Parallel & Distributed Graph algorithms for large graphs, practical challenges

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Who we are

I3S is the computer science laboratory of Université Côte d'Azur.
It is located at the heart of Sophia Antipolis.

- COATI — theoretical and experimental aspects of graph algorithms. Software production: 3 librairies:

MascOPT	network optimization (2001-)
Grph	computing large graphs in-memory (2010-)
BigGrph	platform — distributed library for computing largER graphs (2014-)

- SCALE — theoretical and experimental aspects of distributed computing. Software: ProActive, a platform for component-based computing.

COATI is hosted/supported by Inria.

Graphs, Digraphs, Hypergraphs

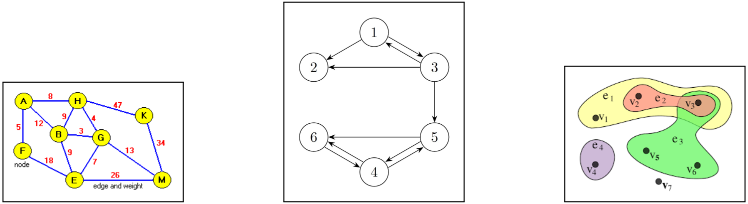


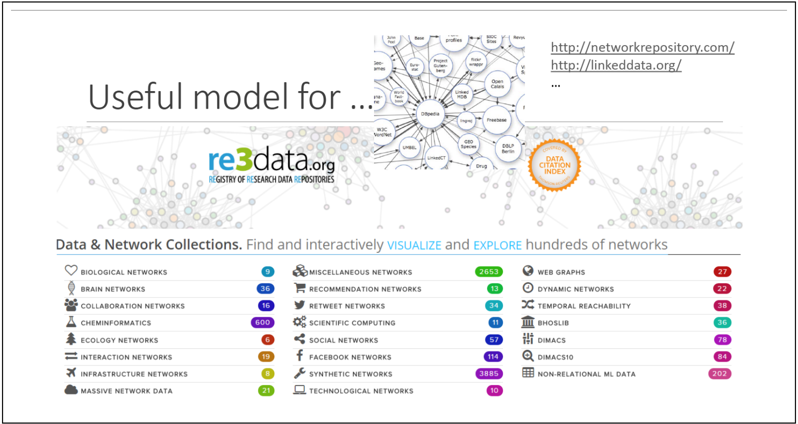
Figure: Weigthed graph, directed graph ad Hypergrah

- Undirected Graph : Vertices + Edges (vertices pairs) $\leftrightarrow$ Symetric binary relation
- Directed graph : Vertices + Arcs = Couple of vertices
- Hypergraphs : (hyper)Edges = Groups of vertices

Mostly study the topology (structure) of the graph, however graphs are often *weighted* $\rightarrow$ values labeling the vertices and arcs.

Graphs : becoming ubiquitous in sciences

some say pervasive ...



Graph representation, memory usage

A graph wtih n vertices m edges graph can be encoded (stored) as:

Its *Adjacency Matrix* $\rightarrow n \times n$ matrice.

for each vertex the list of neighbors $\rightarrow n + m$.

Structure may allow compression.

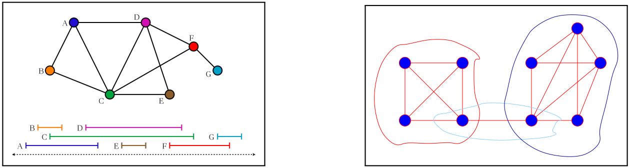


Figure: Interval graph, Union of 3 cliques.

Graph representation, memory usage (II)

Labeling of the vertices matters.

- Hypercube of dimension n + proper labeling $\rightarrow$ edges are encoded in the labels. With a *random* labeling edges appear as arbitrarly
- In a Tree one can always label the sons of a vertex consecutively. A node on store only the ID of its first neighbor and its degree.
- In a subgraph of a Grid one can always label the potential neighbors of a node as $0, 1, 2, 3$.

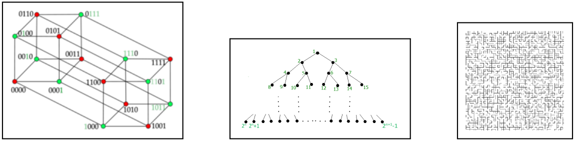


Figure: The hypercube of dimension 4, a Tree, and a subgraph of the grid.

Graph representation : alt representation, hidden constants

There are cases in which the natural representation is not the list of edges.

Using Alternative representation

- For a planar graph, a planar embeding (as example the list of *faces*) may be necessarly to run efficiently the algorithms.
- For an interval graph, the natural representation is to encode node as intervals.
- More generaly additonal information, such as a **Tree decomposition** may be usefull.

Graph representation : Very large graphs

Some specifities of very large graphs

- Constants do matter, using high level abstract data structures increase the memory footprint by a large factor. Efficient solutions are often ad-hoc.
- For very large graph finding and using some hidden specific structure or compressing the graph representation may be unfeasible.
- There are many cases in which some aspect of the structure are known in advance. As example graphs in the plane or physical space, graph for which a natural partitionning do exist.

Graph Properties and Graph Algorithms

We may distinguish two different but related types of questions :

A) Determine some properties of the graph per se.

B) Find some properties of the graph that allow to answer to the questions of type A.

A few Graph properties, type A questions

Statistics

- degree sequence, average distance, average connectivity
- (approx) count small subgraphs, (e.g. count triangles)
- correlation and clustering
  $(Prob[(u,v) \in E \mid \{(u,z),(z,v)\} \in E])$

global properties

- (strongly) connected components, (approximated) Minimum Dominating Set.
- Diameter.

A few Graph properties, type (A+B) questions (II)

Approximated representation & compression

- Find a Map $f : G \rightarrow R^d, l_1$ which "preserve" the distances $\frac{1}{\rho} \leq \frac{d(x,y)}{d(f(x),f(y))} \leq \rho$ (low distorsion mapping).
- Find a simple Random Graph model such that G looks like a *typical event* drawn from the associated distribution (bloc models, preferential attachment models, random graph in the Euclidian plane).
- Fit G into an existing random graph model.
- Determine *clusters in* G, Find congested cuts.

Distributed Algorithm model : Bulk Synchronous Parallel (BSP)

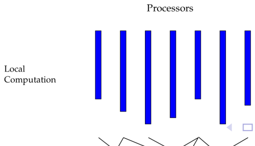
Goal:

One wish to use a cluster of muti-core computer to implement some of these algorithms.

BSP is a message-based iterative distributed algorithm. It runs a sequence of steps. During a step:

- All messages sent at the previous steps are delivered
- All vertices in the graph are scheduled for execution

The algorithm stops when no messages remain.



Practical Implementation for large graphs ?

key performance factors

- Can we manage to fit the graph in the RAM ?
- Multi-threading ! , NEF provides CPU with 48 threads.
- 48 cores $\sim$ PRAM with 48 processing unit.
- Can we split the data or space search without too much synchronization & communications.

Tricks : Sampling, Monte Carlo methods

- Some properties can be derived from a sample of the graph (select randomly a subset of V or a subset of E.
- $\rightarrow$ can work on a smaler graph that fits in the RAM.
- Distant computer can work on different "chunk" of the graph.

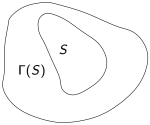
Challenges for Distributed Algorithms

BSP framework

- Each Node is assigned a set of vertices.
- Processing phase = local computations, communication via the RAM.
- Update phase = communications, synchronization,

Performance collapses if the graph is random (or if the vertices are mapped randomly on the nodes).

Amount of communications $|S|\bar{d}|S| \times \frac{|V \setminus S|}{|S|} \sim \bar{d}|S|$



Structured data → low communication overhead

Structure is important

- There are many cases in which communications are lower.
- for grid or planar network the border of a set S is only $\Theta(\sqrt{|S|})$.
- Bad news: for most random networks $|\Gamma(S)| = \Theta(|S|)$.

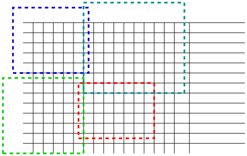


Figure: Grid-like graph, the data is affected to 4 computing nodes.

A practical case : A snapshot of twitter

Input graph

- Twitter data set (crawled by A. Legout/ INRIA -DIANA):
- 240GB on disk, 398M vertices, 23G edges
- average degree of 58 and max degree 24,635,412

Goals

- Compute the Strongly connected Components
- Compute the number of TT_3 and $K_{2,2}$.
- Compute the diameter.

Suitability of existing frameworks

mainly Two platforms: Giraph (atop Hadoop), GraphX (atop Spark).

many flaws

- limited support for graph and programming models
- poor memory performance (GraphX cant load our large Twitter graph dataset)
- unreliable (GraphX again) steep learning curve (GraphX is written in Scala) while lacking flexibility and documentation.
- unsuitable for experimentation (slow startup, low monitoring, etc)

Our own solution : The BigGrph library

- Develloped since 2014 upon Grph (single computation flow library)
- a Java library for the manipulation of very big graphs.
- originally developed in a joint-project of Coati , Scale and Diani Inria teams: Inria provided a Research Engineer during 4 years.
- Objective: running algorithms on bigdata -large graphs

BigGrph workflow

BigGrph's workflow consists of:

1. deploy the executable code
2. bootstrap the application (incremental using rsync ; takes less than a second)
3. partition the graph, by loading each piece on cluster nodes (arbitrary only)
4. perform the duistributed computation (BSP model) .
5. get the result

List of algorithms

- Single-source shortest path (Dijkstra, BFS)
- iFUB (Compute the diamter using a “few” shortest path runs).
- Page Rank
- Connected Strongly Connected components.
- Clustering coefficients, triangle counting
- Numerous stats (degrees, counting, etc)

BigGrph's performance ?

BigGrph :

- loads the graph 20x faster than Giraph
- computes BFS 3x faster than Giraph , 4x faster than GraphX
- uses 3x less memory than Giraph
- can load the big Twitter database (even on 24GB workstations) while GraphX cannot (even on 192GB cluster calculators)

Limitation of BigGrph

Why we decided not to build upon Grph

- Abstract high level library $\rightarrow$ memory intensive.
- not designed for multi-threading.
- designed to hide the implementation $\rightarrow$ not suitable for fine tuning.
- It was too complex (it took many days for our engineer to implement the SCC algorithm

Our solution

Jmaxgrph

- Just like most of others, it is written in Java, because is it the most used, taught, clean, portable, complete language/platform today
- Low memory footprint.
- Non blocking data structures
- target platform: Unix 64-bit (all Linux distributions, MacOSX,
- Use straightforward array stuctures.

Important side functionalities

The framework offer non core functionalities that are essential.

- deploy the executable code
- bootstrap the application
- partition the graph, and load each piece on cluster nodes
- execute in parallel, communicate
- get and centralize the results

Computing strongly connected components

- Tarjan algorithm cannot be implemented transparently.
- Instead we compute local SCC → reduce the instance size.
- The we perform 2 BFS.
- Last we call the algorithm recursively.

Performance Computation time on the NEF cluster:

One node (512 GB RAM)	7:00 hours
8 nodes	3:10 (gc)
12 nodes	2:20
16 nodes	2:35 (more messages)

Largest SCC size = $256M$ vertices (64% of —V—); 141 M of size 1; 651,000 Of size 2; ... typical random graph phenoma of isolated singleton or pairs.