# Storm Data Analysis - Finding the worst type of Storms

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## **Synopsis**

In this analysis storm data from NOAA Storm Database has been used to answer two basic questions about severe weather events:

- Across the United States, which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health?
- Across the United States, which types of events have the greatest economic consequences?

```
library("ggplot2")
library("plyr")
library("tm")
library("gridExtra")
```

## **Data Processing**

This section deals with reading in the data and processing it to do the analysis.

```
data = read.csv("./repdata-data-StormData.csv.bz2")
```

Programmatically extracting the reference categories from the National Weather Service Instruction 10-1605 PDF document.

```
pdf <- readPDF(control = list(c(text = "-layout")))
pdf <- pdf(elem=list(uri="nws_i10_1605.pdf"),language="en")
keep = c(pdf$content[seq(397, 420)], pdf$content[seq(425, 448)])
keep</pre>
```

```
##
   [1] "Astronomical Low Tide"
                                    "Avalanche"
##
   [3] "Blizzard"
                                    "Coastal Flood"
  [5] "Cold/Wind Chill"
                                    "Debris Flow"
   [7] "Dense Fog"
                                    "Dense Smoke"
##
##
  [9] "Drought"
                                    "Dust Devil"
                                    "Excessive Heat"
## [11] "Dust Storm"
## [13] "Extreme Cold/Wind Chill"
                                    "Flash Flood"
## [15] "Flood"
                                    "Frost/Freeze"
## [17] "Funnel Cloud"
                                    "Freezing Fog"
## [19] "Hail"
                                    "Heat"
## [21] "Heavy Rain"
                                    "Heavy Snow"
## [23] "High Surf"
                                    "High Wind"
## [25] "Hurricane (Typhoon)"
                                    "Ice Storm"
## [27] "Lake-Effect Snow"
                                    "Lakeshore Flood"
## [29] "Lightning"
                                    "Marine Hail"
```

```
## [31] "Marine High Wind"
                                    "Marine Strong Wind"
## [33] "Marine Thunderstorm Wind" "Rip Current"
## [35] "Seiche"
                                    "Sleet"
## [37] "Storm Surge/Tide"
                                    "Strong Wind"
## [39] "Thunderstorm Wind"
                                    "Tornado"
## [41] "Tropical Depression"
                                    "Tropical Storm"
## [43] "Tsunami"
                                    "Volcanic Ash"
## [45] "Waterspout"
                                    "Wildfire"
## [47] "Winter Storm"
                                    "Winter Weather"
```

The EVTYPE Variable consists of over 900 factor variables. Most of this is because of spelling mistake and shorthands being used. Most of these occur rarely and can be weeded out without any difference to the final result.

Extracting the 50 most frequent EVTYPE's from the data.

```
freq = count(data, 'EVTYPE')
freq = arrange(freq, desc(freq))
freq = freq[1:50,]
head(freq)
```

```
##
                 EVTYPE
                          freq
## 1
                   HAIL 288661
## 2
             TSTM WIND 219940
## 3 THUNDERSTORM WIND
                         82563
## 4
               TORNADO
                         60652
## 5
           FLASH FLOOD
                         54277
## 6
                 FLOOD 25326
```

The most frequent storm type is **Hail Storm**.

```
detach("package:plyr", unload=TRUE)
library("dplyr")
```

```
##
## Attaching package: 'dplyr'
##
## The following objects are masked from 'package:stats':
##
## filter, lag
##
## The following objects are masked from 'package:base':
##
## intersect, setdiff, setequal, union
```

Subsetting the data to rows which have EVTYPE in freq.

Also, removing the rows where all of property damage, crop damage and fatalities are zero. This is beacause any storm event that does not do any damage is of no use to us in suggesting the most dangerous storm event.

```
df = merge(data, freq, by = "EVTYPE")
df = filter(df, FATALITIES != 0 | PROPDMG != 0)
```

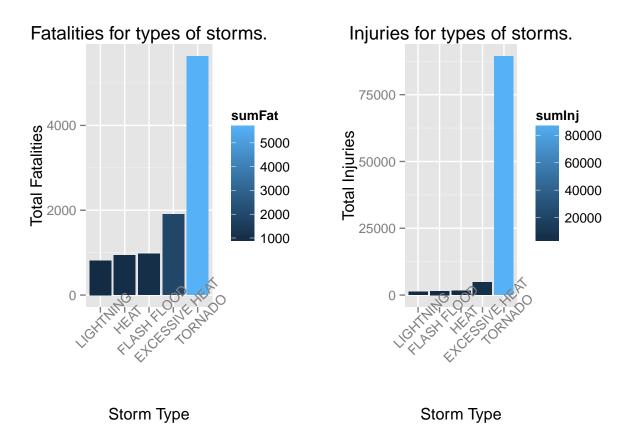
## **Data Analysis**

In this section graphs and tables have been made for the analysis. Specifically, the following graphs are plotted:

- Total fatalities for types of storms
- Total injuries for types of storms
- Total damage for types of storms

#### Damage to population health

```
grouping <- group_by(df, EVTYPE)</pre>
sumHealth = summarize(grouping,sumFat = sum(FATALITIES),
                      sumInj = sum(INJURIES))
sumHealth = arrange(sumHealth, desc(sumFat))
sumHealth = sumHealth[1:5,]
plot1 = ggplot(sumHealth, aes(reorder(factor(EVTYPE), sumFat),
                       y = sumFat, fill = sumFat)) +
  geom_bar(stat = "identity") +
  labs(title = "Fatalities for types of storms.",
       x = "Storm Type", y = "Total Fatalities") +
        theme(axis.text.x = element_text(angle=45))
sumHealth = arrange(sumHealth, desc(sumInj))
sumHealth = sumHealth[1:5,]
plot2 = ggplot(sumHealth, aes(reorder(factor(EVTYPE), sumInj),
                               y = sumInj, fill = sumInj)) +
  geom_bar(stat = "identity") +
  labs(title = "Injuries for types of storms.",
       x = "Storm Type", y = "Total Injuries") +
  theme(axis.text.x = element_text(angle=45))
grid.arrange(plot1, plot2, ncol=2)
```



It is clear from the above graphs that **tornados** have been the worst affecting storm type for the **health of the population**. The fatalities and the injuries caused by tornados far outnumber that of the other storm types.

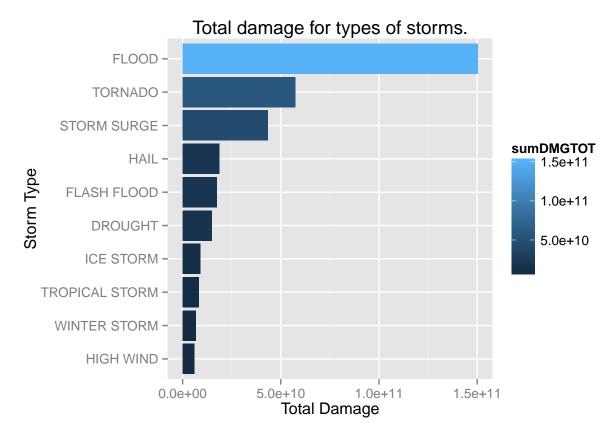
#### **Economic Damage**

In this section the damage to economy has been studied.

```
df$PROPMUL = 0 # Defining a new variable for obtaining the value of the PROPDMGEXP variable
df$CROPMUL = 0 # Defining a new variable for obtaining the value of the CROPDMGEXP variable
df[as.character(df$CROPDMGEXP) == "K",]$CROPMUL = 1000
df[as.character(df$CROPDMGEXP) == "M",]$CROPMUL = 10000000
df[as.character(df$CROPDMGEXP) == "B",]$CROPMUL = 10000000000

df[as.character(df$PROPDMGEXP) == "B",]$PROPMUL = 1000000000
df[as.character(df$PROPDMGEXP) == "M",]$PROPMUL = 10000000
df[as.character(df$PROPDMGEXP) == "K",]$PROPMUL = 1000

df$PROPDMGTOT = df$PROPDMG*df$PROPMUL # property damage for a storm
df$CROPDMGTOT = df$CROPDMG*df$CROPMUL # crop damage for a storm
grouping <- group_by(df, EVTYPE)
sumDMG = summarize(grouping,sumPROPDMG = sum(PROPDMGTOT),</pre>
```



We can see from the above figure that **floods** cause the highest amount of total economic damage. Let us now see which storm types cause the highest amount of damage to property and crop independently.

#### Damage to Property

```
sumDMG = arrange(sumDMG, desc(sumPROPDMG))
sumDMGhead = sumDMG[1:5,]
sumDMGhead
```

## Source: local data frame [5 x 4]

```
##
##
          EVTYPE
                    sumPROPDMG sumCROPDMG
                                              sumDMGTOT
##
          (fctr)
                         (dbl)
                                    (dbl)
                                                  (dbl)
           FLOOD 144657709800 5661968450 150319678250
## 1
## 2
         TORNADO
                  56925660480
                                414953110
                                            57340613590
## 3 STORM SURGE
                  43323536000
                                            43323541000
                                      5000
## 4 FLASH FLOOD
                  16140811510 1421317100
                                            17562128610
                  15727366720 3025537450
## 5
            HAIL
                                            18752904170
```

We can see that **floods** have caused the highest amount of damage to **property**.

#### Damage to Crop

```
sumDMG = arrange(sumDMG, desc(sumCROPDMG))
sumDMGhead = sumDMG[1:5,]
sumDMGhead
## Source: local data frame [5 x 4]
##
##
          EVTYPE
                    sumPROPDMG
                                sumCROPDMG
                                               sumDMGTOT
                                      (db1)
##
                         (db1)
                                                   (db1)
          (fctr)
## 1
         DROUGHT
                    1046106000 13972566000
                                             15018672000
## 2
           FLOOD 144657709800
                                5661968450 150319678250
## 3
       ICE STORM
                    3944927810
                                5022113500
                                              8967041310
## 4
            HAIL
                   15727366720
                                3025537450
                                             18752904170
## 5 FLASH FLOOD
                   16140811510
                                1421317100
                                             17562128610
```

We can see that **droughts** have caused the highest amount of damage to **crop**.

### Results

Looking at the graphs the following points can be ascertained:

- Floods have caused the highest amount of damage to the economy since the time this data has been collected
- Droughts have caused the most amount of damage to the Crops.
- Tornados have had the worst impact on the health of the population.