Dynamic Regression Model Performance

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Model Description

To experiment with Dynamic Regression models, I first needed to select the most likely variables for use as the regressor in the xreg argument. I selected five features by looking for the intersection of the most likely variables identified by their randomForest::importance() according to a Random Forest model, and those identified by their earth::evimp() according to a Multivariate Adaptive Regression Spline (see "dengue/src/FeatureSelection/FeatureSelection.R"). These variables are:

- nonres_guestsstation_max_temp_creanalysis_tdtr_k
- reanalysis_dew_point_temp_k
- reanalysis_specific_humidity_g_per_kg

Experimentation with these five variables revealed that an ARIMA(1,1,1) model with reanalysis_dew_point_temp_k as the regressor was the best (see "dengue/src/Models/4.0.DynamicRegression.R"). The model takes the form:

```
# Fit model
model <- auto.arima(ts.final[,"total_cases"],</pre>
                    xreg = ts.final[,"reanalysis_dew_point_temp_k"])
summary(model)
## Series: ts.final[, "total_cases"]
## Regression with ARIMA(1,1,1) errors
##
  Coefficients:
##
            ar1
                     ma1
                             xreg
##
         0.7084
                 -0.5908
                           0.7578
## s.e. 0.0961
                  0.1090 0.5201
##
## sigma^2 estimated as 180.7:
                                 log likelihood=-3754.79
## AIC=7517.59
                 AICc=7517.63
                                 BIC=7536.95
##
## Training set error measures:
                                   RMSE
                                                                MASE
##
                            ME
                                             MAE MPE MAPE
## Training set -0.0001752054 13.41438 8.061207 NaN Inf 0.2206567
##
## Training set 0.0003965629
```

In order to forecast total_cases with this model, we need a model for forecasting the xreg variable reanalysis_dew_point_temp_k. Experimentation revealed that a fine choice was a Seasonal Naive model (which uses the mean of the value from the season in the past-in this case, the season = the week of the year-as the predicted value for the season in the future). See "dengue/src/Models/4.DynamicRegression.R". This Seasonal Naive model for the xreg term is incorporated into the model for forecasting as below:

Model evaluation

I used the greybox::ro() function to cross validate this model using the forecast evaluation on a rolling origin method (500 origins). I forecast at three horizons: 1 week ahead, 6 weeks ahead, and 6 months ahead. With an MAE of 1.1 for a 1 week horizon, 8.0 for 6 weeks ahead, and 18.0 for 6 months ahead, this model is substantially better than any previous one.

```
# Set up for cross validation
x <- ts.final[,"total_cases"]</pre>
xreg <- ts.final[,"reanalysis_dew_point_temp_k"]</pre>
ourCall <- "predict(arima(x=data, order=c(1,1,1), xreg=xreg[counti]), n.ahead=h, newxreg=xreg[counto])"
ourValue <- "pred"
## 1 week horizon
returnedValues1 <- ro(x,h=1,origins=500,ourCall,ourValue)
# Calculate MAE
print(paste("1 week horizon MAE = ",
            mean(abs(returnedValues1$actuals -
                       returnedValues1$pred),na.rm = TRUE)))
## [1] "1 week horizon MAE = 1.06404117223068"
## 6 week horizon
returnedValues6 <- ro(x,h=6,origins=500,ourCall,ourValue)
# Calculate MAE
print(paste("6 week horizon MAE = ",
            mean(abs(returnedValues6$actuals -
                       returnedValues6$pred),na.rm = TRUE)))
## [1] "6 week horizon MAE = 7.97751927739392"
## 6 month horizon
returnedValues26 <- ro(x,h=26,origins=500,ourCall,ourValue)</pre>
# Calculate MAE
print(paste("6 month horizon MAE = ",
            mean(abs(returnedValues26$actuals -
                       returnedValues26$pred),na.rm = TRUE)))
```

[1] "6 month horizon MAE = 18.0263912097849"