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China 2024

Unlocking LLM Performance with eBPF: Optimizing Training and Inference Pipelines

向阳，云杉网络

Outline

1. **背景**：训练和推理的效率挑战
2. **现状**：传统解决方案和工具的问题
3. **方法**：eBPF 构建零侵扰可观测性
4. **实践**：PyTorch 全栈剖析和追踪

LLM 训练开销大、效率低

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

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

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.

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%

148/54*365/16384 = 6%

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

GPU 年化故障高：6%~11%

故障并不是训练低效的唯一原因

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？

内核计算

```
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).

网络传输

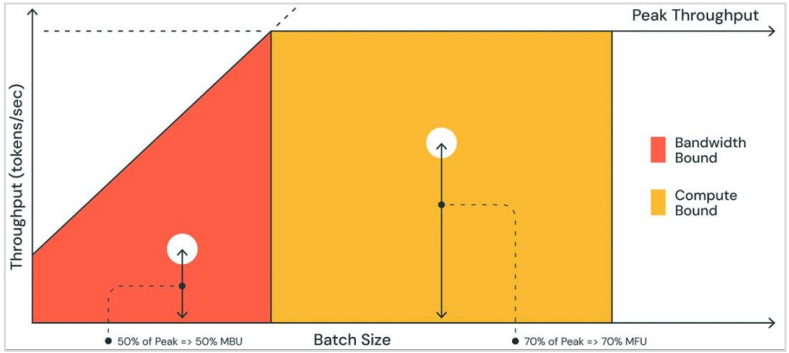
In a distributed job, GPUs consistently share data such as gradients and output tensors. This data exchange between GPUs, whether through the network or PCI Express bus, frequently interrupts their designated tasks and causes a sudden drop in GPU utilization to zero. Within the *Data Exchange* category, 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.

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

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

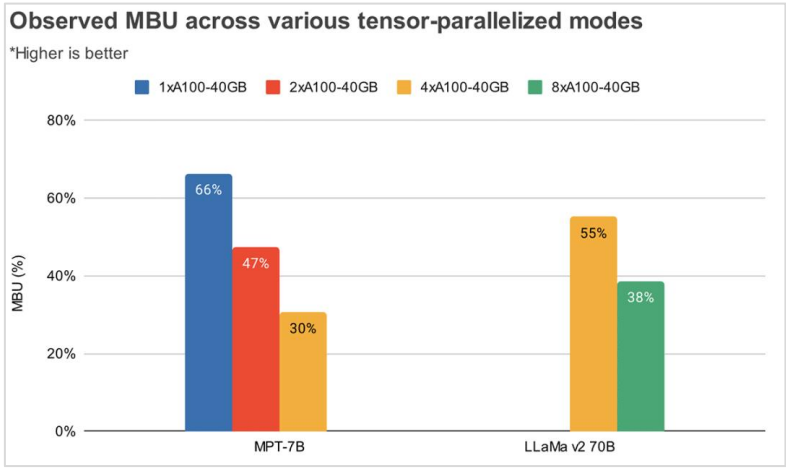
GPU 越少，则每个 GPU 需要加载更多的模型参数。

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



GPU 并非越多越好

GPU 越多，则通信越复杂，内存碎块越多。

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

没有银弹，可观测性是优化的前提。

排查 LLM 推理显存消耗的挑战

- Biz
- vLLM
- PyTorch
- Python / C++

PyTorch

Sig

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.

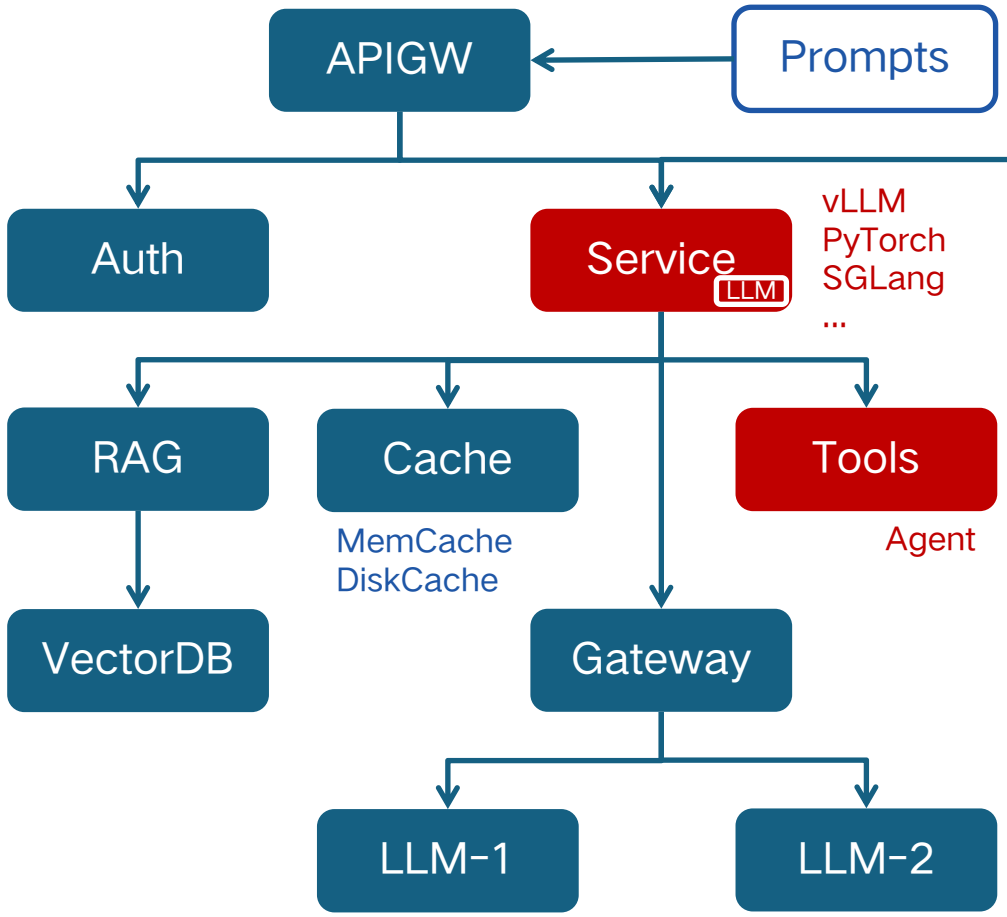
The basic story: vLLM tries to allocate as much memory as possible for KV Cache to accelerate LLM inference. In order to do so, it first profiles the memory usage, guess the maximum size of memory available for KV Cache, and also leave some for storing activation during inference.

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.

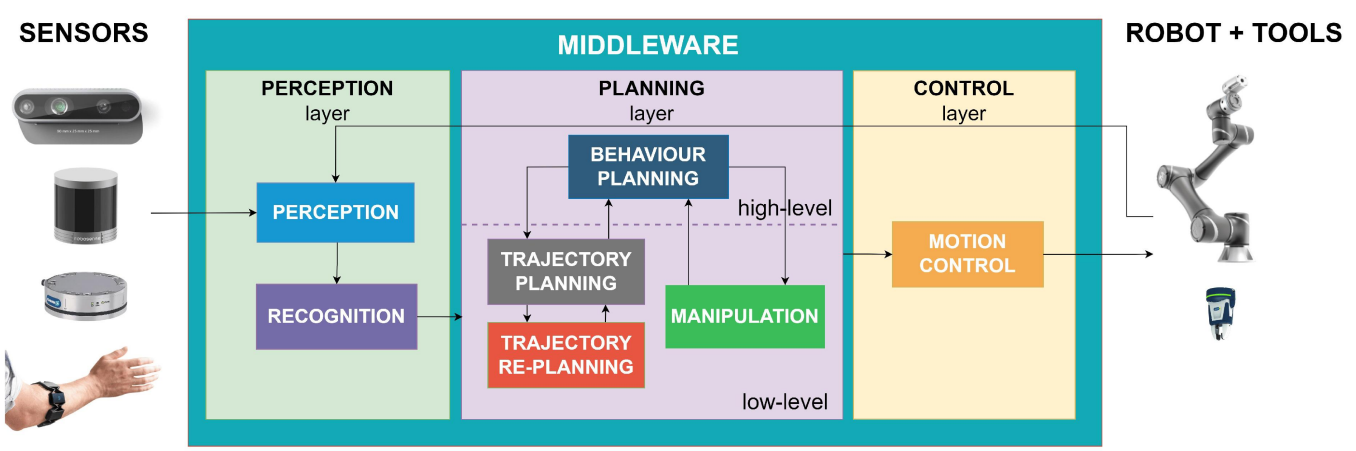
Here are the diagnoses data (produced by `torch.cuda.memory_stats` and `torch.cuda.memory._dump_snapshot`), collected from a server with 2 L4 GPUs:

从推理应用到在线 LLM 推理服务



云 - 在线推理服务是一个复杂的分布式服务
TTFT、TPOT、时延、吞吐

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

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

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

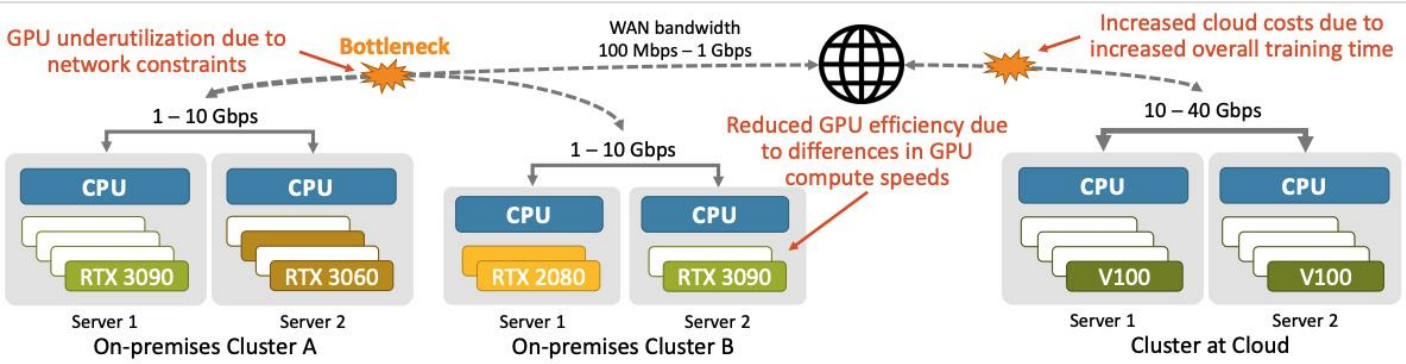
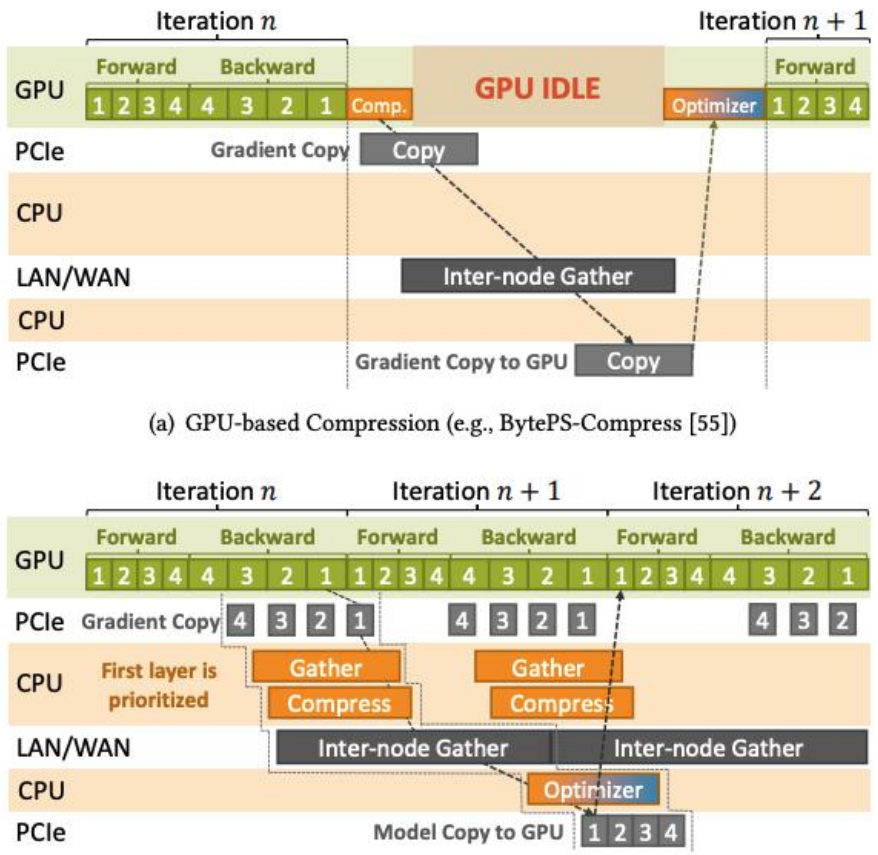


Figure 1: A multi-cluster environment with two on-premises lab clusters and a cloud cluster.

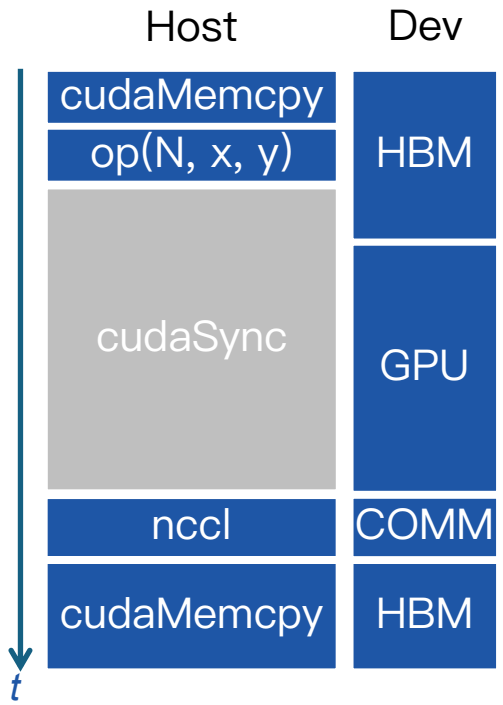


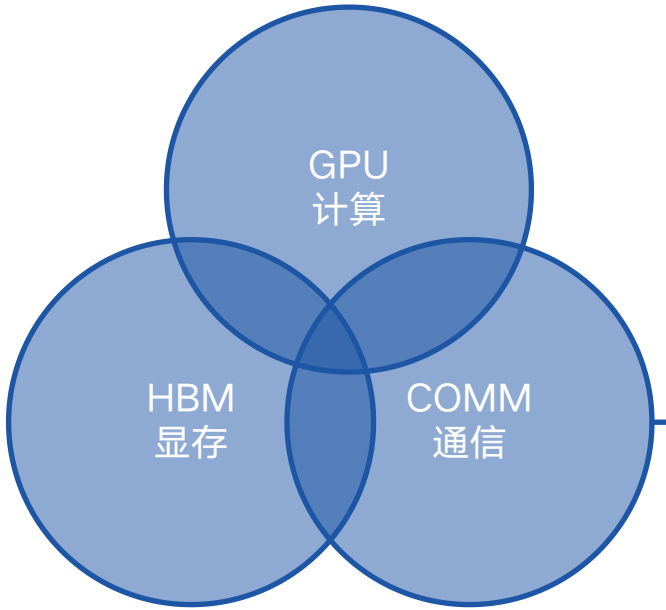
(a) GPU-based Compression (e.g., BytePS-Compress [55])

(b) StellaTrain (Ours)

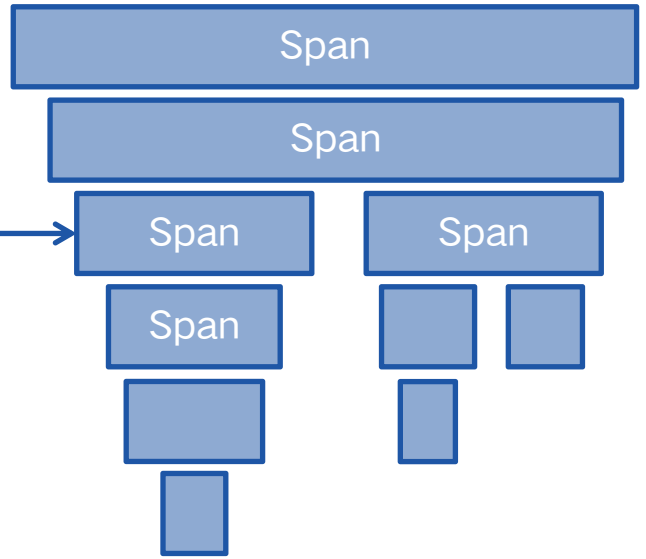
Figure 4: Comparison of training pipelines.

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

Gateway

Auth

3rd

ROS2 Nodes

Gateway

.....

Outline

1. **背景**：训练和推理的效率挑战
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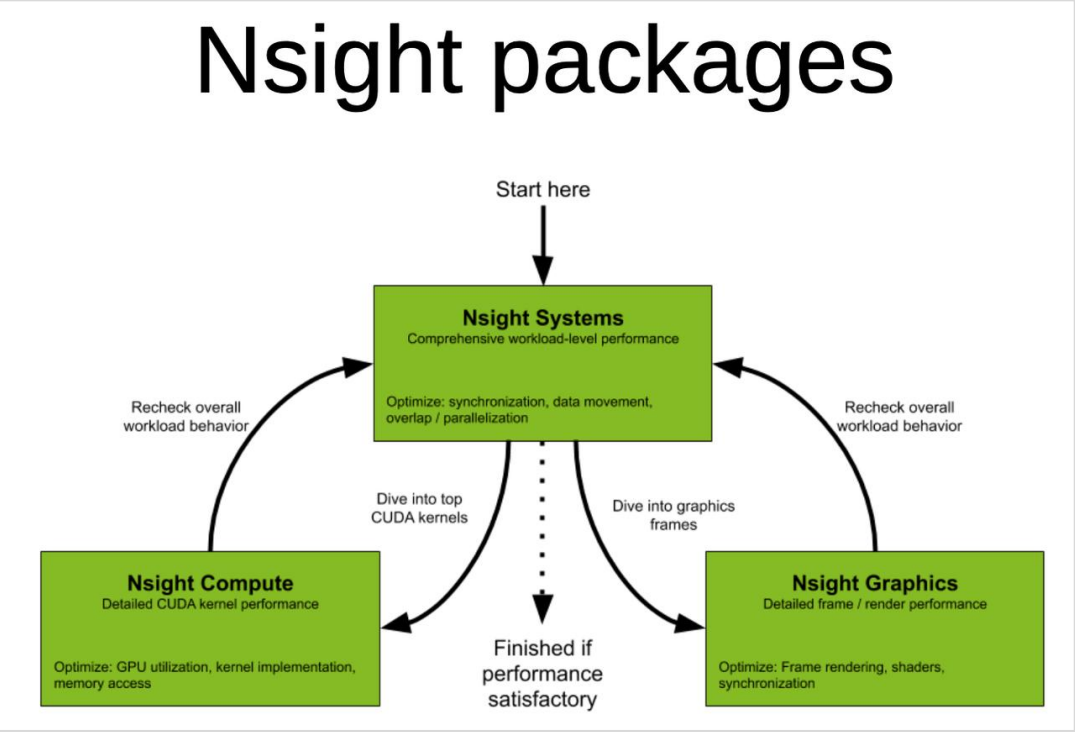
DCGM Prometheus Exporter

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。

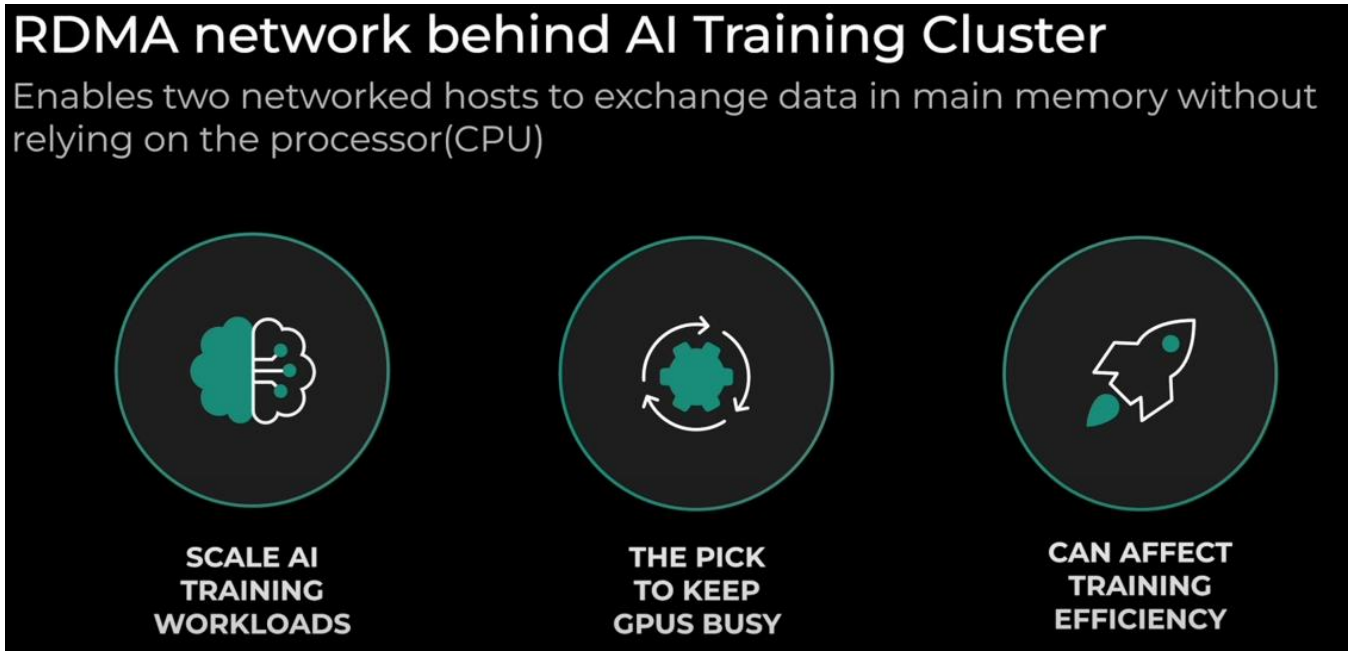
```python
def trace_handler(p):
    output = p.key_averages().table(sort_by="self_cuda_time_total", row_limit=10)
    print(output)
    p.export_chrome_trace("/tmp/trace_" + str(p.step_num) + ".json")

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。

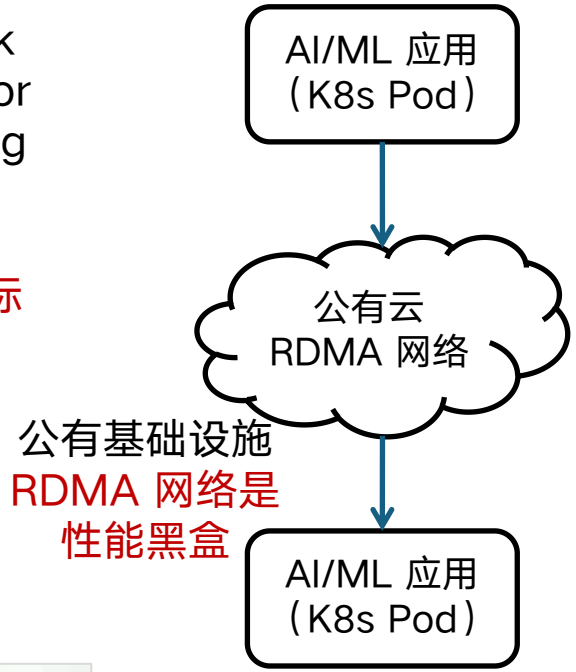
RDMA 网络：网卡/交换机指标、拨测



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

SIGCOMM 2024

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

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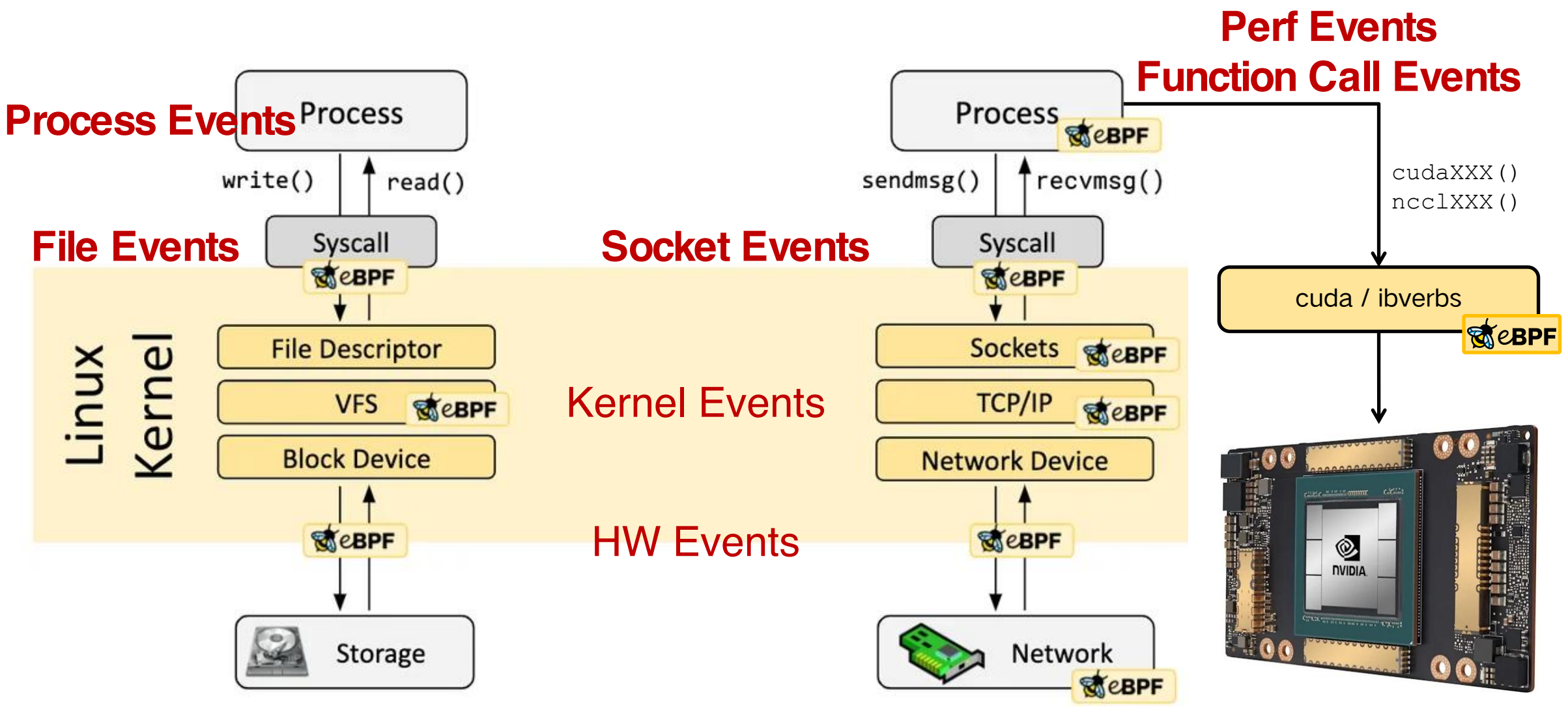
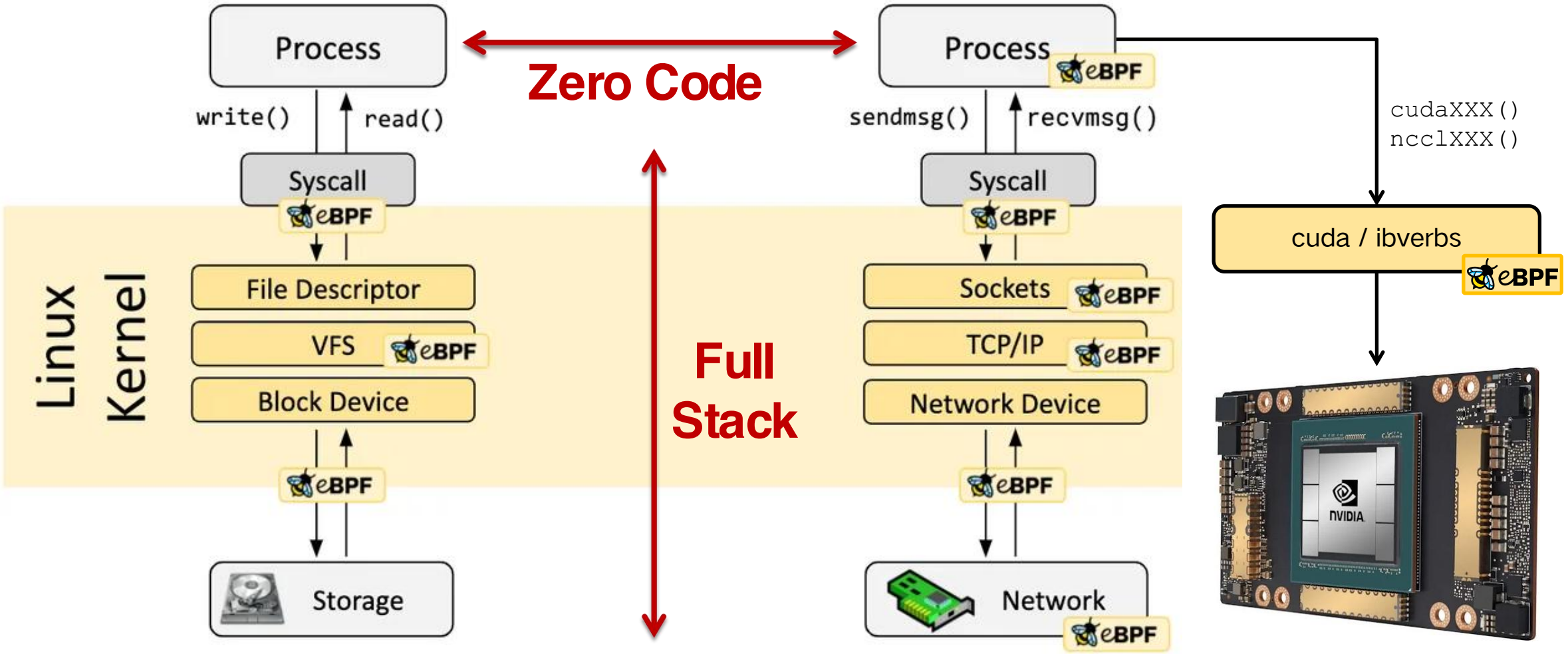
eBPF 的可观测性能力



使用 eBPF 实现可观测性的优势



他山之石：eBPF Profiling & Tracing

Meta：eBPF GPU Profiling

Trace-enabled Timing Model Synthesis for ROS2-based Autonomous Applications

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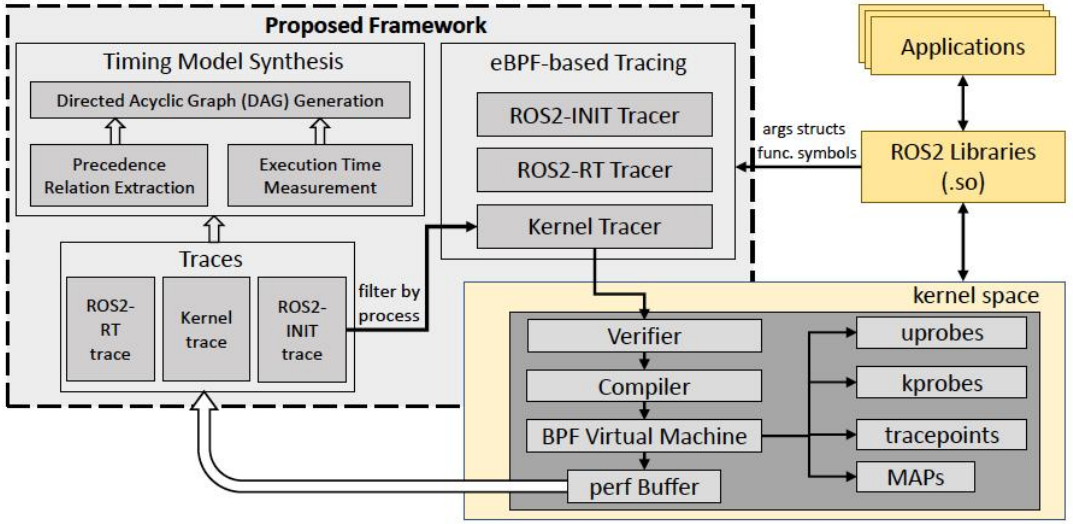


Fig. 1: Proposed trace-enabled timing model synthesis framework.

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

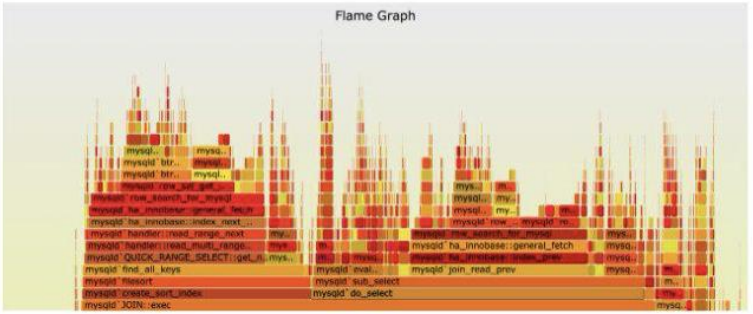
GPU

CPU

Python unwind

DWARF unwind / Frame Pointer

Stack Merge + Thread State Recover



On-CPU
CPU 运算耗时

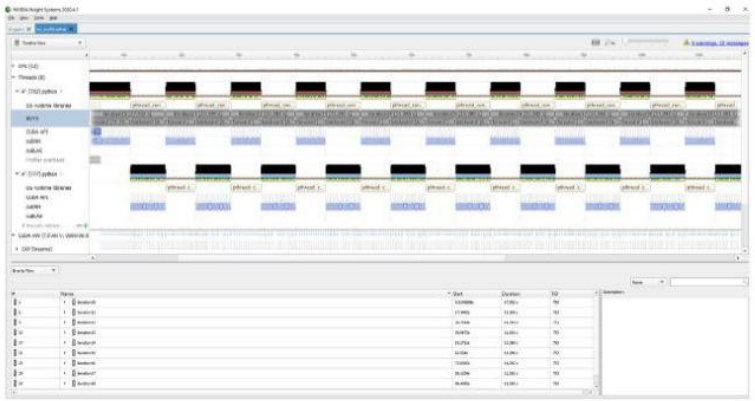
On-GPU
GPU 运算耗时

Off-GPU
GPU 等待耗时

HBM-Malloc
显存申请量

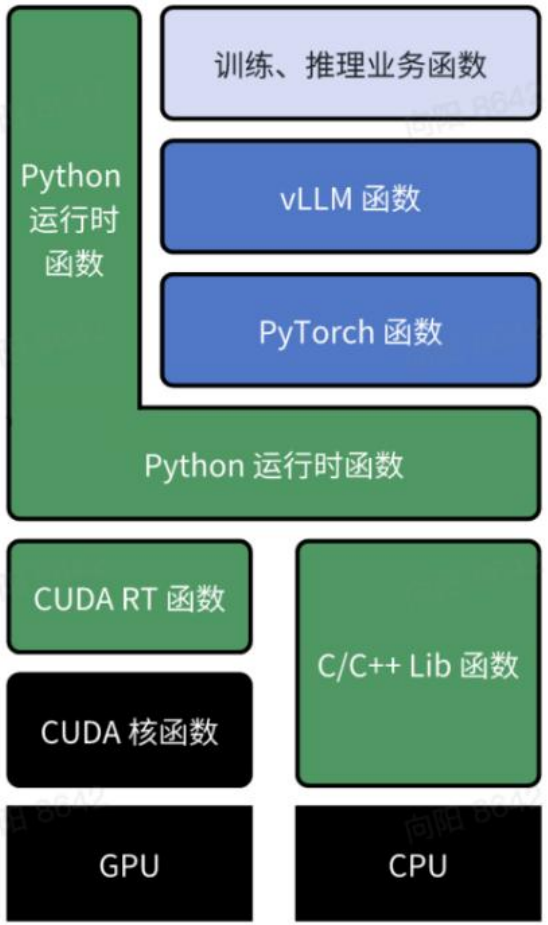
HBM-Inuse
显存用量

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

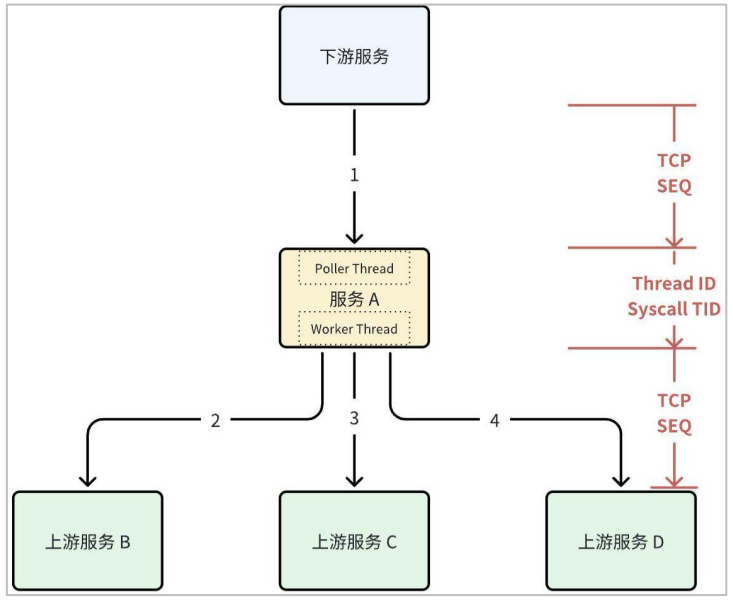
```c
SEC("uretprobe/cuda_malloc")
int uretprobe_cuda_malloc(struct pt_regs *ctx)
{
    __u64 id = bpf_get_current_pid_tgid();
    __u32 tgid = id >> 32;

    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

④ 计算当前
显存消耗

```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;
}
```

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]
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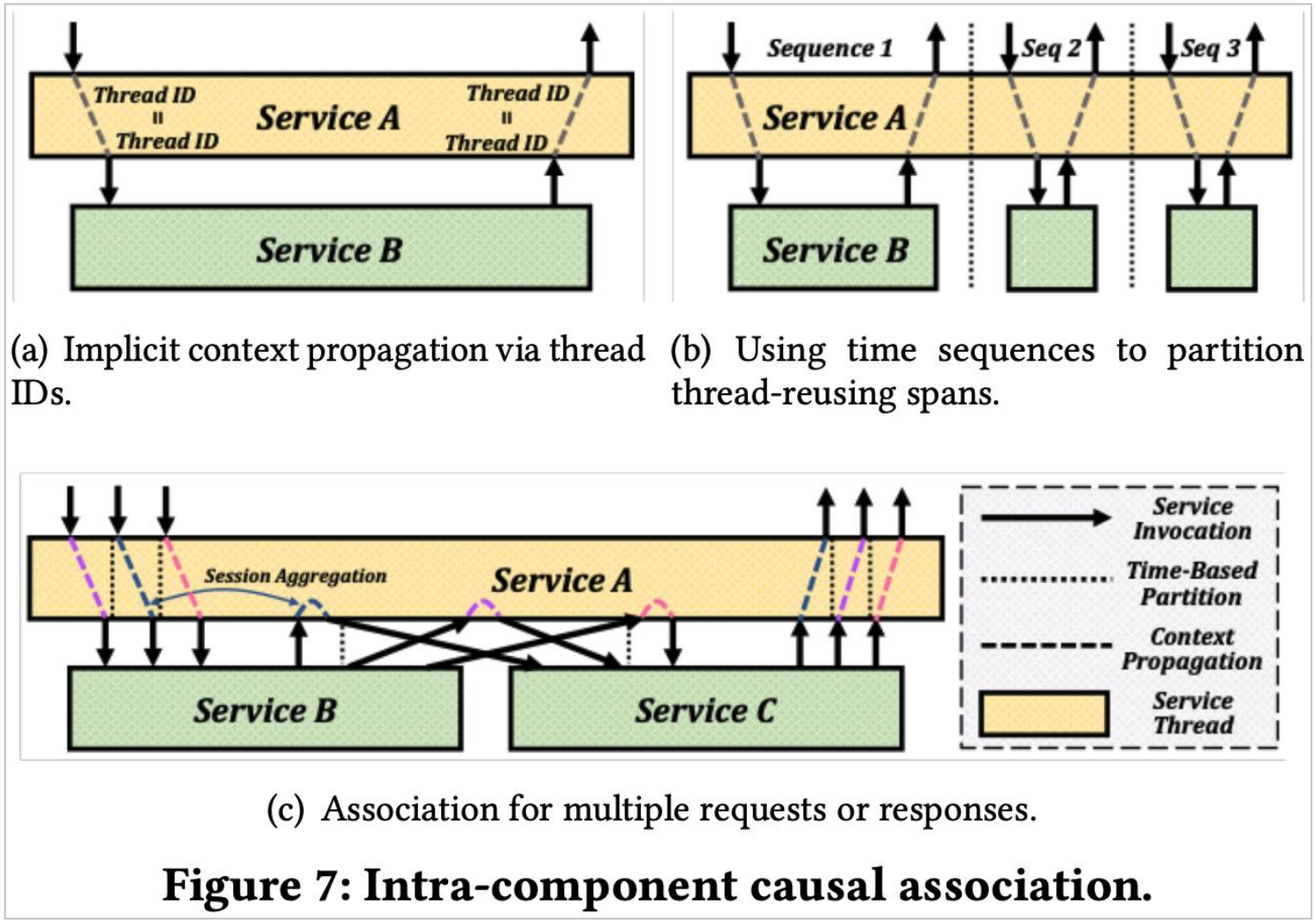
ABSTRACT

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.

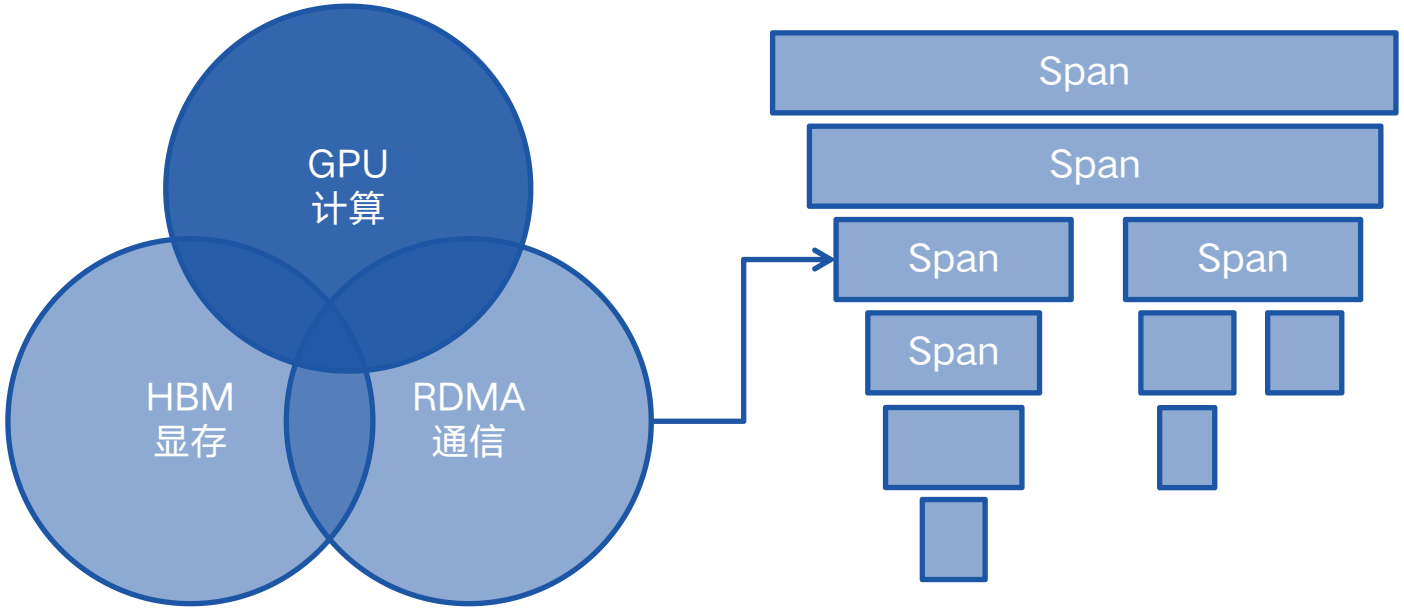
Network-Centric Distributed Tracing with DeepFlow: Troubleshooting Your Microservices in Zero Code

Outline

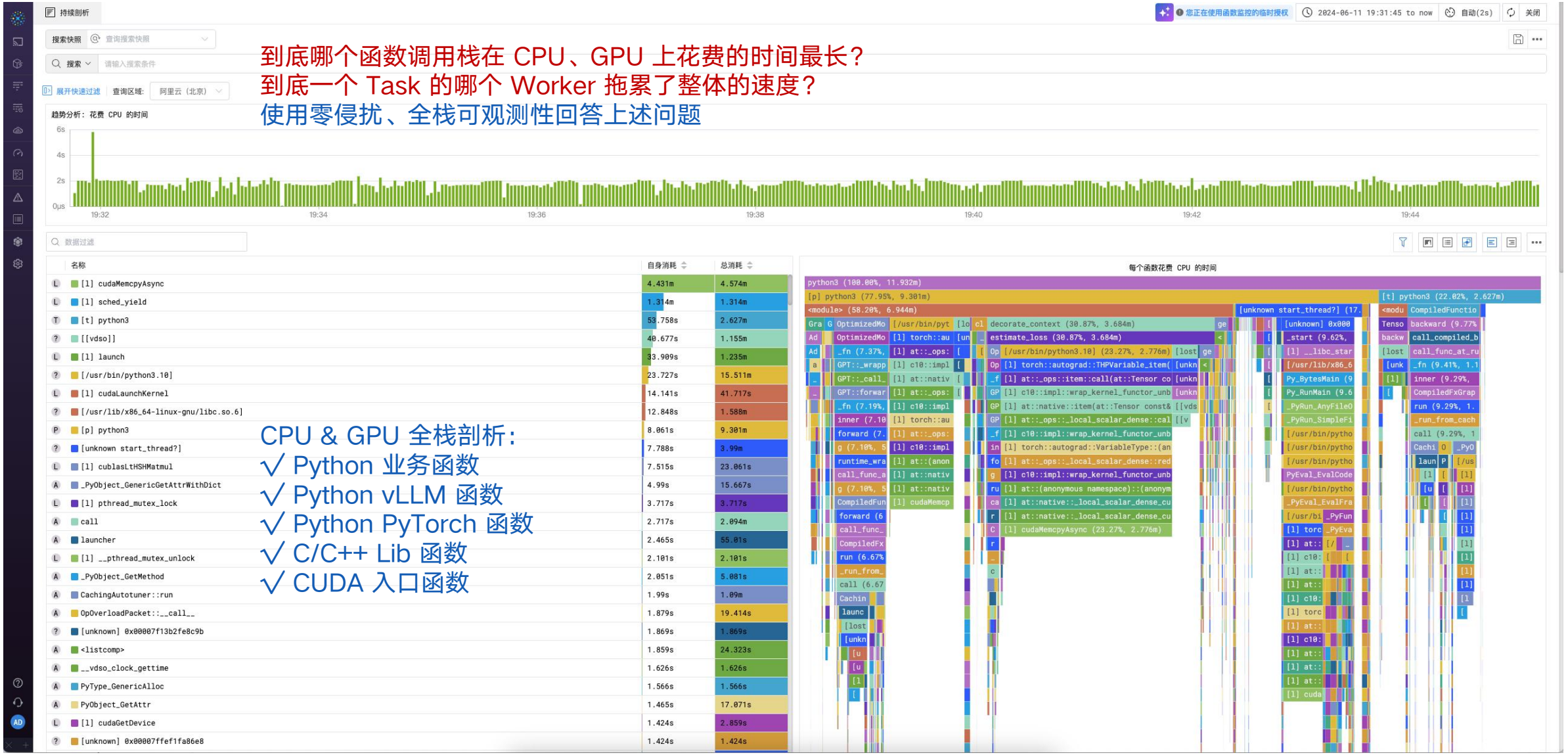
1. **背景**：训练和推理的效率挑战
2. **现状**：传统解决方案和工具的问题
3. **方法**：eBPF 构建零侵扰可观测性
4. **实践**：PyTorch 全栈剖析和追踪

DeepFlow 中的 eBPF AutoProfiling

1. GPU Profiling



PyTorch + nanoGPT CPU & GPU 火焰图



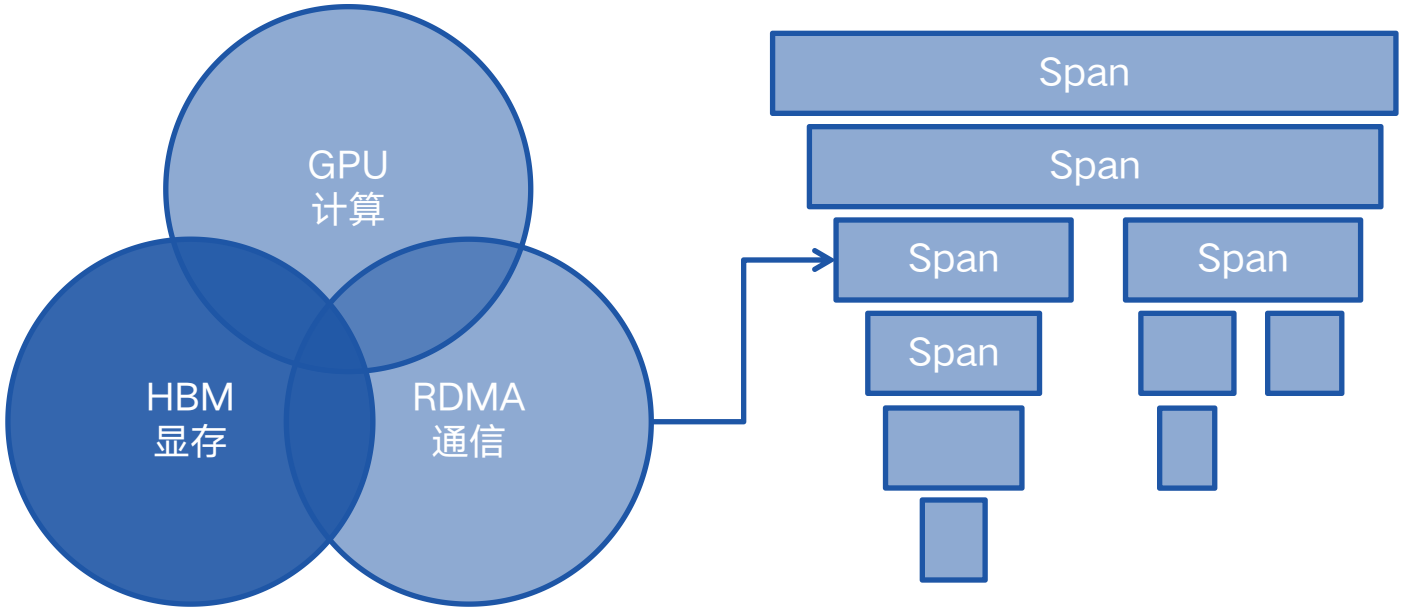
CPU & GPU 全栈剖析：

- √ Python 业务函数
- √ Python vLLM 函数
- √ Python PyTorch 函数
- √ C/C++ Lib 函数
- √ CUDA 入口函数

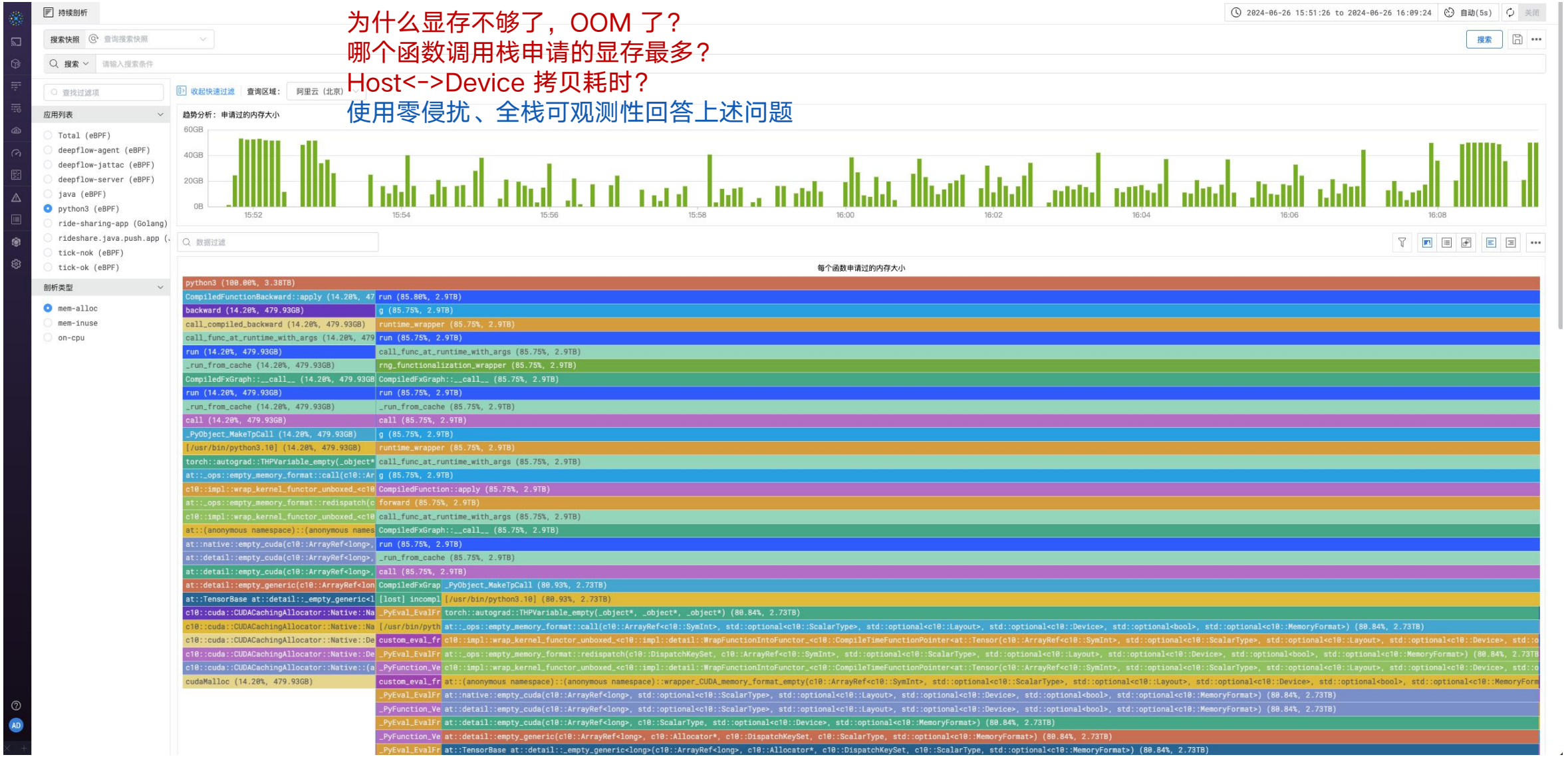
到底哪个函数调用栈在 CPU、GPU 上花费的时间最长？
到底一个 Task 的哪个 Worker 拖累了整体的速度？
使用零侵扰、全栈可观测性回答上述问题

PyTorch + nanoGPT CPU & GPU 火焰图

2. HBM Profiling



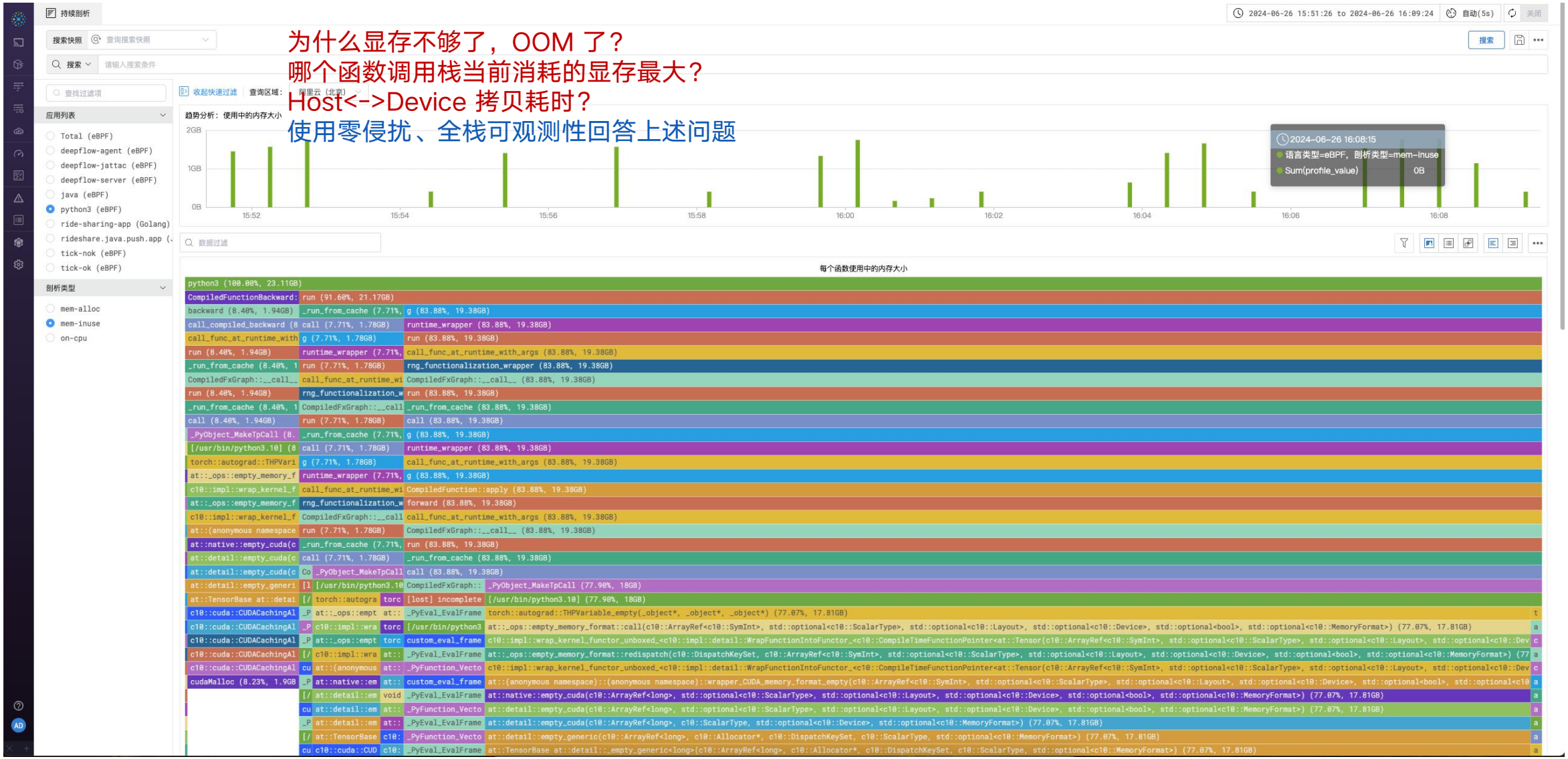
为什么显存不够了，OOM 了？
哪个函数调用栈申请的显存最多？
Host<->Device 拷贝耗时？
使用零侵扰、全栈可观测性回答上述问题



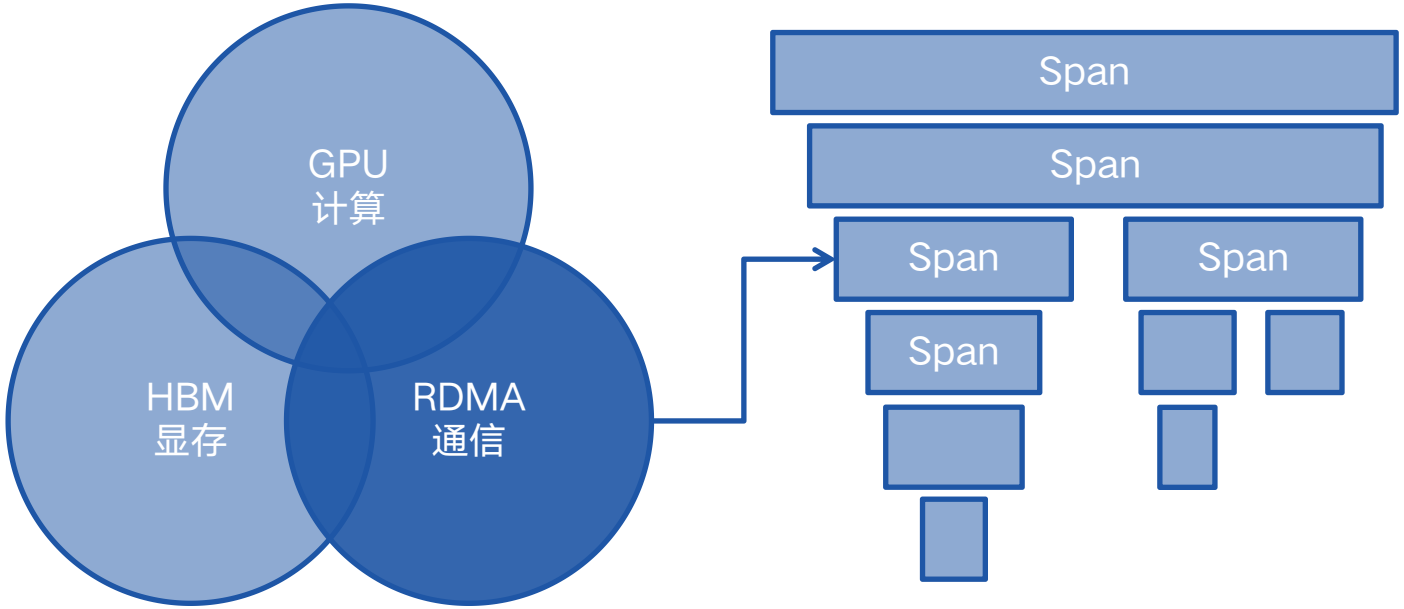
CUDA mem-inuse 显存实时用量火焰图

KubeCon | CloudNativeCon | THE LINUX FOUNDATION OPEN SOURCE SUMMIT | AI_dev
China 2024

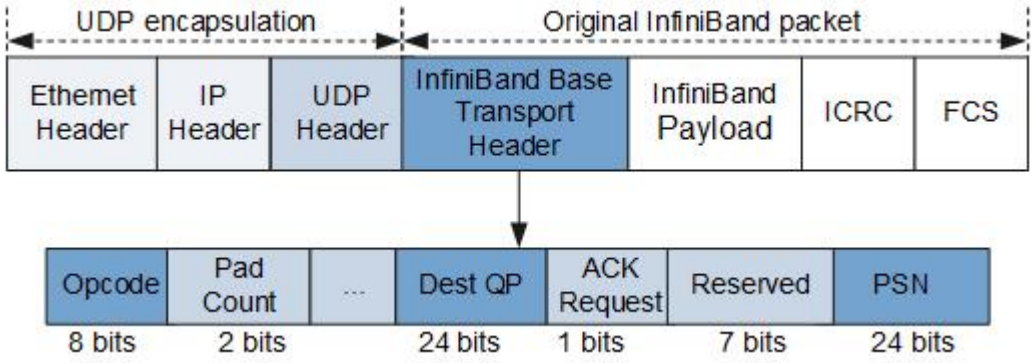
为什么显存不够了，OOM 了？
哪个函数调用栈当前消耗的显存最大？
Host<->Device 拷贝耗时？
使用零侵扰、全栈可观测性回答上述问题



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

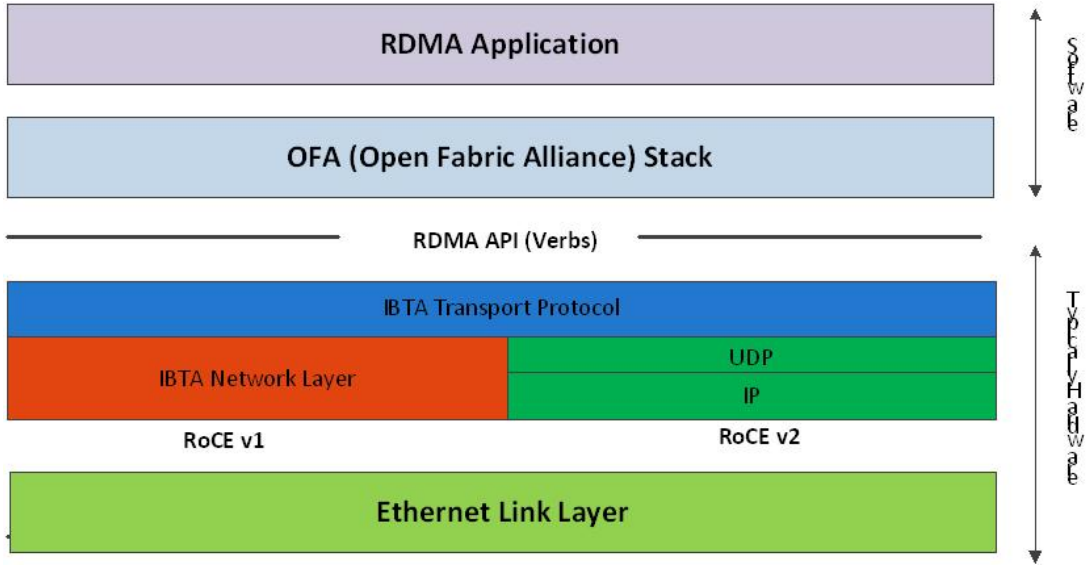
关键指标：

- 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

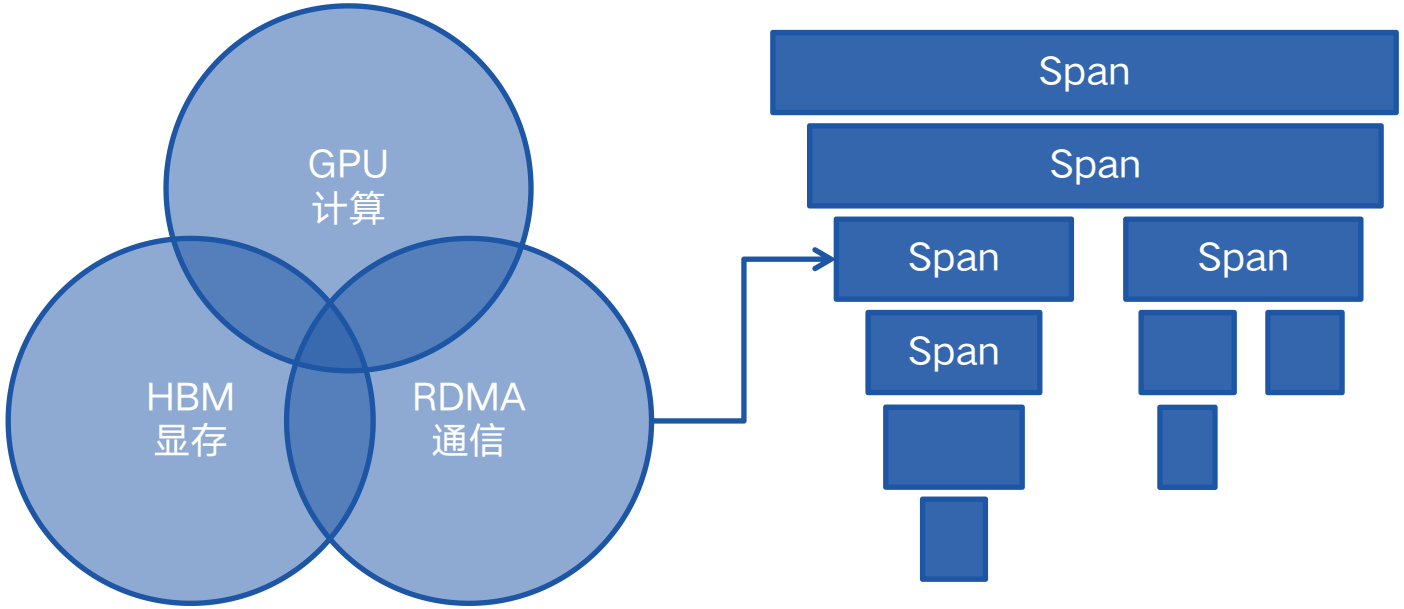
Function	作用
ibv_modify_qp	Queue Pair 状态修改
ibv_reg_mr	Memory Region 注册
ibv_dereg_mr	Memory Region 注销
ibv_post_send	buffer 发送或 RDMA 读写
ibv_poll_cq	等待 wr 完成

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

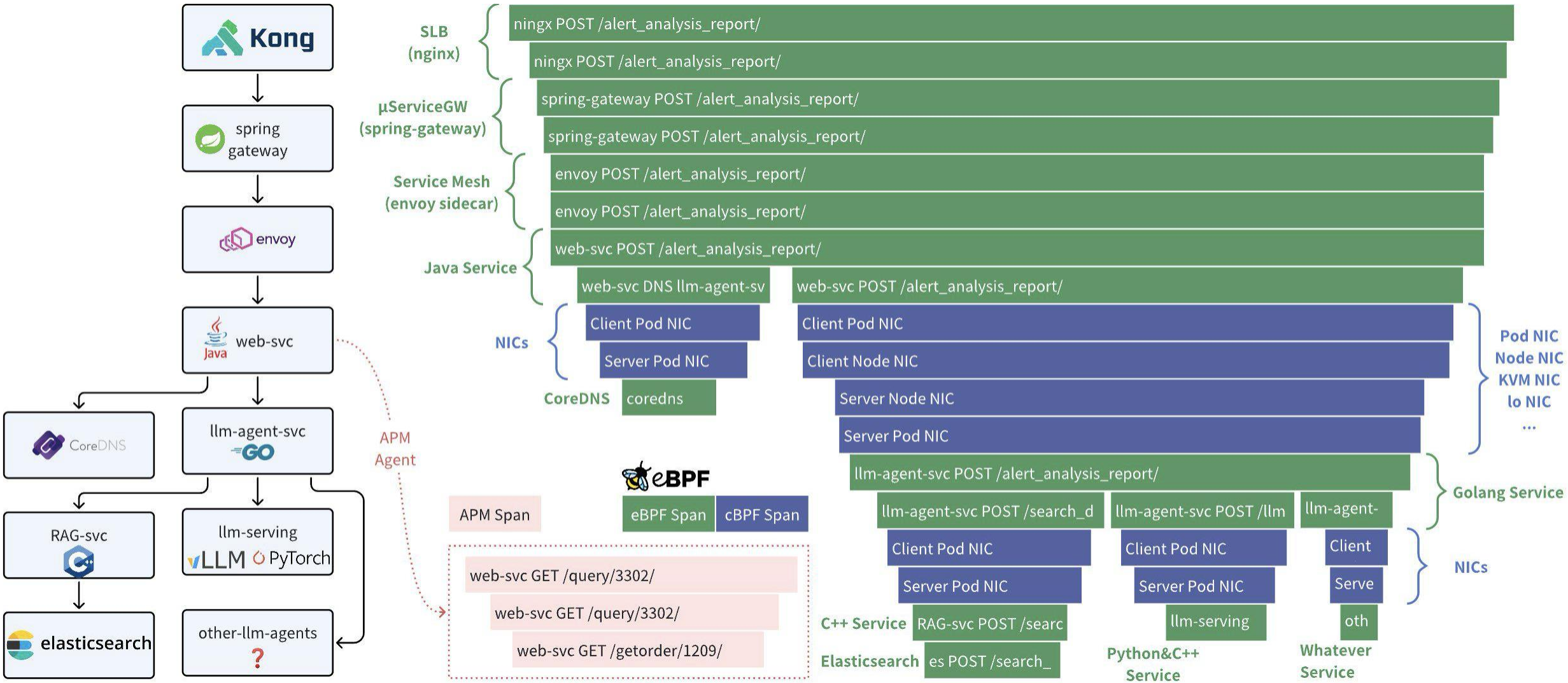


使用 eBPF Hook RDMA API

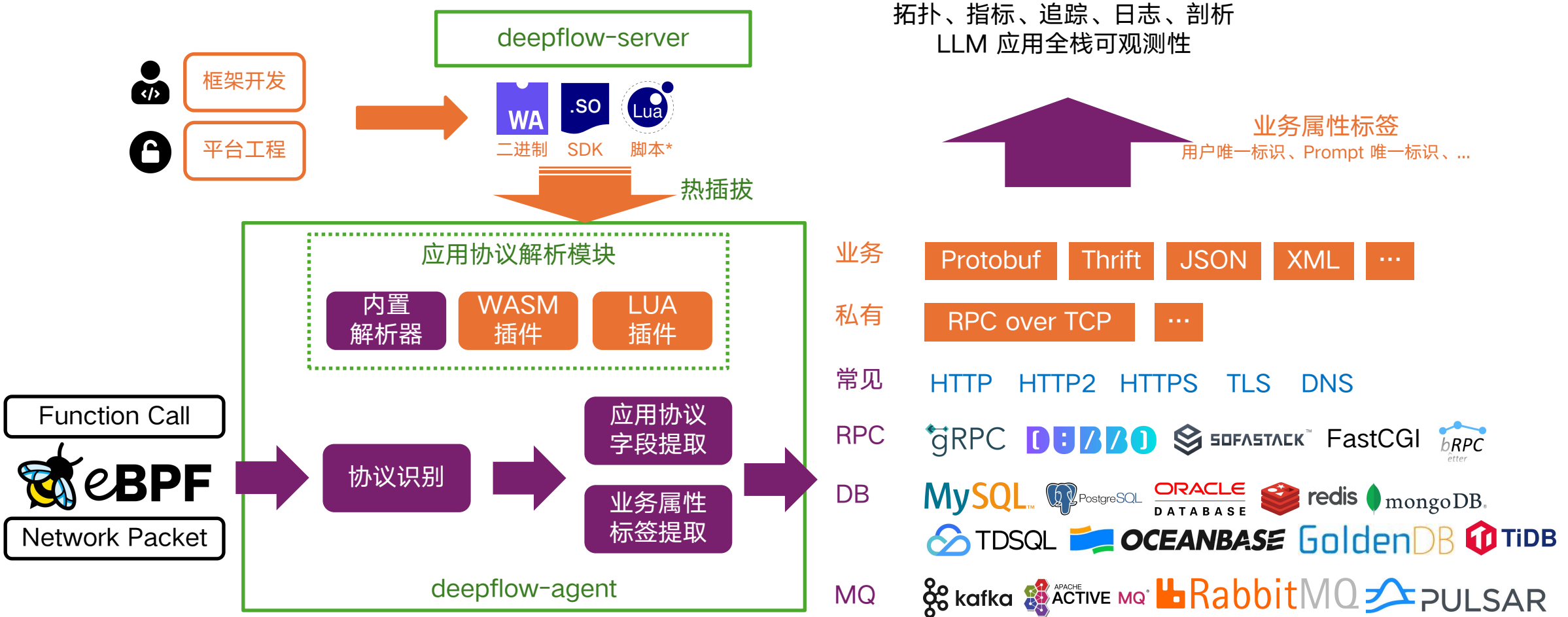
4. Distributed Tracing



云侧、端侧的在线推理服务



内置的及可编程的协议识别能力



DeepFlow：零侵扰实现 AI Infra 和应用的全栈可观测性

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

Prometheus

Open Telemetry

SKYwalking

Pyroscope

VECTOR BY DATADOG

AS SINK

DeepFlow

AS SOURCE

https://deepflow.io

eBPF

Wasm

Grafana

Prometheus

Open Telemetry

SKYwalking

kafka

无需修改代码，无需重启进程