

(sparse) Very Large Graphs  
*A Very New Kind of (Real) Graphs:*  
*Some Problems & and Some Algorithms*

Robert Erra & Alexandre Letois & Mark Angoustures  
 Projet ING 2 Majeure SCIA 2021

19 mai 2021

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
 Letois & Mark  
 Angoustures  
 (s)VLG

A (Sparse) Very  
 Large Graph ?

Graphs are on  
 the Rise!

Basics  
 definitions

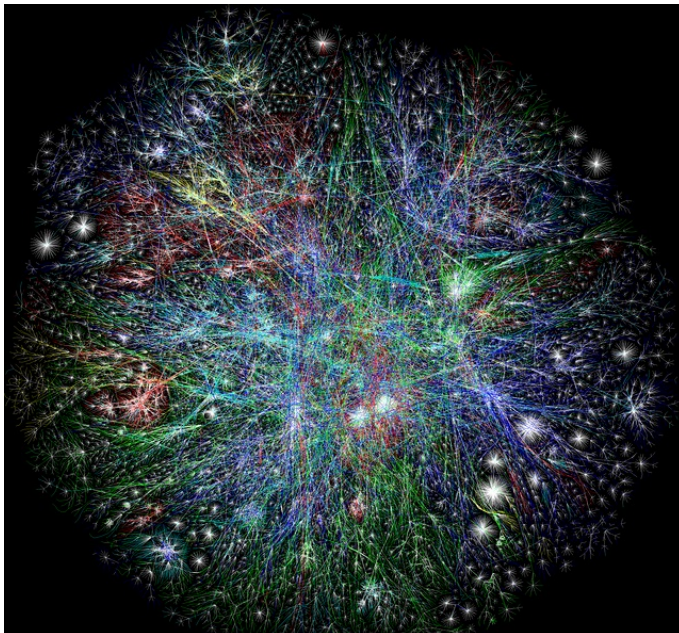
Some  
 interesting  
 (real) Problems

Basics  
 algorithms

A famous  
 algorithm :  
 Pagerank

Very Large  
 Graphs : The  
 $O(n)$  Wall of  
 Big Data

# An example of a (s)VLG (Ref [00]) : a partial view of Internet



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Version $\beta_0$

- 1 Ces notes sont distribuées telles quelles et sont destinées à évoluer.
- 2 Chaque nouvelle version sera mise à disposition lorsque le nombre de changements sera significatif.
- 3 Toute remarque, toute proposition, tout signalement d'erreur, toute idée : n'hésitez pas : [verylargegraphs@gmail.com](mailto:verylargegraphs@gmail.com) (ou Teams).
- 4 Par avance merci.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

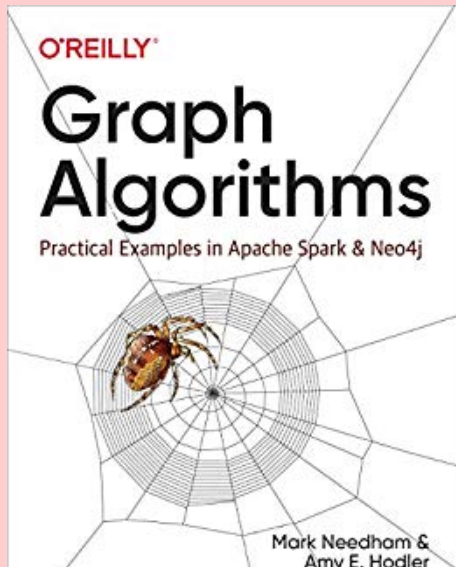
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## The Rising of Graphs (or Graphs are on the Rise)



R. Erra & A. Letois & Mark Angoustures (s)VLG

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very **Large** Graphs

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## Work to do ?

- ① 12 hours : 4 "weeks"
- ② Week 1 : 3 hours of presentation
- ③ Weeks 2, 3 and 4 : 9 hours of Laboratory
- ④ You will have to choose a project (Week 2).

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ① A (Sparse) Very Large Graph ?

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse ) Very Large Graphs [(s)VLG]

## A (Sparse) Very Large Graph [(s)VLG] ? ...

... is a graph,  $G = (V, E)$ , but such that :

- $G$  has a large number  $n = |V|$  of nodes/vertices and  $m = |E|$  edges ;
- with  $m$  (number of edges) : from some millions to some billions ;
- $G$  is *sparse* :  $m = O(n)$  ;
- (we can add this) : it comes from a real-world dataset.

And we can add : these (s)VLGs are generally not static, there are *living* : they evolve dynamically.

So ...

A (Sparse) VLG is a *sparse, large, (possibly) time-evolving graph* that comes from real-world.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ② Graphs are on the Rise!

A (Sparse) Very  
Large Graph ?

**Graphs are on  
the Rise!**

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

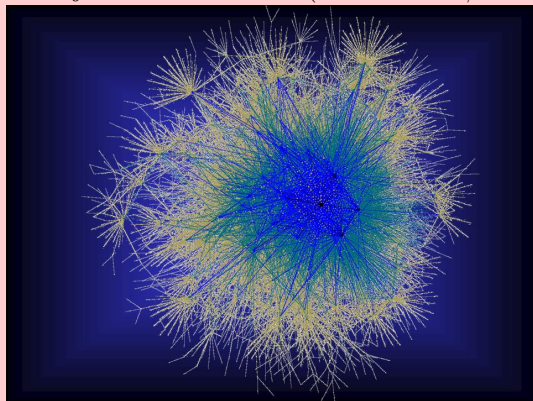
A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## Real-World Data : From [1]

A graph of the BGP (Gateway Protocol) web graph, consisting of major Internet routers (6400 vertices/13000 edges)



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

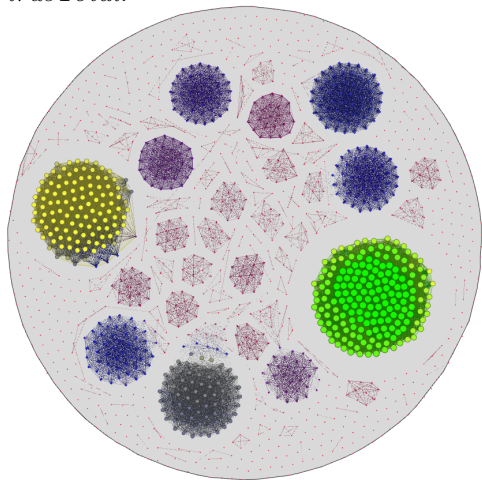
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

*...where we explored some of the idiosyncrasies of mass-malware vs. the ones in targeted malware ... a reasonably diverse corpus of recent malware obtained from VirusTotal.*



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Real-World Data : From [2]

... On a coarse-grained level, the statistics of bio-molecular networks can be studied at the level of the network topology (*i.e.*, the ensemble of its nodes and links).



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

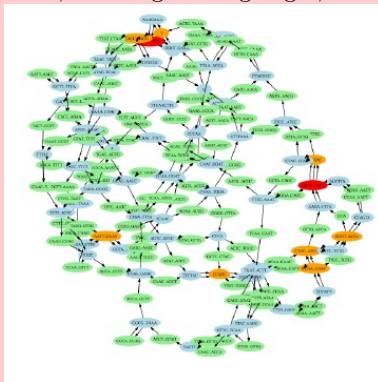
A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

## Real-World Data : From [3]

protein-protein and protein-DNA interaction graphs. Topics include predicting protein function from protein interaction networks, comparing interaction networks from multiple organisms, finding common network motifs, inferring missing edges, and visualizing



biological graphs.

(*sparse*) Very  
Large Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

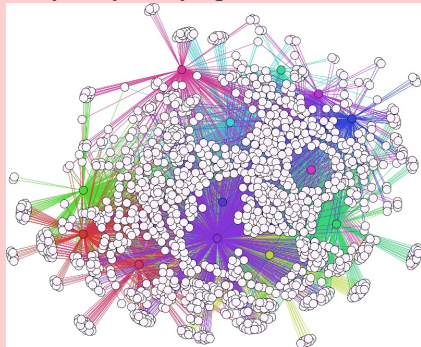
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Real-World Data : From [4]

In the *Social Epidemics, Online Social Networks, and Graphs* course, students learn about graph theory, statistics and computational data analysis by studying their own online social network data.



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

**Graphs are on  
the Rise!**

Basics  
definitions

Some  
interesting  
(real) Problems

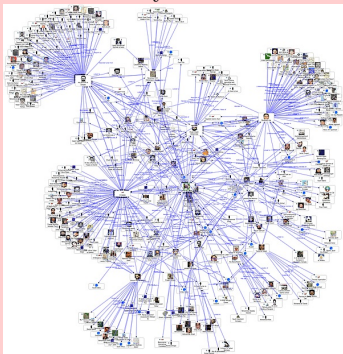
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Real-World Data : From [5]

From a visual standpoint, some clusters and centrality are visible.  
But the density of information makes it difficult to see all the centrality aspects. ...and the program instantly calculates the Social Network Analysis Metrics for the items on the chart.



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

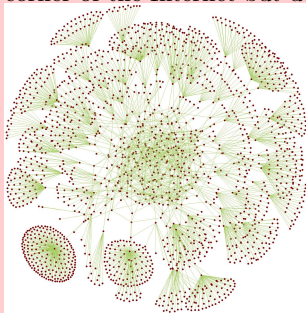
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Real-World Data : From [6]

...a map of the Internet generated by new algorithms ... at UC San Diego. [...] But it is no ordinary map. It is a (mostly) randomly generated graph that retains the essential characteristics of a specific corner of the Internet but doubles the number of nodes.



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ③ Basics definitions

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

**Basics  
definitions**

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## A Graph ?

- $G = (V, E)$
- $V$  : set of nodes/vertices,  $|V| = n$
- $E$  : set of edges,  $|E| = m$ ;  $E \subset \{1, \dots, n\} \times \{1, \dots, n\}$
- $G$  can be undirected :  $(i, j) \in E \Rightarrow (j, i) \in E$
- or  $G$  can be directed :  $(i, j) \in E \not\Rightarrow (j, i) \in E$
- A simple graph :  $(i, i) \notin E \Rightarrow$ , no loops; and no multiple edges
- A node or an edge can have attributes (value)
- The degree of a node is the number of its adjacent nodes.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

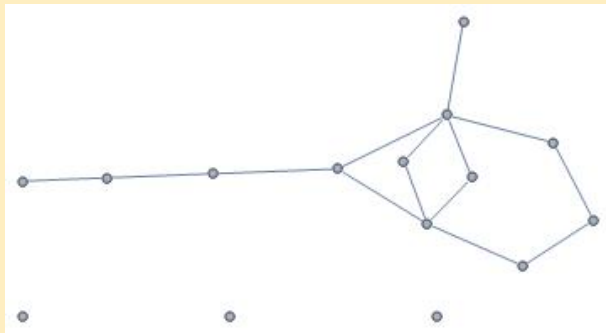
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

## An undirected Graph of 15 nodes



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

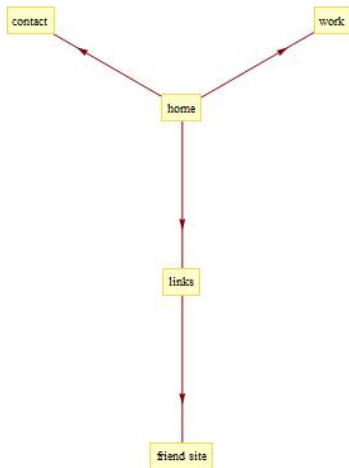
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## A directed Graph



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

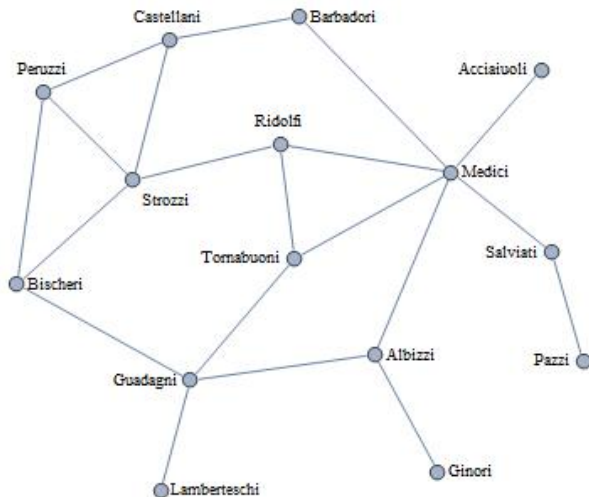
Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

# (sparse ) Very Large Graphs [(s)VLG]

## A real (small) example : The Medici graph



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

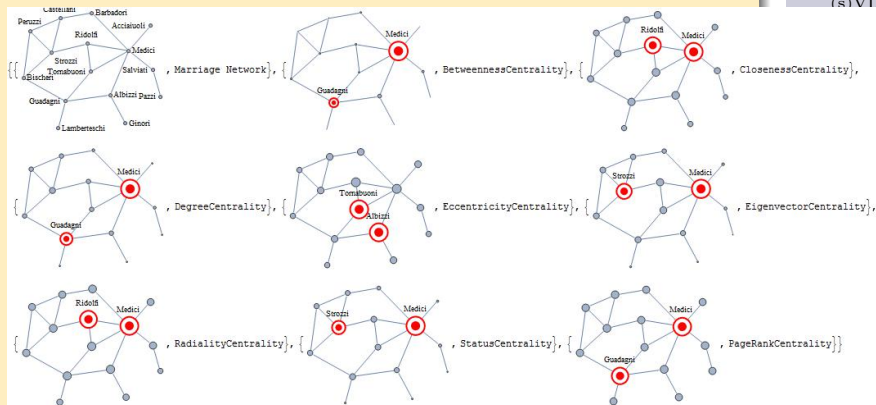
Very Large Graphs : The  $O(n)$  Wall of Big Data

# (sparse) Very Large Graphs [(s)VLG]

(*sparse*) Very  
Large Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A real (small) example : some results about *node centralities* of the Medici graph



## Walks, trails, paths

- 1 A walk is an alternate sequence of vertices and edges, example :  $\{v_2, e_{23}, v_3, e_{37}, v_7\}$
- 2 The length of a walk is the number of edges
- 3 A trail is a walk such that no edge occurs more than once
- 4 A path is a trail such that no (internal) vertex occurs more than once
- 5 The length of a walk/trail/path is the number of its edges
- 6 The distance between  $i$  and  $j$  is the length of the shortest walk between them.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ④ Some interesting (real) Problems

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Some interesting (real) problems

- 1 PageRank : the (famous) ranking algorithm from Google : polynomial (quasi-linear) in floating point arithmetic (so considered as a fast algorithm if the large graph is sparse)
- 2 Diameter and Center of Graphs : polynomial exact algorithms are impracticable [ $O(n^3)$  or  $O(nm)$ ] : develop fast algorithms [ $O(n)$  or  $O(n \log(n))$ ]
- 3 Community : NP-complete (so no polynomial algorithm known)
- 4 A difficult but very interesting problem : compute the approximate diameter and radius/center of the giant component of the graph of the web!

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## (s)VLG : source of graphs

- Graphs from the web
- Graphs from social networks
- Graphs in biological databases
- CFG of large executable graphs
- etc.
- New discipline : *Graph Database Problems*
- SNAP (Stanford Network Analysis Project) :  
<http://snap.stanford.edu/> with a lot of graphs at  
<http://snap.stanford.edu/data/index.html>

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑤ Basics algorithms

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Some classical graph algorithms

- BFS : Breadth First search Search (polynomial algorithm)
- DFS : Depth First Search (polynomial algorithm)
- Diameter : the longest shortest path between two nodes (polynomial algorithm)
- Diameter : it is also the maximum of all eccentricities
- Radius : it is the minimum of all eccentricities
- The All Pairs Shortest Paths (APSP) problem : we want all distances between each couple of nodes (polynomial algorithm).

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑥ A famous algorithm : Pagerank

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## The "web graph" ...

- ❶ is huge (probably today  $> 6 \times 10^{10}$  nodes)
- ❷ is moving /changing (dynamical algorithms or incremental algorithms are needed)
- ❸ is not semantic : just hyperlinks !
- ❹ has a huge giant strong connected component with a lot of "islands"
- ❺ is directed (or oriented) but not weighted (unweighted).

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise !

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## PageRank : The Perron-Frobenius Theorem

Let  $A \in \mathbb{R}^n \times \mathbb{R}^n$  be a positive, column stochastic matrix, *i.e.* each column has a sum=1, then :

- 1 is an eigenvalue of multiplicity one.
- 1 is the largest eigenvalue : all the other eigenvalues are in modulus smaller than 1.
- the eigenvector corresponding  $v$  to eigenvalue 1 has all entries positive :  $v = (v_1, \dots, v_n)$  with  $v_i > 0$ .
- In particular, for the eigenvalue 1 there exists a unique eigenvector  $v^*$  with the sum of its entries equal to 1 :  $A.v^* = v^*$ .

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

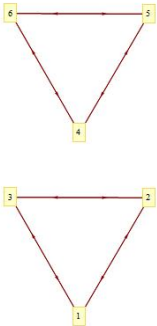
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Problem with disconnected graphs



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

## PageRank : The Brin & Page's Algorithm

Define the Page Rank matrix (aka the Google matrix) :

$$M = (1 - p)A + p.B$$

- $A$  : the transition/adjacent matrix of the " full web graph"
- $p \in ]0, 1[$  : a constant, the famous *damping factor* (typical value : 0.15)
- $B = C/n$ , with  $C(i, j) = 1$  for all  $i, j$
- $M$  remains a column stochastic matrix
- $M$  has only positive entries.

The PageRank vector is the **dominant right eigenvector of  $M$** . We can compute it with the *power algorithm*.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## So is it quite easy to do a PageRank algorithm ?

- For a large and dense graph : No. Why ?
- If  $A$  is a  $(10^{10}, 10^{10})$  dense matrix you need  $O(10^{20})$  to store  $A$  : IMPOSSIBLE
- So : if the graph is sparse, we store a "compressed" representation of  $A$ .
- Use the fact that  $A$  is sparse : a list of lists (list of adjacent nodes for each node)
- So : for a sparse Very Large Graph : PageRank is considered as an "easy" algorithm ...

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise !

Basics  
definitions

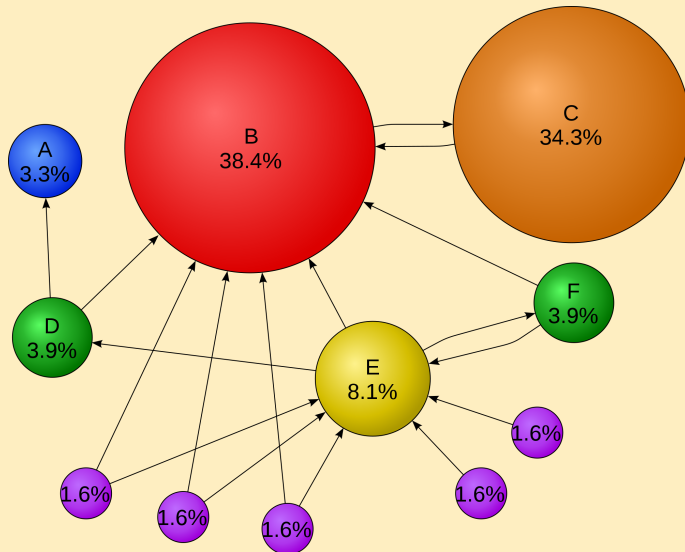
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## A toy example



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

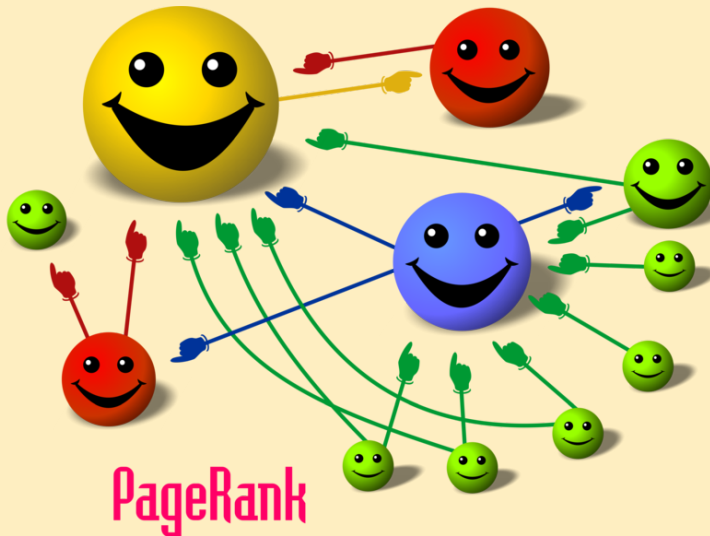
Some interesting (real) Problems

Basics algorithms

A famous algorithm : PageRank

Very Large Graphs : The  $O(n)$  Wall of Big Data

## A funny cartoon view example (Ref Wikipedia)



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
PageRank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑦ Very Large Graphs : The $O(n)$ Wall of Big Data

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Be careful with really *Big Data* : **Small Powers** always **Win**

For a very large set of data, for example with more than  $10^6$ , we can not use, even if there exists, polynomial algorithms of  $O(n^{1+\epsilon})$ .

For  $n = 10^9$

① and  $\epsilon = 0.1$  we have  $O(n^{1+\epsilon}) = n^{1.1} = 7.94328 \times 10^9$

② and  $\epsilon = 0.5$  we have  $O(n^{1+\epsilon}) = n^{1.5} = 3.16228 \times 10^{13}$

③ and  $\epsilon = 1$  we have  $O(n^{1+\epsilon}) = n^2 = 1. \times 10^{18}$

④ and  $\epsilon = 1.5$  we have  $O(n^{1+\epsilon}) = n^{2.5} = 3.16228 \times 10^{22}$

⑤ and  $\epsilon = 2$  we have  $O(n^{1+\epsilon}) = n^3 = 1. \times 10^{27}$  !!!!!!!!!!!

(3) is expensive, (4) and (5) out of reach!!! A complexity of  $O(n)$  or  $O(n \log(n)^{1+\epsilon})$  is a real wall.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

Be careful with really *Big Data* : there is a practical but real wall

- 1 Any (classical) polynomial algorithms in  $O(n^2)$  or  $O(n^3)$  is useless !
- 2 Any (classical) polynomial algorithms in  $O(n^2)$  or  $O(n^3)$  have to be approximated by a  $O(n)$  algorithm (or in some cases  $O(n \log(n)^{1+\epsilon})$ )
- 3 The  $O(n)$  (or  $O(n \log(n)^{1+\epsilon})$ ) is a true Wall !

## An example

- 1 Let  $G$  has  $n = 10^8$  nodes
- 2 So  $n^3 = 10^{24}$
- 3 With a computer doing  $10^{10}$  FLOPS
- 4 A  $O(n^3)$  algorithm will take  $3.17098 \times 10^6$  years !

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise !

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑧ How to compute the diameter of a (s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Diameter & Radius & Center

- Eccentricity of a vertex  $v \in V$  : maximum graph distance between  $v$  and all other vertices of  $G$ .
- For a disconnected graph, all vertices are defined to have infinite eccentricity.
- Eccentricity of  $v$  :  $Ecc(v) = \max_{y \in V} d(v, y)$
- *Maximum eccentricity* : the **graph diameter**. [MAX MAX MIN]
- $Diameter(G) = \max_{x \in V} Ecc(x) = \max_{x, y \in V} d(x, y)$ .
- *Minimum eccentricity* : the **graph radius**. [MIN MAX MIN]
- $Radius\ R(G) = \min_{x \in V} Ecc(x)$
- **Center** : the **set** of vertices with eccentricity equal to the graph's radius.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## Diameter

- Naive but exact algorithms examine each vertex in turn and performs a BFS starting at the chosen vertex.
- Such a sweep starting at vertex  $x$  immediately determines  $Ecc(x)$ .
- But exact algorithm have time complexity in  $O(n^3)$
- For a sparse graph :  $O(nm)$  if  $m \ll n^2$ .
- Too expensive for (s)VLGs [Do not forget  $m = O(n)$ ]
- There exists  $O(n^\omega)$  algorithms with  $\omega \in ]2, 3[$  but not enough "practical" (based on fast matrix multiplication algorithms).

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Diameter

- For a NP-complete or NP-hard problems we compute an *approximate* solution
- Such algorithms are called approximation algorithm
- (Approximation algorithms are algorithms used to find approximate solutions to NP-hard optimization problems)
- We will do the same for all problems with a (s)VLG
- We will search for a not too expensive algorithm for (s)VLGs
- The ideal : a linear algorithm that gives a very good approximation.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑨ Approximation algorithms for the Diameter Problem

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

Basic ideas/1 : For  $x \in V$  then

- $Ecc(x) \leq D(G) \leq 2Ecc(x)$
- Proof of the lower bound :  $Ecc(x) \leq D(G)$  : obvious.
- Proof of the upper bound  $D(G) \leq 2Ecc(x)$  :
  - 1 Take an internal vertex  $z$  between  $x$  and  $y$  such that  $Ecc(x) = (x, y)$
  - 2 Then  $Ecc(x) = d(x, y) \leq d(x, z) + d(z, y) \leq 2Ecc(x)$ .

Idea :

- 1 Use a small set of vertices to refine the bounds, we will have :  $e_L \leq D \leq e_U$ .
- 2 If  $e_L = e_U$  then we have found the true value  $D(G) = e_L = e_U$  !

We will call this type of algorithms **self-checking algorithms**.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise !

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

A toy example : How to use the inequality ...

$$\forall x \in V : Ecc(x) \leq D(G) \leq 2Ecc(x)?$$

- Take  $u_1 \in V$ .
- Compute  $e_1 = Ecc(u_1)$  (with a BFS traversal)
- So we first have :  $R \leq e_1 \leq D \leq 2e_1$
- Now Take  $u_2 \in V$ , different from  $u_1$  of course.
- Compute  $e_2 = Ecc(u_2)$  (with a BFS traversal)
- So we have
$$R \leq \min(e_1, e_2) \leq \max(e_1, e_2) \leq D \leq 2 \min(e_1, e_2)$$

More generally : we will have for  $k$  points/BFS :

$$R \leq \min(e_1, \dots, e_k) \leq \max(e_1, \dots, e_k) \leq D \leq 2 \min(e_1, \dots, e_k)$$

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Basic ideas/2 : a first strategy

- Take  $u \in V$ .
- Compute  $v$  such that  $d(u, v) = Ecc(u)$  with a BFS traversal
- Compute  $w$  such that  $d(v, w) = Ecc(v)$  with a BFS traversal
- This is called the *Magic Double Sweep algorithm*.
- + Ref [23] : iterate and refine the lower and the upper bounds
- ++ Ref [23] : use upper bounds given by spanning tree (which is a subgraphs of  $G$ )
- Of course, again, if the lower bounds and the the upper bound are equal : we have **found** the true diameter.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Basic ideas/3

The Double Sweep algorithm is a special case of a more general algorithm.

### Strategy :

- Take  $u \in V$ .
- Compute the set  $F$  of vertices  $v$  such that  $v \in F : d(u, v) = Ecc(u)$
- Iterate and refine the lower and the upper bounds

### Tactic :

- Choose another  $v \in F$ .
- Compute again the set  $F$  of vertices  $w$  such that  $w \in F : d(v, w) = Ecc(w)$
- Iterate and refine the lower and the upper bounds and so on ...

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

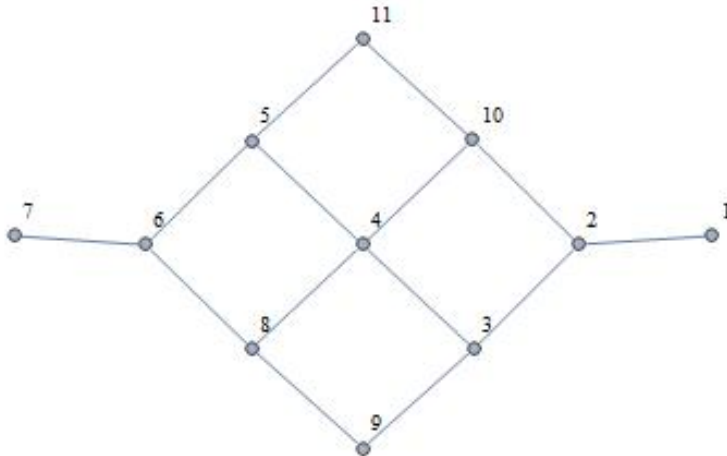
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## The Shuriken Graph :



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures  
(s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm :  
Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data



## An example : the Shuriken Graph (see previous slide)

- Let  $u = 11$  and do a BFS : then  $v = 9$  with  $d(u, v) = 4$ .
- Do a second BFS : then  $w = 11 = u$  and so again : 4.
- But  $D(G) = 6$  with  $D(G) = d(1, 7) = 6$ .
- A conjecture (you don't have to test it) :
  - 1 If  $BFS(BFS(u)) = u$  with  $v = Last(BFS(u))$  but  $D(G) \neq d(u, v)$  and the diameter is not given by a BFS on one of the nodes of the last level then the diameter is given
    - by a BFS on one of the nodes of the **last level** (if  $v$  is not unique).
    - or, by a BFS on one of the nodes of one of the **last but one** level, or not so far.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

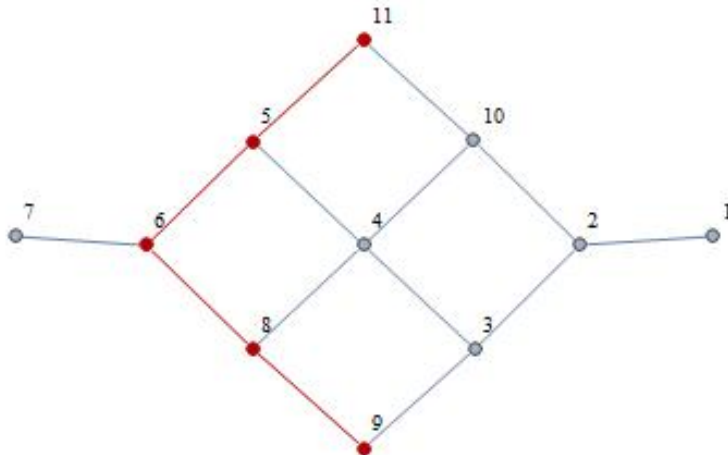
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

The Shuriken Graph : BFS from 11 to 9 and BFS from 9 to 11 : unfortunately length 4



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

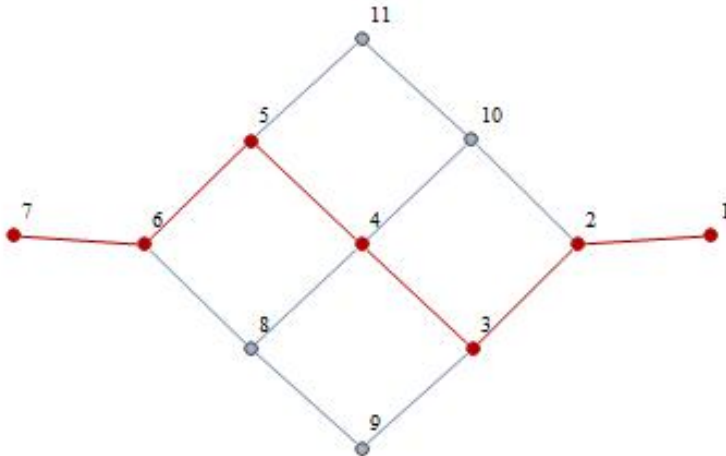
Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

## The Shuriken Graph : BFS from 7 to 1 : length 6



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

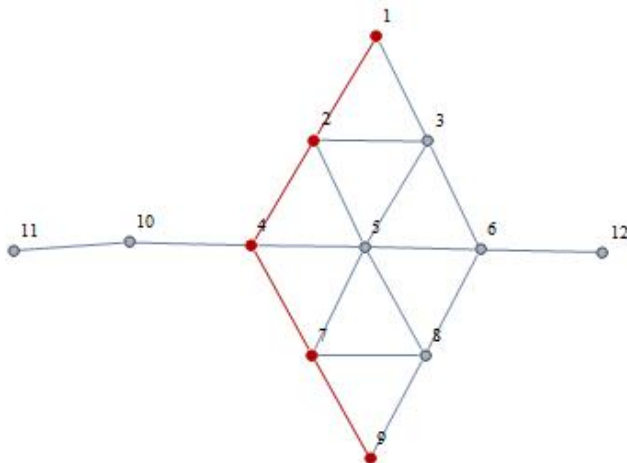
Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

# (sparse ) Very Large Graphs [(s)VLG]

A variant of the Shuriken Graph : BFS From 1 to 9 and  
BFS from 9 to 1 : length 4



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

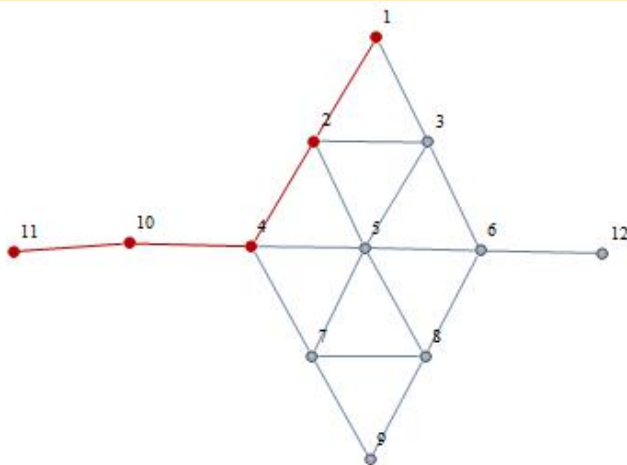
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse ) Very Large Graphs [(s)VLG]

A variant of the Shuriken Graph : BFS from 1 to 9  
(depend of the BFS), length 5



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

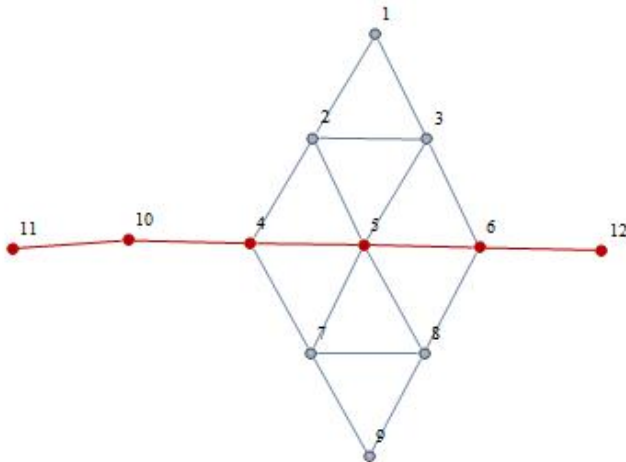
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

A variant of the Shuriken Graph : BFS from 11 to 12 :  
true diameter 5



(*sparse*) Very  
Large Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## A (Sparse) Very Large Graph ?

## Graphs are on the Rise!

## Basics

### definitions

## Some interesting (real) Problems

## Basics algorithms

A famous algorithm :  
Pagerank

## Very Large Graphs : The $O(n)$ Wall of Big Data

## Next week

- Go to <https://www-complexnetworks.lip6.fr/magnien/Diameter/>
- Read the paper (if possible)
- Download the files (diam.c and prelim.c and the graphs [(s)VLG] (see *data* on the web page))
- Compile, Test, Understand.
- (not this year) : Play with the Fringe and the Last But One Fringe.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑩ Two (different but similar) Problems

Known approximate algorithms

A new algorithm for the Graph Problem

Some Open Problems as a Conclusion

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



We consider two different but similar problems :

- ① *The Graph Problem* : we want an approximation of the diameter and the center of a graph, supposed sparse and very large. Exact values are of course interesting.
  - ② *The Point Set Problem* : idem for a very large set of high dimensional points.
- Graph  $G = (V, E)$  :  $|V| = n$  nodes and  $|E| = m$  edges
  - Point Set  $\mathcal{S}$  :  $|\mathcal{S}| = n$  points ,  $\mathcal{S} \subset \mathbb{R}^d$
  - Hypothesis :  $n$  very large,  $d \gg 3$
  - We suppose we can compute a distance  $d(x, y)$  between any two nodes of  $G$  or points of  $\mathcal{S}$ .

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

For both problems, we consider data from real-world datasets, so :

- Very large means : hundred of millions or billions of nodes/points.
- Graphs are sparse :  $m = O(n)$
- For the Graph Problem classical exact algorithms can not be used because of their cubic complexity  $O(n^3)$
- Points are high dimensional and some algorithms are quite expensive if the dimension is high.

There is growing interest in these two problems

- ① The *Graph Problem* is concerned with *web graphs*
- ② The *Point Set Problem* appears when we want to measure the quality of clusters obtained with Machine-Learning algorithms like K-means or KNN.

(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

$G$  : unweighted (or weighted) undirected graph

- *Eccentricity* of a node  $u$  as :  $ecc(u) = \max_{v \in V} d(u, v)$
- *Set Eccentricity* of a node  $u$  as :  
 $\mathcal{E}](u) = \{v | d(u, v) = ecc(u)\}$
- *Diameter* :  $D = \max_x ecc(x) = \max_{x,y} d(x, y)$
- *Radius* :  $R = \min_x ecc(x) = \min_x \max_y d(x, y)$ .
- *Center* : set of all vertices of minimum eccentricity (radius!)
- Some inequalities for the Graph Problem :

$$\forall u : ecc(u) \leq D(G) \leq 2ecc(u)$$

$$R(G) \leq D(G) \leq 2R(G)$$

- We will use these definitions for both problems !

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Graph Problem

- ① For large  $n$  : any exact  $O(n^3)$  or  $O(n^2)$  algorithm is computationally impracticable
- ② We can only use  $O(n)$  or  $O(n \log(n))$  approximate algorithms

## Point Set Problem

- ① For  $d = 2$  or  $3$  there is a fast algorithm
- ② Compute the Convex Hull
- ③ Diameter points are on the Convex Hull
- ④ For  $d > 3$  the Convex Hull can be computed only with a  $O(n^{d/2})$  algorithm
- ⑤ So, again : we can only use  $O(n)$  or  $O(n \log(n))$  approximate algorithms

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑩ Two (different but similar) Problems

Known approximate algorithms

A new algorithm for the Graph Problem

Some Open Problems as a Conclusion

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# Strategies and Tactics for the Graph Problem

Almost all fast approximate algorithms follows the following

## Multiple-Sweep Strategy

- ① Choose  $u \in V$ , make a *Breadth First Search* (BFS) : we will have a node  $v \in \mathcal{E}cc(u)$  so :  $v = \arg ecc(u)$
- ② Use a (small) set of vertices to refine the bounds :  $e_L \leq D(G) \leq e_U$
- ③ If  $e_L = e_U$  then we have found the true value  $D(G) = e_L = e_U$  : it's a **self-checking algorithm** !

## Tactics ? How to choose $u$ ?

- ① Choose  $u$  of low degree/high degree/random degree ?
- ② Our tactic : compute an approximation  $c$  of the Center and choose some nodes  $u \in \mathcal{E}cc(c)$

(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise !

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : PageRank

Very Large Graphs : The  $O(n)$  Wall of Big Data

# Strategies and Tactics for the Point Set Problem

The fastest known approximate algorithm :

Malandain & Boissonat [2001]

- ❶ Choose  $u \in \mathcal{S}$
- ❷ First Sweep : Find a point  $v \in \mathcal{Ecc}(u)$  so :  
 $v = \arg ecc(u)$
- ❸ Do (possibly) Multiple Sweeps
- ❹ Consider the "best" quasi diameter  $[u, v]$  obtained
- ❺ Compute  $c$  : the middle of  $[u, v]$
- ❻ Define  $r = d(u, v)/2$
- ❼ Find all points in the ball  $B(c, r)$
- ❽ Eliminate all these points from  $\mathcal{S}$
- ❾ Iterates with the remainder points
- ❿ Stop when *stopping criterium* is true.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# Multiple Sweep for the Graph Problem

(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

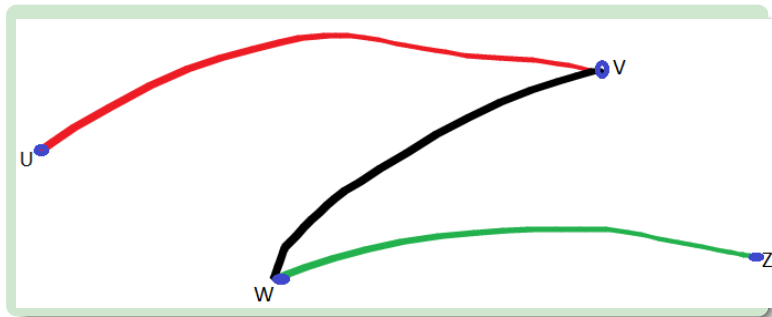
Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm :  
Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data





(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑩ Two (different but similar) Problems

Known approximate algorithms

A new algorithm for the Graph Problem

Some Open Problems as a Conclusion

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# A new algorithm for the Graph Problem 2/

## Description

- 1 Choose  $u \in V$
- 2 First Sweep : Find a point  $v \in \mathcal{E}cc(u)$  so :  
 $v = \arg ecc(u)$
- 3 Do (possibly) Multiple Sweeps
- 4 Consider the "best" quasi diameter  $[u, v]$  obtained  
(and  $e_L, e_U$ )
- 5 Compute  $c$  : the middle of  $[u, v]$
- 6 Define  $r = \lfloor d(u, v)/2 - 1 \rfloor$  (or  $r = \lfloor d(u, v)/2 - 2 \rfloor$ )
- 7 Find all points in the ball " $B(c, r)$ "
- 8 Eliminate all these points from  $V$
- 9 Iterates with the remainder points to refine  $e_L, e_U$
- 10 If we want the exact diameter ; iterate till  
 $e_L = D(G) = e_U$ .

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

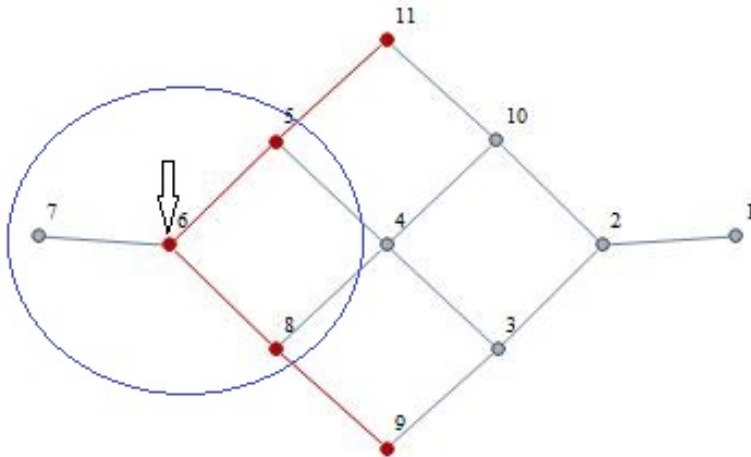
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# A new algorithm for the Graph Problem 1/

The algorithm on a toy example : the *Shuriken* Graph :  
 $u = 11$ , BFS gives  $ecc(u) = 4 = d(u, v = 9)$



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
 Letois & Mark  
 Angoustures  
 (s)VLG

A (Sparse) Very  
 Large Graph ?

Graphs are on  
 the Rise!

Basics  
 definitions

Some  
 interesting  
 (real) Problems

Basics  
 algorithms

A famous  
 algorithm :  
 Pagerank

Very Large  
 Graphs : The  
 $O(n)$  Wall of  
 Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑩ Two (different but similar) Problems

Known approximate algorithms

A new algorithm for the Graph Problem

Some Open Problems as a Conclusion

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# Conclusion : some open problems

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## About the "new" algorithm :

- *Approximate* diameter : it can be very fast (tests with real graphs of  $4 \cdot 10^8$  nodes)
- *Exact* diameter :
  - ❶ Can we obtain in  $O(n)$  the true value for some real world sparse large graphs ?
  - ❷ At least for graphs with low hyperbolicity ?
  - ❸ Or for a specific class of graphs ?
- Can we find a "self-checking" algorithm for the Point Set Problem ?

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ① Representing/Storing a graph

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Sparse ?

- (Wikipedia) : a sparse matrix is a matrix in which most of the elements are zero.
- By contrast, if most of the elements are nonzero, then the matrix is considered dense.
- The fraction of zero elements (non-zero elements) in a matrix is called the *sparsity* (density).

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

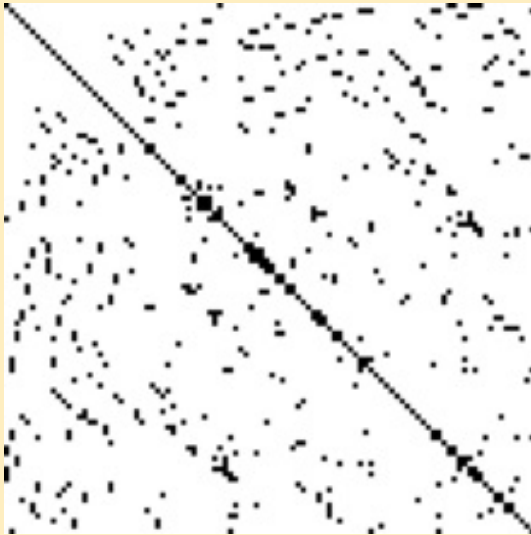
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

A Sparse Matrix/Graph (Black= non zero element)



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## The Yale Format for storing a sparse matrix

- Store only the non zero elements, and the index (i,j) in two separate arrays

- Example :  $A = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 5 & 4 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 2 & 0 \end{bmatrix}$

- will be stored with

- 1  $A = [1, 5, 4, 3, 2]$
- 2 with  $IA = [1, 2, 2, 3, 4]$
- 3 and  $JA = [3, 1, 2, 2, 3]$

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## The LIL Format :List of Lists

- Store one list per row, *i.e.* per node
- With each entry containing the column index and the value.
- Sorted by column index for faster lookup.
- Very good for incremental matrix construction.

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## List of degrees and edges :[21]

\* INPUT FORMAT \*

\*\*\*\*\*

- The first line must be the number  $n$  of nodes ;
- Then comes a series of lines of the form 'i j' meaning that node 'i' has degree 'j',
- And then a series of lines of the form 'u v' meaning that nodes 'u' and 'v' are linked together.
- The nodes must be numbered from 0 to  $n-1$ . There must be no loop (u,u).

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## List of edges : Example : [21]

3

0 2

1 2

2 2

0 1

0 2

2 1

(3 nodes, thus numbered from 0 to 2,  
node 0 has degree 2, node 1  
has degree 2, and node 2 has degree 2  
too, and the links are 0 1,  
0 2 and 2 1)

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Store your (sparse) matrix : and save Space & Time

A toy example in scikit/python :

$$\begin{bmatrix} 14 & 0 & 19 & 0 \\ 0 & 17 & 0 & 0 \\ 0 & 0 & 18 & 0 \\ 0 & 0 & 0 & 15 \end{bmatrix}$$

```
>>> # csr_matrix(arg1[, shape, dtype, copy])
>>> # Compressed Sparse Row matrix
>>> from scipy import sparse
>>> from numpy import array
>>> I = array([0,0,1,2,3])
>>> J = array([0,2,1,2,3])
>>> V = array([14,19,17,18,15])
>>> A = sparse.csr_matrix(I,J,V,shape=(4,4))
```

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
O(n) Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## 12 Complements

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## Complements

The rest of the slides are just complements, there do not concerne the projects of this year. There are related to previous years.

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## 13 Fringe and Last But One Fringe Algorithm

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## The Fringe and the Last But One Fringe

### Algorithme 1 : The Fringe and the Last But One Fringe

(See [101] and [103,104])

**Donnees** : a graph  $G$  (connex) of  $n$  nodes ;

**Procedures externes** : **BFS** ;

**Sortie** : Approximate Diameter( $G$ )

**Debut** :

(1) Choose a vertex  $x_0$  (example : maximum degree) ;

(2) Use a BFS to compute  $d(x_0, v)$  ;

for all  $v \in \{0, \dots, n-1\} \setminus \{v_0\}$   $K = Ecc(x_0)$  ;

(3)  $Inf = K$  ;  $Sup = 2K$  ;

(4) Take the Fringe  $F_k = \{f_1, \dots, f_w\}$

(...) the last level of  $BFS(x_0)$  ;

**Continue**

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise !

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# Fringe and Last But One Fringe Algorithm

## The Fringe and the Last But One Fringe

### Algorithm : The Fringe and the Last But One Fringe

(See [101] and [103,104])

**For**  $i = 1$  **To**  $w$  ;

    Compute  $BFS(f_i)$  ; this gives  $Ecc(f_i)$

**If**  $Ecc(f_i) > Inf$  **Then**

$Inf = Ecc(f_i)$  ;

        ‘[If]  $Inf = Sup$  **Then**  $\{D = Inf$  ; Return  $D$  ;

**EndIf**

**EndFor** ;

**If**  $Ecc(f_i) > Inf$  **Then**  $Inf = Ecc(f_i)$  ;

(5) **If**  $Inf \geq Sup - 2$  **Then**  $\{D = Inf$  ; Return  $D$  ; }

**Else**

$\{Sup = Sup - 2$  ;  $k = k - 1$  ; }

**Continue** with the Previous Fringe **Goto** (4) ;

**Fin.**

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## 14 Communities in a (s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Community in a graph (see [102] and [106] and 107)

- groups of vertices within which connections are dense,
- but between which connections are sparser.
- (See next figure).

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

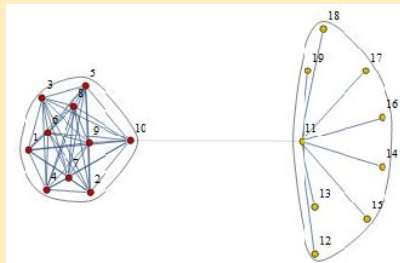
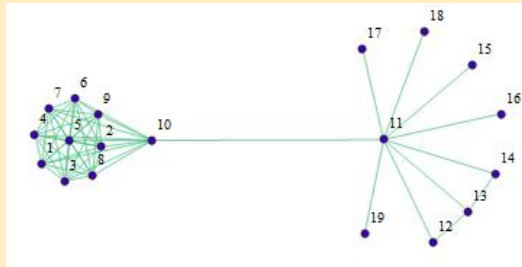
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

## A toy example and its communities



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

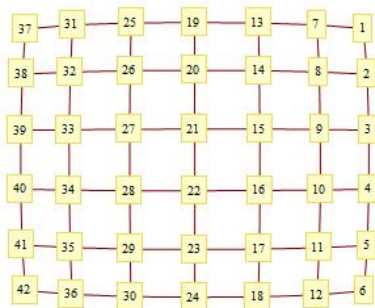
Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Another toy example



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

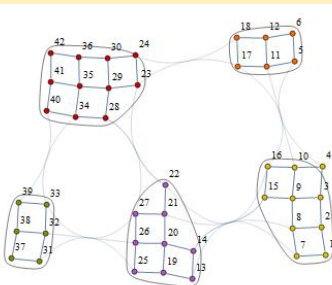
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

## Its communities



(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

<http://digitalinterface.blogspot.fr/2013/05/community-detection-in-graphs.html> : 3 communities

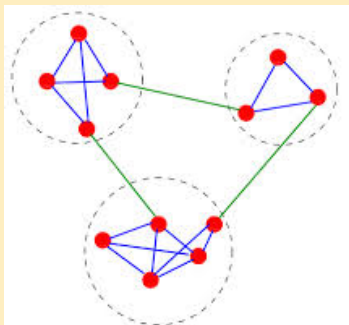


FIG. 1 A simple graph with three communities, enclosed by the dashed circles. Reprinted figure with permission from Ref. (Fortunato and Castellano, 2009). ©2009 by Springer.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## Community in a graph : a mathematical definition of the *Modularity* function $Q(\mathcal{C})$ :

- We suppose  $\mathcal{C} = C_1 \cup C_2 \cdots C_{n_c}$  ,  $\mathcal{C}$  is a community division (no overlapping communities :  $C_i \cap C_j = \emptyset$ ).
- $$Q(\mathcal{C}) = \frac{1}{2m} \sum_{i,j} (A_{i,j} - \frac{k_i k_j}{2m}) \delta(C_i, C_j)$$
- $k_i$  : degree of node  $i$ ,
- $k_j$  : degree of node  $j$
- and  $\delta(C_i, C_j) = 1$  if nodes  $i$  and  $j$  are in the same community, 0 if otherwise.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Community in a graph : another formulation via communities

- The only contributions to the sum come from vertex pairs belonging to the same cluster, so, we can group these contributions together and rewrite the sum over the vertex pairs as a sum over the clusters :

$$Q(\mathcal{C}) = \sum_{i=1}^{n_c} \left[ \frac{l_{C_i}}{m} - \left( \frac{d_{C_i}}{2m} \right)^2 \right]$$

- $n_c$  : the number of different communities
- $l_{C_i}$  the total number of edges joining vertices of community  $C_i$
- and  $d_{C_i}$  the sum of the degrees of the vertices of community  $C_i$ .

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

Modularity function : 4 identical expressions for the most popular function

$$\textcircled{1} \quad Q(\mathcal{C}) = \frac{1}{2m} \sum_{i,j} (A_{i,j} - \frac{k_i k_j}{2m}) \delta(C_i, C_j)$$

$$\textcircled{2} \quad Q(\mathcal{C}) = \sum_{i=1}^{n_c} [\frac{l_{C_i}}{m} - (\frac{d_{C_i}}{2m})^2]$$

$$\textcircled{3} \quad Q(\mathcal{C}) = \sum_{C_i \in \mathcal{C}} [\frac{E(C_i)}{m} - (\frac{Vol(C_i)}{2m})^2]$$

$$\textcircled{4} \quad Q(\mathcal{C}) = \sum_{C_i \in \mathcal{C}} [\frac{Vol(C_i)}{2m} - (\frac{Vol(C_i)}{2m})^2]$$

- $E(C_i)$  : number of edges inside  $C_i$
- $Vol(C_i)$  : volume of  $C_i$  equal to  $\sum_{i \in C_i} k_i$

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Community in a graph : another formulation via communities

- $Q$  is a numerical index of how good a community division  $\mathcal{C}$  is.
- $Q(\mathcal{C}) \in [-1, 1]$ .
- Finding  $\arg_{\mathcal{C}} \max Q(\mathcal{C})$  is a NP-complete problem.

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Community in a graph : The Louvain Algorithm

- THE paper to read, Title : *Fast unfolding of communities in large networks*
- Author : Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte, Etienne Lefebvre,
- Journal of Statistical Mechanics : Theory and Experiment 2008 (10)
- Very Fast : quite linear
- Code (and paper) :  
<https://sites.google.com/site/findcommunities/>

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Community in a graph : The Louvain Algorithm

*The method consists of two phases. First, it looks for "small" communities by optimizing modularity in a local way. Second, it aggregates nodes of the same community and builds a new network whose nodes are the communities. These steps are repeated iteratively until a maximum of modularity is attained.*

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# (sparse) Very Large Graphs [(s)VLG]

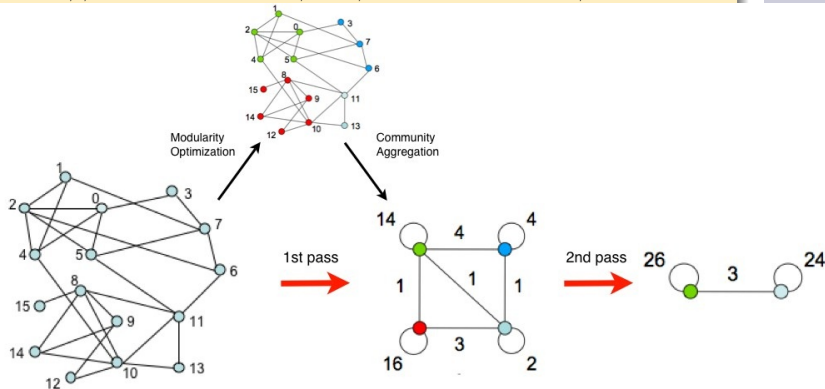
<https://sourceforge.net/projects/louvain/>

Ancienne :

<https://sites.google.com/site/findcommunities/>

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG



(*sparse*) Very  
graph ?

are on  
e !

ons

ing  
problems

ms

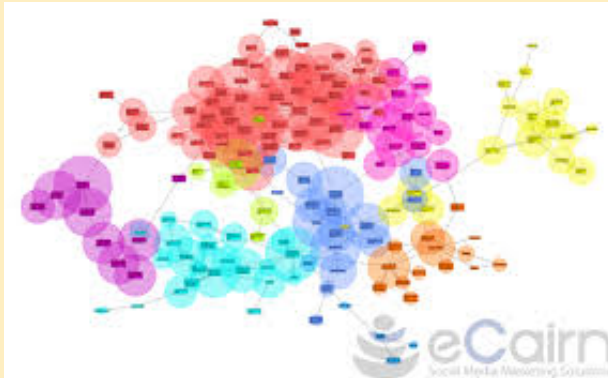
as  
m :  
k

arge  
: The

$O(n)$  Wall of  
Big Data

# VLG : example of communities

<http://blog.ecairn.com/2012/03/22/digital-influence-renaissance-solis/>



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data



# VLG : example of communities

<http://www.hackdiary.com/>



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

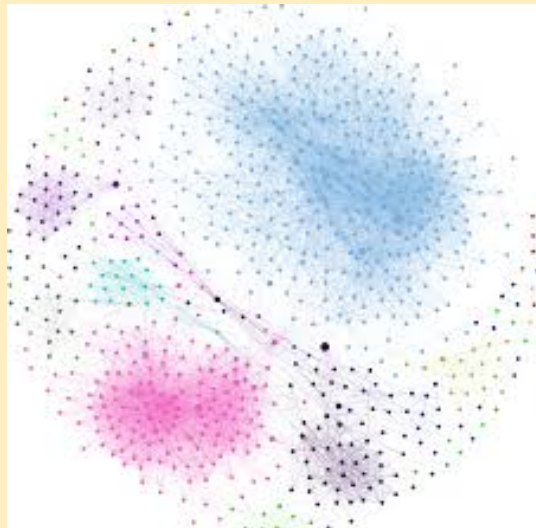
Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

# VLG : example of communities

<https://wisonets.wordpress.com/tag/force-based-algorithms-graph-drawing/>



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

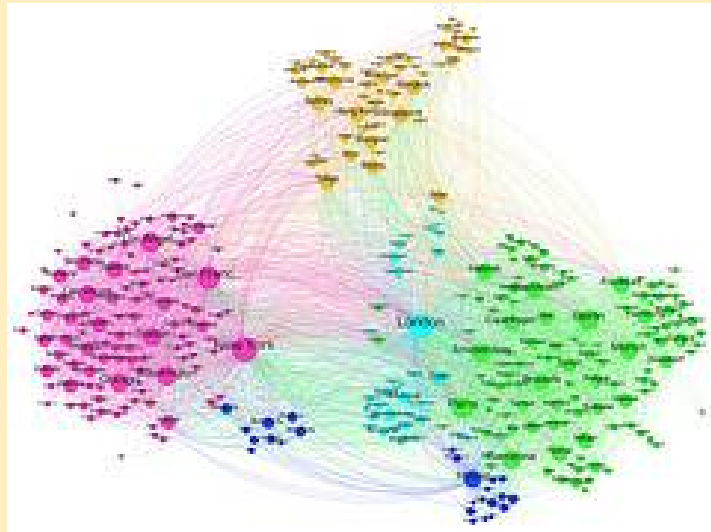
Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

# VLG : example of communities

<https://www.flickr.com/photos/mbiddulph/sets/72157627176352483/details> (sparse) Very Large Graphs



R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## ⑤ Reordering a Graph for Fun & Profit : *MOD versus MUD*

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# Reordering a Graph for Fun & Profit

## Reordering a graph ? $G$ and $G'$ two isomorphic graphs

- Theoretically solving a problem  $\mathcal{P}$  on  $G$  is strictly equivalent to solve the problem on  $G'$ .
- But what about practically with (s)VLG ?  
Surprisingly it is sometimes better (times) to solve the problem  $\mathcal{P}$  on a renumbered version  $G'$  of  $G$ .
- How to renumber ? When ? and Why ?
- We will experimentally explore this on : a BFS traversal, diameter approximation, and the community computation.

## MOD versus MUD

- MUD paradigm : Massive Unordered Data (MAP/REDUCE paradigm)
- MOD : Massive Ordered Data (example : graphs, numerical matrices ...)

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise !

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## MUD :Massive Unordered Data (from Ref [31])

The Massive, Unordered, Distributed-data (MUD) model was recently introduced by Feldman and al. [32] as an abstraction of part of the infrastructure used at Google. It is related to the MapReduce framework presented in [33]. In the multi-round, multi-key MUD model,  $n$  data records are distributed arbitrarily between  $M$  machines. Each machine maps each record to (key, value) pairs. All pairs corresponding to the same key are then 'reduced' to a single record. This reduction is performed by an  $O(\text{polylog}n)$ -space streaming computation. The process repeats for a total of  $l$  rounds. The model is very powerful and it was proven that any EREW-PRAM algorithm can be simulated in the multi-round, multi-key MUD model if the number of keys and rounds is sufficiently large [...]. In practice we are primarily interested in computing with a small number of keys and rounds. What can be computed given  $k$  keys and  $l$  rounds?

(*sparse*) Very  
Large Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Reordering/Renumbering a matrix

- Problem comes from Numerical Analysis : algorithms to solve large linear problems  $Ax = b$  :  $A$  is large and sparse (Difference methods, Finite Elements Methods etc.)
- For each problem (direct solving of  $Ax = b$ ,  $A$  is symmetric, or  $A$  is unsymmetric, iterative solving ...) soon it appeared that renumbering the  $x_i$  could be interesting. [Cuthill-Mackee algorithm : 1969]
- But renumbering the Matrix means renumbering the vertices of  $G(A)$  (the graph  $G$  such that its adjacency matrix is  $A$ )!
- Be careful : Cuthill-Mackee, Sloan, Gibbs-Poole etc. can be very expensive, but Sloan can be used.

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## A simple Reordering/Renumbering of a graph/matrix

- Choose a node  $v_0$
- Make a BFS traversal from  $v_0$ , let  
 $L = BFS(v_0) = \{v_0, v_1, v_2, \dots, v_{n-1}\}$
- Renumber the graph using  $L$ .
- Save the graph.
- Ideas to choose  $v_0$  : make a double sweep. Use the last vertex as  $v_0$ .

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

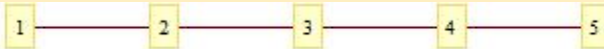
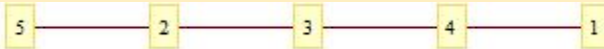


# Reordering a matrix

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

Two views of the same graph : A and B are isomorphic



A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

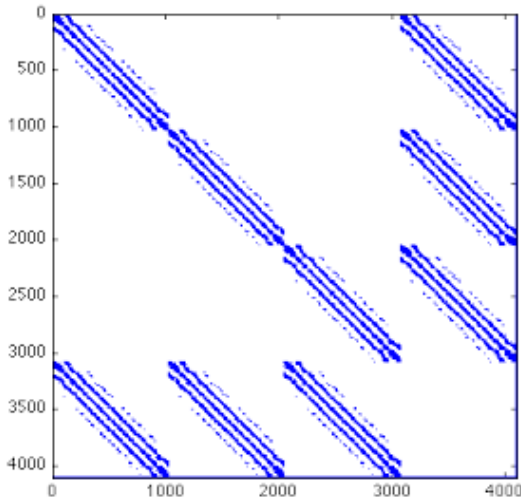
Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# Reordering a matrix : Initial Matrix (FEM)

<http://rbfzone.blogspot.fr/2011/12/cuthill-mckee-ordering-of-boostublas.html>



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

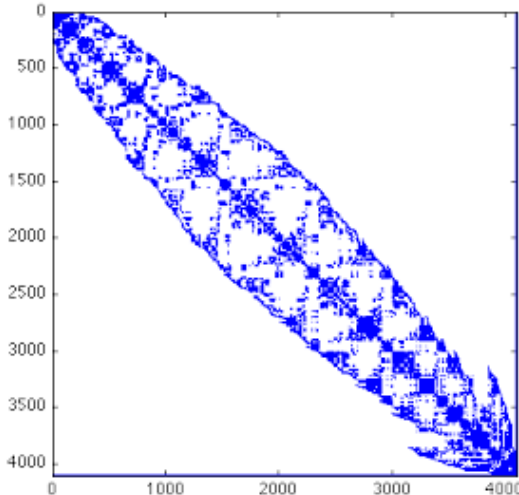
Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

# Reordering a matrix : Reordered Matrix : locality

<http://rbfzone.blogspot.fr/2011/12/cuthill-mckee-ordering-of-boostublas.html>



(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : PageRank

Very Large Graphs : The  $O(n)$  Wall of Big Data

# Reordering a matrix

## Indirection : test case 1/2

```
int A[n];
int B1[n],B2[n],B3[n];
.....
/* Loop 1 B1[i]=i */
for(i=0;i<n,i++)
    A[B1[i]]=i;
/* Loop 2 B1[i]=C[i]*/
for(i=0;i<n,i++)
    A[B2[i]]=i;
/* Loop 3 B3[i]=C[D[i]] */
for(i=0;i<n,i++)
    A[B3[i]]=i;
```

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Indirection : 2/2

- Take a large  $n : n > 10^6, n > 10^7$  or  $n > 10^8$
- Let  $B1 = \{0, \dots, n-1\}$ , compute the cpu time needed for the loop 1
- Let  $B2 = \{n-1, \dots, 0\}$ , compute the cpu time needed for the loop 2
- Let  $B3 = \{n-1, \dots, 0\}$ , again compute the cpu time needed for the loop 3
- Let  $B3$  be a random permutation of  $\{0, \dots, n-1\}$ , again compute the cpu time needed for the loop

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## 16 WorkingPackage to do for 2018?

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

# What ? See the file "Working Packages 2018 ..."

## WorkPackages (WP) : what ?

- Choose a project between :
  - ① Project 1 (diameter : classical version with a modification)
  - ② Project 2 (diameter : a new "suppression" algorithm)
  - ③ Project "special" : A personnel project about (Sparse) Very Large Graphs (but you need to tell us before and we have to sent you our answer).
- Do the job (see after)
- How ? sent a **unique file** (zip, tar)to :  
**verylargegraphs@gmail.com**
- When ? Dead line : before June, 1th 2018 23h42.
- Any question ? Sent it to  
**verylargegraphs@gmail.com**

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## Work to do : : WorkPackages (WP) 2015-2016 (old)

- Choose a WorkPackages from 1 to 4.
- Do the job.
- Write a file *RESULTS\_ <YOUR NAME>.xxx* (max 4 pages in any format) within : Your name, the WP you have chosen, and all the results (specially timing results or any problem)
- Send :
  - ① Every programs (with YOUR NAME)
  - ② The file *RESULTS\_ <YOUR NAME>.xxx* (including the timing results)
  - ③ In a single message please
  - ④ At **verylargegraphs@gmail.com**

(*sparse*) Very  
Large Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data



## Work to do : Workpackage 1 2015-2016 (old)

- Take the graphs `inet` and `ip` : compute and save the giant connected component (see `diam.c`) : `inetgiant` and `ipgiant`
- Implement the double sweep and/or the Fringe algorithms (with bounds)
- Write a reordering algorithms as presented (use a simple BFS from a random node of the giant connected component or a simple BFS from the max degree node)
- Test on `inet/inetgiant` + `ip/ipgiant` (for example with `time.h`)
  - ① with `diam.c` on unordered graphs
  - ② with `diam.c` on reordered graphs
  - ③ with your version of the double sweep
  - ④ and the Fringe algorithms (with bounds)
  - ⑤ with `community.cpp` on unordered graphs and

(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

## Work to do Workpackage 2 : go to (Ref [21]) 2015-2016 (old)

- Take the graphs `inet` and `ip` : compute and save the giant connected component (see `diam.c`) : `inetgiant` and `ipgiant`
- Implement the double sweep and/or the Fringe algorithms (with bounds)
- Use « my » reordering algorithms : send an email to `verylargegraphs@gmail.com` : but you will lose some points
- Test on `inet/inetgiant` + `ip/ipgiant` (for example with `time.h`)
  - ① with `diam.c` on unordered graphs
  - ② with `diam.c` on reordered graphs
  - ③ with your version of the double sweep
  - ④ and the Fringe algorithms (with bounds)
  - ⑤ with `community.cpp` on unordered graphs and

(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

## Work to do : Workpackage 3 : play with community.cpp 2015-2016 (old)

- Take the graphs inet and ip : compute and save the giant component (see diam.c) : inetgiant and ipgiant
- Use the resultst of community.cpp to write a reordering algorithms
- Implement (with time.h) the double sweep and/or the Fringe algorithms (with bounds)
- Test (with time.h) on inet/inetgiant + ip/ipgiant
  - ① with diam.c on unordered graphs
  - ② with diam.c on reordered graphs
  - ③ with your version of the double sweep
  - ④ and he Fringe algorithms (with bounds)
  - ⑤ and (again) with community.cpp on unordered graphs and reordered graphs
- Send everything

(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

## Work to do : Workpackage 4 : play with diam.c and community.cpp 2015-2016 (old)

- If you choose this WP : please write me to discuss : this is a very exploring WP
- Take the graphs inet and ip : compute and save the giant component (see diam.c) : inetgiant and ipgiant
- Use the results of community.cpp to write a reordering algorithms
- Implement a « Fringe like » algorithm using results of community.cpp : Basically this means you create a new graph where each node is a community, we will call this graph the *metagraph*. Compute the diameter of this very smaller metagraph, save the communities involved (and some of the vertices involved, explain how you choose these vertices)) and use them on the true graphs with diam.c using (or your modified newdiam.c) nodes of the community involded. This is a very promising algorithm.

(*sparse*) Very **Large** Graphs

R. Erra & A. Letois & Mark Angoustures (s)VLG

A (Sparse) Very Large Graph ?

Graphs are on the Rise!

Basics definitions

Some interesting (real) Problems

Basics algorithms

A famous algorithm : Pagerank

Very Large Graphs : The  $O(n)$  Wall of Big Data

Work to do : Workpackage 4 : play with diam.c and community.cpp :2015-2016 (old)

- Test (with time.h) on inet/inetgiant + ip/ipgiant
  - ① with diam.c on unordered graphs
  - ② with diam.c on reordered graphs
  - ③ with newdiam.c on unordered graphs
  - ④ with newdiam.c on reordered graphs
  - ⑤ and (again) with community.cpp on unordered graphs and reordered graphs
  - ⑥ and with you program
- Send everything ...

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

## 17 Some Lectures

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## References

- (Ref [00]) <http://matthewgress.com/galleries/Web/Internet-Graph-1069646562-LGL-2D-4096x4096>
- (Ref [1]) : <http://www.math.cornell.edu/mec/Winter2009/RalucaRemus/Lecture2/lecture2.html>
- (Ref [2]) : <http://www.thp.uni-koeln.de/lassig/projects.html>
- (Ref [3]) : <http://www.cs.umd.edu/class/fall2007/cmsc8581/>
- (Ref [4]) : <http://ecsite.cs.colorado.edu/subject-areas/civics/>
- (Ref [5]) : <http://www.fmsasg.com/SocialNetworkAnalysis/>
- (Ref [6]) : [http://www.jacobsschool.ucsd.edu/news/news\\_releases/release.sfe?id=685](http://www.jacobsschool.ucsd.edu/news/news_releases/release.sfe?id=685)
- (Ref [21]) : <https://www-complexnetworks.lip6.fr/magnien/Diameter/>
- (Ref [22]) : <http://mathworld.wolfram.com/GraphEccentricity.html>
- (Ref [31]) : [http://sublinear.info/index.php?title=Open\\_Problems:17](http://sublinear.info/index.php?title=Open_Problems:17)
- (Ref [32]) : Jon Feldman, S. Muthukrishnan, Anastasios Sidiropoulos, Cliff Stein, and Zoya Svitkina. On the complexity of processing massive, unordered, distributed data. 2006.
- (Ref [33]) : Jeffrey Dean and Sanjay Ghemawat. MapReduce : Simplified data processing on large clusters. In OSDI, pages 137-150, 2004.

(*sparse*) Very  
Large Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data

## References

- (Ref [101]) : <https://eudml.org/doc/104856>
- (Ref [102]) : <https://sites.google.com/site/findcommunities/>
- (Ref [102]) : <https://sourceforge.net/projects/loouvain/>
- (Ref [103]) : [http://piluc.dsi.unifi.it/lasagne/?page\\_id=137](http://piluc.dsi.unifi.it/lasagne/?page_id=137)
- (Ref [104]) : [http://piluc.dsi.unifi.it/lasagne/wp-content/uploads/2014/10/leo\\_PhD\\_thesis.pdf](http://piluc.dsi.unifi.it/lasagne/wp-content/uploads/2014/10/leo_PhD_thesis.pdf)
- (Ref [105]) : <http://www.cs.princeton.edu/~chazelle/courses/BIB/pagerank.htm>
- (Ref [106]) : <http://arxiv.org/abs/0906.0612>
- (Ref [107]) : <http://arxiv.org/pdf/1308.0971v1.pdf>
- (Ref [108]) : M. E. Newman and M. Girvan. *Finding and evaluating community structure in networks*. Physical review E, 69(2), 2004.
- (Ref [109]) : <https://hal.archives-ouvertes.fr/hal-01171295/document>

(*sparse*) Very  
**Large** Graphs

R. Erra & A.  
Letois & Mark  
Angoustures  
(s)VLG

A (Sparse) Very  
Large Graph ?

Graphs are on  
the Rise!

Basics  
definitions

Some  
interesting  
(real) Problems

Basics  
algorithms

A famous  
algorithm :  
Pagerank

Very Large  
Graphs : The  
 $O(n)$  Wall of  
Big Data