Covid Analysis

April 7, 2020

Introduction

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Analysis

We use Box Jenkins forecasting to forecast the number of new COVID-19 cases per day in the United States. Below, we will take the following 5 steps of Box Jenkins model fitting.

1. Reducing the observed series to stationary
2. Selecting an appropriate ARMA model for the time series
3. Estimating the parameters of the model
4. Performing diagnostic measures on the fitted models to assess the goodness-of-fit
5. If necessary, examining alternative models for the data

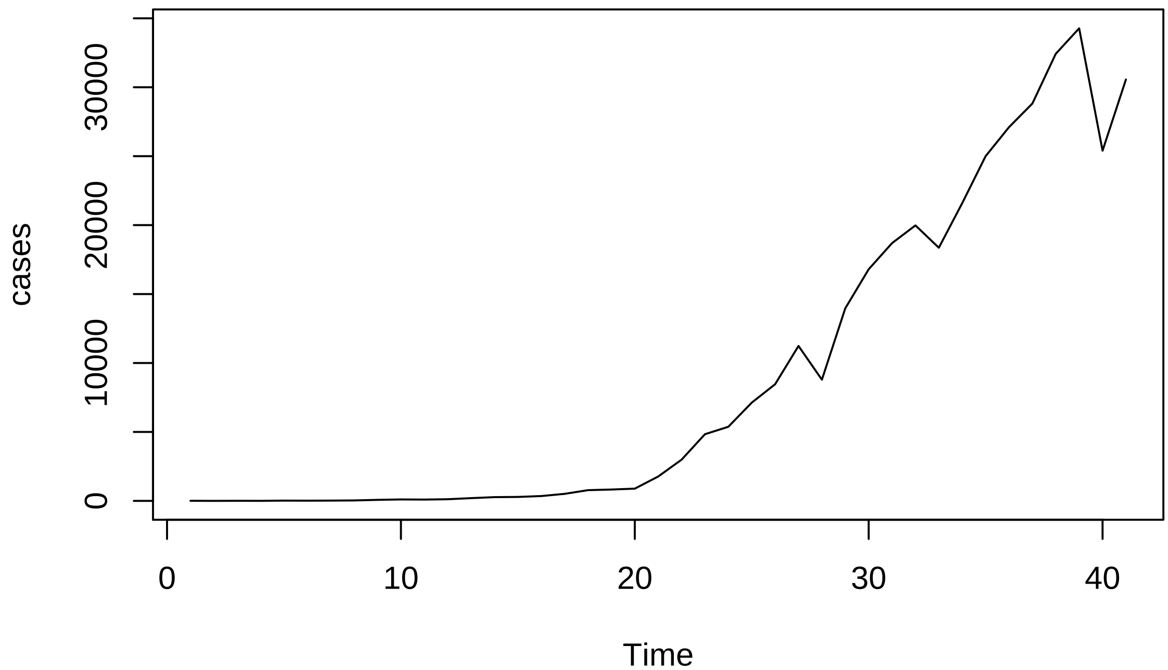
Then, we predict the number of new COVID-19 cases in the United States for the next 5 days assuming no drastic events occur in the spreading of the disease.

Exploratory Analysis

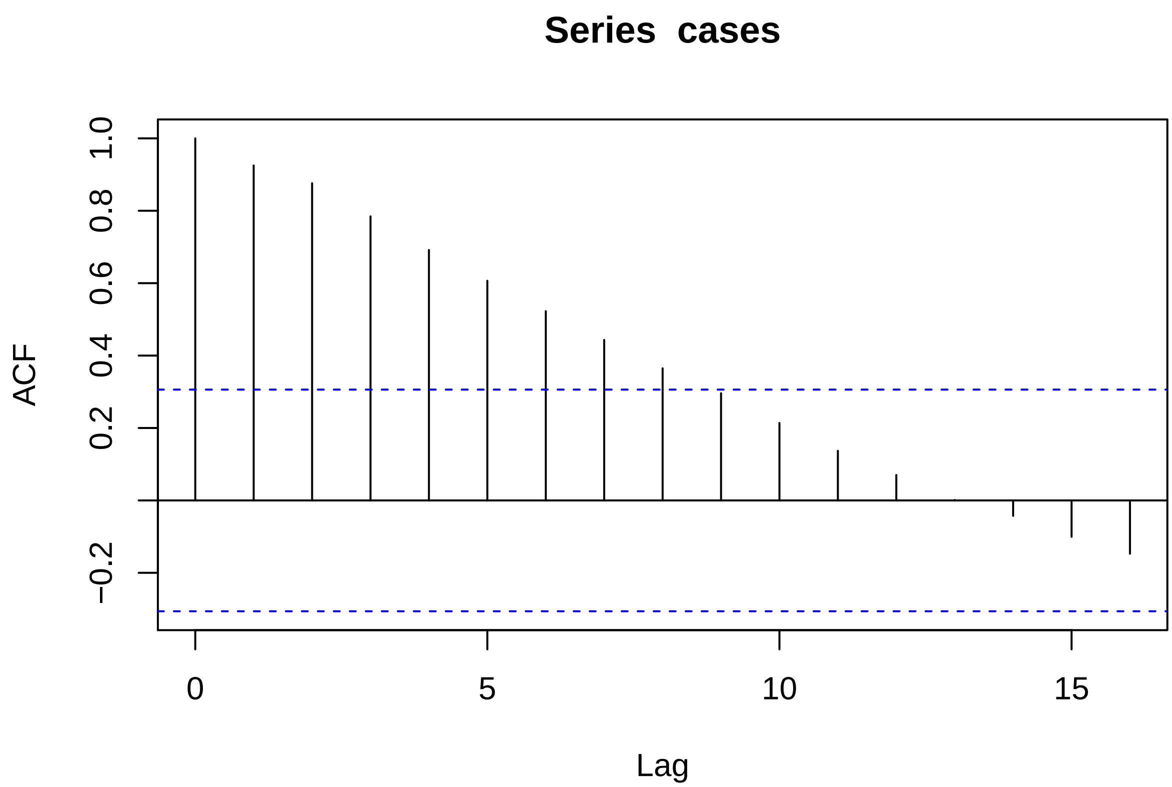
We first plotted our time series and its ACF. It was immediately clear that there was a multiplicative trend due to the series' exponential nature, so we decided to work with the log of the series for the rest of this report.

```r
data = read.csv('us_covid_data.csv')
cases = as.ts(rev(data$cases))
cases = as.ts(cases[59:length(cases)])

plot(cases)
```

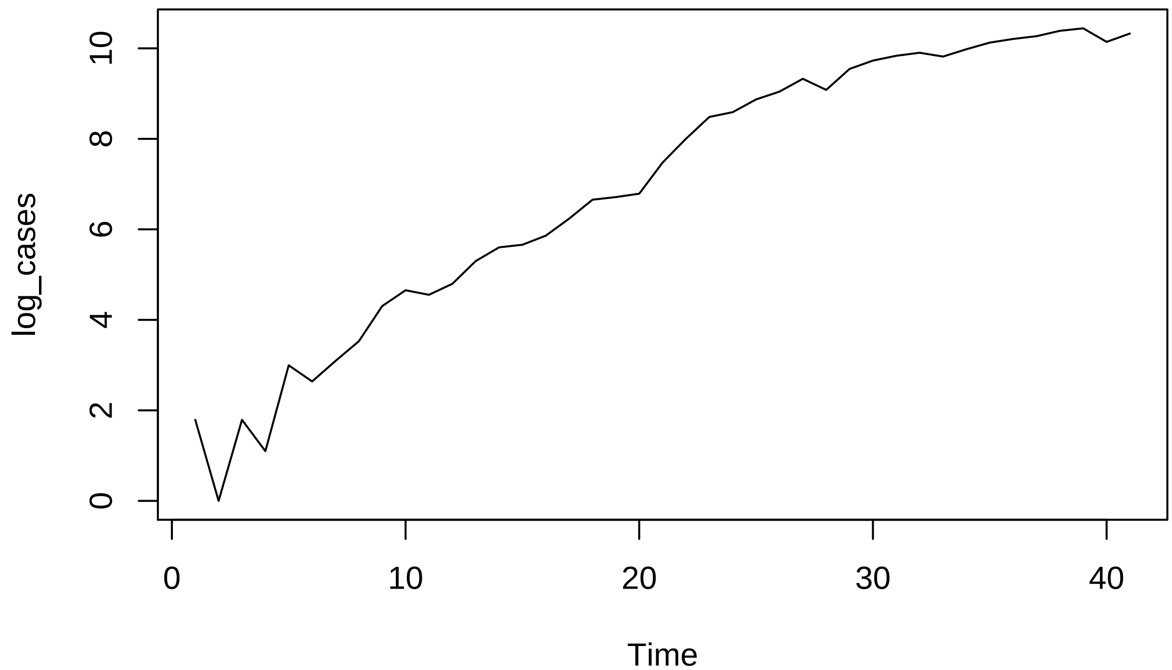



```r
acf(cases)
```

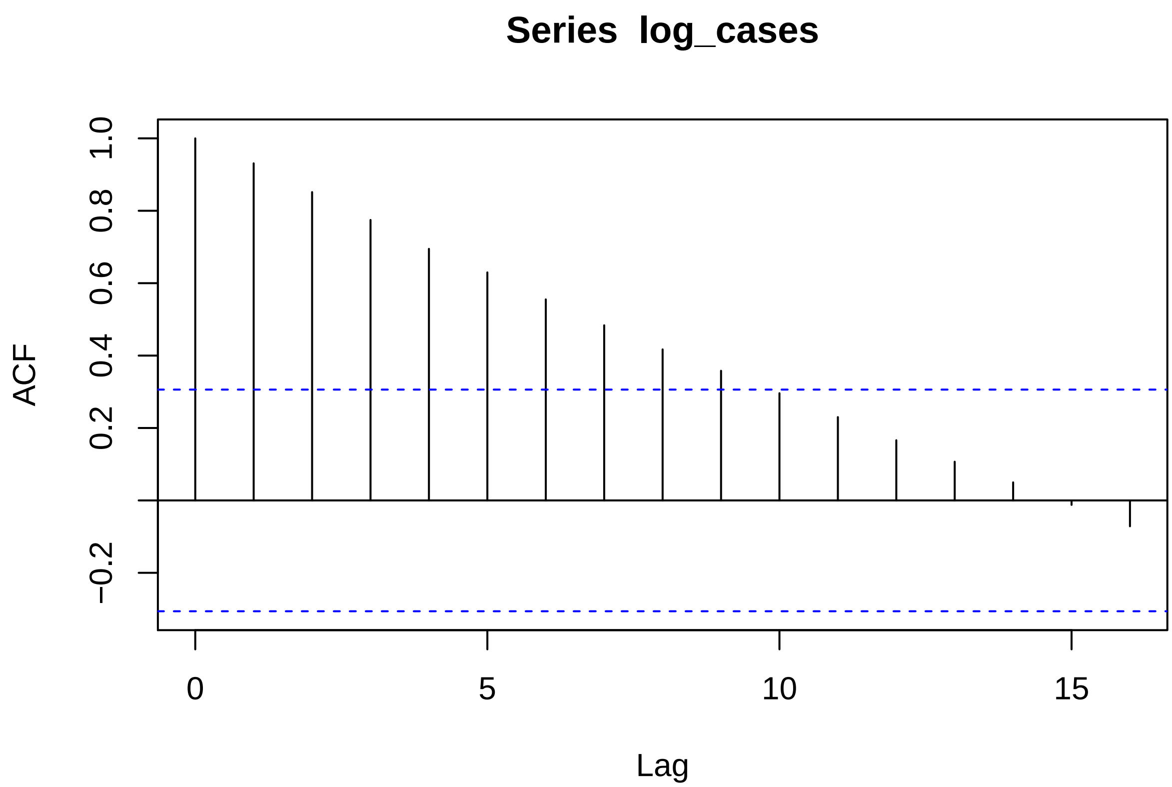



```r
log_cases = log(cases)

plot(log_cases)
```

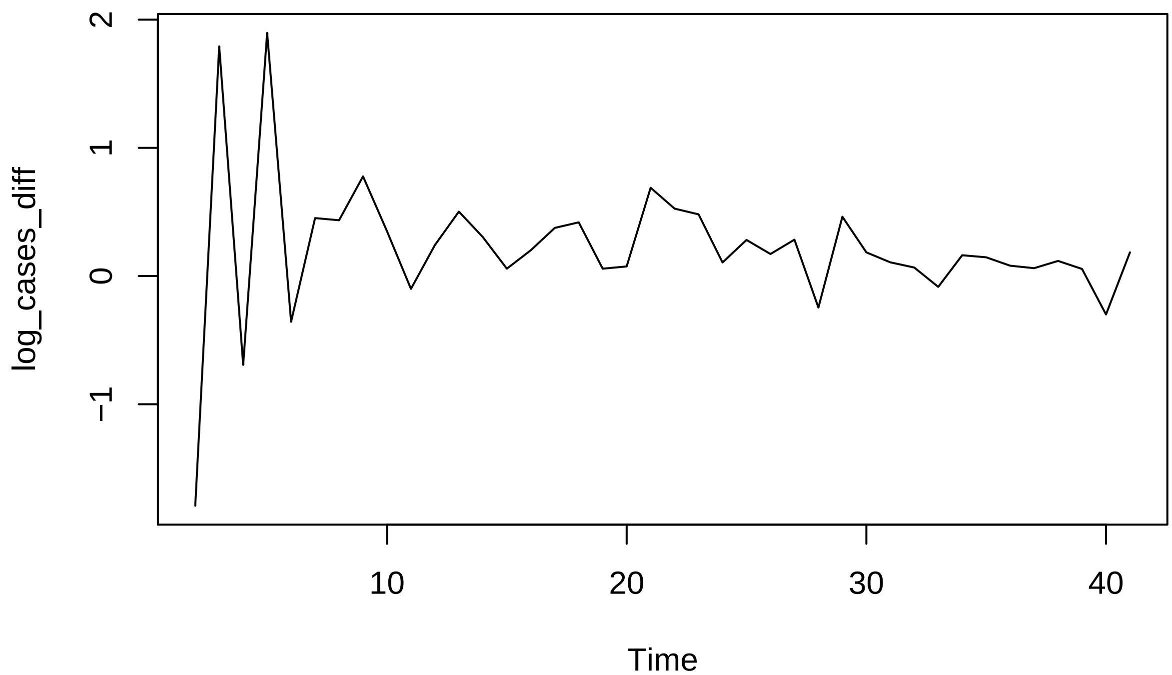



```
acf(log_cases)
```

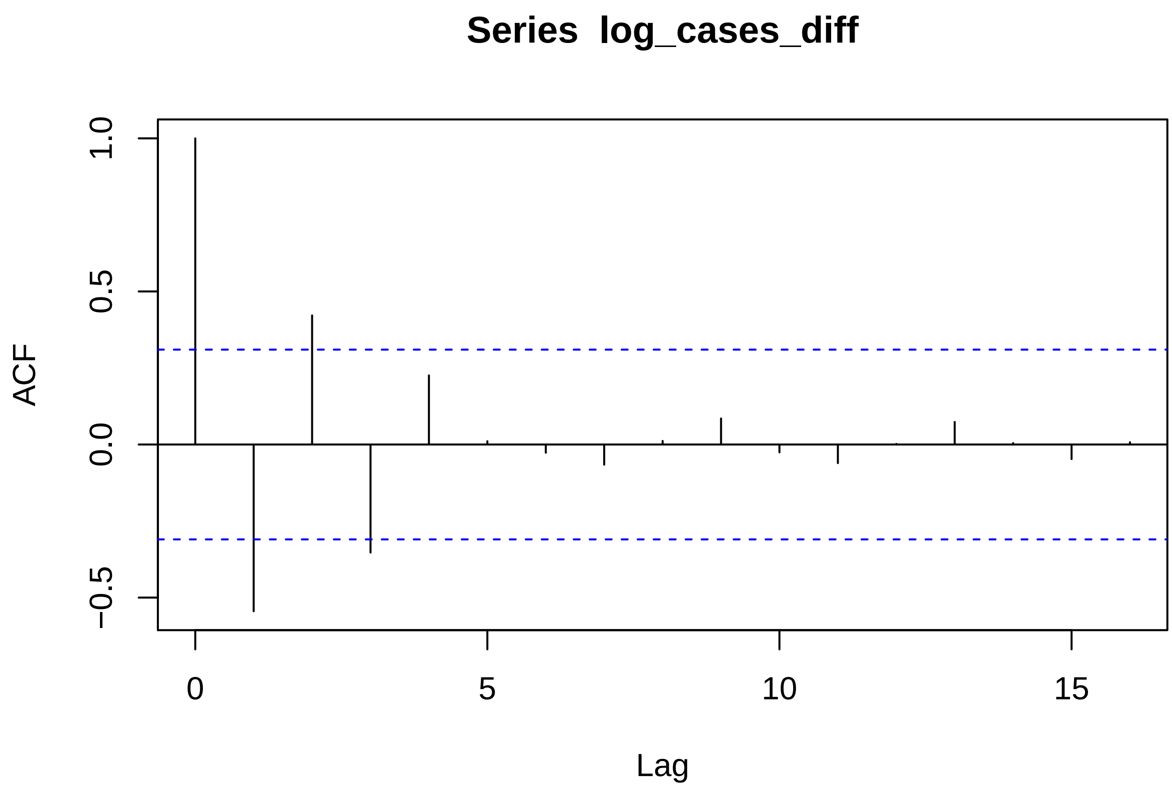


The log of our original series was still non-stationary due to its upward trend. We chose to apply a differencing operator to remove the trend and make the series stationary for further model fitting.

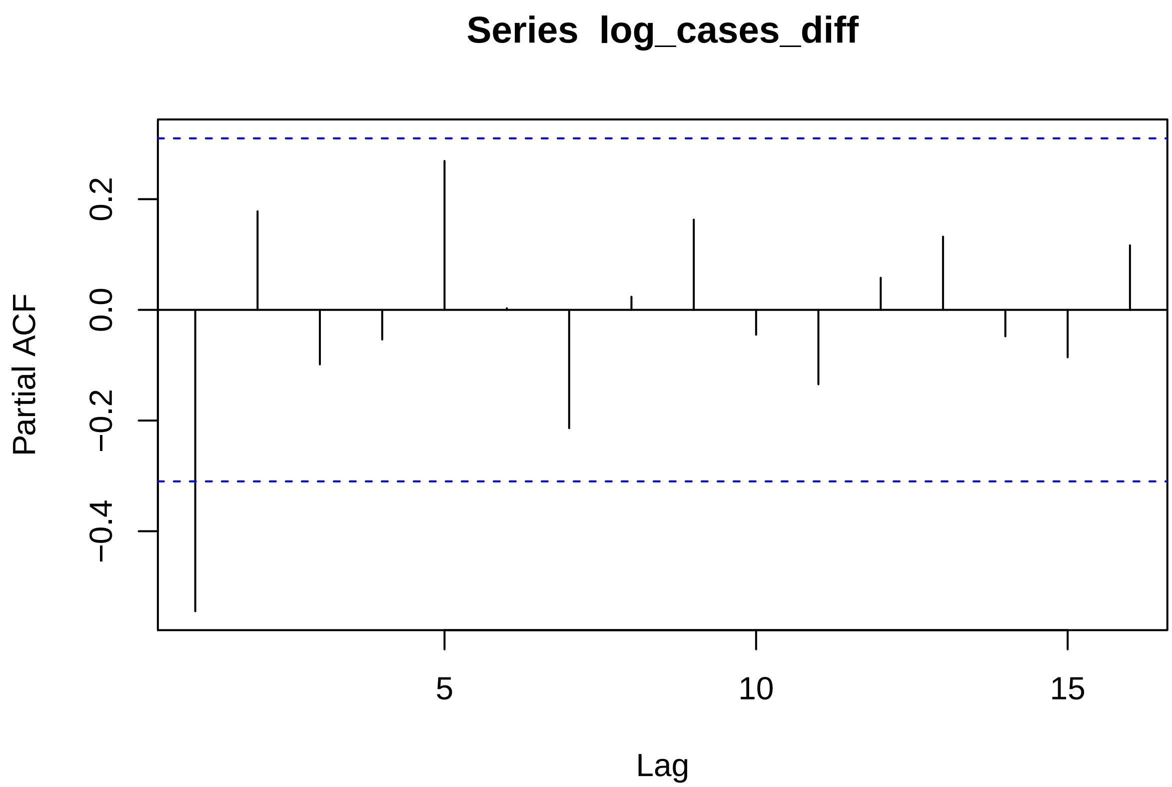
```
log_cases_diff = diff(log_cases)
plot(log_cases_diff)
```




```r
acf(log_cases_diff)
```




```
pacf(log_cases_diff)
```



Model Selection and Fitting

Based on the ACF and PACF of our original time series and its differenced version, we decided to evaluate the models ARIMA(1,1,0) and ARIMA(0,1,3). We chose to difference the time series to remove the trend as the original (log) time series appeared non-stationary. We then chose to evaluate fitting ARMA(1,0) and ARMA(0,3) on the differenced series since the ACF of the differenced series cuts off at 3 and the PACF of the differenced series cuts off at 1 respectively.

We use the CSS-ML method for model fitting.

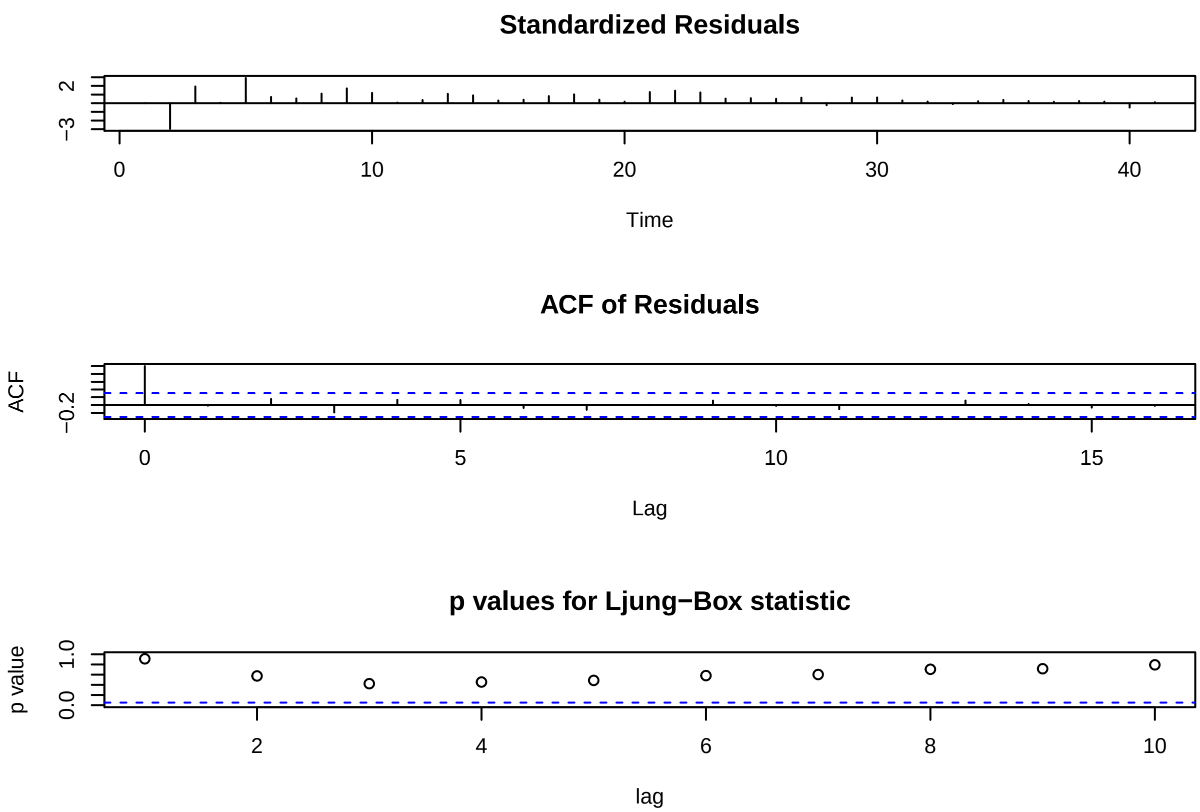
```
arima110 = arima(log_cases, order=c(1,1,0))
arima013 = arima(log_cases, order=c(0,1,3))
```

Diagnostics

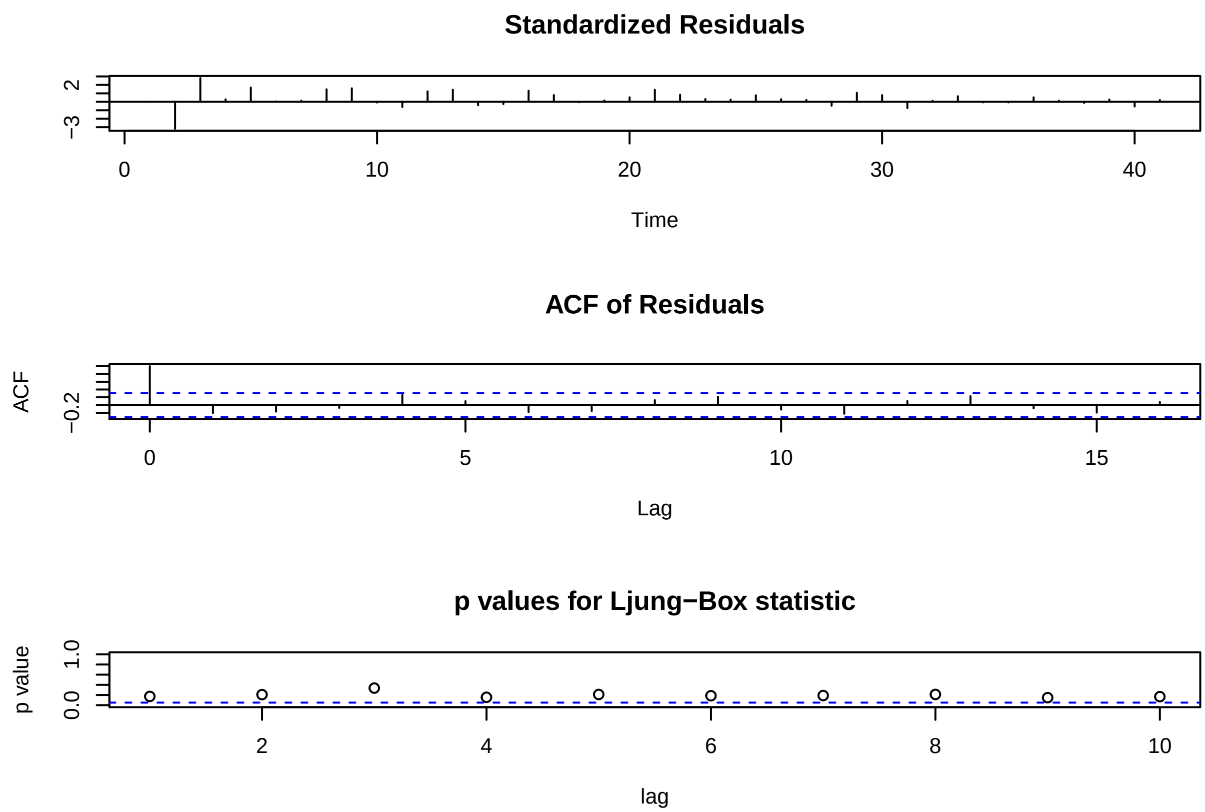
We now run some diagnostics on our models to assess whether they are good or bad fit to our time series data.

1. Ljung-Box Test

```
tsdiag(arima110)
```




```
tsdiag(arima013)
```



The standardized residuals and the ACF of residuals for both ARIMA(1,1,0) and ARIMA(0,1,3) models are generally low and do not display explicit patterns. This suggests that our models are not bad fit for our data at the first glance.

Ljung-Box test assesses whether the ACF of fitted residuals are independent or not. Since the null hypothesis is the statement that the residuals are independent, models with low p-values are not good fit. In our cases, both ARIMA(1,1,0) and ARIMA(0,1,3) models have p-values greater than 0.1 across different lags, and therefore the test suggests that the models are good fit for our data.

2. Model Assessment Through Train-Test Scheme

We decided to fit our ARIMA models on subsets of our series and evalute how good the models are in predicting the remaining entries. Our evaluation metric is Mean Squared Error since Box-Jenkins forecasting is optimal with respect to MSE.

```
train_data = log_cases[1:34]
test_data = log_cases[35:length((log_cases))]

arima110_train = arima(train_data, order=c(1,1,0))
arima110_pred = predict(arima110_train, c(7))
arima110_mse = sum((test_data - arima110_pred$pred)^2)

arima013_train = arima(train_data, order=c(0,1,3))
arima013_pred = predict(arima013_train, c(7))
arima013_mse = sum((test_data - arima013_pred$pred)^2)
```

Mean Squared Error

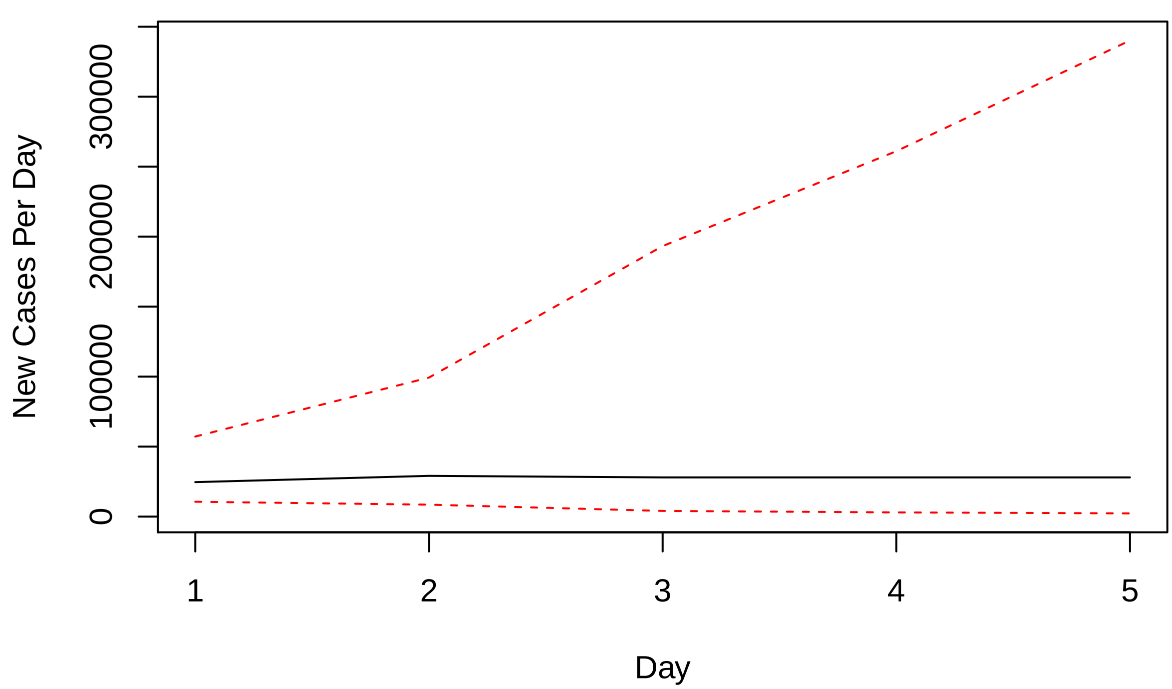
Train/Test Set Sizes	ARIMA(1,1,0) MSE	ARIMA01,1,3) MSE
34 / 7	0.8918	0.7724
36 / 5	0.1378	0.0500
38 / 3	0.0576	0.0465

We find that MSE for both models are relatively low. We decided to use ARIMA(0,1,3) as our final model since it had lower MSE across different configurations of training and test set sizes.

Predicting Future Daily COVID-19 Cases

Using our ARIMA(0,1,3) model, we now predict the progression of COVID-19 for the next 5 days - from April 8th to April 18th - with 95% confidence interval.

```
Pred5 = forecast(arima013, h=5)
LowerBound = exp(Pred5$lower[6:10])
Mean = exp(Pred5$mean)
UpperBound = exp(Pred5$upper[6:10])
Days = seq(1,5)
matplot(
  Days, cbind(LowerBound, Mean, UpperBound), type='l',
  lty=c(2,1,2), col=c('red', 'black', 'red'),
  xlab='Day', ylab='New Cases Per Day'
)
```



The black line denotes the expected number of new cases that will arise and the red line denotes the 95% confidence interval of the prediction. The fitted model shows us that the number of cases to follow will at least be tens of thousands, and in worst case, hundreds of thousands. Our analysis highlights a clear need for the US government to take a drastic measure to curtail the future infections. Otherwise, the number of new infections will continue to increase at a very sharp rate.

Conclusion

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