

Blogpost

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Description of the Dataset:

Our topic is spam email data and our task is to predict whether an email is a spam or not. The data consist of 4601 email items, of which 1813 items were identified as spam. There are 6 predictors, which are the following: * the total length of words in capitals (crl.tot) * the number of occurrences of the \$ symbol (dollar) * the number of occurrences of the ! symbol (bang) * the number of occurrences of the word 'money' (money) * the number of occurrences of the string '000' (n000) * the number of occurrences of the word 'make' (make) and 1 target variable, which is a factor with levels n not spam, y spam (yesno).

Problems in the Dataset:

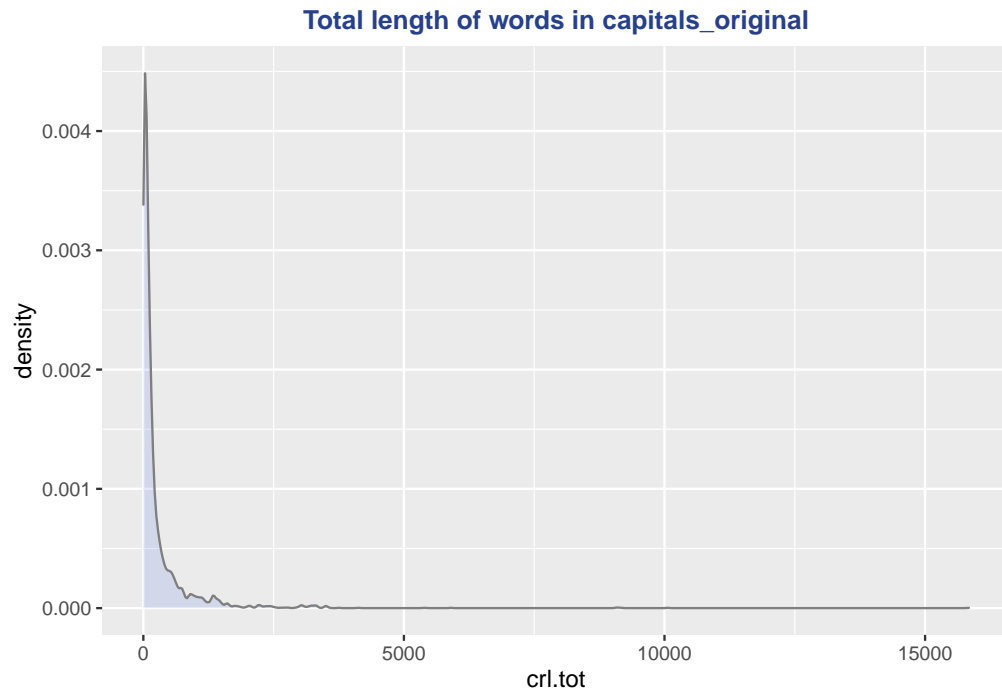
0 values

First of all, we noticed that there are many 0 values in the dataset, we have considered, if we treat them as missing values or real values. Because there are just too much 0s, for example in the column "dollar", there are more than 2 times 0 values than other values. Considering the fact that, in many emails there is just no dollar symbol, we decide to take them as real values and do not handle them.

Missing values, outliers, skewed distribution and new features (continuous variables)

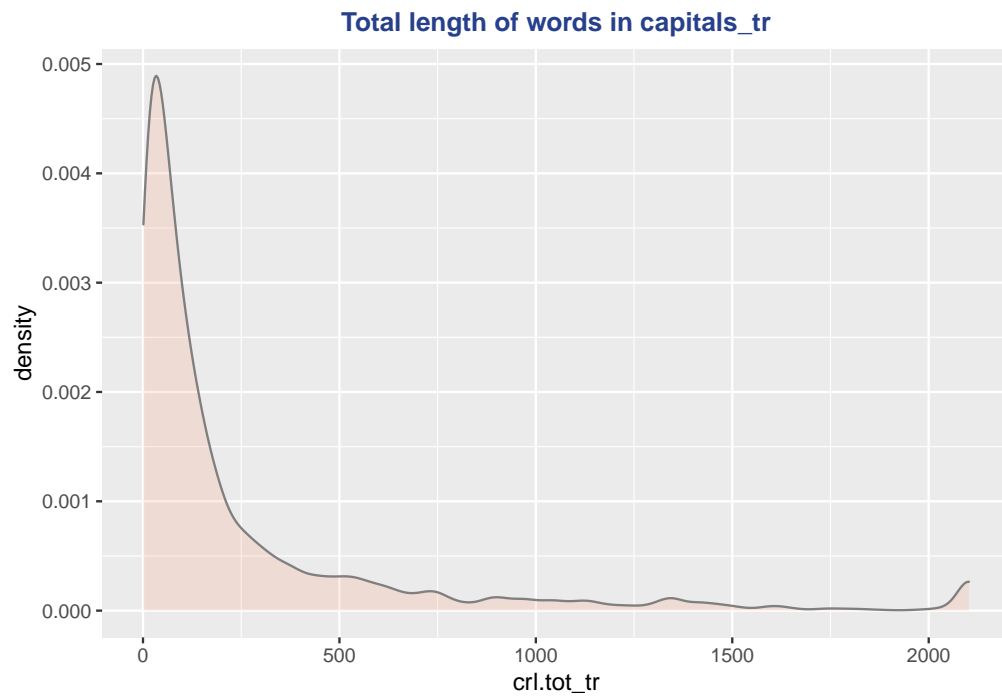
Missing values

There is no missing value in our dataset, either explicit nor implicit. ##### Outliers There are many outliers. Take the column "crl.tot" as an example, we can see from the following plot that, the plot has a really long tail and most of the values are between 0-500.



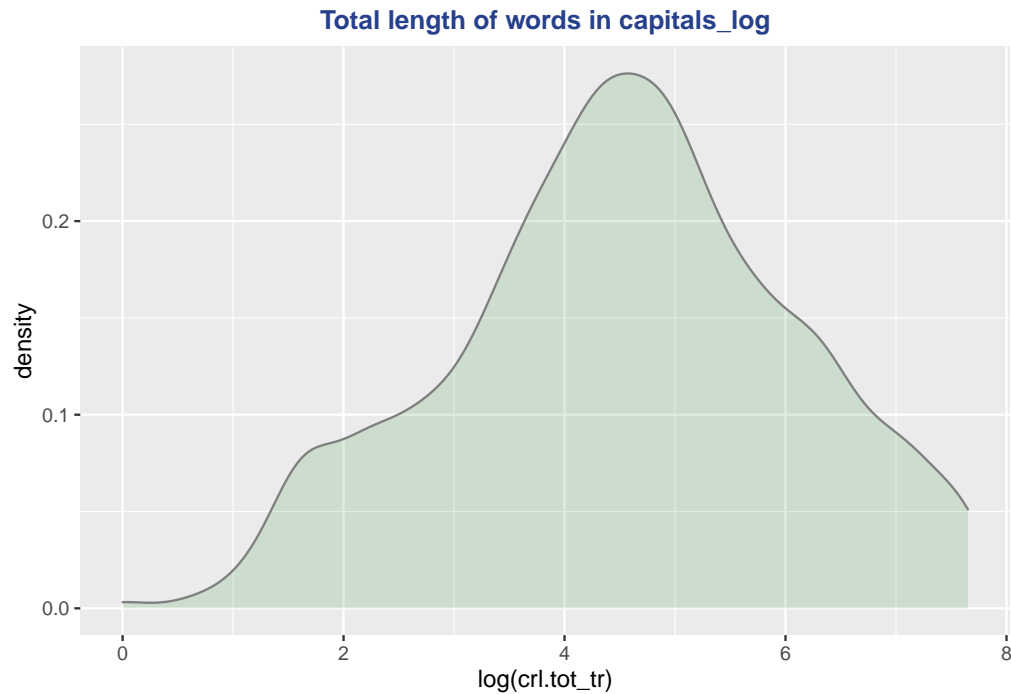
Treating outliers with Zscore

so we used Zscore and created new column “crl.tot_tr” so that we can better deal with the relationship between different predictors and the target variable. After getting rid of the outliers, we got the following plot:



Handling with skewed distribution

From the plot above, we know that outliers are removed and we also kept the intactness the original data. To better finish the modelling tasks, we changed the skeness and then we got the follwing plot:



Treating other continuous variables

We used the same methods for other variables and created for each variable a truncated variable and a log variable.

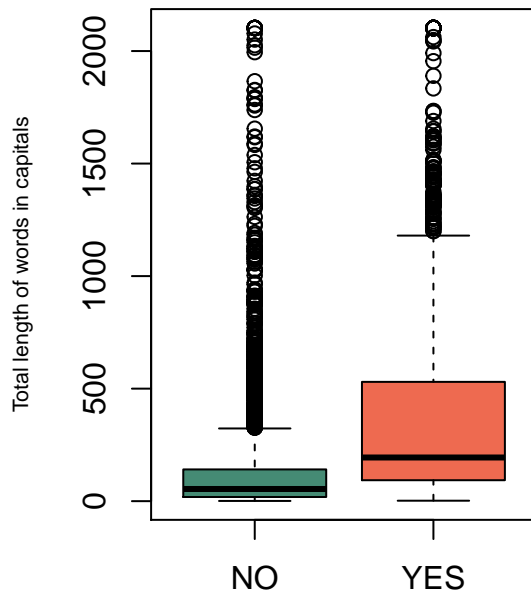
Treating categoriacal variable

There is only one categorical varaibale in our dataset which is yesno. There is no sparse classes in this variable, so we did not treat it.

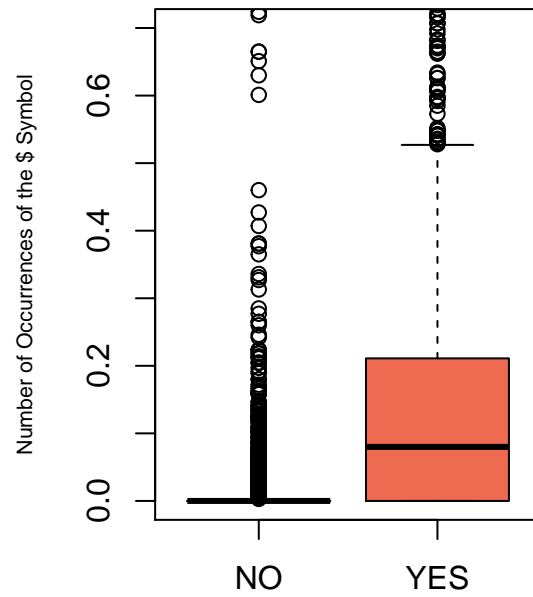
The most valuable insights from EDA

After plotting the relationships between each predicator and the target, it can be easily notice that, generally, the less symbols there are, the more likely that the email is not a spam email. For example, from the plot “The relationship between spam and crl”, we can see that, if the eamil is not a spam email, the total length of words in capitals is approximately in the range of 0-400, the average length is about 100. Compared to nonspam eamils, the range of the total length of capitals words in spam emails varies between 0-750. The avarage value is almost 250. It is the same for the reltionships between other predicators and the target.

The Relationship Between Spam and CRL

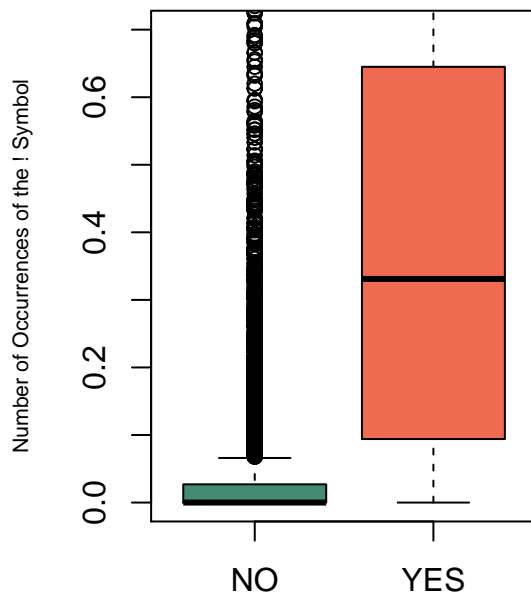


The Relationship Between Spam and dollar symbol



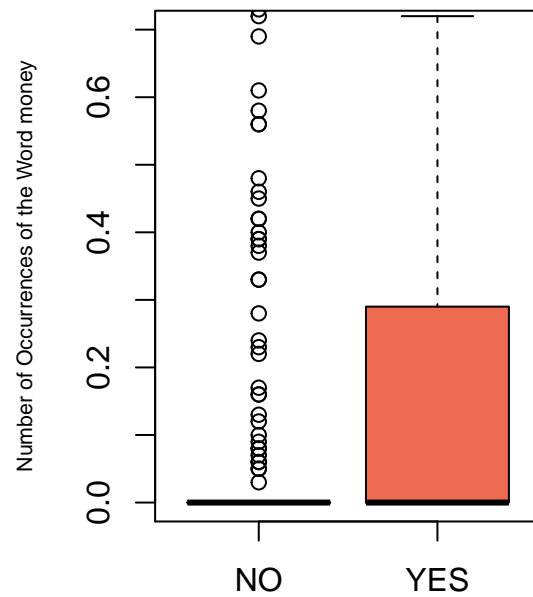
Are They Spam Email?

The Relationship Between Spam and the ! Symbol



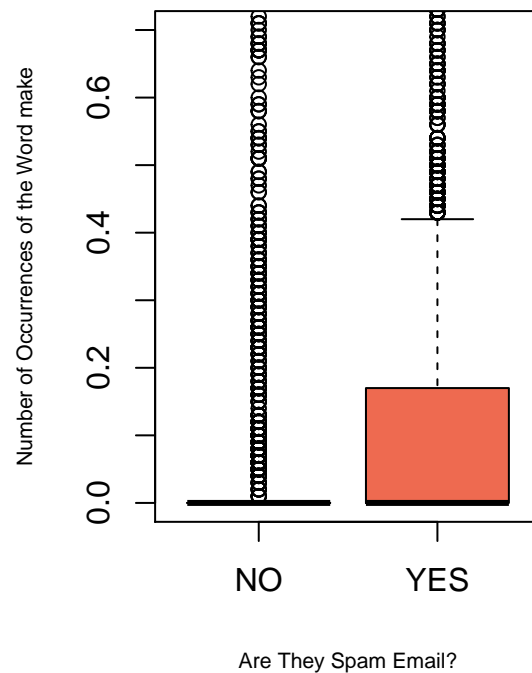
Are They Spam Email?

The Relationship Between Spam and the Word money



Are They Spam Email?

The Relationship Between Spam and Word make



Training Models

We trained four different Logistic Regression Models with one predictor set each. Also, we trained two Ridge Regression Models with predictor set 1 and 2 and two LASSO Regression Models with Predictor Set 3 and 4. Last but not least we created a Decision Tree with all variables as predictors.

5

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set.seed(777)
#set feature set
features.all_features <- c("crl.tot_ln" , "dollar_ln" ,
                          "bang_ln" , "money_ln" , "n000_ln" , "make_ln")

#set train and test data
X.train.all_features <- model.matrix( ~ . -1,
                                     data = spam.train[,features.all_features])
X.test.all_features <- model.matrix( ~ . -1,
                                    data = spam.test[, features.all_features])

#fit LASSO Regression Model
all_features.lasso <- glmnet(X.train.all_features,
                             y.train, alpha= 1,
                             family = "binomial")

#selecting the optimal lambda with the lowest misclassification error
all_features.lasso_cv <- cv.glmnet(X.train.all_features,
                                   y.train, alpha = 1,
                                   type.measure = "class",
                                   lambda = 10^seq(-5, 1, length.out = 100),
                                   family="binomial", nfolds = 10)

#make predictions
pred.all_features.lasso <- as.vector(predict(all_features.lasso,
                                             newx = X.test.all_features,
                                             type = "response",
                                             s = all_features.lasso_cv$lambda.min))

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As the best lambda with the lowest misclassification error we discovered 0.0027.

After it was trained on the training data the model reached an Accuracy of 0.867, a classification Error of 0.133 and a Brier Score of 0.332

Evaluation of prediction task

An Accuracy of 0.867 is good but not outstanding. We still have 186 wrong classifications and declare more emails as spam than the other way around. On the one hand, this can be good because more dangerous spam mails can be intercepted. On the other hand, important e-mails could also be mistakenly viewed as spam and then overlooked.