St344 Individual Coursework U1619685

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```
library(tidyverse)
library(lubridate)
library(broom)
library(car)
library(coin)
library(pgirmess)
library(Hmisc)
library(rio)
library(gridExtra)
```

Lab work

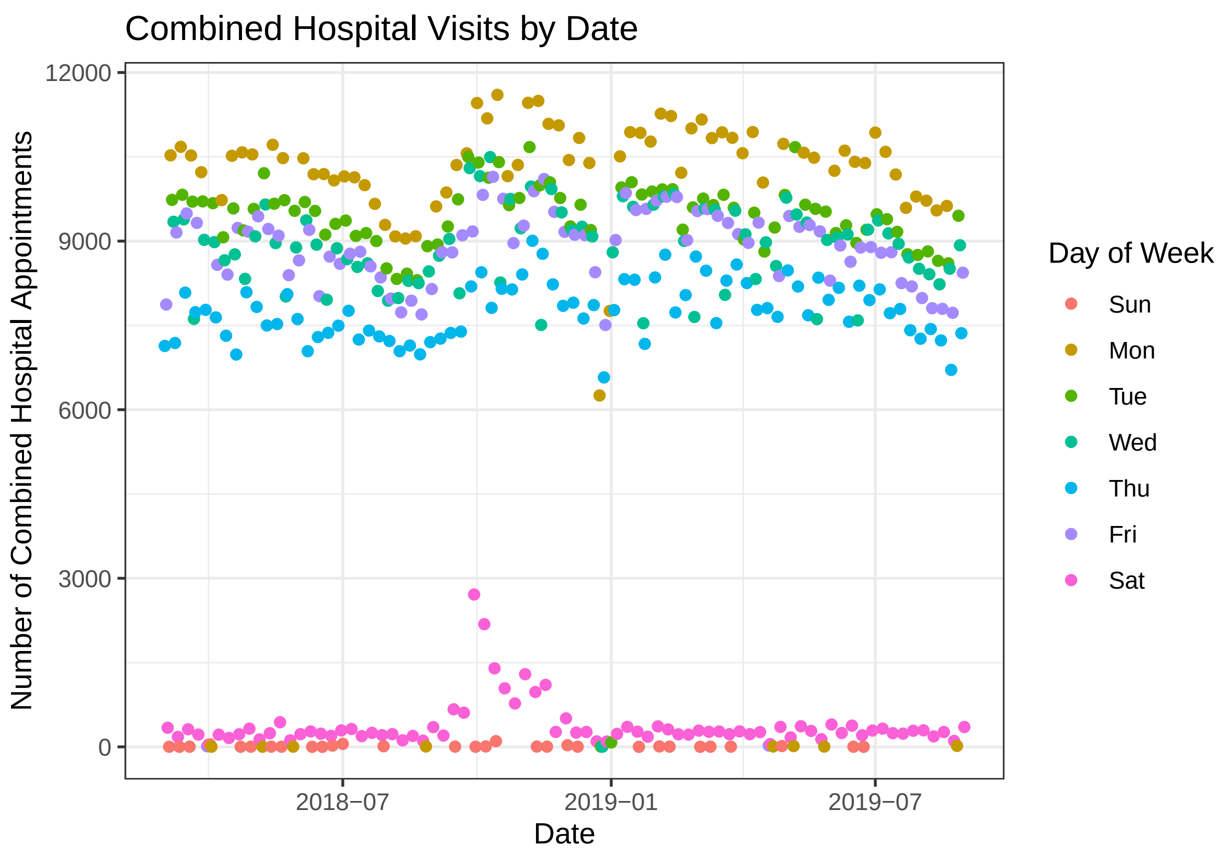
This section of the technical appendix will cover the code produced as part of lab 6, which was used to guide the starting point for the individual project work in general, especially in terms of datasets and provided a good base for exploratory data analysis in particuar for pointing out the effect of different days.

```
#function to lower case column names as in general it is better
#and easier to refer to everything in the lower case + I am a Hadley fanboy
hadley_format <- function(data){
  for (i in 1:length(colnames(data))) {
  colnames(data)[i] = tolower(colnames(data)[i])
  }
  data
}
```

```
#Setting up the file path and loading in the .csv files
file_loc <- "C:/Users/Stephen/Desktop/University Work/Year 3 uni/St344/"
monthYears <- paste0(month.abb[c(3:12,1:8)], "_", c(rep(18,10),rep(19,8)))
d <- list()
for (i in 1:length(monthYears)) {
  filename <- paste0(file_loc, "Appointments_GP_Daily_Aug19/CCG_CSV_", monthYears[i], ".csv")
  d[[i]] <- import(filename, setclass = "tibble")
}

#Checking whether each file has the same number of columns
a <- TRUE
for(i in 1:length(d)){
  cols_1 <- length(d[[1]])
  if(cols_1 - length(d[[i]]) != 0){
    a <- FALSE
  }
  a
}
a
```

```
## [1] TRUE
```

```
#Loading in the Coventry Data from the files
covData <- tibble()
for (i in 1:length(monthYears)) {
  covData <- rbind(covData, filter(d[[i]], CCG_NAME=="NHS Coventry and Rugby CCG"))
}

#This code removes the d variable from the environment and should speed things up
#As the d variable is over 500mb and can cause performance issues in rstudio
remove(d)

covData <- select(covData, Appointment_Date, APPT_STATUS, HCP_TYPE, APPT_MODE, TIME_BETWEEN_BOOK_AND_API
                  COUNT_OF_APPOINTMENTS) %>%
  mutate(Appointment_Date = parse_date_time(Appointment_Date, "%d-%b-%Y")) %>%
  #Changing the letters to lower case to match Hadley Wickhams style guide
  hadley_format() %>%
  #updating the appointment_date variable
  mutate(appointment_data = mdy(appointment_date))

#Looking at number of appointments by each mode
appt_by_mode <- covData %>%
  group_by(appt_mode) %>%
  summarise(count = sum(count_of_appointments))

#Produce a plot line in the lab to ensure my code thus far is correct
covData %>%
  group_by(appointment_date) %>%
  summarise(count = sum(count_of_appointments)) %>%
  ggplot() +
  geom_point(aes(x = appointment_date, y = count,
                 colour = wday(appointment_date, label = TRUE, abbr = TRUE))) +
  labs(x = "Date", y = "Number of Combined Hospital Appointments",
       title = "Combined Hospital Visits by Date",
       colour = "Day of Week") +
  theme_bw() +
  #Can customise colours in due course if required inside next line
  scale_colour_discrete()
```




```
#importing next dataset which involves which patients are registered at each practice
app_gp_coverage <- import(paste0(file_loc,
                                 "Appointments_GP_Daily_Aug19/APPOINTMENTS_GP_COVERAGE.csv"),
                          setclass = "tibble") %>%
  mutate(Appointment_Month = parse_date_time(Appointment_Month, "%d-%b-%Y")) %>%
  hadley_format()

##combining the two datasets for future use
#Filtered to only contain extra information where necessary
data <- left_join(covData, app_gp_coverage, by = c("ccg_code" = "commissioner_organisation_code"))
data <- inner_join(covData, app_gp_coverage, by = c("ccg_code" = "commissioner_organisation_code")) %>%
  filter(year(appointment_date) == year(appointment_month) &
           month(appointment_date) == month(appointment_month))
```

Demand on Coventry GPs

Since there is no data for number of GPs per practice, there is insufficient data to work out an appointment/GP number and hence demand will be modelled by overall appointments in the Cov Area. If this data had been available, then the average time of each visit type and number could have been averaged out over the GPs to find a demand average for GPs but sadly this wasn't available. Appointments which were not attended are still used for the count as the GP still had to be available to answer the person. The counts have been summed by week to take account of differences between days and too try and *absorb* some of that variability and allows for working days to not be a factor. There has also been no subsetting based on hcp_type -> as all appointments is theoretically workload (if admin went through the roof would still be an increased workload for example)

```r
#Seasons data as per: https://www.timeanddate.com/calendar/seasons.html
seasons <- tibble(season = c("winter", "spring", "summer","autumn",
                             "winter", "spring", "summer"),
                  start_date = c(as.Date("2017-12-21"), as.Date("2018-03-20"),
                                 as.Date("2018-06-20"), as.Date("2018-09-23"),
                                 as.Date("2018-12-21"), as.Date("2019-03-20"),
                                 as.Date("2019-06-20")),
                  end_date = c(as.Date("2018-03-19"), as.Date("2018-06-19"),
                               as.Date("2018-09-22"), as.Date("2018-12-20"),
                               as.Date("2019-03-19"), as.Date("2019-06-19"),
                               as.Date("2019-09-22")))

#Some changes to the data, adding in season and week number to each observation
 data <- data %>%
  #Detecting week number of appointment date
  mutate(week_num = isoweek(appointment_date)) %>%
  mutate(year = year(appointment_date)) %>%
  mutate(year = if_else(year == 2018, 0, 1)) %>%
  mutate(week_num = week_num + (52 * year)) %>%
  #Taking account of the fact that 1 actually refers to week 53
  mutate(week_num = if_else(week_num == 1, 53, week_num)) %>%
  mutate(week_num = week_num - 8) %>%
  #Changing class of appointment date variable for easier comparisons
  mutate(appointment_date = appointment_date %>% substr(1,10) %>% as.Date()) %>%
  #Adding
  mutate(season = if_else(between(appointment_date,
                                  seasons$start_date[1],seasons$end_date[1]), "winter",
                  if_else(between(appointment_date,
                                  seasons$start_date[2],seasons$end_date[2]), "spring",
                  if_else(between(appointment_date
                                  , seasons$start_date[3],seasons$end_date[3]), "summer",
                  if_else(between(appointment_date
                                  , seasons$start_date[4],seasons$end_date[4]), "autumn",
                  if_else(between(appointment_date
                                  , seasons$start_date[5],seasons$end_date[5]), "winter",
                  if_else(between(appointment_date
                                  , seasons$start_date[6],seasons$end_date[6]), "spring",
                  if_else(between(appointment_date
                                  , seasons$start_date[7],seasons$end_date[7]), "summer",
                                  "Error"))))))))

# Making adjustment as some weeks may contain dates from different seasons
# Use median as 7 days in a week so only modal one will occur
temp <- data %>%
   mutate(season_num = if_else(season == "winter", 1,
                       if_else(season == "spring", 2,
                       if_else(season == "summer", 3 , 4)))) %>%
   select(week_num, appointment_date,season, season_num) %>%
   unique() %>%
   select(week_num, season,season_num) %>%
   group_by(week_num) %>%
   summarise(count = median(season_num)) %>%
   mutate(season_median = if_else(count == 1, "winter",
```

```r
                              if_else(count == 2, "spring",
                              if_else(count == 3, "summer", "autumn")))) %>%
  select(week_num, season_median)


data <- data %>%
  inner_join(temp)
```

```
## Joining, by = "week_num"
```

```r
#Saving the data before I remove the anonyamous weeks
#For use in part two of the report
part_2_data <- data

#Count summaries of the data by appointment mode and week
appt_by_mode <- data %>%
  group_by(appt_mode, week_num, season_median) %>%
  summarise(count = sum(count_of_appointments)) %>%
  ungroup()

#Looking into the two low results for Face-to-Face
appt_by_mode %>%
  filter(count < 20000 & appt_mode == "Face-to-Face")
```

```
## # A tibble: 2 x 4
##   appt_mode    week_num season_median count
##   <chr>           <dbl> <chr>         <int>
## 1 Face-to-Face        1 winter        12032
## 2 Face-to-Face       44 winter        15428
```

```r
#Returns week 9 (first week and not a full one, only 4 results) and 52 (over Christmas so less visits)
data %>%
  filter(week_num %in% c(9, 52)) %>%
  select(appointment_date) %>%
  unique()
```

```
## # A tibble: 13 x 1
##    appointment_date
##    <date>
##  1 2018-04-23
##  2 2018-04-24
##  3 2018-04-25
##  4 2018-04-26
##  5 2018-04-27
##  6 2018-04-28
##  7 2018-04-29
##  8 2019-02-18
##  9 2019-02-19
## 10 2019-02-20
## 11 2019-02-21
## 12 2019-02-22
## 13 2019-02-23
```

```r
#No appointments on 30th December - CHECK
data %>%
  filter(str_detect(appointment_date, '12-30'))
```

```
## # A tibble: 0 x 20
## # ... with 20 variables: appointment_date <date>, appt_status <chr>,
## #   hcp_type <chr>, appt_mode <chr>, time_between_book_and_appt <chr>,
## #   ccg_code <chr>, count_of_appointments <int>, appointment_data <date>,
## #   stpcd <chr>, regional_local_office_code <chr>, region_code <chr>,
## #   appointment_month <dttm>, `included practices` <int>, `open
## #   practices` <int>, `patients registered at included practices` <int>,
## #   `patients registered at open practices` <int>, week_num <dbl>,
## #   year <dbl>, season <chr>, season_median <chr>
```

```
##Therefore we remove these two weeks (9 and 52) as they seem to be anomalous in comparison to others.
data <- data %>%
  filter(!week_num %in% c(9, 52)) %>%
  filter(appt_mode %in% c("Face-to-Face", "Telephone", "Home Visit"))

#Looking at median season result
median_season <- appt_by_mode %>%
  filter(appt_mode == "Face-to-Face") %>%
  group_by(season_median) %>%
  summarise(F2F = median(count)) %>%
  ungroup() %>%
  cbind(appt_by_mode %>%
  filter(appt_mode == "Telephone") %>%
  group_by(season_median) %>%
  summarise(telephone = median(count)) %>%
  ungroup() %>%
  select(telephone)) %>%
  cbind(appt_by_mode %>%
  filter(appt_mode == "Home Visit") %>%
  group_by(season_median) %>%
  summarise(home_visit = median(count)) %>%
  ungroup() %>%
  select(home_visit))
median_season
```

```
##   season_median   F2F telephone home_visit
## 1        autumn 38791      4244      558.0
## 2        spring 35542      4290      516.5
## 3        summer 33854      4153      519.0
## 4        winter 36603      4770      566.0
```

```
#Percentage of appointments which are telephone: Just approx for using value in report
(100*sum(median_season$telephone))/(sum(median_season$telephone
                                  + median_season$F2F + median_season$home_visit))
```

```
## [1] 10.61819
```

Model exploration

Plotting a couple of models to see whether

```
model1 <- glm(count ~ 0  + week_num, family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Face-to-Face"))
```

```r
model1a <- glm(count ~ week_num, family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Face-to-Face"))
#Face to Face Model
model2 <- glm(count ~ 0  + season_median + week_num , family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Face-to-Face"))
model2a <- glm(count ~ season_median + week_num , family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Face-to-Face"))

model1 %>% summary()
```

```
##
## Call:
## glm(formula = count ~ 0 + week_num, family = "poisson", data = appt_by_mode %>%
##     filter(appt_mode == "Face-to-Face"))
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -513.9   176.8   476.6   632.7   827.6
##
## Coefficients:
##          Estimate Std. Error z value Pr(>|z|)
## week_num 0.1553239  0.0000112   13871   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 51118458  on 79  degrees of freedom
## Residual deviance: 20434126  on 78  degrees of freedom
## AIC: 20435097
##
## Number of Fisher Scoring iterations: 8
```

```r
model1a %>% summary()
```

```
##
## Call:
## glm(formula = count ~ week_num, family = "poisson", data = appt_by_mode %>%
##     filter(appt_mode == "Face-to-Face"))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -137.936    -9.912     7.303    13.652    42.475
##
## Coefficients:
##              Estimate Std. Error  z value Pr(>|z|)
## (Intercept) 1.044e+01  1.229e-03 8488.950  < 2e-16 ***
## week_num    1.187e-04  2.667e-05    4.452 8.52e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 65217  on 78  degrees of freedom
```

```
## Residual deviance: 65198  on 77  degrees of freedom
## AIC: 66170
##
## Number of Fisher Scoring iterations: 4
```

```r
model2 %>% summary()
```

```
##
## Call:
## glm(formula = count ~ 0 + season_median + week_num, family = "poisson",
##     data = appt_by_mode %>% filter(appt_mode == "Face-to-Face"))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -132.527    -5.475     7.944    14.691    28.665
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## season_medianautumn 1.056e+01  1.735e-03 6084.55   <2e-16 ***
## season_medianspring 1.041e+01  1.464e-03 7108.70   <2e-16 ***
## season_mediansummer 1.039e+01  1.673e-03 6212.59   <2e-16 ***
## season_medianwinter 1.040e+01  1.793e-03 5800.15   <2e-16 ***
## week_num            3.146e-04  2.749e-05   11.45   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 51118458  on 79  degrees of freedom
## Residual deviance:    55361  on 74  degrees of freedom
## AIC: 56340
##
## Number of Fisher Scoring iterations: 4
```

```r
model2a %>% summary()
```

```
##
## Call:
## glm(formula = count ~ season_median + week_num, family = "poisson",
##     data = appt_by_mode %>% filter(appt_mode == "Face-to-Face"))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -132.527    -5.475     7.944    14.691    28.665
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)          1.056e+01  1.735e-03 6084.55   <2e-16 ***
## season_medianspring -1.526e-01  1.769e-03  -86.30   <2e-16 ***
## season_mediansummer -1.629e-01  1.801e-03  -90.46   <2e-16 ***
## season_medianwinter -1.561e-01  1.996e-03  -78.21   <2e-16 ***
## week_num             3.146e-04  2.749e-05   11.45   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 65217  on 78  degrees of freedom
## Residual deviance: 55361  on 74  degrees of freedom
## AIC: 56340
##
## Number of Fisher Scoring iterations: 4
```

```
BIC(model1)
```

```
## [1] 20435100
```

```
BIC(model1a)
```

```
## [1] 66175.13
```

```
BIC(model2)
```

```
## [1] 56351.36
```

```
BIC(model2a)
```

```
## [1] 56351.36
```

```
#Model 2 and 2a the same for F2F and significantly better than Model 1 so added seasons improves model
#Both model2 and 2a are equivilent as the intercept term is the same as the spring term in the other

#Let's see if it is the same for Telephone

model1 <- glm(count ~ 0  + week_num, family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Telephone"))

model1a <- glm(count ~ week_num, family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Telephone"))
#Telephone Model
model2 <- glm(count ~ 0  + season_median + week_num , family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Telephone"))
#Home Visit Model
model2 <- glm(count ~ 0  + season_median + week_num , family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Home Visit"))

model1 %>% summary()
```

```
##
## Call:
## glm(formula = count ~ 0 + week_num, family = "poisson", data = appt_by_mode %>%
##     filter(appt_mode == "Telephone"))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -161.01    54.49   142.10   186.40   250.44
##
## Coefficients:
##           Estimate Std. Error z value Pr(>|z|)
## week_num 1.276e-01  3.111e-05    4101   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 5024387  on 79  degrees of freedom
## Residual deviance: 1785395  on 78  degrees of freedom
## AIC: 1786203
##
## Number of Fisher Scoring iterations: 7
```

```r
model1a %>% summary()
```

```
##
## Call:
## glm(formula = count ~ week_num, family = "poisson", data = appt_by_mode %>%
##     filter(appt_mode == "Telephone"))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -39.089   -3.062    1.396    5.548   11.893
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) 8.220e+00  3.590e-03 2289.70   <2e-16 ***
## week_num    3.617e-03  7.532e-05   48.02   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 8806.7  on 78  degrees of freedom
## Residual deviance: 6495.7  on 77  degrees of freedom
## AIC: 7304.8
##
## Number of Fisher Scoring iterations: 4
```

```r
model2a %>% summary()
```

```
##
## Call:
## glm(formula = count ~ season_median + week_num, family = "poisson",
##     data = appt_by_mode %>% filter(appt_mode == "Face-to-Face"))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -132.527    -5.475     7.944    14.691    28.665
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)          1.056e+01  1.735e-03 6084.55   <2e-16 ***
## season_medianspring -1.526e-01  1.769e-03  -86.30   <2e-16 ***
## season_mediansummer -1.629e-01  1.801e-03  -90.46   <2e-16 ***
## season_medianwinter -1.561e-01  1.996e-03  -78.21   <2e-16 ***
## week_num             3.146e-04  2.749e-05   11.45   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 65217  on 78  degrees of freedom
## Residual deviance: 55361  on 74  degrees of freedom
## AIC: 56340
##
## Number of Fisher Scoring iterations: 4
```

```r
BIC(model1)
```

```
## [1] 1786205
```

```r
BIC(model1a)
```

```
## [1] 7309.582
```

```r
BIC(model2a)
```

```
## [1] 56351.36
```

```r
#Again model2(a) is the best so that's what will be used in the plotting function
##Final Models

glm(count ~ 0  + season_median + week_num , family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Face-to-Face")) %>%
  summary()
```

```
##
## Call:
## glm(formula = count ~ 0 + season_median + week_num, family = "poisson",
##     data = appt_by_mode %>% filter(appt_mode == "Face-to-Face"))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -132.527    -5.475     7.944    14.691    28.665
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## season_medianautumn 1.056e+01  1.735e-03 6084.55   <2e-16 ***
## season_medianspring 1.041e+01  1.464e-03 7108.70   <2e-16 ***
## season_mediansummer 1.039e+01  1.673e-03 6212.59   <2e-16 ***
## season_medianwinter 1.040e+01  1.793e-03 5800.15   <2e-16 ***
## week_num            3.146e-04  2.749e-05   11.45   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 51118458  on 79  degrees of freedom
## Residual deviance:    55361  on 74  degrees of freedom
## AIC: 56340
##
## Number of Fisher Scoring iterations: 4
```

```r
glm(count ~ 0  + season_median + week_num , family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Telephone")) %>%
  summary()
```

```
##
## Call:
## glm(formula = count ~ 0 + season_median + week_num, family = "poisson",
##     data = appt_by_mode %>% filter(appt_mode == "Telephone"))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -39.215   -1.978    1.361    5.722   11.142
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## season_medianautumn 8.211e+00  5.125e-03 1602.12   <2e-16 ***
## season_medianspring 8.237e+00  4.200e-03 1961.46   <2e-16 ***
## season_mediansummer 8.184e+00  4.800e-03 1704.92   <2e-16 ***
## season_medianwinter 8.222e+00  5.044e-03 1630.09   <2e-16 ***
## week_num            3.778e-03  7.685e-05   49.16   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 5024386.8  on 79  degrees of freedom
## Residual deviance:    6339.6  on 74  degrees of freedom
## AIC: 7154.8
##
## Number of Fisher Scoring iterations: 4
```

```r
glm(count ~ 0  + season_median + week_num , family = "poisson", data = appt_by_mode %>%
              filter(appt_mode == "Home Visit")) %>%
  summary()
```

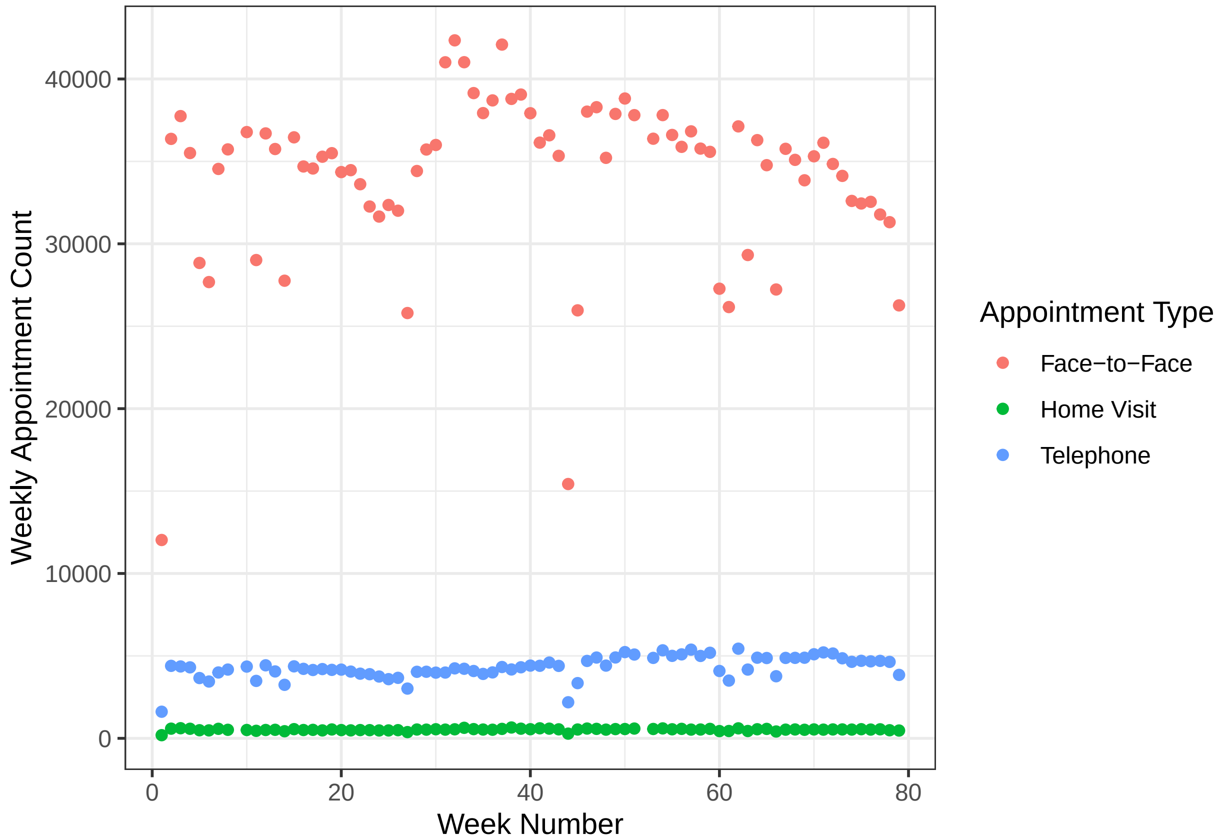
```
##
## Call:
## glm(formula = count ~ 0 + season_median + week_num, family = "poisson",
##     data = appt_by_mode %>% filter(appt_mode == "Home Visit"))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -16.0719   -0.6320    0.2222    1.2904    4.5027
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## season_medianautumn 6.3074293  0.0142006 444.166  < 2e-16 ***
## season_medianspring 6.2025845  0.0118739 522.372  < 2e-16 ***
## season_mediansummer 6.1825092  0.0135689 455.640  < 2e-16 ***
## season_medianwinter 6.2292596  0.0143393 434.419  < 2e-16 ***
## week_num            0.0011161  0.0002213   5.043 4.59e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 438047.05  on 79  degrees of freedom
## Residual deviance:    705.96  on 74  degrees of freedom
## AIC: 1355.2
```

```
##
## Number of Fisher Scoring iterations: 4
```

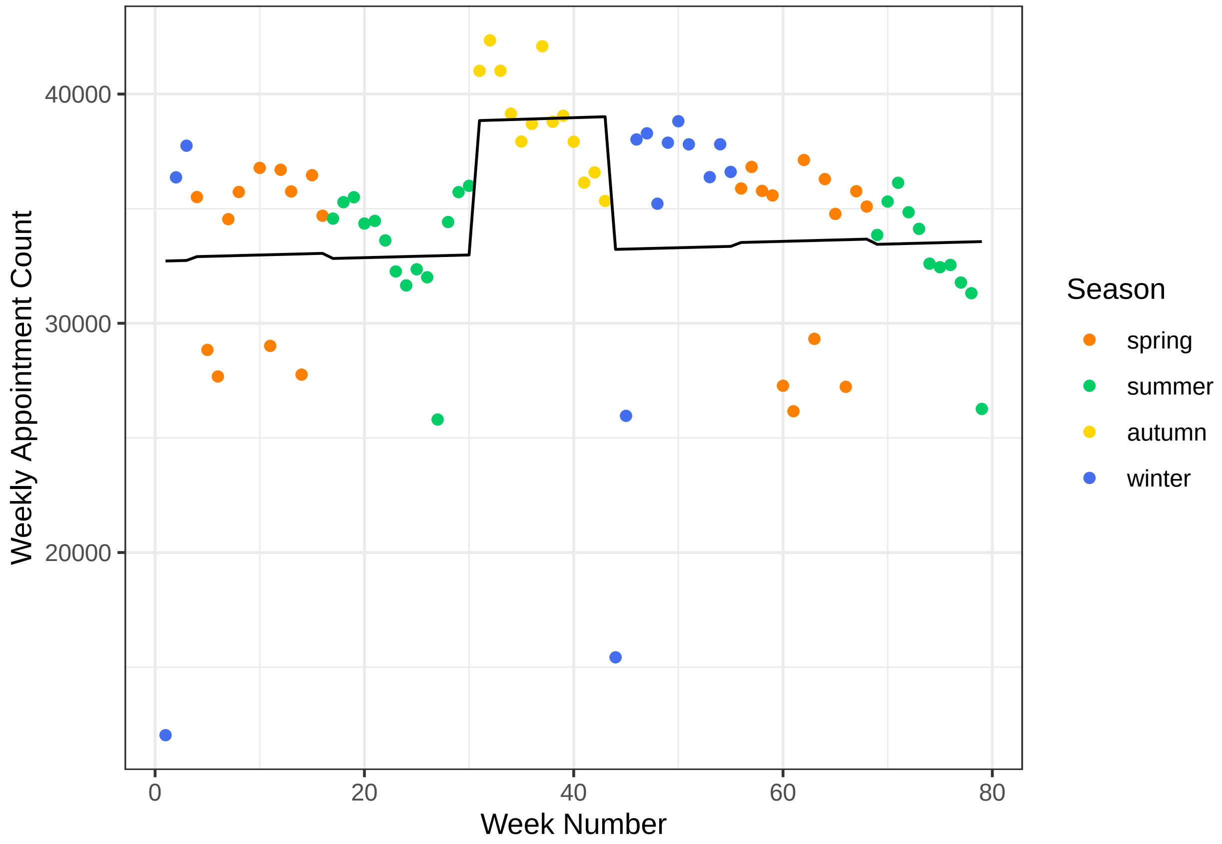
Writing a plotting function to allow for more efficient code for generating plots by appointment type, default option is no filtering (all appointment types combined).

```
#Graphing function for visual aids on the appointment counts
#The filter relates to how the data is subsetted by appointment type.
appt_count <- function(data, filter = "No Filter"){
  if(!filter == "No Filter"){
    #Updating data with filter
    data <- data %>%
      filter(appt_mode == filter)

  model <- glm(count ~ 0  + season_median + week_num , family = "poisson", data = data)
    #Plot with no filter (include legend)
  output <- data %>%
    mutate(poisson_estimate = predict(model, type = "response")) %>%
    ggplot(aes(x = week_num)) +
    geom_point(aes(y = count, colour = season_median)) +
    geom_line(aes(y = poisson_estimate)) +
    theme_bw() +
    #title = paste0(filter, " Weekly Appointment Count with Poisson Regression Line"),
    labs(x = "Week Number", y = "Weekly Appointment Count", colour = "Season") +
    scale_colour_manual("Season", values = c("darkorange1", "springgreen3","gold", "royalblue2"))

  }else{
  output <- data %>%
    ggplot(aes(x = week_num, y = count, colour = appt_mode)) +
    geom_point() +
    theme_bw()  +
    #title = paste0("Weekly Appointment Count by Appointment Type"),
    labs(x = "Week Number", y = "Weekly Appointment Count", colour = "Appointment Type")
  }

  output

}
```

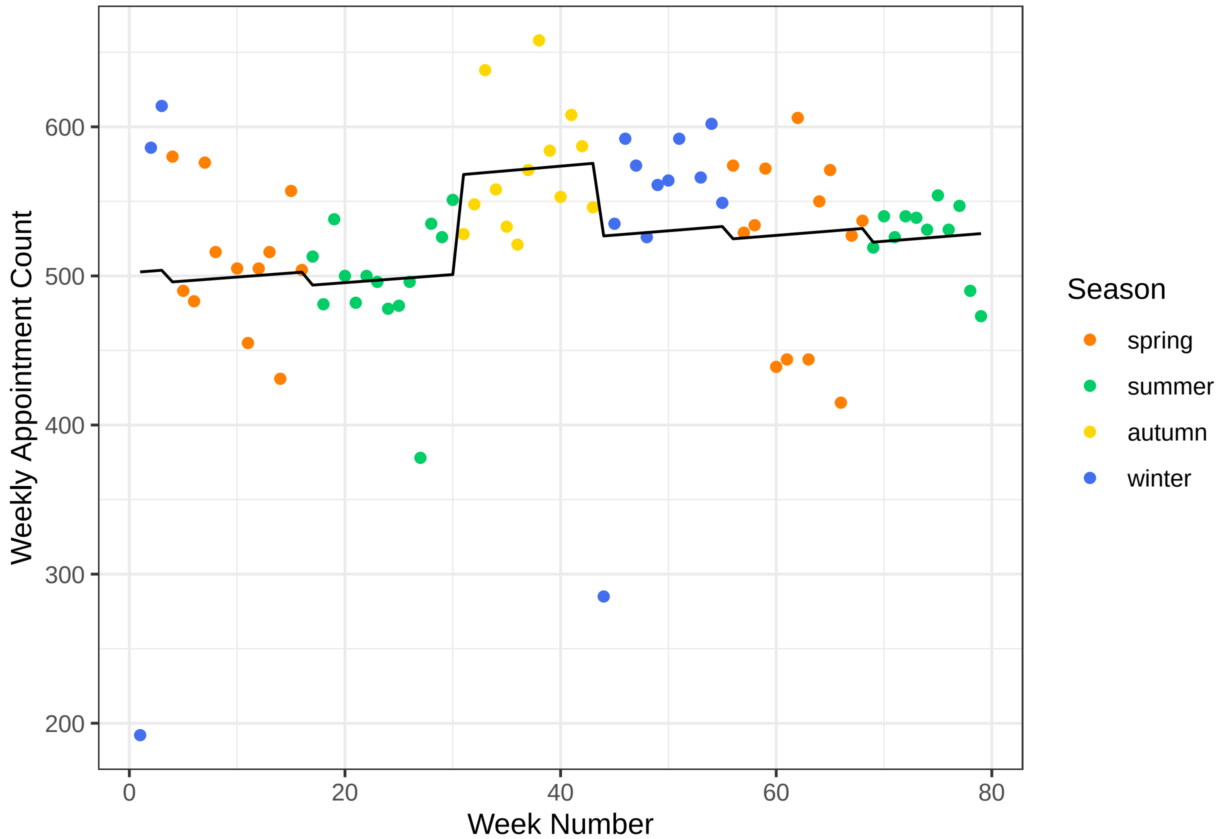
```
#Generating the required dataset to run the appt_count graphing function on:
appt_by_mode <- data %>%
  group_by(appt_mode, week_num, season_median) %>%
  summarise(count = sum(count_of_appointments)) %>%
  ungroup() %>%
  mutate(season_median = factor(season_median,
                                levels = c("spring", "summer","autumn", "winter")))

p1 <- appt_by_mode %>%
  appt_count()
p1
```



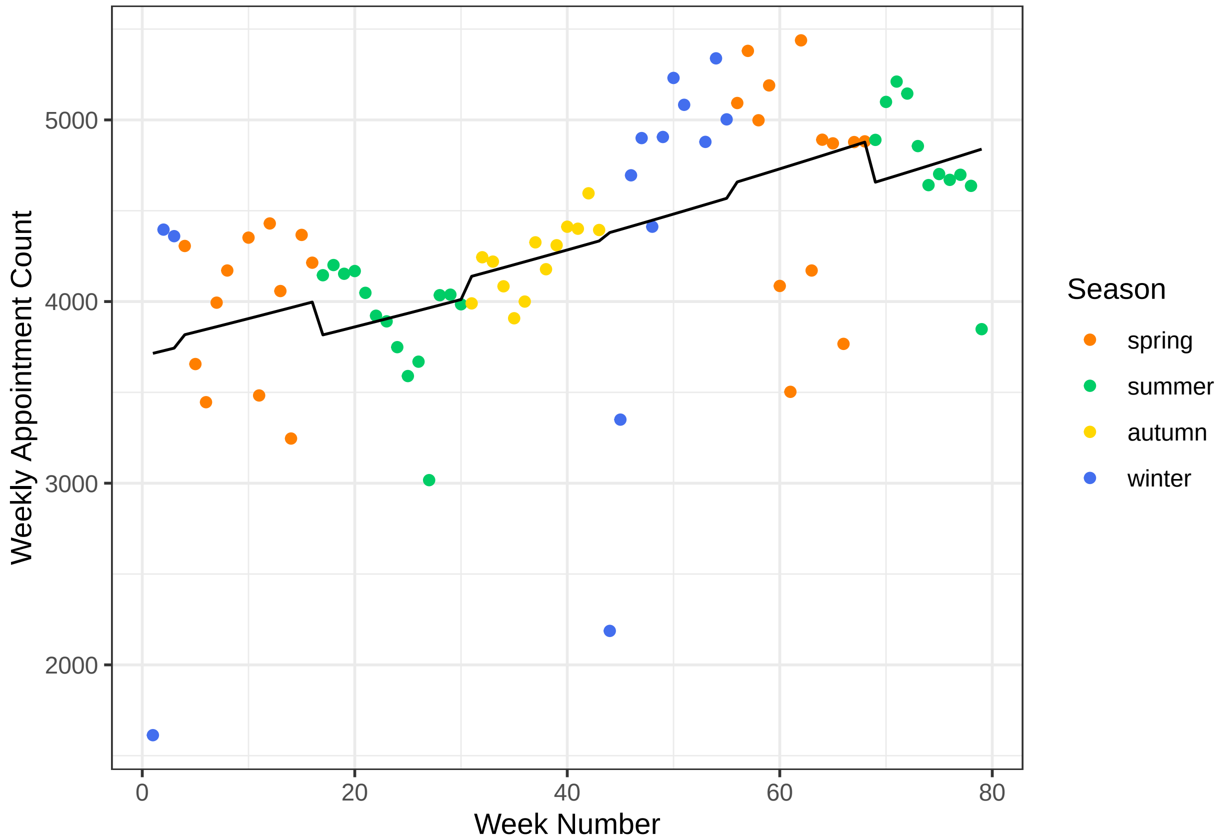

```r
p2 <- appt_by_mode %>%
  appt_count("Face-to-Face")
p2
```




```
#Autumn shift not taken account of in the year 1 vs year 2 comparison and could yeild a no change when
p3 <- appt_by_mode %>%
  appt_count("Home Visit")
p3
```



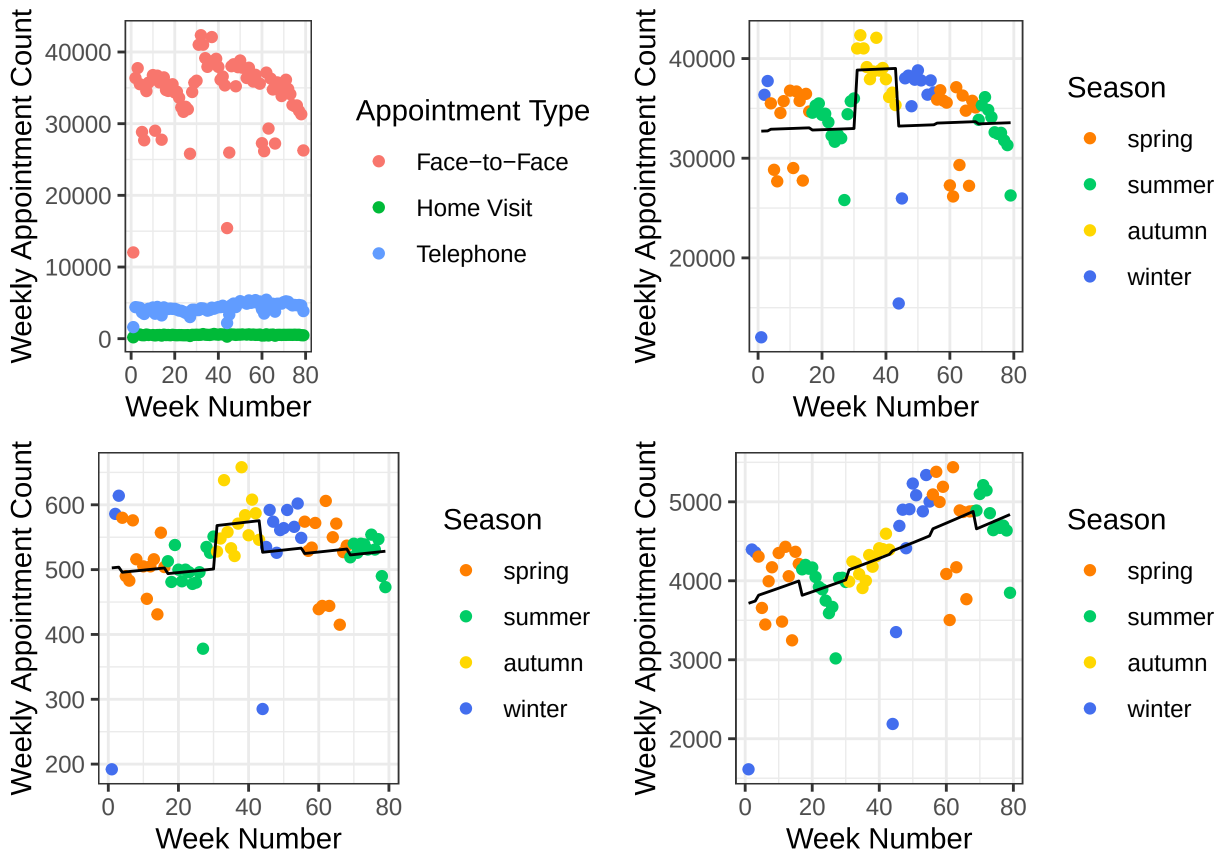

```
p4 <- appt_by_mode %>%
  appt_count("Telephone")
p4
```




```
#For the purposes of the question "Unknown" will not be considered
# appt_by_mode %>%
#   appt_count("Unknown")

#Joining the data appt_by_mode data to original data
data <- data %>%
  inner_join(appt_by_mode)
```

```
## Joining, by = c("appt_mode", "week_num", "season_median")
```

```
#Nice to visualise side by side in Rstudio but not effective in a pdf report.
pic <- grid.arrange(p1,p2,p3,p4,nrow = 2)
```




```
# Telephone Pic for report:
telephone_plot <- p4 + theme(axis.text=element_text(size=12),
        axis.title=element_text(size=14),
        plot.title = element_text(size = 22),
        legend.text = element_text(size = 12),
        legend.title = element_text(size = 14))
```

Statistical significance tests

Looking at the graph generated above, makes sense that season would be a factor to the count. So will be looking into that in the following code. Use Anova test if variance assumption holds - otherwise use the kruskal wallace test. Where the assumption is that all the groups have the same variance.

```
#Function to run the test depending on assumptions
checking_seasons <- function(data, appt_type){
  #Variance assumption (checking they are the same)
  season_check <- data %>% filter(appt_mode == appt_type) %>%
    select(appt_mode, season_median, count) %>%
    unique()
  #if < 0.05 use anova otherwise use kruskal wallace
  var_value <- leveneTest(count ~ season_median, data = season_check)[1,3]
  if(var_value < 0.05){
    test <- "Kruskal"
    #Kruskal Wallace test
    p_value <- kruskal.test(count ~ season_median, data = season_check)$p.value
```

```
  }else{
    test <- "Anova"
    #Running the anova  test
  anova1 <- aov(count ~ season_median, data = season_check)
  p_value <- summary(anova1)[[1]][1,5]
  }
tibble(appt_type = appt_type, test = test, p_value = p_value)
}

#Outputting result of seasons tests by appointment type:
checking_seasons(data, "Face-to-Face") %>%
  bind_rows(checking_seasons(data, "Telephone")) %>%
  bind_rows(checking_seasons(data, "Home Visit"))
```

```
## # A tibble: 3 x 3
##   appt_type    test    p_value
##   <chr>        <chr>     <dbl>
## 1 Face-to-Face Anova   0.00216
## 2 Telephone    Kruskal 0.363
## 3 Home Visit   Anova   0.0715
```

Splitting the data by season for compared t-test would give an option to test if the seasons themselves have increased between the two years. Cold weather could lead to more illnesses. The following function uses a paired t-test to calculate whether the differences are statistically significant or not. It will either use a Welch's test if the variances are not equal, a students t-test if they are or if the data is not normal then it will perform a Wilcoxon Sign Ranked Test on the data. Autumn data cannot be considered as only 1 year of autumn data, which is a shortcoming in the data analysis.

```
#Extracting the data to be used in these tests
stat_data <- data %>%
  #Give a 0 or 1 as a year column for paired t-testing.
  mutate(year == year(appointment_date)) %>%
  select(appt_mode, week_num, season_median, year, count) %>%
  unique()

stat_test <- function(data = stat_data, type = "NA", season = "NA"){
#Updating data

temp_data <- data
  if(type != "NA"){
    temp_data <- temp_data %>%
      filter(appt_mode == type)
  }

  if(season != "NA"){
    temp_data <- temp_data %>%
      filter(season_median == season)
  }

#Test the normality assumption of the data
normal <- TRUE
if(shapiro.test(temp_data$count)$p.value < 0.05){
  normal <- FALSE
}
```

```r
#Checking validity of equal variance
year_1 <- temp_data %>%
  filter(year == 0) %>%
  select(count) %>%
  as_vector()
year_2 <- temp_data %>%
  filter(year == 1) %>%
  select(count) %>%
  as_vector()

#Setting seed to ensure reproducibility
set.seed(666)
min_length <- min(length(year_1), length(year_2))

#Defining data in another format for latter parts
test_data <- tibble(year_1 = year_1 %>% sample(min_length),
                    year_2 = year_2 %>% sample(min_length))

#t-test section
if(normal){

#Sampling for F-test if numbers are different
#Replace = FALSE by default.

variance <- TRUE
#Compares the p.value from F-test and changes the variance check accordingly
if(tidy(var.test(test_data$year_1,
                   test_data$year_2)) %>%
  select(p.value) %>% as_vector() < 0.05){
 #Varaince test significant -> variances NOT Equal
  variance <- FALSE
  }
if(variance == FALSE){
  test <- "Welch"
  #Run Welch test where variance assumption NOT assumed
  p_value <- tidy(t.test((test_data$year_2 - test_data$year_1), mu = 0,
                         alternative = "greater")) %>%
  select(p.value) %>% as_vector()
  if(t_test < 0.05){
    return("H1 True")
  }else{
    return("H0 True")
}
}else{
  test <- "Students"
  #Run students were the variance is assumed
  p_value <- tidy(t.test((test_data$year_2 - test_data$year_1), mu = 0,
                         var.equal=TRUE ,alternative = "greater")) %>%
  select(p.value)  %>% as_vector()

}

}else{
```

```r
  test <- "Wilcoxon"
  #Run the wilcoxon sign ranked test if normality assumption failed
  p_value <- tidy(wilcox.test(test_data$year_2 , test_data$year_1,
                              paired = TRUE, alternative = "greater")) %>%
  select(p.value) %>% as_vector()
}
  #Conclusion
  if(p_value < 0.05){
    outcome <- "H1 True"
  }else{
    outcome <- "H0 True"
}

output <- tibble(appt_mode = type, season = season, test = test,
                 p_value = p_value, conclusion = outcome)
output



}

#Now run the paired T-Test on the data
stat_table <- stat_test(type = "Telephone") %>%
  rbind(stat_test(type = "Face-to-Face")) %>%
  rbind(stat_test(type = "Home Visit")) %>%
  rbind(stat_test(stat_data, "Telephone", "summer")) %>%
  rbind(stat_test(stat_data, "Telephone", "winter")) %>%
  rbind(stat_test(stat_data, "Telephone", "spring")) %>%
  rbind(stat_test(stat_data, "Face-to-Face", "summer")) %>%
  rbind(stat_test(stat_data, "Face-to-Face", "winter")) %>%
  rbind(stat_test(stat_data, "Face-to-Face", "spring")) %>%
  rbind(stat_test(stat_data, "Home Visit", "spring")) %>%
  rbind(stat_test(stat_data, "Home Visit", "winter")) %>%
  rbind(stat_test(stat_data, "Home Visit", "spring"))
```

```
## Multiple parameters; naming those columns num.df, denom.df
## Multiple parameters; naming those columns num.df, denom.df
## Multiple parameters; naming those columns num.df, denom.df
## Multiple parameters; naming those columns num.df, denom.df
```

```r
stat_table
```

```
## # A tibble: 12 x 5
##    appt_mode    season test       p_value conclusion
##    <chr>        <chr>  <chr>        <dbl> <chr>
##  1 Telephone    NA     Wilcoxon 0.0000130 H1 True
##  2 Face-to-Face NA     Wilcoxon 0.815     H0 True
##  3 Home Visit   NA     Wilcoxon 0.0984    H0 True
##  4 Telephone    summer Students 0.0000678 H1 True
##  5 Telephone    winter Wilcoxon 0.0938    H0 True
##  6 Telephone    spring Students 0.00366   H1 True
##  7 Face-to-Face summer Wilcoxon 0.897     H0 True
##  8 Face-to-Face winter Wilcoxon 0.0938    H0 True
##  9 Face-to-Face spring Wilcoxon 0.545     H0 True
## 10 Home Visit   spring Students 0.409     H0 True
```

```
## 11 Home Visit   winter Wilcoxon 0.219     H0 True
## 12 Home Visit   spring Students 0.409     H0 True
```

```
#Only non significant data point in Telephone is winter but not really enough variables to accurately t
```

The outcome from this table demonstrates that there is a only a statistically significant increase in the number of appointments between the 2018 and 2019 dates for telephone appointment types.

Second assignment Questions

```
data_2 <- part_2_data

#Checking unique types of booking times
data_2 %>%
  select(time_between_book_and_appt) %>%
  unique()
```

```
## # A tibble: 8 x 1
##   time_between_book_and_appt
##   <chr>
## 1 1 Day
## 2 Unknown / Data Issue
## 3 Same Day
## 4 8  to 14 Days
## 5 22  to 28 Days
## 6 2 to 7 Days
## 7 More than 28 Days
## 8 15  to 21 Days
```

```
#Checking unique types of appt_status
data_2 %>%
  select(appt_status) %>%
  unique()
```

```
## # A tibble: 4 x 1
##   appt_status
##   <chr>
## 1 Attended
## 2 Unknown
## 3 DNA
## 4 Appt Status Not Provided
```

```
#Discard all data with Unknown / Data Issue and
#Appointment status as Unknown or Appt Status Not Provided
#As only interested in attended/Not attended appointments

data_2 <- data_2 %>%
  filter(!time_between_book_and_appt == "Unknown / Data Issue") %>%
  filter(appt_status %in% c("Attended", "DNA")) %>%
  #Only looking at the GP appointments not attended
  filter(hcp_type == "GP")

#Having a look at mean count
data_2 %>%
```

```r
  group_by(appt_status, time_between_book_and_appt) %>%
  summarise(c = mean(count))
```

```
## # A tibble: 14 x 3
## # Groups:   appt_status [2]
##    appt_status time_between_book_and_appt     c
##    <chr>       <chr>                      <dbl>
##  1 Attended    1 Day                         NA
##  2 Attended    15  to 21 Days                NA
##  3 Attended    2 to 7 Days                   NA
##  4 Attended    22  to 28 Days                NA
##  5 Attended    8  to 14 Days                 NA
##  6 Attended    More than 28 Days             NA
##  7 Attended    Same Day                      NA
##  8 DNA         1 Day                         NA
##  9 DNA         15  to 21 Days                NA
## 10 DNA         2 to 7 Days                   NA
## 11 DNA         22  to 28 Days                NA
## 12 DNA         8  to 14 Days                 NA
## 13 DNA         More than 28 Days             NA
## 14 DNA         Same Day                      NA
```

```r
#temp variance to join by to get the total number of appointments for each day
total_count <- data_2 %>%
  select(appointment_date, time_between_book_and_appt, count_of_appointments) %>%
  group_by(appointment_date, time_between_book_and_appt) %>%
  summarise(total_count = sum(count_of_appointments)) %>%
  ungroup()

#
appt_count <- data_2 %>%
  select(appointment_date, time_between_book_and_appt, appt_status, count_of_appointments) %>%
  group_by(appointment_date, time_between_book_and_appt, appt_status) %>%
  #Has the counts for each day based on both attended and did not attend
  summarise(count = sum(count_of_appointments)) %>%
  ungroup() %>%
  inner_join(total_count) %>%
  mutate(percentage_attendence = 100 *(count/total_count))  %>%
  #Add factoring in for time between appt for future plotting and test outputs
  #Note couple of them had double white spaces
  mutate(time_between_book_and_appt = fct_relevel(time_between_book_and_appt, c("Same Day", "1 Day", "2
                      "8  to 14 Days",    "15  to 21 Days", "22  to 28 Days","More than 28 Days")))
```

```
## Joining, by = c("appointment_date", "time_between_book_and_appt")
```

```r
#Look at minimum and maximum counts to see difference between
appt_count %>%
  filter(appt_status == "DNA") %>%
  group_by(time_between_book_and_appt) %>%
  summarise(min_visits = min(total_count),
            max_visits = max(total_count),
            #median_visits = median(total_count),
            min_dna = min(percentage_attendence),
            max_dna = max(percentage_attendence),
            #median_dna = median(percentage_attendence)
```

```
            )
```

```
## # A tibble: 7 x 5
##   time_between_book_and_appt min_visits max_visits min_dna max_dna
##   <fct>                           <int>      <int>   <dbl>   <dbl>
## 1 Same Day                            3       4325    1.54    33.3
## 2 1 Day                               8        705    3.17    25
## 3 2 to 7 Days                        12       1555    3.33    32.1
## 4 8  to 14 Days                       1        714    4.53   100
## 5 15  to 21 Days                      1        443    3.40   100
## 6 22  to 28 Days                      1        307    2.44   100
## 7 More than 28 Days                   1        209    2.17   100
```

```
#DNA = 100 - Attended so no need to store both
#Variables with < 20 in the number of appointments can lead to a very highly skewed output based on jus
#Did not attends
anova_data <- appt_count %>%
  #Filtering to get did not attend status(reverse for otherone)
  filter(appt_status == "DNA") %>%
  filter(count > 20)

#Variation assumption
leveneTest(percentage_attendence ~ time_between_book_and_appt, data = anova_data)
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##         Df F value    Pr(>F)
## group    6  28.926 < 2.2e-16 ***
##       1090
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Since this assumption is NOT valid, it means the anova is not suitable for this data
#Instead the kruskal-wallis test will be used
kruskal_time <- kruskal.test(percentage_attendence ~ time_between_book_and_appt, data = anova_data)
#https://stackoverflow.com/questions/2478272/kruskal-wallis-test-with-details-on-pairwise-comparisons
#Normally for an anova test a TukeyHSD test would be used to check which ones are not the same
#E.G have different means
#For a kruskal wallis test however, Nemenyi-Damico-Wolfe-Dunn test in the package
library(coin)
oneway_test(percentage_attendence ~ as.factor(time_between_book_and_appt), data = anova_data)
```

```
##
##  Asymptotic K-Sample Fisher-Pitman Permutation Test
##
## data:  percentage_attendence by
##   as.factor(time_between_book_and_appt) (Same Day, 1 Day, 2 to 7 Days, 8  to 14 Days, 15  to 21 Days
## chi-squared = 842.37, df = 6, p-value < 2.2e-16
```

```
#Seems to be all we need
library(pgirmess)

#Looks at which comparisons do NOT have the same mean, individual comparisons
tukey_time <- kruskalmc(anova_data$percentage_attendence, anova_data$time_between_book_and_appt)
tukey_time
```

```
## Multiple comparison test after Kruskal-Wallis
```

```
## p.value: 0.05
## Comparisons
##                                obs.dif critical.dif difference
## Same Day-1 Day               239.50283    107.88478       TRUE
## Same Day-2 to 7 Days         419.01606     86.26360       TRUE
## Same Day-8  to 14 Days       651.36842     86.52620       TRUE
## Same Day-15  to 21 Days      707.88069     92.30922       TRUE
## Same Day-22  to 28 Days      822.66095    165.75877       TRUE
## Same Day-More than 28 Days   945.33082    485.11292       TRUE
## 1 Day-2 to 7 Days            179.51323    107.88478       TRUE
## 1 Day-8  to 14 Days          411.86559    108.09487       TRUE
## 1 Day-15  to 21 Days         468.37786    112.77725       TRUE
## 1 Day-22  to 28 Days         583.15812    177.97103       TRUE
## 1 Day-More than 28 Days      705.82799    489.42034       TRUE
## 2 to 7 Days-8  to 14 Days    232.35236     86.52620       TRUE
## 2 to 7 Days-15  to 21 Days   288.86463     92.30922       TRUE
## 2 to 7 Days-22  to 28 Days   403.64489    165.75877       TRUE
## 2 to 7 Days-More than 28 Days   526.31476    485.11292       TRUE
## 8  to 14 Days-15  to 21 Days    56.51227     92.55466      FALSE
## 8  to 14 Days-22  to 28 Days   171.29253    165.89558       TRUE
## 8  to 14 Days-More than 28 Days 293.96240    485.15969      FALSE
## 15  to 21 Days-22  to 28 Days   114.78026    168.98388      FALSE
## 15  to 21 Days-More than 28 Days 237.45013    486.22436      FALSE
## 22  to 28 Days-More than 28 Days 122.66987    505.34059      FALSE
```

```r
##Looking at number of suitable results per category to analyse the wider variance of values as x axis
anova_data %>%
  group_by(time_between_book_and_appt) %>%
  summarise(count =n())
```

```
## # A tibble: 7 x 2
##   time_between_book_and_appt count
##   <fct>                      <int>
## 1 Same Day                     249
## 2 1 Day                        117
## 3 2 to 7 Days                  249
## 4 8  to 14 Days                246
## 5 15  to 21 Days               193
## 6 22  to 28 Days                39
## 7 More than 28 Days              4
```

```r
plot <- anova_data %>%
  ggplot(aes(x = time_between_book_and_appt, y = percentage_attendence)) +
  geom_violin(aes(fill = time_between_book_and_appt)) +
  geom_boxplot(aes(x = time_between_book_and_appt, y = percentage_attendence), width = 0.10) +
  geom_violin(fill = NA) +
  theme_bw() +
  labs(y = "Percentage of Appointments not Attended",x = "Time between Booking and Appointment") +
  #,title = "Percentage of Appointments not Attended vs Appointment Waiting Time"
  theme(legend.position = "none") +
  #Allowing labels to go onto 2 lines if required
  scale_x_discrete(labels = function(x) str_wrap(x, width = 10))

#Changing axis ready for submission
violin_plot <- plot + theme(axis.text=element_text(size=12),
```

```r
        axis.title=element_text(size=14),
        plot.title = element_text(size = 22))

##Number of DNAs by average number of days + 1 (so as to not divide by 0)
anova_data %>%
  group_by(time_between_book_and_appt) %>%
  summarise(median = median(percentage_attendence)) %>%
  ungroup() %>%
  #Adding +1 to account for same day and giving more than 28 a value of 33
  #to match increase from of 7 between previous
  cbind(ave_day = c(1 , 2, 5.5, 12, 19, 26, 33)) %>%
  mutate(per_day = median/ave_day) %>%
  mutate(per_thousand = median * 10)
```

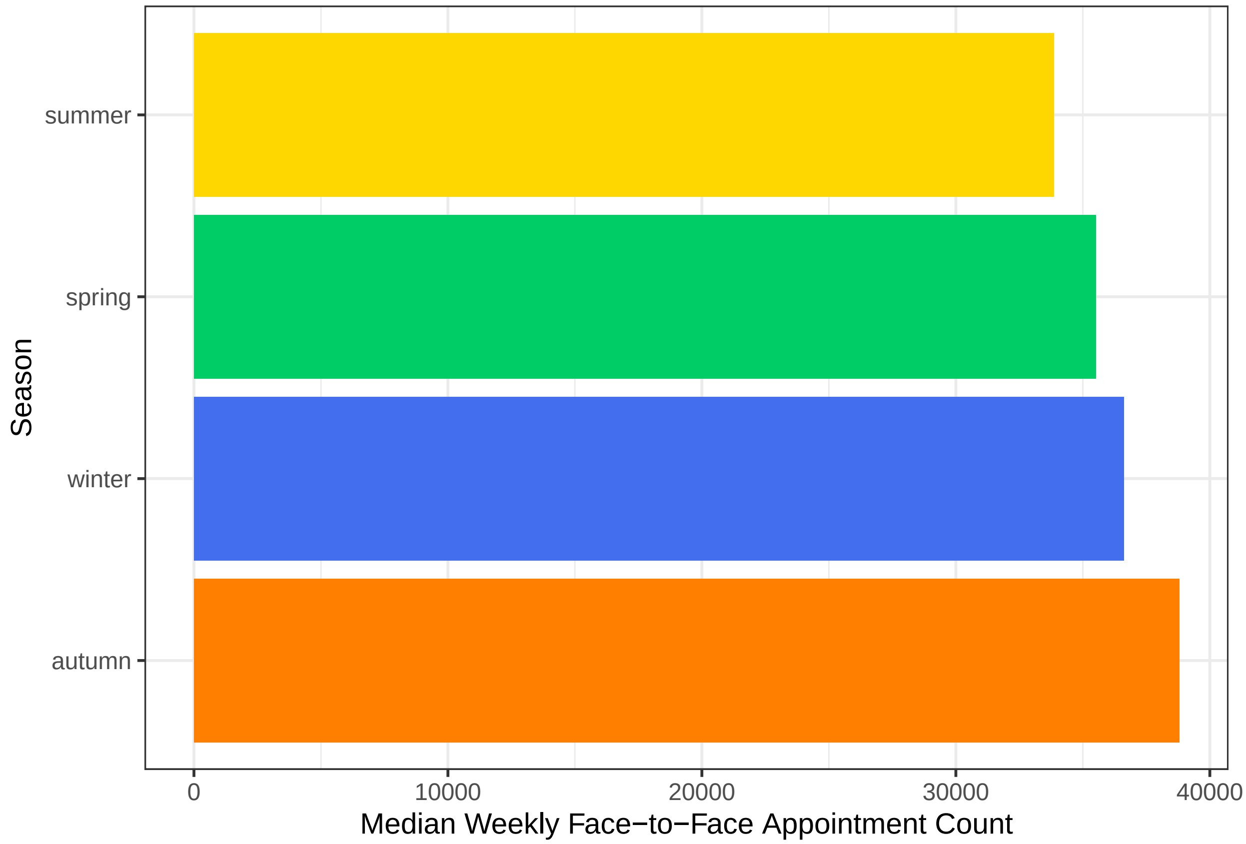
```
##   time_between_book_and_appt    median ave_day   per_day per_thousand
## 1                   Same Day  2.751376     1.0 2.7513757     27.51376
## 2                      1 Day  6.366048     2.0 3.1830239     63.66048
## 3                2 to 7 Days  7.908992     5.5 1.4379986     79.08992
## 4               8  to 14 Days 10.075971    12.0 0.8396643    100.75971
## 5              15  to 21 Days 10.460251    19.0 0.5505395    104.60251
## 6              22  to 28 Days 12.138728    26.0 0.4668742    121.38728
## 7          More than 28 Days 15.332945    33.0 0.4646347    153.32945
```

Extra plots

Implemented a bar chart to showcase difference between seasonal values - using face to face appointments as that had the most obvious difference which is worth highlighting.

```r
#Barchart for season values ~ look at median - to account for bit drop offs or increases.
bar_df <- stat_data %>%
  filter(appt_mode == "Face-to-Face") %>%
  group_by(season_median) %>%
  summarise(count = median(count)) %>%
  arrange(desc(count)) %>%
  #Refactoring to get high to low on the graph
  mutate(season_median = factor(season_median,
                                levels = c("autumn", "winter","spring", "summer")))

#Base R implementation
# barchart <- barplot(height = bar_df$count, names = bar_df$season_median,
#         horiz = T,
#         xlim = c(0,40000),
#         col = c("darkorange1","royalblue2", "springgreen3","gold"),
#         las =1,
#         main = "Median Weekly Appointment Count by Season",
#         xlab = "Median Weekly Count", ylab = "Season")

#GGplot
bar_plot <- bar_df %>%
  ggplot( aes(count, x = season_median)) +
  geom_bar(stat="identity", position = "dodge", aes(fill = season_median)) +
  coord_flip() +
  #Colours to match seasons
```

```
  scale_fill_manual("Season", values = c("darkorange1", "royalblue2",
                                         "springgreen3","gold" )) +
  theme_bw() +
  theme(legend.position = "none") +
  #title ="Median Weekly Face-to-Face Appointment Count by Season",
  labs(y = "Median Weekly Face-to-Face Appointment Count",
       x = "Season")
bar_plot
```




```
#Saving the plots so it can be easily loaded and plotted for the .html file.
save(telephone_plot, violin_plot, bar_plot, file = "html.RData")
```