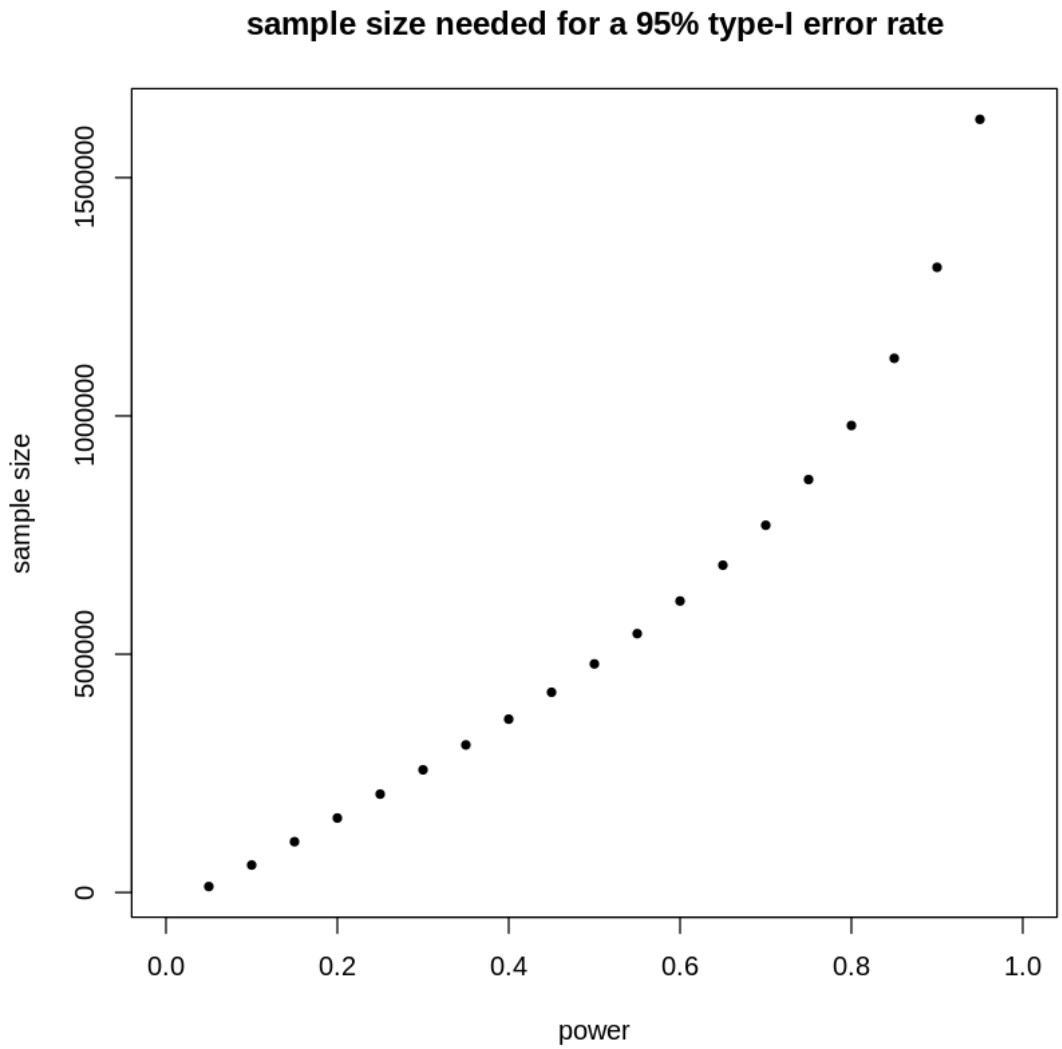
HW1

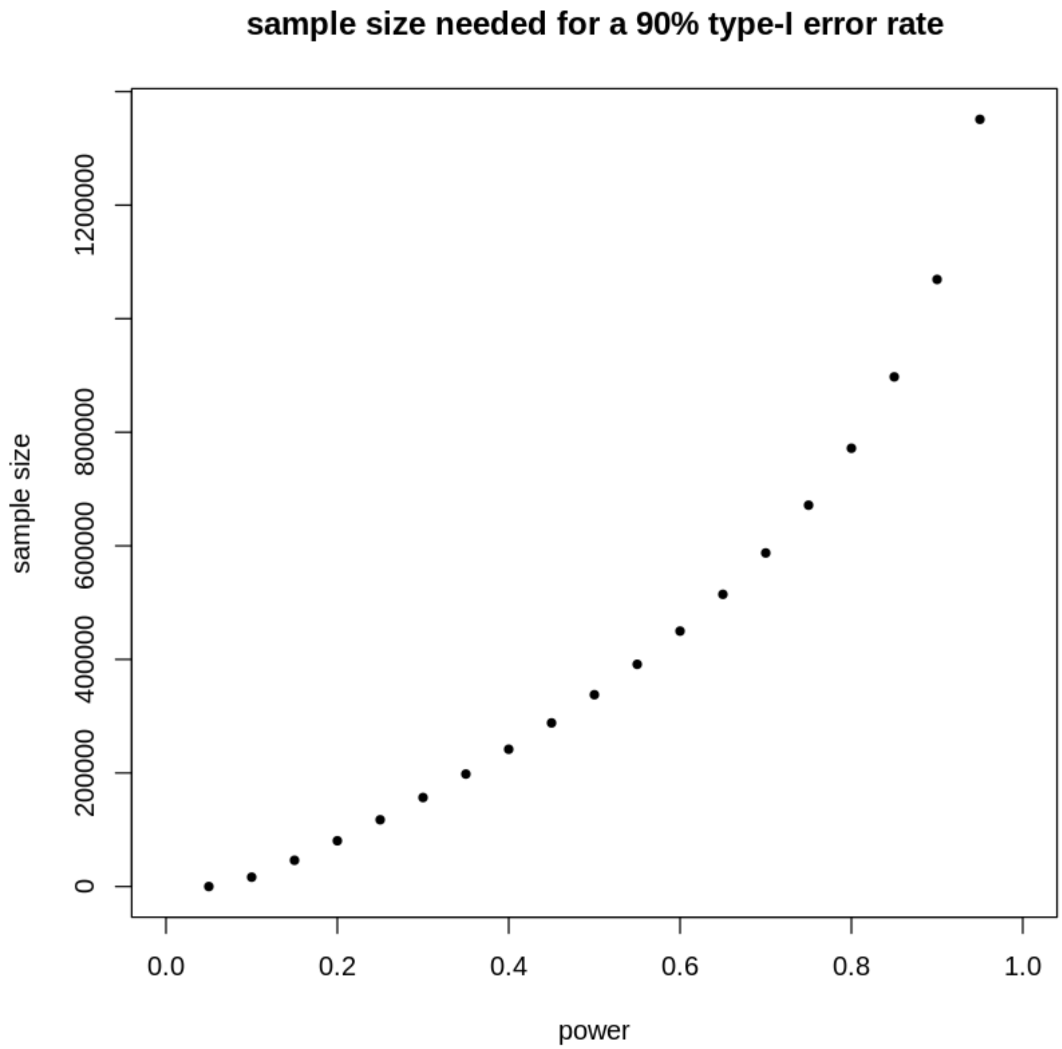
February 20, 2022

1 Problem 1: A/B Testing

Since currently, the company generates an average of \$1.50 per visit, so $\mu_0 = 1.5$. The company decideds that change in revenue with a 1% change in either direction is significant enough to note, so $\mu_1 = 1.5\,(1.01) = 1.515$. The standard deviation $\sigma = 5.3$. The effect size is calculated by $ES = \frac{|\mu_1 - \mu_0|}{\sigma} = \frac{|1.515 - 1.5|}{5.3} = 0.0028$. Since we are assuming a 95% type-I error rate, the sample size required is $n = (\frac{Z_{1-/2} + Z_{1-}}{ES})^2 = \frac{1.96 + Z_{1-}}{0.0028}$. Here, $1-$ is the power of our test.

[2]:
```
ES = (1.515 - 1.5) / 5.3
power = seq(0, 1, 0.05)
sample_size_95 = ((qnorm(1 - 0.05/2) + qnorm(power))/ES)^2
plot(power, sample_size_95, ylab = "sample size", main = "sample size needed␣
 ↪for a 95% type-I error rate", pch = 20)
sample_size_90 = ((qnorm(1 - 0.1/2) + qnorm(power))/ES)^2
plot(power, sample_size_90, ylab = "sample size", main = "sample size needed␣
 ↪for a 90% type-I error rate", pch = 20)
```


sample size needed for a 95% type-I error rate
sample size
0
500000
1000000
1500000
0.0
0.2
0.4
0.6
0.8
1.0
power



From two scatter plots, we can see that sample size needed for a 95% type-I error rate is much higher than a 90% type-I error rate with respect to the same power of the test. For 95% type-I error rate, I will recommend a sample size (visits) around 1300000 to ensure 90% power. For 90% type-I error rate, I will recommend a sample size (visits) around 1000000 to ensure 90% power.

Power is defined as the probability of rejecting null hypothesis given the alternative hypothesis is true, which is represented as $1 -$. Type-I error rate is . As increase, $Z_{1-/2}$ will decrease, so the sample size will decrease. As increase, Z_{1-} will decrease, so the sample size will decrease as well. As effect size increase, the sample size required will decrease. As variance increase, the effect size will decrease, so the sample size required will increase.

2 Problem 2: Missing Data Patterns

[3]:
```
data1 = read.csv("color_test.csv")
head(data1)
attach(data1)
```

A data.frame: 6 × 6

	id <int>	treat <int>	est_age <dbl>	past_cust <int>	past_avg_rev <dbl>	obs_rev <dbl>
1	1	0	36.35849	0	NA	0.00000
2	2	0	31.47492	1	1.553581	0.00000
3	3	1	40.50781	0	NA	0.00000
4	4	0	36.68641	1	1.915854	0.00000
5	5	0	NA	1	0.000000	11.94924
6	6	0	40.05534	1	2.377523	0.00000

[4]:
```
install.packages('naniar')
library(naniar)
```

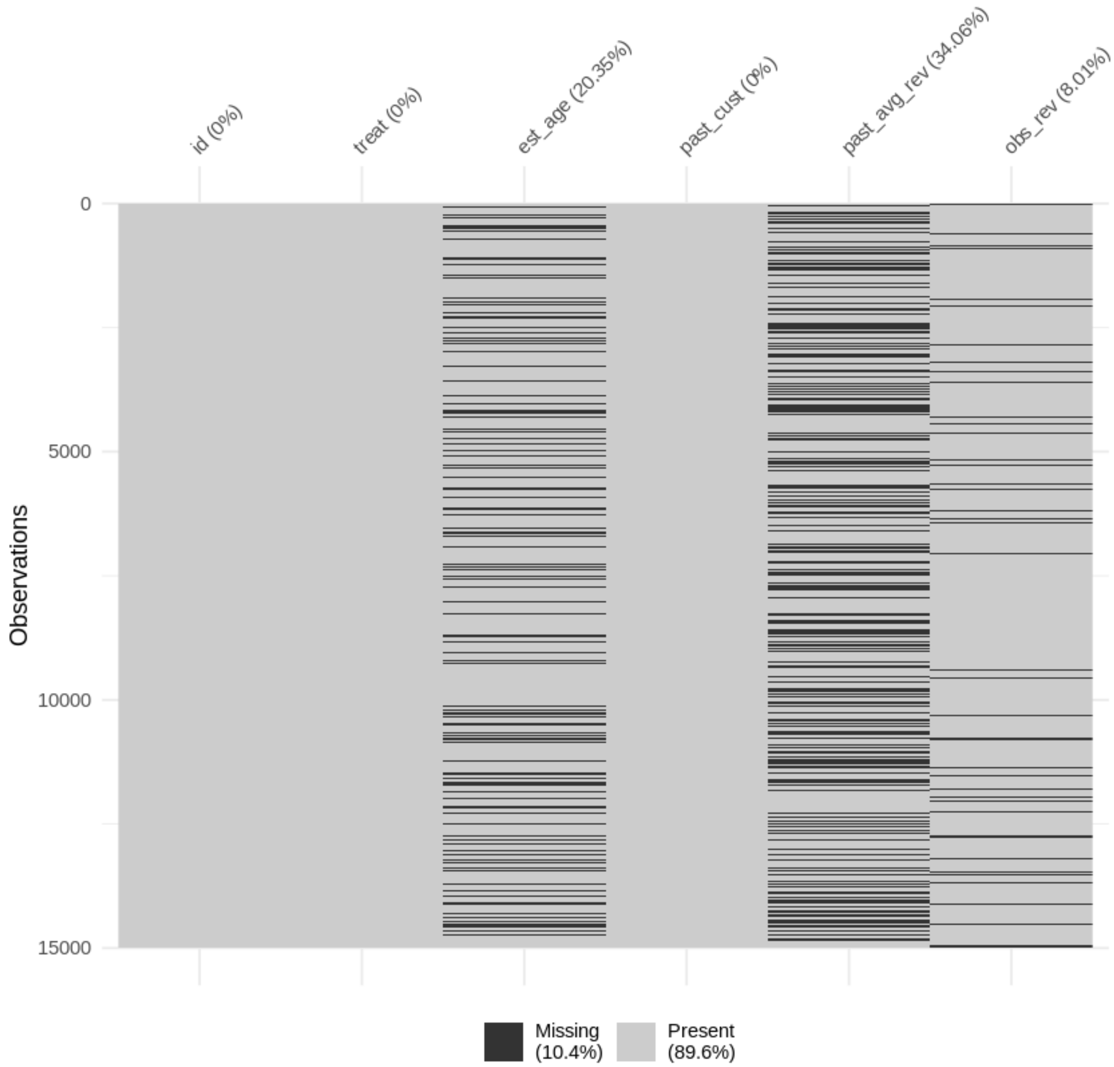
```
Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)
```

[5]:
```
sum(!complete.cases(data1))  # 7843 rows have missing data
nrow(data1) # total number of rows is 15000
```

7843

15000

[6]:
```
vis_miss(data1)
```



[20]:
```
data1 = na.omit(data1) # after omitting the rows containing missing values,␣
↪there are 7157 rows left
nrow(data1)
head(data1)
```

7157

A data.frame: 6 × 6

	id <int>	treat <int>	est_age <dbl>	past_cust <int>	past_avg_rev <dbl>	obs_rev <dbl>
2	2	0	31.47492	1	1.553581	0
4	4	0	36.68641	1	1.915854	0
6	6	0	40.05534	1	2.377523	0
7	7	0	40.05415	1	4.292266	0
9	9	1	45.25272	1	0.000000	0
10	10	1	35.90415	1	0.000000	0

From above graph, we can see that only columns est_age, past_avg_rev, and obs_rev contain missing data. Est_age has 20.35% missing data, past_avg_rev has 34.06% missing data, and obs_rev has 8.01% missing data. Est_age is MAR because it is estimated based on other variables. Past_avg_rev is mar becuase it represents past average revenue. When past_cust is 0 (a new customer), it is definitely NA. Obs_rev is MCAR becuase there is no relationship between the missingness of the data and any values, observed or missing.

For this experiment, we can conduct complete-case analysis since after omitting all the rows containing missing values, we still have 7157 rows left, although this method may introduce bias to our analysis.

[22]:
```
library(tidyverse)
```

```
Warning message in system("timedatectl", intern = TRUE):
"running command 'timedatectl' had status 1"
  Attaching packages                                tidyverse
1.3.1

  tibble  3.1.6      purrr   0.3.4
  tidyr   1.1.4      stringr 1.4.0
  readr   2.1.1      forcats 0.5.1

  Conflicts
tidyverse_conflicts()
  dplyr::filter() masks stats::filter()
  dplyr::lag()    masks stats::lag()
```

[ ]:
```
women_weight <- genderweight %>%
  filter(group == "F") %>%
  pull(weight)
men_weight <- genderweight %>%
  filter(group == "M") %>%
  pull(weight)
# Compute t-test
res <- t.test(women_weight, men_weight)
res
```

[26]:
```
treatment = data1 %>% filter(treat == 1) %>% select(obs_rev)
non_treatment = data1 %>% filter(treat == 0) %>% select(obs_rev)
```

```
t_test <- t.test(treatment, non_treatment)
t_test
```

```
        Welch Two Sample t-test

data:  treatment and non_treatment
t = 9.2936, df = 6765.6, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.8975514 1.3774129
sample estimates:
mean of x mean of y
 3.567782  2.430300
```

Since the p-value is super small, we can reject the null hypothesis that ${}_{treatment} = {}_{nontreatment}$. In other words, there is enough evidence to state that the mean observed revenue for treatment group is different to that of the non-treatment group. The difference for the mean control and test revenue is $3.567782 - 2.4303 = 1.137482$.

3 Problem 3: Exploratory Analysis

[8]:
```
data2 = read.csv("US_Accidents_Dec20_updated.csv")
```

[9]:
```
install.packages('dplyr')
library(dplyr)
```

```
Installing package into ‘/usr/local/lib/R/site-library’
(as ‘lib’ is unspecified)


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
```

[10]:
```
head(data2)
summary(data2)
```

```r
names(data2)
attach(data2)
```

A data.frame: 6 × 47

	ID	Severity	Start_Time	End_Time	Start_Lat	Start_
	<chr>	<int>	<chr>	<chr>	<dbl>	<dbl>
1	A-2716600	3	2016-02-08 00:37:08	2016-02-08 06:37:08	40.10891	-83.092
2	A-2716601	2	2016-02-08 05:56:20	2016-02-08 11:56:20	39.86542	-84.062
3	A-2716602	2	2016-02-08 06:15:39	2016-02-08 12:15:39	39.10266	-84.524
4	A-2716603	2	2016-02-08 06:15:39	2016-02-08 12:15:39	39.10148	-84.523
5	A-2716604	2	2016-02-08 06:51:45	2016-02-08 12:51:45	41.06213	-81.537
6	A-2716605	3	2016-02-08 07:53:43	2016-02-08 13:53:43	39.17239	-84.492

```
      ID               Severity      Start_Time           End_Time        
 Length:1316687     Min.   :1.0   Length:1316687     Length:1316687    
 Class :character   1st Qu.:2.0   Class :character   Class :character  
 Mode  :character   Median :2.0   Mode  :character   Mode  :character  
                    Mean   :2.2                                        
                    3rd Qu.:2.0                                        
                    Max.   :4.0                                        

   Start_Lat        Start_Lng           End_Lat          End_Lng       
 Min.   :24.57   Min.   :-124.50   Min.   :24.57   Min.   :-124.50  
 1st Qu.:33.85   1st Qu.:-118.24   1st Qu.:33.85   1st Qu.:-118.24  
 Median :37.15   Median : -94.60   Median :37.15   Median : -94.60  
 Mean   :36.80   Mean   : -98.89   Mean   :36.80   Mean   : -98.89  
 3rd Qu.:40.67   3rd Qu.: -80.88   3rd Qu.:40.67   3rd Qu.: -80.87  
 Max.   :49.00   Max.   : -67.11   Max.   :49.08   Max.   : -67.11  

  Distance.mi.       Description            Number           Street         
 Min.   :  0.0000   Length:1316687     Min.   :     1    Length:1316687    
 1st Qu.:  0.0000   Class :character   1st Qu.:  1215    Class :character  
 Median :  0.1430   Mode  :character   Median :  3999    Mode  :character  
 Mean   :  0.5711                      Mean   :  8802                      
 3rd Qu.:  0.5730                      3rd Qu.: 10035                      
 Max.   :155.1860                      Max.   :961043                      
                                       NA's   :890371                      
     Side               City              County             State          
 Length:1316687     Length:1316687     Length:1316687     Length:1316687    
 Class :character   Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character  




   Zipcode            Country            Timezone          Airport_Code      
 Length:1316687     Length:1316687     Length:1316687     Length:1316687    
 Class :character   Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character  
```

```
Weather_Timestamp  Temperature.F.   Wind_Chill.F.     Humidity…
Length:1316687     Min.   :-89.00   Min.   :-89.0    Min.   :  1.00
Class :character   1st Qu.: 47.00   1st Qu.: 41.0    1st Qu.: 49.00
Mode  :character   Median : 60.00   Median : 57.0    Median : 68.00
                   Mean   : 59.08   Mean   : 54.8    Mean   : 65.01
                   3rd Qu.: 73.00   3rd Qu.: 70.0    3rd Qu.: 85.00
                   Max.   :170.60   Max.   :113.0    Max.   :100.00
                   NA's   :38428    NA's   :351167   NA's   :40748
 Pressure.in.   Visibility.mi.   Wind_Direction     Wind_Speed.mph.
Min.   : 0.00   Min.   :  0.00   Length:1316687     Min.   :  0.00
1st Qu.:29.41   1st Qu.: 10.00   Class :character   1st Qu.:  3.50
Median :29.87   Median : 10.00   Mode  :character   Median :  7.00
Mean   :29.55   Mean   :  9.09                      Mean   :  7.49
3rd Qu.:30.04   3rd Qu.: 10.00                      3rd Qu.: 10.40
Max.   :58.04   Max.   :130.00                      Max.   :984.00
NA's   :31872   NA's   :38793                       NA's   :103864
Precipitation.in. Weather_Condition    Amenity             Bump
Min.   : 0        Length:1316687     Length:1316687     Length:1316687
1st Qu.: 0        Class :character   Class :character   Class :character
Median : 0        Mode  :character   Mode  :character   Mode  :character
Mean   : 0
3rd Qu.: 0
Max.   :24
NA's   :398289
  Crossing           Give_Way           Junction           No_Exit
Length:1316687     Length:1316687     Length:1316687     Length:1316687
Class :character   Class :character   Class :character   Class :character
Mode  :character   Mode  :character   Mode  :character   Mode  :character



  Railway           Roundabout          Station              Stop
Length:1316687     Length:1316687     Length:1316687     Length:1316687
Class :character   Class :character   Class :character   Class :character
Mode  :character   Mode  :character   Mode  :character   Mode  :character



Traffic_Calming    Traffic_Signal     Turning_Loop       Sunrise_Sunset
Length:1316687     Length:1316687     Length:1316687     Length:1316687
Class :character   Class :character   Class :character   Class :character
Mode  :character   Mode  :character   Mode  :character   Mode  :character
```

```
Civil_Twilight     Nautical_Twilight  Astronomical_Twilight
Length:1316687     Length:1316687     Length:1316687
Class :character   Class :character   Class :character
Mode  :character   Mode  :character   Mode  :character
```

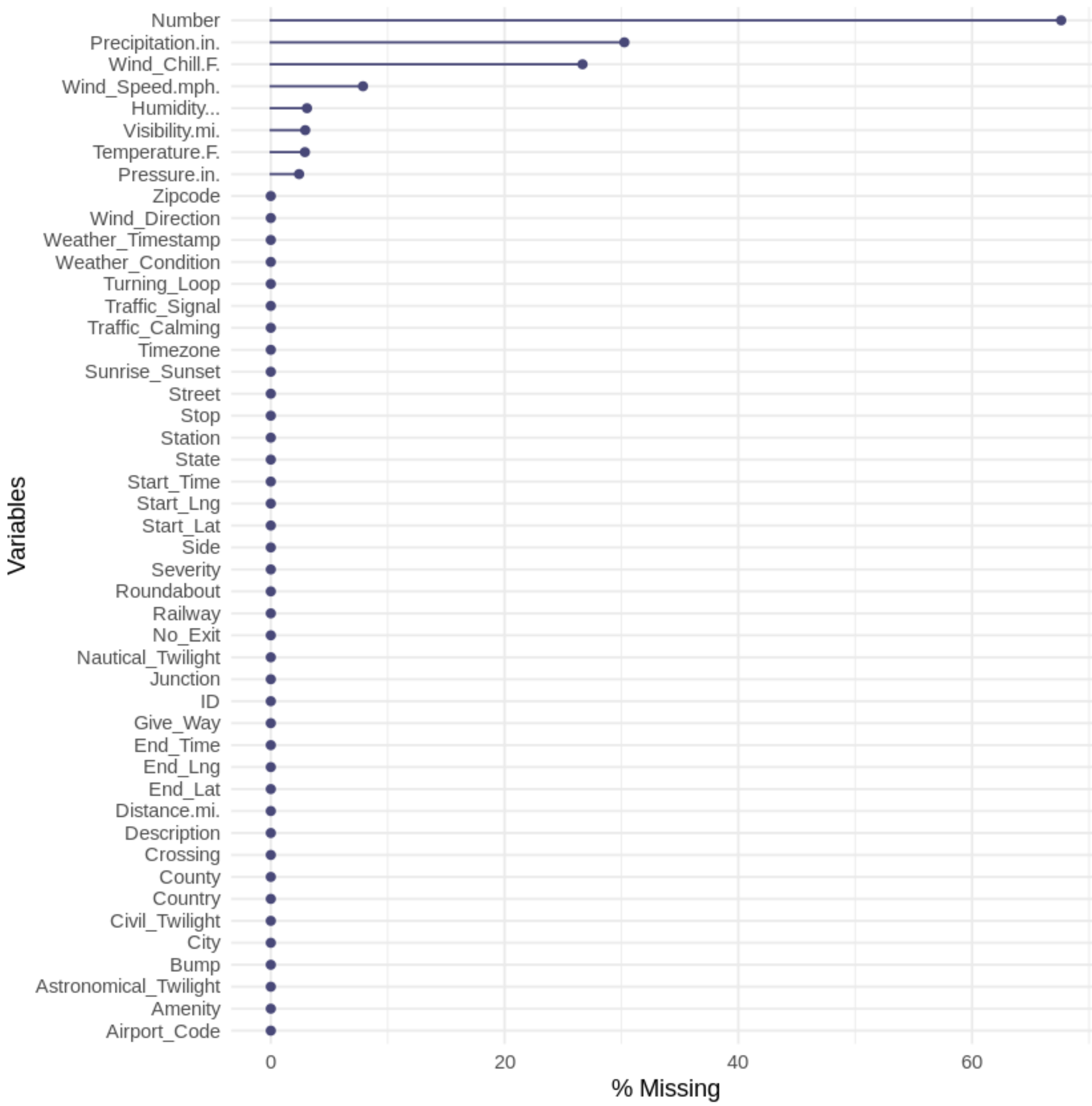
1. 'ID' 2. 'Severity' 3. 'Start_Time' 4. 'End_Time' 5. 'Start_Lat' 6. 'Start_Lng' 7. 'End_Lat' 8. 'End_Lng' 9. 'Distance.mi.' 10. 'Description' 11. 'Number' 12. 'Street' 13. 'Side' 14. 'City' 15. 'County' 16. 'State' 17. 'Zipcode' 18. 'Country' 19. 'Timezone' 20. 'Airport_Code' 21. 'Weather_Timestamp' 22. 'Temperature.F.' 23. 'Wind_Chill.F.' 24. 'Humidity...' 25. 'Pressure.in.' 26. 'Visibility.mi.' 27. 'Wind_Direction' 28. 'Wind_Speed.mph.' 29. 'Precipitation.in.' 30. 'Weather_Condition' 31. 'Amenity' 32. 'Bump' 33. 'Crossing' 34. 'Give_Way' 35. 'Junction' 36. 'No_Exit' 37. 'Railway' 38. 'Roundabout' 39. 'Station' 40. 'Stop' 41. 'Traffic_Calming' 42. 'Traffic_Signal' 43. 'Turning_Loop' 44. 'Sunrise_Sunset' 45. 'Civil_Twilight' 46. 'Nautical_Twilight' 47. 'Astronomical_Twilight'

[11]:
```
sum(!complete.cases(data2))  # 999872 rows have missing data
nrow(data2)
gg_miss_var(data2,show_pct = TRUE)
```

999872

1316687

```
Warning message:
"It is deprecated to specify `guide = FALSE` to remove a guide. Please use
`guide = "none"` instead."
```



From above graph, we can see that almost 70% of the data in column number is missing; 33% of data in column percipitation.in. is missing; 30% of data in column wind_chill.f. is missing; 8% of data in column wind_speed.mph. is missing. There are total eight columns contain missing values. The other four columns don't contain a lot of missing data, rougly around 3%.

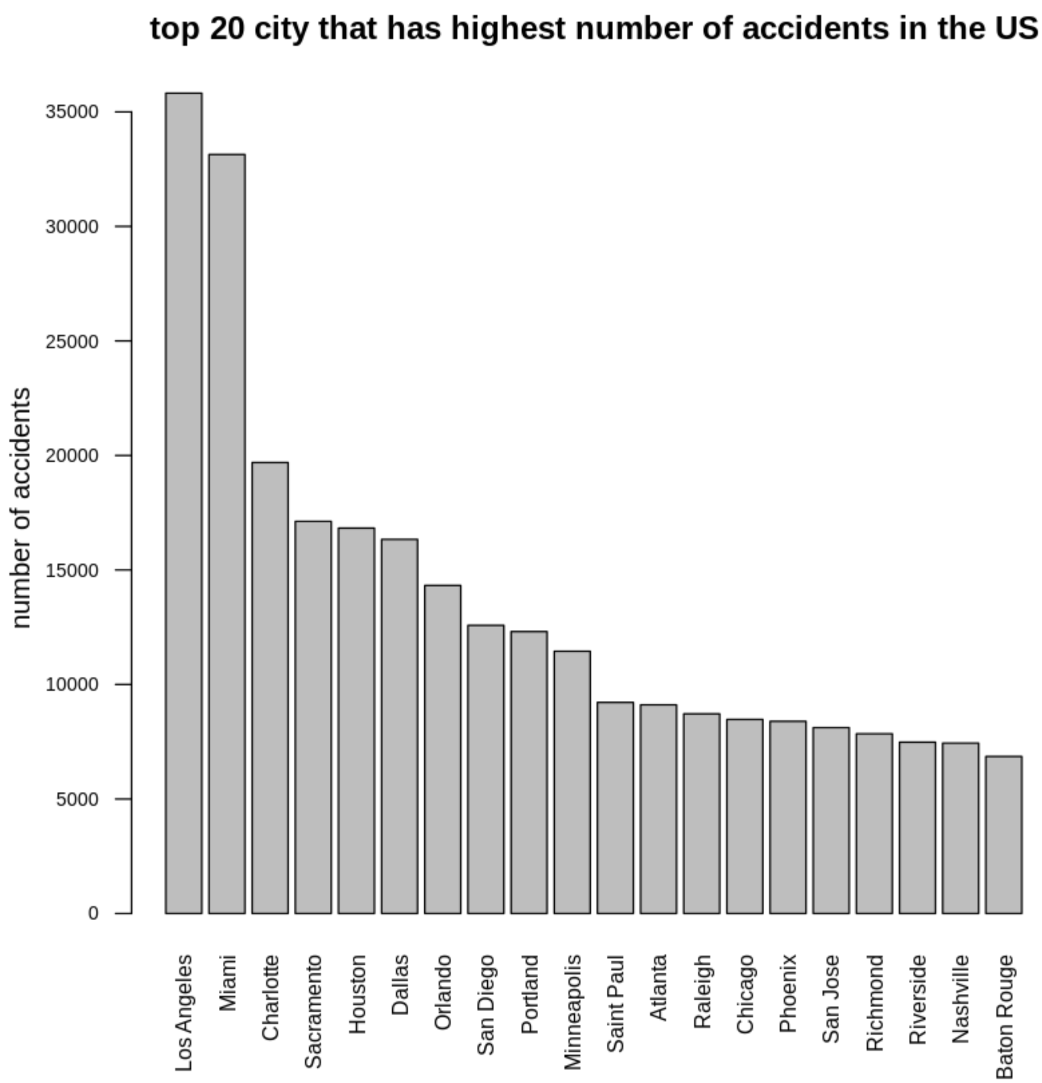
[12]:
```
number_cities = nrow(unique(select(data2, City)))
number_cities # there are total 10658 unique cities in the dataset
top20 = data2 %>% count(City, sort = TRUE) %>% slice(1:20)
print(top20)

barplot(height = top20$n, names.arg = top20$City,las = 2, cex.axis = 0.7, cex.
 ↪names = 0.8, main = "top 20 city that has highest number of accidents in the␣
 ↪US")
```

```r
title(ylab = "number of accidents")
```

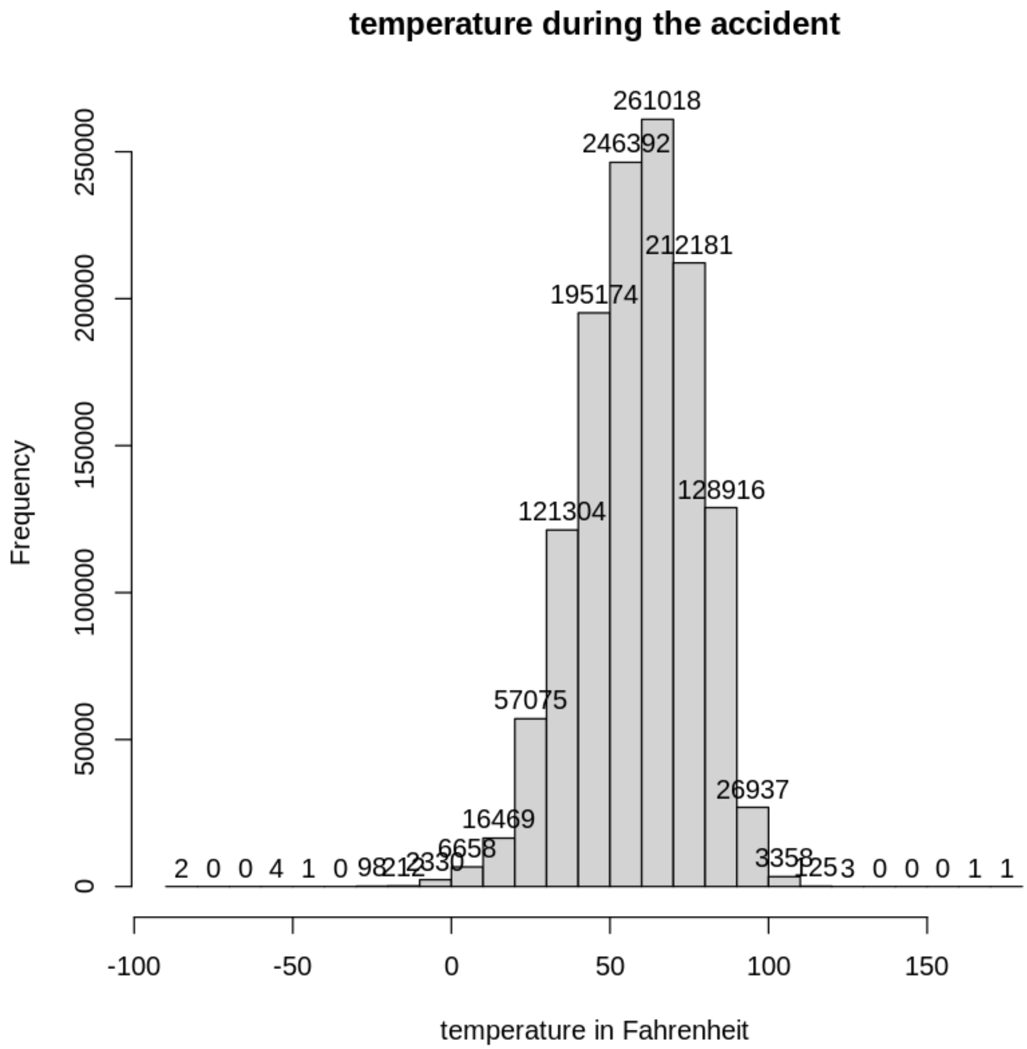
10198

```
          City     n
1  Los Angeles 35818
2        Miami 33139
3    Charlotte 19692
4   Sacramento 17122
5      Houston 16827
6       Dallas 16336
7      Orlando 14324
8    San Diego 12583
9     Portland 12309
10 Minneapolis 11451
11  Saint Paul  9219
12     Atlanta  9110
13     Raleigh  8719
14     Chicago  8474
15     Phoenix  8392
16    San Jose  8117
17    Richmond  7848
18   Riverside  7481
19   Nashville  7439
20 Baton Rouge  6856
```



The above barplot shows the top 20 city in the US that has highest number of accidents. Both Los Angeles and Miami have extremely high number of accidents, more than 30000 cases.City in the third place even doesn't exceed 20000 cases. All the cities after Miami experience a steady decrease in number of accidents.

[13]:
```
hist(Temperature.F., breaks = 20, main = "temperature during the accident",␣
↪xlab = "temperature in Fahrenheit", labels = TRUE)
```



Above graph shows the local terperature when the accident happened. We can see the most common temperature range during accident is from 60 to 70 Fahrenheit.

[14]:

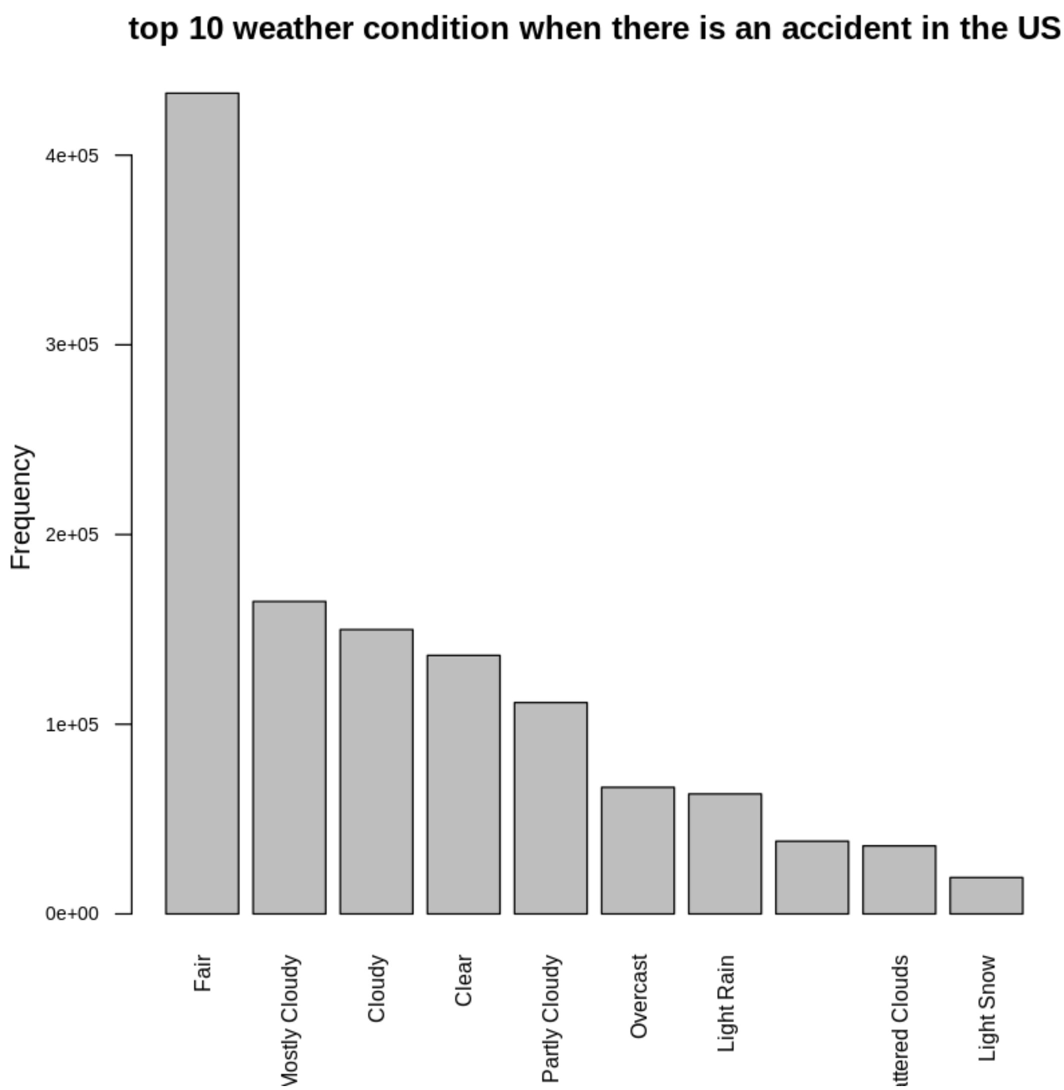
```
#number_cities = nrow(unique(select(data2, City)))
#number_cities # there are total 10658 unique cities in the dataset
#top20 = data2 %>% count(City, sort = TRUE) %>% slice(1:20)
#print(top20)
weather = nrow(unique(select(data2, Weather_Condition)))
weather # there are total 111 unique weather situation
top10 = data2 %>% count(Weather_Condition, sort = TRUE) %>% slice(1:10)
top10
```

```
barplot(height = top10$n, names.arg = top10$Weather_Condition,las = 2, cex.axis␣
↪= 0.7, cex.names = 0.8, main = "top 10 weather condition when there is an␣
↪accident in the US")
title(ylab = "Frequency")
```

111

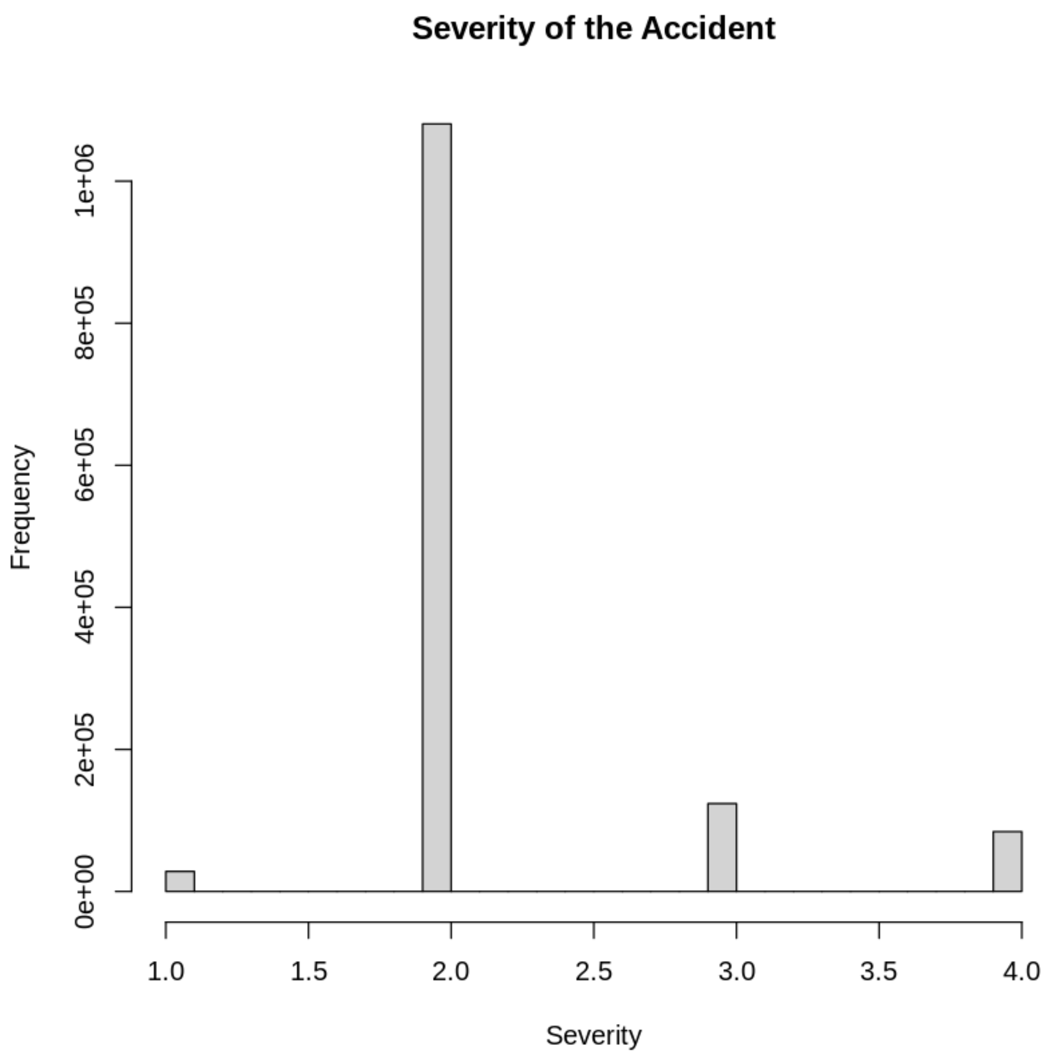
A data.frame: 10 × 2

Weather_Condition	n
<chr>	<int>
Fair	432670
Mostly Cloudy	164722
Cloudy	149902
Clear	136277
Partly Cloudy	111444
Overcast	66749
Light Rain	63259
	38311
Scattered Clouds	35874
Light Snow	19161



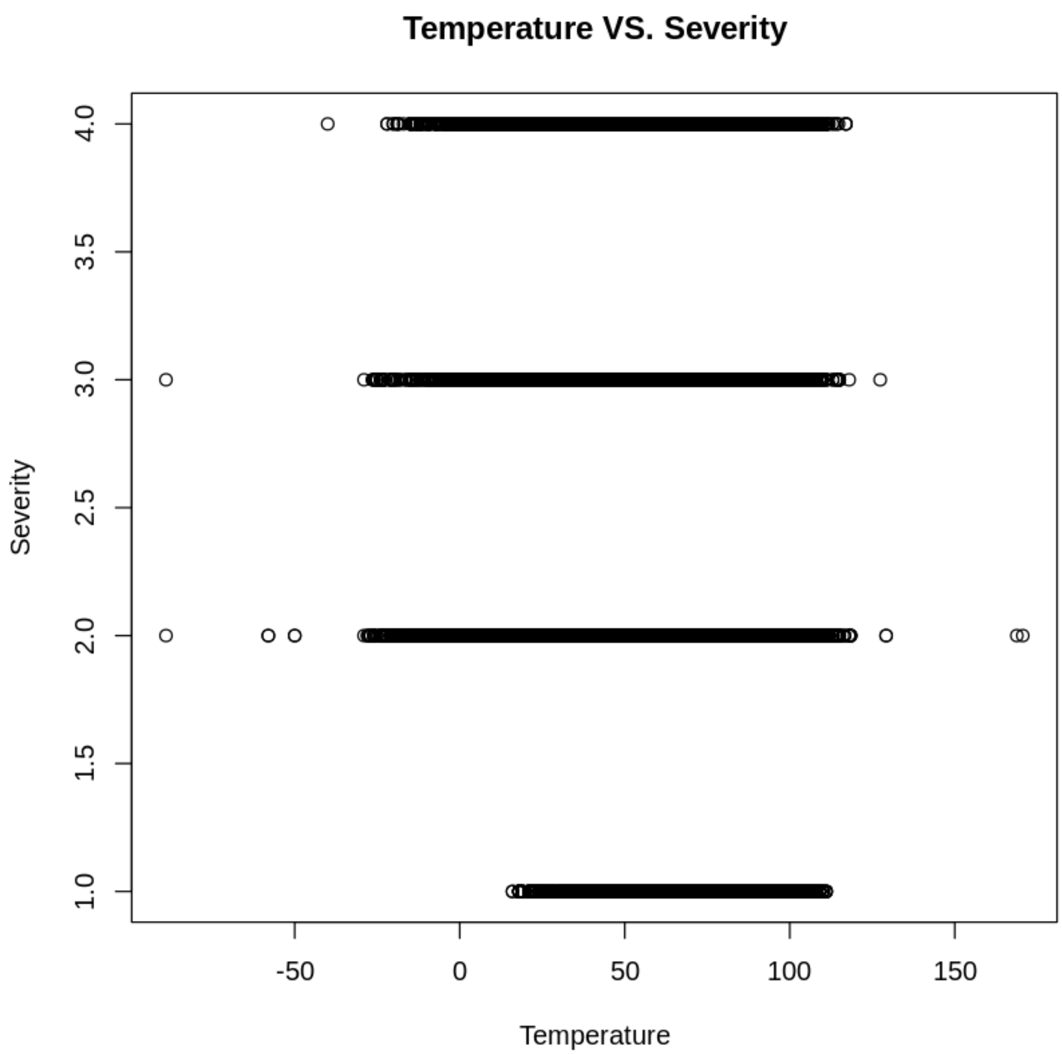
From above graph, we can see that there are more than 400000 times when the accident happened and the weather condition is fair. After that, weather condition associates with the second highest and third highest accident rate is mostly cloudy and cloudy. Fair condition contributes the most compared to others and has extremely high frequency.

[15]:
```
hist(Severity, main = "Severity of the Accident")
```



Above graph show the severity of all the accidents. One indicates the least impact and four indicates a significant impact. We can see that for most of the cases, the severity is 2, meaning that most of the accidents is somewhat severe, but not that severe.

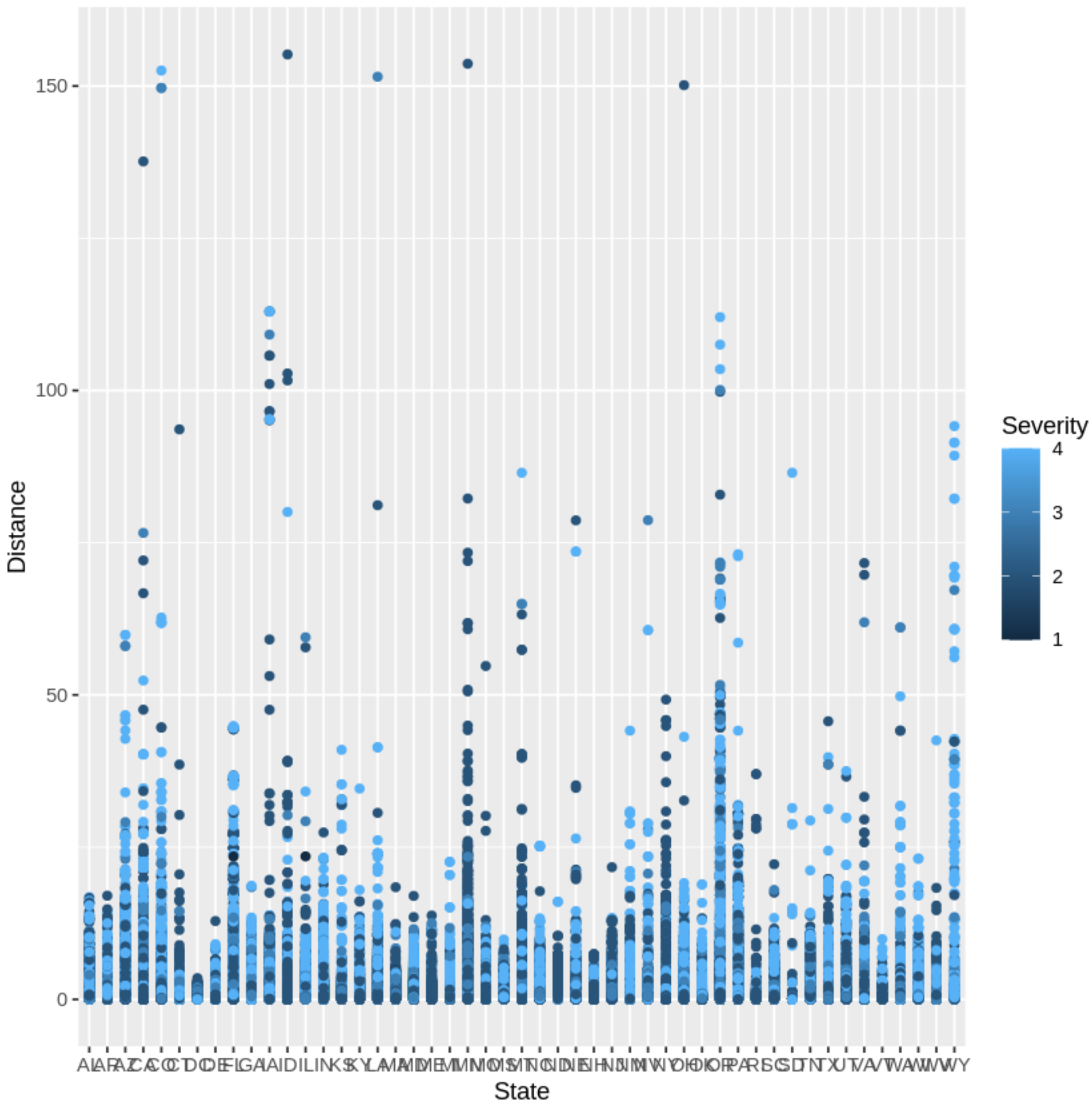
[16]:
```
plot(x=Temperature.F., y=Severity, xlab="Temperature", ylab="Severity", main =␣
 ↪"Temperature VS. Severity")
```



From above plot, we can see that temperature ranges from -20F to 110F all have led to a car accident with severity from 2 to 4. The only exception is that when the severity is 1, the temperature associates with is from approximately 15F to 110F.

[17]:
```
library(ggplot2)
```

[19]:
```
p = ggplot(data = data2)
p = p + geom_point(aes(x=State, y=Distance.mi., group=Severity, color=Severity))
p = p + xlab("State") + ylab("Distance")
p
```



From above graph, we can see that in each state, the length of the road extent affected by the accident (distance) is distributed almost the same. Most of them are clustered around range 0 to 25. Moreover, the severeity of the accidents also doesn't depend on which state you are in and the road extent affected by the accident. The severity is pretty much mixed up in all the states.

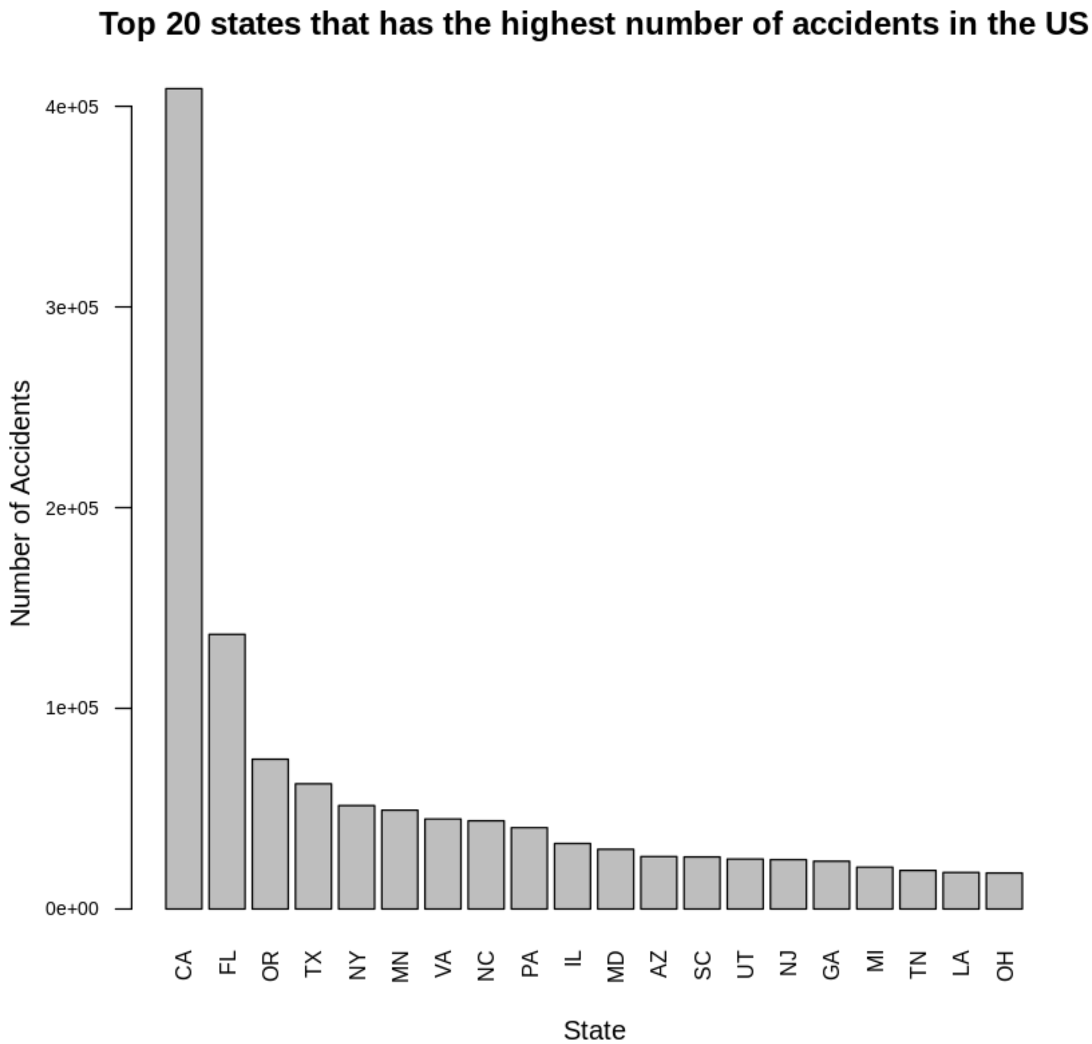
[28]:
```
number_states = nrow(unique(select(data2, State)))
number_states # there are total 49 unique states in the dataset
```

49

[34]:
```
top20_state = data2 %>% count(State, sort = TRUE) %>% slice(1:20)
print(top20_state)
```

```
barplot(height = top20_state$n, names.arg = top20_state$State,las = 2, cex.axis
 = 0.7, cex.names = 0.8, main = "Top 20 states that has the highest number of
 accidents in the US",
ylab = "Number of Accidents", xlab = "State")
```

```
   State      n
1     CA 408771
2     FL 136856
3     OR  74653
4     TX  62390
5     NY  51546
6     MN  49256
7     VA  44853
8     NC  43935
9     PA  40541
10    IL  32635
11    MD  29750
12    AZ  26139
13    SC  25944
14    UT  24882
15    NJ  24612
16    GA  23822
17    MI  20846
18    TN  19224
19    LA  18204
20    OH  17948
```



I think this dataset is representative of the general distribution of accidents in the US since it has a lot of data points and it covers nearly every state in the US. This dataset contains information about 49 states and there are 50 states in the US. One thing I notice is that California has much more accidents than all the other states. In general, I think this dataset reflects the distribution of accidents in the US.