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Special problem, Grocery Store Location. ECE 719  
Optimal systems

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SPRING 2016  
ELECTRICAL ENGINEERING DEPARTMENT  
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DECEMBER 30, 2019

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## Abstract

k-means++ cluster analysis was used to partition the population area such that the center of each partition minimizes the within the partition sum of distance squares of each point in the partition to the center of the partition. The number of customers that would visit our stores located at the center of the partitions was then determined. The number of partitions was increased and the calculation repeated on the larger set by trying all of the different combinations of allocating the stores in the new and larger set of partitions. The largest score was selected. Matlab's kmeans implementation in the Statistics and Machine Learning Toolbox was used to find the set of partitions and their centroids. kmeans++ clustering is known to be computationally NP-hard problem<sup>1</sup>. In addition, the time complexity to analyze each set of partitions is  $\mathcal{O}(N \binom{p}{n})$  where  $p$  is the number partitions and  $N$  is the size of the population. This number quickly becomes very large therefore the implementation limits the number of partitions  $p$  to no more than 15. A number of small test cases with known optimal store locations were constructed and the algorithm was verified to be correct by direct observations. Locations of competitor stores do not affect the decision to where to locate our stores. Competitor stores locations affects the number of customers our stores will attract, but not the optimal locations of our stores.

*Index terms*— k-means++ clustering, NP-hard, optimal store locations

## 0.1 Introduction

The problem is the following: We want to locate  $n$  stores in an area of given population distribution where there already exists  $m$  number of competitor stores. We are given the locations of the competitor stores. We want to find the optimal locations of our  $n$  stores such that we attract the largest number of customers by being close to as many as possible. We are given the locations (coordinates) of the population.

## 0.2 Analysis of the problem

The first important observation found is that the locations of the competitor stores did not affect the decision where the location of our stores should be. This at first seemed counter intuitive. But the optimal solution is to put our stores at the center of the most populated partitions even if the competitor store happened to also be in the same exact location.

The idea is that it is better to split large number of customers with the competition, than locate a store to attract all customers but in a less populated area. This was verified using small test cases (not shown here due to space limitation).

This is where cluster analysis using the kmeans++ algorithm was used. Cluster analysis is known algorithm that partitions population into number of clusters or partitions such that each cluster has the property that its centroid has minimum within-cluster sum of squares of the distance to each point in the cluster. The following is the formal definition of kmeans++ clustering algorithm taken from [https://en.wikipedia.org/wiki/K-means\\_clustering](https://en.wikipedia.org/wiki/K-means_clustering)

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<sup>1</sup>non-deterministic polynomial-time hard

Given a set of observations  $(x_1, x_1, \dots, x_n)$ , where each observation is a  $d$ -dimensional real vector,  $k$ -means clustering aims to partition the  $n$  observations into  $k \leq n$  sets  $S = \{S_1, S_2, \dots, S_k\}$  so as to minimize the within-cluster sum of squares (WCSS) (sum of distance functions of each point in the cluster to the  $K$  center). In other words, its objective is to find:

$$\arg \min_S \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2$$

where  $\mu_i$  is the mean of points in  $S_i$

The main difficulty was in deciding on the number of partitions needed. Should we try smaller number than the number of stores, and therefore put more than one store in same location? Using smaller number of clusters than the number of stores was rejected, since it leads to no improvement in the score (Putting two stores in same location means other areas are not served since we have limited number of stores). Or should we try more partitions than the number of our stores, and then try all the combinations possible between these partitions to find one which gives the larger score? This the approach taken in this algorithm. It was found that by increasing the number of partitions than the number of stores, and trying all possible combinations  $\binom{p}{n}$ , where  $p$  is the number of partitions, a set could be found which has higher than if we used the same number of partitions as the number of stores. The problem with this method is that it has  $\mathcal{O}\left(\binom{p}{n}\right)$  time complexity. This quickly becomes large and not practical when  $p > 15$ . In the test cases used however, there was no case found where  $p$  had to be more than two or three larger than  $n$ . The implementing limits the number of partitions to 15.

When a score is found which is smaller than the previous score, the search stops as this means the maximum was reached. This was determined by number of trials where it was found that once the score become smaller than before, making more partitions did not make it go up again. There is no proof of this, but this was only based on trials and observations. Therefore, the search stops when a score starts to decrease.

The implementation described here is essentially an illustration of the use of cluster analysis, as provided by Matlab, in order to solve the grocery stores location problem. The appendix contains the source code written to solve this problem.

Before describing the algorithm below, we show an example using the early test send to us to illustrate how this method works. This used 500,000 population with 5 competitor stores (the black dots) in the plots that follows and  $n = 4$  (the green dots).

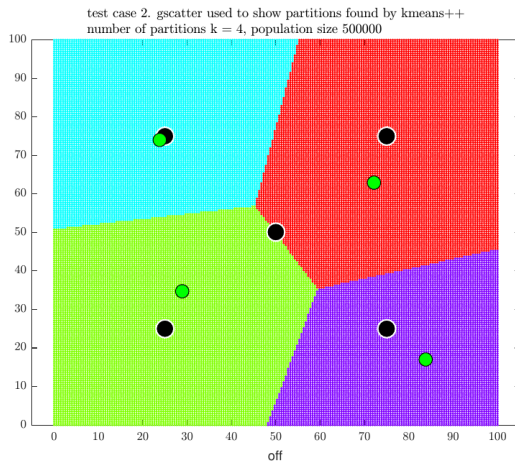


Figure 1: Partitions found by kmeans++ with centroid as green dots and competitor sores as black dots

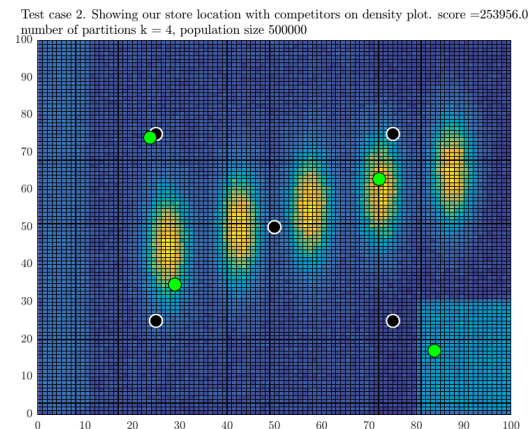


Figure 2: Density of population with corresponding store locations found

The partitions were now increased to 5 and  $\binom{5}{4}$  different combinations were scored to find the 4 best store locations out of these. This resulted in the following result

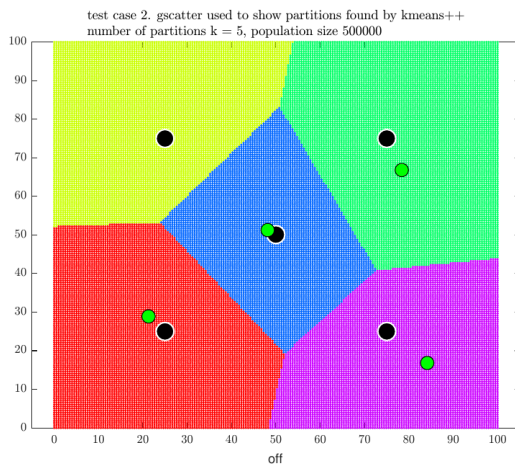


Figure 3: Partitions found by kmeans++ with centroid as green dots and competitor sores as black dots

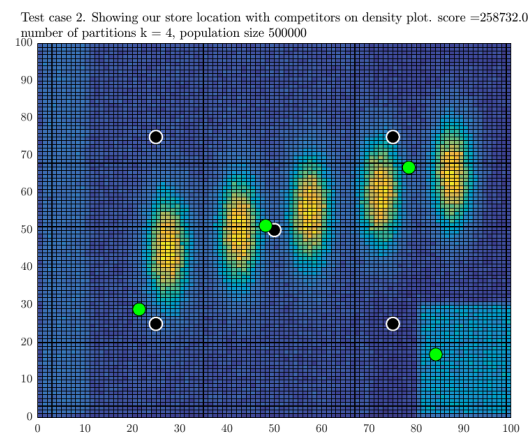


Figure 4: Density of population with corresponding store locations found

When trying 6 partitions, the score was decreased, so the search stopped. The program then printed the final result

J\*=[ 258732.0000] = [%51.75]

x	y
21.356	28.929
78.378	66.732

48.212 51.197  
84.078 16.864

### **0.3 Algorithm description**

This is a description of the algorithm which uses the `kmeans++` cluster analysis function `kmeans()` as part of the Matlab Statistics and Machine Learning Toolbox toolbox, which is included in the student version. This is not a description of the `kmeans++` algorithm itself, since that is well described and documented in many places such as in references [3,4]. This is a description of the algorithm using `kmeans` to solve the grocery location problem.

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**Algorithm 1: Cluster analysis using Kmeans++ for determining optimal store locations**


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**Input:**  $n, X, Y$  where  $n$  is the number of stores to allocate,  $X$  is population coordinates, and  $Y$  is competitor store location coordinates

**Output:** list of coordinates to locate our  $n$  stores at, and  $J^*$  which is size of population our stores will attract when placed at these locations

```

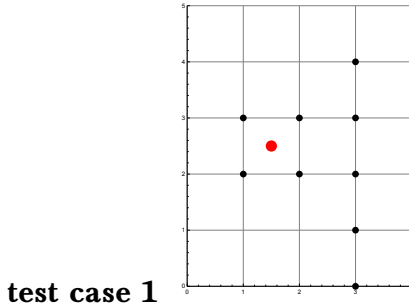
1 currentNumberOfPartitions ← n
2 bestScore ← 0
3 keepSearching ← true
4 bestLocations ← {}
5 while keepSearching do
6   C ← kmeans(currentNumberOfPartitions,X) /* C now contains the centroid of partitions found by kmeans++
   cluster analysis algorithm using Matlab toolbox */
7   partitionSets ← combnk(1:size(C,1),n) /* Find all possible combinations of partitions. Warning, this is  $\binom{k}{n}$ 
   which will quickly grow. In practice, it was found we do not need  $k$  greater than  $n+4$  to find a
   maximum.  $n$  is limited to 10. */
8   partitionScore ← 0
9   winningCombination ← {}
10  foreach  $e \in$  partitionSets do
11    score ← 0
12    foreach  $x_i \in X$  do
13       $d_1 \leftarrow$  shortest distance of  $x_i$  to any of the centroid of the partition  $e$ 
14       $d_2 \leftarrow$  shortest distance of  $x_i$  to any of competitor stores in  $Y$ 
15      if  $d_1 \leq d_2$  /* win this customer or split it. Else competitor is closer */
16        then
17          if  $d_1 = d_2$  then
18            score ← score +  $\frac{1}{2}$ 
19          else
20            score ← score + 1
21          end
22        end
23      end
24      if score  $\geq$  partitionScore then
25        partitionScore ← score
26        winningCombination ←  $e$ 
27      end
28    end
29    if partitionScore  $\geq$  bestScore then
30      /* score did not go down, keep searching. Increase number of population partitions by one and call
31      kmeans++ (above) for new partitions */
32      bestScore ← partitionScore
33      bestLocations ← winningCombination
34      if currentNumberOfPartitions = 15 /* stop search if  $\binom{k \geq 15}{n} \text{ink}$  due to limitation */
35        then
36          keepSearching ← false
37        else
38          currentNumberOfPartitions ← currentNumberOfPartitions + 1
39        end
40      else
41        /* when score goes down, it will not improve any more */
42        keepSearching ← false
43      end
44    end
45  end
46 end
47 return bestScore,bestLocations

```

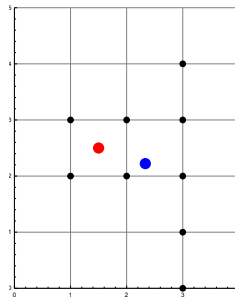
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### 0.3.1 Description of test cases used in development

It was very important to check the correctness of the algorithm using small number of test cases to verify it is generating the optimal store locations as it is very hard to determine the optimal solution for any large size problem by hand. The following are some of the test problems used and the result obtained by the implementation, which shows that the optimal locations were found for each case.



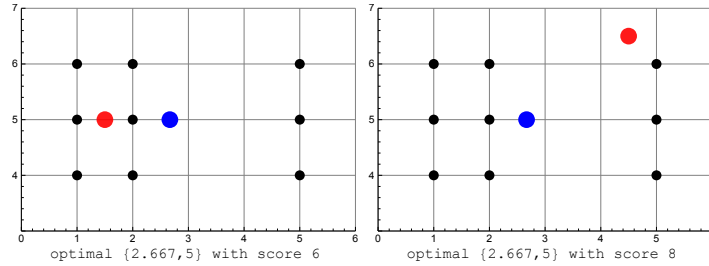
By direct observations, since we have one store only, then we see that by locating it in the center of the population, the score will be 6, which is optimal. The optimal store location found by the program is  $\{2.333, 2.222\}$



**test case 2** This test case shows that the optimal location of our store do not change as the competition store location is changed. Since the optimal location depends on the clustering found and not on the competition location. In the following, the same configuration is used, but one had the competition store is at  $\{1.5, 5\}$  and the other at  $\{4.5, 6.5\}$ . We see by direct counting and observation that the optimal store location is at  $\{2, 5\}$  regardless. The only difference is the number of customers we attract in each case, but not the optimal store location itself. These two plots show this, with the score we obtain given below each configuration.

Clearly when the competitor store is away from the density area, our score will increase. Since the competition also wants to increase its score, then it should also have to locate its store in the same location, which is the kmeans++ optimal location.





Many other test cases were run, using more store locations and they were verified manually that the program result agrees with the finding. It is not possible to verify manually that the result will remain optimal for large population and large number of stores, but these test cases at least show that the algorithm works as expected. Now we will show results of large test cases and the program output generated.

#### 0.4 Result applying the algorithm to the supplied input

The following table summarizes the result of running the store location algorithm on the 5 test cases provided.

Table 1: Summary of store location score of each test case

test case	n	m	X (population)	CPU time (minutes)	$J^*$	percentage
trial/earlier one	4	5	500,000	1.42	258,732	51.75%
1	9	9	500,000	5.49	371,543	74.32%
2	10	10	1,000,000	3.38	637,413	63.74%
3	5	5	130,000	1.16	69,093	53.15%
4	10	10	1,000,000	14.17	683,899	68.39%

For illustration, the following four plots show the locations of our stores (the green dots) for the above final four test cases with the location of the competitor stores (black dots) and the final partitions selected.

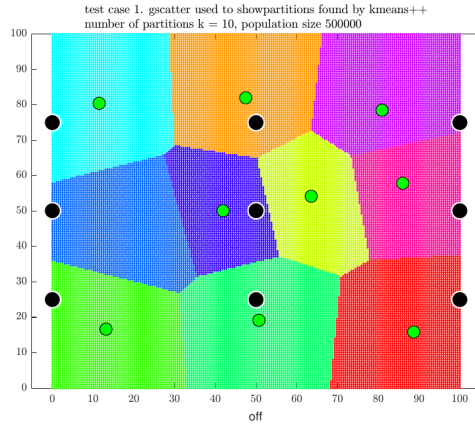


Figure 5: Test case 1

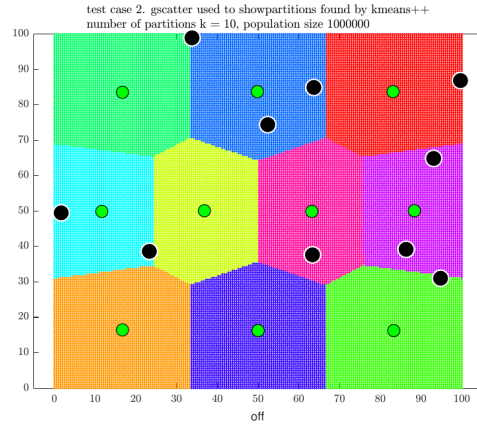


Figure 6: Test case 2

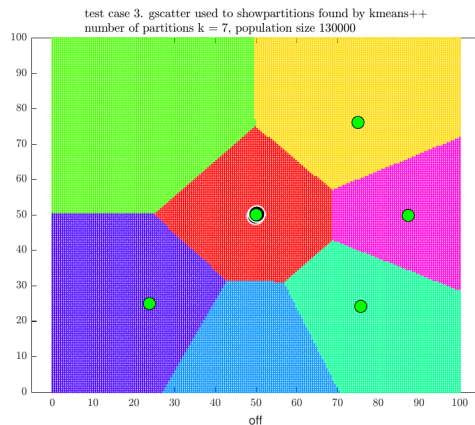


Figure 7: Test case 3

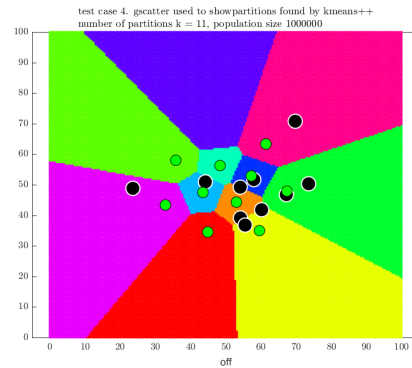


Figure 8: Test case 4

## 0.5 Conclusion

kmeans++ algorithm for cluster analysis appears to be an effective method to use for finding an optimal store locations, but it is only practical for small  $n$  as the algorithm used to obtain the partitions is NP-hard. In addition  $\binom{P}{n}$  combinations of partitions needs to be searched to select the optimal set.

This implementation shows how kmeans++ can be used to solve these types of problems. The location of the competitor stores has no influence on where to locate the stores, but it only affects the final possible score. Generating more partitions (using kmeans++) than the number of stores and selecting from them the best set can lead to improved score. It was found in the test cases used that no more than two of three additional partitions than the number of stores was needed to find the a combination of partitions which gave the maximum score. Generating additional partitions made the score go lower. The score used is the number of customers the stores attract out of the overall population. The algorithm was verified to be correct for small number of tests cases (not shown here due to space

limitation). More research is needed to investigate how feasible this method can be for solving similar resource allocations problems.

## 0.6 References

- 1 Matlab cluster analysis toolbox. Mathworks, Natick, MA
- 2 [https://en.wikipedia.org/wiki/K-means\\_clustering](https://en.wikipedia.org/wiki/K-means_clustering)
- 3 Seber, G.A.F. (1984) Multivariate Observations, Wiley, New York.

## 0.7 Appendix

```

1 function abbasi()
2 %Special problem. ECE 719, spring 2016
3 %by Nasser M. Abbasi
4 %Matlab 2016a
5 %
6
7 clear;      %start with clear env. just in case.
8 close all;  %is it ok to close all windows?
9 commandwindow; %bring command window into focus
10 cd(fileparts(mfilename('fullpath')));
11
12 if license('test','Statistics_Toolbox') ~= 1
13     error(['Warning, the needed toolbox does not', ...
14           'seem to exist in your Matlab. This program needs', ...
15           'the Statistics and Machine Learning Toolbox as', ...
16           'it called kmeans++ cluster analysis\n', ...
17           'Please use the ver command to check you the toolbox\n']);
18 end
19
20 %this window will close when we are done. Ok to do.
21 fig = figure('Position',[370 400 400 30],...
22             'Name','Optimal store locator. ECE 719. UW-Madison',...
23             'NumberTitle','off');
24 set(fig, 'MenuBar', 'none');
25 set(fig, 'ToolBar', 'none');
26 h = uicontrol('Style','text','Position',[4 7 396 15],...
27             'BackgroundColor','w',...
28             'HorizontalAlignment','left');
29 drawnow;
30
31 DEBUG=true; %set to true to see plots
32 %change to false before code lockdown as plots slows down time.
33

```

```

34 OUT(h,'Starting store location program version 1.0....');
35 OUT(h,'Checking for mat files....');
36
37 if ~exist('n.mat','file')
38     error(['file n.mat does not exist in current folder.',...
39         'Please check for lower/upper case and location']);
40 end
41 if ~exist('X.mat','file')
42     error(['file X.mat does not exist in current folder.',...
43         'Please check for lower/upper case and location']);
44 end
45 if ~exist('Y.mat','file')
46     error(['file n.mat does not exist in current folder.',...
47         'Please check for lower/upper case and location']);
48 end
49
50
51 cd('../official_data/4/');
52 load('n');
53 load('X');
54 load('Y');
55 OUT(h,'mat files read ok....');
56 cd(fileparts(mfilename('fullpath')));
57
58 rng(1); %for reproducibility
59 KEEP_TRYING = true; %tells when to stop search
60 best_score_found_so_far = 0;
61 best_locations = [];
62 current_number_of_cluster = n;
63 tstart = tic; %to keep track of CPU time
64 test_case = 4;
65 MAX_CPU = 15; %minutes CPU time limit.
66 status = true;
67 while KEEP_TRYING
68     OUT(h,sprintf(['Best score so far: [%d]. calling kmeans+',...
69         'to make %d partitions...please wait...'],...
70         round(best_score_found_so_far),current_number_of_cluster));
71     [idx,C] = make_cluster(X,current_number_of_cluster,...
72         'sqeuclidean' );
73     active_C = combnk(1:size(C,1),n);
74     OUT(h,sprintf('created active_C, size is [%d,%d]....',...
75         size(active_C,1),size(active_C,2)));
76
77     [status,score,locations]=score_cluster(C,X,Y,active_C,...
78         tstart,h,MAX_CPU);

```

```

79
80     if ~status
81         OUT(h,'Allowed CPU time exceeded, stopping the program');
82         KEEP_TRYING = false;
83     else
84         if score>=best_score_found_so_far
85             best_score_found_so_far=score;
86             best_locations=locations;
87             current_number_of_cluster=current_number_of_cluster+1;
88             %stop search if size too large, or if number of
89             %partitions too large this is due to using k choose m.
90             %For k>15 it will need too much RAM.
91             if current_number_of_cluster>=size(X,1)...
92                 ||current_number_of_cluster>=15
93                 KEEP_TRYING = false;
94             end
95             OUT(h,sprintf('current score %6.2f',...
96                         best_score_found_so_far));
97             if DEBUG
98                 plot_result(test_case,best_locations,X,Y,...
99                             best_score_found_so_far,C);
100            end
101        else
102            OUT(h,sprintf(...
103                'Score is %6.2f. Less than last. Terminating..',...
104                score));
105            KEEP_TRYING = false;
106        end
107        telapsed = toc(tstart);
108        if telapsed>MAX_CPU*60 % CPU limit
109            OUT(h,'CPU time exceeded');
110            KEEP_TRYING = false;
111            status      = false;
112        else
113            OUT(h,sprintf(...
114                'CPU time used to far %6.2f minutes',telapsed/60));
115        end
116    end
117 end
118
119 %final result
120 fprintf('n=%d, X=%d, Y=%d\n',n,size(X,1),size(Y,1));
121
122 fprintf('J*=[%6.2f] = [%%4.2f]\n\n',...
123     best_score_found_so_far,best_score_found_so_far/size(X,1)*100);

```

```

124 fprintf('optimal store coordinates\n');
125 fprintf(' x\t\t y\n');
126
127 for i=1:size(best_locations,1)
128     fprintf('%3.3f\t%3.3f\n',best_locations(i,1),best_locations(i,2));
129 end
130
131 telapsed = toc(tstart);
132
133 if ~status
134     fprintf('\nCPU limit reached. Elapsed time is %6.2f minutes\n',...
135             telapsed/60);
136 else
137     fprintf('\nElapsed time is %6.2f minutes\n',telapsed/60);
138 end
139 if ishandle(fig)
140     close(fig);
141 end
142 end
143 %=====
144 function d = distance_between_2_points(pt1,pt2)
145 %find distance between 2 points, assuming one can only
146 %move N-S or E-W, not diagonal.
147 x1 = pt1(1,1);
148 y1 = pt1(1,2);
149 x2 = pt2(1,1);
150 y2 = pt2(1,2);
151
152 d = abs(x1-x2) + abs(y1-y2);
153 end
154 %=====
155 function best_score_in_cluster = ...
156             find_my_score_in_each_cluster(C,X,Y)
157 %Takes center of each cluster (C) and customers locations (X)
158 %and competition store locations (Y) and returns how many
159 %customers I win in each cluster. Returns an array of number
160 %of customers we attract from competition in each cluster.
161
162 %to store score per cluster
163 best_score_in_cluster = zeros(size(C,1),1);
164
165 for i=1:size(X,1) %loop of all population to see which we win
166     %z1 is competitor, z2 is our store
167     [~,z1] = shortest_distance_to_stores(X(i,:),Y);
168     [idx,z2] = shortest_distance_to_stores(X(i,:),C);

```

```

169     if z2<=z1 %compare with competition to see if we are closer
170         if z1==z2
171             %oh well, split this customer between us and them
172             best_score_in_cluster(idx)=best_score_in_cluster(idx)+0.5;
173         else
174             %good, we are closer, take this customer.
175             best_score_in_cluster(idx)=best_score_in_cluster(idx)+1;
176         end
177     end
178 end
179 end
180
181 %=====
182 function [idx,d] =shortest_distance_to_stores(pt,stores_locations)
183 %find shortest distance from one customer to a set of stores.
184 %The stores can be ours or the competition. Returns the shortest
185 %distance in 'd' and the index of the store who is closest to
186 %this customer
187
188 d = inf;
189 for i=1:size(stores_locations,1)
190     current_distance = distance_between_2_points(pt,...
191                                             stores_locations(i,:));
192     if current_distance <= d
193         d = current_distance;
194         idx = i;
195     end
196 end
197
198 end
199 %=====
200 function [status,best_score,locations]=score_cluster(...
201                                     C,X,Y,active_C,tstart,h,MAX_CPU)
202
203 best_score = 0;
204 status = true;
205 KEEP_TRYING = true;
206
207 while KEEP_TRYING
208     for i=1:size(active_C,1)
209         OUT(h,sprintf(['scoring partition %d of %d in score_cluster() ',...
210                     'Current best score %d'],...
211                     i,size(active_C,1),round(best_score)));
212
213         score = find_my_score_in_each_cluster(...

```

```

214         C(active_C(i,:),:),X,Y);
215     score=sum(score);
216     if score>best_score
217         best_score = score;
218         locations = C(active_C(i,:),:);
219     end
220     telapsed = toc(tstart);
221     if telapsed>MAX_CPU*60
222         OUT(h,sprintf('Exceeded CPU time limit in score_cluster'));
223         KEEP_TRYING = false;
224         status      = false;
225     end
226 end
227 KEEP_TRYING = false;
228 end
229 end
230 %=====
231 function [idx,C] = make_cluster(population,how_many,the_option)
232 %cluster the population. Number of cluster is same as
233 %number of our stores. This was found to be optimal by many
234 %trials and errors. If we use more clusters than number of
235 %stores, the score actually goes down.
236 warning('off','all');
237 [idx,C] = kmeans(population,how_many,'Replicates',5,...
238     'MaxIter',50,'Distance',the_option);
239 warning('on','all');
240 end
241
242 %=====
243 function plot_result(test_case,store_locations,X,Y,...
244     overall_best_score,C)
245
246 %figure;
247 tmp = hist3(X, {0:100 0:100});
248 n1 = tmp';
249 n1(size(tmp,1), size(tmp,2)) = 0;
250 xb = linspace(0,100,101);
251 yb = xb;
252
253 figure;
254 pcolor(xb,yb,n1);
255 hold on;
256 plot(Y(:,1),Y(:,2),'o','MarkerSize',9,...
257     'MarkerFaceColor','black',...
258     'LineWidth',1,'MarkerEdgeColor','white');

```



```

259 plot(store_locations(:,1),store_locations(:,2),...
260       'o','MarkerSize',9,'MarkerFaceColor','green',...
261       'MarkerEdgeColor','black');
262 title( {sprintf(...
263         ['Test case %d$. Showing our store location with',...
264         'competitors on density plot. score =%5.1f'],...
265         test_case,overall_best_score),...
266         sprintf('number of partitions k = %d$, population size %d$',...
267         size(store_locations,1),size(X,1))},...
268         'FontSize',11,'interpreter','Latex');
269 set(gca,'TickLabelInterpreter','Latex','fontsize',8);
270 drawnow;
271 saveas(gcf, sprintf('../images/1_test_case_%d',test_case), 'pdf');
272 saveas(gcf, sprintf('../images/1_test_case_%d',test_case), 'png');
273
274 figure;
275 [x1G,x2G] = meshgrid(linspace(0,100,200),linspace(0,100,200));
276 XGrid = [x1G(:),x2G(:)]; % Defines a fine grid on the plot
277 warning('off','all');
278 idx2Region = kmeans(XGrid,size(C,1),'MaxIter',1,'Start',C);
279 warning('on','all');
280 cmap = hsv(size(C,1));
281 gscatter(XGrid(:,1),XGrid(:,2),idx2Region,cmap,[],[],...
282          'doLeg','off');
283 hold on;
284 plot(Y(:,1),Y(:,2),'o','MarkerSize',12,...
285       'MarkerFaceColor','black',...
286       'LineWidth',1,'MarkerEdgeColor','white');
287 plot(store_locations(:,1),store_locations(:,2),...
288       'o','MarkerSize',9,'MarkerFaceColor','green',...
289       'MarkerEdgeColor','black');
290 title( {sprintf(['test case %d$. gscatter used to show',...
291                 'partitions found by kmeans++'],test_case),...
292         sprintf('number of partitions k = %d$, population size %d$',...
293         size(C,1),size(X,1))},'FontSize',11,'interpreter','Latex');
294 set(gca,'TickLabelInterpreter','Latex','fontsize',8);
295 drawnow;
296 saveas(gcf, sprintf('../images/2_test_case_%d',test_case), 'pdf');
297 saveas(gcf, sprintf('../images/2_test_case_%d',test_case), 'png');
298 end
299 %=====
300 function OUT(h,the_string)
301 fprintf(the_string);
302 fprintf('\n');
303

```

```
304 %if ishandle(h)
305 %   set(h,'String',the_string);
306 %   drawnow;
307 %end
308 end

1  function nma_generate_output(test_case)
2  %Program to generate output to test special problem with
3  %Nasser M. Abbasi
4  %ECE 719, UW Madison
5
6  cd(fileparts(mfilename('fullpath')));
7
8  switch test_case
9      case 1
10         X=[1,2;
11            1,3;
12            2,2;
13            2,3;
14            3,0;
15            3,1;
16            3,2;
17            3,3;
18            3,4];
19         Y=[1.5,2.5];
20         n=1;
21         save('n','n');
22         save('X','X');
23         save('Y','Y');
24         save('test_case','test_case');
25
26     case 105
27         X=[1,2;
28            1,3;
29            2,2;
30            2,3;
31            3,0;
32            3,1;
33            3,2;
34            3,3;
35            3,4];
36         Y=[1.5,2.5];
37         n=2;
38         save('n','n');
39         save('X','X');
40         save('Y','Y');
41         save('test_case','test_case');
```

```
42
43 %         fprintf('best score is %3.3f\n',...
44 %         find_my_score_in_each_cluster([2.5,2.5],X,Y))
45 case 2
46     X=[1,4;
47         1,5;
48         1,6;
49         2,4;
50         2,5;
51         2,6;
52         5,6;
53         5,5;
54         5,4];
55     Y=[4,6.5];
56     n=1;
57     save('n','n');
58     save('X','X');
59     save('Y','Y');
60     save('test_case','test_case');
61
62 %         fprintf('best score is %3.3f\n',...
63 %         find_my_score_in_each_cluster([2,5],X,Y))
64
65 case 3
66     X=[1,4;
67         1,5;
68         1,6;
69         2,4;
70         2,5;
71         2,6;
72         5,6;
73         5,5;
74         5,4];
75     Y=[1.5,5];
76     n=1;
77     save('n','n');
78     save('X','X');
79     save('Y','Y');
80     save('test_case','test_case');
81
82 %         fprintf('best score is %3.3f\n',...
83 %         find_my_score_in_each_cluster([2,5],X,Y))
84
85 case 4
86     X=[1,1;
87         1,2;
88         2,1;
```

```

89         2,2;
90         4,3;
91         4,4;
92         5,3;
93         5,4];
94     Y=[3,2.5];
95     n=1;
96     save('n','n');
97     save('X','X');
98     save('Y','Y');
99     save('test_case','test_case');
100
101 %         fprintf('best score is %3.3f\n',...
102 %             find_my_score_in_each_cluster([2,5],X,Y))
103
104 case 5
105     X=[1,1;
106         1,2;
107         1,3;
108         2,1;
109         2,2;
110         2,3;
111         3,2;
112         4,2;
113         4,3;
114         4,4;
115         4,5;
116         5,1;
117         5,2;
118         5,3;
119         5,4;
120         5,5;
121         6,3;
122         6,4;
123         6,5];
124     Y=[5,4];
125     n=1;
126     save('n','n');
127     save('X','X');
128     save('Y','Y');
129     save('test_case','test_case');
130
131 %         fprintf('best score is %3.3f\n',...
132 %             find_my_score_in_each_cluster([2,5],X,Y))
133
134 case 6
135     X=[ 1,1;

```

```

136         2,1;
137         3,1;
138         1,2;
139         2,2;
140         3,2;
141         1,3;
142         2,3;
143         3,3];
144     Y=[2,2];
145     n=2;
146     save('n','n');
147     save('X','X');
148     save('Y','Y');
149     save('test_case','test_case');
150
151     %         fprintf('best score is %3.3f\n',...
152     %             find_my_score_in_each_cluster([2,5],X,Y))
153
154     case 7
155         rng default; % For reproducibility
156         N=10000;
157         X=[ 30 + 2*randn(N,1),30 + 8*randn(N,1);
158             40 + 2*randn(N,1),40 + 10*randn(N,1);
159             25 + 2*randn(N,1), 50 + 4*randn(N,1);
160             20 + 2*randn(N,1),30 + 4*randn(N,1);
161             50 + 2*randn(N,1),50 + 4*randn(N,1)];
162
163         n=9; %this gives 50%, since competition is already optimal
164         Y=[41.6552   35.4282;
165             24.5046   33.8534;
166             30.5928   30.0431];
167         save('n','n');
168         save('X','X');
169         save('Y','Y');
170         save('test_case','test_case');
171
172
173     case 8
174         rng default; % For reproducibility
175         N=1000;
176         X=[30+randn(N,1),30+randn(N,1);
177             40+randn(N,1),40+randn(N,1);
178             25+randn(N,1),50+randn(N,1);
179             20+randn(N,1),30+randn(N,1);
180             50+randn(N,1),50+randn(N,1)];
181
182         n=4; %this gives 50%, since competition is already optimal

```

```

183     Y=[41.6552    35.4282;
184         24.5046    33.8534;
185         30.5928    30.0431];
186     save('n','n');
187     save('X','X');
188     save('Y','Y');
189     save('test_case','test_case');
190
191     case 9
192         rng default; % For reproducibility
193         N=1000;
194         X=[30+randn(N,1),30+randn(N,1);
195             40+randn(N,1),40+randn(N,1);
196             25+randn(N,1),50+randn(N,1);
197             20+randn(N,1),30+randn(N,1);
198             50+randn(N,1),50+randn(N,1)];
199
200         n=7; %this gives 50%, since competition is already optimal
201         Y=[41.6552    35.4282;
202             24.5046    33.8534;
203             30.5928    30.0431];
204         save('n','n');
205         save('X','X');
206         save('Y','Y');
207         save('test_case','test_case');
208
209     case 10
210         rng default; % For reproducibility
211         N=100000;
212         X=[30+randn(N,1),30+randn(N,1);
213             40+randn(N,1),40+randn(N,1);
214             25+randn(N,1),50+randn(N,1);
215             20+randn(N,1),30+randn(N,1);
216             50+randn(N,1),50+randn(N,1)];
217
218         n=10; %this gives 50%, since competition is already optimal
219         Y=[41.6552    35.4282;
220             24.5046    33.8534;
221             30.5928    30.0431;
222             40.5928    30.0431;
223             70.5928    30.0431];
224         save('n','n');
225         save('X','X');
226         save('Y','Y');
227         save('test_case','test_case');
228
229

```

230 end

231 end