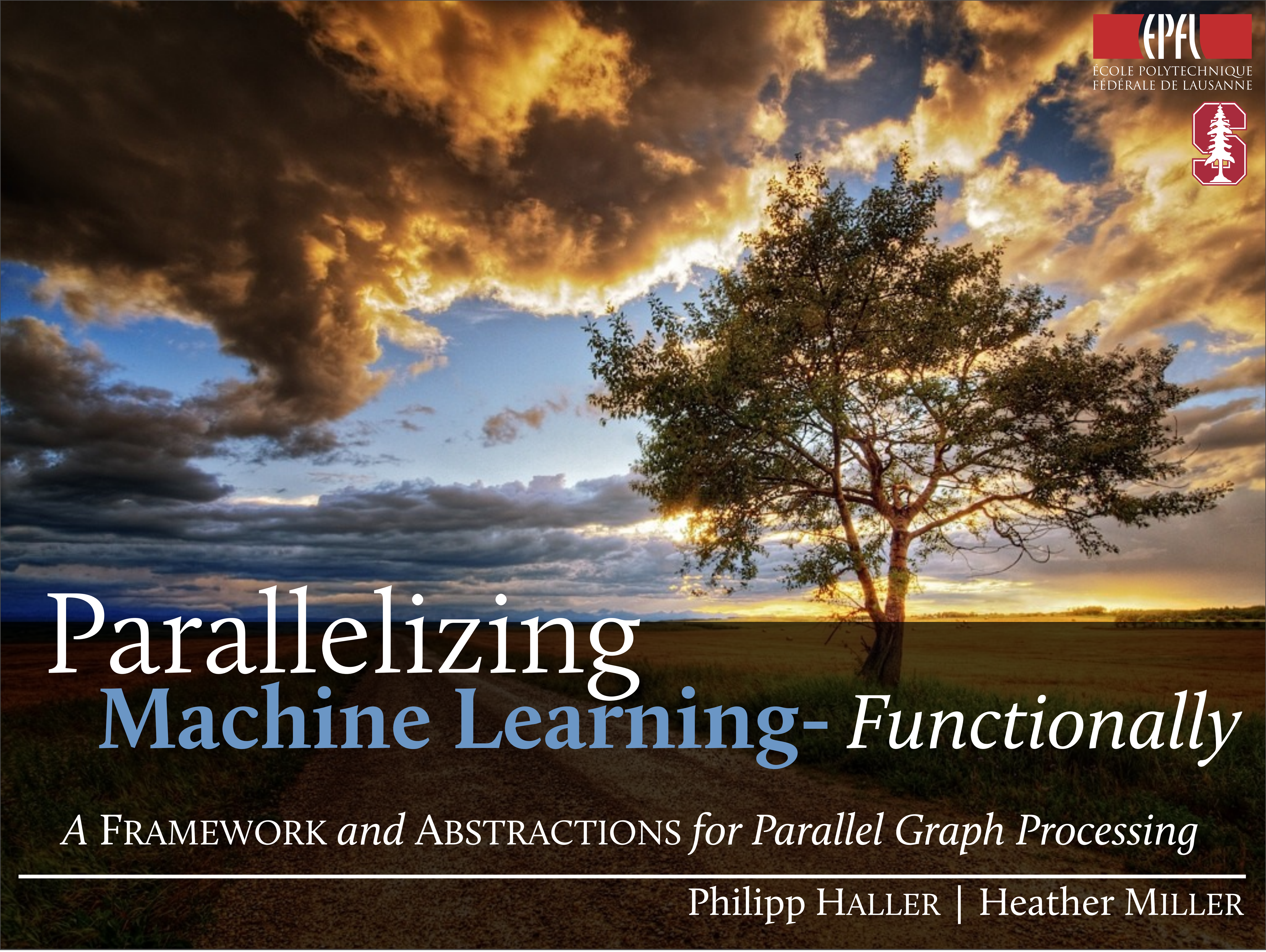


ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

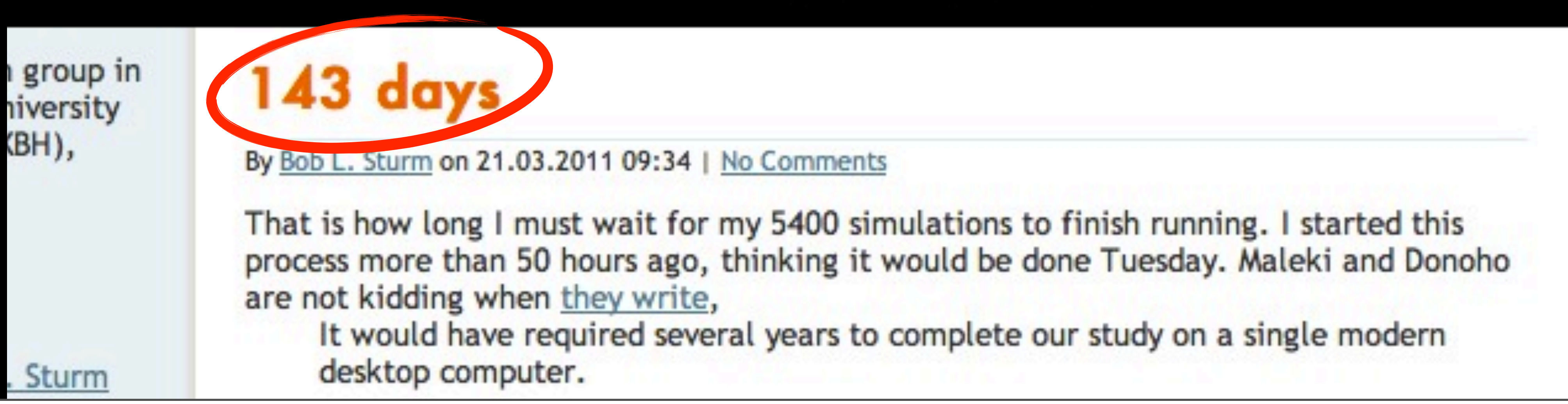
Parallelizing Machine Learning- *Functionally*

A FRAMEWORK *and* ABSTRACTIONS *for Parallel Graph Processing*

Philipp HALLER | Heather MILLER

Data is growing.

At the same time,
there is a growing desire
to ***do MORE with that data.***



143 days

By Bob L. Sturm on 21.03.2011 09:34 | No Comments

That is how long I must wait for my 5400 simulations to finish running. I started this process more than 50 hours ago, thinking it would be done Tuesday. Maleki and Donoho are not kidding when they write,

> It would have required several years to complete our study on a single modern desktop computer.

As an example,

Machine Learning (ML)

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could open up New Applications + New Avenues of Research if ported to a larger scale

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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).

Menthor...

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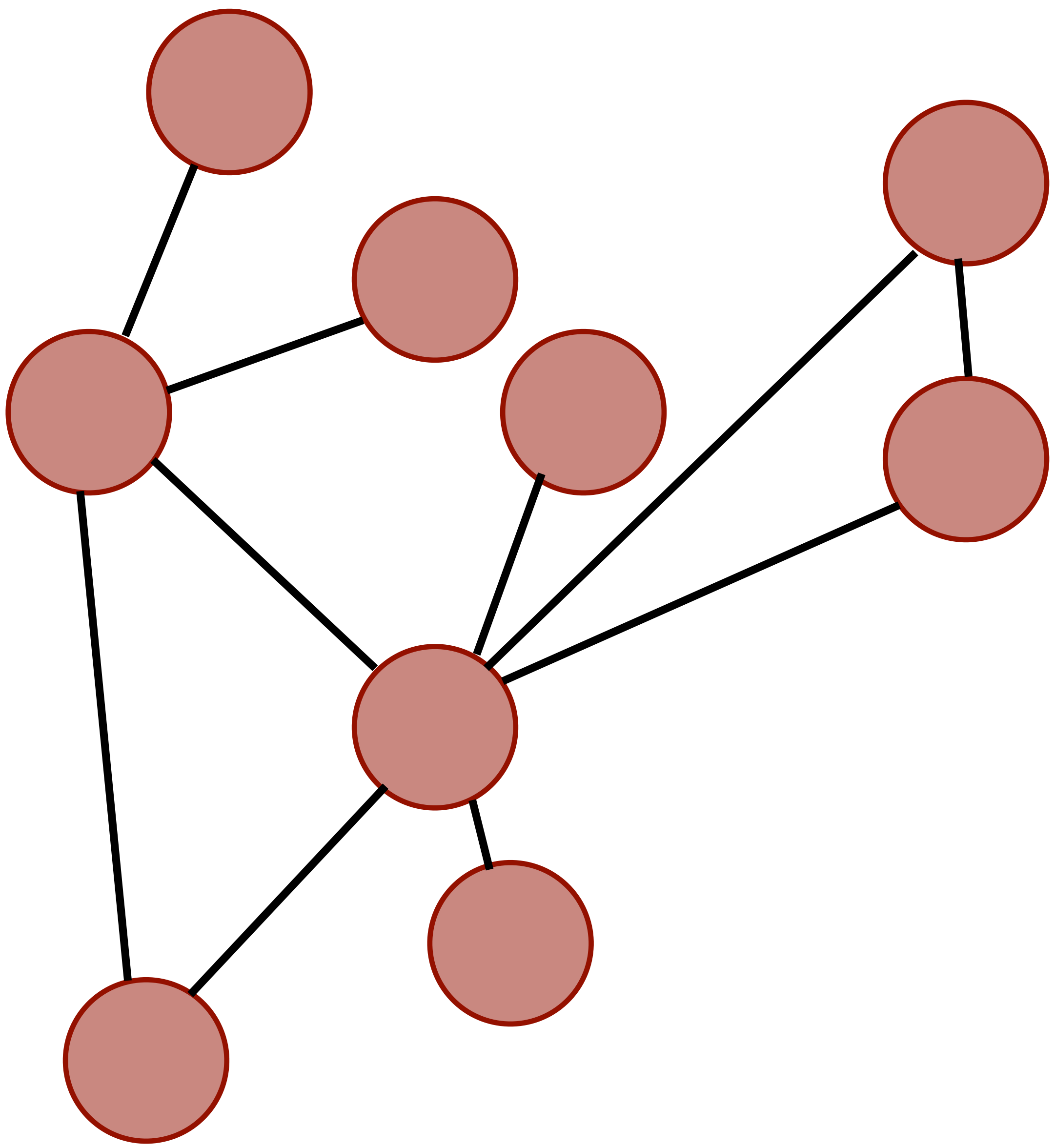
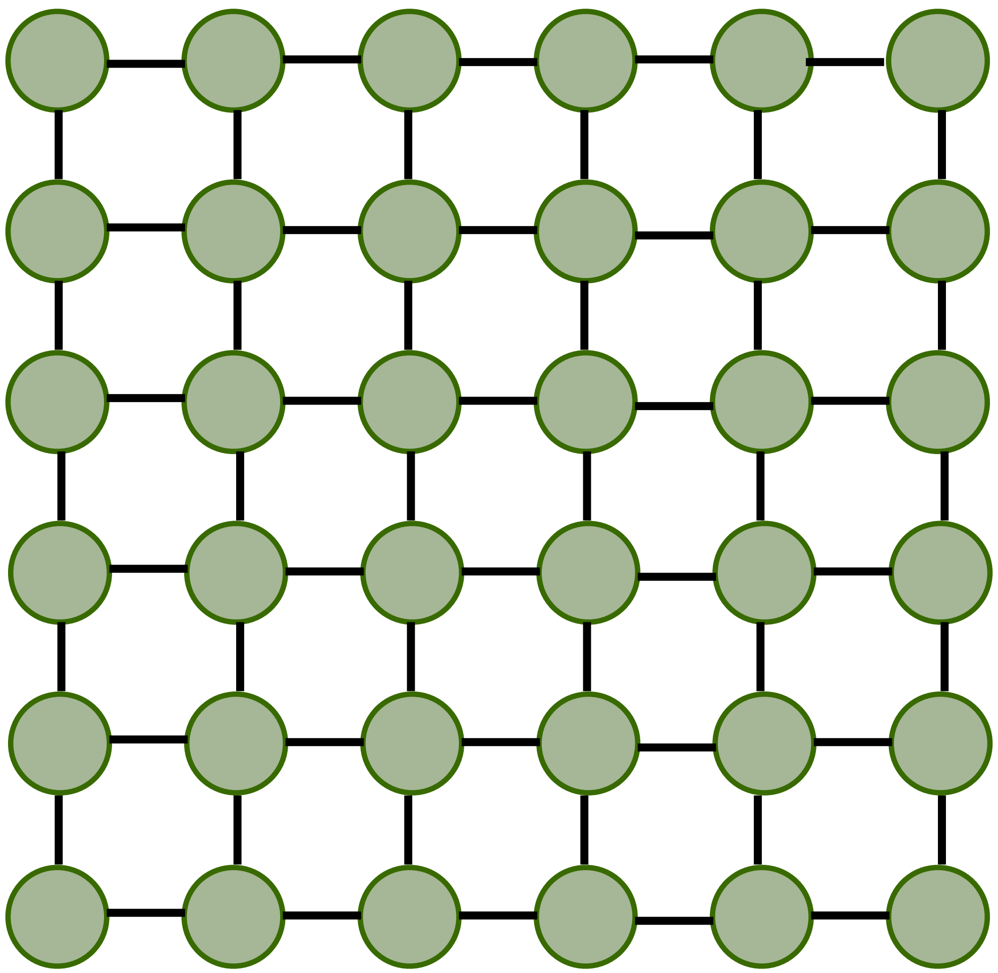
- is a framework for parallel graph processing.
  (But it is not limited to graphs.)
- is inspired by BSP.
  With functional reduction/aggregation mechanisms.
- avoids an inversion of control
  of other BSP-inspired graph-processing frameworks.
- is implemented in Scala,
  and there is a preliminary experimental evaluation.

Menthor's
Model of Computation.

Data.

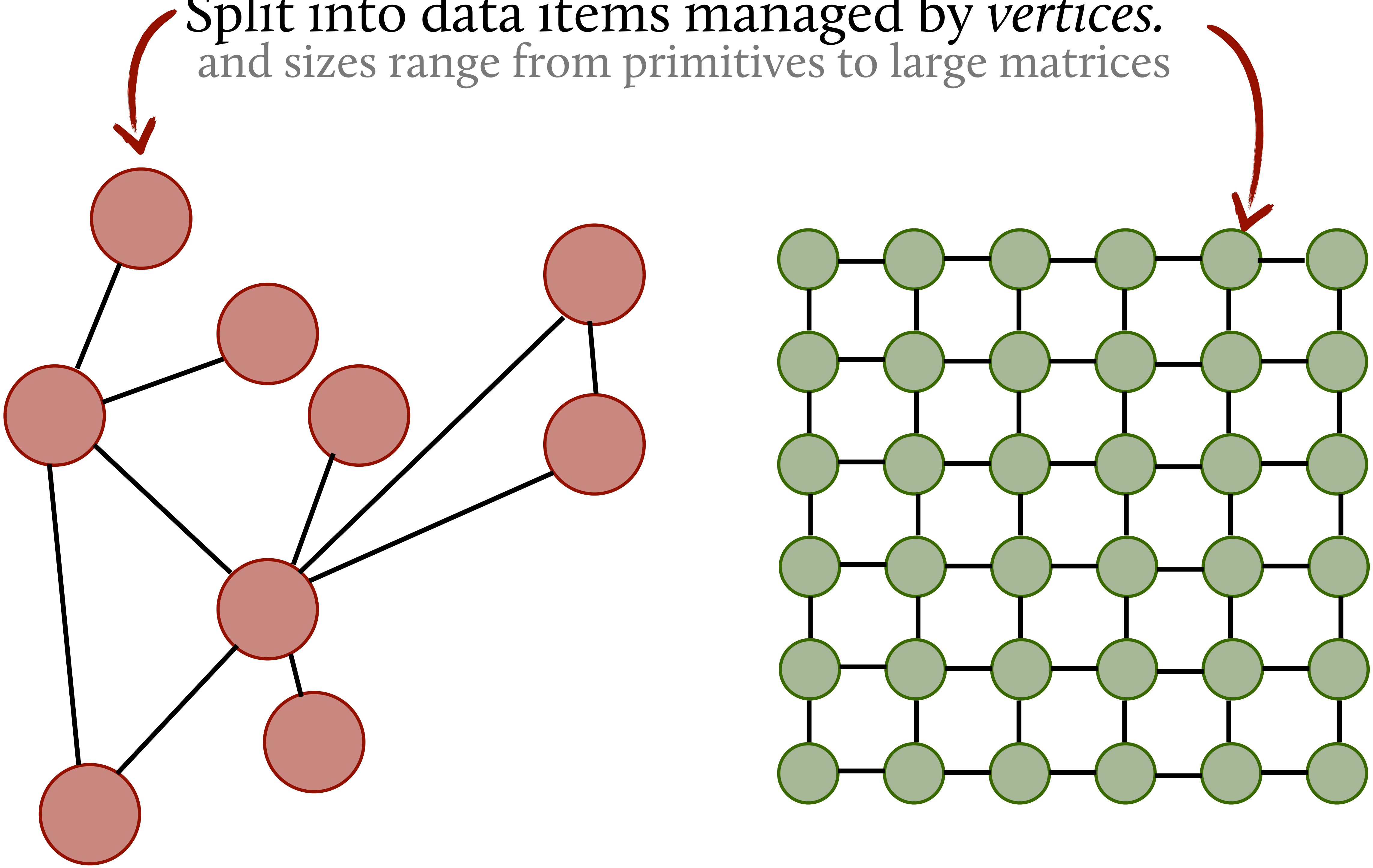




Data.

Split into data items managed by *vertices.*

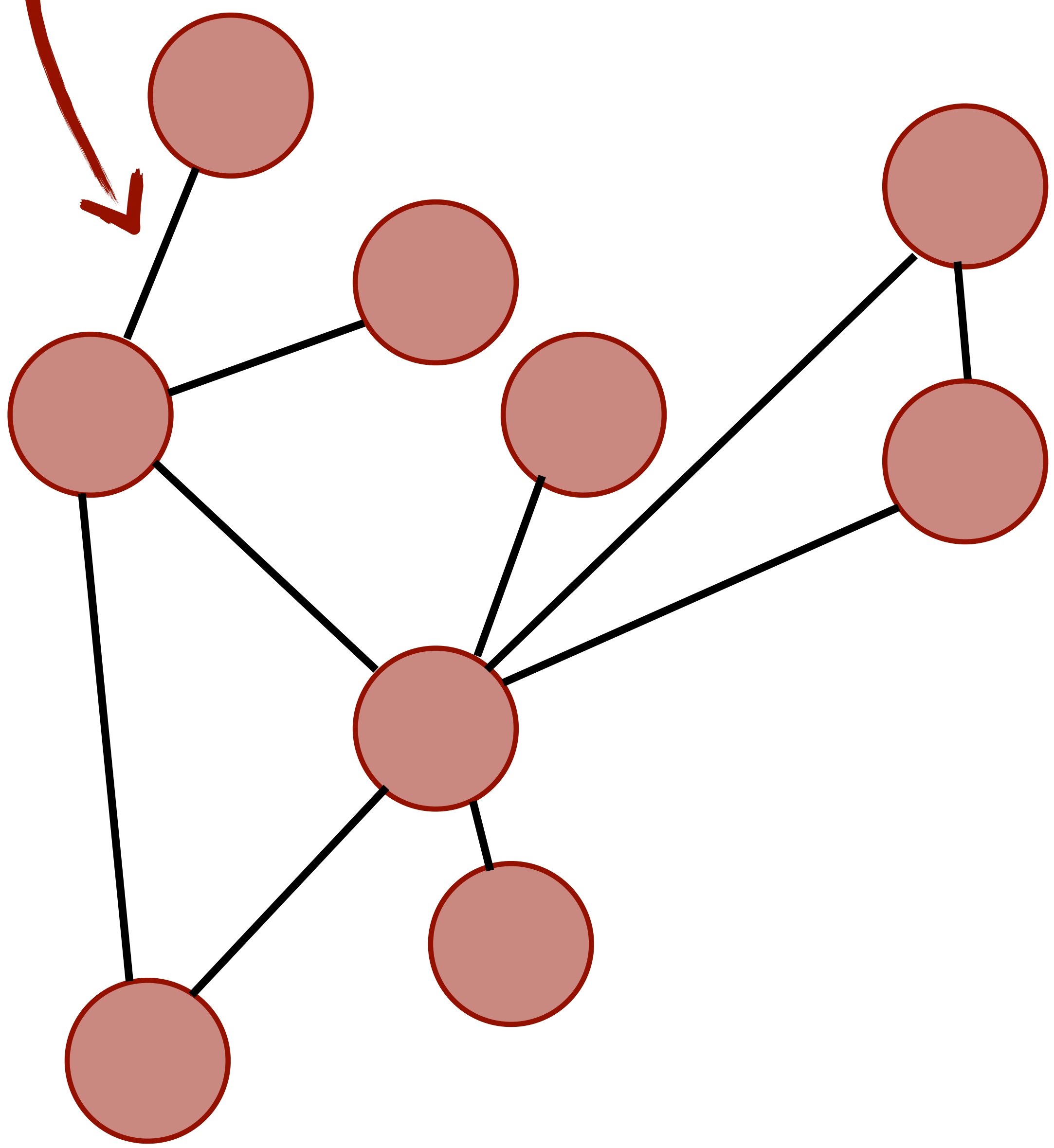
and sizes range from primitives to large matrices

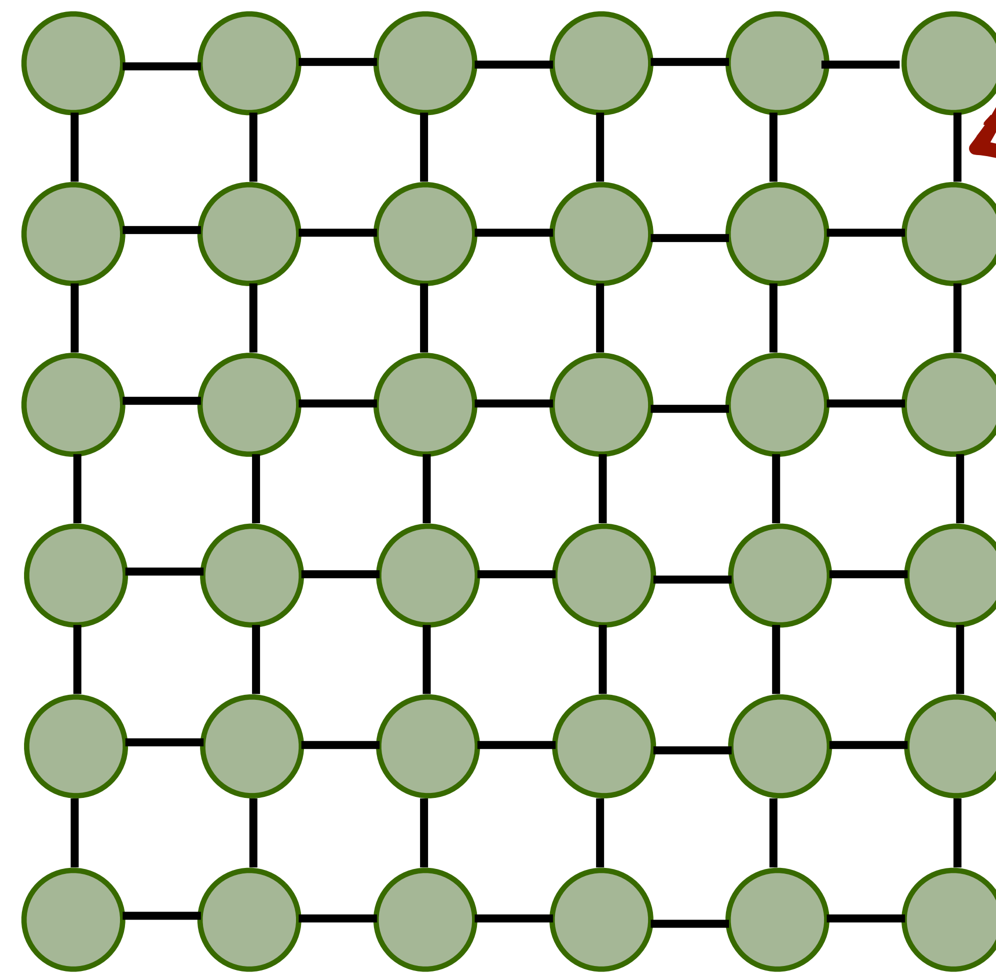


Data.

Split into data items managed by *vertices.*

Relationships expressed using *edges* between vertices.





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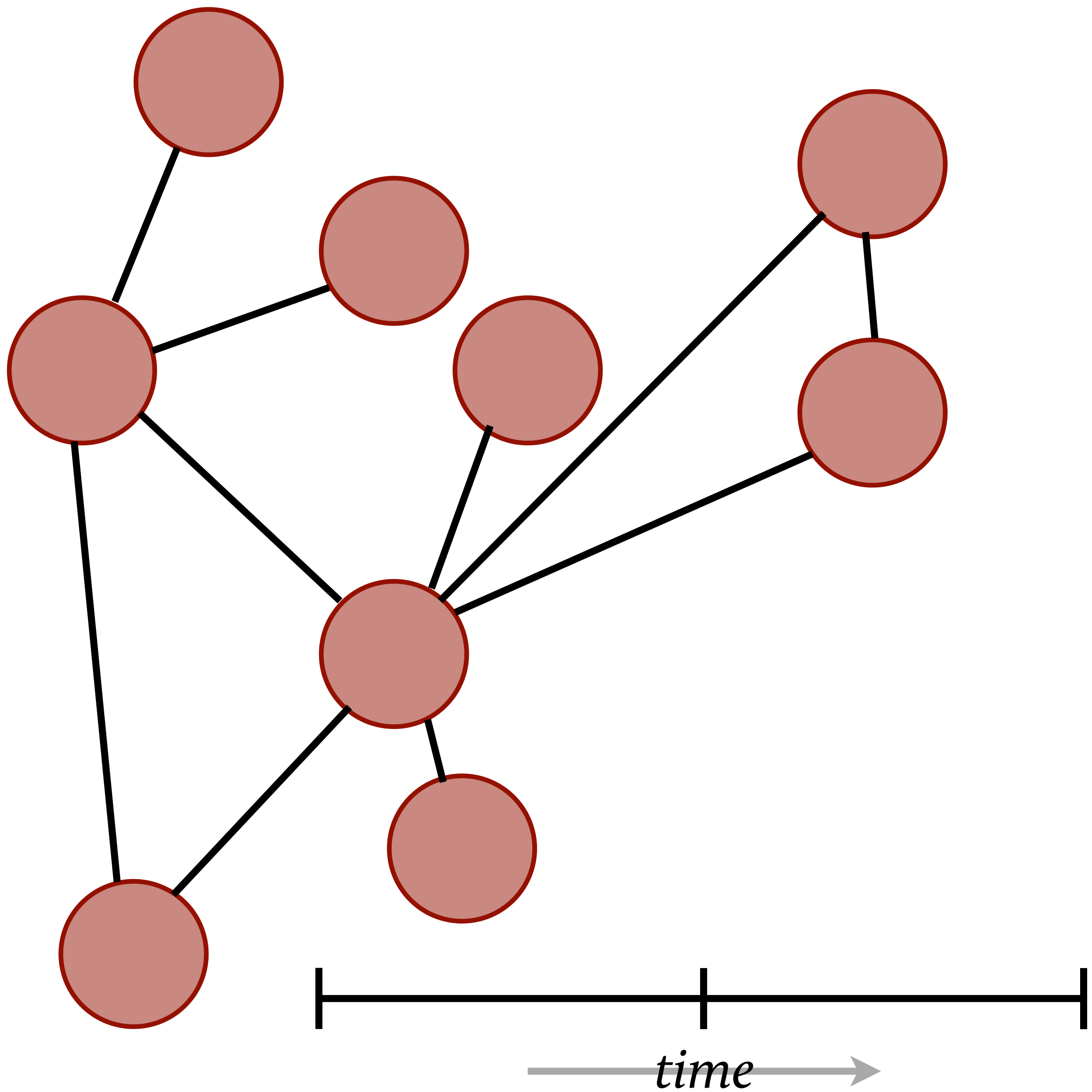

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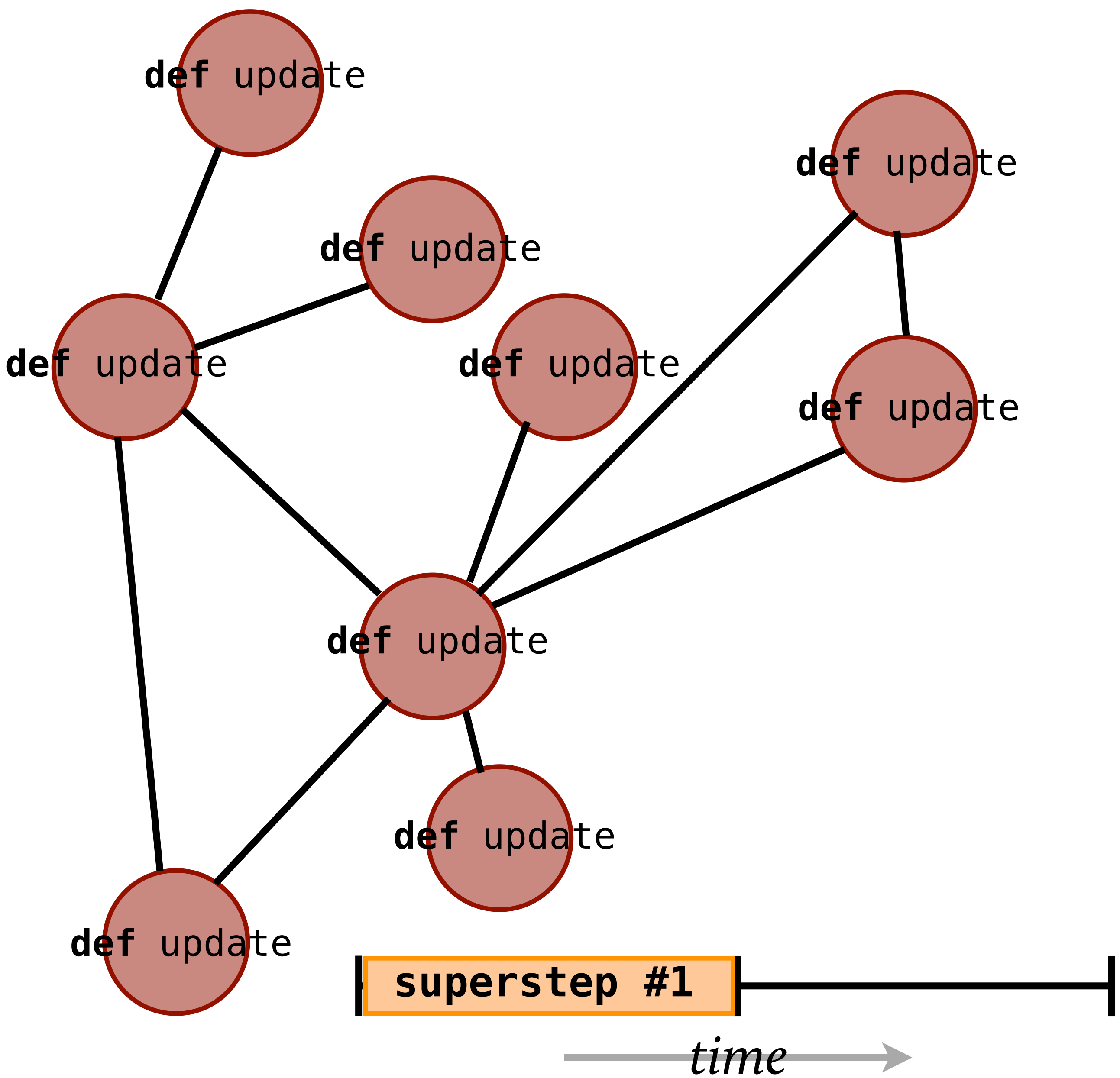

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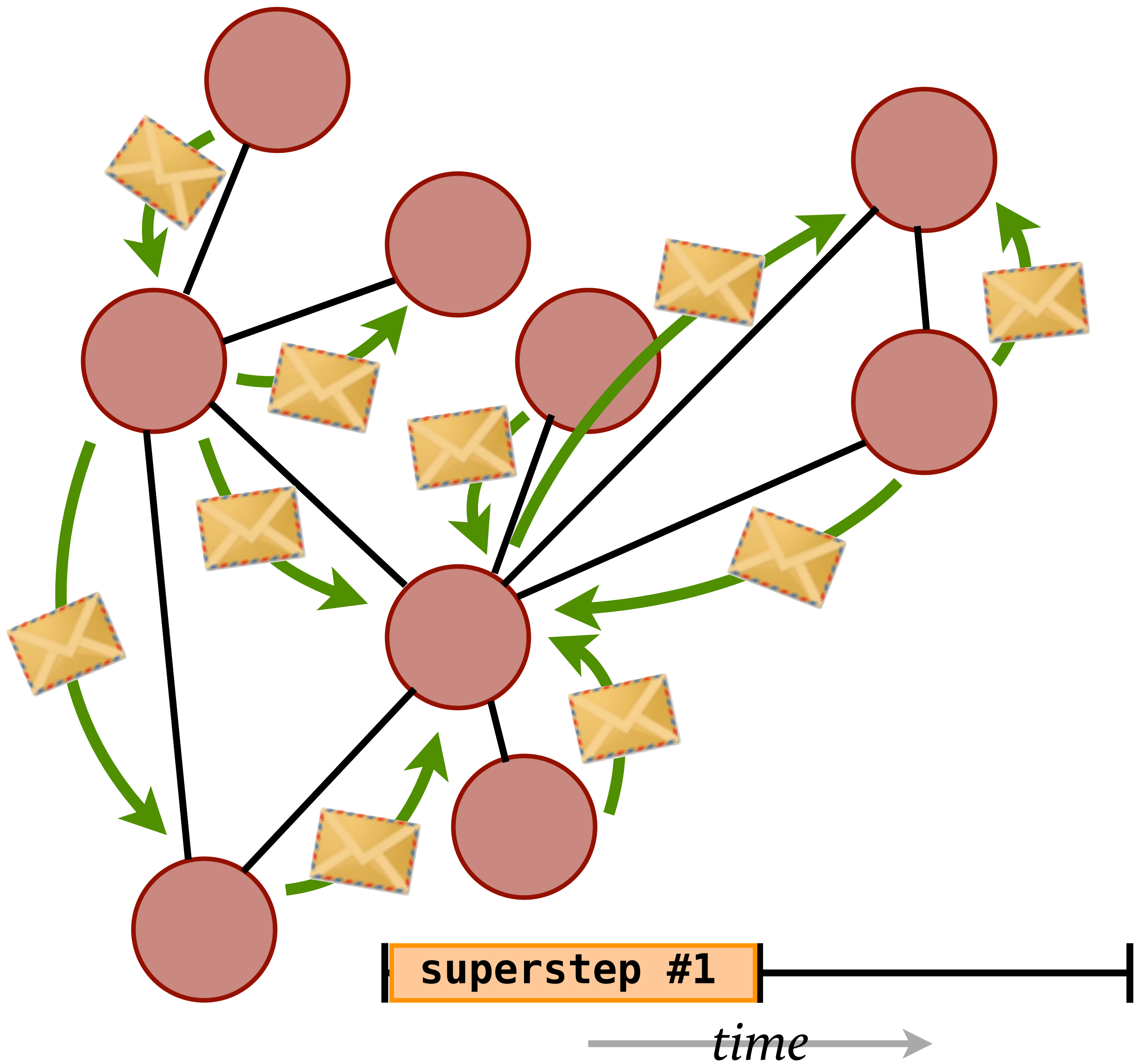

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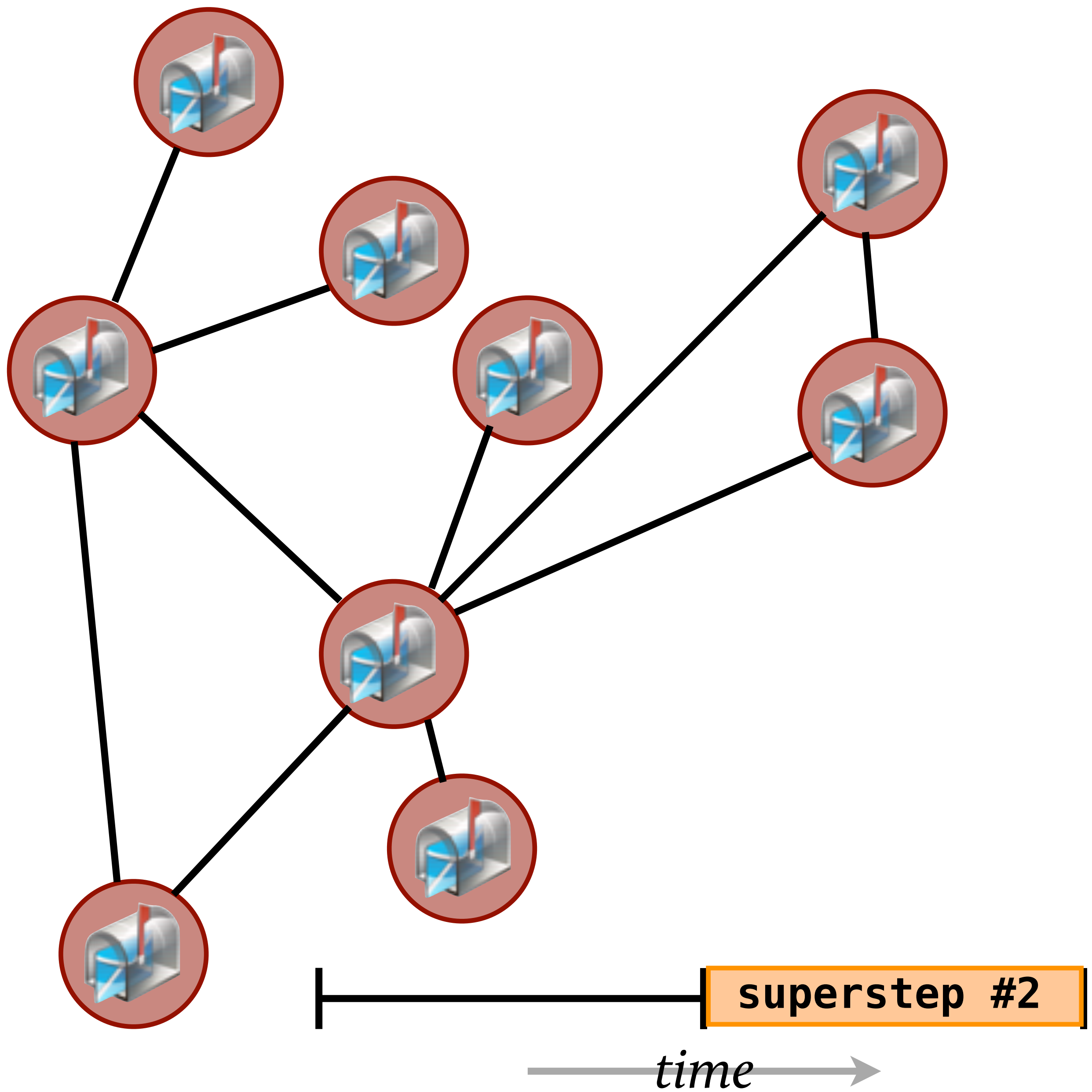

1. update each vertex in *parallel.*
2. `update` produces *outgoing* messages to other vertices
3. incoming messages available at the beginning of the next **SUPERSTEP.**

Substeps. (and Messages)

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case class Message[Data](source: Vertex[Data],
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{
  value = ...
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Examples...

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

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{
```

```
{
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```

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.

```
class PhasedVertex extends Vertex[MyData] {
  var phase = 1
      if (condition)
        phase = 2
    } else if (phase == 2) {
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    }
  }
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```

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

Inverting the Inversion.

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

```
class PhasedVertex extends Vertex[MyData] {

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

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] {

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- Reduction operations important.
  - Replacement for shared data.
  - Global decisions.
- Provided as just another kind of `Substep[Data]`

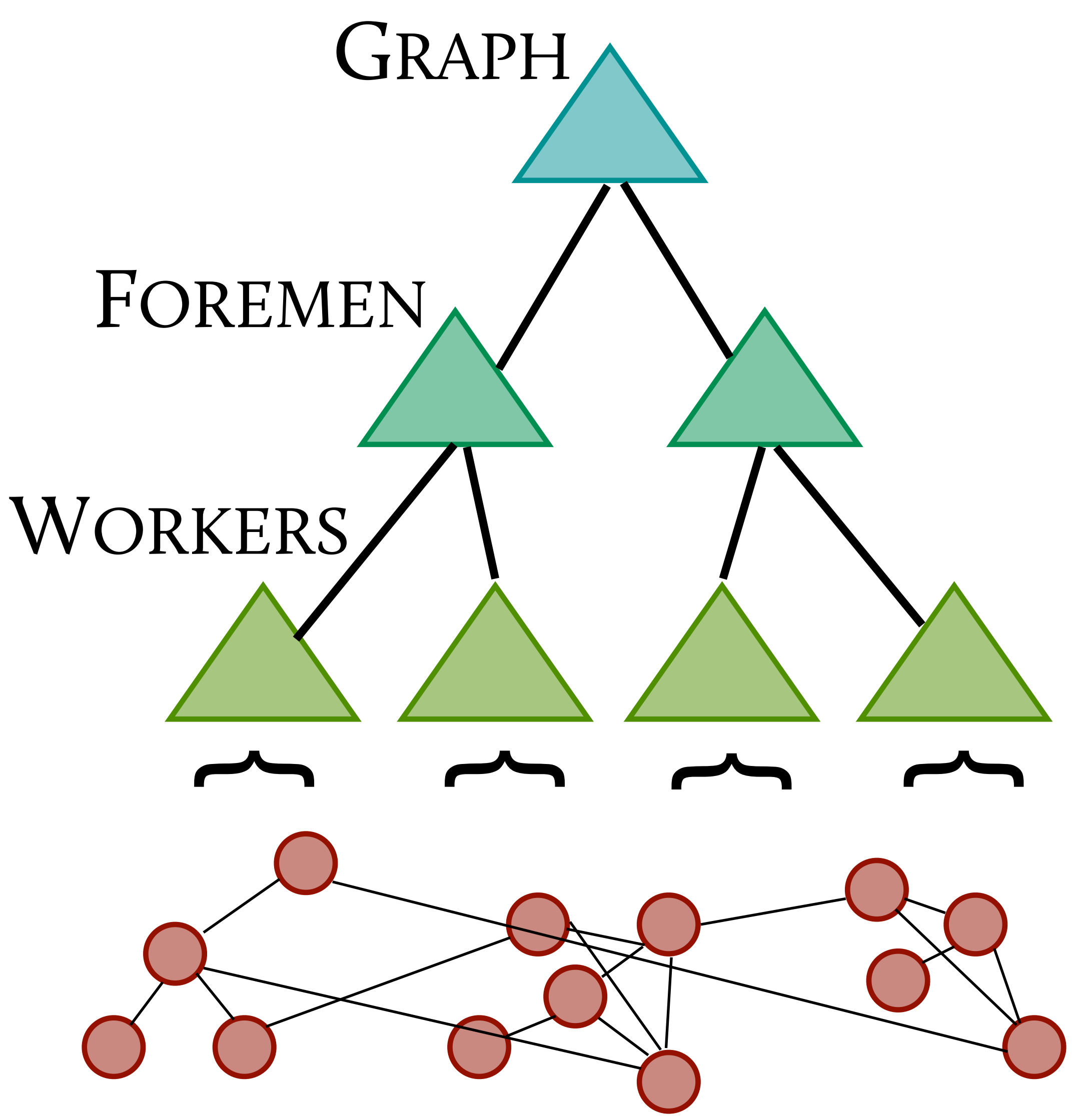
Reduction Combinators: crunch steps.

```
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

Actors.

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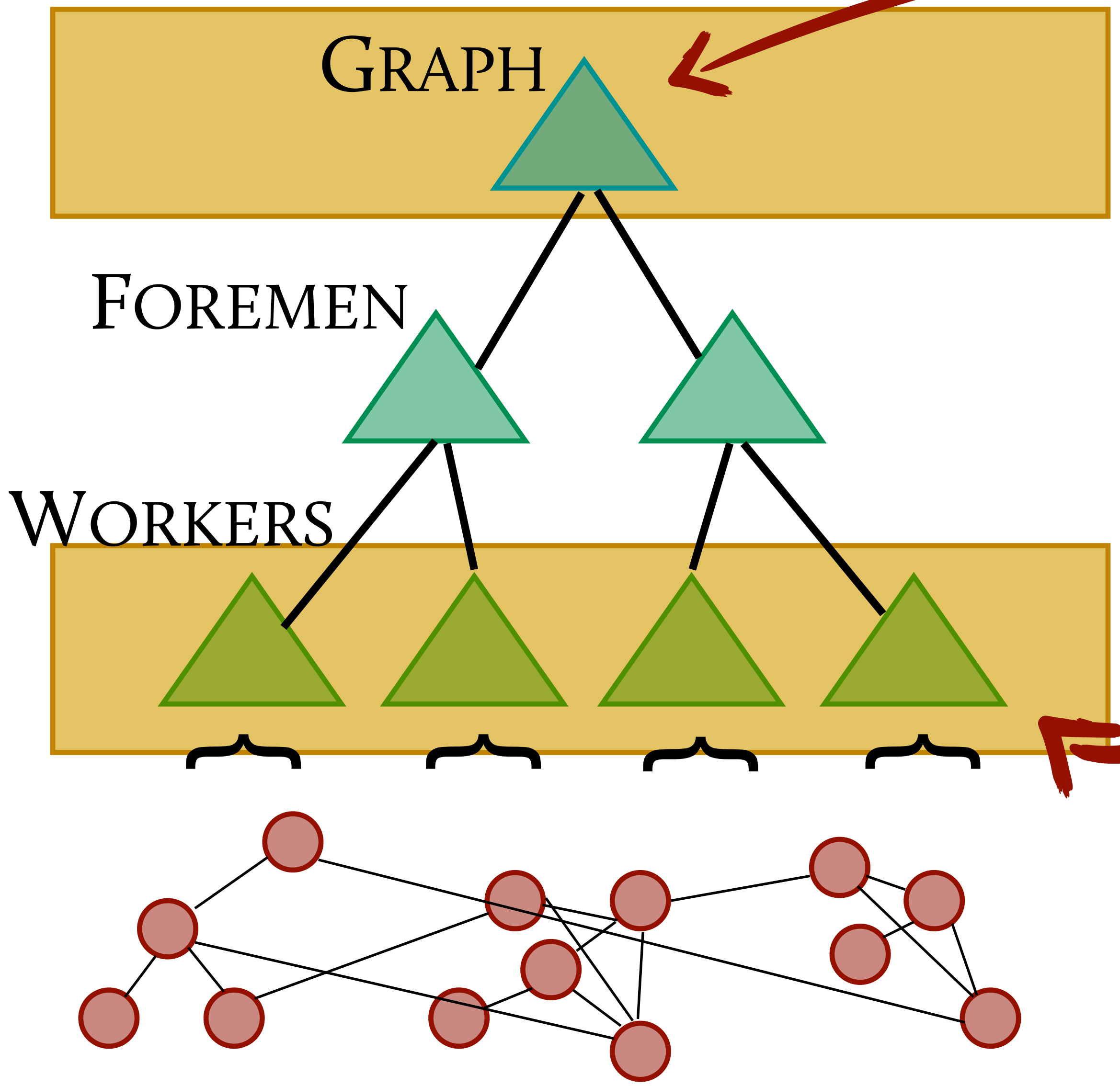

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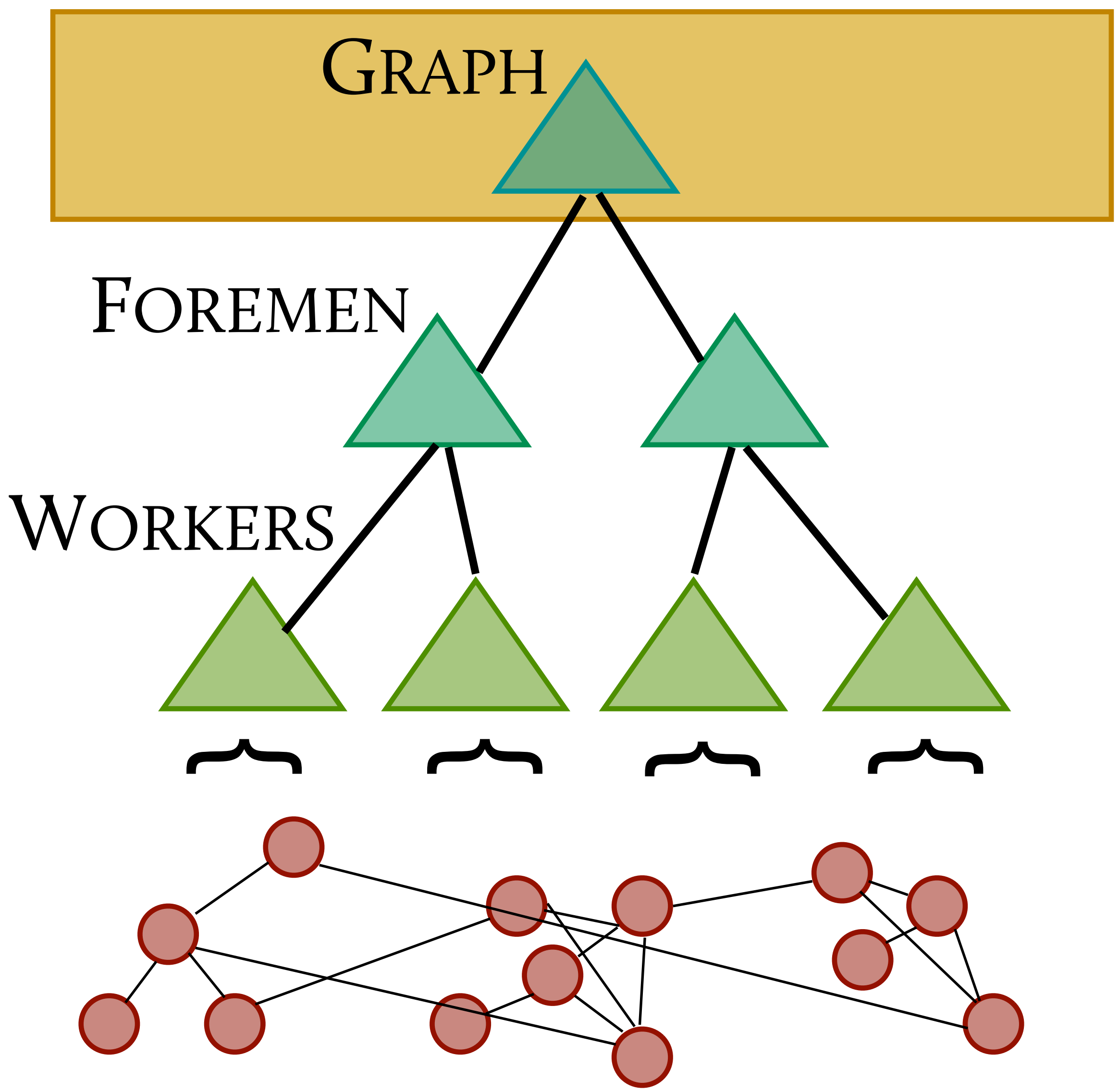

Central GRAPH instance is an actor, which manages a set of WORKER actors

GRAPH synchronizes workers using supersteps.

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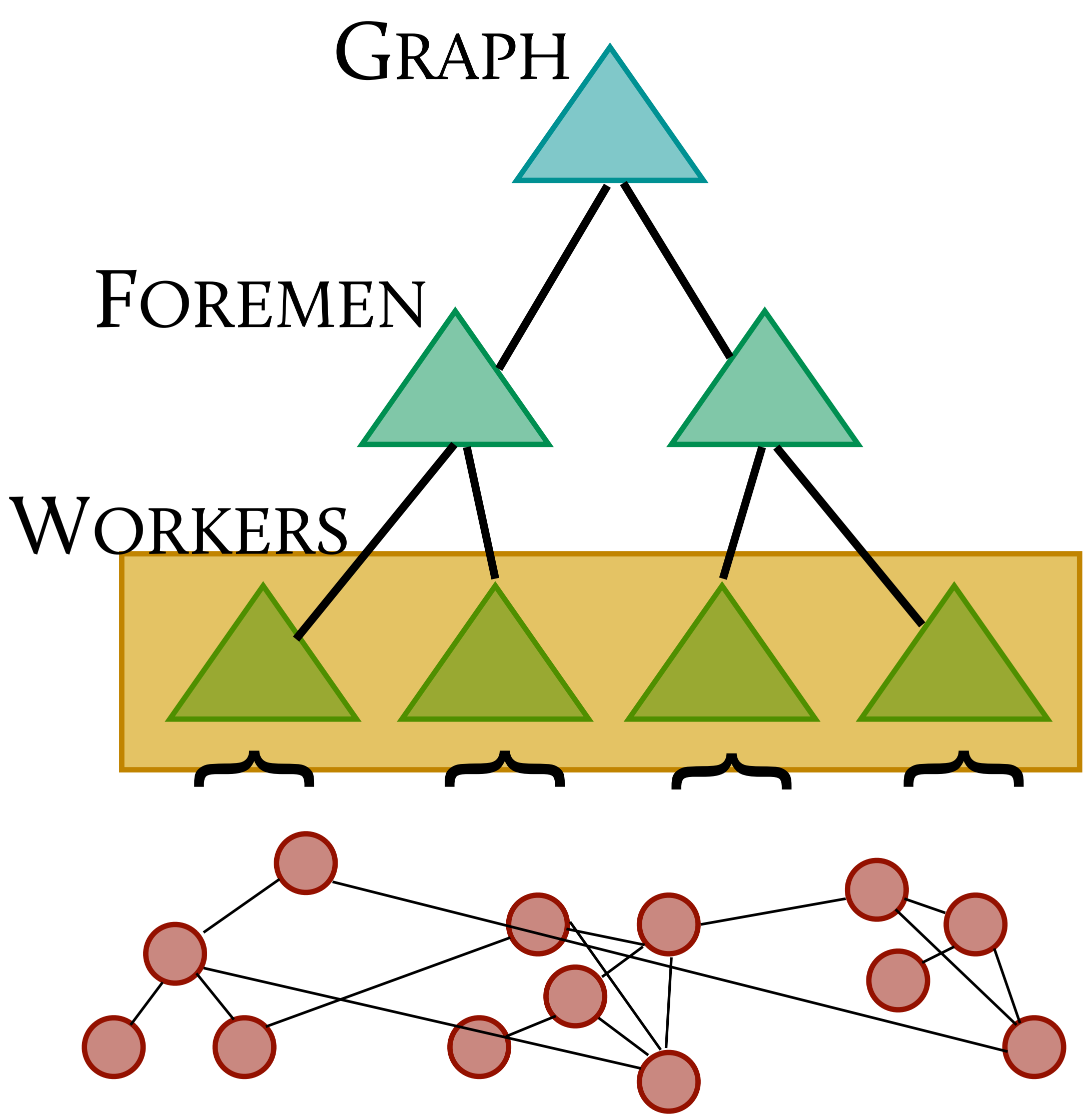
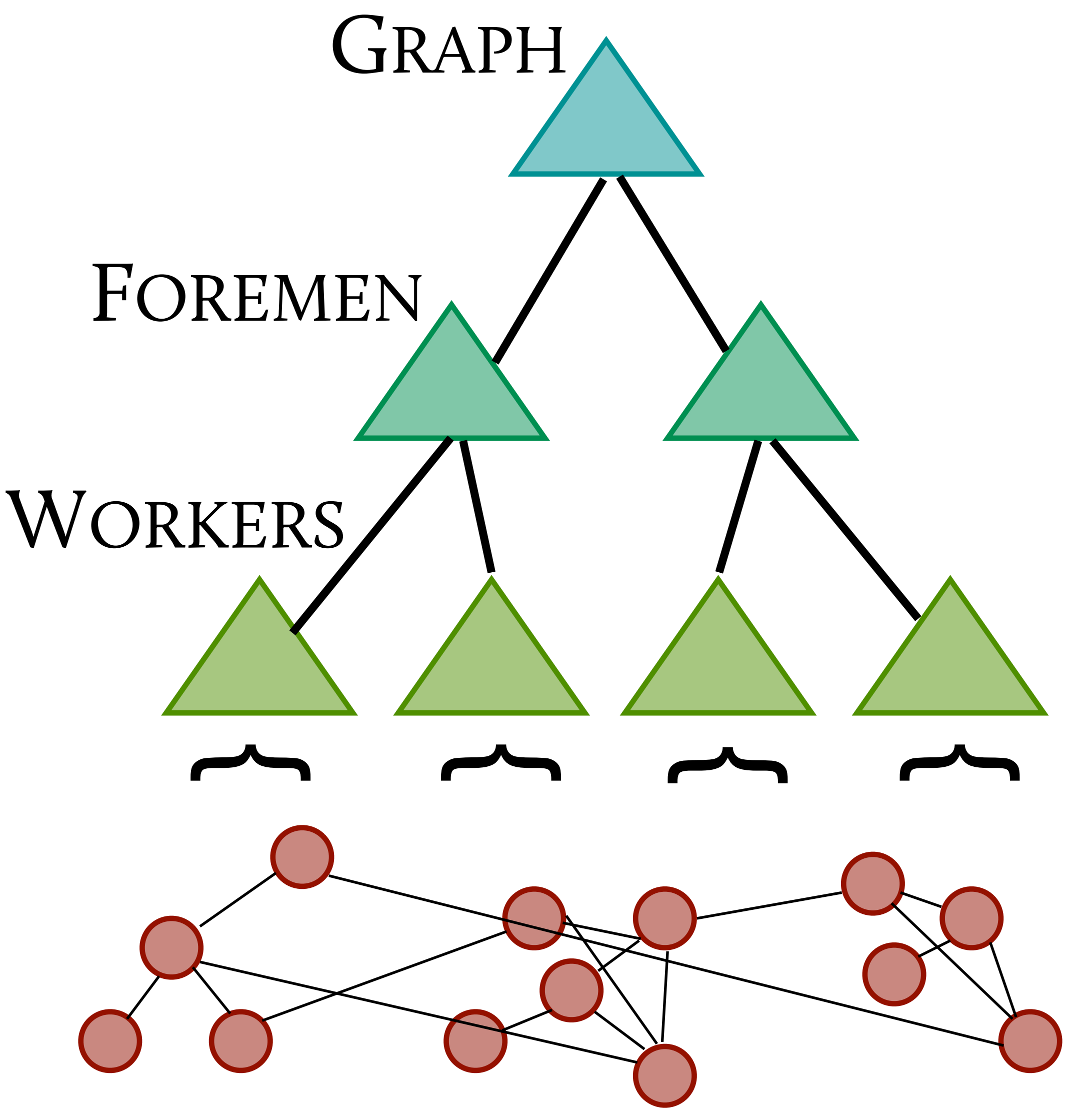


Each WORKER manages a partition of the graph's vertices,

- 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.

Implementing Reduction.



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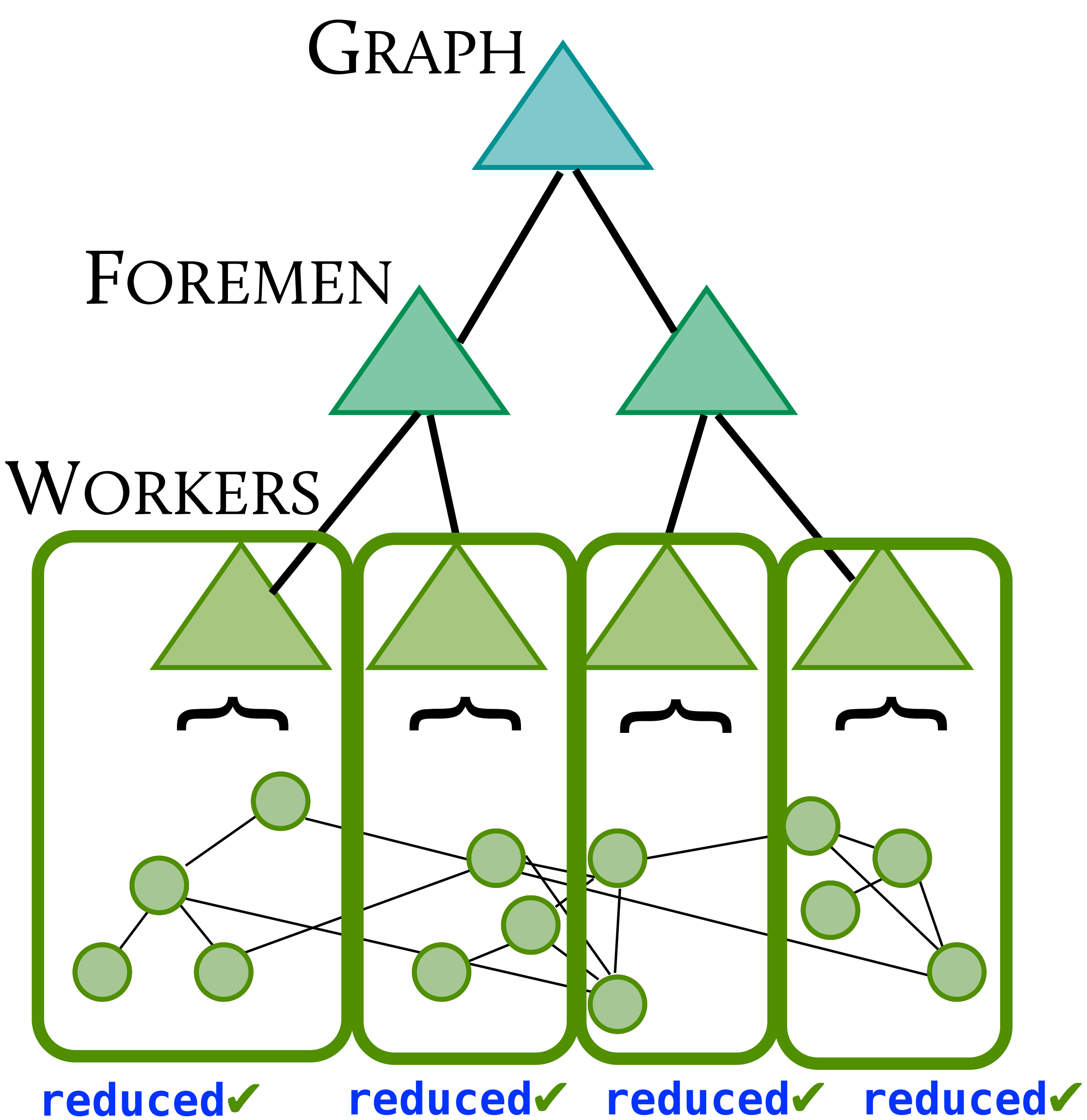

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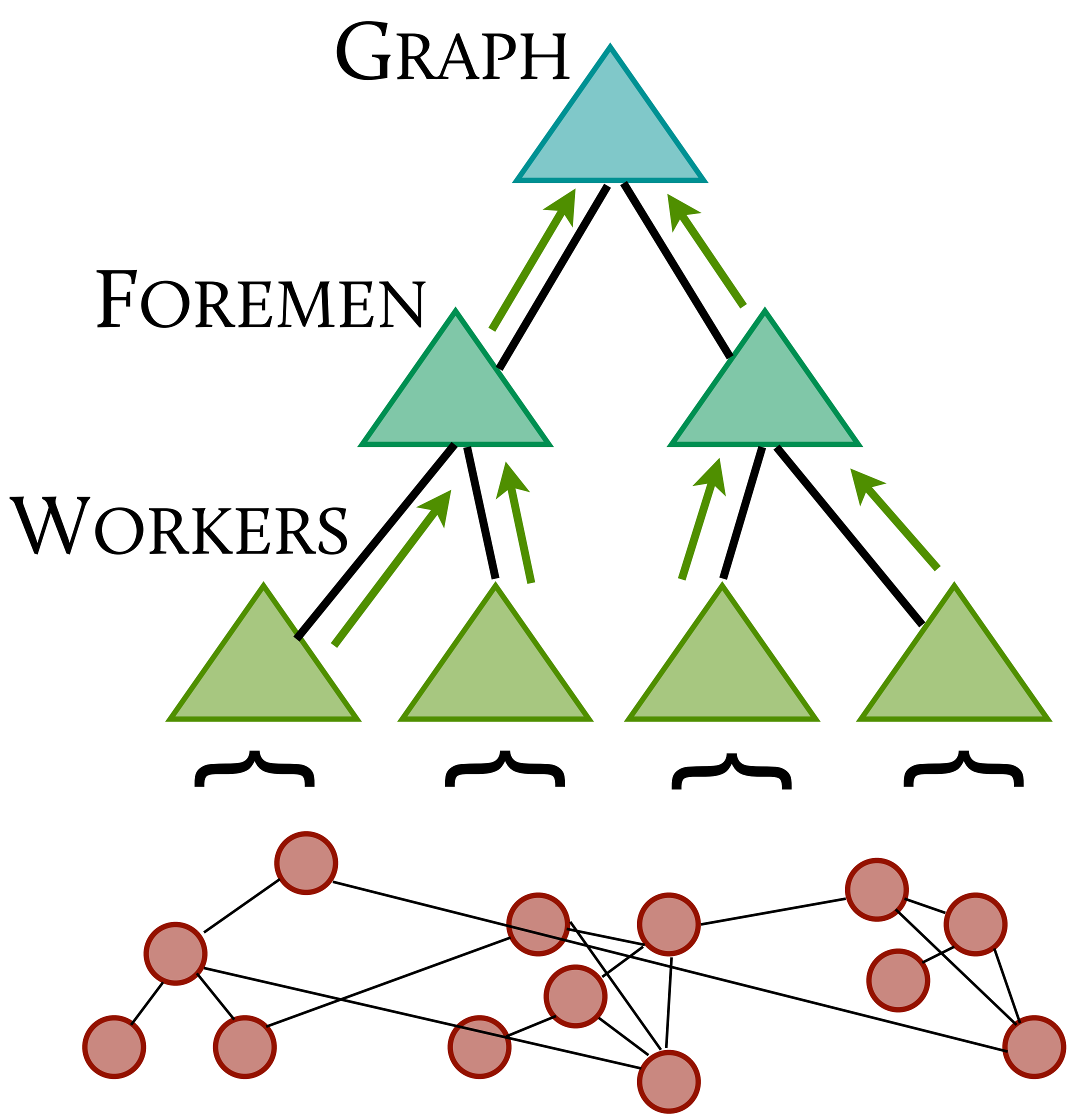

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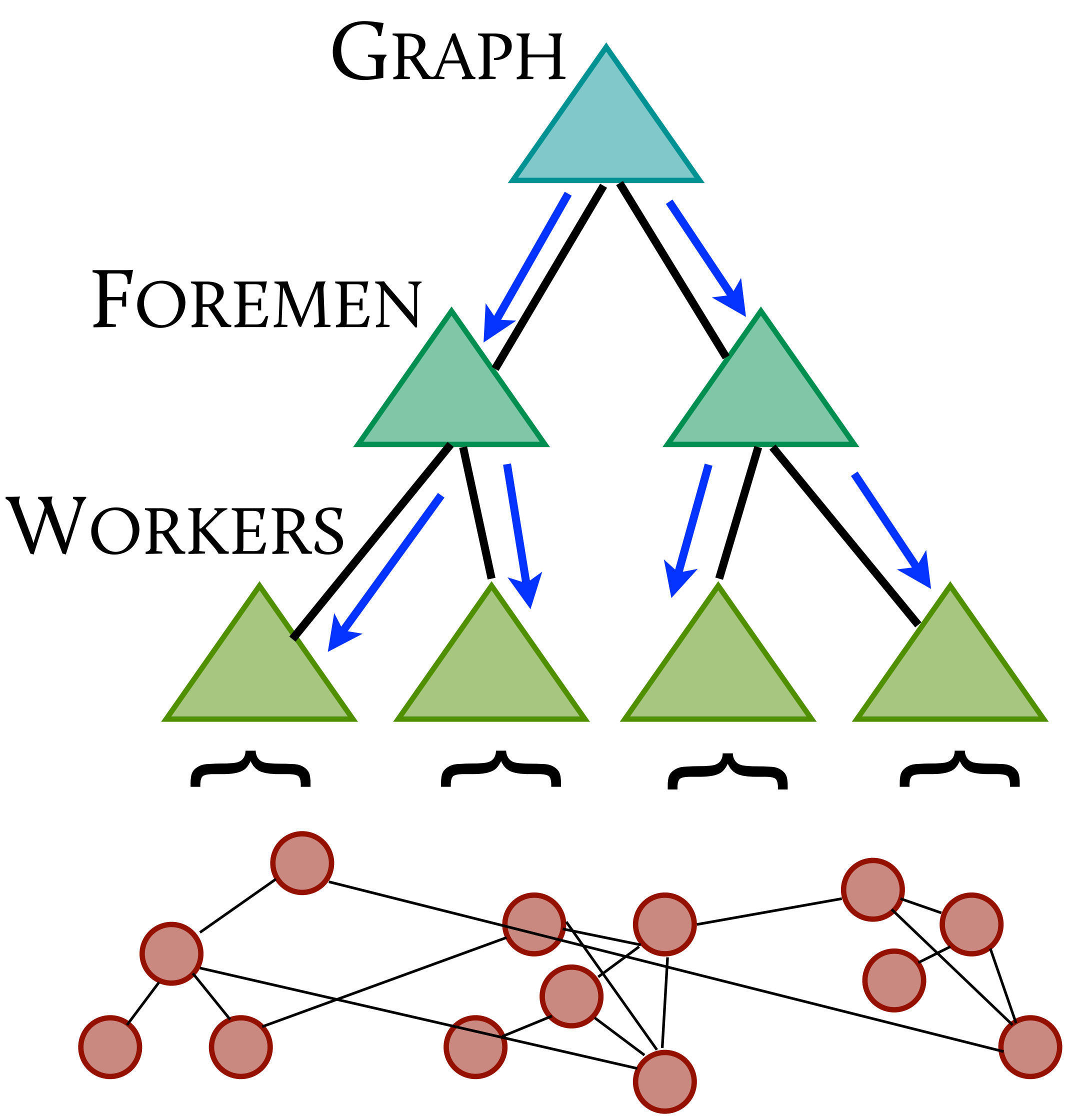

1. WORKER reduces the values of all vertices in its partition.
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3. The final result is passed to all WORKERS which make it available to their vertices as incoming messages (at the beginning of the next superstep)

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- Drawbacks
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  - 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

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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)