

Time Series Covid Project

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#Modeling Covid19 Time Series

Covid19 is a worldwide pandemic that will likely define 2020. In the United States, currently over four million people have been infected and over 150,000 have died as a result of Covid19. As the pandemic continues, limiting infections, serious harm, and death is a primary concern for all involved.

As this is a novel illness, we know relatively little, but understanding how Covid19 is spreading and judging the severity of an outbreak can be approximated with the data we have available. In this report we aim to build effective time series models to forecast future Covid19 cases using the techniques we have learned from this Time Series course. *## Goal One: Data Collection*

The data source we are using is sourced from The Covid Tracking Project.

```
initial_data_fl <- read.csv(file="https://raw.githubusercontent.com/megnn/TimeSeries_Covid/master/covid19_data/florida.csv")
initial_data_us <- read.csv(file="https://raw.githubusercontent.com/megnn/TimeSeries_Covid/master/covid19_data/us.csv")

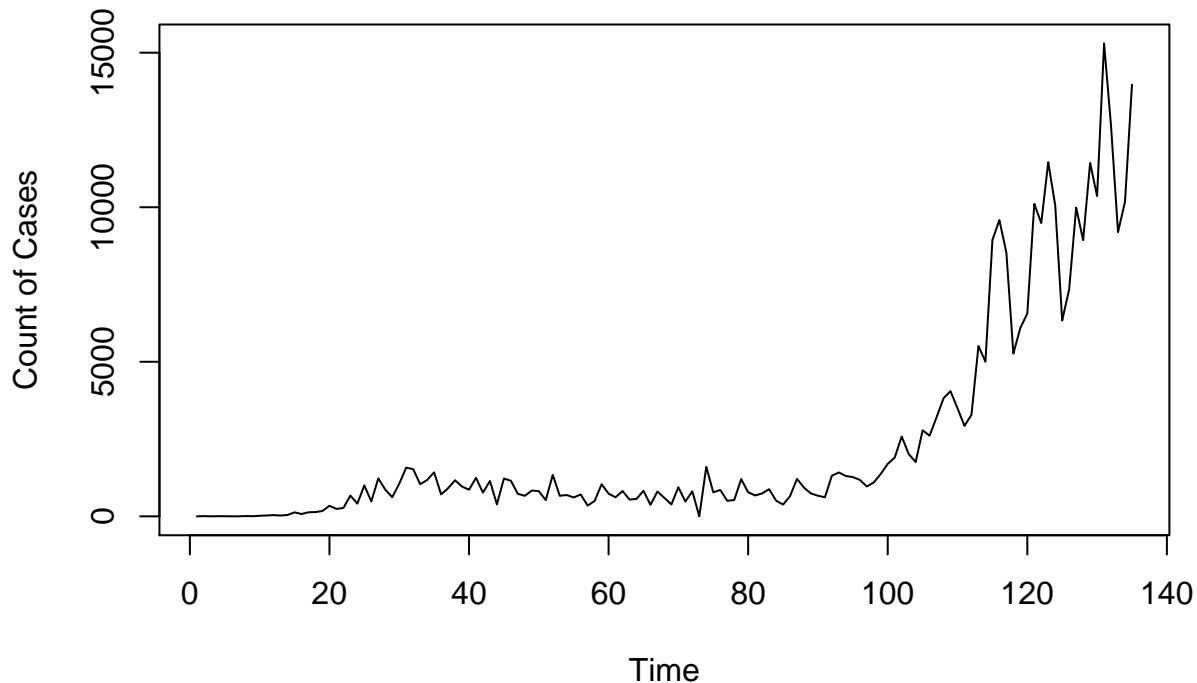
initial_data_fl = initial_data_fl[order(nrow(initial_data_fl)):1,]
initial_data_us = initial_data_us[order(nrow(initial_data_us)):1,]

len_fl = dim(initial_data_fl)[1]
len_us = dim(initial_data_us)[1]
```

Below we plot the realizations of daily new cases from both Florida and the United States as a whole.

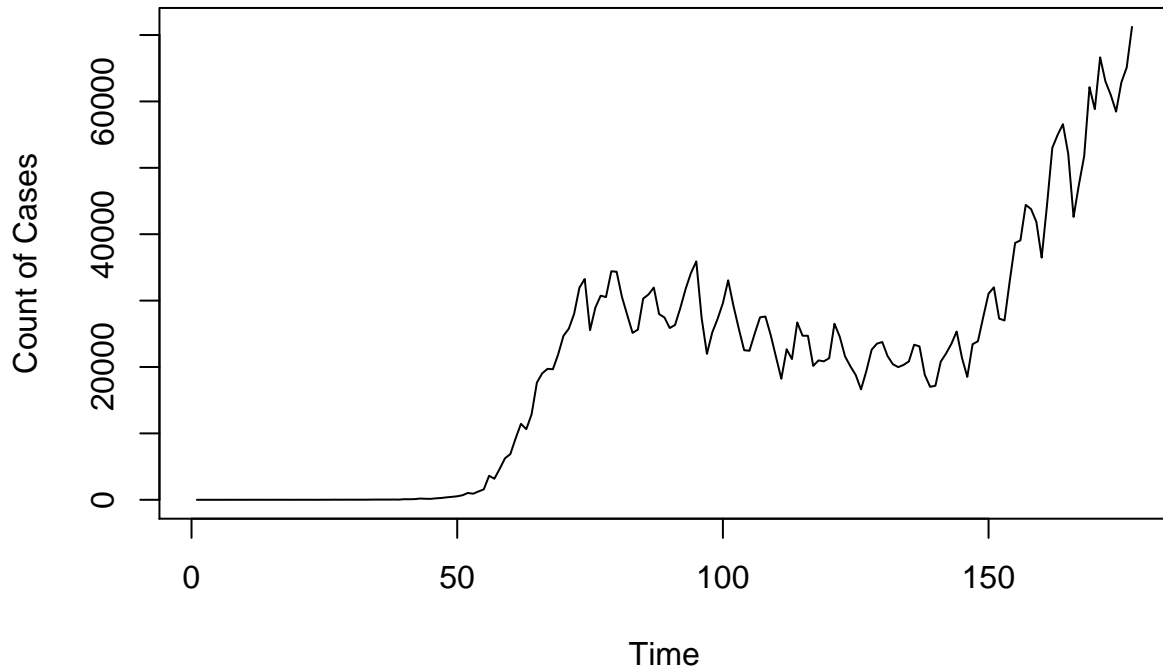
```
plot(x = seq(1,len_fl), y = initial_data_fl$positiveIncrease, type = "l", ylab = "Count of Cases", xlab = "Time")
```

Count of Daily Covid19 Cases – Florida



```
plot(x = seq(1,len_us), y = initial_data_us$positiveIncrease, type = "l", ylab = "Count of Cases", xlab =
```

Count of Daily Covid19 Cases – United States



##Positive Percentage

Positive Percentage is a statistic that calculates daily positive tests as a percentage of daily overall tests returned. We calculated this column and added it to our data below followed by some visual exploration of the statistic itself.

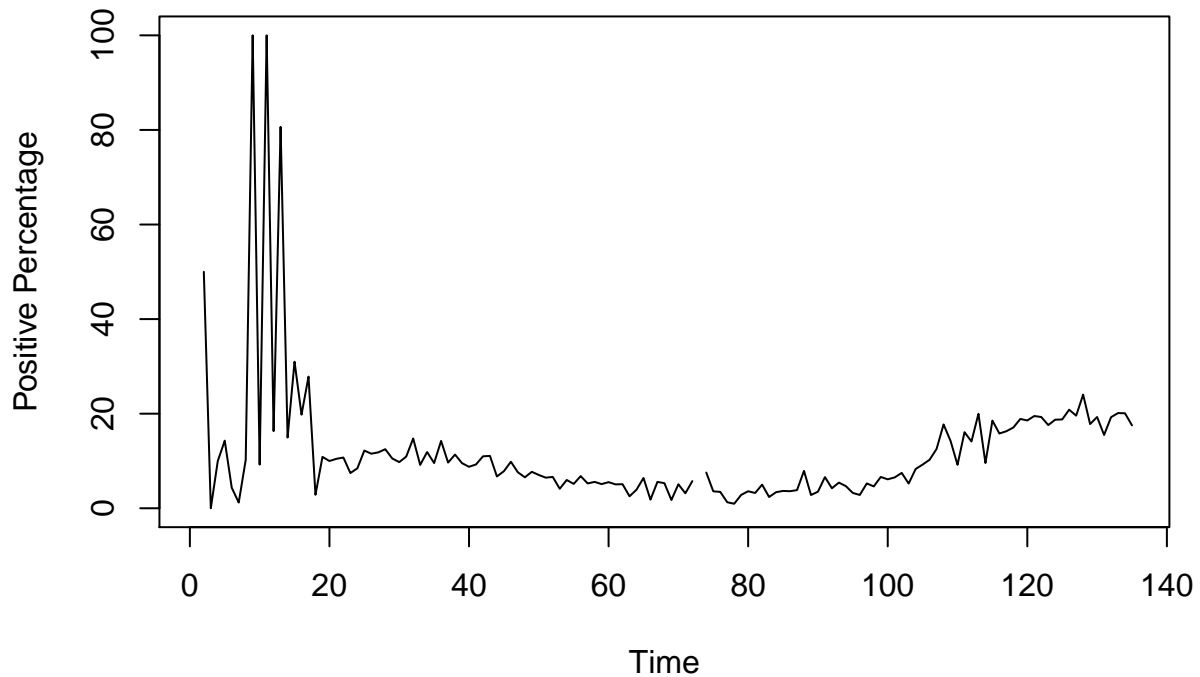
Overall we see a clear instance of high and often 100% positive test rates early on in the first days and weeks of the pandemic spread. We understand this as a result of the fact that Covid19 spread fast and we had more community spread than anticipated early on without the testing available. It is abundantly clear that when we have extremely high percent positive rates near 100% we can expect true positive case numbers at the time to be under represented. But without better epidemiological understanding we can't make judgement calls on true case numbers when percent positives rise from 5% to 10% as we see begin to happen somewhat in recent days in Florida.

```
for (i in 1:nrow(initial_data_fl)) {
  n <- round((initial_data_fl$positiveIncrease / initial_data_fl$totalTestResultsIncrease) * 100, digits = 1)
  initial_data_fl$positive_percentage <- n
}

for (i in 1:nrow(initial_data_us)) {
  n <- round((initial_data_us$positiveIncrease / initial_data_us$totalTestResultsIncrease) * 100, digits = 1)
  initial_data_us$positive_percentage <- n
}

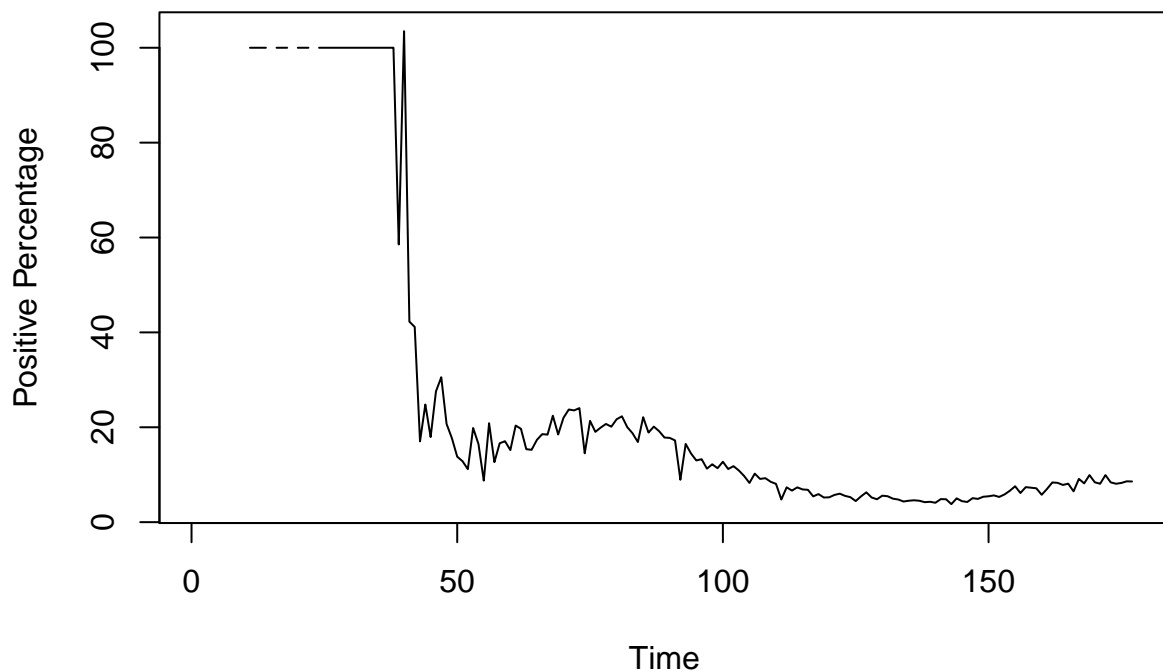
#Percent Positive Exploration
plot(x = seq(1:len_fl), y = initial_data_fl$positive_percentage, type = "l", main = "Florida Positive P
```

Florida Positive Percentage over time



```
plot(x = seq(1:len_us), y = initial_data_us$positive_percentage, type = "l", main = "US Positive Percen
```

US Positive Percentage over time

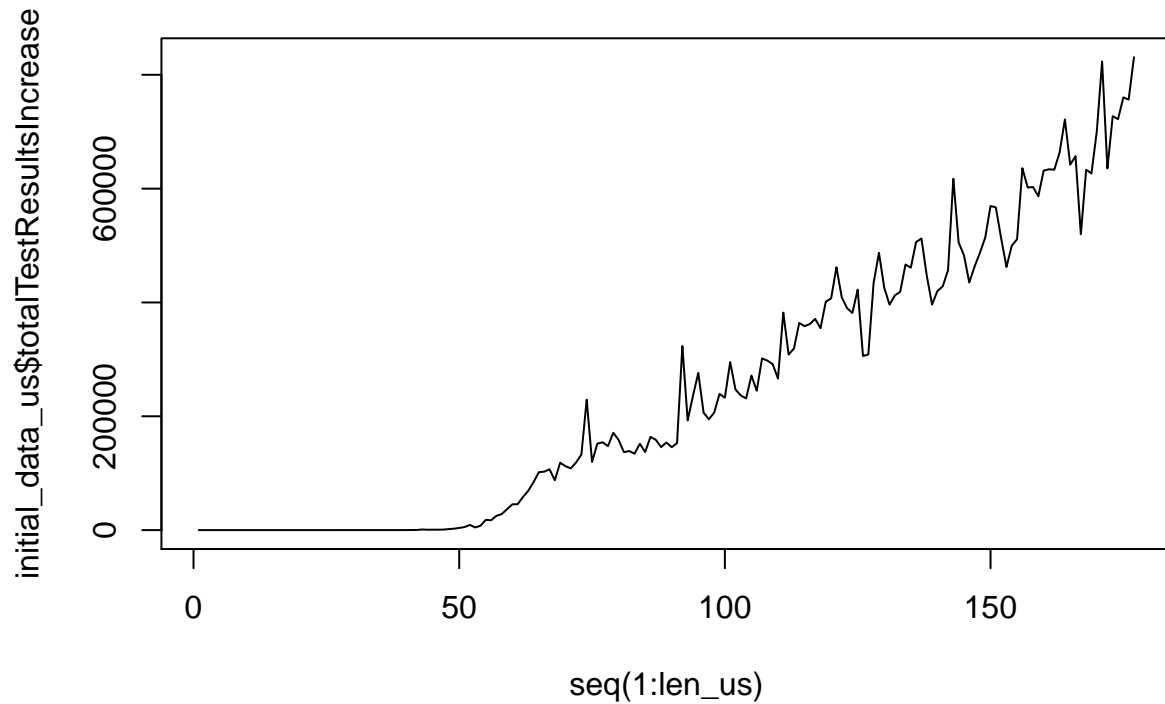


Positive Percentage as a metric is a measure of two main things, how many tests are we administering and how many positives are we receiving. If tests are skyrocketing while positive cases are increasing, we would see a stable or even diminishing line which could indicate not a pandemic under control but simply better testing resources but could be interpreted as a pandemic managed.

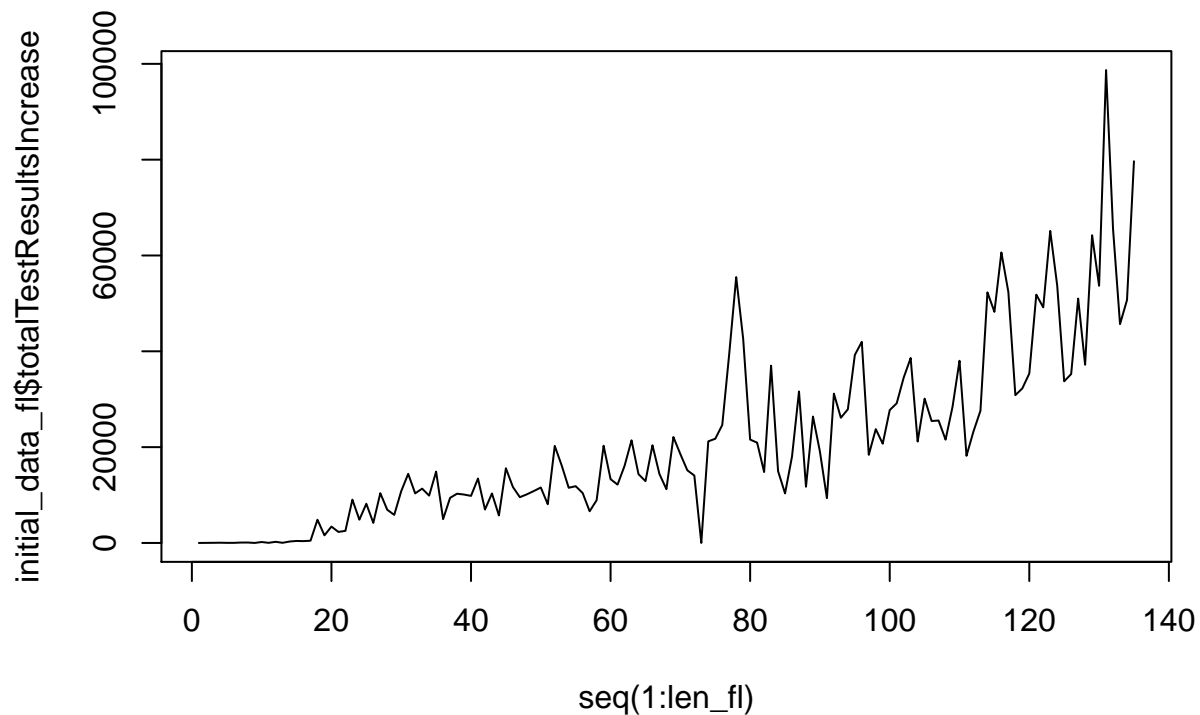
Keeping tests increasing to continue to keep percent positives level is a good indication we have leveled up our resources to continue to diagnose the pandemic at the same level, but if we need to scale up our testing to keep the same positive percentage, there is more covid spread.

However, an increasing positive percentage is a good indicator that our testing resources may not be up to actually up to tracking the current stage of the pandemic.

```
plot(x = seq(1:len_us), y = initial_data_us$totalTestResultsIncrease, type = "l")
```



```
plot(x = seq(1:len_fl), y = initial_data_fl$totalTestResultsIncrease, type = "l")
```



####Data Preperation

In order to model new case numbers by day we set up dataframes with only our date and positive increase amount per day.

```
newcases_fl <- dplyr::select(initial_data_fl, c("date", "positiveIncrease"))
newcases_us <- dplyr::select(initial_data_us, c("date", "positiveIncrease"))
```

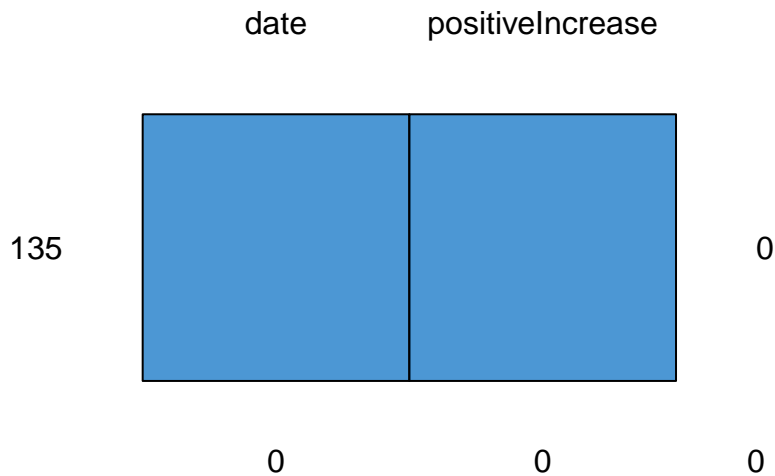
####Checking for NAs

We can see with the missing value analysis below that we have no NAs present in our new case data.

#Checking for NAs

```
md.pattern(newcases_fl)
```

```
## /\      /\
## {  `---'  }
## {  0    0  }
## ==> V <== No need for mice. This data set is completely observed.
## \  \|/  /
## `-----'
```



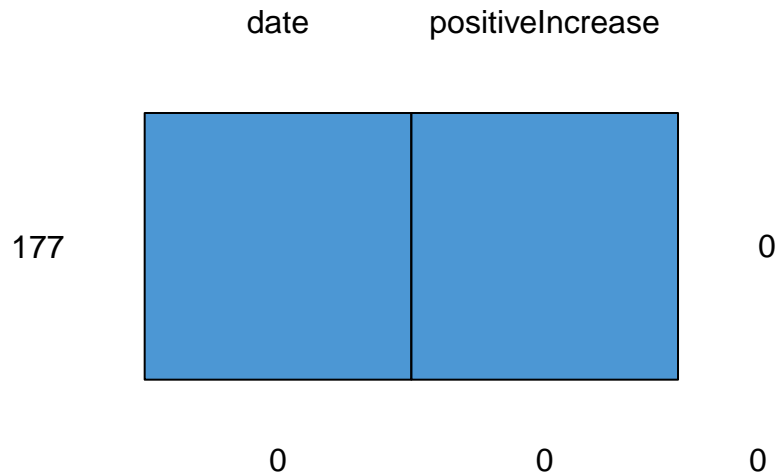
```
##      date positiveIncrease
## 135    1                1 0
##      0                0 0
```

No NAs present

#Checking for NAs

```
md.pattern(newcases_us)
```

```
## /\      /\
## {  `---'  }
## {  0    0  }
## ==> V <== No need for mice. This data set is completely observed.
## \  \|/  /
## `-----'
```

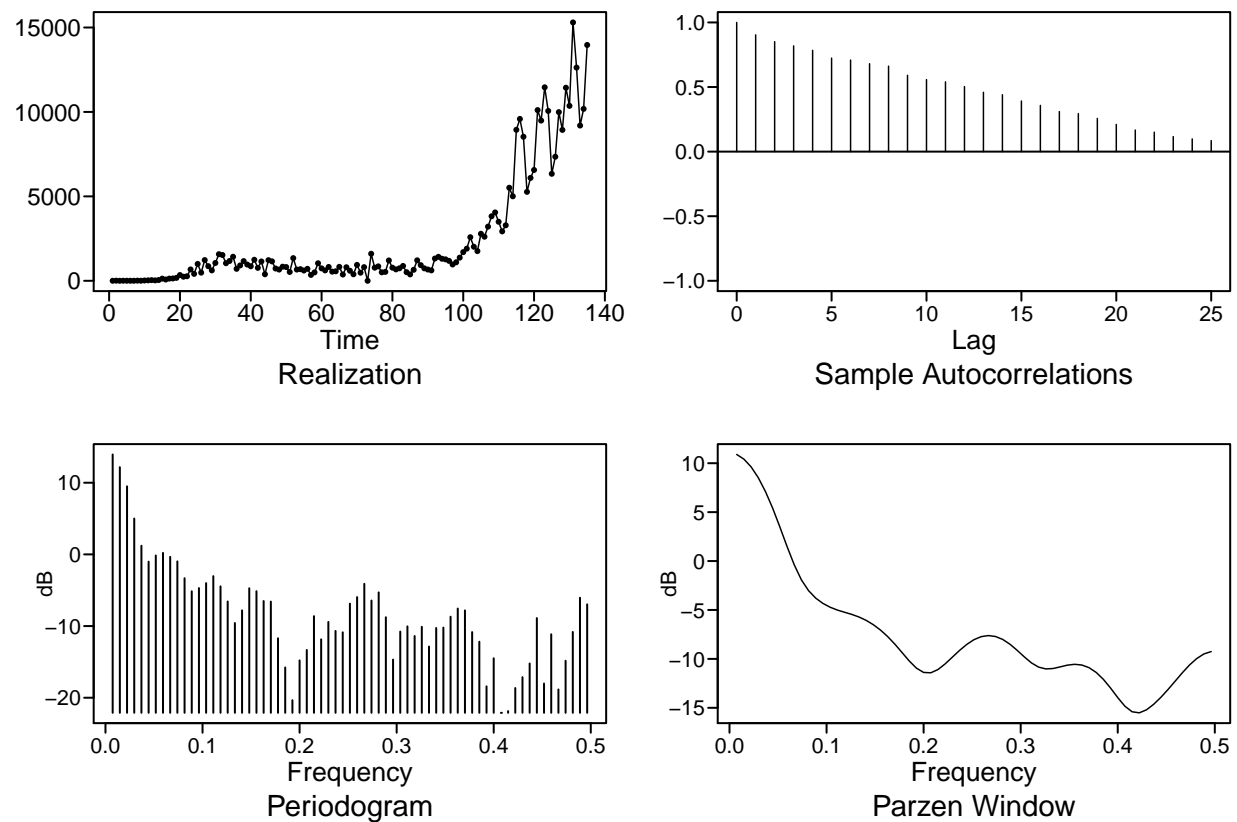


```
##      date positiveIncrease
## 177     1                 1 0
##      0                 0 0
```

#No NAs present

Florida Daily Cases:

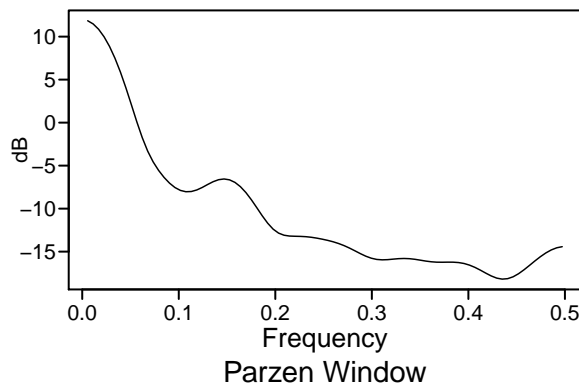
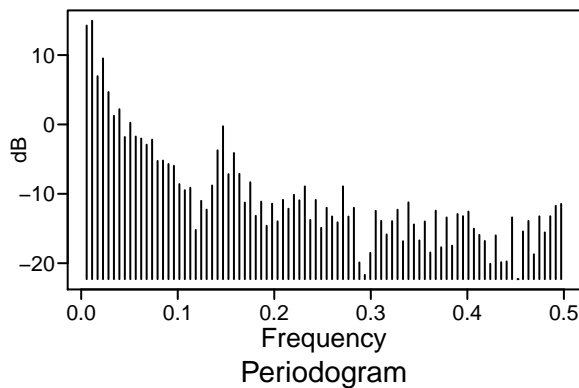
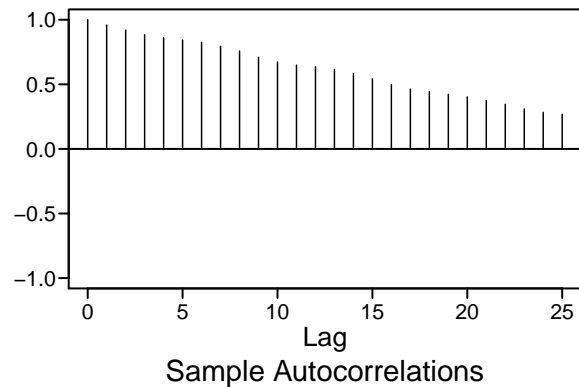
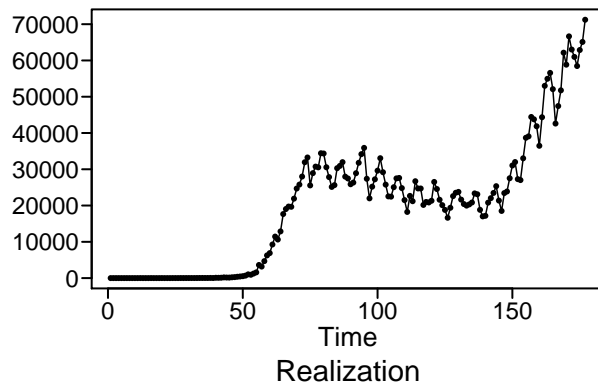
#no text output, just the plots
x = `plotts.sample.wge(newcases_fl$positiveIncrease)`



###US Daily Cases:

```
#no text output
```

```
x = plotts.sample.wge(newcases_us$positiveIncrease)
```



```
dev.off()
```

```
plot(x = seq(1,len_us), y = newcases_us$positiveIncrease, type = "l", main = 'United States Covid-19 Da
```

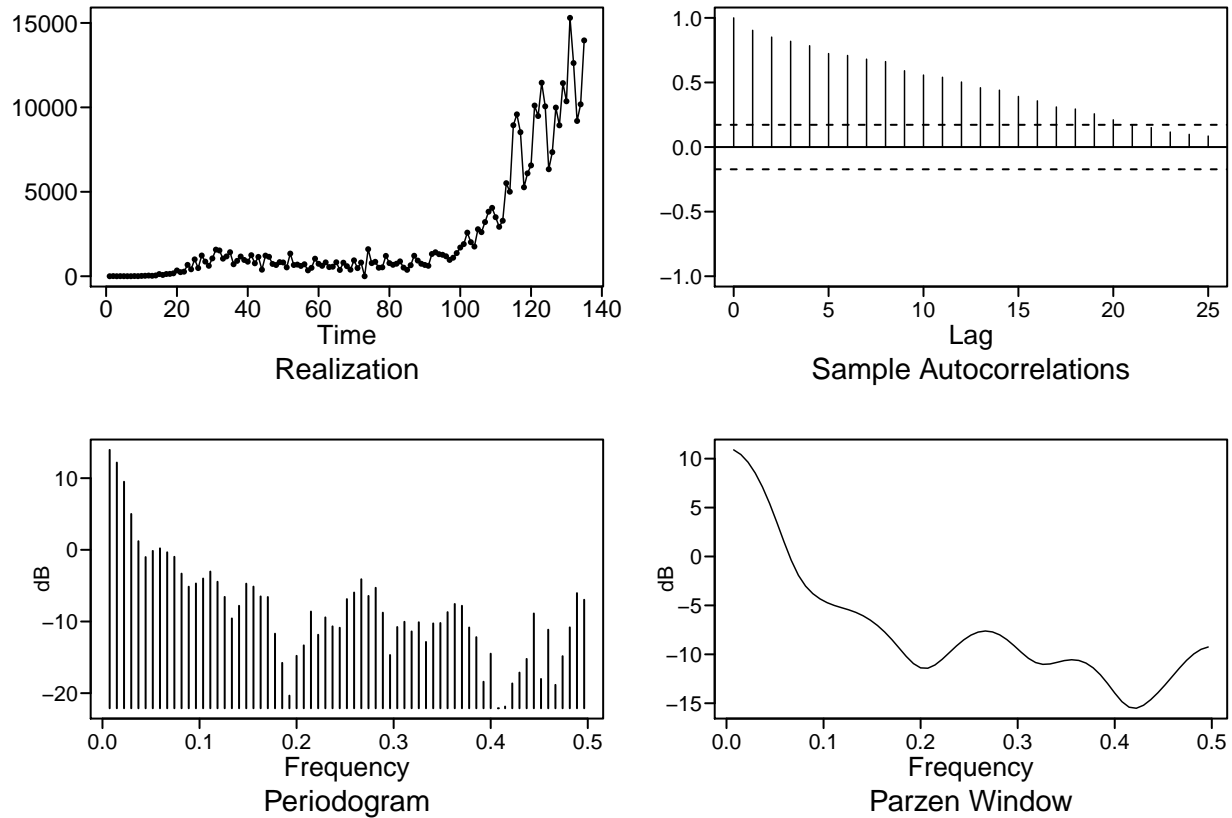
Goal Two: Univariate Analysis

Model Building for Cases in Florida

A. Stationarity vs Non-Stationarity

Overall we see slowly dampening ACFs, combined with a strong aperiodic frequency at zero in our spectral density. These measures alone with a recently quickly rising case count in recent days gives us strong evidence that our data is non-stationary. Given Covid19 spread, it is likely we see continued rising behavior in the short term, some return to lower numbers in the coming months but more uncertainty as new spikes could arise, and in the longest term of years on, we expect new cases to diminish to zero once the pandemic has ended spread.

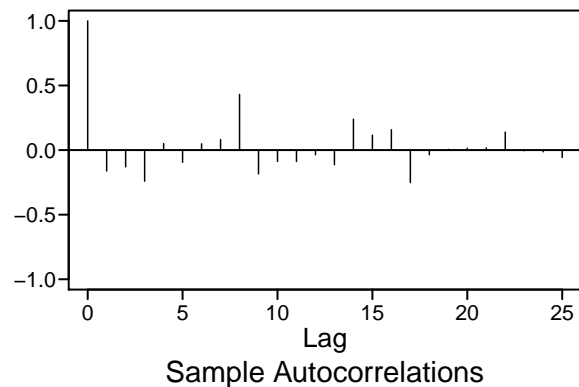
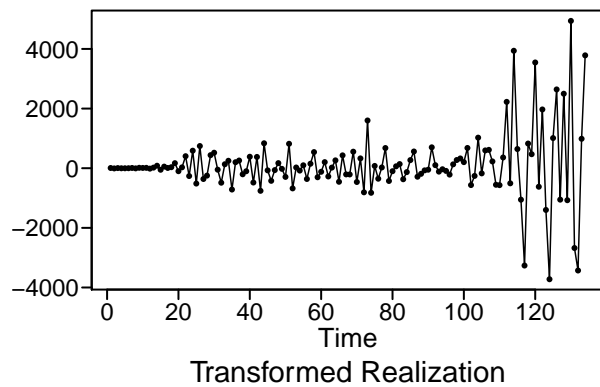
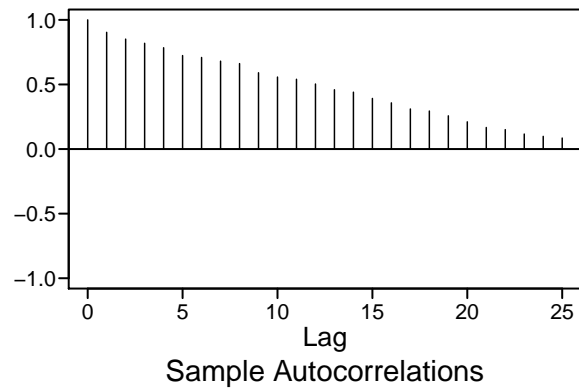
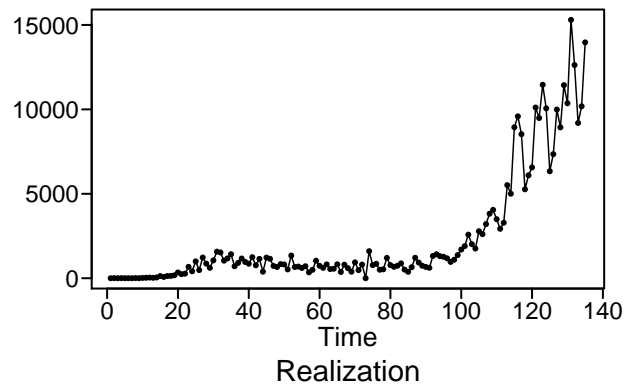
```
x = plotts.sample.wge(newcases_fl$positiveIncrease, arlimits = TRUE)
```



B. Non Stationary Modeling

We did not do any differencing of our data set to account for this non-stationarity. Going into this project we knew that because of the failure to contain the Covid-19 outbreak we would see large spikes of cases in recent time periods compared to distant time periods. We feel that this is an important aspect of our data that we want to portray in our models because we can see empirically in Florida and the United States as a whole that both individual behavior and political policy continue to trend towards further outbreak and rapid, almost exponential daily case growth. While some states with compliant individual behavior and strong political Covid-19 policies have shown “completed” Covid-19 curves, where daily case count begins to trend downwards towards zero, Florida is the opposite. Therefore, since we empirically expect the trend of non-stationarity to continue, we want that represented in our models. This is a fundamental assumption that our models are built on.

```
diff_fl = artrans.wge(newcases_fl$positiveIncrease, 1)
```

C. Model IDing of stationary models

For ARIMA models we identify the stationary components below.

```
#Model Differenced Data
aic5.wge(diff_fl)
```

```
## -----WORKING... PLEASE WAIT...
##
##
## Error in aic calculation at 3 2
## Error in aic calculation at 4 2
## Error in aic calculation at 5 2
## Five Smallest Values of aic
##
##      p      q      aic
## 9      2      2  13.71539
## 16     5      0  13.82831
## 17     5      1  13.83000
## 11     3      1  13.84291
## 14     4      1  13.85759
```

```
aic5.wge(diff_fl, type = "bic") #2,2 produced
```

```
## -----WORKING... PLEASE WAIT...
##
##
## Error in aic calculation at 3 2
## Error in aic calculation at 4 2
## Error in aic calculation at 5 2
```

```
## Five Smallest Values of bic

##      p      q      bic
## 9      2      2  13.82352
## 3      0      2  13.94850
## 11     3      1  13.95104
## 10     3      0  13.95289
## 5      1      1  13.95515

#Modeling original data if stationary
aic5.wge(newcases_fl$positiveIncrease)
```

```
## -----WORKING... PLEASE WAIT...
##
##
## Error in aic calculation at 1 1
## Error in aic calculation at 1 2
## Error in aic calculation at 2 0
## Error in aic calculation at 2 2
## Error in aic calculation at 3 0
## Error in aic calculation at 3 1
## Error in aic calculation at 3 2
## Error in aic calculation at 4 0
## Error in aic calculation at 4 1
## Error in aic calculation at 4 2
## Error in aic calculation at 5 0
## Error in aic calculation at 5 1
## Error in aic calculation at 5 2
## Five Smallest Values of aic
```

```
##      p      q      aic
## 8      2      1  13.97724
## 4      1      0  14.01245
## 3      0      2  14.80561
## 2      0      1  15.43958
## 1      0      0  16.27428
```

```
aic5.wge(newcases_fl$positiveIncrease, type = 'bic')
```

```
## -----WORKING... PLEASE WAIT...
##
##
## Error in aic calculation at 1 1
## Error in aic calculation at 1 2
## Error in aic calculation at 2 0
## Error in aic calculation at 2 2
## Error in aic calculation at 3 0
## Error in aic calculation at 3 1
## Error in aic calculation at 3 2
## Error in aic calculation at 4 0
## Error in aic calculation at 4 1
## Error in aic calculation at 4 2
## Error in aic calculation at 5 0
## Error in aic calculation at 5 1
## Error in aic calculation at 5 2
## Five Smallest Values of bic
```

```
##      p      q      bic
## 4      1      0 14.05549
## 8      2      1 14.06332
## 3      0      2 14.87017
## 2      0      1 15.48262
## 1      0      0 16.29580
```

D. Model Building

Florida Cases - ARIMA Model

```
fl_arima = est.arma.wge(diff_fl, p = 2, q = 2)
```

```
##
## Coefficients of Original polynomial:
## 1.1966 -0.7536
##
## Factor          Roots          Abs Recip      System Freq
## 1-1.1966B+0.7536B^2  0.7939+-0.8346i    0.8681      0.1290
##
##
```

```
fl_arima$aic
```

```
## [1] 13.71539
```

```
trainingSize = 70
```

```
horizon = 12
```

```
ASEHolder = numeric()
```

```
for( i in 1:(135-(trainingSize + horizon) + 1))
{
```

```
  forecasts = fore.aruma.wge(newcases_fl$positiveIncrease[i:(i+(trainingSize-1))],phi = fl_arima$phi, t
```

```
  ASE = mean((newcases_fl$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] - forecas
  ASEHolder[i] = ASE
```

```
}
```

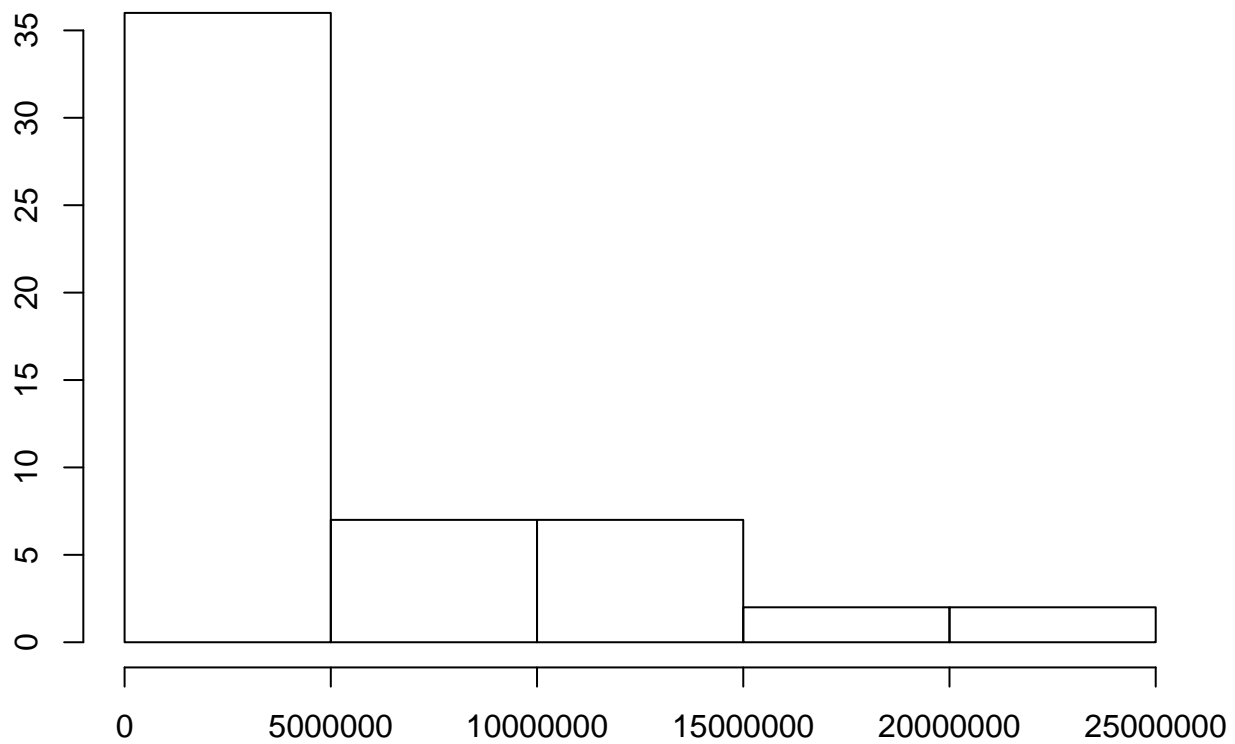
```
ASEHolder
```

```
## [1] 173447.49 229133.67 168384.33 341904.83 191371.33
## [6] 66746.55 106055.45 55793.09 51760.38 98347.57
## [11] 69300.69 139565.30 172736.75 171867.75 247073.12
## [16] 318483.37 249008.34 79288.60 153567.66 232083.96
## [21] 465674.63 679351.45 377844.85 576114.33 618238.92
## [26] 859790.13 1264646.77 2049131.44 2573862.78 2774562.47
## [31] 2726131.29 3450072.02 2727073.18 6406627.51 10231802.96
## [36] 10857622.78 11399600.50 10532859.25 9384763.58 11294574.46
## [41] 14138091.79 20793805.72 23521406.71 17866340.71 18388442.48
## [46] 5099762.18 1515023.47 1884767.08 1726135.90 5054543.44
## [51] 9125960.97 6894983.65 10460145.72 7559902.47
```

```
#Distribution of ASEs on Two Week Periods
```

```
hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for Model ARIMA")
```

ASE Distribution for Model ARIMA(2,1,2) for Florida Data



ASE of model at a given Training Set

```
#Mean ASE
```

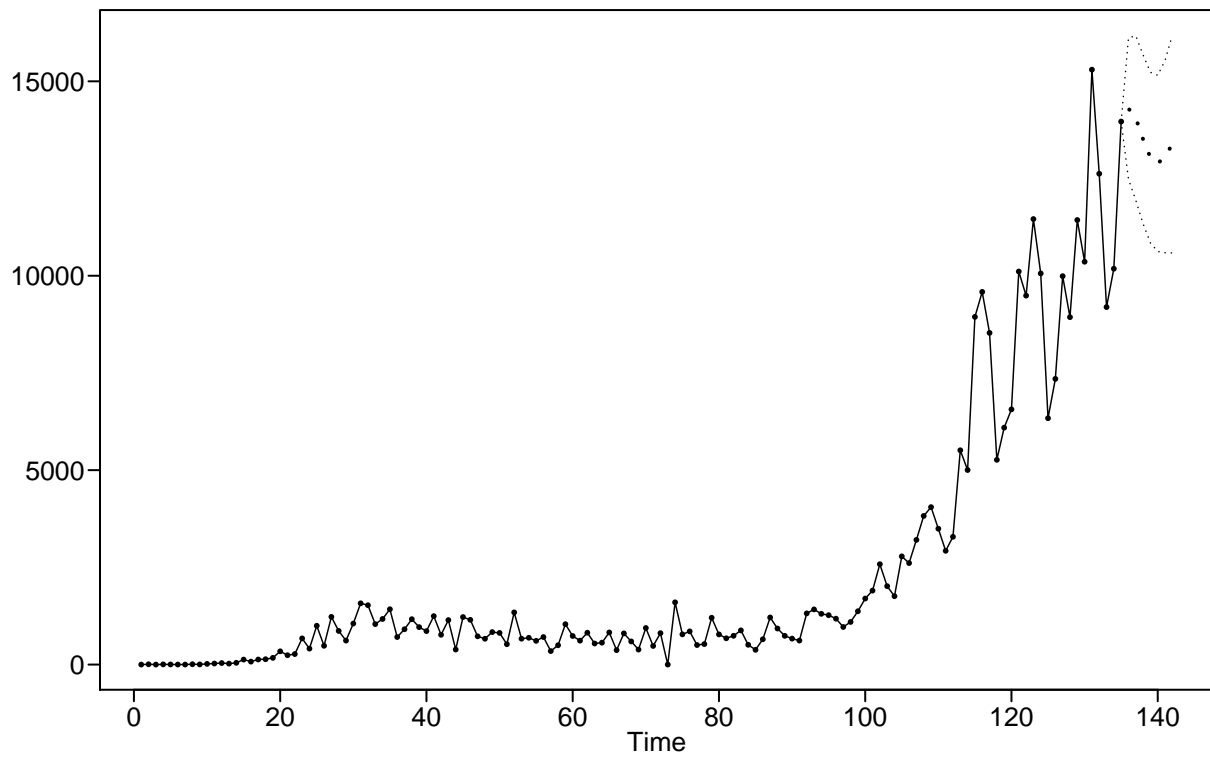
```
WindowedASE = mean(ASEHolder)
```

```
WindowedASE
```

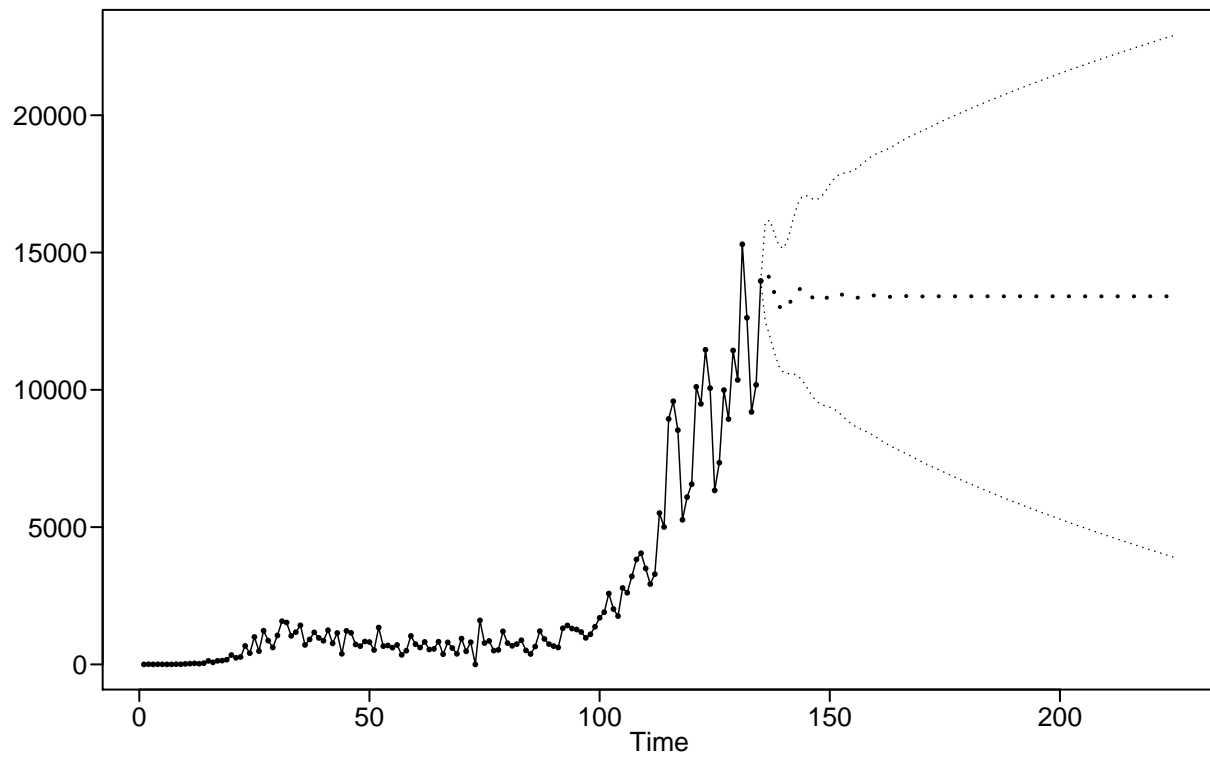
```
## [1] 4418437
```

```
##
```

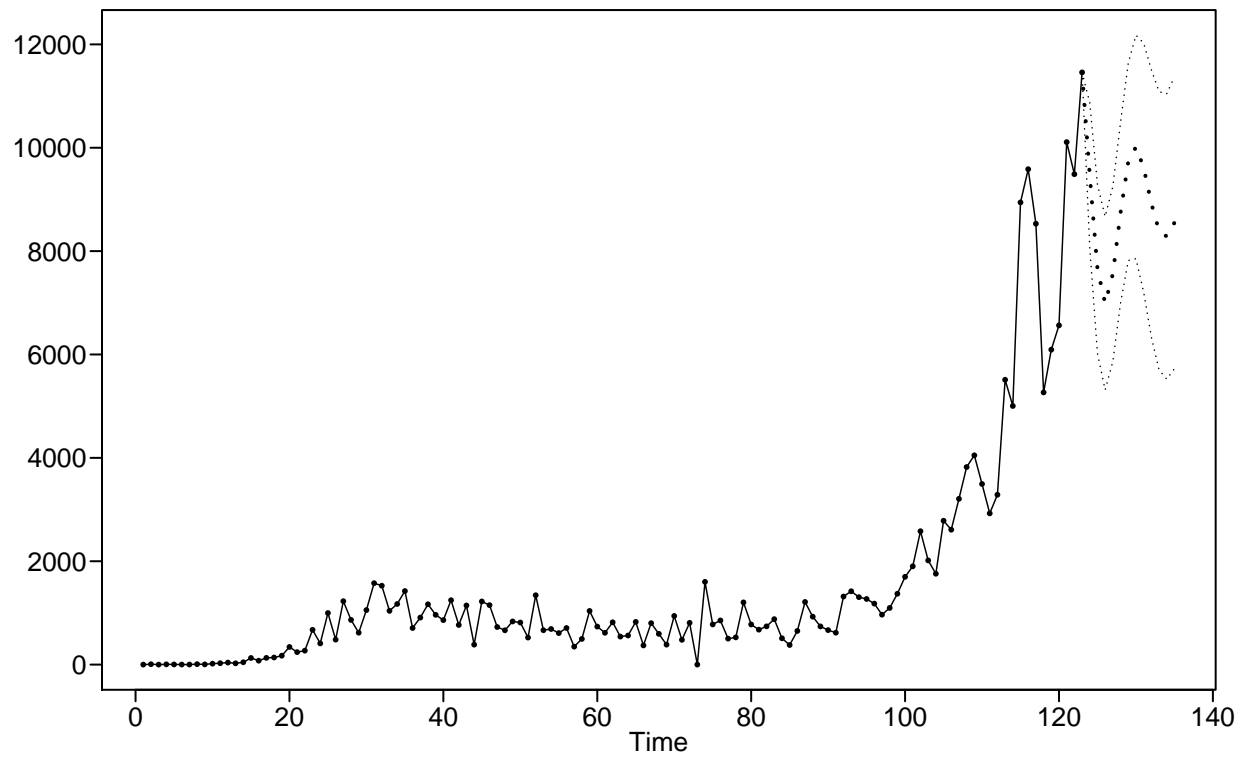
```
short_fl_arima = fore.aruma.wge(newcases_fl$positiveIncrease, phi = fl_arima$phi, theta = fl_arima$theta,
```



```
long_fl_arima = fore.aruma.wge(newcases_fl$positiveIncrease, phi = fl_arima$phi, theta = fl_arima$theta, c
```

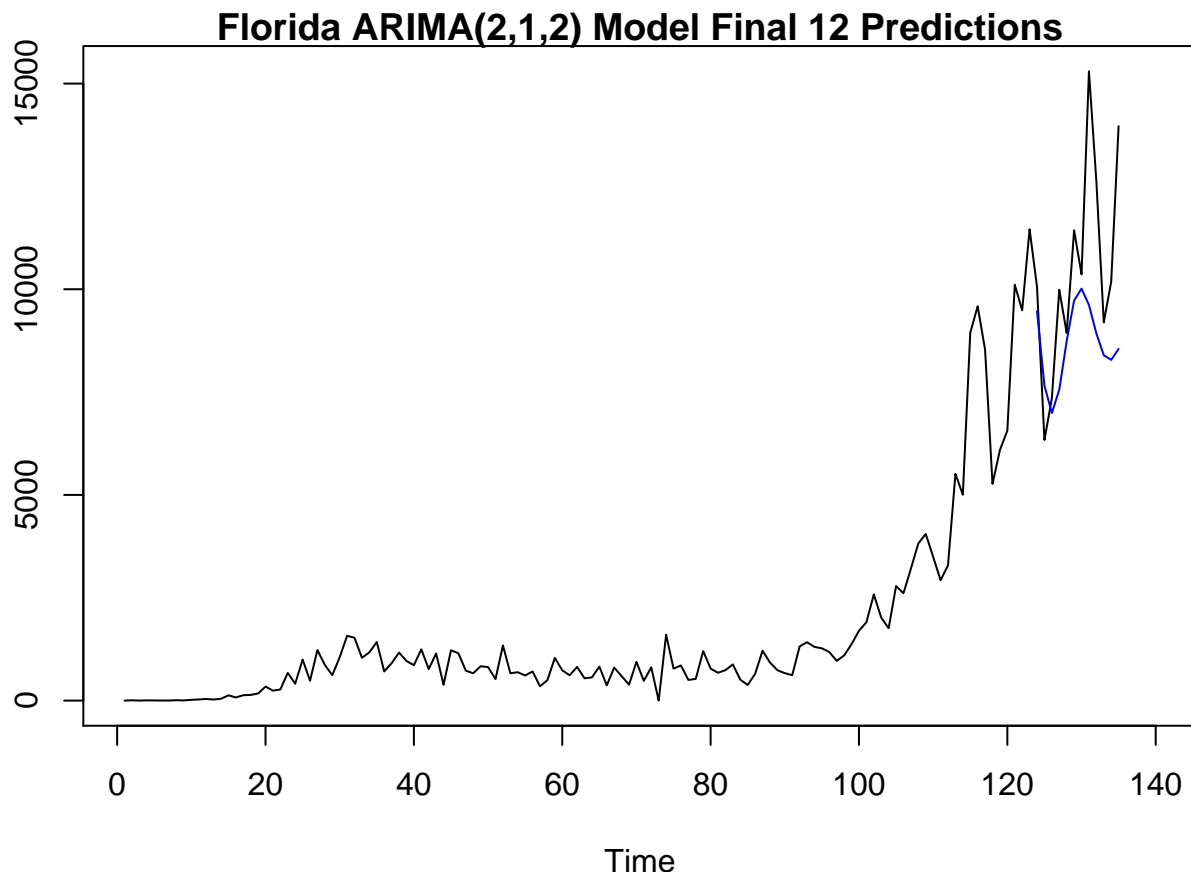


```
final_pred = fore.aruma.wge(newcases_fl$positiveIncrease[1:123], phi = fl_arima$phi, theta = fl_arima$the
```



```
final_pred_df = data.frame(t = seq(124:135), final_pred$f)

plot(newcases_fl$positiveIncrease, type = "l", ylab = "Count of New Cases", xlab = "Time", main = "Florida New Cases",
lines(ts(final_pred$f, start = 124, end = 135), col = "blue"))
```



```
final_ASE = mean((newcases_fl$positiveIncrease[124:135] - final_pred$f)^2)
final_ASE
```

```
## [1] 7562545
```

```
#####MLP Model for Florida Cases
```

```
trainingSize = 70
```

```
horizon = 12
```

```
ASEHolder = numeric()
```

```
for( i in 1:(135-(trainingSize + horizon) + 1))
```

```
{
```

```
  mlp.fit = mlp(ts(newcases_fl$positiveIncrease[1:trainingSize+i]), hd = 5, comb = "median")
```

```
  forecasts = forecast(mlp.fit,h = horizon)
```

```
  ASE = mean((newcases_fl$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] -forecasts)
```

```
  ASEHolder[i] = ASE
```

```
}
```

```
ASEHolder
```

```
## [1] 143763.04 124054.34 278614.85 160612.19 65987.22
```

```
## [6] 90854.71 70154.93 85186.05 59639.47 63197.74
```

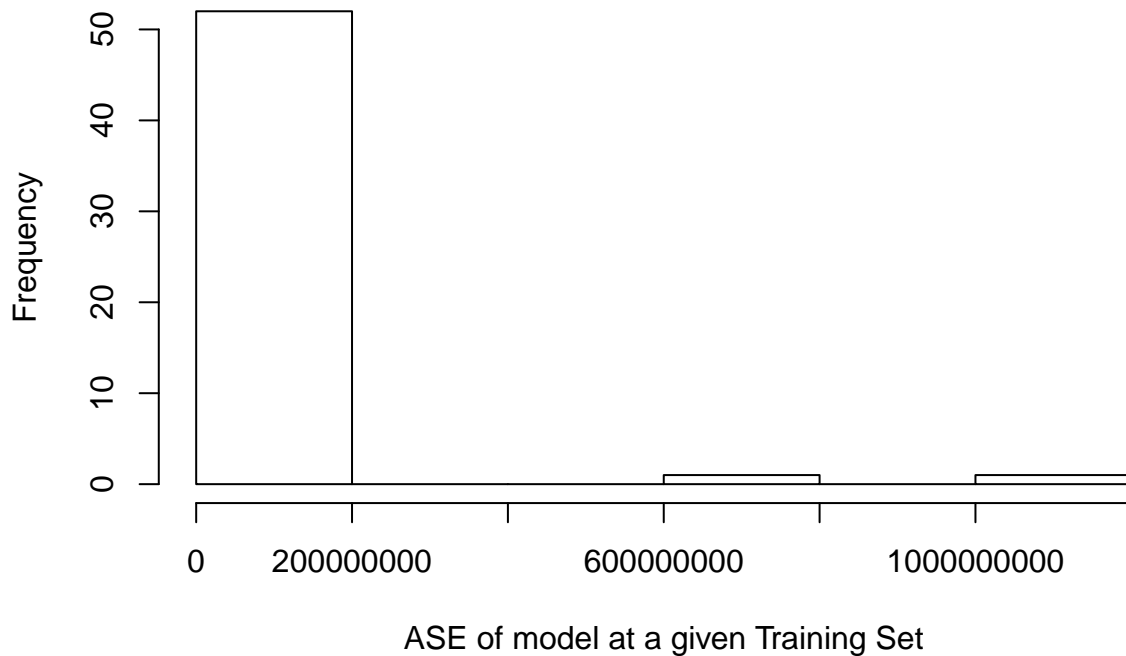
```
## [11] 117068.83 101686.93 110588.72 162454.92 225414.41
```

```
## [16] 295904.65 184371.61 135652.12 143280.42 283467.27
## [21] 1121047.25 620038.17 649608.42 895662.35 896700.96
## [26] 786773.42 1870488.66 2630511.25 3060536.54 2350241.29
## [31] 2310265.12 1579835.32 2739523.67 7000339.51 10742667.16
## [36] 11694236.48 11091932.56 7334210.01 6642625.92 12055258.26
## [41] 17425464.88 21775454.59 16359541.14 11186050.41 636419916.19
## [46] 1175130786.81 5427954.55 33135286.07 15345235.31 25459893.02
## [51] 15272787.02 15055502.44 8893742.66 5273119.84
```

```
#Distribution of ASEs on Two Week Periods
```

```
hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for MLP Model I")
```

ASE Distribution for MLP Model Florida Data



```
#Mean ASE
```

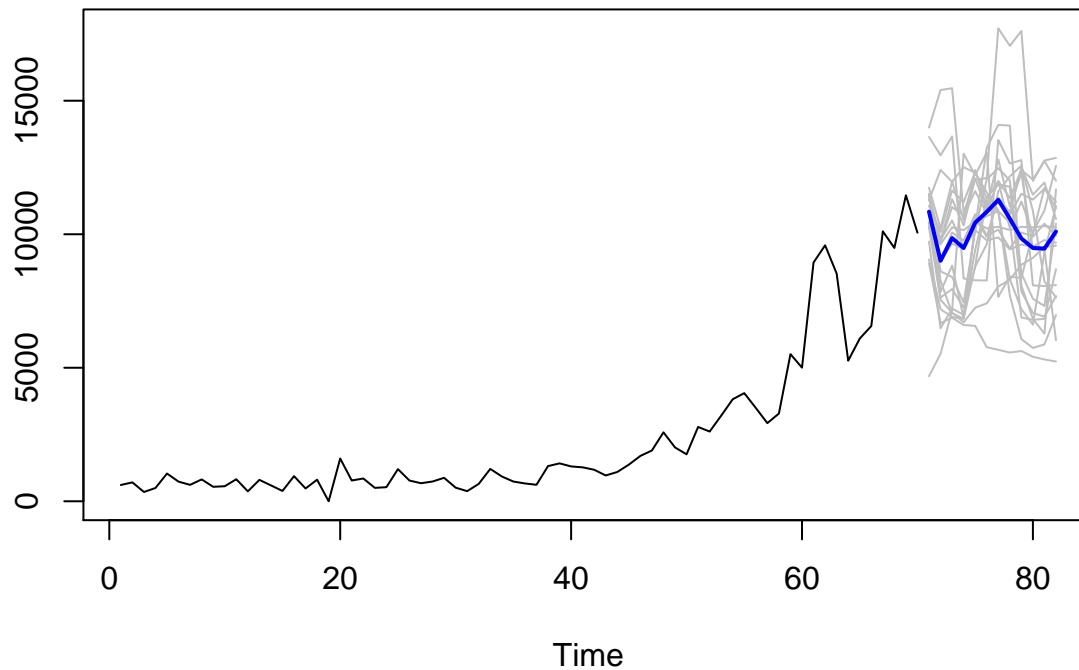
```
WindowedASE = mean(ASEHolder)
```

```
WindowedASE
```

```
## [1] 38761763
```

```
plot(forecasts)
```


Forecasts from MLP

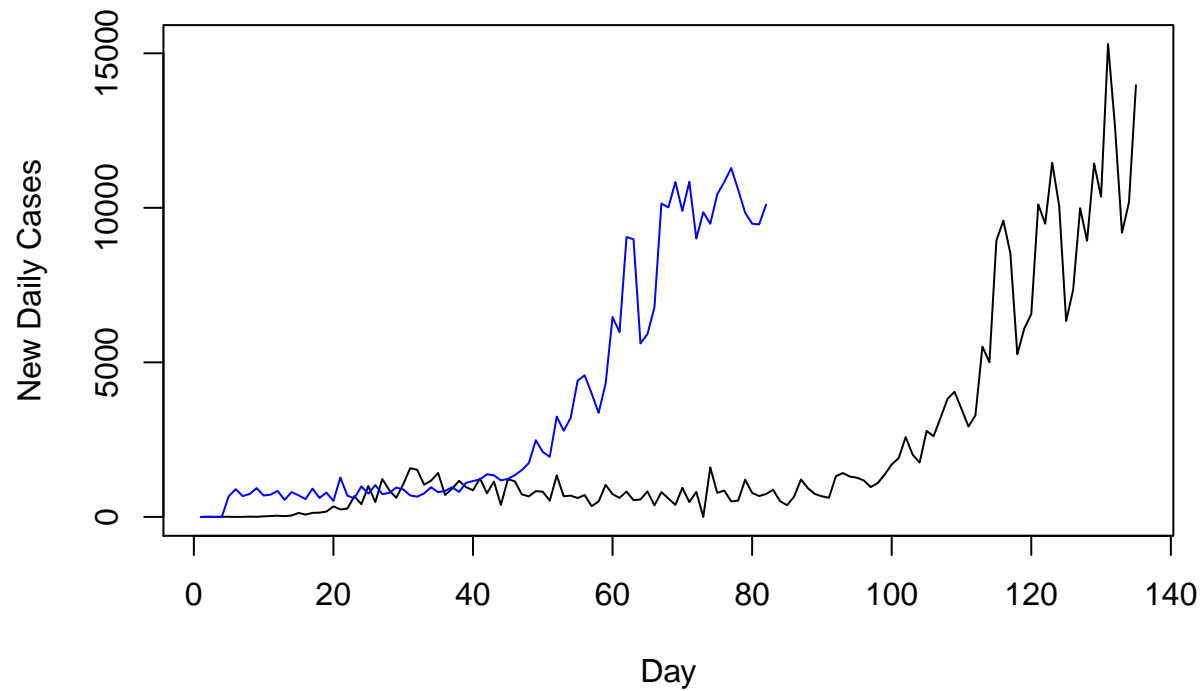


```
#Final Forecasts with data known
mlp.fit_fl_final = mlp(ts(newcases_fl$positiveIncrease[1:123]), hd = 5, comb = "median")
forecasts_fl_mlp = forecast(mlp.fit, h = 12)

final12_ase = mean((newcases_fl$positiveIncrease[124:135] - forecasts_fl_mlp$mean)^2)
final12_ase

## [1] 5273120

all_f = c(rep(1,4), forecasts$fitted, forecasts$mean)
plot(newcases_fl$positiveIncrease, type = "l", ylab = "New Daily Cases", xlab = "Day", main = "")
lines(all_f, col = "blue")
```



```
#Future Forecasts
```

```
mlp.fit_fl_future = mlp(ts(newcases_fl$positiveIncrease), hd = 5, comb = "median")
```

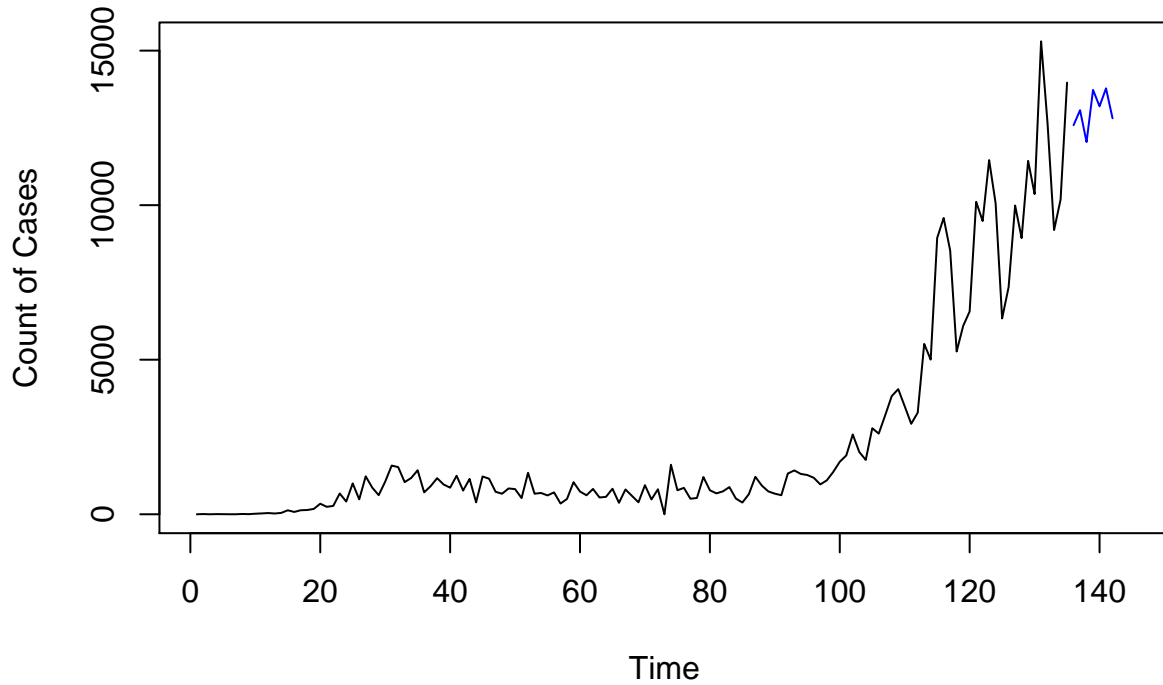
```
short_fl_mlp = forecast(mlp.fit_fl_future, h = 7)
```

```
long_fl_mlp = forecast(mlp.fit_fl_future, h = 90)
```

```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,145), main = "Florida Short Term MLP Forecast")
```

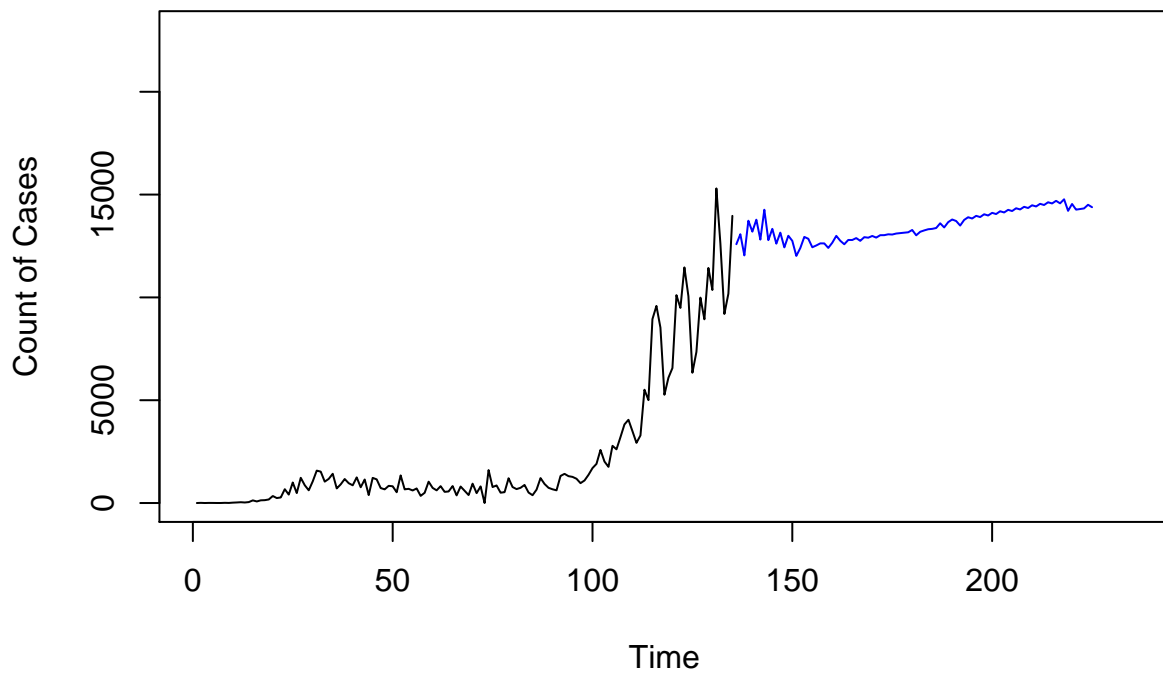
```
lines(short_fl_mlp$mean, col = "blue")
```

Florida Short Term MLP Forecasts



```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,235), ylim = c(0,23000), main = "Florida Long  
lines(long_fl_mlp$mean, col = "blue")
```

Florida Long Term MLP Forecasts



####Florida Cases Ensemble Model

```

#ASE fits for ensemble
mlp.fit_fl_final = mlp(ts(newcases_fl$positiveIncrease[1:123]), hd = 5, comb = "median")
forecasts_fl_mlp = forecast(mlp.fit_fl_final, h = 12)

forecasts_fl_arima = fore.aruma.wge(newcases_fl$positiveIncrease[i:(i+(trainingSize-1))],phi = fl_arima)

ensemble_fl_fore = (forecasts_fl_mlp$mean + final_pred_df$f) / 2

ensemble_ASE = mean((newcases_fl$positiveIncrease[124:135] - ensemble_fl_fore)^2)
ensemble_ASE

```

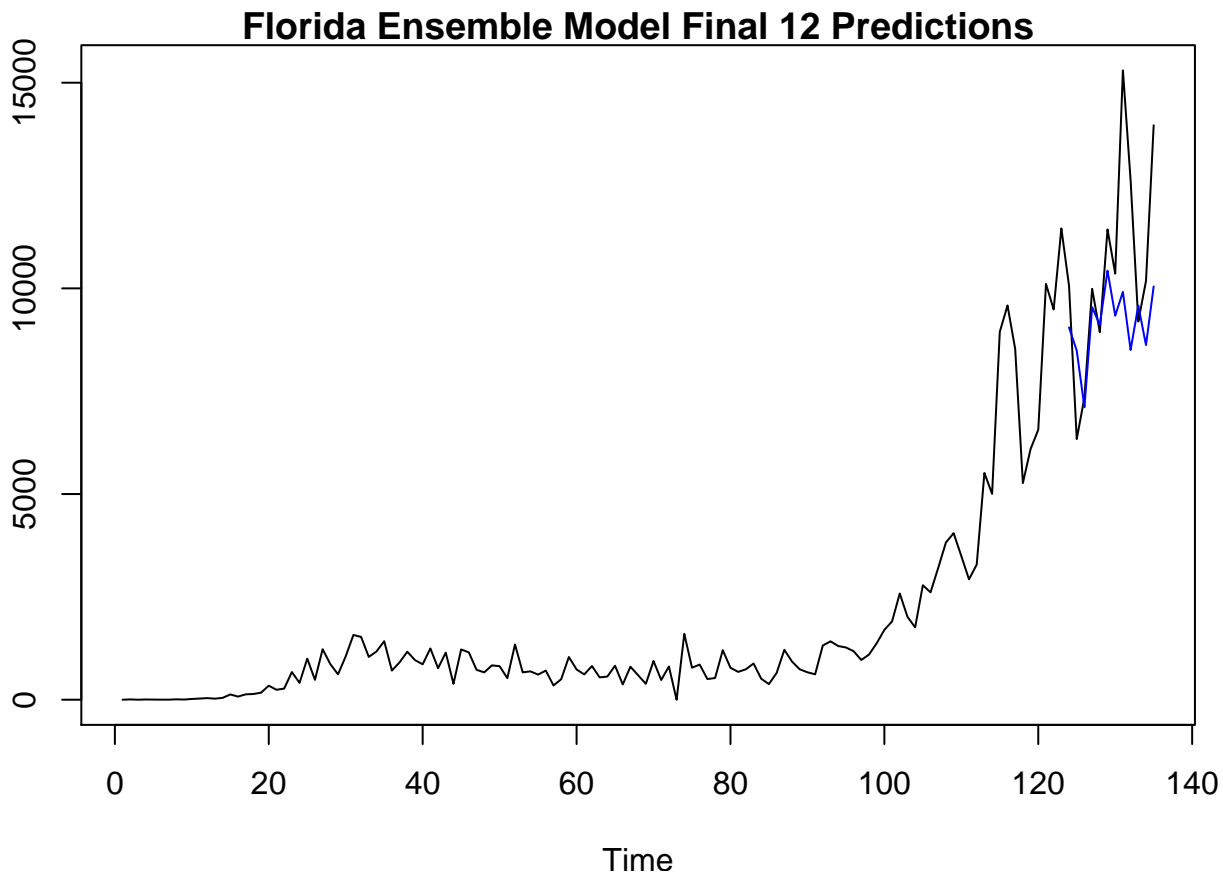
```
## [1] 5990983
```

```
#8.4 Mill
```

```

plot(newcases_fl$positiveIncrease, type = "l", ylab = "Count of New Cases", xlab = "Time", main = "Florida Ensemble Model Final 12 Predictions",
lines(ensemble_fl_fore, col = "blue")

```



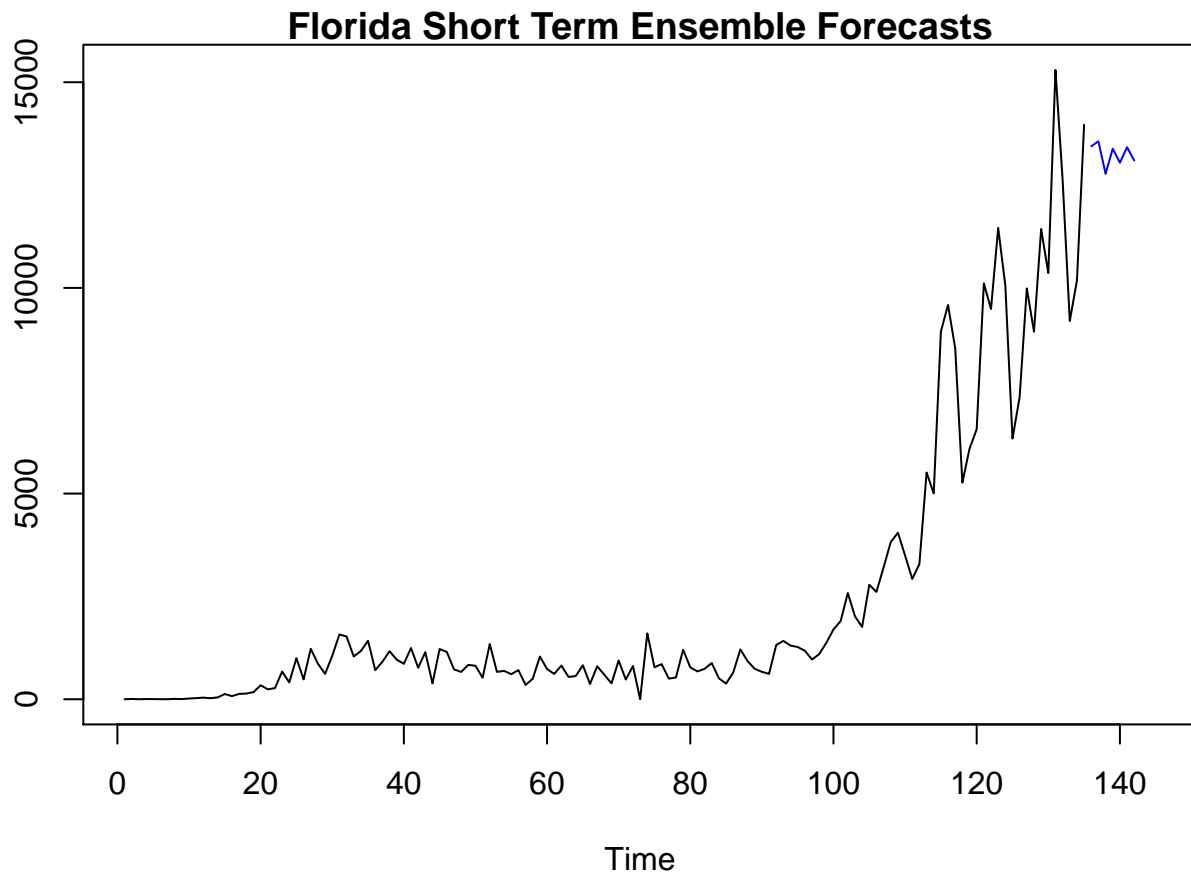
```

#future forecasting

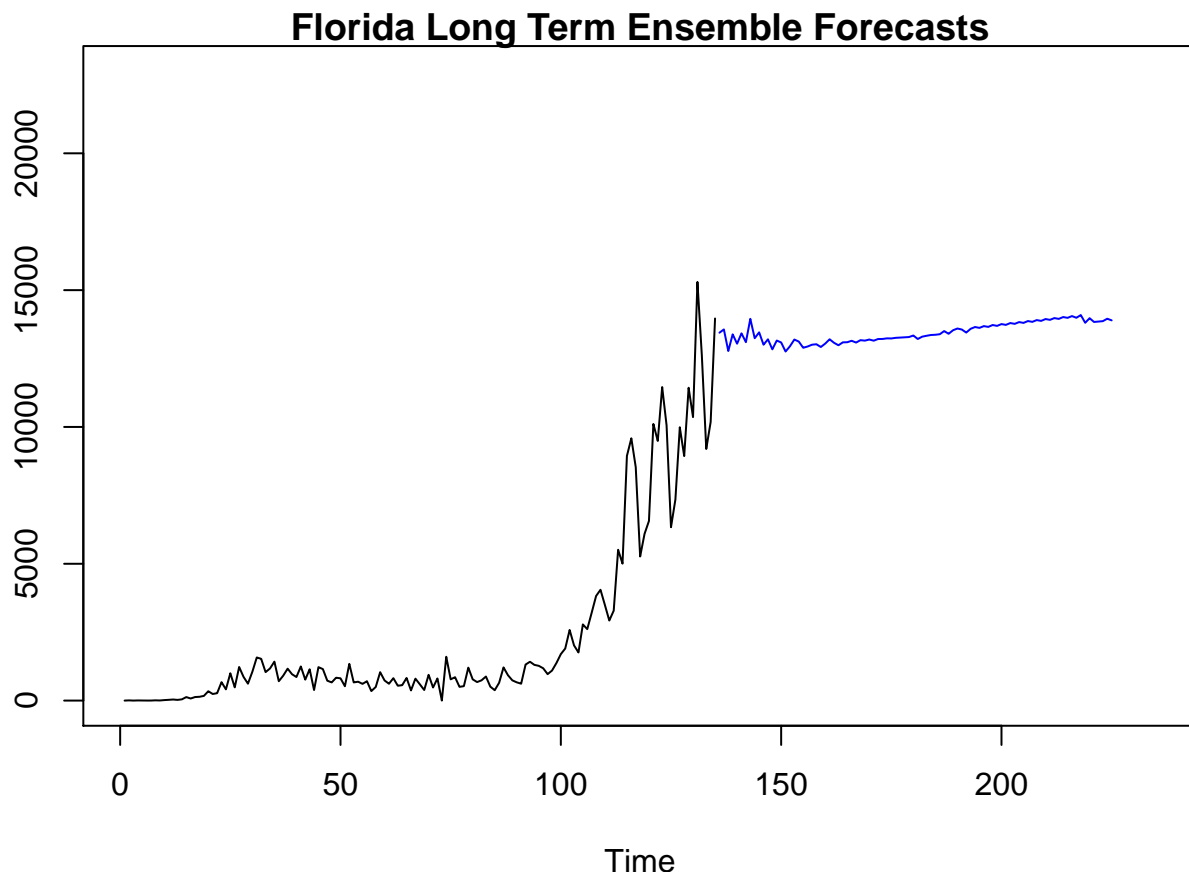
short_fl_ensemble = (short_fl_mlp$mean + short_fl_arima$f)/2
long_fl_ensemble = (long_fl_mlp$mean + long_fl_arima$f)/2

plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,145), main = "Florida Short Term Ensemble Forecast",
lines(short_fl_ensemble, col = "blue")

```



```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,235), ylim = c(0,23000), main = "Florida Long  
lines(long_fl_ensemble, col = "blue")
```



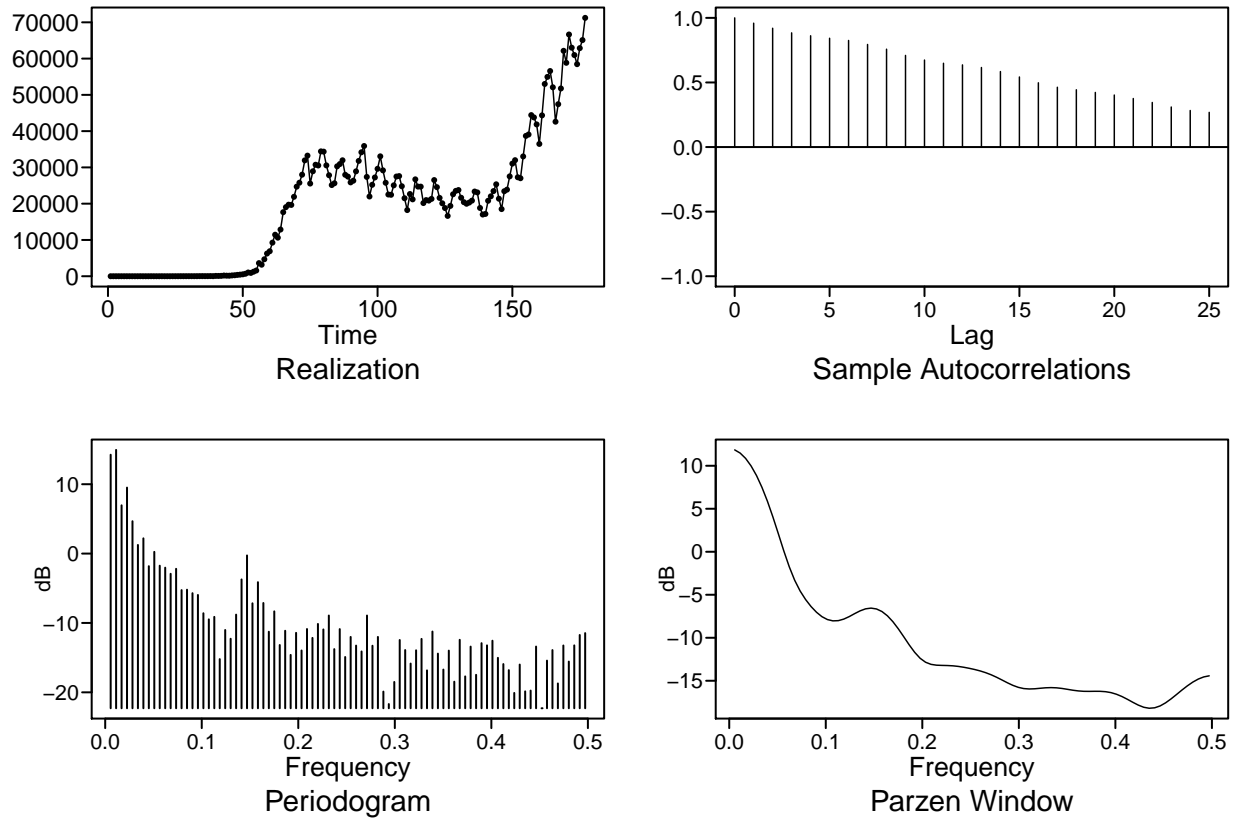
Comparing and Assessing Models

###Model Building for Cases United States

A. Stationarity vs Non-Stationarity

Overall we see slowly dampening ACFs, combined with a strong aperiodic frequency at zero in our spectral density. These measures alone with a recently quickly rising case count in recent days gives us strong evidence that our data is non-stationary. Given Covid19 spread, it is likely we see continued rising behavior in the short term, some return to lower numbers in the coming months but more uncertainty as new spikes could arise, and in the longest term of years on, we expect new cases to diminish to zero once the pandemic has ended spread.

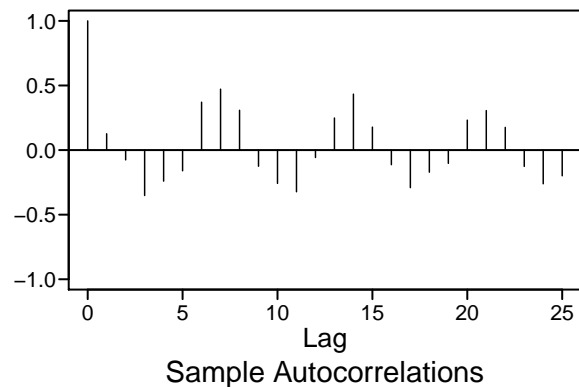
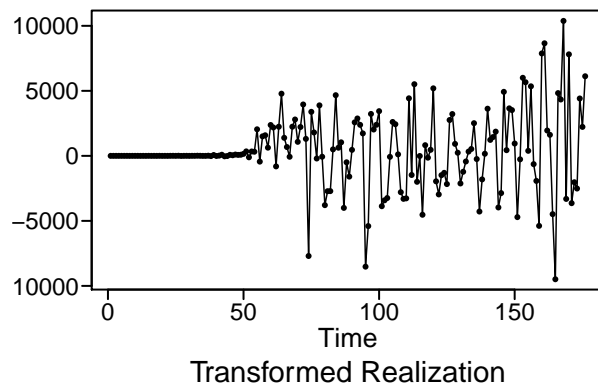
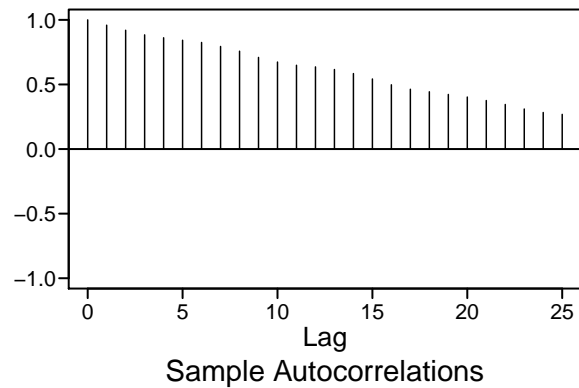
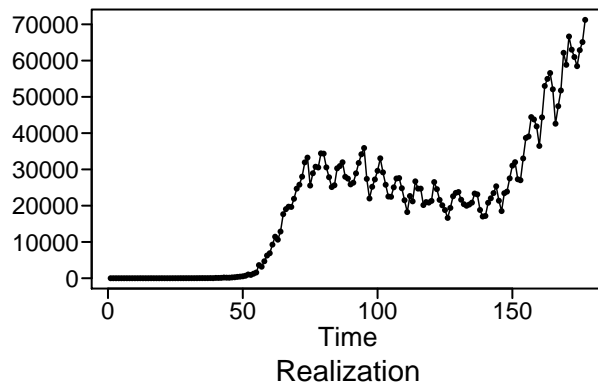
```
#no text output  
x = plotts.sample.wge(newcases_us$positiveIncrease)
```



B. Non-Stationary Modeling

We did not do any differencing of our data set to account for this non-stationarity. Going into this project we knew that because of the failure to contain the Covid-19 outbreak we would see large spikes of cases in recent time periods compared to distant time periods. We feel that this is an important aspect of our data that we want to portray in our models because we can see empirically in Florida and the United States as a whole that both individual behavior and political policy continue to trend towards further outbreak and rapid, almost exponential daily case growth. While some states with compliant individual behavior and strong political Covid-19 policies have shown “completed” Covid-19 curves, where daily case count begins to trend downwards towards zero, Florida is the opposite. Therefore, since we empirically expect the trend of non-stationarity to continue, we want that represented in our models. This is a fundamental assumption that our models are built on.

```
diff_us = artrans.wge(newcases_us$positiveIncrease, 1)
```



C. Model IDing of stationary models

For ARIMA models we identify the stationary components below.

```
#modeling as non-stationary
#0,5 maxes out
aic5.wge(diff_us, p = 3:10)
```

```
## -----WORKING... PLEASE WAIT...
##
##
## Error in aic calculation at 3 2
## Error in aic calculation at 4 2
## Five Smallest Values of aic
##
##      p      q      aic
## 12    6      2  15.35301
## 15    7      2  15.36326
## 18    8      2  15.37452
## 24   10      2  15.37494
## 17    8      1  15.37902
```

```
aic5.wge(diff_us, type = 'bic', p = 3:10)
```

```
## -----WORKING... PLEASE WAIT...
##
##
## Error in aic calculation at 3 2
## Error in aic calculation at 4 2
## Five Smallest Values of bic
```



```
##      p    q      bic
## 12    6    2  15.51514
## 15    7    2  15.54340
## 16    8    0  15.54364
## 14    7    1  15.55598
## 17    8    1  15.55916
```

#Modeling as stationary

```
aic5.wge(newcases_us$positiveIncrease)
```

```
## -----WORKING... PLEASE WAIT...
```

```
##
```

```
##
```

```
## Error in aic calculation at 1 1
## Error in aic calculation at 2 0
## Error in aic calculation at 2 1
## Error in aic calculation at 2 2
## Error in aic calculation at 3 0
## Error in aic calculation at 3 1
## Error in aic calculation at 3 2
## Error in aic calculation at 4 0
## Error in aic calculation at 4 1
## Error in aic calculation at 4 2
## Error in aic calculation at 5 0
## Error in aic calculation at 5 1
## Error in aic calculation at 5 2
## Five Smallest Values of aic
```

```
##      p    q      aic
## 6     1    2  15.95786
## 4     1    0  15.96008
## 3     0    2  17.57501
## 2     0    1  18.44652
## 1     0    0  19.55796
```

```
aic5.wge(newcases_us$positiveIncrease, type = 'bic')
```

```
## -----WORKING... PLEASE WAIT...
```

```
##
```

```
##
```

```
## Error in aic calculation at 1 1
## Error in aic calculation at 2 0
## Error in aic calculation at 2 1
## Error in aic calculation at 2 2
## Error in aic calculation at 3 0
## Error in aic calculation at 3 1
## Error in aic calculation at 3 2
## Error in aic calculation at 4 0
## Error in aic calculation at 4 1
## Error in aic calculation at 4 2
## Error in aic calculation at 5 0
## Error in aic calculation at 5 1
## Error in aic calculation at 5 2
## Five Smallest Values of bic
```

```
##      p    q      bic
```

```
## 4    1    0   15.99597
## 6    1    2   16.02964
## 3    0    2   17.62884
## 2    0    1   18.48240
## 1    0    0   19.57590
```

D. Model Building

US Cases ARIMA

```
us_arima = est.arma.wge(diff_us, p = 6, q = 2)
```

```
##
## Coefficients of Original polynomial:
## 0.9297 -0.4193 -0.1050 0.1192 -0.1654 0.4349
##
## Factor                Roots                Abs Recip      System Freq
## 1-1.2345B+0.9676B^2    0.6379+-0.7916i    0.9837         0.1420
## 1-0.9236B              1.0827            0.9236         0.0000
## 1+0.7898B              -1.2661           0.7898         0.5000
## 1+0.4386B+0.6161B^2    -0.3560+-1.2233i    0.7849         0.2951
##
##
```

```
us_arima$aic
```

```
## [1] 15.35301
```

```
trainingSize = 70
```

```
horizon = 12
```

```
ASEHolder = numeric()
```

```
for( i in 1:(177-(trainingSize + horizon) + 1))
{
```

```
  forecasts = fore.aruma.wge(newcases_us$positiveIncrease[i:(i+(trainingSize-1))],phi = us_arima$phi, t
```

```
  ASE = mean((newcases_us$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] - forecas
  ASEHolder[i] = ASE
```

```
}
```

```
ASEHolder
```

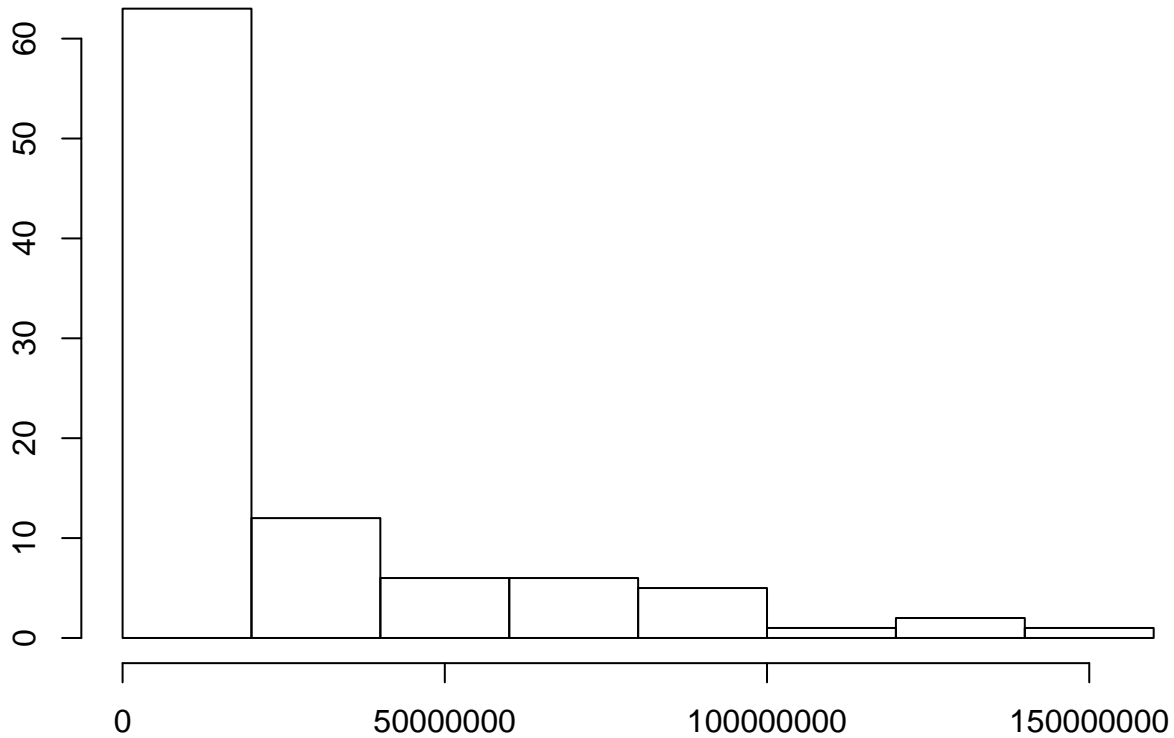
```
## [1] 10675056 18600503 30808202 65947936 107923495 17482463 30122239
## [8] 34296758 18901087 41985555 22196078 8038259 4001099 16220456
## [15] 25623600 10988291 16015628 7577133 11764724 6676069 7463415
## [22] 7011389 8632723 11233687 29607353 92783091 28689956 2678473
## [29] 6273351 3213464 2655246 5598353 2367409 5317189 7163735
## [36] 7454121 9185823 3972393 2978218 9144903 12066578 17419336
## [43] 1643801 5211231 3376700 2165611 4101283 3272886 6092837
## [50] 7387112 2477927 9583839 2591774 3062112 2918252 4802053
## [57] 14084685 16012246 9870509 4635991 3884471 6951811 14030208
## [64] 16685027 7880299 4905266 6986689 12231151 42430184 68416051
## [71] 72678321 36882715 43820966 61733016 41676411 78582278 122236456
## [78] 73735402 97503595 89508118 88460562 90058778 135316356 149071511
## [85] 57389370 16692038 24213370 17023010 16284869 21377733 59860784
```

```
## [92] 35431300 12398822 12621652 14419232 20118462
```

```
#Distribution of ASEs on Two Week Periods
```

```
hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for Model ARIMA(6,1,2) for US Data")
```

ASE Distribution for Model ARIMA(6,1,2) for US Data



ASE of model at a given Training Set

```
#Mean ASE
```

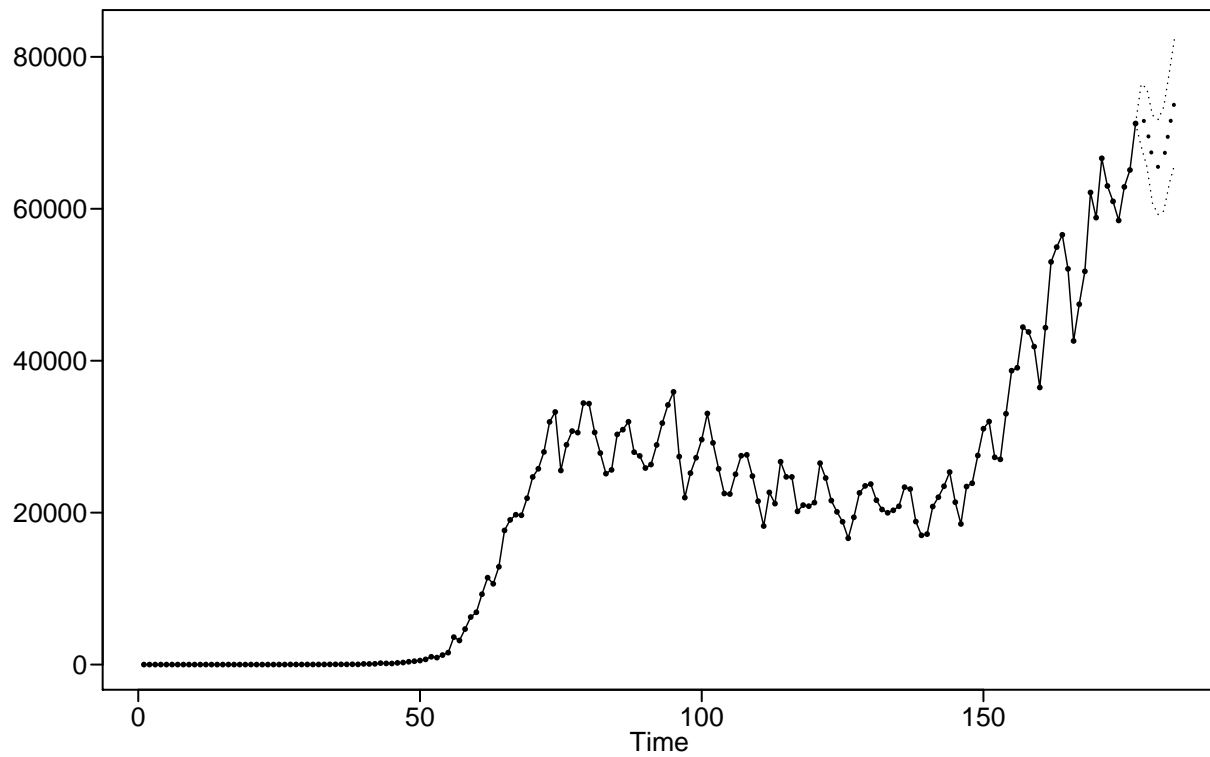
```
WindowedASE = mean(ASEHolder)
```

```
WindowedASE
```

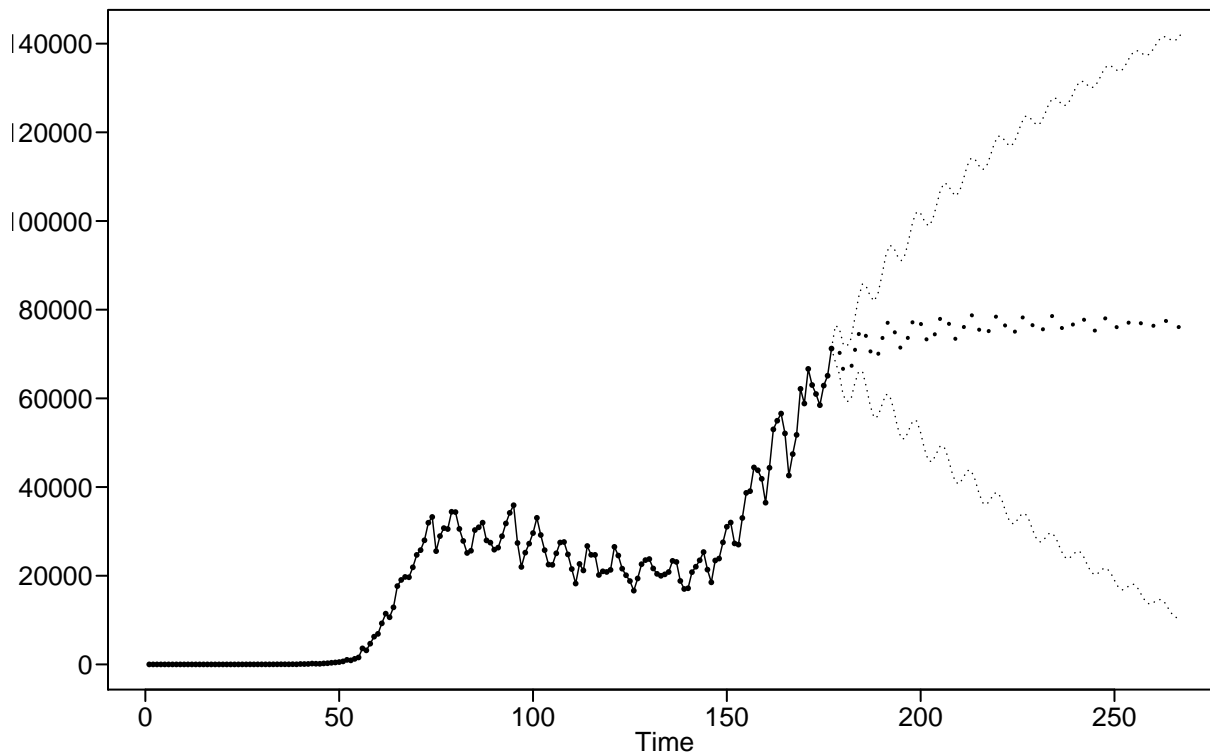
```
## [1] 26724396
```

```
#26724396
```

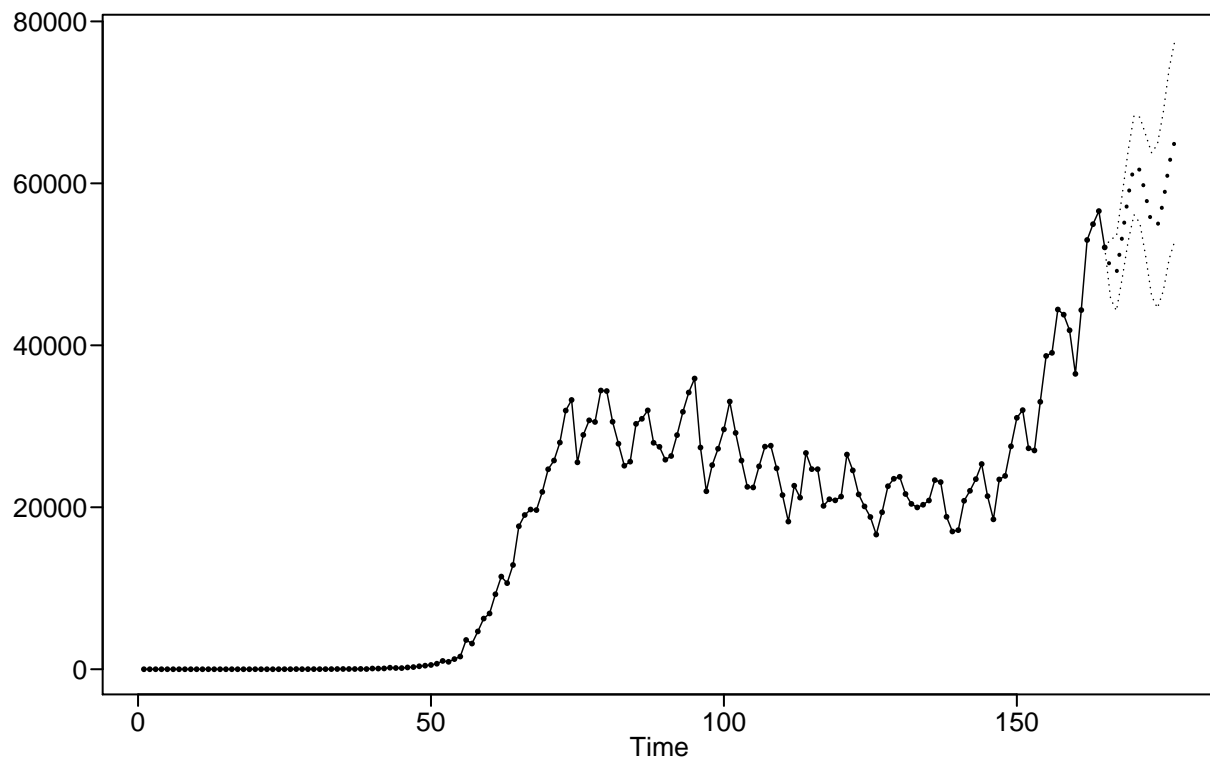
```
short_us_arima = fore.aruma.wge(newcases_us$positiveIncrease, phi = us_arima$phi, theta = us_arima$theta,
```



```
long_us_arima = fore.aruma.wge(newcases_us$positiveIncrease, phi = us_arima$phi, theta = us_arima$theta, c
```



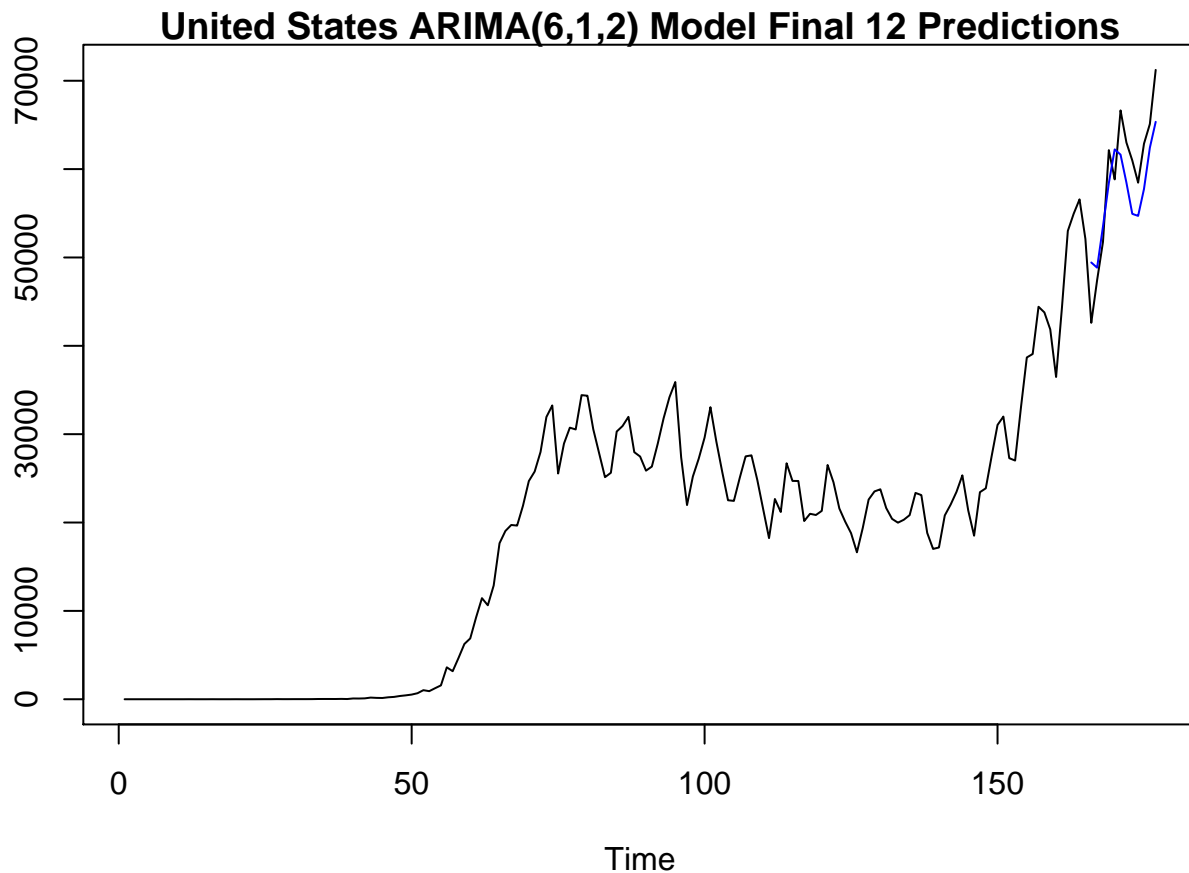
```
final_pred = fore.aruma.wge(newcases_us$positiveIncrease[1:165], phi = us_arima$phi, theta = us_arima$the
```



```
final_12_ase = mean((newcases_us$positiveIncrease[166:177] - final_pred$f)^2)
final_12_ase
```

```
## [1] 20118462
```

```
plot(newcases_us$positiveIncrease, type = "l", ylab = "Count of New Cases", xlab = "Time", main = "Unit
lines(ts(final_pred$f, start = 166, end = 177), col = "blue")
```



####US Cases MLP

trainingSize = 70

horizon = 12

ASEHolder = numeric()

```
for( i in 1:(177-(trainingSize + horizon) + 1))
```

```
{
```

```
  mlp.fit = mlp(ts(newcases_us$positiveIncrease[1:trainingSize+i]), hd = 5, reps = 20, lags = c(1,3,4),
  forecasts = forecast(mlp.fit,h = horizon)
```

```
  ASE = mean((newcases_us$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] -forecasts)
  ASEHolder[i] = ASE
```

```
}
```

ASEHolder

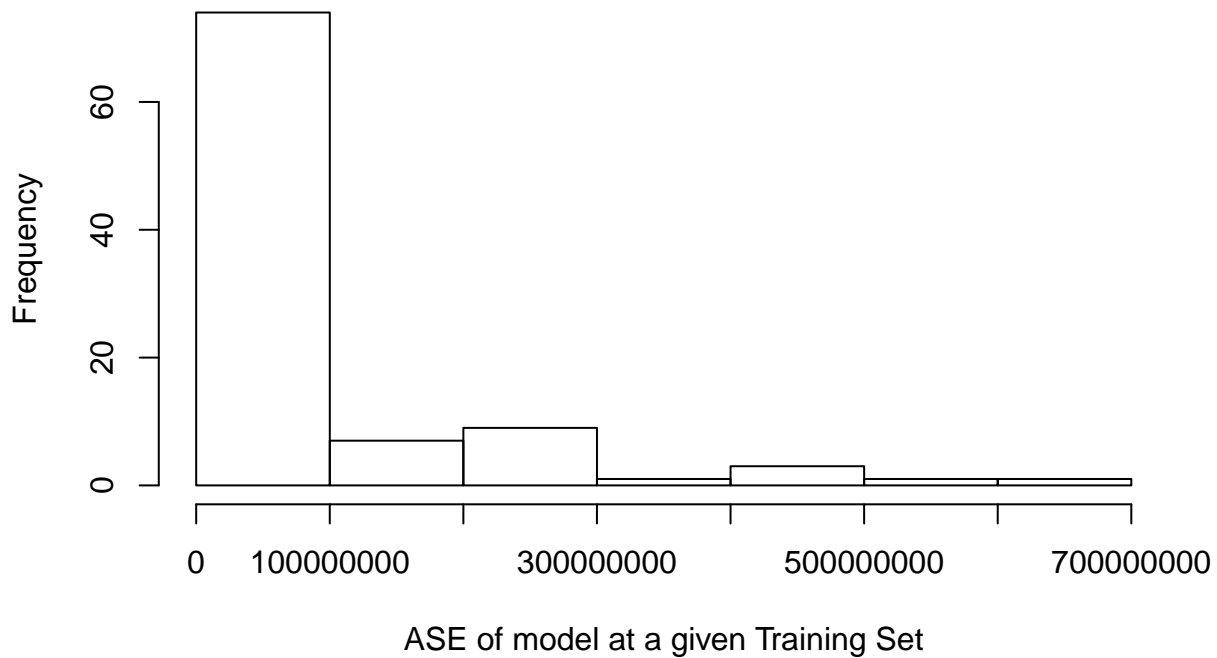
```
## [1] 109816116 297816634 287105287 432385367 11332866 17563339 17526596
## [8] 15298739 164076580 119381783 42150192 10085044 6520820 9779106
## [15] 9096543 14807288 17848664 15161895 14593212 14799941 14789418
## [22] 15167655 18841428 25090063 32408782 19777547 12740601 14610824
## [29] 19662723 31381929 38723313 40435470 34219264 27423156 25621217
## [36] 33618702 40459391 46570671 43760932 34577803 24702177 31271953
## [43] 28995686 38447903 44179583 48224540 36948855 36211173 32297912
## [50] 31926019 42504757 39219494 28823327 32879421 22899968 10935029
```

```
## [57] 4570911 7501687 14534334 8232079 6423252 5877739 6206097
## [64] 4511452 8180231 8006157 8052028 8836821 13545447 19223523
## [71] 21617327 22991811 35571592 60587075 88054709 126461837 167499379
## [78] 214932487 232113012 129809804 208280841 298939040 291724934 395013220
## [85] 403252714 403509101 94337827 218411715 522585766 621589282 183795297
## [92] 80600017 61277318 41403128 79444543 239295383
```

```
#Distribution of ASEs on Two Week Periods
```

```
hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for MLP Model United States Data")
```

ASE Distribution for MLP Model United States Data



```
#Mean ASE
```

```
WindowedASE = mean(ASEHolder)
```

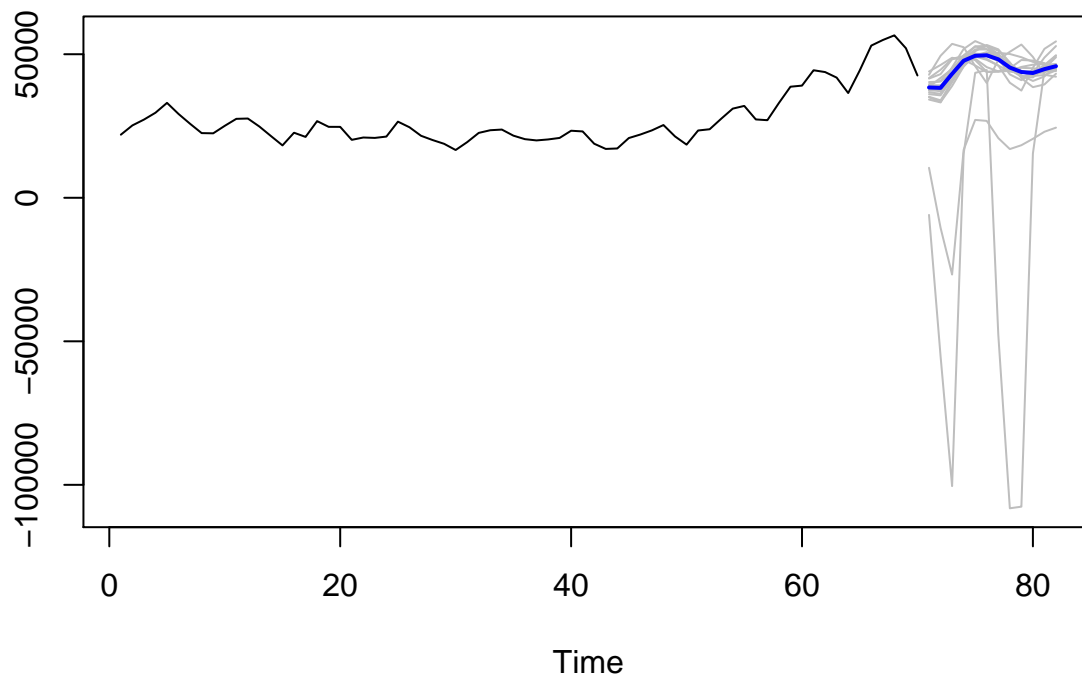
```
WindowedASE
```

```
## [1] 84315579
```

```
#228 mill
```

```
plot(forecasts)
```

Forecasts from MLP



#Actual Forecasting on last segment of data

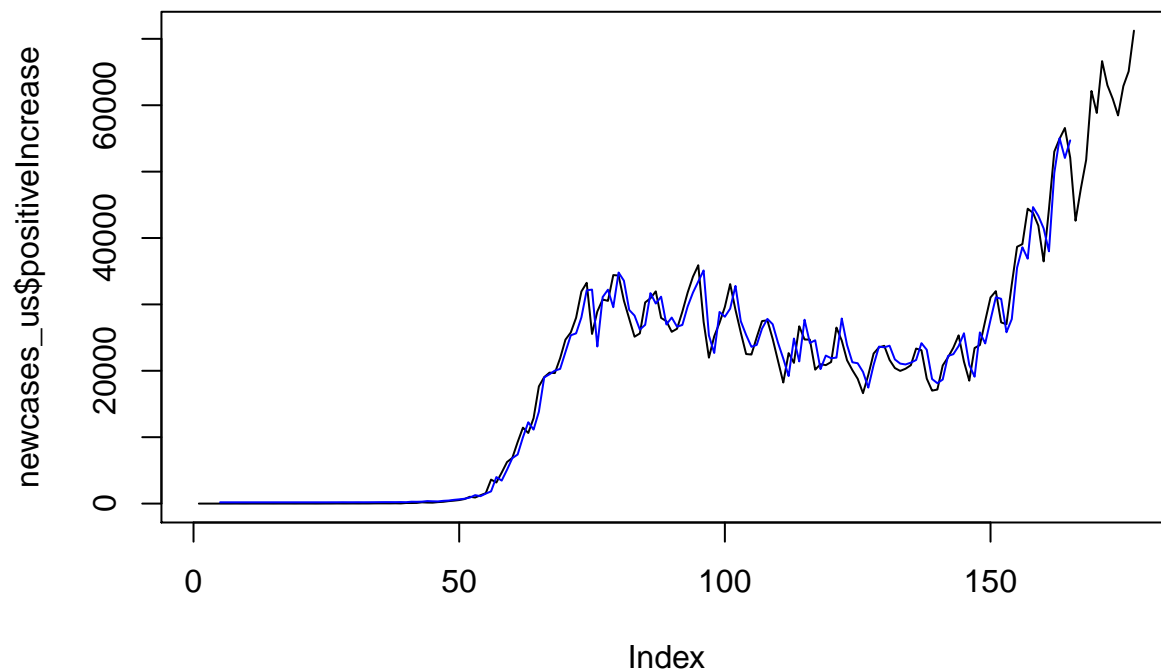
```
mlp.fit = mlp(ts(newcases_us$positiveIncrease[1:165]), hd = 5, comb = "median")
forecasts_us_mlp = forecast(mlp.fit, h = 12)
```

```
ASE = mean((newcases_us$positiveIncrease[166:177] - forecasts_us_mlp$mean)^2)
ASE
```

```
## [1] 52414812
```

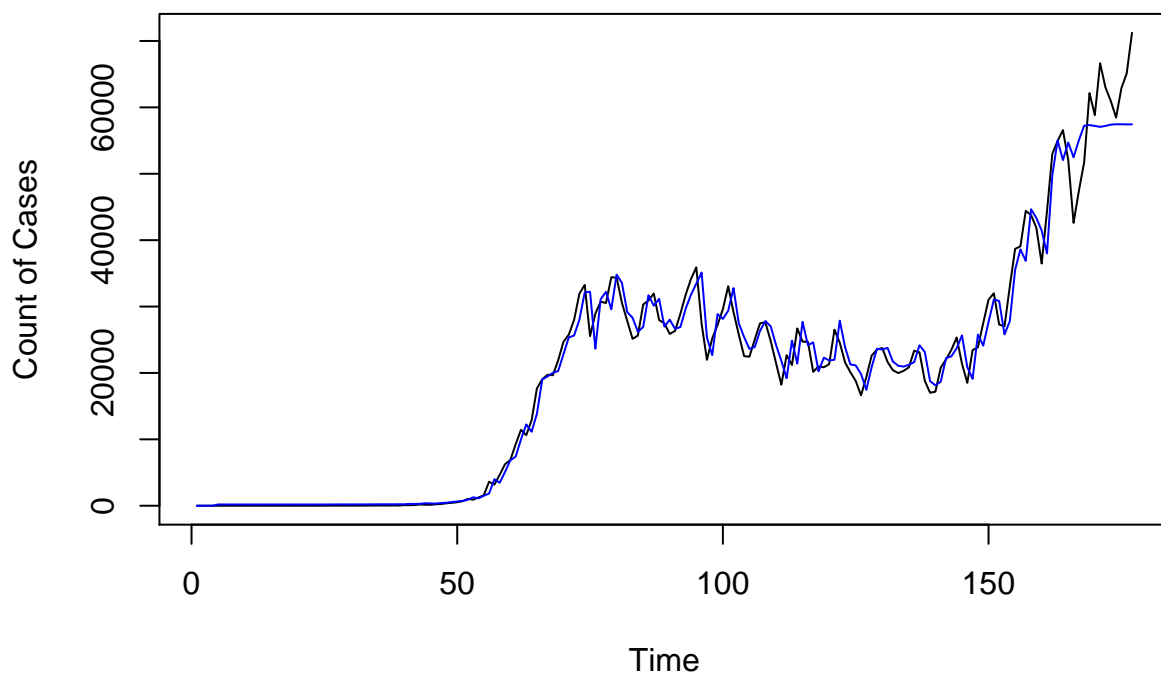
#53,843,551

```
plot(newcases_us$positiveIncrease, type = "l")
lines(forecasts_us_mlp$fitted, col = "blue")
```

```
all_f = c(rep(1,4),forecasts_us_mlp$fitted, forecasts_us_mlp$mean)
plot(newcases_us$positiveIncrease, type = "l", ylab = "Count of Cases", xlab = "Time", main = "US MLP C
lines(all_f, col = "blue")
```

US MLP Cases Model



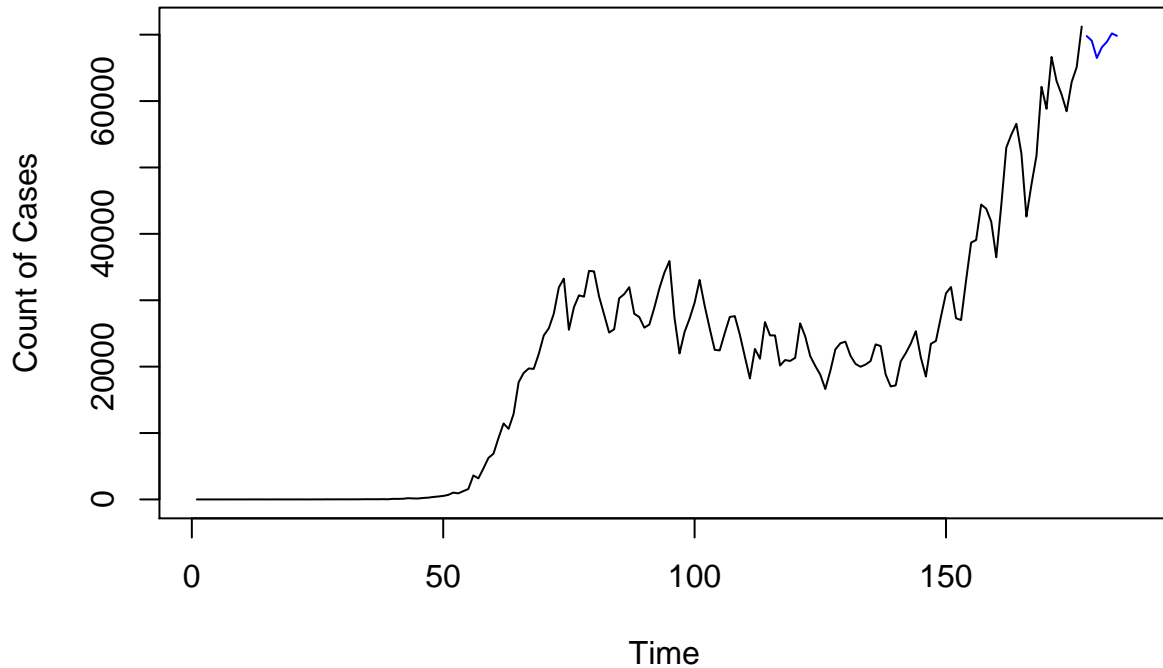
#Future Predictions

```
mlp.fit_us_future =mlp(ts(newcases_us$positiveIncrease), hd = 5, comb = "median")
short_us_mlp = forecast(mlp.fit_us_future,h = 7)
```

```
long_us_mlp = forecast(mlp.fit_us_future,h = 90)
```

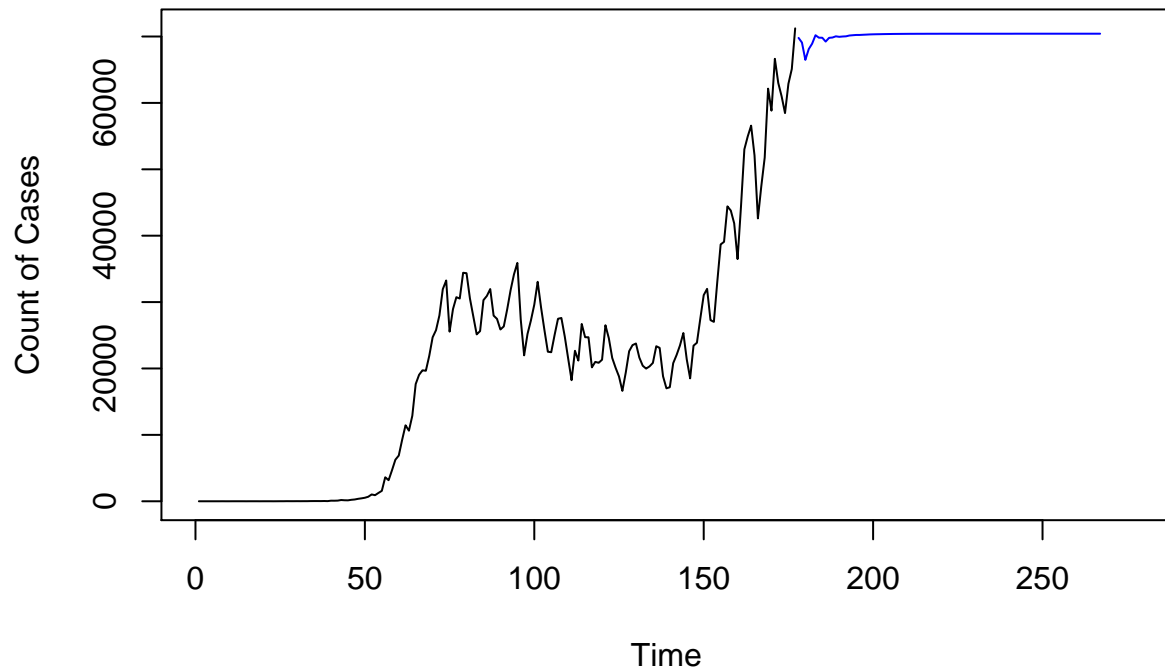
```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,187), main = "United States Short Term MLP For  
lines(short_us_mlp$mean, col = "blue")
```

United States Short Term MLP Forecasts



```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,277), main = "United States Long Term MLP For  
lines(long_us_mlp$mean, col = "blue")
```

United States Long Term MLP Forecasts



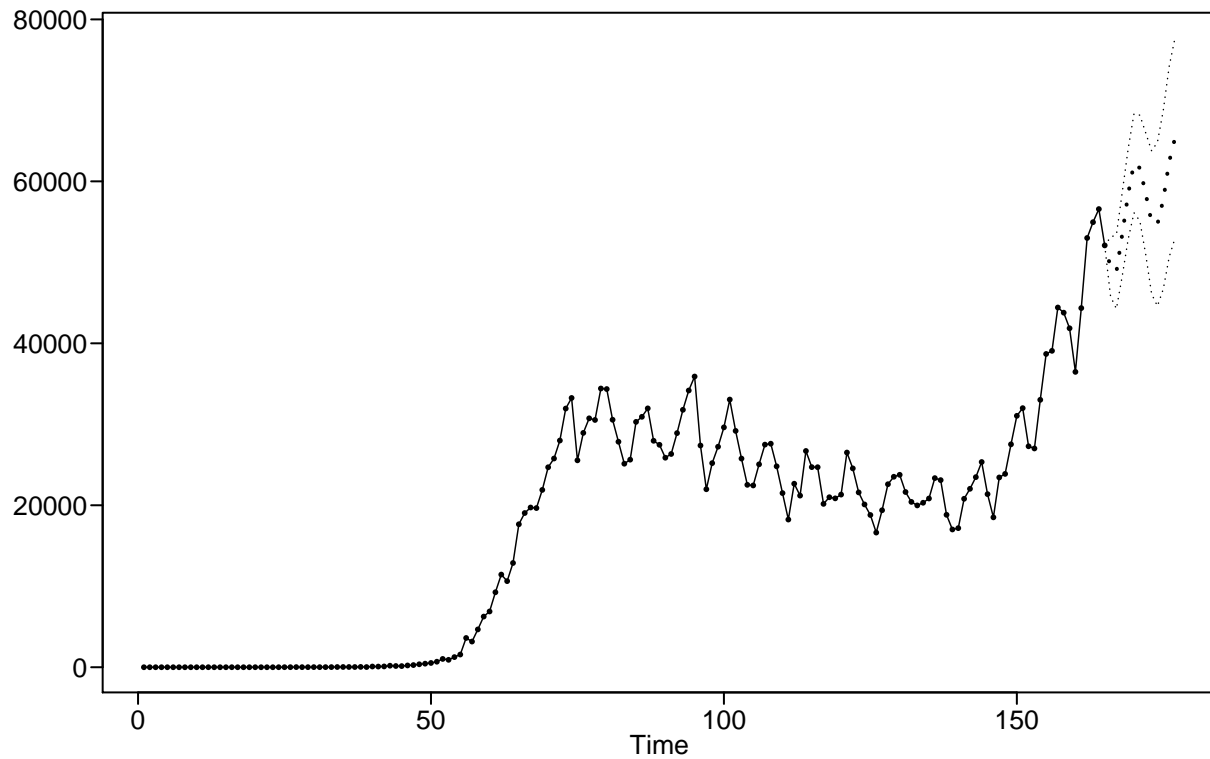
####US Ensemble

```
#ASE fits for ensemble
```

```
#mlp.fit_us_final = mlp(ts(newcases_us$positiveIncrease[1:165]), hd = 5, comb = "median")
```

```
#forecasts_us_mlp = forecast(mlp.fit_us_final,h = 12)
```

```
forecasts_arima_us = fore.aruma.wge(newcases_us$positiveIncrease[1:165],phi = us_arima$phi,theta = us_a
```



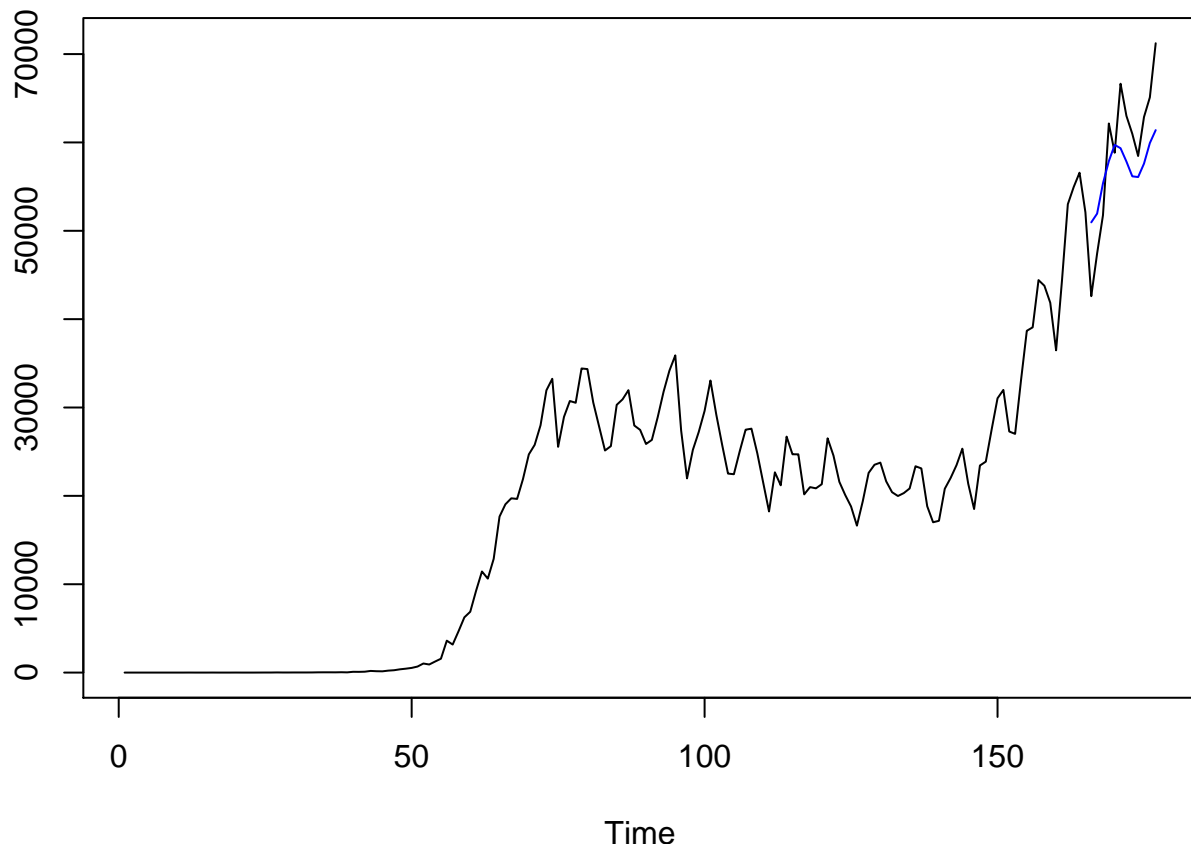
```
ensemble_fore = (forecasts_us_mlp$mean + forecasts_arima_us$f) / 2
```

```
ensemble_ASE = mean((newcases_us$positiveIncrease[166:177] - ensemble_fore)^2)
ensemble_ASE
```

```
## [1] 31855669
```

```
#
```

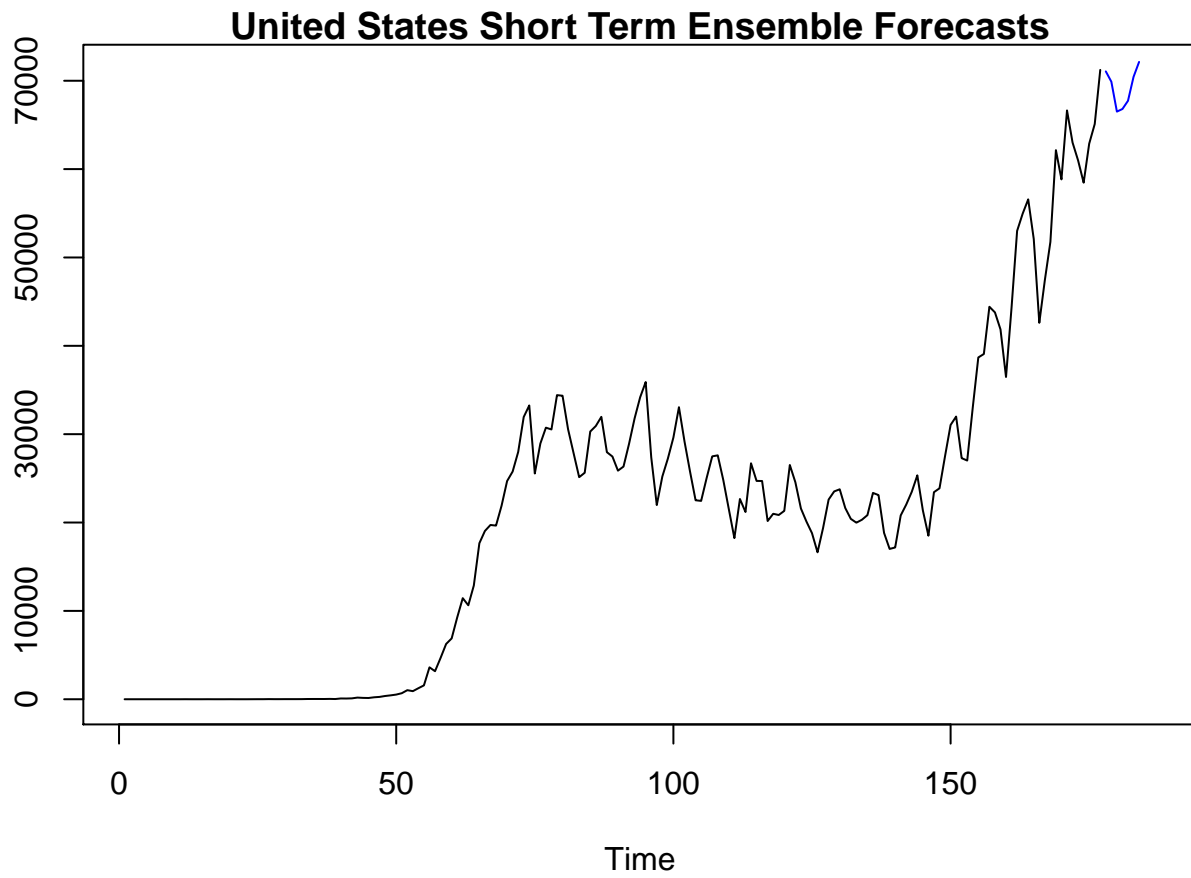
```
plot(newcases_us$positiveIncrease, type = "l", ylab = "Count of New Cases", xlab = "Time")
lines(ensemble_fore, col = "blue")
```



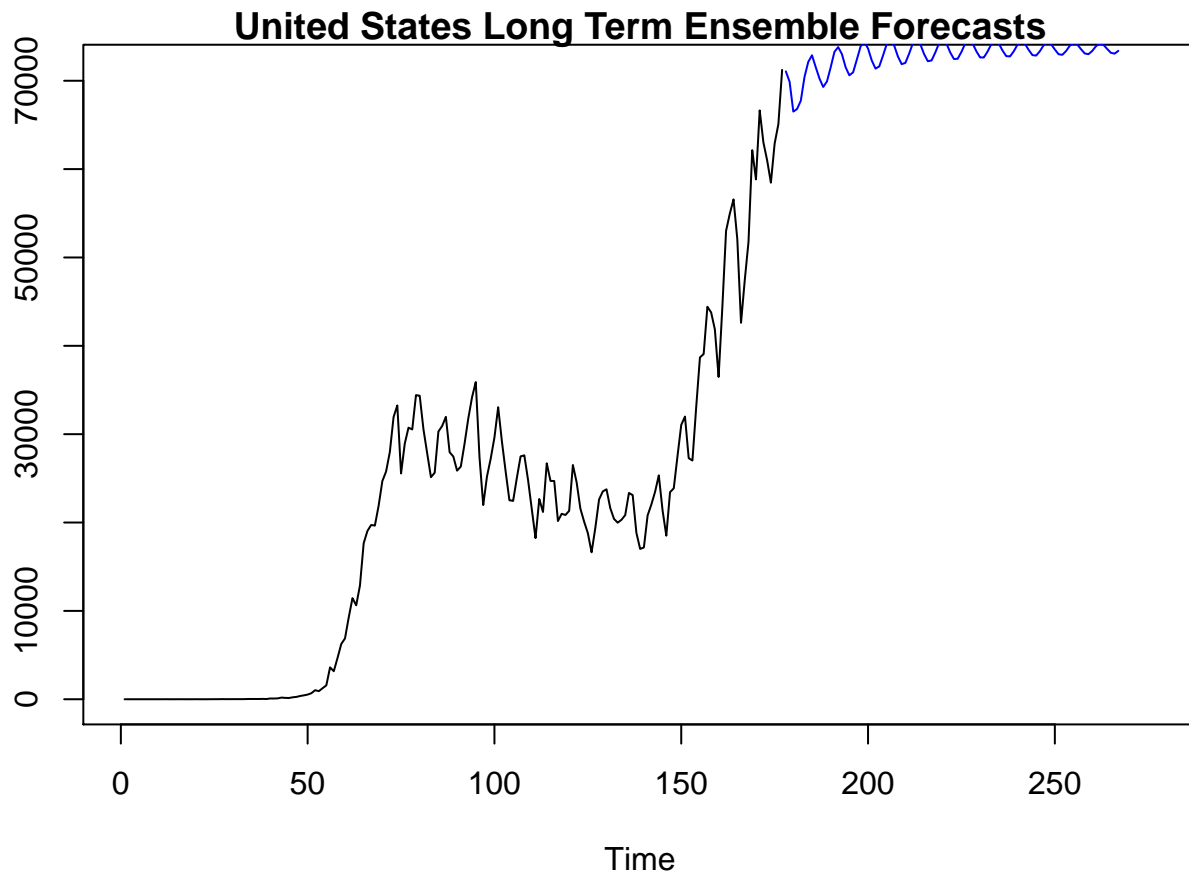
```
#Forecasting ahead
short_ensemble_us = (short_us_mlp$mean + short_us_arima$f)/2

long_ensemble_us = (long_us_mlp$mean + long_us_arima$f)/2

plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,187), main = "United States Short Term Ensemble Forecast",
lines(short_ensemble_us, col = "blue"))
```



```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,277), main = "United States Long Term Ensemble Forecasts")  
lines(long_ensemble_us, col = "blue")
```



Model Building

Goal Three: Multivariate Analysis

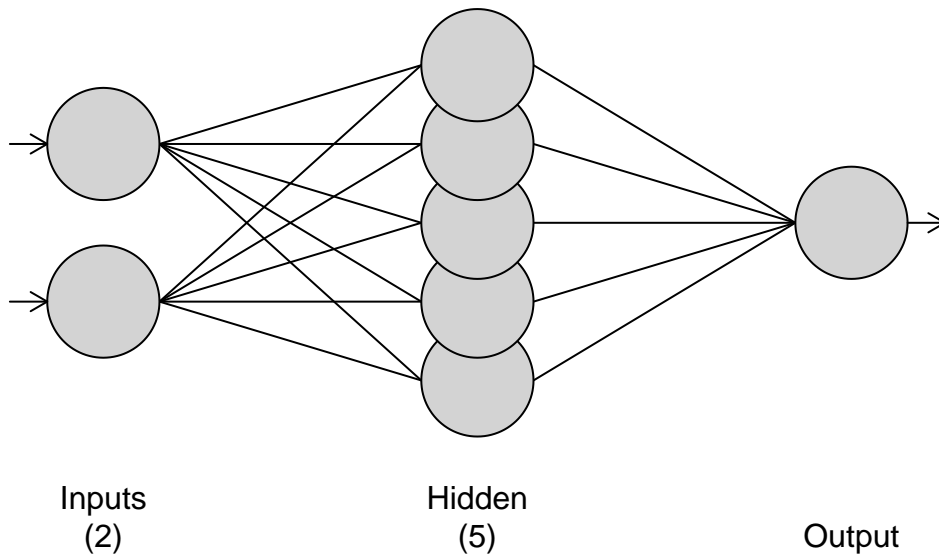
```
newcases_fl_multi = initial_data_fl %>% dplyr::select(positiveIncrease, totalTestResultsIncrease, hosp
```

#Forecast beyond data for Florida

#Forecast future variables

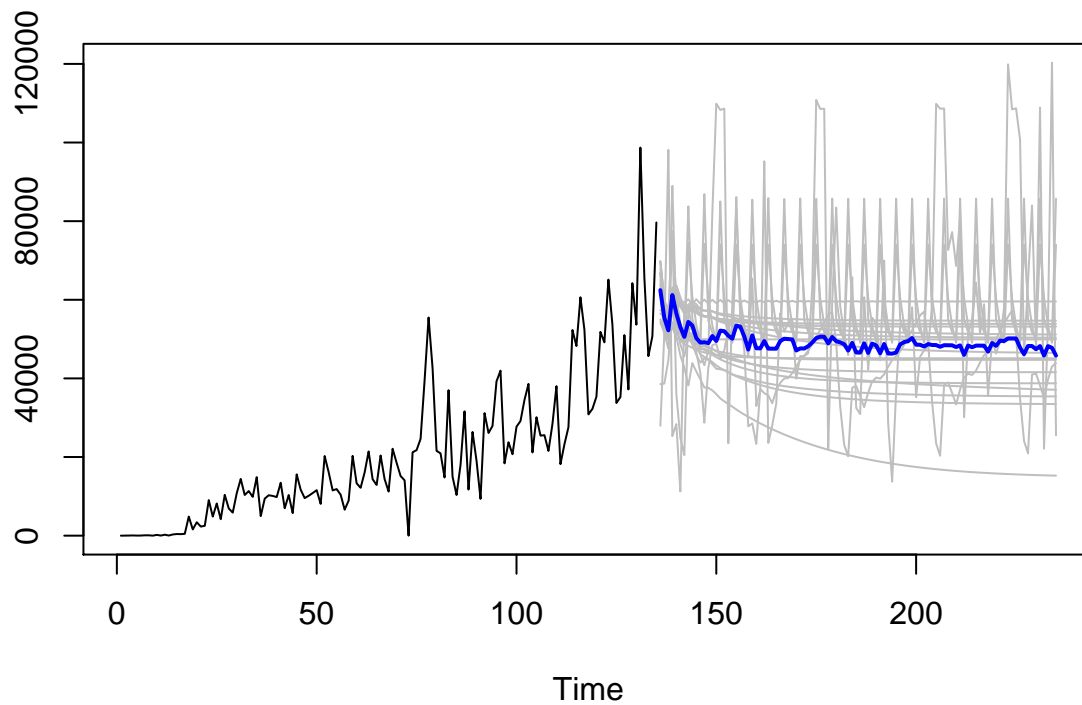
```
fit.mlp.1 = mlp(ts(newcases_fl_multi$totalTestResultsIncrease),reps = 20, comb = "median")  
plot(fit.mlp.1)
```

MLP



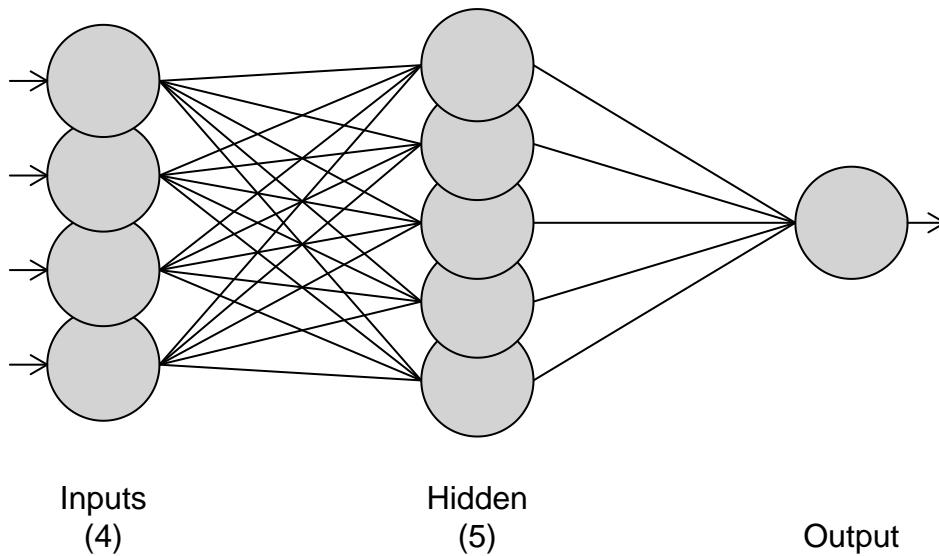
```
fore.mlp.1 = forecast(fit.mlp.1, h = 100)  
plot(fore.mlp.1)
```

Forecasts from MLP



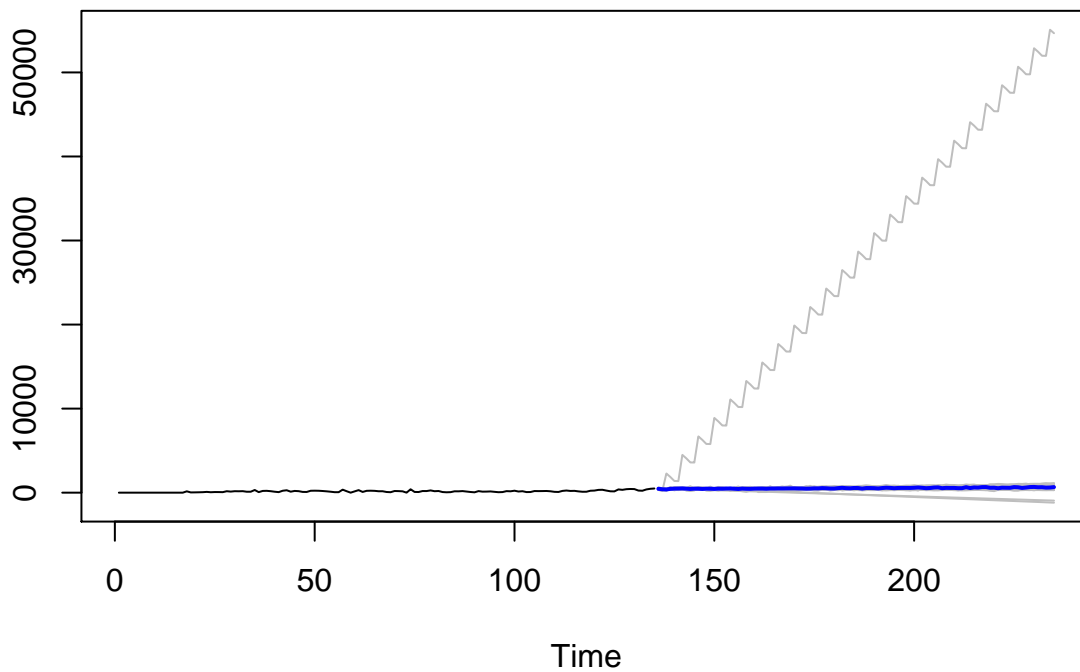
```
fit.mlp.2 = mlp(ts(newcases_fl_multi$hospitalizedIncrease), reps = 20, comb = "median")  
plot(fit.mlp.2)
```


MLP



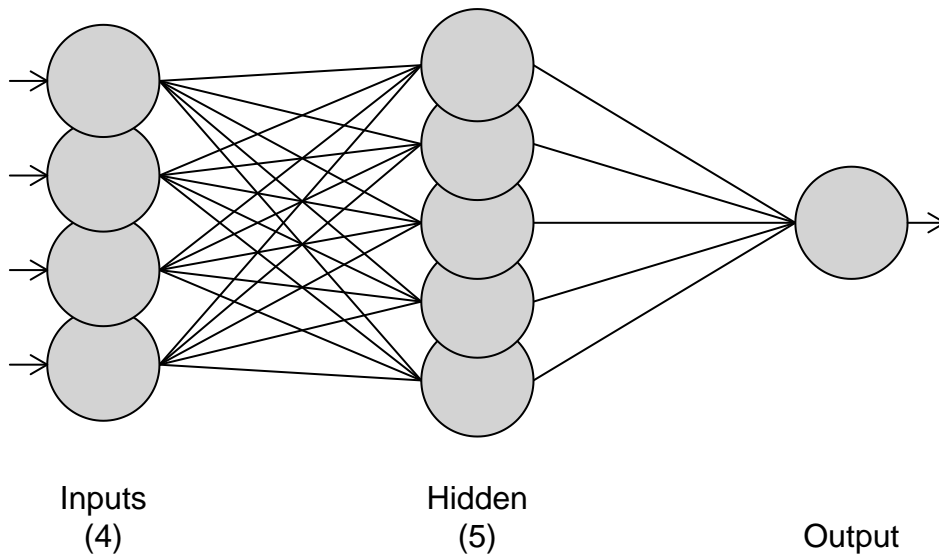
```
fore.mlp.2 = forecast(fit.mlp.2, h = 100)  
plot(fore.mlp.2)
```

Forecasts from MLP



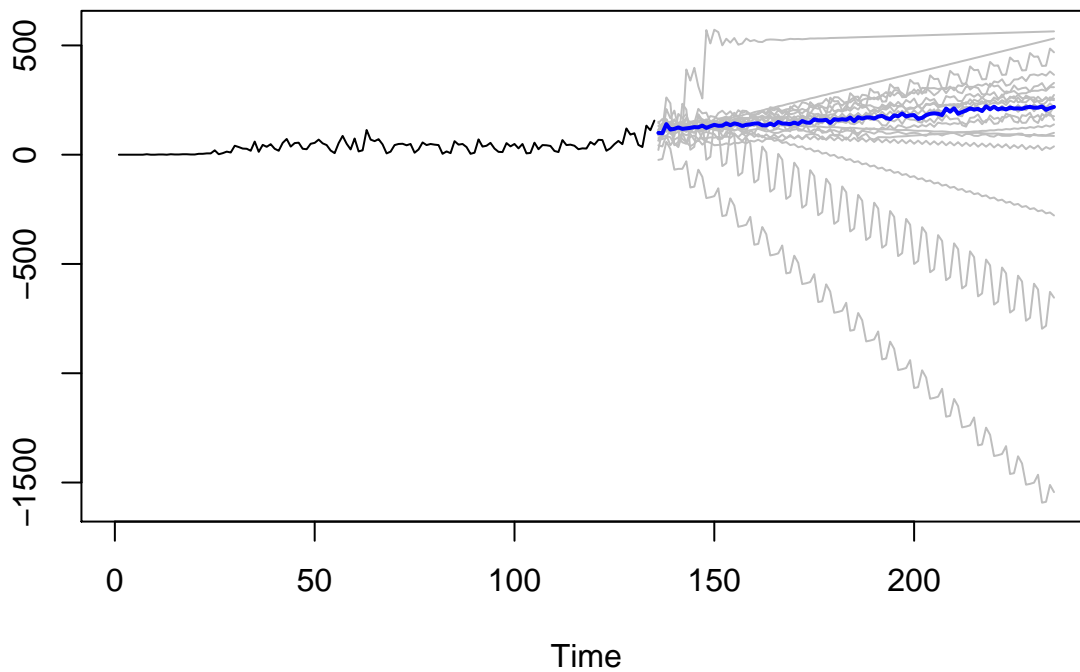
```
fit.mlp.3 = mlp(ts(newcases_fl_multi$deathIncrease), reps = 20, comb = "median")  
plot(fit.mlp.3)
```

MLP



```
fore.mlp.3 = forecast(fit.mlp.3, h = 100)  
plot(fore.mlp.3)
```

Forecasts from MLP



```
#package them up in data frame.  
newvar_fore_fl = data.frame(totalTestResultsIncrease = ts(c(newcases_fl_multi$totalTestResultsIncrease,  
  
#Data has 100 instances beyond current data  
dim(newvar_fore_fl)
```

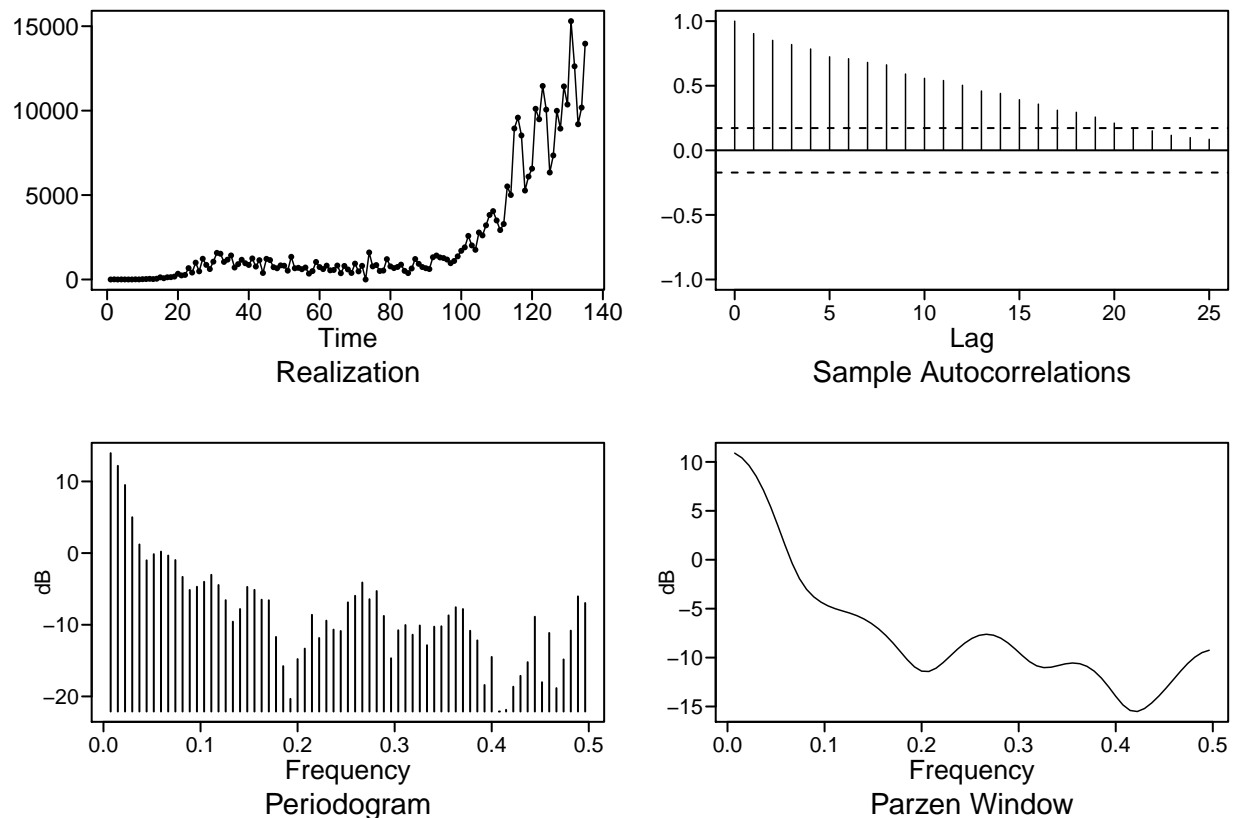
```
## [1] 235 3
```

```
###Multivariate Model Building for Florida Cases
```

A. Stationarity vs Non-Stationarity

Overall we see slowly dampening ACFs, combined with a strong aperiodic frequency at zero in our spectral density. These measures alone with a recently quickly rising case count in recent days gives us strong evidence that our data is non-stationary. Given Covid19 spread, it is likely we see continued rising behavior in the short term, some return to lower numbers in the coming months but more uncertainty as new spikes could arise, and in the longest term of years on, we expect new cases to diminish to zero once the pandemic has ended spread.

```
x = plottts.sample.wge(newcases_fl$positiveIncrease, arlimits = TRUE)
```



B. Non-Stationary Modeling

We did not do any differencing of our data set to account for this non-stationarity. Going into this project we knew that because of the failure to contain the Covid-19 outbreak we would see large spikes of cases in recent time periods compared to distant time periods. We feel that this is an important aspect of our data that we want to portray in our models because we can see empirically in Florida and the United States as a whole that both individual behavior and political policy continue to trend towards further outbreak and rapid, almost exponential daily case growth. While some states with compliant individual behavior and strong political Covid-19 policies have shown “completed” Covid-19 curves, where daily case count begins to trend downwards towards zero, Florida is the opposite. Therefore, since we empirically expect the trend of non-stationarity to continue, we want that represented in our models. This is a fundamental assumption that our models are built on.

C. Model ID

In multivariate modeling, our identification of models occurred specifically for each model and can be found at

the beginning of those sections in particular.

D. Model Building

#####Florida MLR Model

```
fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_fl_multi)
summary(fit)
```

```
##
## Call:
## lm(formula = positiveIncrease ~ totalTestResultsIncrease + hospitalizedIncrease,
##     data = newcases_fl_multi)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6794.8 -1047.8      1.2  1357.6  3712.4
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1358.579010    250.514502  -5.423 0.00000027 ***
## totalTestResultsIncrease    0.137289     0.009719  14.126 < 0.0000000000000002 ***
## hospitalizedIncrease      5.588560     1.626045   3.437 0.000787 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1687 on 132 degrees of freedom
## Multiple R-squared:  0.7585, Adjusted R-squared:  0.7548
## F-statistic: 207.3 on 2 and 132 DF,  p-value: < 0.00000000000000022
```

```
aic5.wge(fit$residuals)#picks 1,1
```

```
## -----WORKING... PLEASE WAIT...
```

```
##
```

```
##
```

```
## Five Smallest Values of aic
```

```
##      p      q      aic
## 5      1      1 13.87980
## 8      2      1 13.89429
## 6      1      2 13.89497
## 11     3      1 13.90310
## 9      2      2 13.90630
```

```
est1 = est.arma.wge(fit$residuals, p = 1, q = 1)
```

```
##
```

```
## Coefficients of Original polynomial:
```

```
## 0.9626
```

```
##
```

```
## Factor          Roots          Abs Recip      System Freq
## 1-0.9626B        1.0388          0.9626          0.0000
```

```
##
```

```
##
```

```

est_tests = mean(tail(newcases_fl_multi$totalTestResultsIncrease))
est_hospital= mean(tail(newcases_fl_multi$hospitalizedIncrease))

for( i in 1:(135-(trainingSize + horizon) ))
{
  fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_fl_multi[1:
  newdata = data.frame(totalTestResultsIncrease = rep(est_tests,horizon), hospitalizedIncrease = rep(es

  preds = predict(fit, newdata = newdata)
  forecasts = fore.arma.wge(fit$residuals,phi = est1$phi,theta = est1$theta, lastn = FALSE,n.ahead = ho

  final_pred = preds + forecasts$f

  ASE = mean((newcases_fl_multi$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] -f
  ASEHolder[i] = ASE

}

```

ASEHolder

```

## [1] 4376563.6 4490588.9 4713585.0 4996534.0 4552540.4
## [6] 3889871.3 1517553.2 461262.7 539850.0 616442.4
## [11] 496137.0 523596.0 524626.6 403695.8 221782.6
## [16] 136819.1 182184.4 193169.1 143050.5 131257.9
## [21] 264319.3 225747.0 213421.5 346797.5 413300.1
## [26] 628089.3 1013180.8 1478979.6 1599746.7 1372768.6
## [31] 1172744.6 1472886.3 1908251.3 5303180.7 8244606.3
## [36] 10064419.8 8986978.8 7931125.0 7225911.1 9791042.3
## [41] 12183663.8 15548906.9 12226294.3 10461543.8 4229821.9
## [46] 4189764.2 4857911.5 5308658.7 4130739.7 6332777.4
## [51] 5791097.6 6141545.0 6741713.6 32879420.5 22899968.2
## [56] 10935029.1 4570911.4 7501687.3 14534334.4 8232078.7
## [61] 6423252.2 5877738.6 6206097.2 4511451.6 8180230.5
## [66] 8006156.6 8052028.0 8836821.1 13545447.0 19223522.8
## [71] 21617326.7 22991810.6 35571592.3 60587074.8 88054709.5
## [76] 126461836.7 167499378.8 214932487.0 232113012.4 129809804.3
## [81] 208280841.0 298939040.5 291724934.3 395013219.6 403252713.6
## [86] 403509101.2 94337827.4 218411714.6 522585765.8 621589282.2
## [91] 183795297.5 80600016.7 61277317.6 41403127.9 79444543.1
## [96] 239295383.3

```

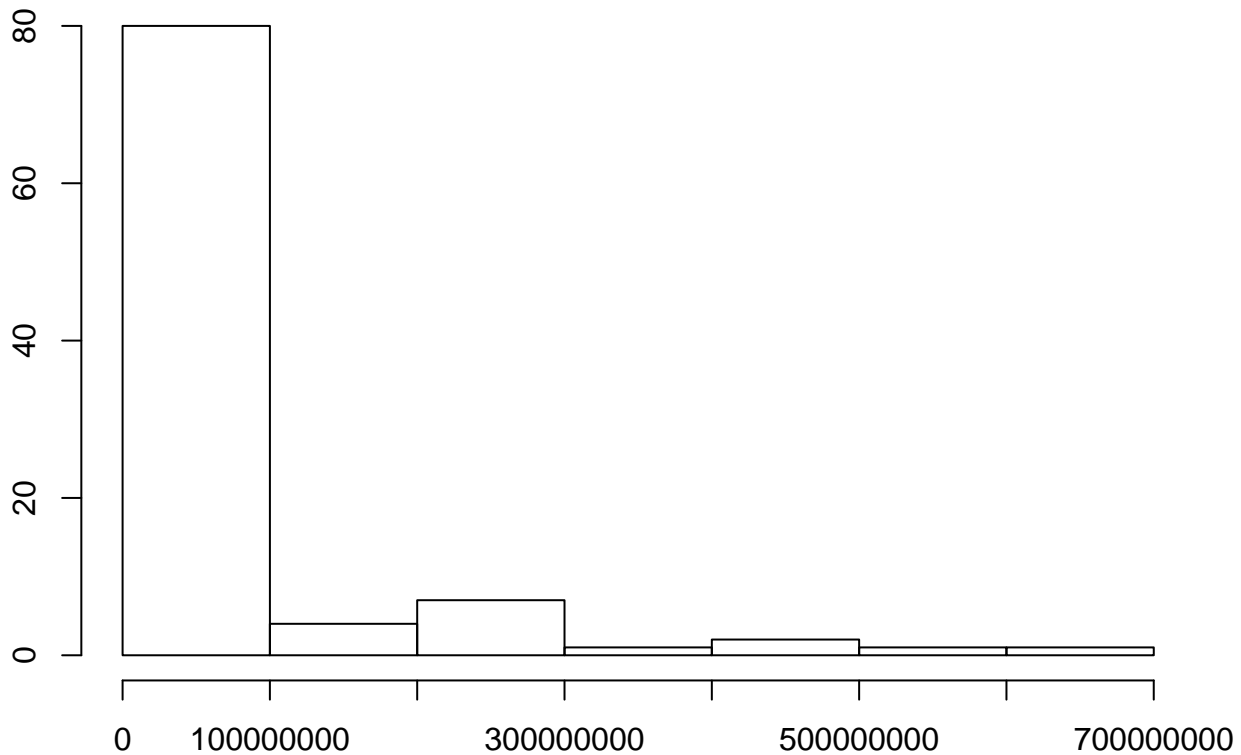
#Distribution of ASEs on Two Week Periods

```

hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for MLR Model 1

```

ASE Distribution for MLR Model Florida Data



ASE of model at a given Training Set

```
#Mean ASE
WindowedASE = mean(ASEHolder)
WindowedASE

## [1] 58691962

fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_fl_multi)
summary(fit)

##
## Call:
## lm(formula = positiveIncrease ~ totalTestResultsIncrease + hospitalizedIncrease,
##     data = newcases_fl_multi)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6794.8 -1047.8      1.2  1357.6  3712.4
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1358.579010    250.514502  -5.423 0.00000027 ***
## totalTestResultsIncrease    0.137289     0.009719  14.126 < 0.0000000000000002 ***
## hospitalizedIncrease     5.588560     1.626045   3.437 0.000787 ***
##
## Pr(>|t|)
## (Intercept)          0.00000027 ***
## totalTestResultsIncrease < 0.0000000000000002 ***
## hospitalizedIncrease          0.000787 ***
```

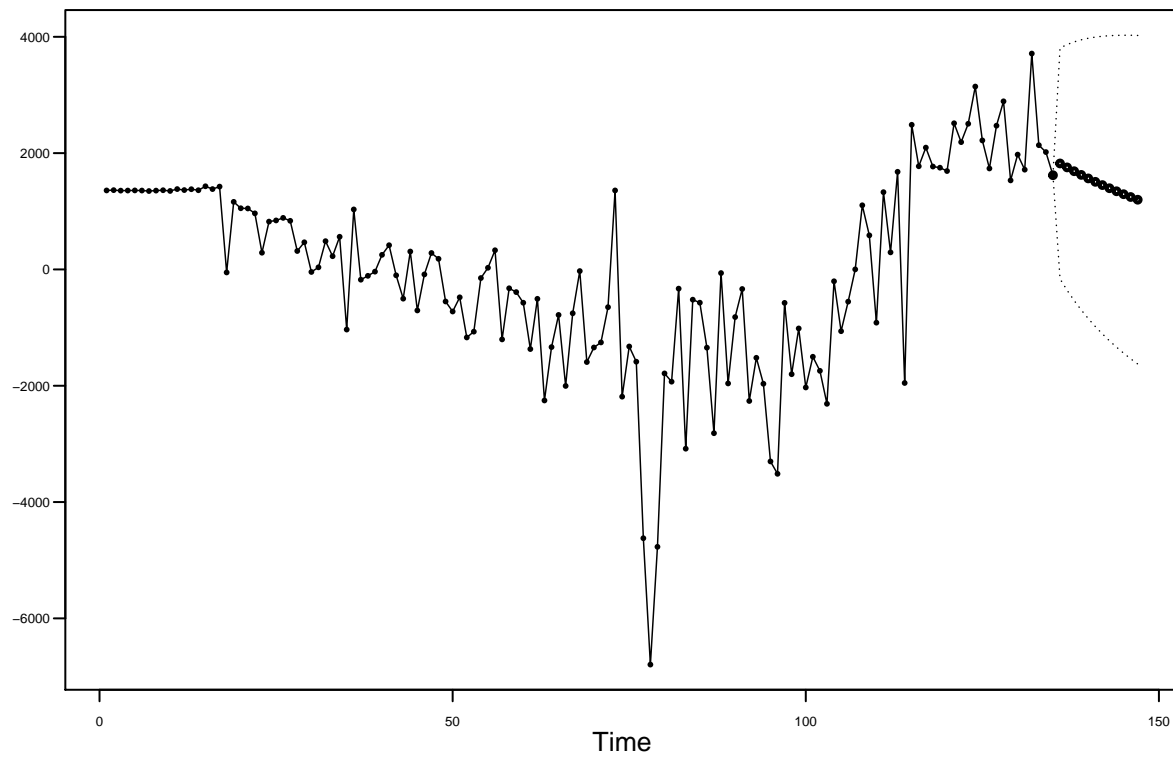
```

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1687 on 132 degrees of freedom
## Multiple R-squared:  0.7585, Adjusted R-squared:  0.7548
## F-statistic: 207.3 on 2 and 132 DF,  p-value: < 0.000000000000000022
newdata = data.frame(totalTestResultsIncrease = rep(est_tests,12), hospitalizedIncrease = rep(est_hospi
preds = predict(fit, newdata = newdata)
aic5.wge(fit$residuals)#picks 1,1

## -----WORKING... PLEASE WAIT...
##
##
## Five Smallest Values of  aic
##      p    q      aic
## 5     1    1  13.87980
## 8     2    1  13.89429
## 6     1    2  13.89497
## 11    3    1  13.90310
## 9     2    2  13.90630
est1 = est.arma.wge(fit$residuals, p = 1, q = 1)

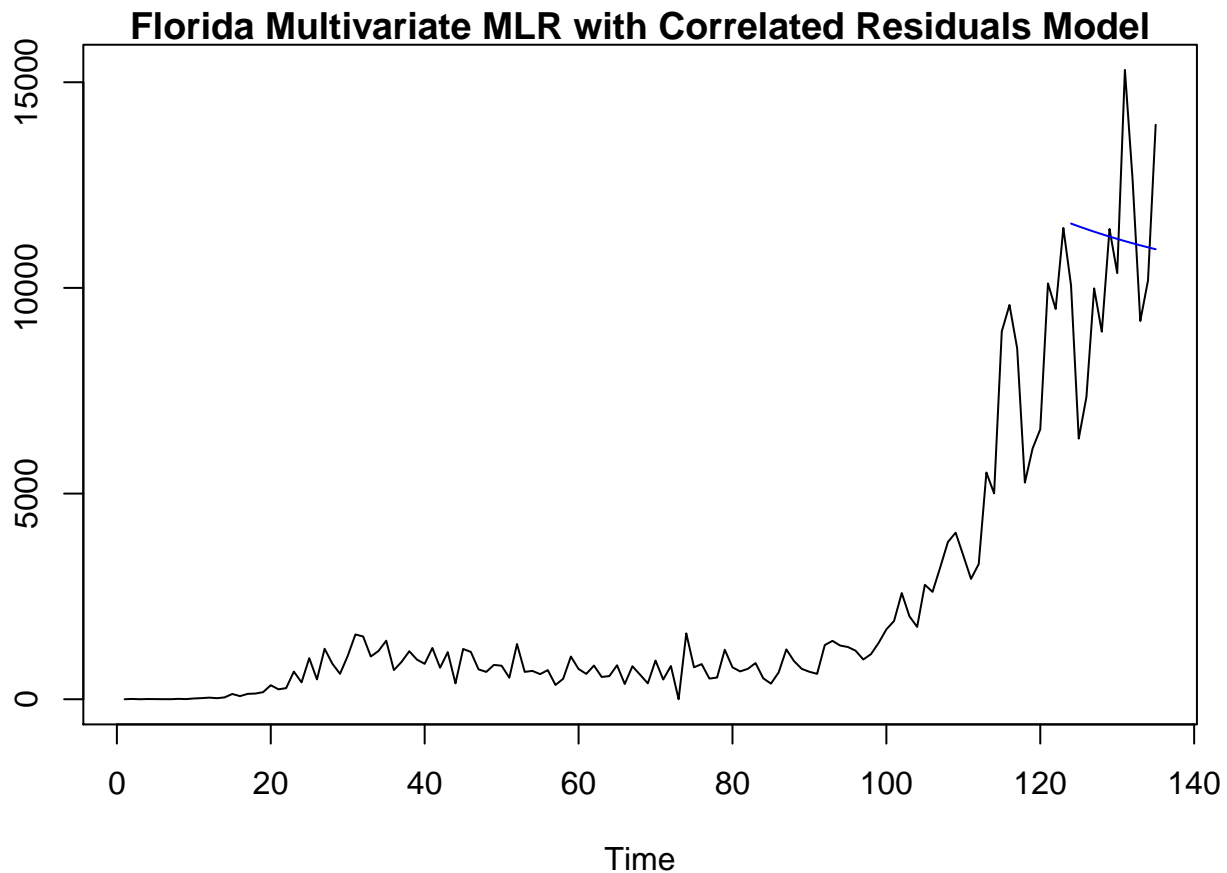
##
## Coefficients of Original polynomial:
## 0.9626
##
## Factor          Roots          Abs Recip      System Freq
## 1-0.9626B       1.0388         0.9626         0.0000
##
##
forecasts = fore.arma.wge(fit$residuals,phi = est1$phi,theta = est1$theta, lastn = FALSE,n.ahead = 12)

```



```
FinalPredictions_fl_MLR = preds + forecasts$f
```

```
plot(newcases_fl$positiveIncrease, type = "l", main = "Florida Multivariate MLR with Correlated Residuals")
lines(ts(FinalPredictions_fl_MLR, start = 124), col = "blue")
```

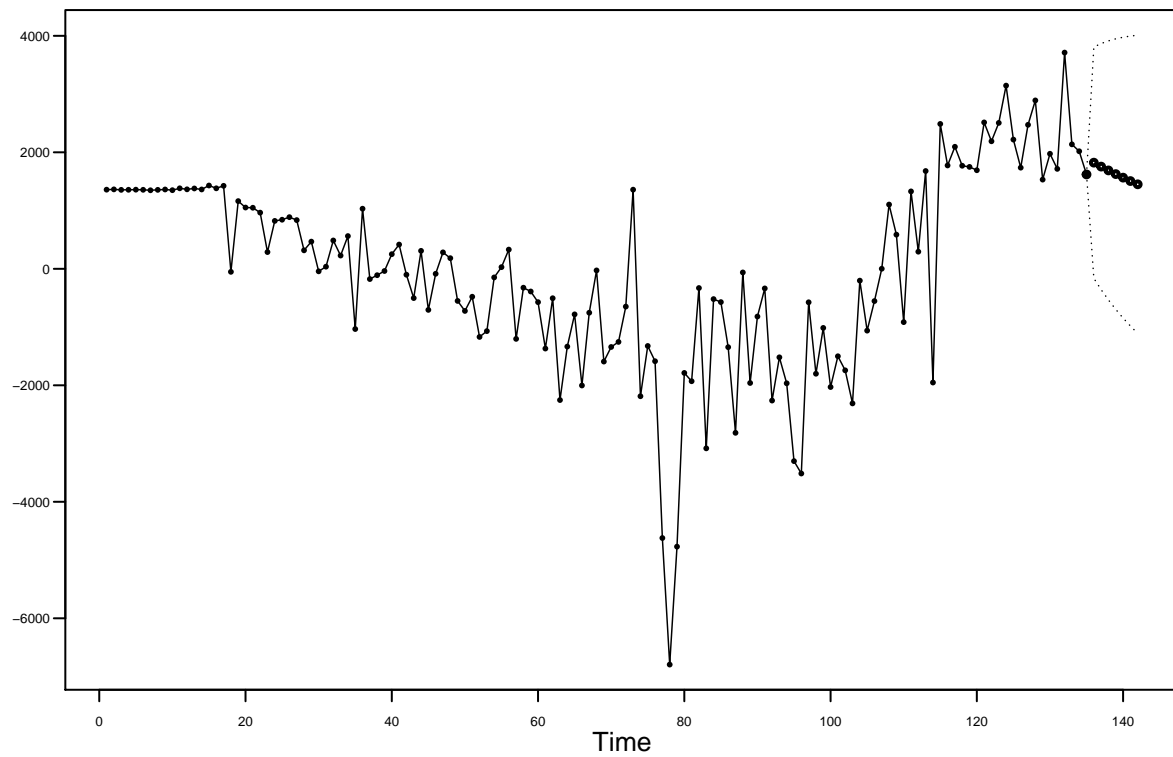
```
ASE = mean((newcases_fl_multi$positiveIncrease[124:135] - FinalPredictions_fl_MLR)^2)
ASE
```

```
## [1] 7223923
```

```
#Forecasting Ahead
```

```
shortdata = data.frame(totalTestResultsIncrease = rep(est_tests,7), hospitalizedIncrease = rep(est_hosp,7))
longdata = data.frame(totalTestResultsIncrease = rep(est_tests,90), hospitalizedIncrease = rep(est_hosp,90))
```

```
fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_fl_multi)
#short
preds = predict(fit, newdata = shortdata)
forecasts = fore.arma.wge(fit$residuals,phi = est1$phi,theta = est1$theta, lastn = FALSE,n.ahead = 7)
```

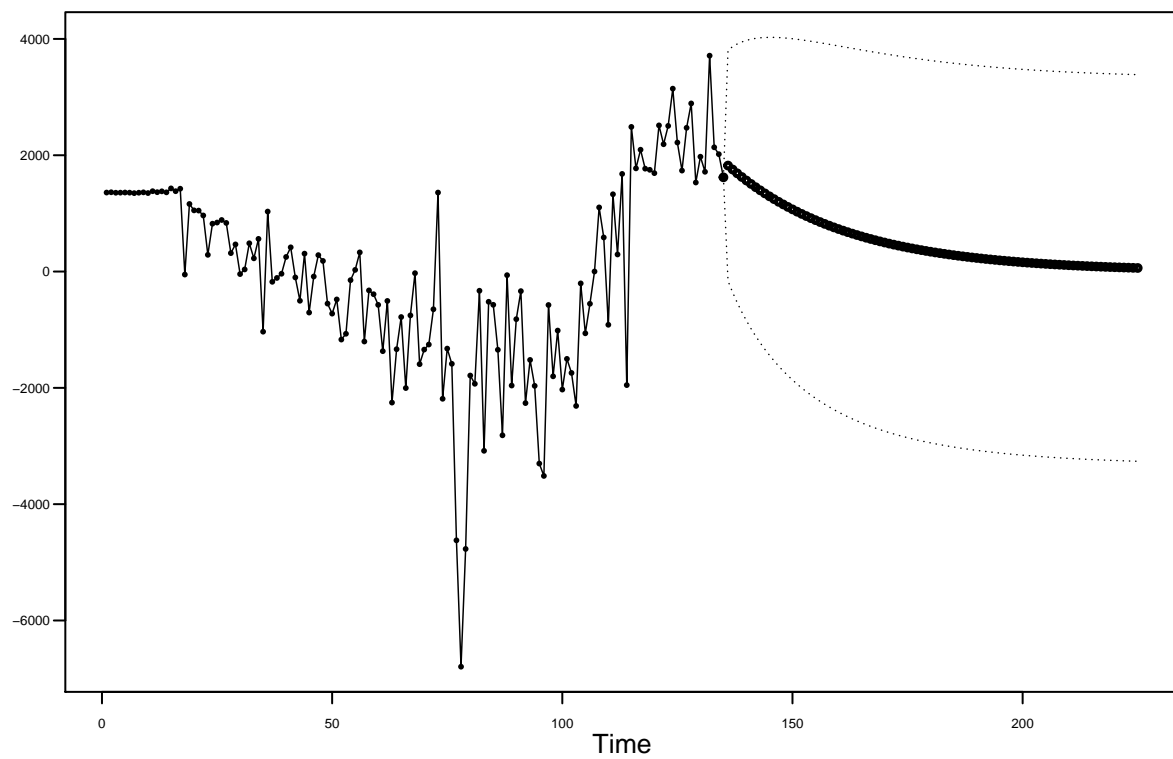


```
short_fl_mlr_m = preds + forecasts$f
```

```
#long
```

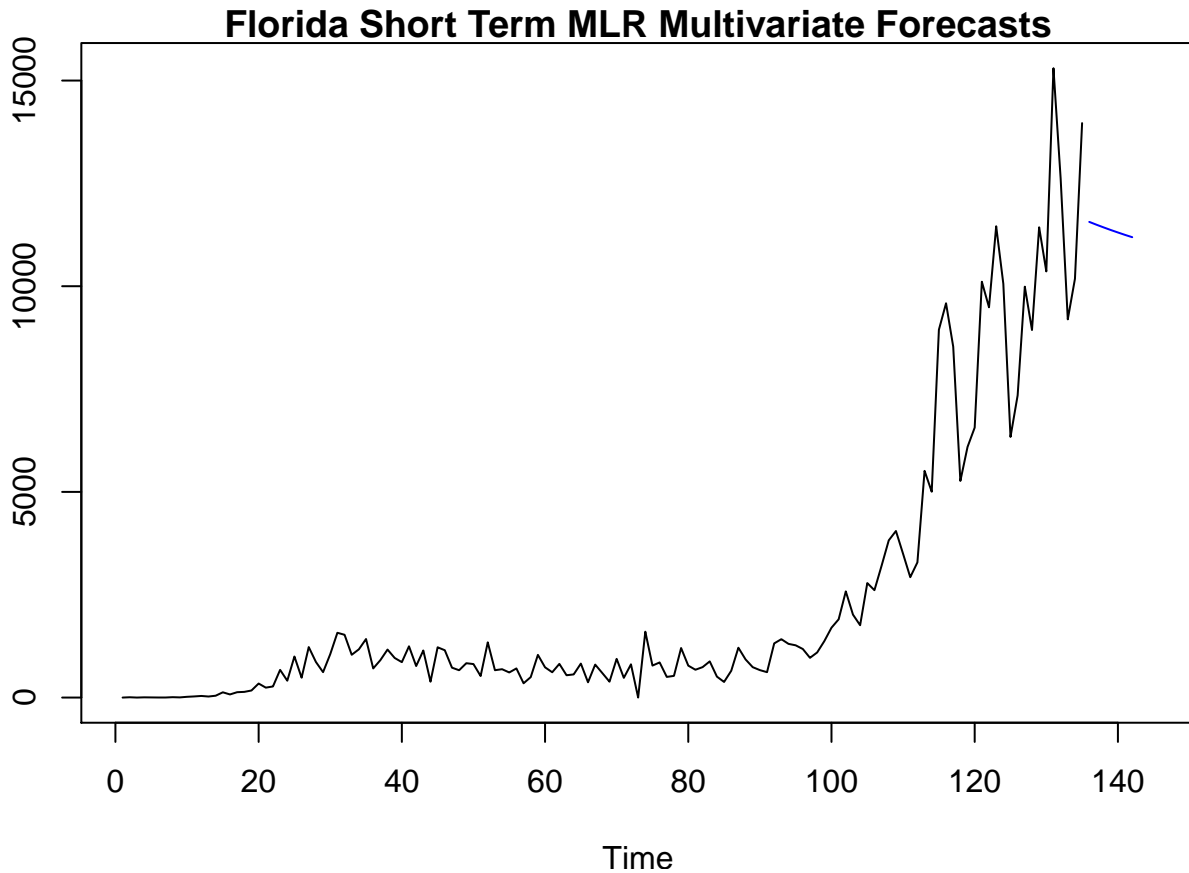
```
preds = predict(fit, newdata = longdata)
```

```
forecasts = fore.arma.wge(fit$residuals, phi = est1$phi, theta = est1$theta, lastn = FALSE, n.ahead = 90)
```

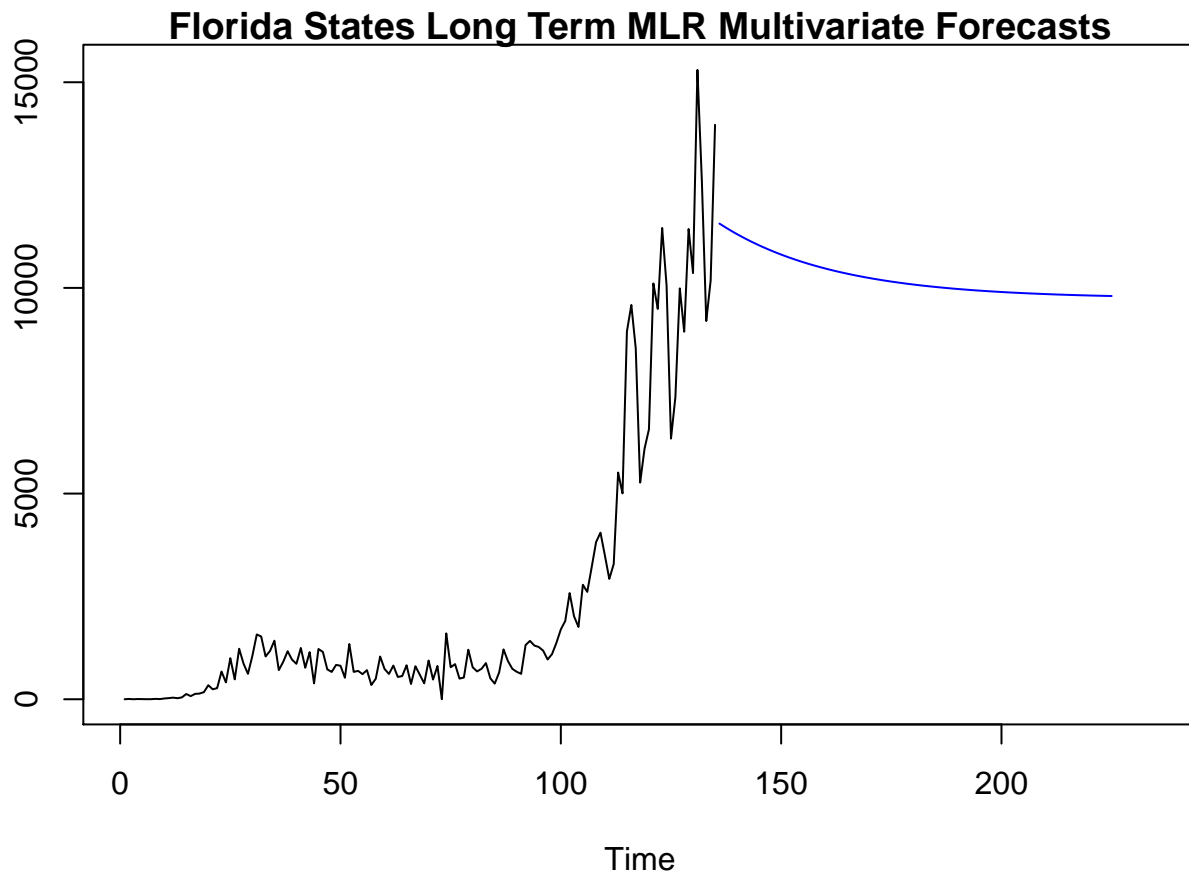


```
long_fl_mlr_m = preds + forecasts$f
```

```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,145), main = "Florida Short Term MLR Multivariate Forecasts", col = "black")
lines(ts(short_fl_mlr_m, start = 136), col = "blue")
```



```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,235), main = "Florida States Long Term MLR Multivariate Forecasts", col = "black")
lines(ts(long_fl_mlr_m, start = 136), col = "blue")
```



```
####Florida Multivariate MLP Cases Model
```

```
newcases_fl_multi = initial_data_fl %>% dplyr::select(positiveIncrease, totalTestResultsIncrease, hosp
newcases_fl_var = cbind(ts(newcases_fl_multi$totalTestResultsIncrease),ts(newcases_fl_multi$hospitalize
```

```
trainingSize = 70
```

```
horizon = 12
```

```
ASEHolder = numeric()
```

```
#Out of bounds if it goes for 54 runs, this ASE will be slightly less wide than the others. But the win
```

```
for( i in 1:(135-(trainingSize + horizon) ))
```

```
{
```

```
  mlp.fit = mlp(ts(newcases_fl_multi$positiveIncrease[1:trainingSize+i]), hd = 5, comb = "median", xreg
```

```
  forecasts = forecast(mlp.fit,h = horizon, xreg = newcases_fl_var[1:(trainingSize + i + 12),])
```

```
  ASE = mean((newcases_fl_multi$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] -f
```

```
  ASEHolder[i] = ASE
```

```
}
```

```
ASEHolder
```

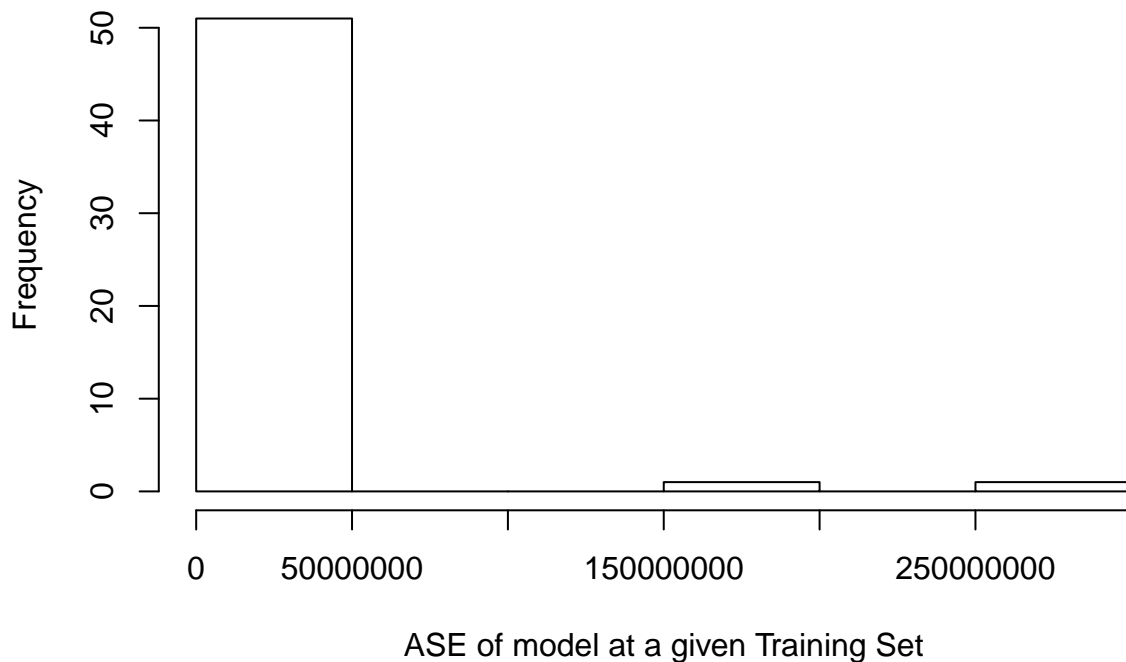
```
## [1] 444153.44 194060.03 712958.65 903230.74 93626.46
## [6] 262553.62 683313.71 1311789.25 525867.47 77420.21
## [11] 151935.46 111753.21 277586.38 221647.60 294752.61
## [16] 401838.94 142857.79 263538.47 162420.22 298807.46
## [21] 612585.87 707084.56 618467.53 1092515.95 1078234.70
```

```
## [26] 860323.96 2116833.27 2896532.04 2513659.93 2965045.82
## [31] 2223309.84 1449933.05 2619105.27 6259345.20 11106408.50
## [36] 11151344.74 10602421.29 8788979.76 8739962.12 8360816.99
## [41] 13457932.79 21281998.77 12992823.99 10721605.74 152094225.32
## [46] 250526636.74 44318528.65 40428553.15 15077537.49 18401073.75
## [51] 16003705.56 16142526.33 8093564.28
```

```
#Distribution of ASEs on Two Week Periods
```

```
hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for MLP Model I")
```

ASE Distribution for MLP Model Florida Data



```
#Mean ASE
```

```
WindowedASE = mean(ASEHolder)
```

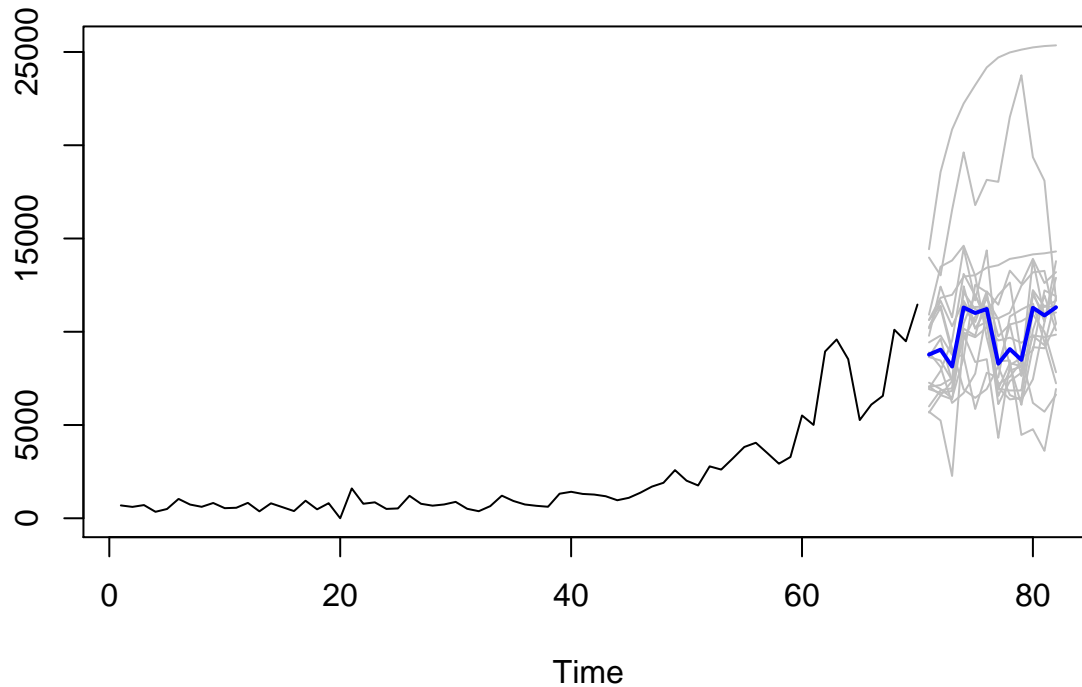
```
WindowedASE
```

```
## [1] 13468674
```

```
#18757436 - 18 mill
```

```
plot(forecasts)
```

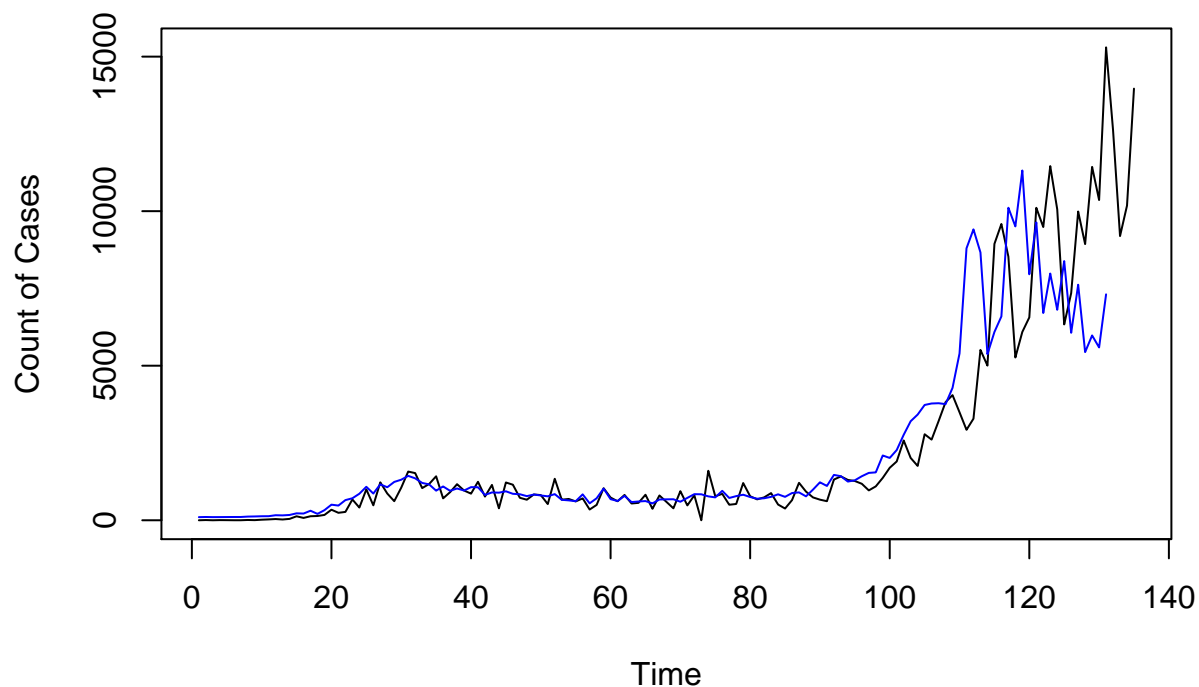
Forecasts from MLP



```
#Final Forecasts with data known
mlp.fit = mlp(ts(newcases_fl_multi$positiveIncrease[1:123]), hd = 5, comb = "median", xreg = newcases_fl.
forecasts = forecast(mlp.fit, h = 12, xreg = newcases_fl_var[1:135,])
fl_multi_mlp_fore = forecasts$mean

all_f = c(forecasts$fitted, forecasts$mean)
plot(newcases_fl_multi$positiveIncrease, type = "l", main = "Florida Multivariate MLP Model with Fits and
lines(all_f, col = "blue")
```

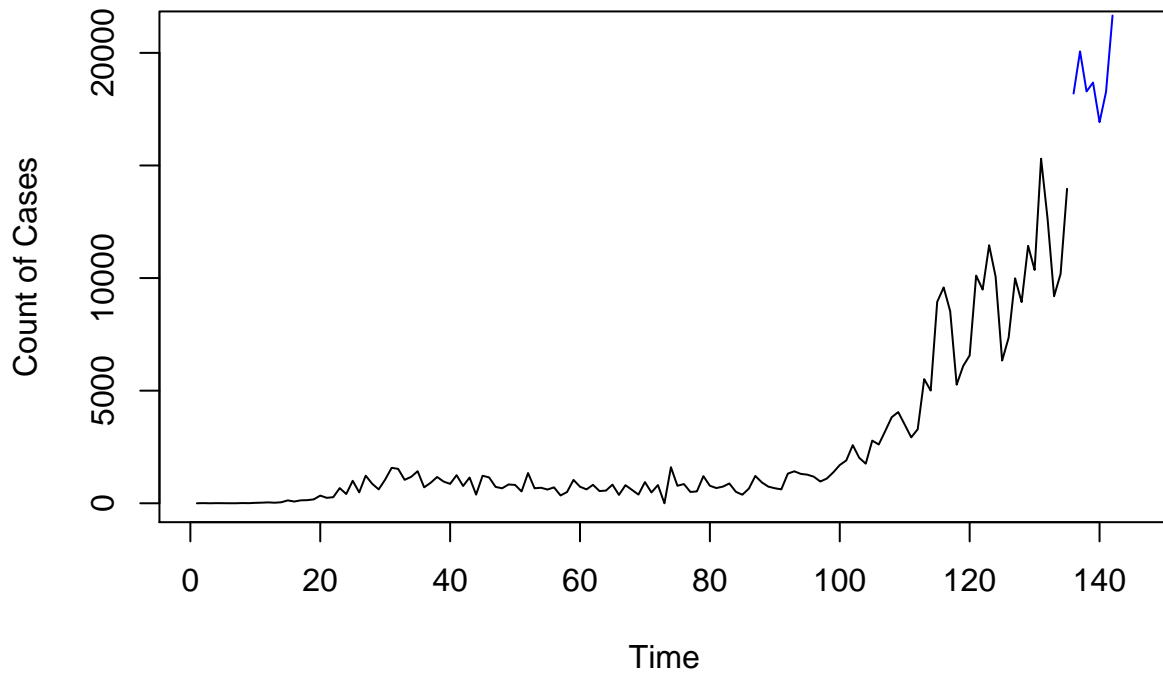
Florida Multivariate MLP Model with Fits and Final 12 Predictions



```
#Forecast beyond data
mlp.fit = mlp(ts(newcases_fl_multi$positiveIncrease), hd = 5, comb = "median", xreg = newvar_fore_fl[1:
short_fl_mlp_m = forecast(mlp.fit,h = 7, xreg = newvar_fore_fl[1:145,])
long_fl_mlp_m = forecast(mlp.fit,h = 90, xreg = newvar_fore_fl[1:225,])

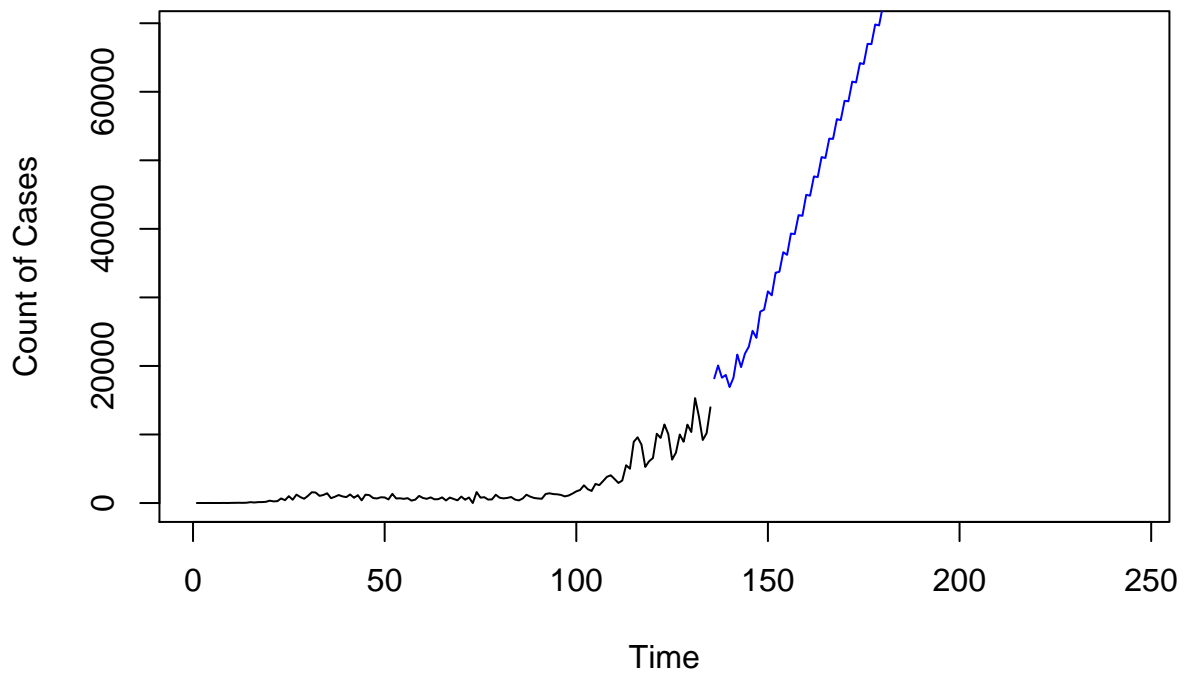
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,145),ylim = c(0,21000), main = "Florida Short
lines(short_fl_mlp_m$mean, col = "blue")
```

Florida Short Term MLP Multivariate Forecasts



```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,245),ylim = c(0,69000), main = "Florida Long Term MLP Multivariate Forecasts")
lines(long_fl_mlp_m$mean, col = "blue")
```

Florida Long Term MLP Multivariate Forecasts



```
final_12_ase = mean((newcases_fl_multi$positiveIncrease[124:135] - fl_multi_mlp_fore)^2)
final_12_ase
```



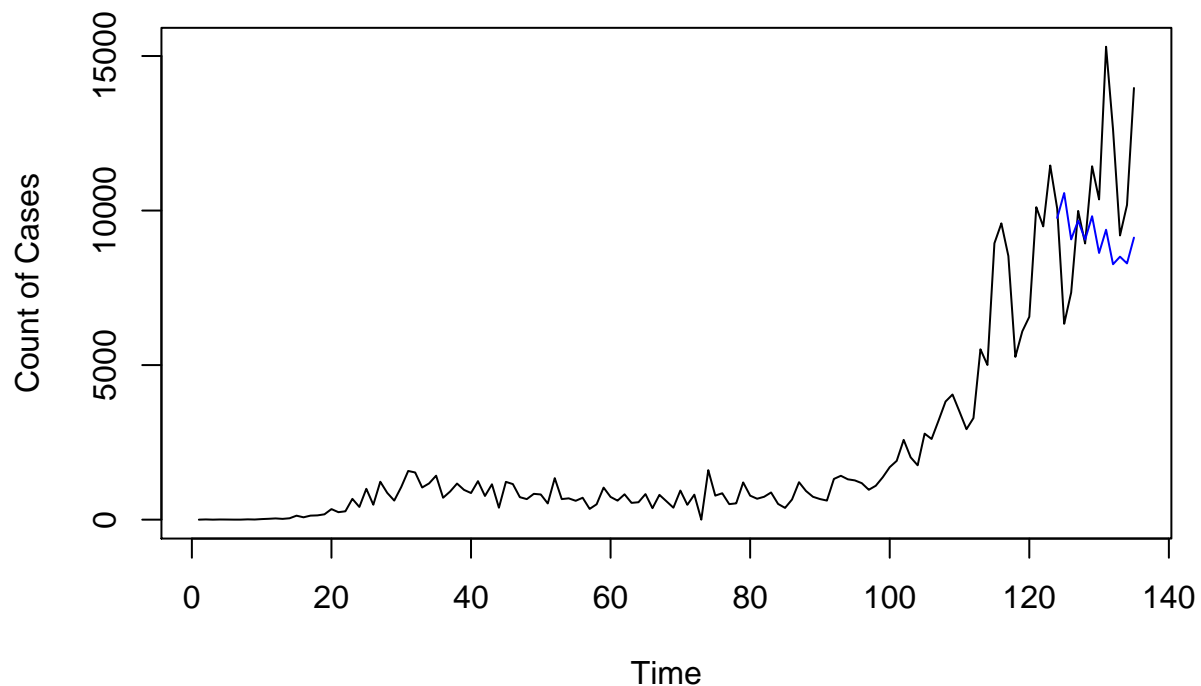
```
## [1] 19855091
```

```
#####Florida Multivariate Ensemble Model
```

```
ensemble_fore = (fl_multi_mlp_fore + FinalPredictions_fl_MLR)/2
```

```
plot(newcases_fl_multi$positiveIncrease, type = "l", main = "Florida Multivariate Ensemble Model with F  
lines(ensemble_fore, col = "blue")
```

Florida Multivariate Ensemble Model with Final 12 Predictions



```
ASE_fl_multi = mean((newcases_fl_multi$positiveIncrease[124:135] - ensemble_fore)^2)  
ASE_fl_multi
```

```
## [1] 9018759
```

```
#ASE of 8,427,522
```

```
#future
```

```
#long_fl_mlp_m
```

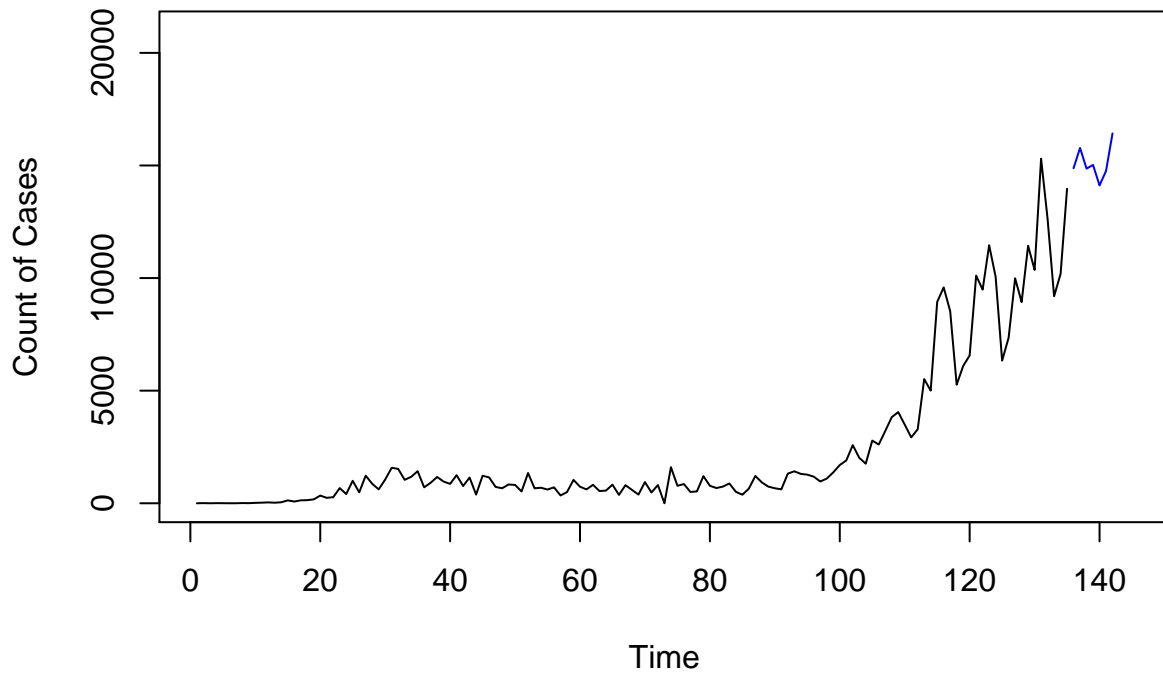
```
#short_fl_mlp_m
```

```
ensemble_fl_fore_short = ( short_fl_mlp_m$mean+ short_fl_mlr_m)/2
```

```
ensemble_fl_fore_long = (long_fl_mlp_m$mean + long_fl_mlr_m)/2
```

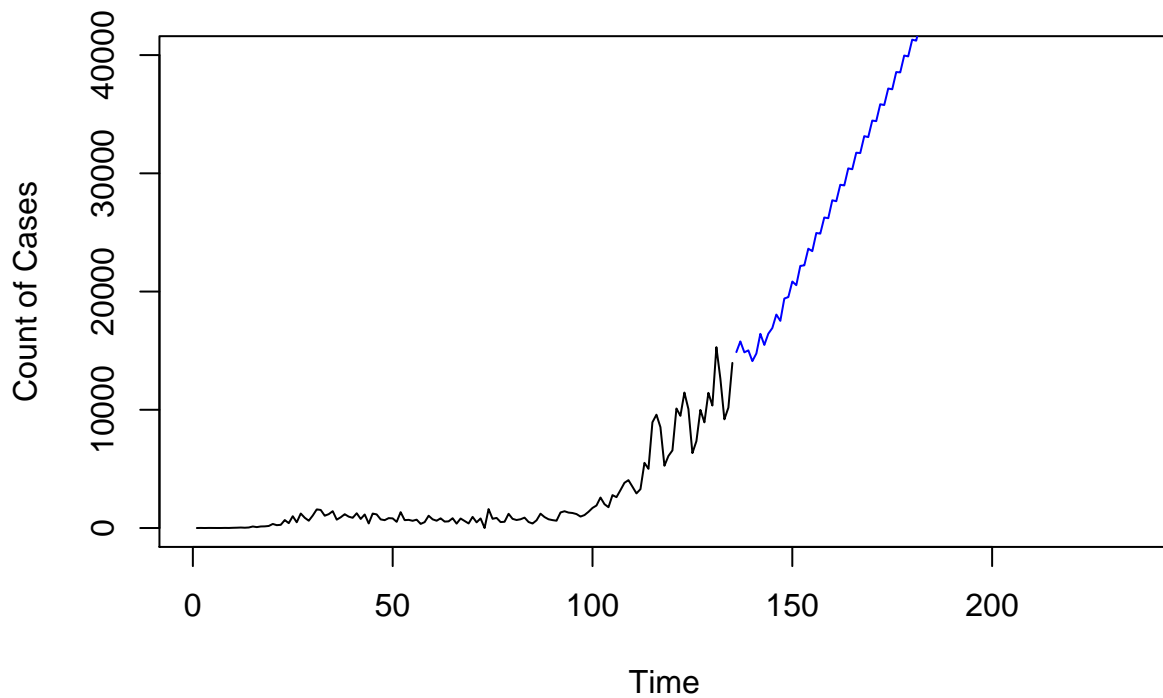
```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,145),ylim = c(0,21000), main = "Florida Short  
lines(ensemble_fl_fore_short, col = "blue")
```

Florida Short Term Multivariate Ensemble Forecasts



```
plot(newcases_fl$positiveIncrease, type = "l", xlim = c(1,235), ylim = c(0,40000),main = "Florida Long Term Multivariate Ensemble Forecasts")
lines(ensemble_fl_fore_long, col = "blue")
```

Florida Long Term Multivariate Ensemble Forecasts



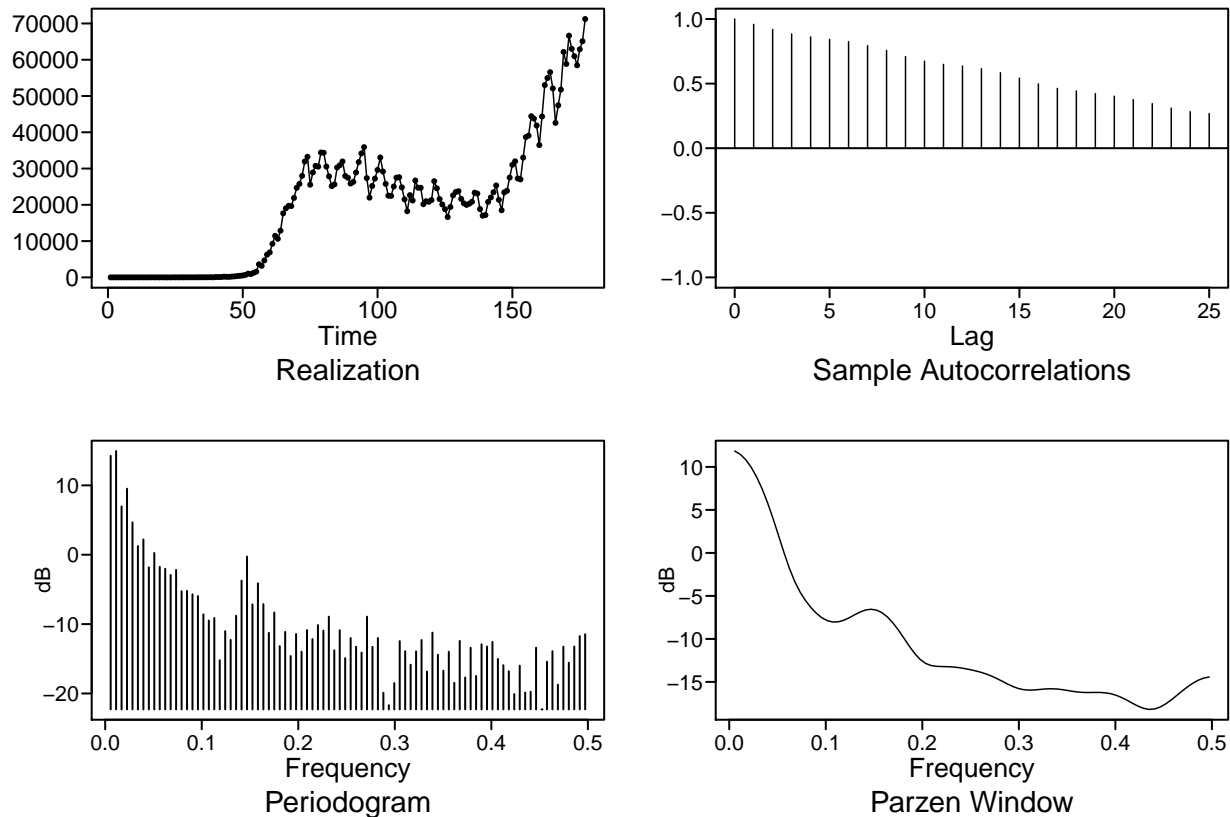
###Multivariate US Models

A. Stationarity vs Non-Stationarity

Overall we see slowly dampening ACFs, combined with a strong aperiodic frequency at zero in our spectral density. These measures alone with a recently quickly rising case count in recent days gives us strong evidence that our data is non-stationary. Given Covid19 spread, it is likely we see continued rising behavior in the short term, some return to lower numbers in the coming months but more uncertainty as new spikes could arise, and in the longest term of years on, we expect new cases to diminish to zero once the pandemic has ended spread.

#no text output

```
x = plottts.sample.wge(newcases_us$positiveIncrease)
```



B. Non-Stationary Modeling

We did not do any differencing of our data set to account for this non-stationarity. Going into this project we knew that because of the failure to contain the Covid-19 outbreak we would see large spikes of cases in recent time periods compared to distant time periods. We feel that this is an important aspect of our data that we want to portray in our models because we can see empirically in Florida and the United States as a whole that both individual behavior and political policy continue to trend towards further outbreak and rapid, almost exponential daily case growth. While some states with compliant individual behavior and strong political Covid-19 policies have shown “completed” Covid-19 curves, where daily case count begins to trend downwards towards zero, Florida is the opposite. Therefore, since we empirically expect the trend of non-stationarity to continue, we want that represented in our models. This is a fundamental assumption that our models are built on.

C. Model IDing of stationary models

In multivariate modeling, our identification of models occurred specifically for each model and can be found at the beginning of those sections in particular.

D. Model Building

In order to forecast multivariate models of new case numbers, we will first fit some new variables for future

MLP type models.

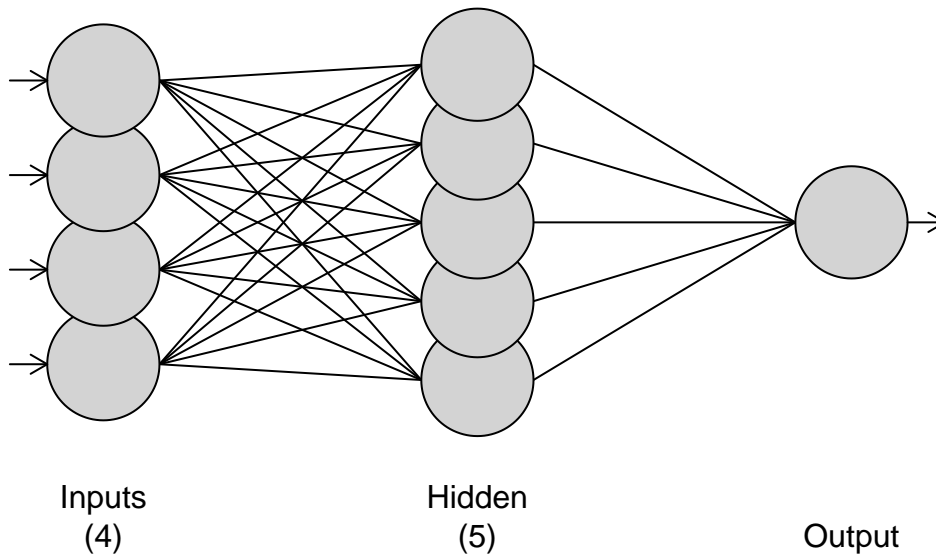
```
newcases_us_multi = initial_data_us %>% dplyr::select(positiveIncrease, totalTestResultsIncrease, hosp
```

```
#Forecast Future
```

```
#Forecast future variables
```

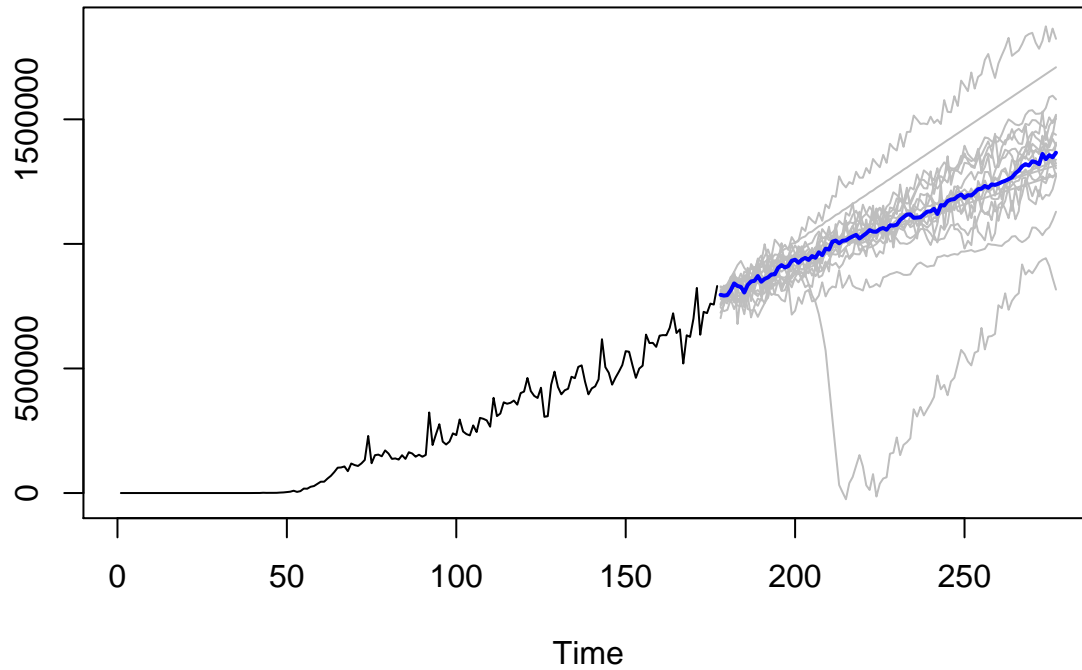
```
fit.mlp.1 = mlp(ts(newcases_us_multi$totalTestResultsIncrease), reps = 20, comb = "median")  
plot(fit.mlp.1)
```

MLP



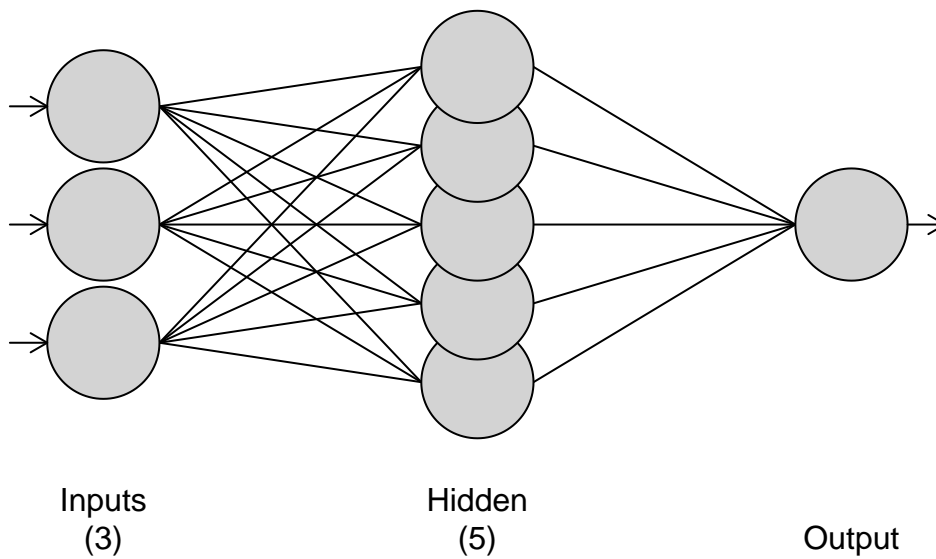
```
fore.mlp.1 = forecast(fit.mlp.1, h = 100)  
plot(fore.mlp.1)
```

Forecasts from MLP



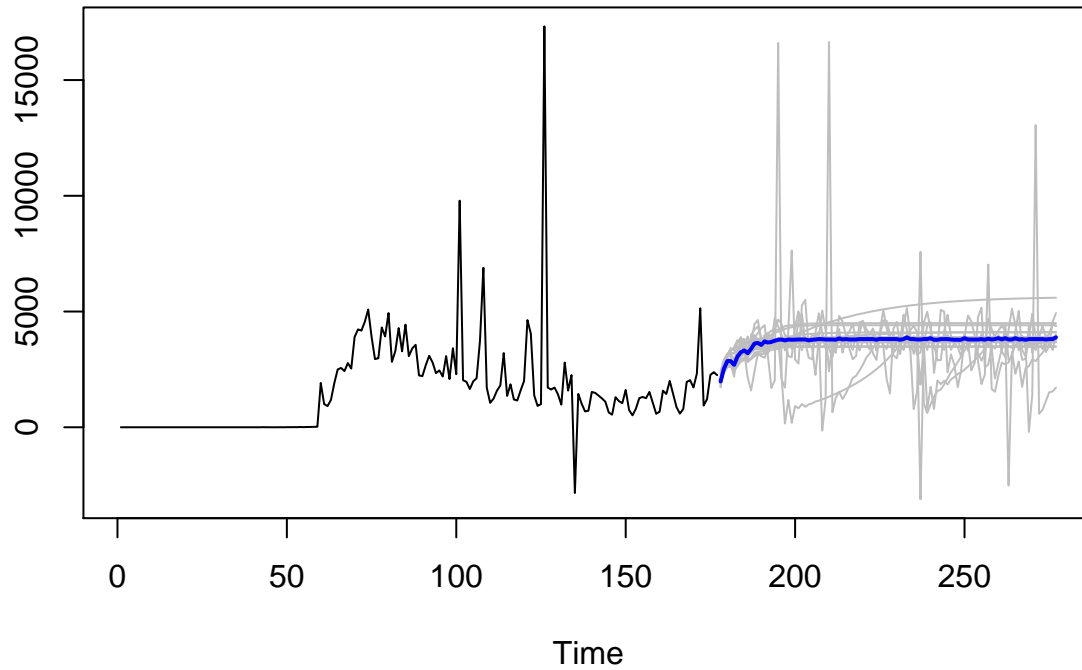
```
fit.mlp.2 = mlp(ts(newcases_us_multi$hospitalizedIncrease), reps = 20, comb = "median")
plot(fit.mlp.2)
```

MLP



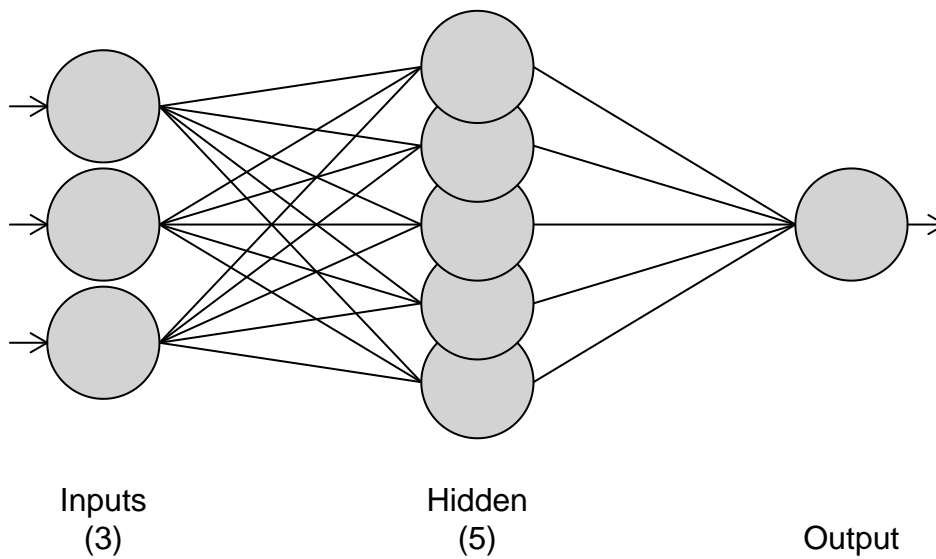
```
fore.mlp.2 = forecast(fit.mlp.2, h = 100)
plot(fore.mlp.2)
```

Forecasts from MLP



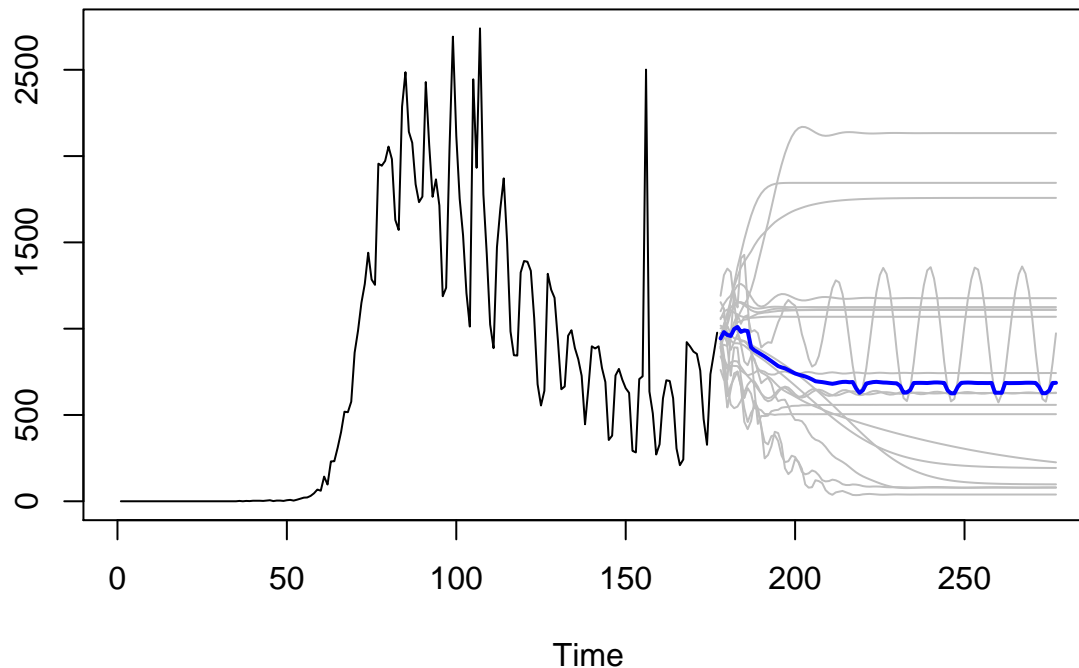
```
fit.mlp.3 = mlp(ts(newcases_us_multi$deathIncrease), reps = 20, comb = "median")  
plot(fit.mlp.3)
```

MLP



```
fore.mlp.3 = forecast(fit.mlp.3, h = 100)  
plot(fore.mlp.3)
```

Forecasts from MLP



```
#package them up in data frame.
newvar_fore_us = data.frame(totalTestResultsIncrease = ts(c(newcases_us_multi$totalTestResultsIncrease,
dim(newvar_fore_us)
```

```
## [1] 277 3
```

```
#####US MLR with Correlated Errors Model
```

```
fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_us_multi[1:165,])
summary(fit)
```

```
##
## Call:
## lm(formula = positiveIncrease ~ totalTestResultsIncrease + hospitalizedIncrease,
##     data = newcases_us_multi[1:165, ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -42222  -3101  -2878   5316  14897
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3101.227341   869.662497   3.566  0.000477 ***
## totalTestResultsIncrease    0.049977    0.002809  17.793  < 0.000000e+00 ***
## hospitalizedIncrease     2.336046    0.290613   8.038  0.000000e+00 ***
## ---
```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7349 on 162 degrees of freedom
## Multiple R-squared:  0.743, Adjusted R-squared:  0.7399
## F-statistic: 234.2 on 2 and 162 DF,  p-value: < 0.00000000000000022

est_tests = mean(tail(newcases_us_multi$totalTestResultsIncrease))
est_hospital= mean(tail(newcases_us_multi$hospitalizedIncrease))
newdata = data.frame(totalTestResultsIncrease = rep(est_tests,12), hospitalizedIncrease = rep(est_hospital,12))

preds = predict(fit, newdata = newdata)

aic5.wge(fit$residuals)#picks 3,2 with full data

## -----WORKING... PLEASE WAIT...
##
##
## Five Smallest Values of  aic
##
##      p      q      aic
## 5      1      1 16.83224
## 6      1      2 16.83708
## 11     3      1 16.83910
## 8      2      1 16.83932
## 13     4      0 16.83996

est1 = est.arma.wge(fit$residuals, p = 3, q = 2)

##
## Coefficients of Original polynomial:
## 1.9444 -0.9016 -0.0473
##
## Factor              Roots              Abs Recip      System Freq
## 1-1.9919B+0.9961B^2   0.9998+-0.0652i    0.9981      0.0104
## 1+0.0474B            -21.0791         0.0474      0.5000
##
##

for( i in 1:(177-(trainingSize + horizon) ))
{
  fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_us_multi[1:trainingSize+i,])
  newdata = data.frame(totalTestResultsIncrease = rep(est_tests,horizon), hospitalizedIncrease = rep(est_hospital,horizon))

  preds = predict(fit, newdata = newdata)
  forecasts = fore.arma.wge(fit$residuals,phi = est1$phi,theta = est1$theta, lastn = FALSE,n.ahead = horizon)

  final_pred  = preds + forecasts$f

  ASE = mean((newcases_us_multi$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] - final_pred)^2)
  ASEHolder[i] = ASE
}

```

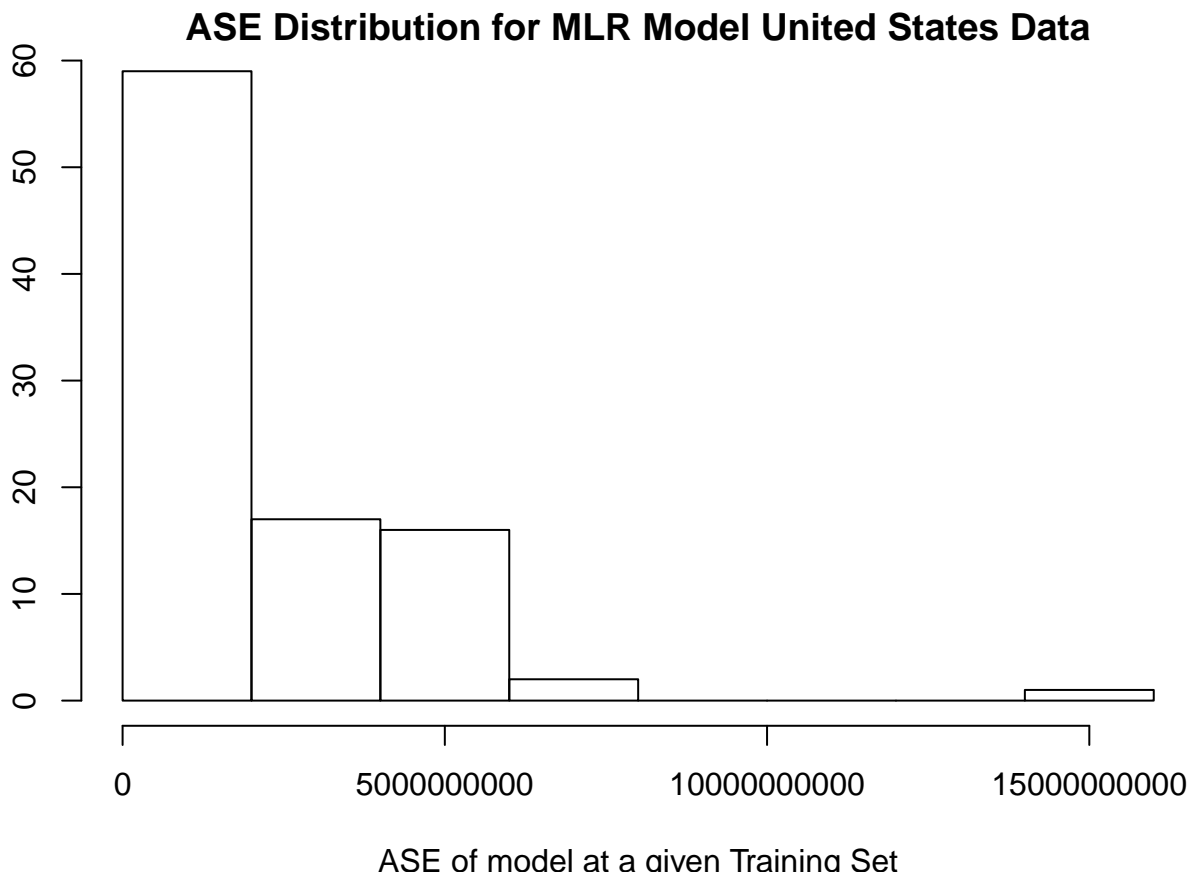


```
ASEHolder
```

```
## [1] 5380274223 4914564759 4555455224 1708071709 1694436967
## [6] 2545354790 3587609643 3594983226 4067557383 4050506483
## [11] 5077832323 5176752257 5348294416 4838019350 4708622612
## [16] 5227841612 5654222458 5676101641 6000663028 6078253699
## [21] 5900331399 1554258063 1809395334 2252786028 2416734053
## [26] 2461093918 2165006104 2061993158 1812244338 1917445023
## [31] 2481645385 2516051039 2398456166 2214123680 1852137279
## [36] 1749588012 1559140675 1356556650 1285173533 1199287506
## [41] 771158389 673913491 642870645 532293973 548308227
## [46] 520596381 438583785 414419021 374067423 251862631
## [51] 205905745 121400107 974304484 23442192 504413661
## [56] 323729831 112461824 1042354738 612690301 97034966
## [61] 339480392 2226182776 152121062 15325519 116703533
## [66] 566689479 474690881 21056191 291275630 1192411920
## [71] 841358069 14317882811 812372140 99566604 332052455
## [76] 974270102 417823732 3699683219 2362942726 2400494736
## [81] 126143855 816363425 83089298 124121842 3827308783
## [86] 512370767 971484081 147200875 119892934 1526454702
## [91] 75284485 49826470 5221093458 4388516429 628353183
```

```
#Distribution of ASEs on Two Week Periods
```

```
hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for MLR Model United States Data")
```



```
#Mean ASE
```

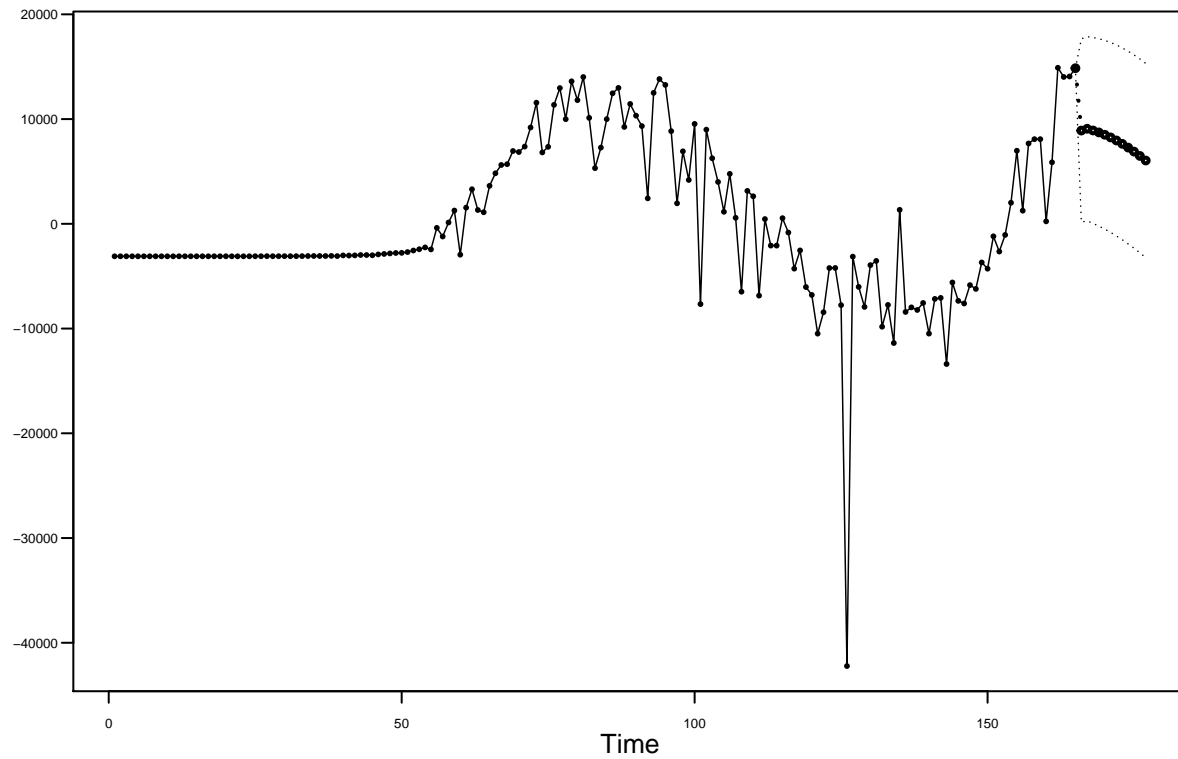
```
WindowedASE = mean(ASEHolder)
```

```
WindowedASE
```

```
## [1] 2024279637
```

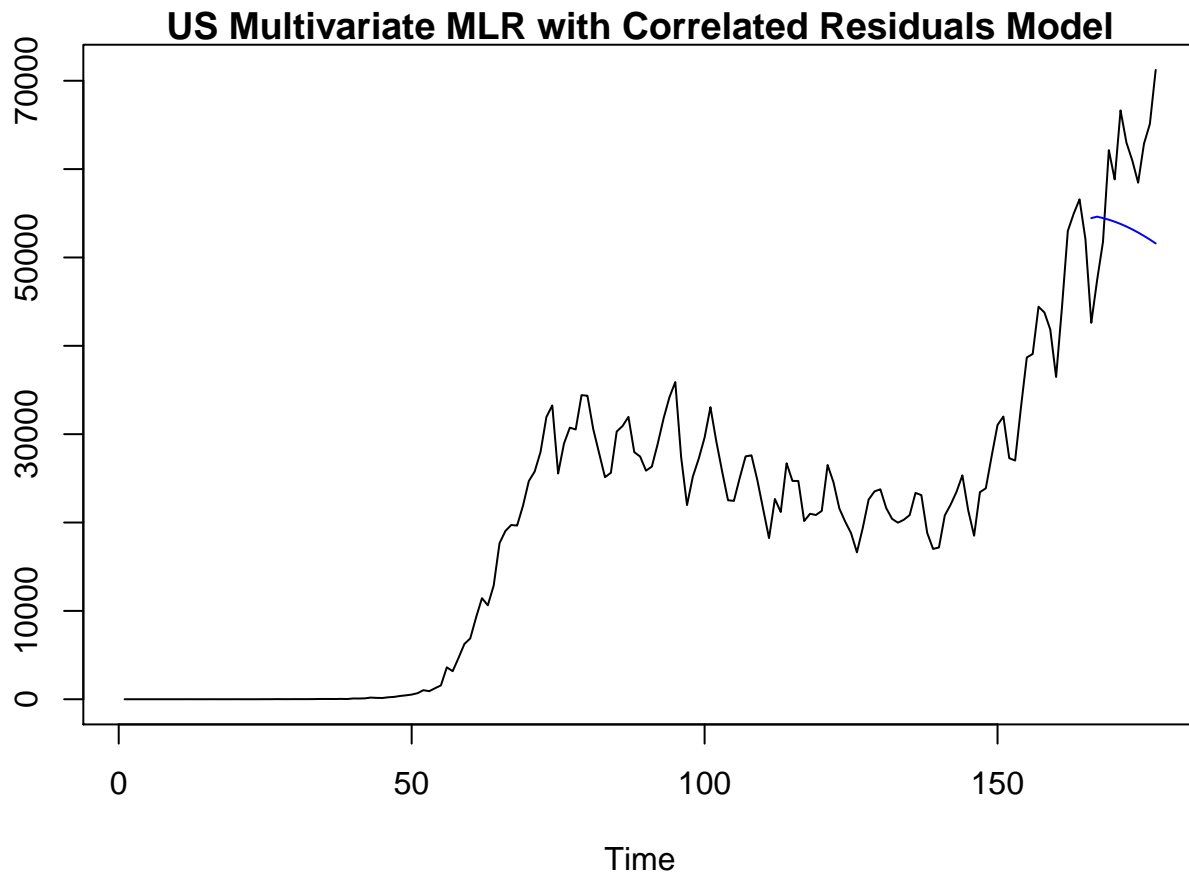
```
fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_us_multi[1:166])  
preds = predict(fit, newdata = newdata)
```

```
forecasts = fore.arma.wge(fit$residuals,phi = est1$phi,theta = est1$theta, lastn = FALSE,n.ahead = 12)
```



```
FinalPredictions_us_MLR = preds + forecasts$f
```

```
plot(newcases_us$positiveIncrease, type = "l", main = "US Multivariate MLR with Correlated Residuals Model")  
lines(ts(FinalPredictions_us_MLR, start = 166), col = "blue")
```



```
ASE = mean((newcases_us_multi$positiveIncrease[166:177] - FinalPredictions_us_MLR)^2)
ASE
```

```
## [1] 108181241
```

```
#
```

```
#Forecasting Ahead
```

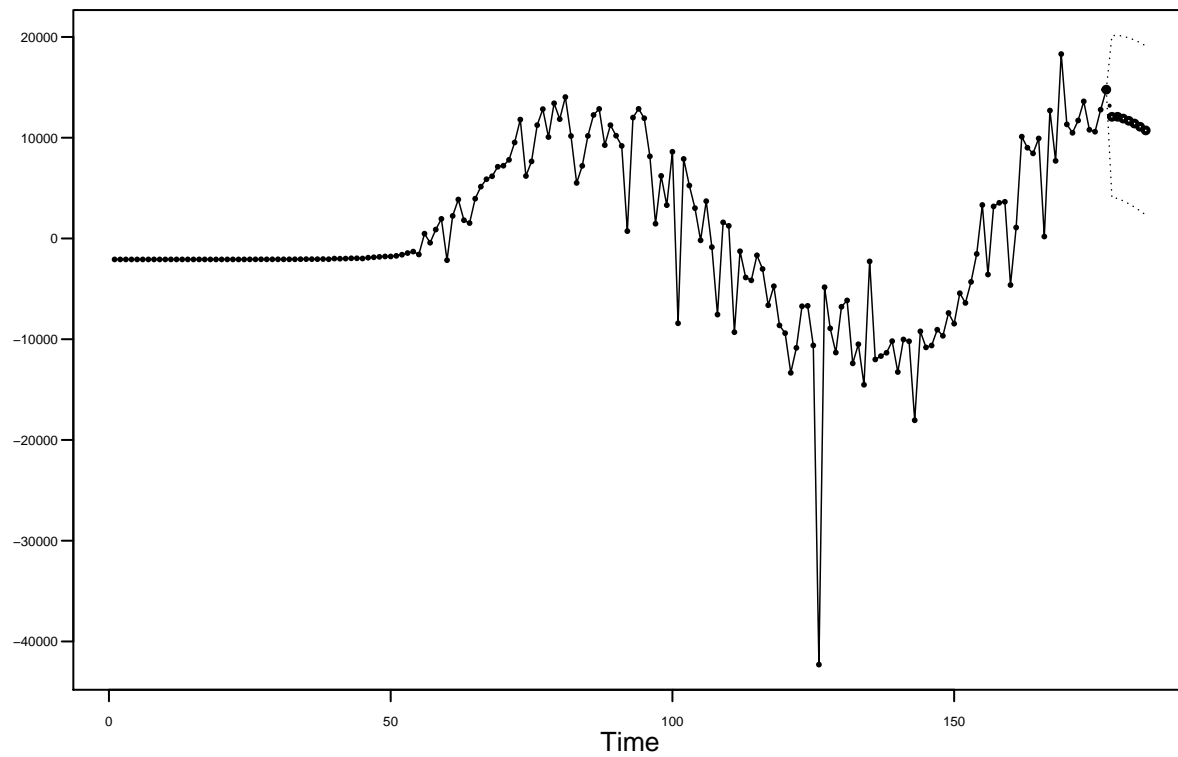
```
shortdata = data.frame(totalTestResultsIncrease = rep(est_tests,7), hospitalizedIncrease = rep(est_hosp,7))
longdata =data.frame(totalTestResultsIncrease = rep(est_tests,90), hospitalizedIncrease = rep(est_hosp,90))
```

```
fit = lm(positiveIncrease~totalTestResultsIncrease + hospitalizedIncrease, data = newcases_us_multi)
```

```
#short
```

```
preds = predict(fit, newdata = shortdata)
```

```
forecasts = fore.arma.wge(fit$residuals,phi = est1$phi,theta = est1$theta, lastn = FALSE,n.ahead = 7)
```

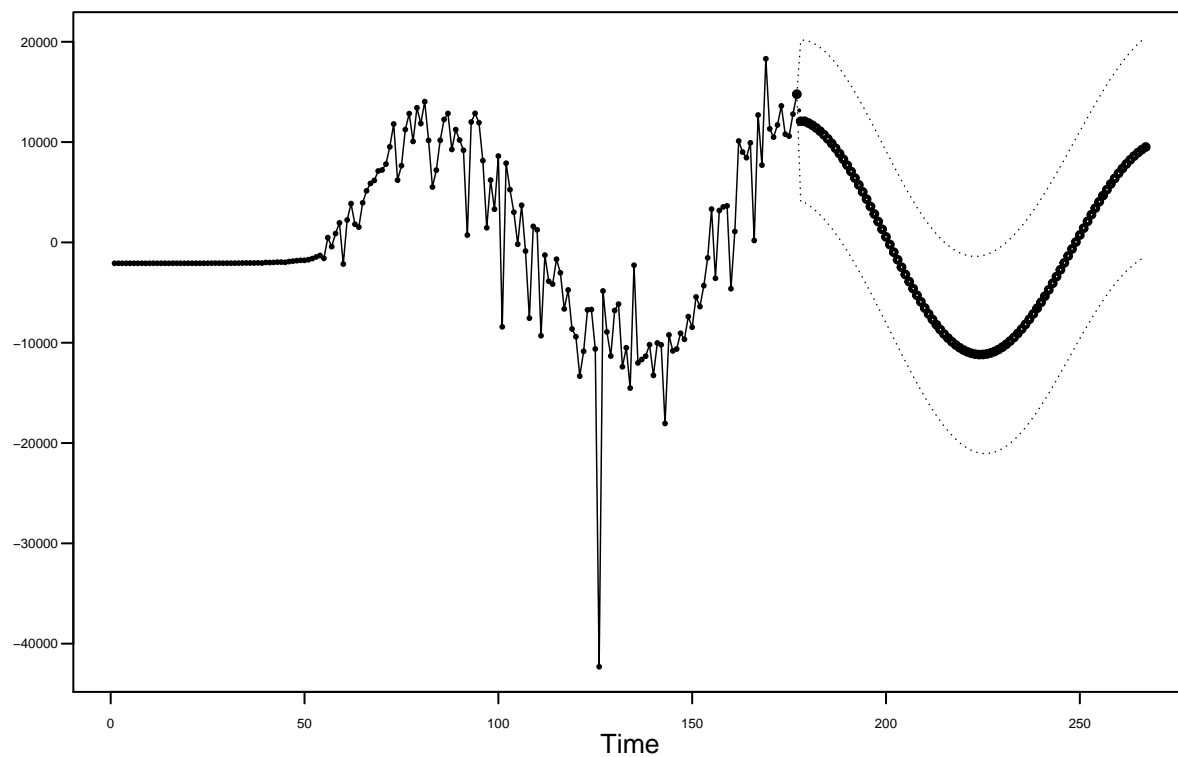


```
short_us_mlr_m = preds + forecasts$f
```

```
#long
```

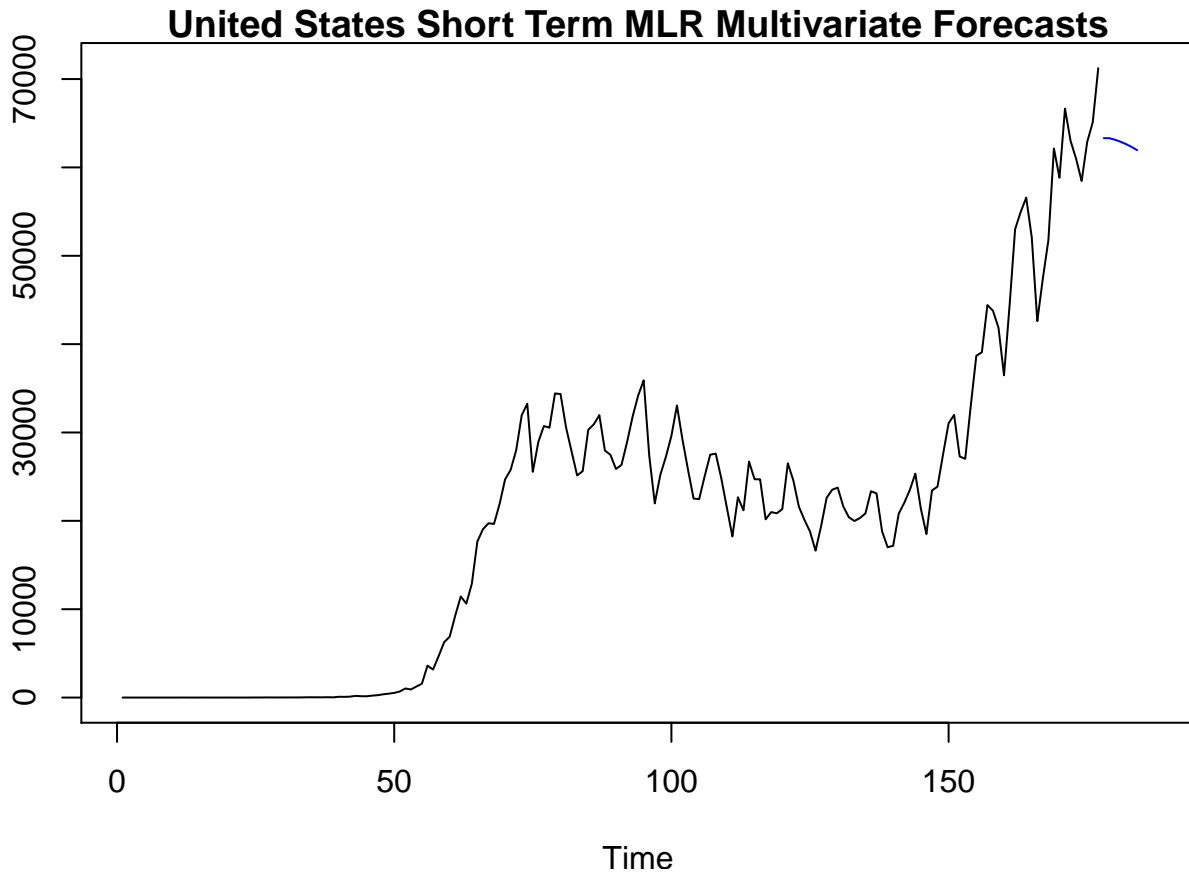
```
preds = predict(fit, newdata = longdata)
```

```
forecasts = fore.arma.wge(fit$residuals, phi = est1$phi, theta = est1$theta, lastn = FALSE, n.ahead = 90)
```

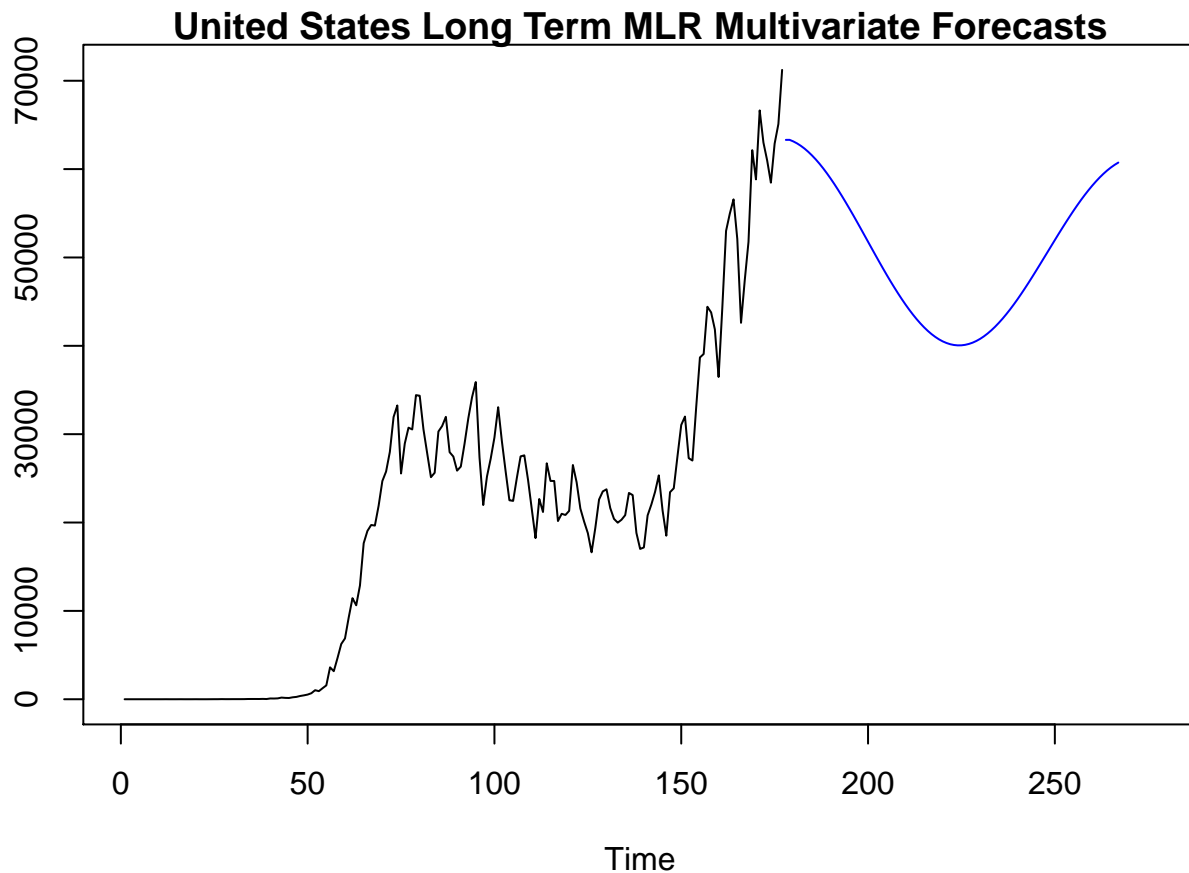


```
long_us_mlr_m = preds + forecasts$f
```

```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,187), main = "United States Short Term MLR Mu  
lines(ts(short_us_mlr_m, start = 178), col = "blue")
```



```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,277), main = "United States Long Term MLR Mu  
lines(ts(long_us_mlr_m,start = 178), col = "blue")
```



####US MLP/RNN Model

```
trainingSize = 70
```

```
horizon = 12
```

```
ASEHolder = numeric()
```

```
for( i in 1:(177-(trainingSize + horizon) + 1))
```

```
{
```

```
  mlp.fit = mlp(ts(newcases_us_multi$positiveIncrease[1:trainingSize+i]), hd = 5, comb = "median", xreg =
```

```
  forecasts = forecast(mlp.fit,h = horizon, xreg = newvar_fore_us[1:(trainingSize + i + 13),])
```

```
  ASE = mean((newcases_us_multi$positiveIncrease[(trainingSize+i):(trainingSize+ i + (horizon) - 1)] -f
```

```
  ASEHolder[i] = ASE
```

```
}
```

```
ASEHolder
```

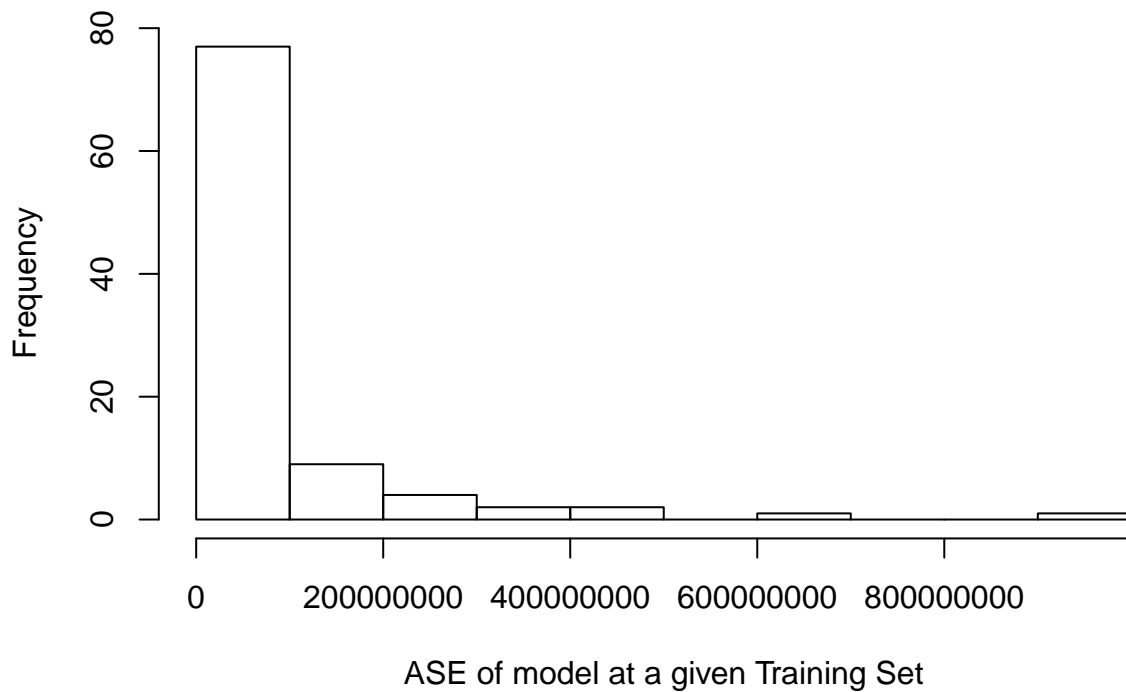
```
## [1] 31611678 295608440 967166724 405102072 695004108 20181861 15107576
## [8] 83099979 303918712 212524108 137064433 67148067 32795839 24937462
## [15] 18441362 33736934 26224626 34670369 38855630 33774080 25651710
## [22] 12259544 16708986 27452912 30499574 43702326 26145257 24846826
## [29] 27941411 43867937 52731830 70910206 61789627 52126325 46466672
## [36] 53222073 55769011 64291897 68278449 68270659 48428787 51984400
## [43] 54120095 70892537 83546948 94144578 88682358 88395125 79435008
## [50] 75032208 82763190 90642265 98382648 91049845 79403607 73247047
## [57] 25748267 40988375 93550417 100912375 107185941 93530400 85980007
```

```
## [64] 64603005 87205883 98720247 98064459 97248332 70454087 42253671
## [71] 77843813 68973543 72465252 66399147 49534046 59976850 60123877
## [78] 71602880 71176770 56921589 83978818 87467857 113859219 247857197
## [85] 157432693 160004389 156337986 110268093 329716206 246679351 425528281
## [92] 63281279 105103364 65869811 77484459 69528459
```

```
#Distribution of ASEs on Two Week Periods
```

```
hist(ASEHolder, xlab = "ASE of model at a given Training Set", main = "ASE Distribution for MLP Model I")
```

ASE Distribution for MLP Model Florida Data



```
#Mean ASE
```

```
WindowedASE = mean(ASEHolder)
```

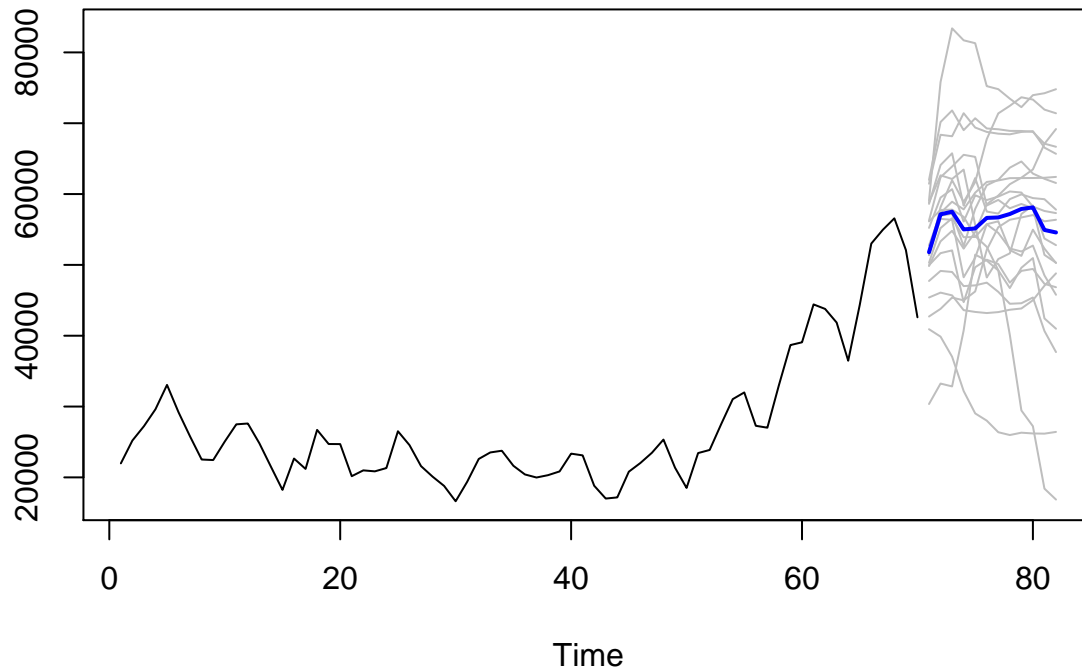
```
WindowedASE
```

```
## [1] 102728319
```

```
#97494363
```

```
plot(forecasts)
```

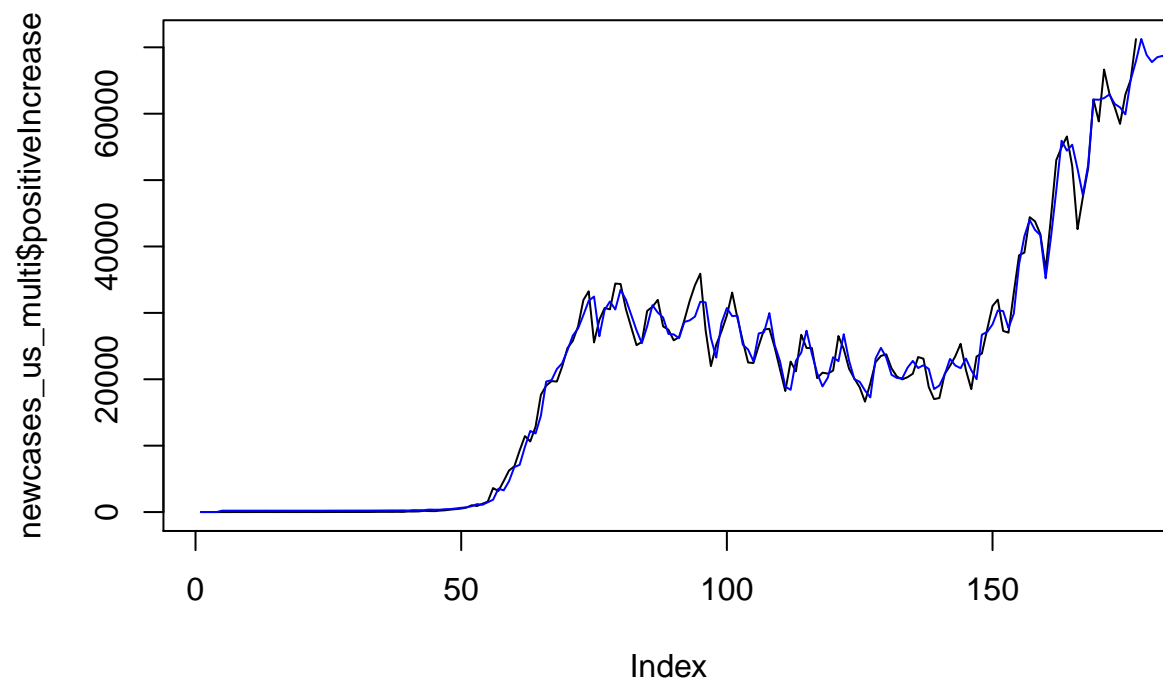
Forecasts from MLP



#Final Forecasts with data known

```
mlp.fit = mlp(ts(newcases_us_multi$positiveIncrease[1:177]), hd = 5, comb = "median", xreg = newvar_for
forecasts_us_mlp = forecast(mlp.fit, h = 12, xreg = newvar_fore_us[1:190,])
```

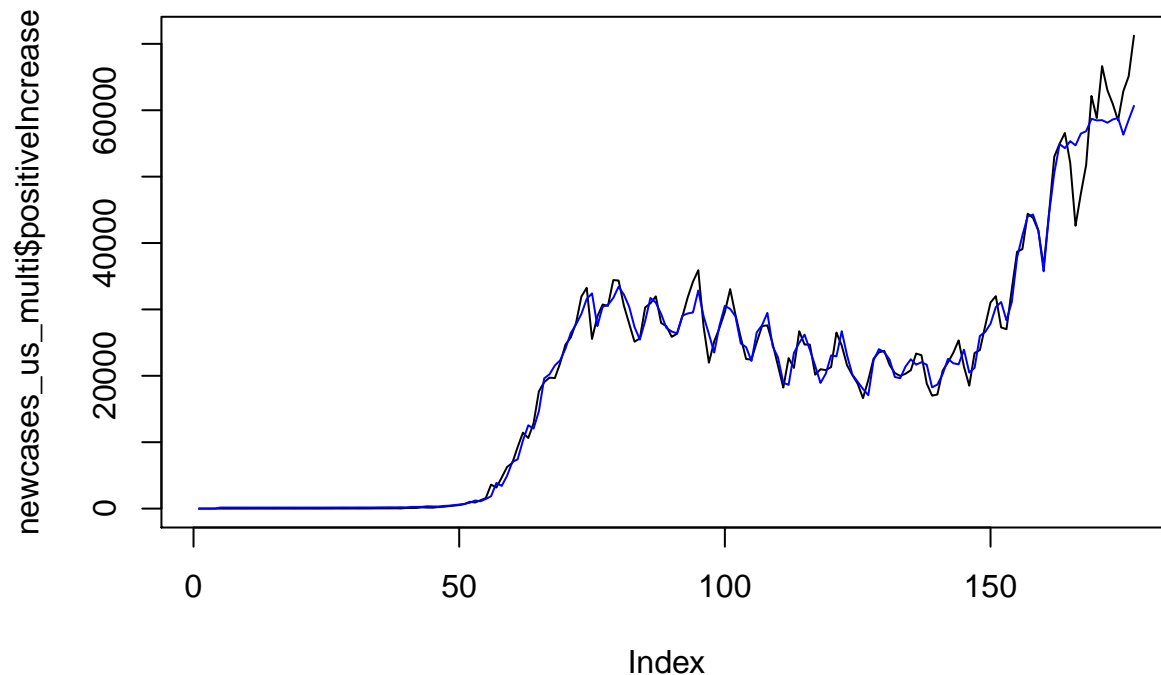
```
all_f = c(rep(1,4),forecasts_us_mlp$fitted, forecasts_us_mlp$mean)
plot(newcases_us_multi$positiveIncrease, type = "l")
lines(all_f, col = "blue")
```




```
#final 12 forecasts
```

```
mlp.fit = mlp(ts(newcases_us_multi$positiveIncrease[1:165]), hd = 5, comb = "median", xreg = newvar_fore_us[1:165])
forecasts_us_mlp = forecast(mlp.fit, h = 12, xreg = newvar_fore_us[1:177,])
```

```
all_f = c(rep(1,4),forecasts_us_mlp$fitted, forecasts_us_mlp$mean)
plot(newcases_us_multi$positiveIncrease, type = "l")
lines(all_f, col = "blue")
```



```
ASE_final12 = mean((newcases_us_multi$positiveIncrease[166:177] -forecasts_us_mlp$mean)^2)
ASE_final12
```

```
## [1] 46652500
```

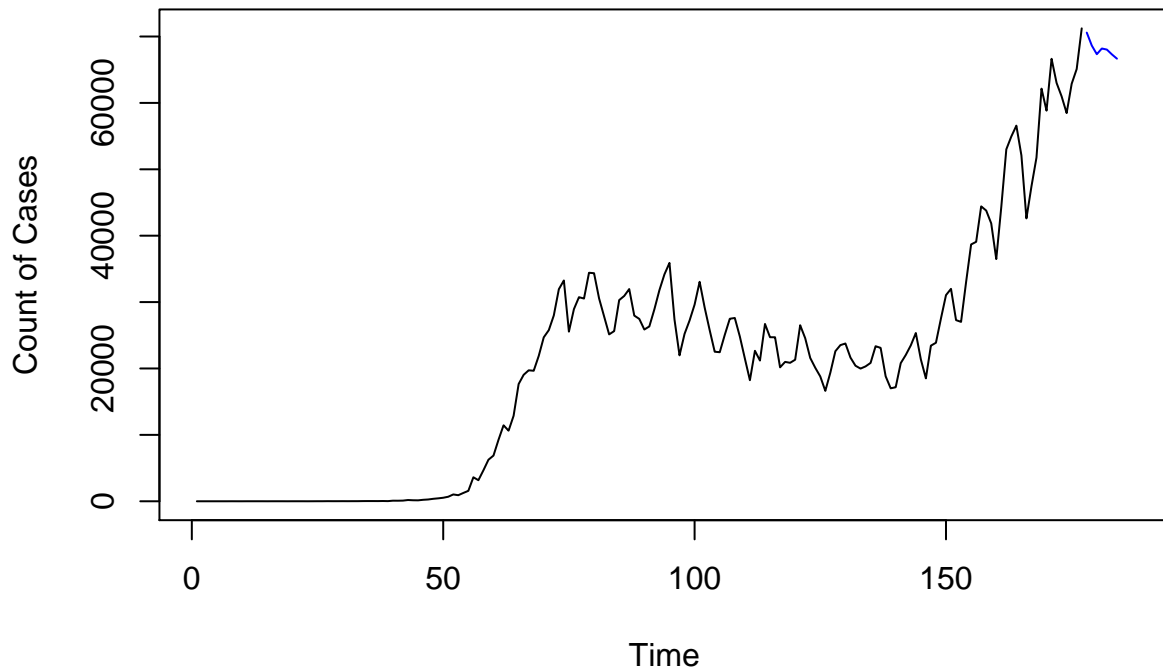
```
#45799110
```

```
#Future Forecasts
```

```
mlp.fit = mlp(ts(newcases_us_multi$positiveIncrease), hd = 5, comb = "median", xreg = newvar_fore_us[1:165])
short_us_mlp_m = forecast(mlp.fit, h = 7, xreg = newvar_fore_us[1:187,])
long_us_mlp_m = forecast(mlp.fit, h = 90, xreg = newvar_fore_us[1:267,])
```

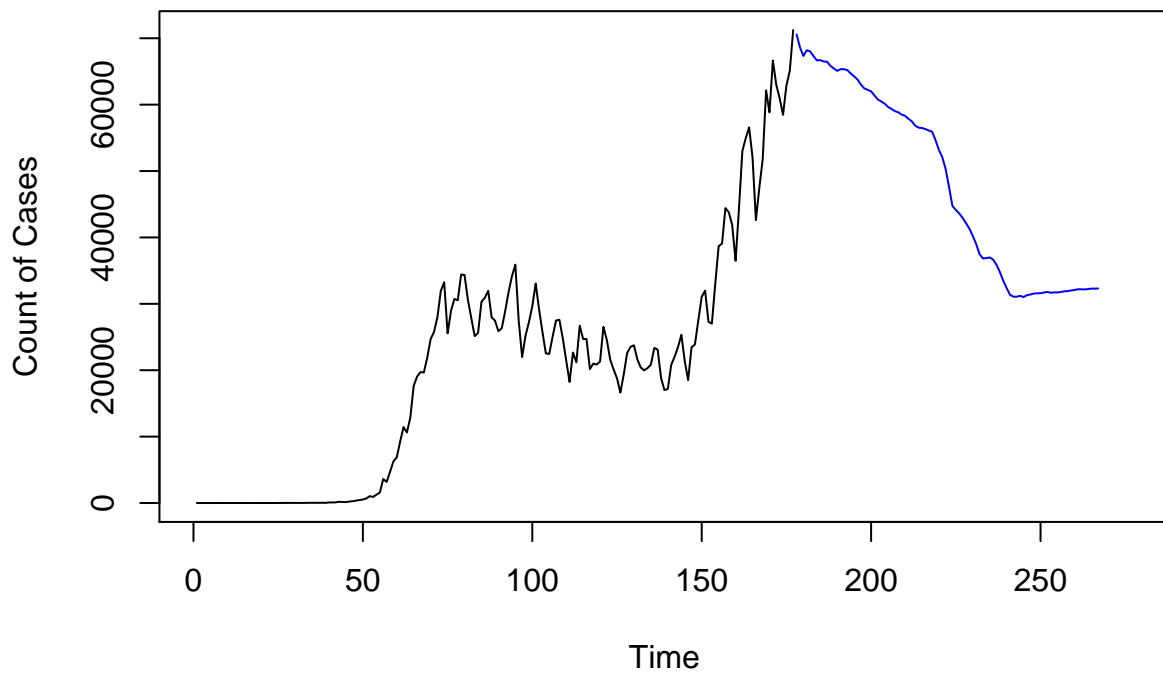
```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,187), main = "United States Short Term MLP Mu")
lines(short_us_mlp_m$mean, col = "blue")
```

United States Short Term MLP Multivariate Forecasts



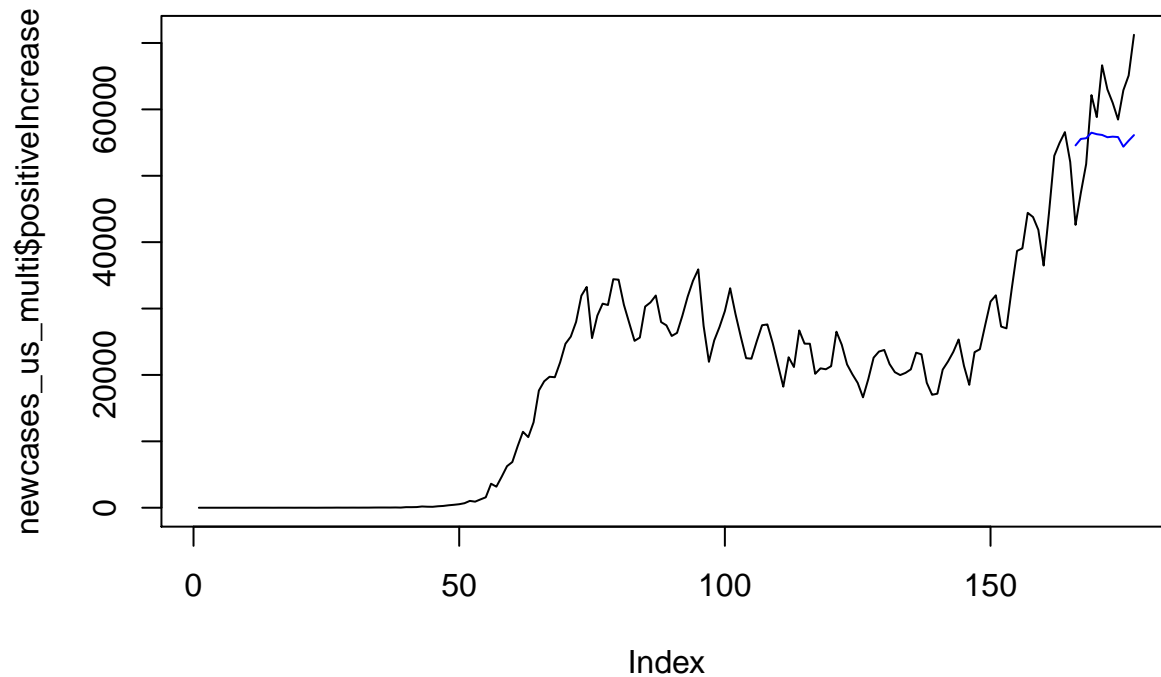
```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,277), main = "United States Long Term MLP Multivariate Forecasts")
lines(long_us_mlp_m$mean, col = "blue")
```

United States Long Term MLP Multivariate Forecasts



####US Ensemble

```
ensemble_us_fore = (forecasts_us_mlp$mean + FinalPredictions_us_MLR)/2
plot(newcases_us_multi$positiveIncrease, type = "l")
lines(ensemble_us_fore, col = "blue")
```



```
#Final 12 ASE
```

```
ASE_final12 = mean((newcases_us_multi$positiveIncrease[166:177] - ensemble_us_fore)^2)
ASE_final12
```

```
## [1] 71221939
```

```
#70596024
```

```
#Forecasting
```

```
#short_us_mlr_m
```

```
#short_us_mlp_m
```

```
#long_us_mlr_m
```

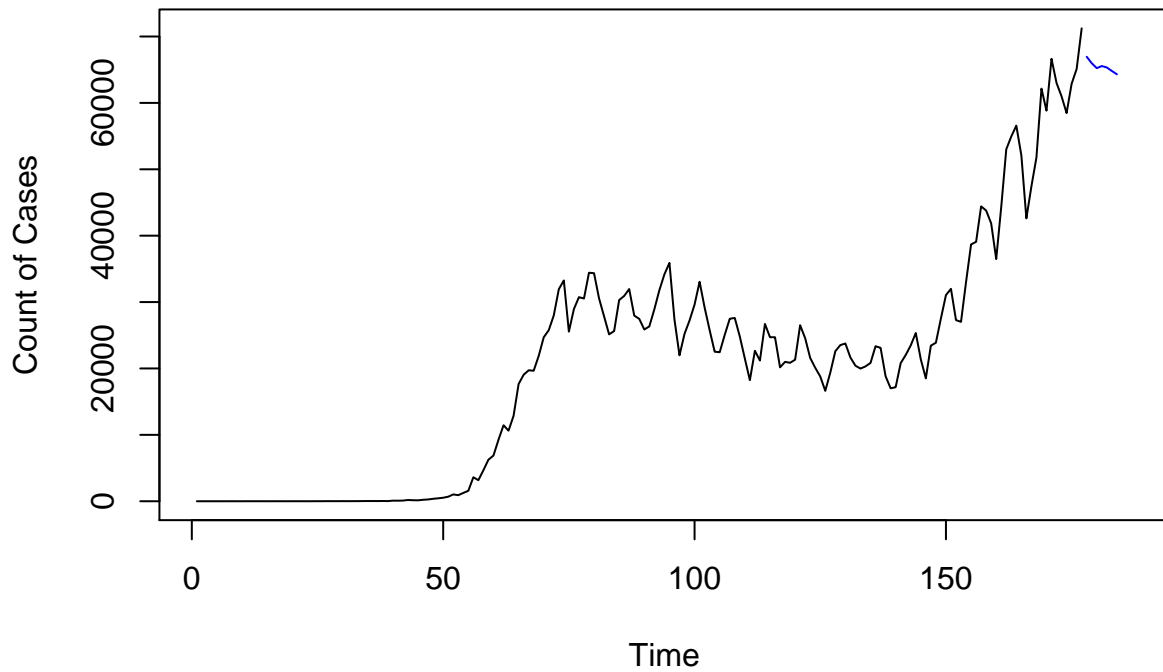
```
#long_us_mlp_m
```

```
ensemble_us_fore_short = ( short_us_mlp_m$mean+ short_us_mlr_m)/2
```

```
ensemble_us_fore_long = (long_us_mlp_m$mean + long_us_mlr_m)/2
```

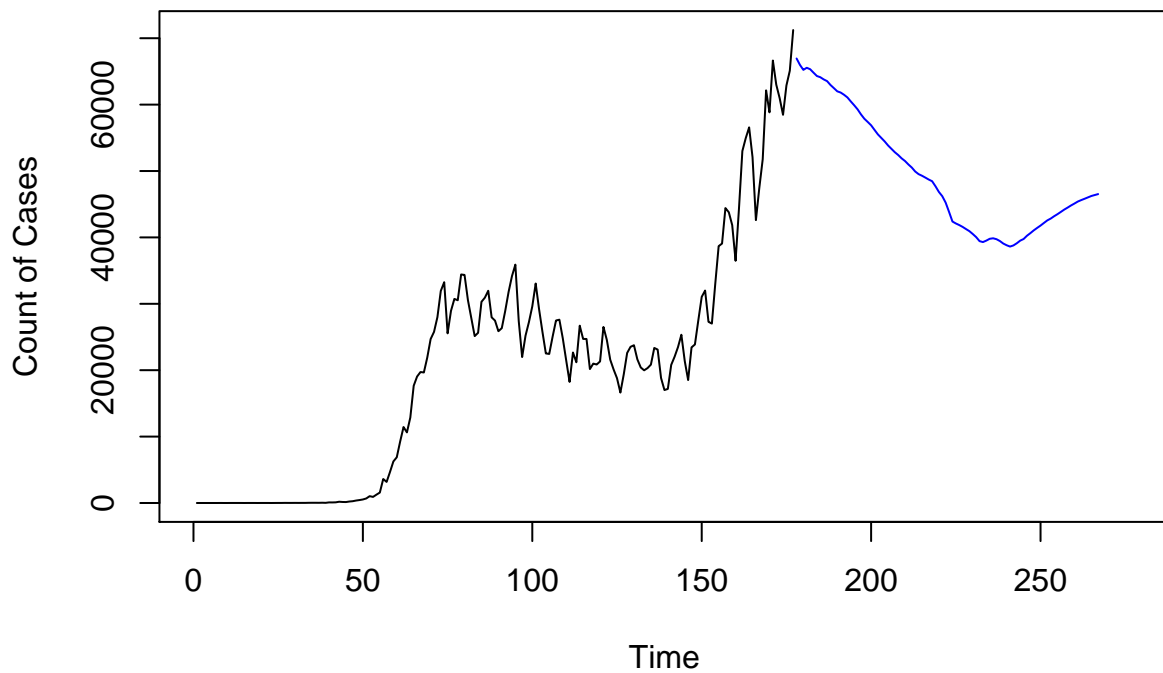
```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,187), main = "United States Short Term Multiv")
lines(ensemble_us_fore_short, col = "blue")
```

United States Short Term Multivariate Ensemble Forecasts



```
plot(newcases_us$positiveIncrease, type = "l", xlim = c(1,277), main = "United States Long Term Multivariate Ensemble Forecasts")
lines(ensemble_us_fore_long, col = "blue")
```

United States Long Term Multivariate Ensemble Forecasts



##Conclusion

Given our data at hand we found our ARIMA(6,1,2) model to offer the best predictions for United States

overall data. We found our Multiple Linear Regression model with correlated errors best predicted our Florida data. Given our current state of spread and recent trends of Covid19 spread, we expect increasing not optimistic forecasts of new case counts to show as most accurate in the coming days and months.