

My Comprehensive Evaluation

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A Comprehensive Evaluation Report

Presented to  
The Statistics Faculty  
Amherst College

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In Partial Fulfillment  
of the Requirements for the Degree  
Bachelor of Arts  
in  
Statistics

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# Acknowledgements

I want to thank my family.



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# Abstract

In recent years, the amount of geographic data has increased immensely. With new technology, the accuracy and complexity of data has also improved. This has provoked statisticians to create techniques to best analyze and draw conclusions from this new-found data. Earlier techniques of spatial data were not equipped to handle the complexity and quantity of the data. This project first explores how and why we analyze data based on geographic information. Next, I will explain some of the newer spatial data algorithms, including PAM (Partitioning Around Medoids), CLARA (Clustering LARge Applications), and CLARANS (Clustering Large Applications based on RANdomized Search). Example data will be used to demonstrate CLARA, and the project will conclude a model to predict cluster.



In recent years, the amount of geographic data has increased immensely. With new technology, the accuracy and complexity of data has also improved. This has provoked statisticians to create techniques to best analyze and draw conclusions from this new-found data. Earlier techniques of spatial data were not equipped to handle the complexity and quantity of the data. This project first explores how and why we analyze data based on geographic information. Next, I will explain some of the newer spatial data algorithms, including PAM (Partitioning Around Medoids), CLARA (Clustering LARge Applications), and CLARANS (Clustering Large Applications based on RANdomized Search). Example data will be used to demonstrate CLARA, and the project will conclude a model to predict cluster.



# Introduction

As mentioned in the abstract, we have much more spatial data than we have had in the past. Spatial data analysis is analyzing data based on topological, geometric, and geographic information. Spatial data may include latitude and longitude, zip code, or street address.

## 0.1 Why Analyze Spatial Data?

We are interested in analyzing spatial data for many reasons, one being because there is so much of it available. Investigating spatial data can help us find dissimilarities and similarities among objects. This can aid us in allocating resources to areas that need them most, discovering changes over time, and categorizing new objects.

## 0.2 Analyzing Spatial Data Algorithms

There are many algorithms out there that handle spatial data; most algorithms are focused around clustering. To get a glimpse of the number of algorithms and strategies to analyze spatial data, the chart below provides some examples.

```
label(path = "clustering_methods.png",  
      caption = "Clustering Methods",  
      label = "Clustering", type = "figure", scale= 0.5)
```

As noted, the methods are aimed around clustering, which we will further explore in the next section.

### 0.2.1 Clustering

Clustering organizes a set of data items into groups so that items in the same group are similar to each other and different from those in other groups [Rec 1]. Clustering

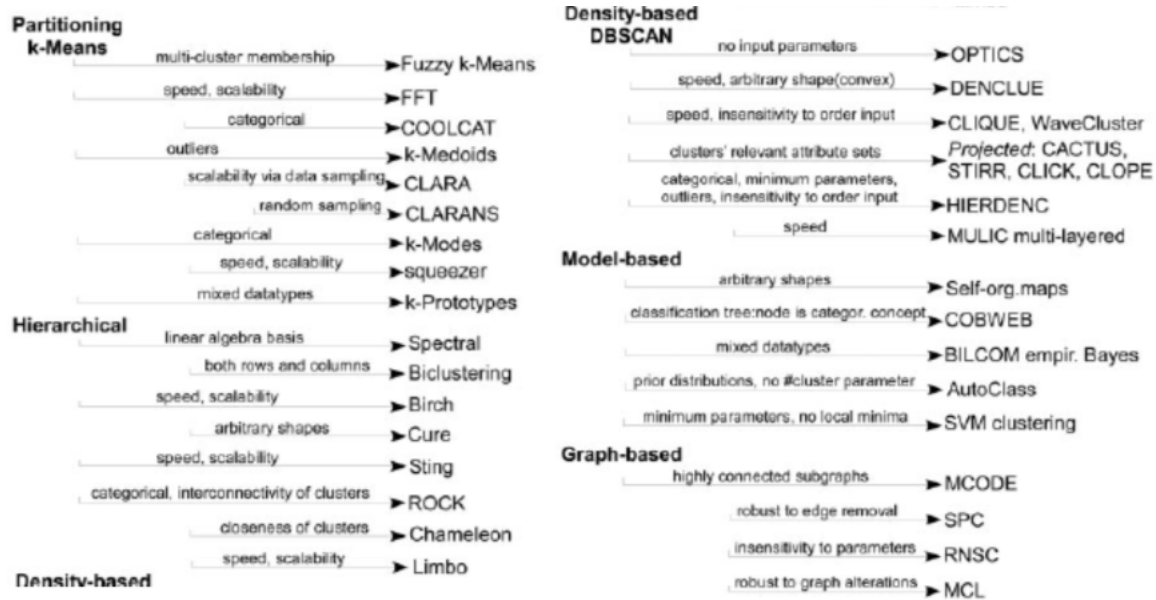


Figure 1: Clustering Methods

is helpful in finding patterns and similarities/differences between data points and groups; however it can be quite subjective. It is up to the statistician to determine how many clusters are appropriate for the data, as well as the cut off for what is considered “dissimilar” or “similar”. Additionally, the statistician must choose which clustering algorithm is best to use... This will be discussed in more detail later on in the project.



# Chapter 1

## How to Cluster

There are many factors to consider when choosing a clustering algorithm, such as the application of the problem (what do you want to find out about this data?), quality vs speed trade off (the size of the data plays a role), characteristics of the data (i.e. numeric distance measures), dimensionality (typically as dimension increases the time it takes to run the method increases and quality of the data clusters decrease), and outliers (some methods are very sensitive to outliers) [Rec 2].

### 1.1 Types of Clustering: Partitioning

There are four main types of clustering: hierarchical, partitioning, density-based, and methods-based. Next, I'll dive into the partitioning clustering technique.

Partitioning cluster methods divide a set of data items into a number of non-overlapping clusters. A data item is typically assigned to a cluster based on a proximity or dissimilarity measure [Rec 2, p. 405].

Usually, there is a data set with  $n$  observations and the goal is to divide the data points into  $K$  clusters so that an objective function is optimized.

The most common objective function is the sum of squared errors (SSE), where  $c_k$  is the centroid or medoid of the cluster  $C_k$ .

$$SSE(C) = \sum_{k=1}^K \sum_{x_i \in C_k} ||x_i - c_k||^2$$

Partitioning clustering algorithms classify the data into  $K$  groups by satisfying both that each group has at least one data point, and that each data point belongs to exactly one group. [Rec 5, p. 18].

## 1.2 Methods to Create Clusters: *K*-Medoids

There are many ways to create clusters. The most basic method is the *K*-means algorithm, which was developed by MacQueen in 1967 [Rec 5, p. 18]. In response to *K*-means being very sensitive to outliers, the *K*-medoid algorithm was created in 1987 [Rec 5, p. 19]. Both partitioning methods use iterative processes to find *K* clusters; however, they use different ways to represent these clusters.

### 1.2.1 *K*-Means

*K*-means algorithm represents its *n* observations in *k* groups, with the center of the groups being the mean/average observation. The goal of the algorithm is to find *k* centroids, one for each cluster. In order to do this, we must minimize an *objective function*, which is the squared error function for *k* means. The objective function is:

$$O = \sum_{j=1}^k \sum_{i=1}^j ||X_i^{(j)} - C_j||^2$$

Where  $|X_i^{(j)} - C_j|$  is an indicator of the distance of the data points from their cluster centers.

The steps of the algorithm are as follows:

1. Choose *K* points in the space to represent the centroid. This works best if they are chosen to be far apart from each other.
2. Assign each object in the data set to the cluster with the closest centroid.
3. When all of the clusters have been made, recalculate the positions of the *K* centroids.
4. Repeat steps 2 and 3 until the centroids no longer move.

This algorithm always terminates; however, it is sensitive both to outliers and to the initial randomly selected *K* cluster centers. Therefore, the algorithm should be run multiple times to reduce the effects from this sensitivity.

[Rec 5, p. 18]

In order to determine how well `_K_`means worked, we use the within cluster sum-of-squares to determine the compactness/“goodness” of the clustering (and we want it as small as possible).

We calculate the WSS by the following equation:

$$WSS = \sum_{k=1}^k \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

Where  $x_i$  is a data point in cluster  $C_k$  and  $\mu_k$  is the mean value assigned to the cluster  $C_k$ . [Rec 7].

### 1.2.2 K Medoids

On the contrary, instead of taking the mean value of the objects in a cluster, the k-medoid method uses the most centrally located object in a cluster to be the cluster center [Rec 2]. This causes the method to be less sensitive to outliers, but also requires more time to run.

Steps for K-medoids: 1. Initial guess for centers  $C_1, C_2, \dots, C_k$  (i.e. randomly select k points from  $X_1, X_2, \dots, X_n$ ) 2. Minimize over C: for each  $i = 1, 2, \dots, n$ , find the cluster center  $C_k$  closest to  $X_i$  and let  $C(i) = k$ . 3. Minimize over  $C_1, C_2, \dots, C_k$ : for each  $k = 1, \dots, K$ ,  $C_k = X_k^*$ , the medoid of points in cluster k. i.e., the point  $X_i$  in the cluster k that minimizes

$$\sum_{c(j)=k} \|X_j - X_i\|^2$$

Basically, K-means and K-medoids follow very similar algorithms; however, K-medoids uses the most centrally located object (medoid) in a cluster to be the cluster center. This causes there to only be at most one center changed for each iteration (makes the algorithm run slower). [rec 2, p. 6].

## 1.3 How to Choose K

Now that we've discussed different kinds of K-means and K-medoids partitioning methods, we know how to find  $K$  clusters of data points; but how do we determine what  $K$  is?

Well, there are many ways to choose  $k$ , which is why these methods are so subjective.

I will describe two of the many ways to determine  $K$ , both of which use visuals to determine what value of  $k$  is appropriate for the data. The elbow method and silhouette method are common ways to find  $K$  when using the  $K$  means and  $K$  medoids algorithms.

### 1.3.1 Elbow Method

To start, the elbow method looks at the total within-cluster sum of squares (WSS) and determines when there are enough clusters so that the next cluster does not improve the total WSS very much. This would be the appropriate  $K$  to choose.

The steps for this algorithm are as follows:

1. Compute the clustering algorithm (i.e. `_k_medoids` method) for different values of  $k$  (i.e.  $k$  from 1 to 10).
2. For each  $k$ , calculate the total WSS. WSS can be calculated as:

$$WSS = \sum_{i=1}^k \sum_{x_i \in C_k} ||x_i - c_k||^2$$

Where  $x_i$  is a data point in cluster  $C_k$  and  $c_k$  is the medoid assigned to the cluster  $C_k$ . [Rec 7].

3. Plot the curve of the total WSSs according to the number of clusters ( $k$ ).
4. The location of the bend in the plot is generally considered an indicator for the appropriate number of clusters.

There will be an example of this method used in Chapter 3.

### 1.3.2 Silhouette Method

The Silhouette Method focuses on the quality of clustering. A high average silhouette width indicates a good clustering (how well each object lies within its cluster).

The steps of the Silhouette Algorithm are:

1. Compute clustering algorithm for different values of  $k$  (i.e.  $k$  from 1 to 10).
2. For each  $k$ , calculate the average silhouette of observations. There is a silhouette method in R that can calculate this for us...
3. Plot the curve of the average silhouettes according to the number of clusters ( $k$ ).
4. The location of the maximum is considered the appropriate number of clusters.

There will also be an example of this method used in Chapter 3. → datanovia website

# Chapter 2

## Clustering Methods Continued

### 2.1 PAM

Partitioning Around Medoids (PAM) is the most commonly used type of k-medoid clustering (Kaufmann & Rousseeuw, 1987).

It iterates through all the k cluster centers and tries to replace the center with one of the other objects (n-k possibilities) [Rec 2]. For a replacement to occur, the squared error function must decrease (if it does not decrease, there is no replacement). The algorithm eventually terminates with a local optimum.

The total complexity of PAM in one iteration is

$$O(k(n - k)^2)$$

(O= each non-medoid data point,  $k$ = # of cluster centers,

$$(n - k)$$

objects to compare to, and

$$(n - k)$$

operations for calculating E). This makes for a costly computation when n is large. The algorithm works best when  $n = 100$  and  $k = 5$ .

Explanation of PAM, REC 6, P. 146-> 4 cases, and algorithm Rec 6 bibliography (Ng & Han, 2000)

## 2.2 CLARA

Because PAM does not scale well to large data sets, Clustering LARge Applications (CLARA) was developed to deal with larger data sets (Kaufmann & Rousseeuw, 1990).

CLARA is a sampling based method, meaning a sample of the data is used to represent the entire data set. Medoids are chosen from this sample data using PAM and then “the average dissimilarity is computed using the whole dataset” (\*\*don’t know what “average dissimilarity” means or how it is calculated). If a new set of medoids gives a lower dissimilarity than a previous best solution, then the best solution is replaced with a new set of medoids [Rec 2, p. 7].

\*PAM on samples

<https://www.coursera.org/lecture/cluster-analysis/3-4-the-k-medoids-clustering-method-nJ0Sb>

## 2.3 CLARANS

(Ng & Han, 1994)

\*Randomized re-sampling, ensuring efficiency and quality

*#How to insert a figure, make sure amherst.png is in main directory*

```
label(path = "clustering_pic.png",  
      caption = "CLARANS searching for a better solution",  
      label = "CLARANS", type = "figure", scale= 0.5)
```

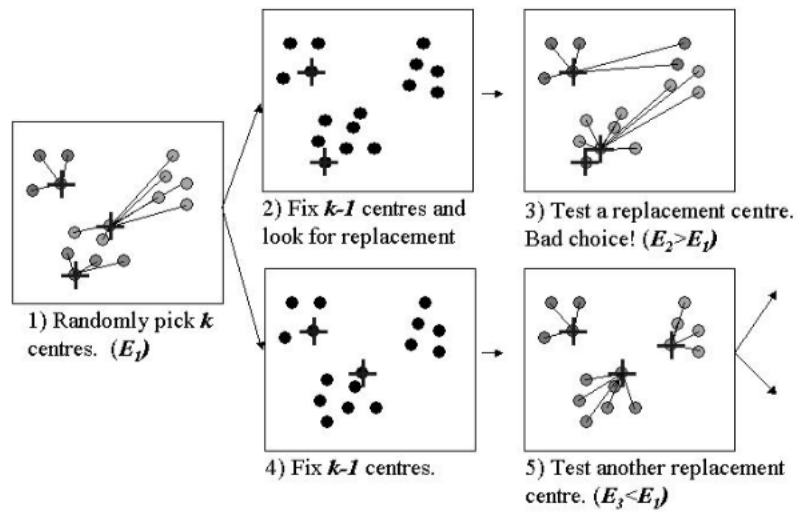


Figure 2.1: CLARANS searching for a better solution





# Chapter 3

## Example

```
#loading in packages  
library(readr)  
library(factoextra)
```

Welcome! Related Books: `Practical Guide To Cluster Analysis in R` at <https://goo.gl/83816t>

```
library(NbClust)  
library(ggplot2)  
library(cluster)  
library(GGally)
```

Attaching package: 'GGally'

The following object is masked from 'package:dplyr':

nasa

### 3.1 Exploring the Data

Data came from Stat 495 final project. (use info from project...). Needed a sample of 1000...

Importing the data:

```
#using data from final stat 495 project
#library(readr)
data_subset <- read_csv("CopyOfdata_subset.csv")
```

Parsed with column specification:

```
cols(
  .default = col_double(),
  geo_name = col_character(),
  geo = col_character(),
  zip = col_character(),
  TRI.ID = col_character(),
  County.x = col_character(),
  County.y = col_character()
)
```

See spec(...) for full column specifications.

```
set.seed(1)
#getting a sample of 1000 observations
mysample <- data_subset[sample(1:nrow(data_subset), 1000,
  replace=FALSE),]
```

Picking variables to focus on-> expanding conclusions from Stat 495 project

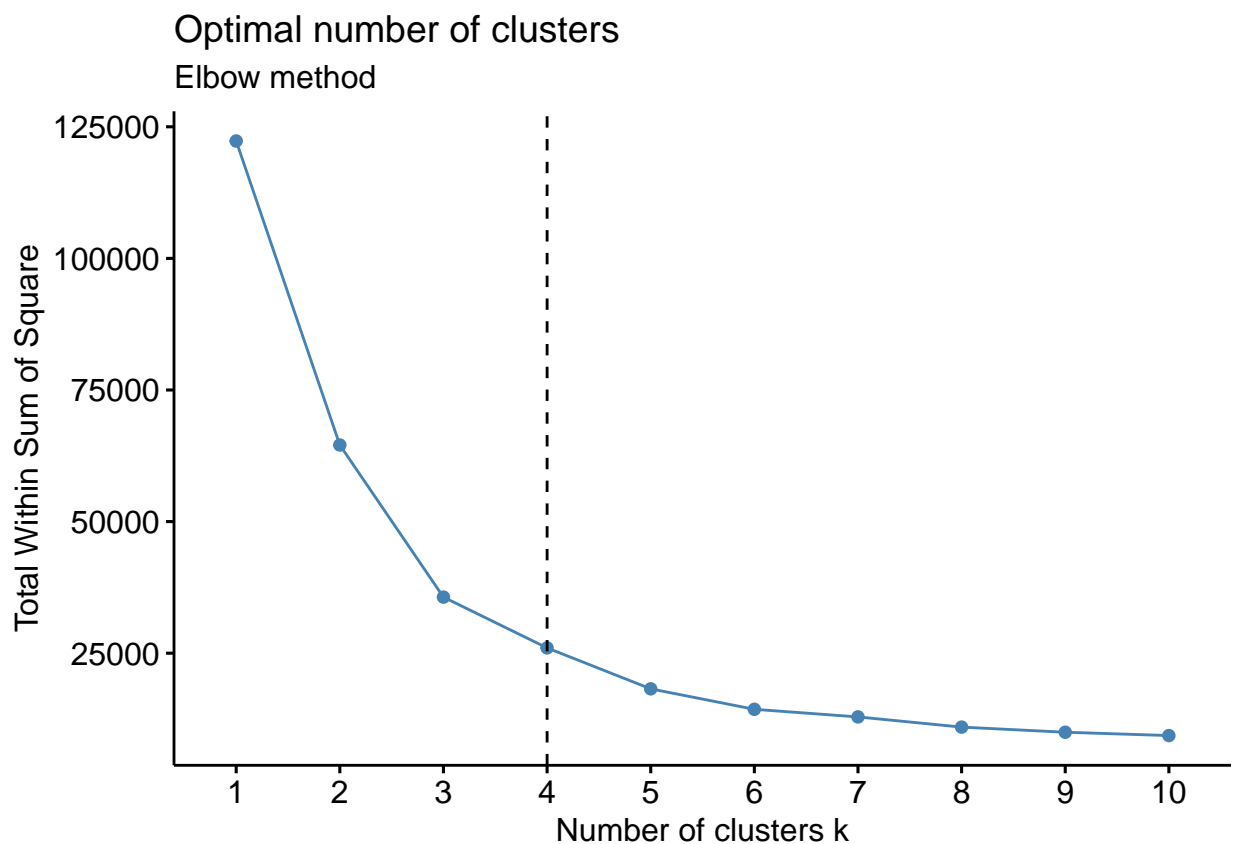
```
#only keeping the variables I want to look at
myvars <- c("Latitude_tri", "Longitude_tri", "poor_or_fair_health", "poor_physical_health")
smallsample <- mysample[myvars]
```

## 3.2 Applying CLARA

Step 1: finding k

```
#finding k with project data, using Elbow Method
#pkgs <- c("factoextra", "NbClust")
#install.packages(pkgs)
```

```
#library(factoextra)
#library(NbClust)
#library(ggplot2)
new<- na.omit(smallsample)
# Elbow method
fviz_nbclust(new, kmeans, method = "wss") +
  geom_vline(xintercept = 4, linetype = 2)+
  labs(subtitle = "Elbow method")
```



Step 2: Run CLARA function

```
#new<- na.omit(smallsample)
#library(cluster)
## run CLARA
clarasamp <- clara(new[1:6], 4)
```

```
## print components of clarax
```

```
print(clarasamp)
```

```
Call:      clara(x = new[1:6], k = 4)
```

```
Medoids:
```

	Latitude_tri	Longitude_tri	poor_or_fair_health	
[1,]	38.6364	-83.6929	0.200	
[2,]	40.3973	-75.9357	0.165	
[3,]	36.1335	-96.0532	0.196	
[4,]	45.4342	-123.0000	0.110	

	poor_physical_health_days	physical_inactivity	adult_obesity
[1,]	4.4	0.299	0.283
[2,]	3.7	0.245	0.308
[3,]	4.6	0.353	0.355
[4,]	3.3	0.137	0.244

```
Objective function: 4.691022
```

```
Clustering vector:  int [1:925] 1 2 1 3 1 3 1 1 1 1 1 3 1 2 1 3 3 3 ...
```

```
Cluster sizes:      453 195 230 47
```

```
Best sample:
```

```
[1]  5  11  24  86 139 149 162 175 177 192 208 224 242 285 306 311 316
[18] 353 361 370 389 400 404 410 429 468 471 478 489 506 589 679 691 703
[35] 719 726 736 741 800 811 815 818 877 882 883 895 902 918
```

```
Available components:
```

```
[1] "sample"      "medoids"      "i.med"        "clustering"   "objective"
[6] "clusinfo"    "diss"         "call"         "silinfo"     "data"
```

```
summary(clarasamp)
```

```
Object of class 'clara' from call:
```

```
  clara(x = new[1:6], k = 4)
```

```
Medoids:
```

	Latitude_tri	Longitude_tri	poor_or_fair_health
[1,]	38.6364	-83.6929	0.200
[2,]	40.3973	-75.9357	0.165
[3,]	36.1335	-96.0532	0.196

```

[4,]      45.4342      -123.0000              0.110
      poor_physical_health_days physical_inactivity adult_obesity
[1,]              4.4              0.299          0.283
[2,]              3.7              0.245          0.308
[3,]              4.6              0.353          0.355
[4,]              3.3              0.137          0.244

```

Objective function: 4.691022

Numerical information per cluster:

```

      size max_diss av_diss isolation
[1,]  453 13.228882 4.578281  1.656594
[2,]  195  8.392191 2.971767  1.050917
[3,]  230 14.554453 6.249473  1.153918
[4,]   47 42.497226 5.284278  1.489171

```

Average silhouette width per cluster:

```
[1] 0.2863797 0.6457187 0.4655863 0.9673973
```

Average silhouette width of best sample: 0.4306859

Best sample:

```

[1]  5 11 24 86 139 149 162 175 177 192 208 224 242 285 306 311 316
[18] 353 361 370 389 400 404 410 429 468 471 478 489 506 589 679 691 703
[35] 719 726 736 741 800 811 815 818 877 882 883 895 902 918

```

Clustering vector:

```

[1] 1 2 1 3 1 3 1 1 1 1 1 3 1 2 1 3 3 3 2 1 3 2 1 1 3 3 2 2 1 1 2 3 1 3
[36] 1 1 1 3 3 1 1 1 1 1 1 1 1 2 1 1 3 1 1 1 1 4 1 1 1 1 2 2 3 3 1 2 1 3
[71] 1 1 3 3 1 3 1 4 1 2 1 2 4 1 1 3 1 2 4 3 3 3 1 1 3 4 4 1 2 2 1 2 3 3 1
[106] 1 1 3 3 4 1 3 3 4 2 1 2 3 2 3 2 2 1 3 1 2 1 1 1 3 2 4 1 2 1 1 2 1 3 3
[141] 1 2 1 1 1 1 2 1 1 2 2 1 1 3 3 1 3 1 3 1 3 1 1 2 1 3 1 4 3 1 1 3 1 3 3
[176] 1 3 1 1 4 2 1 1 1 1 2 1 1 3 1 1 3 2 1 2 3 3 2 1 1 1 2 1 3 2 1 2 1 1 1
[211] 1 1 1 2 1 3 4 2 4 3 1 1 3 2 1 1 3 4 3 2 2 1 1 1 3 3 1 1 3 1 1 2 1 2 3
[246] 2 1 1 3 1 1 3 4 2 1 1 2 3 1 2 1 1 1 3 1 4 2 3 2 1 3 2 2 3 1 1 3 2 1 3
[281] 1 1 3 3 1 1 3 1 2 2 3 1 1 3 1 2 1 1 1 1 1 3 1 1 1 1 3 3 1 3 1 1 3 1 1
[316] 3 1 2 1 1 1 3 2 3 1 1 3 1 1 4 2 1 1 1 3 1 2 1 2 2 1 3 1 1 3 3 4 3 1 1
[351] 1 1 1 1 1 3 1 3 1 1 1 3 3 1 2 1 3 1 2 3 1 3 3 2 2 2 1 1 3 2 3 3 3 1 1
[386] 1 1 2 1 3 1 1 2 1 2 2 1 3 3 2 1 4 2 2 1 1 1 1 1 1 1 3 1 1 1 1 1 2 1 3 1
[421] 3 3 2 3 1 2 1 3 2 1 1 1 1 4 4 1 1 3 1 2 1 1 1 3 1 2 1 1 2 1 3 1 1 2 4
[456] 1 1 2 1 1 1 2 1 1 4 3 1 1 4 4 1 1 3 1 4 1 1 1 1 1 3 4 2 1 1 1 1 2 2 3 1

```

```

[491] 2 3 1 3 3 1 2 2 2 2 1 2 2 3 1 1 2 3 2 1 1 2 3 2 3 3 2 2 2 3 2 1 3 2 3
[526] 3 3 1 4 1 1 2 2 2 1 3 2 1 1 1 3 4 1 1 3 1 1 2 3 1 2 1 3 1 1 3 2 3 3 3
[561] 1 2 1 2 1 3 2 3 1 4 1 1 3 3 2 1 1 3 2 2 1 1 2 1 2 1 1 1 1 3 2 1 3 4 1
[596] 3 1 1 2 1 3 2 3 4 1 3 1 1 1 4 3 1 2 1 1 3 4 2 1 2 3 2 1 2 3 1 1 2 1 2
[631] 1 1 4 3 1 2 3 1 1 3 1 4 3 1 1 1 2 2 3 2 1 1 1 2 1 1 1 2 3 1 3 1 1 3 1
[666] 1 1 1 3 1 2 1 3 1 1 1 1 1 2 2 3 1 2 3 2 2 1 1 2 2 3 2 1 1 1 2 1 3 3 1
[701] 1 1 1 4 2 1 3 1 1 2 4 3 1 1 1 3 3 1 1 1 1 3 1 1 2 4 2 3 1 1 1 3 1 1 3
[736] 1 2 1 2 3 2 2 2 1 3 3 3 1 1 1 2 3 3 3 1 3 3 2 1 2 3 3 1 2 4 2 1 1 3 1
[771] 2 1 1 1 3 1 3 3 1 1 3 3 1 3 1 2 1 1 3 1 4 1 1 1 1 3 2 2 2 4 1 3 3 1 1
[806] 1 3 1 1 1 2 1 1 1 2 2 2 1 1 2 1 3 3 3 3 1 3 2 4 2 1 2 3 1 1 3 2 1 1 4
[841] 2 2 2 2 2 1 3 1 2 1 2 4 3 3 1 1 3 1 1 1 1 1 2 3 3 2 4 1 2 1 1 1 1 2 1
[876] 1 3 1 1 1 3 3 1 1 1 3 1 1 3 1 1 3 1 3 1 3 2 2 2 3 1 2 2 2 1 1 4 1 2 1
[911] 3 1 3 2 3 3 1 1 2 1 3 1 1 3 1

```

Silhouette plot information for best sample:

	cluster	neighbor	sil_width
11	1	2	0.51160188
703	1	2	0.50784463
149	1	3	0.50590891
208	1	2	0.48693148
162	1	3	0.47468187
471	1	2	0.44956360
410	1	2	0.42362707
389	1	2	0.42157038
5	1	2	0.41457596
719	1	2	0.41289559
468	1	2	0.37020730
361	1	2	0.35061984
306	1	2	0.34569720
285	1	2	0.34506744
818	1	3	0.30770633
506	1	3	0.21671937
589	1	2	0.20444489
918	1	2	0.19851903
736	1	3	0.18549695
478	1	2	0.16554915

24	1	2	0.15565598
311	1	2	0.04768370
353	1	3	0.03173421
883	1	2	-0.12930919
895	1	2	-0.24550081
224	2	1	0.76643863
679	2	1	0.75957431
902	2	1	0.74802681
404	2	1	0.74508892
242	2	1	0.73417881
400	2	1	0.73283435
741	2	1	0.61737358
811	2	1	0.47833894
815	2	1	0.43844208
429	2	1	0.43689016
691	3	1	0.62256512
370	3	1	0.62175433
489	3	1	0.61988506
882	3	1	0.60671130
139	3	1	0.58178390
177	3	1	0.55053388
175	3	1	0.43464488
86	3	1	0.29525285
192	3	1	0.28445790
316	3	1	0.27777790
877	3	1	0.22608234
800	4	3	0.96743579
726	4	3	0.96735884

1128 dissimilarities, summarized :

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
	0.0507	6.3776	10.6340	12.8320	15.7130	51.8530

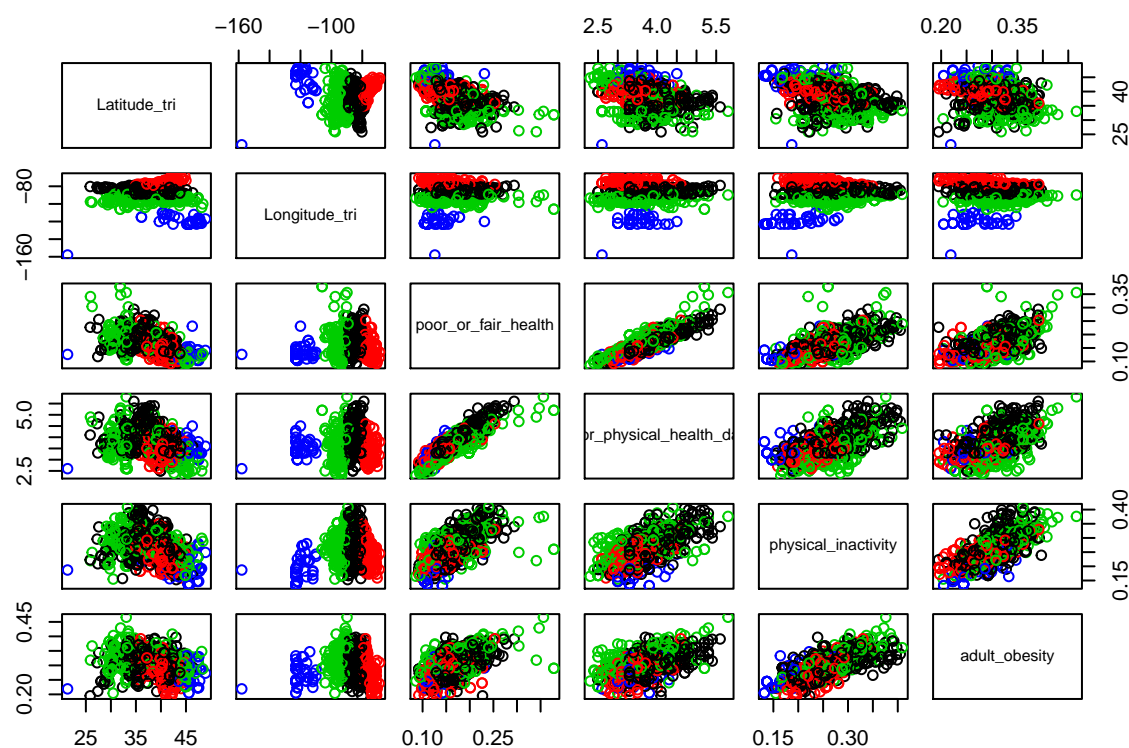
Metric : euclidean

Number of objects : 48

Available components:

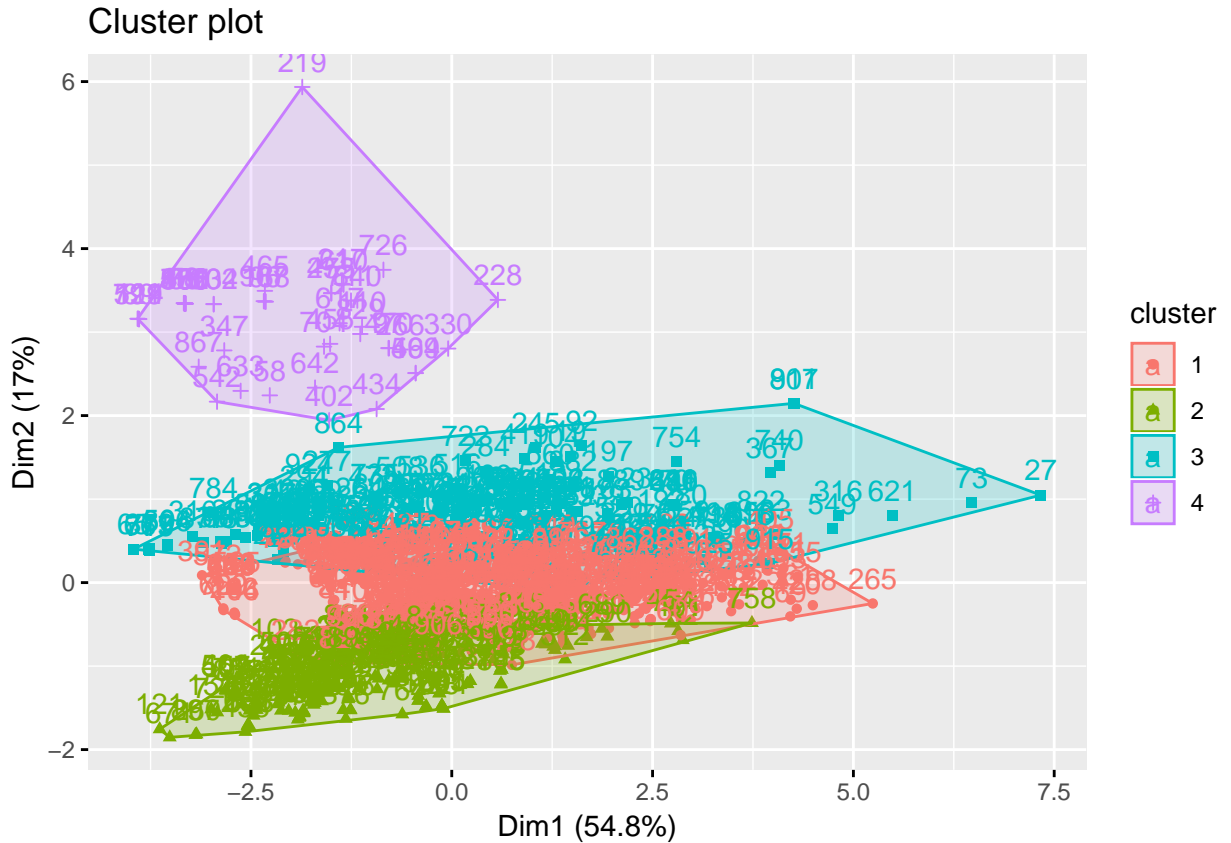
```
[1] "sample"      "medoids"      "i.med"        "clustering"  "objective"
[6] "clusinfo"    "diss"         "call"         "silinfo"     "data"
```

```
## plot clusters
plot(new, col = clarasamp$cluster)
## plot centers
points(clarasamp$centers, col = 1:2, pch = 8)
```



```
#plotting clara
factoextra::fviz_cluster(clarasamp)
```





### 3.3 Evaluation of CLARA

#### 3.3.1 Model to Predict Cluster

First, had to include a cluster variable in the original data set, using the data provided by the CLARA function.

```
#adding each data point's cluster #
cluster<- clarasamp$clustering
cluster_data<- cbind(new, cluster)
```

```
kitchen_sink<- lm(cluster~., data=cluster_data)
summary(kitchen_sink)
```

Call:

```
lm(formula = cluster ~ ., data = cluster_data)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.3742	-0.6013	0.0600	0.6334	1.6092

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-1.373221	0.386769	-3.550	0.000404 ***
Latitude_tri	0.004183	0.006661	0.628	0.530140
Longitude_tri	-0.055900	0.002255	-24.786	< 2e-16 ***
poor_or_fair_health	8.194392	1.457716	5.621	2.51e-08 ***
poor_physical_health_days	-0.913749	0.090846	-10.058	< 2e-16 ***
physical_inactivity	1.395680	0.751308	1.858	0.063536 .
adult_obesity	-0.419444	0.839018	-0.500	0.617249

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

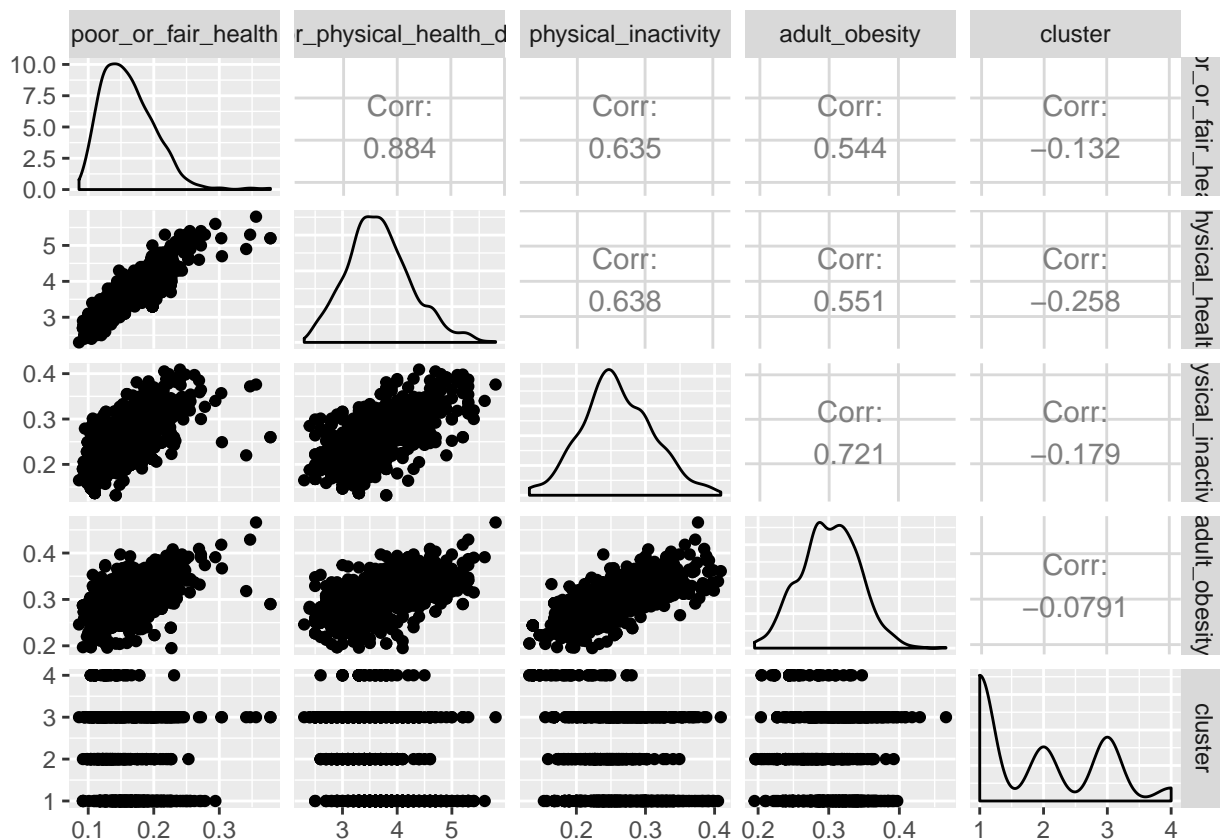
Residual standard error: 0.6984 on 918 degrees of freedom

Multiple R-squared: 0.4751, Adjusted R-squared: 0.4717

F-statistic: 138.5 on 6 and 918 DF, p-value: < 2.2e-16

```
#taking out lat and long
vars <- names(cluster_data) %in% c("Latitude_tri", "Longitude_tri")
cluster_data_new <- cluster_data[!vars]

ggpairs(cluster_data_new)
```



```
fun1<- lm(cluster ~ poor_physical_health_days, data= cluster_data_new)
summary(fun1)
```

Call:

```
lm(formula = cluster ~ poor_physical_health_days, data = cluster_data_new)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.3539	-0.8070	-0.1857	0.8144	2.4875

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	3.40573	0.19278	17.667	< 2e-16 ***
poor_physical_health_days	-0.42072	0.05183	-8.118	1.51e-15 ***

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9288 on 923 degrees of freedom

Multiple R-squared: 0.06664, Adjusted R-squared: 0.06563

F-statistic: 65.9 on 1 and 923 DF, p-value: 1.509e-15

# Conclusion

If we don't want Conclusion to have a chapter number next to it, we can add the `{.unnumbered}` attribute. This has an unintended consequence of the sections being labeled as 3.6 for example though instead of 4.1. The  $\text{\LaTeX}$  commands immediately following the Conclusion declaration get things back on track.

## More info

And here's some other random info: the first paragraph after a chapter title or section head *shouldn't be* indented, because indents are to tell the reader that you're starting a new paragraph. Since that's obvious after a chapter or section title, proper typesetting doesn't add an indent there.



# Appendix A

## The First Appendix

This first appendix includes all of the R chunks of code that were hidden throughout the document (using the `include = FALSE` chunk tag) to help with readability and/or setup.

In the main Rmd file:

```
# This chunk ensures that the acstats package is  
# installed and loaded. This acstats package includes  
# the template files for the thesis and also two functions  
# used for labeling and referencing  
if(!require(devtools))  
  install.packages("devtools", repos = "http://cran.rstudio.com")  
if(!require(acstats)){  
  library(devtools)  
  devtools::install_github("Amherst-Statistics/acstats")  
}  
library(acstats)
```

In :

```
# This chunk ensures that the acstats package is  
# installed and loaded. This acstats package includes  
# the template files for the thesis and also two functions  
# used for labeling and referencing  
if(!require(devtools))  
  install.packages("devtools", repos = "http://cran.rstudio.com")  
if(!require(dplyr))  
  install.packages("dplyr", repos = "http://cran.rstudio.com")  
if(!require(ggplot2))  
  install.packages("ggplot2", repos = "http://cran.rstudio.com")
```

```
if(!require(acstats)){  
  library(devtools)  
  devtools::install_github("Amherst-Statistics/acstats")  
}
```



## Appendix B

The Second Appendix, for Fun



# References

- Angel, E. (2001a). *Batch-file computer graphics : A bottom-up approach with quicktime*. Boston, MA: Wesley Addison Longman.
- Angel, E. (2001b). *Test second book by angel*. Boston, MA: Wesley Addison Longman.
- Ng, R. T., & Han, J. (2000). *Efficient and effective clustering methods for spatial data mining*. San Francisco, CA: Morgan Kaufmann Publishers Inc.