GPUstore: Harnessing GPU Computing for Storage Systems in the OS Kernel

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Presented by *Weibin Sun*

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Motivation

- Storage system performance decided by not only I/O, sometime but also computations
  - e.g. Intel X25-E SSD (256KB I/O size)

	Raw	**dm-crypt**
Read	~250MB/s	~103MB/s
Write	~170MB/s	~95MB/s

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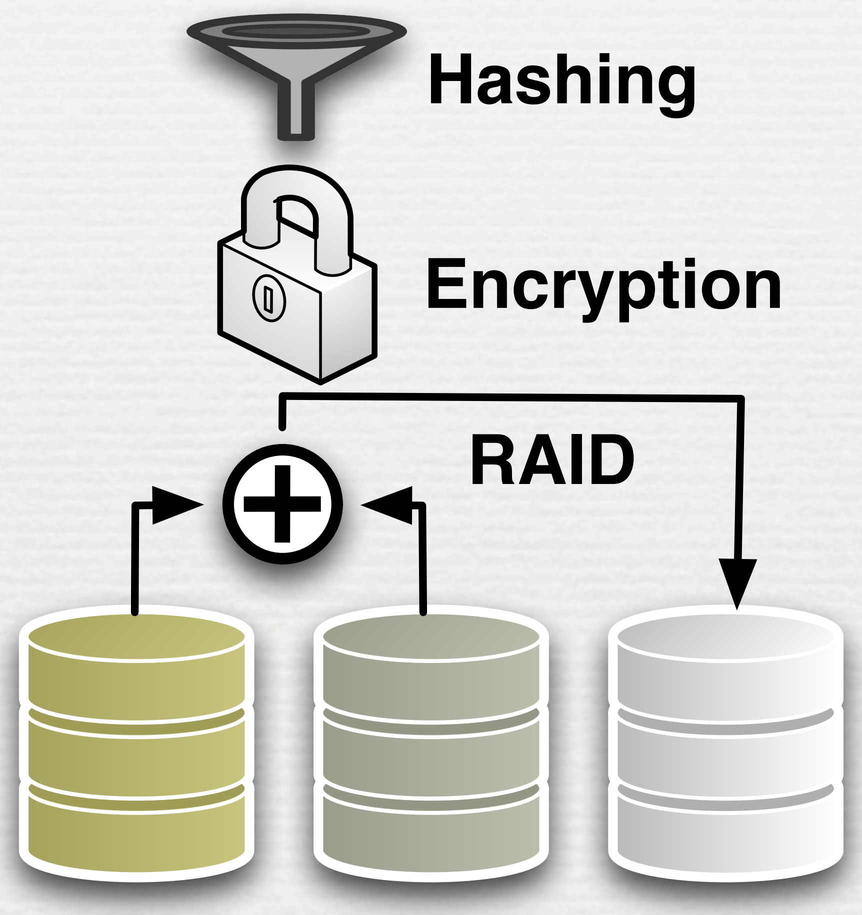

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- Parallel at different scales
  - File, Block, Trunk, Sector, and Row
- Mostly same operations on different data

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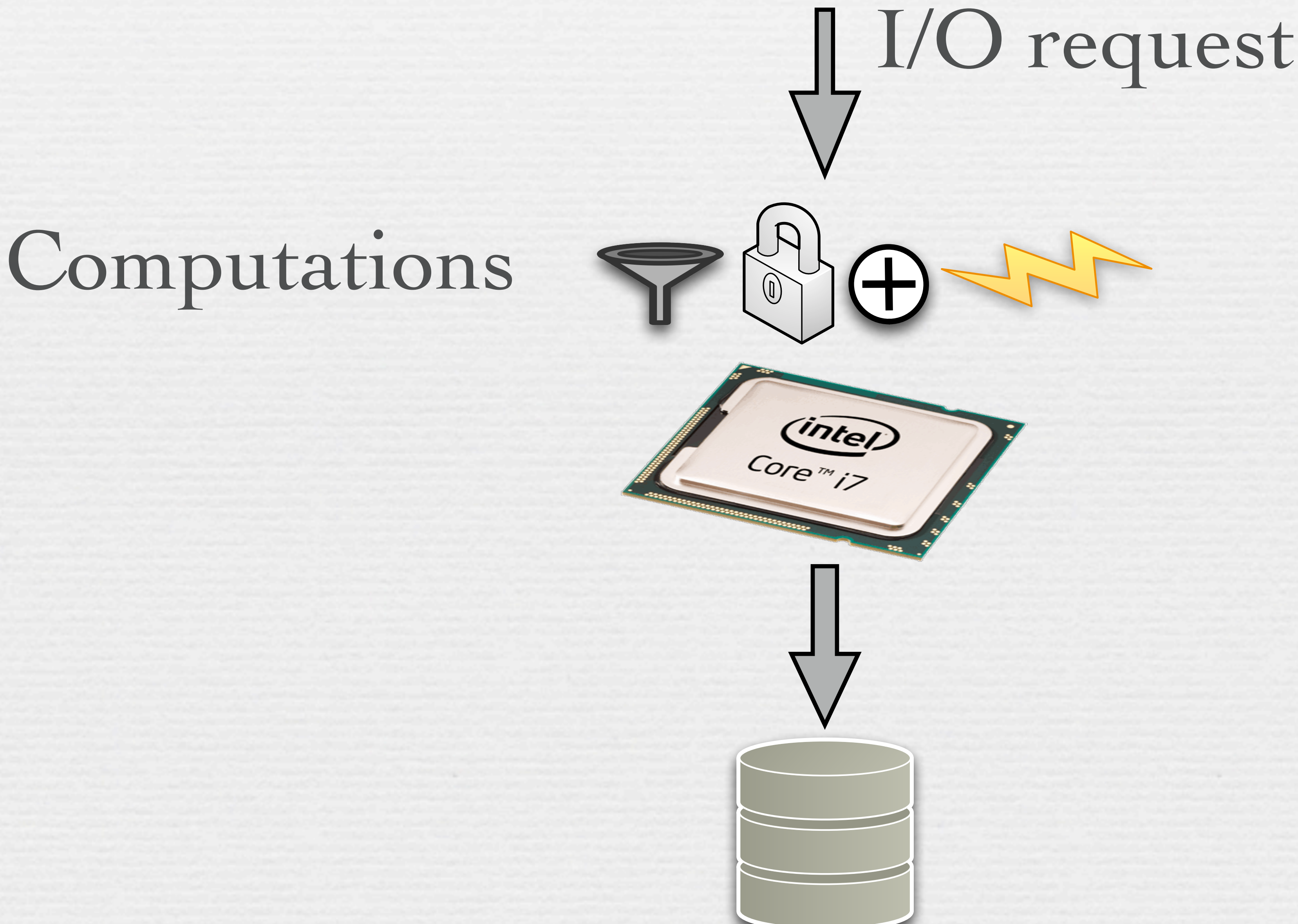
SIMD/STMD
GPU

The idea of GPUstore



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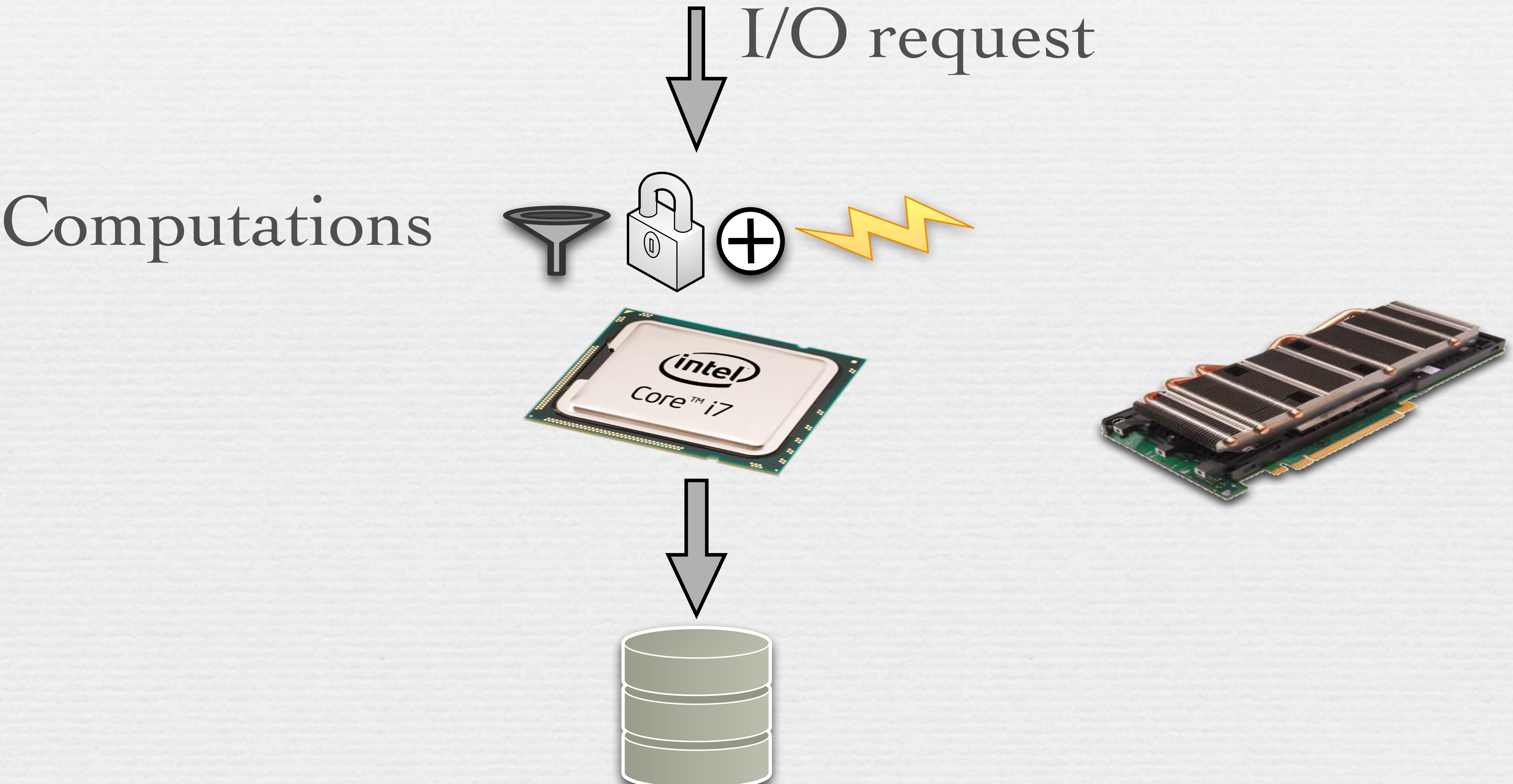
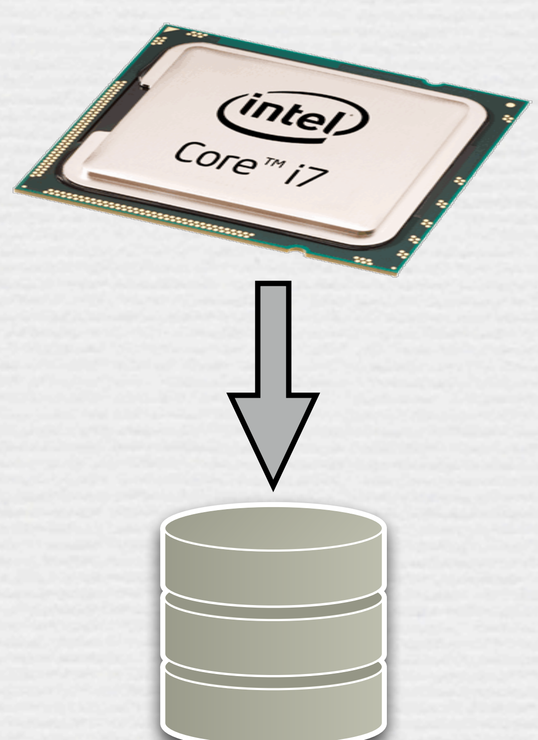
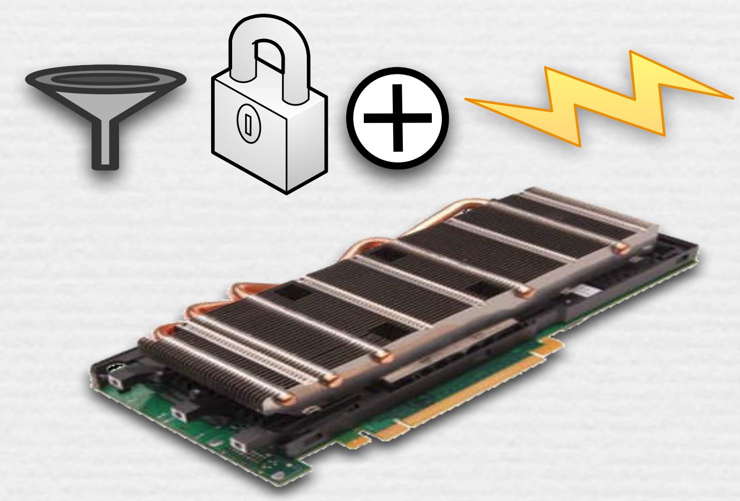


The idea of GPUstore

I/O request

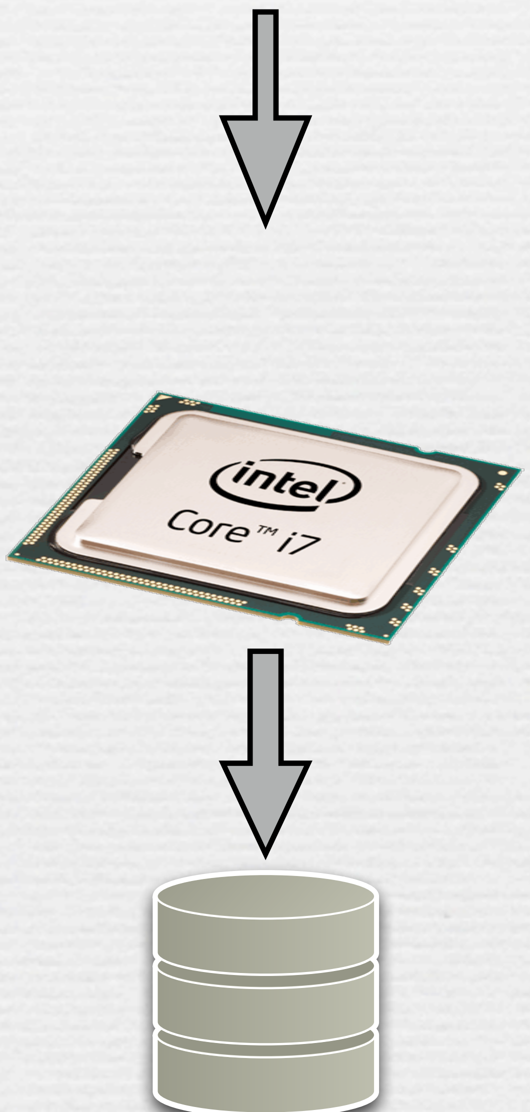
Computations





The idea of GPUstore

I/O request



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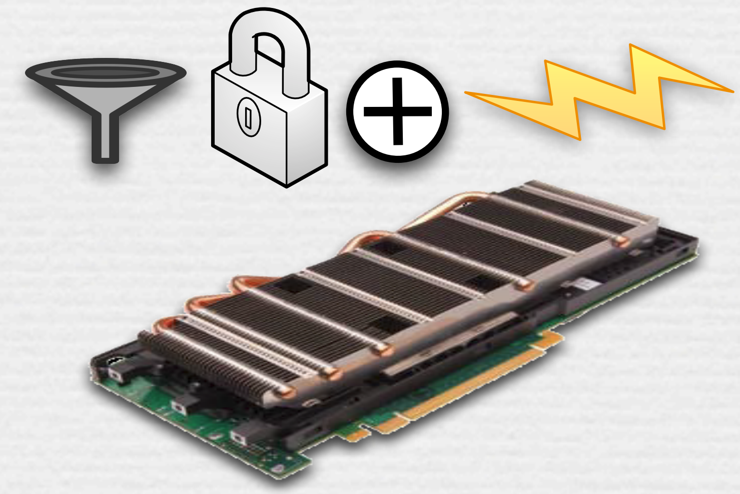

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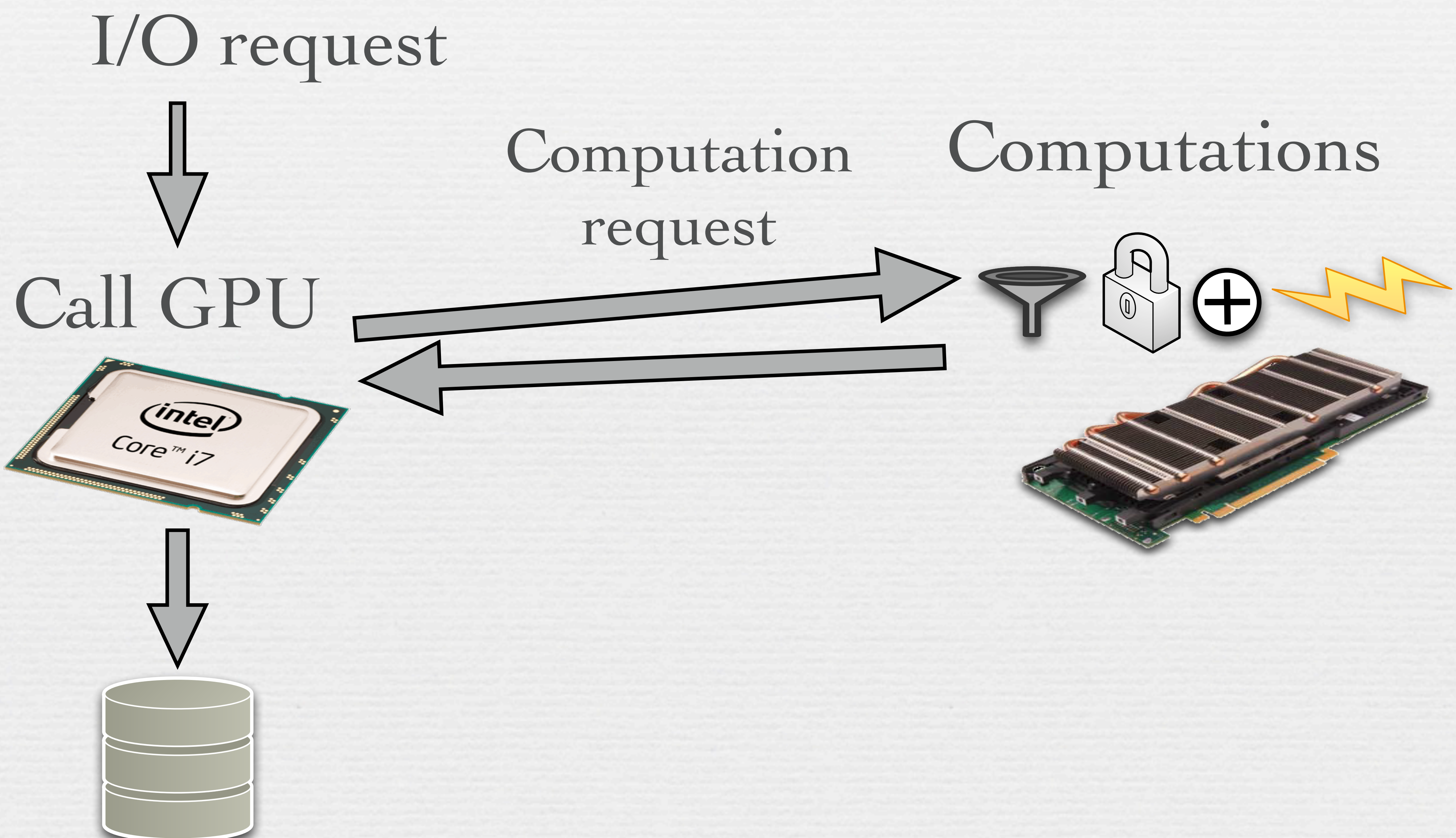

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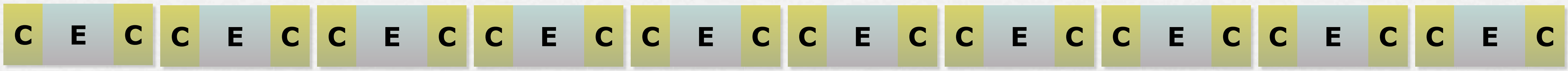
  - Memory management in OS kernel is complicated
- Existing framework/API not for storage
  - TimeGraph, PTask, Sponge, Gdev ...

Some problems

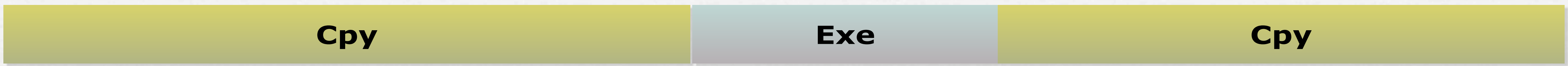
- Too large/too small I/O request
- Redundant buffering (mm problem)
- GPU execution resource abstraction for management

Small I/O => Small Computation



- Small request can't provide enough threads for GPU scheduling
  - e.g. encrypt 64KB disk block with AES CTR
    - 16B AES block size
    - 4K independent blocks = 4K threads
  - To hide mem latency, use all cores
- GPU kernel launch overhead not proportional to req size

Large I/O => Large Computation



- Large request cause long-time waiting/blocking
  - Hard to avoid, e.g. `read(fd, buf, 1024*1024*128);`
    - but we can do better
  - Key to solution: GPU is “multi-task-able”
    - Multiple kernel execution
    - Execution and copy overlapping
    - Multiple DMA engines

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Redundant buffering

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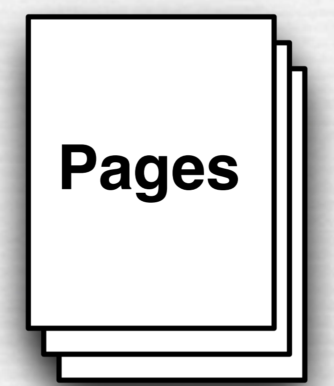
Memory pages allocated at somewhere else in existing code



Storage code's pages

Redundant buffering

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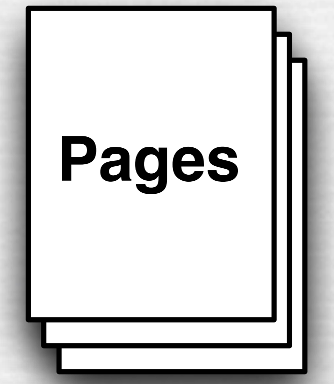

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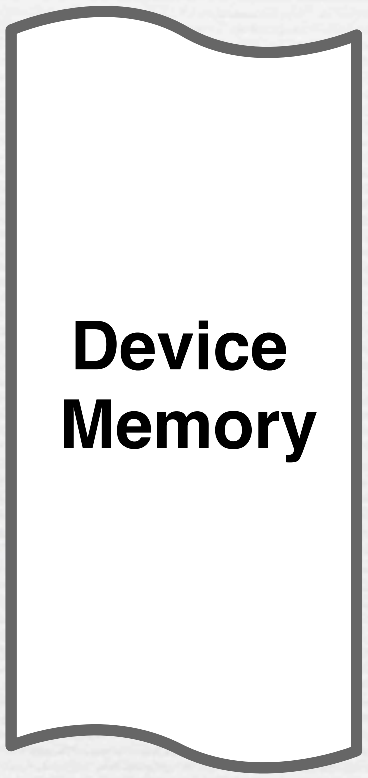

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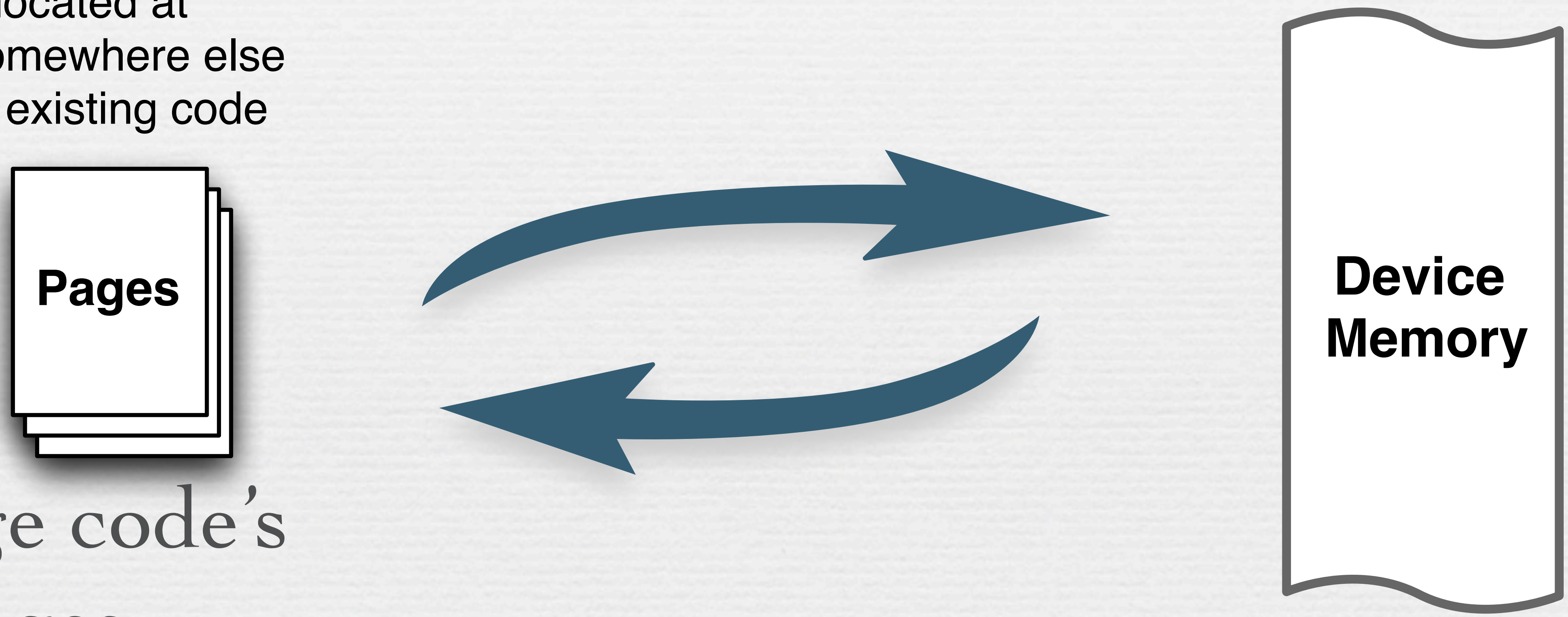

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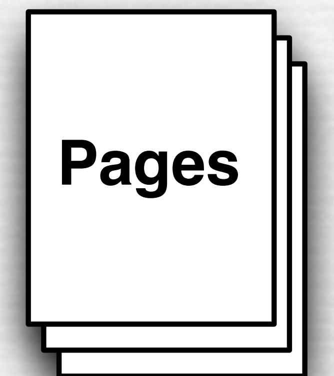

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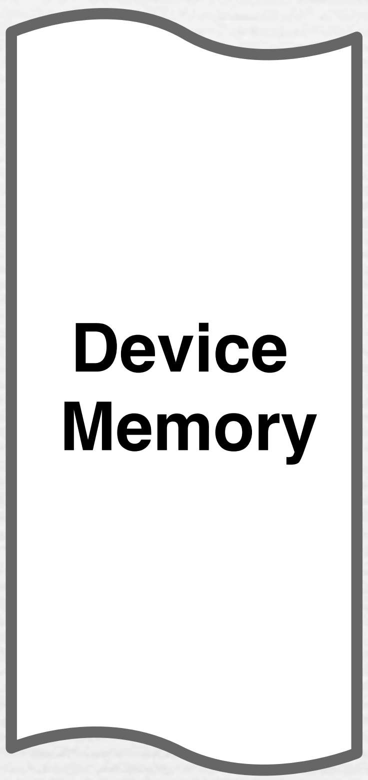

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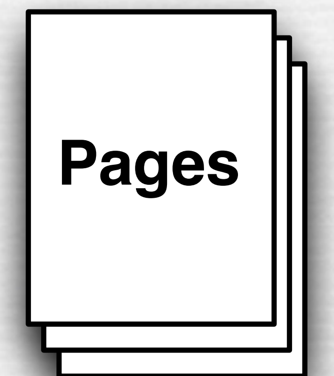

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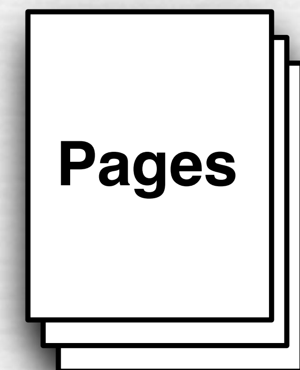
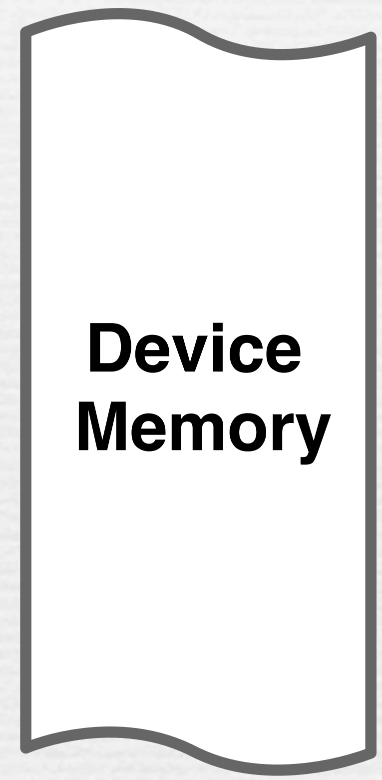


Memory pages
used by GPU
driver for DMA



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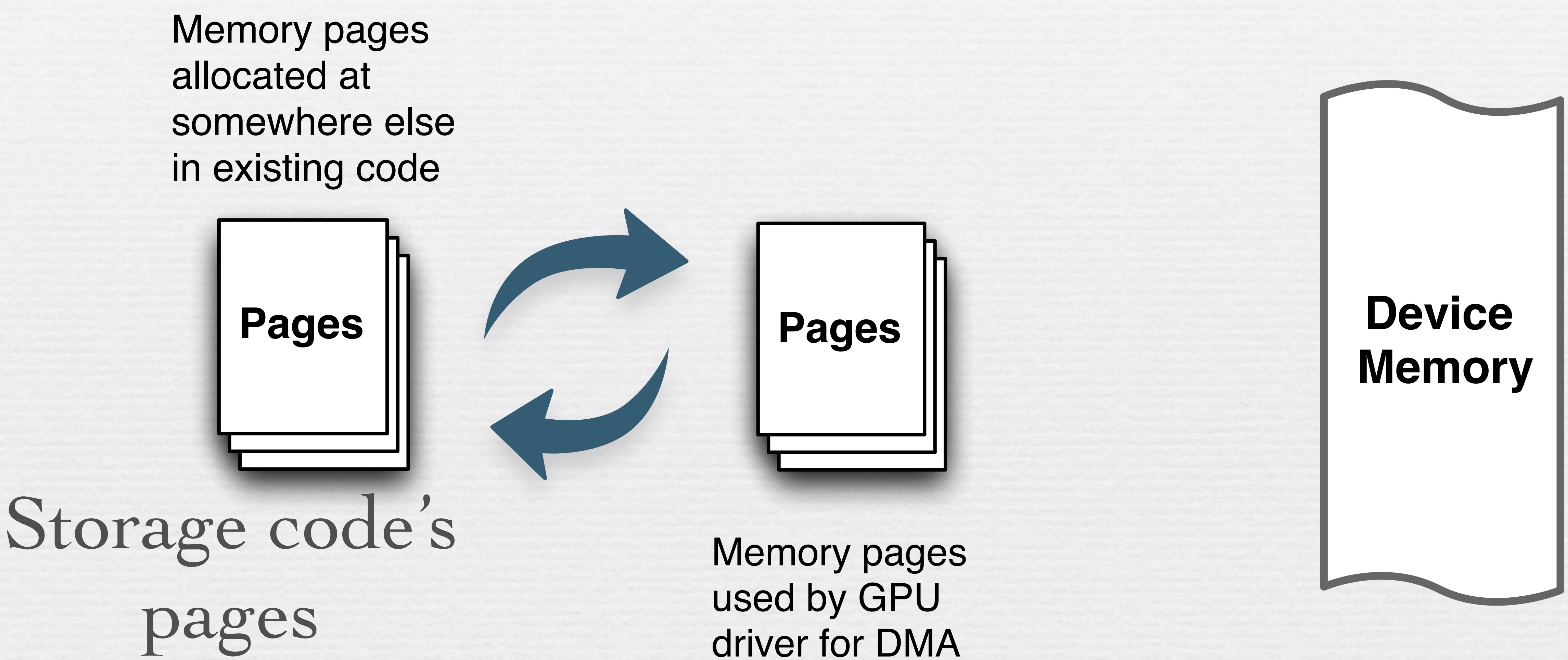

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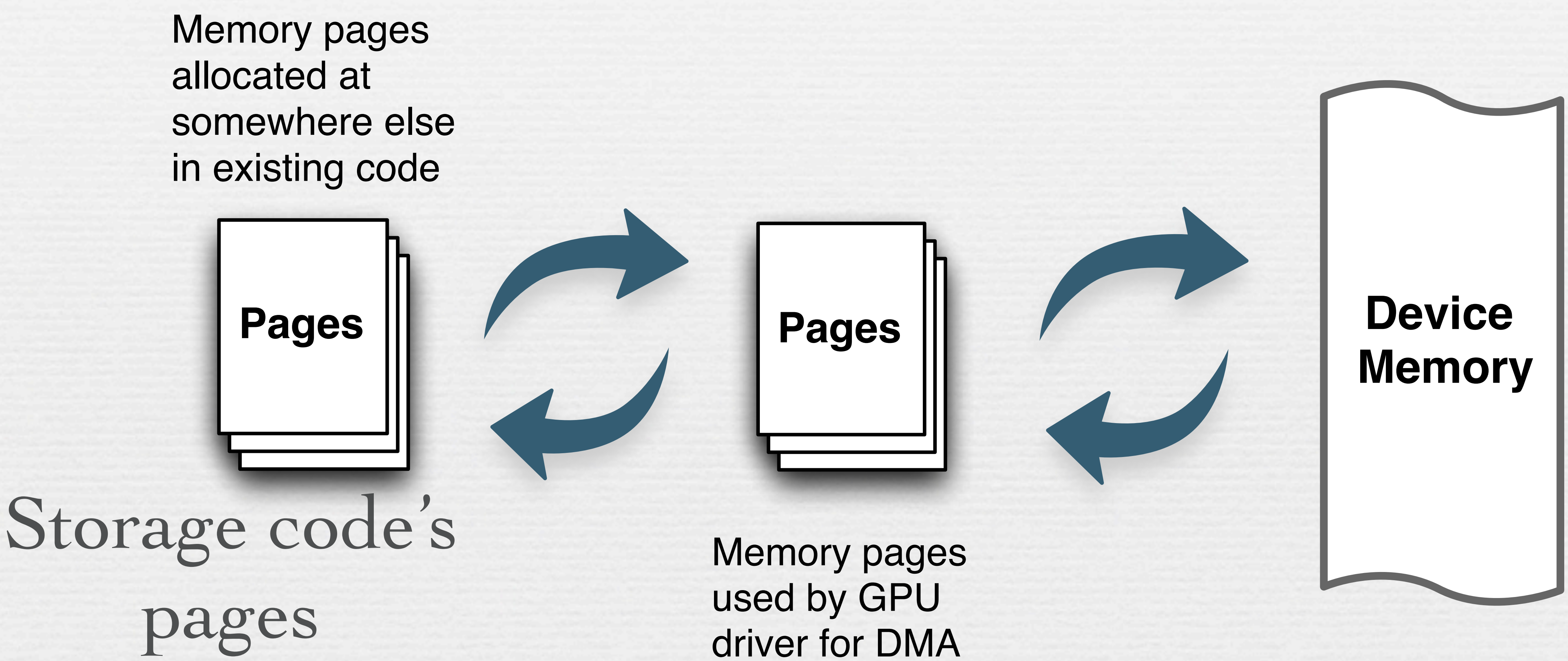

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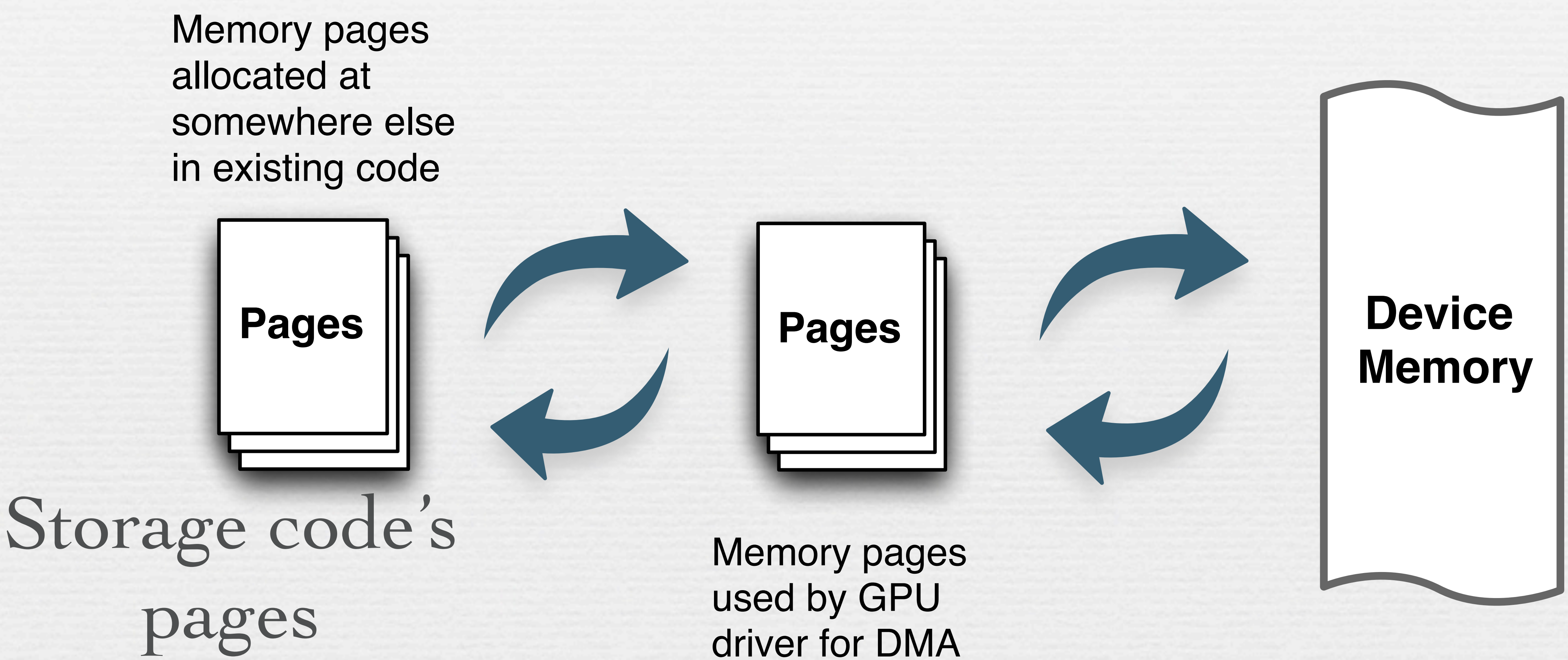

Make existing mechanisms just work: pages from page-cache, scheduled I/O request pages

GPU Execution Resources

- DMA engines
- Ability to run multiple kernels
- Ability to overlap execution and copy
- Multiple GPUs

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Abstract them for management
like CPU cores for CPU execution

GPUstore

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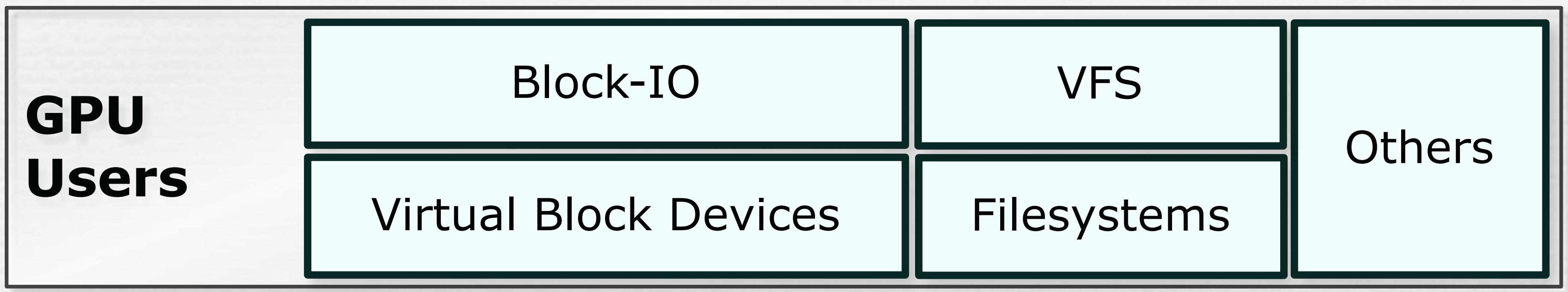
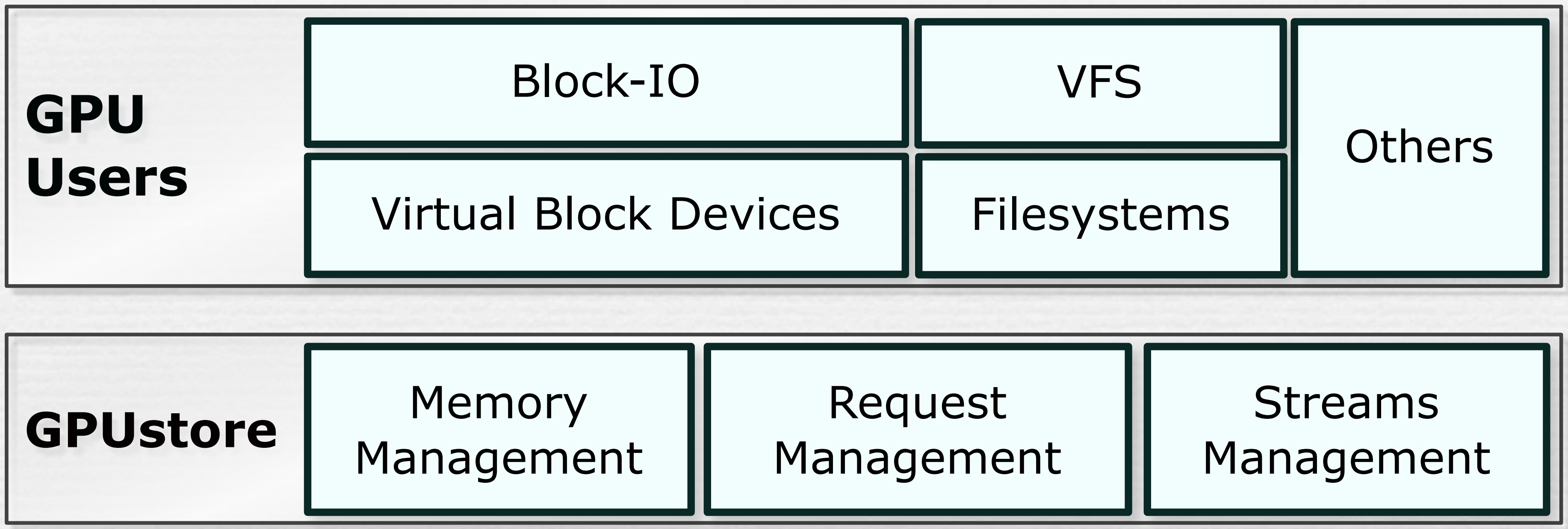
GPUstore


GPU Users
Block-IO
VFS
Virtual Block Devices
Filesystems
Others

GPUstore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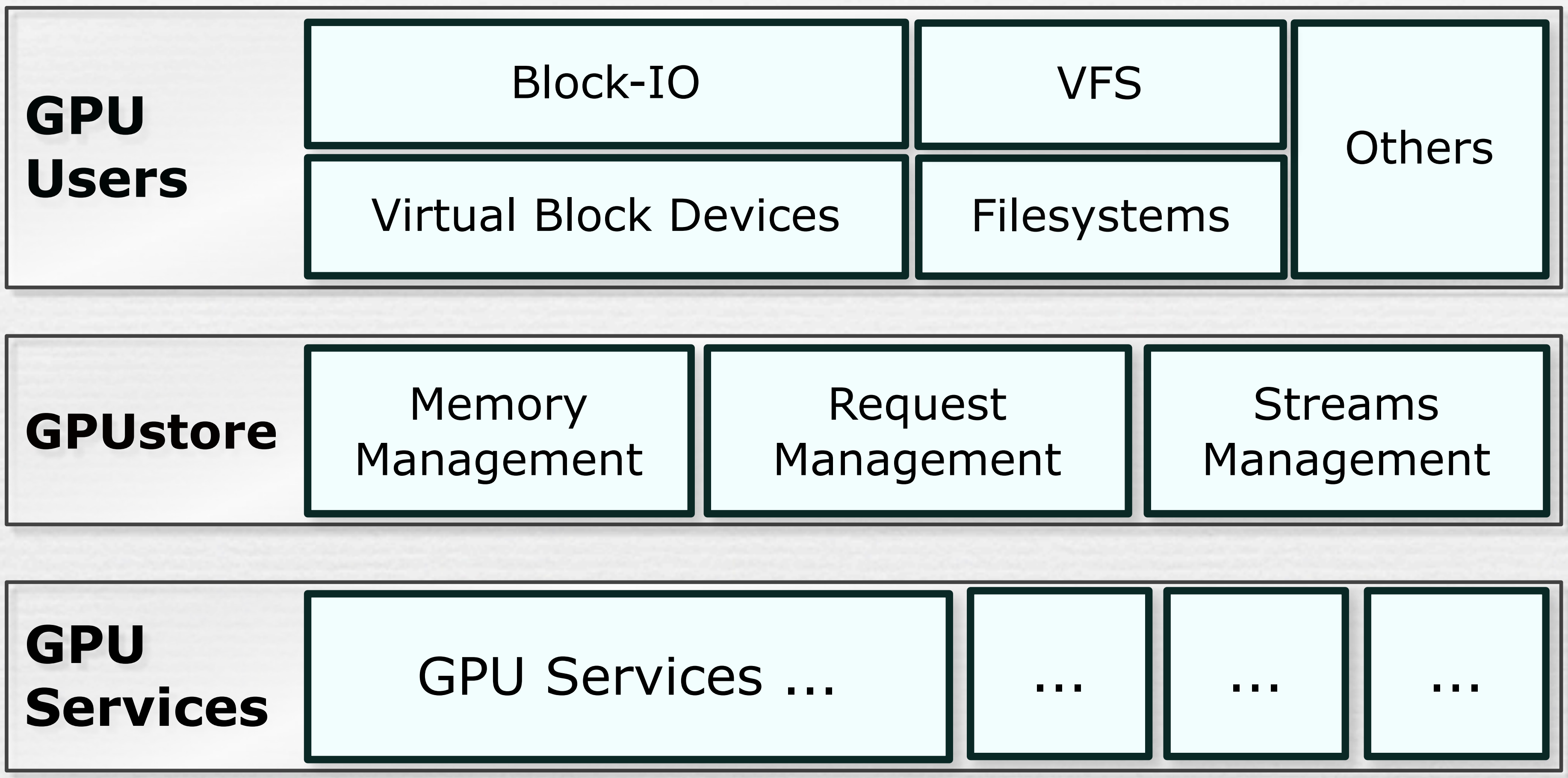
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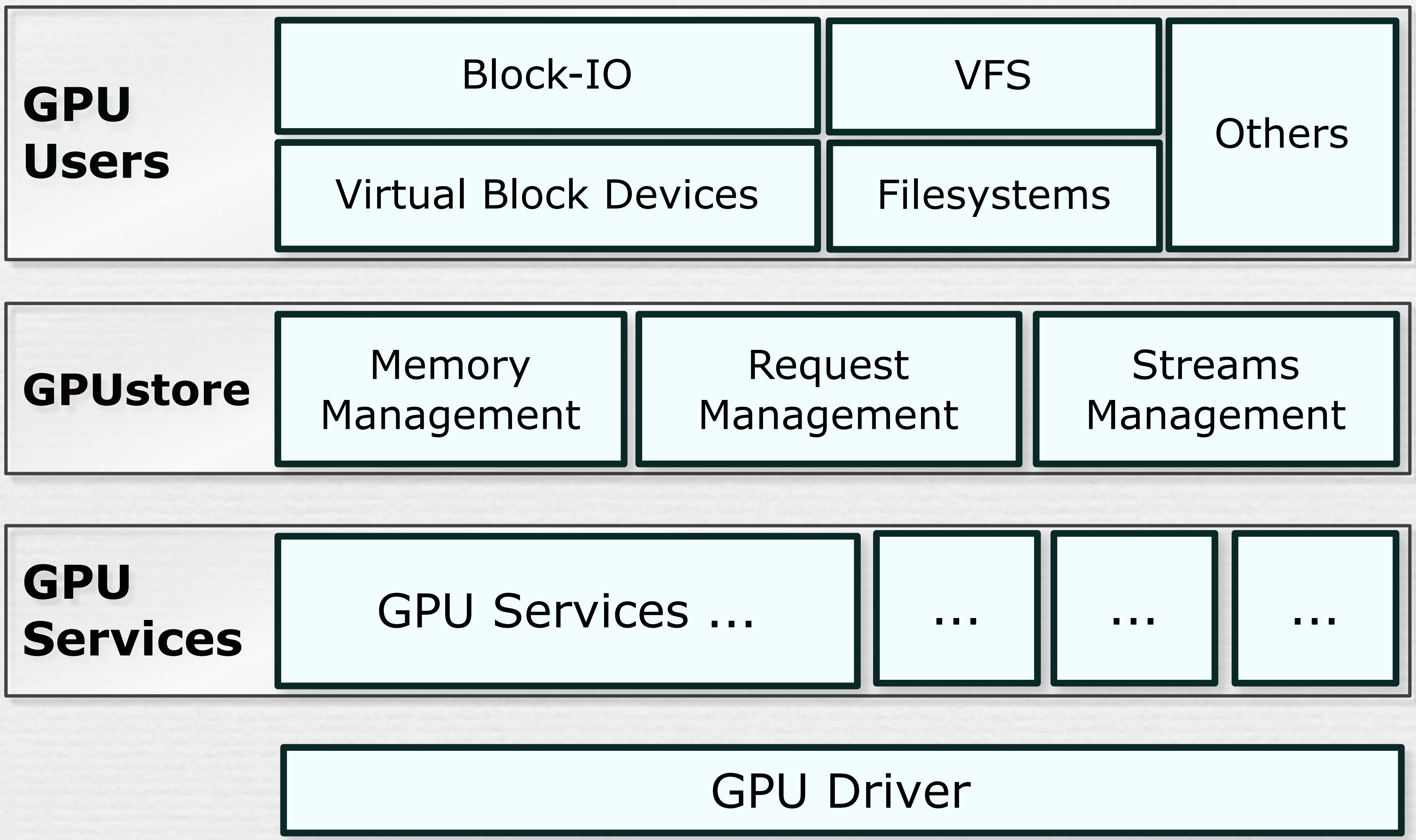
GPUstore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GPU Driver

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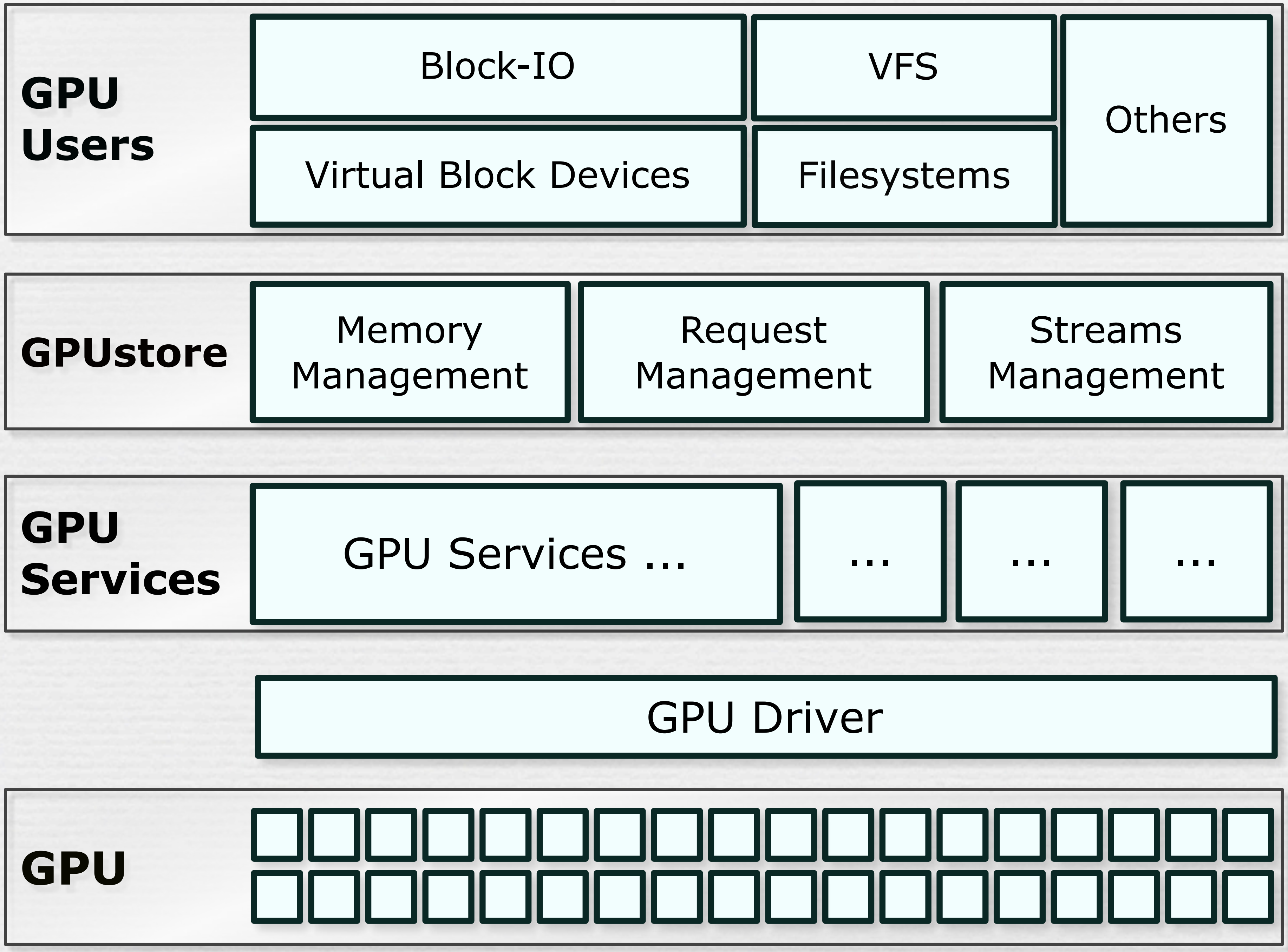
GPUstore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GPUstore

- Stream Management
- Request Management
- Memory Management

"Stream" for resource abstraction

- Term borrowed from CUDA
- A **stream** is an abstract execution pipeline including:
  - DMA engine
  - GPU cores
- Hide real # DMA engines, # cores, # GPUs
- Streams scheduled for request processing
  - First come, first serve now

GPUstore

- ~~Stream Management~~
- Request Management
- Memory Management

Request Management

Request Management

- Computation request scheduling behind all existing mechanisms
  - Just before invoking GPU operations
  - Different from I/O scheduler
    - Considering computing speed, not read/write speed, sectors' locations...

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- Right size?

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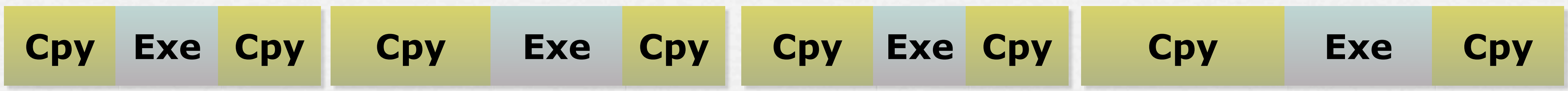

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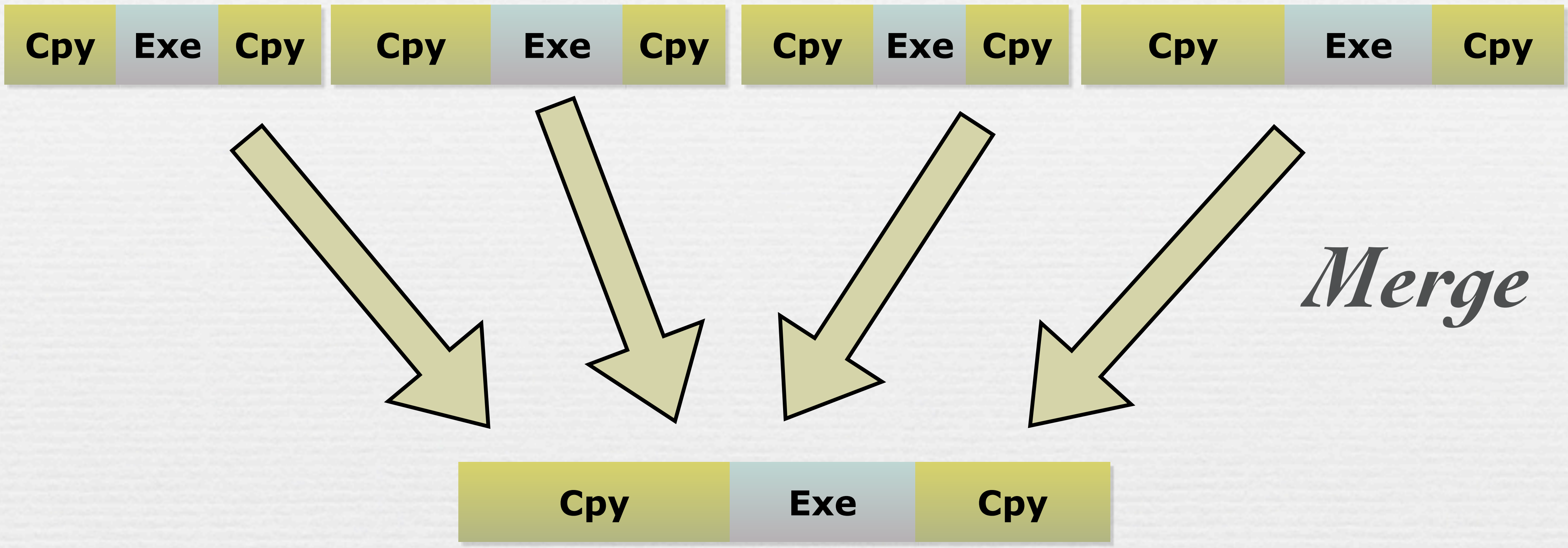

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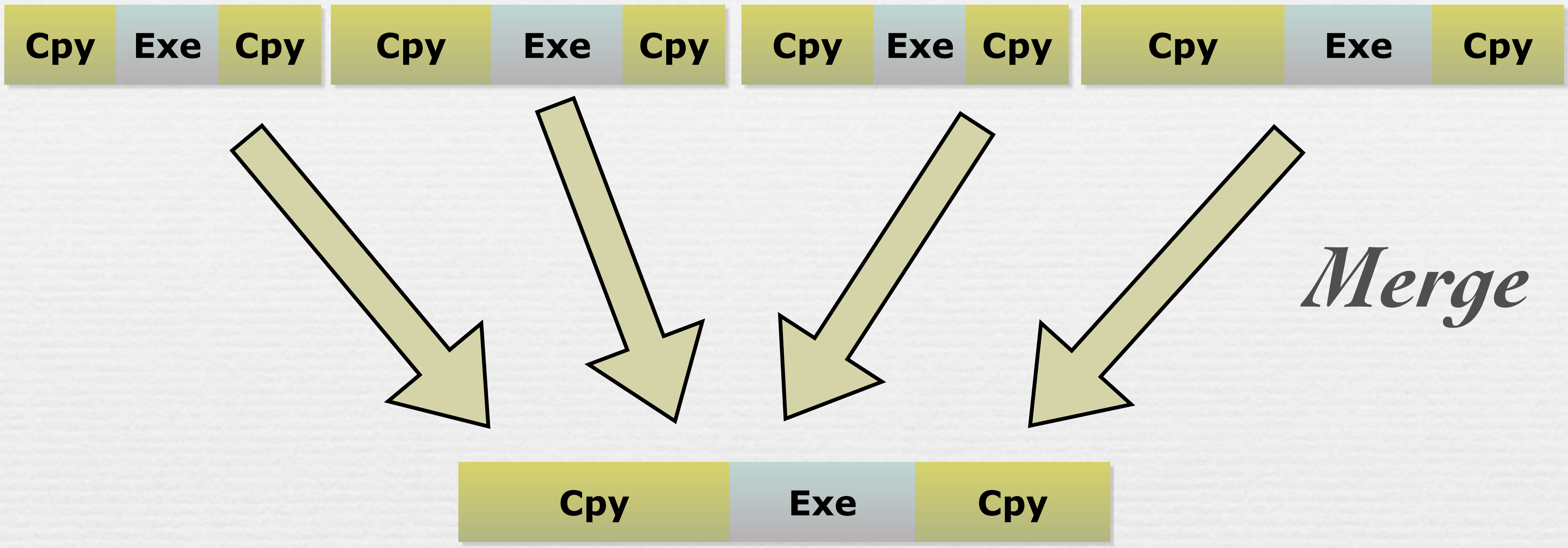
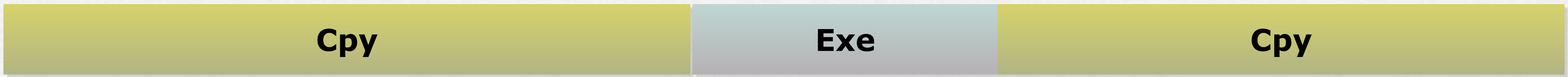


- Merge is not linear addition, total time is not sum of all original ones.
  - GPU utilization, mem latency, launch overhead

Too large I/O causes large computation



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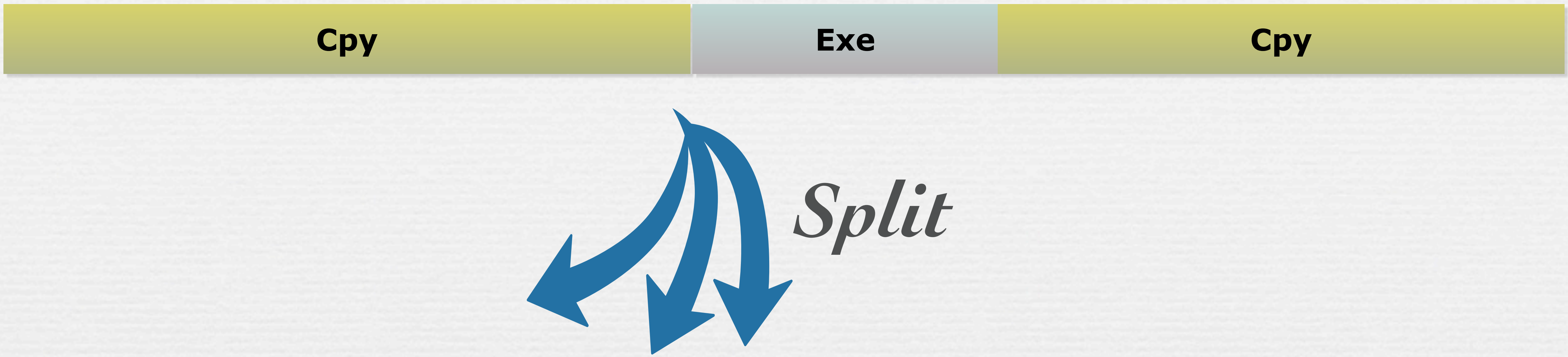

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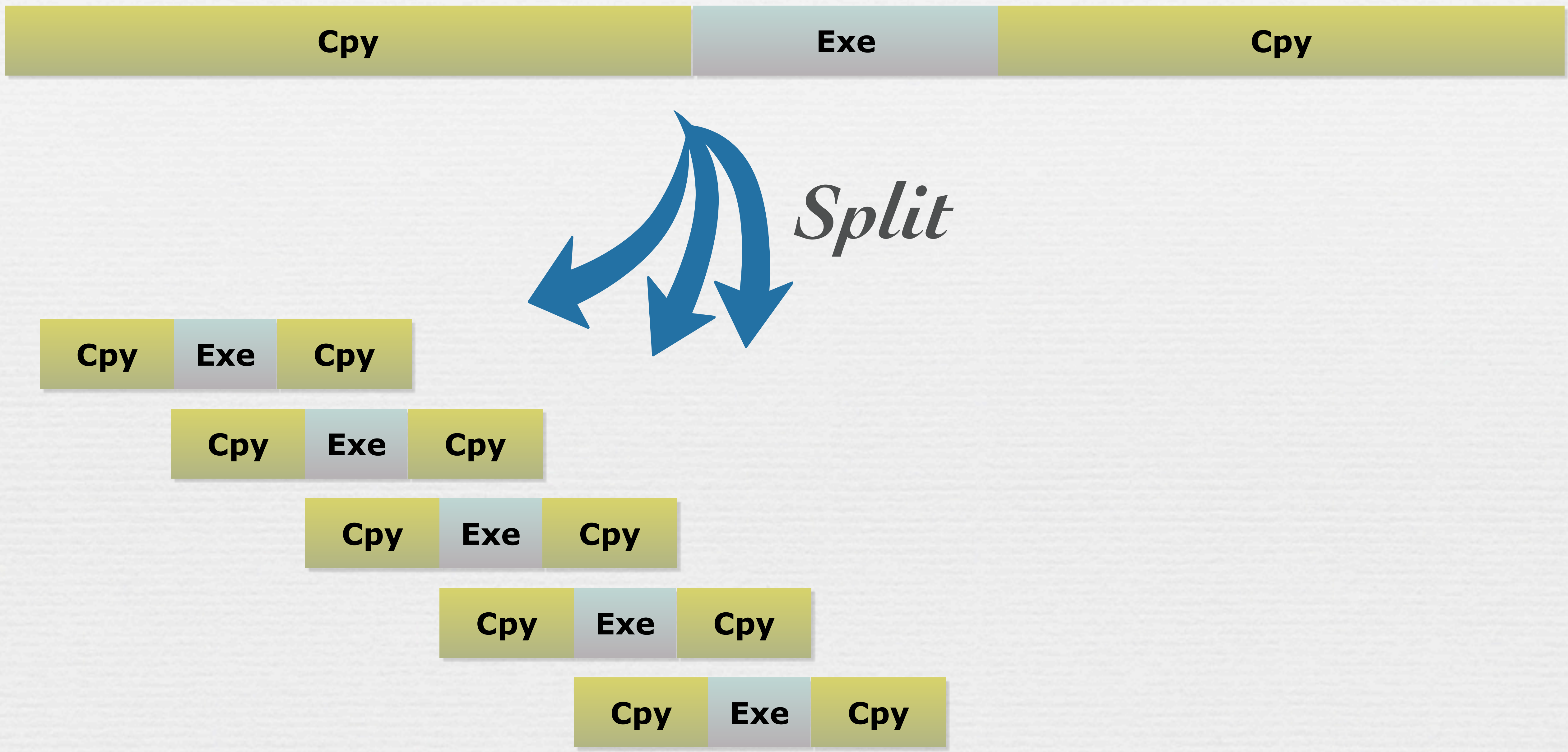

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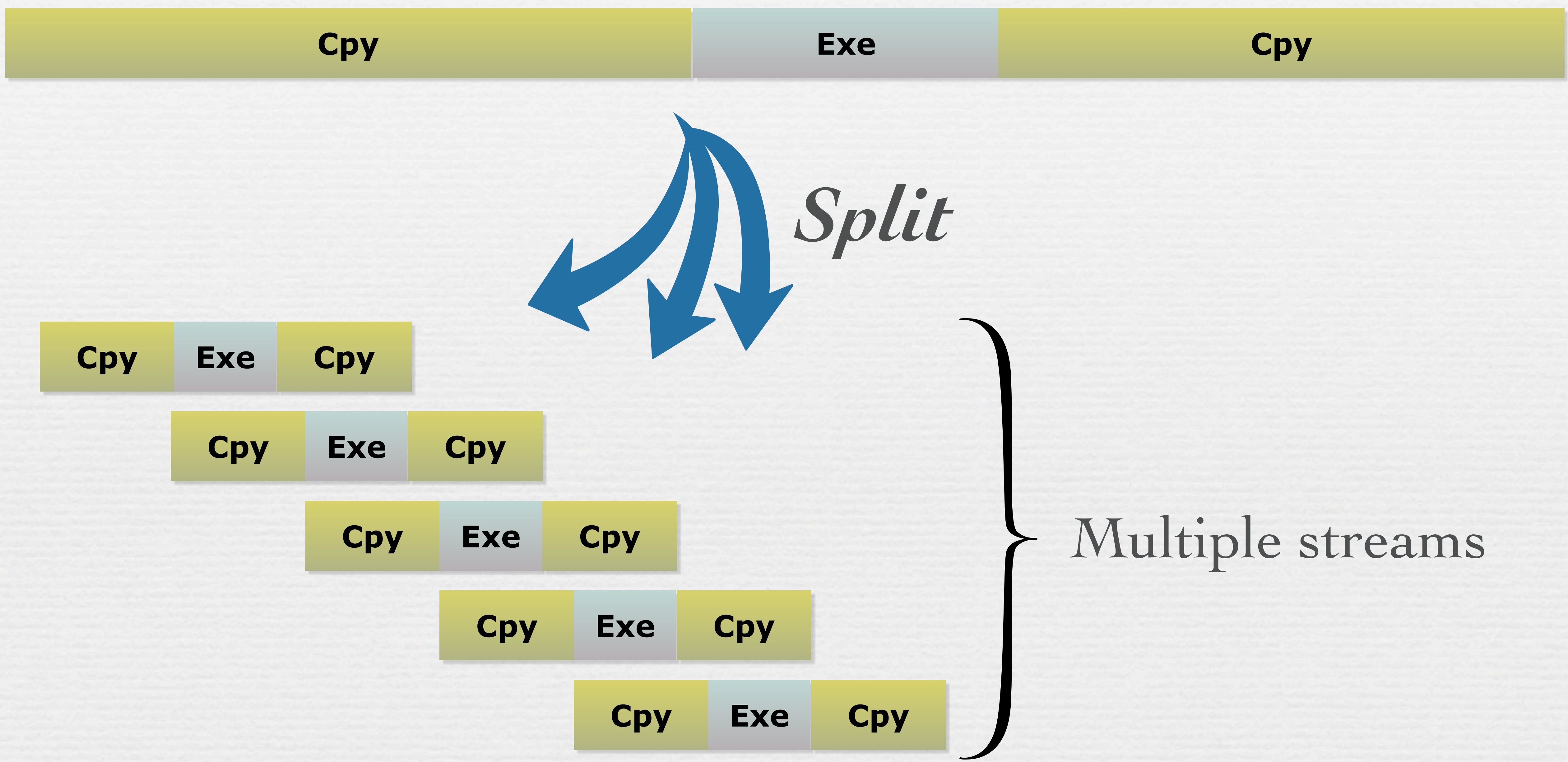

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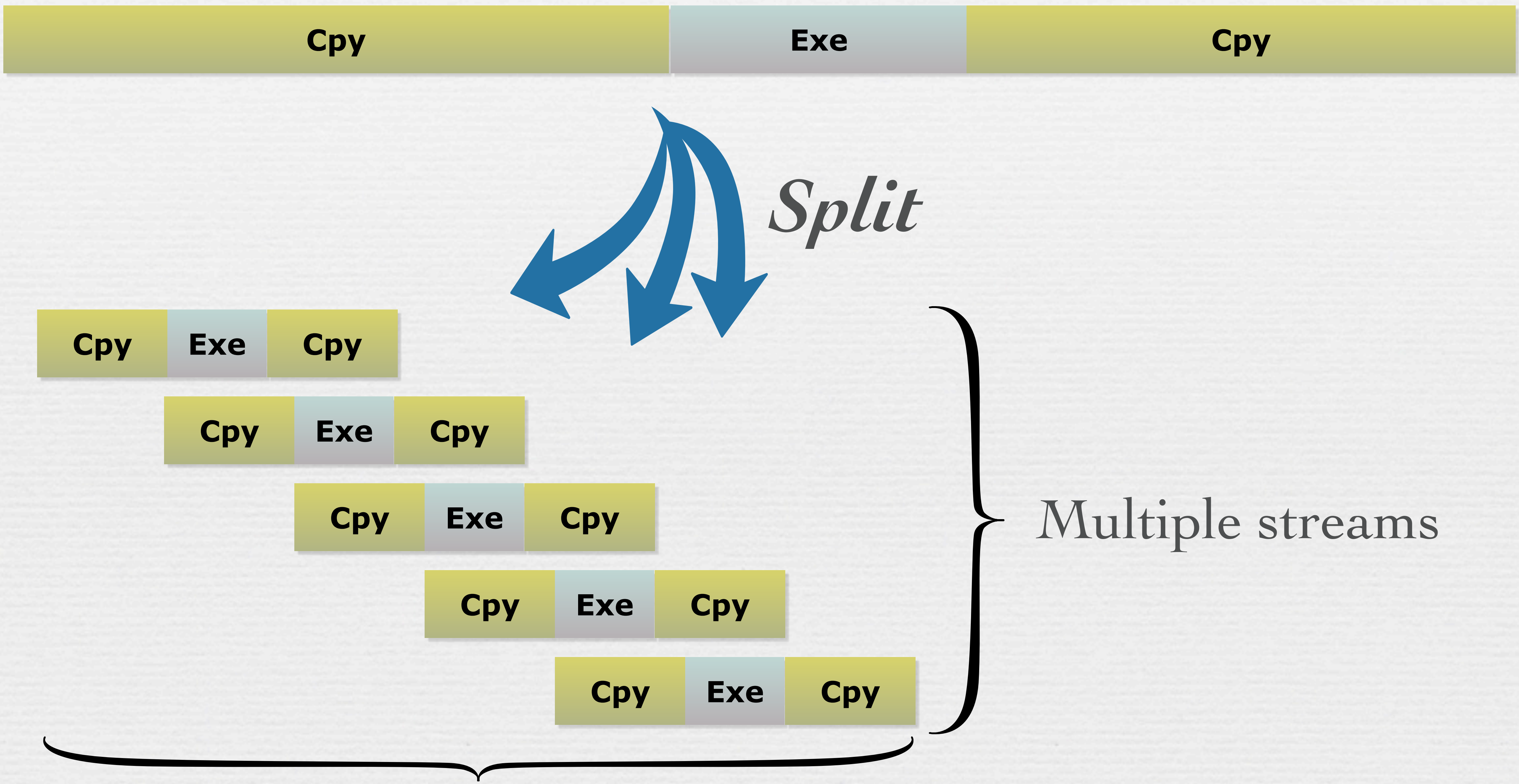

GPU overlapped copy & execution (Multiple DMA engine)

Service-specific request scheduling

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- Not too large, not too small, what's the RIGHT size:
  - Decided by service itself
    - Boot-time benchmark, service logic, computing features...

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- Not too large, not too small, what's the RIGHT size:
  - Decided by service itself
    - Boot-time benchmark, service logic, computing features…
- Make sure correctness: Merge/Split logic:
  - Done by service too
  - Simple ones may use common split/merge

GPUstore

- ~~Stream Management~~
- ~~Request Management~~
- Memory Management

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GPUstore MM

GPUstore MM

- Remap pages for GPU DMA
  - Similar to cudaRegisterHost, but for scattered pages in kernel mode
  - To use existing pages

GPUstore MM

- Remap pages for GPU DMA
  - Similar to cudaRegisterHost, but for scattered pages in kernel mode
  - To use existing pages
- Allocate(and remap) GPU driver's pages directly
  - CUDA Page-locked memory in kernel mode
  - For easily changeable code/new code

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Evaluation

Applications: (Approximated LOC modification)

App.	Modified LOC	%	Request scheduling	MM
eCryptfs	200	2%	Merge/Split	Remapping
dm-crypt	50	3%	Merge/Split	No remapping
MD RAID6	20	0.3%	Merge/Split	No remapping

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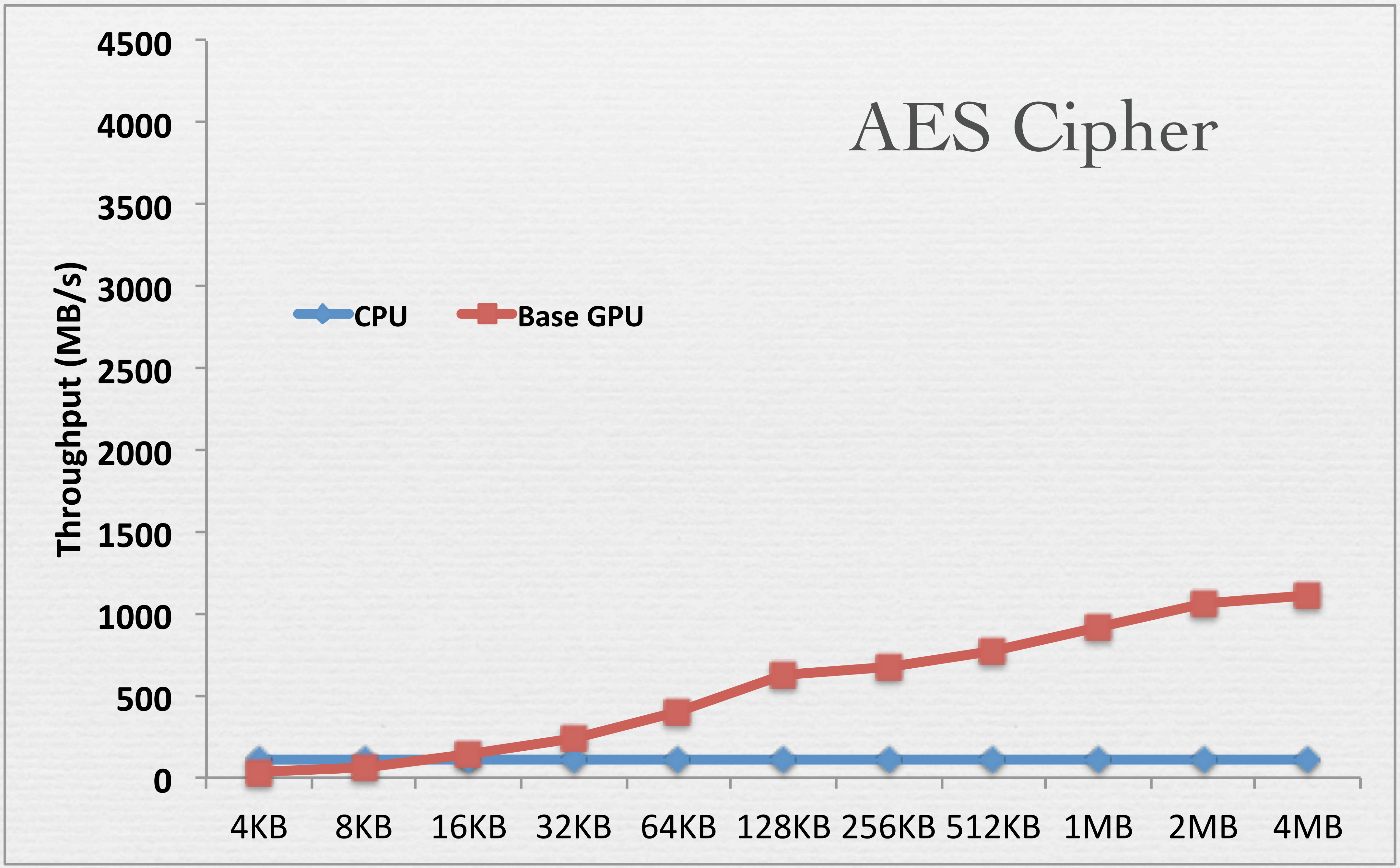
Effectiveness of optimizations



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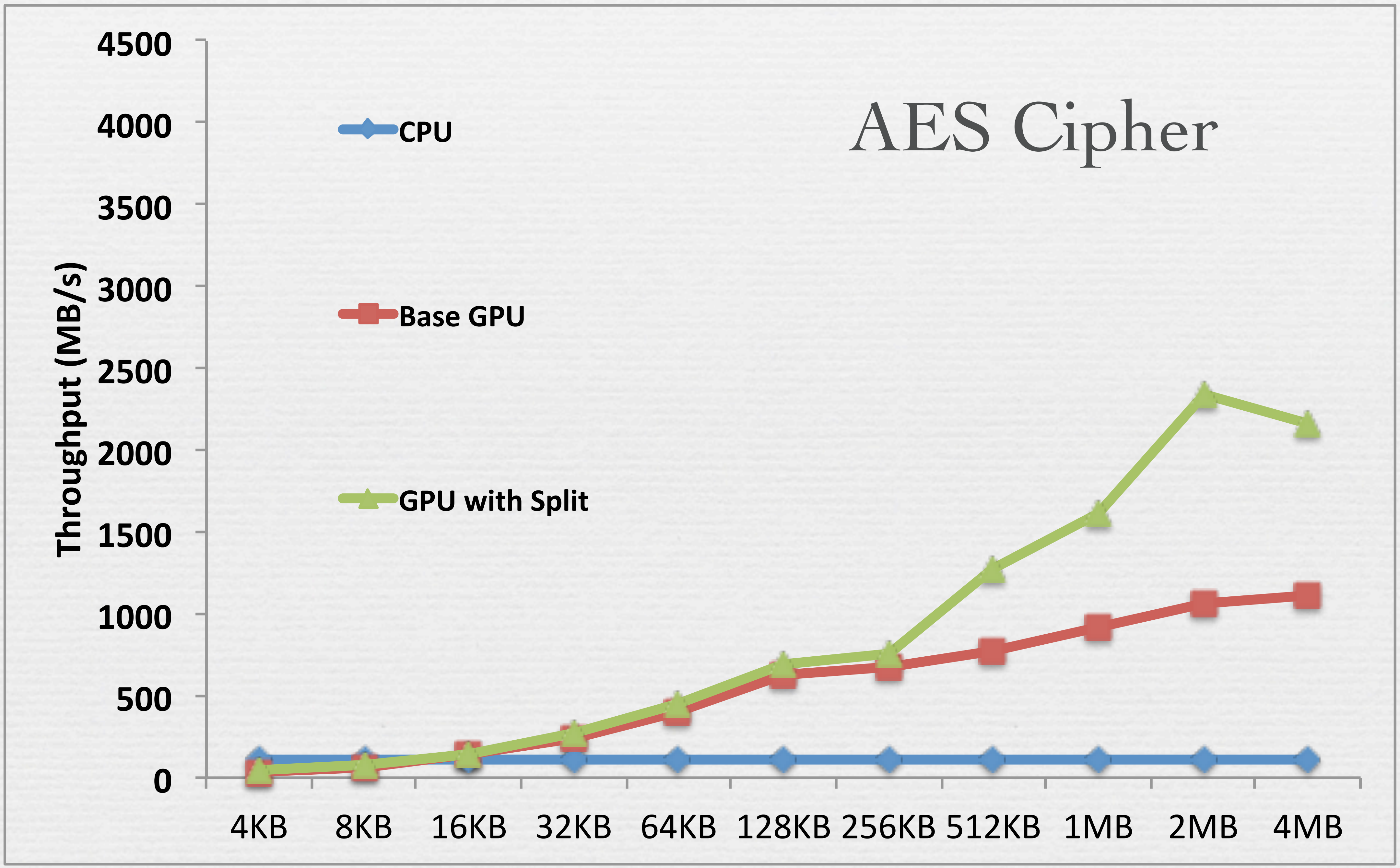

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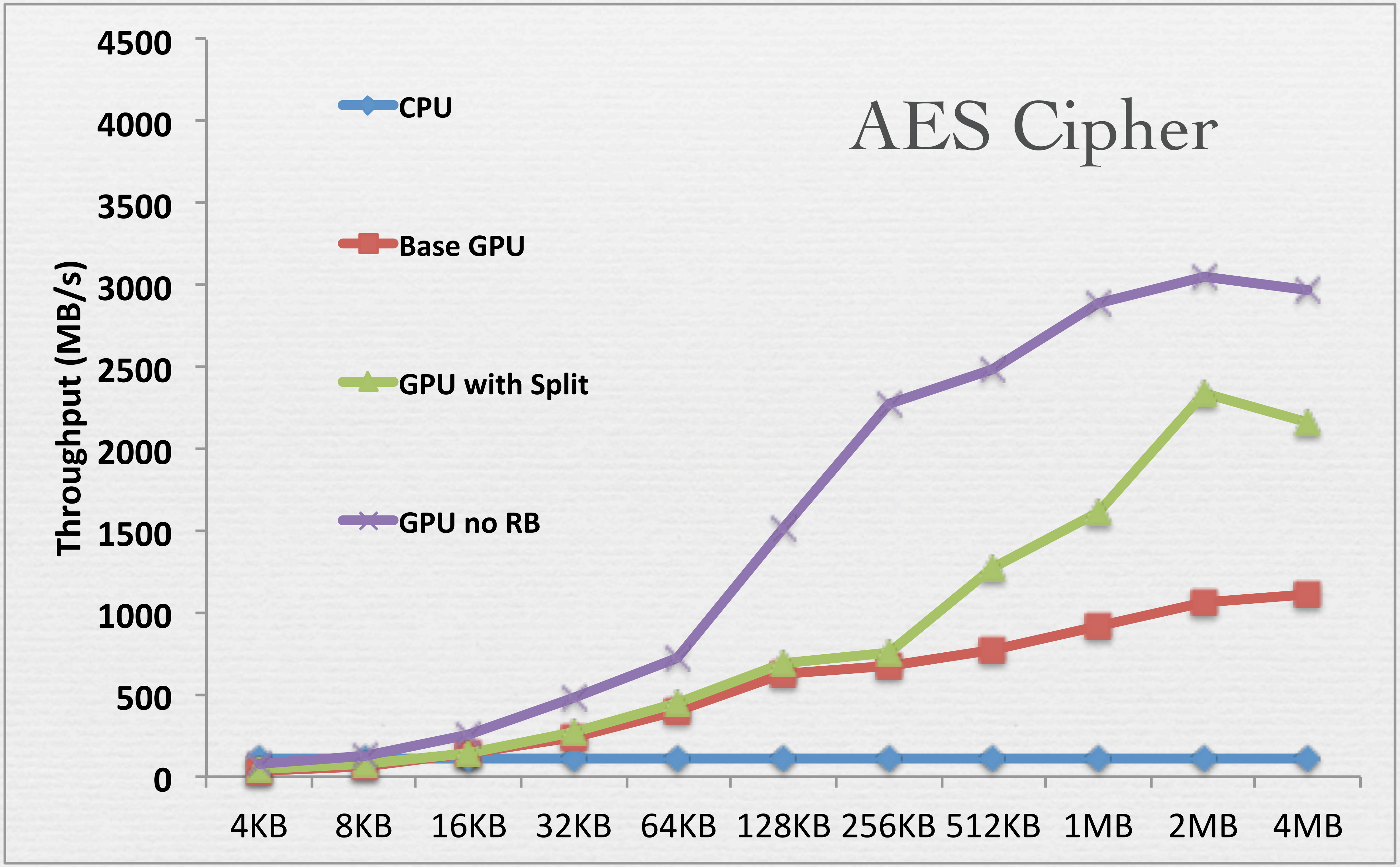

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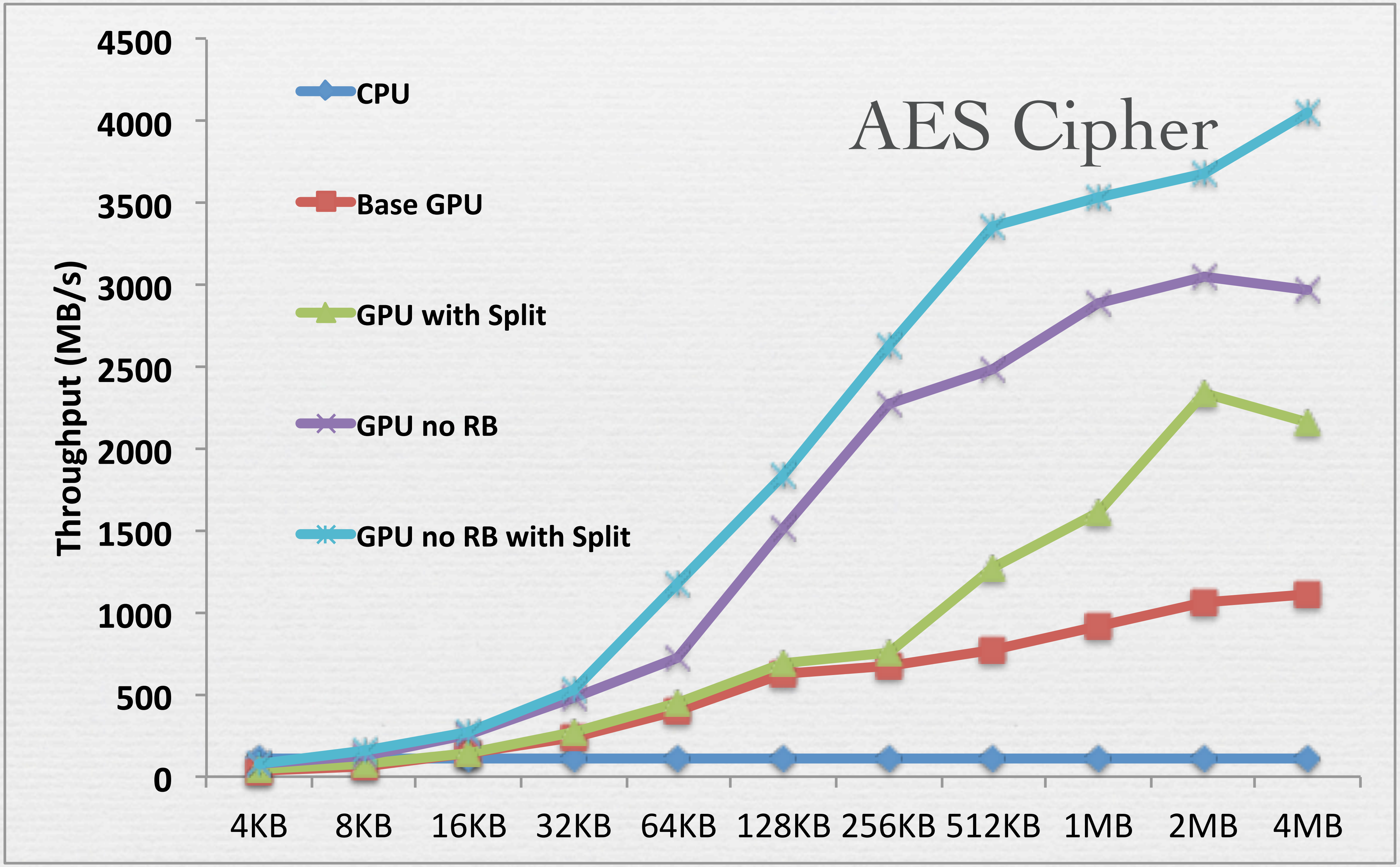

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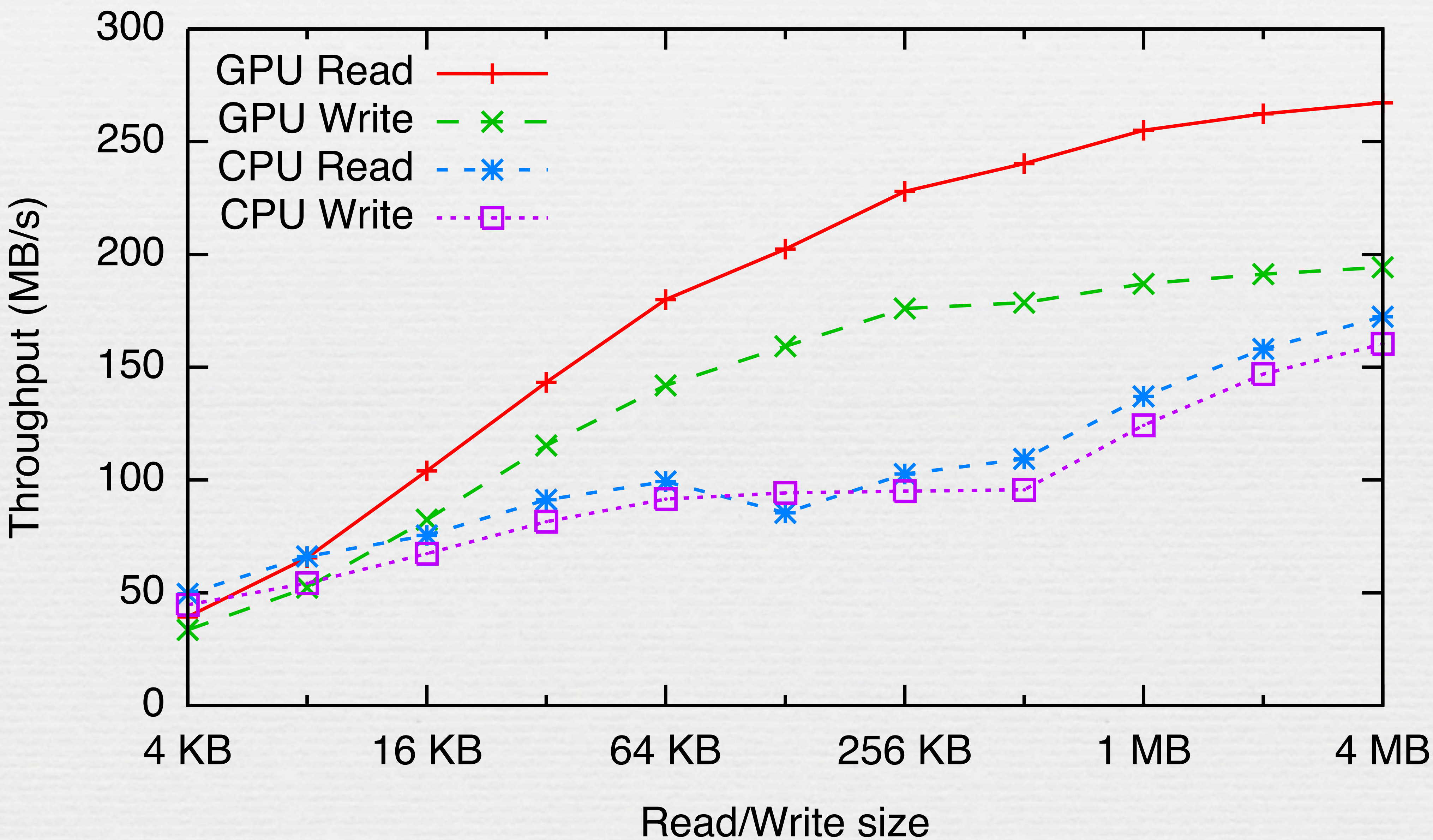
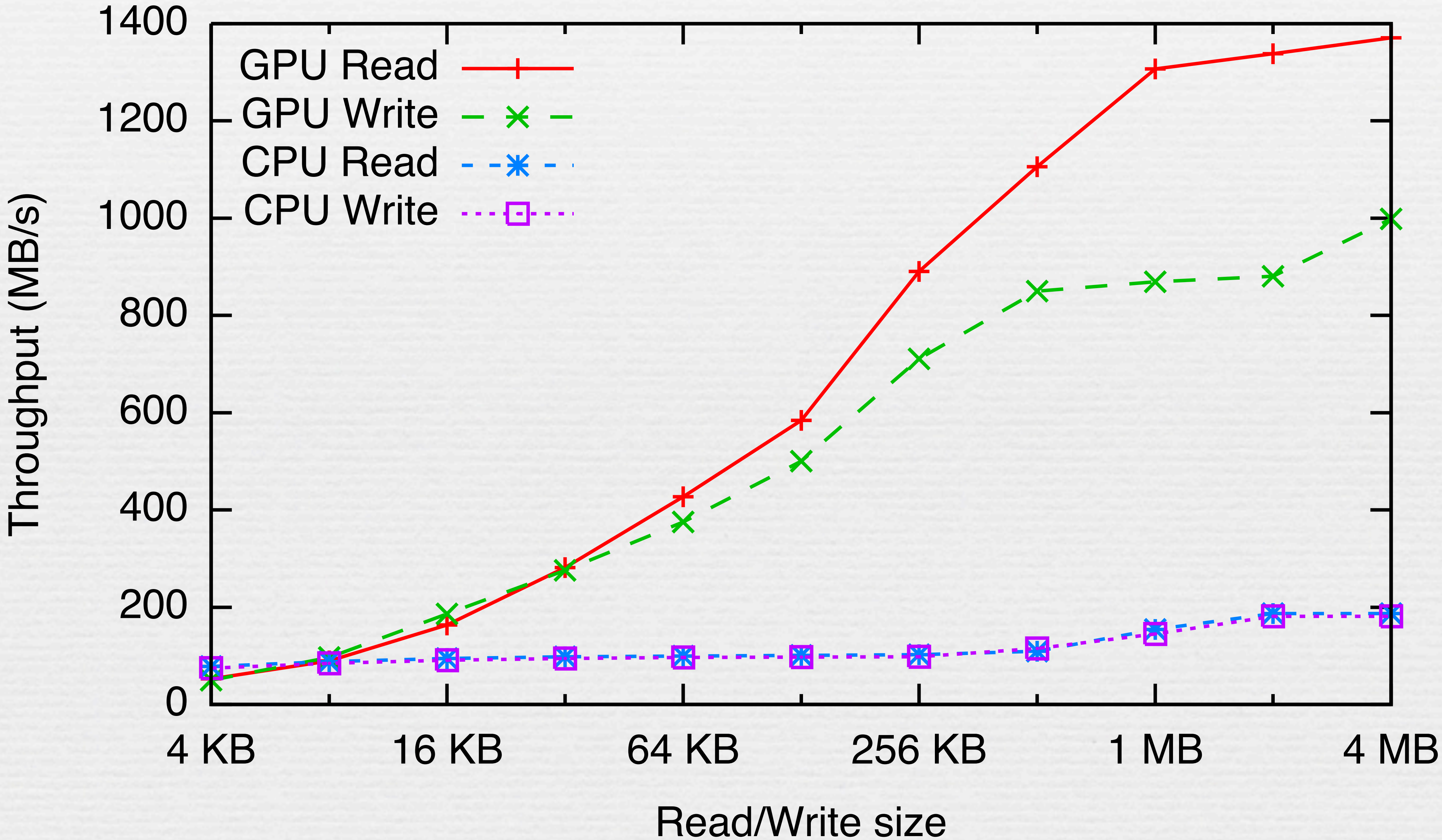
dm-crypt SSD

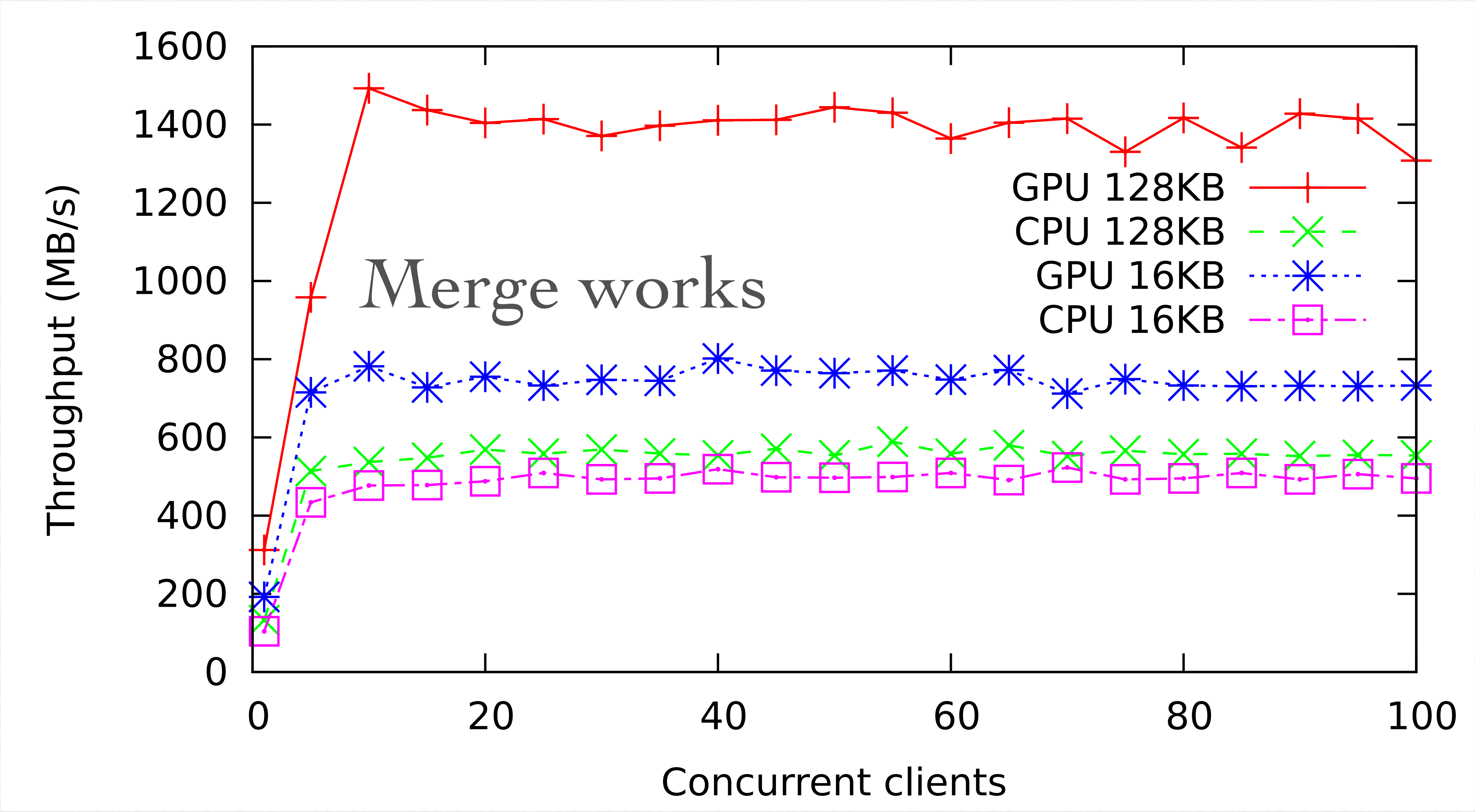


GPU Read
GPU Write
CPU Read
CPU Write
Throughput (MB/s)
300
250
200
150
100
50
0
4 KB
16 KB
64 KB
256 KB
1 MB
4 MB
Read/Write size

Better dm-crypt on RAM disk

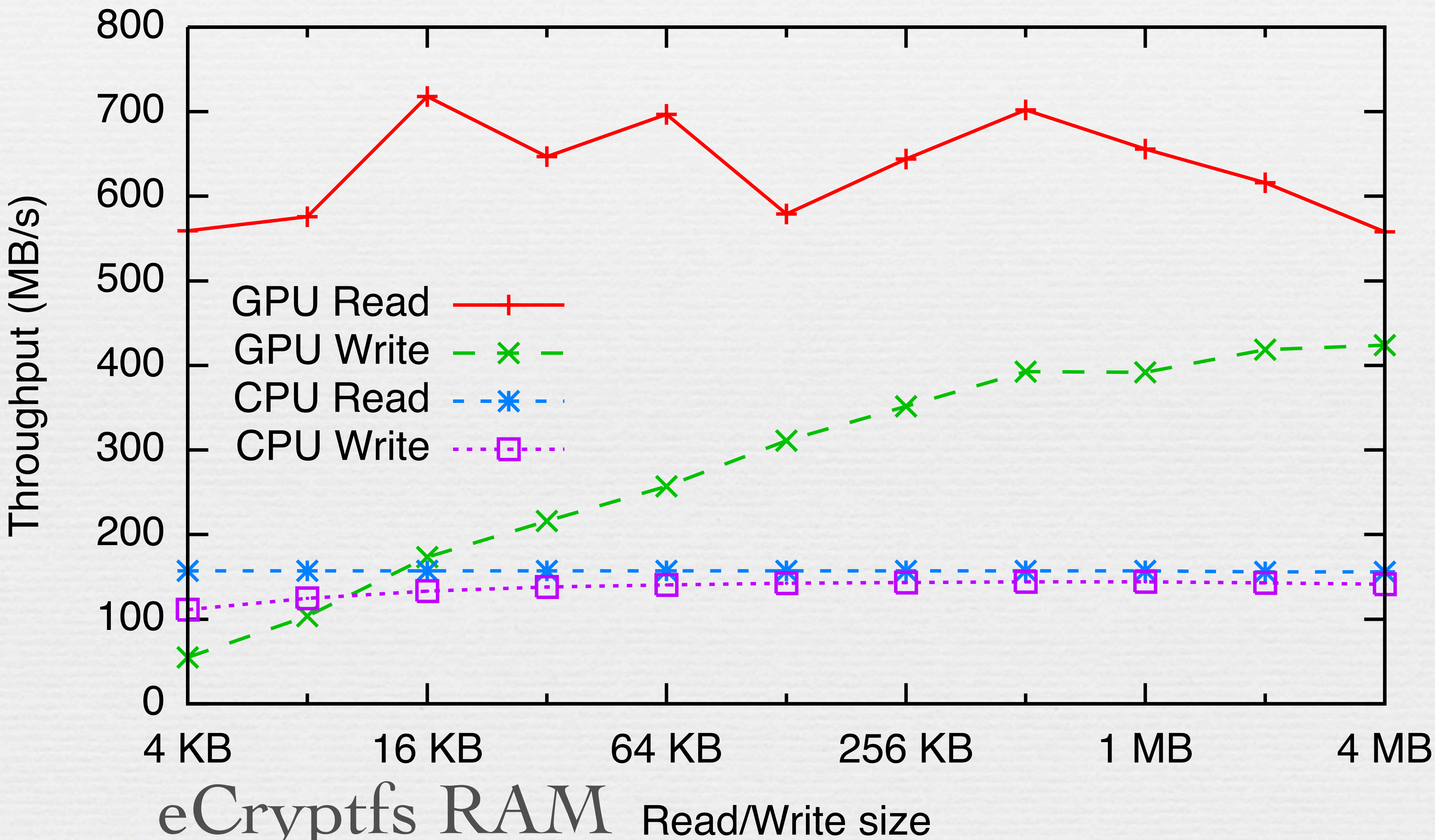


eCryptfs Concurrent clients



RAM Disk, Write only

Existing optimizations still work



eCryptfs RAM

More results in paper

- Upper-bound of best GPUstore framework performance
- eCryptfs on SSD
- RAID6 recovery algorithm
- RAID6 on HDs/RAM disks
- ...

URLs

- Google Code: http://code.google.com/p/kgpu
- Github: https://github.com/wbsun/kgpu
- Being refactored
- Will use Gdev for kernel-level CUDA access

Thanks!
Q&A

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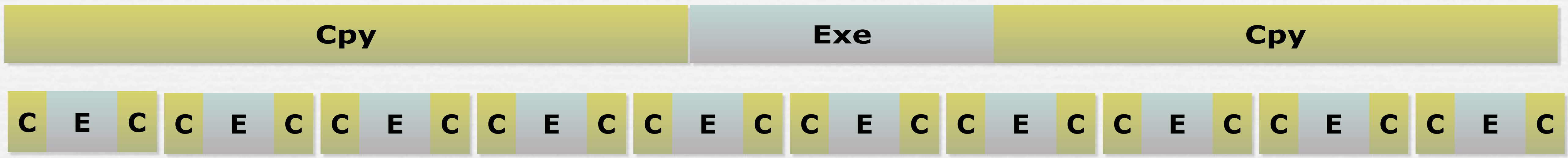
Hate too large/small I/O requests?



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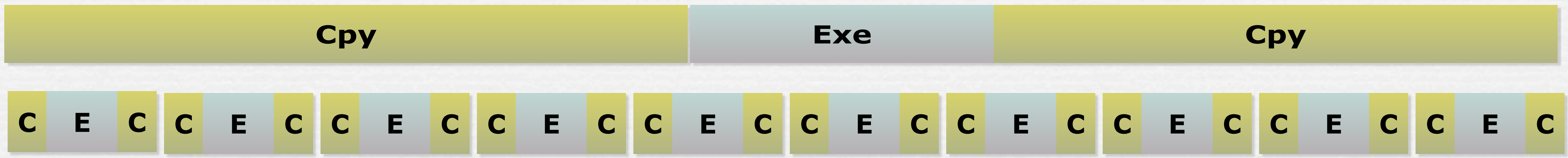

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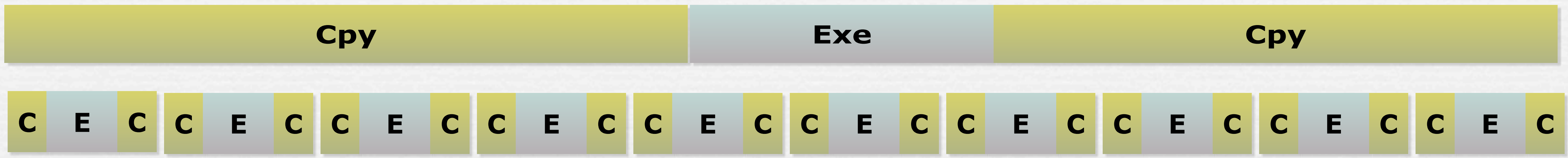

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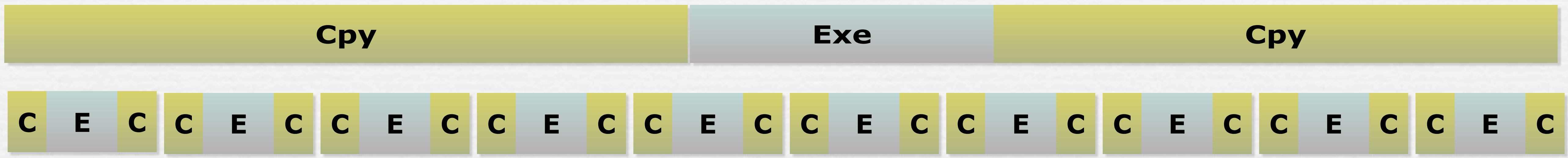

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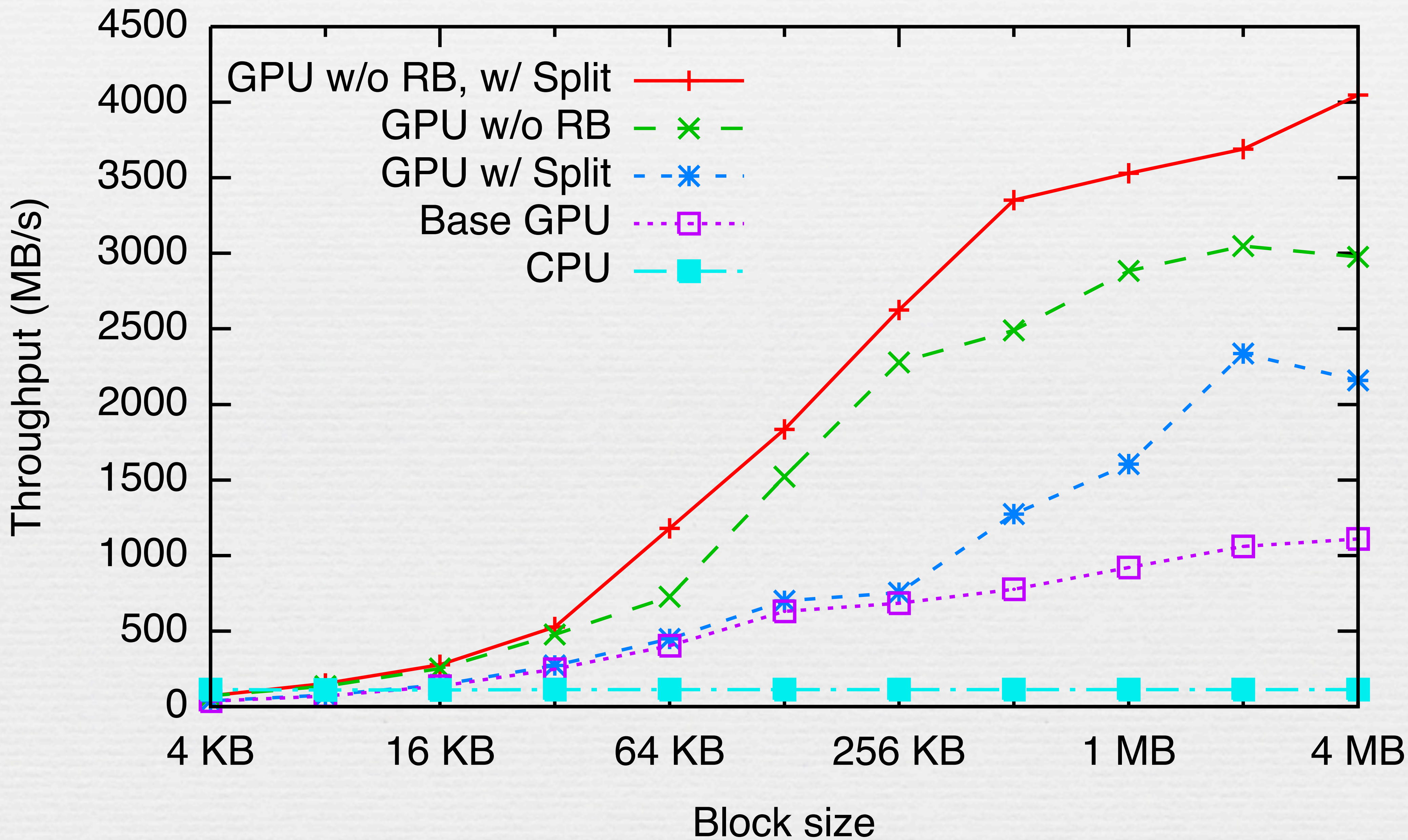

Why GPUstore?

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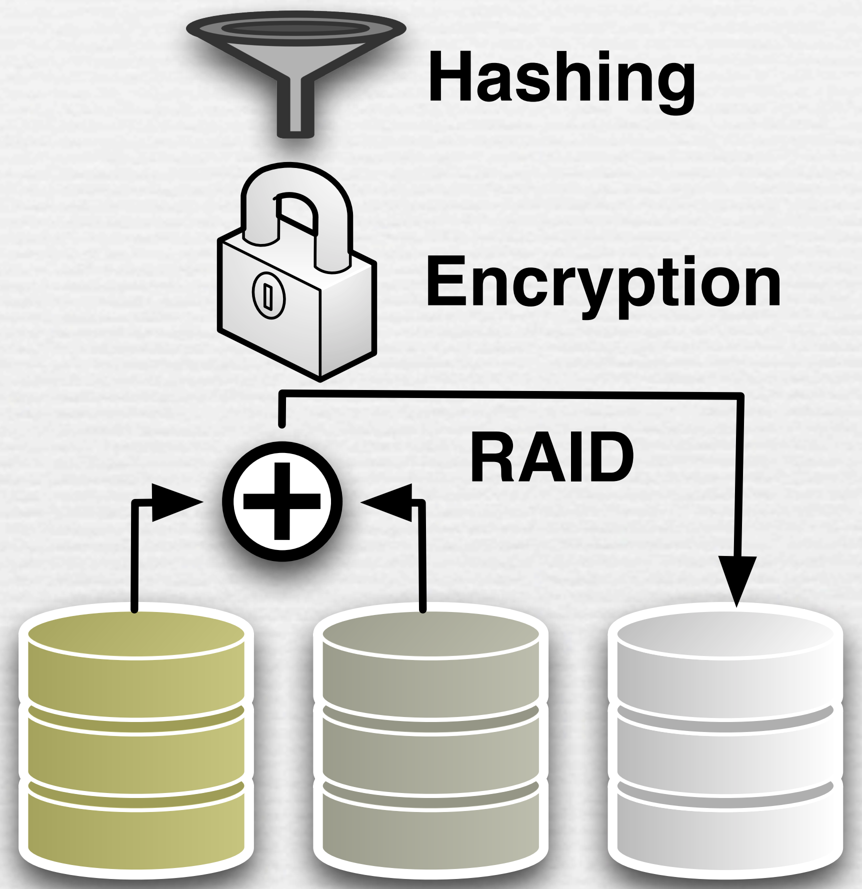
Why GPUstore?



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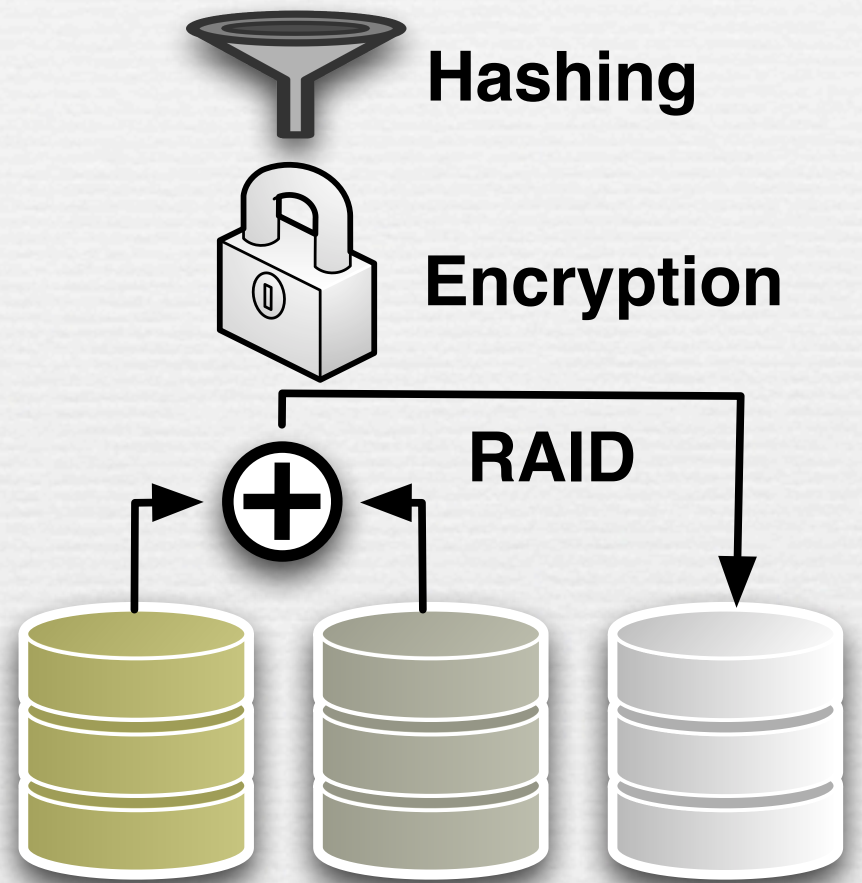

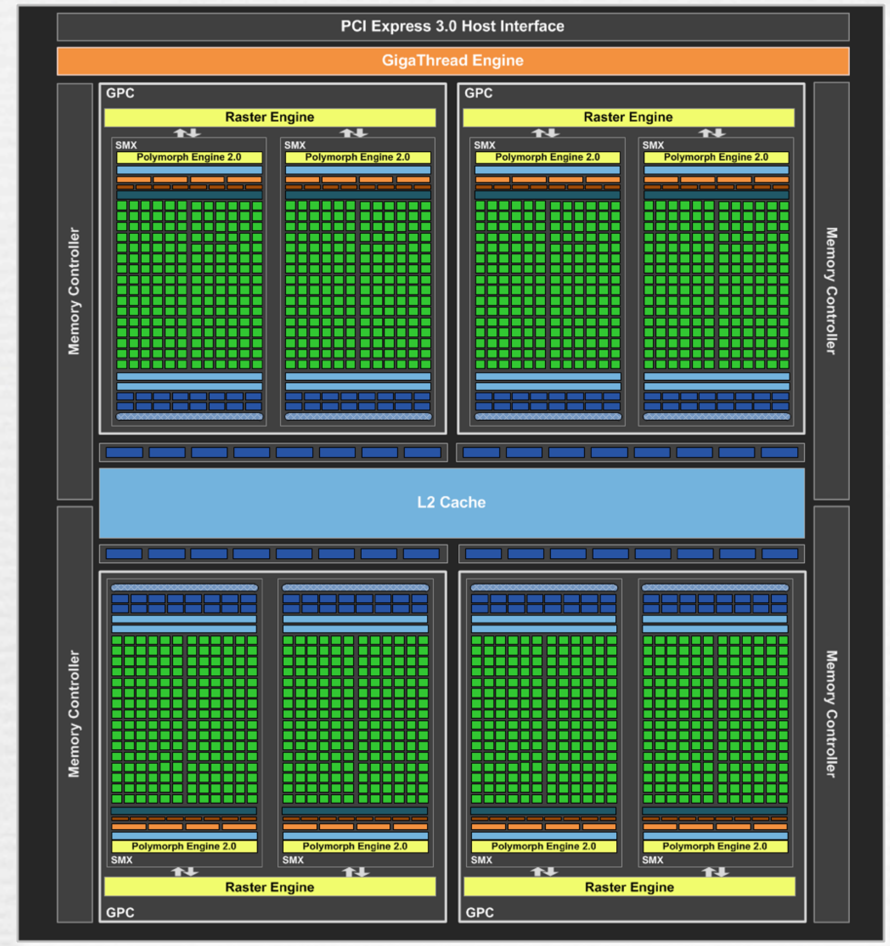

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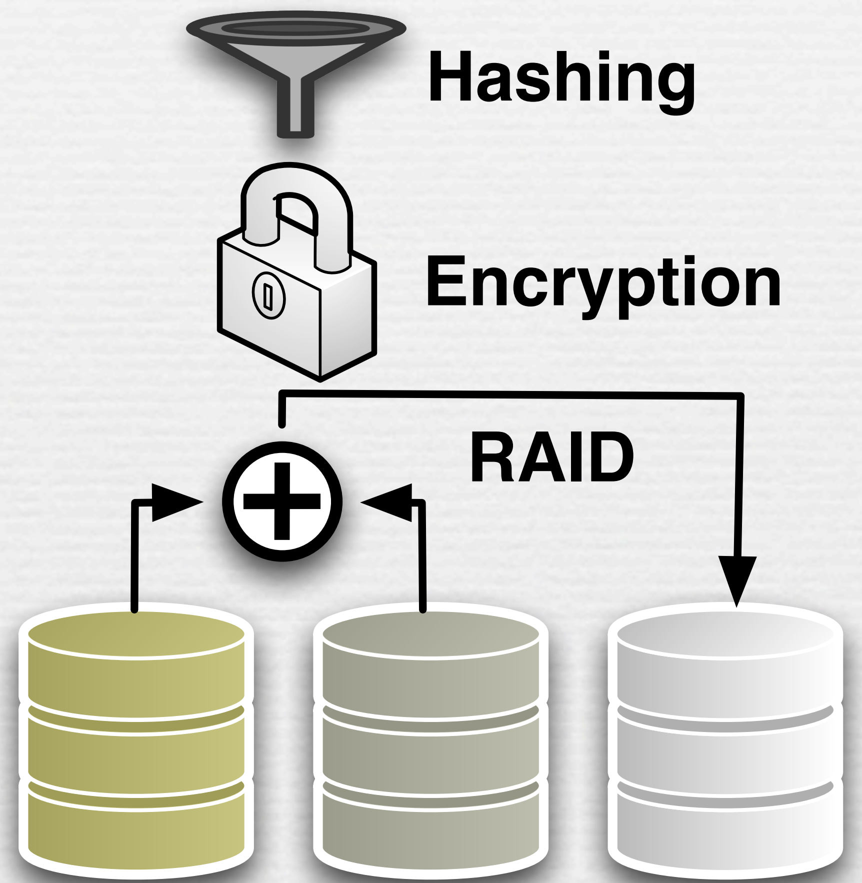
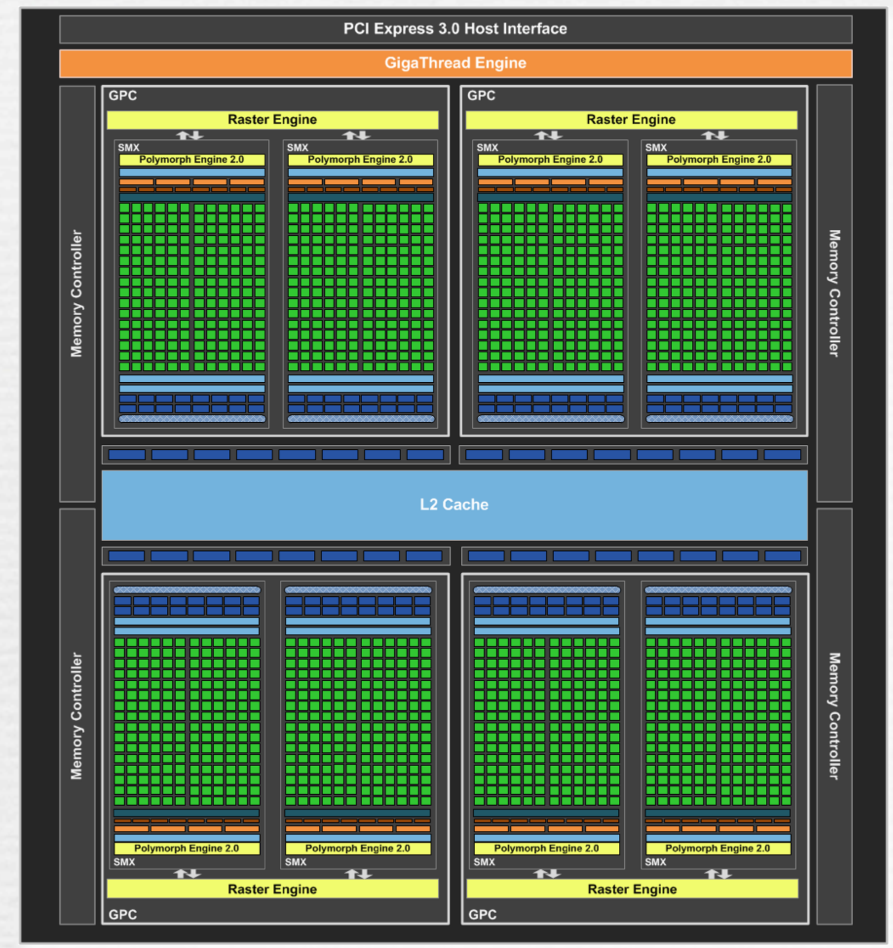




Obstacles

- Computation sizes vary a lot, depend I/O sizes
  - Compared with: long-run, large dataset GPGPU
- No optimizations concerning task sizes in CUDA/OpenCL
- Resources (e.g. memory) management - (because storage systems in kernel is special)

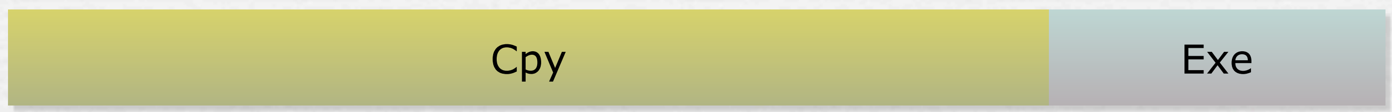
Contribution

- Identified problems in...
  - GPU computing for storage
- A framework:
  - eases integration into existing code
  - REALLY cares about OS kernel

Design - Challenges

- Asynchrony (maybe not a big deal)
- Redundant buffering
- GPU memcpy and access overhead
- Large dataset
- Managing Resources

Large dataset



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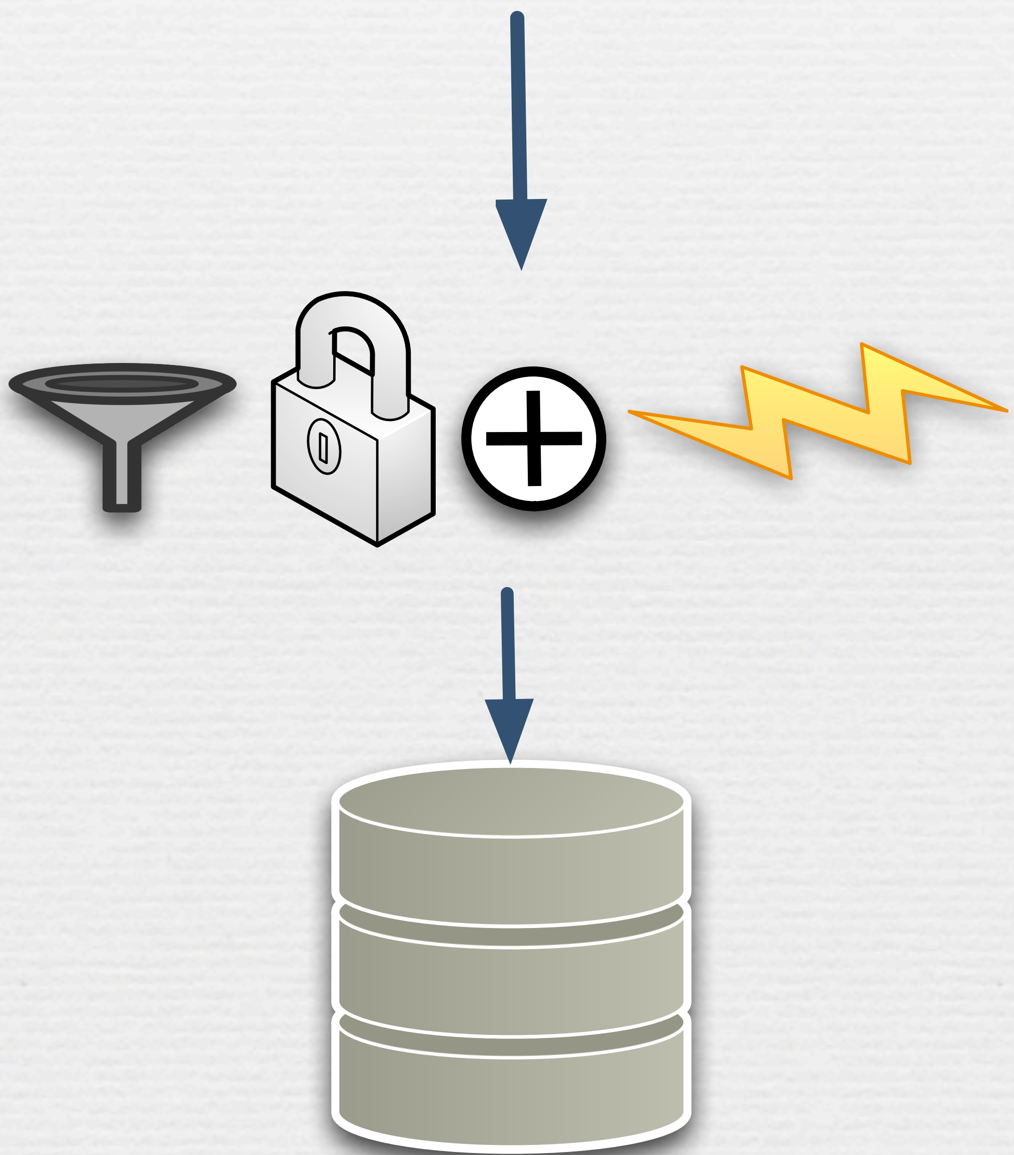
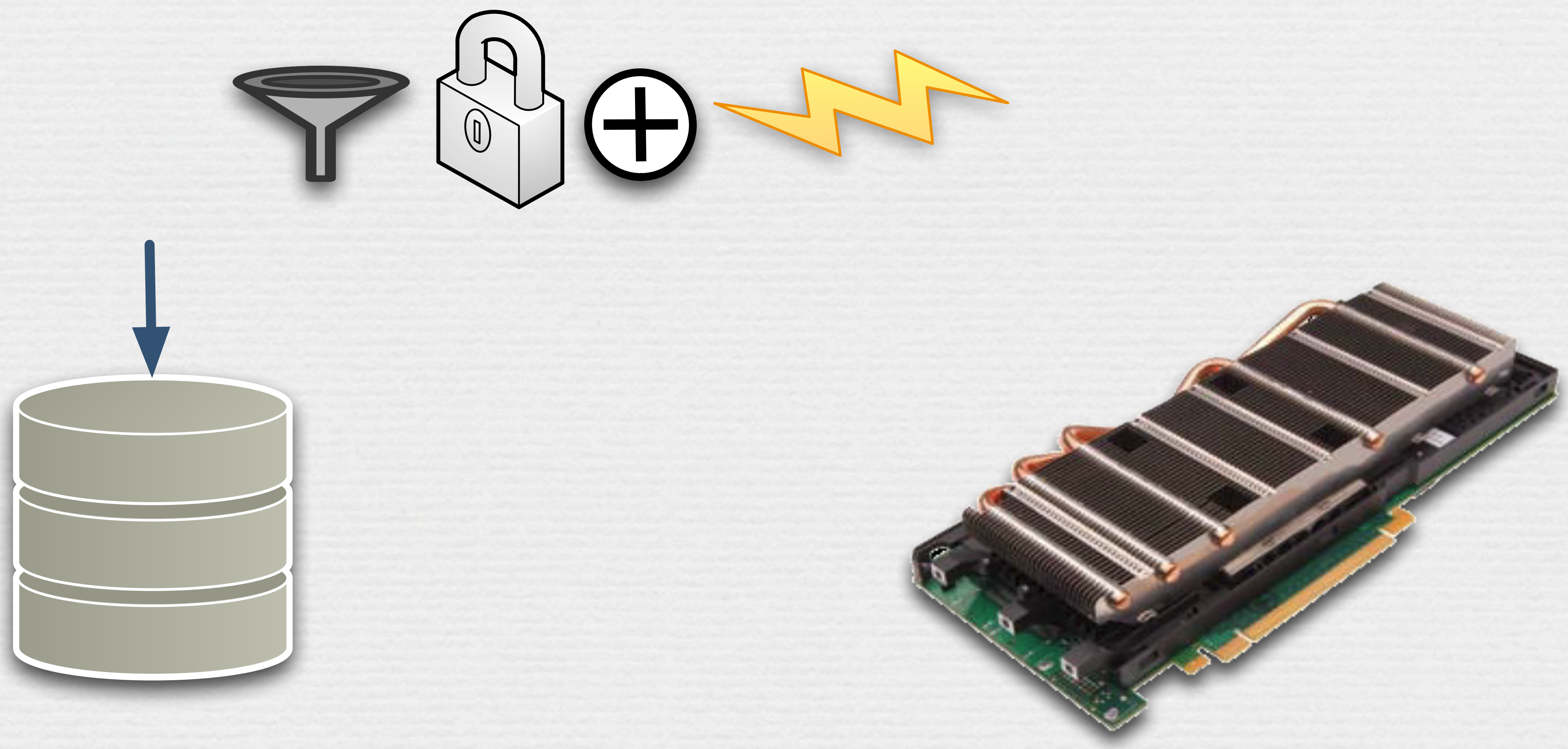
GPUstore



GPUstore



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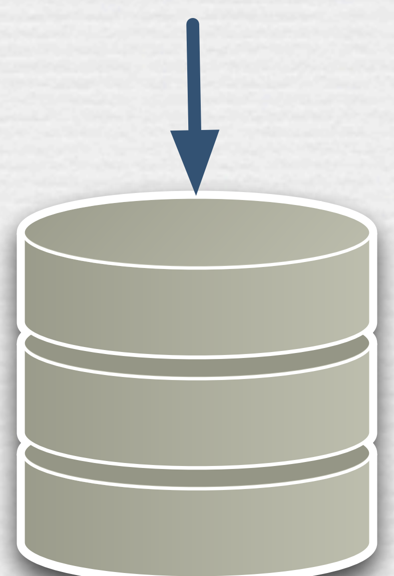
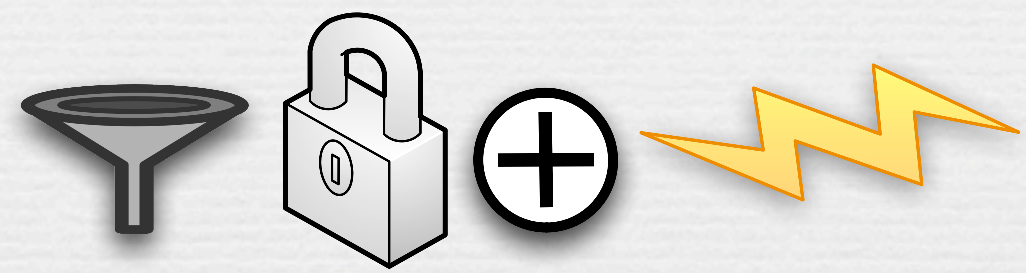
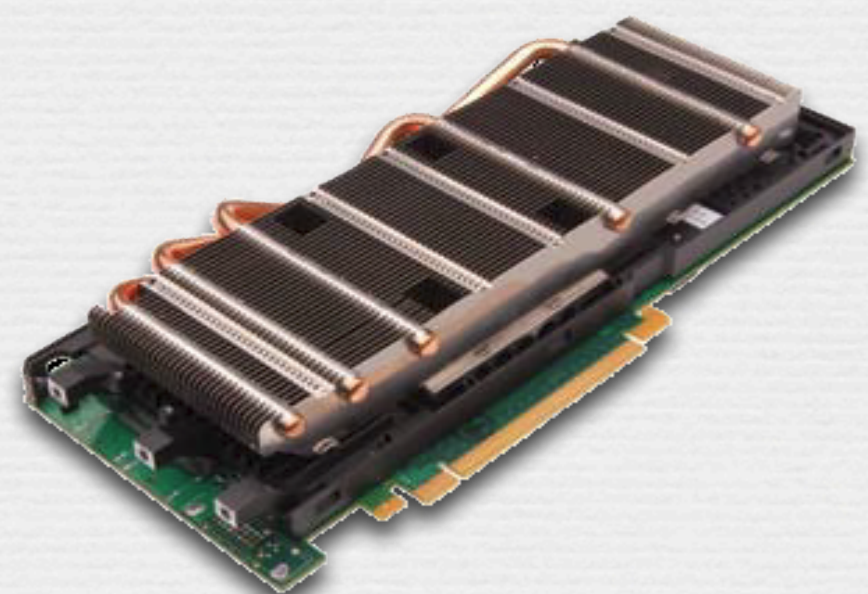
GPUstore







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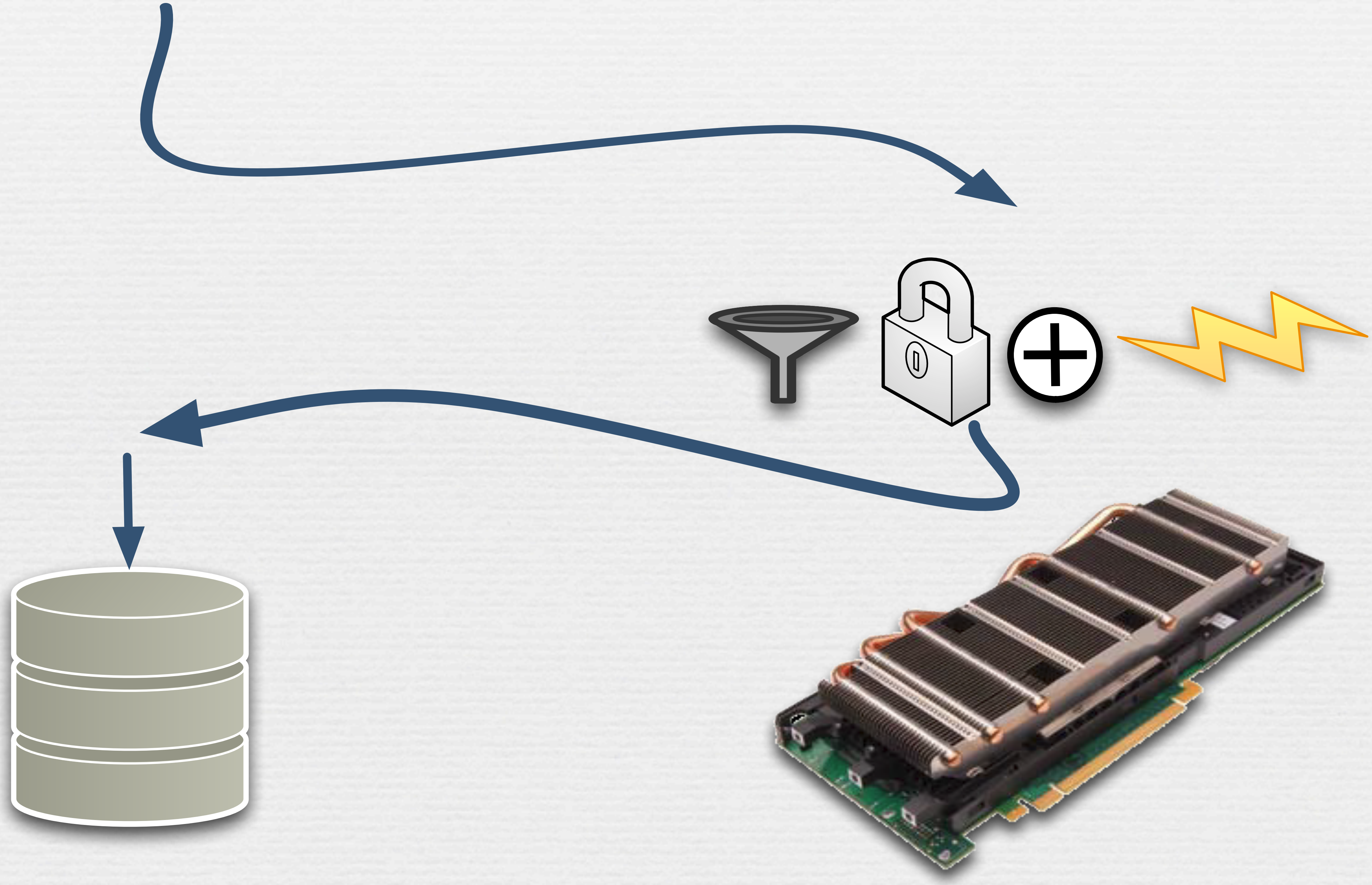

Design

- Request processor
- Functionality -> services

Design - Request Scheduling

- Merge
- Split

Design - Request Scheduling

- Merge
  - To reduce memcpy
  - Hide GPU memory access latency
  - Reduce GPU computing launch overhead

But ...

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But ...

- Computation size matters

But ...

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- We want to help existing storage code, in OS kernel, so:

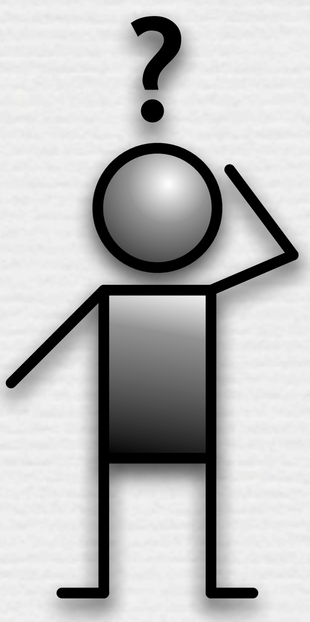
44

But ...

- Computation size matters
- We want to help existing storage code, in OS kernel, so:

Minimum change, maximum performance

Why computation size matters?



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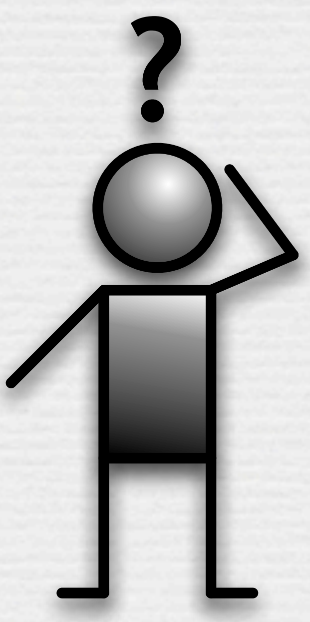
Why computation size matters?

- Size ∝ Time - so not too large



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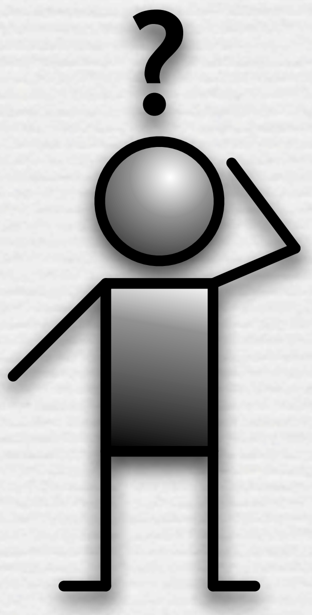

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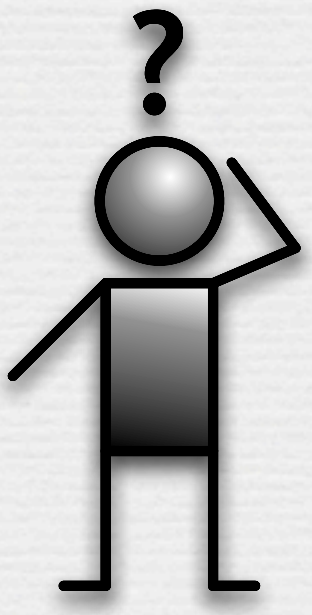

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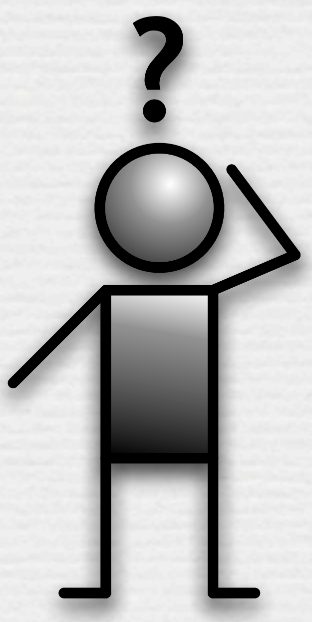
    - Large data/Long run scientific computing/ HPC
    - Kernel storage code should be latency-aware



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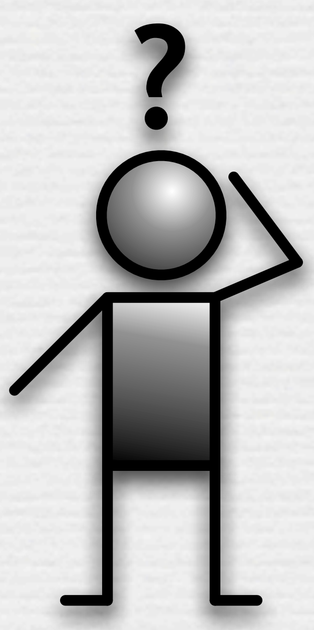

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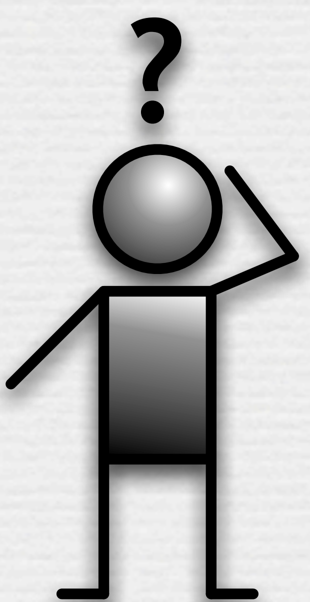
Why computation size matters?

- Size ∝ Number of threads - so not too small



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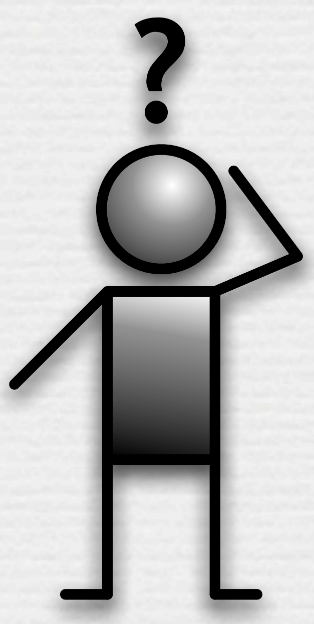

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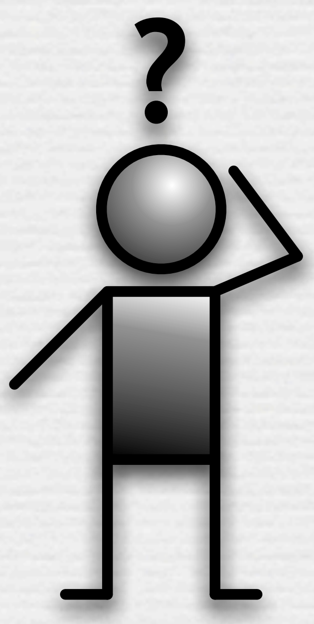

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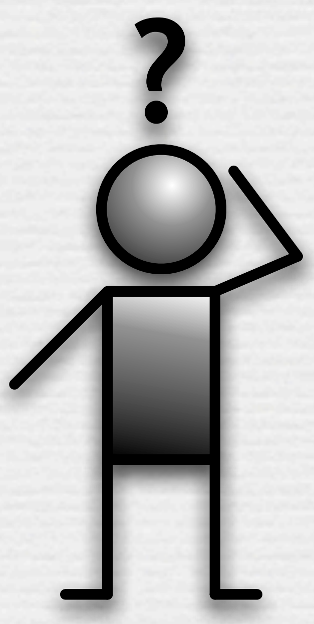

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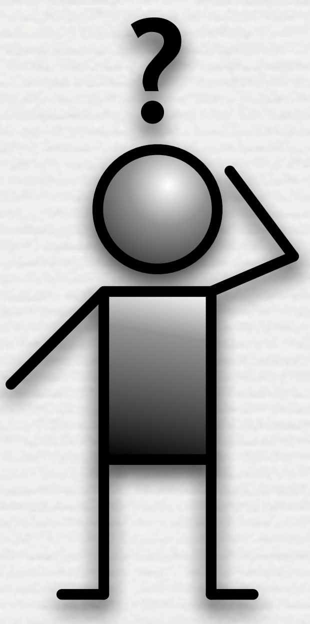

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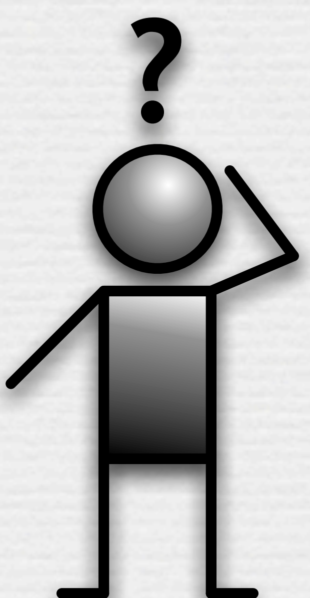

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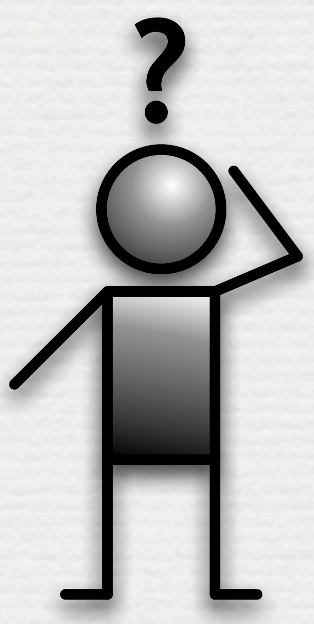

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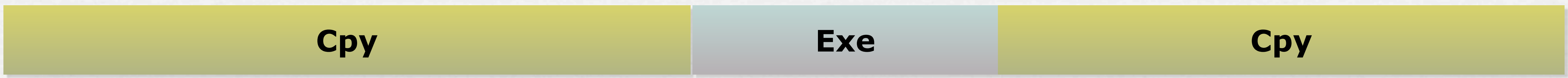
Too large computation



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Too large computation

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- GPU can do:

Too large computation

- GPU can do:
  - Bidirectional DMA with multiple DMA engines

Too large computation

- GPU can do:
    - Bidirectional DMA with multiple DMA engines
    - Overlapped copy and execution

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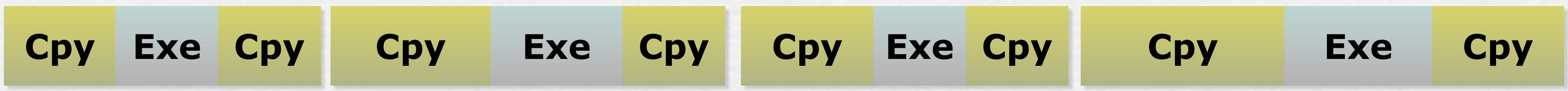
Too large computation

- GPU can do:
  - Bidirectional DMA with multiple DMA engines
  - Overlapped copy and execution
  - Do more than one computation at the same time

Too small computation

Too small computation



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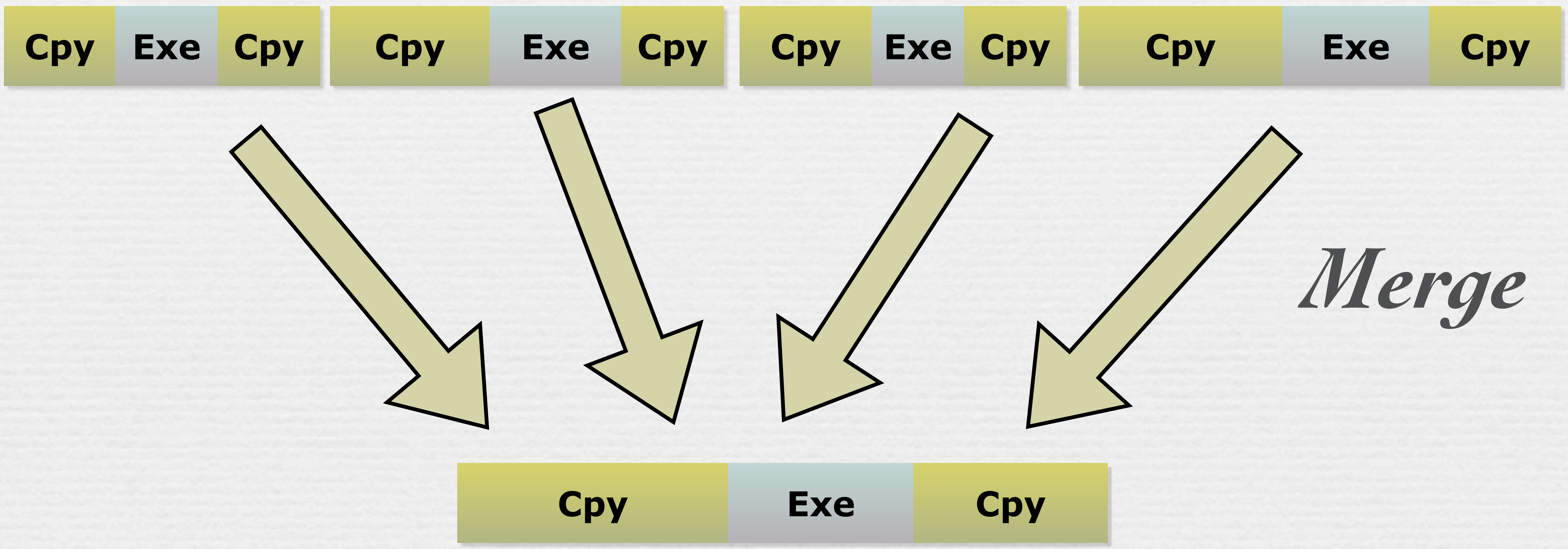

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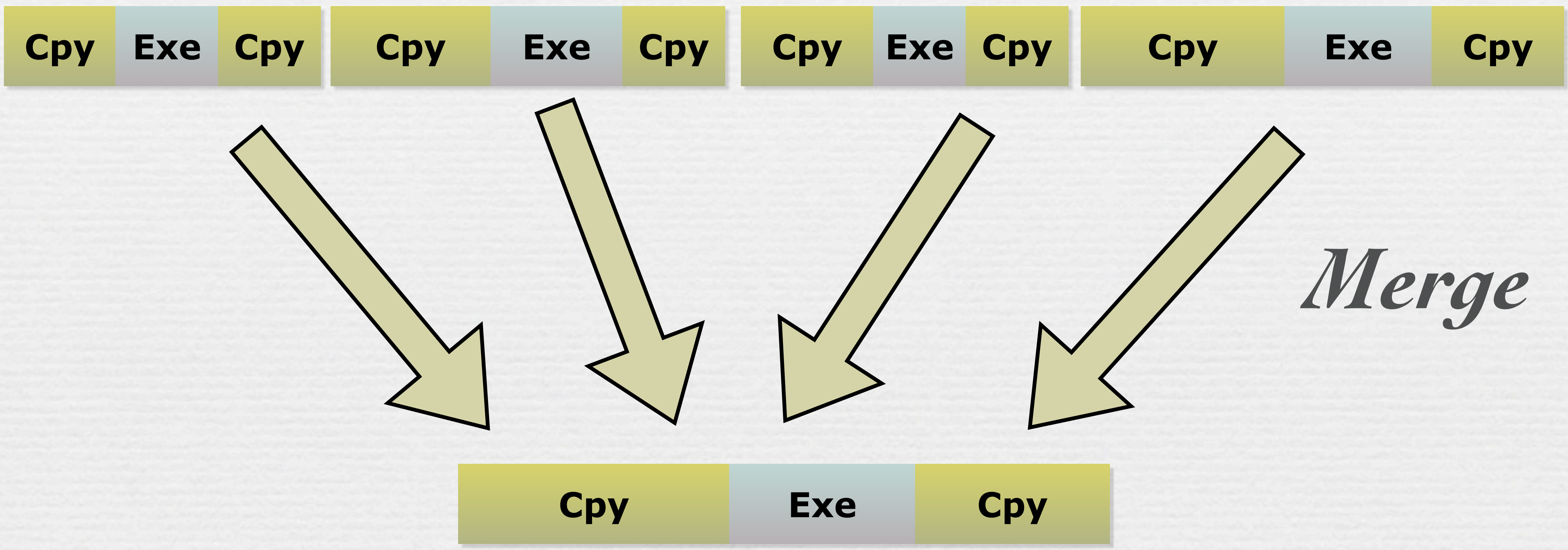
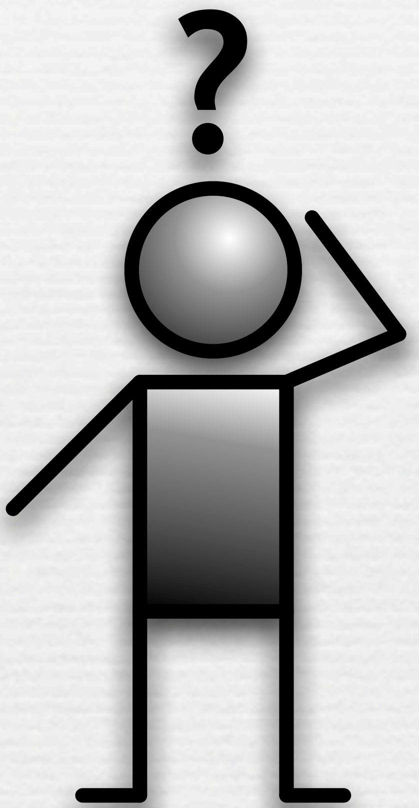


Merge is not linear addition

Okay, but

Okay, but



What is the RIGHT size?

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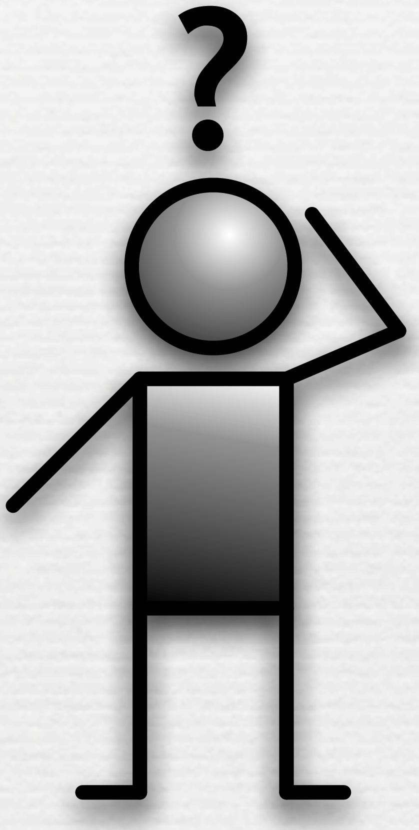

What is the RIGHT size?

How to logical-correctly merge/split?

GPUstore design

- Functionality ➡ Service (simply, code on GPU)
- Using functionality ➡ Request to service

Service-specific request scheduling

Service-specific request scheduling

- Right size:

Service-specific request scheduling

- Right size:
  - Decided by service itself

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Service-specific request scheduling

- Right size:
  - Decided by service itself
    - Boot-time benchmark, service logic, computing features...

Service-specific request scheduling

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- Merge/Split logic:

Service-specific request scheduling

- Right size:
  - Decided by service itself
    - Boot-time benchmark, service logic, computing features...
- Merge/Split logic:
  - Done by service too, or simply nothing

The other “But”

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- Existing code - no big change

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    - In OS kernel: not always be able to control mem allocation - redundant buffering

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The other "But"

- Existing code - no big change
  - In OS kernel: not always be able to control mem allocation - redundant buffering
  - Use functionality as function call
    - Simple: move complex work to service, service as a function call

One more thing

- Other GPU resources
  - Copy engine
  - Overlapping cpy/exec capability

One more thing

- Other GPU resources
  - Copy engine
  - Overlapping cpy/exec capability

Streams

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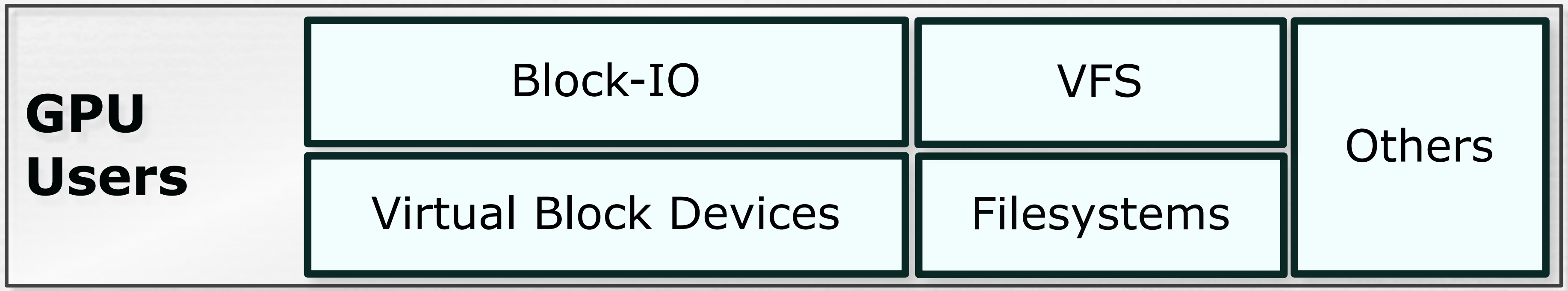
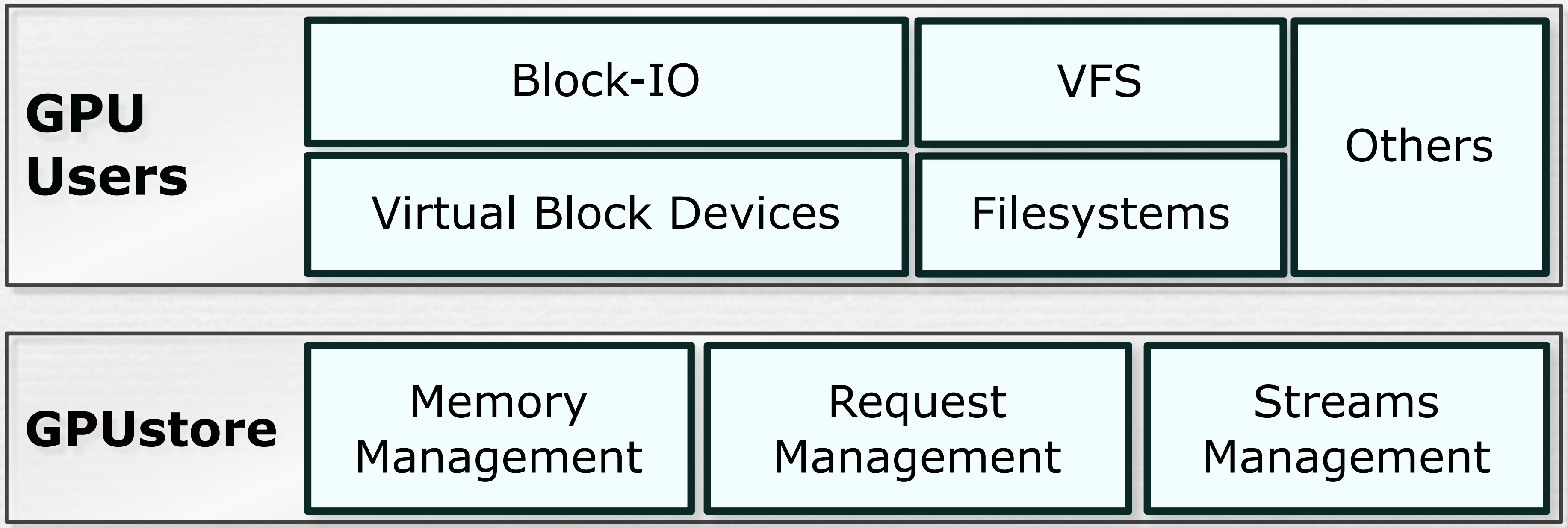
GPUstore

GPUstore

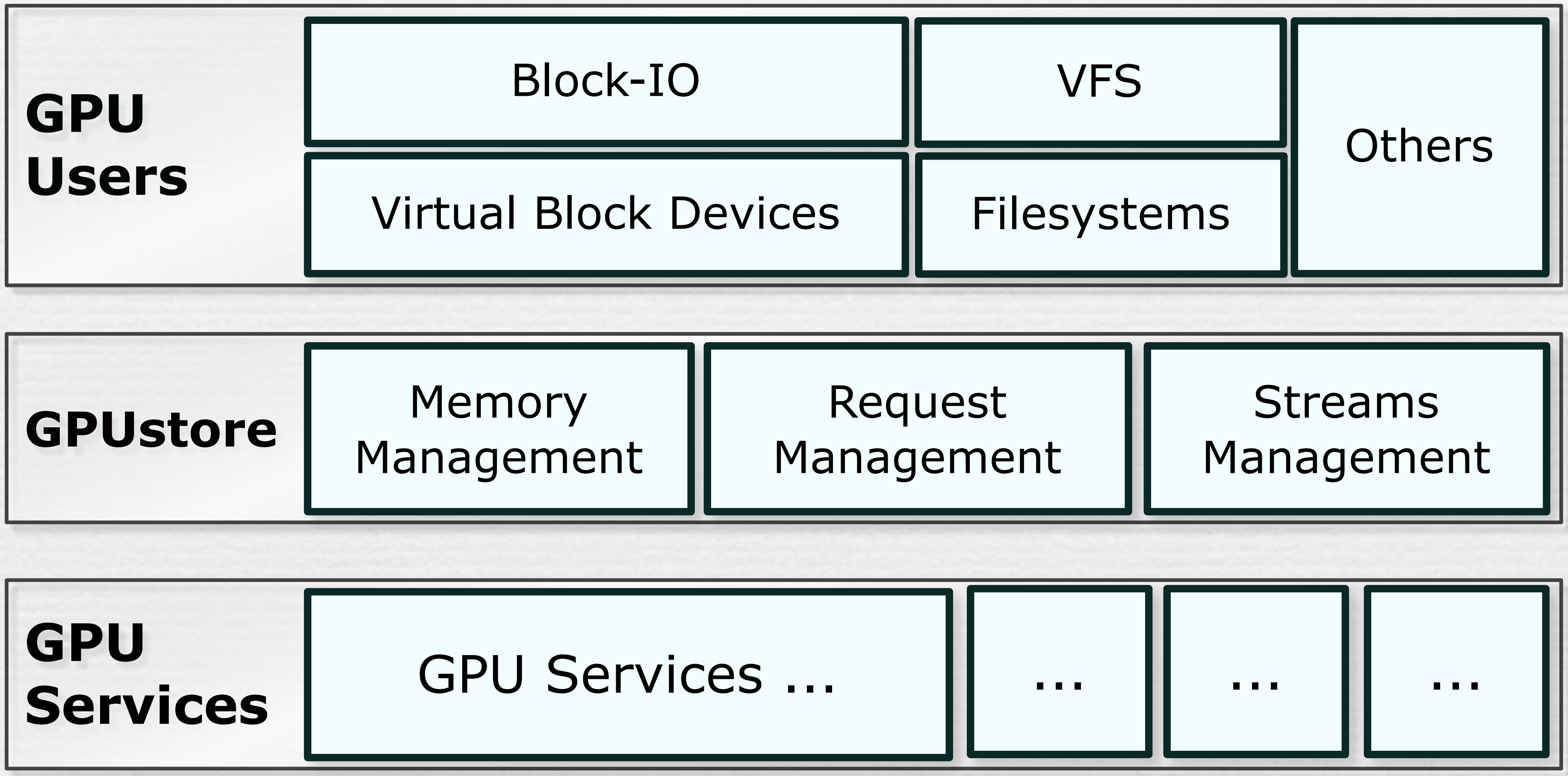

GPU Users
Block-IO
VFS
Virtual Block Devices
Filesystems
Others

GPUstore



GPU Users
Block-IO
VFS
Others
Virtual Block Devices
Filesystems
GPUstore
Memory Management
Request Management
Streams Management

GPUstore


GPU Users
Block-IO
VFS
Others
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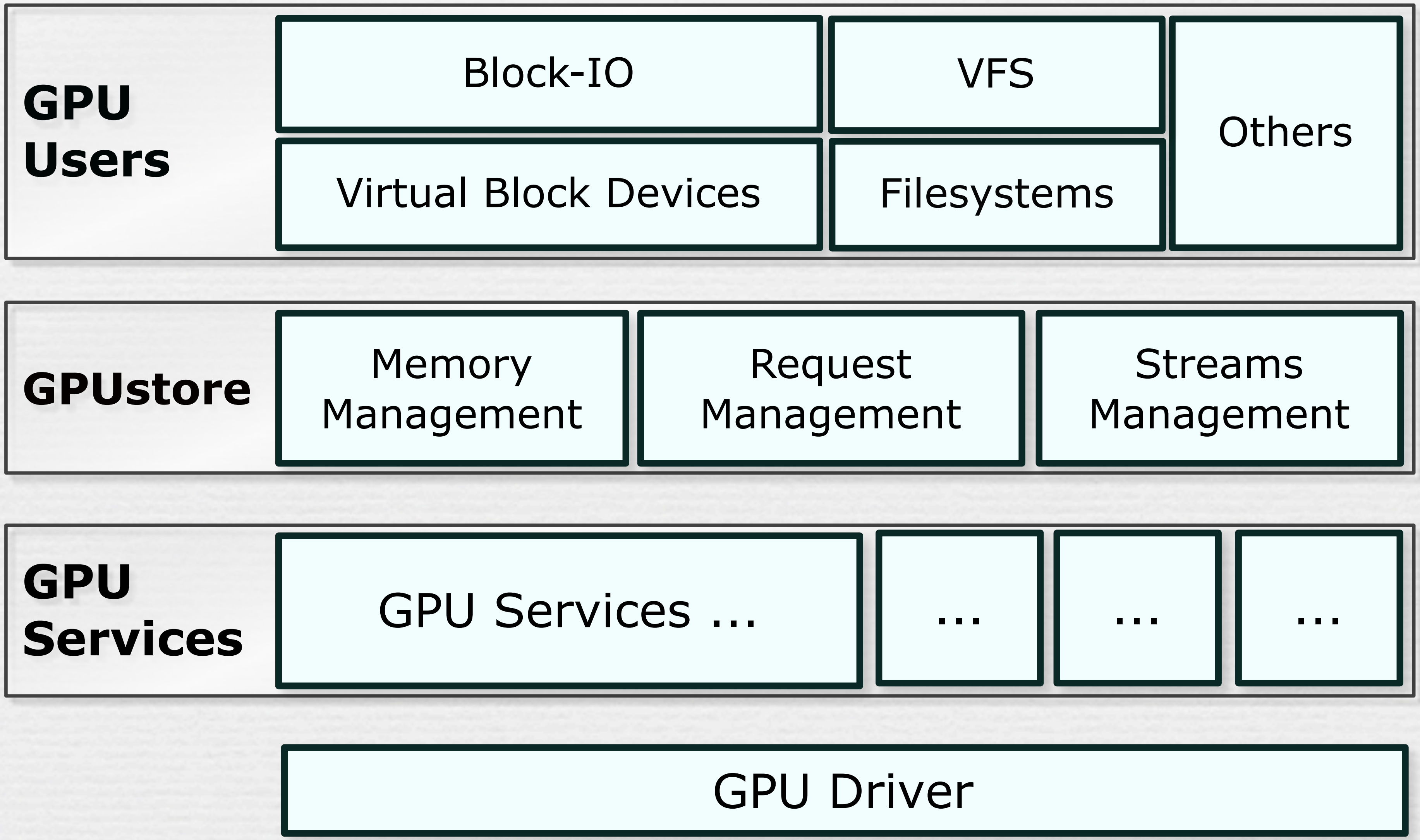
Memory Management
Request Management
Streams Management
GPU Services
GPU Services ...
...
...
...

GPUstore



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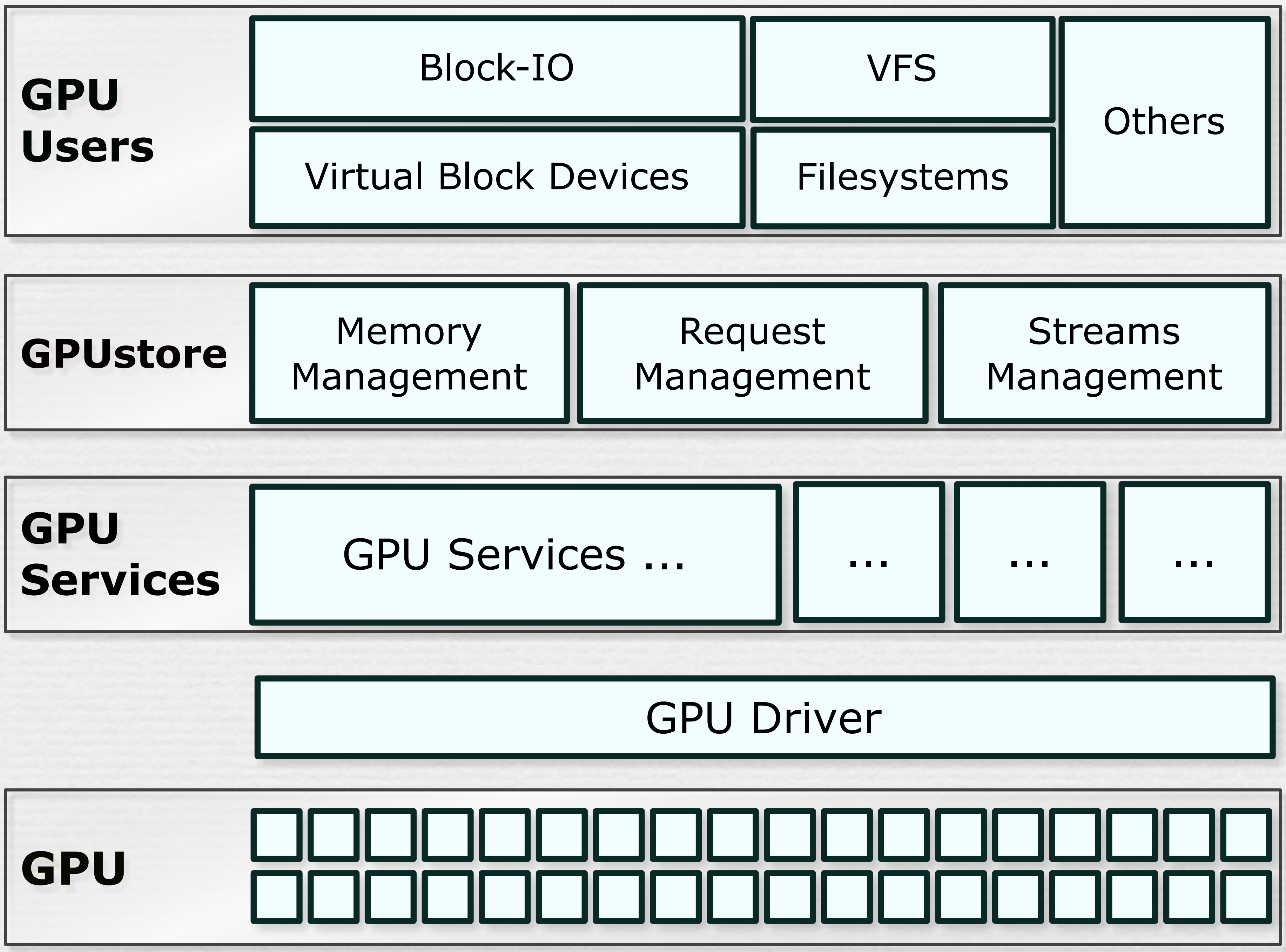
GPU Driver

GPUstore



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GPU Services ...
...
...
...
GPU Driver
GPU

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Design - Request Scheduling

- Split
  - Efficiently using DMA engines
  - Overlapping execution
  - Newer GPU (Fermi)/Multi-GPU preferred

Why merge and split?

- Better performance
- (more fundamental)Simplify GPU computing integration
  - Code deals with single page, single block, small buffers
  - Code accepts a buffer as whole and throws it onto GPU

Design - Memory Management

- Allocating memory from GPU computing runtime
- Using memory from existing code
  - Remapping them

Design - Resource Management

- Managing execution and copy through 'streams' in CUDA
  - First come first serve now
- No preemption currently

Evaluation

- eCryptfs
- dm-crypt
- md RAID 6 (see the paper)