

TinyR1-32B-Preview: Boosting Accuracy with Branch-Merge Distillation

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Abstract

The challenge of reducing the size of Large Language Models (LLMs) while maintaining their performance has gained significant attention. However, existing methods such as model distillation and transfer learning often fail to achieve high accuracy. To address this limitation, we introduce the Branch-Merge distillation approach, which enhances model compression through two phases: (1) the Branch Phase, where knowledge from a large teacher model is *selectively distilled* into specialized student models via domain-specific supervised fine-tuning (SFT); And (2) the Merge Phase, where these student models are merged to enable cross-domain knowledge transfer and improve generalization. We validate our distillation approach using DeepSeek-R1 as the teacher and DeepSeek-R1-Distill-Qwen-32B as the student. The resulting merged model, TinyR1-32B-Preview, outperforms its counterpart DeepSeek-R1-Distill-Qwen-32B across multiple benchmarks, including Mathematics (+5.5 points), Coding (+4.4 points), and Science (+2.9 points), while achieving near-equal performance to DeepSeek-R1 on AIME 2024. The Branch-Merge distillation approach provides a scalable solution for creating smaller, high-performing LLMs with reduced computational cost and time.

developing smaller yet powerful models is a key challenge in Large Language Models (LLMs).

The most effective method, to our knowledge, is distilling a smaller model from a bigger teacher model across various domains (Jiao et al., 2020; DeepSeek-AI, 2025; Team, 2025a; Muennighoff et al., 2025). However, this method has a fundamental limitation: it requires carefully selecting the most relevant data/domains and tuning their proportions for joint training, which is typically time-consuming and error-prone (Guo et al., 2019; Ji et al., 2024). Furthermore, optimizing many domains simultaneously can lead to conflicting gradients, where tasks interfere, impeding overall learning progress (Yu et al., 2020; Jiang et al., 2024). These problems limit the effectiveness and efficiency of naive data mixed distillation, often resulting in models that cannot achieve the performance levels desired for specialized tasks.

To address these issues and optimize performance across multiple areas, we propose an approach, namely branch-merge, which integrates a model-merging technique during the distillation. Our branch-merge distillation approach contains two phases as follows.

- **Branch Phase:** Knowledge is selectively distilled from a unified large teacher model (e.g., DeepSeek-R1 671B) to instruct several specialized student models (e.g., math, coding, science) through domain-specific SFT.
- **Merge Phase:** The specialized models are combined into a single unified model, enabling cross-domain knowledge transfer while preserving their original specialized capabilities.

Contributions

- **Accuracy:** We can see from Figure 1 that the Branch-Merge distillation approach significantly improves model accuracy, approaching the scores

1 Introduction

Recently, the DeepSeek-R1 model has achieved great success, and its released R1-Distill models (DeepSeek-AI, 2025) demonstrated that distilled small models can be superior in reasoning. Building smaller-scale models is also beneficial for deployment and reducing inference costs. However,

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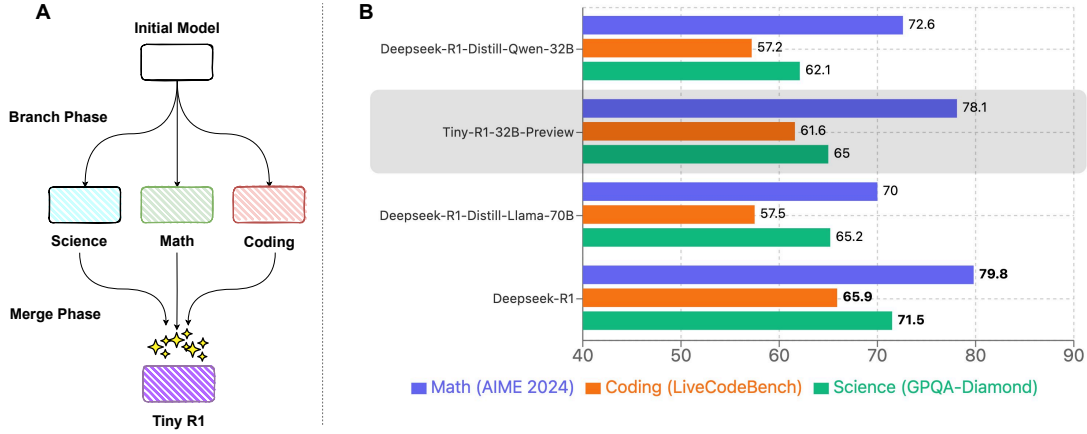


Figure 1: (A) A simplified diagram of our Branch-Merge distillation approach. (1) In the Branch phase, each copy of the Initial Model (backbone) is trained on knowledge from a different domain; (2) In the Merge phase, models are merged based on Arcee Fusion rules. (B) Performance Comparison of different LLM models (Mustar, 2025). TinyR1-32B-Preview outperforms distilled models of the same size in science, math, and coding and achieves comparable results to Deepseek R1. LiveCodeBench here refers to the 24.08-25.02 subset of full LiveCodeBench.

of the R1 teacher model, which traditional distillation methods have not yet achieved. Our distilled Qwen-32B model surpasses DeepSeek-R1-Distill-Qwen-32B with about 5% more accuracy, and its math accuracy approaches that of the original R1 teacher.

- **Simplicity & Low Cost:** Branch-Merge distillation approach significantly reduces the time and computational costs of the merging stage. Compared to traditional methods, we save 90% of the time in the merging phase (0.5 hours with 4 H800 GPUs vs. 23 hours with 32 H800 GPUs for merged data retraining). The ideal reproduction cost for TinyR1-32B-Preview is 744 H800 GPU hours, approximately \$1500 (excluding ablation experiments and parameter search).
- **Openness:** We stand on the shoulders of giants in the open-source community and aim to give back. We will release our model and all data, training code, evaluation code, and logs so anyone can reproduce our results.

2 The Branch-Merge Distillation Approach

This section describes our branch-merge distillation approach (as shown in Figure 1A), which consists of two phases: Branch and Merge. This two-phase distillation strategy directly addresses the issues of data selection and gradient conflict by decoupling training domains (Branch) and then rec-

onciling them (Merge). Each phase is described in detail below.

2.1 The Branch Phase

In the Branch phase, we first constructed separate datasets for math, science, and coding. Then, we fine-tuned DeepSeek-R1-Distill-Qwen-32B on each dataset using SFT, resulting in three specialized expert models.

- **Math:** We sift 58k samples from 94k questions in NuminaMath1.5 (LI et al., 2024) with corresponding solutions from OpenR1 (Team, 2025a) trajectories. The selection is based on three aspects: *question_type*, *source*, and *correctness_math_verify*. Comparative experiments on DeepSeek-R1-Distill-Qwen-14B indicate that these factors have nearly no impact on the results. Ultimately, we adopted a minimal dataset while maintaining comparable performance.
- **Coding:** The OpenThoughts (Team, 2025b) dataset is filtered to form 20k trajectories of coding solutions. An additional modification is replacing “<|begin_of_thought|>” in the original dataset with “<think>” and “<|end_of_solution|>” with “</think>”.
- **Science:** DeepSeek-R1 generates 1 CoT trajectory for each of the 8.6k seed examples (2.7k from the science and health science subsets of data_ablation_full59k in S1 (Muennighoff et al., 2025), 1.0k from S1k (Muennighoff et al., 2025),

4.9k from the science subset of OpenThoughts (Team, 2025b)), resulting in 8.6k CoT trajectories.

We apply SFT on DeepSeek-R1-Distill-Qwen-32B with the three datasets to obtain three specialized models. Detailed experiment setup will be discussed in Section 3.1.

2.2 The Merge Phase

In the Merge phase, we use Arcee Fusion (Goddard et al., 2024) to merge models from different domains.

Two different models are utilized during the Merge Phase. We refer to them as the **Left Model** and the **Right Model**, with their parameters denoted by $\theta_L \in \mathbb{R}^M$ and $\theta_R \in \mathbb{R}^M$, where M is the number of model parameters, respectively.

The merge process is divided into three steps:

1) Computing Importance Score

To measure the impact of each parameter on model performance, an **Importance Score** $S_{IS} \in \mathbb{R}^M$ is defined, and each $S_{IS}^{(i)}$ represents the importance of the i -th parameter.

The Importance Score Matrix S_{IS} is computed based on the Kullback-Leibler (KL) divergence between the softmax-transformed samples drawn from the parameter distributions of the two models. Specifically, we first sample two sets of parameters X and Y from the distributions of the two models:

$$\begin{aligned} X &= \{x_1, x_2, \dots, x_N\}, \quad x_i \sim p(\theta_L), \\ Y &= \{y_1, y_2, \dots, y_N\}, \quad y_i \sim p(\theta_R). \end{aligned} \quad (1)$$

where $p(\theta_L)$ and $p(\theta_R)$ represent the parameter distributions of the two models. Next, we apply the softmax function to X and Y to convert them into two new distributions named \tilde{X} and \tilde{Y} , the definition is shown below:

$$\tilde{x}_i = \frac{e^{x_i}}{\sum_{j=1}^N e^{x_j}} + \epsilon, \quad \tilde{y}_i = \frac{e^{y_i}}{\sum_{j=1}^N e^{y_j}} + \epsilon,$$

where $\epsilon = 1e-8$ is a hyperparameter. The S_{IS} is then calculated as:

$$S_{IS} = D_{KL}(\tilde{X} \parallel \tilde{Y}) \cdot (\theta_L - \theta_R). \quad (2)$$

The importance score serves as a selection criterion for parameter updates.

2) Calculating Dynamic Selection:

We sorted S_{IS} and define the following variables:

- The **median** Q_{Med} : The middle value of the sorted S_{IS} .
- The **lower quartile** $Q_{\frac{3}{4}}$: The median of the lower half of the sorted S_{IS} .
- The **upper quartile** $Q_{\frac{1}{4}}$: The median of the upper half of the sorted S_{IS} .
- The **interquartile range** Q_{IR} : Defined as $Q_{\frac{3}{4}} - Q_{\frac{1}{4}}$, where $Q_{\frac{3}{4}} \geq Q_{\frac{1}{4}}$, ensuring $Q_{IR} \geq 0$.

$S_{THR} \in \mathbb{R}$ is defined via the median Q_{Med} and interquartile range Q_{IR} :

$$S_{THR} = Q_{Med} + \lambda \cdot Q_{IR}, \quad (3)$$

where λ is a hyperparameter defined to balance coefficient.

Since S_{THR} is derived from IS statistics, it dynamically adapts to model parameters, ensuring an optimal update ratio.

3) Selective Integration:

The Merged Model is defined as $\theta_M \in \mathbb{R}^M$. We applied the following rule to merge θ_B and θ_P :

$$\theta_M^i = \theta_L^i + (\theta_R^i - \theta_L^i) \cdot \lceil \max(0, S_{IS}^i - S_{THR}) \rceil. \quad (4)$$

Only Right Model's parameters with an importance score above the threshold are retained; otherwise, Left Model's parameters are kept.

By focusing on the most significant changes, Arcee Fusion avoids over-updating and maintains model stability. Although this method merges only two models at a time, our work involves three models, and we detail the corresponding merge sequence in Section 3.3. A comparison with other model merging methods appears in Figure 2. We compare various merging methods on merging models trained from the math and science domains, and we find that Arcee achieves the highest scores on GPQA-Diamond. We found a similar method ranking on the AIME 2024 benchmark, but no separate graph was drawn due to space limitations.

Model	Math (AIME 2024)	Coding (LiveCodeBench 24.08-25.02)	Science (GPQA-Diamond)
DeepSeek-R1-Distill-Qwen-32B [†]	72.6 (9.6k Tokens)	57.2 (10.1k Tokens)	62.1 (5.3k Tokens)
DeepSeek-R1-Distill-Llama-70B [†]	70.0	57.5	65.2
DeepSeek-R1 [†]	79.8 (9.6k Tokens)	65.9 (10.4k Tokens)	71.5 (5.3k Tokens)
TinyR1-32B-Preview (Ours)	78.1 (11.8k Tokens)	61.6 (12.4k Tokens)	65.0 (8.6k Tokens)

Table 1: Performance comparison on benchmark datasets. All scores are reported as pass@1. Scores reported from DeepSeek-R1 paper (DeepSeek-AI, 2025) are noted with [†]. The number in parentheses represents the average output token length (including the chain of thought), obtained from our testing.

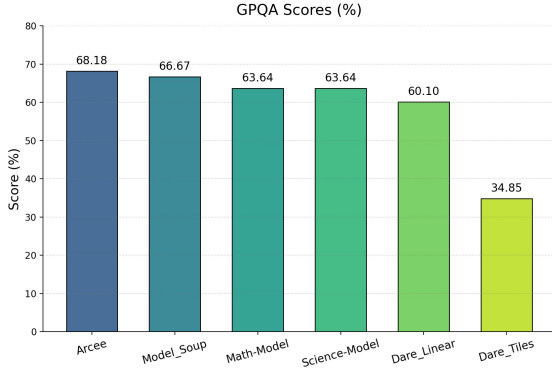


Figure 2: Performance Comparison of merged models on the GPQA-Diamond benchmark.

3 Experiment

We choose Deepseek-R1 (DeepSeek-AI, 2025) and its distilled DeepSeek-R1-Distill-Qwen-32B and DeepSeek-R1-Distill-Llama-70B as baselines. Additionally, we conducted a comprehensive ablation study. We compared TinyR1-32B-Preview with: (a) three domain expert models (Math Expert, Coding Expert, Science Expert) before merging; (b) a ‘Data Mixture’ model trained on a combined Math/Coding/Science dataset; and (c) variants of our model obtained via different merging sequences.

3.1 Experiment Setup

3.1.1 Training Details

We employ DeepSeek-R1-Distill-Qwen-32B as our backbone model. Leveraging the 360-Llama-Factory (Zou et al., 2024) training framework, we develop three domain-specific expert models applying 16384 sequence length with constructed Math, Coding, and Science datasets.

- Math Expert: The math expert model is trained with 5 epochs, batch size 96, and the learning rate is set to constant 1e-5.
- Science Expert: The science expert model is

trained with 5 epochs, batch size 32 with the neat packing mechanism (Tay et al., 2020; Henry et al., 2019; Dean and et al., 2018), and the learning rate is set to cosine 1e-5.

- Coding Expert: The coding expert model is trained with 15 epochs, batch size 96 with the neat packing mechanism, and the learning rate is set to constant 1e-5.

We merged the models trained separately in three fields into a single model. We use the Arcee merging (Goddard et al., 2024) method with the $\theta=1.5$ and threshold THR=0.5. We will compare different model merging methods in Section 3.3.

3.1.2 Evaluation Details

For evaluation, we compare the performance on three benchmark datasets: AIME 2024 for Math, LiveCodeBench (24.08-25.02) for Coding, and GPQA-Diamond for Science. The accuracy is calculated as an average pass@1 across 16, 4, and 4 independent trials for these benchmarks, respectively. Meanwhile, we did not use a greedy way to evaluate the model due to its long-COT output, we set the max tokens to 32768 and evaluated the models with Temperature=0.6 and Top-p=0.95 as recommended in DeepSeek-R1 (DeepSeek-AI, 2025). We tried various open-source frameworks for the evaluation on livecodebench and ultimately selected the evaluation code from FuseAI (Wan et al., 2024) utilizing the vLLM implementation, as it can reproduce the effects of the DeepSeek-R1 and its distilled models.

3.2 Main Results

We compare our TinyR1-32B-Preview model and other models in Table 1.

- In terms of accuracy, we significantly outperform our backbone model, DeepSeek-R1-Distill-Qwen-32B (Math +5.5, Coding +4.4, Science +2.9), and generally surpass

DeepSeek-R1-Distill-Llama-70B (Math +8.1, Coding +4.1, Science -0.2), approaching the performance of DeepSeek-R1 (Math -1.7, Coding -4.3, Science -6.5).

- In terms of inference cost, our model generates slightly more output tokens than R1 (Math +23%, Coding +19%, Science +62%).
- In terms of the model’s parameter size, our model is smaller compared to DeepSeek-R1, making it more suitable for local deployment by users and small groups.

3.3 Ablation Study

As shown in Table 2, we made a comprehensive ablation study to explore if our merging distillation approach works.

Compared to the domain-specific experts, the Data Mixture model surpasses them in math and science but shows decreased performance in coding. This is a seesaw problem that traditional data mixture is difficult to solve (Zamir and Arbeláez, 2018; Liu and Yao, 2019; Radford and W., 2021). In comparison, our merged model improves performance in math and science domains while largely retaining the coding capability. Compared to the Data Mixture, the coding scores of merged models only slightly decreased. We also compared two different model-merging sequences: (1) first merging Math with Coding, then merging with Science; (2) first merging Math with Science, then with Coding. The results show only minor performance differences between these sequences, with the latter yielding a slightly higher average accuracy.

In addition, the average Merging time (GPU hours) of the current Data Mixture is 740 hours¹. On the contrary, the average merging time of Tiny-R1-32B-preview is 4 hours. In summary, we only used 0.5% of the Data-Mixture computational overhead on merging models to surpass the effect of traditional data mixture methods. In addition to reducing computational overhead, model merging significantly accelerates our model release process by avoiding the delays introduced by mixed-data re-SFT on the development model. The model merging is a “free-lunch” approach, as it reduces costs and increases efficiency at the same time.

¹Note that the merging time is the SFT experiment time, excluding the SFT time for single experts and the downstream evaluation time of the Data Mixture model

4 Related Work

4.1 Model Distillation

Knowledge Distillation (KD) (Romero et al., 2015; Hinton et al., 2015) has been proposed to create cheaper strong models (Gou et al., 2021; Hu et al., 2023; Yang et al., 2024; Xu et al., 2024). Primarily, recognizing the disparities between proprietary and open-source LLMs, KD techniques have surged to bridge the performance gap between these models. Distillation methods can be categorized into two types: (1) the logits-based methods (Hinton et al., 2015), which transfer knowledge at the logits level, and (2) the feature-based methods (Romero et al., 2015), which transmit knowledge through intermediate features.

Compared to traditional knowledge distillation techniques (Gou et al., 2021), data augmentation (DA) (Feng et al., 2021) has emerged as an effective method for distilling knowledge in large language models (LLMs). In this approach, a small seed of knowledge is used to prompt LLMs, enabling them to generate additional data tailored to specific domains or skills (Taori et al., 2023). More recently, an API-based strategy has gained attention, where open-source LLMs serve as teachers to self-improve through self-distillation (Yuan et al., 2024; Chen et al., 2024). By applying a range of distillation techniques, this strategy effectively narrows the performance gap between closed-source and open-source models (Chiang et al., 2023; Xu et al., 2023). In this context, the method involves using only the outputs of the teacher model via an API. This strategy includes approaches such as In-Context Learning (Huang et al., 2022), Chain-of-Thought (Li et al., 2022b), and Instruction Following (Wang et al., 2023). In specialized fields, like science (Zhang et al., 2024), where domain-specific knowledge and accuracy are essential, distillation allows open-source models to significantly improve their performance by learning from proprietary models that are extensively trained and fine-tuned in these domains.

4.2 Model Merging

Recent advances in model merging have explored diverse strategies (Ilharco et al., 2022a; Yadav et al., 2023; Davari and Belilovsky, 2024; Deep et al., 2024) to combine neural network parameters while preserving or enhancing performance. Early approaches focused on linear interpolation techniques, such as weight averaging (Wortsman

Model	Math (AIME 2024)	Coding (LiveCodeBench)	Science (GPQA-Diamond)	Merging Time (GPU Hours)
Math Expert	73.1	-	-	-
Coding Expert	-	63.4	-	-
Science Expert	-	-	64.5	-
Data Mixture	75.3	61.0	65.7	740 h
Merging: (Math & Coding) & Science	77.3	63.8	64.0	4h
Merging: (Math & Science) & Coding	78.1	61.6	65.0	4h
TinyR1-32B-Preview	78.1	61.6	65.0	4h

Table 2: Performance comparison between backbone experts, the data-mixture model, and merged model. All scores are reported as pass@1. LiveCodeBench here refers to the 24.08-25.02 subset of full LiveCodeBench.

et al., 2022), where models finetuned from shared pretrained checkpoints are merged via arithmetic mean. While computationally efficient, these methods assume approximate parameter space alignment and often degrade when models exhibit divergent optimization trajectories (Frankle et al., 2020; Izmailov et al., 2018; Neyshabur et al., 2020; Fort et al., 2020; Wortsman et al., 2022; Choshen et al., 2022; Ilharco et al., 2022b).

Theoretical underpinnings for these methods derive from studies on loss landscape geometry (Ilharco et al., 2022a; Li et al., 2018; Garipov et al., 2018; Draxler et al., 2018; Kuditipudi et al., 2019; Fort et al., 2019; Czarnecki et al., 2019; Wortsman et al., 2021; Benton et al., 2021; Entezari et al., 2021; Li et al., 2022a; Lubana et al., 2023). Research on flat local minima (Kaddour et al., 2022; Wortsman et al., 2022; Keskar et al., 2016; Dziugaite and Roy, 2017) dating back from the 1990s (Hochreiter and Schmidhuber, 1994, 1997) suggests that averaged weights reside in flatter regions of the loss surface, correlating with improved out-of-distribution generalization. Further analyses (Daheim et al., 2023; Matena and Raffel, 2022) formalize model merging as identifying connected basins in parameter space, where interpolated solutions maintain low loss. Empirical validations, such as model soups (Wortsman et al., 2022), corroborate that aggregated weights often outperform individual models, particularly under distribution shifts.

5 Conclusion and Future Work

We introduce TinyR1-32B-Preview, a model using the Branch-Merge distillation approach to boost reasoning accuracy while preserving efficiency. We achieve significantly higher accuracy than our backbone model, DeepSeek-R1-Distill-Qwen-32B, and generally outperform DeepSeek-R1-Distill-

Llama-70B while approaching the performance of DeepSeek-R1. Although our model generates slightly more output tokens than R1, its smaller parameter size makes it more efficient and better suited for local deployment by users and small groups.

Potential future directions include:

- **Exploring Alternative Backbones** – For instance, conducting SFT with the Qwen-Instruct model as the backbone. Our preliminary experiments with Qwen-14B-Instruct and Qwen-32B-Instruct for specialized tasks have already yielded similar results.
- **Releasing Models of Various Sizes** – Expanding our model lineup to accommodate different needs.
- **Investigating the Impact of Experiment Details** – Further analyzing how various experiment settings influence final performance.

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