

# **Big data: architectures and data analytics**

# **Graph Analytics in Spark**

## **Part 2**

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# **Graph Algorithms with GraphFrames**

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# Algorithms over graphs

- A graph is just a logical representation of data
- Graph theory provides many algorithms for analyzing data in this format
  - Breadth first search
  - Shortest paths
  - Connected components
  - Strongly connected component
  - Label propagation
  - PageRank
  - ...
- Custom algorithms can be built
- Development continues as new algorithms are added to GraphFrames

# Algorithms over graphs

- A graph is just a logical representation of data
- Graph theory provides many algorithms for analyzing data in this format

- Breadth first search
- Shortest paths
- Connected components
- Strongly connected component
- Label propagation
- PageRank

Here presented

- ...

- Custom algorithms can be built
- Development continues as new algorithms are added to GraphFrames

# Checkpoint directory

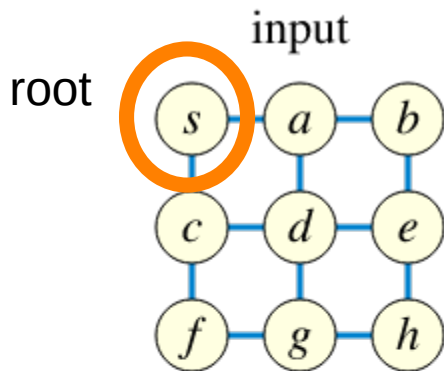
- To run some expensive algorithms, set a checkpoint directory that will store the state of the job at every iteration
- This allow you to continue where you left off if the job crashes
- Create such a folder to set the checkpoint directory with:  
`sc.setCheckpointDir('graphframes_ckpts_dir')`
- graphframes\_ckpts\_dir is your new checkpoint folder
- `sc` is your `spark.sparkContext`

# Breadth first search

- Breadth-first search (BFS) is an algorithm for traversing or searching graph data structures
- It finds the **shortest path** from a vertex to other vertices
- Used in many other algorithms: length of shortest paths, connected components,...

# Breadth first search

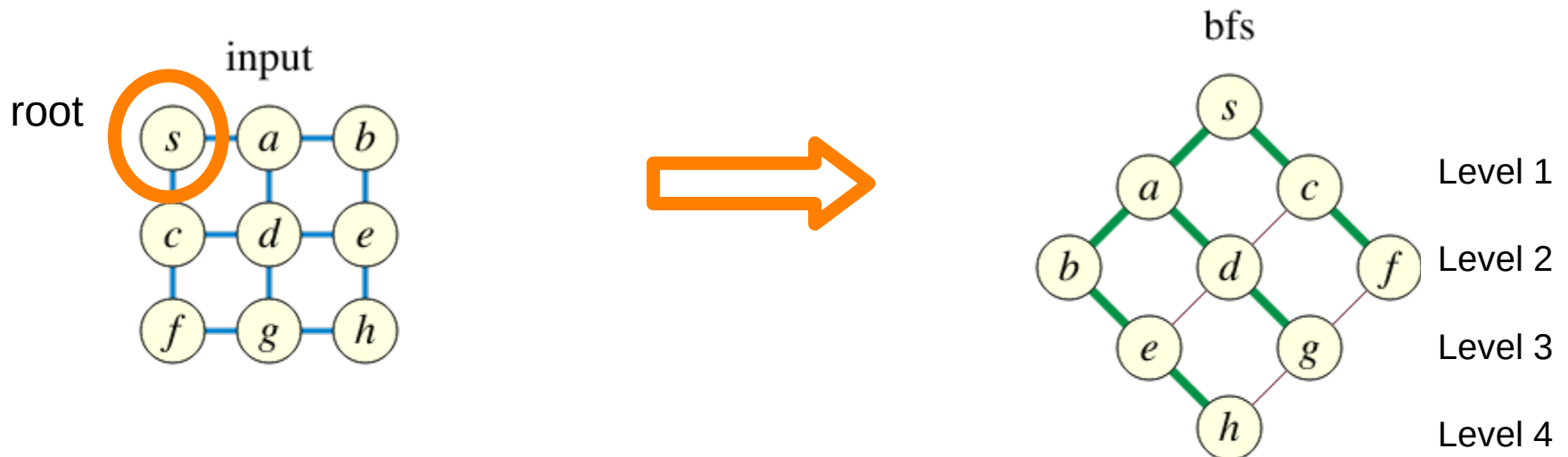
- It starts at an arbitrary node, and explores all of the neighbor nodes at the present depth prior to moving on to the nodes at the next depth level





# Breadth first search

- It starts at an arbitrary node, and explores all of the neighbor nodes at the present depth prior to moving on to the nodes at the next depth level



# Breadth first search

- Breadth-first search (BFS) finds the shortest path(s) from one vertex (or a set of vertices) to another vertex (or a set of vertices)
- `bfs()` method returns a DataFrame of valid shortest paths from vertices matching fromExpr to vertices matching toExpr
- Shortest means globally shortest path. If there are many vertices matching fromExpr and toExpr, only the couple with shortest length is showed
- If multiple paths are valid and **have the same length**, the DataFrame will return one Row for each path

# Breadth first search

- Parameters:
  - fromExpr: Spark SQL expression specifying valid starting vertices for the BFS. E.g., to start from a specific vertex, "id = [start vertex id]"
  - toExpr: Spark SQL expression specifying valid target vertices for the BFS
  - maxPathLength: Limit on the length of paths (default = 10)
  - edgeFilter: Spark SQL expression specifying edges which may be used in the search

# Breadth first search: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

- 1) Find the shortest path from Esther to Charlie
- 2) Find the shortest path from Esther to users of age more than 34, without using edges of type “follow”

# Breadth first search: example

# 1)

# Search shortest path from "Esther" to "Charlie"

```
paths = g.bfs(fromExpr="id = 'e'", toExpr="id = 'c'")
```

```
paths.show()
```

# 2)

# Find the shortest path from Esther to users of age more than 34,  
without using edges of type "follow"

# Specify edge filters or max path lengths.

```
paths2=g.bfs("name = 'Esther'", "age > 34",\
```

```
    edgeFilter="relationship != 'follow'")
```

```
paths2.show()
```

# Breadth first search: example

## 1) Find the shortest path from Esther to Charlie

from	e0	v1	e1	to
[e, Esther, 32]	[e, f, follow]	[f, Fanny, 36]	[f, c, follow]	[c, Charlie, 30]

## 2) Find the shortest path from Esther to users of age more than 34, without using edges of type “follow”

from	e0	v1	e1	v2	e2	to
[e, Esther, 32]	[e, d, friend]	[d, David, 29]	[d, a, friend]	[a, Alice, 34]	[a, b, friend]	[b, Bob, 36]

# Shortest path

- **shortestPaths()** method of a GraphFrame computes length of shortest paths from each vertex to a given set of landmark vertices
- Landmarks are specified by vertex ID.
- It uses the breadth-first search
- The returned DataFrame contains all graph vertex IDs and an additional column
  - a map containing for each reachable landmark vertex (key), the shortest-path distance (value)

# Shortest paths: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Find the shortest paths going to Alice and David**



# Shortest paths: example

```
#list of landmark nodes  
landmarks=["a", "d"]  
results = g.shortestPaths(landmarks=landmarks)  
  
results.show()
```

# Shortest paths: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Find the shortest paths to Alice and David**

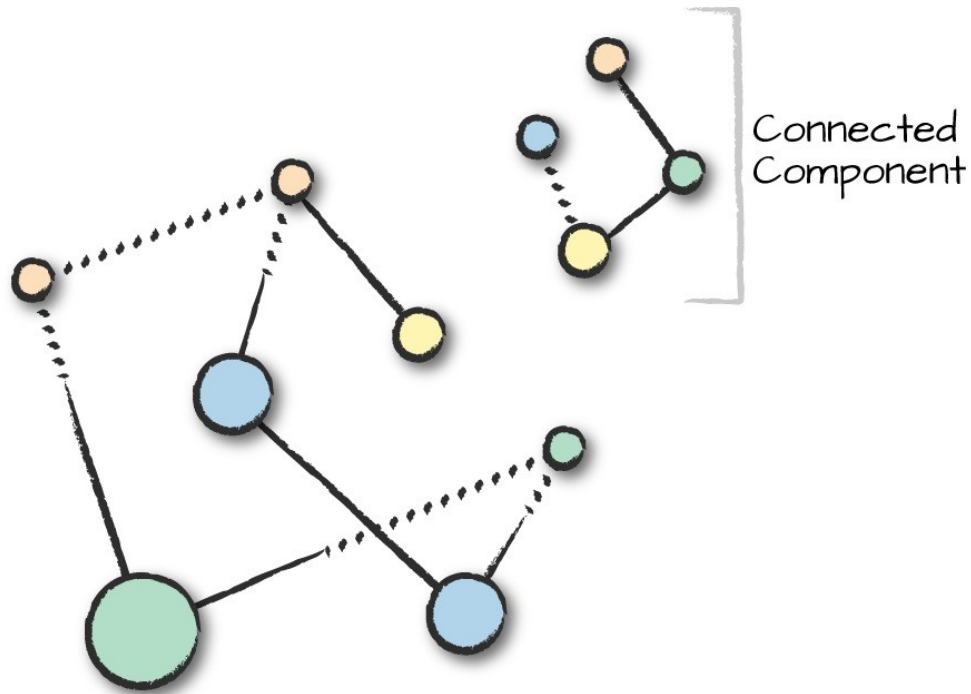
id	name	age	distances
g	Gabby	60	[[]]
b	Bob	36	[[]]
e	Esther	32	[d -> 1, a -> 2]
a	Alice	34	[a -> 0, d -> 2]
f	Fanny	36	[[]]
d	David	29	[d -> 0, a -> 1]
c	Charlie	30	[[]]

# Connected components

- A connected component of a graph is a **subgraph**
- Any two vertices are connected to each other by one or more edges
- The set of vertices is not connected to any additional vertices in the original graph
- Direction of edges is not considered
- Connected components detection can be interesting for clustering, but also to make your computations more efficient

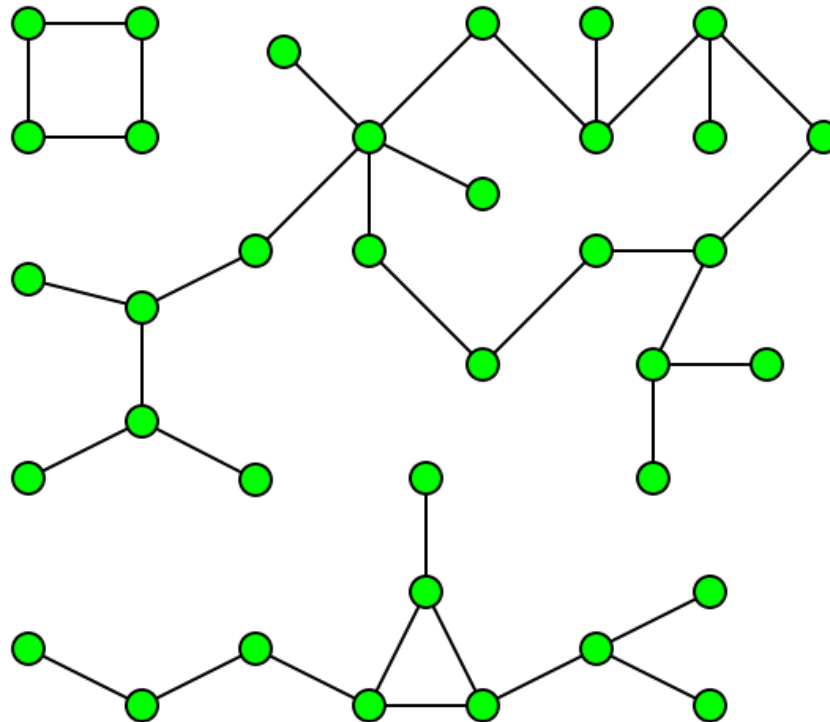
# Connected components

- Two connected components



# Connected components

- Three connected components



# Connected components

- The algorithm to compute the connected components exploit the **breadth-first search**
- For non-distributed graphs, we can compute the components of a graph in linear time (numbers of the vertices and edges)
- A search that begins at some particular vertex  $v$  will find the entire component containing  $v$  (and no more) before returning.
- To find all the components of a graph, loop through its vertices, starting a new breadth first whenever the loop reaches a vertex not included in a found component

# Connected components

- **connectedComponents()** method of a GraphFrame
- It is an expensive algorithm – expect delays
- The default Connected Components algorithm requires setting a Spark **checkpoint** directory
- Parameters:
  - `checkpointInterval` – checkpoint interval in terms of number of iterations (default: 2)
  - `broadcastThreshold` – broadcast threshold in propagating component assignments (default: 1000000)
- Returns:
  - DataFrame with new vertices column “component”

# Connected components: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Find the connected components of the graph**



# Connected components: example

```
#set checkpoint folder  
sc.setCheckpointDir("tmp_ckpts")
```

```
#run the algorithm  
connComp=g.connectedComponents()
```

```
#show results. Order by component in order to have nodes of the  
  same component in adjacent rows  
connComp.orderBy("component").show()
```

```
nComp=connComp.select("component").distinct().count()  
print("Number of connected components: ", nComp)
```

# Connected components: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Find the connected components of the graph**

id	name	age	component
g	Gabby	60	146028888064
c	Charlie	30	412316860416
a	Alice	34	412316860416
b	Bob	36	412316860416
e	Esther	32	412316860416
d	David	29	412316860416
f	Fanny	36	412316860416

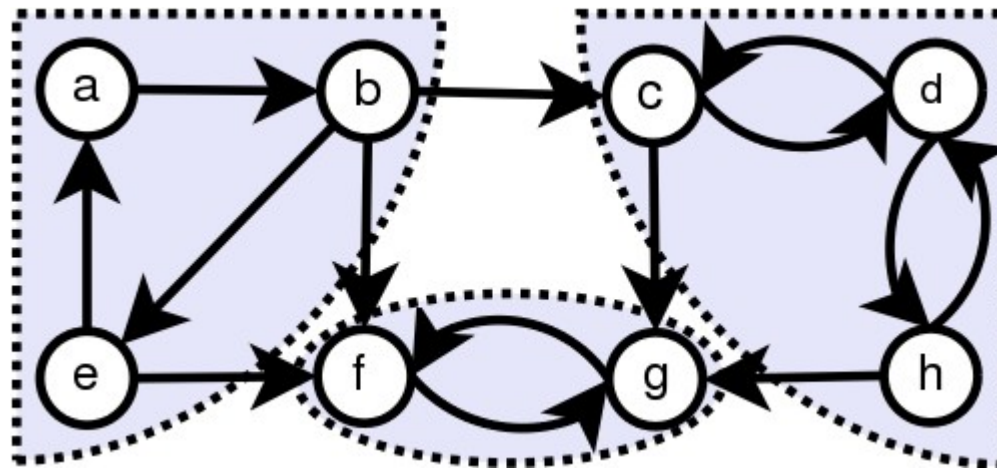
Number of connected components: 2

# Strongly Connected components

- A graph is called strongly connected if there is a path in each direction between each pair of vertices of the graph
- For undirected graph, connected and strongly connected components are the same

# Strongly Connected components

- A graph with 3 strongly connected components



# Strongly Connected components

- **stronglyConnectedComponents()** method of a GraphFrame
- Requires setting a Spark **checkpoint** directory
- Better to run on a cluster with **yarn** scheduler even with small graphs
- Parameters:
  - maxIter – the number of iterations to run
- Returns:
  - DataFrame with new vertices column “component”

# Strongly connected components: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Find the strongly connected components of the graph**

# Strongly connected components: example

```
#set checkpoint folder  
sc.setCheckpointDir("tmp_ckpts")
```

```
#run the algorithm  
strongConnComp = g.stronglyConnectedComponents(maxIter=10)
```

```
#show results. Order by component in order to have nodes of the  
  same components in adjacent rows  
strongConnComp.orderBy("component").show()
```

```
nComp=strongConnComp.select("component").distinct().count()  
print("Number of strongly connected components: ", nComp)
```

# Strongly connected components: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

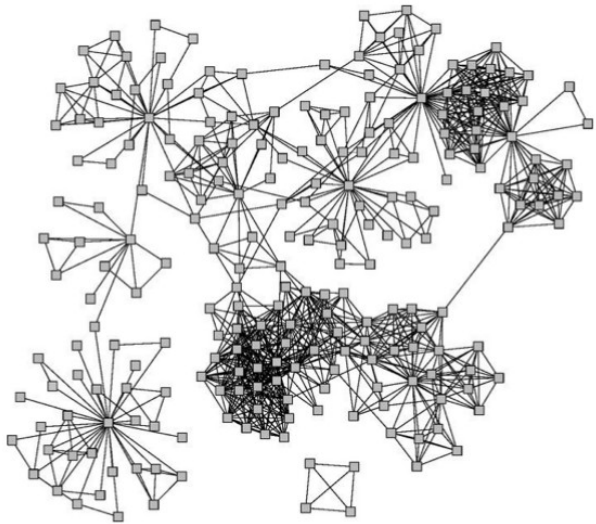
**Find the connected components of the graph**

id	name	age	component
g	Gabby	60	146028888064
f	Fanny	36	412316860416
a	Alice	34	670014898176
e	Esther	32	670014898176
d	David	29	670014898176
b	Bob	36	1047972020224
c	Charlie	30	1047972020224

Number of strongly connected components: 4



# Communities in graphs



What makes a community (cohesive subgroup):

- Mutuality of ties. Everyone in the group has ties (edges) to one another
- Compactness. Closeness or reachability of group members in small number of steps, not necessarily adjacency
- Density of edges. High frequency of ties within the group
- Separation. Higher frequency of ties among group members compared to non-members

# Communities in graphs

Airline flights



image from Lab41 blog

# Label propagation

- Label Propagation an algorithm for **detecting communities in graphs**
- Like clustering but exploiting connectivity
- It is not expensive computationally, but (1) convergence is not guaranteed and (2) one can end up with trivial solutions
- Each node in the network is initially assigned to its own community.
- At every step, nodes send their community affiliation to all neighbors and update their state to the mode community affiliation of incoming messages.

# Label propagation

- **labelPropagation()** method of a GraphFrame
- Parameters:
  - maxIter – the number of iterations to run
- Returns:
  - DataFrame with new vertices column “label”

# Label propagation: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Detect communities with label propagation algorithm**

# Label propagation: example

```
result = g.labelPropagation(maxIter=20)
```

```
result.select("id", "label").orderBy("label").show()
```

# Label propagation: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Detect communities with label propagation algorithm**

id	label
g	146028888064
e	1047972020224
a	1047972020224
c	1047972020224
f	1382979469312
b	1382979469312
d	1382979469312

# Label propagation: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Detect communities with label propagation algorithm**

id	label
g	146028888064
e	1047972020224
a	1047972020224
c	1047972020224
f	1382979469312
b	1382979469312
d	1382979469312

[g] is a community (and a connected components)



# Label propagation: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Detect communities with label propagation algorithm**

id	label
g	146028888064
e	1047972020224
a	1047972020224
c	1047972020224
f	1382979469312
b	1382979469312
d	1382979469312



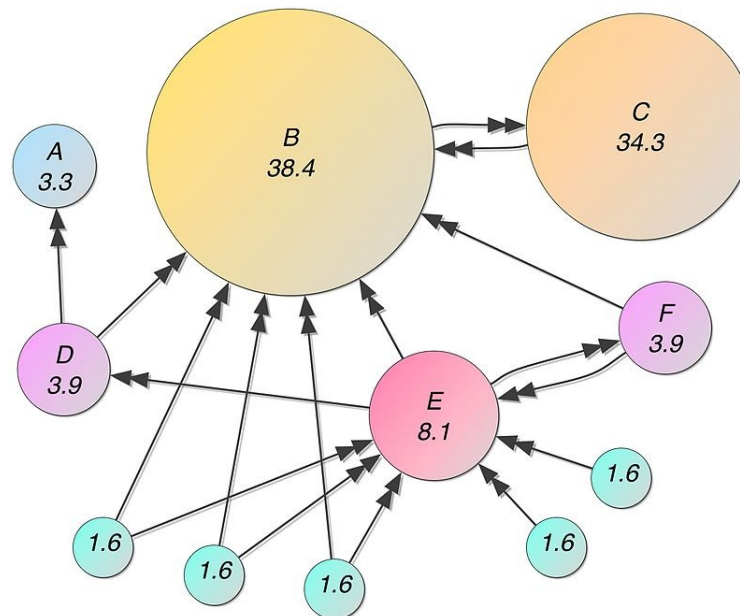
Take care! The algorithm finds two communities [e,a,c] and [f,b,d], but different runs may have different results

# PageRank

- PageRank is the original algorithm used by Google Search to rank vertices in a graph by order of importance
- For Google search, nodes are the pages in the World Wide Web, edges are hyperlinks on the pages
- It is part of the broader algorithms to find **centrality** of nodes
- It assigns a numerical weighting to each node

# PageRank

- It outputs a likelihood that a person randomly clicking on links will arrive at any particular page
- For a page PageRank, it is important not only how many pages link to it, but also their quality (i.e., their PageRank)



# PageRank

- **pageRank()** method of a GraphFrame
- It returns a **GraphFrame** with new vertices column “pagerank” (not normalized) and new edges column “weight”
- Can be run for a fixed number of iterations, by setting **maxIter**
- Can be run until convergence by setting **tol**
- Can be personalized (computing rank with respect to a certain node), by defining **sourceId**

# PageRank: example

## Nodes DataFrame

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

## Edge DataFrame

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**Detect PageRank centrality of nodes**

**Detect PageRank centrality of nodes personalized with respect to Bob**

# PageRank: example

```
# Run PageRank until convergence to tolerance "tol".  
results = g.pageRank(tol=0.03)
```

```
# Display resulting pageranks  
results.vertices.show(truncate=False)
```

```
# Run PersonalizedPageRank until convergence to tolerance "tol".  
resultsPers = g.pageRank(tol=0.03,sourceld="b")
```

```
# Display resulting pageranks  
resultsPers.vertices.show(truncate=False)
```

# PageRank: example

## Detect PageRank centrality of nodes

id	name	age	pagerank
g	Gabby	60	0.2048147336438733
b	Bob	36	2.6151501884736303
e	Esther	32	0.3972957800461296
a	Alice	34	0.4528965797700148
f	Fanny	36	0.36030111878170495
d	David	29	0.36030111878170495
c	Charlie	30	2.609240480502942

## Detect PageRank centrality of nodes personalized with respect to Bob

id	name	age	pagerank
g	Gabby	60	0.0
b	Bob	36	0.542517589576432
e	Esther	32	0.0
a	Alice	34	0.0
f	Fanny	36	0.0
d	David	29	0.0
c	Charlie	30	0.457482410423568

# Custom graph algorithms

- GraphFrames provides primitives for developing yourself other graph algorithms
- It is based on message passing approach
- The two key components are:
  - **aggregateMessages**: Send messages between vertices, and aggregate messages for each vertex.  
[https://graphframes.github.io/graphframes/docs/\\_site/api/python/graphframes.lib.html](https://graphframes.github.io/graphframes/docs/_site/api/python/graphframes.lib.html)
  - **joins**: Join message aggregates with the original graph (DataFrame joins)



# Custom graph algorithm: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**For each user, compute the sum of the ages of adjacent users**

# Custom graph algorithm: example

```
from pyspark.sql.functions import sum as sqlsum
from graphframes.lib import AggregateMessages

# For each user, sum the ages of the adjacent users.
msgToSrc = AggregateMessages.dst["age"]
msgToDst = AggregateMessages.src["age"]
agg = g.aggregateMessages(
    sqlsum(AggregateMessages.msg),
    sendToSrc=msgToSrc,
    sendToDst=msgToDst)
agg.show()
```

# Custom graph algorithm: example

**Nodes DataFrame**

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

**Edge DataFrame**

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

**For each user, compute the sum of the ages of adjacent users**

id	sum(MSG)
f	62
e	99
d	66
c	108
b	94
a	97

# Visualization of a graph

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# Visualize Big Data

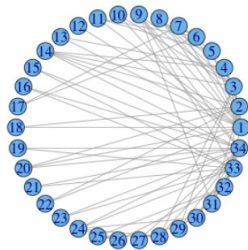
- In general, it is not a good idea to plot Big Data
- After big data processing, often you can plot results → they are no more big data
- You can plot python objects with many libraries, e.g., **matplotlib**
- You can transform spark DataFrame into pandas dataframe: `dfPandas = df.toPandas()`

# Visualize graphs

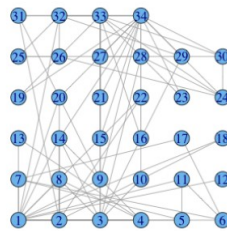
- Why visualize a graph?
  - Get an idea of structure. E.g., A good visualization can show if there are some clusters in a graph
  - To show results of processing. E.g., after performing label propagation, color nodes by labels
  - Some graph visualization algorithms are also dimension reduction tools (e.g., PCA)

# Visualize graphs: layouts

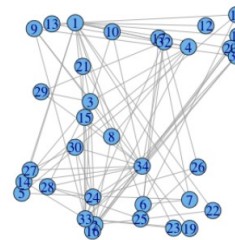
- Layout is a way to map a coordinate to each vertex (usually, on 2D plane)



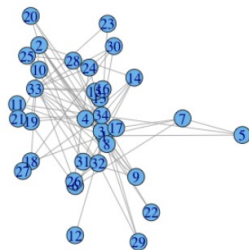
Circular layout



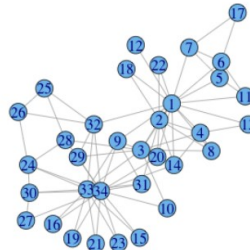
Grid layout



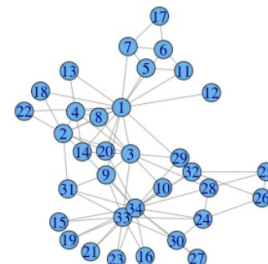
Random layout



Spring based



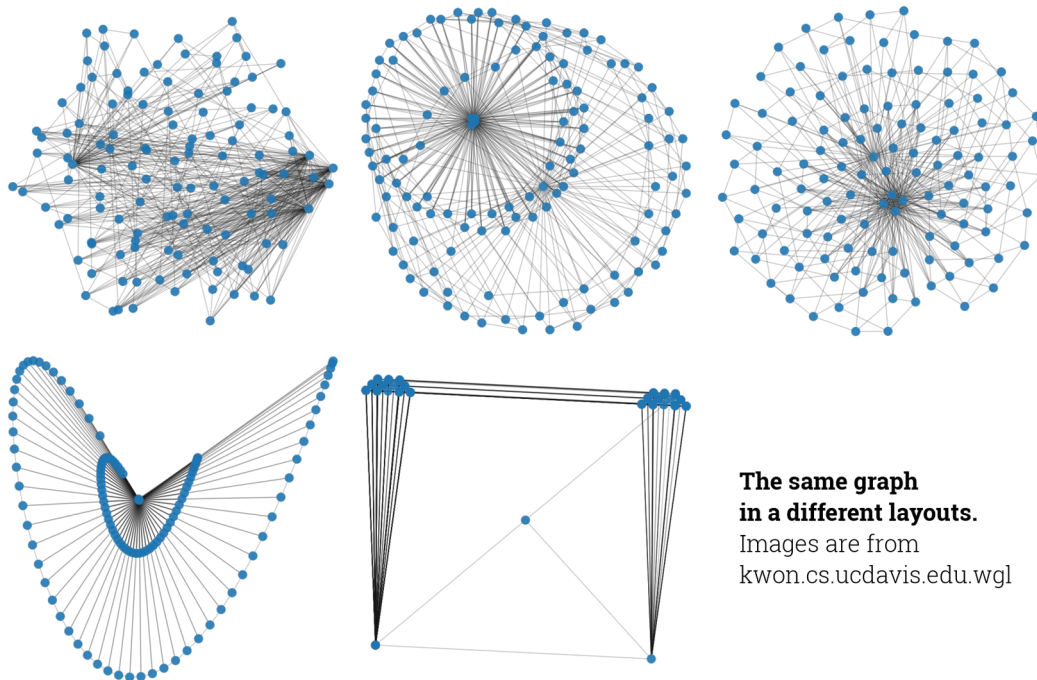
Kamada-Kawai



Fruchterman-Reingold

# Visualize graphs: layouts

- Layout is a way to map a coordinate to each vertex (usually, on 2D plane)
- For the same graph, there are different layouts



**The same graph  
in a different layouts.**

Images are from  
[kwon.cs.ucdavis.edu/wgl](http://kwon.cs.ucdavis.edu/wgl)



# Visualize graphs

- Problems in visualizing large graphs (  $>10k$  vertices and/or edges) :
  - Readability: visualization of a large graph often looks messy because there are too many objects in one plot.
  - Speed: graph visualization algorithms mostly have  $>$  quadratic algorithmic complexity (number of edges or vertices). Too long to find good/optimal parameters.

# Visualize graphs

Readability issue



# Visualize graphs

- There is no native GraphFrame library that visualizes data
- Use python libraries for graph plot
  - **NetworkX, graphviz, matplotlib, pydot,...**
- Use external tools for graph plot
  - **Gephi, LargeViz,...**

<https://towardsdatascience.com/large-graph-visualization-tools-and-approaches-2b8758a1cd59>

# Visualize graphs: networkx

## Nodes DataFrame

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

## Edge DataFrame

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

Create a NetworkX graph from the GraphFrame graph and visualize it

# Visualize graphs: networkx

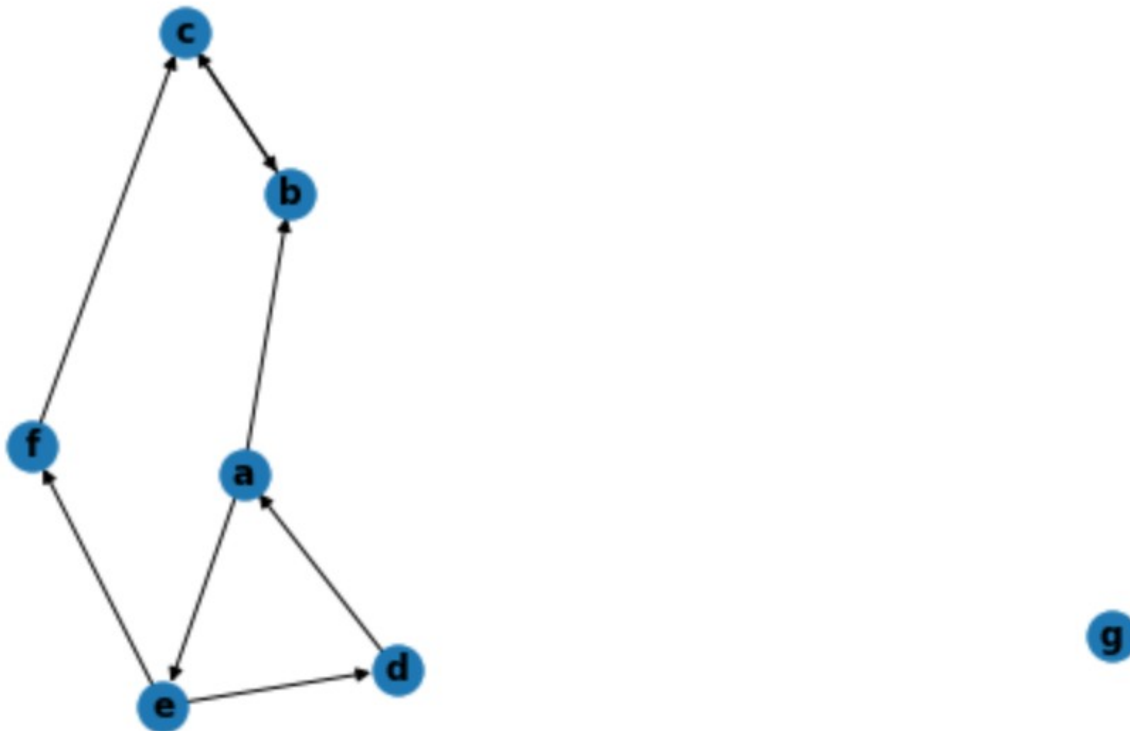
```
import networkx as nx
```

```
def xGraph(edge_list,node_list):  
    Gplot=nx.DiGraph()  
    edges=edge_list.collect()  
    nodes=node_list.collect()  
    for row in edges:  
        Gplot.add_edge(row['src'],row['dst'])  
    for row in nodes:  
        Gplot.add_node(row['id'])  
    return Gplot
```

```
Gplot=xGraph(g.edges,g.vertices)  
nx.draw(Gplot, with_labels=True, font_weight='bold')
```

# Visualize graphs: networkx

Create a NetworkX graph from the GraphFrame graph and visualize it



# Visualize graphs: graphviz

## Nodes DataFrame

id	name	age
a	Alice	34
b	Bob	36
c	Charlie	30
d	David	29
e	Esther	32
f	Fanny	36
g	Gabby	60

## Edge DataFrame

src	dst	relationship
a	b	friend
b	c	follow
c	b	follow
f	c	follow
e	f	follow
e	d	friend
d	a	friend
a	e	friend

Create a graphviz graph from the GraphFrame graph and visualize it

# Visualize graphs: graphviz

```
from graphviz import Digraph
```

```
def vizGraph(edge_list,node_list):  
    Gplot=Digraph()  
    edges=edge_list.collect()  
    nodes=node_list.collect()  
    for row in edges:  
        Gplot.edge(row['src'],row['dst'],label=row['relationship'])  
    for row in nodes:  
        Gplot.node(row['id'],label=row['name'])  
    return Gplot
```

```
Gplot=vizGraph(g.edges,g.vertices)  
Gplot
```



# Visualize graphs: graphviz

Create a graphviz graph from the GraphFrame graph and visualize it

