Bioinformatics III

Second Assignment

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Exercise 2.1: The Scale-Free network

(a) Implement the algorithm given in the lecture to set up a scale-free network according to the Barabási-Albert model (see Lecture 2, slide 8). Start from the first three connected nodes and add each new node with a given number of links. Connect the new links with increasing preference to nodes that have higher degrees. This ScaleFreeNetwork-class should again use the abstract network class that you wrote in the first assignment. To obtain a much faster implementation and full points, think of a method to map the probabilities to connect to nodes somehow instead of computing them from scratch in each iteration.

Implementation of the missing methods for the ScaleFreeNetwork-class. Listing 1 shows source code of ScaleFreeNetwork.py.

```
Listing 1: ScaleFreeNetwork.py
```

```
o #Bioinformatics 3 : Wiebke Schmitt & Thibault Schowing
  import random
  from Node import Node
  from AbstractNetwork import AbstractNetwork
5 class ScaleFreeNetwork(AbstractNetwork):
        ""Scale-free\ network\ implementation\ of\ AbstractNetwork"""
       \mathbf{def} \ \ _{\ \ _{n,n,n}} \mathsf{createNetwork}_{-} (\ \mathsf{self} \ , \ \ \mathsf{amount\_nodes} \ , \ \ \mathsf{amount\_links} \, ) :
10
            Create a network with an amount of n nodes, add m links per iteration
                step
            for n nodes:
                for \ m \ links:
                     link node to other nodes
15
            def symetricConnection(node1, node2):
                node1.addLinkTo(node2)
20
                node2.addLinkTo(node1)
            def genProbList():
                # Generate probability range for each nodes
                prob_list = []
                sumkj = self.degreeSum()
                for key, node in self.nodes.items():
                     # calculate pi
                     \# ki = degree \ of \ node \ i
                     #print("Debug: node degree: ", node.degree())
                     ki = node.degree()
```

```
\# Sum \ kj = sum \ of \ all \ degrees
35
                      prob_list.append(ki / sumkj)
                      #print("Debug select neighbours prob list: ", prob_list)
                 \# now we have a probability list \rightarrow select the number_neighbours
                      future neighbours
40
                 #print("DEBUG probability list generated: ", prob_list)
                 return prob_list
45
            random.seed()
            print("Debug: " , amount_nodes, " _ nodes _ and _ " , amount_links , " links . . . .
50
                 _creating_ScaleFree_network")
            # Initial m0 nodes connected to each other
            # #QUESTION: is 3 fixed ??? Should it be dynamic ?
55
            # Number of links per node
            number_neighbours = amount_links
            # Contains the degrees of the initial complete network
60
            degree\_list = [2,2,2]
            for i in range (0, m0):
                 self.appendNode(Node(i))
65
            symetricConnection (\,self.getNode\,(0)\,,\ self.getNode\,(1)\,)
            \begin{array}{l} symetric Connection (\, self \, . \, getNode \, (1) \, \, , \quad self \, . \, getNode \, (2) \, ) \\ symetric Connection (\, self \, . \, getNode \, (0) \, \, , \quad self \, . \, getNode \, (2) \, ) \end{array}
            \# useless and slow
70
            \#\ http://didar-physics.blogspot.de/2015/02/barabasialbert-model-
                 generated-code.html
            \#\ https://stackoverflow.com/questions/38008748/python-implementing-a-
                 step-by-step-modified-barabasi-albert-model-for-scale-fr
            \# Random failure measure
            random_failure = 0
            \# new nodes id (without the 3 initial nodes)
            for new_node_id in range(3, amount_nodes - 3):
                 #print("Debug: population: ", population)
                 new_node = Node(new_node_id)
                 self.appendNode(new_node)
                 # Just a sequence of all node ids
                 population = list(range(0, self.size()))
85
                 \#\ Generate\ probability\ list\ of\ existing\ nodes
                 prob_list = genProbList()
                 for i in range (amount_links):
90
                      while (True):
                           chosen_neighbour = random.choices(population, weights=
                               \texttt{prob\_list} \ , \ k = 1) \, \lceil 0 \rceil
95
```

```
# if it's a new link and it's not a self-connection
                              if not new_node.hasLinkTo(chosen_neighbour) and not
                                   chosen\_neighbour == new\_node.id:
                                    symetricConnection (new_node, self.getNode(
                                         chosen_neighbour))
                                   break
100
                              # Random failure increment
                              random_failure += 1
                   \# debug info: print degrees
105
                    self.degrees = []
                    for id, node in self.nodes.items():
                         self.degrees.append(node.degree())
                    #print(self.degrees)
110
              \mathbf{print} \, (\, "\, \mathrm{Debug} \, \_\mathrm{Random} \, \_\, \mathrm{failure} \, \_\mathrm{count} \, \colon \_" \, , \, \, \, \mathrm{random} \, \_\mathrm{failure} \, )
```

(b) Determine the degree distributions for scale-free networks of 10 000 and 100 000 nodes (each with two new links per iteration), respectively, and plot them with double logarithmic axes. A new pre-implemented method in Tools.py will help you with that. What are the differences? Next, compare one of the distributions to the degree distribution of an equally sized random network (play around with the plot-scaling). What are the major differences?

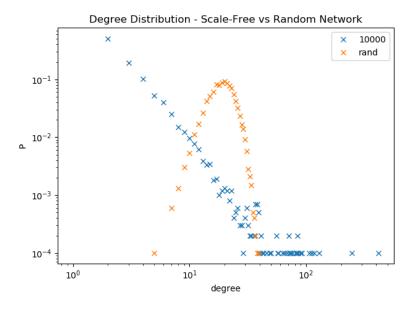


Figure 1: We can observe that the Scale-Free distribution follow a power-law style, as it is almost a straight line when ploted with log-log axes. On the other hand, the random network is more Poisson distributed as seen in Assignment 1.

Listing 2: ScaleFreeTest.py

o #!/usr/bin/python #Bioinformatics 3: Wiebke Schmitt & Thibault Schowing from ScaleFreeNetwork import ScaleFreeNetwork from DegreeDistribution import DegreeDistribution from RandomNetwork import RandomNetwork

```
5 import matplotlib.pyplot as plt
     import Tools as Tools
     if __name__= "__main__":
               # TASK 2.1 a AND b
               # Creating two networks and taking the degree distributions
               small = 100
               \mathrm{big}\,=\,1000
               sf_net = ScaleFreeNetwork(small,2)
               sf_net2 = ScaleFreeNetwork(big,2)
               rand_net = RandomNetwork(10000, 100000)
               sf\_degree \ = \ DegreeDistribution (\, sf\_net \, ) \, . \, getNormalizedDistribution ( \, )
20
               sf_degree2 = DegreeDistribution(sf_net2).getNormalizedDistribution()
               rand_degree = DegreeDistribution(rand_net).getNormalizedDistribution()
               # Plot the degree distribution
               Tools.\,plot Distribution Comparison Log Log \,(\,[\,sf\_degree\,\,,\,\,sf\_degree\,\,2\,\,,\,\,rand\_degree\,\,2)
25
                        [, small, big, "rand"], "Degree_Distribution_Scale-Free_network_")
               Tools.plotDistributionComparisonLogLog\left([sf\_degree2\;,\;rand\_degree]\;,\;[big\;,\;"and\_degree]\;,\;[big\;,\;"and\_degree]\;,\;[big\;,\;"and\_degree]\;,\;[big\;,\;"and\_degree2\;,\; rand\_degree2\;,\; rand\_degree3\;,\; rand\_degree3\;,
                        rand"], "Degree_Distribution_-_Scale-Free_vs_Random_Network")
               # TASK 2.1 c
               sf_net_c = ScaleFreeNetwork(10000, 2)
30
               sf_net_c_degree = DegreeDistribution(sf_net_c).getNormalizedDistribution()
               k = len(sf_net_c_degree)
               gamma_distance = []
35
               # Foreach gamma, calculate the KS distance
               steps = [x * 0.1 for x in range(10, 30)]
               for gamma in steps:
                         theoretical_dist = Tools.getScaleFreeDistributionHistogram(gamma, k)
40
                        \#Normalize
                        {\it \#TODO~normalize~according~to~what~?}
                         distance = Tools.simpleKSdist(sf_net_c_degree, theoretical_dist)
45
                         gamma_distance.append((gamma, distance))
               \# Sort the distances-gamma tuples
               gamma_distance.sort(key=lambda x: x[1], reverse=True)
               print("All_gamma-distance:_", gamma_distance)
50
               print("Best_gamma: _", gamma_distance[0][0])
               \# Optimal theoretical distribution (powerlaw)
               optimal_theoretical = Tools.getScaleFreeDistributionHistogram(
                         gamma_distance[0][0], k)
               Tools.plotDistributionComparisonLogLog([sf_net_c_degree]
                         optimal_theoretical], ['Scale_Free_Network', 'PowerLaw'], 'Compare_
                         theory_to_practice')
```

(c) The degree distribution of a scale-free network follows a power law, which has the form P(k) $k^{-\lambda}$ To simplify the exercise, we assume P(k) $Ck^{-\lambda}$ with C being a fixed normalization constant to obtain a proper distribution. Try to fit this theoretical distribution to the degree distribution of a random network using the Kolmogorov-Smirnov distance.

```
Listing 3: Tools.py
```

```
o import matplotlib.pyplot as plt
import math
```

```
def plotDistributionComparison(histograms, legend, title):
       Plots a list of histograms with matching list of descriptions as the
       ,,,, legend
       # determine max. length
       max_length = max(len(x) for x in histograms)
10
       # extend "shorter" distributions
       for x in histograms:
           x. extend ([0.0]* (max_length-len(x)))
       # plots histograms
15
       for h in histograms:
           plt.plot(range(len(h)), h, marker = 'x')
       # remember: never forget labels!
       plt.xlabel('degree')
20
       plt.ylabel('P')
       # you don't have to do something stuff here
       plt.legend(legend)
25
       plt.title(title)
       plt.tight_layout()
       plt.show()
30 def plotDistributionComparisonLogLog(histograms, legend, title):
       Plots a list of histograms with matching list of descriptions as the
          legend
       fig = plt.figure()
35
       ax = plt.subplot()
       # determine max. length \max_{n} = \max(len(x) | for x in histograms)
       # extend "shorter" distributions
       for x in histograms:
40
           x.extend([0.0]*(max_length-len(x)))
       ax.set_xscale("log")
       ax.set_yscale("log")
45
       # plots histograms
       for h in histograms:
           ax.plot(range(len(h)), h, marker = 'x', linestyle='')
      # remember: never forget labels!
plt.xlabel('degree')
plt.ylabel('P')
50
       # you don't have to do something stuff here
       plt.legend(legend)
55
       plt.title(title)
       plt.tight_layout()
       # Uncomment the line below to display normally
       # plt.show()
60
       # Comment the 2 lines below to display normally
       filename = title + ".png"
       fig.savefig(filename)
65
  def getScaleFreeDistributionHistogram(gamma, k):
```

```
, , ,
       Generates a Power law distribution histogram with slope gamma up to degree
70
       histogram = []
       # NORMALISATION_CONSTANT \
       # Todo here or in ScaleFreeTest.py
       for i in range(1, k):
75
           histogram.append(i**-gamma)
       return histogram
80
  def simpleKSdist(histogram_a, histogram_b):
       Simple \ \ Kolmogorov-Smirnov \ \ distance \ \ implementation
       #print("KSDIST: size hist 1: ", len(histogram_a), " Size hist2: ", len(
           histogram_{-}b))
       \# Assume that the two hists have the same length for i in range(0, len(histogram_a)-1):
           D = \max(D, (histogram_a[i] - histogram_b[i]))
90
       return D
```

Use the KS distance to determine a γ (between 1 and 3, 0.1 steps sufficient) that fits best to the degree distribution of a scale-free network with 10 000 nodes and two new links per iteration. Compare the empirical distribution of the network to the theoretical distribution with optimal γ in a double-log. plot. Comment on the quality of your fit, reason why it may fail and how it could be vastly improved.

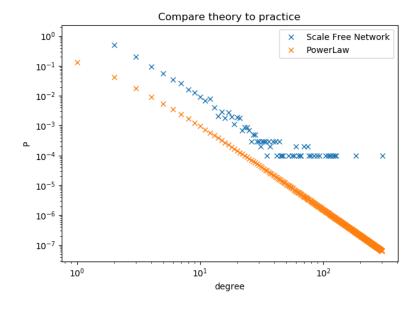


Figure 2:

Figure 3:

Exercise 2.2: Classify real-world network examples

- (a) bla
- (b) bla
- (c) bla

Exercise 2.3: Real interaction networks

(a) Here is the implementation of the BioGRIDReader-class

Listing 4: BioGRIDReader.py

```
o import operator
  from GenericNetwork import GenericNetwork
  from DegreeDistribution import DegreeDistribution
  import Tools as Tools
5 class BioGRIDReader:
        ''', Reads BioGRID tab files'''
      \mathbf{def} __init__(self, filename):
           Initialization, read in file and build any data structure that makes
           you happy
10
           content_start = False
           # Temporary tab -> contains one line
15
           line_tab = []
           self.INTERACTOR\_A =
           self.INTERACTOR_B = 
           self.OFFICIAL\_SYMBOL\_FOR\_A = []
           self.OFFICIAL_SYMBOL_FOR_B = []
20
           self.ALIASES_FOR_A = []
           self.ALIASES\_FOR\_B = [
           self.EXPERIMENTAL_SYSTEM = []
           self.SOURCE = []
           self.PUBMED_ID = []
25
           self.ORGANISM\_A\_ID =
           self.ORGANISM\_B\_ID = []
           with open(filename, "r") as f:
               for line in f:
                   if line.startswith("INTERACTOR_A"):
                       content_start = True
                       continue
                   if content_start:
                       # Process data
35
                       line = line.rstrip()
                       line\_tab = line.split('\t')
                       self.INTERACTOR_A.append(line_tab[0])
                       self.INTERACTOR_B.append(line_tab[1])
40
                        self.OFFICIAL_SYMBOL_FOR_A.append(line_tab[2])
                       self.OFFICIAL_SYMBOL_FOR_B.append(line_tab[3])
                       self.ALIASES_FOR_A.append(line_tab[4])
                       self.ALIASES_FOR_B.append(line_tab[5])
                        \verb|self.EXPERIMENTAL.SYSTEM.append(line\_tab[6])|\\
45
                       self.SOURCE.append(line_tab[7])
                       self.PUBMED_ID.append(line_tab[8])
                       self.ORGANISM_A_ID.append(line_tab[9])
                        self.ORGANISM_B_ID.append(line_tab[10])
           # The file has now been read and all infos are in lists
```

```
# Tuples can store pairwise interactions
55
       def getMostAbundantTaxonIDs(self, n):
           interact = \{\}
           organism_pairs_list = zip(self.ORGANISM_A_ID, self.ORGANISM_B_ID)
60
           for A, B in organism_pairs_list:
               if not A in interact:
                   interact[A] = 1
               else:
                   interact[A] += 1
65
               # If both are the same, the interaction must be counted only once
               if A != B:
                    if not B in interact:
                        interact[B] = 1
70
                    else:
                        interact [B] += 1
           # Sort the dict to retrieve the n first
           \#\ https://stackoverflow.com/questions/613183/how-do-i-sort-a-
               dictionary-by-value
75
           sorted_interact = sorted(interact.items(), key=operator.itemgetter(1))
           nFirst = []
           for i in range (1, n+1):
80
               nFirst.append(sorted\_interact[-i])
           return nFirst
       def getHumanInteraction(self):
           # Search for human-human interactions
           nb\_human\_human\_interact \, = \, 0
           organism_pairs_list = zip(self.ORGANISM_A_ID, self.ORGANISM_B_ID)
           for A, B in organism_pairs_list:
90
               if A == B == "9606":
                   nb\_human\_human\_interact += 1
           print("HUMAN_INTERACTIONS\n")
           print("\nNumber\_of\_Human\_Interactions\_(human\_id\_=\_9606):\_",
95
               nb_human_human_interact)
           # Now we need the indices of the human - human interactions
           # The code below extract the indices where ORGANISM A / ORGANISM B are
               human and take the intersection
           \#\ Order\ dict:\ https://stackoverflow.com/questions/16772071/sort-dict-
               by-value-python
100
           # Get Indexes
           indexesA = [i for i, x in enumerate(self.ORGANISM_AJD) if x == '9606'
           indexesB = [i for i, x in enumerate(self.ORGANISM_B_ID) if x == '9606'
           \# Get intersection
105
           indexes = list(set(indexesA).intersection(indexesB))
           proteins = [self.INTERACTOR_A[i] for i in indexes]
           proteins.extend([self.INTERACTOR_B[i] for i in indexes])
110
           proteins_count = {}
           for prot in proteins:
```

```
if prot not in proteins_count:
                   proteins_count[prot] = 1
115
                   proteins\_count[prot] += 1
           proteins_count = sorted(proteins_count.items(), key=lambda x:x[1])
           \# Obtain the n most used proteins
           n = 10
120
           nFirst = []
           for i in range (1, n + 1):
               nFirst.append(proteins_count[-i])
125
           print("\nThe_", n, "_proteins_with_the_highest_degree_are:_")
           print (nFirst)
       def writeInteractionFile(self, taxon_id, filename):
           organism_pairs_list = zip(self.ORGANISM_AJD, self.ORGANISM_BJD)
130
           file = open(filename, "w+")
           # Get Indexes
           indexesA = [i for i, x in enumerate(self.ORGANISM_A_ID) if x ==
               taxon_id]
           indexesB = [i for i, x in enumerate(self.ORGANISM_BJD) if x = 
135
               taxon_id]
           # Get intersection
           indexes = list(set(indexesA).intersection(indexesB))
140
           for i in indexes:
               file . write(self .INTERACTOR_A[i])
               file.write("\t")
               file . write (self .INTERACTOR_B[i])
               \mathbf{file} \; . \; \mathtt{write} \; \dot{(}\; " \setminus n " \; )
           file.close()
   if __name__= "__main__":
150
       bio = BioGRIDReader("BIOGRID-ALL-3.4.159.tab.txt")
       abundantTaxon = bio.getMostAbundantTaxonIDs(5)
       print("The_most_abundent_TaxonIDs_are_(id,_qty):_", abundantTaxon)
       bio.getHumanInteraction()
155
       # Export human interactions to a file
       EXPORT_FILE_NAME = "humanFile.txt"
      EXPORT_ORGANISM = "9606"
       bio.writeInteractionFile(EXPORT_ORGANISM, EXPORT_FILE_NAME)
160
       # Create GenericNetwork with previously exported file
       gen = GenericNetwork(EXPORT_FILE_NAME)
       print(str(gen))
       # Get distribution
165
       gen_degree = DegreeDistribution(gen).getNormalizedDistribution()
       # Plot the degree distribution
       Distribution_Generic_network_")
```

- (b) The class getMostAbundantTaxonIDs(n) is listed in the listing 4 above.
- (c) How big is the human interaction network and which are the 10 proteins with the highest degree? Take one of them as an example and briefly explain the biology behind the connectivity.

The most abundent TaxonIDs are (id, qty): [('559292', 704012), ('9606', 414501), ('316407',

184023), ('284812', 72149), ('7227', 67935)]

- 559292: Saccharomyces cerevisiae (Baker's Yeast)
- 9606: Human (Homo sapiens)
- 316407: Escherichia coli
- 284812: Schizosaccharomyces pombe (Fission yeast)
- 7227: Drosophila melanogaster

Number of Human-Human interactions (human id = 9606): 386192

The 10 proteins with the highest degree are: [('ETG7157', 3024), ('ETG7706', 2559), ('ETG351', 2454), ('ETG1956', 2134), ('ETG7316', 2042), ('ETG4914', 2002), ('ETG4193', 1939), ('ETG672', 1876), ('ETG1994', 1840), ('RP4-811H24.2', 1646)]

This network has 17087 nodes.

(d) Generic network implementation

```
Listing 5: GenericNetwork.py
```

```
o from AbstractNetwork import AbstractNetwork
  from Node import Node
  # from standard library module
  from itertools import islice
5 import sys
  class GenericNetwork(AbstractNetwork):
      def __init__(self , filename):
10
           Create a network from a file
          self.nodes = \{\}
          # We first need to create all Nodes (unique)
          allEntries = []
          pairs = []
          with open(filename) as f:
20
              # Run through the entire file to make a set of entries
               for line in f:
                   line = line.rstrip()
                   line_tab = line.split('\t')
25
                   pairs.append(line_tab)
                   allEntries.extend(line_tab)
               allUniqueEntries = set(allEntries)
               for n in allUniqueEntries:
                   self.appendNode(Node(n))
30
               for pair in pairs:
                   self.getNode(pair[0]).addLinkTo(self.getNode(pair[1]))
                   self.getNode(pair [1]).addLinkTo(self.getNode(pair [0]))
```