AiDD

2024 AI+研发数字峰会

AI+ Development Digital summit

AI驱动研发变革 促进企业降本增效

北京站 08/16-17

基于 eBPF 和 Agent 构建 LLM 训练推理优化体系

向阳 云杉网络

演讲嘉宾

向阳

清华大学博士 / 云杉网络研发 VP

清华大学博士，云杉网络研发 VP，DeepFlow 开源社区负责人。曾在国际顶级学术会议 ACM SIGCOMM、ACM IMC 上发表可观测性方向的学术论文，现负责可观测性产品 DeepFlow，致力于打造一款为云原生和 AI 应用而生的零侵扰可观测性产品。

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PART 01
背景：训练和推理的效率挑战

LLM 训练开销大、效率低

	GPT-4	Llama-3.1
参数	1.8T	405B
GPU	25K A100	16K H100
时长	90~100 天	54 天
MFU	32%~36%	38%~43%

- Everything We Know About GPT-4 - Klu.ai
- GPT4- All Details Leaked
- The Llama 3 Herd of Models

训练时间长：数月

GPU 数量多：数万

模型参数大：万亿

GPU 利用率低：40%

Component	Category	Interruption Count	% of Interruptions
Faulty GPU	GPU	148	30.1%
GPU HBM3 Memory	GPU	72	17.2%
Software Bug	Dependency	54	12.9%
Network Switch/Cable	Network	35	8.4%
Host Maintenance	Unplanned Maintenance	32	7.6%
GPU SRAM Memory	GPU	19	4.5%
GPU System Processor	GPU	17	4.1%
NIC	Host	7	1.7%
NCCL Watchdog Timeouts	Unknown	7	1.7%
Silent Data Corruption	GPU	6	1.4%
GPU Thermal Interface + Sensor	GPU	6	1.4%
SSD	Host	3	0.7%
Power Supply	Host	3	0.7%
Server Chassis	Host	2	0.5%
IO Expansion Board	Host	2	0.5%
Dependency	Dependency	2	0.5%
CPU	Host	2	0.5%
System Memory	Host	2	0.5%

Table 5 Root-cause categorization of unexpected interruptions during a 54-day period of Llama 3 405B pre-training. About 78% of unexpected interruptions were attributed to confirmed or suspected hardware issues.

148/54*365/16384 = 6%

(148+72+19+17+6+6)/54*365/16384 = 11%

GPU 年化故障高：
6%~11%

代码层面训练低效的主要原因

Classification of the 706 low-GPU-utilization issues discovered across 400 deep learning jobs.

Category	Description	No.	Ratio
Interactive Job	The execution of a job entails regular interaction with its owner.	15	2.12%
GPU Oversubscription	A job requests more GPUs than it actually utilizes.	6	0.85%
Unreleased Job	A job does not terminate promptly after completing its computation.	9	1.27%
Non-DL Job	A job is unrelated to deep learning and does not utilize GPUs at all. For example, the job performs data analysis using CPUs solely.	4	0.57%
Improper Batch Size	Improper values of the batch size are used, which decrease the GPU computation of deep learning operators.	181	25.64%
Insufficient GPU Memory	The GPU memory is not sufficient to support more GPU computation.	22	3.12%
Model Checkpointing	A job saves model checkpoints synchronously to the distributed data store.	116	16.43%
Inefficient Host-GPU Data Transfer	The data transfer between main memory and GPU memory is not efficient.	197	27.90%
Data Preprocessing	Raw input data is preprocessed using CPUs before model training.	28	3.97%
Remote Data Read	A job opens and reads input data directly from the distributed data store.	18	2.55%
External Data Usage	A job accesses input data or model files directly from external sites.	18	2.55%
Intermediate Result Upload	A job saves intermediate training results synchronously to the distributed data store.	14	1.98%
Data Exchange	The GPUs of a distributed job continually exchange data, such as gradients and output tensors, among one another.	50	7.08%
Long Library Installation	The installation of dependent libraries takes too much time (at least 10 minutes).	12	1.70%
API Misuse	API usage violates assumptions.	16	2.27%

- Yanjie Gao (Microsoft Research) et al, ACM ICSE 2024,
  An Empirical Study on Low GPU Utilization of Deep Learning Jobs.
- Yanjie Gao (Microsoft Research) et al, ACM ICSE 2023,
  An Empirical Study on Quality Issues of Deep Learning Platform.

如何知晓你的训练任务是否存在这些问题?

计算效率

```
1 from torch.utils.data import DataLoader
2
3 train_batch_size = ~~32~~ 384
4 eval_batch_size  = ~~32~~ 448
5 train_loader = DataLoader(dataset = train_data, batch_size =
  ↪  train_batch_size, shuffle = True)
6 eval_loader  = DataLoader(dataset = eval_data, batch_size =
  ↪  eval_batch_size, shuffle = True)
```

Figure 2: A simplified example of Improper Batch Size issues. "train_batch_size" and "eval_batch_size" are specified arguments for model training and evaluation, respectively. The fix is to increase their values independently (lines 3–4).

显存拷贝

```
1 import torch
2 from torch.utils.data import DataLoader
3
4 train_loader = DataLoader(train_set,..., num_workers=8,
  ↪  pin_memory=True)
5 eval_loader = DataLoader(eval_set, ..., num_workers=8,
  ↪  pin_memory=True)
6
7 for epoch in range(num_epochs):
8   ...
9   for _, data in enumerate(train_loader, 0):
10    # get the inputs
11    inputs, labels = data
12    inputs = inputs.to(device, non_blocking=True)
13    labels = labels.to(device, non_blocking=True)
```

Figure 4: A simplified example of Inefficient Host-GPU Data Transfer issues. The fix is to enable automatic memory pinning by setting the pin_memory parameter to True (lines 3–4). We further set the non_blocking parameter to True (lines 11–12), which tries asynchronous data transfer if possible.

```
1 import torch
2+import threading
3+import shutil
4+import os
5
6 def main():
7   ...
8   for epoch in range(start_epoch, num_epochs):
9     if step > num_training_steps:
10      break
11    ...
12    for i, batch in enumerate(tqdm(train_loader)):
13      ...
14      logits = model(input_data)
15      ...
16      optimizer.zero_grad()
17      loss.backward()
18      optimizer.step()
19      ...
20      f1, pred = evaluator.evaluate(val_loader, model, step)
21      ...
22      if f1 > max_f1:
23        max_f1 = f1
24        ~~torch.save(model, remote_path)~~
25      + local_path = make_tmp_path(epoch, i)
26      + torch.save(model, local_path)
27
28      + def save_file(local_path, remote_path):
29      +   shutil.copyfile(local_path, remote_path)
30      +   os.remove(local_path)
31
32      + threading.Thread(target = save_file, args = [local_path,
        ↪  remote_path]).start()
33
34 if __name__ == '__main__':
35   main()
```

Figure 3: A simplified example of Model Checkpointing issues. The fix is to save the checkpoint to a local temporary file (lines 25–26), followed by an asynchronous copy to the remote data store in a separate thread (lines 28–32).

In a distributed job, GPUs consistently share data such as gradients and output tensors. This data exchange between GPUs, whether through the network or PCI Express bus, frequently interrupts their designated tasks and causes a sudden drop in GPU utilization to zero. Within the *Data Exchange* category, there are 50 (7.08%) issues. A common fix is to enhance communication efficiency by minimizing the frequency of data exchange (e.g., using large batch sizes) and enabling compressed communication [34, 39]. For users of Horovod [67], enlarging the backward_passes_per_step parameter[5] can help accumulate more local gradient updates and transmit them simultaneously. Developers can also leverage Microsoft DeepSpeed's 3D (data, model, and pipeline) parallelism, whose 1-bit Adam and 0/1 Adam [39] optimizers demonstrate significant reductions in communication volume.

网络传输

LLM 推理开销大、时延高

Llama	8B	70B	405B
FP32	36GB	267GB	**1.48TB**
FP16	20GB	135GB	758GB
INT8	12GB	70GB	382GB
INT4	8GB	37GB	193GB

LLM Memory Requirements

Inference Training

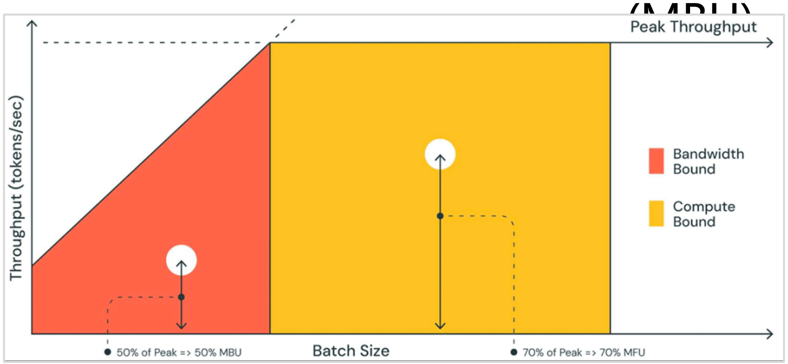
Total Inference Memory: 1.48 TB

- **Model Weights:** 1.47 TB
- **KV Cache:** 2.00 GB
- **Activation Memory:** 3.56 GB

- LLM Memory Requirements
- LLM Inference Performance Engineering: Best Practices

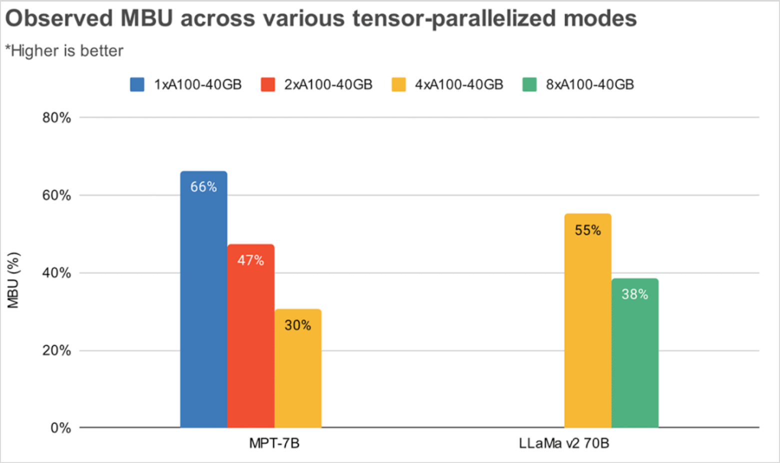
80GB: 1 GPU
640GB: 1 Node x 8 GPU
1.28TB：2 Node x 8 GPU

Time To First Token (TTFT)
Time Per Output Token (TPOT)
Model Bandwidth Utilization (MBU)



GPU 并非越少越好

GPU 越少，则每个 GPU 需要加载更多的模型参数。



GPU 并非越多越好

GPU 越多，则通信越复杂，内存碎块越多。

没有银弹，唯有持续观测 & 优化。

排查 LLM 推理显存消耗的挑战

Biz

vLLM

PyTorch

Python / C++

PyTorch

Help Needed from vLLM team on profiling pytorch cuda memory

youkaichao1 1 Mar 16

Hi, I’m working on GitHub - vllm-project/vllm: A high-throughput and memory-efficient inference and serving engine for LLMs 7 , and the recently release of pytorch 2.2.0 caused some trouble to me. I came here for help in profiling cuda memory usage.

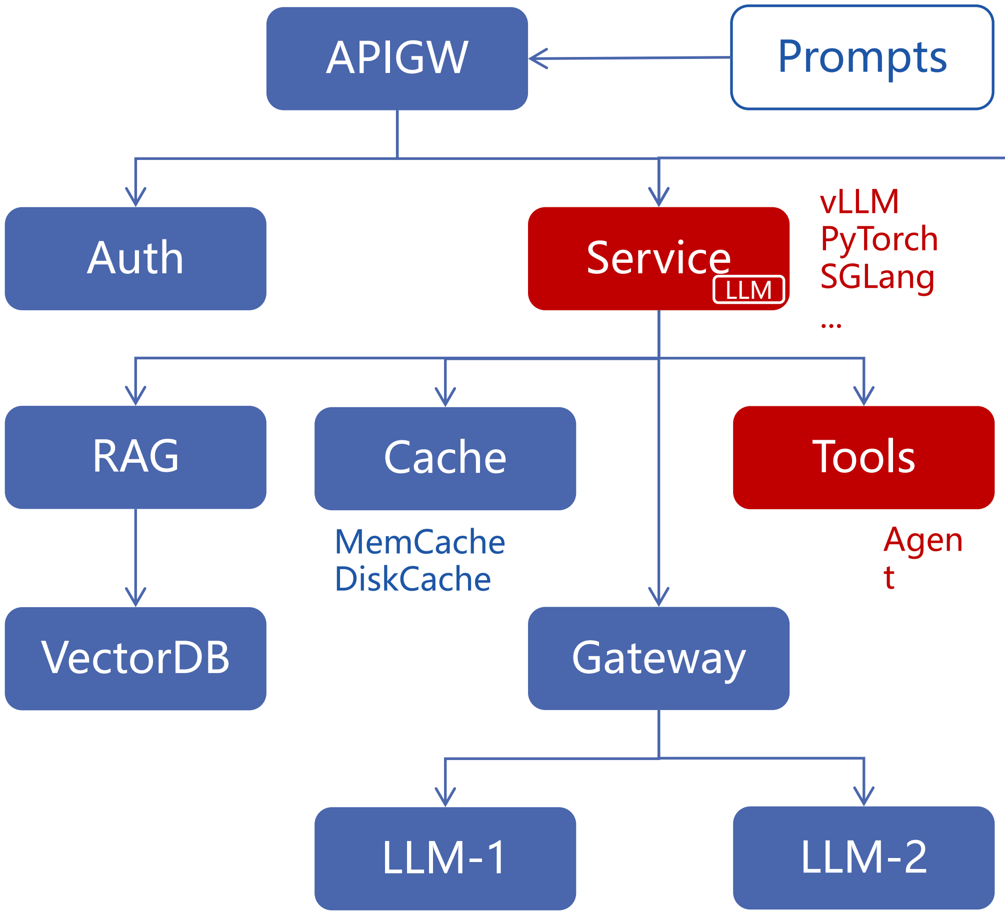
The basic story: vLLM tries to allocate as much memory as possible for KV Cache to accelerate LLM inference. In order to do so, it first profiles the memory usage, guess the maximum size of memory available for KV Cache, and also leave some for storing activation during inference.

What’s more, vLLM uses cuda graph to reduce Python overhead.

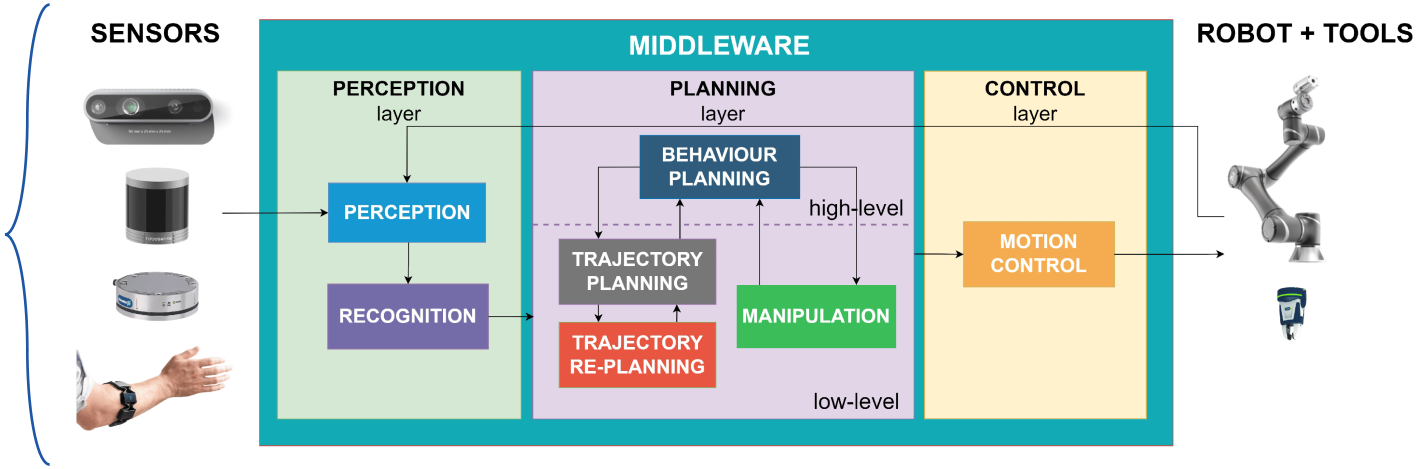
When PyTorch upgrades from 2.1.2 to 2.2.0 , there seems to be some internal change of memory allocator, and the memory that can be used is decreased. It can cause OOM error during inference.

Here are the diagnoses data (produced by `torch.cuda.memory_stats` and `torch.cuda.memory._dump_snapshot`), collected from a server with 2 L4 GPUs:

从推理应用到在线 LLM 推理服务



Perception-Planning-Control
BEV-OCC-Transformer



[Robot Operating System 2 (ROS2)-Based Frameworks for Increasing Robot Autonomy: A Survey]

端 - 自动驾驶、具身智能（ROS2）的端到端
低时延和高稳定性要求

云 - 在线推理服务是一个复杂的分布式服务
TTFT、TPOT、时延、吞吐

从大模型到小模型：消费级 GPU、CPU 协同

Accelerating Model Training in Multi-cluster Environments with Consumer-grade GPUs

Hwijoon Lim
KAIST
Daejeon, Republic of Korea
hwijoon.lim@kaist.ac.kr

Juncheol Ye
KAIST
Daejeon, Republic of Korea
juncheol@kaist.ac.kr

Sangeetha Abdu Jyothi
UC Irvine & VMware Research
Irvine, California, USA
sangeetha.aj@uci.edu

Dongsu Han
KAIST
Daejeon, Republic of Korea
dhan.ee@kaist.ac.kr

Accelerating Model Training in Multi-cluster Environments with Consumer-grade GPUs, SIGCOMM 2024.

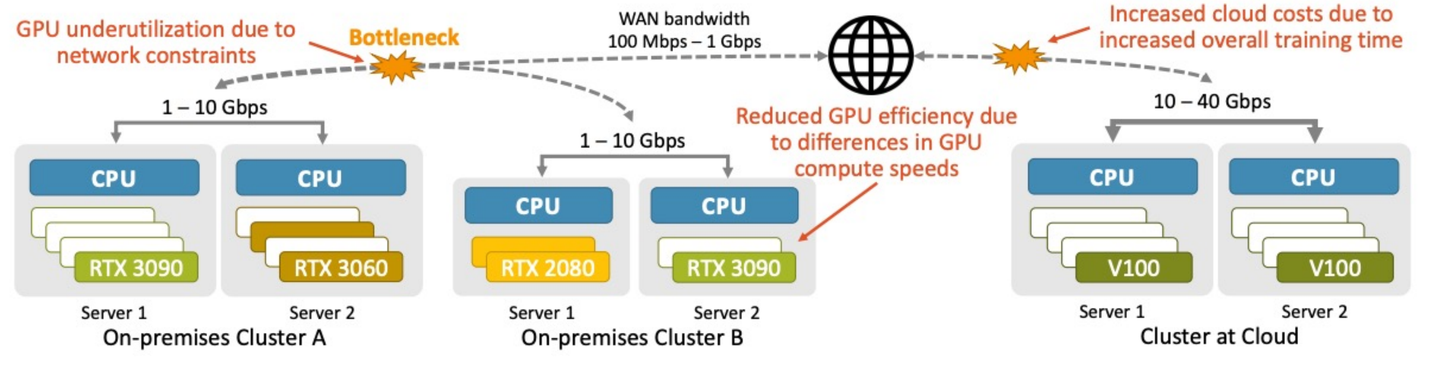


Figure 1: A multi-cluster environment with two on-premises lab clusters and a cloud cluster.

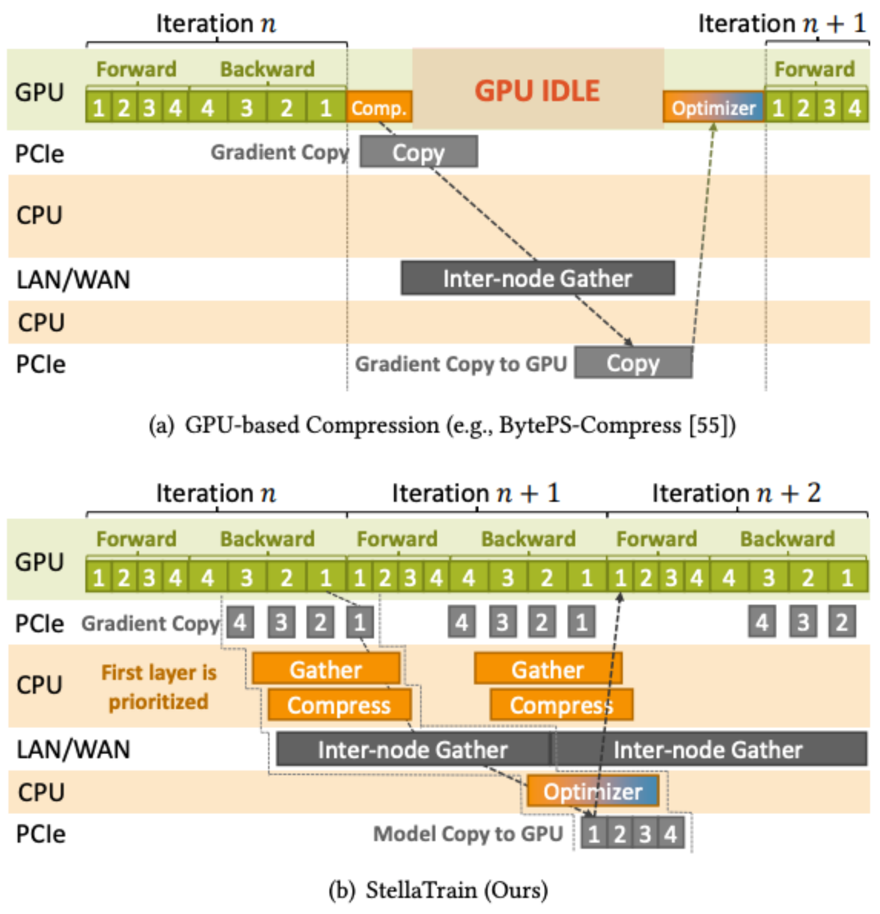
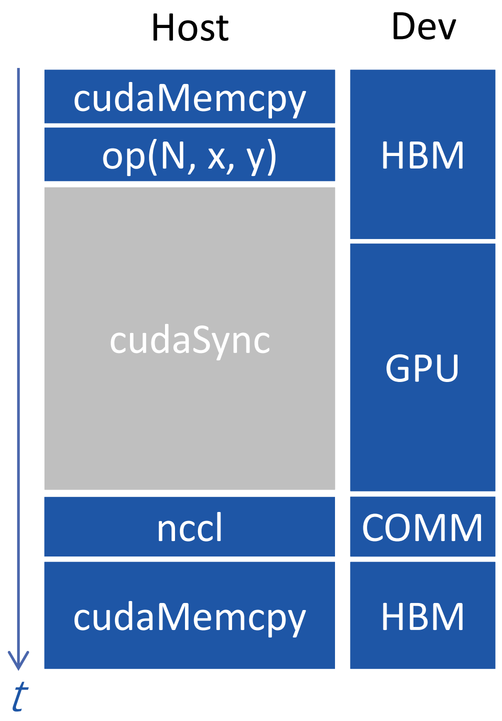
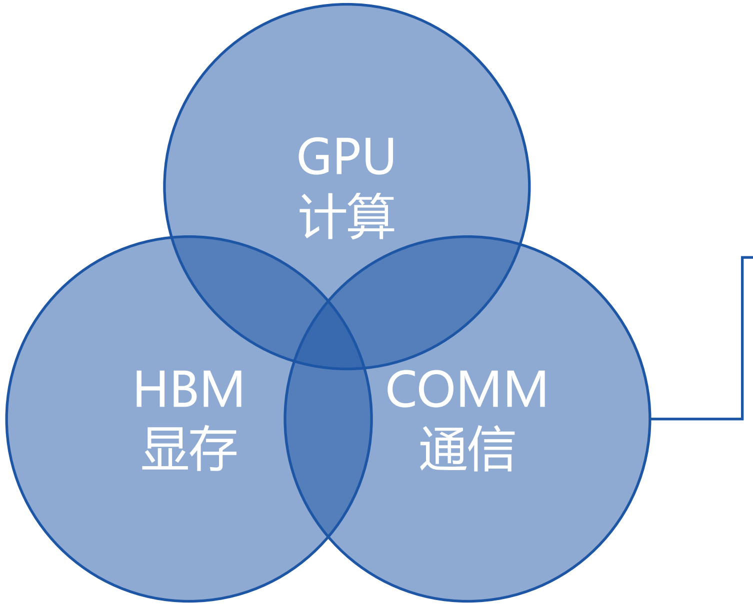


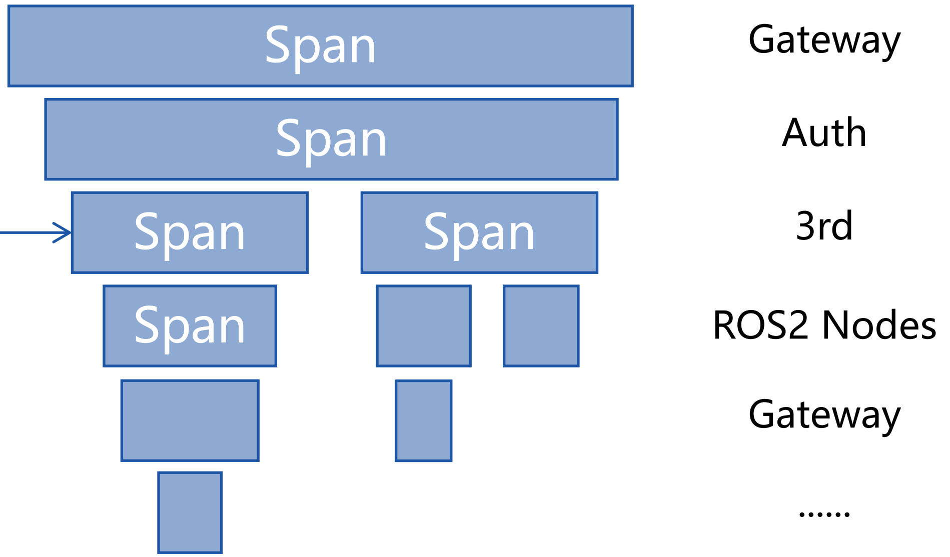
Figure 4: Comparison of training pipelines.

AI 训练和推理的可观测性需求





训练 & 推理



在线、端侧推理服务

PART 02

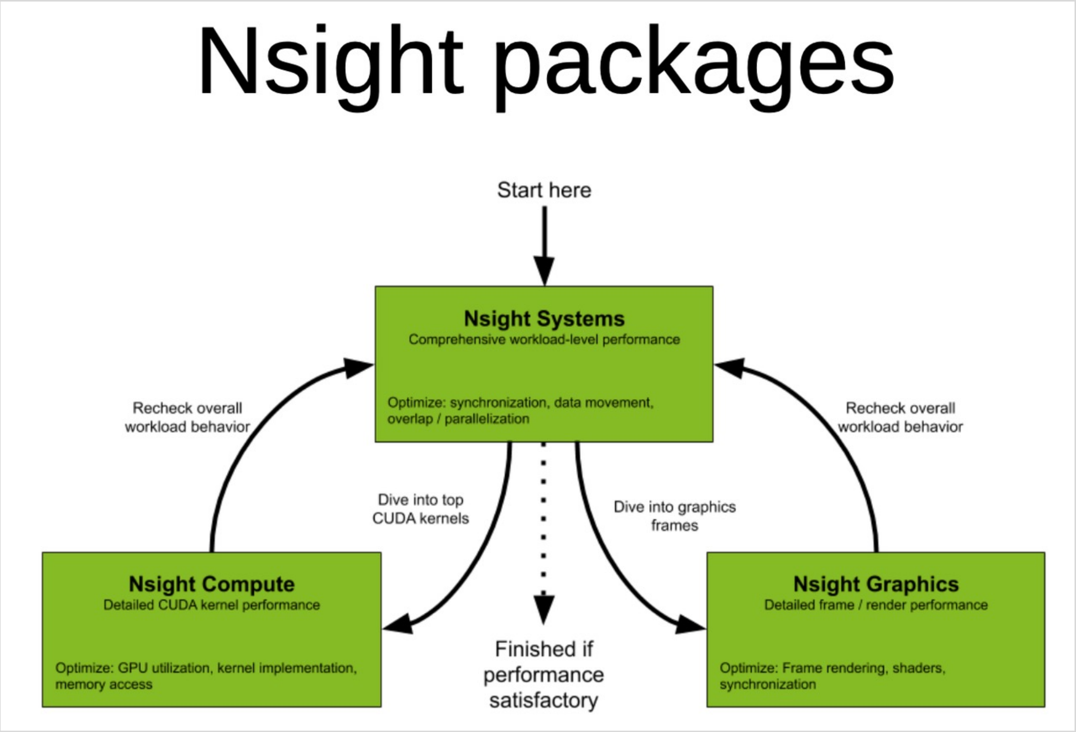
现状：传统解决方案和工具的问题

DCGM Prometheus Exporter

发现故障 √

优化性能 X

GPU：Nvidia Nsight、PyTorch Profiler



Nsight 的问题：

需要重启进程、缺少 CPU Context。

```python
def trace_handler(p):
    output = p.key_averages().table(sort_by="self_cuda_time_total", row_limit=10)
    print(output)
    p.export_chrome_trace("/tmp/trace_" + str(p.step_num) + ".json")

with profile(
    activities=[ProfilerActivity.CPU, ProfilerActivity.CUDA],
    schedule=torch.profiler.schedule(
        wait=1,
        warmup=1,
        active=2),
    on_trace_ready=trace_handler
) as p:
    for idx in range(8):
        model(inputs)
        p.step()
```

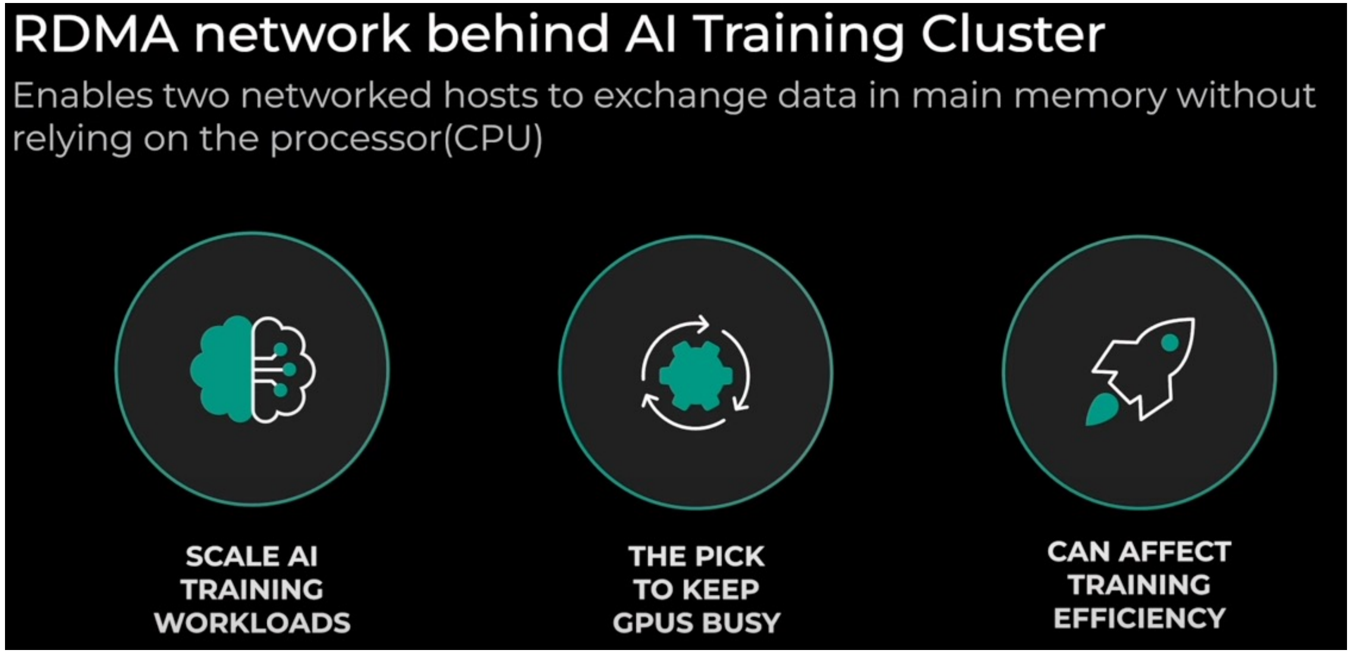
需要手工精心打造插桩、开销

1. Parameter `skip_first` tells profiler that it should ignore the first 10 steps (default value of `skip_first` is zero);
2. After the first `skip_first` steps, profiler starts executing profiler cycles;
3. Each cycle consists of three phases:
   - idling (`wait=5` steps), during this phase profiler is not active;
   - warming up (`warmup=1` steps), during this phase profiler starts tracing, but the results are discarded; this phase is used to discard the samples obtained by the profiler at the beginning of the trace since they are usually skewed by an extra overhead;
   - active tracing (`active=3` steps), during this phase profiler traces and records data;
4. An optional `repeat` parameter specifies an upper bound on the number of cycles. By default (zero value), profiler will execute cycles as long as the job runs.

PyTorch Profiler 的问题：

只能用于 PyTorch；性能影响大；需要改代码、重启进程。

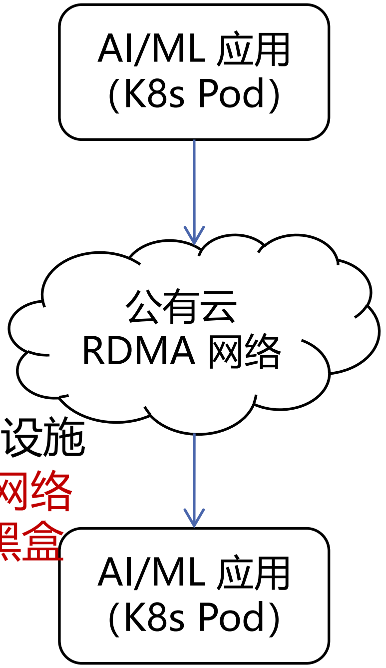
RDMA 网络：网卡/交换机指标、拨测



Meta: Network Observability for AI/HPC Training Workflows

私有基础设施

网卡/交换机指标粒度粗



公有基础设施

RDMA 网络是性能黑盒

R-Pingmesh: A Service-Aware RoCE Network Monitoring and Diagnostic System

Kefei Liu, Zhuo Jiang, Jiao Zhang, Shixian Guo, Xuan Zhang, Yangyang Bai, Yongbin Dong, Feng Luo, Zhang Zhang, Lei Wang, Xiang Shi, Haohan Xu, Yang Bai, Dongyang Song, Haoran Wei, Bo Li, Yongchen Pan, Tian Pan, and Tao Huang

SIGCOMM 2024

Hostping: Diagnosing Intra-host Network Bottlenecks in RDMA Servers

Kefei Liu, Zhuo Jiang, Jiao Zhang, Haoran Wei, Xiaolong Zhong Lizhuang Tan, Tian Pan and Tao Huang

NSDI 2023

字节&北邮

聚焦 RDMA 网络主动拨测

在线推理服务的可观测性：分布式追踪

Python Typescript

```python
from openai import OpenAI
from traceloop.sdk import Traceloop
from traceloop.sdk.decorators import workflow

Traceloop.init(app_name="joke_generation_service")

@workflow(name="joke_creation")
def create_joke():
  client = OpenAI(api_key=os.environ["OPENAI_API_KEY"])
  completion = client.chat.completions.create(
      model="gpt-3.5-turbo",
      messages=[{"role": "user", "content": "Tell me a joke about opentelemetry"}],
  )

  return completion.choices[0].message.content
```

OpenLLMetry

python

```python
@openlit.trace
def generate_one_liner():
    completion = client.chat.completions.create(
        model="gpt-3.5-turbo",
        messages=[
            {
                "role": "system",
                "content": "Return a one liner from any movie for me to guess",
            }
        ],
    )
```

OpenLIT

Python TypeScript

```python
import openai
from langsmith.wrappers import wrap_openai
from langsmith import traceable

# Auto-trace LLM calls in-context
client = wrap_openai(openai.Client())

@traceable # Auto-trace this function
def pipeline(user_input: str):
    result = client.chat.completions.create(
        messages=[{"role": "user", "content": user_input}],
        model="gpt-3.5-turbo"
    )
    return result.choices[0].message.content

pipeline("Hello, world!")
# Out:  Hello there! How can I assist you today?
```

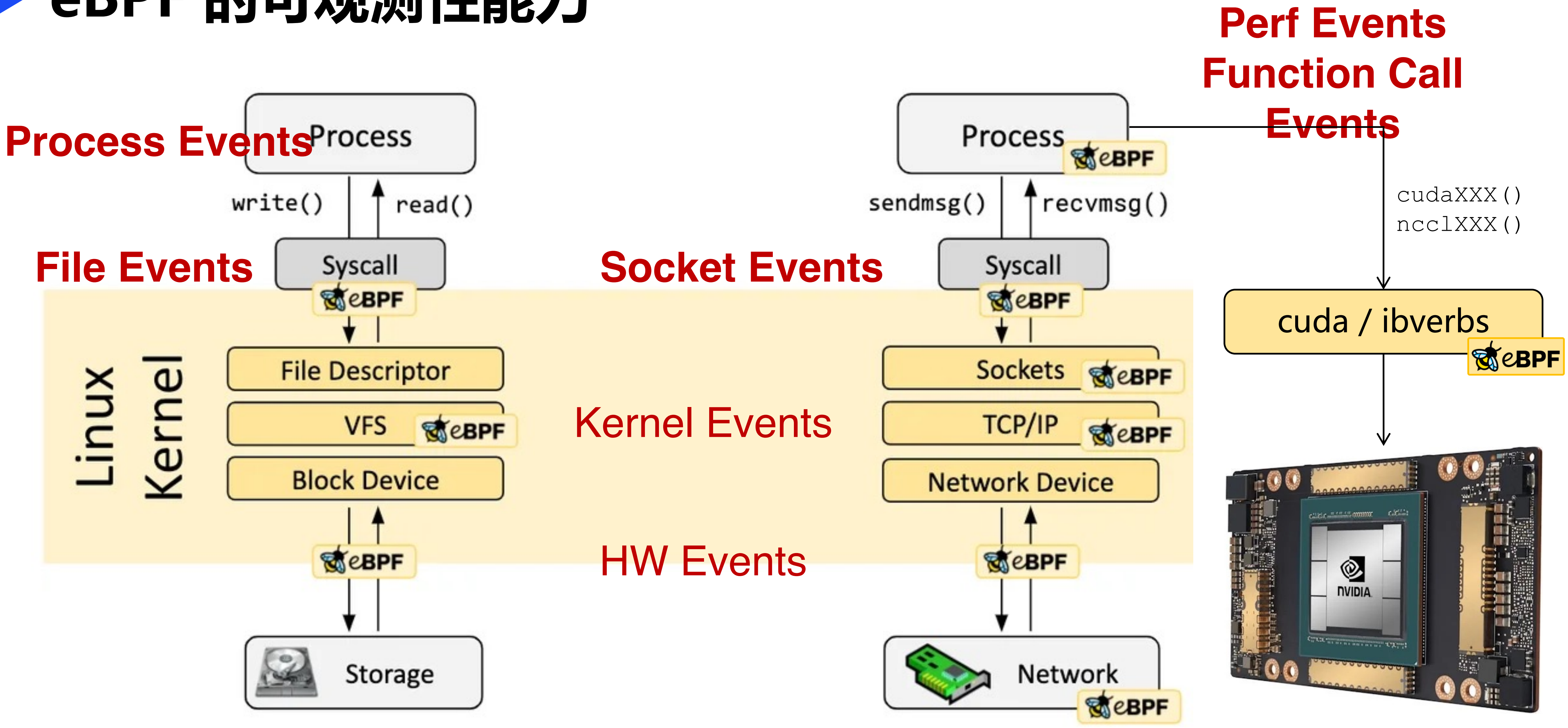
LangSmith

支持的语言有限、需要修改代码

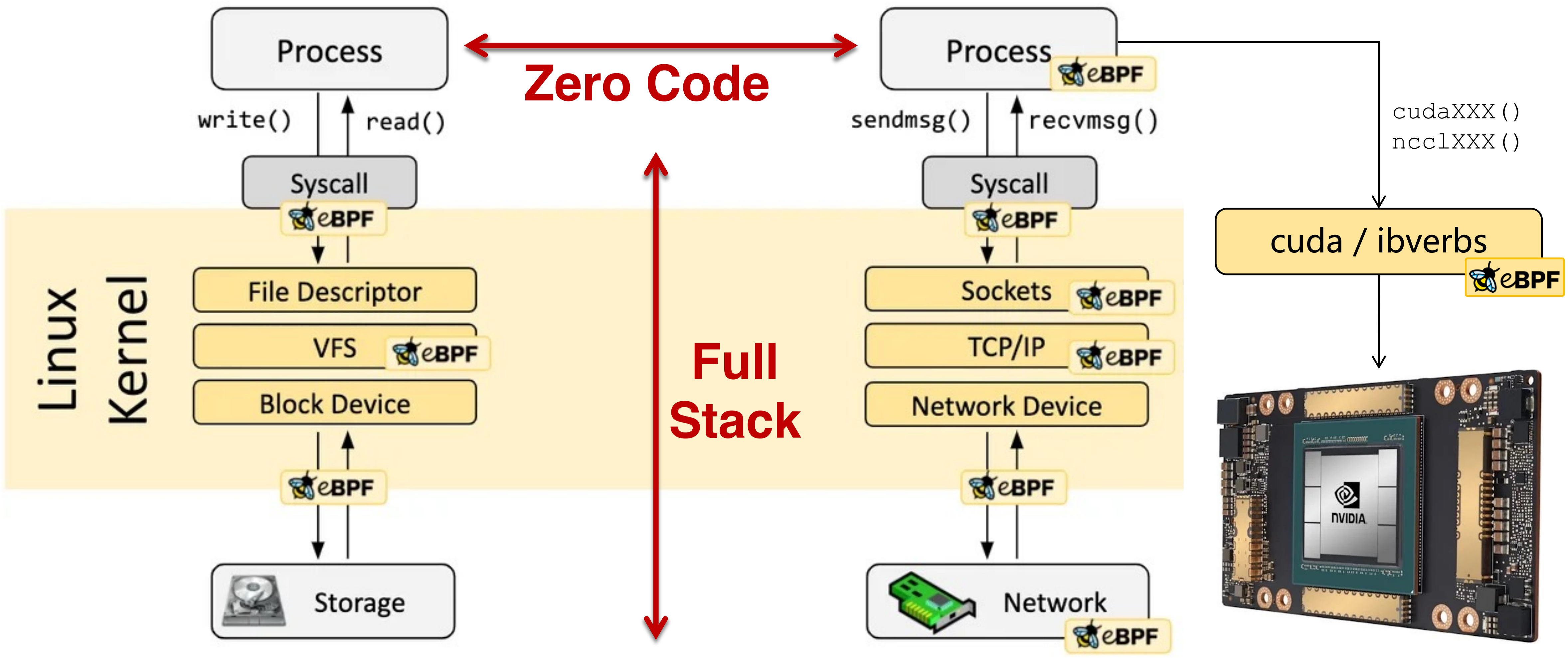
PART 03

方法：eBPF 构建零侵扰可观测性

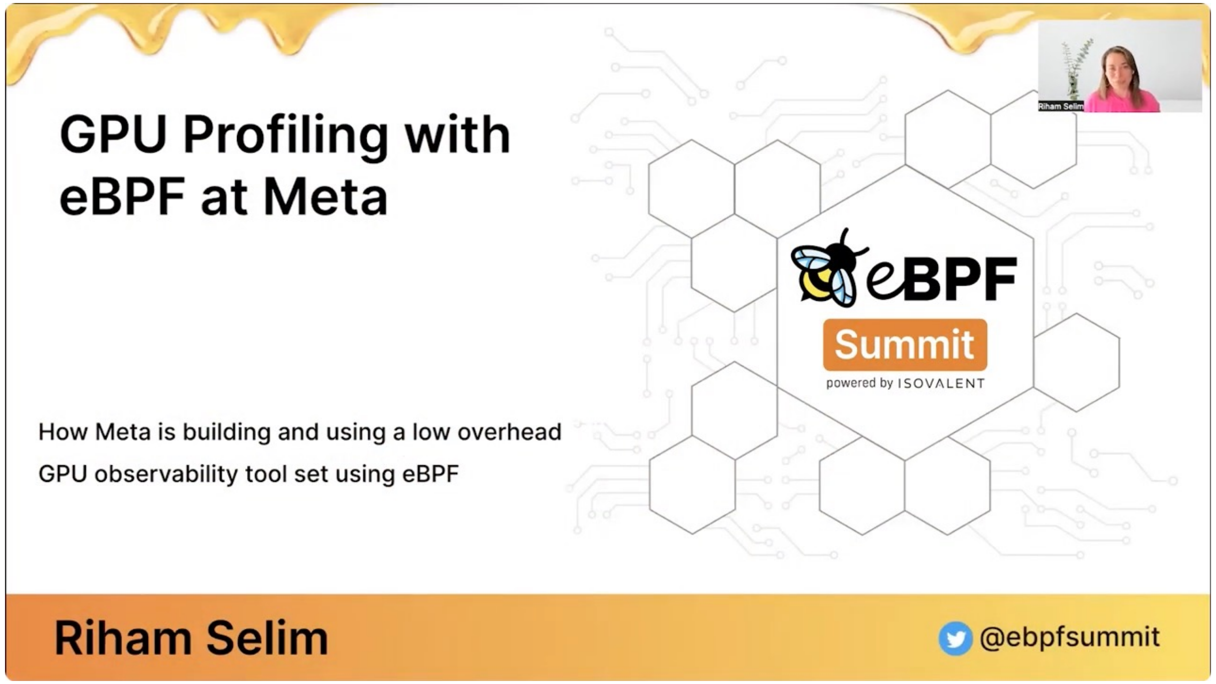
eBPF 的可观测性能力



使用 eBPF 实现可观测性的优势



业内探索：eBPF Profiling & Tracing



Meta：eBPF GPU Profiling

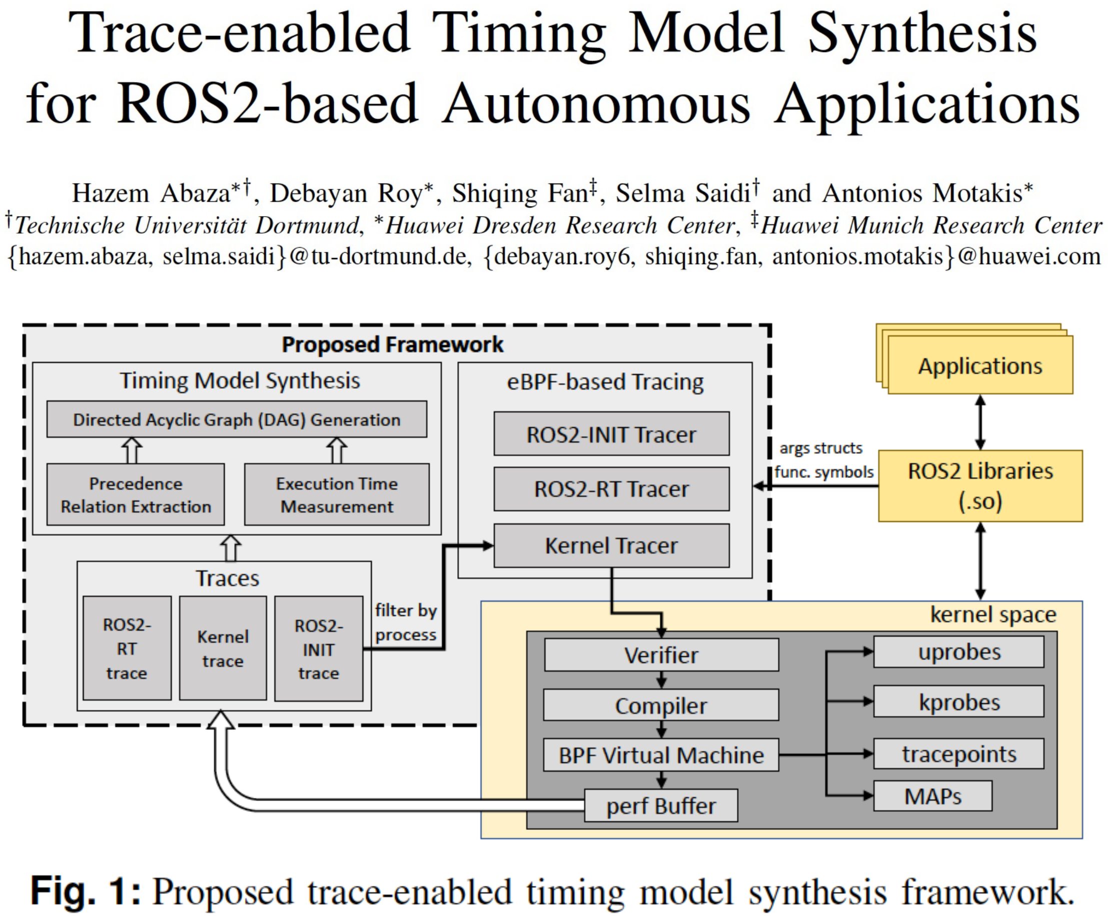


Fig. 1: Proposed trace-enabled timing model synthesis framework.

华为：eBPF Tracing + ROS2

使用 eBPF 实现持续剖析的技术挑战

数据采集	观测对象	数据关联	数据分析

eBPF perf sampling

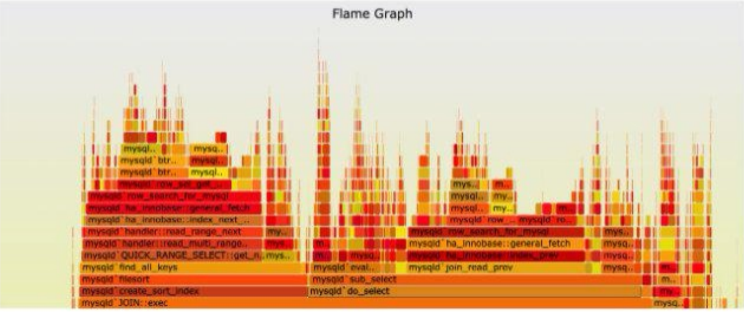
eBPF uprobe hooks
cudaLaunchKernel
cudaMalloc
cudaFree
cudaMemcpy
cudaMemcpyAsync
cudaStreamSynchronize
ncclAllReduce
ncclAllGather

Python 运行时函数
训练、推理业务函数
vLLM 函数
PyTorch 函数
Python 运行时函数
CUDA RT 函数
CUDA 核函数
C/C++ Lib 函数
GPU
CPU

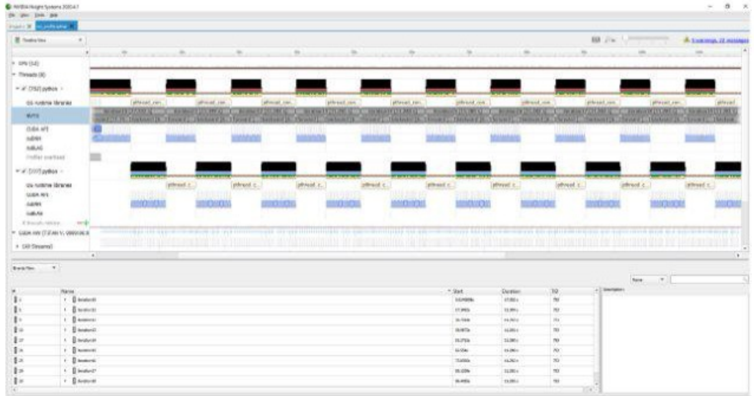
Python unwind

DWARF unwind / Frame Pointer

Stack Merge + Thread State Recover

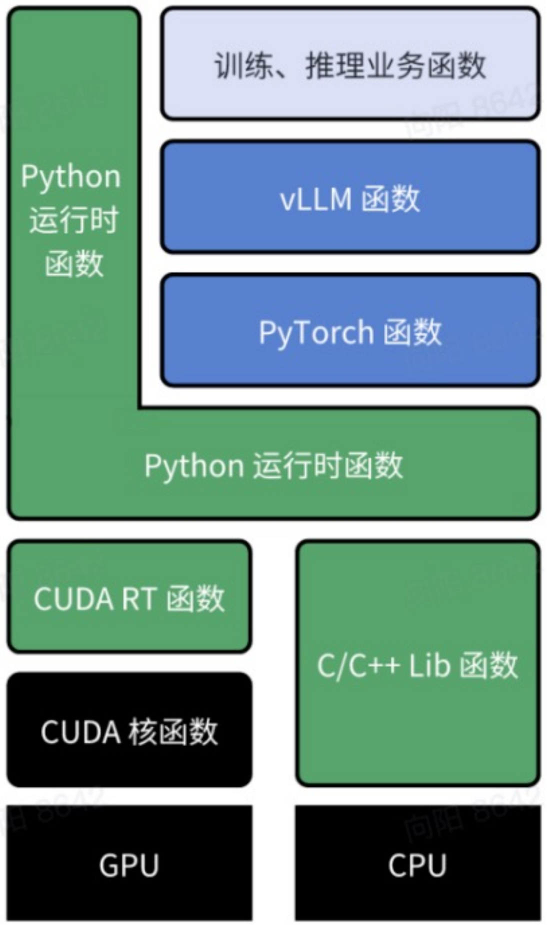


On-CPU CPU 运算耗时	On-GPU GPU 运算耗时	Off-GPU GPU 等待耗时
HBM-Malloc 显存申请量	HBM-Inuse 显存用量	HBM-Copy H2D/D2H



如何合并 Python Stack 和 C/C++ Stack

栈合并目的：全栈剖析




```python
def baz():
    time.sleep(100)

def bar():
    baz()

def foo():
    bar()

def main():
    foo()

main()
```

```
#0  __select_nocancel ()
#1  pysleep
#2  time_sleep
#3  call_function
#4  PyEval_EvalFrameEx
#5  fast_function
#6  call_function
#7  PyEval_EvalFrameEx
#8  fast_function
#9  call_function
#10 PyEval_EvalFrameEx
#11 fast_function
#12 call_function
#13 PyEval_EvalFrameEx
#14 fast_function
#15 call_function
#16 PyEval_EvalFrameEx
#17 _PyEval_EvalCodeWithName
#18 PyEval_EvalCodeEx
#19 PyEval_EvalCode
```

https://github.com/deepflwio/deepflow

例：剖析显存申请和使用量

① eBPF uprobe
Hook cuda_malloc
获取显存申请调用栈

```c
SEC("uprobe/cuda_malloc")
int uprobe_cuda_malloc(struct pt_regs *ctx) {
    __u64 id = bpf_get_current_pid_tgid();
    __u32 tgid = id >> 32;

    void *address = (void *) PT_REGS_PARM1(ctx);
    __u64 size = (__u64) PT_REGS_PARM2(ctx);
    malloc_data_t *data = cuda_malloc_info__lookup(&tgid);
    __u64 call_time = bpf_ktime_get_ns();

    if (data) {
        data->address = address;
        data->size = size;
        data->call_time = call_time;
        data->rip = PT_REGS_IP(ctx);
    } else {
        malloc_data_t newdata = { .address = address, .size = size, .call_time = call_time, .rip = PT_REGS_IP(ctx) };
        cuda_malloc_info__update(&tgid, &newdata);
    }

    return 0;
}
```

② eBPF uretprobe
Hook cuda_malloc
获取申请的显存地址

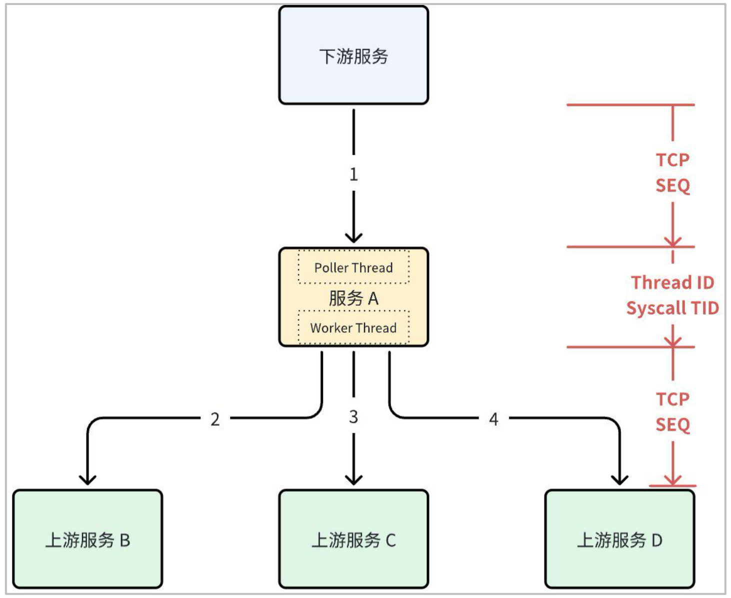
```c
SEC("uretprobe/cuda_malloc")
int uretprobe_cuda_malloc(struct pt_regs *ctx)
{
    __u64 id = bpf_get_current_pid_tgid();
    __u32 tgid = id >> 32;

    long ret = PT_REGS_RC(ctx);
    if (ret != 0) {
        return 0;
    }

    malloc_data_t *data = cuda_malloc_info__lookup(&tgid);
    if (data == NULL) {
        return 0;

    cuda_malloc_info__delete(&tgid);

        __u32 zero = 0;
        unwind_state_t *state = heap__lookup(&zero);
        if (state == NULL) {
                return 0;
        }
        __builtin_memset(state, 0, sizeof(unwind_state_t));

        struct stack_trace_key_t *key = &state->key;
        key->tgid = id >> 32;
        key->pid = (__u32) id;

        /*
         * CPU idle stacks will not be collected.
         */
        if (key->tgid == key->pid && key->pid == 0) {
                return 0;
        }

        key->cpu = bpf_get_smp_processor_id();
        bpf_get_current_comm(&key->comm, sizeof(key->comm));
        key->timestamp = bpf_ktime_get_ns();

        bpf_probe_read_user(&key->mem_addr, sizeof(__u64), (void *)data->address);
        key->mem_size = (__u64) data->size;

    // add one frame for cudaMalloc
    // native unwinding start from uretprobe, which has the reg state after cudaMalloc return
    add_frame(&state->stack, data->rip);

        state->regs.ip = PT_REGS_IP(ctx);
        state->regs.sp = PT_REGS_SP(ctx);
        state->regs.bp = PT_REGS_FP(ctx);
    add_frame(&state->stack, state->regs.ip);
    bpf_tail_call(ctx, &NAME(progs_jmp_uprobe_map), PROG_DWARF_UNWIND_IDX);

    return 0;
}
```

③ eBPF uprobe
Hook cuda_free
获取释放的显存地址

```c
SEC("uprobe/cuda_free")
int uprobe_cuda_free(struct pt_regs *ctx) {
    __u64 id = bpf_get_current_pid_tgid();

        void *addr = (void *) PT_REGS_PARM1(ctx);

        __u32 zero = 0;
        unwind_state_t *state = heap__lookup(&zero);
        if (state == NULL) {
                return 0;
        }
        __builtin_memset(state, 0, sizeof(unwind_state_t));

        struct stack_trace_key_t *key = &state->key;
        key->tgid = id >> 32;
        key->pid = (__u32) id;

        /*
         * CPU idle stacks will not be collected.
         */
        if (key->tgid == key->pid && key->pid == 0) {
                return 0;
        }

        key->cpu = bpf_get_smp_processor_id();
        bpf_get_current_comm(&key->comm, sizeof(key->comm));
        key->timestamp = bpf_ktime_get_ns();

        key->mem_addr = (__u64) addr;

        bpf_perf_event_output(ctx, &NAME(cuda_memory_output), BPF_F_CURRENT_CPU, &state->key, sizeof(state->key));

    return 0;
}
```

④ 计算当前
显存消耗

使用 eBPF 实现分布式追踪的技术挑战



Network-Centric Distributed Tracing with DeepFlow: Troubleshooting Your Microservices in Zero Code

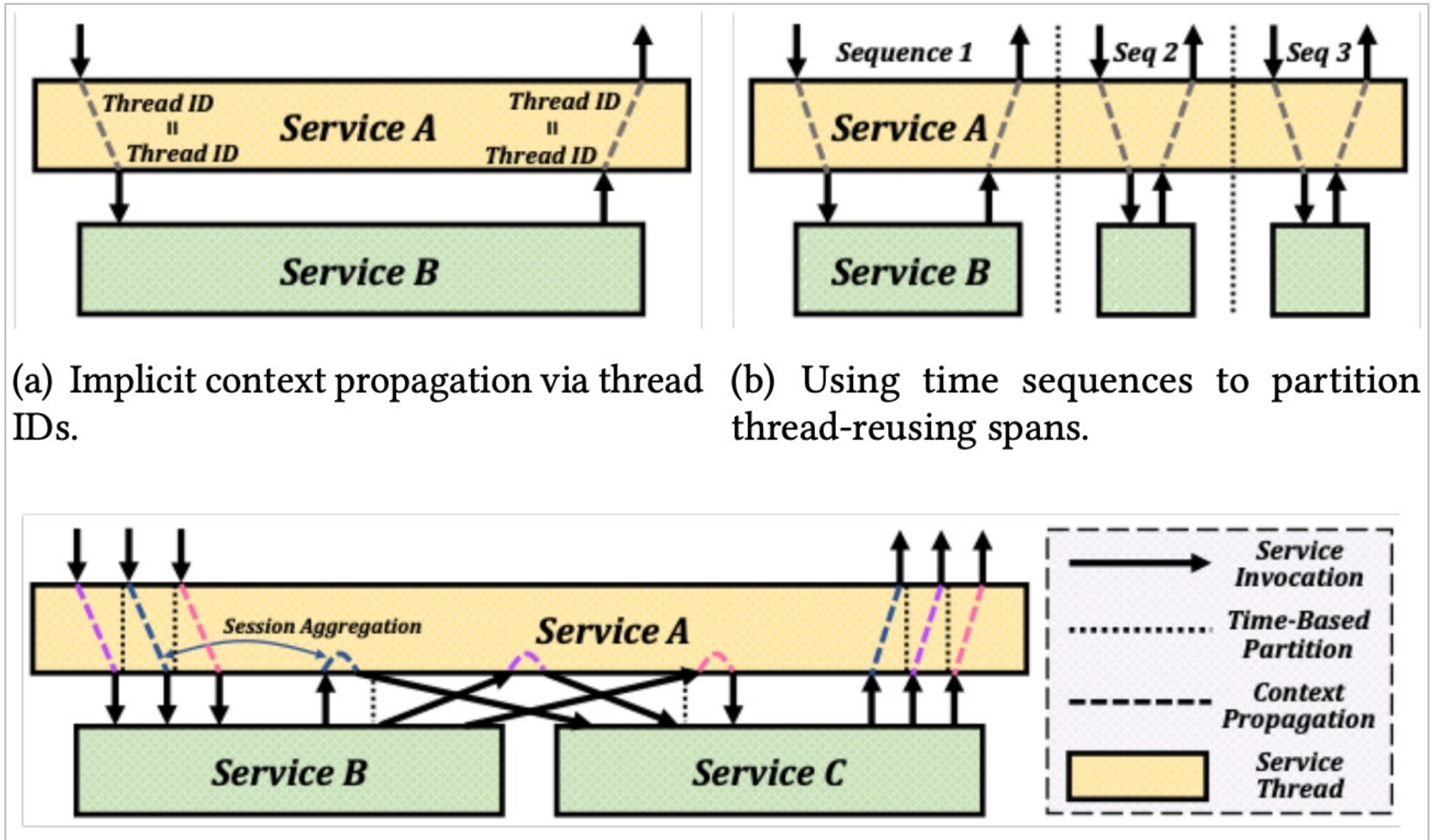
Junxian Shen[1 2 °], Han Zhang[1 4 •], Yang Xiang[2 ⋆], Xingang Shi[1 4], Xinrui Li[3], Yunxi Shen[3], Zijian Zhang[1 2], Yongxiang Wu[3], Xia Yin[3 4], Jilong Wang[1 4], Mingwei Xu[1 4], Yahui Li[1], Jiping Yin[2], Jianchang Song[2], Zhuofeng Li[2], Runjie Nie[2]

[1]Institute for Network Sciences and Cyberspace, Tsinghua University
[2]Yunshan Networks
[3]Department of Computer Science and Technology, Tsinghua University
[4]Zhongguancun Laboratory
°shenjx22@mails.tsinghua.edu.cn •zhhan@tsinghua.edu.cn ⋆xiangyang@yunshan.net

ABSTRACT

Microservices are becoming more complicated, posing new challenges for traditional performance monitoring solutions. On the one hand, the rapid evolution of microservices places a significant

Mingwei Xu[1 4], Yahui Li[1], Jiping Yin[2], Jianchang Song[2], Zhuofeng Li[2], Runjie Nie[2]. 2023. Network-Centric Distributed Tracing with DeepFlow: Troubleshooting Your Microservices in Zero Code. In *ACM SIGCOMM 2023 Conference (ACM SIGCOMM '23), September 10, 2023, New York, NY, USA*. ACM, New York, NY, USA, 18 pages. https://doi.org/10.1145/3603269.3604823



(a) Implicit context propagation via thread IDs.

(b) Using time sequences to partition thread-reusing spans.

(c) Association for multiple requests or responses.

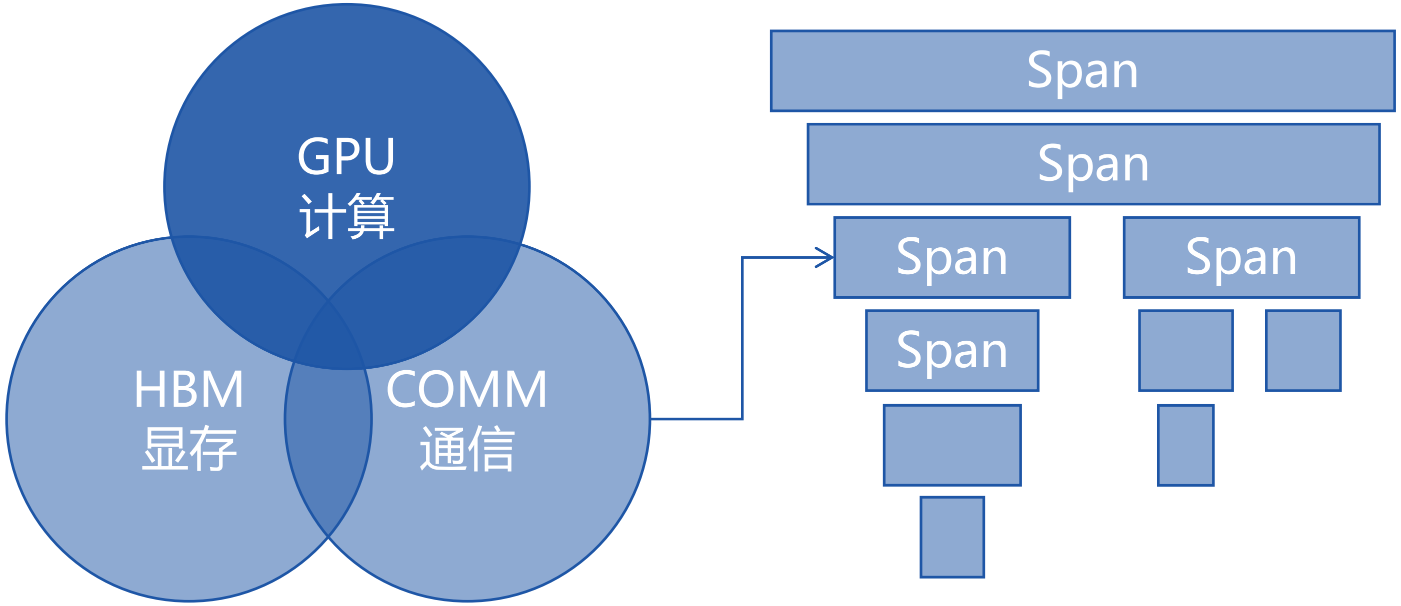
Figure 7: Intra-component causal association.

[Network-Centric Distributed Tracing with DeepFlow: Troubleshooting Your Microservices in Zero Code]()

PART 04
实践：PyTorch 全栈剖析和追踪

DeepFlow 中的 eBPF AutoProfiling

1. Compute Profiling



PyTorch + nanoGPT CPU & GPU 火焰图

到底哪个函数调用栈在 CPU、GPU 上花费的时间最长?

到底一个 Task 的哪个 Worker 拖累了整体的速度?

零侵扰、全栈回答上述问题

CPU & GPU 全栈剖析:

√ Python 业务函数

√ Python vLLM 函数

√ Python PyTorch 函数

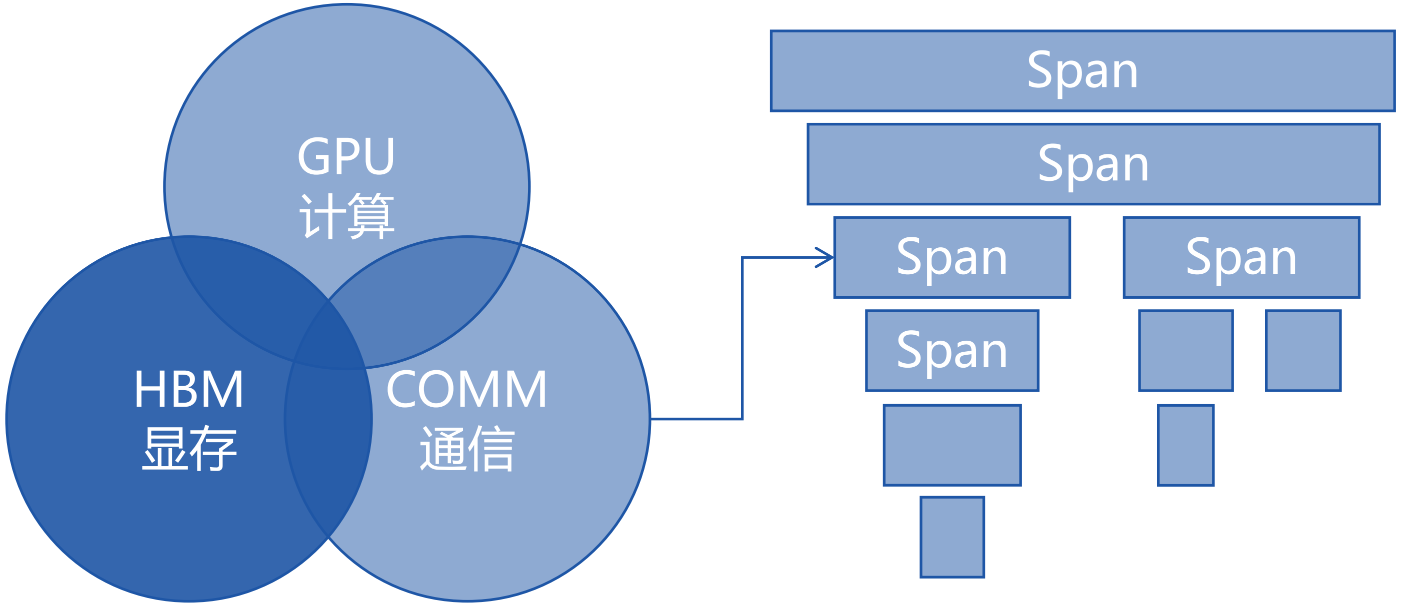
√ C/C++ Lib 函数

√ CUDA 入口函数

PyTorch + nanoGPT CPU & GPU 火焰图

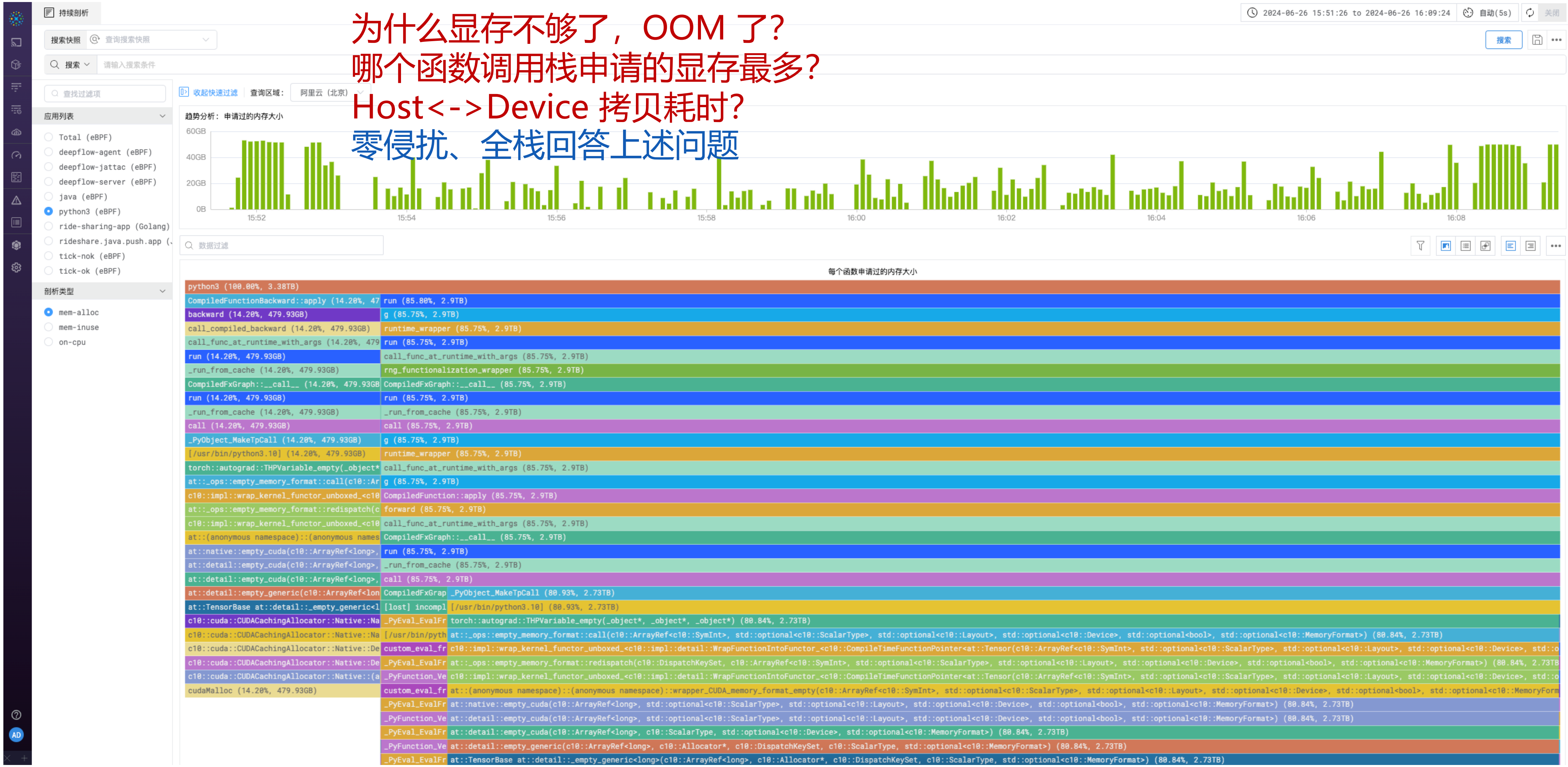
名称	自身消耗	总消耗
[1] cudaMemcpyAsync	4.431m	4.574m
[1] cudaLaunchKernel	14.141s	41.717s
[1] cublasLtHSHMatmul	7.515s	23.061s
[1] cudaGetDevice	1.424s	2.859s
[1] cublasGemmEx	1.414s	25.121s
[1] cublasLtHSHMatmulAlgoGetHeuristic	595.959ms	646.464ms
[1] cuDevicePrimaryCtxGetState	343.434ms	343.434ms
[1] cudaEventQuery	30.303ms	30.303ms
[1] custom_eval_frame_shim	0μs	45.03s

2. HBM Profiling

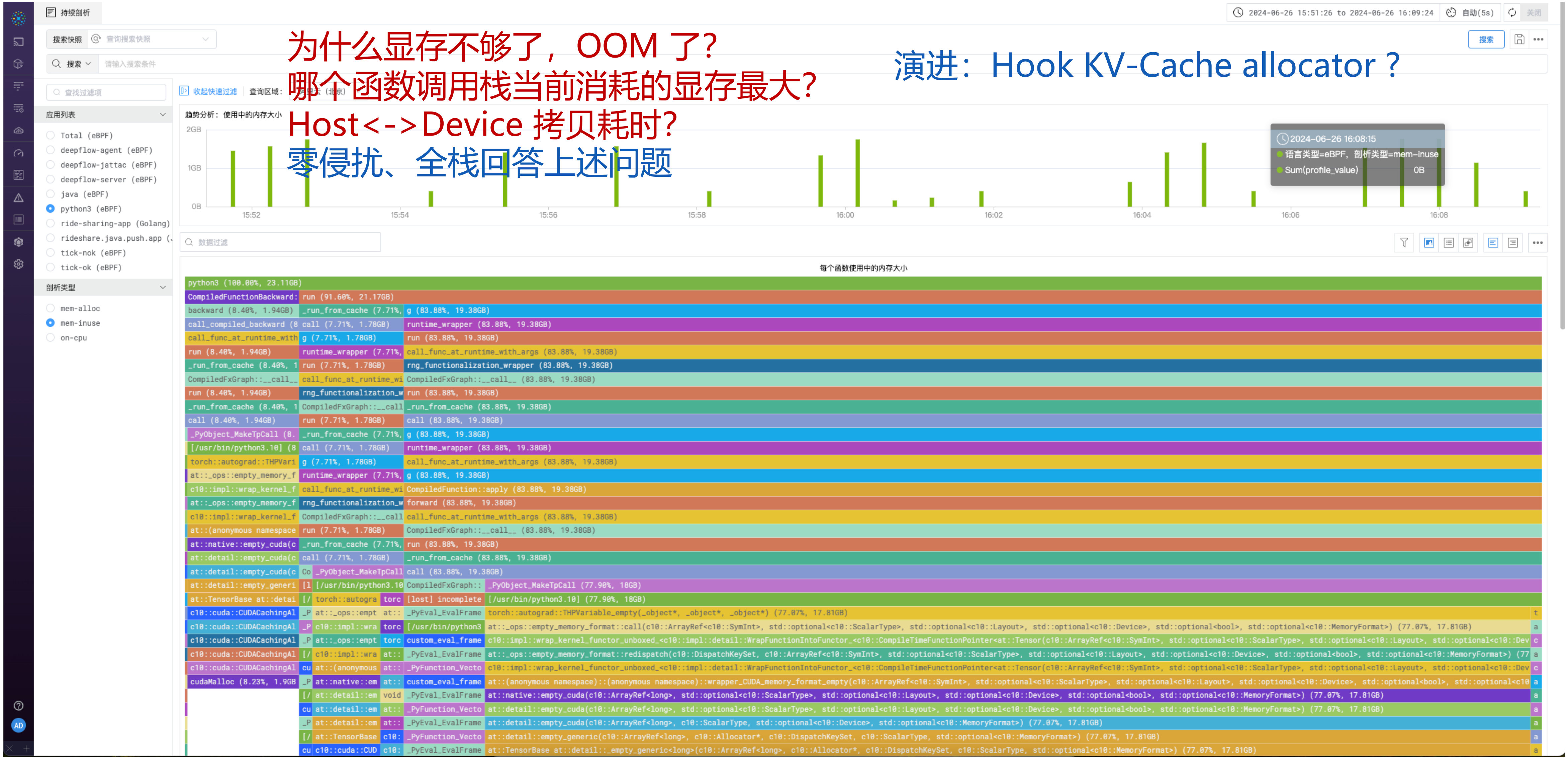


CUDA mem-alloc 显存申请火焰图

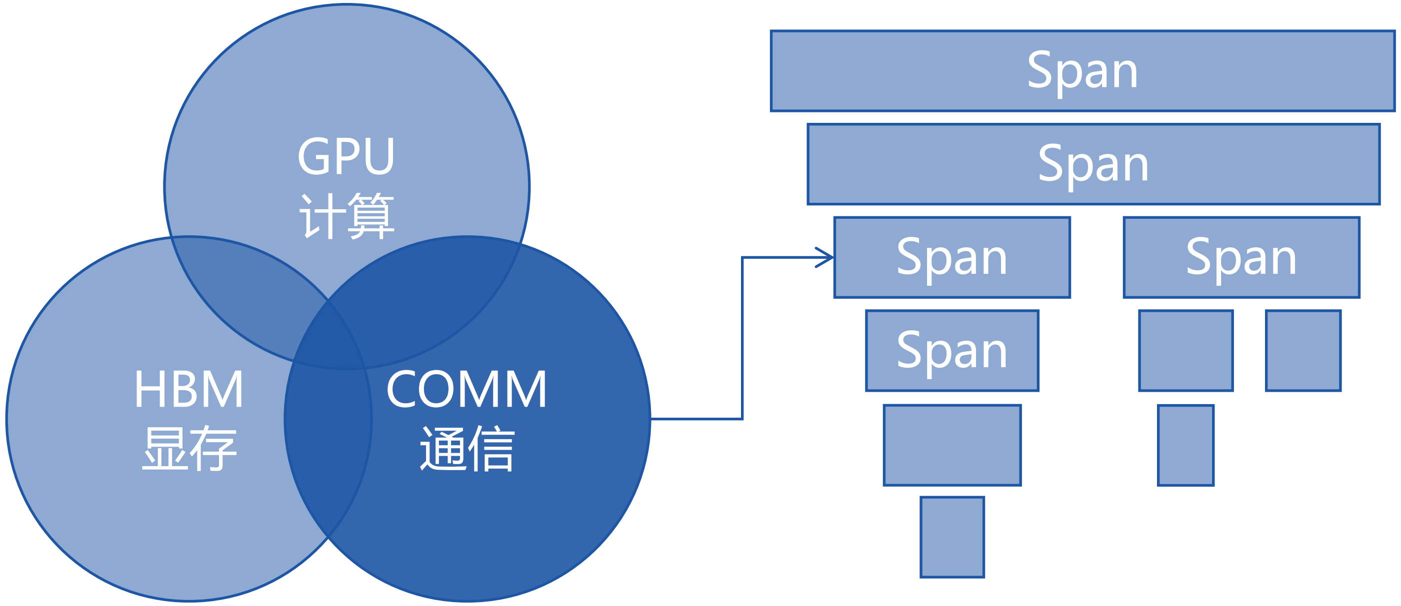
为什么显存不够了，OOM 了?
哪个函数调用栈申请的显存最多?
Host<->Device 拷贝耗时?
零侵扰、全栈回答上述问题



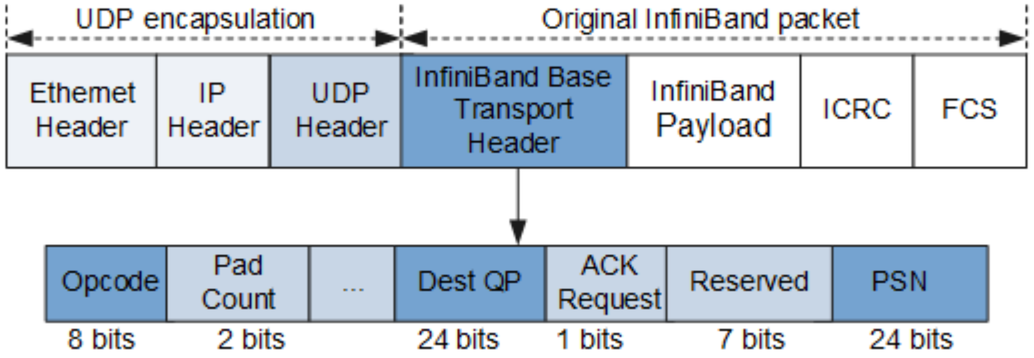
CUDA mem-inuse 显存实时用量火焰图



3. COMM. Profiling



RDMA 网络性能剖析



RoCEv2 Packet

关键标签：

- Client 及其关联的 K8s Pod、标签
- Server 及其关联的 K8s Pod、标签
- Client Queue Pair
- Server Queue Pair

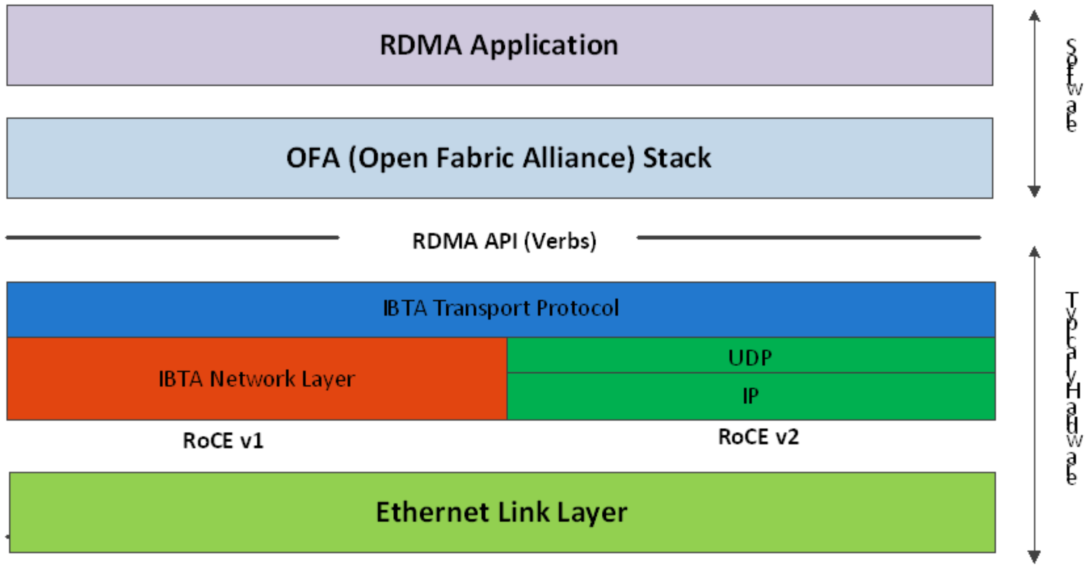
关键指标：

- 丢包率：即 NACK 的比例
- 时延：ACK 的时延
- 吞吐：通信对的 bps、pps 等

eBPF Hooks

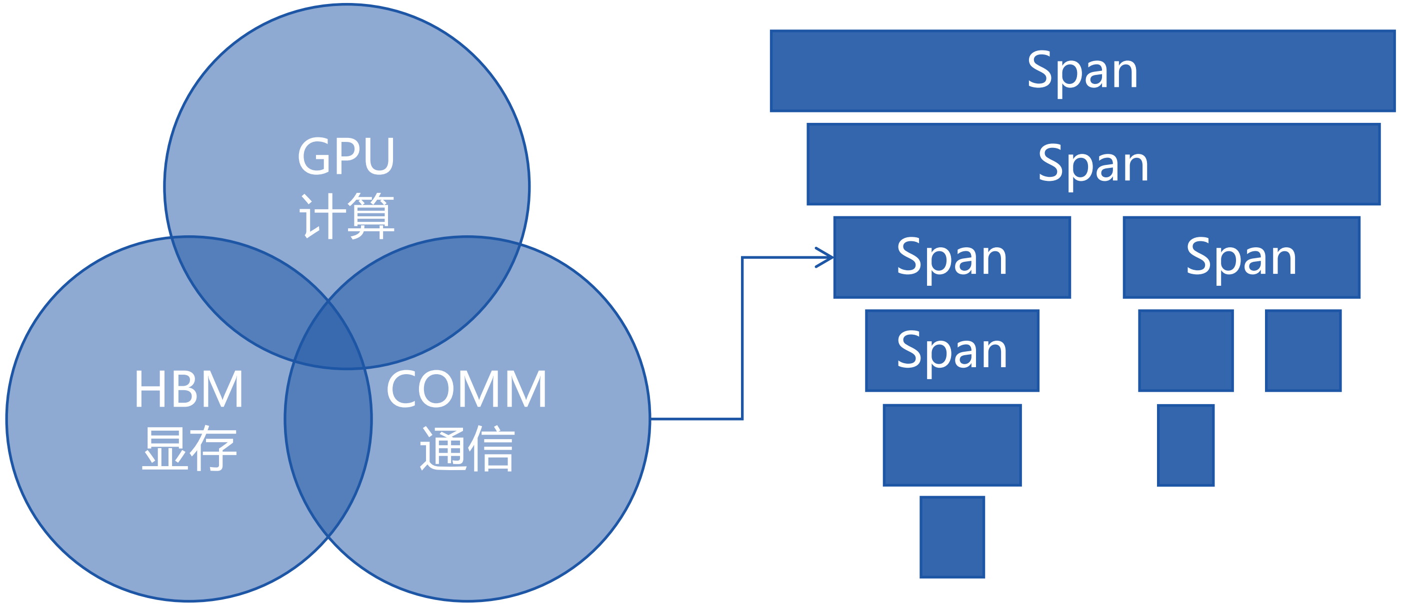
Function	作用
ibv_modify_qp	Queue Pair 状态修改
ibv_reg_mr	Memory Region 注册
ibv_dereg_mr	Memory Region 注销
ibv_post_send	buffer 发送或 RDMA 读写
ibv_poll_cq	等待 wr 完成

libibverbs Hooks, NCCL Hooks, PyTorch Hooks, ...

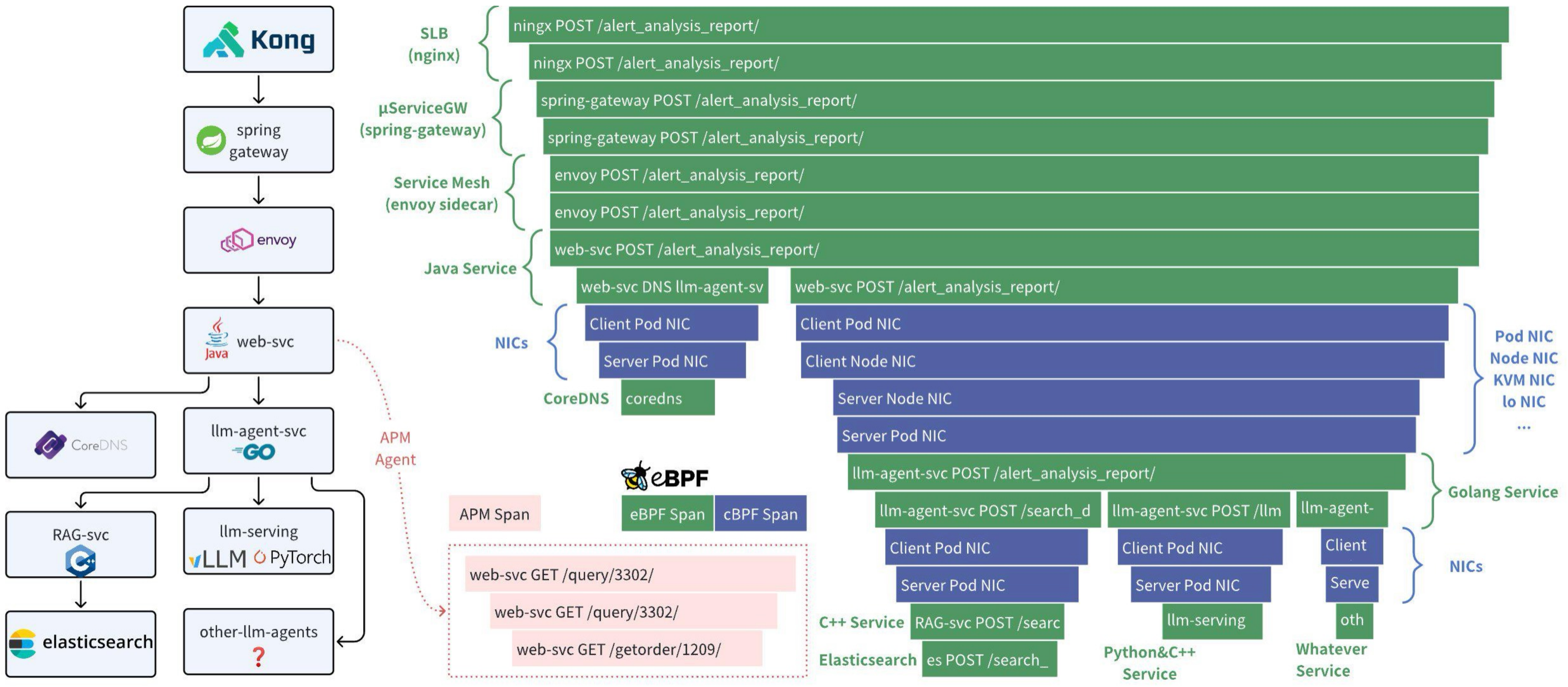


使用 eBPF Hook RDMA API

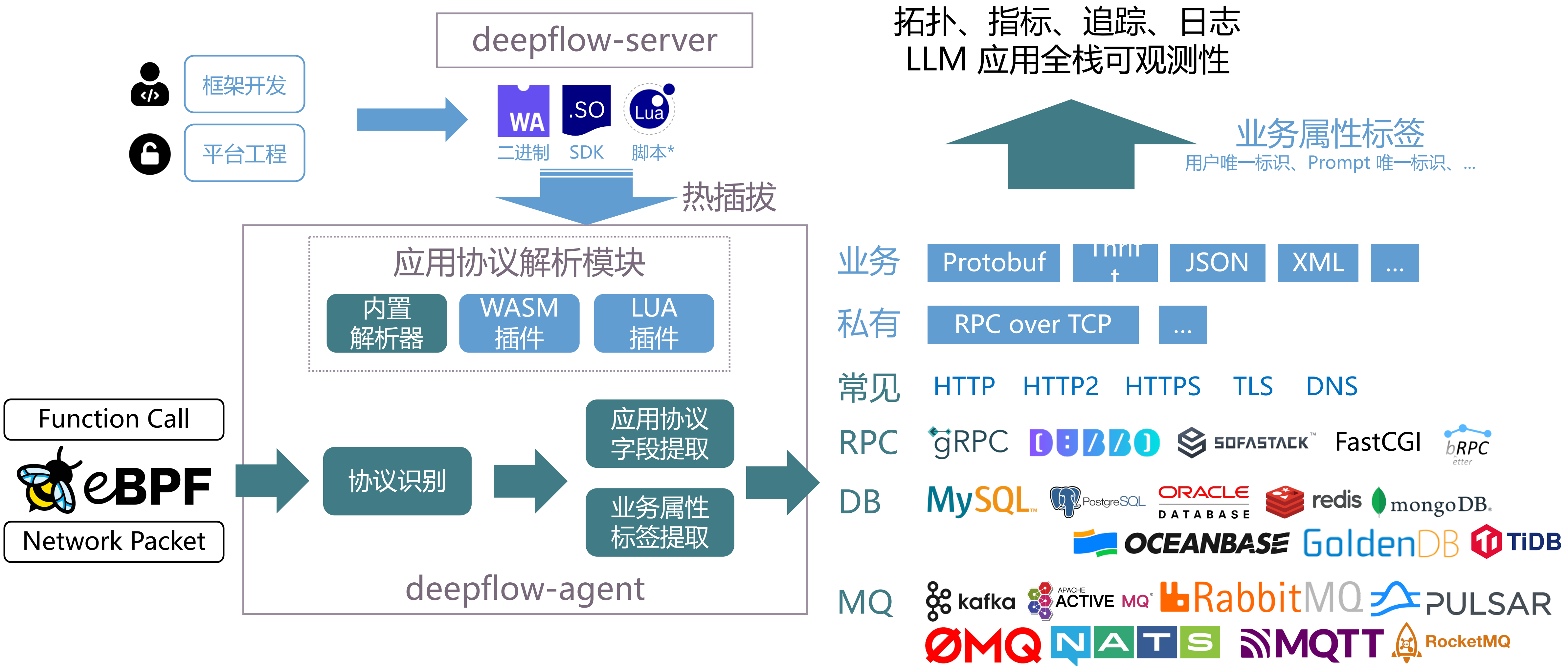
4. Distributed Tracing



在线推理服务、端侧 ROS2 推理服务



内置协议识别能力 + 可编程协议识别能力



PART 05

探索：Agent 自动优化 ML 代码

如何快速高效的理解全栈函数

eBPF

LLM

Business Code

Prompt Engineering
tag.commit_id

python Requests

RAG
Docs / Comments

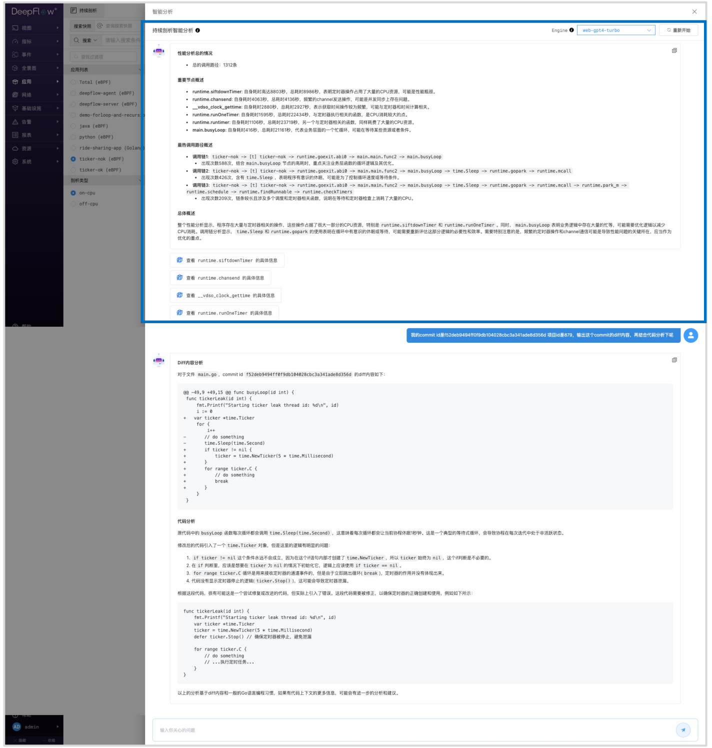
GNU C Library

LLM / 微调

The Linux Kernel

LLM / 微调

利用 LLM Agent 自动优化 ML 代码



持续剖析智能分析

性能分析总的情况

- 总的调用路径：1312条

重要节点概述

- runtime.siftdownTimer: 自身耗时高达8803秒，总耗时8986秒，表明定时器操作占用了大量的CPU资源，可能
- runtime.chansend: 自身耗时4063秒，总耗时4136秒，频繁的channel发送操作，可能是并发同步上存在问题。
- __vdso_clock_gettime: 自身耗时2880秒，总耗时2927秒，表示获取时间操作较为频繁，可能与定时器和时间
- runtime.runOneTimer: 自身耗时1595秒，总耗时22434秒，与定时器执行相关的函数，是CPU消耗较大的点。
- runtime.runtimer: 自身耗时1106秒，总耗时23719秒，另一个与定时器相关的函数，同样耗费了大量的CPU资源
- main.busyLoop: 自身耗时416秒，总耗时21161秒，代表业务层面的一个忙循环，可能在等待某些资源或者条件。

最热调用路径概述

- **调用链1**: `ticker-nok -> [t] ticker-nok -> runtime.goexit.abi0 -> main.main.func2 -> main.busyLoop`
  - 出现次数588次，结合 `main.busyLoop` 节点的高耗时，重点关注业务层函数的循环逻辑及其优化。
- **调用链2**: `ticker-nok -> [t] ticker-nok -> runtime.goexit.abi0 -> main.main.func2 -> main.busyLoop -> time.Sleep -> runtime.gopark -> runtime.mcall`
  - 出现次数426次，含有 `time.Sleep`，表明程序有意识的休眠，可能是为了控制循环速度或等待条件。
- **调用链3**: `ticker-nok -> [t] ticker-nok -> runtime.goexit.abi0 -> main.main.func2 -> main.busyLoop -> time.Sleep -> runtime.gopark -> runtime.mcall -> runtime.park_m -> runtime.schedule -> runtime.findRunnable -> runtime.checkTimers`
  - 出现次数209次，链条较长且涉及多个调度和定时器相关函数，说明在等待和定时器检查上消耗了大量的CPU。

总体概述

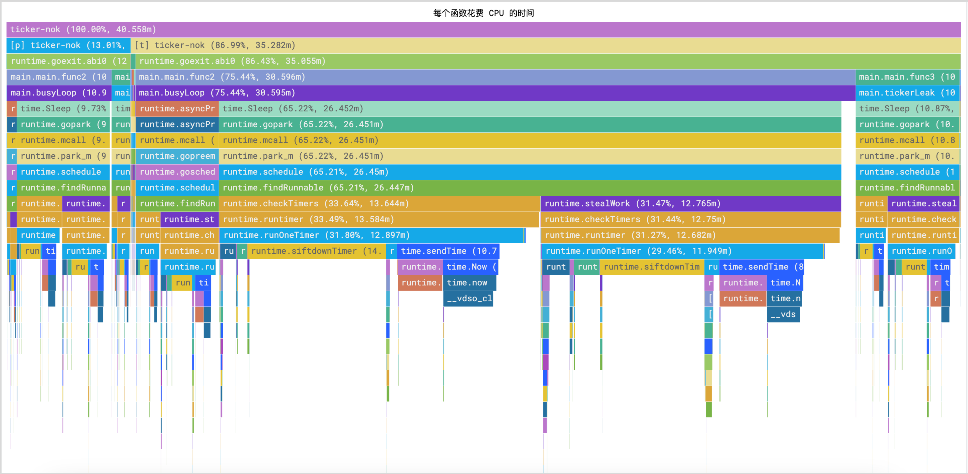
整个性能分析显示，程序存在大量与定时器相关的操作，这些操作占据了很大一部分的CPU资源，特别是 `runtime.siftdownTimer` 和 `runtime.runOneTimer`。同时，`main.busyLoop` 表明业务逻辑中存在大量的忙等，可能需要优化逻辑以减少CPU消耗。调用链分析显示，`time.Sleep` 和 `runtime.gopark` 的使用表明在循环中有意识的休眠或等待，可能需要重新评估这部分逻辑的必要性和效率。需要特别注意的是，频繁的定时器操作和channel通信可能是导致性能问题的关键所在，应当作为优化的重点。

查看 runtime.siftdownTimer 的具体信息

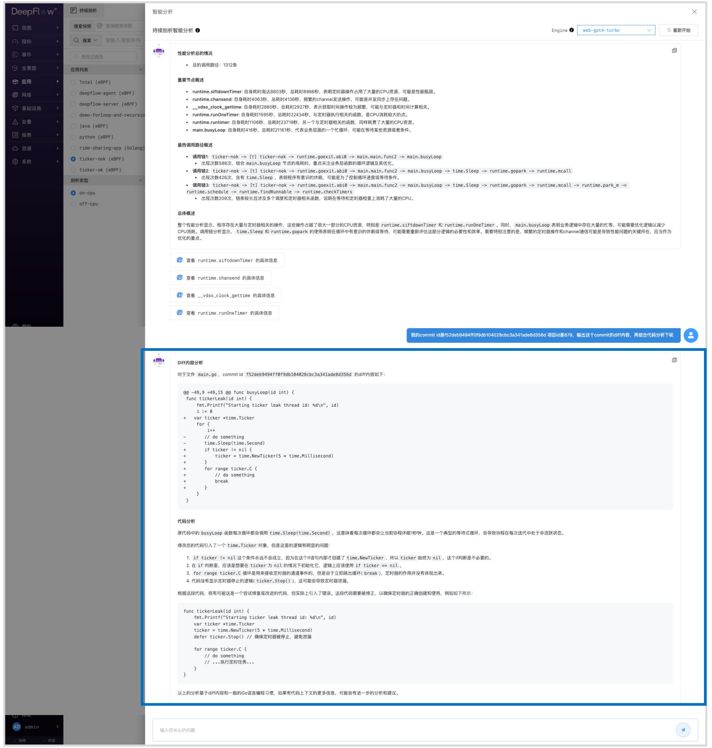
查看 runtime.chansend 的具体信息

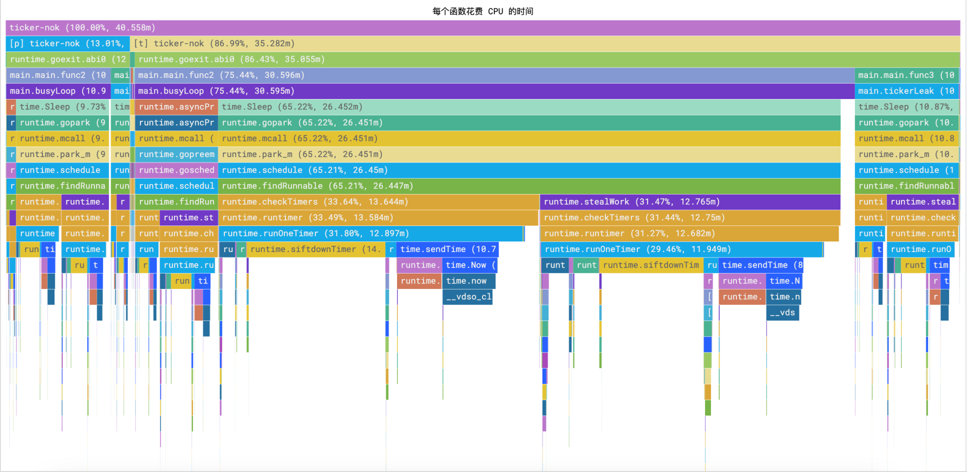
查看 __vdso_clock_gettime 的具体信息

查看 runtime.runOneTimer 的具体信息



利用 LLM Agent 自动优化 ML 代码 / 2





Diff内容分析

对于文件 `main.go`，commit id `f52deb9494ff0f9db104028cbc3a341ade8d356d` 的diff内容如下：

```
@@ -49,9 +49,15 @@ func busyLoop(id int) {
 func tickerLeak(id int) {
     fmt.Printf("Starting ticker leak thread id: %d\n", id)
     i := 0
+    var ticker *time.Ticker
     for {
         i++
-        // do something
-        time.Sleep(time.Second)
+        if ticker != nil {
+            ticker = time.NewTicker(5 * time.Millisecond)
+        }
+        for range ticker.C {
+            // do something
+            break
+        }
     }
 }
```

代码分析

原代码中的 `busyLoop` 函数每次循环都会调用 `time.Sleep(time.Second)`，这意味着每次循环都会让当前协程休眠1秒钟。这是一个典型的等待式循环，会导致协程在每次迭代中处于非活跃状态。

修改后的代码引入了一个 `time.Ticker` 对象，但是这里的逻辑有明显的问题：

1. `if ticker != nil` 这个条件永远不会成立，因为在这个if语句内部才创建了 `time.NewTicker`，所以 `ticker` 始终为 `nil`，这个if判断是不必要的。
2. 在 `if` 判断里，应该是想要在 `ticker` 为 `nil` 的情况下初始化它，逻辑上应该使用 `if ticker == nil`。
3. `for range ticker.C` 循环是用来接收定时器的通道事件的，但是由于立即跳出循环(`break`)，定时器的作用并没有体现出来。
4. 代码没有显示定时器停止的逻辑(`ticker.Stop()`)，这可能会导致定时器泄漏。

根据这段代码，很有可能这是一个尝试修复或改进的代码，但实际上引入了错误。这段代码需要被修正，以确保定时器的正确创建和使用，例如如下所示：

```
func tickerLeak(id int) {
    fmt.Printf("Starting ticker leak thread id: %d\n", id)
    var ticker *time.Ticker
    ticker = time.NewTicker(5 * time.Millisecond)
    defer ticker.Stop() // 确保定时器被停止，避免泄漏

    for range ticker.C {
        // do something
        // ...执行定时任务...
    }
}
```

以上的分析基于diff内容和一般的Go语言编程习惯，如果有代码上下文的更多信息，可能会有进一步的分析和建议。

DeepFlow：零侵扰实现 AI 应用的全栈可观测性

AI+研发数字峰会
AI+ Development Digital summit

CPU+GPU 全栈持续剖析

集合通信网络性能监控

在线推理服务分布式追踪

无需修改代码，无需重启进程

THANKS