Scalable Performance Analysis on Heterogeneous Architectures with HPCToolkit

Milind Chabbi, Karthik Murthy,
Mike Fagan, and John Mellor-Crummey
Rice University

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HPCToolkit

- Performance measurement using statistical sampling of timers and performance counters
- Attribution to hierarchical calling context
- Works on multilingual, fully-optimized, statically or dynamically linked applications (no source modification)
  - Pthread, OMP, MPI, and any combination
- Low overhead (under 5%) for both profiling and tracing
- Scales to large parallel systems
- Analysis of execution costs, inefficiencies, and scaling characteristics

Supporting Heterogeneity in HPCToolkit

- **Heterogeneous** does't mean just GPU kernel
- Most work on the performance analysis of heterogeneous architectures deals with
  - Identifying GPU-kernel-level issues, and improving via: kernel fusion, unrolling, memory access reordering, etc.
- They ignore other parts of heterogeneous systems viz.
  - Nodes with several GPUs and CPUs, and CPUs with several threads
  - GPUs shared by multiple ranks, and concurrent kernel executions
  - Inter-node, and intra-node communication

Should Measure, Analyze and Present

Performance of

- A standalone GPU kernel
  - Timing, and hardware counter values
- Concurrently executing GPU kernels on multiple graphics cards
  - Challenges: concurrent streams, multiple threads, multiple contexts, GPU sharing between threads and processes
- Data communication between CPUs and GPUs
- Multi-threaded processes
- Multiple MPI processes

And It Should Scale

- Should be able to gather data from thousands of nodes
  - Each with several CPUs, Cores, and multiple GPU cards
- Should not distort original execution overlap
- Should have low runtime overhead
- Should produce manageable profile and trace files

Focus on Resource (under) Utilization

- Heterogeneous systems have multiple resources each with disparate capabilities
- Classical "hot-spot" analysis is insufficient
  - Focuses on "most consumed" resources
  - Provides only symptoms of problems
  - Does not indicate causes of problems
- Key to achieving peek performance on heterogeneous systems is to keep all compute resources working simultaneously
  - Overlap computations on multiple resources

Work Balance Between CPU and GPU

- Offloading entire computation to GPUs wastes CPU compute power
- Offloading entire computation to CPUs wastes GPU compute power

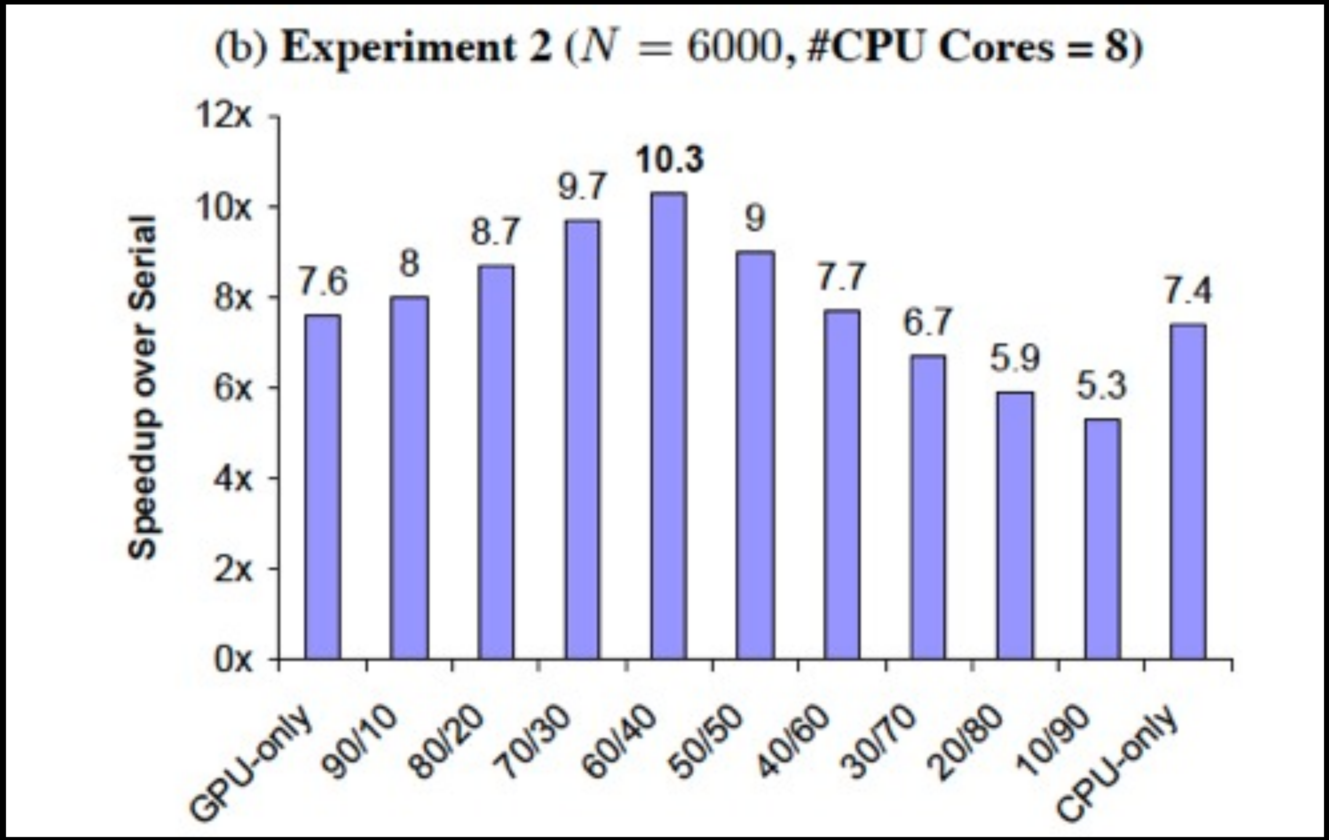


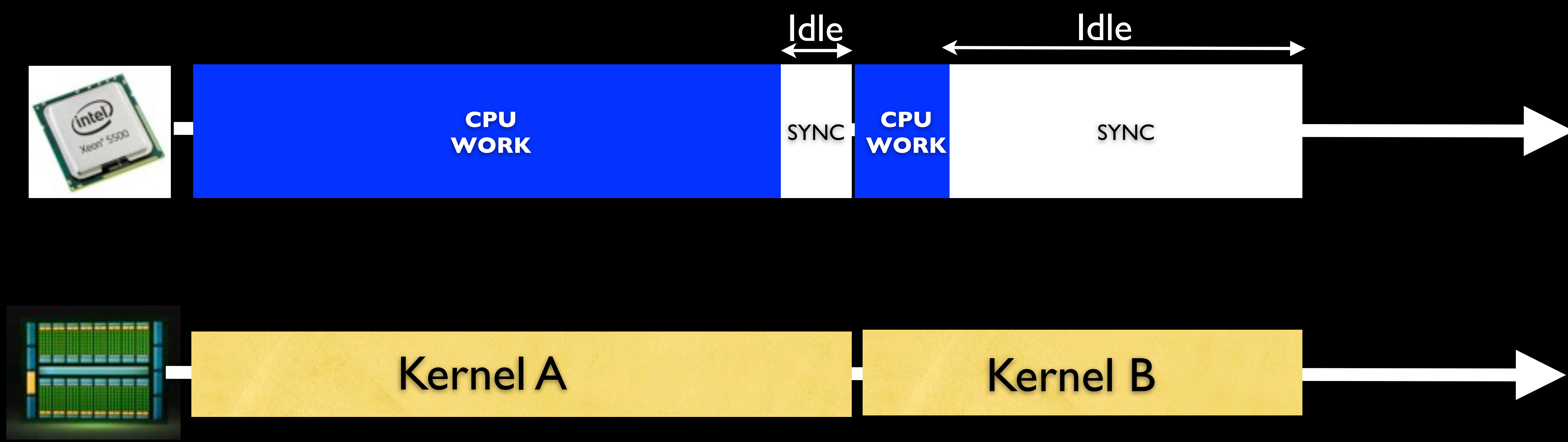
Figure credit: Qilin Exploiting Parallelism on Heterogeneous Multiprocessors

Matrix multiplication on Nvidia 8800 GTX (575 Mhz) and Intel Core2 Quad (2.4Ghz)

Root Cause Analysis with Blame Shifting

- If GPU is idle, code executing on CPU is responsible for not offloading (enough) work to GPU
  - ✦ Attribute blame to CPU code executing while GPU is idle
- If CPU is idle waiting for GPU kernel(s) to finish, executing GPU kernel(s) are responsible for CPU idleness
  - ✦ Attribute proportional blame to each such kernels
- Credit codes that are well overlapped

Performance Expectations for Heterogeneous Systems with Blame Shifting



Top GPU-kernel may not be the best candidate for tuning

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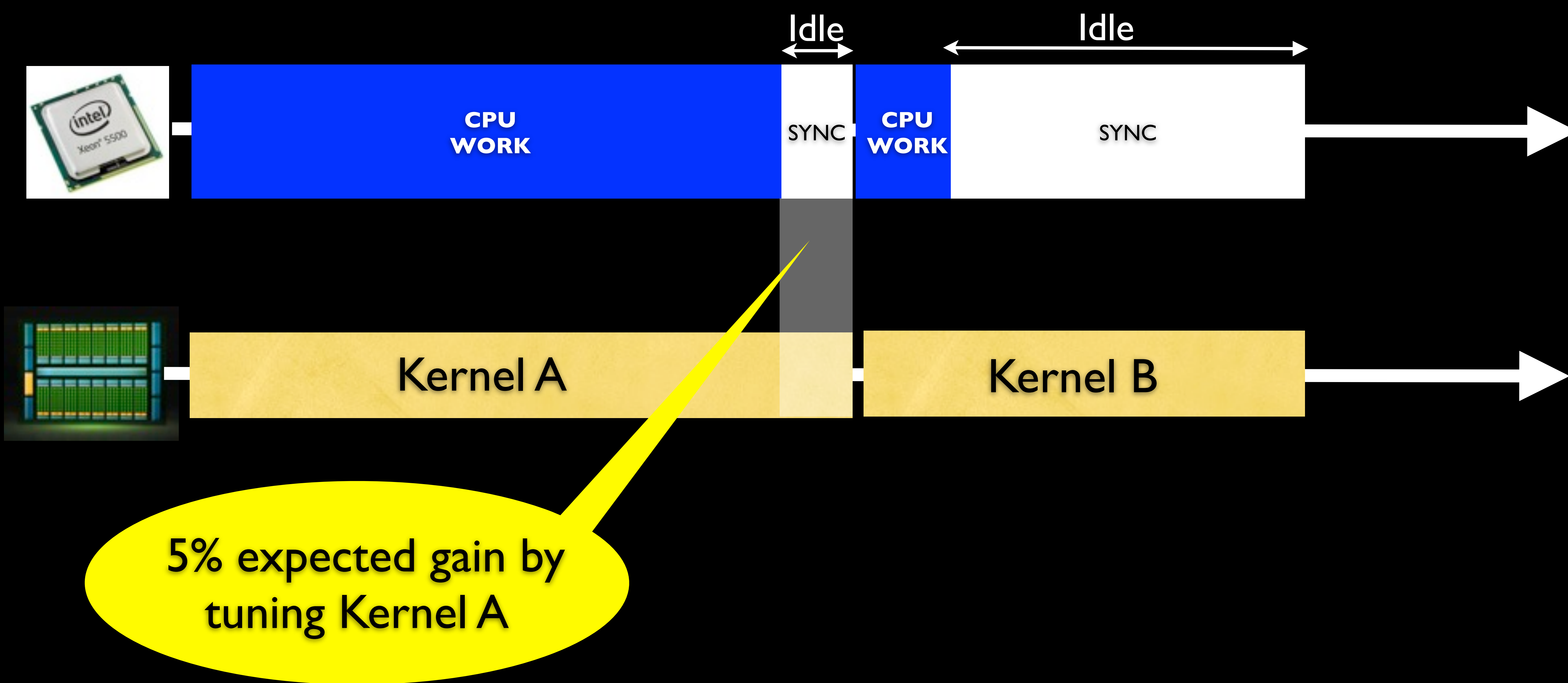

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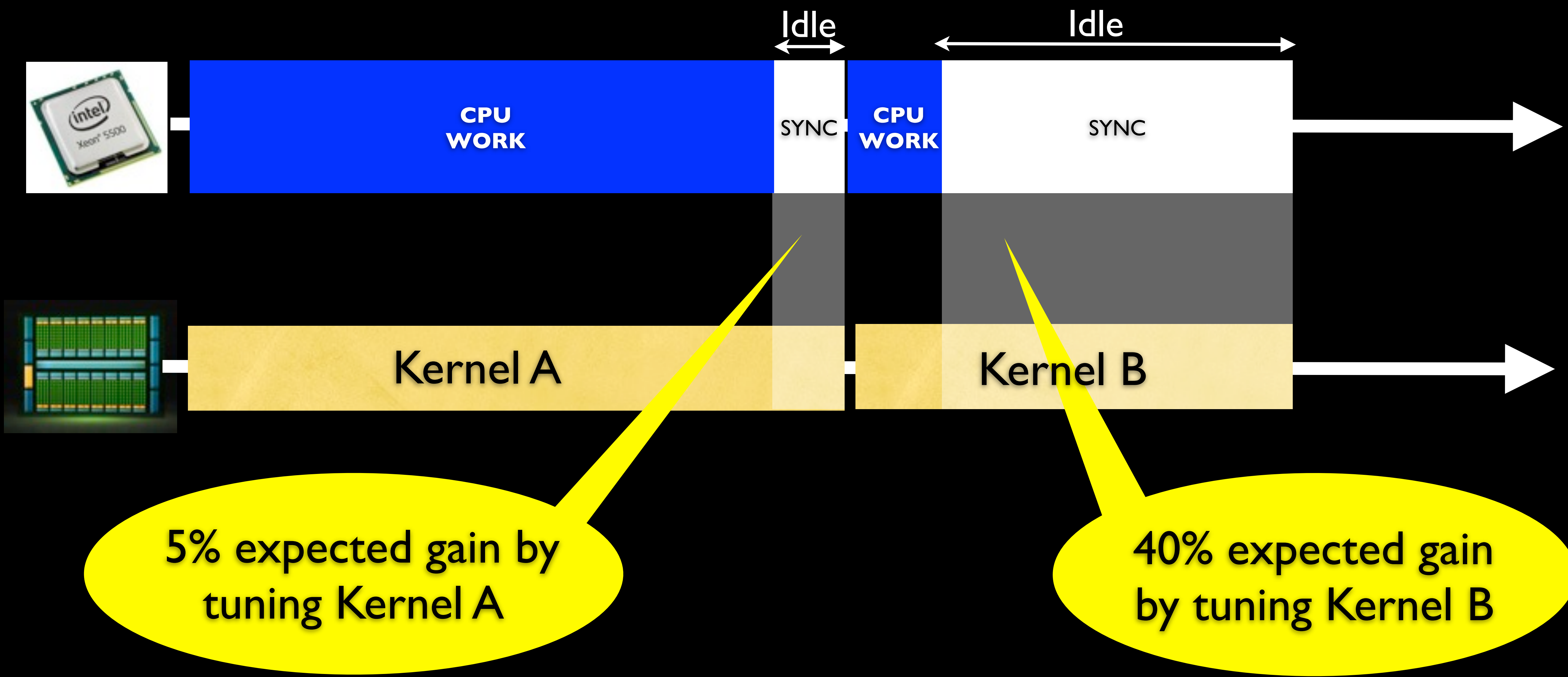

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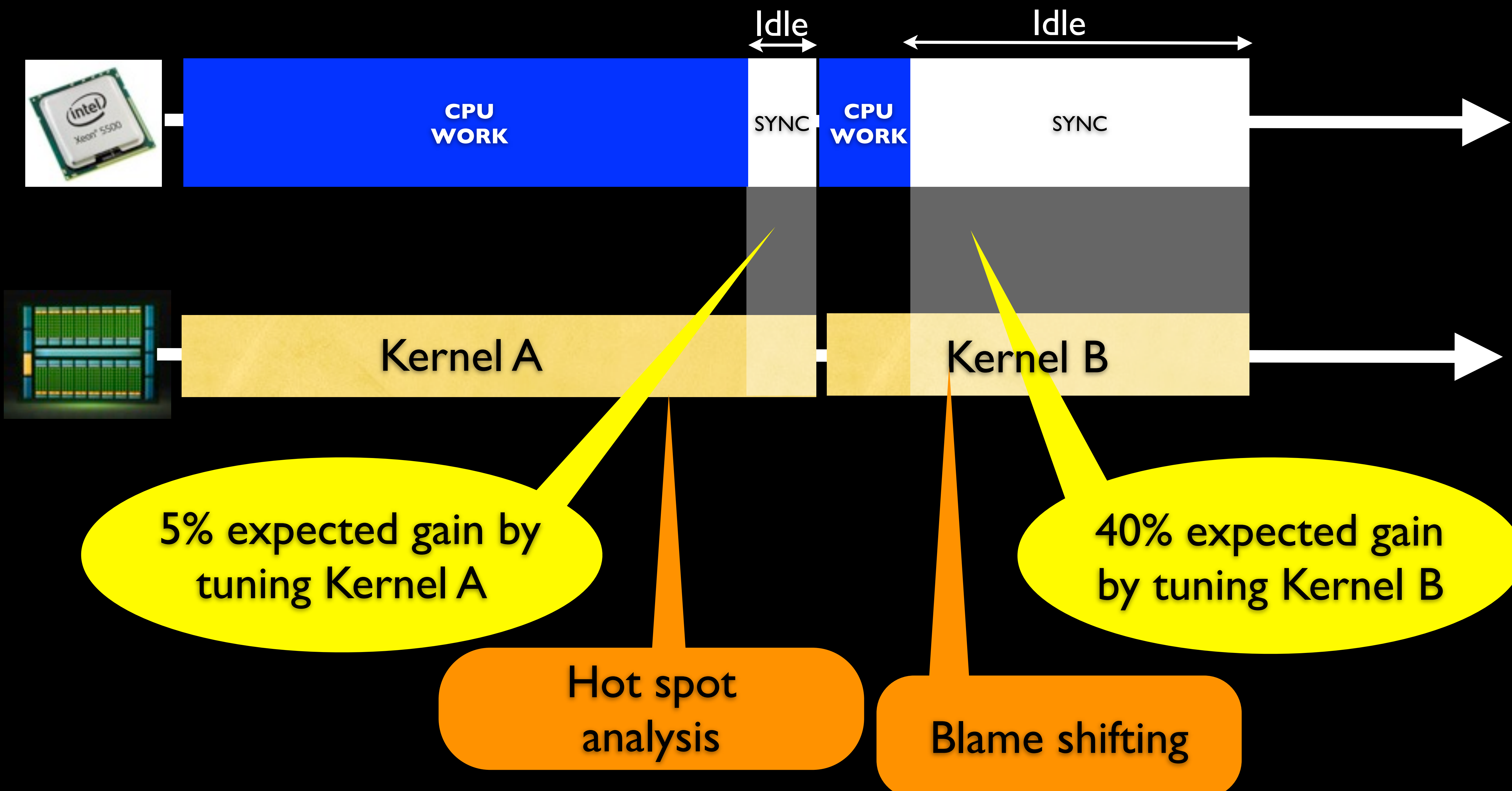

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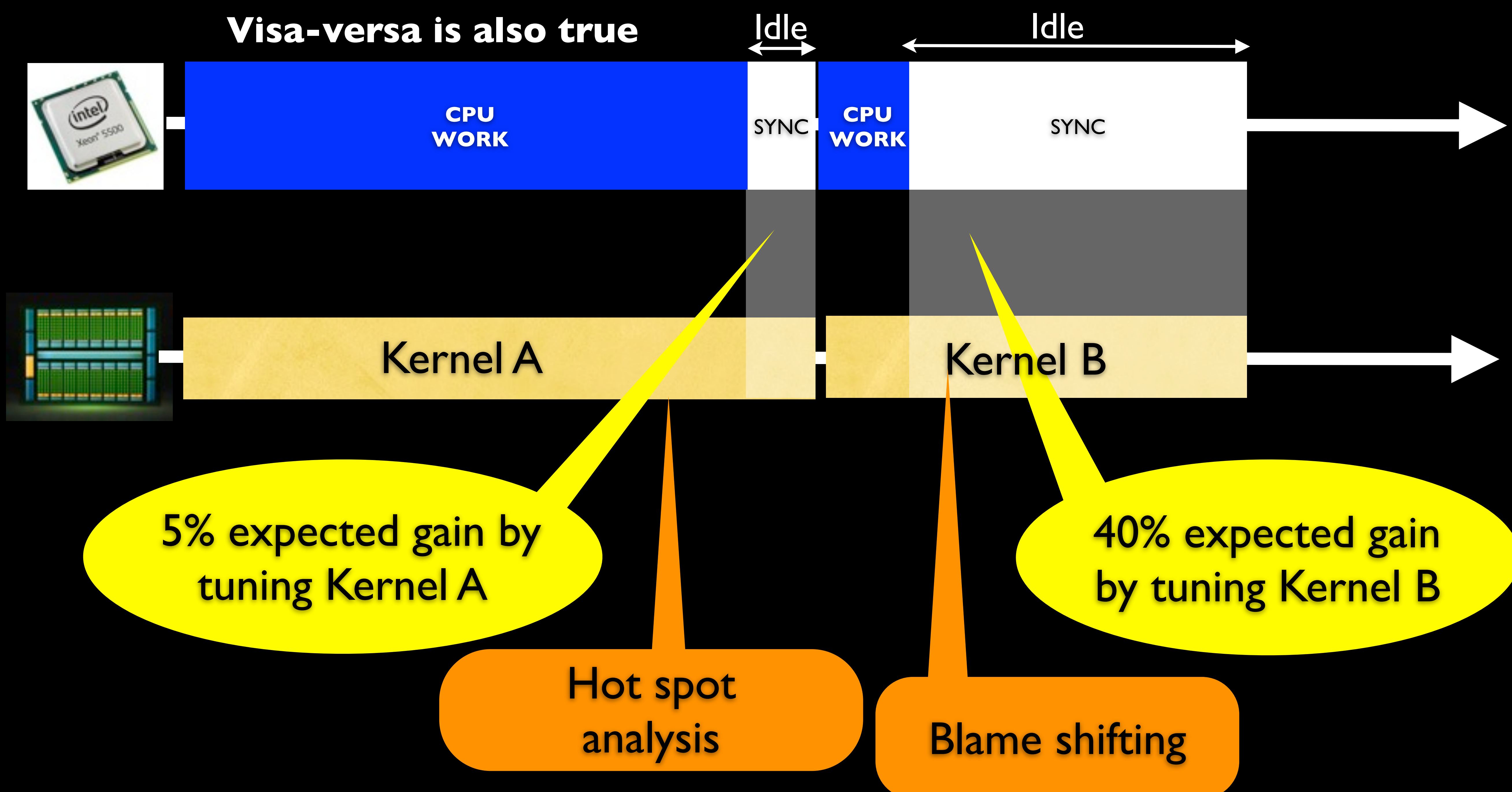

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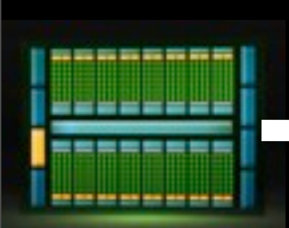
Advantages of Blame Shifting on Heterogeneous Systems

- Pinpoints codes (both GPU kernels and CPU contexts) that benefit most from tuning
  - Improves developer productivity
  - Full calling context to distinguish same kernel, different callpath
- Provides an expectation for the upper bound of performance gain when tuning
- Sampling-based approach keeps overhead low and provides scalability
- Extends naturally to any shared resource
  - GPU, communication network, I/O network

Proxy Sampling of GPU Activities

CPU
thread



GPU
stream

Proxy Sampling of GPU Activities

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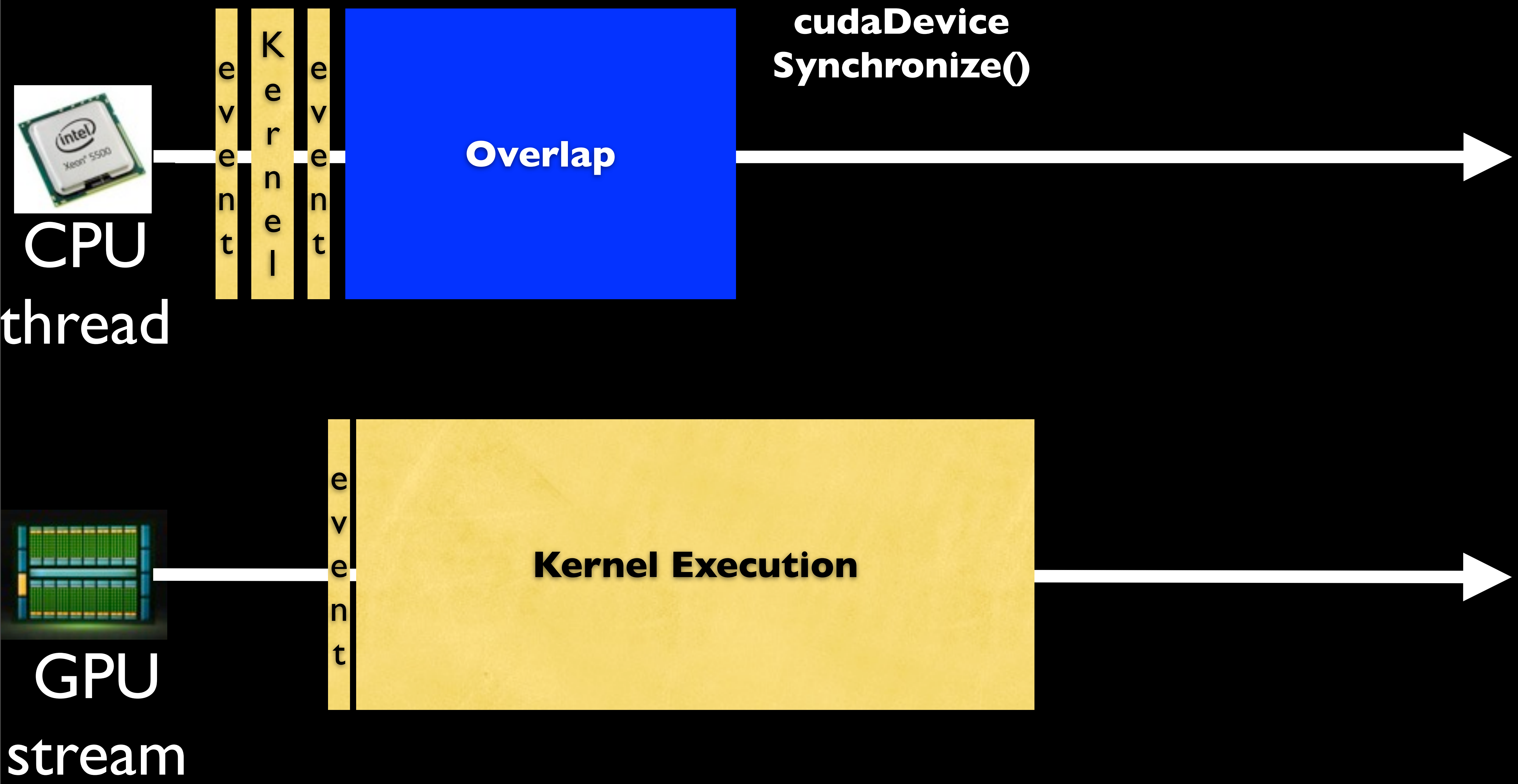

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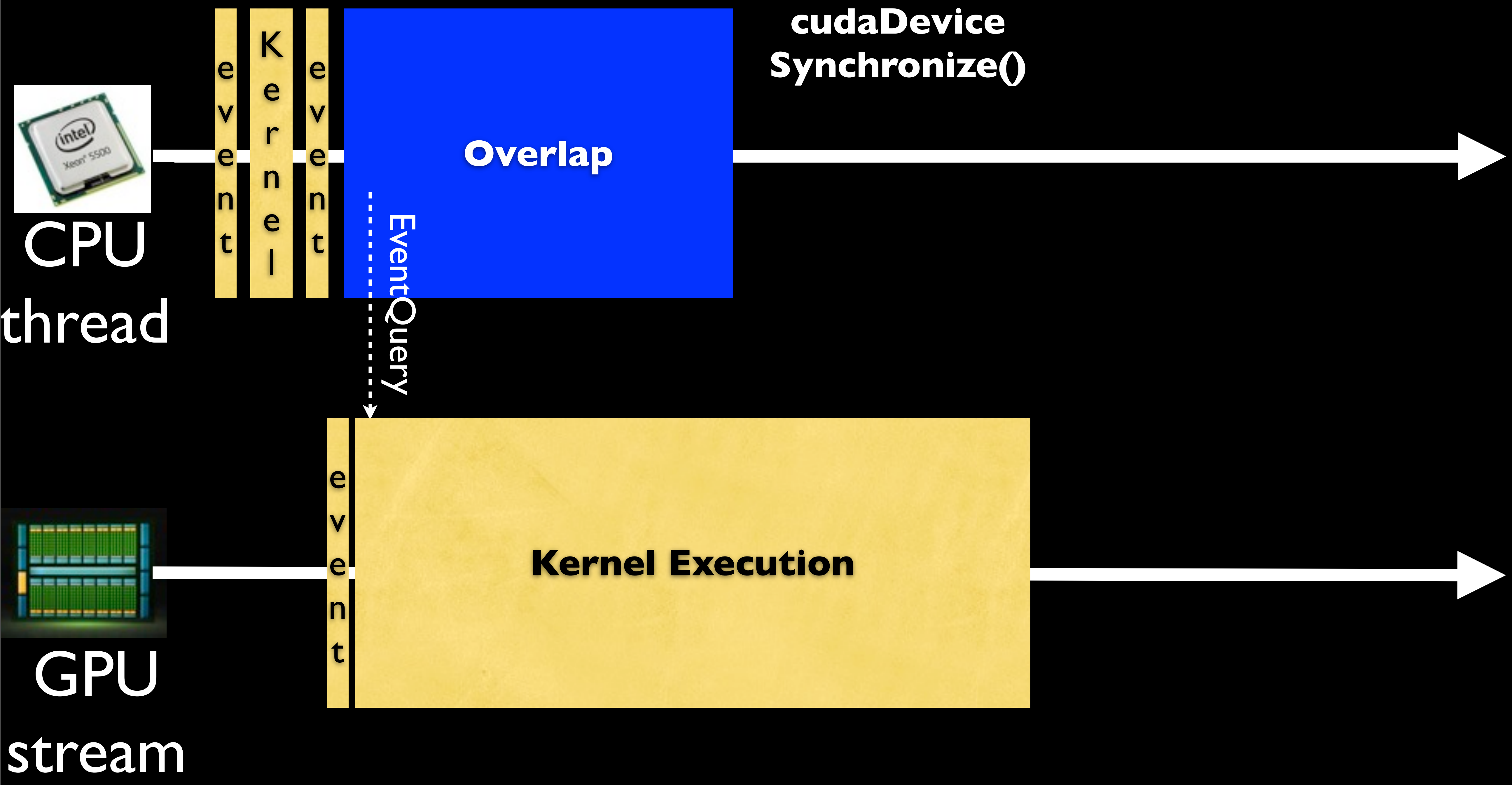

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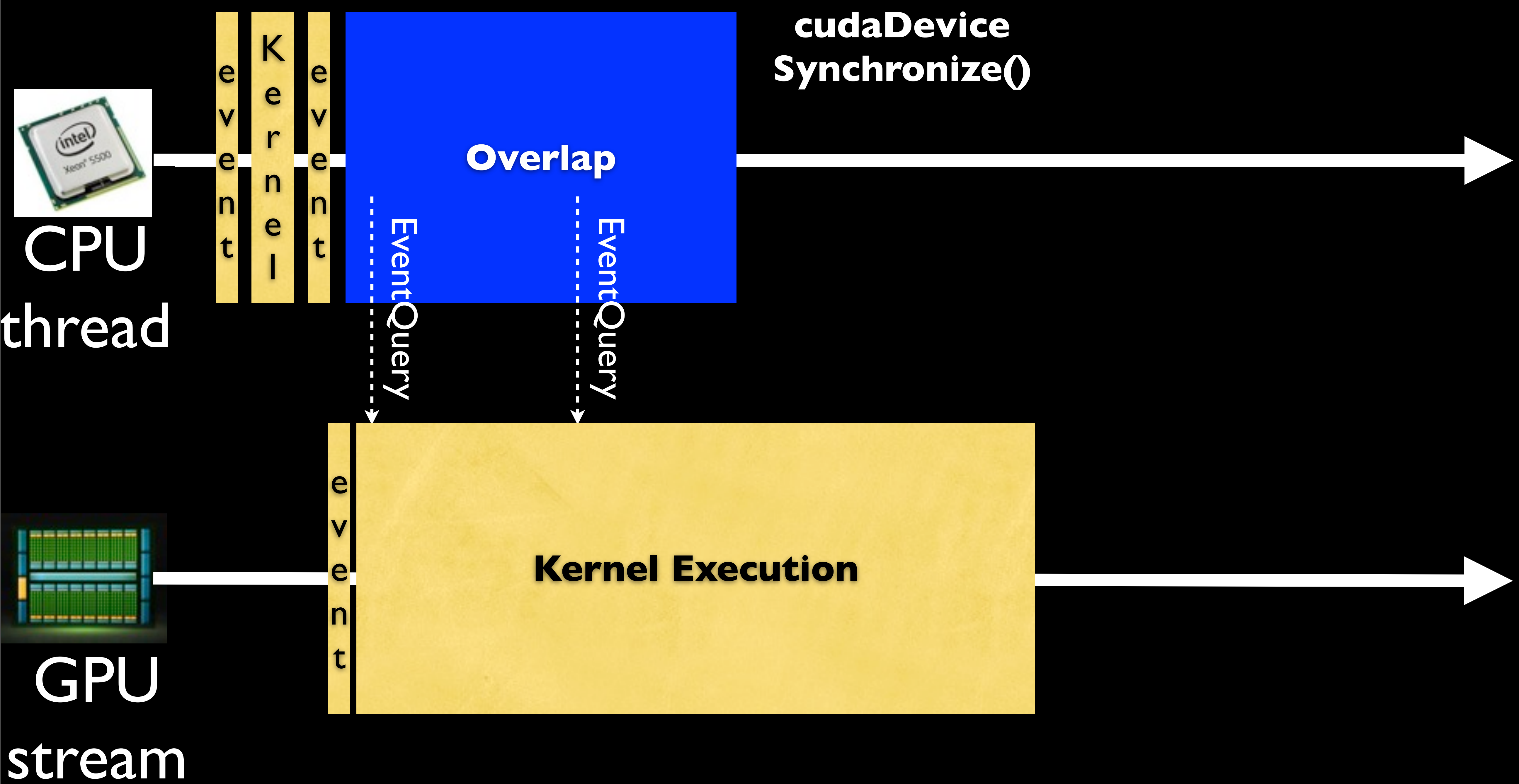

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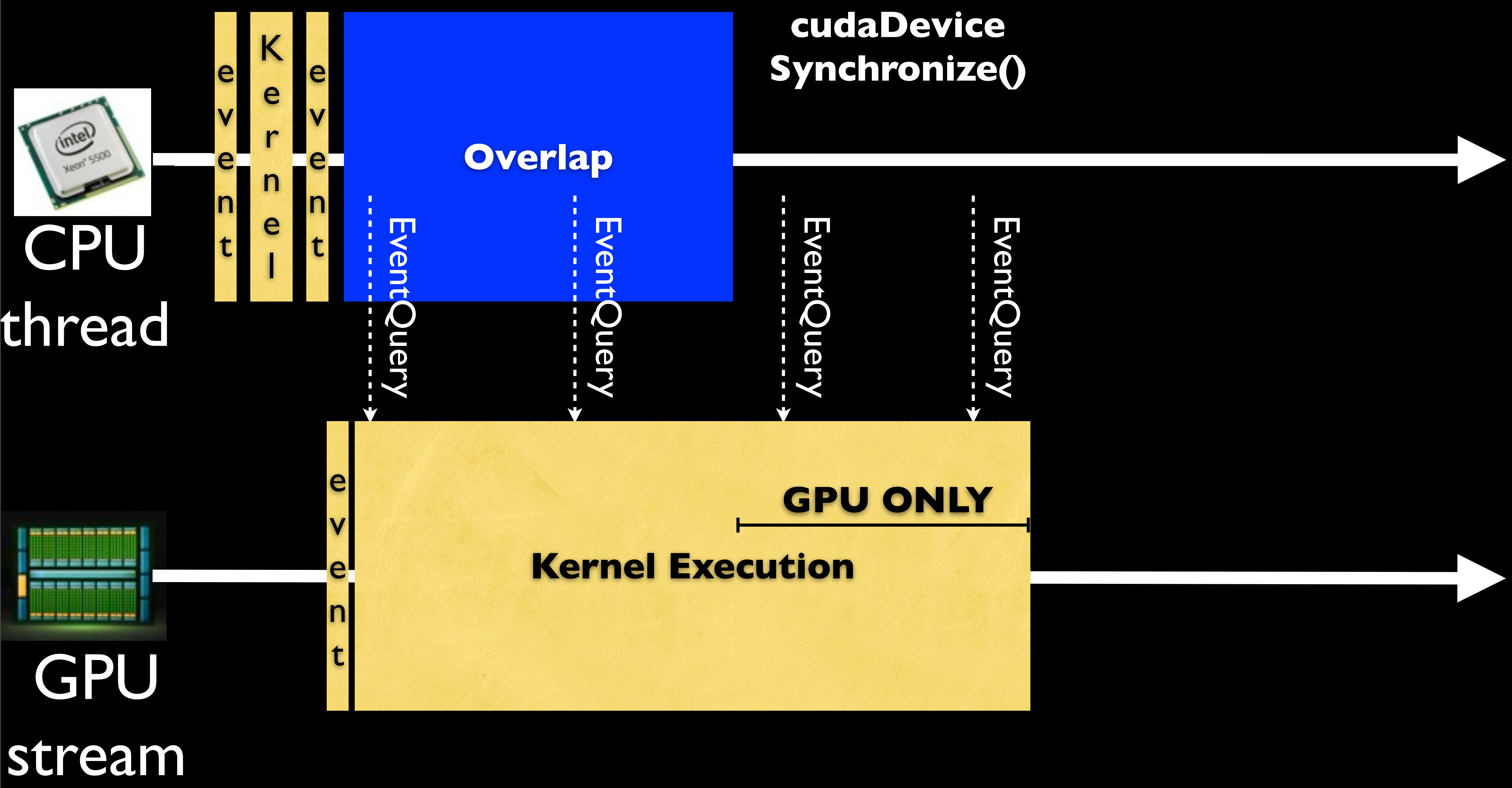

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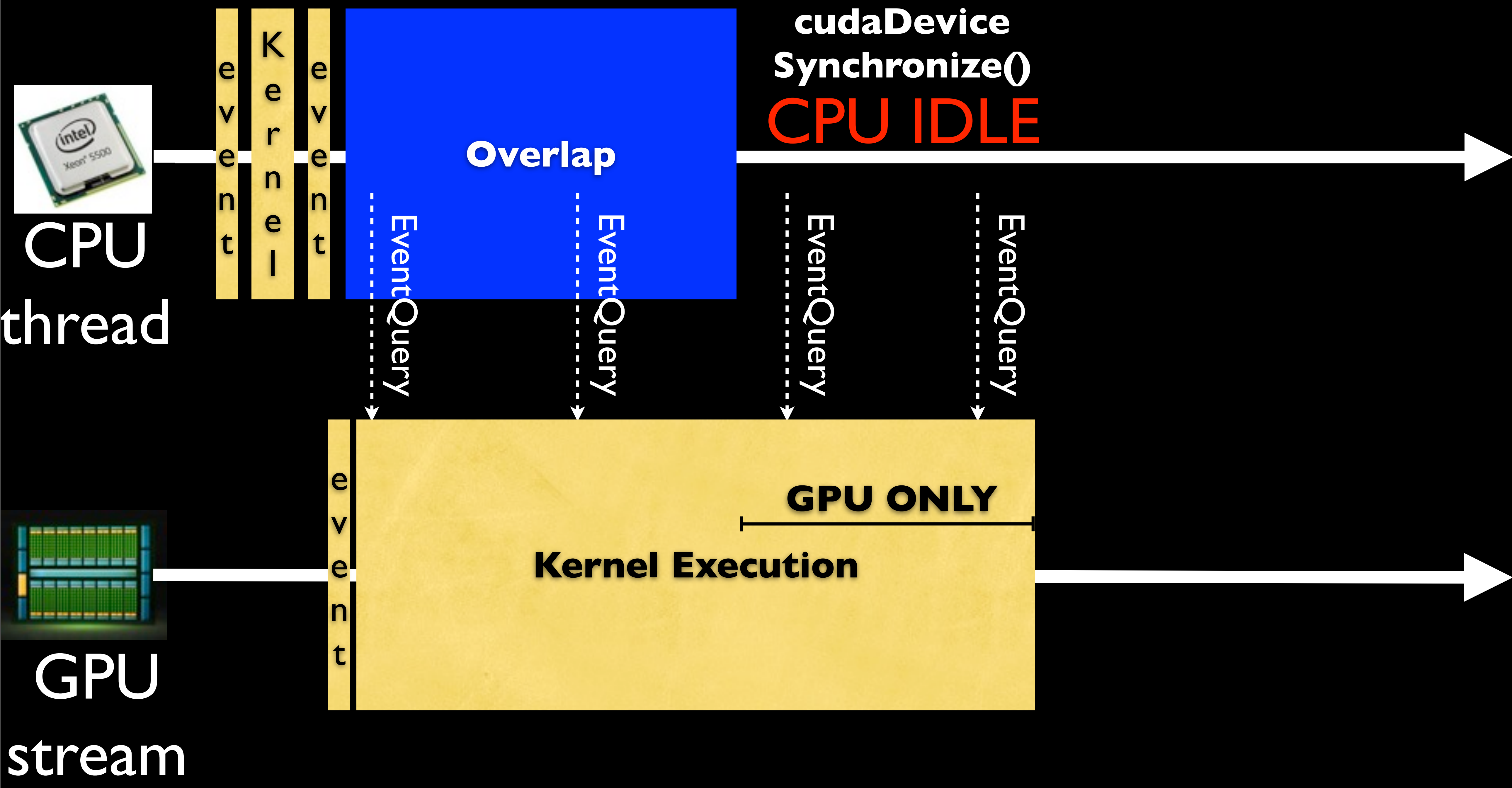

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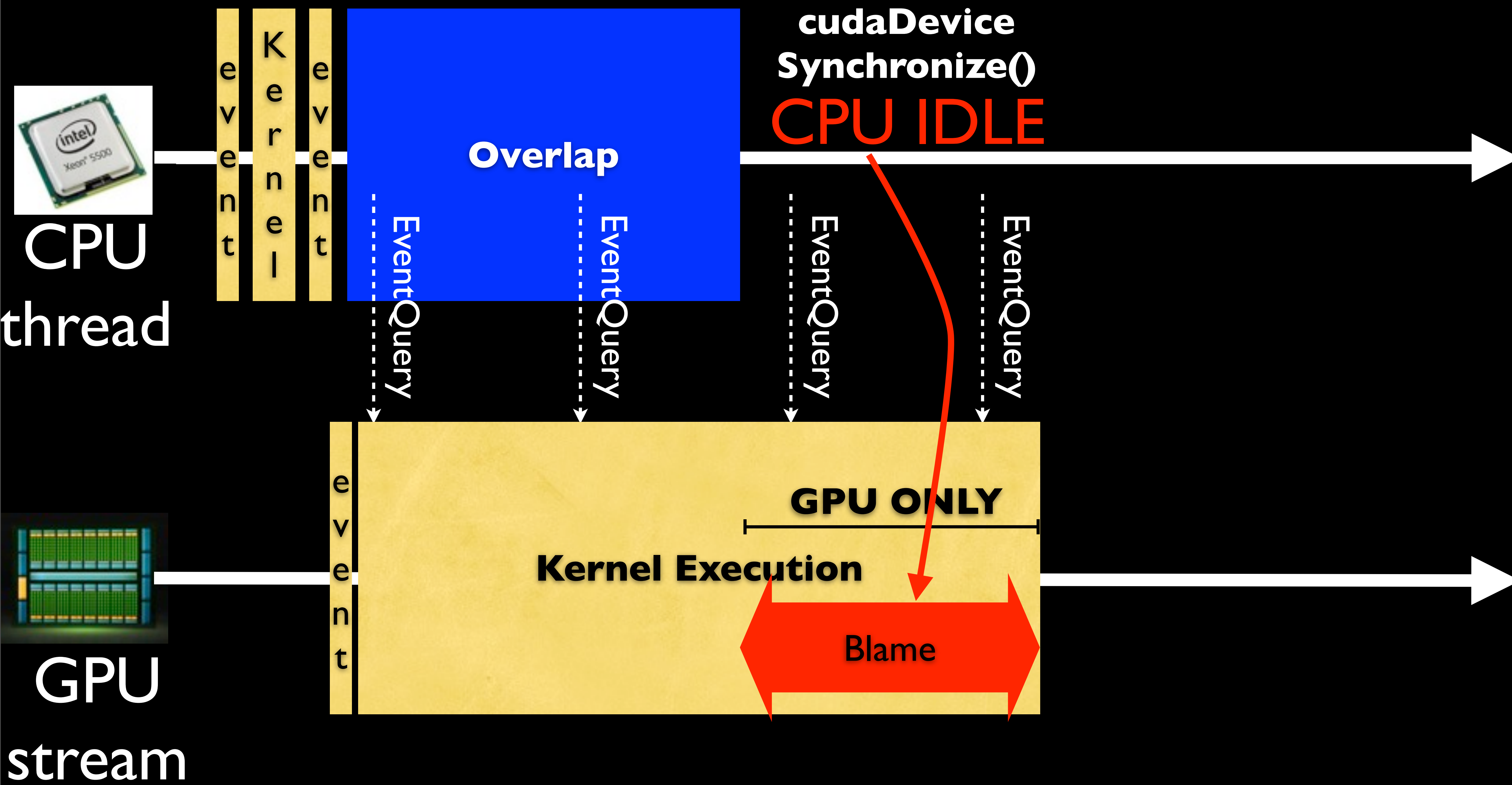

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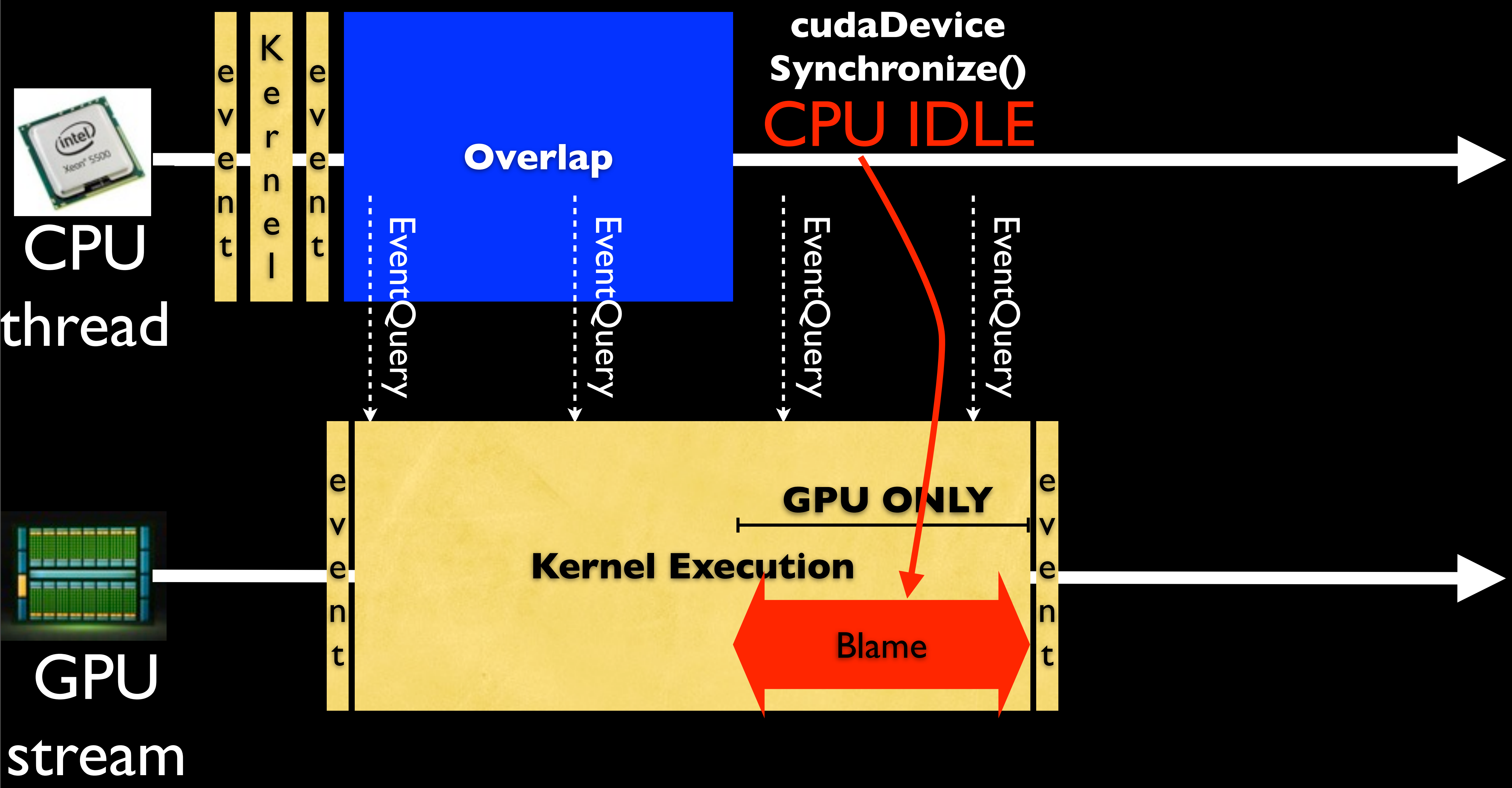

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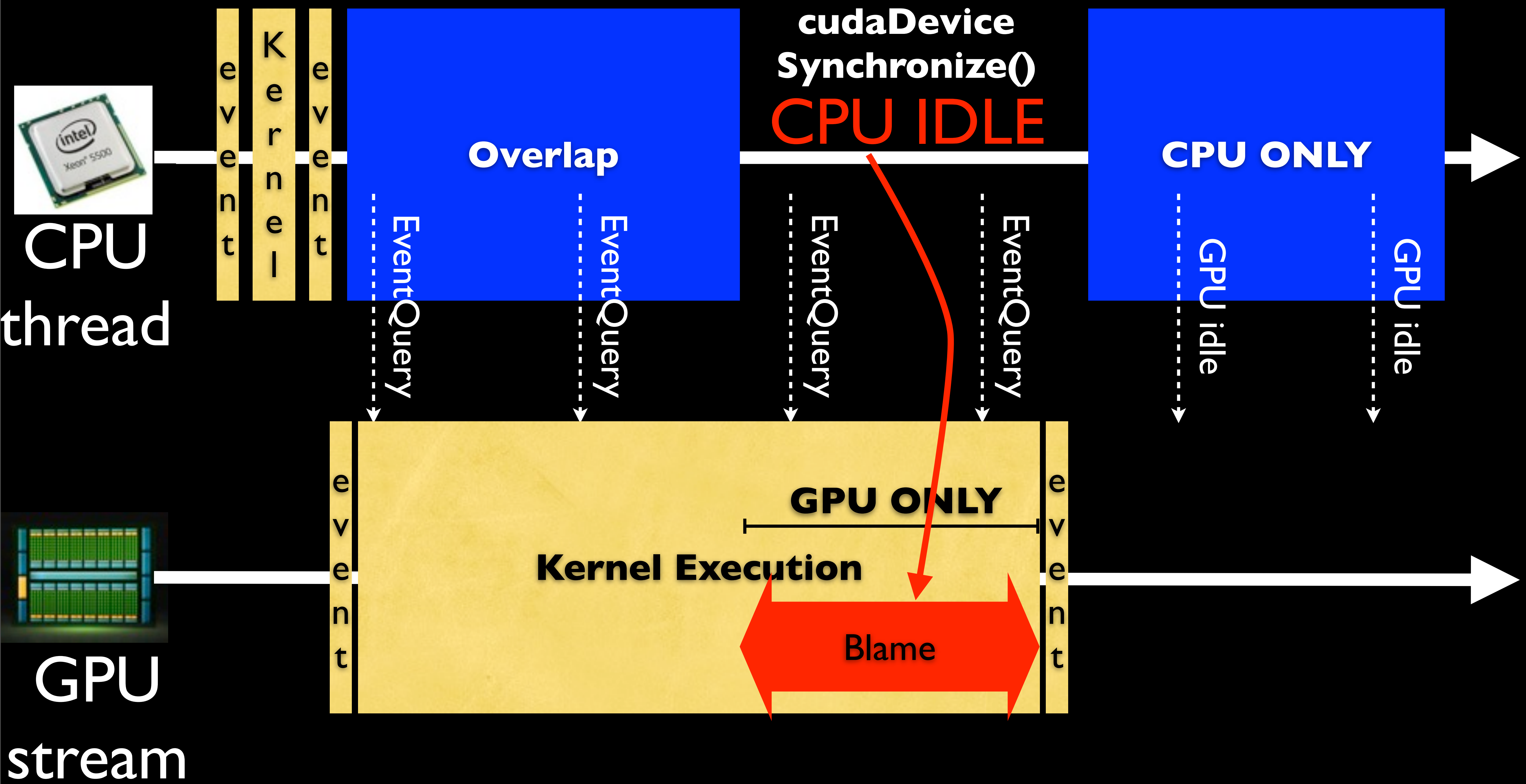

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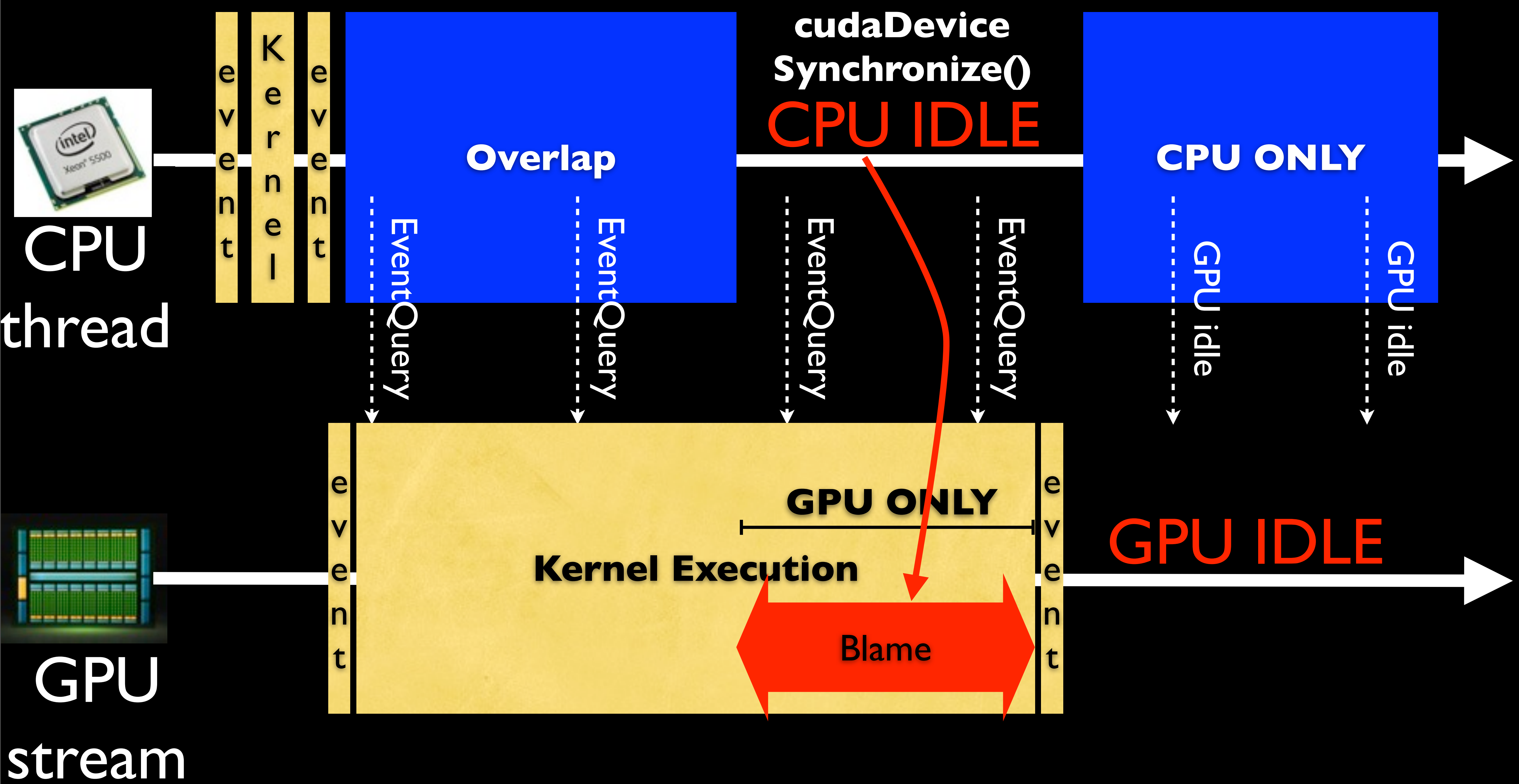

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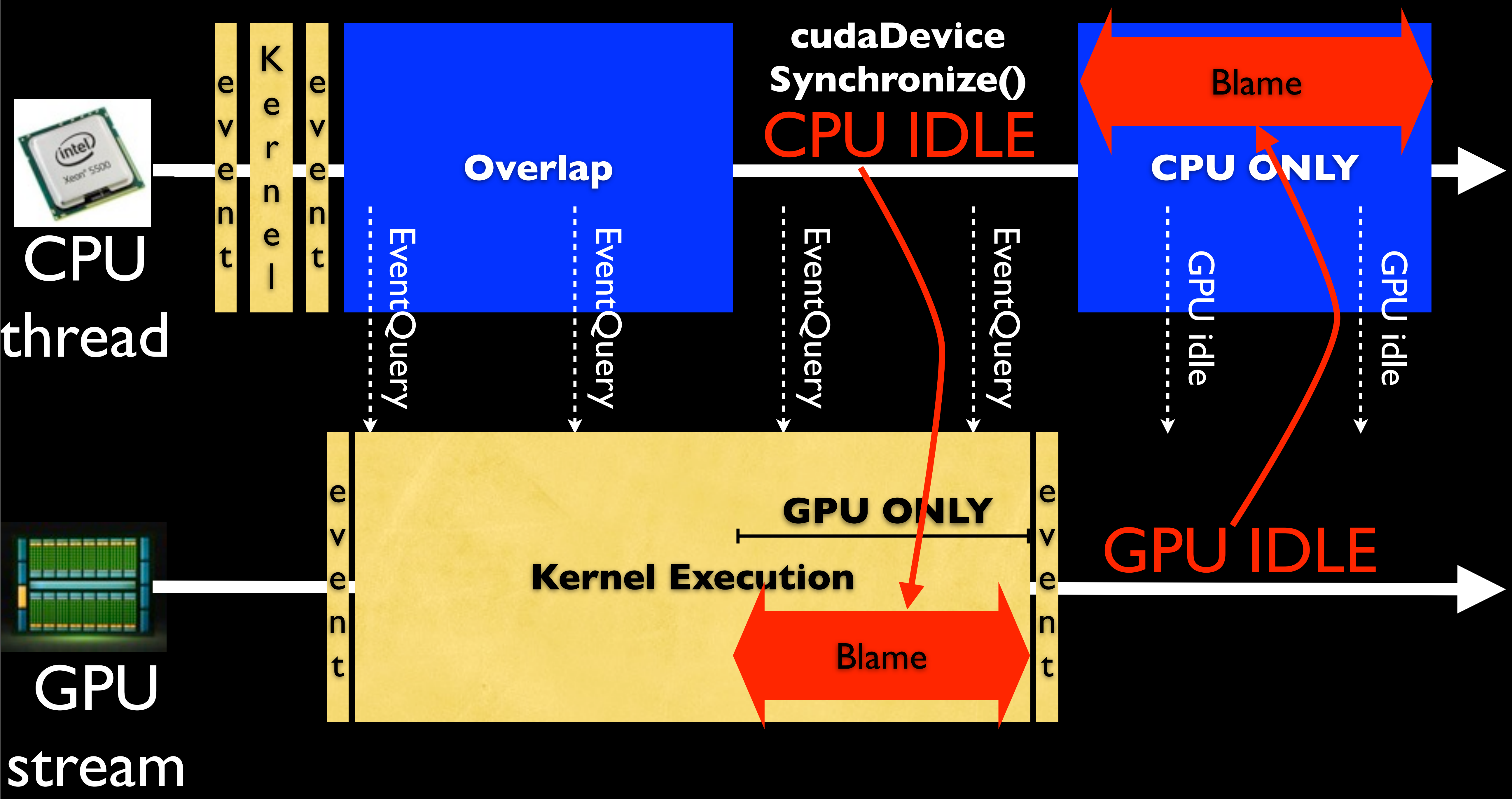


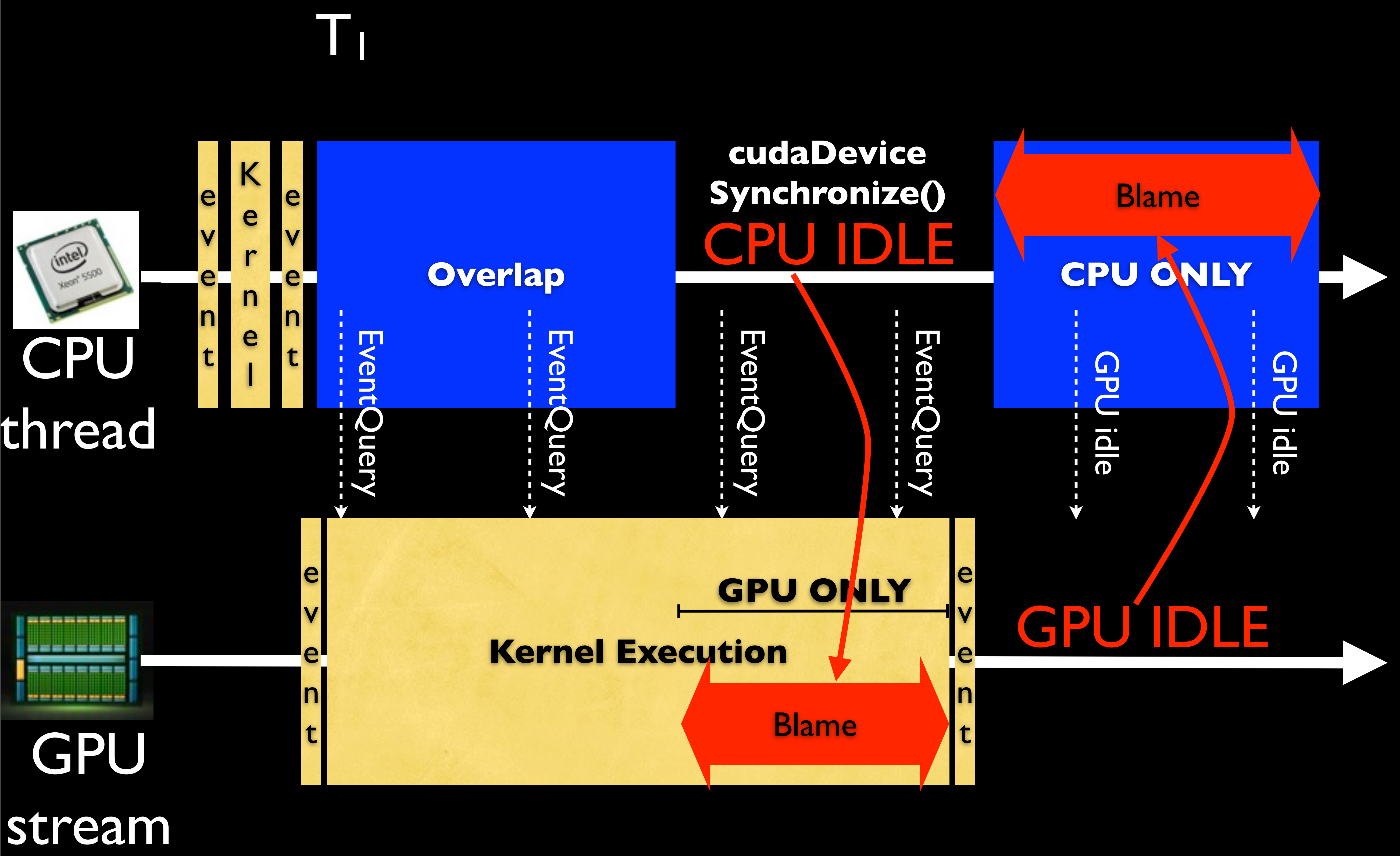
Implementation Challenges

- No sampling support from GPUs
  - ✦ Would have liked timer/counter-based signals from GPUs
- CUPTI has several limitations (some fixed in 5.0RC)
  - ✦ Kernel serialization when using CUPTI
  - ✦ Serialization of CPU threads simultaneously using CUPTI
  - ✦ Activity API is more tracing style, not suitable for profiling
- CUDA limitations (supposed to be fixed in Kepler 2)
  - ✦ Kernel serialization when using events for querying/timing
- Can't poke GPU with cudaEventQuery() from a signal handler when thread is inside a CUDA API call

Workarounds

- CUDA Function wrapping to inject events
  - ✦ Eliminates CPU threads serialization
  - ✦ Waiting for Kepler-2 to fix kernel serialization when using events
- Disable calling cudaEventQuery() from signal handler when CPU is inside CUDA API
  - ✦ Deferred blaming of kernels

Workarounds: Deferred Blaming



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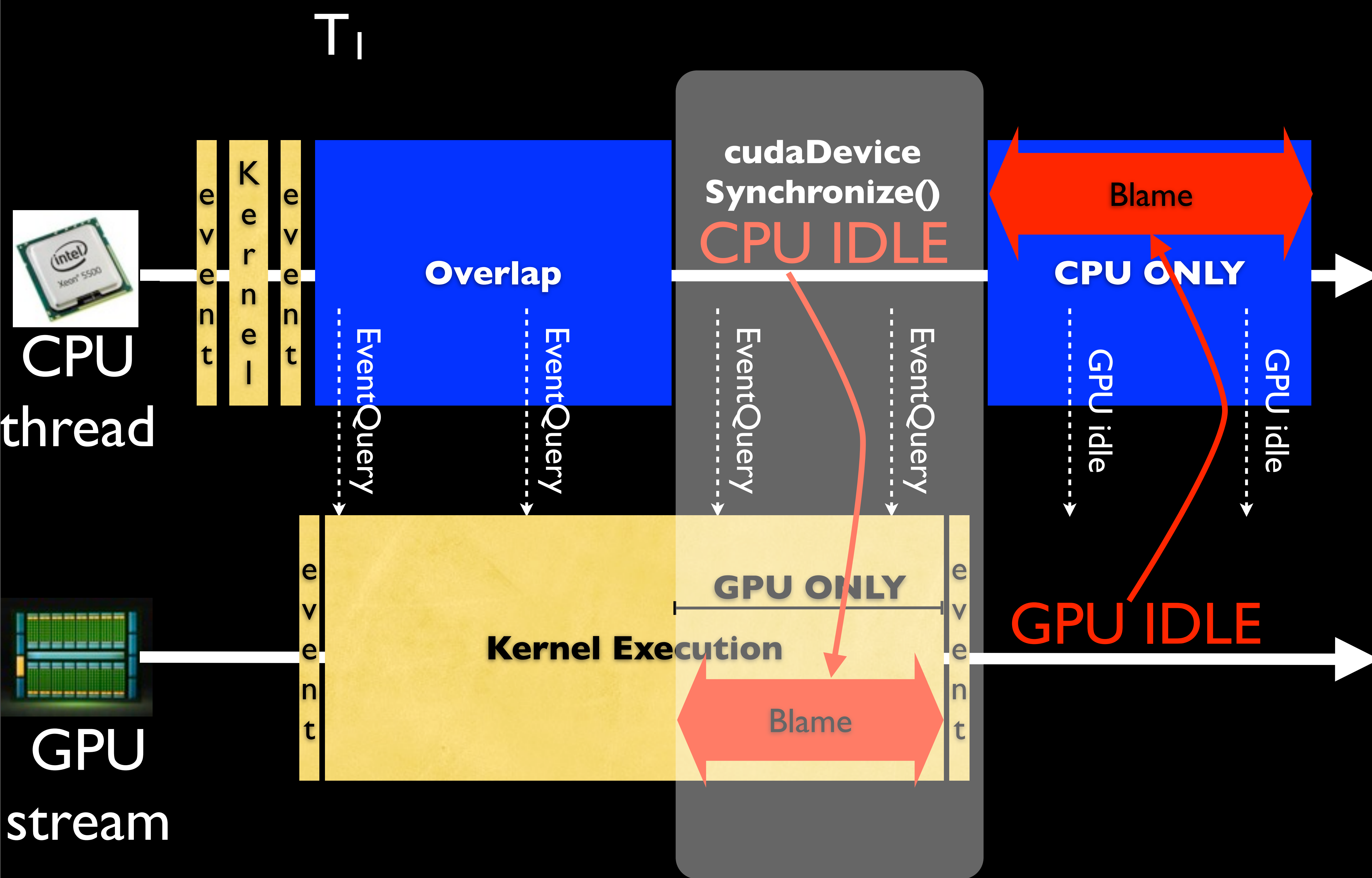

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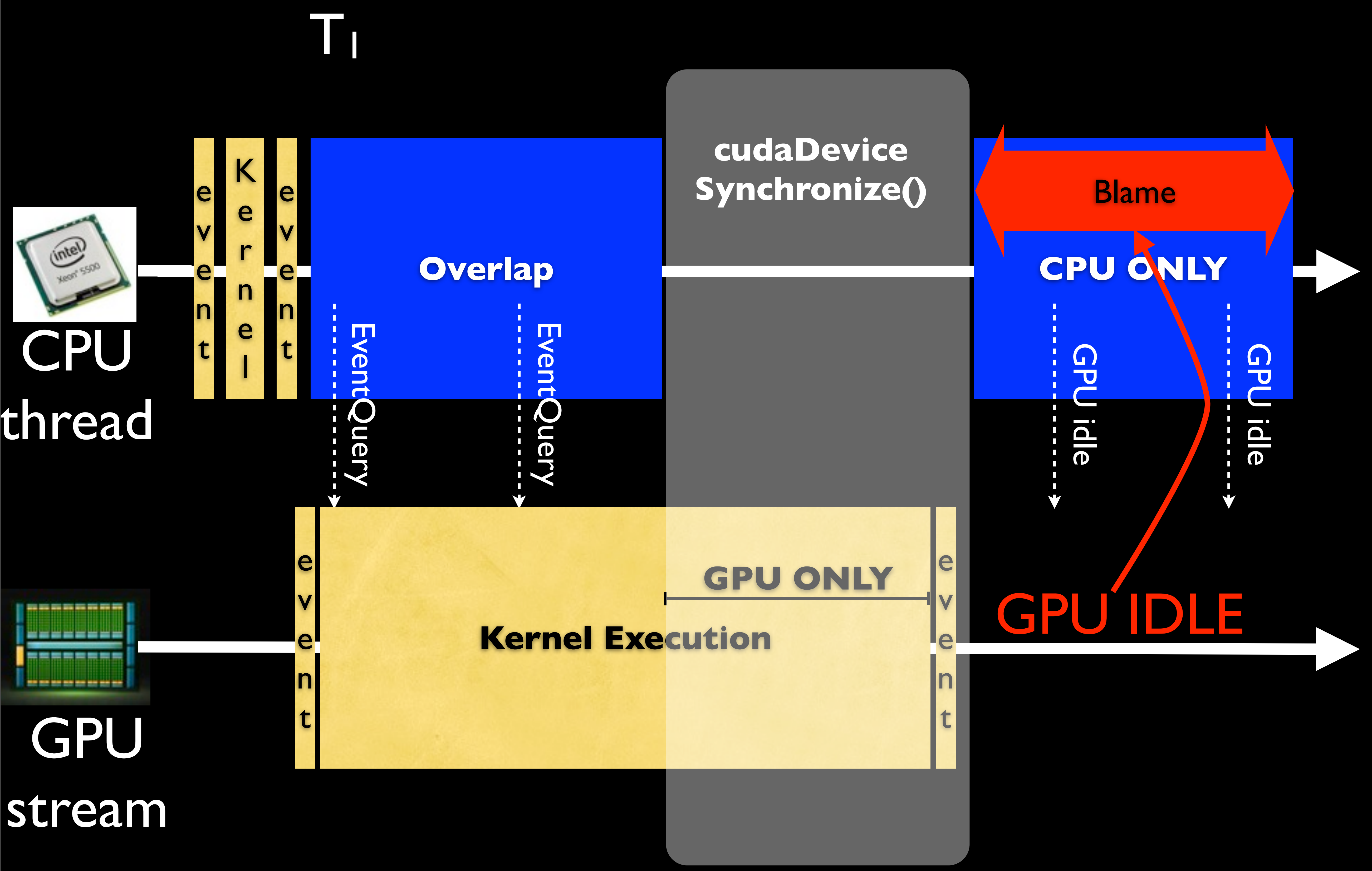

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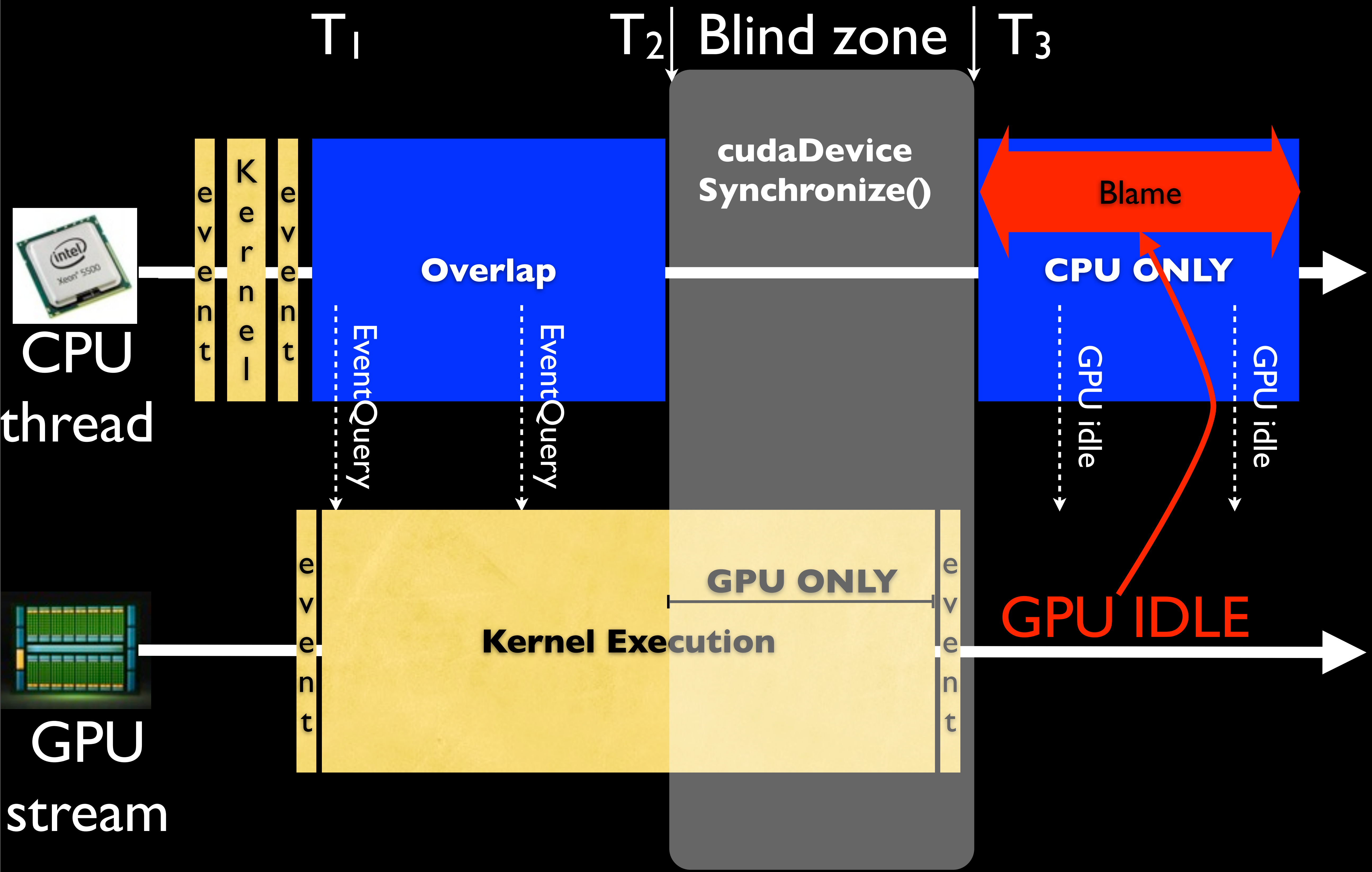

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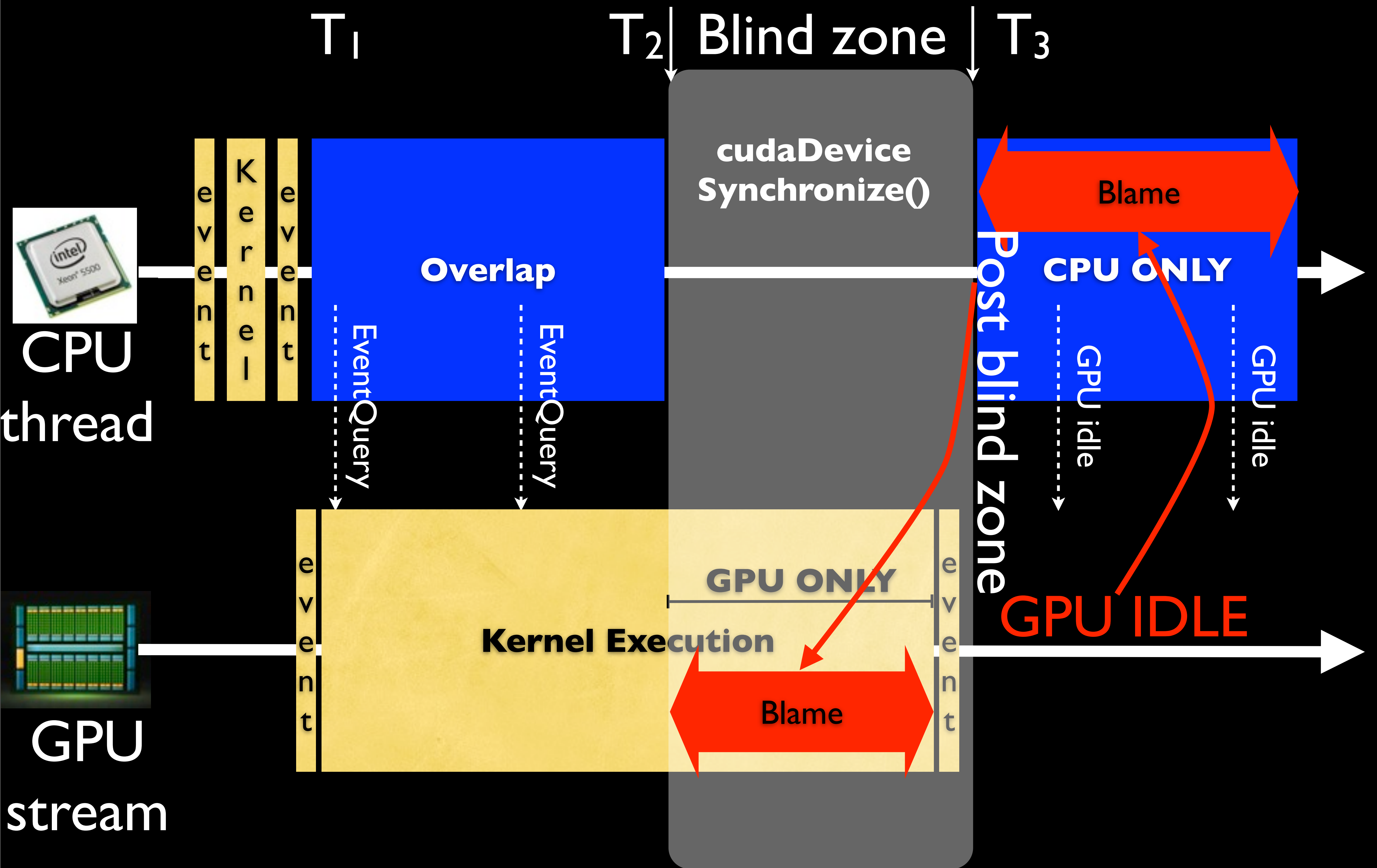

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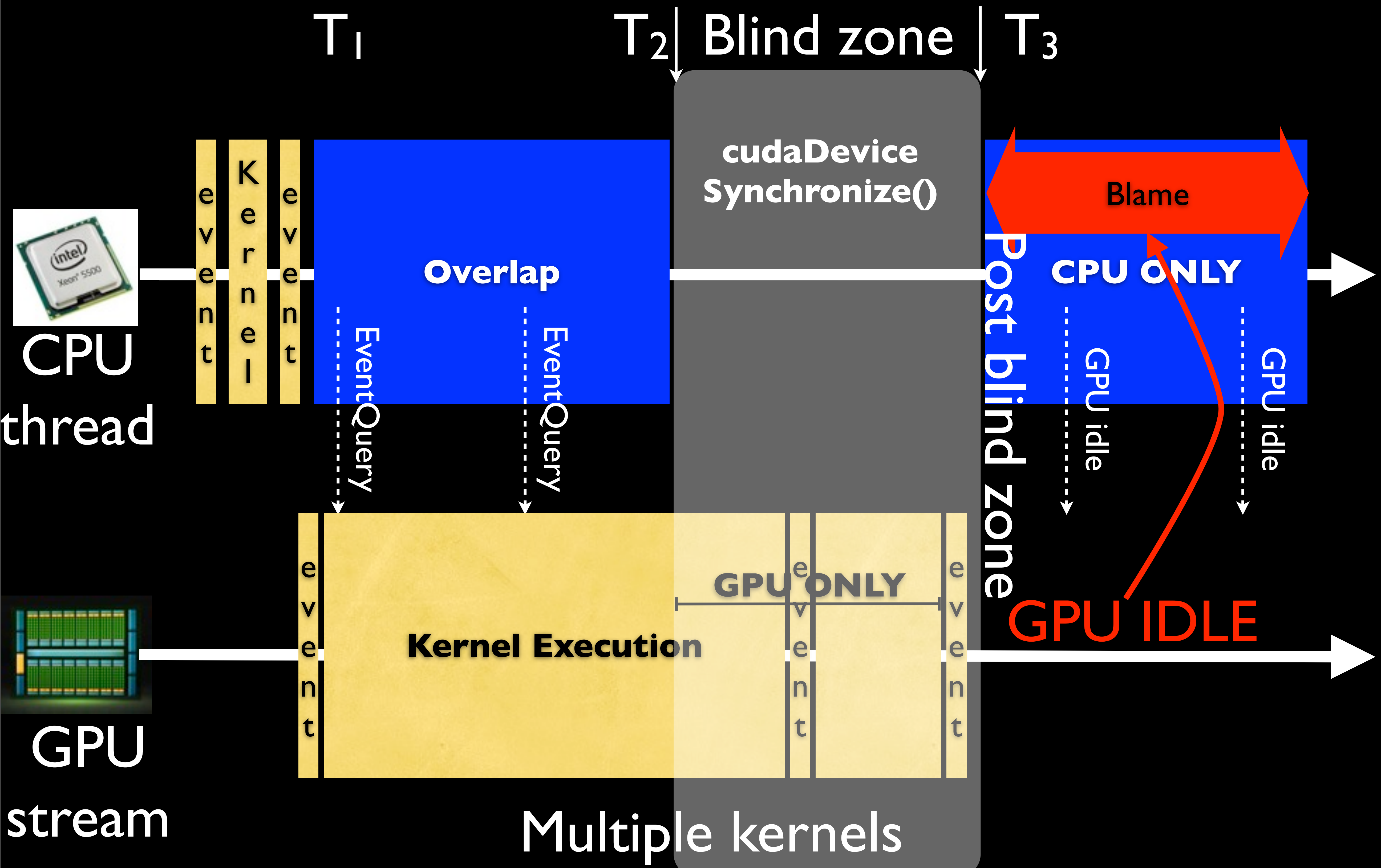

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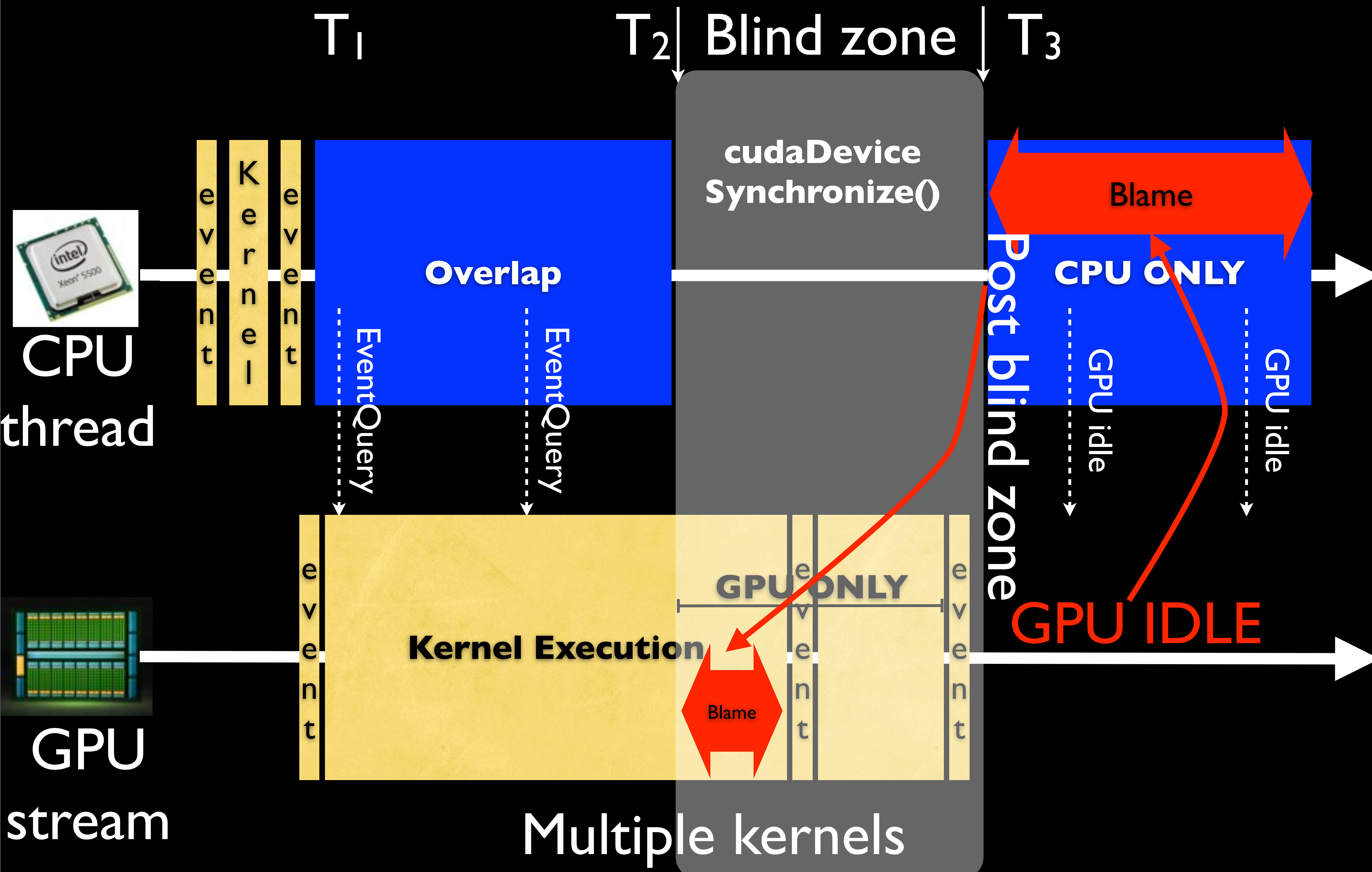

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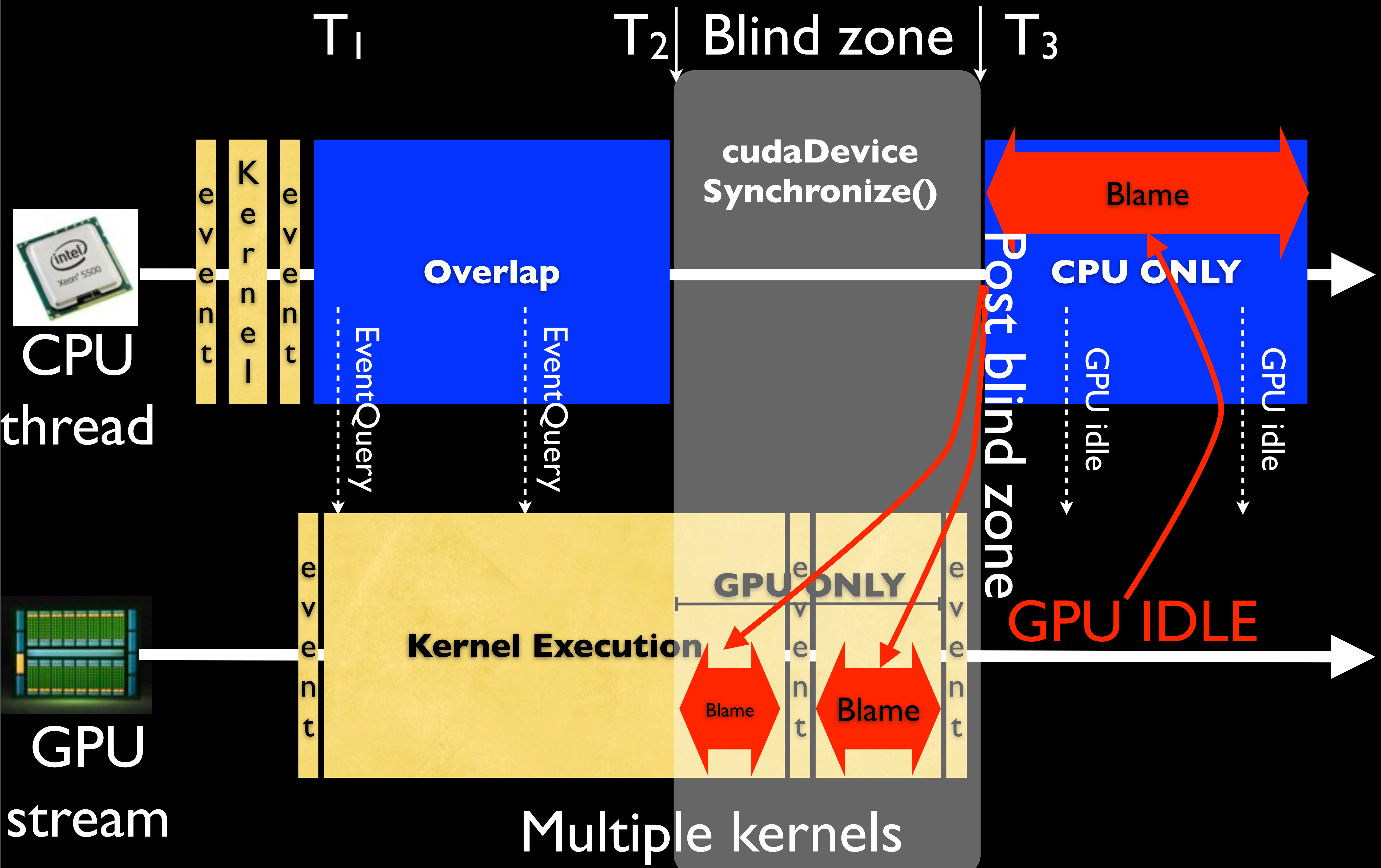


HPCToolkit vs. TAU & Vampir
Time Overhead

Keeneland : Intel Westmere hex-core CPUs@2.8GHz, 24GB,
NVIDIA 6GB Tesla M 2090 GPUs, and a Qlogic QDR InfiniBand interconnect

Program	Base runtime	HPCToolkit		TAU		Vampir
		Profiling	Tracing	Profiling	Tracing	Tracing
LAMMPS rhodopsin protein in solvated lipid bilaye (32procs, 6 nodes, 6ppn, 3 gpu/node)	26.8264 sec	**8.9%** (29.2059s)	**10%** (29.5081s)	**3.1x** (83.6458s)	**3.3x** (89.5835s)	**156x** (4182.72s)
LULESH (1 node, 1proc, 1 gpu)	17.4887 sec	**4.1%** (18.2031s)	**5.8%** (18.5003s)	**47%** (25.7486s)	**44%** (25.1442s)	**5.2X** **(90.8506s)**

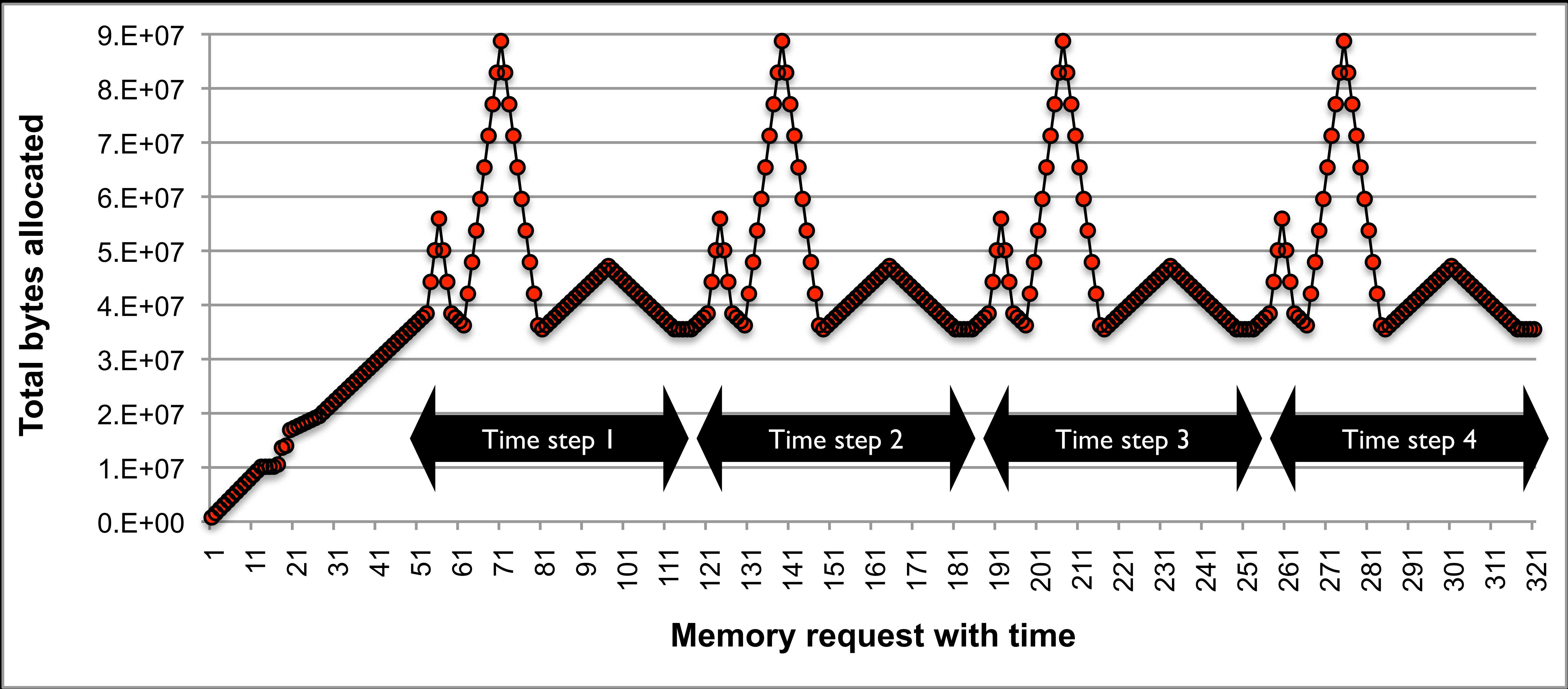
HPCToolkit vs. TAU & Vampir
Data Volume

Program	HPCToolkit		TAU		Vampir
	Profiling	Tracing	Profiling	Tracing	Tracing
LAMMPS (32procs, 6 nodes, 6ppn, 3 gpu/node)	16MB	57MB	**43x** (693MB)	**216x** (12GB)	**1491x** (83GB)
LULESH	268KB	4MB	**3.5x** (948KB)	**42.8x** (171MB)	**140.25x** (561MB)

Insights via Blame Shifting in LULESH CUDA

- Simulations involving complex multi-material motion are one of the the most CPU time consuming applications
  - ✦ LULESH: classic hydro-dynamics code, solves Sedov blast wave problem with “leap frog” time integration scheme
- CUDA version available from LLNL
- DEMO

LULESH CUDA Memory Allocation



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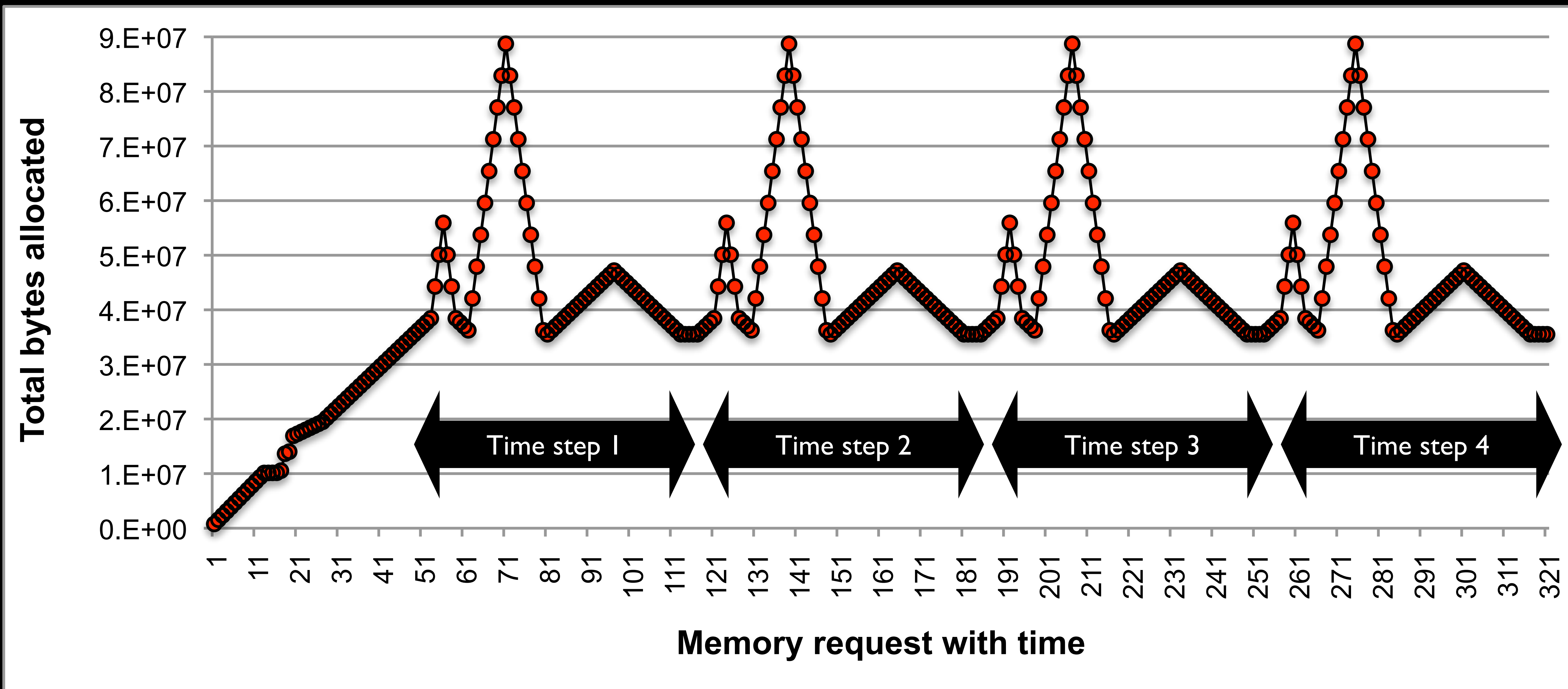

Replaced repeated memory allocation/free with a global allocation: **30%** running time improvement

LAMMPS on LJ

- Large-scale Atomic/Molecular Massively Parallel Simulator (LAMMPS): Classical molecular dynamics code
- Two CUDA versions
  - ✦ GPU
    - ★ Designed to exploit common GPU hardware configurations wAtom-based data (e.g. coordinates, forces) moves back-and-forth between the CPU(s) and GPU every timestep.
    - ★ Neighbor lists can be constructed on the CPU or on the GPU
    - ★ The charge assignment and force interpolation portions of PPPM can be run on the GPU. The FFT portion runs on the CPU.
    - ★ Asynchronous force computations can be performed simultaneously on the CPU(s) and GPU.
  - ✦ USER-CUDA (all on GPU)
    - ★ Many timesteps, to run entirely on the GPU

Conclusions

- Hybrid CPU/GPU blame shifting with HPCToolkit
  - ✦ Provides novel and practical technique for performance analysis of heterogeneous systems
  - ✦ Pinpoints code fragments (CPU and GPU) worth tuning
    - ★ Improves developer productivity
  - ✦ Provides scalable performance measurement and analysis with low space and time overhead compared to state-of-the-art tools
- Several implementation challenges
  - ✦ Better API/hardware support from vendor can eliminate workarounds in all tools

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