

# CSCI 447: Project 1

**George Engel**

GEOENGEL.Z@GMAIL.COM

*Department of Engineering  
Montana State University  
Bozeman, MT 59715, USA*

**Troy Oster**

TOSTER1011@GMAIL.COM

*Department of Engineering  
Montana State University  
Bozeman, MT 59715, USA*

**Dana Parker**

DANAHARMONPARKER@GMAIL.COM

*Department of Engineering  
Montana State University  
Bozeman, MT 59715, USA*

**Henry Soule**

HSOULE427@GMAIL.COM

*Department of Engineering  
Montana State University  
Bozeman, MT 59715, USA*

**Editor:** Engel et al.

## Abstract

A brief, one paragraph abstract summarizing the results of the experiments

**Keywords:** Keywords, Go, Here

## 1. Introduction

The naive Bayes classification model is a simple model for predicting data classification. In this assignment, we implemented this probabilistic model on multiple real-world datasets. We validated our implementation of the algorithm with 10-fold cross-validation and measured the performance of our implementation with two loss functions: 0-1 Loss, and Precision/Recall.

## 2. Problem Statement

Given a data set of which all the correct classifications are known, we can implement and execute a training algorithm on a subset of the data. Then, once trained, the algorithm will guess the classes of another subset of the data and measure the performance. For this assignment, we were provided with 5 real-world data sets. Our task was to implement a training algorithm and guess classifications for each of these 5 data sets and then utilize two different loss functions to measure the accuracy and performance of our predictions. We ran this algorithm on the original versions of each data set, and then introduced noise to each of the data sets by shuffling attribute values among 10% of the values, and ran the

algorithm of the five shuffled versions of the data.

Our hypotheses for each data set are as follows:

*Breast Cancer Wisconsin:* This data set is comprised of 9 quantitative variables, and each data example can be classified as either benign or malignant. We hypothesized that, given that there are only two possible classifications, that we will achieve no less than 75% accuracy (i.e. a 0-1 loss score of 0.75) on our unshuffled data.

*Glass:* This data set is comprised of 7 quantitative variables, and each data example can be classified as one of 7 possible glass types: building\_windows\_float\_processed, building\_windows\_non\_float\_processed, vehicle\_windows\_float\_processed, vehicle\_windows\_non\_float\_processed, containers, tableware, or headlamps. We hypothesize that we will achieve no less than 65% accuracy for this data set, given that there are 7 potential classes.

*Iris:* The iris data set is comprised of 4 quantitative variables, and each data example can be classified as one of three different flower types: iris-setosa, iris-versicolor, iris-virginica. We hypothesize accuracy of no less than 75%.

*Soybean:*

### 3. The Algorithm

Per the instructions of the assignment, we implemented the naive Bayes algorithm on the 5 provided data sets. Given some example  $x \in X$ , where  $X$  is our data set, naive Bayes predicts the correct class  $c$  of  $x$  by computing the probabilities of each possible classification for  $x$ . For class  $c$ , the probability is denoted as  $P(c|a_1, a_2, \dots, a_d)$  where  $a_k$  denotes one of  $d$  attribute values in  $x$ . To compute this probability for each class  $c$ , the probabilities of each attribute value are computed. For each attribute value  $a_k$ , we compute  $P(c) * \prod_{i=0}^d P(a_i|c)$ , where  $P(c)$  is the probability of an attribute being classified as class  $c$ . To predict the correct class for  $x$  we compute  $\underset{c \in C}{\operatorname{argmax}} P(c) * \prod_{i=0}^d P(a_i|c)$ .

### 4. Our Approach

To properly implement naive Bayes on the 5 data sets, we first needed to properly separate and classify each data set. Each data set needed to be separated by class, and then the count and probability of each attribute value for each class needed to be computed. Our approach for this was to create, for each dataset, an associative array, where each possible classifier was a key. For each key, the corresponding values were each their own associative arrays, the keys of which were all the extant attribute values among that class. The value of each key in these inner arrays was a set storing the count and conditional probability of each attribute value given the respective class.

We tested our algorithm's implementation using 10-fold cross-validation. This validation model separates each data set into 10 subsets, or "bins", of equal size. It then runs 10 iterations. During each iteration, one bin is designated as the test data, being the data we

will test our prediction algorithm on. The other 9 bins are designated as training data. It is on this training data subset that we will execute our learning algorithm, from which we will base our predictions. After first running the training algorithm on these 9 bins, we then predict the classifications of each example in the designated test data. For each iteration, a different bin is designated as test data, while the other 9 are designated as the training data.

To assess the performance of our class prediction algorithm, we implemented two loss functions: Precision/Recall, and 0-1 Loss. We ran both loss functions on each iteration of the 10-fold cross-validation process, and then took averages of the values returned during from each iteration and used these values to measure the performance of our prediction algorithm. 0-1 Loss simply computes the fraction of the data our algorithm correctly classified. For each correctly classified data example, a 0 is returned, and for every incorrectly classified value, a 1 is returned. Accuracy is then defined as the percentage of 0's returned [2].

The Precision/Recall loss function computes two values, known as precision and recall, to measure the performance of our class prediction algorithm. This loss function utilizes the amounts of true positive, false positive, and false negative classifications for each class. Precision and recall are computed as follows:

$$Precision = \frac{1}{|C|} \sum_{i=1}^{|C|} \frac{TP_i}{TP_i + FP_i}$$

$$Recall = \frac{1}{|C|} \sum_{i=1}^{|C|} \frac{TP_i}{TP_i + FN_i}$$

$TP_i$  denotes the number of true positive classifications for class  $i$ ,  $FP_i$  denotes the number of false positive classifications for class  $i$ , and  $FN_i$  denotes the number of false negative classifications for class  $i$ .  $C$  is the set of all possible classes. Precision can be interpreted as a measure of how accurate true positive classifications are, as it computes the fraction of all positive classifications for a class that were truly positive. Recall measures accuracy among the values for each class that should have been positive, as it computes the fraction of all values that truly belonged to a class that were classified as positive [1].

## 5. Results

### Acknowledgments

1. Davis, Jesse, and Mark Goadrich. "The Relationship between Precision-Recall and ROC Curves." Proceedings of the 23rd International Conference on Machine Learning - ICML 06, 2006, doi:10.1145/1143844.1143874.
2. Dietterich, Thomas G. "Machine Learning for Sequential Data: A Review." Lecture

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## Appendix A.

In this appendix we prove the following theorem from Section 6.2:

**Theorem** *Let  $u, v, w$  be discrete variables such that  $v, w$  do not co-occur with  $u$  (i.e.,  $u \neq 0 \Rightarrow v = w = 0$  in a given dataset  $\mathcal{D}$ ). Let  $N_{v0}, N_{w0}$  be the number of data points for which  $v = 0, w = 0$  respectively, and let  $I_{uv}, I_{uw}$  be the respective empirical mutual information values based on the sample  $\mathcal{D}$ . Then*

$$N_{v0} > N_{w0} \Rightarrow I_{uv} \leq I_{uw}$$

*with equality only if  $u$  is identically 0.* ■

**Proof.** We use the notation:

$$P_v(i) = \frac{N_v^i}{N}, \quad i \neq 0; \quad P_{v0} \equiv P_v(0) = 1 - \sum_{i \neq 0} P_v(i).$$

These values represent the (empirical) probabilities of  $v$  taking value  $i \neq 0$  and 0 respectively. Entropies will be denoted by  $H$ . We aim to show that  $\frac{\partial I_{uv}}{\partial P_{v0}} < 0 \dots$

*Remainder omitted in this sample. See <http://www.jmlr.org/papers/> for full paper.*