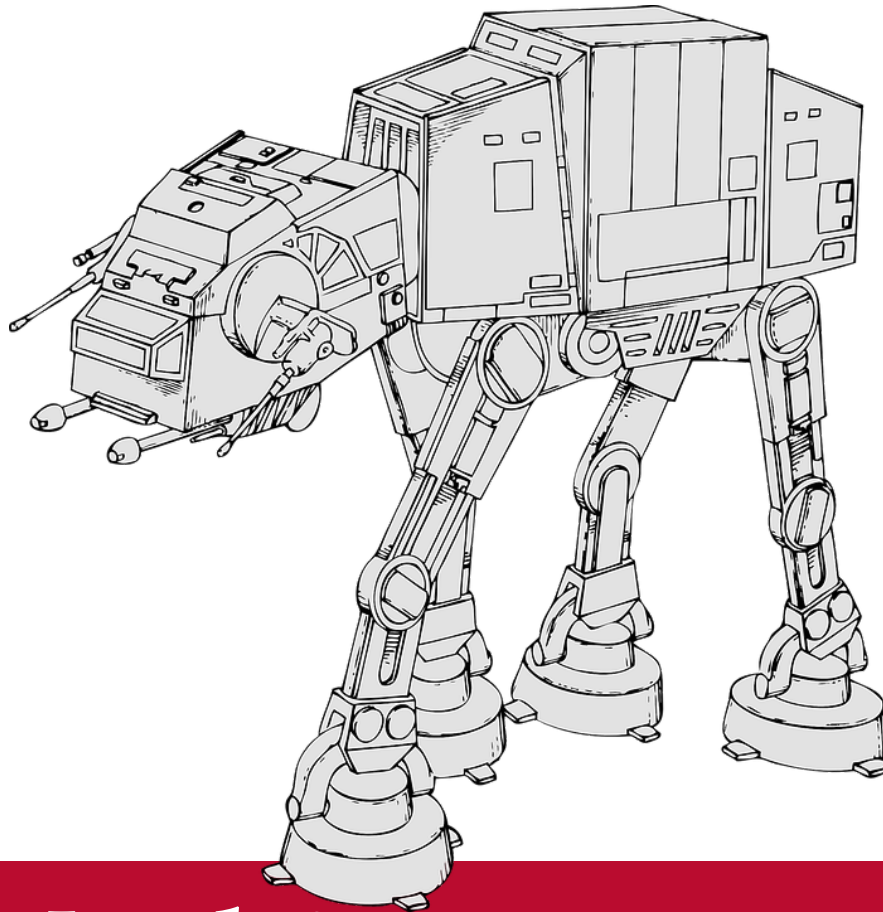


A Machine Learning Study Guide



Machine Learning Handbook

The Definitive Guide

ICS5110, class of 2018/9



**L-Università
ta' Malta**



Copyright © 2018 ICS5110 APPLIED MACHINE LEARNING class of 2018/9, University of Malta.

JEAN-PAUL EBEJER, DYLAN SEYCHELL, LARA MARIE DEMAJO, DANIEL FARRUGIA, KEITH MINTOFF, IVAN SALOMONE **ADD YOUR NAME TO THIS LIST**

Licensed under the Apache License, Version 2.0 (the “License”); you may not use this file except in compliance with the License. You may obtain a copy of the License at <http://www.apache.org/licenses/LICENSE-2.0>. Unless required by applicable law or agreed to in writing, software distributed under the License is distributed on an “AS IS” BASIS, WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied. See the License for the specific language governing permissions and limitations under the License.

First printing, December 2018

Contents

Introduction 5

Activation Functions 7

Confusion Matrix 11

Cross-Validation 17

Noise in datasets 21

Introduction

This book explains popular Machine Learning terms. We focus to explain each term comprehensively, through the use of examples and diagrams. The description of each term is written by a student sitting in for ICS5110 APPLIED MACHINE LEARNING¹ at the University of Malta (class 2018/2019). This study-unit is part of the MSc. in AI offered by the Department of Artificial Intelligence, Faculty of ICT.

¹ <https://www.um.edu.mt/courses/studyunit/ICS5110>

Activation Functions

Caterini (2018) defined artificial neural networks as “a model that would imitate the function of the human brain—a set of neurons joined together by a set of connections. Neurons, in this context, are composed of a weighted sum of their inputs followed by a nonlinear function, which is also known as an activation function.”

Activation functions are used in artificial neural networks to determine whether the output of the neuron should be considered further or ignored. If the activation function chooses to continue considering the output of a neuron, we say that the neuron has been activated. The output of the activation function is what is passed on to the subsequent layer in a multilayer neural network. To determine whether a neuron should be activated, the activation function takes the output of a neuron and transforms it into a value commonly bound to a specific range, typically from 0 to 1 or -1 to 1 depending on the which activation function is applied.

Step Function

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases} \quad (1)$$

$$\frac{d}{d(x)}f(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases} \quad (2)$$

The Heavside step function, visualised in figure 1 and defined by equation 1, is one of the simplest activation functions that can be used in a neural network. This function returns 0 if the input of a node is less than a predetermined threshold (typically 0), or otherwise it returns 1 if the output of the node is greater than or equal to the threshold. This activation function was first used in a machine learning context by Rosenblatt (1957) in his seminal work describing the perceptron, the precursor to the modern day neural network.

Nowadays, the step function is seldom used in practice as it cannot be used to classify more than one class. Furthermore, since the derivative of this function is 0, as defined by equation 2, gradient descent algorithms are not be able to progressively update the weights of a network that makes use of this function (Snyman, 2005).

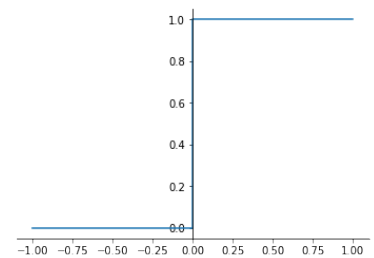


Figure 1: A graph of the step function.

Linear Functions

$$f(x) = ax + b \quad (3)$$

$$\frac{d}{d(x)}f(x) = a \quad (4)$$

A linear activation function, is any function in the format of equation 3, where $a, b \in \mathbb{R}$. This function seeks to solve some of the shortcomings of the step function. The output produced by a linear activation function is proportional to the input. This property means that linear activation functions can be used for multi-class problems. However, linear functions can only be utilised on problems that are linearly separable and can also run into problems with gradient descent algorithms, as the derivative of a linear function is a constant, as seen in equation 4. Additionally, since the output of the linear function is not bound to any range, it could be susceptible to a common problem when training deep neural networks called the exploding gradient problem, which can make learning unstable (Goodfellow et al., 2016).

Sigmoid Function

$$f(x) = \frac{1}{(1 + e^{-x})} \quad (5)$$

$$\frac{d}{d(x)}f(x) = f(x)(1 - f(x)) \quad (6)$$

The sigmoid function or logistic function, visualised in figure 2 and represented by equation 5, is one of the most commonly used activation functions in neural networks, because of its simplicity and desirable properties. The use of this function in neural networks was first introduced by Rumelhart et al. (1986), in one of the most important papers in the field of machine learning, which described the back-propagation algorithm and the introduction of hidden layers, giving rise to modern day neural networks. The values produced by the sigmoid function are bound between 0 and 1, both not inclusive, which help manage the exploding gradient problem. The derivative of this function, represented by equation 6, produces a very steep gradient for a relatively small range of values, typically in the range of -2 to 2 . This means that for most inputs that the function receives it will return values that are very close to either 0 or 1.

On the other hand, this last property makes the sigmoid function very susceptible to the vanishing gradient problem (Bengio et al., 1994). When observing the shape of the sigmoid function we see that towards the ends of the curve, the function becomes very unresponsive to changes in the input. In other words, the gradient of the function for large inputs becomes very close to 0. This can become very problematic for neural networks that are very deep in design, such as recurrent neural networks (RNNs). To address this



Figure 2: A graph of the sigmoid function.

problems in RNNs Long Short-Term Memory (LSTM) units were introduced as a variant of the traditional RNN architecture (Hochreiter and Schmidhuber, 1997).

Hyperbolic Tangent

$$f(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})} \quad (7)$$

$$\frac{d}{d(x)}f(x) = 1 - f(x)^2. \quad (8)$$

The hyperbolic tangent (tanh) function, visualised in figure 3 and represented by equation 7, is another common activation function that is sometimes used instead of sigmoid. The tanh function has the same characteristics of the sigmoid function mentioned above. In fact, when comparing figure 2 to figure 3 one can observe that the tanh function is simply a scaled and translated version of the sigmoid function. As a result of this scaling and translation, the tanh function has a steeper gradient towards the origin, and it returns values between -1 and 1. The derivative of the hyperbolic tangent function is represented by equation 8.

LeCun et al. (2012) analysed various factors that affect the performance of backpropagation, and suggested that tanh may be better suited than sigmoid as an activation function due to its symmetry about the origin, which is more likely to produce outputs that are on average close to zero, resulting in sparser activations. This means that not all nodes in the network need to be computed, leading to better performance. Glorot and Bengio (2010) studied in detail the effects of the sigmoid and tanh activation functions and noted how the sigmoid function in particular is not well suited for deep networks with random initialisation and go on to propose an alternative normalised initialisation scheme which produced better performance in their experiments.

Rectified Linear Unit

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases} \quad (9)$$

$$\frac{d}{d(x)}f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases} \quad (10)$$

The Rectified Linear Unit (ReLU) function, visualised in figure 4 and represented by equation 9, returns 0 if the input of the function is negative, otherwise it outputs the value of the input itself. This function is non-linear in nature even though at first glance it may seem similar to an identity function. The ReLU function is becoming one of the more commonly used activation functions due to its simplicity, performance, and suitability to networks with many layers. Another



Figure 3: A graph of the hyperbolic tangent (tanh) function.



Figure 4: A graph of the ReLU function.

benefit of the ReLU function is that it produces sparse activations unlike many other commonly used functions such as the sigmoid.

The ReLU function has been used in many neural network models to improve their performance. [Nair and Hinton \(2010\)](#) use ReLU to improve the performance of Restricted Boltzmann Machines in object recognition. [Krizhevsky et al. \(2012\)](#) introduced a breakthrough Convolutional Neural Network (CNN) architecture called AlexNet, which pioneered the use of the ReLU activation function together with dropout layers to minimise over fitting in CNNs.

Unfortunately, because the gradient of the function for inputs that are negative is 0, as seen in equation 10, the ReLU function can still be susceptible to the vanishing gradient problem. To manage this problem a variant of the ReLU function, called Leaky ReLU is sometimes used. Rather than simply returning 0 for negative inputs, the leaky ReLU returns a very small value such as $0.01x$. [Maas et al. \(2013\)](#) compared the performance of Sigmoid, ReLU and Leaky ReLU functions and found that while the the performance of both the ReLU and Leaky ReLU functions was better than the performance achieved with the sigmoid function, the performance of the two ReLU functions was nearly identical.

Confusion Matrix

A *Confusion Matrix* (CM), is a contingency table showing how well a model classifies categorical data. By convention (Sammur and Webb, 2017), the CM of an N-class model is an $N \times N$ matrix indexed by the true class in the row dimension and the predicted class in the column dimension (Table 1).

		Predicted Class	
		<i>spam</i>	\neg <i>spam</i>
True Class	<i>spam</i>	10	1
	\neg <i>spam</i>	2	100

Table 1: CM of a hypothetical binary classifier which predicts whether out-of-sample text objects are spam or not. In this example, 10 spam and 100 non-spam objects are classified correctly, whilst 1 spam and 2 non-spam objects are misclassified.

Even though CMs are commonly used to evaluate binary classifiers, they are not restricted to 2-class models (Martin and Jurafsky, 2018). A CM of a multi-class model would show the number of times the classes were predicted correctly and which classes were confused with each other (Table 2).

	<i>M&M's</i>	<i>Skittles</i>	<i>Smarties</i>
<i>M&M's</i>	34	3	8
<i>Skittles</i>	1	28	5
<i>Smarties</i>	2	4	22

Table 2: CM of a hypothetical sweets classifier. The main diagonal of the CM shows the number of correct predictions, whilst the remaining elements indicate how many sweets were misclassified.

The CM of the model $h : X \mapsto C$ over the concept $c : X \mapsto C$ using dataset $S \subset X$ is formally defined as a matrix Ξ such that $\Xi_{c,S}(h)[d_1, d_2] = |S_{h=d_1, c=d_2}|$ (Cichosz, 2014). The CM is constructed by incrementing the element corresponding to the true class *vis-a-vis* the predicted class for each object in the dataset (Algorithm 1).

$\Xi \leftarrow 0$
for $x \in S$ do
$d_1 \leftarrow c(x)$
$d_2 \leftarrow h(x)$
$\Xi_{d_1, d_2} \leftarrow \Xi_{d_1, d_2} + 1$

Algorithm 1: The CM is initialised to the zero matrix, and populated by iterating over all the objects x with corresponding true class d_1 and predicted class d_2 and incrementing the element (d_1, d_2) by 1 for each matching outcome.

In binary classification, the CM consists of 2 specially designated classes called the *positive* class and the *negative* class (Saito and Rehmsmeier, 2015). As indicated in Table 3, positive outcomes from the true class which are classified correctly are called *True Positives* (TP), whilst misclassifications are called *False Negatives* (FN). On the

other hand, negative true class outcomes which are classified correctly are called *True Negatives* (TN), and misclassifications are called *False Positives* (FP). In natural sciences, FP are called *Type I Errors* and FN are known as *Type II Errors* (Fielding and Bell, 1997).

	+ve	-ve
+ve	TP	FN
-ve	FP	TN

Table 3: CMs of binary classifiers have positive (+ve) and negative (-ve) classes, and elements called *True Positives* (TP), *False Positives* (FP), *True Negatives* (TN) and *False Negatives* (FN).

The information presented in the CM can be used to evaluate the performance of different binary classifiers (Lu et al., 2004). A number of statistics (Equations 11-17) derived from the CM have been proposed in the literature (Deng et al., 2016) to gain a better understanding of what are the strengths and weaknesses of different classifiers. Caution should be exercised when interpreting metrics (Jeni et al., 2013), since the CM could be misleading if the data is imbalanced and an important subrange of the domain is underrepresented (Raeder et al., 2012). For instance, an albino zebra classifier which always returns negative will achieve high accuracy since albinism is a rare disorder.

These metrics are important in situations in which a particular type of misclassification, i.e. FP or FN, could have worse consequences than the other (Hassanien and Oliva, 2017). For example, FP are more tolerable than FN in classifiers which predict whether a patient has a disease. Both outcomes are undesirable, but in medical applications it is better to err on the side of caution since FN could be fatal.

Accuracy (ACC) is the proportion of correct predictions (Equation 11). It is a class-insensitive metric because it can give a high rating to a model which classifies majority class objects correctly but misclassifies interesting minority class objects (Branco et al., 2016). The other metrics should be preferred since they are more class-sensitive and give better indicators when the dataset is imbalanced.

$$ACC = \frac{|TP \cup TN|}{|TP \cup FP \cup TN \cup FN|} \quad (11)$$

Negative Predictive Value (NPV) is the ratio of the correct negative predictions from the total negative predictions (Equation 12).

$$NPV = \frac{|TN|}{|TN \cup FN|} \quad (12)$$

True Negative Rate (TNR), or *Specificity*, is the ratio of the correct negative predictions from the total true negatives (Equation 13).

$$TNR = \frac{|TN|}{|TN \cup FP|} \quad (13)$$

True Positive Rate (TPR), also called *Sensitivity* or *Recall*, is the ratio of the correct positive predictions from the total true positives (Equation 14).

$$TPR = \frac{|TP|}{|TP \cup FN|} \quad (14)$$

Sensitivity and Specificity can be combined into a single metric (Equation 15). These metrics are often used in domains in which minority classes are important (Kuhn and Johnson, 2013). For example, the Sensitivity of a medical classifier (El-Dahshan et al., 2010) measures how many patients with the condition tested positive, and Specificity measures how many did not have the condition and tested negative.

$$\text{Sensitivity} \times \text{Specificity} = \frac{|TP| \times |TN|}{|TP \cup FN| \times |TN \cup FP|} \quad (15)$$

Positive Predictive Value (PPV), or *Precision*, is the ratio of the correct positive predictions from the total positive predictions (Equation 16). The difference between accuracy and precision is depicted in Figure 5.

$$\text{PPV} = \frac{|TP|}{|TP \cup FP|} \quad (16)$$

Precision and Recall are borrowed from the discipline of *Information Extraction* (Sokolova and Lapalme, 2009). A composite metric called *F-score*, *F1-score*, or *F-measure* (Equation 17) can be derived by finding their harmonic mean (Kelleher et al., 2015).

$$\text{F-score} = 2 \times \frac{\text{PPV} \times \text{TPR}}{\text{PPV} + \text{TPR}} \quad (17)$$

The complements of ACC, NPV, TNR, TPR and PPV are called, respectively, *Error Rate*, *False Omission Rate*, *false positive rate*, *false negative rate* and *False Discovery Rate*.

The metrics can be adapted for evaluating multi-class models by decomposing an N-class CM into 2-class CMs, and evaluating them individually (Stager et al., 2006). The literature describes two methods for decomposing this kind of CM. In the *1-vs-1* approach, 2-class CMs are constructed for each pairwise class as shown in Table 4.

+ve	-ve
M&M's	{Skittles, Smarties}
Skittles	{M&M's, Smarties}
Smarties	{M&M's, Skittles}

In the *1-vs-rest* approach, 2-class CMs are constructed for each class and the remaining classes combined together as shown in Table 5.

+ve	-ve
M&M's	Skittles \cup Smarties
Skittles	M&M's \cup Smarties
Smarties	Skittles \cup M&M's

Using all metrics could be counterproductive due to information redundancy, but none of the metrics is enough on its own (Ma and Cukic, 2007). For instance, Recall is class-sensitive but it would give a perfect score to an inept model which simply returns the positive



Figure 5: Accuracy vs Precision.

Table 4: 2-class CMs derived from the classes in Table 2. The +ve classes are paired separately with each -ve class.

Table 5: 2-class CMs derived through decomposition of the 3-class CM from Table 2 using the 1-vs-rest approach.

class. Thus, the best approach is to evaluate with complementary pairs (Gu et al., 2009) such as Sensitivity *vs* Specificity, or Precision *vs* Recall; or a combined measure such as the F-score.

Taking into account the above, CMs are suitable for visualising, evaluating, and comparing the performance of binary or multi-class classifiers. They should be used in conjunction with metrics such as the F-measure to avoid bias, especially if the dataset is unbalanced. For further details on the theoretical aspects of CMs and for practical examples in R refer to (Cichosz, 2014); for examples in Python refer to (Müller et al., 2016).

The following example is motivated by the samples in the *Scikit-Learn* documentation and the work of (Géron, 2017). The models in Figure 6 were trained on the *wines* dataset included with Scikit-Learn.

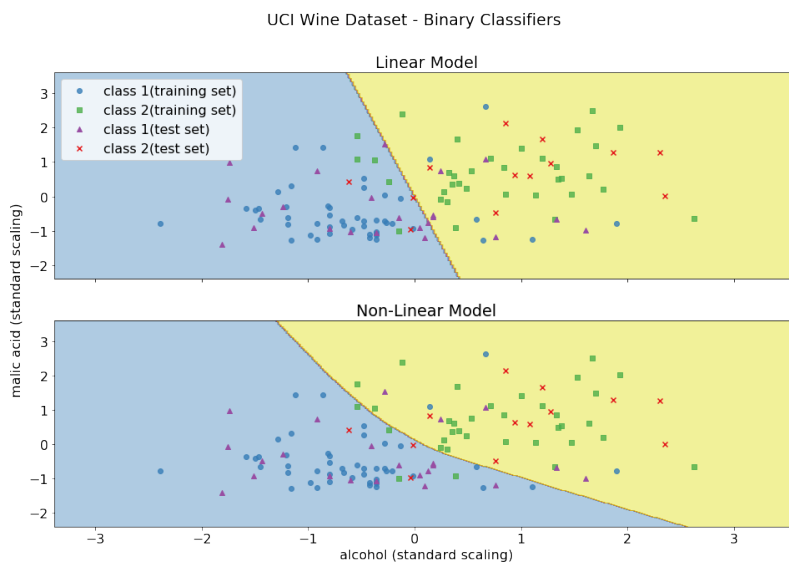


Figure 6: Decision boundary learned by a linear and non-linear binary classifier.

	Linear	Non-Linear
Accuracy	0.72	0.78
Specificity	0.77	0.77
Sensitivity	0.70	0.78
Precision	0.84	0.86
F-score	0.76	0.82

Table 6: Statistics derived from the CMs in Figure 7.

As it can be intuitively deduced from Figure 6, the decision boundary of the non-linear model is a better fit than the linear model. The CMs in Figure 7 also show that non-linear model performs better with a higher TP, and consequently lower TN. The biggest advantage of the non-linear model is the higher Sensitivity resulting in a better F-score.

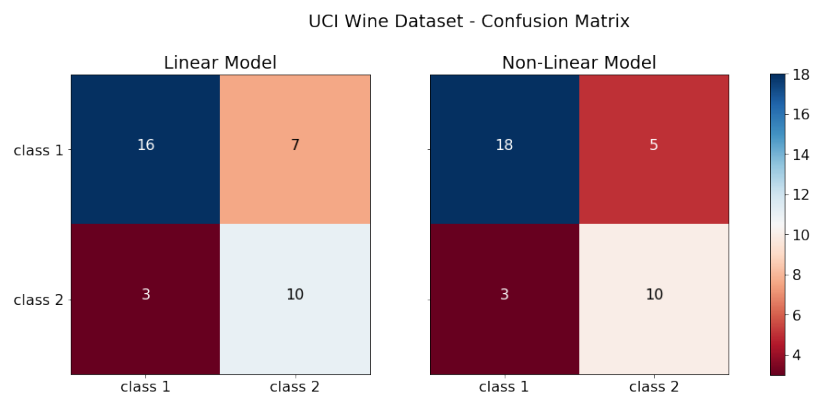


Figure 7: The linear classifier has 16 TP, 10 TN, 7 FN and 3 FP, whilst the non-linear classifier has 18 TP, 10 TN, 5 FN and 3 FP.

Cross-Validation

Cross-validation (CV) is an estimation method used on supervised learning algorithms to assess their ability to predict the output of unseen data (Varma and Simon, 2006; Kohavi, 1995). Supervised learning algorithms are computational tasks like classification or regression, that learn an input-output function based on a set of samples. Such samples are also known as the labeled training data where each example consists of an input vector and its correct output value. After the training phase, a supervised learning algorithm should be able to use the inferred function in order to map new input unseen instances, known as testing data, to their correct output values (Caruana and Niculescu-Mizil, 2006). When the algorithm incorporates supervised feature selection, cross-validation should always be done external to the selection (feature-selection performed within every CV iteration) so as to ensure the test data remains unseen, reducing bias (Ambroise and McLachlan, 2002; Hastie et al., 2001). Therefore, cross-validation, also known as out-of-sample testing, tests the function's ability to generalize to unseen situations (Varma and Simon, 2006; Kohavi, 1995).

Cross-validation has two types of approaches, being i) the exhaustive cross validation approach which divides all the original samples in every possible way, forming training and test sets to train and test the model, and ii) the non-exhaustive cross validation approach which does not consider all the possible ways of splitting the original samples (Arlot et al., 2010).

The above mentioned approaches are further divided into different cross-validation methods, as explained below.

Exhaustive cross-validation

Leave-p-out (LpO)

This method takes p samples from the data set as the test set and keeps the remaining as the training set, as shown in Fig. 9a. This is repeated for every combination of test and training set formed from the original data set and the average error is obtained. Therefore, this method trains and tests the algorithm $\binom{n}{p}$ times when the number of samples in the original data set is n , becoming inapplicable when $p > 1$ (Arlot et al., 2010).

Leave-one-out (LOO)

This method is a specific case of the LpO method having $p = 1$. It requires less computation efforts than LpO since the process is only repeated $n_{choose1} = n$ times, however might still be inapplicable for large values of n (Arlot et al., 2010).

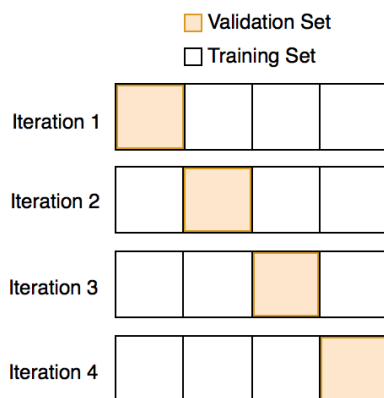
Non-exhaustive cross-validation

Holdout method

This method randomly splits the original data set into two sets being the training set and the test set. Usually, the test set is smaller than the training set so that the algorithm has more data to train on. This method involves a single run and so must be used carefully to avoid misleading results. It is therefore sometimes not considered a CV method (Kohavi, 1995).

k -fold

This method randomly splits the original data set into k equally sized subsets, as shown in Fig. 10. The function is then trained and validated k times, each time taking a different subset as the test data and the remaining $(k - 1)$ subsets as the training data, using each of the k subsets as the test set once. The k results are averaged to produce a single estimation. Stratified k -fold cross validation is a refinement of the k -fold method, which splits the original samples into equally sized and distributed subsets, having the same proportions of the different target labels (Kohavi, 1995).



Repeated random sub-sampling

This method is also known as the Monte Carlo CV. It splits the data set randomly with replacement into training and test subsets using some predefined split percentage, for every run. Therefore, this generates new training and test data for each run but the test data

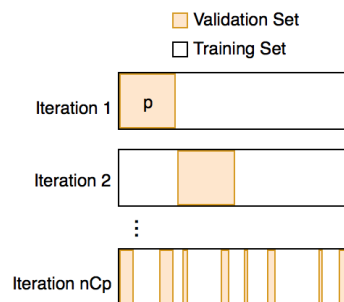


Figure 8: Leave-p-Out Exhaustive Cross Validation

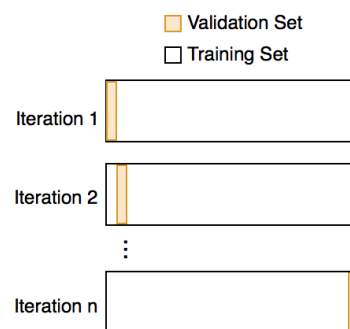


Figure 9: Leave-One-Out Exhaustive Cross Validation

Figure 10: k -Fold Cross Validation where $k=4$

of the different runs might contain repeated samples, unlike that of k -fold (Xu and Liang, 2001).

All of the above cross-validation methods are used to check whether the model has been overfitted or underfitted and hence estimating the model's ability of fitting to independent data. Such ability is measured using quantitative metrics appropriate for the model and data (Kohavi, 1995; Arlot et al., 2010). In the case of classification problems, the misclassification error rate is usually used whilst for regression problems, the mean squared error (MSE) is usually used. MSE is represented by Eq. 18, where n is the total number of test samples, Y_i is the true value of the i^{th} instance and \hat{Y}_i is the predicted value of the i^{th} instance.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (18)$$

Underfitting is when the model has a low degree (e.g. $y = x$, where the degree is 1) and so is not flexible enough to fit the data making the model have a low variance and high bias (Baumann, 2003), as seen in Fig. 12a. Variance is the model's dependence on the training data and bias is model's assumption about the shape of the data (Arlot et al., 2010). On the other hand, as seen in Fig. 12b, overfitting is when the model has a too high degree (e.g. $y = x^{30}$, where the degree is 30) causing it to exactly fit the data as well as the noise and so lacks the ability to generalize (Baumann, 2003), making the model have a high variance. Cross-validation helps reduce this bias and variance since it uses most of the data for both fitting and testing and so helps the model learn the actual relationship within the data. This makes cross-validation a good technique for models to acquire a good bias-variance tradeoff (Arlot et al., 2010).

As stated in (Kohavi, 1995), the LOO method gives a 0% accuracy on the test set when the number of target labels are equal to the number of instances in the dataset. It is shown that the k -fold CV method gives much better results, due to its lower variance, especially when $k = 10, 20$. Furthermore, R. Kohavi et al. state that the best accuracy is achieved when using the stratified cross-validation method, since this has the least bias.

Therefore, let's take an example using the stratified k -fold cross-validation method with $k = 10$. Let's say that we are trying to solve age group classification, using eight non-overlapping age groups being 0-5, 6-10, 11-20, 21-30, 31-40, 41-50, 51-60, and 61+. We are using the FG-NET labelled data set, which contains around 1000 images of individuals aged between 0 and 69. Before we can start training our model (e.g. CNN), we must divide our data set into training and test subsets and this is where cross validation comes in. Therefore, we start by taking the 1000 images of our data set and splitting them according to their target class. Let us assume we have an equal amount of 125 (1000/8) images per class². As depicted in Fig. 13, we can now start forming our 10 folds by taking 10% of each age-group bucket, randomly without replacement. Hence, we will

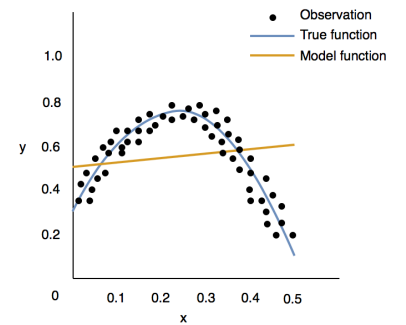


Figure 11: Model Underfitting

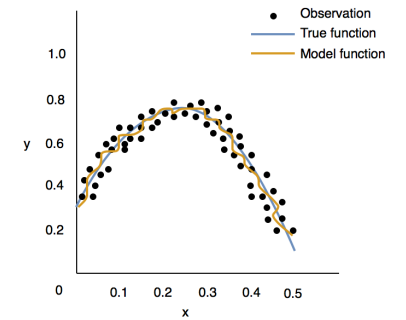


Figure 12: Model Overfitting

² Down-sampling or up-sampling are common techniques used when there is an unequal amount of samples for the different classes.

end up with 10 subsets of 100 images that are equally distributed along all age-groups. With these subsets, we can estimate our model's accuracy with a lower bias-variance tradeoff. Since we are using 10-fold CV, we will train and test our model 10 times. For the first iteration, we shall use subset 1 as the validation set and subsets 2 to 10 as the training set, for the second iteration we use subset 2 as the test set and subsets 1 plus 3 to 10 as our training set, and so on (as shown in Fig. 10). For each iteration we use the misclassification error rate to obtain an accuracy value and we finally average the 10 accuracy rates to obtain the global accuracy of our model when solving age group classification, given the FG-NET data set. Hence, we have now estimated the prediction error of the model and have an idea of how well our model performs in solving such a problem. It is important to note that cross-validation is *just* an estimation method and when using our model in real-life applications we do not apply CV but rather train our model with all the data we have.

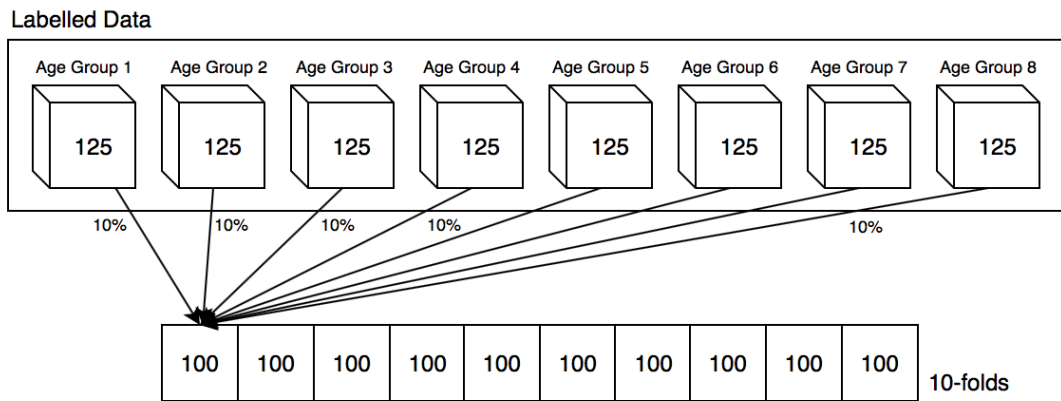


Figure 13: Stratified 10-fold cross-validation on 1000 labelled images of 8 different classes

As concluded by [Varma and Simon \(2006\)](#), cross-validation is well implemented when everything is taken place within every CV iteration (including preprocessing, feature-selection, learning new algorithm parameter values, etc.), and the least bias can be achieved when using nested CV methods.

Noise in datasets

As defined by Hickey (1996), noise is anything that distorts the relationship between the describing attributes and the class. Broadly speaking there are two types of noise: attribute (or feature) noise and class (or label) noise (García et al., 2013; Frénay and Verleysen, 2014). In attribute noise, errors in one or more of the attributes that describe the class distort the true representation of the data. Class noise on the other hand, is the mislabelling of instances in a dataset. Missing observations can exist in both attributes and class, and are also considered as noise (Zhu and Wu, 2004).

The example dataset in Table 7 shows the various forms of noise. Instances 5 and 6 exhibit attribute noise, with instance 5 having a missing value for attribute x_1 , and instance 6 having attribute x_2 erroneously marked as c . Instances 1, 2, 4 and 7 exhibit class noise. Instance 1 was mislabelled as 0, which should read 1. Instances 2 and 4 are contradicting instances, implying that either one was mislabelled or the attribute readings were interpreted differently. Instance 7 has a missing label.

Attribute noise is normally introduced through errors in the data collection or data processing stages, but also by corruption whilst the data are stored or transported (García et al., 2013). Class noise on the other hand can be introduced through (Frénay and Verleysen, 2014):

- insufficient information when labelling the instances;
- expert labelling errors;
- subjectivity of the classes (for example in the case of medical diagnosis where experts can classify differently);
- encoding and communication problems; and
- using a cheap labelling method (such as non-expert or automated approaches).

Unfortunately, noise is very common since reliable, noise free data are expensive and time consuming to obtain (Frénay and Verleysen, 2014). The typical error rate in a dataset is 5%. (Zhu and Wu, 2004).

Effects of noise

When learning a concept, algorithms assume and expect a correct and perfectly labelled dataset (Frénay et al., 2014). Primarily, the noise in the training set reduces the predictive ability of the inferred model (García et al., 2013; Frénay et al., 2014; Frénay and Verleysen, 2014).

#	x_1	x_2	Y
1	a	d	0
2	a	c	1
3	b	c	1
4	a	c	0
5	-	d	0
6	b	c	1
7	b	d	-

Table 7: A sample from a noisy dataset.
Note: Noise is marked in red for ease of demonstration.

This can be seen in Figure 14 that shows the effect of noise on the classification accuracy of various classifiers.

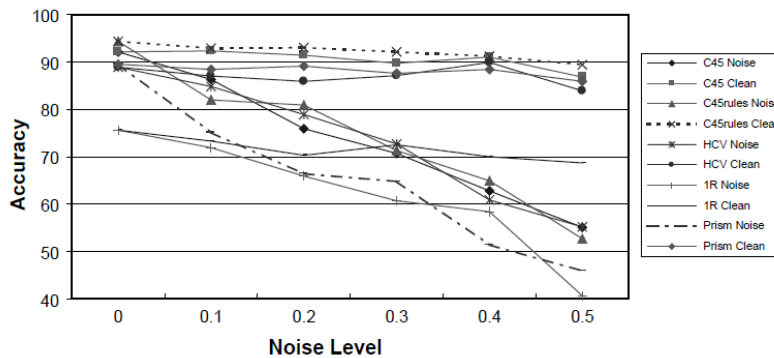


Figure 14: A graph showing the effect of noise on the classification accuracy of various classifiers. Each model was trained on a noisy dataset and on a manually cleaned dataset. These are represented as XXX Noise and XXX Clean respectively, where XXX denotes the classifier in question (Zhu and Wu, 2004).

The extent of the damage caused by noise depends on various factors. Class noise has been found to be more harmful than attribute noise (Zhu and Wu, 2004). The reason for this is that whilst an attribute shares the predictive capability with other attributes, there is only one label and errors confuse the learning algorithm (Zhu and Wu, 2004).

Zhu and Wu (2004) also found that not all attributes are equal in predicting the class and noise in the more important features are more damaging than others. The authors found that the higher the correlation between attribute and class the greater the impact of noise in the attribute.

Learning from a noisy dataset requires a larger training set (Frénay et al., 2014; Frénay and Verleysen, 2014) and is usually lengthier (García et al., 2013). Another cost of noise is the higher complexity of the inferred model (García et al., 2013; Frénay et al., 2014; Frénay and Verleysen, 2014).

Dealing with noise

To improve the performance of the inferred model, the effect of noise must be minimised (Zhu and Wu, 2004). There are various ways addressed in literature by which one can minimise such effects, which can be broadly classified into two categories: (i) improving the quality of the dataset (i.e. cleansing noise); and (ii) building models that are robust to noise.

Cleansing noise

Noise is usually identified by a domain expert since automatic noise identification is difficult (García et al., 2013). However, a domain expert is not always available and manual identification of noise is a lengthy process, therefore automated noise identification techniques are needed that either correct the noisy data or eliminate it.

One cannot identify noise without making assumptions (Frénay

and Verleysen, 2014). Techniques that filter out noise remove instances that appear mislabelled or that disproportionately increase the model complexity (Frénay et al., 2014). In some cases a classifier (noise filter) is trained to identify noisy instances. Other techniques aim at correcting errors or imputing missing values (Zhu and Wu, 2004).

For class noise, filtering out instances that appear noisy was found to improve results, but in the case of attribute noise, removing an instance for a noisy (including missing) attribute would not make sense, especially since other attributes may contain information that is useful for learning (Zhu and Wu, 2004). Instead, correcting or imputing the values was found to achieve better results.

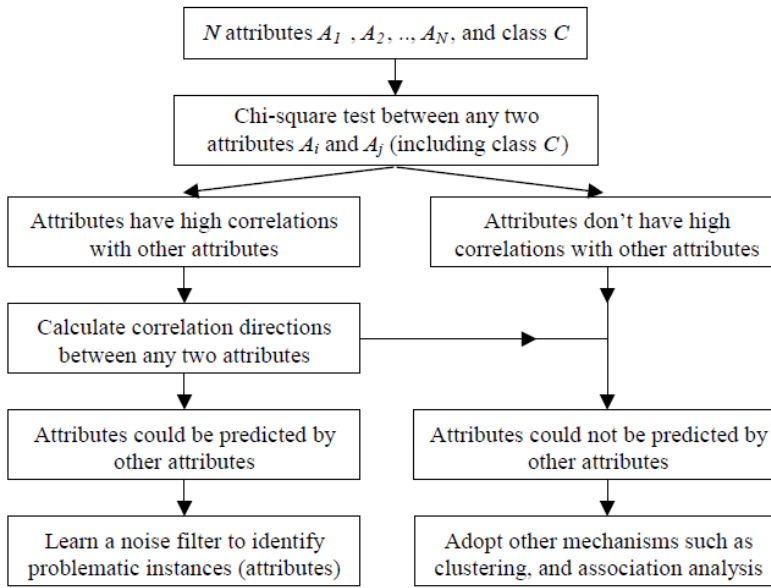


Figure 15: The approach adopted by Zhu and Wu (2004) to filter and correct attribute noise.

Figure 15 depicts the approach taken by Zhu and Wu (2004) to correct attribute noise, where for each attribute a strong correlation with other attributes is sought upon which noisy instances can be predicted (through a learning model) and corrected. If a correlation is not found, corrections are based on other methods such as *clustering* or *k-nearest neighbour*.

The choice of noise filtering method should be based on the task at hand (Frénay and Verleysen, 2014). The effectiveness of the noise filter should be evaluated on a dataset that is degraded with artificial noise. The filtering precision can then be calculated through the number of correct instances that are filtered (*Type I errors* - Equation 19) and the number of incorrect instances that are not filtered (*Type II errors* - Equation 20). These are calculated as follows:

$$ER_1 = \frac{\text{\# of correctly labelled instances which are removed}}{\text{\# of correctly labelled instances}} \quad (19)$$

$$ER_2 = \frac{\text{\# of mislabelled instances which are not removed}}{\text{\# of mislabelled instances}} \quad (20)$$

Consequently, the *Noise Elimination Precision* (NER) can be calculated through Equation 21 (Frénay and Verleysen, 2014).

$$NER = \frac{\text{\# of mislabelled instances which are removed}}{\text{\# of removed instances}} \quad (21)$$

Noise robust models

No learning algorithm is immune to noise but some algorithms perform better than others in the presence of noise (Frénay et al., 2014). Kalapanidas et al. (2003) studied the noise sensitivity of ten different machine learning algorithms against various levels of artificially induced noise. The results show that classifiers are much more noise tolerant than regressors. The *linear regression* algorithm proved to be the regressor least sensitive to noise, whilst the *decision table classifier* proved to be the best performer overall. A similar study (Nettleton et al., 2010) found the *naïve bayes* algorithm to be the most robust to noise.

Bibliography

- Christophe Ambroise and Geoffrey J McLachlan. Selection bias in gene extraction on the basis of microarray gene-expression data. *Proceedings of the national academy of sciences*, 99(10):6562–6566, 2002.
- Sylvain Arlot, Alain Celisse, et al. A survey of cross-validation procedures for model selection. *Statistics surveys*, 4:40–79, 2010.
- Knut Baumann. Cross-validation as the objective function for variable-selection techniques. *TrAC Trends in Analytical Chemistry*, 22(6):395–406, 2003.
- Yoshua Bengio, Patrice Simard, and Paolo Frasconi. Learning long-term dependencies with gradient descent is difficult. *IEEE Transactions on Neural Networks*, 5(2):157–166, March 1994. ISSN 1045-9227.
- Paula Branco, Luís Torgo, and Rita P Ribeiro. A survey of predictive modeling on imbalanced domains. *ACM Computing Surveys (CSUR)*, 49(2):31, 2016.
- Rich Caruana and Alexandru Niculescu-Mizil. An empirical comparison of supervised learning algorithms. In *Proceedings of the 23rd international conference on Machine learning*, pages 161–168. ACM, 2006.
- Anthony L. Caterini. *Deep Neural Networks in a Mathematical Framework (SpringerBriefs in Computer Science)*. Springer, 2018. ISBN 9783319753034.
- Pawel Cichosz. *Data mining algorithms: explained using R*. Wiley, 2014.
- Xinyang Deng, Qi Liu, Yong Deng, and Sankaran Mahadevan. An improved method to construct basic probability assignment based on the confusion matrix for classification problem. *Information Sciences*, 340:250–261, 2016.
- El-Sayed Ahmed El-Dahshan, Tamer Hosny, and Abdel-Badeeh M Salem. Hybrid intelligent techniques for mri brain images classification. *Digital Signal Processing*, 20(2):433–441, 2010.
- Alan H Fielding and John F Bell. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental conservation*, 24(1):38–49, 1997.

- Benoît Frénay and Michel Verleysen. Classification in the presence of label noise: a survey. *IEEE transactions on neural networks and learning systems*, 25(5):845–869, 2014.
- Benoît Frénay, Ata Kabán, et al. A comprehensive introduction to label noise. In *ESANN*, 2014.
- Luís Paulo F. García, André C. P. L. F. de Carvalho, and Ana C. Lorena. Noisy data set identification. In Jeng-Shyang Pan, Marios M. Polycarpou, Michał Woźniak, André C. P. L. F. de Carvalho, Héctor Quintián, and Emilio Corchado, editors, *Hybrid Artificial Intelligent Systems*, pages 629–638, Berlin, Heidelberg, 2013. Springer Berlin Heidelberg. ISBN 978-3-642-40846-5.
- Aurélien Géron. *Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems*. O'Reilly, 2017.
- Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pages 249–256, 2010.
- Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning (Adaptive Computation and Machine Learning series)*. The MIT Press, 2016. ISBN 0262035618.
- Qiong Gu, Li Zhu, and Zhihua Cai. Evaluation measures of the classification performance of imbalanced data sets. In *International Symposium on Intelligence Computation and Applications*, pages 461–471. Springer, 2009.
- Aboul Ella Hassanien and Diego Alberto Oliva. *Advances in Soft Computing and Machine Learning in Image Processing*, volume 730. Springer, 2017.
- Trevor Hastie, Robert Tibshirani, and Jerome Friedman. *The Elements of Statistical Learning*. Springer Series in Statistics. Springer New York Inc., New York, NY, USA, 2001.
- Ray J Hickey. Noise modelling and evaluating learning from examples. *Artificial Intelligence*, 82(1-2):157–179, 1996.
- Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.
- László A Jeni, Jeffrey F Cohn, and Fernando De La Torre. Facing imbalanced data—recommendations for the use of performance metrics. In *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*, pages 245–251. IEEE, 2013.
- Elias Kalapanidas, Nikolaos Avouris, Marian Craciun, and Daniel Neagu. Machine learning algorithms: a study on noise sensitivity. In *Proc. 1st Balcan Conference in Informatics*, pages 356–365, 2003.

- John D Kelleher, Brian Mac Namee, and Aoife D’Arcy. *Fundamentals of machine learning for predictive data analytics*. MIT Press, 2015.
- Ron Kohavi. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *Proceedings of the 14th International Joint Conference on Artificial Intelligence - Volume 2, IJCAI’95*, pages 1137–1143, San Francisco, CA, USA, 1995. Morgan Kaufmann Publishers Inc. ISBN 1-55860-363-8.
- Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.
- Max Kuhn and Kjell Johnson. *Applied predictive modeling*, volume 26. Springer, 2013.
- Yann A LeCun, Léon Bottou, Genevieve B Orr, and Klaus-Robert Müller. Efficient backprop. In *Neural networks: Tricks of the trade*, pages 9–48. Springer, 2012.
- Zhiyong Lu, Duane Szafron, Russell Greiner, Paul Lu, David S Wishart, Brett Poulin, John Anvik, Cam Macdonell, and Roman Eisner. Predicting subcellular localization of proteins using machine-learned classifiers. *Bioinformatics*, 20(4):547–556, 2004.
- Yan Ma and Bojan Cukic. Adequate and precise evaluation of quality models in software engineering studies. In *Proceedings of the third International workshop on predictor models in software engineering*, page 1. IEEE Computer Society, 2007.
- Andrew L Maas, Awni Y Hannun, and Andrew Y Ng. Rectifier nonlinearities improve neural network acoustic models. In *Proc. icml*, volume 30, page 3, 2013.
- James H Martin and Daniel Jurafsky. *Speech and language processing*. Pearson, 2018.
- Andreas C Müller, Sarah Guido, et al. *Introduction to machine learning with Python: a guide for data scientists*. O’Reilly, 2016.
- Vinod Nair and Geoffrey E. Hinton. Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th International Conference on International Conference on Machine Learning, ICML’10*, pages 807–814, USA, 2010. Omnipress. ISBN 978-1-60558-907-7.
- David F Nettleton, Albert Orriols-Puig, and Albert Fornells. A study of the effect of different types of noise on the precision of supervised learning techniques. *Artificial intelligence review*, 33(4):275–306, 2010.
- Troy Raeder, George Forman, and Nitesh V Chawla. Learning from imbalanced data: evaluation matters. In *Data mining: Foundations and intelligent paradigms*, pages 315–331. Springer, 2012.
- Frank Rosenblatt. *The Perceptron, a Perceiving and Recognizing Automation Project Para*. Report: Cornell Aeronautical Laboratory. Cornell Aeronautical Laboratory, 1957.

- David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. Learning representations by back-propagating errors. *Nature*, 323 (6088), 1986. ISSN 0028-0836.
- Takaya Saito and Marc Rehmsmeier. The precision-recall plot is more informative than the roc plot when evaluating binary classifiers on imbalanced datasets. *PloS one*, 10(3):e0118432, 2015.
- Claude Sammut and Geoffrey I Webb. *Encyclopedia of machine learning and data mining*. Springer, 2017.
- Jan Snyman. *Practical Mathematical Optimization: An Introduction to Basic Optimization Theory and Classical and New Gradient-based Algorithms (Applied Optimization Book 97)*. Springer US, 2005. ISBN 978-0-387-24348-1.
- Marina Sokolova and Guy Lapalme. A systematic analysis of performance measures for classification tasks. *Information Processing & Management*, 45(4):427–437, 2009.
- Mathias Stager, Paul Lukowicz, and Gerhard Troster. Dealing with class skew in context recognition. In *26th International Conference on Distributed Computing Systems*, pages 58–58. IEEE, 2006.
- Sudhir Varma and Richard Simon. Bias in error estimation when using cross-validation for model selection. *BMC bioinformatics*, 7(1):91, 2006.
- Qing-Song Xu and Yi-Zeng Liang. Monte carlo cross validation. *Chemometrics and Intelligent Laboratory Systems*, 56(1):1–11, 2001.
- Xingquan Zhu and Xindong Wu. Class noise vs. attribute noise: A quantitative study. *Artificial intelligence review*, 22(3):177–210, 2004.

Index

- activation functions, 7–10
 - hyperbolic tangent, 9
 - linear activation function, 8
 - rectified linear unit (relu), 9
 - sigmoid function, 8
 - step function, 7
- confusion matrix, 11–14
 - 1-vs-1, 13
 - 1-vs-rest, 13
 - accuracy, 12
 - error rate, 13
 - f-score, 13
 - f-measure, 13
 - f1-score, 13
 - false discovery rate, 13
 - false negative rate, 13
 - false omission rate, 13
 - false positive rate, 13
 - negative predictive value, 12
 - positive predictive value, 13
 - precision, 13
 - true negative rate, 12
 - specificity, 12
 - true positive rate, 12
 - recall, 12
 - sensitivity, 12
- cross-validation, 17
 - holdout, 18
 - k-fold, 18
 - leave-one-out, 18
 - leave-p-out, 17
- false negatives, 11
- false positives, 12
- license, 1
- noise in datasets, 21–24
 - artificial, 23
 - attribute noise, 21–23
 - class noise, 21–23
 - cleansing, 22
 - effects, 21
 - filter, 23
 - Noise Elimination Precision, 24
 - noise robust models, 24
 - Type I errors, 23
 - Type II errors, 23
- overfitting, 19
- repeated random sub-sampling, 18
- true negatives, 12
- true positives, 11
- underfitting, 19