

# Determining the best classifier for predicting the value of a boolean field on a blood donor database

Ritabrata Maiti<sup>1</sup>

<sup>1</sup>Delhi Technological University

## Abstract

**Motivation:** Thanks to digitization, we often have access to large databases, consisting of various fields of information, ranging from numbers to texts and even boolean values. Such databases lend themselves especially well to machine learning, classification and big data analysis tasks. We are able to train classifiers, using already existing data and use them for predicting the values of a certain field, given that we have information regarding the other fields. Most specifically, in this study, we look at the Electronic Health Records (EHRs) that are compiled by hospitals. These EHRs are convenient means of accessing data of individual patients, but their processing as a whole still remains a task. However, EHRs that are composed of coherent, well-tabulated structures lend themselves quite well to the application to machine language, via the usage of classifiers. In this study, we look at a Blood Transfusion Service Center Data Set (Data taken from the Blood Transfusion Service Center in Hsin-Chu City in Taiwan). We used scikit-learn machine learning in python. From Support Vector Machines(SVM), we use Support Vector Classification(SVC), from the linear model we import Perceptron. We also used the K.neighborsclassifier and the decision tree classifiers. We segmented the database into the 2 parts. Using the first, we trained the classifiers and the next part was used to verify if the classifier prediction matched that of the actual values.

**Results:** The test program relies on the individual testing of the classifiers. It counts the number of predictions that match the actual value and displays these counts. Using the counts, we are able to decide the best classifier for the given blood donor database. Using the most accurate models, or a collection of these models, we will be able to determine the most accurate prediction for each patient. Here, we wish to determine whether a patient had donated blood in March 2017. This prediction is a boolean value(1 or 0), where 1 denotes that the patient had donated blood and 0 denotes otherwise.

**Contact:** [ritabratamaiti@hiretrex.com](mailto:ritabratamaiti@hiretrex.com)

## 1.Introduction

In the last 20 years, the storage capabilities of electronic media have increased exponentially. As a result, the volume of medical data stored in electronic media has increased exponentially. The various medical data available to us range from images and text to video and audio. These are one of the few data-types that are available and manipulated in medical centers. Often the required data is exploited and analyzed on an individual level. For example, a Magnetic Resonance Imaging(MRI) and a textual health record will be analyzed to establish the diagnosis or disease evolution of a patient.

Among all the different data types, only structured data can be readily used for training machine learning algorithms. This is because tabulated data lends itself especially well to the training of machine language classifiers. Via the classifiers, we are able to work on a dataset, and predict the values present in one field of the given set, provided we have information regarding the other fields of the data set. These machine learning algorithms function by sensing the patterns present in an existing dataset and using those patterns to predict values of missing fields.

However, the problem arises that most of the records in medical databases are unstructured free texts, such as patient health charts and electronic patient reports. These utilize natural languages, i.e languages easily understood and processed by humans but less so by machines. Examples of these include notes on a patients diagnosis, a prescription or even a notes regarding a tissue sample. While the free text can be made machine understandable using NLP algorithms, the most effective pattern reconstruction and predictions in medicine are made using structured databases and classifier algorithms.

The technical core of the program relies on the fact that different training algorithms have different success rates when trained with the same dataset. As a result, we will be able to determine which classifier works best with a given algorithm.

While a doctor's diagnosis remains as invaluable in medicine, with data science, disease diagnosis and prediction becomes far more reliable and efficient.

## 2. Methods

Classification can be thought of as two separate problems – binary classification and multiclass classification. In binary classification, a better-understood task, only two classes are involved, whereas multiclass classification involves assigning an object to one of several classes.

In binary classification, we group an object into one of two classes while in multiclass classification we group an object into one of many classes. Our specific problem requires us to decide whether a specific patient had donated blood on a previous date, and as a result, our classifier provides us with a boolean output of either 1 or 0, wherein 1 denotes that the patient had donated blood and 0 denotes otherwise.

Thus, we have to solve a binary classification problem. In order to find out the most efficient classifier, we should train each classifier by the same dataset. Then, we should predict the values 1 or 0, for a dataset of new patients, and determine whether the predictions match.

By finding out the number of matched predictions, we can calculate the percentage matches of each database and subsequently determine the most efficient classifier.

In machine learning and statistics, a classification is a problem of identifying to which of a set of categories (sub-populations) a new observation belongs, on the basis of a training set of data containing observations (or instances) whose category membership is known. An example would be assigning a given email into "spam" or "non-spam" classes or assigning a diagnosis to a given patient as described by observed characteristics of the patient (gender, blood pressure, presence or absence of certain symptoms, etc.). Classification is an example of pattern recognition.

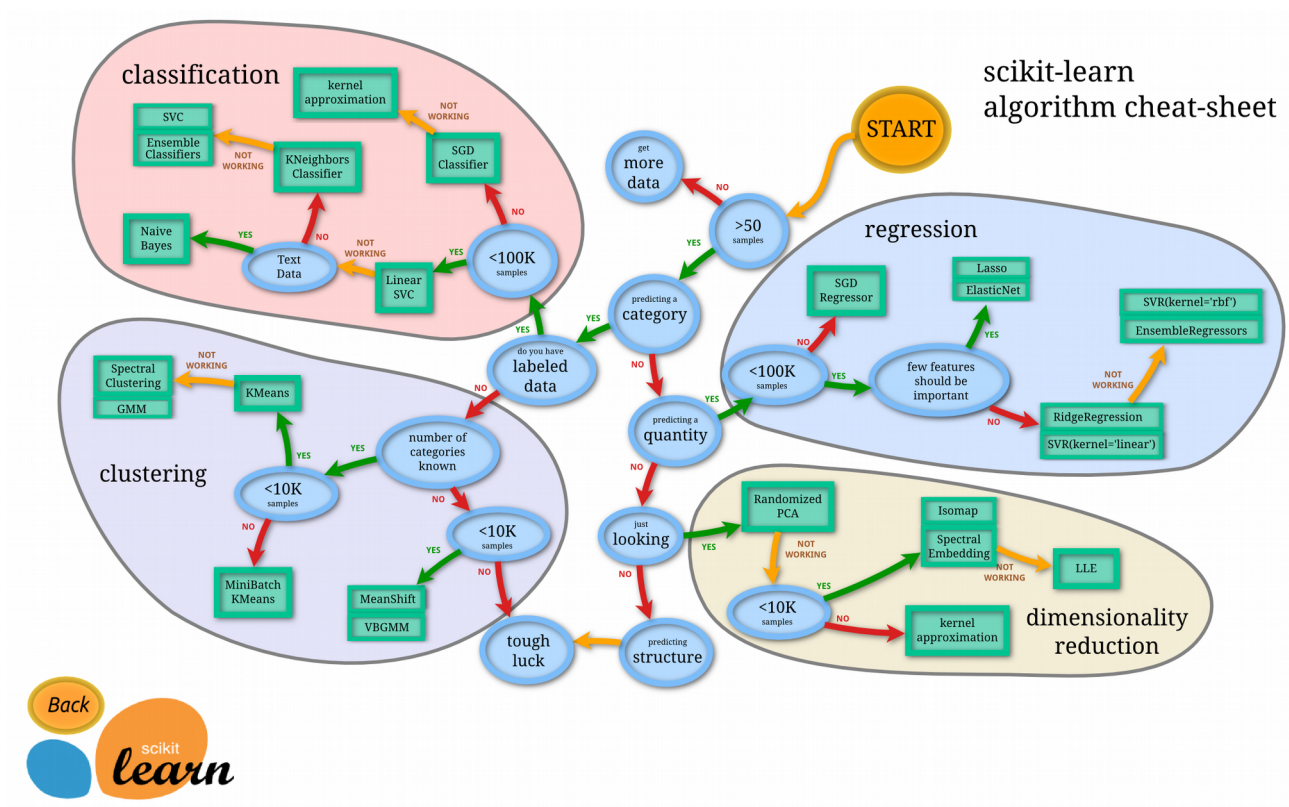
In the terminology of machine learning,[1] classification is considered an instance of supervised learning, i.e. learning where a training set of correctly identified observations is available. The corresponding unsupervised procedure is known as clustering and involves grouping data into categories based on some measure of inherent similarity or distance.

Often, the individual observations are analyzed into a set of quantifiable properties, known variously as explanatory variables or features. These properties may variously be categorical (e.g. "A", "B", "AB" or "O", for blood type), ordinal (e.g. "large", "medium" or "small"), integer-valued (e.g. the number of occurrences of a particular word in an email) or real-valued (e.g. a measurement of blood pressure). Other classifiers work by comparing observations to previous observations by means of a similarity or distance function.

An algorithm that implements classification, especially in a concrete implementation, is known as a classifier. The term "classifier" sometimes also refers to the mathematical function, implemented by a classification algorithm, that maps input data to a category.

Terminology across fields is quite varied. In statistics, where classification is often done with logistic regression or a similar procedure, the properties of observations are termed explanatory variables (or independent variables, regressors, etc.), and the categories to be predicted are known as outcomes, which are considered to be possible values of the dependent variable. In machine learning, the observations are often known as instances, the explanatory variables are termed features (grouped into a feature vector), and the possible categories to be predicted are classes. Other fields may use different terminology: e.g. in community ecology, the term "classification" normally refers to cluster analysis, i.e. a type of unsupervised learning, rather than the supervised learning described in this article.

## 2.1 Classifier Selection



Via usage of the classifier selection diagram given here:

We have subsequently followed the steps:

- >50 samples : Yes
- Predicting a category : Yes
- Labelled Data : Yes
- Therefore classification problem
- <100k samples : Yes

Thus we will be testing the following classifiers:

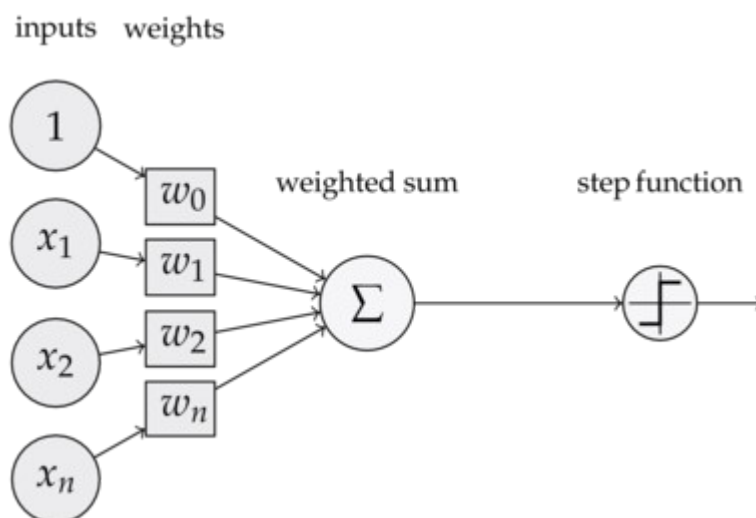
1. SVC
2. Perceptron
3. KNeighborsClassifier
4. Decision Tree Classifier

Using the above-selected classifiers, we run the test programs and determine the results. We observe that the decision tree classifier has a different value for its accuracy in each program run. However, it should also be noted that over a 100 program runs, the decision tree classifier consistently has the low accuracy score. Hence, we may confidently decide that the decision tree classifier is the least accurate. We now record the results and come to a conclusion.

### 3. Results

We observe that the perceptron classifier model consistently scores the highest, and hence we can comfortably say that perceptron is the best model for determining a patient's past decision (with respect to donating blood). After the perceptron model, the SVM model is the second most accurate, and this is followed by the KNN model. The decision tree classifier is the least accurate.

Thus, for such binary predictions using a patient database, usage of the perceptron model is desirable and recommended.



A perceptron model

In fact, perceptron models perform particularly well at binary predictions. Since a patient's decision is binary in nature, perceptron models work the best in this case.

#### 4. Acknowledgements

Source:

(Original Owner and Donor)

Prof. I-Cheng Yeh

Department of Information Management

Chung-Hua University,

Hsin Chu, Taiwan 30067, R.O.C.

e-mail:icyeh '@' chu.edu.tw

TEL:886-3-5186511

Date Donated: October 3, 2008

#### 5. References

1. Har-Peled, S., Roth, D., Zimak, D. (2003) "Constraint Classification for Multiclass Classification and Ranking." In: Becker, B., Thrun, S., Obermayer, K. (Eds) Advances in Neural Information Processing Systems 15: Proceedings of the 2002 Conference, MIT Press. ISBN 0-262-02550-7)
2. Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.
3. Yeh, I-Cheng, Yang, King-Jang, and Ting, Tao-Ming, "Knowledge discovery on RFM model using Bernoulli sequence, "Expert Systems with Applications, 2008
4. Rosenblatt, Frank. x. Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. Spartan Books, Washington DC, 1961
5. Rao, C.R. (1952) Advanced Statistical Methods in Multivariate Analysis, Wiley. (Section 9c)
6. Anderson, T.W. (1958) An Introduction to Multivariate Statistical Analysis, Wiley.
7. Binder, D.A. (1978) "Bayesian cluster analysis", Biometrika, 65, 31-38.
8. Binder, D.A. (1981) "Approximations to Bayesian clustering rules", Biometrika, 68, 275-285.
9. Har-Peled, S., Roth, D., Zimak, D. (2003) "Constraint Classification for Multiclass Classification and Ranking."