


Accurate and Efficient CUDA Generation through Reinforcement Learning

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Problem & Motivation: The CUDA Gap

Problem: GPU kernel implementation is crucial for optimizing ML performance, and **CUDA** is a powerful but low-level programming model that is **specialized, error-prone and time consuming** to implement (i.e., engineers must manage memory hierarchy, warp divergence, performance tuning at hardware level, etc.).

Solution: High-level compiler-based abstraction allows writing GPU code in a Python-like language instead of CUDA C/C++ (e.g., **Triton**).

Problem: Compiler-based GPU programming does not abstract away substantial domain expertise.

	CUDA	TRITON
Memory Coalescing	Manual	Automatic
Shared Memory Management	Manual	Automatic
Scheduling (Within SMs)	Manual	Automatic
Scheduling (Across SMs)	Manual	Manual

Problem with LLM Kernel Generation

Problem: Compiler-based GPU programming does not abstract away substantial domain expertise.

Solution: Large Language Model (LLM) for GPU kernel generation.

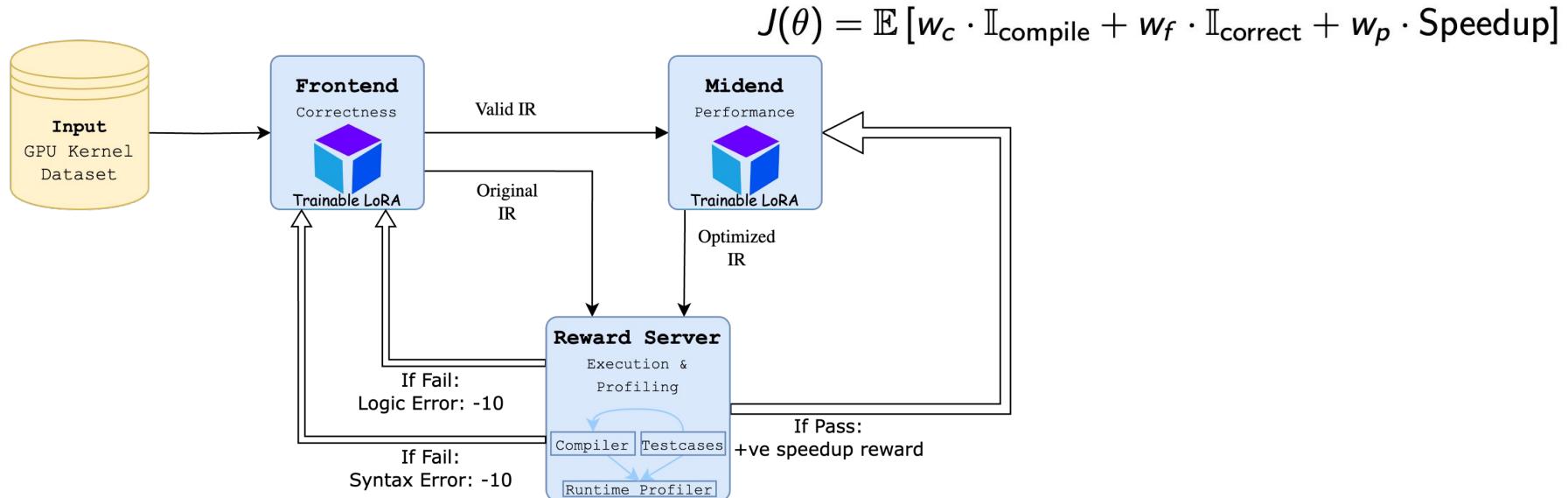
Problem: Inefficient and Inaccurate automatic Triton code generation.

Solution: Supervised Finetuning (SFT) + Reinforcement Learning (RL)

- **SFT** teaches LLM the correct kernel patterns with high-quality code samples.
- **RL** uses CUDA compiler's runtime feedback (e.g., compilation errors, performance metrics) to refine kernel and hyperparameters (e.g., threads per block, block partitioning sizes, shared memory allocation).

System Design: Multi-Agent Architecture

Our pipeline mimics a compiler stack by decoupling **functional correctness** (Frontend) from **runtime optimization** (Mid-end), employing Group Relative Preference Optimization (**GRPO**) for stable RL agent training.



Evaluation Results

Kernel Bench: Benchmark designed to evaluate the ability of LLMs to generate efficient GPU kernels

- Target to Level 1 of Kernel Bench: Simple Kernels

We observed that some kernels failed to compile in the latest version of PyTorch, as it introduced a major, non-backward-compatible API change earlier this year, affecting many of the available data samples.

Future work: finetune the reward function and LLM prompt

```
import torch
import torch.nn as nn
import triton
import triton.language as tl
@triton.jit
def mse_loss_kernel(predictions_ptr, targets_ptr, output_ptr,
n_elements, BLOCK_SIZE:tl.constexpr):
    block_start = tl.program_id(0) * BLOCK_SIZE
    offsets = block_start + tl.arange(0, BLOCK_SIZE)
    mask = offsets < n_elements
    predictions = tl.load(predictions_ptr + offsets, mask=mask,
other=0.0)
    targets = tl.load(targets_ptr + offsets, mask=mask, other=0.0)
    diff = predictions - targets
    squared_diff = diff * diff
    tl.store(output_ptr + offsets, squared_diff, mask=mask)
```

1.5x → speed up

```
def triton_mse_loss(predictions: torch.Tensor, targets: torch.Tensor):
    predictions = predictions.contiguous()
    targets = targets.contiguous()
    n_elements = predictions.numel()
    output = torch.empty_like(predictions)
    BLOCK_SIZE = 1024
    grid = lambda meta: ((n_elements + meta["BLOCK_SIZE"] - 1) //
meta["BLOCK_SIZE"])
    mse_loss_kernel[grid](predictions, targets, output, n_elements,
BLOCK_SIZE=BLOCK_SIZE)
    return torch.mean(output)

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

    def forward(self, predictions, targets):
        return triton_mse_loss(predictions, targets)
```

```
import torch
from torch._inductor.select_algorithm import extern_kernels
import triton
import triton.language as tl
from torch._inductor.runtime.triton_heuristics import gridX
from torch._C import _cuda_getCurrentRawStream as get_raw_stream
import torch.nn as nn
```