

5510-Projecxt

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0.1	How long did it take on average for the CFA brigade to respond to incidents in their own areas for hazard class 2 in Q4 2018/19 and Q4 2019/20? Also, this will be analyzed against the standard time (given in the data for each of the hazard classes). (CFA Emergency Response Time)	1
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0.1 How long did it take on average for the CFA brigade to respond to incidents in their own areas for hazard class 2 in Q4 2018/19 and Q4 2019/20? Also, this will be analyzed against the standard time (given in the data for each of the hazard classes). (CFA Emergency Response Time)

0.1.1 Introduction

There are three critical components of CFA delivery services: Response time: This is measured from when the brigade is alerted to an event to when the brigade arrives at the scene.

Brigade area: Each brigade has a defined brigade area, which specifies the operational footprint of the brigade.

Hazard classes: Hazard class defines the type of risk for a given area. Each brigade area may contain multiple hazard classes. However, each hazard class has a predefined service delivery standards.

In the data we have two variables that record the amount of time it CFA brigade to respond to incidents in specified areas:

- The time in which 90% of emergency incidents were responded to by any brigade; and,
- The time in which 90% of emergency incidents were responded to by the brigade within their own Brigade Area

The variable of interest for us is : The time in which 90% of emergency incidents were responded to by the brigade within their own Brigade Area. The reason is because we want to find out the mean time in which CFA brigade responded to incidents in their own brigade areas.

For this purpose, I did bit of data wrangling:

- renamed variables such that now we have a `TimeResponse` variable, and `TimeResponse_within` variable.
- mutate Number of incidents into a numeric vector.
- Changed the character variables to time using the contributed library `chron`.

For this specific question, we are going to analyze the data for **Hazard Class 2** that covers significant urban areas and is primarily residential including commercial centres, clusters of industrial and/or high density community services e.g. schools, correctional facilities, hospitals.

CFA has service delivery standards, which specify a response time target for a brigade to attend an emergency incident. The service delivery standard (response time) for Hazard Class 2 is **8 minutes**. Hence the analysis will be carried against this standard response time.

```
data_20 <- read.csv("data/dat_q4_2020.csv") %>%
  rename(CFA_district = CFA.District)%>%
  rename(CFA_Brigade_Area = CFA.Brigade.Area)%>%
  rename(Number_of_incidents = `Number.of.emergency.incidents.within.the.Brigade.Area.for.the.reporting`)
  rename(TimeResponse = `The.time.in.which.90..of.emergency.incidents.were.responded.to.by.any.brigade`)
  rename(TimeResponse_within = `The.time.in.which.90..of.emergency.incidents.were.responded.to.by.the.brigade`)
  mutate(`TimeResponse_within` = paste0("00:", `TimeResponse_within`))%>%
  mutate(TimeResponse = paste0("00:", TimeResponse))%>%
  mutate(Number_of_incidents = as.numeric(Number_of_incidents))

data_20
```

##	X	CFA_district	CFA_Brigade_Area	Number_of_incidents	TimeResponse
## 1	1	2	Bendigo	71	00:06:51
## 2	2	2	Eaglehawk	17	00:09:45
## 3	3	2	Golden Square	21	00:07:45
## 4	4	2	Kangaroo Flat	27	00:09:39
## 5	5	4	Portland	12	00:06:30
## 6	6	5	Warrnambool	86	00:07:28
## 7	7	7	Belmont	61	00:06:49
## 8	8	7	Corio	105	00:07:51
## 9	9	7	Geelong City	117	00:06:40
## 10	10	7	Geelong West	16	00:08:21
## 11	11	7	Lara	36	00:11:00
## 12	12	7	Ocean Grove	13	00:05:56
## 13	13	7	Torquay	36	00:11:58
## 14	14	8	Berwick	16	00:05:49
## 15	15	8	Carrum Downs	27	00:10:30
## 16	16	8	Cranbourne	91	00:08:26
## 17	17	8	Dandenong	171	00:08:17
## 18	18	8	Edithvale	13	00:07:18
## 19	19	8	Frankston	143	00:07:19
## 20	20	8	Hallam	106	00:08:10
## 21	21	8	Hampton Park	32	00:08:12
## 22	22	8	Langwarrin	17	00:10:05
## 23	23	8	Mornington	24	00:07:20
## 24	24	8	Mt Eliza	13	00:08:29
## 25	25	8	Noble Park	31	00:06:47
## 26	26	8	Pakenham	28	00:09:19
## 27	27	8	Patterson River	46	00:06:47

```
## 28 28      8      Rosebud      25      00:06:13
##      TimeResponse_within
## 1      00:06:53
## 2      00:13:24
## 3      00:10:14
## 4      00:09:02
## 5      00:06:30
## 6      00:07:28
## 7      00:07:00
## 8      00:07:39
## 9      00:06:40
## 10     00:09:15
## 11     00:10:44
## 12     00:05:56
## 13     00:11:58
## 14     00:05:49
## 15     00:10:44
## 16     00:08:26
## 17     00:08:18
## 18     00:07:20
## 19     00:07:19
## 20     00:08:10
## 21     00:13:12
## 22     00:10:05
## 23     00:07:20
## 24     00:08:29
## 25     00:10:14
## 26     00:09:19
## 27     00:07:35
## 28     00:06:13
```

```
library(chron)
```

```
data_20$TimeResponse_within <- chron(times= data_20$TimeResponse_within)
```

```
data_20
```

```
##      X CFA_district CFA_Brigade_Area Number_of_incidents TimeResponse
## 1  1      2      Bendigo      71      00:06:51
## 2  2      2      Eaglehawk      17      00:09:45
## 3  3      2      Golden Square      21      00:07:45
## 4  4      2      Kangaroo Flat      27      00:09:39
## 5  5      4      Portland      12      00:06:30
## 6  6      5      Warrnambool      86      00:07:28
## 7  7      7      Belmont      61      00:06:49
## 8  8      7      Corio      105      00:07:51
## 9  9      7      Geelong City      117      00:06:40
## 10 10      7      Geelong West      16      00:08:21
## 11 11      7      Lara      36      00:11:00
## 12 12      7      Ocean Grove      13      00:05:56
## 13 13      7      Torquay      36      00:11:58
## 14 14      8      Berwick      16      00:05:49
## 15 15      8      Carrum Downs      27      00:10:30
```

## 16	16	8	Cranbourne	91	00:08:26
## 17	17	8	Dandenong	171	00:08:17
## 18	18	8	Edithvale	13	00:07:18
## 19	19	8	Frankston	143	00:07:19
## 20	20	8	Hallam	106	00:08:10
## 21	21	8	Hampton Park	32	00:08:12
## 22	22	8	Langwarrin	17	00:10:05
## 23	23	8	Mornington	24	00:07:20
## 24	24	8	Mt Eliza	13	00:08:29
## 25	25	8	Noble Park	31	00:06:47
## 26	26	8	Pakenham	28	00:09:19
## 27	27	8	Patterson River	46	00:06:47
## 28	28	8	Rosebud	25	00:06:13
##	TimeResponse_within				
## 1					00:06:53
## 2					00:13:24
## 3					00:10:14
## 4					00:09:02
## 5					00:06:30
## 6					00:07:28
## 7					00:07:00
## 8					00:07:39
## 9					00:06:40
## 10					00:09:15
## 11					00:10:44
## 12					00:05:56
## 13					00:11:58
## 14					00:05:49
## 15					00:10:44
## 16					00:08:26
## 17					00:08:18
## 18					00:07:20
## 19					00:07:19
## 20					00:08:10
## 21					00:13:12
## 22					00:10:05
## 23					00:07:20
## 24					00:08:29
## 25					00:10:14
## 26					00:09:19
## 27					00:07:35
## 28					00:06:13

```
data_20$TimeResponse <- chron(times=data_20$TimeResponse)
```

```
data_20
```

##	X	CFA_district	CFA_Brigade_Area	Number_of_incidents	TimeResponse
## 1	1	2	Bendigo	71	00:06:51
## 2	2	2	Eaglehawk	17	00:09:45
## 3	3	2	Golden Square	21	00:07:45
## 4	4	2	Kangaroo Flat	27	00:09:39
## 5	5	4	Portland	12	00:06:30
## 6	6	5	Warrnambool	86	00:07:28

## 7	7	7	Belmont	61	00:06:49
## 8	8	7	Corio	105	00:07:51
## 9	9	7	Geelong City	117	00:06:40
## 10	10	7	Geelong West	16	00:08:21
## 11	11	7	Lara	36	00:11:00
## 12	12	7	Ocean Grove	13	00:05:56
## 13	13	7	Torquay	36	00:11:58
## 14	14	8	Berwick	16	00:05:49
## 15	15	8	Carrum Downs	27	00:10:30
## 16	16	8	Cranbourne	91	00:08:26
## 17	17	8	Dandenong	171	00:08:17
## 18	18	8	Edithvale	13	00:07:18
## 19	19	8	Frankston	143	00:07:19
## 20	20	8	Hallam	106	00:08:10
## 21	21	8	Hampton Park	32	00:08:12
## 22	22	8	Langwarrin	17	00:10:05
## 23	23	8	Mornington	24	00:07:20
## 24	24	8	Mt Eliza	13	00:08:29
## 25	25	8	Noble Park	31	00:06:47
## 26	26	8	Pakenham	28	00:09:19
## 27	27	8	Patterson River	46	00:06:47
## 28	28	8	Rosebud	25	00:06:13
##	TimeResponse_within				
## 1	00:06:53				
## 2	00:13:24				
## 3	00:10:14				
## 4	00:09:02				
## 5	00:06:30				
## 6	00:07:28				
## 7	00:07:00				
## 8	00:07:39				
## 9	00:06:40				
## 10	00:09:15				
## 11	00:10:44				
## 12	00:05:56				
## 13	00:11:58				
## 14	00:05:49				
## 15	00:10:44				
## 16	00:08:26				
## 17	00:08:18				
## 18	00:07:20				
## 19	00:07:19				
## 20	00:08:10				
## 21	00:13:12				
## 22	00:10:05				
## 23	00:07:20				
## 24	00:08:29				
## 25	00:10:14				
## 26	00:09:19				
## 27	00:07:35				
## 28	00:06:13				

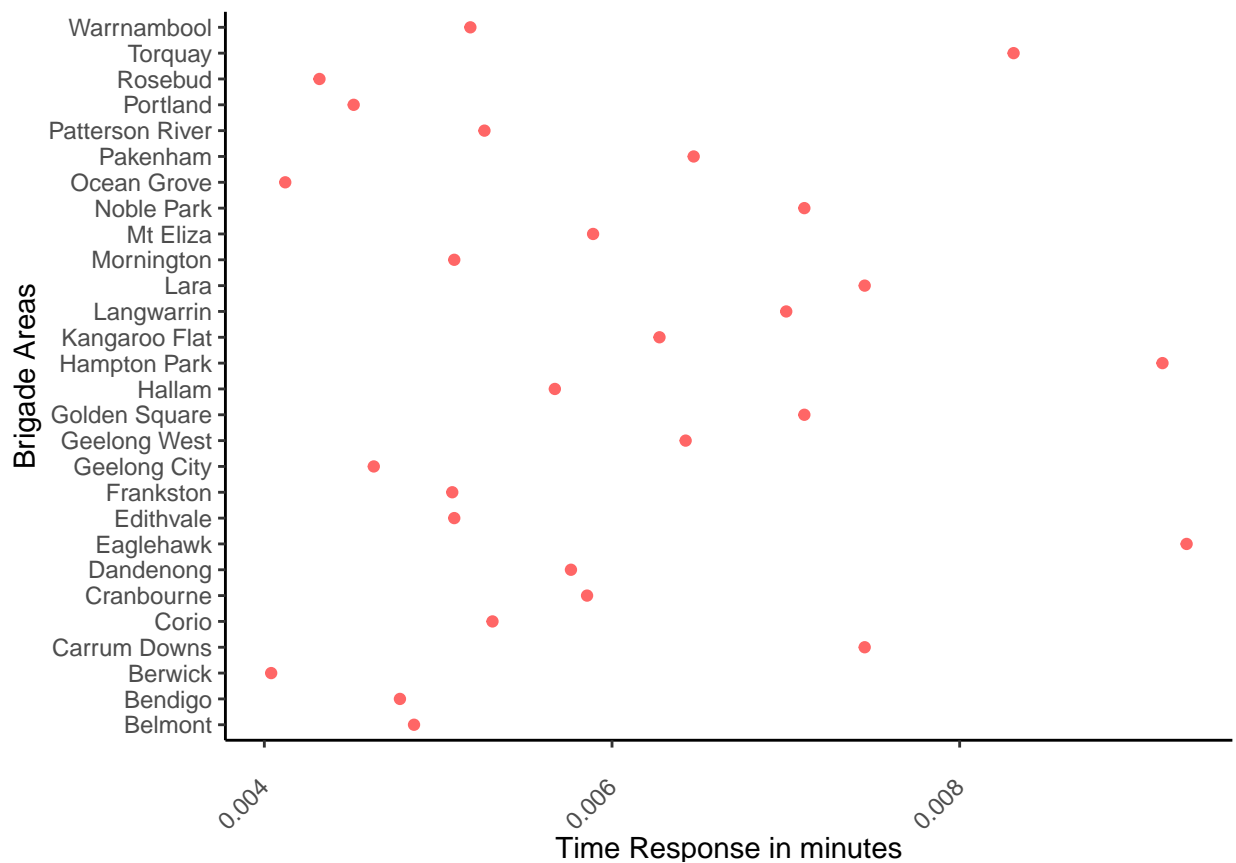
0.1.2 Context

The most recent data from April to June 2020 showed CFA brigades responded to 9,120 incidents, of which 4,893 required an emergency response.

In 87 per cent of incidents that required emergency response, the community received a fire service within the standard response time, which was broadly consistent with previous quarters.CFA News

Let's visualize the data first.

```
ggplot(data_20) +  
  geom_point(data = data_20,  
    aes(x = TimeResponse_within,  
      y = CFA_Brigade_Area),  
    color = "red",  
    alpha = 0.6)+  
  theme_classic()+  
  theme(axis.text.x = element_text(angle = 45, vjust = 0.5, hjust=1), axis.title.x = element_text(vjust=0.5),  
    labs(x = "Time Response in minutes",  
      y = "Brigade Areas"))
```



```
data_20 %>%  
  select(TimeResponse_within)%>%  
  summary(data_20$TimeResponse_within)%>%  
  kable() %>%  
  kable_styling(bootstrap_options = c("striped", "hover"))
```

	TimeResponse_within
	Min. :00:05:49
	1st Qu.:00:07:14
	Median :00:08:14
	Mean :00:08:37
	3rd Qu.:00:10:07
	Max. :00:13:24

The mean time that it took CFA brigades to respond to incidents in their own CFA brigade areas is 0.0059838. This is very close to the target response time for brigades, which is eight minutes.

```
data20_avgRT <- function(TimeResponse_within){
  m = sum(TimeResponse_within)/length(TimeResponse_within)
  return(m)
}
data20_avgRT(data_20$TimeResponse_within)
```

```
## [1] 00:08:37
```

For the year 2018/19, we have used the data belonging to the year 2018/19, which was acquired from the CFA official site.

The most recent data set from July to September 2019 showed CFA brigades responding to 9,830 incidents, of which 5,013 required an emergency response.

In 87 per cent of emergencies, the community received a fire service within the standard response time, which was broadly consistent with previous quarters.CFA News

For this part of the question, I repeated the same data cleaning steps as mentioned above.

```
data_19 <- read.csv("data/dat_q4_2018_19.csv")%>%
  rename(CFA_district = CFA.District)%>%
  rename(CFA_Brigade_Area = CFA.Brigade.Area)%>%
  rename(Number_of_incidents = `Number.of.emergency.incidents.within.the.Brigade.Area.for.the.reporting`)
  rename(TimeResponse = `The.time.in.which.90..of.emergency.incidents.were.responded.to.by.any.brigade`)
  rename(TimeResponse_within = `The.time.in.which.90..of.emergency.incidents.were.responded.to.by.the.brigade`)
  filter(TimeResponse_within != "NULL")%>%
  mutate(`TimeResponse_within` = paste0("00:",`TimeResponse_within`))%>%
  mutate(TimeResponse = paste0("00:",TimeResponse))%>%
  mutate(Number_of_incidents = as.numeric(Number_of_incidents))

data_19
```

```
##      X CFA_district CFA_Brigade_Area Number_of_incidents TimeResponse
## 1    1             2      Bendigo             58      00:07:32
## 2    2             2    Castlemaine             10      00:09:36
## 3    3             2    Eaglehawk              16      00:09:23
## 4    4             2 Kangaroo Flat             12      00:07:48
## 5    5             4    Portland              19      00:07:00
## 6    6             5    Warrnambool            44      00:07:13
## 7    7             6      Colac              10      00:07:46
```

## 8 8	7	Belmont	56	00:07:07
## 9 9	7	Corio	102	00:07:31
## 10 10	7	Geelong City	122	00:06:47
## 11 11	7	Lara	26	00:10:28
## 12 12	7	Ocean Grove	10	00:05:28
## 13 13	7	Torquay	15	00:11:55
## 14 14	8	Berwick	25	00:06:46
## 15 15	8	Carrum Downs	32	00:08:57
## 16 16	8	Cranbourne	78	00:09:51
## 17 17	8	Dandenong	126	00:09:13
## 18 18	8	Edithvale	13	00:06:52
## 19 19	8	Frankston	116	00:07:07
## 20 20	8	Hallam	71	00:07:23
## 21 21	8	Hampton Park	18	00:08:35
## 22 22	8	Mornington	38	00:07:07
## 23 24	8	Pakenham	27	00:08:13
## 24 25	8	Patterson River	29	00:07:33
## 25 26	8	Rosebud	17	00:07:27
## 26 27	8	Springvale	62	00:07:53
## 27 28	11	Bairnsdale	11	00:12:21
## 28 29	13	Bayswater	17	00:06:39
## 29 30	13	Boronia	46	00:06:17
## 30 31	13	Chirnside Park	14	00:08:57
## 31 32	13	Ferntree Gully	24	00:07:30
## 32 33	13	Lilydale	17	00:09:23
## 33 34	13	Montrose	16	00:06:49
## 34 35	13	Rowville	28	00:06:57
## 35 36	13	Scoresby	32	00:09:13
## 36 37	13	Warrandyte	14	00:07:27
## 37 38	14	Caroline Springs	67	00:08:57
## 38 39	14	Craigieburn	52	00:09:43
## 39 40	14	Eltham	25	00:06:48
## 40 41	14	Epping	28	00:09:09
## 41 42	14	Greenvale	17	00:08:51
## 42 43	14	Hoppers Crossing	61	00:08:18
## 43 44	14	Melton	79	00:08:04
## 44 45	14	Mernda	12	00:08:35
## 45 46	14	Point Cook	37	00:09:33
## 46 47	14	South Morang	22	00:07:24
## 47 48	14	Sunbury	44	00:08:20
## 48 49	14	Werribee	20	00:07:13
## 49 50	15	Bacchus Marsh	20	00:10:22
## 50 51	15	Ballarat	25	00:08:03
## 51 52	15	Ballarat City	58	00:05:28
## 52 53	15	Sebastopol	16	00:08:45
## 53 54	15	Wendouree	36	00:09:47
## 54 55	16	Stawell	14	00:09:29
## 55 56	18	Mildura	48	00:06:38
## 56 57	22	Shepparton	79	00:07:13
## 57 58	23	Benalla	13	00:08:34
## 58 59	23	Wangaratta	21	00:05:41
## 59 60	24	Wodonga	40	00:07:45
## 60 62	27	Morwell	39	00:06:28
## 61 63	27	Traralgon	34	00:06:34

##	TimeResponse_within
## 1	00:07:30
## 2	00:09:36
## 3	00:14:45
## 4	00:07:52
## 5	00:07:00
## 6	00:07:13
## 7	00:09:02
## 8	00:08:05
## 9	00:07:56
## 10	00:06:47
## 11	00:10:28
## 12	00:05:28
## 13	00:12:59
## 14	00:06:39
## 15	00:09:21
## 16	00:09:51
## 17	00:09:13
## 18	00:07:13
## 19	00:07:18
## 20	00:08:24
## 21	00:12:16
## 22	00:07:07
## 23	00:07:51
## 24	00:08:20
## 25	00:07:27
## 26	00:08:49
## 27	00:12:23
## 28	00:06:39
## 29	00:06:27
## 30	00:10:30
## 31	00:09:45
## 32	00:09:23
## 33	00:09:07
## 34	00:07:49
## 35	00:12:51
## 36	00:10:31
## 37	00:11:32
## 38	00:09:43
## 39	00:06:48
## 40	00:10:36
## 41	00:11:31
## 42	00:08:18
## 43	00:08:04
## 44	00:08:37
## 45	00:09:33
## 46	00:07:24
## 47	00:08:20
## 48	00:10:03
## 49	00:12:11
## 50	00:10:29
## 51	00:05:27
## 52	00:11:18
## 53	00:16:38

```
## 54      00:09:29
## 55      00:06:38
## 56      00:07:13
## 57      00:08:34
## 58      00:06:15
## 59      00:07:45
## 60      00:06:28
## 61      00:06:26
```

```
library(chron)
```

```
data_19$TimeResponse_within <- chron(times= data_19$TimeResponse_within)
```

```
data_19
```

##	X	CFA_district	CFA_Brigade_Area	Number_of_incidents	TimeResponse
## 1	1	2	Bendigo	58	00:07:32
## 2	2	2	Castlemaine	10	00:09:36
## 3	3	2	Eaglehawk	16	00:09:23
## 4	4	2	Kangaroo Flat	12	00:07:48
## 5	5	4	Portland	19	00:07:00
## 6	6	5	Warrnambool	44	00:07:13
## 7	7	6	Colac	10	00:07:46
## 8	8	7	Belmont	56	00:07:07
## 9	9	7	Corio	102	00:07:31
## 10	10	7	Geelong City	122	00:06:47
## 11	11	7	Lara	26	00:10:28
## 12	12	7	Ocean Grove	10	00:05:28
## 13	13	7	Torquay	15	00:11:55
## 14	14	8	Berwick	25	00:06:46
## 15	15	8	Carrum Downs	32	00:08:57
## 16	16	8	Cranbourne	78	00:09:51
## 17	17	8	Dandenong	126	00:09:13
## 18	18	8	Edithvale	13	00:06:52
## 19	19	8	Frankston	116	00:07:07
## 20	20	8	Hallam	71	00:07:23
## 21	21	8	Hampton Park	18	00:08:35
## 22	22	8	Mornington	38	00:07:07
## 23	24	8	Pakenham	27	00:08:13
## 24	25	8	Patterson River	29	00:07:33
## 25	26	8	Rosebud	17	00:07:27
## 26	27	8	Springvale	62	00:07:53
## 27	28	11	Bairnsdale	11	00:12:21
## 28	29	13	Bayswater	17	00:06:39
## 29	30	13	Boronia	46	00:06:17
## 30	31	13	Chirnside Park	14	00:08:57
## 31	32	13	Ferntree Gully	24	00:07:30
## 32	33	13	Lilydale	17	00:09:23
## 33	34	13	Montrose	16	00:06:49
## 34	35	13	Rowville	28	00:06:57
## 35	36	13	Scoresby	32	00:09:13
## 36	37	13	Warrandyte	14	00:07:27

## 37 38	14 Caroline Springs	67	00:08:57
## 38 39	14 Craigieburn	52	00:09:43
## 39 40	14 Eltham	25	00:06:48
## 40 41	14 Epping	28	00:09:09
## 41 42	14 Greenvale	17	00:08:51
## 42 43	14 Hoppers Crossing	61	00:08:18
## 43 44	14 Melton	79	00:08:04
## 44 45	14 Mernda	12	00:08:35
## 45 46	14 Point Cook	37	00:09:33
## 46 47	14 South Morang	22	00:07:24
## 47 48	14 Sunbury	44	00:08:20
## 48 49	14 Werribee	20	00:07:13
## 49 50	15 Bacchus Marsh	20	00:10:22
## 50 51	15 Ballarat	25	00:08:03
## 51 52	15 Ballarat City	58	00:05:28
## 52 53	15 Sebastopol	16	00:08:45
## 53 54	15 Wendouree	36	00:09:47
## 54 55	16 Stawell	14	00:09:29
## 55 56	18 Mildura	48	00:06:38
## 56 57	22 Shepparton	79	00:07:13
## 57 58	23 Benalla	13	00:08:34
## 58 59	23 Wangaratta	21	00:05:41
## 59 60	24 Wodonga	40	00:07:45
## 60 62	27 Morwell	39	00:06:28
## 61 63	27 Traralgon	34	00:06:34
##	TimeResponse_within		
## 1	00:07:30		
## 2	00:09:36		
## 3	00:14:45		
## 4	00:07:52		
## 5	00:07:00		
## 6	00:07:13		
## 7	00:09:02		
## 8	00:08:05		
## 9	00:07:56		
## 10	00:06:47		
## 11	00:10:28		
## 12	00:05:28		
## 13	00:12:59		
## 14	00:06:39		
## 15	00:09:21		
## 16	00:09:51		
## 17	00:09:13		
## 18	00:07:13		
## 19	00:07:18		
## 20	00:08:24		
## 21	00:12:16		
## 22	00:07:07		
## 23	00:07:51		
## 24	00:08:20		
## 25	00:07:27		
## 26	00:08:49		
## 27	00:12:23		
## 28	00:06:39		

```
## 29      00:06:27
## 30      00:10:30
## 31      00:09:45
## 32      00:09:23
## 33      00:09:07
## 34      00:07:49
## 35      00:12:51
## 36      00:10:31
## 37      00:11:32
## 38      00:09:43
## 39      00:06:48
## 40      00:10:36
## 41      00:11:31
## 42      00:08:18
## 43      00:08:04
## 44      00:08:37
## 45      00:09:33
## 46      00:07:24
## 47      00:08:20
## 48      00:10:03
## 49      00:12:11
## 50      00:10:29
## 51      00:05:27
## 52      00:11:18
## 53      00:16:38
## 54      00:09:29
## 55      00:06:38
## 56      00:07:13
## 57      00:08:34
## 58      00:06:15
## 59      00:07:45
## 60      00:06:28
## 61      00:06:26
```

```
data_19$TimeResponse <- chron(times=data_19$TimeResponse)
```

```
data_19
```

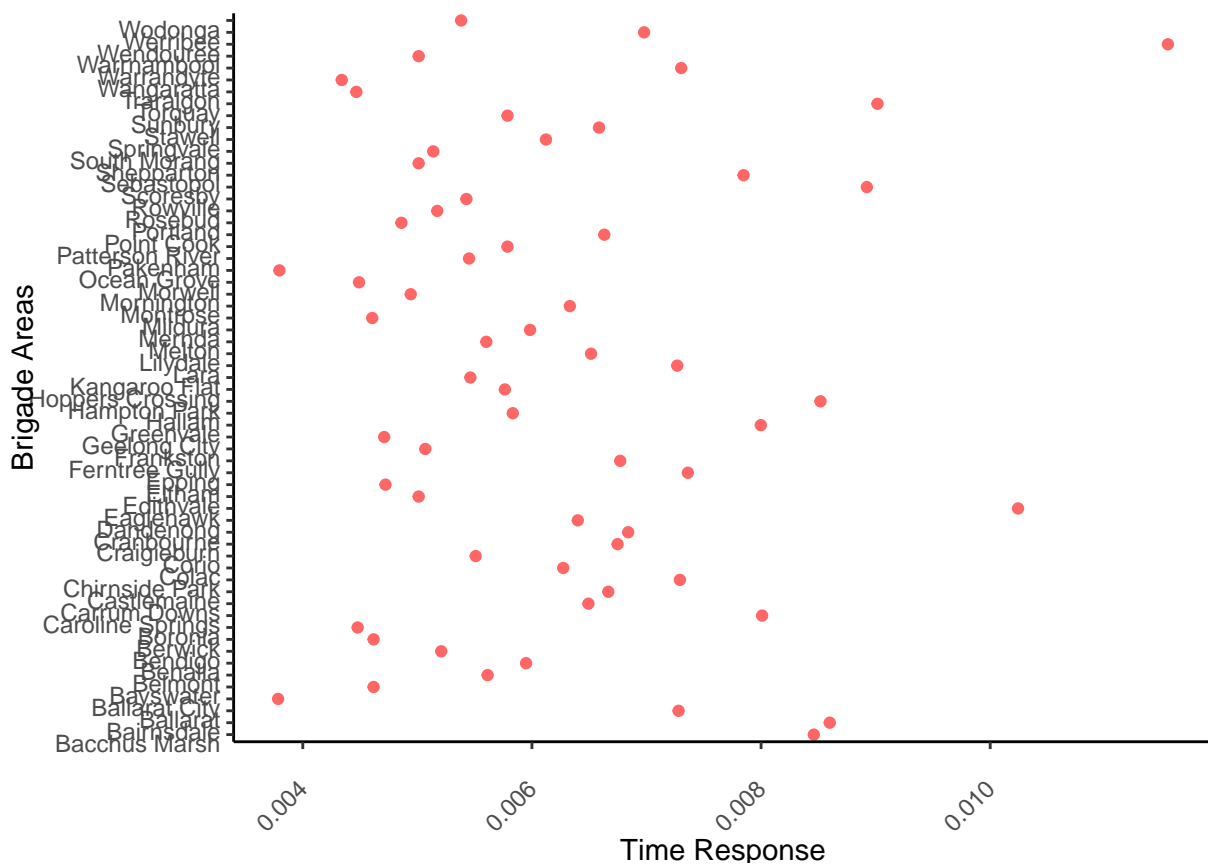
```
##      X CFA_district CFA_Brigade_Area Number_of_incidents TimeResponse
## 1  1      2      Bendigo          58      00:07:32
## 2  2      2      Castlemaine       10      00:09:36
## 3  3      2      Eaglehawk         16      00:09:23
## 4  4      2      Kangaroo Flat      12      00:07:48
## 5  5      4      Portland           19      00:07:00
## 6  6      5      Warrnambool        44      00:07:13
## 7  7      6           Colac          10      00:07:46
## 8  8      7      Belmont           56      00:07:07
## 9  9      7      Corio             102      00:07:31
## 10 10     7      Geelong City       122      00:06:47
## 11 11     7      Lara              26      00:10:28
## 12 12     7      Ocean Grove        10      00:05:28
## 13 13     7      Torquay           15      00:11:55
## 14 14     8      Berwick           25      00:06:46
## 15 15     8      Carrum Downs       32      00:08:57
```

## 16 16	8	Cranbourne	78	00:09:51
## 17 17	8	Dandenong	126	00:09:13
## 18 18	8	Edithvale	13	00:06:52
## 19 19	8	Frankston	116	00:07:07
## 20 20	8	Hallam	71	00:07:23
## 21 21	8	Hampton Park	18	00:08:35
## 22 22	8	Mornington	38	00:07:07
## 23 24	8	Pakenham	27	00:08:13
## 24 25	8	Patterson River	29	00:07:33
## 25 26	8	Rosebud	17	00:07:27
## 26 27	8	Springvale	62	00:07:53
## 27 28	11	Bairnsdale	11	00:12:21
## 28 29	13	Bayswater	17	00:06:39
## 29 30	13	Boronia	46	00:06:17
## 30 31	13	Chirnside Park	14	00:08:57
## 31 32	13	Ferntree Gully	24	00:07:30
## 32 33	13	Lilydale	17	00:09:23
## 33 34	13	Montrose	16	00:06:49
## 34 35	13	Rowville	28	00:06:57
## 35 36	13	Scoresby	32	00:09:13
## 36 37	13	Warrandyte	14	00:07:27
## 37 38	14	Caroline Springs	67	00:08:57
## 38 39	14	Craigieburn	52	00:09:43
## 39 40	14	Eltham	25	00:06:48
## 40 41	14	Epping	28	00:09:09
## 41 42	14	Greenvale	17	00:08:51
## 42 43	14	Hoppers Crossing	61	00:08:18
## 43 44	14	Melton	79	00:08:04
## 44 45	14	Mernda	12	00:08:35
## 45 46	14	Point Cook	37	00:09:33
## 46 47	14	South Morang	22	00:07:24
## 47 48	14	Sunbury	44	00:08:20
## 48 49	14	Werribee	20	00:07:13
## 49 50	15	Bacchus Marsh	20	00:10:22
## 50 51	15	Ballarat	25	00:08:03
## 51 52	15	Ballarat City	58	00:05:28
## 52 53	15	Sebastopol	16	00:08:45
## 53 54	15	Wendouree	36	00:09:47
## 54 55	16	Stawell	14	00:09:29
## 55 56	18	Mildura	48	00:06:38
## 56 57	22	Shepparton	79	00:07:13
## 57 58	23	Benalla	13	00:08:34
## 58 59	23	Wangaratta	21	00:05:41
## 59 60	24	Wodonga	40	00:07:45
## 60 62	27	Morwell	39	00:06:28
## 61 63	27	Traralgon	34	00:06:34
##	TimeResponse_within			
## 1	00:07:30			
## 2	00:09:36			
## 3	00:14:45			
## 4	00:07:52			
## 5	00:07:00			
## 6	00:07:13			
## 7	00:09:02			

## 8	00:08:05
## 9	00:07:56
## 10	00:06:47
## 11	00:10:28
## 12	00:05:28
## 13	00:12:59
## 14	00:06:39
## 15	00:09:21
## 16	00:09:51
## 17	00:09:13
## 18	00:07:13
## 19	00:07:18
## 20	00:08:24
## 21	00:12:16
## 22	00:07:07
## 23	00:07:51
## 24	00:08:20
## 25	00:07:27
## 26	00:08:49
## 27	00:12:23
## 28	00:06:39
## 29	00:06:27
## 30	00:10:30
## 31	00:09:45
## 32	00:09:23
## 33	00:09:07
## 34	00:07:49
## 35	00:12:51
## 36	00:10:31
## 37	00:11:32
## 38	00:09:43
## 39	00:06:48
## 40	00:10:36
## 41	00:11:31
## 42	00:08:18
## 43	00:08:04
## 44	00:08:37
## 45	00:09:33
## 46	00:07:24
## 47	00:08:20
## 48	00:10:03
## 49	00:12:11
## 50	00:10:29
## 51	00:05:27
## 52	00:11:18
## 53	00:16:38
## 54	00:09:29
## 55	00:06:38
## 56	00:07:13
## 57	00:08:34
## 58	00:06:15
## 59	00:07:45
## 60	00:06:28
## 61	00:06:26

Let's visualize the data for the year 2018/19.

```
ggplot(data_19) +
  geom_point(data = data_19,
    aes(x = TimeResponse_within,
      y = CFA_Brigade_Area),
    color = "red",
    alpha = 0.6)+
  theme_classic()+
  theme(axis.text.x = element_text(angle = 45, vjust = 0.5, hjust=1), axis.title.x = element_text(vjust=1),
    axis.text.y = element_text(angle = , vjust = 1, hjust=1), axis.title.y = element_text(vjust=-1))
labs(x = "Time Response",
  y = "Brigade Areas")
```



```
data_19%>%
  select(TimeResponse_within)%>%
  summary(data_19$TimeResponse_within)%>%
  kable() %>%
  kable_styling(bootstrap_options = c("striped", "hover"))
```

Using the summary function, we can see that the mean time taken by the CFA brigades to respond to the incidents in their own areas was 0.0062073. This is again very close to the target standard which was eight minutes.

	TimeResponse_within
	Min. :00:05:27
	1st Qu.:00:07:13
	Median :00:08:24
	Mean :00:08:56
	3rd Qu.:00:10:03
	Max. :00:16:38

```
data19_avgRT <- function(TimeResponse_within){
  m = sum(TimeResponse_within, na.rm = TRUE)/length(TimeResponse_within)
  return(m)
}
data19_avgRT(data_19$TimeResponse_within)
```

```
## [1] 00:08:56
```

0.1.3 Analysis

Keeping it brief, we can state that CFA brigades' performance against standard time of eight minutes for the hazard class 2 was achieved successfully, since we see a little variation in terms of amount of time taken by the CFA.

0.2 Which of the CFA brigade areas have had the highest number of incidents across Hazard classes for the reported period (2019/20) (four quarters). (CFA Emergency Response Time)

0.2.1 Introduction

In this question, we have one variable that records the number of incidents across all hazard classes for all the specified districts. There are three predefined hazard classes: 2, 3 and 4.

- Hazard class 2 (Medium Urban): This includes significant urban areas which are primarily residential including commercial centres, clusters of industrial and/or high density community services e.g. schools, correctional facilities, hospitals. (8 minutes SDS).
- Hazard Class 3 (Low Urban): This includes all urban areas that are not included in Hazard Class 2 and includes predominantly residential occupancies and small industries. (10 minutes SDS).
- Hazard Class 4 (Rural): This includes primarily the natural surroundings in terms of bush and grassland, but also involves isolated dwellings and structures within those areas.

The variable of interest for us is : Number_Incidents_total.

For this purpose, I did bit of data wrangling:

- renamed variables such that now we have a CFA_Brigade_Area variable, and Number_Incidents_total variable in each data set. (I had four datasets for Quarters 1, 2, 3, and 4)
- mutate Number of incidents into a numeric vector.
- Join data using bind_rows

0.2.2 Context

In this question we are concerned with district that has had the highest number of incidents across all hazard classes in the year 2019/20.

Let's first visualize data from each data set for the quarters 1, 2, 3 and 4 for the year 2019/20.

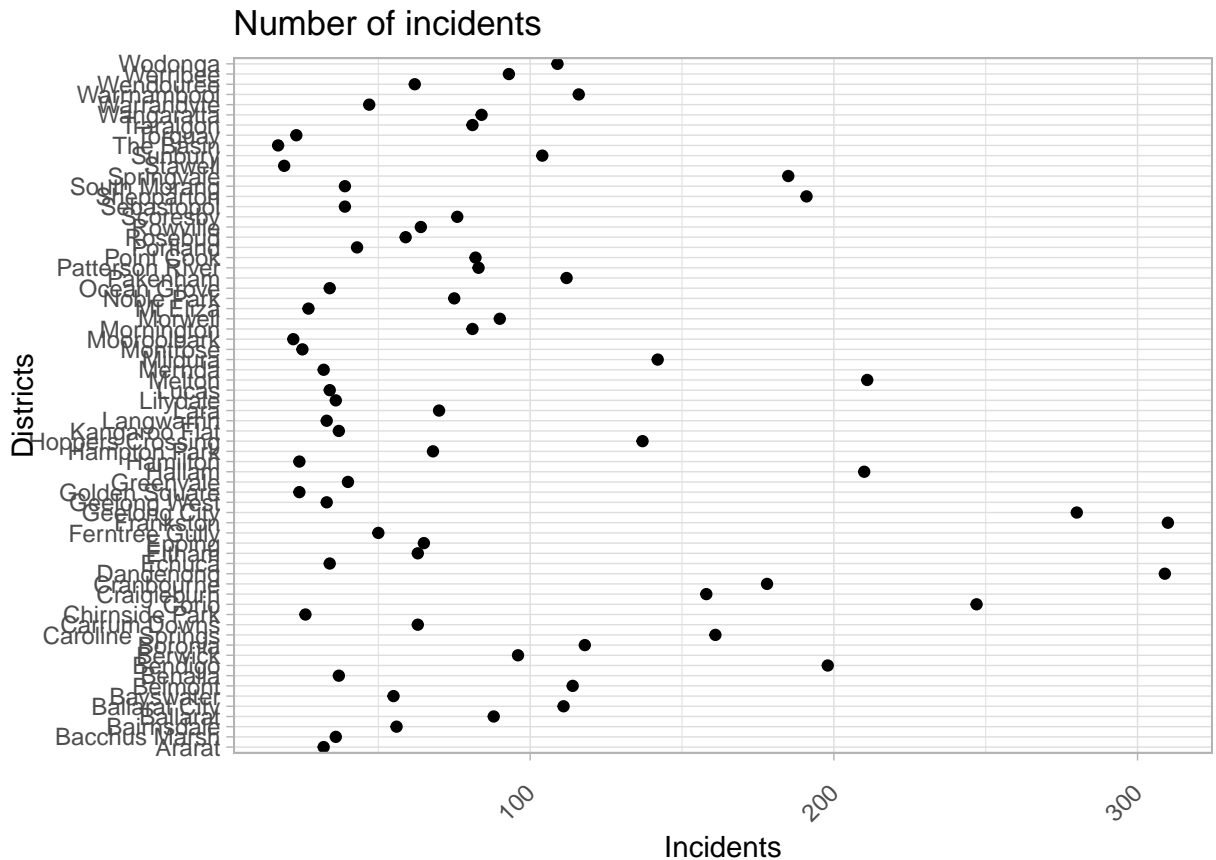
```
dat_Q1_2020 <- read_csv("data/dat_Q1_2020.csv") %>%
  rename(Number_Incidents_total = `Number of incidents within the Brigade Area for the reporting period`)
  rename(CFA_Brigade_Area = `CFA Brigade Area`)

dat_Q1_2020
```

```
## # A tibble: 68 x 4
##       X1 'CFA District' CFA_Brigade_Area Number_Incidents_total
##   <dbl> <chr>          <chr>                                <dbl>
## 1     1 02              Bendigo                                198
## 2     2 02              Golden Square                           24
## 3     3 02              Kangaroo Flat                            37
## 4     4 04              Portland                                 43
## 5     5 05              Hamilton                                 24
## 6     6 05              Warrnambool                             116
## 7     7 07              Belmont                                 114
## 8     8 07              Corio                                   247
## 9     9 07              Geelong City                             280
## 10    10 07             Geelong West                             33
## # ... with 58 more rows
```

```
ggplot(dat_Q1_2020, aes( x = Number_Incidents_total,
                        y = CFA_Brigade_Area)) +
  geom_point() +
  theme_light() +
  theme(axis.text.x = element_text(angle = 45, vjust = 0.5, hjust=1), axis.title.x = element_text(vjust=1),
        axis.text.y = element_text(angle = , vjust = 0.5, hjust=1), axis.title.y = element_text(vjust=1))

  xlab("Incidents") +
  ylab("Districts") +
  ggtitle("Number of incidents")
```



The above plot shows us the number of incidents for the first quarter 2019/20. On the x-axis we have number of incidents and the y-axis we can see the names of districts.

```
dat_Q2_2020 <- read_csv("data/dat_Q2_2020.csv")%>%
  rename(Number_Incidents_total = `Number of incidents within the Brigade Area for the reporting period`)
  rename(CFA_Brigade_Area = `CFA Brigade Area`)
```

```
dat_Q2_2020
```

```
## # A tibble: 77 x 4
##       X1 'CFA District' CFA_Brigade_Area Number_Incidents_total
##       <dbl> <chr>          <chr>                  <dbl>
## 1      1 02            Bendigo                  225
## 2      2 02            Eaglehawk                 47
## 3      3 02            Golden Square            24
## 4      4 02            Kangaroo Flat            47
## 5      5 04            Portland                 35
## 6      6 05            Hamilton                 31
## 7      7 05            Warrnambool             124
## 8      8 06            Colac                    43
## 9      9 07            Belmont                 112
## 10     10 07           Corio                   220
## # ... with 67 more rows
```

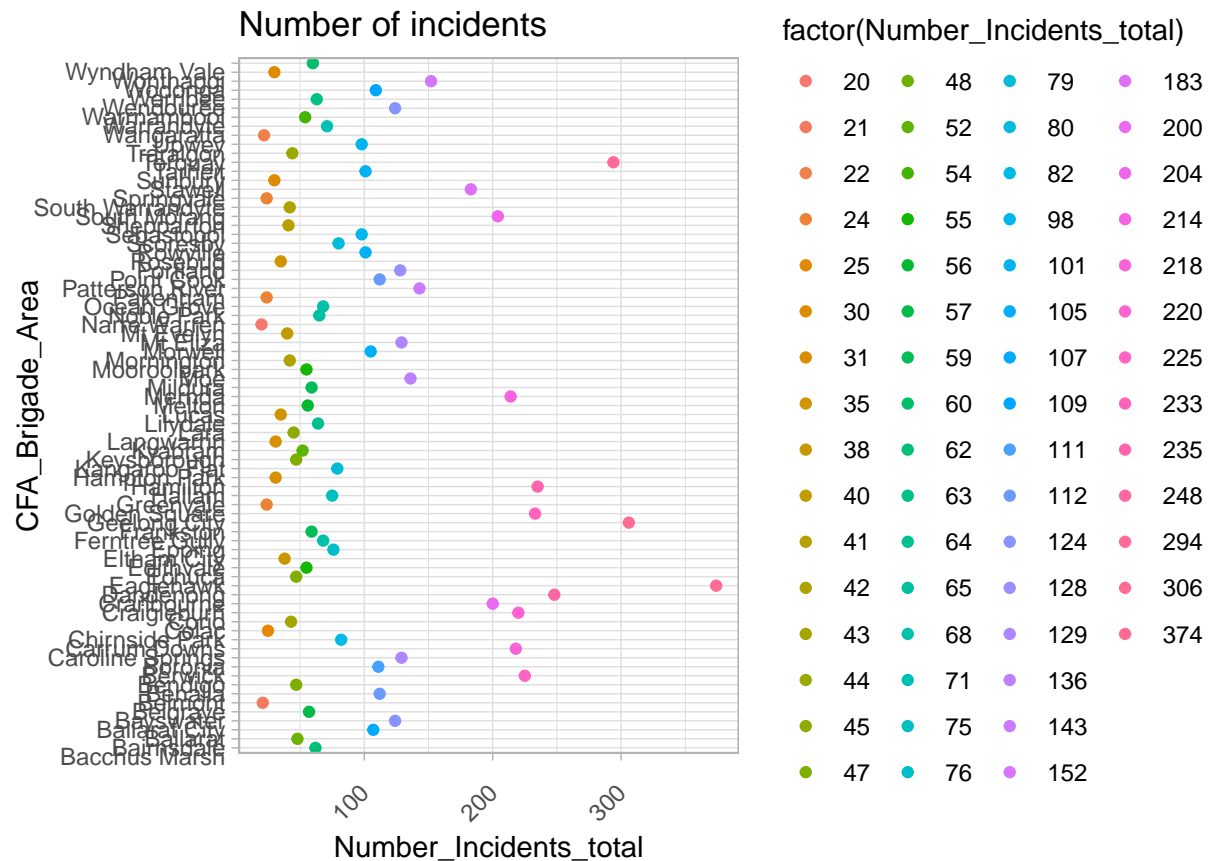
```
ggplot(dat_Q2_2020, aes(x = Number_Incidents_total ,
                        y = CFA_Brigade_Area,
```

```

colour = factor(Number_Incidents_total)))+

geom_point() +
theme_light() +
theme(axis.text.x = element_text(angle = 45, vjust = 0.5, hjust=1), axis.title.x = element_text(vjust=
theme(axis.text.y = element_text(angle = , vjust = 1, hjust=1), axis.title.y = element_text(vjust=
ggtitle("Number of incidents")

```



Similar to the plot above, this plot shows us the number of incidents for the second quarter 2019/20. On the x-axis we have number of incidents and the y-axis we can see the names of districts.

```

dat_Q3_2020 <- read_csv("data/dat_Q3_2020.csv") %>%
  rename(Number_Incidents_total = `Number of incidents within the Brigade Area for the reporting period`)
  rename(CFA_Brigade_Area = `CFA Brigade Area`)

```

```
dat_Q3_2020
```

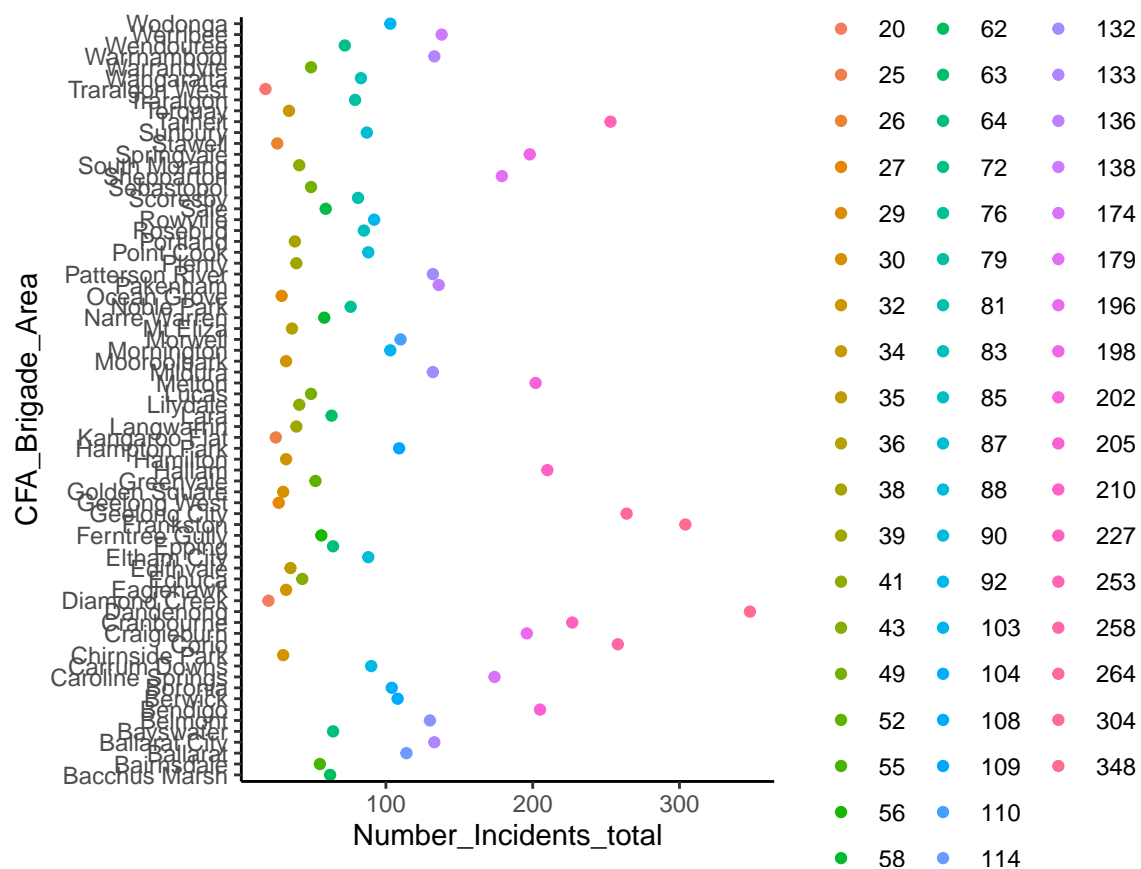
```

## # A tibble: 70 x 4
##       X1 'CFA District' CFA_Brigade_Area Number_Incidents_total
##       <dbl> <chr>         <chr>                  <dbl>
## 1       1 02           Bendigo                  205
## 2       2 02           Eaglehawk                 32
## 3       3 02           Golden Square             30
## 4       4 02           Kangaroo Flat             25

```

```
## 5      5 04      Portland      38
## 6      6 05      Hamilton      32
## 7      7 05      Warrnambool    133
## 8      8 07      Belmont      130
## 9      9 07      Corio        258
## 10     10 07     Geelong City    264
## # ... with 60 more rows
```

```
ggplot(dat_Q3_2020) +
  geom_point(aes(x = Number_Incidents_total,
  y = CFA_Brigade_Area,
  colour = factor(Number_Incidents_total))) +
  theme_classic()
```



The above plot shows us the number of incidents for the third quarter 2019/20. On the x-axis we have number of incidents and the y-axis we can see the names of districts.

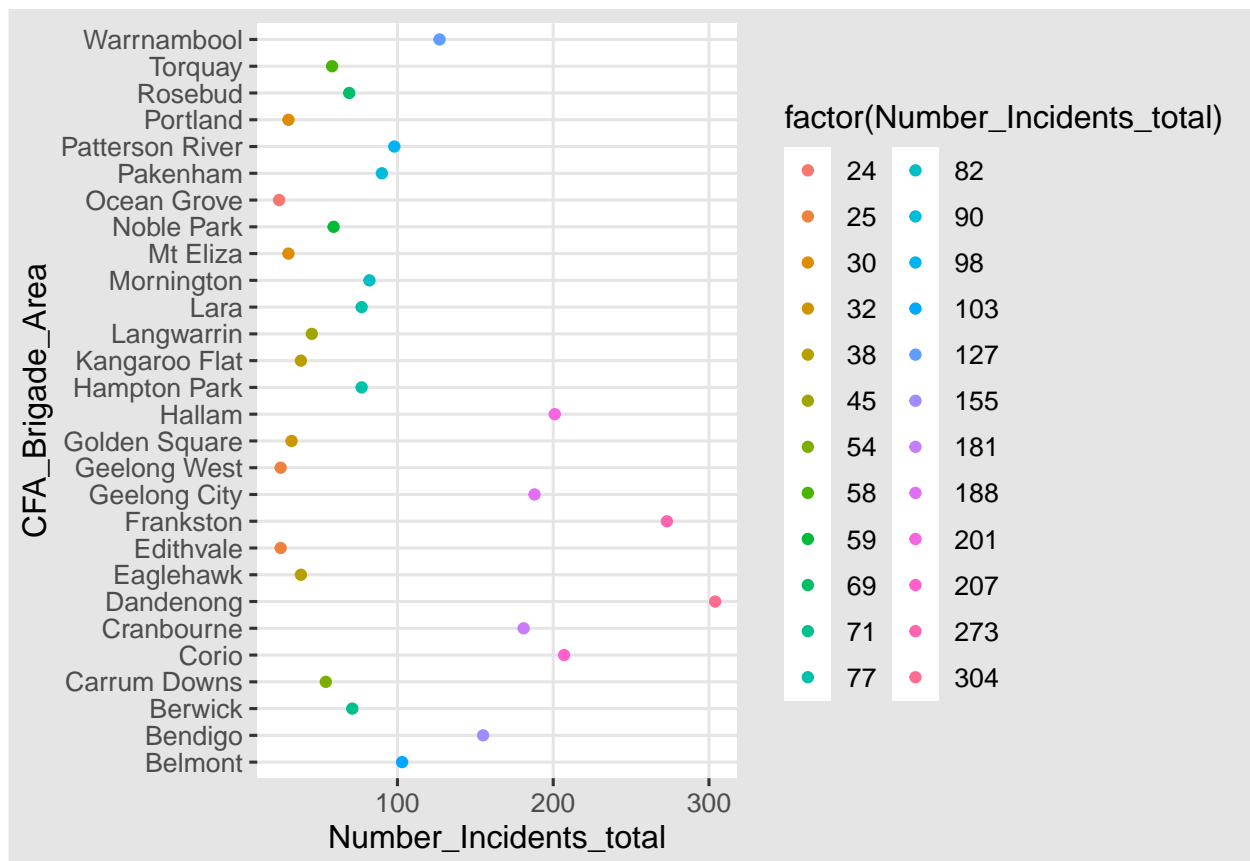
```
dat_Q4_2020 <- read_csv("data/dat_2020Q4.csv")%>%
  select(`CFA District`, `CFA Brigade Area`, `Number of incidents within the Brigade Area for the reporting period`)
  rename(Number_Incidents_total = `Number of incidents within the Brigade Area for the reporting period`)
  rename(CFA_Brigade_Area = `CFA Brigade Area`)

dat_Q4_2020
```

```
## # A tibble: 28 x 3
```

```
##      'CFA District' CFA_Brigade_Area Number_Incidents_total
##      <chr>          <chr>                <dbl>
## 1 02              Bendigo                155
## 2 02              Eaglehawk              38
## 3 02              Golden Square          32
## 4 02              Kangaroo Flat          38
## 5 04              Portland               30
## 6 05              Warrnambool           127
## 7 07              Belmont               103
## 8 07              Corio                 207
## 9 07              Geelong City          188
## 10 07             Geelong West           25
## # ... with 18 more rows
```

```
ggplot(dat_Q4_2020) +
  geom_point(aes(x = Number_Incidents_total,
    y = CFA_Brigade_Area,
    colour = factor(Number_Incidents_total))) +
  theme_igray()
```



The above plot shows us the number of incidents for the fourth quarter 2019/20. On the x-axis we have number of incidents and the y-axis we can see the names of districts.

```
binding_data <- bind_rows(dat_Q1_2020, dat_Q2_2020, dat_Q3_2020, dat_Q4_2020)
```

```
binding_data
```

Table 1: Summary of the incidents.

	Num_incidents1	Num_incidents2	Num_incidents3	Num_incidents4
	Min. : 23.0	Min. : 24.0	Min. : 25.0	Min. : 24.0
	1st Qu.: 63.0	1st Qu.: 52.0	1st Qu.: 76.0	1st Qu.: 54.0
	Median : 83.0	Median :101.0	Median :108.0	Median : 77.0
	Mean :125.5	Mean :126.8	Mean :134.2	Mean :110.1
	3rd Qu.:185.0	3rd Qu.:183.0	3rd Qu.:198.0	3rd Qu.:181.0
	Max. :310.0	Max. :374.0	Max. :348.0	Max. :304.0

```
## # A tibble: 243 x 4
##       X1 'CFA District' CFA_Brigade_Area Number_Incidents_total
##   <dbl> <chr>          <chr>                      <dbl>
## 1     1 02          Bendigo                      198
## 2     2 02      Golden Square                24
## 3     3 02      Kangaroo Flat                 37
## 4     4 04      Portland                   43
## 5     5 05      Hamilton                   24
## 6     6 05      Warrnambool               116
## 7     7 07      Belmont                   114
## 8     8 07      Corio                     247
## 9     9 07      Geelong City              280
## 10    10 07      Geelong West               33
## # ... with 233 more rows
```

0.2.3 Analysis

Using the summary function we can see the maximum number of incidents across all hazard classes for specified districts for the given time frame. Data used here is the merged data of the four data sets, using bind_rows function.

```
DataQ1_4 <- read_csv("data/Question_3_dat_2.csv")%>%
  rename(Num_incidents1=`Number of incidents within the Brigade Area for the reporting period across all
  rename(Num_incidents2=`Number of incidents within the Brigade Area for the reporting period across all
  rename(Num_incidents3=`Number of incidents within the Brigade Area for the reporting period across all
  rename(Num_incidents4=`Number of incidents within the Brigade Area for the reporting period across all
```

```
DataQ1 <- DataQ1_4 %>%
  select(Num_incidents1,
         Num_incidents2,
         Num_incidents3,
         Num_incidents4)%>%
  summary()%>%
  kable(caption = "Summary of the incidents.") %>%
  kable_styling(bootstrap_options = c("striped", "hover"))
```

DataQ1

In the above table, we can see the summary for number of incidents in each quarter; we see that the highest number of incidents was recorded as 374 in the second quarter.

The data used here is the merged data that contains information on all four quarters. For the next steps, we will use the binding_data from above.

Table 2: This is the summary of number of incidents across all hazard classes

Number_Incidents_total
Min. : 17.00
1st Qu.: 39.50
Median : 71.00
Mean : 95.96
3rd Qu.:125.50
Max. :374.00

Table 3: Dandenong district has the highest number of incidents across all hazard classes in all of the four quarters.

CFA_Brigade_Area	Number_Incidents_total
Dandenong	374

```
Highest_NumberIncidents <- binding_data%>%
  select(Number_Incidents_total)%>%
summary()%>%
  kable(caption = "This is the summary of number of incidents across all hazard classes") %>%
  kable_styling(bootstrap_options = c("striped", "hover"))

Highest_NumberIncidents
```

We can see that highest number of incidents are 374, so now using the filter function. let's see which district has 374 incidents.

```
binding_data%>%
  select(-X1,
    -`CFA District`)%>%
  filter(Number_Incidents_total == "374" )%>%
  kable(caption = "Dandenong district has the highest number of incidents across all hazard classes in a")
  kable_styling(bootstrap_options = c("striped", "hover"))
```

From the table we can see that Dandenong has had the highest number of incidents.

0.3 Conclusion

As per the analysis for question on the performance of the brigade, it is safe to say that CFA brigades performed well against the standard delivery service time of eight minutes for the hazard class two incidents. And as per the analysis for the question on the number of incidents, we can see that Dandenong appears to be the area that had highest number of incidents across all hazard classes.

0.4 Fire Detections and Land Type in Bushfire Season

According to the information provided by the department of agriculture of Australian, in the figure 4 below can be seen the number of the fire detections by year. The number of cases registered by the season 2019/2020 were 103.627. The extent of land affected by the bushfires will be detailed i the next part of the report. something interesting to remark it that even though the season 2019/2020 seemed very hard for the country,

Table 4: Total detections by year

Years	Total Counts
2006/2007	3327484
2002/2003	2974094
2013/2014	1016454
2008/2009	784110
2012/2013	736251
2010/2011	685265
2005/2006	557492
2018/2019	545723
2014/2015	523801
2009/2010	487338
2017/2018	469092
2004/2005	461358
2003/2004	446818
2011/2012	416408
2007/2008	381934
2016/2017	377902
2015/2016	315854
2019/2020	103627

in reality this number of cases is not compared with the number of observation for the same season in 2006/2007 and 2002/2003 that hold 3'327484 and 2'974.094 cases respectively in Victoria.

```
fire_total_detects %>%
  select(Years, n) %>%
  arrange(desc(n)) %>%
  rename("Total Counts" = n) %>%
  kable(caption = "Total detections by year") %>%
  kable_styling(c("hover",
                  "condensed",
                  position = "center",
                  fixed_thead = TRUE),
               full_width = FALSE)
```

```
ggplot(fire_total_detects,
       aes(x = Years,
           y = n)) +
  geom_col(fill= 'coral3') +
  coord_flip()+
  labs(y = "Counts") +
  geom_text(aes(label = n, size = 1, hjust= -0.5))+
  theme(legend.position = "none")+
  scale_y_continuous(limits = c(0,3500000))+
  theme_bw()
```

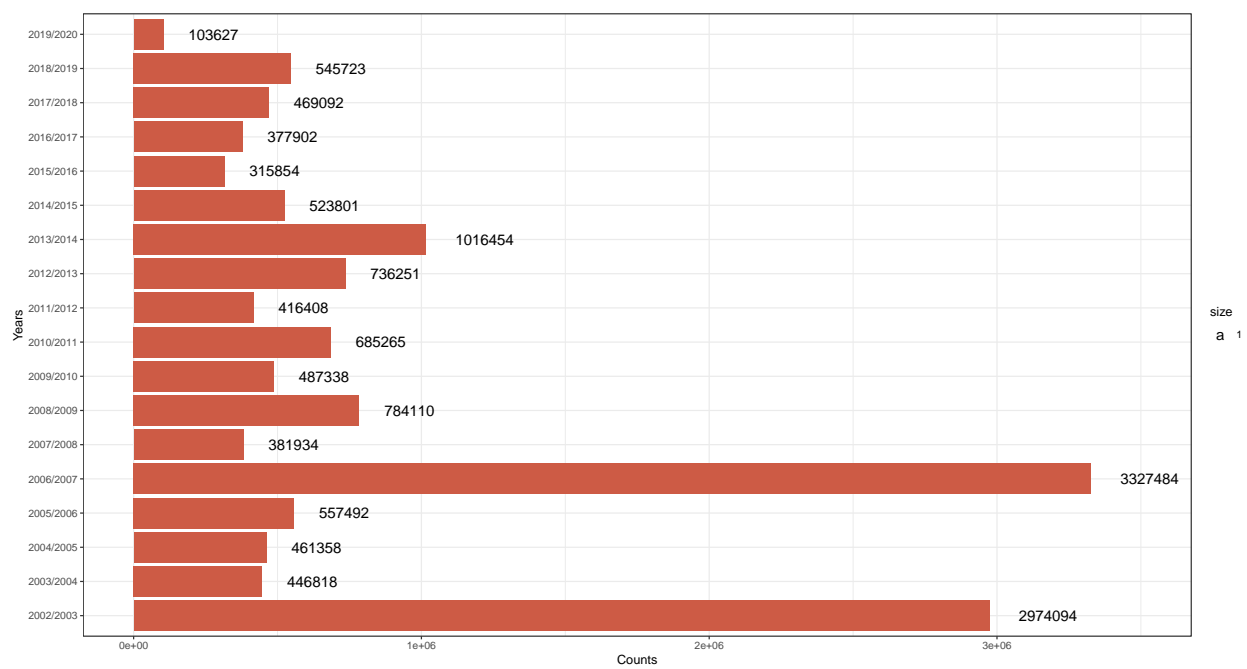



Figure 1: Number of Observations by Year

0.4.1 Percentage of Affected Land by State

Taking in detail the number of the observations by state in the season 2019/2020, we can see that the states with major affectation of the forested land were Australian Capital Territory, Victoria and New south Wales with 92.78%, 92.02% and 90.15% respectively. See Figure 2. The territory with the least affectation was Northern Territory (0%), followed by South Australia with 43.68%.

```
perc_affected_state <- perc_affected_state %>%
  select(Jurisdiction,
         `Proportion of fire area that is forested (perc)` ) %>%
  mutate("Proportion of fire" = 100-`Proportion of fire area that is forested (perc)` ) %>%
  pivot_longer(names_to = "Burnt Area",
               values_to = "Percentage",
               cols = -Jurisdiction)
```

```
ggplot(data = perc_affected_state, aes(x = Jurisdiction,
                                       y = Percentage,
                                       fill= `Burnt Area`)) +
  geom_bar(position="stack",
          stat="identity")+
  geom_text(aes(label = paste0(round(Percentage,2),"%")),
            position = position_stack(vjust = 0.5),
            size = 3)+
  scale_y_continuous(labels = function(x) paste0(x, "%"),
                     breaks = seq(0, 100, 10))+
  coord_flip()+
  theme_bw()+
  theme(legend.position = "bottom")
```

0.4.2 Percentage of Forested Land Affected in Victoria by Type

According to the classification of the land in Victoria, Multiple-use Public Forest got affected by 29%, whereas the Nature Conservation Reserve had 15% of burnt land. similarly the Unresolved tenure land lost 13% of its extent by the fires. In the case of private land, around 6% was consumed by fires. See Figure 3.

```
ft4perc <- ft4perc %>%
  select(...1,Vic.) %>%
  rename("Type of Forest" = ...1, "Burnt Land" = Vic.) %>%
  filter(`Type of Forest` %in%
        c("Leasehold forest",
          "Multiple-use public forest",
          "Nature conservation reserve",
          "Other Crown land",
          "Private forest",
          "Unresolved tenure")) %>%
  mutate("Safe Land" = 100-`Burnt Land`) %>%
  pivot_longer(names_to = "Burnt Area Victoria", values_to = "Percentage", cols = -`Type of Forest`)

ggplot(data = ft4perc, aes(x = `Type of Forest`,
                          y = Percentage, fill= `Burnt Area Victoria`)) +
  geom_bar(position= position_stack(reverse = T), stat="identity")+
  coord_flip()+
```

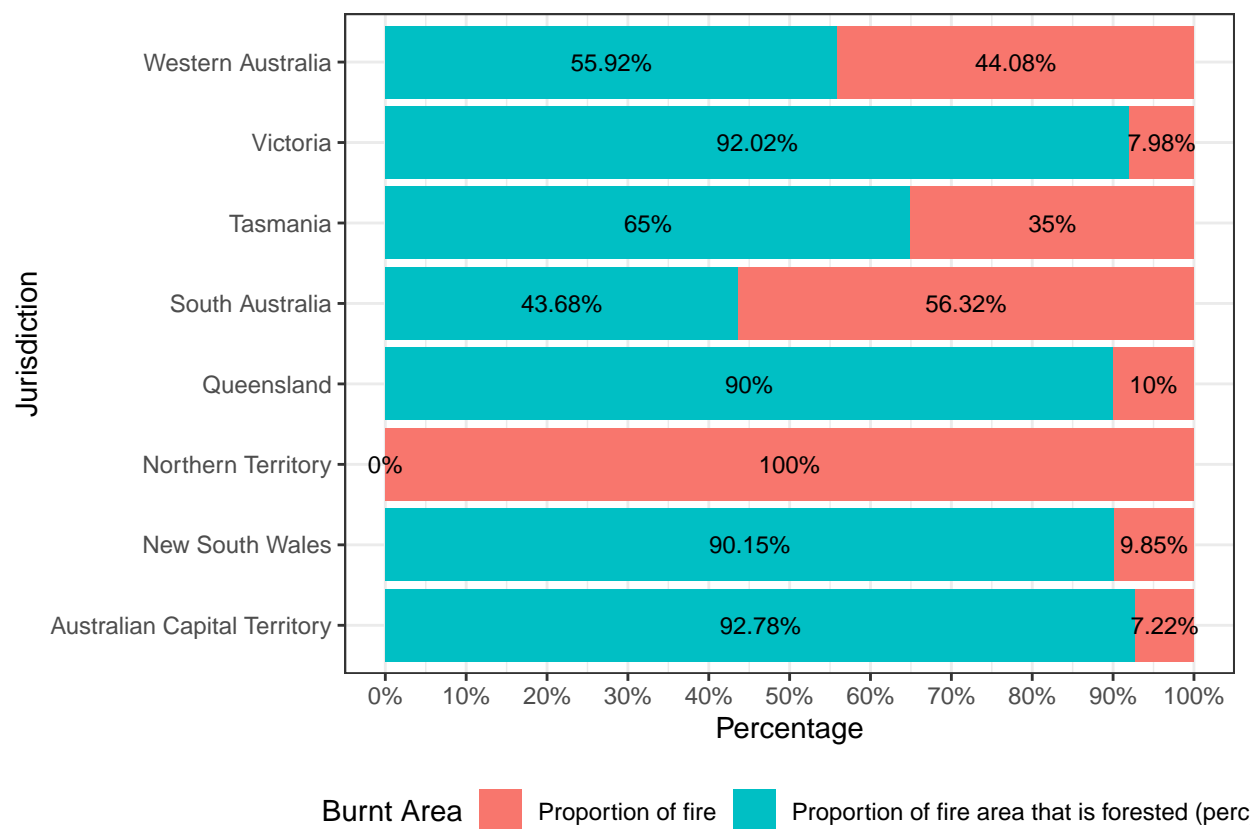


Figure 2: Affection by State

```

theme(legend.position = "bottom")+
theme_bw() +
geom_text(aes(label = paste0(round(Percentage,2),"%")), position = position_stack(vjust = 0.5, reverse = TRUE))

```

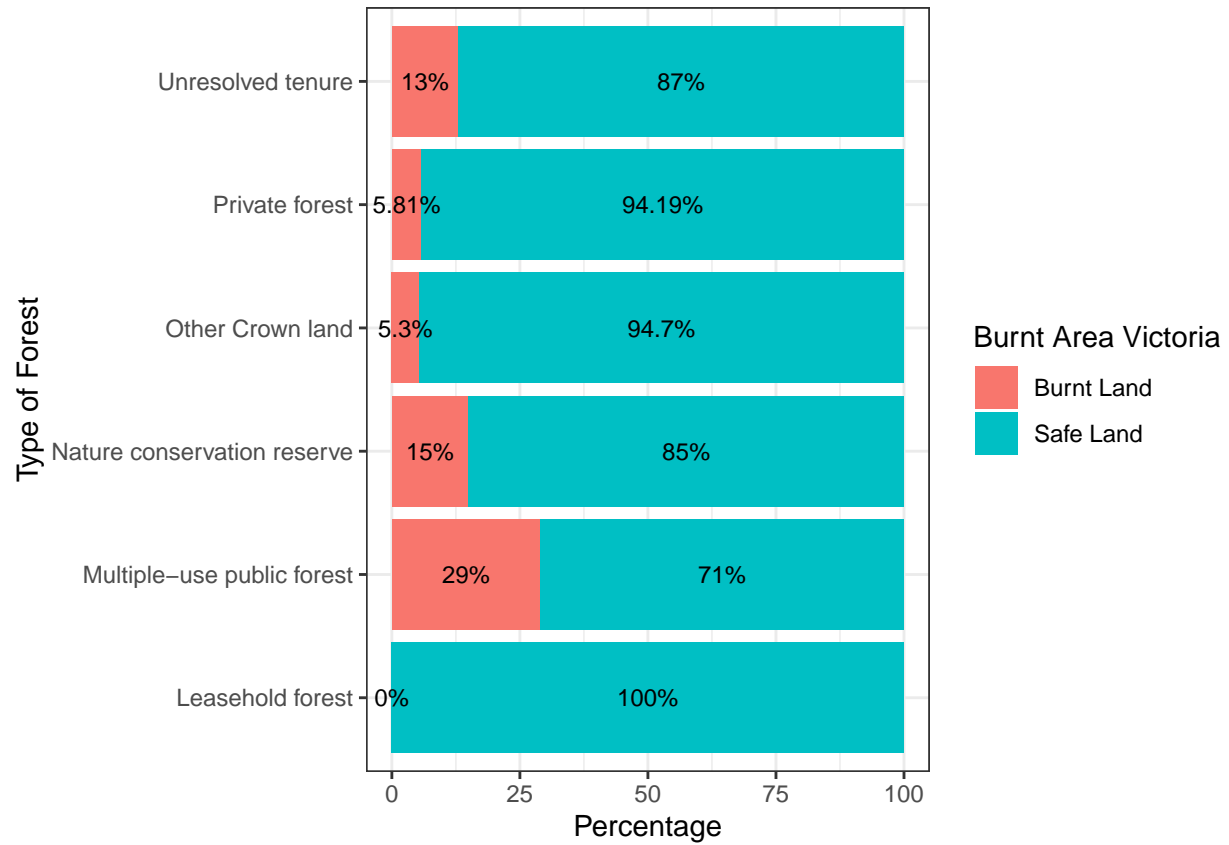


Figure 3: Land Type affected in Victoria

0.5 Melbourne Air Quality Index

The bushfires season had a huge negative impact in the air quality in Victoria, as an example we took data from the Environment Protection Authority in Australia which recorder the PM2.5 (Fine Particulate Matter 2.5) which is an air pollutant concern for the community's health, the higher the rate the worse impact for individuals. In the figure 4 below can be seen the levels for the previous four years, with clearly a huge peak in January 2020.

```
melb_air2 <- melb_air %>% select(date,pm25) %>%  
  mutate(date = as.Date(date, format = "%d/%m/%Y"))  
  
melb_air2 %>%  
  ggplot()+  
  geom_line(aes(x = date,  
                y = pm25),  
            colour = "#FF6600")+  
  theme_bw()+  
  labs(x = "3 Year Historical Melbourne Air Index",  
       y = "Air Index Score")+  
  scale_y_continuous(limits = c(0,280),  
                    breaks = seq(0,280,50))
```

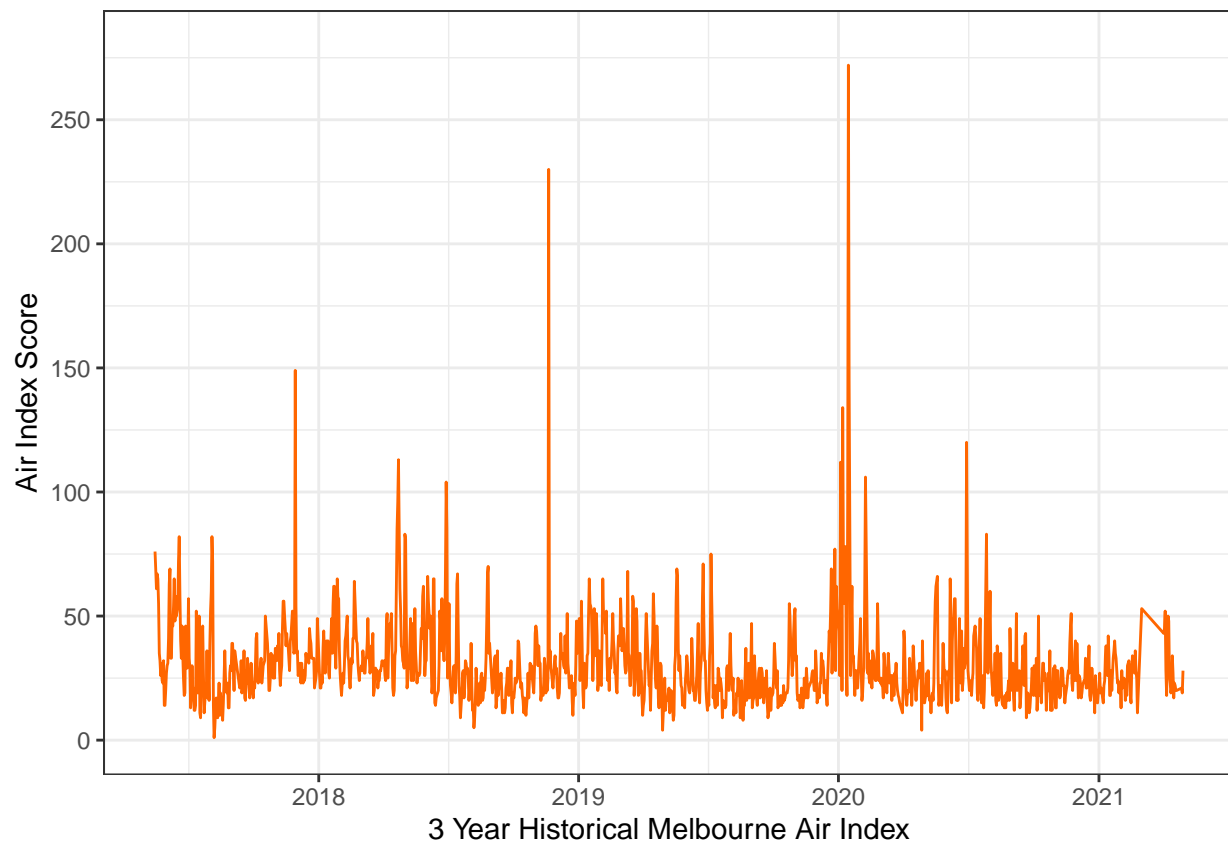


Figure 4: Melbourne Air Quality

The figure below shows the classification of the air quality index, this source will give a clearer idea of the readings of the bushfire season and for previous levels.

```
knitr::include_graphics(here::here('images/polution_table.png'))
```

AQI	Air Pollution Level	Health Implications	Cautionary Statement (for PM2.5)
0 - 50	Good	Air quality is considered satisfactory, and air pollution poses little or no risk	None
51 -100	Moderate	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.	Active children and adults, and people with respiratory disease, such as asthma, should limit prolonged outdoor exertion.
101-150	Unhealthy for Sensitive Groups	Members of sensitive groups may experience health effects. The general public is not likely to be affected.	Active children and adults, and people with respiratory disease, such as asthma, should limit prolonged outdoor exertion.
151-200	Unhealthy	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects	Active children and adults, and people with respiratory disease, such as asthma, should avoid prolonged outdoor exertion; everyone else, especially children, should limit prolonged outdoor exertion
201-300	Very Unhealthy	Health warnings of emergency conditions. The entire population is more likely to be affected.	Active children and adults, and people with respiratory disease, such as asthma, should avoid all outdoor exertion; everyone else, especially children, should limit outdoor exertion.
300+	Hazardous	Health alert: everyone may experience more serious health effects	Everyone should avoid all outdoor exertion

Figure 5: Air Quality Levels

Finally, having a closer look to the most affected months from January to April, we can see that on 15th January the levels recorded was 272, clearly very unhealthy, the population needed to be indoors even more for those with respiratory affections. Certainly the first two weeks were highly affected by the pollution and the fires, all this happened mainly in the first two weeks of the year, leaving highly affected the fauna and flora.

```
melb_air2 %>%
  filter(date >= "2019-12-01" & date <= "2020-03-30" ) %>%

ggplot()+
  geom_line(aes(x = date,
                y = pm25),
            colour = "#FF6600")+
  theme_bw()+
  labs(x = "Melbourne Air Index in 2020 (January to April)",
       y = "Air Index Score")+
  scale_y_continuous(limits = c(0,300),
                    breaks = seq(0,300,20))
```

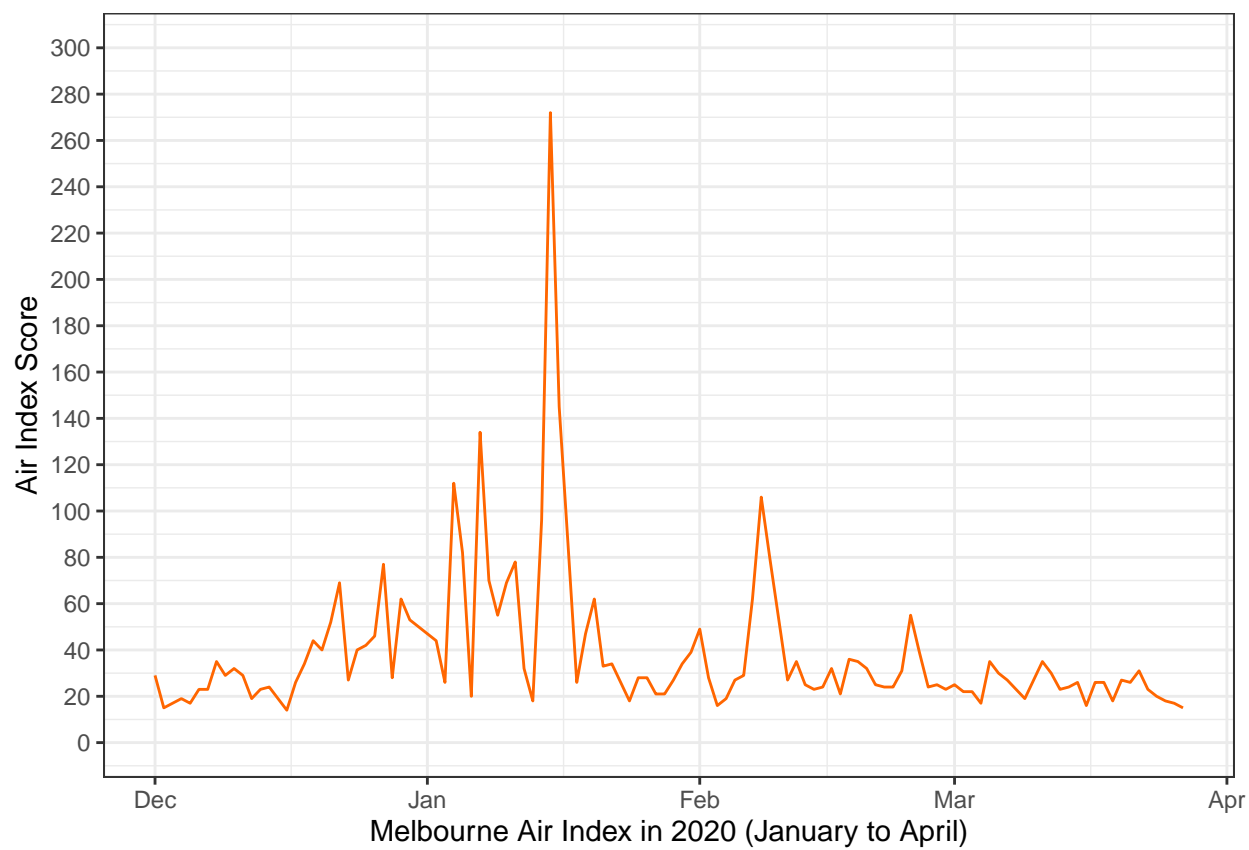


Figure 6: Bushfire Season 2019/2020 Air Quality in Melbourne