

Reproducible Research - Course Project 2

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Introduction

This project involves exploring the U.S. National Oceanic and Atmospheric Administration's (NOAA) storm database. This database tracks characteristics of major storms and weather events in the United States, including when and where they occur, as well as estimates of any fatalities, injuries, and property damage. The analysis below will analyze the major storm events causing injuries and fatalities. Similarly, we will also examine the major Storm Event causing highest property damage.

Synopsis

The analysis on the storm event database revealed that tornadoes are the most dangerous weather event to the populations health. The second most dangerous event type is excessive heat. The economic impact of weather events was also analyzed. Flash floods and thunderstorm winds caused billions of dollars in property damages between 1950 and 2011. The largest damage to crops were caused by droughts, followed by floods and hailing.

Load libraries used

```
library(ggplot2)
library(R.utils)
library(dplyr)
```

Data load

```
if (!file.exists("StormData.csv")) {
  url <- "https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2"
  download.file(url, "StormData.csv.bz2")
  bunzip2("StormData.csv.bz2", "StormData.csv")
}
df <- read.csv("StormData.csv")
```

Data Processing

Health Impact

To evaluate the health impact, the total fatalities and the total injuries for each event type (EVTYPE) are calculated. The codes for this calculation are shown as follows.

```
df.fatalities <- df %>% select(EVTYPE, FATALITIES) %>% group_by(EVTYPE) %>% summarise(total.fatalities = sum(FATALITIES))
head(df.fatalities, 10)
```

```
## # A tibble: 10 x 2
##   EVTYPE          total.fatalities
##   <fct>          <dbl>
## 1 TORNADO          5633
## 2 EXCESSIVE HEAT   1903
## 3 FLASH FLOOD      978
## 4 HEAT             937
## 5 LIGHTNING        816
## 6 TSTM WIND        504
## 7 FLOOD            470
## 8 RIP CURRENT      368
## 9 HIGH WIND        248
## 10 AVALANCHE       224
```

```
df.injuries <- df %>% select(EVTYPE, INJURIES) %>% group_by(EVTYPE) %>% summarise(total.injuries = sum(INJURIES))
head(df.injuries, 10)
```

```
## # A tibble: 10 x 2
##   EVTYPE          total.injuries
##   <fct>          <dbl>
## 1 TORNADO          91346
## 2 TSTM WIND        6957
## 3 FLOOD            6789
## 4 EXCESSIVE HEAT   6525
## 5 LIGHTNING        5230
## 6 HEAT             2100
## 7 ICE STORM        1975
## 8 FLASH FLOOD      1777
## 9 THUNDERSTORM WIND 1488
## 10 HAIL            1361
```

At this point we got the amount of fatalities and injuries per event type.

Economic Impact

The data provides two types of economic impact, namely property damage (PROPDMG) and crop damage (CROPDMG). The actual damage in \$USD is indicated by PROPDMGEXP and CROPDMGEXP parameters.

The indexes in the PROPDMGEXP and CROPDMGEXP have the following multipliers:

H, h -> hundreds = x100 K, K -> kilos = x1,000 M, m -> millions = x1,000,000 B,b -> billions = x1,000,000,000 (+) -> x1 (-) -> x0 (?) -> x0 blank -> x0

So we need to make some math and conversions to get the actual damage values.

```
df.damage <- df %>% select(EVTYPE, PROPDMG, PROPDMGEXP, CROPDMG, CROPDMGEXP)
```

```
Symbol <- sort(unique(as.character(df.damage$PROPDMPGEXP)))
```

```

Multiplier <- c(0,0,0,1,10,10,10,10,10,10,10,10,10,10^9,10^2,10^2,10^3,10^6,10^6)
convert.Multiplier <- data.frame(Symbol, Multiplier)

df.damage$Prop.Multiplier <- convert.Multiplier$Multiplier[match(df.damage$PROPDMGEXP, convert.Multiplier$Symbol)]
df.damage$Crop.Multiplier <- convert.Multiplier$Multiplier[match(df.damage$CROPDMGEXP, convert.Multiplier$Symbol)]

df.damage <- df.damage %>% mutate(PROPDMG = PROPDMG*Prop.Multiplier) %>% mutate(CROPDMG = CROPDMG*Crop.Multiplier)

df.damage.total <- df.damage %>% group_by(EVTYPE) %>% summarize(TOTAL.DMG.EVTYPE = sum(TOTAL.DMG))%>% arrange(desc(TOTAL.DMG.EVTYPE))
head(df.damage.total,10)

```

```

## # A tibble: 10 x 2
##   EVTYPE          TOTAL.DMG.EVTYPE
##   <fct>          <dbl>
## 1 FLOOD          150319678250
## 2 HURRICANE/TYPHOON 71913712800
## 3 TORNADO        57352117607
## 4 STORM SURGE    43323541000
## 5 FLASH FLOOD    17562132111
## 6 DROUGHT        15018672000
## 7 HURRICANE      14610229010
## 8 RIVER FLOOD    10148404500
## 9 ICE STORM      8967041810
## 10 TROPICAL STORM 8382236550

```

At this point we got the amount of economic damage per event type.

Results

Health Impact

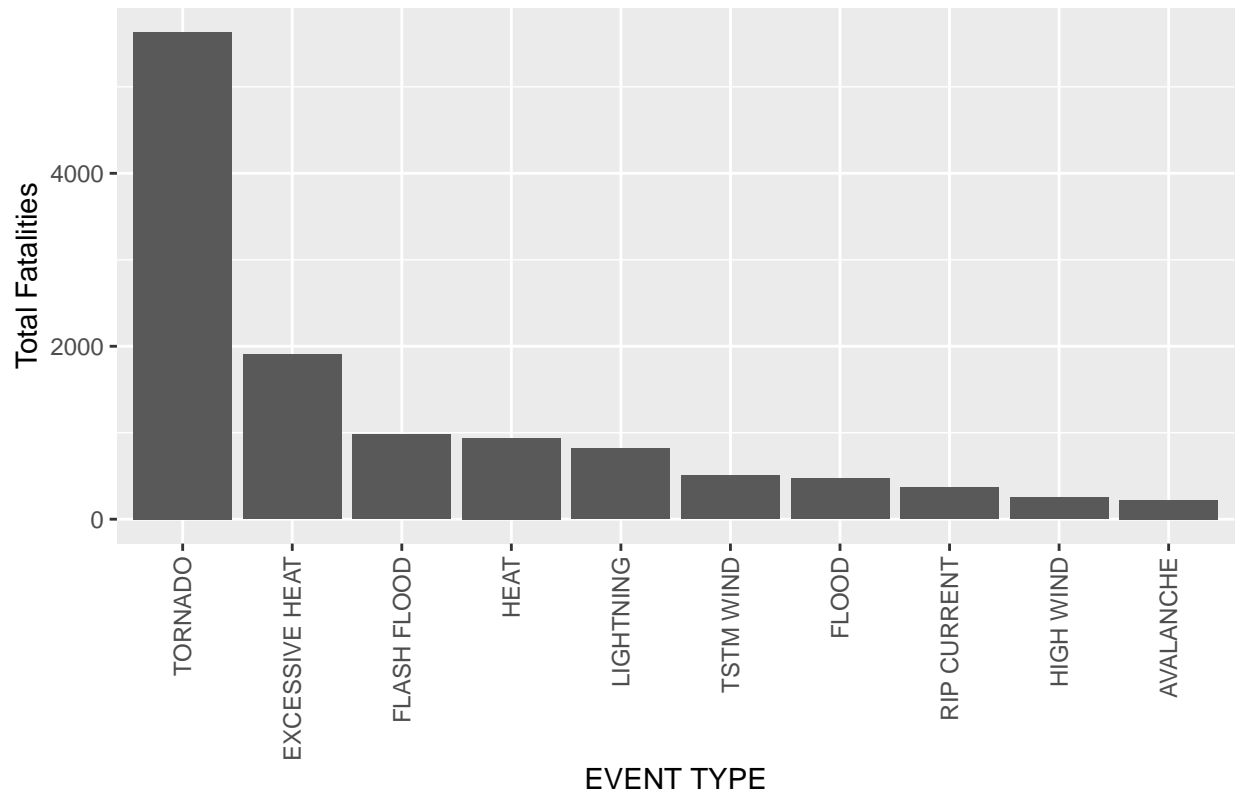
The top 10 events with the highest total fatalities and injuries are shown in the graphic.

```

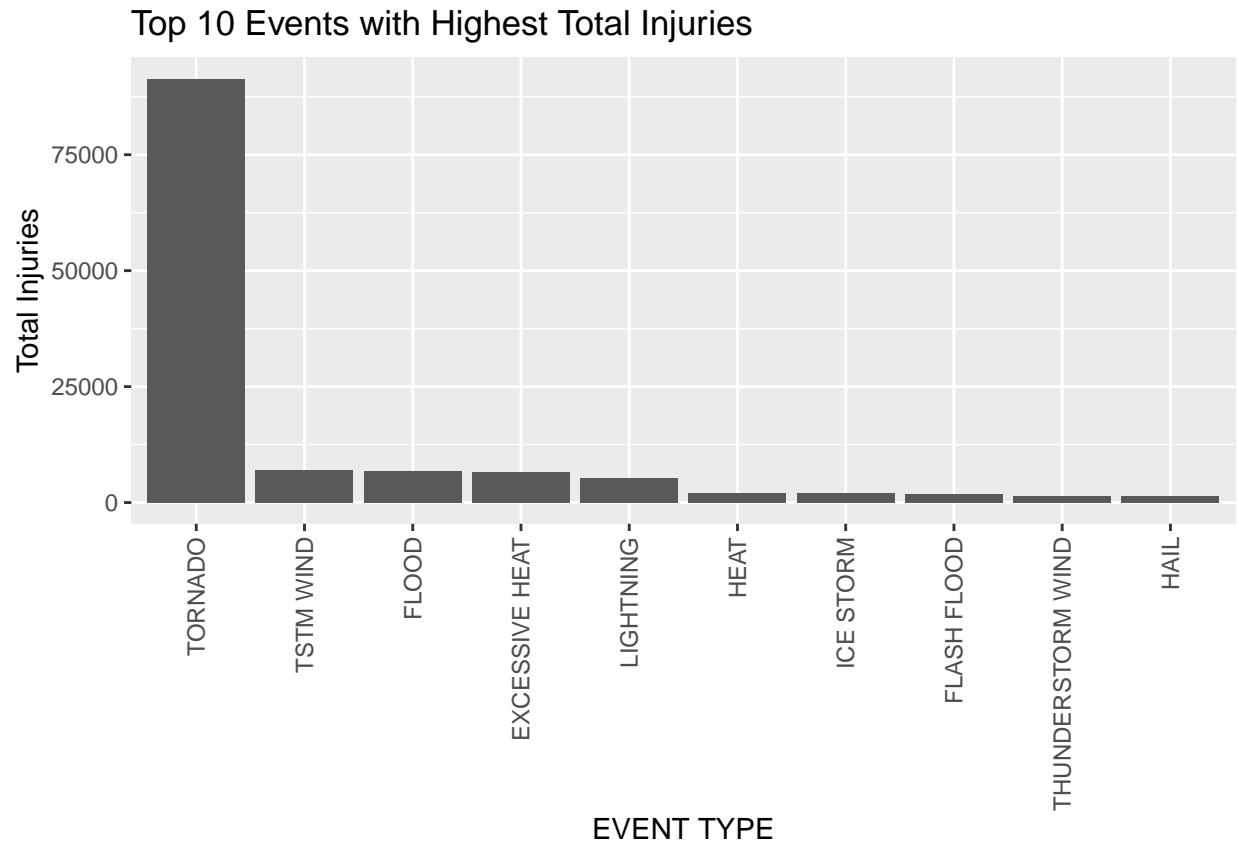
ggplot(df.fatalities[1:10,], aes(x=reorder(EVTYPE, -total.fatalities), y=total.fatalities))+geom_bar(stat="sum")

```

Top 10 Events with Highest Total Fatalities



```
ggplot(df.injuries[1:10,], aes(x=reorder(EVTYPE, -total.injuries), y=total.injuries))+geom_bar(stat="id
```

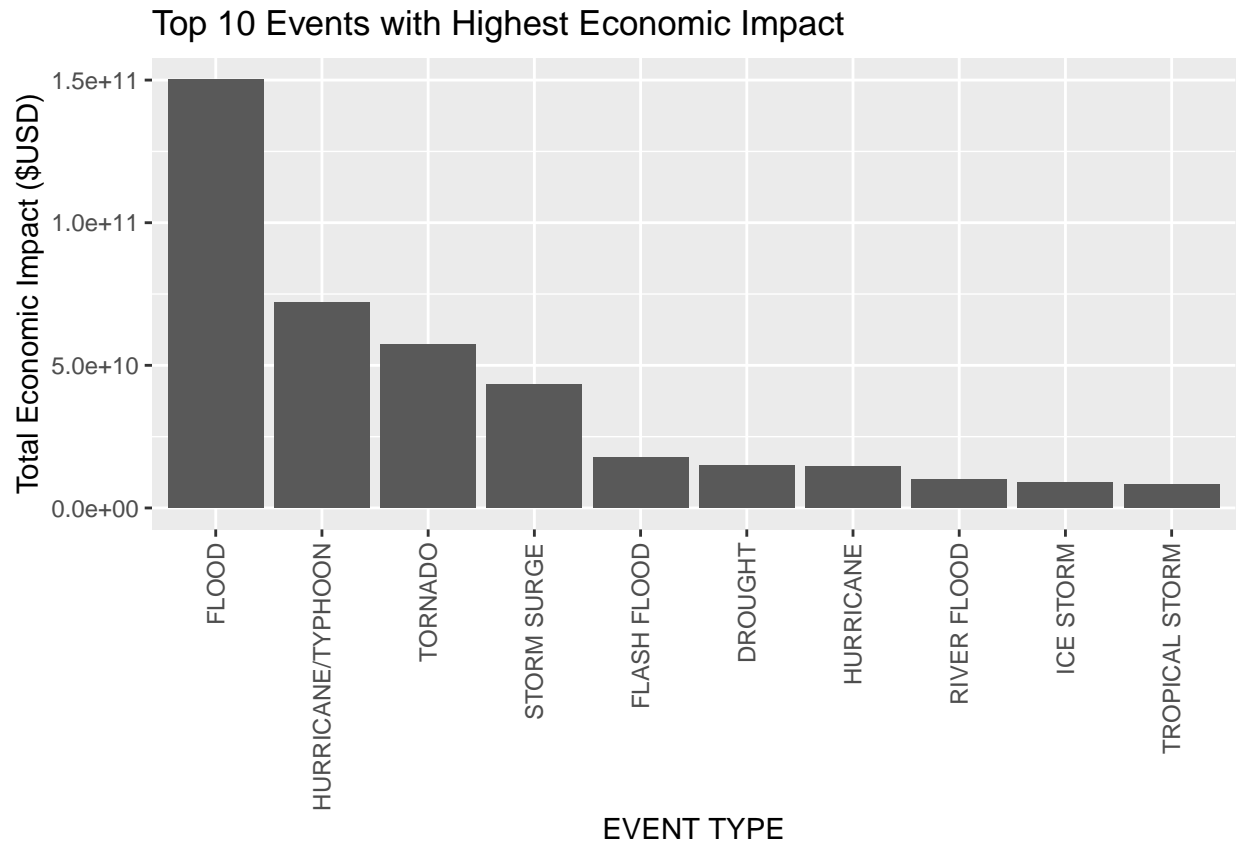


As explained in the synopsis, tornadoes have the highest amount of fatalities and injuries by a long margin.

Economic Impact

The top 10 events with the highest total economic damages are shown in the graphic.

```
ggplot(df.damage.total[1:10,], aes(x=reorder(EVTYPE, -TOTAL.DMG.EVTYPE), y=TOTAL.DMG.EVTYPE))+geom_bar()
```



We can observe that floods cause the highest economic impact.