## Vector Autoregression Model Performance

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## **Model Description**

Vector Autoregression allows for multivariate time series modeling, so in this model I made use of all five variables identified by randomForest::importance() and earth::evimp() (see "dengue/src/FeatureSelection/FeatureSelection.R"). These variables are:

- nonres\_guests
- station\_max\_temp\_c
- reanalysis tdtr k
- reanalysis dew point temp k
- reanalysis\_specific\_humidity\_g\_per\_kg

Experimentation with the parameter p (number of lags in the autoregression) showed that a model with p=1 resulted in residuals = white noise (see "dengue/src/Models/VAR.R").

```
# Fit model
fitvar1 <- VAR(ts.selected, p=1, type = "both")
fitvar1$varresult$total cases
##
## Call:
## lm(formula = y \sim -1 + ., data = datamat)
## Coefficients:
##
                              total_cases.l1
##
                                    9.555e-01
##
                            nonres_guests.11
##
                                   -2.707e-05
##
                       station_max_temp_c.l1
##
                                    7.801e-04
##
                        reanalysis_tdtr_k.l1
##
                                   -7.140e-01
##
             reanalysis_dew_point_temp_k.l1
##
   reanalysis_specific_humidity_g_per_kg.l1
##
                                   -1.523e+00
##
                                        const
##
                                   -6.704e+02
##
                                        trend
```

3.001e-04

## **Model Evaluation**

##

Neither the forecast::tsCV() function nor the greybox::ro() function can be used to cross validate a multivariate time series model, so I wrote a for loop to evaluate 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 6.5 for a 1 week horizon, 14.5 for 6 weeks ahead, and 30.9 for 6 months

ahead, this model is not as good as the Dynamic Regression, in spite of the fact that it includes more variables.

```
# Divide time series with 500 observations in test set
train1 <- subset(ts.selected, end = 436) # subset of series ending at this point
test1 <- subset(ts.selected, start = 437) # subset of series beginning at next point
# Horizon = 1 week
h <- 1 # the horizon
n \leftarrow length(test1[,1]) - h + 1 \# number of obs in test set (500) - horizon (1) + 1
fcmat <- matrix(0, nrow=n, ncol=h) # a matrix of Os that is 500x1
for(i in 1:n)
  x <- subset(ts.selected, end = 436 + (i-1)) # the ts subset (for each iteration)
 refit <- VAR(x, p=1, type="both") # fit the ts subset
 fcmat[i,] <- forecast(refit, h=h)$forecast$total_cases[["mean"]] # forecast, extract the point foreca
# Calculate accuracy
print("1 week horizon accuracy")
## [1] "1 week horizon accuracy"
accuracy(fcmat[,1], test1[,"total_cases"]) # compare forecasts to test set
##
                     ME
                            RMSE
                                      MAE MPE MAPE
                                                           ACF1 Theil's U
## Test set -0.09551088 9.846422 6.484304 -Inf Inf -0.1204734
## Horizon = 6 weeks
h <- 6 # the horizon
n \leftarrow length(test1[,1]) - h + 1 # number of obs in test set (500) - horizon (6) + 1
fcmat <- matrix(0, nrow=n, ncol=h) # a matrix of Os that is 495 x 6
for(i in 1:n)
  x <- subset(ts.selected, end = 436 + (i-1)) # the ts subset (for each iteration)
  refit <- VAR(x, p=1, type="both") # fit the ts subset</pre>
  fcmat[i,] <- forecast(refit, h=h)$forecast$total_cases[["mean"]] # forecast, extract the point foreca</pre>
}
# Calculate accuracy
print("6 week horizon accuracy")
## [1] "6 week horizon accuracy"
accuracy(fcmat[,6], subset(ts.selected, start = 442)[,"total_cases"]) # compare forecasts to true value
                         RMSE
                                  MAE MPE MAPE
                                                     ACF1 Theil's U
## Test set -1.036617 21.7324 14.5005 Inf Inf 0.8037651
                                                                NaN
## Horizon = 6 months
h <- 26 # the horizon
n \leftarrow length(test1[,1]) - h + 1 \# number of obs in test set (500) - horizon (26) + 1
fcmat <- matrix(0, nrow=n, ncol=h) # a matrix of Os that is 475 x 6
```

```
for(i in 1:n)
{
    x <- subset(ts.selected, end = 436 + (i-1)) # the ts subset (for each iteration)
    refit <- VAR(x, p=1, type="both") # fit the ts subset
    fcmat[i,] <- forecast(refit, h=h)$forecast$total_cases[["mean"]] # forecast, extract the point foreca
}

# Calculate accuracy
print("6 month horizon accuracy")

## [1] "6 month horizon accuracy"
accuracy(fcmat[,26], subset(ts.selected, start = 462)[,"total_cases"]) # compare forecasts to true valu

## ME RMSE MAE MPE MAPE ACF1 Theil's U

## Test set -3.193966 42.06621 30.93167 -Inf Inf 0.9476811 0</pre>
```