CS4423 - Networks

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6. Power Laws and Scale-Free Graphs

Lecture 21: Power Laws

```
In [1]: import numpy as np
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
```

Degree Distribution

Recall degree distribution:

The **degree distribution** of an undirected graph G=(X,E) is the function $k\mapsto p_k:=n_k/n$, where n=|X| and n_k is the number of nodes of degree k (and thus p_k is the probability that a random node $x\in X$ has degree k).

In an ensemble of graphs of order n, one sets $p_k := \overline{n_k}/n$, where $\overline{n_k}$ is the expected value of the random variable n_k over the ensemble of graphs.

In this sense, the degree distribution in a random G(n,p) graph is **binomial** :

$$p_k=inom{n-1}{k}p^k(1-p)^{n-1-k},$$

or, in the limit $n o \infty$ and p o 0 with np constant, it is a **Poisson distribution**:

$$p_k = e^{-z}rac{z^k}{k!},$$

where z = np.

A power law degree distribution is strikingly different:

```
p_k = ck^{-\gamma}
```

for certain constants c and γ . (Typically $2 \leq \gamma \leq 3$.)

```
In [2]: def binomial(n, k):
    prd, top, bot = 1, n, 1
    for i in range(k):
        prd = (prd * top) // bot
        top, bot = top - 1, bot + 1
    return prd
```

```
In [3]: def b_dist(n, p, k):
    return binomial(n, k) * p**k * (1-p)**(n-k)
```

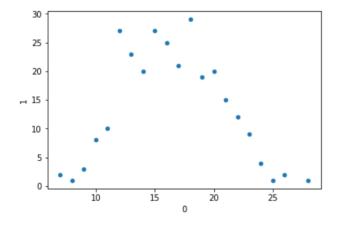
```
In [4]:
         from math import exp, factorial
          def p_dist(l, k):
              return exp(-l) * l**k / factorial(k)
In [5]: n, p = 1000, 0.015
         mm = 50
          l = p * (n-1)
         bb = [b_dist(n-1, p, k) for k in range(mm)]
         pp = [p_dist(l, k) for k in range(mm)]
In [6]: df = pd.DataFrame()
         df['binom'] = bb
         df['poisson'] = pp
         df.plot()
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e66fb6ac8>
                                                      binom
          0.10
                                                      poisson
          0.08
          0.06
          0.04
          0.02
          0.00
                                         30
                                                  40
                                                          50
                        10
                                 20
In [7]:
         def power_dist(c, gamma, k):
              return c * k**(-gamma)
In [8]: c = 0.15
          po1 = [power\_dist(c, 1, k) for k in range(1,mm+1)]
         po2 = [power_dist(c, 2, k) for k in range(1,mm+1)]
po3 = [power_dist(c, 3, k) for k in range(1,mm+1)]
In [9]:
         df['power1'] = po1
         df['power2'] = po2
         df['power3'] = po3
         df.plot()
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e66c67860>
                                                      binom
          0.14
                                                      poisson
                                                      power1
          0.12
                                                      power2
                                                      power3
          0.10
          0.08
          0.06
          0.04
          0.02
          0.00
                                 20
                                         30
                ó
                        10
                                                          50
```

```
In [10]: df.plot(loglog=True)
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e66b9f128>
            10-1
            10-3
            10-5
            10^{-7}
                     binom
            10-9
                      poisson
                     power1
           10-11
                      power2
                      power3
                                          10<sup>1</sup>
In [11]:
          G = nx.read_pajek("c_elegans_undir.net")
          G = nx.Graph(G)
In [12]: n, m = G.number_of_nodes(), G.number_of_edges()
```

A random graph R of same degree n and size m.

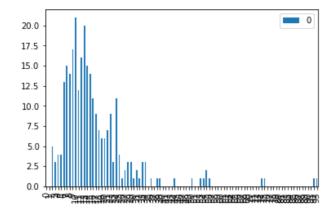
```
In [13]: R = nx.gnm_random_graph(n, m)
    hist = nx.degree_histogram(R)
    hist = [(i, hist[i]) for i in range(len(hist)) if hist[i] > 0]
    df = pd.DataFrame(hist)
    df.plot.scatter(x = 0, y = 1)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e66a57128>



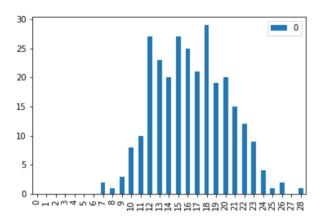
```
In [14]: pd.DataFrame(nx.degree_histogram(G)).plot.bar()
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e66921198>



```
In [15]: pd.DataFrame(nx.degree_histogram(R)).plot.bar()
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e6666d5f8>



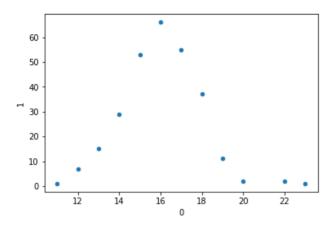
A (n,d,p)-Watts-Strogatz graph has n nodes and dn edges

```
In [16]: d = m//n
    p = 0.2
    W = nx.watts_strogatz_graph(n, 2*d, p)

In [17]: W.number_of_nodes(), W.number_of_edges()
Out[17]: (279, 2232)
```

```
In [18]: hist = nx.degree_histogram(W)
hist = [(i, hist[i]) for i in range(len(hist)) if hist[i] > 0]
df = pd.DataFrame(hist)
df.plot.scatter(x = 0, y = 1)
```

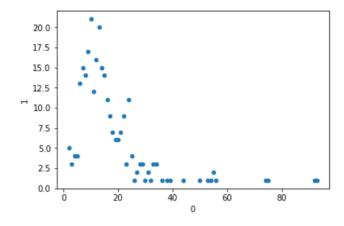
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e6699feb8>



Does the degree histogram of the worm brain network follow a power law degree distribution? Here is a standard plot and a loglog plot of it ...

```
In [19]: hist = nx.degree_histogram(G)
hist = [(i, hist[i]) for i in range(len(hist)) if hist[i] > 0]
df = pd.DataFrame(hist)
df.plot.scatter(x = 0, y = 1)
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e664a0588>



In [20]: df.plot.scatter(x = 0, y = 1, loglog=True)

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e6699f278>

