Decoupling GPU Programming Models from Resource Management for Enhanced Programming Ease, Portability, and Performance

Nandita Vijaykumar\textsuperscript{1}  Kevin Hsieh\textsuperscript{1}  Gennady Pekhimenko\textsuperscript{2,3,1}  Samira Khan\textsuperscript{4}
Ashish Shrestha\textsuperscript{5,1}  Saugata Ghose\textsuperscript{1}  Adwait Jog\textsuperscript{6}  Phillip B. Gibbons\textsuperscript{1}  Onur Mutlu\textsuperscript{7,1}

\textsuperscript{1}Carnegie Mellon University  \textsuperscript{2}University of Toronto  \textsuperscript{3}Microsoft Research
\textsuperscript{4}University of Virginia  \textsuperscript{5}Intel  \textsuperscript{6}College of William and Mary  \textsuperscript{7}ETH Zürich

This paper summarizes the idea of Zorua, which was published in MICRO 2016 \cite{88}, and examines the work’s significance and future potential. The application resource specification—a static specification of several parameters such as the number of threads and the scratchpad memory usage per thread block—forms a critical component of modern GPU programming models. This specification determines the parallelism, and hence performance, of the application during execution because the corresponding on-chip hardware resources are allocated and managed based on this specification. This tight-coupling between the software-provided resource specification and resource management in hardware leads to significant challenges in programming ease, portability, and performance. Zorua is a new resource virtualization framework, that decouples the programmer-specified resource usage of a GPU application from the actual allocation in the on-chip hardware resources. Zorua enables this decoupling by virtualizing each resource transparently to the programmer.

The virtualization provided by Zorua builds on two key concepts—dynamic allocation of the on-chip resources, and their oversubscription using a swap space in memory. Zorua provides a holistic GPU resource virtualization strategy designed to (i) adaptively control the extent of oversubscription, and (ii) coordinate the dynamic management of multiple on-chip resources to maximize the effectiveness of virtualization. We demonstrate that by providing the illusion of more resources than physically available via controlled and coordinated virtualization, Zorua offers several important benefits: (i) Programming Ease. Zorua eases the burden on the programmer to provide code that is tuned to efficiently utilize the physically available on-chip resources. (ii) Portability. Zorua alleviates the necessity of re-tuning an application’s resource usage when porting the application across GPU generations. (iii) Performance. By dynamically allocating resources and carefully oversubscribing them when necessary, Zorua improves or retains the performance of applications that are already highly tuned to best utilize the resources. The holistic virtualization provided by Zorua has many other potential uses, e.g., fine-grained resource sharing among multiple kernels, low-latency preemption of GPU programs, and support for dynamic parallelism.

1. Motivation: Key Challenges in Modern GPUs

Modern Graphics Processing Units (GPUs) offer high performance and energy efficiency for many classes of applications by concurrently executing thousands of threads. In order to execute, each thread requires several major on-chip resources: (i) registers, (ii) scratchpad memory (if used in the program), and (iii) a thread slot in the thread scheduler that keeps all the bookkeeping information required for execution.

Today, these resources are statically allocated to threads based on several parameters—the number of threads per thread block, register usage per thread, and scratchpad usage per block. We refer to these static application parameters as the resource specification of the application. This resource specification forms a critical component of modern GPU programming models (e.g., CUDA \cite{63}, OpenCL \cite{50}). The static allocation over a fixed set of hardware resources based on the software-specified resource specification creates a tight coupling between the program and the physical hardware resources. As a result of this tight coupling, for each application, there are only a few optimized resource specifications that maximize resource utilization. Picking a suboptimal specification leads to underutilization of resources and hence, very often, performance degradation. This leads to three key difficulties related to obtaining good performance on modern GPUs: programming ease, portability, and performance degradation.

Programming Ease. First, the burden falls upon the programmer to optimize the resource specification. For a naive programmer, this is a challenging task because, in addition to selecting a specification suited to an algorithm, the programmer needs to be aware of the details of the GPU architecture to fit the specification to the underlying hardware resources. This tuning is easy to get wrong because there are many highly suboptimal performance points in the specification space, and even a minor deviation from an optimized specification can lead to a drastic drop in performance due to lost parallelism. We refer to such drops as performance cliffs. Even a small change in one resource can result in a significant performance cliff, degrading performance by as much as 50%. Figure 1 depicts multiple sizable cliffs in an example application, when different resource specifications are used.
when the program is run on a real modern GPU, the NVIDIA GTX 745.¹

Portability. Second, different GPUs have varying quantities of each of the resources. Hence, an optimized specification on one GPU may be highly suboptimal on another. This lack of portability necessitates that the programmer re-tune the resource specification of the application for every new GPU generation. This problem is especially significant in virtualized environments, such as data centers, cloud computing, or compute clusters, where the same program may run on a wide range of GPU architectures. Figure 2 depicts the 69% performance loss when porting optimized code from the NVIDIA Kepler [65]/Maxwell [66] architectures to the NVIDIA Fermi [64] architecture.

Performance. Third, for a programmer who chooses to employ software optimization tools (e.g., auto-tuners [21, 24, 49, 74, 75, 79]) or manually tailor the program to fit the hardware, performance is still constrained by the fixed, static resource specification. It is well known [27, 42, 48, 62, 87, 97] that the on-chip resource requirements of a GPU application vary throughout execution. Since the program (even after auto-tuning) has to statically specify its worst-case resource requirements, severe dynamic underutilization of several GPU resources ensues [87], leading to suboptimal performance.

¹Our MICRO 2016 paper [88] describes the experimental methodology for collecting these real system results.

2. A Holistic Approach to Resource Virtualization

To address these three challenges at the same time, we propose Zorua, a new framework that decouples an application’s resource specification from the available hardware resources by virtualizing all three major resources (i.e., scratchpad memory, register file, and thread slots) in a holistic manner. This virtualization provides the illusion of more resources to the GPU programmer and software than physically available, and enables the runtime system and the hardware to dynamically manage multiple resources in a manner that is transparent to the programmer.

2.1. Key Concepts

The virtualization strategy used by Zorua is built upon two key concepts. First, to mitigate performance cliffs when we do not have enough physical resources, we oversubscribe resources by a small amount at runtime, by leveraging their dynamic underutilization and maintaining a swap space (in main memory) for the extra resources required. Second, Zorua improves utilization by determining the runtime resource requirements of an application. It then allocates and deallocates resources dynamically, managing them (i) independently of each other to maximize each resource’s utilization; and (ii) in a coordinated manner, to enable efficient execution of each thread with all its required resources available.

Figure 3 depicts the high-level overview of the virtualization provided by Zorua. The virtual space refers to the illusion of the quantity of available resources. The physical space refers to the actual hardware resources (specific to the target GPU architecture), and the swap space refers to the resources that do not fit in the physical space and hence are spilled to other physical locations. For the register file and scratchpad memory, the swap space is mapped to the global memory space in the memory hierarchy. For threads, only those that are mapped to the physical space are available for scheduling and execution at any given time. If a thread is mapped to the swap space, its state (e.g., the PC) is saved in memory. Resources in the virtual space can be freely remapped between the physical and swap spaces to maintain the illusion of the virtual space resources.

![Figure 1: Performance cliffs in Minimum Spanning Tree (MST) when run on the NVIDIA GTX 745. Reproduced from [88].](image1)

![Figure 2: Performance variation across different GPU generations from NVIDIA (Fermi, Kepler, and Maxwell) for Discrete Fourier Transform (DCT). Reproduced from [88].](image2)

![Figure 3: High-level overview of Zorua. Reproduced from [88].](image3)
2.2. Challenges in Virtualization

Unfortunately, oversubscription means that latency-critical resources, such as registers and scratchpad, may be swapped to memory at the time of access, resulting in high overheads in performance and energy. This leads to two critical challenges in designing a framework to enable virtualization. The first challenge is to effectively determine the extent of virtualization, i.e., by how much each resource appears to be larger than its real physical amount, such that we can minimize oversubscription while still reaping its benefits. This is difficult as the resource requirements continually vary during runtime. The second challenge is to minimize accesses to the swap space. This requires coordination in the virtualized management of multiple resources, so that enough of each resource is available on-chip at the same time when needed.

2.3. Design Ideas

To solve these challenges, Zorua employs two key ideas. First, we leverage the software (the compiler) to provide annotations with information regarding the future resource requirements of each phase of the application. This information enables the framework to make intelligent dynamic decisions ahead of time, with respect to both the extent of oversubscription and the allocation/deallocation of resources. Second, we use an adaptive runtime system to control the allocation of resources. This allows us to (i) dynamically alter the extent of oversubscription; and (ii) continuously coordinate the allocation of multiple on-chip resources and the mapping between their virtual and physical/swap spaces; depending on the varying runtime requirements of each thread. We briefly describe each design idea in turn.

2.3.1. Leveraging Software Annotations of Phase Characteristics

We observe that the runtime variation in resource requirements typically occurs at the granularity of phases of a few tens of instructions. This variation occurs because different parts of kernels perform different operations that require different resources. For example, loops that primarily load/store data from/to scratchpad memory tend to be less register heavy. Sections of code that perform specific computations (e.g., matrix transformation, graph manipulation), can either be register heavy or primarily operate out of scratchpad. Often, scratchpad memory is used for only short intervals [97], e.g., when data exchange between threads is required, such as for a reduction operation.

Figure 4 depicts a few example phases from the N-Queens Solver (NQU). Re-impl. NQU is a scratchpad-heavy application, but it does not use the scratchpad at all during the initial computation phase. During its second phase, it performs its primary computation out of the scratchpad, using as much as 4224B. During its last phase, the scratchpad is used only for reducing results, which requires only 384B. There is also significant variation in the maximum number of live registers in the different phases, as shown in Figure 4.

2.3.2. Control with an Adaptive Runtime System

Phase specifiers provide information to make oversubscription and allocation/deallocation decisions. However, we still need a way to make decisions on the extent of oversubscription and appropriately allocate resources at runtime. To this end, we use an adaptive runtime system, which we refer to as the coordinator. Figure 5 presents an overview of the coordinator.

The virtual space enables the illusion of a larger amount of each of the resources than what is physically available, to adapt to different application requirements. This illusion enables higher thread-level parallelism than what can be achieved with solely the fixed, physically available resources, by allowing more threads to execute concurrently. The size of the virtual space at a given time determines this parallelism, and those threads that are effectively executed in parallel are referred to as active threads. All active threads have thread

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2We refer the reader to Section 4.6 of our MICRO 2016 paper [88] for specific details on how phases are identified.
slots allocated to them in the virtual space (and hence can be executed), but some of them may not be mapped to the physical space at any given time. As discussed previously, the resource requirements of each application continuously change during execution. To adapt to these runtime changes, the coordinator leverages information from the phase specifiers to make decisions on oversubscription. The coordinator makes these decisions at every phase boundary and thereby controls the size of the virtual space for each resource.

2.4. Zorua: An Overview

To address the challenges in virtualization by leveraging the above ideas, Zorua employs a software–hardware codesign that comprises three components: (i) The compiler annotates the program by adding special instructions (phase specifiers) to partition it into phases and to specify the resource needs of each phase of the application. (ii) The coordinator, a hardware-based adaptive runtime system, uses the compiler annotations to dynamically allocate/deallocate resources for each thread at phase boundaries. The coordinator plays the key role of continuously controlling the extent of the oversubscription at each phase boundary. (iii) Hardware virtualization support includes a mapping table for each resource to locate each virtual resource in either the physically available on-chip resources or the swap space in main memory, and the machinery to swap resources between the physical space and the swap space.

Zorua has two key hardware components: (i) the coordinator that contains queues to buffer the pending threads and control logic to make oversubscription and resource management decisions, and (ii) resource mapping tables to map each of the resources to their corresponding physical or swap spaces. Our MICRO 2016 paper [88] provides the detailed implementation of Zorua in Section 4. In particular, we describe several key issues, including how (1) Zorua determines the amount of oversubscription for each resource (Section 4.4 of [88]), (2) Zorua virtualizes each resource (Section 4.5 of [88]), and (3) the compiler identifies each phase (Section 4.6 of [88]).

3. Results

In this section, we evaluate the effectiveness of Zorua in improving programming ease, portability, and performance. Our detailed experimental methodology is described in Section 5 of our MICRO 2016 paper [88]. More results are provided in Section 6 of [88].

3.1. Effect on Performance Variation and Cliffs

We first examine how Zorua alleviates the high variation in performance by reducing the impact of resource specifications on resource utilization. Figure 6 summarizes the range in performance across a wide range of resource specifications (indicating an undesirable dependence on the specification), for the baseline architecture, WLM (which allocates resources at the finer granularity of a warp [91]), and Zorua for a representative set of applications, using a Tukey box plot [61]. The boxes in the box plot represent the range between the first quartile (25%) and the third quartile (75%). The whiskers extending from the boxes represent the maximum and minimum points of the distribution, or $1.5 \times$ the length of the box, whichever is smaller. Any points that lie more than $1.5 \times$ the box length beyond the box are considered to be outliers [61], and are plotted as individual points. The line in the middle of the box represents the median, while the “X” represents the average. We make two major observations from Figure 6.

First, we find that Zorua significantly reduces the performance range across all evaluated resource specifications. Averaged across all of our applications, the worst resource specification for Baseline achieves 96.6% lower performance than the best performing resource specification. For WLM [91], this performance range reduces only slightly, to 88.3%. With Zorua, the performance range drops significantly, to 48.2%. We see drops in the performance range for all applications except SSSP. With SSSP, the range is already small to begin with (23.8% in Baseline), and Zorua exploits the dynamic underutilization, which improves performance but also adds a small amount of variation.

Second, while Zorua reduces the performance range, it also preserves or improves performance of the best performing points. As we examine in more detail in Section 3.2, the reduction in performance range occurs as a result of improved performance mainly at the lower end of the distribution.
First, Zorua successfully mitigates the performance cliffs that occur in Baseline. For example, DCT and MST are both sensitive to the thread block size, as shown in Figures 7a and 7b, respectively. We have circled the locations at which cliffs exist in Baseline. Unlike Baseline, Zorua maintains more steady execution times across the number of threads per block, employing oversubscription to overcome the loss in parallelism due to insufficient on-chip resources. We see similar results across all of our applications.

Second, we observe that while WLM [91] can reduce some of the cliffs by mitigating the impact of large block sizes, many cliffs still exist under WLM (e.g., NQU in Figure 7c). This cliff in NQU occurs as a result of insufficient scratchpad memory, which cannot be handled by warp-level management. Similarly, the cliffs for MST (Figure 7b) also persist with WLM because MST has a lot of barrier operations, and the additional warps scheduled by WLM ultimately stall, waiting for other warps within the same block to acquire resources. We find that, with oversubscription, Zorua is able to smooth out those cliffs that WLM is unable to eliminate.

### 3.2. Effect on Performance

As Figure 6 shows, Zorua either retains or improves the best performing point for each application, compared to the Baseline. Zorua improves the best performing point for each application by 12.8% on average, and by as much as 27.8% (for DCT). This improvement comes from the improved parallelism obtained by exploiting the dynamic underutilization of resources, which exists even for optimized specifications. Applications such as SP and SLA have little dynamic underutilization, and hence do not show any performance improvement. NQU does have significant dynamic underutilization, but Zorua does not significantly improve the best performing point as the overhead of oversubscription outweighs the benefit, and Zorua dynamically chooses not to oversubscribe. We conclude that even for many specifications that are optimized to fit the underlying hardware resources, Zorua is able to further improve performance.

We also note that, in addition to reducing performance variation and improving performance for optimized points, Zorua improves performance by 25.2% on average for all resource specifications across all evaluated applications.

### 3.3. Effect on Portability

Performance cliffs often behave differently across different GPU architectures, and can significantly shift the best performing resource specification point. We study how Zorua can ease the burden of performance tuning if an application has been already tuned for one GPU model, and is later ported to another GPU. To understand this, we define a new metric, porting performance loss, that quantifies the performance impact of porting an application without re-tuning it. To calculate this, we first normalize the execution time of each specification point to the execution time of the best performing specification point. We then pick a source GPU architecture (i.e., the architecture that the GPU was tuned for) and a target GPU architecture (i.e., the architecture that the code will run on), and find the point-to-point drop in performance (when the code is executed on the target GPU) for all points whose performance on the source GPU comes within 5% of the performance at the best performing specification point.\(^3\)

Figure 8 shows the maximum porting performance loss for each application, across any two pairings of our three simulated GPU architectures (NVIDIA Fermi, Kepler, and Maxwell). We find that Zorua greatly reduces the maximum porting performance loss that occurs under both Baseline and WLM for all but one of our applications. On average, the maximum porting performance loss is 52.7% for Baseline, 51.0% for WLM, and only 23.9% for Zorua.

Notably, Zorua delivers significant improvements in portability for applications that previously suffered greatly when ported to another GPU, such as DCT and MST. For both of these applications, the performance variation differs so much

\(^3\)We include any point within 5% of the best performance as there are often multiple points close to the best point, and the programmer may choose any of them.
between GPU architectures that, despite tuning the application on the source GPU to be within 5% of the best achievable performance, their performance on the target GPU is often more than twice as slow as the best achievable performance on the target platform. Zorua significantly lowers this porting performance loss down to 28.1% for DCT and 36.1% for MST. We also observe that for BH, Zorua actually slightly increases the porting performance loss with respect to the Baseline. This is because for Baseline, there are only two points that perform within the 5% margin for our metric, whereas with Zorua, we have five points that fall in that range. Despite this, the increase in porting performance loss for BH is low, deviating only 7.0% from the best performance.

We conclude that Zorua enhances portability of applications by reducing the impact of a change in the hardware resources for a given resource specification. For applications that have already been tuned on one platform, Zorua significantly lowers the penalty of not re-tuning for another platform, allowing programmers to save development time.

4. Related Work

To our knowledge, our MICRO 2016 paper [88] is the first work to propose a holistic software-hardware cooperative approach to virtualizing multiple on-chip resources in a controlled and coordinated manner that addresses these challenges, enabling the different benefits provided by virtualization in modern GPUs.

Prior works propose to virtualize a specific on-chip resource for specific benefits, mostly in the CPU context. For example, in CPUs, the concept of virtualized registers was first used in the IBM 360 [5] and DEC PDP-10 [10] architectures to allow logical registers to be mapped to either fast yet expensive physical registers, or slow and cheap memory. More recent works [67, 93, 94], propose to virtualize registers to increase the effective register file size to much larger register counts. This increases the number of thread contexts that can be supported in a multi-threaded processor [67], or reduces register spills and fills [93, 94]. Other works propose to virtualize on-chip resources in CPUs (e.g., [15,19,25,31,99]). In GPUs, Jeon et al. [42] propose to virtualize the register file by dynamically allocating and deallocating physical registers to enable more parallelism with smaller, more power-efficient physical register files. Concurrent to this work, Yoon et al. [98] propose an approach to virtualize thread slots to increase thread-level parallelism. These works propose specific virtualization mechanisms for a single resource for specific benefits. None of these works provide a cohesive virtualization mechanism for multiple on-chip GPU resources in a controlled and coordinated manner, which forms a key contribution of our MICRO 2016 work.

Enhancing Programming Ease and Portability. There is a large body of work that aims to improve programmability and portability of modern GPU applications using software tools, such as auto-tuners [21, 24, 49, 74, 75, 79], optimizing compilers [17, 37, 47, 59, 95, 96], and high-level programming languages and runtimes [23, 35, 72, 85]. These tools tackle a multitude of optimization challenges, and have been demonstrated to be very effective in generating high-performance portable code. They can also be used to tune the resource

Figure 8: Maximum porting performance loss. Reproduced from [88].
specification. However, there are several shortcomings in these approaches. First, these tools often require profiling runs [17, 21, 75, 79, 95, 96] on the GPU to determine the best performing resource specifications. These runs have to be repeated for each new input set and GPU generation. Second, software-based approaches still require significant programmer effort to write code in a manner that can be exploited by these approaches to optimize the resource specifications. Third, selecting the best performing resource specifications statically using software tools is a challenging task in virtualized environments (e.g., cloud computing, data centers), where it is unclear which kernels may be run together on the same SM or where it is not known, a priori, which GPU generation the application may execute on. Finally, software tools assume a fixed amount of available resources. This leads to runtime underutilization due to static allocation of resources, which cannot be addressed by these tools.

In contrast, the programmability and portability benefits provided by Zorua require no programmer effort in optimizing resource specifications. Furthermore, these auto-tuners and compilers can be used in conjunction with Zorua to further improve performance.

**Efficient Resource Management.** Prior works aim to improve parallelism by increasing resource utilization using hardware-based [6, 7, 30, 42, 45, 46, 55, 57, 62, 71, 84, 86, 91, 97], software-based [32, 36, 53, 58, 68, 92, 97], and hardware-software cooperative [8, 9, 43, 44, 73, 81, 82, 87] approaches. Among these works, the closest to ours are [42, 98] (discussed earlier), [97], and [91]. These approaches propose efficient techniques to dynamically manage a single resource, and can be used along with Zorua to improve resource efficiency further. Yang et al. [97] aim to maximize utilization of the scratchpad with software techniques, and by dynamically allocating/deallocating scratchpad memory. Xiang et al. [91] propose to improve resource utilization by scheduling threads at the finer granularity of a warp rather than a thread block. This approach can help alleviate performance cliffs, but not in the presence of synchronization or scratchpad memory, nor does it address the dynamic underutilization within a thread during runtime. We quantitatively compare to this approach in Section 3 and demonstrate Zorua’s benefits over it.

Other works leverage resource underutilization to improve energy efficiency [2, 27, 28, 29, 42] or perform other useful work [54, 87]. These works are complementary to Zorua.

5. Significance and Long-Term Impact

In this section, we describe the significance and long-term impact of our MICRO 2016 work, Zorua, by delineating its novelty, what it can enable in future systems, and new research directions that it triggers.

5.1. Novelty

• This is the first work that takes a holistic approach to decoupling a GPU application’s resource specification from its physical on-chip resource allocation via the use of virtualization. We develop a comprehensive virtualization framework that provides controlled and coordinated virtualization of multiple on-chip resources to maximize the effectiveness of virtualization.

• Making GPUs easy to program is critical for their widespread use, and also to achieve the high performance promised by the massively parallel architecture. A key limiting factor in GPU programming today is the burden placed on the programmer in finding a hardware resource specification that achieves very high performance. This is the first work to ease that burden without compromising performance by virtualizing the major hardware resources programmers are required to manage today.

• Portability across GPU architectures is vital in environments such as cloud computing and data centers to achieve predictably good performance, irrespective of the GPU generation the application is executing on. This is the first work to tackle the portability challenges that arise from the programmer’s management of the fixed on-chip resources with a holistic resource virtualization strategy.

5.2. What Zorua Can Enable in Future Systems

GPUs have emerged as the dominant massively parallel GPU architecture, used as the platform of choice for a wide range of parallel applications from machine learning to scientific simulation. However, there are a number of key challenges that limit the adoption of GPUs across broader classes of applications and environments, e.g., data centers, cloud computing, etc. Programmability and portability of GPU applications are two such challenges. But future GPUs will need to address several other challenges before truly becoming first-class compute engines. As we describe below, we believe that our work can help address some of these other challenges.

**Multiprogramming in Virtualized Environments.** Zorua lends itself to easily addressing two key challenges in enabling multiprogramming in virtualized environments today:

Fine-grained resource sharing across kernels: Zorua manages the different resources independently and at a fine granularity, using a dynamic runtime system. Hence, Zorua can be extended to support fine-grained sharing and partitioning of resources across multiple kernels to enable efficient multiprogramming in GPUs. Zorua enables better resource utilization in these multiprogrammed environments, while providing the ability to control the partitioning of resources at runtime to provide QoS, fairness, etc., by leveraging the hardware runtime system. Zorua can work synergistically with systems such as Mosaic [8] and MASK [9], which enable efficient memory virtualization techniques for GPUs, to enable true full-system multi-kernel execution.
Preemptive multitasking: Another key challenge in enabling true multiprogramming in GPUs is enabling rapid preemption of kernels [69, 83, 90]. Context switching on GPUs incurs a very high latency and overhead, as a result of the large amount of register file/scratchpad state that needs to be saved before a new kernel can be executed. Zorua enables fine-grained management and virtualization of on-chip resources. It can be naturally extended to enable quick preemption of a task via intelligent management of the swap space and the mapping tables. It can also work synergistically with CABA [87], framework for assist warp execution in GPUs, to provide flexible and efficient support for multitasking and context switching.

Support for Other Parallel Programming Paradigms. The fixed static resource allocation for each thread in modern GPU architectures requires statically dictating the parallelism for the program throughout its execution. Other forms of parallel execution that are dynamic (e.g., CILK [12]) require more flexible allocation of resources at runtime, and are hence more challenging to enable on GPUs. Examples of this include nested parallelism [56], where a kernel can dynamically spawn new kernels or thread blocks, and helper threads [87] to utilize idle resource at runtime to perform different optimizations or background tasks in parallel. Zorua makes it easy to enable these paradigms by providing on-demand dynamic allocation of resources.

Energy Efficiency, Scalability, and Reliability. To support massive parallelism, on-chip resources are a precious and critical resource. However, these resources cannot grow arbitrarily large as GPUs continue to be area-limited and on-chip memory tends to be extremely power hungry and area intensive [2, 27, 28, 42, 73, 98], which are trends we believe will become increasingly important for the foreseeable future. Furthermore, complex thread schedulers that can select a thread for execution from an increasingly large thread pool are required. Zorua enables using smaller register files, scratchpad memory and less complex or fewer thread schedulers to save power and area while still retaining or improving parallelism. The indirect offered by Zorua, along with the dynamic management of resources, could also enable better reliability. The virtualization framework trivially allows portions of a resource that contain hard or soft faults to be remapped to other portions of the resource that do not contain faults, or to spare structures, thereby increasing the error tolerance of these resources.

5.3. New Research Directions Zorua Enables

Zorua opens up several new avenues for more research, which we briefly discuss here.

Flexible Programming Models for GPUs and Heterogeneous Systems. By providing a flexible but dynamically controlled view of the on-chip hardware resources, Zorua changes the abstraction of the on-chip resources that is offered to the programmer and software. This offers the opportunity to rethink resource management in GPUs from the ground up. One could envision more powerful resource allocation and better programmability with programming models that do not require static resource specification, leaving the compiler/runtime system and the underlying virtualized framework to completely handle all forms of on-chip resource allocation, unconstrained by the fixed physical resources in a specific GPU, entirely at runtime. This is especially significant in future systems that are likely to support a wide range of compute engines and accelerators, making it important to be able to write high-level code that can be partitioned easily, efficiently, and at a fine granularity across any set of accelerators, without statically tuning any code segment to run efficiently on the GPU.

Virtualization-Aware Compilation and Auto-Tuning. Zorua changes the contract between the hardware and software to provide a more powerful resource abstraction (in the software) that is flexible and dynamic, by pushing some more functionality to the hardware, which can more easily react to runtime resource requirements of the program. We can re-imagine compilers and auto-tuners to be more intelligent, leveraging this new abstraction and, hence the virtualization, to deliver more efficient and high-performing code optimizations that are not possible with the fixed and static abstractions of today. They could, for example, leverage the oversubscription and dynamic management that Zorua provides to tune the code to more aggressively use resources.

Support for System-Level Tasks on GPUs. As GPUs become increasingly general purpose, a key requirement is better integration with the CPU operating system, and with complex distributed software systems such as those employed for large-scale distributed machine learning [1, 39] or graph processing [3, 4, 60]. If GPUs are architectured to be first-class compute engines, rather than the slave devices they are today, they can be programmed and utilized in the same manner as a modern CPU. This integration requires the GPU execution model to support system-level tasks like interrupts, exceptions, etc. and more generally provide support for access to distributed file systems, disk I/O, or network communication. Support for these tasks and execution models require dynamic provisioning of resources for execution of system-level code. Zorua provides a building block to enable this.

Applicability to General Resource Management in Accelerators. Zorua uses a program phase as the granularity for managing resources. This allows handling resources across phases dynamically, while leveraging static information regarding resource requirements from the software by inserting annotations at phase boundaries. Future work could potentially investigate the applicability of the same approach to manage resources and parallelism in other accelerators (e.g., processing-in-memory accelerators [3, 4, 13, 14, 34, 38, 40, 51, 52, 70, 77, 78, 80, 100] or direct-memory access engines [16, 55, 76]) that require efficient dy-
namic management of large amounts of particular critical resources.

6. Conclusion

We propose Zorua, a new framework that decouples the application resource specification from the allocation in the physical hardware resources (i.e., registers, scratchpad memory, and thread slots) in GPUs. Zorua encompasses a holistic virtualization strategy to effectively virtualize multiple latency-critical on-chip resources in a controlled and coordinated manner. We demonstrate that by providing the illusion of more resources than physically available, via dynamic management of resources and the judicious use of a swap space in main memory, Zorua enhances (i) programming ease (by reducing the performance penalty of suboptimal resource specification), (ii) portability (by reducing the impact of different hardware configurations), and (iii) performance for code with an optimized resource specification (by leveraging dynamic underutilization of resources). We conclude that Zorua is an effective, holistic virtualization framework for GPUs. We believe that the direction provided by Zorua’s virtualization mechanism makes it a generic framework that can address other challenges in modern GPUs. For example, Zorua can enable fine-grained resource sharing and partitioning among multiple kernels/applications, as well as low-latency preemption of GPU programs. We hope that future work explores these promising directions, building on the insights and the framework developed in our MICRO 2016 paper.

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