Knowledge and Information Systems manuscript No.
(will be inserted by the editor)

Instance Reduction for One-Class Classification

**Bartosz Krawczyk · Isaac Triguero ·
Salvador García · Michał Woźniak ·
Francisco Herrera**

Received: date / Accepted: date

Abstract Instance reduction techniques are data preprocessing methods originally developed to enhance the nearest neighbor rule for standard classification. They reduce the training data by selecting or generating representative examples of a given problem. These algorithms have been designed and widely analyzed in multi-class problems providing very competitive results. However, this issue was rarely addressed in the context of one-class classification. In

Michał Woźniak was supported by the Polish National Science Center under the grant no. DEC-2013/09/B/ST6/02264.
Salvador García and Francisco Herrera were supported by the Spanish National Research Project TIN2014-57251-P and the Andalusian Research Plan P11-TIC-7765.

Bartosz Krawczyk
Department of Computer Science
Virginia Commonwealth University, Richmond, VA, USA
E-mail: bkrawczyk@vcu.edu

Isaac Triguero
School of Computer Science
Automated Scheduling, Optimisation and Planning (ASAP) Group
University of Nottingham, Nottingham, UK
E-mail: isaac.triguero@nottingham.ac.uk

Salvador García
Department of Computer Science and Artificial Intelligence
University of Granada, CITIC-UGR, Granada, Spain
E-mail: salvagl@decsai.ugr.es

Michał Woźniak
Department of Systems and Computer Networks
Wrocław University of Technology, Wrocław, Poland
E-mail: michal.wozniak@pwr.edu.pl

Francisco Herrera
Department of Computer Science and Artificial Intelligence
University of Granada, CITIC-UGR, Granada, Spain
Faculty of Computing and Information Technology
King Abdulaziz University, Jeddah, Saudi Arabia
E-mail: herrera@decsai.ugr.es

this specific domain a reduction of the training set may not only decrease the classification time and classifier's complexity, but also allows us to handle internal noisy data and simplify the data description boundary. We propose two methods for achieving this goal. The first one is a flexible framework that adjusts any instance reduction method to one-class scenario by introduction of meaningful artificial outliers. The second one is a novel modification of evolutionary instance reduction technique that is based on differential evolution and uses consistency measure for model evaluation in filter or wrapper modes. It is a powerful native one-class solution that does not require an access to counterexamples. Both of the proposed algorithms can be applied to any type of one-class classifier. On the basis of extensive computational experiments, we show that the proposed methods are highly efficient techniques to reduce the complexity and improve the classification performance in one-class scenarios.

Keywords machine learning · one-class classification · instance reduction · training set selection · evolutionary computing

1 Introduction

Data preprocessing is an essential step within the machine learning process [41, 21, 42]. This kind of techniques aims to simplify the training data by removing noisy and redundant data, so that, machine learning algorithms can be later applied faster and more accurately. In the literature, we can find techniques that focus on the attribute space and others that take into consideration the instance space. From the perspective of attributes, the most well-known data reduction processes are feature selection, feature weighting and feature extraction [4, 7, 30, 44]. Taking into consideration the instance space, we may highlight instance reduction (InR) methods [17, 51].

Instance reduction models search for a reduced set of instances that represents the original training data [14]. These techniques could be grouped into instance selection [17] and instance generation [51] models. The former only selects a subset of instances from the training dataset [35]. The latter may select or generate new artificial instances. Thus, InR can be seen as a combinatorial and optimization problem. Most of the existing InR models have been designed to improve the classification capabilities of the nearest neighbor rule [10], and they are denoted as prototype reduction methods. Among the existing InR methods, evolutionary algorithms have been stressed as the most promising ones [53].

The issue of data preprocessing was so far rarely addressed in the context of one-class classification (OCC) [28]. This branch of machine learning focuses on scenarios in which we do not have access to counterexamples during the training phase. Therefore, a classifier must be trained using objects coming only from a single class, thus creating a data description. Here the quality of training objects has even greater influence on the classification stage than in binary and multi-class problems, as we need to capture such properties of the target class that will allow us to discriminate against unknown outliers. Noisy or rare objects can undermine the performance of one-class classifier, leading to overestimated class boundary [36]. At the same time, training OCC models on large-scale and big data may be of high computational complexity, which will hinder the learning process. This is especially vivid in cases of massive, streaming or complex datasets [33]. Therefore, there is a need for dedicated InR methods.

Our preliminary works on applying InR in OCC [32] showed the potential of this approach. However, this study was limited only to the nearest neighbor data description model and two simple instance reduction techniques. Additionally, we confronted issues with some datasets in which some methods did not provide enough instances to perform the classification step. Therefore, we concluded that there is a need to develop instance reduction methods that can work with any one-class model and are natively tailored to the specific nature of learning in the absence of counterexamples.

In this work, we propose to tackle the issue of InR for OCC from two different perspectives and propose flexible methods that can be used by any one-class classifier.

Our first proposal stems from the intuitive extension of existing InR methods to learning in the absence of counterexamples. We introduce an universal framework for adapting any InR technique to OCC by artificial counterexamples generation and overlapping data cleaning. This way one may transform a given one-class problem into a binary one by creating outliers and then apply any selected InR technique. Generating artificial counterexamples have been used so far in the process of training one-class classifiers [26], but not during the one-class preprocessing phase. This approach could be viewed as a data-level solution, as we modify our training data to allow unaltered usage of any InR algorithm from the literature.

The second proposal is a specific approach tailored to the nature of one-class classification. We introduce a novel modification of evolutionary InR technique that is based on differential evolution [15], and more concretely on a memetic algorithm named SFLSDE (*Scale Factor Local Search Differential Evolution*) [39]. By using a fully unsupervised consistency measure for evaluating set of instances during each iteration we lift the requirement for counterexamples during the reduction phase. Thus, our second proposal is a pure one-class algorithm. We present filter and wrapper modes for our method. This allows user to choose between reduced complexity and a more general solution or a more costly search procedure in order to find a set of instances better fitting the specific one-class learner. This approach could be viewed as an algorithm-level solution, as we modify a specific InR approach to use a criterion suitable for OCC, while leaving our data unaltered.

We present a family of data-level and algorithm-level InR methods for OCC and validate their usefulness and impact on training set reduction, classification accuracy and recognition time on the basis of thorough computational experiments. Such a comparison allows us to gain an insight into how we can reduce the size of the training set in the absence of counterexamples, while maintaining or even improving the obtained predictive performance.

The rest of the manuscript is organized as follows. Next section gives necessary background on OCC and InR. Section 3 discusses the importance of InR in OCC, while Section 4 describe in detail the proposed methodologies. Section 5 presents the evaluation of examined algorithms in a carefully designed experimental study, while final section concludes the paper.

2 Related Works

This section provides the necessary background for the remainder of the paper.

2.1 One-Class Classification

OCC works under the assumption that during the classifier training stage objects originating only from a single class are available [28,38]. We name this specific class as the target class (concept) and denote it as ω_T. The aim of OCC is to derive a decision boundary enclosing all available (or relevant) training objects from ω_T. Thus, we achieve a data (concept) description. As the training procedure is carried out with the usage of only objects from a given class, we may refer to OCC as learning in the absence of counterexamples.

In OCC scenario, during the classification phase, new objects may appear. They may be new instances from the target class or come from previously unknown distribution(s) that are outside of ω_T. Such objects must be rejected by an one-class classifier, as they may be potentially undesirable, harmful or dangerous. We name them as outliers and denote them by ω_O.

A proper OCC method must display good generalization properties in order not to be overfitted on ω_T, and good discrimination abilities to achieve a high rejection rate on ω_O. While this taks may seem as quite similar to binary classification (having positive and negative classes), the primary difference lies in the training procedure of a classifier. In the standard binary problems we may expect objects from the other classes to predominantly come from one direction (the distribution of the given class). In OCC the target class should be separated from all the possible outliers, without any knowledge where does outliers may appear. This leads to a need for the decision boundary to be estimated in all directions in the feature space around the target class.

One may distinguish four main families of OCC classifiers present in the relevant literature:

- **Density-based** methods aim at capturing a distribution of the target class. During prediction phase, a new object is then compared with the estimated distribution and a decision is made on the basis of its resemblance. This approach suffers from a significant limitation, as it requires a high number of available objects from the target class and assumes a flexible density model [45].
- **Reconstruction-based** methods are rooted in clustering and data modeling. They aim at capturing the structure of the target class and during

prediction phase check if new instances will fit into these structures. If the similarity level is below a given threshold, the new instance is labeled as outlier. [46].

- **Boundary-based** methods concentrate on estimating only the enclosing boundary for the target class, assuming that such a boundary will be a sufficient descriptor [3,48]. Thy try to find the optimal size of the volume enclosing the given training objects, as one that is too small can lead to an overtrained model, while one that is too big may lead to an extensive acceptance of outliers into the target class.
- **Ensemble-based** methods [43,58] propose a more flexible data description by utilizing several base classifiers. By combining mutually complementary learners one may achieve a better coverage of the target class, especially when dealing with complex distributions [11]. This requires a proper exploitation of competence areas of each base classifier, like unique model properties (for heterogeneous ensembles [40]), or diversified inputs (for homogeneous ensembles [55]). Additionally, often a classifier selection / ensemble pruning step must be conducted to chose the most complementary and effective learners from the available pool [31].

2.2 Instance Reduction in Standard Classification

This section provides a formal definition about InR techniques and its current trends. A formal notation of the InR problem is as follows: Let $\mathcal{TR}$ be a training dataset and $\mathcal{TS}$ a test set, they are formed by a determined number n and t of samples, respectively. Each sample x_m is a tuple $(x_i^1, x_i^2, ..., x_i^d, \omega_i)$, where, x_i^p is the value of the p-th feature of the i-th sample. This sample belongs to a class ω_i. For the $\mathcal{TR}$ set the class ω_i is known, while it is unknown for $\mathcal{TS}$.

InR techniques aim to reduce the available training set $\mathcal{TR} = \{(x_1, \omega_1), \cdots, (x_n, \omega_n)\}$ of labeled instances to a smaller set of instances $\mathcal{RS} = \{x_1^*, x_2^*, \cdots, x_r^*\}$, with $r < n$ and each x_i^* either drawn from $\mathcal{TR}$ or artificially constructed. The set $\mathcal{RS}$ is later used to train the classifier, rather than the entire set $\mathcal{TR}$, to eventually classify the test set $\mathcal{TS}$. Thus, the instances of $\mathcal{RS}$ should be efficiently computed to represent the distributions of the classes and to discern well when they are used to classify the training objects.

Most of the existing InR models have been designed and combined with the nearest neighbor classifier [10]. As a lazy learning algorithm [1] it classifies unseen instances to the class to which the majority of their k nearest neighbors in the training set belongs based on a certain distance or similarity measure [9]. Thus, the reduction of the training set allows to alleviate the low computational efficiency and high storage requirement of this classifier. Many works extended the application of instance reduction techniques to other classifiers [8] and different domains, such as imbalanced classification [20]. High computational complexity of InR, especially in case of processing large-scale datasets, inspired the development of efficient distributed architectures for this task [13,54].

As we stated before, InR is usually divided into those approaches that are limited to select instances from $\mathcal{TR}$, known as instance selection (InS) [17], and those that may generate artificial examples if needed, named as instance generation (InG) [51]. Both strategies have been deeply studied in the literature. Most of the recent proposals are based on evolutionary algorithms to select [16] or generate [53,27] an appropriate $\mathcal{RS}$.

3 The Role of Instance Reduction in One-Class Classification

In OCC the quality of training data has a direct influence on the estimated data description. If we deal with well-sampled and representative set of examples, then we can assume that it will reflect the true target class distribution. This will allow us to train a classifier displaying at the same time good generalization over the target concept and high discriminative power against outliers, regardless of their nature. This is however an idealized scenario.

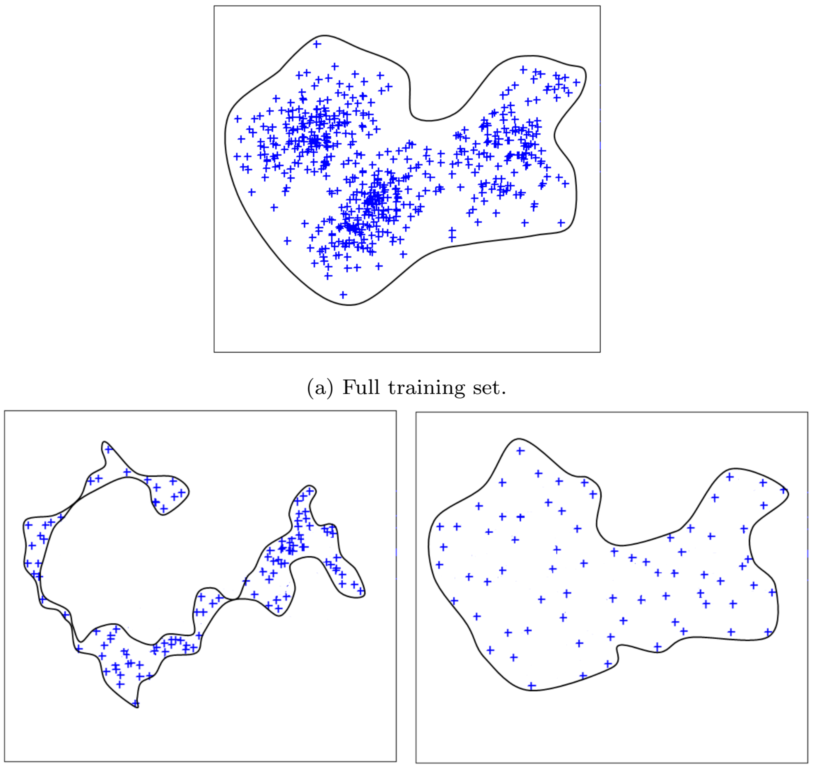
In practice we often deal with uncertain or contaminated training sets in OCC [12]. This means that some objects can be influenced by feature or class label noise, thus offering misleading information regarding the nature of the target concept. When a one-class classifier is being trained on such objects it will output an overestimated decision boundary that will lead to increased acceptance of outliers during the prediction phase. Therefore, to improve the one-class classifier performance such objects should be removed beforehand [37].

Some of training objects may be redundant, not carrying any additional useful information for creating an effective data description. This is especially common in large-scale or big data, where abundance of training examples does not directly translate onto their usefulness. Presence of such objects significantly increase the training and testing times of one-class classifiers. A good example of this can be seen during training one-class methods based on Support Vector Machines [48]. Here one is interested only in objects that have high potential of becoming future support vectors [59]. Thus, reducing the number of potential candidates will speed-up the training procedure.

One must also be aware of the possible negative results of InR in OCC. Firstly, InR methods are unadvised for density-based one-class classifiers. This family of algorithms requires a large sample of the target class in order to properly estimate its density in the feature space. Hence, reducing the size of the training set will negatively impact the quality of the estimation procedure.

From the point of view of any one-class classifier, preserving the original structure of the target class is of uttermost importance. When the training set is subject to a significant level of reduction, the probability of one-class classifier overfitting to a small target concept increases. This will in turn lead to deterioration of generalization capabilities. One cannot assume that only borderline objects within the target concept are important, as outliers may also overlap with the target concept. Therefore, it is highly important to maintain the original object structure, concentrating on removing only redundant or noisy cases. Such a situation is depicted in Figure 1.

Finally, as in standard classification tasks, InR is a trade-off between spending additional computational effort for training set reduction versus achieving a speed-up during the classification phase. As we assume that the classifier, once trained, will be extensively used for continuous decision making, thus improving the classification speed is the priority for us.


(a) Full training set.

(b) Incorrectly reduced instances.

(c) Correctly reduced instances.

Fig. 1: Examples of instance reduction in OCC. Figure (a) depicts an one-class classifier trained on complete set of target class objects. Figure (b) presents an one-class classifier trained on incorrectly reduced set of objects. Here vital objects both within and on the borders of target concept were removed, thus leading to overfitted data description. Figure (c) shows a one-class classifier trained on a reduced set of instances that preserves the characteristics of the original training set.

Instance Reduction for OCC has so far been rarely addressed in the literature. Angiulli [2] introduced a Prototype-based Domain Description rule that is similar to standard nearest neighbor-based one-class classifier but exploits only a selected subset of the training set. Cabral and de Oliviera [6] proposed to analyze every limit of all the feature dimensions to find the true border which describes the normal class. Their method simulates the novelty class by creating artificial prototypes outside the normal description and then uses minimal-distance classification. Hadjadji and Chibani [25] described a special model of Auto-Associative Neural Network that can select samples for its own training in each iteration. This approach is not a strict instance reduction method as it aims only at removing noisy examples. One must notice that these literature proposals are specific only to a given classifier (neighbor-based or neural network). Therefore, there is a lack of universal InR methods for OCC that could be used with any type of one-class classifier.

4 Applying Instance Reduction to One-Class Classification

In this paper we propose two approaches for applying InR for OCC problems:

– A scheme for adapting existing InR solutions to one-class scenarios.
– A new method based on evolutionary InR with one-class evaluation criterion.

Both of these solutions will be described in detail in the following sections.

4.1 Adapting Existing Instance Reduction Methods to One-Class Classification

The first proposed approach is a general framework for adapting any existing InR method to OCC problems. As most of InR methods were designed for binary problems, we need to have access to examples from both classes in order to use them. As in real-life OCC scenarios outliers are not available during the training phase, one needs to find another way to have access to them. We propose to generate artificial counterexamples and use them to transform the input one-class problem into a binary one for the sake of InR procedure. This is a data-level approach that modifies the supplied training set in order to make it applicable to any InR methods, without modifying them in any way.

We will show now how to generate meaningful outliers when only objects from the target class are available. We assume that outliers are distributed uniformly around the target concept. For this, we can use a d-dimensional Gaussian distribution, following these steps [47]:

1. Generate a set of new outlier objects $\mathcal{OS}$ from a specified Gaussian distribution with zero mean and unit variance (making outliers appear all over the decision space similar to white noise):

$$\mathcal{OS} \sim \mathcal{N}(0, 1). \tag{1}$$

2. For each artificial object calculate its squared Euclidean distance from the target concept origin. Please note that this squared distance r^2 is distributed as χ^2 possessing d degrees of freedom. This allows to determine the overlap ratio between outliers and target concept.

$$r^2 = \|x\|^2. \tag{2}$$

3. Apply the cumulative distribution of χ^2_d (denoted here as $\boldsymbol{\chi^2_d}$) in order to transform the r^2 distribution into an uniform distribution $\rho^2 \in [0;1]$, which would lead to determining the new outliers distribution:

$$\rho^2 = \boldsymbol{\chi^2_d}(r^2) = \boldsymbol{\chi^2_d}(\|x\|^2). \tag{3}$$

4. Rescale the obtained distribution ρ^2 using $r' = (\rho^2)^{\frac{2}{d}}$ that r' is distributed as $r' \sim r^d$, where $r \in [0;1]$:

$$r' = (\rho^2)^{\frac{2}{d}} = \left(\boldsymbol{\chi^2_d}(\|x\|^2)\right)^{\frac{2}{d}}. \tag{4}$$

5. Apply rescaling to all of artificially generated objects using obtained factor r' in order to adapt them to the given decision space:

$$x' = \frac{r'}{\|x\|}x. \tag{5}$$

These steps allow us to generate a set of artificial outliers uniformly in a d-dimensional hypersphere. They will be located in all directions surrounding the target class. This way we are able to transform the original one-class problem into a binary setting and apply any InR algorithm on it.

However, this outlier generation method has a significant drawback. There is a high probability that generated artificial outliers will highly overlap with the real target class objects. This can lead to improper selection of prototypes. We are interested in retaining examples that will maintain the best data description. Having outliers within the target class during InR procedure will lead to improper estimation of such potential boundary-building objects. Thus we extend this artificial object generation procedure by a data cleaning step.

For this task we propose to apply Tomek links method [50]. Tomek link is a pair of closest neighbors from opposite classes. Let us assume that we have two objects $(x_i,\ x_j)$, where $x_i \in \omega_T$ and $x_j \in \omega_O$ and $d(x_i, x_j)$ is the distance between these two examples. Such a pair is called a Tomek link if there are no examples x_k in the dataset that satisfy $d(x_i, x_k) < d(x_i, x_j)$ or $d(x_j, x_k) < d(x_i, x_j)$. Therefore if two instances form a Tomek link then one of them is a noisy / overlapping sample or both are located on class borders. One may use this as data cleaning method. Original attempts at this task removed objects from both classes. In the proposed approach we clean only artificial outliers, without affecting the original target class. This leads to removing generated overlapping outliers and obtaining a much better problem representation for InR method.

This data generation approach allows us to run InR methods on a binary set, consisting of target class examples and artificial outliers. As an output, we receive a reduced set of instances. We discard the artificial outliers and use only the ones selected for the target class.

We train a one-class classifier with the usage of reduced set of target class instances.

4.2 Evolutionary Filter and Wrapper Methods for One-Class Instance Reduction

The second proposed approach is a modification of existing InR algorithm that allows to tailor it for OCC scenarios. Here we aim at creating a method that will require only access to target class examples in order to evaluate their usefulness for the classification step. This lifts the requirement for generating artificial counterexamples.

Such an approach may be justified by the fact that introduced artificial objects may not reflect the true nature of outliers. As we do not have any information about the real characteristic of negative objects during the training step we are forced to make certain assumptions. This uncertainty regarding the generated counterexamples highly affects both the pre-processing and training phases.

This is an algorithm-level approach that modifies the specific used InR method, without any alterations on the set of training instances. Let us now present the details of selected InR method (Subsection 4.2.1) and how to change it to a one-class method (Subsection 4.2.2).

4.2.1 Scale Factor Local Search in Differential Evolution for Instance reduction

The Scale Factor Local Search in Differential Evolution (SFLSDE) was originally proposed for continuous optimization problems in [39], and then adapted to perform Instance Reduction in [53], showing to be one of the top performing InG methods in the experimental study. The method uses differential evolution [15], which follows a standard evolutionary framework, evolving a population of candidate solutions over a number of generations.

Specifically, it starts off with a population of NP candidate solutions, so-called individuals. Each of which encodes a reduced set of instances randomly taken from the training set. The size of each individual is typically given by an initial reduction rate parameter that determines the percentage of initial elements selected .

Later, mutation and crossover operators will create new individuals that contain a new positioning for the instances. For each individual c_i, mutation is achieved by randomly selecting two other individuals c_1 and c_2 from the current population. A new individual is created by increasing c_i by the difference of c_1 and c_2, weighted by a scale factor $F > 0$. A number of different mutation operators exist, but we have chosen to use the DE/RandToBest/1 strategy, which makes use of the current fittest c_{best} individual in the population. It increases c_i by both the difference of the two randomly selected individuals as well as the difference of c_i and c_{best}, weighting both terms by F. After mutation, crossover is performed, randomly modifying the mutated individual in certain positions. The crossover is guided by another user-specified parameter Cr.

When new individuals have been generated, a selection operator decides which of those and the previous individuals should survive in the population of the next generation. For this, the one nearest neighbor algorithm is applied classifying the instances of the training set using the instances encoded in each individual as reference. Thus, we obtain a measure of performance of every reduced set that allow us to take the best individuals to the next generation.

The key distinctive point of the the SFLSDE algorithm is that it uses adaptive values for the F and Cr values. Specifically, each individual c_i has their own custom values for F_i and Cr_i, which are encoded within the individual and thus updated in each iteration. The idea of using custom values for F and Cr comes from [5], and the reasoning behind this is that the better the values of the control parameters lead to better individuals, they are therefore more likely to survive and propagate those parameter values F_i and Cr_i to the next generations. When updating the scale factors F_i, two local searches can be used: the golden section search and hill-climbing. We refer to [39] and [53] for further details.

As stated above, SFLSDE was canonically used with measures such as accuracy to evaluate the selected pool of instances. However, as in OCC we do not have access to counterexamples during pre-processing / training stages, we cannot use such measures.

4.2.2 Adapting SFLSDE to OCC

To adapt SFLSDE algorithm to OCC nature we propose to augment it with optimization criterion using the consistency metric. It is a fully unsupervised measure, requiring only access to target class objects. It indicates how consistent a given classifier is in rejecting a pre-set fraction t of the target concept instances.

Let us assume that we have a one-class classifier Ψ trained to reject the fraction t of objects and a validation set $\mathcal{VS}$. Mentioned $\mathcal{VS}$ can be either supplied externally or separated from $\mathcal{TR}$ with constraint that $\mathcal{TR} \cap \mathcal{VS} = \emptyset$.

As in OCC we have an access only to objects from the target concept during the training phase, the error of such classifier may be expressed as false negatives (FN) in a form of:

$$FN = \sum_{i=1}^{|\mathcal{VS}|} \big(1 - I(F_{\omega_T}(x_i) \geq \theta)\big). \tag{6}$$

where $F_{\omega_T}(x_i)$ is the classifier's support for object x_i belonging to the target class, $I(\cdot)$ is the indicator function and θ is the used classification threshold (estimated or inputted by the user).

We can model this as $|\mathcal{VS}|$ binominal experiments. This will allow us to compute the expected number of rejected objects and the variance:

$$E[FN] = \lfloor |\mathcal{VS}| t \rfloor, \tag{7}$$

$$V[FN] = |\mathcal{VS}| t(1-t). \tag{8}$$

When the number of rejected objects from the target class exceeds some bounds around this average (usually 2σ is used [49]), the examined classifier Ψ can be deemed as inconsistent. We may say that Ψ is inconsistent at level t when:

$$\frac{FN}{|\mathcal{VS}|} \geq t + 2\sqrt{|\mathcal{VS}| t(1-t)}. \tag{9}$$

One may compute the consistency for an examined one-class classifier by comparing the rejected fraction t with an estimate of the error on the target class FN:

$$\mathrm{CONS}(\Psi) = |\frac{FN}{|\mathcal{VS}|} - t|. \tag{10}$$

To use this approach, we need to have a number of models to be selected. This is provided by consequent iterations of SFLSDE that supplies us with varying set of target class instances. We order them by their complexity. The model for which the boundary could be estimated with highest reliability, will be selected. Consistency measure prefers the classifier with highest complexity (in order to offer the best possible data description) that can still be considered as consistent.

Therefore, SFLSDE objective is to select such set of instances that maximize the value of one-class classifier's consistency, while satisfying Eq. (9). This allows us to conduct the instance reduction using only objects from the target class.

We propose two versions of our OC-SFLSDE:

- **Filter**. In this version we use an one-class Nearest Neighbor (OCNN) approach for evaluating the consistency of a reduced set of instances in each SFLSDE iteration. The benefits of such an approach is the flexibility of the method (it allows us to select a set of instances once that can be used by any OCC classifier) and reduced computational complexity within each step (OCNN is a lazy classifier, thus no training is required). The main weakness is the fact that filter method will not take into consideration some specific mechanism embedded in training procedures of certain one-class classifiers.

– **Wrapper**. In this version we use an user-specified one-class classifier for evaluating the consistency of reduced set of instances in each SFLSDE iteration. The benefit of the method is the selection of instance set reflecting the data description properties of selected classifier. Drawbacks include increased computational complexity (need to re-train model for each iteration, can be time-consuming for more complex classifiers) and requirement for a priori knowledge of which one-class classifier model will be used for the problem at hand (if an user wants to test more than a single classifier, then OC-SFLSDE must be run for each model independently).

5 Experimental Study

The aim of this experimental study was to compare the proposed InR algorithms for the OCC task with the respect to their reduction rates, influence on classification accuracy and classification times.

5.1 Datasets

To assess the proposed methods we have selected a total of 21 datasets from the UCI Repository. Most of them are binary ones, where the majority class was used as the target concept and the minority class as outliers. For the training purposes we extract only target class object from the given training cross-validation fold, while for testing both target concept examples and outliers from respective test cross-validation fold are used. In case of Contraceptive Method Choice and KDD Cup 1999 datasets, we merged all but one classes as target concept and used the remaining one (with smallest number of samples) as outliers. Details of the chosen datasets are given in Table 1.

We must comment that using binary datasets to transform them into one-class problems is a popular strategy used so far. This way we can simulate a single target concept and a possible outlier distributions with varying overlap ratios, noise or difficult separation boundaries. However, when using binary datasets the outlier distribution will originate from a single class and thus will not cover all areas of the decision space. Such an observed limitation should be a future starting point for developing new one-class benchmarks. However, this is beyond the scope of this paper and we will use here standard approach for evaluating one-class learners.

5.2 Methods

In our experiments, we have selected a number of popular InR methods [22]: 2 InS models, 2 InG and one hybrid InR model:

– The ENN algorithm [56] is an edition-based InS method in which an instance is removed if it does not agree with the majority of its k nearest

Table 1: Details of used datasets. Number of objects in the target class is given in parentheses.

Lp.	Name	Objects	Features	Classes
1.	Climate Model,Simulation Crashes	540 (494)	18	2
2.	Contraceptive Method Choice	1473 (629)	9	3
3.	Credit Approval	690 (307)	15	2
4.	Fertility	100 (88)	10	2
5.	Habermans Survival	306 (225)	3	2
6.	Hepatitis	155 (123)	19	2
7.	Hill-Valley	606 (305)	101	2
8.	Indian Liver Patient Dataset	583 (416)	10	2
9.	Mammographic Mass	961 (516)	9	2
10.	Musk (Version 2)	6598 (2521)	168	2
11.	Ozone Level Detection (One Hour)	2536 (2410)	73	2
12.	Parkinsons	197 (147)	23	2
13.	Pima Indians Diabetes	768 (500)	8	2
14.	Sonar, Mines vs. Rocks	208 (111)	60	2
15.	Statlog (Heart)	270 (150)	13	2
16.	Wisconsin Breast Cancer (Original)	699 (458)	10	2
17.	MiniBooNE	130 065 (93 565)	40	2
18.	Twitter Buzz in Social Media	140 707 (112 932)	77	2
19.	Skin Segmentation	245 057 (50 859)	3	2
20.	Census-Income	299 285 (227 457)	40	2
21.	KDD Cup 1999 (DoS vs. rest)	494 020 (391 458)	41	2

neighbors. As such, the reduction power of this method is limited to remove potential noisy examples.

– The DROP3 [57] procedure combines an edition stage with a decremental approach where the algorithm checks all the instances in order to find those instances which should be deleted. The reduction rate achieved by this InS technique is much higher than the ENN method, eliminating both noisy and unrepresentative examples.
– The ICPL [34] technique is an InG technique that integrates instances by identifying borders and merging those instances that are not located in these borders.
– The IPADE [52] algorithm is an iterative InG model that searches for the smallest reduced set of instances that represent the training data by performing an evolutionary optimization process.
– The SSMA-SFLSDE [53] is a hybrid InS and InG model, in which first the InS method SSMA, determines the best quantity of instances per class for a reduced set, and then the evolutionary method SFLSDE adjusts the positioning of such instances.

We have selected the three following boundary-based one-class classifiers to be used in our experiments:

– One-Class Nearest Neighbor (OCNN) uses only distance to the first nearest neighbor. It works by comparing the distance from the new object to its nearest neighbor from the training set (which consist of labeled target class examples) with the distance from this found nearest neighbor to its own nearest neighbor. This means, that new object is accepted, if it satisfies the local density of objects in the target class.
– Minimum Spanning Tree Data Description (MST) [29] is a distance-based one-class classifier that uses minimum spanning tree structure constructed

on the target class. New instances are classified on the basis of their distance (or similarity) to the closest edge of this tree.

– Support Vector Data Description (SVDD) [48] is a technique that gives a closed boundary around the data in a form of a hypersphere. It is characterized by a center a and radius R. In its basic form it assumes that all objects from the training set must be enclosed by this hypersphere. Slack variables are used to remove inner outliers from the training set, while kernel function allows for searching a better representation in artificial spaces.

5.3 Set-up

Detailed parameters of used methods are given in Table 2. They are selected based on the set-up returning the best averaged performance on examined datasets.

Table 2: Details of algorithm parameters used in the experimental study.

Algorithm	Parameters
OCNN	distance = Euclidean metric
	frac. rejected = 0.05
MST	max. path = 20
	frac. rejected = 0.05
SVDD [29] [48]	kernel type = RBF
	C = 5.0
	γ = 0.0045
	parameter optimization = quadratic programming
	frac. rejected = 0.05
ENN [56]	Number of neighbors = 3, Euclidean distance
DROP3 [57]	Number of neighbors = 3, Euclidean distance
ICPL [34]	Filtering method = RT2
IPADE [52]	Iterations of basic DE = 500, iterSFGSS = 8,
	iterSFHC = 20, Fl = 0.1, Fu = 0.9
SSMA-SFLSDE [53]	PopulationSFLSDE= 50, IterationsSFLSDE = 500
	iterSFGSS =8, iterSFHC=20, Fl=0.1, Fu=0.9
OC-SFLSDE	Population size = 50
	Initial Reduction Rate: 0.95
	Iterations = 500
	iterSFGSS = 8
	iterSFHC = 20
	Fl = 0.1
	Fu = 0.9
	Mutation operator: RandToBest/1/Bin

In order to carry out a thorough comparison, one needs to establish an experimental set-up consisting of evaluation metrics, training / testing modes and statistical analysis [19]. We use the following tools on our framework:

– For evaluating classifiers we use the Balanced Accuracy metric [23] that is skew-insensitive:

$$\text{BAC (TP,FP,TN,FN)} = \frac{1}{2}\left(\frac{\text{TP}}{\text{TP + FN}} + \frac{\text{TN}}{\text{TN + FP}}\right).$$

– Additionally, we check the reduction rate metric, which measures the reduction of storage requirements achieved by a InR algorithm:

$$ReductionRate = 1 - size(\mathcal{RS})/size(\mathcal{TS}).$$

– We use a 10 fold cross validation for training and testing.
– For assessing the ranks of classifiers over all examined benchmarks, we use a Friedman ranking test. It checks if the assigned ranks are significantly different from assigning to each classifier an average rank.
– We use the Finner post-hoc test for an 1 x n comparison. It adjusts the value of α in a step-down manner. We select it due to its high power [18]. Additionally, we examine obtained p-values in order to check how different given two algorithms are.
– We use the Shaffer post-hoc test to find out which of the tested classifiers are distinctive among an n x n comparison. It is a modification of popular Holm's procedure that provides increase in power at the cost of greater complexity of the testing procedure. We have selected it due to its effectiveness in multiple comparison tasks [19]. Additionally, we examine obtained p-values in order to check how different given two algorithms are.
– We fix the significance level $\alpha = 0.05$ for all comparisons.

5.4 General Comments on Obtained Results

Firstly let us compare the two proposed approaches: based on adapting existing methods to OCC and using a consistency-based InR. Regardless of the classifier used, both BAC and statistical tests results clearly point out to superiority of the OC-SFLSDE solution. This can be explained by several factors. The adaptation scheme transforms an original one-class problem into a binary one, assuming a uniform distribution of outliers and generating artificial counterexamples. Despite using data cleaning procedures this approach may potentially lead to ill-defined decision boundaries that may mislead the instance reduction algorithm. One must remember that examined methods use nearest neighbor approach for evaluating the reduced set of instances. There however may not be a direct translation between decision boundaries estimated by binary nearest neighbor and actual shape of data description over the target class. Finally, by transforming a one-class task into a binary problem we overlook some difficulties embedded in the nature of OCC, such as overestimated decision boundaries, empty areas within the data description that lead to classifier's incompetence, or internal noisy samples. These factors may result in a drop of the final accuracy observed for all types of one-class classifiers. The reduction rates displayed by each examined InR algorithm are given in Table 3.

Table 3: Reduction rates [%] obtained by different examined instance reduction approaches.

Dataset	ENN	DROP3	ICPL	IPADE	SSMASFLSDE	OCC-filter	OCC-wrapper-NN	OCC-wrapper-MST	OCC -wrapper-SVDD
Climate	37.04	94.07	88.89	98.89	95.19	81.67	81.67	80.58	80.89
Contraceptive	38.86	74.18	89.01	99.46	97.01	80.25	80.25	78.94	47.28
Credit	20.00	88.99	90.33	99.13	99.42	84.89	84.89	83.92	81.28
Fertility	34.00	94.00	90.00	96.00	94.00	88.73	88.73	88.12	86.73
Habermans	41.18	86.93	87.59	98.04	98.69	85.28	85.28	82.71	83.72
Hepatitis	71.43	71.43	79.23	93.51	92.21	73.08	73.08	70.86	71.24
Hill-Valley	53.80	68.98	71.62	99.34	96.70	75.29	75.29	74.09	72.06
Indian	39.18	78.35	81.45	98.97	98.63	75.82	75.82	74.51	72.88
Mammographic	25.21	82.92	90.00	99.38	98.54	81.03	81.03	78.54	77.90
Musk	74.24	97.73	98.31	99.79	99.36	92.61	92.61	91.30	91.82
Ozone	20.27	97.87	97.85	99.68	95.11	92.30	92.30	88.58	85.60
Parkinsons	36.73	80.61	80.62	94.90	94.90	78.27	78.27	76.37	75.22
Pima	30.99	79.43	80.99	98.70	96.61	73.68	73.68	70.49	68.79
Sonar	31.73	73.08	75.97	97.12	91.35	69.42	69.42	68.76	68.03
Statlog	31.11	89.63	85.93	96.30	96.30	73.12	73.12	72.26	73.12
Wisconsin	15.80	97.70	97.13	99.14	99.14	54.83	54.83	52.64	53.14
MiniBooNE	19.37	93.54	94.19	97.54	97.36	85.49	85.49	82.71	81.09
Twitter Buzz in Social Media	27.43	95.28	97.03	99.01	99.01	87.92	87.92	83.99	80.35
Skin Segmentation	31.54	91.59	91.59	94.12	97.35	81.46	81.46	81.20	80.93
Census-Income	41.54	97.42	95.89	99.11	98.89	79.82	79.82	73.10	71.69
KDD Cup 1999	63.20	89.19	90.86	93.02	93.02	83.19	83.19	82.28	81.93

To cope with these issues OC-SFLSDE (in both wrapper and filter versions) uses a consistency measure which does not require counterexamples. It allows to evaluate the complexity of classifier and how well it captures the target concept without actually being overfitted on training data. Experimental results show that this solution is closer to the nature of one-class problems and offers excellent performance both in filter and wrapper modes. Interestingly OC-SFLSDE is characterized by a slightly lower reduction rates than other methods. This shows that OCC problems cannot be too strongly reduced and a well-represented training set is crucial for proper data description. Additionally, OC-SFLSDE in some cases allows to improve the classification accuracy with respect to the original training set. This shows that by using the proposed hybrid consistency-based solution we are able to filter uncertain or noisy objects that may harm the one-class classifier being trained. While some of the binary methods adopted to OCC offer higher reduction rates and thus increased classification speed-up, OC-SFLSDE returns the best trade-off in terms of classification efficacy and time.

5.5 Results for One-Class Nearest Neighbor

The results obtained by examined InR algorithms with OCNN are presented in Table 4, while the outcomes of post-hoc statistical test are presented in Table 5.

OCNN was the only classifier that displayed good performance with methods other than the proposed filter approach. For some of datasets ENN and SSMASFLSDE approaches augmented with artificial data were able to deliver satisfactory accuracy as well. This can be explained by the minimal-distance classification approach, similar in both binary and one-class scenarios. Hence

Table 4: BAC [%] results for different examined instance reduction methods with One-Class Nearest Neighbor classifier. Please note that for this base classifier both filter and wrapper methods are identical, therefore we present results for only one of them.

Dataset	No reduction	ENN	DROP3	ICPL	IPADE	SSMASFLSDE	OCC-filter
Climate	75.54	75.24	74.68	72.98	70.74	75.24	**78.23**
Contraceptive	89.76	89.03	88.63	87.11	85.93	89.12	**90.76**
Credit	79.63	**79.38**	78.75	76.90	75.69	76.84	**79.38**
Fertility	86.89	86.03	85.64	86.03	85.9	86.04	**87.89**
Haberman	70.98	68.78	68.54	68.37	62.90	68.90	**70.98**
Hepatitis	67.43	**67.22**	67.01	64.37	61.35	66.31	67.00
Hill-Valley	86.94	86.81	86.67	86.12	85.15	86.52	**86.94**
Indian	93.41	**93.41**	93.12	92.53	88.79	92.80	**93.41**
Mammographic	87.37	86.21	86.92	85.11	84.06	86.80	**87.04**
Musk (V2)	71.38	70.79	70.54	69.79	68.94	70.50	**71.27**
Ozone	78.49	76.75	77.32	75.93	75.93	77.83	**77.96**
Parkinsons	67.39	67.04	66.78	67.02	67.12	67.14	**67.39**
Pima	90.52	**89.78**	88.43	88.75	86.42	**89.78**	**89.78**
Sonar	82.66	81.66	81.49	78.34	77.83	81.66	**82.30**
Statlog	68.06	66.18	66.82	64.32	62.11	67.06	**70.02**
Wisconsin	91.36	90.89	90.15	89.74	88.12	90.89	**93.03**
MiniBooNE	72.89	65.35	63.72	60.04	67.83	68.22	**76.44**
Twitter Buzz in Social Media	87.43	82.21	80.10	76.39	82.78	83.19	**88.72**
Skin Segmentation	92.91	84.90	85.18	81.99	84.78	86.11	**93.27**
Census-Income	71.90	59.85	60.14	57.72	63.21	63.99	**70.01**
KDD Cup 1999	72.88	65.31	63.20	58.84	64.25	66.96	**74.06**
Avg. rank		2.69	3.69	4.81	5.72	2.84	1.25

Table 5: Finner test for comparison between the proposed filter instance reduction and reference methods for One-Class Nearest Neighbor classifier. Symbol '=' stands for classifiers without significant differences, '>' for situation in which OCC_f method is superior and '<' for vice versa.

hypothesis	p-**value**
OCC-filter vs no reduction	=0.197458
OCC-filter vs ENN	>0.026588
OCC-filter vs DROP3	>0.000174
OCC-filter vs ICPL	>0.000000
OCC-filter vs IPADE	>0.000000
OCC-filter vs SSMASFLSDE	>0.013132

the evaluation of standard instance selection methods based on two-class nearest neighbor was able to locale useful examples for being preserved in the reduced training set. However, our filter-based solution delivered the best performance in 20 datasets. In this scenario filter and wrapper modes were equivalent due to the base classifier used. Statistical testing confirms the superiority of this approach to reference ones. Additionally, it shows that there are no statistically significant differences between this instance reduction method and classifier trained on the full dataset.

5.6 Results for Minimum Spanning Tree Data Description

The results obtained by examined InR algorithms with MST are presented in Table 6, while the outcomes of post-hoc statistical test are presented in Table 7.

Table 6: BAC [%] results for different examined instance reduction methods with Minimum Spanning Tree Data Description classifier.

Dataset	No reduction	ENN	DROP3	ICPL	IPADE	SSMASFLSDE	OCC-filter	OCC-wrapper-MST
Climate	78.36	77.18	60.12	65.53	64.89	68.54	77.45	**79.45**
Contraceptive	87.75	86.56	76.32	79.32	80.17	80.22	86.89	**87.75**
Credit	82.45	81.36	62.95	69.75	68.65	75.28	81.64	**83.53**
Fertility	87.46	86.89	80.41	82.41	82.24	77.49	**87.46**	**87.46**
Haberman	70.13	68.53	53.58	57.74	58.05	61.93	69.15	**70.02**
Hepatitis	71.38	70.36	59.37	66.12	64.74	64.50	69.36	**71.16**
Hill-Valley	84.23	83.45	76.96	77.43	78.32	77.94	84.23	**85.41**
Indian	94.14	93.72	78.24	78.94	79.27	84.39	**94.51**	**94.51**
Mammographic	85.89	85.02	70.53	77.23	75.51	81.05	**85.11**	**85.11**
Musk (V2)	73.76	72.22	55.85	58.34	57.84	62.63	72.88	**73.41**
Ozone	77.97	77.13	69.93	71.52	72.22	76.86	78.48	**80.39**
Parkinsons	71.84	71.08	58.47	59.32	60.78	60.94	**72.46**	**72.46**
Pima	92.65	91.94	71.04	77.34	75.88	81.56	92.07	**92.43**
Sonar	81.87	80.83	63.68	67.80	69.97	73.74	**81.87**	**81.87**
Statlog	67.27	64.89	50.02	54.53	51.68	61.89	68.37	**70.16**
Wisconsin	93.53	93.21	84.36	87.27	87.09	90.11	93.21	**93.53**
MiniBooNE	74.59	62.18	60.94	58.59	63.93	65.42	74.81	**77.58**
Twitter Buzz in Social Media	88.92	80.05	77.92	74.11	80.22	80.44	85.72	**90.01**
Skin Segmentation	93.44	81.15	82.03	77.22	81.46	82.02	89.17	**94.58**
Census-Income	72.55	58.64	59.23	55.97	61.89	62.36	**70.99**	**70.99**
KDD Cup 1999	72.53	61.18	59.23	54.38	62.05	64.91	72.55	**74.03**
Avg. rank		2.91	6.94	5.31	5.37	4.37	1.94	1.16

Table 7: Shaffer test for comparison between the proposed filter and wrapper instance reduction methods and reference approaches for Minimum Spanning Tree classifier. Symbol '=' stands for classifiers without significant differences, '>' for situation in which the first analyzed method is superior and '<' for vice versa.

hypothesis	***p*-value**	**hypothesis**	***p*-value**
OCC-filter vs no reduction	= 0.614851	OCC-wrapper vs no reduction	> 0.041704
OCC-filter vs ENN	= 0.257327	OCC-wrapper vs ENN	> 0.019860
OCC-filter vs DROP3	> 0.000522	OCC-wrapper vs DROP3	> 0.000000
OCC-filter vs ICPL	> 0.000000	OCC-wrapper vs ICPL	> 0.000000
OCC-filter vs IPADE	> 0.000000	OCC-wrapper vs IPADE	> 0.000000
OCC-filter vs SSMASFLSDE	> 0.00709	OCC-wrapper vs SSMASFLSDE	> 0.000016
OCC-filter vs OCC-wrapper	< 0.044270		

MST works significantly better with OC-SFLSDE than with remaining methods. Here we are able to analyze two operating modes: as a filter and as a wrapper. In the first case we can see that obtained results are statistically not worse than when using full training set. This shows that despite the lack of knowledge which classifier will be used the filter mode can still deliver meaningfully selected training samples. However, Shaffer test pointed that there are no significant differences between this filter method and ENN approach using artificial counterexamples. For the wrapper mode situation changes in favor of the hybrid evolutionary approach. Here we are able not only to significantly outperform all other methods (including filter version), but we also get improved results in comparison to using the entire training set. Using wrapper solution allows us to evaluate the usefulness of training samples for the minimum spanning tree construction and eliminate redundant, similar or noisy samples which contributes to decreased complexity and improved accuracy. Additional cost connected to training MST at each iteration pays off in the improved final model. When comparing classification times we can see that both filter and wrapper solutions achieve similar reduction rates and response times of the trained classifier.

5.7 Results for Support Vector Data Description

The results obtained by examined InR algorithms with SVDD are presented in Table 8, while the outcomes of post-hoc statistical test are presented in Table 9.

Table 8: BAC [%] results for different examined instance reduction methods with Support Vector Data Description classifier. – stands for situation in which the number of instances after reduction was too small to efficiently train SVDD classifier.

Dataset	No reduction	ENN	DROP3	ICPL	IPADE	SSMASFLSDE	OCC-filter	OCC-wrapper-SVDD
Climate	81.73	81.73	–	72.84	–	–	82.38	**84.51**
Contraceptive	85.38	84.79	79.24	74.62	–	65.27	84.90	**85.38**
Credit	83.90	82.58	78.46	63.56	–	–	83.72	**84.43**
Fertility	82.61	79.71	74.07	–	–	–	81.12	**81.94**
Haberman	72.98	71.66	69.31	59.36	–	–	71.35	**72.56**
Hepatitis	70.14	67.48	62.98	63.51	–	–	69.54	**70.00**
Hill-Valley	77.36	75.38	70.93	71.68	–	–	76.30	**77.04**
Indian	93.62	92.54	86.08	82.90	–	–	92.98	**93.18**
Mammographic	87.92	87.44	83.11	59.98	–	–	87.44	**89.03**
Musk (V2)	71.21	70.03	64.82	67.82	48.29	58.58	70.52	**71.06**
Ozone	75.28	74.00	69.05	54.29	44.89	54.48	76.38	**77.81**
Parkinsons	74.02	71.33	66.43	62.74	–	–	72.35	**73.60**
Pima	93.26	91.27	80.27	82.73	–	51.57	92.18	**93.26**
Sonar	79.53	78.18	67.98	71.04	–	–	79.53	**81.13**
Statlog	69.32	**69.90**	–	56.68	–	–	**69.90**	**69.90**
Wisconsin	94.65	**94.65**	–	–	–	–	**94.65**	**94.65**
MiniBooNE	74.23	55.77	54.25	44.46	54.38	57.02	70.05	**76.93**
Twitter Buzz in Social Media	89.41	69.87	68.42	59.93	62.17	63.03	83.98	**91.64**
Skin Segmentation	93.72	68.91	70.01	54.81	64.27	67.72	90.02	**95.03**
Census-Income	76.48	42.20	41.81	39.97	38.55	39.06	69.94	**79.11**
KDD Cup 1999	73.87	53.99	51.95	46.63	48.63	51.89	72.16	**75.86**
Avg. rank		2.78	4.66	4.72	6.47	6.16	2.09	1.12

Table 9: Shaffer test for comparison between the proposed filter and wrapper instance reduction methods and reference approaches for Support Vector Data Description classifier. Symbol '=' stands for classifiers without significant differences, '>' for situation in which the first analyzed method is superior and '<' for vice versa.

hypothesis	***p*-value**	**hypothesis**	***p*-value**
OCC-filter vs no reduction	= 0.162701	OCC-wrapper vs no reduction	> 0.042915
OCC-filter vs ENN	= 0.174658	OCC-wrapper vs ENN	> 0.027993
OCC-filter vs DROP3	> 0.000000	OCC-wrapper vs DROP3	> 0.000000
OCC-filter vs ICPL	> 0.000003	OCC-wrapper vs ICPL	> 0.000001
OCC-filter vs IPADE	> 0.000003	OCC-wrapper vs IPADE	> 0.000000
OCC-filter vs SSMASFLSDE	> 0.000989	OCC-wrapper vs SSMASFLSDE	> 0.000000
OCC-filter vs OCC-wrapper	< 0.028299		

SVDD is characterized by the most atypical behavior from the three examined methods. Here, for some of datasets, the standard InR techniques returned too small training set to build a one-class support vector classifier. This is because they use the nearest neighbor approach which has no lower bound on the size of the training set, while methods based on support vectors require a certain amount of samples for processing. SVDD cannot estimate an enclosing boundary with too few samples, as in cases when some InR methods return less than five training samples. Our proposed method once again returns the best performance, especially in the wrapper mode. This allows us to embed the SVDD training procedure with robustness to internal outliers that is of significant benefit to this classifier. SVDD displays the highest gain in classification efficacy from all of examined classifiers when wrapper selection is applied.

5.8 Impact on the Computational Complexity

The average runtime of examined InR methods are presented in Figure 2. Average classification times before and after reduction for examined classifiers with respect to small datasets (< 10 000 instances) are depicted in Figures 3 – 5, while for large-scale datasets (>= 100 000 instances) are depicted in Figure 6. The red points stand for a baseline classification time, while remaining points stand for reduced classification times after applying examined InR algorithms. This allows us to examine the computational gains from using simplified one-class learners.

In case of OCNN, we can see that our filter is a highly suitable method for OCNN, increasing the classification speed while not decreasing its accuracy. In case of MST, we when comparing classification times we can see that both filter and wrapper solutions achieve similar reduction rates and response times of the trained classifier. As for SVDD, we can see a slightly bigger differences in reduction rates and classification times between filter and wrapper approaches. Using wrapper method results in slightly bigger training set with

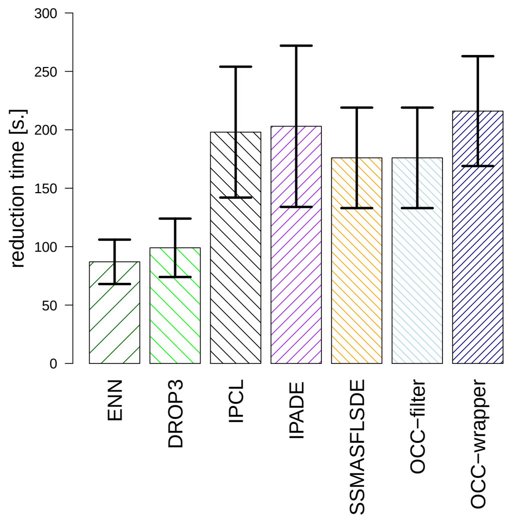


Fig. 2: Average reduction times of examined InR methods over all datasets.

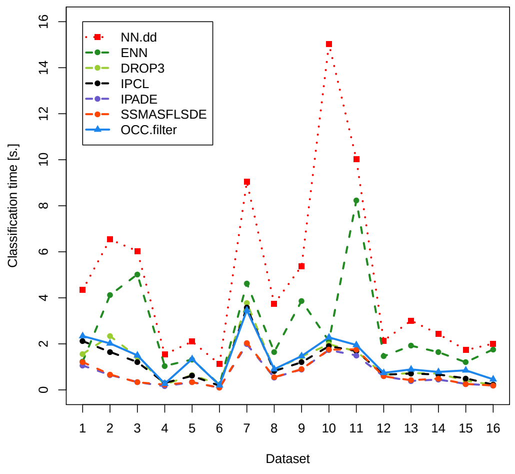


Fig. 3: Average classification times in seconds for One-Class Nearest Neighbor classifier before and after reduction by examined instance reduction methods over small datasets.

potentially higher number of support vectors (which explains the classification time). Still SVDD is characterized by the lowest classification time from all classifiers examined. These additional vectors have a clear positive influence on the classification procedure, which allows us to conclude that wrapper offers

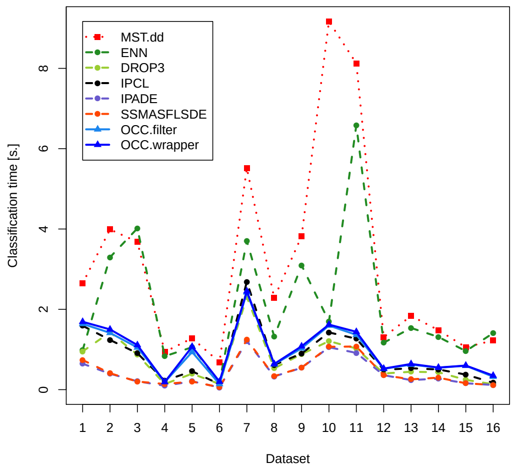


Fig. 4: Average classification times in seconds for Minimum Spanning Tree classifier before and after reduction by examined instance reduction methods over small datasets.

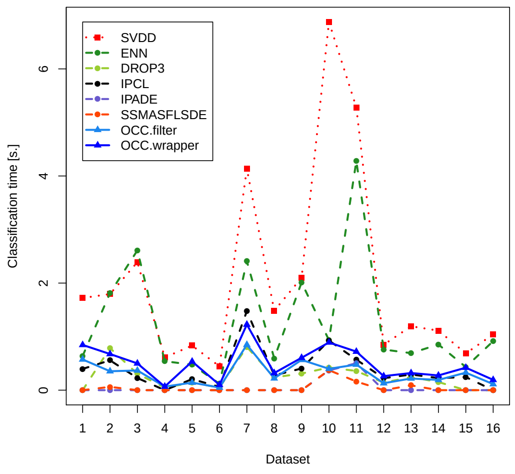


Fig. 5: Average classification times in seconds for Support Vector Data Description classifier before and after reduction by examined instance reduction methods over small datasets. Time equal to 0 stands for a situation in which the dataset after reduction was too small to train a classifier.

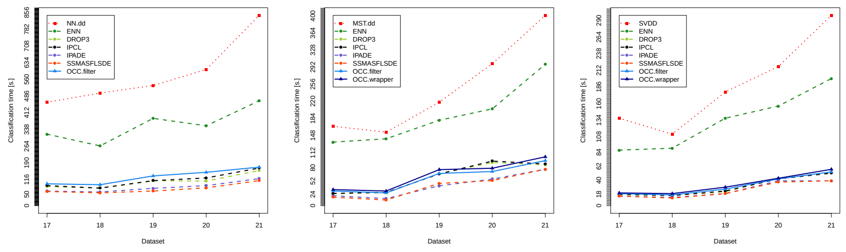


Fig. 6: Average classification times in seconds for (*left*) One-Class Nearest Neighbor, (*center*) Minimum Spanning Tree and (*right*) Support Vector Data Description classifiers before and after reduction by examined instance reduction methods over large-scale datasets.

the best trade-off between reduction rates and classification performance for one-class support vector classifiers.

6 Conclusions and Future Works

In this paper we have discussed the usability of instance reduction methods for one-class classification. We showed, that a carefully conducted InR can lead to a significant lowering of OCC complexity and often to improved classification performance. We have proposed two approaches to applying InR for OCC. Firstly, an universal framework was introduced that allowed to transform any existing InR method to one-class version. It used uniform generation of artificial objects combined with data cleaning procedure to remove overlap between classes. This way we obtained a binary dataset that can be supplied to any conventional InR algorithm. After reduction artificial outliers were discarded and one-class classifier was trained using a reduced set of target concept instances.

We have identified potential shortcoming of methods relying on artificial data generation and proposed a second solution, native to OCC characteristics. It used SFLSDE, method based on differential evolution, to select training samples. We have augmented it with consistency measure in order to evaluate set of instances without a need for counterexamples. Filter and wrapper versions were proposed, varying in complexity and adaptability to selected classification model. Thorough experimental study backed-up by a statistical analysis proved the high usefulness of proposed solutions regardless of the base classifier used. We showed that consistency-based InR significantly outperforms methods that require artificial counterexamples.

Obtained results encourage us to continue work on instance reduction for one-class classification. In future we plan to develop ensemble learning techniques based on diverse subsets of selected examples [24].

References

1. Aha, D.W., Kibler, D., Albert, M.K.: Instance-based learning algorithms. Machine Learning **6**(1), 37–66 (1991)
2. Angiulli, F.: Prototype-based domain description for one-class classification. IEEE Trans. Pattern Anal. Mach. Intell. **34**(6), 1131–1144 (2012)
3. Bicego, M., Figueiredo, M.A.T.: Soft clustering using weighted one-class support vector machines. Pattern Recognition **42**(1), 27–32 (2009)
4. Bolón-Canedo, V., Sánchez-Maroño, N., Alonso-Betanzos, A.: Feature Selection for High-Dimensional Data. Artificial Intelligence: Foundations, Theory, and Algorithms. Springer (2015)
5. Brest, J., Greiner, S., Boskovic, B., Mernik, M., Zumer, V.: Self-adapting control parameters in differential evolution: A comparative study on numerical benchmark problems. IEEE Transactions on Evolutionary Computation **10**(6), 646–657 (2006). DOI 10.1109/TEVC.2006.872133
6. Cabral, G.G., de Oliveira, A.L.I.: A novel one-class classification method based on feature analysis and prototype reduction. In: Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Anchorage, Alaska, USA, October 9-12, 2011, pp. 983–988 (2011)
7. Cano, A., Ventura, S., Cios, K.J.: Multi-objective genetic programming for feature extraction and data visualization. Soft Comput. **21**(8), 2069–2089 (2017)
8. Cano, J.R., Herrera, F., Lozano, M.: Using evolutionary algorithms as instance selection for data reduction in KDD: an experimental study. IEEE Transactions on Evolutionary Computation **7**(6), 561–575 (2003)
9. Chen, Y., Garcia, E.K., Gupta, M.R., Rahimi, A., Cazzanti, L.: Similarity-based classification: Concepts and algorithms. Journal of Machine Learning Research **10**, 747–776 (2009)
10. Cover, T.M., Hart, P.E.: Nearest neighbor pattern classification. IEEE Transactions on Information Theory **13**(1), 21–27 (1967)
11. Cyganek, B.: One-class support vector ensembles for image segmentation and classification. Journal of Mathematical Imaging and Vision **42**(2-3), 103–117 (2012)
12. Cyganek, B., Wiatr, K.: Image contents annotations with the ensemble of one-class support vector machines. In: NCTA 2011 - Proceedings of the International Conference on Neural Computation Theory and Applications [part of the International Joint Conference on Computational Intelligence IJCCI 2011], Paris, France, 24-26 October, 2011, pp. 277–282 (2011)
13. Czarnowski, I.: Prototype selection algorithms for distributed learning. Pattern Recognition **43**(6), 2292–2300 (2010)
14. Czarnowski, I.: Cluster-based instance selection for machine classification. Knowl. Inf. Syst. **30**(1), 113–133 (2012)
15. Das, S., Suganthan, P.: Differential evolution: A survey of the state-of-the-art. IEEE Transactions on Evolutionary Computation **15**(1), 4–31 (2011)
16. García, S., Cano, J.R., Herrera, F.: A memetic algorithm for evolutionary prototype selection: A scaling up approach. Pattern Recognition **41**(8), 2693–2709 (2008)
17. García, S., Derrac, J., Cano, J., Herrera, F.: Prototype selection for nearest neighbor classification: Taxonomy and empirical study. IEEE Transactions on Pattern Analysis and Machine Intelligence **34**(3), 417–435 (2012)
18. García, S., Fernández, A., Luengo, J., Herrera, F.: Advanced nonparametric tests for multiple comparisons in the design of experiments in computational intelligence and data mining: Experimental analysis of power. Inf. Sci. **180**(10), 2044–2064 (2010)
19. García, S., Herrera, F.: An extension on "Statistical comparisons of classifiers over multiple data sets" for all pairwise comparisons. Journal of Machine Learning Research **9**, 2677–2694 (2008)
20. García, S., Herrera, F.: Evolutionary under-sampling for classification with imbalanced data sets: Proposals and taxonomy. Evolutionary Computation **17**(3), 275–306 (2009)
21. García, S., Luengo, J., Herrera, F.: Data Preprocessing in Data Mining. Springer Publishing Company, Incorporated (2014)

22. García, S., Luengo, J., Herrera, F.: Tutorial on practical tips of the most influential data preprocessing algorithms in data mining. Knowledge-Based Systems **98**, 1–29 (2016)
23. García, V., Mollineda, R.A., Sánchez, J.S.: Index of balanced accuracy: A performance measure for skewed class distributions. In: Pattern Recognition and Image Analysis, 4th Iberian Conference, IbPRIA 2009, Póvoa de Varzim, Portugal, June 10-12, 2009, Proceedings, pp. 441–448 (2009)
24. García-Pedrajas, N., de Haro-García A.: Boosting instance selection algorithms. Knowledge-Based Systems **67**, 342–360 (2014)
25. Hadjadji, B., Chibani, Y.: Optimized selection of training samples for one-class neural network classifier. In: 2014 International Joint Conference on Neural Networks, IJCNN 2014, Beijing, China, July 6-11, 2014, pp. 345–349 (2014)
26. Hempstalk, K., Frank, E., Witten, I.H.: One-class classification by combining density and class probability estimation. In: Machine Learning and Knowledge Discovery in Databases, European Conference, ECML/PKDD 2008, Antwerp, Belgium, September 15-19, 2008, Proceedings, Part I, pp. 505–519 (2008)
27. Hu, W., Tan, Y.: Prototype generation using multiobjective particle swarm optimization for nearest neighbor classification. IEEE Transactions on Cybernetics **46**(12), 2719–2731 (2016)
28. Japkowicz, N., Myers, C., Gluck, M.: A novelty detection approach to classification. In: Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence, IJCAI 95, Montréal Québec, Canada, August 20-25 1995, 2 Volumes, pp. 518–523 (1995)
29. Juszczak, P., Tax, D.M.J., Pekalska, E., Duin, R.P.W.: Minimum spanning tree based one-class classifier. Neurocomputing **72**(7-9), 1859–1869 (2009)
30. Kim, K., Lin, H., Choi, J.Y., Choi, K.: A design framework for hierarchical ensemble of multiple feature extractors and multiple classifiers. Pattern Recognition **52**, 1–16 (2016)
31. Krawczyk, B.: One-class classifier ensemble pruning and weighting with firefly algorithm. Neurocomputing **150**, 490–500 (2015)
32. Krawczyk, B., Triguero, I., García, S., Woźniak, M., Herrera, F.: A first attempt on evolutionary prototype reduction for nearest neighbor one-class classification. In: Proceedings of the IEEE Congress on Evolutionary Computation, CEC 2014, Beijing, China, July 6-11, 2014, pp. 747–753 (2014). DOI 10.1109/CEC.2014.6900469
33. Krawczyk, B., Woźniak, M., Herrera, F.: On the usefulness of one-class classifier ensembles for decomposition of multi-class problems. Pattern Recognition **48**(12), 3969 – 3982 (2015)
34. Lam, W., Keung, C.K., Liu, D.: Discovering useful concept prototypes for classification based on filtering and abstraction. IEEE Transactions on Pattern Analysis and Machine Intelligence **14**(8), 1075–1090 (2002)
35. Leyva, E., Muñoz, A.G., Pérez, R.: Three new instance selection methods based on local sets: A comparative study with several approaches from a bi-objective perspective. Pattern Recognition **48**(4), 1523–1537 (2015)
36. Li, Y.: Selecting training points for one-class support vector machines. Pattern Recognition Letters **32**(11), 1517–1522 (2011)
37. Liu, W., Hua, G., Smith, J.R.: Unsupervised one-class learning for automatic outlier removal. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2014, Columbus, OH, USA, June 23-28, 2014, pp. 3826–3833 (2014)
38. Moya, M., Hush, D.: Network constraints and multi-objective optimization for one-class classification. Neural Networks **9**(3), 463–474 (1996)
39. Neri, F., Tirronen, V.: Scale factor local search in differential evolution. Memetic Computing **1**(2), 153–171 (2009)
40. Parhizkar, E., Abadi, M.: Beeowa: A novel approach based on ABC algorithm and induced OWA operators for constructing one-class classifier ensembles. Neurocomputing **166**, 367–381 (2015)
41. Pyle, D.: Data Preparation for Data Mining. The Morgan Kaufmann Series in Data Management Systems. Morgan Kaufmann (1999)
42. Ramírez-Gallego, S., Krawczyk, B., García, S., Wozniak, M., Herrera, F.: A survey on data preprocessing for data stream mining: Current status and future directions. Neurocomputing **239**, 39–57 (2017)

43. Rokach, L.: Decision forest: Twenty years of research. Information Fusion **27**, 111–125 (2016)
44. Shu, W., Shen, H.: Multi-criteria feature selection on cost-sensitive data with missing values. Pattern Recognition **51**, 268–280 (2016)
45. Sonnenburg, S., Ratsch, G., Schafer, C., Scholkopf, B.: Large scale multiple kernel learning. Journal of Machine Learning Research **7**, 1531–1565 (2006)
46. Spurek, P., Wójcik, M., Tabor, J.: Cross-entropy clustering approach to one-class classification. In: Artificial Intelligence and Soft Computing - 14th International Conference, ICAISC 2015, Zakopane, Poland, June 14-18, 2015, Proceedings, Part I, pp. 481–490 (2015)
47. Tax, D.J.M., Duin, R.P.W.: Uniform object generation for optimizing one-class classifiers. Journal of Machine Learning Research **2**, 155–173 (2001)
48. Tax, D.M.J., Duin, R.P.W.: Support vector data description. Machine Learning **54**(1), 45–66 (2004)
49. Tax, D.M.J., Müller, K.: A consistency-based model selection for one-class classification. In: 17th International Conference on Pattern Recognition, ICPR 2004, Cambridge, UK, August 23-26, 2004., pp. 363–366 (2004)
50. Tomek, I.: Two modifications of cnn. Systems, Man and Cybernetics, IEEE Transactions on **SMC-6**(11), 769–772 (1976)
51. Triguero, I., Derrac, J., García, S., Herrera, F.: A taxonomy and experimental study on prototype generation for nearest neighbor classification. IEEE Transactions on Systems, Man, and Cybernetics–Part C: Applications and Reviews **42**(1), 86–100 (2012)
52. Triguero, I., García, S., Herrera, F.: IPADE: Iterative prototype adjustment for nearest neighbor classification. IEEE Transactions on Neural Networks **21**(12), 1984–1990 (2010)
53. Triguero, I., García, S., Herrera, F.: Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition **44**(4), 901–916 (2011)
54. Triguero, I., Peralta, D., Bacardit, J., García, S., Herrera, F.: MRPR: A mapreduce solution for prototype reduction in big data classification. Neurocomputing **150**, 331–345 (2015)
55. Wilk, T., Woźniak, M.: Soft computing methods applied to combination of one-class classifiers. Neurocomputing **75**, 185–193 (2012)
56. Wilson, D.L.: Asymptotic properties of nearest neighbor rules using edited data. IEEE Transactions on System, Man and Cybernetics **2**(3), 408–421 (1972)
57. Wilson, D.R., Martinez, T.R.: Reduction techniques for instance-based learning algorithms. Machine Learning **38**(3), 257–286 (2000)
58. Woźniak, M., Grana, M., Corchado, E.: A survey of multiple classifier systems as hybrid systems. Information Fusion **16**(1), 3–17 (2014)
59. Zhu, F., Ye, N., Yu, W., Xu, S., Li, G.: Boundary detection and sample reduction for one-class support vector machines. Neurocomputing **123**, 166–173 (2014)