Zoomer Challenge

Hossain Pezeshki

2015-04-19

Goal

We are given observations of numbers of restaurant orders for different dates, as well as the number of restaurants that were open on the given dates and the ambient weather conditions including minimum and maximum temperature, the amount of percipitation and weather events such as fog, rain or snow. The objective is to build a predictive model of restaurant orders.

```
## Loading required package: lattice
## Loading required package: ggplot2
## randomForest 4.6-10
## Type rfNews() to see new features/changes/bug fixes.
```

Exploratory Analysis

One looks for missing values. We observe that there are none.

```
zmr.train <- read.csv (file = "Zoomer_take_home_challenge_training_set.csv", header=TRUE)
sum (is.na (zmr.train))
```

```
## [1] 0
```

One also examines the skewness of the response variable; we observe that it is just over 0.7, indicating only moderate skewness. Therefore, there is no need for a Box-Cox transformation.

```
skewness (zmr.train$order_count)
```

```
## [1] 0.701062443806
```

One looks for and removes any covariates with near zero variance. We observe that the given data set has no near zero variance predictors.

```
nearZeroVar (zmr.train[,-3])
```

```
## integer(0)
```

Examining the prevalence of the levels of the factor variable `events`, we see that some levels have only a few entries, indicating that these levels are overly finely divided.

```
table (zmr.train$events)
```

```
##
##                Fog            Fog-Rain       Fog-Rain-Snow            Fog-Snow
##                  1                   5                   1                   3
##               None                Rain           Rain-Snow Rain-Thunderstorm
##                 89                  31                   6                   2
##               Snow
##                 14
```

Consequently, we replace the `event` column with three binary factors:

- `Fog` whether or not there was fog
- `Rain` whether or not there was rain
- `Snow` whether or not there was snow

Clearly the absent level `None` corresponds to the above three being `FALSE`.

Additionally, we make `calendar_code` a factor variable. These transformations are implemented by the function `mytrns` given below:

```
mytrns <- function (indf) {
 outdf <- data.frame (weekday =as.factor (weekdays (as.Date (indf$X, '%Y-%m-%d'))))
 outdf$calendar_code <- as.factor (indf$calendar_code)
 outdf$restaurant_count <- as.numeric (indf$restaurant_count)

 outdf$max_temp <- indf$max_temp
 outdf$min_temp <- indf$min_temp
 outdf$precipitation <- indf$precipitation

 tmp <- grep ("Fog", indf$events)
 v <- vector ("logical", dim(indf)[1])
 v[tmp] <- TRUE; v[-tmp] <- FALSE
 outdf$Fog <- as.factor (v)

 tmp <- grep ("Rain", indf$events)
 v[tmp] <- TRUE; v[-tmp] <- FALSE
 outdf$Rain <- as.factor (v)

 tmp <- grep ("Snow", indf$events)
 v[tmp] <- TRUE; v[-tmp] <- FALSE
 outdf$Snow <- as.factor (v)

  outdf
}

trans.zmr.train <- mytrns (zmr.train)  # Transformed covariates
y <- zmr.train$order_count  # The response variable
```

Model fitting

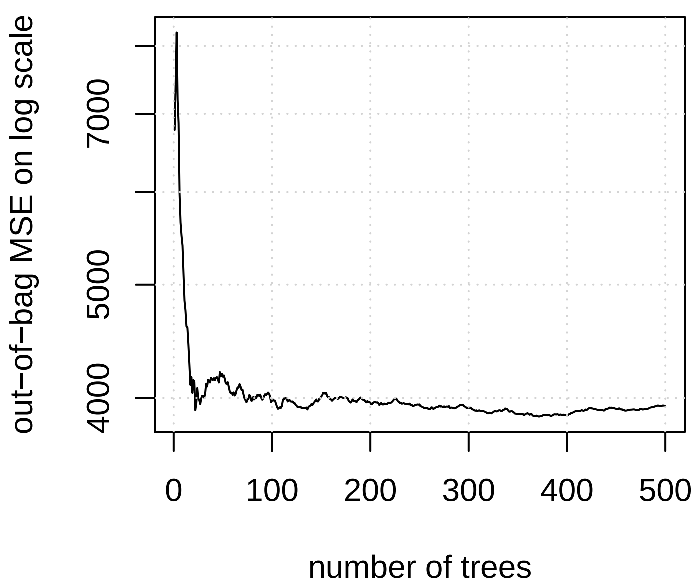
After applying the above transformation, we experiment with two different models. First we fit a linear regression model, and observe that the apparent RMSE error is `53.2`.

```r
fitlm <- lm (y~0+., data=trans.zmr.train)
prdlm <- predict (fitlm, newdata=trans.zmr.train)

RMSE <- function (x, y) {
  stopifnot (length(x) == length(y))
  s <- sqrt (mean ((x-y)^2))
  s
}

cat ("Linear model apparent error = ", RMSE (prdlm, y), '\n')
```

```
## Linear model apparent error =  53.2364122578
```

Next we fit a random forest to the transformed data, and observe that the greatest reduction in out-of-bag MSE estimate is achieved by the first 200 trees; so we refit the forest with `ntree=200`.

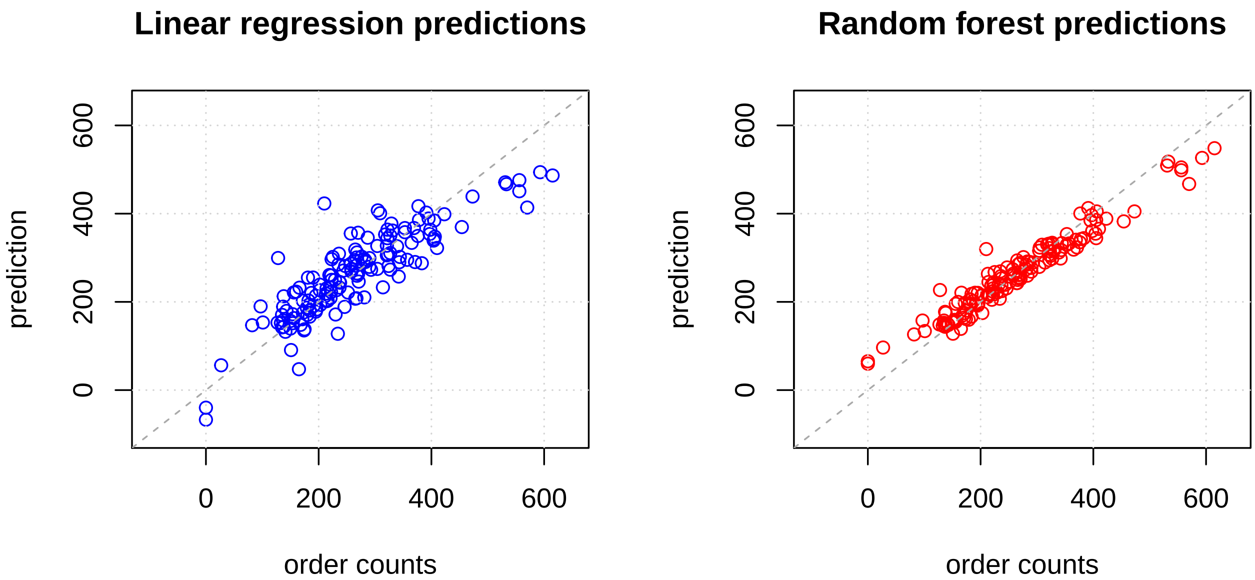
```r
rffit <- randomForest (y~., data=trans.zmr.train, importance=TRUE)
plot (rffit$mse, type='l', xlab="number of trees",
      ylab = "out-of-bag MSE on log scale", log="y"); grid()
```




```r
rffit <- randomForest (y~., data=trans.zmr.train, importance=TRUE, ntree=200)
rfprd <- predict (rffit, newdata=trans.zmr.train)
cat ("Re-fitted random forest apparent error = ", RMSE (rfprd, y), '\n')
```

```
## Re-fitted random forest apparent error =  30.8563476019
```

As expected the random forest model has superior apparent error performance `30.4`. We can visualize the relative performance of the two models by plotting their respective predictions versus the response on the training set itself.



The transformed covariates are listed in decreasing order of their importance (to the random forest model) below. We see that the weather events are not very important, and that the day of the week is less significant than the air temperature.

```
sgnf <- importance (rffit, scale=TRUE)
ind <- order (sgnf[,2], decreasing = TRUE)
print (sgnf[ind,])
```

```
##                       %IncMSE   IncNodePurity
## restaurant_count 18.771791080883 577875.11232360
## max_temp         12.999824734487 389844.90021410
## min_temp          9.986181641856 282743.61419122
## weekday           6.368729042091 172090.45762653
## calendar_code    19.293714165647 162246.86065638
## precipitation     1.821516931947  79386.82050887
## Snow              2.471740383949  46953.58847137
## Rain              3.446159629509  21494.30943387
## Fog              -0.588681894894   9133.58814316
```

Prediction

We transform the test data as above (using `mytrns`) before applying the prediction. The predicted values are written in a file called `end_product.csv`.

```
zmr.test <- read.csv ("Zoomer_take_home_challenge_test_set.csv", header=TRUE)
trans.zmr.test <- mytrns (zmr.test)
# The following line is necessary since the test set has only calendar_code==1.
levels (trans.zmr.test$calendar_code) <- levels (trans.zmr.train$calendar_code)

prd <- predict (rffit, newdata=trans.zmr.test)
write (round(prd), file="end_product.csv", sep='\n')
```

Additional questions

Information about whether a given day is a holiday or a long weekend might help improve the prediction.

Saturdays appear to have the largest number of orders averaging 313, while Thursdays appear to have the fewest averaging 220. The mean numbers of orders per day of the week and the associated t-confidence bands are calculated using the following code fragment.

```
days <- levels (trans.zmr.train$weekday)
m <- list()
for (d in days) {
  ind <- which (trans.zmr.train$weekday == d)
  bydaydat <- zmr.train[ind,]
  m[[d]] <- mean (bydaydat$order_count)
  s <- sd (bydaydat$order_count)
  n <- length(ind)
  ci <- m[[d]] + s * qt(p=0.95, df=n-1) * c(-1,1)/sqrt(n)
  str <- sprintf ("mean for %s = %f, tCI=[%f, %f]\n", d, m[[d]], ci[1], ci[2])
  cat (str)
}
```

```
## mean for Friday = 300.857143, tCI=[250.622679, 351.091607]
## mean for Monday = 234.434783, tCI=[205.231987, 263.637578]
## mean for Saturday = 313.090909, tCI=[271.714332, 354.467486]
## mean for Sunday = 295.818182, tCI=[249.442259, 342.194105]
## mean for Thursday = 219.571429, tCI=[181.675709, 257.467148]
## mean for Tuesday = 230.045455, tCI=[198.571965, 261.518944]
## mean for Wednesday = 248.047619, tCI=[209.466787, 286.628451]
```

```
d <-which.max (m)
cat ("Most average orders ", m[[d]], " on ", days[d], '\n')
```

```
## Most average orders  313.090909091  on  Saturday
```

```
d <- which.min (m)
cat ("Fewest orders ", m[[d]], " on ", days[d], '\n')
```

```
## Fewest orders  219.571428571  on  Thursday
```