Backbone Determination in a Wireless Sensor Network

Jake Carlson

February 18, 2018

Abstract

A report on implementing algorithms to partition a random geometric graph into bipartite subgraphs. Three different graph geometries are explored: unit square, unit disk, and unit sphere. Nodes are uniformly distributed in the geometry. Then the edges are determined and the verticies are colored using smallest-last vertex ordering.

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Benchmark	Order	Avg Deg	Topology	r	Size	Realized Avg Deg	Max Deg	Min Deg	Max Deg Del
1	1000	32	Square	0.101	14397	28	45	8	19
2	8000	64	Square	0.050	245884	61	95	17	39
3	16000	32	Square	0.025	250059	31	51	8	25
4	64000	64	Square	0.018	2016843	63	97	10	40
5	64000	128	Square	0.025	4005101	125	181	30	75
6	128000	64	Square	0.013	4052365	63	97	12	42
7	128000	128	Square	0.018	8070473	126	179	38	73
8	8000	64	Disk	0.045	245420	61	89	20	38
9	64000	64	Disk	0.016	2021818	63	101	18	42
10	64000	128	Disk	0.022	4018364	125	180	48	74
11	16000	64	Sphere	0.126	513208	64	94	38	41
12	32000	128	Sphere	0.126	2048539	128	170	83	89
13	64000	128	Sphere	0.089	4095131	127	188	88	88

Table 1: Benchmarks for Generating and Coloring RGGs

1 Executive Summary

1.1 Introduction

Random geometric graphs (RGGs) are useful for simulating wireless sensor networks placed in different topologies. This project examines three different geometries: Square, Disk, and Sphere. The user supplies parameters for how many nodes they want in the network and how many connections they want for each node. Then, the simulation finds the average radius needed for that number of connections, finds multiple backbones for the RGG, and displays the results graphically.

1.2 Environment Description

The data structures and topologies for this simulation are implemented in Python 2.7. The graphics are done using Processing.py. All development and benchmarking has been done on a 2014 MackBook Pro with a 3 GHz Intel Core i7 processor and 16 GB of DDR 3 RAM running macOS High Sierra 10.13.3.

I elected to use Processing because of the simple API used to draw and render shapes in two- and three-dimensional space. I choose to use Processing.py over Java Processing because of my familiarity and comfort with the Python programming language. I could have writen the graph generation, coloring, and backbone determination in another language and saved the data to a file for loading in processing, but since I intend to implement all of the algorithms in linear time, I don't think there will be a performance issue with using an interpreted language instead of a compiled one.

A separate data generation script was used to generate the summary table and graphs using matplotlib. This library, and a variety of others, could not be imported into Processing.py because the jython interpreter used by Processing only accepts libraries written in raw Python.

The different geometries were implemented in a stand alone Python file and imported into the Processing.py script or the data generation script depending on what was being run. These classes can then be used directly by Processing or the data generation script. Because there is no intermediary file to hold the generated nodes and edges, there is no additional disk space needed to run the simulation. Everything can be done in system memory managed by Processing.

2 Reduction to Practice

2.1 Data Structure Design

The primary data structure used for this project is an adjacency list. However, to allow for constant time lookup of edges of a node, I used a Python dictionary where the keys are nodes and the values are a list of indicies of adjacent nodes in the original list of nodes. The space needed by the adjacency list is

 $\Theta(|V|+2|E|)$. Two entries are used for each edge because they are undirected. This is superior to the adjacency matrix data structure which would require $\Theta(|E|^2)$ space.

In order to make this project maintainable as it is developed along the semester, I used the object-oriented capabilities Python has to offer to design the different geometries. I start with a base Topology class that creates the interface Processing uses to draw the graphs. This base class implements all of the methods needed for node placement and edge detection in 2D graphs. Then, I create three subclasses: Square, Disk, and Sphere.

The Square and Disk topologies simply need to override the methods for generating nodes and calculating the node radius needed for the desired average degree. The Sphere subclass needs to override a few additional functions because it exists in a 3D space. Other than the methods for generating nodes and calculating the node radius, it also needs to override the function used to draw the graph so that Processing will render the graph properly in 3D.

2.2 Algorithm Descriptions

2.2.1 Node Placement

A different node placement algorithm is required for each of the geometries. For the Square, the coordinates for each node are generated as two random numbers taken from a unifrom distribution on the range [0, 1]. All of these points are guaranteed to be in the unit square.

For the Disk, a similar method is used. The coordinates for nodes are randomly sampled from a uniform distribution; however, if a node has a distance from the center of the Disk greater than the radius of 1, the coordinates for that node are resampled.

For the Sphere a different method must be used so that all of the nodes are placed on the surface of the Sphere and the volume is vacant. For this geometry, I used the following equations:

$$x = \sqrt{1 - u^2} \cos \theta \tag{1}$$

$$y = \sqrt{1 - u^2} \sin \theta \tag{2}$$

$$z = u \tag{3}$$

where $\theta \in [0, 2\pi]$ and $u \in [-1, 1]$. This is guaranteed to uniformly distribute nodes on the surface area of the sphere [1].

All of these algorithms can be solved in $\Theta(|V|)$ where because each node only needs to be assigned a position once.

2.2.2 Edge Determination

There are several methods for finding the edges in the graph. The brute force method checks every node, and for each node checks all other nodes to see if they are close enough to form an edge. The brute force method is $\Theta(|V|^2)$.

The second method to find the edges is the sweep method. This method first sorts the nodes along the x-axis. Then, for any node, we only need to search left and right until the distance along the x-axis is greater than the connection radius for the nodes. This dramatically reduces the search space. The sweep method is $O(nlg(n) + 2rn^2)$ where n = |V| an r is the connection radius. The nlg(n) portion is for the sorting and the $2rn^2$ portion is for measuring the distance between nodes in a sweep step.

The final method to find edges is the cell method. This method places the nodes into cells of area $r \times r$ based on their position in the topology. When the edge detection runs, each node needs to be visited once, but only the cell the node populates and the neighboring cells need to be searched for connections.

The only method that needs to be adjusted for the Sphere is the cell method. Instead of using a two dimensional grid of cells, a three dimensional mesh is needed to divide the topology. The cells then have volume $r \times r \times r$. Only the current cell and the neighboring cells need to be searched.

2.2.3 Graph Coloring

Two algorithms are used for coloring the graphs. The first is smallest-last vertex ordering, which sorts the verticies based on the number of degrees they have. The second is the greedy graph coloring algorithm.

Smallest-last vertex ordering is used to order the nodes for coloring. The steps to this algorithm are as follows [3]:

1. Initialize a representation of your target graph

- 2. Find the vertex v_i of minimum degree in your representation
- 3. Update your representation to simulate deleting v_i
- 4. If there are still verticies in the representation, return to step 1, otherwise terminate with the sequence of verticies removed

This algorithm is linear if each of the above steps is linear. Step 1 is linear if we can build a representation of the graph in linear time. For this, we can use an array of buckets, where each bucket holds the verticies that have the same number of edges as the position of the bucket in the array of buckets. To build this data structure, each node only needs to be visited once, making this linear in both space and time. Next, finding the vertex of minimum degree simply requires finding the lowest index bucket that has a node. This is bounded by the number of buckets, which is bounded by the number of nodes, making Step 2 linear. Next, we have to update the representation of the graph. To do this, we have to look at each node that shares an edge with v_j and move it to the bucket for nodes with one fewer degree. This requires traversing the list of edges for v_j which means Step 3 is linear. Since this is repeated for each node, the runtime of this program is $\Theta(|E| + |V|)$ and the space needed is $\Theta(|V|)$.

After this, a single traversal of the smallest-last vertex ordering is needed to color the graph. As we traverse this list, we check to see if the nodes before it (that are already colored) share an edge with the current node. The node can then be colored with any color it does not share an edge with or, if it shares an edge with all currently used colors, it is assigned a new color. This algorithm is also linear. Each node needs to be visited once and when a node is visited, all previous nodes are checked to see if they are in the edge list of the current node. Because we used smallest last vertex ordering, as we have to check more and more nodes, we get to check fewer and fewer edges. This makes the greedy coloring algorithm O(|V| + |E|).

2.3 Algorithm Engineering

2.3.1 Node Placement

It is easy to implement the algorithms for placing nodes in the different geometries using Python's math library. This library offers functions for sampling points on a uniform distribution. For the Square, sampling on a range [0,1] is sufficient for all of the nodes. Since each node only needs to be placed once, this runs at $\Theta(|V|)$ where.

For the Disk, the node needs to be resampled if it is too far from the center. To do this, the distance function is used to find the distance between the node and the center. If the node is further than 1 from the center, node generation falls into a while loop which iterates until the node is within the unit circle. Since nodes are taken from a uniform distribution, the number of nodes that will need to be resampled is approximately equal to the ratio of the area of the square that circumscribes the unit circle which falls outside of the unit circle to the total area of the square. This is given by:

$$\frac{(2r)^2 - \pi r^2}{(2r)^2} = \frac{4 - \pi}{4} = 0.2146 \tag{4}$$

Since the placement algorithm for each node of the Disk will iterate until the node falls within the unit circle, the total number of iterations N can be found as the sum of the geometric series:

$$N = \sum_{k=0}^{\infty} n(0.2146)^k = \frac{n}{1 - 0.2146} = 1.273n \tag{5}$$

where n = |V|. This shows this implementation is $\Theta(n)$.

For the node placement algorithm of the Sphere, again the math library in Python makes this easy. Each node needs two random values pulled from a uniform distribution, two square root operations, one sine operation, and one cosine operation. Each node only needs to be placed once so the runtime of this algorithm is $\Theta(n)$ where n = |V|.

2.3.2 Edge Determination

Each method implemented for finding edges has a different time complexity. The brute force method uses an outer loop and an inner loop, which each iterate over every node in the graph. An edge is saved to the adjacency list if the nodes are not the same and the distance between them is less than or equal to the calculated node radius. This is guaranteed to run in $\Theta(n^2)$ where n = |V|. The number of times

the distance needs to be calculated is $n \times (n-1)$ because it will not be calculated when the nodes are the same (distance would be zero, but no edge is drawn here). No additional space is needed for the brute force method so the space complexity is O(1).

The implementation of sweep starts by sorting the nodes along the x-axis. Python lists have a builtin sort function that has O(nlg(n)) time complexity [2]. After this stage, it iterates over every node
building a search space which will be scaned for edges. For each node, the list of nodes is searched right $r \times n$ nodes to find those within one radius length of the current node. With the search space built, the
search space is iterated over once to find nodes that have a distance less than or equal the node radius.
Then, the indicies of the nodes are added to the adjacency list entry for each other. My implementation
of this runs in O(nlg(n) + 2rn) where n = |V| and r is the node connection radius. Because the list sort
method sorts inplace, the only additional space needed is for the search space. This saves O(rn) nodes
and is reset after every iteration.

The cell method implementation works in linear time. In the first step of the method, the cells are initialized as a list of empty lists. There are $(1/r+1)^2$ cells. The nodes are then iterated over and assigned a cell by dividing their x and y coordinates by the node radius. At this point, the cells are iterated over and, for each node in the cell, the nodes in the current cell and the four forward adjacent cells and the are checked to see if they fall within the node radius of the current node. All together, this implementation runs at $O(n+n+5nr^2) = O((2+5r^2)n)$ where n=|V|. The amount of additional space needed is equal to the number of nodes because they are coppied into their respective cells. This places the space complexity at $\Theta(n)$.

2.3.3 Graph Coloring

Implementing the smallest-last coloring algorithm involves implementing the smallest-last vertex ordering algorithm and the greedy graph coloring algorithm. For smallest-last vertex ordering, the first thing to do is build the data structure used to represent the graph with deleted nodes. The number of sets needed is equal to the maximum degree of the nodes. Then, the index of each node is placed in the set corresponding to the number of edges it has then the RGG. Simultaneously, a dictionary is created that maps each node to the number of degrees it has in the graph with deletions. Each value starts at the number of edges the corresponding node has in the RGG. At this point, we have iterated over all of the nodes once and allocated space for twice the number of nodes by copying them into the sets and using them as the keys for the degrees dictionary.

Because Python dictionaries resize at specific numbers of entries, we can determine the number of additional insertions caused by rehashing while the degrees dictionary is built. Python dictionaries start out with space for 8 entries and quadruple in size until the number of entries is above 50,000, at which point it begins to double in size. Clearly the dictionary grows at a logarithmic rate, but the total number of insertions I for an input size of n is given by:

$$I = \begin{cases} n + 8 \sum_{k=1}^{\log_4 \lceil n/8 \rceil} 4^k & n \le 50,000\\ n + 8 \sum_{k=1}^6 4^k + 32768 \sum_{k=1}^{\log_2 \lceil n/32768 \rceil} 2^k & n > 50,000 \end{cases}$$
(6)

Fortunately, because the entire dictionary is built before it is used by the smallest-last vertex ordering algorithm, it will never again be resized once the algorithm starts. Unfortunately, the sets resize at a similar rate and it is more difficult to predict how large the sets will need to be when performing smallest-last vertex ordering. The degree dictionary will also be used to index into the sets, so we gain a speed up here by not having to iterate over all of the edges for a node and determining if the node it shares an edge with are in the remaining graph each time we want to sift nodes down to lower set.

Next, the smallest-last vertex ordering algorithm is run until every node has been removed from the sets. For each node, I iterate over the sets from lowest degree to highest degree to find the first non-empty set. This set must contain the next node to remove becuase it contains all nodes with smallest degree. Before deleting the node from the graph and moving all adjacent nodes down a set, I check to see if the current set has all remaining nodes. If this is the case, the terminal clique has been found, and the size of the terminal clique must be saved. After this check, a node is popped from the end of the current set, and appended to the smallest-last ordering result. Then, for all the adjacent nodes to the popped node in the original graph, I check if the node is in the set with its degree. If it is, the number of degrees for that node can be decremented and the node can be placed into the correct set for its new degree.

The last step is to reverse the order of the smallest-last ordering result because it was built in the opposite order (smallest-first). All together, excluding the initialization of accessory data structures, this implementation runs in $\Theta(2|V|+2|E|)$ time and $\Theta(2|V|)$ space since nodes are removed from the buckets and added to the result.

After this the graph needs to be colored. For this I initially assign each node a color of -1 in a node color array that is parallel to the original list of nodes. I iterate over all of the nodes in the smallest-last vertex ordering. At each node, I generate a set of colors that is already used by the neighbors of that node by iterating over all of its edge nodes and grabbing their color from the node color array. Then, I just have to increment color from 0 until it does not exist in the search space set and I have the color to assign to the node.

Since the smallest-last odering is used, each time I check to see if a node is adjacent to the current node, I am searching nodes with fewer and fewer edges. This means that the nodes with the most neighbors are searched first, when the number of other nodes to check is lowest, and the nodes with the festest neighbors are searched last, when we have the most nodes to check if they share an edge with the current node. All together, this implementation runs in $\Theta(|V|+2|E|)$ time and $\Theta(|V|)$ space because we need a new array for the colors assigned to each of the nodes.

2.4 Verification

2.4.1 Node Placement

The nodes can be verified to be distributed uniformly if the distribution of degrees follows a normal distribution. To show that the distribution of degrees for each of my geometries are following a normal distribution, I plotted degree histograms for each of the geometries with 32,000 nodes and an average degree of 16. The histogram for Square is given in Figure 1, Disk is given in Figure 2, and Sphere is given in Figure 3. These histograms clearly follow a normal distribution.

2.4.2 Edge Determination

The runtime for the edge detection methods can be varified by varying the number of nodes and measuring the runtime of each algorithm. By looking at how the runtime grows, we can calculate the trendline that best fits the growth rate. For the first comparison, I vary the number of nodes from 4,000 to 64,000 in steps of 4,000, while holding the desired average dgree constant at 16. As we can see in Figure 4, the growth rates of the brute force and sweep methods are quadratic, while the growth rate of the cell method. The trendline functions are given on the graph.

For the second metric, I held the number of nodes constant at 32,000 and varied the desired average degree from 2 to 32 in steps of 2. The graph is given in Figure 5. The cell method clearly grows linearly, but the sweep method is harder to gauge. Since varying the desired average degree should only change the node radius, I would expect this to grow linearly as well. However, because each graph is randomly generated, some graphs can have nodes that are closer to sorted order than others. This can effect the measured runtime. It would be easier to gauge the trend if it I ran the data collection multiple times and averaged the results.

2.4.3 Graph Coloring

References

- [1] Weisstein, Eric W., Wolfram MathWorld

 Sphere Point Picking

 http://mathworld.wolfram.com/SpherePointPicking.html
- [2] Peters, Tim
 Timsort
 http://svn.python.org/projects/python/trunk/Objects/listsort.txt
- [3] Matula, David and Beck, Leland Smallest-Last Ordering and Clustering and Graph Coloring Algorithms
- [4] Johnson, Ian

 Linear-Time Computation of High-Converage Backbones for Wireless Sensor Networks

 https://github.com/ianjjohnson/SensorNetwork/blob/master/Report/Report.pdf

3 Appendix A - Figures

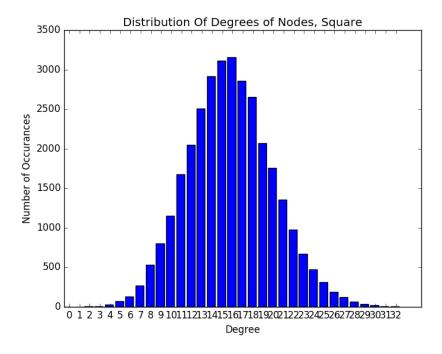


Figure 1: Distribution of Degree counts for Square. 32,000 Nodes, Average Degree of 16

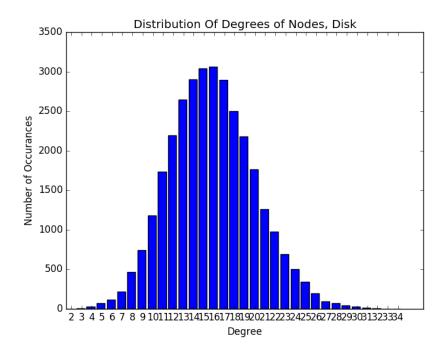


Figure 2: Distribution of Degree counts for Disk. 32,000 Nodes, Average Degree of 16

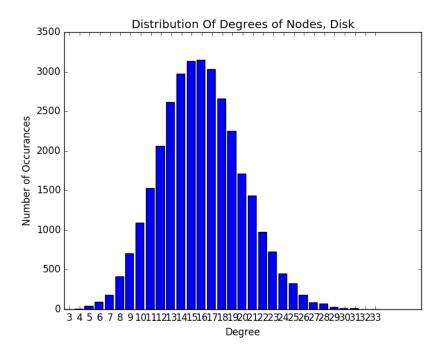


Figure 3: Distribution of Degree counts for Sphere. 32,000 Nodes, Average Degree of 16

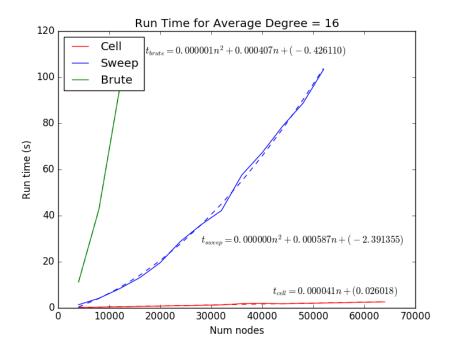


Figure 4: Runtime for Each Edge Detection Method, Average Degree of 16

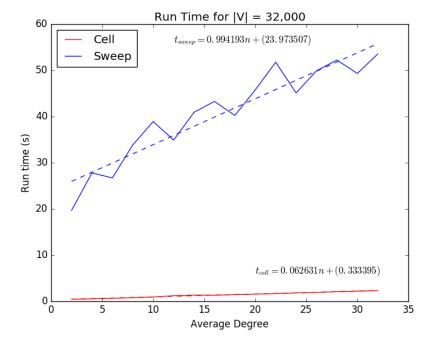


Figure 5: Runtime for Cell and Sweep Edge Detection, Variable Average Degree

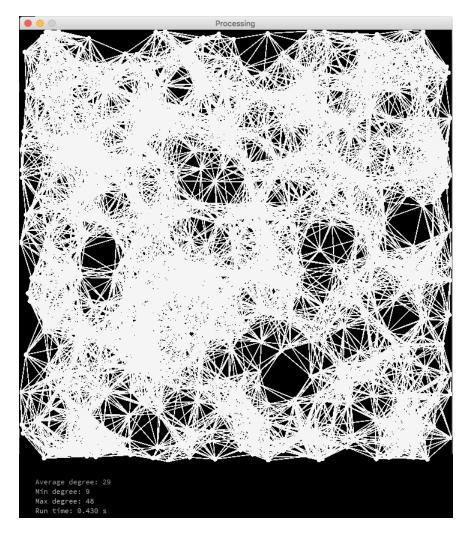


Figure 6: Square Benchmark Number 1. 1000 Nodes, Average Degree of $32\,$

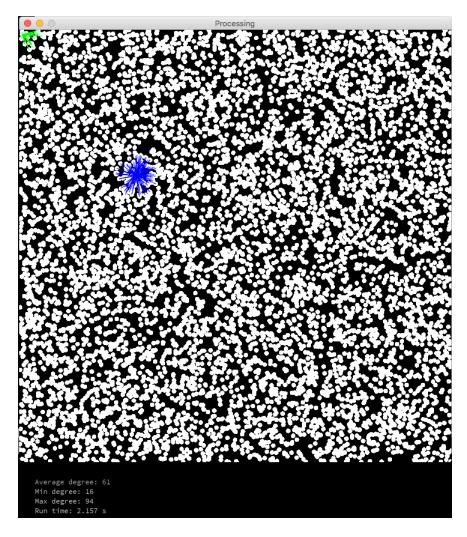


Figure 7: Square Benchmark Number 2. 8000 Nodes, Average Degree of $64\,$

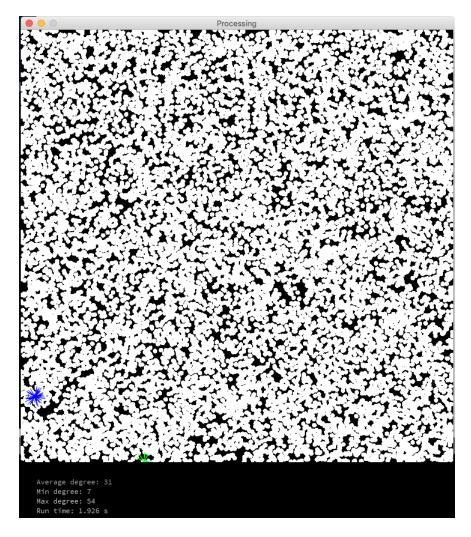


Figure 8: Square Benchmark Number 3. 16000 Nodes, Average Degree of $32\,$

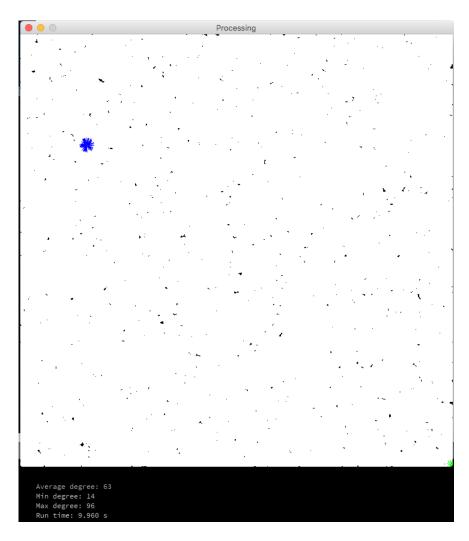


Figure 9: Square Benchmark Number 4. 64000 Nodes, Average Degree of $64\,$

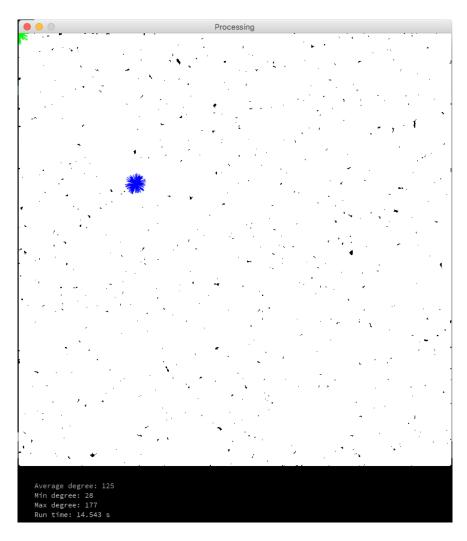


Figure 10: Square Benchmark Number 5. 64000 Nodes, Average Degree of 128

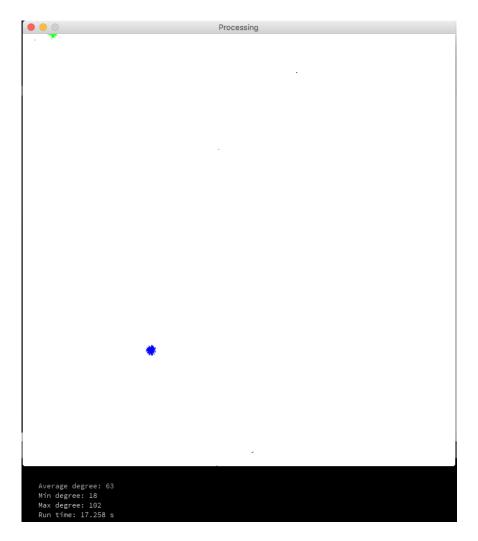


Figure 11: Square Benchmark Number 6. 128000 Nodes, Average Degree of 64

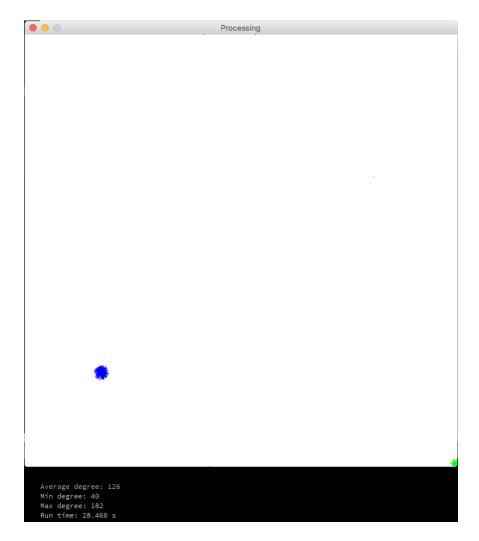


Figure 12: Square Benchmark Number 7. 128000 Nodes, Average Degree of 128

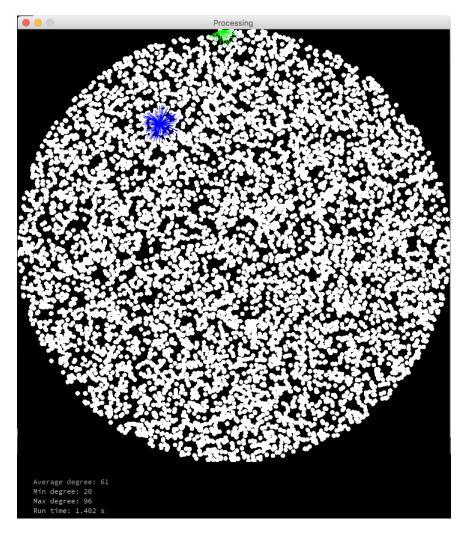


Figure 13: Disk Benchmark Number 1. 8000 Nodes, Average Degree of $64\,$

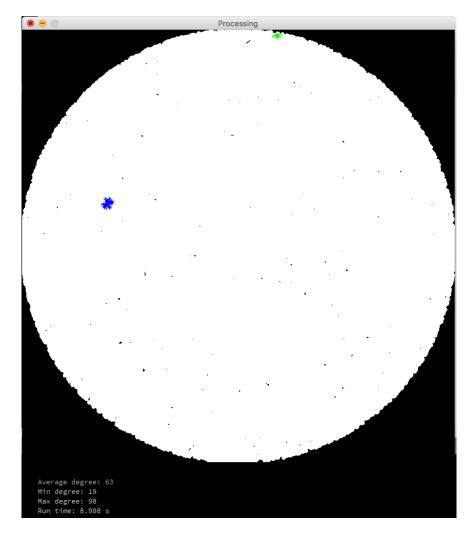


Figure 14: Disk Benchmark Number 2. 64000 Nodes, Average Degree of 64

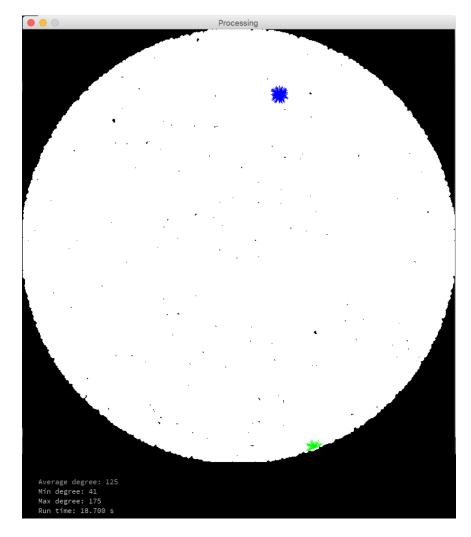


Figure 15: Disk Benchmark Number 3. 64000 Nodes, Average Degree of $128\,$

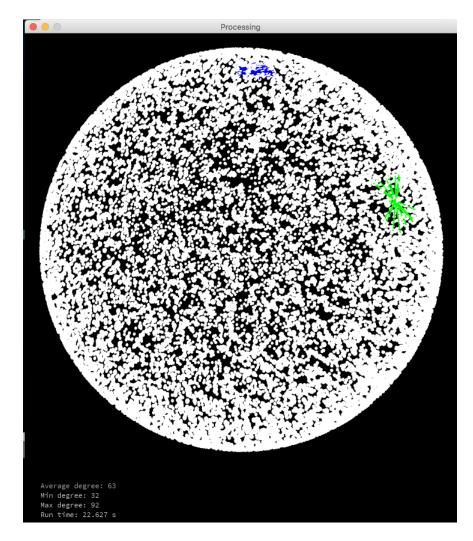


Figure 16: Sphere Benchmark Number 1. 16000 Nodes, Average Degree of $64\,$

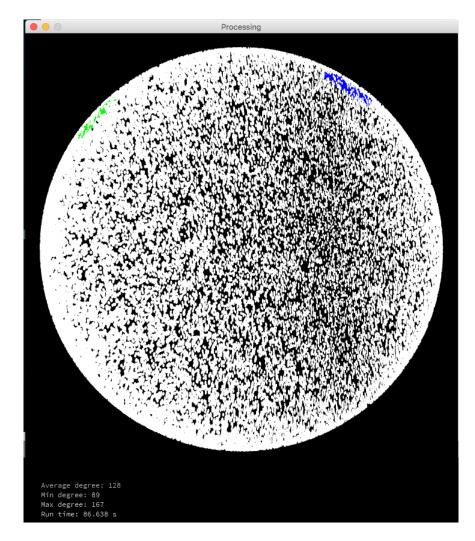


Figure 17: Sphere Benchmark Number 2. 32000 Nodes, Average Degree of 128

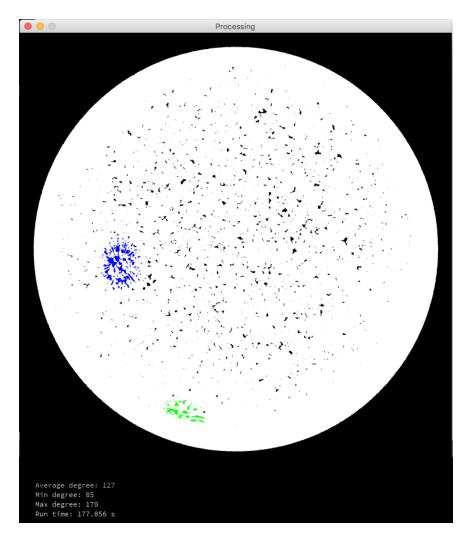


Figure 18: Sphere Benchmark Number 3. 64000 Nodes, Average Degree of 128

4 Appendix B - Code Listings

Listing 1: Processing driver

```
1 import random
 2 import time
3 import math
 4 from collections import Counter
5 from objects.topology import Square, Disk, Sphere
_{7} CANVAS_HEIGHT = 720
8 \text{ CANVAS\_WIDTH} = 720
10 NUM_NODES = 100
11 AVG.DEG = 10
12
13 MAX_NODES_TO_DRAW_EDGES = 8000
_{15} RUN_BENCHMARK = False
16
17 def setup():
        size (CANVAS_WIDTH, CANVAS_HEIGHT, P3D)
18
        background(0)
20
21 def draw():
        topology . drawGraph (MAX_NODES_TO_DRAW_EDGES)
22
23
24 def main():
        global topology
25
        # topology = Square()
        # topology = Disk()
27
28
        topology = Sphere()
29
        topology.num_nodes = NUM_NODES
30
        topology.avg\_deg = AVG\_DEG
31
        topology.canvas_height = CANVAS_HEIGHT
32
        topology.canvas_width = CANVAS_WIDTH
33
34
35
        if RUN_BENCHMARK:
             n\_benchmark\,=\,0
             topology.prepBenchmark(n_benchmark)
37
        run_time = time.clock()
39
40
        topology.generateNodes()
41
        topology.findEdges(method="cell")
42
43
        topology.colorGraph()
44
        print "Average degree: {}".format(topology.findAvgDegree())
print "Min degree: {}".format(topology.getMinDegree())
print "Max degree: {}".format(topology.getMaxDegree())
46
47
        print "Num edges: {}".format(topology.findNumEdges())
48
        print "Terminal clique size: {}".format(topology.term_clique_size)
print "Number of colors: {}".format(len(set(topology.node_colors)))
print "Max degree when deleted: {}".format(max(topology.deg_when_del.values())
49
51
        color_cnt = Counter(topology.node_colors)
        print "Max color set size: {} color: {}".format(color_cnt.most_common(1)
        [0][1],
                                                                       color_cnt.most_common(1)
        [0][0]
55
        run_time = time.clock() - run_time
56
        print "Run time: {0:.3f} s".format(run_time)
57
59 main()
```

Listing 2: Topology class and subclasses

```
1 import random
2 import math
3 import time
5 # benchmarks (num_nodes, avg_deg)
_{6} SQUARE BENCHMARKS = [(1000,32), (8000,64), (16000,32), (64000,64), (64000,128),
                         (128000,64), (128000, 128)]
8 DISK_BENCHMARKS = [(8000,64), (64000,64), (64000,128)]
9 SPHERE BENCHMARKS = [(16000,64), (32000,128), (64000,128)]
10
11 """
12 Topology - super class for the shape of the random geometric graph
13 ",",
14 class Topology(object):
15
      num\_nodes = 100
16
       avg_deg = 0
17
       canvas_height = 720
18
       canvas_width = 720
19
20
21
       def = init = (self):
           self.nodes = []
22
23
           self.edges = \{\}
           self.node_r = 0.0
24
           self.minDeg = ()
25
26
           self.maxDeg = ()
           self.s_last = []
27
28
           self.deg\_when\_del = \{\}
           self.node_colors = []
29
30
      # public funciton for generating nodes of the graph, must be subclassed
31
32
       def generateNodes(self):
           print "Method for generating nodes not subclassed"
33
34
      # public function for finding edges
       def findEdges(self, method="brute"):
36
           self._getRadiusForAverageDegree()
37
           self._addNodesAsEdgeKeys()
38
39
           if method == "brute":
40
               self._bruteForceFindEdges()
41
           elif method == "sweep":
42
               self._sweepFindEdges()
43
           elif method == "cell":
44
               self._cellFindEdges()
45
           else:
46
               print "Find edges method not defined: {}".format(method)
48
49
           self._findMinAndMaxDegree()
50
51
      # brute force edge detection
       def _bruteForceFindEdges(self):
           for i, n in enumerate(self.nodes):
               for j, m in enumerate(self.nodes):
                   if i != j and self._distance(n, m) <= self.node_r:</pre>
                        self.edges[n].append(j)
56
57
      # sweep edge detection
58
59
       def _sweepFindEdges(self):
           self.nodes.sort(key=lambda x: x[0])
60
61
           for i, n in enumerate(self.nodes):
62
               search_space = []
63
               for j in range(1, self.num_nodes-i):
                    if abs(n[0] - self.nodes[i+j][0]) \le self.node_r:
65
                        search_space.append(i+j)
67
                    else:
```

```
break
68
                for j in search_space:
69
                     if self._distance(n, self.nodes[j]) <= self.node_r:</pre>
70
71
                         self.edges[n].append(j)
                         self.edges[self.nodes[j]].append(i)
73
       # cell edge detection
74
       def _cellFindEdges(self):
75
            num_cells = int(1/self.node_r) + 1
76
            cells = []
77
78
            for i in range (num_cells):
                cells.append([[] for j in range(num_cells)])
79
80
            for i, n in enumerate(self.nodes):
81
                 cells [int(n[0]/self.node_r)][int(n[1]/self.node_r)].append(i)
82
83
84
            for i in range(num_cells):
                for j in range(num_cells):
85
                     for n_i in cells[i][j]:
86
                         for c in self._findAdjCells(i, j, num_cells):
87
88
                              for m_i in cells [c[0]][c[1]]:
                                  if self._distance(self.nodes[n_i], self.nodes[m_i]) <=
89
        self.node_r:
                                       self.edges[self.nodes[n_i]].append(m_i)
90
                                       self.edges[self.nodes[m_i]].append(n_i)
91
                         for m_i in cells[i][j]:
92
                              if self._distance(self.nodes[n_i], self.nodes[m_i]) <=
93
        self.node_r and n_i != m_i:
                                  self.edges[self.nodes[n_i]].append(m_i)
94
95
       # cell edge detection helper function
96
       def _findAdjCells(self, i, j, n):
97
            adj_cells = [(1,-1), (0,1), (1,1), (1,0)]
            return (((i+x[0])\%n,(j+x[1])\%n) for x in adj_cells)
99
       # function for finding the radius needed for the desired average degree
       # must be subclassed
       def _getRadiusForAverageDegree(self):
            print "Method for finding necessary radius for average degree not
       subclassed"
       # helper function for findEdges, initializes edges dict
       def _addNodesAsEdgeKeys(self):
            self.edges = {n:[] for n in self.nodes}
108
109
       # claculates the distance between two nodes (2D)
       def _distance(self, n, m):
             \begin{array}{lll} \textbf{return} & \textbf{math.sqrt} \; ((\, n \, [\, 0\, ] \; - \; m[\, 0\, ]\,) \; **2 + (n \, [\, 1\, ] \; - \; m[\, 1\, ]\,) \; **2) \\ \end{array} 
       # public function for finding the number of edges
       def findNumEdges (self):
            sigma_edges = 0
            for k in self.edges.keys():
117
                sigma_edges += len(self.edges[k])
118
119
            return sigma_edges/2
121
       # public function for finding the average degree of nodes
       def findAvgDegree(self):
            return 2*self.findNumEdges()/self.num_nodes
       # helper function for finding nodes with min and max degree
126
       def _findMinAndMaxDegree(self):
            self.minDeg = self.edges.keys()[0]
129
            self.maxDeg = self.edges.keys()[0]
            for k in self.edges.keys():
                if \ len(self.edges[k]) < len(self.edges[self.minDeg]):
```

```
self.minDeg = k
                if len(self.edges[k]) > len(self.edges[self.maxDeg]):
                     self.maxDeg = k
136
       # public function for getting the minimum degree
137
       def getMinDegree(self):
            return len (self.edges[self.minDeg])
139
140
       # public functino for getting the maximum degree
141
       def getMaxDegree(self):
142
            return len (self.edges[self.maxDeg])
143
144
       # public function for setting up the benchmark to run, must be subclassed
145
       def prepBenchmark(self, n):
146
            print "Method for preparing benchmark not subclassed"
147
148
       # public function for drawing the graph
149
       def drawGraph(self, n_limit):
            self._drawNodes()
            if self.num_nodes <= n_limit:
                self._drawEdges()
            else:
                self._drawMinMaxDegNodes()
       # responsible for drawing the nodes in the canvas
       def _drawNodes(self):
158
            strokeWeight(2)
159
            stroke (255)
160
            fill (255)
161
            for n in range (self.num_nodes):
163
                ellipse (self.nodes[n][0]*self.canvas\_width, self.nodes[n][1]*self.\\
164
       canvas_height, 5, 5)
165
       # responsible for drawing the edges in the canavas
       def _drawEdges(self):
167
            strokeWeight(1)
168
169
            stroke (245)
            fill (255)
170
            for n in self.edges.keys():
                for m_i in self.edges[n]:
                    line(n[0]*self.canvas_width, n[1]*self.canvas_height, self.nodes[
       m_i][0] * self.canvas_width, self.nodes[m_i][1] * self.canvas_height)
       # responsible for drawing the edges of the min and max degree nodes
176
       def _drawMinMaxDegNodes(self):
            strokeWeight(1)
178
            stroke (0,255,0)
179
            fill (255)
            for n_i in self.edges[self.minDeg]:
181
                line(self.minDeg[0]*self.canvas_width, self.minDeg[1]*self.
       canvas_height, self.nodes[n_i][0]*self.canvas_width, self.nodes[n_i][1]*self.
       canvas_height)
            stroke(0,0,255)
184
            for n_i in self.edges[self.maxDeg]:
185
                line(self.maxDeg[0]*self.canvas\_width, self.maxDeg[1]*self.
186
       can vas\_height \;,\;\; self \;. nodes [\; n\_i \;] [\; 0] * self \;. can vas\_width \;,\;\; self \;. nodes [\; n\_i \;] [\; 1] * self \;.
       canvas_height)
187
       # uses smallest last vertex ordering to color the graph
188
       def colorGraph (self):
189
            self.s_last, self.deg_when_del = self._smallestLastVertexOrdering()
190
191
            self.node_colors = self._assignNodeColors(self.s_last)
       # constructs a degree structure and determines the smallest last vertex
       ordering
```

```
def _smallestLastVertexOrdering(self):
             deg_sets = {l:set() for l in range(len(self.edges[self.maxDeg])+1)}
195
             deg\_when\_del = \{n: len(self.edges[n]) for n in self.nodes\}
196
197
             for i, n in enumerate (self.nodes):
198
                 deg_sets [deg_when_del[n]].add(i)
200
            smallest_last_ordering = []
201
202
             clique_found = False
203
            j = len(self.nodes)
204
             while j > 0:
205
                 # get the current smallest bucket
                 curr_bucket = 0
207
208
                 while len(deg_sets[curr_bucket]) == 0:
                     curr_bucket += 1
209
210
                 # if all the remaining nodes are connected we have the terminal clique
211
                 if not clique_found and len(deg_sets[curr_bucket]) == j:
212
                      clique_found = True
213
                      self.term_clique_size = curr_bucket
                 # get node with smallest degree
216
                 v_i = deg_sets[curr_bucket].pop()
217
                 smallest_last_ordering.append(v_i)
218
219
                 # decrement position of nodes that shared an edge with v
                 for n_i in (n_i for n_i in self.edges[self.nodes[v_i]] if n_i in
221
        deg\_sets\left[\,deg\_when\_del\left[\,self.nodes\left[\,n\_i\,\right]\right]\right]\right):
                      deg_sets [deg_when_del[self.nodes[n_i]]].remove(n_i)
                      deg\_when\_del[self.nodes[n\_i]] = 1
                      deg\_sets \left[ \, deg\_when\_del \left[ \, self \, . \, nodes \left[ \, n\_i \, \right] \right] \right]. \, add \left( \, n\_i \, \right)
                 j -= 1
226
            # reverse list since it was built shortest-first
            return smallest_last_ordering[::-1], deg_when_del
229
230
        # assigns the colors to nodes given in a smallest-last vertex ordering as a
        parallel array
        def _assignNodeColors(self , s_last):
             colors = [-1 \text{ for } \_in \text{ range}(len(s\_last))]
             for i in s_last:
                 adj_colors = set([colors[j] for j in self.edges[self.nodes[i]]])
235
                 color = 0
                 while color in adj_colors:
                     color += 1
238
                 colors [i] = color
239
240
            return colors
241
242
243 """
244 Square - inherits from Topology, overloads generateNodes and
        _getRadiusForAverageDegree
245 for a unit square topology
246 """
247 class Square (Topology):
248
249
        def __init__(self):
            super(Square, self).__init__()
250
251
        # places nodes uniformly in a unit square
        def generateNodes(self):
253
             for i in range (self.num_nodes):
                 self.nodes.append((random.uniform(0,1), random.uniform(0,1)))
256
        # calculates the radius needed for the requested average degree in a unit
257
        square
```

```
def _getRadiusForAverageDegree(self):
258
            self.node_r = math.sqrt(self.avg_deg/(self.num_nodes * math.pi))
259
260
261
       # gets benchmark setting for square
       def prepBenchmark(self, n):
262
            self.num\_nodes = SQUARE.BENCHMARKS[n][0]
263
            self.avg_deg = SQUARE_BENCHMARKS[n][1]
264
265
266 """
267 Disk - inherits from Topology, overloads generateNodes and
       _getRadiusForAverageDegree
268 for a unit circle topology
269 """
270 class Disk (Topology):
271
       def __init__(self):
272
            super(Disk, self).__init__()
274
       # places nodes uniformly in a unit square and regenerates the node if it falls
       # outside of the circle
       def generateNodes(self):
            for i in range(self.num_nodes):
278
                p = (random.uniform(0,1), random.uniform(0,1))
279
                while self._distance(p, (0.5,0.5)) > 0.5:
280
                    p = (random.uniform(0,1), random.uniform(0,1))
281
                self.nodes.append(p)
283
       # calculates the radius needed for the requested average degree in a unit
284
       circle
       def _getRadiusForAverageDegree(self):
285
            self.node_r = math.sqrt((self.avg_deg + 0.0)/self.num_nodes)/2
287
       # gets benchmark setting for disk
        def prepBenchmark(self, n):
289
            self.num\_nodes = DISK\_BENCHMARKS[n][0]
            self.avg\_deg = DISK\_BENCHMARKS[n][1]
291
292
293 """
294 Sphere - inherits from Topology, overloads generateNodes,
       _getRadiusForAverageDegree,
295 and _distance for a unit sphere topology. Also updates the drawGraph function for
296 a 3D canvas
297 """
298 class Sphere (Topology):
299
       # adds rotation and node limit variables
300
       def __init__(self):
301
            super(Sphere, self).__init__()
302
            self.rot = (0, math.pi/4, 0) \# this may move to Topology if rotation is
303
        given to the 2D shapes
           # used to control _drawNodes functionality
304
            self.n_limit = 8000
305
306
       # places nodes in a unit cube and projects them onto the surface of the sphere
307
308
       def generateNodes(self):
            for i in range (self.num_nodes):
309
310
                # equations for uniformly distributing nodes on the surface area of
311
                # a sphere: http://mathworld.wolfram.com/SpherePointPicking.html
                u = random.uniform(-1,1)
                theta = random.uniform (0, 2*math.pi)
314
                    \operatorname{math.sqrt}(1 - u **2) * \operatorname{math.cos}(\operatorname{theta}),
                    math.sqrt(1 - u**2) * math.sin(theta),
316
317
                    u
318
                self.nodes.append(p)
       # calculates the radius needed for the requested average degree in a unit
321
```

```
sphere
        def _getRadiusForAverageDegree(self):
             self.node_r = math.sqrt((self.avg_deg + 0.0)/self.num_nodes)*2
324
        # calculates the distance between two nodes (3D)
        def _distance(self, n, m):
             return math.sqrt ((n[0] - m[0]) **2 + (n[1] - m[1]) **2 + (n[2] - m[2]) **2)
328
        # gets benchmark setting for sphere
        def prepBenchmark(self, n):
             self.num\_nodes = SPHERE\_BENCHMARKS[n][0]
             self.avg\_deg = SPHERE\_BENCHMARKS[n][1]
        # public function for drawing graph, updates node limit if necessary
334
        def drawGraph(self , n_limit):
             self.n_limit = n_limit
             self._drawNodesAndEdges()
        # responsible for drawing nodes and edges in 3D space
        def _drawNodesAndEdges(self):
340
            # positions camera
            camera (self.canvas_width/2, self.canvas_height/2, self.canvas_width*-2,
342
        0.5, 0.5, 0, 0, 1, 0
            # updates rotation
344
             self.rot = (self.rot[0], self.rot[1] - math.pi/100, self.rot[2])
346
347
            background (0)
348
            strokeWeight (2)
            stroke (255)
349
             fill (255)
350
351
             for n in range (self.num_nodes):
                 pushMatrix()
353
354
355
                 # sets new rotation
                 rotateZ(self.rot[2])
357
                 rotateY(-1*self.rot[1])
358
359
                 # sets drawing origin to current node
                 translate((self.nodes[n][0])*self.canvas_width, (self.nodes[n][1])*
360
        self.canvas_height, (self.nodes[n][2]) * self.canvas_width)
                 # places ellipse at origin
362
                 ellipse (0, 0, 10, 10)
363
364
                 # draw all edges
365
                 if self.num_nodes <= self.n_limit:</pre>
366
                      for e_i in self.edges[self.nodes[n]]:
367
                          e = self.nodes[e_i]
                          # draws line from origin to neighboring node
369
                          line(0,0,0, (e[0] - self.nodes[n][0])*self.canvas_width, (e[1]
370
         -\ self.nodes[n][1])*self.canvas\_height,\ (e[2]-\ self.nodes[n][2])*self.
        canvas_width)
                 # draw edges for min degree node
                 elif self.nodes[n] == self.minDeg:
                      stroke (0,255,0)
373
                      for e_i in self.edges[self.nodes[n]]:
                          e = self.nodes[e_i]
                          # draws line from origin to neighboring node
                          line \, (0\,,\!0\,,\!0\,, \ (e\,[\,0\,] \ - \ self\,.\,nodes\,[\,n\,]\,[\,0\,]\,) * self\,.\,canvas\_width\,\,, \ (\,e\,[\,1\,] \ - \ self\,.\,nodes\,[\,n\,]\,[\,0\,]\,) * self\,.\,nodes\,[\,n\,]\,[\,0\,]\,) * self\,.\,nodes\,[\,n\,]\,[\,0\,]\,,
         - self.nodes[n][1]) *self.canvas_height, (e[2] - self.nodes[n][2]) *self.
        canvas_width)
                      stroke (255)
                 # draw edges for max degree node
                 elif self.nodes[n] == self.maxDeg:
380
                      stroke (0,0,255)
381
                      for e_i in self.edges[self.nodes[n]]:
382
```