Background

I am going to explore a large data set or traffic crashes to learn about what factors are connected with injuries. I will use data from the city of Chicago's open data portal. (This activity is derived from a blog post by Julia Silge). Along with this I am going to do some mutating of the original data set to answer some questions at the bottom.

```
years_ago <- mdy("01/01/2022") # data from last 2 years. May take time to load!
crash_url <- glue::glue("https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3i
crash_raw <- as_tibble(read.socrata(crash_url)) # a new way to read in data, don't worry about it!
```

This data set has a lot of different variables that are unnecessary for the Exploratory Data Analysis that we are going to do today. Therefore we are going to manipulate it into a few smaller data sets so it is easier to work through and get graphs out of. One important aspect of the data set that we don't have but want is a variable called `injuries` which indicates if the crash involved injuries or not. So we are going to first create that variable. We are then going to create an unknown category for missing `report_type`s and decide any other variables to keep in our new data set.

```
crash <- crash_raw %>%
  transmute(
    injuries = as.factor(if_else(injuries_total > 0, "injuries", "none")),
    report_type = replace(crash_raw$report_type, crash_raw$report_type == "", "Unknown"),
    # choose your variables here (use ?transmute to see what this does)
    latitude, longitude, crash_date, crash_day_of_week, weather_condition
  )
```

```
crash <- crash %>%
    mutate(
    crash_day_name = wday(crash_day_of_week, label = T, abbr = F)
    )
tibble(crash)
```

```
## # A tibble: 228,423 x 8
##    injuries report~1 latit~2 longi~3 crash_date          crash~4 weath~5 crash~6
##    <fct>    <chr>       <dbl>   <dbl> <dttm>                <int> <chr>   <ord>
##  1 injuries ON SCENE     41.8   -87.6 2022-02-28 10:21:00       2 CLEAR   Monday
##  2 injuries ON SCENE     41.9   -87.7 2022-04-27 09:30:00       4 CLEAR   Wednes~
##  3 none     ON SCENE     41.9   -87.7 2023-03-05 01:13:00       1 CLEAR   Sunday
##  4 none     ON SCENE     41.8   -87.7 2022-11-30 08:50:00       4 CLEAR   Wednes~
##  5 none     NOT ON ~     41.8   -87.7 2022-03-04 10:30:00       6 CLEAR   Friday
##  6 none     ON SCENE     41.7   -87.6 2022-09-20 15:47:00       3 CLEAR   Tuesday
##  7 none     ON SCENE     41.7   -87.7 2023-07-03 21:09:00       2 CLEAR   Monday
##  8 none     ON SCENE     41.7   -87.6 2022-05-10 21:18:00       3 CLEAR   Tuesday
##  9 injuries ON SCENE     41.9   -87.6 2023-02-22 15:43:00       4 RAIN    Wednes~
## 10 injuries ON SCENE     41.9   -87.6 2022-07-21 13:26:00       5 CLEAR   Thursd~
## # ... with 228,413 more rows, and abbreviated variable names 1: report_type,
## #   2: latitude, 3: longitude, 4: crash_day_of_week, 5: weather_condition,
## #   6: crash_day_name
```

```
J_D_Crash <- crash_raw %>%
  transmute(
    injuries = as.factor(if_else(injuries_total > 0, "injuries", "none")),
```

```
    crash_month, crash_day_of_week) %>%
  mutate(
    month = month(crash_month, label =T),
    week_day = wday(crash_day_of_week, label = T, abbr = F)
  ) %>%
  filter(month == "Jan" | month == "Dec",
         !is.na(injuries)) %>%
  group_by(week_day, injuries) %>%
  summarize(number_of_crahses = n())
```

```
## `summarise()` has grouped output by 'week_day'. You can override using the
## `.groups` argument.
```

```
tibble(J_D_Crash)
```

```
## # A tibble: 14 x 3
##    week_day  injuries number_of_crahses
##    <ord>     <fct>                <int>
##  1 Sunday    injuries               826
##  2 Sunday    none                  4684
##  3 Monday    injuries               777
##  4 Monday    none                  5011
##  5 Tuesday   injuries               850
##  6 Tuesday   none                  5083
##  7 Wednesday injuries               799
##  8 Wednesday none                  4741
##  9 Thursday  injuries               843
## 10 Thursday  none                  5111
## 11 Friday    injuries               925
## 12 Friday    none                  6139
## 13 Saturday  injuries               928
## 14 Saturday  none                  5658
```

Exploratory Data Analysis

Now that we have taken away some of the clatter that was in our original data set, by making new ones, we are going to answer a few questions.

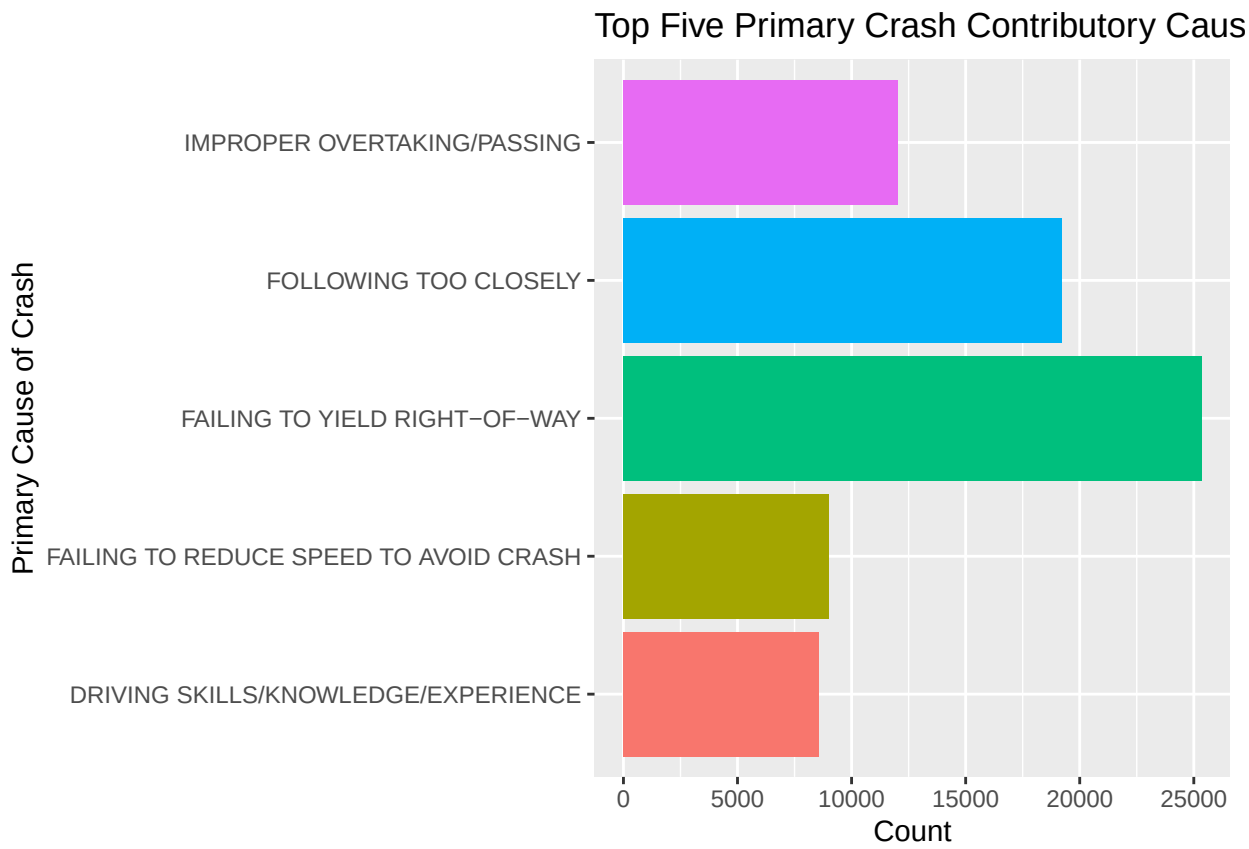
1. Take a look at crashes by latitude and longitude, colored by injuries. What do you notice?

```
ggplot(
  crash %>% filter(latitude > 0),
  mapping=aes(x=longitude, y=latitude)
) +
  geom_point(mapping=aes(color=injuries))
```

One thing I notice is that the outline that forms looks like the city limits of Chicago. Along with this there doesn't seem to be much else that we can take away from this graph. It is a little jumbled and doesn't tell a clear story.

2. What are the most common contributing factors to a crash?

```
top_causes <- crash_raw %>%
  filter(prim_contributory_cause != "UNABLE TO DETERMINE" &
    prim_contributory_cause != "NOT APPLICABLE") %>%
  group_by(prim_contributory_cause) %>%
  summarize(count = n()) %>%
  top_n(5, count)

top5_filtered <- crash_raw %>%
  filter(prim_contributory_cause %in% top_causes$prim_contributory_cause)

top5_filtered$prim_contributory_cause <- factor(top5_filtered$prim_contributory_cause, levels = top_caus

ggplot(top5_filtered,
       aes(x = prim_contributory_cause, fill = prim_contributory_cause)) +
  geom_bar(show.legend = FALSE) +
  coord_flip() +
  labs(title = "Top Five Primary Crash Contributory Causes",
       x="Primary Cause of Crash",
       y="Count")
```

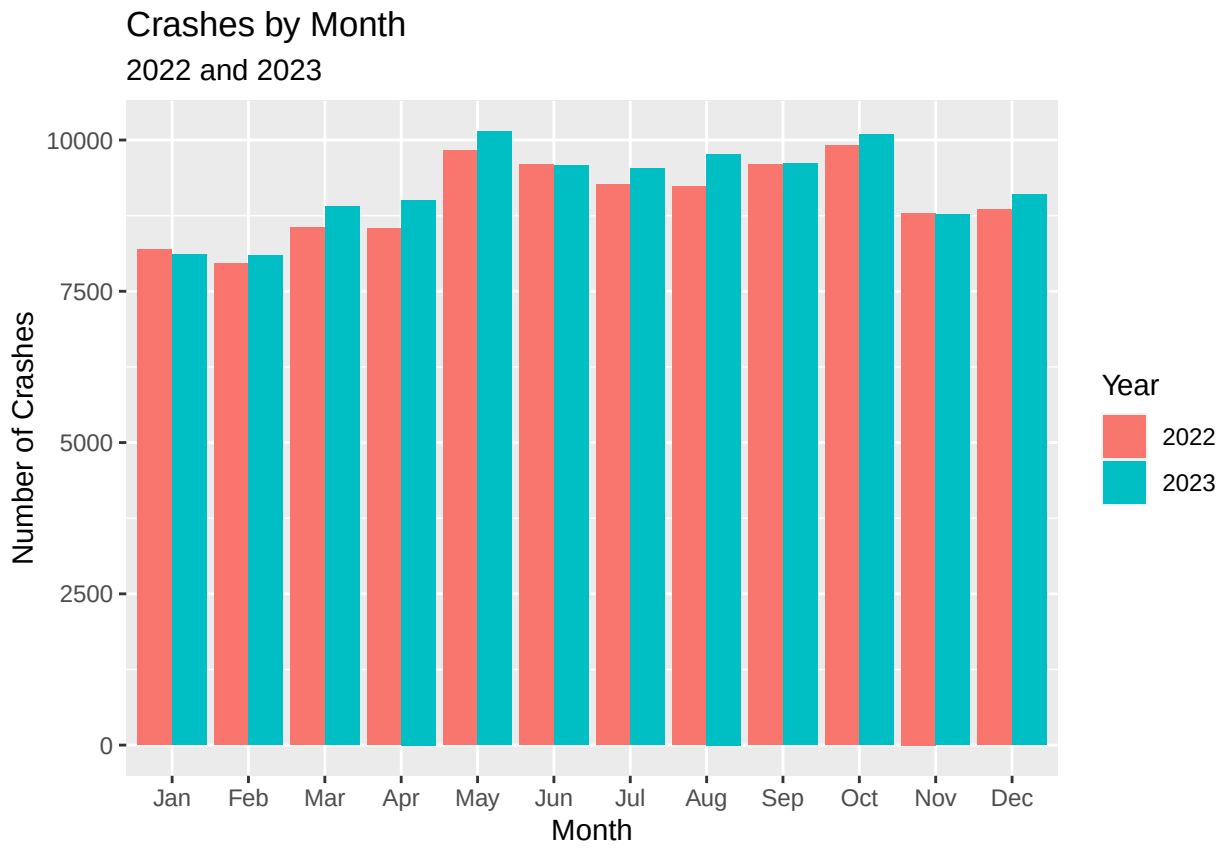


Here we are able to extract the top five primary factors for a car crash. These are; 1) Failing to yield right of way, 2) Following too closely, 3) Improper overtaking/passing, 4) Failing to reduce speed to avoid crash, 5) driving skills/knowledge/experience.

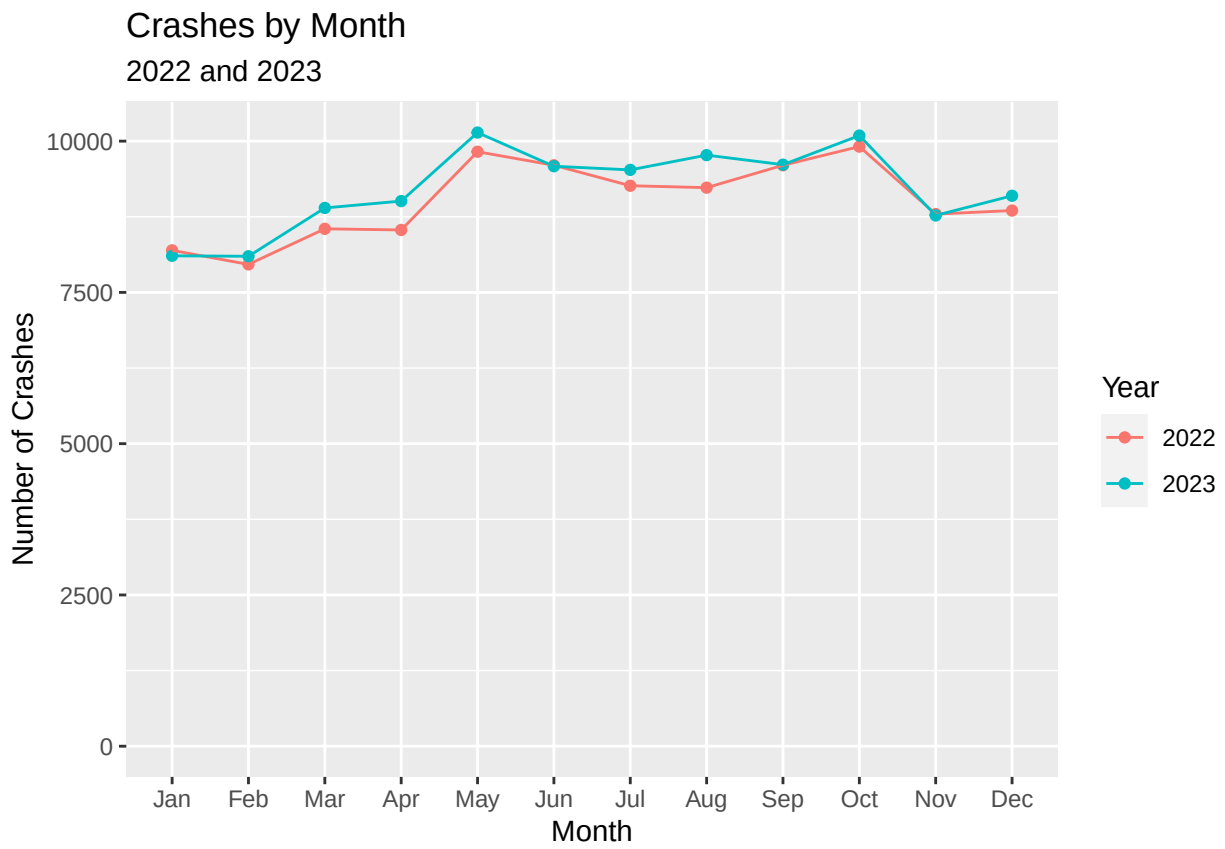
3. How do crashes vary month by month? Compare crashes by month in 2022 to 2023.

```
crash_raw <- crash_raw %>%
  mutate(
    month = month(crash_month, label =T))
crash_2022 <- crash_raw %>% filter(as.Date(crash_date) >= as.Date('2022-01-01') & as.Date(crash_date) <

crash_2023 <- crash_raw %>% filter(as.Date(crash_date) >= as.Date('2023-01-01') & as.Date(crash_date) <

crash_2022_month <- crash_2022 %>%
  group_by(month) %>%
  summarise(crash_count = n())

crash_2023_month <- crash_2023 %>%
  group_by(month) %>%
  summarise(crash_count = n())

combined_years <- bind_rows(
  mutate(crash_2022, year = 2022),
  mutate(crash_2023, year = 2023))

combined_years_month <- bind_rows(
```

```
  mutate(crash_2022_month, year = 2022),
  mutate(crash_2023_month, year = 2023))


ggplot(combined_years, aes(x = month, fill = as.factor(year))) +
  geom_bar(position = "dodge", stat = "count") +
  labs(title = "Crashes by Month",
       subtitle = "2022 and 2023",
       x="Month",
       y="Number of Crashes",
       fill="Year")
```



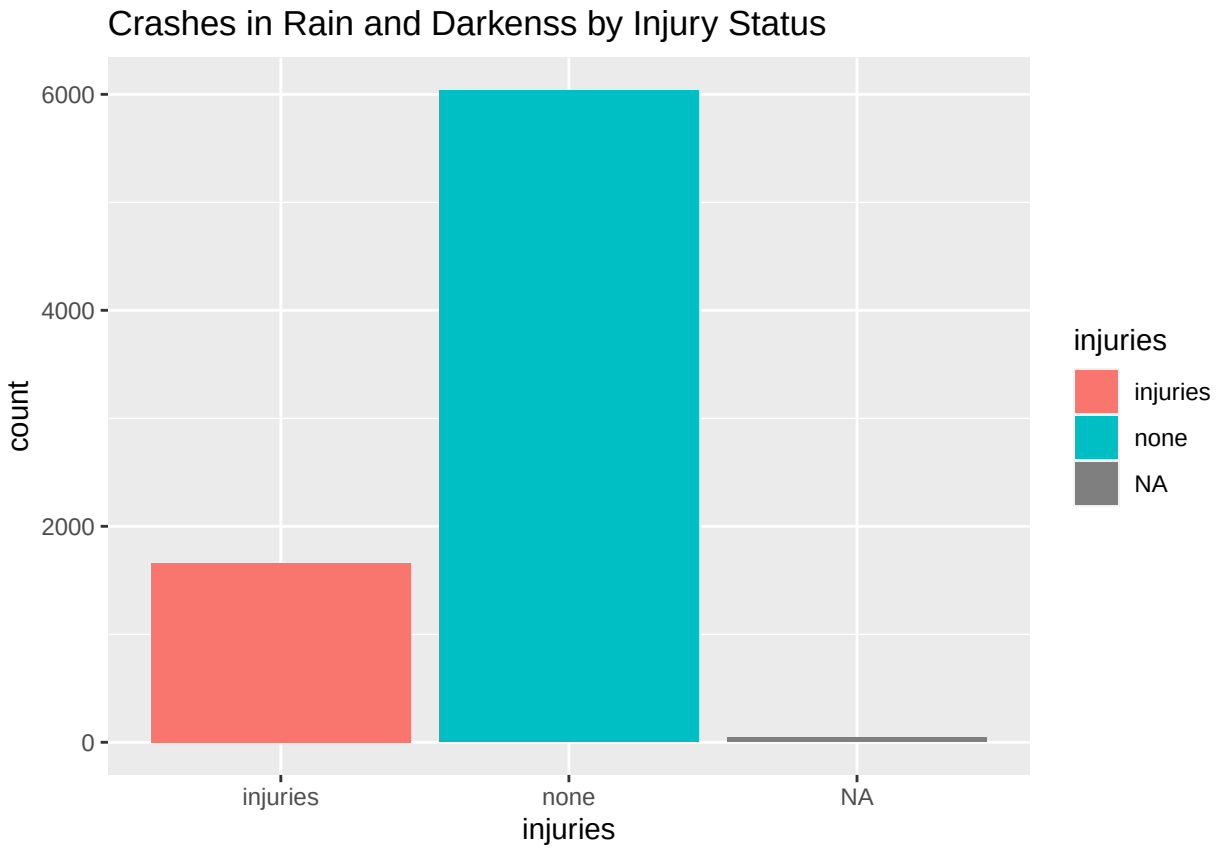

```
ggplot(combined_years_month, aes(x = month, y = crash_count, group = year, color = as.factor(year))) +
  geom_point() +
  geom_line() +
  labs(title = "Crashes by Month",
       subtitle = "2022 and 2023",
       x = "Month",
       y = "Number of Crashes",
       color = "Year") +
  expand_limits(y = 0)
```



When looking at all the data, both May and October are the two months that have the most crashes. As you can see by looking at these graphs, there seems to be a very similar distribution of crashes throughout the months.

4. Are crashes more likely to cause injuries when it is rainy and dark? Use the variables `weather_condition` and `lighting_condition` to explore.

```
ggplot(
  crash_raw %>%
    filter(weather_condition == "RAIN" & (lighting_condition == "DARKNESS" | lighting_condition == "DARI
    mutate(injuries = if_else(injuries_total > 0, "injuries", "none")),
  aes(x = injuries)
) +
geom_bar(aes(fill=injuries)) +
labs(title = "Crashes in Rain and Darkenss by Injury Status")
```



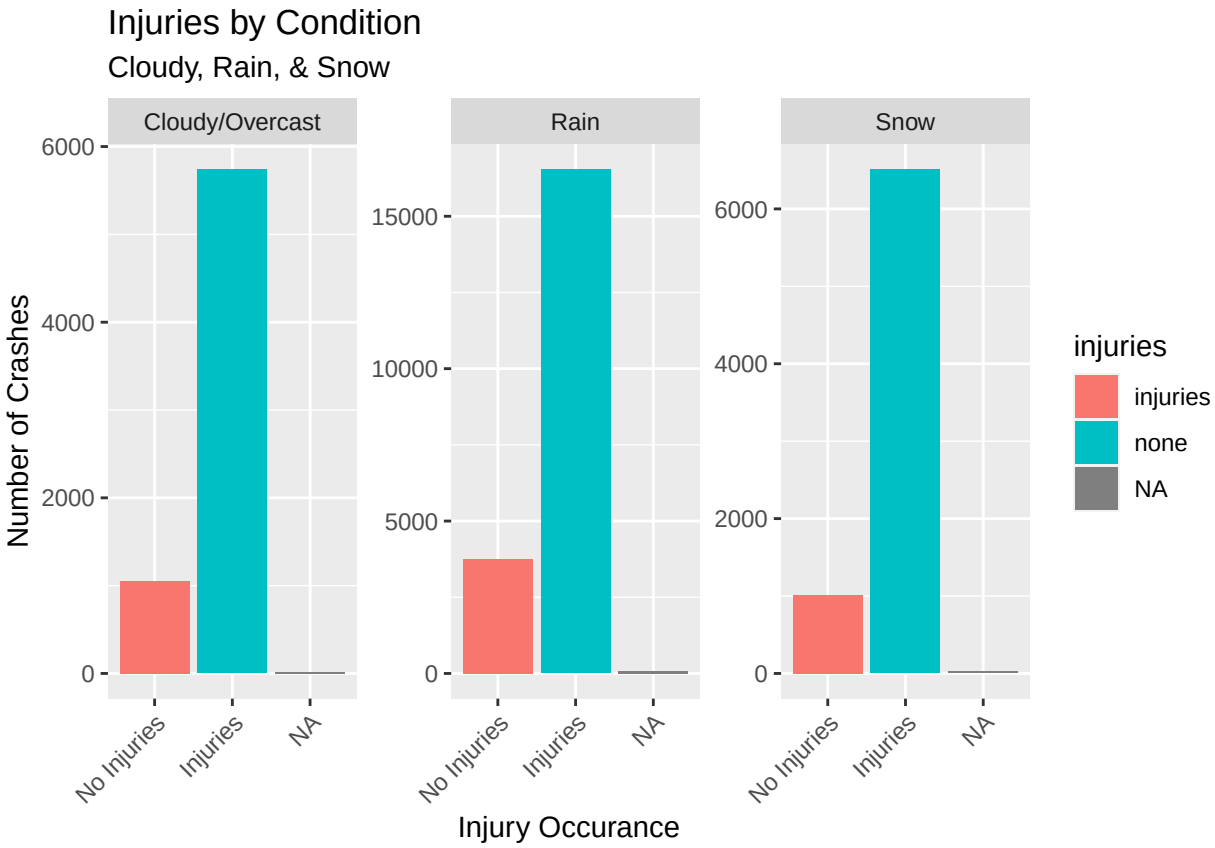
When looking at injuries that occurred under the conditions when it was rainy and dark, with or without lighted roads, injuries do not occur more often then not. As you can see in the graph above, of the many crashes that occurred under these conditions injuries happened in roughly 1 out of every 5 crashes.

5. Choose a question you want to explore, and create an appropriate visual.

What conditions cause the highest percentage of injuries?

```
snow <- crash_raw %>% filter(weather_condition == "SNOW")
rain <- crash_raw %>% filter(weather_condition == "RAIN")
cloudy <- crash_raw %>% filter(weather_condition == "CLOUDY/OVERCAST")

combined_conditions <- bind_rows(
  mutate(snow, condition = "Snow"),
  mutate(rain, condition = "Rain"),
  mutate(cloudy, condition = "Cloudy/Overcast"))

ggplot(combined_conditions %>%
    mutate(injuries = if_else(injuries_total > 0, "injuries", "none")),
    aes(x = injuries)
) +
  geom_bar(aes(fill=injuries)) +
  labs(title = "Injuries by Condition",
       subtitle = "Cloudy, Rain, & Snow",
       y = "Number of Crashes",
       x = "Injury Occurance") +
```

```
facet_wrap(~condition, scales = "free_y") +
scale_x_discrete(labels = c("No Injuries", "Injuries"))  +
theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



By looking at these even though we can see the y-axis are set to different scales, the bars that depict when there were no injuries are all at a equal height. Therefore we can then look at the proportions of each graph to determine which condition has the highest probability to have an injury in an accident. Out of these three conditions we can see that Rain has the highest probability, followed by Cloudy or Overcast and then lastly, Snow.