Clustering High Collision Areas in Toronto

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Extract, Transform, and Loading the Dataset

The differences between this dataset and the original collisions.csv dataset are that the following ETL processes were applied to it:

- only car-on-pedestrian and car-on-cyclist collisions were kept; car-on-car, car-on-property collisions were excluded
- spatial joined in QGIS using the Toronto Neighbourhoods shapefile, which added a Neighourhood ID and Neighbourhood name field to each observation (if a collision took place within the boundaries of a neighbourhood, it was given the corresponding Neighbourhood label)
- spatial joined in QGIS using the Toronto Centrelines shapefile, which added a unique street ID (LFN_ID) and total length in kilometres of the primary road the collision took place on as new fields to the dataset

- street name columns were merged into a single column called street1
- engineered several binary features which check whether an area has above the city's average for that measure. E.g. businessess_check checks whether the area has more than the average number of businesses or not.

Pre-processing the Data

Once the different datasets from different sources are ready, they need to be joined.

```
library(readr)
# Main dataset

collisions <- read_csv("D:/Google Drive/Data Analysis/136/capstone-
repo/Datasets/Collisions - Processed.csv",
    col_types = cols(collision_date = col_date(format = "%m/%d/%Y")))

# Datasets to be joined on Neighbourhood ID to collisions dataframe

hood_profiles <- read_csv("D:/Google Drive/Data Analysis/136/capstone-
repo/Datasets/Joined Sets (Neighbourhood-level Data)/Processed - Hood
Profiles 2016.csv")

income <- read_csv("D:/Google Drive/Data Analysis/136/capstone-
repo/Datasets/Joined Sets (Neighbourhood-level Data)/Processed - Income.csv")

civics <- read_csv("D:/Google Drive/Data Analysis/136/capstone-
repo/Datasets/Joined Sets (Neighbourhood-level Data)/Processed - Civics.csv")

economics <- read_csv("D:/Google Drive/Data Analysis/136/capstone-
repo/Datasets/Joined Sets (Neighbourhood-level Data)/Processed -
Economics.csv")

transportation <- read_csv("D:/Google Drive/Data Analysis/136/capstone-
repo/Datasets/Joined Sets (Neighbourhood-level Data)/Processed -
Transportation.csv")

language <- read_csv("D:/Google Drive/Data Analysis/136/capstone-
repo/Datasets/Joined Sets (Neighbourhood-level Data)/Processed -
Language.csv")

# join the above tables to the collisions dataset
main.df <- merge(collisions, hood_profiles, by.x = "AREA_S_CD", by.y = "Hood
ID", all.x = T)
main.df <- merge(main.df, income, by.x = "AREA_S_CD", by.y = "HOOD ID", all.x
= T)
main.df <- merge(main.df, language, by.x = "AREA_S_CD", by.y = "HOOD ID",
all.x = T)
main.df <- merge(main.df, civics, by.x = "AREA_S_CD", by.y = "Neighbourhood
Id", all.x = T)
```

```r
main.df <- merge(main.df, economics, by.x = "AREA_S_CD", by.y =
"Neighbourhood Id", all.x = T)
main.df <- merge(main.df, transportation, by.x = "AREA_S_CD", by.y =
"Neighbourhood Id", all.x = T)
colnames(main.df)

# turn four-digit integer into time
library(caret)

summary(main.df$collision_time)
main.df$collision_time <- substr(as.POSIXct(sprintf("%04.0f",
main.df$collision_time), format='%H%M'), 12, 16)
main.df$collision_time <- as.POSIXct(main.df$collision_time, format =
'%H:%M')
head(main.df$collision_time)

# drop redundant columns

main.df$`HOOD NAME.x` <- NULL
main.df$`Hood Name`<- NULL
main.df$`HOOD NAME.y`<- NULL
main.df$Neighbourhood.x <- NULL
main.df$Neighbourhood.y <- NULL
main.df$Neighbourhood <- NULL
main.df$`Total % In LIM-AT.y` <- NULL
main.df$`Total % In LIM-AT` <- main.df$`Total % In LIM-AT.x`
main.df$`Total % In LIM-AT.x` <- NULL
colnames(main.df)

# remove all rows containing non-pedestrian collisions
pedestrian.df <- main.df[which(main.df$involved_class == "PEDESTRIAN"),]
unique(pedestrian.df$involved_class)

# drop non-pedestrian columns
pedestrian.df <- pedestrian.df[,-c(14,24,27,30:31)]
dim(pedestrian.df)
```

Data Cleaning

```r
# Remove variables with 50% or more missing values
pedestrian.df <- pedestrian.df[, colMeans(is.na(pedestrian.df)) <= .5]
dim(pedestrian.df)

# Remove variables with zero or near zero variance (aka nearly all rows have
same value)
library(caret)
nzv <- nearZeroVar(pedestrian.df)
nzv
```

```
# the below columns have near zero variance
colnames(pedestrian.df)[12]
colnames(pedestrian.df)[20]

pedestrian.df <- pedestrian.df[,-nzv]
dim(pedestrian.df)

# how many missing values?
sum(is.na(pedestrian.df))

# where are the missing values located?
na_count <- sapply(pedestrian.df, function(x)
  sum(length(which(is.na(x)))))
na_count <- data.frame(na_count)
print(na_count)

# there are 107 rows with no identifiable neighbourhood ID so these can be
removed
pedestrian.df <- pedestrian.df[-which(is.na(pedestrian.df$AREA_S_CD)),]

# px isn't used in our analysis since its a unique id for joining to some
other table
# streets with unknown LFN_IDs mean no length could be calculated for that
street; since street length is important in our analysis to measure collision
density, these unknown streets should be removed
# involved_age and light are also important variables we'd like to correlate
so we can remove records with NAs for these

dim(pedestrian.df)

# prior to cleaning, there are 16665 rows, 84 features
pedestrian.df <- pedestrian.df[,-5]
pedestrian.df <- pedestrian.df[-which(is.na(pedestrian.df$LFN_ID)),]
pedestrian.df <- pedestrian.df[-which(is.na(pedestrian.df$involved_age)),]
pedestrian.df <- pedestrian.df[-which(is.na(pedestrian.df$light)),]
dim(pedestrian.df)

#for street_2 and street_type 2 -- many times when a collision is reported,
only the street the collision took place on is reported, not the intersecting
street. street_type_2 contains the type of street the intersecting street is
which is not useful. We will keep street_2 since it could be useful for human
understanding where we tend to think of streets in terms of intersections not
GPS coordinates

pedestrian.df <- pedestrian.df[,-9]

#Remove all records where collisions didn't result in any injury
dim(pedestrian.df)
pedestrian.df <- pedestrian.df[!pedestrian.df$involved_injury_class ==
```

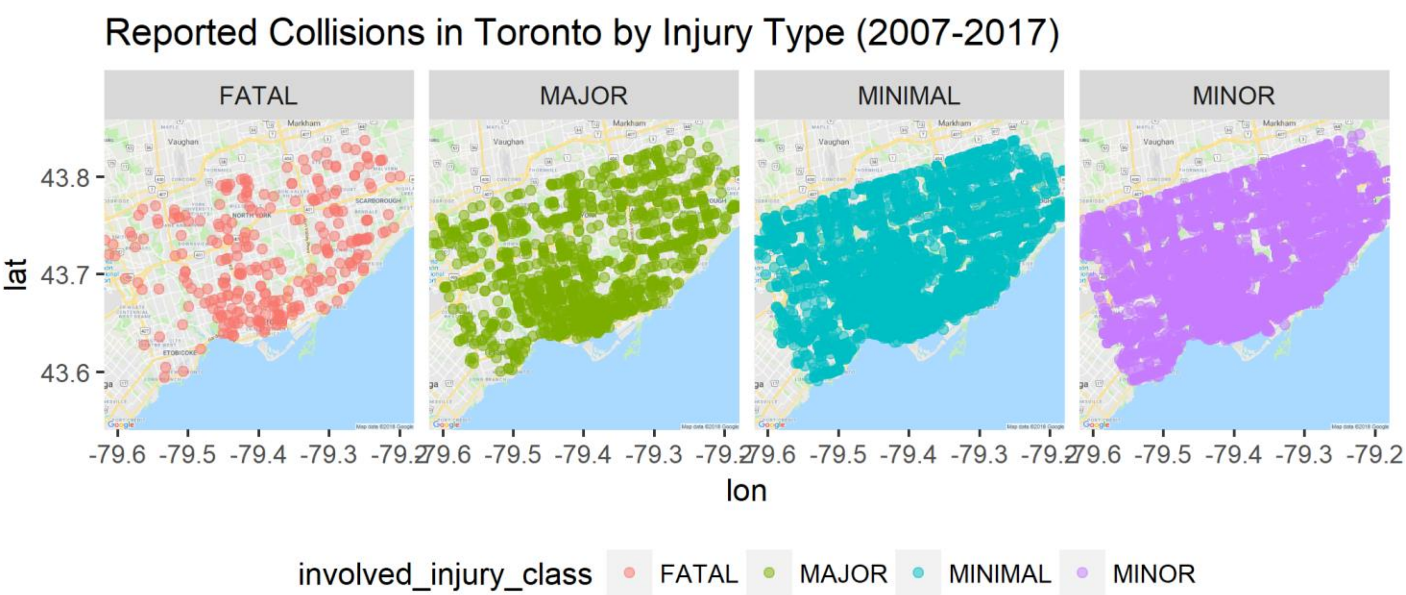
```
"NONE",]
dim(pedestrian.df)

# missing values in cleaned data set
na_count <- sapply(pedestrian.df, function(x)
  sum(length(which(is.na(x)))))
na_count <- data.frame(na_count)
na_count

# location_desc, intital_dir, pedestrian_action, pedestrian_collision_type
# all 4 of these features are qualitative, categorical variables that further
describe the collision so they represent either truly unknown or non-
applicable situations

unique(pedestrian.df$location_desc)
unique(pedestrian.df$initial_dir)
unique(pedestrian.df$pedestrian_action)
unique(pedestrian.df$pedestrian_collision_type)
```

Exploring the Data

Prior to modelling, we should obtain an untuitive understanding of the problem of collisions in Toronto.

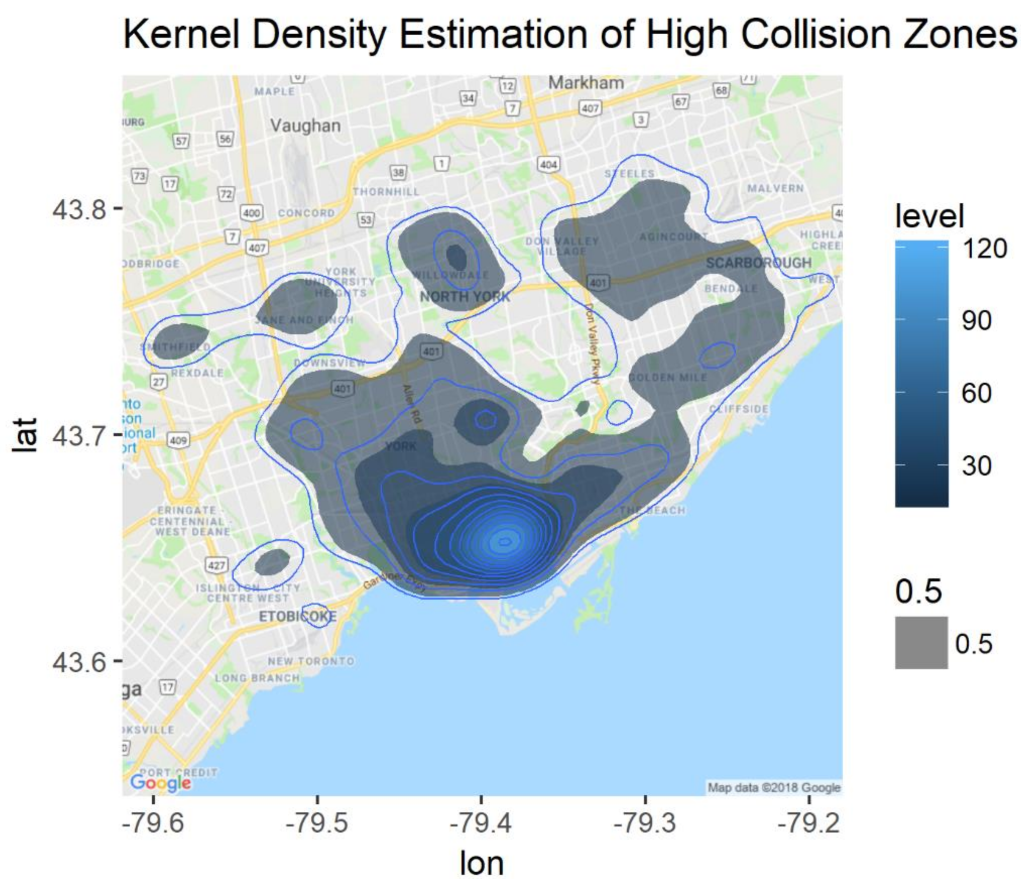
```
# Missing Values
sum(is.na(pedestrian.df))

## [1] 4060

na_count

##                                                          na_count
## street_2                                                     1468
## location_desc                                                  41
## initial_dir                                                  1331
## pedestrian_action                                             596
## pedestrian_collision_type                                     624


# 4060 missing values, all of them categorical variables

# Summary of the dataset
str(pedestrian.df)

# The dataset contains many features that are related to each other so
Principal Component Analysis (PCA) will help reduce the dimensionality
greatly

# Let's map these collisions to get an intuition for the problem the city is
```

```
facing
# install dev build of ggmap library
#if(!requireNamespace("devtools")) install.packages("devtools")
#devtools::install_github("dkahle/ggmap", ref = "tidyup", force = T)

library(maptools)

library(ggmap)

library(rgeos)

register_google(key = "AIzaSyBwXArBPS6-g3f2-rzWXJyz0NhcK5I5eUc")
toronto_map <- ggmap(get_googlemap(center = c(-79.4, 43.7), zoom = 11, scale
= 1, maptype = "roadmap"))

## Source : https://maps.googleapis.com/maps/api/staticmap?center=43.7,-
79.4&zoom=11&size=640x640&scale=1&maptype=roadmap&key=xxx-g3f2-
rzWXJyz0NhcK5I5eUc

toronto_map + geom_point(aes(x = longitude, y = latitude, color =
involved_injury_class), data = pedestrian.df, alpha = 0.5, size = 1.5) +
theme(legend.position="bottom") + facet_grid(~ involved_injury_class) +
```




```
labs(title = "Reported Collisions in Toronto by Injury Type (2007-2017)")
```

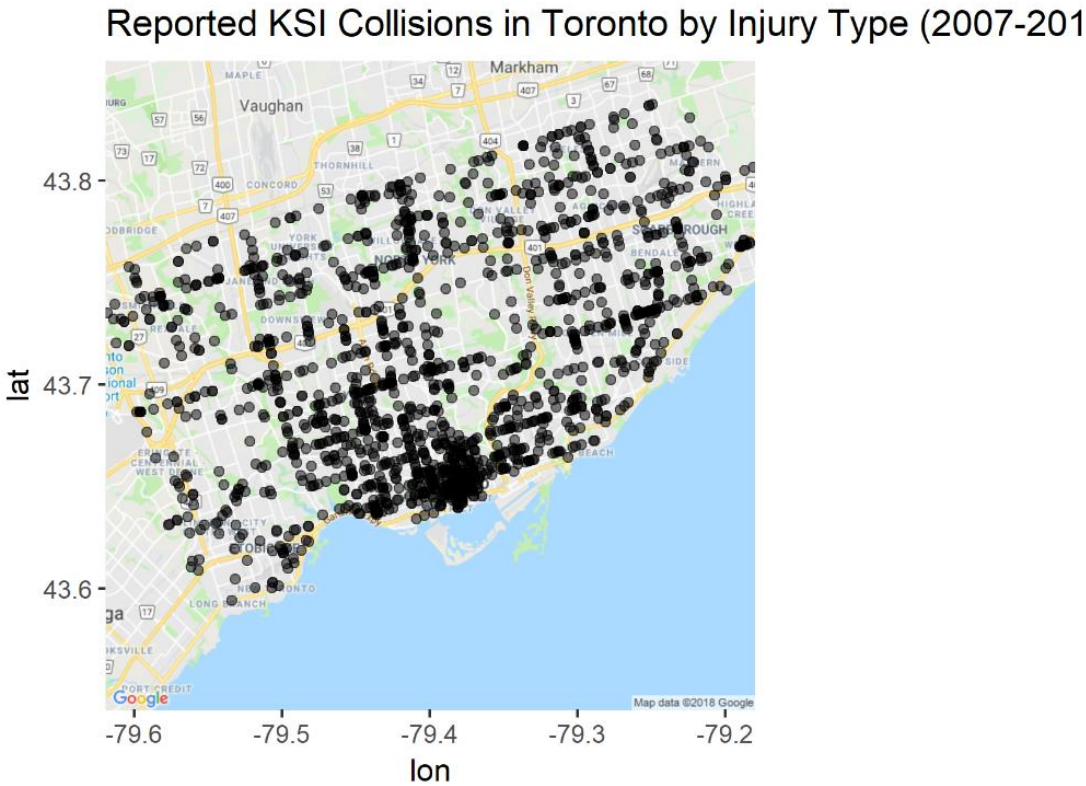
```
# Hard to tell if there are any particular areas that are more prone to collisions which we address below. What we do see is that fatal collisions are rare events

# Use Kernal Density Estimation (KDE) to show the density of collisions in Toronto
toronto_map + stat_density2d(aes(x = longitude, y = latitude, fill = ..level.., alpha = 0.5), data = pedestrian.df, size = 0.1, bins = 10, geom = "polygon") + geom_density2d(data = pedestrian.df, aes(x = longitude, y = latitude), size = 0.3) + labs(title = "Kernel Density Estimation of High
```



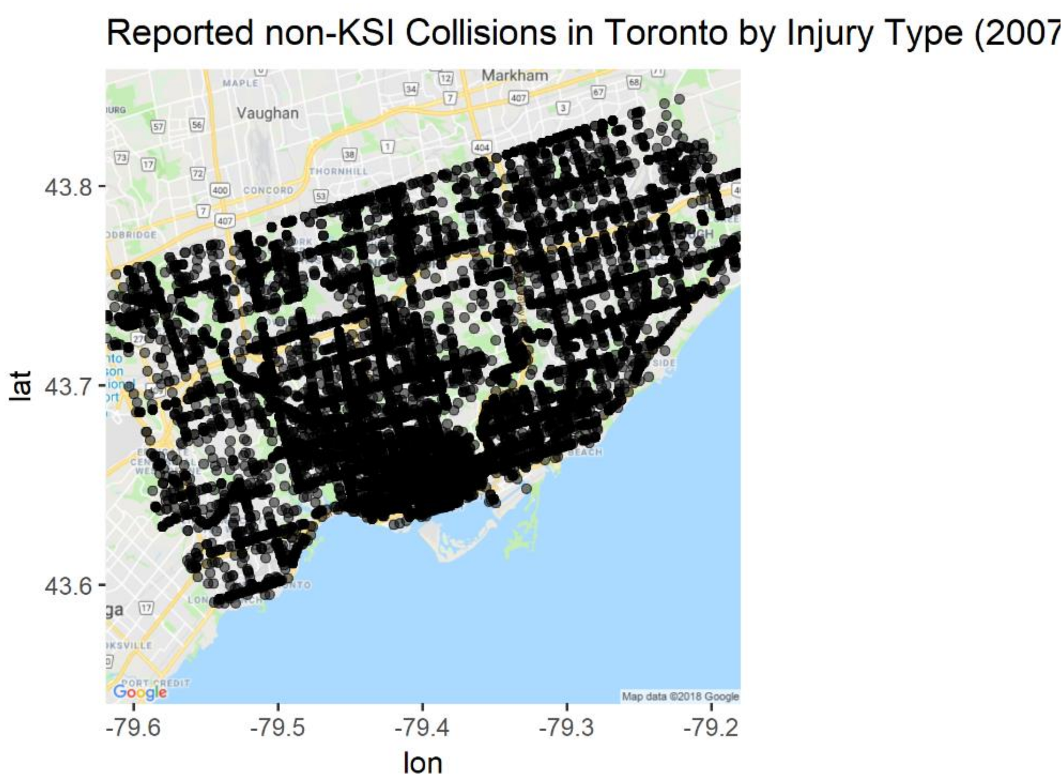

```
Collision Zones")
```

```
# this does a much better job of showing high colliaion areas

# perhaps a trend can be observed if we differentiate between collisions resulting in death or seriously injury vs. non-KSI collisions so we look at that below

# subset the Killed or Seriously Injured incidents and non-KSIs
ksi_df <- pedestrian.df[pedestrian.df$involved_injury_class == "FATAL" |
```

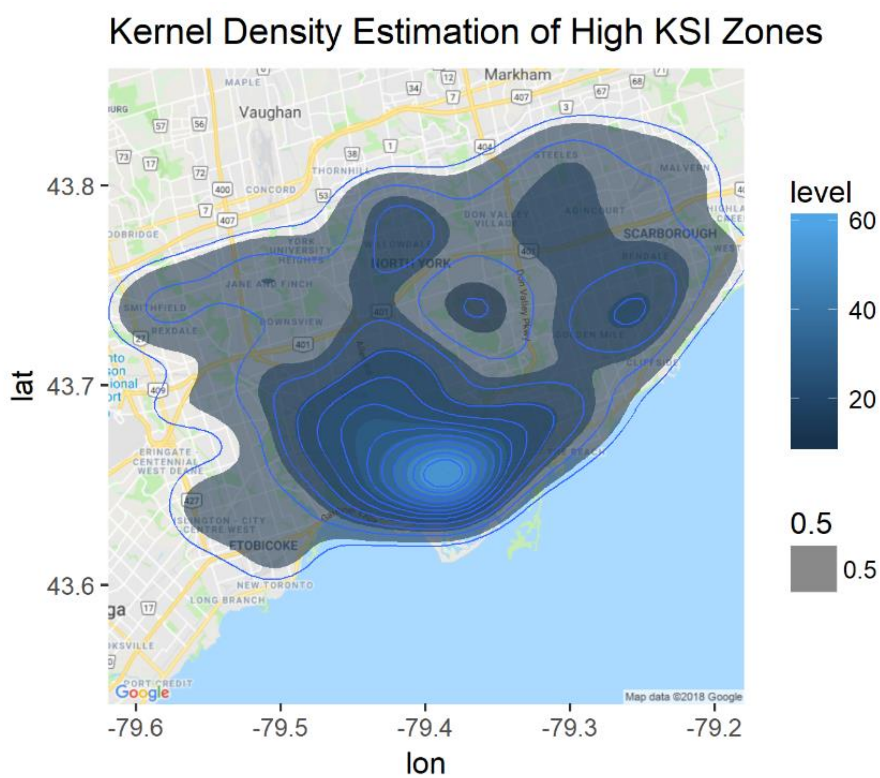
```
pedestrian.df$involved_injury_class == "MAJOR",]
dim(ksi_df)

## [1] 1606   87

nonksi_df <- pedestrian.df[-(pedestrian.df$involved_injury_class == "FATAL" |
pedestrian.df$involved_injury_class == "MAJOR"),]
dim(nonksi_df)

## [1] 15532    87

# is there a pattern in where pedestrians were killed or seriously injured?
toronto_map + geom_point(aes(x = longitude, y = latitude), data = ksi_df,
alpha = 0.5, size = 1.5) +   theme(legend.position="bottom") + labs(title =
"Reported KSI Collisions in Toronto by Injury Type (2007-2017)")
```



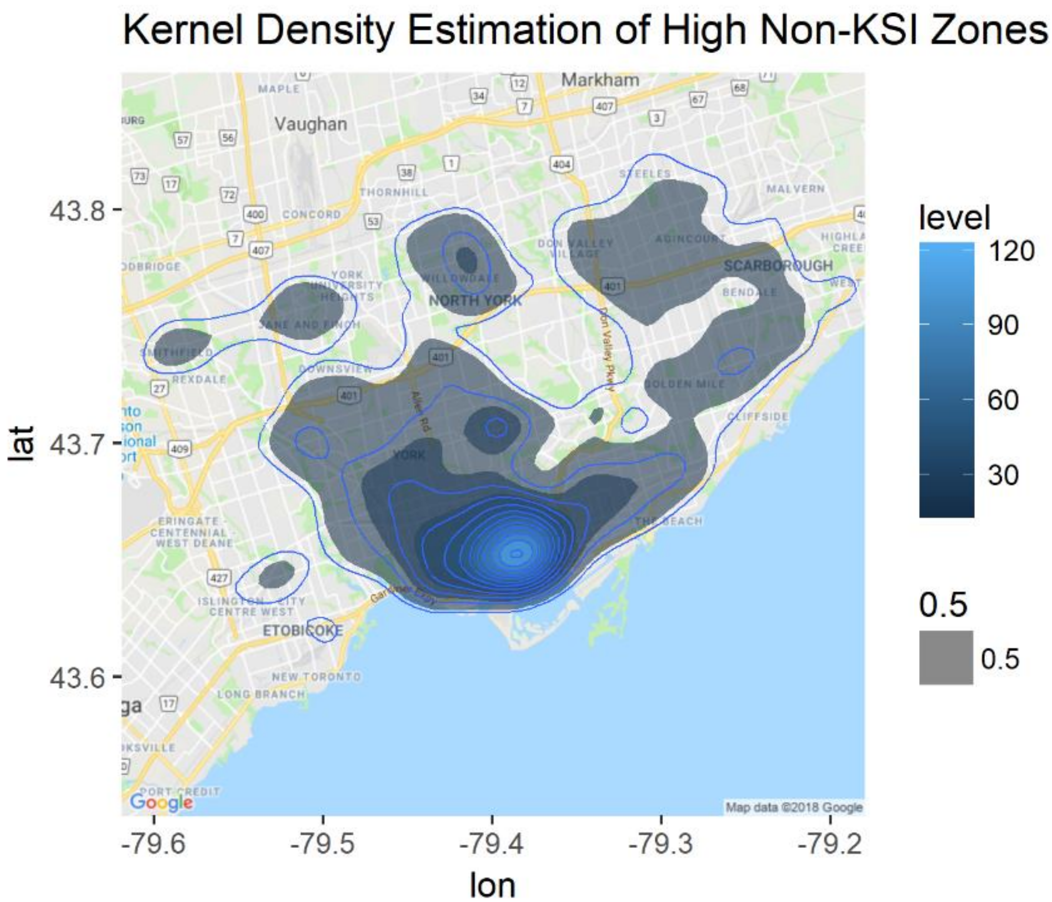

```
toronto_map + geom_point(aes(x = longitude, y = latitude), data = nonksi_df,
alpha = 0.5, size = 1.5) +   theme(legend.position="bottom") + labs(title =
"Reported non-KSI Collisions in Toronto by Injury Type (2007-2017)")
```



```
# KSIs seem to roughly correspond to areas that have high collisions in general.. lets use KDE to see the densities better to compare

# Use Kernal Density Estimation (KDE) to show the density of KSI vs non-KSI collisions in Toronto
toronto_map + stat_density2d(aes(x = longitude, y = latitude, fill = ..level.., alpha = 0.5), data = ksi_df, size = 0.1, bins = 10, geom = "polygon") + geom_density2d(data = ksi_df, aes(x = longitude, y = latitude), size = 0.3) + labs(title = "Kernel Density Estimation of High KSI Zones")
```




```
# Use Kernal Density Estimation (KDE) to show the density of non-KSI collisions in Toronto
toronto_map + stat_density2d(aes(x = longitude, y = latitude, fill = ..level.., alpha = 0.5), data = nonksi_df, size = 0.1, bins = 10, geom = "polygon") + geom_density2d(data = nonksi_df, aes(x = longitude, y = latitude), size = 0.3) + labs(title = "Kernel Density Estimation of High Non-KSI Zones")

## Warning: Removed 130 rows containing non-finite values (stat_density2d).

## Warning: Removed 130 rows containing non-finite values (stat_density2d).
```



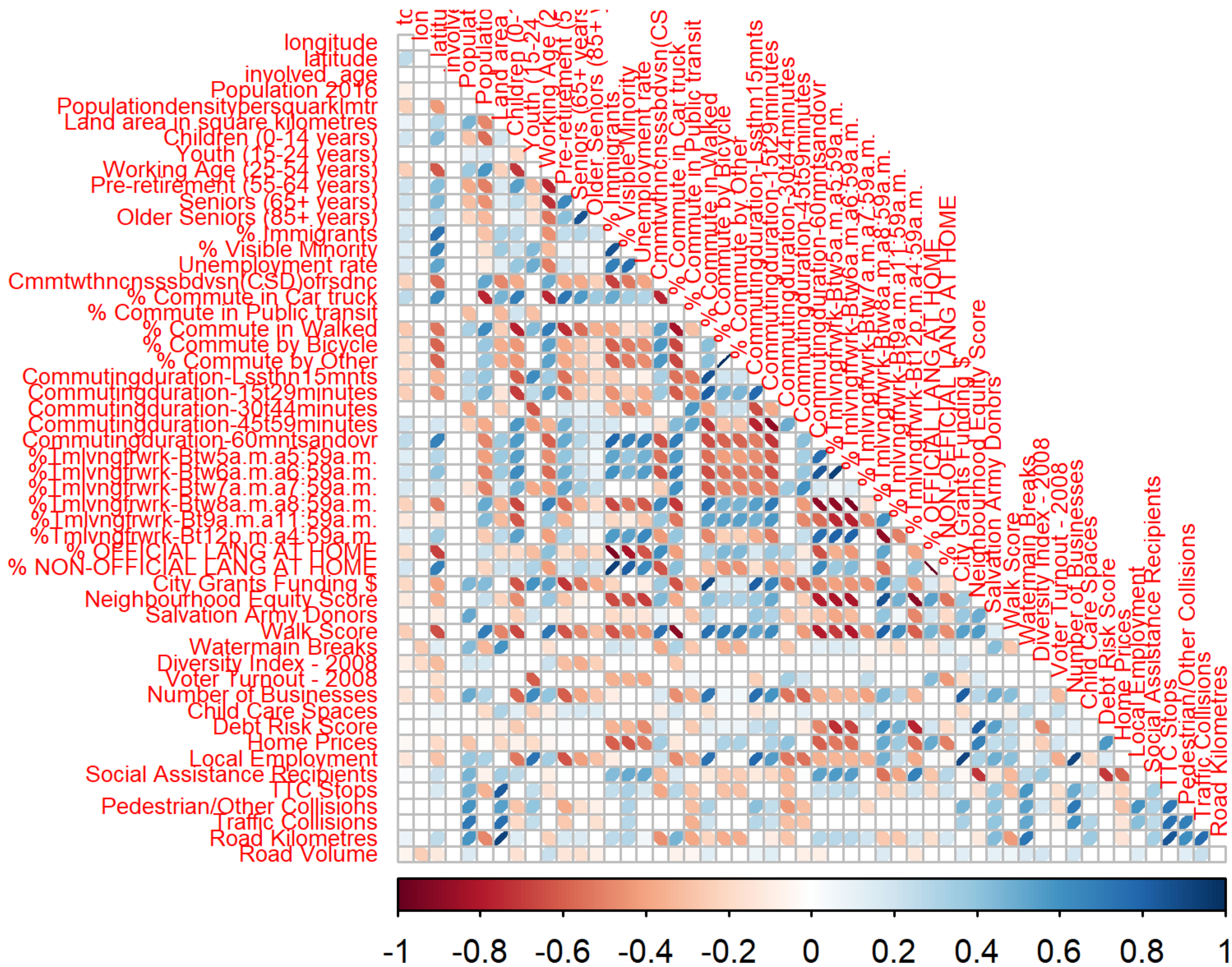

```
# The non-KSIs seem to be more diffuse when compared to KSI collisions, but
both seem to occur with more frequency in the same locations.. the shape of
the kernal densities look very similar. Just in case I want to study this
further, I will engineer a new feature called ksi_check where "1" means the
collision is a KSI, "0" not.

pedestrian.df$ksi_check <- ifelse(pedestrian.df$involved_injury_class ==
"FATAL" | pedestrian.df$involved_injury_class == "MAJOR", 1, 0)
prop.table(table(pedestrian.df$ksi_check))

##
##         0         1
## 0.8966072 0.1033928

pedestrian.df$ksi_check <- as.factor(pedestrian.df$ksi_check)

# major imbalance between non-ksi vs. ksi collisions (9:1 ratio)

# pair-wise correlations of numerical variables
pedestrian.df$AREA_S_CD <- as.character(pedestrian.df$AREA_S_CD)
pedestrian.df$collision_id <- as.character(pedestrian.df$collision_id)
```

```r
pedestrian.df$LFN_ID <- as.character(pedestrian.df$LFN_ID)
pedestrian.df$child_check <- as.factor(pedestrian.df$child_check)
pedestrian.df$senior_check <- as.factor(pedestrian.df$senior_check)
pedestrian.df$minority_check <- as.factor(pedestrian.df$minority_check)
pedestrian.df$immigrants_check <- as.factor(pedestrian.df$immigrants_check)
pedestrian.df$commute_car_check <- as.factor(pedestrian.df$commute_car_check)
pedestrian.df$businesses_check <- as.factor(pedestrian.df$businesses_check)
pedestrian.df$childcare_check <- as.factor(pedestrian.df$childcare_check)
pedestrian.df$homeprice_check <- as.factor(pedestrian.df$homeprice_check)
pedestrian.df$localemployment_check <-
as.factor(pedestrian.df$localemployment_check)
pedestrian.df$socialasst_check <- as.factor(pedestrian.df$socialasst_check)
pedestrian.df$ttc_check <- as.factor(pedestrian.df$ttc_check)
pedestrian.df$road_km_check <- as.factor(pedestrian.df$road_km_check)
pedestrian.df$road_vol_check <- as.factor(pedestrian.df$road_vol_check)
pedestrian.df <- unique(pedestrian.df)

library(mlbench)
library(caret)
library(corrplot)

cor_pedestrian.df <- cor(Filter(is.numeric, pedestrian.df))
pedestrian.df_num <- Filter(is.numeric, pedestrian.df)

# looking for very strong pair-wise correlation aka colinearity
# find attributes that are highly corrected i.e. >|0.9| (candidates for
removal due to pair-wise correlations)
highlyCorrelated <- findCorrelation(cor_pedestrian.df, cutoff=0.9, verbose =
T)

## Compare row 31  and column  29 with corr  0.938
##   Means:  0.434 vs 0.285 so flagging column 31
## Compare row 29  and column  28 with corr  0.938
##   Means:  0.398 vs 0.28 so flagging column 29
## Compare row 14  and column  35 with corr  0.935
##   Means:  0.357 vs 0.276 so flagging column 14
## Compare row 36  and column  47 with corr  0.912
##   Means:  0.357 vs 0.272 so flagging column 36
## Compare row 43  and column  47 with corr  0.918
##   Means:  0.333 vs 0.269 so flagging column 43
## Compare row 21  and column  22 with corr  1
##   Means:  0.325 vs 0.266 so flagging column 21
## Compare row 35  and column  34 with corr  1
##   Means:  0.294 vs 0.264 so flagging column 35
## Compare row 7  and column  52 with corr  0.923
##   Means:  0.275 vs 0.263 so flagging column 7
## All correlations <= 0.9
```

```
# print names of highly correlated attributes
highlyCorrelated_names <- colnames(cor_pedestrian.df)[highlyCorrelated]
highlyCorrelated_names
```

```
## [1] "% Time leaving for work - Between 8 a.m. and 8:59 a.m."
## [2] "% Time leaving for work - Between 6 a.m. and 6:59 a.m."
## [3] "% Immigrants"
## [4] "City Grants Funding $"
## [5] "Number of Businesses"
## [6] "% Commute by Bicycle"
## [7] "% NON-OFFICIAL LANG AT HOME"
## [8] "Land area in square kilometres"
```

```
# none of these variables having very high correlation seem to matter much
for our analysis so they are to be kept in for now.. PCA will combine these
attributes anyway

# Function to calc p values in correlation matrix
cor.mtest <- function(mat, ...) {
  mat <- as.matrix(mat)
  n <- ncol(mat)
  p.mat<- matrix(NA, n, n)
  diag(p.mat) <- 0
  for (i in 1:(n - 1)) {
    for (j in (i + 1):n) {
      tmp <- cor.test(mat[, i], mat[, j], ...)
      p.mat[i, j] <- p.mat[j, i] <- tmp$p.value
    }
  }
  colnames(p.mat) <- rownames(p.mat) <- colnames(mat)
  p.mat
}

p.mat <- cor.mtest(cor_pedestrian.df)
colnames(cor_pedestrian.df) <- abbreviate(colnames(cor_pedestrian.df),
minlength=30)
rownames(cor_pedestrian.df) <- abbreviate(rownames(cor_pedestrian.df),
minlength=30)

corrplot(cor_pedestrian.df, method = "ellipse", type = "lower", diag = F,
insig = "blank", sig.level = 0.05, p.mat = p.mat, tl.cex = 0.55)
```



```
# there are way too many statistically significant correlations between
variables so need to reduce dimensions further to make any sense of it
```

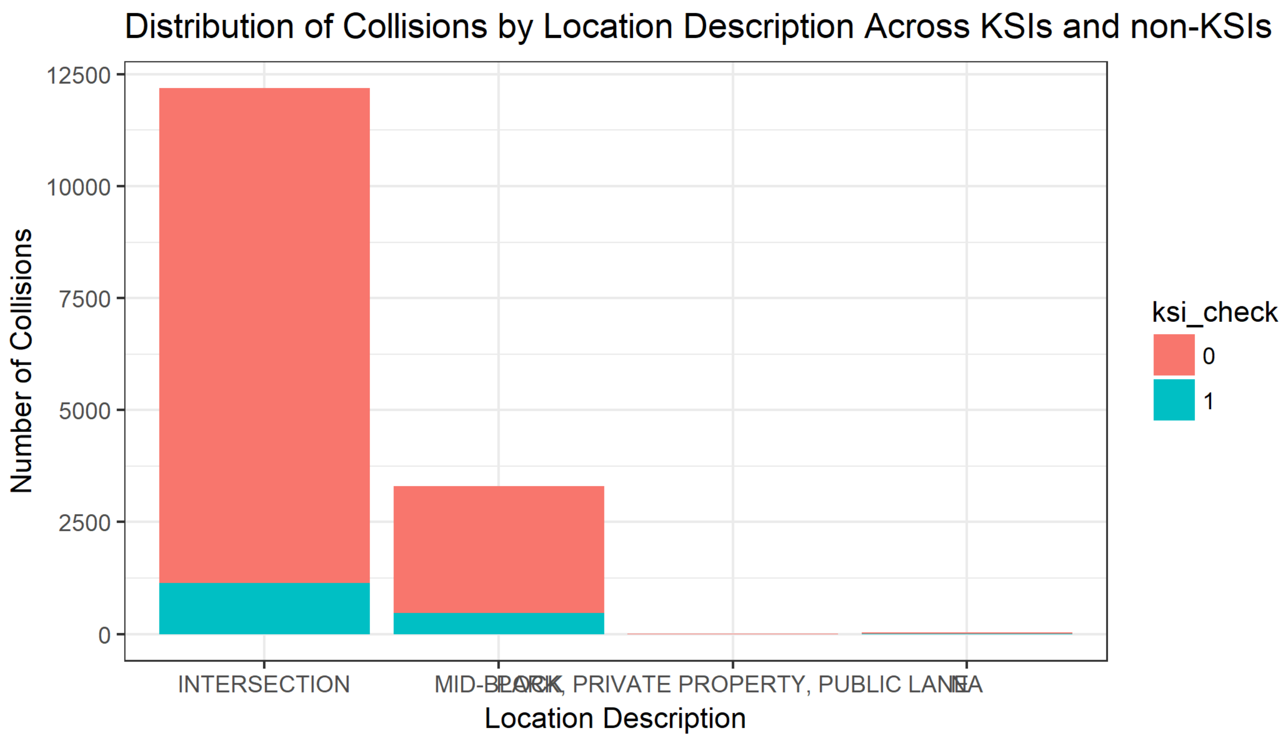
Neighbourhood	Collisions
Waterfront Communities-The Island (77)	608
Bay Street Corridor (76)	567
Church-Yonge Corridor (75)	367
Downsview-Roding-CFB (26)	286
Islington-City Centre West (14)	286
West Humber-Clairville (1)	280
Kensington-Chinatown (78)	272
Annex (95)	253
Moss Park (73)	241

York University Heights (27)	237
Woburn (137)	236
South Riverdale (70)	232
Niagara (82)	226
Weston (113)	211
Trinity-Bellwoods (81)	199
Newtonbrook West (36)	196
Dovercourt-Wallace Emerson-Junction (93)	195
High Park-Swansea (87)	187
South Parkdale (85)	182
Agincourt South-Malvern West (128)	176

Street	Collisions
YONGE ST	555
DUNDAS ST W	371
BATHURST ST	366
BLOOR ST W	326
EGLINTON AVE E	319
JANE ST	293
QUEEN ST W	268
FINCH AVE W	266
SHEPPARD AVE E	254
LAWRENCE AVE E	245
DUFFERIN ST	240
EGLINTON AVE W	232
DANFORTH AVE	219
FINCH AVE E	212
VICTORIA PARK AVE	208
KEELE ST	203
KING ST W	192
LAWRENCE AVE W	185
ST CLAIR AVE W	184
KINGSTON RD	182

Road Type	Collisions
MAJOR ARTERIAL	10318

MINOR ARTERIAL	2645
COLLECTOR	1294
LOCAL	1276



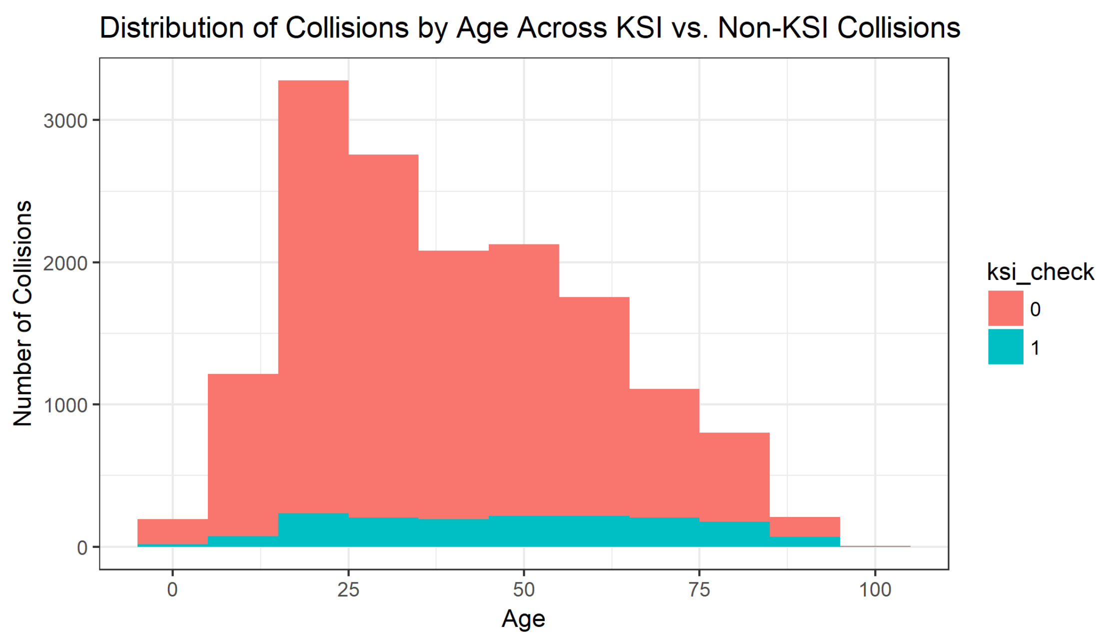
Location	Collisions
INTERSECTION	12186
MID-BLOCK	3304
NA	41
PARK, PRIVATE PROPERTY, PUBLIC LANE	2

Road Type	Collisions
MAJOR ARTERIAL	10318
MINOR ARTERIAL	2645
COLLECTOR	1294
LOCAL	1276

Light Condition	Collisions
DAYLIGHT	9685

DARK	5233
DUSK	391
DAWN	222
OTHER	2

Visibility Condition	Collisions
CLEAR	12311
RAIN	2563
SNOW	457
OTHER	72
FREEZING RAIN	41
FOG, MIST, SMOKE, DUST	40
DRIFTING SNOW	29
STRONG WIND	20



Clustering Collision Densities by Location

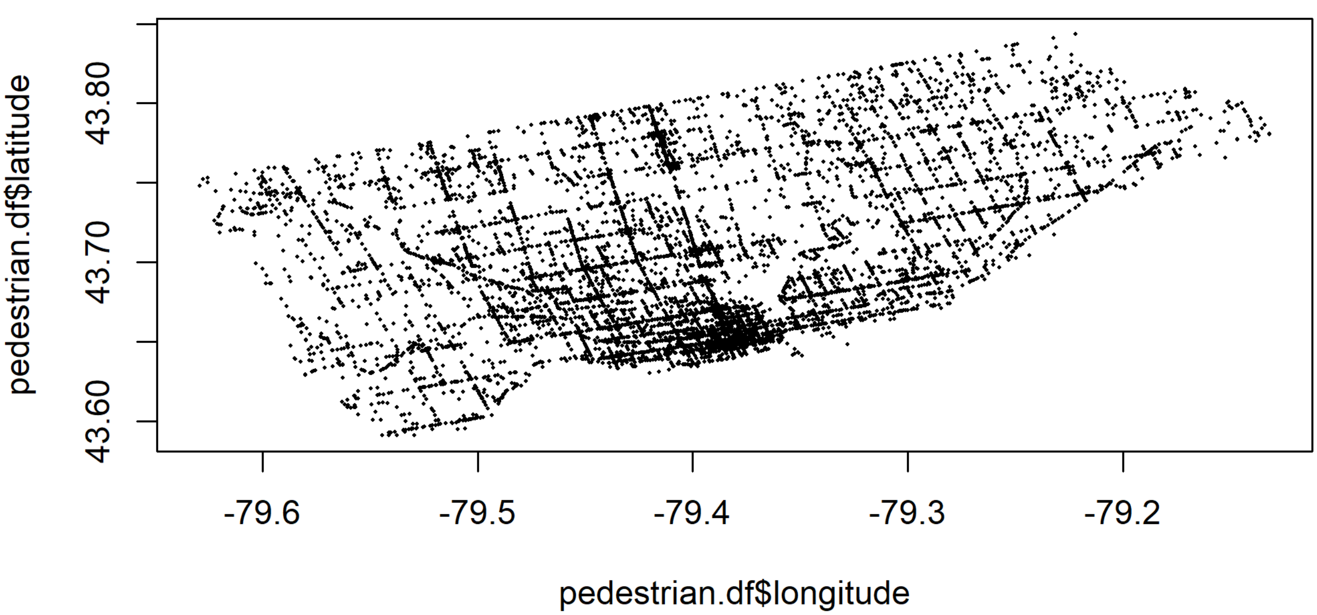
Prior to classification, we need to group the collision densities (where collisions occur within a set radius). We use three methods of grouping collision densities:

1. Kernel Density Estimation (KDE)
2. K-means Clustering
3. Density Based Spatial Clustering and Application with Noise (DBSCAN)

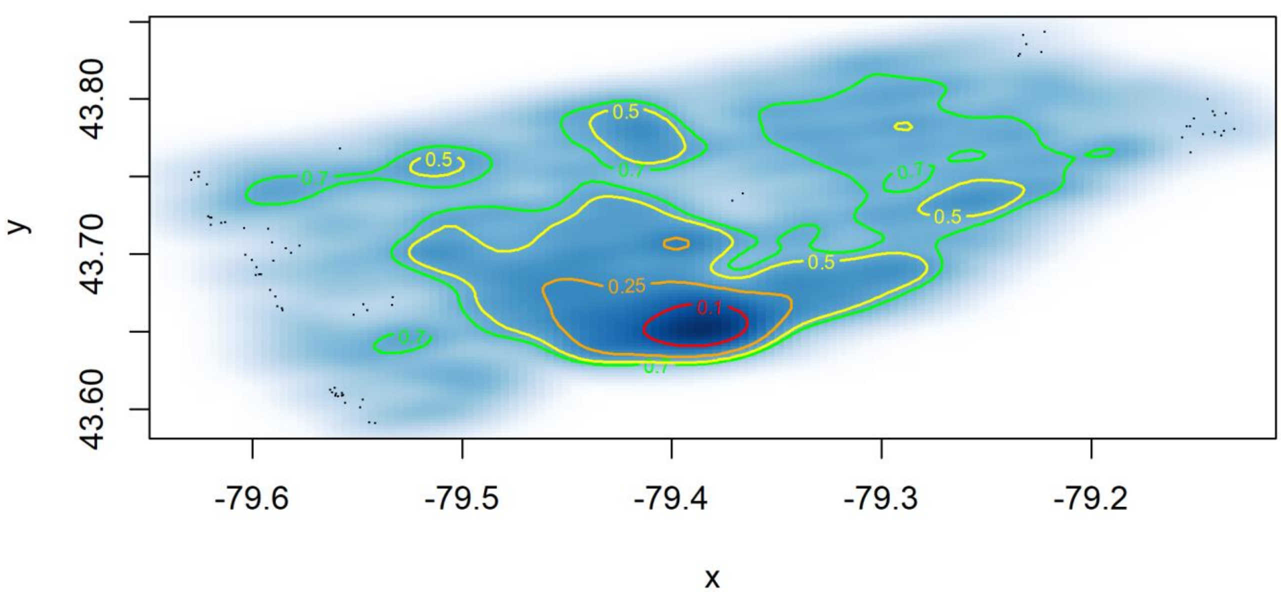
By using unsupervised learning to group these collision densities we can create a map of collision hotspots and then model the data to examine shared chareristics and classify unseen data.

Kernel Density Estimation (KDE)

```
#KDE is the standard method used in most of the traffic safety literature. KDE groups densities of points into 3-dimensional "humps" or kernels along a specified threshold. I used a KDE in the exploratory data analysis stage above, but didn't pull those high collision zones into the data set as a new feature.

# Below, I reconstruct the KDE to my specifications and then create a new feature in the dataset called zone which assigns every collision falling within at least 70% of the surface area of the KDE one of four zones according to the levels set below (70%, 50%, 25%, 10%).

# I can then use the zone attribute to look at shared characteristics of collisions within each zone beyond geographic proximity during classification.

library(MASS)
library(sp)
library(reshape2)

# Reference plot showing all collision points plotted
plot(pedestrian.df$longitude, pedestrian.df$latitude, pch = 16, cex = .25)
```



```
# use kde2d function to create kernel density estimates
x <- pedestrian.df$longitude
y <- pedestrian.df$latitude
dens <- kde2d(x, y, n=100)

# create the contours to plot - 70%, 50%, 25%, 10% of density contained in
each contour
prob <- c(0.7, 0.5, 0.25, 0.1)
dx <- diff(dens$x[1:4])
dy <- diff(dens$y[1:4])
sz <- sort(dens$z)
c1 <- cumsum(sz) * dx * dy

levels <- sapply(prob, function(x) {
    approx(c1, sz, xout = 1 - x)$y
})

#create the contour plot using smoothScatter which smooths the collisions
into kernel densities

smoothScatter(x,y) + contour(dens, levels=levels, labels=prob, col =
c("green", "yellow", "orange", "red"), lwd = 1.5, add=T)
```



```r
# points within polygons to identify which collisions lie within which of the four contours
# show how many polygons created per level
ls <- contourLines(dens, level=levels)
sort(table(sapply(ls, `[[`, "level")))

##
## 70.2266571229002 29.7050372913424 15.5351922832459 11.5092342683039
##                1                2                5                7

# there are 15 polygons in total but 4 levels; this is bc each polygon is on a separate layer

setNames(
  lapply(ls, function(poly) sum(sp::point.in.polygon(pedestrian.df$longitude, pedestrian.df$latitude, poly$x, poly$y))),
  sapply(ls, `[[`, "level")
) -> level_cts

# show sum of collisions per contour level
sapply(
  split(level_cts, names(level_cts)),
  function(level) sum(unlist(level))
) -> pt_cts

pt_cts <- as.data.frame(pt_cts)
pt_cts <- t(pt_cts)
colnames(pt_cts) <- c("Zone 4 (70%)", "Zone 3 (50%)", "Zone 2 (25%)", "Zone 1 (10%)")
rownames(pt_cts) <- "Number of Collisions"
pt_cts <- t(pt_cts)
library(knitr)
kable(pt_cts)
```

	Number of Collisions
Zone 4 (70%)	12017
Zone 3 (50%)	8469
Zone 2 (25%)	4325
Zone 1 (10%)	2054

```r
# below, I attempted to add Zone labels as a new feature to the dataset but the function didnt work as expected as it generated more non-duplicate records than the dataset contained. As a result, I wasn't able to test the clustering performance of KDE on location coordinates as of December 4, 2018. I will update the notebook if I'm able to succeed with this later.

#do.call(
#  rbind.data.frame,
```

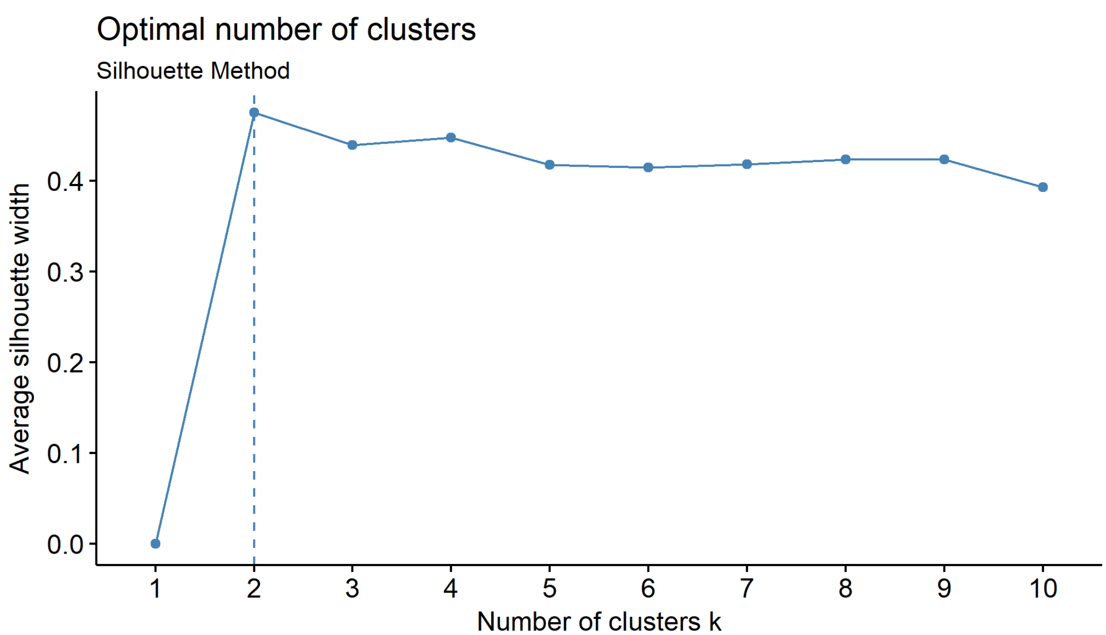
```
#  lapply(ls, function(poly) {
#    which_pts <- as.logical(sp::point.in.polygon(pedestrian.df$longitude,
pedestrian.df$latitude, poly$x, poly$y))
#    tdf <- pedestrian.df[which_pts,] # assign them to a temp data frame
#    tdf$level <- poly$level # add the level
#    tdf
#  })
#) -> pedestrian.df2

#library(dplyr)
#dplyr::glimpse(pedestrian.df2)

#new_xdf$level_num <- as.integer(factor(new_xdf$level, levels,
labels=1:length(levels)))
#new_xdf$prob <- as.numeric(as.character(factor(new_xdf$level, levels,
labels=prob)))

#pedestrian.kde <- pedestrian.df
#prop.table(table(pedestrian.kde$zone))
```

K-means Clustering

Rather than clustering collisions by kernel densities, we can also cluster using k-means clustering which is an unsupervised learning algorithm. Below we find the optimal value for **k**, which is the number of clusters our model will attempt to fit the points. Effectively, this will cluster collisions into discrete concentrations based on location not unlike KDE, but using the shortest Eucledean distance to the centroid rather than kernel density. Thus, I expect the two models to look somewhat similar to each other, but k-means will have potentially many elliptically-shaped clusters rather than the organic, blob-like shape KDE creates.

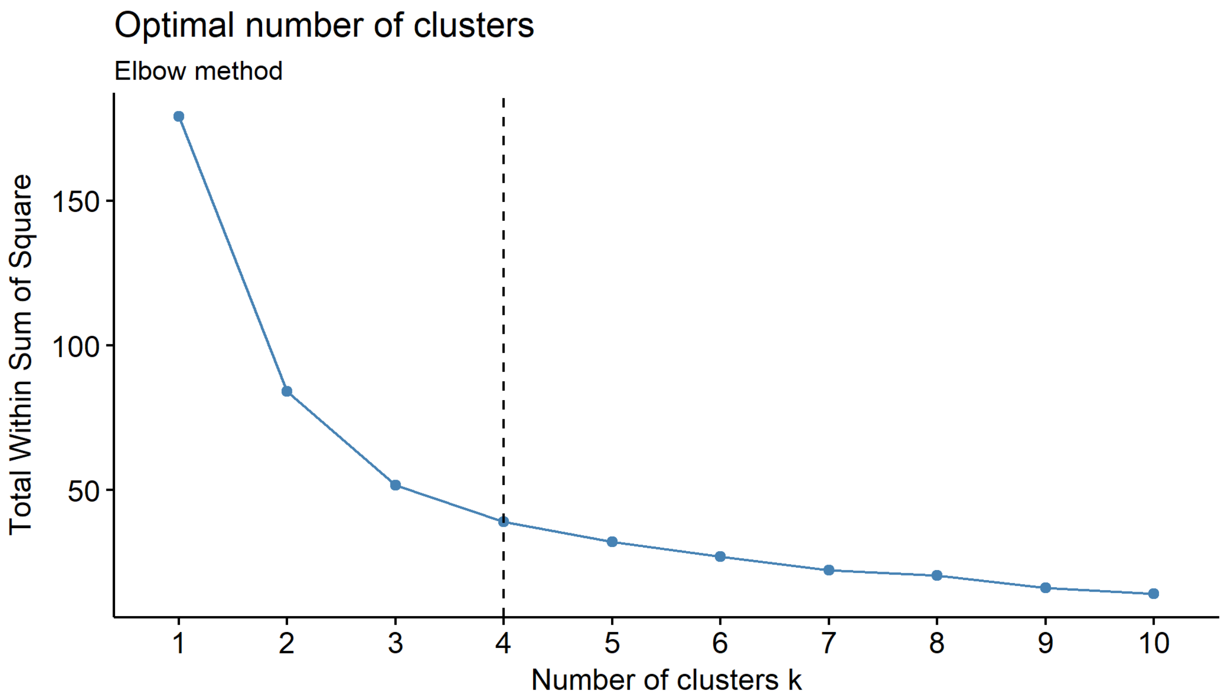
```
# Before applying k-means, we must find k, the optimal number of clusters
library(factoextra)

library(NbClust)

library(doSNOW)

library(caret)

# creating subset of main dataset to only contain lon and lat coordinates of
collisions
pedestrian.coords <- pedestrian.df[,c("longitude", "latitude")]
pedestrian.kmeans <- pedestrian.df[,c("longitude", "latitude")]
# create a stratified sample of the above so that the training and test sets
contains the same proportion of collisions by location in case this
influences collisions

#pedestrian.df$location_desc <- as.factor(pedestrian.df$location_desc)
```

```
#set.seed(123)
#index <- createDataPartition(pedestrian.coords$location_desc, times = 1, p =
0.75, list = F)
#train_pedestrian.kmeans <- pedestrian.coords[index,]
#test_pedestrian.kmeans <- pedestrian.coords[-index,]

# remove location_desc since it is a classifier and we are using an
unsupervised algorithm
#train_pedestrian.kmeans <- train_pedestrian.kmeans[,-3]
#test_pedestrian.kmeans <- test_pedestrian.kmeans[,-3]

# creating parallel processing clusters to speed up calculations
# WARNING - these calculations are resource intensive on both CPU and RAM
# Need at least 3 cores and 16 GB of RAM to run

cl <- makeCluster(3, type = "SOCK")
registerDoSNOW(cl)

# Using avg silhouette to determine optimal k clusters
fviz_nbclust(pedestrian.kmeans, kmeans, method = "silhouette") +
labs(subtitle = "Silhouette Method")
```

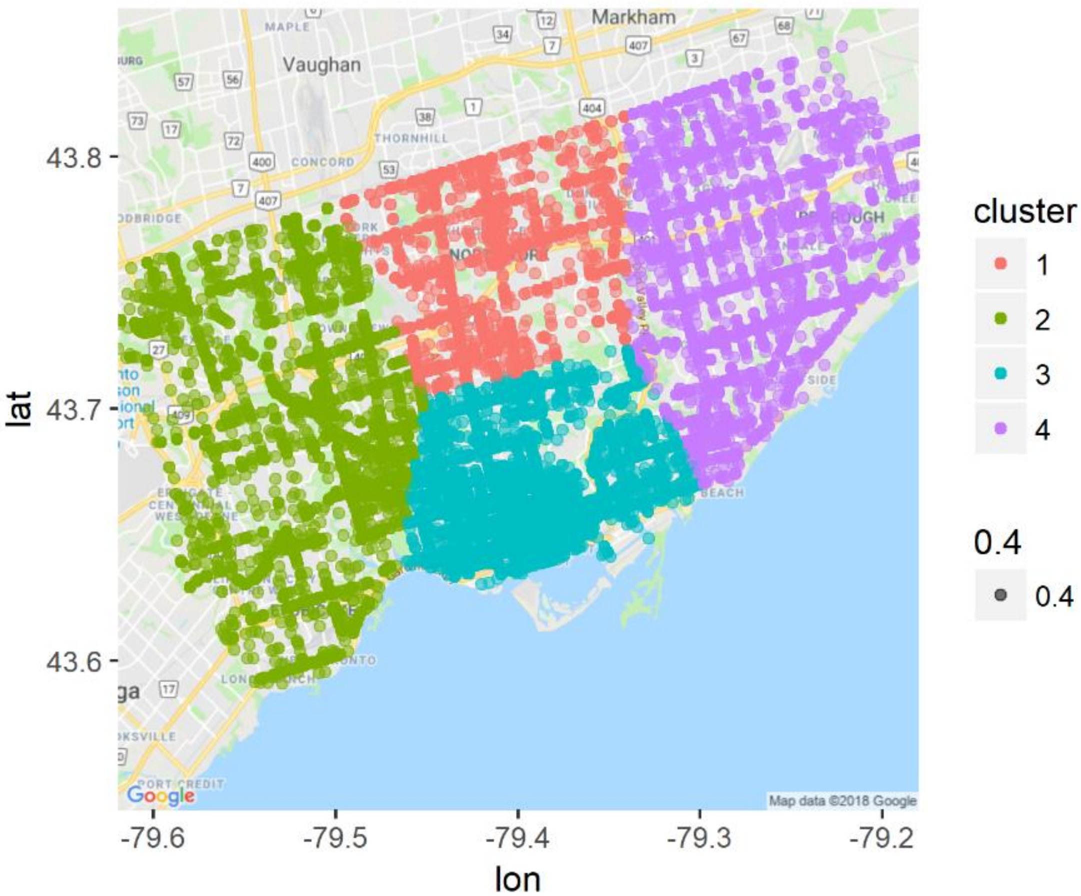



```
# silhouette method suggests 2 clusters

# Elbow method
fviz_nbclust(pedestrian.kmeans, kmeans, method = "wss") +
geom_vline(xintercept = 4, linetype = 2) +
  labs(subtitle = "Elbow method")
```

```
# elbow method suggests 4 clusters

#we will try 4 clusters since having only 2 clusters with so many points and
noise will lead to a useless outcome
```

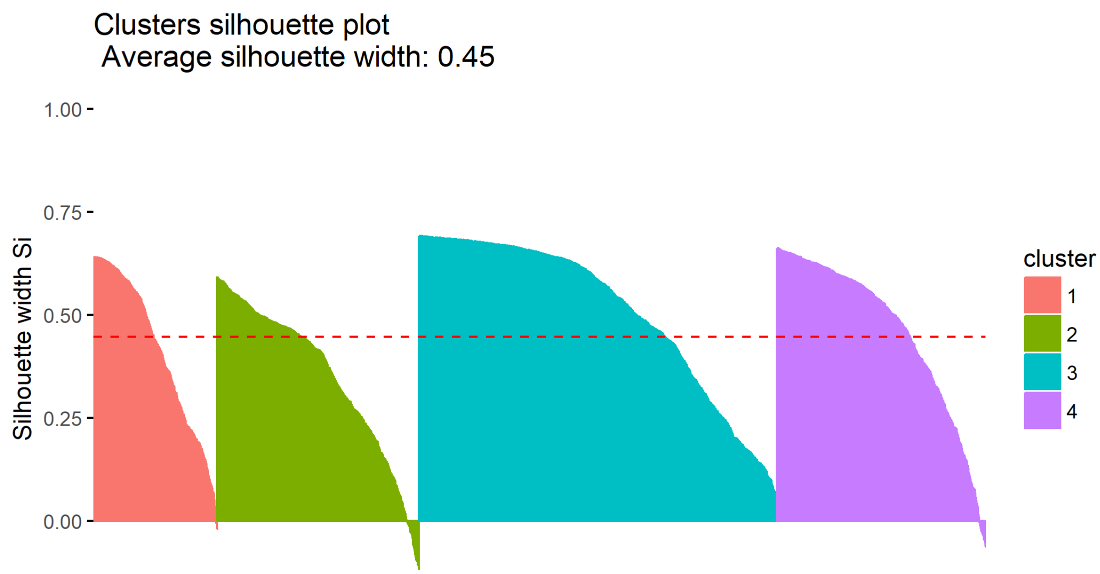



```
# k-means clustering
set.seed(123)
kmeans_model <- kmeans(pedestrian.kmeans, 4, nstart = 25)
pedestrian.kmeans$cluster <- as.factor(kmeans_model$cluster)

stopCluster(cl)
gc()

toronto_map + geom_point(aes(x = longitude, y = latitude, color = cluster,
alpha = 0.4), data = pedestrian.kmeans)
```




```
# interestingly, the kmeans clustering grouped the points roughly according
to the boundaries of North York, Etobicoke, Downtown, and Scarborough, even
though all it had was lat and lon data.

# create a disimilarity matrix for use in silhouette
dm <- as.matrix(dist(pedestrian.coords))

# use the identified clusters and dissimilarity matrix to calculate the
silhouette
# our cluster labels need to be turned back into numerical values not factor
to work
library(cluster)

## Warning: package 'cluster' was built under R version 3.3.3

pedestrian.kmeans$cluster <- as.numeric(pedestrian.kmeans$cluster)
silhouette_kmeans <- silhouette(pedestrian.kmeans$cluster, dm)

# plot results
fviz_silhouette(silhouette_kmeans, print.summary = T)

##   cluster size ave.sil.width
## 1       1 2161          0.41
```

```
## 2        2 3506          0.35
## 3        3 6237          0.51
## 4        4 3629          0.46
```



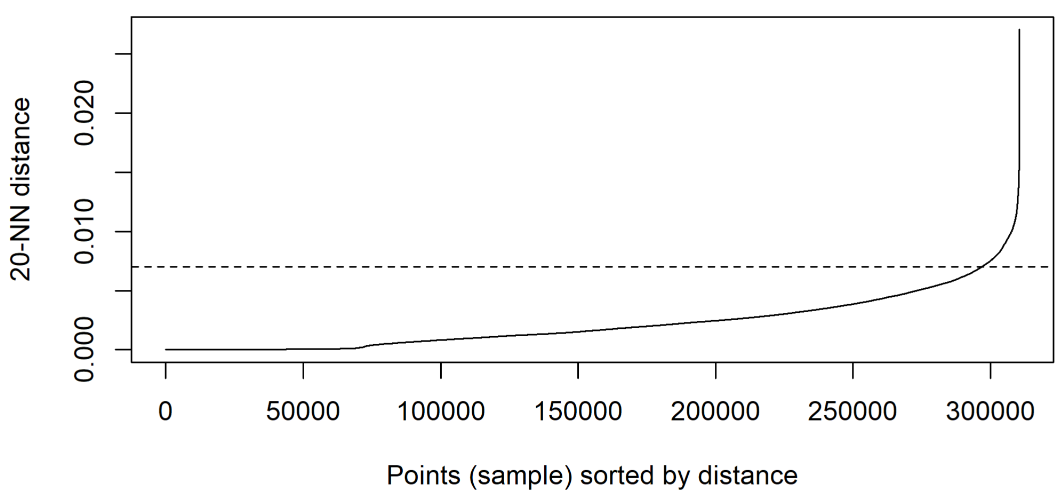

```
# With an average silhouette of 0.45, the structure of the clusters is
acceptable, but not strong. Notably cluster 2 is quite weak with an average
silhouette length of 0.35. This perhaps means that clustering by kmeans on
collision locations is reasonable, but not necessarily solid.

#add kmeans clusters to main dataset
pedestrian.df$kmeans_cluster <- pedestrian.kmeans$cluster
```

Density-based Spatial Clustering and Application with Noise (DBSCAN)

Similar in logic to both KNN and KDE, this clustering algorithm is said to have better performance for clusters of linear shape. Since my data is based on collisions on streets which have a linear shape and a lot of outliers (aka noise), it is expected for DBSCAN to perform well in this case vs. k-means which is effective at clustering points in an eliptical shape and with little noise. Another benefit of DBSCAN is that it requires no **k** to be set ahead of time. Much like KNN, it requires the minimum amount of neighbours to be set, as well as **epsilon**, which is the radius of the neighbourhood. In DBSCAN, it is possible for a point to not belong to any cluster which is beneficial in this case since we want to prioritize areas with high concentrations of collisions.

```
# for Density-based Clustering (DBSCAN) and visualization of clusters
library("dbscan")
library("factoextra")
library("knitr")

# Determining optimal epsilon
```

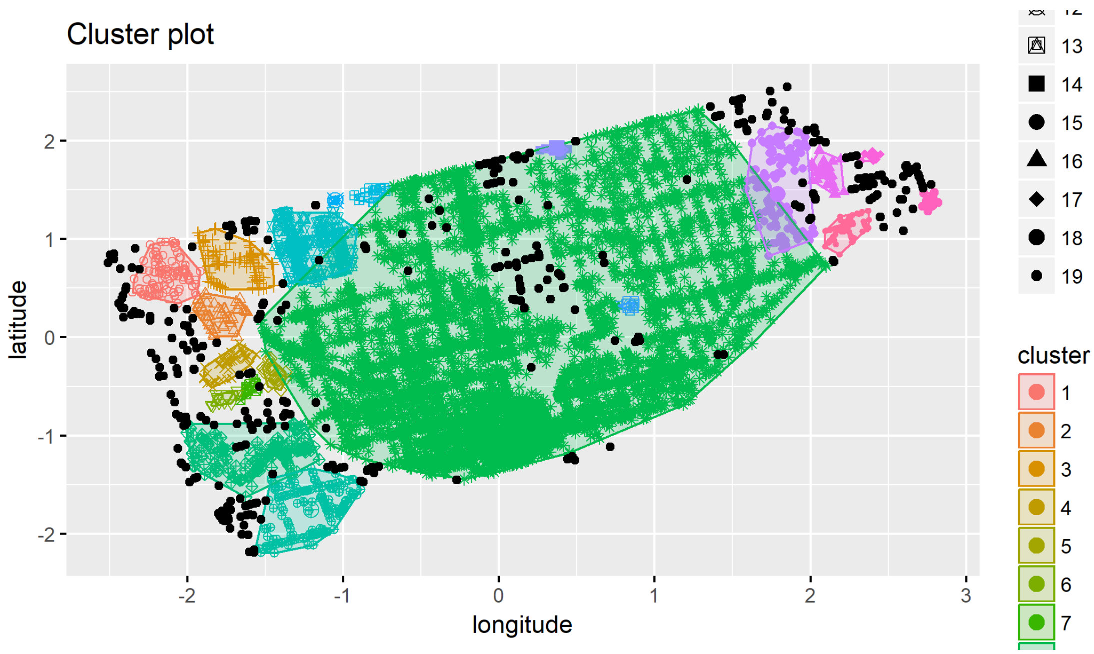
```r
# Just like k in k-means, there are methods to determine the optimal epsilon
in DBSCAN using k-nearest neighbours. The value of k in our KNN corresponds
to the min points value in DBSCAN.

# These k-distances are plotted and similar to the elbow method used above
for k-means, a sharp bend occurs which corresponds to optimal eps.

pedestrian.dbscan <- pedestrian.coords


# prepare our training and test sets
#pedestrian.dbscan <- pedestrian.coords[index,]
#test_pedestrian.dbscan <- pedestrian.coords[-index,]

# remove ksi_check since it is a classifier and we are using an unsupervised
algorithm
#train_pedestrian.dbscan <- train_pedestrian.dbscan[,-3]
#test_pedestrian.dbscan <- test_pedestrian.dbscan[,-3]

# Check for optimal epsilson value using KNN
dbscan::kNNdistplot(pedestrian.dbscan, k =  20) + abline(h = 0.007, lty = 2)
```




```
## numeric(0)
```

```r
#therefore, for dbscan, we set eps = 0.006 and minPts = 18

# However, keep in mind that an epsilon of 0.001 is equivalent to a radius of
111 metres since the coordinates are using longitude and latitude. This means
too high an eps can easily span across the entire city, leading to one giant
cluster.
```

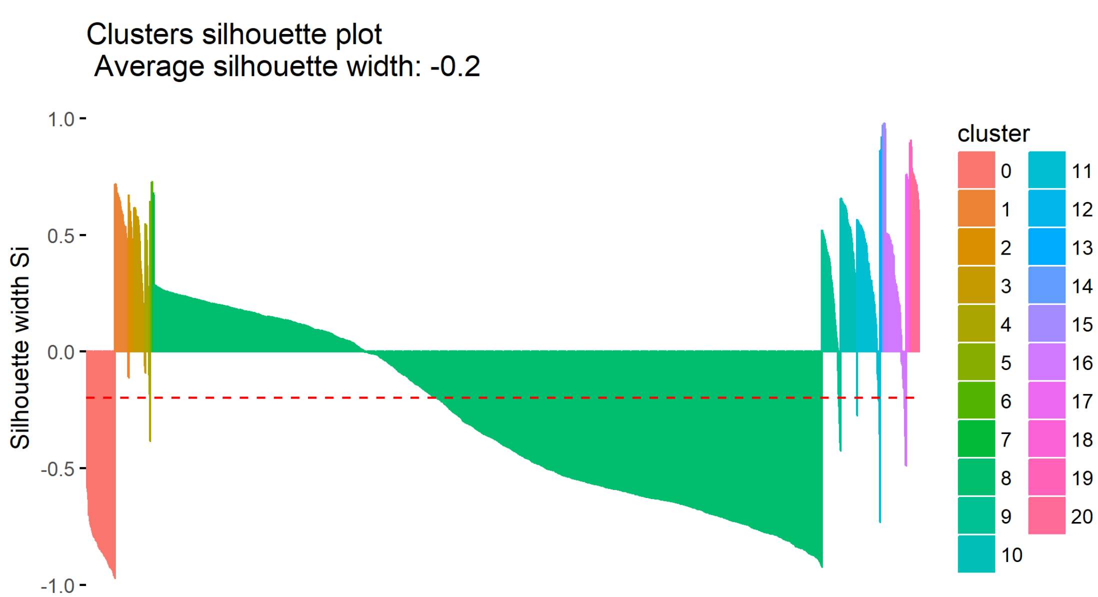
```
set.seed(123)
dbscan_model <- dbscan::dbscan(pedestrian.dbscan, 0.007, minPts = 20)

# plot the results
fviz_cluster(dbscan_model, pedestrian.dbscan, geom = "point")
```




```
# show results in text form
dbscan_model

## DBSCAN clustering for 15533 objects.
## Parameters: eps = 0.007, minPts = 20
## The clustering contains 20 cluster(s) and 538 noise points.
##
##     0     1     2     3     4     5     6     7     8     9    10    11
##   538   257    99   210    93    29    26    16 12442   349   310   429
##    12    13    14    15    16    17    18    19    20
##    32    18    17    33   386    64    20    20   145
##
## Available fields: cluster, eps, minPts

# The column names are cluster numbers - cluster 0 are the black points in
the plot. They do not fit in any cluster (considered noise)
# our model created 19 clusters and the shape of the clusters aren't as
intuitive as the kmeans model but they do seem to highlight specific
collision hotspots unlike kmeans.

# Now lets see if DBSCAN performed better than kmeans using silhouette

# use the identified clusters and dissimilarity matrix to calculate the
```

```r
silhouette
# our cluster labels need to be turned back into numerical values not factor
to work
library(cluster)
dbscan_clusters <- dbscan_model$cluster

silhouette_dbscan <- silhouette(dbscan_model$cluster, dm)

# plot results
fviz_silhouette(silhouette_dbscan, print.summary = T)
```

```
##    cluster  size ave.sil.width
## 0        0   538         -0.82
## 1        1   257          0.57
## 2        2    99          0.51
## 3        3   210          0.41
## 4        4    93          0.25
## 5        5    29          0.52
## 6        6    26          0.49
## 7        7    16          0.61
## 8        8 12442         -0.30
## 9        9   349          0.25
## 10      10   310          0.50
## 11      11   429          0.30
## 12      12    32          0.74
## 13      13    18          0.90
## 14      14    17          0.96
## 15      15    33          0.97
## 16      16   386          0.23
## 17      17    64          0.63
## 18      18    20          0.86
## 19      19    20          0.87
## 20      20   145          0.70
```



```
# With an average silhouette of -0.2, this is a far worse way to cluster the
collisions when compared to kmeans. However, certain clusters have very
strong fits. Unfortunately, the weak fit of the largest cluster - which spans
a large part of the city and is represented by the bright green colour -
brings the average silhouette down significantly.

# One thing the City could do is look at the clusters that the model
identified that have strong silhouettes (above 0.65 for example) and target
those areas for intervention. Because clusters with low silhouette scores
could easily belong to other clusters, the clusters that have high
silhouettes are quite durable.

# Due to the overall low silhouette score, however, We will exclude the
cluster labels from dbscan from further analysis and see if it is better with
multiple dimensions rather than just longitude and latitude.
```

Classification

We have so far used 3 clustering methods to group collisions based on their geo-spatial attributes. These clusters were then added as new features to the dataset so we can see whether they are good predictors. For classification purposes, we can't use KDE, but we can use both k-means and DBSCAN in order to see if there are shared characteristics between collisions and come up with a way to profile high collision zones.

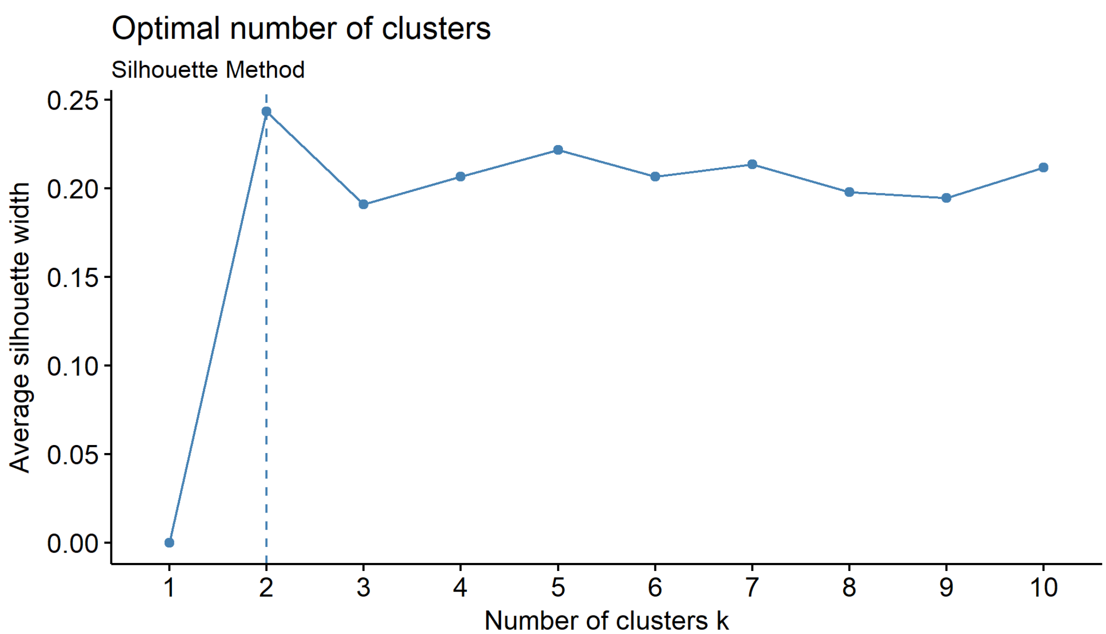
Creating a Training and Test Set I created a training and test set in case I want to use a supervised machine learning algorithm for classifcation.

```
library(caret)
pedestrian.df$kmeans_cluster <- as.factor(pedestrian.df$kmeans_cluster)

# create random stratified sample so that the proportion of k-means clusters
is similar across the training set and test set
set.seed(123)
index <- createDataPartition(pedestrian.df$kmeans_cluster, times = 1, p =
0.75, list = F)
train_pedestrian <- pedestrian.df[index,]
test_pedestrian <- pedestrian.df[-index,]

# verifying the stratified samples have similar distributions of collisions
based on location
prop.table(table(train_pedestrian$kmeans_cluster))

##
##         1         2         3         4
## 0.1391297 0.2257317 0.4015106 0.2336280

prop.table(table(test_pedestrian$kmeans_cluster))
```

```
##
##         1         2         3         4
## 0.1391036 0.2256569 0.4015971 0.2336425
```

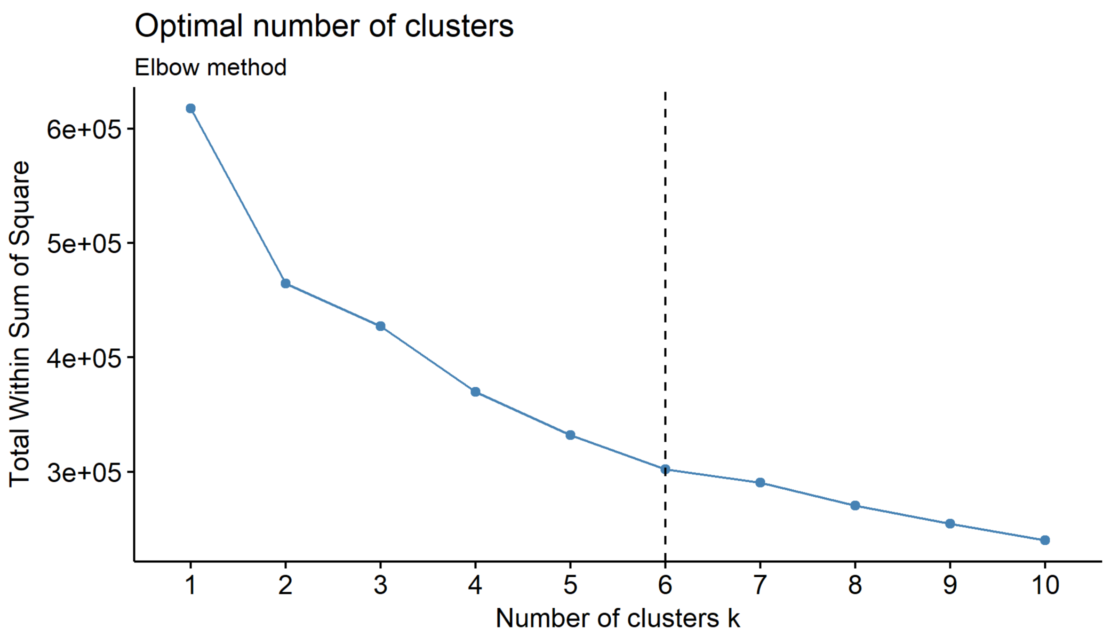
K-means Clustering Classification Model

```
# Before applying k-means, we must find k, the optimal number of clusters
library(factoextra)
library(NbClust)
library(doSNOW)

# Normalizing numerical values
train_pedestrian_num <- Filter(is.numeric, train_pedestrian)
train_pedestrian_num_norm <- scale(train_pedestrian_num)
train_pedestrian_num_norm <- as.data.frame(train_pedestrian_num_norm)

# creating parallel processing clusters
# WARNING be sure your computer has at least 4 processing cores and 16 GB of
RAM
cl <- makeCluster(3, type = "SOCK")
registerDoSNOW(cl)

# Using avg silhouette to determine optimal k clusters
fviz_nbclust(train_pedestrian_num_norm, kmeans, method = "silhouette") +
labs(subtitle = "Silhouette Method")
```

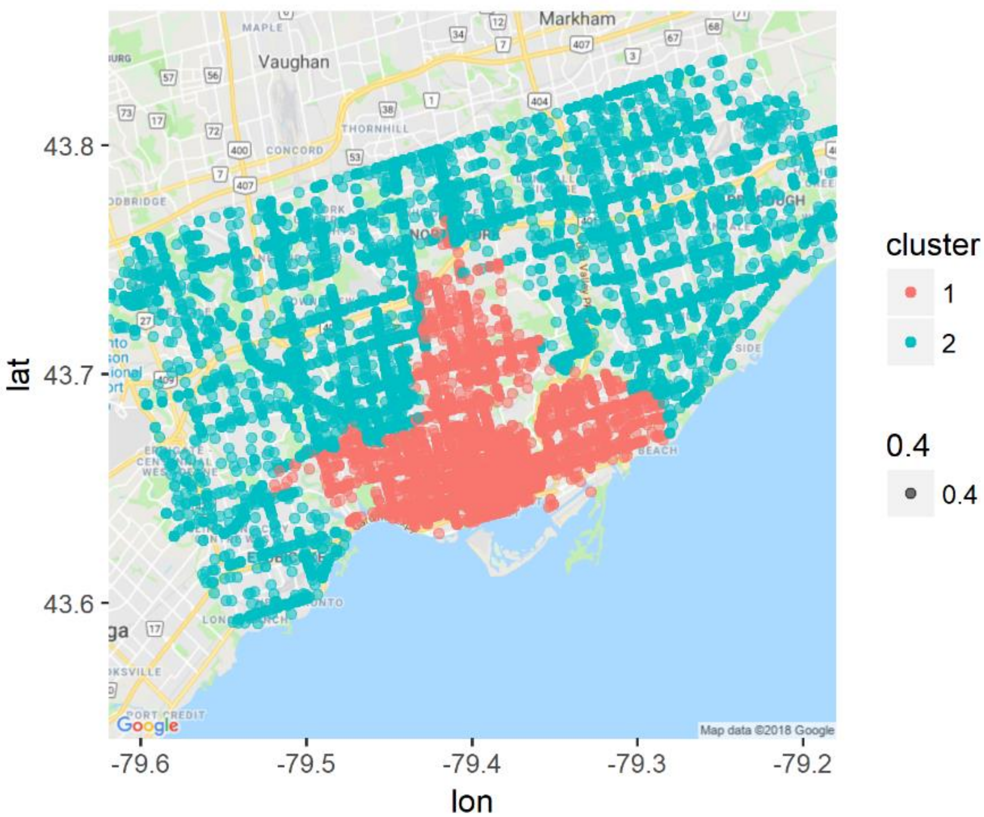



```
# silhouette method suggests 2 clusters

# Elbow method
fviz_nbclust(train_pedestrian_num_norm, kmeans, method = "wss") +
```

```r
geom_vline(xintercept = 6, linetype = 2) +
  labs(subtitle = "Elbow method")
```

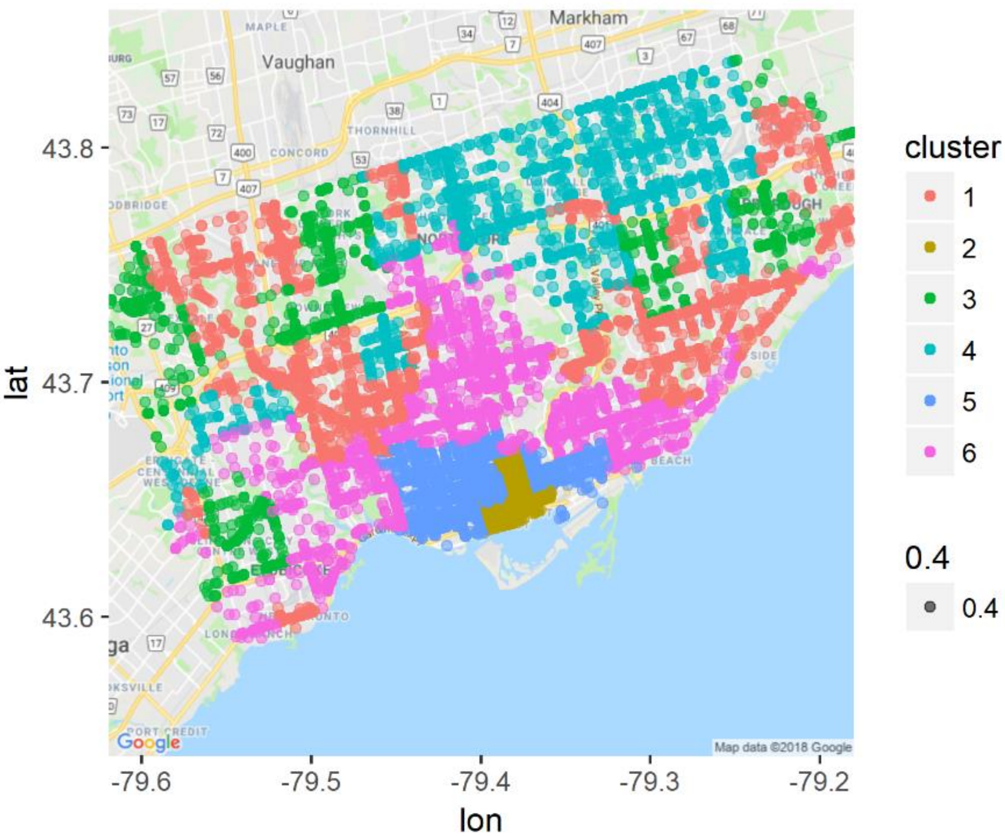



```r
# elbow method suggests 6 clusters


# we can go either 2 or 6 clusters - I will try both and see which has better
silhouette score
# k = 2
set.seed(123)
train_kmeans_k2 <- kmeans(train_pedestrian_num_norm, 2, nstart = 25)
train_pedestrian_num_norm_k2 <- train_pedestrian_num_norm
train_pedestrian_num_norm_k2$cluster <- as.factor(train_kmeans_k2$cluster)
train_pedestrian_num_norm_k2$longitude <- train_pedestrian_num$longitude
train_pedestrian_num_norm_k2$latitude <- train_pedestrian_num$latitude

toronto_map + geom_point(aes(x = longitude, y = latitude, color = cluster,
alpha = 0.4), data = train_pedestrian_num_norm_k2)
```

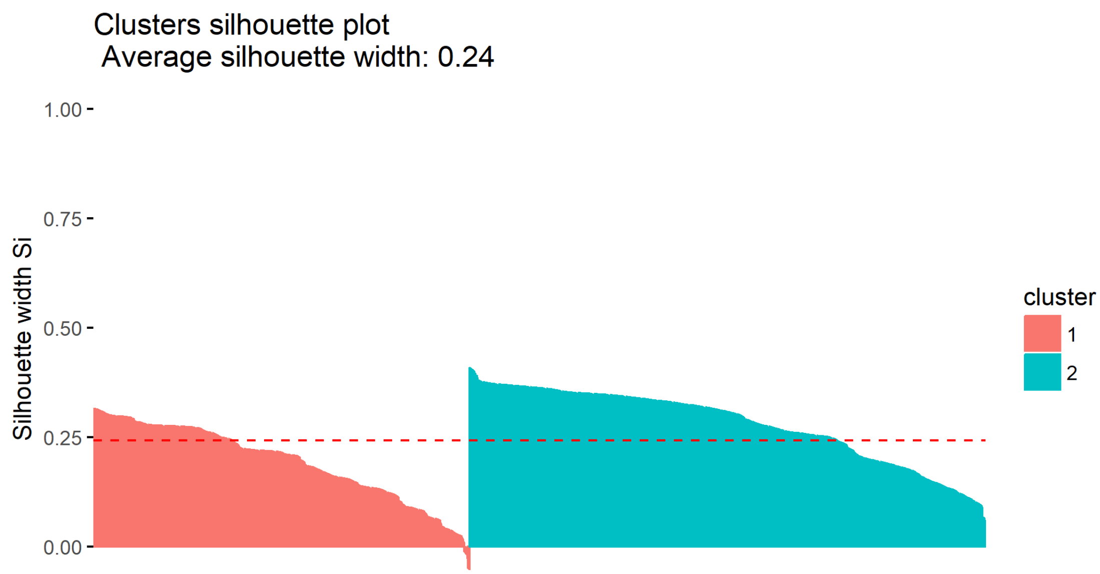



```r
# This cluster pattern is quite intuitive -- cluster 1 is the downtown core,
cluster 2 is everything outside the core. Let's see what it looks like when
we use 6 as suggested by the Elbow Method.

# k = 6
set.seed(123)
train_kmeans_k6 <- kmeans(train_pedestrian_num_norm, 6, nstart = 25)
train_pedestrian_num_norm_k6 <- train_pedestrian_num_norm
train_pedestrian_num_norm_k6$cluster <- as.factor(train_kmeans_k6$cluster)
train_pedestrian_num_norm_k6$longitude <- train_pedestrian_num$longitude
train_pedestrian_num_norm_k6$latitude <- train_pedestrian_num$latitude

toronto_map + geom_point(aes(x = longitude, y = latitude, color = cluster,
alpha = 0.4), data = train_pedestrian_num_norm_k6)
```

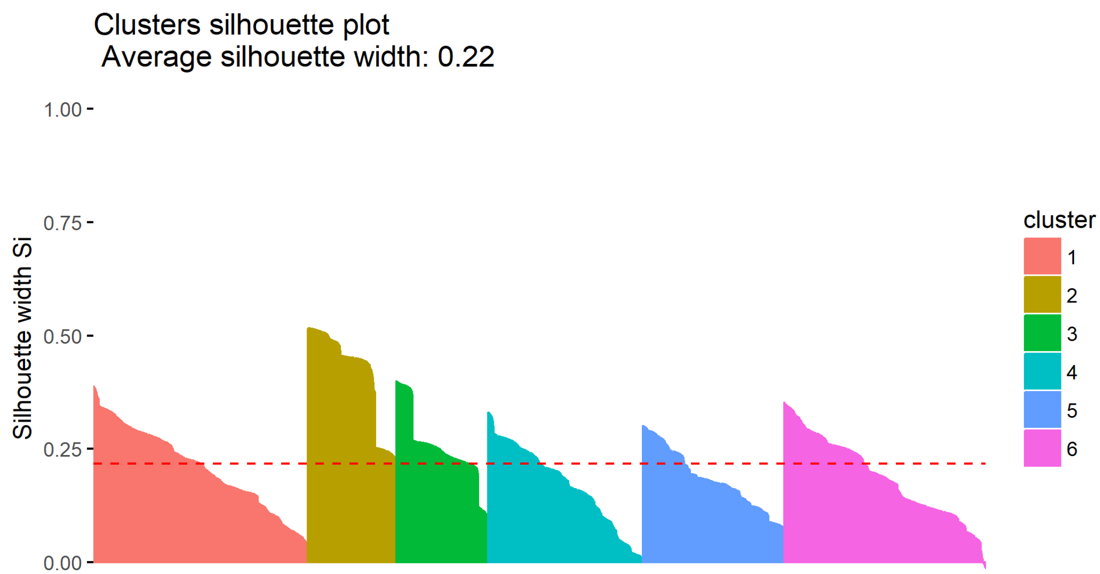
```
# here too the downtown core is clearly identifiable, but the outlying clusters are mixed together and it is hard to tell from the plot what characteristics the points within these clusters share. Later, we will use Random Forest to see which variables are most important to each cluster to answer this question.
```




```
# performance testing using silhouette
library(cluster)
# create a disimilarity matrix for use in silhouette
dm <- as.matrix(dist(train_pedestrian_num_norm))
train_pedestrian_num_norm_k2$cluster <-
as.numeric(train_pedestrian_num_norm_k2$cluster)
train_pedestrian_num_norm_k6$cluster <-
as.numeric(train_pedestrian_num_norm_k6$cluster)

# calculate and plot silhouette for k = 2 model
silhouette_k2 <- silhouette(train_pedestrian_num_norm_k2$cluster, dm)
fviz_silhouette(silhouette_k2, print.summary = T)

##   cluster size ave.sil.width
## 1       1 4910          0.19
## 2       2 6741          0.28
```



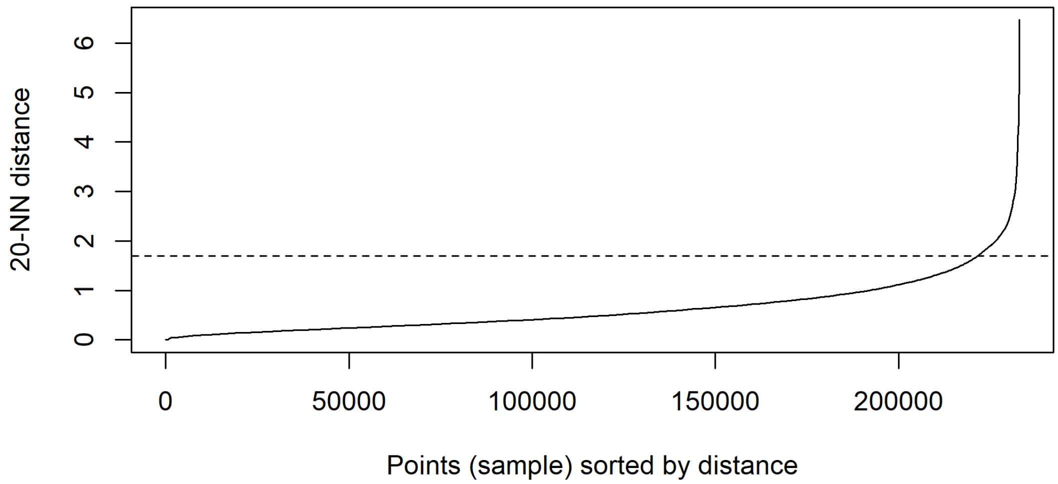

```
# with an average silhouette of 0.24, the clusters are quite weak

# calculate and plot silhouette for k = 6 model
silhouette_k6 <- silhouette(train_pedestrian_num_norm_k6$cluster, dm)
fviz_silhouette(silhouette_k6, print.summary = T)

##   cluster size ave.sil.width
## 1       1 2804          0.21
## 2       2 1152          0.42
## 3       3 1199          0.25
## 4       4 2022          0.17
## 5       5 1847          0.18
## 6       6 2627          0.19
```



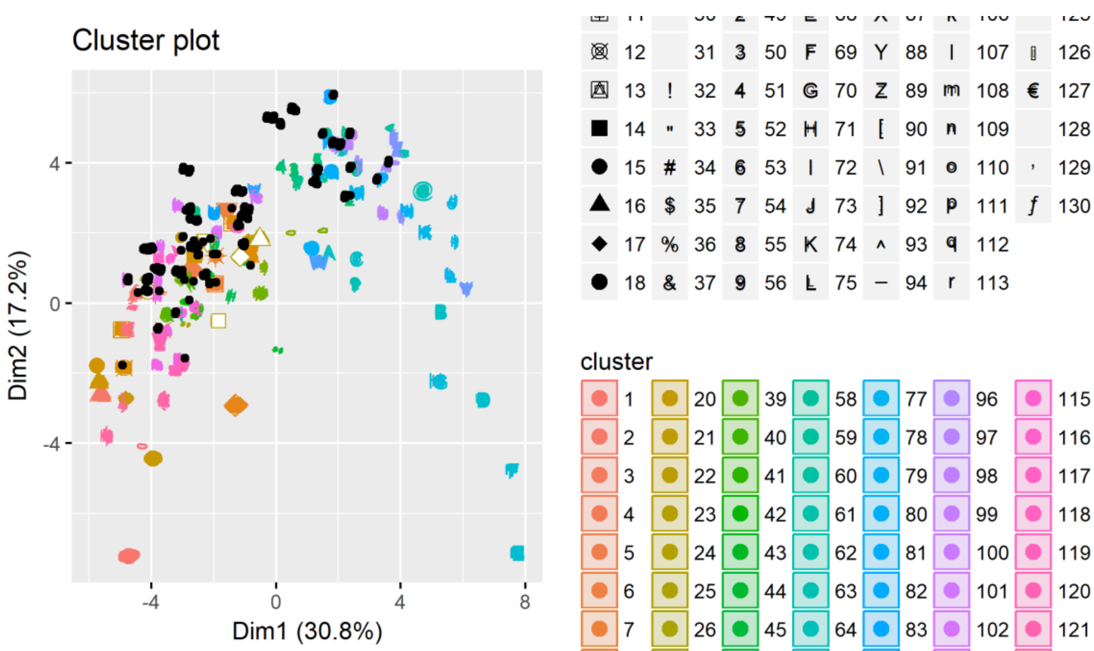

```
# with an average silhouette of 0.21, this is a very poor model
stopCluster(cl)
gc()

##             used   (Mb) gc trigger   (Mb)   max used    (Mb)
## Ncells   2362853  126.2    3886542  207.6    3886542   207.6
## Vcells 149209943 1138.4  670484527 5115.4 1313139997 10018.5

# Considering how both k = 2 and k = 6 let to poor clustering performance, we
will not use kmeans any further.
```

DBSCAN Classification

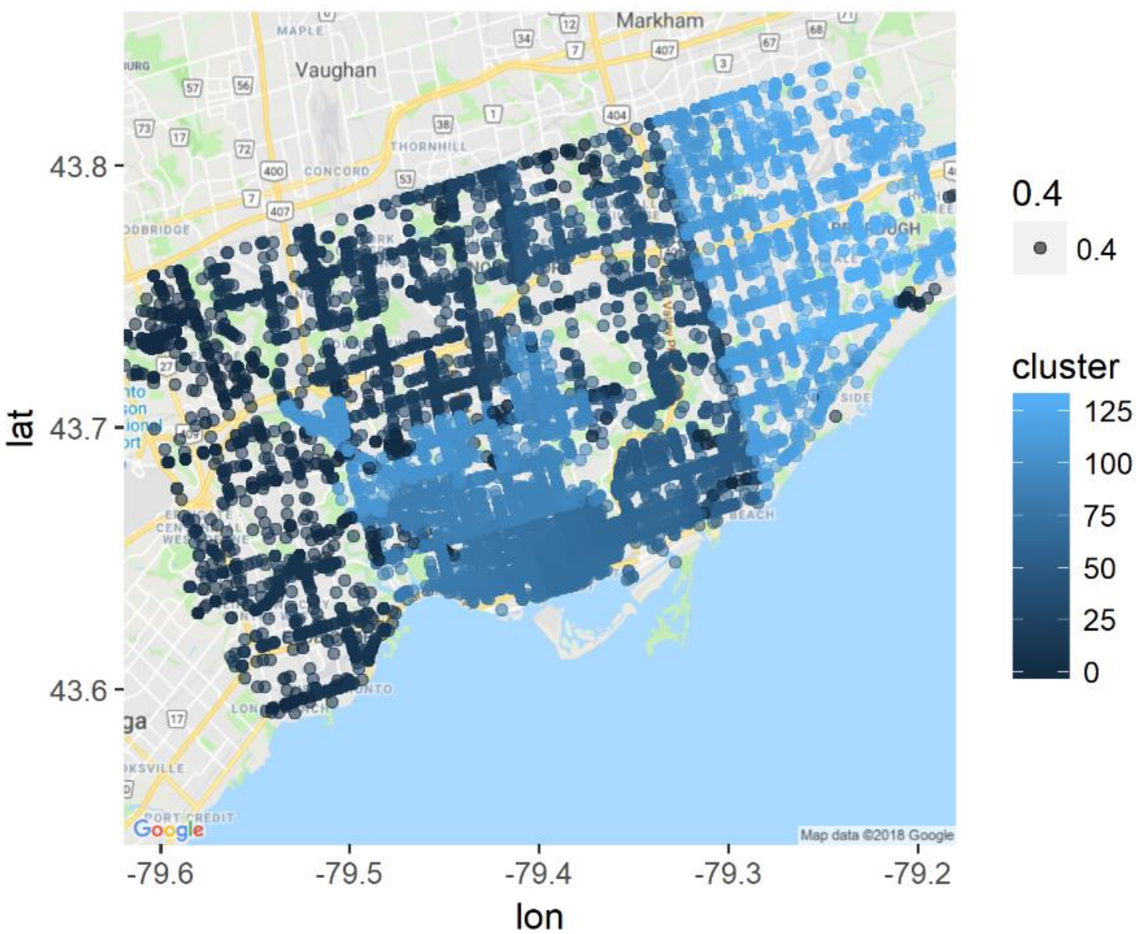
```
# for Density-based Clustering (DBSCAN) and visualization of clusters
library("dbscan")
library("factoextra")
library("knitr")

# Determining optimal epsilon

train_dbscan <- train_pedestrian_num_norm

# Check for optimal epsilson value using KNN
dbscan::kNNdistplot(train_dbscan, k =  20) + abline(h = 1.7, lty = 2)
```




```
## numeric(0)

#therefore, for dbscan, we set eps = 1.7 and minPts = 20

set.seed(123)
train_dbscan_model <- dbscan::dbscan(train_dbscan, 1.7, minPts = 20)

# plot the results
fviz_cluster(train_dbscan_model, train_dbscan, geom = "point")
```

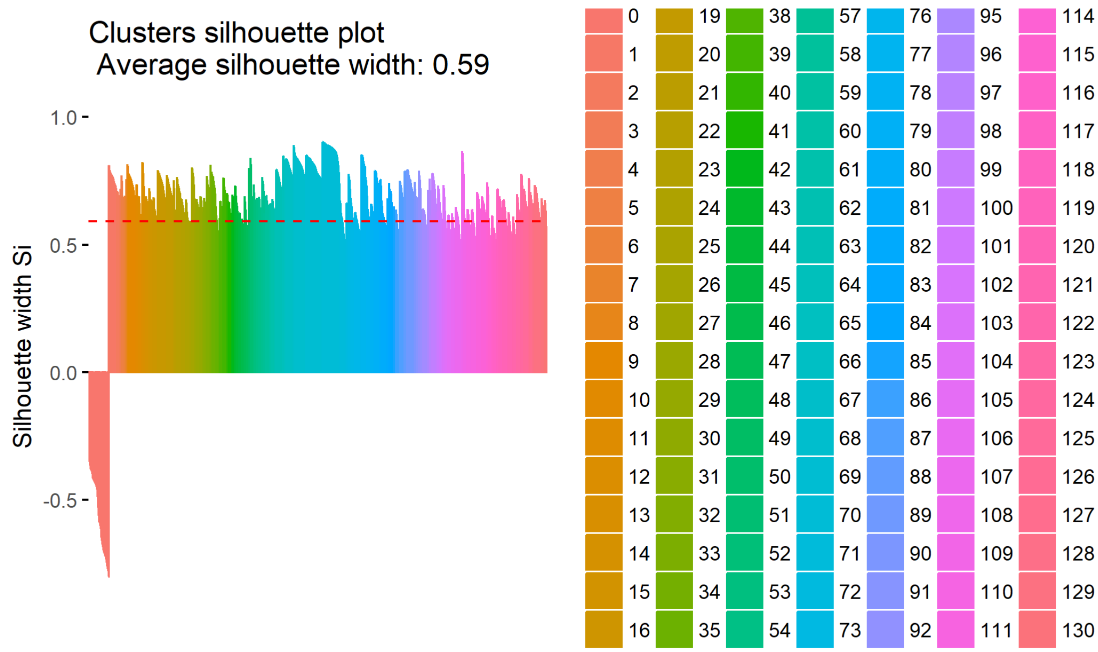


```
# show results in text form
train_dbscan_model

# our model created 133 clusters and the shape of the clusters aren't as intuitive as the kmeans model since lon and lat were normalized. However, I replot the clusters using actual lon and lat coordinates and we are able to see what the clusters look like in real space:

train_dbscan_17 <- train_pedestrian_num_norm
train_dbscan_17$cluster <- train_dbscan_model$cluster
train_dbscan_17$longitude <- train_pedestrian_num$longitude
train_dbscan_17$latitude <- train_pedestrian_num$latitude

toronto_map + geom_point(aes(x = longitude, y = latitude, color = cluster, alpha = 0.4), data = train_dbscan_17)
```




```
# This clustering pattern is very different from kmeans - first, there are a lot more clusters, and second, the clusters that are away from the downtown core are in a grid-like pattern -- a pattern we could expect due to the grid-like layout of toronto's streets!
```

```
# Now lets see if DBSCAN performed better than kmeans using silhouette

silhouette_dbscan_17 <- silhouette(train_dbscan_17$cluster, dm)
fviz_silhouette(silhouette_dbscan_17, print.summary = T)
```



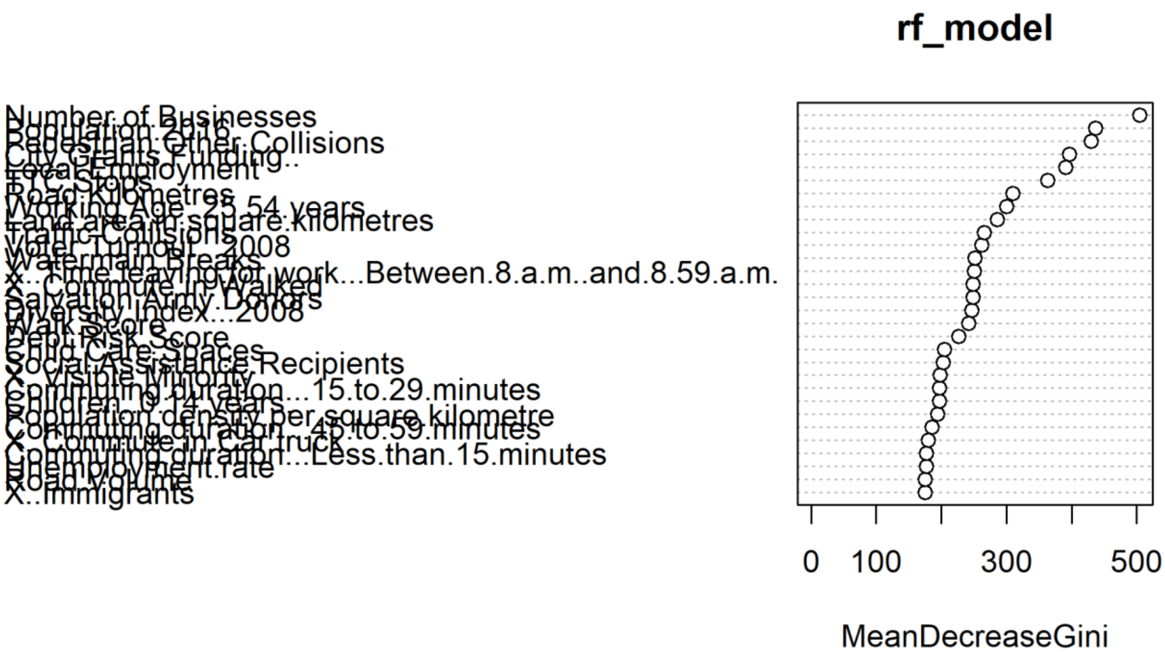

```
# with an average silhouette of 0.59, the clusters are quite strong. Only
cluster 0 is problematic, which we would expect since in DBSCAN, cluster 0 is
classified as noise.
```

Using Random Forest to Profile Clusters

We now have a reliable way to cluster the collision zones in Toronto, but no real idea of what are the shared characteristics of the points within each cluster. The visualization of the clusters hint that location (Scarborough, Downtown Core) play an important role, but what other variables are important to determining a collision's membership in a cluster? We use Random Forest to find out.

```
library(randomForest)

# remove cluster 0 since they are classified as noise by DBSCAN - I set all
cluster 0 to NA so that I can easily remove them
train_dbscan_17$cluster <- as.numeric(train_dbscan_17$cluster)
train_dbscan_17_clean <- train_dbscan_17
train_dbscan_17_clean$cluster[train_dbscan_17_clean$cluster == 0] <- NA
train_dbscan_17_clean <-
train_dbscan_17_clean[complete.cases(train_dbscan_17_clean),]

# random forest process
train_dbscan_17$cluster <- as.factor(train_dbscan_17$cluster)
```

```r
names(train_dbscan_17) <- make.names(names(train_dbscan_17))

# parallel processing
cl <- makeCluster(3, type = "SOCK")
registerDoSNOW(cl)

# RF model
set.seed(123)
rf_model <- randomForest(cluster ~ ., data = train_dbscan_17)
varImpPlot(rf_model)
```




```r
stopCluster(cl)

# Random Forest suggests that Number of businesses, population of the
neighbourhood, city grant funding, TTC stops, total road kilometrage in the
neighbourhood, and living in a neighbourhood of working age people all
contribute to the cluster characteristics.
```