TDDD43
Advanced Data Models and Databases

Topic: Graph Data

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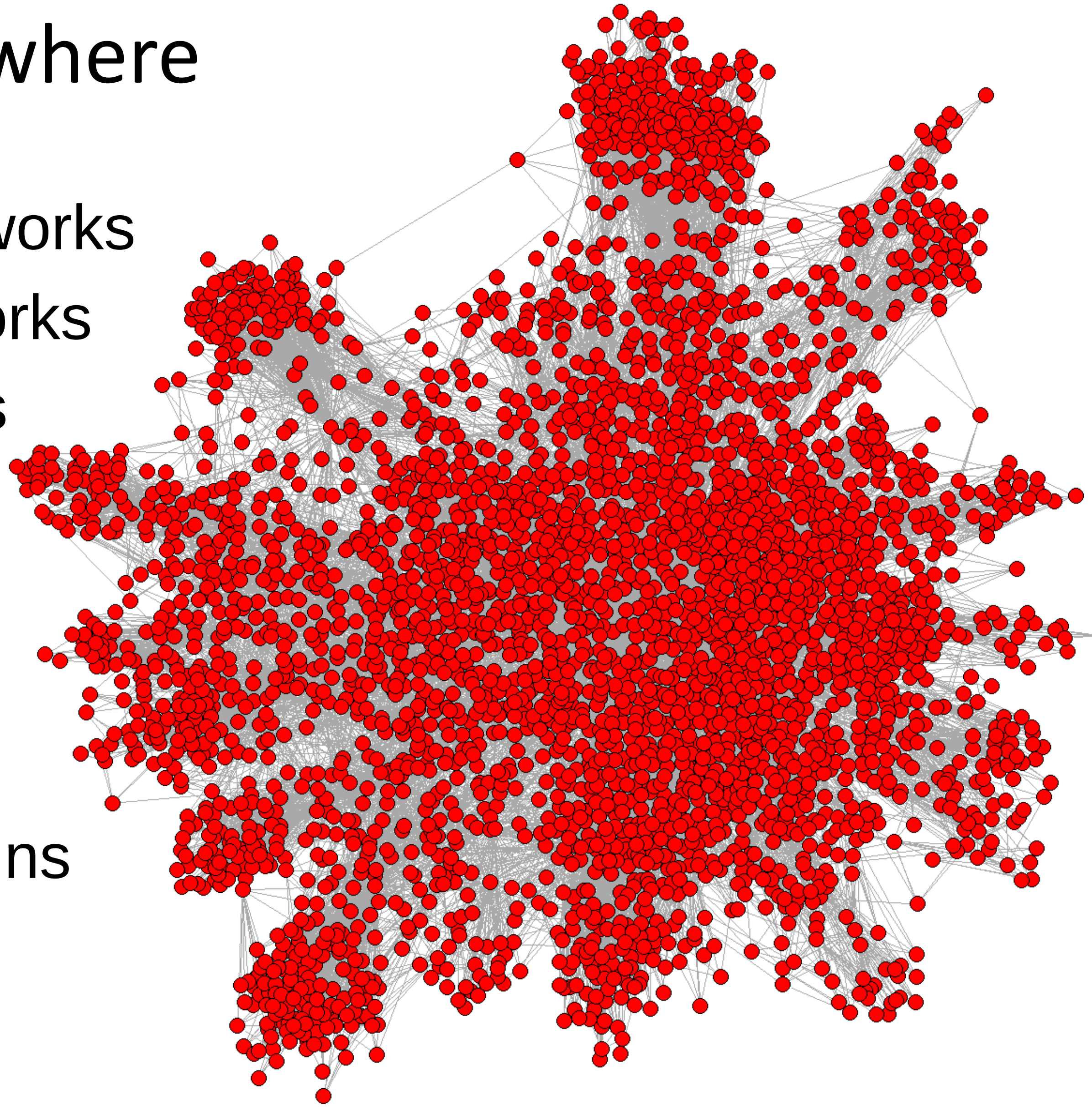
Graphs are Everywhere

- Transportation networks
- Bibliographic networks
- Computer networks
- Social networks
- Topic maps
- Knowledge bases
- Protein interactions
- Biological food chains
- etc.



Categories of Graph Data Systems

- **Triple stores**
  - Typically, pattern matching queries
  - Data model: RDF
- **Graph databases**
  - Typically, navigational queries
  - Prevalent data model: property graphs
- **Graph processing systems**
  - Typically, complex graph analysis tasks
  - Prevalent data model: generic graphs

Remember my earlier lecture on RDF and SPARQL

Graph Data Models

RDF Data Model

Remember
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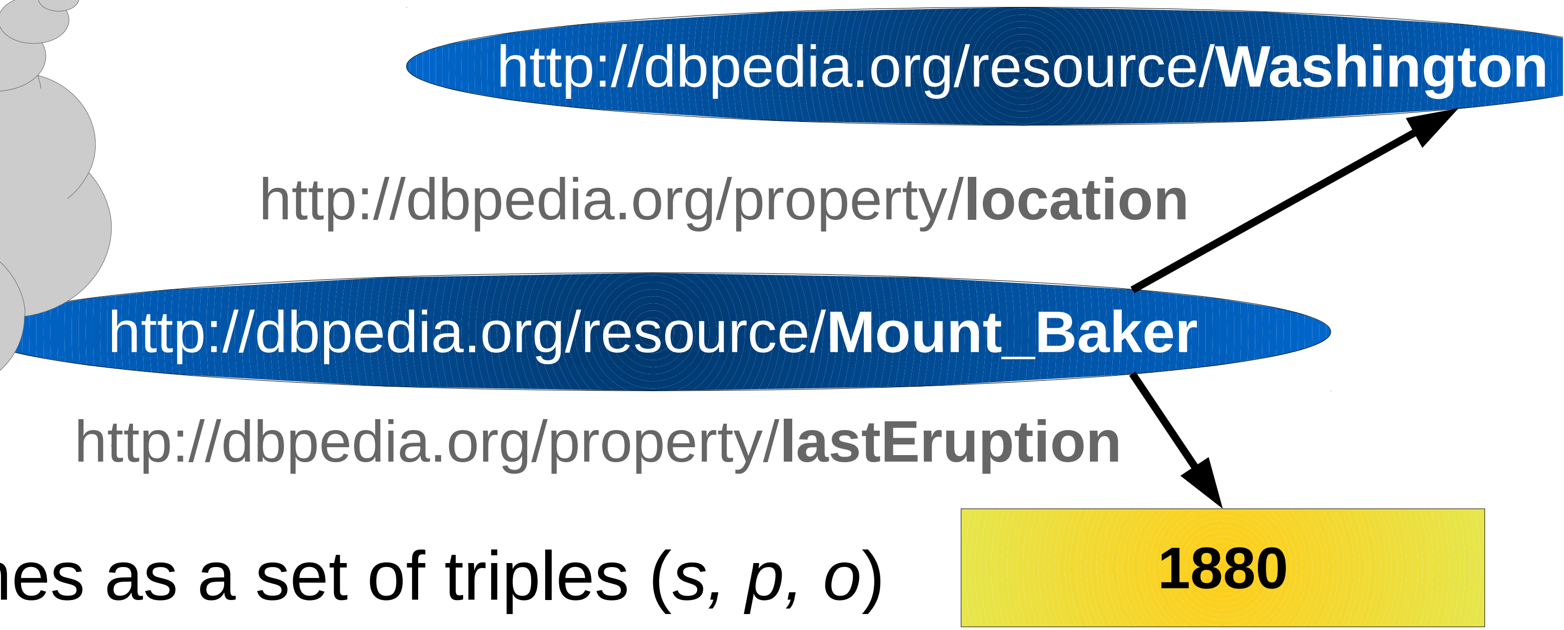
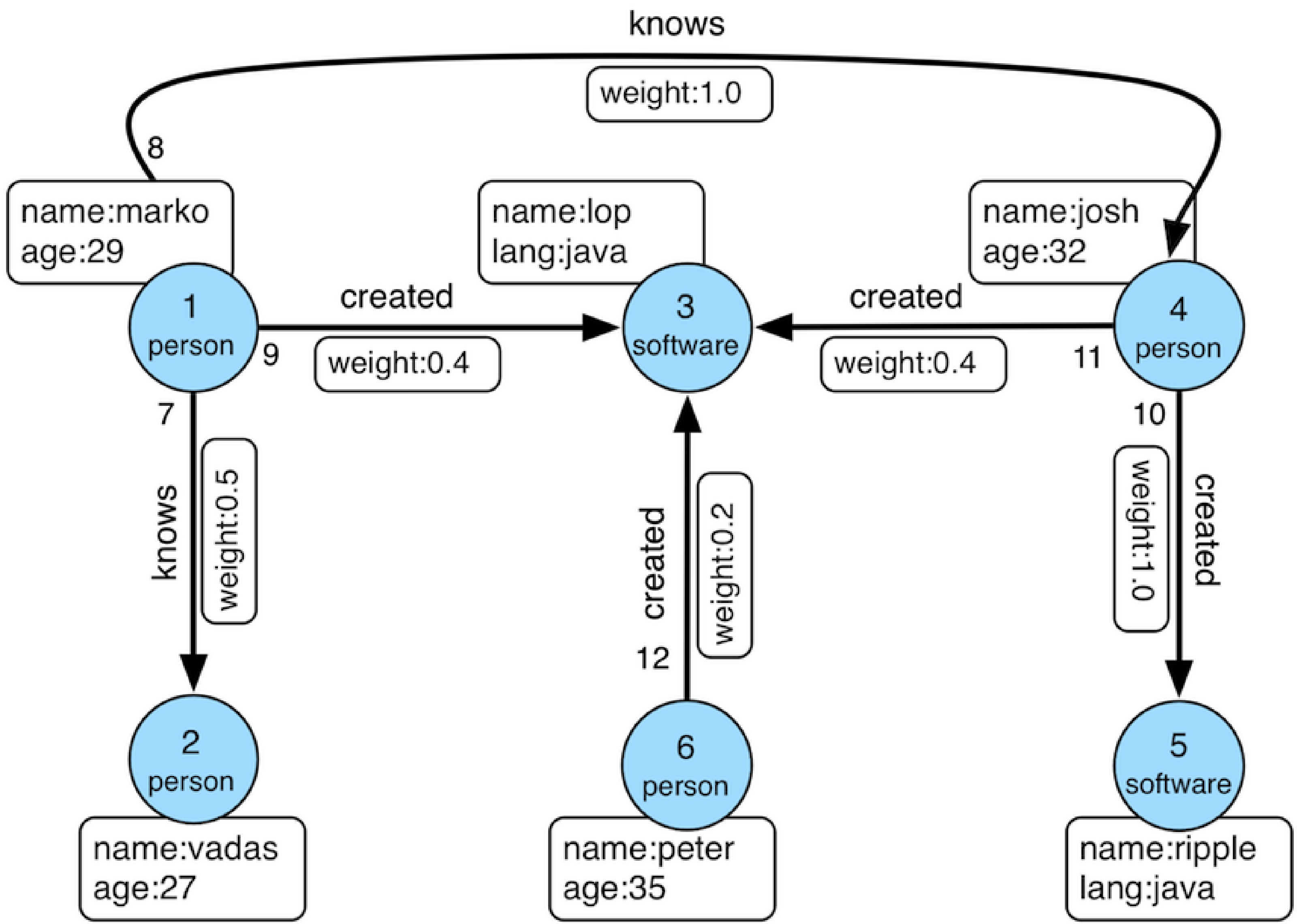
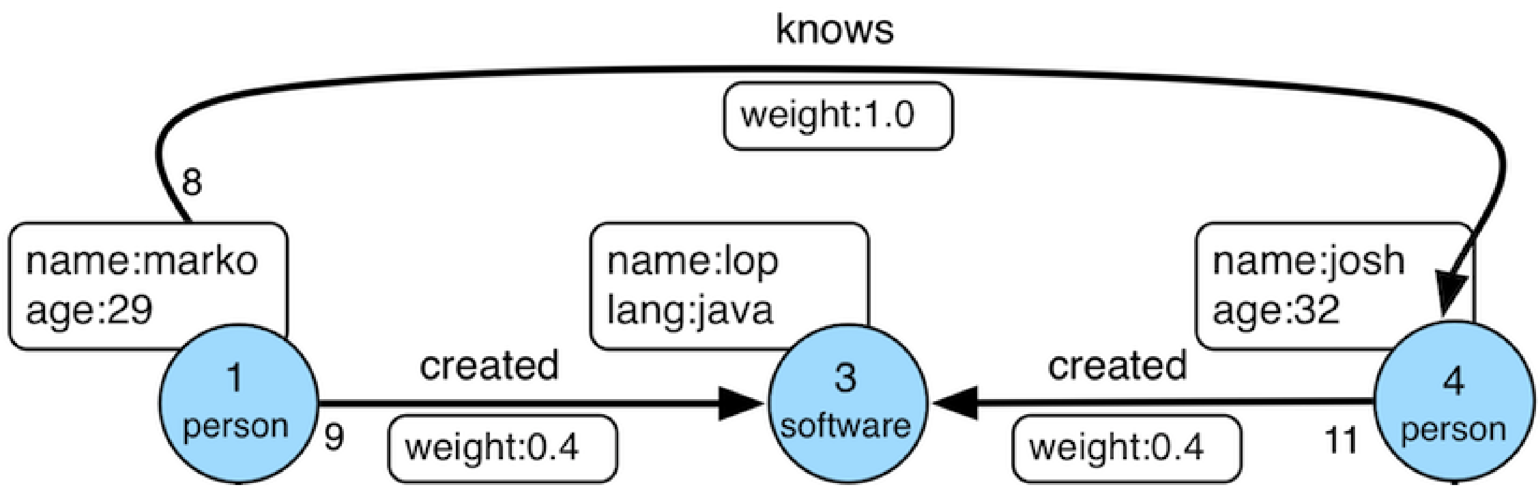


- Data comes as a set of triples (*s*, *p*, *o*)
  - ***s***ubject: URI
  - ***p***redicate: URI
  - ***o***bject: URI or literal
- Such a set may be understood as a graph
  - Triples as directed edges
  - Subjects and objects as vertexes
  - Edges labeled by predicate

Property Graph



Property Graph (cont'd)



- Directed multigraph
  - multiple edges between the same pair of nodes
- Any node and any edge may have a label
- Additionally, any node and any edge may have an arbitrary set of key-value pairs (“properties”)

Property Graphs versus RDF Graphs

- Both data models have a lot of similarities:
  - Directed multigraphs
  - Labels on edges and on vertexes
  - Attributes with values on vertexes
- However, there are some subtle differences:
  - No edge properties in RDF graphs
  - Edge labels cannot appear as nodes in a PG (in RDF we may have <s1,p1,o1> and <p1,p2,o2>)
  - No multivalued (vertex) properties in a PG (unless we use a collection object as the value)
  - Node and edge identifiers in a PG are local to the PG, whereas URIs are globally unique identifiers (important for data integration)

Generic Graphs

- Data model
  - Directed multigraphs
  - Arbitrary user-defined data structure can be used as value of a vertex or an edge (e.g., a Java object)
- Example (Flink Gelly API):

```
// create new vertexes with a Long ID and a String value
Vertex<Long, String> v1 = new Vertex<Long, String>(1L, "foo");
Vertex<Long, String> v2 = new Vertex<Long, String>(2L, "bar");

Edge<Long, Double> e = new Edge<Long, Double>(1L, 2L, 0.5);
```

- Advantage: give users maximum flexibility
- Drawback: systems cannot provide built-in operators related to vertex data or edge data

Graph Databases

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Examples of Graph DB Systems

- Systems that focus on graph databases
  - Neo4j
  - Sparksee
  - Titan
  - InfiniteGraph
- Multi-model NoSQL stores with support for graphs:
  - OrientDB
  - ArangoDB
- Triple stores with TinkerPop support
  - Blazegraph
  - Stardog
  - IBM System G

Apache TinkerPop

- Graph computing framework
  - Vendor-agnostic
- Includes a graph structure API
  - Formerly known as Blueprints API
  - For creating and modifying Property Graphs
  - Example:

```
Graph graph = …
Vertex marko = graph.addVertex(T.label, "person", T.id, 1, "name", "marko", "age", 29);
Vertex vadas = graph.addVertex(T.label, "person", T.id, 2, "name", "vadas", "age", 27);
marko.addEdge("knows", vadas, T.id, 7, "weight", 0.5f);
```

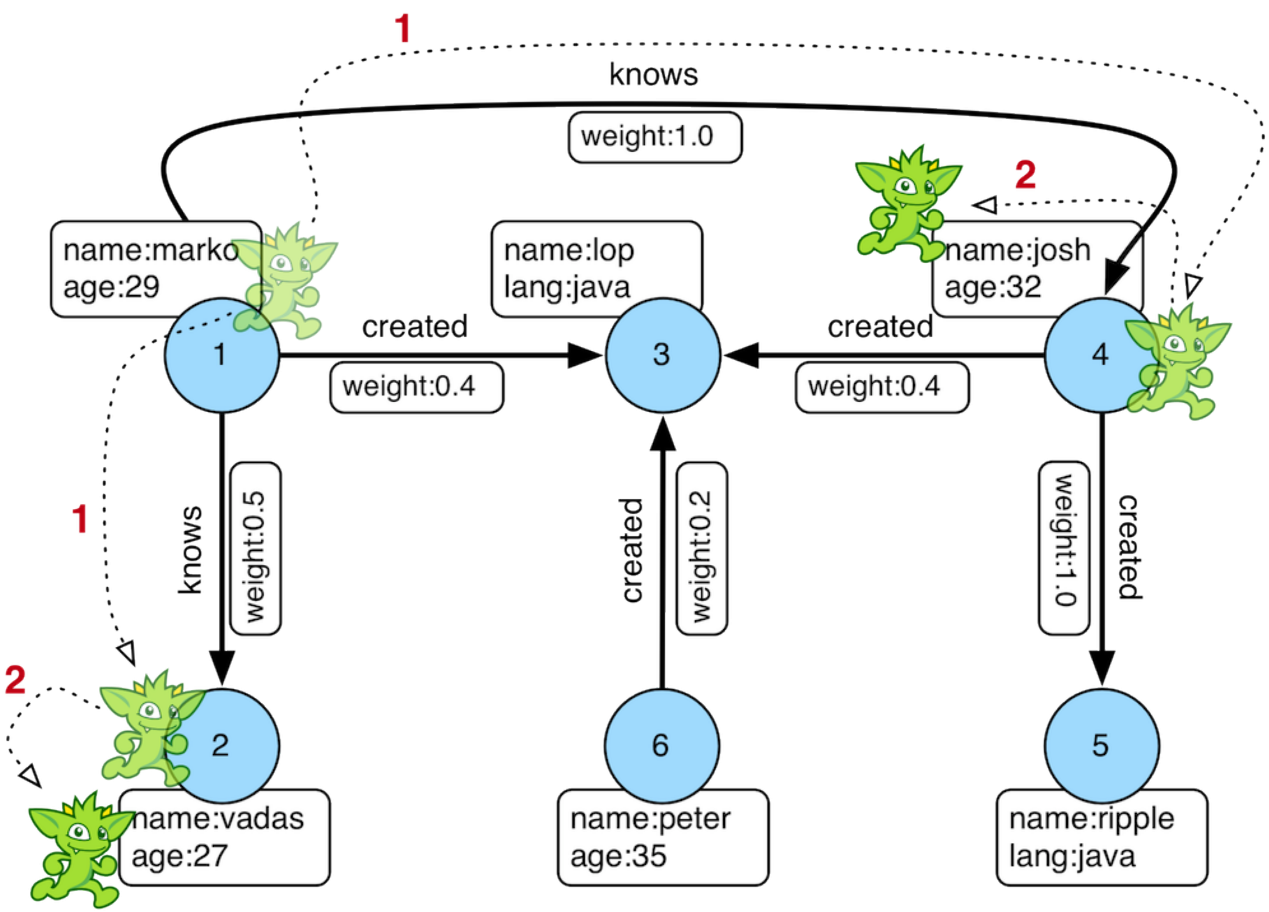
- Also includes a process API
  - Graph-parallel engine
  - Graph traversal, based on a language called Gremlin

Gremlin Graph Traversal Language

- Part of the TinkerPop framework
- Powerful domain-specific language (DSL) with embeddings in various programming languages
- Expressions specify a concatenation of traversal steps

Gremlin Example

g.V().has('name','marko').out('knows').values('name')



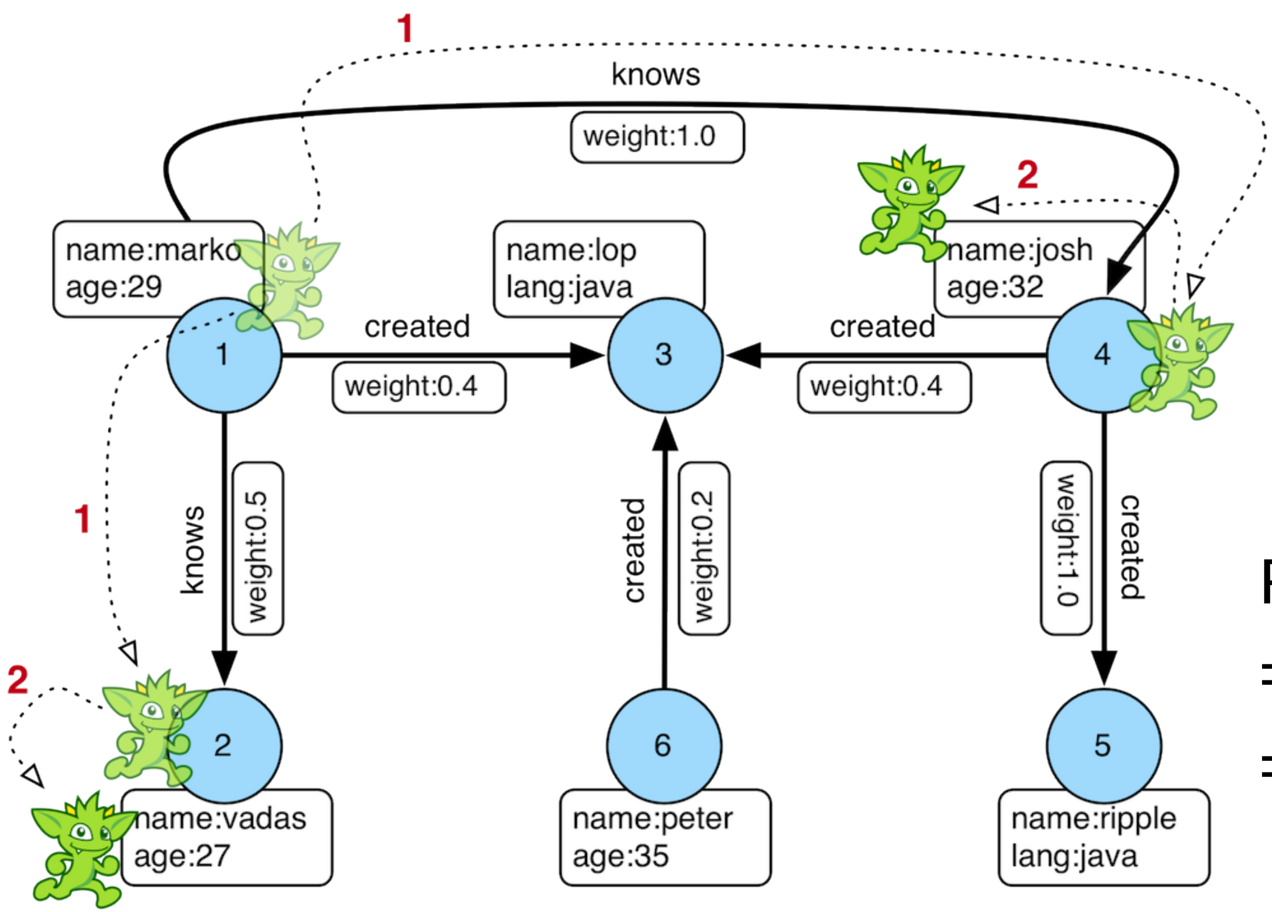
Result:

==>vadas

==>josh

Gremlin Example

g.V().has('name','marko').out('knows').values('name').path()



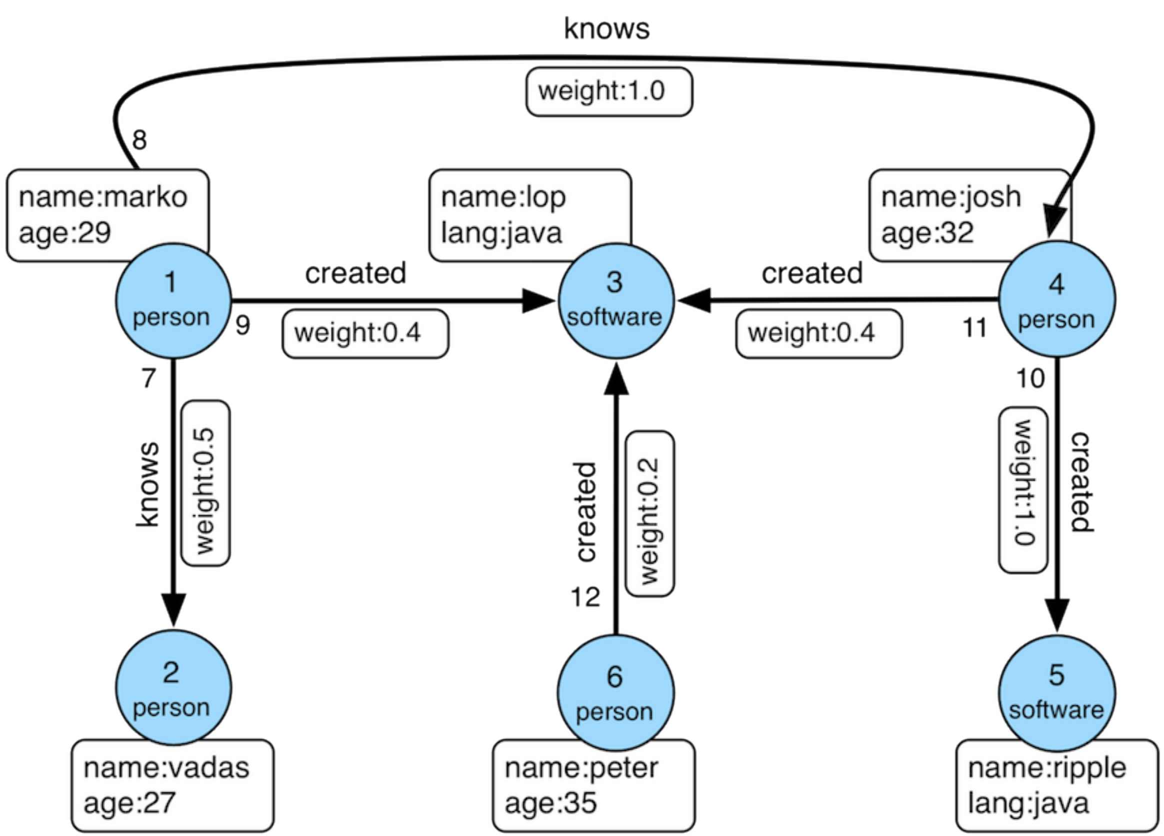
Result:

==>[v[1],v[2],vadas]

==>[v[1],v[4],josh]

Gremlin Example

g.V().has('name','marko').repeat(out()).times(2).values('name')



Result:

==>ripple

==>lop

Cypher

- Declarative graph database query language
- Proprietary (used by Neo4j)
- The OpenCypher project aims to deliver an open specification
- Example
  - Recall our initial Gremlin example:

    ```
    g.V().has('name','marko').out('knows').values('name')
    ```

  - In Cypher we could express this query as follows:

    ```
    MATCH ( {name:'marko'} )-[:knows]->( x )
    RETURN x.name
    ```

Possible Clauses in Cypher Queries

CREATE - creates nodes and edges

DELETE - removes nodes, edges, properties

SET - sets values of properties

MATCH - specifies a *pattern* to match in the data graph

WHERE - filters pattern matching results

RETURN - which nodes / edges / properties in the matched data should be returned

UNION - merges results from two or more queries

WITH - chains subsequent query parts (like piping in Unix commands)

Node Patterns in Cypher

- Node patterns may have different forms:

  ( ) - matches any node

  (:person) - matches nodes whose label is *person*

  ({name:'marko'}) - matches nodes that have a property *name='marko'*

  (:person {name:'marko'}) - matches nodes that have both the label *person* and a property *name='marko'*

- Every node pattern can be assigned a *variable*
  - Can be used to refer to the matching node in another query clause or to express joins
  - For instance, (x), (x:person)

Relationship Patterns in Cypher

- Relationship pattern must be placed between two node patterns and it may have different forms
  - --> or <-- - matches any edge (with the given direction)
  - -[:knows]-> - matches edges whose label is *knows*
  - -[{weight:0.5}]-> - matches edges that have a property *weight=0.5*
  - -[:knows {weight:0.5}]-> - matches edges that have both the label *knows* and a property *weight=0.5*
  - -[:knows*..4]-> - matches paths of *knows* edges of up to length 4
- Every relationship pattern can be assigned a *variable*
  - For instance, <-[x:knows]-

More Complex Cypher Patterns

- Node patterns and relationship patterns are just basic building blocks that can be combined into more complex patterns
- Examples:
  - ```
    MATCH (a)-[:knows]->()-[:knows]->(a)
    RETURN a
    ```
  - ```
    MATCH p = shortestPath(
          (:person {name:'marko'})-[*]->(:person {name:'josh'})
    )
    RETURN p
    ```

Filtering in Cypher

- Pattern matching results can be filtered out by using the WHERE clause (similar to SQL)
- Examples:
  - ```
    MATCH (a:person)-[x:knows]->(b:person)
    WHERE x.weight > 0.5 AND x.weight < 0.9
    RETURN a , b
    ```
  - ```
    MATCH ()-[x:knows]->()
    WHERE exists(x.weight)
    RETURN x
    ```
  - ```
    MATCH (a)-[:knows]->(b)-[x:knows]->(c)
    WHERE NOT (a)-[:knows]->(c)
    RETURN *
    ```
    ```

Graph Processing Systems

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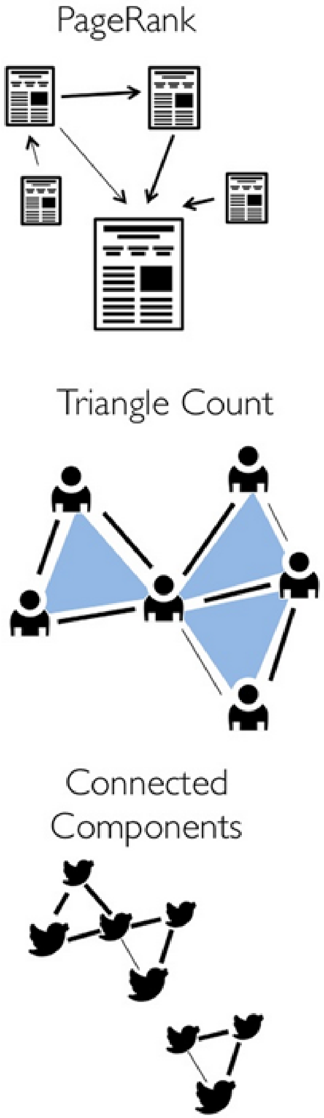
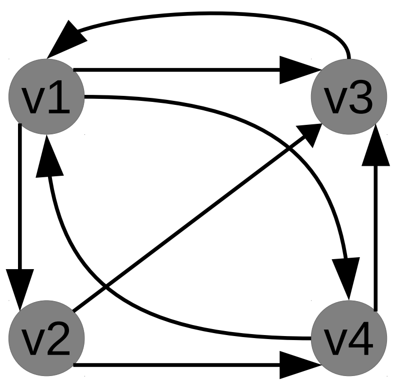
Complex Graph Analysis Tasks???

- Tasks that require an *iterative processing* of the *entire graph* or large portions thereof
- Examples:
  - Centrality analysis (e.g., PageRank)
  - Clustering, connected components
  - Graph coloring
  - Diameter finding
  - All-pairs shortest path
  - Graph pattern mining (e.g., frequent subgraphs, community detection)
  - Machine learning (e.g., belief propagation, Gaussian non-negative matrix factorization)



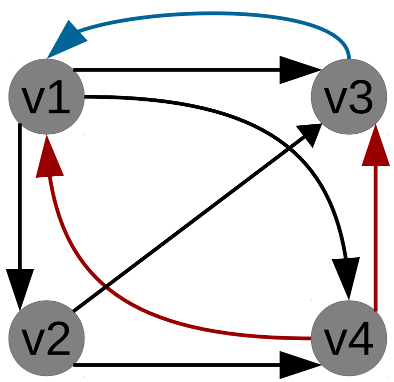
Example: PageRank



$$PR_{k+1}(v) = \sum_{v_{IN}} PR_k(v_{IN}) \,/\, |Out(v_{IN})|$$

	k=0	k=1	k=2	k=3	k=4	k=5	k=6
PR(v1)	0.25						
PR(v2)	0.25						
PR(v3)	0.25						
PR(v4)	0.25						

Example: PageRank

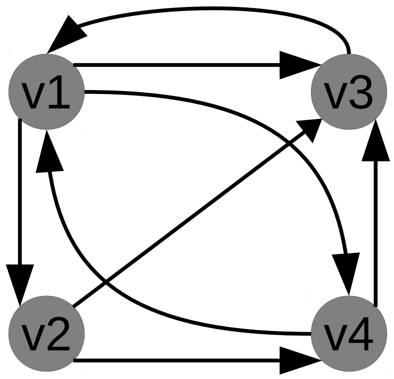


$$PR_{k+1}(v) = \sum_{v_{IN}} PR_k(v_{IN}) \,/\, |Out(v_{IN})|$$

$$\begin{aligned} PR_2(v1) &= PR_1(v3)/1 + PR_1(v4)/2 \\ &= 0.25/1 + 0.25/2 \\ &= 0.25 + 0.125 \\ &= 0.375 \end{aligned}$$

	k=0	*k*=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6
PR(v1)	0.25	0.37					
PR(v2)	0.25						
PR(v3)	0.25						
PR(v4)	0.25						

Example: PageRank



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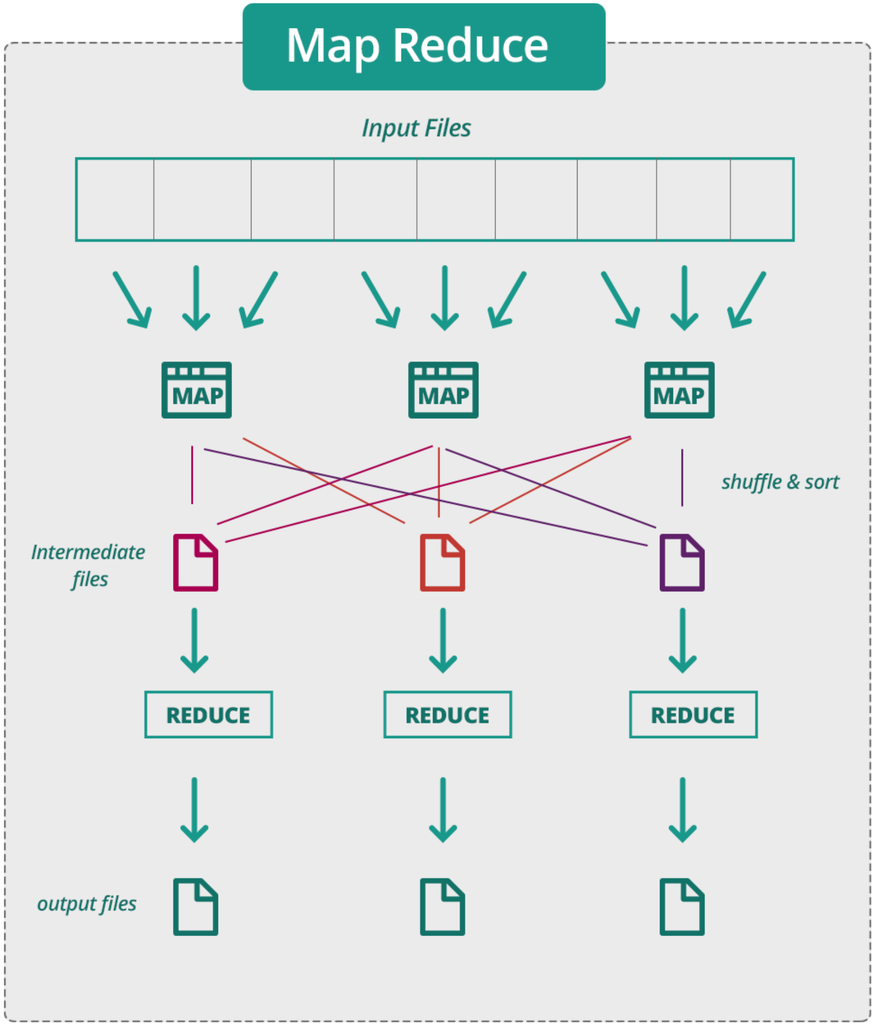
PR(v1)	0.25	0.37	0.43	0.35	0.39	0.38	0.38
PR(v2)	0.25	0.08	0.12	0.14	0.11	0.13	0.13
PR(v3)	0.25	0.33	0.27	0.29	0.29	0.28	0.28
PR(v4)	0.25	0.20	0.16	0.20	0.19	0.19	0.19

Convergence

Observation

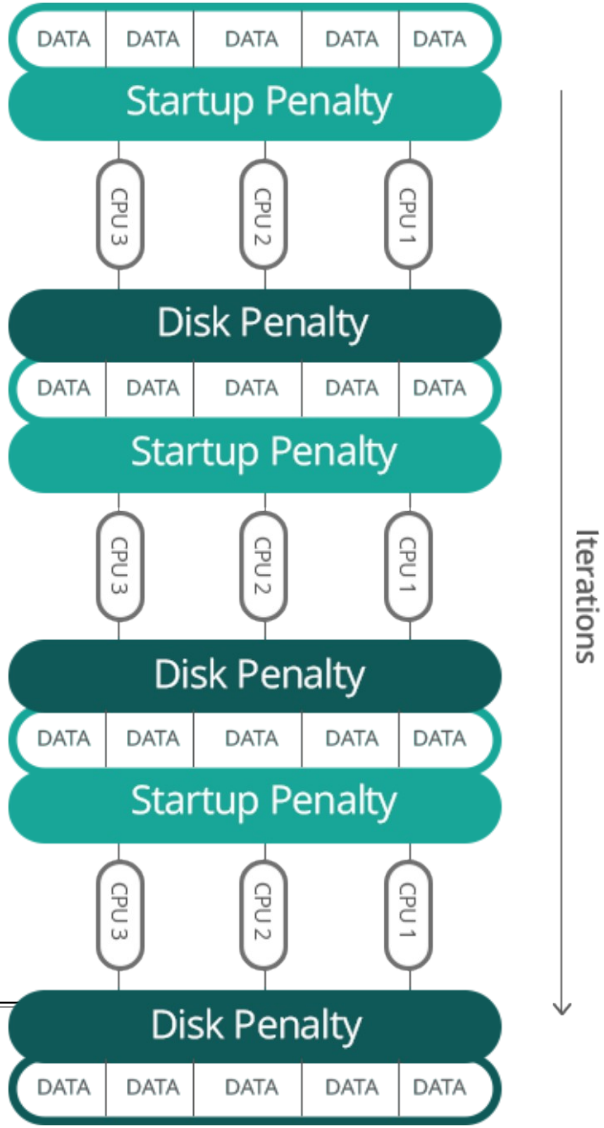
- Many such algorithms iteratively propagate data along the graph structure by transforming intermediate vertex and edge values

Can we use MapReduce for this?



Can we use MapReduce for this?

- M/R does not directly support iterative algorithms
- Materializing intermediate results at each M/R iteration harms performance
- Extra M/R job on each iteration for checking whether a fixed point has been reached
- Additional issue for graph algorithms
  - Invariant graph-topology data reloaded and reprocessed at each iteration
  - Wastes I/O, CPU, and network bandwidth



Graph Processing Systems

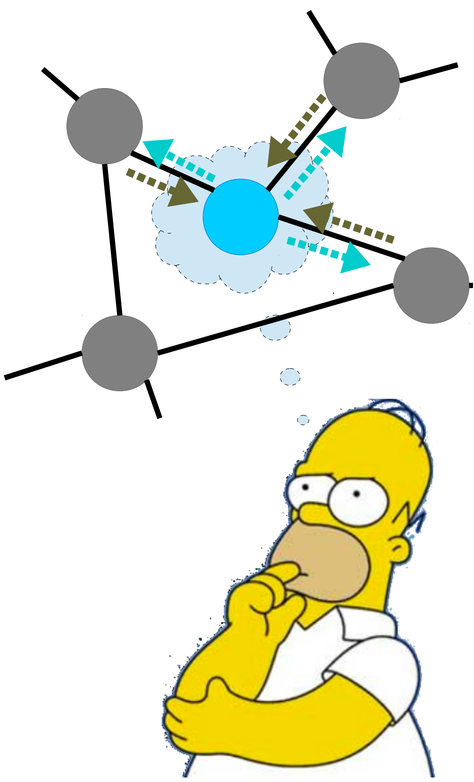
Pregel Family
- Pregel
- Giraph
- Giraph++
- Mizan
- GPS
- Pregelix
- Pregel+

GraphLab Family
- GraphLab
- PowerGraph
- GraphChi (*centralized*)

Other Systems
- Trinity
- TurboGraph (*centralized*)
- Signal/Collect

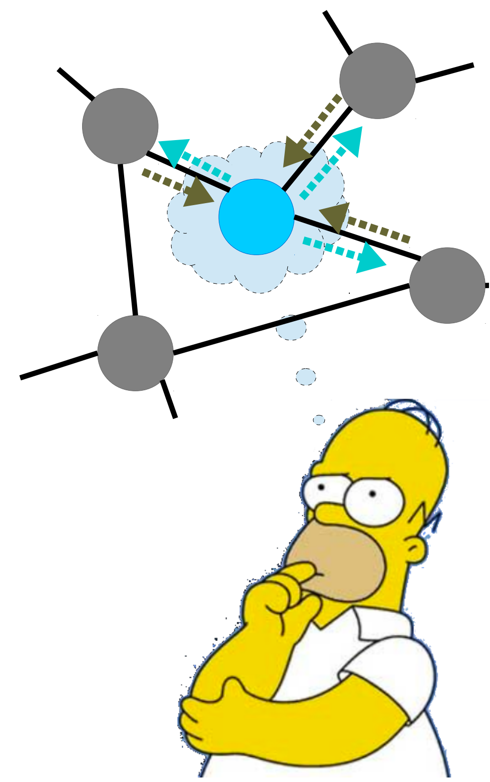
Vertex-Centric Abstraction

- Many such algorithms iteratively propagate data along the graph structure by transforming intermediate vertex and edge values
  - These transformations are defined in terms of functions on the values of adjacent vertexes and edges
  - Hence, such algorithms can be expressed by specifying a function that can be applied to any vertex separately
- "Think like a vertex"



Vertex-Centric Abstraction (cont'd)

- Vertex compute function consists of three steps:
  1. Read all incoming messages from neighbors
  2. Update the value of the vertex
  3. Send messages to neighbors
- Additionally, function may "vote to halt" if a local convergence criterion is met
- Overall execution can be parallelized
  - Terminates when all vertexes have halted and no messages in transit



Example: Vertex-Centric PageRank

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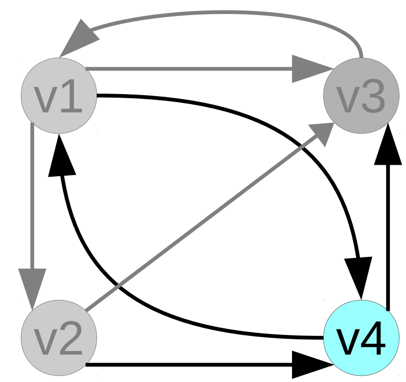

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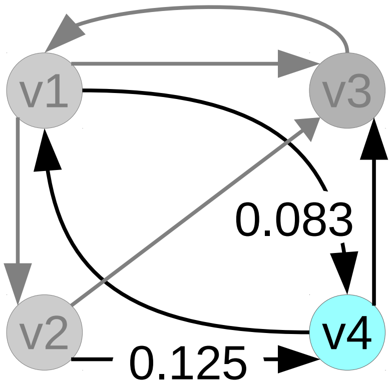

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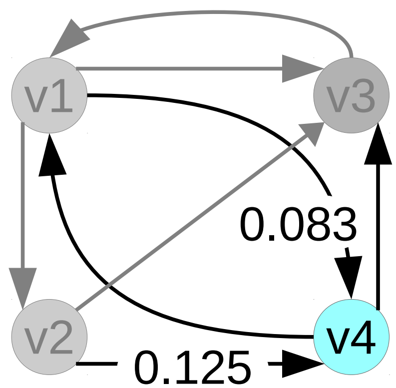

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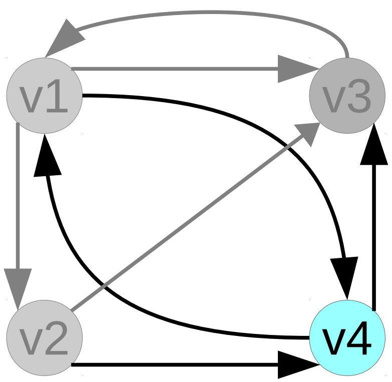

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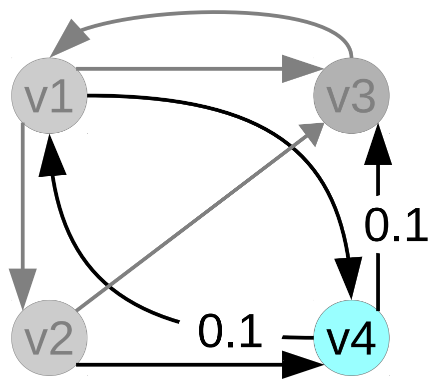

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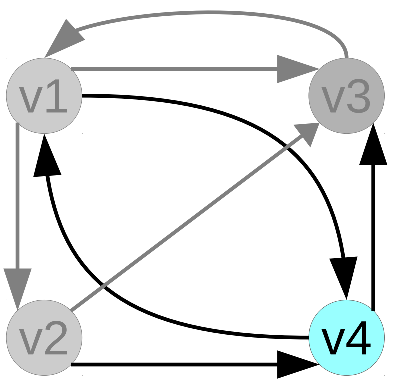

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local convergence

Example: Vertex-Centric PageRank

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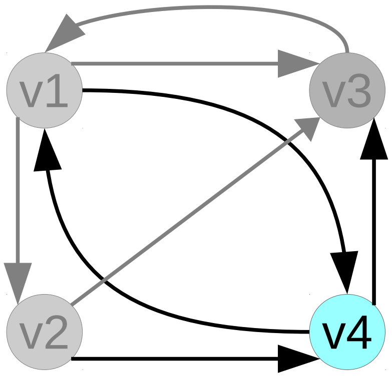

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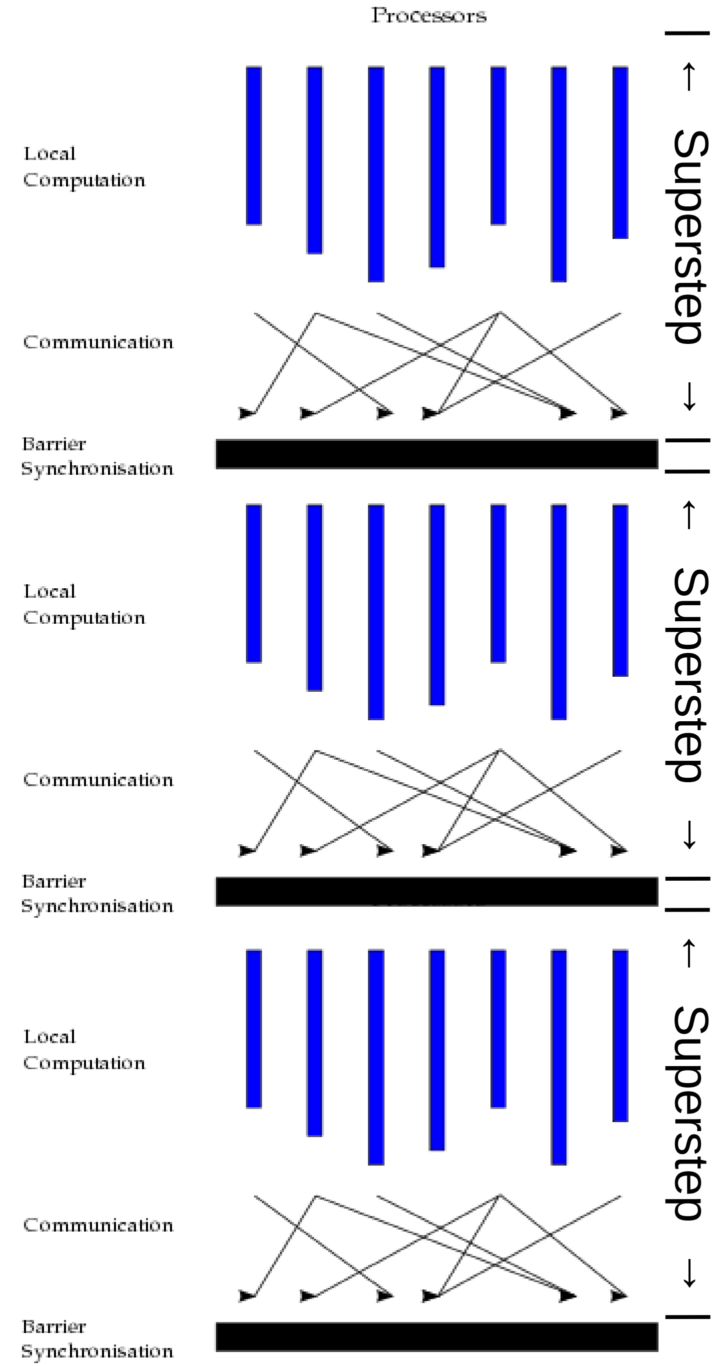
Google Pregel

- First system that implemented vertex-centric computation for shared-nothing clusters
  - Communication through message passing
- Based on the *bulk synchronous parallel (BSP)* programming model
  - Supersteps with synchronization barriers
- Apache Giraph was a first open source implementation of Pregel



MapReduce versus Pregel

MapReduce

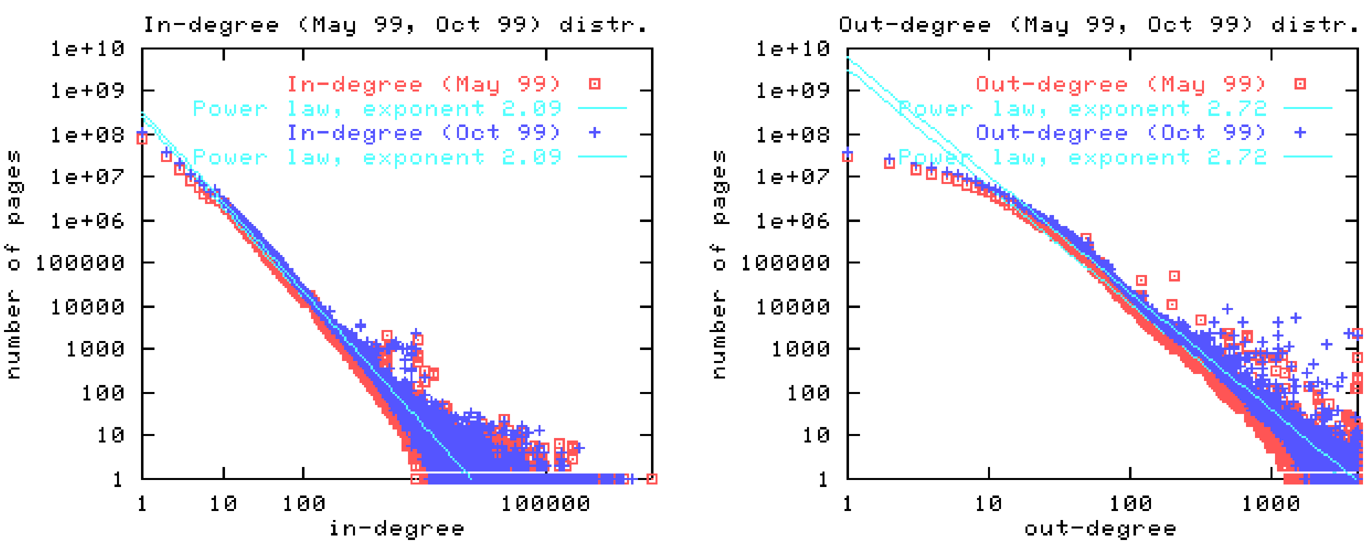
- Requires passing of entire graph topology from one iteration to the next
- Intermediate result after each iteration is stored on disk and then read again from disk
- Programmer needs to write a driver program to support iterations, and another M/R job to check for fixed point

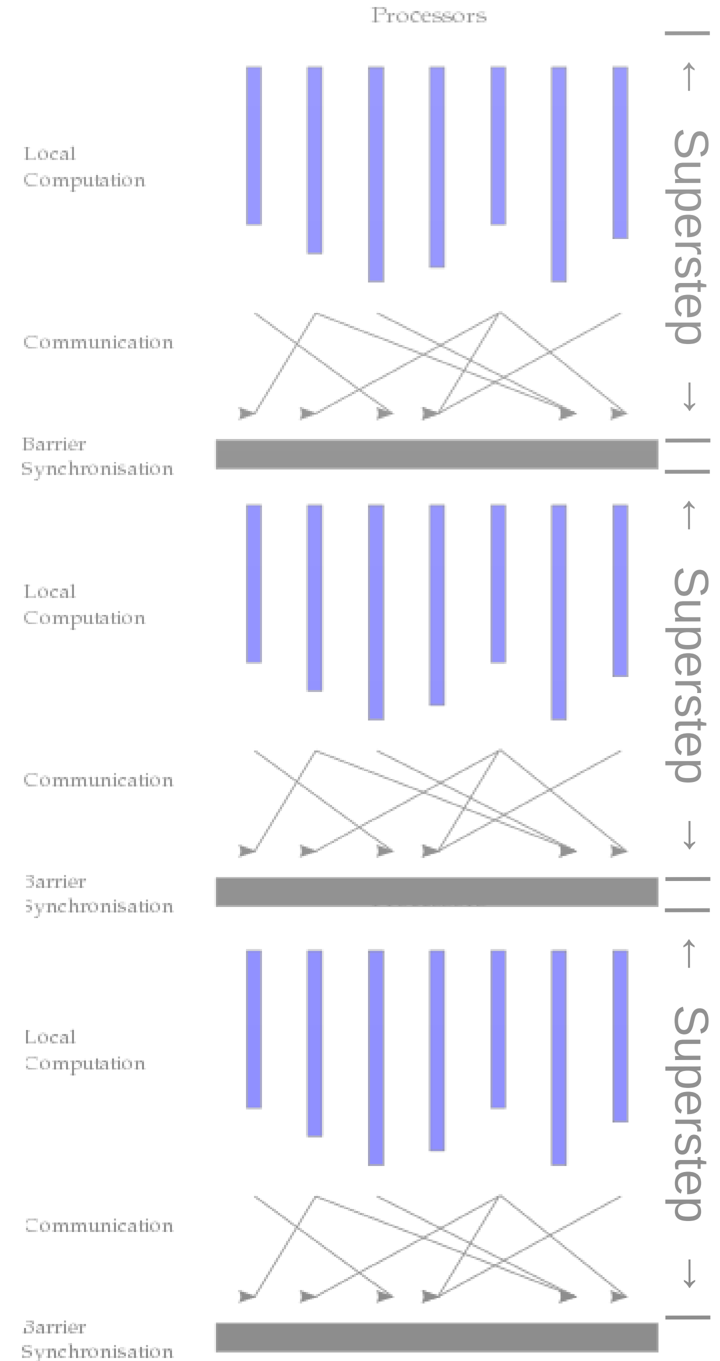
Pregel

- Graph topology is not passed across iterations, vertexes only send their state to their neighbors
- Main memory based
- Usage of supersteps and master-client architecture makes programming easy

Limitation of Pregel

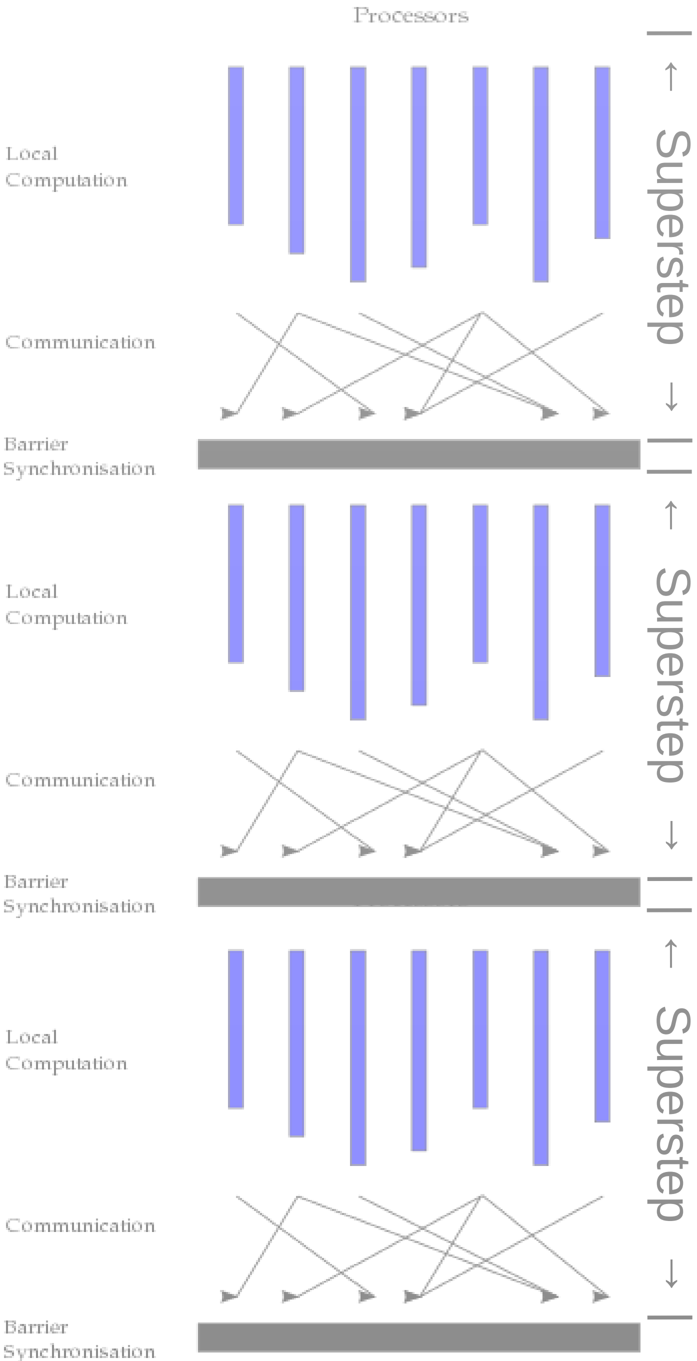
- In the BSP model, performance is limited by slowest worker machine
  - Many real-world graphs have power-law degree distribution, which may lead to few highly-loaded workers





Limitation of Pregel

- In the BSP model, performance is limited by slowest worker machine
  - Many real-world graphs have power-law degree distribution, which may lead to few highly-loaded workers
- Possible optimizations to balance the workload:
  - Decompose the vertex program
  - Sophisticated graph partitioning
  - Graph-centric abstraction
- Another possibility: asynchronous execution (instead of BSP)



Combiner

- Takes two messages and combines them into one
  - Associative, commutative function
- Can be used to aggregate messages before sending them to the worker node that has the target vertex

- Example:
  - In the vertex-centric PageRank, messages are values $m_{IN} = (Pr_k(v_{IN}) \,/\, |Out(v_{IN})|)$ of each incoming neighbor v_{IN}
  - In the vertex function these values are summed up:
    $$(Pr_k(v_{IN1}) \,/\, |Out(v_{IN1})|) + (Pr_k(v_{IN2}) \,/\, |Out(v_{IN2})|) + \ldots$$
  - Parts of this sum may be computed by worker nodes that have some of the incoming neighbor vertexes

Signal/Collect Model

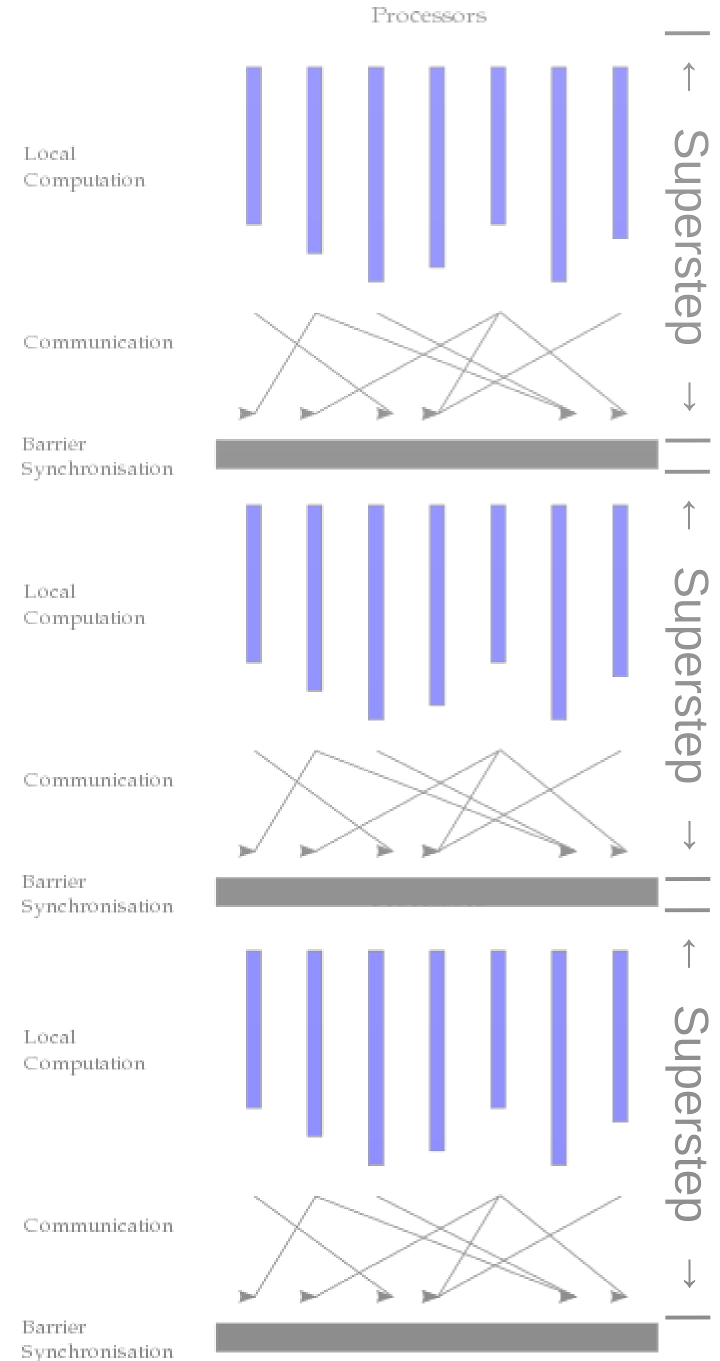
- Signaling (edge function):
  - Every edge uses the value of its source vertex to compute a message ("signal") for the target vertex
  - Executed on the worker that has the source vertex
- Collecting (vertex function):
  - Every vertex computes its new value based on the messages received from its incoming edges
  - Executed on the worker that has the target vertex

Gather, Apply, Scatter (GAS) Model

- Gather:
  - Accumulate incoming messages, i.e., same purpose as a combiner
- Apply:
  - Update the vertex value based on the accumulated information
  - Operates only on the vertex
- Scatter:
  - Computes outgoing messages
  - Can be executed in parallel for each adjacent edge

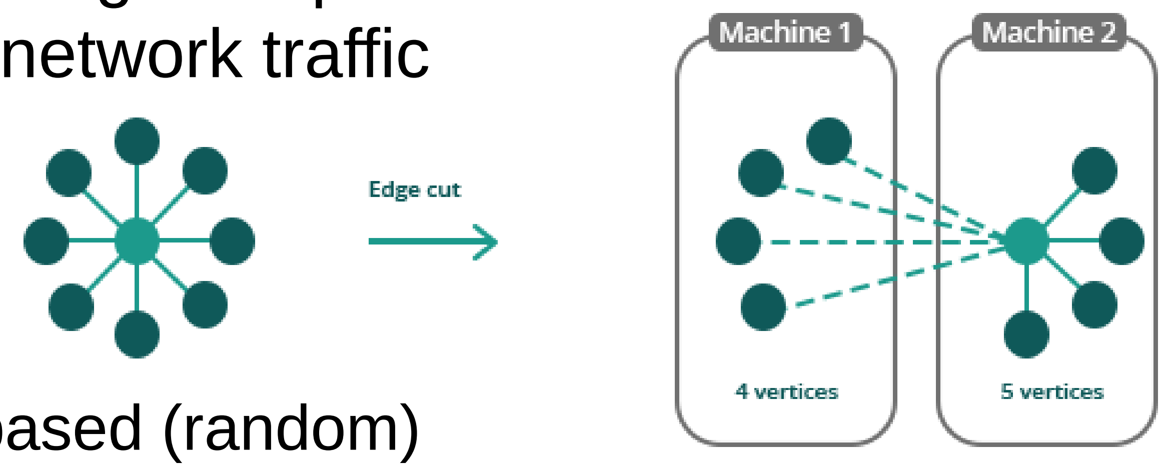
Limitation of Pregel

- In the BSP model, performance is limited by slowest worker machine
  - Many real-world graphs have power-law degree distribution, which may lead to few highly-loaded workers
- Possible optimizations to balance the workload:
  - Decompose the vertex program
  - Sophisticated graph partitioning
  - Graph-centric abstraction
- Another possibility: asynchronous execution (instead of BSP)



Partitioning

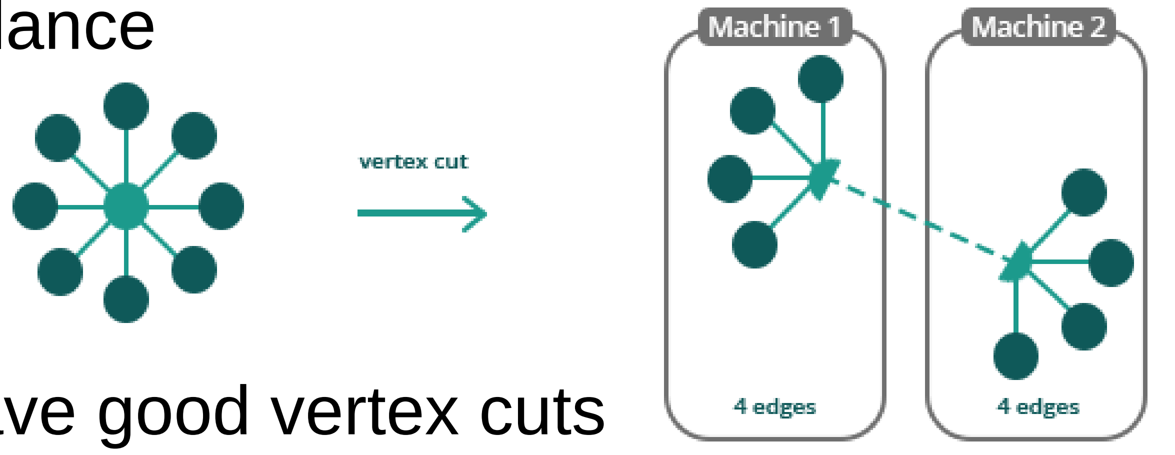
- **Goal:** distribute the vertexes to achieve a balanced workload while minimizing inter-partition edges to avoid costly network traffic



  - For instance, hash-based (random) partitioning has extremely poor locality
- Unfortunately, the problem is NP-complete
  - k-way graph partitioning problem
- Various heuristics and approximation algorithms

Vertex-Cut

- PowerGraph introduced a partitioning scheme that “cuts” vertexes such that the edges of high-degree vertexes are handled by multiple workers
  - improved work balance



- Power-law graphs have good vertex cuts
  - Communication is linear in the number of machines each vertex spans
  - Vertex-cut minimizes this number
  - Hence, reduced network traffic

Limitation of Pregel

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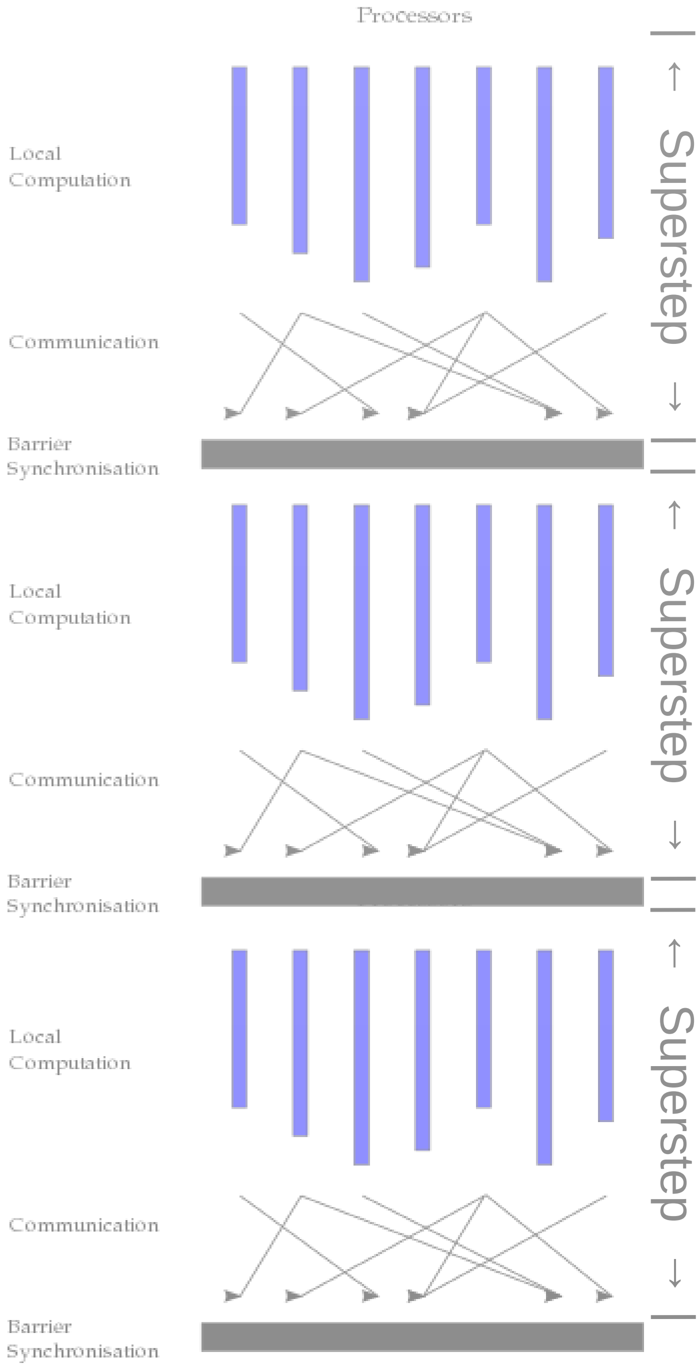

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Image sources:
- Example Property Graph http://tinkerpop.apache.org/docs/current/tutorials/getting-started/
- BSP Illustration https://en.wikipedia.org/wiki/Bulk_synchronous_parallel
- Smiley https://commons.wikimedia.org/wiki/File:Face-smile.svg
- Frowny https://commons.wikimedia.org/wiki/File:Face-sad.svg
- Powerlaw charts http://www9.org/w9cdrom/160/160.html

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