W271 Assignment 8

```
theme_set(theme_minimal())
```

(14 points total) Question-1: Is Unemployment an Autoregressive or a Moving Average Process?

You did work in a previous homework to produce a data pipeline that pulled the unemployment rate from official BLS sources. Reuse that pipeline to answer this final question in the homework:

> "Are unemployment claims in the US an autoregressive, or a moving average process?

(1 point) Part-1: Why is the distinction important?

Why is it important to know whether a process is a AR or an MA (or a combination of the two) process? What changes in the ways that you would talk about the process, what changes in the ways that you would fit a model to the process, and what changes with how you would produce a forecast for this process? > Knowing what model fits the time-series better will allow us to select the model that is more likely to make valid predicitons. Autoregressive mofdels imply that there is a strong influence of one day over another, while moving average models assume that there are random shocks that happen independently. Therefore, AR model will take into account shocks that go beyond its order p, while MA has no memnory whatsoever about what happened beyonfd the lag of it order q. Producing forecast for AR(p) model we would use a linear regression and last p values, while forecasting with MA(q) model we would use the last q shocks.

(1 point) Part-2: Pull in (and clean up) your data pipeline.

In the previous homework, you built a data pipeline to draw data from the BLS. We are asking you to re-use, and if you think it is possible, to improve the code that you wrote for this pipeline in the previous homework.

- Are there places where you took "shortcuts" that could be more fully developed?
- Are the processes that could be made more modular, or better documented so that they are easier for you to understand what they are doing? You've been away from the code that you wrote for a few weeks, and so it might feel like "discovering" the code of a *mad-person* (Who even wrote this???)

```
# Generate a list of timeseries we would like to obtain
series_ids <- list(uer.total ="LNS14000000",
                   uer.men ="LNS14000001",
                   uer.women = 'LNS14000002')

# API call to retrieve the data
uer_series <- get_n_series_table(series_ids,
                                 '913c5fe448924ea584e043f736c95080',
                                 start_year = 2000,
                                 end_year = 2023)
```

```
## Year 2000 to 2023 is longer than 20 year API limit. Performing 2 requests.
```

```
# Generate time period variable from the text column for month
uer_series$period <- as.integer(str_sub(uer_series$period, 2, 3))
```

```r
# Set descriptive names
names(uer_series) <- c("year", "month", "overall", "male", "female")

# Produce tydiverse-friendly long form of the data frame
unemployment <- pivot_longer(uer_series, cols = 3:5,
                             names_to = "name",
                             values_to = "value")

# Generate timeindex
unemployment$time_index<-yearmonth(paste(unemployment$year, unemployment$month))

unemployment <- as_tsibble(unemployment[3:5], key = name, index = time_index)
```

```r
head(unemployment)
```

```
## # A tsibble: 6 x 3 [1M]
## # Key:       name [1]
##   name   value time_index
##   <chr>  <dbl>      <mth>
## 1 female   4.1   2000 Jan
## 2 female   4.1   2000 Feb
## 3 female   4.3   2000 Mar
## 4 female   4     2000 Apr
## 5 female   4.2   2000 May
## 6 female   4.1   2000 Jun
```

(5 points) Part-3: Conduct an EDA of the data and comment on what you see.

We have presented four **core** plots that are a part of the EDA for time-serires data. Produce each of these plots, and comment on what you see.

```r
TS_plot <- unemployment %>% filter (name == 'overall') %>% autoplot()
```

```
## Plot variable not specified, automatically selected `.vars = value`
```

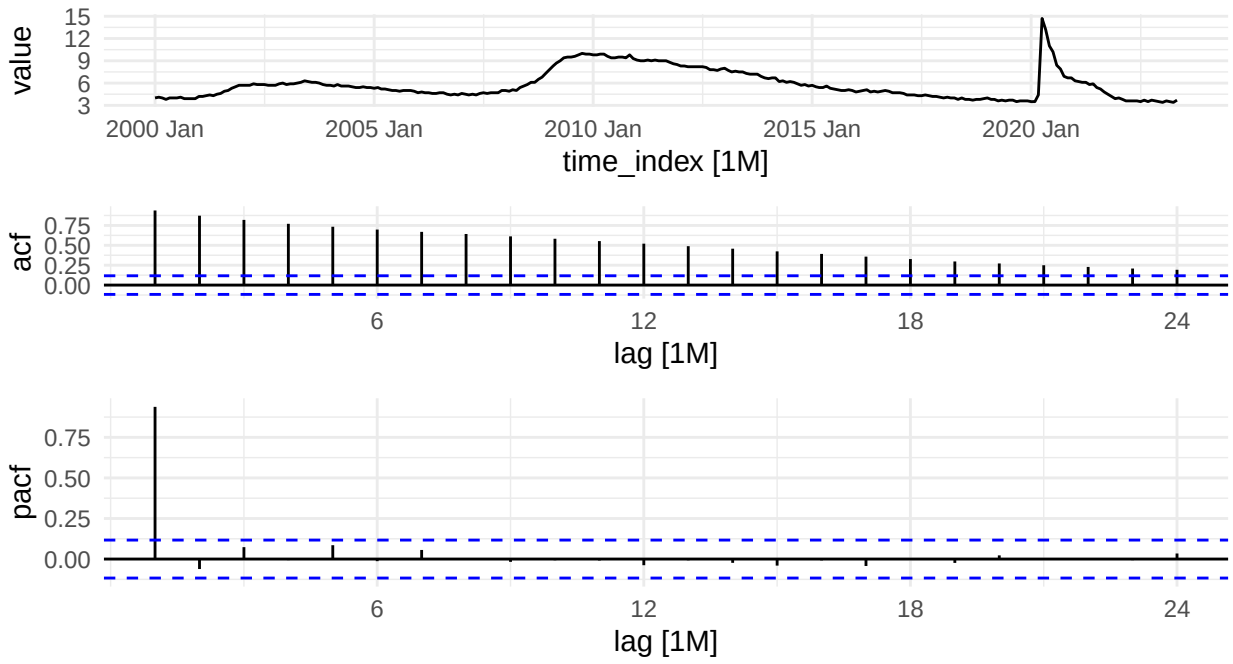
```r
ACF_plot <- unemployment %>% filter(name == 'overall') %>% ACF() %>% autoplot()
```

```
## Response variable not specified, automatically selected `var = value`
```

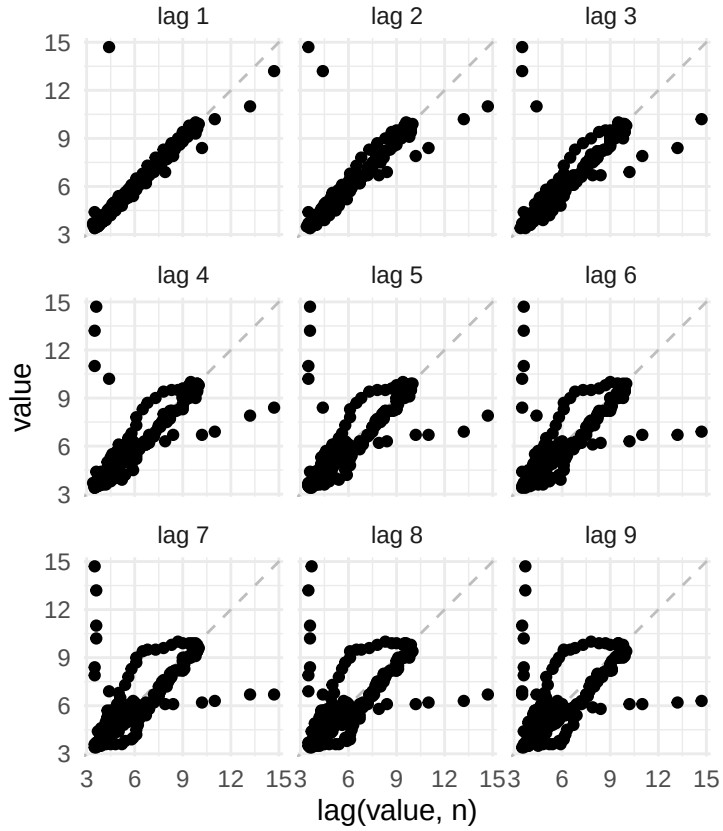
```r
PACF_plot <- unemployment %>% filter(name == 'overall') %>% PACF() %>% autoplot()
```

```
## Response variable not specified, automatically selected `var = value`
```

```r
plot_grid(TS_plot, ACF_plot, PACF_plot, align = "v", nrow = 4, rel_heights = c(2, 2, 3), scale = c(1,1,
```



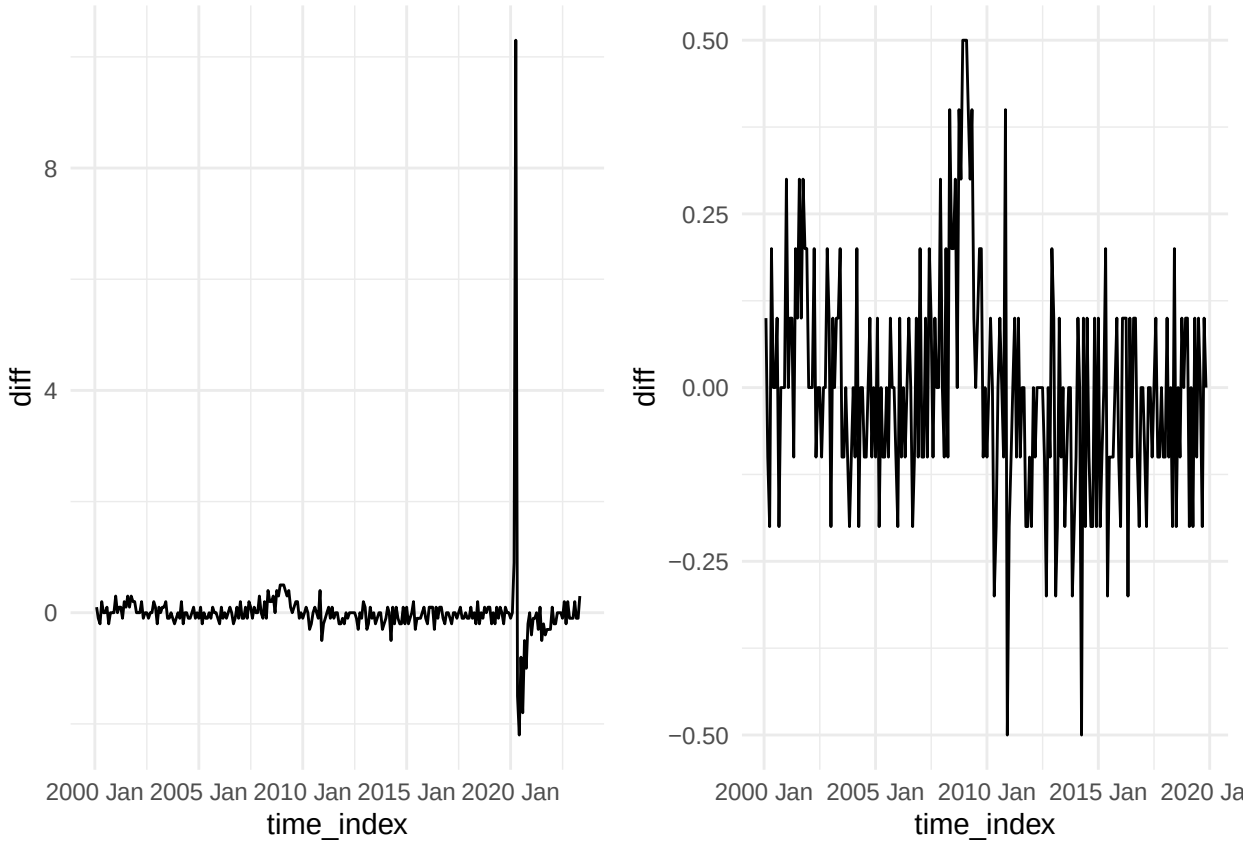

```
unemployment %>% filter(name == 'overall') %>%  gg_lag(value, lag = 1:9, geom = "point", color = 1)
```



I assume that the conclusions about overall unemployment can be extrapolated to gender-specific data, therefore I focus on overall unemployment here. From the look of the series it is obvious that expectation of the series is not constant, i.e. the series os not stationary. This is also reflected on the ACF plot that has many non-zero lags and only gradual decrease in significance. That might mean an AR component in the series, but in this case is more likely is due to strong trend. PACF

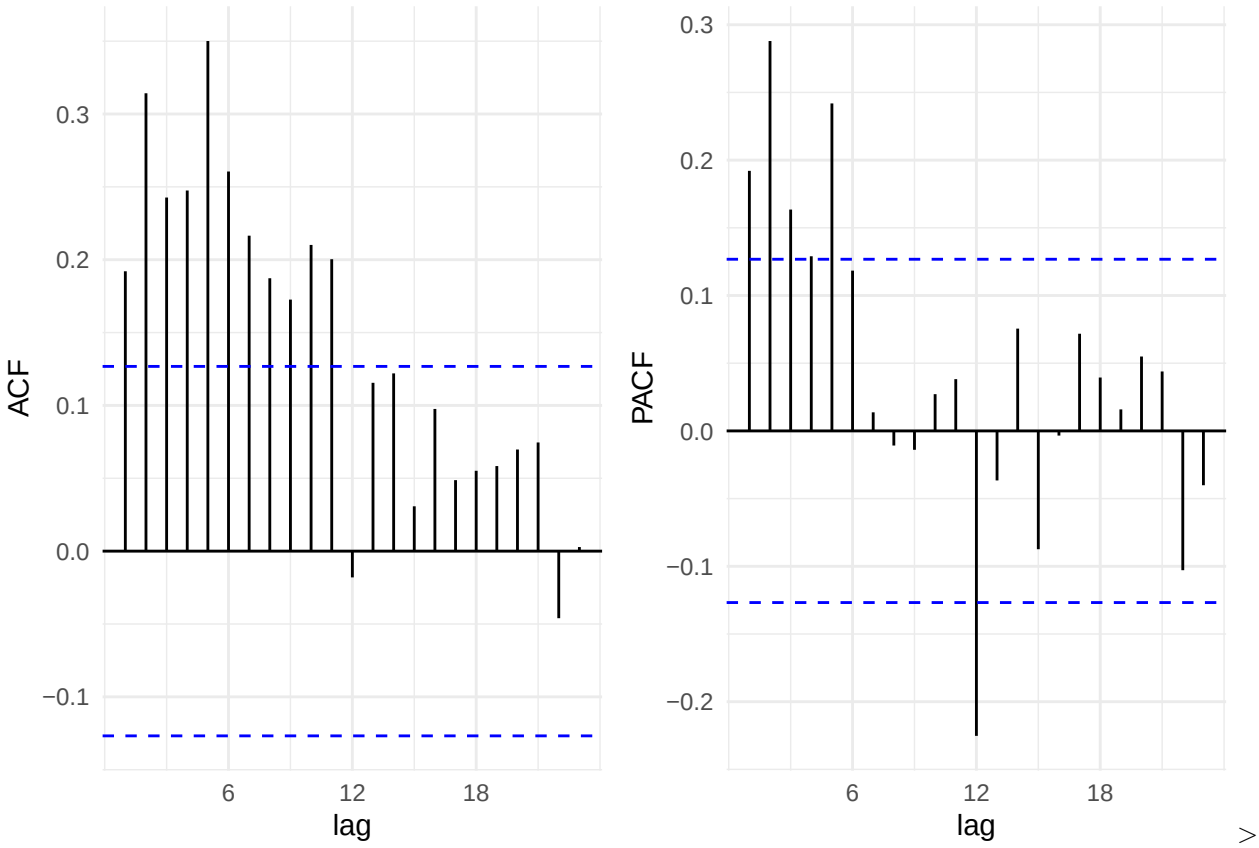
plot also exhibit strong correlation with lag 1, but no oscilatory beheviour typical for MA model.

```
overall_ts <- unemployment %>% filter(name == "overall")
overall_ts <- mutate(overall_ts, diff = difference(value, lag=1))
overall_ts <- overall_ts[3:4]

short <- overall_ts %>% filter(time_index < ym('2019 Dec')) %>%
  ggplot() + aes(x = time_index, y = diff) + geom_line()

full <- overall_ts %>% ggplot() + aes(x = time_index, y = diff) + geom_line()

grid.arrange(full,short,nrow=1)
```



Differenceing yields an almost stationary series, but a huge spike at the beginning of the 2020 introduces perturbation that is not charachteristic of the series and can skew predictions.

```
g1<-overall_ts %>% filter(time_index < ym('2019 Dec')) %>%
  ACF(diff, type="correlation") %>% autoplot()  + labs (x = "lag", y = "ACF")

g2<-overall_ts %>% filter(time_index < ym('2019 Dec')) %>%
  ACF(diff, type="partial") %>% autoplot() + labs (x = "lag", y = "PACF")

grid.arrange(g1,g2,nrow=1)
```



>

Focusing on detrended series, we can see that ACF plot decays quickly, loosing signoficance after lag 11. This is not consistent with a pure AR process that should show exponential decay in ACF plot. Therefore, based on ACF plot, we might conclude MA(11) model. At the same time, PACF plot is consistently significant up to lag 6, with a negative spike at lag 12. This is not consistent with a pure MA process that should have oscillations in PACF plot and based on ACF plot we might conclude AR(6), possibly up to AR(12) process.

(1 point) Part-4: Make a Call

Based on what you have plotted and written down in the previous section, would you say that the unemployment rate is an AR, MA or a mix of the two? > Form the analysis above its is difficult to be completely certain what dgrees of AR and MA would be the most appropriate. It is likely to be a mix of the two, and detrending as also nessesary. ## (6 points total) Part-5: Estimate a model

Report the best-fitting parameters from the best-fitting model, and then describe what your model is telling you. In this description, you should:

- (1 point) State, and justify your model selection criteria.
- (1 point) Interpret the model selection criteria in context of the other models that you also fitted.
- (2 points) Interpret the coefficients of the model that you have estimated.
- (2 points) Produce and interpret the model diagnostic plots to evaluate how well your best-fitting model is performing.
- (1 (optional) point) If, after fitting the models, and interpreting their diagnostics plots, you determine that the model is doing poorly – for example, you notice that the residuals are not following a white-noise process – then, make a note of the initial model that you fitted then propose a change to the data or the model in order to make the model fit better. If you take this action, you should focus your interpretation of the model's coefficients on the model that you think does the best job, which might be the model after some form of variable transformation.

  Becasue diagnostic plots did not yield a definitive indication of the degree of MA amd AR

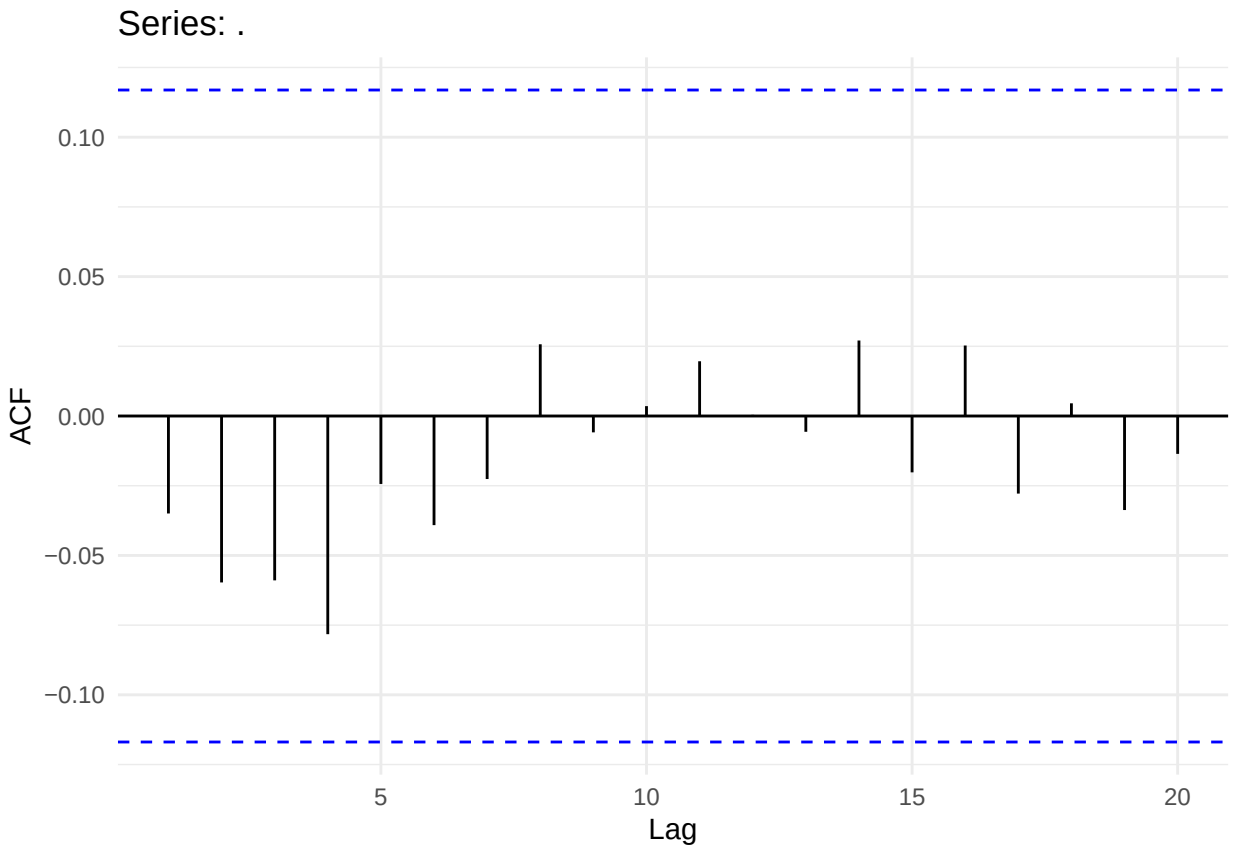
component of the models, we will perform a grid search of various combinations of AR, MA and detrending parameters. We will use BIC criterion as it is more stringent than AIC. We will be fitting a large number of models, therefore stringent criterion is needed to avoid unreliable conclusions.

```
# Generate a set of models AR(1)-AR(10) and MA(1)-MA(10)
# with first and second degree of differencing.
# Select the model with the lowest BIC
model.bic<-unemployment %>% filter(name == "overall") %>%
model(ARIMA(value ~ 1 + pdq(1:10,1:2,1:10) + PDQ(0,0,0), ic="bic", stepwise=F, greedy=F))

# Report the winning model parameters
model.bic %>% report()
```

```
## Series: value
## Model: ARIMA(1,1,1) w/ drift
##
## Coefficients:
##           ar1     ma1  constant
##       -0.7277  0.8019   -0.0018
## s.e.   0.1594  0.1363    0.0720
##
## sigma^2 estimated as 0.4521:  log likelihood=-284.66
## AIC=577.33   AICc=577.47   BIC=591.87
```

With the winning ARIMA model (1,1,1) in hand we will check its residuals to make sure that the residuals are as close to white noise as possible.

```
# Obtain the winning model as a separate instance of Arima class
dat <- unemployment %>% filter(name == "overall")
arima.model <- arima(dat$value, order = c(1,1,1), include.mean = T)

# Visualize ACF plot of its residuals
arima.model %>% residuals() %>% acf(plot = FALSE) %>% autoplot() + coord_cartesian(xlim = c(1, 20))
```



The residuals do not appear to be a white noise, but we will use Ljung Box test to investigate if they are indeed not random.

```
resid.ts <- as.ts(arima.model %>% residuals())
Box.test(resid.ts, lag = 1, type = "Ljung-Box")
```

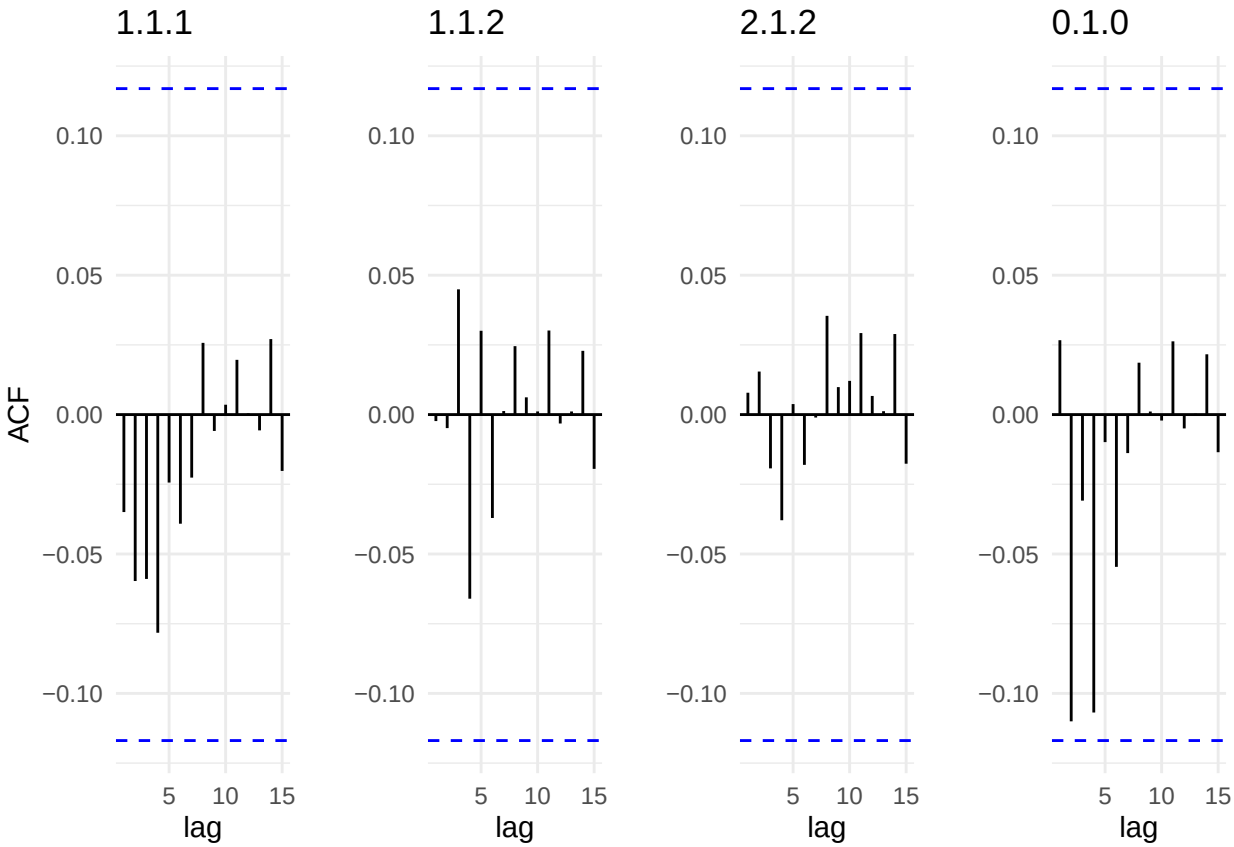
```
##
##  Box-Ljung test
##
## data:  resid.ts
## X-squared = 0.34698, df = 1, p-value = 0.5558
```

The test fails to reject the null hypothesis, therefore we do not have statistical evidence against random distribution of the residuals of this model.

The selected model, therefore, is ARIMA (1,1,1) with coefficients autoregressive coefficient -0.7277, moving average coefficeint and a constant term (average) of -0.0018. I.e. after one level of differencing, in the resulting autoregressive model the predicted value will depend on the lag 1 series with coeff -0.7277, lag 1 error with coeff 0.8019, and the average of the model is almoset excatly zero.

```
# Obtain residuals ACF plot for selected model
dat <- unemployment %>% filter(name == "overall")
arima1_1_1 <- arima(dat$value, order = c(1,1,1), include.mean = T)
plot111 <- arima1_1_1 %>% residuals() %>% acf(plot = FALSE) %>% autoplot() +
  coord_cartesian(xlim = c(1, 15)) + labs(x = "lag", y = "ACF", title = "1.1.1")

# Obtain residuals plot for alternative ARIMA(1,1,2)
dat <- unemployment %>% filter(name == "overall")
```

```r
arima1_1_2 <- arima(dat$value, order = c(1,1,2), include.mean = T)
plot112 <- arima1_1_2 %>% residuals() %>% acf(plot = FALSE) %>% autoplot() +
  coord_cartesian(xlim = c(1, 15)) + labs(x = "lag", y = "", title = "1.1.2")

# Obtain residuals plot for for alternative ARIMA(2,1,2)
dat <- unemployment %>% filter(name == "overall")
arima2_1_2 <- arima(dat$value, order = c(2,1,2), include.mean = T)
plot212 <- arima2_1_2 %>% residuals() %>% acf(plot = FALSE) %>% autoplot() +
  coord_cartesian(xlim = c(1, 15)) + labs(x = "lag", y = "", title = "2.1.2")

# Obtain residuals plot for random walk
dat <- unemployment %>% filter(name == "overall")
arima0_1_0 <- arima(dat$value, order = c(0,1,0), include.mean = T)
plot010 <- arima0_1_0 %>% residuals() %>% acf(plot = FALSE) %>% autoplot() +
  coord_cartesian(xlim = c(1, 15)) + labs(x = "lag", y = "", title = "0.1.0")

grid.arrange(plot111, plot112, plot212, plot010, nrow=1)
```



Interestingly, simple random walk model ARIMA (0,1,0) has lower BIC than the selected model (583.87 vs 591.87), but showes clear autoregressive features in its residuals (see plot above). Also, ARIMA (1,1,2) (BIC 593.54) visually has residuals closer to white noise and ARIMA (2,1,2) ACF plot has no significant lags at all, albiet at the expense of higher BIC. More detailed evaluations and testing of predictions would be needed to make the final judgement on the suitability of these models.

(14 Points Total) Question-2: COVID-19

The United States Centers for Disease Control maintains the authoritative dataset of confirmed and probable COVID-19 cases.

- This data is described on this page [link].
- The data is made available via an API link on this page as well.

(1 point) Part-1: Access Data

Use the public API to download the CDC COVID-19 data and store in a useful dataframe. A useful dataframe:

- Should have useful variable names;
- Should be in a format that can be used for time series modeling;

- Should have appropriate time indexes (and possibly keys) set; but,
- At this point, should not have derivative features mutated onto the data frame; nor,
- Should it be aggregated or summarized.

```
covid_df <- read.socrata("https://data.cdc.gov/resource/pwn4-m3yp.json")
```

```
columns_to_select <- c(1,2,5,6,7,8)
covid_df$date_updated <- ymd(covid_df$date_updated)
covid_df <- covid_df %>% mutate_at(c(5,6,7,8), as.numeric)
covid_ts <- covid_df[columns_to_select] %>% as_tsibble(key = 'state', index = 'date_updated')
```

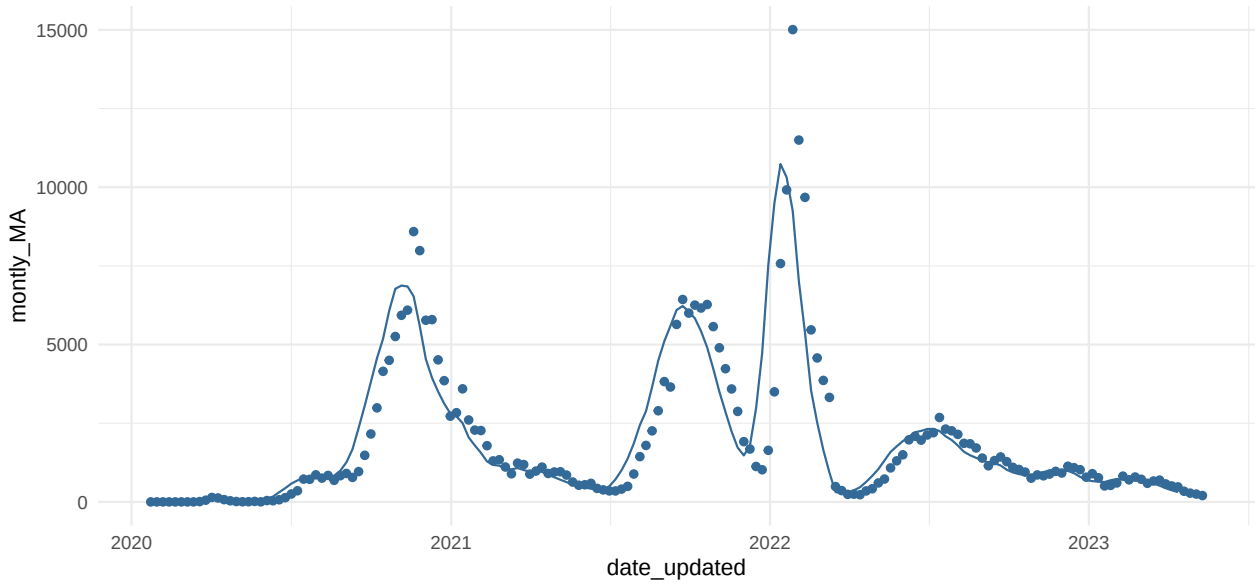
(5 points) Part-2: Pick a State and Produce a Model

1. Choose a state that is not California (we are putting this criteria in so that we see many different states chosen);
2. Produce a 7-day, backward smoother of the total case rate; then,

3. Produce a model of COVID cases in that state. This should include:

- Conducting a full EDA and description of the data that you observe
- Estimating a model (either AR or MA) that you believe is appropriate after conducting your EDA
- Evaluating the model performance through diagnostic plots

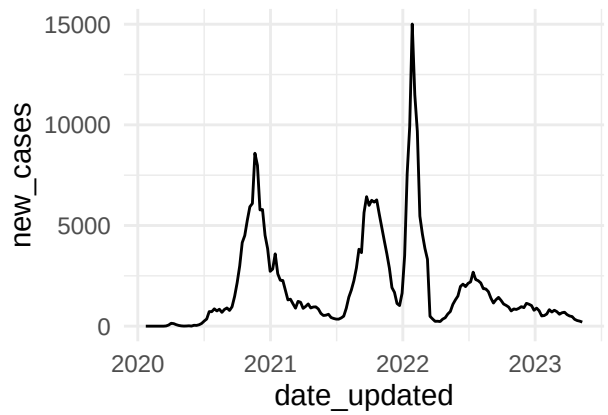
```
# Let's pick Montana, home of the Glacier NP
covid_MT <- covid_ts %>% filter(state == "MT")

# The data that we eneded up using is already aggregated by week
# Therefore weekly moving average is pointless
# Smoothing over 4-week periods (not exactly monthly, but close enough):

# Produce new column with smoothed values
covid_MT <- covid_MT%>% mutate(
    `montly_MA` = slider::slide_dbl(new_cases, mean,
    .before = 0, .after = 4, .complete = TRUE))

# Generate a plot to show smoothing effect
covid_MT %>% ggplot() +
  geom_line(aes(x = date_updated, y = montly_MA , colour = origin)) +
  geom_point(aes(x = date_updated, y = new_cases , colour = origin)) +
  theme_minimal() +
  theme(legend.position = "none")
```

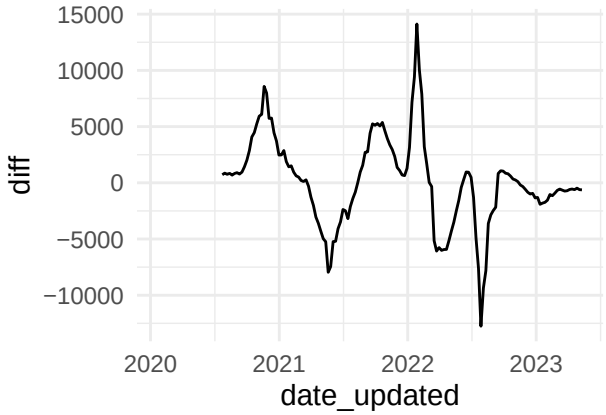


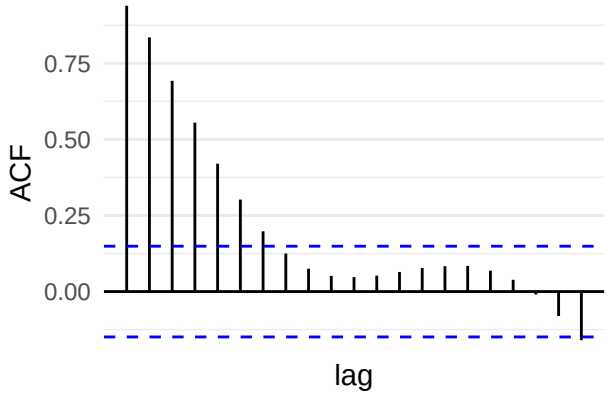
Smoothing effect does not appear to add any value to the analysis, therefore in the following analysis we will use unmsoothed weekly data, equivalent to what we would have, had we gotten the daily data form the source.

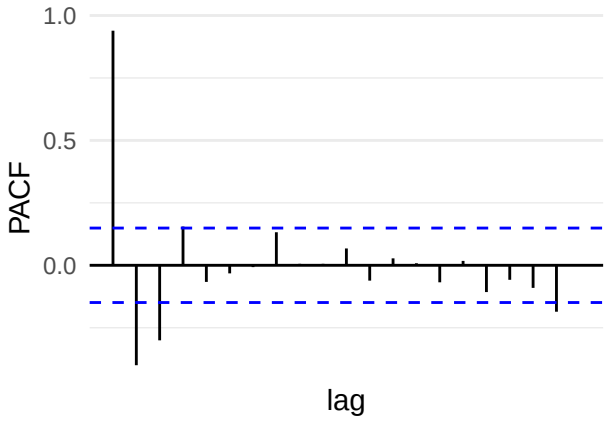
```
covid_MT <- mutate(covid_MT, diff = difference(new_cases, lag=26))

ts_plot <- covid_MT %>% ggplot() + aes(x = date_updated, y = new_cases) + geom_line()

ts_diff_plot <- covid_MT %>% ggplot() + aes(x = date_updated, y = diff) + geom_line()

acf_plot<-covid_MT %>%
  ACF(diff, type="correlation") %>% autoplot()  + labs (x = "lag", y = "ACF")

pacf_plot<-covid_MT %>%
  ACF(diff, type="partial") %>% autoplot() + labs (x = "lag", y = "PACF")

grid.arrange(ts_plot , ts_diff_plot, acf_plot, pacf_plot, nrow=2)
```

```
## Warning: Removed 26 rows containing missing values (`geom_line()`).
```





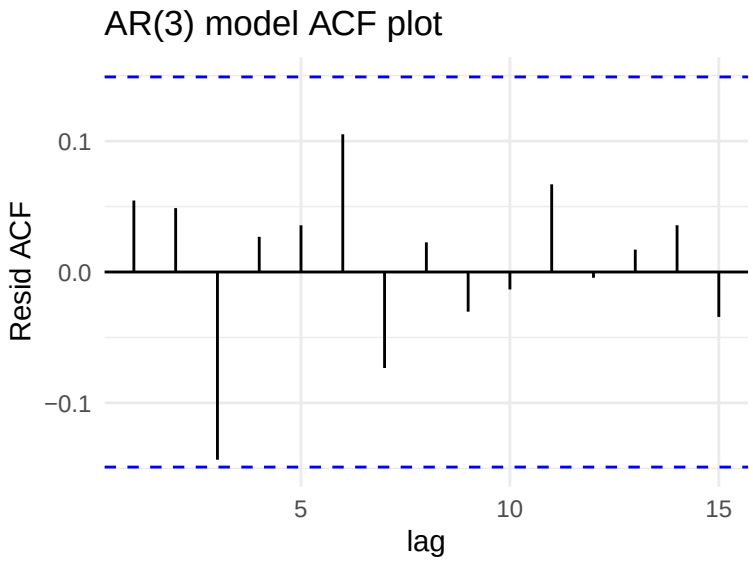





```
model.bic<-covid_MT %>%
model(ARIMA(diff~ 1 + pdq(0:10,0:2,0:10) + PDQ(0,0,0), ic="bic", stepwise=F, greedy=F))
model.bic %>%
report()
```

```
## Series: diff
## Model: ARIMA(3,0,0) w/ mean
##
## Coefficients:
##          ar1      ar2      ar3  constant
##       1.1874  -0.0040  -0.2958   11.1739
## s.e.  0.0779   0.1254   0.0778   94.9349
##
## sigma^2 estimated as 1193134:  log likelihood=-1248.61
## AIC=2507.22   AICc=2507.58   BIC=2522.99
```

```
MT_AR3 <- arima(covid_MT$diff, order = c(3,0,0), seasonal = c(0, 0, 0), include.mean = T)
MT_AR3_plot <- MT_AR3 %>% residuals() %>% acf(plot = FALSE, na.action = na.pass) %>% autoplot() +
  coord_cartesian(xlim = c(1, 15)) + labs(x = "lag", y = "Resid ACF", title = "AR(3) model ACF plot")
```




```
resid.ar3 <- as.ts(MT_AR3 %>% residuals())
LBT <- Box.test(resid.ar3, lag = 1, type = "Ljung-Box")
```

The residuals look like random white noise. Ljung-Box test fials to reject hypothesis that the residuals are random (p value 0.504)

(5 points) Part-3: Produce a Nationwide Model

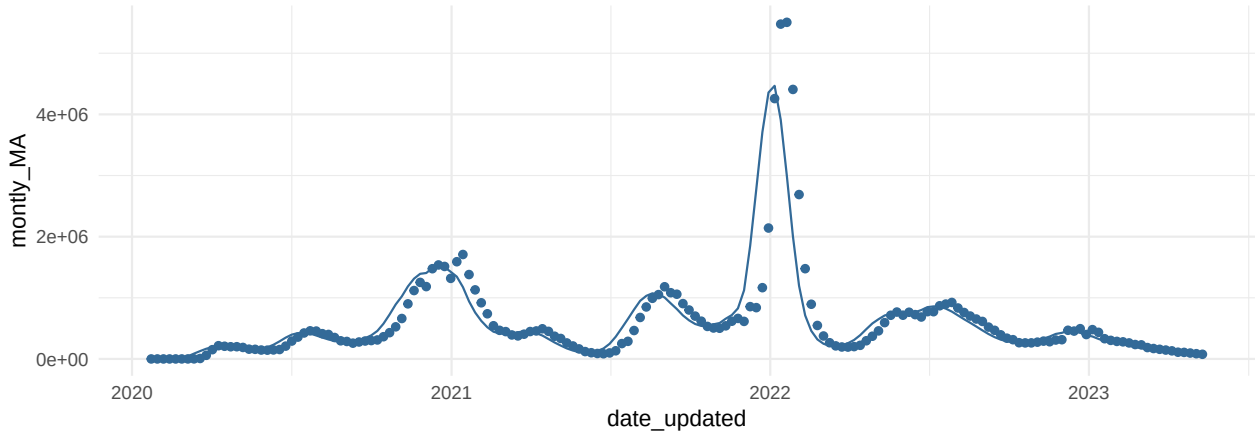
1. Aggregate the state-day data into nationwide-day level data;
2. Produce a 7-day, backward smoother of the total case rate; then,
3. Produce a model of COVID cases across the US. Like the state model, this should include:

- Conducting a full EDA and description of the data that you observe
- Estimating a model (either AR or MA) that you believe is appropriate after conducting your EDA
- Evaluating the model performance through diagnostic plots

```
# I could not figure out how to aggregate on a tsibble
# So will aggregate on dataframe

# Subset the original df to make final ts smaller
columns_to_select <- c(1,6)
nation_df <- covid_df[columns_to_select]

# Aggregate on the dataframe
nation_ts <- aggregate(nation_df["new_cases"], by = nation_df["date_updated"], sum)

# Convert back to tsibble
nation_ts <- as_tsibble(nation_ts, index = date_updated)
```

```
# The data that we eneded up using is already aggregated by week
# Therefore weekly moving average is pointless
# Smoothing over 4-week periods (not exactly monthly, but close enough):

# Produce new column with smoothed values
nation_ts <- nation_ts%>% mutate(
    `montly_MA` = slider::slide_dbl(new_cases, mean,
    .before = 0, .after = 4, .complete = TRUE))
```

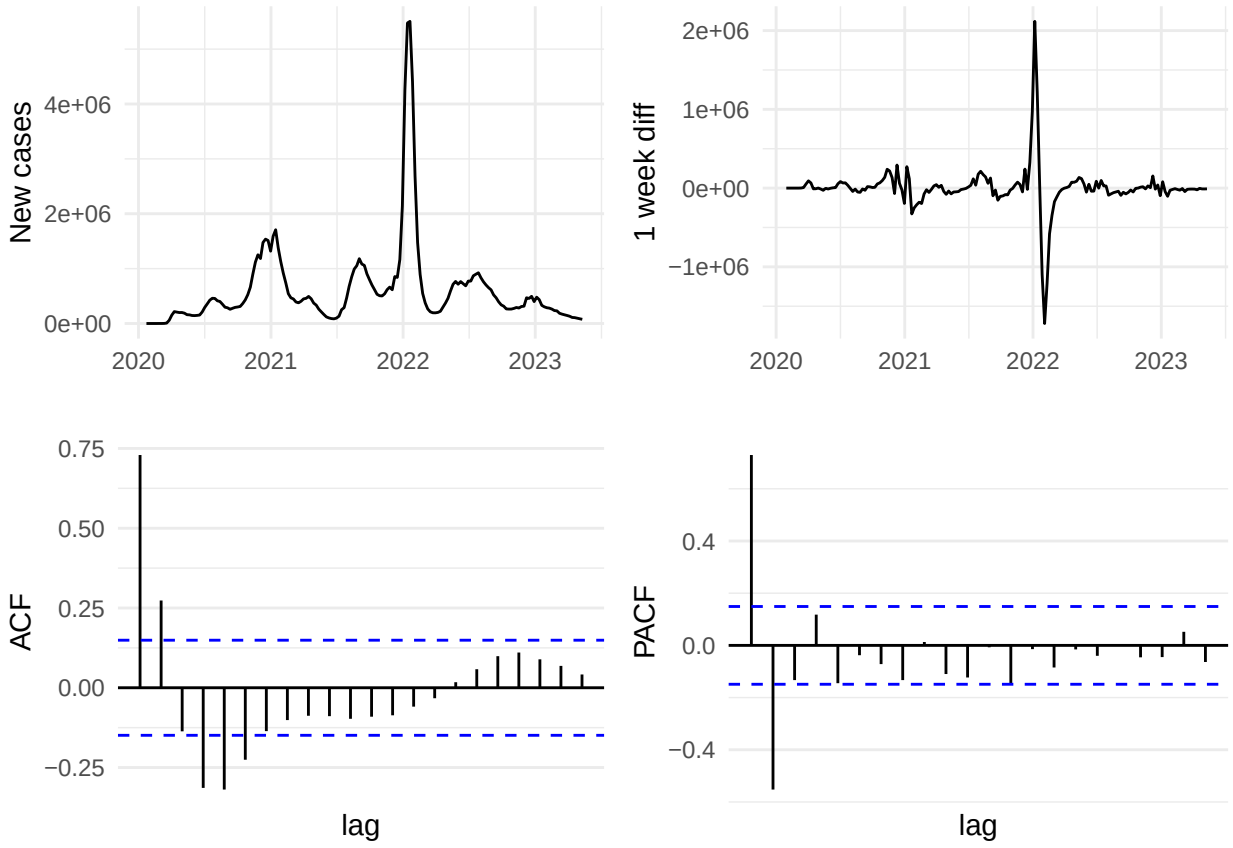
```r
# Generate a plot to show smoothing effect
nation_ts %>% ggplot() +
  geom_line(aes(x = date_updated, y = montly_MA , colour = origin)) +
  geom_point(aes(x = date_updated, y = new_cases , colour = origin)) +
  theme_minimal() + theme(legend.position = "none")
```



Smoothing effect does not appear to add any value to the analysis, therefore in the following analysis we will use unmsoothed weekly data, equivalent to what we would have, had we gotten the daily data form the source.

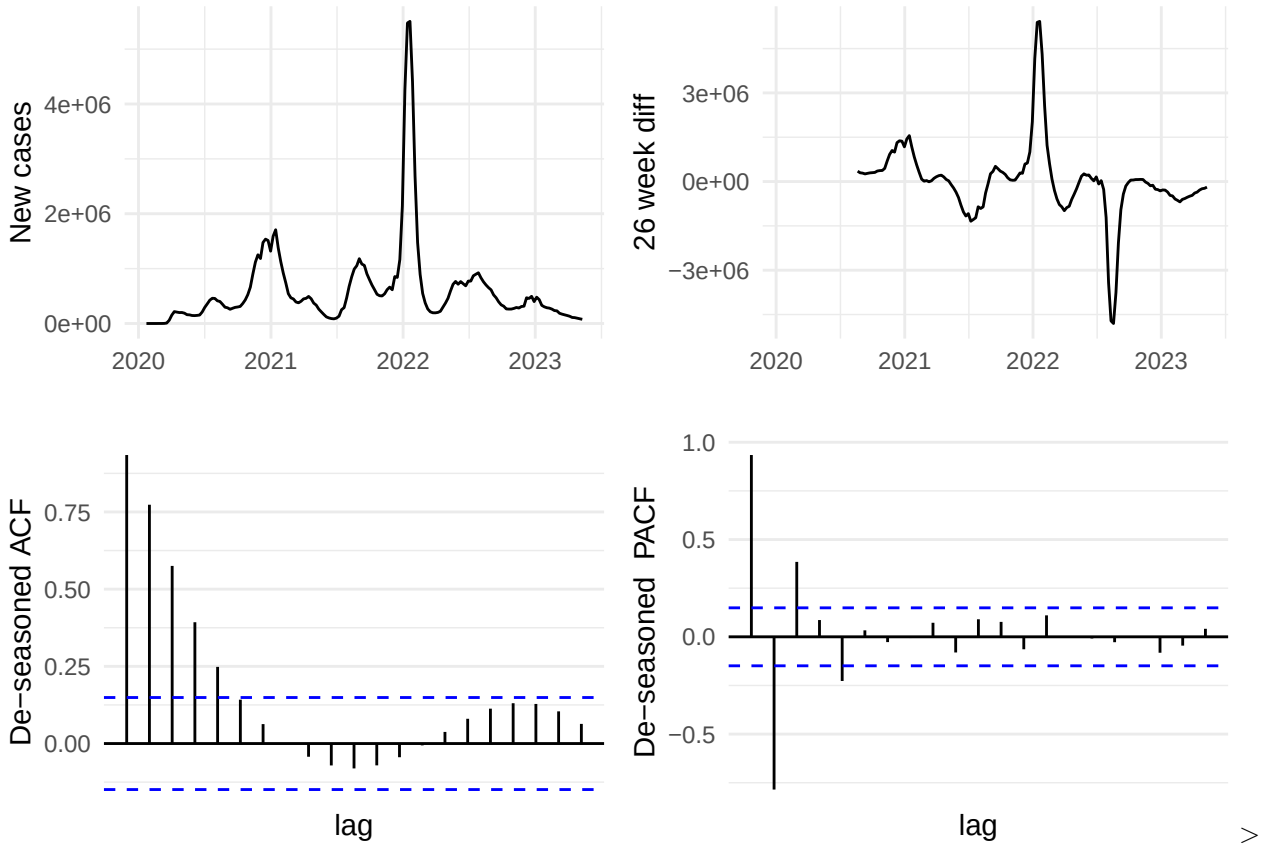
We know from previous analysis that the series requires de-trending. Below we plot the series itself, along side with the differenced series, ACF and PACF of the differenced series

```r
nation_ts<- mutate(nation_ts, diff = difference(new_cases, lag=1))

ts_plot <- nation_ts %>% ggplot() + aes(x = date_updated, y = new_cases) +
  geom_line() + labs (x = "", y = "New cases")

ts_diff_plot <- nation_ts %>% ggplot() + aes(x = date_updated, y = diff) +
  geom_line()   + labs (x = "", y = "1 week diff")

acf_plot<-nation_ts %>%
  ACF(diff, type="correlation") %>% autoplot()  + labs (x = "lag", y = "ACF")

pacf_plot<-nation_ts %>%
  ACF(diff, type="partial") %>% autoplot() + labs (x = "lag", y = "PACF")

grid.arrange(ts_plot , ts_diff_plot, acf_plot, pacf_plot, nrow=2)
```



Even after differencing the series remains non-stationary, with variance strongly dependent on time. Additionally, ACF resembles dampened oscillations, indicating underlying seasonality. It was not clear what would cause the seasonality, but running a few experiemtns we can find that de-trending with lag around half a year significantly reduces these artefacts. It is unlikely to be caused by the actual season, but probably a combinaton of how fast the virus spreads and how fast political descisions on shut down are made.

```
nation_ts<- mutate(nation_ts, diff = difference(new_cases, lag=30))

ts_plot <- nation_ts %>% ggplot() + aes(x = date_updated, y = new_cases) +
  geom_line()   + labs (x = "", y = "New cases")

ts_diff_plot <- nation_ts %>% ggplot() + aes(x = date_updated, y = diff) +
  geom_line()  + labs (x = "", y = "26 week diff")

acf_plot<-nation_ts %>%
  ACF(diff, type="correlation") %>% autoplot()  + labs (x = "lag", y = "De-seasoned ACF")

pacf_plot<-nation_ts %>%
  ACF(diff, type="partial") %>% autoplot() + labs (x = "lag", y = "De-seasoned  PACF")

grid.arrange(ts_plot , ts_diff_plot, acf_plot, pacf_plot, nrow=2)
```



After de-seasoning, the timeseries appears to be closer to stationary, with mean around 0 and standard deviation relatievely stable. Characteristic decay of ACF fanction indicates an AR process, which is consistent with quick decay of PACF plot. From these graphs it apperas that it might be an AR(5) process, becasue 5'th lag is the last one significant on PACF plot. It is worth noting that ACF plot still has significant oscilations. More complex de-trending procedures than just differencing might be required.

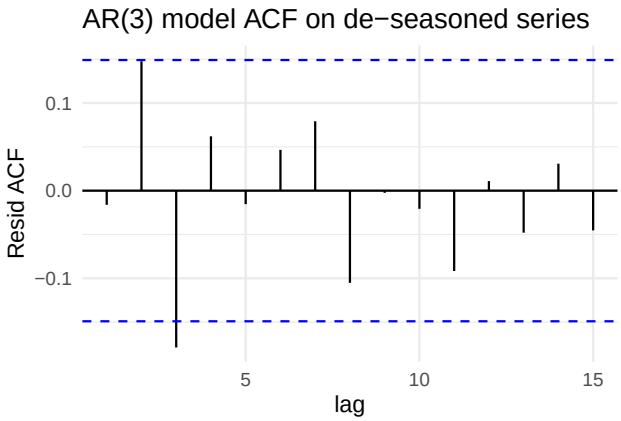
Next, we will perform a grid search using BIC to evaluate goodness of fit.

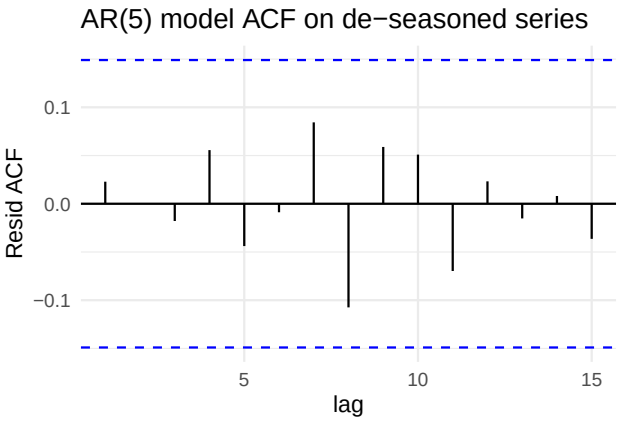
```
nation.bic<-nation_ts%>%
model(ARIMA(diff~ 1 + pdq(0:10,0:2,0:10) + PDQ(0,0,0), ic="bic", stepwise=F, greedy=F))
nation.bic %>%
report()
```

```
## Series: diff
## Model: ARIMA(3,0,0) w/ mean
##
## Coefficients:
##          ar1      ar2     ar3   constant
##       1.9776  -1.4447  0.3957   1833.972
## s.e.  0.0758   0.1348  0.0755  20514.645
##
## sigma^2 estimated as 5.384e+10:  log likelihood=-1983.81
## AIC=3977.61   AICc=3977.97   BIC=3993.38
```

```
Nation_AR3 <- arima(nation_ts$diff, order = c(3,0,0), seasonal = c(0, 0, 0), include.mean = T)
Nation_AR3_plot <- Nation_AR3 %>% residuals() %>% acf(plot = FALSE, na.action = na.pass) %>% autoplot()
  coord_cartesian(xlim = c(1, 15)) + labs(x = "lag", y = "Resid ACF", title = "AR(3) model ACF on de-sea

Nation_AR5 <- arima(nation_ts$diff, order = c(5,0,0), seasonal = c(0, 0, 0), include.mean = T)
```

```
Nation_AR5_plot <- Nation_AR5 %>% residuals() %>% acf(plot = FALSE, na.action = na.pass) %>% autoplot()
  coord_cartesian(xlim = c(1, 15)) + labs(x = "lag", y = "Resid ACF", title = "AR(5) model ACF on de-sea
```





> The grid search yielded the lowest BIC for AR(2) model, however, residual ACF plot for AR3 model has a few strongly significant lags. AR(5) model that we infered from the analysis of ACF and PACF of de-seasoned series demonstrates a lot more random beheviour. Therefore we will move forward with the AR(5) model.

(www3 points) Part-4: Write a few paragraphs about this modeling task

The nationwide model that you just produced contains much **more** data than went into your state-level model. Does this make it a better model? Why or why not?

Without a requirement that you actually produce the model that you propose: If you were trying to produce a nationwide model, knowing: (a) what you know about the state model that you fit; (b) what you know about the nationwide model that you fit; and (c) what you, as a citizen of this world who has lived through these past years: *propose a modeling strategy you think will produce the best nationwide forecasting model.*

This could be, for example, the nationwide model that you have fitted above. Or, you might propose some other forms of data aggregation before modeling, or model aggregation but not data aggregation. In writing about your strategy, justify choices that you are making.

Our goal with this question is to ask that you not only conduct the narrow technical work, but also that you do the higher-level reasoning about the technical work. We would like you to write in full paragraphs, rather than bullet points that address specific parts of the prompt above.