Project1

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Data Importing and Indexing

```
data_start_ind <- 1
data_end_ind <- 1622
forecast_stary_ind <- 1623
forecast_end_ind <- 1722

path <- paste(getwd(), '/Data Set for Class.xls', sep="")
sheet_name <- 'S01'

# Read the specified sheet from the Excel file
s01 <- read_excel(path, sheet = sheet_name)</pre>
```

Data Visualization

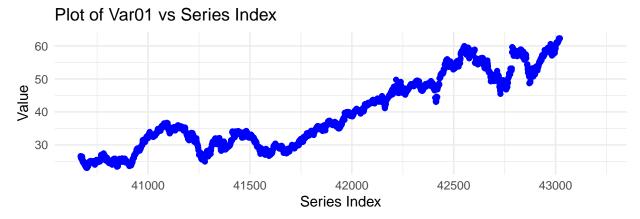
```
var1_plot <- ggplot(s01, aes(x = SeriesInd, y = Var01)) +
    geom_point(color = "blue") +
    labs(title = "Plot of Var01 vs Series Index", x = "Series Index", y = "Value") +
    theme_minimal()

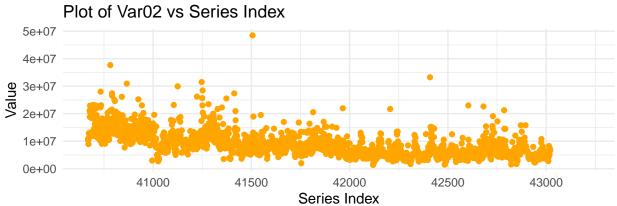
var2_plot <- ggplot(s01, aes(x = SeriesInd, y = Var02)) +
    geom_point(color = "orange") +
    labs(title = "Plot of Var02 vs Series Index", x = "Series Index", y = "Value") +
    theme_minimal()

grid.arrange(var1_plot, var2_plot, nrow = 2)

## Warning: Removed 142 rows containing missing values or values outside the scale range
## ('geom_point()').</pre>

## Warning: Removed 140 rows containing missing values or values outside the scale range
## ('geom_point()').
```





Data Imputation

I'm using linear imputation, so creating a line of best fit between the last two known points and filling in missing values along that line. This works for Var01, however for Var02, I will impute the median given how it contains more static.

Values to forecast: 43022 - 43221 index numbers: 1623 - 1762

Checking for Stationarity

```
acf_var1 <- acf(s01$Var01[data_range], plot = FALSE)
acf_var2 <- acf(s01$Var02[data_range], plot = FALSE)

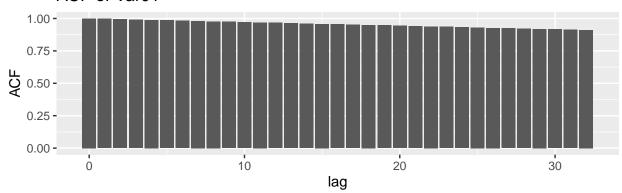
acf_var1_df <- data.frame(lag = acf_var1$lag, acf = acf_var1$acf)
acf_var2_df <- data.frame(lag = acf_var2$lag, acf = acf_var2$acf)

acf1 <- ggplot(acf_var1_df, aes(x = lag, y = acf)) +
    geom_bar(stat = "identity") +
    labs(title = "ACF of Var01", y = 'ACF')

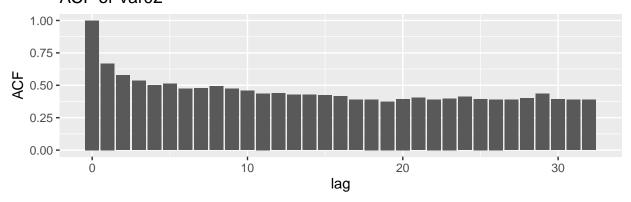
acf2 <- ggplot(acf_var2_df, aes(x = lag, y = acf)) +
    geom_bar(stat = "identity") +
    labs(title = "ACF of Var02", y = 'ACF')

grid.arrange(acf1, acf2, nrow=2)</pre>
```

ACF of Var01



ACF of Var02



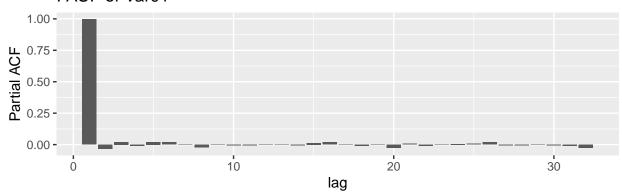
```
pacf_var1 <- pacf(s01$Var01[data_range], plot = FALSE)
pacf_var2 <- pacf(s01$Var02[data_range], plot = FALSE)

pacf_var1_df <- data.frame(lag = pacf_var1$lag, pacf = pacf_var1$acf)
pacf_var2_df <- data.frame(lag = pacf_var2$lag, pacf = pacf_var2$acf)

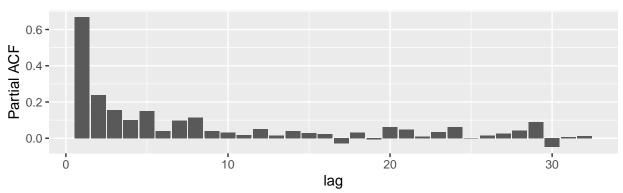
pacf1 <- ggplot(pacf_var1_df, aes(x = lag, y = pacf)) +
    geom_bar(stat = "identity") +
    labs(title = "PACF of Var01", y = 'Partial ACF')</pre>
```

```
pacf2 <- ggplot(pacf_var2_df, aes(x = lag, y = pacf)) +
   geom_bar(stat = "identity") +
   labs(title = "PACF of Var02", y = 'Partial ACF')
grid.arrange(pacf1, pacf2, nrow=2)</pre>
```

PACF of Var01



PACF of Var02



Var01 is non-stationary while Var02 is stationary.

We will preforming differencing to make Var01 stationary.

```
var1_diff <- diff(s01$Var01[data_range], differences = 1)

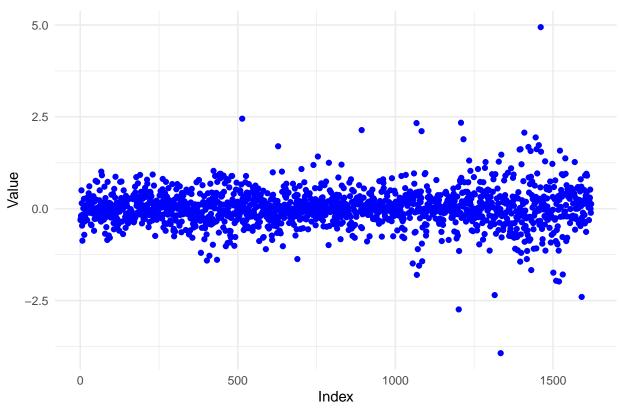
var1_diff_df <- data.frame(Index = seq_along(var1_diff), Value = var1_diff)

var1_plot <- ggplot(var1_diff_df, aes(x = Index, y = Value)) +
    geom_point(color = "blue") +
    labs(title = "Plot of Var01 differenced vs Index", x = "Index", y = "Value") +</pre>
```

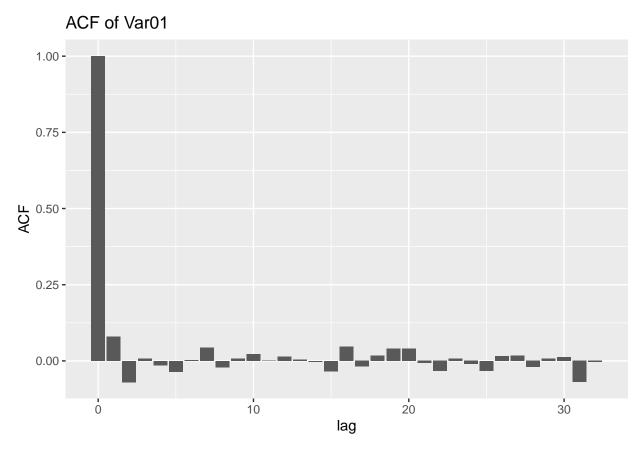
```
grid.arrange(var1_plot, nrow = 1)
```

theme minimal()

Plot of Var01 differenced vs Index



```
acf_var1 <- acf(var1_diff, plot = FALSE)
acf_var1_df <- data.frame(lag = acf_var1$lag, acf = acf_var1$acf)
acf1 <- ggplot(acf_var1_df, aes(x = lag, y = acf)) +
    geom_bar(stat = "identity") +
    labs(title = "ACF of Var01", y = 'ACF')
grid.arrange(acf1, nrow = 1)</pre>
```



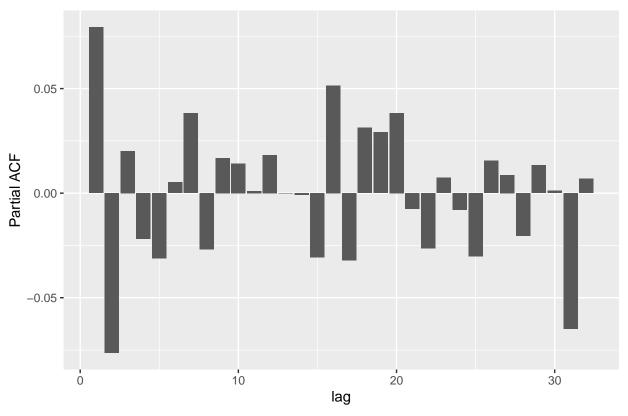
```
pacf_var1 <- pacf(var1_diff, plot = FALSE)

pacf_var1_df <- data.frame(lag = pacf_var1$lag, pacf = pacf_var1$acf)

pacf1 <- ggplot(pacf_var1_df, aes(x = lag, y = pacf)) +
    geom_bar(stat = "identity") +
    labs(title = "PACF of Var01", y = 'Partial ACF')

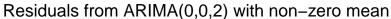
grid.arrange(pacf1, nrow=1)</pre>
```

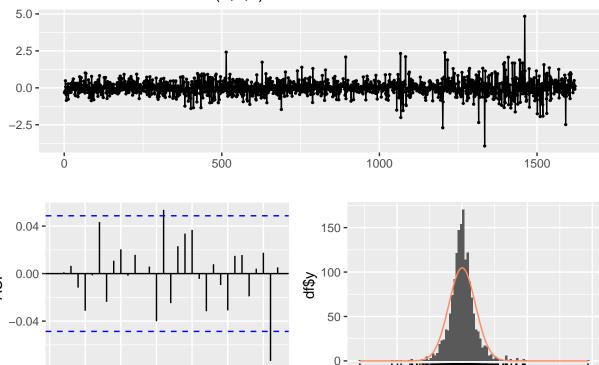
PACF of Var01



Forecasting

```
fit_var1 <- auto.arima(var1_diff, stationary = TRUE)</pre>
summary(fit_var1)
## Series: var1_diff
## ARIMA(0,0,2) with non-zero mean
##
## Coefficients:
##
                    ma2
##
        0.0875 -0.0731 0.0220
## s.e. 0.0248 0.0250 0.0129
## sigma^2 = 0.2612: log likelihood = -1210.39
## AIC=2428.77 AICc=2428.79 BIC=2450.33
##
## Training set error measures:
                                  RMSE
                                            MAE MPE MAPE
                                                               MASE
## Training set 2.867594e-06 0.5105564 0.3473101 NaN Inf 0.7076254 -0.0003393583
checkresiduals(fit_var1)
```





```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(0,0,2) with non-zero mean
## Q* = 6.7689, df = 8, p-value = 0.5618
##
## Model df: 2. Total lags used: 10
```

20

Lag

25

30

-2.5

0.0

residuals

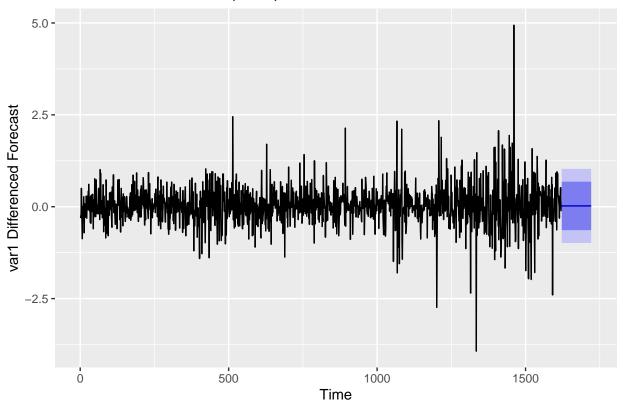
2.5

5.0

10

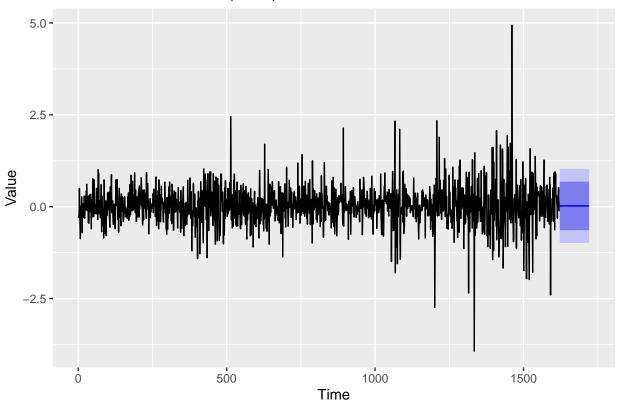
```
fc_var1 <- forecast(fit_var1, h=100)
autoplot(fc_var1) + ylab('var1 Differenced Forecast')</pre>
```

Forecasts from ARIMA(0,0,2) with non-zero mean



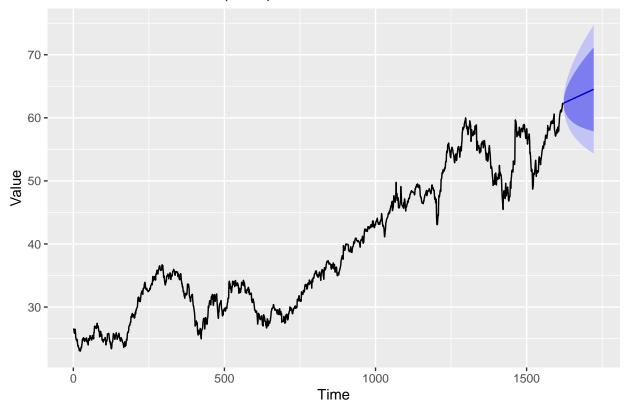
```
fit <- Arima(var1_diff, order=c(2,1,3), include.constant=FALSE)
fc <- forecast(fit, h=100)
autoplot(fc) + ylab('Value')</pre>
```

Forecasts from ARIMA(2,1,3)



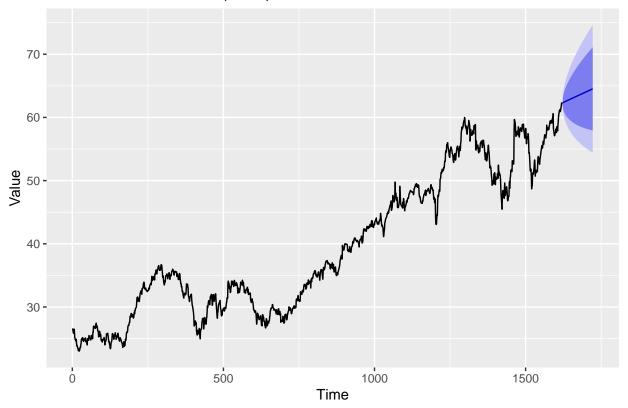
```
fit <- auto.arima(s01$Var01[data_range])
fc <- forecast(fit, h=100)
autoplot(fc) + ylab('Value')</pre>
```

Forecasts from ARIMA(0,1,2) with drift



```
fit <- Arima(s01$Var01[data_range], order=c(2,1,3), include.drift=TRUE)
fc <- forecast(fit, h=100)
autoplot(fc) + ylab('Value')</pre>
```

Forecasts from ARIMA(2,1,3) with drift

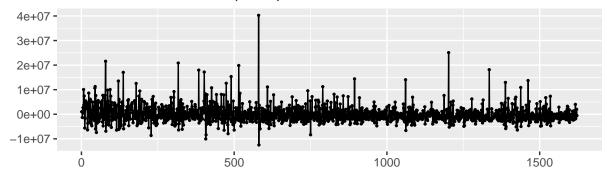


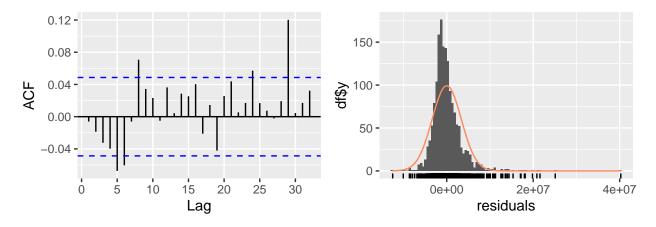
```
fit_var2 <- auto.arima(s01$Var02[data_range], stationary = TRUE)
summary(fit_var2)</pre>
```

```
## Series: s01$Var02[data_range]
## ARIMA(5,0,0) with non-zero mean
##
## Coefficients:
##
            ar1
                     ar2
                             ar3
                                     ar4
                                              ar5
                                                        mean
##
         0.4398 \quad 0.1268 \quad 0.0875 \quad 0.0313 \quad 0.1514
                                                   8905853.1
## s.e. 0.0245 0.0268 0.0269 0.0268 0.0245
                                                    575822.3
##
## sigma^2 = 1.142e+13: log likelihood = -26683.01
## AIC=53380.01 AICc=53380.08
                                  BIC=53417.75
##
## Training set error measures:
                                                  MPE
                                                          MAPE
                              RMSE
                                       MAE
                                                                    MASE
## Training set -3637.317 3373476 2243121 -12.14313 28.10484 0.888227 -0.005976824
```

checkresiduals(fit_var2)

Residuals from ARIMA(5,0,0) with non-zero mean

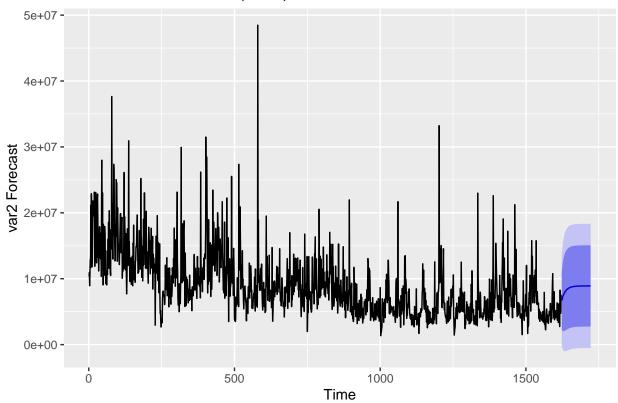




```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(5,0,0) with non-zero mean
## Q* = 29.281, df = 5, p-value = 2.043e-05
##
## Model df: 5. Total lags used: 10
```

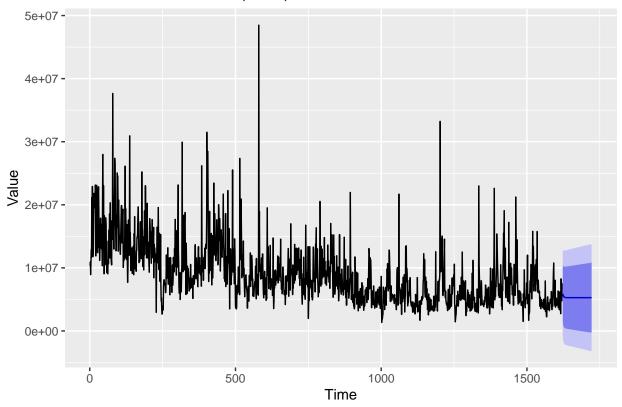
```
fc_var2 <- forecast(fit_var2, h=100)
autoplot(fc_var2) + ylab('var2 Forecast')</pre>
```

Forecasts from ARIMA(5,0,0) with non-zero mean



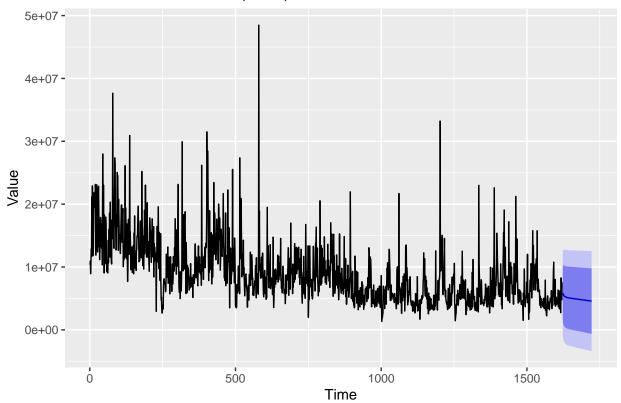
```
fit <- Arima(s01$Var02[data_range], order=c(2,1,3), include.constant=FALSE)
fc <- forecast(fit, h=100)
autoplot(fc) + ylab('Value')</pre>
```

Forecasts from ARIMA(2,1,3)



```
fit <- auto.arima(s01$Var02[data_range])
fc <- forecast(fit, h=100)
autoplot(fc) + ylab('Value')</pre>
```

Forecasts from ARIMA(1,1,3) with drift



```
fit <- Arima(s01$Var02[data_range], order=c(2,1,3), include.drift=TRUE)
fc <- forecast(fit, h=100)
autoplot(fc) + ylab('Value')</pre>
```

Forecasts from ARIMA(2,1,3) with drift

