"Topic: GPU+PyTorch+Triton" Starting Tutorial

0. Hardware Information

> **Hardware**: `NVIDIA A100`
>
> **Driver**: `cuda_12.3.r12.3/compiler.33281558_0`

表： GPU硬件的信息汇总

架构	GPU型号	计算能力	`-arch` 参数	备注	CUDA版本要求
Volta	V100	7.0	`-arch=sm_70`	数据中心卡	9.0+
Volta	Titan V	7.0	`-arch=sm_70`	消费级卡	9.0+
Ampere	A100	8.0	`-arch=sm_80`	数据中心卡	11.0+
Ampere	A30	8.0	`-arch=sm_80`	数据中心卡	11.0+
Ampere	RTX 30系列	8.6	`-arch=sm_86`	消费级卡	11.0+
Hopper	H100	9.0	`-arch=sm_90`	数据中心卡	11.8+
Blackwell	B200	9.0+	`-arch=sm_90`	目前使用Hopper参数	12.0+

1. Building Environment

```
wget https://repo.anaconda.com/miniconda/Miniconda3-latest-Linux-x86_64.sh
bash ~/Miniconda3-latest-Linux-x86_64.sh
```

2. PyTorch + Triton + vLLM

```
pip3 install torch torchvision --index-url https://download.pytorch.org/whl/cu121
```

```
pip install triton==3.4.0
```

```
pip install vllm==0.9.2
```

Verify the installations:

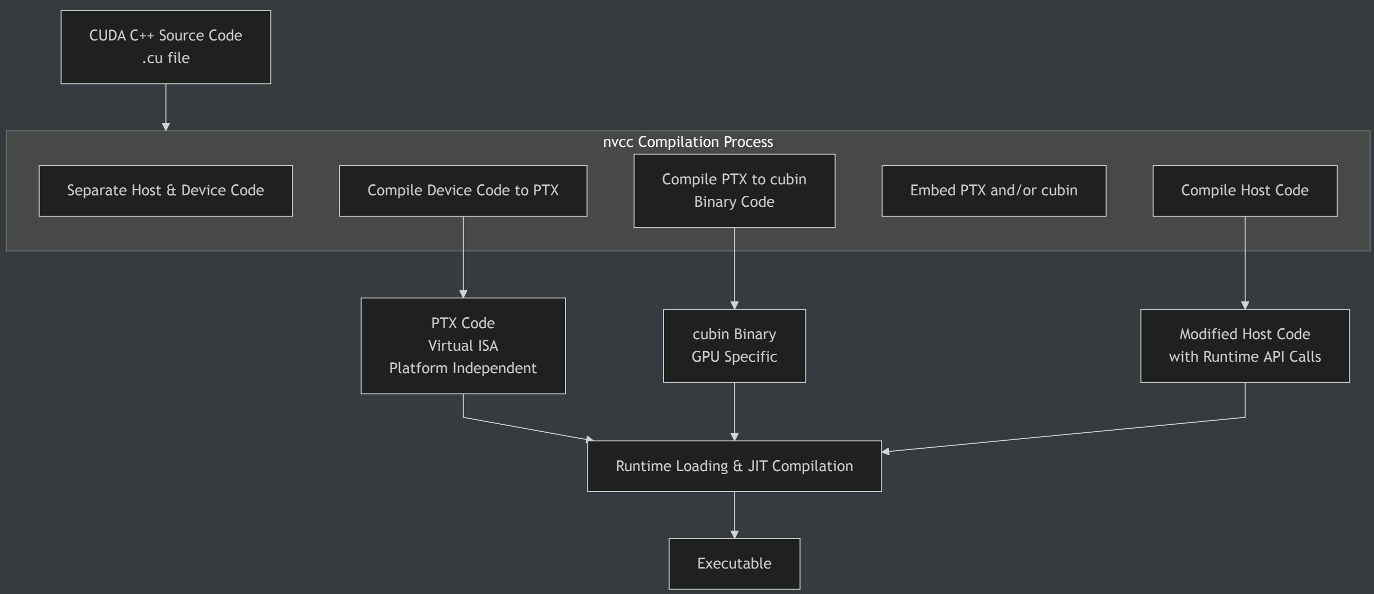
```
# 验证脚本 verify_installation.py
import torch
import triton
import vllm

print(f"PyTorch 版本: {torch.__version__}")
print(f"PyTorch CUDA 可用: {torch.cuda.is_available()}")
print(f"PyTorch CUDA 版本: {torch.version.cuda}")
print(f"Triton 版本: {triton.__version__}")
print(f"vLLM 版本: {vllm.__version__}")

# 测试GPU计算
if torch.cuda.is_available():
    device = "cuda"
    x = torch.tensor([1.0, 2.0, 3.0]).to(device)
    y = x * 2
    print(f"GPU计算测试成功: {y}")
else:
    print("CUDA不可用！")
```

3. CUDA编程基础

CUDA相关的编程编译流程可以总结为如下流程图：



"Hello World"样例代码：

```
// add.cu
#include <iostream>
#include <math.h>

// Kernel function to add the elements of two arrays
__global__
void add(int n, float *x, float *y)
{
 for (int i = 0; i < n; i++)
   y[i] = x[i] + y[i];
}

int main(void)
{
 int N = 1<<20;
 float *x, *y;
```

```
    // Allocate Unified Memory – accessible from CPU or GPU
    cudaMallocManaged(&x, N*sizeof(float));
    cudaMallocManaged(&y, N*sizeof(float));

    // initialize x and y arrays on the host
    for (int i = 0; i < N; i++) {
      x[i] = 1.0f;
      y[i] = 2.0f;
    }

    // Run kernel on 1M elements on the GPU
    add<<<1, 1>>>(N, x, y);

    // Wait for GPU to finish before accessing on host
    cudaDeviceSynchronize();

    // Check for errors (all values should be 3.0f)
    float maxError = 0.0f;
    for (int i = 0; i < N; i++) {
      maxError = fmax(maxError, fabs(y[i]-3.0f));
    }
    std::cout << "Max error: " << maxError << std::endl;

    // Free memory
    cudaFree(x);
    cudaFree(y);
     return 0;
   }
```

(1) Kernel Function: 设备侧函数主要以 `__global__` 关键词修饰

```
__global__ add(int n, float* x, float* y) {
  for (int i = 0; i < n; ++i) {
    y[i] = x[i] + y[i];
  }
}
```

(2) Unified Memory: host-device统一编址的显存分配，利用 `cudaMallocManaged()` 分配统一内存，返回可访问的指针， `kernel` 执行完毕需要手动利用 `cudaFree()` 释放内存（ `cudaMallocManaged-cudaFree` 和标准 `C++` 中的 `new-delete` 对应）

```
// Allocate Unified Memory -- accessible from CPU or GPU
float *x, *y, *sum;
cudaMallocManaged(&x, N*sizeof(float));
cudaMallocManaged(&y, N*sizeof(float));

...

// Free memory
cudaFree(x);
cudaFree(y);
```

(3) Kernal Launch: 从host侧启动Kernel函数，使用cuda的三重角度括号语法 `<<<Dg, Db, Ns, S>>>`

> **注释**：
>
> (a) `Dg` 代表整个grid的尺寸（一个grid有多少个block），数据类型为dim3，例如：Dim3 Dg(Dg.x, Dg.y, 1)代表grid中每行有Dg.x个block，每列有Dg.y个block，第三个纬度恒定为1，因此整个grid一共有 `Dg.x * Dg.y` 个block，且 $Dg.x, Dg.y <= 65535;$
>
> (b) Db定义一个block的尺寸（一个block有多少thread），数据类型为dim3，例如：Dim3 Db(Db.x, Db.y, Db.z)代表block中每行有Db.x个thread，每列有Db.y个thread，高度方向有Db.z个thread，因此一个block有$Db.x * Db.y * Db.z$个thread.

> (c) Ns为可选参数，用于设置每个block除了静态分配的共享内存外，最多能动态分配的共享内存大小，单位为Byte。如果不需要，则$Ns = 0$或者参数缺省.
>
> (d) S时cudaStream_t类型的可选参数，默认值为$S = 0$，标识核函数位于哪个stream中（指定核函数在哪个stream中执行）

```
// 代表一个block，一个thread
add<<<1, 1>>>(N, sum, x, y);
```

(4) nvcc编译

- 基础编译命令：直接得到可执行文件

```
nvcc -o add add.cu
```

- 指定平台：从V100, A100, H100到B200不同GPU型号，nvcc可以编译得到特定平台二进制、ptx指令或者通用平台指令（就是各个平台的指令打包）

```
# 查询当前使用GPU平台的卡型号等信息
nvidia-smi
# 查询当前使用的GPU平台的计算能力
nvidia-smi --query-gpu=compute_cap --format=csv
```

```
# 编译到特定平台

## (1) V100及所有计算能力7.0的GPU
nvcc -arch=sm_70 -o your_program your_program.cu
# 如果需要包含PTX代码以支持未来兼容性
nvcc -arch=sm_70 -gencode arch=compute_70,code=sm_70 -o your_program
your_program.cu
## (2) A100及所有计算能力8.0的GPU
nvcc -arch=sm_80 -o your_program your_program.cu
# 如果需要包含PTX代码以支持未来兼容性
```

```
nvcc -arch=sm_80 -gencode arch=compute_80,code=sm_80 -o your_program your_program.cu
## (3) H100及所有计算能力9.0的GPU
nvcc -arch=sm_90 -o your_program your_program.cu
# 如果需要包含PTX代码以支持未来兼容性
nvcc -arch=sm_90 -gencode arch=compute_90,code=sm_90 -o your_program your_program.cu
## (4) B200及所有计算能力9.0的GPU
nvcc -arch=sm_90 -o your_program your_program.cu
# 如果需要包含PTX代码以支持未来兼容性
nvcc -arch=sm_90 -gencode arch=compute_90,code=sm_90 -o your_program your_program.cu
```

```
# 编译到通用平台
# 支持V100到H100的通用二进制
nvcc -gencode arch=compute_70,code=sm_70 -gencode arch=compute_80,code=sm_80 -gencode arch=compute_90,code=sm_90 -o universal_program program.cu
```

当前使用的GPU硬件为A100，因此以上 `add.cu` 代表编译命令为：

```
nvcc -arch=sm_80 -o add add.cu
```

执行后得到结果：

```
(pytorch) lthpc@gnode02:~/chengl/Programming> ./add
Max error: 0
```

(5) cuda原生性能Profiling采集工具: `nsys`

- 直接采集完整性能统计数据

```
nsys profile -t cuda --stats=true ./add
```

结果会生成如下详细性能信息：包括内存分配（`cudaMallocManaged`），同步，内存释放，Kernel启动时间，Kernel执行时间等

```
(pytorch) lthpc@gnode02:~/chengl/Programming> nsys profile -t cuda --
stats=true ./add
Max error: 0
Generating '/tmp/nsys-report-94b0.qdstrm'
[1/6] [========================100%] report2.nsys-rep
[2/6] [========================100%] report2.sqlite
[3/6] Executing 'cuda_api_sum' stats report

 Time (%)  Total Time (ns)  Num Calls    Avg (ns)       Med (ns)
Min (ns)     Max (ns)     StdDev (ns)           Name
 --------  ---------------  ---------  -------------  -------------  -
----------  -----------  -------------  ----------------------
     64.2      308,780,682          2  154,390,341.0  154,390,341.0
    19,020  308,761,662  218,314,015.8  cudaMallocManaged
     35.7      171,461,980          1  171,461,980.0  171,461,980.0
 171,461,980  171,461,980            0.0  cudaDeviceSynchronize
      0.1          468,500          2      234,250.0      234,250.0
   183,820      284,680       71,318.8  cudaFree
      0.0          197,110          1      197,110.0      197,110.0
   197,110      197,110            0.0  cudaLaunchKernel
      0.0              840          1          840.0          840.0
       840          840            0.0  cuModuleGetLoadingMode

[4/6] Executing 'cuda_gpu_kern_sum' stats report

 Time (%)  Total Time (ns)  Instances    Avg (ns)       Med (ns)
Min (ns)     Max (ns)    StdDev (ns)            Name
 --------  ---------------  ---------  -------------  -------------  -
----------  -----------  -----------  -------------------------
    100.0      171,458,500          1  171,458,500.0  171,458,500.0
 171,458,500  171,458,500          0.0  add(int, float *, float *)

[5/6] Executing 'cuda_gpu_mem_time_sum' stats report
```

```
 Time (%)  Total Time (ns)  Count  Avg (ns)  Med (ns)  Min (ns)  Max
(ns)  StdDev (ns)               Operation
 --------  ---------------  -----  --------  --------  --------  -----
---  -----------  ----------------------------------
     61.3          978,906     48  20,393.9   6,575.5     3,679
105,411     29,701.5  [CUDA memcpy Unified Host-to-Device]
     38.7          617,794     24  25,741.4   5,167.5     2,655
151,107     43,848.0  [CUDA memcpy Unified Device-to-Host]

[6/6] Executing 'cuda_gpu_mem_size_sum' stats report

 Total (MB)  Count  Avg (MB)  Med (MB)  Min (MB)  Max (MB)  StdDev
(MB)               Operation
 ----------  -----  --------  --------  --------  --------  ----------
-  ----------------------------------
      8.389     48     0.175     0.033     0.004     1.044
 0.304  [CUDA memcpy Unified Host-to-Device]
      4.194     24     0.175     0.033     0.004     1.044
 0.307  [CUDA memcpy Unified Device-to-Host]

Generated:
    /home/lthpc/chengl/Programming/report2.nsys-rep
    /home/lthpc/chengl/Programming/report2.sqlite
```

- 简化性能统计信息：Mark Harris 写了一个简单的nsys_easy脚本(https://github.com/harrism/nsys_easy)，用来简化输出信息

```
# 修改执行权限
chmod 755 ~/nsys_easy/nsys_easy
# 添加nsys_easy环境变量
export PATH=~/nsys_easy:$PATH
# 采集性能信息
nsys_easy ./add
```

结果会生成如下简化信息：

```
(pytorch) lthpc@gnode02:~/chengl/Programming> nsys_easy ./add
Max error: 0
Generating '/tmp/nsys-report-66ad.qdstrm'
[1/1] [========================100%] nsys_easy.nsys-rep
Generated:
    /home/lthpc/chengl/Programming/nsys_easy.nsys-rep
Generating SQLite file nsys_easy.sqlite from nsys_easy.nsys-rep
Processing 939 events:
[=====================================================100%]
Processing [nsys_easy.sqlite] with [/home/software/cuda-12.3/nsight-
systems-2023.3.3/host-linux-x64/reports/cuda_gpu_sum.py]...

 ** CUDA GPU Summary (Kernels/MemOps) (cuda_gpu_sum):

 Time (%)  Total Time (ns)  Instances    Avg (ns)       Med (ns)
Min (ns)     Max (ns)     StdDev (ns)   Category
Operation
 --------  ---------------  ---------  -------------  -------------  -
----------  -----------  -----------  -----------  -------------------
-----------------
     99.1      172,191,985          1  172,191,985.0  172,191,985.0
 172,191,985  172,191,985          0.0  CUDA_KERNEL  add(int, float *,
float *)
      0.6          979,518         48       20,406.6        6,527.5
     3,647      105,666     29,680.1  MEMORY_OPER  [CUDA memcpy
Unified Host-to-Device]
      0.4          618,691         24       25,778.8        5,199.5
     2,495      151,235     43,882.6  MEMORY_OPER  [CUDA memcpy
Unified Device-to-Host]
```

(6) PyTorch + CUDA原生集成开发 + pyTorch统一性能Profiling采集工具：`torch.profiler`

参考PyTorch官网说明：https://docs.pytorch.org/docs/stable/profiler.html

目前LLM基本都是在PyTorch的pythonic环境下开发使用，为了实现CUDA函数在PyTorch的自然集成，需要用到 `torch.utils.cpp_extension` 和 `torch/extension.h` ，并利用 `pybind11` 完成pytorch下对CUDA-C/C++函数的调用。https://github.com/gau-nernst/learn-cuda中了给了10个示例教程，这里给出 `01-vector addition` 的代码示例。

Name	Description
01. Vector addition	Simple example to get everything working.
02a. Matrix multiplication SIMT	Block tiling, thread tiling, warp tiling.
02b. Matrix multiplication TensorOp	Inline PTX, `cvta`, `ldmatrix`, `mma`.
03. Sum	Reduction in general. Prepare for softmax (max and sum).
04. Softmax	Naive (safe) softmax, online softmax. `atomicCAS()`. Single-block and multi-block per row.
05. FP6	FP6 primitives (FP32/FP16/BF16<->FP6).
06. Box blur	2D CUDA blocks/threads. TODO: optimize with separable filters, moving average.
07. Attention	Flash attention
08. Row-scaled matmul	Simple epilogue
09. Block-scaled matmul	MXFP8

```
// add.cu
#include <torch/extension.h>

#define CHECK_CUDA(x) TORCH_CHECK(x.device().is_cuda(), #x " must be a CUDA tensor")
#define CHECK_CONTIGUOUS(x) TORCH_CHECK(x.is_contiguous(), #x " must be contiguous")
#define CHECK_INPUT(x)                                                    \
  CHECK_CUDA(x);                                                          \
  CHECK_CONTIGUOUS(x)

__global__ void add_kernel(const float *input1, const float *input2, float *output, int size) {
```

```
  const int idx = blockIdx.x * blockDim.x + threadIdx.x;
  if (idx < size)
    output[idx] = input1[idx] + input2[idx];
}

torch::Tensor add(torch::Tensor input1, torch::Tensor input2) {
  CHECK_INPUT(input1);
  CHECK_INPUT(input2);
  int size = input1.numel();
  TORCH_CHECK(size == input2.numel(), "input1 and input2 must have the
same size");
  torch::Tensor output = torch::empty(size, input1.options());

  int n_threads = 256;
  int n_blocks = (size + n_threads - 1) / n_threads;
  add_kernel<<<n_blocks, n_threads>>>(input1.data_ptr<float>(),
input2.data_ptr<float>(), output.data_ptr<float>(), size);

  return output;
}

PYBIND11_MODULE(TORCH_EXTENSION_NAME, m) { m.def("add", &add, "Add two
vectors"); }
```

实际上就是添加了一个tensor的wrapper，因为tensor是pytorch的基础数据类型，因此核心步骤就是将原始cuda的入参和返回参数等转成tensor（指针），传给torch实现包装。下面是pytorch中的调用代码（可以看到就是重新声明了cuda函数，将其归类为一类module，从而下面可以直接从module中调用原始封装后的cuda函数，如果需要将函数注册进torch，即torch.add，后续会涉及）：

```
# main.py
import torch
import torch.utils.cpp_extension
from torch.profiler import profile, record_function, ProfilerActivity
import matplotlib.pyplot as plt
```

```
module = torch.utils.cpp_extension.load(
    "module",
    sources=["add.cu"],
    extra_cuda_cflags=["-O3"],
    verbose=True,
)

# Example usage
input1 = torch.randn(1024000, device="cuda")
input2 = torch.randn(1024000, device="cuda")
output = module.add(input1, input2)
```

下面给出torch.profiler采集以上封装后的cuda函数方法。

- **(a) 最基础的 `torch.profiler` 裸测试调用采集性能数据**

```
# 核心结构
from torch.profiler import profile, record_function, ProfilerActivity
with torch.profiler.profile(
    activities=[
        torch.profiler.ProfilerActivity.CPU,
        torch.profiler.ProfilerActivity.CUDA,
    ]
) as p:
    code_to_profile() # 替换成需要采集的torch代码（函数）
print(p.key_averages().table(sort_by="self_cuda_time_total",
row_limit=-1))
```

完整测试代码如下：

```
import torch
import torch.utils.cpp_extension
from torch.profiler import profile, record_function, ProfilerActivity
import matplotlib.pyplot as plt
```

```python
module = torch.utils.cpp_extension.load(
    "module",
    sources=["add.cu"],
    extra_cuda_cflags=["-O3"],
    verbose=True,
)

# Example usage
input1 = torch.randn(1024000, device="cuda")
input2 = torch.randn(1024000, device="cuda")

with torch.profiler.profile(
    activities=[
        torch.profiler.ProfilerActivity.CPU,
        torch.profiler.ProfilerActivity.CUDA,
    ]
) as p:
    output = module.add(input1, input2)
print(p.key_averages().table(sort_by="self_cuda_time_total",
row_limit=-1))
p.export_chrome_trace("trace.json")  # 可以生成程序运行的timeline
```

运行后的结果如下：

```
(pytorch) lthpc@gnode02:~/chengl/Programming/learn-
cuda/1_vector_addition> CUDA_VISIBLE_DEVICES=0 python main.py
Using /home/lthpc/.cache/torch_extensions/py310_cu126 as PyTorch
extensions root...
Detected CUDA files, patching ldflags
Emitting ninja build file
/home/lthpc/.cache/torch_extensions/py310_cu126/module/build.ninja...
Building extension module module...
Allowing ninja to set a default number of workers... (overridable by
setting the environment variable MAX_JOBS=N)
```

```
ninja: no work to do.
Loading extension module module...
-------------------------------------------------------  ------------
 ------------  ------------  ------------  ------------  ------------
 ------------  ------------  ------------  ------------
                                                   Name    Self CPU %
     Self CPU   CPU total %     CPU total  CPU time avg     Self CUDA
  Self CUDA %    CUDA total  CUDA time avg    # of Calls
-------------------------------------------------------  ------------
 ------------  ------------  ------------  ------------  ------------
 ------------  ------------  ------------  ------------
    add_kernel(float const*, float const*, float*, int)         0.00%
      0.000us         0.00%       0.000us       0.000us       9.824us
      100.00%       9.824us       9.824us             1
                                            aten::empty         5.96%
     52.520us        75.63%     666.350us     666.350us       0.000us
        0.00%       0.000us       0.000us             1
                                           Unrecognized        69.67%
    613.830us        69.67%     613.830us     613.830us       0.000us
        0.00%       0.000us       0.000us             1
                                       cudaLaunchKernel         8.46%
     74.530us        23.81%     209.810us     209.810us       0.000us
        0.00%       0.000us       0.000us             1
                        Runtime Triggered Module Loading        15.35%
    135.280us        15.35%     135.280us      67.640us       0.000us
        0.00%       0.000us       0.000us             2
                                  cudaDeviceSynchronize         0.56%
      4.910us         0.56%       4.910us       4.910us       0.000us
        0.00%       0.000us       0.000us             1
-------------------------------------------------------  ------------
 ------------  ------------  ------------  ------------  ------------
 ------------  ------------  ------------  ------------
Self CPU time total: 881.070us
Self CUDA time total: 9.824us
```

从上面列表中找到 `Name = add_kernel` 对应的 `Self CUDA= 9.824us` 即为GPU上add_kernel执行的完整时间，下面还可以发现 `cudaLaunchKernel` 代表从host侧启动GPU侧核函数花费时间为 `209.810us` ，可以看到远远长于Kernel本身在GPU上执行时间。

- **(b) 考虑预热等因素后的 `torch.profiler` 调用性能采集方法**

```
# 核心结构
with torch.profiler.profile(
    activities=[
        torch.profiler.ProfilerActivity.CPU,
        torch.profiler.ProfilerActivity.CUDA,
    ]
) as p:
    code_to_profile_0()
    // turn off collection of all CUDA activity
    p.toggle_collection_dynamic(False,
[torch.profiler.ProfilerActivity.CUDA])
    code_to_profile_1()
    // turn on collection of all CUDA activity
    p.toggle_collection_dynamic(True,
[torch.profiler.ProfilerActivity.CUDA])
    code_to_profile_2()
print(p.key_averages().table(sort_by="self_cuda_time_total",
row_limit=-1))
```

完整测试代码：

```
import torch
import torch.utils.cpp_extension
from torch.profiler import profile, record_function, ProfilerActivity
import matplotlib.pyplot as plt

module = torch.utils.cpp_extension.load(
    "module",
    sources=["add.cu"],
```

```python
    extra_cuda_cflags=["-O3"],
    verbose=True,
)

# Example usage
input1 = torch.randn(1024000, device="cuda")
input2 = torch.randn(1024000, device="cuda")

# Non-default profiler schedule allows user to turn profiler on and
off
# on different iterations of the training loop;
# trace_handler is called every time a new trace becomes available
def trace_handler(prof):
    print(
        prof.key_averages().table(sort_by="self_cuda_time_total",
row_limit=-1)
    )
    prof.export_chrome_trace("/tmp/test_trace_" + str(prof.step_num) +
".json")

with torch.profiler.profile(
    activities=[
        torch.profiler.ProfilerActivity.CPU,
        torch.profiler.ProfilerActivity.CUDA,
    ],
    # In this example with wait=1, warmup=1, active=2, repeat=1,
    # profiler will skip the first step/iteration,
    # start warming up on the second, record
    # the third and the forth iterations,
    # after which the trace will become available
    # and on_trace_ready (when set) is called;
    # the cycle repeats starting with the next step
    schedule=torch.profiler.schedule(wait=1, warmup=1, active=7,
repeat=1),
    on_trace_ready=trace_handler,
    record_shapes=True,
```

```
    # on_trace_ready=torch.profiler.tensorboard_trace_handler('./log')
    # used when outputting for tensorboard
) as p:
    for iter in range(10):
        output = module.add(input1, input2)
        # send a signal to the profiler that the next iteration has
started
        p.step()
```

采集结果如下：

```
(pytorch) lthpc@gnode02:~/chengl/Programming/learn-
cuda/1_vector_addition> CUDA_VISIBLE_DEVICES=0 python main.py
Using /home/lthpc/.cache/torch_extensions/py310_cu126 as PyTorch
extensions root...
Detected CUDA files, patching ldflags
Emitting ninja build file
/home/lthpc/.cache/torch_extensions/py310_cu126/module/build.ninja...
Building extension module module...
Allowing ninja to set a default number of workers... (overridable by
setting the environment variable MAX_JOBS=N)
ninja: no work to do.
Loading extension module module...
-------------------------------------------------------  ------------
 ------------  ------------  ------------  ------------  ------------
 ------------  ------------  ------------  ------------
                                                   Name    Self CPU %
     Self CPU   CPU total %     CPU total  CPU time avg     Self CUDA
  Self CUDA %    CUDA total  CUDA time avg    # of Calls
-------------------------------------------------------  ------------
 ------------  ------------  ------------  ------------  ------------
 ------------  ------------  ------------  ------------
    add_kernel(float const*, float const*, float*, int)         0.00%
      0.000us         0.00%       0.000us       0.000us      45.956us
      100.00%      45.956us       6.565us             7
```

```
                                        ProfilerStep*         0.00%
       0.000us         0.00%       0.000us       0.000us      45.956us
     100.00%      45.956us       6.565us             7
                                        ProfilerStep*        71.61%
     380.100us        96.98%     514.710us      73.530us       0.000us
         0.00%       0.000us       0.000us             7
                                          aten::empty        12.90%
      68.450us        12.90%      68.450us       9.779us       0.000us
         0.00%       0.000us       0.000us             7
                                     cudaLaunchKernel        12.47%
      66.160us        12.47%      66.160us       9.451us       0.000us
         0.00%       0.000us       0.000us             7
                                cudaDeviceSynchronize         3.02%
      16.050us         3.02%      16.050us      16.050us       0.000us
         0.00%       0.000us       0.000us             1
-------------------------------------------------------  ------------
 ------------  ------------  ------------  ------------  ------------
 ------------  ------------  ------------  ------------
Self CPU time total: 530.760us
Self CUDA time total: 45.956us
```

可以看到考虑预热和多次平均后的 `add_kernel` 时间为 `6.565us` ，并且多次运行时间差别也不大。

(c) 考虑预热等因素 + 仅采集部分代码的 `torch.profiler` 调用性能采集方法：`toggle_collection_dynamic`

```
with torch.profiler.profile(
    activities=[
        torch.profiler.ProfilerActivity.CPU,
        torch.profiler.ProfilerActivity.CUDA,
    ]
) as p:
    code_to_profile_0()
    // turn off collection of all CUDA activity
```

```
    p.toggle_collection_dynamic(False,
[torch.profiler.ProfilerActivity.CUDA])
    code_to_profile_1()
    // turn on collection of all CUDA activity
    p.toggle_collection_dynamic(True,
[torch.profiler.ProfilerActivity.CUDA])
    code_to_profile_2()
print(p.key_averages().table(sort_by="self_cuda_time_total",
row_limit=-1))
```

完整代码如下：

```
import torch
import torch.utils.cpp_extension
from torch.profiler import profile, record_function, ProfilerActivity
import matplotlib.pyplot as plt

module = torch.utils.cpp_extension.load(
    "module",
    sources=["add.cu"],
    extra_cuda_cflags=["-O3"],
    verbose=True,
)

# Non-default profiler schedule allows user to turn profiler on and
off
# on different iterations of the training loop;
# trace_handler is called every time a new trace becomes available
def trace_handler(prof):
    print(
        prof.key_averages().table(sort_by="self_cuda_time_total",
row_limit=-1)
    )
    prof.export_chrome_trace("/tmp/test_trace_" + str(prof.step_num) +
".json")
```

```
with torch.profiler.profile(
    activities=[
        torch.profiler.ProfilerActivity.CPU,
        torch.profiler.ProfilerActivity.CUDA,
    ],
    # In this example with wait=1, warmup=1, active=2, repeat=1,
    # profiler will skip the first step/iteration,
    # start warming up on the second, record
    # the third and the forth iterations,
    # after which the trace will become available
    # and on_trace_ready (when set) is called;
    # the cycle repeats starting with the next step
    schedule=torch.profiler.schedule(wait=1, warmup=1, active=7,
repeat=1),
    on_trace_ready=trace_handler,
    record_shapes=True,
    # on_trace_ready=torch.profiler.tensorboard_trace_handler('./log')
    # used when outputting for tensorboard
) as p:
    for iter in range(10):
        p.toggle_collection_dynamic(False,
[torch.profiler.ProfilerActivity.CPU,
torch.profiler.ProfilerActivity.CUDA])  # 同时关掉CPU和GPU上的性能采集
        input1 = torch.randn(1024000, device="cuda")  # 为了测试效果，将
数据生成也考虑如下采集
        input2 = torch.randn(1024000, device="cuda")
        p.toggle_collection_dynamic(True,
[torch.profiler.ProfilerActivity.CUDA]) # 仅仅打开GPU上的性能采集
        output = module.add(input1, input2)
        # send a signal to the p
        p.step()
```

profiling结果如下：

Name	Self CPU %	Self CPU	CPU total %	CPU total	CPU time avg	Self CUDA	Self CUDA %	CUDA total	CUDA time avg	# of Calls
add_kernel(float const*, float const*, float*, int)	0.00%	0.000us	0.00%	0.000us	0.000us	54.114us	100.00%	54.114us	6.764us	8
ProfilerStep*	0.00%	0.000us	0.00%	0.000us	0.000us	5.888us	10.88%	5.888us	5.888us	1
ProfilerStep*	45.61%	1.301ms	45.95%	1.311ms	1.311ms	0.000us	0.00%	0.000us	0.000us	1
cudaLaunchKernel	1.77%	50.440us	1.77%	50.440us	7.206us	0.000us	0.00%	0.000us	0.000us	7
cudaDeviceSynchronize	52.62%	1.501ms	52.62%	1.501ms	1.501ms	0.000us	0.00%	0.000us	0.000us	1

Self CPU time total: 2.852ms
Self CUDA time total: 54.114us

作为对比：

(a) 类型一

```
for iter in range(10):
        p.toggle_collection_dynamic(False,
[torch.profiler.ProfilerActivity.CPU,
torch.profiler.ProfilerActivity.CUDA])  # 同时关掉CPU和GPU上的性能采集
        input1 = torch.randn(1024000, device="cuda")  # 为了测试效果，将
数据生成也考虑如下采集
        input2 = torch.randn(1024000, device="cuda")
        output = module.add(input1, input2)
        # send a signal to the p
        p.step()
```

ninja: no work to do.
Loading extension module module...

Name	Self CPU %	Self CPU	CPU total %	CPU total	CPU time avg	# of Calls
ProfilerStep*	100.00%	127.950us	100.00%	127.950us	127.950us	1

Self CPU time total: 127.950us

(b) 类型二

```python
for iter in range(10):
        p.toggle_collection_dynamic(False,
[torch.profiler.ProfilerActivity.CPU,
torch.profiler.ProfilerActivity.CUDA])  # 同时关掉CPU和GPU上的性能采集
        input1 = torch.randn(1024000, device="cuda")  # 为了测试效果，将
数据生成也考虑如下采集
        input2 = torch.randn(1024000, device="cuda")
        p.toggle_collection_dynamic(True,
[torch.profiler.ProfilerActivity.CPU]) # 仅仅打开CPU上的性能采集
        output = module.add(input1, input2)
        # send a signal to the p
        p.step()
```

```
-----------------  ------------  ------------  ------------  ------------  ------------  ------------
             Name    Self CPU %      Self CPU   CPU total %     CPU total  CPU time avg    # of Calls
-----------------  ------------  ------------  ------------  ------------  ------------  ------------
    ProfilerStep*        96.15%     900.710us       100.00%     936.750us     133.821us             7
      aten::empty         3.85%      36.040us         3.85%      36.040us       5.149us             7
-----------------  ------------  ------------  ------------  ------------  ------------  ------------
Self CPU time total: 936.750us
```

(c) 类型三

```python
for iter in range(10):
        p.toggle_collection_dynamic(False,
[torch.profiler.ProfilerActivity.CPU,
torch.profiler.ProfilerActivity.CUDA])  # 同时关掉CPU和GPU上的性能采集
        input1 = torch.randn(1024000, device="cuda")  # 为了测试效果，将
数据生成也考虑如下采集
        input2 = torch.randn(1024000, device="cuda")
        p.toggle_collection_dynamic(True,
[torch.profiler.ProfilerActivity.CPU,
torch.profiler.ProfilerActivity.CUDA]) # 打开CPU+GPU上的性能采集
        output = module.add(input1, input2)
        # send a signal to the p
        p.step()
```

Name	Self CPU %	Self CPU	CPU total %	CPU total	CPU time avg	Self CUDA	Self CUDA %	CUDA total	CUDA time avg	# of Calls
add_kernel(float const*, float const*, float*, int)	0.00%	0.000us	0.00%	0.000us	0.000us	41.474us	100.00%	41.474us	5.925us	7
ProfilerStep*	0.00%	0.000us	0.00%	0.000us	0.000us	41.474us	100.00%	41.474us	5.925us	7
ProfilerStep*	91.86%	17.944ms	92.29%	18.029ms	2.576ms	0.000us	0.00%	0.000us	0.000us	7
aten::empty	0.19%	37.720us	0.19%	37.720us	5.389us	0.000us	0.00%	0.000us	0.000us	7
cudaLaunchKernel	0.24%	47.080us	0.24%	47.080us	6.726us	0.000us	0.00%	0.000us	0.000us	7
cudaDeviceSynchronize	7.71%	1.506ms	7.71%	1.506ms	1.506ms	0.000us	0.00%	0.000us	0.000us	1

Self CPU time total: 19.535ms
Self CUDA time total: 41.474us

(d) 类型四

```python
for iter in range(10):
        p.toggle_collection_dynamic(True,
[torch.profiler.ProfilerActivity.CPU,
torch.profiler.ProfilerActivity.CUDA])  # 同时关掉CPU和GPU上的性能采集
        input1 = torch.randn(1024000, device="cuda")  # 为了测试效果，将
数据生成也考虑如下采集
        input2 = torch.randn(1024000, device="cuda")
        p.toggle_collection_dynamic(True,
[torch.profiler.ProfilerActivity.CPU,
torch.profiler.ProfilerActivity.CUDA]) # 打开CPU+GPU上的性能采集
        output = module.add(input1, input2)
        # send a signal to the p
        p.step()
```

Name	Self CPU %	Self CPU	CPU total %	CPU total	CPU time avg	Self CUDA	Self CUDA %	CUDA total	CUDA time avg	# of Calls
ProfilerStep*	0.00%	0.000us	0.00%	0.000us	0.000us	374.888us	188.10%	374.888us	53.555us	7
aten::normal_	10.47%	106.230us	23.78%	241.180us	17.227us	159.298us	79.93%	159.298us	11.378us	14
void at::native::(anonymous namespace)::distribution...	0.00%	0.000us	0.00%	0.000us	0.000us	159.298us	79.93%	159.298us	11.378us	14
add_kernel(float const*, float const*, float*, int)	0.00%	0.000us	0.00%	0.000us	0.000us	40.001us	20.07%	40.001us	5.714us	7
ProfilerStep*	53.96%	547.360us	99.12%	1.005ms	143.636us	0.000us	0.00%	159.298us	22.757us	7
aten::randn	7.24%	73.400us	38.33%	388.780us	27.770us	0.000us	0.00%	159.298us	11.378us	14
aten::empty	10.20%	103.470us	10.20%	103.470us	4.927us	0.000us	0.00%	0.000us	0.000us	21
cudaStreamIsCapturing	1.67%	16.980us	1.67%	16.980us	0.606us	0.000us	0.00%	0.000us	0.000us	28
cudaLaunchKernel	15.58%	158.010us	15.58%	158.010us	7.524us	0.000us	0.00%	0.000us	0.000us	21
cudaDeviceSynchronize	0.88%	8.880us	0.88%	8.880us	8.880us	0.000us	0.00%	0.000us	0.000us	1

Self CPU time total: 1.014ms
Self CUDA time total: 199.299us

(7) CUDA Kernel基本优化方法