Parallelizing Machine Learning—Functionally

A Framework and Abstractions for Parallel Graph Processing

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Data is growing.

At the same time, there is a growing desire to do **MORE** with that data.
As an example, **Machine Learning (ML)** has provided elegant and sophisticated solutions to many complex problems on a small scale,
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has provided elegant and sophisticated solutions to many complex problems on a small scale,

could open up **NEW APPLICATIONS + NEW AVENUES OF RESEARCH** if ported to a larger scale
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- typically focus on optimizing sequential algorithms when faced with scaling problems.
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but efforts are routinely limited by complexity and running time of **sequential** algorithms.

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typically focus on optimizing sequential algorithms when faced with scaling problems. **Need to make it easier to experiment with parallelism**
What about MapReduce?
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Poor support for iteration.

MapReduce instances must be chained together in order to achieve iteration.

Not always straightforward.
Even building non-cyclic pipelines is hard (e.g., FlumeJava, PLDI’10).

Overhead is significant.
Communication, serialization (e.g., Phoenix, IISWC’09).
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  With functional reduction/aggregation mechanisms.
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- is inspired by BSP.  
  With functional reduction/aggregation mechanisms.

- avoids an inversion of control  
  of other BSP-inspired graph-processing frameworks.

- is implemented in Scala,  
  and there is a preliminary experimental evaluation.
Menthor's Model of Computation.
Data.
Data.

Split into data items managed by *vertices*, and sizes range from primitives to large matrices.
Data.

Split into data items managed by vertices.
Relationships expressed using edges between vertices.
Algorithms.
Algorithms.

Data items stored inside of vertices *iteratively* updated.
Algorithms.

Data items stored inside of vertices \textit{iteratively} updated.

Iterations happen as \textbf{S}YNCHRONIZED \textbf{S}UPERSTEPS.

(inspired by the BSP model)
Algorithms.

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Iterations happen as SYNCHRONIZED SUPERSTEPS.

\[ \text{time} \]
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Data items stored inside of vertices *iteratively* updated. Iterations happen as *Synchronized Supersteps*.

I. Update each vertex in *parallel*.
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1. update each vertex in parallel.
2. update produces *outgoing* messages to other vertices.

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1. update each vertex in parallel.
2. update produces *outgoing* messages to other vertices
3. incoming messages available at the beginning of the next **Superstep**.
Substeps. (and Messages)

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2. return a list of messages:

   ```scala
case class Message[Data](source: Vertex[Data], dest: Vertex[Data], value: Data)
   ```
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**Examples...**

```scala
{
  value = ...
  List()
}
```
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**Examples...**

```
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  value = ...
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}
{  
  ...
  for (nb <- neighbors)
    yield Message(this, nb, value)
}
```
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```scala
{ value = ... List() }
{ ... for (nb <- neighbors) yield Message(this, nb, value) }
```

Each is *implicitly* converted to a **Substep** [Data]
Some Examples...
PageRank.

class PageRankVertex extends Vertex[Double](0.0d) {
  def update() = {
    var sum = incoming.foldLeft(0)(_ + _.value)
    value = (0.15 / numVertices) + 0.85 * sum

    if (superstep < 30) {
      for (nb <- neighbors) yield
        Message(this, nb, value / neighbors.size)
    } else
      List()
  }
}
Another Example.

class PhasedVertex extends Vertex[MyData] {
  var phase = 1

  def update() = {
    if (phase == 1) {
      ...
      if (condition)
        phase = 2
    } else if (phase == 2) {
      ...
    }
  }
}
Another Example.

```java
class PhasedVertex extends Vertex[MyData] {
    var phase = 1

    def update() = {
        if (phase == 1) {
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        } else if (phase == 2) {
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        }
    }
}
```

**INVERSION OF CONTROL!!**
Thus, manual stack management...

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Inverting the Inversion.

Use high-level combinators to build expressions of type \texttt{Substep[Data]}

```scala
class PhasedVertex extends Vertex[MyData] {

  def update() = {
    thenUntil(condition) {
      ...
    } then {
      ...
    }
  }
}
```
Inverting the Inversion.

Use high-level combinators to build expressions of type `Substep[Data]`

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Inverting the Inversion.

Use high-level combinators to build expressions of type `Substep[Data]`.

Thus avoiding manual stack management.

class PhasedVertex extends Vertex[MyData] {
    def update() = {
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Reduction Combinators: crunch steps.
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- Reduction operations important.
  - Replacement for shared data.
  - Global decisions.
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  - Replacement for shared data.
  - Global decisions.

- Provided as just another kind of Substep[Data]
Reduction Combinators: crunch steps.

def update() = {
    then {
        value = ...
    }
    crunch ((v1: Double, v2: Double) => v1 + v2) then {
        incoming match { case List(reduced) =>
            ...
        }
    }
    ...
}
Menthor's Implementation
Actors.

Implementation based upon Actors.

Central GRAPH instance is an actor, which manages a set of WORKER actors.
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GRAPH synchronizes workers using supersteps.
Each WORKER manages a partition of the graph’s vertices,

- Deliver incoming messages that were sent in the previous superstep;
- Select and execute update step on each vertex in its partition;
- Forward outgoing messages generated by its vertices in the current superstep.
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**I.** WORKER reduces the values of all vertices in its partition.
Implementing Reduction.

1. WORKER reduces the values of all vertices in its partition.

2. The result and the closure that was used to compute it is sent to the GRAPH actor, which computes the final reduced value.
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2. The result and the closure that was used to compute it is sent to the GRAPH actor, which computes the final reduced value.

3. The final result is passed to all WORKERS which make it available to their vertices as incoming messages (at the beginning of the next superstep)
Implementation Principles.
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✗ A pure Scala library
  - No staging and code generation.
  - No dependency on language virtualization.
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✗ Benefits
  - Compatible with mainline Scala compiler.
  - Fast compilation.
  - Simple debugging and troubleshooting.
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✗ Benefits
- Compatible with mainline Scala compiler.
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✗ Drawbacks
- No aggressive optimizations.
- No support for heterogeneous hardware platforms.
Related Work.

**Google’s Pregel**
- **GraphLab**
- **Signal/Collect**

**Main Inspiration**
- Graphs/BSP

**Control**
- Inverted

**Async Execution**
- Non-determinism

**OptiML**
- Aggressive Optimizations
- Requires Staging
- Debugging
- Not optimal, yet

**Spark**
- Designed for Iteration
- Cluster support
- No graph support
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Be sure to see their talk!
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(Many more discussed in the paper.)
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http://lamp.epfl.ch/~phaller/menthor/

Questions?
Experimental Results.

Applications
- PageRank on (subset of) Wikipedia
- Hierarchical clustering
- Loopy belief propagation

Very preliminary results
- Evaluating BSP-based model
- Implementation details changing
- Parallel collections (extensions)