

Qwen3 Technical Report

Qwen Team



<https://huggingface.co/Qwen>



<https://modelscope.cn/organization/qwen>






<https://github.com/QwenLM/Qwen3>

Abstract

In this work, we present Qwen3, the latest version of the Qwen model family. Qwen3 comprises a series of large language models (LLMs) designed to advance performance, efficiency, and multilingual capabilities. The Qwen3 series includes models of both dense and Mixture-of-Expert (MoE) architectures, with parameter scales ranging from 0.6 to 235 billion. A key innovation in Qwen3 is the integration of thinking mode (for complex, multi-step reasoning) and non-thinking mode (for rapid, context-driven responses) into a unified framework. This eliminates the need to switch between different models—such as chat-optimized models (e.g., GPT-4o) and dedicated reasoning models (e.g., QwQ-32B)—and enables dynamic mode switching based on user queries or chat templates. Meanwhile, Qwen3 introduces a thinking budget mechanism, allowing users to allocate computational resources adaptively during inference, thereby balancing latency and performance based on task complexity. Moreover, by leveraging the knowledge from the flagship models, we significantly reduce the computational resources required to build smaller-scale models, while ensuring their highly competitive performance. Empirical evaluations demonstrate that Qwen3 achieves state-of-the-art results across diverse benchmarks, including tasks in code generation, mathematical reasoning, agent tasks, etc., competitive against larger MoE models and proprietary models. Compared to its predecessor Qwen2.5, Qwen3 expands multilingual support from 29 to 119 languages and dialects, enhancing global accessibility through improved cross-lingual understanding and generation capabilities. To facilitate reproducibility and community-driven research and development, all Qwen3 models are publicly accessible under Apache 2.0.

QWEN3技术报告

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抽象的

在这项工作中，我们介绍了Qwen3，这是QWEN模型系列的最新版本。QWEN3包括一系列旨在提高性能，效率和多语言功能的大型语言模型（LLM）。QWEN3系列包括稠密和混合物（MOE）架构的模型，参数尺度范围为0.6至2350亿。QWEN3中的一个关键创新是整合思维模式（用于复杂，多步推理）和非思考模式（用于快速，上下文驱动响应）中的统一框架。这无需在不同模型之间进行切换，例如聊天优化的模型（例如GP T-4O）和专用的推理模型（例如QWQ-32B） - 并根据用户查询或聊天模板启用动态模式切换。同时，QWEN3引入了一种思维预算机制，使用户可以在推理过程中自适应地分配计算资源，从而根据任务复杂性平衡延迟和性能。此外，通过利用旗舰模型中的知识，我们大大减少了建立较小规模的模型所需的计算资源，同时确保其竞争激烈的性能。经验评估表明，QWEN3在不同的基准中取得了最新的结果，包括代码生成，数学推理，代理任务等方面的任务，与更大的MOE模型和专有模型竞争。与其前身QWEN2.5相比，QWEN3将多语言支持从29种到119种语言和方言扩展，从而提高跨语言理解和发电能力来增强全球可访问性。为了促进可重复性和社区驱动的研发，所有QWEN3模型均可在Apache 2.0下公开访问。

1 Introduction

The pursuit of artificial general intelligence (AGI) or artificial super intelligence (ASI) has long been a goal for humanity. Recent advancements in large foundation models, e.g., GPT-4o (OpenAI, 2024), Claude 3.7 (Anthropic, 2025), Gemini 2.5 (DeepMind, 2025), DeepSeek-V3 (Liu et al., 2024a), Llama-4 (Meta-AI, 2025), and Qwen2.5 (Yang et al., 2024b), have demonstrated significant progress toward this objective. These models are trained on vast datasets spanning trillions of tokens across diverse domains and tasks, effectively distilling human knowledge and capabilities into their parameters. Furthermore, recent developments in reasoning models, optimized through reinforcement learning, highlight the potential for foundation models to enhance inference-time scaling and achieve higher levels of intelligence, e.g., o3 (OpenAI, 2025), DeepSeek-R1 (Guo et al., 2025). While most state-of-the-art models remain proprietary, the rapid growth of open-source communities has substantially reduced the performance gap between open-weight and closed-source models. Notably, an increasing number of top-tier models (Meta-AI, 2025; Liu et al., 2024a; Guo et al., 2025; Yang et al., 2024b) are now being released as open-source, fostering broader research and innovation in artificial intelligence.

In this work, we introduce Qwen3, the latest series in our foundation model family, Qwen. Qwen3 is a collection of open-weight large language models (LLMs) that achieve state-of-the-art performance across a wide variety of tasks and domains. We release both dense and Mixture-of-Experts (MoE) models, with the number of parameters ranging from 0.6 billion to 235 billion, to meet the needs of different downstream applications. Notably, the flagship model, Qwen3-235B-A22B, is an MoE model with a total of 235 billion parameters and 22 billion activated ones per token. This design ensures both high performance and efficient inference.

Qwen3 introduces several key advancements to enhance its functionality and usability. First, it integrates two distinct operating modes, thinking mode and non-thinking mode, into a single model. This allows users to switch between these modes without alternating between different models, e.g., switching from Qwen2.5 to QwQ (Qwen Team, 2024). This flexibility ensures that developers and users can adapt the model’s behavior to suit specific tasks efficiently. Additionally, Qwen3 incorporates thinking budgets, providing users with fine-grained control over the level of reasoning effort applied by the model during task execution. This capability is crucial to the optimization of computational resources and performance, tailoring the model’s thinking behavior to meet varying complexity in real-world applications. Furthermore, Qwen3 has been pre-trained on 36 trillion tokens covering up to 119 languages and dialects, effectively enhancing its multilingual capabilities. This broadened language support amplifies its potential for deployment in global use cases and international applications. These advancements together establish Qwen3 as a cutting-edge open-source large language model family, capable of effectively addressing complex tasks across various domains and languages.

The pre-training process for Qwen3 utilizes a large-scale dataset consisting of approximately 36 trillion tokens, curated to ensure linguistic and domain diversity. To efficiently expand the training data, we employ a multi-modal approach: Qwen2.5-VL (Bai et al., 2025) is finetuned to extract text from extensive PDF documents. We also generate synthetic data using domain-specific models: Qwen2.5-Math (Yang et al., 2024c) for mathematical content and Qwen2.5-Coder (Hui et al., 2024) for code-related data. The pre-training process follows a three-stage strategy. In the first stage, the model is trained on about 30 trillion tokens to build a strong foundation of general knowledge. In the second stage, it is further trained on knowledge-intensive data to enhance reasoning abilities in areas like science, technology, engineering, and mathematics (STEM) and coding. Finally, in the third stage, the model is trained on long-context data to increase its maximum context length from 4,096 to 32,768 tokens.

To better align foundation models with human preferences and downstream applications, we employ a multi-stage post-training approach that empowers both thinking (reasoning) and non-thinking modes. In the first two stages, we focus on developing strong reasoning abilities through long chain-of-thought (CoT) cold-start finetuning and reinforcement learning focusing on mathematics and coding tasks. In the final two stages, we combine data with and without reasoning paths into a unified dataset for further fine-tuning, enabling the model to handle both types of input effectively, and we then apply general-domain reinforcement learning to improve performance across a wide range of downstream tasks. For smaller models, we use strong-to-weak distillation, leveraging both off-policy and on-policy knowledge transfer from larger models to enhance their capabilities. Distillation from advanced teacher models significantly outperforms reinforcement learning in performance and training efficiency.

We evaluate both pre-trained and post-trained versions of our models across a comprehensive set of benchmarks spanning multiple tasks and domains. Experimental results show that our base pre-trained models achieve state-of-the-art performance. The post-trained models, whether in thinking or non-thinking mode, perform competitively against leading proprietary models and large mixture-of-experts (MoE) models such as o1, o3-mini, and DeepSeek-V3. Notably, our models excel in coding, mathematics, and agent-related tasks. For example, the flagship model Qwen3-235B-A22B achieves 85.7 on AIME’24

1 简介

追求人工通用情报（AGI）或人工超级智能（ASI）长期以来一直是人类的目标。大型基础模型的最新进展，例如GPT-4O（OpenAI, 2024），Claude 3.7（Anthropic, 2025），Gemini 2.5（DeepMind, 2025），DeepSeek-V3（Liu等人, 2024a），Llama-4（Meta-ai-4, 2025）和Qwen2.5（Yan et al., 2025）和Qwen2.5（Meta-ai-4）（Yan et al., 2025）2.5（Meta-ai-ai ext）。这个目标。这些模型在跨不同领域和任务的庞大数据集上进行了培训，有效地将人类的知识 and 能力提炼成其参数。此外，推理模型的最新发展通过增强学习优化，强调了基础模型增强推理时间缩放并实现更高智能水平的潜力，例如O3（OpenAI, 2025），DeepSeek-R1（Guo等人, 2025年）。尽管大多数最先进的模型仍然是专有的，但开源社区的快速增长已大大缩小了开放量和闭源模型之间的性能差距。值得注意的是，越来越多的顶级模型（Meta-AI, 2025; Liu等, 2024a; Guo等, 2025; Yang等人, 2024b）现在被释放为开放源，促进了人工智能领域的更广泛的研究和创新。

在这项工作中，我们介绍了基础模型家族中最新系列Qwen3。QWEN3是一系列开放式大型语言模型（LLMs），可在各种任务和域中实现最先进的性能。我们释放了一个密度和混合物（MOE）模型，参数范围从6亿到2350亿，以满足不同下游应用的需求。值得注意的是，旗舰型号QWEN3-235B-A22B是MOE模型，每个令牌的参数总计为2350亿个，激活的参数为220亿。这种设计可确保高性能和有效的推理。

Qwen3引入了几个关键进步，以增强其功能和可用性。首先，它将两个不同的操作模式集成到一个模型中。这允许用户在这些模式之间切换，而无需在不同模型之间交替，例如从QWEN2.5切换到QWQ（Qwen Team, 2024）。这种灵活性可确保开发人员和用户可以调整模型的行为以有效地适合特定任务。此外，QWEN3结合了思考预算，为用户提供了对模型执行过程中模型所应用的推理工作水平的精细控制。这种能力对于优化计算资源和绩效至关重要，该模型的思维行为可以满足现实世界应用中各种复杂性。此外，QWEN3已在36万亿个代币中进行了预先培训，最多可掩盖119种语言和方言，从而有效增强了其多语言能力。这种扩大的语言支持扩大了其在全球用例和国际应用程序中部署的潜力。这些进步共同将QWEN3建立一个尖端的开源大语言模型家族，能够有效解决跨各种领域和语言的复杂任务。

QWEN3的预训练过程采用了一个大规模数据集，该数据集由大约36万亿代币组成，以确保语言和领域的多样性进行策划。为了有效地扩展培训数据，我们采用了一种多模式方法：QWEN2.5-VL（Bai等, 2025）被列出，以从广泛的PDF文档中提取文本。我们还使用域特异性模型来生成合成数据：QWEN2.5-MATH（Yang等, 2024c）用于数学内容，QWEN2.5-CODER（Hui等, 2024）用于代码相关的数据。训练过程遵循三阶段的策略。在第一阶段，该模型接受了约300万亿代币的培训，以建立强大的常识基础。在第二阶段，对知识密集型数据进行了进一步的培训，以增强科学，技术，工程和数学（STEM）和编码等领域的推理能力。最后，在第三阶段，对模型进行了长篇文化数据的培训，以将其最大上下文长度从4,096增加到32,768个令牌。

为了使基础模型与人类的偏好和下游应用更好，我们采用多阶段的训练后方法，赋予思维（推理）和非思维模式。在前两个阶段中，我们专注于通过长期思考（COT）冷启动填充和加强学习的关键关注数学和编码任务，以发展强大的推理能力。在最后两个阶段中，我们将数据结合在一起，没有推理路径，将数据集中到一个统一的数据集中，以进一步进行微调，从而使模型能够有效地处理两种类型的输入，然后我们应用一般域增强学习以提高各种下游任务的性能。对于较小的型号，我们使用强对准的蒸馏，利用从较大型号的非政策和上政策的知识转移来增强其功能。高级教师模型的蒸馏极大地超过了绩效和培训效率方面的强化学习。

我们在跨越多个任务和域的一组综合基准中评估了模型的预训练和训练后版本。实验结果表明，我们的基本预培训模型达到了最新的性能。无论是在思维还是非思维模式中，受过训练的模型，都在针对领先的专有模型和大型专家（MOE）模型（例如O1，O3 Mini和DeepSeek-V3）进行竞争性能。值得注意的是，我们的模型在编码，数学和与代理相关的任务方面表现出色。例如，旗舰型QWEN3-235B-A22B在Aim v24上实现85.7

and 81.5 on AIME’25 (AIME, 2025), 70.7 on LiveCodeBench v5 (Jain et al., 2024), 2,056 on CodeForces, and 70.8 on BFCL v3 (Yan et al., 2024). In addition, other models in the Qwen3 series also show strong performance relative to their size. Furthermore, we observe that increasing the thinking budget for thinking tokens leads to a consistent improvement in the model’s performance across various tasks.

In the following sections, we describe the design of the model architecture, provide details on its training procedures, present the experimental results of pre-trained and post-trained models, and finally, conclude this technical report by summarizing the key findings and outlining potential directions for future research.

2 Architecture

The Qwen3 series includes 6 dense models, namely Qwen3-0.6B, Qwen3-1.7B, Qwen3-4B, Qwen3-8B, Qwen3-14B, and Qwen3-32B, and 2 MoE models, Qwen3-30B-A3B and Qwen3-235B-A22B. The flagship model, Qwen3-235B-A22B, has a total of 235B parameters with 22B activated ones. Below, we elaborate on the architecture of the Qwen3 models.

The architecture of the Qwen3 dense models is similar to Qwen2.5 (Yang et al., 2024b), including using Grouped Query Attention (GQA, Ainslie et al., 2023), SwiGLU (Dauphin et al., 2017), Rotary Positional Embeddings (RoPE, Su et al., 2024), and RMSNorm (Jiang et al., 2023) with pre-normalization. Besides, we remove QKV-bias used in Qwen2 (Yang et al., 2024a) and introduce QK-Norm (Dehghani et al., 2023) to the attention mechanism to ensure stable training for Qwen3. Key information on model architecture is provided in Table 1.

The Qwen3 MoE models share the same fundamental architecture as the Qwen3 dense models. Key information on model architecture is provided in Table 2. We follow Qwen2.5-MoE (Yang et al., 2024b) and implement fine-grained expert segmentation (Dai et al., 2024). The Qwen3 MoE models have 128 total experts with 8 activated experts per token. Unlike Qwen2.5-MoE, the Qwen3-MoE design excludes shared experts. Furthermore, we adopt the global-batch load balancing loss (Qiu et al., 2025) to encourage expert specialization. These architectural and training innovations have yielded substantial improvements in model performance across downstream tasks.

Qwen3 models utilize Qwen’s tokenizer (Bai et al., 2023), which implements byte-level byte-pair encoding (BBPE, Brown et al., 2020; Wang et al., 2020; Sennrich et al., 2016) with a vocabulary size of 151,669.

Table 1: Model architecture of Qwen3 dense models.

Models	Layers	Heads (Q / KV)	Tie Embedding	Context Length
Qwen3-0.6B	28	16 / 8	Yes	32K
Qwen3-1.7B	28	16 / 8	Yes	32K
Qwen3-4B	36	32 / 8	Yes	128K
Qwen3-8B	36	32 / 8	No	128K
Qwen3-14B	40	40 / 8	No	128K
Qwen3-32B	64	64 / 8	No	128K

Table 2: Model architecture of Qwen3 MoE models.

Models	Layers	Heads (Q / KV)	# Experts (Total / Activated)	Context Length
Qwen3-30B-A3B	48	32 / 4	128 / 8	128K
Qwen3-235B-A22B	94	64 / 4	128 / 8	128K

3 Pre-training

In this section, we describe the construction of our pretraining data, the details of our pretraining approach, and present experimental results from evaluating the base models on standard benchmarks.

3.1 Pre-training Data

Compared with Qwen2.5 (Yang et al., 2024b), we have significantly expanded the scale and diversity of our training data. Specifically, we collected twice as many pre-training tokens—covering three times more languages. All Qwen3 models are trained on a large and diverse dataset consisting of **119 languages and dialects**, with a total of **36 trillion tokens**. This dataset includes high-quality content in various

在Aime’ 25 (Aime, 2025) 上的81.5, LiveCodeBench V5上的70.7 (Jain等, 2024), CodeForces的2,056, BFCL V3上的70.8 (Yan等人, 2024年)。此外, QWEN3系列中的其他模型也相对于它们的大小表现出很强的性能。此外, 我们观察到, 增加思考代币的思维预算会导致模型在各种任务中的表现持续改善。

在以下各节中, 我们描述了模型体系结构的设计, 提供有关其培训程序的详细信息, 介绍了预培训和训练后模型的实验结果, 最后通过总结了关键发现并概述了未来研究的潜在方向来结束这项技术报告。

2个体系结构

QWEN3系列包括6种密集型号, 即Qwen3-0.6b, Qwen3-1.7b, Qwen3-4b, Qwen3-8b, Qwen3-14b和Qwen3-32b和2个MOE型号, Qwen3-30b-a3b和Qwen3-30b-a3b和qwen3b and qwen3b and qwen3-235b-aaba-aa22222222b。旗舰模型QWEN3-235B-A22B, 共有235b参数, 其激活为22B。下面, 我们详细介绍了QWEN3模型的架构。

Qwen3致密模型的结构与Qwen2.5 (Yang等, 2024b) 相似, 包括使用分组的查询注意 (GQA, Ainslie等, 2023), Swiglu (Dauphin等, 2017, 2017), 旋转位置嵌入 (Rope, Su等) (rope, su et al., 2024) 等 (JIAN) 等 (JIAN) 等 (JIAN) (JIAN) (JIAN等) (JIAN) (RSNOMN) (RSNOMN) (RSN) (RSNOMN) (RSN)。前归一化。此外, 我们删除了QWEN2中使用的QKV偏置 (Yang等, 2024a), 并将QK-Norm (Dehghani等, 2023) 引入注意机制, 以确保Qwen3的稳定训练。表1中提供了有关模型体系结构的关键信息。

QWEN3 MOE模型与QWEN3密集模型具有相同的基本体系结构。表2中提供了有关模型架构的关键信息。我们遵循QWEN2.5-MOE (Yang等, 2024b) 并实施细粒的专家细分 (Dai等, 2024)。QWEN3 MOE模型有128个专家, 每个令牌有8个激活的专家。与Qwen2.5-Moe不同, QWEN3-MOE设计不包括共享专家。此外, 我们采用了全球批次负载平衡损失 (Qiu等, 2025) 来鼓励专家专业。这些建筑和培训创新在下游任务中取得了重大改进。

QWEN3模型利用Qwen的令牌 (Bai等, 2023), 它实现了字节级字节置编码 (BBPE, Brown等, 2020; Wang等, 2020; Sennrich等, 2016) 的词汇大小为151,6699。

表1: Qwen3密集模型的模型结构。

Models	Layers	Heads (Q / KV)	Tie Embedding	Context Length
Qwen3-0.6B	28	16 / 8	Yes	32K
Qwen3-1.7B	28	16 / 8	Yes	32K
Qwen3-4B	36	32 / 8	Yes	128K
Qwen3-8B	36	32 / 8	No	128K
Qwen3-14B	40	40 / 8	No	128K
Qwen3-32B	64	64 / 8	No	128K

表2: QWEN3 MOE模型的模型结构。

Models	Layers	Heads (Q / KV)	# Experts (Total / Activated)	Context Length
Qwen3-30B-A3B	48	32 / 4	128 / 8	128K
Qwen3-235B-A22B	94	64 / 4	128 / 8	128K

3预训练

在本节中, 我们描述了我们的训练数据的构建, 我们的训练方法的细节, 并通过评估标准基准的基础模型提出了实验性结果。

3.1预训练数据

与QWEN2.5 (Yang等人, 2024b) 相比, 我们已经显着扩大了培训数据的规模和多样性。具体来说, 我们收集了两倍的预训练令牌, 覆盖了三倍的语言。所有QWEN3模型均经过大型多样的数据集培训, 该数据集由119种语言和方言组成, 共有36万亿代币。该数据集包括各种高质量的内容

domains such as coding, STEM (Science, Technology, Engineering, and Mathematics), reasoning tasks, books, multilingual texts, and synthetic data.

To further expand the pre-training data corpus, we first employ the Qwen2.5-VL model (Bai et al., 2025) to perform text recognition on a large volume of PDF-like documents. The recognized text is then refined using the Qwen2.5 model (Yang et al., 2024b), which helps improve its quality. Through this two-step process, we are able to obtain an additional set of high-quality text tokens, amounting to trillions in total. Besides, we employ Qwen2.5 (Yang et al., 2024b), Qwen2.5-Math (Yang et al., 2024c), and Qwen2.5-Coder (Hui et al., 2024) models to synthesize trillions of text tokens in different formats, including textbooks, question-answering, instructions, and code snippets, covering dozens of domains. Finally, we further expand the pre-training corpus by incorporating additional multilingual data and introducing more languages. Compared to the pre-training data used in Qwen2.5, the number of supported languages has been significantly increased from 29 to 119, enhancing the model’s linguistic coverage and cross-lingual capabilities.

We have developed a multilingual data annotation system designed to enhance both the quality and diversity of training data. This system has been applied to our large-scale pre-training datasets, annotating over 30 trillion tokens across multiple dimensions such as educational value, fields, domains, and safety. These detailed annotations support more effective data filtering and combination. Unlike previous studies (Xie et al., 2023; Fan et al., 2023; Liu et al., 2024b) that optimize the data mixture at the data source or domain level, our method optimizes the data mixture at the instance-level through extensive ablation experiments on small proxy models with the fine-grained data labels.

3.2 Pre-training Stage

The Qwen3 models are pre-trained through a three-stage process:

- (1) **General Stage (S1):** At the first pre-training stage, all Qwen3 models are trained on over 30 trillion tokens using a sequence length of 4,096 tokens. At this stage, the models have been fully pre-trained on language proficiency and general world knowledge, with training data covering 119 languages and dialects.
- (2) **Reasoning Stage (S2):** To further improve the reasoning ability, we optimize the pre-training corpus of this stage by increasing the proportion of STEM, coding, reasoning, and synthetic data. The models are further pre-trained with about 5T higher-quality tokens at a sequence length of 4,096 tokens. We also accelerate the learning rate decay during this stage.
- (3) **Long Context Stage:** In the final pre-training stage, we collect high-quality long context corpora to extend the context length of Qwen3 models. All models are pre-trained on hundreds of billions of tokens with a sequence length of 32,768 tokens. The long context corpus includes 75% of text between 16,384 to 32,768 tokens in length, and 25% of text between 4,096 to 16,384 in length. Following Qwen2.5 (Yang et al., 2024b), we increase the base frequency of RoPE from 10,000 to 1,000,000 using the ABF technique (Xiong et al., 2023). Meanwhile, we introduce YARN (Peng et al., 2023) and Dual Chunk Attention (DCA, An et al., 2024) to achieve a four-fold increase in sequence length capacity during inference.

Similar to Qwen2.5 (Yang et al., 2024b), we develop scaling laws for optimal hyper-parameters (e.g., learning rate scheduler, and batch size) predictions based on three pre-training stages mentioned above. Through extensive experiments, we systematically study the relationship between model architecture, training data, training stage, and optimal training hyper-parameters. Finally, we set the predicted optimal learning rate and batch size strategy for each dense or MoE model.

3.3 Pre-training Evaluation

We conduct comprehensive evaluations of the base language models of the Qwen3 series. The evaluation of base models mainly focuses on their performance in general knowledge, reasoning, mathematics, scientific knowledge, coding, and multilingual capabilities. The evaluation datasets for pre-trained base models include 15 benchmarks:

- **General Tasks:** MMLU (Hendrycks et al., 2021a) (5-shot), MMLU-Pro (Wang et al., 2024) (5-shot, CoT), MMLU-redux (Gema et al., 2024) (5-shot), BBH (Suzgun et al., 2023) (3-shot, CoT), SuperGPQA (Du et al., 2025) (5-shot, CoT).
- **Math & STEM Tasks:** GPQA (Rein et al., 2023) (5-shot, CoT), GSM8K (Cobbe et al., 2021) (4-shot, CoT), MATH (Hendrycks et al., 2021b) (4-shot, CoT).

为了进一步扩展培训前数据语料库，我们首先采用QWEN2.5-VL模型（Bai等，2025）对大量类似PDF的文档进行文本识别。然后，使用QWEN2.5模型（Yang等，2024b）来完善公认的文本，这有助于提高其质量。通过这个两步的过程，我们能够获得一组额外的高质量文本令牌，总计总计数万亿。此外，我们采用Qwen2.5（Yang等，2024b），Qwen2.5-MATH（Yang等人，2024c）和Qwen2.5-Coder（Hui等，2024）模型，以合成不同格式的文本代币的批量，包括教科书，询问书籍，指示，指示，指示，指示，指示，指示，并涵盖了编码，以及编码，以及编码。最后，我们通过合并其他多语言数据并引入更多语言来进一步扩展培训前语料库。与QWEN2.5中使用的预培训数据相比，支持语言的数量已从29升至119，增强了该模型的语言覆盖范围和跨语言功能。

3.2预训练阶段

(1) 一般阶段 (S1)：在第一个预训练阶段，所有QWEN3模型均使用4,096个令牌的序列长度在30万亿代币上训练。在此阶段，这些模型已经在语言水平和一般世界知识上进行了全面培训，培训数据涵盖了119种语言和方言。(2) 推理阶段 (S2)：为了进一步提高推理能力，我们通过增加茎，编码，推理和合成数据的比例来优化此阶段的前训练语料库。这些模型以4,096个代币的序列长度为4,096个代币进一步预训练。在此阶段，我们还加速了学习率的衰减。

与QWEN2.5 (Yang等人, 2024b)类似, 我们根据上述三个预训练阶段开发了最佳超参数(例如学习率调度程序和批次大小)预测的最佳超参数(例如, 学习率调度程序和批次大小)的预测。通过广泛的实验, 我们系统地研究了模型架构, 训练数据, 训练阶段和最佳培训超参数之间的关系。最后, 我们为每个密集或MOE模型设置了预测的最佳学习率和批处理大小策略。

我们对QWEN3系列的基本语言模型进行全面评估。基本模型的评估主要集中于他们在一般知识，推理，数学，科学知识，编码和多语言能力中的表现。预先训练的基本模型的评估数据集包括15个基准：

- [illegible]

- **Coding Tasks:** EvalPlus (Liu et al., 2023a) (0-shot) (Average of HumanEval (Chen et al., 2021), MBPP (Austin et al., 2021), Humaneval+, MBPP+) (Liu et al., 2023a), MultiPL-E (Cassano et al., 2023) (0-shot) (Python, C++, JAVA, PHP, TypeScript, C#, Bash, JavaScript), MBPP-3shot (Austin et al., 2021), CRUX-O of CRUXEval (1-shot) (Gu et al., 2024).
- **Multilingual Tasks:** MGSM (Shi et al., 2023) (8-shot, CoT), MMMLU (OpenAI, 2024) (5-shot), INCLUDE (Romanou et al., 2024) (5-shot).

For the base model baselines, we compare the Qwen3 series base models with the Qwen2.5 base models (Yang et al., 2024b) and other leading open-source base models, including DeepSeek-V3 Base (Liu et al., 2024a), Gemma-3 (Team et al., 2025), Llama-3 (Dubey et al., 2024), and Llama-4 (Meta-AI, 2025) series base models, in terms of scale of parameters. All models are evaluated using the same evaluation pipeline and the widely-used evaluation settings to ensure fair comparison.

Summary of Evaluation Results Based on the overall evaluation results, we highlight some key conclusions of Qwen3 base models.

- (1) Compared with the previously open-source SOTA dense and MoE base models (such as DeepSeek-V3 Base, Llama-4-Maverick Base, and Qwen2.5-72B-Base), Qwen3-235B-A22B-Base outperforms these models in most tasks with significantly fewer total parameters or activated parameters.
- (2) For the Qwen3 MoE base models, our experimental results indicate that: (a) Using the same pre-training data, Qwen3 MoE base models can achieve similar performance to Qwen3 dense base models with only $1/5$ activated parameters. (b) Due to the improvements of the Qwen3 MoE architecture, the scale-up of the training tokens, and more advanced training strategies, the Qwen3 MoE base models can outperform the Qwen2.5 MoE base models with less than $1/2$ activated parameters and fewer total parameters. (c) Even with $1/10$ of the activated parameters of the Qwen2.5 dense base model, the Qwen3 MoE base model can achieve comparable performance, which brings us significant advantages in inference and training costs.
- (3) The overall performance of the Qwen3 dense base models is comparable to the Qwen2.5 base models at higher parameter scales. For example, Qwen3-1.7B/4B/8B/14B/32B-Base achieve comparable performance to Qwen2.5-3B/7B/14B/32B/72B-Base, respectively. Especially in STEM, coding, and reasoning benchmarks, the performance of Qwen3 dense base models even surpasses Qwen2.5 base models at higher parameter scales.

The detailed results are as follows.

Qwen3-235B-A22B-Base We compare Qwen3-235B-A22B-Base to our previous similar-sized MoE Qwen2.5-Plus-Base (Yang et al., 2024b) and other leading open-source base models: Llama-4-Maverick (Meta-AI, 2025), Qwen2.5-72B-Base (Yang et al., 2024b), DeepSeek-V3 Base (Liu et al., 2024a). From the results in Table 3, the Qwen3-235B-A22B-Base model attains the highest performance scores across most of the evaluated benchmarks. We further compare Qwen3-235B-A22B-Base with other baselines separately for the detailed analysis.

- (1) Compared with the recently open-source model Llama-4-Maverick-Base, which has about **twice** the number of parameters, Qwen3-235B-A22B-Base still performs better on most benchmarks.
- (2) Compared with the previously state-of-the-art open-source model DeepSeek-V3-Base, Qwen3-235B-A22B-Base outperforms DeepSeek-V3-Base on 14 out of 15 evaluation benchmarks with only about $1/3$ the total number of parameters and $2/3$ activated parameters, demonstrating the powerful and cost-effectiveness of our models.
- (3) Compared with our previous MoE Qwen2.5-Plus of similar size, Qwen3-235B-A22B-Base significantly outperforms it with fewer parameters and activated parameters, which shows the remarkable advantages of Qwen3 in pre-training data, training strategy, and model architecture.
- (4) Compared with our previous flagship open-source dense model Qwen2.5-72B-Base, Qwen3-235B-A22B-Base surpasses the latter in all benchmarks and uses fewer than $1/3$ of the activated parameters. Meanwhile, due to the advantage of the model architecture, the inference costs and training costs on each trillion tokens of Qwen3-235B-A22B-Base are much cheaper than those of Qwen2.5-72B-Base.

Qwen3-32B-Base Qwen3-32B-Base is our largest dense model among the Qwen3 series. We compare it to the baselines of similar sizes, including Gemma-3-27B (Team et al., 2025) and Qwen2.5-32B (Yang et al., 2024b). In addition, we introduce two strong baselines: the recently open-source MoE model Llama-4-Scout, which has three times the parameters of Qwen3-32B-Base but half the activated parameters;

- 编码任务: evalplus (Liu等, 2023a) (0-shot) (人类VAL的平均值 (Chen等, 2021), MBPP (Austin等, 2021), HumaneVal +}, MBPP +) (V2)} (v2)} (liu等, liu等, 2023a), 跨度 (2023a), 2023.203。 (Python, C ++, Java, PHP, Typescript, C#, Bash, JavaScript), M BPP-3Shot (Austin等, 2021), Cruxeval (1-Shot) 的Crux-O (Gu等, 2024)。
- 多语言任务: MGSM (Shi等, 2023) (8-Shot, cot), mmmlu (Openai, 2024) (5-Shot) (Romanou等, 2024) (5-Shot)。

对于基本模型基线, 我们将QWEN3系列基本模型与QWEN2.5基本模型 (Yang等, 2024b) 和其他领先的开源基本模型 (包括DeepSeek-V3基础) (Liu等, 2024a), Gemma-3, Gemma-3 (Team等) (Team等, 2025年, 2025年), Llama-3 (Llama-3 (Dubey et al all llama et al and), 和2024 (MET)。2025) 串联基本模型, 就参数的规模而言。使用相同的评估管道和广泛使用的评估设置对所有模型进行评估, 以确保公平比较。

评估结果的摘要基于总体评估结果, 我们重点介绍了QWEN3基本模型的一些关键结论。

(1) 与以前开源的SOTA密集和MOE基础模型 (例如DeepSeek-V3基础, Llama-4-Maverick基础和Qwen2.5-72b基本), QWEN3-235B-A22B-BASE在大多数任务中具有较少的任务中的这些模型在大多数任务中均优于这些模型, 这些模型在大多数任务中都差不多。(2) 对于QWEN3 MOE基础模型, 我们的实验结果表明: (a) 使用相同的训练数据, QWEN3 MOE基本模型可以实现与仅具有1/5激活参数的QWEN3密集基本模型相似的性能。(b) 由于QWEN3 MOE架构的改进, 训练令牌的扩展以及更高级的培训策略, QWEN3 MOE基础模型的表现可以胜过QWEN2.5 MOE基础模型, 该模型的激活参数小于1/2, 总参数较少。(c) 即使使用QWEN2.5密度基本模型的激活参数的1/10, QWEN3 MOE基础模型也可以实现可比的性能, 这为推理和培训成本带来了显着优势。

(3) QWEN3致密基本模型的总体性能与较高参数尺度的QWEN2.5基本模型相当。例如, QWEN3-1.7B/4B/8B/14B/32B基数分别达到了与QWEN2.5-3B/7B/14B/32B/72B基数相当的性能。尤其是在茎, 编码和推理基准中, QWEN3致密基本模型的性能甚至超过了较高参数尺度的QWEN2.5基本模型。

详细的结果如下。

QWEN3-235B-A22B基准群我们将QWEN3-235B-A22B-BASE与以前的类似大小的Moe Qwen2.5-Plus-base (Yang等, 2024b) 和其他领先的开源基础模型: Llama-4-Maverick (Meta-4-Maverick (Meta-ai, 2025), QWEN2.5-BASE ET), YANG 2.5-BASE (YANGAI-4-MAVERICK), YANG 2.5-BASE, YANG 2.42 BASE, YANG.2BBASE, DeepSeek-V3基础 (Liu等, 2024a)。从表3的结果中, QWEN3-235B-A22B-BASE模型在大多数评估的基准中获得了最高的性能得分。我们进一步将QWEN3-235B-A22B-BASE与其他基线分别进行了比较, 以进行详细分析。

(1) 与最近的开源模型Llama-4-Maverick-base相比, 该基线的参数次数约为两倍, QWEN3-235B-A22B基准群在大多数基准测试中仍然表现更好。(2) 与以前最先进的开源模型DeepSeek-V3基键相比, Qwen3-235b-a22b-base在15个评估基准中的14个中的14个, 只有1/3的评估基准中的14个, 只有1/3个参数总数和2/3激活的参数和2/3的激活参数, 证明了强大的和成本的型号。(3) 与我们以前的MOE QWEN2.5以上相似的大小相比, QWEN3-235B-A22B-base Sigsigsigsig在较少的参数和激活的参数中表现出了较少的优于它, 这表明了QWEN3在预训练数据, 训练策略和模型架构中的显着优势。

(4) 与我们以前的旗舰开源密集模型QWEN2.5-72B基础相比, Qwen3-235b-a22b-base在所有基准中都超过了后者, 并且使用了激活参数的1/3。同时, 由于模型体系结构的优势, QWEN3-235B-A22B基数的每万亿代币的推理成本和培训成本比QWEN2.5-72B基准的便宜得多。

QWEN3-32B-base QWEN3-32B-base是我们在QWEN3系列中最大的密集模型。我们将其与类似尺寸的基准进行比较, 包括Gemma-3-27b (Team等, 2025) 和Qwen2.5-32b (Yang等, 2024b)。此外, 我们介绍了两个强大的基线: 最近开源的MOE模型Llama-4-Scout, 其具有QWEN3-32B基数的参数的三倍, 但是激活参数的一半;

Table 3: Comparison among Qwen3-235B-A22B-Base and other representative strong open-source baselines. The highest, the second-best scores are shown in bold and underlined, respectively.

	Qwen2.5-72B Base	Qwen2.5-Plus Base	Llama-4-Maverick Base	DeepSeek-V3 Base	Qwen3-235B-A22B Base
Architecture	Dense	MoE	MoE	MoE	MoE
# Total Params	72B	271B	402B	671B	235B
# Activated Params	72B	37B	17B	37B	22B
<i>General Tasks</i>					
MMLU	86.06	85.02	85.16	<u>87.19</u>	87.81
MMLU-Redux	83.91	82.69	84.05	<u>86.14</u>	87.40
MMLU-Pro	58.07	63.52	<u>63.91</u>	59.84	68.18
SuperGPQA	36.20	37.18	40.85	<u>41.53</u>	44.06
BBH	<u>86.30</u>	85.60	83.62	86.22	88.87
<i>Math & STEM Tasks</i>					
GPQA	45.88	41.92	43.94	41.92	47.47
GSM8K	91.50	<u>91.89</u>	87.72	87.57	94.39
MATH	62.12	62.78	<u>63.32</u>	62.62	71.84
<i>Coding Tasks</i>					
EvalPlus	65.93	61.43	<u>68.38</u>	63.75	77.60
MultiPL-E	58.70	62.16	57.28	<u>62.26</u>	65.94
MBPP	<u>76.00</u>	74.60	75.40	74.20	81.40
CRUX-O	66.20	68.50	<u>77.00</u>	76.60	79.00
<i>Multilingual Tasks</i>					
MGSM	82.40	82.21	79.69	82.68	83.53
MMMLU	84.40	83.49	83.09	<u>85.88</u>	86.70
INCLUDE	69.05	66.97	<u>73.47</u>	75.17	73.46

Table 4: Comparison among Qwen3-32B-Base and other strong open-source baselines. The highest and second-best scores are shown in bold and underlined, respectively.

	Qwen2.5-32B Base	Qwen2.5-72B Base	Gemma-3-27B Base	Llama-4-Scout Base	Qwen3-32B Base
Architecture	Dense	Dense	Dense	MoE	Dense
# Total Params	32B	72B	27B	109B	32B
# Activated Params	32B	72B	27B	17B	32B
<i>General Tasks</i>					
MMLU	83.32	86.06	78.69	78.27	<u>83.61</u>
MMLU-Redux	81.97	83.91	76.53	71.09	<u>83.41</u>
MMLU-Pro	55.10	<u>58.07</u>	52.88	56.13	65.54
SuperGPQA	33.55	<u>36.20</u>	29.87	26.51	39.78
BBH	84.48	<u>86.30</u>	79.95	82.40	87.38
<i>Math & STEM Tasks</i>					
GPQA	<u>47.97</u>	45.88	26.26	40.40	49.49
GSM8K	<u>92.87</u>	91.50	81.20	85.37	93.40
MATH	57.70	62.12	51.78	51.66	<u>61.62</u>
<i>Coding Tasks</i>					
EvalPlus	<u>66.25</u>	65.93	55.78	59.90	72.05
MultiPL-E	<u>58.30</u>	<u>58.70</u>	45.03	47.38	67.06
MBPP	73.60	<u>76.00</u>	68.40	68.60	78.20
CRUX-O	<u>67.80</u>	66.20	60.00	61.90	72.50
<i>Multilingual Tasks</i>					
MGSM	78.12	<u>82.40</u>	73.74	79.93	83.06
MMMLU	82.40	84.40	77.62	74.83	<u>83.83</u>
INCLUDE	64.35	69.05	<u>68.94</u>	68.09	67.87

表3: QWEN3-235B-A22B基础与其他代表性强的开源基线之间的比较。最高的，第二好的分数分别以粗体和下划线显示。

	Qwen2.5-72B Base	Qwen2.5-Plus Base	Llama-4-Maverick Base	DeepSeek-V3 Base	Qwen3-235B-A22B Base
Architecture	Dense	MoE	MoE	MoE	MoE
# Total Params	72B	271B	402B	671B	235B
# Activated Params	72B	37B	17B	37B	22B
<i>General Tasks</i>					
MMLU	86.06	85.02	85.16	<u>87.19</u>	87.81
MMLU-Redux	83.91	82.69	84.05	<u>86.14</u>	87.40
MMLU-Pro	58.07	63.52	<u>63.91</u>	59.84	68.18
SuperGPQA	36.20	37.18	40.85	<u>41.53</u>	44.06
BBH	<u>86.30</u>	85.60	83.62	86.22	88.87
<i>Math & STEM Tasks</i>					
GPQA	<u>45.88</u>	41.92	43.94	41.92	47.47
GSM8K	91.50	<u>91.89</u>	87.72	87.57	94.39
MATH	62.12	62.78	<u>63.32</u>	62.62	71.84
<i>Coding Tasks</i>					
EvalPlus	65.93	61.43	<u>68.38</u>	63.75	77.60
MultiPL-E	58.70	62.16	57.28	<u>62.26</u>	65.94
MBPP	<u>76.00</u>	74.60	75.40	74.20	81.40
CRUX-O	66.20	68.50	<u>77.00</u>	76.60	79.00
<i>Multilingual Tasks</i>					
MGSM	82.40	82.21	79.69	82.68	83.53
MMMLU	84.40	83.49	83.09	<u>85.88</u>	86.70
INCLUDE	69.05	66.97	<u>73.47</u>	75.17	73.46

表4: QWEN3-32B碱基和其他强大的开源基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

	Qwen2.5-32B Base	Qwen2.5-72B Base	Gemma-3-27B Base	Llama-4-Scout Base	Qwen3-32B Base
Architecture	Dense	Dense	Dense	MoE	Dense
# Total Params	32B	72B	27B	109B	32B
# Activated Params	32B	72B	27B	17B	32B
<i>General Tasks</i>					
MMLU	83.32	86.06	78.69	78.27	<u>83.61</u>
MMLU-Redux	81.97	83.91	76.53	71.09	<u>83.41</u>
MMLU-Pro	55.10	<u>58.07</u>	52.88	56.13	65.54
SuperGPQA	33.55	<u>36.20</u>	29.87	26.51	39.78
BBH	84.48	<u>86.30</u>	79.95	82.40	87.38
<i>Math & STEM Tasks</i>					
GPQA	<u>47.97</u>	45.88	26.26	40.40	49.49
GSM8K	<u>92.87</u>	91.50	81.20	85.37	93.40
MATH	57.70	62.12	51.78	51.66	<u>61.62</u>
<i>Coding Tasks</i>					
EvalPlus	<u>66.25</u>	65.93	55.78	59.90	72.05
MultiPL-E	<u>58.30</u>	<u>58.70</u>	45.03	47.38	67.06
MBPP	73.60	<u>76.00</u>	68.40	68.60	78.20
CRUX-O	<u>67.80</u>	66.20	60.00	61.90	72.50
<i>Multilingual Tasks</i>					
MGSM	78.12	<u>82.40</u>	73.74	79.93	83.06
MMMLU	82.40	84.40	77.62	74.83	<u>83.83</u>
INCLUDE	64.35	69.05	<u>68.94</u>	68.09	67.87

Table 5: Comparison among Qwen3-14B-Base, Qwen3-30B-A3B-Base, and other strong open-source baselines. The highest and second-best scores are shown in bold and underlined, respectively.

	Gemma-3-12B Base	Qwen2.5-14B Base	Qwen2.5-32B Base	Qwen2.5-Turbo Base	Qwen3-14B Base	Qwen3-30B-A3B Base
Architecture	Dense	Dense	Dense	MoE	Dense	MoE
# Total Params	12B	14B	32B	42B	14B	30B
# Activated Params	12B	14B	32B	6B	14B	3B
<i>General Tasks</i>						
MMLU	73.87	79.66	83.32	79.50	81.05	<u>81.38</u>
MMLU-Redux	70.70	76.64	81.97	77.11	79.88	<u>81.17</u>
MMLU-Pro	44.91	51.16	55.10	55.60	<u>61.03</u>	61.49
SuperGPQA	24.61	30.68	33.55	31.19	<u>34.27</u>	35.72
BBH	74.28	78.18	84.48	76.10	81.07	<u>81.54</u>
<i>Math & STEM Tasks</i>						
GPQA	31.31	32.83	47.97	41.41	39.90	<u>43.94</u>
GSM8K	78.01	90.22	92.87	88.32	<u>92.49</u>	91.81
MATH	44.43	55.64	57.70	55.60	62.02	<u>59.04</u>
<i>Coding Tasks</i>						
EvalPlus	52.65	60.70	66.25	61.23	72.23	<u>71.45</u>
MultiPL-E	43.03	54.79	58.30	53.24	<u>61.69</u>	66.53
MBPP	60.60	69.00	<u>73.60</u>	67.60	73.40	74.40
CRUX-O	52.00	61.10	<u>67.80</u>	60.20	68.60	67.20
<i>Multilingual Tasks</i>						
MGSM	64.35	74.68	78.12	70.45	79.20	<u>79.11</u>
MMMLU	72.50	78.34	82.40	79.76	79.69	<u>81.46</u>
INCLUDE	63.34	60.26	64.35	59.25	<u>64.55</u>	67.00

Table 6: Comparison among Qwen8B-Base and other strong open-source baselines. The highest and second-best scores are shown in bold and underlined, respectively.

	Llama-3-8B Base	Qwen2.5-7B Base	Qwen2.5-14B Base	Qwen3-8B Base
Architecture	Dense	Dense	Dense	Dense
# Total Params	8B	7B	14B	8B
# Activated Params	8B	7B	14B	8B
<i>General Tasks</i>				
MMLU	66.60	74.16	79.66	76.89
MMLU-Redux	61.59	71.06	76.64	<u>76.17</u>
MMLU-Pro	35.36	45.00	<u>51.16</u>	56.73
SuperGPQA	20.54	26.34	30.68	31.64
BBH	57.70	70.40	<u>78.18</u>	78.40
<i>Math & STEM Tasks</i>				
GPQA	25.80	<u>36.36</u>	32.83	44.44
GSM8K	55.30	85.36	90.22	<u>89.84</u>
MATH	20.50	49.80	<u>55.64</u>	60.80
<i>Coding Tasks</i>				
EvalPlus	44.13	62.18	60.70	67.65
MultiPL-E	31.45	50.73	<u>54.79</u>	58.75
MBPP	48.40	63.40	<u>69.00</u>	69.80
CRUX-O	36.80	48.50	<u>61.10</u>	62.00
<i>Multilingual Tasks</i>				
MGSM	38.92	63.60	74.68	76.02
MMMLU	59.65	71.34	78.34	<u>75.72</u>
IINCLUDE	44.94	53.98	60.26	<u>59.40</u>

表5: QWEN3-14B基数, QWEN3-30B-A3B基准和其他强大的开源基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

	Gemma-3-12B Base	Qwen2.5-14B Base	Qwen2.5-32B Base	Qwen2.5-Turbo Base	Qwen3-14B Base	Qwen3-30B-A3B Base
Architecture	Dense	Dense	Dense	MoE	Dense	MoE
# Total Params	12B	14B	32B	42B	14B	30B
# Activated Params	12B	14B	32B	6B	14B	3B
<i>General Tasks</i>						
MMLU	73.87	79.66	83.32	79.50	81.05	<u>81.38</u>
MMLU-Redux	70.70	76.64	81.97	77.11	79.88	<u>81.17</u>
MMLU-Pro	44.91	51.16	55.10	55.60	<u>61.03</u>	61.49
SuperGPQA	24.61	30.68	33.55	31.19	<u>34.27</u>	35.72
BBH	74.28	78.18	84.48	76.10	81.07	<u>81.54</u>
<i>Math & STEM Tasks</i>						
GPQA	31.31	32.83	47.97	41.41	39.90	<u>43.94</u>
GSM8K	78.01	90.22	92.87	88.32	<u>92.49</u>	91.81
MATH	44.43	55.64	57.70	55.60	62.02	<u>59.04</u>
<i>Coding Tasks</i>						
EvalPlus	52.65	60.70	66.25	61.23	72.23	<u>71.45</u>
MultiPL-E	43.03	54.79	58.30	53.24	<u>61.69</u>	66.53
MBPP	60.60	69.00	<u>73.60</u>	67.60	73.40	74.40
CRUX-O	52.00	61.10	<u>67.80</u>	60.20	68.60	67.20
<i>Multilingual Tasks</i>						
MGSM	64.35	74.68	78.12	70.45	79.20	<u>79.11</u>
MMMLU	72.50	78.34	82.40	79.76	79.69	<u>81.46</u>
INCLUDE	63.34	60.26	64.35	59.25	<u>64.55</u>	67.00

表6: QWEN8B基准和其他强大的开源基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

	Llama-3-8B Base	Qwen2.5-7B Base	Qwen2.5-14B Base	Qwen3-8B Base
Architecture	Dense	Dense	Dense	Dense
# Total Params	8B	7B	14B	8B
# Activated Params	8B	7B	14B	8B
<i>General Tasks</i>				
MMLU	66.60	74.16	79.66	76.89
MMLU-Redux	61.59	71.06	76.64	<u>76.17</u>
MMLU-Pro	35.36	45.00	<u>51.16</u>	56.73
SuperGPQA	20.54	26.34	30.68	31.64
BBH	57.70	70.40	<u>78.18</u>	78.40
<i>Math & STEM Tasks</i>				
GPQA	25.80	<u>36.36</u>	32.83	44.44
GSM8K	55.30	85.36	90.22	<u>89.84</u>
MATH	20.50	49.80	<u>55.64</u>	60.80
<i>Coding Tasks</i>				
EvalPlus	44.13	62.18	60.70	67.65
MultiPL-E	31.45	50.73	<u>54.79</u>	58.75
MBPP	48.40	63.40	<u>69.00</u>	69.80
CRUX-O	36.80	48.50	<u>61.10</u>	62.00
<i>Multilingual Tasks</i>				
MGSM	38.92	63.60	74.68	76.02
MMMLU	59.65	71.34	78.34	<u>75.72</u>
IINCLUDE	44.94	53.98	60.26	<u>59.40</u>

Table 7: Comparison among Qwen3-4B-Base and other strong open-source baselines. The highest and second-best scores are shown in bold and underlined, respectively.

	Gemma-3-4B Base	Qwen2.5-3B Base	Qwen2.5-7B Base	Qwen3-4B Base
Architecture	Dense	Dense	Dense	Dense
# Total Params	4B	3B	7B	4B
# Activated Params	4B	3B	7B	4B
<i>General Tasks</i>				
MMLU	59.51	65.62	74.16	<u>72.99</u>
MMLU-Redux	56.91	63.68	<u>71.06</u>	72.79
MMLU-Pro	29.23	34.61	<u>45.00</u>	50.58
SuperGPQA	17.68	20.31	<u>26.34</u>	28.43
BBH	51.70	56.30	<u>70.40</u>	72.59
<i>Math & STEM Tasks</i>				
GPQA	24.24	26.26	36.36	36.87
GSM8K	43.97	79.08	<u>85.36</u>	87.79
MATH	26.10	42.64	<u>49.80</u>	54.10
<i>Coding Tasks</i>				
EvalPlus	43.23	46.28	62.18	63.53
MultiPL-E	28.06	39.65	<u>50.73</u>	53.13
MBPP	46.40	54.60	<u>63.40</u>	67.00
CRUX-O	34.00	36.50	<u>48.50</u>	55.00
<i>Multilingual Tasks</i>				
MGSM	33.11	47.53	63.60	67.74
MMMLU	59.62	65.55	<u>71.34</u>	71.42
INCLUDE	49.06	45.90	<u>53.98</u>	56.29

Table 8: Comparison among Qwen3-1.7B-Base, Qwen3-0.6B-Base, and other strong open-source baselines. The highest and second-best scores are shown in bold and underlined, respectively.

	Qwen2.5-0.5B Base	Qwen3-0.6B Base	Gemma-3-1B Base	Qwen2.5-1.5B Base	Qwen3-1.7B Base
Architecture	Dense	Dense	Dense	Dense	Dense
# Total Params	0.5B	0.6B	1B	1.5B	1.7B
# Activated Params	0.5B	0.6B	1B	1.5B	1.7B
<i>General Tasks</i>					
MMLU	47.50	52.81	26.26	60.90	62.63
MMLU-Redux	45.10	51.26	25.99	<u>58.46</u>	61.66
MMLU-Pro	15.69	24.74	9.72	<u>28.53</u>	36.76
SuperGPQA	11.30	15.03	7.19	<u>17.64</u>	20.92
BBH	20.30	41.47	28.13	<u>45.10</u>	54.47
<i>Math & STEM Tasks</i>					
GPQA	24.75	<u>26.77</u>	24.75	24.24	28.28
GSM8K	41.62	59.59	2.20	<u>68.54</u>	75.44
MATH	19.48	32.44	3.66	<u>35.00</u>	43.50
<i>Coding Tasks</i>					
EvalPlus	31.85	36.23	8.98	<u>44.80</u>	52.70
MultiPL-E	18.70	24.58	5.15	<u>33.10</u>	42.71
MBPP	29.80	36.60	9.20	<u>43.60</u>	55.40
CRUX-O	12.10	27.00	3.80	<u>29.60</u>	36.40
<i>Multilingual Tasks</i>					
MGSM	12.07	30.99	1.74	32.82	50.71
MMMLU	31.53	50.16	26.57	<u>60.27</u>	63.27
INCLUDE	24.74	34.26	25.62	<u>39.55</u>	45.57

表7: QWEN3-4B碱基和其他强大的开源基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

	Gemma-3-4B	Qwen2.5-3B	Qwen2.5-7B	Qwen3-4B
	Base	Base	Base	Base
Architecture	Dense	Dense	Dense	Dense
# Total Params	4B	3B	7B	4B
# Activated Params	4B	3B	7B	4B
<i>General Tasks</i>				
MMLU	59.51	65.62	74.16	<u>72.99</u>
MMLU-Redux	56.91	63.68	<u>71.06</u>	72.79
MMLU-Pro	29.23	34.61	<u>45.00</u>	50.58
SuperGPQA	17.68	20.31	<u>26.34</u>	28.43
BBH	51.70	56.30	<u>70.40</u>	72.59
<i>Math & STEM Tasks</i>				
GPQA	24.24	26.26	36.36	36.87
GSM8K	43.97	79.08	<u>85.36</u>	87.79
MATH	26.10	42.64	<u>49.80</u>	54.10
<i>Coding Tasks</i>				
EvalPlus	43.23	46.28	62.18	63.53
MultiPL-E	28.06	39.65	<u>50.73</u>	53.13
MBPP	46.40	54.60	<u>63.40</u>	67.00
CRUX-O	34.00	36.50	<u>48.50</u>	55.00
<i>Multilingual Tasks</i>				
MGSM	33.11	47.53	63.60	67.74
MMMLU	59.62	65.55	<u>71.34</u>	71.42
INCLUDE	49.06	45.90	<u>53.98</u>	56.29

表8: QWEN3-1.7B基础, QWEN3-0.6B基础和其他强大的开源基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

	Qwen2.5-0.5B	Qwen3-0.6B	Gemma-3-1B	Qwen2.5-1.5B	Qwen3-1.7B
	Base	Base	Base	Base	Base
Architecture	Dense	Dense	Dense	Dense	Dense
# Total Params	0.5B	0.6B	1B	1.5B	1.7B
# Activated Params	0.5B	0.6B	1B	1.5B	1.7B
<i>General Tasks</i>					
MMLU	47.50	52.81	26.26	60.90	62.63
MMLU-Redux	45.10	51.26	25.99	<u>58.46</u>	61.66
MMLU-Pro	15.69	24.74	9.72	<u>28.53</u>	36.76
SuperGPQA	11.30	15.03	7.19	<u>17.64</u>	20.92
BBH	20.30	41.47	28.13	<u>45.10</u>	54.47
<i>Math & STEM Tasks</i>					
GPQA	24.75	<u>26.77</u>	24.75	24.24	28.28
GSM8K	41.62	59.59	2.20	<u>68.54</u>	75.44
MATH	19.48	32.44	3.66	<u>35.00</u>	43.50
<i>Coding Tasks</i>					
EvalPlus	31.85	36.23	8.98	<u>44.80</u>	52.70
MultiPL-E	18.70	24.58	5.15	<u>33.10</u>	42.71
MBPP	29.80	36.60	9.20	<u>43.60</u>	55.40
CRUX-O	12.10	27.00	3.80	<u>29.60</u>	36.40
<i>Multilingual Tasks</i>					
MGSM	12.07	30.99	1.74	32.82	50.71
MMMLU	31.53	50.16	26.57	<u>60.27</u>	63.27
INCLUDE	24.74	34.26	25.62	<u>39.55</u>	45.57

and our previous flagship open-source dense model Qwen2.5-72B-Base, which has more than twice the number of parameters compared to Qwen3-32B-Base. The results are shown in Table 4, which support three key conclusions:

- (1) Compared with the similar-sized models, Qwen3-32B-Base outperforms Qwen2.5-32B-Base and Gemma-3-27B Base on most benchmarks. Notably, Qwen3-32B-Base achieves 65.54 on MMLU-Pro and 39.78 on SuperGPQA, significantly outperforming its predecessor Qwen2.5-32B-Base. In addition, Qwen3-32B-Base achieves significantly higher encoding benchmark scores than all baseline models.
- (2) Surprisingly, we find that Qwen3-32B-Base achieves competitive results compared to Qwen2.5-72B-Base. Although Qwen3-32B-Base has less than half the number of parameters of Qwen2.5-72B-Base, it outperforms Qwen2.5-72B-Base in 10 of the 15 evaluation benchmarks. On coding, mathematics, and reasoning benchmarks, Qwen3-32B-Base has remarkable advantages.
- (3) Compared to Llama-4-Scout-Base, Qwen3-32B-Base significantly outperforms it on all 15 benchmarks, with only one-third of the number of parameters of Llama-4-Scout-Base, but twice the number of activated parameters.

Qwen3-14B-Base & Qwen3-30B-A3B-Base The evaluation of the Qwen3-14B-Base and Qwen3-30B-A3B-Base is compared against baselines of similar sizes, including Gemma-3-12B Base, Qwen2.5-14B Base. Similarly, we also introduce two strong baselines: (1) Qwen2.5-Turbo (Yang et al., 2024b), which has 42B parameters and 6B activated parameters. Note that its activated parameters are twice those of Qwen3-30B-A3B-Base. (2) Qwen2.5-32B-Base, which has 11 times the activated parameters of Qwen3-30B-A3B and more than twice that of Qwen3-14B. The results are shown in Table 5, where we can draw the following conclusions.

- (1) Compared with the similar-sized models, Qwen3-14B-Base significantly performs better than Qwen2.5-14B-Base and Gemma-3-12B-Base on all 15 benchmarks.
- (2) Similarly, Qwen3-14B-Base also achieves very competitive results compared to Qwen2.5-32B-Base with less than half of the parameters.
- (3) With only 1/5 activated non-embedding parameters, Qwen3-30B-A3B significantly outperforms Qwen2.5-14B-Base on all tasks, and achieves comparable performance to Qwen3-14B-Base and Qwen2.5-32B-Base, which brings us significant advantages in inference and training costs.

Qwen3-8B / 4B / 1.7B / 0.6B-Base For edge-side models, we take similar-sized Qwen2.5, Llama-3, and Gemma-3 base models as the baselines. The results can be seen in Table 6, Table 7, and Table 8. All Qwen3 8B / 4B / 1.7B / 0.6B-Base models continue to maintain strong performance across nearly all benchmarks. Notably, Qwen3-8B / 4B / 1.7B-Base models even outperform larger size Qwen2.5-14B / 7B / 3B Base models on over half of the benchmarks, especially on STEM-related and coding benchmarks, reflecting the significant improvement of the Qwen3 models.

4 Post-training

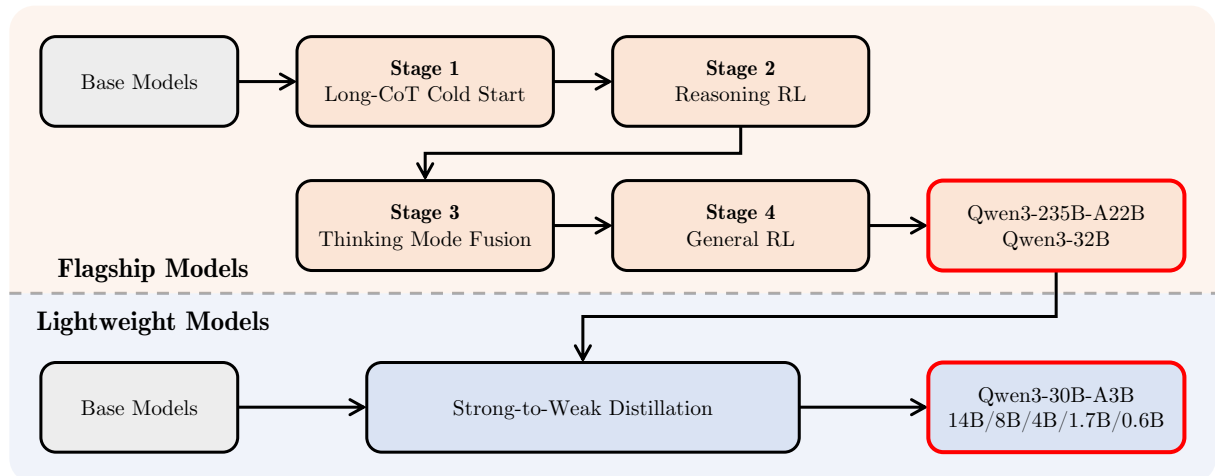


Figure 1: Post-training pipeline of the Qwen3 series models.

以及我们以前的旗舰开源密集型QWEN2.5-72B基础，与QWEN3-32B基本相比，参数数量是参数数的两倍以上。结果显示在表4中，该表4支持三个关键结论：

- (1) 与相似大小的模型相比，QWEN3-32B基本在大多数基准上都优于QWEN2.5-32B-base和Gemma-3-27b基础。值得注意的是，QWEN3-32B基数在MMLU-PRO上达到65.54，而SuperGPQA上的39.78在39.78上的表现显着优于其前身QWEN2.5-32B基础。此外，QWEN3-32B基本的编码得分明显高于所有基线模型。
- (2) 令人惊讶的是，与QWEN2.5-72B基础相比，QWEN3-32B基础可取得竞争性结果。尽管QWEN3-32B基础的参数数量少于QWEN2.5-72B基数的一半，但在15个评估基准中的10个中，它的表现优于QWEN2.5-72B基数。关于编码，数学和推理基准，QWEN3-32B基础具有显著的优势。
- (3) 与Llama-4-Scout-base相比，QWEN3-32B基础在所有15个基准上都显着胜过它，只有三分之一的llama-4-Scout-base参数次数，但是激活参数的数量的两倍。

QWEN3-14B-BASE和QWEN3-30B-A3B-BASE对QWEN3-14B基本和QWEN3-30B-A3B碱基的评估与包括Gemma-3-12b碱基QWEN2.5-14B基础在内的类似尺寸的基线相比。同样，我们还引入了两个强基线：（1）QWEN2.5-TURBO（Yang等，2024b），它具有42B参数和6B激活的参数。请注意，其激活参数是QWEN3-30B-A3B基数的两倍。（2）QWEN2.5-32B基本，其具有QWEN3-30B-A3B的激活参数的11倍，是Qwen3-14b的两倍以上。结果显示在表5中，我们可以得出以下结论。

- (1) 与类似大小的模型相比，在所有15个基准上，QWEN3-14B基础的性能明显优于QWEN2.5-14B-base和Gemma-3-12b-base。
- (2) 类似地，与QWEN2.5-32B基本相比，QWEN3-14B基础也获得了非常具竞争力的结果，而参数的一半却少于一半。
- (3) QWEN3-30B-A3B只有1/5个激活的非安装参数，在所有任务上都显着优于QWEN2.5-14B基本，并且在QWEN3-14B-BASE和QWEN2.5-32B基础上的表现可比性可比性可比性，从而带来了巨大的优势，从而带来了我们的优势和培训成本。

QWEN3-8B / 4B / 1.7B / 0.6B基准用于边缘型号，我们将相似大小的Qwen2.5，Llama-3和Gemma-3基本模型作为基准。结果可以在表6，表7和表8中看到。所有QWEN3 8B / 4B / 1.7B / 0.6B基本模型继续在几乎所有基准测试中都保持强劲的性能。值得注意的是，QWEN3-8B / 4B / 1.7B基本模型甚至超过较大的QWEN 2.5-14B / 7B / 3B基本模型在超过一半的基准分析上，尤其是在与STEM相关的基准和编码基准上，反映了QWEN3模型的显着改善。

4训练后

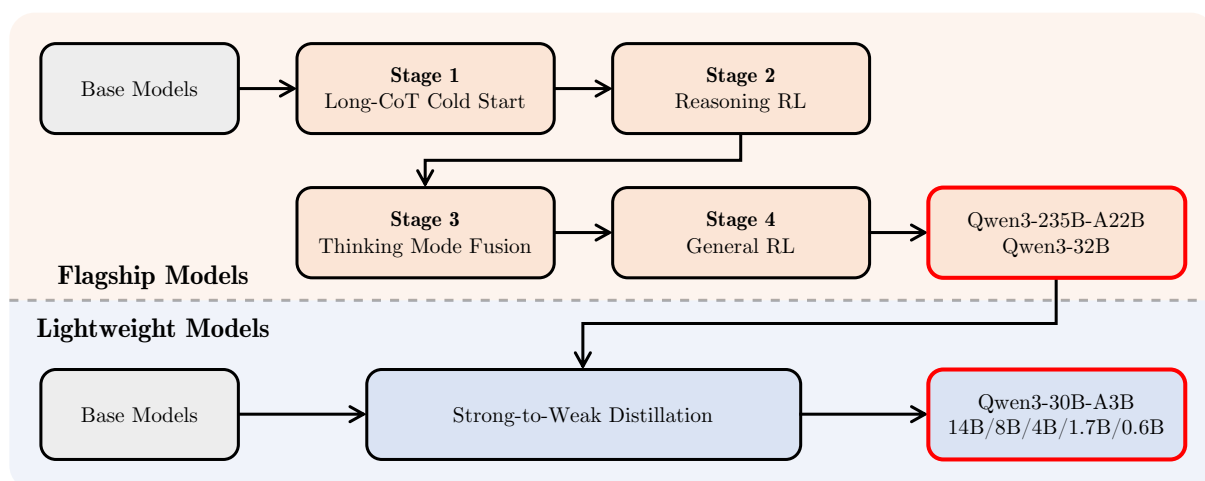


图1：QWEN3系列模型的训练后管道。

The post-training pipeline of Qwen3 is strategically designed with two core objectives:

- (1) **Thinking Control:** This involves the integration of two distinct modes, namely the “non-thinking” and “thinking” modes, providing users with the flexibility to choose whether the model should engage in reasoning or not, and to control the depth of thinking by specifying a token budget for the thinking process.
- (2) **Strong-to-Weak Distillation:** This aims to streamline and optimize the post-training process for lightweight models. By leveraging the knowledge from large-scale models, we substantially reduce both the computational costs and the development efforts required for building smaller-scale models.

As illustrated in Figure 1, the flagship models in the Qwen3 series follow a sophisticated four-stage training process. The first two stages focus on developing the models’ “thinking” abilities. The next two stages aim to integrate strong “non-thinking” functionalities into the models.

Preliminary experiments suggest that directly distilling the output logits from teacher models into lightweight student models can effectively enhance their performance while maintaining fine-grained control over their reasoning processes. This approach eliminates the necessity of performing an exhaustive four-stage training process individually for every small-scale model. It leads to better immediate performance, as indicated by higher Pass@1 scores, and also improves the model’s ability of exploration, as reflected in improved Pass@64 results. In addition, it achieves these gains with much greater training efficiency, requiring only 1/10 of the GPU hours compared to the four-stage training method.

In the following sections, we present the four-stage training process and provide a detailed explanation of the Strong-to-Weak Distillation approach.

4.1 Long-CoT Cold Start

We begin by curating a comprehensive dataset that spans a wide range of categories, including math, code, logical reasoning, and general STEM problems. Each problem in the dataset is paired with verified reference answers or code-based test cases. This dataset serves as the foundation for the “cold start” phase of long Chain-of-Thought (long-CoT) training.

The dataset construction involves a rigorous two-phase filtering process: query filtering and response filtering. In the query filtering phase, we use Qwen2.5-72B-Instruct to identify and remove queries that are not easily verifiable. This includes queries containing multiple sub-questions or those asking for general text generation. Furthermore, we exclude queries that Qwen2.5-72B-Instruct can answer correctly without using CoT reasoning. This helps prevent the model from relying on superficial guessing and ensures that only complex problems requiring deeper reasoning are included. Additionally, we annotate each query’s domain using Qwen2.5-72B-Instruct to maintain balanced domain representation across the dataset.

After reserving a validation query set, we generate N candidate responses for each remaining query using QwQ-32B (Qwen Team, 2025). When QwQ-32B consistently fails to generate correct solutions, human annotators manually assess the accuracy of the responses. For queries with positive Pass@ N , further stringent filtering criteria are applied to remove responses that (1) yield incorrect final answers, (2) contain substantial repetition, (3) clearly indicate guesswork without adequate reasoning, (4) exhibit inconsistencies between the thinking and summary contents, (5) involve inappropriate language mixing or stylistic shifts, or (6) are suspected of being overly similar to potential validation set items. Subsequently, a carefully selected subset of the refined dataset is used for the initial cold-start training of the reasoning patterns. The objective at this stage is to instill foundational reasoning patterns in the model without overly emphasizing immediate reasoning performance. This approach ensures that the model’s potential is not limited, allowing for greater flexibility and improvement during the subsequent reinforcement learning (RL) phase. To achieve this objective effectively, it is preferable to minimize both the number of training samples and the training steps during this preparatory phase.

4.2 Reasoning RL

The query-verifier pairs used in the Reasoning RL stage must satisfy the following four criteria: (1) They were not used during the cold-start phase. (2) They are learnable for the cold-start model. (3) They are as challenging as possible. (4) They cover a broad range of sub-domains. We ultimately collect a total of 3,995 query-verifier pairs, and employed GRPO (Shao et al., 2024) to update the model parameters. We observe that using a large batch size and a high number of rollouts per query, along with off-policy training to improve sample efficiency, is beneficial to the training process. We have also addressed how to balance exploration and exploitation by controlling the model’s entropy to increase steadily or remain

QWEN3的训练后管道在战略上设计了两个核心目标：

(1) 思考控制：这涉及两种不同的模式的集成，即“无思想”和“思考”模式，使用户可以灵活地选择该模型是否应参与推理，并通过为思维过程指定标志性预算来控制思维的深度。

(2) 强到潜在的蒸馏：这旨在简化和优化轻质模型的训练后过程。通过利用大型模型的知识，我们大大减少了构建较小规模模型所需的计算成本和开发工作。

如图1所示，QWEN3系列中的旗舰模型遵循复杂的四阶段训练过程。前两个阶段的重点是开发模型的“思考”能力。接下来的两个阶段旨在将强大的“无思考”功能整合到模型中。

初步实验表明，将输出逻辑从教师模型直接提炼为轻量级学生模型可以有效地提高其性能，同时保持对推理过程的细粒度控制。这种方法消除了每个小规模模型单独执行详尽的四阶段训练过程的必要性。如较高的传球@1分数所表明的那样，它可以提高即时性能，并提高模型的勘探能力，如改进的Pass@64结果所反映的。此外，它以更高的训练效率实现了这些收益，与四阶段训练方法相比，GPU小时仅需要1/10。

在以下各节中，我们介绍了四个阶段的训练过程，并提供了对强对准蒸馏方法的详细说明。

4.1 长点冷启动

我们首先策划一个跨越广泛类别的全面数据集，包括数学，代码，逻辑推理和一般的茎问题。数据集中的每个问题与已验证的参考答案或基于代码的测试用例配对。该数据集是长期思想链（长时间）培训的“冷启动”阶段的基础。

数据集构造涉及严格的两阶段过滤过程：查询过滤和响应过滤。在查询过滤阶段，我们使用QWEN2.5-72B - 教学来识别和删除不容易验证的查询。这包括包含多个子问题或要求一般文本生成的查询。此外，我们排除了QWEN2.5-72B-INSTRUCTION可以正确回答而无需使用COT推理的问题。这有助于防止模型依靠表面的猜测，并确保仅包括需要更深入推理的复杂问题。此外，我们使用QWEN2.5-72B教学来注释每个查询的域，以维护整个数据集的平衡域表示。

保留验证查询集后，我们使用QWQ-32B（QWEN Team, 2025）为每个剩余查询生成N候选响应。当QWQ-32B始终无法生成正确的解决方案时，人体注释者手动评估响应的准确性。对于积极通过@N的查询，应用进一步的严格过滤标准来删除（1）产生不正确的最终答案的答案，（2）包含实质性重复，（3）明确表示猜测，（3）没有适当的推理，（4）在思维和总体上涉及不适当的语言之间的不适当范围，（4）涉及到不适当的语言，（5）涉及到不适当的范围，（5）涉及到不适当的范围，（5）验证集项目。随后，精心选择的精制数据集的子集用于推理模式的初始冷启动训练。此阶段的目的是在模型中灌输基本的推理模式，而不会过分强调直接的推理性能。这种方法可确保模型的潜力不受限制，从而在随后的强化学习（RL）阶段可以更大的灵活性和提高。为了有效地实现这一目标，最好将训练样本的数量和训练步骤最小化。

4.2 推理RL

在推理RL阶段中使用的查询佛教配对必须满足以下四个标准：（1）在寒冷阶段未使用它们。（2）对于冷启动模型来说，它们是可以学习的。（3）他们尽可能具有挑战性。（4）它们涵盖了广泛的子域。最终，我们总共收集了3,995个查询驱动程序对，并使用GRPO（Shao等，2024）来更新模型参数。我们观察到，使用较大的批量尺寸和每个查询的大量推出，以及可提高样品效率的额外培训，对培训过程有益。我们还通过控制模型的熵来稳定增加或保持

Table 9: **Examples of SFT data for thinking and non-thinking modes during the thinking mode fusion stage.** For the thinking mode, the `/think` flag can be omitted since it represents the default behavior. This feature has been implemented in the chat template¹ supported by the Hugging Face’s tokenizer, where the thinking mode can be disabled using an additional parameter `enable_thinking=False`.

Thinking Mode	Non-Thinking Mode
<code>< im_start >user</code> <code>{query} /think< im_end ></code> <code>< im_start >assistant</code> <code><think></code> <code>{thinking-content}</code> <code></think></code> <code>{response}< im_end ></code>	<code>< im_start >user</code> <code>{query} /no_think< im_end ></code> <code>< im_start >assistant</code> <code><think></code> <code></think></code> <code>{response}< im_end ></code>

stable, which is crucial for maintaining stable training. As a result, we achieve consistent improvements in both training reward and validation performance over the course of a single RL run, without any manual intervention on hyperparameters. For instance, the AIME’24 score of the Qwen3-235B-A22B model increases from 70.1 to 85.1 over a total of 170 RL training steps.

4.3 Thinking Mode Fusion

The goal of the Thinking Mode Fusion stage is to integrate the “non-thinking” capabilities into the previously developed “thinking” model. This approach allows developers to manage and control reasoning behaviors, while also reducing the cost and complexity of deploying separate models for thinking and non-thinking tasks. To achieve this, we conduct continual supervised fine-tuning (SFT) on the Reasoning RL model and design a chat template to fuse the two modes. Moreover, we find that models capable of handling both modes proficiently perform consistently well under different thinking budgets.

Construction of SFT data. The SFT dataset combines both the “thinking” and “non-thinking” data. To ensure that the performance of the Stage 2 model is not compromised by the additional SFT, the “thinking” data is generated via rejection sampling on Stage 1 queries using the Stage 2 model itself. The “non-thinking” data, on the other hand, is carefully curated to cover a diverse range of tasks, including coding, mathematics, instruction-following, multilingual tasks, creative writing, question answering, and role-playing. Additionally, we employ automatically generated checklists for assessing the response quality of “non-thinking” data. To enhance the performance on tasks with low-resource languages, we particularly increase the proportion of translation tasks.

Chat Template Design. To better integrate the two modes and enable users to dynamically switch the model’s thinking process, we design chat templates for Qwen3, as shown in Table 9. Specifically, for samples in thinking mode and non-thinking mode, we introduce `/think` and `/no_think` flags in the user query or system message, respectively. This allows the model to follow the user’s input and select the appropriate thinking mode accordingly. For non-thinking mode samples, we retain an empty thinking block in the assistant’s response. This design ensures internal format consistency within the model and allows developers to prevent the model from engaging in thinking behavior by concatenating an empty think block in the chat template. By default, the model operates in thinking mode; therefore, we add some thinking mode training samples where the user queries do not include `/think` flags. For more complex multi-turn dialogs, we randomly insert multiple `/think` and `/no_think` flags into users’ queries, with the model response adhering to the last flag encountered.

Thinking Budget. An additional advantage of Thinking Mode Fusion is that, once the model learns to respond in both non-thinking and thinking modes, it naturally develops the ability to handle intermediate cases—generating responses based on incomplete thinking. This capability lays the foundation for implementing budget control over the model’s thinking process. Specifically, when the length of the model’s thinking reaches a user-defined threshold, we manually halt the thinking process and insert the stop-thinking instruction: “Considering the limited time by the user, I have to give the solution based on the thinking directly now.\n</think>.\n\n”. After this instruction is inserted, the model proceeds to generate a final response based on its accumulated reasoning up to that point. It is worth noting that this ability is not explicitly trained but emerges naturally as a result of applying Thinking Mode Fusion.

表9：在思维模式融合阶段，用于思考和非思维模式的SFT数据的示例。对于思考模式，可以省略/ think标志，因为它表示默认行为。此功能已在聊天模板¹中实现，由拥抱面的令牌支持，可以使用附加参数 enable_thinking=False禁用思维模式。

Thinking Mode	Non-Thinking Mode
< im_start >user {query} /think< im_end > < im_start >assistant <think> {thinking_content} </think> {response}< im_end >	< im_start >user {query} /no_think< im_end > < im_start >assistant <think> </think> {response}< im_end >

稳定，这对于维持稳定的培训至关重要。结果，我们在一次RL运行过程中，无需对超参数的任何手动干预，我们就可以在培训奖励和验证绩效方面进行一致的改进。例如，在170 RL训练步骤中，QWEN3-235 B-A22B模型的Aime’ 24分数从70.1增加到85.1。

4.3思维模式融合

思维模式融合阶段的目标是将“无思考”功能集成到先前开发的“思维”模型中。这种方法使开发人员可以管理和控制推理行为，同时还降低了部署单独的思维和无思想任务模型的成本和复杂性。为了实现这一目标，我们对推理RL模型进行了连续监督的微调（SFT），并设计一个聊天模板以融合两种模式。此外，我们发现能够在不同的思维预算下能够熟练地处理两种模式的模型。

SFT数据的构建。SFT数据集结合了“思考”和“非思维”数据。为了确保阶段2模型的性能不会受到其他SFT的损害，使用阶段2模型本身在阶段1查询上进行拒绝采样生成“思考”数据。另一方面，对“无思考”数据进行了仔细的策划，以涵盖各种任务，包括编码，数学，跟随指导，多语言任务，创意写作，问题答案和角色扮演。此外，我们采用自动生成的清单来评估“无思考”数据的响应质量。为了提高低资源语言的任务的性能，我们特别增加了翻译任务的比例。

聊天模板设计。为了更好地整合这两种模式并使用户能够动态切换模型的思维过程，我们为QWEN3设计聊天模板，如表9所示。具体来说，对于思维模式和非思想模式的样本，我们分别介绍了/ think和/ think和/ no_think flag在用户查询或系统消息中。这使模型可以遵循用户的输入并相应地选择适当的思维模式。对于非思维模式样本，我们在助手的回应中保留一个空的思维块。该设计确保了模型内部格式的一致性，并允许开发人员通过在聊天模板中加成空的思想块来防止模型参与思考行为。默认情况下，模型在思维模式下运行；因此，我们添加了一些思维模式培训样本，其中用户查询不包括/ think标志。对于更复杂的多转话对话框，我们将多个/ think和/ no_think标志随机插入用户的查询中，并符合遇到最后一个标志的模型响应。

思维预算。思考模式融合的另一优点是，一旦模型学会了以非思维方式和思考模式做出响应，它自然会发展出处理中间情况的能力 - 基于不完整的思维而产生响应。该能力为对模型的思维过程实施预算控制奠定了基础。具体而言，当模型思维的长度达到用户定义的阈值时，我们会手动停止思维过程并插入停止思维的指令：“Considering the limited time by the user, I have to give the solution based on the thinking directly now.\n</think>.\n\n”。插入此指令后，该模型将根据其累积的推理产生最终响应。值得注意的是，这种能力没有明确训练，而是由于应用思维模式融合而自然出现的。

4.4 General RL

The General RL stage aims to broadly enhance the models’ capabilities and stability across diverse scenarios. To facilitate this, we have established a sophisticated **reward system** covering **over 20 distinct tasks**, each with customized scoring criteria. These tasks specifically target enhancements in the following core capabilities:

- **Instruction Following:** This capability ensures that models accurately interpret and follow user instructions, including requirements related to content, format, length, and the use of structured output, delivering responses that align with user expectations.
- **Format Following:** In addition to explicit instructions, we expect the model to adhere to specific formatting conventions. For instance, it should respond appropriately to the `/think` and `/no.think` flags by switching between thinking and non-thinking modes, and consistently use designated tokens (e.g., `<think>` and `</think>`) to separate the thinking and response parts in the final output.
- **Preference Alignment:** For open-ended queries, preference alignment focuses on improving the model’s helpfulness, engagement, and style, ultimately delivering a more natural and satisfying user experience.
- **Agent Ability:** This involves training the model to correctly invoke tools via designated interfaces. During the RL rollout, the model is allowed to perform complete multi-turn interaction cycles with real environment execution feedback, thereby improving its performance and stability in long-horizon decision-making tasks.
- **Abilities for Specialized Scenarios:** In more specialized scenarios, we design tasks tailored to the specific context. For example, in Retrieval-Augmented Generation (RAG) tasks, we incorporate reward signals to guide the model toward generating accurate and contextually appropriate responses, thereby minimizing the risk of hallucination.

To provide feedback for the aforementioned tasks, we utilized three distinct types of rewards:

- (1) **Rule-based Reward:** The rule-based reward has been widely used in the reasoning RL stage, and is also useful for general tasks such as instruction following (Lambert et al., 2024) and format adherence. Well-designed rule-based rewards can assess the correctness of model outputs with high precision, preventing issues like reward hacking.
- (2) **Model-based Reward with Reference Answer:** In this approach, we provide a reference answer for each query and prompt Qwen2.5-72B-Instruct to score the model’s response based on this reference. This method allows for more flexible handling of diverse tasks without requiring strict formatting, avoiding false negatives that can occur with purely rule-based rewards.
- (3) **Model-based Reward without Reference Answer:** Leveraging human preference data, we train a reward model to assign scalar scores to model responses. This approach, which does not depend on a reference answer, can handle a broader range of queries while effectively enhancing the model’s engagement and helpfulness.

4.5 Strong-to-Weak Distillation

The Strong-to-Weak Distillation pipeline is specifically designed to optimize lightweight models, encompassing 5 dense models (Qwen3-0.6B, 1.7B, 4B, 8B, and 14B) and one MoE model (Qwen3-30B-A3B). This approach enhances model performance while effectively imparting robust mode-switching capabilities. The distillation process is divided into two primary phases:

- (1) **Off-policy Distillation:** At this initial phase, we combine the outputs of teacher models generated with both `/think` and `/no.think` modes for response distillation. This helps lightweight student models develop basic reasoning skills and the ability to switch between different modes of thinking, laying a solid foundation for the next on-policy training phase.
- (2) **On-policy Distillation:** In this phase, the student model generates on-policy sequences for fine-tuning. Specifically, prompts are sampled, and the student model produces responses in either `/think` or `/no.think` mode. The student model is then fine-tuned by aligning its logits with those of a teacher model (Qwen3-32B or Qwen3-235B-A22B) to minimize the KL divergence.

4.6 Post-training Evaluation

To comprehensively evaluate the quality of instruction-tuned models, we adopted automatic benchmarks to assess model performance under both thinking and non-thinking modes. These benchmarks are

4.4一般RL

一般的RL阶段旨在广泛地增强模型的能力和稳定性。为了促进这一点，我们建立了一个复杂的奖励系统，涵盖了20多个不同的任务，每个任务都具有定制的评分标准。这些任务在以下核心功能中专门针对增强功能：

- 指令以下：此功能可确保模型准确解释和遵循用户说明，包括与内容，格式，长度和结构化输出使用相关的要求，并提供与用户期望相符的响应。
- 格式以下：除了明确的说明外，我们还希望该模型遵守特定的格式约定。例如，它应该通过在思维和非思想模式之间切换/`think`和/`no_think`标志，并始终使用指定的令牌（例如`<think>`和`</think>`）来分离最终输出中的思维和响应零件。
- 偏好一致性：对于开放式查询，偏好对齐侧重于改善模型的帮助，参与度和风格，最终提供更自然和令人满意的用户体验。
- 代理能力：这涉及训练模型通过指定接口正确调用工具。在RL推出期间，允许模型使用真实的环境执行反馈执行完整的多转交互周期，从而改善了长距离决策任务的性能和稳定性。
- 专业场景的能力：在更专业的方案中，我们设计了针对特定上下文的任务。例如，在检索功能的生成（RAG）任务中，我们合并了奖励信号，以指导模型产生准确且上下文适当的响应，从而最大程度地减少了幻觉的风险。

为了提供上述任务的反馈，我们利用了三种不同类型的奖励：

（1）基于规则的奖励：基于规则的奖励已被广泛用于推理RL阶段，并且对于诸如教学之类的一般任务（Lambert等，2024）和格式依从性等一般任务也很有用。精心设计的基于规则的奖励可以以高精度评估模型输出的正确性，从而防止奖励黑客攻击。（2）基于参考的基于模型的奖励：在这种方法中，我们为每个查询提供一个参考答案，并提示QWEN2.5-72B-INSTRUCTION，根据此参考为模型的响应评分。此方法允许在不需要严格格式的情况下更灵活地处理各种任务，避免使用纯粹基于规则的奖励发生的虚假负面因素。（3）基于模型的奖励没有参考答案：利用人类偏好数据，我们训练奖励模型，将标量分数分配给模型响应。这种不取决于参考答案的方法可以处理更广泛的查询，同时有效地增强了模型的参与度和帮助。

4.5强到蒸馏蒸馏

强驾驶的蒸馏管线是专门设计的，可以优化轻巧的型号，包括5个密集的型号（Qwen3-0.6b, 1.7b, 1.7b, 4b, 4b, 8b和14b）和一个MOE模型（QWEN3-30B-A3B）。这种方法增强了模型性能，同时有效地传达了强大的模式转换功能。蒸馏过程分为两个主要阶段：

（1）非政策蒸馏：在此初始阶段，我们将生成的教师模型的输出与/`think`和/`no_think`模式一起生成的响应蒸馏。这有助于轻巧的学生模型发展基本的推理技能以及在不同的思维方式之间切换的能力，为下一个政策培训阶段奠定了坚实的基础。（2）上蒸馏：在此阶段，学生模型会生成用于微调的式序列。具体来说，提示进行采样，学生模型在/`think`或/`no_think`模式下产生响应。然后，通过将其逻辑与教师模型（QWEN3-32B或QWEN3-235B-A22B）保持一致，以微调学生模型，以最大程度地减少KL差异。

4.6训练后评估

为了全面评估教学调整模型的质量，我们采用了自动基准来评估在思维和非思考模式下的模型性能。这些基准是

Table 10: **Multilingual benchmarks and the included languages.** The languages are identified in IETF language tags.

Benchmark	# Langs	Languages
Multi-IF	8	en, es, fr, hi, it, pt, ru, zh
INCLUDE	44	ar, az, be, bg, bn, de, el, es, et, eu, fa, fi, fr, he, hi, hr, hu, hy, id, it, ja, ka, kk, ko, lt, mk, ml, ms, ne, nl, pl, pt, ru, sq, sr, ta, te, tl, tr, uk, ur, uz, vi, zh
MMMLU	14	ar, bn, de, en, es, fr, hi, id, it, ja, ko, pt, sw, zh
MT-AIME2024	55	af, ar, bg, bn, ca, cs, cy, da, de, el, en, es, et, fa, fi, fr, gu, he, hi, hr, hu, id, it, ja, kn, ko, lt, lv, mk, ml, mr, ne, nl, no, pa, pl, pt, ro, ru, sk, sl, so, sq, sv, sw, ta, te, th, tl, tr, uk, ur, vi, zh-Hans, zh-Hant
PolyMath	18	ar, bn, de, en, es, fr, id, it, ja, ko, ms, pt, ru, sw, te, th, vi, zh
MLogiQA	10	ar, en, es, fr, ja, ko, pt, th, vi, zh

categorized into several dimensions:

- **General Tasks:** We utilize benchmarks including MMLU-Redux (Gema et al., 2024), GPQA-Diamond (Rein et al., 2023), C-Eval (Huang et al., 2023), and LiveBench (2024-11-25) (White et al., 2024). For GPQA-Diamond, we sample 10 times for each query and report the averaged accuracy.
- **Alignment Tasks:** To evaluate how well the model aligns with human preferences, we employ a suite of specialized benchmarks. For instruction-following performance, we report the strict-prompt accuracy of IFEval (Zhou et al., 2023). To assess alignment with human preferences on general topics, we utilize Arena-Hard (Li et al., 2024) and AlignBench v1.1 (Liu et al., 2023b). For writing tasks, we rely on Creative Writing V3 (Paech, 2024) and WritingBench (Wu et al., 2025) to evaluate the model’s proficiency and creativity.
- **Math & Text Reasoning:** For evaluating mathematical and logical reasoning skills, we employ high-level math benchmarks including MATH-500 (Lightman et al., 2023), AIME’24 and AIME’25 (AIME, 2025), and text reasoning tasks including ZebraLogic (Lin et al., 2025) and AutoLogi (Zhu et al., 2025). For AIME problems, each year’s questions include Part I and Part II, totaling 30 questions. For each question, we sample 64 times and take the average accuracy as the final score.
- **Agent & Coding:** To test the model’s proficiency in coding and agent-based tasks, we use BFCL v3 (Yan et al., 2024), LiveCodeBench (v5, 2024.10-2025.02) (Jain et al., 2024), and Codeforces Ratings from CodeElo (Quan et al., 2025). For BFCL, all Qwen3 models are evaluated using the FC format, and yarn was used to deploy the models to a context length of 64k for Multi-Turn evaluation. Some baselines are derived from the BFCL leaderboard, taking the higher scores between FC and Prompt formats. For models not reported on the leaderboard, the Prompt formats are evaluated. For LiveCodeBench, for the non-thinking mode, we use the officially recommended prompt, while for the thinking mode, we adjust the prompt template to allow the model to think more freely, by removing the restriction `You will not return anything except for the program.` To evaluate the performance gap between models and competitive programming experts, we use CodeForces to calculate Elo ratings. In our benchmark, each problem is solved by generating up to eight independent reasoning attempts.
- **Multilingual Tasks:** For multilingual capabilities, we evaluate four kinds of tasks: instruction following, knowledge, mathematics, and logical reasoning. Instruction following is assessed using Multi-IF (He et al., 2024), which focuses on 8 key languages. Knowledge assessment consisted of two types: regional knowledge evaluated through INCLUDE (Romanou et al., 2024), covering 44 languages, and general knowledge assessed with MMMLU (OpenAI, 2024) across 14 languages, excluding the unoptimized Yoruba language; for these two benchmarks, we sample only 10% of the original data to improve evaluation efficiency. The mathematics task employ MT-AIME2024 (Son et al., 2025), encompassing 55 languages, and PolyMath (Wang et al., 2025), which includes 18 languages. Logical reasoning is evaluated using MlogiQA, covering 10 languages, sourced from Zhang et al. (2024).

For all Qwen3 models in the thinking mode, we utilize a sampling temperature of 0.6, a top-p value of 0.95, and a top-k value of 20. Additionally, for Creative Writing v3 and WritingBench, we apply a presence penalty of 1.5 to encourage the generation of more diverse content. For Qwen3 models in the non-thinking mode, we configure the sampling hyperparameters with temperature = 0.7, top-p = 0.8, top-k = 20, and presence penalty = 1.5. For both the thinking and non-thinking modes, we set the max output length to 32,768 tokens, except AIME’24 and AIME’25 where we extend this length to 38,912 tokens to provide sufficient thinking space.

表10: 多语言基准和随附的语言。这些语言是在IETF语言标签中标识的。

Benchmark	# Langs	Languages
Multi-IF	8	en, es, fr, hi, it, pt, ru, zh
INCLUDE	44	ar, az, be, bg, bn, de, el, es, et, eu, fa, fi, fr, he, hi, hr, hu, hy, id, it, ja, ka, kk, ko, lt, mk, ml, ms, ne, nl, pl, pt, ru, sq, sr, ta, te, tl, tr, uk, ur, uz, vi, zh
MMMLU	14	ar, bn, de, en, es, fr, hi, id, it, ja, ko, pt, sw, zh
MT-AIME2024	55	af, ar, bg, bn, ca, cs, cy, da, de, el, en, es, et, fa, fi, fr, gu, he, hi, hr, hu, id, it, ja, kn, ko, lt, lv, mk, ml, mr, ne, nl, no, pa, pl, pt, ro, ru, sk, sl, so, sq, sv, sw, ta, te, th, tl, tr, uk, ur, vi, zh-Hans, zh-Hant
PolyMath	18	ar, bn, de, en, es, fr, id, it, ja, ko, ms, pt, ru, sw, te, th, vi, zh
MLogiQA	10	ar, en, es, fr, ja, ko, pt, th, vi, zh

分为几个维度：

- 一般任务：我们利用包括MMLU-REDUX（Gema等，2024），GPQA-Diamond（Rein等，2023），C-Eval（Huang等，2023）和LiveBench（2024-11-25）（2024-11-25）（White等，2024）。对于GPQA-Diamond，我们为每个查询采样10次，并报告平均准确性。
- 一致性任务：为了评估该模型与人类偏好的一致性如何，我们采用了一套专门的基准测试。对于跟随指导性的性能，我们报告了IFEVAL的严格及时准确性（Zhou等，2023）。为了评估与人类对一般主题的偏好的一致性，我们利用竞技场（Li等，2024）和Alignbench v1.1（Liu等，2023b）。为了写作任务，我们依靠创意写作V3（Paech，2024）和写作Bench（Wu等，2025）来评估模型的熟练程度和创造力。
- 数学和文本推理：为了评估数学和逻辑推理技能，我们采用了高水平的数学基准，包括Math-500（Lightman等，2023），Aime’ 24和Aime’ 24和Aime’ 25（Aime，2025），以及文本推理任务，包括ZebraLogic（包括ZebraLogic）（Lin等，2025）和Autalogie（2025）和2025。对于AIME问题，每年的问题包括第一部分和第二部分，总共30个问题。对于每个问题，我们采样64次，并将平均准确度作为最终得分。
- 代理和编码：为了测试模型在编码和基于代理的任务方面的熟练程度，我们使用BFCL V3（Yan等，2024），LiveCodeBench（V5，2024.10-2025.02）（Jain等，2024），以及Codeelo（Quan等，20225）的CodeForces等级。对于BFCL，使用FC格式评估所有QWEN3模型，并使用纱线将模型部署到64K的上下文长度进行多转化评估。一些基线源自BFCL排行榜，在FC和及时格式之间取得更高的分数。对于未在排行榜上报告的模型，评估了及时格式。对于LiveCodeBench，对于非思考模式，我们使用正式推荐的提示，而对于思考模式，我们调整了提示模板，以允许模型通过删除限制You will not return anything except for the program来更自由地思考。为了评估模型和竞争性编程专家之间的性能差距，我们使用CodeForces来计算ELO评分。在我们的基准中，通过产生多达八次独立推理尝试来解决每个问题。
- 多语言任务：对于多语言功能，我们评估了四种任务：指令以下，知识，数学和逻辑推理。使用Multif（He等，2024）评估以下指令，该指令重点介绍了8种关键语言。知识评估由两种类型组成：通过Inclubence（Romanou等，2024）评估的区域知识，涵盖了44种语言，以及用MMMLU（OpenAI，2024）评估的14种语言评估的一般知识，不包括未取代的Yoruba语言；对于这两个基准，我们仅采样了原始数据的10%以提高评估效率。数学任务采用了MT-AIME2024（Son等，2025），包括55种语言和Polymath（Wang等，2025），其中包括18种语言。使用Mlogiqa评估逻辑推理，涵盖了Zhang等人的10种语言。（2024）。

对于以思考模式下的所有QWEN3模型，我们使用0.6的采样温度为0.6，TOP-P值为0.95，TOP-K值为20。此外，对于创意写作V3和Writingbench，我们将其施加1.5的存在惩罚来鼓励生成更多多样化的内容。对于在非思考模式下的QWEN3模型，我们以温度= 0.7，top-p = 0.8，top-k = 20和存在惩罚= 1.5配置采样超参数。对于思维和非思想模式，我们将最大输出长度设置为32,768个令牌，除了Aime’ 24和Aime’ 25，我们将此长度扩展到38,912代币，以提供足够的思维空间。

Table 11: Comparison among Qwen3-235B-A22B (Thinking) and other reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		OpenAI-o1	DeepSeek-R1	Grok-3-Beta (Think)	Gemini2.5-Pro	Qwen3-235B-A22B
	Architecture	-	MoE	-	-	MoE
	# Activated Params	-	37B	-	-	22B
	# Total Params	-	671B	-	-	235B
General Tasks	MMLU-Redux	92.8	<u>92.9</u>	-	93.7	92.7
	GPQA-Diamond	78.0	71.5	<u>80.2</u>	84.0	71.1
	C-Eval	85.5	91.8	-	82.9	<u>89.6</u>
	LiveBench 2024-11-25	75.7	71.6	-	82.4	<u>77.1</u>
Alignment Tasks	IFEval strict prompt	92.6	83.3	-	89.5	83.4
	Arena-Hard	92.1	92.3	-	96.4	<u>95.6</u>
	AlignBench v1.1	8.86	8.76	-	9.03	<u>8.94</u>
	Creative Writing v3	81.7	85.5	-	86.0	84.6
	WritingBench	7.69	7.71	-	8.09	<u>8.03</u>
Math & Text Reasoning	MATH-500	96.4	97.3	-	98.8	<u>98.0</u>
	AIME'24	74.3	79.8	83.9	92.0	<u>85.7</u>
	AIME'25	79.2	70.0	77.3	86.7	<u>81.5</u>
	ZebraLogic	<u>81.0</u>	78.7	-	87.4	80.3
	AutoLogi	<u>79.8</u>	<u>86.1</u>	-	85.4	89.0
Agent & Coding	BFCL v3	<u>67.8</u>	56.9	-	62.9	70.8
	LiveCodeBench v5	<u>63.9</u>	64.3	<u>70.6</u>	70.4	70.7
	CodeForces (Rating / Percentile)	1891 / 96.7%	2029 / 98.1%	-	2001 / 97.9%	2056 / 98.2%
Multilingual Tasks	Multi-IF	48.8	67.7	-	77.8	71.9
	INCLUDE	<u>84.6</u>	82.7	-	85.1	78.7
	MMMLU 14 languages	88.4	86.4	-	<u>86.9</u>	84.3
	MT-AIME2024	67.4	73.5	-	<u>76.9</u>	80.8
	PolyMath	38.9	47.1	-	<u>52.2</u>	54.7
	MLogiQA	75.5	73.8	-	<u>75.6</u>	77.1

Table 12: Comparison among Qwen3-235B-A22B (Non-thinking) and other non-reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		GPT-4o -2024-11-20	DeepSeek-V3	Qwen2.5-72B -Instruct	LLaMA-4 -Maverick	Qwen3-235B-A22B
	Architecture	-	MoE	Dense	MoE	MoE
	# Activated Params	-	37B	72B	17B	22B
	# Total Params	-	671B	72B	402B	235B
General Tasks	MMLU-Redux	87.0	89.1	86.8	91.8	<u>89.2</u>
	GPQA-Diamond	46.0	59.1	49.0	69.8	<u>62.9</u>
	C-Eval	75.5	86.5	84.7	83.5	<u>86.1</u>
	LiveBench 2024-11-25	52.2	<u>60.5</u>	51.4	59.5	62.5
Alignment Tasks	IFEval strict prompt	<u>86.5</u>	86.1	84.1	86.7	83.2
	Arena-Hard	85.3	<u>85.5</u>	81.2	82.7	96.1
	AlignBench v1.1	8.42	<u>8.64</u>	7.89	7.97	8.91
	Creative Writing v3	81.1	74.0	61.8	61.3	<u>80.4</u>
	WritingBench	<u>7.11</u>	6.49	7.06	5.46	7.70
Math & Text Reasoning	MATH-500	77.2	90.2	83.6	90.6	91.2
	AIME'24	11.1	<u>39.2</u>	18.9	38.5	40.1
	AIME'25	7.6	28.8	15.0	15.9	<u>24.7</u>
	ZebraLogic	27.4	42.1	26.6	40.0	37.7
	AutoLogi	65.9	<u>76.1</u>	66.1	75.2	83.3
Agent & Coding	BFCL v3	72.5	57.6	63.4	52.9	68.0
	LiveCodeBench v5	32.7	33.1	30.7	37.2	<u>35.3</u>
	CodeForces (Rating / Percentile)	864 / 35.4%	<u>1134 / 54.1%</u>	859 / 35.0%	712 / 24.3%	1387 / 75.7%
Multilingual Tasks	Multi-IF	65.6	55.6	65.3	75.5	<u>70.2</u>
	INCLUDE	<u>78.8</u>	76.7	69.6	80.9	75.6
	MMMLU 14 languages	80.3	81.1	76.9	82.5	79.8
	MT-AIME2024	9.2	20.9	12.7	<u>27.0</u>	32.4
	PolyMath	13.7	20.4	16.9	<u>26.1</u>	27.0
	MLogiQA	57.4	58.9	59.3	<u>59.9</u>	67.6

表11: QWEN3-235B-A22B（思维）和其他推理基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		OpenAI-o1	DeepSeek-R1	Grok-3-Beta (Think)	Gemini2.5-Pro	Qwen3-235B-A22B
	Architecture	-	MoE	-	-	MoE
	# Activated Params	-	37B	-	-	22B
	# Total Params	-	671B	-	-	235B
General Tasks	MMLU-Redux	92.8	<u>92.9</u>	-	93.7	92.7
	GPQA-Diamond	78.0	71.5	<u>80.2</u>	84.0	71.1
	C-Eval	85.5	91.8	-	82.9	<u>89.6</u>
	LiveBench 2024-11-25	75.7	71.6	-	82.4	<u>77.1</u>
Alignment Tasks	IFEval strict prompt	92.6	83.3	-	89.5	83.4
	Arena-Hard	92.1	92.3	-	96.4	<u>95.6</u>
	AlignBench v1.1	8.86	8.76	-	9.03	<u>8.94</u>
	Creative Writing v3	81.7	85.5	-	86.0	84.6
	WritingBench	7.69	7.71	-	8.09	<u>8.03</u>
Math & Text Reasoning	MATH-500	96.4	97.3	-	98.8	<u>98.0</u>
	AIME'24	74.3	79.8	83.9	92.0	<u>85.7</u>
	AIME'25	79.2	70.0	<u>77.3</u>	86.7	<u>81.5</u>
	ZebraLogic	<u>81.0</u>	78.7	-	87.4	80.3
	AutoLogi	<u>79.8</u>	<u>86.1</u>	-	85.4	89.0
Agent & Coding	BFCL v3	<u>67.8</u>	56.9	-	62.9	70.8
	LiveCodeBench v5	<u>63.9</u>	64.3	<u>70.6</u>	70.4	70.7
	CodeForces (Rating / Percentile)	1891 / 96.7%	2029 / 98.1%	-	2001 / 97.9%	2056 / 98.2%
Multilingual Tasks	Multi-IF	48.8	67.7	-	77.8	71.9
	INCLUDE	<u>84.6</u>	82.7	-	85.1	78.7
	MMMLU 14 languages	88.4	86.4	-	<u>86.9</u>	84.3
	MT-AIME2024	67.4	73.5	-	<u>76.9</u>	80.8
	PolyMath	38.9	47.1	-	<u>52.2</u>	54.7
	MLogiQA	75.5	73.8	-	<u>75.6</u>	77.1

表12: QWEN3-235B-A22B（非思维）和其他非争议基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		GPT-4o -2024-11-20	DeepSeek-V3	Qwen2.5-72B -Instruct	LLaMA-4 -Maverick	Qwen3-235B-A22B
	Architecture	-	MoE	Dense	MoE	MoE
	# Activated Params	-	37B	72B	17B	22B
	# Total Params	-	671B	72B	402B	235B
General Tasks	MMLU-Redux	87.0	89.1	86.8	91.8	<u>89.2</u>
	GPQA-Diamond	46.0	59.1	49.0	69.8	<u>62.9</u>
	C-Eval	75.5	86.5	84.7	83.5	<u>86.1</u>
	LiveBench 2024-11-25	52.2	<u>60.5</u>	51.4	59.5	62.5
Alignment Tasks	IFEval strict prompt	<u>86.5</u>	86.1	84.1	86.7	83.2
	Arena-Hard	85.3	<u>85.5</u>	81.2	82.7	96.1
	AlignBench v1.1	8.42	<u>8.64</u>	7.89	7.97	8.91
	Creative Writing v3	81.1	74.0	61.8	61.3	<u>80.4</u>
	WritingBench	<u>7.11</u>	6.49	7.06	5.46	7.70
Math & Text Reasoning	MATH-500	77.2	90.2	83.6	90.6	91.2
	AIME'24	11.1	<u>39.2</u>	18.9	38.5	40.1
	AIME'25	7.6	28.8	15.0	15.9	<u>24.7</u>
	ZebraLogic	27.4	42.1	26.6	40.0	37.7
	AutoLogi	65.9	<u>76.1</u>	66.1	75.2	83.3
Agent & Coding	BFCL v3	72.5	57.6	63.4	52.9	68.0
	LiveCodeBench v5	32.7	33.1	30.7	37.2	<u>35.3</u>
	CodeForces (Rating / Percentile)	864 / 35.4%	<u>1134 / 54.1%</u>	859 / 35.0%	712 / 24.3%	1387 / 75.7%
Multilingual Tasks	Multi-IF	65.6	55.6	65.3	75.5	<u>70.2</u>
	INCLUDE	<u>78.8</u>	76.7	69.6	80.9	75.6
	MMMLU 14 languages	80.3	81.1	76.9	82.5	79.8
	MT-AIME2024	9.2	20.9	12.7	<u>27.0</u>	32.4
	PolyMath	13.7	20.4	16.9	<u>26.1</u>	27.0
	MLogiQA	57.4	58.9	59.3	<u>59.9</u>	67.6

Summary of Evaluation Results From the evaluation results, we summarize several key conclusions of the finalized Qwen3 models as follows:

- (1) Our flagship model, Qwen3-235B-A22B, demonstrates the state-of-the-art overall performance among open-source models in both the thinking and non-thinking modes, surpassing strong baselines such as DeepSeek-R1 and DeepSeek-V3. Qwen3-235B-A22B is also highly competitive to closed-source leading models, such as OpenAI-o1, Gemini2.5-Pro, and GPT-4o, showcasing its profound reasoning capabilities and comprehensive general abilities.
- (2) Our flagship dense model, Qwen3-32B, outperforms our previous strongest reasoning model, QwQ-32B, in most of the benchmarks, and performs comparably to the closed-source OpenAI-o3-mini, indicating its compelling reasoning capabilities. Qwen3-32B is also remarkably performant in the non-thinking mode and surpasses our previous flagship non-reasoning dense model, Qwen2.5-72B-Instruct.
- (3) Our lightweight models, including Qwen3-30B-A3B, Qwen3-14B, and other smaller dense ones, possess consistently superior performance to the open-source models with a close or larger amount of parameters, proving the success of our Strong-to-Weak Distillation approach.

The detailed results are as follows.

Qwen3-235B-A22B For our flagship model Qwen3-235B-A22B, we compare it with the leading reasoning and non-reasoning models. For the thinking mode, we take OpenAI-o1 (OpenAI, 2024), DeepSeek-R1 (Guo et al., 2025), Grok-3-Beta (Think) (xAI, 2025), and Gemini2.5-Pro (DeepMind, 2025) as the reasoning baselines. For the non-thinking mode, we take GPT-4o-2024-11-20 (OpenAI, 2024), DeepSeek-V3 (Liu et al., 2024a), Qwen2.5-72B-Instruct (Yang et al., 2024b), and LLaMA-4-Maverick (Meta-AI, 2025) as the non-reasoning baselines. We present the evaluation results in Table 11 and 12.

- (1) From Table 11, with only 60% activated and 35% total parameters, Qwen3-235B-A22B (Thinking) outperforms DeepSeek-R1 on 17/23 the benchmarks, particularly on the reasoning-demanded tasks (e.g., mathematics, agent, and coding), demonstrating the state-of-the-art reasoning capabilities of Qwen3-235B-A22B among open-source models. Moreover, Qwen3-235B-A22B (Thinking) is also highly competitive to the closed-source OpenAI-o1, Grok-3-Beta (Think), and Gemini2.5-Pro, substantially narrowing the gap in the reasoning capabilities between open-source and close-source models.
- (2) From Table 12, Qwen3-235B-A22B (Non-thinking) exceeds the other leading open-source models, including DeepSeek-V3, LLaMA-4-Maverick, and our previous flagship model Qwen2.5-72B-Instruct, and also surpasses the closed-source GPT-4o-2024-11-20 in 18/23 the benchmarks, indicating its inherent strong capabilities even when not enhanced with the deliberate thinking process.

Qwen3-32B For our flagship dense model, Qwen3-32B, we take DeepSeek-R1-Distill-Llama-70B, OpenAI-o3-mini (medium), and our previous strongest reasoning model, QwQ-32B (Qwen Team, 2025), as the baselines in the thinking mode. We also take GPT-4o-mini-2024-07-18, LLaMA-4-Scout, and our previous flagship model, Qwen2.5-72B-Instruct, as the baselines in the non-thinking mode. We present the evaluation results in Table 13 and 14.

- (1) From Table 13, Qwen3-32B (Thinking) outperforms QwQ-32B on 17/23 the benchmarks, making it the new state-of-the-art reasoning model at the sweet size of 32B. Moreover, Qwen3-32B (Thinking) also competes with the closed-source OpenAI-o3-mini (medium) with better alignment and multilingual performance.
- (2) From Table 14, Qwen3-32B (Non-thinking) exhibits superior performance to all the baselines on almost all the benchmarks. Particularly, Qwen3-32B (Non-thinking) performs on par with Qwen2.5-72B-Instruct on the general tasks with significant advantages on the alignment, multilingual, and reasoning-related tasks, again proving the fundamental improvements of Qwen3 over our previous Qwen2.5 series models.

Qwen3-30B-A3B & Qwen3-14B For Qwen3-30B-A3B and Qwen3-14B, we compare them with DeepSeek-R1-Distill-Qwen-32B and QwQ-32B in the thinking mode, and Phi-4 (Abdin et al., 2024), Gemma-3-27B-IT (Team et al., 2025), and Qwen2.5-32B-Instruct in the non-thinking mode, respectively. We present the evaluation results in Table 15 and 16.

- (1) From Table 15, Qwen3-30B-A3B and Qwen3-14B (Thinking) are both highly competitive to QwQ-32B, especially on the reasoning-related benchmarks. It is noteworthy that Qwen3-30B-A3B achieves comparable performance to QwQ-32B with a smaller model size and less than

评估结果的评估结果摘要，我们总结了最终QWEN3模型的几个关键结论：如下：

(1) 我们的旗舰模型QWEN3-235B-A22B在思维和非思想模式中展示了开源模型之间的最先进的整体性能，超过了诸如DeepSeek-R1和DeepSeek-V3之类的强大基线。QWEN3-235B-A22B在封闭源领先的模型中也具有很高的竞争力，例如OpenAI-O1，Gemini2.5-Pro和GPT-4O，展示了其深刻的推理能力和全面的一般能力。(2) 在大多数基准测试中，我们的旗舰密集模型QWEN3-32B优于我们先前最强的推理模型QWQ-32B，并且与封闭的OpenAI-O3-mini相当执行，表明其令人信服的推理能力。QWEN3-32B在非思考模式下也表现出色，超过了我们以前的旗舰非争议密集模型QWEN2.5-72B-Instruct。(3) 我们的轻质模型，包括QWEN3-30B-A3B，QWEN3-14B和其他较小的密集模型，其始终如一的性能超过了具有接近或更大参数的开源模型，这证明了我们强涉及的涉足蒸馏方法的成功。

详细的结果如下。

QWEN3-235B-A22B为我们的旗舰型QWEN3-235B-A22B，我们将其与主要的理由和非推理模型进行了比较。对于思考模式，我们采用OpenAI-O1 (OpenAI, 2024)，DeepSeek-R1 (Guo等, 2025)，Grok-3-Beta (Think) (Think) (XAI, 2025) 和Gemini2.5-Pro (DeepMind, 2025) 作为推理基线。对于非思维模式，我们将GPT-4O-2024-11-20 (OpenAI, 2024)，DeepSeek-V3 (Liu等, 2024a)，Qwen2.5-72b-Instruct (Yang等人, 2024b) 和Llama-4-Maverick (Meta-4-Maverick (Meta-Maibick, 2025) as Baseins as asterali nes。我们在表11和12中介绍了评估结果。

(1) From Table 11, with only 60% activated and 35% total parameters, Qwen3-235B-A22B (Thinking) outperforms DeepSeek-R1 on 17/23 the benchmarks, particularly on the reasoning-demanded tasks (e.g., mathematics, agent, and coding), demonstrating the state-of-the-art reasoning capabilities of Qwen3-235B-A22B among开源型号。此外，QWEN3-235B-A22B（思维）也与封闭源OpenAI-O1，Grok-3-beta（Think）和Gemini2.5-Pro具有高度的竞争力，从而显着缩小了开源能力和近距离源模型之间推理能力的差距。

(2) 从表12中，QWEN3-235B-A22B（非思考）超过了其他领先的开源模型，包括DeepSeek-V3，Llama-4-Maverick以及我们以前的旗舰型QWEN2.5-72B-指令，并超过了封闭式的GPT-4O-4O-204O-204-20-224-11-11-20 in 18/23 in 18/23 in nimand compandity command command compant in bench当不进行故意的思考过程中增强时。

QWEN3-32B对于我们的旗舰密集型号，QWEN3-32B，我们采用DeepSeek-R1-Distill-lalama-70B，Openai-O3-Mini（中）以及以前最强的推理模型，QWQ-32B（QWQ-32B（QWEN TEAK, 2025），作为思维模式的基础。我们还将GPT-4O-MINI-2024-07-18，LLAMA-4-SCOUT和我们的先前旗舰型号QWEN2.5-72B-Instruct作为非思维模式的基准。我们在表13和14中介绍了评估结果。

(1) 从表13中，Qwen3-32b（思维）在17/23上优于QWQ-32B，这使其成为32B的甜味大小的新的最新推理模型。此外，QWEN3-32B（思考）还与封闭源OpenAI-O3-Mini（中）竞争，具有更好的对齐和多语言性能。(2) 从表14中，Qwen3-32b（非思想）几乎所有基准的基准表现出卓越的性能。尤其是，QWEN3-32B（非思想）在一般任务上与QWEN2.5-72B的教学表现出色，在对齐，多语言和与推理相关的任务上具有显著优势，再次证明了与以前的QWEN2.5系列模型相比QWEN3的基本改进。

QWEN3-30B-A3B和QWEN3-14B用于QWEN3-30B-A3B和QWEN3-14B，我们将它们与思维模式中的DeepSeek-R1-Distill-Qwen-32B和QWQ-32B进行了比较，以及PHI-4，PHI-4 (Abdin等, 2024)，Gemma-3-3-2 7B-IT (Abdin等人)，AI-3-27b-It，AL。QWEN2.5-32B - 分别在非思考模式下。我们在表15和16中介绍了评估结果。

(1) 从表15中，QWEN3-30B-A3B和QWEN3-14B（思维）都对QWQ-32B具有很高的竞争力，尤其是在与推理相关的基准方面。值得注意的是，QWEN3-30B-A3B的性能与QWQ-32B相当，型号尺寸较小，少于

Table 13: Comparison among Qwen3-32B (Thinking) and other reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		DeepSeek-R1 -Distill-Llama-70B	QwQ-32B	OpenAI-o3-mini (medium)	Qwen3-32B
	Architecture	Dense	Dense	-	Dense
	# Activated Params	70B	32B	-	32B
	# Total Params	70B	32B	-	32B
<i>General Tasks</i>	MMLU-Redux	89.3	<u>90.0</u>	<u>90.0</u>	90.9
	GPQA-Diamond	65.2	<u>65.6</u>	76.8	<u>68.4</u>
	C-Eval	71.8	88.4	75.1	<u>87.3</u>
	LiveBench 2024-11-25	54.5	<u>72.0</u>	70.0	74.9
<i>Alignment Tasks</i>	IFEval strict prompt	79.3	83.9	91.5	<u>85.0</u>
	Arena-Hard	60.6	<u>89.5</u>	89.0	93.8
	AlignBench v1.1	6.74	<u>8.70</u>	8.38	8.72
	Creative Writing v3	62.1	82.4	74.8	<u>81.0</u>
	WritingBench	6.08	<u>7.86</u>	7.52	7.90
<i>Math & Text Reasoning</i>	MATH-500	94.5	98.0	98.0	<u>97.2</u>
	AIME'24	70.0	79.5	<u>79.6</u>	81.4
	AIME'25	56.3	69.5	74.8	<u>72.9</u>
	ZebraLogic	71.3	76.8	88.9	<u>88.8</u>
	AutoLogi	83.5	88.1	86.3	<u>87.3</u>
<i>Agent & Coding</i>	BFCL v3	49.3	<u>66.4</u>	64.6	70.3
	LiveCodeBench v5	54.5	62.7	66.3	<u>65.7</u>
	CodeForces (Rating / Percentile)	1633 / 91.4%	<u>1982 / 97.7%</u>	2036 / 98.1%	1977 / 97.7%
<i>Multilingual Tasks</i>	Multi-IF	57.6	<u>68.3</u>	48.4	73.0
	INCLUDE	62.1	69.7	<u>73.1</u>	73.7
	MMMLU 14 languages	69.6	80.9	79.3	<u>80.6</u>
	MT-AIME2024	29.3	68.0	<u>73.9</u>	75.0
	PolyMath	29.4	<u>45.9</u>	38.6	47.4
	MLogiQA	60.3	<u>75.5</u>	71.1	76.3

Table 14: Comparison among Qwen3-32B (Non-thinking) and other non-reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		GPT-4o-mini -2024-07-18	LLaMA-4 -Scout	Qwen2.5-72B -Instruct	Qwen3-32B
	Architecture	-	MoE	Dense	Dense
	# Activated Params	-	17B	72B	32B
	# Total Params	-	109B	72B	32B
<i>General Tasks</i>	MMLU-Redux	81.5	<u>86.3</u>	86.8	85.7
	GPQA-Diamond	40.2	57.2	49.0	<u>54.6</u>
	C-Eval	66.3	78.2	84.7	<u>83.3</u>
	LiveBench 2024-11-25	41.3	47.6	<u>51.4</u>	59.8
<i>Alignment Tasks</i>	IFEval strict prompt	80.4	84.7	<u>84.1</u>	83.2
	Arena-Hard	74.9	70.5	<u>81.2</u>	92.8
	AlignBench v1.1	7.81	7.49	<u>7.89</u>	8.58
	Creative Writing v3	70.3	55.0	61.8	78.3
	WritingBench	5.98	5.49	<u>7.06</u>	7.54
<i>Math & Text Reasoning</i>	MATH-500	78.2	82.6	<u>83.6</u>	88.6
	AIME'24	8.1	<u>28.6</u>	18.9	31.0
	AIME'25	8.8	10.0	<u>15.0</u>	20.2
	ZebraLogic	20.1	24.2	<u>26.6</u>	29.2
	AutoLogi	52.6	56.8	<u>66.1</u>	78.5
<i>Agent & Coding</i>	BFCL v3	64.0	45.4	<u>63.4</u>	63.0
	LiveCodeBench v5	27.9	29.8	<u>30.7</u>	31.3
	CodeForces (Rating / Percentile)	<u>1113 / 52.6%</u>	981 / 43.7%	859 / 35.0%	1353 / 71.0%
<i>Multilingual Tasks</i>	Multi-IF	62.4	64.2	<u>65.3</u>	70.7
	INCLUDE	66.0	74.1	<u>69.6</u>	<u>70.9</u>
	MMMLU 14 languages	72.1	77.5	<u>76.9</u>	76.5
	MT-AIME2024	6.0	19.1	<u>12.7</u>	24.1
	PolyMath	12.0	<u>20.9</u>	16.9	22.5
	MLogiQA	42.6	53.9	<u>59.3</u>	62.9

表13: QWEN3-32B（思维）和其他推理基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		DeepSeek-R1 -Distill-Llama-70B	QwQ-32B	OpenAI-o3-mini (medium)	Qwen3-32B
	Architecture	Dense	Dense	-	Dense
	# Activated Params	70B	32B	-	32B
	# Total Params	70B	32B	-	32B
General Tasks	MMLU-Redux	89.3	<u>90.0</u>	<u>90.0</u>	90.9
	GPQA-Diamond	65.2	<u>65.6</u>	76.8	<u>68.4</u>
	C-Eval	71.8	88.4	75.1	<u>87.3</u>
	LiveBench 2024-11-25	54.5	<u>72.0</u>	70.0	74.9
Alignment Tasks	IFEval strict prompt	79.3	83.9	91.5	<u>85.0</u>
	Arena-Hard	60.6	<u>89.5</u>	89.0	93.8
	AlignBench v1.1	6.74	<u>8.70</u>	8.38	8.72
	Creative Writing v3	62.1	82.4	74.8	<u>81.0</u>
	WritingBench	6.08	<u>7.86</u>	7.52	7.90
Math & Text Reasoning	MATH-500	94.5	98.0	98.0	<u>97.2</u>
	AIME'24	70.0	79.5	<u>79.6</u>	81.4
	AIME'25	56.3	69.5	74.8	<u>72.9</u>
	ZebraLogic	71.3	76.8	88.9	<u>88.8</u>
	AutoLogi	83.5	88.1	86.3	<u>87.3</u>
Agent & Coding	BFCL v3	49.3	<u>66.4</u>	64.6	70.3
	LiveCodeBench v5	54.5	<u>62.7</u>	66.3	<u>65.7</u>
	CodeForces (Rating / Percentile)	1633 / 91.4%	<u>1982 / 97.7%</u>	2036 / 98.1%	1977 / 97.7%
Multilingual Tasks	Multi-IF	57.6	<u>68.3</u>	48.4	73.0
	INCLUDE	62.1	69.7	<u>73.1</u>	73.7
	MMMLU 14 languages	69.6	80.9	79.3	<u>80.6</u>
	MT-AIME2024	29.3	68.0	<u>73.9</u>	75.0
	PolyMath	29.4	<u>45.9</u>	38.6	47.4
	MLogiQA	60.3	<u>75.5</u>	71.1	76.3

表14: QWEN3-32B（非思维）和其他非争议基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		GPT-4o-mini -2024-07-18	LLaMA-4 -Scout	Qwen2.5-72B -Instruct	Qwen3-32B
	Architecture	-	MoE	Dense	Dense
	# Activated Params	-	17B	72B	32B
	# Total Params	-	109B	72B	32B
General Tasks	MMLU-Redux	81.5	<u>86.3</u>	86.8	85.7
	GPQA-Diamond	40.2	57.2	49.0	<u>54.6</u>
	C-Eval	66.3	78.2	84.7	<u>83.3</u>
	LiveBench 2024-11-25	41.3	47.6	<u>51.4</u>	59.8
Alignment Tasks	IFEval strict prompt	80.4	84.7	<u>84.1</u>	83.2
	Arena-Hard	74.9	70.5	<u>81.2</u>	92.8
	AlignBench v1.1	7.81	7.49	<u>7.89</u>	8.58
	Creative Writing v3	70.3	55.0	61.8	78.3
	WritingBench	5.98	5.49	<u>7.06</u>	7.54
Math & Text Reasoning	MATH-500	78.2	82.6	<u>83.6</u>	88.6
	AIME'24	8.1	<u>28.6</u>	18.9	31.0
	AIME'25	8.8	10.0	<u>15.0</u>	20.2
	ZebraLogic	20.1	24.2	<u>26.6</u>	29.2
	AutoLogi	52.6	56.8	<u>66.1</u>	78.5
Agent & Coding	BFCL v3	64.0	45.4	<u>63.4</u>	63.0
	LiveCodeBench v5	27.9	29.8	<u>30.7</u>	31.3
	CodeForces (Rating / Percentile)	<u>1113 / 52.6%</u>	981 / 43.7%	859 / 35.0%	1353 / 71.0%
Multilingual Tasks	Multi-IF	62.4	64.2	<u>65.3</u>	70.7
	INCLUDE	66.0	74.1	<u>69.6</u>	<u>70.9</u>
	MMMLU 14 languages	72.1	77.5	<u>76.9</u>	76.5
	MT-AIME2024	6.0	19.1	<u>12.7</u>	24.1
	PolyMath	12.0	<u>20.9</u>	16.9	22.5
	MLogiQA	42.6	53.9	<u>59.3</u>	62.9

Table 15: Comparison among Qwen3-30B-A3B / Qwen3-14B (Thinking) and other reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		DeepSeek-R1 -Distill-Qwen-32B	QwQ-32B	Qwen3-14B	Qwen3-30B-A3B
	Architecture	Dense	Dense	Dense	MoE
	# Activated Params	32B	32B	14B	3B
	# Total Params	32B	32B	14B	30B
General Tasks	MMLU-Redux	88.2	90.0	88.6	<u>89.5</u>
	GPQA-Diamond	62.1	<u>65.6</u>	64.0	65.8
	C-Eval	82.2	88.4	86.2	<u>86.6</u>
	LiveBench 2024-11-25	45.6	<u>72.0</u>	71.3	74.3
Alignment Tasks	IFEval strict prompt	72.5	83.9	<u>85.4</u>	86.5
	Arena-Hard	60.8	89.5	91.7	<u>91.0</u>
	AlignBench v1.1	7.25	8.70	8.56	8.70
	Creative Writing v3	55.0	82.4	<u>80.3</u>	79.1
	WritingBench	6.13	7.86	<u>7.80</u>	7.70
Math & Text Reasoning	MATH-500	94.3	98.0	96.8	98.0
	AIME'24	72.6	<u>79.5</u>	79.3	80.4
	AIME'25	49.6	<u>69.5</u>	70.4	70.9
	ZebraLogic	69.6	76.8	<u>88.5</u>	89.5
	AutoLogi	74.6	88.1	89.2	<u>88.7</u>
Agent & Coding	BFCL v3	53.5	66.4	70.4	<u>69.1</u>
	LiveCodeBench v5	54.5	<u>62.7</u>	63.5	<u>62.6</u>
	CodeForces (Rating / Percentile)	1691 / 93.4%	1982 / 97.7%	1766 / 95.3%	<u>1974 / 97.7%</u>
Multilingual Tasks	Multi-IF	31.3	68.3	74.8	<u>72.2</u>
	INCLUDE	68.0	69.7	<u>71.7</u>	71.9
	MMMLU 14 languages	<u>78.6</u>	80.9	77.9	78.4
	MT-AIME2024	44.6	68.0	<u>73.3</u>	73.9
	PolyMath	35.1	<u>45.9</u>	45.8	46.1
	MLogiQA	63.3	75.5	<u>71.1</u>	70.1

Table 16: Comparison among Qwen3-30B-A3B / Qwen3-14B (Non-thinking) and other non-reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		Phi-4	Gemma-3 -27B-IT	Qwen2.5-32B -Instruct	Qwen3-14B	Qwen3-30B-A3B
	Architecture	Dense	Dense	Dense	Dense	MoE
	# Activated Params	14B	27B	32B	14B	3B
	# Total Params	14B	27B	32B	14B	30B
General Tasks	MMLU-Redux	85.3	82.6	83.9	82.0	<u>84.1</u>
	GPQA-Diamond	56.1	42.4	49.5	<u>54.8</u>	<u>54.8</u>
	C-Eval	66.9	66.6	80.6	<u>81.0</u>	82.9
	LiveBench 2024-11-25	41.6	49.2	50.0	59.6	<u>59.4</u>
Alignment Tasks	IFEval strict prompt	62.1	80.6	79.5	84.8	<u>83.7</u>
	Arena-Hard	75.4	<u>86.8</u>	74.5	86.3	88.0
	AlignBench v1.1	7.61	7.80	7.71	<u>8.52</u>	8.55
	Creative Writing v3	51.2	82.0	54.6	<u>73.1</u>	68.1
	WritingBench	5.73	<u>7.22</u>	5.90	7.24	<u>7.22</u>
Math & Text Reasoning	MATH-500	80.8	90.0	84.6	90.0	<u>89.8</u>
	AIME'24	22.9	<u>32.6</u>	18.8	31.7	32.8
	AIME'25	17.3	24.0	12.8	<u>23.3</u>	21.6
	ZebraLogic	32.3	24.6	26.1	<u>33.0</u>	33.2
	AutoLogi	66.2	64.2	65.5	82.0	<u>81.5</u>
Agent & Coding	BFCL v3	47.0	59.1	62.8	<u>61.5</u>	58.6
	LiveCodeBench v5	25.2	26.9	26.4	<u>29.0</u>	29.8
	CodeForces (Rating / Percentile)	1280 / 65.3%	1063 / 49.3%	903 / 38.2%	1200 / 58.6%	<u>1267 / 64.1%</u>
Multilingual Tasks	Multi-IF	49.5	69.8	63.2	72.9	<u>70.8</u>
	INCLUDE	65.3	71.4	67.5	<u>67.8</u>	<u>67.8</u>
	MMMLU 14 languages	<u>74.7</u>	76.1	74.2	72.6	73.8
	MT-AIME2024	13.1	23.0	15.3	<u>23.2</u>	24.6
	PolyMath	17.4	20.3	18.3	<u>22.0</u>	23.3
	MLogiQA	53.1	<u>58.5</u>	58.0	58.9	53.3

表15: QWEN3-30B-A3B / QWEN3-14B（思维）和其他推理基准之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		DeepSeek-R1 -Distill-Qwen-32B	QwQ-32B	Qwen3-14B	Qwen3-30B-A3B
	Architecture	Dense	Dense	Dense	MoE
	# Activated Params	32B	32B	14B	3B
	# Total Params	32B	32B	14B	30B
General Tasks	MMLU-Redux	88.2	90.0	88.6	<u>89.5</u>
	GPQA-Diamond	62.1	<u>65.6</u>	64.0	65.8
	C-Eval	82.2	88.4	86.2	<u>86.6</u>
	LiveBench 2024-11-25	45.6	<u>72.0</u>	71.3	74.3
Alignment Tasks	IFEval strict prompt	72.5	83.9	<u>85.4</u>	86.5
	Arena-Hard	60.8	89.5	91.7	<u>91.0</u>
	AlignBench v1.1	7.25	8.70	8.56	8.70
	Creative Writing v3	55.0	82.4	<u>80.3</u>	79.1
	WritingBench	6.13	7.86	<u>7.80</u>	7.70
Math & Text Reasoning	MATH-500	94.3	98.0	96.8	98.0
	AIME'24	72.6	<u>79.5</u>	79.3	80.4
	AIME'25	49.6	<u>69.5</u>	70.4	70.9
	ZebraLogic	69.6	76.8	<u>88.5</u>	89.5
	AutoLogi	74.6	88.1	89.2	<u>88.7</u>
Agent & Coding	BFCL v3	53.5	66.4	70.4	<u>69.1</u>
	LiveCodeBench v5	54.5	<u>62.7</u>	63.5	<u>62.6</u>
	CodeForces (Rating / Percentile)	1691 / 93.4%	1982 / 97.7%	1766 / 95.3%	<u>1974 / 97.7%</u>
Multilingual Tasks	Multi-IF	31.3	68.3	74.8	<u>72.2</u>
	INCLUDE	68.0	69.7	<u>71.7</u>	71.9
	MMMLU 14 languages	<u>78.6</u>	80.9	77.9	78.4
	MT-AIME2024	44.6	68.0	<u>73.3</u>	73.9
	PolyMath	35.1	<u>45.9</u>	45.8	46.1
	MLogiQA	63.3	75.5	<u>71.1</u>	70.1

表16: QWEN3-30B-A3B / QWEN3-14B（非思维）和其他非推理基准之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		Phi-4	Gemma-3 -27B-IT	Qwen2.5-32B -Instruct	Qwen3-14B	Qwen3-30B-A3B
	Architecture	Dense	Dense	Dense	Dense	MoE
	# Activated Params	14B	27B	32B	14B	3B
	# Total Params	14B	27B	32B	14B	30B
General Tasks	MMLU-Redux	85.3	82.6	83.9	82.0	<u>84.1</u>
	GPQA-Diamond	56.1	42.4	49.5	<u>54.8</u>	<u>54.8</u>
	C-Eval	66.9	66.6	80.6	<u>81.0</u>	82.9
	LiveBench 2024-11-25	41.6	49.2	50.0	59.6	<u>59.4</u>
Alignment Tasks	IFEval strict prompt	62.1	80.6	79.5	84.8	<u>83.7</u>
	Arena-Hard	75.4	<u>86.8</u>	74.5	86.3	88.0
	AlignBench v1.1	7.61	7.80	7.71	<u>8.52</u>	8.55
	Creative Writing v3	51.2	82.0	54.6	<u>73.1</u>	68.1
	WritingBench	5.73	<u>7.22</u>	5.90	7.24	<u>7.22</u>
Math & Text Reasoning	MATH-500	80.8	90.0	84.6	90.0	<u>89.8</u>
	AIME'24	22.9	<u>32.6</u>	18.8	31.7	32.8
	AIME'25	17.3	24.0	12.8	<u>23.3</u>	21.6
	ZebraLogic	32.3	24.6	26.1	<u>33.0</u>	33.2
	AutoLogi	66.2	64.2	65.5	82.0	<u>81.5</u>
Agent & Coding	BFCL v3	47.0	59.1	62.8	<u>61.5</u>	58.6
	LiveCodeBench v5	25.2	26.9	26.4	<u>29.0</u>	29.8
	CodeForces (Rating / Percentile)	1280 / 65.3%	1063 / 49.3%	903 / 38.2%	1200 / 58.6%	<u>1267 / 64.1%</u>
Multilingual Tasks	Multi-IF	49.5	69.8	63.2	72.9	<u>70.8</u>
	INCLUDE	65.3	71.4	67.5	<u>67.8</u>	<u>67.8</u>
	MMMLU 14 languages	<u>74.7</u>	76.1	74.2	72.6	73.8
	MT-AIME2024	13.1	23.0	15.3	<u>23.2</u>	24.6
	PolyMath	17.4	20.3	18.3	<u>22.0</u>	23.3
	MLogiQA	53.1	<u>58.5</u>	58.0	58.9	53.3

Table 17: Comparison among Qwen3-8B / Qwen3-4B (Thinking) and other reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		DeepSeek-R1 -Distill-Qwen-14B	DeepSeek-R1 -Distill-Qwen-32B	Qwen3-4B	Qwen3-8B
	Architecture	Dense	Dense	Dense	Dense
	# Activated Params	14B	32B	4B	8B
	# Total Params	14B	32B	4B	8B
General Tasks	MMLU-Redux	84.1	88.2	83.7	<u>87.5</u>
	GPQA-Diamond	59.1	62.1	55.9	<u>62.0</u>
	C-Eval	78.1	<u>82.2</u>	77.5	83.4
	LiveBench 2024-11-25	52.3	45.6	<u>63.6</u>	67.1
Alignment Tasks	IFEval strict prompt	72.6	72.5	<u>81.9</u>	85.0
	Arena-Hard	48.0	60.8	<u>76.6</u>	85.8
	AlignBench v1.1	7.43	7.25	<u>8.30</u>	8.46
	Creative Writing v3	54.2	55.0	<u>61.1</u>	75.0
	WritingBench	6.03	6.13	<u>7.35</u>	7.59
Math & Text Reasoning	MATH-500	93.9	94.3	<u>97.0</u>	97.4
	AIME'24	69.7	72.6	<u>73.8</u>	76.0
	AIME'25	44.5	49.6	<u>65.6</u>	67.3
	ZebraLogic	59.1	69.6	<u>81.0</u>	84.8
	AutoLogi	78.6	74.6	<u>87.9</u>	89.1
Agent & Coding	BFCL v3	49.5	53.5	<u>65.9</u>	68.1
	LiveCodeBench v5	45.5	<u>54.5</u>	<u>54.2</u>	57.5
	CodeForces (Rating / Percentile)	1574 / 89.1%	<u>1691 / 93.4%</u>	1671 / 92.8%	1785 / 95.6%
Multilingual Tasks	Multi-IF	29.8	31.3	<u>66.3</u>	71.2
	INCLUDE	59.7	68.0	61.8	<u>67.8</u>
	MMMLU 14 languages	73.8	78.6	69.8	<u>74.4</u>
	MT-AIME2024	33.7	44.6	<u>60.7</u>	65.4
	PolyMath	28.6	35.1	<u>40.0</u>	42.7
	MLogiQA	53.6	63.3	<u>65.9</u>	69.0

Table 18: Comparison among Qwen3-8B / Qwen3-4B (Non-thinking) and other non-reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		LLaMA-3.1-8B -Instruct	Gemma-3 -12B-IT	Qwen2.5-7B -Instruct	Qwen2.5-14B -Instruct	Qwen3-4B	Qwen3-8B
	Architecture	Dense	Dense	Dense	Dense	Dense	Dense
	# Activated Params	8B	12B	7B	14B	4B	8B
	# Total Params	8B	12B	7B	14B	4B	8B
General Tasks	MMLU-Redux	61.7	77.8	75.4	80.0	77.3	<u>79.5</u>
	GPQA-Diamond	32.8	40.9	36.4	45.5	41.7	39.3
	C-Eval	52.0	61.1	76.2	78.0	72.2	<u>77.9</u>
	LiveBench 2024-11-25	26.0	43.7	34.9	42.2	<u>48.4</u>	53.5
Alignment Tasks	IFEval strict prompt	75.0	80.2	71.2	81.0	<u>81.2</u>	83.0
	Arena-Hard	30.1	82.6	52.0	68.3	66.2	<u>79.6</u>
	AlignBench v1.1	6.01	7.77	7.27	7.67	<u>8.10</u>	8.38
	Creative Writing v3	52.8	79.9	49.8	55.8	53.6	<u>64.5</u>
	WritingBench	4.57	<u>7.05</u>	5.82	5.93	6.85	7.15
Math & Text Reasoning	MATH-500	54.8	<u>85.6</u>	77.6	83.4	84.8	87.4
	AIME'24	6.3	22.4	9.1	15.2	<u>25.0</u>	29.1
	AIME'25	2.7	18.8	12.1	13.6	<u>19.1</u>	20.9
	ZebraLogic	12.8	17.8	12.0	19.7	35.2	26.7
	AutoLogi	30.9	58.9	42.9	57.4	<u>76.3</u>	76.5
Agent & Coding	BFCL v3	49.6	50.6	55.8	<u>58.7</u>	57.6	60.2
	LiveCodeBench v5	10.8	25.7	14.4	21.9	21.3	<u>22.8</u>
	CodeForces (Rating / Percentile)	473 / 14.9%	462 / 14.7%	191 / 0.0%	<u>904 / 38.3%</u>	842 / 33.7%	1110 / 52.4%
Multilingual Tasks	Multi-IF	52.1	<u>65.6</u>	47.7	55.5	61.3	69.2
	INCLUDE	34.0	65.3	53.6	<u>63.5</u>	53.8	62.5
	MMMLU 14 languages	44.4	<u>70.0</u>	61.4	70.3	61.7	66.9
	MT-AIME2024	0.4	16.7	5.5	8.5	13.9	16.6
	PolyMath	5.8	<u>17.6</u>	11.9	15.0	16.6	18.8
	MLogiQA	41.9	54.5	49.5	51.3	49.9	<u>51.4</u>

表17: QWEN3-8B / QWEN3-4B（思维）和其他推理基准之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		DeepSeek-R1 -Distill-Qwen-14B	DeepSeek-R1 -Distill-Qwen-32B	Qwen3-4B	Qwen3-8B
	Architecture	Dense	Dense	Dense	Dense
	# Activated Params	14B	32B	4B	8B
	# Total Params	14B	32B	4B	8B
General Tasks	MMLU-Redux	84.1	88.2	83.7	<u>87.5</u>
	GPQA-Diamond	59.1	62.1	55.9	<u>62.0</u>
	C-Eval	78.1	<u>82.2</u>	77.5	83.4
	LiveBench 2024-11-25	52.3	45.6	<u>63.6</u>	67.1
Alignment Tasks	IFEval strict prompt	72.6	72.5	<u>81.9</u>	85.0
	Arena-Hard	48.0	60.8	<u>76.6</u>	85.8
	AlignBench v1.1	7.43	7.25	<u>8.30</u>	8.46
	Creative Writing v3	54.2	55.0	<u>61.1</u>	75.0
	WritingBench	6.03	6.13	<u>7.35</u>	7.59
Math & Text Reasoning	MATH-500	93.9	94.3	<u>97.0</u>	97.4
	AIME'24	69.7	72.6	<u>73.8</u>	76.0
	AIME'25	44.5	49.6	<u>65.6</u>	67.3
	ZebraLogic	59.1	69.6	<u>81.0</u>	84.8
	AutoLogi	78.6	74.6	<u>87.9</u>	89.1
Agent & Coding	BFCL v3	49.5	53.5	<u>65.9</u>	68.1
	LiveCodeBench v5	45.5	<u>54.5</u>	<u>54.2</u>	57.5
	CodeForces (Rating / Percentile)	1574 / 89.1%	<u>1691 / 93.4%</u>	1671 / 92.8%	1785 / 95.6%
Multilingual Tasks	Multi-IF	29.8	31.3	<u>66.3</u>	71.2
	INCLUDE	59.7	68.0	61.8	<u>67.8</u>
	MMMLU 14 languages	73.8	78.6	69.8	<u>74.4</u>
	MT-AIME2024	33.7	44.6	<u>60.7</u>	65.4
	PolyMath	28.6	35.1	<u>40.0</u>	42.7
	MLogiQA	53.6	63.3	<u>65.9</u>	69.0

表18: QWEN3-8B / QWEN3-4B（非思维）和其他非争议基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		LLaMA-3.1-8B -Instruct	Gemma-3 -12B-IT	Qwen2.5-7B -Instruct	Qwen2.5-14B -Instruct	Qwen3-4B	Qwen3-8B
	Architecture	Dense	Dense	Dense	Dense	Dense	Dense
	# Activated Params	8B	12B	7B	14B	4B	8B
	# Total Params	8B	12B	7B	14B	4B	8B
General Tasks	MMLU-Redux	61.7	77.8	75.4	80.0	77.3	<u>79.5</u>
	GPQA-Diamond	32.8	40.9	36.4	45.5	41.7	39.3
	C-Eval	52.0	61.1	76.2	78.0	72.2	<u>77.9</u>
	LiveBench 2024-11-25	26.0	43.7	34.9	42.2	<u>48.4</u>	53.5
Alignment Tasks	IFEval strict prompt	75.0	80.2	71.2	81.0	<u>81.2</u>	83.0
	Arena-Hard	30.1	82.6	52.0	68.3	66.2	<u>79.6</u>
	AlignBench v1.1	6.01	7.77	7.27	7.67	<u>8.10</u>	8.38
	Creative Writing v3	52.8	79.9	49.8	55.8	53.6	<u>64.5</u>
	WritingBench	4.57	<u>7.05</u>	5.82	5.93	6.85	7.15
Math & Text Reasoning	MATH-500	54.8	<u>85.6</u>	77.6	83.4	84.8	87.4
	AIME'24	6.3	22.4	9.1	15.2	<u>25.0</u>	29.1
	AIME'25	2.7	18.8	12.1	13.6	<u>19.1</u>	20.9
	ZebraLogic	12.8	17.8	12.0	19.7	35.2	26.7
	AutoLogi	30.9	58.9	42.9	57.4	<u>76.3</u>	76.5
Agent & Coding	BFCL v3	49.6	50.6	55.8	<u>58.7</u>	57.6	60.2
	LiveCodeBench v5	10.8	25.7	14.4	21.9	21.3	<u>22.8</u>
	CodeForces (Rating / Percentile)	473 / 14.9%	462 / 14.7%	191 / 0.0%	<u>904 / 38.3%</u>	842 / 33.7%	1110 / 52.4%
Multilingual Tasks	Multi-IF	52.1	<u>65.6</u>	47.7	55.5	61.3	69.2
	INCLUDE	34.0	65.3	53.6	<u>63.5</u>	53.8	62.5
	MMMLU 14 languages	44.4	<u>70.0</u>	61.4	70.3	61.7	66.9
	MT-AIME2024	0.4	16.7	5.5	8.5	13.9	16.6
	PolyMath	5.8	<u>17.6</u>	11.9	15.0	16.6	18.8
	MLogiQA	41.9	54.5	49.5	51.3	49.9	<u>51.4</u>

Table 19: Comparison among Qwen3-1.7B / Qwen3-0.6B (Thinking) and other reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		DeepSeek-R1 -Distill-Qwen-1.5B	DeepSeek-R1 -Distill-Llama-8B	Qwen3-0.6B	Qwen3-1.7B
	Architecture	Dense	Dense	Dense	Dense
	# Activated Params	1.5B	8B	0.6B	1.7B
	# Total Params	1.5B	8B	0.6B	1.7B
<i>General Tasks</i>	MMLU-Redux	45.4	<u>66.4</u>	55.6	73.9
	GPQA-Diamond	33.8	49.0	27.9	<u>40.1</u>
	C-Eval	27.1	<u>50.4</u>	<u>50.4</u>	68.1
	LiveBench 2024-11-25	24.9	<u>40.6</u>	30.3	51.1
<i>Alignment Tasks</i>	IFEval strict prompt	39.9	59.0	<u>59.2</u>	72.5
	Arena-Hard	4.5	<u>17.6</u>	8.5	43.1
	AlignBench v1.1	5.00	<u>6.24</u>	6.10	7.60
	Creative Writing v3	16.4	51.1	30.6	<u>48.0</u>
	WritingBench	4.03	5.42	<u>5.61</u>	7.02
<i>Math & Text Reasoning</i>	MATH-500	83.9	<u>89.1</u>	77.6	93.4
	AIME'24	28.9	50.4	10.7	<u>48.3</u>
	AIME'25	22.8	<u>27.8</u>	15.1	36.8
	ZebraLogic	4.9	<u>37.1</u>	30.3	63.2
	AutoLogi	19.1	<u>63.4</u>	61.6	83.2
<i>Agent & Coding</i>	BFCL v3	14.0	21.5	<u>46.4</u>	56.6
	LiveCodeBench v5	13.2	42.5	12.3	<u>33.2</u>
<i>Multilingual Tasks</i>	Multi-IF	13.3	27.0	<u>36.1</u>	51.2
	INCLUDE	21.9	34.5	<u>35.9</u>	51.8
	MMMLU 14 languages	27.3	40.1	<u>43.1</u>	59.1
	MT-AIME2024	12.4	<u>13.2</u>	7.8	36.1
	PolyMath	<u>14.5</u>	10.8	11.4	25.2
	MLogiQA	29.0	32.8	<u>40.9</u>	56.0

Table 20: Comparison among Qwen3-1.7B / Qwen3-0.6B (Non-thinking) and other non-reasoning baselines. The highest and second-best scores are shown in bold and underlined, respectively.

		Gemma-3 -1B-IT	Phi-4-mini	Qwen2.5-1.5B -Instruct	Qwen2.5-3B -Instruct	Qwen3-0.6B	Qwen3-1.7B
	Architecture	Dense	Dense	Dense	Dense	Dense	Dense
	# Activated Params	1.0B	3.8B	1.5B	3.1B	0.6B	1.7B
	# Total Params	1.0B	3.8B	1.5B	3.1B	0.6B	1.7B
<i>General Tasks</i>	MMLU-Redux	33.3	67.9	50.7	<u>64.4</u>	44.6	<u>64.4</u>
	GPQA-Diamond	19.2	25.2	29.8	30.3	22.9	28.6
	C-Eval	28.5	40.0	53.3	68.2	42.6	<u>61.0</u>
	LiveBench 2024-11-25	14.4	<u>25.3</u>	18.0	23.8	21.8	35.6
<i>Alignment Tasks</i>	IFEval strict prompt	54.5	68.6	42.5	58.2	54.5	<u>68.2</u>
	Arena-Hard	17.8	<u>32.8</u>	9.0	23.7	6.5	36.9
	AlignBench v1.1	5.3	6.00	5.60	<u>6.49</u>	5.60	7.20
	Creative Writing v3	52.8	10.3	31.5	42.8	28.4	<u>43.6</u>
	WritingBench	5.18	4.05	4.67	<u>5.55</u>	5.13	6.54
<i>Math & Text Reasoning</i>	MATH-500	46.4	<u>67.6</u>	55.0	67.2	55.2	73.0
	AIME'24	0.9	<u>8.1</u>	0.9	6.7	3.4	13.4
	AIME'25	0.8	<u>5.3</u>	0.4	4.2	2.6	9.8
	ZebraLogic	1.9	2.7	3.4	4.8	4.2	12.8
	AutoLogi	16.4	28.8	22.5	29.9	<u>37.4</u>	59.8
<i>Agent & Coding</i>	BFCL v3	16.3	31.3	47.8	<u>50.4</u>	44.1	52.2
	LiveCodeBench v5	1.8	<u>10.4</u>	5.3	<u>9.2</u>	3.6	11.6
<i>Multilingual Tasks</i>	Multi-IF	32.8	<u>40.5</u>	20.2	32.3	33.3	44.7
	INCLUDE	32.7	43.8	33.1	43.8	34.4	<u>42.6</u>
	MMMLU 14 languages	32.5	<u>51.4</u>	40.4	51.8	37.1	48.3
	MT-AIME2024	0.2	0.9	0.7	<u>1.6</u>	1.5	4.9
	PolyMath	3.5	6.7	5.0	<u>7.3</u>	4.6	10.3
	MLogiQA	31.8	39.5	<u>40.9</u>	39.5	37.3	41.1

表19: qwen3-1.7b / qwen3-0.6b（思维）和其他推理基准之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		DeepSeek-R1 -Distill-Qwen-1.5B	DeepSeek-R1 -Distill-Llama-8B	Qwen3-0.6B	Qwen3-1.7B
	Architecture	Dense	Dense	Dense	Dense
	# Activated Params	1.5B	8B	0.6B	1.7B
	# Total Params	1.5B	8B	0.6B	1.7B
<i>General Tasks</i>	MMLU-Redux	45.4	<u>66.4</u>	55.6	73.9
	GPQA-Diamond	33.8	49.0	27.9	<u>40.1</u>
	C-Eval	27.1	<u>50.4</u>	<u>50.4</u>	68.1
	LiveBench 2024-11-25	24.9	<u>40.6</u>	30.3	51.1
<i>Alignment Tasks</i>	IFEval strict prompt	39.9	59.0	<u>59.2</u>	72.5
	Arena-Hard	4.5	<u>17.6</u>	8.5	43.1
	AlignBench v1.1	5.00	<u>6.24</u>	6.10	7.60
	Creative Writing v3	16.4	51.1	30.6	<u>48.0</u>
	WritingBench	4.03	5.42	<u>5.61</u>	7.02
<i>Math & Text Reasoning</i>	MATH-500	83.9	<u>89.1</u>	77.6	93.4
	AIME'24	28.9	50.4	10.7	<u>48.3</u>
	AIME'25	22.8	<u>27.8</u>	15.1	36.8
	ZebraLogic	4.9	<u>37.1</u>	30.3	63.2
	AutoLogi	19.1	<u>63.4</u>	61.6	83.2
<i>Agent & Coding</i>	BFCL v3	14.0	21.5	<u>46.4</u>	56.6
	LiveCodeBench v5	13.2	42.5	12.3	<u>33.2</u>
<i>Multilingual Tasks</i>	Multi-IF	13.3	27.0	<u>36.1</u>	51.2
	INCLUDE	21.9	34.5	<u>35.9</u>	51.8
	MMMLU 14 languages	27.3	40.1	<u>43.1</u>	59.1
	MT-AIME2024	12.4	<u>13.2</u>	7.8	36.1
	PolyMath	<u>14.5</u>	10.8	11.4	25.2
	MLogiQA	29.0	32.8	<u>40.9</u>	56.0

表20: QWEN3-1.7B / QWEN3-0.6B（非思考）和其他非争议基线之间的比较。最高和第二好的分数分别以粗体和下划线显示。

		Gemma-3 -1B-IT	Phi-4-mini	Qwen2.5-1.5B -Instruct	Qwen2.5-3B -Instruct	Qwen3-0.6B	Qwen3-1.7B
	Architecture	Dense	Dense	Dense	Dense	Dense	Dense
	# Activated Params	1.0B	3.8B	1.5B	3.1B	0.6B	1.7B
	# Total Params	1.0B	3.8B	1.5B	3.1B	0.6B	1.7B
<i>General Tasks</i>	MMLU-Redux	33.3	67.9	50.7	<u>64.4</u>	44.6	<u>64.4</u>
	GPQA-Diamond	19.2	25.2	29.8	30.3	22.9	28.6
	C-Eval	28.5	40.0	<u>53.3</u>	68.2	42.6	<u>61.0</u>
	LiveBench 2024-11-25	14.4	<u>25.3</u>	18.0	23.8	21.8	35.6
<i>Alignment Tasks</i>	IFEval strict prompt	54.5	68.6	42.5	58.2	54.5	68.2
	Arena-Hard	17.8	<u>32.8</u>	9.0	23.7	6.5	36.9
	AlignBench v1.1	5.3	6.00	5.60	<u>6.49</u>	5.60	7.20
	Creative Writing v3	52.8	10.3	31.5	42.8	28.4	<u>43.6</u>
	WritingBench	5.18	4.05	4.67	<u>5.55</u>	5.13	6.54
<i>Math & Text Reasoning</i>	MATH-500	46.4	<u>67.6</u>	55.0	67.2	55.2	73.0
	AIME'24	0.9	<u>8.1</u>	0.9	6.7	3.4	13.4
	AIME'25	0.8	<u>5.3</u>	0.4	4.2	2.6	9.8
	ZebraLogic	1.9	2.7	3.4	4.8	4.2	12.8
	AutoLogi	16.4	28.8	22.5	29.9	<u>37.4</u>	59.8
<i>Agent & Coding</i>	BFCL v3	16.3	31.3	47.8	<u>50.4</u>	44.1	52.2
	LiveCodeBench v5	1.8	<u>10.4</u>	5.3	<u>9.2</u>	3.6	11.6
<i>Multilingual Tasks</i>	Multi-IF	32.8	<u>40.5</u>	20.2	32.3	33.3	44.7
	INCLUDE	32.7	43.8	33.1	43.8	34.4	<u>42.6</u>
	MMMLU 14 languages	32.5	<u>51.4</u>	40.4	51.8	37.1	48.3
	MT-AIME2024	0.2	0.9	0.7	<u>1.6</u>	1.5	4.9
	PolyMath	3.5	6.7	5.0	<u>7.3</u>	4.6	10.3
	MLogiQA	31.8	39.5	<u>40.9</u>	39.5	37.3	41.1

1/10 activated parameters, demonstrating the effectiveness of our Strong-to-Weak Distillation approach in endowing lightweight models with profound reasoning capabilities.

- (2) From Table 16, Qwen3-30B-A3B and Qwen3-14B (Non-thinking) surpass the non-reasoning baselines in most of the benchmarks. They exceed our previous Qwen2.5-32B-Instruct model with significantly fewer activated and total parameters, allowing for more efficient and cost-effective performance.

Qwen3-8B / 4B / 1.7B / 0.6B For Qwen3-8B and Qwen3-4B, we compare them with DeepSeek-R1-Distill-Qwen-14B and DeepSeek-R1-Distill-Qwen-32B in the thinking mode, and LLaMA-3.1-8B-Instruct (Dubey et al., 2024), Gemma-3-12B-IT (Team et al., 2025), Qwen2.5-7B-Instruct, and Qwen2.5-14B-Instruct in the non-thinking mode, respectively. For Qwen3-1.7B and Qwen3-0.6B, we compare them with DeepSeek-R1-Distill-Qwen-1.5B and DeepSeek-R1-Distill-Llama-8B in the thinking mode, and Gemma-3-1B-IT, Phi-4-mini, Qwen2.5-1.5B-Instruct, and Qwen2.5-3B-Instruct in the non-thinking mode, respectively. We present the evaluation results of Qwen3-8B and Qwen3-4B in Table 17 and 18 and those of Qwen3-1.7B and Qwen3-0.6B in Table 19 and 20, respectively. Overall, these edge-side models exhibit impressive performance and outperform baselines even with more parameters, including our previous Qwen2.5 models, in either the thinking or the non-thinking mode. These results, once again, demonstrate the efficacy of our Strong-to-Weak Distillation approach, making it possible for us to build the lightweight Qwen3 models with remarkably reduced costs and efforts.

4.7 Discussion

The Effectiveness of Thinking Budget To verify that Qwen3 can enhance its intelligence level by leveraging an increased thinking budget, we adjust the allocated thinking budget on four benchmarks across Mathematics, Coding, and STEM domains. The resulting scaling curves are presented in Figure 2, Qwen3 demonstrates scalable and smooth performance improvements correlated to the allocated thinking budget. Moreover, we observe that if we further extend the output length beyond 32K, the model’s performance is expected to improve further in the future. We leave this exploration as future work.

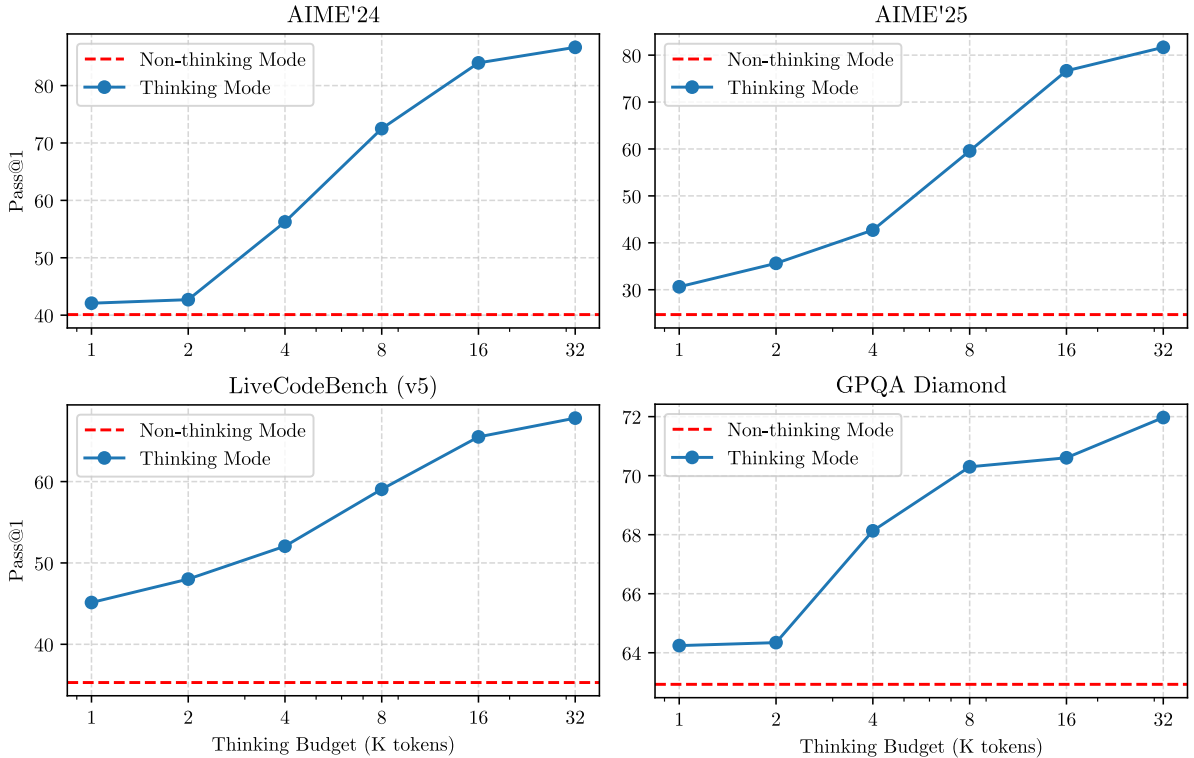


Figure 2: Performance of Qwen3-235B-A22B with respect to the thinking budget.

The Effectiveness and Efficiency of On-Policy Distillation We evaluate the effectiveness and efficiency of on-policy distillation by comparing the performance and computational cost—measured in GPU hours—after undergoing distillation versus direct reinforcement learning, both starting from the same off-policy distilled 8B checkpoint. For simplicity, we focus solely on math and code-related queries in

1/10激活的参数，证明了我们强大的蒸馏方法在赋予具有深刻推理能力的轻质模型中的有效性。

(2) 从表16中，QWEN3-30B-A3B和QWEN3-14B（非思维）在大多数基准中都超过了非争议的基线。它们超过了我们以前的QWEN2.5-32B教学模型，其激活和总参数明显少得多，从而可以提高效率和具有成本效益的性能。

QWEN3-8B / 4B / 1.7B / 0.6B用于QWEN3-8B和QWEN3-4B，我们将它们与DeepSeek-R1-Distill-Qwen-14b和DeepSeek-R1-distill-Qwen-14b和DeepSeek-R1-Distill-distill-qwen-32b在思维模式下，以及Llama-3.1-3.1-3.1-3.1-8b-buststruct（dubey et al dubey等）2025），QWEN2.5-7B教学和QWEN2.5-14B教学分别在非思考模式下。For Qwen3-1.7B and Qwen3-0.6B, we compare them with DeepSeek-R1-Distill-Qwen-1.5B and DeepSeek-R1-Distill-Llama-8B in the thinking mode, and Gemma-3-1B-IT, Phi-4-mini, Qwen2.5-1.5B-Instruct, and Qwen2.5-3B-Instruct in the non-thinking mode, respectively.我们介绍了表17和18中QWEN3-8B和QWEN3-4B的评估结果以及表19和20中Qwen3-1.7b和Qwen3-1.7b和Qwen3-0.6b的评估结果。总体而言，这些边缘侧模型在思维模式或非思维模式下，即使有更多参数，包括我们以前的QWEN2.5模型在内的更多参数也表现出令人印象深刻的性能和表现优于基线。这些结果再次证明了我们强大的蒸馏方法的功效，这使我们有可能以大幅降低的成本和努力来构建轻量级的QWEN3模型。

4.7讨论

思考预算验证QWEN3的有效性可以通过利用增加的思维预算来提高其情报水平，我们调整了数学，编码和STEM领域的四个基准测试的分配思维预算。所得的缩放曲线如图2所示，QWEN3显示了与分配的思维预算相关的可扩展性能改进。此外，我们观察到，如果我们将输出长度进一步扩展到32K以上，则预计该模型的性能将在未来进一步提高。我们将这一探索作为未来的工作。

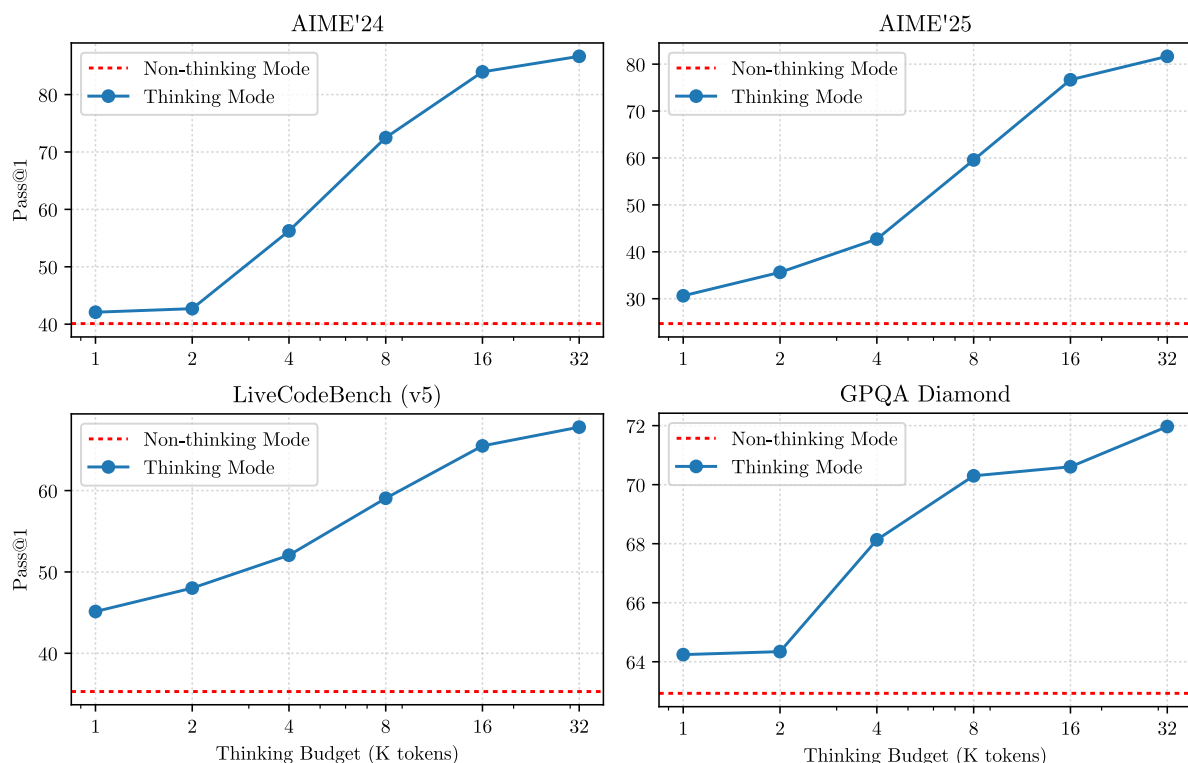


图2：关于思维预算的QWEN3-235B-A22B的性能。

在上蒸馏蒸馏的有效性和效率我们通过比较蒸馏与直接增强学习后的性能和计算成本（在GPU小时内进行测量）来评估上彻底蒸馏的有效性和效率，这两者都从相同的非上政策蒸馏8B检查点开始。为简单起见，我们仅关注与数学和代码相关的查询

this comparison. The results, summarized in Table 21, show that distillation achieves significantly better performance than reinforcement learning while requiring approximately only 1/10 of the GPU hours. Furthermore, distillation from teacher logits enables the student model to expand its exploration space and enhance its reasoning potential, as evidenced by the improved pass@64 scores on the AIME’24 and AIME’25 benchmarks after distillation, compared to the initial checkpoint. In contrast, reinforcement learning does not lead to any improvement in pass@64 scores. These observations highlight the advantages of leveraging a stronger teacher model in guiding student model learning.

Table 21: Comparison of reinforcement learning and on-policy distillation on Qwen3-8B. Numbers in parentheses indicate pass@64 scores.

Method	AIME’24	AIME’25	MATH500	LiveCodeBench v5	MMLU -Redux	GPQA -Diamond	GPU Hours
Off-policy Distillation	55.0 (90.0)	42.8 (83.3)	92.4	42.0	86.4	55.6	-
+ Reinforcement Learning	67.6 (90.0)	55.5 (83.3)	94.8	52.9	86.9	61.3	17,920
+ On-policy Distillation	74.4 (93.3)	65.5 (86.7)	97.0	60.3	88.3	63.3	1,800

The Effects of Thinking Mode Fusion and General RL To evaluate the effectiveness of Thinking Mode Fusion and General Reinforcement Learning (RL) during the post-training, we conduct evaluations on various stages of the Qwen-32B model. In addition to the datasets mentioned earlier, we introduce several in-house benchmarks to monitor other capabilities. These benchmarks include:

- **CounterFactQA**: Contains counterfactual questions where the model needs to identify that the questions are not factual and avoid generating hallucinatory answers.
- **LengthCtrl**: Includes creative writing tasks with length requirements; the final score is based on the difference between the generated content length and the target length.
- **ThinkFollow**: Involves multi-turn dialogues with randomly inserted /think and /no_think flags to test whether the model can correctly switch thinking modes based on user queries.
- **ToolUse**: Evaluates the stability of the model in single-turn, multi-turn, and multi-step tool calling processes. The score includes accuracy in intent recognition, format accuracy, and parameter accuracy during the tool calling process.

Table 22: Performance of Qwen3-32B after Reasoning RL (Stage 2), Thinking Mode Fusion (Stage 3), and General RL (Stage 4). Benchmarks with * are in-house datasets.

Benchmark		Stage 2 Reasoning RL	Stage 3 Thinking Mode Fusion		Stage 4 General RL	
		Thinking	Thinking	Non-Thinking	Thinking	Non-Thinking
<i>General Tasks</i>	LiveBench 2024-11-25	68.6	70.9 ^{+2.3}	57.1	74.9 ^{+4.0}	59.8 ^{+2.8}
	Arena-Hard	86.8	89.4 ^{+2.6}	88.5	93.8 ^{+4.4}	92.8 ^{+4.3}
	CounterFactQA*	50.4	61.3 ^{+10.9}	64.3	68.1 ^{+6.8}	66.4 ^{+2.1}
<i>Instruction & Format Following</i>	IFEval strict prompt	73.0	78.4 ^{+5.4}	78.4	85.0 ^{+6.6}	83.2 ^{+4.8}
	Multi-IF	61.4	64.6 ^{+3.2}	65.2	73.0 ^{+8.4}	70.7 ^{+5.5}
	LengthCtrl*	62.6	70.6 ^{+8.0}	84.9	73.5 ^{+2.9}	87.3 ^{+2.4}
	ThinkFollow*	-	88.7		98.9 ^{+10.2}	
<i>Agent</i>	BFCL v3	69.0	68.4 ^{-0.6}	61.5	70.3 ^{+1.9}	63.0 ^{+1.5}
	ToolUse*	63.3	70.4 ^{+7.1}	73.2	85.5 ^{+15.1}	86.5 ^{+13.3}
<i>Knowledge & STEM</i>	MMLU-Redux	91.4	91.0 ^{-0.4}	86.7	90.9 ^{-0.1}	85.7 ^{-1.0}
	GPQA-Diamond	68.8	69.0 ^{+0.2}	50.4	68.4 ^{-0.6}	54.6 ^{+4.3}
<i>Math & Coding</i>	AIME’24	83.8	81.9 ^{-1.9}	28.5	81.4 ^{-0.5}	31.0 ^{+2.5}
	LiveCodeBench v5	68.4	67.2 ^{-1.2}	31.1	65.7 ^{-1.5}	31.3 ^{+0.2}

The results are shown in Table 22, where we can draw the following conclusions:

- (1) Stage 3 integrates the non-thinking mode into the model, which already possesses thinking capabilities after the first two stages of training. The ThinkFollow benchmark score of 88.7 indicates that the model has developed an initial ability to switch between modes, though it still occasionally makes errors. Stage 3 also enhances the model’s general and instruction-following capabilities in thinking mode, with CounterFactQA improving by 10.9 points and LengthCtrl by 8.0 points.

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<i>Knowledge & STEM</i>	MMLU-Redux	91.4	91.0 ^{-0.4}	86.7	90.9 ^{-0.1}	85.7 ^{-1.0}
	GPQA-Diamond	68.8	69.0 ^{+0.2}	50.4	68.4 ^{-0.6}	54.6 ^{+4.3}
<i>Math & Coding</i>	AIME’24	83.8	81.9 ^{-1.9}	28.5	81.4 ^{-0.5}	31.0 ^{+2.5}
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-
- (2) Stage 4 further strengthens the model’s general, instruction-following, and agent capabilities in both thinking and non-thinking modes. Notably, the ThinkFollow score improves to 98.9, ensuring accurate mode switching.
 - (3) For Knowledge, STEM, Math, and Coding tasks, Thinking Mode Fusion and General RL do not bring significant improvements. In contrast, for challenging tasks like AIME’24 and Live-CodeBench, the performance in thinking mode actually decreases after these two training stages. We conjecture this degradation is due to the model being trained on a broader range of general tasks, which may compromise its specialized capabilities in handling complex problems. During the development of Qwen3, we choose to accept this performance trade-off to enhance the model’s overall versatility.

5 Conclusion

In this technical report, we introduce Qwen3, the latest version of the Qwen series. Qwen3 features both thinking mode and non-thinking mode, allowing users to dynamically manage the number of tokens used for complex thinking tasks. The model was pre-trained on an extensive dataset containing 36 trillion tokens, enabling it to understand and generate text in 119 languages and dialects. Through a series of comprehensive evaluations, Qwen3 has shown strong performance across a range of standard benchmarks for both pre-trained and post-trained models, including tasks related to code generation, mathematics, reasoning, and agents.

In the near future, our research will focus on several key areas. We will continue to scale up pretraining by using data that is both higher in quality and more diverse in content. At the same time, we will work on improving model architecture and training methods for the purposes of effective compression, scaling to extremely long contexts, etc. In addition, we plan to increase computational resources for reinforcement learning, with a particular emphasis on agent-based RL systems that learn from environmental feedback. This will allow us to build agents capable of tackling complex tasks that require inference time scaling.

6 Authors

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In the near future, our research will focus on several key areas. We will continue to scale up pretraining by using data that is both higher in quality and more diverse in content. At the same time, we will work on improving model architecture and training methods for the purposes of effective compression, scaling to extremely long contexts, etc. In addition, we plan to increase computational resources for reinforcement learning, with a particular emphasis on agent-based RL systems that learn from environmental feedback. This will allow us to build agents capable of tackling complex tasks that require inference time scaling.

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A Appendix

A.1 Additional Evaluation Results

A.1.1 Long-Context Ability

Table 23: Performance of Qwen3 Models on the RULER benchmark.

		RULER						
		Avg.	4K	8K	16K	32K	64K	128K
<i>Non-thinking Mode</i>	Qwen2.5-7B-Instruct	85.4	96.7	95.1	93.7	89.4	82.3	55.1
	Qwen2.5-14B-Instruct	91.4	97.7	96.8	95.9	93.4	86.7	78.1
	Qwen2.5-32B-Instruct	92.9	96.9	97.1	95.5	95.5	90.3	82.0
	Qwen2.5-72B-Instruct	95.1	97.7	97.2	97.7	96.5	93.0	88.4
	Qwen3-4B	85.2	95.1	93.6	91.0	87.8	77.8	66.0
	Qwen3-8B	89.1	96.3	96.0	91.8	91.2	82.1	77.4
	Qwen3-14B	94.6	98.0	97.8	96.4	96.1	94.0	85.1
	Qwen3-32B	93.7	98.4	96.0	96.2	94.4	91.8	85.6
	Qwen3-30B-A3B	91.6	96.5	97.0	95.3	92.4	89.1	79.2
	Qwen3-235B-A22B	95.0	97.7	97.2	96.4	95.1	93.3	90.6
	Qwen3-4B	83.5	92.7	88.7	86.5	83.2	83.0	67.2
	Qwen3-8B	84.4	94.7	94.4	86.1	80.8	78.3	72.0
	Qwen3-14B	90.1	95.4	93.6	89.8	91.9	90.6	79.0
	Qwen3-32B	91.0	94.7	93.7	91.6	92.5	90.0	83.5
<i>Thinking Mode</i>	Qwen3-30B-A3B	86.6	94.1	92.7	89.0	86.6	82.1	75.0
	Qwen3-235B-A22B	92.2	95.1	94.8	93.0	92.3	92.0	86.0

For evaluating long-context processing capabilities, we report the results on the RULER benchmark (Hsieh et al., 2024) in Table 23. To enable length extrapolation, we utilize YARN (Peng et al., 2023) with a `scaling_factor=4`. In thinking mode, we set the thinking budget to 8192 tokens to mitigate overly verbose reasoning on the extremely long inputs.

The results show that:

1. In non-thinking mode, Qwen3 outperforms Qwen2.5 models of a similar size in long-context processing tasks.
2. In thinking mode, the model’s performance slightly degrades. We hypothesize that the thinking content does not provide significant benefits for these retrieval tasks, which do not rely on reasoning and may instead interfere with the retrieval process. We are committed to enhancing the long-context capability in the thinking mode in future versions.

A.1.2 Multilingual Ability

Table 24-35 presents the detailed benchmark scores across various languages, including Spanish, French, Portuguese, Italian, Arabic, Japanese, Korean, Indonesian, Russian, Vietnamese, German, and Thai. The results of these tables demonstrate that the Qwen3 series models achieve competitive performance across all evaluated benchmarks, showcasing their strong multilingual capabilities.

To evaluate the performance of Qwen3 across a broader range of languages, we utilize Belebele (Bandarkar et al., 2023), a benchmark for natural language understanding. We conduct evaluations on 80 supported languages from the benchmark, excluding 42 unoptimized languages, as shown in Table 36 (organized by language family). The performance comparison between Qwen3 and other baseline models on the Belebele benchmark is presented in Table 37. The results show that Qwen3 achieves comparable performance to similarly-sized Gemma models while outperforming Qwen2.5 significantly.

A Appendix

A.1 Additional Evaluation Results

A.1.1 Long-Context Ability

Table 23: Performance of Qwen3 Models on the RULER benchmark.

		RULER						
		Avg.	4K	8K	16K	32K	64K	128K
Non-thinking Mode	Qwen2.5-7B-Instruct	85.4	96.7	95.1	93.7	89.4	82.3	55.1
	Qwen2.5-14B-Instruct	91.4	97.7	96.8	95.9	93.4	86.7	78.1
	Qwen2.5-32B-Instruct	92.9	96.9	97.1	95.5	95.5	90.3	82.0
	Qwen2.5-72B-Instruct	95.1	97.7	97.2	97.7	96.5	93.0	88.4
	Qwen3-4B	85.2	95.1	93.6	91.0	87.8	77.8	66.0
	Qwen3-8B	89.1	96.3	96.0	91.8	91.2	82.1	77.4
	Qwen3-14B	94.6	98.0	97.8	96.4	96.1	94.0	85.1
	Qwen3-32B	93.7	98.4	96.0	96.2	94.4	91.8	85.6
	Qwen3-30B-A3B	91.6	96.5	97.0	95.3	92.4	89.1	79.2
	Qwen3-235B-A22B	95.0	97.7	97.2	96.4	95.1	93.3	90.6
	Qwen3-4B	83.5	92.7	88.7	86.5	83.2	83.0	67.2
	Qwen3-8B	84.4	94.7	94.4	86.1	80.8	78.3	72.0
	Qwen3-14B	90.1	95.4	93.6	89.8	91.9	90.6	79.0
	Qwen3-32B	91.0	94.7	93.7	91.6	92.5	90.0	83.5
Thinking Mode	Qwen3-30B-A3B	86.6	94.1	92.7	89.0	86.6	82.1	75.0
	Qwen3-235B-A22B	92.2	95.1	94.8	93.0	92.3	92.0	86.0

For evaluating long-context processing capabilities, we report the results on the RULER benchmark (Hsieh et al., 2024) in Table 23. To enable length extrapolation, we utilize YARN (Peng et al., 2023) with a `scaling_factor=4`. In thinking mode, we set the thinking budget to 8192 tokens to mitigate overly verbose reasoning on the extremely long inputs.

The results show that:

1. In non-thinking mode, Qwen3 outperforms Qwen2.5 models of a similar size in long-context processing tasks.
2. In thinking mode, the model’s performance slightly degrades. We hypothesize that the thinking content does not provide significant benefits for these retrieval tasks, which do not rely on reasoning and may instead interfere with the retrieval process. We are committed to enhancing the long-context capability in the thinking mode in future versions.

A.1.2 Multilingual Ability

Table 24-35 presents the detailed benchmark scores across various languages, including Spanish, French, Portuguese, Italian, Arabic, Japanese, Korean, Indonesian, Russian, Vietnamese, German, and Thai. The results of these tables demonstrate that the Qwen3 series models achieve competitive performance across all evaluated benchmarks, showcasing their strong multilingual capabilities.

To evaluate the performance of Qwen3 across a broader range of languages, we utilize Belebele (Bandarkar et al., 2023), a benchmark for natural language understanding. We conduct evaluations on 80 supported languages from the benchmark, excluding 42 unoptimized languages, as shown in Table 36 (organized by language family). The performance comparison between Qwen3 and other baseline models on the Belebele benchmark is presented in Table 37. The results show that Qwen3 achieves comparable performance to similarly-sized Gemma models while outperforming Qwen2.5 significantly.

Table 24: **Benchmark scores for language: Spanish (es)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.1	70.0	96.4	88.7	90.0	54.4	79.9
	QwQ-32B	70.0	<u>75.0</u>	81.8	84.5	76.7	52.2	73.4
	Qwen3-235B-A22B	74.2	76.2	89.1	<u>86.7</u>	<u>86.7</u>	57.3	<u>78.4</u>
	Qwen3-32B	74.7	68.8	90.9	82.8	76.7	51.8	74.3
	Qwen3-30B-A3B	74.9	71.2	80.0	81.9	76.7	48.5	72.2
	Qwen3-14B	<u>76.2</u>	67.5	83.6	81.1	73.3	50.3	72.0
	Qwen3-8B	<u>74.1</u>	70.0	78.2	79.2	70.0	43.7	69.2
	Qwen3-4B	69.1	68.8	72.7	75.7	66.7	42.3	65.9
	Qwen3-1.7B	56.0	55.0	72.7	64.5	46.7	30.2	54.2
	Qwen3-0.6B	39.2	42.5	54.5	48.8	13.3	14.3	35.4
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	67.5	52.5	89.1	<u>80.6</u>	10.0	15.5	52.5
	Gemma-3-27b-IT	73.5	57.5	89.1	<u>77.7</u>	30.0	22.4	58.4
	Qwen2.5-72B-Instruct	66.7	61.3	80.0	80.1	20.0	18.8	54.5
	Qwen3-235B-A22B	71.7	66.2	83.6	83.7	<u>33.3</u>	29.5	61.3
	Qwen3-32B	72.1	<u>65.0</u>	83.6	80.4	<u>26.7</u>	24.7	58.8
	Qwen3-30B-A3B	72.1	53.8	<u>85.5</u>	78.3	<u>33.3</u>	<u>25.0</u>	58.0
	Qwen3-14B	76.2	63.7	78.2	77.4	40.0	<u>25.0</u>	<u>60.1</u>
	Qwen3-8B	73.1	50.0	80.0	73.7	16.7	21.3	52.5
	Qwen3-4B	65.8	50.0	60.0	68.3	13.3	17.3	45.8
	Qwen3-1.7B	47.9	43.8	50.9	54.3	10.0	11.6	36.4
	Qwen3-0.6B	35.5	37.5	43.6	39.5	3.3	5.8	27.5

Table 25: **Benchmark scores for language: French (fr)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.5	73.8	85.7	88.3	80.0	<u>52.8</u>	<u>76.8</u>
	QwQ-32B	72.4	<u>78.8</u>	76.2	84.0	80.0	49.4	73.5
	Qwen3-235B-A22B	77.3	<u>78.8</u>	85.7	<u>86.6</u>	86.7	57.4	78.8
	Qwen3-32B	76.7	81.2	76.2	<u>82.1</u>	<u>83.3</u>	47.1	74.4
	Qwen3-30B-A3B	75.2	67.5	<u>83.3</u>	81.0	76.7	46.9	71.8
	Qwen3-14B	<u>77.6</u>	71.2	73.8	80.4	73.3	44.2	70.1
	Qwen3-8B	<u>73.8</u>	66.2	85.7	77.9	70.0	45.3	69.8
	Qwen3-4B	71.3	63.7	71.4	74.5	66.7	40.2	64.6
	Qwen3-1.7B	52.6	56.2	54.8	64.8	60.0	28.7	52.8
	Qwen3-0.6B	36.1	48.8	47.6	48.4	6.7	14.0	33.6
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	67.8	56.2	<u>85.7</u>	81.8	10.0	15.3	52.8
	Gemma-3-27b-IT	73.9	57.5	<u>73.8</u>	78.3	23.3	21.5	54.7
	Qwen2.5-72B-Instruct	72.1	55.0	81.0	80.2	26.7	15.7	55.1
	Qwen3-235B-A22B	73.2	65.0	88.1	<u>81.1</u>	36.7	28.1	62.0
	Qwen3-32B	<u>75.8</u>	60.0	73.8	79.5	30.0	23.0	57.0
	Qwen3-30B-A3B	75.6	52.5	69.0	77.9	26.7	<u>27.3</u>	54.8
	Qwen3-14B	78.4	63.7	73.8	75.1	<u>33.3</u>	24.4	<u>58.1</u>
	Qwen3-8B	71.9	52.5	71.4	71.7	<u>20.0</u>	21.4	51.5
	Qwen3-4B	64.2	47.5	61.9	67.6	20.0	19.2	46.7
	Qwen3-1.7B	46.1	43.8	64.3	53.2	3.3	11.6	37.0
	Qwen3-0.6B	32.8	35.0	38.1	39.4	6.7	4.6	26.1

Table 24: **Benchmark scores for language: Spanish (es)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.1	70.0	96.4	88.7	90.0	54.4	79.9
	QwQ-32B	70.0	<u>75.0</u>	81.8	84.5	76.7	52.2	73.4
	Qwen3-235B-A22B	74.2	76.2	89.1	<u>86.7</u>	<u>86.7</u>	57.3	<u>78.4</u>
	Qwen3-32B	74.7	68.8	90.9	82.8	76.7	51.8	74.3
	Qwen3-30B-A3B	74.9	71.2	80.0	81.9	76.7	48.5	72.2
	Qwen3-14B	<u>76.2</u>	67.5	83.6	81.1	73.3	50.3	72.0
	Qwen3-8B	<u>74.1</u>	70.0	78.2	79.2	70.0	43.7	69.2
	Qwen3-4B	69.1	68.8	72.7	75.7	66.7	42.3	65.9
	Qwen3-1.7B	56.0	55.0	72.7	64.5	46.7	30.2	54.2
	Qwen3-0.6B	39.2	42.5	54.5	48.8	13.3	14.3	35.4
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	67.5	52.5	89.1	<u>80.6</u>	10.0	15.5	52.5
	Gemma-3-27b-IT	73.5	57.5	89.1	<u>77.7</u>	30.0	22.4	58.4
	Qwen2.5-72B-Instruct	66.7	61.3	80.0	80.1	20.0	18.8	54.5
	Qwen3-235B-A22B	71.7	66.2	83.6	83.7	<u>33.3</u>	29.5	61.3
	Qwen3-32B	72.1	<u>65.0</u>	83.6	80.4	<u>26.7</u>	24.7	58.8
	Qwen3-30B-A3B	72.1	53.8	<u>85.5</u>	78.3	<u>33.3</u>	<u>25.0</u>	58.0
	Qwen3-14B	76.2	63.7	78.2	77.4	40.0	<u>25.0</u>	<u>60.1</u>
	Qwen3-8B	73.1	50.0	80.0	73.7	16.7	21.3	52.5
	Qwen3-4B	65.8	50.0	60.0	68.3	13.3	17.3	45.8
	Qwen3-1.7B	47.9	43.8	50.9	54.3	10.0	11.6	36.4
	Qwen3-0.6B	35.5	37.5	43.6	39.5	3.3	5.8	27.5

Table 25: **Benchmark scores for language: French (fr)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.5	73.8	85.7	88.3	80.0	<u>52.8</u>	<u>76.8</u>
	QwQ-32B	72.4	<u>78.8</u>	76.2	84.0	80.0	49.4	73.5
	Qwen3-235B-A22B	77.3	<u>78.8</u>	85.7	<u>86.6</u>	86.7	57.4	78.8
	Qwen3-32B	76.7	81.2	76.2	<u>82.1</u>	<u>83.3</u>	47.1	74.4
	Qwen3-30B-A3B	75.2	67.5	<u>83.3</u>	81.0	76.7	46.9	71.8
	Qwen3-14B	<u>77.6</u>	71.2	73.8	80.4	73.3	44.2	70.1
	Qwen3-8B	<u>73.8</u>	66.2	85.7	77.9	70.0	45.3	69.8
	Qwen3-4B	71.3	63.7	71.4	74.5	66.7	40.2	64.6
	Qwen3-1.7B	52.6	56.2	54.8	64.8	60.0	28.7	52.8
	Qwen3-0.6B	36.1	48.8	47.6	48.4	6.7	14.0	33.6
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	67.8	56.2	<u>85.7</u>	81.8	10.0	15.3	52.8
	Gemma-3-27b-IT	73.9	57.5	<u>73.8</u>	78.3	23.3	21.5	54.7
	Qwen2.5-72B-Instruct	72.1	55.0	81.0	80.2	26.7	15.7	55.1
	Qwen3-235B-A22B	73.2	65.0	88.1	<u>81.1</u>	36.7	28.1	62.0
	Qwen3-32B	<u>75.8</u>	60.0	73.8	79.5	30.0	23.0	57.0
	Qwen3-30B-A3B	75.6	52.5	69.0	77.9	26.7	<u>27.3</u>	54.8
	Qwen3-14B	78.4	63.7	73.8	75.1	<u>33.3</u>	24.4	<u>58.1</u>
	Qwen3-8B	71.9	52.5	71.4	71.7	<u>20.0</u>	21.4	51.5
	Qwen3-4B	64.2	47.5	61.9	67.6	20.0	19.2	46.7
	Qwen3-1.7B	46.1	43.8	64.3	53.2	3.3	11.6	37.0
	Qwen3-0.6B	32.8	35.0	38.1	39.4	6.7	4.6	26.1

Table 26: **Benchmark scores for language: Portuguese (pt)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.5	73.8	83.9	88.9	73.3	52.2	75.4
	QwQ-32B	70.5	70.0	<u>80.4</u>	84.0	80.0	48.7	72.3
	Qwen3-235B-A22B	73.6	78.8	78.6	<u>86.2</u>	86.7	58.3	77.0
	Qwen3-32B	74.1	<u>76.2</u>	76.8	82.6	80.0	52.4	73.7
	Qwen3-30B-A3B	76.1	71.2	71.4	81.0	76.7	49.3	71.0
	Qwen3-14B	<u>77.3</u>	68.8	75.0	81.6	<u>83.3</u>	46.7	72.1
	Qwen3-8B	<u>73.9</u>	67.5	75.0	78.6	<u>56.7</u>	44.8	66.1
	Qwen3-4B	70.6	62.5	71.4	75.1	73.3	44.2	66.2
	Qwen3-1.7B	55.6	60.0	53.6	64.6	46.7	28.2	51.4
	Qwen3-0.6B	38.7	33.8	42.9	47.5	10.0	12.7	30.9
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	66.8	57.5	<u>78.6</u>	80.7	10.0	15.0	51.4
	Gemma-3-27b-IT	<u>72.9</u>	55.0	75.0	77.1	33.3	20.9	55.7
	Qwen2.5-72B-Instruct	68.8	55.0	71.4	<u>82.2</u>	23.3	11.3	52.0
	Qwen3-235B-A22B	72.5	67.5	82.1	83.5	33.3	28.3	61.2
	Qwen3-32B	71.1	<u>61.3</u>	73.2	80.6	30.0	23.9	56.7
	Qwen3-30B-A3B	72.3	47.5	67.9	77.8	26.7	24.0	52.7
	Qwen3-14B	75.5	58.8	75.0	76.5	26.7	<u>25.8</u>	56.4
	Qwen3-8B	71.9	56.2	71.4	72.9	20.0	19.7	52.0
	Qwen3-4B	66.1	50.0	73.2	66.7	10.0	18.1	47.4
	Qwen3-1.7B	49.5	33.8	39.3	52.9	6.7	12.8	32.5
	Qwen3-0.6B	36.6	37.5	42.9	37.5	3.3	5.7	27.2

Table 27: **Benchmark scores for language: Italian (it)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.9	100.0	87.2	90.0	<u>54.1</u>	82.4
	QwQ-32B	71.2	<u>96.4</u>	84.9	76.7	49.3	75.7
	Qwen3-235B-A22B	73.7	<u>96.4</u>	<u>85.7</u>	<u>80.0</u>	57.4	78.6
	Qwen3-32B	76.6	<u>90.9</u>	<u>81.6</u>	<u>80.0</u>	49.7	<u>75.8</u>
	Qwen3-30B-A3B	75.9	94.5	81.9	<u>80.0</u>	48.1	76.1
	Qwen3-14B	<u>79.0</u>	94.5	80.2	70.0	47.0	74.1
	Qwen3-8B	<u>74.6</u>	89.1	77.5	76.7	46.1	72.8
	Qwen3-4B	69.8	83.6	74.4	76.7	44.5	69.8
	Qwen3-1.7B	54.6	74.5	64.2	53.3	29.6	55.2
	Qwen3-0.6B	37.8	45.5	45.9	6.7	13.3	29.8
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	67.6	98.2	<u>80.7</u>	13.3	15.2	55.0
	Gemma-3-27b-IT	<u>74.6</u>	90.9	78.4	23.3	20.5	57.5
	Qwen2.5-72B-Instruct	67.2	<u>94.5</u>	<u>80.7</u>	16.7	16.7	55.2
	Qwen3-235B-A22B	72.9	92.7	82.6	33.3	28.6	62.0
	Qwen3-32B	71.4	92.7	79.5	<u>30.0</u>	23.0	59.3
	Qwen3-30B-A3B	73.9	87.3	77.7	33.3	24.8	<u>59.4</u>
	Qwen3-14B	75.8	89.1	75.7	26.7	<u>27.6</u>	59.0
	Qwen3-8B	72.1	85.5	72.9	13.3	23.8	53.5
	Qwen3-4B	63.0	78.2	67.8	23.3	19.3	50.3
	Qwen3-1.7B	46.1	70.9	53.4	6.7	11.9	37.8
	Qwen3-0.6B	35.1	43.6	39.0	0.0	4.5	24.4

Table 26: **Benchmark scores for language: Portuguese (pt)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.5	73.8	83.9	88.9	73.3	52.2	75.4
	QwQ-32B	70.5	70.0	<u>80.4</u>	84.0	80.0	48.7	72.3
	Qwen3-235B-A22B	73.6	78.8	78.6	<u>86.2</u>	86.7	58.3	77.0
	Qwen3-32B	74.1	<u>76.2</u>	76.8	82.6	80.0	52.4	73.7
	Qwen3-30B-A3B	76.1	71.2	71.4	81.0	76.7	49.3	71.0
	Qwen3-14B	<u>77.3</u>	68.8	75.0	81.6	<u>83.3</u>	46.7	72.1
	Qwen3-8B	<u>73.9</u>	67.5	75.0	78.6	<u>56.7</u>	44.8	66.1
	Qwen3-4B	70.6	62.5	71.4	75.1	73.3	44.2	66.2
	Qwen3-1.7B	55.6	60.0	53.6	64.6	46.7	28.2	51.4
	Qwen3-0.6B	38.7	33.8	42.9	47.5	10.0	12.7	30.9
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	66.8	57.5	<u>78.6</u>	80.7	10.0	15.0	51.4
	Gemma-3-27b-IT	72.9	55.0	75.0	77.1	33.3	20.9	55.7
	Qwen2.5-72B-Instruct	68.8	55.0	71.4	<u>82.2</u>	23.3	11.3	52.0
	Qwen3-235B-A22B	72.5	67.5	82.1	83.5	33.3	28.3	61.2
	Qwen3-32B	71.1	<u>61.3</u>	73.2	80.6	30.0	23.9	56.7
	Qwen3-30B-A3B	72.3	47.5	67.9	77.8	26.7	24.0	52.7
	Qwen3-14B	75.5	58.8	75.0	76.5	26.7	<u>25.8</u>	56.4
	Qwen3-8B	71.9	56.2	71.4	72.9	20.0	19.7	52.0
	Qwen3-4B	66.1	50.0	73.2	66.7	10.0	18.1	47.4
	Qwen3-1.7B	49.5	33.8	39.3	52.9	6.7	12.8	32.5
	Qwen3-0.6B	36.6	37.5	42.9	37.5	3.3	5.7	27.2

Table 27: **Benchmark scores for language: Italian (it)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	80.9	100.0	87.2	90.0	<u>54.1</u>	82.4
	QwQ-32B	71.2	<u>96.4</u>	84.9	76.7	49.3	75.7
	Qwen3-235B-A22B	73.7	<u>96.4</u>	<u>85.7</u>	<u>80.0</u>	57.4	78.6
	Qwen3-32B	76.6	<u>90.9</u>	<u>81.6</u>	<u>80.0</u>	49.7	<u>75.8</u>
	Qwen3-30B-A3B	75.9	94.5	81.9	<u>80.0</u>	48.1	76.1
	Qwen3-14B	<u>79.0</u>	94.5	80.2	70.0	47.0	74.1
	Qwen3-8B	<u>74.6</u>	89.1	77.5	76.7	46.1	72.8
	Qwen3-4B	69.8	83.6	74.4	76.7	44.5	69.8
	Qwen3-1.7B	54.6	74.5	64.2	53.3	29.6	55.2
	Qwen3-0.6B	37.8	45.5	45.9	6.7	13.3	29.8
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	67.6	98.2	<u>80.7</u>	13.3	15.2	55.0
	Gemma-3-27b-IT	<u>74.6</u>	90.9	<u>78.4</u>	23.3	20.5	57.5
	Qwen2.5-72B-Instruct	67.2	<u>94.5</u>	<u>80.7</u>	16.7	16.7	55.2
	Qwen3-235B-A22B	72.9	92.7	82.6	33.3	28.6	62.0
	Qwen3-32B	71.4	92.7	79.5	<u>30.0</u>	23.0	59.3
	Qwen3-30B-A3B	73.9	87.3	<u>77.7</u>	33.3	24.8	<u>59.4</u>
	Qwen3-14B	75.8	89.1	75.7	26.7	<u>27.6</u>	59.0
	Qwen3-8B	72.1	85.5	72.9	13.3	<u>23.8</u>	53.5
	Qwen3-4B	63.0	78.2	67.8	23.3	19.3	50.3
	Qwen3-1.7B	46.1	70.9	53.4	6.7	11.9	37.8
	Qwen3-0.6B	35.1	43.6	39.0	0.0	4.5	24.4

Table 28: **Benchmark scores for language: Arabic (ar)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	75.0	89.3	87.8	76.7	52.6	76.3
	QwQ-32B	<u>75.0</u>	67.9	81.8	80.0	41.3	69.2
	Qwen3-235B-A22B	80.0	71.4	<u>83.6</u>	76.7	53.7	<u>73.1</u>
	Qwen3-32B	66.2	73.2	<u>80.1</u>	86.7	47.0	70.6
	Qwen3-30B-A3B	66.2	66.1	77.2	<u>83.3</u>	47.3	68.0
	Qwen3-14B	71.2	67.9	77.4	<u>83.3</u>	46.6	69.3
	Qwen3-8B	65.0	67.9	74.4	<u>76.7</u>	44.9	65.8
	Qwen3-4B	62.5	55.4	67.7	66.7	41.2	58.7
	Qwen3-1.7B	55.0	44.6	53.2	36.7	25.8	43.1
	Qwen3-0.6B	40.0	41.1	38.9	10.0	11.7	28.3
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	51.2	78.6	80.9	13.3	12.9	47.4
	Gemma-3-27b-IT	56.2	62.5	74.4	26.7	22.8	48.5
	Qwen2.5-72B-Instruct	<u>56.2</u>	66.1	77.2	6.7	14.7	44.2
	Qwen3-235B-A22B	66.2	67.9	<u>79.5</u>	40.0	28.2	56.4
	Qwen3-32B	55.0	69.6	<u>75.7</u>	23.3	25.4	49.8
	Qwen3-30B-A3B	48.8	64.3	71.6	<u>30.0</u>	22.6	47.5
	Qwen3-14B	52.5	60.7	69.5	23.3	23.5	45.9
	Qwen3-8B	45.0	58.9	64.6	13.3	16.4	39.6
	Qwen3-4B	52.5	42.9	56.7	13.3	15.3	36.1
	Qwen3-1.7B	31.2	37.5	43.6	3.3	9.4	25.0
	Qwen3-0.6B	40.0	39.3	35.4	0.0	3.8	23.7

Table 29: **Benchmark scores for language: Japanese (ja)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	72.5	74.5	<u>83.8</u>	83.3	55.4	<u>73.9</u>
	QwQ-32B	<u>73.8</u>	86.3	82.3	53.3	39.9	67.1
	Qwen3-235B-A22B	75.0	94.1	84.8	73.3	<u>52.7</u>	76.0
	Qwen3-32B	70.0	<u>90.2</u>	80.2	<u>76.7</u>	47.7	73.0
	Qwen3-30B-A3B	66.2	88.2	79.9	73.3	47.4	71.0
	Qwen3-14B	68.8	88.2	79.4	66.7	45.7	69.8
	Qwen3-8B	71.2	86.3	74.9	73.3	44.7	70.1
	Qwen3-4B	63.7	80.4	72.5	53.3	40.7	62.1
	Qwen3-1.7B	53.8	74.5	61.8	36.7	28.5	51.1
	Qwen3-0.6B	47.5	47.1	45.1	13.3	14.5	33.5
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	60.0	<u>92.2</u>	81.9	10.0	12.5	51.3
	Gemma-3-27b-IT	66.2	86.3	76.5	20.0	17.3	53.3
	Qwen2.5-72B-Instruct	55.0	94.1	77.7	16.7	17.7	52.2
	Qwen3-235B-A22B	67.5	<u>92.2</u>	<u>80.9</u>	26.7	26.9	58.8
	Qwen3-32B	58.8	<u>92.2</u>	78.0	20.0	20.5	<u>53.9</u>
	Qwen3-30B-A3B	51.2	82.4	74.9	<u>30.0</u>	<u>20.6</u>	51.8
	Qwen3-14B	55.0	84.3	73.8	33.3	19.8	53.2
	Qwen3-8B	47.5	82.4	69.9	20.0	18.5	47.7
	Qwen3-4B	46.2	76.5	64.8	13.3	15.1	43.2
	Qwen3-1.7B	40.0	68.6	46.3	3.3	11.6	34.0
	Qwen3-0.6B	37.5	37.3	37.9	3.3	3.7	23.9

Table 28: **Benchmark scores for language: Arabic (ar)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	75.0	89.3	87.8	76.7	52.6	76.3
	QwQ-32B	<u>75.0</u>	67.9	81.8	80.0	41.3	69.2
	Qwen3-235B-A22B	80.0	71.4	<u>83.6</u>	76.7	53.7	<u>73.1</u>
	Qwen3-32B	66.2	73.2	<u>80.1</u>	86.7	47.0	70.6
	Qwen3-30B-A3B	66.2	66.1	77.2	<u>83.3</u>	47.3	68.0
	Qwen3-14B	71.2	67.9	77.4	<u>83.3</u>	46.6	69.3
	Qwen3-8B	65.0	67.9	74.4	<u>76.7</u>	44.9	65.8
	Qwen3-4B	62.5	55.4	67.7	66.7	41.2	58.7
	Qwen3-1.7B	55.0	44.6	53.2	36.7	25.8	43.1
	Qwen3-0.6B	40.0	41.1	38.9	10.0	11.7	28.3
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	51.2	78.6	80.9	13.3	12.9	47.4
	Gemma-3-27b-IT	56.2	62.5	74.4	26.7	22.8	48.5
	Qwen2.5-72B-Instruct	<u>56.2</u>	66.1	77.2	6.7	14.7	44.2
	Qwen3-235B-A22B	66.2	67.9	<u>79.5</u>	40.0	28.2	56.4
	Qwen3-32B	55.0	69.6	<u>75.7</u>	23.3	25.4	49.8
	Qwen3-30B-A3B	48.8	64.3	71.6	<u>30.0</u>	22.6	47.5
	Qwen3-14B	52.5	60.7	69.5	23.3	23.5	45.9
	Qwen3-8B	45.0	58.9	64.6	13.3	16.4	39.6
	Qwen3-4B	52.5	42.9	56.7	13.3	15.3	36.1
	Qwen3-1.7B	31.2	37.5	43.6	3.3	9.4	25.0
	Qwen3-0.6B	40.0	39.3	35.4	0.0	3.8	23.7

Table 29: **Benchmark scores for language: Japanese (ja)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	72.5	74.5	<u>83.8</u>	83.3	55.4	<u>73.9</u>
	QwQ-32B	<u>73.8</u>	86.3	82.3	53.3	39.9	67.1
	Qwen3-235B-A22B	75.0	94.1	84.8	73.3	<u>52.7</u>	76.0
	Qwen3-32B	70.0	<u>90.2</u>	80.2	<u>76.7</u>	47.7	73.0
	Qwen3-30B-A3B	66.2	88.2	79.9	73.3	47.4	71.0
	Qwen3-14B	68.8	88.2	79.4	66.7	45.7	69.8
	Qwen3-8B	71.2	86.3	74.9	73.3	44.7	70.1
	Qwen3-4B	63.7	80.4	72.5	53.3	40.7	62.1
	Qwen3-1.7B	53.8	74.5	61.8	36.7	28.5	51.1
	Qwen3-0.6B	47.5	47.1	45.1	13.3	14.5	33.5
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	60.0	<u>92.2</u>	81.9	10.0	12.5	51.3
	Gemma-3-27b-IT	66.2	86.3	76.5	20.0	17.3	53.3
	Qwen2.5-72B-Instruct	55.0	94.1	77.7	16.7	17.7	52.2
	Qwen3-235B-A22B	67.5	<u>92.2</u>	<u>80.9</u>	26.7	26.9	58.8
	Qwen3-32B	58.8	<u>92.2</u>	78.0	20.0	20.5	<u>53.9</u>
	Qwen3-30B-A3B	51.2	82.4	74.9	<u>30.0</u>	<u>20.6</u>	51.8
	Qwen3-14B	55.0	84.3	73.8	33.3	19.8	53.2
	Qwen3-8B	47.5	82.4	69.9	20.0	18.5	47.7
	Qwen3-4B	46.2	76.5	64.8	13.3	15.1	43.2
	Qwen3-1.7B	40.0	68.6	46.3	3.3	11.6	34.0
	Qwen3-0.6B	37.5	37.3	37.9	3.3	3.7	23.9

Table 30: **Benchmark scores for language: Korean (ko)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	75.0	88.0	85.9	<u>76.7</u>	50.0	75.1
	QwQ-32B	76.2	72.0	81.8	60.0	40.0	66.0
	Qwen3-235B-A22B	71.2	<u>80.0</u>	<u>84.7</u>	80.0	55.7	<u>74.3</u>
	Qwen3-32B	71.2	<u>74.0</u>	<u>79.2</u>	80.0	48.5	70.6
	Qwen3-30B-A3B	68.8	72.0	78.6	<u>76.7</u>	46.6	68.5
	Qwen3-14B	67.5	74.0	79.6	<u>76.7</u>	46.0	68.8
	Qwen3-8B	60.0	<u>80.0</u>	74.7	<u>76.7</u>	42.3	66.7
	Qwen3-4B	66.2	74.0	68.8	70.0	40.6	63.9
	Qwen3-1.7B	53.8	66.0	57.8	43.3	25.2	49.2
	Qwen3-0.6B	33.8	52.0	41.5	13.3	11.8	30.5
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	63.7	80.0	80.5	13.3	12.9	50.1
	Gemma-3-27b-IT	58.8	<u>76.0</u>	75.9	20.0	18.3	49.8
	Qwen2.5-72B-Instruct	58.8	68.0	76.7	6.7	17.7	45.6
	Qwen3-235B-A22B	63.7	<u>76.0</u>	<u>79.8</u>	33.3	27.9	56.1
	Qwen3-32B	60.0	<u>74.0</u>	<u>77.2</u>	<u>26.7</u>	21.2	51.8
	Qwen3-30B-A3B	52.5	72.0	72.5	16.7	20.7	46.9
	Qwen3-14B	52.5	68.0	73.3	20.0	18.7	46.5
	Qwen3-8B	52.5	<u>76.0</u>	66.5	23.3	16.3	46.9
	Qwen3-4B	46.2	74.0	59.9	13.3	16.6	42.0
	Qwen3-1.7B	48.8	58.0	46.0	6.7	9.0	33.7
	Qwen3-0.6B	40.0	52.0	36.9	0.0	5.5	26.9

Table 31: **Benchmark scores for language: Indonesian (id)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	<u>80.0</u>	<u>86.3</u>	83.3	<u>51.3</u>	75.2
	QwQ-32B	76.4	83.7	73.3	47.3	70.2
	Qwen3-235B-A22B	<u>80.0</u>	87.2	<u>80.0</u>	53.5	75.2
	Qwen3-32B	<u>80.0</u>	82.0	<u>76.7</u>	45.6	71.1
	Qwen3-30B-A3B	81.8	80.4	<u>80.0</u>	44.9	<u>71.8</u>
	Qwen3-14B	78.2	79.6	70.0	45.3	68.3
	Qwen3-8B	72.7	77.7	70.0	43.8	66.0
	Qwen3-4B	70.9	72.3	66.7	41.2	62.8
	Qwen3-1.7B	63.6	61.2	36.7	26.8	47.1
	Qwen3-0.6B	36.4	46.6	10.0	12.6	26.4
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	<u>80.0</u>	<u>81.1</u>	10.0	14.7	46.4
	Gemma-3-27b-IT	<u>76.4</u>	<u>75.9</u>	13.3	22.6	47.0
	Qwen2.5-72B-Instruct	74.5	78.8	10.0	16.6	45.0
	Qwen3-235B-A22B	81.8	81.9	33.3	27.5	56.1
	Qwen3-32B	81.8	77.2	23.3	24.3	<u>51.6</u>
	Qwen3-30B-A3B	70.9	76.4	<u>30.0</u>	<u>25.9</u>	50.8
	Qwen3-14B	70.9	74.1	26.7	24.6	49.1
	Qwen3-8B	78.2	69.6	20.0	21.6	47.4
	Qwen3-4B	67.3	66.5	13.3	19.0	41.5
	Qwen3-1.7B	52.7	49.0	3.3	10.8	29.0
	Qwen3-0.6B	52.7	40.0	3.3	5.1	25.3

Table 30: **Benchmark scores for language: Korean (ko)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	75.0	88.0	85.9	<u>76.7</u>	50.0	75.1
	QwQ-32B	76.2	72.0	81.8	60.0	40.0	66.0
	Qwen3-235B-A22B	71.2	<u>80.0</u>	<u>84.7</u>	80.0	55.7	<u>74.3</u>
	Qwen3-32B	71.2	<u>74.0</u>	<u>79.2</u>	80.0	48.5	70.6
	Qwen3-30B-A3B	68.8	72.0	78.6	<u>76.7</u>	46.6	68.5
	Qwen3-14B	67.5	74.0	79.6	<u>76.7</u>	46.0	68.8
	Qwen3-8B	60.0	<u>80.0</u>	74.7	<u>76.7</u>	42.3	66.7
	Qwen3-4B	66.2	74.0	68.8	70.0	40.6	63.9
	Qwen3-1.7B	53.8	66.0	57.8	43.3	25.2	49.2
	Qwen3-0.6B	33.8	52.0	41.5	13.3	11.8	30.5
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	63.7	80.0	80.5	13.3	12.9	50.1
	Gemma-3-27b-IT	58.8	<u>76.0</u>	75.9	20.0	18.3	49.8
	Qwen2.5-72B-Instruct	58.8	68.0	76.7	6.7	17.7	45.6
	Qwen3-235B-A22B	63.7	<u>76.0</u>	<u>79.8</u>	33.3	27.9	56.1
	Qwen3-32B	60.0	<u>74.0</u>	<u>77.2</u>	<u>26.7</u>	21.2	51.8
	Qwen3-30B-A3B	52.5	72.0	72.5	16.7	20.7	46.9
	Qwen3-14B	52.5	68.0	73.3	20.0	18.7	46.5
	Qwen3-8B	52.5	<u>76.0</u>	66.5	23.3	16.3	46.9
	Qwen3-4B	46.2	74.0	59.9	13.3	16.6	42.0
	Qwen3-1.7B	48.8	58.0	46.0	6.7	9.0	33.7
	Qwen3-0.6B	40.0	52.0	36.9	0.0	5.5	26.9

Table 31: **Benchmark scores for language: Indonesian (id)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	<u>80.0</u>	<u>86.3</u>	83.3	<u>51.3</u>	75.2
	QwQ-32B	76.4	83.7	73.3	47.3	70.2
	Qwen3-235B-A22B	<u>80.0</u>	87.2	<u>80.0</u>	53.5	75.2
	Qwen3-32B	<u>80.0</u>	82.0	<u>76.7</u>	45.6	71.1
	Qwen3-30B-A3B	81.8	80.4	<u>80.0</u>	44.9	<u>71.8</u>
	Qwen3-14B	78.2	79.6	70.0	45.3	68.3
	Qwen3-8B	72.7	77.7	70.0	43.8	66.0
	Qwen3-4B	70.9	72.3	66.7	41.2	62.8
	Qwen3-1.7B	63.6	61.2	36.7	26.8	47.1
	Qwen3-0.6B	36.4	46.6	10.0	12.6	26.4
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	<u>80.0</u>	<u>81.1</u>	10.0	14.7	46.4
	Gemma-3-27b-IT	<u>76.4</u>	<u>75.9</u>	13.3	22.6	47.0
	Qwen2.5-72B-Instruct	74.5	78.8	10.0	16.6	45.0
	Qwen3-235B-A22B	81.8	81.9	33.3	27.5	56.1
	Qwen3-32B	81.8	77.2	23.3	24.3	<u>51.6</u>
	Qwen3-30B-A3B	70.9	76.4	<u>30.0</u>	<u>25.9</u>	50.8
	Qwen3-14B	70.9	74.1	26.7	24.6	49.1
	Qwen3-8B	78.2	69.6	20.0	21.6	47.4
	Qwen3-4B	67.3	66.5	13.3	19.0	41.5
	Qwen3-1.7B	52.7	49.0	3.3	10.8	29.0
	Qwen3-0.6B	52.7	40.0	3.3	5.1	25.3

Table 32: **Benchmark scores for language: Russian (ru)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	INCLUDE	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	68.1	80.4	70.0	<u>52.3</u>	<u>67.7</u>
	QwQ-32B	61.2	73.2	<u>76.7</u>	43.6	63.7
	Qwen3-235B-A22B	62.2	80.4	80.0	53.1	68.9
	Qwen3-32B	62.5	73.2	63.3	46.5	61.4
	Qwen3-30B-A3B	60.7	<u>76.8</u>	73.3	45.4	64.0
	Qwen3-14B	<u>63.6</u>	80.4	66.7	46.4	64.3
	Qwen3-8B	<u>62.9</u>	69.6	63.3	37.7	58.4
	Qwen3-4B	52.8	69.6	56.7	36.6	53.9
	Qwen3-1.7B	37.8	46.4	20.0	22.8	31.8
	Qwen3-0.6B	26.4	46.4	3.3	7.0	20.8
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	52.0	80.4	20.0	13.7	41.5
	Gemma-3-27b-IT	57.3	71.4	23.3	21.6	43.4
	Qwen2.5-72B-Instruct	54.1	67.9	20.0	13.3	38.8
	Qwen3-235B-A22B	56.7	<u>75.0</u>	40.0	26.1	49.4
	Qwen3-32B	58.6	71.4	30.0	23.3	45.8
	Qwen3-30B-A3B	58.0	73.2	<u>30.0</u>	21.1	45.6
	Qwen3-14B	60.3	71.4	26.7	<u>24.2</u>	45.6
	Qwen3-8B	<u>59.3</u>	58.9	20.0	22.8	40.2
	Qwen3-4B	46.1	58.9	13.3	17.8	34.0
	Qwen3-1.7B	34.8	41.1	3.3	13.2	23.1
	Qwen3-0.6B	25.5	46.4	0.0	5.8	19.4

Table 33: **Benchmark scores for language: Vietnamese (vi)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	<u>72.5</u>	89.1	70.0	<u>52.1</u>	<u>70.9</u>
	QwQ-32B	71.2	69.1	70.0	49.2	64.9
	Qwen3-235B-A22B	75.0	<u>87.3</u>	83.3	55.1	75.2
	Qwen3-32B	67.5	<u>81.8</u>	83.3	44.0	69.2
	Qwen3-30B-A3B	68.8	78.2	<u>76.7</u>	46.1	67.4
	Qwen3-14B	<u>72.5</u>	72.7	73.3	45.8	66.1
	Qwen3-8B	65.0	72.7	73.3	42.9	63.5
	Qwen3-4B	68.8	63.6	60.0	42.2	58.6
	Qwen3-1.7B	52.5	61.8	30.0	26.9	42.8
	Qwen3-0.6B	33.8	38.2	6.7	9.8	22.1
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	57.5	<u>81.8</u>	10.0	13.0	40.6
	Gemma-3-27b-IT	52.5	<u>74.5</u>	<u>33.3</u>	20.6	45.2
	Qwen2.5-72B-Instruct	61.3	72.7	26.7	18.6	44.8
	Qwen3-235B-A22B	70.0	83.6	36.7	27.1	54.4
	Qwen3-32B	60.0	<u>81.8</u>	23.3	21.8	46.7
	Qwen3-30B-A3B	52.5	<u>81.8</u>	20.0	<u>24.7</u>	44.8
	Qwen3-14B	<u>63.7</u>	67.3	20.0	21.6	43.2
	Qwen3-8B	48.8	65.5	20.0	19.1	38.4
	Qwen3-4B	48.8	65.5	20.0	19.0	38.3
	Qwen3-1.7B	36.2	60.0	3.3	10.9	27.6
	Qwen3-0.6B	30.0	36.4	3.3	3.9	18.4

Table 32: **Benchmark scores for language: Russian (ru)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	Multi-IF	INCLUDE	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	68.1	80.4	70.0	<u>52.3</u>	<u>67.7</u>
	QwQ-32B	61.2	73.2	<u>76.7</u>	43.6	63.7
	Qwen3-235B-A22B	62.2	80.4	80.0	53.1	68.9
	Qwen3-32B	62.5	73.2	63.3	46.5	61.4
	Qwen3-30B-A3B	60.7	<u>76.8</u>	73.3	45.4	64.0
	Qwen3-14B	<u>63.6</u>	80.4	66.7	46.4	64.3
	Qwen3-8B	<u>62.9</u>	69.6	63.3	37.7	58.4
	Qwen3-4B	52.8	69.6	56.7	36.6	53.9
	Qwen3-1.7B	37.8	46.4	20.0	22.8	31.8
	Qwen3-0.6B	26.4	46.4	3.3	7.0	20.8
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	52.0	80.4	20.0	13.7	41.5
	Gemma-3-27b-IT	57.3	71.4	23.3	21.6	43.4
	Qwen2.5-72B-Instruct	54.1	67.9	20.0	13.3	38.8
	Qwen3-235B-A22B	56.7	<u>75.0</u>	40.0	26.1	49.4
	Qwen3-32B	58.6	71.4	30.0	23.3	45.8
	Qwen3-30B-A3B	58.0	73.2	<u>30.0</u>	21.1	45.6
	Qwen3-14B	60.3	71.4	26.7	<u>24.2</u>	45.6
	Qwen3-8B	<u>59.3</u>	58.9	20.0	22.8	40.2
	Qwen3-4B	46.1	58.9	13.3	17.8	34.0
	Qwen3-1.7B	34.8	41.1	3.3	13.2	23.1
	Qwen3-0.6B	25.5	46.4	0.0	5.8	19.4

Table 33: **Benchmark scores for language: Vietnamese (vi)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	INCLUDE	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	<u>72.5</u>	89.1	70.0	<u>52.1</u>	<u>70.9</u>
	QwQ-32B	71.2	69.1	70.0	49.2	64.9
	Qwen3-235B-A22B	75.0	<u>87.3</u>	83.3	55.1	75.2
	Qwen3-32B	67.5	<u>81.8</u>	83.3	44.0	69.2
	Qwen3-30B-A3B	68.8	78.2	<u>76.7</u>	46.1	67.4
	Qwen3-14B	<u>72.5</u>	72.7	73.3	45.8	66.1
	Qwen3-8B	65.0	72.7	73.3	42.9	63.5
	Qwen3-4B	68.8	63.6	60.0	42.2	58.6
	Qwen3-1.7B	52.5	61.8	30.0	26.9	42.8
	Qwen3-0.6B	33.8	38.2	6.7	9.8	22.1
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	57.5	<u>81.8</u>	10.0	13.0	40.6
	Gemma-3-27b-IT	52.5	<u>74.5</u>	<u>33.3</u>	20.6	45.2
	Qwen2.5-72B-Instruct	61.3	72.7	26.7	18.6	44.8
	Qwen3-235B-A22B	70.0	83.6	36.7	27.1	54.4
	Qwen3-32B	60.0	<u>81.8</u>	23.3	21.8	46.7
	Qwen3-30B-A3B	52.5	<u>81.8</u>	20.0	<u>24.7</u>	44.8
	Qwen3-14B	<u>63.7</u>	67.3	20.0	21.6	43.2
	Qwen3-8B	48.8	65.5	20.0	19.1	38.4
	Qwen3-4B	48.8	65.5	20.0	19.0	38.3
	Qwen3-1.7B	36.2	60.0	3.3	10.9	27.6
	Qwen3-0.6B	30.0	36.4	3.3	3.9	18.4

Table 34: **Benchmark scores for language: German (de)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	50.0	85.6	86.7	53.8	69.0
	QwQ-32B	57.1	83.8	76.7	51.0	67.2
	Qwen3-235B-A22B	71.4	86.0	<u>83.3</u>	55.4	74.0
	Qwen3-32B	<u>64.3</u>	81.9	86.7	48.1	<u>70.2</u>
	Qwen3-30B-A3B	<u>64.3</u>	81.9	80.0	46.6	68.2
	Qwen3-14B	57.1	80.9	70.0	48.1	64.0
	Qwen3-8B	<u>64.3</u>	78.1	66.7	43.6	63.2
	Qwen3-4B	57.1	74.0	73.3	43.1	61.9
	Qwen3-1.7B	<u>64.3</u>	63.4	36.7	26.8	47.8
	Qwen3-0.6B	57.1	47.6	10.0	13.7	32.1
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	57.1	<u>80.4</u>	10.0	13.5	40.2
	Gemma-3-27b-IT	57.1	76.1	26.7	20.2	45.0
	Qwen2.5-72B-Instruct	<u>64.3</u>	79.9	16.7	19.3	45.0
	Qwen3-235B-A22B	71.4	81.7	40.0	25.9	54.8
	Qwen3-32B	57.1	77.2	30.0	21.9	46.6
	Qwen3-30B-A3B	57.1	77.7	23.3	<u>25.2</u>	45.8
	Qwen3-14B	57.1	76.0	<u>30.0</u>	24.5	<u>46.9</u>
	Qwen3-8B	<u>64.3</u>	70.8	20.0	19.9	43.8
	Qwen3-4B	<u>64.3</u>	66.0	26.7	16.4	43.4
	Qwen3-1.7B	42.9	53.2	10.0	10.6	29.2
	Qwen3-0.6B	42.9	37.8	3.3	5.7	22.4

Table 35: **Benchmark scores for language: Thai (th)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	<u>73.8</u>	80.0	<u>50.7</u>	68.2
	QwQ-32B	75.0	60.0	41.3	58.8
	Qwen3-235B-A22B	73.8	86.7	53.6	71.4
	Qwen3-32B	<u>73.8</u>	76.7	46.9	65.8
	Qwen3-30B-A3B	63.7	<u>80.0</u>	45.2	63.0
	Qwen3-14B	65.0	76.7	44.4	62.0
	Qwen3-8B	68.8	70.0	41.3	60.0
	Qwen3-4B	60.0	60.0	39.4	53.1
	Qwen3-1.7B	48.8	33.3	23.7	35.3
	Qwen3-0.6B	33.8	13.3	11.4	19.5
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	52.5	10.0	11.9	24.8
	Gemma-3-27b-IT	50.0	16.7	19.0	28.6
	Qwen2.5-72B-Instruct	<u>58.8</u>	6.7	17.4	27.6
	Qwen3-235B-A22B	61.3	<u>23.3</u>	27.6	37.4
	Qwen3-32B	61.3	13.3	22.2	32.3
	Qwen3-30B-A3B	50.0	30.0	<u>22.3</u>	<u>34.1</u>
	Qwen3-14B	47.5	<u>23.3</u>	22.1	31.0
	Qwen3-8B	42.5	10.0	17.2	23.2
	Qwen3-4B	43.8	13.3	16.1	24.4
	Qwen3-1.7B	42.5	6.7	9.5	19.6
	Qwen3-0.6B	37.5	0.0	3.6	13.7

Table 34: **Benchmark scores for language: German (de)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	INCLUDE	MMMLU	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	50.0	85.6	86.7	53.8	69.0
	QwQ-32B	57.1	83.8	76.7	51.0	67.2
	Qwen3-235B-A22B	71.4	86.0	<u>83.3</u>	55.4	74.0
	Qwen3-32B	<u>64.3</u>	81.9	86.7	48.1	<u>70.2</u>
	Qwen3-30B-A3B	<u>64.3</u>	81.9	80.0	46.6	68.2
	Qwen3-14B	57.1	80.9	70.0	48.1	64.0
	Qwen3-8B	<u>64.3</u>	78.1	66.7	43.6	63.2
	Qwen3-4B	57.1	74.0	73.3	43.1	61.9
	Qwen3-1.7B	<u>64.3</u>	63.4	36.7	26.8	47.8
	Qwen3-0.6B	57.1	47.6	10.0	13.7	32.1
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	57.1	<u>80.4</u>	10.0	13.5	40.2
	Gemma-3-27b-IT	57.1	76.1	26.7	20.2	45.0
	Qwen2.5-72B-Instruct	<u>64.3</u>	79.9	16.7	19.3	45.0
	Qwen3-235B-A22B	71.4	81.7	40.0	25.9	54.8
	Qwen3-32B	57.1	77.2	30.0	21.9	46.6
	Qwen3-30B-A3B	57.1	77.7	23.3	<u>25.2</u>	45.8
	Qwen3-14B	57.1	76.0	<u>30.0</u>	24.5	<u>46.9</u>
	Qwen3-8B	<u>64.3</u>	70.8	20.0	19.9	43.8
	Qwen3-4B	<u>64.3</u>	66.0	26.7	16.4	43.4
	Qwen3-1.7B	42.9	53.2	10.0	10.6	29.2
	Qwen3-0.6B	42.9	37.8	3.3	5.7	22.4

Table 35: **Benchmark scores for language: Thai (th)**. The highest and second-best scores are shown in **bold** and underlined, respectively.

	Model	MLogiQA	MT-AIME24	PolyMath	Average
<i>Thinking Mode</i>	Gemini2.5-Pro	<u>73.8</u>	80.0	<u>50.7</u>	68.2
	QwQ-32B	75.0	60.0	41.3	58.8
	Qwen3-235B-A22B	73.8	86.7	53.6	71.4
	Qwen3-32B	<u>73.8</u>	76.7	46.9	65.8
	Qwen3-30B-A3B	63.7	<u>80.0</u>	45.2	63.0
	Qwen3-14B	65.0	76.7	44.4	62.0
	Qwen3-8B	68.8	70.0	41.3	60.0
	Qwen3-4B	60.0	60.0	39.4	53.1
	Qwen3-1.7B	48.8	33.3	23.7	35.3
	Qwen3-0.6B	33.8	13.3	11.4	19.5
<i>Non-thinking Mode</i>	GPT-4o-2024-1120	52.5	10.0	11.9	24.8
	Gemma-3-27b-IT	50.0	16.7	19.0	28.6
	Qwen2.5-72B-Instruct	<u>58.8</u>	6.7	17.4	27.6
	Qwen3-235B-A22B	61.3	<u>23.3</u>	27.6	37.4
	Qwen3-32B	61.3	13.3	22.2	32.3
	Qwen3-30B-A3B	50.0	30.0	<u>22.3</u>	<u>34.1</u>
	Qwen3-14B	47.5	<u>23.3</u>	22.1	31.0
	Qwen3-8B	42.5	10.0	17.2	23.2
	Qwen3-4B	43.8	13.3	16.1	24.4
	Qwen3-1.7B	42.5	6.7	9.5	19.6
	Qwen3-0.6B	37.5	0.0	3.6	13.7

Table 36: Language families and language codes supported by Qwen3 in Belebele Benchmark

Language family	# Langs	Language code (ISO 639-3 ISO 15924)
Indo-European	40	por_Latn, deu_Latn, tsk_Cyrl, ces_Latn, nob_Latn, dan_Latn, snd_Arab, spa_Latn, isl_Latn, slv_Latn, eng_Latn, ory_Orya, hrv_Latn, ell_Grek, ukr_Cyrl, pan_Guru, srp_Cyrl, npi_Deva, mkd_Cyrl, guj_Gujr, nld_Latn, swe_Latn, hin_Deva, rus_Cyrl, asm_Beng, cat_Latn, als_Latn, sin_Sinh, urd_Arab, mar_Deva, lit_Latn, slk_Latn, ita_Latn, pol_Latn, bul_Cyrl, afr_Latn, ron_Latn, fra_Latn, ben_Beng, hye_Armn
Sino-Tibetan	3	zho_Hans, mya_Mymr, zho_Hant
Afro-Asiatic	8	heb_Hebr, apc_Arab, acm_Arab, ary_Arab, ars_Arab, arb_Arab, mlt_Latn, erz_Arab
Austronesian	7	ilo_Latn, ceb_Latn, tgl_Latn, sun_Latn, jav_Latn, war_Latn, ind_Latn
Dravidian	4	mal_Mlym, kan_Knda, tel_Telu, tam_Taml
Turkic	4	kaz_Cyrl, azj_Latn, tur_Latn, uzn_Latn
Tai-Kadai	2	tha_Thai, lao_Lao
Uralic	3	fin_Latn, hun_Latn, est_Latn
Austroasiatic	2	vie_Latn, khm_Khmr
Other	7	eus_Latn, kor_Hang, hat_Latn, swl_Latn, kea_Latn, jpn_Jpan, kat_Geor

Table 37: Comparison of Belebele Benchmark performance between Qwen3 and other baseline models. Scores are highlighted with the highest in **bold** and the second-best underlined.

Model	Indo-European	Sino-Tibetan	Afro-Asiatic	Austronesian	Dravidian	Turkic	Tai-Kadai	Uralic	Austroasiatic	Other
Gemma-3-27B-IT	<u>89.2</u>	86.3	85.9	<u>84.1</u>	83.5	86.8	81.0	<u>91.0</u>	86.5	87.0
Qwen2.5-32B-Instruct	85.5	82.3	80.4	<u>70.6</u>	67.8	80.8	74.5	87.0	79.0	72.6
QwQ-32B	86.1	83.7	81.9	71.3	69.3	80.3	77.0	88.0	83.0	74.0
Qwen3-32B (Thinking)	90.7	89.7	84.8	86.7	84.5	89.3	83.5	91.3	88.0	83.1
Qwen3-32B (Non-thinking)	89.1	<u>88.0</u>	<u>82.3</u>	83.7	<u>84.0</u>	85.0	85.0	88.7	88.0	<u>81.3</u>
Gemma-3-12B-IT	85.8	83.3	83.4	79.3	<u>79.0</u>	82.8	77.5	89.0	83.0	81.6
Qwen2.5-14B-Instruct	82.7	78.9	80.4	69.1	66.2	74.2	72.2	83.9	77.9	70.4
Qwen3-14B (Thinking)	88.6	87.3	<u>82.4</u>	82.4	81.0	83.8	83.5	91.0	82.5	81.7
Qwen3-14B (Non-thinking)	<u>87.4</u>	82.7	80.1	<u>80.7</u>	78.0	81.8	<u>80.5</u>	87.7	81.5	77.0
Gemma-3-4B-IT	71.8	72.0	63.5	61.7	64.8	64.0	61.5	70.7	71.0	62.6
Qwen2.5-3B-Instruct	58.0	62.3	57.2	47.9	36.9	<u>45.1</u>	49.8	50.6	56.8	<u>48.4</u>
Qwen3-4B (Thinking)	82.2	77.7	74.1	73.0	74.3	76.3	68.5	83.0	74.5	67.9
Qwen3-4B (Non-thinking)	<u>76.0</u>	<u>77.0</u>	<u>65.6</u>	<u>65.6</u>	<u>65.5</u>	<u>64.0</u>	60.5	<u>74.0</u>	<u>74.0</u>	61.0
Gemma-3-1B-IT	36.5	36.0	30.0	29.1	28.8	27.3	28.0	32.7	33.0	30.9
Qwen2.5-1.5B-Instruct	41.5	43.0	39.6	34.8	28.6	29.7	39.4	33.8	42.0	36.0
Qwen3-1.7B (Thinking)	69.7	66.0	59.4	58.6	52.8	57.8	53.5	70.3	63.5	53.4
Qwen3-1.7B (Non-thinking)	<u>58.8</u>	<u>62.7</u>	<u>50.8</u>	<u>53.0</u>	<u>43.3</u>	<u>48.0</u>	<u>46.0</u>	<u>54.3</u>	<u>54.0</u>	<u>43.9</u>

Table 36: Language families and language codes supported by Qwen3 in Belebele Benchmark

Language family	# Langs	Language code (ISO 639-3 ISO 15924)
Indo-European	40	por_Latn, deu_Latn, tsk_Cyrl, ces_Latn, nob_Latn, dan_Latn, snd_Arab, spa_Latn, isl_Latn, slv_Latn, eng_Latn, ory_Orya, hrv_Latn, ell_Grek, ukr_Cyrl, pan_Guru, srp_Cyrl, npi_Deva, mkd_Cyrl, guj_Gujr, nld_Latn, swe_Latn, hin_Deva, rus_Cyrl, asm_Beng, cat_Latn, als_Latn, sin_Sinh, urd_Arab, mar_Deva, lit_Latn, slk_Latn, ita_Latn, pol_Latn, bul_Cyrl, afr_Latn, ron_Latn, fra_Latn, ben_Beng, hye_Armn
Sino-Tibetan	3	zho_Hans, mya_Mymr, zho_Hant
Afro-Asiatic	8	heb_Hebr, apc_Arab, acm_Arab, ary_Arab, ars_Arab, arb_Arab, mlt_Latn, erz_Arab
Austronesian	7	ilo_Latn, ceb_Latn, tgl_Latn, sun_Latn, jav_Latn, war_Latn, ind_Latn
Dravidian	4	mal_Mlym, kan_Knda, tel_Telu, tam_Taml
Turkic	4	kaz_Cyrl, azj_Latn, tur_Latn, uzn_Latn
Tai-Kadai	2	tha_Thai, lao_Lao
Uralic	3	fin_Latn, hun_Latn, est_Latn
Austroasiatic	2	vie_Latn, khm_Khmr
Other	7	eus_Latn, kor_Hang, hat_Latn, swl_Latn, kea_Latn, jpn_Jpan, kat_Geor

Table 37: Comparison of Belebele Benchmark performance between Qwen3 and other baseline models. Scores are highlighted with the highest in **bold** and the second-best underlined.

Model	Indo-European	Sino-Tibetan	Afro-Asiatic	Austronesian	Dravidian	Turkic	Tai-Kadai	Uralic	Austroasiatic	Other
Gemma-3-27B-IT	<u>89.2</u>	86.3	85.9	<u>84.1</u>	83.5	86.8	81.0	<u>91.0</u>	86.5	87.0
Qwen2.5-32B-Instruct	85.5	82.3	80.4	<u>70.6</u>	67.8	80.8	74.5	<u>87.0</u>	79.0	72.6
QwQ-32B	86.1	83.7	81.9	71.3	69.3	80.3	77.0	88.0	83.0	74.0
Qwen3-32B (Thinking)	90.7	89.7	84.8	86.7	84.5	89.3	83.5	91.3	88.0	83.1
Qwen3-32B (Non-thinking)	89.1	<u>88.0</u>	<u>82.3</u>	83.7	<u>84.0</u>	85.0	85.0	88.7	88.0	<u>81.3</u>
Gemma-3-12B-IT	85.8	<u>83.3</u>	83.4	79.3	<u>79.0</u>	<u>82.8</u>	77.5	<u>89.0</u>	83.0	81.6
Qwen2.5-14B-Instruct	82.7	78.9	80.4	69.1	66.2	74.2	72.2	83.9	77.9	70.4
Qwen3-14B (Thinking)	88.6	87.3	<u>82.4</u>	82.4	81.0	83.8	83.5	91.0	82.5	81.7
Qwen3-14B (Non-thinking)	<u>87.4</u>	82.7	<u>80.1</u>	<u>80.7</u>	78.0	81.8	<u>80.5</u>	87.7	81.5	77.0
Gemma-3-4B-IT	71.8	72.0	63.5	61.7	64.8	64.0	61.5	70.7	71.0	62.6
Qwen2.5-3B-Instruct	58.0	62.3	57.2	47.9	36.9	<u>45.1</u>	49.8	50.6	56.8	<u>48.4</u>
Qwen3-4B (Thinking)	82.2	77.7	74.1	73.0	74.3	76.3	68.5	83.0	74.5	67.9
Qwen3-4B (Non-thinking)	<u>76.0</u>	<u>77.0</u>	<u>65.6</u>	<u>65.6</u>	<u>65.5</u>	<u>64.0</u>	60.5	<u>74.0</u>	<u>74.0</u>	61.0
Gemma-3-1B-IT	36.5	36.0	30.0	29.1	28.8	27.3	28.0	32.7	33.0	30.9
Qwen2.5-1.5B-Instruct	41.5	43.0	39.6	34.8	28.6	29.7	39.4	33.8	42.0	36.0
Qwen3-1.7B (Thinking)	69.7	66.0	59.4	58.6	52.8	57.8	53.5	70.3	63.5	53.4
Qwen3-1.7B (Non-thinking)	<u>58.8</u>	<u>62.7</u>	<u>50.8</u>	<u>53.0</u>	<u>43.3</u>	<u>48.0</u>	<u>46.0</u>	<u>54.3</u>	<u>54.0</u>	<u>43.9</u>

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