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MRPR: A MapReduce Solution for Prototype Reduction in Big Data Classification

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Abstract

In the era of big data, analyzing and extracting knowledge from large-scale data sets is a very interesting and challenging task. The application of standard data mining tools in such data sets is not straightforward. Hence, a new class of scalable mining method that embraces the huge storage and processing capacity of cloud platforms is required. In this work, we propose a novel distributed partitioning methodology for prototype reduction techniques in nearest neighbor classification. These methods aim at representing original training data sets as a reduced number of instances. Their main purposes are to speed up the classification process and reduce the storage requirements and sensitivity to noise of the nearest neighbor rule. However, the standard prototype reduction methods cannot cope with very large data sets. To overcome this limitation, we develop a MapReduce-based framework to distribute the functioning of these algorithms through a cluster of computing elements, proposing several algorithmic strategies to integrate multiple partial solutions (reduced sets of prototypes) into a single one. The proposed model enables prototype reduction algorithms to be applied over big data classification problems without significant accuracy loss. We test the speeding up capabilities of our model with data sets up to 5.7 millions of

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instances. The results show that this model is a suitable tool to enhance the performance of the nearest neighbor classifier with big data.

Keywords:
Big data, Mahout, Hadoop, Prototype reduction, Prototype generation, Nearest neighbor classification

1. Introduction

The term of big data is increasingly being used to refer to the challenges and advantages derived from collecting and processing vast amounts of data [1]. Formally, it is defined as the quantity of data that exceeds the processing capabilities of a given system [2] in terms of time and/or memory consumption. It is attracting much attention in a wide variety of areas such as industry, medicine or financial businesses because they have progressively acquired a lot of raw data. Nowadays, with the availability of cloud platforms [3] they could take some advantages from these massive data sets by extracting valuable information. However, the analysis and knowledge extraction process from big data become very difficult tasks for most of the classical and advanced data mining and machine learning tools [4, 5].

Data mining techniques should be adapted to the emerging technologies [6, 7] to overcome their limitations. In this sense, the MapReduce framework [8, 9] in conjunction with its distributed file system [10], originally introduced by Google, offers a simple but robust environment to tackling the processing of large data sets over a cluster of machines. This scheme is currently taken into consideration in data mining, rather than other parallelization schemes such as MPI (Message Passing Interface) [11], because of its fault-tolerant mechanism, which is crucial for time-consuming jobs, and because of its simplicity. In the specialized literature, several recent proposals have focused on the parallelization of machine learning tools based on the MapReduce approach [12, 13]. For example, some classification techniques such as [14, 15, 16] have been implemented within the MapReduce paradigm. They have shown that the distribution of the data and the processing under a cloud computing infrastructure is very useful for speeding up the knowledge extraction process.

Data reduction techniques [17] emerged as preprocessing algorithms that aim to simplify and clean the raw data, enabling data mining algorithms to be applied not only in a faster way, but also in a more accurate way by removing noisy and redundant data. From the perspective of the attributes space, the most well-known data reduction processes are feature selection and feature extraction [18]. Taking into consideration the instance space, we highlight instance reduction methods. This latter is usually divided into instance selection [19] and instance generation or abstraction [20]. Advanced models that tackle simultaneously both problems are [21, 22, 23]. As such, these techniques should ease data mining algorithms to address with big data problems, however, these methods are also affected by the increase of the size and complexity of data sets and they are unable to provide a preprocessed data set in a reasonable time.

This work is focused on Prototype Reduction (PR) techniques [20], which are instance reduction methods that aim to improve the classification capabilities of the Nearest Neighbor rule (NN) [24]. These techniques may select instances from the original data set, or build new artificial prototypes, to form a resulting set of prototypes that better adjusts the decision boundaries between classes in NN classification. PR techniques have proved to be very competitive at reducing the computational cost and high storage requirements of the NN algorithm, and also improving its classification performance [25, 26, 27].

Large-scale data cannot be tackled by standard data reduction techniques because their runtime becomes impractical. Several solutions have been developed to enable data reduction techniques to deal with this problem. For PR, we can find a data-level approach that is based on a distributed partitioning model that maintains the class distribution (also called stratification). This splits the original training data into several subsets that are individually addressed. Then, it joins each partial reduced set into a global solution. This approach has been used for instance selection [28, 29] and generation [30] with promising results. However, two main problems appear when we increase the data set size:

- A stratified partitioning process could not be carried out when the size of the data set is so big that it occupies all the available RAM memory.
- This scheme does not consider that joining each partial solution into a global one could generate a reduced set with redundant or noisy instances that may damage the classification performance.

In this work, we propose a new distributed framework for PR, based on the stratification procedure, which handles the drawbacks mentioned above.

To do so, we rely on the success of the MapReduce framework, designing carefully the map and reduce tasks to perform a proper PR process. Concretely, the map phase corresponds to the splitting procedure and the application of the PR technique. The reduce stage performs a filtering or fusion of prototypes to avoid the introduction of harmful prototypes to the resulting preprocessed data set.

We will denote this framework "MapReduce for Prototype Reduction" (MRPR). The idea of splitting the data into several subsets, and processing them separately, fits better with the MapReduce philosophy, than with other parallelization schemes because of two reasons: Firstly, each subset is individually processed, so that, it does not need data exchange between nodes to proceed [31]. Secondly, the computational cost of each chunk could be so high that a fault-tolerant mechanism is mandatory. For the reduce stage we study three different strategies, of varying computational effort, for the integration of the partial solutions generated by the mappers.

Developing a distributed partitioning scheme based on MapReduce for PR motivates the global purpose of this work, which can be divided into three objectives:

- To enable PR techniques to deal with big data classification problems.
- To analyze and illustrate the scalability of the proposed scheme in terms of classification accuracy and runtime.
- To study how PR techniques enhance the NN rule when dealing with big data.

To test the performance of our model, we will conduct experiments on big data sets focusing on an advanced PR technique, called SSMA-SFLSDE, which was recently proposed in [27]. Moreover, some additional experiments with other PR techniques will be also carried out. The experimental study includes an analysis of training and test accuracy, runtime and reduction capabilities of PR techniques under the proposed framework. Several variations of the proposed model will be investigated with different number of mappers and four data sets of up to 5.7 millions instances.

The rest of the paper is organized as follows. In Section 2, we provide some background material about PR and MapReduce. In Section 3, we describe the MapReduce implementation proposed for PR and discuss which PR methods are candidates to be adapted to this framework. We present and discuss the empirical results in Section 4. Finally, Section 5 summarizes the conclusions of the paper.

2. Background

In this section we provide some background information about the topics used in this paper. Section 2.1 presents the PR problem and its weaknesses to deal with big data. Section 2.2 introduces the MapReduce paradigm and the implementation used in this work.

2.1. Prototype reduction and big data

This section defines the PR problem, its current trends and the drawbacks of tackling big data with PR techniques. A formal notation of the PR problem is the following: Let TR be a training data set and TS a test set, they are formed by a determined number $\mathbf{n}$ and $\mathbf{t}$ of samples, respectively. Each sample $\mathbf{x}_p$ is a tuple $(\mathbf{x}_{p1}, \mathbf{x}_{p2}, ..., \mathbf{x}_{pD}, \omega)$, where, $\mathbf{x}_{pf}$ is the value of the f-th feature of the p-th sample. This sample belongs to a class ω, given by $\mathbf{x}_{p\omega}$, and a D-dimensional space. For the TR set the class ω is known, while it is unknown for TS.

The purpose of PR is to provide a reduced set RS which consists of $\mathbf{rs}$, $\mathbf{rs} < \mathbf{n}$, prototypes, which are either selected or generated from the examples of TR. The prototypes of RS should be calculated to efficiently represent the distributions of the classes and to discern well when they are used to classify the training objects. The size of RS should be sufficiently reduced to deal with the storage and evaluation time problems of the NN classifier.

As we stated above, PR is usually divided into those approaches that are limited to select instances from TR, known as prototype selection, and those that may generate artificial examples (prototype generation). Both strategies have been deeply studied in the literature. Most of the recent proposals are based on evolutionary algorithms to select [32, 33] or generate [25, 26] an appropriate RS. Furthermore, there is a hybrid approach between prototype selection and generation in [27]. Recent reviews about these topics are [19] and [20]. More information about PR can be found at the SCI2S thematic public website on *Prototype Reduction in Nearest Neighbor Classification: Prototype Selection and Prototype Generation* [1].

[1] `http://sci2s.ugr.es/pr/`

Despite the promising results shown by PR techniques with small and medium data sets, they lack of scalability to address big TR data sets (from tens of thousands of instances onwards [29]). The main problems found to deal with large-scale data are:

- Runtime: The complexity of PR models is $O((n \cdot D)^2)$ or higher, where n is the number of instances and D the number of features. Although these techniques are only applied once on a TR, if this process takes too long, its application could become inoperable for real applications.

- Memory consumption: Most of PR methods need to store in the main memory many partial calculations, intermediate solutions, and/or also the entire TR. When TR is too big, it could easily exceed the available RAM memory.

As we will see in further sections, these weaknesses motivate the use of distributed partitioning procedures, which divide the TR into disjoint subsets that can be manage by PR methods [28].

2.2. Mapreduce

MapReduce is a paradigm of parallel programming [8, 9] designed to process or generate large data sets. It allows us to tackle big data sets over a computer cluster regardless the underlying hardware or software. It is characterized by its highly transparency for programmers, which allows to parallelize applications in a easy and comfortable way.

Based on functional programming, this model works in two different steps: the map phase and the reduce phase. Each one has key-value ($< k, v >$) pairs as input and output. Both phases are defined by a programmer. The map phase takes each $< k, v >$ pair and generates a set of intermediate $< k, v >$ pairs. Then, MapReduce merges all the values associated with the same intermediate key as a list (known as shuffle phase). The reduce phase takes that list as input for producing the final values. Figure 1 depicts a flowchart of the MapReduce framework. In a MapReduce program, all map and reduce operations run in parallel. First of all, all map functions are independently run. Meanwhile, reduce operations wait until their respective maps are finished. Then, they process different keys concurrently and independently. Note that inputs and outputs of a MapReduce job are stored in an associated distributed file system that is accessible from any computer of the used cluster.

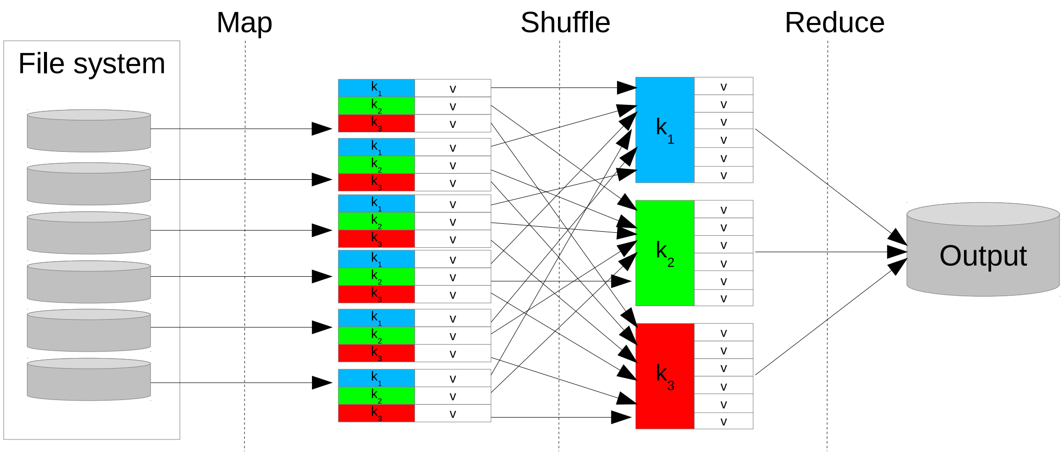


Figure 1: Flowchart of the MapReduce framework

An illustrative example about the way of working of MapReduce could be find the average costs per year from a big list of cost records. Each record may be composed by a variety of values, but it at least includes the year and the cost. The map function extracts from each record the pairs $< year, cost >$ and transmits them as its output. The shuffle stage groups the $< year, cost >$ pairs by its corresponding year, creating a list of costs per year $< year, list(cost) >$. Finally, the reduce phase performs the average of all the costs contained in the list of each year.

Different implementations of the MapReduce framework are possible [8], depending on the available cluster architecture. Some implementations of MapReduce are: Mars [34], Phoenix [35] and Apache Hadoop [36, 37]. In this paper we will focus on the Hadoop implementation because of its performance, open source nature, installation facilities and its distributed file system (Hadoop Distributed File System, HDFS).

A Hadoop cluster is formed by a master-slave architecture, where one master node manages an arbitrary number of slave nodes. The HDFS replicates file data in multiple storage nodes that can concurrently access to the data. As such cluster, a certain percentage of these slave nodes may be out of order temporarily. For this reason, Hadoop provides a fault-tolerant mechanism, so that, when one node fails, Hadoop restarts automatically the task on another node.

As we commented above, the MapReduce approach can be useful for many different tasks. In terms of data mining, it offers a propitious environment to successfully speed up these kinds of techniques. In fact, there is a growing open source project, called Apache Mahout [38], that collects distributed and scalable machine learning algorithms implemented on top of Hadoop. Nowadays, it supplies an implementation of several specific techniques, such as, k-means for clustering, a naive bayes classifier, a collaborative filtering, etc. We based our implementations on this library.

3. MRPR: MapReduce for prototype reduction

In this section we present the proposed MapReduce approach for PR. Firstly, we argue the motivation that justify our proposal (Section 3.1). Then, we detail the proposed model in depth (Section 3.2). Finally, we comment which PR methods can be implemented within the proposed framework depending on their main characteristics (Section 3.3)

3.1. Motivation

As mentioned before, PR methods decrease their performance when dealing with large amounts of instances. The distribution and parallelization of workload in different sub-processes may ease the problems previously enumerated (runtime and memory consumption). To tackle this challenge we have to create an efficient and flexible PR design that takes advantage of parallelization schemes and cloud-enable infrastructures. The designed framework should enable PR techniques to be applied with data sets of unlimited number of instances without major algorithmic modifications, just by using more computers. Furthermore, this model should guarantee that the objectives of PR models are maintained, so that, it should provide high reduction rates without significant accuracy loss.

In our previous work [30], a distributed partitioning approach was proposed to alleviate these issues. This model splits the training set, called TR, into disjoint d subsets $(TR_1, TR_2, ..., TR_d)$ with equal class distribution and size. Then, a PR model is applied to each TR_j, obtaining a resulting reduced set RS_j. Finally, all RS_j $(1 \leq j \leq d)$ are merged into a final reduced set, called RS, which is used to classify the instances of TS with the NN rule.

This partitioning process shows to perform well in medium size domains. However, it has some limitations:

- Maintaining the proportion of examples per class of TR within each subset TR_j cannot be accomplished when the size of the data set does not fit in the main memory. Hence, this strategy cannot scale to data sets of arbitrary size.

- Joining all the partial reduced sets RS_j into a final RS may lead to the introduction of noisy and/or redundant examples. Each resulting RS_j tries to represent, with the minimum number of instances, a proportion of the entire TR. Thus, when the size of TR tends to be very high, the instances contained in some TR_j subsets may be located very near in the D-dimensional space. Therefore, the final RS may enclose unnecessary instances to represent the training data. The likelihood of this issue increases with the number of partitions.

Moreover, it is important to note that this distributed model was not implemented within any parallel environment that ensures high scalability and fault tolerance. These weaknesses motivate the design of a parallel PR system based on cloud technologies.

In [30], we compared some relevant PR methods with the distributed partitioning model. We concluded that the best performing approach was the SSMA-SFLSDE model [27]. In our experiments, we will mainly focus on this PR model (although other models will be investigated).

3.2. Parallelizing PR with MapReduce

This section explains how to parallelize PR techniques following a MapReduce procedure. Section 3.2.1 details the map phase and Section 3.2.2 presents the reduce stage. At the end of the section, Figure 3 illustrates a high level scheme of the proposed parallel system MRPR.

3.2.1. Map phase

Suppose a training set TR, of a determined size, stored in the HDFS as a single file. The first step of MRPR is devoted to split TR into a given number of disjoint subsets. Within a Hadoop perspective, the TR file is composed by h HDFS blocks that are accessible from any computer of the cluster independently of its size. Let m the number of map tasks (a user-defined parameter). Each map task ($Map_1, Map_2, ..., Map_m$) will form an associated TR_j, where $1 \leq j \leq m$, with the instances of each chunk in which is divided the training set file. It is noteworthy that this partitioning process is performed sequentially, so that, the Map_j corresponds to the j data chunk of h/m HDFS blocks. So, each map will process approximately the same number of instances.

```
function MAP(Number of splits j)
    Constitute TR_j with the instances of split j.
    RS_j=PrototypeReduction(TR_j)
    return RS_j
end function
function REDUCE(RS_j,typeOfReducer)                    ▷ Initially RS = ∅
    RS = RS ∪ RS_j
    if typeOfReducer==Filtering then
        RS=Filtering(RS)
    end if
    if typeOfReducer==Fusion then
        RS=Fusion(RS)
    end if
    return RS
end function
```

Figure 2: Map and reduce functions

Under this scheme, if the partitioning procedure is directly applied over TR, the class distribution of each subset TR_j could be biased to the original distribution of instances in its corresponding file. As we stated before, a proper stratified partitioning could not be carried out if the size of TR does not fit in the main memory. In order to develop a scheme easily scalable to any number of instances, we previously randomize the entire file. This operation is not time-consuming in comparison with the application of the PR technique and should be applied only once. It does not ensure that every class is represented proportionally to its number of instances in TR. However, probabilistically, each chunk should include approximately a number of instances of class ω according to the probability of belonging to this class in the original TR.

When each map has formed its corresponding TR_j, a PR step is performed using TR_j as the input training data. This step generates a reduced set RS_j. Note that PR techniques may consume different computational times although they are applied with data sets of similar characteristics. It mainly depends on the stopping criteria of each PR model. Nevertheless, MapReduce starts the reduce phase as the first mapper has finalized. Figure 2 contains the pseudo-code of the map function. This function is basically the application of the PR technique for each training partition.

As each map finishes its processing the results are forwarded to a single reduce task.

3.2.2. Reduce phase

The reduce phase will consist of the iterative aggregation of all the RS_j as a single one RS. Figure 2 shows the pseudo-code of the implemented reduce function. Initially $RS = \emptyset$. To do so, we propose different alternatives:

- *Join*: This simple option, based on stratification, concatenates all the RS_j sets into a final reduce set RS. Instruction 7 indicates how the reduce function progressively joins all the RS_j as the mappers finish their processing. This type of reducer implements the same strategy used in the distributed partitioning procedure that we previously proposed [30]. As such, this joining process does not guarantee that the resulting RS does not contain irrelevant or even harmful instances, but it is included as a baseline.

- *Filtering*: This alternative explores the idea of a filtering stage that removes noisy instances during the formation of RS. This is based on those prototype selection methods belonging to the edition family of methods [19].

  This kind of methods is commonly based on simple heuristics that discard points that are noisy or do not agree with their neighbors. They supply smoother decision boundaries for the NN classifier. In general, edition schemes enhance generalization capabilities by performing a slight reduction of the original training set.

  These characteristics are very appropriates for the current stage of our framework. At this stage, the map phase has reduced each partition to a subset of representative instances. To aggregate them into a single RS set, we do not pursue to reduce more the RS, we focus on removing noisy instances, if any. Therefore, the reduce function iteratively applies a filtering of the current RS. It means that as the mappers end their execution, the reduce function is run and the next RS is computed as the filtered set obtained with its current content and the new RS_j. It is described in instructions 8-10 of Figure 2.

- *Fusion*: In this variant we aim to eliminate redundant prototypes. To accomplish this objective we rely on the success of centroid-based methods for prototype generation [20]. These techniques reduce a prototype set by merging similar examples [39]. Since in this step we have to

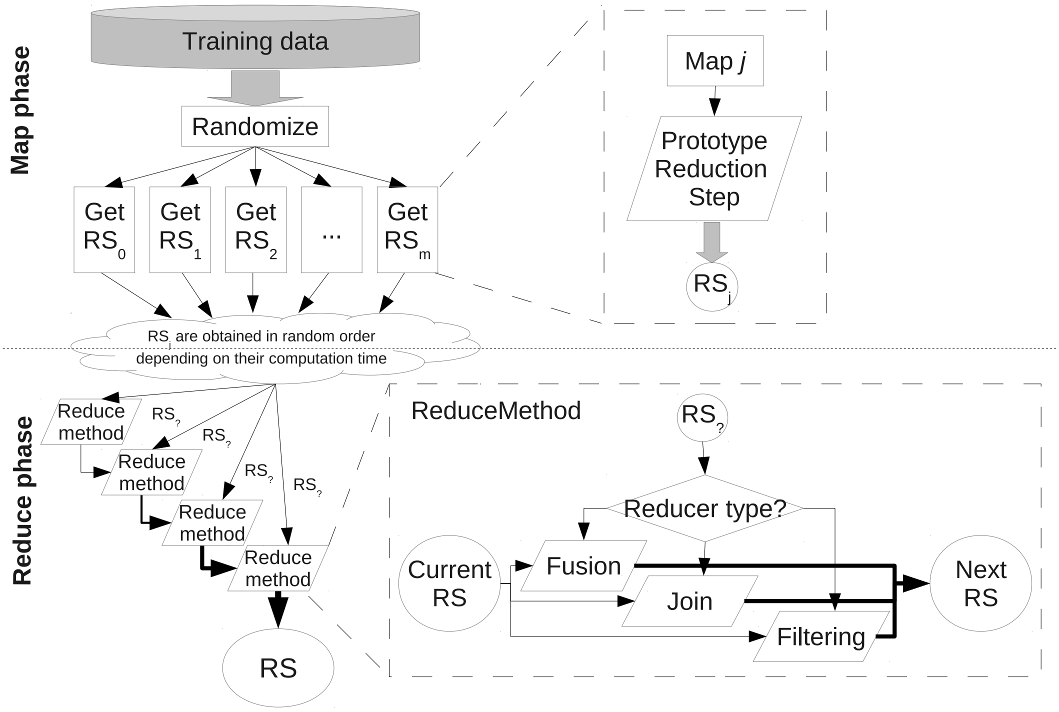


Figure 3: MRPR scheme

fuse all the RS_j into a single one, these methods can be very useful to generate a final set without redundant or very similar prototypes.

As in the previous scheme, the fusion phase will be progressively applied during the creation of RS. Instructions 11-13 of Figure 2 explain how to apply the fusion phase in the MapReduce framework.

As we have explained, MRPR only uses one single reducer that is run every time that a mapper is completed. With the adopted strategy, the use of a single reducer is computationally less expensive than use more than one. It decreases the Mapreduce overhead (especially network overhead) [40].

As summary, Figure 3 outlines the way of working of the MRPR framework, differentiating between the map and reduce phases. It puts emphasis on how the single reducer works and it forms the final RS. The resulting RS will be used as training set for the NN rule to classify the unseen data of the TS set.

3.3. Which PR methods are more suitable for the MRPR framework?

In this subsection we explain which kind of PR techniques fit with the proposed MRPR framework in its respective stages. In the map phase, the main prototype reduction process is carried out by a PR technique. Then, depending on the selected reduce type we should select a filtering or a fusion PR technique to combine the resulting reduced sets. In what follows, we discuss which PR techniques are more appropriate for these stages and how to combine them.

All PR algorithms utilize a training set (in our case TR_j) as input and then return a reduced set RS_j. Therefore, all of them could be implemented in the map phase of MRPR according to the description performed above. However, depending on their characteristics (reduction, accuracy and runtime), we should take into consideration the following aspects to select a proper PR algorithm:

- A very accurate PR technique is desirable. However, in many PR techniques it implies a low reduction rate. A resulting RS with an excessive number of instances can negatively influence in the time needed by the reduce phase.
- The runtime consumption of a PR algorithm will determine the necessary number of mappers in which the TR set of a given problem should be divided. Depending on the problem tackled, a very high number of mappers may result in a non representative subset TR_j from the original TR.

According to [19, 20], there are six main PR families: edition [41], condensation [42], hybrid approaches [43], positioning adjustment [25], centroids-based [44] and space splitting [45]. Although there are differences between the methods of each family, most of them perform in a similar way. With these previous notes in mind, we can state the following general recommendations:

- Edition-based methods are focused on cleaning the training set by removing noisy data. Thus, these methods are usually very fast and accurate but they obtain a very low reduction rate. To implement these methods in our framework we recommend the use of a very fast reduce phase. For instance, a simple join scheme, a filtering reducer with the ENN method [41] or a fusion reducer based on PNN [39].

- Condensation, hybrid and space splitting approaches commonly offer a good trade-off between reduction, accuracy and runtime. Their reduction rate is normally around 60-80%, so that, depending on the problem addressed, the reducer should have a moderate time consumption. For example, we recommend the use of ENN [41] or Depur [46] for filtering reducers and GMCA [44] for fusion.

- Positioning adjustment techniques may offer a very high reduction rate or even adjustable as a user-defined parameter. These techniques can provide very accurate results in a relatively moderate runtime. To implement these techniques we suggest the inclusion of very accurate reducers, such as ICPL [47] for fusion, because the high reduction rate will allow them to be applied in a fast way.

- Centroid-based algorithms are very accurate, with a moderate reduction power but (in general) very time-consuming. Although its implementation is feasible and could be useful in some problems, we assume that their use should be limited to the later stage (reduce phase).

As general suggestions to combine PR techniques in the map and reduce phases, we can establish the following rules:

- High reduction rates in the map phase permit very accurate reducers.

- Low reduction rates in the map phase need fast reducers (join, filtering or a fast fusion).

As commented in the previous section, we propose the use of edition-based methods for the filtering reduce type and centroid-based algorithms to fuse prototypes. In our experiments, we will focus on a simple but effective edition technique: the edited nearest neighbor (ENN) [41]. This algorithm removes an instance from a set of prototypes if it does not agree with the majority of its k nearest neighbors. As algorithms to fuse prototype, we will use the ICLP2 method presented in [47] as a more accurate option and the GMCA model for a faster reduce phase [44]. The ICPL2 model integrates several prototypes by identifying borders and merging those instances that are not located in these borders. It highlights as the best performing model of the centroid-based family in [20]. The GMCA approach merges prototype based on a hierarchical clustering. This method provides a good trade-off between accuracy and runtime needed.

4. Experimental study

In this section we present all the questions raised with the experimental study and the results obtained. Section 4.1 describes the performance measures used to evaluate the MRPR model. Section 4.2 defines and details the hardware and software support used in our experiments. Section 4.3 shows the parameters of the involved algorithms and the data sets chosen. Section 4.4 presents and discusses the results achieved. Finally, Section 4.5 includes additional experiments using different PR techniques within the MRPR model.

4.1. Performance measures

In this work we study the performance of a parallel PR system to improve the NN classifier. Hence, we need several types of measures to characterize the abilities of the proposed approach and its variants. In the following, we briefly describe the considered measures:

- *Accuracy:* It counts the number of correct classifications regarding the total number of instances classified [4, 48]. In our experiments we will compute training and test classification accuracy.

- *Reduction rate:* It measures the reduction of storage requirements achieved by a PR algorithm.

  $$ReductionRate = 1 - size(RS)/size(TR) \tag{1}$$

  Reducing the stored instances in the TR set will yield a time reduction to classify a new input sample.

- *Runtime:* We will quantify the total time spent by MRPR to generate the RS, including all the computations performed by the MapReduce framework.

- *Test classification time:* It refers to the time needed to classify all the instances of TS regarding a given TR. For PR, it is directly related to the reduction rate.

- *Speed up:* It usually checks the efficiency achieved by a parallel system in comparison with the sequential version of the algorithm. Thus, it measures the relation between the runtime of sequential and parallel versions. If the calculation is executed in c processing cores and it is considered fully parallelizable, the maximum theoretical speed up would be equal to the number of used cores, according to the the Amdahl's Law [49]. With a MapReduce parallelization scheme, each map will correspond to a single core, so that, the number of used mappers determines the maximum attainable speed up. However, due to the magnitude of the data sets used, we cannot run the sequential version of the selected PR technique (SSMA-SFLSDE) because its execution is extremely slow. For this reason, we will take the runtime with the minimum number of mappers as reference time to calculate the speed up. Therefore, the speed up will be computed as:

$$Speedup = \frac{parallel\_time}{parallel\_time\_with\_minimum\_number\_of\_mappers} \tag{2}$$

4.2. Hardware and software used

The experiments have been carried out on twelve nodes in a cluster: The master node and eleven compute nodes. Each one of these compute nodes has the following features:

- **Processors**: 2 x Intel Xeon CPU E5-2620
- **Cores**: 6 per processor (12 threads)
- **Clock Speed**: 2.00 GHz
- **Cache**: 15 MB
- **Network**: Gigabit Ethernet (1 Gbps)
- **Hard drive**: 2 TB
- **RAM**: 64 GB

The master node works as the user interface and hosts both Hadoop master processes: the NameNode and the JobTracker. The NameNode handles the HDFS, coordinating the slave machines by the means of their respective DataNode processes, keeping track of the files and the replications of each

HDFS block. The JobTracker is the MapReduce framework master process that manages the TaskTrackers of each compute node. Its responsibilities are maintaining the load-balance and the fault-tolerance in the system, ensuring that all nodes get their part of the input data chunk and reassigning the parts that could not be executed.

The specific details of the software used are the following:

- **MapReduce implementation:** Hadoop 2.0.0-cdh4.4.0. MapReduce 1 runtime(Classic). Cloudera's open-source Apache Hadoop distribution [50].
- **Maximum maps tasks:** 128.
- **Maximum reducer tasks:** 1.
- **Machine learning library:** Mahout 0.8.
- **Operating system:** Cent OS 6.4.

Note that the total number of cores of the cluster is 132. However, the maximum number of map tasks are limited to 128 and one for the reducers.

4.3. Data sets and methods

In this experimental study we will use four big classification data sets taken from the UCI repository [51]. Table 1 summarizes the main characteristics of these data sets. For each data set, we show the number of examples (#Examples), number of attributes (#Dimension), and the number of classes (#ω).

Table 1: Summary description of the used big data classification

Data set	**#Examples**	**#Dimension**	**#ω.**
PokerHand	1025010	10	10
KddCup 1999 (DOS vs. normal classes)	4856151	41	2
Susy	5000000	18	2
RLCP	5749132	4	2

These data sets have been partitioned using a 5 fold cross-validation (5-fcv) scheme. It means that the data set is split into 5 folds, each one containing 20% of the examples of the data set. For each fold, a PR algorithm is run over the examples presented in the remaining folds (that is, in the

Table 2: Approximate number of instances in each TR_j subset according to the number of mappers used.

	Number of mappers				
Data set	**64**	**128**	**256**	**512**	**1024**
PokerHand	12813	6406	3203	1602	801
Kddcup (10%)	6070	3035	1518	759	379
Kddcup (50%)	**30351**	15175	7588	3794	1897
Kddcup (100%)	**60702**	**30351**	15175	7588	3794
Susy	**62469**	**31234**	15617	7809	3904
RLCP	**71862**	**35931**	17965	8983	4491

training partition, TR). Then, the resulting RS is tested with the current fold using the NN rule. Test partitions are kept aside during the PR phase in order to analyze the generalization capabilities provided by the generated RS. Because of the randomness of some operations that these algorithms perform, they have been run three times per partition.

Aiming to investigate the effect of the number of instances in our MRPR scheme, we will create three different versions of the KDD Cup data set by selecting (randomly) 10%, 50% and 100% of the instances of the original data set. We will denote these versions as Kddcup (10%), Kddcup (50%) and Kddcup (100%). The number of instances of a data set and the number of mappers used in our scheme have a straight relation. Table 2 shows the approximate number of instances per chunk, that is, the size of each TR_j for MRPR, attending to the number of mappers established. When the number of instances per chunk exceeds twenty thousand, the execution of the PR is not feasible in time. Therefore, we are unable to carry out these experiments.

As we stated before, we will focus on the hybrid SSMA-SFLSDE algorithm [27] to test the MRPR model. However, in Section 4.5, we will conduct some additional experiments with other PR techniques. Concretely, we will use LVQ3 [52] and RSP3 [45] as pure prototype generation algorithms as well as DROP3 [43] and FCNN [53] as prototype selection algorithms.

Furthermore, we will use the ENN algorithm [41] as edition method for the filtering-based reducer. For the fusion-based reducer, we will apply a very accurate centroid-based technique called ICLP2 [47] when SSMA-SFLSDE and LVQ3 are run in the map phase. It is motivated by the high reduction ratio of these positioning adjustment methods. For RSP3, DROP3 and FCNN we will based on a faster fusion method known as GMCA [44]

Table 3: Parameter specification for all the methods involved in the experimentation

Algorithm	***Parameters***
MRPR	Number of mappers = 64/128/256/512/1024. Number of reducers=1
	Type of Reduce = Join/Filtering/Fusion.
SSMA-SFLSDE	PopulationSFLSDE= 40, IterationsSFLSDE = 500,
	iterSFGSS =8, iterSFHC=20, Fl=0.1, Fu=0.9
ICLP2 (Fusion)	Filtering method = RT2
ENN (Filtering)	Number of neighbors = 3, Euclidean distance.
NN	Number of neighbors = 1, Euclidean distance.
LVQ3	Iterations = 100, *alpha* = 0.1, WindowWidth=0.2, *epsilon* = 0.1
RSP3	Subset Choice = Diameter
DROP3	Number of neighbors = 3, Euclidean distance.
FCNN	Number of neighbors = 3, Euclidean distance.
GMCA (Fusion)	Number of neighbors = 1, Euclidean distance.

In addition, the NN classifier has been included as baseline limit of performance. Table 3 presents all the parameters involved in our experimental study. These parameters have been fixed according to the recommendation of the corresponding authors of each algorithm. Note that our research is not devoted to optimize the accuracy obtained with a PR method over a specific problem. We focus our experiments on the analysis of the behavior of the proposed parallel system. To do so, we will study the influence of the number mappers and type of reduce regarding to the accuracy achieved and the runtime needed. In some of the experiments we will use a higher number of mappers than the available map tasks (128). In these cases, the Hadoop system queues the remaining tasks and they are dispatched as soon as any map task has finished its processing.

A brief description of the used PR methods is:

- **SSMA-SFLSDE**: This algorithm is a hybridization of prototype selection and generation. First, a prototype selection step is performed based on the memetic algorithm SSMA [32]. This approach makes use of a local search specifically developed for prototype selection. This initial step allows us to find a promising selection of prototypes per class. Then, its resulting RS is inserted as one of the individuals of the population of an adaptive differential evolution algorithm [54, 55], acting as a prototype generation model to adjust the positioning of the selected prototypes.

- **LVQ3**: This method combines strategies to "punish" or "reward" the positioning of a prototype in order to adjust the positioning of a set of initial prototypes (adjustable). Therefore, it is included in the positioning adjustment family.

- **RSP3**: This technique tries to avoid drastic changes in the form of decision boundaries associated with $TR$by splitting it in different subsets according to the highest overlapping degree [45]. As such, it belongs to the family of space-splitting PR techniques.

- **DROP3**: This model combine a noise-filtering stage and a decremental approach to remove instances from the original TR set that are considered as harmful within the nearest neighbors. It is included in the family of hybrid edition and condensation PR techniques.

- **FCNN**: With an incremental methodology, this algorithm starts by introducing to the resulting RS the centroids of each class. Then, a prototype contained in TR will be added according to the nearest neighbor of each centroid. It belongs to the condensation-based family.

4.4. Exhaustive evaluation of the MRPR framework for the SSMA-SFLSDE method

This section presents and analyzes the results collected in the experimental study with the SSMA-SFLSDE method from two different points of view:

- Firstly, we study the accuracy and reduction results obtained with the three implemented reducers of the MRPR model. We will check the performance achieved in comparison with the NN rule (Section 4.4.1).

- Secondly, we analyze the scalability of the proposed approach in terms of runtime and speed up (Section 4.4.2).

Tables 4, 5, 6 and 7 summarize all the results obtained on the considered data sets. They show training/test accuracy, runtime and reduction rate obtained by the SSMA-SFLSDE algorithm, in our MRPR framework, depending on the number of mappers (#Mappers) and reduce type. For each one of these measures, average (Avg.) and standard deviation (Std.) results are presented (from the 5-fcv experiment). Moreover, the average classification time in the TS is computed as the time needed to classify all the

Table 4: Results obtained for the PokerHand problem.

Reduce type	**#Mappers**	**Training**		**Test**		**Runtime**		**Reduction rate**		**Classification**
		Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.	**time** (TS)
Join	64	**0.5158**	0.0007	**0.5102**	0.0008	13236.6012	147.8684	97.5585	0.0496	1065.1558
Filtering	64	***0.5212***	0.0008	**0.5171**	0.0014	13292.8996	222.3406	98.0714	0.0386	848.0034
Fusion	64	**0.5201**	0.0011	***0.5181***	0.0015	14419.3926	209.9481	99.1413	0.0217	374.8814
Join	128	**0.5111**	0.0005	**0.5084**	0.0011	3943.3628	161.4213	97.2044	0.0234	1183.6378
Filtering	128	**0.5165**	0.0007	**0.5140**	0.0007	3949.2838	135.4213	97.7955	0.0254	920.8190
Fusion	128	**0.5157**	0.0012	**0.5139**	0.0006	4301.2796	180.5472	99.0250	0.0119	419.6914
Join	256	**0.5012**	0.0010	0.4989	0.0010	2081.0662	23.6610	96.5655	0.0283	1451.1200
Filtering	256	**0.5045**	0.0010	**0.5024**	0.0006	2074.0048	25.4510	97.2681	0.0155	1135.2452
Fusion	256	**0.5161**	0.0004	**0.5151**	0.0007	2231.4050	14.3391	98.8963	0.0045	478.8326
Join	512	**0.5066**	0.0007	**0.5035**	0.0009	1101.8868	16.6405	96.2849	0.0487	1545.4300
Filtering	512	**0.5114**	0.0010	**0.5091**	0.0005	1101.2614	13.0263	97.1122	0.0370	1472.6066
Fusion	512	**0.5088**	0.0008	**0.5081**	0.0009	1144.8080	18.3065	98.7355	0.0158	925.1834
Join	1024	0.4685	0.0008	0.4672	0.0008	598.2918	11.6175	95.2033	0.0202	2132.7362
Filtering	1024	0.4649	0.0009	0.4641	0.0010	585.4320	8.4529	96.2073	0.0113	1662.5460
Fusion	1024	**0.5052**	0.0003	**0.5050**	0.0009	601.0838	7.4914	98.6249	0.0157	1345.6998
NN	–	0.5003	0.0007	0.5001	0.0011	–	–	–	–	48760.8242

Table 5: Results obtained for the Kddcup (100%) problem.

Reduce type	**#Mappers**	**Training**		**Test**		**Runtime**		**Reduction rate**		**Classification**
		Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.	**time**(TS)
Join	256	0.9991	0.0003	0.9993	0.0003	8536.4206	153.7057	99.9208	0.0007	1630.8426
Filtering	256	0.9991	0.0003	0.9991	0.0003	8655.6950	148.6363	99.9249	0.0009	1308.1294
Fusion	256	***0.9994***	0.0000	***0.9994***	0.0000	8655.6950	148.6363	99.9279	0.0008	1110.4478
Join	512	0.9991	0.0001	0.9992	0.0001	4614.9390	336.0808	99.8645	0.0010	5569.8084
Filtering	512	0.9989	0.0001	0.9989	0.0001	4941.7682	44.8844	99.8708	0.0013	5430.4020
Fusion	512	0.9992	0.0001	**0.9993**	0.0001	5018.0266	62.0603	99.8660	0.0006	2278.2806
Join	1024	0.9990	0.0002	0.9991	0.0002	2620.5402	186.5208	99.7490	0.0010	5724.4108
Filtering	1024	0.9989	0.0000	0.9989	0.0001	3103.3776	15.4037	99.7606	0.0011	4036.5422
Fusion	1024	0.9991	0.0002	0.9991	0.0002	3191.2468	75.9777	99.7492	0.0010	4247.8348
NN	0	0.9994	0.0001	0.9993	0.0001	–	–	–	–	2354279.8650

instances of TS with the corresponding RS generated by MRPR. Furthermore, we compare these results with the accuracy and the test classification time achieved by the NN classifier. It uses the whole TR set to classify all the instances of TS. In these tables, average accuracies higher or equal than the obtained with the NN algorithm have been highlighted in bold. The best ones in overall, on training and test phases, are stressed in italic.

4.4.1. Analysis of accuracy and reduction capabilities

This section is focused on comparing the resulting accuracy and reduction rates of the different versions of MRPR. Figure 4 depicts the test accuracy achieved according to the number of mappers in the data sets considered. It represents the average accuracy depending on the reduce type utilized. The average accuracy result of the NN rule is presented as a line

Table 6: Results obtained for the Susy problem.

Reduce type	**#Mappers**	**Training**		**Test**		**Runtime**		**Reduction rate**		**Classification**
		Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.	**time(TS)**
Join	256	**0.6953**	0.0005	**0.7234**	0.0004	69153.3210	4568.5774	97.4192	0.0604	30347.0420
Filtering	256	**0.6941**	0.0001	***0.7282***	0.0003	66370.7020	4352.1144	97.7690	0.0046	24686.3550
Fusion	256	0.6870	0.0002	**0.7240**	0.0002	69796.7260	4103.9986	98.9068	0.0040	11421.6820
Join	512	0.6896	0.0012	**0.7217**	0.0003	26011.2780	486.6898	97.2050	0.0052	35067.5140
Filtering	512	0.6898	0.0002	**0.7241**	0.0003	28508.2390	484.5556	97.5609	0.0036	24867.5478
Fusion	512	0.6810	0.0002	**0.7230**	0.0002	30344.2770	489.8877	98.8337	0.0302	12169.2180
Join	1024	**0.6939**	0.0198	**0.7188**	0.0417	13524.5692	1941.2683	97.1541	0.5367	45387.6154
Filtering	1024	0.6826	0.0005	**0.7226**	0.0006	14510.9125	431.5152	97.3203	0.0111	32568.3810
Fusion	1024	0.6757	0.0004	**0.7208**	0.0008	15562.1193	327.8043	98.7049	0.0044	12135.8233
NN	0	0.6899	0.0001	0.7157	0.0001	–	–	–	–	1167200.3250

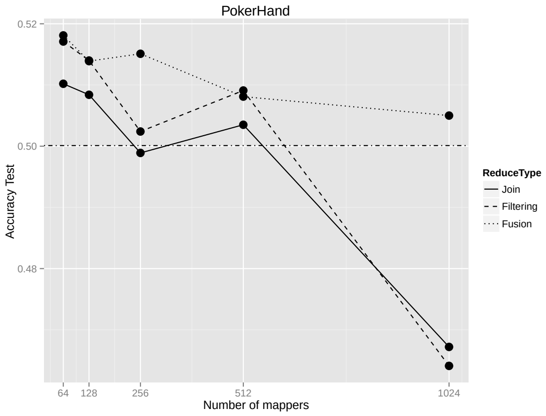
Table 7: Results obtained for the RLCP problem.

Reduce type	**#Mappers**	**Training**		**Test**		**Runtime**		**Reduction rate**		**Classification**
		Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.	**time(TS)**
Join	256	***0.9963***	0.0000	***0.9963***	0.0000	29549.0944	62.4140	98.0091	0.0113	10534.0450
Filtering	256	***0.9963***	0.0000	***0.9963***	0.0000	29557.2276	62.7051	98.0091	0.0113	10750.9012
Fusion	256	***0.9963***	0.0000	***0.9963***	0.0000	26814.9270	1574.4760	98.6291	0.0029	10271.0902
Join	512	**0.9962**	0.0001	**0.9962**	0.0000	10093.9022	61.6980	97.9911	0.0019	11767.8596
Filtering	512	**0.9962**	0.0001	**0.9962**	0.0000	10916.6962	951.5328	97.9919	0.0016	11689.1144
Fusion	512	**0.9962**	0.0001	***0.9963***	0.0000	11326.7812	85.6898	98.3012	0.0036	10856.8888
Join	1024	**0.9960**	0.0001	**0.9960**	0.0001	5348.4346	20.6944	97.9781	0.0010	10930.7026
Filtering	1024	**0.9960**	0.0001	**0.9960**	0.0001	5328.0388	14.8981	97.9781	0.0010	11609.2740
Fusion	1024	**0.9960**	0.0001	**0.9960**	0.0001	5569.2214	16.5025	98.2485	0.0015	10653.3659
NN	0	0.9946	0.0001	0.9946	0.0001	–	–	–	–	769706.2186

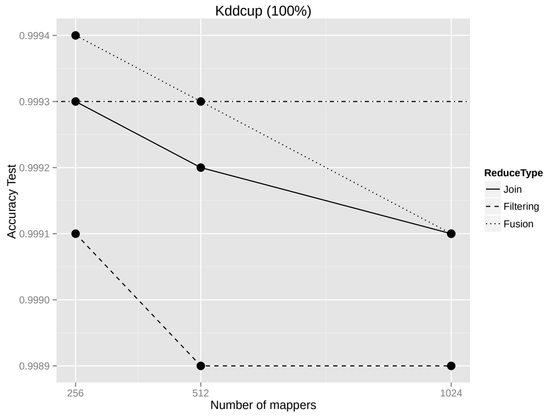
$y = AverageAccuracy$, to show the accuracy differences between using the whole TR or a generated RS as training data set. In addition, Figure 5 plots the reduction rates attained by each type of reduce for both problems. In each sub-figure the average reduction rate with 256 mappers has been drawn.

According to these graphics and tables we can make several observations from these results:

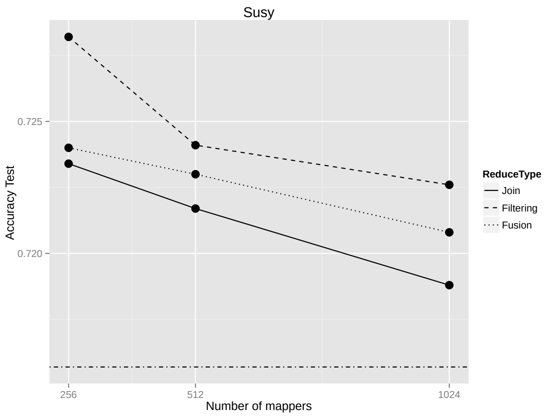
- Since that within the MRPR framework a PR algorithm does not dispose of the full information about the whole addressed problem, it is expected that the accuracy obtained decreases according as the number of available instances in the used training set is reduced. This statement and the way in which the accuracy is reduced depends crucially on the specific problem tackled and its complexity. However, it could be generalizable and extensible to most of the problems because there will be a minimum number of instances in which the performance decrease drastically. Observing previous tables and graphics, we can see that in the case of the PokerHand problem its performance is markedly



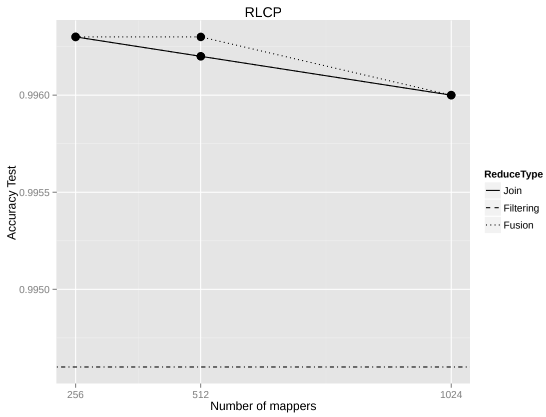
(a) PokerHand: Test accuracy.



(b) Kddcup (100%): Test accuracy.



(c) Susy: Test accuracy.



(d) RLCP: Test accuracy.

Figure 4: Test accuracy results

deteriorated when the problem is divided into 1024 subsets (mappers) in both training and test phases. In Susy data set, the accuracy is gradually deteriorated as the number of mapper is incremented. For the Kddcup (100%) and RCLP problems, their performance is very slightly reduced when the number of mappers is increased (the order of three or four ten-thousandths).

- Nevertheless, it is important to highlight that although the accuracy of the PR algorithm may be gradually decreased it is not very far from

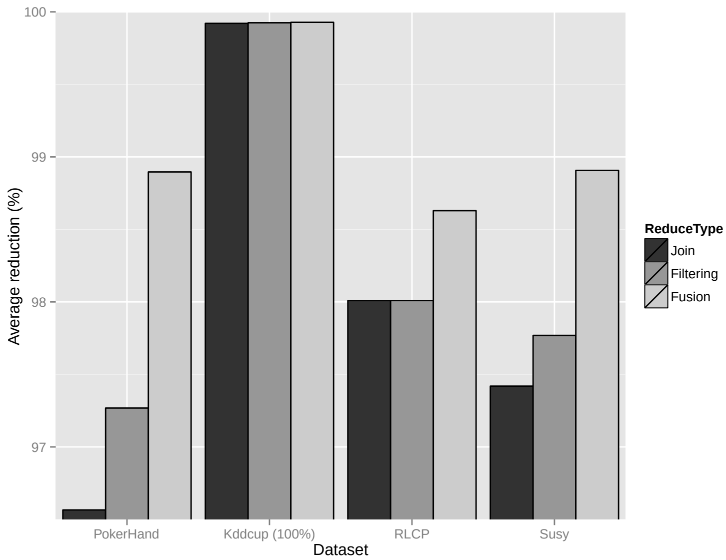


Figure 5: Reduction rate achieved with 256 mappers.

the achieved with the NN rule. In fact, it could be even higher as happens in the cases of PokerHand, Susy and RLCP problems. This situation occurs because PR techniques remove noisy instances from the TR set that damage the classification performance of the NN rule. Moreover, PR models typically smooth the decision boundaries between classes that usually rebounds in an improvement of the generalization capabilities (test accuracy).

- When tackling large-scale problems, the reduction rate of a PR technique becomes much more important, maintaining the premise that the accuracy is not very deteriorated. A high reduction rate implies a significant decrement in the computational time spent to classify new instances. As we commented before, the accuracy obtained by our model is not dramatically decreased when the number of mappers is augmented. The same behavior is found in terms of reduction capabilities. This number also influences in the reduction rate achieved because the lack of information about the whole problem may produce a degradation of the reduction capabilities of PR techniques. However, in general, the reduction rates presented are very high, representing the original problem with less than a 5% of the total number of instances.

It allows us to classify the TS in a very fast time.

- Independently to the number of mappers and type of reduce, there are no differences between the results of training a test phases. The partitioning process slightly reduces accuracy and reduction rate because of the lack of the whole information. By contrast, this mechanism assists not to fall into the overfitting problem, that is, the overlearning of the training set.

- Comparing the different reduce types, we can check that in general the fusion approach outperforms to the rest kinds of reducers in most of the data sets. The fusion scheme results in a better training and test accuracy. It is noteworthy that in the case of PokerHand data set, when the other types of reducers decrease their performance, the fusion reducer is able to preserve its accuracy with 1024 mappers. We can also observe that the filtering reducer also provides higher accuracy results than the join approach in PokerHand and Susy problems, while its results are very similar for the Kddcup (100%) and RLCP sets.

- Taking a quick glance at Figure 5, it reveals that the fusion scheme always reports the higher reduction rate, followed by the filtering scheme. Beside the fusion reducer promotes a higher reduction rate it has shown the best accuracy. Therefore, it shows that merging the resultant RS_j sets with a fusion or a filtering process provides a better accuracy and reduction rates than a joining phase.

- Considering the results provided by the NN rule and the whole TR, Figure 4 shows that in terms of accuracy, the MRPR model with the fusion scheme overcomes to the NN rule in PokerHand, Susy and RCLP problems. A very similar behavior is reached for the Kddcup (100%) data set. Nevertheless, the reduction rate attained by the MRPR model implies a lower test classification time. For example, we can see in Table 4 that we can perform the classification of PokerHand data set up to 130 times faster than the NN classifier when the fusion method and 64 mappers are used. A similar improvement is achieved in Susy and RLCP problems. However, for the Kddcup (100%) data set this improvement is much more accentuated and classifying the test set can be approximately 2120 times faster (using the fusion reducer and 256 mappers). These results demonstrate and exemplify the necessity of applying PR techniques to large-scale problems.

4.4.2. Analysis of the scalability

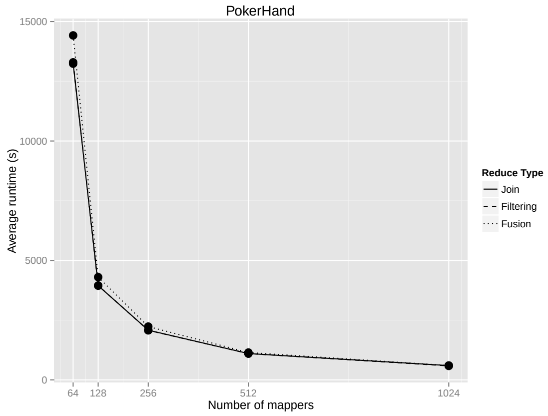
In this part of the experimental study we concentrate on the analysis of runtime and speed up of the MRPR model. As defined in Section 4.3, we divided the Kddcup problem into three sets with different number of instances. We aim to study the influence of the number of instances in the same problem. Figure 6 draws the average runtime (obtained in the 5-fcv experiment) according to the number of mappers used in the problem considered. Moreover, Figure 7 depicts the speed up achieved by MRPR and the fusion reducer.

Note that, as we clarified in Section 4.1, the speed up has been computed using the runtime with the minimum number of mappers ($minMaps$) as the reference time. Therefore, it implies that the speed up does not represent the gain obtained regarding the number of cores. In this chart, the speed up of MRPR with $minMaps$ in each data set is set as 1. Since the complexity of SSMA-SFLSDE is $O((n{\cdot}D)^2)$, we cannot expect a quadratic speed up because the proposed scheme is focused on the number of instances. Furthermore, it is very important to remember that, in the used cluster, the maximum available mappers at the same time is 128 and the rest of tasks are queued.

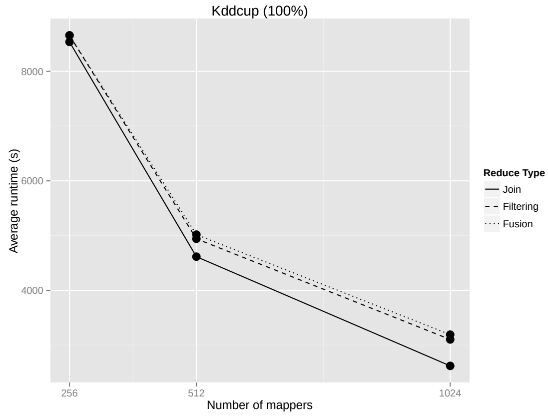
Figure 8 presents an average runtime comparison between the results obtained in the three versions of the Kddcup problem. It shows for each set its average runtime with 256, 512 and 1024 mappers of the MRPR approach using the reducer based on fusion.

Given these figures and previous tables, we want to outline the following comments:

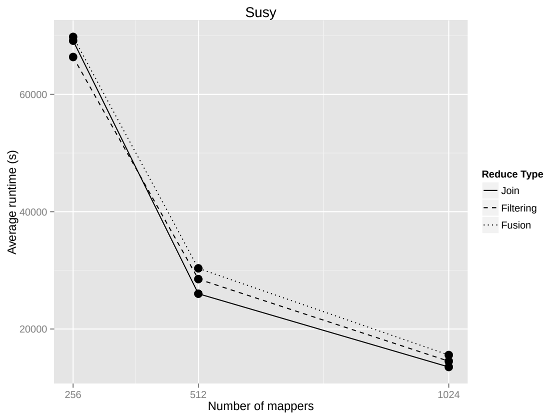
- Despite the performance showed by the filtering and fusion reducers in comparison with the joining scheme, all the reduce alternatives spend very similar runtimes to generate a final RS. It means that although the fusion and filtering reducers require extra computations regarding to the join approach, we take advantage from the way of working of MapReduce, so that, the reduce stage is being executed while the mappers are still finishing. In this way, most of the extra calculations needed by filtering and fusion approaches are performed before all the mappers have finished.



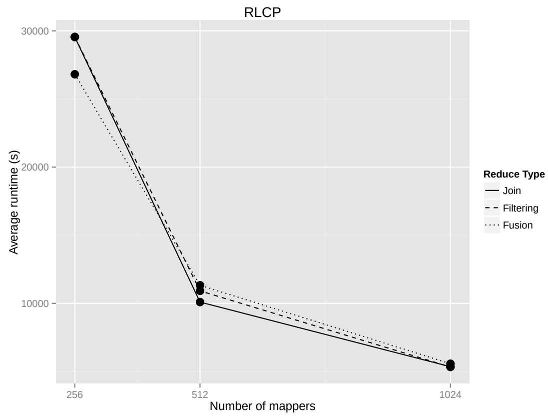
(a) PokerHand: Runtime.



(b) Kddcup (100%): Runtime.



(c) Susy: Runtime.



(d) RLCP: Runtime.

Figure 6: Average runtime obtained by MRPR

- In Figure 7, we can observe different tendencies depending on the used data set. It is due to the fact that these problems have a different number of features that also determine the complexity of the PR technique. For this reason, it easier to obtain a higher speed up with PokerHand, rather than, for instance, in the Kddcup problem, because it has a lesser number of characteristics. The same behavior is shown in Susy and RLCP problems, with a similar number of instances, a slightly better speed up is achieved with RLCP. In addition, according with this figure, we can mention that we the same resources (128 mappers)

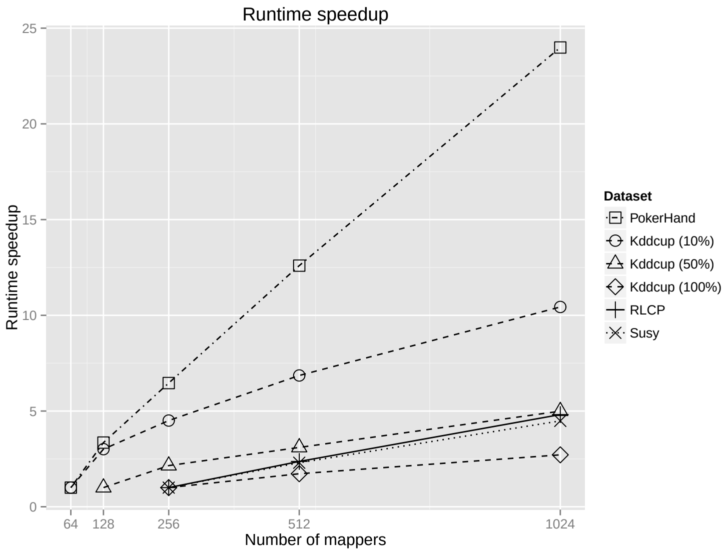


Figure 7: Speed up achieved by MRPR with the fusion reducer

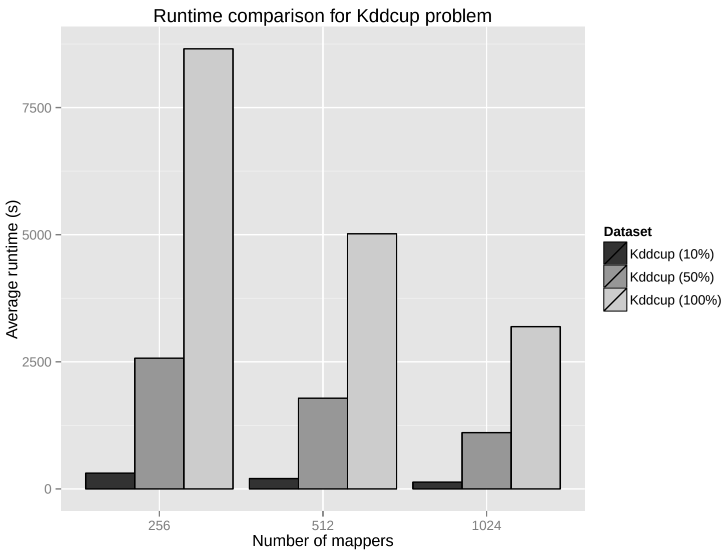


Figure 8: Runtime comparison on the three versions of the Kddcup problem, using MRPR with the fusion reducer.

MRPR is able to accelerate the processing of PR techniques by dividing in the TR set in a higher number of subsets. As we checked in the previous section, these speed ups do not fall into a significant accuracy loss.

- Figure 8 illustrates the increment of average runtime when the size of the same problem is increased. In problems with quadratic complexity, we could expect that with the same number of mappers this increment should be also quadratic. In this figure, we can see that the increment of runtime is much lesser than a quadratic increment. For example, for 512 mappers, MRPR spends 2571.0068 seconds in Kddcup (50%) and 8655.6950 seconds for the full problem. As we can see in Table 2, the approximate number of instances in each TR_j subset is the double for Kddcup 100% than Kddcup 50% with 512 mappers. Therefore, its computational cost is not incremented quadratically.

4.5. Experiments on different PR techniques

In this section we perform some additional experiments using four different PR techniques in the proposed MRPR framework. In these experiments, the number of mappers has been fixed to 64 and we focus on the PokerHand problem. Table 8 shows the results obtained.

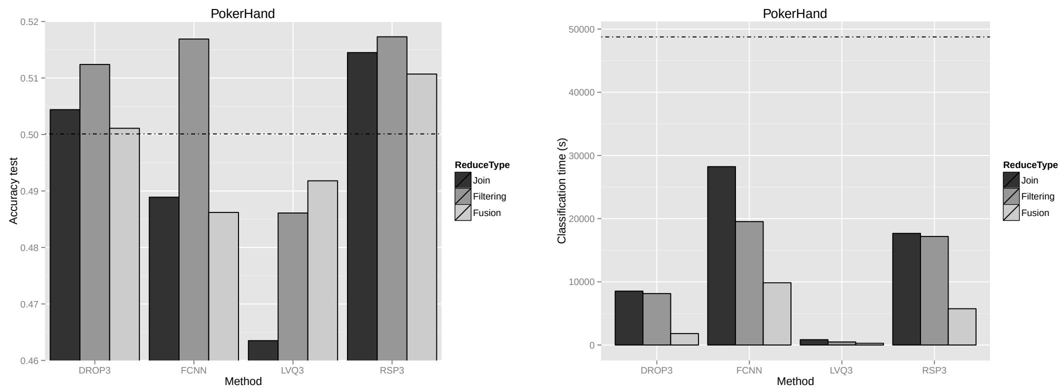
Figure 9 presents a comparison across the four techniques within MRPR. Figure 9a depicts the accuracy test obtained by the four techniques using the three reduce types. Figure 9b shows the time needed to classify the test set. In both plots, the results of the NN rule have been presented as baseline. As before, those results that are better than the NN rule have been stressed in bold and the best ones in overall are highlighted in italic.

Observing these results, we can see that the MRPR model works appropriately with these techniques. Nevertheless, we can point out several differences in comparison with the results obtained with SSMA-SFLSDE:

- Since LVQ3 is a positioning adjustment method with a high reduction rate, we observe a similar behavior between this technique and SSMA-SFLSDE within the MRPR model. Note that this algorithm has been also run with ICLP2 as fusion method. We can highlight that the filtering and fusion reduce schemes greatly improve the performance of LVQ3 in accuracy and reduction rates.

Table 8: Results obtained for the PokerHand problem with 64 Mappers.

PR technique	Reduce type	Training Avg.	Training Std.	Test Avg.	Test Std.	Runtime Avg.	Runtime Std.	Reduction rate Avg.	Reduction rate Std.	Classification time (TS)
LVQ3	Join	0.4686	0.0005	0.4635	0.0014	15.3526	0.8460	97.9733	0.0001	841.5352
	Filtering	0.4892	0.0007	0.4861	0.0013	17.7602	0.1760	98.6244	0.0101	487.0822
	Fusion	0.4932	0.0010	0.4918	0.0012	83.7830	4.8944	99.3811	0.0067	273.4192
FCNN	Join	0.4883	0.0008	0.4889	0.0010	39.8196	2.1829	17.7428	0.0241	28232.4110
	Filtering	**0.5185**	0.0006	**0.5169**	0.0005	5593.4358	23.1895	47.3255	0.0310	19533.5424
	Fusion	**0.6098**	0.0002	0.4862	0.0006	3207.8540	37.2208	72.5604	0.0080	9854.8956
DROP3	Join	**0.5073**	0.0004	**0.5044**	0.0014	69.5268	2.5605	77.0352	0.0141	8529.0618
	Filtering	**0.5157**	0.0005	**0.5124**	0.0013	442.9670	2.6939	81.2203	0.0169	8139.5878
	Fusion	**0.5390**	0.0004	**0.5011**	0.0005	198.1450	5.2750	92.3467	0.0043	1811.0866
RSP3	Join	***0.6671***	0.0003	**0.5145**	0.0007	219.2912	2.8126	53.0566	0.0554	17668.5268
	Filtering	**0.6491**	0.0003	***0.5173***	0.0008	1898.5854	10.8303	58.8459	0.0280	17181.5448
	Fusion	**0.5786**	0.0004	**0.5107**	0.0010	1448.4272	60.5462	84.3655	0.0189	5741.6588
NN	–	0.5003	0.0007	0.5001	0.0011	–	–	–	–	48760.8242



(a) PokerHand: Accuracy Test.

(b) PokerHand: Classification Time.

Figure 9: Results obtained by MRPR in different PR techniques

- In the previous section we observed that the filtering and fusion stages provide a greater reduction rate than the join scheme. In this section, we can see that for FCNN, DROP3 and RSP3, their effect is even more accentuated due to the fact that these techniques have a lesser reduction power than SSMA-SFLSDE and LVQ3. Therefore, the filtering and fusion algorithms become more important with these techniques in order to achieve a high reduction ratio.

- The runtime needed by filtering and fusion schemes crucially depends on the reduction rate of the use technique. For example, the FCNN method initially provides a very reduced reduction rate (around 18%), so that, the runtime of filtering and fusion reducers is greater than the time needed by the join reducer. However, as commented before, the application of these reduces increases the reduction rate, resulting in a faster classification time.

- As commented previously, we have used a fusion reducer based on GMCA when FCNN, DROP3 and RSP3 are applied. It is noteworthy that this fusion approach has resulted in a faster runtime in comparison with the filtering scheme. Nevertheless, as we expected, the performance reached with this fusion reducer, in terms of accuracy, is lower than the obtained with ICLP2 in combination with SSMA-SFLSDE.

- Comparing the results obtained with these techniques and SSMA-SFLSDE, we can observe that the best accuracy test results is obtained with RSP3 and the filtering scheme (0.5173) with a medium reduction ratio (58.8459%). However, the SSMA-SFLSDE algorithm was able to achieve a higher accuracy test (0.5181) using the fusion reducer with a very high reduction rate (99.1413%).

5. Concluding remarks

In this paper we have developed a MapReduce solution for prototype reduction, denominated as MRPR. The proposed scheme enables to these kinds of techniques to be applied over big classification data sets with promising results. Otherwise, these techniques would be limited to tackle small or medium problems that does not contain more than several thousand of examples, due to memory and runtime restrictions. The MapReduce paradigm has offered a simple, transparent and efficient environment to parallelize the prototype reduction computation. Three different reduce types have been investigated: Join, Filtering and Fusion; aiming to provide more accurate preprocessed sets. We have found that a reducer based on fusion of prototypes permits to obtain reduced sets with higher reduction rates and accuracy performance.

The experimental study carried out has shown that MRPR obtains very competitive results. We have tested its behavior with different kinds of PR techniques, analyzing the accuracy, the reduction rate and the computational cost obtained. In particular, we have studied two prototype selection methods (FCNN and DROP3), two prototype generation (LVQ3 and RSP3) techniques and the hybrid SSMA-SFLSDE algorithm.

The main achievements of MRPR have been:

- It has allowed us to apply PR techniques in large-scale problems.
- No significant accuracy and reduction losses with very good speed up.
- Its application has resulted in a very big reduction of storage requirements and classification time for the NN rule, when dealing with big data sets.

As future work, we consider the study of new frameworks that enable PR techniques to deal with both large-scale and high dimensional data sets.

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References

[1] V. Marx, The big challenges of big data, Nature 498 (7453) (2013) 255–260.

[2] M. Minelli, M. Chambers, A. Dhiraj, Big Data, Big Analytics: Emerging Business Intelligence and Analytic Trends for Today's Businesses (Wiley CIO), 1st Edition, Wiley Publishing, 2013.

[3] D. Plummer, T. Bittman, T. Austin, D. Cearley, D. S. Cloud, Defining and describing an emerging phenomenon. Technical report, Gartner (2008).

[4] E. Alpaydin, Introduction to Machine Learning, 2nd Edition, MIT Press, Cambridge, MA, 2010.

[5] M. Woniak, M. Graña, E. Corchado, A survey of multiple classifier systems as hybrid systems, Information Fusion 16 (2014) 3–17.

[6] S. Sakr, A. Liu, D. Batista, M. Alomari, A survey of large scale data management approaches in cloud environments, IEEE Communications Surveys and Tutorials 13 (3) (2011) 311–336.

[7] J. Bacardit, X. Llorà, Large-scale data mining using genetics-based machine learning, Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 3 (1) (2013) 37–61.

[8] J. Dean, S. Ghemawat, Mapreduce: simplified data processing on large clusters, Communications of the ACM 51 (1) (2008) 107–113.

[9] J. Dean, S. Ghemawat, Map reduce: A flexible data processing tool, Communications of the ACM 53 (1) (2010) 72–77.

[10] S. Ghemawat, H. Gobioff, S.-T. Leung, The google file system, in: Proceedings of the nineteenth ACM symposium on Operating systems principles, SOSP '03, 2003, pp. 29–43.

[11] M. Snir, S. Otto, MPI-The Complete Reference: The MPI Core, MIT Press, 1998.

[12] W. Zhao, H. Ma, Q. He, Parallel k-means clustering based on mapreduce, in: M. Jaatun, G. Zhao, C. Rong (Eds.), Cloud Computing, Vol. 5931 of Lecture Notes in Computer Science, Springer Berlin Heidelberg, 2009, pp. 674–679.

[13] A. Srinivasan, T. Faruquie, S. Joshi, Data and task parallelism in ILP using mapreduce, Machine Learning 86 (1) (2012) 141–168.

[14] Q. He, C. Du, Q. Wang, F. Zhuang, Z. Shi, A parallel incremental extreme svm classifier, Neurocomputing 74 (16) (2011) 2532 – 2540.

[15] I. Palit, C. Reddy, Scalable and parallel boosting with mapreduce, IEEE Transactions on Knowledge and Data Engineering 24 (10) (2012) 1904–1916.

[16] G. Caruana, M. Li, Y. Liu, An ontology enhanced parallel SVM for scalable spam filter training, Neurocomputing 108 (2013) 45 – 57.

[17] D. Pyle, Data Preparation for Data Mining, The Morgan Kaufmann Series in Data Management Systems, Morgan Kaufmann, 1999.

[18] H. Liu, H. Motoda (Eds.), Computational Methods of Feature Selection, Chapman & Hall/Crc Data Mining and Knowledge Discovery Series, Chapman & Hall/Crc, 2007.

[19] S. García, J. Derrac, J. Cano, F. Herrera, Prototype selection for nearest neighbor classification: Taxonomy and empirical study, IEEE Transactions on Pattern Analysis and Machine Intelligence 34 (3) (2012) 417–435.

[20] I. Triguero, J. Derrac, S. García, F. Herrera, 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) (2012) 86–100.

[21] J. Derrac, S. García, F. Herrera, IFS-CoCo: Instance and feature selection based on cooperative coevolution with nearest neighbor rule, Pattern Recognition 43 (6) (2010) 2082–2105.

[22] J. Derrac, C. Cornelis, S. García, F. Herrera, Enhancing evolutionary instance selection algorithms by means of fuzzy rough set based feature selection, Information Sciences 186 (1) (2012) 73–92.

[23] N. García-Pedrajas, A. de Haro-García, J. Pérez-Rodríguez, A scalable approach to simultaneous evolutionary instance and feature selection, Information Sciences 228 (2013) 150–174.

[24] T. M. Cover, P. E. Hart, Nearest neighbor pattern classification, IEEE Transactions on Information Theory 13 (1) (1967) 21–27.

[25] L. Nanni, A. Lumini, Particle swarm optimization for prototype reduction, Neurocomputing 72 (4-6) (2008) 1092–1097.

[26] I. Triguero, S. García, F. Herrera, IPADE: Iterative prototype adjustment for nearest neighbor classification, IEEE Transactions on Neural Networks 21 (12) (2010) 1984–1990.

[27] I. Triguero, S. García, F. Herrera, Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification, Pattern Recognition 44 (4) (2011) 901–916.

[28] J. R. Cano, F. Herrera, M. Lozano, Stratification for scaling up evolutionary prototype selection, Pattern Recognition Letters 26 (7) (2005) 953–963.

[29] J. Derrac, S. García, F. Herrera, Stratified prototype selection based on a steady-state memetic algorithm: a study of scalability, Memetic Computing 2 (3) (2010) 183–199.

[30] I. Triguero, J. Derrac, S. García, F. Herrera, A study of the scaling up capabilities of stratified prototype generation, in: Proceedings of the third World Congress on Nature and Biologically Inspired Computing (NABIC'11), 2011, pp. 304–309.

[31] W.-Y. Chen, Y. Song, H. Bai, C.-J. Lin, E. Chang, Parallel spectral clustering in distributed systems, Pattern Analysis and Machine Intelligence, IEEE Transactions on 33 (3) (2011) 568–586.

[32] S. García, J. R. Cano, F. Herrera, A memetic algorithm for evolutionary prototype selection: A scaling up approach, Pattern Recognition 41 (8) (2008) 2693–2709.

[33] N. García-Pedrajas, J. Pérez-Rodríguez, Multi-selection of instances: A straightforward way to improve evolutionary instance selection, Applied Soft Computing 12 (11) (2012) 3590 – 3602.

[34] B. He, W. Fang, Q. Luo, N. K. Govindaraju, T. Wang, Mars: A mapreduce framework on graphics processors, in: Proceedings of the 17th International Conference on Parallel Architectures and Compilation Techniques, PACT '08, ACM, New York, NY, USA, 2008, pp. 260–269.

[35] J. Talbot, R. M. Yoo, C. Kozyrakis, Phoenix++: Modular mapreduce for shared-memory systems, in: Proceedings of the Second International Workshop on MapReduce and Its Applications, ACM, New York, NY, USA, 2011, pp. 9–16. doi:10.1145/1996092.1996095.

[36] T. White, Hadoop: The Definitive Guide, 3rd Edition, O'Reilly Media, Inc., 2012.

[37] A. H. Project, Apache hadoop (2013).
URL `http://hadoop.apache.org/`

[38] A. M. Project, Apache mahout (2013).
URL `http://mahout.apache.org/`

[39] C.-L. Chang, Finding prototypes for nearest neighbor classifiers, IEEE Transactions on Computers 23 (11) (1974) 1179–1184.

[40] C.-T. Chu, S. Kim, Y.-A. Lin, Y. Yu, G. Bradski, A. Ng, K. Olukotun, Map-reduce for machine learning on multicore, in: Advances in Neural Information Processing Systems, 2007, pp. 281–288.

[41] D. L. Wilson, Asymptotic properties of nearest neighbor rules using edited data, IEEE Transactions on System, Man and Cybernetics 2 (3) (1972) 408–421.

[42] P. E. Hart, The condensed nearest neighbor rule, IEEE Transactions on Information Theory 18 (1968) 515–516.

[43] D. R. Wilson, T. R. Martinez, Reduction techniques for instance-based learning algorithms, Machine Learning 38 (3) (2000) 257–286.

[44] R. Mollineda, F. Ferri, E. Vidal, A merge-based condensing strategy for multiple prototype classifiers, IEEE Transactions on Systems, Man and Cybernetics B 32 (5) (2002) 662–668.

[45] J. S. Sánchez, High training set size reduction by space partitioning and prototype abstraction, Pattern Recognition 37 (7) (2004) 1561–1564.

[46] J. S. Sánchez, R. Barandela, A. I. Marqués, R. Alejo, J. Badenas, Analysis of new techniques to obtain quality training sets, Pattern Recognition Letters 24 (7) (2003) 1015–1022.

[47] W. Lam, C. K. Keung, D. Liu, Discovering useful concept prototypes for classification based on filtering and abstraction., IEEE Transactions on Pattern Analysis and Machine Intelligence 14 (8) (2002) 1075–1090.

[48] I. H. Witten, E. Frank, Data Mining: Practical machine learning tools and techniques, 2nd Edition, Morgan Kaufmann, San Francisco, 2005.

[49] G. M. Amdahl, Validity of the single processor approach to achieving large scale computing capabilities, in: Proc. Spring Joint Comput. Conf., ACM, 1967, pp. 483–485.

[50] Cloudera, Cloudera distribution including apache hadoop (2013).
URL http://www.cloudera.com

[51] A. Frank, A. Asuncion, UCI machine learning repository (2010).
URL http://archive.ics.uci.edu/ml

[52] T. Kohonen, The self organizing map, Proceedings of the IEEE 78 (9) (1990) 1464–1480.

[53] F. Angiulli, Fast nearest neighbor condensation for large data sets classification, IEEE Transactions on Knowledge and Data Engineering 19 (11) (2007) 1450–1464.

[54] K. V. Price, R. M. Storn, J. A. Lampinen, Differential Evolution A Practical Approach to Global Optimization, Natural Computing Series, 2005.

[55] F. Neri, V. Tirronen, Scale factor local search in differential evolution, Memetic Computing 1 (2) (2009) 153–171.