Leveraging the GPU on Spark

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Motivation

- Initial motivation: Time series analysis in Chronix
Motivation

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- Accelerating operations with high arithmetic intensity is “easy”:
  - copy from Spark to accelerated native application
  - compute...
  - copy back results
Motivation

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- More generally: accelerate operations with low arithmetic intensity
- Typically CPU ↔ GPU slow, GPU RAM fast
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- More generally: accelerate operations with low arithmetic intensity
- Typically CPU ↔ GPU slow, GPU RAM fast
- Can we just keep the data on the GPU all the time?
GPU ↔ Java

- Project Sumatra aimed for deep integration into Hotspot. Didn’t happen (project is “currently inactive”).
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- OpenCL and CUDA are native APIs, interfacing via JNI possible but tedious
- There has yet to emerge a standard way of GPU acceleration for Java
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- OpenCL and CUDA are native APIs, interfacing via JNI possible but tedious
- There has yet to emerge a standard way of GPU acceleration for Java
- Many publications, but few publish code
Transpilers

There are two serious transpilers publicly available:

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Both could use some love...
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Challenges

jocl/jcuda

Near 1:1 wrappers around OpenCL/CUDA

- Very flexible in usage
jocl/jcuda

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➤ Direct OpenCL usage makes runtime code generation easy.
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Near 1:1 wrappers around OpenCL/CUDA
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Near 1:1 wrappers around OpenCL/CUDA

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Currently the only reasonable choices.
CUDA vs. OpenCL

CUDA
- has a mature ecosystem
- needs separate compilation
- works only on Nvidia GPUs

OpenCL
- “works” on lots of devices (CPUs, GPUs, FPGAs, etc)
- supports JIT compilation of kernels (from C)
- most implementations are fragile/quirky
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Challenges

GPU ↔ Spark

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- IBM GPUEabler (Tungsten prototype?)
  - looks promising
Leveraging the GPU on Spark

Challenges

GPU ↔ Spark

- Project Tungsten (theoretically)
- IBM GPUEnabler (Tungsten prototype?)
  - looks promising
  - but mostly undocumented
  - uses internal Spark APIs
  - had randomly failing tests
  - their example code is faster on the CPU
CLRDD

CLRDD[T](val wrapped: RDD[CLPartition[T]]) extends RDD[T]

- One CLPartition yields one context and an iterator of binary chunks
  - The context provides asynchronous methods on chunks
CLRDD

\[ \text{CLRDD}[T](\text{val wrapped: RDD[CLPartition[T]]}) \text{ extends RDD}[T] \]

- One \textit{CLPartition} yields one context and an iterator of binary chunks
  - The context provides asynchronous methods on chunks
- Provides GPU functions on the RDD
- The user can choose caching on the GPU at runtime
- If data is not cached on the GPU, it is streamed as needed
Storage

- all useful operations on `CLRDD[T]` require a typeclass instance `CLType[T]`
- minimal definition includes OpenCL type, mapping to/from ByteBuffer storage
- optionally: OpenCL arithmetics
- macro generated instances for all primitive vector/tuple types
Operations

Operations are represented as composable case classes that can generate a kernel source:

```scala
case class MapReduceKernel[A, B](
  f: MapKernel[A, B],
  reduceBody: String,
  identity: String,
  cpu: Boolean,
  implicit val clA: CLType[A],
  implicit val clB: CLType[B]
) extends CLProgramSource {
  def generateSource(supply: Iterator[String]): Array[String] = ...
  ...
}
```
Functions on the GPU

High level functions that are implemented:

- One to one map functions (inplace/copying):
  
  \[
  \text{crdd.map[\textbf{Byte}]}(\"return \ x\%2;\")
  \]
Functions on the GPU

High level functions that are implemented:

- One to one map functions (inplace/copying):
  ```scala
  crdd.map[Byte]("return x%2;")
  ```

- Simple reduction:
  ```scala
  def sum(implicit num: Numeric[T]) : T = {
    val clT = implicitly[CLType[T]]
    reduce(MapReduceKernel(
      MapKernel.identity[T], // first map
      "return x+y;", // then reduce
      clT.zeroName, // string zero
      useCPU, // algorithm selection
      clT, clT // explicit typeclasses
    ), num.zero, ((x: T, y: T) => num.plus(x,y)))
  }
  ```
Functions on the GPU

- Many to one sliding window map

```scala
def movingAverage(width: Int)(implicit clT: CLType[T])
//polymorphic return type, e.g.CLRDD[(Double,Double)]
: CLRDD[clT.doubleCLInstance.elemType] = {
  val clRes = clT.doubleCLInstance
  sliding[clT.doubleCLInstance.elemType](
    width, 1, // width, stride
    s"""${clRes.clName} res = ${clRes.zeroName};
    for(int i=0; i<$width; ++i)
      res += convert_${clRes.clName}(GET(i));
    return res/$width;""
  )//just scala things...
  (clT.doubleCLInstance.selfInstance,
   clT.doubleCLInstance.elemClassTag)
}
```
Benchmarking Setup

Workstation

- Spark local mode
- Intel i7-3770: 4 cores, 8 threads, ~20GiB/s
- Radeon HD 7950, ~200GiB/s
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Benchmarks

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Cluster

- Spark standalone cluster mode
- 4 nodes, 40Gbit/s Infiniband interconnect
- two Xeon 2660v2: 20 cores, 40 threads, \( \sim 100 \text{GiB/s} \)
- two K20m, \( \sim 400 \text{GiB/s} \)
Benchmarks

- All benchmarks operate on RDD[Double]s.
- AMD’s OpenCL implementation for the CPUs
Benchmarks

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- All data cached in RAM/graphics RAM before benchmarking
Benchmarks

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- AMD’s OpenCL implementation for the CPUs
- all data cached in RAM/graphics RAM before benchmarking
- solid lines show throughput
- dashed lines show time to process one RDD
Workstation sum

1 “Scala” result with neither rdd.sum(), nor rdd.reduce()
**Workstation stats**

![Graph showing throughput and time for different sizes of data with GPU, CPU, and Scala comparisons.](image)
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Benchmarks

Workstation moving Average

![Graph showing throughput vs. size and time for GPU, CPU, and Scala.](image)

- **Throughput** measured in MiB/s.
- **Size** measured in MiB.
- **Time** measured in seconds.

The graph compares the performance of GPU, CPU, and Scala for different sizes of data. The GPU consistently shows higher throughput compared to CPU and Scala across various sizes of data.
Cluster sum

![Graph showing throughput and time for different sizes and frameworks (GPU, CPU, Scala).]
Cluster stats

![Cluster stats graph](image)

Throughput [MiB/s] vs. size [MiB] for GPU, CPU, and Scala.

- **GPU** line: solid black
- **CPU** line: blue
- **Scala** line: green

**Y-axis**: Throughput [MiB/s] (log scale)

**X-axis**: Size [MiB] (log scale)

**Legend**:
- GPU
- CPU
- Scala
Cluster moving Average

![Graph showing throughput and time for different sizes and architectures](image-url)
Conclusions

- simple aggregations could be faster even without GPUs.
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- Large speedups for big datasets in GPU memory.
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- simple aggregations could be faster even without GPUs.
- large speedups for big datasets in GPU memory
- implementation effort vs. plain Spark is a lot higher
  - fit data into GPU RAM
  - special GPU code?
  - debugging
  - deploying
The Way Forward

- Efficiently using GPUs (for arbitrary tasks) is a hard problem.
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- Builtins could benefit, especially with intelligent caching in GPU memory (typically scarce).
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- Builtins could benefit, especially with intelligent caching in GPU memory (typically scarce).
- Bytecode inspection for simple operations (see SPARK-14083)?
- Spark as a compiler?
Remember that complaint about not publishing code?

Fully functioning prototype implementation at: https://github.com/TPolzer/spark-clrdd.
Code

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- Fully functioning prototype implementation at: https://github.com/TPolzer/spark-clrdd.
Questions?