Big Data Analytics with Delite

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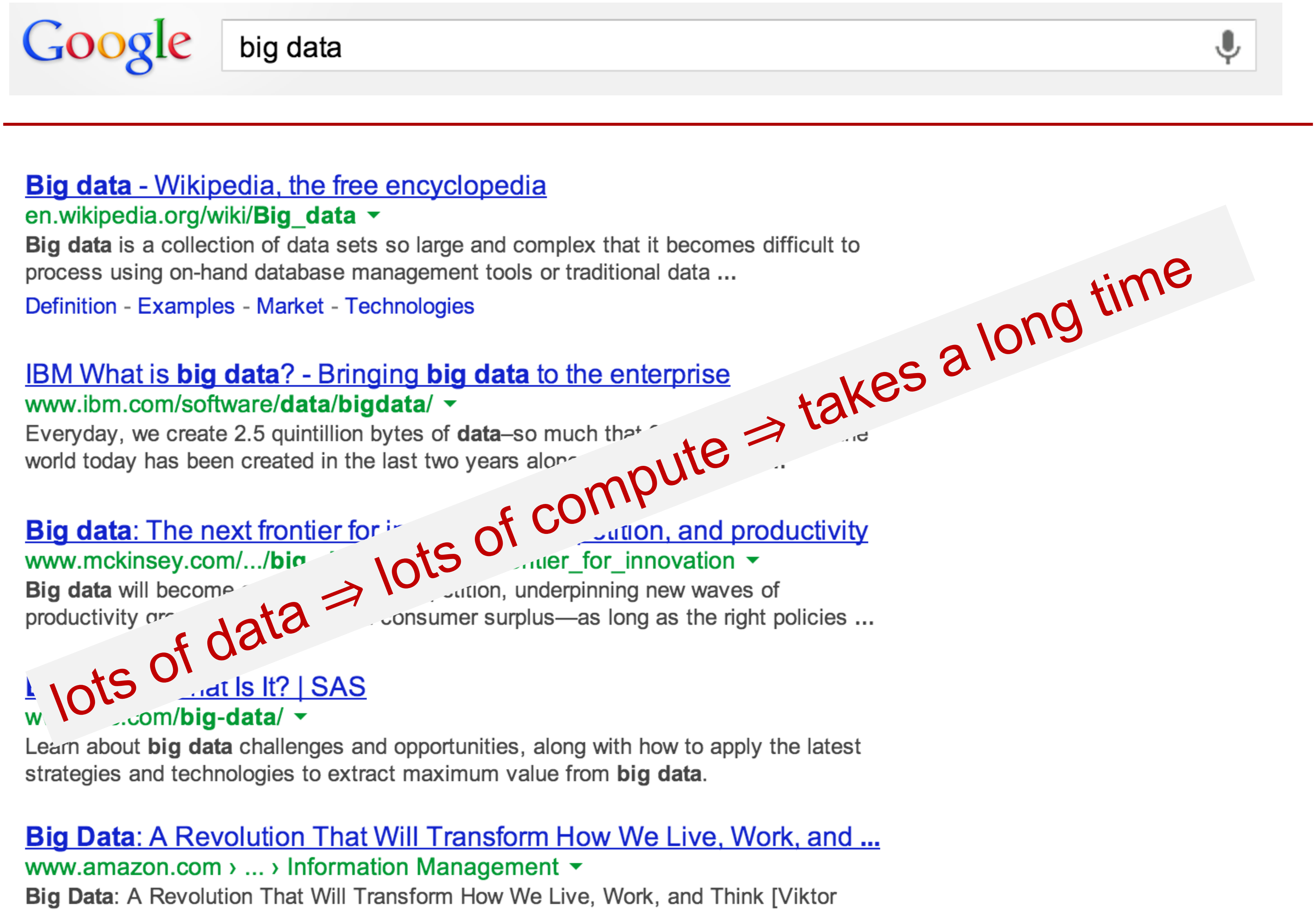
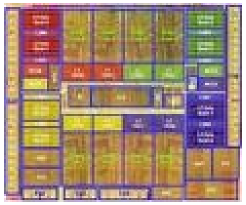
Stanford University, EPFL


Google
big data
Big data - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/Big_data
Big data is a collection of data sets so large and complex that it becomes difficult to process using on-hand database management tools or traditional data ...
Definition - Examples - Market - Technologies
IBM What is big data? - Bringing big data to the enterprise
www.ibm.com/software/data/bigdata/
Everyday, we create 2.5 quintillion bytes of data–so much that
world today has been created in the last two years alon
Big data: The next frontier for
ition, and productivity
www.mckinsey.com/.../big
ntier_for_innovation
Big data will become
ition, underpinning new waves of
productivity
consumer surplus—as long as the right policies ...
at Is It? | SAS
.com/big-data/
Learn about big data challenges and opportunities, along with how to apply the latest strategies and technologies to extract maximum value from big data.
Big Data: A Revolution That Will Transform How We Live, Work, and ...
www.amazon.com › ... › Information Management
Big Data: A Revolution That Will Transform How We Live, Work, and Think [Viktor
lots of data ⇒ lots of compute ⇒ takes a long time

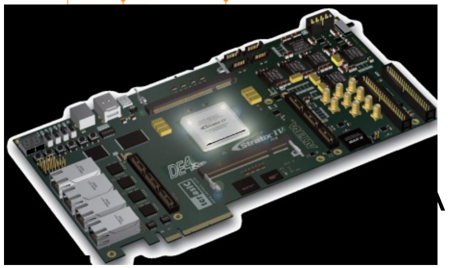
Heterogeneous Parallel Architectures Today

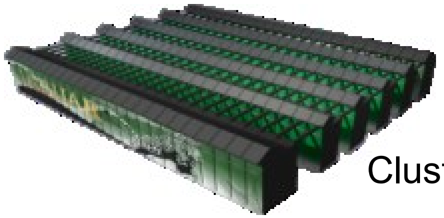
- High performance capability



Multicore CPU

GPU



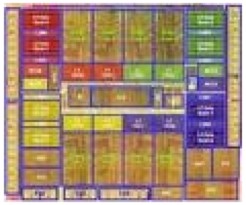


Cluster

Heterogeneous Parallel Programming

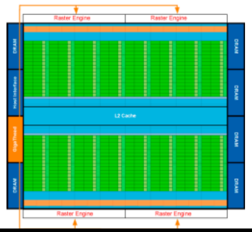
- But high effort

Threads
OpenMP



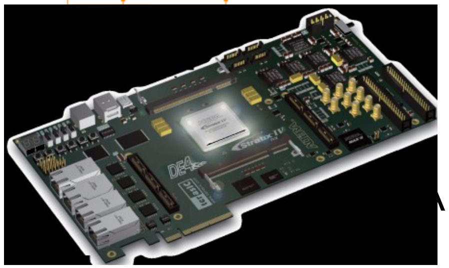
Multicore
CPU

CUDA
OpenCL

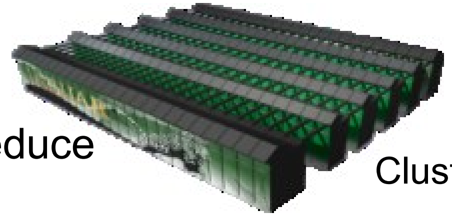


GPU

Verilog
VHDL



MPI
MapReduce



Cluster

Programmability Chasm

Applications

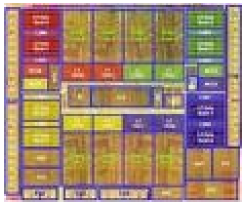
Scientific Engineering

Virtual Worlds

Personal Robotics

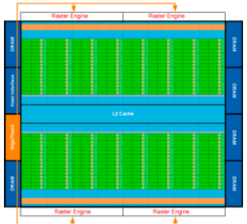
Data Isnformatics

Threads
OpenMP



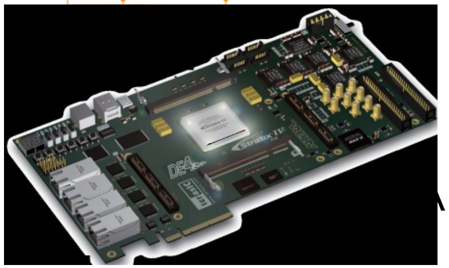
Multicore
CPU

CUDA
OpenCL

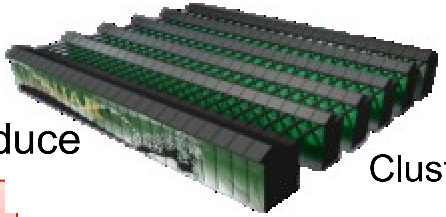


GPU

Verilog
VHDL



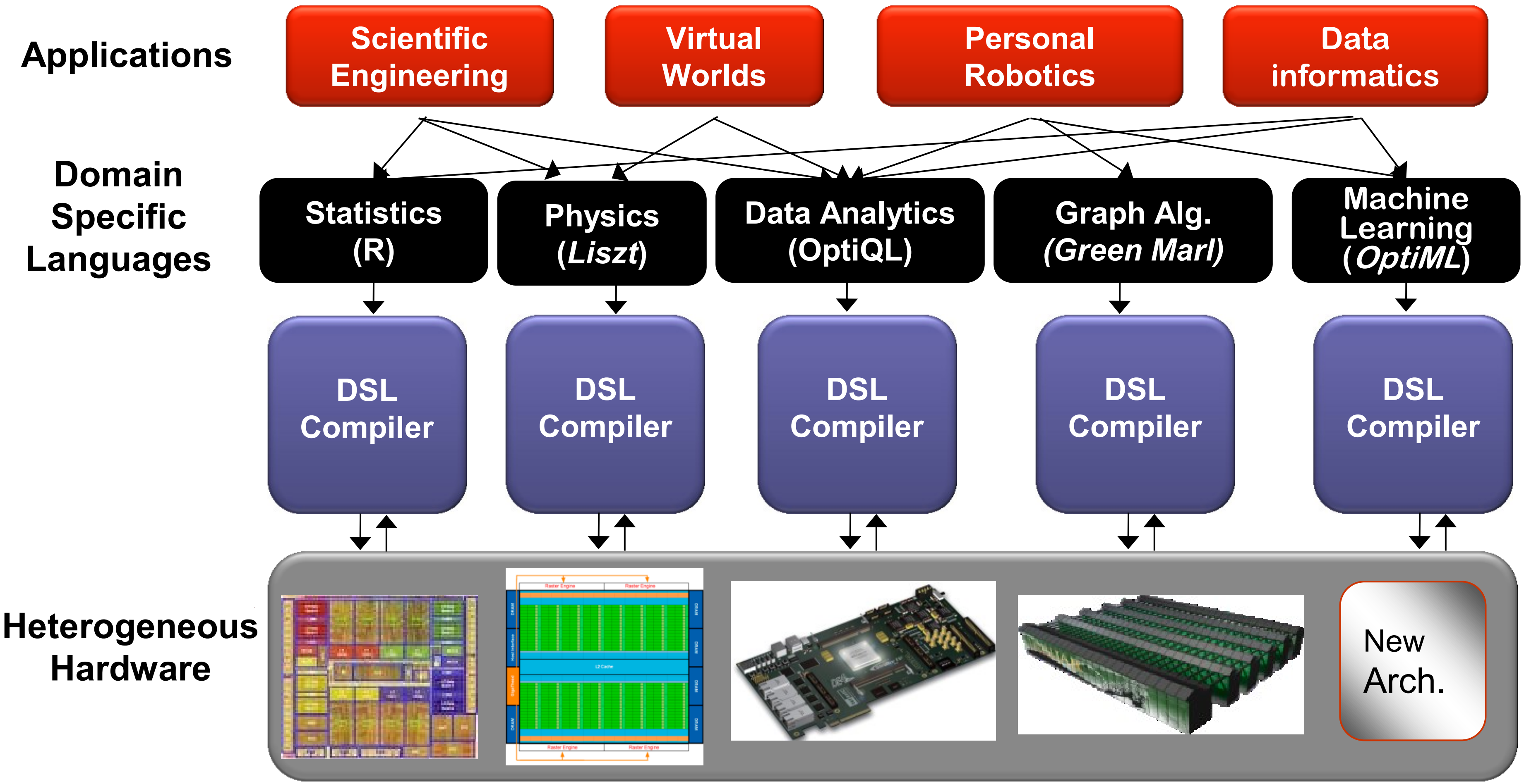
MPI
MapReduce



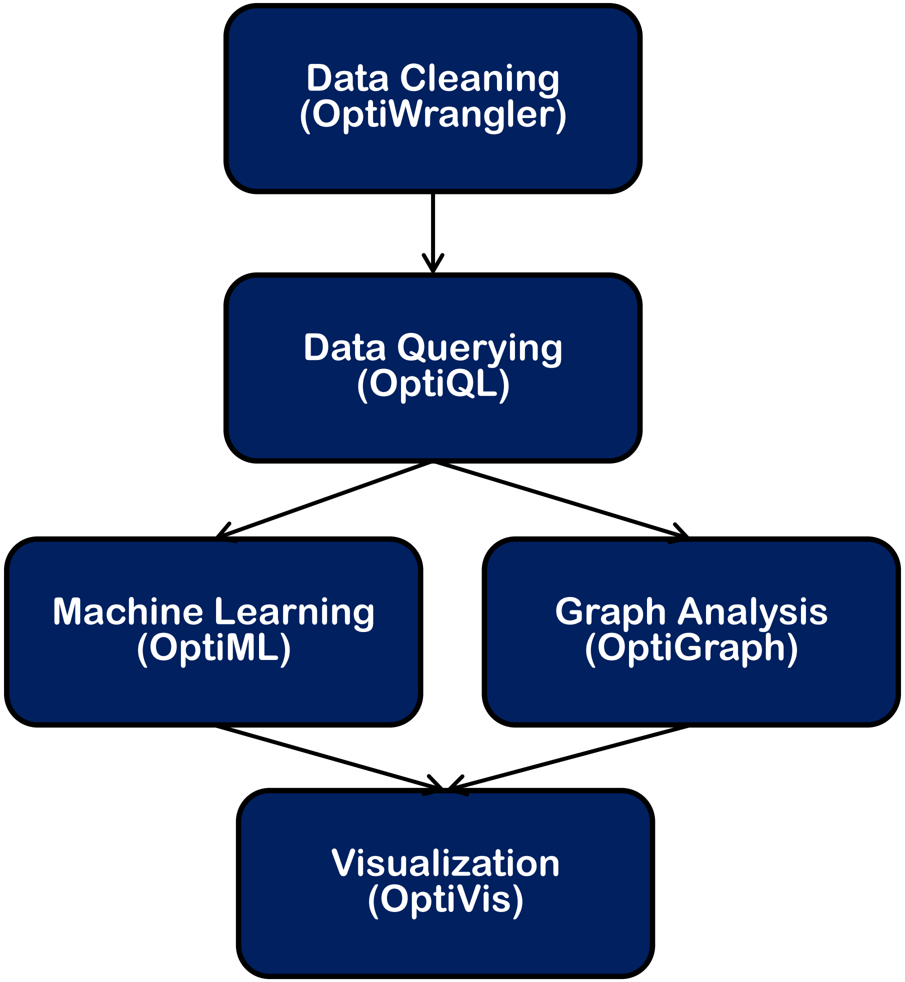
Cluster

Too many different programming models

Bridging the Programmability Chasm



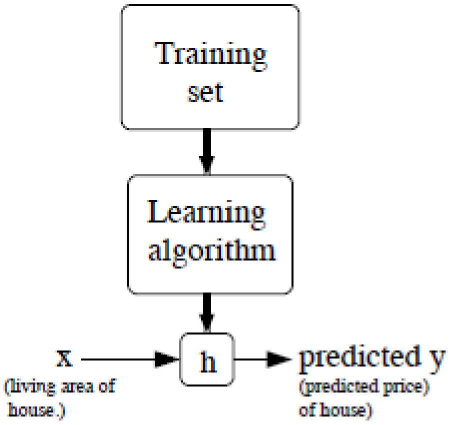
Big Data Pipeline



Domain Expertise

Gradient Descent

Images, Video, Audio



Convex Optimization

Message-passing graphs

Probability

Linear Algebra

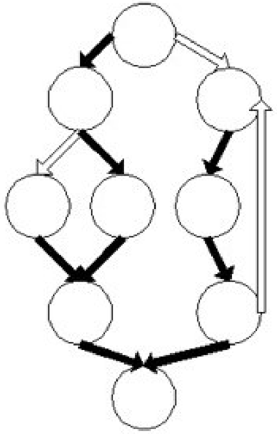
Streaming training sets

Expressing the important problems

Language Expertise

Abstract Syntax Tree

Control Flow Graph



Program Transformation

Alias Analysis

Code Generation

Loop-invariant Code Motion

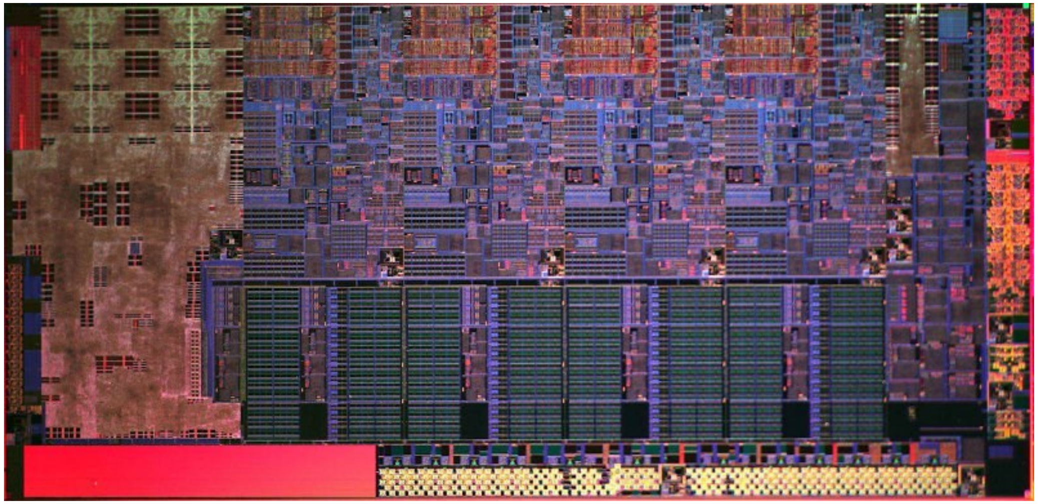
Performance Expertise

Thread

False Sharing

Locality

Mutex



SSE

Synchronization

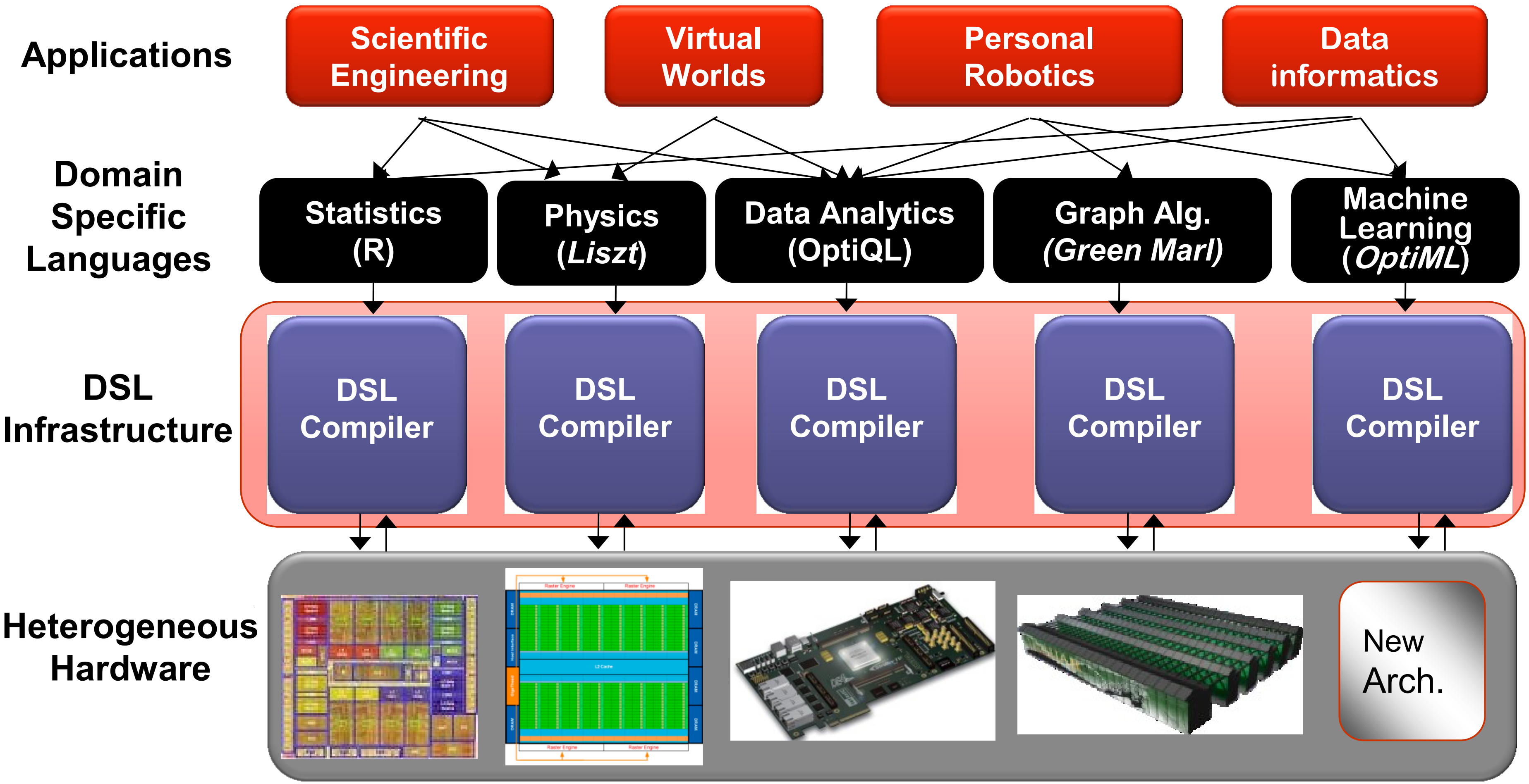
Coherency Protocol

TLB Shootdown

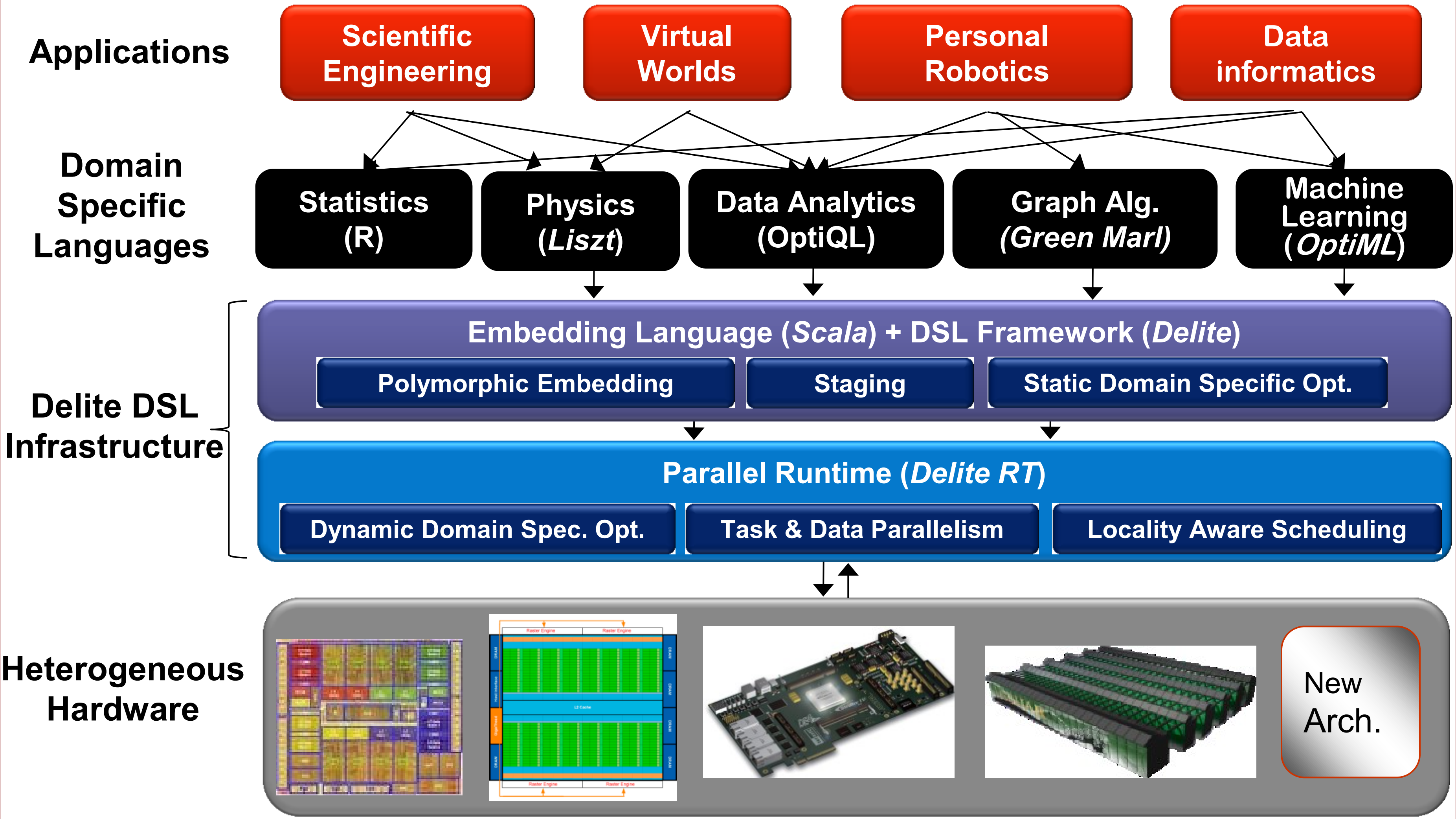
Bandwidth

Implementing efficiently and portably

Common DSL Infrastructure



Delite DSL Framework

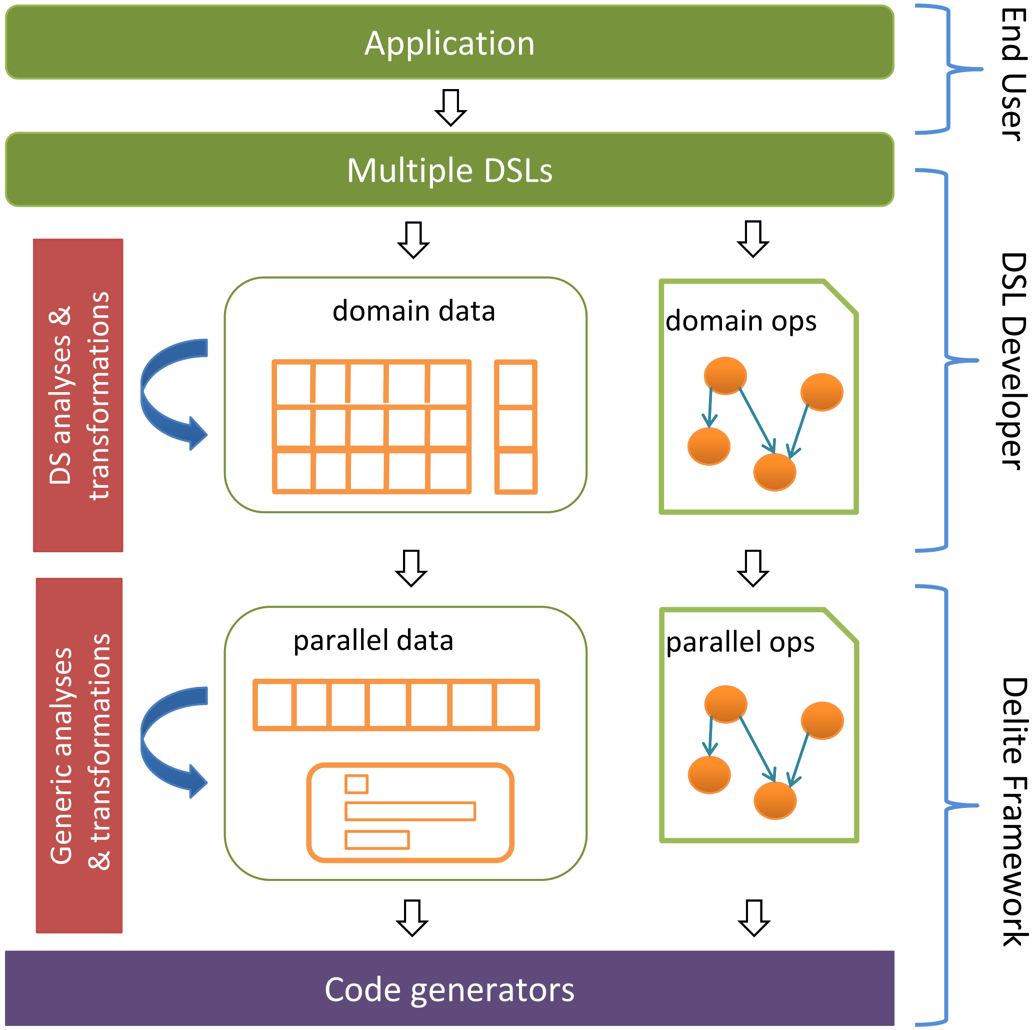


Outline

- Building high performance DSLs for heterogeneous cluster computing in Delite
- Case study: Tackling nested parallel patterns on clusters with existing Delite DSLs
- Performance results

Delite Programming Model

- Parallel Patterns
  - Map, Zip, Filter, FlatMap, Reduce, GroupBy, …
  - Composable
    - e.g., Filter-GroupBy
    - e.g., Map{Reduce}
- Restricted Data
  - Records of primitives and arrays
    - Per-target implementations



Delite Example

- DSL author writes:

```
trait VectorOps {
  trait Vector[A] //user-facing types (abstract)

  //DSL methods on abstract types create domain-specific IR nodes
  def infix_max[A:Manifest:Ordering](v: Rep[Vector[A]]) = VectorMax(v)

  //DSL ops implemented using Delite parallel patterns; Delite handles codegen
  case class VectorMax[A:Manifest:Ordering](in: Rep[Vector[A]])
    extends DeliteOpReduce[A] {

    def func = (a,b) => if (a > b) a else b
 }

  //DSL data structures implemented using Delite structs
  case class VectorNew[A:Manifest](length: Rep[Int])
    extends DeliteStruct[Vector[A]] {

    val elems = (“_data” -> DeliteArray[A](length), “_length” -> length)
  }
}
```

DSL Optimizations

```
trait MatrixOpsOpt extends MatrixOps {
  override def matrix_plus[A:Manifest:Arith]
   (x: Rep[Matrix[A]], y: Rep[Matrix[A]]) = (x, y) match {
     // (AB + AD) == A(B + D)
     case (Def(MatrixTimes(a, b)), Def(MatrixTimes(c, d))) if (a == c) =>
       matrix_times(a, matrix_plus(b,d)) //return optimized version

      //case … (other rewrites)
      case _ => super.matrix_plus(x, y)
  }
}

trait MyDSL extends VectorOpsOpt with MatrixOpsOpt
trait MyApp extends MyDSL {
  def main() {
    val v = Vector(1,2,3,4,5)
    v.max //can run on CPU, GPU, across a cluster, …
  }
}
```

Delite Advantages

- *Parallel pattern IR* makes it easy for DSL authors to expose parallelism in their domain
- Provides code generators for Scala, C++, OpenCL, CUDA, and clusters thereof
- Uses staging (LMS) to build the IR (POPL '13)
  - Systematically removes abstraction
  - Simple transformation interface based on rewrites
    - Each DSL can add new domain-specific optimizations
- Provides reusable, composable optimizations
  - High-level operator fusion, AoS to SoA, code motion, dead field elimination, CSE

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- Performance results

Nested Parallel Patterns

- Parallelization decisions are much more difficult
  - What if a big loop nested inside a small loop?
  - Unroll the outer loop, flatten the loops, interchange the loops, …
- Nesting order determines the data access stencil
  - Affects freedom to physically partition data across the cluster
  - Want to distribute over the "big" dataset
- Optimal traversal order is architecture dependent
  - No one "correct" way of writing the program
  - Often reversed for CPU vs. GPU (row-oriented vs. column-oriented)
- Compiler needs to be able to transform between both versions to maintain architecture-agnostic source code

OptiQL

- Data querying of in-memory collections
  - inspired by LINQ to Objects
- SQL-like declarative language
- Use high-level semantic knowledge to implement query optimizer

OptiQL: TPCH-Q1

```
// lineItems: Table[LineItem]
// Similar to Q1 of the TPC-H benchmark
val q = lineItems Where(_.l_shipdate <= Date(‘‘19981201’’)).
  GroupBy(l => l.l_linestatus).
  Select(g => new Record {
    val lineStatus = g.key
    val sumQty = g.Sum(_.l_quantity)
    val sumDiscountedPrice =
      g.Sum(r => r.l_extendedprice*(1.0-r.l_discount))
    val avgPrice = g.Average(_.l_extendedprice)
    val countOrder = g.Count
  }) OrderBy(_.returnFlag) ThenBy(_.lineStatus)
```

hoisted

fused

TPC-H LineItem

- User-defined struct

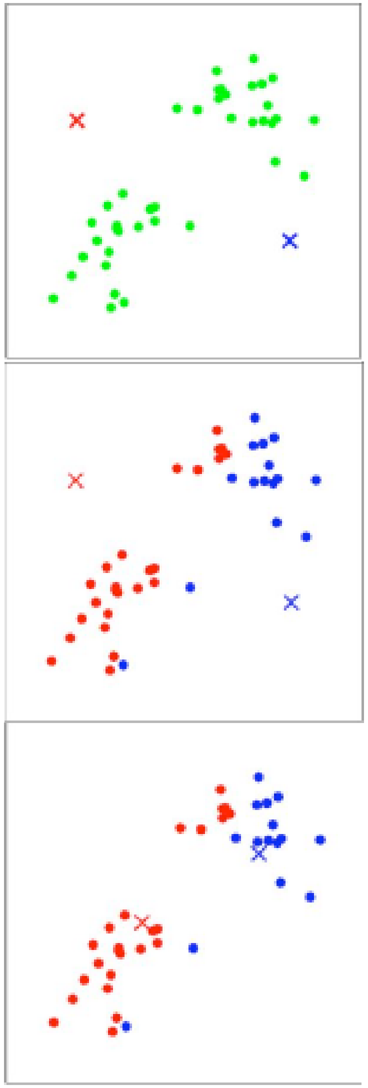
```
type LineItem = Record {
  val l_orderkey: Int;          val l_partkey: Int
  val l_suppkey: Int;           val l_linenumber: Int
  val l_quantity: Double;       val l_extendedprice: Double
  val l_discount: Double;       val l_tax: Double
  val l_returnflag: Char;       val l_linestatus: Char
  val l_shipdate: Date;         val l_commitdate: Date
  val l_receiptdate: Date
  val l_shipinstruct: String;   val l_shipmode: String
  val l_comment: String
}
```

OptiML

OptiML: An Implicitly Parallel Domain-Specific Language for Machine Learning, **ICML 2011**

- Provides a familiar (MATLAB-like) language and API for writing ML applications
  - Ex. `val c = a * b` (a, b are Matrix[Double])
- Implicitly parallel data structures
  - Base types: Vector[T], Matrix[T], Graph[V,E], Stream[T]
  - Subtypes: TrainingSet, IndexVector, Image, …
- Implicitly parallel control structures
  - sum{…}, (0::end) {…}, gradient { … }, untilconverged { … }
  - Arguments to control structures are anonymous functions with restricted semantics

OptiML: *k*-means Clustering

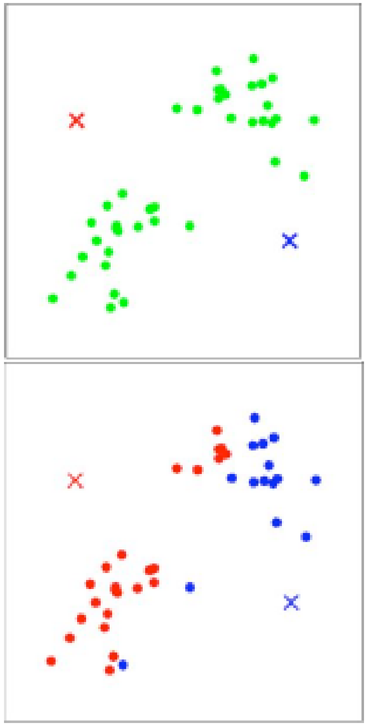


```
untilconverged(mu, tol){ mu =>
    // assign each sample to the closest centroid
    val clusters = x.groupRowsBy { row =>
      // calculate distances to current centroids
      val allDistances = mu mapRows { centroid =>
        dist(row, centroid)
      }
     allDistances.minIndex
    }

    // move each cluster centroid to the
    // mean of the points assigned to it
    val newMu = clusters.map(e => e.sum / e.length)
    newMu
}
```

fused

OptiML: *k*-means Clustering (2)



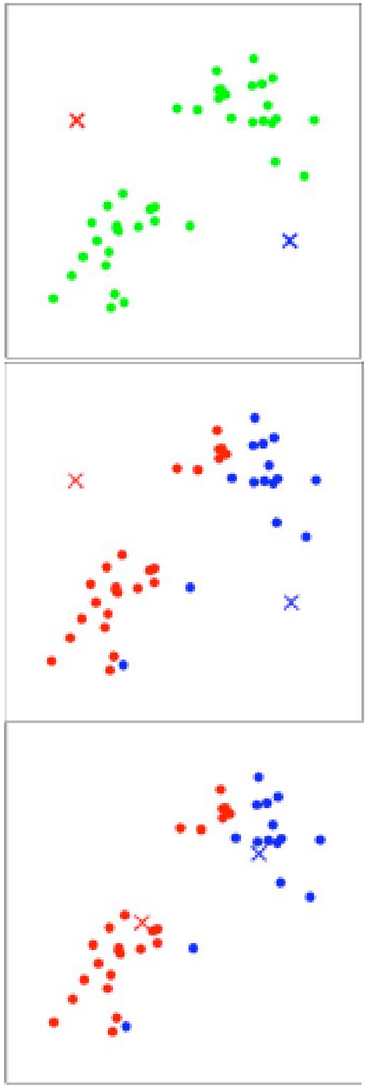
```
untilconverged(mu, tol){ mu =>
    // calculate distances to current centroids
    val c = (0::m){i =>
       val allDistances = mu mapRows { centroid =>
          dist(x(i), centroid)
       }
       allDistances.minIndex
    }

    // move each cluster centroid to the
    // mean of the points assigned to it




}
```

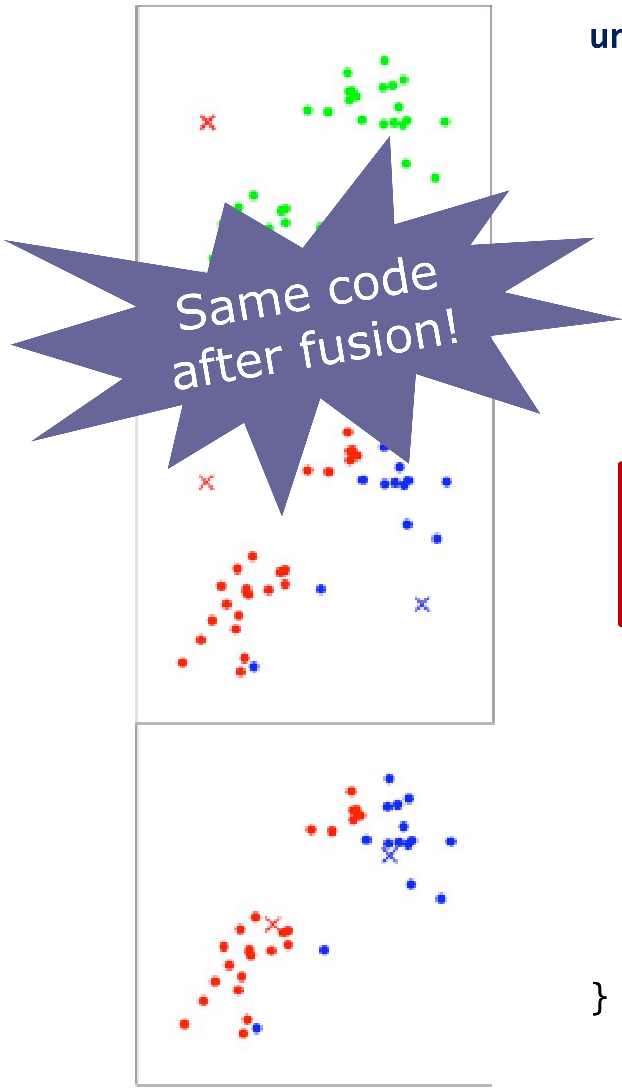
OptiML: *k*-means Clustering (2)



```
untilconverged(mu, tol){ mu =>
    // calculate distances to current centroids
    val c = (0::m){i =>
       val allDistances = mu mapRows { centroid =>
          dist(x(i), centroid)
       }
       allDistances.minIndex
    }

    // move each cluster centroid to the
    // mean of the points assigned to it
    val newMu = (0::k,*){ cluster =>
       val weightedpoints =
         sumRowsIf(0,m)(i => c(i) == cluster){ i => x(i) }
       val points = c.count(i => i == cluster)
       weightedpoints / points
    }
    newMu
}
```

OptiML: *k*-means Clustering (3)




```
untilconverged(mu, tol){ mu =>
    // calculate distances to current centroids
    val c = (0::m){i =>
        val allDistances = mu mapRows { centroid =>
            dist(x(i), centroid)
        }
        allDistances.minIndex
    }

val allWP = bucketReduce(0::m)(i => c(i), i => x(i), _ + _)
val allP =  bucketReduce(0::m)(i => c(i), i => 1,    _ + _)

  val newMu = (0::k,*){ cluster =>
        val weightedpoints = allWP(cluster)
        val points = allP(cluster)
        weightedpoints / points
    }
    newMu
}
```

fused

OptiML: Logistic Regression

```
untilconverged(theta, tol){ theta =>
  (0::x.numFeatures){ j => //vector of sums
    val gradient = sum(0, x.numSamples){ i =>
      x(i)(j)*(y(i) - hyp(theta,x(i)))
    }
    theta(j) + alpha*gradient
  }
}
```

$$\Downarrow$$

```
untilconverged(theta, tol){ theta =>
  val gradientVec = sum(0, x.numSamples){ i => //sum of vectors
    (0::x.numFeatures){ j =>
       x(i)(j)*(y(i) – hyp(theta,x(i)))
    }
  }
  (0::x.numFeatures){ j =>
    val gradient = gradientVec(j)
    theta(j) + alpha*gradient
  }
}
```

Logistic Regression on the GPU

- For GPU execution the original traversal order is actually superior!
  - Better to compute a vector of multiple scalar sums than a sum of vectors
- But we need the transformation to optimally partition the app across a cluster

- Solution: Apply the inverse transformation within the CUDA kernel implementation and transpose each chunk of the input matrix when shipped to the GPU
  - Distribute matrix by samples (rows) across the cluster, iterate and sum by features (columns) within each GPU

Stencil Analysis and Data Partitioning

- Delite analyzes the access pattern for each input of a parallel op
  - Possible Stencils: *One*, *Interval* (distribute); *All* (broadcast); *Unknown* (runtime message passing)

- Stencil for each op is joined conservatively to determine a partition for each data structure / schedule for each op
  - Consider constraints on input locations & constraints on output locations
  - Attempt to create a schedule that requires no data re-shuffling

Runtime Management

- Runtime uses master/slave model for cluster
  - Master runs all effectful / sequential ops
  - Pure parallel ops can be executed across multiple slaves using RPC calls
  - Efficient serialization using Protocol Buffers
  - Each slave can utilize multi-core and GPU
- Each slave keeps its portion of distributed data structures in memory for future ops
  - Garbage collection handled using DEG information (liveness analysis)
  - GC the GPU's memory in a similar way

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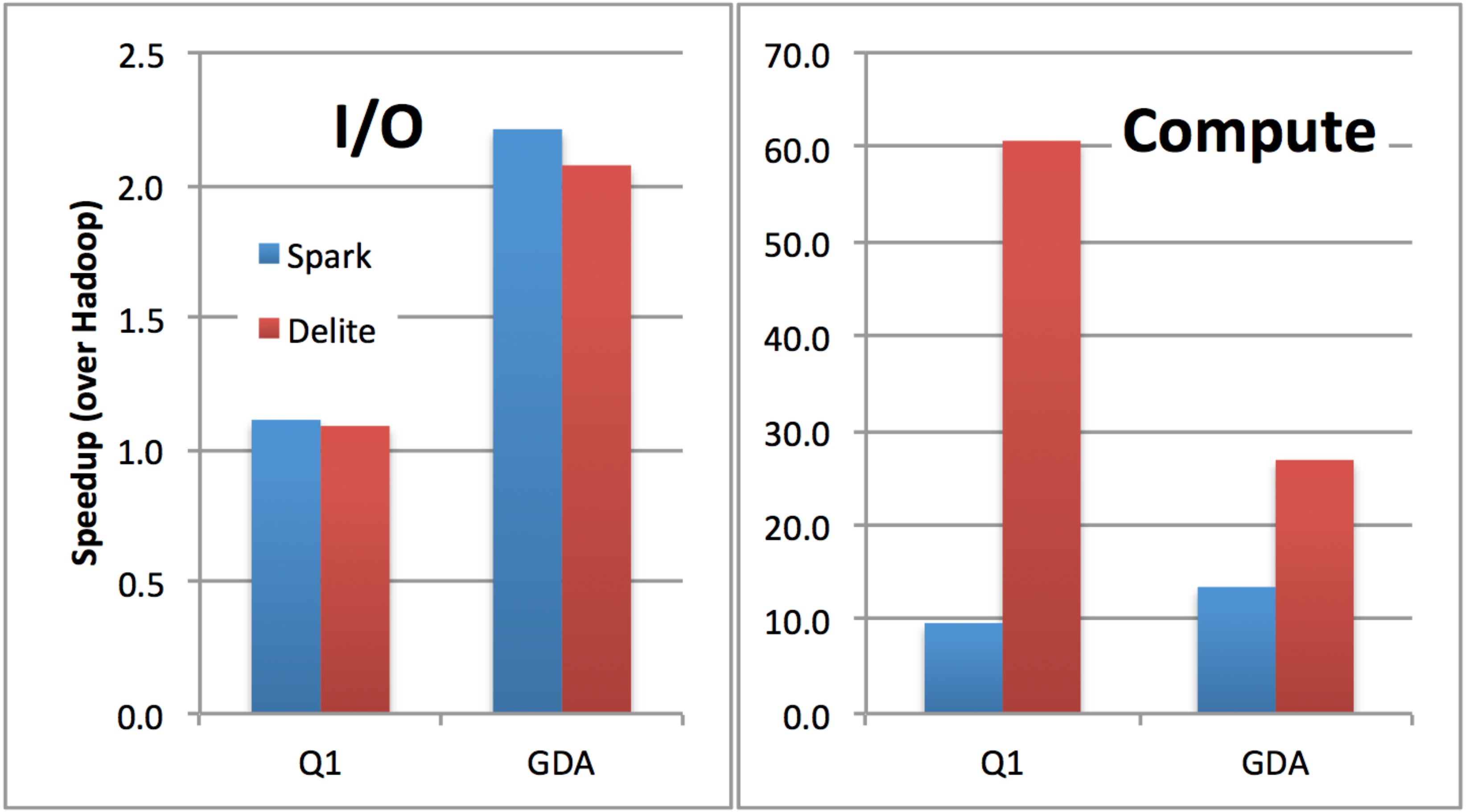
Experimental Setup

- Amazon EC2 Cluster: 20 nodes
  - m1.xlarge instances
    - 4 virtual cores, 15GB RAM, 1Gb Ethernet
- Local Cluster: 4 nodes
  - 12 Intel Xeon X5680 cores (2 sockets)
  - 48 GB RAM
  - NVIDIA Tesla C2050 GPU
  - 1Gb Ethernet

3 versions of every app

- 1) Deliteful languages (OptiML, OptiQL)
- 2) Apache Hadoop
- 3) Spark
  - Scala library for cluster parallelization
  - Solves many of the inefficiencies related to Hadoop by keeping data in memory
  - Provides data-parallel operators on distributed datastructures
  - Stay for the next talk!

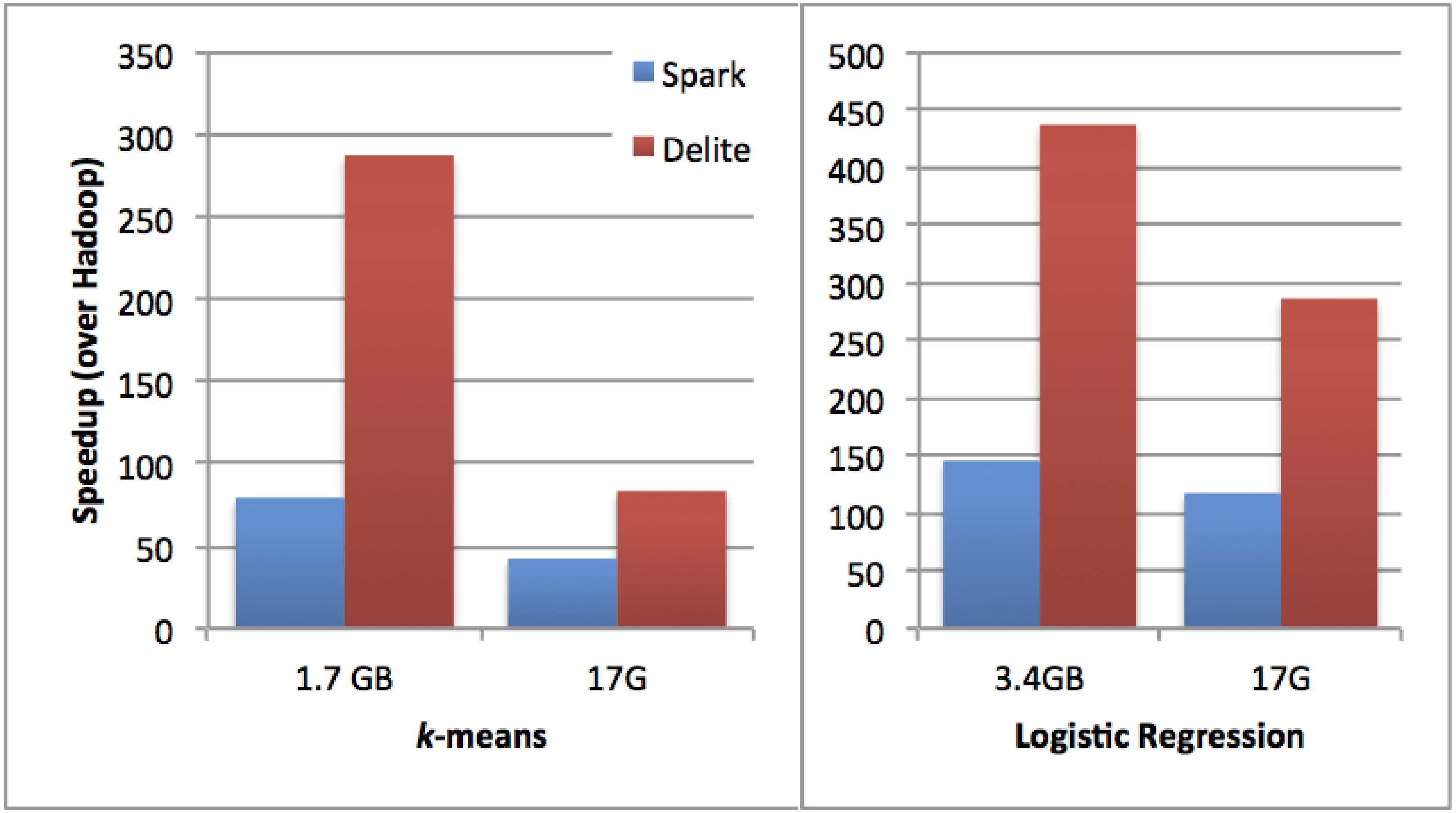
OptiQL: TPC-H Query 1 & OptiML: GDA



20 node Amazon cluster

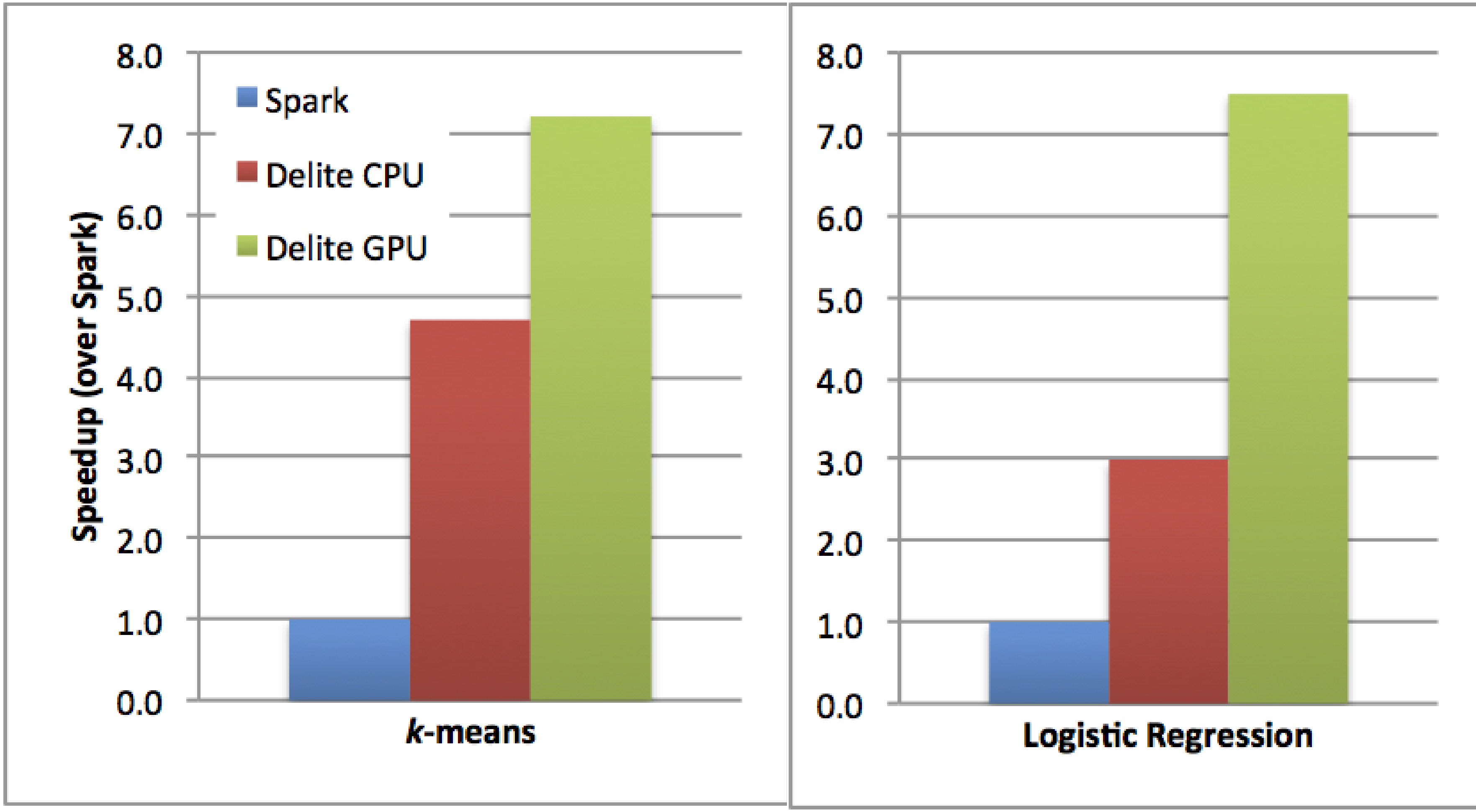
Q1: TPC-H 5GB dataset; GDA: 17GB dataset

OptiML: *k*-means & logistic regression



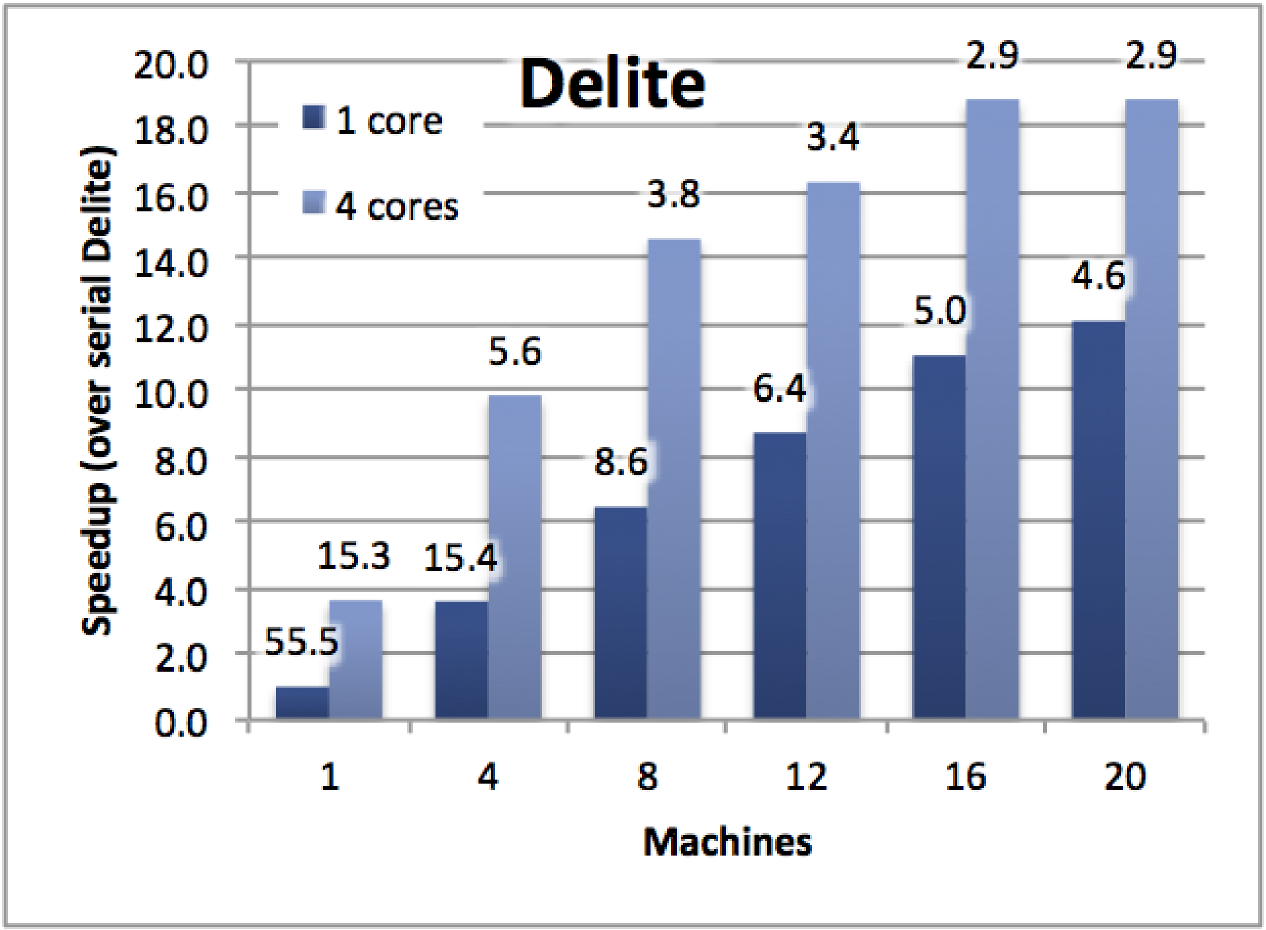
20 node Amazon cluster

OptiML: *k*-means and logistic regression



4 node local cluster: 3.4 GB dataset

Strong Scaling Results on Amazon



k-means 50MB dataset
(execution time in seconds above bars)

Thank You!

- Delite repository
  - http://github.com/stanford-ppl/Delite

- Stanford Pervasive Parallelism Lab
  - Links to publications and related projects
  - http://ppl.stanford.edu