

Stochastic Models and Optimization: Problem Set 1

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Problem 5. TSP Computational Assignment:

Visit the website: <http://www.math.uwaterloo.ca/tsp/world/countries.html>. Solve the Traveling Salesman Problem for Uruguay based on the dataset provided. You can use your favorite programming language and solution method for the TSP. Provide a printout of your code with detailed documentation, and compare the optimal solution you obtain to the one available at the website.

The code has been done in R. We used 3 heuristic approaches to find approximate the problem: The nearest neighbor, the greedy algorithm and the simulation annealing. We can see that the best approach (annealing) is above the optimal solution by 12%, however comparing to the second best it just 1% below. Furthermore, this 1% represented an important loose in terms of efficiency. In the following table you can see some important results:

	optimal	nearest neighbor	greedy	annealing
distance	79114.00	100056.45	89559.29	88985.51
distance/optimal		1.26	1.13	1.12
run time (min)		0.19	2.55	11.69

```
1 library(fields)
2 library(dplyr)
3
4 # Read data and estimate distances between cities
5 data_uy734 <- read.csv("/home/chpmoreno/Dropbox/Documents/BGSE/Second_Term/
  SMO/Problemsets/PS2/uy734.csv")[, -1]
6 cities_distances <- rdist(data_uy734) # euclidean distance estimation
7
8 # //////////////////////////////////////
9 # nearest Neighbor approach ####
10 # //////////////////////////////////////
11 city_path_nearest_neighbor <- function(cities_distances, city = round(runif(1, 1,
  nrow(cities_distances)))) {
12   # Create an auxiliar distance matrix for eliminating selected cities
13   cities_distances_aux <- cities_distances
14   # Impose big distances for 0 diagonal values of distance matrix. If we do not
    do this the diagonal will be
15   # the minimum distance for each city.
16   cities_distances_aux[cities_distances_aux == 0] <- 1000000000
17   n_cities <- nrow(cities_distances_aux) # number of cities
18
19   city_path <- city # initial city (by default usually random)
20
21   # nearest neighbor O(n^2) algorithm:
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22  # 1. Select a random city.
23  # 2. Find the nearest unvisited city and go there.
24  # 3. Are there any unvisited cities left? If yes, repeat step 2.
25  # 4. Return to the first city.
26  i = 1
27  while(length(city_path) < (n_cities + 1)) {
28      current_city_distances ← cities_distances_aux[, city_path[i]] # current
        city
29      nearest_city_to_current ← which.min(current_city_distances) # find the
        minimum available distance
30      city_path ← c(city_path, nearest_city_to_current) # add the nearest city to
        the path
31      cities_distances_aux[city_path, city_path[i + 1]] ← 1000000000 # eliminate
        the new current city distance
32      i = i + 1
33  }
34  city_path ← c(city_path, city_path[1]) # return to the first city
35
36  # Calculate the total distance of the path
37  total_distance ← 0
38  for(i in 1:(length(city_path) - 1)){
39      total_distance ← total_distance + cities_distances[city_path[i], city_path[i
        + 1]]
40  }
41
42  # return the path and its distance
43  return(list(path = city_path, distance = total_distance))
44 }
45
46 # Compute the best nearest Neighbor path from all the cities as initial ones
47 best_path_nearest_neighbor ← function(cities_distances) {
48     nearest_neighbor_paths ← NULL
49     nearest_neighbor_distances ← NULL
50     for(i in 1:nrow(cities_distances)) {
51         estimator_aux ← city_path_nearest_neighbor(cities_distances, i)
52         nearest_neighbor_paths ← cbind(nearest_neighbor_paths, estimator_aux$
            path)
53         nearest_neighbor_distances ← c(nearest_neighbor_distances, estimator_aux$
            distance)
54     }
55
56     return(list(best_path = nearest_neighbor_paths[, which.min(nearest_neighbor_
        distances)],
57                 distance = min(nearest_neighbor_distances)))
58 }
59
60 # //////////////////////////////////////
61 # Greedy Algorithm approach ####
62 # //////////////////////////////////////
63 city_path_greedy ← function(cities_distances) {
64     n_cities ← nrow(cities_distances)
65     # Take all the edges and weights from distance matrix
66     edges_and_weights_matrix ← NULL
67     for(i in 1:n_cities) {

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68   city_distance_vector      ← cities_distances[i:n_cities,i][-1]
69   if(length(city_distance_vector) > 0)
70     edges_and_weights_matrix ← rbind(edges_and_weights_matrix, cbind(rep(i,
71                                     length(city_distance_vector)),
72                                     seq(i+1,
73                                           n_cities
74                                           ),
75                                     city_distance_vector
76                                     ))
77 }
78 # Order the edges by weights
79 edges_and_weights_df      ← as.data.frame(edges_and_weights_matrix)
80 edges_and_weights_ordered_df ← arrange(edges_and_weights_df, city_distance_
81                                     vector)
82
83 # greedy  $O(n^2 \log_2(n))$  algorithm:
84 # Constrains: gradually constructs the by
85 # repeatedly selecting the shortest edge and adding it to
86 # the path as long as it does not create a cycle with less
87 # than N edges, or increases the degree of any node to
88 # more than 2. We must not add the same edge twice. Then:
89 # 1. Sort all edges.
90 # 2. Select the shortest edge and add it to our
91 # path if it does not violate any of the constraints.
92 # 3. Do we have N edges in our tour? If no, repeat
93 # step 2.
94 city_path ← edges_and_weights_ordered_df[1, 1:2]
95 total_distance ← 0
96 for(i in 2:nrow(edges_and_weights_ordered_df)) {
97   # Constrains
98   if((sum(city_path == edges_and_weights_ordered_df[i, 1]) < 2 &
99       sum(city_path == edges_and_weights_ordered_df[i, 2]) < 2) &
100      sum((city_path[edges_and_weights_ordered_df[i, 1] == city_path[, 1], 2]
101          ==
102          city_path[edges_and_weights_ordered_df[i, 2] == city_path[, 2], 1]))
103      == 0) {
104     # path fill
105     city_path ← rbind(city_path, edges_and_weights_ordered_df[i, 1:2])
106     # compute the distance
107     total_distance ← total_distance + edges_and_weights_ordered_df[i, 3]
108   }
109 }
110 return(list(best_path = city_path, distance = total_distance))
111 }
112
113 # //////////////////////////////////////
114 # Simulated annealing approach ####
115 # //////////////////////////////////////
116
117 # This approach is based on Todd W. Schneider code and his blog post, availables

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      on:
111 # * http://toddschneider.com/posts/traveling-salesman-with-simulated-annealing-
      r-and-shiny/
112 # * https://github.com/toddschneider/shiny-salesman
113
114 # Calculate the path distance
115 calculate_path_distance = function(path, distance_matrix) {
116   sum(distance_matrix[embed(c(path, path[1]), 2)])
117 }
118
119 # Compute the current temperature
120 current_temperature = function(iter, s_curve_amplitude, s_curve_center, s_curve_
      width) {
121   s_curve_amplitude * s_curve(iter, s_curve_center, s_curve_width)
122 }
123
124 s_curve = function(x, center, width) {
125   1 / (1 + exp((x - center) / width))
126 }
127
128 # simulation annealing O() algorithm:
129 # 1. Start with a random path through the selected cities.
130 # 2. Pick a new candidate path at random from all neighbors of the existing path
      .
131 # This candidate path might be better or worse compared to the existing one.
132 # 3. If the candidate path is better than the existing path, accept it as the
      new path. If the candidate
133 # path is worse than the existing tour, still maybe accept it, according to some
      probability. The probability
134 # of accepting an inferior tour is a function of how much longer the candidate
      is compared to the current tour,
135 # and the temperature of the annealing process. A higher temperature makes you
      more likely to accept an inferior
136 # path.
137 # 4. Go back to step 2 and repeat as many times as you want or can.
138 city_path_annealing_process = function(distance_matrix, path, path_distance,
      best_path = c(), best_distance = Inf,
139                                     starting_iteration = 0, number_of_
      iterations = 1000000,
140                                     s_curve_amplitude = 400000, s_curve_
      center = 0, s_curve_width = 300000) {
141
142   n_cities = nrow(distance_matrix) # number of cities
143
144   for(i in 1:number_of_iterations) {
145     iter = starting_iteration + i
146     # computation of temperature
147     temp = current_temperature(iter, s_curve_amplitude, s_curve_center, s_curve_
      width)
148
149     candidate_path = path # initial path
150     swap = sample(n_cities, 2) # new path
151     candidate_path[swap[1]:swap[2]] = rev(candidate_path[swap[1]:swap[2]])
152     candidate_dist = calculate_path_distance(candidate_path, distance_matrix) #

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153         compute the distance for new path
154     # ratio indicator
155     if (temp > 0) {
156         ratio = exp((path_distance - candidate_dist) / temp)
157     } else {
158         ratio = as.numeric(candidate_dist < path_distance)
159     }
160     # probabilistic decision
161     if (runif(1) < ratio) {
162         path = candidate_path
163         path_distance = candidate_dist
164         # best path and best distance
165         if (path_distance < best_distance) {
166             best_path = path
167             best_distance = path_distance
168         }
169     }
170 }
171 return(list(path=path, path_distance=path_distance,
172            best_path=best_path, distance=best_distance))
173 }
174
175 # //////////////////////////////////////
176 # Code execution #####
177 # //////////////////////////////////////
178 # Optimal solution given by http://www.math.uwaterloo.ca/tsp/world/uytour.html
179 optimal = 79114
180 # nearest Neighbor
181 nearest_neighbor_time <- Sys.time()
182 nearest_neighbor_distance <- best_path_nearest_neighbor(cities_distances)$
183     distance
184 nearest_neighbor_time <- Sys.time() - nearest_neighbor_time
185 # Greedy
186 greedy_time <- Sys.time()
187 greedy_distance <- city_path_greedy(cities_distances)$distance
188 greedy_time <- Sys.time() - greedy_time
189 # Annealing
190 distance_matrix = cities_distances
191 path = sample(nrow(distance_matrix))
192 path_distance = calculate_path_distance(path, distance_matrix)
193 annealing_time <- Sys.time()
194 annealing_distance <- city_path_annealing_process(distance_matrix = distance_
195     matrix,
196     path = path,
197     path_distance = path_distance)$
198     distance
199 annealing_time <- Sys.time() - annealing_time
200 # Comparison table
201 comparison_table <- rbind(c(optimal, nearest_neighbor_distance, greedy_distance,
202     annealing_distance),
203     c(NA, nearest_neighbor_distance / optimal, greedy_
204     distance / optimal,
205     annealing_distance / optimal),

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201             c(NA, nearest_neighbor_time / 60, greedy_time,
                annealing_time))
202 comparison_table ← round(as.data.frame(comparison_table), 2)
203 colnames(comparison_table) ← c("optimal", "nearest_neighbor", "greedy", "
    annealing")
204 rownames(comparison_table) ← c("distance", "distance/optimal", "run time (min)")

```