## STAT S4240 002, Homework 3

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## Problem 1: Naive Bayes Text Classification: Data Preparation

See  $hw03_q1.R$  for code.

## **Problem 2: Naive Bayes Function**

We first estimate the log priors based on the log of the proportion of training documents attributed to each author.

$$p(\text{author} = \text{author}) = \log \left( \frac{\# \text{ of training documents attributed to author}}{\text{total } \# \text{ of training documents}} \right)$$

Then, using (1) the log probabilities for the dictionary in a Hamilton-authored document and (2) the log probabilities for the dictionary in a Madison-authored document (as computed in **Problem 1**), we can input a new document-term-matrix and classify each document as belonging to one of the authors.

```
naive.bayes <- function(logp.hamilton.train, logp.madison.train,</pre>
                        log.prior.hamilton, log.prior.madison, dtm.test){
  # Performs naive bayes classification
  # Inputs: logp.hamilton.train : vector of log probabilities of words
  #
                                         occurring in the hamilton training data
  #
                                       vector of log probabilities of words
             logp.madison.train
  #
                                         occurring in the madison training data
             log.prior.hamilton
                                       the log prior of hamilton documents
             log.prior.madison
                                       the log prior of madison documents
             dtm.test
                                       a document-term-matrix to classify
  # Output: Classification labels for each document in dtm.test
  # calculate the log posterior probabilities
  log.post.hamilton <- log.prior.hamilton + (dtm.test %*% logp.hamilton.train)</pre>
  log.post.madison <- log.prior.madison + (dtm.test %*% logp.madison.train)</pre>
  # compare the log posterior probabilities and assign to the author
  # with highest probability
 prediction <- data.frame(logPostHam=log.post.hamilton,</pre>
                            logPostMad=log.post.madison)
 prediction$pred <- (log.post.hamilton >= log.post.madison)
  prediction$pred <- gsub(TRUE, "Hamilton", prediction$pred)</pre>
  prediction$pred <- gsub(FALSE, "Madison", prediction$pred)</pre>
  # return a vector of the predictions
 return(prediction$pred)
}
```

## Problem 3: question 3

Using the confusionMatrix function from the caret library

- Accuracy: 63% accurate (% of the test papers that are classified correctly)
- True Positive Rate: 100% (Hamilton classified as Hamilton divided by the total amount of testing Hamilton papers)
- True Negative Rate: 9% (Madison classified as Madison divided by the total amount of testing Madison papers)
- False Positive Rate: 91% (Madison classified as Hamilton divided by the total amount of testing Madison)
- False Negative Rate: 0% (Hamilton classified as Madison divided by the total amount of testing Hamilton)

```
> confusionMatrix(data=predictions$pred,
+
                 reference=predictions$trueValue,
                 dnn=c("Prediction", "True Value"),
                 positive="Hamilton")
Confusion Matrix and Statistics
         True Value
Prediction Hamilton Madison
 Hamilton 16
 Madison
               0
                       1
              Accuracy : 0.6296
                95% CI: (0.4237, 0.806)
   No Information Rate: 0.5926
   P-Value [Acc > NIR] : 0.427258
                 Kappa : 0.106
Mcnemar's Test P-Value: 0.004427
           Sensitivity: 1.00000
           Specificity: 0.09091
        Pos Pred Value: 0.61538
        Neg Pred Value : 1.00000
            Prevalence: 0.59259
        Detection Rate: 0.59259
  Detection Prevalence: 0.96296
     Balanced Accuracy: 0.54545
      'Positive' Class : Hamilton
```