

## 5 - Developing Algorithms

Drew Conway and Aric Hagberg

June 29, 2010

- ▶ Examples of some simple algorithms
- ▶ Writing a new algorithm

## Directed Scale-Free Graphs

Béla Bollobás\*

Christian Borgs†

Jennifer Chayes‡

Oliver Riordan§

### 2 The model

We consider a directed graph which grows by adding single edges at discrete time steps. At each such step a vertex may or may not also be added. For simplicity we allow multiple edges and loops. More precisely, let  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta_{in}$  and  $\delta_{out}$  be non-negative real numbers, with  $\alpha + \beta + \gamma = 1$ . Let  $G_0$  be any fixed initial directed graph, for example a single vertex without edges, and let  $t_0$  be the number of edges of  $G_0$ . (Depending on the parameters, we may have to assume  $t_0 \geq 1$  for the first few steps of our process to make sense.) We set  $G(t_0) = G_0$ , so at time  $t$  the graph  $G(t)$  has exactly  $t$  edges, and a random number  $n(t)$  of vertices. In what follows, to choose a vertex  $v$  of  $G(t)$  according to  $d_{out} + \delta_{out}$  means to choose  $v$  so that  $\Pr(v = v_i)$  is proportional to  $d_{out}(v_i) + \delta_{out}$ , i.e., so that  $\Pr(v = v_i) = (d_{out}(v_i) + \delta_{out}) / (t + \delta_{out}n(t))$ . To choose  $v$  according to  $d_{in} + \delta_{in}$  means to choose  $v$  so that  $\Pr(v = v_i) = (d_{in}(v_i) + \delta_{in}) / (t + \delta_{in}n(t))$ . Here  $d_{out}(v_i)$  and  $d_{in}(v_i)$  are the out-degree and in-degree of  $v_i$ , measured in the graph  $G(t)$ .

For  $t \geq t_0$  we form  $G(t+1)$  from  $G(t)$  according to the following rules:

(A) With probability  $\alpha$ , add a new vertex  $v$  together with an edge from  $v$  to an existing vertex  $w$ , where  $w$  is chosen according to  $d_{in} + \delta_{in}$ .

(B) With probability  $\beta$ , add an edge from an existing vertex  $v$  to an existing vertex  $w$ , where  $v$  and  $w$  are chosen independently,  $v$  according to  $d_{out} + \delta_{out}$ , and  $w$  according to  $d_{in} + \delta_{in}$ .

(C) With probability  $\gamma$ , add a new vertex  $w$  and an edge from an existing vertex  $v$  to  $w$ , where  $v$  is chosen according to  $d_{out} + \delta_{out}$ .

## Feature: Compact code - building new generators

```
1 import bisect
2 import random
3 from networkx import MultiDiGraph
4
5 def scale_free_graph(n, alpha=0.41,beta=0.54,delta_in=0.2,delta_out=0):
6     def _choose_node(G,distribution ,delta ):
7         cumsum=0.0
8         psum=float(sum( distribution .values()))+float(delta)*len( distribution )
9         r=random.random()
10        for i in range(0,len( distribution )):
11            cumsum+=(distribution[i]+delta)/psum
12            if r < cumsum:
13                break
14        return i
15
16    G=MultiDiGraph()
17    G.add_edges_from([(0,1),(1,2),(2,0)])
18    gamma=1-alpha-beta
19
20    while len(G)<n:
21        r = random.random()
22        if r < alpha:
23            v = len(G)
24            w = _choose_node(G, G.in_degree(), delta_in)
25        elif r < alpha+beta:
26            v = _choose_node(G, G.out_degree(), delta_out)
27            w = _choose_node(G, G.in_degree(), delta_in)
28        else:
29            v = _choose_node(G, G.out_degree(), delta_out)
30            w = len(G)
31        G.add_edge(v,w)
32    return G
```

Python is easy to write and read

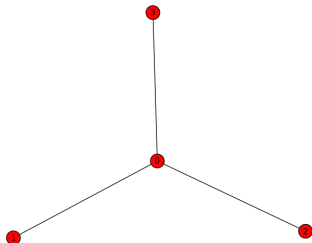
### Breadth First Search

```
1 from collections import deque
2
3 def breadth_first_search(g, source):
4     queue = deque([(None, source)])
5     enqueued = set([source])
6     while queue:
7         parent, n = queue.popleft()
8         yield parent, n
9         new = set(g[n]) - enqueued
10        enqueued |= new
11        queue.extend([(n, child) for child in new])
```

Credit: Matteo Dell'Amico

For a graph with  $n$  nodes

$$C_D(v) = \frac{\deg(v)}{n-1}$$



```
1 >>> G=nx.star_graph(3)
2 >>> print G.edges()
3 [(0, 1), (0, 2), (0, 3)]
4 >>> print G.degree(0)
5 2
6 >>> print len(G) # # of nodes
7 4
8 >>> print G.degree(0)/3
9 0
10 >>> print G.degree(0)/3.0
11 1
12 >>> for v in G:
13 ...     print v, G.degree(v)/3.0
14 0 1.0
15 1 0.33333333333333
16 2 0.33333333333333
17 3 0.33333333333333
```

## Degree centrality 1

```
1 import networkx as nx
2
3 def degree centrality(G):
4
5     n=len(G)-1.0 # forces floating point for n
6     for v in G:
7         print v, G.degree(v)/n
8
9     return
10
11 G=nx.star_graph(3)
12 degree centrality(G)
```

## Degree centrality 2

```
1 import networkx as nx
2
3 def degree_centrality(G):
4
5     centrality = {} # empty dictionary
6     n=len(G)-1.0 # forces floating point for n
7     for v in G:
8         centrality[v]=G.degree(v)/n
9
10    return centrality
11
12 G=nx.star_graph(3)
13 dc=degree_centrality(G)
14 for v in dc:
15     print v,dc[v]
16
17 print dc
```



```
1 def degree centrality(G):
2
3     centrality = {} # empty dictionary
4     n=len(G)-1.0 # forces floating point for n
5     for v in G:
6         centrality[v]=G.degree(v)/n
7
8     return centrality
9
10 if __name__=='__main__':
11     import networkx as nx
12     G=nx.star_graph(3)
13     for v,c in degree centrality(G).items():
14         print v,c
```

```
1 def degree centrality(G):
2     """Compute degree centrality for nodes.
3
4     The degree centrality for a node is the fraction of all other
5     nodes it is connected to.
6
7     >>> import networkx as nx
8     >>> G=nx.star_graph(3)
9     >>> print degree centrality(G)[0]
10    1.0
11    """
12    centrality = {} # empty dictionary
13    n=len(G)-1.0 # forces floating point for n
14    for v in G:
15        centrality[v]=G.degree(v)/n
16    return centrality
```

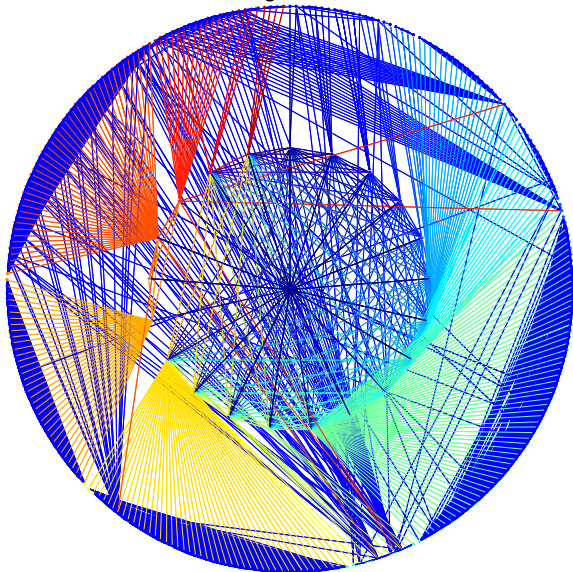
# Degree centrality in NetworkX

```
1 def degree_centrality(G):
2     """Compute the degree centrality for nodes.
3
4     The degree centrality for a node  $v$  is the fraction of nodes it
5     is connected to.
6
7     Parameters
8     -----
9     G : graph
10         A networkx graph
11
12     Returns
13     -----
14     nodes : dictionary
15         Dictionary of nodes with degree centrality as the value.
16
17     See Also
18     -----
19     betweenness_centrality, load_centrality, eigenvector_centrality
20
21     Notes
22     -----
23     The degree centrality values are normalized by dividing by the maximum
24     possible degree in a simple graph  $n-1$  where  $n$  is the number of nodes in  $G$ .
25
26     For multigraphs or graphs with self loops the maximum degree might
27     be higher than  $n-1$  and values of degree centrality greater than 1
28     are possible.
29     """
30     centrality={}
31     s=1.0/(len(G)-1.0)
32     centrality=dict((n,d*s) for n,d in G.degree_iter())
33     return centrality
```

This algorithm is really a one-liner:

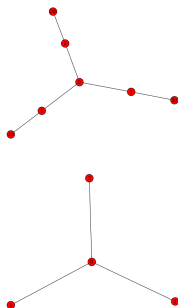
```
1 def degree_centrality(G):  
2     return dict((n,d/(len(G)-1.0)) for n,d in G.degree_iter())
```

Create network of neighbors centered at node n



# Ego Graph: getting started

```
1 import networkx as nx
2
3 def ego(G,v):
4     """Returns Graph of neighbors centered
5     at node n and including n.
6
7     >>> import networkx as nx
8     >>> G=nx.star_graph(3)
9     >>> G.add_edge(1,10)
10    >>> G.add_edge(2,20)
11    >>> G.add_edge(3,30)
12    >>> E=nx.ego_graph(G,0)
13    >>> print E.nodes()
14    [0, 1, 2, 3]
15    >>> print E.edges()
16    [(0, 1), (0, 2), (0, 3)]
17    """
18    return # E — the ego graph
19
20 if __name__=='__main__':
21     G=nx.star_graph(3)
22     G.add_edges_from([(1,10),(2,20),(3,30)])
23     E=ego(G,0)
```



## Hints:

- ▶ only consider Graph()
- ▶ use `G.neighbors(v)`
- ▶ same as `G[v]`
- ▶ don't worry about attributes

My solution