MA20277 - Coursework 1

PLEASE ENTER YOUR CANDIDATE NUMBER

```
library(dplyr)
library(lubridate)
library(ggplot2)
library(patchwork)
library(tidyr)
library(tibble)
```

Question 1

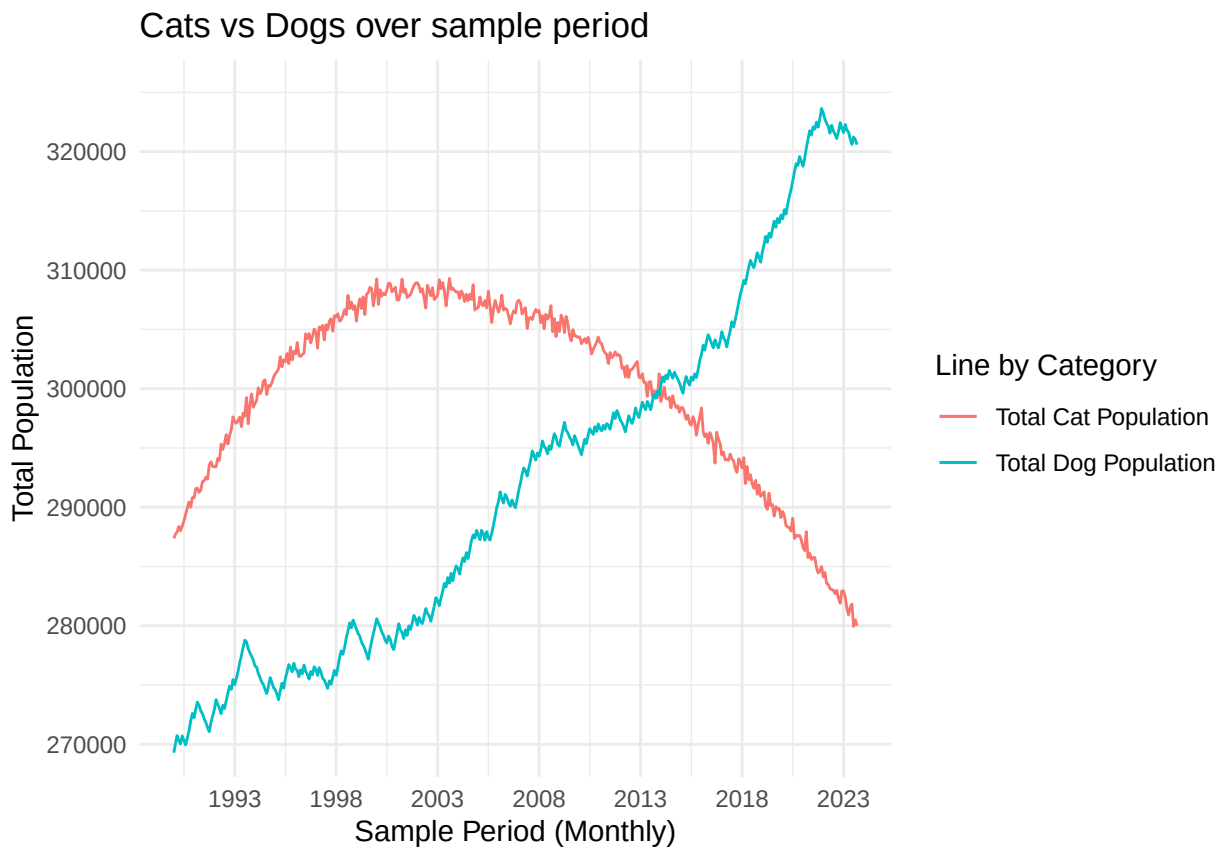
The Utopian charity *Respect for Pets* has collected data on cats and dogs for 1990-2023. Utopia only allows three dog breeds, Beagle, Dachshund and Maltese, and all pets have to be registered. The charity would like to gain some insight regarding the following questions:

a) How has the number of dogs and cats changed over time? How has the popularity of the different dog breeds evolved since 1990?

```
pets = read.csv("Data/Pets.csv")
maltese_Dogs = read.csv("Data/Maltese.csv")
respiratory_Cases = read.csv("Data/Cases.csv")
```

1A - Cats and Dogs Population Analysis

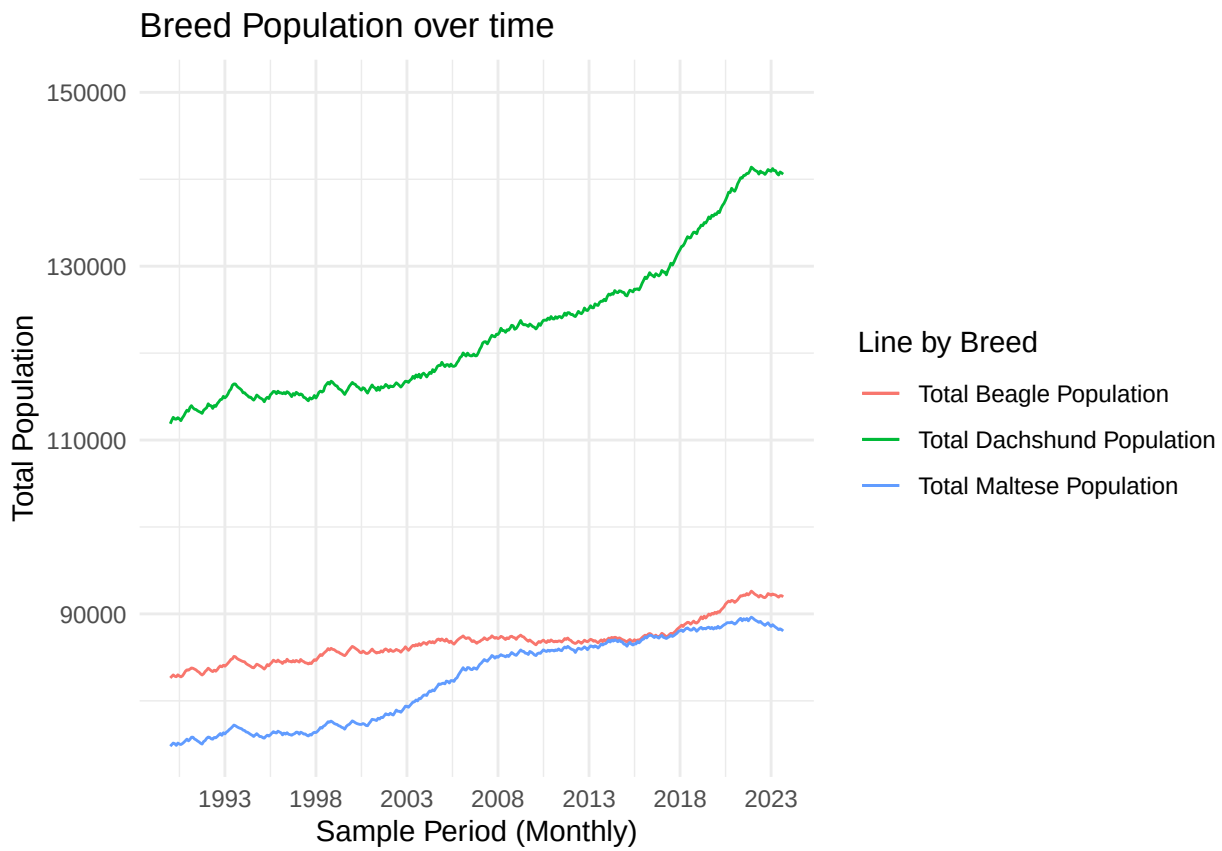
```
Cats_Dogs_Aggregated_Data = pets %>% mutate(Total_Cats = (Cats + CatRescue),
                                 Total_Dogs = (Beagles + Dachshund + Maltese +
                                 Date_col = make_date(Year,Month,1)) %>%
# Add columns calculating total for Cats and Dogs,
# and combining year and month columns using lubridate
select(Date_col,Total_Cats,Total_Dogs)
# Selecting only needed columns for analysis

ggplot(Cats_Dogs_Aggregated_Data,aes(Date_col)) +
  geom_line(aes(y = Total_Cats, color = "Total Cat Population")) +
  geom_line(aes(y = Total_Dogs, color = "Total Dog Population")) +
  theme(legend.title = element_text(face = "bold")) +
  labs(colour = "Line by Category", title = "Cats vs Dogs over sample period") +
  xlab("Sample Period (Monthly)") +
  ylab("Total Population") +
  coord_cartesian(xlim = c(make_date(1990,1,1),make_date(2023,9,1)),
                  ylim = c(270000,325000)) + theme_minimal() +
    scale_x_date(date_breaks = "5 years",date_labels = "%Y")
```



We are able to see that while cats used to have a higher population than dogs within our data in the period 1990 to 2014, however dogs have a much higher population than cats post 2014. The population of cats has been steadily decreasing since the early 2000's.

1A - Breed population analysis

```
Breed_Analysis = pets %>% mutate(Total_Beagles = Beagles + BeaglesRescue,
                                 Total_Dachshund = Dachshund + DachshundRescue,
                                 Total_Maltese = Maltese + MalteseRescue,
                                 Date_col = make_date(Year,Month,1)) %>%
  select(Date_col,Total_Beagles,Total_Dachshund,Total_Maltese)

ggplot(Breed_Analysis,aes(Date_col)) +
  geom_line(aes(y = Total_Beagles, color = "Total Beagle Population")) +
  geom_line(aes(y = Total_Dachshund, color = "Total Dachshund Population")) +
  geom_line(aes(y = Total_Maltese, color = "Total Maltese Population")) +
  theme(legend.title = element_text(face = "bold")) +
  labs(colour = "Line by Breed",
       title = "Breed Population over time",
       x = "Sample Period (Monthly)",
       y = "Total Population") +
  coord_cartesian(xlim = c(make_date(1990,1,1),make_date(2023,9,1)),
                  ylim = c(75000,150000)) + theme_minimal() +
  scale_x_date(date_breaks = "5 years",date_labels = "%Y")
```



We are able to see that Maltese and Beagle breeds have stayed consistently similar throughout the sample period, with a mean of 82,000 and 87,000 respectively. The Dachshund breed has been higher throughout the sample period and continues to grow, reaching a maximum of 141,000 and a mean of 123,000.

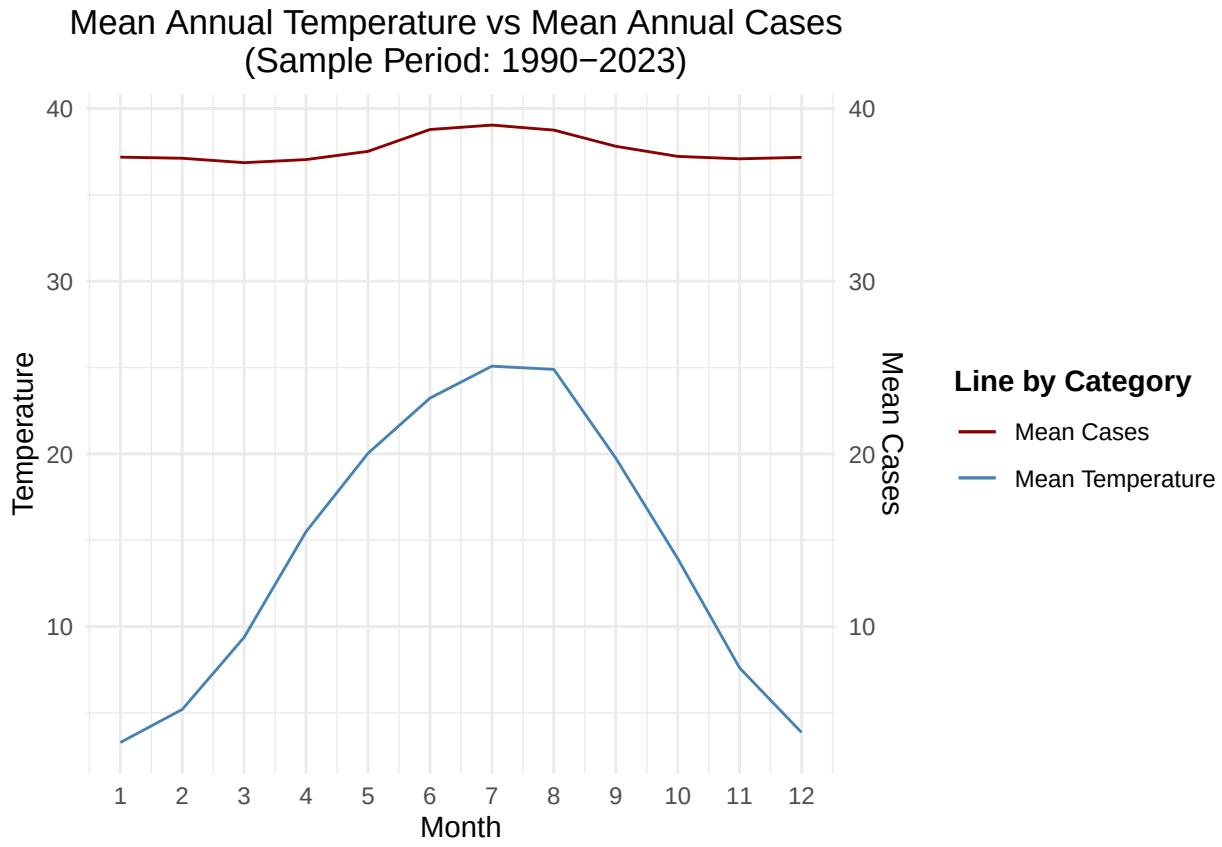
b) Maltese are known to experience respiratory issues, such as wheezing or asthma. How do environmental and physiological factors affect the risk of a Maltese experiencing these issues?

From the preliminary analysis above, we are able to determine a periodic cycle in temperature throughout each year, and therefore can group each year and analyse cases on a month-by-month basis instead.

1B - Maltese Respiratory Issue Analysis

```
respiratory_Cases_Clean = respiratory_Cases %>%
mutate(Date = ymd(Date))

respiratory_Cases_Monthly = respiratory_Cases_Clean %>%
                        mutate(Date = month(Date)) %>%
                        group_by(Date) %>%
                        summarise('Mean_Temp' = mean(Temperature),
                                  'Mean_Cases' = mean(Number))

 ggplot(respiratory_Cases_Monthly, aes(x = Date)) +
  geom_line(aes(y = Mean_Temp, color = "Mean Temperature")) +
  geom_line(aes(y = Mean_Cases, color = "Mean Cases")) +
```

```
  scale_color_manual(values = c("Mean Temperature" = "steelblue",
                                "Mean Cases" = "darkred")) +
  labs(x = "Month",
       y = "Temperature",
       colour = "Line by Category") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5),
        legend.title = element_text(face = "bold")) +
  ggtitle("Mean Annual Temperature vs Mean Annual Cases \n (Sample Period: 1990-2023)") +
  scale_y_continuous(sec.axis = sec_axis(~ ., name = "Mean Cases")) +
  scale_x_continuous(limits = c(1, 12),breaks = seq(1, 12, by = 1))
```




```
#  ggplot(respiratory_Cases_Clean, aes(x = Temperature, y = Number)) +
#   geom_point() +
#   geom_smooth(method = "lm", se = FALSE, color = "blue") +
#   labs(title = "Temperature vs. Cases",
#        x = "Temperature",
#        y = "Cases")
#
#
# ggplot(respiratory_Cases_Clean, aes(x = Temperature, y = Number)) +
#   geom_bin2d(bins = 25) +
#   scale_fill_gradient(low = "antiquewhite", high = "darkred") +
#   labs(title = "Two Dimensional Histogram showing frequency of cases vs temperature",
#        y = "Cases") +
```

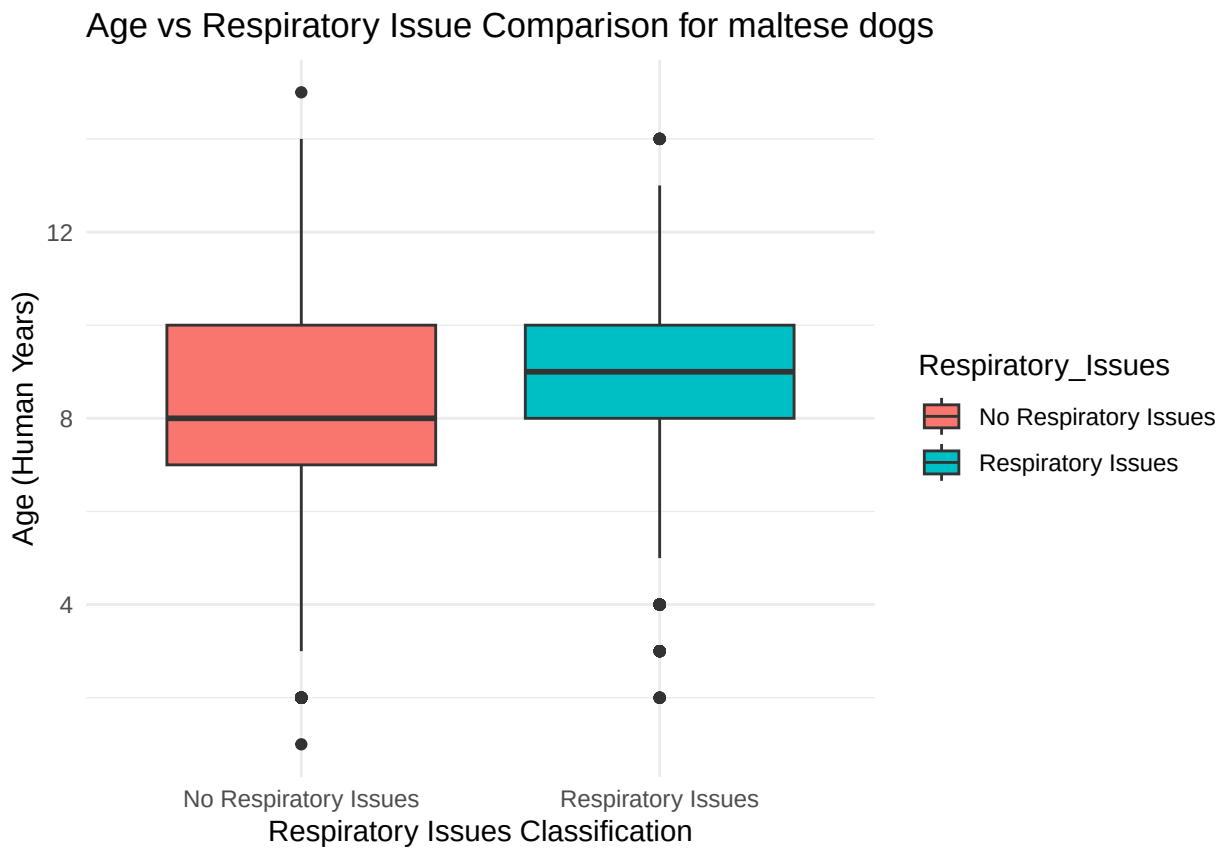
```
#   theme(plot.title = element_text(hjust = 0.5),
#         legend.title = element_text(face = "bold")) +
#   theme_minimal()
```

We use monthly mean temperature vs monthly mean cases not to analyse a trend between temperature and respiratory cases, but instead to analyse the seasonality of both occurring.

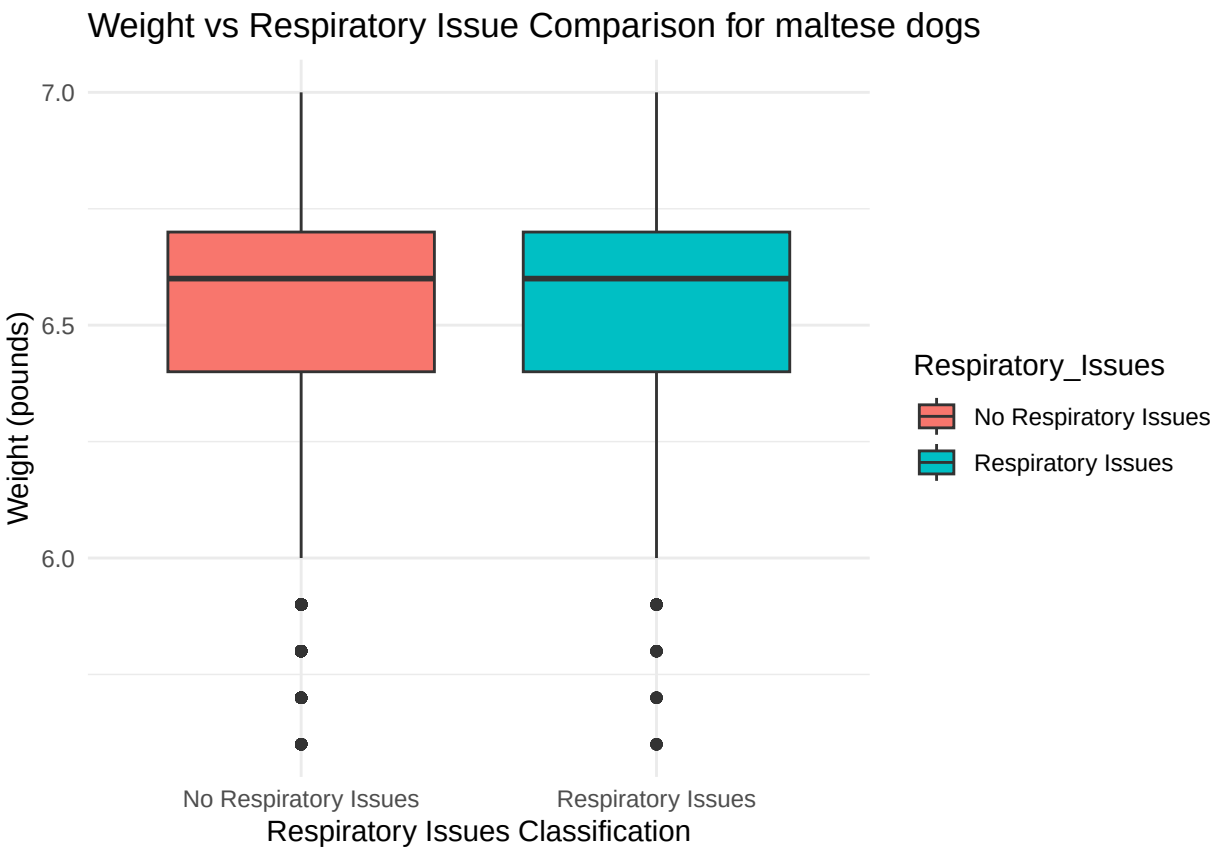
We may conclude that while cases increase when temperature increases, this may not be the causation, and could be down to something else such as allergies or increased respiration rates at that time of year. This is backed up by the correlation coefficient between temperature and cases being around 0.14, suggesting no clear correlation.

1B - Box plots

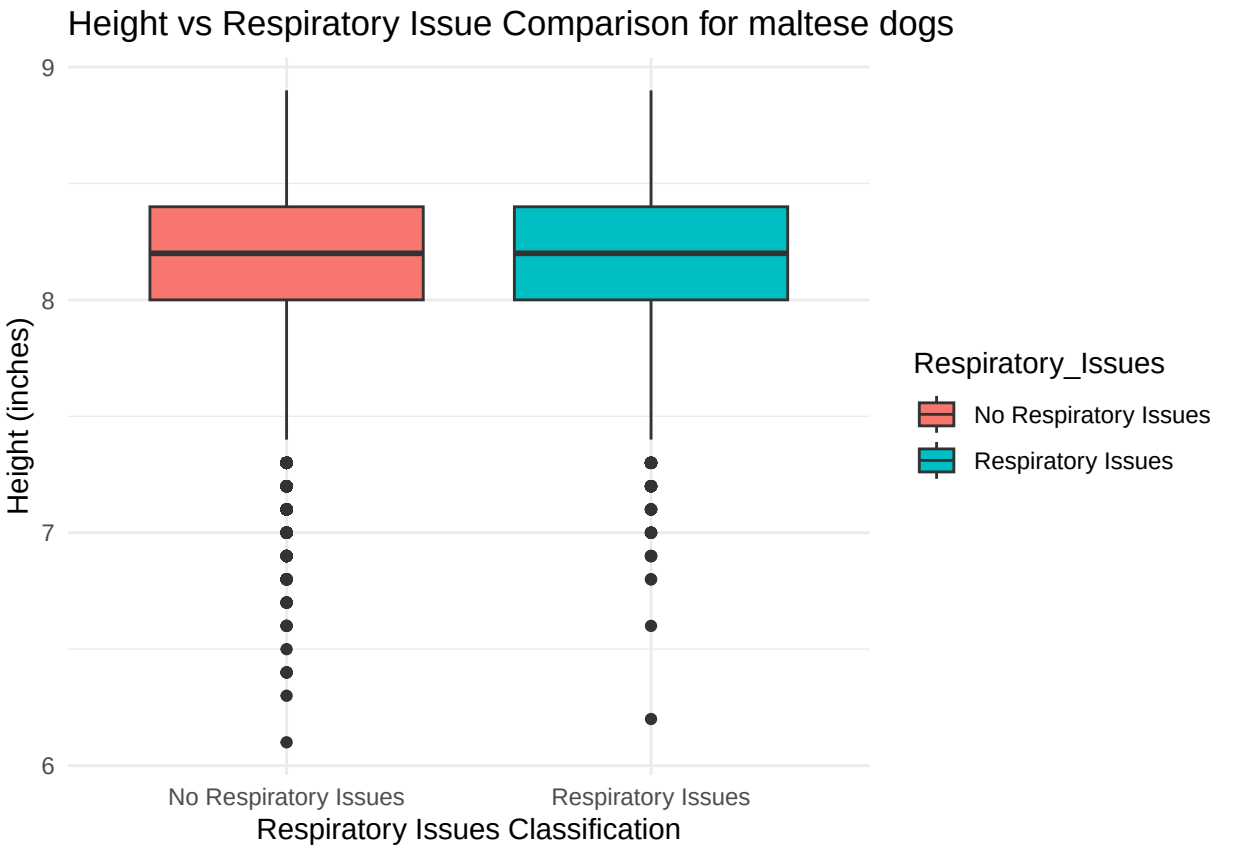
```
maltese_Dogs = mutate(maltese_Dogs,Respiratory_Issues = case_when(
              RespiratoryIssues == 1 ~ "Respiratory Issues",
              RespiratoryIssues == 0 ~ "No Respiratory Issues"))

Age_Plot = ggplot(maltese_Dogs,
                  aes(x=Respiratory_Issues, y=Age, fill = Respiratory_Issues)) +
    geom_boxplot() +
    theme_minimal() +
    labs(title = "Age vs Respiratory Issue Comparison for maltese dogs",
         x = "Respiratory Issues Classification",
         y = "Age (Human Years)")

Weight_Plot = ggplot(maltese_Dogs,
                     aes(x=Respiratory_Issues, y=Weight, fill = Respiratory_Issues)) +
    geom_boxplot() +
    theme_minimal() +
    labs(title = "Weight vs Respiratory Issue Comparison for maltese dogs",
       x = "Respiratory Issues Classification",
       y = "Weight (pounds)")

Height_Plot = ggplot(maltese_Dogs,
                     aes(x=Respiratory_Issues, y=Height, fill = Respiratory_Issues)) +
    geom_boxplot() +
    theme_minimal() +
    labs(title = "Height vs Respiratory Issue Comparison for maltese dogs",
         x = "Respiratory Issues Classification",
         y = "Height (inches)")

print(Age_Plot)
```




```
print(Weight_Plot)
```




```
print(Height_Plot)
```



While we can see that analysing height and weight for both classifications shows no significant difference, when we look at age, we are able to draw a conclusion that generally higher aged dogs are more susceptible to respiratory issues, with a higher median, Q1, Q3 and smaller IQR. We are however limited by our data, since we only have 2,500 observations with Respiratory issues, compared to 17,000 without any.

Question 2

The Utopian Fire Department has gathered data on their activities for 2022. They also managed to provide you with access to some data for the houses in Utopia. The Utopian Fire Department asks you to address the following questions:

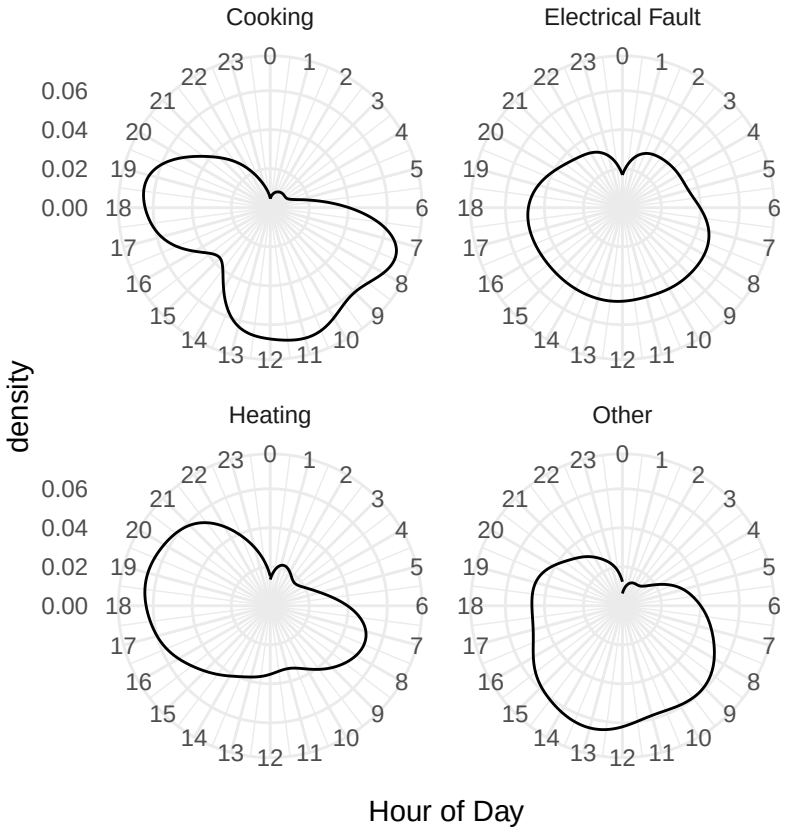
a) How does the frequency of the different causes for fires vary other time? How many casualties were attributed to each cause and are there differences in the frequency with which casualties occur across causes?

```
Fires = read.csv("Data/Fires.csv")
Housing_Reg = read.csv("Data/Housing Register.csv")
```

2A - Hourly density plots

```
Fires = Fires %>% mutate(Date_Clean = ymd_hm(Date),
                         minute = minute(Date_Clean),
                         hour = hour(Date_Clean),
```

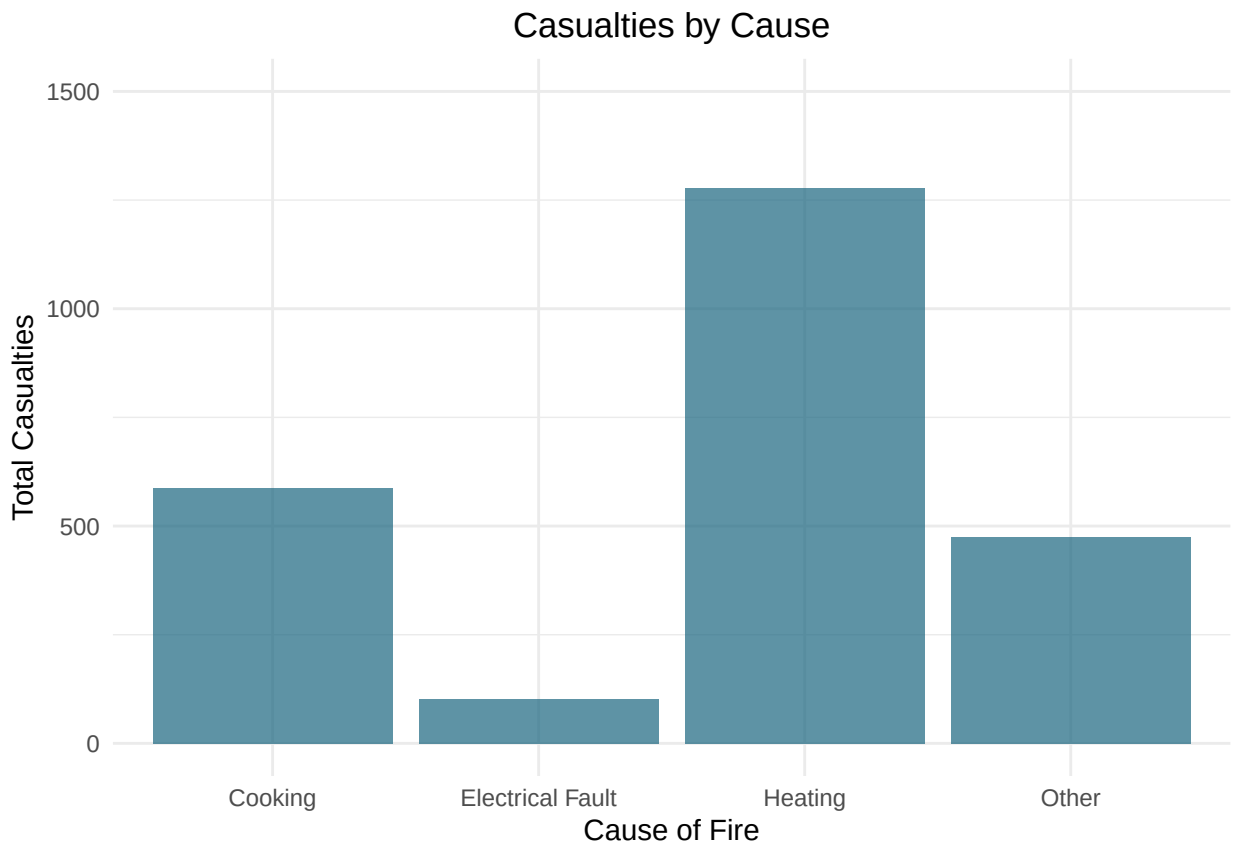
```
                  day = day(Date_Clean),
                  month = month(Date_Clean),
                  year = year(Date_Clean),
                  time = hour + (minute/60),
                  Casualties_Involved = case_when(
                                        Casualties > 0 ~ "Casualties Involved",
                                        Casualties == 0 ~ "No Casualties Involved"))

ggplot(Fires,aes(x = time)) + coord_polar(theta = 'x') +
  geom_density() +
  labs(x = 'Hour of Day',
       Title = "A plot showing the frequency of fires each day") +
  facet_wrap(vars(Cause)) +
  scale_x_continuous(breaks = seq(0,23,1),limits = c(0,24)) +
  theme_minimal()
```



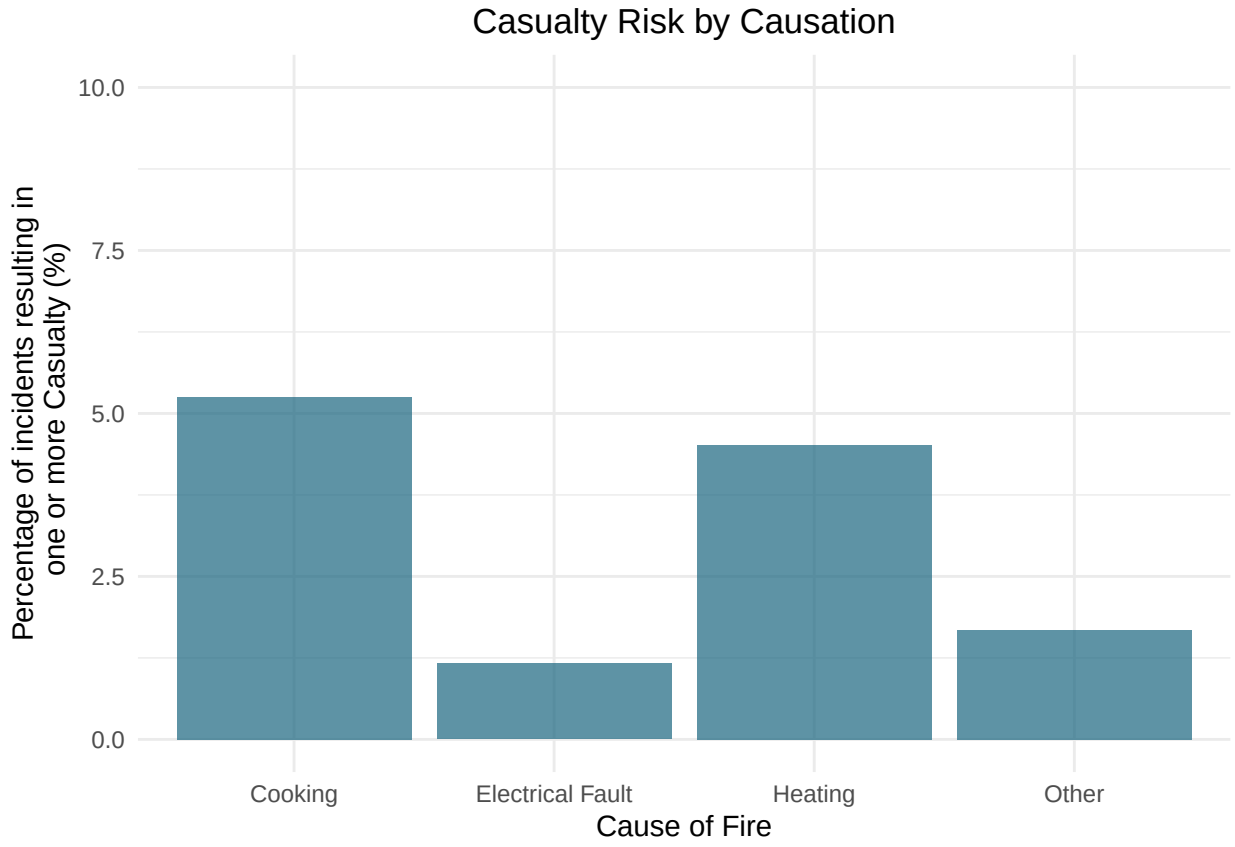
From the density function graphs above, we are able to analyse that each category has a different probability density function over a given 24 hrs. Cooking has the highest frequencies between the ranges 7am-8am, 11am-1pm and 5pm to 8pm; all times associated to breakfast, lunch and dinner. Electrical faults are evenly distributed over 8am to 7pm, Heating has the highest density over 5pm to 9pm, and Other has no identifiable trends apart from being evenly distributed during sociable hours.

2A - Casualties by causation

```
# Summarise the data by Cause, and calculate some fields for analysis.
Casualties_by_causation_analysis = Fires %>%
  group_by(Cause) %>%
  summarise(Total_Casualties = sum(Casualties),
            Count_Casualties = sum(Casualties > 0),
            Total_Incidents = n(),
            risk_likelihood = 100*(Count_Casualties/Total_Incidents))

# Note, care must be taken to distinguish the difference
# between there being a casualty (a count) and the sum of casualties.
# Both are useful for analysis, however for the proportion of incidents
# where casualties have been involved, we will use the count.

ggplot(Casualties_by_causation_analysis, aes(x = Cause, y = Total_Casualties)) +
  geom_bar(stat = "identity", fill=rgb(0.1,0.4,0.5,0.7)) +
  theme_minimal() +
  labs(x = "Cause of Fire",
       y = "Total Casualties",
       title = "Casualties by Cause") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian(ylim = c(0,1500))
```



```r
# Showing the proportion of casualties vs incidents

ggplot(Casualties_by_causation_analysis, aes(x = Cause, y = risk_likelihood)) +
  geom_bar(stat = "identity", fill=rgb(0.1,0.4,0.5,0.7)) +
  theme_minimal() +
  labs(x = "Cause of Fire",
       y = "Percentage of incidents resulting in\n one or more Casualty (%)",
       title = "Casualty Risk by Causation") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian(ylim = c(0,10))
```

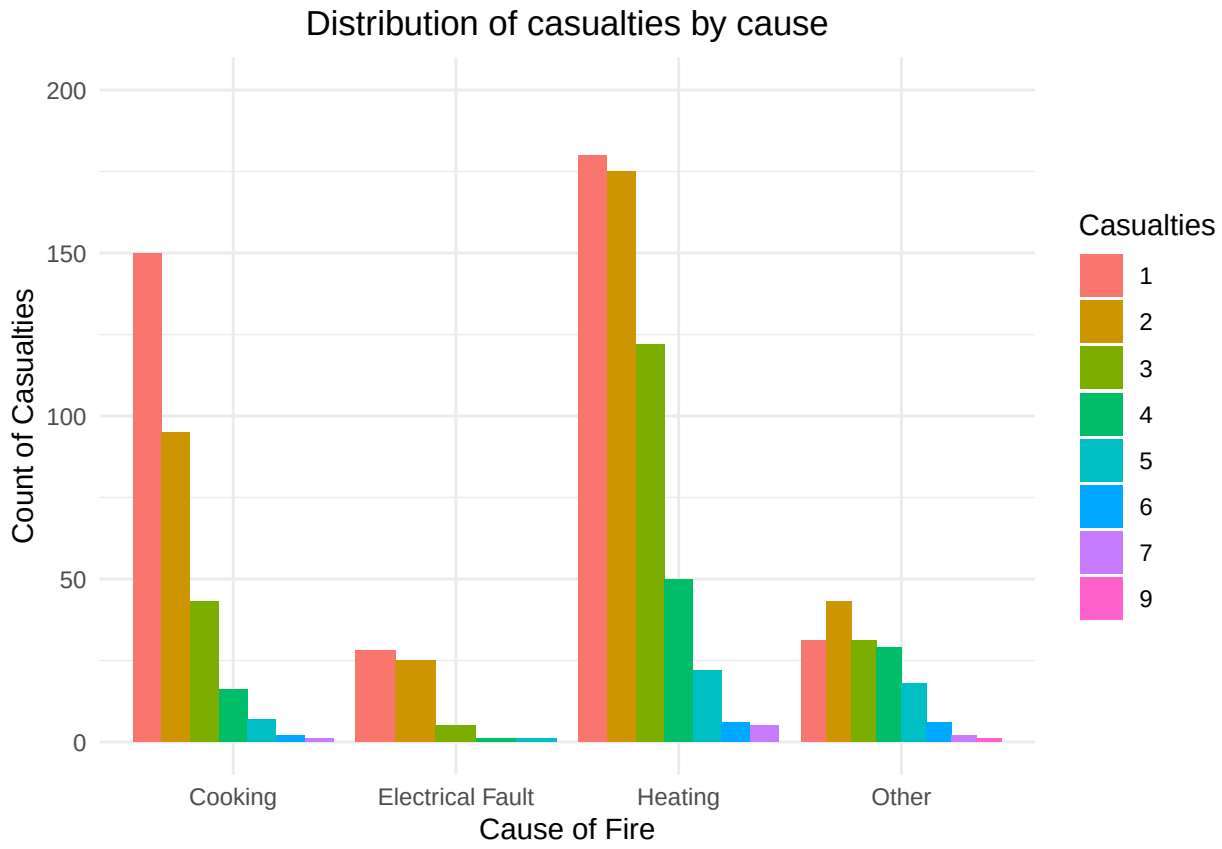


By examining total casualties by cause, and their likelihood to involve casualties, we can examine while Heating fires tend to have the most casualties involved, cooking fires are more likely to involve casualties.

2A - Casualty Distribution

```r
# Calculate Casualty distribution, filtering on where casualties occur.
Casualty_Distribution = Fires %>% filter(Casualties > 0) %>%
  group_by(Cause,Casualties) %>%
  summarise(Count_Of_Incidents = n())

# Distribution of casualties
ggplot(Casualty_Distribution,
       aes(fill = as.character(Casualties),
```

```
          x = Cause,
          y = Count_Of_Incidents)) +
geom_bar(position="dodge",stat = "identity") +
theme_minimal() +
labs(x = "Cause of Fire",
     y = "Count of Casualties",
     title = "Distribution of casualties by cause") +
theme(plot.title = element_text(hjust = 0.5)) +
coord_cartesian(ylim = c(0,200)) +
 scale_fill_discrete(name = "Casualties")
```



This is further examined in the distribution of casualties by cause, where heating fires tend to have a higher number of casualties involved.

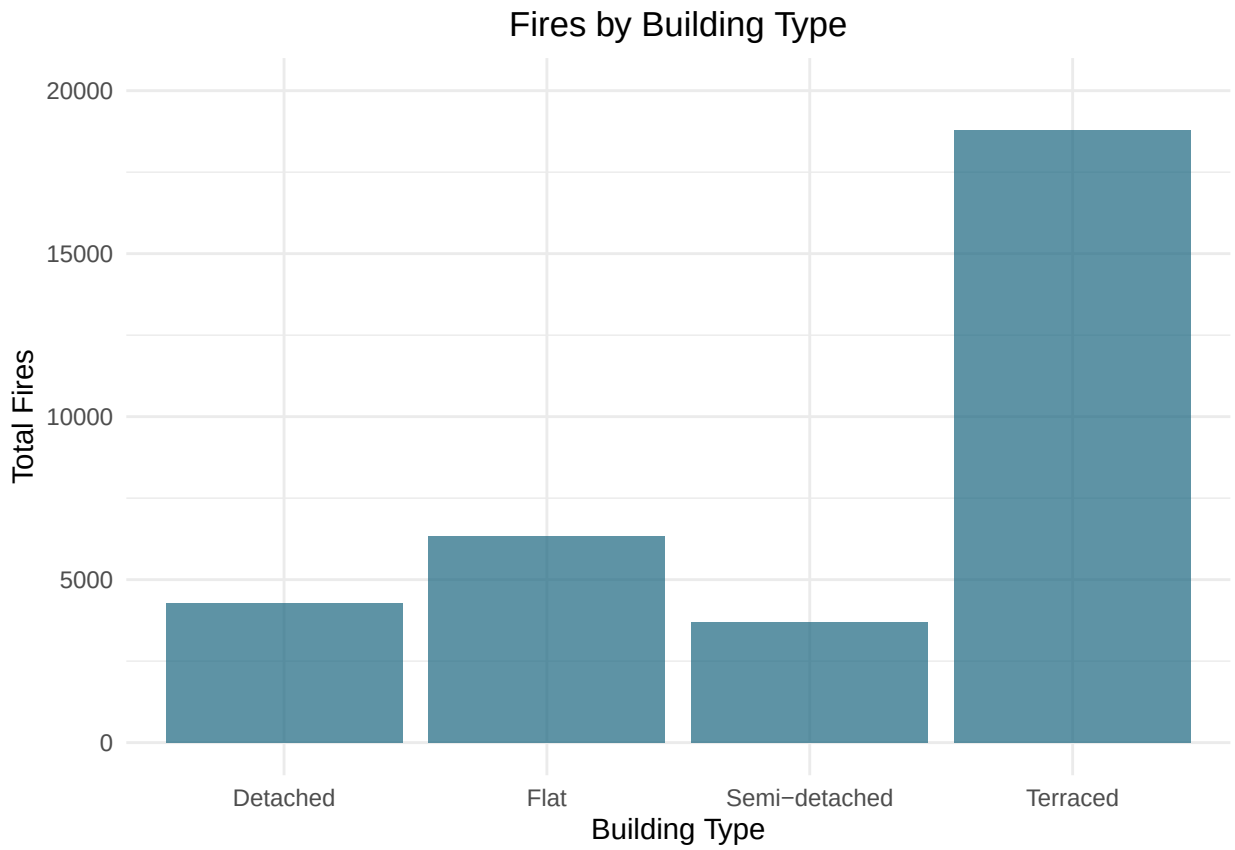
b) Are there any differences in the risk of fire for the different types of property? What is the relation between the year a property was built and the risk of fire?

```
# Join housing registry to fire dataset.
Fire_join = Fires %>% left_join(Housing_Reg, by = c("RegisterNumber" = "ID"))
```

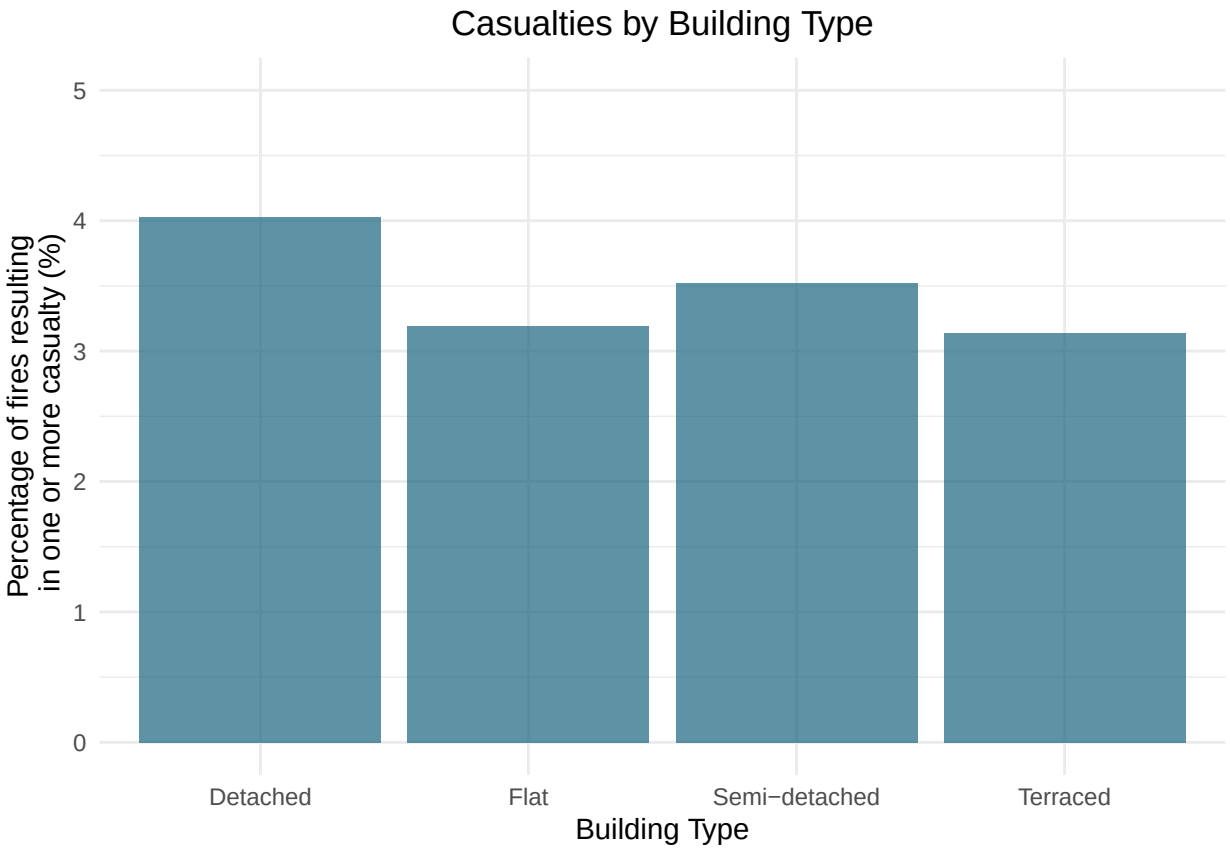
2B - Building Analysis

```
# Summarise data for building analysis
Building_Type_Analysis = Fire_join %>%  group_by(Type) %>%
```

```
summarise(Total_Fires = n(),
          Fires_Involving_Casualties = sum(Casualties > 0),
          Fires_Involving_Casualties_Perc = 100*Fires_Involving_Casualties/Total_Fires)

# Analyse Total fires by building type
ggplot(Building_Type_Analysis, aes(x = Type, y = Total_Fires)) +
  geom_bar(stat = "identity", fill=rgb(0.1,0.4,0.5,0.7)) +
  theme_minimal() +
  labs(x = "Building Type",
       y = "Total Fires",
       title = "Fires by Building Type") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian(ylim = c(0,20000))
```




```
# Analyse casualties by building type
ggplot(Building_Type_Analysis, aes(x = Type, y = Fires_Involving_Casualties_Perc)) +
  geom_bar(stat = "identity", fill=rgb(0.1,0.4,0.5,0.7)) +
  theme_minimal() +
  labs(x = "Building Type",
       y = "Percentage of fires resulting\n in one or more casualty (%)",
       title = "Casualties by Building Type") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian(ylim = c(0,5))
```

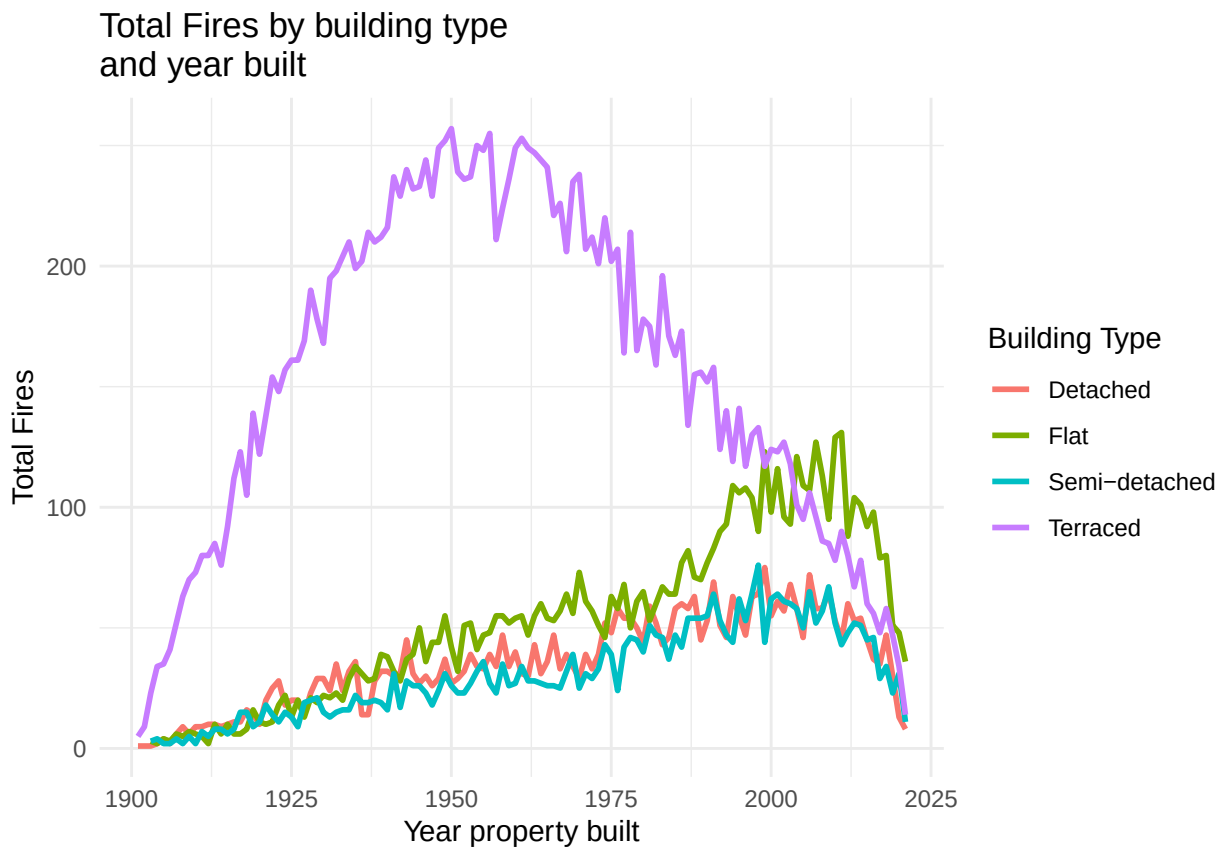


We can see that in our sample terraced houses tend to have a significantly higher number of fires associated with them, however we are unsure of the total amount in Utopia, and therefore must proceed with caution.

It may however be a fair assertation that fires are more likely to occur in terraced houses since of the higher likelihood of fire spreading house-to-house. While we have a clear outlier comparing the total amount of fires, when we look at the likelihood of one or more casualties we find a uniform distribution across all house types, inferring that none are more likely to have casualties than others.

2B - Fires by Building Type

```
  # summarise data to find the yearly
  Fire_BuildingAge_Analysis = Fire_join %>% group_by(Type,Year) %>%
                              summarise(Total_Fires = n())

# Analyse Fires by building type and year built
ggplot(Fire_BuildingAge_Analysis, aes(x = Year, y = Total_Fires, color = Type)) +
  geom_line(linewidth = 1) +
  labs(title = "Total Fires by building type \nand year built",
       x = "Year property built",
       y = "Total Fires") +
  scale_color_discrete(name = "Building Type") +
  theme(plot.title = element_text(hjust = 0.5))+
  theme_minimal()
```



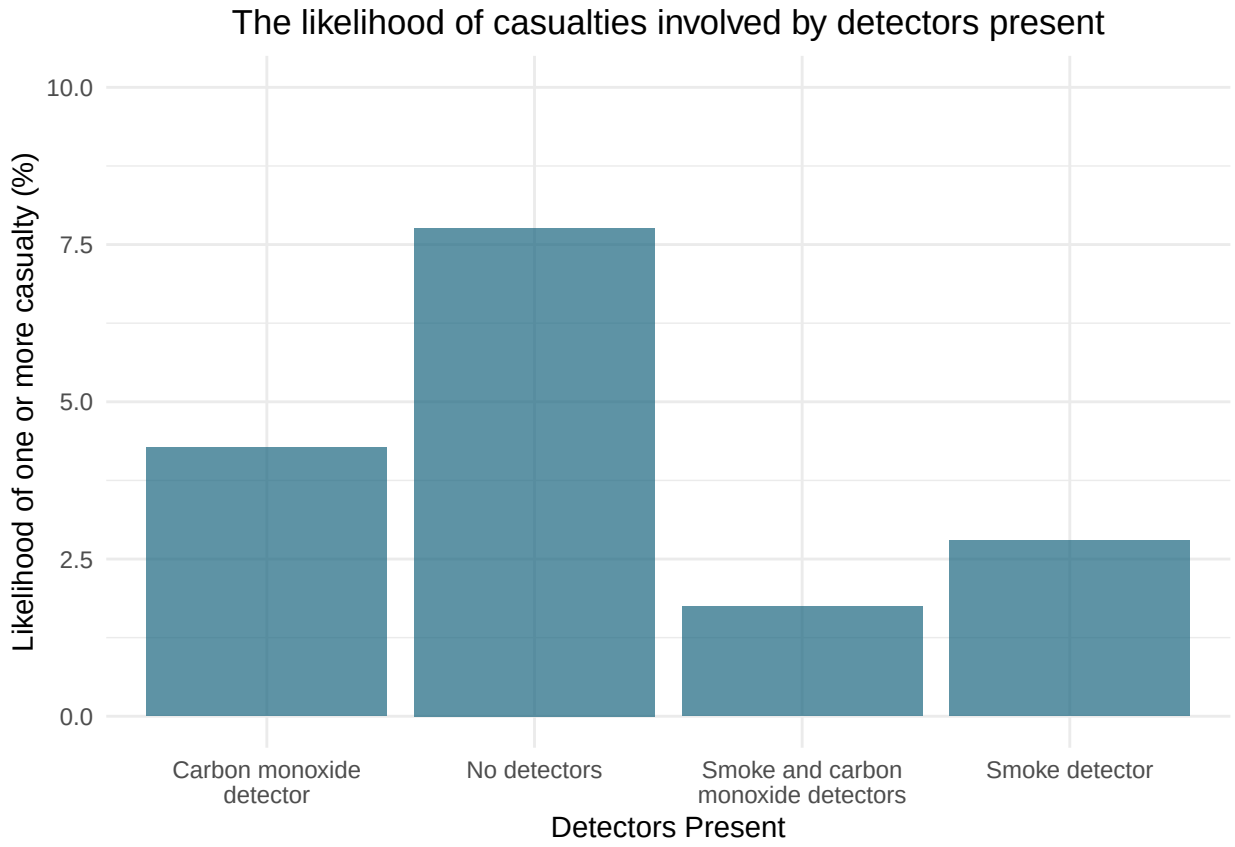
When we analyse fires by year built we find that terraced houses built in the early to late 1900s are involved in a greater number of fires. We can see a downwards trend towards the end of the sample period. It is important to note this does not necessarily mean that newer houses have less fires, since they have had less time for fires to occur in the sample period.

c) The Fire Department wishes to run a campaign which encourages home owners to install smoke and carbon monoxide detectors. What does the data reveal regarding the benefits of installing smoke and carbon monoxide detectors?

2C - Casualties by Detectors Present

```
# Classify data into groups and summarise

Fires = Fires %>% mutate(Detectors_Present = case_when(
            (Smoke == 1) & (CO == 1) ~ "Smoke and carbon\nmonoxide detectors",
            (Smoke == 1) & (CO == 0) ~ "Smoke detector",
            (Smoke == 0) & (CO == 1) ~ "Carbon monoxide\ndetector",
            (Smoke == 0) & (CO == 0) ~ "No detectors"))

Detector_Analysis = Fires %>%
            group_by(Detectors_Present) %>%

            summarise(Total_Fires = n(),
                      Total_Casualties = sum(Casualties),
```

```
                    Count_Casualties = sum(Casualties > 0),
                    Casualty_likelihood = 100*Count_Casualties / Total_Fires,
                    Average_Property_Damage = mean(Damage, na.rm = TRUE))


ggplot(Detector_Analysis, aes(x = Detectors_Present, y = Casualty_likelihood)) +
  geom_bar(stat = "identity", fill=rgb(0.1,0.4,0.5,0.7)) +
  theme_minimal() +
  labs(x = "Detectors Present",
       y = "Likelihood of one or more casualty (%)",
       title = "The likelihood of casualties involved by detectors present") +
  theme(plot.title = element_text(hjust = 0.5)) +
  coord_cartesian(ylim = c(0,10))
```

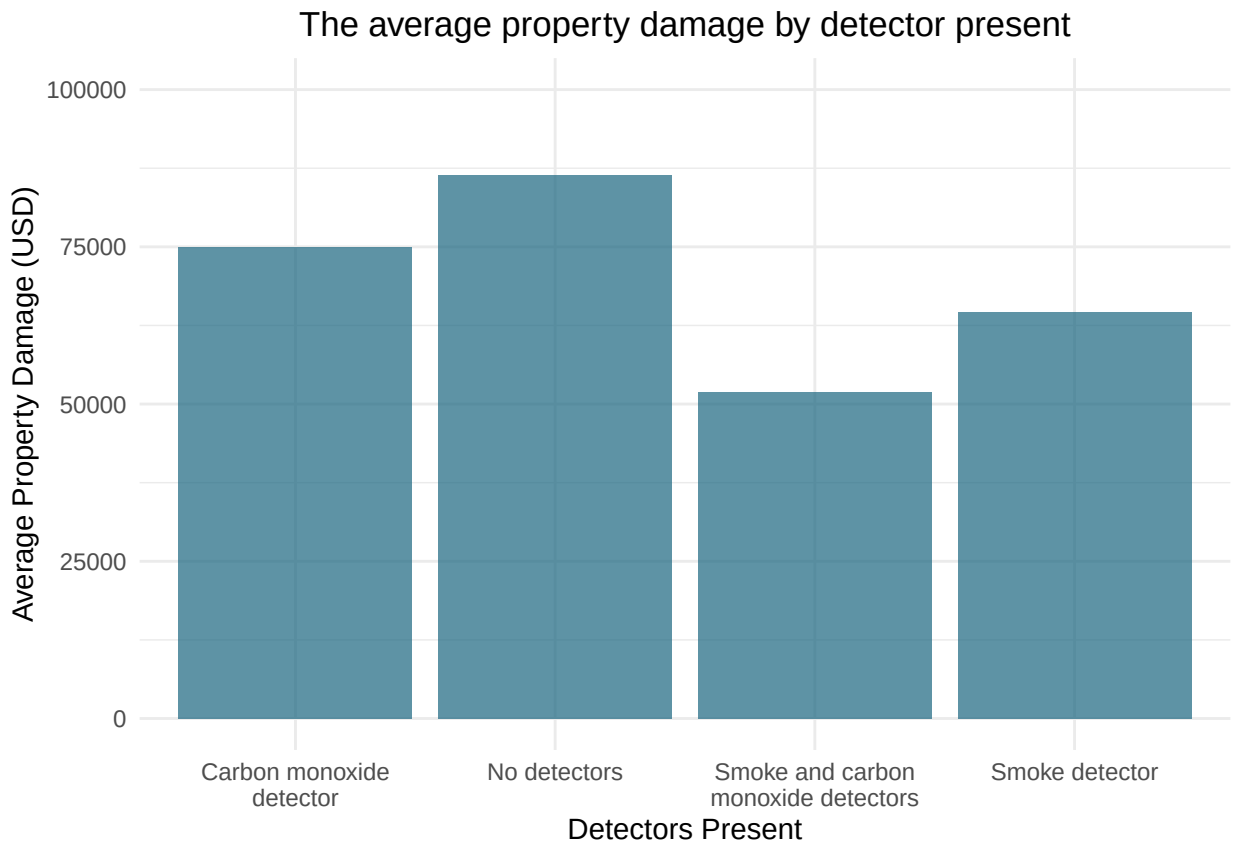


We are able to analyse that fires where no detectors are present have a significantly higher likelihood in resulting in one or more casualty. The likelihood of casualties is over 4 times higher in properties without detectors.

2C - Property Damage by Detectors Present

```
ggplot(Detector_Analysis, aes(x = Detectors_Present, y = Average_Property_Damage)) +
  geom_bar(stat = "identity", fill=rgb(0.1,0.4,0.5,0.7)) +
  theme_minimal() +
  labs(x = "Detectors Present",
```

```
      y = "Average Property Damage (USD)",
      title = "The average property damage by detector present") +
theme(plot.title = element_text(hjust = 0.5)) +
coord_cartesian(ylim = c(0,100000))
```



We are able to conclude that properties with no detectors are more likely to have a higher monetary loss than those with detectors. It could be possible that since detectors are able to give early warning of a fire, the emergency services are called sooner and therefore respond quicker than if there were no detector - leading to less damage.

look at property year and detectors present!

2C - Property year and detectors present