了一个多标记预测（MTP）目标，并证明它对模型性能有益。它还可以用于推测性解码以加速推理。

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，并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，实现了近乎完全的计算-通信重叠。这显著提高了我们的训练效率，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。
- 以仅2.664M H800 GPU小时的经济成本，我们完成了在14.8T token上对DeepSeek-V3的预训练，生成了当前最强的开源基础模型。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，特别是DeepSeek R1系列模型之一的推理能力提炼到标准的大语言模型（LLM）中，尤其是DeepSeek-V3。我们的管道优雅地将R1的验证和反思模式融入DeepSeek-V3，显著提高了其推理性能。同时，我们还控

- 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 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,

制了DeepSeek-V3的输出风格和长度。

核心评估结果总结

- 知识：(1) 在如MMLU、MMLU-Pro和GPQA等教育基准测试中，DeepSeek-V3超越了所有其他开源模型，分别在MMLU、MMLU-Pro和GPQA上取得了88.5、75.9和59.1的分数。其性能与GPT-4o和Claude-Sonnet-3.5等领先的闭源模型相当，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上均表现出色，优于其他开源模型。尽管在英文事实知识（SimpleQA）方面落后于GPT-4o和Claude-Sonnet-3.5，但在中文事实知识（中文SimpleQA）方面超过了这些模型，突显了其在中文事实知识方面的优势。
- 代码、数学和推理：(1) DeepSeek-V3 在所有非长链CoT的开源和闭源模型中，在与数学相关的基准测试中实现了最先进的性能。值得注意的是，它甚至在特定的基准测试中（如MATH-500）超过了o1-preview，展示了其强大的数学推理能力。(2) 在与编码相关的任务中，DeepSeek-V3 成为了编码竞赛基准测试（如LiveCodeBench）中的顶级模型，巩固了其在该领域的领先地位。对于与工程相关的任务，虽然 DeepSeek-V3 的表现略低于Claude-Sonnet-3.5，但它仍然显著领先于所有其他模型，展示了其在各种技术基准测试中的竞争力。

在本文的其余部分，我们首先详细介绍了我们的DeepSeek-V3模型架构（第 2节）。随后，我们介绍了我们的基础设施，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，我们描述了我们的预训练过程，包括训练数据的构建、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，我们讨论了我们在后训练方面的努力，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，我们总结了这项工作，讨论了DeepSeek-V3的现有局限性，并提出了未来研究的潜在方向（第6节）。

2. Architecture

我们首先介绍 DeepSeek-V3 的基本架构，其特点包括多头潜在注意力（MLA） (DeepSeek-AI, 2024c) 用于高效的推理，以及 DeepSeekMoE (Dai et al., 2024) 用于经济的训练。然后，我们提出一个多标记预测（MTP）训练目标，我们观察到这可以增强在评估基准上的整体性能。对于未明确提及的其他次要细节，DeepSeek-V3 遵循 DeepSeek-V2 (DeepSeek-AI, 2024c) 的设置。

2.1. Basic Architecture

DeepSeek-V3 的基本架构仍然在 Transformer (Vaswani et al., 2017) 框架内。为了高效推理和经济的训练，DeepSeek-V3 也采用了 MLA 和 DeepSeekMoE，这些已经在 DeepSeek-V2 中得到了充分验证。与 DeepSeek-V2 相比，一个例外是我们为 DeepSeekMoE 引入了一种无辅助损失的负载均衡策略 (Wang et al., 2024a)，以减轻确保负载均衡所导致的性能下降。图 2 描述了 DeepSeek-V3 的基本架构，我们将在本节中简要回顾 MLA 和 DeepSeekMoE 的细节。

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 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 $\mathbf{h}_t \in \mathbb{R}^d$

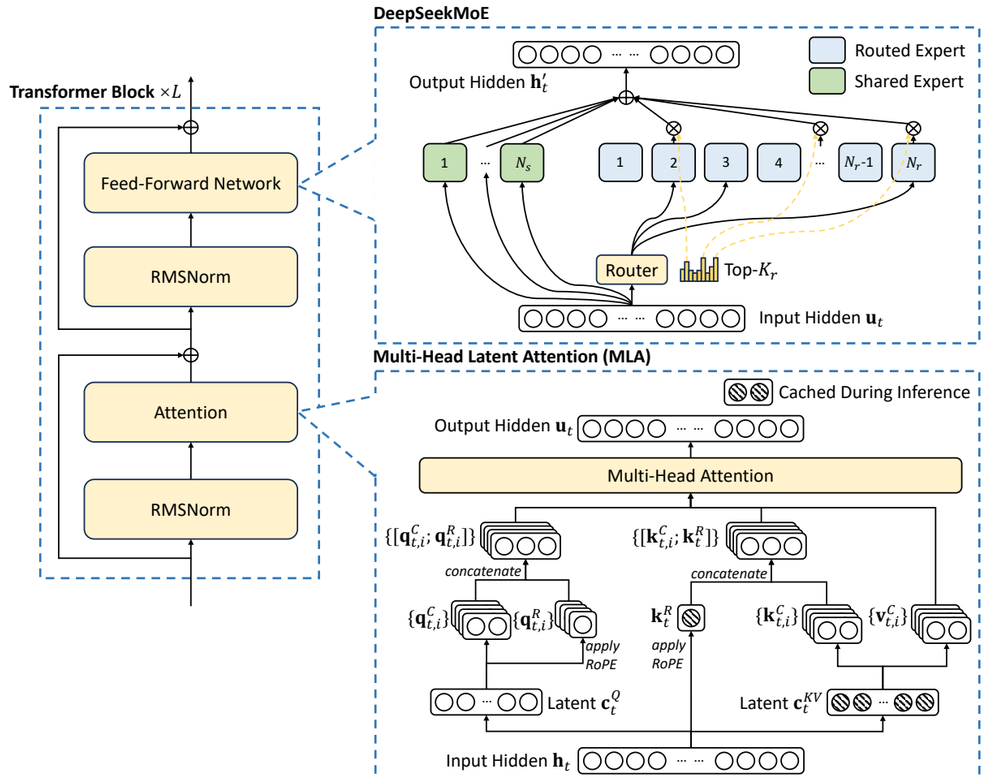


Figure 2 | DeepSeek-V3 基本架构的说明。沿用 DeepSeek-V2，我们采用 MLA 和 DeepSeekMoE 以实现高效的推理和经济的训练。

2.1.1. *Multi-Head Latent Attention*

对于注意力机制，DeepSeek-V3 采用了 MLA 架构。设 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，$\mathbf{h}_t \in \mathbb{R}^d$ 表示在给定注意力层中第 t 个标记的注意力输入。 MLA 的核心是注意力键和值的低秩联合压缩，以减少推理过程中的键值（KV）缓存：

$$\boxed{\mathbf{c}^{KV}_t} = W^{DKV}\mathbf{h}_t, \tag{1}$$

$$[\mathbf{k}^C_{t,1}; \mathbf{k}^C_{t,2}; \ldots; \mathbf{k}^C_{t,n_h}] = \mathbf{k}^C_t = W^{UK}\mathbf{c}^{KV}_t, \tag{2}$$

$$\boxed{\mathbf{k}^R_t} = \mathrm{RoPE}(W^{KR}\mathbf{h}_t), \tag{3}$$

$$\mathbf{k}_{t,i} = [\mathbf{k}^C_{t,i}; \mathbf{k}^R_t], \tag{4}$$

$$[\mathbf{v}^C_{t,1}; \mathbf{v}^C_{t,2}; \ldots; \mathbf{v}^C_{t,n_h}] = \mathbf{v}^C_t = W^{UV}\mathbf{c}^{KV}_t, \tag{5}$$

其中 $\mathbf{c}^{KV}_t \in \mathbb{R}^{d_c}$ 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； $W^{DKV} \in \mathbb{R}^{d_c \times d}$ 表示降维投影矩阵； $W^{UK}, W^{UV} \in \mathbb{R}^{d_h n_h \times d_c}$ 分别是键和值的升维投影矩阵； $W^{KR} \in \mathbb{R}^{d^R_h \times d}$ 是用于生成

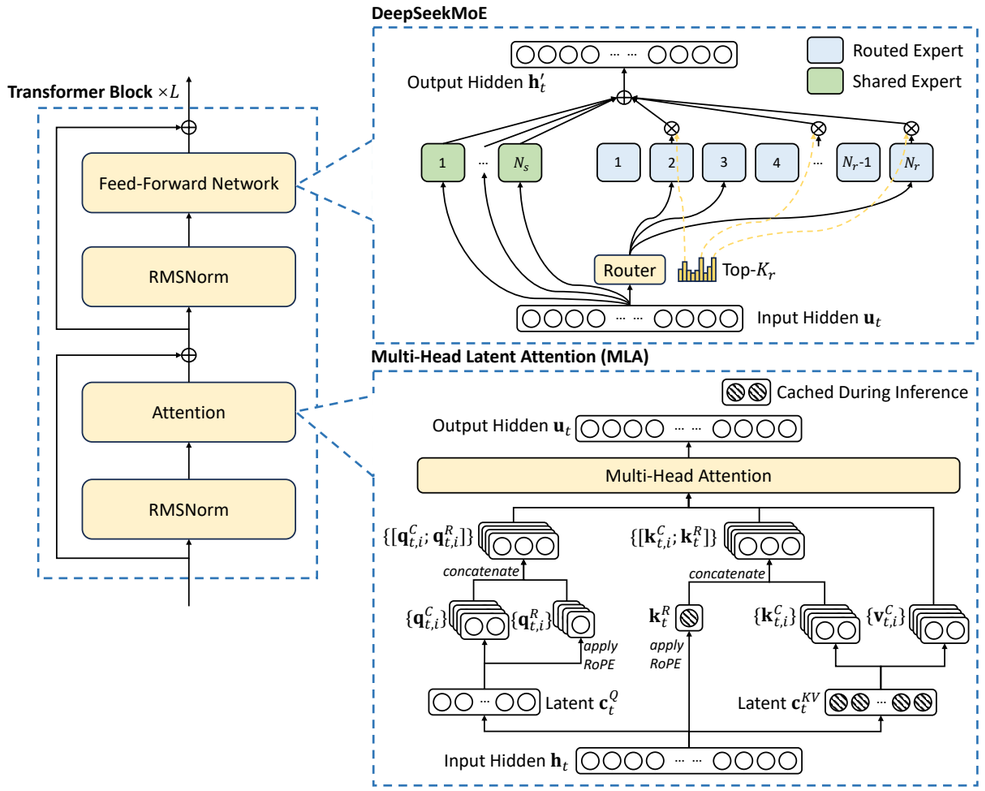


Figure 2 | Illustration of the basic architecture of DeepSeek-V3. Following DeepSeek-V2, we adopt MLA and DeepSeekMoE for efficient inference and economical training.

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:

$$\boxed{\mathbf{c}^{KV}_t} = W^{DKV}\mathbf{h}_t, \tag{1}$$

$$[\mathbf{k}^C_{t,1};\mathbf{k}^C_{t,2};\ldots;\mathbf{k}^C_{t,n_h}] = \mathbf{k}^C_t = W^{UK}\mathbf{c}^{KV}_t, \tag{2}$$

$$\boxed{\mathbf{k}^R_t} = \mathrm{RoPE}(W^{KR}\mathbf{h}_t), \tag{3}$$

$$\mathbf{k}_{t,i} = [\mathbf{k}^C_{t,i};\mathbf{k}^R_t], \tag{4}$$

$$[\mathbf{v}^C_{t,1};\mathbf{v}^C_{t,2};\ldots;\mathbf{v}^C_{t,n_h}] = \mathbf{v}^C_t = W^{UV}\mathbf{c}^{KV}_t, \tag{5}$$

where $\mathbf{c}^{KV}_t \in \mathbb{R}^{d_c}$ 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; $W^{KR} \in \mathbb{R}^{d^R_h \times d}$ is the matrix used to produce the decoupled key that carries Rotary Positional Embedding (RoPE) (Su et al., 2024);

携带旋转位置嵌入（Rotary Positional Embedding, RoPE）的解耦键的矩阵 (Su et al., 2024)；RoPE(·) 表示应用 RoPE 矩阵的操作；$[\cdot;\cdot]$ 表示拼接。注意，对于 MLA，仅需在生成过程中缓存蓝色框中的向量（即 $\mathbf{c}^{KV}_t$ 和 $\mathbf{k}^R_t$），这显著减少了 KV 缓存，同时保持了与标准多头注意力（MHA） (Vaswani et al., 2017) 相当的性能。

对于注意力查询，我们还执行低秩压缩，这可以在训练期间减少激活内存：

$$\mathbf{c}^Q_t = W^{DQ}\mathbf{h}_t, \tag{6}$$

$$[\mathbf{q}^C_{t,1};\mathbf{q}^C_{t,2};\ldots;\mathbf{q}^C_{t,n_h}] = \mathbf{q}^C_t = W^{UQ}\mathbf{c}^Q_t, \tag{7}$$

$$[\mathbf{q}^R_{t,1};\mathbf{q}^R_{t,2};\ldots;\mathbf{q}^R_{t,n_h}] = \mathbf{q}^R_t = \mathrm{RoPE}(W^{QR}\mathbf{c}^Q_t), \tag{8}$$

$$\mathbf{q}_{t,i} = [\mathbf{q}^C_{t,i};\mathbf{q}^R_{t,i}], \tag{9}$$

其中 $\mathbf{c}^Q_t \in \mathbb{R}^{d'_c}$ 是查询的压缩潜在向量；$d'_c (\ll d_h n_h)$ 表示查询压缩维度；$W^{DQ} \in \mathbb{R}^{d'_c \times d}, W^{UQ} \in \mathbb{R}^{d_h n_h \times d'_c}$ 分别是查询的降维和升维矩阵；$W^{QR} \in \mathbb{R}^{d^R_h n_h \times d'_c}$ 是生成携带 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 $(\mathbf{v}^C_{j,i})$ 被组合以生成最终的注意力输出 $\mathbf{u}_t$：

$$\mathbf{o}_{t,i} = \sum_{j=1}^{t} \mathrm{Softmax}_j\left(\frac{\mathbf{q}^T_{t,i}\mathbf{k}_{j,i}}{\sqrt{d_h + d^R_h}}\right)\mathbf{v}^C_{j,i}, \tag{10}$$

$$\mathbf{u}_t = W^O[\mathbf{o}_{t,1};\mathbf{o}_{t,2};\ldots;\mathbf{o}_{t,n_h}], \tag{11}$$

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 with Auxiliary-Loss-Free Load Balancing*

DeepSeekMoE 的基本架构。 对于前馈网络（FFNs），DeepSeek-V3 采用了 DeepSeekMoE 架构 (Dai et al., 2024)。与传统的 MoE 架构如 GShard (Lepikhin et al., 2021) 相比，DeepSeekMoE 使用了更细粒度的专家，并将一些专家隔离为共享专家。设 $\mathbf{u}_t$ 表示第 t 个 token 的 FFN 输入，我们按以下方式计算 FFN 输出 $\mathbf{h}'_t$：

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

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

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

$$s_{i,t} = \mathrm{Sigmoid}\left(\mathbf{u}_t{}^T\mathbf{e}_i\right), \tag{15}$$

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:

$$\mathbf{c}_t^Q = W^{DQ}\mathbf{h}_t, \tag{6}$$

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

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

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

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 $W^{QR} \in \mathbb{R}^{d_h^R n_h \times d_c'}$ 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 $\mathbf{u}_t$:

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

$$\mathbf{u}_t = W^O[\mathbf{o}_{t,1}; \mathbf{o}_{t,2}; ...; \mathbf{o}_{t,n_h}], \tag{11}$$

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

其中 N_s 和 N_r 分别表示共享专家和路由专家的数量； $\text{FFN}_i^{(s)}(\cdot)$ 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数量； $g_{i,t}$ 是第 i 个专家的门控值； $s_{i,t}$ 是令牌到专家的亲和度； $\mathbf{e}_i$ 是第 i 个路由专家的质心向量； $\text{Topk}(\cdot, K)$ 表示第 t 个令牌与所有路由专家计算的亲和度得分中最高的 K 个得分组成的集合。与 DeepSeek-V2 略有不同，DeepSeek-V3 使用 Sigmoid 函数来计算亲和度得分，并对所有选定的亲和度得分进行归一化以生成门控值。

无辅助损失的负载均衡。 对于 MoE 模型，不平衡的专家负载将导致路由崩溃 (Shazeer et al., 2017) 并降低专家并行场景下的计算效率。传统的解决方案通常依赖于辅助损失 (Fedus et al., 2021; Lepikhin et al., 2021) 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 et al., 2024a)。为了在负载均衡和模型性能之间取得更好的平衡，我们开创了一种无辅助损失的负载均衡策略 (Wang et al., 2024a) 以确保负载均衡。具体来说，我们为每个专家引入一个偏置项 b_i，并将其添加到相应的亲和度得分 $s_{i,t}$ 中以确定 top-K 路由：

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

请注意，偏差项仅用于路由。门控值仍从原始亲和力得分 $s_{i,t}$ 导出，该值将与前馈网络（FFN）输出相乘。在训练过程中，我们持续监控每个训练步骤中整个批次的专家负载。在每个步骤结束时，如果某个专家过载，我们将减少其对应的偏差项 γ；如果某个专家负载不足，我们将增加其对应的偏差项 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 在训练过程中保持了专家负载的平衡，并且比通过纯辅助损失鼓励负载平衡的模型表现更好。

互补的序列级辅助损失。 尽管 DeepSeek-V3 主要依赖于无辅助损失的策略来实现负载平衡，为了防止任何单个序列内的极端不平衡，我们还采用了一个互补的序列级平衡损失：

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

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

$$s_{i,t}' = \frac{s_{i,t}}{\sum_{j=1}^{N_r} s_{j,t}}, \tag{19}$$

$$P_i = \frac{1}{T} \sum_{t=1}^{T} s_{i,t}', \tag{20}$$

其中平衡因子 α 是一个超参数，对于 DeepSeek-V3 将被赋予一个极小的值； $\mathbb{1}(\cdot)$ 表示指示函数； T 表示序列中的标记数量。序列级平衡损失鼓励每个序列上的专家负载保持平衡。

the FFN output $\mathbf{h}'_t$ as follows:

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

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

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

$$s_{i,t} = \mathrm{Sigmoid}\left(\mathbf{u}_t{}^T \mathbf{e}_i\right), \tag{15}$$

where N_s and N_r denote the numbers of shared experts and routed experts, respectively; $\mathrm{FFN}_i^{(s)}(\cdot)$ and $\mathrm{FFN}_i^{(r)}(\cdot)$ 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 $\mathrm{Topk}(\cdot, K)$ 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:

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

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

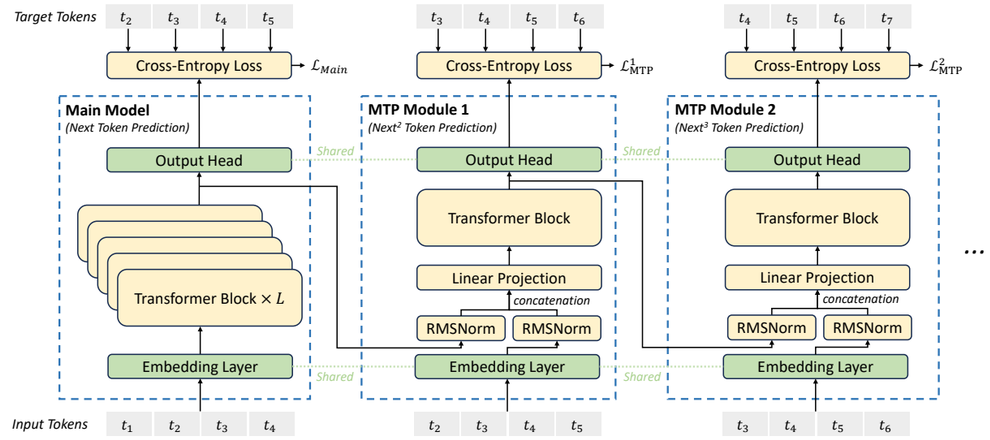


Figure 3 | 我们的多标记预测（MTP）实现的说明。我们在每个深度为每个标记的预测保持完整的因果链。

节点限制路由。 与 DeepSeek-V2 使用的设备限制路由类似，DeepSeek-V3 也使用一种受限的路由机制来限制训练期间的通信成本。简而言之，我们确保每个标记最多只会被发送到 M 个节点，这些节点的选择依据是每个节点上分布的专家的最高 $\frac{K_r}{M}$ 亲和度分数之和。在这种约束下，我们的 MoE 训练框架几乎可以实现计算和通信的完全重叠。

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

2.2. Multi-Token Prediction

受 Gloeckle et al. (2024) 的启发，我们为 DeepSeek-V3 设定了一个多标记预测（MTP）目标，该目标将每个位置的预测范围扩展到多个未来的标记。一方面，MTP 目标密集化了训练信号，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，以更好地预测未来的标记。图 3 说明了我们对 MTP 的实现。与 Gloeckle et al. (2024) 不同，后者使用独立的输出头并行预测 D 个额外的标记，我们顺序预测额外的标记，并在每个预测深度保持完整的因果链。我们在本节中介绍我们 MTP 实现的详细信息。

MTP 模块。 具体来说，我们的 MTP 实现使用 D 个顺序模块来预测 D 个额外的标记。第 k 个 MTP 模块由一个共享的嵌入层 $\mathrm{Emb}(\cdot)$、一个共享的输出头 $\mathrm{OutHead}(\cdot)$、一个 Transformer 块 $\mathrm{TRM}_k(\cdot)$ 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 $\mathbf{h}_i^{k-1} \in \mathbb{R}^d$ 和第 $(i+k)$ 个标记的嵌入 $Emb(t_{i+k}) \in \mathbb{R}^d$

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:

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

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

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

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

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.

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.

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.

2.2. Multi-Token Prediction

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

通过线性投影结合：

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

其中 $[\cdot;\cdot]$ 表示连接操作。特别是，当 $k = 1$ 时，$\mathbf{h}^{k-1}_i$ 指的是主模型给出的表示。注意，对于每个 MTP 模块，其嵌入层与主模型共享。组合后的 $\mathbf{h}'^{k}_i$ 作为第 k 层 Transformer 块的输入，以生成当前层的输出表示 $\mathbf{h}^{k}_i$：

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

其中 T 表示输入序列的长度，$_{i:j}$ 表示切片操作（包括左右边界）。最后，以 $\mathbf{h}^{k}_i$ 作为输入，共享输出头将计算第 k 个附加预测标记的概率分布 $P^{k}_{i+1+k} \in \mathbb{R}^V$，其中 V 是词汇表的大小：

$$P^{k}_{i+k+1} = \text{OutHead}(\mathbf{h}^{k}_i). \tag{23}$$

输出头 $\text{OutHead}(\cdot)$ 线性地将表示映射到 logits，然后应用 $\text{Softmax}(\cdot)$ 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 et al., 2024b) 类似，但其主要目标是推测解码 (Leviathan et al., 2023; Xia et al., 2023)，而我们则利用 MTP 来改进训练。

MTP 训练目标。 对于每个预测深度，我们计算一个交叉熵损失 $\mathcal{L}^{k}_{\text{MTP}}$：

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

其中 T 表示输入序列的长度，t_i 表示第 i 个位置的真实标记，$P^{k}_i[t_i]$ 表示第 k 个 MTP 模块给出的 t_i 的预测概率。最后，我们计算所有深度的 MTP 损失的平均值，并乘以一个权重因子 λ，以获得总体的 MTP 损失 $\mathcal{L}_{\text{MTP}}$，这作为 DeepSeek-V3 的额外训练目标：

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

推理中的MTP。 我们的MTP策略主要旨在提高主模型的性能，因此在推理过程中，我们可以直接丢弃MTP模块，主模型可以独立且正常地运行。此外，我们还可以将这些MTP模块重新用于推测解码，以进一步降低生成延迟。

3. Infrastructures

3.1. Compute Clusters

DeepSeek-V3 在配备有 2048 个 NVIDIA H800 GPU 的集群上进行训练。 H800 集群中的每个节点包含 8 个通过 NVLink 和 NVSwitch 连接的 GPU。在不同节点之间，使用 InfiniBand (IB) 互

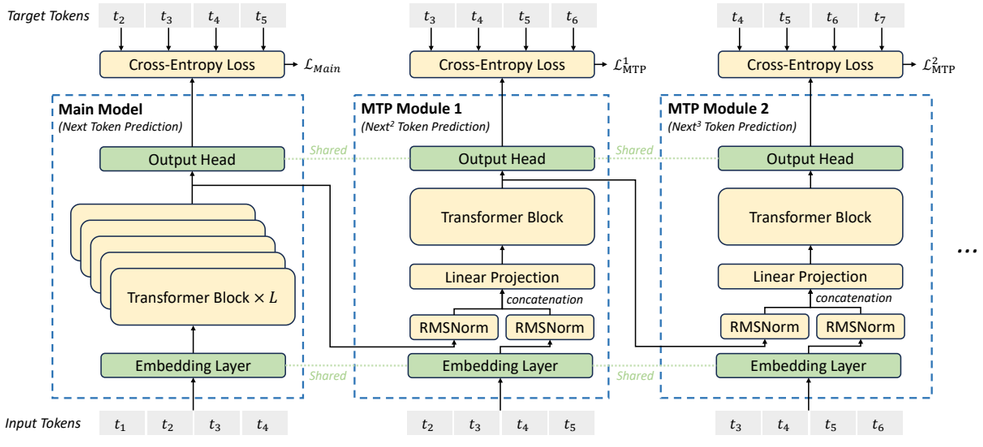


Figure 3 | Illustration of our Multi-Token Prediction (MTP) implementation. We keep the complete causal chain for the prediction of each token at each depth.

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.

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 $\mathrm{Emb}(\cdot)$, a shared output head $\mathrm{OutHead}(\cdot)$, a Transformer block $\mathrm{TRM}_k(\cdot)$, 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 $Emb(t_{i+k}) \in \mathbb{R}^d$ with the linear projection:

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

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 $\mathbf{h}_i^k$:

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

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 $P_{i+1+k}^k \in \mathbb{R}^V$, where

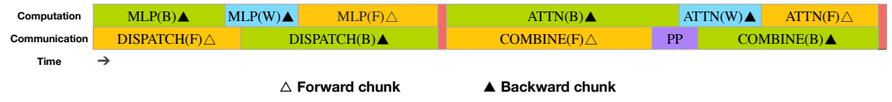


Figure 4 | 一对前向和后向块的重叠策略（变压器块的边界未对齐）。橙色表示前向，绿色表示“输入的后向”，蓝色表示“权重的后向”，紫色表示PP通信，红色表示屏障。全对全通信和PP通信都可以完全隐藏。

连来促进通信。

3.2. Training Framework

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打造的高效且轻量级的训练框架。总体而言，DeepSeek-V3 应用了 16 路管道并行（PP） (Qi et al., 2023a)，64 路专家并行（EP） (Lepikhin et al., 2021) 跨 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 算法以实现高效的管道并行。与现有的 PP 方法相比，DualPipe 的管道气泡更少。更重要的是，它在前向和后向过程中重叠了计算和通信阶段，从而解决了由跨节点专家并行引入的通信开销大的问题。其次，我们开发了高效的跨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（SMs）。最后，我们仔细优化了训练期间的内存占用，从而能够在不使用昂贵的张量并行（TP）的情况下训练 DeepSeek-V3。

3.2.1. DualPipe and Computation-Communication Overlap

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的比例约为 1:1，效率较低。为了解决这一挑战，我们设计了一种创新的流水线并行算法 DualPipe，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，还减少了流水线中的空闲时间。

DualPipe 的核心思想是在一对单独的前向和后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`。特别是，对于后向块，`attention` 和 `MLP` 进一步分为两部分，即 `backward for input` 和 `backward for weights`，类似于 ZeroBubble (Qi et al., 2023b)。此外，我们还添加了一个 `PP communication` 组件。如图 4 所示，对于一对前向和后向块，我们重新排列这些组件并手动调整用于通信和计算的 GPU SMs 的比例。通过这种重叠策略，我们可以在执行过程中确保所有 all-to-all 和 PP 通信都能完全隐藏。鉴于高效的重叠策略，完整的 DualPipe 调度如图 5 所示。它采用双向流水线调度，同时从流水线的两端输入微批次，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，只要我们保持恒定的计算与通信比例，仍然可以在节点间使用细粒度的专家，同时实现接近零的 all-to-all 通信开销。

此外，即使在没有沉重通信负担的更一般场景中，DualPipe 仍然表现出效率优势。在表 2 中，我们总结了不同 PP 方法的流水线气泡和内存使用情况。如表所示，与 ZB1P (Qi et al.,

V is the vocabulary size:

$$P_{i+k+1}^{k} = \text{OutHead}(\mathbf{h}_i^k). \tag{23}$$

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 $\mathcal{L}_{\text{MTP}}^{k}$:

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

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 $\mathcal{L}_{\text{MTP}}$, which serves as an additional training objective for DeepSeek-V3:

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

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.

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,

Figure 5 | 示例 DualPipe 调度，8 个 PP 级和两个方向的 20 个微批次。反向的微批次与前向的微批次对称，因此为了简化说明，我们省略了它们的批次 ID。被共享黑色边框包围的两个单元格具有相互重叠的计算和通信。

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

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

2023b) 和 1F1B (Harlap et al., 2018) 相比，DualPipe 显著减少了流水线气泡，而峰值激活内存仅增加了 $\frac{1}{PP}$ 倍。尽管 DualPipe 需要保留两份模型参数，但这并不会显著增加内存消耗，因为我们在训练过程中使用了较大的 EP 尺寸。与 Chimera (Li and Hoefler, 2021) 相比，DualPipe 仅要求流水线阶段和微批次可被 2 整除，而不要求微批次必须被流水线阶段整除。此外，对于 DualPipe，无论是气泡还是激活内存都不会随着微批次数量的增加而增加。

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

为了确保 DualPipe 具有足够的计算性能，我们定制了高效的跨节点全对全通信内核（包括调度和组合），以减少用于通信的 SM 数量。内核的实现与我们的集群中的 MoE 门控算法和网络拓扑共同设计。具体来说，在我们的集群中，跨节点的 GPU 通过 IB 完全互连，而节点内部的通信则通过 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 限制为最多分发到 4 个节点，从而减少 IB 流量。对于每个 token，当其路由决策确定后，它将首先通过 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，我们将努力确保它通过 NVLink 即时转发到托管其目标专家的特定 GPU，而不被随后到达的 token 阻塞。通过这种方式，IB 和 NVLink 之间的通信完全重叠，每个 token 可以高效地在每个节点上平均选择 3.2 个专家，而不会产生额外的 NVLink 开销。这意味着，虽然 DeepSeek-V3 实际上只选择 8 个路由专家，但它可以在保持相同通信成本的情况下将此数量扩展到最多 13 个专家（4 个节点 × 3.2 个专家/节点）。总体而言，在这种通信策略下，仅 20 个 SM 就足以充分利用 IB 和 NVLink 的带宽。

具体来说，我们采用了 warp 专业化技术 (Bauer et al., 2014)，并将 20 个 SM 分成 10 个通信通道。在调度过程中，(1) IB 发送，(2) IB 到 NVLink 转发，以及 (3) NVLink 接收分别由各自的 warp 处理。分配给每个通信任务的 warp 数量根据所有 SM 的实际工作负载动态调整。同样，

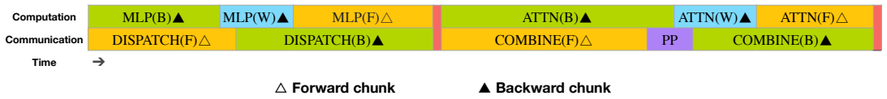


Figure 4 | Overlapping strategy for a pair of individual forward and backward chunks (the boundaries of the transformer blocks are not aligned). Orange denotes forward, green denotes "backward for input", blue denotes "backward for weights", purple denotes PP communication, and red denotes barriers.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

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

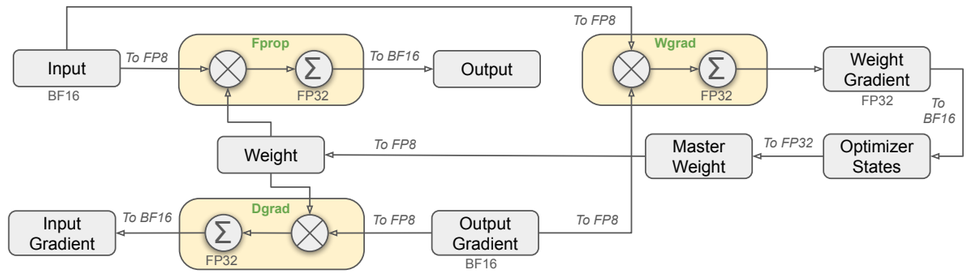


Figure 6 | 整体的混合精度框架采用FP8数据格式。为便于说明，仅展示了`Linear`算子。

在组合过程中，(1) NVLink 发送，(2) NVLink 到 IB 转发和累积，以及 (3) IB 接收和累积也由动态调整的 warp 处理。此外，调度和组合内核与计算流重叠，因此我们还考虑了它们对其他 SM 计算内核的影响。具体来说，我们使用定制的 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 缓存的使用和对其他 SM 的干扰。

3.2.3. *Extremely Memory Saving with Minimal Overhead*

为了减少训练期间的内存占用，我们采用了以下技术。

RMSNorm 和 MLA 上投影的重新计算。 我们在反向传播过程中重新计算所有的 RMSNorm 操作和 MLA 上投影，从而消除了持久存储其输出激活的需要。虽然会带来轻微的开销，但这种策略显著减少了存储激活所需的内存。

CPU 中的指数移动平均。 在训练过程中，我们保留模型参数的指数移动平均 (EMA)，以便在学习率衰减后提前估计模型性能。 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增加额外内存或时间开销的情况下维护 EMA 参数。

多标记预测的共享嵌入和输出头。 通过 DualPipe 策略，我们将模型的最浅层（包括嵌入层）和最深层（包括输出头）部署在同一 PP 级别上。这种安排使得 MTP 模块和主模型之间可以物理共享共享嵌入和输出头的参数和梯度。这种物理共享机制进一步提高了我们的内存效率。

3.3. FP8 Training

受到近期低精度训练进展的启发 (Dettmers et al., 2022; Noune et al., 2022; Peng et al., 2023b)，我们提出了一种利用FP8数据格式训练DeepSeek-V3的细粒度混合精度框架。虽然低精度训练前景广阔，但激活、权重和梯度中的异常值往往限制了其应用 (Fishman et al., 2024; He et al.; Sun et al., 2024)。尽管在推理量化方面已经取得了显著进展 (Frantar et al., 2022; Xiao et al., 2023)，但在大规模语言模型预训练中成功应用低精度技术的研究相对较少 (Fishman et al., 2024)。为了解决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化策略：以$1 \times N_c$元素

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×	PP
ZB1P	$(PP-1)(F+B-2W)$	1×	PP
DualPipe (Ours)	$(\frac{PP}{2}-1)(F\&B+B-3W)$	2×	$PP+1$

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.

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.

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,

的平铺分组或以$N_c \times N_c$元素的块分组。在我们增加精度的累加过程中，相关的反量化开销得到了很大程度的缓解，这是实现准确的FP8通用矩阵乘法 (GEMM)的关键方面。此外，为了进一步减少MoE训练中的内存和通信开销，我们在FP8中缓存和调度激活，同时在BF16中存储低精度优化器状态。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，训练了大约1万亿个标记（详见附录 B.1）。值得注意的是，与BF16基线相比，我们的FP8训练模型的相对损失误差始终低于0.25%，这一水平在训练随机性的可接受范围内。

3.3.1. *Mixed Precision Framework*

在广泛采用的低精度训练技术 (Kalamkar et al., 2019; Narang et al., 2017)的基础上，我们提出了一种用于FP8训练的混合精度框架。在这个框架中，大多数计算密集型操作以FP8进行，而少数关键操作则战略性地保持其原始数据格式，以平衡训练效率和数值稳定性。整体框架如图 6所示。

首先，为了加速模型训练，大多数核心计算内核，即GEMM操作，都以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的输出。如图 6所示，与`Linear`算子相关的三个GEMM，即`Fprop`（前向传播）、`Dgrad`（激活反向传播）和`Wgrad`（权重反向传播），都在FP8中执行。这种设计理论上将计算速度提高了一倍，与原始的BF16方法相比。此外，FP8 `Wgrad` GEMM允许以FP8存储激活，以便在反向传播中使用。这显著减少了内存消耗。

尽管FP8格式具有效率优势，但某些算子由于对低精度计算的敏感性仍需要更高的精度。此外，一些低开销的算子也可以利用更高的精度，对整体训练成本的影响可以忽略不计。因此，经过仔细调查，我们保持以下组件的原始精度（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。这些高精度的针对性保留确保了DeepSeek-V3的稳定训练动态。为了进一步保证数值稳定性，我们以更高的精度存储主权重、权重梯度和优化器状态。虽然这些高精度组件会带来一些内存开销，但通过在分布式训练系统中高效地跨多个DP等级分片，可以将其影响最小化。

3.3.2. *Improved Precision from Quantization and Multiplication*

基于我们的混合精度FP8框架，我们介绍了几种增强低精度训练准确性的策略，重点在于量化方法和乘法过程。

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，溢出和下溢是常见的挑战，这受到其减少的指数位的限制。作为标准做法，通过将输入张量的最大绝对值缩放到FP8的最大可表示值，将输入分布对齐到FP8格式的可表示范围内 (Narang et al., 2017)。这种方法使得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上应用缩放。如图 7 (a)所示，(1) 对于激活值，我们以`1x128`的块为单位对元素进行分组和缩放（即每个token每128个通道）；(2) 对于权重，我

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 selects only 8 routed experts in practice, it can scale up this number to a maximum of 13 experts (4 nodes × 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

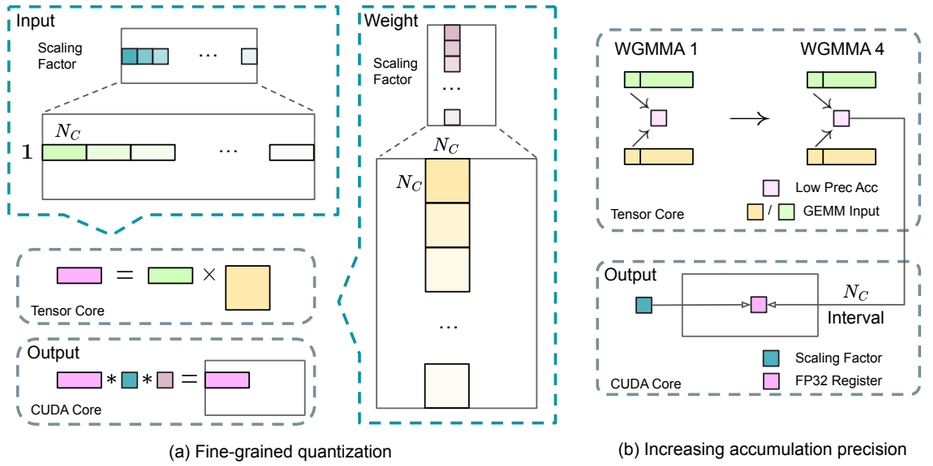


Figure 7 | (a) 我们提出了一种细粒度量化方法，以减轻特征异常值引起的量化误差；为了简化说明，仅展示了Fprop。 (b) 结合我们的量化策略，我们通过在每 N_C = 128 个元素 MMA 间隔提升到 CUDA 核心，提高了 FP8 GEMM 的精度，以实现高精度累加。

们以128x128的块为单位对元素进行分组和缩放（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的元素组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对激活值进行分组和缩放时的训练不稳定性。

我们方法中的一个关键修改是在GEMM操作的内部维度上引入每组缩放因子。此功能在标准FP8 GEMM中不直接支持。然而，结合我们的精确FP32累加策略，它可以高效地实现。

值得注意的是，我们的细粒度量化策略与微缩放格式的概念高度一致 (Rouhani et al., 2023b)，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放格式 (NVIDIA, 2024a)。我们希望我们的设计可以作为未来工作的参考，以跟上最新的GPU架构。

提高累加精度。 低精度GEMM操作通常会遇到下溢问题，其准确性很大程度上取决于高精度累加，这通常在FP32精度下进行 (Kalamkar et al., 2019; Narang et al., 2017)。然而，我们观察到，在NVIDIA H800 GPU上，FP8 GEMM的累加精度仅限于保留大约14位，这远低于FP32累加精度。当内部维度K较大时，这个问题将变得更加明显 (Wortsman et al., 2023)，这是在大规模模型训练中常见的场景，其中批量大小和模型宽度增加。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加精度导致的最大相对误差接近2%。尽管存在这些问题，有限的累加精度仍然是少数FP8框架的默认选项 (NVIDIA, 2024b)，严重限制了训练精度。

为了解决这个问题，我们采用了提升到CUDA核心以实现更高精度的策略 (Thakkar et al., 2023)。过程如图 7 (b)所示。具体来说，在张量核心上执行矩阵乘加（MMA）时，中间结果使用有限的位宽累加。一旦达到N_C的间隔，这些部分结果将被复制到CUDA核心上的FP32寄存器

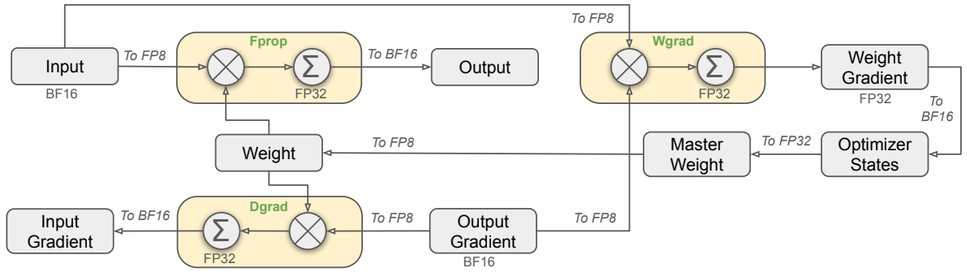


Figure 6 | The overall mixed precision framework with FP8 data format. For clarification, only the `Linear` operator is illustrated.

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 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

中，在那里进行全精度FP32累加。如前所述，我们的细粒度量化在内部维度K上应用每组缩放因子。这些缩放因子可以在CUDA核心上高效地乘以，作为去量化过程的一部分，而不会增加额外的计算成本。值得注意的是，这种修改减少了单个线程组的WGMMA（Warpgroup-level Matrix Multiply-Accumulate）指令的发布率。然而，在H800架构上，通常有两个WGMMA会持续并发：当一个线程组执行提升操作时，另一个线程组能够执行MMA操作。这种设计使得两个操作可以重叠，保持Tensor Core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，代表了可以显著提高精度而不引入大量开销的最小累积间隔。

尾数优于指数。 与先前工作(NVIDIA, 2024b; Peng et al., 2023b; Sun et al., 2019b)采用的混合FP8格式不同，后者在`Fprop`中使用`E4M3`（4位指数和3位尾数），在`Dgrad`和`Wgrad`中使用`E5M2`（5位指数和2位尾数），我们对所有张量采用`E4M3`格式以获得更高的精度。我们认为这种方法的可行性归功于我们的细粒度量化策略，即块和瓦片级缩放。通过在较小的元素组上操作，我们的方法有效地在这些分组元素之间共享指数位，减轻了动态范围有限的影响。

在线量化。 在张量级量化框架中(NVIDIA, 2024b; Peng et al., 2023b)，延迟量化被采用，该方法保持先前迭代中最大绝对值的历史记录以推断当前值。为了确保准确的缩放比例并简化框架，我们在线计算每个`1x128`激活瓦片或`128x128`权重块的最大绝对值。基于此，我们推导出缩放因子，然后将激活或权重在线量化为FP8格式。

3.3.3. Low-Precision Storage and Communication

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

低精度优化器状态。 我们采用BF16数据格式而不是FP32来跟踪AdamW (Loshchilov and Hutter, 2017)优化器中的第一和第二矩，而不会导致性能显著下降。然而，主权重（由优化器存储）和梯度（用于批量大小累积）仍然保留为FP32，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，自然选择在FP8格式中缓存激活，以供`Linear`操作符的反向传播使用。然而，为了实现低成本高精度训练，对某些操作符进行了特别考虑：

> **(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 `1x128` quantization tile to an `128x1` tile in the backward pass. To avoid introducing extra quantization error, all the scaling factors are round scaled, i.e., integral power of 2.

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.

3.3.1. Mixed Precision Framework

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.

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.

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 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.

3.3.2. Improved Precision from Quantization and Multiplication

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.

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

(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.

低精度通信。 通信带宽是MoE模型训练中的关键瓶颈。为了解决这一挑战，我们在MoE上投影之前对激活进行量化到FP8，然后应用`dispatch`组件，这与MoE上投影中的FP8 `Fprop`兼容。类似于注意力操作符后的`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下投影之前的激活梯度。对于前向和后向`combine`组件，我们保留它们为BF16，以在训练管道的关键部分保持训练精度。

3.4. Inference and Deployment

我们在H800集群上部署DeepSeek-V3，其中每个节点内的GPU通过NVLink互连，整个集群中的所有GPU通过IB完全互连。为了同时确保在线服务的服务水平目标（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。

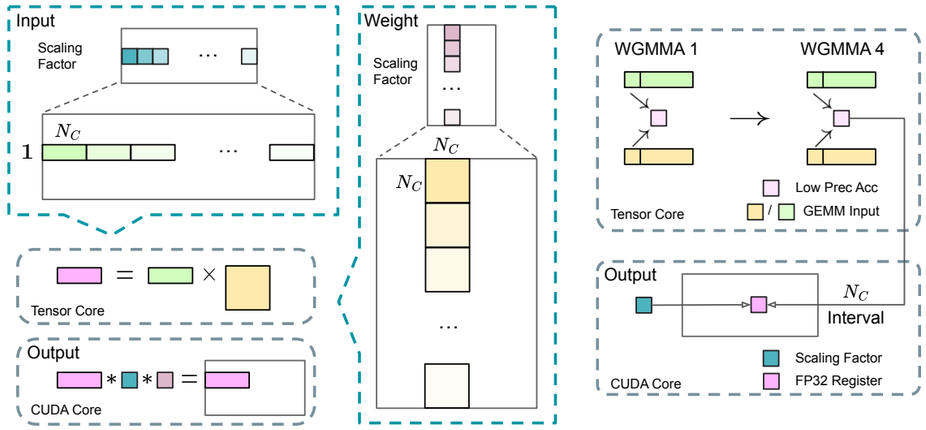
3.4.1. Prefilling

预填充阶段的最小部署单元由4个节点组成，每个节点配备32个GPU。`attention` 部分采用4路张量并行（TP4）与序列并行（SP），结合8路数据并行（DP8）。其较小的TP规模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），确保每个专家处理足够大的批次，从而提高计算效率。对于 `MoE` 的全对全通信，我们使用与训练相同的策略：首先通过IB在节点间传输令牌，然后通过NVLink在节点内的GPU间转发。特别是，我们对浅层的密集MLP使用1路张量并行，以减少TP通信。

为了在 `MoE` 部分的不同专家之间实现负载均衡，我们需要确保每个GPU处理的令牌数量大致相同。为此，我们引入了一种 冗余专家 的部署策略，即复制高负载专家并冗余部署。高负载专家的检测基于在线部署期间收集的统计信息，并定期调整（例如，每10分钟一次）。确定冗余专家集后，我们根据观察到的负载，仔细重新安排节点内GPU上的专家，尽量在不增加跨节点全对全通信开销的情况下平衡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，除了它原本托管的8个专家外，还将托管一个额外的冗余专家。

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，我们同时处理两个具有相似计算工作量的微批次，使一个微批次的 `attention` 和 `MoE` 与另一个微批次的 `dispatch` 和 `combine` 重叠。

最后，我们正在探索一种 动态冗余 策略，每个GPU托管更多的专家（例如，16个专家），但在每个推理步骤中只激活9个。在每层的全对全操作开始之前，我们实时计算全局最优路由方案。鉴于预填充阶段涉及大量的计算，计算此路由方案的开销几乎可以忽略不计。



(a) Fine-grained quantization (b) Increasing accumulation precision

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.

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 1x128 tile basis (i.e., per token per 128 channels); and (2) for weights, we group and scale elements on a 128x128 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.

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 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.

3.4.2. *Decoding*

在解码过程中，我们将共享专家视为路由专家。从这个角度来看，每个标记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个节点组成，每个节点配备320个GPU。attention部分采用TP4与SP结合，同时使用DP80，而MoE部分使用EP320。对于MoE部分，每个GPU仅托管一个专家，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直接点对点传输实现，以达到低延迟。此外，我们利用IBGDA (NVIDIA, 2022)技术进一步减少延迟并提高通信效率。

类似于预填充，我们定期根据在线服务中的统计专家负载在一定间隔内确定冗余专家的集合。然而，我们不需要重新安排专家，因为每个GPU仅托管一个专家。我们还在探索解码阶段的动态冗余策略。然而，这需要更仔细地优化计算全局最优路由方案的算法，并与dispatch内核融合以减少开销。

此外，为了提高吞吐量并隐藏全对全通信的开销，我们还在探索在解码阶段同时处理两个计算工作量相似的微批次。与预填充不同，attention在解码阶段占用更多时间。因此，我们将一个微批次的attention与另一个微批次的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个标记以内），瓶颈是内存访问而非计算。由于MoE部分仅需加载一个专家的参数，内存访问开销极小，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，我们可以仅分配一小部分SM给dispatch+MoE+combine。

3.5. Suggestions on Hardware Design

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

3.5.1. *Communication Hardware*

在 DeepSeek-V3 中，我们实现了计算和通信的重叠，以在计算过程中隐藏通信延迟。这显著减少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，我们在 H800 GPU 可用的 132 个 SM 中分配了 20 个用于此目的），这将限制计算吞吐量。此外，使用 SM 进行通信会导致显著的效率低下，因为张量核心完全未被利用。

目前，SM 主要执行以下任务以实现全对全通信：

- 在 IB (InfiniBand) 和 NVLink 域之间转发数据，同时从单个 GPU 聚合 destined for 多个 GPU 的 IB 流量，这些 GPU 位于同一节点内。
- 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 用于 `all-to-all combine`。
- 管理细粒度内存布局 在通过 IB 和 NVLink 域向多个专家传输分块数据时。

我们希望看到未来的供应商开发出能够将这些通信任务从宝贵的计算单元SM中卸载出来的硬件，作为GPU协处理器或类似于NVIDIA SHARP Graham et al. (2016)的网络协处理器。此

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 WGMMAs, 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.

外，为了减少应用程序编程的复杂性，我们希望这种硬件能够从计算单元的角度统一IB（扩展）和NVLink（扩展）网络。通过这种统一的接口，计算单元可以通过提交基于简单原语的通信请求，轻松地在整个IB-NVLink统一域中完成诸如`read`、`write`、`multicast`和`reduce`等操作。

3.5.2. Compute Hardware

在 Tensor Core 中提高 FP8 GEMM 积累精度。 在当前 NVIDIA Hopper 架构的 Tensor Core 实现中，FP8 GEMM（通用矩阵乘法）采用定点积累，通过根据最大指数右移来对齐尾数乘积。我们的实验表明，它仅使用每个尾数乘积经过符号填充右移后的最高 14 位，并截断超出此范围的位。然而，例如，要从 32 个 FP8×FP8 乘法的积累中获得精确的 FP32 结果，至少需要 34 位精度。因此，我们建议未来的芯片设计增加 Tensor Core 中的积累精度，以支持全精度积累，或根据训练和推理算法的精度要求选择适当的积累位宽。这种方法确保误差保持在可接受的范围内，同时保持计算效率。

支持分块和分片量化。 当前的 GPU 仅支持张量级量化，缺乏对我们的分块和分片量化等细粒度量化的原生支持。在当前实现中，当达到 N_C 间隔时，部分结果将从 Tensor Core 复制到 CUDA 核心，乘以缩放因子，并加到 CUDA 核心上的 FP32 寄存器中。尽管结合我们的精确 FP32 积累策略显著减轻了去量化的开销，但 Tensor Core 和 CUDA 核心之间的频繁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启用 Tensor Core 接收缩放因子并实现组缩放的 MMA 来支持细粒度量化。这样，整个部分和积累和去量化可以直接在 Tensor Core 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。 尽管我们的研究表明在线量化非常有效，但当前的实现难以有效支持在线量化。在现有过程中，我们需要从 HBM（高带宽内存）读取 128 个 BF16 激活值（前一次计算的输出）进行量化，然后将量化的 FP8 值写回 HBM，仅为了再次读取进行 MMA。为了解决这种低效问题，我们建议未来的芯片将 FP8 转换和 TMA（张量内存加速器）访问整合为单一融合操作，以便在将激活从全局内存传输到共享内存时完成量化，避免频繁的内存读写。我们还建议支持用于加速的线程级转换指令，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 HBM 附近。在这种情况下，BF16 元素可以直接在从 HBM 读取到 GPU 时转换为 FP8，减少大约 50% 的片外内存访问。

支持转置 GEMM 操作。 当前架构使得将矩阵转置与 GEMM 操作融合变得复杂。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，需要读取矩阵，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 操作之前直接从共享内存中读取矩阵的转置，对于训练和推理所需的精度。结合 FP8 格式转换和 TMA 访问的融合，这一增强将显著简化量化工作流程。

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 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 `1x128` activation tile or `128x128` 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 `1x128` quantization tile to an `128x1` 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

4. Pre-Training

4.1. Data Construction

与 DeepSeek-V2 相比，我们通过增加数学和编程样本的比例来优化预训练语料库，同时扩展了多语言覆盖范围，不仅限于英语和中文。此外，我们的数据处理管道经过优化，以最大限度地减少冗余，同时保持语料库的多样性。受 Ding et al. (2024) 的启发，我们实施了文档打包方法以确保数据完整性，但在训练过程中没有引入跨样本注意力掩码。最后，DeepSeek-V3 的训练语料库由 14.8T 高质量和多样化的标记符组成。

在 DeepSeekCoder-V2 (DeepSeek-AI, 2024a) 的训练过程中，我们观察到 Fill-in-Middle (FIM) 策略不会削弱下一个标记预测能力，同时使模型能够根据上下文线索准确预测中间文本。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，我们使用 Prefix-Suffix-Middle (PSM) 框架来结构化数据，如下所示：

$$\texttt{<|fim\_begin|>}f_{\text{pre}}\texttt{<|fim\_hole|>}f_{\text{suf}}\texttt{<|fim\_end|>}f_{\text{middle}}\texttt{<|eos\_token|>}.$$

这种结构在预打包过程中应用于文档级别。 FIM 策略以 0.1 的速率应用，与 PSM 框架保持一致。

DeepSeek-V3 的分词器采用字节级 BPE (Shibata et al., 1999)，词汇量扩展至 128K 个标记。我们的分词器的预分词器和训练数据已修改，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符号和换行的标记。然而，当模型处理没有终止换行的多行提示时，尤其是对于少量样本评估提示，这种技巧可能会引入标记边界偏差 (Lundberg, 2023)。为了解决这个问题，我们在训练过程中随机分割了一定比例的此类组合标记，使模型接触到更广泛的特殊情况，从而减轻这种偏差。

4.2. Hyper-Parameters

模型超参数. 我们将Transformer层的数量设置为61，隐藏维度设置为7168。所有可学习参数均以0.006的标准差随机初始化。在MLA中，我们将注意力头的数量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。对于解耦的查询和键，我们将每个头的维度d^R_h设置为64。我们用MoE层替换了除前三个层之外的所有FFN层。每个MoE层由1个共享专家和256个路由专家组成，每个专家的中间隐藏维度为2048。在路由专家中，每个标记将激活8个专家，并确保每个标记最多被发送到4个节点。多标记预测深度D设置为1，即除了下一个确切的标记外，每个标记还将预测一个额外的标记。如同DeepSeek-V2一样，DeepSeek-V3也在压缩的潜在向量之后使用额外的RMSNorm层，并在宽度瓶颈处乘以额外的缩放因子。在这种配置下，DeepSeek-V3包含671B总参数，其中37B参数在每个标记上被激活。

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.

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.

训练超参数。 我们使用AdamW优化器 (Loshchilov and Hutter, 2017)，其超参数设置为$\beta_1 = 0.9$，$\beta_2 = 0.95$，weight_decay $= 0.1$。我们在预训练期间将最大序列长度设置为4K，并在14.8T标记上预训练DeepSeek-V3。关于学习率调度，我们首先在前2K步中将学习率线性增加到2.2×10^{-4}。然后，我们将学习率保持在2.2×10^{-4}，直到模型消耗10T训练标记。随后，我们逐渐在4.3T标记中将学习率衰减至2.2×10^{-5}，遵循余弦衰减曲线。在训练最后500B标记期间，我们在前333B标记中保持学习率为2.2×10^{-5}，在剩余167B标记中切换到另一个恒定学习率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，在训练前469B标记期间，批量大小逐渐从3072增加到15360，然后在剩余训练中保持15360。我们利用管道并行性将模型的不同层部署在不同的GPU上，对于每一层，路由专家将均匀部署在属于8个节点的64个GPU上。对于节点限制路由，每个标记最多被发送到4个节点（即，$M = 4$）。对于无辅助损失的负载平衡，我们为前14.3T标记设置偏置更新速度γ为0.001，为剩余500B标记设置为0.0。对于平衡损失，我们设置α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在前10T标记中设置为0.3，在剩余4.8T标记中设置为0.1。

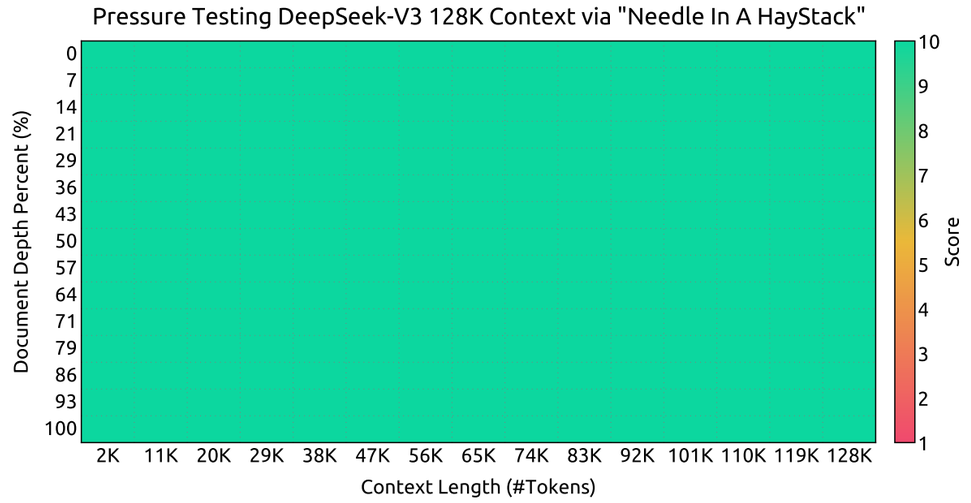


Figure 8 | 在“大海捞针”（NIAH）测试中的评估结果。 DeepSeek-V3 在所有上下文窗口长度（最高达128K）上表现良好。

4.3. Long Context Extension

我们采用与 DeepSeek-V2 (DeepSeek-AI, 2024c) 类似的方法，以在 DeepSeek-V3 中实现长上下文能力。在预训练阶段之后，我们应用 YaRN (Peng et al., 2023a) 进行上下文扩展，并进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，然后再扩展到 128K。 YaRN 的配置与 DeepSeek-V2 中使用的配置一致，仅应用于解耦的共享键 $\mathbf{k}_t^R$。两个阶段的超参数保持一致，比例尺 $s = 40$，$\alpha = 1$，$\beta = 32$，缩放因子 $\sqrt{t} = 0.1 \ln s + 1$。在第一阶段，序列长度设置为 32K，批量大小为 1920。在第二阶段，序列长度增加到 128K，批量大小减少到

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.

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.

480。两个阶段的学习率均设置为 7.3×10^{-6}，与预训练阶段的最终学习率相匹配。

通过这两个阶段的扩展训练，DeepSeek-V3 能够处理长达 128K 的输入，同时保持强大的性能。图 8 显示，经过监督微调后，DeepSeek-V3 在 "针尖上的 haystack" (NIAH) 测试中表现出显著的性能，证明了在上下文窗口长度高达 128K 时的一致稳健性。

4.4. Evaluations

4.4.1. Evaluation Benchmarks

DeepSeek-V3 的基础模型是在一个包含英语和中文为主的多语言语料库上预训练的，因此我们主要在一系列英语和中文基准测试以及一个多语言基准测试上评估其性能。我们的评估基于我们HAI-LLM框架中集成的内部评估框架。考虑的基准测试按类别列出如下，其中 下划线 标记的基准测试是中文的，双下划线 标记的基准测试是多语言的：

多学科多项选择 数据集包括 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) 和 CMMLU (Li et al., 2023)。

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

闭卷问答 数据集包括 TriviaQA (Joshi et al., 2017) 和 NaturalQuestions (Kwiatkowski et al., 2019)。

阅读理解 数据集包括 RACE Lai et al. (2017)，DROP (Dua et al., 2019)，C3 (Sun et al., 2019a) 和 CMRC (Cui et al., 2019)。

指代消解 数据集包括 CLUEWSC (Xu et al., 2020) 和 WinoGrande Sakaguchi et al. (2019)。

语言建模 数据集包括 Pile (Gao et al., 2020)。

中文理解和文化 数据集包括 CCPM (Li et al., 2021)。

数学 数据集包括 GSM8K (Cobbe et al., 2021)，MATH (Hendrycks et al., 2021)，MGSM (Shi et al., 2023) 和 CMath (Wei et al., 2023)。

代码 数据集包括 HumanEval (Chen et al., 2021)，LiveCodeBench-Base (0801-1101) (Jain et al., 2024)，MBPP (Austin et al., 2021) 和 CRUXEval (Gu et al., 2024)。

标准化考试 包括 AGIEval (Zhong et al., 2023)。请注意，AGIEval 包括英语和中文子集。

遵循我们之前的工作 (DeepSeek-AI, 2024b,c)，我们对包括 HellaSwag，PIQA，WinoGrande，RACE-Middle，RACE-High，MMLU，MMLU-Redux，MMLU-Pro，MMMLU，ARC-Easy，ARC-Challenge，C-Eval，CMMLU，C3 和 CCPM 的数据集采用基于困惑度的评估，对 TriviaQA，NaturalQuestions，DROP，MATH，GSM8K，MGSM，HumanEval，MBPP，LiveCodeBench-

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 -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 (General Matrix Multiply) employs fixed-point accumulation, aligning the mantissa products by right-shifting based on the maximum exponent before addition. Our experiments reveal that it only uses the highest 14 bits of each mantissa product after sign-fill right shifting, and truncates bits exceeding this range. However, for example, to achieve precise FP32 results from the accumulation of 32 FP8×FP8 multiplications, at least 34-bit precision is required. Thus, we recommend that future chip designs increase accumulation precision in Tensor Cores to support full-precision accumulation, or select an appropriate accumulation bit-width according to the accuracy requirements of training and inference algorithms. This approach ensures that errors remain within acceptable

Base，CRUXEval，BBH，AGIEval，CLUEWSC，CMRC 和 CMath 的数据集采用基于生成的评估。此外，我们对 Pile-test 进行基于语言建模的评估，并使用每字节比特数 (BPB) 作为指标，以确保使用不同分词器的模型之间的公平比较。

	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	**65.2**
	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**
	MGSM (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 | DeepSeek-V3-Base 与其他代表性开源基础模型的比较。所有模型都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 的被认为是同一水平。 DeepSeek-V3-Base 在大多数基准测试中表现最佳，特别是在数学和代码任务上。

4.4.2. *Evaluation Results*

在表3中，我们将DeepSeek-V3的基础模型与最先进的开源基础模型进行了比较，包括DeepSeek-V2-Base (DeepSeek-AI, 2024c)（我们之前的版本），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对所有这些模型进行了评估，并确保它们具有相同的评估设置。请注意，由于我们评估框架在过去几个月的变化，DeepSeek-V2-

bounds while maintaining computational efficiency.

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.

Base的性能与我们之前报告的结果存在轻微差异。总体而言，DeepSeek-V3-Base全面超越了DeepSeek-V2-Base和Qwen2.5 72B Base，并在大多数基准测试中超过了LLaMA-3.1 405B Base，基本上成为最强的开源模型。

从更详细的视角来看，我们将DeepSeek-V3-Base与其它开源基础模型分别进行了比较。 (1) 与DeepSeek-V2-Base相比，由于我们在模型架构上的改进、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（最先进的中文开源模型）相比，尽管激活参数只有其一半，DeepSeek-V3-Base仍展现出显著的优势，特别是在英语、多语言、代码和数学基准测试中。对于中文基准测试，除了CMMLU（中文多学科多项选择任务）外，DeepSeek-V3-Base也表现出比Qwen2.5 72B更好的性能。 (3) 与LLaMA-3.1 405B Base（拥有11倍激活参数的最大的开源模型）相比，DeepSeek-V3-Base在多语言、代码和数学基准测试中也表现出更好的性能。对于英语和中文语言基准测试，DeepSeek-V3-Base表现出竞争性或更好的性能，尤其在BBH、MMLU系列、DROP、C-Eval、CMMLU和CCPM上表现优异。

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，训练DeepSeek-V3每万亿令牌仅需180K H800 GPU小时，这比训练72B或405B密集模型便宜得多。

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 (BPB)	-	**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 | MTP策略的消融结果。 MTP策略在大多数评估基准上持续提升模型性能。

4.5. Discussion

4.5.1. Ablation Studies for Multi-Token Prediction

在表 4中，我们展示了MTP策略的消融结果。具体来说，我们在两个基线模型的不同规模上验证了MTP策略。在小规模上，我们在1.33万亿个标记上训练了一个包含157亿个总参数的基线MoE模型。在大规模上，我们在5400亿个标记上训练了一个包含2287亿个总参数的基线MoE模型。在此基础上，保持训练数据和其他架构不变，我们在其上附加了一个1层的MTP模块，并使用MTP策略训练了两个模型以进行比较。请注意，在推理过程中，我们直接丢弃了MTP模块，

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 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:

$$\texttt{<|fim\_begin|>}f_{\text{pre}}\texttt{<|fim\_hole|>}f_{\text{suf}}\texttt{<|fim\_end|>}f_{\text{middle}}\texttt{<|eos\_token|>}.$$

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^R_h to 64. We substitute all FFNs except for the first three layers with MoE layers. Each MoE layer consists of 1

Benchmark (Metric)	# Shots	Small MoE Aux-Loss-Based	Small MoE Aux-Loss-Free	Large MoE Aux-Loss-Based	Large MoE 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 | 辅助损失自由平衡策略的消融结果。与纯粹基于辅助损失的方法相比，辅助损失自由策略在大多数评估基准上始终实现更好的模型性能。

因此所比较模型的推理成本完全相同。从表中可以看出，MTP策略在大多数评估基准上一致地提升了模型性能。

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

在表 5中，我们展示了无辅助损失平衡策略的消融结果。我们在两个不同规模的基线模型上验证了这一策略。在小规模上，我们在1.33万亿个标记上训练了一个包含157亿个参数的基线MoE模型。在大规模上，我们在5780亿个标记上训练了一个包含2287亿个参数的基线MoE模型。这两个基线模型纯粹使用辅助损失来促进负载平衡，并使用带有top-K亲和力归一化的sigmoid门函数。它们控制辅助损失强度的超参数分别与DeepSeek-V2-Lite和DeepSeek-V2相同。在这些基线模型的基础上，保持训练数据和其他架构不变，我们移除了所有辅助损失并引入了无辅助损失的平衡策略进行对比。从表中可以看出，无辅助损失的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. *Batch-Wise Load Balance VS. Sequence-Wise Load Balance*

辅助损失自由平衡与序列级辅助损失之间的关键区别在于它们的平衡范围：批量级与序列级。与序列级辅助损失相比，批量级平衡施加了更灵活的约束，因为它不要求每个序列在域内平衡。这种灵活性使专家能够更好地专注于不同的领域。为了验证这一点，我们在Pile测试集的不同领域中记录并分析了一个基于16B辅助损失的基线模型和一个16B辅助损失自由模型的专家负载。如图 9所示，我们观察到辅助损失自由模型确实表现出更高的专家专业化模式。

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，我们还设计并验证了一种批量级辅助损失，该损失鼓励在每个训练批次上而不是每个序列上实现负载平衡。实验结果表明，在实现相似的批量级负载平衡水平时，批量级辅助损失也可以实现与辅助损失自由方法相似的模型性能。具体来说，在我们使用1B MoE模型的实验中，验证损失分别为：使用序列级辅助损

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 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.

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

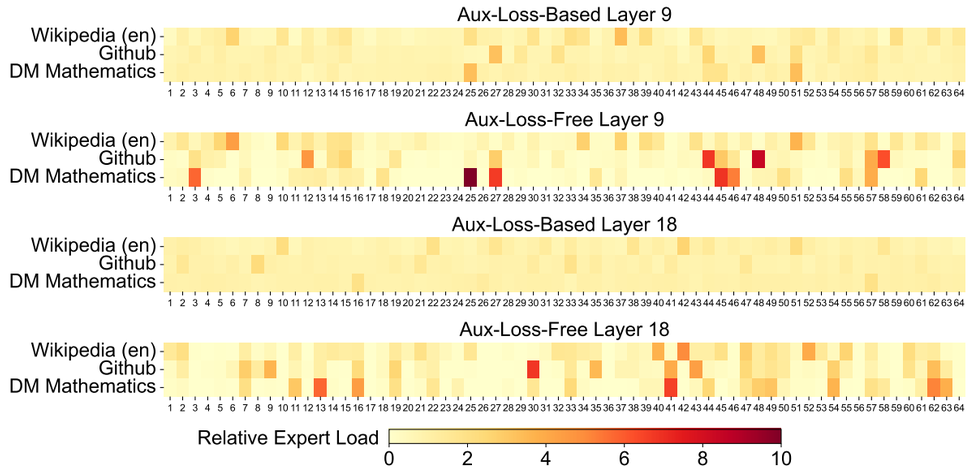


Figure 9 | 在Pile测试集的三个领域中，无辅助损失和基于辅助损失模型的专家负载。无辅助损失模型显示出比基于辅助损失模型更强的专家专业化模式。相对专家负载表示实际专家负载与理论平衡专家负载之间的比率。由于篇幅限制，我们仅以两层的结果为例，所有层的结果见附录 C。

失为2.258，使用辅助损失自由方法为2.253，使用批量级辅助损失为2.253。我们还在3B MoE模型上观察到类似的结果：使用序列级辅助损失的模型验证损失为2.085，而使用辅助损失自由方法或批量级辅助损失的模型验证损失均为2.080。

此外，尽管批量级负载平衡方法表现出一致的性能优势，它们也面临两个潜在的效率挑战：(1) 某些序列或小批次内的负载不平衡，以及 (2) 推理过程中由于领域转移引起的负载不平衡。第一个挑战通过我们使用大规模专家并行和数据并行的训练框架自然解决，该框架保证了每个微批次的较大规模。对于第二个挑战，我们还设计并实现了一个高效的推理框架，采用冗余专家部署，如第3.4节所述，以克服这一问题。

5. Post-Training

5.1. Supervised Fine-Tuning

我们整理了我们的指令调优数据集，包括1.5M个实例，涵盖多个领域，每个领域采用特定的数据创建方法以满足其特定需求。

推理数据。 对于涉及推理的数据集，包括数学、编程竞赛问题和逻辑谜题，我们利用内部的DeepSeek-R1模型生成数据。具体来说，虽然R1生成的数据表现出强大的准确性，但它存在过度思考、格式不佳和过长等问题。我们的目标是平衡R1生成的推理数据的高准确性和常规格式化推理数据的清晰性和简洁性。

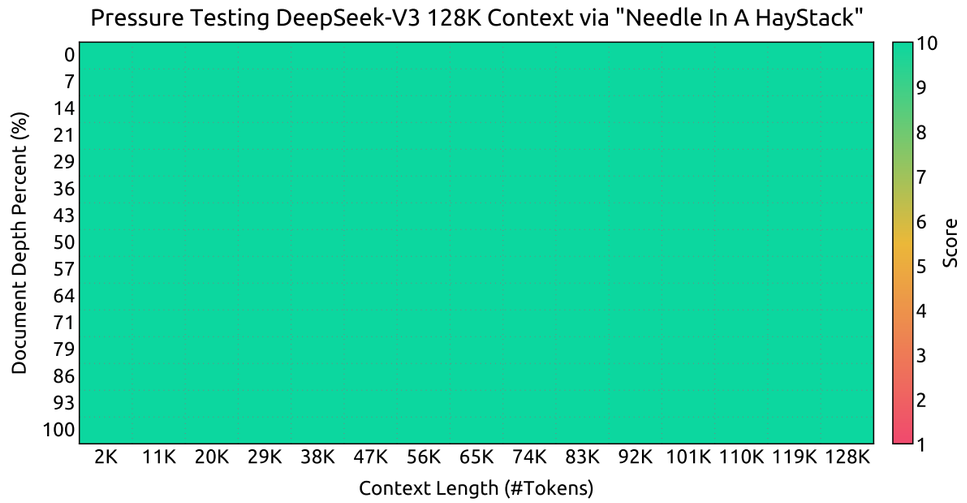


Figure 8 | Evaluation results on the "Needle In A Haystack" (NIAH) tests. DeepSeek-V3 performs well across all context window lengths up to 128K.

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.

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).

为了建立我们的方法，我们首先开发一个针对特定领域的专家模型，如代码、数学或一般推理，使用结合监督微调（SFT）和强化学习（RL）的训练管道。这个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>的格式结合，第二种则在问题和R1响应中加入系统提示，格式为<系统提示, 问题, R1响应>。

系统提示精心设计，包括指导模型生成包含反思和验证机制的响应的指令。在RL阶段，模型利用高温采样生成响应，即使在没有明确的系统提示的情况下，也能整合R1生成数据和原始数据的模式。经过数百次RL步骤后，中间的RL模型学会了整合R1模式，从而战略性地提高整体性能。

完成RL训练阶段后，我们实施拒绝采样以整理最终模型的高质量SFT数据，其中专家模型作为数据生成源。这种方法确保最终训练数据保留DeepSeek-R1的优势，同时生成简洁有效的响应。

非推理数据。 对于非推理数据，如创意写作、角色扮演和简单问答，我们使用DeepSeek-V2.5生成响应，并聘请人工标注者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进行两个周期的微调，采用从5×10^{-6}逐渐降低到1×10^{-6}的余弦衰减学习率调度。在训练过程中，每个单序列由多个样本组成。然而，我们采用样本掩码策略，确保这些示例保持隔离且互不可见。

5.2. Reinforcement Learning

5.2.1. Reward Model

我们在RL过程中采用了基于规则的奖励模型（RM）和基于模型的RM。

基于规则的RM。 对于可以使用特定规则验证的问题，我们采用基于规则的奖励系统来确定反馈。例如，某些数学问题有确定的结果，我们要求模型在指定的格式（例如，在框内）提供最终答案，使我们能够应用规则来验证其正确性。同样，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，因为这种方法不易受到操纵或利用。

基于模型的RM。 对于具有自由形式真实答案的问题，我们依赖奖励模型来确定响应是否与预期的真实答案匹配。相反，对于没有确定真实答案的问题，例如涉及创意写作的问题，奖励模型的任务是基于问题和相应的答案作为输入提供反馈。奖励模型是从DeepSeek-V3 SFT检查点训练的。为了增强其可靠性，我们构建了偏好数据，不仅提供最终的奖励，还包括导致奖励的思考链。这种方法有助于减轻特定任务中的奖励欺骗风险。

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 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-

5.2.2. Group Relative Policy Optimization

类似于 DeepSeek-V2 (DeepSeek-AI, 2024c)，我们采用了组相对策略优化（Group Relative Policy Optimization, GRPO） (Shao et al., 2024)，该方法放弃了通常与策略模型大小相同的批评模型，并从组得分中估计基线。具体来说，对于每个问题 q，GRPO 从旧的策略模型 $\pi_{\theta_{old}}$ 中采样一组输出 $\{o_1, o_2, \cdots, o_G\}$，然后通过最大化以下目标来优化策略模型 π_θ：

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

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

其中 ε 和 β 是超参数；π_{ref} 是参考模型；A_i 是优势值，从每组输出对应的一系列奖励 $\{r_1, r_2, \ldots, r_G\}$ 中得出：

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

我们在强化学习（RL）过程中融入了来自不同领域的提示，如编程、数学、写作、角色扮演和问答。这种方法不仅使模型更贴近人类偏好，还提高了在基准测试中的表现，特别是在可用的SFT数据有限的情况下。

5.3. Evaluations

5.3.1. Evaluation Settings

评估基准。 除了用于基础模型测试的基准外，我们还评估了指令模型在 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)、Aider [1]、LiveCodeBench (Jain et al., 2024)（2024年8月至11月的问题）、Codeforces [2]、中国全国高中数学奥林匹克竞赛（CNMO 2024）[3] 和美国数学邀请赛 2024（AIME 2024）(MAA, 2024) 上的表现。

对比基线。 我们对我们的聊天模型与多个强大的基线模型进行了全面评估，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，评估是通过它们各自的 API 进行的。

[1] https://aider.chat
[2] https://codeforces.com
[3] https://www.cms.org.cn/Home/comp/comp/cid/12.html

	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	**65.2**
	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**
	MGSM (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.

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, 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

详细的评估配置。 对于包括 MMLU、DROP、GPQA 和 SimpleQA 在内的标准基准，我们采用了 simple-evals 框架[4] 的评估提示。我们在零样本设置中使用 Zero-Eval 提示格式 (Lin, 2024) 评估 MMLU-Redux。对于其他数据集，我们遵循数据集创建者提供的原始评估协议和默认提示。对于代码和数学基准，HumanEval-Mul 数据集包括 8 种主流编程语言（Python、Java、Cpp、C#、JavaScript、TypeScript、PHP 和 Bash）。我们在 LiveCodeBench 上使用 CoT 和非 CoT 方法评估模型性能，数据收集时间为 2024 年 8 月至 11 月。 Codeforces 数据集使用竞争对手的百分比进行评估。 SWE-Bench verified 使用无代理框架 (Xia et al., 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 以 0.7 的温度进行评估，结果取 16 次运行的平均值，而 MATH-500 采用贪婪解码。我们允许所有模型在每个基准上输出最多 8192 个标记。

	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.**
	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	**82.6**
	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	**39.2**
	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 | DeepSeek-V3 与其他代表性聊天模型的比较。所有模型都在限制输出长度为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多次测试，以得出稳健的最终结果。 DeepSeek-V3 是表现最好的开源模型，同时也表现出与前沿闭源模型竞争的性能。

5.3.2. Standard Evaluation

表 6 展示了评估结果，表明 DeepSeek-V3 是表现最佳的开源模型。此外，它在与前沿的闭源模型如 GPT-4o 和 Claude-3.5-Sonnet 的竞争中也表现出色。

[4] https://github.com/openai/simple-evals

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 (BPB)	-	**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.

英文基准测试。 MMLU 是一个广泛认可的基准测试，旨在评估大型语言模型在不同知识领域和任务中的表现。 DeepSeek-V3 展现了竞争力，与顶级模型如 LLaMA-3.1-405B、GPT-4o 和 Claude-Sonnet 3.5 持平，同时显著超越 Qwen2.5 72B。此外，DeepSeek-V3 在 MMLU-Pro 中表现出色，这是一个更具挑战性的教育知识基准测试，其表现紧随 Claude-Sonnet 3.5 之后。在 MMLU-Redux 中，这是一个经过修正标签的 MMLU 的改进版本，DeepSeek-V3 超越了其竞争对手。此外，在 GPQA-Diamond 中，这是一个博士水平的评估平台，DeepSeek-V3 取得了显著的成绩，排名仅次于 Claude 3.5 Sonnet，且大幅超越所有其他竞争对手。

在长上下文理解基准测试如 DROP、LongBench v2 和 FRAMES 中，DeepSeek-V3 继续展示其顶级模型的地位。在 DROP 的 3-shot 设置中，DeepSeek-V3 达到了令人印象深刻的 91.6 F1 分，超越了该类别中的所有其他模型。在 FRAMES 中，这是一个需要处理 100k 令牌上下文的问答基准测试，DeepSeek-V3 紧随 GPT-4o 之后，但大幅超越所有其他模型。这表明 DeepSeek-V3 在处理极长上下文任务方面具有强大的能力。 DeepSeek-V3 的长上下文能力进一步通过其在 LongBench v2 中的最佳表现得到验证，该数据集是在 DeepSeek V3 发布前几周发布的。在事实知识基准测试 SimpleQA 中，DeepSeek-V3 落后于 GPT-4o 和 Claude-Sonnet，这主要是由于其设计重点和资源分配。 DeepSeek-V3 分配了更多的训练令牌来学习中文知识，从而在 C-SimpleQA 中表现出色。在指令遵循基准测试中，DeepSeek-V3 显著超越了其前身 DeepSeek-V2-系列，突显了其在理解和遵守用户定义的格式约束方面的能力提升。

代码和数学基准测试。 编码是 LLMs 面临的一项具有挑战性和实用性的任务，包括以工程为重点的任务如 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，但显著超越了开源模型。开源的 DeepSeek-V3 预计将促进编码相关工程任务的进展。通过提供其强大功能的访问，DeepSeek-V3 可以推动软件工程和算法开发等领域的创新和改进，使开发人员和研究人员能够突破开源模型在编码任务中所能实现的界限。在算法任务中，DeepSeek-V3 展现了卓越的性能，在 HumanEval-Mul 和 LiveCodeBench 等基准测试中超越了所有基线模型。这一成功可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 展现了卓越的性能，显著超越了基线模型，并为非 o1 类模型设定了新的最先进水平。具体而言，在 AIME、MATH-500 和 CNMO 2024 中，DeepSeek-V3 超越了第二好的模型 Qwen2.5 72B，绝对分数高出约 10%，这在如此具有挑战性的基准测试中是一个显著的差距。这一显著的能力突显了来自 DeepSeek-R1 的蒸馏技术的有效性，该技术已被证明对非 o1 类模型非常有益。

中文基准测试。 Qwen 和 DeepSeek 是两个具有强大中英文支持的代表性模型系列。在事实基准测试 Chinese SimpleQA 中，DeepSeek-V3 超越了 Qwen2.5-72B 16.4 分，尽管 Qwen2.5 是在更大的语料库上训练的，该语料库包含 18T 个令牌，比 DeepSeek-V3 预训练的 14.8T 个令牌多 20%。在C-Eval（一个代表性的中文教育知识评估基准）和CLUEWSC（中文Winograd Schema Challenge）上，DeepSeek-V3 和 Qwen2.5-72B 展现了相似的性能水平，表明这两个模型都已

Benchmark (Metric)	# Shots	Small MoE Aux-Loss-Based	Small MoE Aux-Loss-Free	Large MoE Aux-Loss-Based	Large MoE 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.

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. 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.

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 | 英文开放对话评估。对于AlpacaEval 2.0，我们使用长度控制胜率作为评估指标。

针对具有挑战性的中文推理和教育任务进行了良好的优化。

5.3.3. Open-Ended Evaluation

除了标准基准测试外，我们还使用大型语言模型（LLMs）作为评委，对我们的模型在开放生成任务上的表现进行了评估，结果如表 7所示。具体而言，我们遵循AlpacaEval 2.0 (Dubois et al., 2024) 和 Arena-Hard (Li et al., 2024a) 的原始配置，这些配置利用GPT-4-Turbo-1106作为评委进行成对比较。在Arena-Hard上，DeepSeek-V3 对基线模型GPT-4-0314的胜率超过86%，表现与顶级模型如Claude-Sonnet-3.5-1022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 达到了一个开创性的里程碑，成为首个在Arena-Hard基准测试中超过85%的开源模型。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中所能实现的目标树立了新的标准。

同样，DeepSeek-V3 在AlpacaEval 2.0上的表现也非常出色，超过了闭源和开源模型。这表明它在写作任务和处理简单问答场景方面表现出色。值得注意的是，它以20%的显著优势超过了DeepSeek-V2.5-0905，突显了其在处理简单任务方面的显著改进，并展示了其进步的有效性。

5.3.4. DeepSeek-V3 as a Generative Reward Model

我们比较了DeepSeek-V3与最先进模型GPT-4o和Claude-3.5的判断能力。表 8展示了这些模型在RewardBench (Lambert et al., 2024)中的性能。 DeepSeek-V3的性能与GPT-4o-0806和Claude-3.5-Sonnet-1022的最佳版本相当，同时超过了其他版本。此外，通过投票技术也可以增强DeepSeek-V3的判断能力。因此，我们采用DeepSeek-V3和投票技术来对开放性问题提供自我反馈，从而提高对齐过程的有效性和鲁棒性。

5.4. Discussion

5.4.1. Distillation from DeepSeek-R1

我们基于DeepSeek-V2.5 从 DeepSeek-R1 中消融了蒸馏的贡献。基线模型是在短 CoT 数据上训练的，而其竞争对手则使用上述专家检查点生成的数据。

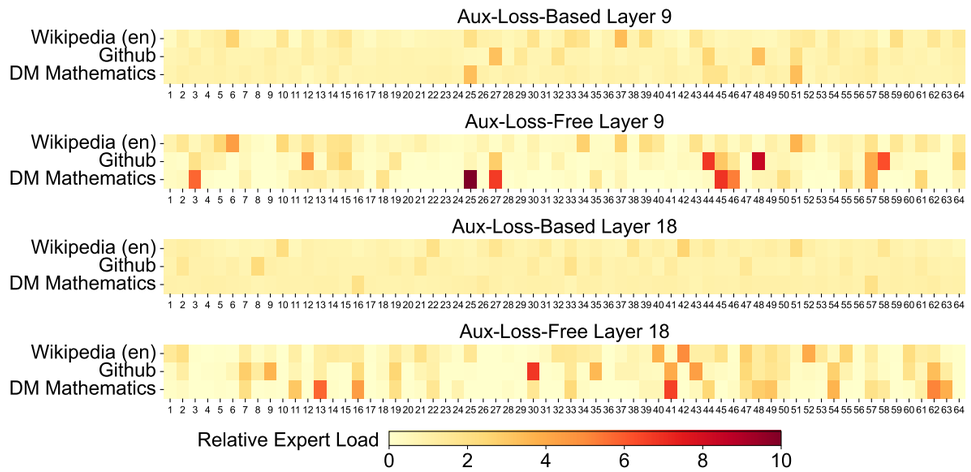


Figure 9 | Expert load of auxiliary-loss-free and auxiliary-loss-based models on three domains in the Pile test set. The auxiliary-loss-free model shows greater expert specialization patterns than the auxiliary-loss-based one. The relative expert load denotes the ratio between the actual expert load 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.

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 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.

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 | GPT-4o、Claude-3.5-sonnet 和 DeepSeek-V3 在 RewardBench 上的表现。

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 | DeepSeek-R1 的蒸馏贡献。 LiveCodeBench 和 MATH-500 的评估设置与表 6 中相同。

表 9 展示了蒸馏数据的有效性，显示在 LiveCodeBench 和 MATH-500 基准测试中都有显著的改进。我们的实验揭示了一个有趣的权衡：蒸馏虽然提高了性能，但也显著增加了平均响应长度。为了在模型准确性和计算效率之间保持平衡，我们为 DeepSeek-V3 在蒸馏过程中仔细选择了最优设置。

我们的研究表明，从推理模型中进行知识蒸馏为训练后优化提供了一个有前景的方向。虽然我们目前的工作集中在从数学和编码领域蒸馏数据，但这种方法在各种任务领域中具有广泛的应用潜力。在这些特定领域的有效性表明，长 CoT 蒸馏可能对提高其他需要复杂推理的认知任务的模型性能有价值。在不同领域进一步探索这种方法仍然是未来研究的一个重要方向。

5.4.2. Self-Rewarding

奖励在强化学习（RL）中起着关键作用，引导优化过程。在可以通过外部工具轻松验证的领域，如某些编程或数学场景，RL表现出卓越的效率。然而，在更普遍的情况下，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，为了应对这些更广泛的情境，我们采用了宪法AI方法 (Bai et al., 2022)，利用 DeepSeek-V3 本身的投票评估结果作为反馈来源。这种方法产生了显著的对齐效果，显著提高了 DeepSeek-V3 在主观评估中的表现。通过整合额外的宪法输入，DeepSeek-V3 可以朝着宪法方向优化。我们认为，这种结合补充信息与大语言模型（LLM）作为反馈来源的范式至关重要。 LLM 作为一个多功能处理器，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 LLM 的自我改进。除了自我奖励外，我们还致力于发现其他通用且可扩展的奖励方法，以持续提升模型在一般场景中的能力。

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 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.

5.4.3. Multi-Token Prediction Evaluation

DeepSeek-V3 不仅仅预测下一个单一的标记，而是通过 MTP 技术预测接下来的 2 个标记。结合投机解码框架 (Leviathan et al., 2023; Xia et al., 2023)，它可以显著加速模型的解码速度。一个自然的问题是关于额外预测的标记的接受率。根据我们的评估，第二个标记预测的接受率在各种生成主题中保持在 85% 到 90% 之间，表现出一致的可靠性。这一高接受率使 DeepSeek-V3 能够显著提高解码速度，达到 1.8 倍的 TPS（每秒标记数）。

6. Conclusion, Limitations, and Future Directions

在本文中，我们介绍了 DeepSeek-V3，这是一个具有 6710 亿总参数和 370 亿激活参数的大规模 MoE 语言模型，训练使用了 14.8 万亿个 token。除了 MLA 和 DeepSeekMoE 架构外，它还开创了一种无辅助损失的负载平衡策略，并设定了多 token 预测训练目标以实现更强的性能。由于支持 FP8 训练和精心的工程优化，DeepSeek-V3 的训练成本效益高。后训练也在从 DeepSeek-R1 系列模型中提取推理能力方面取得了成功。全面评估表明，DeepSeek-V3 已成为目前最强的开源模型，并且其性能可与 GPT-4o 和 Claude-3.5-Sonnet 等领先的闭源模型相媲美。尽管性能强大，它还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。

虽然承认其强大的性能和成本效益，我们也认识到 DeepSeek-V3 存在一些部署上的局限性。首先，为了确保高效的推理，DeepSeek-V3 的推荐部署单元相对较大，这可能对小型团队构成负担。其次，尽管我们的 DeepSeek-V3 部署策略已实现比 DeepSeek-V2 高出两倍以上的端到端生成速度，但仍存在进一步提升的潜力。幸运的是，随着更先进硬件的发展，这些局限性有望得到自然解决。

DeepSeek 一贯坚持长期主义的开源模型路线，旨在稳步接近 AGI（人工智能通用智能）的最终目标。未来，我们计划在以下方向上战略性地投入研究。

- 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的效率，努力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。
- 我们将不断迭代训练数据的数量和质量，并探索引入额外的训练信号源，旨在推动数据在更广泛的维度上进行扩展。
- 我们将持续探索和迭代我们模型的深度思考能力，旨在通过扩展其推理的长度和深度来提高它们的智能和解决问题的能力。
- 我们将探索更全面和多维度的模型评估方法，以防止在研究过程中优化一组固定基准的倾向，这可能会对模型能力产生误导性的印象，并影响我们的基础评估。

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.

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 $\{o_1, o_2, \cdots, o_G\}$ from the old policy model $\pi_{\theta_{old}}$ and then optimizes the policy model π_θ by maximizing the following objective:

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

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

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

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

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), Aider [1], LiveCodeBench (Jain et al., 2024) (questions from August 2024 to November 2024), Codeforces [2], 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 framework[4]. 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

[1] https://aider.chat
[2] https://codeforces.com
[3] https://www.cms.org.cn/Home/comp/comp/cid/12.html
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	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.**
	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	**82.6**
	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	**39.2**
	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.

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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

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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.

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 compromising 18T tokens, which are 20% more than the 14.8T tokens that DeepSeek-V3 is 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.

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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.

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.

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 promis-

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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.

ing 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 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

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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.
- 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

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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.

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Appendix

A. Contributions and Acknowledgments

研究与工程
刘爱新
邢雪
王冰萱
吴博超
卢成达
赵成刚
邓成启
张晨宇*
阮冲
戴大脉
郭大雅
杨德建
陈德立
李尔航
林方云
戴福聪
罗福立*
郝光博
陈冠廷
李国威
张H.
包汉
徐汉伟
王浩成*
张浩伟
丁红辉
辛华建*
高华作
屈辉
郭建忠
李家石
王家伟*
陈景昌
袁景阳
邱俊杰
李俊龙
李俊翔
宋俊晓
董凯
胡凯*
高凯歌
关康
黄克欣
余快
王连
张乐聪
赵亮
王立通
张立月
张明川
张明华
唐明辉
黄盼盼
王培一
王乾成
朱启豪
陈勤宇
杜秋石
葛瑞琪
张瑞松
潘瑞泽
王润基
徐润新
张若愚
卢上浩
周上炎
陈山煌

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叶胜锋
马世荣
王世宇
余水萍
周顺风
潘姝婷
云涛
天培
王鼎曾
万家赵*
文刘
文峰梁
文军高
文琴余
文涛张
晓彪
晓东刘
晓涵王
晓康陈
晓康张
晓涛聂
新程
新刘
新谢
行超刘
行凯余
心宇杨
心远李
学成苏
徐恒林
Y.K. 李
Y.Q. 王
Y.X. 魏
杨张
燕红徐
姚李
姚赵
姚峰孙
姚辉王
一余
一超张
一帆施
一良熊
英何
一石卞
一松王
一轩谭
一阳马*
一元刘
永强郭
余武
源欧
玉端王
越巩
愈恒邹
愈嘉何
云帆熊
玉香罗
玉香尤
玉轩刘
玉阳周
Z.F. 武
Z.Z. 任
泽辉任
章力沙
择付
择安徐
钊达谢
郑岩张
郑文郝
志斌郭
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子佳朱
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子维谢
宋子阳
高子怡
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数据标注
冯蓓
李辉
蔡杰
倪佳琪
徐磊
李萌
田宁
陈荣杰
金荣亮
陈茹意
李双
周爽
孙天宇
李小庆
金翔岳
沈晓瑾
陈晓莎
孙晓雯
王晓翔
宋欣楠
周欣怡

朱燕霞
徐燕红
黄亚萍
李耀辉
郑毅
朱玉辰
马云娴
黄振
徐志鹏
张中宇

商务与合规
季东杰
梁健
陈瑾
夏磊毅
王妙君
李明明
张鹏
吴少青
叶胜锋
王涛
肖文龙
安伟
王献祖
单新霞
唐颖
查玉坤
严玉婷
张震

在每个角色中，作者按名字的首字母顺序列出。带有 * 标记的名字表示已离开我们团队的个人。

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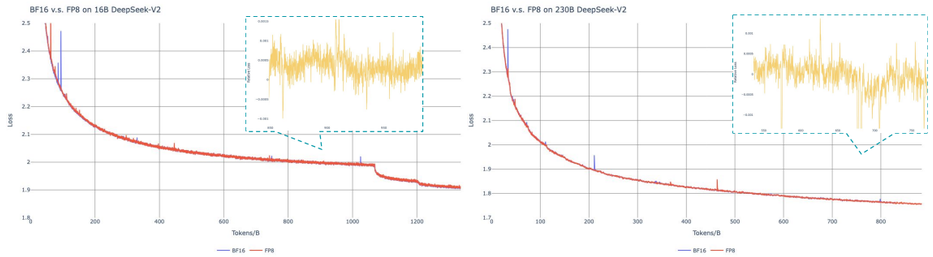

Figure 10 | BF16 和 FP8 训练的损失曲线对比。结果通过指数移动平均 (EMA) 平滑，系数为 0.9。

B. Ablation Studies for Low-Precision Training

B.1. FP8 v.s. BF16 Training

我们通过与BF16训练的比较来验证我们的FP8混合精度框架，该比较基于两个不同规模的基线模型。在小规模上，我们在1.33万亿个标记上训练了一个包含大约160亿个总参数的基线MoE模型。在大规模上，我们在大约0.9万亿个标记上训练了一个包含大约2300亿个总参数的基线MoE模型。我们在图 10中展示了训练曲线，并证明了相对误差在我们的高精度累加和细粒度量化策略下保持在0.25%以下。

B.2. Discussion About Block-Wise Quantization

虽然我们的分块细粒度量化有效地减轻了特征异常值引入的误差，但它要求对激活量化采用不同的分组，即前向传播时为1x128，反向传播时为128x1。激活梯度也需要类似的过程。一种直接的策略是像量化模型权重那样，对每个128x128元素应用块量化。这样，反向传播时只需要进行转置。因此，我们进行了一项实验，其中所有与Dgrad相关的张量都以块为单位进行量化。结果表明，Dgrad操作，即以链式方式计算激活梯度并反向传播到浅层，对精度高度敏感。具体来说，激活梯度的块量化导致了一个包含约160亿参数的MoE模型在训练约3000亿个token时出现模型发散。我们假设这种敏感性是由于激活梯度在token之间高度不平衡，导致了与token相关的异常值 (Xi et al., 2023)。这些异常值无法通过块量化方法有效管理。

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

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中都表现出更高的专家专业化程度，如图 10所示。

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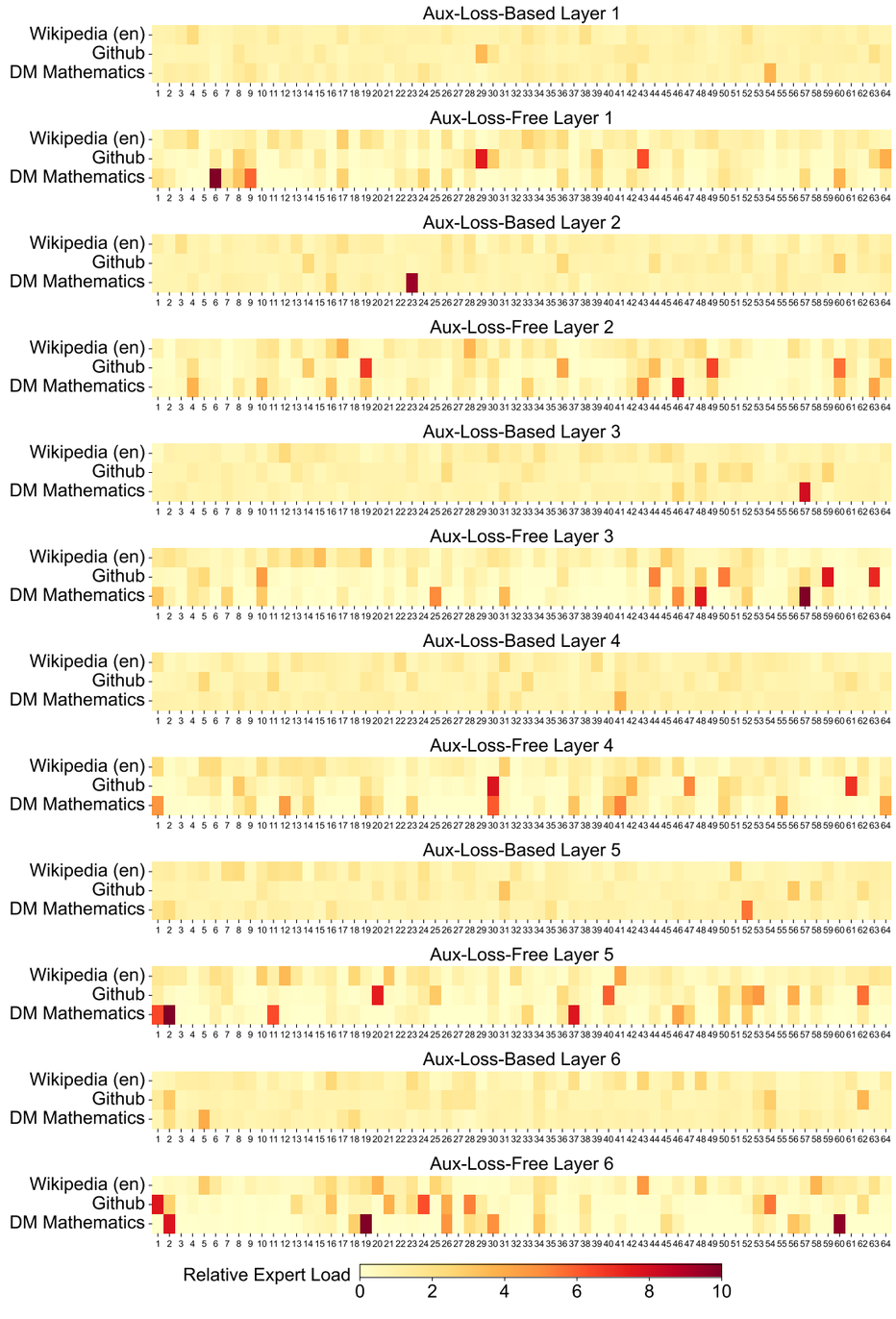

(a) Layers 1-7

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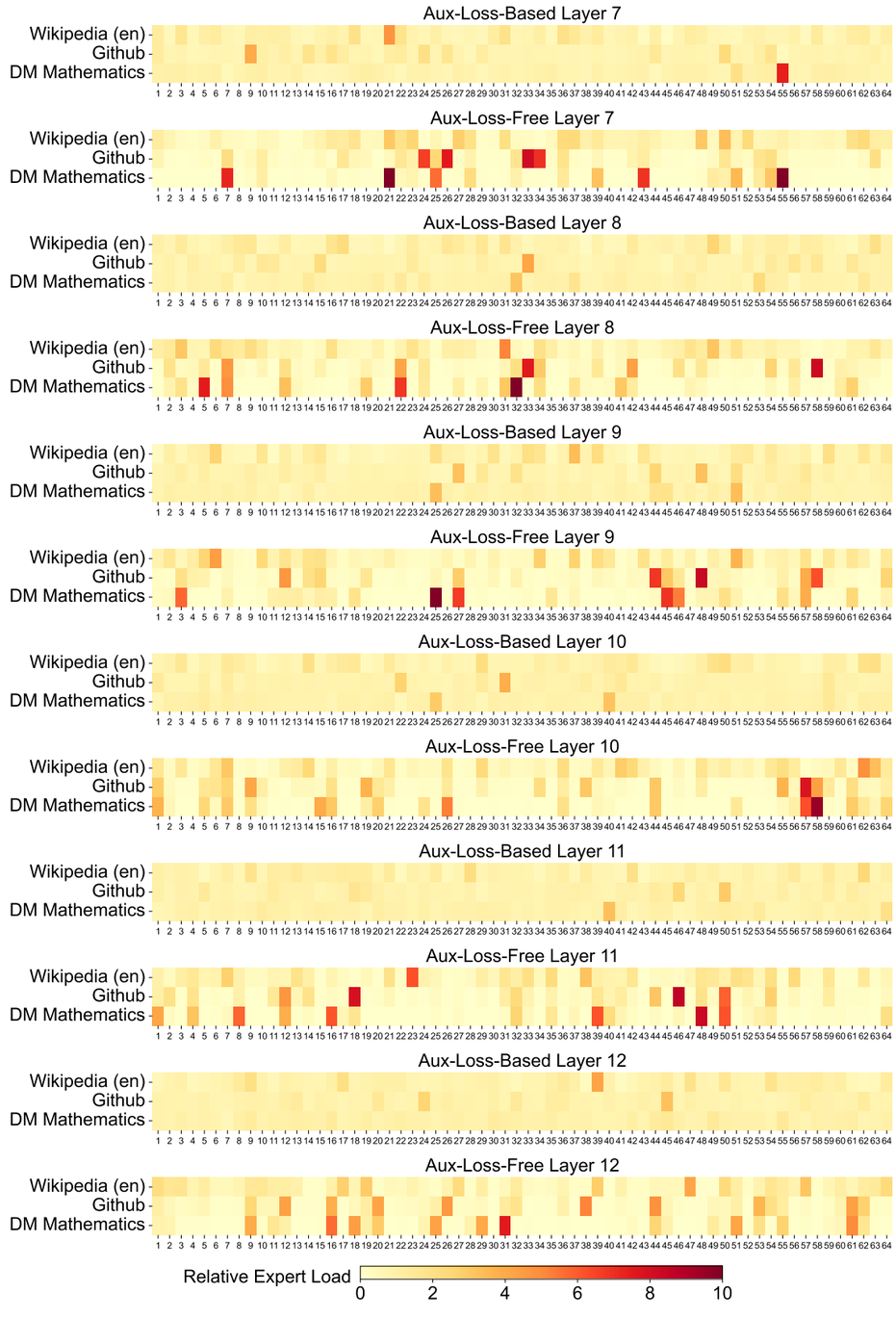

(b) Layers 7-13

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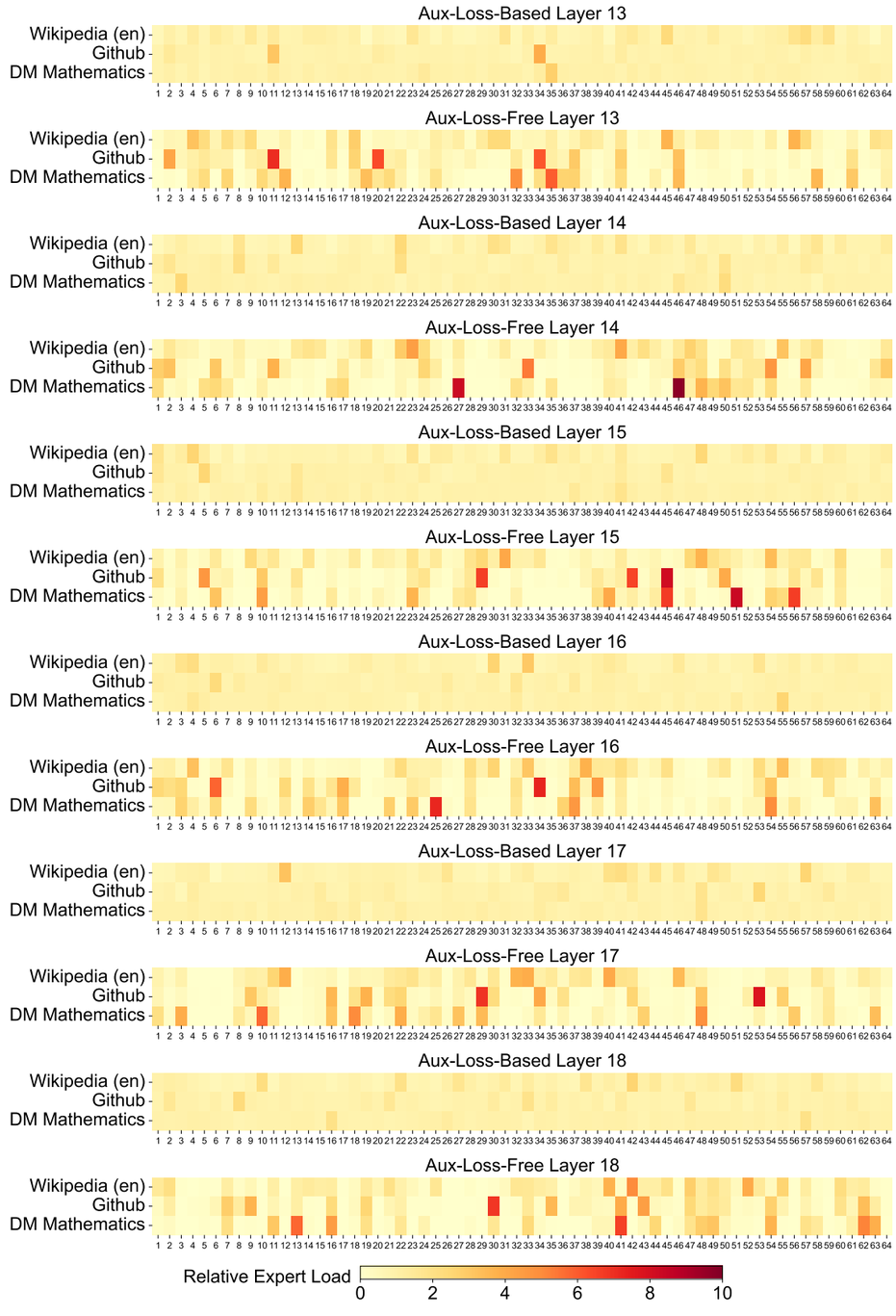

(c) Layers 13-19

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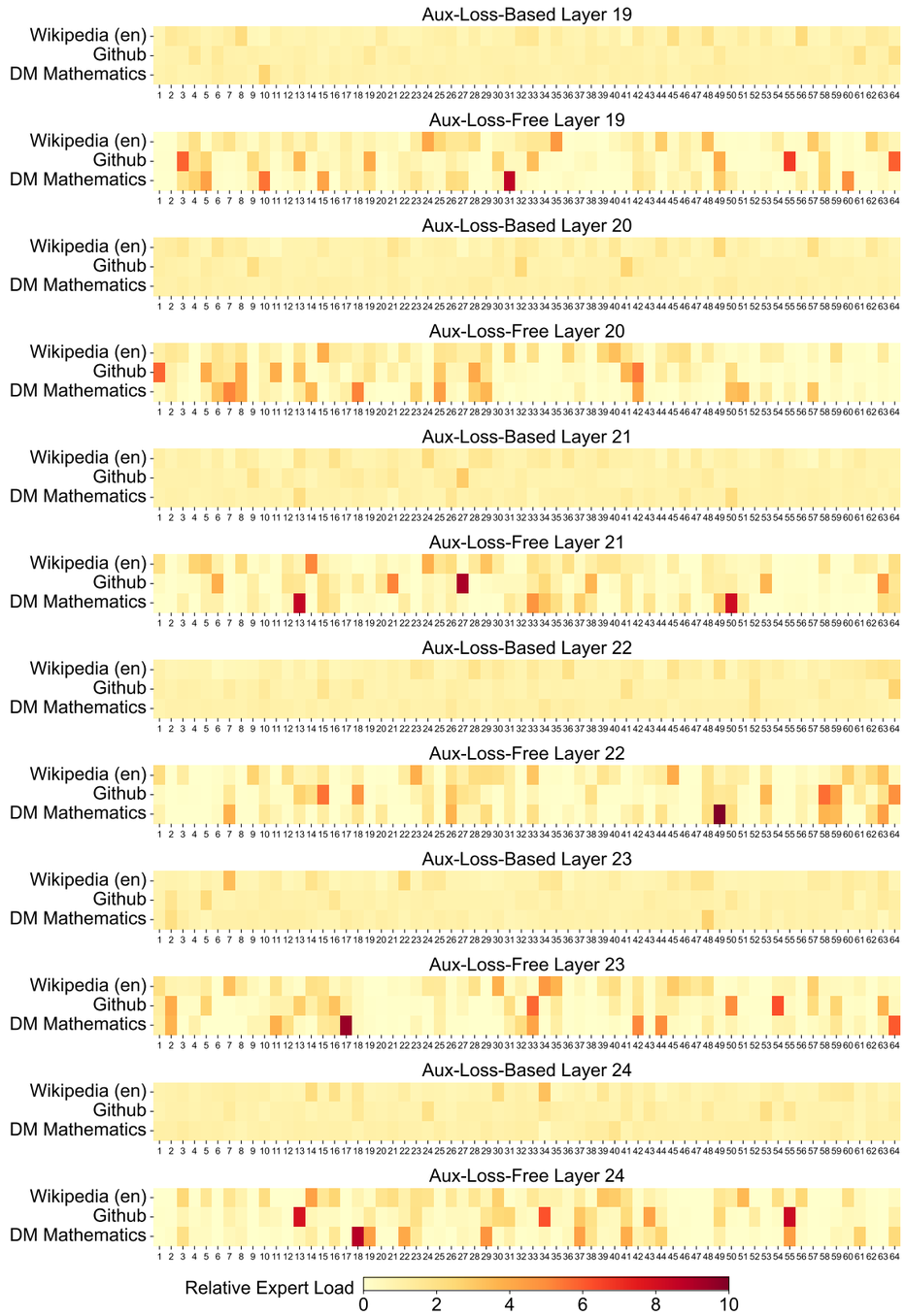


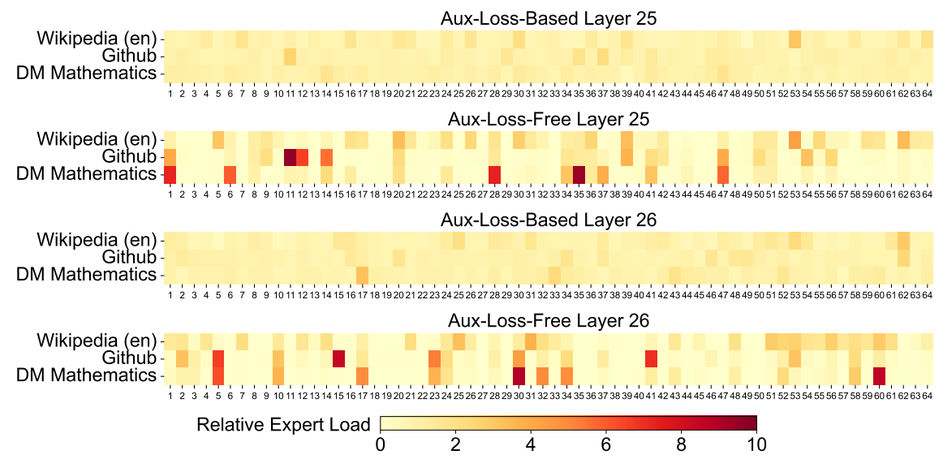
(d) Layers 19-25

Appendix

A. Contributions and Acknowledgments

Research & Engineering

Aixin Liu
Bing Xue
Bingxuan Wang
Bochao Wu
Chengda Lu
Chenggang Zhao
Chengqi Deng
Chenyu Zhang*
Chong Ruan
Damai Dai
Daya Guo
Dejian Yang
Deli Chen
Erhang Li
Fangyun Lin
Fucong Dai
Fuli Luo*
Guangbo Hao
Guanting Chen
Guowei Li
H. Zhang
Han Bao*
Hanwei Xu
Haocheng Wang*
Haowei Zhang
Honghui Ding
Huajian Xin*
Huazuo Gao
Hui Qu
Jianzhong Guo
Jiashi Li
Jiawei Wang*
Jingchang Chen
Jingyang Yuan
Junjie Qiu
Junlong Li
Junxiao Song
Kai Dong
Kai Hu*
Kaige Gao
Kang Guan
Kexin Huang
Kuai Yu
Lean Wang
Lecong Zhang
Liang Zhao
Litong Wang
Liyue Zhang
Mingchuan Zhang
Minghua Zhang
Minghui Tang
Panpan Huang
Peiyi Wang
Qiancheng Wang
Qihao Zhu
Qinyu Chen
Qiushi Du
Ruiqi Ge
Ruisong Zhang
Ruizhe Pan
Runji Wang
Runxin Xu
Ruoyu Zhang
Shanghao Lu
Shangyan Zhou
Shanhuang Chen
Shengfeng Ye



(e) Layers 25-27

Figure 10 | 在Pile测试集的三个领域中，无辅助损失和基于辅助损失模型的专家负载。无辅助损失模型显示出比基于辅助损失模型更强的专家专业化模式。相对专家负载表示实际专家负载与理论平衡专家负载之间的比率。

Shirong Ma
Shiyu Wang
Shuiping Yu
Shunfeng Zhou
Shuting Pan
Tao Yun
Tian Pei
Wangding Zeng
Wanjia Zhao*
Wen Liu
Wenfeng Liang
Wenjun Gao
Wenqin Yu
Wentao Zhang
Xiao Bi
Xiaodong Liu
Xiaohan Wang
Xiaokang Chen
Xiaokang Zhang
Xiaotao Nie
Xin Cheng
Xin Liu
Xin Xie
Xingchao Liu
Xingkai Yu
Xinyu Yang
Xinyuan Li
Xuecheng Su
Xuheng Lin
Y.K. Li
Y.Q. Wang
Y.X. Wei
Yang Zhang
Yanhong Xu
Yao Li
Yao Zhao
Yaofeng Sun
Yaohui Wang
Yi Yu
Yichao Zhang
Yifan Shi
Yiliang Xiong
Ying He
Yishi Piao
Yisong Wang
Yixuan Tan
Yiyang Ma*
Yiyuan Liu
Yongqiang Guo
Yu Wu
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Yuduan Wang
Yue Gong
Yuheng Zou
Yujia He
Yunfan Xiong
Yuxiang Luo
Yuxiang You
Yuxuan Liu
Yuyang Zhou
Z.F. Wu
Z.Z. Ren
Zehui Ren
Zhangli Sha
Zhe Fu
Zhean Xu
Zhenda Xie
Zhengyan Zhang
Zhewen Hao
Zhibin Gou
Zhicheng Ma
Zhigang Yan
Zhihong Shao
Zhiyu Wu
Zhuoshu Li
Zihui Gu

Zijia Zhu
Zijun Liu*
Zilin Li
Ziwei Xie
Ziyang Song
Ziyi Gao
Zizheng Pan

Data Annotation

Bei Feng
Hui Li
J.L. Cai
Jiaqi Ni
Lei Xu
Meng Li
Ning Tian
R.J. Chen
R.L. Jin
Ruyi Chen
S.S. Li
Shuang Zhou
Tianyu Sun
X.Q. Li
Xiangyue Jin
Xiaojin Shen
Xiaosha Chen
Xiaowen Sun
Xiaoxiang Wang
Xinnan Song
Xinyi Zhou
Y.X. Zhu
Yanhong Xu
Yanping Huang
Yaohui Li
Yi Zheng
Yuchen Zhu
Yunxian Ma
Zhen Huang
Zhipeng Xu
Zhongyu Zhang

Business & Compliance

Dongjie Ji
Jian Liang
Jin Chen
Leyi Xia
Miaojun Wang
Mingming Li
Peng Zhang
Shaoqing Wu
Shengfeng Ye
T. Wang
W.L. Xiao
Wei An
Xianzu Wang
Xinxia Shan
Ying Tang
Yukun Zha
Yuting Yan
Zhen Zhang

Within each role, authors are listed alphabetically by the first name. Names marked with * denote individuals who have departed from our team.

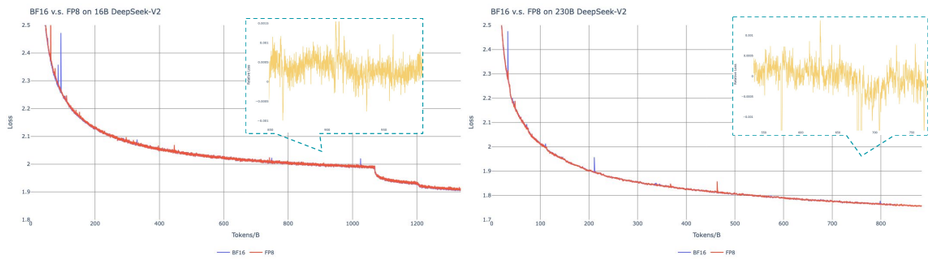


Figure 10 | Loss curves comparison between BF16 and FP8 training. Results are smoothed by Exponential Moving Average (EMA) with a coefficient of 0.9.

B. Ablation Studies for Low-Precision Training

B.1. FP8 v.s. BF16 Training

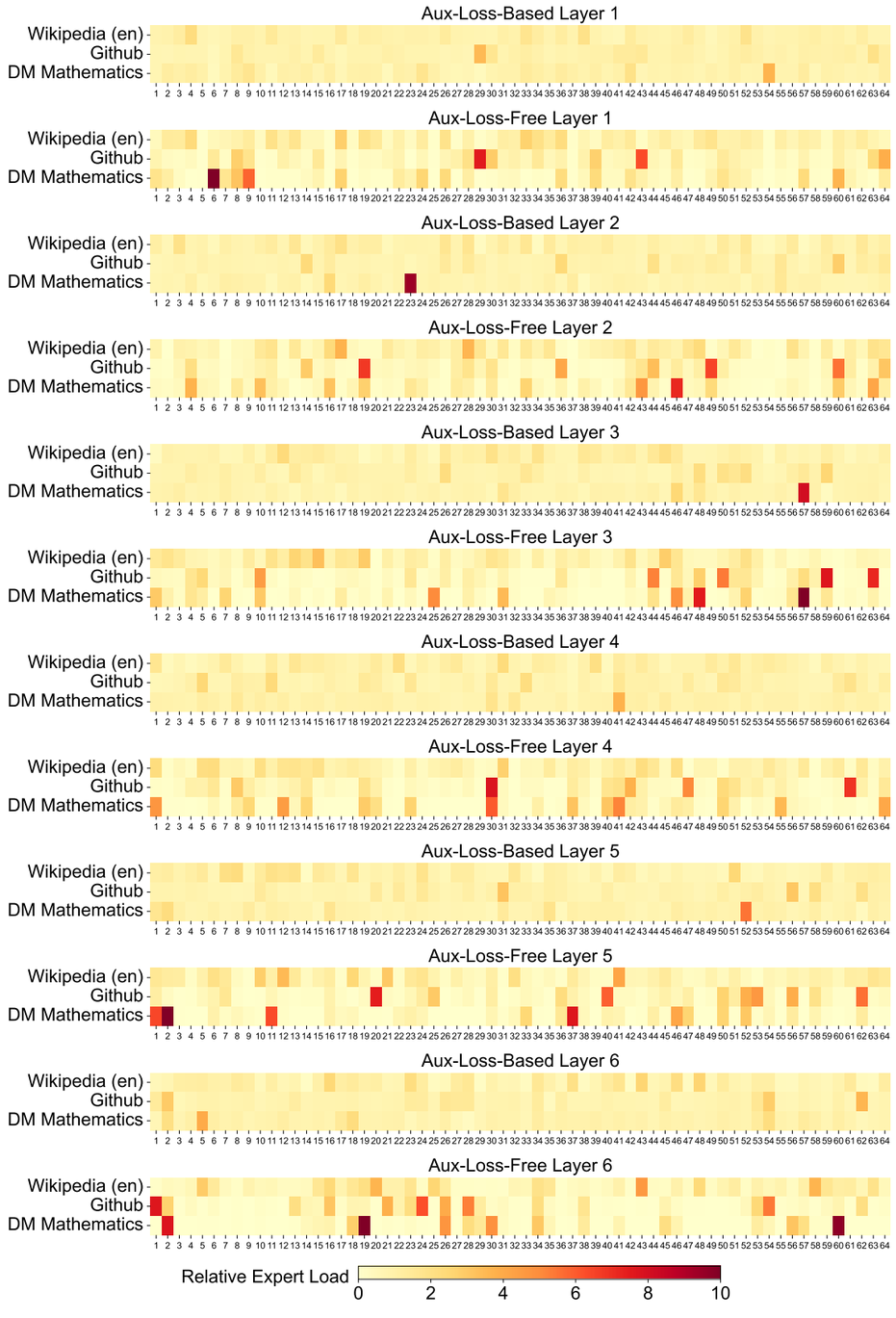
We validate our FP8 mixed precision framework with a comparison to BF16 training on top of two baseline models across different scales. At the small scale, we train a baseline MoE model comprising approximately 16B total parameters on 1.33T tokens. At the large scale, we train a baseline MoE model comprising 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.

B.2. Discussion About Block-Wise Quantization

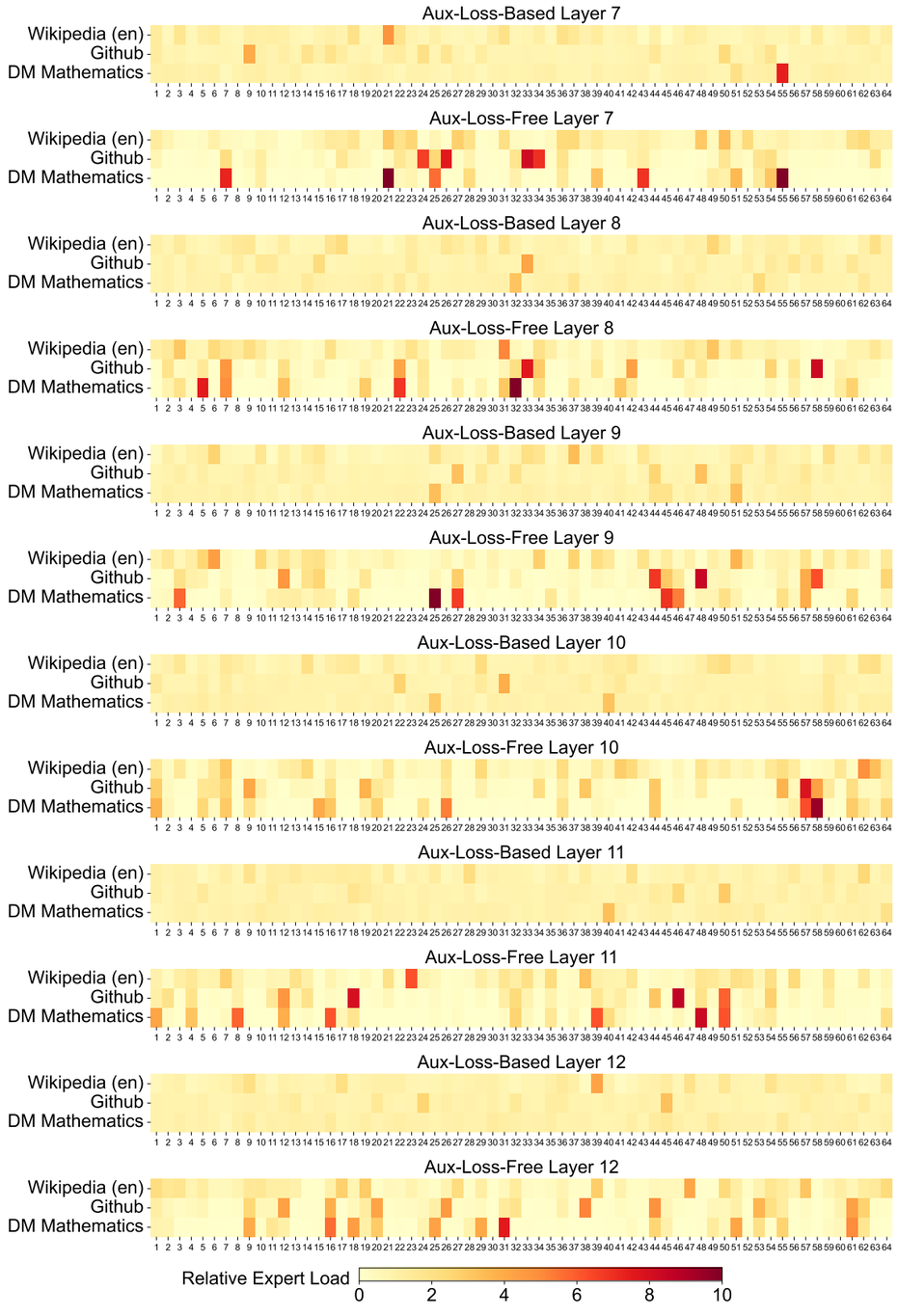
Although our tile-wise fine-grained quantization effectively mitigates the error introduced by feature outliers, it requires different groupings for activation quantization, i.e., `1x128` in forward pass and `128x1` for backward pass. A similar process is also required for the activation gradient. A straightforward strategy is to apply block-wise quantization per `128x128` 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 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

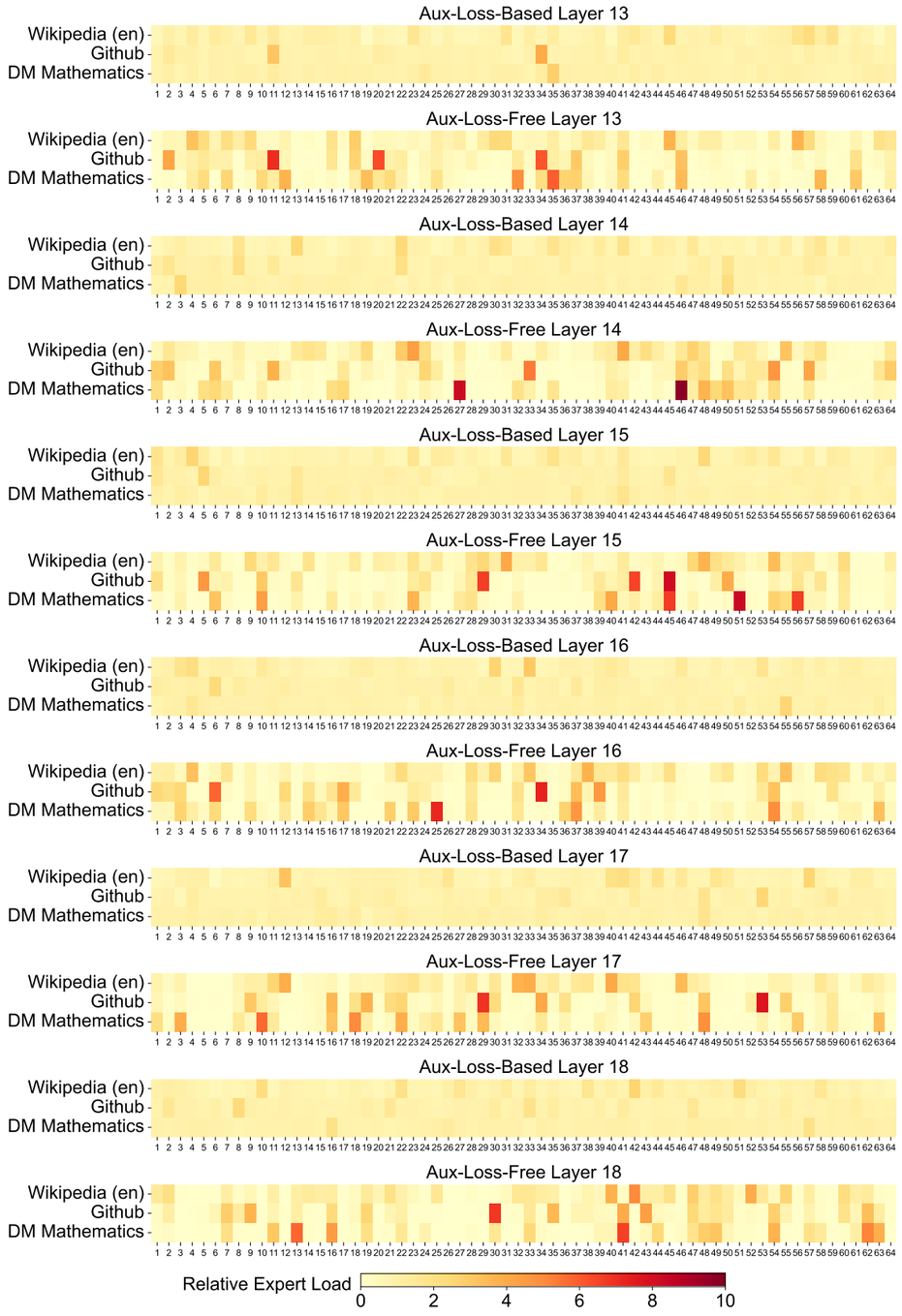
We record the expert load of the 16B auxiliary-loss-based baseline and the auxiliary-loss-free model on the Pile test set. The auxiliary-loss-free model tends to have greater expert specialization across all layers, as demonstrated in Figure 10.


Aux-Loss-Based Layer 1
Aux-Loss-Free Layer 1
Aux-Loss-Based Layer 2
Aux-Loss-Free Layer 2
Aux-Loss-Based Layer 3
Aux-Loss-Free Layer 3
Aux-Loss-Based Layer 4
Aux-Loss-Free Layer 4
Aux-Loss-Based Layer 5
Aux-Loss-Free Layer 5
Aux-Loss-Based Layer 6
Aux-Loss-Free Layer 6
Wikipedia (en)
Github
DM Mathematics
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64
Relative Expert Load
0 2 4 6 8 10

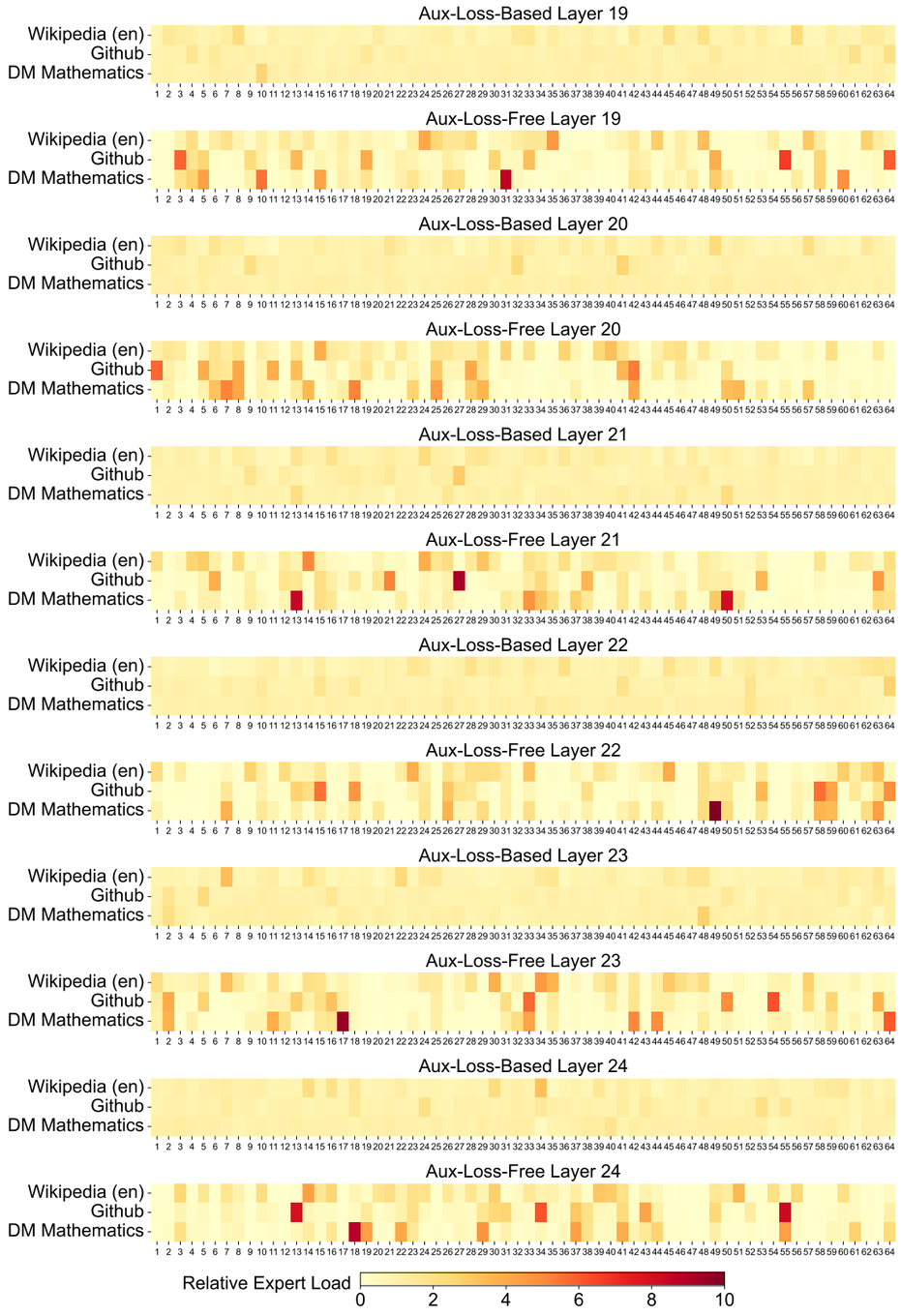
(a) Layers 1-7


Aux-Loss-Based Layer 7
Aux-Loss-Free Layer 7
Aux-Loss-Based Layer 8
Aux-Loss-Free Layer 8
Aux-Loss-Based Layer 9
Aux-Loss-Free Layer 9
Aux-Loss-Based Layer 10
Aux-Loss-Free Layer 10
Aux-Loss-Based Layer 11
Aux-Loss-Free Layer 11
Aux-Loss-Based Layer 12
Aux-Loss-Free Layer 12
Wikipedia (en)
Github
DM Mathematics
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64
Relative Expert Load
0 2 4 6 8 10

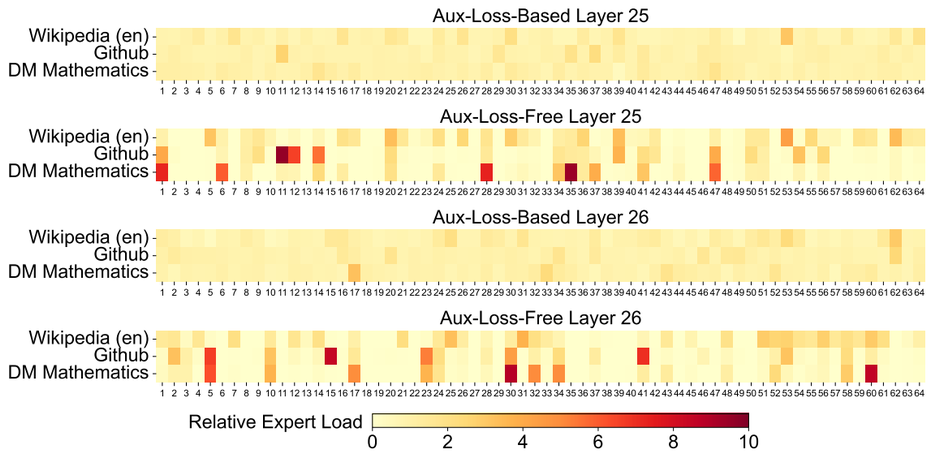
(b) Layers 7-13



(c) Layers 13-19



(d) Layers 19-25



(e) Layers 25-27

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.