

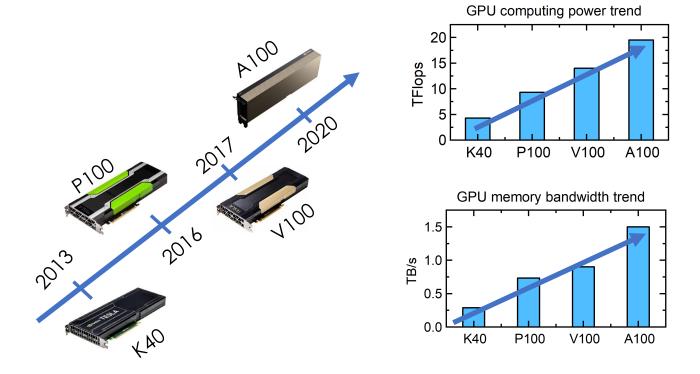
ShadowVM: Accelerating Data Plane for Data Analytics with Bare Metal CPUs and GPUs

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Background

https://www.nvidia.com/



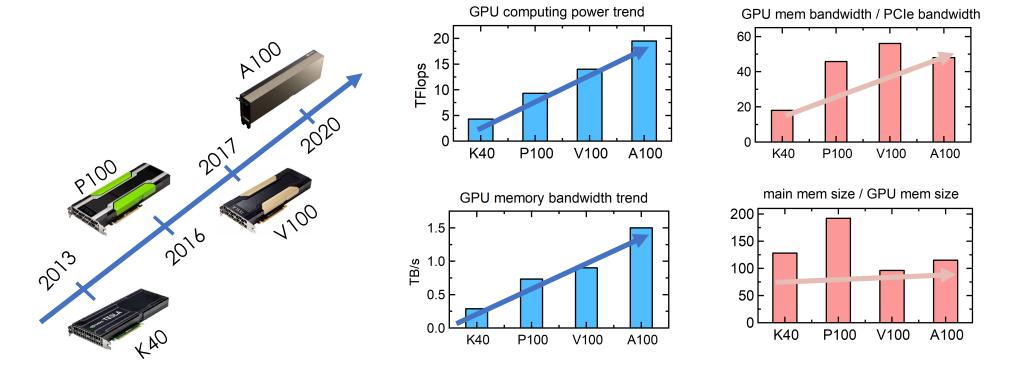
GPU itself continues to improve in the pass decade, luckily for Graphics, HPC, Deep Learning, etc.





Background

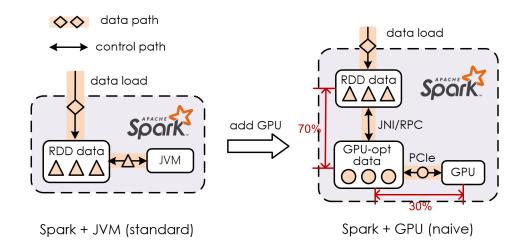
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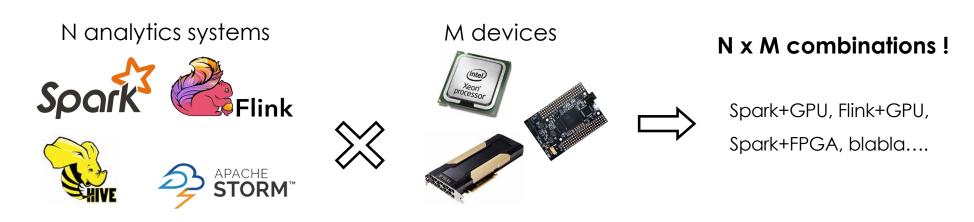
However, owing to the nature of CPU-GPU architecture, how to exploit GPU in data analytics is still an open issue!



- Challenge 1: a long data path moving data to GPU
 - Standard Spark abstracts partitioned data as RDD and computes RDD with JVM
 - When adding GPU to compute RDD, it involves extra JNI/RPC calls before data reaches
 GPU through PCIe

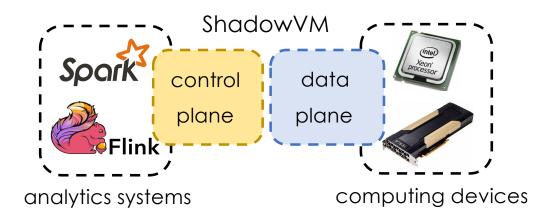


- Challenge 2: current works are based on the case-by-case approach
 - Diverse analytics systems and devices will lead to tedious engineering
 - Needs to modify current analytics systems or even build new systems
 - Implementations and optimizations are hard to reuse among different combinations

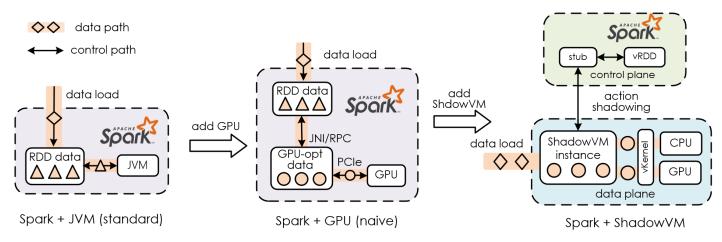


- Challenge 3: the underlying optimization space of GPU is restricted by the upper analytics systems
 - RDD data is stateless, while GPU context is stateful (initialization is costly)
 - RDD processing model is row-oriented (optimized for CPU), while GPU prefers a column-oriented approach
 - RDD scheduling only consider homogeneous resources (CPU or GPU), while a heterogeneous machine contains both CPU and GPU

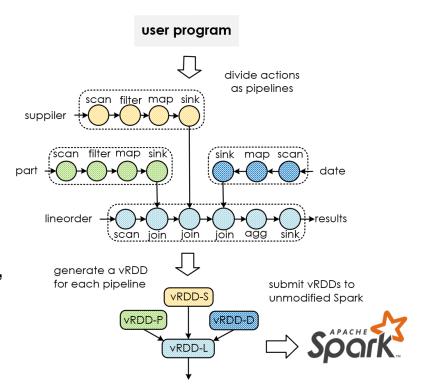
- Our key idea to solve all challenges
 - Decouple control plane & data plane in the end-to-end data path
- ShadowVM
 - A lightweight control plane to adapt analytics systems
 - An efficient data plane to utilize CPUs and GPUs without the restrictions from the control plane



- Core abstracts in ShadowVM
 - vRDD (control plane): a "virtual" RDD that holds control information rather than real data
 - vKernel (data plane): an execution unit that runs on a pod of bare metal CPUs and GPUs
 - Action shadowing: offloading computing from vRDD to vKernel



- How to generate and execute vRDDs
 - Write a user program with ShadowVM control plane API
 - Divide computing actions as pipelines (actions in a pipeline can be executed without blocking)
 - Generate a vRDD for each pipeline (reduce pthread/kernel launching in data plane)
 - Submit vRDDs to unmodified Spark (vRDD is still a "normal" RDD)



- Compare the implementations of RDD and vRDD
 - Take a simple map (one to one) as an example

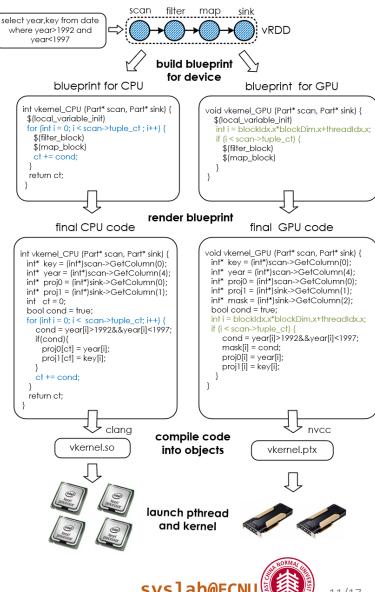
```
rdd.mapPartitions(
......
@Override
public Iterator<Integer> call(Iterator<Integer> input){
    List<Integer> output = new ArrayList<>();
    /* compute each input value */
    while(input.hasNext()){
        Integer value = input.next();
        output.add(value +1);
    }
    return output.iterator();
}
```

RDD: directly compute and deliver data

vRDD: offload computing and deliver barrier

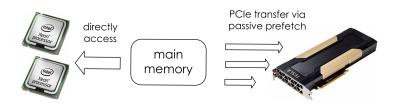


- How to execute vkernel in the data plane
 - Generate CPU and GPU code code with two steps
 - 1. build blueprint for device (CPU/GPU)
 - 2. render blueprint with implementations
 - Compile code into target objects (.so/.ptx)
 - Launch pthread for CPU and CUDA kernel for GPU
 - partitioned parallelism
 - CPU/GPU ratio is based on runtime statistics
 - speculative execution to narrow scheduling errors





- Traditional active copy: put data to GPU memory as far as possible
 - Restrict the workload size (below GPU memory)
 - Restrict the opportunity to reduce PCIe transfer
- Passive prefetch: put data in host memory and delay real transfer to vkernel runtime
 - vkernel is executed in a pipelined manner (locality is low)
 - Skip unused data when there are multiple selective actions in a pipeline (e.g., filters/joins)
 - Integrate in vkernel codegen by using UVM pointers and skip conditions for GPU thread
 - Decoupled data plane allows to reuse GPU memory context (UVM initialization is costly)

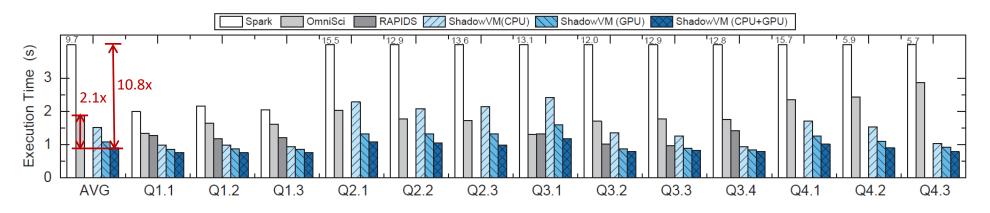


Evaluation

- CPU node: 16 CPU cores (Intel Xeon Silver 4110x2)
- Het node: 16 CPU cores + 1 GPU card (NVIDIA Titan RTX)
- Main memory: 128 GB
- GPU memory: 24 GB
- Ubuntu Server 18.04 + CUDA 10.0 + Clang 6.0 + OpenJDK 8.0
- 3 x CPU nodes for JVM-based **Spark**
- 1 x Het node for GPU-aware systems, including ShadowVM, OmniSci, RAPIDS
- Star Schema Benchmark (SSB) with all 13 analytics SQLs

Evaluation

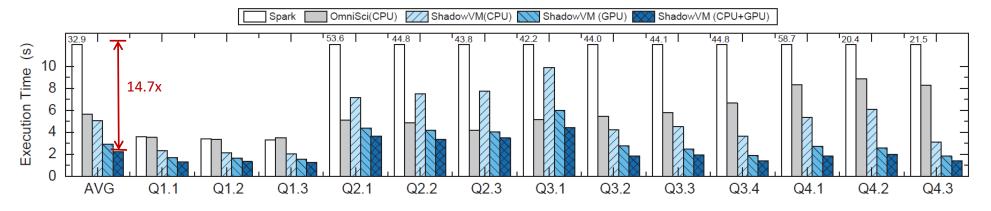
- ShadowVM outperforms Spark by $6.4\times$, $8.9\times$, and $10.8\times$ on three modes
- ShadowVM (mixed CPU-GPU) outperforms GPU-centric OmniSci by up to 2.1×
- RAPIDS is slightly faster than OmniSci by using overlapping but fails in some SQLs



medium-scale workload (SSB, scale factor = 20GB)

Evaluation

- ShadowVM outperforms Spark by up to 14.7×
- OmniSci is switched to the CPU mode due to out of GPU memory
- RAPIDS fails due to out of GPU memory



large-scale workload (SSB, scale factor = 100GB)

Conclusion

- ShadowVM introduces a new approach to harness data analytics systems with modern computing devices
 - A lightweight control plane to adapt upper analytics systems
 - An efficient data plane to directly utilize bare metal CPUs and GPUs without the restrictions from the control plane
 - Offloading computing from control plane to data plane
- ShadowVM code (Java control plane + CPP/CUDA data plane) is available at https://github.com/syslab-ecnu/ShadowVM

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Thank you Q&A

