

Data Analysis on Severe Weather events in the USA

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This report shows uses data from the National Weather Service and National Climatic Data Center Storm Events in order to study the impacts of severe weather condition regarding the health of human population and economic consequences. In order to adress theses problems we are going to simplify the data set, acting only regarding from year by begining date and relevant data, we did not make any consideration regarding the location which might have been usefull in order to adress a specific city. To start this we imported the data :

```
## Data Processing :  
RawData <- read.csv("repdata-data-StormData.csv")  
RawData$EVTYPE = as.character(RawData$EVTYPE)  
RawData$BGN_DATE <- as.Date(as.character(RawData$BGN_DATE), "%m/%d/%Y")  
Data <- RawData[,c("BGN_DATE", "EVTYPE", "MAG", "FATALITIES", "INJURIES", "PROPDMGEXP", "CROPDMGEXP")]  
## Furthermore I have normalized the data in the following way, giving growing integer numbers to the facto  
r :  
Data$PROPDMGEXP <- as.numeric(Data$PROPDMGEXP)  
Data$CROPDMGEXP <- as.numeric(Data$CROPDMGEXP)
```

Regarding the danger toward population health we started by looking for “human health” in the document “Storm Data Documentation” and extracted the corresponding daa from the Raw Data.

We are going to look at the event that have more that average of Injuries and Fatalities.

```

### Results : on Human Health
## Let us compute criteria of our analysis :
Mean_Inj <- mean(Data$INJURIES)
Mean_Fat <- mean(Data$FATALITIES)
M_Mean_Pop_Risk <- which(Data$INJURIES > Mean_Inj & Data$FATALITIES > Mean_Fat)
## Risk Event Data Set is :
Risk_Event_Data <- Data[M_Mean_Pop_Risk,]

##The 15 most likely to happen which are also the more dangerous than average
Count_By_Type <- tapply(Risk_Event_Data$EVTYPE, Risk_Event_Data$EVTYPE, length)
Rank <- sort(Count_By_Type, decreasing = TRUE)
head(Rank, 15)

```

##	TORNADO	LIGHTNING	TSTM WIND	FLASH FLOOD
##	1378	263	148	85
##	HIGH WIND	EXCESSIVE HEAT	WINTER STORM	RIP CURRENT
##	69	64	52	47
##	FLOOD	AVALANCHE	THUNDERSTORM WIND	HEAVY SNOW
##	44	42	40	32
##	RIP CURRENTS	ICE STORM	FOG	
##	29	24	23	

```

## Weight of different components in Population health : \n 1) Injuries
Weight_Inj_By_Type <- tapply(Risk_Event_Data$INJURIES, Risk_Event_Data$EVTYPE, sum)
Weight_Inj_By_Type <- sort(Weight_Inj_By_Type, decreasing = TRUE)
head(Weight_Inj_By_Type, 15)

```

##	TORNADO	EXCESSIVE HEAT	FLOOD	ICE STORM
##	60187	4791	2679	1720
##	HEAT	HURRICANE/TYPHOON	BLIZZARD	LIGHTNING
##	1420	1219	718	649
##	TSTM WIND	FLASH FLOOD	WINTER STORM	FOG
##	646	641	599	308
##	HIGH WIND	TROPICAL STORM	HEAT WAVE	
##	308	274	269	

2) Fatalities

```
Weight_Fat_By_Type <- tapply(Risk_Event_Data$FATALITIES, Risk_Event_Data$EVTYPE, sum)
Weight_Fat_By_Type <- sort(Weight_Fat_By_Type, decreasing = TRUE)
head(Weight_Fat_By_Type, 15)
```

##	TORNADO	EXCESSIVE HEAT	LIGHTNING	TSTM WIND
##	5227	402	283	199
##	FLASH FLOOD	FLOOD	HIGH WIND	WINTER STORM
##	171	104	102	85
##	HEAT	WILDFIRE	THUNDERSTORM WIND	AVALANCHE
##	73	55	54	52
##	HEAVY SNOW	RIP CURRENT	BLIZZARD	
##	51	50	48	

3) Sum of the Two :

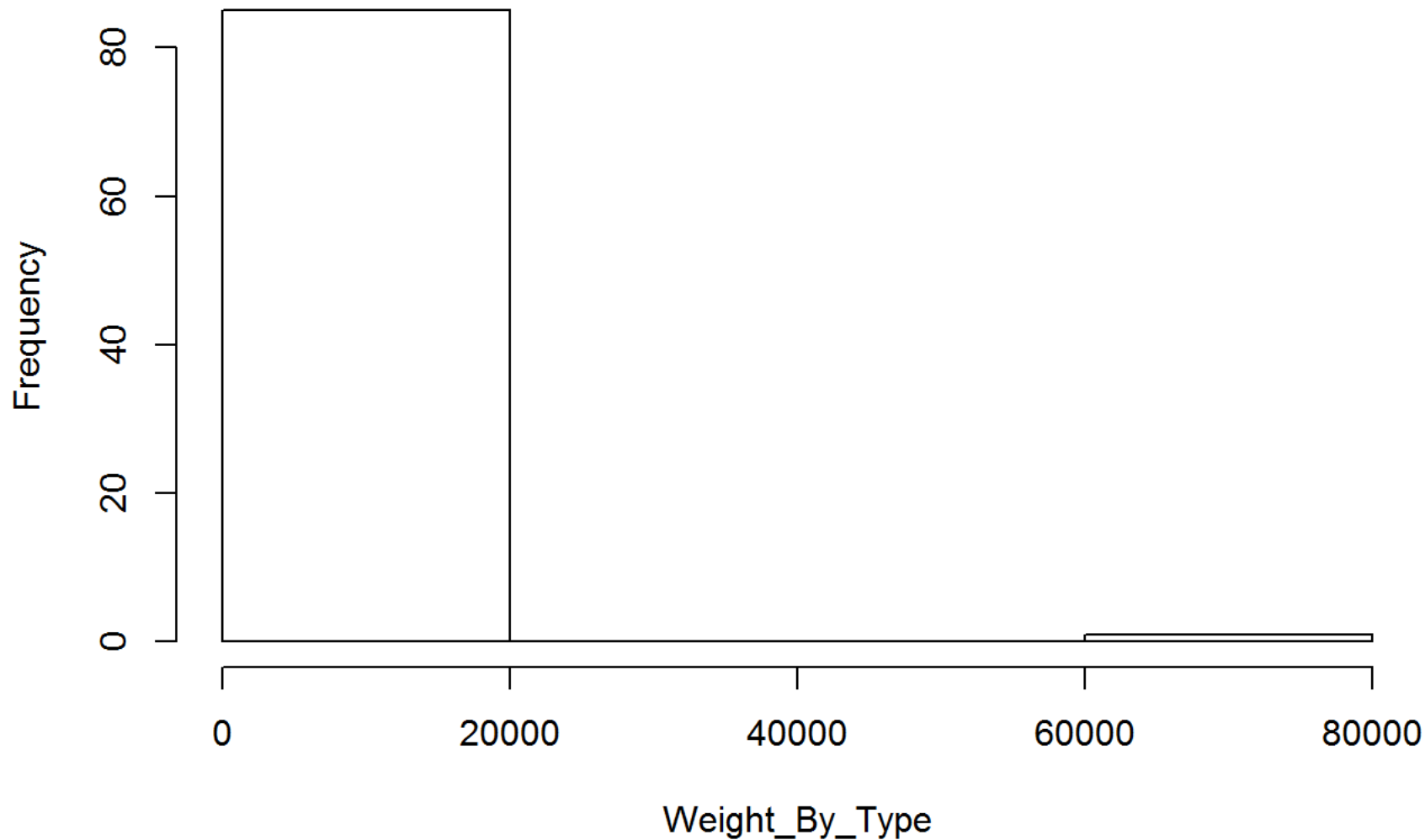
```
Weight_By_Type <- Weight_Inj_By_Type + Weight_Fat_By_Type
head(Weight_By_Type, 15)
```

##	TORNADO	EXCESSIVE HEAT	FLOOD	ICE STORM
##	65414	5193	2962	1919
##	HEAT	HURRICANE/TYPHOON	BLIZZARD	LIGHTNING
##	1591	1323	820	734
##	TSTM WIND	FLASH FLOOD	WINTER STORM	FOG
##	719	696	653	360
##	HIGH WIND	TROPICAL STORM	HEAT WAVE	
##	359	324	317	

4) Lets us revue the proportion of damages caused by thoses envents :

```
hist(Weight_By_Type, breaks = 3)
```

Histogram of Weight_By_Type



We see here

that the immense majority of these events have a very small impact on the Population health side of the problem. Only a few at the far right are causing big problems.

We note that the greatest overall factor of destruction toward human health are Tornados. Given what we have said before, an approach to the problem could be to focus emergency resources on the top 4 or 5 most harmful risks.

Let us study the impacts on Econmical critera, we will repeat the same analysis :

```
### Results : on Economic Consequences :
```

```
Mean_Cro <- mean(Data$CROPDMGEXP)
```

```
Mean_Pro <- mean(Data$PROPDMGEXP)
```

```
M_Mean_Ec_Risk <- which(Data$CROPDMGEXP > Mean_Cro & Data$PROPDMGEXP > Mean_Pro)
```

```
## Risk Event Data Set is :
```

```
Risk_Event_Data <- Data[M_Mean_Ec_Risk,]
```

```
##The 15 most likely to happen which are also the more dangerous than average
```

```
Count_By_Type <- tapply(Risk_Event_Data$EVTYPE, Risk_Event_Data$EVTYPE, length)
```

```
Rank <- sort(Count_By_Type, decreasing = TRUE)
```

```
head(Rank, 15)
```

##	THUNDERSTORM WIND	HAIL	FLASH FLOOD
##	81417	79967	21623
##	FLOOD	HIGH WIND	TORNADO
##	13548	11494	9382
##	WINTER STORM	WINTER WEATHER	HEAVY SNOW
##	6714	6659	6014
##	MARINE THUNDERSTORM WIND	TSTM WIND	HEAVY RAIN
##	5812	5613	5258
##	LIGHTNING	STRONG WIND	FUNNEL CLOUD
##	4168	2572	2382

```
## Weight of differents components regarding Economic consequence: \n 1) Crop :
```

```
Weight_Cro_By_Type <- tapply(Risk_Event_Data$CROPDMGEXP, Risk_Event_Data$EVTYPE, sum)
```

```
Weight_Cro_By_Type <- sort(Weight_Cro_By_Type, decreasing = TRUE)
head(Weight_Cro_By_Type, 15)
```

```
##          THUNDERSTORM WIND          HAIL          FLASH FLOOD
##          570059          560566          151689
##          FLOOD          HIGH WIND          TORNADO
##          95502          80548          65824
##          WINTER STORM          WINTER WEATHER          HEAVY SNOW
##          47010          46615          42114
## MARINE THUNDERSTORM WIND          TSTM WIND          HEAVY RAIN
##          40684          39555          36854
##          LIGHTNING          STRONG WIND          FUNNEL CLOUD
##          29180          18008          16674
```

2) Property :

```
Weight_Pro_By_Type <- tapply(Risk_Event_Data$PROPDMGEXP, Risk_Event_Data$EVTYPE, sum)
Weight_Pro_By_Type <- sort(Weight_Pro_By_Type, decreasing = TRUE)
head(Weight_Pro_By_Type, 15)
```

```
##          THUNDERSTORM WIND          HAIL          FLASH FLOOD
##          1384613          1360169          368953
##          FLOOD          HIGH WIND          TORNADO
##          232122          195716          161065
##          WINTER STORM          WINTER WEATHER          HEAVY SNOW
##          114238          113215          102284
## MARINE THUNDERSTORM WIND          TSTM WIND          HEAVY RAIN
##          98804          95599          89442
```

##	LIGHTNING	STRONG WIND	FUNNEL CLOUD
##	70962	43732	40494

3) Sum of the Two :

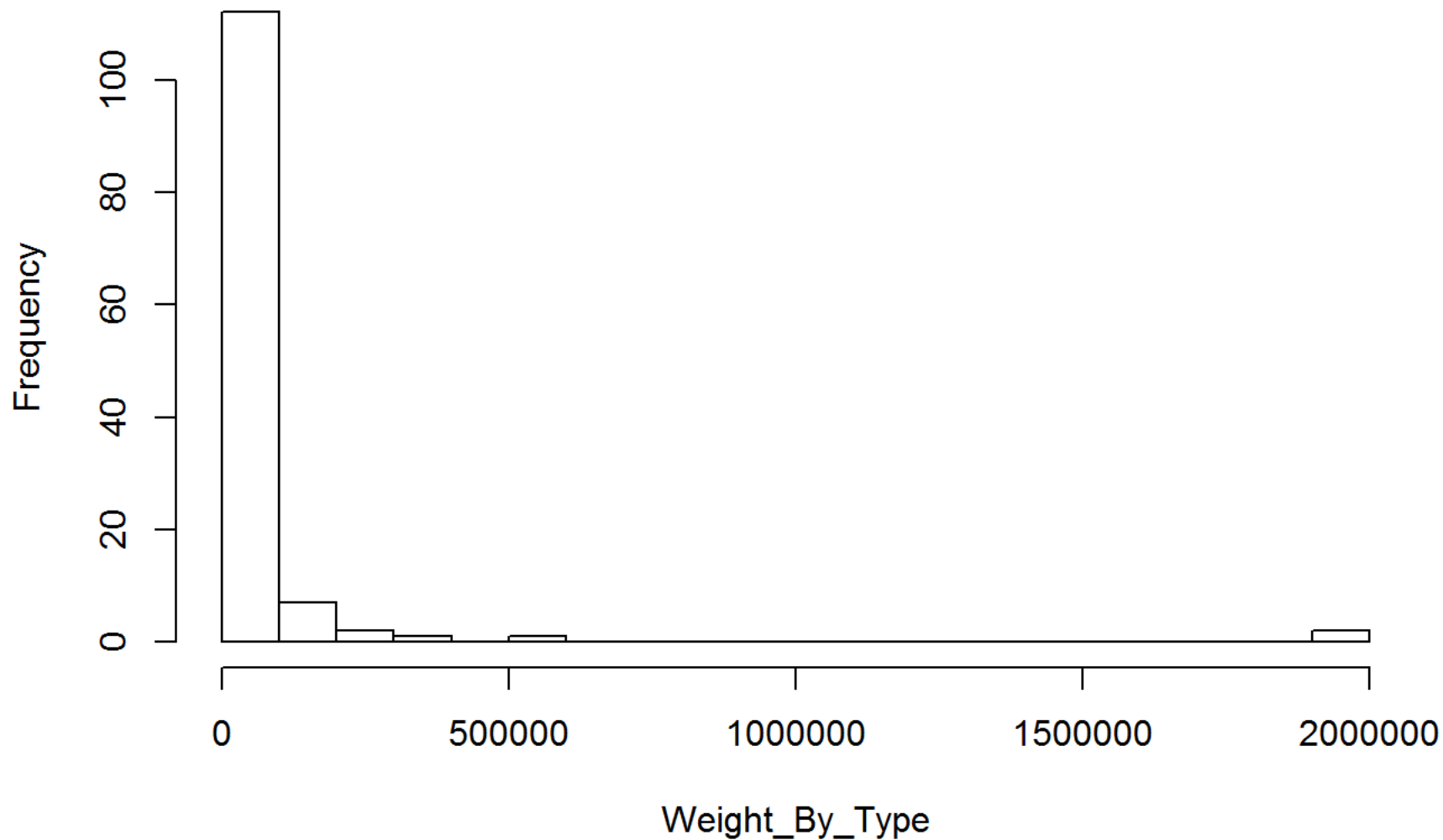
```
Weight_By_Type <- Weight_Cro_By_Type + Weight_Pro_By_Type
head(Weight_By_Type, 15)
```

##	THUNDERSTORM WIND	HAIL	FLASH FLOOD
##	1954672	1920735	520642
##	FLOOD	HIGH WIND	TORNADO
##	327624	276264	226889
##	WINTER STORM	WINTER WEATHER	HEAVY SNOW
##	161248	159830	144398
##	MARINE THUNDERSTORM WIND	TSTM WIND	HEAVY RAIN
##	139488	135154	126296
##	LIGHTNING	STRONG WIND	FUNNEL CLOUD
##	100142	61740	57168

4) Lets us revue the proportion of damages caused by thoses envents :

```
hist(Weight_By_Type, breaks = 25)
```


Histogram of Weight_By_Type



We note a very strong correlation between the 2 Economic sets.

However the relation between Economic

risks and Human health is very thin, there are not many top risks identified here for human health and for the Economie.