Crash Fatalities

JAlexandra

2025-05

Purpose

I am looking at understanding the relationship between fatalCount (the count of fatalities associated with a crash) and the rest of the variables in this data set.

Looking at the data descriptions

On https://opendata-nzta.opendata.arcgis.com/pages/cas-data-field-descriptions there are the descriptions of the variables along with their variable names in the Crash data set.

I found that the variables crashDistance, easting, northing, and roadMarkings are listed as in the data set on that page, but are not in this csv.

The variables X, Y, objectID, and crashRoadSideRoad are in the data set but are not listed on this page.

The X-coordinate is often referred to as the "Easting", it seems like a reasonable assumption to say that the easting variable is the X variable and the northing variable is the Y variable in this dataset.

However there is no obvious link between the variables crashDistance, roadMarkings, objectID and crashRoadSideRoad.

Because I cannot determine the exact meanings of the variables objectID, and crashRoadSideRoad I will be removing them from the data set.

Small discrepencies in variable names when comparing the field descriptions variable names to the data sets variable names:

The variable intersectionMidblock mentioned in the field descriptions appears to be the variable intersection in the dataset.

Likewise with roadCharacter1 and roadCharacter.

The variables fatalCount, crashSeverity, seriousInjuryCount and minorInjuryCount contain similar information and I'm choosing to drop crashSeverity, seriousInjuryCount and minorInjuryCount

There are a significant amount variables that give location data, such as X, Y, and region. For the purposes of this research much of this information is redundant, as a result I will be removing the following variables crashLocation1, crashLocation2, directionRoleDescription and tlaName.

The variables crashYear and crashFinancialYear contain similar information, and I am choosing to drop crashFinancialYear.

The variable urban is derived from the variable speedLimit, since it contains the same information I will be removing it from the data set.

Libraries

```
library(readxl)
library(finalfit)
library(naniar)
library(scales)
library(psych)
library(ggcorrplot)
library(caret)
library(moments)
library(MVN)
library(reshape2)
library(ggplot2)
library(pander)
library(car)
library(MASS)
library(dplyr)
library(AER)
library(performance)
```

Loading Data

```
Crash <- read.csv("Crash_Analysis_System_(CAS)_data.csv",
                  na.strings = c("", "Unknown", "Null", "Nil"))
```

Dropping unknown variables:

```
Crash <- subset(Crash, select = -c(OBJECTID, crashRoadSideRoad))
```

Dropping unnecessary variables:

```
Crash <- subset(Crash, select = c(-crashSeverity, -crashLocation1, -crashLocation2,
        -crashFinancialYear, -tlaName, -tlaId, -directionRoleDescription,
        -seriousInjuryCount, -minorInjuryCount, -urban))
```

EDA

Quantitative analysis

```
pander(data.frame(
  mean = sapply(select_if(Crash, is.numeric), mean, na.rm = TRUE),
  median = sapply(select_if(Crash, is.numeric), median, na.rm = TRUE),
  iqr = sapply(select_if(Crash, is.numeric), IQR, na.rm = TRUE)
))
```

	mean	median	iqr
X	1721397	1757428	89494
Y	5644547	5802445	479769
advisorySpeed	54.21	55	25
areaUnitID	546282	536651	53813
bicycle	0.02873	0	0
bridge	0.0137	0	0
bus	0.01593	0	0
carStationWagon	1.302	1	1
cliffBank	0.1063	0	0
crashYear	2012	2011	13
debris	0.00844	0	0
ditch	0.09428	0	0
fatalCount	0.01045	0	0
fence	0.2104	0	0
guardRail	0.08129	0	0
houseOrBuilding	0.02353	0	0
kerb	0.03547	0	0
meshblockId	1351845	1177900	1525399
moped	0.007022	0	0
motorcycle	0.03711	0	0
NumberOfLanes	2.332	2	0
objectThrownOrDropped	0.002169	0	0
otherObject	0.02378	0	0
otherVehicleType	0.005422	0	0
overBank	0.0422	0	0
parkedVehicle	0.2575	0	0
pedestrian	1.044	1	0
phoneBoxEtc	0.01256	0	0
postOrPole	0.1221	0	0
roadworks	0.003147	0	0
schoolBus	0.0008131	0	0
slipOrFlood	0.002536	0	0
speedLimit	65.94	50	50
strayAnimal	0.004231	0	0
suv	0.107	0	0
taxi	0.01064	0	0
temporarySpeedLimit	45.33	40	20
trafficIsland	0.0288	0	0
trafficSign	0.04928	0	0
train	0.001449	0	0
tree	0.1029	0	0
truck	0.0799	0	0
unknownVehicleType	0.003839	0	0
vanOrUtility	0.1783	0	0
vehicle	0.02407	0	0
waterRiver	0.009777	0	0

The variables are on extremely different scales, which could affect the values of regression coefficients, but will not affect the statistical significance or interpretation of the coefficients for the later regression.

```r
pander(summary(Crash))
```

Table 2: Table continues below

X	Y	advisorySpeed	areaUnitID
Min. :1150346	Min. :4721798	Min. :15.00	Min. :500100
1st Qu.:1704319	1st Qu.:5434056	1st Qu.:40.00	1st Qu.:519710
Median :1757428	Median :5802445	Median :55.00	Median :536651
Mean :1721397	Mean :5644547	Mean :54.21	Mean :546282
3rd Qu.:1793813	3rd Qu.:5913825	3rd Qu.:65.00	3rd Qu.:573523
Max. :2465388	Max. :6190095	Max. :95.00	Max. :626801
NA	NA	NA's :836776	NA's :4

Table 3: Table continues below

bicycle	bridge	bus	carStationWagon
Min. :0.00000	Min. :0.00	Min. :0.00000	Min. : 0.000
1st Qu.:0.00000	1st Qu.:0.00	1st Qu.:0.00000	1st Qu.: 1.000
Median :0.00000	Median :0.00	Median :0.00000	Median : 1.000
Mean :0.02873	Mean :0.01	Mean :0.01593	Mean : 1.302
3rd Qu.:0.00000	3rd Qu.:0.00	3rd Qu.:0.00000	3rd Qu.: 2.000
Max. :5.00000	Max. :4.00	Max. :3.00000	Max. :11.000
NA's :5	NA's :513897	NA's :5	NA's :5

Table 4: Table continues below

cliffBank	crashDirectionDescription	crashSHDescription	crashYear
Min. :0.00	Length:870753	Length:870753	Min. :2000
1st Qu.:0.00	Class :character	Class :character	1st Qu.:2005
Median :0.00	Mode :character	Mode :character	Median :2011
Mean :0.11	NA	NA	Mean :2012
3rd Qu.:0.00	NA	NA	3rd Qu.:2018
Max. :3.00	NA	NA	Max. :2025
NA's :513897	NA	NA	NA

Table 5: Table continues below

debris	ditch	fatalCount	fence
Min. :0.00	Min. :0.00	Min. :0.00000	Min. :0.00
1st Qu.:0.00	1st Qu.:0.00	1st Qu.:0.00000	1st Qu.:0.00
Median :0.00	Median :0.00	Median :0.00000	Median :0.00
Mean :0.01	Mean :0.09	Mean :0.01045	Mean :0.21
3rd Qu.:0.00	3rd Qu.:0.00	3rd Qu.:0.00000	3rd Qu.:0.00
Max. :7.00	Max. :3.00	Max. :9.00000	Max. :4.00
NA's :513897	NA's :513897	NA's :1	NA's :513897

Table 6: Table continues below

flatHill	guardRail	holiday	houseOrBuilding
Length:870753	Min. :0.00	Length:870753	Min. :0.00
Class :character	1st Qu.:0.00	Class :character	1st Qu.:0.00
Mode :character	Median :0.00	Mode :character	Median :0.00
NA	Mean :0.08	NA	Mean :0.02
NA	3rd Qu.:0.00	NA	3rd Qu.:0.00
NA	Max. :4.00	NA	Max. :2.00
NA	NA's :513897	NA	NA's :513897

Table 7: Table continues below

intersection	kerb	light	meshblockId
Mode:logical	Min. :0.00	Length:870753	Min. : 100
NA's:870753	1st Qu.:0.00	Class :character	1st Qu.: 602401
NA	Median :0.00	Mode :character	Median :1177900
NA	Mean :0.04	NA	Mean :1351845
NA	3rd Qu.:0.00	NA	3rd Qu.:2127800
NA	Max. :3.00	NA	Max. :3209003
NA	NA's :513897	NA	NA's :4

Table 8: Table continues below

moped	motorcycle	NumberOfLanes	objectThrownOrDropped
Min. :0.000000	Min. :0.00000	Min. :0.000	Min. :0
1st Qu.:0.000000	1st Qu.:0.00000	1st Qu.:2.000	1st Qu.:0
Median :0.000000	Median :0.00000	Median :2.000	Median :0
Mean :0.007021	Mean :0.03711	Mean :2.332	Mean :0
3rd Qu.:0.000000	3rd Qu.:0.00000	3rd Qu.:2.000	3rd Qu.:0
Max. :4.000000	Max. :8.00000	Max. :9.000	Max. :4
NA's :5	NA's :5	NA's :2094	NA's :513897

Table 9: Table continues below

otherObject	otherVehicleType	overBank	parkedVehicle	pedestrian
Min. :0.00	Min. :0.000000	Min. :0.00	Min. :0.00	Min. :1.00
1st Qu.:0.00	1st Qu.:0.000000	1st Qu.:0.00	1st Qu.:0.00	1st Qu.:1.00
Median :0.00	Median :0.000000	Median :0.00	Median :0.00	Median :1.00
Mean :0.02	Mean :0.005422	Mean :0.04	Mean :0.26	Mean :1.04
3rd Qu.:0.00	3rd Qu.:0.000000	3rd Qu.:0.00	3rd Qu.:0.00	3rd Qu.:1.00
Max. :5.00	Max. :3.000000	Max. :4.00	Max. :8.00	Max. :7.00
NA's :513897	NA's :5	NA's :513897	NA's :513897	NA's :842125

Table 10: Table continues below

phoneBoxEtc	postOrPole	region	roadCharacter
Min. :0.00	Min. :0.00	Length:870753	Length:870753
1st Qu.:0.00	1st Qu.:0.00	Class :character	Class :character
Median :0.00	Median :0.00	Mode :character	Mode :character
Mean :0.01	Mean :0.12	NA	NA
3rd Qu.:0.00	3rd Qu.:0.00	NA	NA
Max. :3.00	Max. :4.00	NA	NA
NA's :513897	NA's :513897	NA	NA

Table 11: Table continues below

roadLane	roadSurface	roadworks	schoolBus
Length:870753	Length:870753	Min. :0	Min. :0.0000000
Class :character	Class :character	1st Qu.:0	1st Qu.:0.0000000
Mode :character	Mode :character	Median :0	Median :0.0000000
NA	NA	Mean :0	Mean :0.0008131
NA	NA	3rd Qu.:0	3rd Qu.:0.0000000
NA	NA	Max. :3	Max. :3.0000000
NA	NA	NA's :513897	NA's :5

Table 12: Table continues below

slipOrFlood	speedLimit	strayAnimal	streetLight
Min. :0	Min. : 2.00	Min. :0	Length:870753
1st Qu.:0	1st Qu.: 50.00	1st Qu.:0	Class :character
Median :0	Median : 50.00	Median :0	Mode :character
Mean :0	Mean : 65.94	Mean :0	NA
3rd Qu.:0	3rd Qu.:100.00	3rd Qu.:0	NA
Max. :4	Max. :110.00	Max. :3	NA
NA's :513897	NA's :1148	NA's :513897	NA

Table 13: Table continues below

suv	taxi	temporarySpeedLimit	trafficControl
Min. :0.000	Min. :0.00000	Min. : 10.00	Length:870753
1st Qu.:0.000	1st Qu.:0.00000	1st Qu.: 30.00	Class :character
Median :0.000	Median :0.00000	Median : 40.00	Mode :character
Mean :0.107	Mean :0.01064	Mean : 45.33	NA
3rd Qu.:0.000	3rd Qu.:0.00000	3rd Qu.: 50.00	NA
Max. :6.000	Max. :5.00000	Max. :100.00	NA
NA's :5	NA's :5	NA's :856353	NA

Table 14: Table continues below

trafficIsland	trafficSign	train	tree	truck
Min. :0.00	Min. :0.00	Min. :0	Min. :0.0	Min. :0.0000
1st Qu.:0.00	1st Qu.:0.00	1st Qu.:0	1st Qu.:0.0	1st Qu.:0.0000
Median :0.00	Median :0.00	Median :0	Median :0.0	Median :0.0000
Mean :0.03	Mean :0.05	Mean :0	Mean :0.1	Mean :0.0799
3rd Qu.:0.00	3rd Qu.:0.00	3rd Qu.:0	3rd Qu.:0.0	3rd Qu.:0.0000
Max. :4.00	Max. :4.00	Max. :1	Max. :4.0	Max. :5.0000
NA's :513897	NA's :513897	NA's :513897	NA's :513897	NA's :5

Table 15: Table continues below

unknownVehicleType	vanOrUtility	vehicle	waterRiver
Min. :0.000000	Min. :0.0000	Min. :0.00	Min. :0.00
1st Qu.:0.000000	1st Qu.:0.0000	1st Qu.:0.00	1st Qu.:0.00
Median :0.000000	Median :0.0000	Median :0.00	Median :0.00
Mean :0.003839	Mean :0.1783	Mean :0.02	Mean :0.01
3rd Qu.:0.000000	3rd Qu.:0.0000	3rd Qu.:0.00	3rd Qu.:0.00
Max. :3.000000	Max. :6.0000	Max. :4.00	Max. :2.00
NA's :5	NA's :5	NA's :513897	NA's :513897

weatherA	weatherB
Length:870753	Length:870753
Class :character	Class :character
Mode :character	Mode :character
NA	NA
NA	NA
NA	NA
NA	NA

Count data: fatalCount, bicycle, bridge, bus, carStationWagon, cliffBank, debris, ditch, fence, guardRail, houseOrBuilding, kerb, moped, motorcycle, NumberOfLanes, objectThrownOrDropped, otherObject, otherVehicleType, overBank, parkedVehicle, pedestrian, phoneBoxEtc, postOrPole, roadworks, schoolBus, slipOrFlood, strayAnimal, suv, taxi, trafficIsland, trafficSign, train, tree, truck, unknownVehicleType, vanOrUtility, vehicle, waterRiver.

A large amount of the count data variables are derived variables.

Discrete variables (not including count data): crashYear

Continuous variables: X, Y, advisorySpeed, areaUnitID, meshblockId, speedLimit, temporarySpeedLimit

All of the categorical variables are nominal (lack an inherent order).

The data set is majority made up of count data and categorical variables.

There is one logical variable in the data set named intersection it has 870753 NA's which is equal to the total amount of observations in the data set. This means that this variable has no data for any of the observations. As a result I will be removing it

```r
Crash <- subset(Crash, select = -c(intersection))
```

```r
pander(head(Crash))
```

Table 17: Table continues below

X	Y	advisorySpeed	areaUnitID	bicycle	bridge	bus
1243177	4849584	NA	611210	0	NA	0
1832358	5584384	NA	559220	0	0	0
1749496	5918077	NA	514801	0	NA	0
2038048	5708026	NA	544701	0	NA	0
1834941	5642955	NA	554900	0	0	0
1693702	5676441	NA	551800	0	NA	0

Table 18: Table continues below

carStationWagon	cliffBank	crashDirectionDescription	crashSHDescription
2	NA	NA	Yes
0	0	South	Yes
1	NA	NA	Yes
2	NA	NA	No
0	1	South	Yes
2	NA	West	Yes

Table 19: Table continues below

crashYear	debris	ditch	fatalCount	fence	flatHill	guardRail
2003	NA	NA	0	NA	Flat	NA
2003	0	1	0	1	Flat	0
2003	NA	NA	0	NA	Flat	NA
2004	NA	NA	0	NA	Flat	NA
2005	0	0	0	0	Flat	0
2003	NA	NA	0	NA	Flat	NA

Table 20: Table continues below

holiday	houseOrBuilding	kerb	light	meshblockId	moped
NA	NA	NA	Overcast	3109000	0
NA	0	0	Dark	1748400	0
NA	NA	NA	Dark	390401	0
NA	NA	NA	Overcast	1382300	0
NA	0	0	Overcast	1673301	0
NA	NA	NA	Bright sun	1594000	0

Table 21: Table continues below

motorcycle	NumberOfLanes	objectThrownOrDropped	otherObject
0	4	NA	NA
0	2	0	0
0	3	NA	NA
0	2	NA	NA
0	2	0	0
0	4	NA	NA

Table 22: Table continues below

otherVehicleType	overBank	parkedVehicle	pedestrian	phoneBoxEtc
0	NA	NA	NA	NA
0	0	0	NA	0
0	NA	NA	NA	NA
0	NA	NA	NA	NA
0	0	0	NA	0
0	NA	NA	NA	NA

Table 23: Table continues below

postOrPole	region	roadCharacter	roadLane
NA	Southland Region	NA	2-way
0	Manawatū-Whanganui Region	NA	2-way
NA	Auckland Region	Motorway ramp	1-way
NA	Gisborne Region	NA	2-way
0	Manawatū-Whanganui Region	NA	2-way
NA	Taranaki Region	NA	1-way

Table 24: Table continues below

roadSurface	roadworks	schoolBus	slipOrFlood	speedLimit	strayAnimal
Sealed	NA	0	NA	50	NA
Sealed	0	0	0	100	0
Sealed	NA	0	NA	100	NA
Sealed	NA	0	NA	50	NA
Sealed	0	0	0	100	0
Sealed	NA	0	NA	50	NA

Table 25: Table continues below

streetLight	suv	taxi	temporarySpeedLimit	trafficControl
NA	0	0	NA	Traffic Signals
None	0	0	NA	NA
On	0	0	NA	NA
NA	0	0	NA	Give way

streetLight	suv	taxi	temporarySpeedLimit	trafficControl
NA	0	0	NA	NA
NA	0	0	NA	NA

Table 26: Table continues below

trafficIsland	trafficSign	train	tree	truck	unknownVehicleType
NA	NA	NA	NA	0	0
0	0	0	0	0	0
NA	NA	NA	NA	1	0
NA	NA	NA	NA	0	0
0	0	0	0	1	0
NA	NA	NA	NA	0	0

vanOrUtility	vehicle	waterRiver	weatherA	weatherB
0	NA	NA	Fine	NA
1	0	0	Fine	NA
0	NA	NA	Heavy rain	NA
0	NA	NA	Fine	NA
0	0	0	Heavy rain	NA
0	NA	NA	Fine	NA

I can see that some variables have lots of NA's such as advisorySpeed which has 836776 NA's - almost the entire variable's data is missing data.

Data cleaning

Converting Categorical data for regression

All categorical variables in the data set:

```
colnames(select_if(Crash, is.character))
```

```
##  [1] "crashDirectionDescription" "crashSHDescription"
##  [3] "flatHill"                  "holiday"
##  [5] "light"                     "region"
##  [7] "roadCharacter"             "roadLane"
##  [9] "roadSurface"               "streetLight"
## [11] "trafficControl"            "weatherA"
## [13] "weatherB"
```

```
sort(unique(Crash[["crashSHDescription"]]))
```

```
## [1] "No"  "Yes"
```

Note: crashSHDescription "Indicates where a crash is reported to have occurred on a State Highway (SH) marked '1', or on another road type marked '2'" according to the field descriptions, but in this data set it is coded with "No" and "Yes".

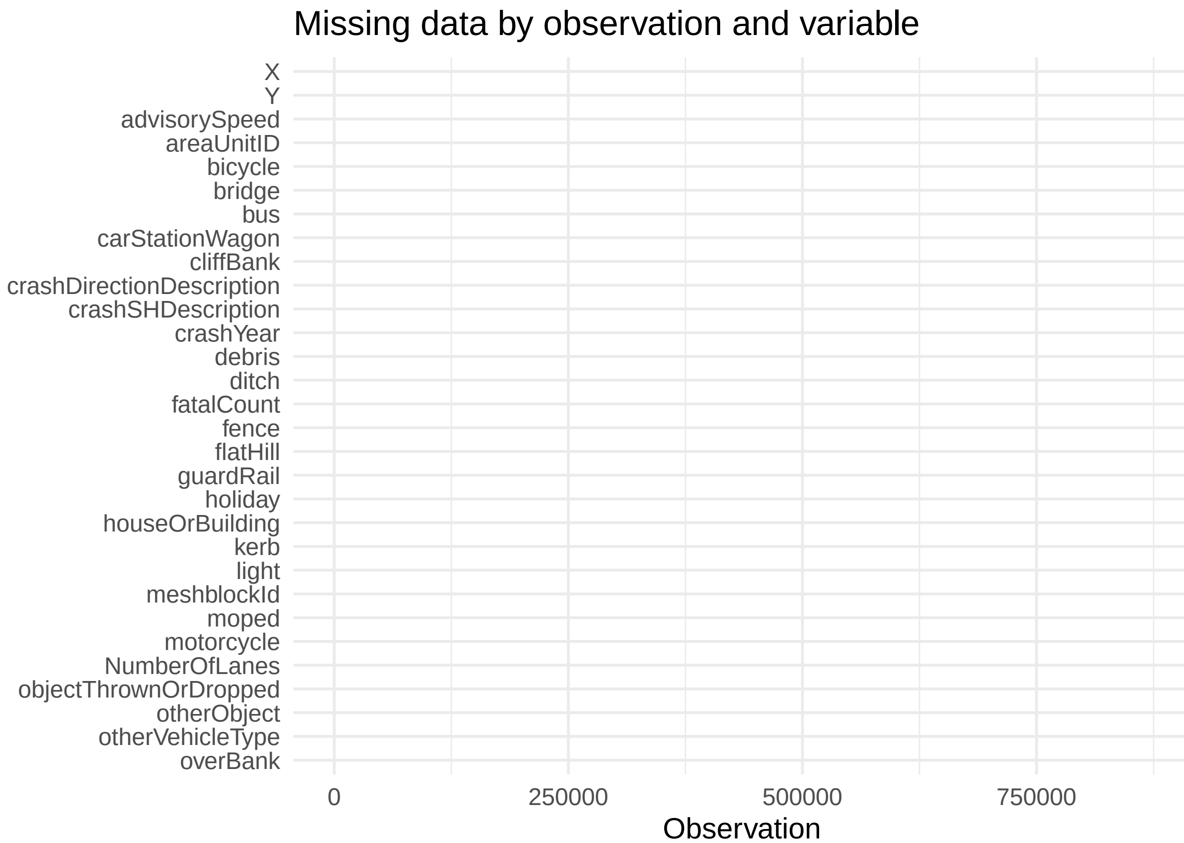
Turning all categorical variables into factors for regression:

```
Crash$crashSHDescription <- as.factor(Crash$crashSHDescription)
Crash$flatHill <- as.factor(Crash$flatHill)
Crash$holiday <- as.factor(Crash$holiday)
Crash$light <- as.factor(Crash$light)
Crash$region <- as.factor(Crash$region)
Crash$roadCharacter <- as.factor(Crash$roadCharacter)
Crash$roadLane <- as.factor(Crash$roadLane)
Crash$roadSurface <- as.factor(Crash$roadSurface)
Crash$streetLight <- as.factor(Crash$streetLight)
Crash$trafficControl <- as.factor(Crash$trafficControl)
Crash$weatherA <- as.factor(Crash$weatherA)
Crash$weatherB <- as.factor(Crash$weatherB)
Crash$crashDirectionDescription <- as.factor(Crash$crashDirectionDescription)
```

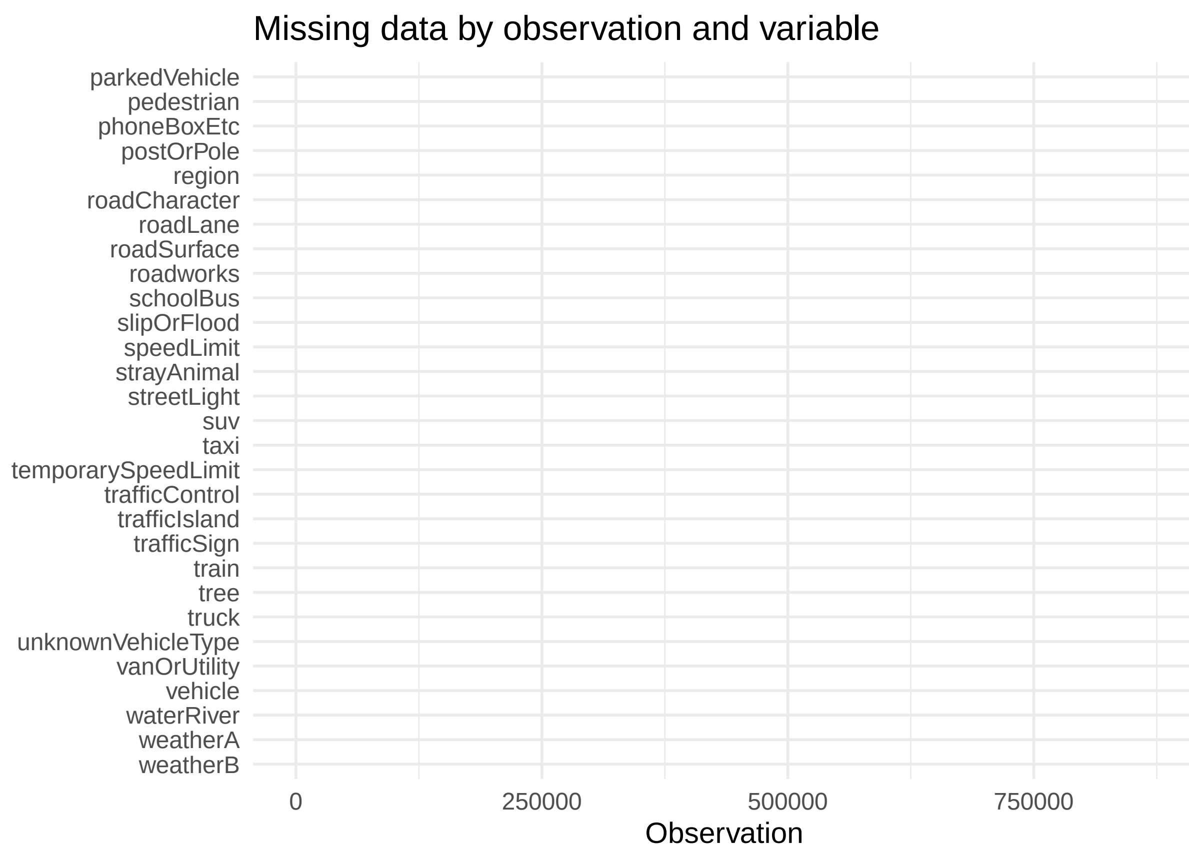
Missing data

There are 59 variables and trying to place them onto one plot caused it to be unreadable. To resolve this it has been split into separate plots.

```
# Producing a missing data plot for the data frame.
missing_plot(Crash[,1:30], title = "Missing data by observation and variable")
```




```
missing_plot(Crash[,31:59], title = "Missing data by observation and variable")
```



It seems that most variables in the Crash data set have large amounts of missing data. Particularly temporarySpeedLimit, pedestrian, the encoded WeatherB variables, the encoded holiday variables, and advisorySpeed which appear to be majority missing data.

Calculating how many variables have missing data:

```
percentages <- c()
missing_percents_colnames <- c()
x = 0
for (i in colnames(Crash)){
  if (sum(is.na(Crash[[i]])) > 0){
    percentages <- append(percentages, prop_miss(Crash[[i]]))
    missing_percents_colnames <- append(missing_percents_colnames, colnames(Crash[i]))
    x = x + 1
  }
}
print(x)
```

```
## [1] 56
```

```
# Turning proportion to percentage
percentages <- percent(percentages, accuracy = 0.01)
```

There are 55 variables with missing data out of 59.

Finding out what proportion of each variables data is missing:

```r
missing.table <- do.call(rbind, Map(data.frame, variable = missing_percents_colnames,
                                    percentage = percentages))
missing.table <- missing.table[rev(order(missing.table$percentage)), ]
row.names(missing.table) <- c(1:nrow(missing.table))
missing.table
```

```
##                     variable percentage
## 1         temporarySpeedLimit     98.35%
## 2                    weatherB     96.79%
## 3                  pedestrian     96.71%
## 4               advisorySpeed     96.10%
## 5               roadCharacter     95.99%
## 6                     holiday     94.49%
## 7              trafficControl     66.31%
## 8                  waterRiver     59.02%
## 9                     vehicle     59.02%
## 10                       tree     59.02%
## 11                      train     59.02%
## 12                trafficSign     59.02%
## 13              trafficIsland     59.02%
## 14                strayAnimal     59.02%
## 15                slipOrFlood     59.02%
## 16                  roadworks     59.02%
## 17                 postOrPole     59.02%
## 18                phoneBoxEtc     59.02%
## 19              parkedVehicle     59.02%
## 20                   overBank     59.02%
## 21                otherObject     59.02%
## 22        objectThrownOrDropped     59.02%
## 23                       kerb     59.02%
## 24            houseOrBuilding     59.02%
## 25                  guardRail     59.02%
## 26                      fence     59.02%
## 27                      ditch     59.02%
## 28                     debris     59.02%
## 29                  cliffBank     59.02%
## 30                     bridge     59.02%
## 31 crashDirectionDescription     37.61%
## 32                streetLight     34.45%
## 33                   weatherA      1.85%
## 34                      light      0.96%
## 35                   flatHill      0.74%
## 36                     region      0.38%
## 37              NumberOfLanes      0.24%
## 38                 speedLimit      0.13%
## 39                roadSurface      0.12%
## 40                   roadLane      0.06%
## 41          crashSHDescription      0.02%
## 42               vanOrUtility      0.00%
## 43          unknownVehicleType      0.00%
## 44                      truck      0.00%
## 45                       taxi      0.00%
## 46                        suv      0.00%
```

```
## 47                 schoolBus      0.00%
## 48          otherVehicleType      0.00%
## 49                motorcycle      0.00%
## 50                     moped      0.00%
## 51               meshblockId      0.00%
## 52                fatalCount      0.00%
## 53           carStationWagon      0.00%
## 54                       bus      0.00%
## 55                   bicycle      0.00%
## 56                areaUnitID      0.00%
```

30 variables have more than 59% of their data missing. Another 2 variables have around 30% of their data missing.

I think it would be best to drop these variables as other methods such as imputation for the missing data would be too computationally expensive given the scale of the data.

```
# Dropping variables
Crash <- Crash %>% select(-missing.table$variable[1:32])
```

There are now have 27 variables in the data set.

Reducing the data down to complete cases only:

```
Crash <- Crash[complete.cases(Crash), ]
# making the dependent variable the first column
Crash <- Crash %>% relocate(fatalCount)
```

This causes the amount of observations I have to go from 870,753 to 844,965, a reduction of 2.96% (to 2 d.p).

Plotting data

Boxplots of categorical data

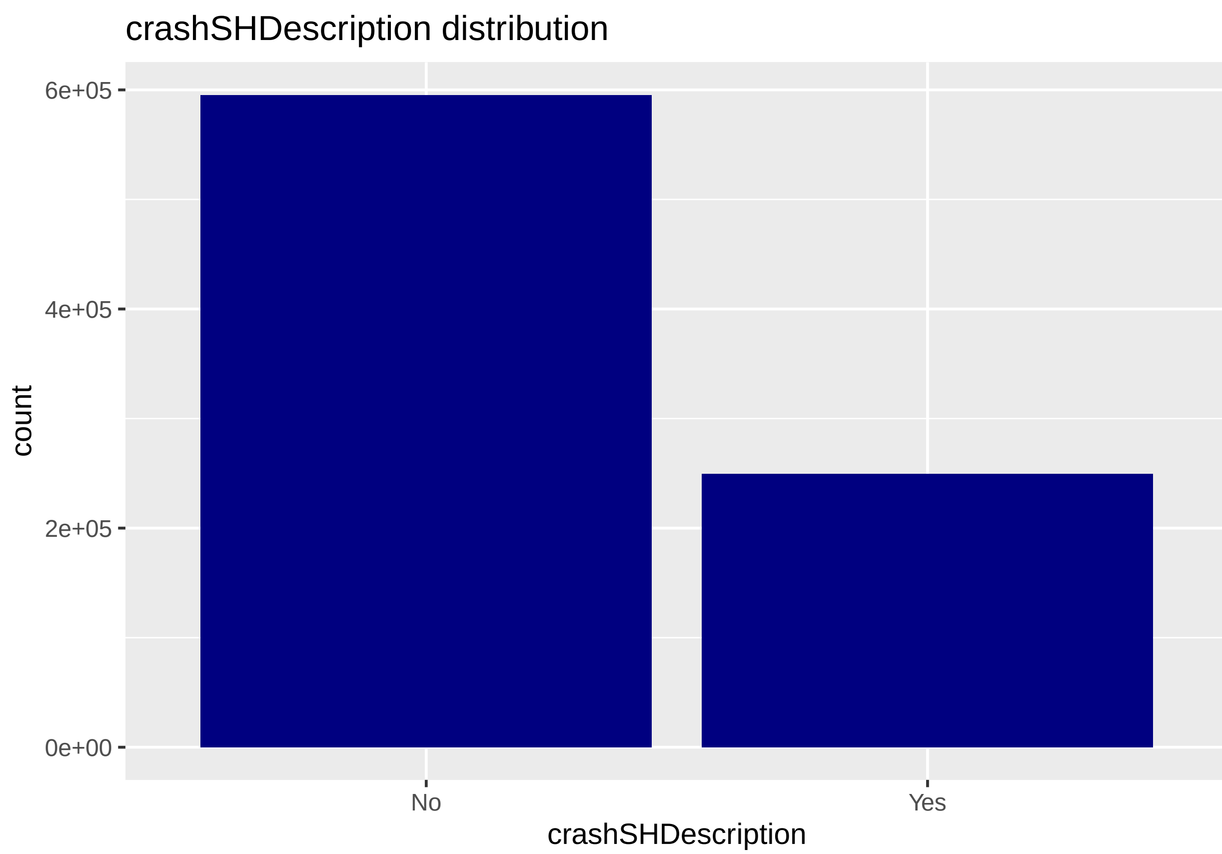
All categorical variables:

```
colnames(select_if(Crash, is.factor))
```

```
## [1] "crashSHDescription" "flatHill"           "light"
## [4] "region"             "roadLane"           "roadSurface"
## [7] "weatherA"
```

Bar plot of crashSHDescription:

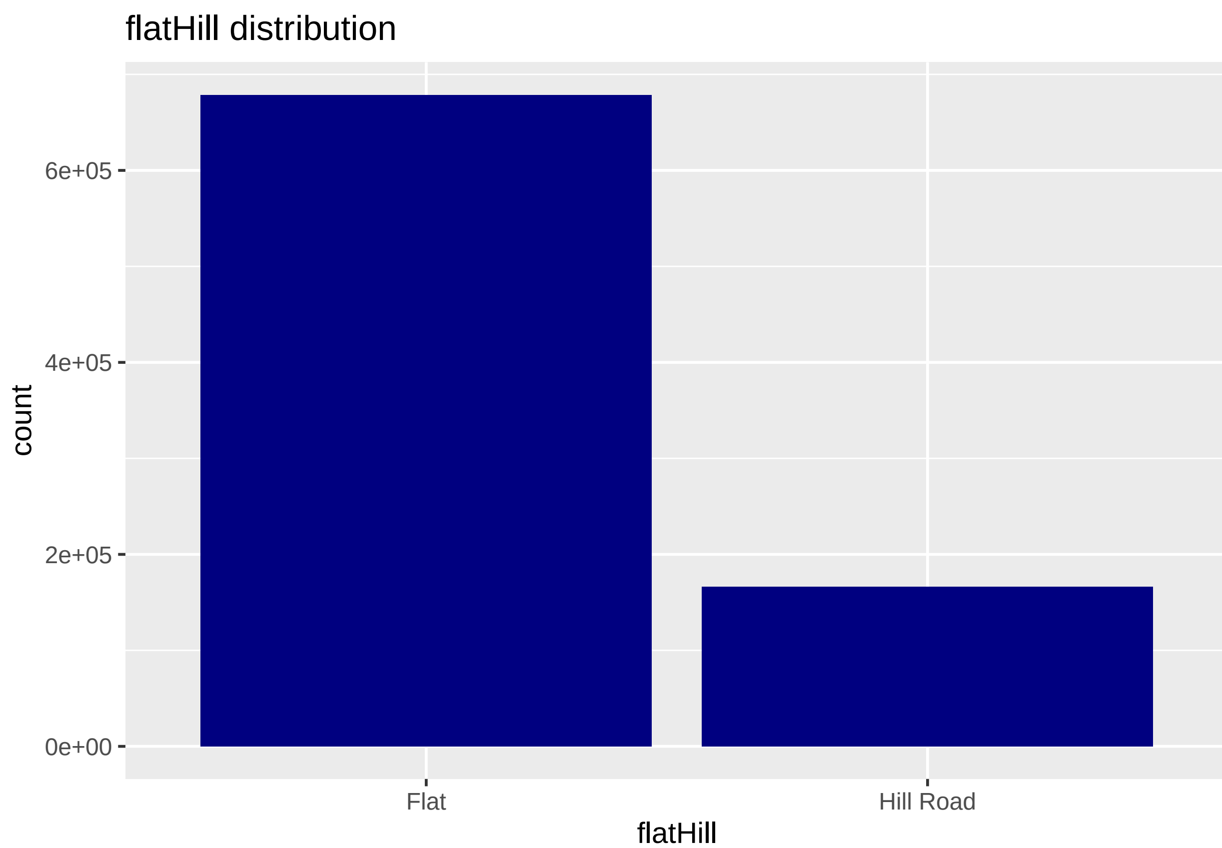
```
ggplot(Crash, aes(x = crashSHDescription)) +
  geom_bar(fill = "navy") +
  ggtitle("crashSHDescription distribution")
```



There are less twilight observations (around 500,000).

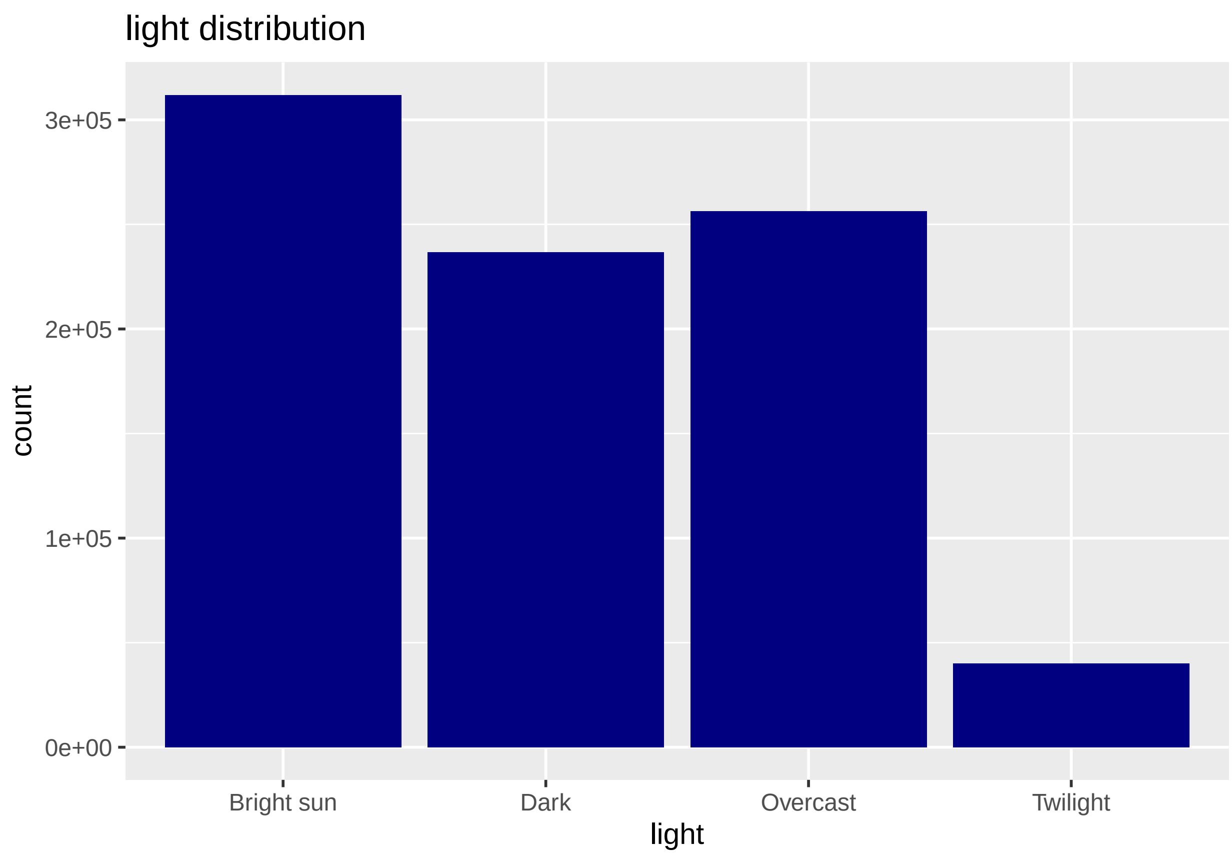
Bar plot of flatHill:

```
ggplot(Crash, aes(x = flatHill)) +
  geom_bar(fill = "navy") +
  ggtitle("flatHill distribution")
```



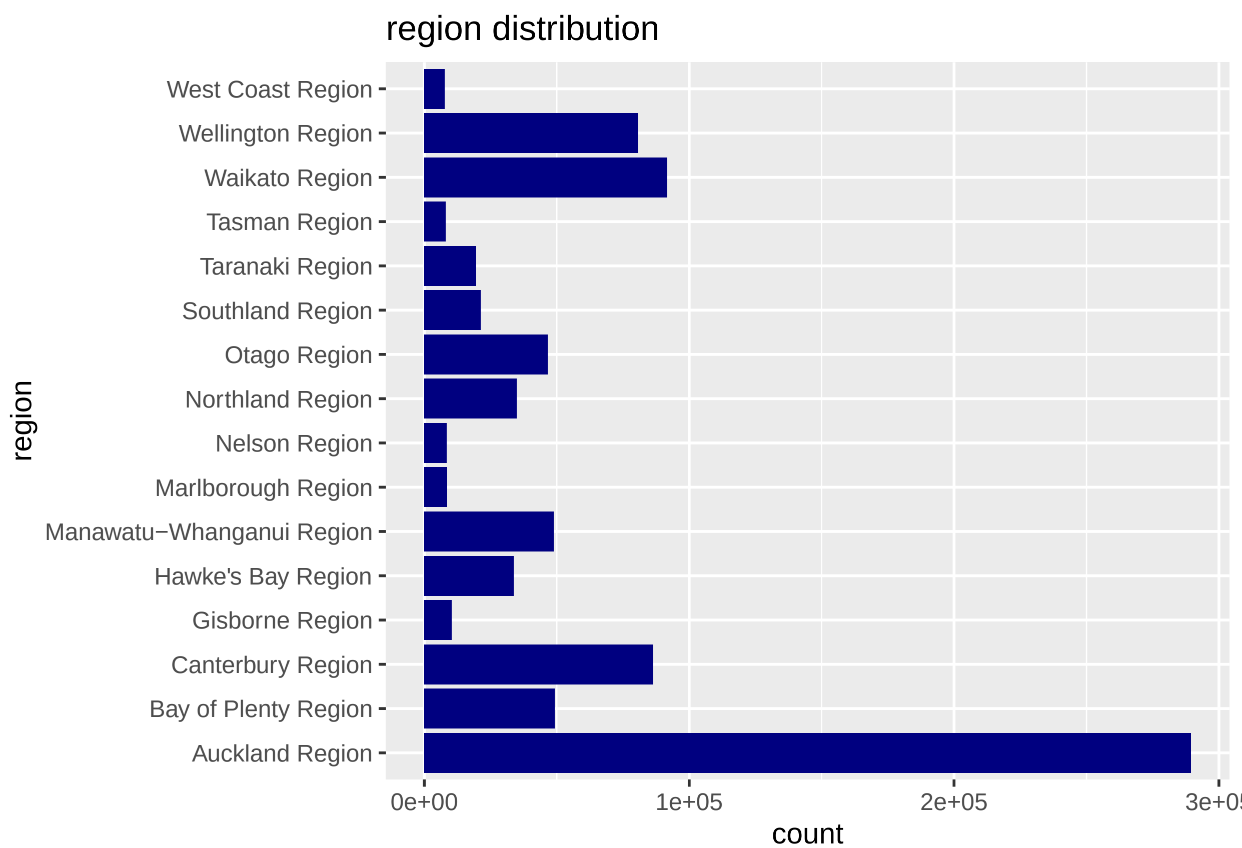
Bar plot of light:

```
ggplot(Crash, aes(x = light)) +
  geom_bar(fill = "navy") +
  ggtitle("light distribution")
```



Bar plot of region:

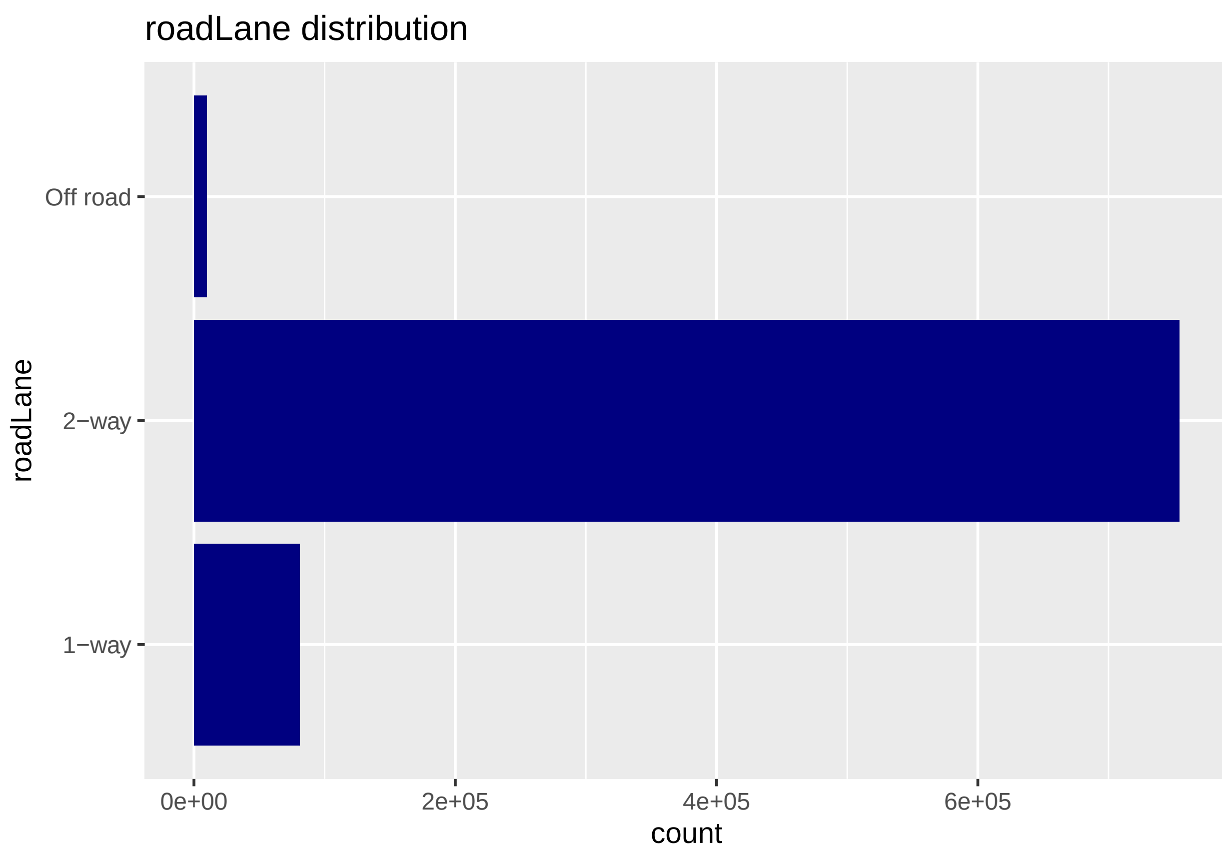
```
ggplot(Crash, aes(x = region)) +
  geom_bar(fill = "navy") +
  coord_flip() +
  ggtitle("region distribution")
```



The majority of car crashes occur in Auckland.

Bar plot of roadLane:

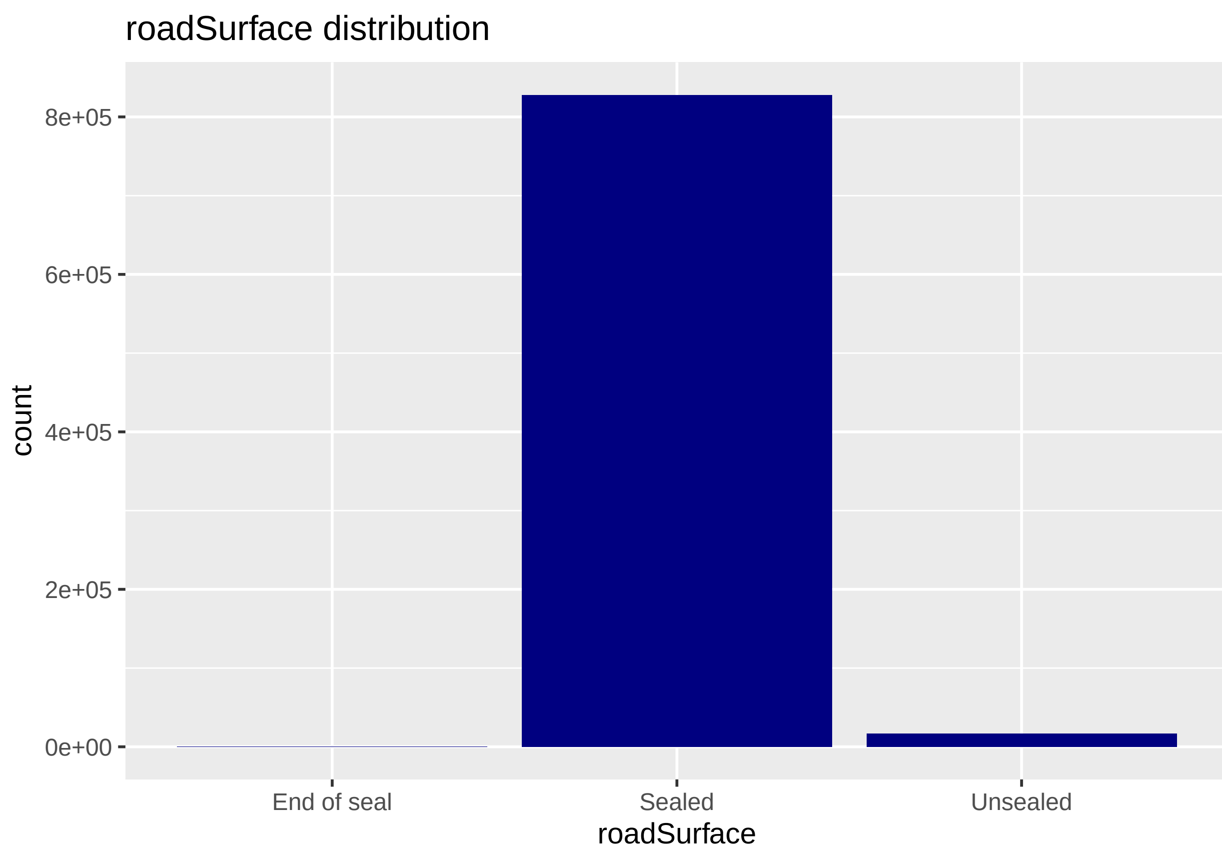
```
ggplot(Crash, aes(x = roadLane)) +
  geom_bar(fill = "navy") +
  coord_flip() +
  ggtitle("roadLane distribution")
```



Few Off road observations

Bar plot of roadSurface:

```
ggplot(Crash, aes(x = roadSurface)) +
  geom_bar(fill = "navy") +
  ggtitle("roadSurface distribution")
```



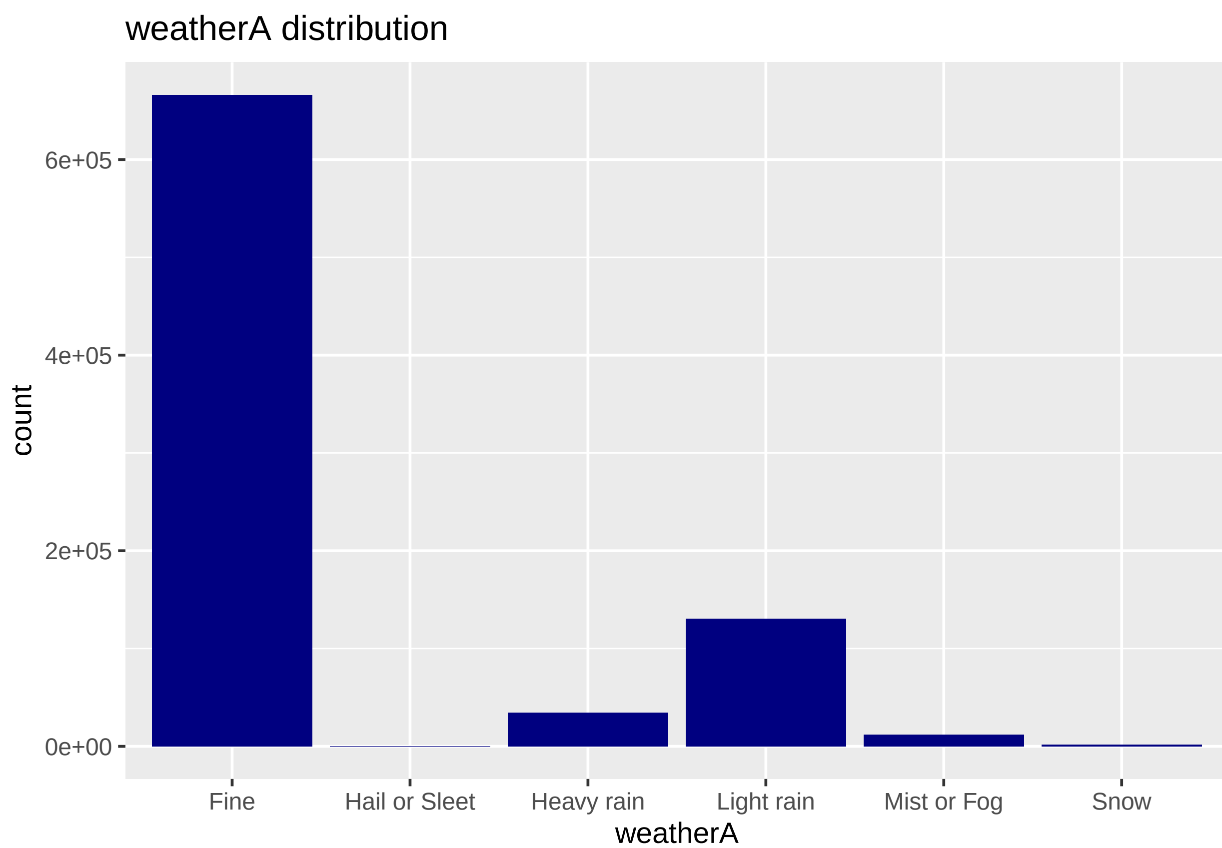
There are very few End of seal observations

```
sum(Crash$roadSurface == "End of seal")
```

```
## [1] 122
```

Bar plot of weatherA:

```
ggplot(Crash, aes(x = weatherA)) +
  geom_bar(fill = "navy") +
  ggtitle("weatherA distribution")
```




```
sum(Crash$weatherA == "Hail or Sleet")
```

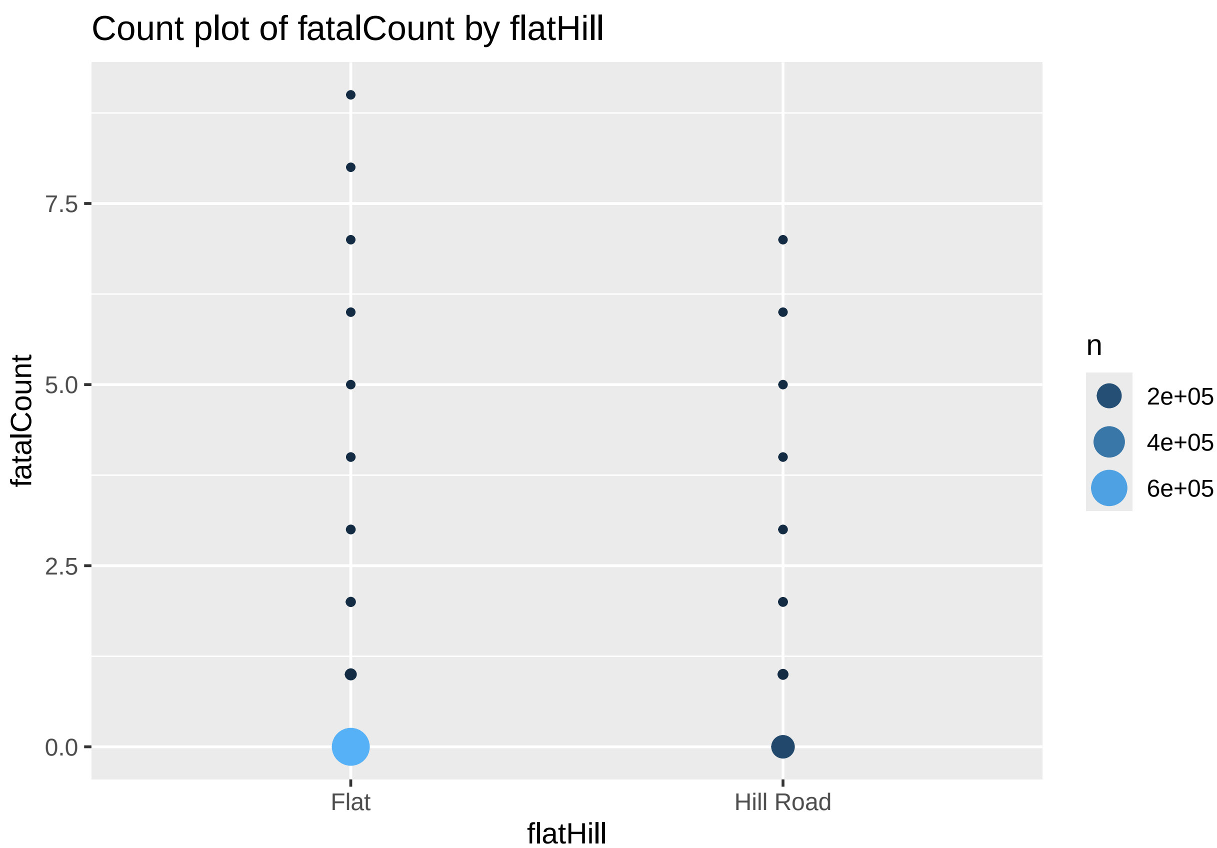
```
## [1] 172
```

There are only 172 Hail or Sleet observations Many of the categorical variables are imbalanced

Numerical data plots

Count plot of response variable fatalCount:

```
ggplot(Crash, aes(x = flatHill, y = fatalCount)) +
  geom_count(aes(color = after_stat(n), size = after_stat(n))) +
  guides(color = 'legend') + ggtitle("Count plot of fatalCount by flatHill")
```



There are few observations with at least 1 death.

```r
sum(Crash$fatalCount == 0)
```

```
## [1] 836997
```

```r
sum(Crash$fatalCount >= 1)
```

```
## [1] 7968
```

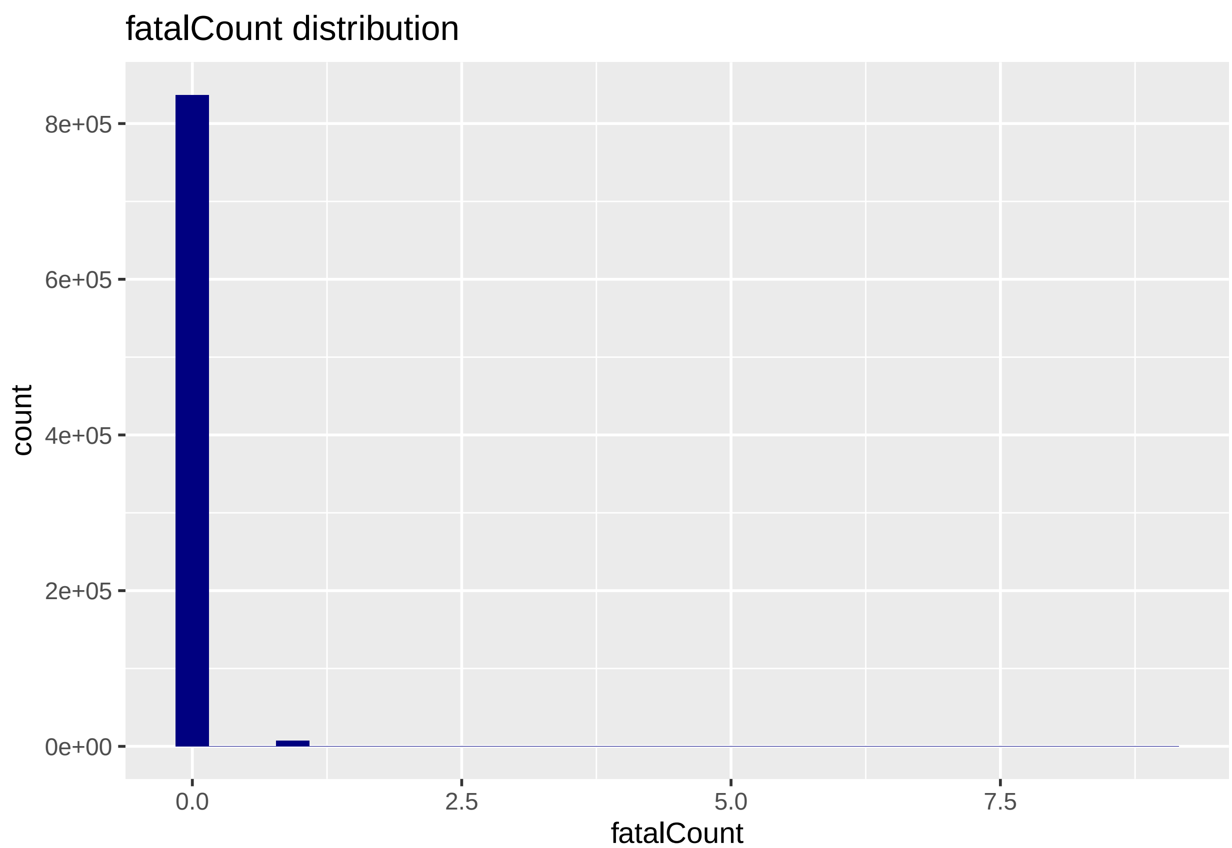
```r
round((7968/836997)*100, 2)
```

```
## [1] 0.95
```

Observations with 1 or more deaths make up only 0.95% of observations.

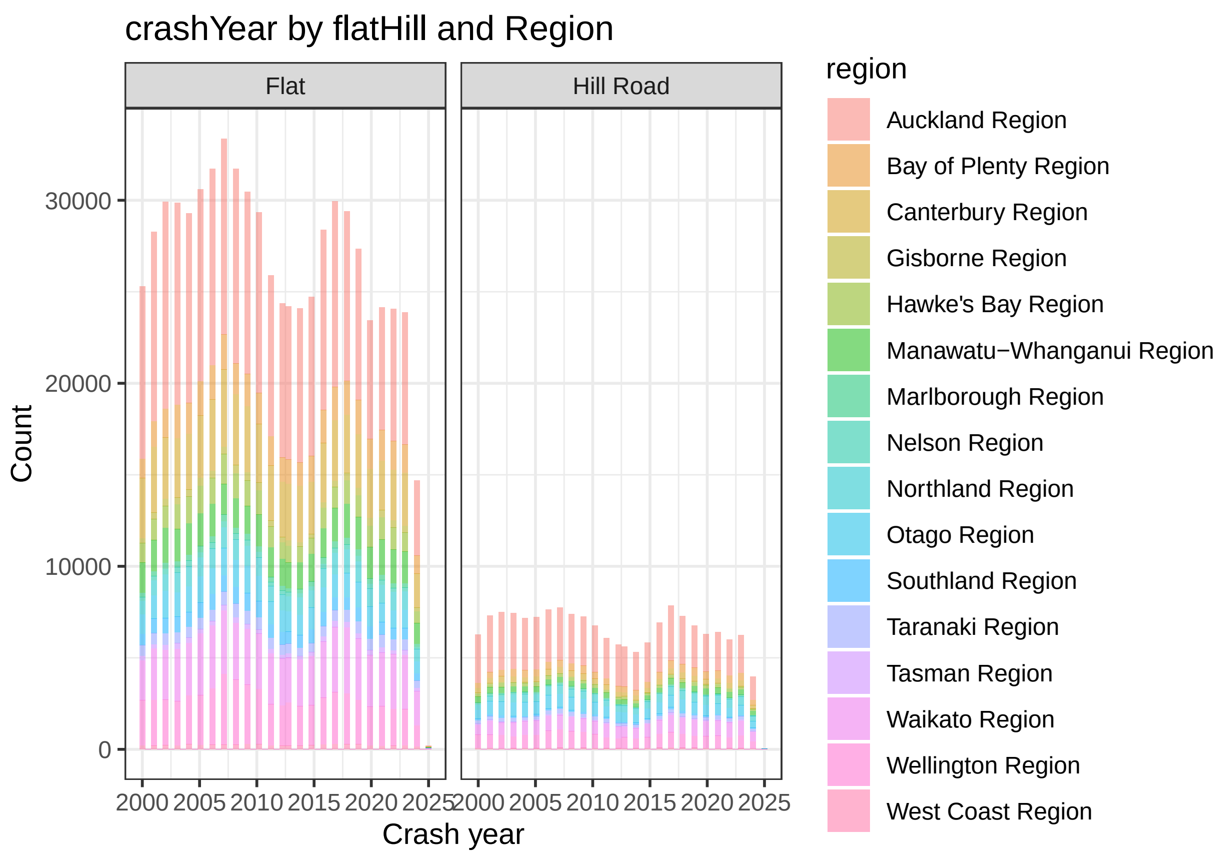
```r
ggplot(Crash, aes(x = fatalCount)) +
  geom_histogram(fill = "navy")  + ggtitle("fatalCount distribution")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



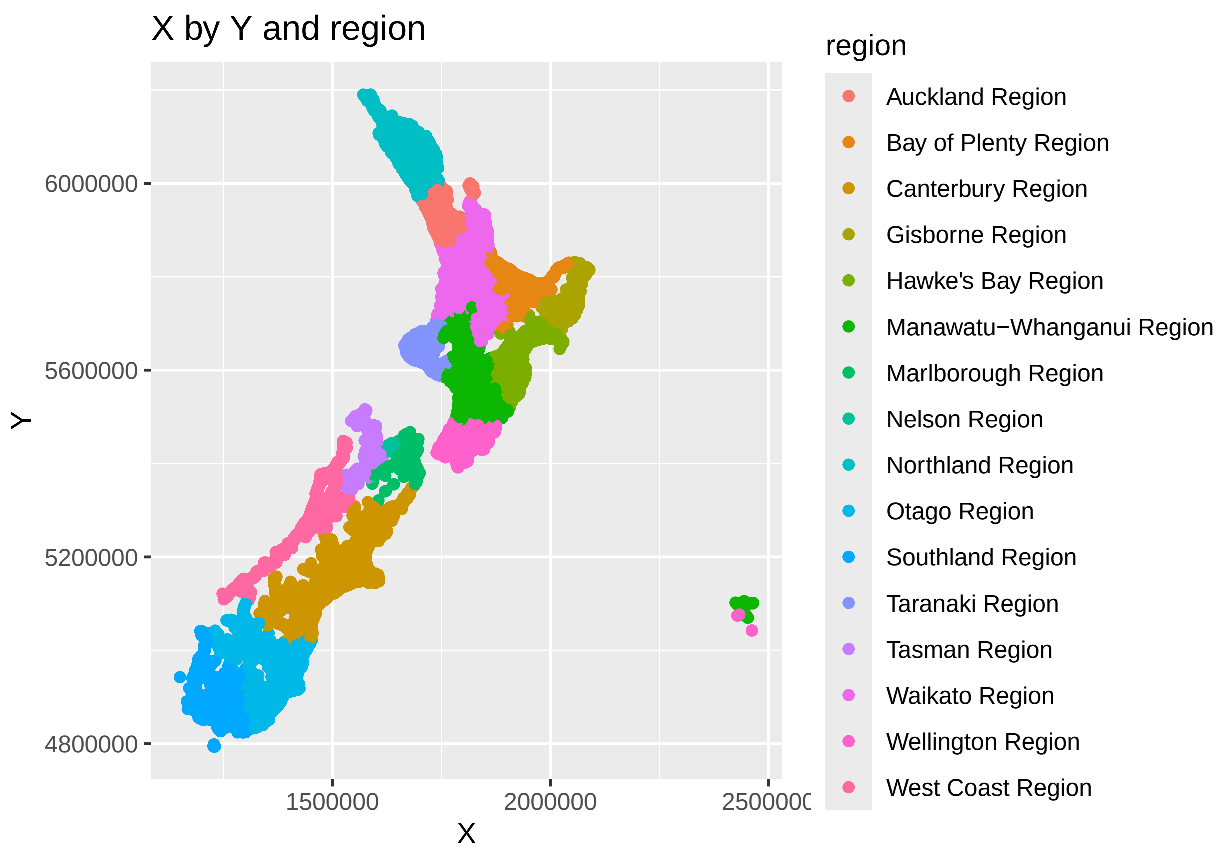
Zero deaths appear to be the vast majority of car crashes, this could potentially indicate zero inflation.

```
ggplot(data = Crash,
       mapping = aes(x = crashYear, fill = region)) +
  geom_histogram(alpha = 0.5, bins = 50) +
  labs(x = "Crash year", y = "Count",
       title = "crashYear by flatHill and Region") +
  facet_grid(. ~ flatHill) +
  theme_bw()
```



More crashes occur on flat roads than hill roads for every year recorded. But that could be due to there being more flat roads overall in New Zealand than there are hill roads.

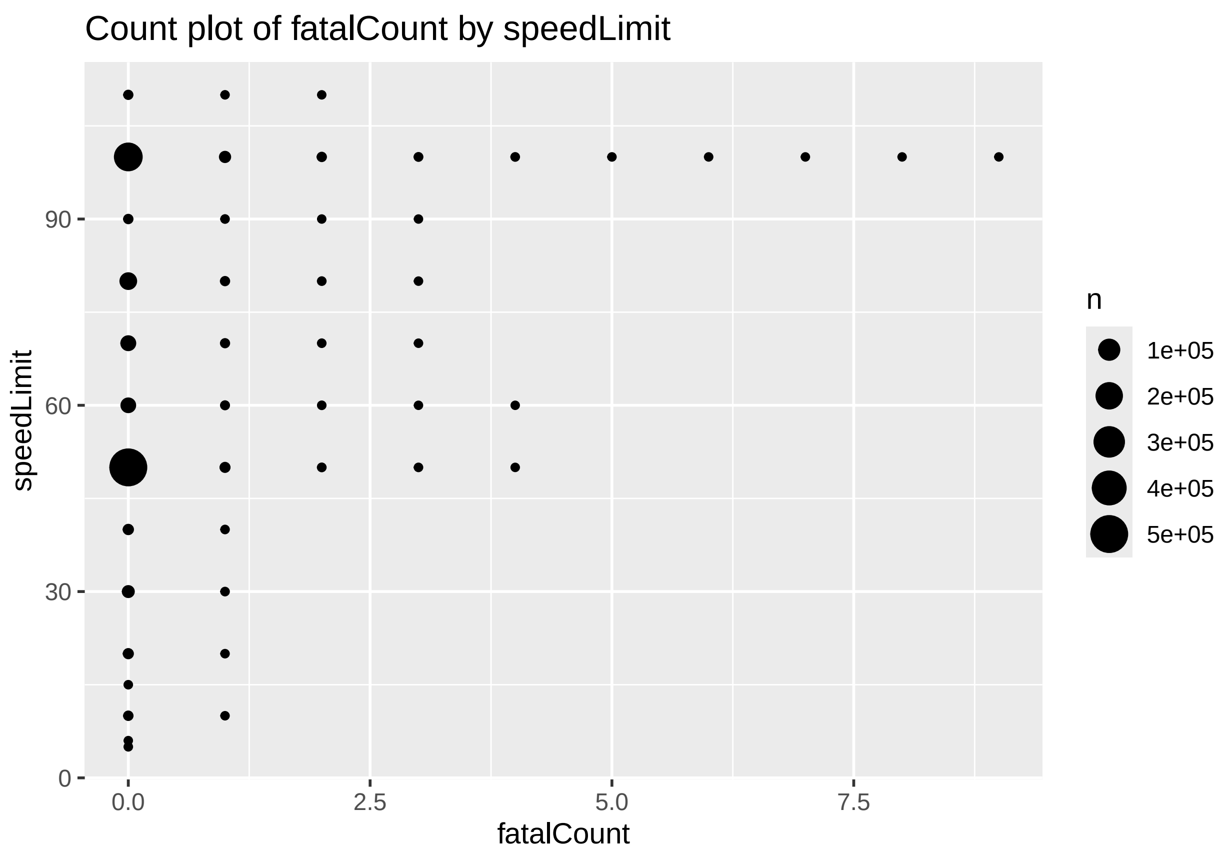
```
ggplot(Crash, aes(x = X, y = Y, color = region)) +
  geom_point() + ggtitle("X by Y and region")
```



It appears that X and Y contain redundant information that can be modeled by region.

Count plot of response variable fatalCount:

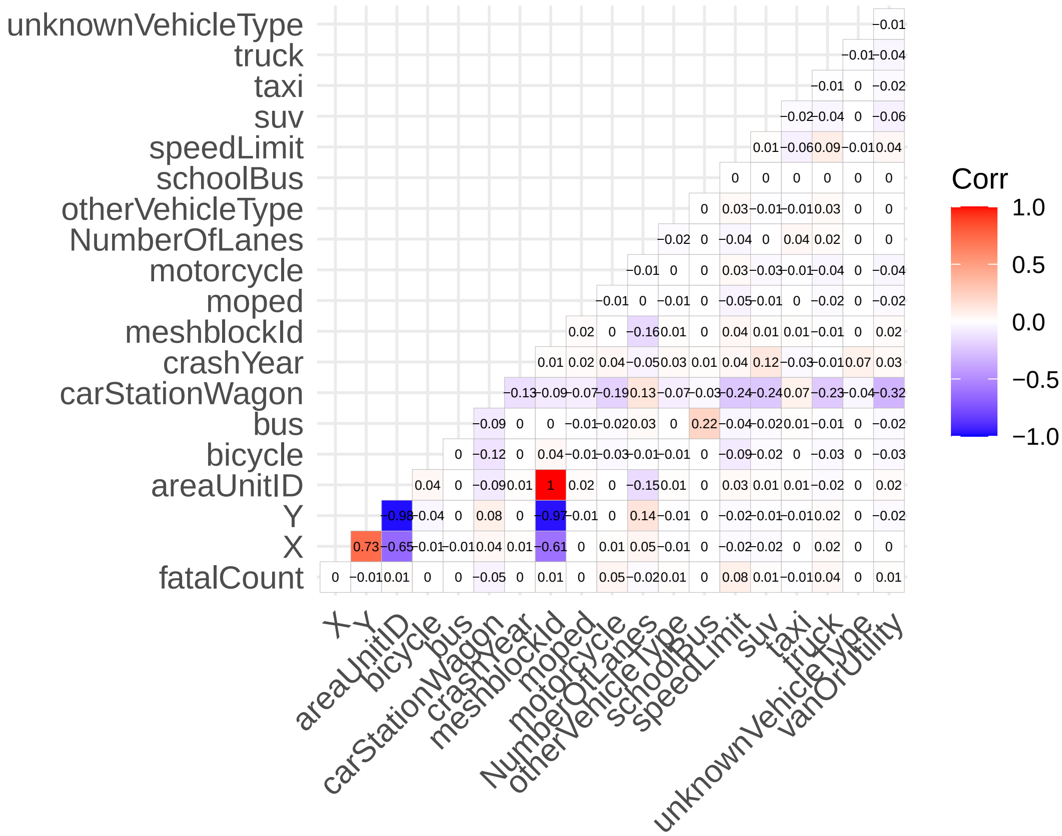
```
ggplot(Crash, aes(x = fatalCount, y = speedLimit)) +
  geom_count() + ggtitle("Count plot of fatalCount by speedLimit")
```



fatalCount's of 5 and above appear to only occur when speedLimit is above 90

Correlation plot

```
ggcorrplot(cor(select_if(Crash, is.numeric)),
method = "square",
lab = TRUE,
lab_size = 1.9,
type = "lower")
```




```r
findCorrelation(cor(select_if(Crash, is.numeric)), cutoff = 0.7, names = TRUE)
```

```
## [1] "areaUnitID" "Y"
```

Y is strongly correlated with areaUnitID and meshblockID with a correlation of -0.98 and -0.97 respectively.

The variable areaUnitID is strongly correlated with meshblockID with a correlation of 1.

Due to X and Y being strongly correlated with a correlation of 0.73 and that they contain redundant information already contained in region, I will be dropping X and Y.

Due to the strong correlation between these variables I will be removing the following variables: areaUnitID and meshblockId

```r
Crash <- Crash %>% select(-areaUnitID, -meshblockId, -Y, -X)
```

I now have 23 variables in the Crash data set.

Skewness

```r
pander(skewness(select_if(Crash, is.numeric)))
```

Table 28: Table continues below

fatalCount	bicycle	bus	carStationWagon	crashYear	moped
15.07	6.129	8.042	0.4287	0.0966	11.93

Table 29: Table continues below

motorcycle	NumberOfLanes	otherVehicleType	schoolBus	speedLimit	suv
5.651	1.802	14.3	36.35	0.6734	3.158

taxi	truck	unknownVehicleType	vanOrUtility
10.5	3.555	19.54	2.227

The response variable fatalCount has a skewness of 15.07 this is significant departure from the normal distribution which has a skewness of 0.

The majority of the numerical variables have a skewness value above 3. Only vanOrUtility, speedLimit, NumberOfLanes, crashYear and carStationWagon aren't skewed.

Kurtosis

```r
pander(kurtosis(select_if(Crash, is.numeric)))
```

Table 31: Table continues below

fatalCount	bicycle	bus	carStationWagon	crashYear	moped
363.7	45.68	69.04	4.26	1.804	146.3

Table 32: Table continues below

motorcycle	NumberOfLanes	otherVehicleType	schoolBus	speedLimit	suv
44.27	7.582	219.8	1421	1.726	13.28

taxi	truck	unknownVehicleType	vanOrUtility
128.8	15.91	410.4	7.649

The response variable fatalCount has a kurtosis of 363.7, which means it has a leptokurtic distribution (high peak) this is significant departure from the normal distribution where the absolute kurtosis value should not exceed 7.1.

The variables taxi, motorcycle, bus, moped, otherVehicleType, schoolBus and unknownVehicleType all have extremely high kurtosis values, indicating leptokurtic distributions.

The distributions of most of the variables seem highly skewed with high peaks.

The kurtosis and skewness of fatalCount (the response variable) indicates that the variables distribution deviates significantly from a normal distribution meaning that the assumption of normality has been violated.

Due to the non-normality of the data I will fit a generalized linear model to the data due to its robustness to non-normality (particularly when the data set is large).

Given that the response variable is discrete count data (counting the number of deaths per car crash) I will attempt to fit a poisson model to the data first.

Feature selection:

Feature importance:

```
roc_imp <- filterVarImp(x = Crash[,-1], y = Crash$fatalCount, nonpara = TRUE)
roc_imp <- data.frame(cbind(variable = rownames(roc_imp), score = roc_imp[,1]))
roc_imp$score <- as.double(roc_imp$score)
roc_imp <- roc_imp[order(roc_imp$score,decreasing = TRUE),]
pander(roc_imp)
```

	variable	score
16	speedLimit	0.006846
3	carStationWagon	0.002264
9	motorcycle	0.002249
4	crashSHDescription	0.002016
19	truck	0.001523
12	region	0.0005017
10	NumberOfLanes	0.000402
13	roadLane	0.0003068
6	flatHill	0.0001869
11	otherVehicleType	0.0001188
21	vanOrUtility	6.696e-05
17	suv	5.021e-05
18	taxi	4.436e-05
14	roadSurface	4.328e-05
8	moped	2.239e-05
15	schoolBus	1.841e-05
20	unknownVehicleType	1.511e-05
2	bus	9.198e-06
5	crashYear	6.401e-06
7	light	2.277e-06
22	weatherA	6.409e-07
1	bicycle	5.928e-07

Reducing the data set to the ten most important variables:

```
Crash2 <- Crash %>% select(fatalCount, roc_imp$variable[1:10])
```

Poisson Regression

Fitting a poisson regression model:

```r
model_glm_P <- glm(fatalCount ~ speedLimit + motorcycle + roadLane + truck + region +
                     NumberOfLanes + otherVehicleType + crashSHDescription +
                     carStationWagon + flatHill, data = Crash2, family = poisson)
pander(summary(model_glm_P))
```

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-8.228	0.09641	-85.34	0
speedLimit	0.03274	0.0006049	54.13	0
motorcycle	0.8625	0.02125	40.59	0
roadLane2-way	1.406	0.06512	21.59	2.436e-103
roadLaneOff road	1.594	0.1403	11.36	6.532e-30
truck	0.6601	0.02501	26.39	1.586e-153
regionBay of Plenty Region	0.439	0.04721	9.3	1.403e-20
regionCanterbury Region	0.3516	0.0431	8.157	3.435e-16
regionGisborne Region	0.1095	0.09288	1.178	0.2387
regionHawke's Bay Region	0.1822	0.05687	3.203	0.001359
regionManawatū-Whanganui Region	0.3092	0.04726	6.542	6.062e-11
regionMarlborough Region	0.2506	0.09092	2.756	0.005849
regionNelson Region	-0.227	0.1538	-1.476	0.1399
regionNorthland Region	0.3633	0.04938	7.358	1.874e-13
regionOtago Region	-0.1165	0.05793	-2.011	0.04431
regionSouthland Region	0.04354	0.06932	0.6282	0.5299
regionTaranaki Region	0.2113	0.06679	3.163	0.00156
regionTasman Region	-0.08718	0.09632	-0.9051	0.3654
regionWaikato Region	0.3614	0.03952	9.145	5.962e-20
regionWellington Region	-0.1379	0.05483	-2.515	0.0119
regionWest Coast Region	0.2326	0.08259	2.817	0.004851
NumberOfLanes	-0.168	0.01778	-9.45	3.401e-21
otherVehicleType	0.3089	0.08474	3.645	0.0002674
crashSHDescriptionYes	0.1974	0.02434	8.112	4.968e-16
carStationWagon	-0.1577	0.01641	-9.608	7.412e-22
flatHillHill Road	-0.02073	0.0247	-0.8395	0.4012

(Dispersion parameter for poisson family taken to be 1)

Null deviance:	85086 on 844964 degrees of freedom
Residual deviance:	74307 on 844939 degrees of freedom

Checking model assumptions:

I need to check if the response variable fatalCount follows a poisson distribution:

```r
dispersiontest(model_glm_P, alternative = "two.sided")
```

```
##
##  Dispersion test
##
```

```
## data:  model_glm_P
## z = 13.104, p-value < 2.2e-16
## alternative hypothesis: true dispersion is not equal to 1
## sample estimates:
## dispersion
##   1.199071
```

```r
dispersiontest(model_glm_P, alternative = "greater")
```

```
##
##  Overdispersion test
##
## data:  model_glm_P
## z = 13.104, p-value < 2.2e-16
## alternative hypothesis: true dispersion is greater than 1
## sample estimates:
## dispersion
##   1.199071
```

The small p-value indicates that the data does not fit a poisson distribution. Overdispersion means the assumptions of the model are not met.

To handle the overdispersion I could fit a quasipoission distribution or a negative binomial distribution to the data instead of a poisson distribution.

Because I want to use AIC or BIC for model selection I will fit a negative binomial model, as quasi-poisson models cannot use AIC or BIC for model selection. This is due to quasi-Poisson models using quasi-likelihood rather than true likelihood.

```r
model_nb <- glm.nb(fatalCount ~ speedLimit + motorcycle + roadLane + truck + region +
                     NumberOfLanes + otherVehicleType + crashSHDescription +
                     carStationWagon + flatHill, data = Crash2)
```

Previously I found that only 0.95% of fatalCount data (the response variable) had a count different from 0.

I am going to test for zero inflation due to this:

```r
check_zeroinflation(model_nb)
```

```
## # Check for zero-inflation
##
##    Observed zeros: 836997
##   Predicted zeros: 837009
##             Ratio: 1.00
```

```
## Model seems ok, ratio of observed and predicted zeros is within the
##   tolerance range (p = 0.840).
```

The ratio of observed and predicted zeros is within the tolerance range which means that zero inflation is not an issue for the negative binomial model, so there is no need to fit a zero-inflated negative binomial model.

Variable selection

stepwise BIC:

```
step(model_nb, direction = "both", k = log(844965))
```

```
## Start:  AIC=87960.88
## fatalCount ~ speedLimit + motorcycle + roadLane + truck + region +
##     NumberOfLanes + otherVehicleType + crashSHDescription + carStationWagon +
##     flatHill
##
##                      Df Deviance   AIC
## - flatHill            1    45059 87947
## - otherVehicleType    1    45068 87956
## <none>                     45059 87961
## - crashSHDescription  1    45118 88005
## - region             15    45313 88009
## - NumberOfLanes       1    45143 88031
## - carStationWagon     1    45177 88065
## - truck               1    45501 88388
## - roadLane            2    45640 88514
## - motorcycle          1    45757 88645
## - speedLimit          1    47823 90711
##
## Step:  AIC=87947.38
## fatalCount ~ speedLimit + motorcycle + roadLane + truck + region +
##     NumberOfLanes + otherVehicleType + crashSHDescription + carStationWagon
##
##                      Df Deviance   AIC
## - otherVehicleType    1    45064 87942
## <none>                     45056 87947
## + flatHill            1    45056 87961
## - crashSHDescription  1    45114 87992
## - region             15    45311 87998
## - NumberOfLanes       1    45139 88017
## - carStationWagon     1    45174 88052
## - truck               1    45497 88375
## - roadLane            2    45637 88501
## - motorcycle          1    45753 88631
## - speedLimit          1    47881 90759
##
## Step:  AIC=87942.07
## fatalCount ~ speedLimit + motorcycle + roadLane + truck + region +
##     NumberOfLanes + crashSHDescription + carStationWagon
##
##                      Df Deviance   AIC
## <none>                     45042 87942
## + otherVehicleType    1    45034 87947
## + flatHill            1    45042 87956
## - crashSHDescription  1    45100 87986
## - region             15    45299 87994
## - NumberOfLanes       1    45125 88012
## - carStationWagon     1    45164 88050
```

```
## - truck               1    45486 88373
## - roadLane            2    45623 88496
## - motorcycle          1    45737 88623
## - speedLimit          1    47876 90762
```

```
##
## Call:  glm.nb(formula = fatalCount ~ speedLimit + motorcycle + roadLane +
##     truck + region + NumberOfLanes + crashSHDescription + carStationWagon,
##     data = Crash2, init.theta = 0.1058491131, link = log)
##
## Coefficients:
##                     (Intercept)                       speedLimit
##                        -8.19342                          0.03255
##                      motorcycle                     roadLane2-way
##                         1.04272                          1.40044
##                  roadLaneOff road                            truck
##                         1.62812                          0.66806
##      regionBay of Plenty Region          regionCanterbury Region
##                         0.44174                          0.35175
##         regionGisborne Region         regionHawke's Bay Region
##                         0.12660                          0.18296
## regionManawatū-Whanganui Region         regionMarlborough Region
##                         0.32061                          0.23741
##            regionNelson Region           regionNorthland Region
##                        -0.22859                          0.37625
##             regionOtago Region           regionSouthland Region
##                        -0.12013                          0.04669
##          regionTaranaki Region              regionTasman Region
##                         0.20279                         -0.09298
##           regionWaikato Region          regionWellington Region
##                         0.37086                         -0.14220
##        regionWest Coast Region                    NumberOfLanes
##                         0.22566                         -0.16826
##          crashSHDescriptionYes                  carStationWagon
##                         0.20877                         -0.19644
##
## Degrees of Freedom: 844964 Total (i.e. Null);  844941 Residual
## Null Deviance:       54580
## Residual Deviance: 45040     AIC: 87660
```

BIC stepwise regression selected all variables already in the model.

Diagnostic measures

Is there severe multicollinearity in the data set:

```r
pander(vif(model_nb))
```

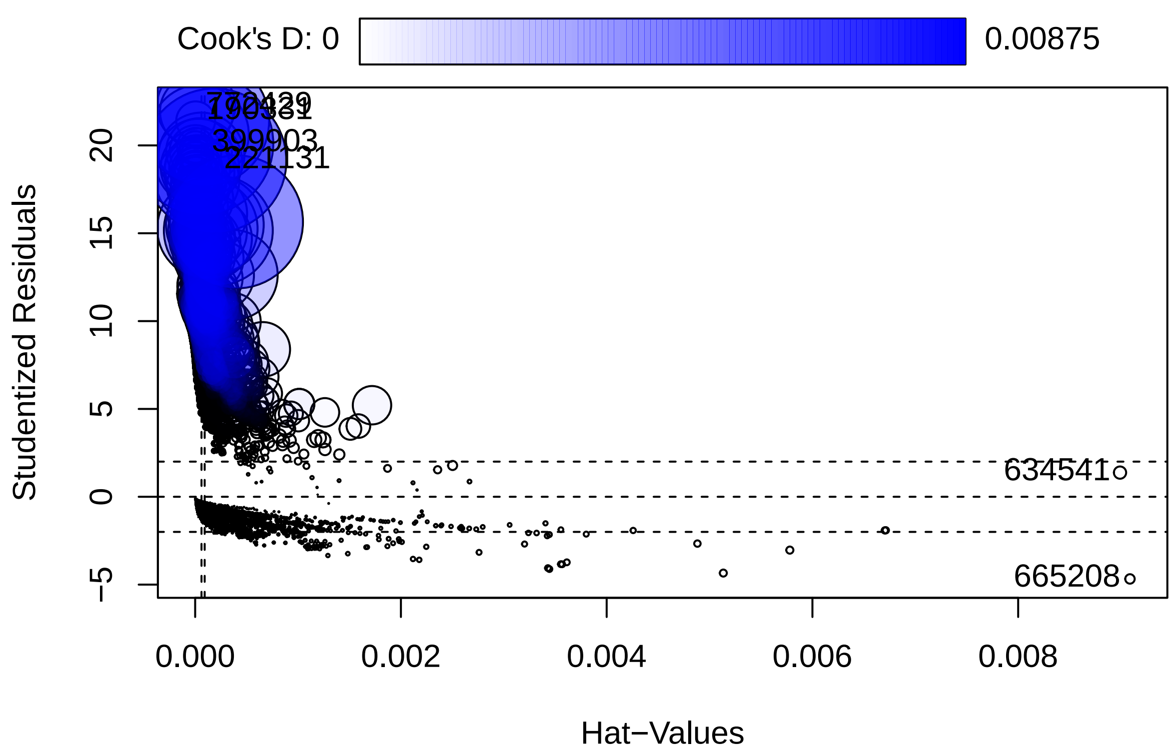
	GVIF	Df	GVIF^(1/(2*Df))
speedLimit	1.466	1	1.211

	GVIF	Df	GVIF^(1/(2*Df))
motorcycle	1.112	1	1.055
roadLane	1.237	2	1.055
truck	1.141	1	1.068
region	1.401	15	1.011
NumberOfLanes	1.195	1	1.093
otherVehicleType	1.009	1	1.004
crashSHDescription	1.355	1	1.164
carStationWagon	1.326	1	1.152
flatHill	1.054	1	1.027

The variance inflation factors (VIF's) are all below 10, meaning there is no evidence of severe multicollinearity of the predictors.

Cook's distance:

```
influencePlot(model_nb)
```




```
##            StudRes          Hat        CookD
## 190331 21.934360 1.531365e-05 2.278637e-03
## 221131 19.138611 1.864857e-04 8.753667e-03
## 399903 20.106231 6.764269e-05 8.546707e-03
## 634541  1.376228 8.990071e-03 6.349918e-05
## 665208 -4.676156 9.086875e-03 3.759999e-05
## 772429 22.223502 8.801727e-06 2.604160e-03
```

There are six oberservations that are influential points according to cook's distance, I will remove them from the data set.

```
Crash2 <- Crash2[-c(190331, 221131, 399903, 634541, 665208, 772429),]
```

Interpretting model coefficients

```
# refitting model using data excluding influential points
model_nb <- glm.nb(fatalCount ~ speedLimit + motorcycle + roadLane + truck + region +
                   NumberOfLanes + otherVehicleType + crashSHDescription +
                   carStationWagon + flatHill, data = Crash2)

pander(summary(model_nb))
```

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-8.196	0.1016	-80.64	0
speedLimit	0.03254	0.0006478	50.23	0
motorcycle	1.045	0.03686	28.36	6.469e-177
roadLane2-way	1.402	0.06759	20.74	1.47e-95
roadLaneOff road	1.625	0.1519	10.7	1.019e-26
truck	0.6662	0.03052	21.83	1.258e-105
regionBay of Plenty Region	0.4397	0.05209	8.442	3.112e-17
regionCanterbury Region	0.3486	0.04692	7.429	1.09e-13
regionGisborne Region	0.1266	0.1024	1.236	0.2163
regionHawke's Bay Region	0.1815	0.0627	2.894	0.003802
regionManawatū-Whanganui Region	0.3178	0.05207	6.104	1.035e-09
regionMarlborough Region	0.2317	0.1035	2.239	0.02516
regionNelson Region	-0.2287	0.1632	-1.401	0.1612
regionNorthland Region	0.3742	0.0547	6.84	7.92e-12
regionOtago Region	-0.1199	0.06276	-1.91	0.05609
regionSouthland Region	0.04058	0.07598	0.5341	0.5933
regionTaranaki Region	0.1997	0.07446	2.682	0.007313
regionTasman Region	-0.0952	0.106	-0.8979	0.3693
regionWaikato Region	0.3686	0.04314	8.544	1.293e-17
regionWellington Region	-0.1426	0.05817	-2.452	0.01421
regionWest Coast Region	0.2252	0.09396	2.396	0.01656
NumberOfLanes	-0.1684	0.01898	-8.876	6.92e-19
otherVehicleType	0.3119	0.1042	2.993	0.002764
crashSHDescriptionYes	0.2098	0.02736	7.667	1.765e-14
carStationWagon	-0.1937	0.01839	-10.54	5.946e-26
flatHillHill Road	-0.01067	0.02777	-0.3844	0.7007

(Dispersion parameter for Negative Binomial(0.1061) family taken to be 1)

Null deviance:	54604 on 844958 degrees of freedom
Residual deviance:	45059 on 844933 degrees of freedom

Interpretation of coefficients. For a one unit change in the speedLimit, the log of expected counts of fatalCount changes by 0.0325426, given that the other predictor variables in the model are held constant. This change is statistically significant at a significance level of 0.05

For a one unit change in the motorcycle, the log of expected counts of fatalCount changes by 1.0454277, given that the other predictor variables in the model are held constant. This change is statistically significant at a significance level of 0.05

The expected log count for 2-way road lane is 1.4018498 higher than the expected log count for a 1-way road lane. This is statistically significant at a significance level of 0.05

The expected log count for Off road lane is 1.6252327 higher than the expected log count for a 1-way road lane. This is statistically significant at a significance level of 0.05

For a one unit change in the truck, the log of expected counts of fatalCount changes by 0.6661703, given that the other predictor variables in the model are held constant. This change is statistically significant at a significance level of 0.05

The expected log count for the Bay of Plenty region is 0.4397231 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the Canterbury region is 0.3485874 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the Gisborne region is 0.1265755 higher than the expected log count for the Auckland region. This is not statistically significant at a significance level of 0.05

The expected log count for the Hawke's Bay region is 0.1814586 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the Manawatū-Whanganui region is 0.3178115 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the Marlborough region is 0.2317315 higher than the expected log count for the Auckland region. This is not statistically significant at a significance level of 0.05

The expected log count for the Nelson region is -0.2286856 higher than the expected log count for the Auckland region. This is not statistically significant at a significance level of 0.05

The expected log count for the Northland region is 0.3741685 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the Otago region is -0.1199022 higher than the expected log count for the Auckland region. This is not statistically significant at a significance level of 0.05

The expected log count for the Southland region is 0.0405806 higher than the expected log count for the Auckland region. This is not statistically significant at a significance level of 0.05

The expected log count for the Taranaki region is 0.1997085 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the Tasman region is -0.0951974 higher than the expected log count for the Auckland region. This is not statistically significant at a significance level of 0.05

The expected log count for the Waikato region is 0.3686458 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the Wellington region is -0.1426382 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

The expected log count for the West Coast region is 0.2251500 higher than the expected log count for the Auckland region. This is statistically significant at a significance level of 0.05

For a one unit change in the NumberOfLanes, the log of expected counts of fatalCount changes by -0.1684421, given that the other predictor variables in the model are held constant. This change is statistically significant at a significance level of 0.05

For a one unit change in the otherVehicleType, the log of expected counts of fatalCount changes by 0.3119136, given that the other predictor variables in the model are held constant. This change is statistically significant at a significance level of 0.05

For a one unit change in the crashSHDescriptionYes, the log of expected counts of fatalCount changes by 0.2097563, given that the other predictor variables in the model are held constant. This change is statistically significant at a significance level of 0.05

For a one unit change in the carStationWagon, the log of expected counts of fatalCount changes by -0.1937036, given that the other predictor variables in the model are held constant. This change is statistically significant at a significance level of 0.05

For a one unit change in the flatHillHill, the log of expected counts of fatalCount changes by -0.0106745, given that the other predictor variables in the model are held constant. This change is not statistically significant at significance level of 0.05

Using model for prediction

Estimating count of deaths in a car crash based on new data:

```
newdata1 <- data.frame(speedLimit = 100,
                       motorcycle = 2,
                       roadLane = "2-way",
                       truck = 5,
                       region = "Bay of Plenty Region",
                       NumberOfLanes = 4,
                       otherVehicleType = 3,
                       crashSHDescription = "Yes",
                       carStationWagon = 3,
                       flatHill = "Hill Road")
predict(model_nb, newdata = newdata1)
```

```
##        1
## 2.201431
```