Pregel: A System for Large-Scale Graph Processing

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Large Graphs are Everywhere

We can use graphs to represent

- Social networks
- Transportation routes
- Citation maps between published work
- Disease outbreaks

with **billions** of vertices and edges each. But graph algorithms do a poor job with

- Memory access locality
- Optimizing parallel allocation
- **Distribution over multiple machines**

Pregel

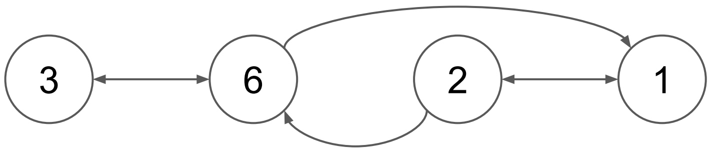
Idea: A framework that executes the same user-defined function `Compute()` for each vertex in a sequence of ***supersteps*** until the algorithm reaches completion.

A **superstep** is a synchronous iteration that performs `Compute()` on all **active** vertices at the step.

Pregel utilizes **message passing** to communicate updates in the state of the graph immediately.

Pregel: Maximum Value Example

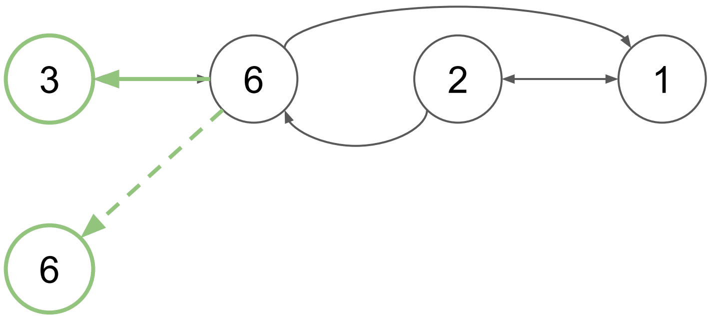
All vertices begin as ***active***



Superstep 0

Pregel: Maximum Value Example

At superstep *S*, vertices send messages to outgoing edges at superstep *S+1*

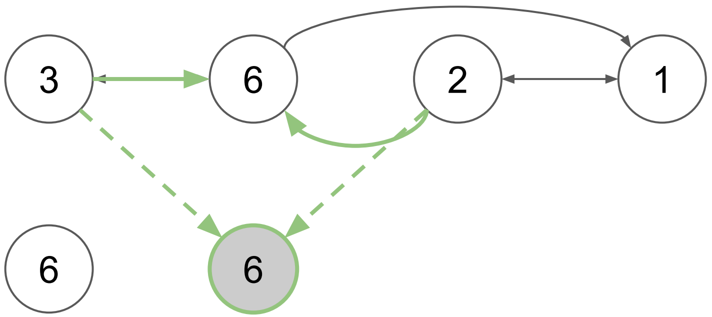


Superstep 0

Superstep 1

Pregel: Maximum Value Example

At superstep *S*, vertices send messages to outgoing edges at superstep *S+1*

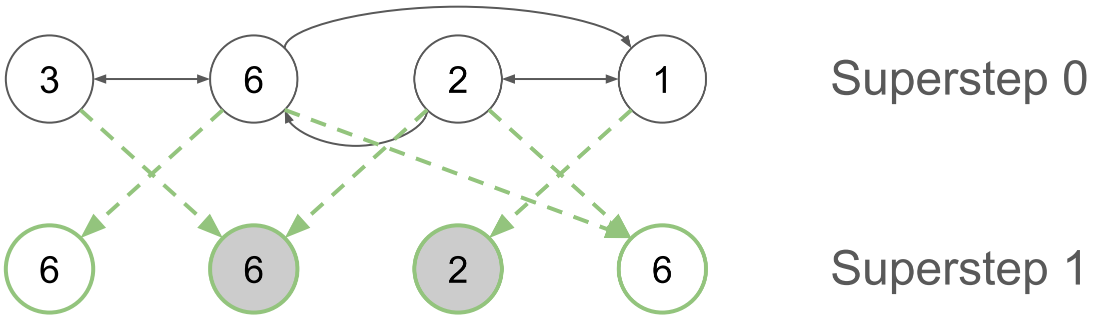


Superstep 0

Superstep 1

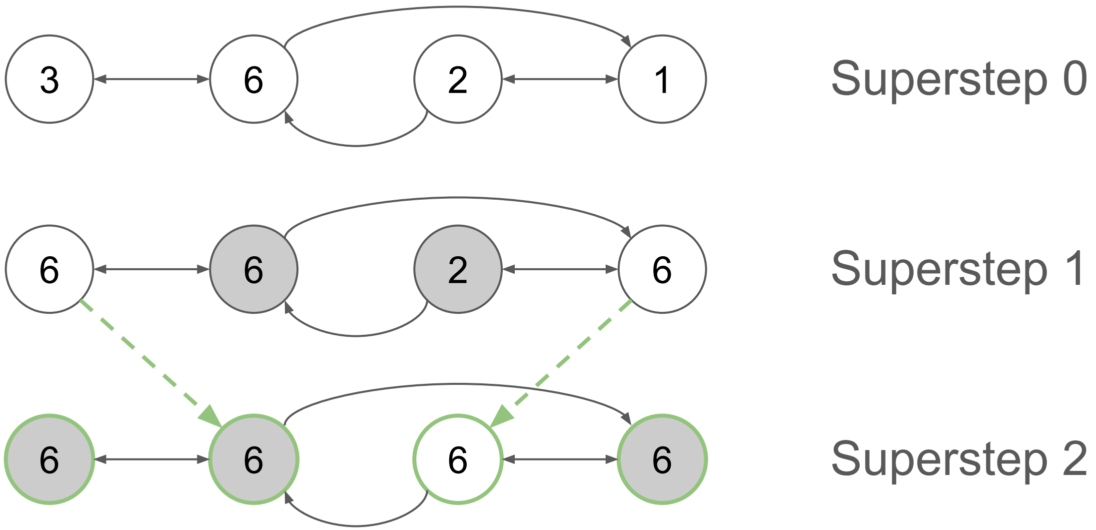
Vertices that do not change are ***voted to a halt***

Pregel: Maximum Value Example

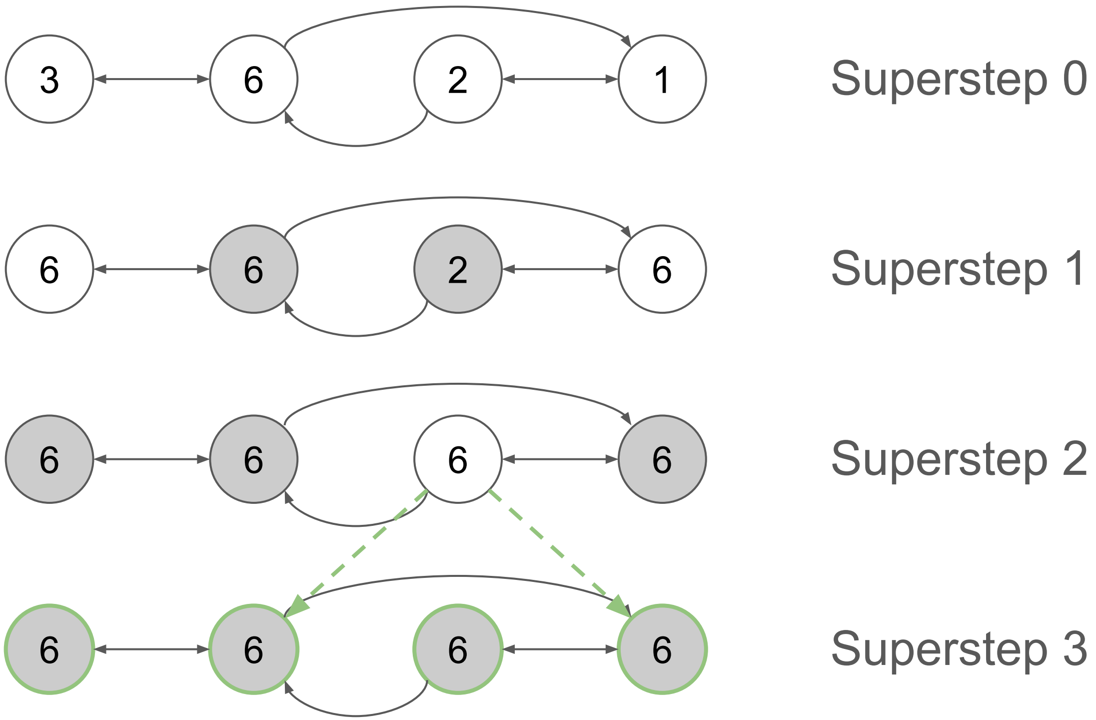


Pregel: Maximum Value Example

A vertex can become active again if another vertex sends it a message at superstep *S-1*



Pregel: Maximum Value Example

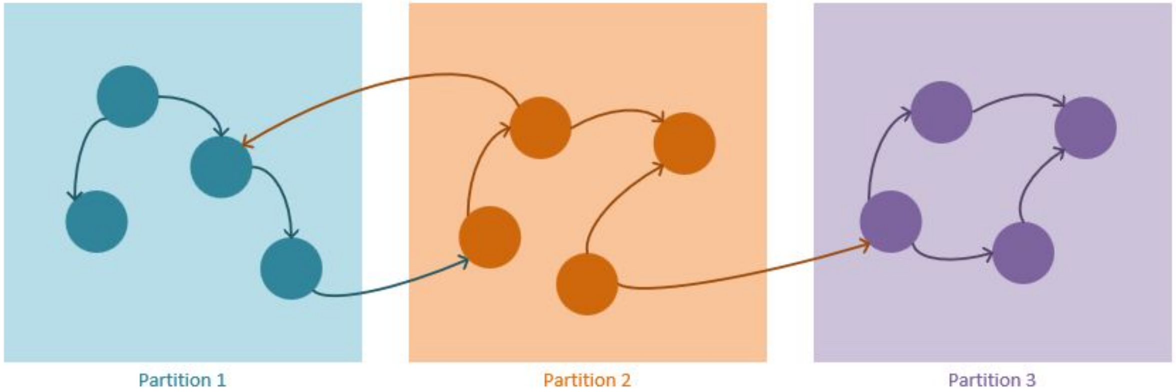


The process completes once all vertices are deactivated simultaneously

Pregel Framework: API Details

- Message passing between vertices
  - Messages sent to *V* at *S* are iterated through at *S+1*
  - Non-neighbors can send messages
- Topology Mutations
  - Edge removals, vertex removals, vertex addition, edge addition
  - Partial ordering and handlers to avoid data races
- `Combine()` to condense several messages into one
- `Aggregator()` for global coordination
- Support for flexible input/output graph formats

Pregel Architecture: A Distributed System



The input graph is broken into partitions, where each vertex is assigned a partition based on the hash value of its vertex ID

Program Execution

At the start, one worker machine is assigned **master**. A master must

- Divide and allocate partitions to the workers
- Instruct each worker to perform a superstep
- Instruct workers to save its state

At each superstep, each **worker** is in charge of

- Maintaining the state of its own partition
- Sending messages to remote peers
- Loop through its active vertices and call `Compute()`
- Signal to the master when complete

Fault Tolerance

Basic **Checkpointing**

- Failed worker at *S’* : Master → X → Worker - - - - Master
- Recover supersteps since most recent checkpoint *S*

Confined Recovery

- Workers log their outgoing messages
- Recover from *S* to *S’* only for the lost partitions
- Adds overhead --
- Saves compute resources ++

Applications to Real Problems

PageRank

Problem: Ranking webpages based on the quality of quantity of links to the page

Vertex: Potential page rank, all initialized the same

Outgoing messages: Inversely proportional to the number of outgoing edges

PageRank

```
class PageRankVertex
    : public Vertex<double, void, double> {
 public:
  virtual void Compute(MessageIterator* msgs) {
    if (superstep() >= 1) {
      double sum = 0;
      for (; !msgs->Done(); msgs->Next())
        sum += msgs->Value();
      *MutableValue() =
          0.15 / NumVertices() + 0.85 * sum;
    }

    if (superstep() < 30) {
      const int64 n = GetOutEdgeIterator().size();
      SendMessageToAllNeighbors(GetValue() / n);
    } else {
      VoteToHalt();
    }
  }
};
```

Single-Source Shortest Paths (SSSP)

Problem: Finding the shortest distance between a source and all other vertices

Vertex: distance from source initialized to INF

Outgoing messages: Potential minimum distances + its own edge weight

Uses a `Combiner()` to reduce data sent

Single-Source Shortest Paths (SSSP)

```
class ShortestPathVertex
    : public Vertex<int, int, int> {
  void Compute(MessageIterator* msgs) {
    int mindist = IsSource(vertex_id()) ? 0 : INF;
    for (; !msgs->Done(); msgs->Next())
      mindist = min(mindist, msgs->Value());
    if (mindist < GetValue()) {
      *MutableValue() = mindist;
      OutEdgeIterator iter = GetOutEdgeIterator();
      for (; !iter.Done(); iter.Next())
        SendMessageTo(iter.Target(),
                      mindist + iter.GetValue());
    }
    VoteToHalt();
  }
};
```

```
class MinIntCombiner : public Combiner<int> {
  virtual void Combine(MessageIterator* msgs) {
    int mindist = INF;
    for (; !msgs->Done(); msgs->Next())
      mindist = min(mindist, msgs->Value());
    Output("combined_source", mindist);
  }
};
```

*Much better than single-machine implementations

Maximal Bipartite Matching

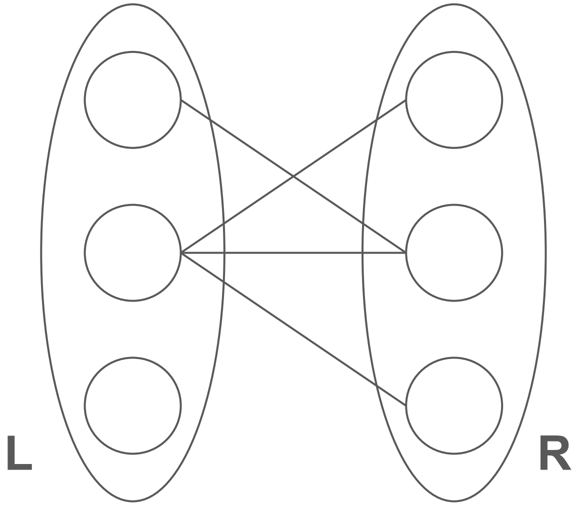
Problem: Find a set of edges such that no two edges share an endpoint from a bipartite graph, using the maximum number of edges

Vertex: (<L/R>, <matched_vertex_ID>)

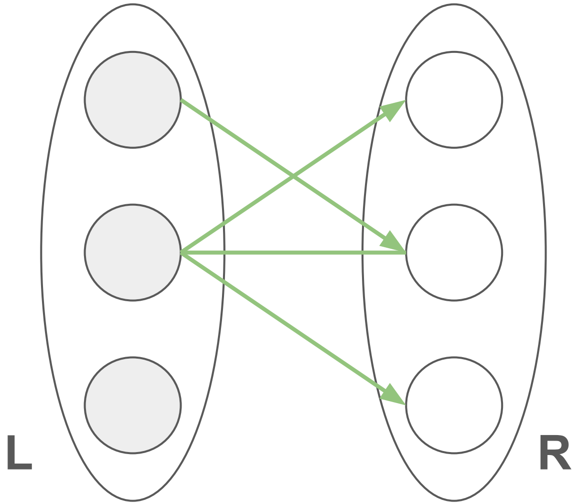
Outgoing messages: boolean

Supersteps work in cycles of 4 phases

Maximal Bipartite Matching

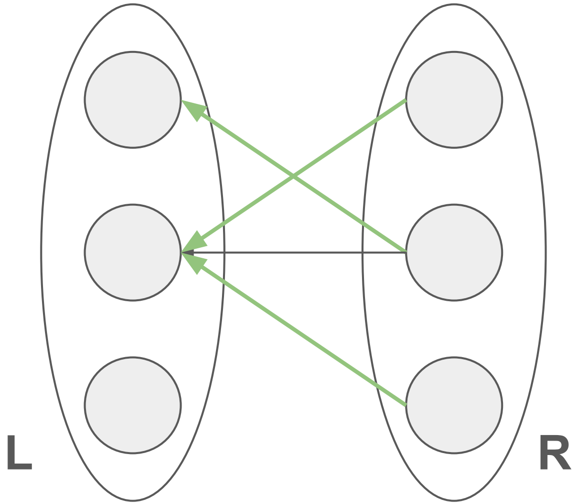


Maximal Bipartite Matching



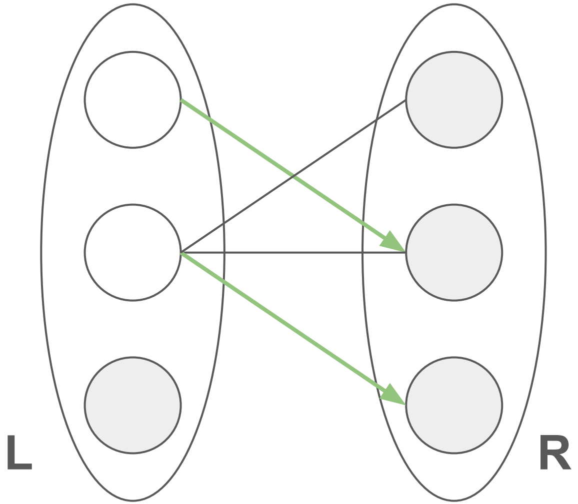
Phase 0 (Superstep 0)

Maximal Bipartite Matching



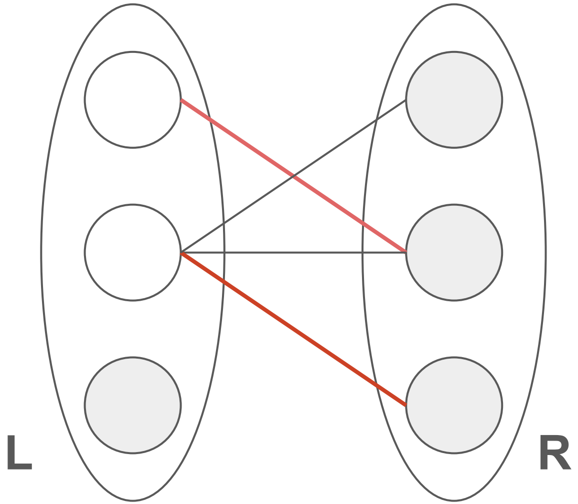
Phase 1 (Superstep 1)

Maximal Bipartite Matching



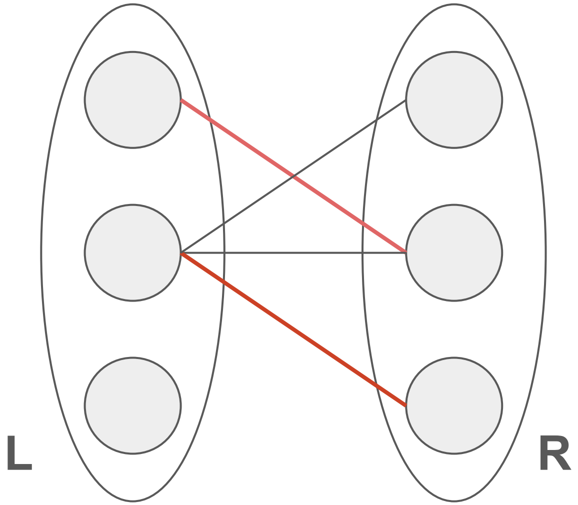
Phase 2 (Superstep 2)

Maximal Bipartite Matching



Phase 3 (Superstep 3)

Maximal Bipartite Matching



Phase 0 (Superstep 4)

Semi-Clustering

Problem: Finding groups of people who interact frequently with each other and less frequently with others

Vertex: list of at most C_{max} semi-clusters sorted by score

Outgoing message: its semi-cluster *c*

Score: $$S_c = \frac{I_c - f_B B_c}{V_c(V_c - 1)/2}$$

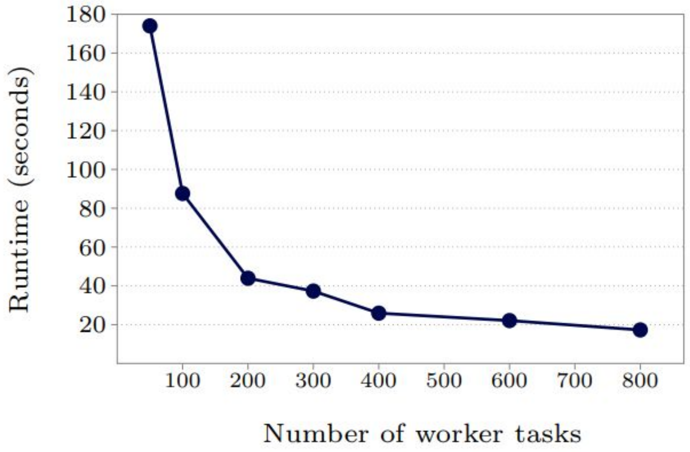
I_c = sum of weights of edges within *c*
B_c = sum of weights of edges outgoing c
V_c = number of vertices in *c*
f_B = boundary edge score factor (parameter between 0-1)

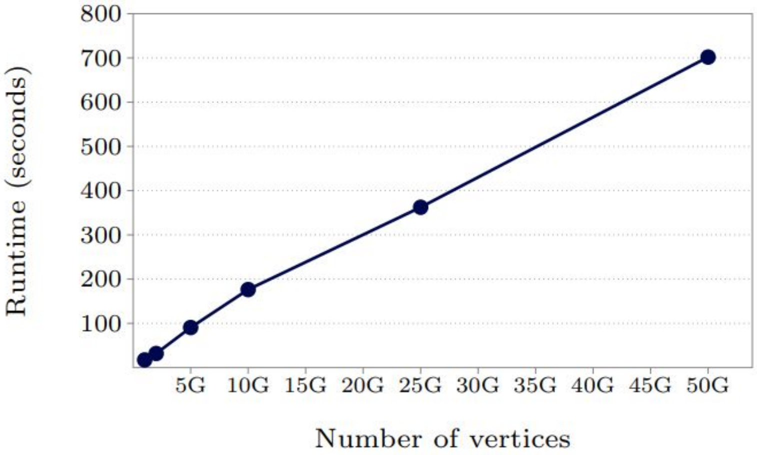
Semi-Clustering

- Vertex V iterates over the semi-clusters $c_1,...,c_k$ sent to it on the previous superstep. If a semi-cluster c does not already contain V, and $V_c < M_{\mathtt{max}}$, then V is added to c to form c'.
- The semi-clusters $c_1, ..., c_k, c'_1, ..., c'_k$ are sorted by their scores, and the best ones are sent to V's neighbors.
- Vertex V updates its list of semi-clusters with the semi-clusters from $c_1, ..., c_k, c'_1, ..., c'_k$ that contain V.

Experiments

Evaluated performance for SSSP on binary trees using clusters of 300 multicore machines

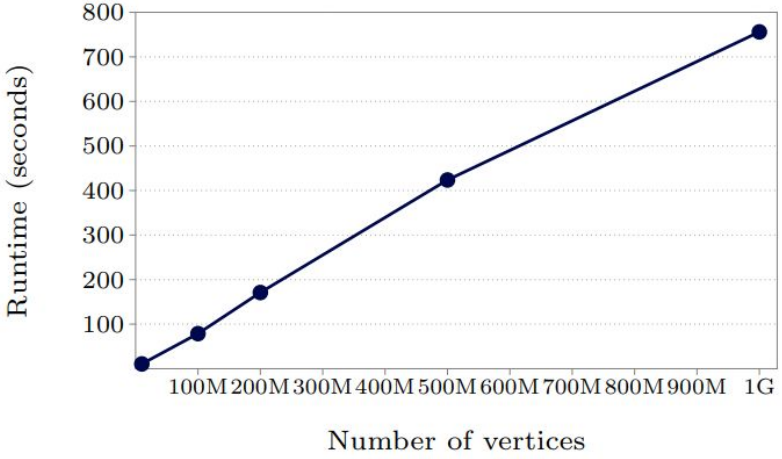




Experiments

Evaluated performance for SSSP on log-normal distribution of outdegrees to better represent real world graphs

$$p(d) = \frac{1}{\sqrt{2\pi}\,\sigma d}\, e^{-(\ln d - \mu)^2/2\sigma^2}$$



Comparison to Existing Models

MapReduce

-- No graph API

Bulk Synchronous Parallel (BSP)

++ Same synchronous superstep model

-- No graph-specific API

-- Not tested beyond dozens of machines

Comparison to Existing Models

Parallel Boost Graph Library (BGL)

++ Implements multiple algorithms on MPI

-- Uses *ghost cells*, can cause scaling issues

-- Poor fault tolerance

CGMgraph

++ Implements multiple algorithms on MPI

-- Not generic, user cannot implement their own algorithms

Conclusion

Strengths:

- Flexible and intuitive API explanation
- Simple applications to real problems

Weaknesses:

- Shallow evaluations
- Message passing catered towards sparse graphs only

Future Directions:

- Scaling to even larger graphs
- Topology-aware partitioning