Bioinformatics III

Fifth Assignment

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Exercise 5.1: Cliques and Network Evolution

(a) Reading network files

The class GenericNetwork contains the functions to read the network from a file and also the function to count cliques.

```
Listing 1: generic_network.py
```

```
o from node import Node
  import itertools
  import copy
  class GenericNetwork:
      \mathbf{def} __init__(self):
           # key: node identifier, value: Node-object
           self.nodes = \{\}
           self.nb\_edges = 0
10
      def read_from_tsv(self , file_path):
           Reads\ white-space-separated\ files\ that\ contain\ two\ or\ more\ columns.
               The first two columns contain the
           identifiers of two nodes that have an undirected edge. The two nodes
15
               are added to the network.
           : param \ file\_path: \ path \ to \ the \ file
          # clear the prior content of the network
           self.nodes = \{\}
20
          # open the file for reading
           with open(file_path, 'r') as file:
               # iterate over the lines in the file
               for line in file:
25
                   columns = line.split()
                   # skip lines that do not have two node identifiers
                   if len(columns) < 2:
                       continue
30
                   # We ignore if there is more than one connection
                   # create the two nodes and remove potential whitespace such as
                        new-line from their identifiers
                   node_1 = Node(columns[0].strip())
                   node_2 = Node(columns[1].strip())
                   # add the nodes and the edge between them to the network
                   self.add_node(node_1)
                   self.add_node(node_2)
```

```
self.add_edge(node_1, node_2)
40
       def get_nodes(self):
            :return: the dict of nodes
45
            return copy.deepcopy(self.nodes)
       def add_node(self, node):
50
            Adds the specified node to the network.
            : param \ \ node: \ \ \stackrel{ \, {\scriptstyle \  \, }}{Node-object}
            if node.identifier not in self.nodes.keys():
55
                 self.nodes [\,node.identifier\,] \,\,=\,\, node
       def add_edge(self, node_1, node_2):
            Adds an (undirected) edge between the two specified nodes.
60
            :param node_1: Node-object
:param node_2: Node-object
            :raises: KeyError if either node is not in the network
            \# raise an error if the nodes are not in the network
65
            if node_1.identifier not in self.nodes.keys():
                 raise KeyError('There_is_no_node_in_the_network_with_identifier:',
                       node_1)
            if node_2.identifier not in self.nodes.keys():
                 raise KeyError('There_is_no_node_in_the_network_with_identifier:',
                       node_2)
70
            # add the (undirected) edge
            self.nodes[node_1.identifier].add_edge(node_2)self.nodes[node_2.identifier].add_edge(node_1)
            # increment the number of edge of 1
75
            self.nb\_edges += 1
       \mathbf{def}\ \mathtt{get\_node}(\mathtt{self}\ ,\ \mathtt{identifier}) :
            : param \quad identifier: \quad node \quad identifier
80
            :return: Node-object corresponding to the given node identifier, if
                 the\ node\ is\ in\ the\ network
            :raises: KeyError if there is no node with that identifier in the
                network
            if identifier not in self.nodes.keys():
                 raise KeyError('There_is_no_node_in_the_network_with_identifier:',
85
                       identifier)
            return self.nodes[identifier]
       def has_edge(self, node_1, node_2):
            : param node_1: Node-object
90
            :param\ node\_2:\ Node-object
            : return: \ \mathit{True} \ if \ the \ \mathit{two} \ \mathit{nodes} \ \mathit{have} \ \mathit{an} \ (\mathit{undirected}) \ \mathit{edge} \, , \ \mathit{False}
                 otherwise
            :raises: KeyError if either node is not in the network
            # raise an error if the nodes are not in the network
95
            if node_1.identifier not in self.nodes.keys():
                 raise KeyError('There_is_no_node_in_the_network_with_identifier:',
                       node_1)
            if node_2.identifier not in self.nodes.keys():
```

```
raise KeyError ('There_is_no_node_in_the_network_with_identifier:',
                      node_2)
100
            return node_1.has_edge_to(node_2) and node_2.has_edge_to(node_1)
        def size (self):
            :return: number of nodes in the network
105
            return len(self.nodes.keys())
        def nb_edges(self):
110
            : return: \ number \ of \ edges
            return self.nb_edges()
115
        def max_degree(self):
            :return: highest node degree in the network, 0 if there are no nodes
            in the network
            return max([node.degree() for node in self.nodes.values()], default=0)
120
        def __str__(self):
            Any string-representation of the network (something simply is enough)
^{125}
            # will contain: {identifier : neighbours} -> dict are printed pretty
                nicely
            self.networkdict = {}
            for n in self.nodes.values():
                \# n is a node \rightarrow contains identifier and neighbours
130
                 nblist = []
                 for elem in n.neighbour_nodes:
                     nblist.append(elem)
                 self.networkdict[n.identifier] = nblist
            \label{eq:niceprint} \mbox{niceprint} \, = \, \mbox{str} \, (("\n".join\,("\{\}\t\t\{\}".\mbox{format}(k\,,\ v)\ \mbox{for}\ k\,,\ v\ \mbox{in}\ \mbox{self} \,.
135
                networkdict.items())) + " \n\n")
            {\bf return} \ {\tt niceprint}
        # remove the link between two nodes and return true or false if link don't
             exist.
        def remove_link(self, node1, node2):
140
            :param\ node1:
            :param\ node2:
            : return:
145
            if isinstance(node1, str):
                 node1 = self.nodes[node1]
            if isinstance(node2, str):
                 node2 = self.nodes[node2]
150
            if node1.has_edge_to(node2) and node2.has_edge_to(node1):
                 node1.remove_edge(node2)
                 node2.remove_edge(node1)
                 self.nb_edges -= 1
155
                return True
            else:
                 return False
        # Find all the cliques of k nodes in the network
160
```

```
# We tried an other recursive manner (Bron-Kerbosch with pivot) but missed
            time to succeed
       def find_cliques(self, k):
           \# main loop (recursive)
           def clique_loop(k, list):
165
               # Recursivity stop condition
                if k == 1:
                    return list
170
                else:
                    tmp_list = []
                    for tuple in list:
                        for node1 in self.nodes.keys():
                            if node1 in tuple:
                                 break
175
                             else:
                                 for node2 in tuple:
                                     hasLink = True
                                     if not self.nodes[node1].has_edge_to(self.
180
                                         nodes [node2]):
                                         hasLink = False
                                 \verb|tmp_list.append|(\mathbf{tuple} + (\verb|node1|,))|
185
                    return clique_loop(k - 1, tmp_list)
           # Here we call the main loop, the list argument contains a map object
           # nodelist == iterable containing all the nodes keys formatted: (x, )
190
           \#\ http://www.secnetix.de/olli/Python/lambda\_functions.hawk
           nodelist = map(lambda x: (x,), self.nodes.keys())
            lst = clique_loop(k, nodelist)
           ret = sorted(lst)
195
           ret = [ret for ret, _ in itertools.groupby(ret)]
           return ret
```

(b) Finding Cliques

The function to find cliques of n nodes in a network is in the class generic_network.py in listing 7. This function returns the list of cliques of size n. In the main program (listing 3), the function remove_contained_cliques remove the smaller cliques contained in the bigger one as requested. The code seems to work, but the execution time is too long. We are aware that this is not the optimal solution.

(c) Evolving Network

In the listing 3, the main program is executed and different functions are implemented. The function evolve takes a network and a number of time steps and randomly remove or add edges in the network.

```
Listing 2: main5.py
o from generic_network import GenericNetwork
  import random
  from random import randint
  import matplotlib.pyplot as plt
  {\bf from} \ {\bf randomized\_network} \ {\bf import} \ {\bf RandomizedNetwork}
5 from motif_enrichment import MotifEnrichment
  def remove_contained_cliques(res1, res2, res3):
10
       :param clik3: cliques of 3 nodes
      :param clik4: cliques of 4 nodes
       : param \ clik 5: \ cliques \ of \ 5 \ nodes
       :return: remove the smaller cliques contained in the big ones as requested
15
      # If the clique of 4 is already in a clique of 5 -> remove
      for clique5 in res3:
           for clique4 in res2:
               if contains(clique5, clique4):
                   res2.remove(clique4)
20
           # Same with size 3
           for clique3 in res1:
               if contains(clique5, clique3):
                    res1.remove(clique3)
25
      for clique4 in res2:
           for clique3 in res1:
               if contains(clique4, clique3):
                    res1.remove(clique3)
  \mathbf{def} contains (list1, list2):
       http://\,thispointer.com/python-check-if-a-list-contains-all-the-elements-of
           -another-list
       check if list1 contains all elements in list2
35
       : param list1:
      : param list 2:
       :return: boolean value
      result = all(elem in list1 for elem in list2)
40
      return bool(result)
  def evolve(t, network, plot = None):
      Randomly select two nodes and delete the edge if existing or add it
```

otherwise

```
:param t: number of time steps
       :param network: network class object
       : return:
50
       def get_two_random_nodes(add):
            :add: if "add" is true, we want to add an edge so the two nodes must
55
               not be connected
            : return: \ two \ different \ random \ nodes \ from \ the \ network
           \# Pick a node with a degree > 1
           \verb|node1| = \verb|network.get_node| (\verb|random.sample| (\verb|list| (\verb|network.get_nodes| ()) , 1)
60
                [0])
           node2 = network.get_node(random.sample(list(network.get_nodes()), 1)
                [0])
           while not node1.degree() > 1:
                node1 = network.get_node(random.sample(list(network.get_nodes())),
                    1) [0])
65
           while not node2.degree() > 1:
                node2 = network.get_node(random.sample(list(network.get_nodes())),
                    1)[0])
           # If we want to add an edge, the two nodes mustn't be connected. To
                avoid \ blockage
70
           # it is necessary to rechoose both nodes.
           if add:
                while node1.has_edge_to(node2) or node1 == node2:
                    node1 = network.get_node(random.sample(list(network.get_nodes
                        ()), 1)[0])
                    node2 = network.get_node(random.sample(list(network.get_nodes
                        ()), 1)[0])
75
            else:
                # if the node are note connected, take a random neighbour of node1
                while not node1.has_edge_to(node2) or node1 == node2:
                    node1_list = node1.get_neighbours()
                    node2 = network.get_node(node1_list[randint(0,len(node1_list)
                        -1)])
80
           return (node1, node2)
       \# return \ cliques \ values \ for \ t = 100
       ret1 = []
       ret2 = []
85
       ret3 = []
       for _{-} in range (0, t):
           print("Evolution_step:_", _)
90
           \# 1 = Add or 0 = delete edge
           add = bool(random.getrandbits(1))
           # Get to nodes according to the decision to add or remove an edge
           nodes = get_two_random_nodes(add)
95
            if not add:
               network.remove_link(nodes[0], nodes[1])
                network.add_edge(nodes[0], nodes[1])
100
           \# For t = 100 - plot each step.
            if t = 100:
                print("Calculating_intermediate_cliques...")
```

```
res1 = network.find_cliques(3)
105
                res2 = network.find_cliques(4)
                res3 = network.find_cliques(5)
                remove_contained_cliques(res1, res2, res3)
               # Save the number of cliques of size 3, 4 and 5 after each step
110
               ret1.append(len(res1))
               ret2.append(len(res2))
               ret3.append(len(res3))
       \# return the different clique values for all the 100 steps (empty if t !=
       return (ret1, ret2, ret3)
   #
       120 #
      MAIN
  #
       if -name = "-main = ":
125
       \mathbf{print} \, (\, \text{``Assignment $\_5$} \, \text{\_\_Schmitt $\_$Schowing $\setminus n \setminus n$''} \, )
       # (b) - Read Network
PATH = "../Data/sup53/rat_network.tsv"
       net = GenericNetwork()
130
       net.read_from_tsv(PATH)
       \# \# (c) - Count \ cliques
       \# res1 = net. find\_cliques(3)
       \# res2 = net. find\_cliques(4)
135
       \# res3 = net.find\_cliques(5)
       ## Total number of cliques
       # print("\n\nUmber of cliques of 3 nodes: ", len(res1))
       # print("Number of cliques of 4 nodes: ", len(res2))
# print("Number of cliques of 5 nodes: ", len(res3))
140
       #
       #
       \#\ \#\ \#\ Do\ not\ count\ the\ cliques\ of\ smaller\ size\ that\ are\ contained\ in\ a
       \# \# \# clique.
145
       ## remove_contained_cliques(res1, res2, res3)
       ##
       # #
       ## print("Number of cliques of 4 nodes after cleaning: ", len(res2))
## print("Number of cliques of 5 nodes after cleaning: ", len(res3))
150
       #
       #
       #
155
       #
       \#\ \#\ 100\ EVOLUTION-\ reset\ the\ network
       \# print("\n\n
                "\n
       #
                                           Network Evolution"
                "\setminus n
       #
                                                                               -\langle n"\rangle
       #
```

```
# print("Start evolution 100 time steps.")
165
       # evo100_net = GenericNetwork()
       #
         evo100\_net.read\_from\_tsv(PATH)
         evolution\_data\_100 = evolve(100, evol00\_net)
       #
       #
170
       # print("Evolution done. Counting cliques.")
       #
       #
         evo100\_res1 = evo100\_net.find\_cliques(3)
         evo100\_res2 = evo100\_net.find\_cliques(4)
       \# evo100\_res3 = evo100\_net.find\_cliques(5)
175
       #
       ## remove_contained_cliques(evo100_res1, evo100_res2, evo100_res3)
         print("\n\nNumber of cliques of 3 nodes after 100 evolutions: ", len(
           evo100_res1))
         print ("Number of cliques of 4 nodes after 100 evolutions: ", len (
180
           evo100\_res2))
         print ("Number of cliques of 5 nodes after 100 evolutions: ", len (
           evo100\_res3))
         print("Plot Evolution Data")
       #
       #
       \# \ plt. \ plot \ (\ evolution\_data\_100 \ [0] \ , \ \ label = \ 'Cliques \ \ of \ \ size \ \ 3')
185
       # plt. xlabel ("Evolution")
       # plt.ylabel("Number of cliques")
190
       # plt.legend()
       # plt.show()
       #
       #
       #
195
       ## Too damn long!
       \# # 1000 EVOLUTION - reset the network
       #
       #
         print ("Reset Network")
       #
         evo1000_net = GenericNetwork()
200
       #
         evo1000\_net.read\_from\_tsv(PATH)
       #
       #
       # print("Start evolution 1000 time steps.")
         evolution\_data\_1000 = evolve(1000, evo1000\_net)
       #
205
       #
       # print("Counting cliques for the 1000 time evolved network")
       \# evo1000\_res1 = evo1000\_net.find\_cliques(3)
       \# evo1000\_res2 = evo1000\_net.find\_cliques(4)
         evo1000\_res3 = evo1000\_net.find\_cliques(5)
       #
       #
210
       \# \# remove\_contained\_cliques(evo1000\_res1, evo1000\_res2, evo1000\_res3)
       #
       #
         print("\n\n) number of cliques of 3 nodes after 1000 evolutions: ", len(
           evo1000_res1))
         print("Number of cliques of 4 nodes after 1000 evolutions: ", len(
215
           evo1000_res2))
         print ("Number of cliques of 5 nodes after 1000 evolutions: ", len (
           evo1000_res3))
       \# print("\n\n
220
                "\backslash\, n
                                           Randomized network"
       #
                "\backslash n
       #
                                                                              —\n")
```

```
# print("Original Network ")
225
       # rat_net = GenericNetwork()
       \# \ rat\_net.read\_from\_tsv\left("../Data/sup53/rat\_network.tsv"\right)
       \# print("nb cliques 3: ", len(rat_net.find_cliques(3)))
230
       \# print ("Randomized Network")
       \# randomized\_net = RandomizedNetwork(rat\_net).get\_randomized\_network()
       \# print("nb cliques rand: ", len(randomized_net.find_cliques(3)))
235
            Motif\ Enrichment
       #
        rat_net = GenericNetwork()
240
        rat_net.read_from_tsv("../Data/sup53/rat_network.tsv")
       print("Start_Motif_Enrichment")
enrich = MotifEnrichment(100, rat_net)
        print("P-Values: ", enrich.pis)
```

(d) Cliques in evolving networks. Due to the execution time, this has been run on a minimized version of the rat network.

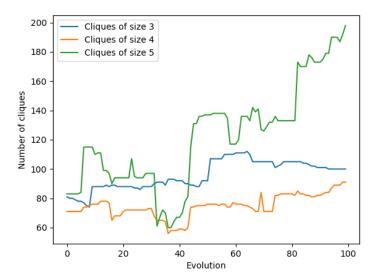


Figure 1: Evolution of the number of cliques during 100 randomization steps on a randomly minimized version of the rat network.

(e) Randomizing Network The class randomized_network builds a randomized network. Randomizing a network this way, keep its degree (number of edges) the same but change the topological structure of the graph. According to the Wikipedia definition of Degree-preserving randomization: "Degree Preserving Randomization is a technique used in Network Science that aims to assess whether or not variations observed in a given graph could simply be an artifact of the graph's inherent structural properties rather than properties unique to the nodes, in an observed network. "(https://en.wikipedia.org/wiki/Degree-preserving_randomization, Mai 2018). In other words, we use the randomization to verify whether the topology of the original graph is due to randomness or has a specific structure.

Listing 3: randomized_network.py

```
20
          m = self.rand\_network.nb\_edges
           for _{-} in range (0, 2*m):
               #print("debug loop: ", _)
25
               \# Randomly select 2 nodes with degree > 0
               def choose_random_node():
                   return self.rand_network.get_node(random.sample(list(self.
                       rand_network.get_nodes()), 1)[0])
               def choose_two_nodes_condition():
30
                   Chose two nodes
                    - not the same nodes
                    - with more than 0 neighbour
35
                   : return:\\""
                   node01 = choose_random_node()
                   node11 = choose_random_node()
40
                   while not node01.degree() > 0 or node01.has_edge_to(node11):
                       node01 = choose_random_node()
                   while (not node11.degree() > 0 and node11 != node01) or node11
45
                       . has_edge_to(node01):
                       node11 = choose\_random\_node()
                   return node01, node11
50
               \# CHOSE TWO RANDOM NODES - not identical, with degree > 1
               node01, node11 = choose_two_nodes_condition()
               # Randomly select a neighbour in the neighbours lists !!!!! not
                   already connected to node 11 !!!!
               \# #TODO proof to self link and duplicate link \# #UPDATE self link ok, as the two nodes are different
55
               \# Below: choose two node in the neighbour list of node01 and node
               # the resulting edges should be switched without producing
                   duplicate nodes
60
               def chose_rand_neighbour(list):
                   return self.rand_network.get_node(list[randint(0, len(list) -
                       1)])
               \# chose 02 and 12 a random neighbour of 01 and 11
               # In the next while loop, all random operation a executed again to
65
                    avoid blockage.
               node02 = chose_rand_neighbour(node01.get_neighbours())
               node12 = chose_rand_neighbour(node11.get_neighbours())
               # chose a random other neighbour !! Might cause blockage if
70
                   neighbour are all connected to node 01
               while node01.has_edge_to(node12) or node11.has_edge_to(node02):
                   node01, node11 = choose_two_nodes_condition()
                   node02 = chose_rand_neighbour(node01.get_neighbours())
                   node12 = chose_rand_neighbour(node11.get_neighbours())
75
               \# e1 = (node01, node02) \rightarrow (node01, node12)
```

```
# e2 = (node11, node12) -> (node 11, node02)

node01.remove_edge(node02)
node01.add_edge(node12)

node11.remove_edge(node12)
node11.add_edge(node02)

def get_randomized_network(self):
return self.rand_network
```

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Bioinformatics III Fifth Assignment

(f) $Examining\ motif\ enrichment$ Please be aware that the function to extract the cliques is still not optimal here.

Exercise 5.2: Annotations in Protein-Protein-Interaction Networks

(a) Adding annotations to PPI-networks

The listings for this exercise are at the end of the document.

(b) Generating an overview

For Chicken:

Table 1: Chicken network overview

Interactions in the network	300				
Proteins in the network	281	Protein without annotation	44	Percentage	15.6
Annotation per protein					
Smallest number	0	Average number	7.7	Biggest number	88
Protein per annotation					
Smallest number	1	Average number	1.55	Biggest number	27

For pig:

Table 2: Pig network overview

Interactions in the network	50				
Proteins in the network	51	Protein without annotation	13	Percentage	25.5
Annotation per protein					
Smallest number	0	Average number	5.5	Biggest number	40
Protein per annotation					
Smallest number	1	Average number	1.13	Biggest number	5

for Human:

Table 3: Human network overview

Interactions in the network	275472				
Proteins in the network	17087	Protein without annotation	2262	Percentage	13.2
Annotation per protein					
Smallest number	0	Average number	7.22	Biggest number	184
Protein per annotation					
Smallest number	1	Average number	10.6	Biggest number	1554

(c) Examining the most/least common annotations Implement a function that returns the n most common and n least common GO identifiers in a given annotated network. If there are several GO identifiers that are associated with the same number of proteins, choose the ones with the lower lexicographical order first.

Table 4: Function of the 5 most common GO identifiers of the human network.

GO id	Quantity	Biological Process	
GO:0006351	1562	The cellular synthesis of RNA on a template of DNA.	
GO:0045944	1029	Any process that activates or increases the frequency,	
GO.0045944	1029	rate or extent of transcription from an RNA polymerase II promoter.	
GO:0007165	1010	Signal transduction	
GO:0006357	960	Any process that modulates the frequency, rate or extent	
GO:0006557	900	of transcription mediated by RNA polymerase II.	
GO:0006355	765	Any process that modulates the frequency, rate or extent	
GO.0000333	100	of cellular DNA-templated transcription	

We can observe that these annotations concerns general process happening almost in every cell. This explains why they are the most common in opposition as the annotations in the table below, which concerns specific reaction or process concerning particular location or molecules.

Table 5: Function of the 5 least common GO identifiers of the human network

GO id	Quantity	Biological Process
GO:0000003	1	Reproduction
GO:0000011	1	Vacuole inheritance
GO:0000032	1	Cell wall mannoprotein biosynthetic process
GO:0000053	1	Argininosuccinate metabolic process
GO:0000097	1	Sulfur amino acid biosynthetic process

(d) **Investigating annotation enrichment** The hypergeometric distribution can be used to find out if a given annotation is significantly overrepresented in interacting compared to non-interacting protein pairs. Implement a function that computes pA for every annotation A in a given annotated network.

Table 6: Number and percentage of annotation with certain p-value

p-value	Number	Percentage
p < 0.05	35	2.721%
p > 0.5	43	3.343%
p > 0.95	1243	96.656%

Table 7: Annotations with the five lowest pA and five highest pA

GO:ID	pA	Nb Protein	Nb Interact. protein	Annotation
GO:0009409	4.3907e-07	3	3	Response to cold
GO:0030154	1.7908e-05	7	4	Cell differentiation
GO:0007169	0.0002	3	2	Transmembrane receptor protein tyrosine kinase signaling pathway
GO:0000712	0.0002	3	2	Resolution of meiotic recombination intermediates
GO:0032570	0.0002	3	2	Response to progesterone
GO:0007049	1	10	0	Cell cycle
GO:0006096	1	9	0	Glycotic process
GO:0055114	1	9	0	Oxydation-reduction process
GO:0006457	1	9	0	Protein folding
GO:0006094	1	8	0	Gluconeogenesis

TODO

The closer the p-value to zero, the more significant the GO term associated with the group of protein is. The five GO term with the lowest p-value describe very specific process in opposition to the ones with the five highest p-value.

Are interacting proteins functionally more similar than non-interacting protein? ???????? No real similarity between the interacting protein and the non-interacting.

Was this to be expected? Why (not)?

(e) **e) Investigating annotation combinations**: Implement a function that computes if certain annotation combinations occur more frequently than expected. The function should take the combination size k and the number of random distributions r. Additionally, let n be the number of proteins in the network and nA the number of proteins with annotation

Table 8: Number and percentage of combination with certain p-value

p-value	Number	Percentage
p < 0.05	9794	49.25%
p > 0.5	0	0.0%
p >0.95	1252	6.295%

Table 9: The m combinations with the smallest pc and the m combinations with the highest pc

Three smallest Pc:				
GO:IDs	Occurence	p-Value	Annotation 1	Annotation 2
'GO:0006897',	1	0.0	endocytosis	Receptor-mediated
'GO:0006898'	0.0		endocytosis	endocytosis
'GO:0006898',	2	0.0	Receptor-mediated	Ventral spinal cord
'GO:0021517'		0.0	endocytosis	development
'GO:0008203',	1	0.0	Cholesterole metabolism	Dendrites
'GO:0048813'	1	0.0	process	morphogenesis
Three biggest Pc:				
'GO:0006355',	1	0.71	Regulation of transcription	Regulation of transcription
'GO:0006355'	1	0.71	DNA-templated	DNA-templated
'GO:0006351',	1	0.71	Transcription	Protein stabilization
'GO:0050821'	1	0.11	DNA-templated	1 Totem stabilization
'GO:0006351',	1	0.69	Transcription	Negative regulation of
'GO:0043066'	1	0.03	DNA-templated	apoptotic process

TODO - COMMENT

(f) Listings:

```
Listing 4: task52_main.py
o from UniprotReader import UniprotReader
  from generic_network import GenericNetwork
  from GOreader import GOReader
  {\bf from} \ \ {\bf annotated\_network} \ \ {\bf import} \ \ {\bf AnnotatedNetwork}
     __name__= "__main__":
       #
                             ____Chicken_Annotated_Network"
10
            #
      #TODO check version (mini)
path_chicken_network = "../Data/sup51/chicken_network.tsv"
15
       chicken_network = GenericNetwork()
       chicken_network.read_from_tsv(path_chicken_network)
       path_chicken_uniprot = "../Data/sup51/chicken_uniprot.tsv"
       chicken_uniprot = UniprotReader(path_chicken_uniprot)
20
       path_chicken_ontology = "../Data/sup51/chicken_GO.gaf"
       chicken_GO = GOReader(path_chicken_ontology)
       Anet_chicken = AnnotatedNetwork(path_chicken_network,
25
           path_chicken_ontology , path_chicken_uniprot )
       # GENERATE OVERVIEW
       Anet_chicken.generate_overview()
       \# \# COMMON GO: IDs - Only requested for human
30
       \# common\_chicken\_GOids = Anet\_chicken.get\_common\_GOid(5)
       # ANNOTATION ENRICHMENT
       \mathbf{print} (" \setminus \mathsf{n} \setminus \mathsf{nInvestigating\_annotation\_enrichment\_for\_the\_chicken\_network \setminus \mathsf{n"})
       Anet_chicken.annotation_enrichment(5)
35
       # ANNOTATION COMBINATION
       print("\n\nInvestigating_annotation_combinations_for_the_chicken_network\n
       Anet_chicken.annotation_combination(2, 100, 3)
40
       #
       print"("\n\n
              "\n____Pig_Annotated_Network"
45
                  n")
       path_pig_network = "../Data/sup53/pig_network.tsv"
       pig_network = GenericNetwork()
50
```

```
pig_network.read_from_tsv(path_pig_network)
      path_pig_uniprot = "../Data/sup53/pig_uniprot.tsv"
      pig_uniprot = UniprotReader(path_pig_uniprot)
55
      path_pig_ontology = "../Data/sup53/pig_GO.gaf"
      pig_GO = GOReader(path_pig_ontology)
      Anet_pig = AnnotatedNetwork(path_pig_network, path_pig_ontology,
          path_pig_uniprot)
60
      Anet_pig.generate_overview()
      \# \# Only requested for human
      \# \# common\_pig\_GOids = Anet\_pig.get\_common\_GOid(5)
65
      #
      \mathbf{print}^{''}("\setminus n\setminus n
             "\n____Human_Annotated_Network"
             " \ n-
70
           #
      path_human_network = "../Data/sup53/human_network.tsv"
      human_network = GenericNetwork()
      human_network.read_from_tsv(path_human_network)
75
      path\_human\_uniprot = "../Data/sup53/human\_uniprot.tsv"
      human_uniprot = UniprotReader(path_human_uniprot)
      path\_human\_ontology \ = \ "../\,Data/sup53/human\_GO.\,gaf"
80
      human_GO = GOReader(path_human_ontology)
      Anet_human = AnnotatedNetwork(path_human_network, path_human_ontology,
          path_human_uniprot)
      Anet_human.generate_overview()
      common_human_GOids = Anet_human.get_common_GOid(5)
```

Listing 5: UniprotReader.py

```
o from collections import defaultdict
  class UniprotReader:
      Reads uniprot tab files
5
          __init__(self, filename):
      \mathbf{def}
           Initialization, read in file and build any data structure that makes
           you happy
10
          \# structure containing ENTRY : [list of other names]
           self.mapping = defaultdict(set)
          # structure containing other names : ENTRY
           self.reverse_mapping = defaultdict(set)
15
           self.ENTRY = []
           self.ENTRY.NAME = []
           self.STATUS = []
           self.PROTEIN_NAMES = []
20
           self.GENE\_NAMES = []
           self.ORGANISM = []
          # Read file
           content_start = False
25
           with open(filename, "r") as f:
               for line in f:
                   if content_start:
                       # Process data
                       line = line.rstrip()
30
                       line_tab = line.split('\t')
                       self.ENTRY.append(line_tab[0])
                       self.ENTRY.NAME.append(line\_tab[1])
                       self.STATUS.append(line_tab[2])
35
                       # Split the different names
                        self.PROTEIN_NAMES.append(line_tab[3].split('_'))
                        self.GENE.NAMES.append(line_tab[4].split('_'))
                       self.ORGANISM.append(line_tab[5])
40
                   if line.startswith("Entry"):
                       content_start = True
                       continue
          # Construct mapping and reverse mapping
45
          for i in range(0, len(self.ENTRY)):
               for gene in self.GENE.NAMES[i]:
                   self.mapping[self.ENTRY[i]].add(gene)
                   self.reverse_mapping[gene].add(self.ENTRY[i])
50
      def get_uniprot_names_mapping(self):
          return self.mapping
      def get_names_uniprot_mapping(self):
          return self.reverse_mapping
55
      # Print mapping to file or to console
      # OPTIONAL
      def print_mapping(self):
          print("TODO")
60
      def print_reverse_mapping(self):
          \mathbf{print}\,(\,\text{"TODO"}\,)
```

Listing 6: GOreader.py

```
_{0} from collections import default dict
  class GOReader:
       ''', 'Reads GO files'''
      def __init__(self, filename):
          Initialization, read in file and build any data structure that makes
             you happy
          self.DB_NAME = []
          self.ACCESS_NUMBER = []
          self.ALTERNATIVE.NAME = []
          self.GO_IDENTIFIER = []
          self.ONTOLOGY\_INDICATOR = []
          with open(filename, "r") as f:
15
              for line in f:
                  if line.startswith("UniProtKB"):
                      # Process data
                      line = line.rstrip()
                      line_tab = line.split('\t')
20
                      # Skip all entries not belonging to biological process
                          ontology
                      if line_tab[8] != 'P':
                          continue
25
                      self.DBNAME.append(line_tab[0])
                      self.ACCESS_NUMBER.append(line_tab[1]) # Protein name to
                          map
                      self.ALTERNATIVE.NAME.append(line_tab[2])
                      self.GO_IDENTIFIER.append(line_tab[4])
                      self.ONTOLOGY.INDICATOR.append(line\_tab[8])
          ONTOLOGY_INDICATOR [i]
          # Create a data structure with all information
35
          self.DATA = []
          for i in range(0, len(self.DB_NAME)):
              #TODO delete DATA if not used
40
              self.ALTERNATIVE.NAME[i],
                                self.GO_IDENTIFIER[i]
45
                                self.ONTOLOGY\_INDICATOR[i]]
              self.DATA.append(entry_line)
          # Create 4 dictionaries to map all GO ids of the GO file with the
50
              other\ data\ (\mathit{prot}\ \mathit{names})
            dict {GOID : access_number}
          # dict {GOID : alternative_name}
# dict {alternative_name : GOID}
          \# dict \{access\_number : GOID\}
55
          self.goid_accessnb = defaultdict(set)
          self.accessnb_goid = defaultdict(set)
          self.alternativename_goid = defaultdict(set)
          self.goid_alternativename = defaultdict(set)
```

```
60
            # For readability
            idx_db_name = 0
            idx_access_nb = 1
             idx_alter_name = 2
65
             idx_go_id = 3
             idx_onto_id = 4
            \# For every entry, fill the mappers.
            # The commented mappers are not used but could be useful
            for entry_line in self.DATA:
                 \#self.\ goid\_accessnb\ [\ entry\_line\ [\ idx\_go\_id\ ]\ ].\ add\ (\ entry\_line\ [\ idx\_go\_id\ ]\ ].
                      idx_access_nb )
                  self.accessnb_goid [entry_line[idx_access_nb]].add(entry_line[
                      idx_go_id])
                 \#self.alternativename\_goid[entry\_line[idx\_alter\_name]].add(
                      entry\_line[idx\_go\_id])
75
                 \#self.goid\_alternative name\ [\ entry\_line\ [\ idx\_go\_id\ ]\ ].\ add\ (\ entry\_line\ [\ idx\_go\_id\ ])
                      idx\_alter\_name/)
80
            # print("Verify mapers")
               for key in self.goid_accessnb:
            #
                    print("\nKey: ", key) for elem in self.goid_accessnb[key]:
            #
85
            #
                        print (elem)
            #
        def get_GO_IDs(self , proteinID):
             Get a protein name, returns all GO ids related to it
90
             : param \ protein ID:
             : return: \\
             lst1 = []
95
             for prot in proteinID:
                 tmp = self.accessnb_goid[prot]
                  lst1.extend(list(tmp))
            return lst1
100
        def get_data(self):
             return self.DATA
```

```
Listing 7: annotated_network.py
{\scriptsize 0} \;\; \mathbf{from} \;\; \mathbf{UniprotReader} \;\; \mathbf{import} \;\; \mathbf{UniprotReader}
  from generic_network import GenericNetwork
  from GOreader import GOReader
  import numpy as np
  from collections import defaultdict
5 import itertools
  from itertools import combinations
  import math
10 def nCr(n,r):
       \#\ https://stackoverflow.com/questions/4941753/is-there-a-math-ncr-function
           -in\!-\!python
       :param n: Total number of object in the set
       :param r: Number of object in the subset
       :return: Number of possible subset
15
       return math.factorial(n) // math.factorial(r) // math.factorial(n-r)
20 class AnnotatedNetwork:
       def __init__(self, network_path, GO_path, uniprot_path):
            self.network = GenericNetwork()
            self.network.read_from_tsv(network_path)
25
            self.uniprot = UniprotReader(uniprot_path)
            self.GO = GOReader(GO_path)
            self.to_uniprot_mapper = self.uniprot.get_names_uniprot_mapping()
30
           \#self.to\_othername\_mapper = self.uniprot.get\_uniprot\_names\_mapping()
           # dict containing network node { network node id : go ids}
            self.net_go = defaultdict(list)
35
           # Mapping protein to GOs
           # { nodeid : [GO, GO, ...]}
for id, node in self.network.nodes.items():
40
                \# Convert the protein id
                uniprot_id = self.to_uniprot_mapper[id]
                 \# \ uniprot\_id \ can \ contains \ 0, \ 1 \ or \ more \ names \\ \# \ map \ the \ protein \ names \ with \ the \ GO \ ids 
45
                goids = self.GO.get_GO_IDs(uniprot_id)
                self.net_go[id] = goids
           # Reverse mapping GO to proteins (net)
           \# \{GO \ annot : [node, node, ...]\}
50
            self.go_net = defaultdict(set)
           for node in self.net_go:
                list_annot = self.net_go[node]
55
                for annot in list_annot:
                     self.go_net[annot].add(node)
           # Completing GO in the network and quantity
           \# \{GO : qty\}
60
            self.go_qty = defaultdict(int)
           for key in self.go_net:
                self.go_qty[key] = len(self.go_net[key])
```

```
65
            # COMPUTE ANNOTATION QUANTITY OCCURRENCE
            \# number of protein
            self.nb\_prot = 0
            \# number of protein without annotation
            self.nb_prot_wo_annotation = 0
70
            # {number of annotation : occurence}
            self.nb_annotqty_occurence = dict()
            # total annotation (Not unique, see total_annot_unique
            self. total_annot = 0
75
            # for every node
             \mbox{ for } \mbox{ key } \mbox{ in } \mbox{ self.net\_go:} 
                 self.nb\_prot += 1
                 nb_annotation = len(self.net_go[key])
80
                 self.total_annot += nb_annotation
                 if nb_annotation == 0:
                     self.nb_prot_wo_annotation += 1
                # increment quantity of annotation
                 if nb_annotation in self.nb_annotqty_occurence:
                     self.nb_annotqty_occurence[nb_annotation] += 1
                     self.nb\_annotqty\_occurence[nb\_annotation] = 1
90
            # PROTEIN PER ANNOTATION
            self.total_prot_per_annot = 0
95
            # dict {number of prot/annot : occurence}
            self.nb_prot_occurence = dict()
            # for every annotation in {GO: nodes}
100
            for annot in self.go_net:
                 nb_prot = len(self.go_net[annot])
                 self.total\_prot\_per\_annot += nb\_prot
                # increment quantity of annotation
105
                 if nb_prot in self.nb_prot_occurence:
                     self.nb_prot_occurence[nb_prot] += 1
                 else:
                     self.nb_prot_occurence[nb_prot] = 1
                #print annotation: proteins
#print(annot, "\t\t", self.go_net[annot])
110
115
       def generate_overview(self):
            Generate the overview of the network
            : return: nada
120
            \# Task 52
            print("\n-
                             —Annotated_Network_Overview———
            print("Total_protein_in_the_network: ", len(self.network.nodes))
            print("Total_interactions_in_the_network: ", len(self:network.nb_edges)
print("Total_unique_annotation: ", len(self.go_net))
125
            print("Nb_prot:_", self.nb_prot, "\t\tNb_without_annotation:_", self.
                 nb_prot_wo_annotation, "\t\tPercentage:_",
                   (self.nb_prot_wo_annotation / self.nb_prot) * 100)
            print("Smallest_number_of_annotation:_", sorted(self.
130
```

```
\label{eq:nb_annotqty_occurence} $$ nb_annotqty_occurence \) [0] \ , \ "\t\t\Average_number_of_annotation: \_" \ , \\ self.total_annot \ / \ self.nb_prot \ , \ "\t\t\Biggest_number_of\_ \\ annotation: \_" \ , \ sorted \( self.nb_annotqty_occurence \) [-1]) $$
              \mathbf{print} \ ("\, S\, mallest\, \_number\, \_of\, \_protein\, \_per\, \_annotation\, :\, \_" \ , \ \mathbf{sorted} \ (s\, elf \ .
                   nb\_prot\_occurence) \ [0] \ , \ "\ t\ Average\_number\_of\_protein: \_" \ ,
                     self.total\_prot\_per\_annot \ / \ \textbf{len} ( \, self.go\_net \, ) \, , \ " \setminus t \setminus t \\ Biggest \, \_
                          number_of_protein:_", sorted(self.nb_prot_occurence)[-1])
135
              \mathbf{print}(" \setminus n \setminus n")
        def get_common_GOid(self, n):
              Return the n most common GO identifiers of the annotated network
140
              :param n: number of GO wanted
              return: tuple of lists (n most common, n least common)
             \#sorted\_go\_qty = sorted(self.go\_qty.items(), key=lambda x: x[1])
145
             # Table of sorted GO quantity (DESC) and sorted GO id (ASC)
              sorted\_go\_qty1 = [v[0] \ \textbf{for} \ v \ \textbf{in} \ \textbf{sorted} (self.go\_qty.items(), \ key= \textbf{lambda})
                    kv: (-kv[1], kv[0]))
             # Table of sorted GO quantity (ASC) and sorted GO id (ASC)
              sorted_go_qty2 = [v[0] for v in sorted(self.go_qty.items(), key=lambda
150
                    kv: (kv[1], kv[0]))
              print("Most_common_GO_ids")
              n_most_common = list(itertools.islice(sorted_go_qty1, n))
155
              for goid in n_most_common:
                   print(goid, "\t", self.go_qty[goid])
              print("Least_common_GO_ids")
              n_least_common = list(itertools.islice(sorted_go_qty2, n))
160
              for goid in n_least_common:
                   print(goid, "\t", self.go_qty[goid])
             return (n_most_common, n_least_common)
165
        def annotation_enrichment(self, top):
              :param top: number of top annotation probability
              :return: the n highest and lowest p(a)
             \#\ List\ of\ all\ possible\ protein\ pairs\ in\ the\ network
              protein_pairs = list(itertools.combinations(self.network.nodes, 2))
175
             # Number of possible pair
             N = len(protein_pairs)
             # Number of interacting protein pairs
             n = self.network.nb_edges
180
             # Annotation and interacting pairs {GO: [(prot1, prot2), (prot2, prot3)]
              self.annot_all_pairs = defaultdict(list)
              self.annot_interaction_pairs = defaultdict(list)
              self.annot_probability = defaultdict(float)
185
             ncr_Nn = nCr(N, n)
              # For each annotation in the network
              for A in self.go_net:
190
```

```
# For every possible pair in the network, check if both have
                                                annotation \ A
                                          If they have both annotation A, check if the two proteins are
                                                interacting (connected in the network)
                                      for pair in protein_pairs:
                                                 \textbf{if} \ A \ \textbf{in} \ self.net\_go [ pair [0] ] \ \textbf{and} \ A \ \textbf{in} \ self.net\_go [ pair [1] ] : \\
195
                                                          self.annot_all_pairs[A].append(pair)
                                                          # if pair 0 and pair 1 are interacting
                                                           \textbf{if} \hspace{0.1in} \texttt{self.network.get\_node} \hspace{0.1in} (\hspace{0.1em} \texttt{pair} \hspace{0.1em} [\hspace{0.1em} 0\hspace{0.1em}] \hspace{0.1em}) \hspace{0.1em} .\hspace{0.1em} \texttt{has\_edge\_to} \hspace{0.1em} (\hspace{0.1em} \texttt{self.network} \hspace{0.1em} .
                                                                   .get_node(pair[1])):
                                                                    self.annot_interaction_pairs[A].append(pair)
200
                                     # Ka = number of protein pairs where both proteins have annotation
                                     Ka = len(self.annot_all_pairs[A])
                                     \# ka = number of interacting protein pairs where both proteins
205
                                                have annotation A
                                      ka = len(self.annot_interaction_pairs[A])
                                      N_{minus}Ka = N - Ka
                                     # Trying to optimize here ! (not bad, can do better !)
210
                                      if ka == 0:
                                                self.annot\_probability[A] = 1
                                               \# print(A, "\ t pA: ", 1)
                                                continue
215
                                     pA = 0
                                      for i in range (ka, min(Ka, n) + 1):
                                                \begin{array}{ll} nCr\_Ka\_i &= nCr(Ka, \ i) \\ nCr\_N\_minus\_Ka\_n\_i &= nCr(N\_minus\_Ka, \ n-i) \end{array}
220
                                                   print("\nn = ", n, ", n, "\nN = ", N, "\nKa = ", Ka, " \nA = ", Ka, " \nA = " \nA = " \nA = ", Ka, " \nA = ",
                                               #
                                               #
                                               #
                                                                    " \setminus nka = ", ka,
" \setminus ni = ", i,
                                               #
                                                #
225
                                                                    #
                                                #
230
                                               pA += (nCr_Ka_i * nCr_N_minus_Ka_n_i) / ncr_Nn
                                      self.annot\_probability[A] = pA
                           # The number and percentage of annotations A with pA < 0.05, pA > 0.5,
                                      pA > 0
                            pa_005 = pa_05 = pa_095 = 0
235
                            for A in self.annot_probability:
                                      if self.annot_probability [A] <= 0.05:
                                              pa_005 += 1
                                      if self.annot_probability [A] < 0.95:
240
                                                pa_-05 += 1
                                      if self.annot_probability [A] >= 0.95:
                                                pa_-095 += 1
                           # Percentages
                            tot_annot = len(self.go_net)
245
                           pct_005 = pa_005 / tot_annot
pct_05 = pa_05 / tot_annot
                           pct_095 = pa_095 / tot_annot
                           250
                                        pct_005*100, "%")
```

```
print("Number_of_annotation_with_pA_>_0.5 & _< _0.95_:_", pa_05, "->_",
                  pct_05*100, "%")
             print("Number_of_annotation_with_pA_>_0.95_____:_", pa_095, "->",
                  pct_095*100, "%")
             \mathbf{print}(" \setminus n")
             \# The n annotations with the smallest pA and the n annotations with
255
                  the highest pA.
                If there are several annotations with the same pA, choose the ones
                  that \ are \ associated
             # with more proteins first
             \# Create a (GO, pA, Nb-prot) list for the later sort
             annot_prob_prot = []
260
             for A in self.annot_probability:
                  \verb"annot_prob_prot.append" ((A, self.annot_probability" [A], \verb"len" (self.annot_probability")] and the self.annot_probability [A] annot_probability [A].
                       go_net[A]), len(self.annot_interaction_pairs[A])))
             ## All the Annotation A with their probabilities and number of
                  protein
265
             \# for e in annot_prob_prot:
                    print(e)
             # gives [(GO-id', p(A), nb-protein), (..., ..., ...)] with P(a)
                  ordered ASC
             sorted\_probabilities\_ASC = \left[ \left( v\left[ 0 \right], \ v\left[ 1 \right], \ v\left[ 2 \right], \ v\left[ 3 \right] \right) \ \textbf{for} \ v \ \textbf{in} \ \textbf{sorted} (\\ annot\_prob\_prot, \ key=lambda \ kv: \ \left( kv\left[ 1 \right], \ kv\left[ 2 \right] \right) \right) \right]
270
             \# \ gives \ [(\ 'GO-id\ ',\ p(A),\ nb\_protein),\ (\ldots,\ \ldots,\ \ldots)] \ with\ P(a)
                  ordered DSC
             annot_prob_prot, key=lambda kv: (-kv[1], -kv[2]))]
             \# Take the "top" firsts
             smallest_prob = list(itertools.islice(sorted_probabilities_ASC, top))
275
             biggest_prob = list(itertools.islice(sorted_probabilities_DSC, top))
             print("\n\n(GO: id _ _ | _ _pA_ _ | _ _Nb_Protein _ | _Nb_Interact . _Protein )\n")
             print ("Five_smallest_Pa:_\n")
for e in smallest_prob:
280
                  print(e)
             print("\nFive_biggest_Pa:_\n")
             for e in biggest_prob:
                  \mathbf{print}\,(\,\mathrm{e}\,)
285
        def annotation_combination(self, k, r, m):
              :param\ k:\ combination\ size
290
              : param \ r: \ number \ of \ random \ distribution
              :param m: m combinations with the smallest pc and the m annotations
                  with \ the \ highest \ pc
              : return:
295
             annotation_probability = defaultdict(float)
             # number of protein in the network
             n = self.network.size()
300
             # number of protein with annotation A
             \# len(self.go_net[A]
             # For each annotation, compute its probability
             \# go\_net \rightarrow \{GO\_id : [prot1, prot2, \ldots]\}
305
             for A in self.go_net:
```

```
annotation_probability[A] = len(self.go_net[A]) / n
           # Generate a list of all annotation combinations of size k that occur
               in the annotated network
             https://stackoverflow.com/questions/22799053/combinations-of-
310
               elements-of-different-tuples-in-the-list
           \#all\_combinations = list(combinations(self.go\_net, k))
           # Combination set contains all combination of k annotation contained
               in the network
           combination_dict = defaultdict(list)
           for node in self.net_go:
315
               if len(self.net_go[node]) < k:</pre>
                   continue
               tmp_combinations = combinations(self.net_go[node], k)
320
               # For each k-combination for this node
               for combination in tmp_combinations:
                   # The combination are sorted in order to avoid adding (a,b)
                       and (b,a)
                   s_combination = tuple(sorted(combination))
                   if s_combination in combination_dict:
325
                       combination\_dict[s\_combination][0] += 1
                       combination_dict[s_combination].append(1)
330
           annotation\_probability[A])
           \# For each combination (C1, C2, ...) in the network...
           for C in combination_dict:
335
               \# Cn = how often this combination occurs in the network
                \#nc = combination\_dict[C]
               Pe_c = annotation\_probability[C[0]] * annotation\_probability[C[1]]
               combination_dict[C].append(Pe_c)
340
           \# \ \mathit{DEBUG} - \ \mathit{infos}
           # for key in combination_dict:
                 print (key, ": \ t", combination\_dict [key])
           for key in combination_dict:
345
               \#probability\_list = [combination\_dict[key][1]] * n
               prob = combination_dict[key][1]
               \# nr = number of random sample in which C occurs at least as much
                   as in the original network
               nr = 0
350
               for _{-} in range (0, r):
                   random\_list = np.random.choice([0, 1], size=n, p=[1 - prob,
                       prob])
                   \# C in the actual network appears combination\_dict[key][0]
                       times
                   # number of occurence in random network
355
                   nb_occ = np.count_nonzero(random_list)
                   if nb\_occ >= combination\_dict[key][0]:
                       nr += 1
360
               \# Calculating and adding the probability pc to the dict "
                   combination\_dict"
               pc = nr / r
               combination_dict [key].append(pc)
```

```
\# IMPORTANT - structure of combination dict.
365
                  \# combination_dict = (c1, c2) : [nb_occ, expect_prob, rand_prob]
                  pc_0001 = pc_005 = pc_05 = 0
                  nb_C = len(combination_dict)
370
                  for c in combination_dict:
                        pc = combination_dict[c][2]
                         if pc < 0.001:
                         pc_{-}0001 += 1
elif pc < 0.005:
375
                               pc_{-}005 += 1
                         \mathbf{elif}\ \mathrm{pc}\ >\ 0.05\colon
                               pc_05 += 1
380
                  # percentages
                  pct_0001 = pc_0001/nb_C
                  pct_{005} = pc_{005}/nb_{C}
                  pct_05 = pc_05/nb_C
                 print("pc_<_0.001_:_", pc_0001, "->_", pct_0001 * 100, "%")
print("pc_<_0.005_:_", pc_005, "->_", pct_005 * 100, "%")
print("pc_<_0.05_:_", pc_05, "->_", pct_05 * 100, "%")
385
                  combination_dict_sorted_ASC = sorted(combination_dict.items(), key=
                        \textbf{lambda} \ e \colon \ e \left[ \ 1 \ \right] \left[ \ 2 \ \right] )
                  combination_dict_sorted_DSC = sorted(combination_dict.items(), key=
390
                        lambda e: -e[1][2]
                  # Take the "m" firsts
                  smallest_prob = list(itertools.islice(combination_dict_sorted_ASC, m))
                  biggest_prob = list(itertools.islice(combination_dict_sorted_DSC, m))
395
                  \begin{array}{l} \mathbf{print}\,(\,\text{``} \backslash n \backslash n (GO: ids\_\_|\, \_\_Occurence\_in\_the\_data\_\_|\, \_\_Pe(C)\_|\, \_Pc) \backslash n\,\text{''}\,) \\ \mathbf{print}\,(\,\text{``Three\_smallest}\_Pc: \_\backslash n\,\text{''}\,) \end{array}
                  for e in smallest_prob:
                        print(e)
400
                  \begin{array}{lll} \mathbf{print} \, (\, "\, \backslash n \\ \mathbf{Three\_biggest\_Pc} : \, \_ \backslash n" \, ) \\ \mathbf{for} \ e \ \mathbf{in} \ biggest\_prob : \end{array}
                        print(e)
```