Forecasting Event Data

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Introduction

In this tutorial, I compare forecasting utility of PHOENIX and ICEWS event datasets using the output from random forest model.

Loading libraries:

```
rm(list=ls())
library(here)
library(caret)
library(stats)
library(plyr)
library(data.table)
library(tidyverse)
library(randomForest)
```

Making sure the results of this script are reproducible

```
set.seed(0927)
```

In order to compare forecasting utility I am using The Ground Truth Data Set (GTDS), which which provides information on 5 events of interests (EOI): International Crisis, Ethnic/Religious Conflict, Domestic Crisis, Rebellion, and Insurgency. It covers 168 states from January 2001 through 2014. The unit is country-month.

```
eoi = read.csv("gtds_2001.to.may.2014.csv")
head(eoi)
```

```
##   ccode country year month   time ins reb dpc erv ic notes
## 1    20  Canada 2001     1 2001m1   0   0   0   0  0
## 2    20  Canada 2001     2 2001m2   0   0   0   0  0
## 3    20  Canada 2001     3 2001m3   0   0   0   0  0
## 4    20  Canada 2001     4 2001m4   0   0   0   0  0
## 5    20  Canada 2001     5 2001m5   0   0   0   0  0
## 6    20  Canada 2001     6 2001m6   0   0   0   0  0
##                coder insnotes dpcnotes rebnotes ervnotes icnotes
## 1 Bentley & Leonard
## 2 Bentley & Leonard
## 3 Bentley & Leonard
## 4 Bentley & Leonard
## 5 Bentley & Leonard
## 6 Bentley & Leonard
```

Here, I'll focus on on International Crisis. For the purpose of forecasting I create an onset variable:

```
eoi_int = eoi %>%
  select(ccode, year, month, ic)

eoi_d = eoi_int[eoi_int$ic==1,]
eoi_d$onset <- with(eoi_d, ave(year, month, ccode, FUN = function(x)
  as.integer(c(TRUE, tail(x, -1L) != head(x, -1L) + 1L))))
eoi_d = eoi_d[eoi_d$onset==1,]
```

```r
eoi_final = merge(eoi_int, eoi_d, all.x=T)
eoi_final$onset[is.na(eoi_final$onset)==T] <-0
eoi_final$ic = NULL
```

I've already preprocessed both PHOENIX and ICEWS. I aggregated both datasets to the country - month level and selected conflicts with government and military actors for international conflict. In this aggregated form, both datasets provide information on counts of events for quad classes: verbal cooperation, material cooperation, verbal conflict, material conflict.

```r
phoenix_int = read.csv("pho_international.csv")
head(phoenix_int)
```

```
##   X ccode year month vcp mcp vcf mcf
## 1 1   100 2001     2   3   0   0   0
## 2 2   100 2001     4   1   0   0   0
## 3 3   100 2001     5   2   0   0   0
## 4 4   100 2001     6   6   0   0   0
## 5 5   100 2001     7   1   0   1   0
## 6 6   100 2001     9   1   0   0   1
```

I lagged quad categories by 3 and 6 months

```r
pho_int_lag = phoenix_int %>%
  group_by(ccode) %>%
  arrange(ccode, year) %>%
  do(data.frame(., setNames(shift(.$vcp, c(3,6)), paste("vcp_l", c(3,6), sep=".")))) %>%
  do(data.frame(., setNames(shift(.$mcp, c(3,6)), paste("mcp_l", c(3,6), sep=".")))) %>%
  do(data.frame(., setNames(shift(.$vcf, c(3,6)), paste("vcf_l", c(3,6), sep=".")))) %>%
  do(data.frame(., setNames(shift(.$mcf, c(3,6)), paste("mcf_l", c(3,6), sep=".")))) %>%
  select(ccode, year, month, vcp_l.3, mcp_l.3, vcf_l.3, mcf_l.3,
         vcp_l.6, mcp_l.6, vcf_l.6, mcf_l.6)

pho_int_lag = na.omit(pho_int_lag)
```

I merge GTDS and PHOENIX datasets together

```r
df = merge(pho_int_lag, eoi_final, by=c("ccode", "year", "month"))
df$onset = as.factor(df$onset)
```

I split the data on training and test samples. In this example, I train the model on 2001 - 2005 data and test it on 2006

```r
train_data = df[which(df$year<=2005),]
train_data_l3 = subset(train_data, select=c("ccode", "year", "month",
                                            "vcp_l.3", "mcp_l.3", "vcf_l.3", "mcf_l.3", 'onset'))
train_data_l6 = subset(train_data, select=c("ccode", "year", "month",
                                            "vcp_l.6", "mcp_l.6", "vcf_l.6", "mcf_l.6", 'onset'))


test_data = df[which(df$year==2006),]
test_data_l3 = subset(test_data, select=c("ccode", "year", "month",
                                          "vcp_l.3", "mcp_l.3", "vcf_l.3", "mcf_l.3", 'onset'))
test_data_l6 = subset(test_data, select=c("ccode", "year", "month",
                                          "vcp_l.6", "mcp_l.6", "vcf_l.6", "mcf_l.6", 'onset'))
```

I train the model using random forest and 5-fold cross validation.

```r
rf_model<-train(onset~.,data=train_data_l3,method="rf",
                trControl=trainControl(method="cv",number=5, savePredictions = T),
                prox=TRUE,allowParallel=TRUE)
print(rf_model)
```

```
## Random Forest
##
## 5273 samples
##    7 predictor
##    2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 4219, 4219, 4217, 4218, 4219
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##   2     0.9624513  0.3002987
##   4     0.9736396  0.6060027
##   7     0.9806565  0.7469173
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 7.
```

Looking at the results

```r
print(rf_model$finalModel)
```

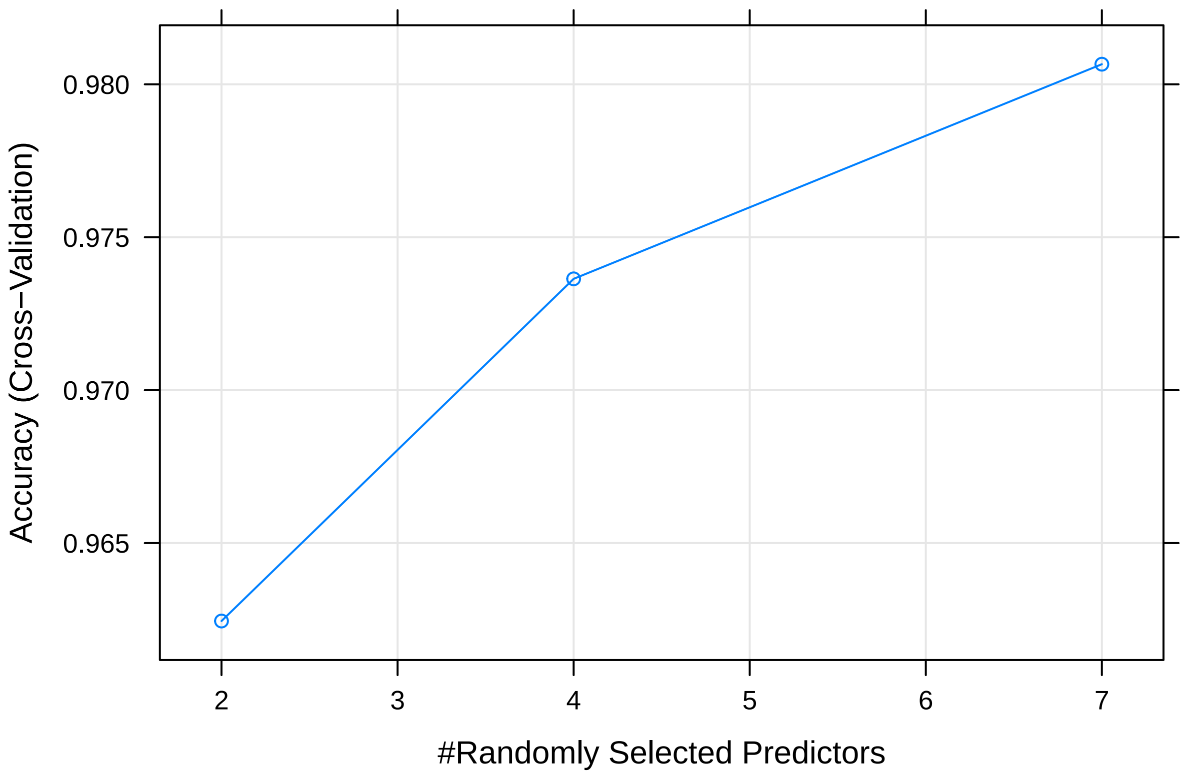
```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry, proximity = TRUE,      allowParallel = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 7
##
##         OOB estimate of  error rate: 1.54%
## Confusion matrix:
##      0   1 class.error
## 0 5020  26 0.005152596
## 1   55 172 0.242290749
```

```r
testclass <- predict(rf_model, newdata = test_data_l3)
cfMatrix <- confusionMatrix(data = testclass, test_data_l3$onset)
print(cfMatrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 936  23
##          1  43   0
##
##                Accuracy : 0.9341
##                  95% CI : (0.917, 0.9487)
##     No Information Rate : 0.977
##     P-Value [Acc > NIR] : 1.00000
```

```
##
##                   Kappa : -0.0308
##  Mcnemar's Test P-Value : 0.01935
##
##             Sensitivity : 0.9561
##             Specificity : 0.0000
##          Pos Pred Value : 0.9760
##          Neg Pred Value : 0.0000
##              Prevalence : 0.9770
##          Detection Rate : 0.9341
##    Detection Prevalence : 0.9571
##       Balanced Accuracy : 0.4780
##
##        'Positive' Class : 0
##
```

```
plot(rf_model)
```




```
test.probs <- predict(rf_model,test_data_l3,type="prob")

library(pROC)

pROC::roc(test_data_l3$onset, testclass)

rf.ROC <- roc(predictor=testclass,
              response=test_data_l3$onset,
              levels=rev(levels(test_data_l3$onset)))
rf.ROC$auc

plot(rf.ROC,main="RF ROC Phoenix")
```

I am doing the same for ICEWS data:

```
icw_int = read.csv("icw_international.csv")
head(icw_int)
```

```
##   X ccode year month  vcp mcp vcf mcf
## 1 1     2 2001     1 1377  11  27  13
## 2 2     2 2001     2 2189  10  69  14
## 3 3     2 2001     3 2431  23  58  32
## 4 4     2 2001     4 1710   7  34  16
## 5 5     2 2001     5 2385   9  52  13
## 6 6     2 2001     6 3032  27  71  18
```

```
# lag variables by 3 and 6 months
icw_int_lag = icw_int %>%
  group_by(ccode) %>%
  arrange(ccode, year) %>%
  do(data.frame(., setNames(shift(.$vcp, c(3,6)), paste("vcp_l", c(3,6), sep=".")))) %>%
  do(data.frame(., setNames(shift(.$mcp, c(3,6)), paste("mcp_l", c(3,6), sep=".")))) %>%
  do(data.frame(., setNames(shift(.$vcf, c(3,6)), paste("vcf_l", c(3,6), sep=".")))) %>%
  do(data.frame(., setNames(shift(.$mcf, c(3,6)), paste("mcf_l", c(3,6), sep=".")))) %>%
  select(ccode, year, month, vcp_l.3, mcp_l.3, vcf_l.3, mcf_l.3,
         vcp_l.6, mcp_l.6, vcf_l.6, mcf_l.6)

icw_int_lag = na.omit(icw_int_lag)

# merge 2 datasets
df2 = merge(icw_int_lag, eoi_final, by=c("ccode", "year", "month"))
df2$onset = as.factor(df2$onset)

# split the data
train_data = df2[which(df2$year<=2005),]
train_data_l3 = subset(train_data, select=c("ccode", "year", "month",
                                            "vcp_l.3", "mcp_l.3", "vcf_l.3", "mcf_l.3", 'onset'))
train_data_l6 = subset(train_data, select=c("ccode", "year", "month",
                                            "vcp_l.6", "mcp_l.6", "vcf_l.6", "mcf_l.6", 'onset'))


test_data = df2[which(df2$year==2006),]
test_data_l3 = subset(test_data, select=c("ccode", "year", "month",
                                          "vcp_l.3", "mcp_l.3", "vcf_l.3", "mcf_l.3", 'onset'))
test_data_l6 = subset(test_data, select=c("ccode", "year", "month",
                                          "vcp_l.6", "mcp_l.6", "vcf_l.6", "mcf_l.6", 'onset'))




# train the model
rf_model2<-train(onset~.,data=train_data_l3,method="rf",
                trControl=trainControl(method="cv",number=5, savePredictions = T),
                prox=TRUE,allowParallel=TRUE)
print(rf_model2)
```

```
## Random Forest
##
```

```
## 7742 samples
##    7 predictor
##    2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 6194, 6194, 6194, 6193, 6193
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##   2     0.9711958  0.4508524
##   4     0.9814000  0.7083704
##   7     0.9855332  0.7843434
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 7.
```

```r
print(rf_model2$finalModel)
```

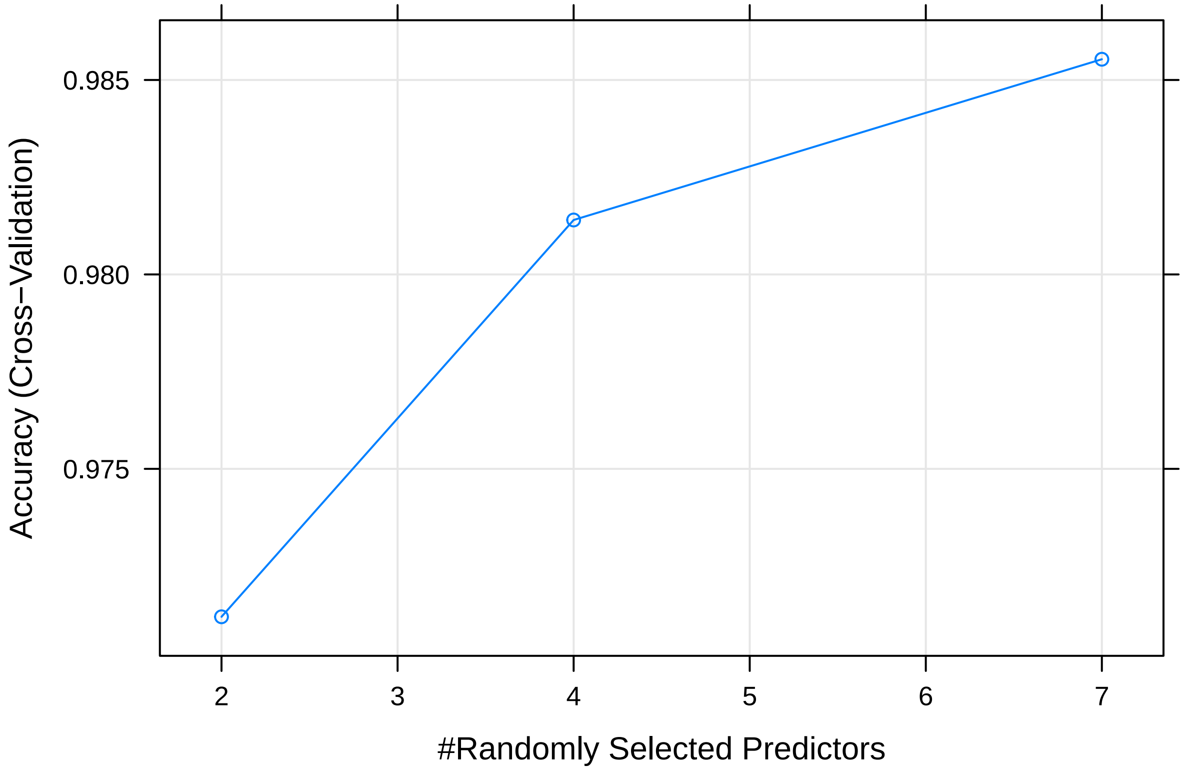
```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry, proximity = TRUE,      allowParallel = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 7
##
##         OOB estimate of  error rate: 1.25%
## Confusion matrix:
##      0   1 class.error
## 0 7416  26 0.003493684
## 1   71 229 0.236666667
```

```r
testclass <- predict(rf_model2, newdata = test_data_l3)
cfMatrix <- confusionMatrix(data = testclass, test_data_l3$onset)
print(cfMatrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1703   32
##          1   57    0
##
##                Accuracy : 0.9503
##                  95% CI : (0.9392, 0.9599)
##     No Information Rate : 0.9821
##     P-Value [Acc > NIR] : 1.00000
##
##                   Kappa : -0.0234
##  Mcnemar's Test P-Value : 0.01096
##
##             Sensitivity : 0.9676
##             Specificity : 0.0000
##          Pos Pred Value : 0.9816
##          Neg Pred Value : 0.0000
```

```
##               Prevalence : 0.9821
##           Detection Rate : 0.9503
##     Detection Prevalence : 0.9682
##        Balanced Accuracy : 0.4838
##
##         'Positive' Class : 0
##
```

```
plot(rf_model2)
```




```
test.probs <- predict(rf_model2,test_data_l3,type="prob")

library(pROC)

pROC::roc(test_data_l3$onset, testclass)

rf.ROC <- roc(predictor=testclass,
              response=test_data_l3$onset,
              levels=rev(levels(test_data_l3$onset)))
rf.ROC$auc
# Area under the curve: 1

plot(rf.ROC,main="RF ROC ICEWS")
```