

Scientific Computing (M3SC) - Project 1

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1 APPROACH AND SOLUTION STRATEGY

In order to model the flow of traffic through Rome in the models given to us, I defined a function (which is explained thoroughly in Section 2) called **trafficFlow** which takes as arguments numerous parameters which can be altered to simulate different traffic flows through the network. In the 3 models that we were required to simulate, the starting node is node 13 (St. Peter's Square) of python-index 12 and the end destination of the cars is node 52 (Coliseum) of python-index 51, and at each iteration some of the cars move to the next node in the current optimal path from the current node to node 52, which is determined by Dijkstra's algorithm (which was provided to us), whilst others are forced to remain behind.

The function **trafficFlow** will complete 200 iterations as instructed, each time updating the number of cars at each node as we model the cars moving through the network. I start off assuming that there are no cars in the network, so inevitably there is no movement of cars during the first iteration, but then I inject 20 cars at node 13 so at the end of the first iteration there are 20 cars at node 13 and no cars everywhere else; I then add 20 cars to node 13 at the end of the next 179 iterations (so 180 injections of 20 cars in total).

At each iteration, I see where there are currently cars and using Dijkstra's algorithm I determine where these cars should move to in that current iteration based on the shortest path, which may change at every iteration due to the fact that the weights of the edges will change as the cars traverse through the network and therefore affect the Dijkstra path. For the cars not at node 52, I compute 70% of the number of cars at these nodes and round this number to the nearest integer; I add this number to the number of cars at the next node of the current Dijkstra path, and subtract this number from the number of cars at the current node to ensure that the number of cars in the network is conserved, so that cars only leave the network via node 52. This is implemented by considering cars at node 52 separately, and as instructed I compute 40% of the number of cars at node 52 and round it to the nearest

integer, before subtracting this number from the number of cars currently there to ensure that 60% of the cars remain as described.

Once the cars have been moved through the network, I update the weight matrix according to the following formula:

$$w_{ij} = w_{ij}^{(0)} + \xi \frac{c_i + c_j}{2}$$

where $w_{ij}^{(0)}$ represents the original weight value of the edge connecting node i and node j at the start of the simulation, and c_i, c_j represent the new number of cars at nodes i and j respectively. This gives a new updated weight matrix, and is then used in the next iteration when Dijkstra's algorithm is called upon.

The number of cars is stored in an array called *carFreq*, and the t -th row gives the number of cars at each of the 58 nodes at the end of iteration t , where $1 \leq t \leq 200$. From this, I determine information such as what was the maximum load of cars for each node over the 200 iterations, which is stored in the array *maximumLoad*; from this, I then find which 5 nodes were the most congested over the 200 iterations, which is stored in the array *mostCongested* and the actual values of these maximum loads is stored in *loadCongested*. In addition to this, I also determine which edges in the network were used over the course of the simulation and return these in the list *usedUnique*, whilst *unusedUnique* is a list consisting of the unused edges.

2 PYTHON CODE TO IMPLEMENT MODELS

Below is my python function **trafficFlow**, with comments explaining the functionality and thinking behind the approach and implementation of my function to simulate the model.

```
1 #Define a function where we can model the traffic flow easily
2 #for different parameter values
3 def trafficFlow(ist,iend,wei0,minutes,numInject,freqInject,e):
4
5     #ist = index of the starting node
6     #iend = index of the end node
7     #wei0 = weight matrix at start of the traffic flow
8     #minutes = number of iterations we simulate
9     #numInject = number of cars to inject at the end of
10    #           each iteration we are adding cars at
11    #freqInject = number of times we inject new cars into
12    #           the network
13    #e = parameter used when updating the weight matrix
14
15    #Initialise the weight matrix as the original one, but
16    #note that wei will be updated at the end of each
17    #iteration after the cars have moved through the network
18    wei = wei0.copy()
19
20    #Initialise the matrix carFreq which stores the number of
21    #cars at each node at the end of each iteration once
22    #the cars have moved and we have added more cars to the
23    #network if necessary.
24
25    #Note: the first row i.e. carFreq[0,:] is a row of zeros
26    #because I start off the simulation with no cars in the
27    #network.
28
29    #Note: numNodes is the number of nodes in the network, and
30    #can be determined by looking at the size of the weight
31    #matrix
32    numNodes = int(np.shape(wei0)[0])
33    carFreq = np.zeros((minutes,numNodes),dtype=int)
34
35    #Initialise an empty list which will update and store the
36    #edges that we use as we simulate the traffic flow
37    usedEdges = []
38
39    #Complete the iterations using a for loop, iterating
40    #over t
41    for t in range(minutes):
42
```

```

43     #After the first iteration is complete i.e. once we
44     #have cars in the network, update the current row of
45     #zeros by the previous row so we know how many cars are
46     #at each node at the start of the current iteration
47
48     #Note: we start with no cars in the network, so at
49     #the start of the first iteration with python-index
50     #t=0 we have that carFreq[0,:] is a row of zeros
51     if t > 0:
52         carFreq[t,:] = carFreq[t-1,:]
53
54     #Make a copy of how many cars are at each node at the
55     #start of the current iteration so we can refer back
56     #to it when computing how many cars (if any) need to
57     #move from each node
58     tempVec = carFreq[t,:].copy()
59
60     #Loop through each of the nodes and determine the next
61     #node that the cars should move to using the path
62     #given by Dijkstra's algorithm, where we use the
63     #current weight matrix to find the current optimal
64     #Dijkstra path
65     for i in range(numNodes):
66
67         #Only apply DIjkstra's algorithm to nodes where
68         #there are currently cars using the indexes of
69         #these nodes and the current weight matrix,
70         #because otherwise we will compute a path but
71         #won't have any cars to move
72         if tempVec[i] != 0:
73
74             #Store the Dijkstra path in the list shpath so
75             #that we can obtain the next node to move the
76             #cars to later on
77             shpath = Dijkst(i,iend,wei)
78
79             #Assign numCars to be the current number of
80             #cars at the node we are currently interested
81             #in, so we can refer to it later when
82             #computing how many cars to move
83             numCars = tempVec[i]
84
85             #Move cars through the network if we are not
86             #at the end of the path i.e. not at node with
87             #python-index iend, so that we do not lose
88             #cars incorrectly
89             if i != iend:
90

```

```

91         #If we aren't at the end node, compute 70%
92         #of the number of cars currently there to
93         #the nearest integer so these are the cars
94         #to be moved. Note that we only compute
95         #this value once and we add it to the next
96         #node and subtract it from the current
97         #node in order to conserve the number of
98         #cars in the network, so there is no net
99         #gain nor loss of cars in the network
100        numMove = int(round(numCars*0.7))
101
102        #Obtain the python-index of the next node
103        #for the cars to move to from the Dijkstra
104        #path
105        nextNode = shpath[1]
106
107        #Add the cars to be moved to the number of
108        #cars at the next node
109        carFreq[t,nextNode] = carFreq[t,nextNode]
110                               + numMove
111
112        #Remove these cars from the node that they
113        #were at when the iteration started
114        carFreq[t,i] = carFreq[t,i] - numMove
115
116        #Add the edge used by the cars moving from
117        #node i+1 (python-index i) to node
118        #nextNode+1 (python-index nextNode) to the
119        #list of used edges using append
120        usedEdges.append([i+1,nextNode+1])
121
122        #If we are at the end node, then compute 40%
123        #of the cars that are currently there to the
124        #nearest integer and remove them from the
125        #network by subtracting them from the end node
126        else:
127            numMove = int(round(numCars*0.4))
128            carFreq[t,i] = carFreq[t,i] - numMove
129
130        #If we haven't completed the first freqInject
131        #iterations, add numInject cars into the network at
132        #the starting node with python-index ist in
133        #conjunction with the function argument
134        if t <= (freqInject-1):
135            carFreq[t,ist] = carFreq[t,ist] + numInject
136
137
138

```

```

139         #Update the weight matrix wei for the elements that
140         #are non-zero, since we only update the weights
141         #corresponding to places where there are actually
142         #links between the nodes. We do this using the formula
143         #given to us, so we add the original weight to e
144         #(argument of the function) multiplied by half of the
145         #sum of the new number of cars which are there at the
146         #end of the current iteration
147         for i in range(numNodes):
148             for j in range(numNodes):
149                 if wei[i,j] != 0:
150                     wei[i,j] = wei0[i,j] + e*(carFreq[t,i]
151                                     + carFreq[t,j])/2
152
153     #Note: at this point, we have completed the simulation of
154     #the model
155
156     #Find the maximum number of cars at each node by finding
157     #the maximum value in each column, since each column
158     #contains the number of cars at each node at the end of
159     #each iteration
160     maximumLoad = np.amax(carFreq, axis = 0)
161
162     #Find the 5 most congested nodes from the array
163     #maximumLoad, and list them from the most congested in
164     #descending order in the array mostCongested.
165     #Note: I need to add 1 to the indexes since python-indexes
166     #start from 0 and not 1
167     indexCongested = np.argsort(maximumLoad)[-5:][::-1]
168     mostCongested = indexCongested + 1
169
170     #Find how many cars are at each of the 5 most congested
171     #nodes using the indexes of these nodes, and store these
172     #in the array loadCongested
173     loadCongested = maximumLoad[indexCongested]
174
175     #Find the unvisited nodes by finding where the maximum
176     #load of cars over all iterations was 0 in maximumLoad,
177     #meaning there were never any cars there at any point
178     #in the flow model. Again, I need to add 1 to remove the
179     #effect of python-indexes
180     unvisitedNodes = np.where(maximumLoad == 0)[0] + 1
181
182     #Make a list of the used edges called usedUnique, which
183     #removes the repeats of the used edges in usedEdges
184     usedUnique = []
185     [usedUnique.append(edge) for edge in usedEdges if edge not
186                                     in usedUnique]

```

```

187 #Using the edge list, which is a list of lists called
188 #edgeList and will be computed from the files RomeVertices
189 #and RomeEdges before using this function trafficFlow,
190 #take out the edges which have been used so that we can
191 #obtain the unused edges. To do this, set unusedUnique to
192 #be edgeList, and then remove any edges that have been
193 #used from it to obtain the unused edges in the simulation
194 unusedUnique = edgeList[:]
195 for edge in usedUnique:
196     if edge in unusedUnique:
197         unusedUnique.remove(edge)
198
199 #If e = 0, then there is one flow path for the traffic so
200 #I want this path to be returned by the function along
201 #with the other bits of useful information computed by the
202 #function
203 if e == 0:
204
205     #Compute the Dijkstra path
206     flowPattern = Dijkst(ist,iend,wei0)
207
208     #Add 1 to each of the python-indexes in flowPattern so
209     #we obtain the nodes of the Dijkstra path and not
210     #their python-indexes
211     for i in range(len(flowPattern)):
212         flowPattern[i] = flowPattern[i] + 1
213
214     #Return all of this data
215     return carFreq,maximumLoad,mostCongested,
216           loadCongested,unvisitedNodes,usedUnique,
217           unusedUnique,flowPattern
218
219 #If e != 0, just return the relevant information and no
220 #path since there wouldn't be a unique path taken by all
221 #of the cars injected into the network as there would be
222 #so many different paths taken by different sets of cars
223 else:
224     return carFreq,maximumLoad,mostCongested,
225           loadCongested,unvisitedNodes,usedUnique,
226           unusedUnique

```

3 RESULTS FOR MODELS

For reference in the subsections below in which I report on my findings, I have included the code below which I used to simulate the 3 models of interest. Note that I used the given function **calcWei** to initialise the weight matrix using the information contained in the given data files **RomeVertices** and **RomeEdges**, and then I computed a unique edge list called *edgeList* which consists of a unique list of the set of edges in the network; I do this because within my python function **trafficFlow**, I refer to *edgeList* in order to determine the list of unused edges by removing the used edges from a list to leave behind the unused edges.

```
1 if __name__ == '__main__':
2     import numpy as np
3     import scipy as sp
4     import math as ma
5     import sys
6     import time
7     import csv
8
9     #Initialise weight matrix using the given data files
10    RomeX = np.empty(0,dtype=float)
11    RomeY = np.empty(0,dtype=float)
12    with open('RomeVertices','r') as file:
13        AAA = csv.reader(file)
14        for row in AAA:
15            RomeX = np.concatenate((RomeX,[float(row[1])]))
16            RomeY = np.concatenate((RomeY,[float(row[2])]))
17        file.close()
18
19    RomeA = np.empty(0,dtype=int)
20    RomeB = np.empty(0,dtype=int)
21    RomeV = np.empty(0,dtype=float)
22    with open('RomeEdges','r') as file:
23        AAA = csv.reader(file)
24        for row in AAA:
25            RomeA = np.concatenate((RomeA,[int(row[0])]))
26            RomeB = np.concatenate((RomeB,[int(row[1])]))
27            RomeV = np.concatenate((RomeV,[float(row[2])]))
28        file.close()
29
30    #Make a copy of the original weight matrix using the
31    #provided function calcWei and the data from RomeVertices
32    #and RomeEdges, and call this original weight matrix
33    #weiOriginal
34    weiOriginal = calcWei(RomeX,RomeY,RomeA,RomeB,RomeV)
35
36
37
```



```

38 #Using RomeA and RomeB which came from the file RomeEdges,
39 #I make an edge list of all of the edges which can be
40 #referred to when the traffic flow is modelled below
41 #within the function.
42 #Note: I will make a list of lists, so each element of the
43 #list is in fact a list consisting of an edge in the
44 #network
45 edgeList1 = []
46 for i in range(np.size(RomeA)):
47     edge = []
48     edge.append(RomeA[i])
49     edge.append(RomeB[i])
50     edgeList1.append(edge)
51
52 #Ensure that the edge list has no repeated edges in it for
53 #when it is referred to when the function trafficFlow is
54 #called upon below
55 edgeList = []
56 [edgeList.append(x) for x in edgeList1 if x not in
57                                     edgeList]
58 #Make a copy of the original weight matrix to use in the
59 #first 2 models
60 wei0 = weiOriginal.copy()
61
62 #Model 1: start at node 13 (python-index 12) and end at
63 #node 52 (python-index 51) with e = 0.01 and no blocked
64 #nodes
65 carFreq1,maximumLoad1,mostCongested1,loadCongested1,
66 unvisitedNodes1,usedUnique1,unusedUnique1 =
67 trafficFlow(12,51,wei0,200,20,180,0.01)
68
69 #Model 2: same as Model 1, but for e = 0 instead
70 carFreq2,maximumLoad2,mostCongested2,loadCongested2,
71 unvisitedNodes2,usedUnique2,unusedUnique2,flowPattern1 =
72 trafficFlow(12,51,wei0,200,20,180,0)
73
74 #Get the weight matrix for Model 3 where node 30 is
75 #blocked, so that any edges linked to node 30
76 #(python-index 29) are blocked off so we do not use any of
77 #the edges connected to node 30, and call it wei1
78 wei1 = weiOriginal.copy()
79 wei1[29,:] = 0
80 wei1[:,29] = 0
81
82 #Model 3: same as Model 1, but with node 30 blocked
83 carFreq3,maximumLoad3,mostCongested3,loadCongested3,
84 unvisitedNodes3,usedUnique3,unusedUnique3 =
85 trafficFlow(12,51,wei1,200,20,180,0.01)

```

3.1 MODEL 1: $\xi = 0.01$ AND NO BLOCKED NODES

The results for this simulation can be found in my python code, but I will reference to the necessary output when analysing the model now. The maximum load for each node over the 200 iterations was returned and stored in the array *maximumLoad1*, and this was found to be:

```
1 maximumLoad1
2 = array([ 1,  2,  0,  7,  0,  8,  8,  0, 16, 14,  0,  8, 28,
3          0, 28, 22,  7, 28, 11, 28, 38, 11,  7, 24, 40, 23,
4          6, 10, 13, 32, 12, 19, 15, 15, 23,  9,  3, 14, 19,
5          30, 30, 11, 31, 28,  4,  0,  0, 11,  0, 23, 18, 63,
6          17, 15, 12, 14, 11, 11  ])
```

From this, I was able to determine the 5 most congested nodes, and these were returned and stored in the array *mostCongested1*:

```
1 mostCongested1 = array([52, 25, 21, 30, 43], dtype=int64)
```

so I can conclude that, in descending order, the most congested nodes were 52, 25, 21, 30 and 43. The maximum loads at each of these nodes was stored in *loadCongested1*:

```
1 loadCongested1 = array([63, 40, 38, 32, 31])
```

It is worth noting that after having analysed the map of Rome provided, and where these 5 nodes are in relation to the network as a whole, it is not surprising that these nodes happened to be the 5 most congested nodes. This is because node 52 is obviously the desired end destination of all of the cars, and therefore all of the cars are aiming to get to node 52. Node 25 lies near node 13 and is the starting point of a one-way system (given we start at node 13) that leads directly to node 52 that avoids much of the city, which could explain why it was a very congested node. Nodes 21, 30 and 43 all lie pretty centrally in the network and are very well-connected to many other nodes in terms of the number of edges emanating from them, hence they provide focal points from which the cars can take many routes to node 52 and possibly explains why they were amongst the most congested nodes.

The unused edges were stored in *unusedUnique1* as follows:

```
1 unusedUnique1
2 = [ [1, 2], [2, 3], [3, 2], [3, 5], [5, 8], [8, 11],
3     [11, 14], [14, 18], [14, 15], [18, 15], [15, 13], [56, 54],
4     [55, 56], [57, 55], [58, 57], [52, 58], [54, 49], [49, 47],
5     [47, 48], [48, 46], [46, 37], [37, 24], [8, 9], [9, 8],
6     [11, 16], [16, 11], [21, 18], [4, 1], [12, 4], [23, 12],
7     [27, 23], [31, 27], [42, 31], [52, 42], [1, 7], [7, 1],
8     [19, 10], [29, 19], [41, 29], [44, 41], [52, 44], [17, 19],
9     [28, 17], [36, 28], [44, 36], [44, 42], [42, 44], [31, 36],
10    [28, 29], [4, 7], [7, 6], [10, 9], [32, 22], [33, 22],
```

```

11 [41, 43], [43, 49], [49, 43], [32, 26], [33, 32], [34, 33],
12 [29, 34], [38, 35], [39, 38], [41, 39], [43, 30], [43, 48],
13 [48, 45], [46, 45], [45, 46], [45, 30], [30, 21] ]

```

Also note the unvisited nodes for this model, stored in *unvisitedNodes1*:

```

1 unvisitedNodes1
2 = array([3, 5, 8, 11, 14, 46, 47, 49], dtype=int64)

```

After examining the unused edges in this model, and also observing which nodes were not visited, it appears that the unused edges mostly either lie in a one-way system or simply would be taking us backwards and away from the end destination of node 52. Taking a closer look at the list of edges, *edgeList*, reveals that there are one-way systems (running along either side of the river) which form the following paths between the nodes going from left to right:

- [3 – 5 – 8 – 11 – 14 – 18 – 25 – 40 – 50 – 51 – 53 – 54]
- [3 – 5 – 8 – 11 – 14 – 15]
- [54 – 49 – 47 – 48 – 46 – 37 – 24 – 21 – 20 – 16 – 9 – 6 – 2]

Comparing the unvisited nodes to the edges that appear in the one-way systems and the list of unused edges, namely *unusedUnique1*, we observe that there is clearly a correlation; if we disregard the edges that in effect take us backwards in the sense that they don't take a car towards node 52 but rather away from it, all of the other unused edges with the exception of [44 - 42] and [42 - 44] are in the one-way systems that do not take us towards node 52 given that we start at node 13, so we can conclude that the unused edges are mainly those that lie on one-way systems and do not take us towards node 52 given that we started at node 13. Also note that all of the unvisited nodes lie on one-way systems which take a car away from node 52, and every other node was used in some way.

3.2 MODEL 2: $\xi = 0$ AND NO BLOCKED NODES

Setting the parameter $\xi = 0$ in the formula used to update the weights in effect results in a non-changing weight matrix. Because of this, the accumulation of cars at a particular node has no effect on the shortest path to node 52 at any given time, hence all of the cars follow the same path from node 13 to node 52 which is the first Dijkstra path. This flow pattern, which I called *flowPattern1*, was found to be:

```

1 flowPattern1
2 = [13, 15, 18, 25, 40, 50, 51, 53, 54, 56, 55, 57, 58, 52]

```

Observe that this path is part of a one-way system that is on the outskirts of Rome, so it makes sense that this would be the shortest path since it is a very direct path from node 13 to node 52.

3.3 MODEL 3: $\xi = 0.01$ AND NODE 30 BLOCKED

In order to simulate this model after an accident occurred at node 30, I had to modify the weight matrix which was inputted into the function **flowPattern** to account for this. As can be seen in the code at the start of this section, I set the 30th row and column (with python-index 29) to 0 so that no cars could ever go through node 30 when making the journey to node 52. Since node 30 is fairly central to the network, and was the 4th most congested node in Model 1, one would expect removing node 30 to have an effect on the flow of the cars through the network as we modelled the simulation.

In this model, the most congested nodes, stored in *mostCongested3*, were:

```
1 mostCongested3 = array([52, 25, 21, 15, 18], dtype=int64)
```

so clearly the first 3 most congested nodes haven't changed compared with Model 1 but we see that nodes 15 and 18 now become relatively more congested after blocking node 30. The maximum loads of these most congested nodes was stored in *loadCongested3*:

```
1 loadCongested3 = array([56, 35, 29, 28, 28])
```

so we do observe a decrease in the peak values at nodes 52, 25 and 21 of 7, 5 and 9 respectively.

In order to be able to observe which nodes decreased or increased most in peak value, I computed the difference between *maximumLoad1* and *maximumLoad3* as follows:

```
1 maximumLoad3 - maximumLoad1
2 = array([ 1,  1,  0,  3,  0,  5,  3,  0,  2,  1,
3           0,  2,  0,  0,  0,  0,  1,  0,  1, -2,
4          -9,  4,  2, -6, -5, -4,  2,  1,  0, -32,
5          -1,  1,  3, -1, -9,  1, -3,  0, -7, -3,
6          -9, -2, -14, -6, -4,  0,  0,  3,  0, -2,
7           1, -7, -2, -1, -1, -2, -1, -2])
```

There was inevitably a massive decrease (of 32) in the maximum load at node 30 since it was blocked, but other nodes that noticeably decreased in peak value in descending order were nodes 43, 21, 35, and 41 with a range of decrease from 9 to 14, all of which are directly connected to node 30 or in the case of node 41 connected to node 30 via node 43; we would expect there to be a reduction in the peak value of cars at the nodes closely connected to node 30 if node 30 is blocked. Nodes that increased noticeably in peak value in descending order were nodes 6, 22, 7, 33 and 48, but not by that great an amount as the range of increase in the maximum loads at these nodes was between 3 and 5.