STA457 Final Project - ETS Model

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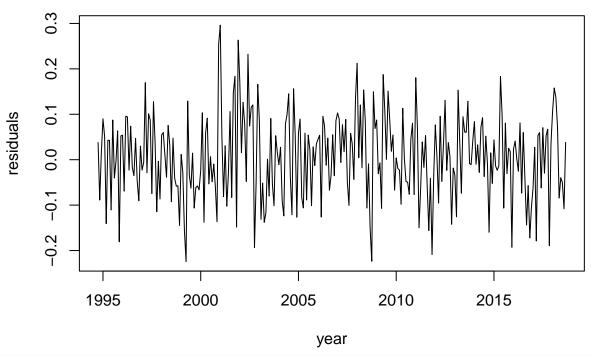
Monthly Average Price Over Time



price_ts <- ts(cocoa_data\$Price_Monthly_Avg, start = c(1994, 10), frequency = 12)</pre>

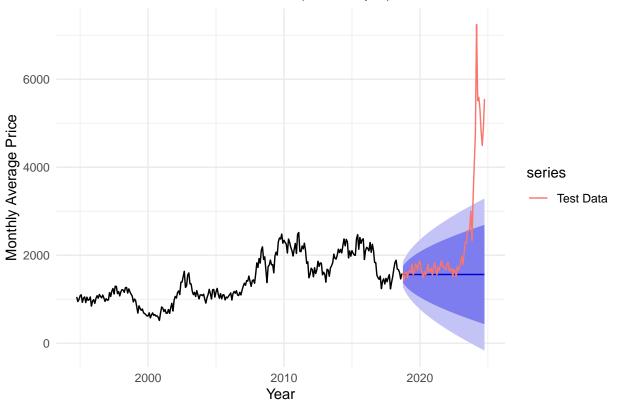
```
n <- length(price_ts)</pre>
split_index <- floor(0.8 * n)</pre>
train_data <- window(price_ts, end = time(price_ts)[split_index])</pre>
test_data <- window(price_ts, start = time(price_ts)[split_index + 1])</pre>
ets_model <- ets(train_data, model = "ZZZ")</pre>
summary(ets_model)
## ETS(M,N,N)
## Call:
## ets(y = train_data, model = "ZZZ")
##
     Smoothing parameters:
##
##
       alpha = 0.6515
##
##
     Initial states:
##
       1 = 1015.4246
##
##
     sigma: 0.0936
##
##
        AIC
                AICc
## 4421.590 4421.675 4432.579
## Training set error measures:
                       ME
                              RMSE
                                        MAE
                                                    MPE
                                                             MAPE
                                                                       MASE
## Training set 2.919422 136.2439 106.3791 -0.3609434 7.638507 0.4127703
##
                       ACF1
## Training set 0.03449358
plot(residuals(ets_model), main = "Residual from ETS Model", xlab = "year", ylab = "residuals")
```

Resiudal from ETS Model



```
forecast1 <- forecast(ets_model, h = length(test_data))
autoplot(forecast1) +
  autolayer(test_data, series = "Test Data") +
  ggtitle("Price Forecast with ETS Model (80/20 Split)") +
  xlab("Year") +
  ylab("Monthly Average Price") +
  theme_minimal()</pre>
```

Price Forecast with ETS Model (80/20 Split)



accuracy(forecast1, test_data)

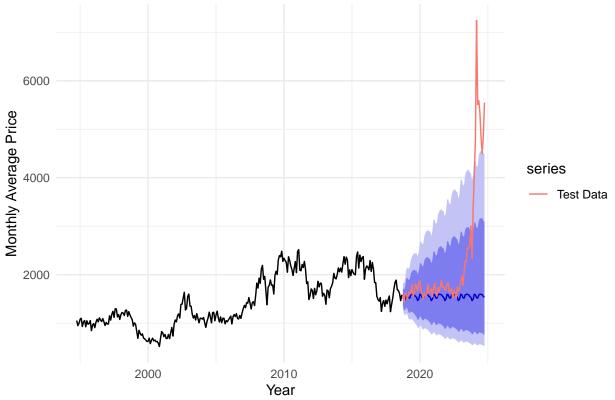
##

gamma = 1e-04

```
RMSE
                                            MAE
                                                                  MAPE
                   2.919422 136.2439 106.3791 -0.3609434 7.638507 0.4127703
## Training set
## Test set
                712.279961 1446.2536 723.3655 19.0506738 19.800260 2.8067899
                       ACF1 Theil's U
##
## Training set 0.03449358
## Test set
                 0.89187094 2.731099
log_price_ts <- ts(cocoa_data$log_price, start = c(1994, 10), frequency = 12)</pre>
n <- length(price_ts)</pre>
split_index <- floor(0.8 * n)</pre>
log_train_data <- window(log_price_ts, end = time(log_price_ts)[split_index])</pre>
log_test_data <- window(log_price_ts, start = time(log_price_ts)[split_index + 1])</pre>
log_ets_model <- ets(log_train_data, model = "ZZZ")</pre>
summary(log_ets_model)
## ETS(A,N,A)
##
## Call:
    ets(y = log_train_data, model = "ZZZ")
##
##
     Smoothing parameters:
##
       alpha = 0.6995
```

```
##
##
     Initial states:
##
       1 = 6.9154
       s = 0 \ 0.0221 \ 0.0265 \ 0.0292 \ 0.0201 \ -0.0232
##
              -0.0186 0.0206 0.0289 -0.0366 -0.0576 -0.0115
##
##
##
     sigma: 0.0909
##
##
        AIC
                 AICc
                           BIC
## 265.5331 267.2978 320.4775
## Training set error measures:
                                   RMSE
                                               MAE
                                                           MPE
                                                                    MAPE
                                                                              MASE
                         ME
## Training set 0.00214092 0.08869351 0.07231002 0.01998717 1.009136 0.3876736
##
## Training set -0.07071379
log_forecast <- forecast(log_ets_model, h = length(log_test_data))</pre>
# Back-transform
log_forecast$mean <- exp(log_forecast$mean)</pre>
log_forecast$lower <- exp(log_forecast$lower)</pre>
log_forecast$upper <- exp(log_forecast$upper)</pre>
log_forecast$x <- exp(log_forecast$x)</pre>
autoplot(log_forecast) +
  autolayer(test_data, series = "Test Data") +
  ggtitle("ETS Forecast on Log-Transformed Prices (Back-Transformed)") +
  xlab("Year") +
  ylab("Monthly Average Price") +
  theme_minimal()
```

ETS Forecast on Log-Transformed Prices (Back-Transformed)



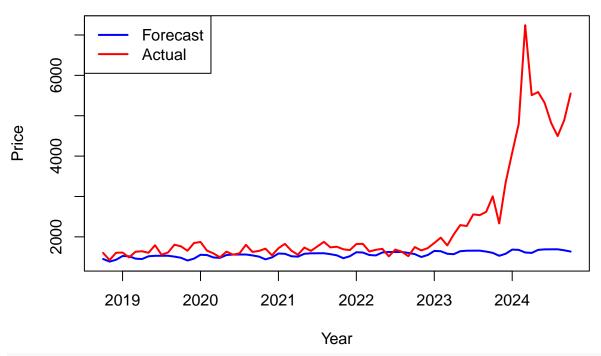
```
# Compare to test data
accuracy(log_forecast, test_data)
```

```
ME
                              RMSE
                                          MAE
                                                    MPE
                                                            MAPE
                                                                      MASE
                                                                                ACF1
## Training set 1433.911 1521.199 1433.9110 99.43856 99.43856 5.563835 0.9593853
                 724.049 1449.538 733.3112 19.74428 20.35921 2.845381 0.8913310
## Test set
##
                 Theil's U
## Training set
                        NA
## Test set
                  2.749785
diff_log_price <- ts(cocoa_data$diff_log_price, start = c(1994, 10), frequency = 12)
n <- length(diff_log_price)</pre>
split_index <- floor(0.8 * n)</pre>
diff_log_train <- window(diff_log_price, end = time(price_ts)[split_index])</pre>
diff_log_test <- window(diff_log_price, start = time(price_ts)[split_index + 1])</pre>
diff_log_ets_model <- ets(diff_log_train, model = "ZZZ")</pre>
summary(diff_log_ets_model)
```

```
## ETS(A,N,A)
##
## Call:
## ets(y = diff_log_train, model = "ZZZ")
##
## Smoothing parameters:
## alpha = 1e-04
```

```
##
       gamma = 1e-04
##
##
     Initial states:
##
       1 = 0.0017
##
       s = -0.0161 - 0.0013 - 9e - 04 0.0056 0.0443 - 0.0081
              -0.0411 -0.0058 0.0611 0.031 -0.0481 -0.0207
##
##
##
     sigma: 0.0967
##
                           BIC
##
        AIC
                AICc
## 301.0174 302.7821 355.9618
##
## Training set error measures:
                                     RMSE
                                                                    MAPE
                                                                               MASE
##
                                                  MAE
                                                            MPE
## Training set -0.0002304408 0.09432926 0.07645199 58.53721 162.9805 0.7983175
##
                       ACF1
## Training set -0.3195361
diff_log_forecast <- forecast(diff_log_ets_model, h = length(diff_log_test))</pre>
forecasted_diffs <- diff_log_forecast$mean</pre>
last_log_price <- tail(cocoa_data$log_price, 1)</pre>
# Reconstruct & back-transform
log_price_forecast <- ts(cumsum(forecasted_diffs) + 7.3,</pre>
                          start = time(diff_log_test)[1], frequency = 12)
price_forecast <- exp(log_price_forecast)</pre>
actual_price_test <- window(price_ts, start = time(diff_log_test)[1])</pre>
# Plot forecast vs actual
plot(price_forecast, col = "blue", lwd = 2, ylim = range(c(price_forecast, actual_price_test)),
     main = "Forecasted vs Actual Prices BY ETS (Back-Transformed)", ylab = "Price", xlab = "Year")
lines(actual_price_test, col = "red", lwd = 2)
legend("topleft", legend = c("Forecast", "Actual"), col = c("blue", "red"), lty = 1, lwd = 2)
```

Forecasted vs Actual Prices BY ETS (Back-Transformed)



accuracy(price_forecast, actual_price_test)

ME RMSE MAE MPE MAPE ACF1 Theil's U
Test set 710.5973 1410.485 716.5764 19.69213 20.08671 0.8878682 2.666692