

Sydney Rainfall Forecast

Logan Sartain

12/7/2022

PROJECT SETUP

Install Required Libraries (If Necessary)

```
install.packages("fpp3", repos = "http://cran.us.r-project.org")
```

```
## Installing package into 'C:/Users/logan/AppData/Local/R/win-library/4.2'  
## (as 'lib' is unspecified)
```

```
## package 'fpp3' successfully unpacked and MD5 sums checked  
##  
## The downloaded binary packages are in  
## C:\Users\logan\AppData\Local\Temp\RtmpQ3abA8\downloaded_packages
```

```
install.packages("lubridate", repos = "http://cran.us.r-project.org")
```

```
## Installing package into 'C:/Users/logan/AppData/Local/R/win-library/4.2'  
## (as 'lib' is unspecified)
```

```
## package 'lubridate' successfully unpacked and MD5 sums checked
```

```
## Warning: cannot remove prior installation of package 'lubridate'
```

```
## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying  
## C:\Users\logan\AppData\Local\R\win-library\4.2\00LOCK\lubridate\libs\x64\lubridate.dll  
## to  
## C:\Users\logan\AppData\Local\R\win-library\4.2\lubridate\libs\x64\lubridate.dll:  
## Permission denied
```

```
## Warning: restored 'lubridate'
```

```
##  
## The downloaded binary packages are in  
## C:\Users\logan\AppData\Local\Temp\RtmpQ3abA8\downloaded_packages
```

```
install.packages("fastDummies", repos = "http://cran.us.r-project.org")
```

```
## Installing package into 'C:/Users/logan/AppData/Local/R/win-library/4.2'  
## (as 'lib' is unspecified)
```

```
## package 'fastDummies' successfully unpacked and MD5 sums checked  
##  
## The downloaded binary packages are in  
## C:\Users\logan\AppData\Local\Temp\RtmpQ3abA8\downloaded_packages
```

```
install.packages("gplots", repos = "http://cran.us.r-project.org")
```

```
## Installing package into 'C:/Users/logan/AppData/Local/R/win-library/4.2'  
## (as 'lib' is unspecified)
```

```
## package 'gplots' successfully unpacked and MD5 sums checked  
##  
## The downloaded binary packages are in  
## C:\Users\logan\AppData\Local\Temp\RtmpQ3abA8\downloaded_packages
```

```
install.packages("ggplot2", repos = "http://cran.us.r-project.org")
```

```
## Installing package into 'C:/Users/logan/AppData/Local/R/win-library/4.2'  
## (as 'lib' is unspecified)
```

```
## package 'ggplot2' successfully unpacked and MD5 sums checked  
##  
## The downloaded binary packages are in  
## C:\Users\logan\AppData\Local\Temp\RtmpQ3abA8\downloaded_packages
```

```
install.packages("tidyverse", repos = "http://cran.us.r-project.org")
```

```
## Installing package into 'C:/Users/logan/AppData/Local/R/win-library/4.2'  
## (as 'lib' is unspecified)
```

```
## package 'tidyverse' successfully unpacked and MD5 sums checked  
##  
## The downloaded binary packages are in  
## C:\Users\logan\AppData\Local\Temp\RtmpQ3abA8\downloaded_packages
```

Load Required Libraries

```
library(fpp3)
```

```
## — Attaching packages ————— fpp3 0.4.0 —
```

```
## ✓ tibble      3.1.8      ✓ tsibble      1.1.3
## ✓ dplyr       1.0.10     ✓ tsibbledata 0.4.1
## ✓ tidyr       1.2.1      ✓ feasts      0.3.0
## ✓ lubridate   1.9.0      ✓ fable       0.3.2
## ✓ ggplot2     3.4.0
```

```
## — Conflicts ————— fpp3_conflicts —
## X lubridate::date()      masks base::date()
## X dplyr::filter()       masks stats::filter()
## X tsibble::intersect()  masks base::intersect()
## X tsibble::interval()   masks lubridate::interval()
## X dplyr::lag()          masks stats::lag()
## X tsibble::setdiff()    masks base::setdiff()
## X tsibble::union()      masks base::union()
```

```
library(lubridate)
library(fastDummies)
library(gplots)
```

```
##
## Attaching package: 'gplots'
```

```
## The following object is masked from 'package:stats':
##
##      lowess
```

```
library(ggplot2)
library(tidyverse)
```

```
## — Attaching packages
## —————
## tidyverse 1.3.2 —
```

```
## ✓ readr      2.1.3      ✓ stringr 1.5.0
## ✓ purrr      0.3.5      ✓ forcats 0.5.2
## — Conflicts ————— tidyverse_conflicts() —
## X lubridate::as.difftime() masks base::as.difftime()
## X lubridate::date()       masks base::date()
## X dplyr::filter()         masks stats::filter()
## X tsibble::intersect()    masks lubridate::intersect(), base::intersect()
## X tsibble::interval()     masks lubridate::interval()
## X dplyr::lag()            masks stats::lag()
## X tsibble::setdiff()      masks lubridate::setdiff(), base::setdiff()
## X tsibble::union()        masks lubridate::union(), base::union()
```

Import Dataset

```
options(max.print = 175)
url <- "https://github.com/LoganSartain/Final-Project-Bana-4090/blob/main/weatherAUS.csv?raw=true"
AUS <- read.csv(url, header = TRUE)
print(AUS)
```

```
##      Date Location MinTemp MaxTemp Rainfall Evaporation Sunshine WindGustDir
## 1 2008-12-01  Albury    13.4    22.9     0.6          NA        NA         W
## 2 2008-12-02  Albury     7.4    25.1     0.0          NA        NA        WNW
## 3 2008-12-03  Albury    12.9    25.7     0.0          NA        NA        WSW
## 4 2008-12-04  Albury     9.2    28.0     0.0          NA        NA         NE
## 5 2008-12-05  Albury    17.5    32.3     1.0          NA        NA         W
## 6 2008-12-06  Albury    14.6    29.7     0.2          NA        NA        WNW
## 7 2008-12-07  Albury    14.3    25.0     0.0          NA        NA         W
##      WindGustSpeed WindDir9am WindDir3pm WindSpeed9am WindSpeed3pm Humidity9am
## 1              44          W      WNW             20             24          71
## 2              44        NNW      WSW              4             22          44
## 3              46          W      WSW             19             26          38
## 4              24          SE         E             11              9          45
## 5              41        ENE        NW              7             20          82
## 6              56          W         W             19             24          55
## 7              50          SW         W             20             24          49
##      Humidity3pm Pressure9am Pressure3pm Cloud9am Cloud3pm Temp9am Temp3pm
## 1              22      1007.7      1007.1        8        NA      16.9      21.8
## 2              25      1010.6      1007.8       NA        NA      17.2      24.3
## 3              30      1007.6      1008.7       NA         2      21.0      23.2
## 4              16      1017.6      1012.8       NA        NA      18.1      26.5
## 5              33      1010.8      1006.0        7         8      17.8      29.7
## 6              23      1009.2      1005.4       NA        NA      20.6      28.9
## 7              19      1009.6      1008.2        1        NA      18.1      24.6
##      RainToday RainTomorrow
## 1          No          No
## 2          No          No
## 3          No          No
## 4          No          No
## 5          No          No
## 6          No          No
## 7          No          No
## [ reached 'max' / getOption("max.print") -- omitted 145453 rows ]
```

INTRODUCTION

This dataset has 10 years of weather data taken around multiple locations in Australia. I decided to focus on Temperature in Sydney, Australia. It includes many weather variables that would be useful in predicting and forecasting temperature.

The dataset is from Kaggle.

This dataset was created by Joe Young and Adam Young. They gathered data from the Australia government and compiled it to create this dataset.

Index: Date

Key: Location

Forecast Variable: MaxTemp

Predictor Variables: MinTemp, Rainfall, Evaporation, Sunshine, WindGustDir, WindGustSpeed, WindDir9am, WindDir3pm, WindSpeed9am, WindSpeed3pm, Humidity9am, Humidity3pm, Pressure9am, Pressure3pm, Cloud9am, Cloud3pm, Temp9am, Temp3pm, RainToday, and RainTomorrow.

I chose this dataset because I have always found weather and storms interesting. I would love to be able to predict the weather for a meteorologist/news station as a future job. It is also interesting to me how hard it can be to accurately predict the weather so I thought it would be cool to see how accurate I could be.

The forecast on this data can be leveraged to make better decisions by a multitude of different organizations in Australia. An obvious one would be weather/news stations making more accurate predictions on temperature but, this forecast could also be useful for farmers, sporting events, wedding venues, outdoor concert coordinators, Uber drivers, restaurants with outdoor dining, and airlines just to name a few. This would allow all of these different types of organizations to plan better according to the weather. For example, a restaurant may want to schedule less waiters on a night where it is going to be too hot or too cold because they won't need anyone for outdoor dining. Or a wedding venue may need to prepare a backup plan in case of extreme heat or cold. The forecast would overall allow for better planning and decision making in this regard.

DATA WRANGLING

Convert to a tsibble

```
AUS$Date <- as.Date(AUS$Date , format="%Y-%m-%d")

AUS <- AUS %>%
  as_tsibble(index = Date, key = Location)
```

Deal with Missing Data

```
summary(Filter(is.numeric, AUS))
```

##	MinTemp	MaxTemp	Rainfall	Evaporation
##	Min. : -8.50	Min. : -4.80	Min. : 0.000	Min. : 0.00
##	1st Qu.: 7.60	1st Qu.: 17.90	1st Qu.: 0.000	1st Qu.: 2.60
##	Median : 12.00	Median : 22.60	Median : 0.000	Median : 4.80
##	Mean : 12.19	Mean : 23.22	Mean : 2.361	Mean : 5.47
##	3rd Qu.: 16.90	3rd Qu.: 28.20	3rd Qu.: 0.800	3rd Qu.: 7.40
##	Max. : 33.90	Max. : 48.10	Max. : 371.000	Max. : 145.00
##	NA's : 1485	NA's : 1261	NA's : 3261	NA's : 62790
##	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm
##	Min. : 0.00	Min. : 6.00	Min. : 0.00	Min. : 0.00
##	1st Qu.: 4.80	1st Qu.: 31.00	1st Qu.: 7.00	1st Qu.: 13.00
##	Median : 8.40	Median : 39.00	Median : 13.00	Median : 19.00
##	Mean : 7.61	Mean : 40.03	Mean : 14.04	Mean : 18.66
##	3rd Qu.: 10.60	3rd Qu.: 48.00	3rd Qu.: 19.00	3rd Qu.: 24.00
##	Max. : 14.50	Max. : 135.00	Max. : 130.00	Max. : 87.00
##	NA's : 69835	NA's : 10263	NA's : 1767	NA's : 3062
##	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm
##	Min. : 0.00	Min. : 0.00	Min. : 980.5	Min. : 977.1
##	1st Qu.: 57.00	1st Qu.: 37.00	1st Qu.: 1012.9	1st Qu.: 1010.4
##	Median : 70.00	Median : 52.00	Median : 1017.6	Median : 1015.2
##	Mean : 68.88	Mean : 51.54	Mean : 1017.6	Mean : 1015.3
##	3rd Qu.: 83.00	3rd Qu.: 66.00	3rd Qu.: 1022.4	3rd Qu.: 1020.0
##	Max. : 100.00	Max. : 100.00	Max. : 1041.0	Max. : 1039.6
##	NA's : 2654	NA's : 4507	NA's : 15065	NA's : 15028
##	Cloud9am	Cloud3pm	Temp9am	Temp3pm
##	Min. : 0.00	Min. : 0.00	Min. : -7.20	Min. : -5.40
##	1st Qu.: 1.00	1st Qu.: 2.00	1st Qu.: 12.30	1st Qu.: 16.60
##	Median : 5.00	Median : 5.00	Median : 16.70	Median : 21.10
##	Mean : 4.45	Mean : 4.51	Mean : 16.99	Mean : 21.68
##	3rd Qu.: 7.00	3rd Qu.: 7.00	3rd Qu.: 21.60	3rd Qu.: 26.40
##	Max. : 9.00	Max. : 9.00	Max. : 40.20	Max. : 46.70
##	NA's : 55888	NA's : 59358	NA's : 1767	NA's : 3609

```
# Replacing missing data with the median value of the predictor variable for numeric
AUS$MinTemp[is.na(AUS$MinTemp)] <- median(AUS$MinTemp,na.rm=TRUE)
AUS$MaxTemp[is.na(AUS$MaxTemp)] <- median(AUS$MaxTemp,na.rm=TRUE)
AUS$Rainfall[is.na(AUS$Rainfall)] <- median(AUS$Rainfall,na.rm=TRUE)
AUS$Evaporation[is.na(AUS$Evaporation)] <- median(AUS$Evaporation,na.rm=TRUE)
AUS$Sunshine[is.na(AUS$Sunshine)] <- median(AUS$Sunshine,na.rm=TRUE)
AUS$WindGustSpeed[is.na(AUS$WindGustSpeed)] <- median(AUS$WindGustSpeed,na.rm=TRUE)
AUS$WindSpeed9am[is.na(AUS$WindSpeed9am)] <- median(AUS$WindSpeed9am,na.rm=TRUE)
AUS$WindSpeed3pm[is.na(AUS$WindSpeed3pm)] <- median(AUS$WindSpeed3pm,na.rm=TRUE)
AUS$Humidity9am[is.na(AUS$Humidity9am)] <- median(AUS$Humidity9am,na.rm=TRUE)
AUS$Humidity3pm[is.na(AUS$Humidity3pm)] <- median(AUS$Humidity3pm,na.rm=TRUE)
AUS$Pressure9am[is.na(AUS$Pressure9am)] <- median(AUS$Pressure9am,na.rm=TRUE)
AUS$Pressure3pm[is.na(AUS$Pressure3pm)] <- median(AUS$Pressure3pm,na.rm=TRUE)
AUS$Cloud9am[is.na(AUS$Cloud9am)] <- median(AUS$Cloud9am,na.rm=TRUE)
AUS$Cloud3pm[is.na(AUS$Cloud3pm)] <- median(AUS$Cloud3pm,na.rm=TRUE)
AUS$Temp9am[is.na(AUS$Temp9am)] <- median(AUS$Temp9am,na.rm=TRUE)
AUS$Temp3pm[is.na(AUS$Temp3pm)] <- median(AUS$Temp3pm,na.rm=TRUE)

summary(Filter(is.numeric, AUS))
```

```
##      MinTemp      MaxTemp      Rainfall      Evaporation
## Min.    :-8.50  Min.    :-4.80  Min.     : 0.000  Min.     : 0.00
## 1st Qu.: 7.70   1st Qu.:18.00  1st Qu.: 0.000  1st Qu.: 4.00
## Median :12.00   Median :22.60  Median : 0.000  Median : 4.80
## Mean   :12.19   Mean    :23.22  Mean    : 2.308  Mean    : 5.18
## 3rd Qu.:16.80   3rd Qu.:28.20  3rd Qu.: 0.600  3rd Qu.: 5.20
## Max.    :33.90   Max.     :48.10  Max.     :371.000  Max.     :145.00
##      Sunshine      WindGustSpeed      WindSpeed9am      WindSpeed3pm
## Min.     : 0.00   Min.     : 6.00   Min.     : 0.00   Min.     : 0.00
## 1st Qu.: 8.20   1st Qu.: 31.00  1st Qu.: 7.00   1st Qu.:13.00
## Median : 8.40   Median : 39.00  Median : 13.00  Median :19.00
## Mean    : 7.99   Mean    : 39.96  Mean    : 14.03  Mean    :18.67
## 3rd Qu.: 8.70   3rd Qu.: 46.00  3rd Qu.: 19.00  3rd Qu.:24.00
## Max.    :14.50   Max.     :135.00  Max.     :130.00  Max.     :87.00
##      Humidity9am      Humidity3pm      Pressure9am      Pressure3pm
## Min.     : 0.0   Min.     : 0.00   Min.     : 980.5   Min.     : 977.1
## 1st Qu.: 57.0   1st Qu.: 37.00  1st Qu.:1013.5   1st Qu.:1011.1
## Median : 70.0   Median : 52.00  Median :1017.6   Median :1015.2
## Mean    : 68.9   Mean    : 51.55  Mean    :1017.6   Mean    :1015.3
## 3rd Qu.: 83.0   3rd Qu.: 65.00  3rd Qu.:1021.8   3rd Qu.:1019.4
## Max.    :100.0   Max.     :100.00  Max.     :1041.0   Max.     :1039.6
##      Cloud9am      Cloud3pm      Temp9am      Temp3pm
## Min.     :0.00   Min.     :0.00   Min.     :-7.20   Min.     :-5.40
## 1st Qu.:3.00   1st Qu.:4.00   1st Qu.:12.30   1st Qu.:16.70
## Median :5.00   Median :5.00   Median :16.70   Median :21.10
## Mean    :4.66   Mean    :4.71   Mean    :16.99   Mean    :21.67
## 3rd Qu.:6.00   3rd Qu.:6.00   3rd Qu.:21.50   3rd Qu.:26.20
## Max.     :9.00   Max.     :9.00   Max.     :40.20   Max.     :46.70
```

```
# Removing missing data entirely for RainToday and RainTomorrow
```

```
AUS <- AUS %>%  
  mutate(RainToday = ifelse(is.na(RainToday), "Unknown", RainToday))
```

```
AUS <- AUS %>%  
  mutate(RainTomorrow = ifelse(is.na(RainTomorrow), "Unknown", RainTomorrow))
```

```
summary(AUS)
```



```

##      Date      Location      MinTemp      MaxTemp
## Min.      :2007-11-01  Length:145460  Min.      :-8.50  Min.      :-4.80
## 1st Qu.:2011-01-11  Class :character  1st Qu.: 7.70  1st Qu.:18.00
## Median :2013-06-02  Mode  :character  Median :12.00  Median :22.60
## Mean   :2013-04-04                Mean  :12.19  Mean   :23.22
## 3rd Qu.:2015-06-14                3rd Qu.:16.80  3rd Qu.:28.20
## Max.   :2017-06-25                Max.   :33.90  Max.   :48.10
##      Rainfall      Evaporation      Sunshine      WindGustDir
## Min.      : 0.000  Min.      : 0.00  Min.      : 0.00  Length:145460
## 1st Qu.: 0.000  1st Qu.: 4.00  1st Qu.: 8.20  Class :character
## Median : 0.000  Median : 4.80  Median : 8.40  Mode  :character
## Mean   : 2.308  Mean   : 5.18  Mean   : 7.99
## 3rd Qu.: 0.600  3rd Qu.: 5.20  3rd Qu.: 8.70
## Max.   :371.000  Max.   :145.00  Max.   :14.50
## WindGustSpeed  WindDir9am      WindDir3pm      WindSpeed9am
## Min.      : 6.00  Length:145460  Length:145460  Min.      : 0.00
## 1st Qu.: 31.00  Class :character  Class :character  1st Qu.: 7.00
## Median : 39.00  Mode  :character  Mode  :character  Median : 13.00
## Mean   : 39.96                Mean   : 14.03
## 3rd Qu.: 46.00                3rd Qu.: 19.00
## Max.   :135.00                Max.   :130.00
## WindSpeed3pm  Humidity9am      Humidity3pm      Pressure9am
## Min.      : 0.00  Min.      : 0.0  Min.      : 0.00  Min.      : 980.5
## 1st Qu.:13.00  1st Qu.: 57.0  1st Qu.: 37.00  1st Qu.:1013.5
## Median :19.00  Median : 70.0  Median : 52.00  Median :1017.6
## Mean   :18.67  Mean   : 68.9  Mean   : 51.55  Mean   :1017.6
## 3rd Qu.:24.00  3rd Qu.: 83.0  3rd Qu.: 65.00  3rd Qu.:1021.8
## Max.   :87.00  Max.   :100.0  Max.   :100.00  Max.   :1041.0
## Pressure3pm  Cloud9am      Cloud3pm      Temp9am      Temp3pm
## Min.      : 977.1  Min.      :0.00  Min.      :0.00  Min.      : -7.20  Min.      : -5.40
## 1st Qu.:1011.1  1st Qu.:3.00  1st Qu.:4.00  1st Qu.:12.30  1st Qu.:16.70
## Median :1015.2  Median :5.00  Median :5.00  Median :16.70  Median :21.10
## Mean   :1015.3  Mean   :4.66  Mean   :4.71  Mean   :16.99  Mean   :21.67
## 3rd Qu.:1019.4  3rd Qu.:6.00  3rd Qu.:6.00  3rd Qu.:21.50  3rd Qu.:26.20
## Max.   :1039.6  Max.   :9.00  Max.   :9.00  Max.   :40.20  Max.   :46.70
## RainToday      RainTomorrow
## Length:145460  Length:145460
## Class :character  Class :character
## Mode  :character  Mode  :character
##
##
##

```

```
# Remove variables WindGustDir, WindDir9am, and WindDir3pm
```

```
AUS <- AUS[,!names(AUS) %in% c("WindGustDir", "WindDir9am", "WindDir3pm")]
```

Create New Variables to aid in Forecasting

```
AUS$Year <- year(ymd(AUS$Date)) # Add Year Column
AUS$Month <- month(ymd(AUS$Date)) # Add Month Column
AUS2 <- AUS %>% mutate(TempDiff = MaxTemp - MinTemp) # Temperature Difference Variable
```

Aggregate time series to desired format for forecasting

```
# Create Dummy Variables for RainToday and RainTomorrow

AUS3 <- dummy_cols(AUS2,
  select_columns = c("RainToday", "RainTomorrow"),
  remove_selected_columns = TRUE)

# Checking for variables with autocorrelation to see if we want to remove any

colfunc <- colorRampPalette(c("red", "white", "green"))
heatmap.2(cor(Filter(is.numeric, AUS3), use = "complete.obs"), Rowv = FALSE,
  Colv = FALSE, dendrogram = "none", lwid=c(0.1,4), lhei=c(0.1,4),
  col = colfunc(15),
  cellnote = round(cor(Filter(is.numeric, AUS3), use = "complete.obs"),2),
  notecol = "black", key = FALSE, trace = 'none')
```

1	0.73	0.10	0.36	0.03	0.17	0.17	0.17	0.23	0.04	0.42	0.43	0.04	0	0.9	0.7	0.04	0.20	0.24	0.06	0.10	0.05	0.08	0.10	0.08	MinTemp	
0.73	1	0.07	0.45	0.32	0.07	0.01	0.05	0.5	0.50	0.31	0.40	0.23	0.22	0.88	0.97	0.06	0.16	0.49	0.22	0.01	0.23	0.15	0.04	0.16	MaxTemp	
0.1	0.07	1	0.04	0.17	0.13	0.08	0.06	0.22	0.25	0.16	0.12	0.16	0.14	0.01	0.08	0.01	0.03	0.24	0.47	0.04	0.5	0.22	0.01	0.23	Rainfall	
0.36	0.45	0.04	1	0.28	0.15	0.15	0.1	0.38	0.29	0.24	0.23	0.17	0.16	0.43	0.43	0.04	0.02	0.17	0.14	0.02	0.14	0.09	0.04	0.09	Evaporation	
0.03	0.32	0.17	0.28	1	0.03	0.01	0.02	0.33	0.43	0.04	0	0.5	0.53	0.19	0.33	0.04	0.02	0.41	0.23	0.01	0.23	0.31	0.04	0.32	Sunshine	
0.17	0.07	0.13	0.15	0.03	1	0.58	0.66	0.24	0.03	0.43	0.38	0.05	0.07	0.15	0.03	0.03	0.06	0.13	0.15	0.02	0.15	0.22	0.02	0.22	WindGustSp	
0.17	0.01	0.08	0.15	0.01	0.58	1	0.54	0.27	0.03	0.22	0.17	0.01	0.03	0.13	0	0.02	0.05	0.20	0.1	0.03	0.1	0.09	0.03	0.09	WindSpeed	
0.17	0.05	0.06	0.10	0.02	0.66	0.51	1	0.14	0.02	0.28	0.24	0.03	0.01	0.16	0.03	0.03	0.06	0.15	0.08	0.02	0.08	0.09	0.02	0.08	WindSpeed	
0.23	0.5	0.22	0.38	0.33	0.24	0.27	0.14	1	0.66	0.13	0.18	0.36	0.28	0.47	0.49	0.04	0.09	0.42	0.34	0.01	0.35	0.25	0.02	0.25	Humidity9ar	
0.01	0.5	0.25	0.29	0.43	0.03	0.03	0.02	0.66	1	0.03	0.05	0.4	0.4	0.22	0.56	0.04	0.02	0.72	0.36	0.02	0.37	0.43	0.02	0.43	Humidity3pr	
0.42	0.34	0.16	0.2	0.04	0.43	0.22	0.28	0.13	0.03	1	0.96	0.1	0.14	0.40	0.27	0.03	0.03	0.10	0.17	0	0.18	0.22	0	0.23	Pressure9ar	
0.43	0.40	0.12	0.23	0.01	0.38	0.17	0.24	0.18	0.05	0.96	1	0.04	0.06	0.44	0.36	0.02	0.02	0.10	0.1	0	0.10	0.21	0	0.21	Pressure3pr	
0.04	0.23	0.16	0.17	0.5	0.05	0.01	0.03	0.60	0.4	0.10	0.04	1	0.56	0.12	0.24	0.06	0.04	0.39	0.24	0.04	0.24	0.25	0.03	0.24	Cloud9am	
0	0.22	0.14	0.16	0.53	0.07	0.03	0.01	0.28	0.4	0.14	0.06	0.56	1	0.14	0.25	0.05	0	0.34	0.2	0.03	0.21	0.29	0.02	0.29	Cloud3pm	
0.90	0.88	0.01	0.43	0.19	0.15	0.13	0.16	0.47	0.22	0.40	0.44	0.12	0.11	1	0.85	0.05	0.14	0.10	0.09	0	0	0.10	0.02	0	0.03	Temp9am
0.70	0.97	0.08	0.43	0.33	0.03	0	0.03	0.49	0.56	0.27	0.36	0.24	0.25	0.85	1	0.05	0.17	0.49	0.22	0.01	0.23	0.18	0.04	0.19	Temp3pm	
0.04	0.06	0.01	0.04	0.04	0.03	0.02	0.03	0.04	0.01	0.03	0.02	0.06	0.05	0.05	0.05	1	0.1	0.03	0	0.03	0.01	0	0.03	0.01	Year	
-0.20	0.16	0.03	0.02	0.02	0.06	0.05	0.06	0.09	0.02	0.03	0.02	0.01	0	-0.14	0.17	0.11	1	0.03	0.04	0.01	0.04	0.04	0.01	0.01	Month	
0.24	0.49	0.24	0.17	0.41	0.13	0.20	0.15	0.42	0.72	0.1	0.01	0.39	0.31	0.10	0.49	0.03	0.03	1	0.39	0.02	0.39	0.33	0.02	0.33	TempDiff	
0.06	0.22	0.47	0.14	0.23	0.15	0.14	0.08	0.34	0.36	0.17	0.1	0.24	0.20	0.09	0.22	0	0.00	0.39	1	-0.27	0.94	0.34	0.16	0.29	RainToday_	
0.04	0.04	0.04	0.02	0.01	0.02	0.03	0.02	0.01	0.02	0	0	0.04	0.03	0	0.01	0.03	0.04	0.02	0.27	1	-0.08	0.19	0.56	0	RainToday_	
0.05	0.23	0.5	0.14	0.23	0.15	0.10	0.08	0.35	0.37	0.18	0.10	0.24	0.21	0.10	0.23	0.01	0.04	0.39	0.94	0.08	1	-0.28	0.03	0.31	RainToday_	
0.08	0.15	0.22	0.09	0.31	0.22	0.09	0.09	0.25	0.43	0.22	0.24	0.25	0.29	0.02	0.18	0	0.00	0.33	0.34	0.19	0.28	1	-0.27	0.94	RainTomorr	
0.04	0.04	0.04	0.01	0.01	0.02	0.03	0.02	0.02	0.02	0	0	0.03	0.02	0	0.01	0.03	0.04	0.02	0.16	0.56	0.03	0.27	1	-0.08	RainTomorr	
0.08	0.16	0.23	0.09	0.32	0.22	0.09	0.08	0.25	0.43	0.23	0.24	0.24	0.29	0.03	0.19	0.01	0.04	0.33	0.29	0	0.34	0.94	0.08	1	RainTomorr	

MinTemp
MaxTemp
Rainfall
Evaporation
Sunshine
dGustSpeed
dSpeed9am
dSpeed3pm
Humidity9am
Humidity3pm
Pressure9am
Pressure3pm
Cloud9am
Cloud3pm
Temp9am
Temp3pm
Year
Month
TempDiff
inToday_No
ay_Unknown
inToday_Yes
morrow_No
w_Unknown
morrow_Yes

```

# Look to see which variables are highly correlated with MaxTemp.
# MinTemp, Temp9am, and Temp3pm are all highly positively correlated with MaxTemp
# We will remove these three variables as they may likely cause problems with autocorrelation.

drop <- c("MinTemp", "Temp9am", "Temp3pm")
AUS4 = AUS3[,!(names(AUS3) %in% drop)]

# Convert processed dataset to tsibble again

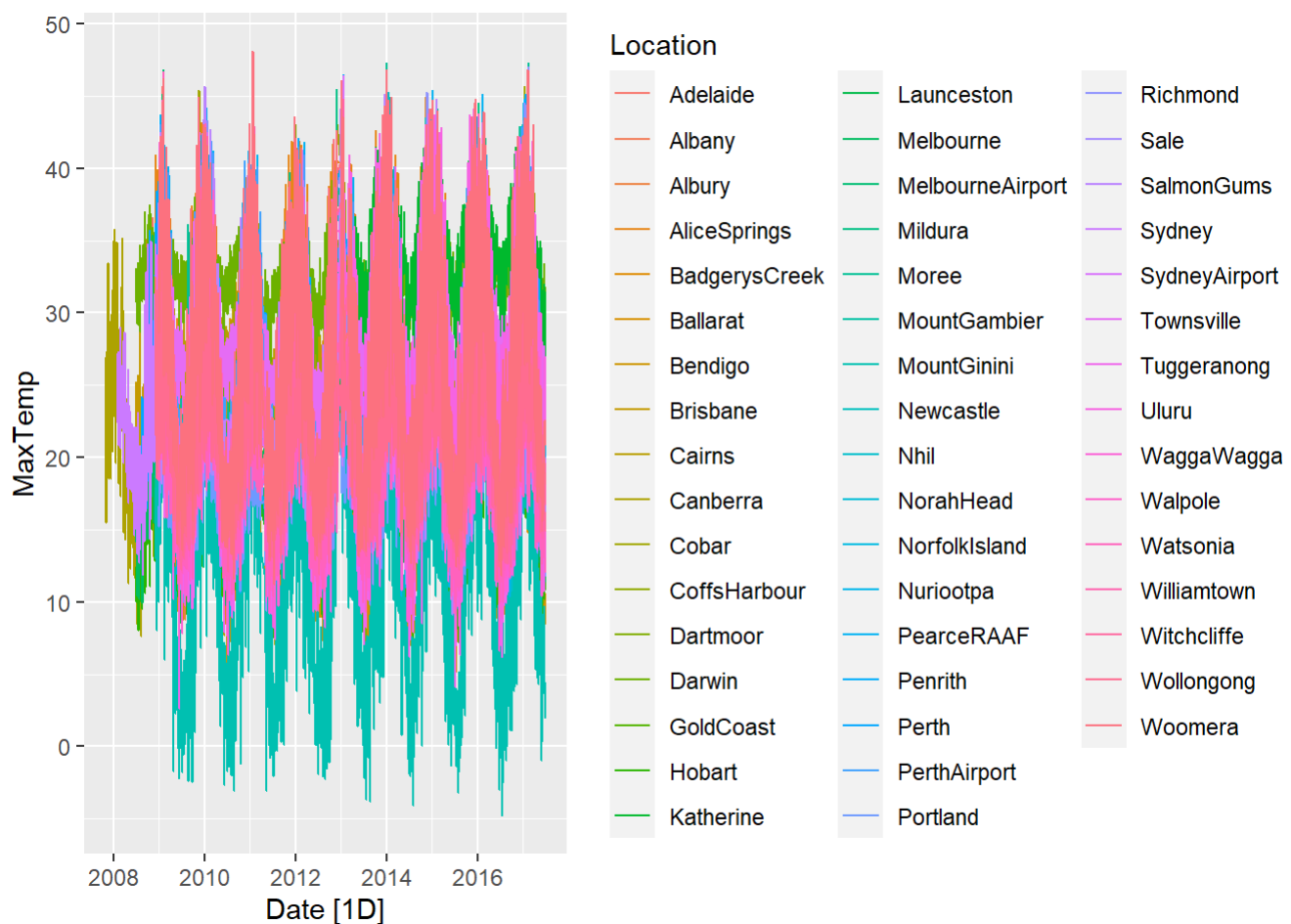
AUS_Final <- AUS4 %>%
  as_tsibble(index = Date, key = Location)

```

EXPLORATORY ANALYSIS AND VISUALIZATION FOR THE DATASET

Visualize the dataset and comment on characteristics of time series

```
AUS_Final %>% autoplot(MaxTemp)
```

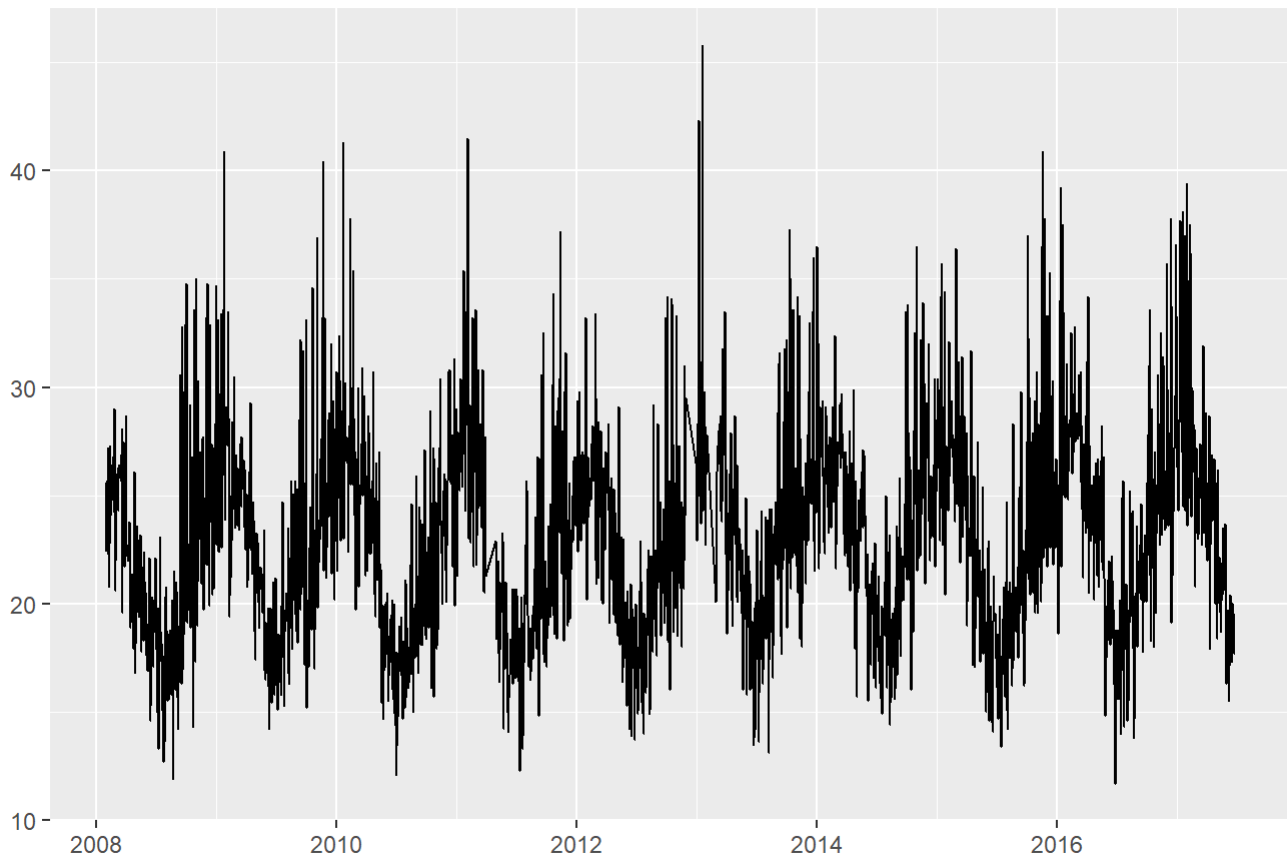


```
# Since there are so many different locations, it makes the plot hard to read. To fix this problem
# we will turn our focus on the largest city, Sydney, to further look for seasonality.

Sydney <- AUS_Final %>%
  filter(Location == "Sydney")

Sydney %>%
  autoplot(MaxTemp) + labs(title = "Temperature Highs in Sydney (degrees celsius)", x = " ", y =
" ")
```

Temperature Highs in Sydney (degrees celsius)



Comment on any anomalies in the data

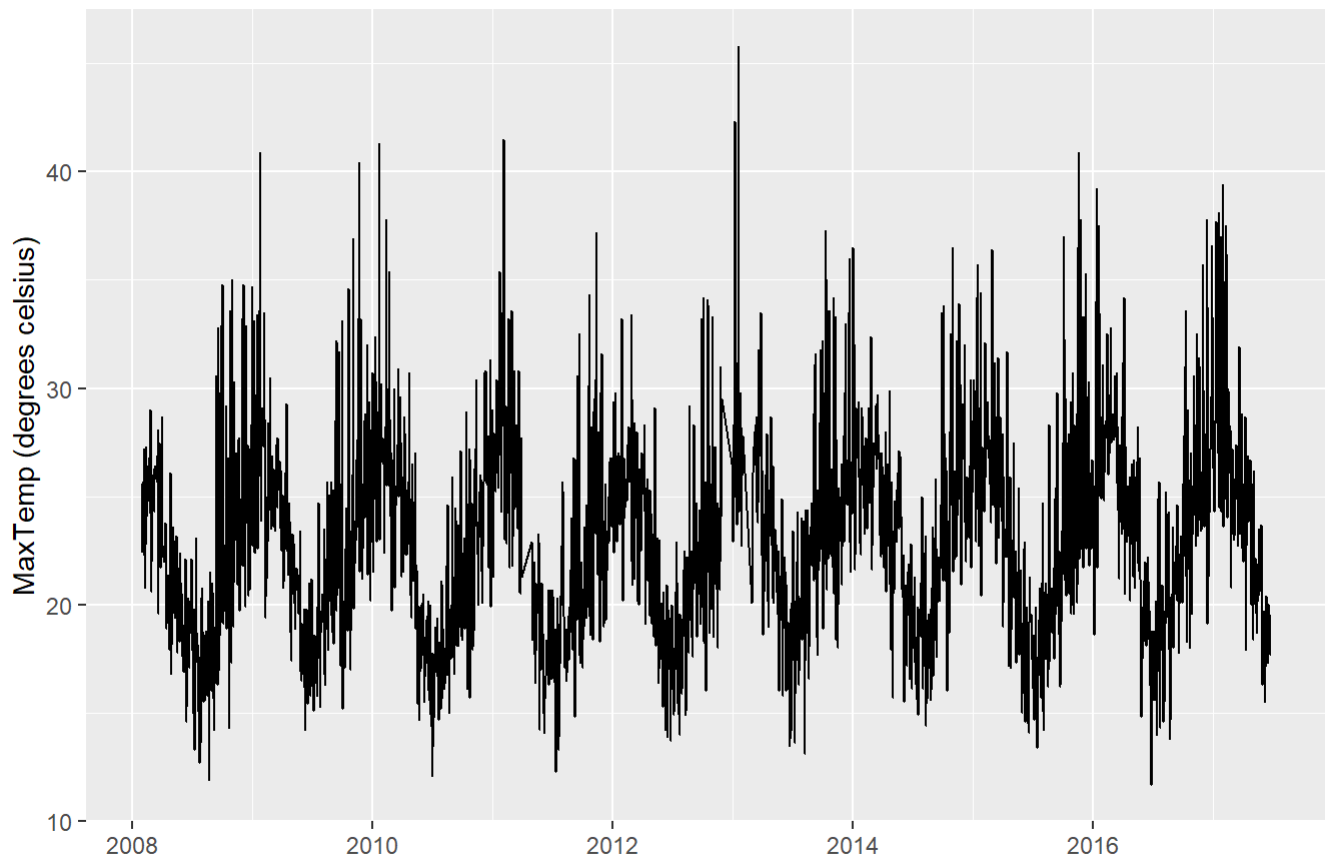
It looks like there is a huge spike upwards in temperature in Jan 2013. There are also some abnormally low drops in temperature in may/june of 2016.

Describe trend/seasonality/cycles with supporting charts:

Trend

```
Sydney %>%
  autoplot(MaxTemp) + labs(y = "MaxTemp (degrees celsius)", x = " ", title = "Temperature in Sydney")
```

Temperature in Sydney



There is no apparent trend in Temperature.

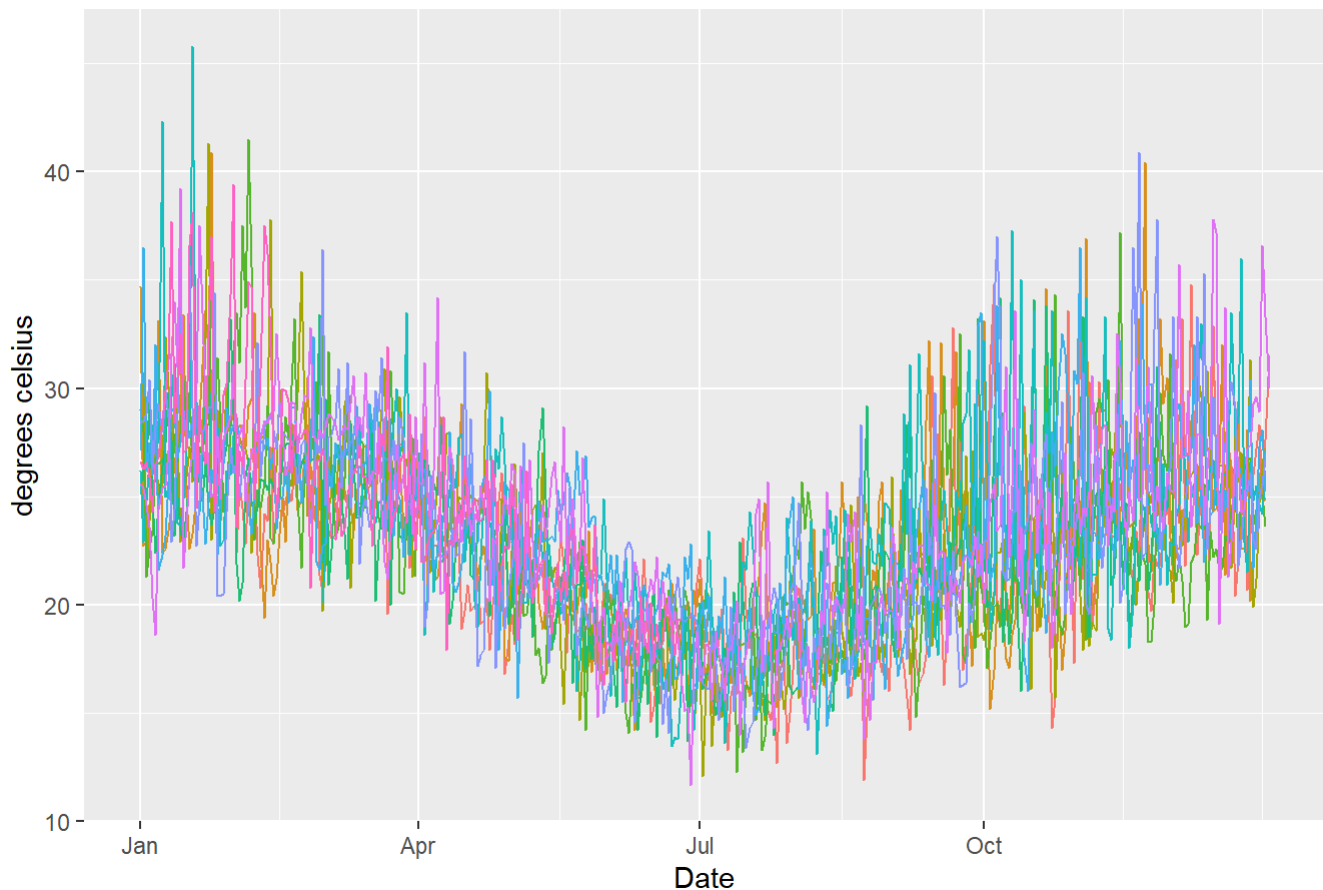
Seasonality

```
Syd_Fill <- Sydney %>% fill_gaps()

Syd_Fill %>% gg_season(MaxTemp, period = "year") +
  theme(legend.position = "none") +
  labs(y="degrees celsius", title="Seasonality of Temp in Sydney")
```

```
## Warning: Removed 31 rows containing missing values (`geom_line()`).
```

Seasonality of Temp in Sydney

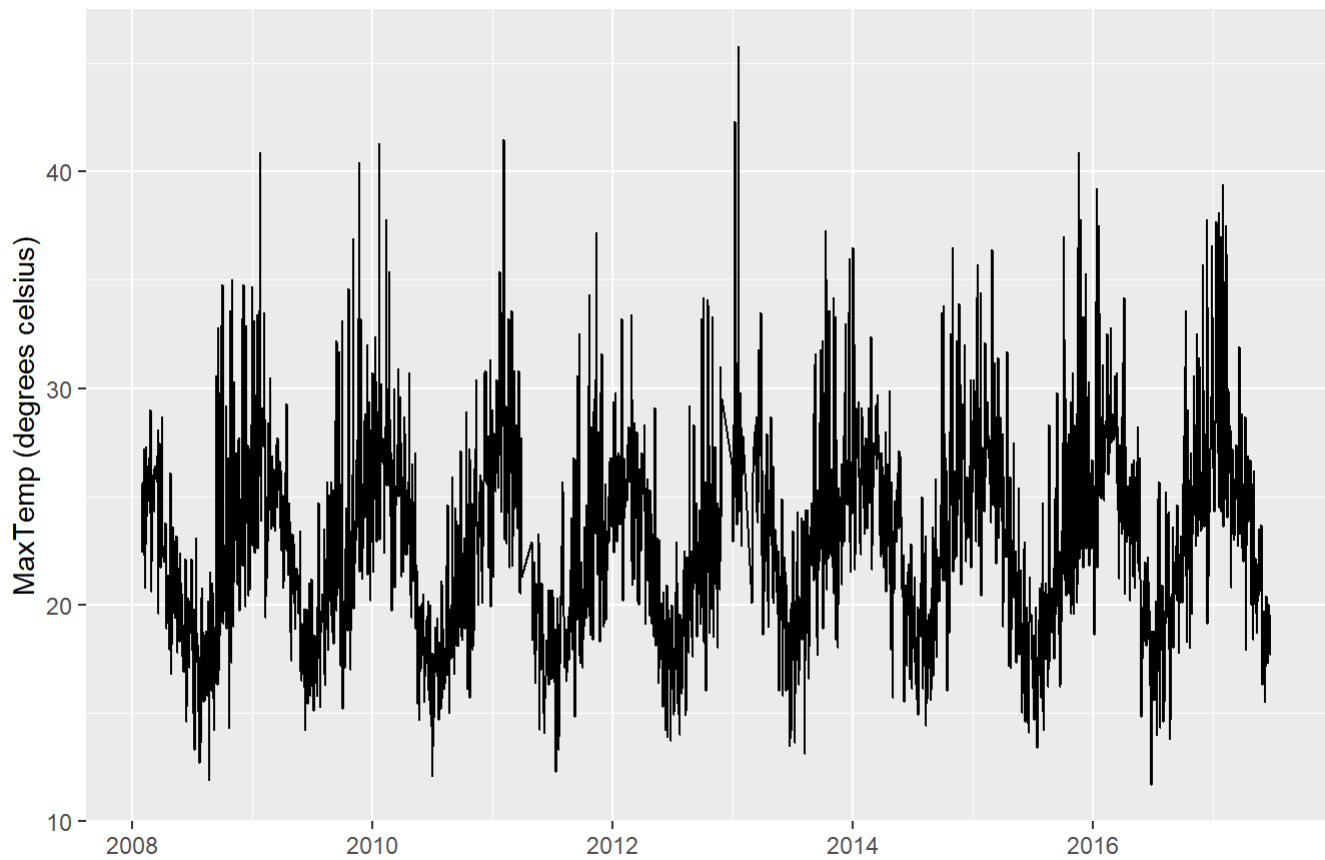


There is a very apparent season trend in the Temperature in Sydney. It starts off with the hottest temperatures in January and February, and then stays warm until the start of a slow decline in temperature in April. The decline in temperature continues until July where we see the lowest temperatures. The temperature then slowly increases until November where it stays very warm through December going into the next year.

Cycles

```
Sydney %>%  
  autoplot(MaxTemp) + labs(y = "MaxTemp (degrees celsius)", x = " ", title = "Temperature in Sydney")
```

Temperature in Sydney



There is no evidence of any cyclic behavior here.

MODEL FITTING

Split dataset into training and test sets

```
View(Sydney)
train <- Syd_Fill %>%
  filter(year(Date) < '2015-01-01')
test <- Syd_Fill %>%
  filter(year(Date) >= '2015-01-01')
```

```
train$MaxTemp[is.na(train$MaxTemp)] <- median(train$MaxTemp,na.rm=TRUE)
train$Rainfall[is.na(train$Rainfall)] <- median(train$Rainfall,na.rm=TRUE)
train$Evaporation[is.na(train$Evaporation)] <- median(train$Evaporation,na.rm=TRUE)
train$Sunshine[is.na(train$Sunshine)] <- median(train$Sunshine,na.rm=TRUE)
train$WindGustSpeed[is.na(train$WindGustSpeed)] <- median(train$WindGustSpeed,na.rm=TRUE)
train$WindSpeed9am[is.na(train$WindSpeed9am)] <- median(train$WindSpeed9am,na.rm=TRUE)
train$WindSpeed3pm[is.na(train$WindSpeed3pm)] <- median(train$WindSpeed3pm,na.rm=TRUE)
train$Humidity9am[is.na(train$Humidity9am)] <- median(train$Humidity9am,na.rm=TRUE)
train$Humidity3pm[is.na(train$Humidity3pm)] <- median(train$Humidity3pm,na.rm=TRUE)
train$Pressure9am[is.na(train$Pressure9am)] <- median(train$Pressure9am,na.rm=TRUE)
train$Pressure3pm[is.na(train$Pressure3pm)] <- median(train$Pressure3pm,na.rm=TRUE)
train$Cloud9am[is.na(train$Cloud9am)] <- median(train$Cloud9am,na.rm=TRUE)
train$Cloud3pm[is.na(train$Cloud3pm)] <- median(train$Cloud3pm,na.rm=TRUE)
train$Year[is.na(train$Year)] <- median(train$Year,na.rm=TRUE)
train$Month[is.na(train$Month)] <- median(train$Month,na.rm=TRUE)
train$TempDiff[is.na(train$TempDiff)] <- median(train$TempDiff,na.rm=TRUE)
train$RainToday_1[is.na(train$RainToday_1)] <- median(train$RainToday_1,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainToday_1`.
## Unknown or uninitialised column: `RainToday_1`.
## Unknown or uninitialised column: `RainToday_1`.
```

```
train$RainToday_2[is.na(train$RainToday_2)] <- median(train$RainToday_2,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainToday_2`.
```

```
## Warning: Unknown or uninitialised column: `RainToday_2`.
## Unknown or uninitialised column: `RainToday_2`.
```

```
train$RainToday_Unknown[is.na(train$RainToday_Unknown)] <- median(train$RainToday_Unknown,na.rm=
TRUE)
train$RainTomorrow_1[is.na(train$RainTomorrow_1)] <- median(train$RainTomorrow_1,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_1`.
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_1`.
## Unknown or uninitialised column: `RainTomorrow_1`.
```

```
train$RainTomorrow_2[is.na(train$RainTomorrow_2)] <- median(train$RainTomorrow_2,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_2`.
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_2`.
## Unknown or uninitialised column: `RainTomorrow_2`.
```



```
train$RainTomorrow_Unknown[is.na(train$RainTomorrow_Unknown)] <- median(train$RainTomorrow_Unkno  
wn,na.rm=TRUE)
```

```
summary(train)
```

```

##      Date      Location      MaxTemp      Rainfall
##  Min.   :2008-02-01  Length:2891  Min.   :11.90  Min.   : 0.000
##  1st Qu.:2010-01-23  Class :character  1st Qu.:19.60  1st Qu.: 0.000
##  Median :2012-01-16  Mode  :character  Median :22.60  Median : 0.000
##  Mean   :2012-01-16                      Mean   :22.78  Mean   : 3.059
##  3rd Qu.:2014-01-07                      3rd Qu.:25.60  3rd Qu.: 1.000
##  Max.   :2015-12-31                      Max.   :45.80  Max.   :119.400
##
##  Evaporation      Sunshine      WindGustSpeed      WindSpeed9am
##  Min.   : 0.000    Min.   : 0.000    Min.   :17.00    Min.   : 0.00
##  1st Qu.: 3.200    1st Qu.: 4.400    1st Qu.:37.00    1st Qu.:11.00
##  Median : 4.800    Median : 8.300    Median :39.00    Median :15.00
##  Mean   : 5.084    Mean   : 7.203    Mean   :40.77    Mean   :15.01
##  3rd Qu.: 6.800    3rd Qu.:10.100    3rd Qu.:43.00    3rd Qu.:20.00
##  Max.   :18.400    Max.   :13.600    Max.   :96.00    Max.   :54.00
##
##  WindSpeed3pm      Humidity9am      Humidity3pm      Pressure9am
##  Min.   : 0.00    Min.   : 19.00    Min.   :10.00    Min.   : 986.7
##  1st Qu.:15.00    1st Qu.: 59.00    1st Qu.:45.00    1st Qu.:1014.1
##  Median :19.00    Median : 70.00    Median :56.00    Median :1018.6
##  Mean   :19.31    Mean   : 68.78    Mean   :55.01    Mean   :1018.4
##  3rd Qu.:24.00    3rd Qu.: 80.00    3rd Qu.:64.00    3rd Qu.:1023.1
##  Max.   :50.00    Max.   :100.00    Max.   :99.00    Max.   :1038.8
##
##  Pressure3pm      Cloud9am      Cloud3pm      Year
##  Min.   : 989.8    Min.   :0.000    Min.   :0.000    Min.   :2008
##  1st Qu.:1011.6    1st Qu.:2.000    1st Qu.:2.000    1st Qu.:2010
##  Median :1016.3    Median :5.000    Median :5.000    Median :2012
##  Mean   :1016.1    Mean   :4.338    Mean   :4.379    Mean   :2012
##  3rd Qu.:1020.8    3rd Qu.:7.000    3rd Qu.:6.000    3rd Qu.:2014
##  Max.   :1036.7    Max.   :9.000    Max.   :8.000    Max.   :2015
##
##  Month      TempDiff      RainToday_No      RainToday_Unknown
##  Min.   : 1.000    Min.   : 0.200    Min.   :0.0000    Min.   :0.000000
##  1st Qu.: 4.000    1st Qu.: 6.100    1st Qu.:0.0000    1st Qu.:0.000000
##  Median : 7.000    Median : 8.000    Median :1.0000    Median :0.000000
##  Mean   : 6.608    Mean   : 8.116    Mean   :0.7402    Mean   :0.002421
##  3rd Qu.: 9.000    3rd Qu.:10.000    3rd Qu.:1.0000    3rd Qu.:0.000000
##  Max.   :12.000    Max.   :24.100    Max.   :1.0000    Max.   :1.000000
##
##  RainToday_Yes      RainTomorrow_No      RainTomorrow_Unknown      RainTomorrow_Yes
##  Min.   :0.0000    Min.   :0.0000    Min.   :0.000000    Min.   :0.000
##  1st Qu.:0.0000    1st Qu.:0.0000    1st Qu.:0.000000    1st Qu.:0.000
##  Median :0.0000    Median :1.0000    Median :0.000000    Median :0.000
##  Mean   :0.2573    Mean   :0.7405    Mean   :0.002421    Mean   :0.257
##  3rd Qu.:1.0000    3rd Qu.:1.0000    3rd Qu.:0.000000    3rd Qu.:1.000
##  Max.   :1.0000    Max.   :1.0000    Max.   :1.000000    Max.   :1.000
##  NA's   :89      NA's   :89      NA's   :89

```

```
test$MaxTemp[is.na(test$MaxTemp)] <- median(test$MaxTemp,na.rm=TRUE)
test$Rainfall[is.na(test$Rainfall)] <- median(test$Rainfall,na.rm=TRUE)
test$Evaporation[is.na(test$Evaporation)] <- median(test$Evaporation,na.rm=TRUE)
test$Sunshine[is.na(test$Sunshine)] <- median(test$Sunshine,na.rm=TRUE)
test$WindGustSpeed[is.na(test$WindGustSpeed)] <- median(test$WindGustSpeed,na.rm=TRUE)
test$WindSpeed9am[is.na(test$WindSpeed9am)] <- median(test$WindSpeed9am,na.rm=TRUE)
test$WindSpeed3pm[is.na(test$WindSpeed3pm)] <- median(test$WindSpeed3pm,na.rm=TRUE)
test$Humidity9am[is.na(test$Humidity9am)] <- median(test$Humidity9am,na.rm=TRUE)
test$Humidity3pm[is.na(test$Humidity3pm)] <- median(test$Humidity3pm,na.rm=TRUE)
test$Pressure9am[is.na(test$Pressure9am)] <- median(test$Pressure9am,na.rm=TRUE)
test$Pressure3pm[is.na(test$Pressure3pm)] <- median(test$Pressure3pm,na.rm=TRUE)
test$Cloud9am[is.na(test$Cloud9am)] <- median(test$Cloud9am,na.rm=TRUE)
test$Cloud3pm[is.na(test$Cloud3pm)] <- median(test$Cloud3pm,na.rm=TRUE)
test$Year[is.na(test$Year)] <- median(test$Year,na.rm=TRUE)
test$Month[is.na(test$Month)] <- median(test$Month,na.rm=TRUE)
test$TempDiff[is.na(test$TempDiff)] <- median(test$TempDiff,na.rm=TRUE)
test$RainToday_1[is.na(test$RainToday_1)] <- median(test$RainToday_1,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainToday_1`.
```

```
## Warning: Unknown or uninitialised column: `RainToday_1`.
## Unknown or uninitialised column: `RainToday_1`.
```

```
test$RainToday_2[is.na(test$RainToday_2)] <- median(test$RainToday_2,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainToday_2`.
```

```
## Warning: Unknown or uninitialised column: `RainToday_2`.
## Unknown or uninitialised column: `RainToday_2`.
```

```
test$RainToday_Unknown[is.na(test$RainToday_Unknown)] <- median(test$RainToday_Unknown,na.rm=TRUE)
test$RainTomorrow_1[is.na(test$RainTomorrow_1)] <- median(test$RainTomorrow_1,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_1`.
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_1`.
## Unknown or uninitialised column: `RainTomorrow_1`.
```

```
test$RainTomorrow_2[is.na(test$RainTomorrow_2)] <- median(test$RainTomorrow_2,na.rm=TRUE)
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_2`.
```

```
## Warning: Unknown or uninitialised column: `RainTomorrow_2`.  
## Unknown or uninitialised column: `RainTomorrow_2`.
```

```
test$RainTomorrow_Unknown[is.na(test$RainTomorrow_Unknown)] <- median(test$RainTomorrow_Unknown,  
na.rm=TRUE)  
  
summary(test)
```

```
##      Date      Location      MaxTemp      Rainfall
## Min.      :2016-01-01  Length:542      Min.      :11.70  Min.      : 0.000
## 1st Qu.:2016-05-15  Class :character  1st Qu.:20.60  1st Qu.: 0.000
## Median :2016-09-27  Mode  :character  Median :24.20  Median : 0.000
## Mean      :2016-09-27      Mean      :24.11  Mean      : 4.154
## 3rd Qu.:2017-02-09      3rd Qu.:27.00  3rd Qu.: 1.400
## Max.      :2017-06-25      Max.      :39.40  Max.      :94.400
##      Evaporation      Sunshine      WindGustSpeed      WindSpeed9am
## Min.      : 0.00  Min.      : 0.000  Min.      :19.00  Min.      : 0.00
## 1st Qu.: 3.40  1st Qu.: 4.500  1st Qu.:31.00  1st Qu.:11.00
## Median : 5.20  Median : 8.400  Median :39.00  Median :15.00
## Mean      : 5.65  Mean      : 7.272  Mean      :41.28  Mean      :15.29
## 3rd Qu.: 7.80  3rd Qu.:10.100  3rd Qu.:49.50  3rd Qu.:20.00
## Max.      :15.80  Max.      :13.500  Max.      :96.00  Max.      :44.00
##      WindSpeed3pm      Humidity9am      Humidity3pm      Pressure9am
## Min.      : 2.00  Min.      :21.00  Min.      :14.00  Min.      : 998.3
## 1st Qu.:15.00  1st Qu.:56.00  1st Qu.:43.00  1st Qu.:1013.2
## Median :19.00  Median :66.00  Median :54.00  Median :1018.0
## Mean      :19.36  Mean      :65.57  Mean      :53.14  Mean      :1017.9
## 3rd Qu.:24.00  3rd Qu.:76.00  3rd Qu.:62.75  3rd Qu.:1022.6
## Max.      :57.00  Max.      :92.00  Max.      :91.00  Max.      :1039.0
##      Pressure3pm      Cloud9am      Cloud3pm      Year      Month
## Min.      : 994  Min.      :0.000  Min.      :0.000  Min.      :2016  Min.      : 1.000
## 1st Qu.:1011  1st Qu.:1.000  1st Qu.:2.000  1st Qu.:2016  1st Qu.: 3.000
## Median :1016  Median :5.000  Median :4.500  Median :2016  Median : 5.000
## Mean      :1015  Mean      :4.332  Mean      :4.304  Mean      :2016  Mean      : 5.515
## 3rd Qu.:1020  3rd Qu.:7.000  3rd Qu.:7.000  3rd Qu.:2017  3rd Qu.: 8.000
## Max.      :1036  Max.      :8.000  Max.      :8.000  Max.      :2017  Max.      :12.000
##      TempDiff      RainToday_No      RainToday_Unknown  RainToday_Yes
## Min.      : 0.400  Min.      :0.0000  Min.      :0      Min.      :0.0000
## 1st Qu.: 6.400  1st Qu.:0.0000  1st Qu.:0      1st Qu.:0.0000
## Median : 8.150  Median :1.0000  Median :0      Median :0.0000
## Mean      : 8.232  Mean      :0.7325  Mean      :0      Mean      :0.2675
## 3rd Qu.:10.200  3rd Qu.:1.0000  3rd Qu.:0      3rd Qu.:1.0000
## Max.      :17.100  Max.      :1.0000  Max.      :0      Max.      :1.0000
##      RainTomorrow_No  RainTomorrow_Unknown  RainTomorrow_Yes
## Min.      :0.0000  Min.      :0      Min.      :0.0000
## 1st Qu.:0.0000  1st Qu.:0      1st Qu.:0.0000
## Median :1.0000  Median :0      Median :0.0000
## Mean      :0.7325  Mean      :0      Mean      :0.2675
## 3rd Qu.:1.0000  3rd Qu.:0      3rd Qu.:1.0000
## Max.      :1.0000  Max.      :0      Max.      :1.0000
```

```
test <- test %>%
  as_tsibble(index = Date, key = NULL)
train <- train %>%
  as_tsibble(index = Date, key = NULL)
```

I chose to split the data at the year 2015 because it is close to 80% of the records in the training set and 20% of the records into the test set.

Fit TSLM, ETS and ARIMA model(s):

TSLM and ETS

```
TSLM_ETS_Models <- train %>%
  model(
    TSLM = TSLM(MaxTemp ~ trend()),
    SES = ETS(log(MaxTemp) ~ error("A") + trend("N") + season("N")),
    Holt = ETS(log(MaxTemp) ~ error("A") + trend("A") + season("N")),
    Damped = ETS(log(MaxTemp) ~ error("A") + trend("Ad") + season("N")),
    Additive = ETS(log(MaxTemp) ~ error("A") + trend("A") + season("A")),
    Multiplicative = ETS(log(MaxTemp) ~ error("M") + trend("A") + season("M"))
  )

glance(TSLM_ETS_Models)
```

```
## # A tibble: 6 × 18
##   .model  r_squa...1 adj_r_...2 sigma2 stati...3 p_value    df log_lik    AIC    AICc
##   <chr>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl> <int>  <dbl>  <dbl>  <dbl>
## 1 TSLM      0.00535    0.00500  1.89e+1    15.5  8.32e-5     2  -8352.  8507.  8507.
## 2 SES       NA         NA      1.66e-2    NA   NA          NA  -5597. 11200. 11200.
## 3 Holt      NA         NA      1.67e-2    NA   NA          NA  -5606. 11221. 11221.
## 4 Damped    NA         NA      1.67e-2    NA   NA          NA  -5605. 11222. 11222.
## 5 Additi... NA         NA      1.67e-2    NA   NA          NA  -5598. 11220. 11220.
## 6 Multip... NA         NA      1.72e-3    NA   NA          NA  -5587. 11198. 11199.
## # ... with 8 more variables: BIC <dbl>, CV <dbl>, deviance <dbl>,
## #   df.residual <int>, rank <int>, MSE <dbl>, AMSE <dbl>, MAE <dbl>, and
## #   abbreviated variable names 1r_squared, 2adj_r_squared, 3statistic
```

The lowest AICc of the TSLM and different ETS models is the TSLM model at 8507.

ARIMA

```
# Check for stationarity
```

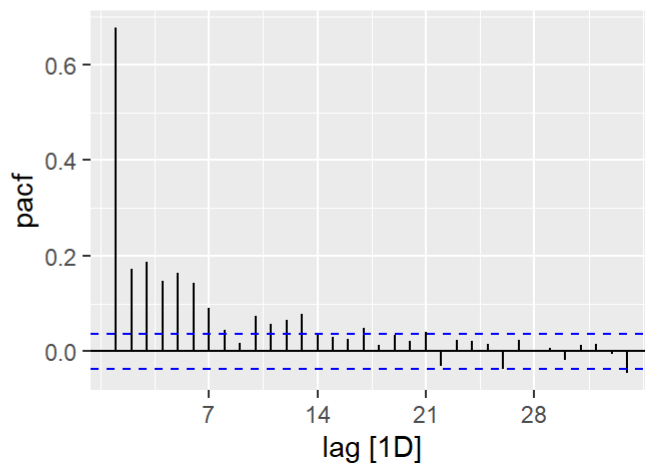
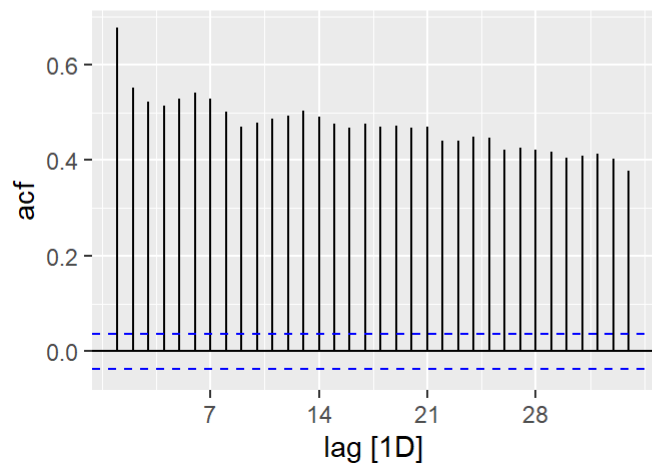
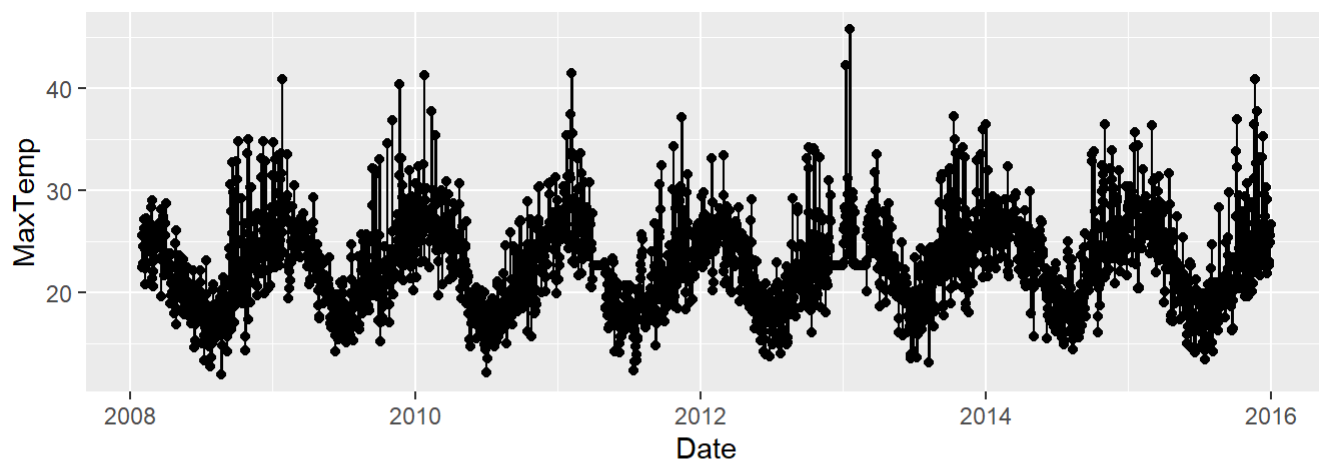
```
train %>% features(MaxTemp, unitroot_nsdiffs)
```

```
## # A tibble: 1 × 1
##   nsdiffs
##   <int>
## 1      0
```

```
# 0 nsdiffs recommended therefore data is stationary and we can continue with ARIMA model
```

```
# Plot ACF and PACF
```

```
train %>% gg_tsdisplay(MaxTemp, plot_type = 'partial')
```



PACF dies in somewhat sine wave manner but acf does not die out at all. Therefore there is no clear ar or

ma choice based on the ACF and PACF plot.

Create ARIMA models

```
ARIMA_Models <- train %>%
  model(
    arima_auto = ARIMA(MaxTemp),
    automatic_exhaustive = ARIMA(MaxTemp, stepwise = FALSE), #exhaustive search
    automatic_no_seas_exhaustive = ARIMA(MaxTemp ~ PDQ(0, 0, 0), stepwise = FALSE), #exhaustive search no seasonal differences
    automatic_no_seas = ARIMA(MaxTemp ~ PDQ(0,0,0)) #fable algorithm no seasonal differencing
  )

glance(ARIMA_Models)
```

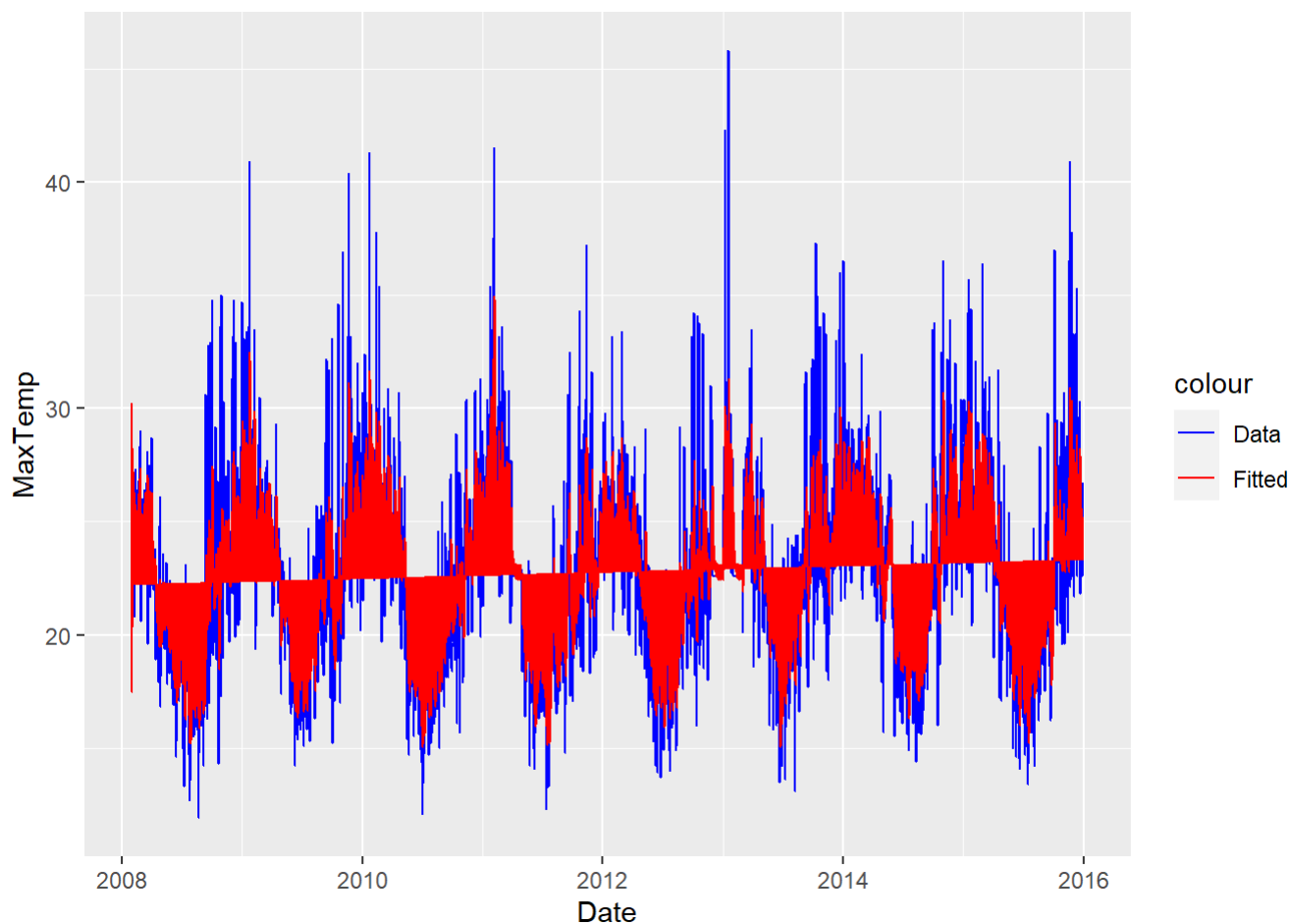
```
## # A tibble: 4 × 8
##   .model          sigma2 log_lik    AIC    AICc    BIC ar_ro...1 ma_ro...2
##   <chr>          <dbl>   <dbl> <dbl> <dbl> <dbl> <list> <list>
## 1 arima_auto      8.77  -7238. 14491. 14491. 14539. <cpl> <cpl>
## 2 automatic_exhaustive 8.77  -7238. 14491. 14491. 14539. <cpl> <cpl>
## 3 automatic_no_seas_exhaust... 8.78  -7239. 14495. 14495. 14543. <cpl> <cpl>
## 4 automatic_no_seas    9.41  -7341. 14691. 14691. 14714. <cpl> <cpl>
## # ... with abbreviated variable names 1ar_roots, 2ma_roots
```

Lowest AICc of ARIMA models is arima_auto with 14491

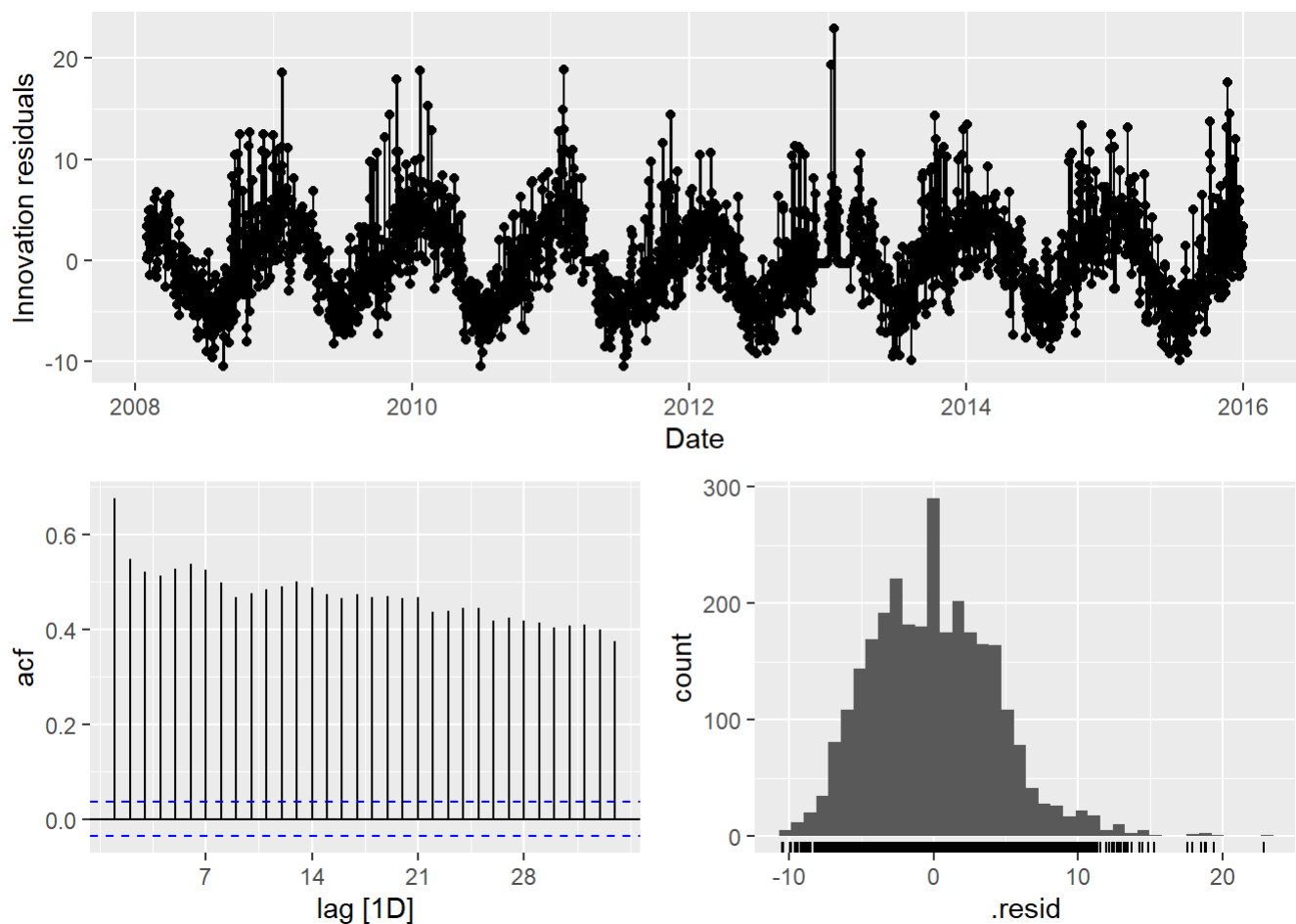
Evaluate residuals of TSLM, ETS, and ARIMA models:

TSLM and ETS residuals

```
aug_TSLM_ETS <- augment(TSLM_ETS_Models)
aug_TSLM_ETS %>%
  ggplot(aes(x = Date)) +
  geom_line(aes(y = MaxTemp, color = "Data")) +
  geom_line(aes(y = .fitted, color = "Fitted")) +
  scale_color_manual(values = c(Data = "Blue", Fitted = "Red"))
```



```
# Using best model for gg_tsresiduals()
TSLM_ETS_Models %>% select(TSLM) %>% gg_tsresiduals()
```

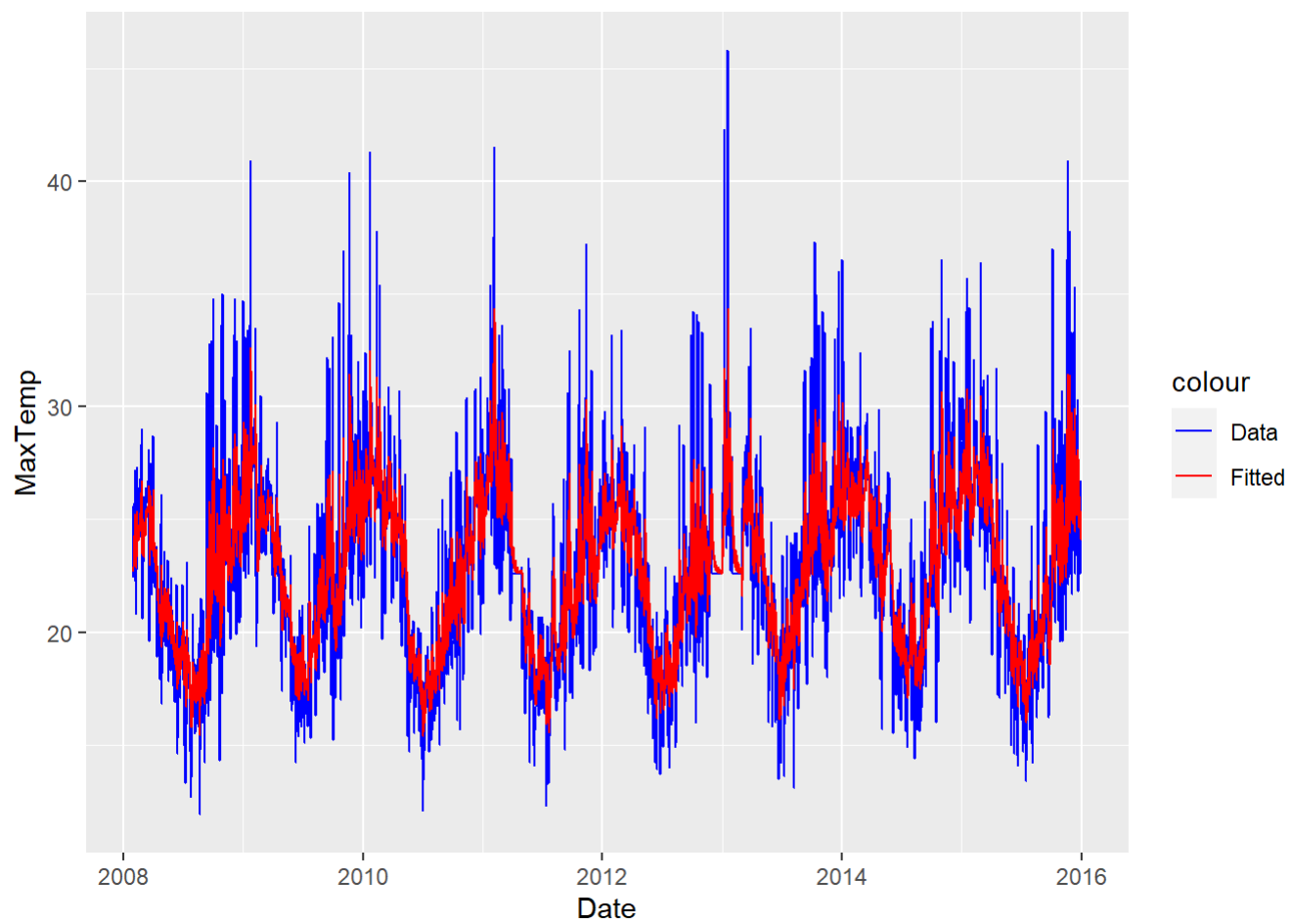
```
# Check if residuals are stationary
aug_TSLM_ETS %>% features(.innov, unitroot_kpss)
```

```
## # A tibble: 6 × 3
##   .model      kpss_stat kpss_pvalue
##   <chr>      <dbl>      <dbl>
## 1 Additive    0.0198      0.1
## 2 Damped     0.117       0.1
## 3 Holt       0.0145      0.1
## 4 Multiplicative 0.0398      0.1
## 5 SES        0.0140      0.1
## 6 TSLM       0.123       0.1
```

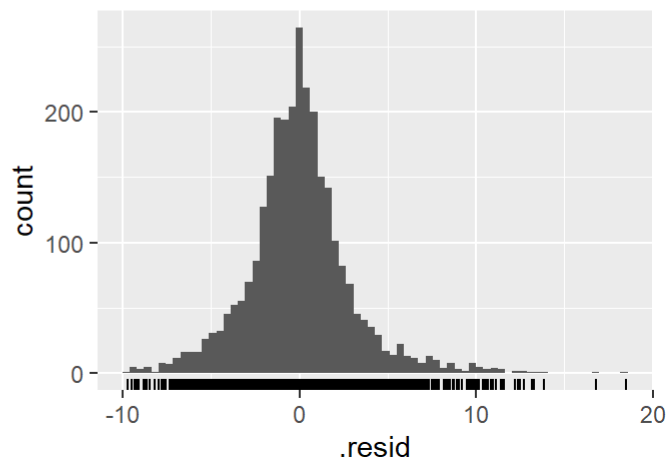
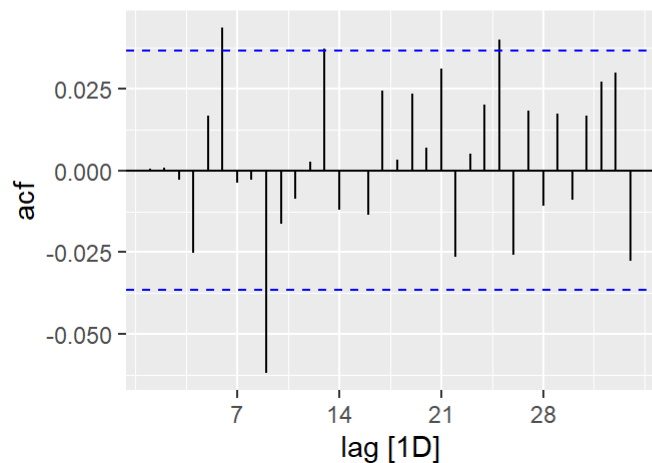
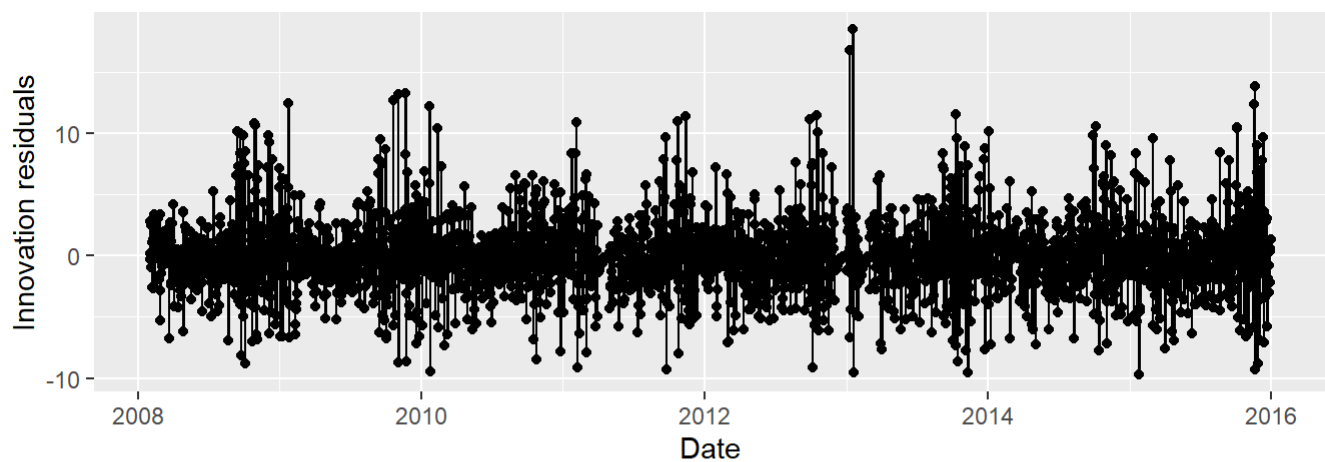
Because the model residuals each have a p-value of 0.1, this means that they are all stationary.

ARIMA residuals

```
aug_ARIMA <- augment(ARIMA_Models)
aug_ARIMA %>%
  ggplot(aes(x = Date)) +
  geom_line(aes(y = MaxTemp, color = "Data")) +
  geom_line(aes(y = .fitted, color = "Fitted")) +
  scale_color_manual(values = c(Data = "Blue", Fitted = "Red"))
```



```
# Using best model for gg_tsresiduals()  
ARIMA_Models %>% select(arima_auto) %>% gg_tsresiduals()
```



```
# Check if residuals are stationary
aug_ARIMA %>% features(.innov, unitroot_kpss)
```

```
## # A tibble: 4 × 3
##   .model                kpss_stat kpss_pvalue
##   <chr>                 <dbl>     <dbl>
## 1 arima_auto            0.0553      0.1
## 2 automatic_exhaustive  0.0553      0.1
## 3 automatic_no_seas     0.0765      0.1
## 4 automatic_no_seas_exhaustive 0.0549      0.1
```

Because the model residuals each have a p-value of 0.1, this means that they are all stationary.

If there are predictor variables – fit a TSLM with predictor variables, Regression with ARIMA errors:

TSLM with Predictor Variables

```

TSLM_Predictors <- train %>%
  model(
    lm = TSLM(MaxTemp ~ TempDiff),
    lm2 = TSLM(MaxTemp ~ TempDiff + Rainfall),
    lm3 = TSLM(MaxTemp ~ Evaporation + Humidity3pm + Cloud3pm),
    lm4 = TSLM(MaxTemp ~ Humidity9am + Humidity3pm + Pressure9am + Pressure3pm + TempDiff),
    lm5 = TSLM(MaxTemp ~ Humidity9am + Humidity3pm + Pressure9am + Pressure3pm),
    lm6 = TSLM(MaxTemp ~ Rainfall + Evaporation + Humidity9am + Humidity3pm),
    lm7 = TSLM(MaxTemp ~ Sunshine + Humidity9am + Humidity3pm),
    lm8 = TSLM(MaxTemp ~ Sunshine + Cloud9am + Cloud3pm + TempDiff),
    lm9 = TSLM(MaxTemp ~ TempDiff + Sunshine + Evaporation + Humidity9am + Humidity3pm + Pressur
e9am +
              Pressure3pm + Rainfall)
  )

glance(TSLM_Predictors)

```

```

## # A tibble: 9 × 15
##   .model r_squared adj_r_sq...1 sigma2 stati...2 p_value    df log_lik    AIC    AICc
##   <chr>      <dbl>      <dbl> <dbl>    <dbl>    <dbl> <int>  <dbl> <dbl> <dbl>
## 1 lm        0.106      0.106  17.0    343. 1.69e- 72    2  -8198.  8198.  8198.
## 2 lm2       0.112      0.112  16.9    183. 1.60e- 75    3  -8188.  8179.  8179.
## 3 lm3       0.262      0.261  14.1    341. 1.11e-189    4  -7921.  7649.  7649.
## 4 lm4       0.289      0.288  13.5    235. 7.69e-211    6  -7867.  7543.  7543.
## 5 lm5       0.200      0.199  15.2    181. 2.03e-138    5  -8037.  7882.  7882.
## 6 lm6       0.282      0.281  13.7    283. 1.34e-205    5  -7882.  7571.  7571.
## 7 lm7       0.114      0.113  16.9    124. 1.33e- 75    4  -8185.  8176.  8176.
## 8 lm8       0.181      0.180  15.6    160. 1.11e-123    5  -8071.  7950.  7950.
## 9 lm9       0.533      0.531   8.92   410. 0                9  -7261.  6337.  6337.
## # ... with 5 more variables: BIC <dbl>, CV <dbl>, deviance <dbl>,
## #   df.residual <int>, rank <int>, and abbreviated variable names
## #   1adj_r_squared, 2statistic

```

Lowest AICc is lm9 with 6337.

ARIMA with Errors

```

ARIMA_Errors <- train %>%
  model(
    ARIMA1 = ARIMA(MaxTemp ~ TempDiff),
    ARIMA2 = ARIMA(MaxTemp ~ TempDiff + Rainfall),
    ARIMA3 = ARIMA(MaxTemp ~ Evaporation + Humidity3pm + Cloud3pm),
    ARIMA4 = ARIMA(MaxTemp ~ Humidity9am + Humidity3pm + Pressure9am + Pressure3pm + TempDiff),
    ARIMA5 = ARIMA(MaxTemp ~ Humidity9am + Humidity3pm + Pressure9am + Pressure3pm),
    ARIMA6 = ARIMA(MaxTemp ~ Rainfall + Evaporation + Humidity9am + Humidity3pm),
    ARIMA7 = ARIMA(MaxTemp ~ Sunshine + Humidity9am + Humidity3pm),
    ARIMA8 = ARIMA(MaxTemp ~ Sunshine + Cloud9am + Cloud3pm + TempDiff),
    ARIMA9 = ARIMA(MaxTemp ~ TempDiff + Sunshine + Evaporation + Humidity9am + Humidity3pm + Press
ure9am +
      Pressure3pm + Rainfall)
  )
glance(ARIMA_Errors)

```

```

## # A tibble: 9 × 8
##   .model sigma2 log_lik    AIC    AICc    BIC ar_roots  ma_roots
##   <chr>   <dbl>   <dbl> <dbl> <dbl> <dbl> <list>   <list>
## 1 ARIMA1    3.14  -5753. 11522. 11522. 11570. <cpl [1]> <cpl [16]>
## 2 ARIMA2    3.13  -5749. 11515. 11516. 11569. <cpl [1]> <cpl [16]>
## 3 ARIMA3    6.71  -6851. 13724. 13724. 13789. <cpl [8]> <cpl [16]>
## 4 ARIMA4    2.43  -5380. 10785. 10785. 10857. <cpl [1]> <cpl [4]>
## 5 ARIMA5    5.41  -6537. 13095. 13095. 13154. <cpl [3]> <cpl [2]>
## 6 ARIMA6    6.68  -6843. 13708. 13708. 13774. <cpl [8]> <cpl [9]>
## 7 ARIMA7    6.50  -6805. 13630. 13630. 13690. <cpl [8]> <cpl [9]>
## 8 ARIMA8    3.09  -5728. 11478. 11478. 11543. <cpl [1]> <cpl [16]>
## 9 ARIMA9    2.39  -5354. 10738. 10738. 10827. <cpl [1]> <cpl [4]>

```

The lowest AICc is ARIMA9 with 10738

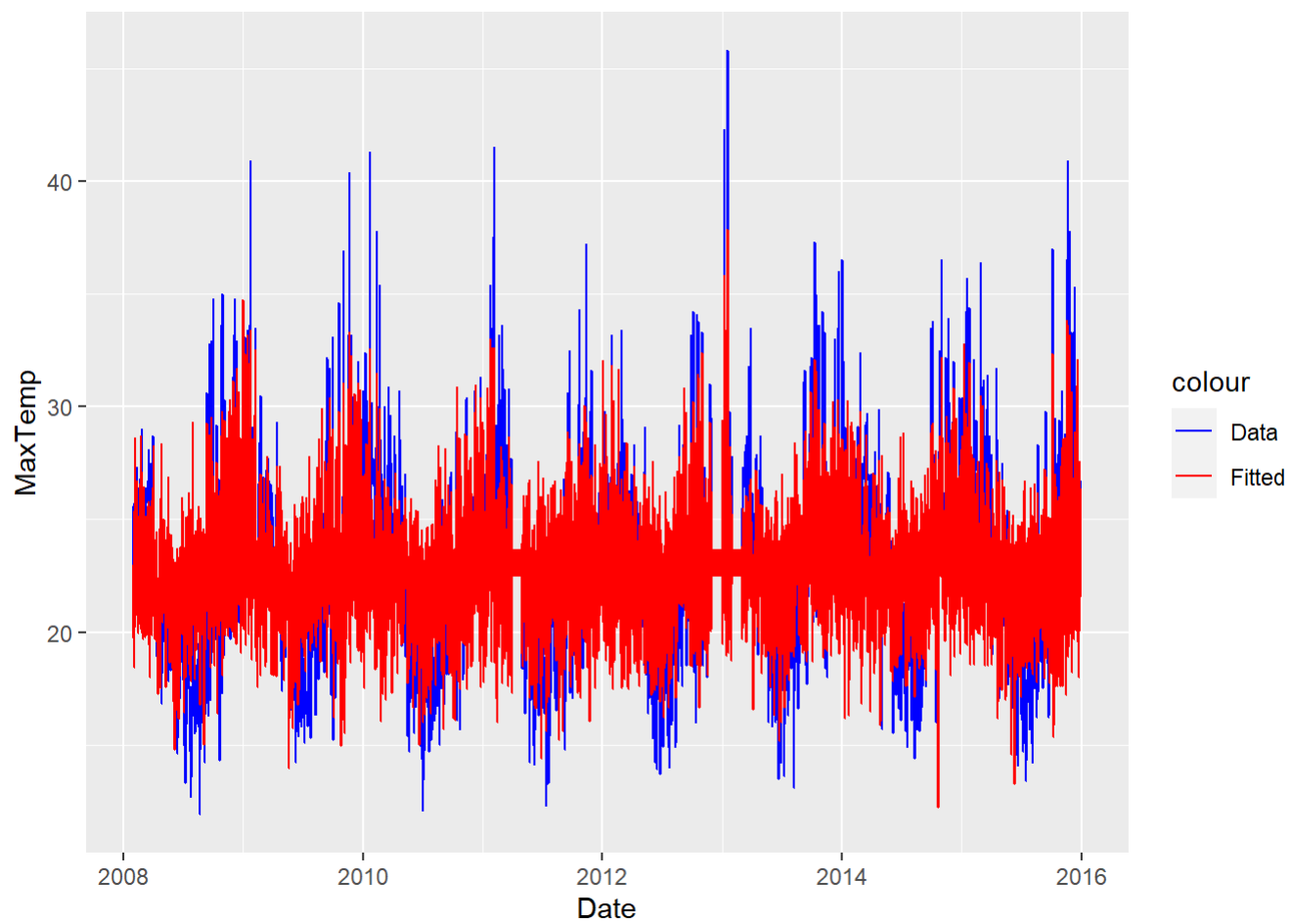
Evaluate Residuals of TSLM w/ predictors and ARIMA with errors:

TSLM w/ Predictors residuals

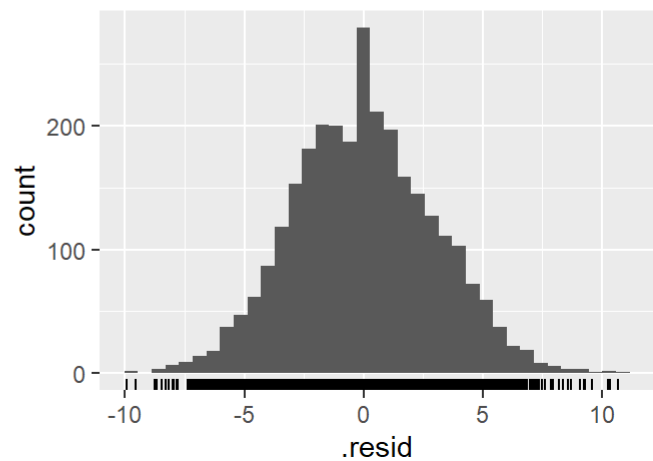
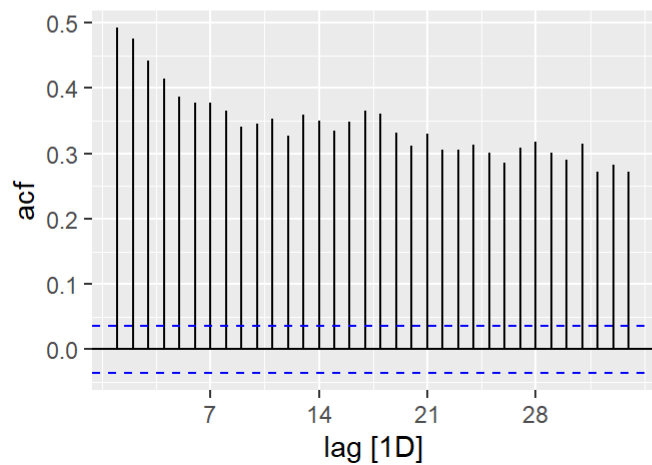
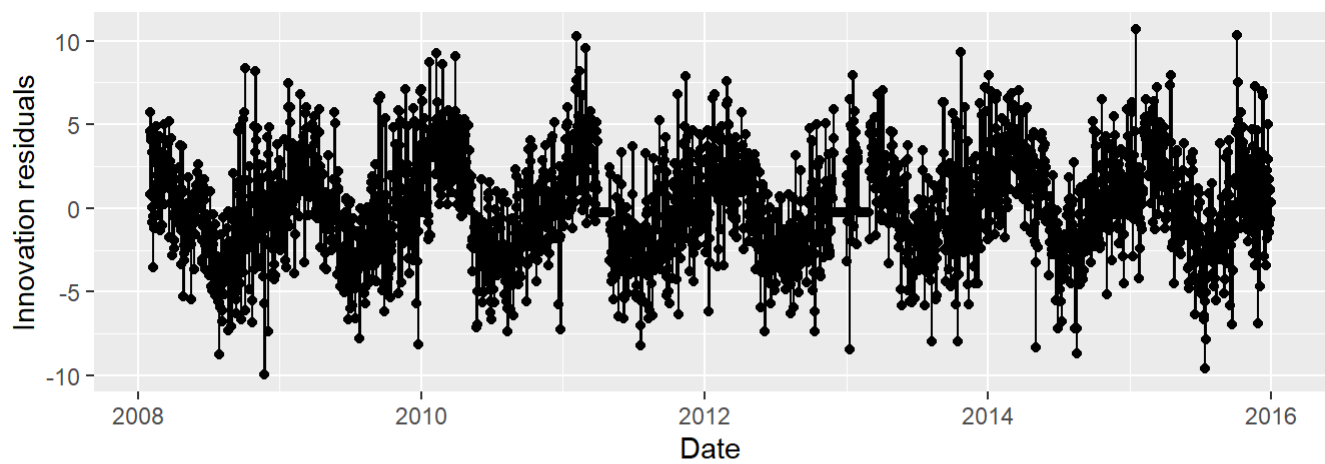
```

aug_TSLM_Predictors <- augment(TSLM_Predictors)
aug_TSLM_Predictors %>%
  ggplot(aes(x = Date)) +
  geom_line(aes(y = MaxTemp, color = "Data")) +
  geom_line(aes(y = .fitted, color = "Fitted")) +
  scale_color_manual(values = c(Data = "Blue", Fitted = "Red"))

```



```
# Using best model for gg_tsresiduals()  
TSLM_Predictors %>% select(lm9) %>% gg_tsresiduals()
```



```
# Check if residuals are stationary
aug_TSLM_Predictors %>% features(.innov, unitroot_kpss)
```

```
## # A tibble: 9 × 3
##   .model kpss_stat kpss_pvalue
##   <chr>      <dbl>      <dbl>
## 1 lm        0.202        0.1
## 2 lm2       0.209        0.1
## 3 lm3       0.306        0.1
## 4 lm4       0.343        0.1
## 5 lm5       0.492       0.0434
## 6 lm6       0.400       0.0772
## 7 lm7       0.340        0.1
## 8 lm8       0.237        0.1
## 9 lm9       0.427       0.0656
```

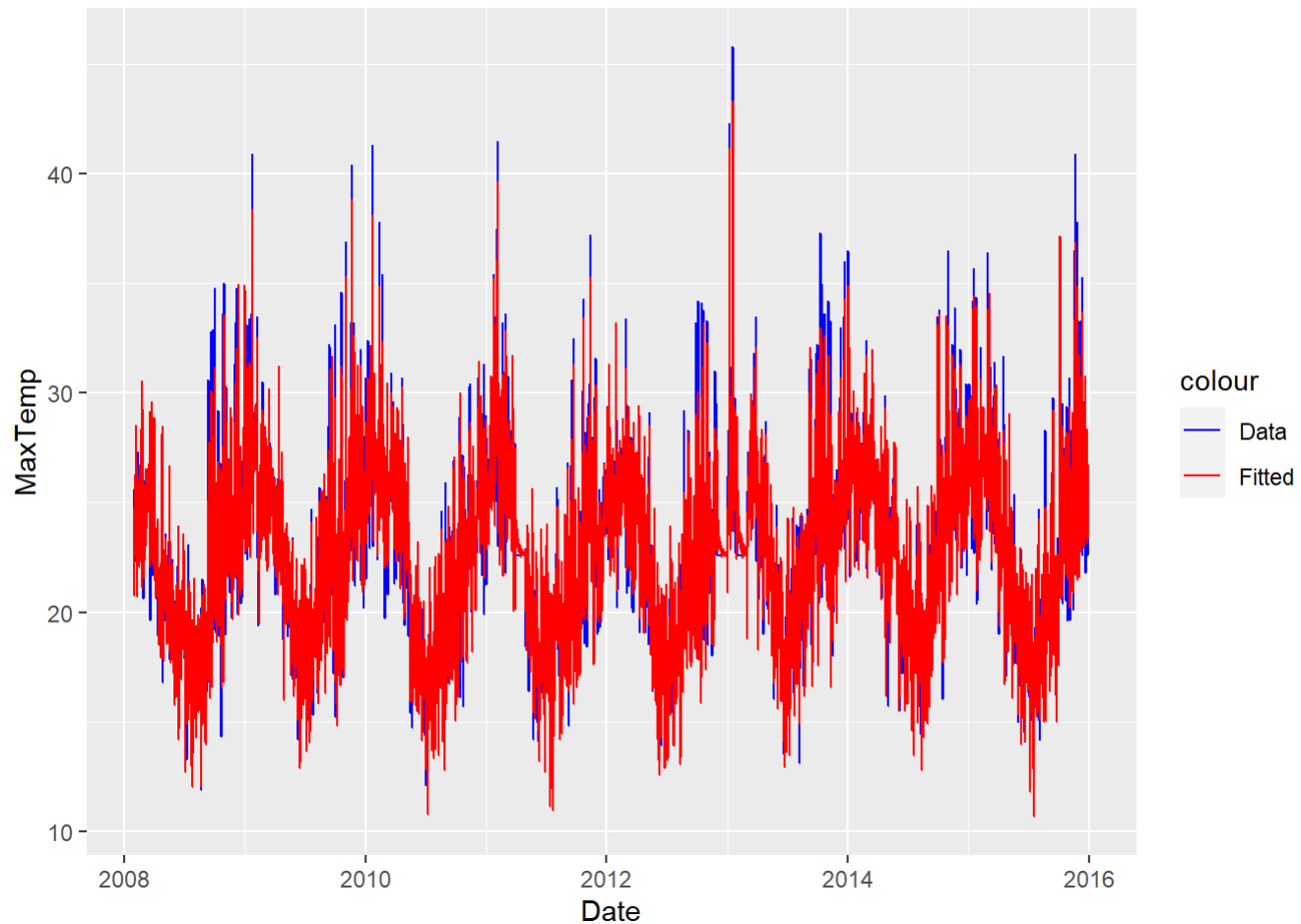
The residuals are stationary for lm1, lm2, lm3, lm4, lm7, and lm8 because they are the only ones with a p-value of 0.1. The others have smaller p-values making them not stationary.

ARIMA w/ Errors residuals

```

aug_ARIMA_e <- augment(ARIMA_Errors)
aug_ARIMA_e %>%
  ggplot(aes(x = Date)) +
  geom_line(aes(y = MaxTemp, color = "Data")) +
  geom_line(aes(y = .fitted, color = "Fitted")) +
  scale_color_manual(values = c(Data = "Blue", Fitted = "Red"))

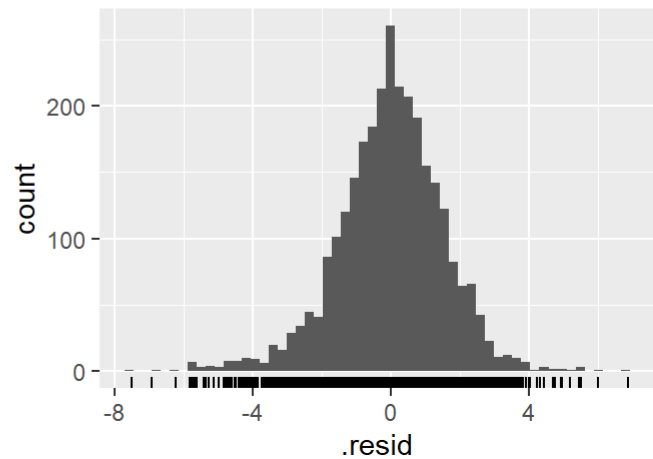
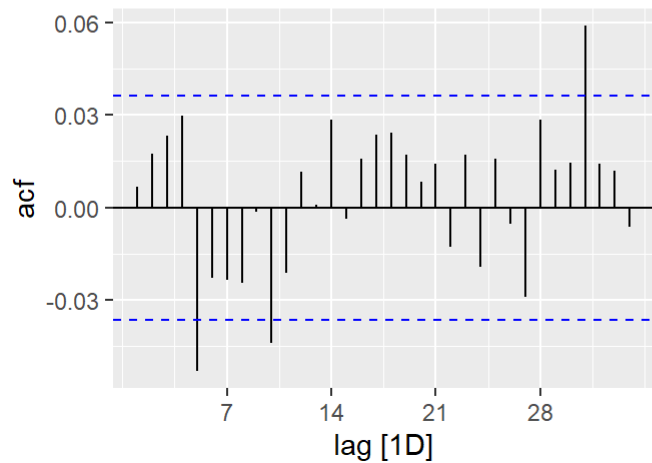
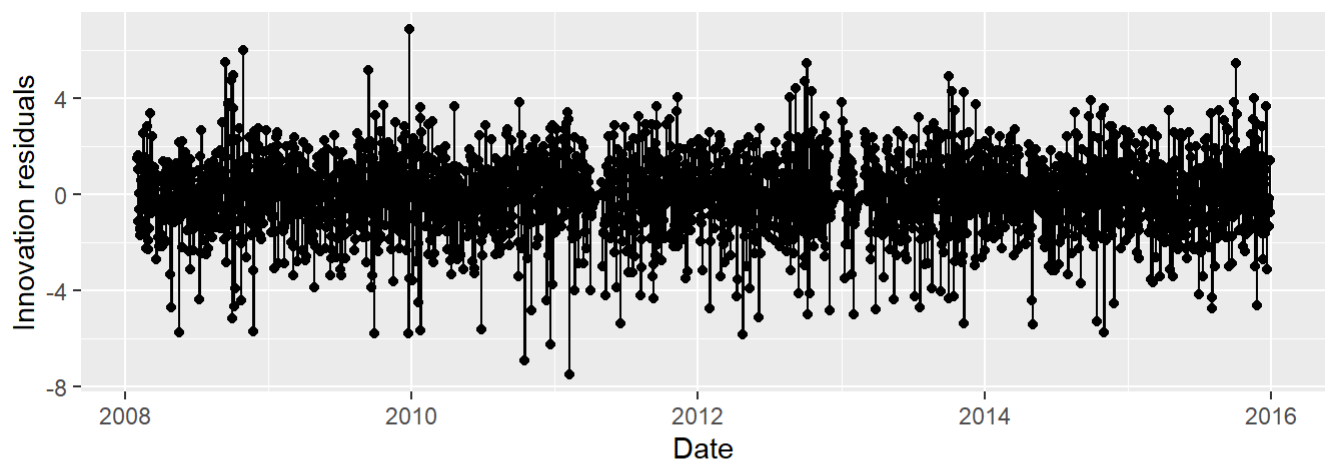
```



```

# Using best model for gg_tsresiduals()
ARIMA_Errors %>% select(ARIMA9) %>% gg_tsresiduals()

```

```
# Check if residuals are stationary
aug_ARIMA_e %>% features(.innov, unitroot_kpss)
```

```
## # A tibble: 9 × 3
##   .model kpss_stat kpss_pvalue
##   <chr>      <dbl>      <dbl>
## 1 ARIMA1    0.0377      0.1
## 2 ARIMA2    0.0382      0.1
## 3 ARIMA3    0.0462      0.1
## 4 ARIMA4    0.0460      0.1
## 5 ARIMA5    0.0408      0.1
## 6 ARIMA6    0.0479      0.1
## 7 ARIMA7    0.0489      0.1
## 8 ARIMA8    0.0370      0.1
## 9 ARIMA9    0.0454      0.1
```

All of the models have stationary residuals here because they all have a p-value of 0.1.

Benchmark Methods

```
benchmark <- train %>%
  model(
    mean = MEAN(MaxTemp),
    naive = NAIVE(MaxTemp),
    s_naive = SNAIVE(MaxTemp),
    drift = RW(MaxTemp ~ drift())
  )
glance(benchmark)
```

```
## # A tibble: 4 × 2
##   .model  sigma2
##   <chr>    <dbl>
## 1 mean      19.0
## 2 naive     12.3
## 3 s_naive   18.0
## 4 drift     12.3
```

ACCURACY

Used glance from each of the 4 model families I built

```
glance(TSLM_ETS_Models)
```

```
## # A tibble: 6 × 18
##   .model  r_squa...1 adj_r_...2 sigma2 stati...3 p_value    df log_lik    AIC    AICc
##   <chr>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl> <int>    <dbl>    <dbl>    <dbl>
## 1 TSLM      0.00535  0.00500  1.89e+1   15.5  8.32e-5     2  -8352.   8507.   8507.
## 2 SES       NA      NA      1.66e-2   NA    NA          NA  -5597.  11200.  11200.
## 3 Holt      NA      NA      1.67e-2   NA    NA          NA  -5606.  11221.  11221.
## 4 Damped   NA      NA      1.67e-2   NA    NA          NA  -5605.  11222.  11222.
## 5 Additi... NA      NA      1.67e-2   NA    NA          NA  -5598.  11220.  11220.
## 6 Multip... NA      NA      1.72e-3   NA    NA          NA  -5587.  11198.  11199.
## # ... with 8 more variables: BIC <dbl>, CV <dbl>, deviance <dbl>,
## #   df.residual <int>, rank <int>, MSE <dbl>, AMSE <dbl>, MAE <dbl>, and
## #   abbreviated variable names 1r_squared, 2adj_r_squared, 3statistic
```

```
glance(ARIMA_Models)
```

```
## # A tibble: 4 × 8
##   .model                sigma2 log_lik    AIC    AICc    BIC ar_ro...1 ma_ro...2
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl>    <dbl> <list>    <list>
## 1 arima_auto           8.77  -7238.  14491.  14491.  14539. <cpl>    <cpl>
## 2 automatic_exhaustive 8.77  -7238.  14491.  14491.  14539. <cpl>    <cpl>
## 3 automatic_no_seas_exhaust... 8.78  -7239.  14495.  14495.  14543. <cpl>    <cpl>
## 4 automatic_no_seas     9.41  -7341.  14691.  14691.  14714. <cpl>    <cpl>
## # ... with abbreviated variable names 1ar_roots, 2ma_roots
```

```
glance(TSLM_Predictors)
```

```
## # A tibble: 9 × 15
##   .model r_squared adj_r_sq...1 sigma2 stati...2 p_value    df log_lik    AIC    AICc
##   <chr>      <dbl>      <dbl> <dbl>    <dbl>    <dbl> <int>  <dbl> <dbl> <dbl>
## 1 lm        0.106      0.106  17.0     343. 1.69e- 72    2  -8198. 8198. 8198.
## 2 lm2       0.112      0.112  16.9     183. 1.60e- 75    3  -8188. 8179. 8179.
## 3 lm3       0.262      0.261  14.1     341. 1.11e-189    4  -7921. 7649. 7649.
## 4 lm4       0.289      0.288  13.5     235. 7.69e-211    6  -7867. 7543. 7543.
## 5 lm5       0.200      0.199  15.2     181. 2.03e-138    5  -8037. 7882. 7882.
## 6 lm6       0.282      0.281  13.7     283. 1.34e-205    5  -7882. 7571. 7571.
## 7 lm7       0.114      0.113  16.9     124. 1.33e- 75    4  -8185. 8176. 8176.
## 8 lm8       0.181      0.180  15.6     160. 1.11e-123    5  -8071. 7950. 7950.
## 9 lm9       0.533      0.531   8.92    410. 0          9  -7261. 6337. 6337.
## # ... with 5 more variables: BIC <dbl>, CV <dbl>, deviance <dbl>,
## #   df.residual <int>, rank <int>, and abbreviated variable names
## #   1adj_r_squared, 2statistic
```

```
glance(ARIMA_Errors)
```

```
## # A tibble: 9 × 8
##   .model sigma2 log_lik    AIC    AICc    BIC ar_roots ma_roots
##   <chr>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl> <list>  <list>
## 1 ARIMA1   3.14  -5753. 11522. 11522. 11570. <cpl [1]> <cpl [16]>
## 2 ARIMA2   3.13  -5749. 11515. 11516. 11569. <cpl [1]> <cpl [16]>
## 3 ARIMA3   6.71  -6851. 13724. 13724. 13789. <cpl [8]> <cpl [16]>
## 4 ARIMA4   2.43  -5380. 10785. 10785. 10857. <cpl [1]> <cpl [4]>
## 5 ARIMA5   5.41  -6537. 13095. 13095. 13154. <cpl [3]> <cpl [2]>
## 6 ARIMA6   6.68  -6843. 13708. 13708. 13774. <cpl [8]> <cpl [9]>
## 7 ARIMA7   6.50  -6805. 13630. 13630. 13690. <cpl [8]> <cpl [9]>
## 8 ARIMA8   3.09  -5728. 11478. 11478. 11543. <cpl [1]> <cpl [16]>
## 9 ARIMA9   2.39  -5354. 10738. 10738. 10827. <cpl [1]> <cpl [4]>
```

MODELS BEST MODEL AICc TSLM and ETS TSLM 8507 ARIMA arima_auto 14491 TSLM_Predictors lm9 6337
ARIMA Errors ARIMA9 10738

The overall model with the lowest AICc is the lm9 model from TSLM_Predictors.

I selected AICc because it was an easy method to compare accuracy of my models performance while also accounting for model complexity.

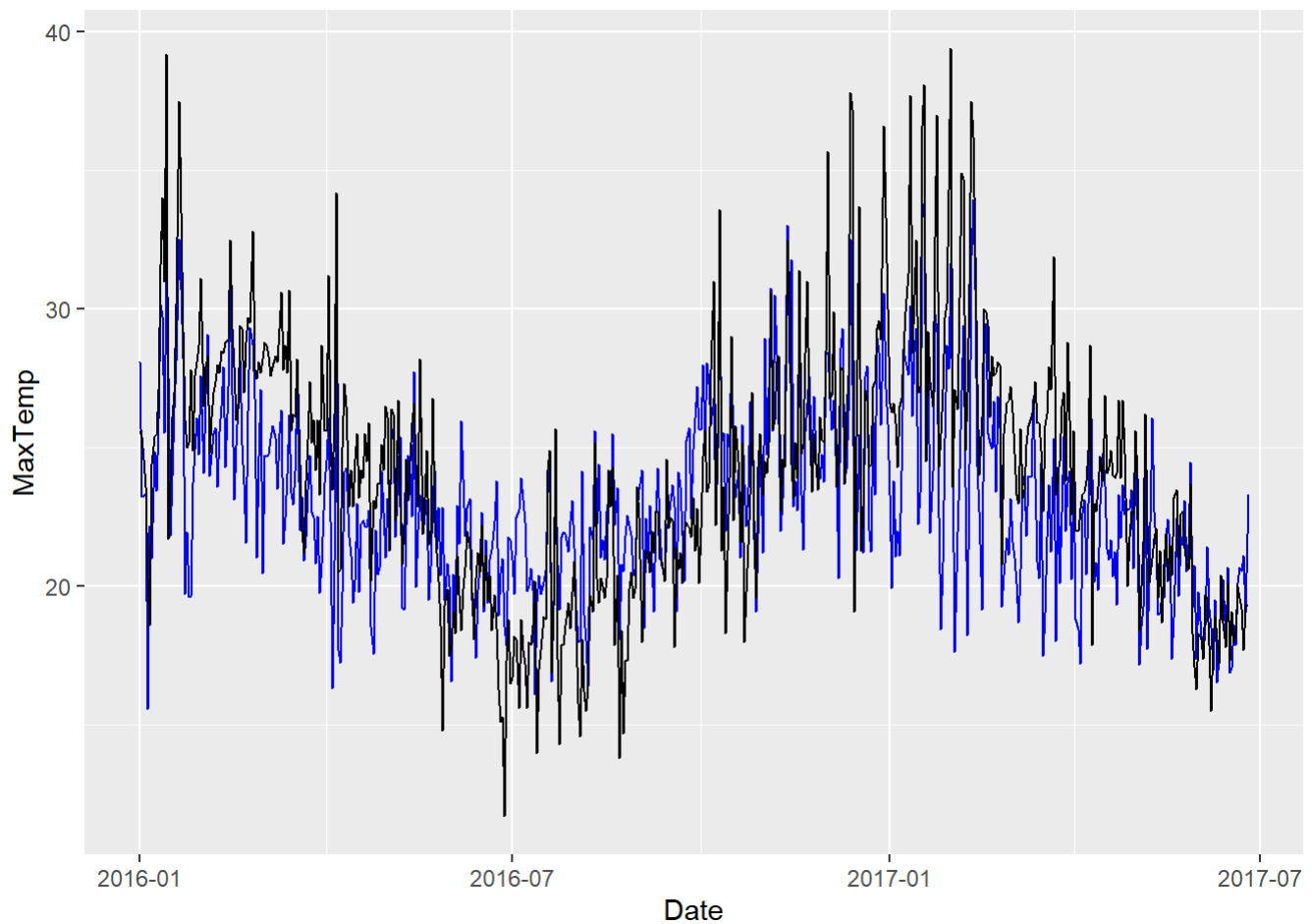
Final Model

```
final_model <- TSLM_Predictors %>% select(lm9)
```

The final model that I will use is lm9 because it had the lowest AICc of any of the models I was able to build.

FORECAST

```
fc <- final_model %>%
  forecast(new_data = test)
fc %>% autoplot(test, level = NULL)
```



```
fc %>% accuracy(test)
```

```
## # A tibble: 1 × 10
##   .model .type    ME  RMSE   MAE   MPE  MAPE  MASE  RMSSE  ACF1
##   <chr>  <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 lm9    Test  0.986  3.31  2.65  2.34  11.2   NaN    NaN  0.530
```

I am forecasting about 2 years into the future. This is because the test dataset contains about 20% of the records which ends up being about 2 years out of the almost 10 years of data.

Some considerations when implementing this dataset is that this is the peak temperature recorded of each day, not the average temperature of the day. It is also important to consider that I only focused on temperature in Sydney, not all of Australia. As the many different locations have very different climates and temperatures in the country/continent. So using this forecast to predict on another location would not result in accurate results despite them both being in Australia.