The Beginnings of a Search Engine

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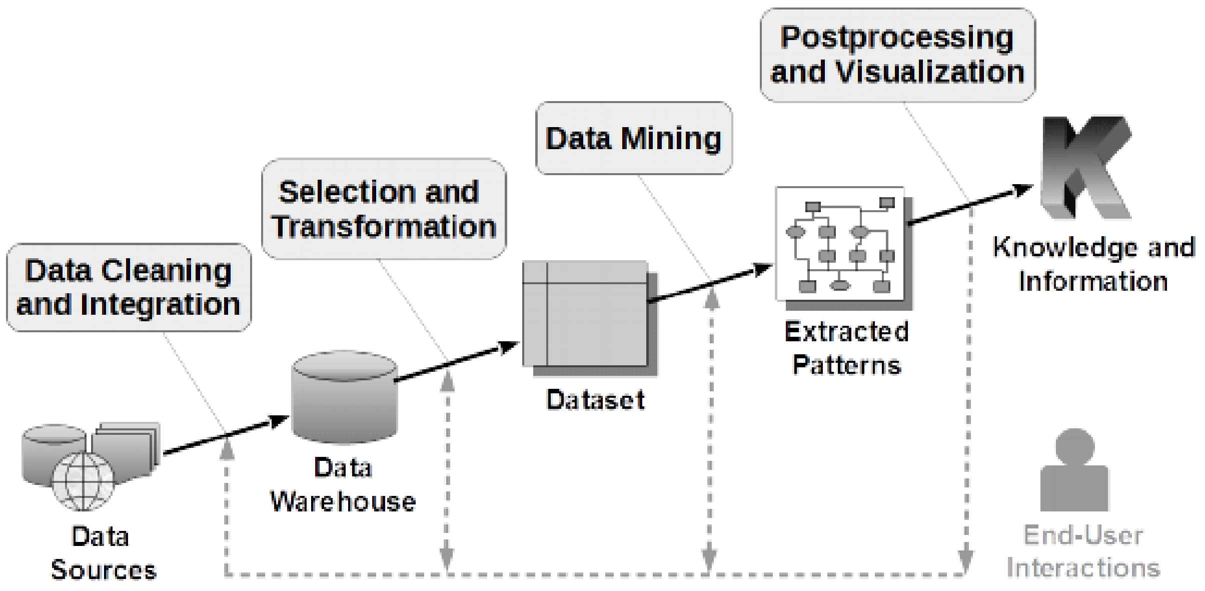
Abstract

The objective of this project is to determine the relevance of various url queries based on an array of 12 different predictors. The classifiers tried include Random Forests, Support Vector Machines, Decision Trees, and Naive Bayes. Based on our experimentation, Support Vector Machines had the lowest error and highest accuracy, therefore we decided to generate the text file of 0s and 1s using this classifier. We further tuned the SVM model to increase the accuracy and minimize the misclassification error of predictions. The diagram below shows the process that was followed for the duration of the project.


Postprocessing and Visualization
Data Mining
Selection and Transformation
Data Cleaning and Integration
Knowledge and Information
Extracted Patterns
Dataset
Data Warehouse
Data Sources
End-User Interactions

Selection

Before employing any methods onto the training data, we decided to determine which of the 12 variables were significant. Performing a logistic regression, there were 8 variables that were found to be significant due to their low p-values. This entire process is shown in the Figure 1. The three asterisks depict which variables were significant. From this, we were also able to understand that the variables query_id and url_id were both highly correlated to each other. Our future model making was done to keep these variables as independent from each other as possible.

Pre-Processing

The main pre-processing of this data was understanding the meaning of the values of the variables and the variables themselves. This was crucial in the next steps because further model making would be tougher without a thorough understanding of the data and its structure.

Transforming the Data

The main transforming of the data was done using k-fold cross validation. We were able to set up an environment, in which we ran 10-fold cross validation. This cross validation helped us verify that all of our classifiers were working properly and were trained enough to perform well on the test set.

Data Mining

The majority of the project took place in this stage. We tested the performance of 4 different methods and then decided which method to employ on the test data. The 4 methods we chose included Support Vector Machines, Random Forests, Decision Trees, and Naive Bayes. The results of the 4 classifiers are shown in the sub sections below.. As Support Vector Machines had the lowest error, we decided to move on with this method and further tune it to decrease the error and maximize the accuracy of our model.

1. Decision Trees

The decision tree model that we built had an accuracy of approximately 61.5%. This was a significantly low accuracy, therefore we had low hopes for the future tuning we would perform for decision trees. Yet, we still went ahead with our tuning in the two methods shown below.

a. Tuning: Omitting Variables

To tune the parameters in the decision tree model from before, we decided to omit variables one at a time. This helped us determine which variables had a significant impact to the outcome. The table below shows several trials of variables that were left out against the accuracy of the model.

Omitted Variable	Accuracy	Misclassification Error
None Omitted	61.05%	38.95%
query_id	61.6%	38.4%
url_id	61.34%	38.66%
query_length	62.02%	37.98%
is_homepage	60.93%	39.07%
sig1	61.3%	38.7%
sig2	61.88%	38.12%
sig3	62.1%	37.9%
sig4	62.01%	37.98%
sig5	61.14%	38.86
sig6	60.9%	39.1%
sig7	61.75%	38.25%
sig8	61.25%	38.75%

b. Tuning: Pruning

To further test the effectiveness of the decision tree model, we decided to use pruning to remove the unnecessary elements of the decision tree. This gave us much more accurate results and provided us an accuracy value of approximately 64%. Although this was not very close to the accuracy of Random Forests or SVM, it was worthwhile to understand how pruning works on the training dataset.

2. Naive Bayes

The results from the Naive Bayes model are shown in Figure 2. The overall accuracy came to be around 60%. This was a very low value compared to our various other models. We tried to implement an lplace smoothing metric on our Naive Bayes model, however, it did not result in a significant increase in accuracy. Due to this and the limited time, we decided not to go further with Naive Bayes and not further tune the model.

3. Random Forest

The main results from running Random Forests are shown in the figures at the end. The error, using a validation set for predictions, came to be around 34%. To further analyze the causes of the error and in hopes to increase accuracy, we tuned the random forest by removing the less important predictors (found from logistic regression). This tuning, however, did not have a significant impact on decreasing the error.

a. Tuning: Changing Number of Trees

The table below shows how accuracy changed based on the number of trees inputted to our Random Forest model. As you can see, there is a gradually increasing pattern, however, the accuracy is not significantly changing.

Number of Trees in Model	**Accuracy**	**Misclassification Error**
100	65.2%	34.8%
500	65.6%	34.4%
1000	66.1%	33.9%
2000	66.4%	33.6%

b. Tuning: Omitting Variables

The next form of tuning we tried for our Random Forest model was omitting one variable from the model and calculating the accuracy. The table below shows the results of the omitting trials. Although there is a higher accuracy in some models than others, SVM was an overall better model, due to its high accuracy rate. Therefore, we decided to move on to tuning our last classifier: Support Vector Machines.

Omitted Variable	**Accuracy**	**Misclassification Error**
None Omitted	66.1%	33.9%
query_id	65.92%	34.08%
url_id	65.93%	34.07%
query_length	65.1%	34.9%
is_homepage	65.86%	34.14%
sig1	65.65%	34.35%
sig2	64.03%	35.97%
sig3	64.54%	35.46%
sig4	65.12%	34.88%
sig5	65.34%	34.66%
sig6	64.87%	35.13%
sig7	64.73%	35.27%
sig8	65.34%	34.66%

4. Support Vector Machine

SVM turned out to have the highest accuracy, 67%, out of all of our models. Although it had an accuracy very close to that of Random Forest, we decided to move on with tuning our SVM to reduce the error. The two main ways we tuned our model were using different types of kernels and changing the cost for each model.

a. Tuning: Changing Kernels

We began our testing with a linear kernel model. This model constantly gave an accuracy of about 67%, therefore we decided to try out polynomial kernel SVM. This method did not increase the accuracy, but rather decreased by a few percentages. This immediate drop in accuracy alerted us to try radial based kernel, which increased our accuracy to the highest it ever was, 67.8%. From these positive results of the radial kernel SVM, we decided to move on by tuning this radial model through changing the cost of each model.

Kernel Type with Cost of 1	**Accuracy**	**Misclassification Error**
Linear	67.34%	32.66%
Polynomial	65.76%	34.24%
Radial	67.8%	32.2%

b. Tuning: Changing Cost

After determining that radial kernel SVM was the best model for our training data, we decided to tune the model even more by changing the cost. We started off by putting the cost very low and gradually increasing it. At the start, with the default cost of 1, the model had an accuracy of about 67.8%. We continued to increase the cost until we reached 263. At this 263 cost value, we achieved a 69% accuracy for our predictions. We continued to slowly add the cost, in an effort to decrease the error even more. However, the accuracy continually decreased. We reverted back to our 263 cost radial kernel model and created our text file of relevance predictions.

Cost Value with Radial Kernel	**Accuracy**	**Misclassification Error**
1	67.8%	32.2%
50	67.94%	32.06%
100	68.2%	31.8%
263	68.8%	31.2%
300	68.3%	31.7%

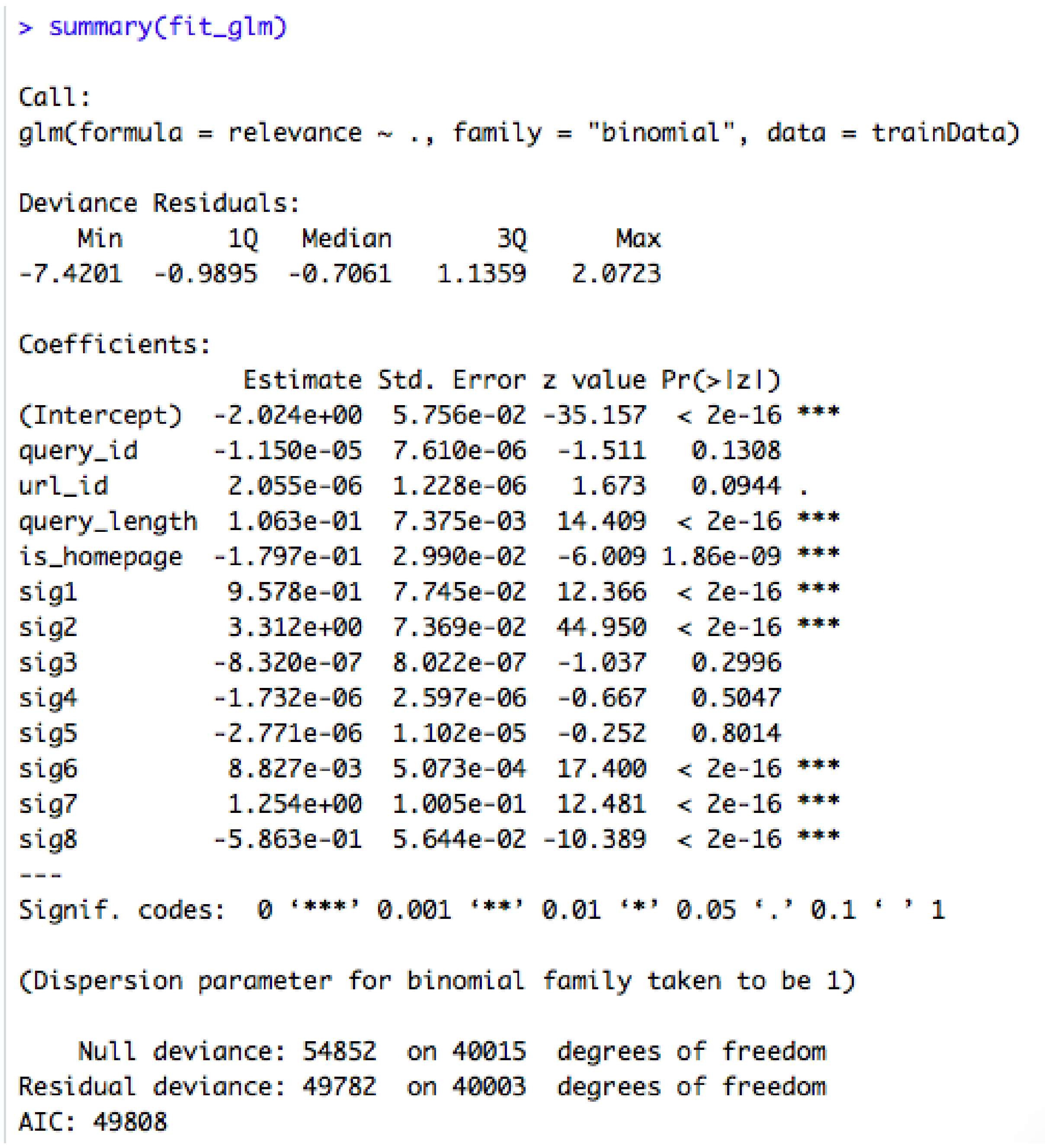
Evaluation

After creating the four models mentioned above, the following table was formed.

Model Type	**Max. Accuracy**	**Misclassification Error**
Decision Trees	64.05%	35.95%
Naive Bayes	60.14%	39.86%
Random Forest	66.4%	33.6%
SVM	68.8%	31.2%

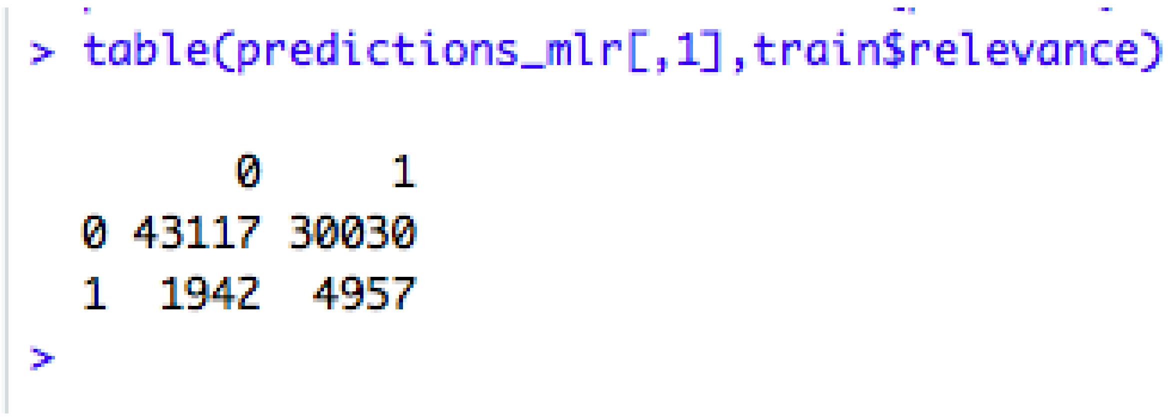
This table shows that SVM had the highest accuracy value and would be the most effective in predicting relevance correctly for the test data set. The tuning done to the original SVM model brought the accuracy to a maximum of around 68.8%.

Note: The next three pages display several images and graphs that are referred to in the body of this document.



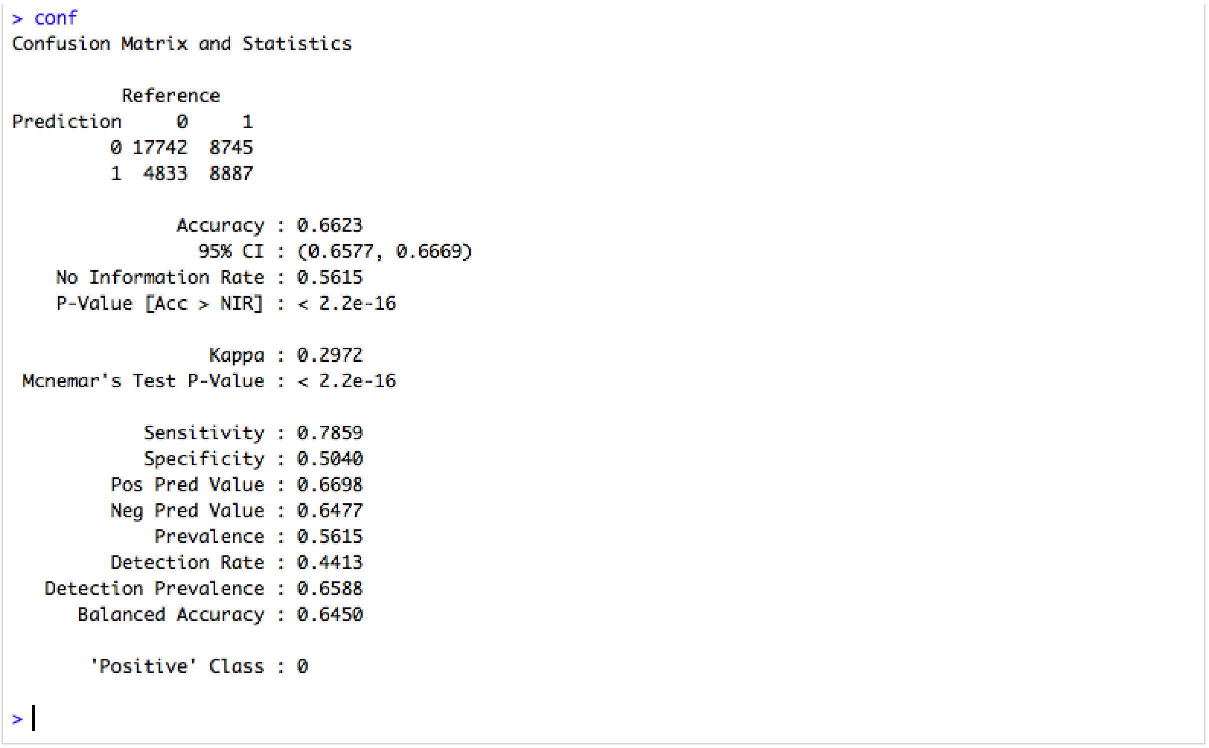
```
> summary(fit_glm)

Call:
glm(formula = relevance ~ ., family = "binomial", data = trainData)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-7.4201  -0.9895  -0.7061   1.1359   2.0723

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)  -2.024e+00  5.756e-02 -35.157  < 2e-16 ***
query_id     -1.150e-05  7.610e-06  -1.511   0.1308
url_id        2.055e-06  1.228e-06   1.673   0.0944 .
query_length  1.063e-01  7.375e-03  14.409  < 2e-16 ***
is_homepage  -1.797e-01  2.990e-02  -6.009 1.86e-09 ***
sig1          9.578e-01  7.745e-02  12.366  < 2e-16 ***
sig2          3.312e+00  7.369e-02  44.950  < 2e-16 ***
sig3         -8.320e-07  8.022e-07  -1.037   0.2996
sig4         -1.732e-06  2.597e-06  -0.667   0.5047
sig5         -2.771e-06  1.102e-05  -0.252   0.8014
sig6          8.827e-03  5.073e-04  17.400  < 2e-16 ***
sig7          1.254e+00  1.005e-01  12.481  < 2e-16 ***
sig8         -5.863e-01  5.644e-02 -10.389  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 54852  on 40015  degrees of freedom
Residual deviance: 49782  on 40003  degrees of freedom
AIC: 49808
```

Figure 1: This screen shot shows the logistic regression for the training data. This was used to figure out which of the 12 predictors were significant and will be most important in the classifiers. The three asterisks show which of the 12 different variables were most important, which is based on the p-value.



```
> table(predictions_mlr[,1],train$relevance)

        0     1
  0 43117 30030
  1  1942  4957
>
```

Figure 2: This is the resulting matrix of the Naive Bayes method. This can be used to calculate the accuracy values mentioned in the document above



```
> conf
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 17742  8745
         1  4833  8887

               Accuracy : 0.6623
                 95% CI : (0.6577, 0.6669)
    No Information Rate : 0.5615
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.2972
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.7859
            Specificity : 0.5040
         Pos Pred Value : 0.6698
         Neg Pred Value : 0.6477
             Prevalence : 0.5615
         Detection Rate : 0.4413
   Detection Prevalence : 0.6588
      Balanced Accuracy : 0.6450

       'Positive' Class : 0

> |
```

Figure 3: This image shows the confusion matrix and accuracy results for the Random Forest model. As you can see, the accuracy is approximately 66%, therefore it is not as good as the final SVM model.

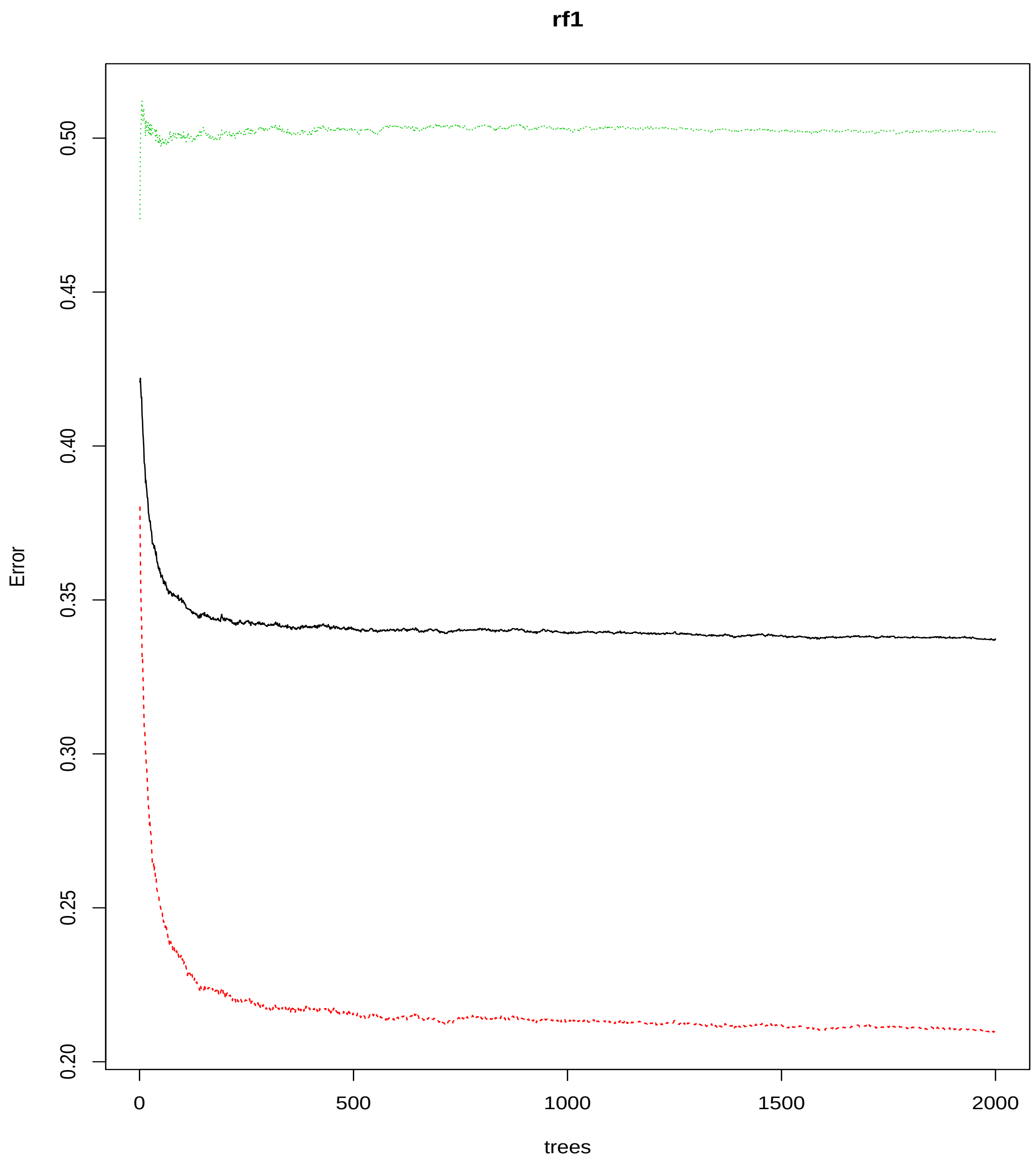


Figure 4: This graph displays the errors of the Random Forest model from Fiure 3. The middle black line is the most important line to us, as it is the misclassification error. As seen in the image, the misclassification error never seems to decrease much below 34%.