Over Sampling for Time Series Classification

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Contents

Abstract

The `OSTSC` package is a powerful oversampling approach for classifying univariant, but multinomial time series data. This vignette provides a brief overview of the over-sampling methodology implemented by the package. A tutorial of the OSTSC package is provided. We begin by providing three test cases for the user to quickly validate the functionality in the package. To demonstrate the performance impact of OSTSC, we then provide two medium size imbalanced time series datasets. Each example applies a TensorFlow implementation of a Long Short-Term Memory (LSTM) classifier - a type of a Recurrent Neural Network (RNN) classifier - to imbalanced time series. The classifier performance is compared with and without oversampling. Finally, larger versions of these two datasets are evaluated to demonstrate the scalability of the package. The examples demonstrate that the OSTSC package improves the performance of RNN classifiers applied to highly imbalanced time series data. In particular, OSTSC is observed to increase the AUC of LSTM from 0.543 to 0.784 on a high frequency trading dataset consisting of 30,000 time series observations.

Introduction

A significant number of learning problems involve the accurate classification of rare events or outliers from time series data. For example, the detection of a flash crash, rogue trading, or heart arrhythmia from an electrocardiogram. Due to the rarity of these events, machine learning classifiers for detecting these events may be biased towards avoiding false positives. This is because any potential for false positives is greatly exaggerated by the number of negative samples in the data set.

Class imbalance problems are most easily addressed by treating the observations as conditionally independent. Then standard statistical techniques, such as oversampling the minority class or undersampling the majority class, or both, are applicable. More (2016) compared a batch of resampling techniques' classification performances on imbalanced datasets. Besides the conventional resampling approaches, More showed how ensemble methods retain as much original information from the majority class as possible when performing undersampling. Ensemble methods perform well and have gained popularity in the data mining literature. Dubey et al. (2014) studied an ensemble system of feature selection and data sampling from an imbalanced Alzheimer's Disease Neuroimaging Initiative dataset.

However the imbalanced time series classification problem is more complex when the time dimension needs to be accounted for. Not only is the assumption that the observations are conditionally independent too strong, but also the predictors may be cross-correlated too. The sample correlation structure may weaken or be entirely lost under application of the conventional resampling approaches described above.

There are two existing research directions for imbalanced time series classification. One is to preserve the covariance structure during oversampling proposed by Cao et al. (2011). Another is to conduct undersampling with various learning algorithms, proposed by Liang and Zhang (2012). Both approaches are limited to binary classification and do not consider the more general problem of multi-classification.

A key assertation by Cao, Tan, and Pang (2014) is that a time series sampling scheme should preserve the covariance structure. When the observations are conditionally dependent, this approach has been shown to outperform other sampling approaches such as undersampling the majority class, oversampling the minority class, and SMOTE. Our R package `Over Sampling for Time Series Classification` (OSTSC) is built on this idea. OSTSC first implements Enhanced Structure Preserving Oversampling (EPSO) of the minority class. It then uses a nearest neighbor method from the SMOTE family to generate synthetic positives. Specifically, it uses an Adaptive Synthetic Sampling Approach for Imbalanced Learning (ADASYN). Note that other packages such as Siriseriwan (2017) already implement SMOTE sampling techniques, including ADASYN. However an implementation of ADASYN has been provided in OSTSC for compatibility with the format required for use with EPSO and TensorFlow.

For examining the performance of oversampling for times series classification, RNNs are preferred (Graves (2013)). Recently Dixon (2017) applied RNNs to imbalanced times series data used in high frequency trading. The RNN classifier predicts a price-flip in the limit order book based on a sequence of limit order book depths and market orders. The approach uses standard under-sampling of the majority class to improve the classifier performance. OSTSC provides a uni-variate sample of this data and demonstrates the application of EPSO and ADASYN to improve the performance of the RNN. The RNN is implemented in 'TensorFlow' (Abadi et al. (2016)) and made available in R by using a wrapper for 'Keras' (Allaire and Chollet (2017)), a high-level API for 'TensorFlow'.

The current version of the package currently only supports univariant classification of time series. The extension to multi-features requires tensor computations which are not implemented here.

Overview

This vignette provides a brief description of the sampling methodologies implemented. We introduce the OSTSC package and illustrate its application using various examples. For validation purposes only, we first apply OSTSC to three small built-in toy datasets. These datasets are not sufficiently large to demonstrate the methodology. However, they can be used to quickly verify that the OSTSC function generates a balanced dataset.

For demonstrating the effect of OSTSC on LSTM performance, we provide two medium size datasets that can be computed with moderate computation. Finally, to demonstrate scalability, we evaluate OSTSC on two larger datasets. The reader is advised that the total amount of computation in this case is significant. We would therefore expect a user to test the OSTSC functionality on the small or medium size datasets, but reserve running the larger dataset examples on a higher performance machine. The medium and large datasets are not built-in to keep the package size within 5MB.

Background

ESPO is used to generate a large percentage of the synthetic minority samples from univariate labeled time series under the modeling assumption that the predictors are Gaussian. EPSO estimates the covariance structure of the minority-class samples and applies a spectral filter to reduce noise. ADASYN is a nearest neighbor interpolation approach which is subsequently applied to the EPSO samples (Cao et al. (2013)).

More formally, given the time series of positive labeled predictors $P = \left\{x_{11}, x_{12}, ..., x_{1|P|}\right\}$ and the negative time series $N = \left\{x_{01}, x_{02}, ..., x_{0|N|}\right\}$, where $|N| \gg |P|$, $x_{ij} \in \mathbb{R}^{n\times 1}$, the new samples are generated by the following steps:

1. Removal of the Common Null Space

Let $q_{ij} = L_s^T x_{ij}$ represent x_{ij} in a lower-dimensional signal space, where L_s consists of eigenvectors in the signal space.

2. ESPO

Let

$$W_p = \frac{1}{|P|}\sum_{j=1}^{|P|}(q_{1j} - \bar{q_1})(q_{1j} - \bar{q_1})^T.$$

and let $\hat{D} = V^T W_p V$ be the eigendecomposition with the diagonal matrix $\hat{D}$ of regularized eigenvalues $\left\{\hat{d_1}, ..., \hat{d_n}\right\}$, sorted in descending order, and with orthogonal eigenvector matrix V. Then we generate a synthetic positive sample from

$$b = \hat{D}^{1/2} V^T z + \bar{q_1}.$$

z is drawn from a zero-mean mixed Gaussian distribution and $\bar{q_1}$ is the corresponding positive-class mean vector. The oversampling is repeated until all $(|N| - |P|)r$ required synthetic samples are generated, where $r \in [0, 1]$ is the integration percentage of synthetic samples contributed by ESPO, which is chosen empirically. The remaining $(1 - r)$ percentage of the samples are generated by the interpolation procedure described next.

3. ADASYN

Given the transformed positive data $P_t = \{q_{1i}\}$ and negative data $N_t = \{q_{0j}\}$, each sample q_{1i} is replicated $\Gamma_i = |S_{i:k-NN} \bigcap N_t| / Z$ times, where $S_{i:k-NN}$ is this sample's kNN in the entire dataset, Z is a normalization factor so that $\sum_{i=1}^{|P_t|} \Gamma_i = 1$.

See Cao et al. (2013) for further technical details of this approach.

Functionality

The package imports 'parallel' (R Core Team (2017)), 'doParallel' (Microsoft Corporation and Weston (2017b)), 'doSNOW' (Microsoft Corporation and Weston (2017a)) and 'foreach' (Revolution Analytics and Weston (2015)) for multi-threaded execution on shared memory architectures. Parallel execution is strongly suggested for datasets consisting of at least 30,000 observations. OSTSC also imports 'mvrnorm' from 'MASS' (Venables and Ripley (2002)) to generate random vectors from the multivariate normal distribution, and 'rdist' from 'fields' (Douglas Nychka et al. (2015)) in order to calculate the Euclidean distance between vectors and matrices.

This vignette displays some simple examples below. For calling the RNN and examining the classifier's performance, 'keras' (Allaire and Chollet (2017)), 'dummies' (Brown (2012)) and 'pROC' (Robin et al. (2011)) are required.

Examples

Data loading & oversampling

The OSTSC package provides three small built-in datasets for verification that OSTSC has correctly installed and generates balanced time series. The first two examples use OSTSC to balance binary data while the third balances multinomial data.

The synthetically generated control dataset

The dataset `Dataset_Synthetic_Control` is a time series of sensor measurements of human body motion generated by Alcock et al. (1999). We introduce the following labeling: Class 1 represents the 'Normal' state, while Class 0 represents one of 'Cyclic', 'Increasing trend', 'Decreasing trend', 'Upward shift' or 'Downward shift' (Pham and Chan (1998)). Users load the dataset by calling `data()`.

```r
data(Dataset_Synthetic_Control)

train.label <- Dataset_Synthetic_Control$train.y
train.sample <- Dataset_Synthetic_Control$train.x
test.label <- Dataset_Synthetic_Control$test.y
test.sample <- Dataset_Synthetic_Control$test.x
```

Each row of the dataset is a sequence of observations. The sequence is of length 60 and there are 300 observations.

```r
dim(train.sample)
```

```
## [1] 300  60
```

The imbalance ratio of the training data is 1:5.

```r
table(train.label)
```

```
## train.label
##   0   1
## 250  50
```

We now provide a simple example demonstrating oversampling of the minority data to match the number of observations of the majority class. The output 'MyData' stores the samples (a.k.a. features) and labels. There are ten parameters in the OSTSC function, the details of which can be found in the help documentation. Calling the OSTSC function requires the user to provide at least the labels and sample data - the other parameters have default values. It is important to note that the labels are separated from the samples.

```r
MyData <- OSTSC(train.sample, train.label, parallel = FALSE)
over.sample <- MyData$sample
over.label <- MyData$label
```

The positive and negative observations are now balanced. Let us check the (im)balance of the new dataset.

```r
table(over.label)
```

```
## over.label
##   0   1
## 250 250
```

The minority class data is oversampled to produce a balanced feature set. The minority-majority formation uses a one-vs-rest strategy. For this binary dataset, the Class 1 data has been oversampled to yield the same number of observations as Class 0.

```r
dim(over.sample)
```

```
## [1] 500  60
```

The automatic diatoms identification dataset

The dataset `Dataset_Adiac` is generated from a pilot study identifying diatoms (unicellular algae) from images by Jalba, Wilkinson, and Roerdink (2004) originally has 37 classes. For the purpose of demonstrating OSTSC we selected only one class as the positive class (Class 1) and all others are set as the negative class (Class 0) to form a highly imbalanced dataset. Users load the dataset into R by calling `data()`.

```
data(Dataset_Adiac)

train.label <- Dataset_Adiac$train.y
train.sample <- Dataset_Adiac$train.x
test.label <- Dataset_Adiac$test.y
test.sample <- Dataset_Adiac$test.x
```

The training dataset consists of 390 observations of a 176 length sequence.

```
dim(train.sample)
```

```
## [1] 390 176
```

The imbalance ratio of the training data is 1:29.

```
table(train.label)
```

```
## train.label
##   0   1
## 377  13
```

The OSTSC function generates a balanced dataset:

```
MyData <- OSTSC(train.sample, train.label, parallel = FALSE)
over.sample <- MyData$sample
over.label <- MyData$label
```

table() provides a summary of the balanced dataset.

```
table(over.label)
```

```
## over.label
##   0   1
## 377 377
```

The high frequency trading dataset

The OSTSC function provides support for multinomial classification. The user specifies which classes should be oversampled. Typically, oversampling is first applied to the minority class - the class with the least number of observations. The dataset `Dataset_HFT300` is extracted from a real high frequency trading datafeed (Dixon (2017)). It contains a feature representing instantaneous liquidity imbalance using the best bid to ask ratio. The data is labeled so that $Y = 1$ for a next event mid-price up-tick, $Y = -1$ for a down-tick, and $Y = 0$ for no mid-price movement.
Users load the dataset into the R environment by calling `data()`.

```
data(Dataset_HFT300)

train.label <- Dataset_HFT300$y
train.sample <- Dataset_HFT300$x
```

The sequence length is set to 10 and 300 sequence observations are randomly drawn for this example dataset.

```
dim(train.sample)
```

```
## [1] 300  10
```

The imbalance ratio of the three class dataset is 1:48:1.

```
table(train.label)
```

```
## train.label
##  -1   0   1
##   6 288   6
```

This example demonstrates the case when there are two minority classes and both are over-sampled. The oversampling is processed using a one-vs-rest strategy, which means that each minority class is oversampled to the same count as the sum of the count of all other classes. This results in a slight imbalance in the total number of labels.

```
MyData <- OSTSC(train.sample, train.label, parallel = FALSE)
over.sample <- MyData$sample
over.label <- MyData$label
```

We observe the ratio of the classes after oversampling.

```
table(over.label)
```

```
## over.label
##  -1   0   1
## 294 288 294
```

The above examples illustrate how OSTSC oversamples small datasets. In the next section, we demonstrate and evaluate the oversampled data on two medium size datasets.

Applying OSTSC to medium size datasets

The Electrical Devices dataset

The dataset `Dataset_ElectricalDevices` is a sample collected from the 'Powering the Nation' study (Lines et al. (2011)). This study seeks to reduce the UK's carbon footprint by collecting behavioural data on how consumers use electricity within the home. Each class represent a signal from a different electrical device. Classes 5 and 6 in the original dataset are set as the negative and positive respectively. The dataset is split into training and testing feature vectors and labels.

```
ElectricalDevices <- Dataset_ElectricalDevices()

train.label <- ElectricalDevices$train.y
train.sample <- ElectricalDevices$train.x
test.label <- ElectricalDevices$test.y
test.sample <- ElectricalDevices$test.x
vali.label <- ElectricalDevices$vali.y
vali.sample <- ElectricalDevices$vali.x
```

Each row in the data represents a sequence of length 96.

```
dim(train.sample)
```

```
## [1] 2200   96
```

The imbalance ratio of the training data is 1:21.

```
table(train.label)
```

```
## train.label
##    0    1
## 2100  100
```

After oversampling with OSTSC, the positive and negative observations are balanced.

```
MyData <- OSTSC(train.sample, train.label, parallel = FALSE)
over.sample <- MyData$sample
over.label <- MyData$label
```

```
table(over.label)
```

```
## over.label
##    0    1
## 2100 2100
```

An LSTM classifier is used as the basis for performance assessment of oversampling with OSTSC. We use 'keras' (Allaire and Chollet (2017)) to configure the architecture, hyper-parameters and learning schedule of the LSTM classifier for sequence classification.

As a baseline for OSTSC, we assess the performance of LSTM trained on the unbalanced and balanced data. All performances are evaluated out-of-sample unless stated otherwise. Note that for the multi-classification examples, each F1 history is shown separately but is evaluated on the same validation set during training. The procedure for applying Keras is next outlined:

1. One-hot encode the categorical label vectors as binary class matrices using 'dummy()' function. Then transform the feature matrices to tensors for LSTM.

```
library(keras)
library(dummies)
train.y <- dummy(train.label)
test.y <- dummy(test.label)
train.x <- array(train.sample, dim = c(dim(train.sample),1))
test.x <- array(test.sample, dim = c(dim(test.sample),1))
vali.y <- dummy(vali.label)
vali.x <- array(vali.sample, dim = c(dim(vali.sample),1))
over.y <- dummy(over.label)
over.x <- array(over.sample, dim = c(dim(over.sample),1))
```

2. Initialize a sequential model, add layers and then compile it. Train the LSTM classifier on both of the imbalanced and the oversampled data.

```
K <- backend()

metric_f1_0 <- function(y_true, y_pred) { # positive is 0
  true_positives <- K$sum(y_true*y_pred, axis=K$cast(0,dtype='int32'))[1]
  possible_positives <- K$sum(y_true,axis=K$cast(0,dtype='int32'))[1]
  recall <- true_positives / (possible_positives + K$epsilon())

  predicted_positives<- K$sum(y_pred,axis=K$cast(0,dtype='int32'))[1]
  precision <- true_positives / (predicted_positives + K$epsilon())
  return(2*((precision*recall)/(precision+recall+ K$epsilon())))
}

metric_f1_1 <- function(y_true, y_pred) { # positive is 1
  true_positives <- K$sum(y_true*y_pred, axis=K$cast(0,dtype='int32'))[2]
  possible_positives <- K$sum(y_true,axis=K$cast(0,dtype='int32'))[2]
  recall <- true_positives / (possible_positives + K$epsilon())
  predicted_positives<- K$sum(y_pred,axis=K$cast(0,dtype='int32'))[2]
  precision <- true_positives / (predicted_positives + K$epsilon())
  return(2*((precision*recall)/(precision+recall+ K$epsilon())))
}
```

```
metric_f1_2 <- function(y_true, y_pred) { # positive is 2
  true_positives <- K$sum(y_true*y_pred, axis=K$cast(0,dtype='int32'))[3]
  possible_positives <- K$sum(y_true,axis=K$cast(0,dtype='int32'))[3]
  recall <- true_positives / (possible_positives + K$epsilon())
  predicted_positives<- K$sum(y_pred,axis=K$cast(0,dtype='int32'))[3]
  precision <- true_positives / (predicted_positives + K$epsilon())
  return(2*((precision*recall)/(precision+recall+ K$epsilon())))
}

LossHistory <- R6::R6Class("LossHistory",
  inherit = KerasCallback,

  public = list(

    losses = NULL,
    f1_0s    = NULL,
    f1_1s    = NULL,
    f1_2s    = NULL,
    val_f1_0s= NULL,
    val_f1_1s= NULL,
    val_f1_2s= NULL,

    on_epoch_end = function(epoch, logs = list()) {
      self$losses <- c(self$losses, logs[["loss"]])
      self$f1_0s    <- c(self$f1_0s, logs[["f1_score_0"]])
      self$f1_1s    <- c(self$f1_1s, logs[["f1_score_1"]])
      self$f1_2s    <- c(self$f1_2s, logs[["f1_score_2"]])
      self$val_f1_0s    <- c(self$val_f1_0s, logs[["val_f1_score_0"]])
      self$val_f1_1s    <- c(self$val_f1_1s, logs[["val_f1_score_1"]])
      self$val_f1_2s    <- c(self$val_f1_2s, logs[["val_f1_score_2"]])
    }
))

model <- keras_model_sequential()
model %>%
    layer_lstm(10, input_shape = c(dim(train.x)[2], dim(train.x)[3])) %>%
    #layer_dropout(rate = 0.1) %>%
    layer_dense(dim(train.y)[2]) %>%
    layer_dropout(rate = 0.1) %>%
    layer_activation("softmax")
history <- LossHistory$new()
model %>% compile(
    loss = "categorical_crossentropy",
    optimizer = optimizer_adam(lr = 0.005),
    metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1)
)
lstm.before <- model %>% fit(
    x = train.x,
    y = train.y,
    validation_data=list(vali.x,vali.y),
    batch_size = 256,
    callbacks = list(history),
    epochs = 50
)

model.over <- keras_model_sequential()
model.over %>%
    layer_lstm(10, input_shape = c(dim(over.x)[2], dim(over.x)[3])) %>%
    #layer_dropout(rate = 0.1) %>%
    layer_dense(dim(over.y)[2]) %>%
    layer_dropout(rate = 0.1) %>%
    layer_activation("softmax")
history.over <- LossHistory$new()
model.over %>% compile(
    loss = "categorical_crossentropy",
    optimizer = optimizer_adam(lr = 0.005),
    metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1)
)
lstm.after <- model.over %>% fit(
    x = over.x,
    y = over.y,
    validation_data=list(vali.x,vali.y),
    batch_size = 256,
    callbacks = list(history.over),
    epochs = 50
)
```

3. From the training history, Figures 1 and 2 compare the F1 scores of the two models without and with oversampling. Figure 3 compares the losses of the two models.

In addition to the training history, Figures 4 and 5 compare the confusion matrices of the two models without and with oversampling. Figure 6 compares the receiver operating characteristic (ROC) curves of the models. The final out-of-sample F1 scores of the two trained models are also shown below for comparison.

```
pred.label <- model %>% predict_classes(test.x)
pred.label.over <- model.over %>% predict_classes(test.x)
```

```
## The class 1 F1 score without oversampling:  0.6712329

## The class 0 F1 score without oversampling:  0.9817768

## The class 1 F1 score with oversampling:  0.7368421

## The class 0 F1 score with oversampling:  0.9847793
```

The Electrocardiogram dataset

The dataset `Dataset_ECG` was originally created by Goldberger et al. (2000) and records heartbeats from patients with severe congestive heart failure. The dataset was pre-processed to extract heartbeat sequences and add labels by Chen et al. (2015). The vignettes uses 5,000 randomly selected heartbeat sequences.

```
ECG <- Dataset_ECG()

train.label <- ECG$train.y
train.sample <- ECG$train.x
test.label <- ECG$test.y
test.sample <- ECG$test.x
vali.label <- ECG$vali.y
vali.sample <- ECG$vali.x
```

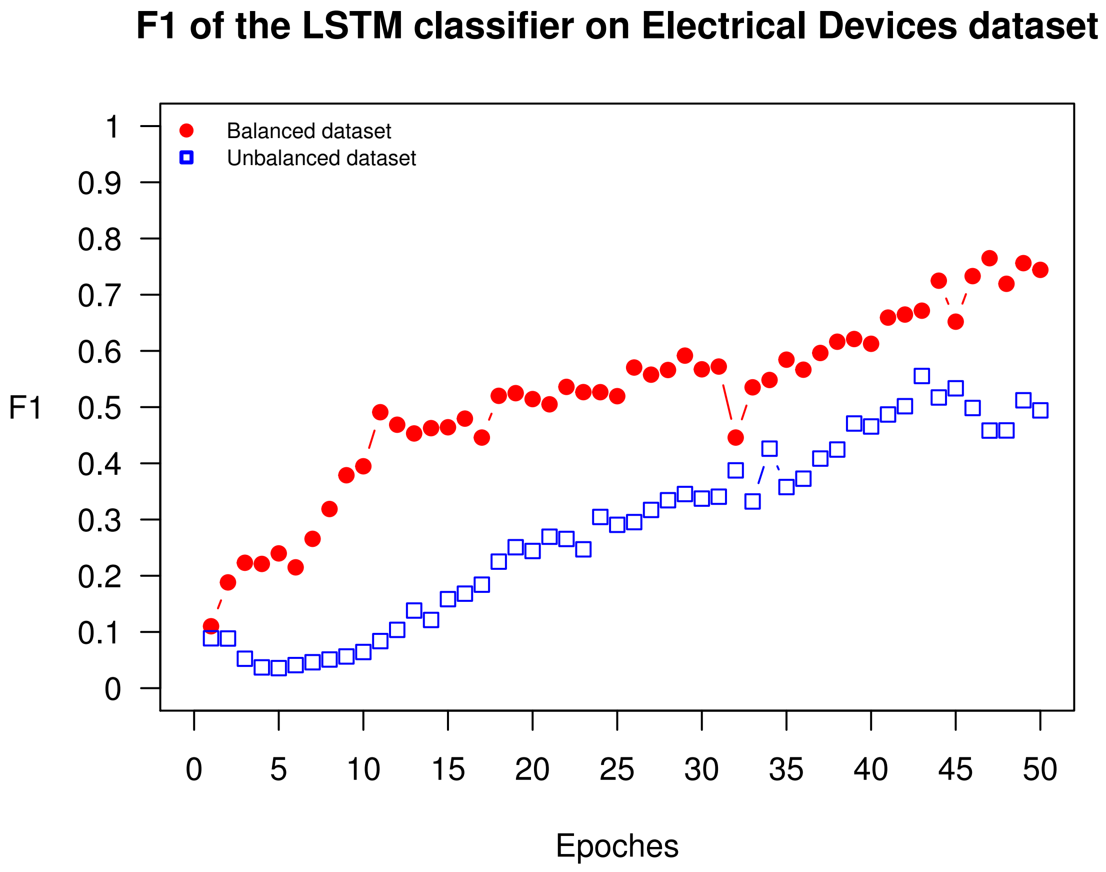


Figure 1: The F1 scores (class 1) of the LSTM classifier trained on the unbalanced and balanced Electrical Devices dataset. Both metrics are evaluated at the end of each epoch.

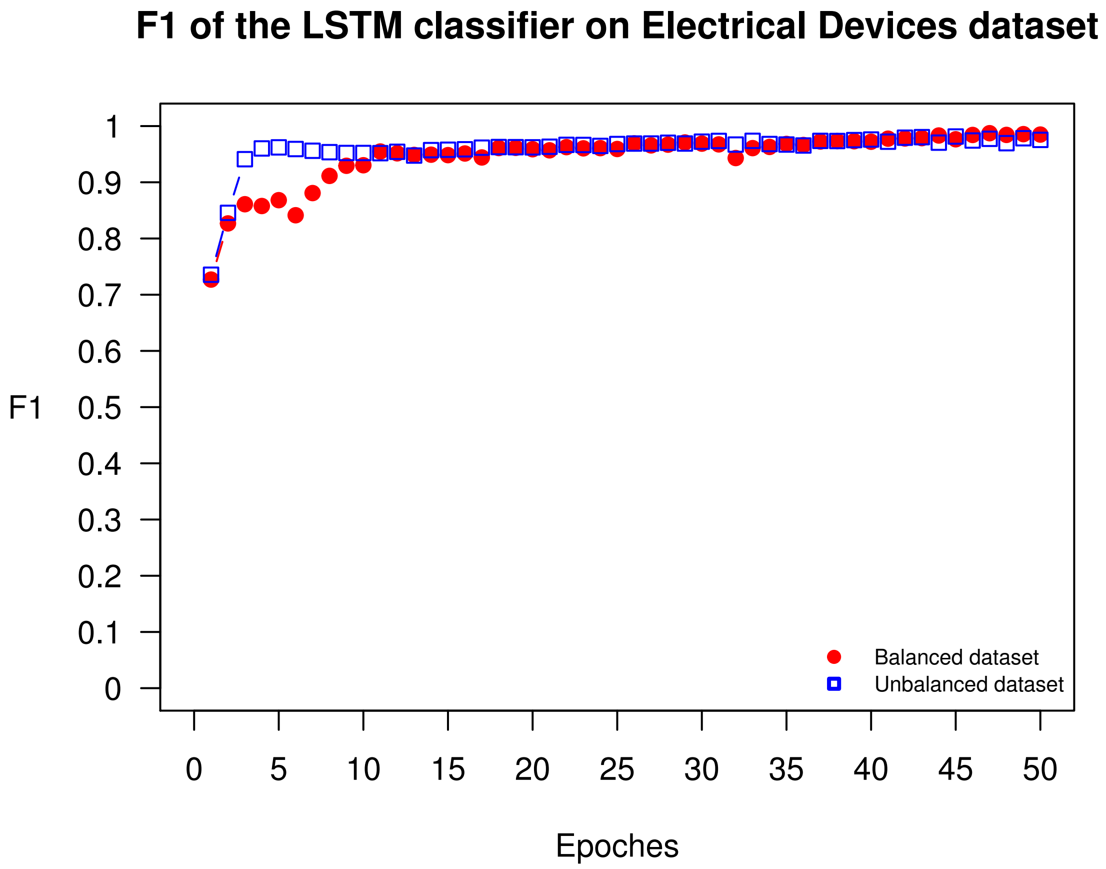


Figure 2: The F1 scores (class 0) of the LSTM classifier trained on the unbalanced and balanced Electrical Devices dataset. Both metrics are evaluated at the end of each epoch.

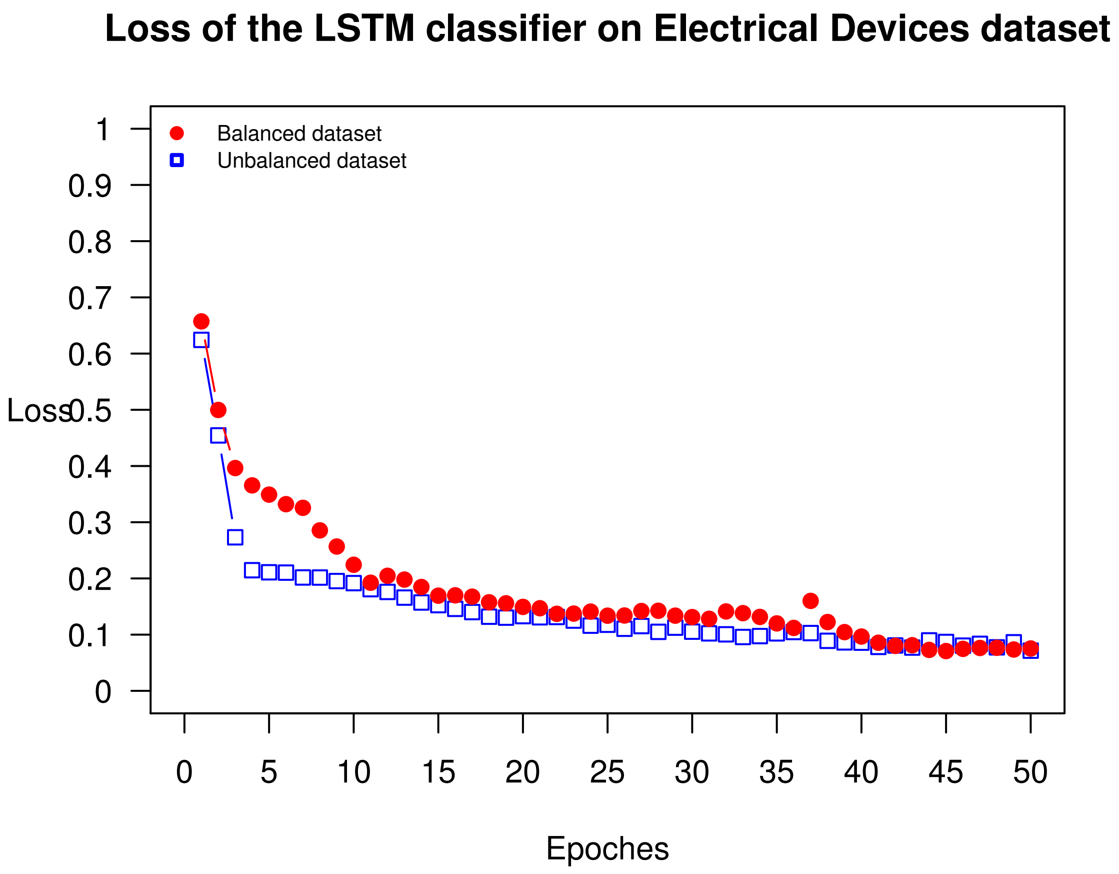


Figure 3: The losses of the LSTM classifier trained on the unbalanced and balanced Electrical Devices dataset. Both metrics are evaluated at the end of each epoch.

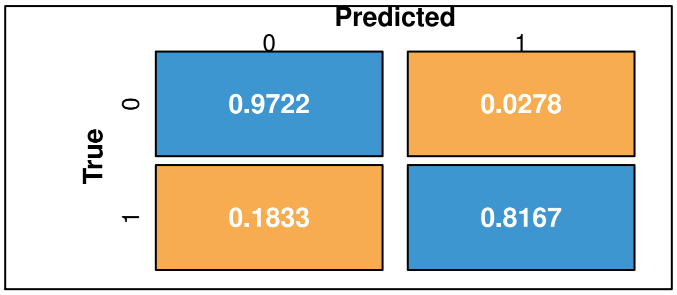


Figure 4: Normalized confusion matrix of LSTM applied to the Electrical Devices dataset without oversampling.

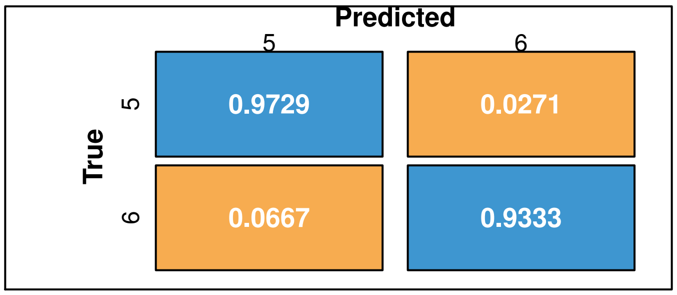


Figure 5: Normalized confusion matrix of LSTM applied to the Electrical Devices dataset with oversampling.

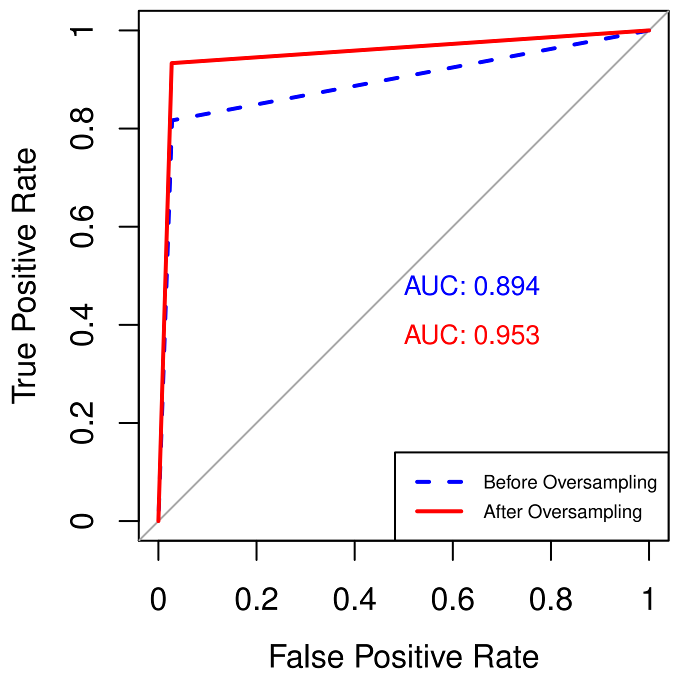


Figure 6: ROC curves comparing the effect of oversampling on the performance of LSTM applied to the Electrical Devices dataset.

Each row in the data represents a sequence of length 140.

```
dim(train.sample)
```

```
## [1] 2296  140
```

This experiment uses 3 classes of the dataset to ensure a high degree of imbalance: the imbalance ratio is 32:1:2.

```
table(train.label)
```

```
## train.label
##    0    1    2
## 2100   66  130
```

Let us check that the data is balanced after oversampling.

```
MyData <- OSTSC(train.sample, train.label, parallel = FALSE)
over.sample <- MyData$sample
over.label <- MyData$label
```

```
table(over.label)
```

```
## over.label
##    0    1    2
## 2100 2230 2166
```

We evaluate the effect of oversampling on the performance of LSTM following Steps 1-3 above. First the data is transformed. During configuring and training the model, the F1 scores and losses are measured at the end of each epoch using the same validation set.

```
library(keras)
library(dummies)
```

```r
train.y <- dummy(train.label)
test.y <- dummy(test.label)
train.x <- array(train.sample, dim = c(dim(train.sample),1))
test.x <- array(test.sample, dim = c(dim(test.sample),1))
vali.y <- dummy(vali.label)
vali.x <- array(vali.sample, dim = c(dim(vali.sample),1))
over.y <- dummy(over.label)
over.x <- array(over.sample, dim = c(dim(over.sample),1))

model <- keras_model_sequential()
model %>%
    layer_lstm(10, input_shape = c(dim(train.x)[2], dim(train.x)[3])) %>%
    #layer_dropout(rate = 0.1) %>%
    layer_dense(dim(train.y)[2]) %>%
    layer_dropout(rate = 0.1) %>%
    layer_activation("softmax")
history <- LossHistory$new()
model %>% compile(
    loss = "categorical_crossentropy",
    optimizer = optimizer_adam(lr = 0.001),
    metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1,
                'f1_score_2' = metric_f1_2)
)
lstm.before <- model %>% fit(
    x = train.x,
    y = train.y,
    validation_data=list(vali.x,vali.y),
    batch_size = 256,
    callbacks = list(history),
    epochs = 50
)

model.over <- keras_model_sequential()
model.over %>%
    layer_lstm(10, input_shape = c(dim(over.x)[2], dim(over.x)[3])) %>%
    #layer_dropout(rate = 0.1) %>%
    layer_dense(dim(over.y)[2]) %>%
    layer_dropout(rate = 0.1) %>%
    layer_activation("softmax")
history.over <- LossHistory$new()
model.over %>% compile(
    loss = "categorical_crossentropy",
    optimizer = optimizer_adam(lr = 0.001),
    metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1,
                'f1_score_2' = metric_f1_2)
)
lstm.after <- model.over %>% fit(
    x = over.x,
    y = over.y,
    validation_data=list(vali.x,vali.y),
    batch_size = 256,
    callbacks = list(history.over),
    epochs = 50
)
```

Keeping the number of epoches fixed, Figures 7, 8 and 9 respectively compare the F1 scores of three different classes of the two models without and with oversampling. Figure 10 compares the losses of the two models. From the losses and F1 scores, we note that the model has not yet been adequately trained after 50 epoches. We are trying to demonstrate the utility of OSTSC with only a modest amount of computation. The user can of course choose to increase the number of epoches, but will this require more computation. The user should refer to the larger dataset examples below for comparative evaluations which use more epoches for training LSTM.

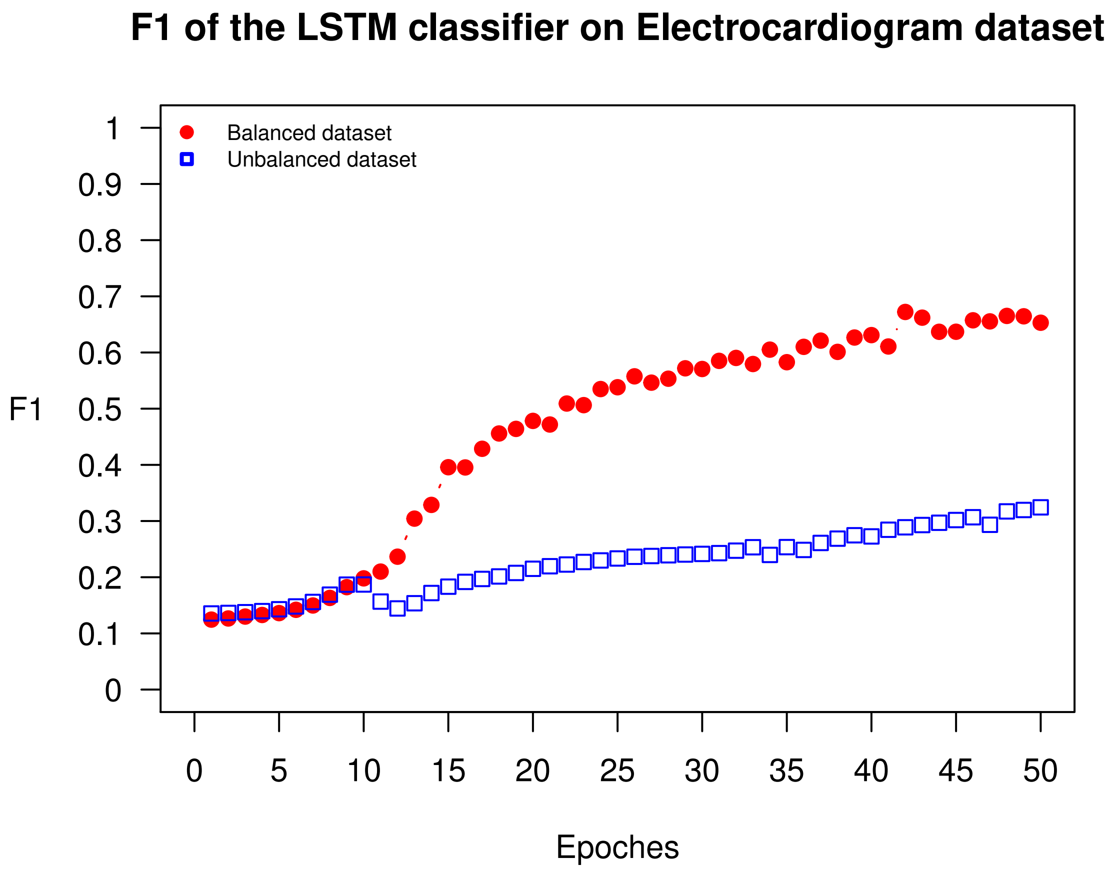


Figure 7: The F1 scores (class 2) of the LSTM classifier trained on the unbalanced and balanced Electrocardiogram dataset. Both metrics are evaluated at the end of each epoch.

In addition to the training history, Figures 11 and 12 compare the confusion matrices of the two models without and with oversampling. Figure 13 compares the receiver operating characteristic (ROC) curves of the models. The final F1 scores of the two trained models, using the same validation set, are also shown below for comparison.

```
pred.label <- model %>% predict_classes(test.x)
pred.label.over <- model.over %>% predict_classes(test.x)
```

```
## The class 2 F1 score without oversampling:  0.36

## The class 1 F1 score without oversampling:  0.64

## The class 0 F1 score without oversampling:  0.9698858

## The class 2 F1 score with oversampling:  0.6969697
```

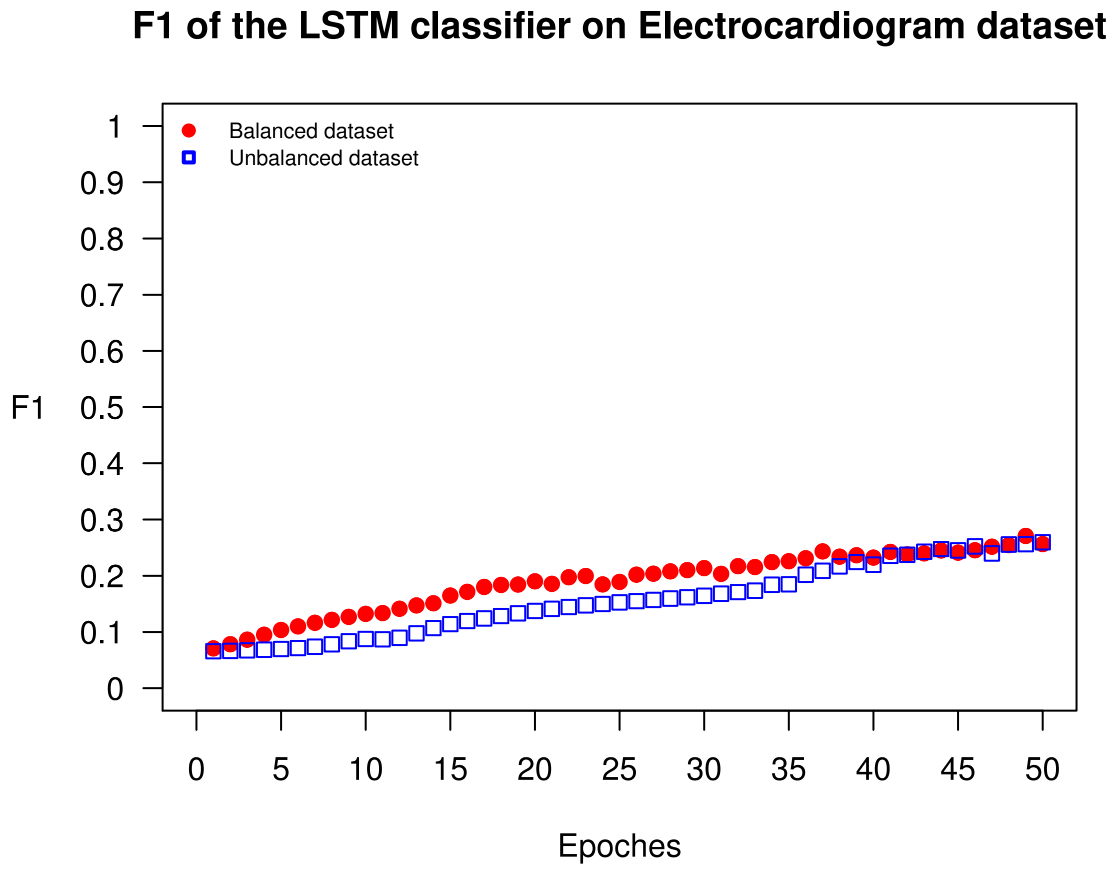


Figure 8: The F1 scores (class 1) of the LSTM classifier trained on the unbalanced and balanced Electrocardiogram dataset. Both metrics are evaluated at the end of each epoch.

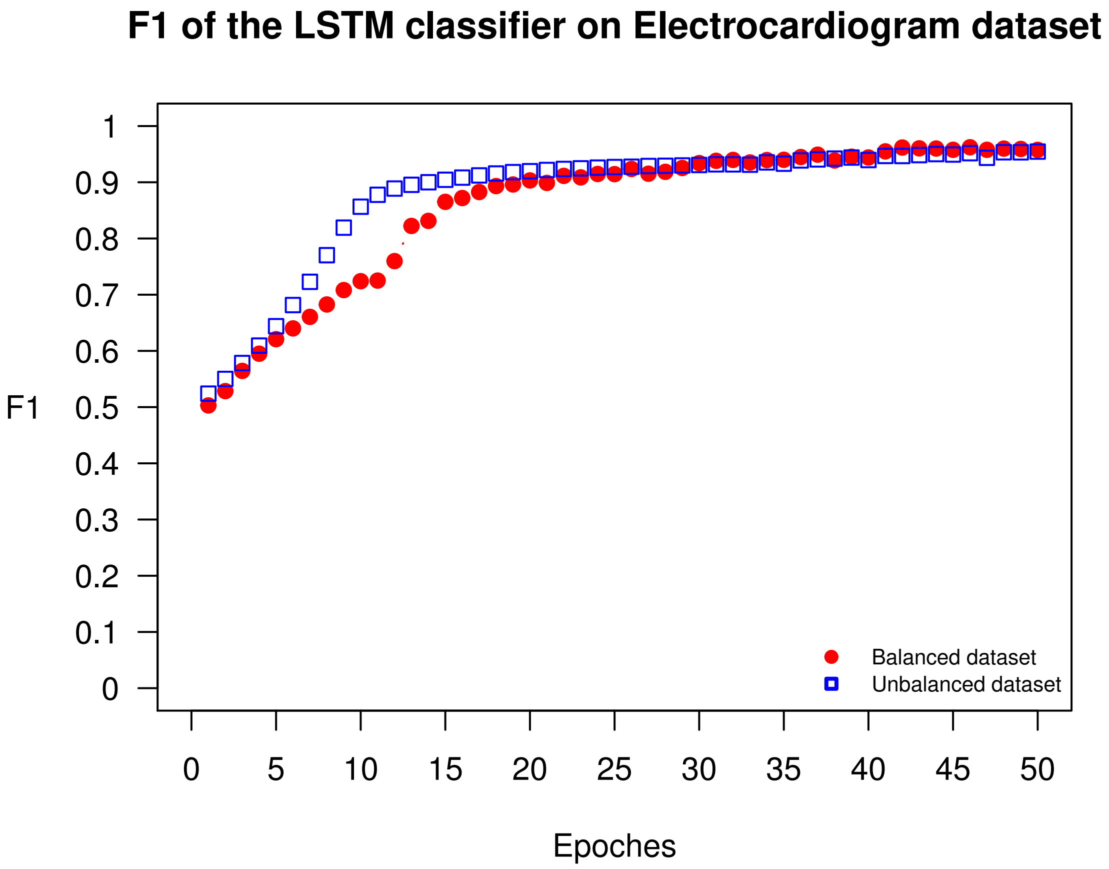


Figure 9: The F1 scores (class 0) of the LSTM classifier trained on the unbalanced and balanced Electrocardiogram dataset. Both metrics are evaluated at the end of each epoch.

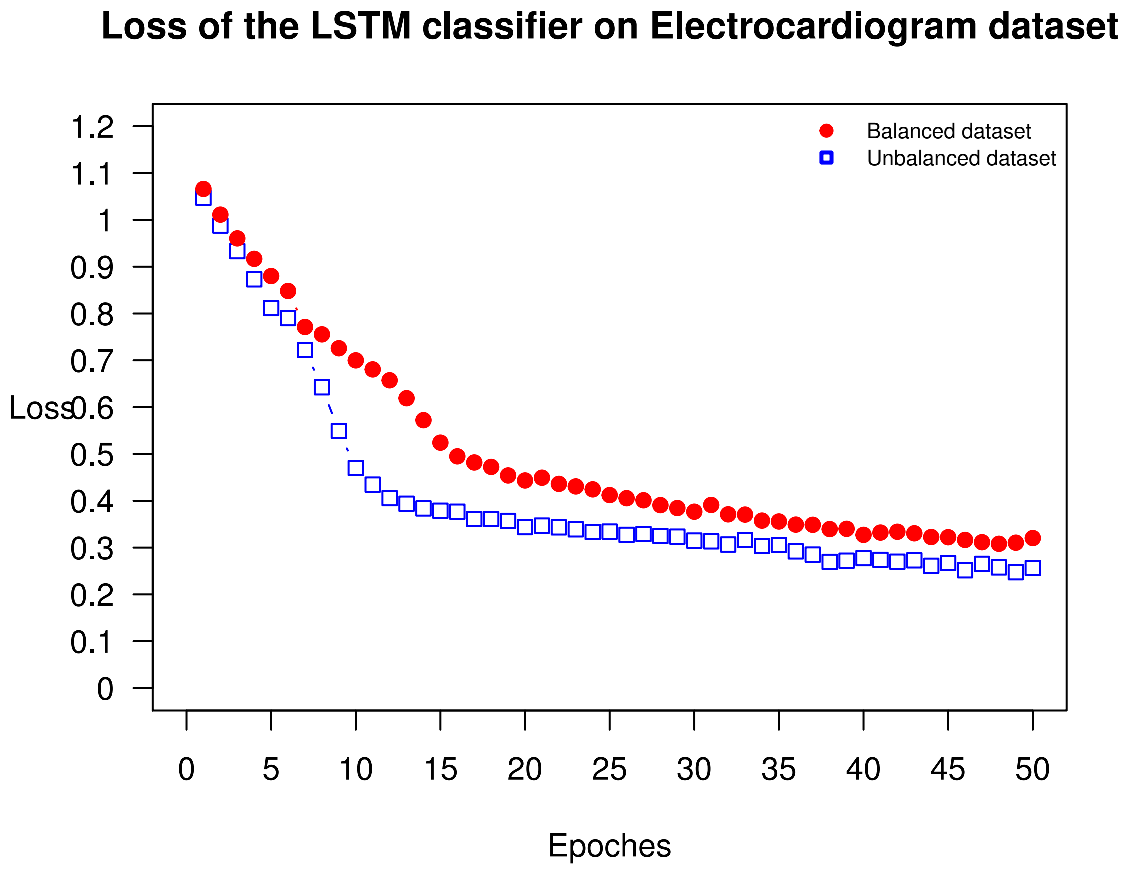


Figure 10: The losses of the LSTM classifier trained on the unbalanced and balanced Electrocardiogram dataset. Both metrics are evaluated at the end of each epoch.

```
## The class 1 F1 score with oversampling:  0.5909091
```

```
## The class 0 F1 score with oversampling:  0.9784483
```

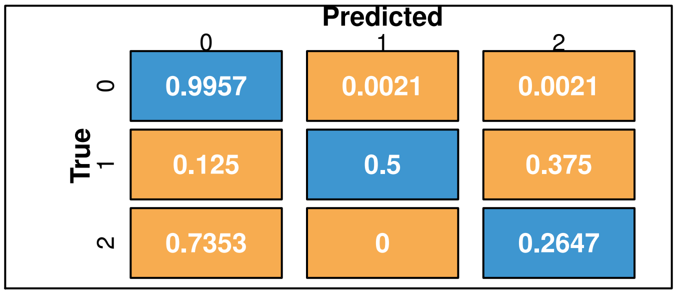


Figure 11: Normalized confusion matrices of LSTM applied to the Electrocardiogram dataset without oversampling.

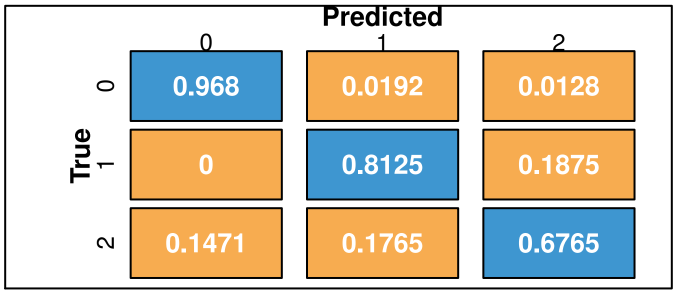


Figure 12: Normalized confusion matrix of LSTM applied to the Electrocardiogram dataset with oversampling.

Evaluating OSTSC on the large datasets

The evaluation of oversampling uses larger datasets: the MHEALTH and HFT datasets. The purpose of this evaluation is to demonstrate how OSTSC performs at scale. We increase the data sizes by a factor of up to 10x. The evaluation of each dataset takes approximately three hours on a 1.7 GHz four-core laptop with 8GM of RAM.

The MHEALTH dataset

The dataset `Dataset_MHEALTH` benchmarks techniques for human behavioral analysis applied to multimodal body sensing (Banos et al. (2014)). In this experiment, only Subjects 1-5 and Feature 12 (the x coordinate of the magnetometer reading from the left-ankle sensor) are used. The dataset is labeled with a dichotonomous response (Banos et al. (2015)). Class 11 (Running) is set as the positive and the remaining states are the negative. The dataset is split into training and testing feature vectors and labels.

```
MHEALTH <- Dataset_MHEALTH()

train.label <- MHEALTH$train.y
train.sample <- MHEALTH$train.x
test.label <- MHEALTH$test.y
test.sample <- MHEALTH$test.x
vali.label <- MHEALTH$vali.y
vali.sample <- MHEALTH$vali.x
```

Each row in the data represents a sequence of length 30.

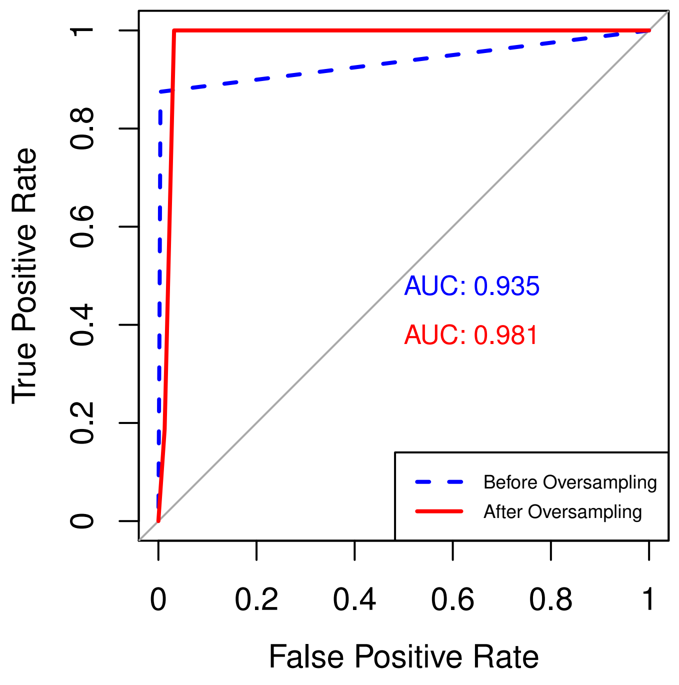


Figure 13: ROC curves of LSTM applied to the Electrocardiogram dataset, with and without oversampling.

```
dim(train.sample)
```

```
## [1] 10250    30
```

Class 1 represents the positive data and class 0 represents the negative. The imbalance ratio of the train dataset is 1:40.

```
table(train.label)
```

```
## train.label
##     0     1
## 10000   250
```

After oversampling, the positive and negative observations are balanced.

```
MyData <- OSTSC(train.sample, train.label, parallel = FALSE)
over.sample <- MyData$sample
over.label <- MyData$label
```

```
table(over.label)
```

```
## over.label
##     0     1
## 10000 10000
```

We are concerned more here with the comparative performance without and with oversampling and less with the absolute gain (which is subject to further parameter tuning). Keeping the number of epoches fixed, Figures 14 and 15 compare the F1 scores of the two models without and with oversampling, Figure 16 compares the losses of the two models, Figures 17 and 18 compare the confusion matrices of the two models without and with oversampling, and Figure 19 compares the ROC curves of the models. The final F1 scores of the two trained models, using the same validation set, are also shown below for comparison.

```r
train.y <- dummy(train.label)
test.y <- dummy(test.label)
train.x <- array(train.sample, dim = c(dim(train.sample),1))
test.x <- array(test.sample, dim = c(dim(test.sample),1))
vali.y <- dummy(vali.label)
vali.x <- array(vali.sample, dim = c(dim(vali.sample),1))
over.y <- dummy(over.label)
over.x <- array(over.sample, dim = c(dim(over.sample),1))

model <- keras_model_sequential()
model %>%
  layer_lstm(10, input_shape = c(dim(train.x)[2], dim(train.x)[3])) %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(dim(train.y)[2]) %>%
  layer_dropout(rate = 0.2) %>%
  layer_activation("softmax")
history <- LossHistory$new()
model %>% compile(
  loss = "categorical_crossentropy",
  optimizer = "adam",
  metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1)
)
lstm.before <- model %>% fit(
  x = train.x,
  y = train.y,
  validation_data=list(vali.x,vali.y),
  callbacks = list(history),
  epochs = 50
)

model.over <- keras_model_sequential()
model.over %>%
  layer_lstm(10, input_shape = c(dim(over.x)[2], dim(over.x)[3])) %>%
  layer_dropout(rate = 0.1) %>%
  layer_dense(dim(over.y)[2]) %>%
  layer_dropout(rate = 0.1) %>%
  layer_activation("softmax")
history.over <- LossHistory$new()
model.over %>% compile(
  loss = "categorical_crossentropy",
  optimizer = "adam",
  metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1)
)
lstm.after <- model.over %>% fit(
  x = over.x,
  y = over.y,
  validation_data=list(vali.x,vali.y),
  callbacks = list(history.over),
  epochs = 50
)

pred.label <- model %>% predict_classes(test.x)
pred.label.over <- model.over %>% predict_classes(test.x)
```

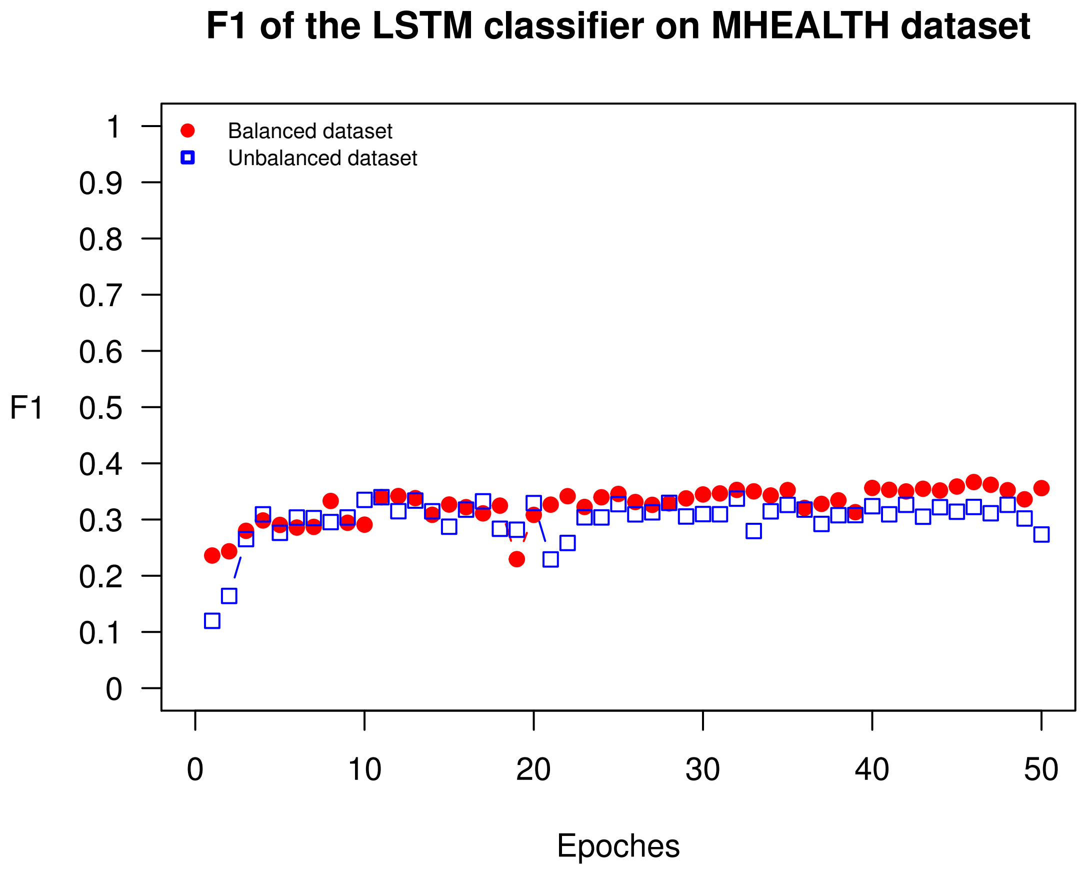


Figure 14: The F1 scores (class 1) of the LSTM classifier trained on the unbalanced and balanced MHEALTH dataset. Both metrics are evaluated at the end of each epoch.

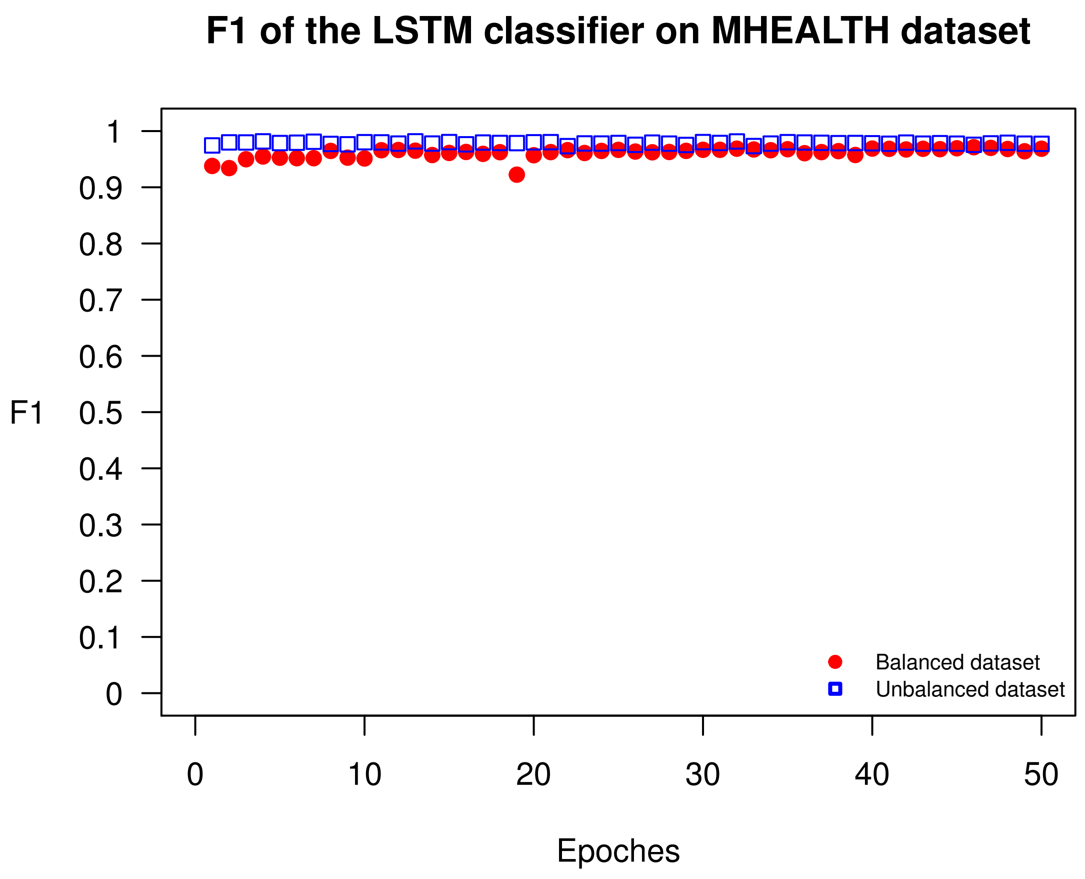


Figure 15: The F1 scores (class 0) of the LSTM classifier trained on the unbalanced and balanced MHEALTH dataset. Both metrics are evaluated at the end of each epoch.

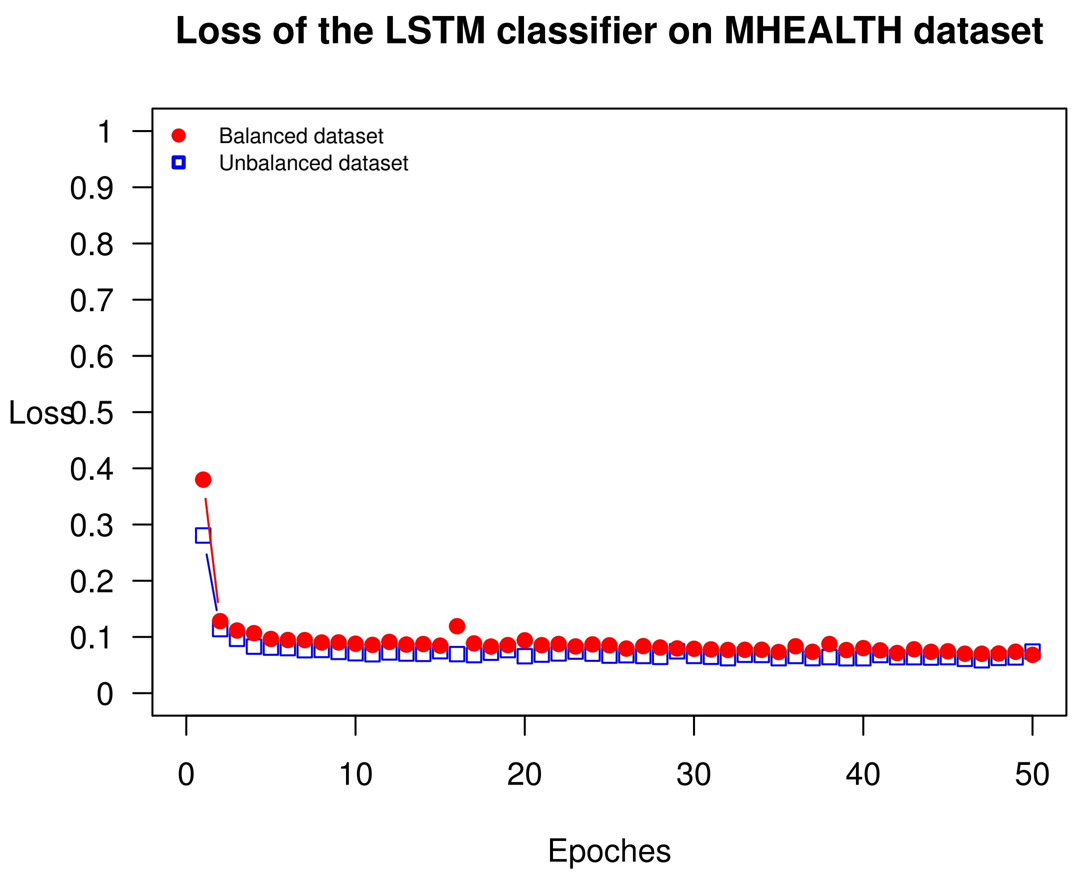


Figure 16: The losses of the LSTM classifier trained on the unbalanced and balanced MHEALTH dataset. Both metrics are evaluated at the end of each epoch.

```
## The class 1 F1 score without oversampling:  0.4496487

## The class 0 F1 score without oversampling:  0.985566

## The class 1 F1 score with oversampling:  0.493992

## The class 0 F1 score with oversampling:  0.9762516
```

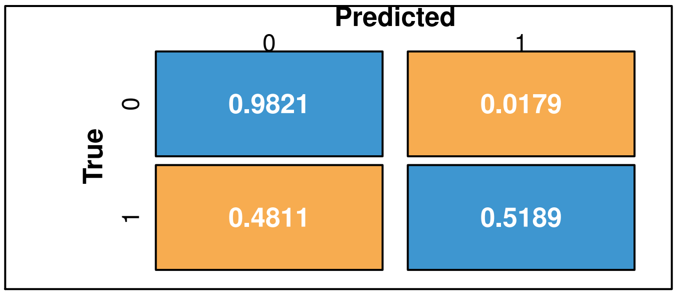


Figure 17: Normalized confusion matrix of LSTM applied to the MHEALTH dataset without oversampling.

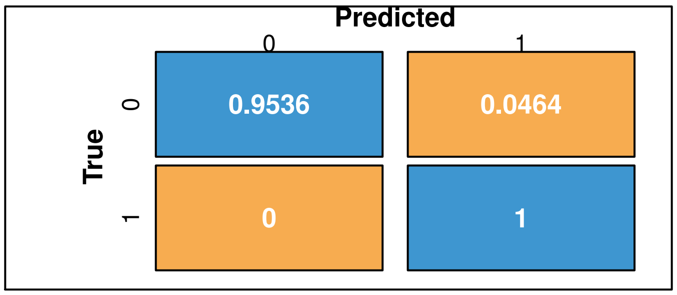


Figure 18: Normalized confusion matrix of LSTM applied to the MHEALTH dataset with oversampling.

The high frequency trading dataset

The dataset `Dataset_HFT` has already been introduced in the `Data loading & oversampling` section. The purpose of this example is to demonstrate the application of oversampling to a large sized dataset consisting of 30,000 observations instead of 300. For control, the imbalance ratio of the dataset is configured to be the same as the smaller dataset. We split the training, validating and testing data by a ratio of 20:3:7.

```
HFT <- Dataset_HFT()

label <- HFT$y
sample <- HFT$x
train.label <- label[1:20000]
train.sample <- sample[1:20000, ]
test.label <- label[23001:30000]
test.sample <- sample[23001:30000, ]
vali.label <- label[20001:23000]
vali.sample <- sample[20001:23000, ]
```

The imbalance ratio of the training data is 1:48:1.

```
table(train.label)
```

```
## train.label
##    -1     0     1
```

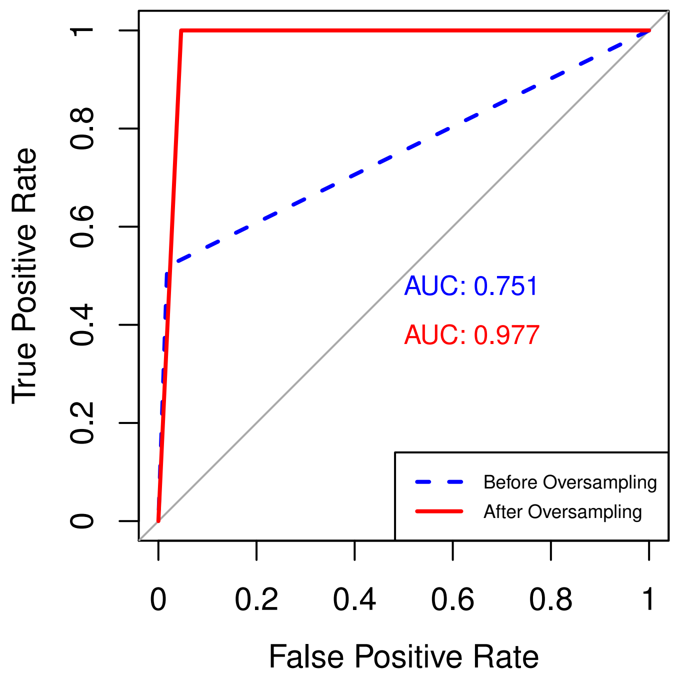


Figure 19: ROC curves of LSTM applied to the MHEALTH dataset, with and without oversampling.

```
##   383 19269   348
```

After oversampling the data is balanced.

```
MyData <- OSTSC(train.sample, train.label, parallel = FALSE)
over.sample <- MyData$sample
over.label <- MyData$label
```

```
table(over.label)
```

```
## over.label
##    -1     0     1
## 19617 19269 19652
```

We increase the number of epoches to 100. Figures 20, 21 and 22 compare the F1 scores of the two models without and with oversampling. Figure 23 compares the losses of the two models. Figures 24 and 25 compare the confusion matrices of the two models without and with oversampling. Figure 26 compares the ROC curves of the models. The final F1 scores of the two trained models, using the same validation set, are also shown below for comparison.

```
train.y <- dummy(train.label)
test.y <- dummy(test.label)
train.x <- array(train.sample, dim = c(dim(train.sample),1))
test.x <- array(test.sample, dim = c(dim(test.sample),1))
vali.y <- dummy(vali.label)
vali.x <- array(vali.sample, dim = c(dim(vali.sample),1))
over.y <- dummy(over.label)
over.x <- array(over.sample, dim = c(dim(over.sample),1))

model <- keras_model_sequential()
model %>%
  layer_lstm(10, input_shape = c(dim(train.x)[2], dim(train.x)[3])) %>%
```

```r
  layer_dropout(rate = 0.1) %>%
  layer_dense(dim(train.y)[2]) %>%
  layer_dropout(rate = 0.1) %>%
  layer_activation("softmax")
history <- LossHistory$new()
model %>% compile(
  loss = "categorical_crossentropy",
  optimizer = "adam",
  metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1,
              'f1_score_2' = metric_f1_2)
)
lstm.before <- model %>% fit(
  x = train.x,
  y = train.y,
  validation_data=list(vali.x,vali.y),
  callbacks = list(history),
  epochs = 100
)

model.over <- keras_model_sequential()
model.over %>%
  layer_lstm(10, input_shape = c(dim(train.x)[2], dim(train.x)[3])) %>%
  layer_dropout(rate = 0.1) %>%
  layer_dense(dim(train.y)[2]) %>%
  layer_dropout(rate = 0.1) %>%
  layer_activation("softmax")
history.over <- LossHistory$new()
model.over %>% compile(
  loss = "categorical_crossentropy",
  optimizer = "adam",
  metrics = c("accuracy",'f1_score_0' = metric_f1_0, 'f1_score_1' = metric_f1_1,
              'f1_score_2' = metric_f1_2)
)
lstm.after <- model.over %>% fit(
    x = over.x,
    y = over.y,
    validation_data=list(vali.x,vali.y),
    callbacks = list(history.over),
    epochs = 100
)
```

```r
pred.label <- model %>% predict_classes(test.x)
pred.label.over <- model.over %>% predict_classes(test.x)
```

```
## The class 1 F1 score without oversampling:  0.1538462

## The class 0 F1 score without oversampling:  0.9757571

## The class -1 F1 score without oversampling:  0.1826923

## The class 1 F1 score with oversampling:  0.2854311

## The class 0 F1 score with oversampling:  0.9007458

## The class -1 F1 score with oversampling:  0.2810127
```

The comparative results are similar to the MHEALTH dataset - oversampling improves the performance and

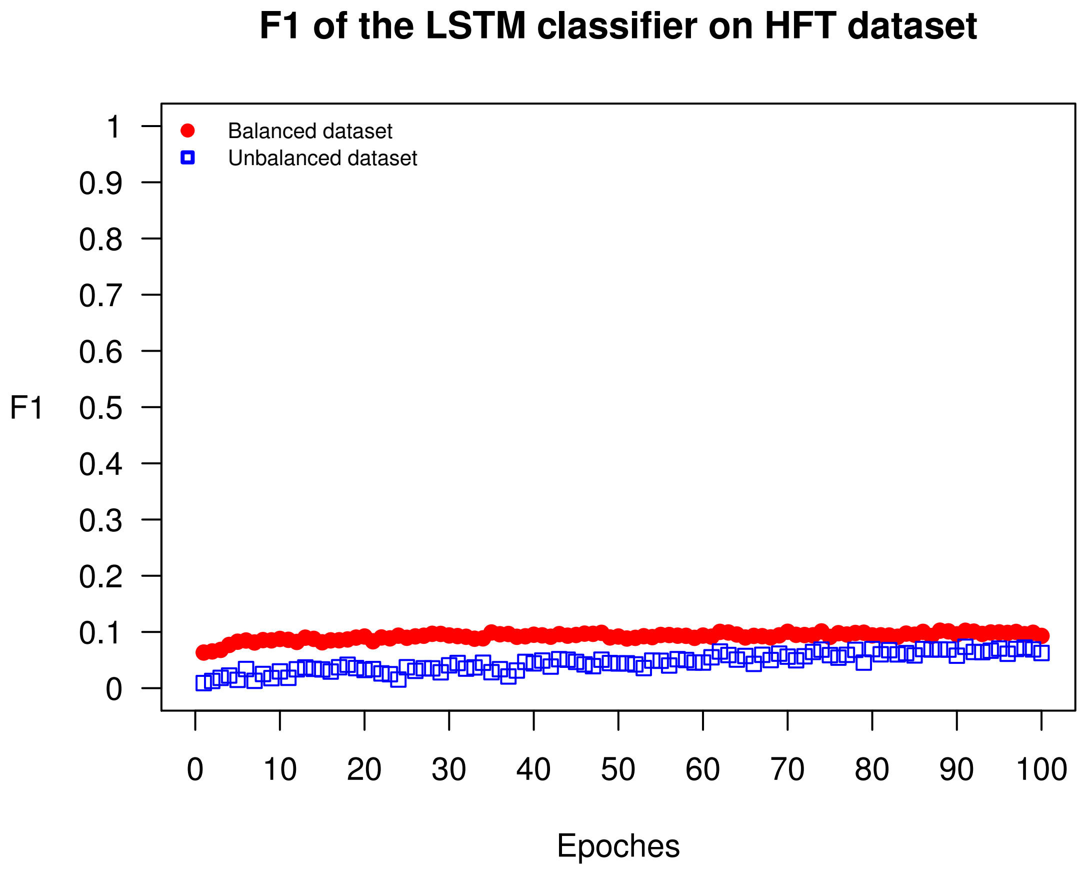


Figure 20: The F1 scores (class 1) of the LSTM classifier trained on the unbalanced and balanced HFT dataset. Both metrics are evaluated at the end of each epoch.

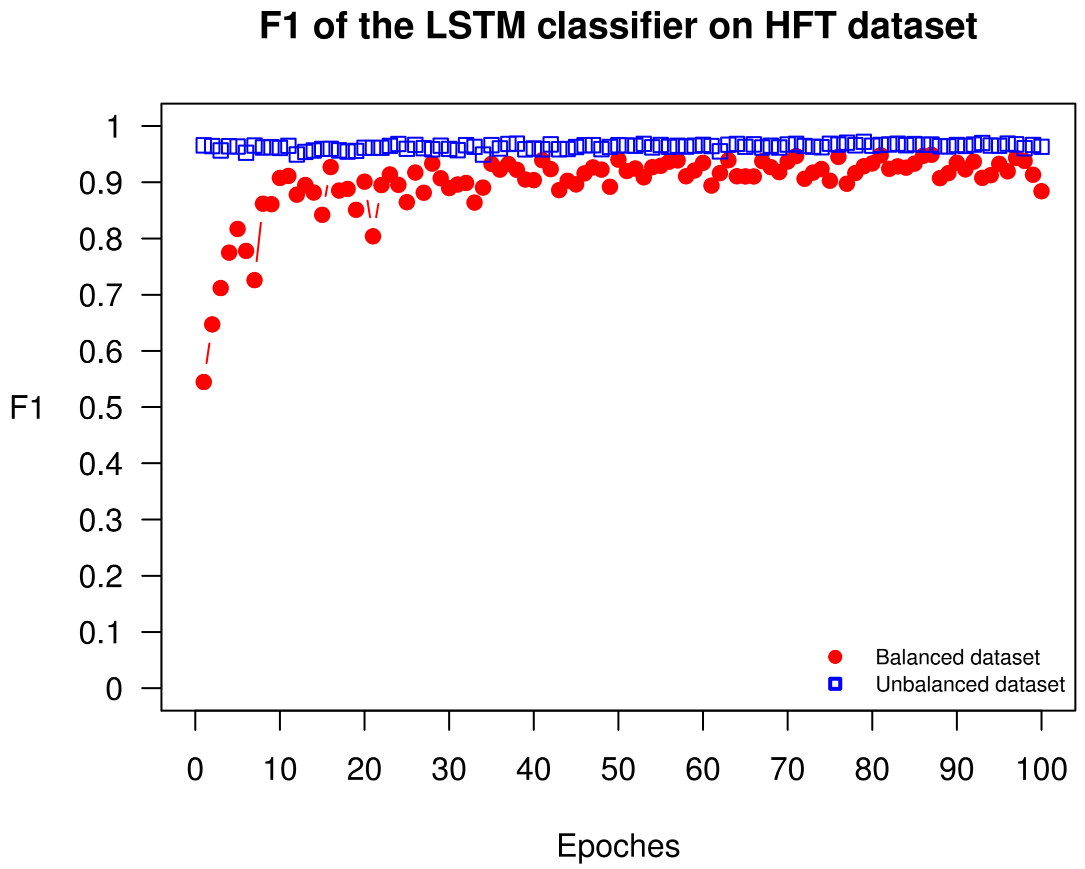


Figure 21: The F1 scores (class 0) of the LSTM classifier trained on the unbalanced and balanced HFT dataset. Both metrics are evaluated at the end of each epoch.

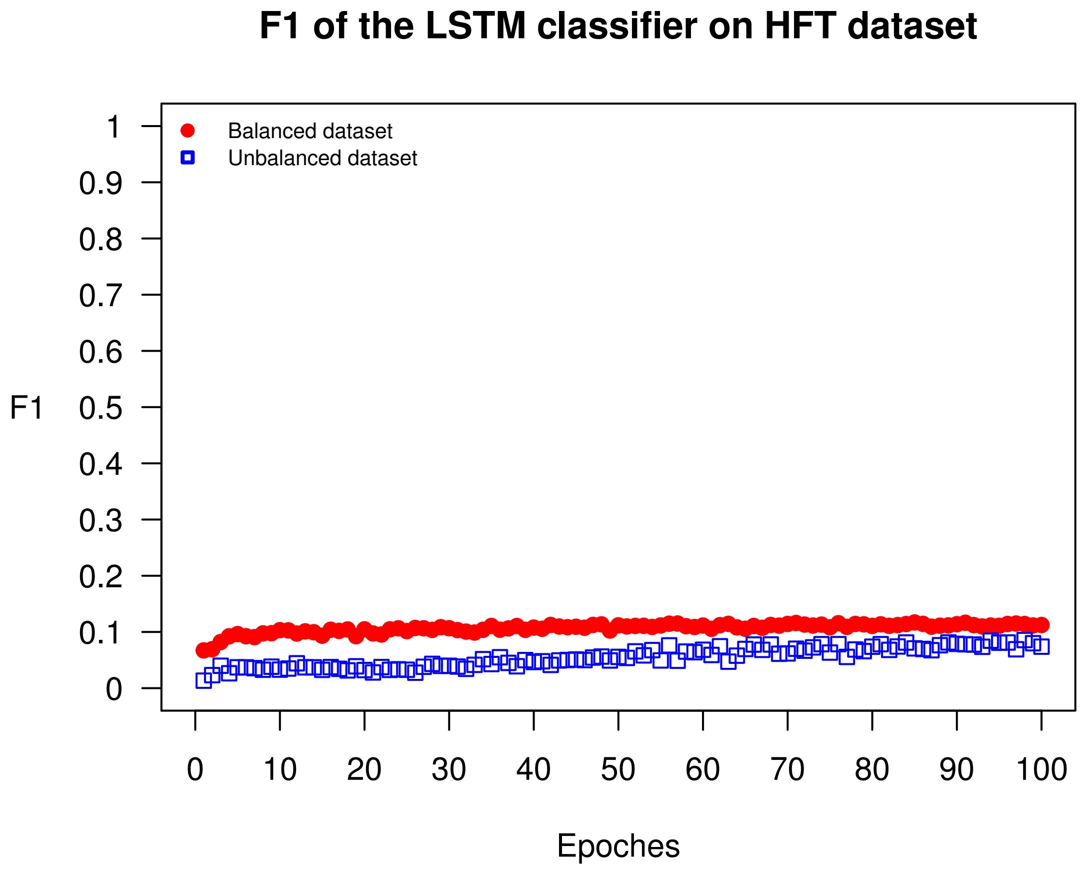


Figure 22: The F1 scores (class -1) of the LSTM classifier trained on the unbalanced and balanced HFT dataset. Both metrics are evaluated at the end of each epoch.

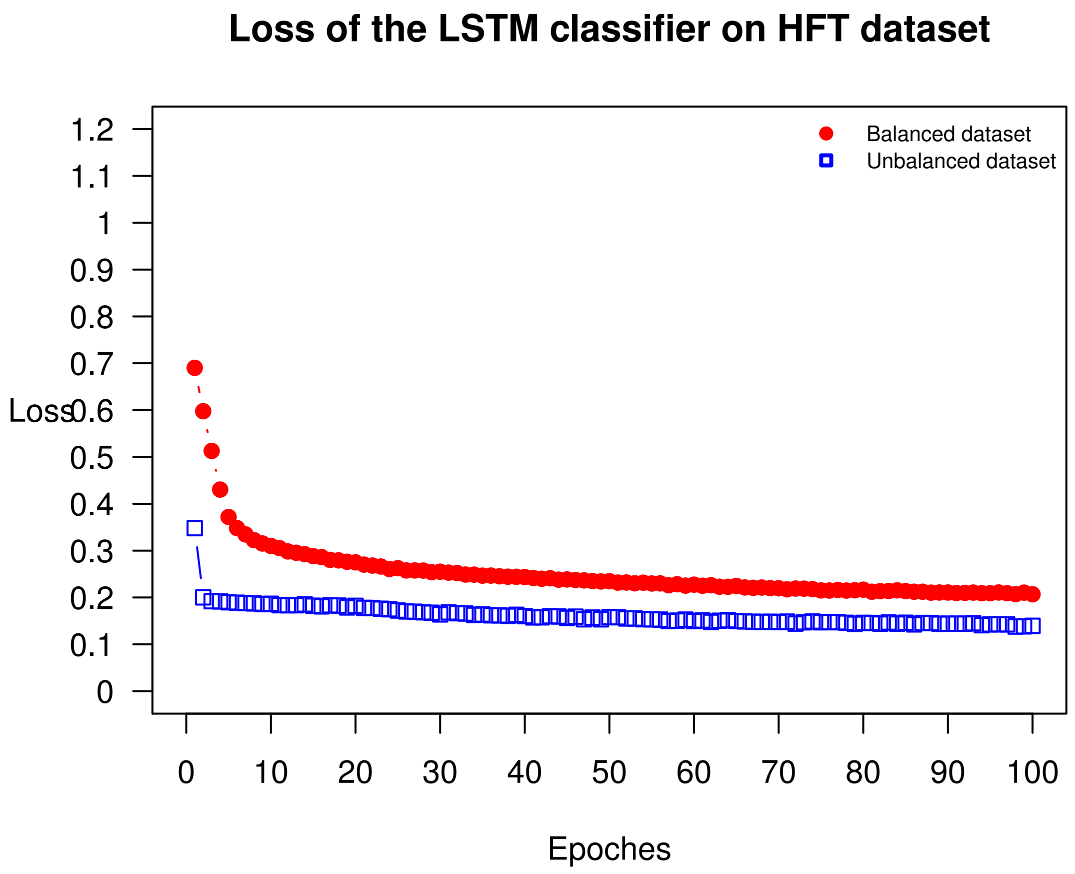
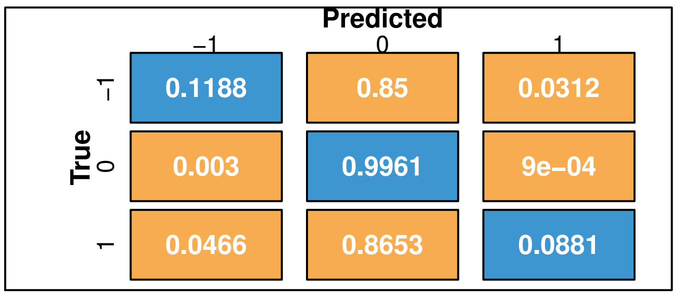
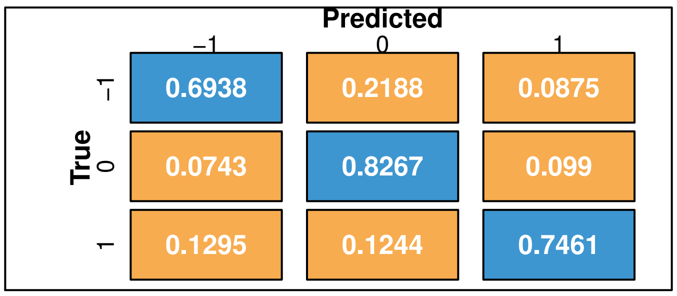


Figure 23: The losses of the LSTM classifier trained on the unbalanced and balanced HFT dataset. Both metrics are evaluated at the end of each epoch.


Predicted
True

True \ Predicted	−1	0	1
−1	0.1188	0.85	0.0312
0	0.003	0.9961	9e−04
1	0.0466	0.8653	0.0881

Figure 24: Normalized confusion matrices of LSTM applied to the HFT dataset without oversampling.


Predicted
True

True \ Predicted	−1	0	1
−1	0.6938	0.2188	0.0875
0	0.0743	0.8267	0.099
1	0.1295	0.1244	0.7461

Figure 25: Normalized confusion matrix of LSTM applied to the HFT dataset with oversampling.

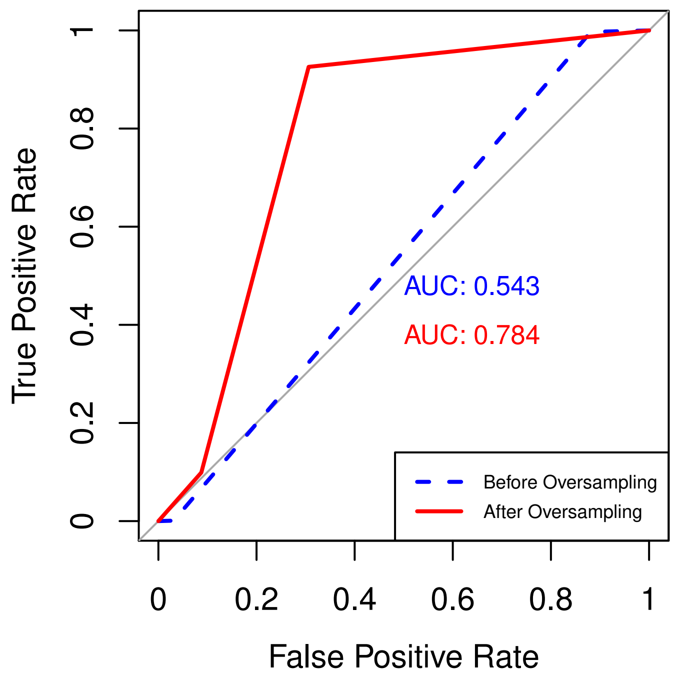


Figure 26: ROC curves of LSTM applied to the HFT dataset with and without oversampling.

the comparative gain from using OSTSC only increases with more training observations and more epoches.

Summary

The `OSTSC` package is a powerful oversampling approach for classifying univariant, but multinomial time series data. This vignette provides a brief overview of the over-sampling methodology implemented by the package. We first provide three examples for the user to verify correct package installation and reproduceability of the results. Using a 'TensorFlow' implementation of an LSTM architecture, we compared the classifier with and without oversampling. We then repeated the evaluation on two medium size datasets which demonstrate the performance gains from using OSTSC and do not require significant computation. Finally, two large datasets are evaluated to demonstrate the scalability of the package. The examples serve to demonstrate that the OSTSC package improves the performance of RNN classifiers applied to highly imbalanced time series data.

References

Abadi, Martin, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, and others. 2016. "TensorFlow: A System for Large-Scale Machine Learning." In *Proceedings of the 12th Usenix Conference on Operating Systems Design and Implementation*, 265–83. OSDI'16. Berkeley, CA, USA: USENIX Association. http://dl.acm.org/citation.cfm?id=3026877.3026899.

Alcock, R. J., Y. Manolopoulos, Data Engineering Laboratory, and Department Of Informatics. 1999. "Time-Series Similarity Queries Employing a Feature-Based Approach." In *7th Hellenic Conference on Informatics, Ioannina*, 27–29.

Allaire, JJ, and Francois Chollet. 2017. *Keras: R Interface to 'Keras'*. https://CRAN.R-project.org/package=keras.

Banos, Oresti, Rafael Garcia, Juan A. Holgado-Terriza, Miguel Damas, Hector Pomares, Ignacio Rojas, Alejandro Saez, and Claudia Villalonga. 2014. "mHealthDroid: A Novel Framework for Agile Development of Mobile Health Applications." In *Ambient Assisted Living and Daily Activities: 6th International Work-Conference, IWAAL 2014, Belfast, UK, December 2-5, 2014.*, edited by Leandro Pecchia, Liming Luke Chen, Chris Nugent, and Jos Bravo, 91–98. Cham: Springer International Publishing.

Banos, Oresti, Claudia Villalonga, Rafael Garcia, Alejandro Saez, Miguel Damas, Juan A. Holgado-Terriza, Sungyong Lee, Hector Pomares, and Ignacio Rojas. 2015. "Design, implementation and validation of a novel open framework for agile development of mobile health applications." *BioMedical Engineering OnLine* 14 (2): S6.

Brown, Christopher. 2012. *Dummies: Create Dummy/Indicator Variables Flexibly and Efficiently.* https://CRAN.R-project.org/package=dummies.

Cao, Hong, Xiaoli Li, David Yew-Kwong Woon, and See-Kiong Ng. 2011. "SPO: Structure Preserving Oversampling for Imbalanced Time Series Classification." *2011 IEEE 11th International Conference on Data Mining*, 1008–13.

———. 2013. "Integrated Oversampling for Imbalanced Time Series Classification." *IEEE Transactions on Knowledge and Data Engineering* 25: 2809–22.

Cao, Hong, Vincent Y. F. Tan, and John Z. F. Pang. 2014. "A Parsimonious Mixture of Gaussian Trees Model for Oversampling in Imbalanced and Multimodal Time-Series Classification." *IEEE Transactions on Neural Networks and Learning Systems* 25: 2226–39.

Chen, Yanping, Yuan Hao, Thanawin Rakthanmanon, Jesin Zakaria, Bing Hu, and Eamonn Keogh. 2015. "A General Framework for Never-Ending Learning from Time Series Streams." *Data Mining and Knowledge Discovery* 29 (6): 1622–64. doi:10.1007/s10618-014-0388-4.

Dixon, M. F. 2017. "Sequence Classification of the Limit Order Book using Recurrent Neural Networks." *ArXiv E-Prints*, July.

Douglas Nychka, Reinhard Furrer, John Paige, and Stephan Sain. 2015. "Fields: Tools for Spatial Data." Boulder, CO, USA: University Corporation for Atmospheric Research. doi:10.5065/D6W957CT.

Dubey, Rashmi, Jiayu Zhou, Yalin Wang, Paul M. Thompson, and Jieping Ye. 2014. "Analysis of Sampling Techniques for Imbalanced Data: An N = 648 Adni Study." *NeuroImage* 87: 220–41.

Goldberger, Ary L., Luis A. N. Amaral, Leon Glass, Jeffrey M. Hausdorff, Plamen Ch. Ivanov, Roger G. Mark, Joseph E. Mietus, George B. Moody, Chung-Kang Peng, and H. Eugene Stanley. 2000. "PhysioBank, Physiotoolkit, and Physionet." *Circulation* 101 (23). American Heart Association, Inc.: e215–e220. doi:10.1161/01.CIR.101.23.e215.

Graves, Alex. 2013. "Generating Sequences with Recurrent Neural Networks." *CoRR* abs/1308.0850. http://arxiv.org/abs/1308.0850.

Jalba, Andrei C, Michael HF Wilkinson, and Jos BTM Roerdink. 2004. "Automatic Segmentation of Diatom Images for Classification." *Microscopy Research and Technique* 65 (1-2). Wiley Online Library: 72–85.

Liang, Guohua, and Chengqi Zhang. 2012. "A Comparative Study of Sampling Methods and Algorithms for Imbalanced Time Series Classification." In *AI 2012: Advances in Artificial Intelligence: 25th Australasian Joint Conference, Sydney, Australia, December 4-7, 2012.*, edited by Michael Thielscher and Dongmo Zhang, 637–48. Berlin, Heidelberg: Springer Berlin Heidelberg.

Lines, Jason, Anthony Bagnall, Patrick Caiger-Smith, and Simon Anderson. 2011. "Classification of Household Devices by Electricity Usage Profiles." In *Intelligent Data Engineering and Automated Learning-Ideal 2011*, 403–12. Springer.

Microsoft Corporation, and Stephen Weston. 2017a. *DoSNOW: Foreach Parallel Adaptor for the 'Snow' Package.* https://CRAN.R-project.org/package=doSNOW.

Microsoft Corporation, and Steve Weston. 2017b. *DoParallel: Foreach Parallel Adaptor for the 'Parallel'*

Package. https://CRAN.R-project.org/package=doParallel.

More, A. 2016. "Survey of resampling techniques for improving classification performance in unbalanced datasets." *ArXiv E-Prints*, August.

Pham, D, and AB Chan. 1998. "Control Chart Pattern Recognition Using a New Type of Self-Organizing Neural Network." In *Proceedings of the Institution of Mechanical Engineers Part I-Journal of Systems and Control Engineering - Proc Inst Mech Eng I-J Syst c*, 212:115–27.

R Core Team. 2017. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Revolution Analytics, and Steve Weston. 2015. *Foreach: Provides Foreach Looping Construct for R*. https://CRAN.R-project.org/package=foreach.

Robin, Xavier, Natacha Turck, Alexandre Hainard, Natalia Tiberti, Frédérique Lisacek, Jean-Charles Sanchez, and Markus Müller. 2011. "PROC: An Open-Source Package for R and S+ to Analyze and Compare Roc Curves." *BMC Bioinformatics* 12: 77.

Siriseriwan, Wacharasak. 2017. *Smotefamily: A Collection of Oversampling Techniques for Class Imbalance Problem Based on Smote*. https://CRAN.R-project.org/package=smotefamily.

Venables, W. N., and B. D. Ripley. 2002. *Modern Applied Statistics with S*. Fourth. New York: Springer. http://www.stats.ox.ac.uk/pub/MASS4.