SEG-SSC: A Framework Based on Synthetic Examples Generation for Self-Labeled Semi-Supervised Classification

Isaac Triguero, Salvador García, and Francisco Herrera

***Abstract*—Self-labeled techniques are semi-supervised classification methods that address the shortage of labeled examples via a self-learning process based on supervised models. They progressively classify unlabeled data and use them to modify the hypothesis learned from labeled samples. Most relevant proposals are currently inspired by boosting schemes to iteratively enlarge the labeled set. Despite their effectiveness, these methods are constrained by the number of labeled examples and their distribution, which in many cases is sparse and scattered. The aim of this paper is to design a framework, named synthetic examples generation for self-labeled semi-supervised classification, to improve the classification performance of any given self-labeled method by using synthetic labeled data. These are generated via an oversampling technique and a positioning adjustment model that use both labeled and unlabeled examples as reference. Next, these examples are incorporated in the main stages of the self-labeling process. The principal aspects of the proposed framework are: 1) introducing diversity to the multiple classifiers used by using more (new) labeled data; 2) fulfilling labeled data distribution with the aid of unlabeled data; and 3) being applicable to any kind of self-labeled method. In our empirical studies, we have applied this scheme to four recent self-labeled methods, testing their capabilities with a large number of data sets. We show that this framework significantly improves the classification capabilities of self-labeled techniques.**

***Index Terms*—Co-training, self-labeled methods, semi-supervised classification, synthetic examples.**

I. Introduction

HAVING a multitude of unlabeled data and few labeled ones occurs quite often in many practical applications such as medical diagnosis, spam filtering, bioinformatics, etc. In this scenario, learning appropriate hypotheses with traditional supervised classification methods [1] is not straightforward because they only can exploit labeled data. Nevertheless, semi-supervised classification (SSC) [2]–[4] approaches also utilize unlabeled data to improve the predictive performance, modifying the learned hypothesis obtained from labeled examples alone.

With SSC we may pursue two different objectives: transductive and inductive classification [5]. The former is devoted to predicting the correct labels of a set of unlabeled examples that is also used during the training phase. The latter refers to the problem of predicting unseen data by learning from labeled and unlabeled data as training examples. In this paper, we will analyze both settings.

Existing SSC algorithms are usually classified depending on the conjectures they make about the relation of labeled and unlabeled data distributions. Broadly speaking, they are based on the manifold and/or cluster assumption. The manifold assumption is satisfied if data lie approximately on a manifold of lower dimensionality than the input space [6]. The cluster assumption states that similar examples should have the same label. Graph-based models [7] are the most common approaches to implementing the manifold assumption [8]. As regards examples of models based on the cluster assumption, we can find generative models [9] or semi-supervised support vector machines [10]. Recent studies have addressed multiple assumptions in one model [5], [11], [12].

Self-labeled techniques are SSC methods that do not make any specific suppositions about the input data [13]. These models use unlabeled data within a supervised framework via a self-training process. First attempts correspond to the self-training algorithm [14] that iteratively enlarges the labeled training set by adding the most confident predictions of the supervised classifier used. The standard co-training [15] methodology splits the feature space into two different conditionally independent views. Then, it trains one classifier in each specific view, and the classifiers teach each other the most confidently predicted examples. Advanced approaches do not require explicit feature splits or the iterative mutual-teaching procedure imposed by co-training, as they are commonly based on disagreement-based classifiers [16]–[18]. These models have been successfully applied to many real applications such as image classification [19], shadow detection [20], computer-aided diagnosis [21], etc.

Self-labeled techniques are limited by the number of labeled points and their distribution to identifying reliable unlabeled examples. This problem is more pronounced when the labeled ratio is greatly reduced and labeled examples do not minimally represent the domain. Moreover, most of the advanced models use some diversity mechanisms, such as bootstrapping [22], to

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provide differences between the hypotheses learned with the multiple classifiers. However, these mechanisms may provide a similar performance to classical self-training or co-training approaches if the number of labeled data is insufficient to achieve different learned hypotheses.

The aim of this paper is to alleviate these weaknesses by using new synthetic labeled examples to introduce diversity to multiple classifier approaches and fulfill the labeled data distribution. A complete motivation for the use of synthetic labeled examples is discussed in Section III-A.

We propose a framework applicable to any self-labeled method that incorporates synthetic examples in the self-learning process. We will denote this framework synthetic examples generation for self-labeled SSC (SEG-SSC). It is composed of two main parts: generation and incorporation.

1) The generation process consists of an oversampling technique and a later adjustment of the positioning of the examples. It is initially inspired by the SMOTE algorithm [23] to generate new synthetic examples, for all the classes, based on both the small labeled set and the unlabeled data. Then, this process is refined using a positioning adjustment of prototypes model [24] based on a differential evolution algorithm [25].
2) New labeled points are then included in two of the main steps of a self-labeling method: the initialization phase and the update of the labeled training set, so that it introduces new examples in a progressive manner during the self-labeling process.

An extensive experimental analysis is carried out to check the performance of the proposed framework. We apply the SEG-SSC scheme to four recent self-labeled techniques that have different characteristics, comparing the performance obtained with the original proposals. We conduct experiments over 55 standard classification data sets extracted from the KEEL and UCI repositories [26], [27] and 11 high dimensional data sets from the book by Chapelle *et al*. [2]. The results will be contrasted with nonparametric statistical tests [28], [29].

The remainder of this paper is organized as follows. Section II defines the SSC problem and sums up the classical and current self-labeled approaches. Then, Section III presents the proposed framework, explaining its motivation and the details of its implementation. Section IV describes the experimental setup and discusses the results obtained. Finally, Section V summarizes the conclusions drawn in this paper.

II. Self-Labeled Semi-Supervised Classification

This section provides the definition of the SSC problem (Section II-A) and briefly describes the most relevant self-labeled approaches proposed in the literature (Section II-B).

A. Semi-Supervised Classification

A formal description of the SSC problem is as follows: Let $\mathbf{x}_p$ be an example where $\mathbf{x}_p = (\mathbf{x}_{p1}, \mathbf{x}_{p2}, \ldots, \mathbf{x}_{pD}, \omega)$, with $\mathbf{x}_p$ belonging to a class ω and a D-dimensional space in which $\mathbf{x}_{pi}$ is the value of the ith feature of the pth sample. Then, let us assume that there is a labeled set L which consists of n instances $\mathbf{x}_p$ with ω known and an unlabeled set U which consists of m instances $\mathbf{x}_q$ with ω unknown, let $m > n$. The $L \cup U$ set forms the training set TR. Moreover, there is a test set TS composed of t unseen instances $\mathbf{x}_r$ with ω unknown, which has not been used at the training stage.

The aim of SSC is to obtain a robust learned hypothesis using TR instead of L alone. It can be applied in two slightly different settings. On the one hand, transductive learning is devoted to classify all the m instances $\mathbf{x}_q$ of U with their correct class. The class assignation should represent the distribution of the classes efficiently, based on the input distribution of L and U. On the other hand, the inductive learning phase consists of correctly classifying the instances of TS based on the previously learned hypothesis.

B. Self-Labeled Techniques: Previous Work

Self-labeled techniques form an important family of methods in SSC [3]. They are not intrinsically geared to learning in the presence of both labeled and unlabeled data, but they use unlabeled points within a supervised learning paradigm. These techniques aim to obtain one (or several) enlarged labeled set/s, based on the most reliable predictions. Thus, these models do not make any specific assumptions about the input data, but the models accept that their own predictions tend to be correct. Some authors state that self-labeling is likely to be the case when the classes form well-separated clusters [3] (cluster assumption).

The major benefits of this family of methods are: simplicity and being a wrapper methodology. The former is related to the facility of implementation and applicability. The latter means that any kind of classifier can be used regardless of its complexity, which is very important depending on the problem tackled. As caveats, the addition of wrongly labeled examples during the self-labeling process can lead to an even worse performance. Several mechanisms have been proposed to reduce this problem [30].

A preeminent work with this philosophy is the self-training paradigm designed by Yarowsky [14]. In self-training, a supervised classifier is initially trained with the L set. Then it is retrained with its own most confident predictions, enlarging its labeled training set. Thus, it is defined as a wrapper method for SSC. This idea was later extended by Blum and Mitchell [15] with the method known as co-training. This consists of two classifiers that are trained on two sufficient and redundant sets of attributes. This requirement implies that each subset of features should be able to perfectly define the frontiers between classes. Then, the method follows a mutual teaching procedure that works as follows: each classifier labels the most confidently predicted examples from its point of view and they are added to the L set of the other classifier. It is also known that usefulness is constrained by the imposed requirement [31], which is not satisfied in many real applications. Nevertheless, this method has become an example for recent models thanks to the idea of using the agreement (or disagreement) of multiple classifiers and the mutual teaching approach. A good study of when co-training works can be found in [32].

Due to the success of co-training and its relatively limited application, many works have proposed the improvement of

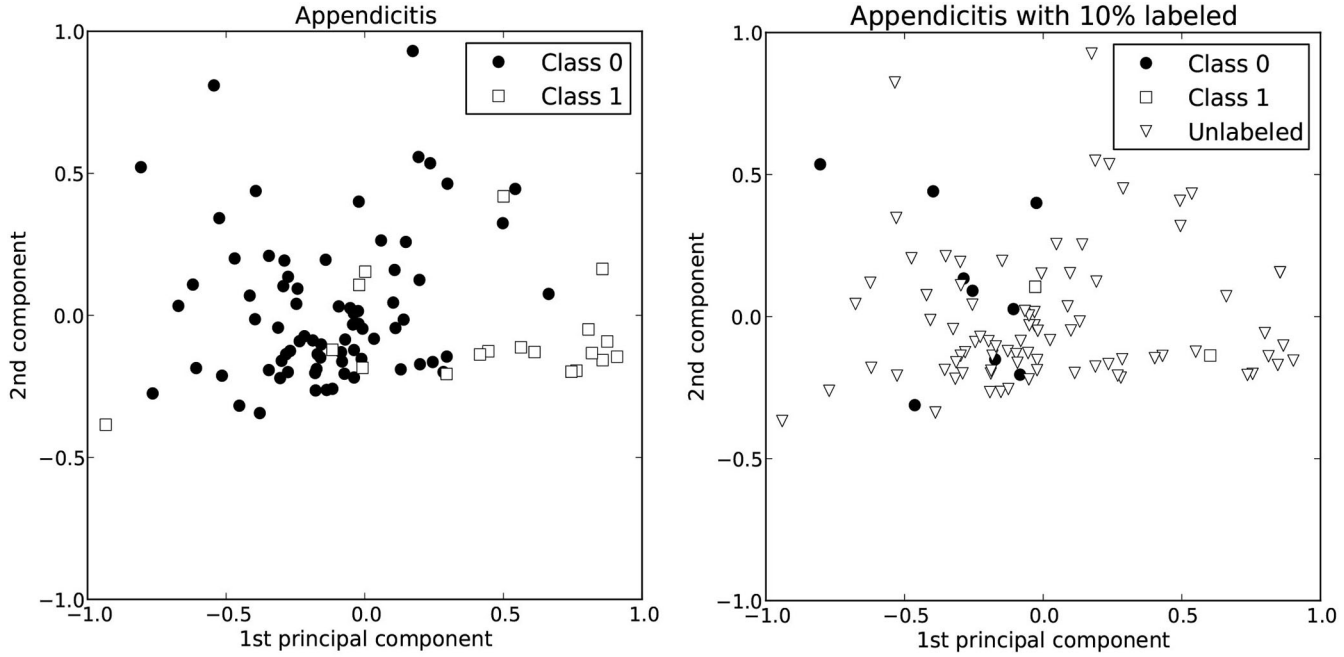


Fig. 1. 2-D projections of appendicitis. Red circles, class 0. Blue squares, class 1. White triangles, unlabeled. (a) Appendicitis problem. (b) Appendicitis problem: 10% labeled points (Democratic—0.7590 accuracy).

standard co-training by eliminating the established conditions. Goldman and Zhou [33] proposed a multilearning approach, so that two different supervised learning algorithms were used without splitting the feature space. They showed that this mechanism divides the instance space into a set of equivalence classes. Later, the same authors proposed a faster and more precise alternative, named Democractic co-learning (Democratic-Co) [34], which is also based on multilearning. As an alternative, which requires neither sufficient and redundant views nor several supervised learning algorithms, Zhou and Li [35] presented the Tri-Training algorithm, which attempts to determine the most reliable unlabeled data as the agreement of three classifiers (same learning algorithm). Then, they proposed the Co-Forest algorithm [21] as a similar approach that uses Random Forest [36]. A further similar approach is Co-Bagging [37], [38] where confidence is estimated from the local accuracy of committee members. Other recent self-labeled approaches are [39]–[43].

In summary, all of these recent schemes work on the hypothesis that several weak classifiers, learned with a small number of instances, can produce better generalizations than only one weak classifier. These methods are also known as disagreement-based models that are motivated, in part, by the empirical success of ensemble learning. The term disagreement-based was recently coined by Zhou and Li [17].

III. Synthetic Examples Generation for Self-Labeled Methods

In this section we present the SEG-SSC framework. Firstly, Section III-A enumerates the arguments that justify our proposal. Secondly, Section III-B explains how to generate useful synthetic examples in a semi-supervised scenario. Finally, Section III-C describes the SEG-SSC framework, emphasizing when synthetic data should be used.

A. Motivation: Why Add Synthetic Examples?

The most important weakness of self-labeling models can occur when erroneous labeled examples are added to the labeled training set. This will incorrectly modify the learned model, which may lead to the addition of wrong examples in successive iterations. Why does this situation occur?

1) There may be outliers in the original unlabeled set. This problem can be avoided if they are detected and not included in the labeled training set. For this problem, there are several solutions in the literature such as edition schemes [30], [44], [45] or some other mechanisms [33]. Recent models, such as Tri-Training [35] or Co-Forest [21], establish some criteria to compensate for the negative influence of noise by augmenting the labeled training set with sufficient new labeled data.
2) Independently of the number of unlabeled examples, they can be limited by the distribution of labeled input data. If the available labeled instances do not represent a reliable domain of the problem, it may complicate the estimation of confidence predictions because the supervised classifiers used do not have enough information to establish coherent hypotheses. Furthermore, it is even more difficult if these labeled points are very close to the decision boundaries. Fig. 1 shows an example with the appendicitis problem [27]. This picture presents a 2-D projection (obtained with PCA [46]) of the problem and a partition with 10 % of labeled examples. As we can observe, not only is the problem not well represented

by labeled points, it also shows that some of the nearest unlabeled points to the two labeled examples of class 1 (blue circles) belong to class 0 (red crosses). This fact can affect confidence of a self-labeled method estimated with the base classifier.

3) A greatly reduced labeled ratio may produce a lack of diversity among self-labeling methods with more than one classifier. As we have established above, multiple classifier approaches work as a combination of several weak classifiers. However, if there are only a few labeled data it is very difficult to obtain different hypotheses, and therefore, the classifiers are identical. For example, the Tri-Training algorithm is based on a bootstrapping approach [22]. This resampling technique creates new labeled sets for each classifier by modifying the original L. In general, this operation yields different labeled sets to the original, but it is not significant in the case of small labeled data sets and the existence of outliers in the sample. As a consequence, it could lead to biased examples which will not accurately represent the domain of the problem. Although multilearning approaches attempt to achieve diversity by using different kinds of learning models, a reduced number of instances usually damages their performance because the models are too weak.

The first limitation has already been addressed in the literature with different mechanisms [47]. However, the last two issues are currently open problems.

In order to ease both situations, mainly induced by the shortage of labeled points, we introduce new labeled data into the self-labeling process. To do this, we rely on the success of oversampling approaches in imbalanced domains [48]–[51], but with the difference that we deal with all the classes of the problem.

Nevertheless, the use of synthetic data for self-labeling methods is not straightforward and must be carefully performed. The aim of using an oversampling method is to effectively reinforce the decision regions between classes. To do so, we will be aided by the distribution of unlabeled data in conjunction with the labeled ones, because if we focus only on labeled examples, it may lead to generate noisy instances when the second issue explained above happens. The effectiveness of this idea will be empirically checked in Section IV.

B. Generation of Synthetic Examples

To generate new labeled data in an SSC context we perform certain operations on the available data, so that we use both labeled and unlabeled sets. Algorithm 1 outlines the pseudocode of the oversampling technique proposed. This method is initially based on the SMOTE algorithm proposed in [23] which was designed for imbalanced domains [52] and is limited to oversampling the minority class. In our proposal, we use the underlying idea of SMOTE as an initialization procedure, to generate new examples of all the classes. Furthermore, the resulting synthetic set of prototypes is then readjusted with a positioning adjustment of prototypes scheme [24]. Therefore, this mechanism is divided into two phases: initialization and adjustment of prototypes.

Algorithm 1 Generation of Synthetic Examples

```
1: Input: Labeled set L, Unlabeled set U, Oversampling factor f,
   Number of Neighbors k.
2: Output: OverSampled set.
3: OverSampled = ∅
4: TR = L ∪ U
5: ratio = (f · #TR) / #L
6: Randomize TR
7: for i = 1 to NumberOfClasses do
8:    PerClass[i] = getFromClass (L, i)
9:    for j = 1 to #PerClass[i] do
10:      Generated = 0
11:      repeat
12:         neighbors[1..k] = Compute k nearest neighbors
            for PerClass[i][j] in TR
13:         nn = Random number between 1 and k
14:         Sample = PerClass[j]
15:         Nearest = TR[neighbors[nn]]
16:         for m = 1 to NumberOfAttributes do
17:            dif = Nearest[m] − Sample[m]
18:            gap = Random number between 0 and 1.
19:            Synthetic[m] = Sample[m] + gap ∗ dif
20:         end for
21:         OverSampled = OverSampled ∪ Synthetic
22:         Generated + +
23:      until Generated < ratio
24:   end for
25: end for
26: OverSampled = DE_adjustment(OverSampled, L)
27: return OverSampled
```

1) Initialization: We start from the L and U sets as well as an user-defined oversampling factor f and a number k of nearest neighbors. We will generate a set of synthetic prototypes *OverSampled* that is initialized as empty (Instruction 3).

The ratio of synthetic examples to be generated is computed according to f and the proportion of labeled examples in the training set *TR* (see Instructions 4 and 5). Furthermore, to prevent the influence of the order of labeled and unlabeled instances when computing distances, the *TR* set is randomized (Instruction 6).

Next, the algorithm enters a loop (Instructions 7–25) to proportionally oversample each class, using its own labeled samples as the base. Thus, we extract from L a set of examples *PerClass* that belong to the current class (Instruction 8). Each one will serve as the base prototype and will be oversampled as many times as the previous computed ratio indicates (Instructions 11–23).

New synthetic examples are located along the line segments joining any of the k nearest neighbors (randomly chosen). To face the SSC scenario, the nearest neighbors are not only being looked for in the L set, but are searched for in the *TR* set (Instruction 12). In this way, we try to avoid the negative effects of the second weakness of self-labeled techniques explained before. Following the idea of SMOTE, synthetic examples are initially generated as the difference between an existing sample and one of its nearest neighbors (Instruction 17). Then, this difference is scaled by a random number in the range [0, 1], and is added to the base example (Instructions 18 and 19). It is noteworthy that the class value of the generated example is the same as the considered base sample. The generated prototypes are iteratively stored in *OverSampled* until the stopping condition is satisfied.

2) Adjustment of Prototypes: Can we use this process to improve the distribution of labeled input data? The answer depends on the specific problem and partition used. Although the generation algorithm provides more labeled examples that may be very useful in many domains, they are not totally confident. It may suffer from the same problem as the self-labeling approaches and their confidence predictions. It is well-known that SMOTE can generate noisy data [53] which are usually eliminated with edition schemes. Because we are not interested in removing synthetic data, we will apply an evolutionary adjustment process to the *OverSampled* set (Instruction 26) based on the differential evolution algorithm used in [54].

Differential evolution [25] follows the general procedure of an evolutionary algorithm [55]. It starts with a set of candidate solutions, the so-called individuals, which evolve during a determined number of generations through different operators: mutation, crossover, and selection; aiming to minimize/maximize a fitness function. For our purposes, this algorithm is adapted in the following way.

1) Each individual encodes a single prototype. The process consists of the optimization of the location of all the individuals of the population.
2) Mutation and crossover operators guide the optimization of the positioning of the prototypes. These operators only produce modifications to the attributes of the prototypes of the *OverSampled* set, keeping the class value unchangeable throughout the evolutionary cycle. We will focus on the *DE/CurrentToRand/1* strategy to generate new prototypes [56].
3) Then, we obtain a new set of synthetic prototypes that should be evaluated to decide whether it is better or not than the current set. To make this decision, we use the most reliable data we have, that is, the labeled data L. The generated data should be able to correctly classify L. To check this, the nearest neighbor rule is used as the base classifier to obtain the corresponding fitness value. We try to maximize this value.

The stopping criteria is achieved when the generated data perfectly classify L, or a given number of iterations have been performed. More details are in [54, Sec. III-B].

It is worth mentioning that this optimization process is only applied to cases in which the former oversampling approach generates synthetic data that is not able to classify L. We thereby endow our model with greater robustness. Fig. 2 shows an example of a resulting set of over-sampled prototypes in the appendicitis problem. We can observe that in comparison with Fig. 1, the available labeled data points better represent the domain of the problem.

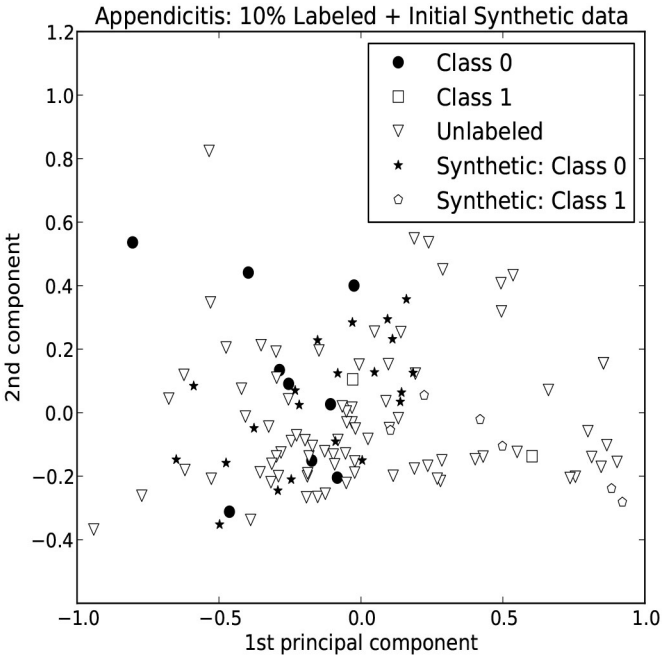


Fig. 2. Example of data generation in the appendicitis problem. 2-D projections of appendicitis. Red circles, class 0. Blue squares, class 1. White triangles, unlabeled. Red stars, synthetic class 0. Blue pentagons, synthetic class 1 (SEG-SSC+Democratic—0.8072 accuracy).

C. Self-Labeling With Synthetic Data

In this subsection, we describe the SEG-SSC framework in depth. With the generation method presented, we obtain new labeled data that can be directly used to improve the generalization capabilities of self-labeled approaches. Nevertheless, the aim of this framework is to be as flexible as possible, so that it can be applied to different self-labeled algorithms. Although each method proceeds in a different way, they either share some operations or are very similar. Therefore, we explain how to incorporate synthetic examples in the self-learning process in order to address the limitations on the distribution of labeled data and the lack of diversity in multiple classifier methods.

In general, self-labeled methods use a set of N classifiers C_i, where $i \in [1, N]$, to predict the class of unlabeled instances. Each C_i has an associated labeled set L_i that is iteratively enlarged. In what follows, we describe the three main operations that support our proposal. For clarity, Fig. 3 depicts a flowchart of the proposed scheme, outlining its more general operations and way of working.

1) *Initialization of Classifiers:* In current approaches, L_i is initially formed from the available data in L. Depending on the particular method, they may use the same labeled data for each L_i or apply a bootstrapping to introduce diversity. As we showed before, both alternatives can lead to a lack of diversity when more than one classifier is used. To solve this, we promote the generation of different synthetic examples for each classifier C_i. In this way, the generation mechanism is applied a total of N times. Because L data are the most confident examples, we ensure that they belong to each L_i in conjunction with synthetic examples. Note that the generation method has some randomness, so different executions generate distinct synthetic points. This ensures the diversity between L_i sets.
2) *Self-Labeling Stage:* After the initialization phase, each classifier is trained with its respective L_i. Then, the learned hypotheses are used to classify unlabeled points,

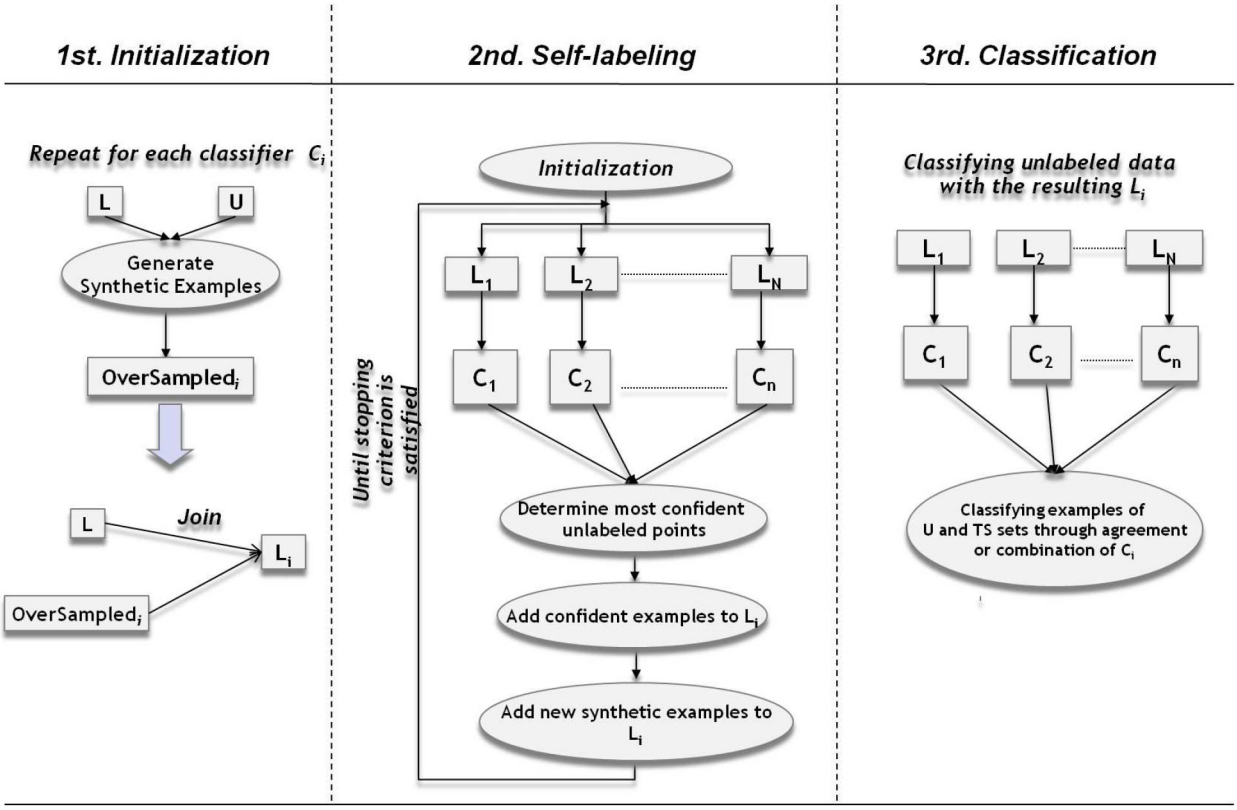


Fig. 3. SEG-SSC flowchart.

determining the most reliable examples. There are several ways to perform this operation. Single classifier approaches extract their confidence from the base classifier and multiple classifiers calculate confidence predictions in terms of the agreement or combination of hypotheses. Independently of the procedure followed, each classifier obtains a set L_i' that will be used to enlarge L_i. At this point, there are two possibilities: self or mutual teaching. The former uses its own predictions to augment its L_i. With a mutual teaching approach, a classifier C_j teaches its confidence predictions to the rest of the classifiers, that is, it increases L_i, $\forall\ i \neq j$. When all the L_i are increased, a new oversampling stage is performed for each L_i, using its prototypes and the remaining unlabeled examples. The resulting L_i sets are ready to be used in the next iteration.

3) *Final Classification:* The stopping criteria depends on the specific self-labeled method used, which is usually defined by a given number of iterations or by the condition of the learned hypotheses of the classifiers used, which does not change. When it is satisfied, not all the unlabeled instances have had to be added to one of the L_i sets. For this reason, the resulting L_i sets have to be used to classify the remaining instances of U and the TS set.

As such, this scheme is applicable to any self-labeling method and should provide better generalization capabilities to all of them. To test the proposed framework, we have applied these ideas to four self-labeling approaches: Democratic-Co [34], Tri-Training [35], Co-Forest [21] and Co-Bagging [37], [38]. These models have different characteristics, such as distinct mechanisms to determine confident examples (agreement or combination), teaching schemes, uses of different learning algorithms or having a different initialization scheme. Table I summarizes the main properties of these models. We modify these models by adding synthetic examples, as explained above, to have an idea of how flexible our framework is. The modified versions of these algorithms will be denoted: SEG-SSC+Democratic-Co, SEG-SSC+Tri-Training, SEG-SSC+Co-Forest and SEG-SS+Co-Bagging.

TABLE I
MAIN CHARACTERISTICS OF SELECTED SELF-LABELED METHODS

Algorithm	Initialization	Classifiers	Teaching scheme	Confidence rule
Democratic-Co	Simple	Different learning algorithms	Self-teaching	Weighted majority
Tri-Training	Bootstrapping	Same learning algorithms	Mutual-teaching	Majority
Co-Forest	Bootstrapping	Same learning algorithms	Self-teaching	Majority
Co-Bagging	Simple	Same learning algorithms	Self-teaching	Majority

As an additional comment of the proposed model, we can note that the generation of synthetic data is based on meta-heuristics that may lack of solid theoretical insights. In the specialized literature, these kinds of techniques, such as in [23] and [50], do not provide any theoretical analyses because of the stochastic nature of the models. However, their applicability and effectiveness has been proved in many real world applications [52], [53]. This fact motivates the large experimental study that we will perform in the following section to support the usefulness and soundness of our model.

TABLE II
SUMMARY DESCRIPTION OF STANDARD CLASSIFICATION DATA SETS

Data set	#Ex.	#D.	#ω.	Data set	#Ex.	#D.	#ω.
abalone	4174	8	28	movement_libras	360	90	15
appendicitis	106	7	2	mushroom	8124	22	2
australian	690	14	2	nursery	12 690	8	5
autos	205	25	6	pageblocks	5472	10	5
banana	5300	2	2	penbased	10 992	16	10
breast	286	9	2	phoneme	5404	5	2
bupa	345	6	2	pima	768	8	2
chess	3196	36	2	ring	7400	20	2
cleveland	297	13	5	saheart	462	9	2
coil2000	9822	85	2	satimage	6435	36	7
contraceptive	1473	9	3	segment	2310	19	7
crx	125	15	2	sonar	208	60	2
dermatology	366	33	6	spambase	4597	55	2
ecoli	336	7	8	spectheart	267	44	2
flare-solar	1066	9	2	splice	3190	60	3
german	1000	20	2	tae	151	5	3
glass	214	9	7	texture	5500	40	11
haberman	306	3	2	tic-tac-toe	958	9	2
heart	270	13	2	thyroid	7200	21	3
hepatitis	155	19	2	titanic	2201	3	2
housevotes	435	16	2	twonorm	7400	20	2
iris	150	4	3	vehicle	846	18	4
led7digit	500	7	10	vowel	990	13	11
lymphography	148	18	4	wine	178	13	3
magic	19 020	10	2	wisconsin	683	9	2
mammographic	961	5	2	yeast	1484	8	10
marketing	8993	13	9	zoo	101	17	7
monks	432	6	2				

TABLE III
SUMMARY DESCRIPTION OF HIGH DIMENSIONAL DATA SETS

Data set	#Ex.	#D.	#ω.	Reference
bci	400	117	2	
coil	1500	241	6	
coil2	1500	241	2	
digit1	1500	241	2	
g241c	1500	241	2	
g241n	1500	241	2	
secstr	83 679	315	2	
text	1500	11 960	2	
usps	1500	241	2	[2]
bbc	2225	9636	5	
bbcsport	737	4613	5	[57]

TABLE IV
PARAMETER SPECIFICATION FOR THE BASE LEARNERS AND THE SELF-LABELED METHODS USED IN THE EXPERIMENTATION

Algorithm	*Parameters*
KNN	Number of Neighbors = 3, Euclidean Distance
C4.5	Confidence level: $c = 0.25$ Mininum number of item-sets per leaf: $i = 2$ Prune after the tree building
Democratic-Co	Classifiers = 3NN, C4.5, NB
Tri-Training	No parameters specified
Co-Forest	Number of RandomForest Classifiers = 6, Threshold = 0.75
Co-Bagging	MAX_ITER = 40, Committee members = 3 Ensemble Learning = *Bagging*, Pool U = 100
SEG-SSC	Oversampling factor=0.25, Number of Neighbors = 5
Differential evolution parameters	Iterations = 100, iterSFGSS = 8,iterSFHC =20 Fl=0.1, Fu=0.9

IV. EXPERIMENT SETUP AND ANALYSIS OF RESULTS

This section presents all of the issues related to the experimental framework used in this paper and the analysis of results. Section IV-A describes the main properties of the data sets used and the parameters of the selected algorithms. Section IV-B presents and analyzes the results obtained with standard classification data sets. Finally, Section IV-C studies the behavior of the proposed framework when dealing with high dimensional problems.

A. Data Sets and Parameters

The experimentation is based on 55 standard classification data sets taken from the UCI repository [27] and the KEEL-dataset repository[1] [26] and 11 high dimensional problems extracted from the book by Chapelle *et al*. [2] and the BBC News web page [57]. Tables II and III summarize the properties of the selected data sets. They show, for each data set, the number of examples (#Ex.), the number of attributes (#D.), and the number of classes (#ω.). The standard classification data sets considered contain between 100 and 19 000 instances, the number of attributes ranges from 2 to 90 and the number of classes varies between 2 and 28. However, the 11 high dimensional data sets contain between 400 and 83 679 instances and the number of features oscillates from 117 to 11 960.

All the data sets have been partitioned using the tenfold cross-validation procedure, that is, the data set has been split into tenfolds, each one containing 10% of the examples of the data set. For each fold, an algorithm is trained with the examples contained in the rest of the folds (training partition) and then tested with the current fold. Note that test partitions are kept aside to assess the performance of the learned hypothesis.

Each training partition is then divided into two parts: labeled and unlabeled examples. Using the recommendation established in [41], in the division process we do not maintain the class proportion in the labeled and unlabeled sets since the main aim of SSC is to exploit unlabeled data for better classification results. Hence, we use a random selection of examples that will be marked as labeled instances, and the class label of the rest of the instances will be removed. We ensure that every class has at least one representative instance. In standard classification data sets we have taken a labeled ratio of 10%. For high dimensional data sets, we will use two splits for training partitions with 10 and 100 labeled examples, respectively. In both cases, the remaining instances are marked as unlabeled points.

Regarding the parameters of the algorithms, the selected values are fixed for all problems, and they have been chosen according to the recommendation of the corresponding authors of each algorithm. From our point of view, the approaches analyzed should be as general and as flexible as possible. It is known that a good choice of parameters boosts their better performance over different data sources, but their way of working should offer good enough results in spite of the fact that the parameters are not optimized for a specific data set. This is the main purpose of this experimental setup, to show how the proposed framework can improve the efficacy of self-labeled techniques. Table IV specifies the configuration parameters of all the methods. Because these algorithms carry out some random operations during the labeling process, they have been run three times per partition.

In this table, we also present the parameters involved in our framework: the oversampling factor, the number of

[1] http://sci2s.ugr.es/keel/datasets

neighbors, and the parameters needed for the differential evolution optimization. They can also be adjusted for each problem, however, with the same aim of being as flexible as possible. We have fixed these values empirically in previous experiments. The parameters used for the differential evolution optimization are the same as those established in [54], except for the number of iterations that have been reduced. We decrease this value because, under this framework, the reference set used by differential evolution contains a smaller number of instances than in the case of supervised learning.

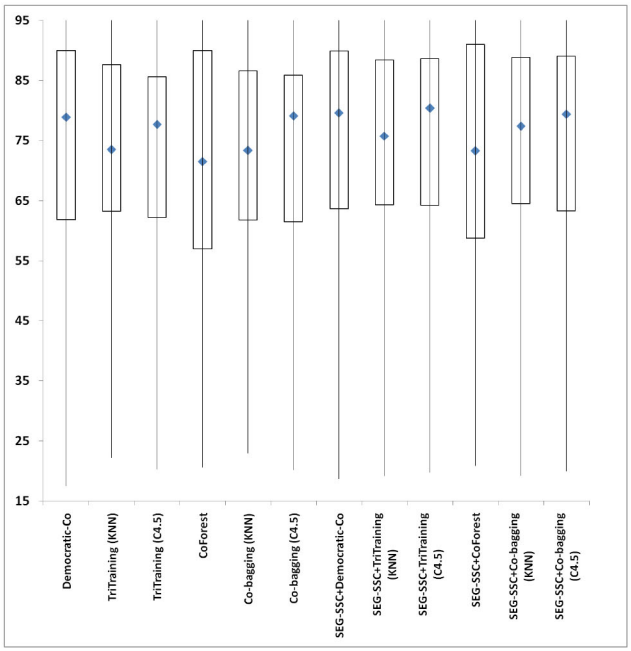
The Co-Forest and Democractic-Co algorithms were designed and tested with determined base classifiers. In this paper, these algorithms maintain their classifiers. However, the interchange of the base classifiers is allowed in the Tri-Training and Co-Bagging approaches. In these cases, we will test two base classifiers, the K-Nearest Neighbor [58], and the C4.5 algorithms [59]. A brief description of these base classifiers and their associated confidence prediction computation are given as follows.

1) *K-Nearest Neighbor (KNN):* This is an instance-based learning algorithm that belongs to the lazy learning family of methods [60]. As such, it does not build a model during the learning process and is based on dissimilarities among a set of instances. For those self-labeled methods that need to estimate confidence predictions from this classifier, they can approximate it in terms of distance from the currently labeled set.
2) *C4.5:* This is a decision tree algorithm [59] that induces classification rules for a given training set. The decision tree is built with a top-down scheme, using the normalized information gain (difference in entropy) that is obtained from choosing an attribute for splitting the data. The attribute with the highest normalized information gain is the one used to make the decision. Confidence predictions can be obtained from the accuracy of the leaf that makes the prediction. The accuracy of a leaf is the percentage of correctly classified train examples from the total number of covered train instances.

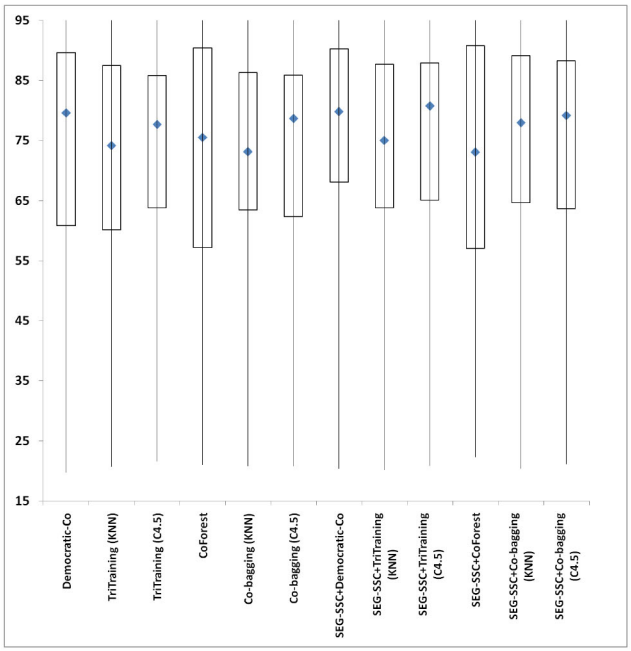
B. Experiments on Standard Classification Data Sets

In this subsection we compare the modified versions of the selected self-labeled methods (within SEG-SSC) with the original ones, focusing on the results obtained on the 55 standard classification data sets and a labeled ratio of 10%. We analyze the transductive and inductive accuracy capabilities of these methods. Both results are presented in Tables V and VI, respectively. In these tables, we have specified the base classifier between brackets for Tri-Training and Co-Bagging algorithms. The best result of each row has been highlighted in bold face.

Aside from these tables, Fig. 4 depicts two box plot representations of the results obtained in transductive and inductive settings, respectively. With these box plots we show a graphical comparison of the performance of the algorithms, indicating their most important characteristics such as the median, extreme values and spread of values about the median in the form of quartiles (Q1 and Q3).



(a)



(b)

Fig. 4. Box plot of transductive and inductive accuracy rates. The boxes contain 50% of the data (Q1–Q3), blue points are the median values and the lines extend to the most extreme values. (a) Transductive accuracy. (b) Inductive accuracy.

Observing these tables and the figure we can appreciate differences between each of the original proposals and the improvement achieved by the addition of synthetic examples. Nevertheless, the use of hypothesis testing methods is mandatory in order to contrast the results of a new proposal with several comparison methods. The aim of these techniques is to identify the most relevant differences found between methods, which is highly recommended in the data mining field [29]. To do this, we focus on the Wilcoxon signed-ranks test [61]

TABLE V
TRANSDUCTIVE ACCURACY RESULTS OVER STANDARD CLASSIFICATION DATA SETS

Datasets	Original Proposals						SEG-SSC					
	Democratic-Co	Tri-Training (KNN)	Tri-Training (C4.5)	Co-Forest	Co-Bagging (KNN)	Co-Bagging (C4.5)	Democratic-Co	Tri-Training (KNN)	Tri-Training (C4.5)	Co-Forest	Co-Bagging (KNN)	Co-Bagging (C4.5)
abalone	19.7700	22.1300	20.2800	20.5500	**22.9200**	20.1100	18.6274	19.1120	19.6966	20.8546	19.2365	19.9401
appendicitis	80.6000	78.1400	82.7300	81.9000	80.3700	**82.2600**	80.1273	79.6511	80.3736	80.1847	79.4376	81.3013
australian	82.6800	79.0200	82.7700	82.4900	82.0200	81.3200	**83.2558**	80.7156	80.8587	83.1306	80.6082	80.5546
automobile	32.8500	**45.6100**	37.7200	41.5600	36.9300	35.1900	43.8713	45.1214	39.0806	41.3491	45.3764	35.4917
banana	84.2700	86.9500	85.1000	53.9400	**87.6300**	85.7200	85.9003	86.7179	86.7622	54.9849	86.8274	86.9113
breast	70.2000	69.3400	68.6900	**71.4800**	69.8400	68.9500	71.0801	68.6319	68.3242	69.4731	68.9862	67.7848
bupa	54.2800	55.7900	58.5700	59.4700	55.3100	59.8900	58.1093	56.8213	58.6070	**61.1814**	56.6096	59.5062
chess	92.0000	79.6200	95.4300	94.3700	81.4600	95.0800	92.0444	82.7566	95.3117	93.9368	84.1663	**95.4083**
cleveland	53.8000	52.4800	50.2800	51.8500	53.2200	50.8100	**54.2972**	50.7729	51.3120	53.6428	51.5208	50.8462
coil2000	93.0300	88.2500	**93.4300**	92.8300	92.3700	93.6300	90.2300	89.0100	92.1800	92.9300	90.2400	90.6400
contraceptive	45.0000	42.0000	47.6600	48.6300	41.7400	47.9700	44.7097	42.4225	48.0525	**49.6524**	42.8332	46.4188
crx	84.6100	80.8500	84.8100	82.7200	82.7300	**84.8300**	82.3222	80.4531	83.1333	82.6423	82.1320	81.8868
dermatology	88.0000	89.4800	87.6200	89.3000	87.2400	86.9700	90.2394	90.8924	90.2385	91.6161	**91.7198**	88.8587
ecoli	63.6400	66.4800	65.9200	66.5600	68.1700	65.7000	65.4363	67.1914	64.9134	**69.8830**	67.3791	63.4947
flare	**71.3300**	62.9700	71.1600	39.8700	61.9800	71.2700	70.7523	63.7500	70.1389	39.3403	66.8634	68.7963
german	70.1200	66.2100	68.5800	67.8500	68.5200	69.2000	**72.0370**	68.1605	68.7778	68.1358	69.0000	69.0617
glass	48.7100	51.2600	49.5500	55.2600	47.7900	45.9700	49.8987	54.2011	51.7359	**56.3432**	53.1702	50.7878
haberman	**73.2300**	65.5800	71.6200	58.7000	66.8700	71.4500	72.3424	66.1459	71.2583	62.1837	66.6686	68.9213
heart	78.8600	73.4700	75.6600	71.0500	76.6700	73.7000	**79.2694**	74.3836	74.2009	73.2877	74.3379	75.0228
hepatitis	81.4200	81.4000	81.4200	**84.8800**	82.5300	81.4200	78.9245	80.2432	78.9000	84.1557	81.5418	79.3906
housevotes	89.8500	89.1000	92.9500	91.3500	89.0500	**93.5400**	89.6435	89.7856	92.2012	89.6818	89.4874	92.5117
iris	91.6400	92.1300	75.9000	90.1600	92.3000	80.3300	93.9344	**94.1803**	83.6066	90.8197	94.0164	83.0328
led7digit	60.0500	59.4300	60.3000	62.9400	**66.1700**	57.3100	61.8272	61.3333	63.5062	63.3580	63.6790	63.1111
lymphography	51.9000	64.7600	58.9600	61.8000	61.0900	57.6200	58.9634	**65.4149**	59.0391	62.5010	63.0386	54.8241
magic	78.7300	78.0800	82.0100	84.2000	79.8500	83.2700	79.6235	77.7595	82.4028	**84.3311**	78.0042	81.6811
mammographic	80.4300	73.8900	**81.5600**	76.6700	76.3300	81.3600	80.8290	75.7620	81.2622	77.4400	77.3973	80.5495
marketing	27.8800	25.6800	28.1500	28.7900	26.6500	27.8300	26.0327	26.2354	27.0427	**28.7900**	25.6569	26.4127
monk-2	90.1100	70.5700	**97.0300**	96.0700	68.5400	**97.0300**	86.7461	72.0527	92.4715	91.2758	76.5598	88.3120
movement_libras	17.5200	40.2800	22.4800	30.4800	36.3800	20.9300	28.8276	**44.1379**	26.9655	32.9310	43.8276	26.7931
mushroom	99.2600	99.5200	99.5100	90.9200	99.2000	99.4700	99.5213	99.6088	99.7049	90.9362	99.5957	**99.7705**
nursery	89.6300	76.3200	90.3300	37.6600	73.4900	90.2400	89.5509	78.3274	**91.5057**	37.8782	78.5675	89.2461
page-blocks	90.6000	93.4200	95.4300	**95.7900**	93.1300	95.3300	93.7309	93.3202	95.5446	95.6912	93.3789	95.1814
penbased	94.7300	97.7400	90.0200	95.5900	96.8200	90.5000	95.6400	**98.0345**	92.3247	95.9388	98.0155	93.5455
phoneme	78.6000	80.8000	78.0900	80.4700	79.8800	79.0700	79.9137	80.7817	80.6835	**81.8896**	80.9576	81.0970
pima	**71.9600**	65.0600	68.2900	68.5500	65.6200	64.4200	70.4932	66.7475	70.6701	69.6090	67.0209	68.0663
ring	88.7200	66.6000	85.0400	88.4400	61.5200	85.8900	**94.6296**	82.5375	81.7150	81.5349	86.7901	79.1859
saheart	**67.4500**	63.3900	65.6600	64.3800	65.6300	65.8700	65.9012	64.8068	65.1284	66.2758	65.3412	65.3147
satimage	85.0600	86.0700	82.3000	86.5500	85.9500	82.1500	85.6518	87.8005	84.1478	86.9986	**88.1784**	84.3185
segment	90.5900	90.0200	90.3700	90.8600	87.6900	90.9800	90.6197	91.6346	91.0150	**92.0726**	91.5652	91.5438
sonar	64.3100	65.1900	63.8900	69.2100	65.7800	63.0100	70.3383	67.0835	66.3745	**71.2210**	67.2593	66.9614
spambase	88.1700	82.8400	88.3700	92.1400	83.3700	89.4700	88.7979	85.9357	90.0437	**92.6510**	86.9667	90.9567
spectfheart	73.0900	69.6300	72.8200	77.7600	73.3700	72.1200	76.2400	73.3690	75.1242	**80.2129**	74.2972	76.5126
splice	**93.4900**	66.5700	81.9500	50.3800	69.5400	81.9700	92.7786	79.8181	87.6393	49.5666	81.2926	89.2918
tae	39.6300	40.7600	39.3700	37.8300	40.6000	38.6400	39.9467	41.0862	40.8437	37.1800	**42.3864**	41.8213
texture	88.2700	94.4200	85.2600	90.7000	93.4100	84.8800	88.7026	96.4669	89.1021	92.6218	**96.4916**	90.3681
thyroid	94.1500	90.6400	**99.1200**	98.6100	92.0300	98.9700	96.7147	91.0460	98.0864	97.5103	91.1094	96.6907
tic-tac-toe	69.7600	70.3200	71.0000	61.8500	67.9700	71.4500	70.5093	70.6640	**73.0610**	62.8186	72.8934	72.6751
titanic	77.1800	74.6000	77.6900	70.9800	67.7400	77.7700	77.5310	74.5973	**77.7834**	70.8566	75.5737	77.5086
twonorm	97.0300	93.8000	85.9200	91.3300	95.2200	85.9300	**97.3390**	96.3664	87.0871	92.0938	96.4097	88.1198
vehicle	47.8700	56.9700	60.4800	64.1500	55.6500	59.0200	57.9951	60.7683	62.1831	**66.5154**	61.7747	62.1973
vowel	40.6700	48.0400	44.9000	51.9800	37.7200	43.6400	50.3616	50.9601	50.9726	54.4140	51.5586	**51.9202**
wine	93.0700	92.8500	78.9800	87.5200	93.7600	80.9900	**95.1475**	93.9660	83.9114	91.0536	92.9243	87.4473
wisconsin	96.2400	95.5000	92.5900	93.4800	95.9400	92.9400	**96.6413**	95.9910	93.9148	95.6295	96.1535	94.9061
yeast	48.9500	46.3300	49.7300	45.8800	45.9300	48.0800	48.0431	49.5750	**50.2999**	48.3013	49.2672	49.1259
zoo	92.6200	92.2300	75.4100	89.7800	78.4400	75.5800	86.4836	**93.7834**	88.2045	93.5267	92.8808	90.2835
Average	73.0475	71.4651	72.5611	71.1002	71.0558	72.3462	**74.3477**	73.0708	73.6259	71.7279	73.6177	73.3147

because it establishes a pairwise comparison between methods. In this way, we can see if there are significant differences between the original and modified versions. More information about this test and other statistical procedures can be found at http://sci2s.ugr.es/sicidm/.

Table VII collects the results of the application of the Wilcoxon signed-ranks test to the transductive and inductive accuracy rates. It shows the rankings $R+$ and $R-$ values achieved and its associate p-value. Adopting a level of significance of $\alpha = 0.1$, we emphasize in bold face those comparisons in which SEG-SSC significantly outperforms the original algorithm.

With these results we can make the following analysis.

1) In Tables V and VI we can see that our framework provides a great improvement in accuracy to the self-labeled techniques used in most of the data sets and rarely does it significantly reduce its performance level. On average, the versions that use synthetic examples always outperform the algorithms upon which they are based in both the transductive and inductive phases. In general, the average improvement achieved for one algorithm in the transductive setting is more or less maintained in the inductive test, which shows the robustness of the models. Co-Bagging (KNN) seems to be the algorithm that benefits most when it uses synthetic instances, by contrast, SEG-SSC does not significantly increase the average performance of Co-Forest. Comparing all the algorithms, the best performing approach is SEG-SSC+Democratic-co.
2) It is known that the performance of self-labeled algorithms depends firstly on the general abilities of their base classifiers [62]. We notice that C4.5 is a better base classifier than KNN for the Tri-Training philosophy. However, the Co-Bagging algorithm performs in a similar way with both classifiers. As expected, the results obtained with our framework are also affected by the base classifier. At this point, we can see that those algorithms that are based on KNN offer a greater average improvement.
3) In Fig. 4, the size of the boxes are related to the robustness of the algorithms. Thus, we observe that, in many cases, SEG-SSC finds more compact boxes than the original

TABLE VI
INDUCTIVE ACCURACY RESULTS OVER STANDARD CLASSIFICATION DATA SETS

Datasets	Original Proposals						SEG-SSC					
	Democratic-Co	Tri-Training (KNN)	Tri-Training (C4.5)	Co-Forest	Co-Bagging (KNN)	Co-Bagging (C4.5)	Democratic-Co	Tri-Training (KNN)	Tri-Training (C4.5)	Co-Forest	Co-Bagging (KNN)	Co-Bagging (C4.5)
abalone	21.0600	20.7200	21.6100	21.0100	20.7700	20.8200	20.3408	20.1730	20.8922	**22.3287**	20.3636	21.1299
appendicitis	82.1800	73.8200	80.4500	82.2700	74.7300	80.4500	76.5455	75.7273	79.4545	79.2727	74.7273	**83.3636**
australian	**84.4900**	80.2900	**84.4900**	84.0600	81.3000	82.7500	84.3478	80.4348	82.1739	83.0435	81.5942	82.3188
automobile	36.0100	43.0700	38.8900	**45.6900**	31.0500	33.6600	44.1879	43.5711	40.7375	40.2639	43.9220	42.4181
banana	84.1700	86.8100	84.8100	52.7000	**87.3600**	85.5300	85.7736	86.4717	86.8868	55.5472	86.6792	86.7736
breast	72.8700	70.8100	72.1600	**73.3900**	70.9000	72.5200	72.5921	70.4380	71.9036	70.9338	69.0904	68.7853
bupa	51.0400	54.1600	57.4200	58.5100	57.6600	61.1900	61.9745	54.7159	**63.2280**	58.5091	57.3746	62.5796
chess	91.9900	83.0900	**95.7800**	94.4000	80.8800	95.4300	91.4895	78.5345	94.9313	93.2094	83.8238	95.7745
cleveland	52.2300	**56.6200**	47.6100	53.6600	54.9600	53.3500	55.7156	55.9584	51.0575	53.2235	56.0482	50.6689
coil2000	93.2200	87.9500	**93.5700**	92.9900	92.2700	93.4800	90.1955	88.2800	92.1100	93.1000	90.1500	90.2500
contraceptive	43.5800	42.1600	48.1300	48.5300	41.0700	48.2700	46.0953	41.7549	47.5188	**49.6920**	42.9100	47.1824
crx	84.9500	80.3400	**85.5500**	82.0600	81.0200	84.9600	83.6402	79.2744	83.4395	82.0433	81.7268	80.3731
dermatology	87.6000	89.3000	88.1600	90.4700	87.0800	87.6000	89.3233	90.1495	87.6332	90.6976	**91.5388**	87.3709
ecoli	63.7000	66.7000	65.8500	62.8300	66.7300	65.5800	68.1907	67.2727	65.5437	67.5758	**70.2674**	65.8556
flare	**72.1400**	63.8900	71.5800	40.2400	63.2300	71.4000	71.3939	64.4507	70.3624	38.8415	66.8877	68.5779
german	71.6000	66.7000	71.7000	68.6000	68.8000	71.1000	**71.7000**	68.5000	68.0000	68.6000	68.3000	70.2000
glass	48.6800	**59.4100**	49.2100	55.8900	48.2400	48.9800	52.7294	57.1968	56.1803	51.6927	54.2606	54.6483
haberman	71.5600	59.7800	70.8800	60.1400	67.9900	71.2200	**71.8602**	64.7419	69.2043	59.2903	65.3226	65.2688
heart	**80.0000**	76.6700	71.4800	69.2600	78.5200	70.3700	**80.0000**	77.0370	72.5926	71.8519	75.9259	71.8519
hepatitis	83.4300	79.6900	83.4300	81.0900	81.1800	83.4300	82.7446	77.3506	81.2673	**90.5032**	78.4383	77.7403
housevotes	88.9900	89.3900	91.5800	**92.1600**	90.3600	91.9500	90.2963	89.0168	88.2021	90.8505	90.3950	90.9857
iris	91.3300	92.0000	72.6700	93.3300	93.3300	80.0000	91.3333	**93.3333**	83.3333	92.0000	92.6667	84.0000
led7digit	61.6000	59.4000	60.4000	63.4000	**66.0000**	56.4000	59.8000	60.4000	63.0000	62.6000	61.8000	61.2000
lymphography	49.0100	67.8700	61.1800	64.6400	66.0800	59.4800	68.1709	65.2129	65.2829	68.2017	**68.8683**	61.5182
magic	78.4200	76.7800	82.4500	84.3600	79.8100	83.1900	79.8370	77.1819	82.3554	**84.7266**	77.9443	81.9821
mammographic	79.6300	76.9900	**81.8300**	79.4100	77.5800	80.8500	80.6285	76.5328	81.7016	79.6800	78.3287	79.7660
marketing	27.1000	26.2000	26.9400	29.2300	26.9300	27.0600	25.8285	26.7307	27.5396	**29.6700**	25.8699	27.1754
monk-2	90.7500	64.6000	96.5700	**93.9200**	67.0700	96.5700	86.4930	64.3084	92.0869	88.8386	77.0660	86.3375
movement_libras	19.7200	**44.4400**	27.5000	31.1100	34.1700	24.1700	29.7222	43.0556	29.4444	32.5000	43.3333	27.2222
mushroom	99.2700	99.4700	99.5500	90.8400	99.0100	99.5400	99.5531	99.5009	99.7678	90.8713	99.4826	**99.8040**
nursery	89.5100	86.9800	90.3900	38.0900	73.8500	90.0600	88.4568	75.7330	**91.3117**	37.3148	78.2330	89.1512
page-blocks	90.7700	93.6400	95.6100	95.8500	93.4900	95.6700	94.3714	93.3847	95.6873	**95.8699**	93.5306	95.3398
penbased	94.7400	98.0100	90.2700	95.5100	96.8200	90.4900	95.8151	**98.2351**	92.2486	96.1066	98.0441	93.6136
phoneme	78.7400	80.4600	77.7000	80.0700	79.8300	78.8900	79.4957	80.7726	80.7542	**81.3837**	80.9578	81.1430
pima	**69.6700**	62.6500	65.6400	66.2700	63.5800	63.4200	68.1074	64.4723	67.7110	68.6167	65.8994	66.9233
ring	87.4100	60.4100	85.4200	88.2300	61.7600	85.8200	**94.3784**	69.4189	81.5270	80.2568	86.8649	79.1757
saheart	**68.1900**	62.7700	67.7600	65.5900	64.0800	64.9700	67.9880	63.2239	66.6744	67.1045	65.6059	64.7317
satimage	84.6200	85.2100	82.2400	86.0000	85.6400	82.0500	85.5945	87.0244	83.8226	86.5584	**88.0969**	84.3355
segment	90.2600	90.7400	90.0000	90.3000	87.0600	91.6000	91.0390	**91.8182**	91.2554	**91.8182**	91.7749	91.5584
sonar	60.0500	63.4500	70.1900	**75.5000**	65.8800	70.1400	71.0714	66.3571	64.8095	73.0476	63.9524	70.0476
spambase	87.7700	81.1000	88.1000	91.8600	83.2700	89.5100	88.0794	82.4662	90.2108	**92.6257**	86.5782	90.8852
spectfheart	73.7900	69.0500	75.7400	77.5100	73.1100	75.7100	76.7379	74.9858	79.4444	79.3875	**79.8291**	79.0456
splice	89.7800	77.5900	82.5400	50.6600	69.7500	82.4800	**92.2257**	65.8307	88.1191	50.0000	81.7555	89.2476
tae	37.7100	40.4200	**45.7100**	37.7900	42.8700	42.3700	38.4583	38.3750	38.5417	36.4600	39.0417	39.1667
texture	89.4400	95.2400	85.2400	90.6500	94.3100	85.0000	90.9455	**96.8182**	89.4909	92.3818	**96.8182**	90.6727
thyroid	93.9300	90.6700	**99.1800**	98.5800	92.1000	99.0600	94.2917	91.1250	98.1528	97.6528	91.4444	96.8611
tic-tac-toe	69.0000	70.6700	70.8800	59.7100	67.9600	70.3500	71.5154	71.3004	72.0252	59.0833	72.4452	**72.7522**
titanic	77.5600	74.1500	77.6500	70.6500	67.4800	**78.3700**	77.6018	74.1512	78.2378	70.5140	75.1940	77.2394
twonorm	96.4500	91.0900	86.1600	89.8900	95.1800	85.9700	**96.8919**	93.6351	87.0135	90.6216	96.5270	87.8243
vehicle	50.2300	55.2000	61.9400	61.2400	55.5500	60.3000	59.4664	60.6373	61.7129	63.8459	62.4034	**62.5266**
vowel	41.6200	49.8000	45.2500	52.2200	39.2900	45.5600	49.1919	52.5253	52.2222	**54.3434**	52.5253	53.0303
wine	94.9300	92.6500	82.0300	85.8800	93.2700	78.6600	95.5229	93.2026	85.9150	91.0131	**96.0784**	88.7582
wisconsin	**96.5000**	94.6200	93.1200	93.5800	95.9300	92.8400	96.3694	95.2032	93.7194	94.6063	95.7938	94.7580
yeast	48.8600	47.5100	49.0700	45.6200	46.7000	47.6500	46.5645	50.1383	**50.3387**	47.4420	50.2091	47.8501
zoo	93.1400	**93.4700**	71.9200	90.8900	78.3300	74.5600	88.5000	92.7222	86.9167	92.6389	92.7222	87.3889
Average	73.0362	71.7576	72.9669	71.2424	70.9667	72.7782	**74.7488**	72.0157	73.9217	71.4700	73.7715	73.5845

algorithms. In the cases in which the boxes have more or less the same size, we can see that they are higher in the plot. Median results also help us to identify algorithms that perform well in many domains. Thus, we observe again that most of the median values of modified versions are higher than the original proposals. Taking into account median values, SEG-SSC+Tri-Training (C4.5) may be considered the best model.

4) According to the Wilcoxon signed-ranks test, SEG-SSC achieves that all the methods significantly overcome their original proposals in terms of transductive learning, supporting previous conclusions. However, in the inductive phase, we find that Co-Forest and Co-Bagging (C4.5) have not been significantly improved. Even so, they report higher $R+$ rankings than the original models, which means that they perform slightly better.

C. Experiments on High Dimensional Problems With Small Labeled Ratio

This subsection is devoted to studying the behavior of the proposed framework when it is applied to high dimensional data and a very reduced labeled ratio. Most of the considered data sets (9 of 11) were provided in the book by Chapelle *et al*. [2], in which the studies were performed using only 10 and 100 labeled instances. We attempt to perform a similar study with the difference that we also investigate the inductive abilities of the models. Furthermore, BBC and BBCsport data sets have been also analyzed in a semi-supervised context with a few number of labeled instances [63].

TABLE VII
RESULTS OF THE WILCOXON SIGNED-RANKS TEST ON TRANSDUCTIVE AND INDUCTIVE PHASES

Comparison	Transductive phase			Test phase		
	$R+$	$R-$	p-value	$R+$	$R-$	p-value
SEG-SSC+Democratic-Co vs. Democratic-Co	1086	454	**0.0080**	1057	428	**0.0067**
SEG-SSC+Tri-Training (KNN) vs. Tri-Training (KNN)	1371	169	**0.0000**	995	545	**0.0588**
SEG-SSC+Tri-Training (C4.5) vs. Tri-Training (C4.5)	1083	457	**0.0086**	966	574	**0.0997**
SEG-SSC+Co-Forest vs. Co-Forest	1132	353	**0.0008**	863	622	0.2970
SEG-SSC+Co-Bagging (KNN) vs. Co-Bagging (KNN)	1201	339	**0.0003**	1204	336	**0.0003**
SEG-SSC+Co-Bagging (C4.5) vs. Co-Bagging (C4.5)	966	574	**0.0997**	943	597	0.1460

In the scatterplots of Fig. 5 we depict transductive and inductive accuracy results obtained with 10 and 100 labeled data. In these plots, the x-axis position of the point is the accuracy of the original self-labeled method on a single data

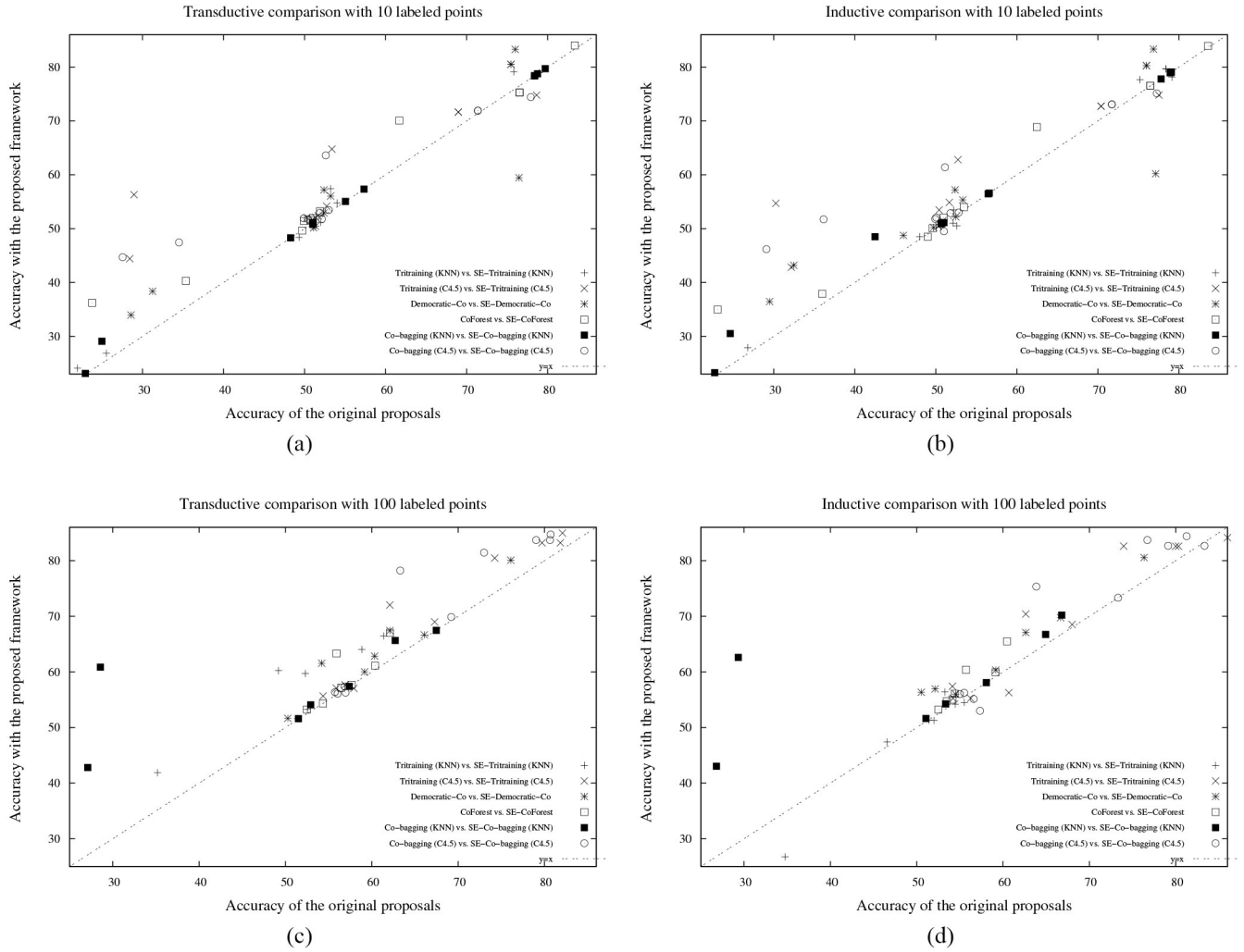


Fig. 5. High dimensional data sets: transductive and inductive accuracy results. (a) Ten labeled points: transductive accuracy. (b) Ten labeled points: inductive accuracy. (c) Hundred labeled points: transductive accuracy. (d) Hundred labeled points: inductive accuracy.

TABLE VIII
HIGH DIMENSIONAL DATA SETS: AVERAGE RESULTS OBTAINED IN TRANSDUCTIVE (TRS) AND INDUCTIVE (TST) PHASES

#L	Phase	Democratic-Co	Tri-Training (KNN)	Tri-Training (C4.5)	Co-Forest	Co-Bagging (KNN)	Co-Bagging (C4.5)
10	TRS	56.6987	56.1988	53.1233	55.5031	56.8976	53.8810
	TST	56.5331	55.9070	53.3841	55.6181	56.3126	53.8852
100	TRS	70.8563	66.5833	68.7295	68.0144	65.4552	68.7148
	TST	70.1286	65.4899	69.1031	67.1261	66.1272	69.7143

#L	Phase	SEG-SSC+ Democratic-Co	SEG-SSC+ Tri-Training (KNN)	SEG-SSC+ Tri-Training (C4.5)	SEG-SSC+ Co-Forest	SEG-SSC+ Co-Bagging (KNN)	SEG-SSC+ Co-Bagging (C4.5)
10	TRS	58.4330	57.1121	58.7192	58.0919	57.2811	57.8010
	TST	58.8520	56.0891	58.3297	57.6709	57.4786	58.1651
100	TRS	73.4449	70.1754	71.7133	70.1887	70.4770	72.4768
	TST	73.5080	65.1796	71.1483	69.2605	71.0570	71.9971

set, and the y-axis position is the accuracy of the modified algorithm. Therefore, points above the $y = x$ line correspond to data sets for which new proposals perform better than the original algorithm.

Table VIII tabulates the average results obtained in the 11 data sets considered, including transductive and inductive phases for both 10 and 100 splits.

Given Fig. 5 and Table VIII, we can make the following comments.

1) In all the plots of Fig. 5, most of the points are above the $y = x$ line, which means that, with the proposed framework, the self-labeled techniques perform better than the original algorithms. Differentiating between 10 and 100 available labeled points, we can see that when we have 100 labeled examples, there are more points above this line in both the transductive and inductive phases. We do not discern great differences between the performance obtained in both learning phases which shows that the hypotheses learned with the available labeled and unlabeled data were appropriate.
2) Table VIII shows that, on average, the proposed scheme obtains a better performance level than the original ones in most cases, independently of the learning phase and the number of labeled data considered. Attending to the difference between transductive and inductive results, we observe that, in general, SEG-SSC increments both proportionally. Nevertheless, there are significant differences between the results obtained with 10 and 100 labeled points.
3) With these results in mind, we can see the good synergy between synthetic examples and self-labeled techniques

in these domains, but, what are the main differences with the results obtained in the previous subsection? We observe great differences between those algorithms that use KNN as a base classifier and those that use C4.5. With standard classification data sets, we ascertained that C4.5 was the best base classifier for Tri-Training and performs similarly to KNN for Co-Bagging. These statements are maintained in these domains, where C4.5 performs better. In this paper, SEG-SSC+Democratic may be highlighted as the best performing model, obtaining the highest transductive and inductive accuracy results with 10 and 100 labeled examples.

V. Conclusion

In this paper we have developed a novel framework called SEG-SSC to improve the performance of any self-labeled SSC method. It is focused on the idea of using synthetic examples in order to diminish the drawbacks occasioned by the absence of labeled examples, which deteriorates the efficiency of this family of methods.

The proposed self-labeled scheme with synthetic examples has been incorporated in four well-known self-labeled techniques that have been modified by introducing the necessary elements to follow the designed framework. These models are able to overcome the original self-labeled methods due to the fact that the addition of new labeled data implies a better diversity of multiple classifier approaches and fulfills the distribution of labeled data.

The wide experimental study carried out has allowed us to investigate the behavior of the proposed scheme with a high number of data sets with a varied number of instances and features. The results have been statistically compared, supporting the assertion that our proposal is a suitable tool for enhancing self-labeled methods.

Among the used data sets, we have tackled problems related to diverse applications with a high practical interest. For instance, our model can be used to address practical problems such as computer-aided diagnosis, image-classification, spam filtering, etc., [21], [47].

There are many possible variations of our proposed semi-supervised scheme that could be interesting to explore as future work. In our opinion, the use of oversampling techniques with self-labeled techniques is not only a new way to improve the capabilities of this family of techniques, but could also be useful for most of the existing semi-supervised learning algorithms.

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