Knowledge-Based Systems 117 (2017) 3–15

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

kNN-IS: An Iterative Spark-based design of the k-Nearest Neighbors classifier for big data

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ARTICLE INFO

Article history:
Received 31 January 2016
Revised 10 June 2016
Accepted 12 June 2016
Available online 14 June 2016

Keywords:
K-nearest neighbors
Big data
Apache Hadoop
Apache Spark
MapReduce

ABSTRACT

The k-Nearest Neighbors classifier is a simple yet effective widely renowned method in data mining. The actual application of this model in the big data domain is not feasible due to time and memory restrictions. Several distributed alternatives based on MapReduce have been proposed to enable this method to handle large-scale data. However, their performance can be further improved with new designs that fit with newly arising technologies.

In this work we provide a new solution to perform an exact k-nearest neighbor classification based on Spark. We take advantage of its in-memory operations to classify big amounts of unseen cases against a big training dataset. The map phase computes the k-nearest neighbors in different training data splits. Afterwards, multiple reducers process the definitive neighbors from the list obtained in the map phase. The key point of this proposal lies on the management of the test set, keeping it in memory when possible. Otherwise, it is split into a minimum number of pieces, applying a MapReduce per chunk, using the caching skills of Spark to reuse the previously partitioned training set. In our experiments we study the differences between Hadoop and Spark implementations with datasets up to 11 million instances, showing the scaling-up capabilities of the proposed approach. As a result of this work an open-source Spark package is available.

1. Introduction

Over the last few years, gathering information has become an automatic and relatively inexpensive task, thanks to technology improvements. This has resulted in a severe increment of the amount of available data. Social media, biomedicine or physics are just a few examples of areas that are producing tons of data every day [1]. This data is useless without a proper knowledge extraction process that can somehow take advantage of it. This fact poses a significant challenge to the research community because standard machine learning methods can not deal with the volume, diversity and complexity that this data brings [2]. Therefore, existing learning techniques need to be remodeled and updated to deal with such volume of data.

The k-Nearest Neighbor algorithm (kNN) [3] is an intuitive and effective nonparametric model used for both classification and regression purposes. In [4], the kNN was claimed to be one of the ten most influential data mining algorithms. In this work, we are focused on classification tasks. As a lazy learning model, the kNN requires that all the training data instances are stored. Then, for each unseen case and every training instance, it performs a pairwise computation of a certain distance or similarity measure [5,6], selecting the k closest instances to them. This operation has to be repeated for all the input examples against the whole training dataset. Thus, the application of this technique may become impractical in the big data context. In what follows, we refer to this original algorithm as the exact kNN method, w.r.t. partial and approximate variants of the kNN model that reduce the computational time, assuming that distances are computed using any class of approximation error bound [7].

Recent cloud-based technologies offer us an ideal environment to handle this issue. The MapReduce framework [8], and its open-source implementation in Hadoop [9], were the precursor tools to

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http://dx.doi.org/10.1016/j.knosys.2016.06.012
0950-7051/

tackle data-intensive applications [10] based on the principle of data locality [11], which is implemented through its distributed file system. Its application in data mining has been widely spread [12–14], to the detriment of other parallelization schemes such as Message Passing Interface [15], because of its fault-tolerant mechanism (recommendable for time-consuming tasks) and its ease of use [16]. Despite its unquestionable breakthrough, researchers have found several limitations in Hadoop Mapreduce to design scalable machine learning tools [17]. MapReduce is inefficient for applications that share data across multiple steps, including iterative algorithms or interactive queries. Multiple platforms for large-scale processing have recently emerged to overcome the issues presented by Hadoop MapReduce [18,19]. Among them, Spark [20] highlights as one of the most flexible and powerful engines to performed faster distributed computing in big data by using in-memory primitives. This platform allows user programs to load data into memory and query it repeatedly, making it more suitable for online, iterative or data streams algorithms [21].

The use of the kNN algorithm and similar approaches has been already considered in the big data context. On the one hand, some works incorporate a kNN classifier in a MapReduce process [22], but their purpose is not to carry out an exact kNN classification, but use a partial kNN (kNN is applied over subsets of the training data) as part of a larger pipeline of experiments. In [23] the authors proposed a novel approach for clustering in large datasets by adding kNN and Principal Component Analysis as part of the technique proposed. The method proposed in [24] have two different stages. The first stage used a k-means in order to separate the whole dataset in different parts. The second stage computes a kNN in each split providing approximate results. On the other hand, without aiming at classification or regression tasks, several approaches have been proposed to perform a distributed computation of kNN join queries in MapReduce. For example, in [25] the authors apply kNN-join (exact or approximate) queries within a two-stage MapReduce process. In [26] the authors proposed *Spitfire*, an efficient and scalable kNN queries model composed of multiple distributed stages. We further discuss these methods in Section 2.2. When focused on pure classification, the MapReduce process can be greatly simplified because it is not necessary to provide the k nearest neighbors themselves, but rather their classes. In [27], an iterative Hadoop MapReduce process (iHMR-kNN) was presented for kNN based image classification. This approach iteratively performs MapReduce for every single test instance, with the consequent time consumption of Hadoop-based systems for iterations. In [28], however, we proposed a single Hadoop MapReduce process that can simultaneously classify large amounts of test samples against a big training dataset, avoiding start-up costs of Hadoop. To do so, we read the test set line by line from the Hadoop File System, which make this model fully scalable but its performance can be further improved by in-memory solutions.

In this paper, we propose an iterative MapReduce-based approach for kNN algorithm implemented under Apache Spark. In our implementation, we aim to exploit the flexibility provided by Spark, by using other in-memory operations that alleviate the consumption costs of existing MapReduce alternatives. To manage enormous test sets as well, this method will iteratively address chunks of this set, if necessary. The maximum number of possible test examples, depending on memory limitations, will be used to minimize the number of iterations. In each iteration, a kNN MapReduce process will be applied. The map phase consists of deploying the computation of similarity between a subset of the test examples and splits of the training set through a cluster of computing nodes. As a result of each map, the class label of the k nearest neighbors together with their computed distance values will be emitted to the reduce stage. Multiple reducers will determine which are the final k nearest neighbors from the list provided by the maps. This process is repeated until the whole test set is classified. Through the text, we will denote this approach as a kNN design based on Spark (kNN-IS).

In summary, the contributions of this work are as follows:

- We extend the MapReduce scheme proposed in [28] by using multiples reducers to speed up the processing when the number of maps needed is very high.
- A fully parallel implementation of the kNN classifier that makes use of in-memory Spark operations to accelerate all the stages of the method, including normalization of the data, processing of big test datasets, and computation of pairwise similarities, without incurring in Hadoop startup costs.

To test the performance of the proposed classification model, we will conduct experiments on big datasets with up to 11 millions instances. We investigate the influence of number of maps and reducers and we will establish a comparison among existing Hadoop MapReduce alternatives and the proposed approach. A repository of code with the implementation of this technique can be found at https://github.com/JMailloH/kNN_IS.

The remainder of this paper is organized as follows. Section 2 introduces the big data technologies used in this work and the current state-of-art in kNN big data classification. Then, Section 3 details the proposed kNN-IS model. Section 4 describes the experimental setup and Section 5 includes multiple analyses of results. Finally, Section 6 outlines the conclusions drawn in this work. The Appendix provides a quick start guide with the developed Spark package.

2. Preliminaries

This section provides the necessary background for the remainder of the paper. First, Section 2.1 introduces the concept of MapReduce and the platforms Hadoop and Spark. Then, Section 2.2 formally defines the kNN algorithm and its weaknesses to tackle big data problems, presenting the current alternatives to alleviate them.

2.1. MapReduce programming model and frameworks: Hadoop and Spark

The MapReduce programming paradigm [8] is a scale-out data processing tool for Big Data, designed by Google in 2003. This was thought to be the most powerful search-engine on the Internet, but it rapidly became one of the most effective techniques for general-purpose data parallelization.

MapReduce is based on two separate user-defined primitives: Map and Reduce. The Map function reads the raw data in form of key-value ($<$ *key, value* $>$) pairs, and transforms them into a set of intermediate $<$ *key, value* $>$ pairs, conceivably of different types. Both key and value types must be defined by the user. Then, MapReduce merges all the values associated with the same intermediate key as a list (shuffle phase). Finally, the Reduce function takes the grouped output from the maps and aggregates it into a smaller set of pairs. This process can be schematized as shown in Fig. 1.

This transparent and scalable platform automatically processes data in a distributed cluster, relieving the user from technical details, such as: data partitioning, fault-tolerance or job communication. We refer to [16] for an exhaustive review of this framework and other distributed paradigms.

Apache Hadoop [29,30] is the most popular open-source implementation of MapReduce for large-scale processing and storage on commodity clusters. The use of this framework has become widespread in many fields because of its performance, open source nature, installation facilities and its distributed file system

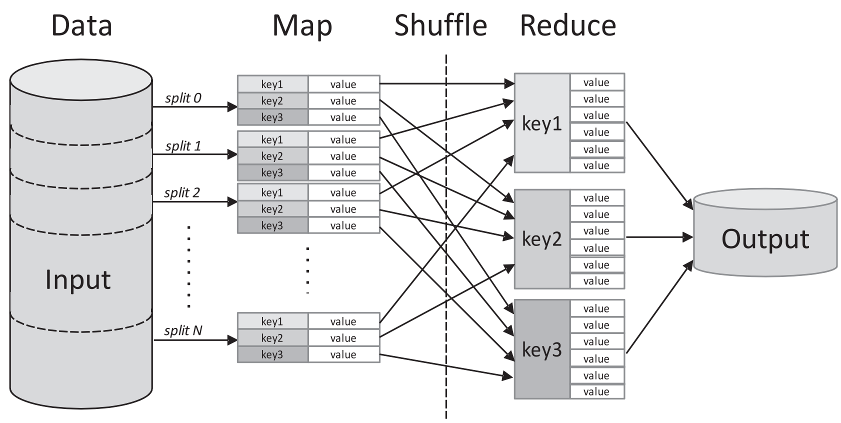


Fig. 1. Data flow overview of MapReduce.

(Hadoop Distributed File System, HDFS). In spite of its great popularity, Hadoop and MapReduce have shown not to fit well in many cases, like online or iterative computing [31]. Its inability to reuse data through in-memory primitives makes the application of Hadoop for many machine learning algorithms unfeasible.

Apache Spark, a novel solution for large-scale data processing, was thought to be able to solve the Hadoop's drawbacks [32,33]. Spark was introduced as part of the Hadoop Ecosystem and it is designed to cooperate with Hadoop, specially by using its distributed file system. This framework proposes a set of in-memory primitives, beyond the standard MapReduce, with the aim of processing data more rapidly on distributed environments, up to 100x faster than Hadoop.

Spark is based on Resilient Distributed Datasets (RDDs), a special type of data structure used to parallelize the computations in a transparent way. These parallel structures let us persist and reuse results, cached in memory. Moreover, they also let us manage the partitioning to optimize data placement, and manipulate data using a wide set of transparent primitives. All these features allow users to easily design new data processing pipelines.

A scalable machine learning library (MLlib) [34] was built on top of Spark, thanks to its implicit suitability for iterative processes. The current version of MLlib (v1.6.0) contains a large set of standard learning algorithms and statistic tools, which covers many important fields in the knowledge discovery process, such as: classification, regression, clustering, optimization or data preprocessing. The MLlib is a key component of the MLbase [35] platform. It provides a high-level API that makes easier for the user to connect multiple machine learning algorithms. However, this platform does not include lazy learning algorithms such as the kNN algorithm.

2.2. The kNN classifier and big data

The kNN algorithm is a non-parametric method that can be used for either classification and regression tasks. Here, we define the kNN problem, its current trends and the drawbacks to manage big data. A formal notation for the kNN algorithm is the following:

Let *TR* be a training dataset 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*. For each sample $\mathbf{x}_{test}$ included in the *TS* set, the kNN algorithm searches the *k* closest samples in the *TR* set. Thus, the kNN calculates the distances between $\mathbf{x}_{test}$ and all the samples of *TR*. The Euclidean distance is the most widely-used measure for this purpose. The training samples are ranked in ascending order according to the computed distance, taking the *k* nearest samples $(\mathbf{neigh}_1, \mathbf{neigh}_2, ..., \mathbf{neigh}_k)$. Then, they are used to compute the most predominant class label. The chosen value of *k* may influence the performance and the noise tolerance of this technique.

Although the kNN has shown outstanding performance in a wide variety of problems, it lacks the scalability to manage big *TR* datasets. The main problems found for dealing with large-scale data are:

- Runtime: The complexity to find the nearest neighbor training example of a single test instance is $O((n \cdot D))$, where n is the number of training instances and D the number of features. This becomes computationally more expensive when it involves finding the *k* closets neighbors, since it requires the sorting of the computed distances, so that, an extra complexity $O(n \cdot log(n))$. Finally, this process needs to be repeated for every test example.
- Memory consumption: For a rapid computation of the distances, the kNN model requires the training data to be stored in memory. When *TR* and the *TS* sets are too big, they may easily exceed the available RAM memory.

These drawbacks motivate the use of big data technologies to distribute the processing of kNN over a cluster of nodes.

In the literature, we can find a family of approaches that perform kNN joins with MapReduce. A recent review on this topic can be found in [36]. The kNN joins differs from kNN classifier in the expected output. While the kNN classifier aims to provide the predicted class, the kNN join outputs the neighbors themselves for a single test. Thus, these methods cannot be applied for classification.

For an exact kNN join, two main alternatives have been proposed in [25]. The first one, named H-BkNNJ, consists of a single round of MapReduce in which *TR* and *TS* sets are partitioned together, so that, every map task processes a pair TS_i and TR_i, and carries out the pairwise distance comparison between each training and test splits. Let m the number of used partitions, it creates m^2 blocks by performing a linear scan on both sets. The reduce task then processes all computed distances for a given test instance and sorts them in ascending order to output the top k results. A second alternative called H-BNLJ is proposed, by using two MapReduce processes, in order to reduce the complexity of the sort phase. However, it still requires m^2 tasks. The main deficiencies of these approaches are: (1) they generate extra blocks of data, and therefore, they make the size of the problem tackled even bigger; (2) they square the complexity of the solution (m^2 tasks); (3) it relied on Hadoop MapReduce, so that, the two-stage MapReduce model needs to serialize intermediate data into disk, with its consequent cost. Some other models, such as PGBJ [37], perform a preprocessing phase and distance based partitioning strategy to reduce the number of task to m. Nevertheless, it adds an extra computational cost to carry out this phase. More recently, a new alternative called Spitfire was proposed in [26]. Following its own distributed procedure (i.e. not a MapReduce model), it calculates the k nearest neighbors of all the elements of a single set. To do so, it first partitions the search space, and then, calculates and replicates the k nearest neighbors in each split. The last phase computes a local kNN to provide the final result.

Focusing on classification tasks (also valid for regression), existing methods are simpler than kNN join approaches, since they do not need to provide the neighbors themselves (or reference to them to search for them later), only their classes. Two main approaches have been presented so far, and they are both focused on using the Map phase to split the training data in m disjoint parts. The former was presented in [27], and it proposes iteratively repeating a MapReduce process (without an explicitly defined reduce function) for each single test example, which is very time consuming in both Hadoop and also in Spark (as we will discuss further in the experiment section). The latter was proposed in [28], denoted as MR-kNN, in which a single MapReduce process manages the classification of the (big) test set. To do that, Hadoop primitives are used to read line by line the test data within the map phase. As such, this model is scalable but its performance can be further improved by in-memory solutions.

3. kNN-IS: An Iterative Spark-based design of the kNN classifier for Big Data

In this section we present an alternative distributed kNN model for big data classification using Spark. We will denote our method as kNN-IS. We focus on the reduction of the runtime of the kNN classifier, when both training and test sets are big datasets. As stated in [36], when computing kNN within a parallel framework, many additional factors may impact the execution time, such as number of MapReduce jobs j or number of Map m and Reduce r tasks required. Therefore, writing an efficient exact kNN in Spark is challenging, and multiple key-points must be taken into account to obtain an efficient and scalable model.

Aiming to alleviate the main issues presented by previously MapReduce solutions for kNN, we introduce the following ideas in our proposal:

- As in [28] and [27], a MapReduce process will split the training dataset, as it is usually the biggest dataset, into m tasks. In contradistinction to kNN-join approaches that need m^2 tasks, we reduce the complexity of kNN to m tasks without requiring any preprocessing in advanced.
- To tackle large test datasets, we rely on Spark to reuse the previously split training set with different chunks of the test set. The use of multiple MapReduce jobs over the same data does not imply significant extra costs in Spark, but we keep this number to a minimum. The MR-kNN approach only performs m tasks independently of the test data size, by reading line-by-line the test set within the maps. Here we show how in-memory operations highly reduce the cost of every task.
- It is also noteworthy that none of the alternatives proposed for pure kNN classification (e.g. [27,28]) discuss the influence of the number of reducers, which can be determinant when the size of the dataset becomes very big (See Section 5.3).
- In addition, every single operation will be performed within the RDD objects provided by Spark. It means that even simple operations such as normalization, are also efficient and fully scalable.

This is the reasoning behind our model. In what follows, we detail its main components. First of all, we will present the main MapReduce process that classifies a subset of the test set against the whole training set (Section 3.1). Then, we give a global overview of the method, showing the details to carry out the iterative computation over the test data (Section 3.2).

3.1. MapReduce for kNN classification within Spark

This subsection introduces the MapReduce process that will manage the classification of subsets of test data that fit in memory. As such, this MapReduce process is based on our previously proposed alternative MR-kNN, with the distinction that it allows for multiple reducers, checks the iterations required to run avoiding memory swap, and is implemented under Spark.

As a MapReduce model, this divides the computation into two main phases: the map and the reduce operations. The map phase splits the training data and calculates for each chunk the distances and the corresponding classes of the k nearest neighbors for every test sample. The reduce stage aggregates the distances of the k nearest neighbors from each map and makes a definitive list of k nearest neighbors. Ultimately, it conducts the usual majority voting procedure of the kNN algorithm to predict the resulting class. Map and reduce functions are now defined in Sections 3.1.1 and 3.1.2, respectively.

3.1.1. Map phase

Let us assume that the training set TR and the corresponding subset of test samples TS_i have been previously read from HDFS as RDD objects. Hence, the training dataset TR has already been split into a user-defined number m of disjoint subsets when it was read. Each map task (Map_1, Map_2, ..., Map_m) tackles a subset TR_j, where $1 \le j \le m$, with the samples of each chunk in which the training set file is divided. Therefore, each map approximately processes a similar number of training instances.

To obtain an exact implementation of kNN, the input test set TS_i is not split together with the training set, but it is read in each map in order to compare every test sample against the whole training set. It implies that both TS_i and TR_j are supposed to fit altogether in memory.

Algorithm 1 contains the pseudo-code of this function. In our implementation in Spark we make use of the *mapPartitions(func)* transformation, which runs the function defined in Algorithm 1 on each block of the RDD separately.

Algorithm 1 Map function

Require: TR_j TS_i; k
1: **for** $t = 0$ **to** $size(TS_i)$ **do**
2: $CD_{t,j} \leftarrow$ Compute kNN (TR_j, $TS_i(x)$, k)
3: $result_j \leftarrow (< key: t, value: CD_{t,j} >)$
4: EMIT($result_j$)
5: **end for**

Every map j will constitute a class-distance vector $CD_{t,j}$ of pairs $<$ *class, distance* $>$ of dimension k for each test sample t in TS_i. To do so, Instruction 2 computes for each test sample the class and the distance to its k nearest neighbors. To accelerate the posterior actualization of the nearest neighbors in the reducers, every vector $CD_{t,j}$ is sorted in ascending order regarding the distance to the test sample, so that, $Dist(neigh_1) < Dist(neigh_2) < .... < Dist(neigh_k)$.

Unlike the MapReduce proposed in [28], every map sends multiple outputs, e.g. one per test instance. The vector $CD_{t,j}$ is outputted as value together with an identifier of test instance t as key (Instruction 3). In this way, we allow this method to use multiple reducers. Having more reducers may be useful when the used training and test datasets are very big.

3.1.2. Reduce phase

The reduce phase consists of collecting, from the tentative k nearest neighbors provided by the maps, the closest ones for the examples contained in TS_i. After the map phase, all the elements with the same key have been grouped. A reducer is run over a list($CD_{t,\,0}$, $CD_{t,\,1}$, .., $CD_{t,\,m}$) and determines the k nearest neighbors of this test example t.

This function will process every element of such list one after another. Instructions 2 to 7 update a resulting list $results_{reducer}$ with the k neighbors. Since the vectors coming from the maps are ordered according to the distance, the update process becomes faster. This consists of merging two sorted lists up to get k values, so that, the complexity in the worst case is O(k). Therefore, this function compares every distance value of each of the neighbors one by one, starting with the closest neighbor. If the distance is lesser than the current value, the class and the distance of this position is updated with the corresponding values, otherwise we proceed with the following value. Algorithm 2 provides the details of the reduce operation.

Algorithm 2 Reduce by key operation

Require: $result_{key}$, k
1: cont=0
2: **for** $i = 0$ **to** k **do**
3:   **if** $result_{key}(cont).Dist < result_{reducer}(i).Dist$ **then**
4:     $result_{reducer}(i) = result_{key}(cont)$
5:     cont++
6:   **end if**
7: **end for**

In summary, for every instance in the test set, the reduce function will aggregate the values according to function described before. To ease the implementation of this idea, we use the transformation *ReduceByKey(func)* from Spark. Algorithm 2 corresponds to the function required in Spark.

3.2. General scheme of kNN-IS

When the size of the test set is very large, we may exceed the memory allowance of the map tasks. In this case, we also have to split the test dataset and carry out multiple iterations of the MapReduce process defined above. Fig. 2 depicts the general work-flow of the method. Algorithm 3 shows the pseudo-code of the whole method with precise details of the functions utilized in Spark. In the following, we describe the most significant instructions, enumerated from 1 to 13.

Algorithm 3 kNN-IS

Require: TR; TS; k; $\#Maps$; $\#Reduces$; $\#MemAllow$
1: $TR-RDD_{raw} \leftarrow$ textFile(TR, $\#Maps$)
2: $TS-RDD_{raw} \leftarrow$ textFile(TS).zipWithIndex()
3: $TR-RDD \leftarrow TR-RDD_{raw}$.map(normalize).cache
4: $TS-RDD \leftarrow TS-RDD_{raw}$.map(normalize).cache
5: $\#Iter \leftarrow$ calIter($TR-RDD$.weight(), $TS-RDD$.weight, $MemAllow$)
6: $TS-RDD$.RangePartitioner($\#Iter$)
7: **for** $i = 0$ **to** $\#Iter$ **do**
8:   $TS_i \leftarrow$ broadcast($TS-RDD$.getSplit(i))
9:   resultKNN $\leftarrow TR-RDD$.mapPartition($TR_j \rightarrow$ kNN(TR_j, TS_i, k))
10:   result $\leftarrow$ $resultKNN.reduceByKey(combineResult$, #Reduces).collect
11:   right-predictedClasses[i] $\leftarrow$ calculateRightPredicted(result)
12: **end for**
13: cm $\leftarrow$ calculateConfusionMatrix(right-predictedClasses)

As input, we receive the path in the HDFS for both training and test data as well as the number of maps m and reducers r. We also dispose of the number of neighbors k and the memory allowance for each map.

Firstly, we create an RDD object with the training set TR formed by m blocks (Instruction 1). The test set TS is also read as an RDD without specifying a number of partitions. As this is read, we establish the key of every single test instance according to its position in the dataset (Instruction 2, function *zipWithIndex()* in Spark).

Since we will use Euclidean distance to compute the similarity between instances, normalizing both datasets becomes a mandatory task. Thus, Instructions 3 and 4 both perform a parallel operation to normalize the data into the range [0,1]. Both datasets are also cached for future reuse.

Even though Spark can be iteratively applied with the same data without incurring excessive time consumption, we reduce the number of iterations to a minimum because the fewer iterations there are, the better the performance will be. Instruction 5 calculates the minimum number of iterations $\#Iter$ that we will have to perform to manage the input data. To do so, it will use the size of every chunk of the training dataset, the size of the test set and the memory allowance for each map.

With the computed number of iterations $\#Iter$, we can easily split the test dataset into subsets of a similar number of samples. To do that, we make use of the previously established keys in TS (in Instruction 2). Instruction 6 will perform the partitioning of the test dataset by using the function *RangePartitioner*.

Next, the algorithm enters into a loop in which we classify subsets of the test set (Instructions 7-12). Instruction 7 firstly gets the split corresponding to the current iteration. We use the transformation *filterByRange(lowKey, maxKey)* to efficiently take the corresponding subset. This function takes advantage of the split performed in Instruction 6, to only scan the matching elements. Then, we broadcast this subset TS_i into the main memory of all the computing nodes involved. The *broadcast* function of Spark allows us to keep a read-only variable cached on each machine rather than copying it with the tasks.

After that, the main map phase starts in Instruction 9. As stated before, the *mapPartition* function computes the kNN for each partitions of TR_j and TS_i and emits a pair RDD with key equals to the number of instance and value equals to a list of *class-distance*. The reduce phase joins the results of each map grouping by key (Instruction 9). As a result, we obtain the k neighbors with the smallest distance and their classes for each test input in TS_i. More details can be found in the previous section.

The last step in this loop collects the right and predicted classes storing them as an array in every iteration (Instruction 11).

Finally, when the loop is done, Instruction 13 computes the resulting confusion matrix and outputs the desired performance measures.

4. Experimental set-up

In this section, we show the factors and points related to the experimental study. We provide the performance measures used (Section 4.1), the details of the problems chosen for the experimentation (Section 4.2) and the involved methods with their respective parameters (Section 4.3). Finally, we specify the hardware and software resources that support our experiments (Section 4.4).

4.1. Performance measures

In this work we assess the performance and scalability with the following three measures:

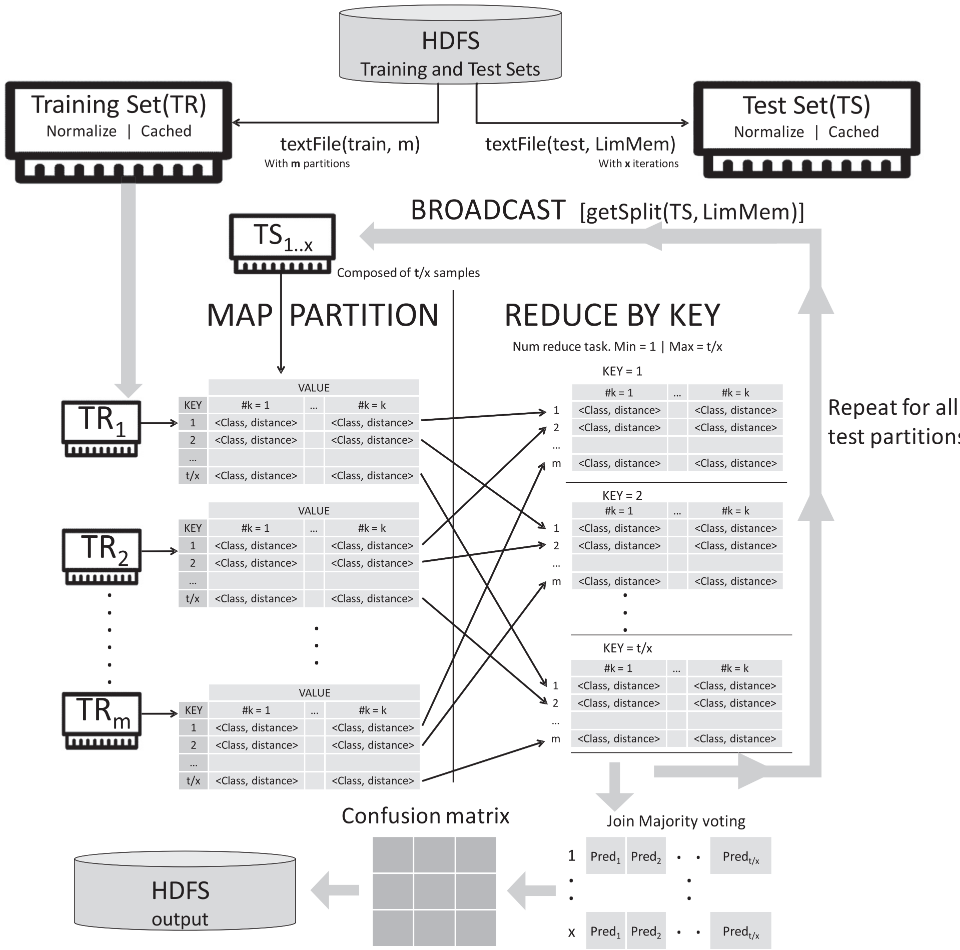


Fig. 2. Flowchart of the proposed kNN-IS algorithm.

- *Accuracy:* Represents the number of correct classifications against the total number of classified instances. This is calculated from a resulting confusion matrix, dividing the sum of the diagonal elements between the total of the elements of the confusion matrix. This is the most commonly used metric for assessing the performance of classifiers for years in standard classification ([38] [39]).
- *Runtime:* We will collect the total time spent by the kNN classifier to classify a given test set against the training dataset. Moreover, we will take intermediate times from the map phase and the reduce phase to better analyze the behavior of our proposal. The total runtime for the parallel approach includes reading and distributing all the data, in addition to calculating k nearest neighbors and majority vote.
- *Speed up:* Proves the efficiency of a parallel algorithm comparing against the sequential version of the algorithm. Thus, it measures the relation between the runtime of sequential and parallel versions. In a fully parallelism environment, the maximum theoretical speed up would be the same as the number of used cores, according to the Amdahl's Law [40].

$$Speedup = \frac{base\_line}{parallel\_time} \quad (1)$$

where *base_line* is the runtime spent with the sequential version and *parallel_time* is the total runtime achieved with its improved version.

Table 1
Summary description of the used datasets.

Dataset	#Examples	#Features	$\#\omega$
PokerHand	1,025,010	10	10
ECBDL'14	2,063,187	631	2
Susy	5,000,000	18	2
Higgs	11,000,000	28	2

4.2. Datasets

In this experimental study we will use four big data classification problems. PokerHand, Susy and Higgs are extracted from the UCI machine learning repository [41]. Moreover, we take an extra dataset that comes from the ECBDL'14 competition [42]. This is a highly imbalanced problem (Imbalanced ratio $>$ 45), in which the kNN may be biased towards the negative class. Thus, we randomly sample said dataset to obtain more balance. The point of using said dataset, is that apart from containing a substantial number of instances, it has a relatively high number of features, so that, we can see how this fact affects the proposed model.

Table 1 summarizes the characteristics of these datasets. We show the number of examples (*#Examples*), number of features (*#Features*), and the number of classes ($\#\omega$). Note that with a fewer number of instances, the ECBLD'14 datasets become the larger datasets in terms of size because of its number of features.

For the experimental study all datasets have been partitioned using a 5 fold cross-validation (5-fcv) scheme. It means that the

Table 2
Approximate number of instances in the training subset depending on the number of mappers.

	Number of maps						
Dataset	32	64	128	256	512	1024	2048
PokerHand	25,626	12,813	6,406	*3,203*	*1,602*	*800*	*400*
ECBDL'14	*51,580*	*25,790*	12,895	6,448	3,224	1,612	*806*
Susy	*62,468*	31,234	15,617	7,809	3,905	1,953	976
Higgs	*275,000*	*137,500*	68,750	34,375	17,188	8,594	4,297

Table 3
Approximate number of instances in the test subset depending on the number of reducers.

	Number of reducers			
Dataset	1	32	64	128
PokerHand	205,002	*102,501*	*51,250*	*25,625*
ECBDL'14	412,637	12,895	6,448	*3,224*
Susy	1,000,000	31,250	15,625	*7,813*
Higgs	2,200,000	*68,750*	34,375	17,188

Table 4
Parameter settings for the used methods.

Method	**Parameter values**
MR-kNN [28]	k=1,3,5,7; Number Of Maps = 32/64/128; Number Of Reducers:1 Implementation: Hadoop MapReduce; Euclidean Distance
kNN-IS	k=1,3,5,7; Number Of Maps = 32/64/128/256/512/1024/2048; Number Of Reducers: 1/32/64/128 Implementation: Spark; Euclidean Distance Memory allowance per Map: 2GB Multiple iterations: Automatically determined or Fixed.

dataset is partitioned into 5 folds, each one including 80% training samples and the rest test examples. For each fold, the kNN algorithm computes the nearest neighbors from the *TS* against *TR*.

In the presented MapReduce scheme, the number of instances of a dataset and the number of maps used have a direct relation, so that, the greater the number of maps is, the fewer number of instances there are in them. Table 2 presents the number of instances in each training set according to the number of maps used. In italics we represent the settings that are not used in our experiments because there are either too few instances or too many.

The number of reducers also plays an important role in how the test dataset is managed in kNN-IS. The larger the number of reducers, the smaller the number of test instances that have to be processed for each reducer. Table 3 shows this relation, assuming that the test set is not split because of memory restrictions (so, number of iterations = 1). Once again, we point out in italics those settings that have not been explored.

4.3. Methods and parameters

Among the existing distributed kNN models based on MapReduce, we establish a comparison with the model proposed in [28], MR-kNN, as the most promising alternative proposed so far, which is based in Hadoop MapReduce.

As stated in Section 2.2, kNN-join methods [36] were originally designed for other purposes rather than classification. They also require the data size to increase and even a squared number of Map tasks. Therefore, their theoretical complexity is so much higher than the proposed technique that we have discarded a comparison of such models, as it would be very time consuming.

We have also conducted preliminary experiments in order to apply the iterative method proposed iHMR-kNN [27]. However, the iterative processing becomes so slow that we have not been able to apply it to any of the datasets considered in a timely manner.

This work is mainly devoted to testing the scalability capabilities of the proposed model, showing how it palliates the weaknesses of previously proposed models stated in Section 2.2. To do so, we will analyze the effect of the number of neighbors, and the number of maps and reducers. Table 4 summarizes the parameters used for both MR-kNN and kNN-IS models.

4.4. Hardware and software used

All the experiments have been executed on a cluster which is composed of sixteen nodes: the master node and sixteen computing nodes. All the nodes have the following features:

- Processors: 2x Intel Xeon CPU E5-2620
- Cores: 6 cores (12 threads)
- Clock speed: 2 GHz
- Cache: 15 MB
- Network: Infiniband (40Gb/s)
- RAM: 64 GB

The specific details of the software used and its configuration are the following:

- MapReduce implementations: Hadoop 2.6.0-cdh5.4.2 and Spark 1.5.1
- Maximum number of map tasks: 256
- Maximum number of reduce tasks: 128
- Maximum memory per task: 2GB.
- Operating System: Cent OS 6.5

Note that the total number of available cores is 192, which becomes 384 by using hyper-threading technology. Thus, when we explore a number of maps greater than 384, we cannot expect linear speedups, since there will be queued tasks. For these cases, we will focus on analyzing the map and reduce runtimes.

5. Analysis of results

In this section, we study the results collected from different experimental studies. Specifically, we analyze the next four points:

- First, we establish a comparison between kNN-IS and MR-kNN (Section 5.1).
- Second, we deeply analyze the influence of the number of neighbors k value in the performance proposed model (Section 5.2).
- Third, we check the impact of the number of reducers in relation to the number of maps when tackling very large datasets (Section 5.3).
- Finally, we study the behavior of kNN-IS with huge test datasets, in which the method is obliged to perform multiple iterations (Section 5.4).

Table 5
Sequential kNN performance.

Dataset	Number of Neighbors	Runtime(s)	AccTest
	1	105475.0060	0.5019
PokerHand	3	105507.8470	0.4959
	5	105677.1990	0.5280
	7	107735.0380	0.5386
	1	3258848.8114	0.6936
Susy	3	3259619.4959	0.7239
	5	3265185.9036	0.7338
	7	3325338.1457	0.7379

Table 6
Results obtained by MR-kNN and kNN-IS algorithms in PokerHand dataset.

		MR-kNN		**kNN-IS**	
Dataset	#Map	AvgRunTime	Speedup	AvgRuntime	Speedup
	128	804.4560	131.1135	102.9380	1024.6460
PokerHand	64	1470.9524	71.7052	179.2381	588.4631
	32	3003.3630	35.1190	327.5347	322.0270
	256	12367.9657	263.4911	1900.0393	1715.1481
Susy	128	26438.5201	123.2614	3163.9710	1029.9869
	64	50417.4493	64.6373	6332.8108	514.5975

5.1. Comparison with MR-kNN

This section compares kNN-IS with MR-kNN, as the potentially fastest alternative proposed so far. To do this, we make use of PokerHand and Susy datasets. We could not go further than these datasets in order to obtain the results of the sequential kNN. In these datasets, kNN-IS only needs to conduct one iteration, since the test datasets fits in the memory in a every map. The number of reducers in kNN-IS has been also fixed to 1, to establish a comparison between very similar MapReduce alternatives under Hadoop (MR-kNN) or Spark (kNN-IS).

First of all, we run the sequential version of kNN over these datasets as a baseline. As in [28], this sequential version reads the test set line by line, as done by MR-kNN, as a straightforward solution to avoid memory problems. We understand that this scenario corresponds to the worst possible case for the sequential version, and better sequential versions could be designed. However, our aim here is to compare with the simplest sequential version, assuming that large test sets do not fit in memory together with the training set.

Table 5 shows the runtime (in seconds) and the average accuracy (AccTest) results obtained by the standard kNN algorithm, depending on the number of neighbors.

Table 6 summarizes the results obtained with both methods with k=1. The next Section will detail the influence of the value of k. It shows, for each number of maps (#Maps) the average total time (AvgRuntime) and the speedup achieved against the sequential version. As stated before, both methods correspond to exact implementation of the kNN, so that, we obtain exactly the same average accuracy as presented in Table 5.

Fig. 3 plots speed up comparisons of both approaches against the sequential version as the number of maps is increased ($k = 1$).

According to all these tables and figures, we can make the following analysis:

- As we can observe in Table 5, that the required runtime for this sequential version of the kNN method is considerably high in both datasets. However, Table 6 shows how this runtime can be greatly reduced in both approaches as the number of maps is increased. As stated above, both alternatives always provide the same accuracy as the sequential version.
- According to Fig. 3, a linear speed up for the hadoop-based kNN model has been achieved since both models read the test dataset set line-by-line, which is sometimes even superlinear what is related to memory-consumption problems of the original kNN model to manage the training set. However, kNN-IS presents a faster speed up than a linear speed up in respect to this sequential version. This is because of the use of in-memory data structures that allowed us to avoid reading test data from HDFS line-by-line.
- Comparing MR-kNN and kNN-IS, the results show how Spark has allowed us to reduce the runtime needed almost 10-fold in comparison to Hadoop.

Table 7
Results obtained with Susy dataset.

k	#Map	AvgMapTime	AvgRedTime	AvgTotalTime
1	512	730.3893	560.4334	2042.2533
	256	1531.6145	345.5664	1900.0393
	128	2975.3013	166.3976	3163.9710
	64	6210.6177	92.8188	6332.8108
3	512	770.3924	736.8489	2298.3384
	256	1553.4222	410.2235	2615.0150
	128	3641.9363	253.5656	3921.3640
	64	6405.3132	152.9890	6593.5531
5	512	781.3855	928.2620	2511.8909
	256	1773.3579	479.0801	2273.6377
	128	3685.3194	332.9783	4042.1755
	64	6582.0373	194.7054	6802.8159
7	512	782.5756	930.5107	2516.5011
	256	1827.9189	522.6219	2372.4100
	128	3401.2547	414.2961	3838.2360
	64	6637.8837	224.7191	6890.8242

5.2. Influence of the number of neighbors

To deeply analyze the influence of the number of neighbors we focus on the Susy dataset, and we set the number of reducer tasks to one again. We analyze its effect in both map and reduce phases.

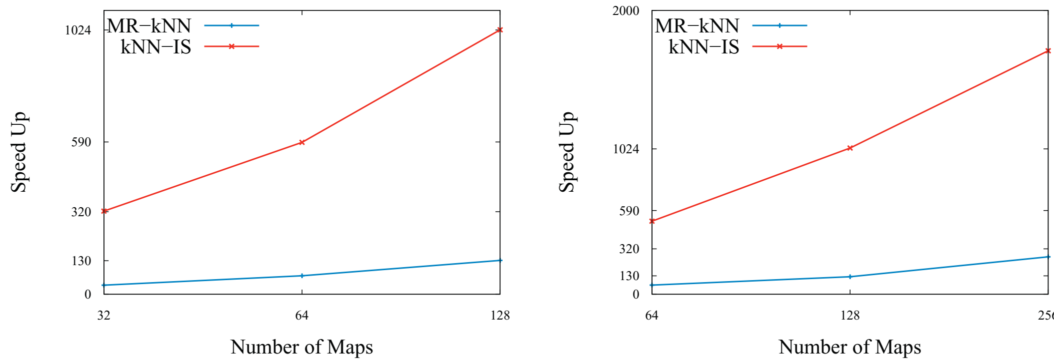
Table 7 collects for each number of neighbors (#Neigh) and number of maps (#Maps), the average map execution time (AvgMapTime), the average reduce time (AvgRedTime) and the average total runtime (AvgTotalTime). Recall that in our cluster the maximum number of map tasks is set to 256. Thus, the total runtime for 512 maps does not show a linear reduction, but it can be appreciated in the reduction of the map runtime.

Fig. 4 presents how the value of k influences in map runtimes. It depicts the map runtimes in terms of number of maps for $k = 1, 3, 5$ and 7. Fig. 5 plots the reduce runtime in relation to the k value and number of maps.

According to these tables and plots, we can conclude that:

- Even though larger values of k imply that the data transferred from the maps to the reducers is bigger, this value does not drastically affect the total runtimes. In Table 7, we can appreciate that, in general, the total runtime slightly increments.
- Comparing Figs. 4 and 5, we can see that the number of neighbors seem to have more influence on the reduce runtime than on the map phase. This is because the number of neighbors does not affect the main computation cost (computing the distances between test and training instances) of the map phase, while it may affect the updating process performed in the reducers since its complexity is $O(k)$.

Finally, as a general appreciation, Fig. 5 reveals that when a larger number of maps is used, which is clearly necessary to deal big datasets, the reduce runtimes increase considerably. This has motivated the study carried out in the next Section.



(a) Poker-Hand (b) Susy

Fig. 3. Speedup comparisons between MR-kNN and kNN-IS against the sequential kNN.

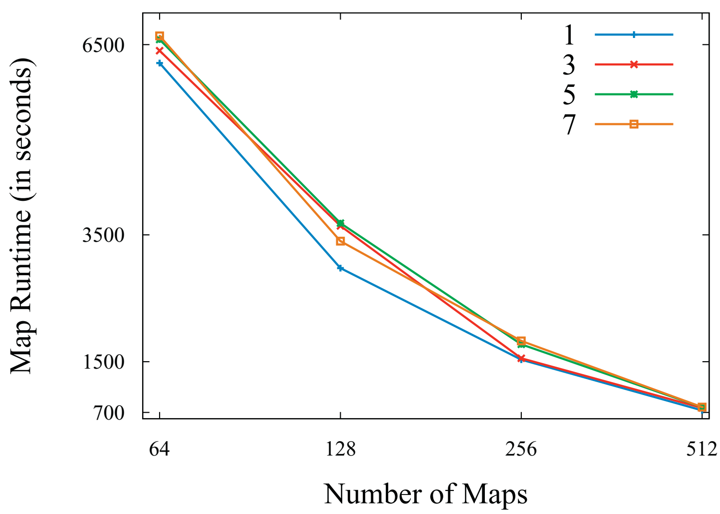


Fig. 4. Influence of parameter k in the map phase: Susy dataset.

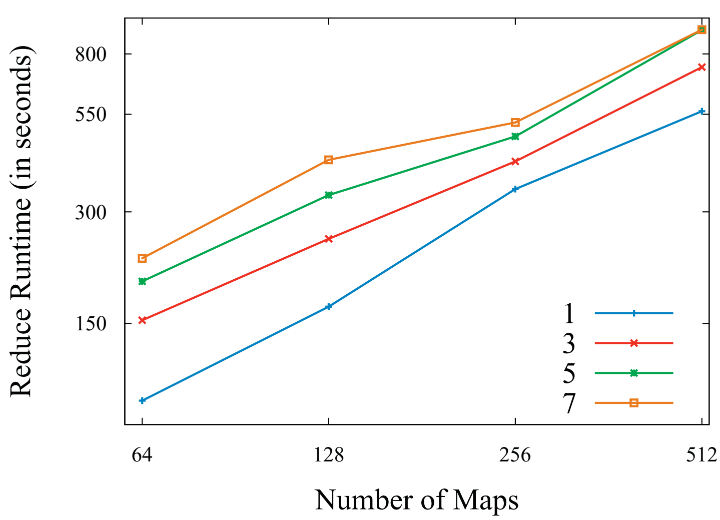


Fig. 5. Influence of parameter k in the reduce phase. Susy dataset.

5.3. Influence of the number of reducers

As we just saw in the previous section, a high number of maps greatly increases the load of the reduce phase. However, the use of a large number of maps may be absolutely necessary to tackle very big datasets. This section investigates how the proposed idea of managing different test instances in multiple reducers may help to alleviate such an issue.

In this experiment, we involve the three biggest datasets: ECBLD'14, Susy, Higgs. Once again, kNN-IS does not require multiple iterations for these test datasets' sizes. To be concise, in this study we only focus on k=1.

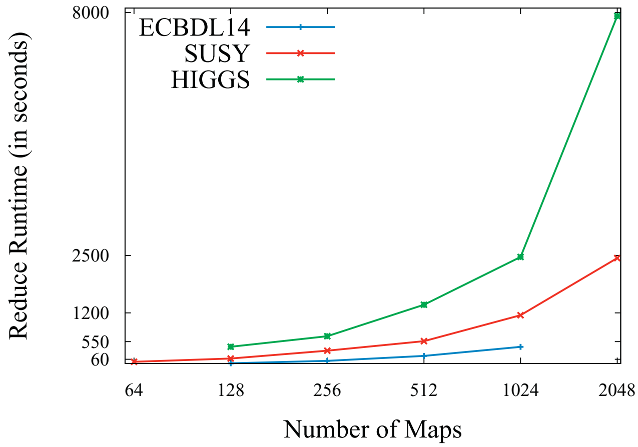


Fig. 6. Reduce runtime required against the number of map tasks, k=1, Number of reducers = 1.

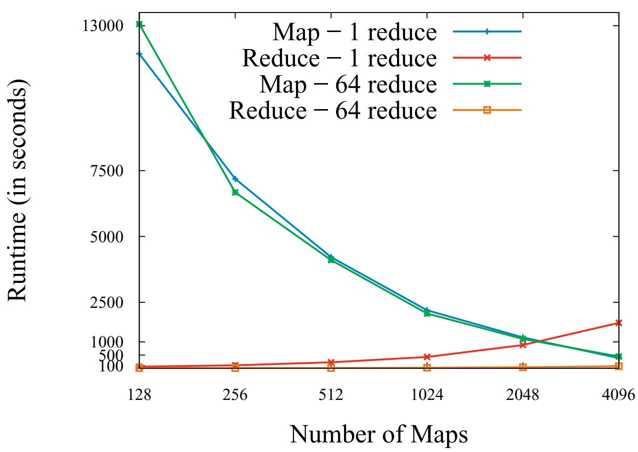


Fig. 7. Map and Reduce runtimes required according to the number of maps - ECBDL.

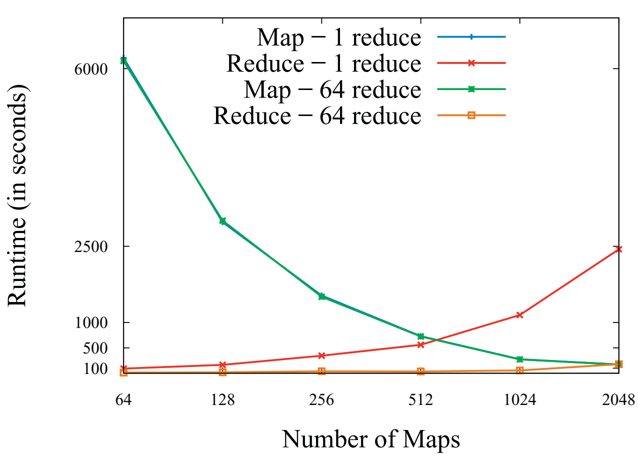


Fig. 8. Map and Reduce runtimes required according to the number of maps - SUSY.

Fig. 6 plots the reduce time required with a single reducer for all these problems. It confirms, as pointed out in the previous section, the drastic increment when the number of maps is very high. It is actually even more accentuated as Higgs and ECBLD'14 are larger datasets that require a greater number of maps.

For sake of clarity, we do not present the associated tables of results for the three considered problems, but we visually present such results in Figs. 7, 8 and 9. These figures plot the map and

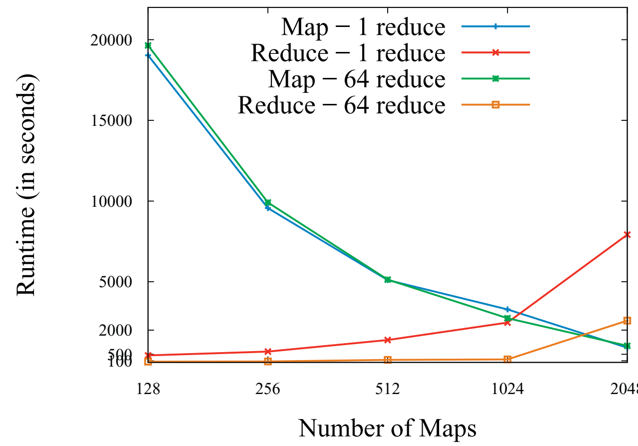


Fig. 9. Map and Reduce runtimes required according to the number of maps - HIGGS.

Table 8
Results obtained with more than one iteration.

Dataset	#Iter	AvgMapTime	AvgRedTime	AvgTotalTime
ECBDL'14	3	7309.7122	8.8911	28673.7015
#Red=64	5	4303.7106	5.2520	28918.2992
	10	2027.5685	2.8076	29121.0583
SUSY	2	2385.6183	34.2682	6723.7762
#Red=64	5	1156.9453	14.1350	9493.5098
	10	649.7218	5.9823	10278.2612
HIGGS	2	16835.6982	144.3371	44414.1423
#Red=128	5	7145.7838	59.3202	46806.8294
	10	3668.4418	29.7266	51836.9468

reduce runtimes spent in ECBLD'14, Susy and Higgs, respectively, in terms of the number of maps and reduces utilized.

These figures reveal that:

- Using multiple reducers effectively softens the runtime spent in the reduce phase when it is necessary to use a larger number of maps. In the previous plots, we can see how the version with a single reducer rapidly increases its computational cost in comparison to the version with more reducers.
- The reduction in the required time is not linear in respect to the number of reducers. As pointed out in [43], an excessive number of reducers can also lead to a MapReduce overhead in the network. As we can see, for example in Figure 10, there are no great differences when using 32 or 64 reducers.
- The use of multiple reducers is devised to use with a high number of maps. Otherwise, its behavior may damage the efficiency. For example, for the Susy dataset, it is not convenient to use more than 32 reducers unless we have more than 512 maps.

In conclusion, it is important to find a trade-off between the number of maps and reducers according to the cluster and the dataset that we dispose.

5.4. Dealing with large amounts of test data

To test the behavior of the full model presented here, we carry out a study in which both training and test sets are composed of the same number of instances. In this way, we ensure that kNN-IS is obliged to perform multiple iterations. To do so, we test training versus training datasets.

Table 8 presents the results of the three datasets with more than one iteration (#Iter), average reduce runtime (AvgRedTime) and the average total runtime (AvgTotalTime). To study the influence of test size, we focus on k=1, with 256 maps, 64 reduces

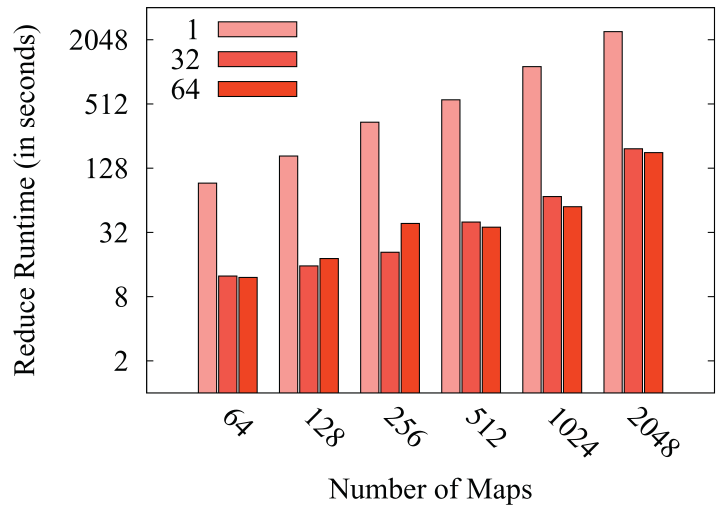


Fig. 10. Reduce Runtime vs. number of maps and reducers — SUSY.

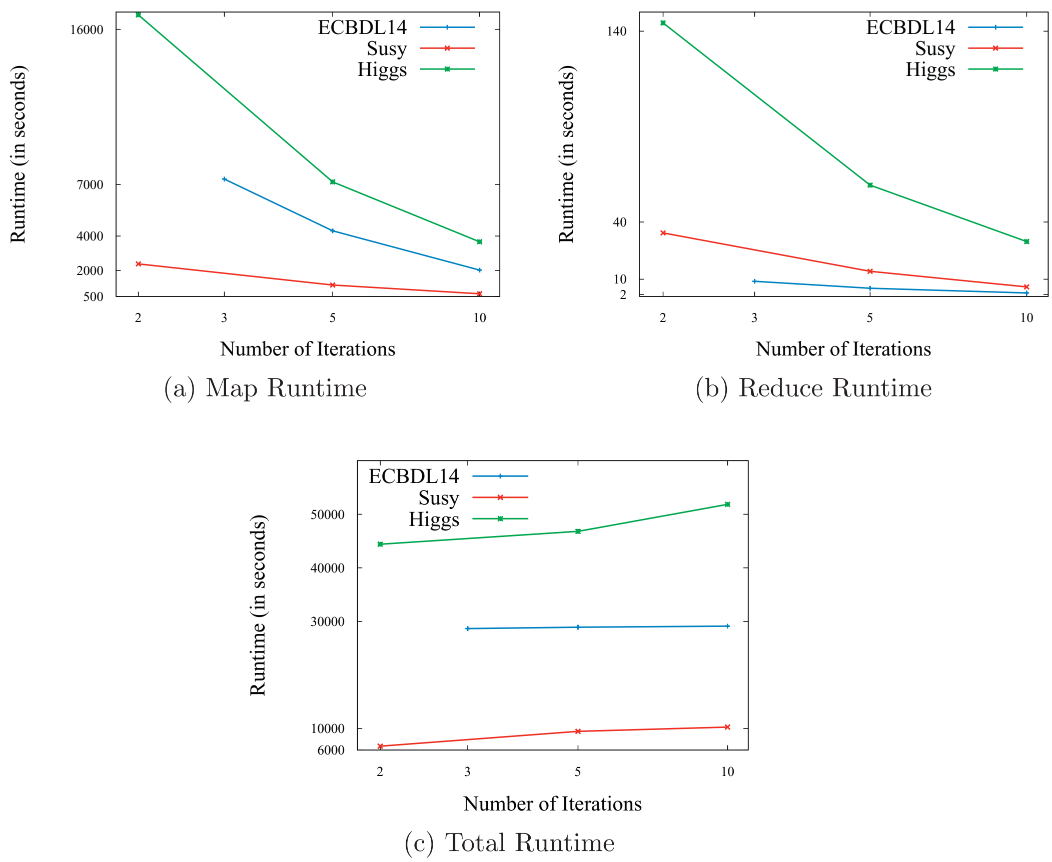


Fig. 11. Runtimes vs number of iterations.

for Susy and ECBDL'14 datasets and 128 reduce tasks for the Higgs dataset (#Red).

Fig. 11 presents the influence of the number of iterations. The ECBDL'14 dataset needs 3 iterations to fit the main memory. The other datasets only need 2 iterations. Fig. 11a shows the map time with a different number of iterations for the three datasets used. Fig. 11b presents how the number of iterations influences the reduce runtimes and Fig. 11c plots the total runtime versus the number of iterations.

Analyzing these tables and plots, we can observe that:

- As Fig. 11 shows and as we can expected, when more than one iteration is used, the map and reduce runtimes decrease. This occurs because the number of instances to be calculated on each core are less than a simple iteration.
- However, Fig. 11c shows how it slightly increases the total runtime. This behavior could be caused by a network saturation of the cluster. For ECBDL'14 dataset, the total runtime increases less than other two datasets. This happens because it has fewer samples as shown in Table 1. Thus, it produces less network traffic in spite of having more features.

In conclusion, the iterative functionality of kNN-IS has to be used when the size of datasets exceeds the available memory of a core of the cluster because it becomes slower in total runtimes and network traffic is increased.

6. Conclusions and further work

In this paper we have developed a Iterative MapReduce solution for the k-Nearest Neighbors algorithm based on Spark. It is denominated as kNN-IS. The proposed scheme is an exact model of the kNN algorithm that we have enabled to apply with large-datasets. Thus, kNN-IS obtains the same accuracy as kNN. However, the kNN algorithm has two main issues when dealing with large-scale data: Runtime and Memory consumption. The use of Apache Spark has provided us with a simple, transparent and efficient environment to parallelize the kNN algorithm as an iterative MapReduce process.

The experimental study carried out has shown that kNN-IS obtains a very competitive runtime. We have tested its behavior with datasets of different sizes (different number of features and different number of samples).

The main achievements obtained are the following:

- kNN-IS is an exact parallel approach and obtains the same accuracy and very good achievements on runtimes.
- kNN-IS (Spark) has allowed us to reduce the runtime needed by almost 10 times in comparison to MR-kNN (Hadoop).
- Despite producing more transfer from the map to reduce, the number of neighbors (k) does not drastically affect to the total runtime.
- We can optimize the runtime with a trade-off between the number of maps and reducers according to the cluster and the dataset used
- When datasets are enormous and it exceed the memory capacity of the cluster, kNN-IS calculates the solution with more than one iteration by splitting the test set. Therefore, it has allowed us to apply the kNN algorithm in large-scale problems.
- The software of this contribution can be found as a spark-package at http://spark-packages.org/package/JMailloH/kNN_IS. The source code of this technique can be found in the next repository https://github.com/JMailloH/kNN_IS

As future work, we aim to tackle big datasets that contain missing values [44] by using kNN-IS to impute them, and datasets with a very large number of features by using multi-view approaches. We are planning to extend the use of kNN-IS to instance selection techniques for big data [45], where it reports good results. Another direction for future work is to extend the application of the presented kNN-IS approach to a big data semi-supervised learning [46] context.

Acknowledgments

This work has been supported by the Spanish National Research Project TIN2014-57251-P and the Andalusian Research Plan P11-TIC-7765. J. Maillo and S. Ramírez hold FPU scholarships from the Spanish Ministry of Education. I. Triguero held a BOF postdoctoral fellowship from Ghent University during part of the development of this work.

Appendix

As consequence of this work, we have developed a Spark package with the kNN-IS implementation. It has all the functionalities exposed in this study. In addition, we have developed kNN-IS for the machine learning library on Spark, as part of the MLlib library and the MLbase platform.

Prerequisites: You must have Spark 1.5.1, Scala 2.10 and Maven 3.3.3 or higher installed. Java Virtual Machine 1.7.0 is necessary because Scala runs over it.

The implementation allows us to determine the:

- Number of Cores to be used: Number of cores to compute the MapReduce approach.
- Number of neighbors: Number of neighbors. The value of k.
- Number of maps: Number of map tasks.
- Number of reduces: Number of reduce tasks.
- Number of iterations: Number of iterations. Setting to -1 to auto-setting the iterations. We give optional parameter (*Maximum memory per node*) limit on GB for each map task. This selects the minimum number of iterations within the limit provided.

The input data is expected to be in KEEL Dataset format [47]. The datasets are previously stored in HDFS.

The output will be stored in HDFS in the following format: ./*outputPath*/Predictions.txt/part-00000 contains the predicted and right class in two column. ./*outputPath*/Result.txt/part-00000 shows confusion matrix, accuracy and total runtime. ./*outputPath*/Times.txt/part-00000 presents higher map time, higher reduce time, average iterative time and total runtime.

For more details, please refer to the README in the GitHub repository: https://github.com/JMailloH/kNN_IS/blob/master/README.md

The proposed kNN-IS is now available as a Spark Package at http://spark-packages.org/package/JMailloH/kNN_IS

References

[1] C. Lynch, Big data: how do your data grow? Nature 455 (7209) (2008) 28–29, doi:10.1038/455028a.

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

[4] X. Wu, V. Kumar (Eds.), The Top Ten Algorithms in Data Mining, Chapman & Hall/CRC Data Mining and Knowledge Discovery, 2009.

[5] Y. Chen, E.K. Garcia, M.R. Gupta, A. Rahimi, L. Cazzanti, Similarity-based classification: concepts and algorithms, J. Mach. Learn. Res. 10 (2009) 747–776.

[6] K.Q. Weinberger, L.K. Saul, Distance metric learning for large margin nearest neighbor classification, J. Mach. Learn. Res. 10 (2009) 207–244.

[7] S. Arya, D.M. Mount, N.S. Netanyahu, R. Silverman, A.Y. Wu, An optimal algorithm for approximate nearest neighbor searching fixed dimensions, J. ACM 45 (6) (1998) 891–923, doi:10.1145/293347.293348.

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

[9] 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.

[10] C.P. Chen, C.-Y. Zhang, Data-intensive applications, challenges, techniques and technologies: a survey on big data, Inf. Sci. 275 (2014) 314–347, doi:10.1016/j.ins.2014.01.015.

[11] Z. Guo, G. Fox, M. Zhou, Investigation of data locality in mapreduce, in: Cluster, Cloud and Grid Computing (CCGrid), 2012 12th IEEE/ACM International Symposium on, 2012, pp. 419–426, doi:10.1109/CCGrid.2012.42.

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

[13] I. Triguero, S. del Río, V. López, J. Bacardit, J.M. Benítez, F. Herrera, ROSEFW-RF: The winner algorithm for the ecbdl'14 big data competition: An extremely imbalanced big data bioinformatics problem, Know. Based Syst. 87 (C) (2015) 69–79, doi:10.1016/j.knosys.2015.05.027.

[14] X. Yan, J. Zhang, Y. Xun, X. Qin, A parallel algorithm for mining constrained frequent patterns using mapreduce, Soft Comput. (2015) 1–13, doi:10.1007/s00500-015-1930-z.

[15] W. Gropp, E. Lusk, A. Skjellum, Using MPI: portable parallel programming with the message-passing interface, 1, MIT press, 1999.

[16] A. Fernández, S. Río, V. López, A. Bawakid, M. del Jesus, J. Benítez, F. Herrera, Big data with cloud computing: an insight on the computing environment, mapreduce and programming frameworks, WIREs Data Min. Knowl. Discov. 4 (5) (2014) 380–409.

[17] K. Grolinger, M. Hayes, W. Higashino, A. L'Heureux, D. Allison, M. Capretz, Challenges for mapreduce in big data, in: Services (SERVICES), 2014 IEEE World Congress on, 2014, pp. 182–189, doi:10.1109/SERVICES.2014.41.

[18] Y. Low, J. Gonzalez, A. Kyrola, D. Bickson, C. Guestrin, J.M. Hellerstein, Graphlab: a new parallel framework for machine learning, in: Conference on Uncertainty in Artificial Intelligence (UAI), 2010. Catalina Island, California

[19] Y. Bu, B. Howe, M. Balazinska, M.D. Ernst, Haloop: efficient iterative data processing on large clusters, Proc. VLDB Endow. 3 (1-2) (2010) 285–296, doi:10.14778/1920841.1920881.

[20] M. Zaharia, M. Chowdhury, T. Das, A. Dave, J. Ma, M. McCauley, M.J. Franklin, S. Shenker, I. Stoica, Resilient distributed datasets: a fault-tolerant abstraction for in-memory cluster computing, in: Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation, USENIX Association, 2012, pp. 1–14.

[21] M. Ghesmoune, M. Lebbah, H. Azzag, Micro-batching growing neural gas for clustering data streams using spark streaming, Procedia Comput. Sci. 53 (2015) 158–166, doi:10.1016/j.procs.2015.07.290. INNS Conference on Big Data 2015 Program San Francisco, CA, USA 8-10 August 2015

[22] I. Triguero, D. Peralta, J. Bacardit, S. García, F. Herrera, MRPR: a mapreduce solution for prototype reduction in big data classification, Neurocomputing 150, Part A (0) (2015) 331–345, doi:10.1016/j.neucom.2014.04.078.

[23] S. Ding, M. Du, H. Jia, Study on density peaks clustering based on k-nearest neighbors and principal component analysis, Knowl. Based Syst. 99 (2016) 135–145, doi:10.1016/j.knosys.2016.02.001.

[24] D. Deng, X. Zhu, D. Cheng, M. Zong, S. Zhang, Efficient knn classification algorithm for big data, Neurocomputing 195 (2016) 143–148, doi:10.1016/j.neucom.2015.08.112. Learning for Medical Imaging

[25] C. Zhang, F. Li, J. Jestes, Efficient parallel knn joins for large data in mapreduce, in: Proceedings of the 15th International Conference on Extending Database Technology, in: EDBT '12, ACM, New York, NY, USA, 2012, pp. 38–49, doi:10.1145/2247596.2247602.

[26] G. Chatzimilioudis, C. Costa, D. Zeinalipour-Yazti, W.C. Lee, E. Pitoura, Distributed in-memory processing of all k nearest neighbor queries, IEEE Trans. Knowl. Data Eng. 28 (4) (2016) 925–938, doi:10.1109/TKDE.2015.2503768.

[27] K. Sun, H. Kang, H.-H. Park, Tagging and classifying facial images in cloud environments based on kNN using mapreduce, Optik 126 (21) (2015) 3227–3233, doi:10.1016/j.ijleo.2015.07.080.

[28] J. Maillo, I. Triguero, F. Herrera, A mapreduce-based k-nearest neighbor approach for big data classification, in: 9th International Conference on Big Data Science and Engineering (IEEE BigDataSE-15), 2015, pp. 167–172.

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

[30] A.H. Project, Apache Hadoop, 2015.

[31] J. Lin, Mapreduce is good enough? if all you have is a hammer, throw away everything that's not a nail!, Big Data 1:1 (2013) 28–37.

[32] H. Karau, A. Konwinski, P. Wendell, M. Zaharia, Learning Spark: Lightning-Fast Big Data Analytics, O'Reilly Media, Incorporated, 2015.

[33] A. Spark, Apache Spark: Lightning-fast cluster computing, 2015. [Online; accessed July 2015].

[34] A. Spark, Machine Learning Library (MLlib) for Spark, 2016. [Online; accessed May 2016].

[35] A. Spark, Machine Learning API (ML) for Spark, 2016. [Online; accessed May 2016].

[36] G. Song, J. Rochas, F. Huet, F. Magoules, Solutions for processing k nearest neighbor joins for massive data on mapreduce, in: Parallel, Distributed and Network-Based Processing (PDP), 2015 23rd Euromicro International Conference on, 2015, pp. 279–287, doi:10.1109/PDP.2015.79.

[37] W. Lu, Y. Shen, S. Chen, B.C. Ooi, Efficient processing of k nearest neighbor joins using mapreduce, Proc. VLDB Endow. 5 (10) (2012) 1016–1027, doi:10.14778/2336664.2336674.

[38] E. Alpaydin, Introduction to Machine Learning, 2nd, The MIT Press, 2010.

[39] I.H. Witten, E. Frank, Data Mining: Practical Machine Learning Tools and Techniques, Second Edition (Morgan Kaufmann Series in Data Management Systems), Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2005.

[40] G.M. Amdahl, Validity of the single processor approach to achieving large scale computing capabilities, in: Proceedings of the April 18-20, 1967, Spring Joint Computer Conference, in: AFIPS'67 (Spring), ACM, New York, NY, USA, 1967, pp. 483–485, doi:10.1145/1465482.1465560.

[41] M. Lichman, UCI Machine Learning Repository, 2013.

[42] I. Arnaldo, K. Veeramachaneni, U. O'Reilly and J. Bacardit. ECBDL14 dataset: Protein structure prediction and contact map for the ECBDL2014 big data competition, 2014, http://cruncher.ncl.ac.uk/bdcomp/.

[43] 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.

[44] J. Luengo, S. García, F. Herrera, On the choice of the best imputation methods for missing values considering three groups of classification methods, Knowl. Inf. Syst. 32 (1) (2011) 77–108, doi:10.1007/s10115-011-0424-2.

[45] Á. Arnaiz-González, J.F. Díez-Pastor, J.J. Rodríguez, C. García-Osorio, Instance selection of linear complexity for big data, Knowl. Based Syst. (2016), doi:10.1016/j.knosys.2016.05.056.

[46] I. Triguero, S. García, F. Herrera, Self-labeled techniques for semi-supervised learning: taxonomy, software and empirical study, Knowl. Inf. Syst. 42 (2) (2013) 245–284, doi:10.1007/s10115-013-0706-y.

[47] J. Alcalá-Fdez, A. Fernandez, J. Luengo, J. Derrac, S. García, L. Sánchez, F. Herrera, KEEL data-mining software tool: data set repository, integration of algorithms and experimental analysis framework, J. Mult. Valued Logic Soft Comput. 17 (2-3) (2011) 255–287.