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+

sm_75	Turing support
sm_80, sm_86 and sm_87, sm_88	NVIDIA Ampere GPU architecture support
sm_89	Ada support
sm_90, sm_90a	Hopper support
sm_100, sm_100f, sm_100a, sm_103, sm_103f, sm_103a, sm_110, sm_110f, sm_110a, sm_120, sm_120f, sm_120a, sm_121, sm_121f, sm_121a	Blackwell support

(From NVIDIA CUDA Compiler Driver, same with PTX)

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
```

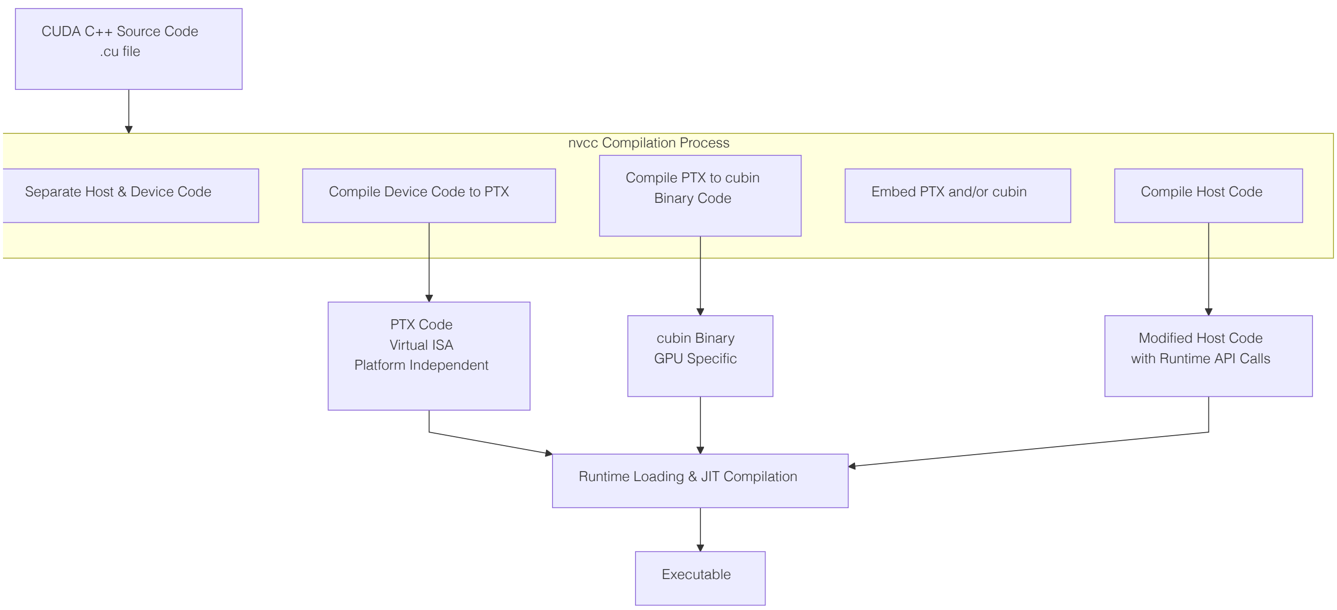
Verify the installations:

```
# 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

> ***编译选项:***
>
> *--gpu-architecture：指定virtual architecture(PTX)，例如：compute_80, compute_90*
>
> *--gpu-code: 指定real architecture, 例如：sm_80, sm_86*

- 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
```

- CUDA编译基本设计原理

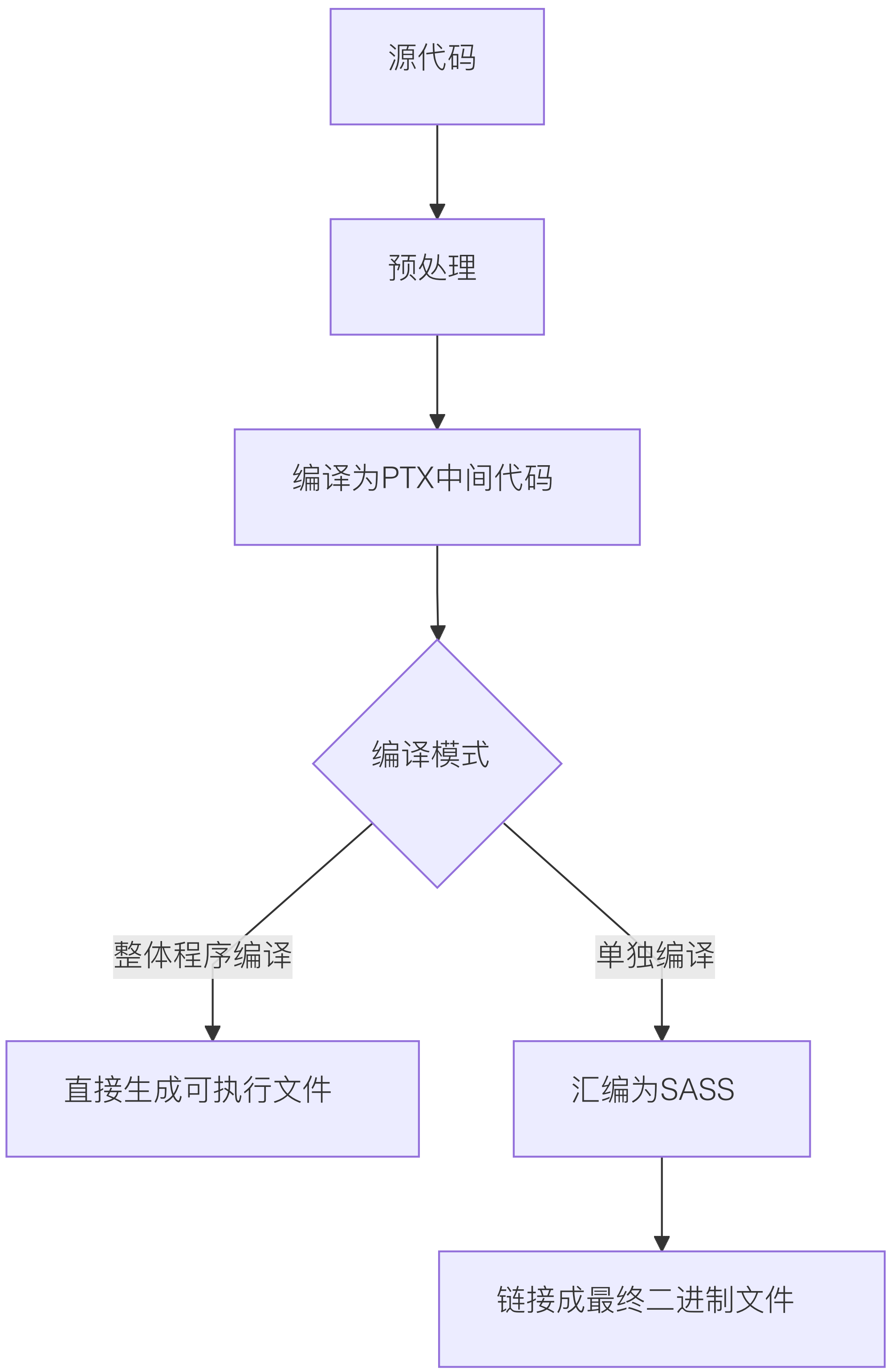
为了尽可能提升CUDA代码的跨平台兼容性，CUDA的编译过程分别针对两级架构: virtual intermediate architecture(VIA)和real GPU architecture(RGA). 两级架构的中间表示为PTX，PTX可以看做VIA的Assembly code和RGA的源代码，PTX的选择应该使VIA尽可能low-level，而RGA尽可能的high-level. 如果需要尽可能提高应用代码的可移植性(不确定GPU的平台)，可以采用just-in-time编译方式，但是JIT一个缺点是程序startup delay过长，解决该问题的两个方法分别是: compilation cache和Fatbinaries。

```
# JIT compilation
nvcc x.cu --gpu-architecture=compute_90 --gpu-code=compute_90
```

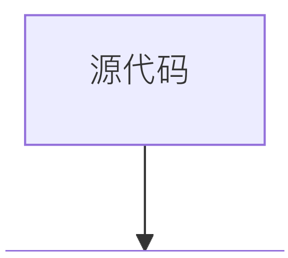
```
# Fatbinaries: This command generates exact code for two architectures,
plus PTX code for use by JIT in case a next generation GPU is
encountered.
nvcc x.cu --gpu-architecture=compute_80 --gpu-
code=compute_80,sm_86,sm_89
```

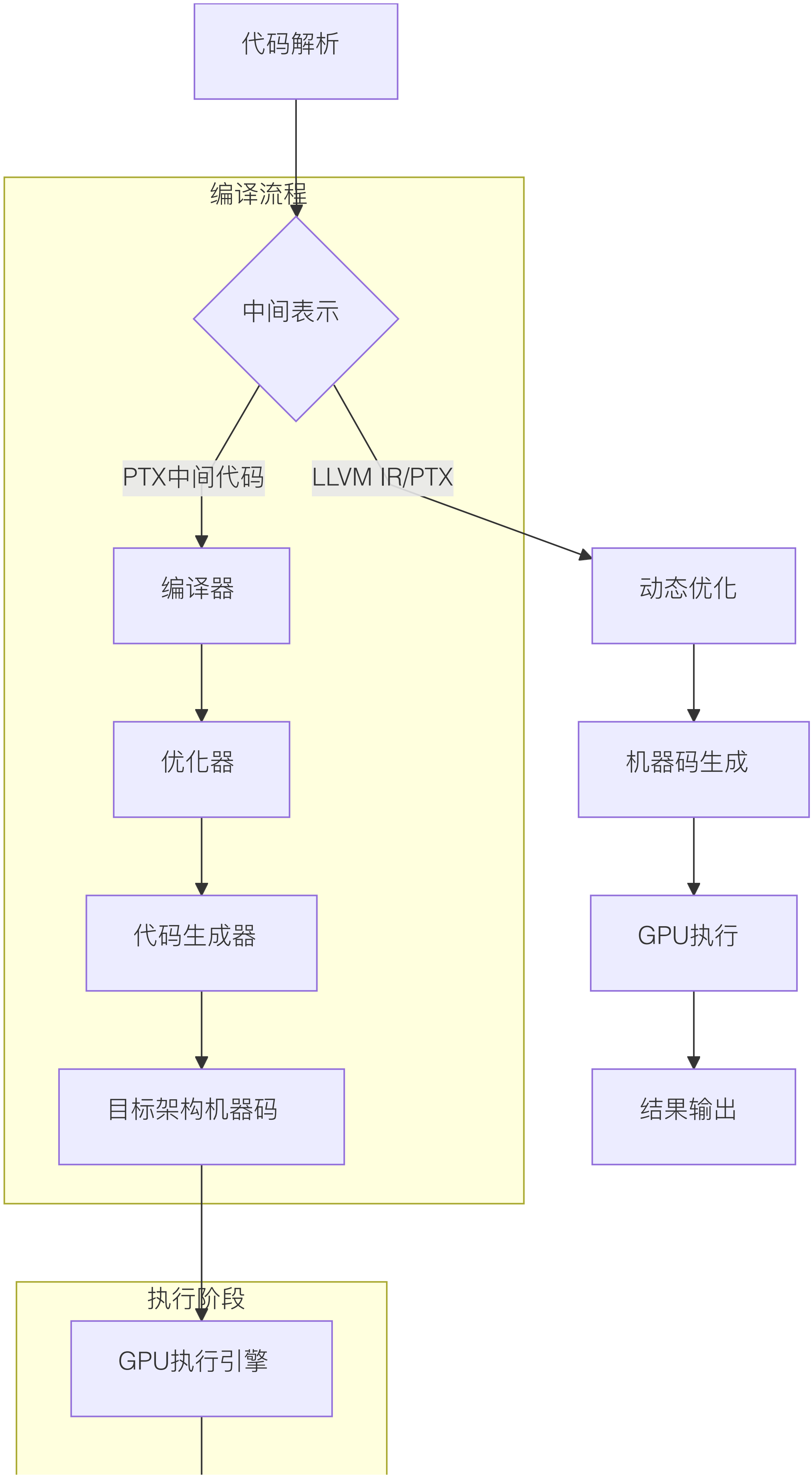
下面给出了CUDA代码常规两级编译流程和JIT编译流程示意图。

（1）CUDA代码常规两级编译流程

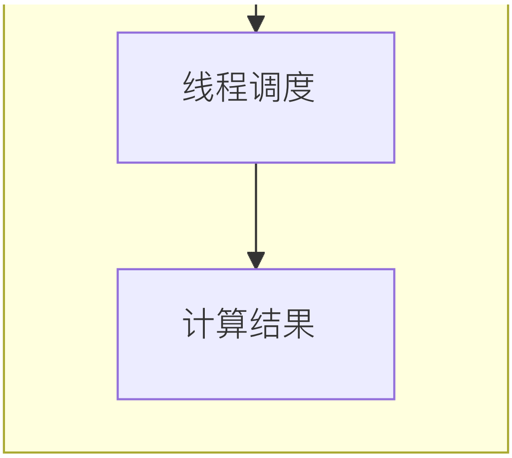

源代码
预处理
编译为PTX中间代码
编译模式
整体程序编译
单独编译
直接生成可执行文件
汇编为SASS
链接成最终二进制文件

（2）JIT编译流程


源代码



代码解析
编译流程
中间表示
PTX中间代码
LLVM IR/PTX
编译器
优化器
代码生成器
目标架构机器码
动态优化
机器码生成
GPU执行
结果输出
执行阶段
GPU执行引擎



(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

```bash
# 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

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"],
    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

```
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

4. TensorRT-LLM

在NVIDIA A100 GPU上部署TensorRT-LLM能显著提升大语言模型的推理性能。下面我将为你梳理详细的安装步骤、模型部署流程以及性能测试方法。

🛠️ TensorRT-LLM 安装指南

TensorRT-LLM的安装主要有以下几种方式，你可以根据需求选择：

安装方式	适用场景	说明
PIP 安装	快速开始，无需复杂配置	一条命令即可完成，适合体验和快速原型验证。
NGC 容器	保证环境一致性和隔离性	推荐用于生产环境，避免了依赖冲突。
源码编译	需要最新特性或特定定制	过程最复杂，但能获取最前沿的功能。

考虑到你已具备PyTorch和GPU驱动环境，**推荐使用PIP安装**以快速上手。

1. **安装依赖**：确保系统具备必要的编译工具和库。

   ```
   sudo apt-get -y install libopenmpi-dev python3-pip
   ```

2. **安装TensorRT-LLM**：使用pip从NVIDIA官方索引安装。

   ```
   pip3 install --upgrade pip setuptools
   pip3 install tensorrt_llm -U --extra-index-url
   https://pypi.nvidia.com
   ```

   安装成功后，可以在终端中输入`pip list | grep tensorrt`来确认安装版本。

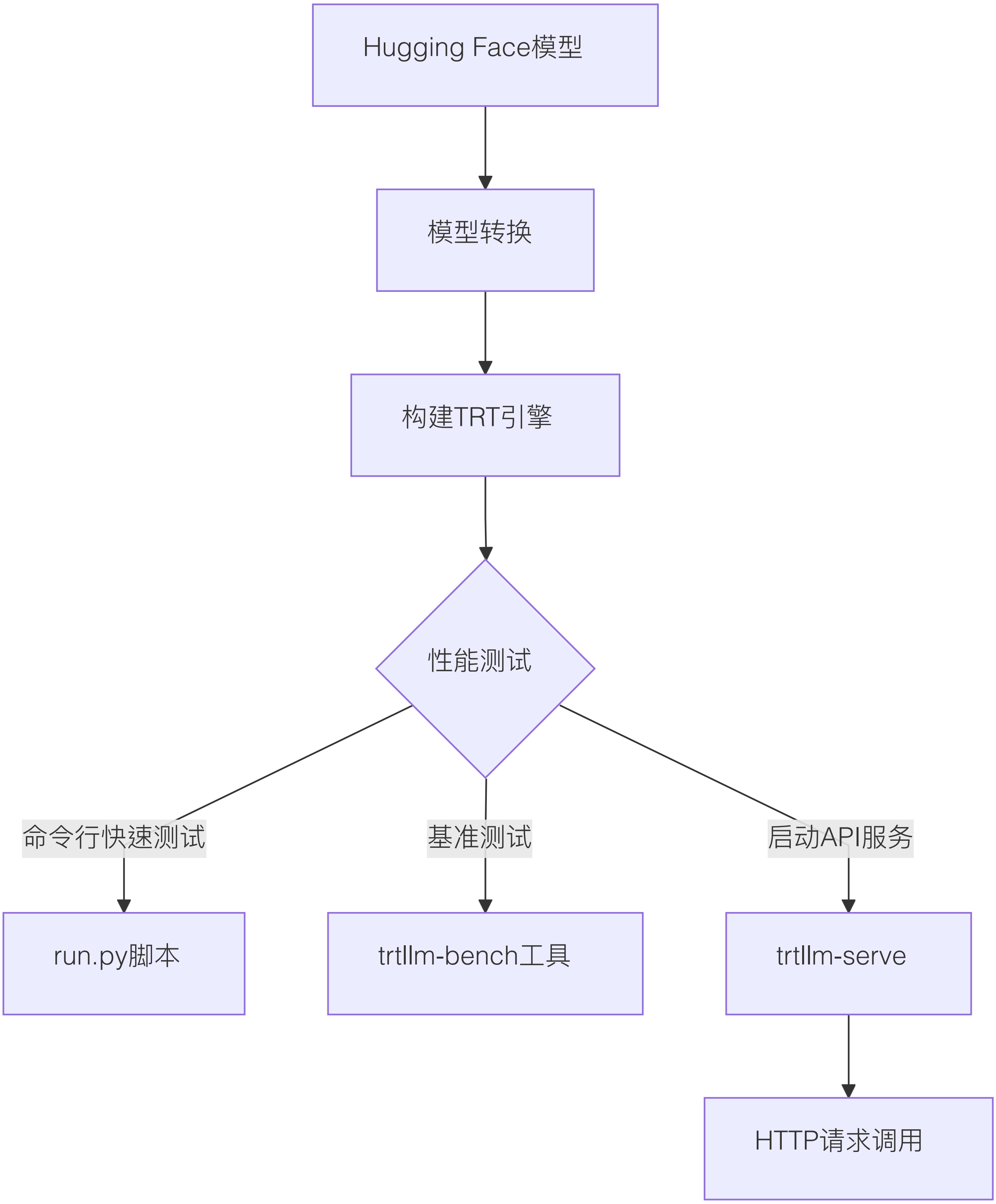
3. **验证安装**：在Python环境中导入TensorRT-LLM包来验证安装是否成功。

   ```
   python3 -c "import tensorrt_llm; print(tensorrt_llm.__version__)"
   ```

   如果能够成功导入并打印出版本号，则说明安装成功。

🚀 大模型部署与推理

TensorRT-LLM部署模型的核心流程是：先将Hugging Face格式的模型转换为TensorRT-LLM格式，然后构建优化后的推理引擎，最后执行推理。



我们以 **Qwen1.5-4B-Chat** 模型为例，展示部署的全过程。

1. **获取模型**
   从魔搭社区（ModelScope）下载模型：

```
git lfs install
git clone https://modelscope.cn/qwen/Qwen1.5-4B-Chat.git
```

2. **模型转换与引擎构建**
   首先需要获取TensorRT-LLM的示例代码：

```
wget https://github.com/NVIDIA/TensorRT-
LLM/archive/refs/tags/v0.10.0.tar.gz
tar xvf v0.10.0.tar.gz
cd TensorRT-LLM-0.10.0/examples/qwen
```

   安装模型依赖并执行转换：

```
pip install -r requirements.txt
# 将模型转换为TensorRT-LLM格式的检查点
python3 convert_checkpoint.py --model_dir /path/to/Qwen1.5-4B-Chat
\
                              --output_dir /path/to/trt_checkpoint
\
                              --dtype float16
# 构建TensorRT推理引擎
trtllm-build --checkpoint_dir /path/to/trt_checkpoint \
             --output_dir /path/to/trt_engines/qwen/1-gpu \
             --gemm_plugin float16
```

   关键参数说明：

   - `--model_dir`: 输入模型路径。
   - `--output_dir`: 转换后或构建引擎的输出路径。
   - `--dtype`: 计算精度，`float16` 在A100上能较好平衡性能与精度。
   - `--gemm_plugin`: 使用插件加速矩阵乘法，建议开启。

3. **执行推理测试**
   引擎构建成功后，可以使用附带的`run.py`脚本进行快速推理测试：

```
python3 ../run.py --input_text "你好，请介绍一下你自己" \
                  --max_output_len 500 \
                  --tokenizer_dir /path/to/Qwen1.5-4B-Chat \
                  --engine_dir /path/to/trt_engines/qwen/1-gpu
```

📊 性能测试与基准测试

为了全面评估优化后的模型性能，TensorRT-LLM提供了专业的基准测试工具。

1. **使用 `trtllm-bench` 进行基准测试**
   这个工具可以详细评估模型的吞吐量和延迟指标。

```bash
# 首先准备一个包含测试提示词的JSONL数据集
trtllm-bench throughput \
  --model /path/to/your/engine/directory \  # 使用构建好的引擎目录
  --dataset /path/to/dataset.jsonl \
  --tp 1 \          # 张量并行数，单卡设为1
  --backend tensorrt \
  --report_json benchmark_results.json
```

   关键性能指标解读：

   - **Request Throughput (req/sec)**: 每秒处理的请求数。
   - **Total Output Throughput (tokens/sec)**: 每秒生成的令牌数，衡量**生成速度**的核心指标。
   - **Time-to-First-Token (TTFT)**: 从发送请求到收到第一个令牌的时间，影响用户体验。
   - **Time-Per-Output-Token (TPOT)**: 平均生成每个令牌所需时间，与生成速度成反比。

2. **启动推理API服务**
   若要提供类似OpenAI的API服务，可以使用`trtllm-serve`命令：

```bash
trtllm-serve /path/to/trt_engines/qwen/1-gpu \
             --host localhost \
             --port 8000 \
             --max_batch_size 64
```

   服务启动后，即可通过HTTP请求调用：

```bash
curl http://localhost:8000/v1/completions \
  -H "Content-Type: application/json" \
  -d '{
    "model": "qwen",
    "prompt": "太阳为什么东升西落？",
    "max_tokens": 500,
    "temperature": 0.8
  }'
```

💎 关键提示与优化技巧

- **精度选择**：在A100上，`float16` (FP16) 和 `bfloat16` (BF16) 是常用的推理精度。

FP8是更新的低精度格式，可以进一步提升吞吐量并降低显存占用，部分模型已支持。

- **插件启用**：在构建引擎时，`--gemm_plugin` 和 `--gpt_attention_plugin` 等插件能通过融合算子来提升性能，建议启用。
- **利用A100特性**：A100支持**MIG（多实例GPU）**技术，可以将单块80GB GPU划分为多个小型GPU实例，从而同时服务多个推理任务，提升资源利用率。
- **性能调优**：基准测试时，通过调整 `--concurrency` (并发请求数) 等参数，可以模拟不同负载，找到最优的吞吐量和延迟平衡点。