

# Machine Learning Project

## *Classification of news articles*

Jakob Sahlström  
jasa5691@student.uu.se

Anders Lindström  
anli6945@student.uu.se

Jesper Dürebrandt  
jedu6357@student.uu.se

Uppsala University

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### Abstract

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## 1 Introduction

## 2 Theory

### 2.1 Naive Bayes classifier

Let  $c$  be the class and  $A = a_1, \dots, a_n$  be the attributes of a document. Then with Bayes Theorem

$$p(c|A) = \frac{p(A|c)p(c)}{p(A)}, \quad (1)$$

the attributes  $A$  is classified as class  $C$  if and only if

$$f_b(A) = \frac{p(c|A)}{p(\neg c|A)} \geq 1, \quad (2)$$

where  $f_b(A)$  is called a *Bayesian* classifier. Assuming all attributes are independent given the class,

$$p(A|c) = p(a_1, \dots, a_n|c) = \prod_{i=1}^n p(a_i|c)$$

the final classifier can be written as

$$f_{nb}(A) = \frac{p(c)}{p(\neg c)} \prod_{i=1}^n \frac{p(a_i|c)}{p(a_i|\neg c)} \quad (3)$$

where  $f_{nb}$  is called the *Naive Bayesian* (NB) classifier.

Two models that uses the Naive Bayes assumption are the *multi-variate Bernoulli* model and the *multinomial* model. The main difference is that in the Bernoulli model the attributes are binary, indicating if a word from a vocabulary has occurred at least once or not. In the multinomial model the frequency of words are taken into account.

### 2.2 Random Forest

Random Forest (RF) is based on building several considerably small decision trees. Consider having a feature vector that is of length  $N$ , then randomly select  $n \ll N$  of those features. Build the trees with some kind of algorithm (e.g. C4.5), where information gain is taken into consideration when splitting, and no pruning is done (i.e. expand the tree fully). Then repeat selecting  $n$  new variables from  $N$  until the wanted number of trees are built.

After all the trees are built, they can be used to let a new vector of data pass through all the trees and then letting each tree *vote* on what class the vector most probably should be a part

of.

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**Algorithm 1** Random Forest

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Let  $x = (x_1, x_2, \dots, x_N)$  be a set of features;  
**while** *not enough trees* **do**  
    Randomly pick with replacement a subset  
    containing  $n \ll N$  features;  
    Use training set to build a decision tree us-  
    ing a classification algorithm, e.g. C4.5, except  
    no pruning is done.  
**end while**

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### 2.3 Support Vector Machine Classifier

Support vector machine classifiers (SVM's) clas-  
sifies data belonging to two classes by finding the  
hyperplane with the widest margin that separates  
the classes. The data vectors that restrict the  
margin of the hyperplane are referred to as suport  
vectors. This results in a maximization problem,  
where the objective function describes the width  
of the margin. This is solved using quadratic pro-  
gramming. An advantage with this approach is  
that the maximization problem is convex, mean-  
ing that the maximum found is guaranteed to be  
the global maximum. This requires, however,  
that the classes are linearly separable.

## 3 Method

### 3.1 News Crawler

A crawler was written and used that extracted  
articles from BBC<sup>1</sup>. The crawler extracts which  
topic the article belongs to, which is written in the  
HTML-code of the page on BBC's articles. In to-  
tal, about --NUMBER-- articles where extracted  
under --NUMBER-- different topics. This will be  
used as training and test data for the classifiers.

### 3.2 Coding

Pythons has been chosen as programming lan-  
guage to extend our knowledge and experience  
of implementing different types of classifiers with  
different classify-packages and further understand  
how the data has to be prepared and presented  
to the classifiers.

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<sup>1</sup><http://www.bbc.com/>

### 3.3 Preparation of Data

To classify the articles as accurately and fast as  
possible, the data has to be prepared in such  
way that it contains as much information as  
possible in a format as dense as possible. To  
achieve this, the articles were parsed into words  
with white-space as separator, then removed of  
all characters not found in the English alphabet,  
though keeping the '-' character. After that,  
the words were stemmed so that similar words  
would be on the same form, and not be seen as  
two different words. (E.g. "argued", "argues",  
"arguing" reduce to "argu".) When they had  
been stemmed, all so called stop words were  
removed (such as "a", "the", etc.)

When the crawler was extracting articles,  
the crawler sometimes for various reasons failed  
to obtain the body text for some of the articles.  
The result was an empty field where all the body  
text would go. This was of course removed from  
the set of articles.

### 3.4 Vocabulary

To

### 3.5 Datatypes

There are many different ways to represent a fea-  
ture vector, and different classifiers might want it  
represented in different ways. We have chosen to  
investigate four different types of representations  
of the vocabulary. The different datatypes were

**Binary:**

Does article contain word or not.

**Count:**

How many times does article contain word.

**Normalized Count by article length:**

The Count array divided by the number of  
words in article (sum < 1).

**Normalized Count by sum of Count:**

The Count array divided by the sum of the  
Count array (sum = 1).

### 3.6 Classifiers

In the Scikit-learn package<sup>2</sup> there are plenty of  
different classifiers, amongst them the four we

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<sup>2</sup><http://scikit-learn.org/>

want to investigate. The four classifiers we will be investigating are

- Naïve Bayes: Bernoulli
- Naïve Bayes: Multinomial
- Support Vector machines (SVM)
- Random forest

## 4 Results

### 4.1 Naive Bayes Classifier

### 4.2 Support Vector Machine Classifier

## 5 Related work

### 5.1 Naive Bayes Classifier

Naive Bayes models are widely used because of it's simplicity and efficiency. A. McCallum and K. Nigam compares the two most common models, the multi-variate Bernoulli and the multinomial model, in the realm of document classification. They are explained in detailed both theoretically and empirically and in general the multinomial model outperforms the Bernoulli model [7].

### 5.2 Random Forest Classifier

Random Forest is a decision tree based classification model. It has been used to classify web documents by keywords, where it for five and seven topics performed better than e.g. Naive Bayes and MLP [2]. In I. Kopriska, J. Poon, J. Clark, J. Chan's paper, they use Random Forest for classifying e-mails. Random Forest was able to outperform other methods, such as DT, SVM and NB[3].

### 5.3 Support Vector Machine Classifier

Support vector machine classifiers performs well on data that is linearly separable and is guaranteed to find the optimal hyperplane that separates the data. They can however only separate data into two classes, but if combined they are able to perform multi-class classification. A simple approach is to use  $k$  SVMs to solve a  $k$ -class classification problem. The SVMs may also be combined in a more sophisticated fashion, so that less than  $k$  SVMs can be used. Both methods are investigated in [5].

## 6 Conclusions & Future work

## References

- [1] R. Berwick. An Idiots guide to Support vector machines, 2003.
- [2] Myungsook Klassen and Nikhila Paturi. Web document classification by keywords using random forests, 2010.
- [3] Irena Koprinska, Josiah Poon, James Clark, and Jason Chan. Learning to classify e-mail, 2006.
- [4] V. Tampakas M. Ikonomakis, S. Kotsiantis. Text Classification Using Machine Learning Techniques, 2005.
- [5] Eddy Mayoraz and Ethem Alpaydin. Support Vector Machines for Multi-class Classification, 1999.
- [6] Andrew McCallum and Kamal Nigam. A comparison of event models for Naive Bayes text classification, 1998.
- [7] Harry Zhang. The Optimality of Naive Bayes, 2004.