TRITONRL: TRAINING LLMS TO THINK AND CODE TRITON WITHOUT CHEATING

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ABSTRACT

With the rapid evolution of large language models (LLMs), the demand for automated, high-performance system kernels has emerged as a key enabler for accelerating development and deployment. We introduce TRITONRL, a domain-specialized LLM for Triton kernel generation, trained with a novel training framework that enables robust and automated kernel synthesis. Unlike general-purpose programming languages, Triton kernel generation faces unique challenges due to data scarcity and incomplete evaluation criteria, vulnerable to reward hacking. Our approach addresses these challenges end-to-end by distilling Triton-specific knowledge through supervised fine-tuning on curated datasets, and further improving code quality via reinforcement learning (RL) with robust, verifiable rewards and hierarchical reward assignment. Our RL framework robustly detects reward hacking and guides both reasoning traces and code tokens through fine-grained verification and hierarchical reward decomposition, enabling the model to generate high-quality Triton kernels that can truly replace existing modules. With robust and fine-grained evaluation, our experiments on KernelBench demonstrate that TRITONRL achieves state-of-the-art correctness and speedup, surpassing all other Triton-specific models and underscoring the effectiveness of our RL-based training paradigm.

1 INTRODUCTION

The exponential growth in demand for GPU computing resources has driven the need for highly optimized GPU kernels that improve computational efficiency, yet with the emergence of numerous GPU variants featuring diverse hardware specifications and the corresponding variety of optimization kernels required for each, developing optimized kernels has become an extremely time-consuming and challenging task. In response to this need, there is growing interest in leveraging large language models (LLMs) for automated kernel generation. While there have been attempts introducing inference frameworks that utilize general-purpose models, such as OpenAI models and DeepSeek, for generating kernels (Ouyang et al., 2025; Lange et al., 2025; Li et al., 2025a; NVIDIA Developer Blog, 2025; Muhamed et al., 2023), they often struggle with even basic kernel implementations, thereby highlighting the critical need for domain-specific models specifically tailored for kernel synthesis.

As the need for specialized models for kernel generation has emerged, several works have focused on fine-tuning LLMs for CUDA or Triton. In the CUDA domain, recent RL-based approaches include Kevin-32B Baronio et al. (2025), which progressively improves kernels using execution feedback as reward signals, and CUDA-L1, which applies contrastive RL to DeepSeek-V3 Li et al. (2025c). While these large models (32B-671B parameters) achieve strong CUDA performance, their training costs remain prohibitively expensive. To address these limitations, researchers have proposed specialized 8B Triton models, including KernelLLM Fisches et al. (2025) (supervised training on torch compiler-generated code) and AutoTriton Li et al. (2025b), fine-tuned via LLM distillation and RL using execution feedback. Though these smaller models outperform their base models, significant room remains for improving efficiency and accuracy compared to larger counterparts.

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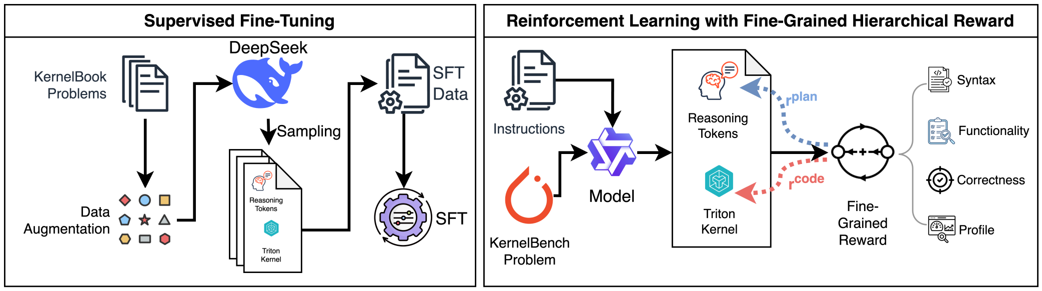

Figure 1: TRITONRL components and workflow.

Furthermore, there is a common issue reported across kernel generation works, reward hacking (Baronio et al., 2025; Li et al., 2025b). Due to the scarcity of high-quality kernel examples compared to other programming languages, most approaches rely on RL training using runtime measurements and correctness rewards from unit tests after kernel execution. However, models frequently learn to exploit unit test loopholes, such as direct use of high-level PyTorch modules, rather than generating proper code, and this phenomenon is particularly prevalent in smaller models (8B and below) (Baronio et al., 2025). This issue fundamentally undermines the core objective of developing more efficient custom kernels to replace existing pre-optimized libraries, while current approaches predominantly rely on simple rule-based syntax verification whose effectiveness remains uncertain.

In this paper, we present TRITONRL, an 8B-scale LLM specialized for Triton programming that achieves state-of-the-art performance in both correctness and runtime speedup, while effectively mitigating reward hacking. To enable high-quality Triton kernel generation with small models (up to 8B), we design a training pipeline with the following key contributions:

- **Simplified dataset curation with distillation**: Instead of large-scale web crawling, we build on the curated *KernelBook* problems. Their solutions are refined and augmented through DeepSeek-R1 distillation (Guo et al., 2025), providing high-quality supervision for SFT of our base model Qwen3-8B (Team, 2025).
- **Fine-grained and robust verification**: We incorporate enhanced rule-based checks (e.g., `nn.Module`) together with LLM-based judges (e.g., Qwen3-235B-Instruct) to construct verifiable rewards. This enables reliable diagnosis across commercial and open-source models, while preventing reward hacking that arises from naive syntax-only verification.
- **Hierarchical reward decomposition with data mixing**: Our RL stage decomposes rewards into multiple dimensions (e.g., correctness, efficiency, style) and applies token-level credit assignment. Combined with strategic data mixing across SFT and RL, this yields better kernel quality, generalization, and robustness.
- **Comprehensive evaluation and open-sourcing**: Through rigorous validity analysis that filters out syntactically or functionally invalid code, we reveal true performance differences among models. Ablation studies further confirm the effectiveness of our hierarchical reward design and data mixing. At the 8B scale, TRITONRL surpasses existing Triton-specific LLMs, including KernelLLM (Fisches et al., 2025) and AutoTriton (Li et al., 2025b). We release our datasets and codes, including training and evaluation frameworks, to ensure reproducibility and foster future research.[1]

2 TRITONRL

In this section, we present TRITONRL, a specialized model designed for Triton programming. Our objective is to develop a model that can generate Triton code that is both correct and highly optimized for speed, outperforming the reference implementation. To achieve this, we adopt a two-stage training strategy: we first apply supervised fine-tuning (SFT) to instill fundamental Triton syntax and kernel optimization skills, followed by reinforcement learning (RL) with fine-grained verifiable rewards to further refine the model for correctness and efficiency. We will first detail the SFT procedure, and subsequently present the design of the reinforcement learning framework.

[1] Codes and datasets will be available soon.

2.1 TRITON KNOWLEDGE DISTILLATION VIA SUPERVISED FINE-TUNING

Recent work (Fisches et al., 2025; Li et al., 2025b) has demonstrated that large language models (LLMs) exhibit weak Triton programming ability at the 8B scale, struggling both with syntax and with performance-oriented design patterns. Effective dataset curation is therefore essential, not only to expose Triton-specific primitives and coding structures but also to preserve the reasoning traces that guide kernel optimization. To address this, our pipeline follows three key steps: (i) data augmentation, (ii) synthesis of reasoning traces paired with corresponding code, and (iii) construction of high-quality training pairs for supervised fine-tuning.

(i) **Data augmentation:** We start from the problem sets in KernelBook (Paliskara & Saroufim, 2025), which provides curated pairs of PyTorch programs and equivalent Triton kernels. To enrich this dataset, we augment the tasks with additional variations (e.g., diverse input shapes), thereby exposing the model to broader performance scenarios.

(ii) **Data synthesis:** To obtain diverse reasoning traces that guide correct and efficient Triton generation, we employ DeepSeek-R1 (Guo et al., 2025) to jointly synthesize reasoning steps and Triton implementations. For each task wrapped with instruction and Pytorch reference, multiple candidate kernels are collected, each paired with an explicit reasoning trace. This yields a dataset of $\mathcal{D} = \{(q, o_i)\} = \{(\texttt{task query, Triton code with CoT})\}$. See concrete template in Appendix F.5). Rather than directly using the Triton code from KernelBook as the target, we instead utilize Triton implementations generated by DeepSeek-R1. This choice ensures higher quality supervision, as KernelBook's original Triton code frequently relies on high-level PyTorch modules (see Appendix F.2 for examples).

(iii) **Supervised fine-tuning:** In the SFT stage, the model is trained to produce valid Triton code as well as reproduce the associated reasoning traces from the instruction. This distillation process transfers essential Triton programming patterns while reinforcing reasoning ability.

2.2 REINFORCEMENT LEARNING WITH HIERARCHICAL REWARD DECOMPOSITION

While supervised fine-tuning (SFT) equips the base model with basic Triton syntax and kernel optimization abilities, the resulting code may still contain errors or lack efficiency. To further improve the quality of Triton code generation of TRITONRL, we train the model via reinforcement learning (RL) with verifiable rewards, which incentivize model to generate more correct and efficient Triton code yielding higher rewards. In RL, designing effective reward feedback is essential since crude reward designs not perfectly aligned with original objectives of tasks often lead to reward hacking, guiding models to exploit loopholes. To address this, we first introduce robust and fine-grained verifiers that rigorously assess the quality of Triton code in diverse aspects, forming the basis for constructing reward functions. Building on these verifiers, we present a GRPO-based RL framework with hierarchical reward decomposition that provides targeted feedback for reasoning traces and Triton code, thereby improving the correctness and efficiency of generated Triton kernels.

Fine-Grained Verification for High-Quality Triton Code. We denote i-th generated output sample o_i for a given prompt or task q. Recall that q and o_i include Pytorch reference q^{ref} and Triton code o_i^{code} that is executable on some proper input x, i.e., $q^{\text{ref}}(x), o^{\text{code}}(x)$. We introduce fine-grained verifiers v that comprehensively evaluate different aspects of code quality as follows.

- Robust verifier: Sequential verifier to check output is a valid Triton code without non-nonsensical hacking. See Figure 2 for an illustration
  - `syntax` : A binary verifier that assesses whether code o^{code} is valid Triton syntax. We use a rule-based linter to verify the presence of Triton kernels annotated with @triton.jit.
  - `func`: A binary functionality verifier to detect whether o^{code} constitutes a valid Triton kernel. Syntax checks alone are insufficient, since models may output code that superficially passes verification but defers computations to high-level PyTorch modules (e.g., torch.nn, @) or hardcodes constants, as in Figure 2 (b). To address this, we combine a rule-based linter—which ensures Triton kernels are invoked and flags reliance on PyTorch modules—with an LLM-based judge that evaluates semantic correctness against task specifications.

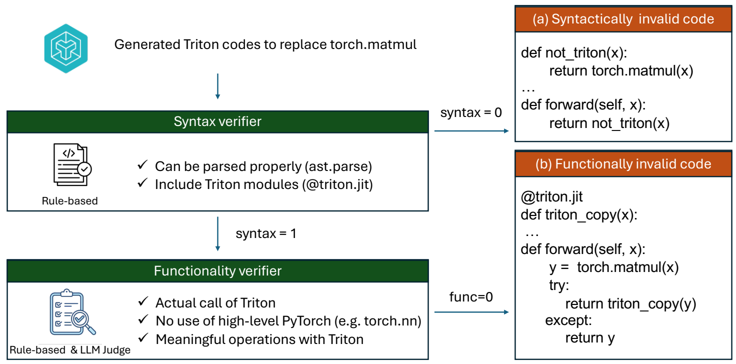

Figure 2: Illustration of the flow of our robust verifier incorporating syntax and functionality checkers and the examples of invalid Triton codes. (a) invalid syntax: the code lacks any Triton blocks and consists solely of PyTorch code. (b) invalid functionality: the code include dummy Triton code that just copies data without meaningful operation delegating core operation (matrix multiplication) to PyTorch modules (torch.matmul).

- `compiled`: A binary verifier that checks whether the generated Triton code can be successfully compiled without errors.
- `correct`: A binary verifier that evaluates whether the generated Triton code produces correct outputs by compiling and comparing its results against those of the reference PyTorch code using provided test input x.

$$\texttt{correct}(q, o) \;=\; \texttt{compile}\big(o^{\text{code}}\big) \cdot \mathbb{1}\big[\, o^{\text{code}}(x) == q^{\text{ref}}(x) \,\big]$$

- `speedup`: A scalar score that quantifies the execution time improvement of the generated Triton code relative to the reference PyTorch implementation. For a prompt q with reference Pytorch code q^{ref} and corresponding triton code o^{code} generated, speed-up is defined as, given test input x,

$$\texttt{speedup}(q, o) = \frac{\tau(o^{\text{code}}, x)}{\tau(q^{\text{ref}}, x)} \cdot \texttt{correct}(q, o),$$

  where $\tau(\cdot, x)$ measure the runtimes of given code and input x.

For notational simplicity, for a given prompt q and output sample o_i, we define $v(q, o_i)$ as v_i any verification function v throughout the paper.

While prior works (Li et al., 2025b; Baronio et al., 2025) addressed reward hacking with rule-based linters, such methods remain vulnerable to loopholes. Our verifier combines rule-based and LLM-based checks to capture both syntactic and semantic errors, offering stronger guidance during training (see Appendix F.4 for examples and Section 3 for evaluation). Building on these fine-grained verifiers, we develop an RL framework that delivers targeted feedback to both reasoning traces and Triton code, improving kernel correctness and efficiency.

Hierarchical Reward Decomposition. Training LLMs with long reasoning traces remains challenging because providing appropriate feedback across lengthy responses is difficult. When a single final reward is uniformly applied to all tokens, it fails to distinguish between those that meaningfully contribute to correctness or efficiency and those that do not. This issue is particularly pronounced in kernel code generation, where reasoning traces often outline complex optimization strategies for GPU operations while the subsequent code implements these plans. Even if the reasoning trace proposes a promising optimization, errors in the Triton implementation may result in the entire response being penalized. Thus, a single reward signal fails to provide appropriate feedback to both reasoning and solution (Qu et al., 2025), conflating high-quality reasoning with poor execution and preventing effective learning of good optimization strategies.

To address this, we propose a GRPO with hierarchical reward decomposition for Triton code generation. Specifically, Triton code generation o_i can be viewed as two-level hierarchy action pairs,

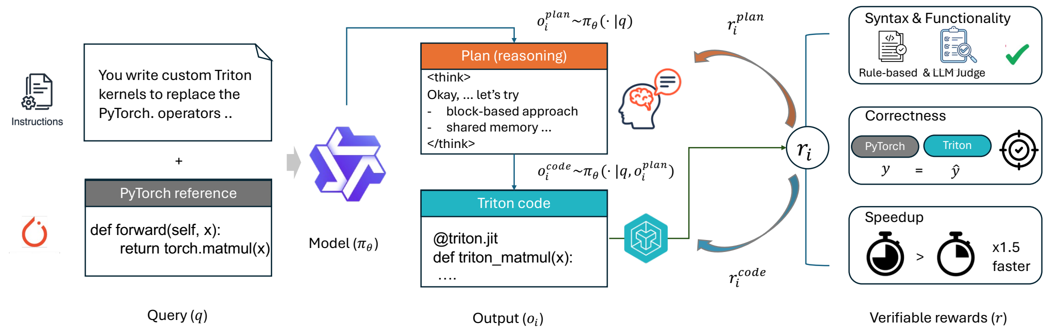

Figure 3: An example LLM output for Triton code generation, showing a reasoning trace (plan) and the generated Triton kernel code conditioned on the plan.

- o_i^{plan}: CoT reasoning traces correspond to high-level planning actions, providing abstract kernel optimization strategies, such as tiling or shared memory.
- o_i^{code}: final Triton code answers correspond to low-level coding actions that execute the plan given by the previous reasoning traces.

The key idea is to assign different reward credit for different class of output tokens between plan and code as illustrated in Figure 3. By jointly optimizing rewards for both levels, we can train the model to better align its reasoning with the desired code output as follows:

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}_{q\sim P(Q),\ \{o_i=(o_i^{\text{plan}}, o_i^{\text{code}})\}_{i=1}^{G}\sim\pi_{\theta_{old}}(\cdot|q)}\left[\frac{1}{G}\sum_{i=1}^{G}\alpha\mathcal{F}_{\text{GRPO}}^{\text{plan}}(\theta,i)+\mathcal{F}_{\text{GRPO}}^{\text{code}}(\theta,i)\right] \tag{1}$$

where π_θ and $\pi_{\theta_{old}}$ are the policy model and reference model, q denotes a prompt given to the model, defining a task to implement in Triton, and $o_i = (o_i^{\text{plan}}, o_i^{\text{code}})$ represents i-th response generated by the model for q in the group G. Here we denote $o_{i,t}^{\text{plan}}$ and $o_{i,t}^{\text{code}}$ as t-th token of output plan and code, and T_i^{plan} and T_i^{code} as the sets of token positions in the plan and code, respectively. The GRPO losses $\mathcal{F}^{\text{plan}}(\theta)$ and $\mathcal{F}^{\text{code}}(\theta)$ are computed over the tokens in generated plans and Triton codes, respectively, and $\alpha \in [0,1]$ is a weighting factor that balances the training speed of planning and coding policy. Here, α is set to a small value (e.g., 0.1) so that the planning distribution is updated slowly, allowing the coding policy sufficient time to learn correct implementations conditioned on those high-level plans. The detailed formulation of each loss component is as follows:

$$\begin{aligned}
\mathcal{F}_{\text{GRPO}}^{\text{plan}} &= \frac{1}{|o_i^{\text{plan}}|}\sum_{t\in T_i^{\text{plan}}} A_i^{\text{plan}}\cdot\min\left\{\frac{\pi_\theta(o_{i,t}^{\text{plan}}|q,o_{i,<t}^{\text{plan}})}{\pi_{\theta_{old}}(o_{i,t}^{\text{plan}}|q,o_{i,<t}^{\text{plan}})}, \text{clip}\left(\frac{\pi_\theta(o_{i,t}^{\text{plan}}|q,o_{i,<t}^{\text{plan}})}{\pi_{\theta_{old}}(o_{i,t}^{\text{plan}}|q,o_{i,<t}^{\text{plan}})}, 1-\epsilon, 1+\epsilon\right)\right\}, \\
\mathcal{F}_{\text{GRPO}}^{\text{code}} &= \frac{1}{|o_i^{\text{code}}|}\sum_{t\in T_i^{\text{code}}} A_i^{\text{code}}\cdot\min\left\{\frac{\pi_\theta(o_{i,t}^{\text{code}}|q,o_i^{\text{plan}},o_{i,<t}^{\text{code}})}{\pi_{\theta_{old}}(o_{i,t}^{\text{code}}|q,o_i^{\text{plan}},o_{i,<t}^{\text{code}})}, \text{clip}\left(\frac{\pi_\theta(o_{i,t}^{\text{code}}|q,o_i^{\text{plan}},o_{i,<t}^{\text{code}})}{\pi_{\theta_{old}}(o_{i,t}^{\text{code}}|q,o_i^{\text{plan}},o_{i,<t}^{\text{code}})}, 1-\epsilon, 1+\epsilon\right)\right\},
\end{aligned} \tag{2}$$

where A_i^{plan} and A_i^{code} are the group-wise advantages for plan and code tokens, computed as $A_i = r_i - \frac{1}{G}\sum_{j=1}^{G} r_j$, with rewards for plan and code tokens defined as:

$$r_i^{\text{plan}} = \texttt{syntax}_i \cdot \texttt{func}_i \cdot \texttt{speedup}_i, \quad r_i^{\text{code}} = \texttt{syntax}_i \cdot \texttt{func}_i \cdot \texttt{correct}_i. \tag{3}$$

Here, we note that the syntax and functionality checks serve as necessary conditions for correctness and speedup evaluations. If either the syntax or functionality check fails, the generated code is deemed invalid, and both correctness and speedup rewards are set to zero.

To provide separate feedback for the *hierarchical* actions of planning and coding with their respective contributions, we design distinct reward functions for each action. As described in equation 3, we decouple rewards for high-level plan tokens and low-level code tokens based on their main contributions to the final output, assigning speedup-based rewards to plan tokens and correctness-based rewards to code tokens. This approach ensures that reasoning traces are encouraged to propose optimization strategies that yield efficient kernels, while code generation is guided to produce valid implementations that faithfully realize these plans. In this way, our hierarchical reward decomposition provides a more targeted and effective learning signal compared to *uniform* reward designs used in prior work Li et al. (2025b); Baronio et al. (2025), which apply a uniform reward to all tokens.

Another key aspect of our reward decomposition is the use of the weighting factor α to balance the training speed of planning and coding policies. To effectively learn both planning and coding skills, it is important to ensure that the model has sufficient time to learn correct Triton implementation given the current planning distribution. If α is set to 1.0, the planning and coding policies are updated at the same rate, which may lead to instability in learning, as the coding policy may struggle to keep up with rapidly changing plans. In contrast, if α is too small (e.g., 0.0), the planning policy remains static and only the coding policy is updated, which may limit the model's ability to explore promising kernel optimization plans. By setting α to an appropriately small value (e.g., 0.1), we ensure that the planning distribution is updated slowly, allowing the coding policy sufficient time to learn correct implementations conditioned on those high-level plans. This helps avoid overly penalizing the reasoning trace due to code generation instability in early training, thus preserving promising optimization plans that may yield higher speedup once the code generation stabilizes.

In our experiments, we compare our hierarchical reward decomposition with uniform reward designs explored by prior work Li et al. (2025b); Baronio et al. (2025), and evaluate different choices of α to highlight the advantages of the hierarchical reward decomposition.

Difficulty-Aware Data Mixing. The selection of training data is crucial for effective RL post-training, and many works have shown that selective sampling by leveraging additional information, such as difficulty or interaction between data points, can significantly improve model performance (Yu et al., 2025; Chen et al., 2025; 2024). While KernelBook Paliskara & Saroufim (2025) is a large-scale dataset containing diverse kernel generation tasks, uniformly sampling from the entire dataset may be inefficient and lead to suboptimal model performance. In this work, we augment each task in KernelBook with a difficulty label and explore different data mixtures to construct an optimal training set for RL post-training.

We use an LLM labeler to create difficulty labels for each data point in KernelBook based on the difficulty levels defined in KernelBench (Ouyang et al., 2025), which categorizes tasks into three levels based on the complexity of kernel implementation, and we denote the subset of training data with difficulty level d as $\mathcal{D}_{train}^{(d)}$ for $d \in \{1, 2, 3\}$. Forcusing on level 1 and 2 tasks, we form various data mixtures by sampling from these subsets with data mixing probabilities $\boldsymbol{p} = (p_1, p_2)$, where p_d denotes the probability of sampling from $\mathcal{D}_{train}^{(d)}$. By varying the mixture probabilities $\boldsymbol{p}$, we can construct different training data mixtures. In our experiments, we explore multiple mixtures and evaluate the performance of the post-trained model on KernelBench to identify the optimal training data configuration. Additional details are provided in Appendix F.1.

3 EXPERIMENTS

This section provides the detailed recipe of training and evaluation of TRITONRL, followed by the main results and ablation studies.

3.1 TRAINING AND EVALUATION SETUPS

Data Preparation. For both SFT and RL, we use 11k tasks from KernelBook (Paliskara & Saroufim, 2025). We expand each task with five reasoning traces and corresponding Triton implementations generated by DeepSeek-R1 (Guo et al., 2025), yielding 58k `<task query, Triton code with CoT>` pairs. Prompts adopt a one-shot format, where the reference PyTorch code is given and the model is asked to produce an optimized Triton alternative (examples in Appendix F.5). To support curriculum in RL training, we further label tasks into three difficulty levels using Qwen3-235B-Instruct (Team, 2025), following the task definitions in Ouyang et al. (2025), yielding 11k `<task query, level>` pairs. See detailed generation and classification in Appendix H and F.1.

Training Configuration. We begin by fine-tuning the base model Qwen3-8B on KernelBook tasks. After SFT, we move to RL training on the same KernelBook tasks, but without output la-

Model	#Params	LEVEL1 (ROBUST VERIFIER)				LEVEL1 (W/O ROBUST VERIFIER)	
		valid	compiled / correct	fast_1 / fast_2	mean speedup	valid	compiled / correct
Qwen3 (base)	8B	73.0	40.0 / 14.0	0.0 / 0.0	0.03	54.0	52.0 / 15.0
Qwen3	14B	82.0	65.0 / 17.0	0.0 / 0.0	0.04	66.0	71.0 / 16.0
Qwen3	32B	75.0	61.0 / 16.0	2.0 / 0.0	0.06	52.0	50.0 / 15.0
KernelLLM	8B	42.0	40.0 / 20.0	0.0 / 0.0	0.05	100.0	98.0 / 29.0
AutoTriton	8B	97.0	78.0 / 50.0	2.0 / 1.0	0.25	100.0	95.0 / 70.0
TRITONRL (ours)	8B	99.0	82.0 / **56.0**	**5.0** / 1.0	**0.33**	99.0	83.0 / 58.0
w/o RL (SFT only)	8B	97.0	**88.0** / 44.0	4.0 / **2.0**	**0.33**	98.0	93.0 / 47.0
Claude-3.7	-	99.0	**99.0** / 53.0	3.0 / 1.0	0.32	100.0	100.0 / 64.0

Table 1: Main results on KernelBench Level 1. All metrics are reported as pass@10 (%). Our model achieves the best results among models with fewer than 32B parameters. The left block reports evaluation with the robust verifier (syntax + functionality). The right block (w/o robust verifier) lacks functionality checks, leading to misleading correctness estimates.

bels—rewards are computed directly from code execution-so the RL dataset consists only of task instructions. An example of such instructions is shown in Appendix F.5. We implement training under the VeRL framework (Sheng et al., 2025). Unlike SFT, we use the subset of KernelBook tasks labeled as Level 1 and Level 2 for RL training. We explore different data mixtures from Level 1 and Level 2 tasks for RL training, where the default mixture is $\boldsymbol{p} = [1.0, 0.0]$ unless specified otherwise. Hyperparameters for both SFT and RL are provided in Appendix H. By default, we use the reward function r from equation 3, setting $\alpha^* = 0.1$ unless specified otherwise.

Evaluation Benchmarks. We evaluate TRITONRL on KernelBench (Li et al., 2025a)[2]. KernelBench offers an evaluation framework covering 250 tasks, divided into Level 1 (100 single-kernel tasks, such as convolution), Level 2 (100 simple fusion tasks, such as conv+bias+ReLU), and Level 3 (50 full architecture tasks, such as MobileNet), to assess LLM proficiency in generating efficient CUDA kernels. We conduct experiments mainly on the Level 1 and Level 2 tasks from KernelBench. The prompts used for these benchmarks are provided in Appendix G.1.

Metrics. We evaluate the performance of LLMs for generating Triton code in terms of (1) Validity (syntax and functionality); (2) Correctness (compilation and correct output); (3) Speedup (relative execution time improvement). We report $\texttt{fast}_1$ and $\texttt{fast}_2$ to indicate the model's ability to generate Triton code that is at least as fast as or twice as fast as the reference PyTorch implementation, respectively. The formal definition of metrics is provided in Appendix D. We measure the pass@k metrics for each aspect, which indicates the ratio of generating at least one successful solution among k sampled attempts. We use $k = 10$ as a default unless specified. We test both Triton codes and reference PyTorch codes on an NVIDIA L40S.

Baselines. We compare TRITONRL with several baselines, including KernelLLM (Fisches et al., 2025) and AutoTriton (Li et al., 2025b), which are fine-tuned LLMs specifically for Triton programming. We also include our base model Qwen3-8B (Team, 2025) without any fine-tuning, fine-tuned Qwen3-8B only after SFT, and larger Qwen3 models (e.g., Qwen3-14B and Qwen3-32B). Additionally, we evaluate Claude-3.7 (Anthropic, 2025) with unknown model size. For large model classes beyond 100B (e.g., GPT-OSS 120B (OpenAI, 2025), DeepSeek-R1-0528 (NVIDIA Developer Blog, 2025)), we report the numbers to the Appendix I.1 as a reference.

3.2 MAIN EXPERIMENT RESULTS

Overall Performance on Level 1 Tasks. The left side of Table 1 presents the performance comparison results for pass@10 evaluated with robust verifiers (syntax and functionality) on KernelBench Level 1 tasks. TRITONRL consistently outperforms most baseline models with < 32B parameter sizes in terms of validity, correctness, and speedup. In particular, TRITONRL surpasses AutoTriton, which also leverages SFT and RL, by achieving higher correctness and speedup, underscoring the advantages of our hierarchical reward assignment. Notably, the correctness metric improves from 44% (SFT only) to 55% after RL, indicating that RL provides substantial gains in

[2]We use the Triton backend version of KernelBench from `https://github.com/ScalingIntelligence/KernelBench/pull/35`.

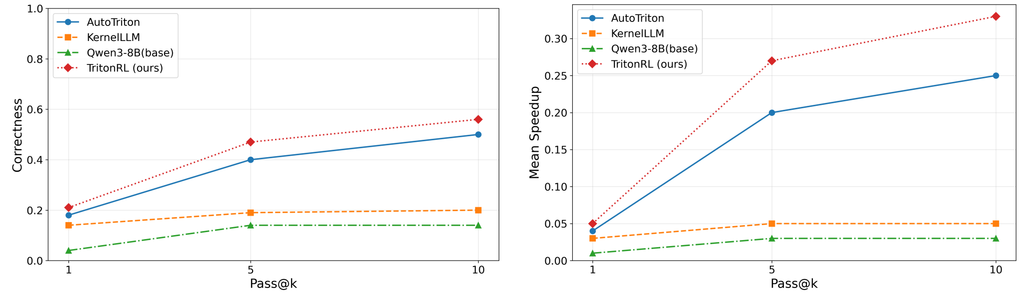

Figure 4: Pass@k correctness and mean speedup for $k = 1, 5, 10$ on KernelBench Level 1 tasks. The figures show how performance (correctness on the left, mean speedup on the right) of TRITONRL and baseline models scales as the number of attempts increases.

addition to supervised fine-tuning. Furthermore, TRITONRL achieves on-par performance to much larger models, highlighting the efficiency of our approach in enabling smaller models to excel in specialized code generation tasks. We further evaluated inference scaling by varying the number of sampled attempts ($k = 1, 5, 10$), as illustrated in Figure 4. The correctness of TRITONRL increases with more samples, whereas KernelLLM and Qwen3-8B show limited improvement, suggesting that TRITONRL generates a more diverse set of codes and benefits from additional sampling during inference. Additional pass@1 and pass@5 results are provided in Appendix I.2.

Effectiveness of Validity Reward. We analyze the validity of Triton codes generated by fine-tuned models to understand the types of errors each model is prone to. To examine the effects of fine-tuning on validity, we also include the base models of TRITONRL and the baseline models. In Figure 5, although both AutoTriton and TRITONRL achieve relatively high rates of validity compared to KernelLLM, a more detailed breakdown reveals that AutoTriton exhibits a much higher proportion of functionally invalid codes. Interestingly, the base model of AutoTriton shows a low rate of functionally and syntactically invalid codes, indicating that the fine-tuning process of AutoTriton may have led to learn functionally invalid codes. In contrast, TRITONRL generates significantly fewer invalid codes in terms of both syntax and functionality after fine-tuning, demonstrating the effectiveness of our robust verification in enhancing code quality.

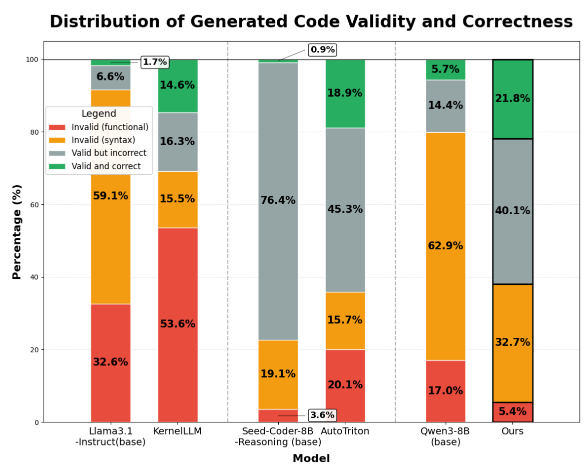

Figure 5: Side-by-side comparison of base models and their post-trained variants. Successful training should reduce invalid syntax errors (yellow) and functional invalidity (red), while increasing correctness (green) from individual base model. Only TRITONRL shows this outcome. For each metric, the numbers represent the ratio of corresponding samples among 10 generated samples for each of the 100 tasks in KernelBench Level 1.

Moreover, Table 1 highlights how heavily prior models relied on cheating shortcuts. Without functionality verification (w/o robust), AutoTriton's correctness jumps from 50% to 70%, revealing its tendency to exploit reward-driven shortcuts rather than produce true Triton code. In contrast, TRITONRL shows only a slight increase (56% to 58%), suggesting it learned to generate genuine code.

Effectiveness of Hierarchical Reward Decomposition. To validate the effectiveness of our hierarchical reward decomposition, we compare it with a *uniform* reward assignment approach, where a single reward is uniformly applied to all tokens without distinguishing between plan and code tokens, which is the reward design chosen by Li et al. (2025b); Baronio et al. (2025). To generalize the reward function used in Li et al. (2025b) and Baronio et al. (2025), we define a uniform reward as a weighted combination of correctness and speedup conditioned on validity, which can be expressed as

$$r_i = \texttt{syntax}_i \cdot \texttt{func}_i \cdot (\beta \cdot \texttt{correct}_i + (1-\beta) \cdot \texttt{speedup}_i), \tag{4}$$

where $\beta \in [0, 1]$ is a hyperparameter that the ratio of correctness in the reward mixture. In Li et al. (2025b), the reward is computed only based on correctness conditioned and validity, which corresponds to $\beta = 1.0$, while in Baronio et al. (2025), the reward is defined as the sum of correctness and speedup with some fixed weights. We defer the detailed GRPO formulation for uniform reward to Appendix E. We compare TRITONRL using hierarchical reward decomposition against models trained with uniform reward designs for various β values, keeping all other RL training settings (GRPO algorithm, hyperparameters, and pre-RL fine-tuning) consistent.

Table 2 demonstrates that hierarchical reward decomposition consistently yields higher correctness and speedup than any uniform reward configuration. While prior works (Li et al., 2025b; Baronio et al., 2025) explored single reward functions with various mixtures of correctness and speedup, our results demonstrate that such uniform designs have limitations in achieving the best model performance. This suggests that decoupling rewards by token class provides more targeted learning signals, better aligning with the distinct roles of planning and coding and leading to higher-quality Triton code generation.

Reward Type	Correctness ratio (β)	valid	compiled / correct	fast_1 / fast_2
Hierarchical (α^*)	-	99.0	82.0 / **56.0**	**5.0** / 1.0
Uniform	0.0	94.0	87.0 / 47.0	3.0 / 1.0
Uniform	0.3	100.0	**90.0** / 38.0	2.0 / 1.0
Uniform	0.5	92.0	77.0 / 43.0	3.0 / 1.0
Uniform	0.7	98.0	78.0 / 40.0	1.0 / 1.0
Uniform	1.0	95.0	75.0 / 38.0	2.0 / 1.0

Table 2: Comparison of hierarchical versus uniform reward designs on KernelBench Level 1 tasks. All metrics are reported as pass@10 (%). Reward type specifies whether the single reward is assigned uniformly across all tokens (Uniform), or the reward signal is decomposed by token class (Hierarchical) as in equation 3. The hyperparameter β in the uniform reward design controls the proportion of correctness in the single reward function applied to all tokens. See equation 4 for details.

Effect of Plan-to-Code Update Ratio (α). We also analyze the effect of the hyperparameter α in our hierarchical reward decomposition, which controls the relative update rate of planning versus coding actions during RL training. Smaller α values slow down plan token updates, allowing coding actions to adapt to more stable planning distributions. As shown in Table 3, $\alpha = 0.1$ achieves the best overall performance, while higher values (e.g., $\alpha = 1.0$) lead to instability and reduced correctness and speedup. Conversely, setting $\alpha = 0.0$, disabling plan updates, also degrades results, and this indicates that some plan adaptation is necessary. These findings highlight the importance of balancing plan and code updates to avoid premature convergence and maximize Triton code quality.

α	valid	compiled / correct	fast_1 / fast_2
0.0	98.0	78.0 / 37.0	3.0 / 1.0
0.1 (α^*)	99.0	82.0 / **56.0**	**5.0** / 1.0
0.3	100.0	**96.0** / 55.0	1.0 / 1.0
0.5	100.0	85.0 / 48.0	2.0 / 1.0
1.0	98.0	64.0 / 33.0	2.0 / 1.0

Table 3: Ablation study of the hyperparameter α in TRITONRL on KernelBench Level 1 tasks. All metrics are reported as pass@10 (%). α is the weighting factor for plan rewards in equation 3, determining how quickly plan tokens are updated relative to code tokens during training. The default configuration uses $\alpha^* = 0.1$.

Effect of Data Mixture for RL Training. We explore different data mixtures for RL training of TRITONRL to understand how training data composition affects model performance. Our training dataset consists of two levels of tasks, with the ratio controlled by a data mixture probability vector $\boldsymbol{p} = [p_1, p_2]$, where p_1 and p_2 represent the probabilities of sampling Level 1 and Level 2 tasks, respectively. We evaluate TRITONRL on KernelBench Level 1 and 2 tasks using three data mixing strategies for RL training: training exclusively on Level 1 tasks ($\boldsymbol{p} = [1, 0]$), exclusively on Level 2 tasks ($\boldsymbol{p} = [0, 1]$), and a balanced mixture of both ($\boldsymbol{p} = [0.5, 0.5]$), as summarized in Table 4. Training only on Level 1 tasks ($\boldsymbol{p} = [1, 0]$) yields the best correctness and fast$_1$ on Level 1 evaluation, while training only on Level 2 tasks does not improve Level 2 performance. This may be because Level 2 tasks are inherently more complex, and reward signals from those tasks are very sparse, making it difficult for the model to learn effectively (as confirmed in Table 5). This observation motivates future work to explore adaptive $\boldsymbol{p}$ scheduling during post-training.

Train Data Mixture	**Mixing Prob. $\boldsymbol{p}$**	LEVEL1			LEVEL2		
		valid	**compiled / correct**	**fast$_1$ / fast$_2$**	**valid**	**compiled / correct**	**fast$_1$ / fast$_2$**
Level 1	$[1, 0]$	99.0	82.0 / 56.0	5.0 / 1.0	66.0	29.0 / 7.0	0.0 / 0.0
Level 1+2	$[0.5, 0.5]$	99.0	92.0 / 43.0	2.0 / 1.0	74.0	35.0 / 8.0	0.0 / 0.0
Level 2	$[0, 1]$	100.0	97.0 / 49.0	3.0 / 1.0	57.0	37.0 / 6.0	0.0 / 0.0

Table 4: Ablation study on data mixture for RL training of TRITONRL, where the performance is evaluated on KernelBench level 1 and level 2 tasks.

Limited Performance on Fusion Tasks (Level 2). We evaluated TRITONRL and baseline models on KernelBench Level 2 tasks, which involve fused implementations such as Conv+Relu. As shown in Table 5, TRITONRL outperforms other 8B-scale Triton-specific models in correctness and speedup. However, all models show a marked drop from Level 1 to Level 2, reflecting the increased difficulty of generating fully valid Triton code for fusion tasks. Fusion tasks require integrating multiple kernels, making it more challenging to produce correct implementations compared to single-operation replacements. Models often take shortcuts by implementing only part of the task in Triton and relying on high-level PyTorch APIs for the remainder, resulting in incomplete or invalid solutions (see Appendix F.3 for examples). Additionally, these tasks yield much sparser reward signals, since successful fusion implementations are rare, making effective learning more difficult even when similar fusion tasks are frequently encountered during training, as shown in Table 4. This pronounced performance gap highlights the need for improved optimization strategies and leaves substantial room for future progress.

Model	**#Params**	LEVEL2			LEVEL2 (W/O ROBUST)
		valid	**compiled / correct**	**fast$_1$ / fast$_2$**	**compiled / correct**
Qwen3 (base)	8B	56.0	1.0 / 0.0	0.0 / 0.0	52.0 / 11.0
Qwen3	14B	35.0	24.0 / 1.0	0.0 / 0.0	94.0 / 65.0
Qwen3	32B	31.0	16.0 / 0.0	0.0 / 0.0	73.0 / 22.0
KernelLLM	8B	0.0	0.0 / 0.0	0.0 / 0.0	96.0 / 3.0
AutoTriton	8B	70.0	3.0 / 0.0	0.0 / 0.0	97.0 / 76.0
TRITONRL (ours)	8B	69.0	29.0 / **7.0**	0.0 / 0.0	88.0 / 42.0
w/o RL (SFT only)	8B	67.0	**32.0** / 6.0	0.0 / 0.0	98.0 / 41.0
Claude-3.7	-	34.0	34.0 / **12.0**	1.0 / 0.0	98.0 / 60.0

Table 5: Main results on KernelBench Level 2. The left block reports evaluation with the robust verifier (syntax + functionality). The right block (w/o robust verifier) lacks functionality checks, leading to misleading correctness estimates, more severe than Level 1 evaluation.

4 CONCLUSION

In this work, we introduce TRITONRL, a specialized LLM for Triton code generation, trained with a novel RL framework featuring robust verifiable rewards and hierarchical reward assignment. Our experiments on KernelBench show that TRITONRL surpasses existing fine-tuned Triton models in validity, correctness, and efficiency. Ablation studies demonstrate that both robust reward design and hierarchical reward assignment are essential for achieving correctness and efficiency. We believe TRITONRL marks a significant advancement toward fully automated and efficient GPU kernel generation with LLMs.

Reproducibility Statement

Our code-base is built upon publicly available frameworks (Verl (Sheng et al., 2025). Section 3.1 and the Appendix H G describe the experimental settings in detail.

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A LLM USAGE

We used an LLM to improve the writing by correcting grammar in our draft. It was not used to generate research ideas.

B RELATED WORK

B.1 LLM FOR KERNEL GENERATION

The exponential growth in demand for GPU computing resources has driven the need for highly optimized GPU kernels that improves computational efficiency. However, writing efficient GPU kernels is a complex and time-consuming task that requires specialized knowledge of GPU architectures and programming models. This has spurred significant interest in leveraging Large Language Models (LLMs), for automated kernel generation, especially for CUDA and Triton (Shao et al., 2024; Ouyang et al., 2025; Li et al., 2025a; NVIDIA Developer Blog, 2025). While these general-purpose models excel at a variety of programming tasks, they often struggle with custom kernel generation, achieving low success rates on specialized gpu programming tasks (Ouyang et al., 2025), highlighting the need for domain-specific models tailored to kernel synthesis.

For CUDA kernel generation, Ouyang et al. (2025) introduced KERNELBENCH, an open-source framework for evaluating LMs' ability to write fast and correct kernels on a suite of 250 carefully selected PyTorch ML workloads. Furthermore, Lange et al. (2025) presented an agentic framework, which leverages LLMs to translate PyTorch code into CUDA kernels and iteratively optimize them using performance feedback. Additionally, several works have focused on fine-tuning LLMs tailored for CUDA kernel generation. For example, Kevin-32B (Baronio et al., 2025) is a 32B parameter model fine-tuned via multi-turn RL to enhance kernel generation through self-refinement, and CUDA-L1 (Li et al., 2025c) applies contrastive reinforcement learning to DeepSeek-V3-671B, achieving notable speedup improvements in CUDA optimization tasks.

Another line of research focuses on Triton kernel generation. Li et al. (2025a) introduced TRITONBENCH, providing evaluations of LLMs on Triton programming tasks and highlighting the challenges of Triton's domain-specific language and GPU programming complexity. To further enhance LLMs' capabilities in Triton programming, Fisches et al. (2025) has introduced KernelLLM, a fine-tuned model of Llama3.1-8B-Instruct via supervised fine-tuning with Pytorch and Triton code pairs in KernelBook Paliskara & Saroufim (2025), but its performance is limited by the quality of training data. Similarly, Li et al. (2025b) introduced AutoTriton, a model fine-tuned specifically for Triton programming from Seed-Coder-8B-Reasoning Zhang et al. (2025), which achieves improved performance via SFT and RL with verifiable rewards based on correctness and rule-based Triton syntax verification, which may have limited improvement in runtime efficiency due to correctness-focused rewards. Both KernelLLM and AutoTriton are concurrent works developed alongside our work, and we provide a detailed comparison in Section 3.2.

B.2 REINFORCEMENT LEARNING WITH VERIFIABLE REWARDS

Reinforcement Learning (RL) has become a key technique for training Large Language Models (LLMs), especially in domains where verifiable reward signals are available. Unlike supervised fine-tuning (SFT), which relies on curated examples, RL enables models to learn through trial and error, guided solely by reward feedback. This makes the design of accurate reward functions critical, as the model's behavior is shaped entirely by the reward signal. As a result, RL with verifiable rewards (RLVR) (Lambert et al., 2025; Team et al., 2025; Guo et al., 2025) has gained significant traction in applications like mathematics and code generation (Shao et al., 2024; Li et al., 2022), where external verification is feasible through solution correctness or unit test outcomes.

In math and coding applications, the reward can be directly computed solely based on the final outcomes when ground-truth answers or unit tests are available. For tasks where validation is not available or noisy, rule-based verification or LLM-based judges can be employed to verify the quality of generated content (Guha et al., 2025; Guo et al., 2025). For coding tasks, unit tests are commonly used to measure whether generated code meets the specified requirements (Le et al., 2022; Ouyang et al., 2025). However, unit tests often fail to cover edge cases or fully capture the problem requirements, leading to potential "reward hacking" (Skalse et al., 2022) where the model generates code that passes the tests but does not genuinely solve the task (Sharma et al., 2024; Gao et al., 2024). Such reward hacking has been observed in kernel generation tasks, where models produce superficially correct codes passing unit tests by using high-level Pytorch modules instead of implementing custom kernels. To address this, some works Li et al. (2025b); Baronio et al. (2025) have introduced rule-based verification, which checks kernel syntax or use of specific high-level modules.

C NOTATIONS

The following notations will be used throughout this paper. For notational simplicity, we denote any function $f(q, o_i)$ as f_i when the context is clear.

- q: prompt given to the model, defining a task to implement in Triton
- o: output sequence generated by the model, which includes both reasoning trace and Triton code
- π_θ: policy model with parameters θ
- G: group size for GRPO
- o_i: i-th sample in the group G, which includes a reasoning trace that provides the "plan" for Triton code optimization and implementation and the final "Triton code", i.e. $o_i = \{o_{i,\text{plan}}, o_{i,\text{triton}}\}$
- T_i^c: set of token indices corresponding to token class $c \in \{\text{plan}, \text{triton}\}$ in the i-th sample
- $r^c(q, o_i) = r_i^c$: reward function for token class $c \in \{\text{plan}, \text{triton}\}$.
- $\hat{A}_t^c(q, o_i) = r^c(q, o_i) - \frac{1}{G}\sum_{j=1}^{G} r^c(q, o_j)$: token-level advantage of the t-th token of the i-th sample belonging to token class $c \in \{\text{plan}, \text{triton}\}$, shortened as $\hat{A}_{i,t}^c$.

D METRICS

We provide the formal definitions of the evaluation metrics used in this paper. Given a set of N tasks $\{q_n\}_{n=1}^N$ and k samples $\{o_i\}_{i=1}^k$ generated by the model for each task, we define the following metrics:

$$\begin{aligned}
&\text{valid} = \frac{1}{N}\sum_{n=1}^{N}\max_{i\in[k]} \mathbb{1}(\texttt{syntax}(q_n, o_i)\cdot\texttt{func}(q_n, o_i) = 1)\\
&\text{compiled} = \frac{1}{N}\sum_{n=1}^{N}\max_{i\in[k]} \mathbb{1}(\texttt{syntax}(q_n, o_i)\cdot\texttt{func}(q_n, o_i)\cdot\texttt{compiled}(q_n, o_i) = 1)\\
&\text{correct} = \frac{1}{N}\sum_{n=1}^{N}\max_{i\in[k]} \mathbb{1}(\texttt{syntax}(q_n, o_i)\cdot\texttt{func}(q_n, o_i)\cdot\texttt{correct}(q_n, o_i) = 1)\\
&\text{fast}_p = \frac{1}{N}\sum_{n=1}^{N}\max_{i\in[k]} \mathbb{1}(\texttt{syntax}(q_n, o_i)\cdot\texttt{func}(q_n, o_i)\cdot\texttt{correct}(q_n, o_i)\cdot\texttt{speedup}(q_n, o_i) > p)\\
&\text{mean_speedup} = \frac{1}{N}\sum_{n=1}^{N}\max_{i\in[k]}(\texttt{syntax}(q_n, o_i)\cdot\texttt{func}(q_n, o_i)\cdot\texttt{correct}(q_n, o_i)\cdot\texttt{speedup}(q_n, o_i))
\end{aligned} \tag{5}$$

E GRPO WITH UNIFORM REWARD ASSIGNMENT

Here we provide the detailed formulation of GRPO with uniform reward assignment, which is used in our experiments (Section 3.2) to compare with our proposed hierarchical reward assignment. The GRPO objective with uniform reward assignment is defined as

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}_{q\sim P(Q),\ \{o_i=(o_i^{\text{plan}}, o_i^{\text{code}})\}_{i=1}^G \sim \pi_{\theta_{old}}(\cdot|q)} \left[\frac{1}{G}\sum_{i=1}^{G}\mathcal{L}_{\text{GRPO}}(\theta, i)\right] \tag{6}$$

where π_θ and $\pi_{\theta_{old}}$ are the policy model and reference model, q denotes a prompt given to the model, defining a task to implement in Triton, and o_i represents i-th response generated by the model for q in the group G. The GRPO losses $\mathcal{L}(\theta, i)$ is computed as

$$\mathcal{L}_{\text{GRPO}}(\theta, i) = \frac{1}{G}\sum_{i=1}^{G}\frac{1}{|o_i|}\sum_{t=1}^{|o_i|} A_i \cdot \min\left\{\frac{\pi_\theta(o_{i,t}|q, o_{i,<t})}{\pi_{\theta_{old}}(o_{i,t}|q, o_{i,<t})}, \text{clip}\left(\frac{\pi_\theta(o_{i,t}|q, o_{i,<t})}{\pi_{\theta_{old}}(o_{i,t}|q, o_{i,<t})}, 1-\epsilon, 1+\epsilon\right)\right\}, \tag{7}$$

where A_i denotes the group-wise advantage uniformly applied to all tokens, computed as $A_i = r_i - \frac{1}{G}\sum_{j=1}^{G} r_j$, with r_i being the reward for the i-th sample. In the uniform reward assignment, we define the reward as a weighted combination of correctness and speedup conditioned on validity, which can be expressed as

$$r_i = \texttt{syntax}_i \cdot \texttt{func}_i \cdot (\beta \cdot \texttt{correct}_i + (1-\beta) \cdot \texttt{speedup}_i), \tag{8}$$

where $\beta \in [0, 1]$ is a hyperparameter that the ratio of correctness in the reward mixture.

F Data curation and examples

F.1 Data Mixing Subset Creation

We labeled difficulty level of 11k PyTorch reference codes in KernelBook based on the complexity of kernel implementation using Qwen3-235B-Instruct (Team, 2025). For each given PyTorch reference code, we prompt Qwen3-235B-Instruct (temperature=0.7, top_p=0.8) to label the difficulty level of replacing the PyTorch reference with Triton code as follows:

Instruction (input) example

``` <PyTorch reference code> ```
Assign a kernel implementation complexity level (1, 2, or 3) of the provided reference PyTorch architecture according to the criteria below:
• Level 1: Single primitive operation. This level includes the foundational building blocks of AI (e.g. convolutions, matrix-vector and matrix-matrix multiplications, losses, activations, and layer normalizations). Since PyTorch makes calls to several well-optimized and often closed-source kernels under-the-hood, it can be challenging for LMs to outperform the baseline for these primitive operations. However, if an LM succeeds, the open-source kernels could be an impactful alternative to the closed-source (e.g., CuBLAS [27]) kernels.
• Level 2: Operator sequences. This level includes AI workloads containing multiple primitive operations, which can be fused into a single kernel for improved performance (e.g., a combination of a convolution, ReLU, and bias). Since compiler-based tools such as the PyTorch compiler are effective at fusion, it can be challenging for LMs to outperform them. However, LMs may propose more complex algorithms compared to compiler rules. • Level 3: This level includes architectures that power popular AI models, such as AlexNet and MiniGPT, collected from popular PyTorch repositories on GitHub.

Data Mixing for Reinforcement Learning. In our task, we have a training dataset $\mathcal{D}_{train}$ that is made of examples from KernelBook. We have an evaluation dataset $\mathcal{D}_{test}$ from KernelBench. We regard the problem of selecting the right examples to post-train our LLM model as a data mixing optimization problem, and we formulate the problem as follows.

Given a training dataset $\mathcal{D}_{train}$ and a test dataset $\mathcal{D}_{test}$, either dataset can be divided into m subsets. we suppose the probability of selecting m training data subsets forms a probability simplex $\mathbf{p} \in \Delta$, which represents the probability of drawing different subsets in the training set. We define the reward function $R^i_{test}(\boldsymbol{p}) = \frac{1}{|\mathcal{D}^i_{test}|}\sum_{q \in \mathcal{D}^i_{test}} \max_{o \in \pi^{\boldsymbol{p}}(q)} r\big(q, o\big)$, where $\pi^{\boldsymbol{p}}$ is the policy that is trained under the data mixture $\boldsymbol{p}$. In this problem, we use a static mixture $\boldsymbol{p}$ for all post-training steps. Following the proposal by Chen et al. (2024), we can express a data mixture optimization problem as the following optimization problem:

$$\underset{\boldsymbol{p} \in \Delta}{\text{maximize}} \sum_{j=1}^{m} R^j_{test}(\boldsymbol{p}) \text{ s.t. } R^j_{test}(\boldsymbol{p}) = \zeta(S, \boldsymbol{p}), \text{where } S \in \mathbb{R}^{m \times m}. \tag{9}$$
```

We define $\mathcal{S}$ as the reward interaction matrix, where $\mathcal{S}_{ij}$ captures the effect of post-training on the i-th subset in $\mathcal{D}_{train}$ and then using the learned policy π to generate corresponding kernels for the j-th $\mathcal{D}_{test}$. We use a general function ζ to leverage this information to predict the reward obtained on the j-th subset in $\mathcal{D}_{test}$.

We make two crucial changes to prior data mixing work. First, unlike the typical data mixing work that assumes ζ can be parametrized as a linear function, we do not make specific assumptions (Chen et al., 2023; Xie et al., 2023; Fan et al., 2023). Second, we do not create random subsets of our data. Instead, we note that KernelBench (Ouyang et al., 2025) has three complexity levels. We use an LLM labeler to create difficulty labels for each data point in $\mathcal{D}_{train}$. Since we focus on difficulty level 1 and 2, we create two subsets for training and test: $\mathcal{D}_{train} = \{\mathcal{D}_{train}^{L1}, \mathcal{D}_{train}^{L2}\}$, $\mathcal{D}_{test} = \{\mathcal{D}_{test}^{L1}, \mathcal{D}_{test}^{L2}\}$. Since the problem is under-constrained without a known parametric form of ζ, we simply evaluate three candidate initializations, $\boldsymbol{p} \in [1, 0], [0, 1], [0.5, 0.5]$, and choose the best-performing mixture rather than fully modeling S and ζ or solving for p exhaustively.

F.2 Example of invalid Triton codes in KernelBook

The following is an example of invalid Triton code from KernelBook. The intended objective is to implement a convolution layer with bias addition using Triton. However, the generated code fails to correctly realize the convolution operation and bias addition within the Triton kernel, resulting in incorrect functionality. Specifically, this is not a valid Triton implementation of conv2d because the actual convolution is performed outside the Triton kernel using PyTorch modules. The Triton kernel itself only adds a bias term to the convolution output by loading and adding per-channel bias values; it does not perform any of the core convolution computations, such as sliding window access, dot products, or handling stride, padding, or dilation. Thus, while the Triton code is syntactically valid and functionally correct for bias addition, it does not implement conv2d and cannot be considered a genuine Triton-based convolution.

```
import torch
import torch.nn as nn
import triton
import triton.language as tl

from torch._inductor.select_algorithm import extern_kernels
from torch._inductor.runtime.triton_heuristics import grid
from torch._C import _cuda_getCurrentRawStream as get_raw_stream
from torch._C._dynamo.guards import assert_size_stride


@triton.jit
def triton_poi_fused_convolution_0(in_out_ptr0, in_ptr0, xnumel, XBLOCK:
    tl.constexpr):
   xoffset = tl.program_id(0) * XBLOCK
   xindex = xoffset + tl.arange(0, XBLOCK)[:]

   tl.full([XBLOCK], True, tl.int1)

   x3 = xindex
   x1 = xindex // 4096 % 2

   tmp0 = tl.load(in_out_ptr0 + x3, None)
   tmp1 = tl.load(in_ptr0 + x1, None, eviction_policy='evict_last')

   tmp2 = tmp0 + tmp1

   tl.store(in_out_ptr0 + x3, tmp2, None)


def call(args):
   primals_1, primals_2, primals_3 = args
   args.clear()

   assert_size_stride(primals_1, (2, 3, 1, 1), (3, 1, 1, 1))
```

```
    assert_size_stride(primals_2, (2,), (1,))
    assert_size_stride(primals_3, (4, 3, 64, 64), (12288, 4096, 64, 1))

    with torch.cuda._DeviceGuard(0):
        torch.cuda.set_device(0)

        buf0 = extern_kernels.convolution(
            primals_3,
            primals_1,
            stride=(1, 1),
            padding=(0, 0),
            dilation=(1, 1),
            transposed=False,
            output_padding=(0, 0),
            groups=1,
            bias=None
        )

        assert_size_stride(buf0, (4, 2, 64, 64), (8192, 4096, 64, 1))

        buf1 = buf0
        del buf0

        get_raw_stream(0)

        triton_poi_fused_convolution_0[grid(32768)](
            buf1, primals_2, 32768,
            XBLOCK=128,
            num_warps=4,
            num_stages=1
        )

        del primals_2

    return buf1, primals_1, primals_3


class ModelNew(nn.Module):
    def __init__(self, num_classes=2, in_channels=3, is_deconv=False,
        is_batchnorm=False, *args, **kwargs):
        super(ModelNew, self).__init__()
        self.is_deconv = is_deconv
        self.in_channels = in_channels
        self.is_batchnorm = is_batchnorm

        self.final = nn.Conv2d(self.in_channels, num_classes, kernel_size
            =1)

    def forward(self, input_0):
        primals_1 = self.final.weight
        primals_2 = self.final.bias
        primals_3 = input_0

        output = call([primals_1, primals_2, primals_3])
        return output[0]
```

F.3 Example of invalid Triton codes for Level 2 tasks

The following is an example of invalid Triton code generated during RL training of TritonRL. This level 2 task aims to implement a two-branch linear transformation with message passing, structured like a Graph Neural Network (GNN) layer. However, while the code implment linear transformations using a custom Triton kernel, it fails to fully realize the intended GNN functionality with only Triton kernels by using torch.bmm.

```
import torch
import torch.nn as nn
import triton
import triton.language as tl

@triton.jit
def _linear_triton_kernel(
   input_ptr, weight_ptr, bias_ptr, output_ptr,
   B, M, N, K,
   stride_input_b, stride_input_m, stride_input_k,
   stride_weight_n, stride_weight_k,
   stride_output_b, stride_output_m, stride_output_n,
   BLOCK_SIZE_M: tl.constexpr, BLOCK_SIZE_N: tl.constexpr, BLOCK_SIZE_K:
      tl.constexpr,
):
   pid_b = tl.program_id(0)
   pid_m = tl.program_id(1)
   pid_n = tl.program_id(2)

   pid_m = tl.multiple_of(pid_m * BLOCK_SIZE_M, BLOCK_SIZE_M)
   pid_n = tl.multiple_of(pid_n * BLOCK_SIZE_N, BLOCK_SIZE_N)

   input_ptr += pid_b * stride_input_b
   output_ptr += pid_b * stride_output_b

   offs_m = pid_m + tl.arange(0, BLOCK_SIZE_M)
   offs_n = pid_n + tl.arange(0, BLOCK_SIZE_N)
   offs_k = tl.arange(0, BLOCK_SIZE_K)

   input_ptrs = input_ptr + (offs_m[:, None] * stride_input_m + offs_k[
      None, :] * stride_input_k)
   weight_ptrs = weight_ptr + (offs_n[:, None] * stride_weight_n + offs_k
      [None, :] * stride_weight_k)

   acc = tl.zeros((BLOCK_SIZE_M, BLOCK_SIZE_N), dtype=tl.float32)

   for k in range(0, K, BLOCK_SIZE_K):
      mask_k = (offs_k[None, :] < K - k)
      mask_m = (offs_m[:, None] < M)
      mask_n = (offs_n[None, :] < N)

      a = tl.load(input_ptrs, mask=mask_k & mask_m, other=0.0)
      b = tl.load(weight_ptrs, mask=mask_k & mask_n, other=0.0)

      b = tl.trans(b)
      acc += tl.dot(a, b)

      input_ptrs += BLOCK_SIZE_K * stride_input_k
      weight_ptrs += BLOCK_SIZE_K * stride_weight_k

   bias_ptrs = bias_ptr + offs_n
   bias = tl.load(bias_ptrs, mask=offs_n < N, other=0.0)
   acc += bias[None, :]

   offs_out_m = pid_m + tl.arange(0, BLOCK_SIZE_M)
   offs_out_n = pid_n + tl.arange(0, BLOCK_SIZE_N)
   out_ptrs = output_ptr + (offs_out_m[:, None] * stride_output_m +
      offs_out_n[None, :] * stride_output_n)

   mask = (offs_out_m[:, None] < M) & (offs_out_n[None, :] < N)
   tl.store(out_ptrs, acc, mask=mask)


def linear_triton(input, weight, bias):
```

```
    B, M, K = input.shape
    N = weight.shape[0]
    output = torch.empty((B, M, N), device=input.device, dtype=input.dtype
        )

    grid = (B, triton.cdiv(M, 64), triton.cdiv(N, 64))

    _linear_triton_kernel[grid](
        input, weight, bias, output,
        B, M, N, K,
        input.stride(0), input.stride(1), input.stride(2),
        weight.stride(0), weight.stride(1),
        output.stride(0), output.stride(1), output.stride(2),
        BLOCK_SIZE_M=64, BLOCK_SIZE_N=64, BLOCK_SIZE_K=64
    )

    return output


class ModelNew(nn.Module):
    def __init__(self, state_dim, name='', out_state_dim=None):
        super().__init__()
        self.state_dim = state_dim
        self.out_state_dim = out_state_dim if out_state_dim is not None
            else state_dim
        self.fc1 = nn.Linear(in_features=self.state_dim, out_features=self.
            out_state_dim)
        self.fc2 = nn.Linear(in_features=self.state_dim, out_features=self.
            out_state_dim)
        self.name = name

    def forward(self, input, adj):
        state_in = linear_triton(input, self.fc1.weight, self.fc1.bias)
        temp = torch.bmm(adj, input)
        forward_input = linear_triton(temp, self.fc2.weight, self.fc2.bias)
        return state_in + forward_input
```

F.4 Invalid Triton code examples

Here, we provide some examples of invalid Triton code generated by the baseline models.

Example 1: Triton syntax failure (`syntax` = 0) – no Triton kernel. This is not a Triton kernel because it does not include any custom `@triton.jit` kernel.

```
import torch
import torch.nn as nn
import triton
import triton.language as tl
import torch.nn.functional as F

# To replace with Triton, a custom kernel would be needed (not provided
    here)
class ModelNew(nn.Module):
    def __init__(self) -> None:
        super().__init__()

    def forward(self, x):
        return F.avg_pool2d(x, kernel_size=3, stride=None, padding=0)

def get_inputs():
    a = torch.randn(1, 128).cuda()
    b = torch.randn(1, 128).cuda()
    return [a, b]
```

```
def get_init_inputs():
    return []
```

Example 2: Functional failure (`syntax` = 1, `func` = 0) – use of high-level PyTorch module. This implementation contains a Triton kernel, but the main computation (convolution) is still handled by the PyTorch `nn.Conv3d` module. The Triton kernel is only used for a simple addition, rather than implementing the full intended operation.

```
import torch
import torch.nn as nn
import triton
import triton.language as tl


@triton.jit
def add_bias_kernel(
    out_ptr,
    bias_ptr,
    n_elements,
    out_C,
    out_D,
    out_W,
    out_H,
    BLOCK_SIZE: tl.constexpr,
):
    pid = tl.program_id(0)
    block_start = pid * BLOCK_SIZE
    offsets = block_start + tl.arange(0, BLOCK_SIZE)
    mask = offsets < n_elements

    out = tl.load(out_ptr + offsets, mask=mask, other=0.0)

    stride_channel = out_D * out_W * out_H
    channel_idx = (offsets // stride_channel) % out_C
    bias = tl.load(bias_ptr + channel_idx, mask=mask, other=0.0)

    out = out + bias
    tl.store(out_ptr + offsets, out, mask=mask)


def triton_add_bias(out: torch.Tensor, bias: torch.Tensor):
    assert out.is_cuda and bias.is_cuda, "Tensors must be on CUDA."

    out = out.contiguous()
    bias = bias.contiguous()
    n_elements = out.numel()
    BLOCK_SIZE = 128

    grid = lambda meta: (
        (n_elements + meta["BLOCK_SIZE"] - 1) // meta["BLOCK_SIZE"],
    )

    batch_size, out_channels, D, W, H = out.shape

    add_bias_kernel[grid](
        out,
        bias,
        n_elements,
        out_channels,
        D,
        W,
        H,
        BLOCK_SIZE=BLOCK_SIZE
```

```
    )

    return out


class ModelNew(nn.Module):
    def __init__(
        self,
        in_channels: int,
        out_channels: int,
        kernel_size: int,
        stride: int = 1,
        padding: int = 0,
        dilation: int = 1,
        groups: int = 1,
        bias: bool = False
    ):
        super(ModelNew, self).__init__()
        self.conv3d = nn.Conv3d(
            in_channels,
            out_channels,
            (kernel_size, kernel_size, kernel_size),
            stride=stride,
            padding=padding,
            dilation=dilation,
            groups=groups,
            bias=bias
        )

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        out = self.conv3d(x)
        if self.conv3d.bias is not None:
            out = triton_add_bias(out, self.conv3d.bias)
        return out
```

Example 3: Functional failure (`syntax` = 1, `func` = 0) – hardcoded output and no meaningful computation. While the Triton kernel is syntactically correct, but it doesn't actually implement the intended operation (Group Normalization). The kernel doesn't compute mean or variance, which are essential for GroupNorm. To implement real GroupNorm, you'd need to compute per-group statistics and normalize accordingly. Also, it only loads the input tensor and writes it back unchanged.

```
import torch
import torch.nn as nn
import triton
import triton.language as tl


@triton.jit
def groupnorm_kernel(
    x_ptr, # Pointer to x tensor
    y_ptr, # Pointer to y tensor (not used here)
    out_ptr, # Pointer to output tensor
    n_elements, # Total number of elements
    BLOCK_SIZE: tl.constexpr,
):
    # Each program handles a contiguous block of data of size BLOCK_SIZE
    block_start = tl.program_id(0) * BLOCK_SIZE
    # Create a range of offsets [0..BLOCK_SIZE-1]
    offsets = block_start + tl.arange(0, BLOCK_SIZE)
    # Mask to ensure we don't go out of bounds
    mask = offsets < n_elements
    # Load input value
```

```
    x = tl.load(x_ptr + offsets, mask=mask, other=0.0)
    # Compute x squared
    x_squared = x * x
    # Store the result
    tl.store(out_ptr + offsets, x, mask=mask)


def triton_groupnorm(x: torch.Tensor, y: torch.Tensor):
    assert x.is_cuda and y.is_cuda, "Tensors␣must␣be␣on␣CUDA."
    x = x.contiguous()
    y = y.contiguous()

    # Prepare output tensor
    out = torch.empty_like(x)

    # Number of elements in the tensor
    n_elements = x.numel()
    BLOCK_SIZE = 128 # Tunable parameter for block size

    # Determine the number of blocks needed
    grid = lambda meta: ((n_elements + meta["BLOCK_SIZE"] - 1) // meta["
        BLOCK_SIZE"],)

    # Launch the Triton kernel
    groupnorm_kernel[grid](x, y, out, n_elements, BLOCK_SIZE=BLOCK_SIZE)
    return out


class ModelNew(nn.Module):
    def __init__(self, num_features: int, num_groups: int) -> None:
        super().__init__()
        self.num_features = num_features
        self.num_groups = num_groups

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        # Use Triton kernel for elementwise operations
        x_triton = triton_groupnorm(x, x)
        # Manually compute mean and variance (as Triton kernel only handles
            x)
        # Actual GroupNorm logic would go here
        # For this example, we return the Triton processed tensor
        return x_triton
```

F.5 SFT AND RL DATASET CONSTRUCTION WITH KERNELBOOK

To synthesize SFT dataset, we extract 11,621 PyTorch reference codes from KernelBook, executable without errors, such as

```
import torch
import torch.nn as nn


class Model(nn.Module):

def __init__(self):
super(Model, self).__init__()

def forward(self, neighbor):
return torch.sum(neighbor, dim=1)


def get_inputs():
return [torch.rand([4, 4, 4, 4])]
```

```
def get_init_inputs():
return [[], {}]
```

For each given PyTorch reference code, we construct an instruction for DeepSeek-R1 to generate CoTs and Triton kernels as:

Instruction (input) example

Your task is to write custom Triton kernels to replace as many PyTorch operators as possible in the given architecture, aiming for maximum speedup. You may implement multiple custom kernels, explore operator fusion (such as combining matmul and relu), or introduce algorithmic improvements (like online softmax). You are only limited by your imagination. You are given the following architecture:
``` <PyTorch reference code> ```
You have to optimize the architecture named Model with custom Triton kernels. Optimize the architecture named Model with custom Triton kernels! Name your optimized output architecture ModelNew. Output the new code in codeblocks. Please generate real code, NOT pseudocode, make sure the code compiles and is fully functional. Just output the new model code, no other text, and NO testing code! Before writing a code, reflect on your idea to make sure that the implementation is correct and optimal.

Given the instruction for each PyTorch reference code, we collect (CoT, Triton kernel code) pairs fom DeepSeek-R1 and construct outputs for SFT by concatenating the pairs as follows:

Triton kernel with CoT (output) example

````
 <think>
CoT
</think>
```
<Triton kernel code>
```
````

In this manner, for each Pytorch reference code in KernelBook, we construct 5 (input, output) SFT samples.

For RL training, we use the same instruction input as a prompt for the same set of Pytorch reference codes in KernelBook, without the output synthesized by DeepSeek-R1 because RL training only requires reward feedback, which can be directly obtained from executing the generated Triton code.

G Evaluation and examples

G.1 Evaluation with KernelBench

To evaluate the trained models, we construct prompts for 250 tasks in KernelBench. Similar to KernelBook, KernelBench provides a reference PyTorch code for each task. For each given reference PyTorch code, we construct a prompt with one simple example pair of (PyTorch code, Triton kernel code), similarly to the one-shot prompting format in KernelBench. Here, we use the following PyTorch and Triton codes for a simple add operation as an example:

```
### PyTorch reference code ###
import torch
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self) -> None:
        super().__init__()
```
```

```
    def forward(self, a, b):
        return a + b

def get_inputs():
    # randomly generate input tensors based on the model architecture
    a = torch.randn(1, 128).cuda()
    b = torch.randn(1, 128).cuda()
    return [a, b]

def get_init_inputs():
    # randomly generate tensors required for initialization based on the
        model architecture
    return []

### Triton kernel code ###

import torch
import torch.nn as nn
import torch.nn.functional as F
import triton
import triton.language as tl

@triton.jit
def add_kernel(
    x_ptr, # Pointer to first input
    y_ptr, # Pointer to second input
    out_ptr, # Pointer to output
    n_elements, # Total number of elements in input/output
    BLOCK_SIZE: tl.constexpr,
):
    # Each program handles a contiguous block of data of size BLOCK_SIZE
    block_start = tl.program_id(0) * BLOCK_SIZE
    # Create a range of offsets [0..BLOCK_SIZE-1]
    offsets = block_start + tl.arange(0, BLOCK_SIZE)
    # Mask to ensure we don't go out of bounds
    mask = offsets < n_elements
    # Load input values
    x = tl.load(x_ptr + offsets, mask=mask, other=0.0)
    y = tl.load(y_ptr + offsets, mask=mask, other=0.0)
    # Perform the elementwise addition
    out = x + y
    # Store the result
    tl.store(out_ptr + offsets, out, mask=mask)

def triton_add(x: torch.Tensor, y: torch.Tensor):
    """
␣␣␣␣This␣function␣wraps␣the␣Triton␣kernel␣call.␣It:
␣␣␣␣␣␣1.␣Ensures␣the␣inputs␣are␣contiguous␣on␣GPU.
␣␣␣␣␣␣2.␣Calculates␣the␣grid␣(blocks)␣needed.
␣␣␣␣␣␣3.␣Launches␣the␣Triton␣kernel.
␣␣␣␣"""
    assert x.is_cuda and y.is_cuda, "Tensors␣must␣be␣on␣CUDA."
    x = x.contiguous()
    y = y.contiguous()

    # Prepare output tensor
    out = torch.empty_like(x)

    # Number of elements in the tensor
    n_elements = x.numel()
    BLOCK_SIZE = 128 # Tunable parameter for block size

    # Determine the number of blocks needed
    grid = lambda meta: ((n_elements + meta["BLOCK_SIZE"] - 1) // meta["
        BLOCK_SIZE"],)
```

```
    # Launch the Triton kernel
    add_kernel[grid](x, y, out, n_elements, BLOCK_SIZE=BLOCK_SIZE)
    return out

class ModelNew(nn.Module):
    def __init__(self) -> None:
        super().__init__()

    def forward(self, a, b):
        # Instead of "return a + b", call our Triton-based addition
        return triton_add(a, b)
```

Prompt (input) example

You write custom Triton kernels to replace the pytorch operators in the given architecture to get speedups.
You have complete freedom to choose the set of operators you want to replace. You may make the decision to replace some operators with custom Triton kernels and leave others unchanged. You may replace multiple operators with custom implementations, consider operator fusion opportunities (combining multiple operators into a single kernel, for example, combining matmul+relu), or algorithmic changes (such as online softmax). You are only limited by your imagination.
Here's an example to show you the syntax of inline embedding custom Triton kernels in torch. The example given architecture is:
``` <Example PyTorch code> ```
The example new architecture with custom Triton kernels looks like this:
``` <Example Triton kernel code> ```
You are given the following architecture:
``` <PyTorch reference code> ```
Optimize the architecture named Model with custom Triton kernels! Name your optimized output architecture ModelNew. Output the new code in codeblocks. Please generate real code, NOT pseudocode, make sure the code compiles and is fully functional. Just output the new model code, no other text, and NO testing code!

G.2 Example of Triton codes with speedup > 1

Problem 12 in KernelBench Level 1: diagonal matrix multiplication with x11 speedup.

```
import torch
import triton
import triton.language as tl

@triton.jit
def fused_diag_matmul_kernel(
  vec_a_ptr, # Pointer to the diagonal vector A (N,)
  mat_b_ptr, # Pointer to the input dense matrix B (N, M)
  output_ptr, # Pointer to the output matrix (N, M)
  # --- Matrix dimensions ---
  N, # The size of the diagonal vector A
  M, # The number of columns in matrix B
  TOTAL_ELEMENTS, # Total number of elements in the output matrix (N * M)
  # --- Tuning parameters ---
  BLOCK_SIZE: tl.constexpr, # Number of elements each Triton program will
      handle
):
  """
␣␣Computes␣C␣=␣diag(A)␣*␣B,␣where␣A␣is␣a␣vector␣representing␣the␣diagonal
    .
␣␣This␣kernel␣treats␣the␣operation␣as␣a␣simple␣element-wise␣
    multiplication
```
```

```
␣␣where␣each␣row␣of␣B␣is␣scaled␣by␣the␣corresponding␣element␣of␣A.
␣␣"""
  # 1. CALCULATE OFFSETS: Determine which elements this program instance
      will process.
  pid = tl.program_id(axis=0)
  block_start_offset = pid * BLOCK_SIZE
  offsets = block_start_offset + tl.arange(0, BLOCK_SIZE)

  # 2. CREATE BOUNDARY-CHECK MASK: Prevent out-of-bounds memory access.
  mask = offsets < TOTAL_ELEMENTS

  # 3. COMPUTE 2D INDICES FROM 1D OFFSETS: Find the row for vector A.
  row_indices = offsets // M

  # 4. LOAD DATA EFFICIENTLY: Read from global memory into registers.
  vec_a_elements = tl.load(vec_a_ptr + row_indices, mask=mask, other=0.0)
  mat_b_elements = tl.load(mat_b_ptr + offsets, mask=mask, other=0.0)

  # 5. PERFORM THE CORE COMPUTATION: The actual fused operation.
  output = vec_a_elements * mat_b_elements

  # 6. STORE THE RESULT: Write the computed values back to global memory.
  tl.store(output_ptr + offsets, output, mask=mask)
```

Problem 61 in KernelBench Level 1: 3D Transposed Convolution with x1.5 speedup.

```
import torch
import torch.nn as nn
import triton
import triton.language as tl


@triton.jit
def conv_transpose3d_kernel(
    input_ptr, weight_ptr, output_ptr,
    B, IC, OC, D_in, H_in, W_in, D_out, H_out, W_out,
    input_batch_stride, input_channel_stride, input_d_stride,
        input_h_stride, input_w_stride,
    weight_in_channels_stride, weight_out_channels_stride, weight_d_stride
        , weight_h_stride, weight_w_stride,
    output_batch_stride, output_channel_stride, output_d_stride,
        output_h_stride, output_w_stride,
    BLOCK_SIZE: tl.constexpr,
):
    # Each block handles BLOCK_SIZE output elements
    pid = tl.program_id(0)
    n_elements = B * OC * D_out * H_out * W_out

    block_start = pid * BLOCK_SIZE
    offsets = block_start + tl.arange(0, BLOCK_SIZE)

    # Mask to avoid out-of-bounds access in last block
    mask = offsets < n_elements

    # Precompute for flattening and indexing
    OC_D_outH_outW_out = OC * D_out * H_out * W_out
    D_outH_outW_out = D_out * H_out * W_out

    # Decompose flat index into (batch, channel, depth, height, width)
    b_idx = offsets // OC_D_outH_outW_out
    residual = offsets % OC_D_outH_outW_out
    oc_idx = residual // D_outH_outW_out
    spatial_idx = residual % D_outH_outW_out

    d_idx = spatial_idx // (H_out * W_out)
```

```
hw_idx = spatial_idx % (H_out * W_out)
h_idx = hw_idx // W_out
w_idx = hw_idx % W_out

# Accumulator for output value (per element)
acc = tl.zeros((BLOCK_SIZE,), dtype=tl.float32)

# Loop over all input channels and 3x3x3 kernel positions
for ic in range(IC):
   for kd in range(3):
      for kh in range(3):
         for kw in range(3):
            # Compute corresponding input position for each output
            d_in = d_idx - kd
            h_in = h_idx - kh
            w_in = w_idx - kw

            # Check input bounds to avoid invalid memory access
            in_bounds = (
               (d_in >= 0) & (d_in < D_in) &
               (h_in >= 0) & (h_in < H_in) &
               (w_in >= 0) & (w_in < W_in)
            )

            # Compute input tensor offset
            input_offsets = (
               b_idx * input_batch_stride +
               ic * input_channel_stride +
               d_in * input_d_stride +
               h_in * input_h_stride +
               w_in * input_w_stride
            )

            # Load input values with masking (zeros for out-of-bounds)
            input_val = tl.load(input_ptr + input_offsets, mask=
                in_bounds, other=0.0)

            # Compute weight tensor offset (flipped in transpose)
            weight_offsets = (
               oc_idx * weight_out_channels_stride +
               ic * weight_in_channels_stride +
               kd * weight_d_stride +
               kh * weight_h_stride +
               kw * weight_w_stride
            )

            weight_val = tl.load(weight_ptr + weight_offsets)

            # Accumulate product into output accumulator
            acc += input_val * weight_val

# Store the final output value
output_offsets = (
   b_idx * output_batch_stride +
   oc_idx * output_channel_stride +
   d_idx * output_d_stride +
   h_idx * output_h_stride +
   w_idx * output_w_stride
)

# Store with mask for thread-safety
tl.store(output_ptr + output_offsets, acc, mask=mask)
```

```
def triton_conv_transpose3d(x: torch.Tensor, weight: torch.Tensor) ->
    torch.Tensor:
   B, IC, D_in, H_in, W_in = x.shape
   OC = weight.shape[1]

   # Output dimensions for stride=1, padding=0, kernel=3
   D_out = D_in + 2
   H_out = H_in + 2
   W_out = W_in + 2

   # Allocate output tensor
   output = torch.empty((B, OC, D_out, H_out, W_out), device=x.device,
       dtype=x.dtype)

   # Launch grid size: enough blocks to cover all output elements
   BLOCK_SIZE = 256
   grid = (triton.cdiv(B * OC * D_out * H_out * W_out, BLOCK_SIZE),)

   # Launch the kernel
   conv_transpose3d_kernel[grid](
      x, weight, output,
      B, IC, OC, D_in, H_in, W_in, D_out, H_out, W_out,
      x.stride(0), x.stride(1), x.stride(2), x.stride(3), x.stride(4),
      weight.stride(0), weight.stride(1), weight.stride(2), weight.stride
          (3), weight.stride(4),
      output.stride(0), output.stride(1), output.stride(2), output.stride
          (3), output.stride(4),
      BLOCK_SIZE
   )

   return output


class ModelNew(nn.Module):
   def __init__(
      self,
      in_channels: int,
      out_channels: int,
      kernel_size: int,
      stride: int = 1,
      padding: int = 0,
      output_padding: int = 0,
      groups: int = 1,
      bias: bool = False
   ):
      super().__init__()

      # This implementation is hardcoded for kernel_size=3, stride=1, no
          padding, no bias
      assert (
         kernel_size == 3 and stride == 1 and
         padding == 0 and output_padding == 0 and
         groups == 1 and not bias
      )

      self.in_channels = in_channels
      self.out_channels = out_channels

      # Weight shape: [in_channels, out_channels, 3, 3, 3]
      self.weight = nn.Parameter(torch.empty(in_channels, out_channels,
          3, 3, 3))

      # Initialize with Kaiming uniform
      nn.init.kaiming_uniform_(self.weight, a=5**0.5)
```

```
    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return triton_conv_transpose3d(x, self.weight)
```

Problem 35 in KernelBench Level 1: Group Normalization with x1.1 speedup.

```
import torch
import torch.nn as nn
import triton
import triton.language as tl


@triton.jit
def group_norm_reduce_kernel(
    x_ptr,
    mean_group_ptr,
    var_group_ptr,
    N, C, H, W, num_groups, M,
    BLOCK_SIZE_REDUCE: tl.constexpr
):
    # Program IDs for parallel execution across batch and groups
    pid0 = tl.program_id(0) # batch index
    pid1 = tl.program_id(1) # group index

    group_size = M * H * W
    group_start = pid0 * (C * H * W) + pid1 * group_size

    # Use float accumulators for numerical stability
    sum1 = 0.0
    sum2 = 0.0

    # Loop over the group in chunks for better cache usage
    for i in range(0, group_size, BLOCK_SIZE_REDUCE):
        offset = i + tl.arange(0, BLOCK_SIZE_REDUCE)
        mask = offset < group_size # avoid out-of-bounds loads

        offsets = group_start + offset

        # Efficient memory access with masking and zero-padding
        chunk = tl.load(x_ptr + offsets, mask=mask, other=0.0)

        # Accumulate sum and squared sum
        sum1 += tl.sum(chunk, axis=0)
        sum2 += tl.sum(chunk * chunk, axis=0)

    # Numerically stable variance computation
    mean = sum1 / group_size
    var = (sum2 - mean * sum1) / group_size

    # Store per-group mean and variance
    mean_idx = pid0 * num_groups + pid1
    tl.store(mean_group_ptr + mean_idx, mean)
    tl.store(var_group_ptr + mean_idx, var)


@triton.jit
def group_norm_forward_kernel(
    x_ptr,
    out_ptr,
    mean_group_ptr,
    var_group_ptr,
    weight_ptr,
    bias_ptr,
    N, C, H, W, num_groups, M, eps,
    BLOCK_SIZE: tl.constexpr
):
```

```
    # 1D parallelism across total number of elements
    pid = tl.program_id(0)
    total_elements = N * C * H * W

    block_start = pid * BLOCK_SIZE
    offsets = block_start + tl.arange(0, BLOCK_SIZE)
    mask = offsets < total_elements # bounds checking

    # Flattened indexing to recover n, c from offset
    total2 = H * W
    total3 = C * total2

    n = offsets // total3
    rest = offsets - n * total3
    c = rest // total2
    group_index = c // M # which group the channel belongs to

    # Memory load with masking
    x_offsets = offsets
    x_val = tl.load(x_ptr + x_offsets, mask=mask)

    # Load per-sample, per-group mean and variance
    mean_idx = n * num_groups + group_index
    mean_val = tl.load(mean_group_ptr + mean_idx)
    var_val = tl.load(var_group_ptr + mean_idx)

    # Load affine transformation parameters per channel
    gamma = tl.load(weight_ptr + c)
    beta = tl.load(bias_ptr + c)

    # Avoid negative variance (numerical safety)
    var_val = tl.maximum(var_val, 0)
    std = tl.sqrt(var_val + eps)

    # Normalize and apply affine transformation
    normalized = (x_val - mean_val) / std
    out_val = normalized * gamma + beta

    # Store result with mask to handle edge threads
    tl.store(out_ptr + x_offsets, out_val, mask=mask)


class ModelNew(nn.Module):
    def __init__(self, num_features, num_groups):
        super().__init__()
        self.num_groups = num_groups
        self.num_features = num_features

        # Learnable affine parameters
        self.weight = nn.Parameter(torch.ones(num_features))
        self.bias = nn.Parameter(torch.zeros(num_features))

    def forward(self, x):
        x = x.contiguous() # ensure contiguous memory layout for Triton

        N, C, H, W = x.shape
        M = C // self.num_groups # channels per group

        # Allocate buffers for per-group statistics
        mean_group = torch.empty((N, self.num_groups), device=x.device)
        var_group = torch.empty((N, self.num_groups), device=x.device)

        # Launch reduction kernel: one thread per (N, group)
        grid_reduce = (N, self.num_groups)
        group_norm_reduce_kernel[grid_reduce](
```

```
            x, mean_group, var_group,
            N, C, H, W, self.num_groups, M,
            BLOCK_SIZE_REDUCE=1024 # large block size for better throughput
        )

        # Allocate output tensor
        out = torch.empty_like(x)
        total_elements = N * C * H * W

        # Launch forward kernel: 1D block across all elements
        grid_forward = (triton.cdiv(total_elements, 1024),)
        group_norm_forward_kernel[grid_forward](
            x, out, mean_group, var_group,
            self.weight, self.bias,
            N, C, H, W, self.num_groups, M, 1e-5,
            BLOCK_SIZE=1024 # tuneable block size
        )

        return out
```

H HYPERPARAMETERS OF SFT AND RL TRAINING

For data preparation, we use temperature=0.6, top_p=0.95 for DeepSeek-R1 (Guo et al., 2025). To label difficulty, we further label tasks into three difficulty levels using Qwen3-235B-Instruct (Team, 2025) (temperature=0.7, top_p=0.8).

For SFT, we training for 2 epochs with a batch size of 16, a learning rate of 1×10^{-5}, and a maximum sequence length of 12,288 tokens. We train the model for 2 epochs using the VeRL framework (Sheng et al., 2025) with a batch size of 32, a learning rate of 1×10^{-6}, the maximum prompt length $2,048$, and the maximum response length $16,384$. We use 8 NVIDIA A100 80GB GPUs for both SFT and RL training.

I ADDITIONAL EXPERIMENT RESULTS

I.1 OVERALL PERFORMANCE COMPARISON

Model	#Params	LEVEL1			LEVEL1 (W/O ROBUST)		
		valid	compiled / correct	fast_1 / fast_2	valid	compiled / correct	fast_1 / fast_2
Qwen3 (base)	8B	73.0	40.0 / 14.0	0.0 / 0.0	54.0	52.0 / 15.0	0.0 / 0.0
Qwen3	14B	82.0	65.0 / 17.0	0.0 / 0.0	66.0	71.0 / 16.0	0.0 / 0.0
Qwen3	32B	75.0	61.0 / 16.0	2.0 / 0.0	52.0	50.0 / 15.0	2.0 / 0.0
KernelLLM	8B	42.0	40.0 / 20.0	0.0 / 0.0	100.0	98.0 / 29.0	2.0 / 0.0
AutoTriton	8B	97.0	78.0 / 50.0	2.0 / 1.0	100.0	95.0 / 70.0	8.0 / 1.0
TRITONRL (ours)	8B	99.0	82.0 / 56.0	5.0 / 1.0	99.0	83.0 / 58.0	5.0 / 1.0
w/o RL (SFT only)	8B	97.0	88.0 / 44.0	4.0 / 2.0	98.0	93.0 / 47.0	5.0 / 2.0
GPT-oss	120B	100.0	100.0 / 74.0	7.0 / 2.0	100.0	100.0 / 78.0	7.0 / 2.0
Claude-3.7	-	99.0	99.0 / 53.0	3.0 / 1.0	100.0	100.0 / 64.0	8.0 / 1.0
DeepSeek-R1	685B	100.0	100.0 / 66.0	6.0 / 2.0	100.0	100.0 / 72.0	6.0 / 2.0

Table 6: Main results on KernelBench Level 1. All metrics are reported in terms of pass@10 (%). We obtained the best result in model parameter sizes $<$ 32B. The left side shows the results where the validity of generated codes is verified using the robust verifier, checking both syntax and functionality. The right side (w/o robust) shows the results without the robust verifier, where functionality is not checked.

I.2 PASS@K RESULTS

In addition to the pass@10 results shown in the main text, we also report pass@1 and pass@5 results for KernelBench Level 1 and Level 2 tasks in Table 8 and Table 9. These results further demonstrate

Model	#Params	LEVEL2			LEVEL2 (W/O ROBUST)		
		valid	compiled / correct	fast_1 / fast_2	valid	compiled / correct	fast_1 / fast_2
Qwen3 (base)	8B	56.0	1.0 /0.0	0.0 / 0.0	94.0	52.0 / 11.0	1.0 / 0.0
Qwen3	14B	35.0	24.0 / 1.0	0.0 / 0.0	100.0	94.0 / 65.0	14.0 / 1.0
Qwen3	32B	31.0	16.0 / 0.0	0.0 / 0.0	90.0	73.0 / 22.0	7.0 / 1.0
KernelLLM	8B	0.0	0.0 / 0.0	0.0 / 0.0	98.0	96.0 / 3.0	3.0 / 1.0
AutoTriton	8B	70.0	3.0 / 0.0	0.0 / 0.0	100.0	97.0 / 76.0	15.0 / 0.0
TRITONRL (ours)	8B	69.0	41.0 / 10.0	0.0 / 0.0	100.0	88.0 / 42.0	13.0 / 1.0
w/o RL (SFT only)	8B	67.0	32.0 / 6.0	0.0 / 0.0	100.0	98.0 / 41.0	11.0 / 1.0
GPT-oss	120B	39.0	38.0 / 12.0	0.0 / 0.0	100.0	99.0 / 74.0	23.0 / 1.0
Claude-3.7	-	34.0	34.0 / 12.0	1.0 / 0.0	100.0	98.0 / 60.0	18.0 / 1.0
DeepSeek-R1	685B	30.0	29.0 / 10.0	0.0 / 0.0	100.0	98.0 / 72.0	25.0 / 3.0

Table 7: Main results on KernelBench level 2 tasks. All metrics are reported in terms of pass@10 (%). We obtained the best result in model parameter sizes < 32B. The left side shows the results where the validity of generated codes is verified using the robust verifier, checking both syntax and functionality. The right side (w/o robust) shows the results without the robust verifier, where functionality is not checked.

the strong performance of TRITONRL in generating valid, correct, and efficient Triton code across various pass@k metrics.

Model	PASS@1			PASS@5			PASS@10		
	valid	compiled / correct	fast_1 / fast_2	valid	compiled / correct	fast_1 / fast_2	valid	compiled / correct	fast_1 / fast_2
Qwen3 (8B)	24.0	14.0 / 4.0	0.0 / 0.0	54.0	33.0 / 14.0	0.0 / 0.0	73.0	40.0 / 14.0	0.0 / 0.0
Qwen3 (14B)	25.0	22.0 / 10.0	0.0 / 0.0	66.0	53.0 / 14.0	0.0 / 0.0	82.0	65.0 / 17.0	0.0 / 0.0
Qwen3 (32B)	19.0	16.0 / 4.0	0.0 / 0.0	52.0	41.0 / 14.0	2.0 / 0.0	75.0	61.0 / 16.0	2.0 / 0.0
KernelLLM	32.0	29.0 / 14.0	0.0 / 0.0	41.0	39.0 / 19.0	0.0 / 0.0	42.0	40.0 / 20.0	0.0 / 0.0
AutoTriton	61.0	42.0 / 18.0	0.0 / 0.0	94.0	73.0 / 40.0	1.0 / 1.0	97.0	78.0 / 50.0	2.0 / 1.0
TRITONRL (ours)	70.0	51.0 / 21.0	0.0 / 0.0	97.0	80.0 / 47.0	3.0 / 1.0	99.0	82.0 / 56.0	5.0 / 1.0
w/o RL (SFT only)	48.0	37.0 /12.0	0.0 / 0.0	94.0	77.0 / 31.0	2.0 /1.0	97.0	88.0 / 44.0	4.0 / 2.0
GPT-oss	82.0	82.0 / 38.0	3.0 / 1.0	100.0	100.0 / 64.0	7.0 / 2.0	100.0	100.0 / 74.0	7.0 / 2.0
Claude-3.7	78.0	73.0 / 25.0	1.0 / 1.0	99.0	98.0 / 40.0	1.0 / 1.0	99.0	99.0 / 53.0	3.0 / 1.0
DeepSeek-R1	87.0	86.0 / 29.0	1.0 / 0.0	99.0	98.0 / 51.0	4.0 / 2.0	100.0	100.0 / 66.0	6.0 / 2.0

Table 8: Pass@k performance comparison for $k = 1, 5, 10$ on KernelBench Level 1 tasks.

Model	PASS@1			PASS@5			PASS@10		
	valid	compiled / correct	fast_1 / fast_2	valid	compiled / correct	fast_1 / fast_2	valid	compiled / correct	fast_1 / fast_2
Qwen3 (8B)	9.0	0.0 / 0.0	0.0 / 0.0	30.0	1.0 / 0.0	0.0 / 0.0	56.0	1.0 / 0.0	0.0 / 0.0
Qwen3 (14B)	4.0	2.0 / 1.0	0.0 / 0.0	23.0	17.0 / 1.0	0.0 / 0.0	35.0	24.0 / 1.0	0.0 / 0.0
Qwen3 (32B)	4.0	3.0 / 0.0	0.0 / 0.0	19.0	9.0 / 0.0	0.0 / 0.0	31.0	16.0 / 0.0	0.0 / 0.0
KernelLLM	0.0	0.0 / 0.0	0.0 / 0.0	0.0	0.0 / 0.0	0.0 / 0.0	0.0	0.0 / 0.0	0.0 / 0.0
AutoTriton	21.0	0.0 / 0.0	0.0 / 0.0	57.0	1.0 / 0.0	0.0 / 0.0	70.0	3.0 / 0.0	0.0 / 0.0
TRITONRL (ours)	16.0	10.0 / 0.0	0.0 / 0.0	56.0	20.0 / 4.0	0.0 / 0.0	71.0	29.0 / 7.0	0.0 / 0.0
w/o RL (SFT only)	15.0	8.0 / 0.0	0.0 / 0.0	51.0	25.0 / 5.0	0.0 / 0.0	67.0	32.0 / 6.0	0.0 / 0.0
GPT-oss	9.0	8.0 / 2.0	0.0 / 0.0	30.0	28.0 / 7.0	0.0 / 0.0	39.0	38.0 / 12.0	0.0 / 0.0
Claude-3.7	15.0	13.0 / 1.0	0.0 / 0.0	31.0	30.0 / 10.0	1.0 / 0.0	34.0	34.0 / 12.0	1.0 / 0.0
DeepSeek-R1	6.0	4.0 / 0.0	0.0 / 0.0	23.0	22.0 / 4.0	0.0 / 0.0	30.0	29.0 / 10.0	0.0 / 0.0

Table 9: Pass@k performance comparison for $k = 1, 5, 10$ on KernelBench Level 2 tasks.