

US Covid-19 Cases Time Series Analysis

Stefan Maciolek

5/28/2020

```
#importing Covid Data from Johns Hopkins
uscases <-
read.csv(url("https://raw.githubusercontent.com/CSSEGISandData/COVID-
19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_co
nfirmes_US.csv"))
usdeaths <-
read.csv(url("https://raw.githubusercontent.com/CSSEGISandData/COVID-
19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_de
aths_US.csv"))
uscases <- uscases[, -c(1:5,8:11)]
usdeaths <- usdeaths[, -c(1:5,8:12)]
n <- ncol(uscases)-2
date <- 1:n
date <- as.Date(date,origin = "2020-01-21")
format(date,format = "%b %d %y")

## [1] "Jan 22 20" "Jan 23 20" "Jan 24 20" "Jan 25 20" "Jan 26 20" "Jan 27
20"
## [7] "Jan 28 20" "Jan 29 20" "Jan 30 20" "Jan 31 20" "Feb 01 20" "Feb 02
20"
## [13] "Feb 03 20" "Feb 04 20" "Feb 05 20" "Feb 06 20" "Feb 07 20" "Feb 08
20"
## [19] "Feb 09 20" "Feb 10 20" "Feb 11 20" "Feb 12 20" "Feb 13 20" "Feb 14
20"
## [25] "Feb 15 20" "Feb 16 20" "Feb 17 20" "Feb 18 20" "Feb 19 20" "Feb 20
20"
## [31] "Feb 21 20" "Feb 22 20" "Feb 23 20" "Feb 24 20" "Feb 25 20" "Feb 26
20"
## [37] "Feb 27 20" "Feb 28 20" "Feb 29 20" "Mar 01 20" "Mar 02 20" "Mar 03
20"
## [43] "Mar 04 20" "Mar 05 20" "Mar 06 20" "Mar 07 20" "Mar 08 20" "Mar 09
20"
## [49] "Mar 10 20" "Mar 11 20" "Mar 12 20" "Mar 13 20" "Mar 14 20" "Mar 15
20"
## [55] "Mar 16 20" "Mar 17 20" "Mar 18 20" "Mar 19 20" "Mar 20 20" "Mar 21
20"
## [61] "Mar 22 20" "Mar 23 20" "Mar 24 20" "Mar 25 20" "Mar 26 20" "Mar 27
20"
## [67] "Mar 28 20" "Mar 29 20" "Mar 30 20" "Mar 31 20" "Apr 01 20" "Apr 02
20"
## [73] "Apr 03 20" "Apr 04 20" "Apr 05 20" "Apr 06 20" "Apr 07 20" "Apr 08
20"
```

```
## [79] "Apr 09 20" "Apr 10 20" "Apr 11 20" "Apr 12 20" "Apr 13 20" "Apr 14
20"
## [85] "Apr 15 20" "Apr 16 20" "Apr 17 20" "Apr 18 20" "Apr 19 20" "Apr 20
20"
## [91] "Apr 21 20" "Apr 22 20" "Apr 23 20" "Apr 24 20" "Apr 25 20" "Apr 26
20"
## [97] "Apr 27 20" "Apr 28 20" "Apr 29 20" "Apr 30 20" "May 01 20" "May 02
20"
## [103] "May 03 20" "May 04 20" "May 05 20" "May 06 20" "May 07 20" "May 08
20"
## [109] "May 09 20" "May 10 20" "May 11 20" "May 12 20" "May 13 20" "May 14
20"
## [115] "May 15 20" "May 16 20" "May 17 20" "May 18 20" "May 19 20" "May 20
20"
## [121] "May 21 20" "May 22 20" "May 23 20" "May 24 20" "May 25 20" "May 26
20"
## [127] "May 27 20"
```

The data were imported from Johns Hopkins, cleaned up, and a date variable was created for plotting purposes. For this analysis the case data wasn't used, just the case numbers

#finding total cases and turning them into a time series object
library(TSA)

```
##
## Attaching package: 'TSA'

## The following objects are masked from 'package:stats':
##
##   acf, arima

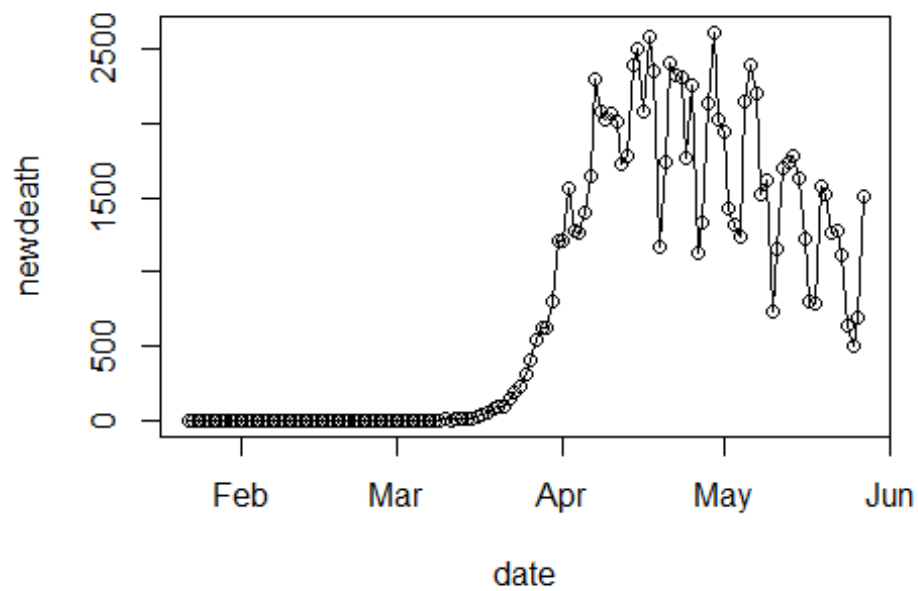
## The following object is masked from 'package:utils':
##
##   tar

totdeath <- colSums(usdeaths[,3:(n+2)])
newdeath <- rep(0,n)
newdeath[1] <- totdeath[1]
newdeath[2:n] <- diff(totdeath)
newdeath <- ts(data=newdeath,start=c(2020,01,22),frequency = 365)
```

A the data were turned into a time series object

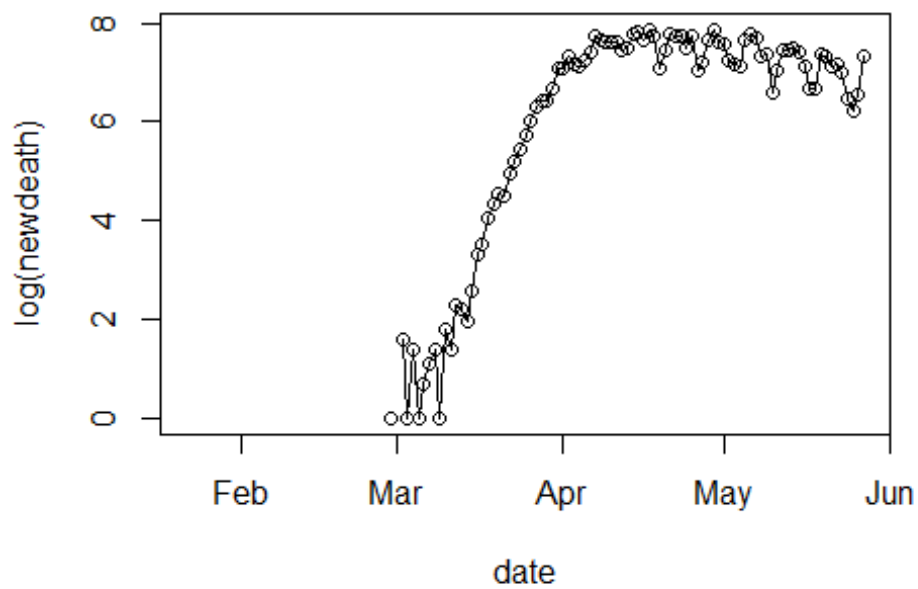
#trying various transformations
wkday <- c("W","T","F","S","S","M","T")
plot(date,newdeath,type="o",main="Untransformed time series")

Untransformed time series

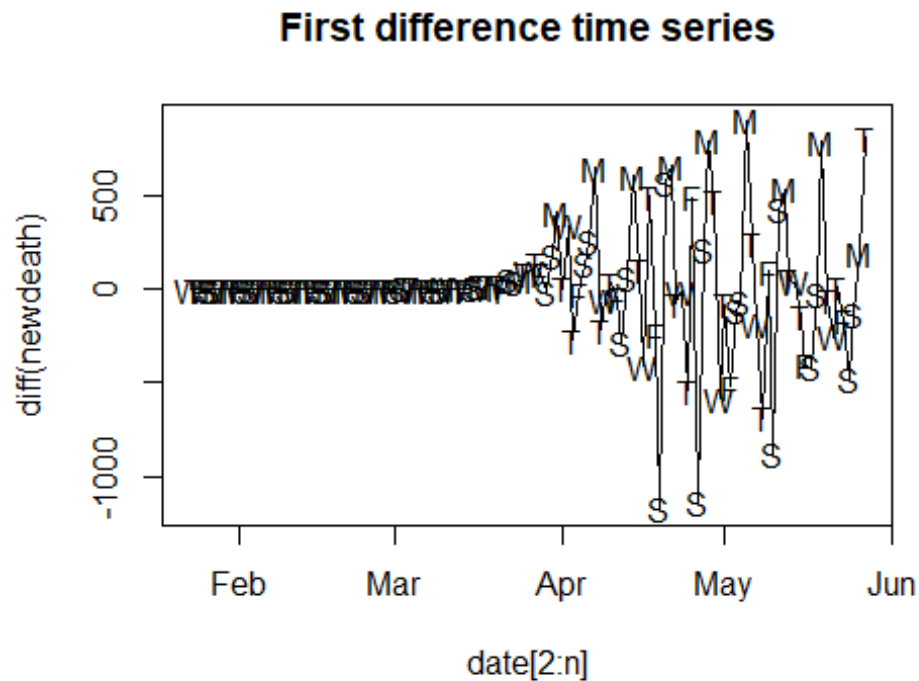


```
plot(date,log(newdeath),type="o",main="Log time series")
```

Log time series



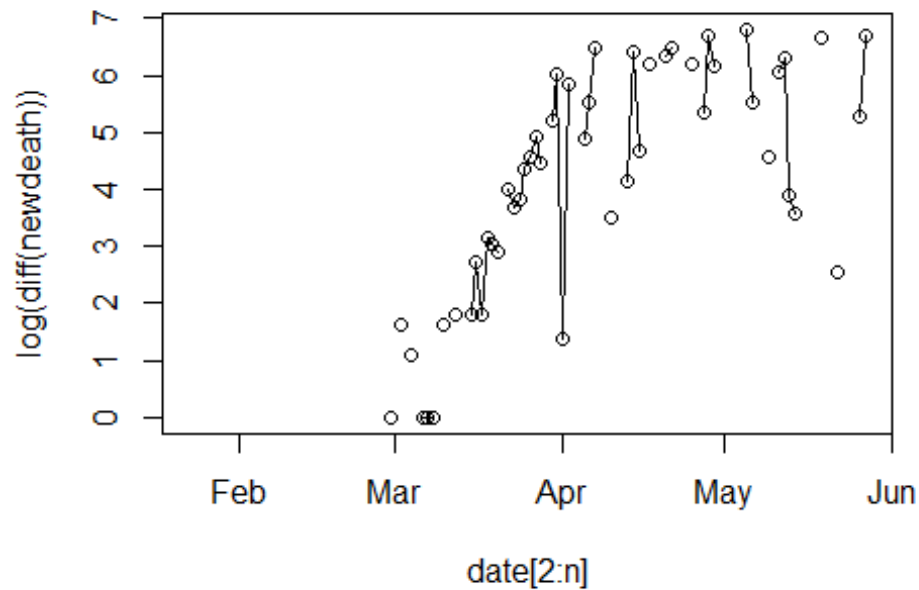
```
plot(date[2:n],diff(newdeath),type="o",main="First difference time series",pch=wkday)
```



```
plot(date[2:n],log(diff(newdeath)),type="o",main="Log of first difference time series")
```

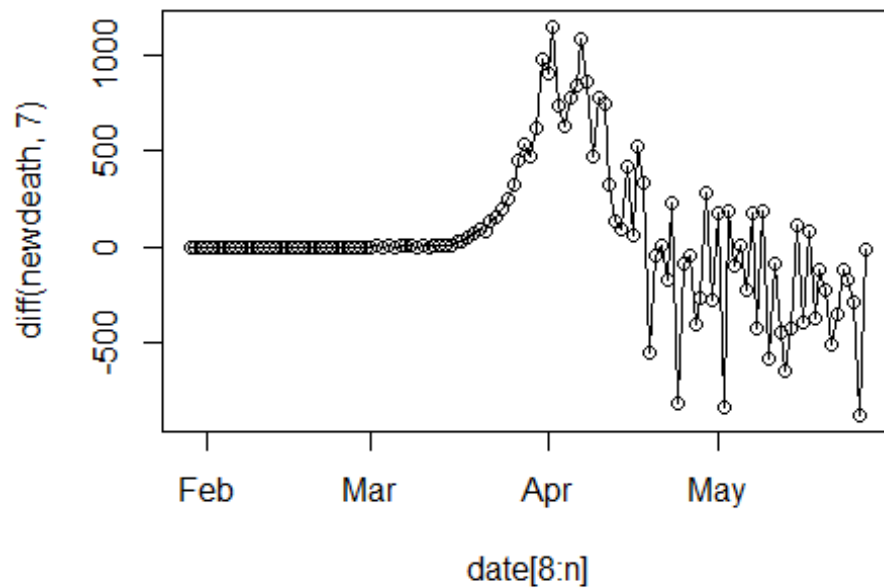
```
## Warning in log(diff(newdeath)): NaNs produced
```

Log of first difference time series

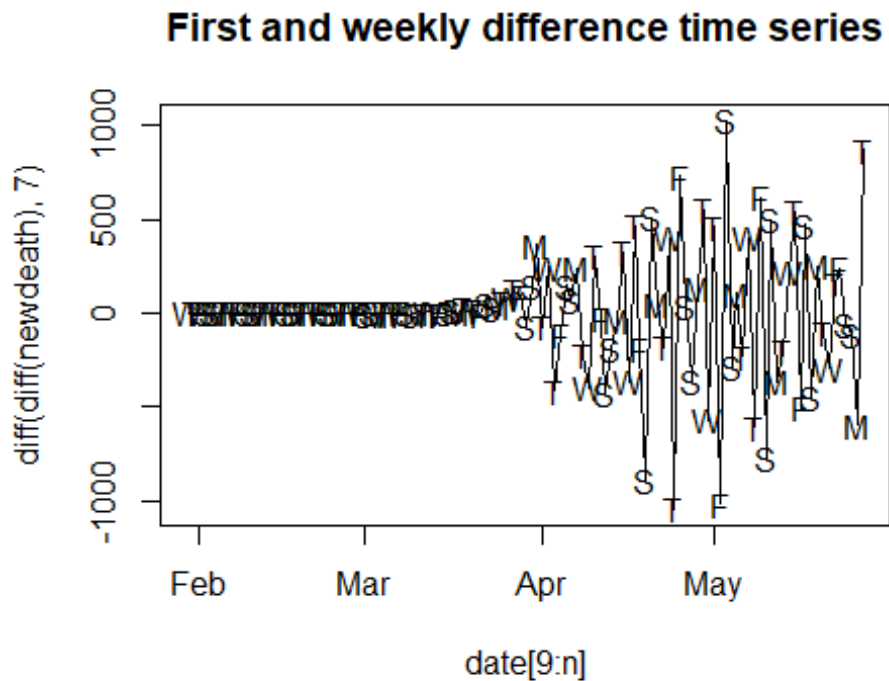


```
plot(date[8:n],diff(newdeath,7),type="o",main="First weekly difference time series")
```

First weekly difference time series



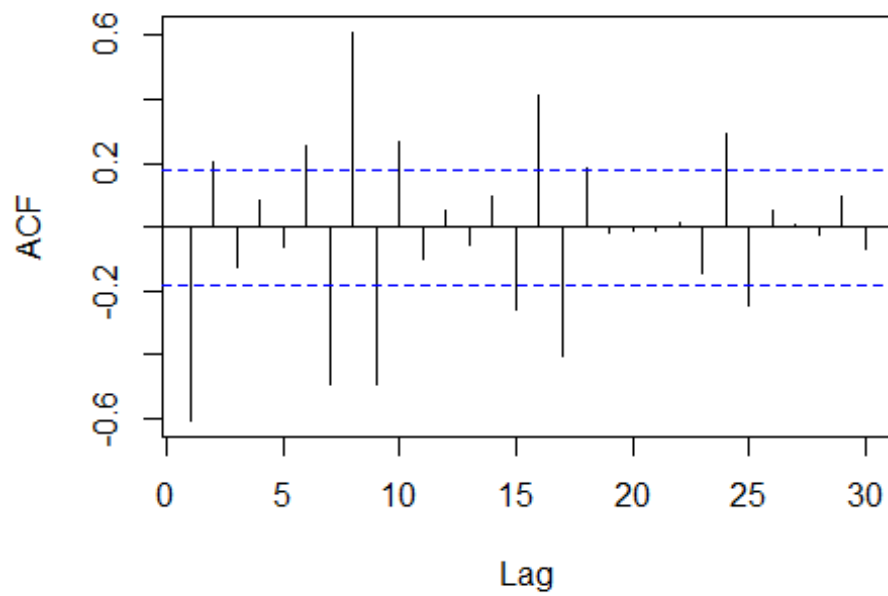
```
plot(date[9:n],diff(diff(newdeath),7),type="o",main="First and weekly  
difference time series",pch=wkday)
```



Several transformations and combinations of transformations were tested to see if they made the data random. In the end, a first and first seasonal difference with a weekly period were chosen.

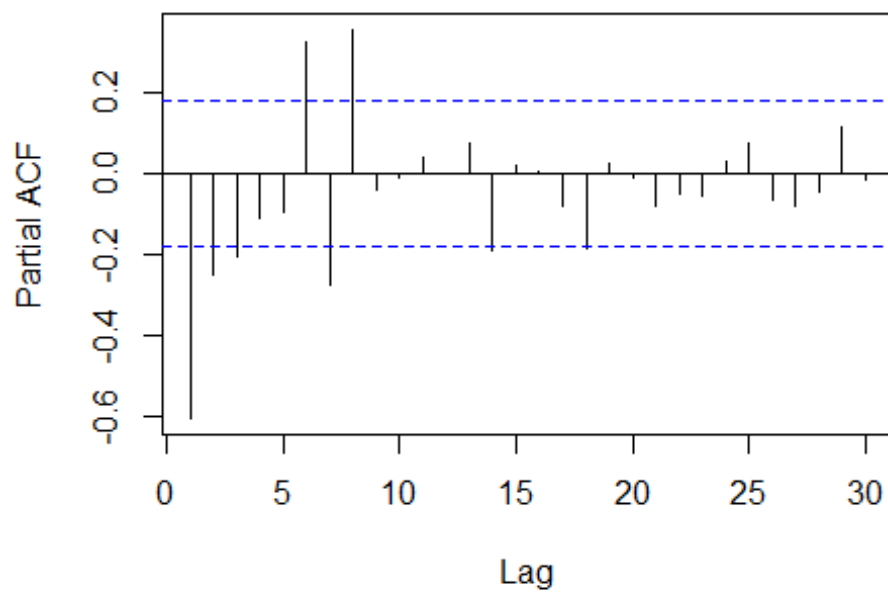
```
#starting with an ARIMA model with both a first and first weekly difference  
#preliminary analysis  
transdeath <- diff(diff(newdeath),7)  
acf(as.vector(transdeath),main="ACF of transformed series",lag.max=30)
```

ACF of transformed series

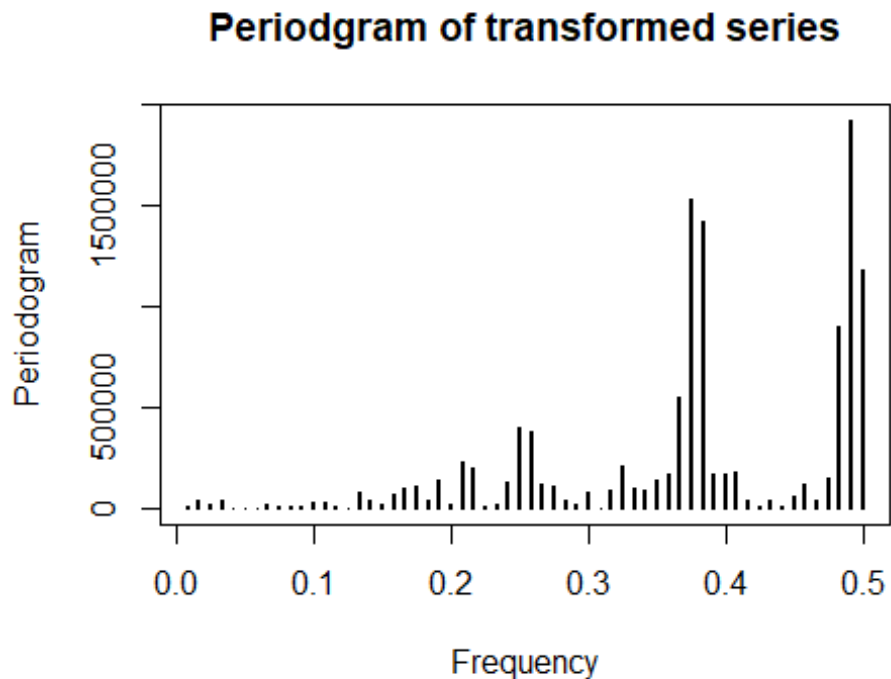


```
pacf(as.vector(transdeath),main="PACF of transformed series",lag.max=30)
```

PACF of transformed series



```
periodogram(transdeath,main="Periodgram of transformed series")
```



The ACF and PACF of the series suggest a starting model with at least 1 AR and 1 seasonal AR component.

```
#model fitting:
#looking at the periodograms, it appears a ARIMA(1,1,0)x(1,1,0)_7 is
justified to start
tsmodel <- function(ar,ma,ars,mas){
  mod <-
  arima(newdeath,order=c(ar,1,ma),seasonal=list(order=c(ars,1,mas),period=7))
  return(mod)
}
tsmodel(1,0,1,0)

##
## Call:
## arima(x = newdeath, order = c(ar, 1, ma), seasonal = list(order = c(ars,
1,
##     mas), period = 7))
##
## Coefficients:
##          ar1      sar1
##      -0.5466  -0.2685
## s.e.    0.0906   0.1036
##
## sigma^2 estimated as 57435:  log likelihood = -821.32,  aic = 1646.64

tsmodel(2,0,1,0)
```



```
##
## Call:
## arima(x = newdeath, order = c(ar, 1, ma), seasonal = list(order = c(ars,
1,
##     mas), period = 7))
##
## Coefficients:
##           ar1           ar2           sar1
##      -0.6753   -0.2538   -0.2696
## s.e.    0.1081    0.0912    0.1144
##
## sigma^2 estimated as 53876:  log likelihood = -817.58,  aic = 1641.16
tsmodel(3,0,1,0)

##
## Call:
## arima(x = newdeath, order = c(ar, 1, ma), seasonal = list(order = c(ars,
1,
##     mas), period = 7))
##
## Coefficients:
##           ar1           ar2           ar3           sar1
##      -0.7311   -0.3754   -0.1811   -0.2368
## s.e.    0.1097    0.1113    0.0942    0.1126
##
## sigma^2 estimated as 52266:  log likelihood = -815.77,  aic = 1639.53
tsmodel(3,0,2,0) #not significant

##
## Call:
## arima(x = newdeath, order = c(ar, 1, ma), seasonal = list(order = c(ars,
1,
##     mas), period = 7))
##
## Coefficients:
##           ar1           ar2           ar3           sar1           sar2
##      -0.7192   -0.3509   -0.2095   -0.2779   -0.1595
## s.e.    0.1151    0.1128    0.0945    0.1214    0.1000
##
## sigma^2 estimated as 51011:  log likelihood = -814.52,  aic = 1639.04
tsmodel(3,1,1,0) #not significant

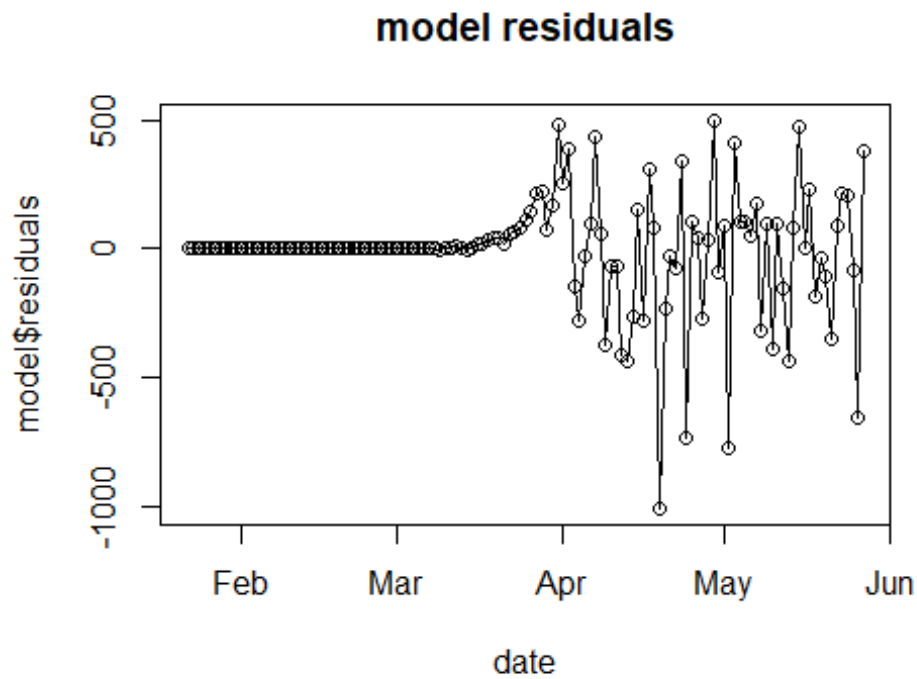
##
## Call:
## arima(x = newdeath, order = c(ar, 1, ma), seasonal = list(order = c(ars,
1,
##     mas), period = 7))
##
```

```
## Coefficients:
##          ar1      ar2      ar3      ma1      sar1
##      -0.4764 -0.2002 -0.1231 -0.2702 -0.2286
## s.e.   0.2999  0.2281  0.1276  0.2892  0.1140
##
## sigma^2 estimated as 51999:  log likelihood = -815.46,  aic = 1640.92
tsmodel(3,0,1,1) #not stationary

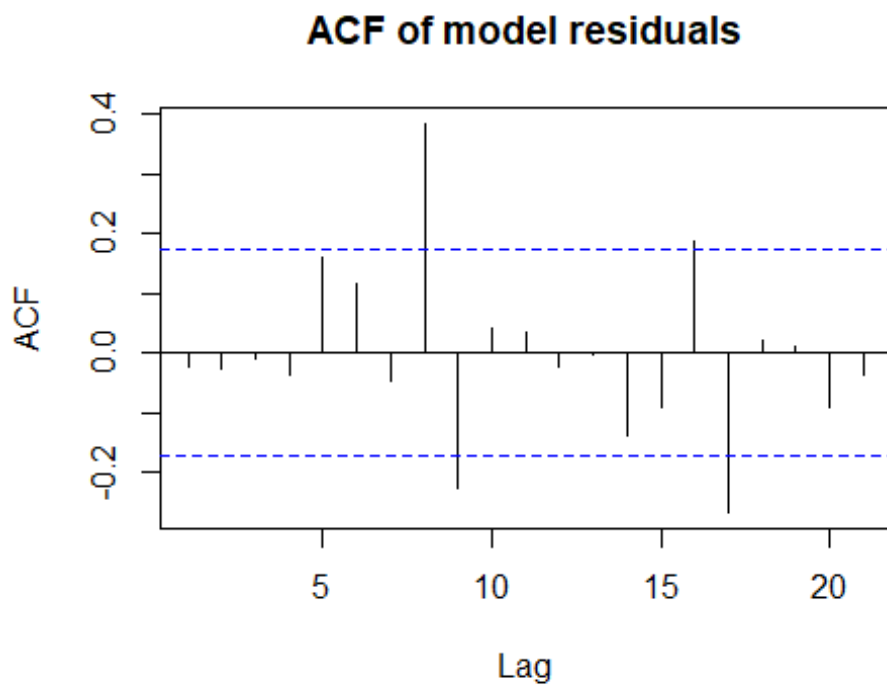
##
## Call:
## arima(x = newdeath, order = c(ar, 1, ma), seasonal = list(order = c(ars,
1,
##      mas), period = 7))
##
## Coefficients:
##          ar1      ar2      ar3      sar1      sma1
##      -0.7197 -0.3460 -0.1837  0.3006 -0.5915
## s.e.   0.1150  0.1142  0.0934  0.3352  0.2677
##
## sigma^2 estimated as 50672:  log likelihood = -814.19,  aic = 1638.37
#the final model is an ARIMA(3,1,0)X(1,1,0)_7
```

The order of the model was raised one component at a time until adding further components were no longer significant. The final model was an ARIMA(3,1,0)X(1,1,0)_7

```
#diagnostics:
model<-tsmodel(3,0,1,0)
plot(date,model$residuals,main="model residuals",type="o")
```

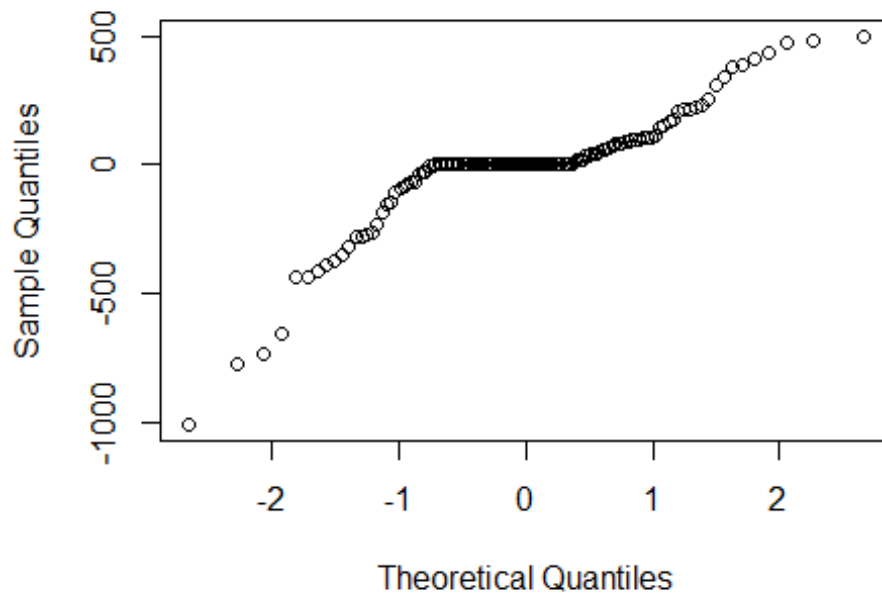


```
acf(as.vector(model$residuals),main="ACF of model residuals")
```



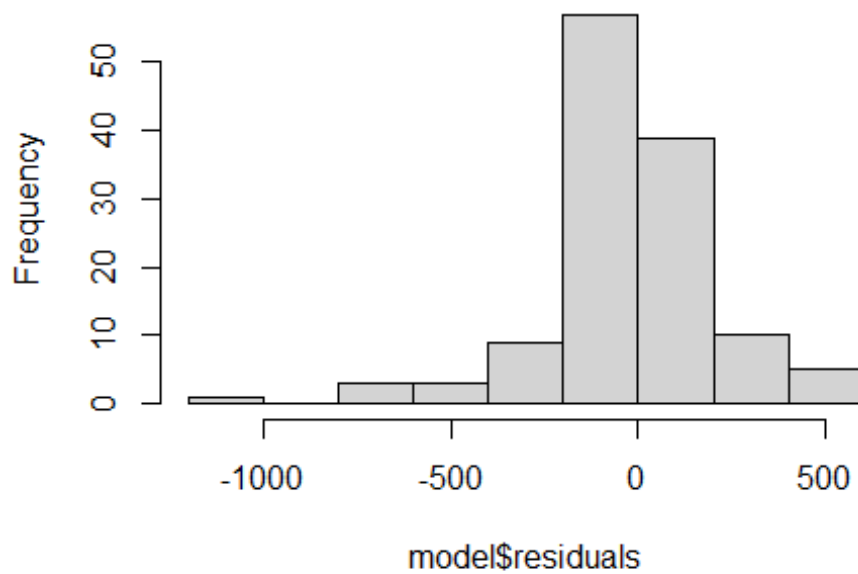
```
qqnorm(model$residuals,main="QQ plot of model residuals")
```

QQ plot of model residuals



```
hist(model$residuals,main="histogram of model residuals")
```

histogram of model residuals

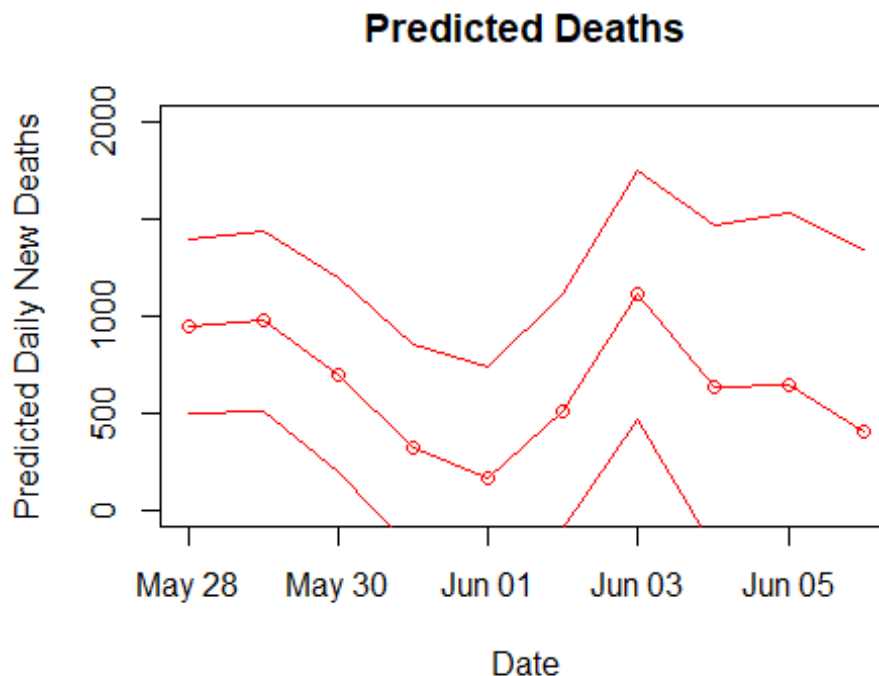


The residuals were analyzed and diagnostics produced. The residuals are more or less normal, and although they have a high autocorrelation at lag 8, it doesn't appear large enough to justify a more complex model

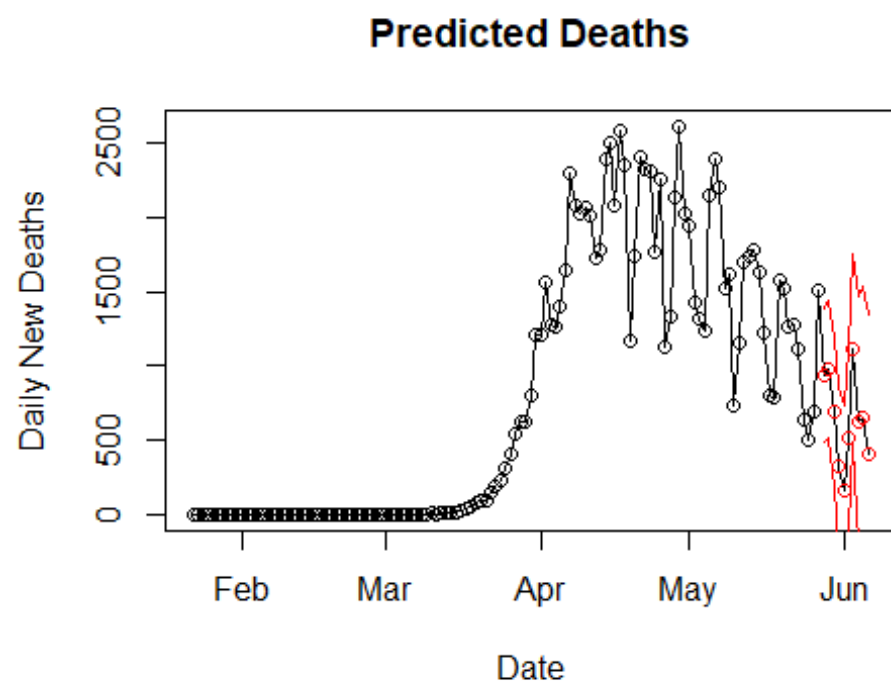
```
#predictions
predictions <- predict(model,n.ahead=10)
dateahead<- seq(from=(n+1),to=(n+10))
dateahead <- as.Date(dateahead,origin = "2020-01-21")
format(dateahead,format = "%b %d %y")

## [1] "May 28 20" "May 29 20" "May 30 20" "May 31 20" "Jun 01 20" "Jun 02 20"
## [7] "Jun 03 20" "Jun 04 20" "Jun 05 20" "Jun 06 20"

plot(dateahead,predictions$pred,main="Predicted
Deaths",type="o",ylim=c(0,2000),ylab="Predicted Daily New
Deaths",xlab="Date",col="red")
lines(dateahead,(predictions$pred - 1.96*predictions$se),type="l",col="red")
lines(dateahead,(predictions$pred + 1.96*predictions$se),type="l",col="red")
```



```
datenew <- c(date,dateahead)
total <- c(newdeath,predictions$pred)
plot(datenew,total,col=c(rep("black",n),rep("red",10)),main="Predicted
Deaths",type="o",ylab="Daily New Deaths",xlab="Date")
lines(dateahead,(predictions$pred - 1.96*predictions$se),type="l",col="red")
lines(dateahead,(predictions$pred + 1.96*predictions$se),type="l",col="red")
```



The model was used to create predictions for 10 days out.