

cpts591_Mengxiao_hw1

February 18, 2020

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[1]: from igraph import *

[2]: # At first, we need to read the three networks and generate three Erdos-Renyi
    ↪ random networks.

[3]: # Political blogs
g_PB = Graph.Read_GML('polblogs.gml')
# Neural network
g_NN = Graph.Read_GML('celegansneural.gml')
# Internet
g_In = Graph.Read_GML('as-22july06.gml')
# With n = 2000, p = 0.01
g_01 = Graph.GRG(2000, 0.01)
# With n = 2000, p = 0.005
g_005 = Graph.GRG(2000, 0.005)
# With n = 2000, p = 0.0025
g_0025 = Graph.GRG(2000, 0.0025)

[4]: # Q1. calculate the information for each of the six networks.

[5]: g = {}
g['PB']={'model': g_PB, 'Network': 'Political blogs'}
g['NN']={'model': g_NN, 'Network': 'Neural network'}
g['In']={'model': g_In, 'Network': 'Internet'}
g['01']={'model': g_01, 'Network': 'G(2000,0.01)'}
g['005']={'model': g_005, 'Network': 'G(2000,0.005)'}
g['0025']={'model': g_0025, 'Network': 'G(2000, 0.0025)'}
names = ['PB', 'NN', 'In', '01', '005', '0025']

[6]: for i in names:
    g[i]['Type'] = g[i]['model'].is_directed()
    g[i]['n'] = g[i]['model'].vcount()
    g[i]['m'] = g[i]['model'].ecount()
    if g[i]['Type']:
        g[i]['c-strong'] = g[i]['model'].components().summary()
        g[i]['c-weak'] = g[i]['model'].components(WK).summary()
    else:
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        g[i]['c'] = g[i]['model'].components().summary()
    g[i]['d'] = g[i]['model'].maxdegree()
    g[i]['l'] = g[i]['model'].average_path_length()
    g[i]['L'] = g[i]['model'].diameter()
    g[i]['ccl'] = g[i]['model'].transitivity_avglocal_undirected()
    g[i]['ccg'] = g[i]['model'].transitivity_undirected()

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[7]: g
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[7]: {'PB': {'model': <igraph.Graph at 0x7f35cc03ee58>,
  'Network': 'Political blogs',
  'Type': True,
  'n': 1490,
  'm': 19090,
  'c-strong': 'Clustering with 1490 elements and 688 clusters',
  'c-weak': 'Clustering with 1490 elements and 268 clusters',
  'd': 468,
  'l': 3.3901837252152363,
  'L': 9,
  'ccl': 0.3600286522101186,
  'ccg': 0.2259585173589758},
  'NN': {'model': <igraph.Graph at 0x7f35b3fbb048>,
  'Network': 'Neural network',
  'Type': True,
  'n': 297,
  'm': 2359,
  'c-strong': 'Clustering with 297 elements and 57 clusters',
  'c-weak': 'Clustering with 297 elements and 1 clusters',
  'd': 139,
  'l': 3.9918839808408726,
  'L': 14,
  'ccl': 0.30791453707858335,
  'ccg': 0.18071147126607687},
  'In': {'model': <igraph.Graph at 0x7f359a088408>,
  'Network': 'Internet',
  'Type': False,
  'n': 22963,
  'm': 48436,
  'c': 'Clustering with 22963 elements and 1 clusters',
  'd': 2390,
  'l': 3.842426273858345,
  'L': 11,
  'ccl': 0.3499153584893828,
  'ccg': 0.011146383847822162},
  '01': {'model': <igraph.Graph at 0x7f359a0884f8>,
  'Network': 'G(2000,0.01)',
  'Type': False,

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'n': 2000,
'm': 633,
'c': 'Clustering with 2000 elements and 1428 clusters',
'd': 6,
'l': 1.4457274826789839,
'L': 6,
'ccl': 0.5620967741935483,
'ccg': 0.5431034482758621},
'005': {'model': <igraph.Graph at 0x7f359a0885e8>,
'Network': 'G(2000,0.005)',
'Type': False,
'n': 2000,
'm': 153,
'c': 'Clustering with 2000 elements and 1850 clusters',
'd': 2,
'l': 1.0254777070063694,
'L': 2,
'ccl': 0.6923076923076923,
'ccg': 0.6923076923076923},
'0025': {'model': <igraph.Graph at 0x7f359a0886d8>,
'Network': 'G(2000, 0.0025)',
'Type': False,
'n': 2000,
'm': 34,
'c': 'Clustering with 2000 elements and 1966 clusters',
'd': 2,
'l': 1.0285714285714285,
'L': 2,
'ccl': 0.0,
'ccg': 0.0}}

```

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[8]: # Q2. Plot the degree distribution of each network.
import cairocffi
from igraph import plot

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[9]: for i in names:
    plot(g[i]['model'].degree_distribution(),
        g[i]['Network']+"_degree_distribution.png",
        bbox=(300, 300), margin=20)

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[31]: # A2. According to the graph, I find that the degree distribution graph of
# the Neural network and Internet is obviously fit the Poisson distribution,
# so that they are the E-R random graph, but the other network look
# like power law distribution, but according to the theory, what our
# build is an E-R random graph, so their degree distribution graph may
# be still a Poisson distribution but just shifted left.

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[10]: # Q3. Plot the pathlength distribution of each network.
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[11]: for i in names:
        plot(g[i]['model'].path_length_hist(),
             g[i]['Network']+"_path_length_hist.png",
             bbox=(300, 300), margin=20)
        print("-"*20+g[i]['Network']+"-"+20)
        print(g[i]['model'].path_length_hist())
```

*****Political blogs*****

N = 981248, mean +- sd: 3.3902 +- 1.1302

Each * represents 5901 items

```
[ 1,  2): *** (19022)
[ 2,  3): ***** (193830)
[ 3,  4): ***** (348198)
[ 4,  5): ***** (275702)
[ 5,  6): ***** (107394)
[ 6,  7): **** (25602)
[ 7,  8): * (10092)
[ 8,  9): (1371)
[ 9, 10): (37)
```

*****Neural network*****

N = 67644, mean +- sd: 3.9919 +- 2.0243

Each * represents 339 items

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[ 1,  2): ***** (2345)
[ 2,  3): ***** (11767)
[ 3,  4): ***** (20346)
[ 4,  5): ***** (14133)
[ 5,  6): ***** (6421)
[ 6,  7): ***** (4323)
[ 7,  8): ***** (3318)
[ 8,  9): ***** (1984)
[ 9, 10): **** (1442)
[10, 11): ** (946)
[11, 12): * (454)
[12, 13): (142)
[13, 14): (21)
[14, 15): (2)
```

*****Internet*****

N = 263638203, mean +- sd: 3.8424 +- 0.8957

Each * represents 2024692 items

```
[ 1,  2): (48436)
[ 2,  3): ***** (11063714)
[ 3,  4): ***** (84546313)
[ 4,  5): ***** (113382789)
[ 5,  6): ***** (44950231)
[ 6,  7): **** (8674704)
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[ 7, 8): (913431)
[ 8, 9): (56317)
[ 9, 10): (2214)
[10, 11): (53)
[11, 12): (1)
*****G(2000,0.01)*****
N = 866, mean +- sd: 1.4457 +- 0.9085
Each * represents 9 items
[1, 2): *****
(633)
[2, 3): ***** (147)
[3, 4): **** (44)
[4, 5): ** (22)
[5, 6): * (15)
[6, 7): (5)
*****G(2000,0.005)*****
N = 157, mean +- sd: 1.0255 +- 0.1581
Each * represents 2 items
[1, 2):
*****
(153)
[2, 3): ** (4)
*****G(2000, 0.0025)*****
N = 35, mean +- sd: 1.0286 +- 0.1690
[1, 2): ***** (34)
[2, 3): * (1)

```

[32]: *# A3. From the graph I can find that all of three real-world network given
by professor are Poisson distribution and most of the path length are
3 to 5. But all of the three E-R random graph built by us still like
power law distribution and their path length are most 1.*

[39]: *# Q4. Choose one real-world network and do the analysis in (1)-(3).
I choose the network "Les Miserables" on the web given by professor.
It contains the weighted network of coappearances of characters in
Victor Hugo's novel "Les Miserables". Nodes represent characters as
indicated by the labels and edges connect any pair of characters that
appear in the same chapter of the book. The values on the edges are
the number of such coappearances.*

```

g_LM = Graph.Read_GML('lesmis.gml')
g['LM']={'model': g_LM, 'Network': 'Les Miserables'}
g['LM']['Type']=g_LM.is_directed()
g['LM']['n']=g_LM.vcount()
g['LM']['m']=g_LM.ecount()
if g['LM']['Type']:
    g['LM']['c-strong']=g_LM.components().summary()

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    g['LM']['c-weak']=g_LM.components(WEAK).summary()
else:
    g['LM']['c']=g_LM.components(WEAK).summary()
g['LM']['d']=g_LM.maxdegree()
g['LM']['l']=g_LM.average_path_length()
g['LM']['L']=g_LM.diameter()
g['LM']['ccl']=g_LM.transitivity_avglocal_undirected()
g['LM']['ccg']=g_LM.transitivity_undirected()
plot(g_LM.degree_distribution(), g['LM']['Network']+"_degree_distribution.png",
bbox=(300, 300), margin=20)
plot(g_LM.path_length_hist(), g['LM']['Network']+"_path_length_hist.png",
bbox=(300, 300), margin=20)
print(g['LM'])
print('*'*20+"Les Miserables"+"*"*20)
print("degree distribution: ")
print(g_LM.degree_distribution())
print("path length hist")
print(g_LM.path_length_hist())

```

```

{'model': <igraph.Graph object at 0x7f359a0888b8>, 'Network': 'Les Miserables',
'Type': False, 'n': 77, 'm': 254, 'c': 'Clustering with 77 elements and 1
clusters', 'd': 36, 'l': 2.6411483253588517, 'L': 5, 'ccl': 0.735525495746084,
'ccg': 0.49893162393162394}

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*****Les Miserables*****

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degree distribution:

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N = 77, mean +- sd: 6.5974 +- 6.0399

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[ 1,  2): ***** (17)
[ 2,  3): ***** (10)
[ 3,  4): ***** (6)
[ 4,  5): *** (3)
[ 5,  6): (0)
[ 6,  7): ***** (5)
[ 7,  8): ***** (10)
[ 8,  9): * (1)
[ 9, 10): *** (3)
[10, 11): ***** (5)
[11, 12): ***** (6)
[12, 13): ** (2)
[13, 14): ** (2)
[14, 15): (0)
[15, 16): ** (2)
[16, 17): * (1)
[17, 18): * (1)
[18, 19): (0)
[19, 20): * (1)
[20, 21): (0)
[21, 22): (0)

```

```

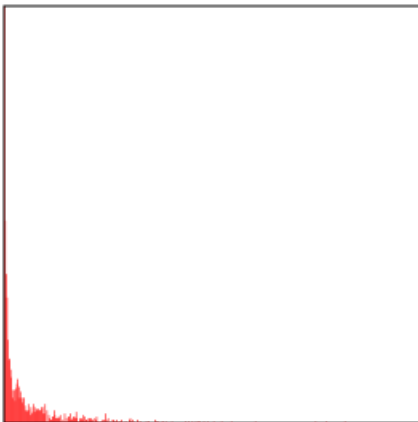
[22, 23): * (1)
[23, 24): (0)
[24, 25): (0)
[25, 26): (0)
[26, 27): (0)
[27, 28): (0)
[28, 29): (0)
[29, 30): (0)
[30, 31): (0)
[31, 32): (0)
[32, 33): (0)
[33, 34): (0)
[34, 35): (0)
[35, 36): (0)
[36, 37): * (1)
path length hist
N = 2926, mean +- sd: 2.6411 +- 0.8556
Each * represents 19 items
[1, 2): ***** (254)
[2, 3): ***** (995)
[3, 4): ***** (1251)
[4, 5): ***** (399)
[5, 6): * (27)

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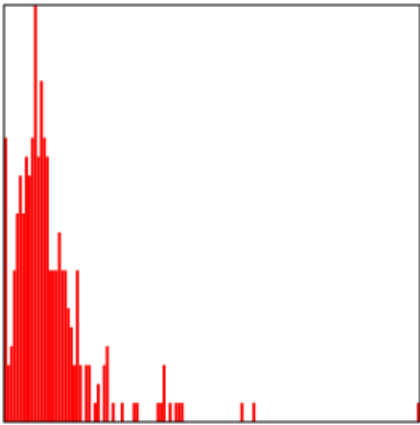
[34]: *# A4. According to the graph, we can find the degree distribution of
 # the Les Miserables network is still Poisson distribution but it's
 # path length hist is clearly not Poisson distribution or power law
 # distribution. But there exist a point with 36 degree, this point may
 # be very important.*

—————Degree distribution graph—————

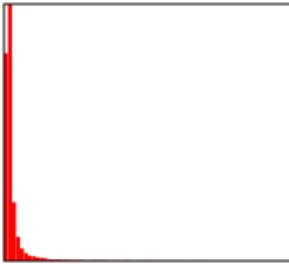
Political blogs:



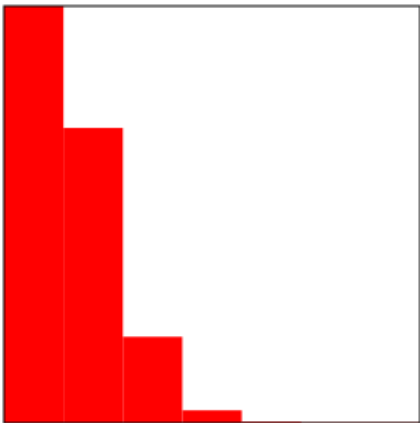
Neural network:



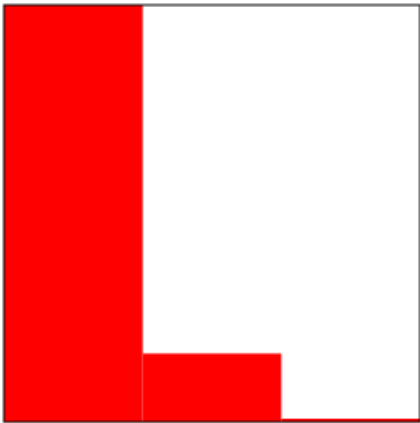
Internet:



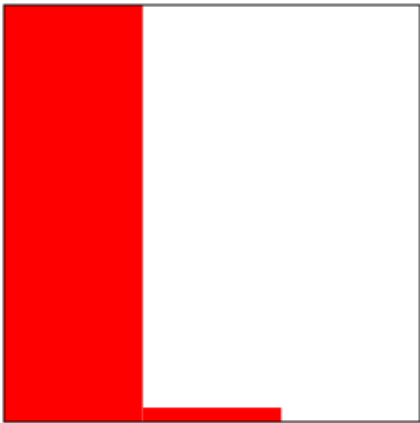
$G(2000,0.01)$



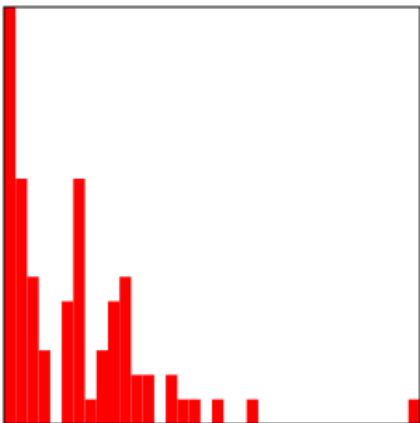
$G(2000,0.005)$



G(2000,0.0025)

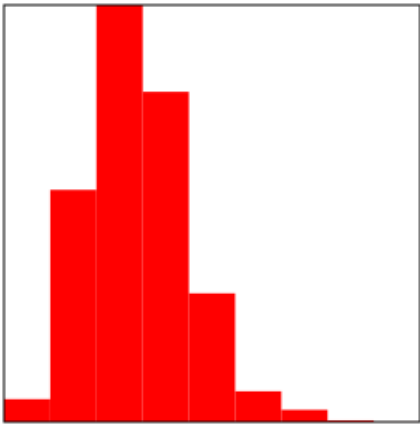


Les Miserables:

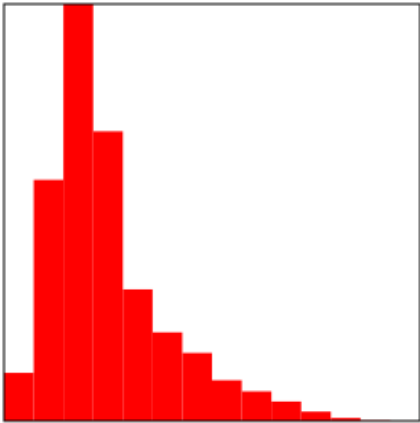


—————path length hist—————

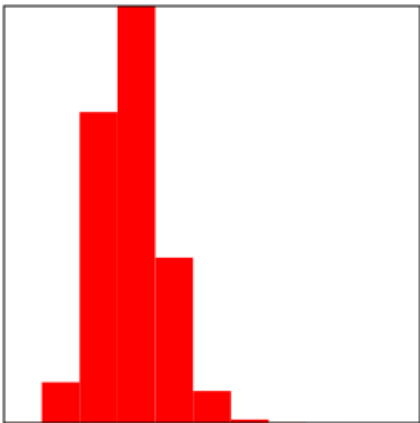
Political blogs:



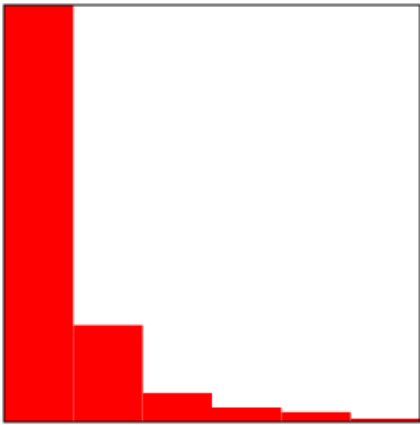
Neural network:



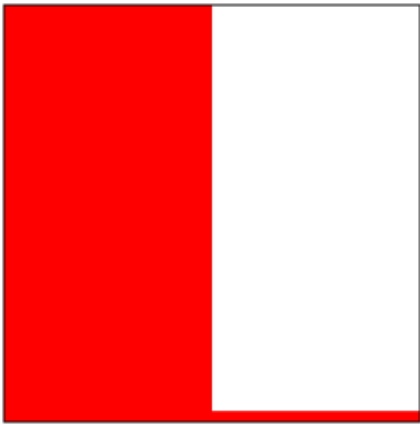
Internet:



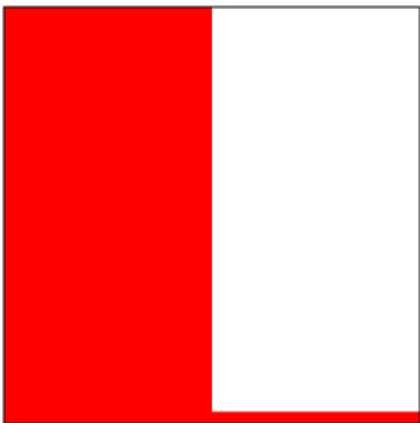
$G(2000,0.01)$



G(2000,0.005)



G(2000,0.0025)



Les Miserables:

