Feature selection in high-dimensional dataset using MapReduce

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Abstract. This paper describes a distributed MapReduce implementation of the minimum Redundancy Maximum Relevance algorithm, a popular feature selection method in bioinformatics and network inference problems. The proposed approach handles both *tall/narrow* and *wide/short* datasets. We further provide an open source implementation based on Hadoop/Spark, and illustrate its scalability on datasets involving millions of observations or features.

1 Introduction

The exponential growth of data generation, measurements and collection in scientific and engineering disciplines leads to the availability of huge and high-dimensional datasets, in domains as varied as text mining, social network, astronomy or bioinformatics to name a few. The only viable path to the analysis of such datasets is to rely on data-intensive distributed computing frameworks [1].

MapReduce has in the last decade established itself as a reference programming model for distributed computing. The model is articulated around two main classes of functions, *mappers* and *reducers*, which greatly decrease the complexity of a distributed program while allowing to express a wide range of computing tasks. MapReduce was popularised by Google research in 2008 [2], and may be executed on parallel computing platforms ranging from specialised hardware units such as parallel field programmable gate arrays (FPGAs) and graphics processing units, to large clusters of commodity machine using for example the Hadoop or Spark frameworks [2–4].

In particular, the expressiveness of the MapReduce programming model has led to the design of advanced distributed data processing libraries for machine learning and data mining, such as Hadoop Mahout and Spark MLlib. Many of the standard supervised and unsupervised learning techniques (linear and logistic regression, naive Bayes, SVM, random forest, PCA) are now available from these libraries [5–7].

Little attention has however yet been given to feature selection algorithms (FSA), which form an essential component of machine learning and data mining workflows. Besides reducing a dataset size, FSA also generally allow to improve the performance of classification and regression models by selecting the most relevant features and reducing the noise in a dataset [8].

Three main classes of FSA can be distinguished: *filter*, *wrapper* and *embedded* methods [8, 9]. Filter methods are model-agnostic, and rank features according to some metric of information conservation such as mutual information or variance. Wrapper methods use the model as a black-box to select the most relevant features. Finally, in embedded methods, feature evaluation is performed alongside the model training. In this paper, feature metrics are named hereafter *feature score* functions.

Early research on distributing FSA mostly concerned wrapper methods, in which parallel processing was used to simultaneously assess different subsets of variables [10–14]. These approaches effectively speed up the search for relevant subsets of variables, but require the dataset to be sent to each computing unit, and therefore do not scale as the dataset size increases.

MapReduce based approaches, which address this scalability issue by splitting datasets in chunks, have more recently been proposed [15–21]. In [15], an embedded approach is proposed for logistic regression. Scalability in the dataset size is obtained by relying on an approximation of the logistic regression model performance on subsets of the training set. In [16], a wrapper method based on an evolutionary algorithm is used to drive the feature search. The first approaches based on filter methods were proposed in [17, 18], using variance preservation and mutual information as feature selection metrics, respectively. Two other implementations of filter-based methods have lately been proposed, addressing the column subset selection problem (CSSP) [19], and the distribution of data by features in [20]. Recently, a filter-based feature selection framework based on information theory [22] has been implemented using Apache Spark [21].

In this paper we tackle the implementation of *minimal Redundancy Maximal Relevance* (*mRMR*) [23], a forward feature selection algorithm belonging to filter methods. mRMR was shown to be particularly effective in the context of network inference problems, where relevant features have to be selected out of thousands of other noisy features [1, 24].

The main contributions of the paper are the following: *i*) design of minimum Redundancy Maximum Relevance algorithm using MapReduce paradigm; *ii*) open-source implementation for Apache Spark available on a public repository; *iii*) analysis of the scalability properties of the algorithm. In an extended version [25], we also detail how to customize the feature score function during the feature selection process.

The paper is structured as follows. Section 2 provides an overview of the MapReduce paradigm, and Section 3 describes the two main layouts along which data can be stored. Section 4 presents our distributed implementation of mRMR. Section 5 finally provides a thorough experimental evaluation, where we illustrate the scalability of the proposed implementation by varying the number of rows and columns of the datasets, the number of selected features in the feature selection step and the number of nodes in the cluster.

2 MapReduce paradigm

MapReduce [2] is a programming paradigm designed to analyse large volumes of data in a parallel fashion. Its goal is to process data in a scalable way, and to seamlessly adapt to the available computational resources.

A MapReduce job transforms lists of input data elements into lists of output data elements. This process happens twice in a program, once for the *Map* step and once for the *Reduce* step. Those two steps are executed sequentially, and the Reduce step begins once the Map step is completed.

In the Map step, the data elements are provided as a list of key-value objects. Each element of that list is loaded, one at a time, into a function called *mapper*. The mapper transforms the input, and outputs any number of intermediate key-value objects. The original data is not modified, and the mapper output is a list of new objects.

In the Reduce step, intermediate objects that share the same key are grouped together by a *shuffling* process, and form the input to a function called *reducer*. The reducer is invoked as many times as there are keys, and its value is an iterator over the related grouped intermediate values.

Mappers and reducers run on some or all of the nodes in the cluster in an isolated environment, i.e. each function is not aware of the other ones and their task is equivalent in every node. Each mapper loads the set of files local to that machine and processes it. This design choice allows the framework to scale without any constraints about the number of nodes in the cluster. An overview of the MapReduce paradigm is reported in Figure 1a.

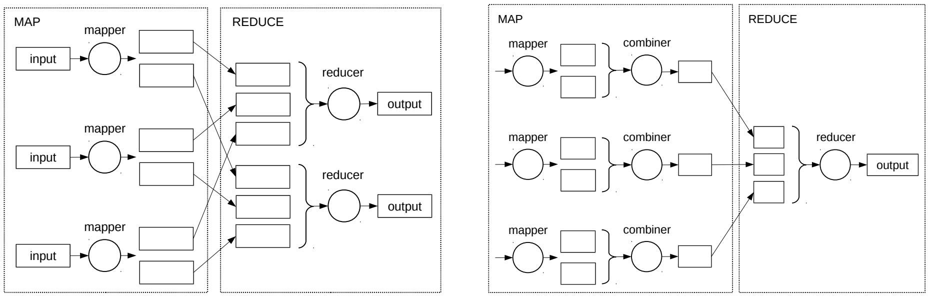
Algorithms written in MapReduce scale with the cluster size, and Execution Time (ET) can be decreased by increasing the number of nodes. The design of the algorithm and the data layout are important factors impacting ET [26].

In ET terms, jobs perform better in MapReduce when transformations are executed locally during the Map step, and when the amount of information transferred during the shuffling step is minimised [27]. In particular, MapReduce is very well-suited for associative and commutative operators, such as *sum* and *multiplication*. These can indeed be partially processed using an intermediate *Combine* step, which can be applied between the Map and Reduce stages.

The combiner is an optional functionality in MapReduce [2]. It locally aggregates mapper output objects before they are sent over the network. It operates by taking as input the intermediate key-value objects produced by the mappers, and output key-value pairs for the Reduce step. This optional process allows to reduce data transfer over the network, therefore reducing the global ET of the job. An illustration of the use and advantages of the combiner is given in Figure 1b.

3 Data Layout

In learning problems, training data from a phenomenon is usually encoded in tables, using rows as observations, and columns as features. Let M be the number of observations, and N be the number of features. Training data can be



(a) MapReduce overview of the data flow. The dataset stored in the distributed storage system is split into chunks across nodes (rectangular *input* boxes). Each chunk is fed as input to the mapper functions, which may output intermediate objects. These objects are shuffled and grouped by keys across the network. Finally, the reducers generate the groups of intermediate objects and output the results. All objects (input, intermediate, output) are identified by a key-value pair.

(b) MapReduce overview of the data flow with the additional combiner function. Intermediate objects produced by mappers are locally aggregated by a commutative and associative function implemented in the combiner logic. In this example three, instead of six, intermediate objects are sent over the network to the reducer function. Combiners provide an efficient way to reduce the amount of shuffled data, and to reduce the overall execution time of the job.

Fig. 1: MapReduce data flow overview with and without combiner.

represented as a collection of vectors, $\mathbf{X}$,

$$\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_M)$$

where

$$\mathbf{x}_j = (x_{j,1}, x_{j,2}, \ldots, x_{j,N}) \qquad \forall j \in (1, \ldots, M)\,.$$

We will refer to this type of structure as the *conventional* encoding, see Table 1.

It is however worth distinguishing two types of tables: *tall and narrow* (T/N) tables, where $M \gg N$, and *short and wide* (S/W) tables, where $M \ll N$.

The distinction is important since MapReduce divides input data in chunks of rows, that are subsequently processed by the mappers. MapReduce is therefore well suited to ingest T/N table, but much less S/W tables, since data cannot be efficiently split along columns. S/W tables are for example encountered in domains such as text mining or bioinformatics [28, 29], where the number of features can be on the order of tens or hundreds of thousands, while observations may only be on the order of hundreds or thousands.

In such cases, it can be beneficial to transform S/W into T/N tables, by storing observations as columns and features as rows. We refer to this type of structure as *alternative* encoding, see Table 2.

$x_{1,1}$	$x_{1,2}$	$\dots$	$\dots$	$x_{1,N}$
$x_{2,1}$	$x_{2,2}$	$\dots$	$\dots$	$x_{2,N}$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
$x_{M,1}$	$x_{M,2}$	$\dots$	$\dots$	$x_{M,N}$

Table 1: Conventional encoding: Observations ($x_{i,\cdot}$) are stored along rows, and features ($x_{\cdot,j}$) are stored along columns.

$x_{1,1}$	$x_{2,1}$	$\dots$	$\dots$	$x_{M,1}$
$x_{1,2}$	$x_{2,2}$	$\dots$	$\dots$	$x_{M,2}$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
$x_{1,N}$	$x_{2,N}$	$\dots$	$\dots$	$x_{M,N}$

Table 2: Alternative encoding: Observation ($x_{i,\cdot}$) are stored along columns, and features ($x_{\cdot,j}$) are stored along rows.

4 Iterative feature selection framework

This section first recalls the standard mRMR algorithm [23]. We then detail our MapReduce implementation, for both conventional and alternative encodings. An implementation of a custom feature score function using the Pearson correlation coefficient is reported in the extended article [25].

4.1 minimal Redundancy Maximal Relevance

Let us define the dataset as the table $\mathbf{X}$ with M rows, N columns and discrete values. We define $\mathbf{x}_k$ as the $k-th$ column vector of the dataset and $\mathbf{c}$ as the class vector. Furthermore, let us define L as the number of features to select and i_c^l and i_s^l as the sets at step l ($1 \leqslant l \leqslant L$) of candidate and selected features indices, respectively. At $l = 1$, we have $i_c^1 = \{1, ..., N\}$ and $i_s^1 = \varnothing$. The pseudo-code of the algorithm is reported in Listing 1.1.

Listing 1.1: minimum Redundancy Maximum Relevance Pseudo-code. $I(\cdot)$ is the function that, given two vectors, returns their mutual information. $\mathbf{x}_k$ is the $k - th$ column vector of the dataset and $\mathbf{c}$ is the class vector. L is the number of features to select, i_c^l and i_s^l as the sets at step l ($1 \leqslant l \leqslant L$) of candidate and selected features indices.

```
$i_c^1 = \{1, ..., N\}$
$i_s^1 = \varnothing$
for $l = 1 \rightarrow L$
  for $k \in i_c^l$
    $I_{\mathbf{x}_k,\mathbf{c}} \leftarrow I(\mathbf{x}_k, \mathbf{c})$
    for $j \in i_s^l$
      $I_{\mathbf{x}_k,\mathbf{x}_j} \leftarrow I(\mathbf{x}_k, \mathbf{x}_j)$
    $g_k \leftarrow I_{\mathbf{x}_k,\mathbf{c}} - \frac{1}{|i_s^l|} \sum_{j \in i_s^l} I_{\mathbf{x}_k,\mathbf{x}_j}$
  $k^* \leftarrow$ argmax($g_k$)
  $i_c^{l+1} \leftarrow i_c^l \backslash k^*$
  $i_s^{l+1} \leftarrow i_s^l \cup k^*$
```

```
12 output $i_s^L$
```

mRMR is an iterative greedy algorithm: at each step the candidate feature is selected based on a combination of its mutual information with the class and the selected features:

$$\operatorname{argmax}_{k \in i_c^l} g_k(\cdot)$$

$$g_k(\cdot) = \begin{cases} I(\mathbf{x}_k; \mathbf{c}) & l = 1 \\ I(\mathbf{x}_k; \mathbf{c}) - \frac{1}{|i_s^l|} \sum_{j \in i_s^l} I(\mathbf{x}_k; \mathbf{x}_j) & l > 1 \end{cases} \tag{1}$$

where $I(\cdot)$ returns the mutual information of two vectors. The *feature score* $g(\cdot)$ is assessed in Lines 5-8 in Listing 1.1.

We redesigned the algorithm using MapReduce paradigm on Apache Spark, distributing the feature evaluation into the cluster. Besides the core features of MapReduce previously described, our design takes advantage of the *broadcast* operator provided in Apache Spark. Broadcasted variables are commonly used in machine learning algorithms to efficiently send additional data to every mapper and reducer as read-only variables [30].

4.2 mRMR in MapReduce with conventional encoding

Let us define the dataset as a Resilient Distributed Dataset (RDD) [31] of M tuples $(\mathbf{x}, c)$, where $\mathbf{x}$ is the input (observation) vector and c is the target class value.

Considering the dataset with only discrete values, we represent with d_c the set of categorical values of the class, and with d_v the (union) set of unique categorical values of all features. If the dataset has binary values, then $d_c = d_v = \{0, 1\}$. In case of having features with different sets of categorical values, then d_v is the union of unique categorical values of all features.

The input vector is partitioned in candidate and selected features, labeled respectively as $\mathbf{x}_c$ and $\mathbf{x}_s$ ($\mathbf{x}_c \cup \mathbf{x}_s = \mathbf{x}$, $|\mathbf{x}| = N$). Variables L, i_c^l and i_s^l are defined as in the previous section and i_{class} is the class column index. Listings 1.2, 1.3 and 1.4 report the MapReduce job, the mapper and reducer functions, respectively, while an illustrative overview of the data flow is reported in Fig. 2.

Listing 1.2: mRMR MapReduce job with conventional data encoding. L is the number of features to select, i_c^l and i_s^l are the sets at step l ($1 \leqslant l \leqslant L$) of candidate and selected features indices. i_{class} is the class column index. d_c is the set of categorical values of the class, and d_v is the (union) set of unique categorical values of all features.

```
$i_c^1 = \{1, ..., N\}$
$i_s^1 = \varnothing$
for $l = 1 \to L$
  broadcast $i_{class}$, $i_c^l$, $i_s^l$, $d_v$, $d_c$
  scores <- mapreduce(RDD, mapper, reducer)
  $k^*$ ← collectArgmax(scores)
  $i_c^{l+1} \leftarrow i_c^l \backslash k^*$
  $i_s^{l+1} \leftarrow i_s^l \cup k^*$
output $i_s^L$
```

Listing 1.3: mRMR MapReduce mapper function with conventional data encoding. i_c^l and i_s^l as the sets at step l ($1 \leqslant l \leqslant L$) of candidate and selected features indices. i_{class} is the class column index. d_c is the set of categorical values of the class, and d_v is the (union) set of unique categorical values of all features. e is a single observation fed as input to the mapper, k and j represent column indices and *contTable* is the function that creates a contingency table.

```
# broadcasted vars: $i_{class}$, $i_c^l$, $i_s^l$, $d_v$, $d_c$
mapper(·, $e$)
  for $k \in i_c^l$
    output ($k$, contTable($e_k$, $e_{i_{class}}$, $d_v$, $d_c$))
    for $j \in i_s^l$
      output ($k$, contTable($e_k$, $e_j$, $d_v$, $d_c$))
```

Listing 1.4: mRMR MapReduce reducer function with conventional data encoding. k is a column index and t is a collection of contingency tables. The *score* function process all the contingency tables associated with the column with index k and return the feature score.

```
reducer($k$, $t$)
  output($k$, score($t$))
```

For every $(e_k, e_{i_{class}})$ pair, the mapper task outputs a contingency table, *contTable*, with rows defined as the categorical values in d_c and columns defined as the categorical values in d_v. The element corresponding to row $e_{i_{class}}$ and column e_k is set to 1, while all the others are set to 0. Considering the dataset in Table 3, having one binary class column and four categorical features (with three possible values: *-2*, *0*, *2*), an example of emitted contingency table is reported in Table 4. In this example the class vector can only have two possible values: *0* and *1*; any feature can only have three possible values: *-2*, *0* and *2*. The input pair $(e_k, e_{i_{class}})$ is $(2, 0)$, therefore the element corresponding to row *0* and column *2* is set to 1, all the others are set to 0.

In case of (e_k, e_j) pair, the contingency table has both rows and columns defined by categorical values in d_v.

At the cost of managing discrete values only, the commutative and associative properties of the contingency table allows the use of the combiner function, thus minimizing the amount of data exchanged across the cluster during shuffling. While the single mapper outputs one or more contingency tables for each

#entry	class	features			
	c	$\mathbf{x}_1$	$\mathbf{x}_2$	$\mathbf{x}_3$	$\mathbf{x}_4$
1	0	2	0	0	-2
2	0	0	-2	2	0
3	0	0	2	0	-2
4	1	-2	0	0	0
...	...	...	...	...	...

Table 3: Example of dataset encoded with conventional layout.

candidate feature, those tables emitted by mappers executed on a given node can be locally reduced via the Combine step. Assuming that the first four entries in Table 3 are processed by four mappers in the same machine, Table 5 is the result of the combiner after the aggregation of four contingency tables of the $\mathbf{x}_1$ feature produced by the mappers. In this example, the combiner performs an element-wise sum of the contingency tables given as input.

		d_v		
		-2	**0**	**2**
d_c	**0**	0	0	1
	1	0	0	0

Table 4: Contingency table emitted by the mapper function as a result of processing the pair $(\mathbf{x}_1, c)$ of the first entry in Table 3.

		d_v		
		-2	**0**	**2**
d_c	**0**	0	2	1
	1	1	0	0

Table 5: Aggregated contingency table emitted by the combiner function as a result of processing the pair $(\mathbf{x}_1, c)$ of the first four entries in Table 3.

4.3 mRMR in MapReduce with alternative encoding

Data stored in alternative encoding has one column per observation and one row per feature. In this case, let us define the dataset as a RDD of N tuples $(k, \mathbf{x})$, where $\mathbf{x}$ is the feature vector and k is the row index ($k \in \{1, ..., N\}$). Feature and class values could be discrete and continuous as well. With respect to the design of mRMR in MapReduce with conventional encoding, a set of vectors are broadcasted across the cluster: $\mathbf{v}_{class}$ is the class vector, v_s is the collection of selected feature vectors and i_s is the collection of selected feature indices. Variable L is defined as in the previous section and *getEntry* function is a MapReduce task that retrieves the feature vector from the RDD, given a feature index. Listings 1.5 and 1.6 report the MapReduce job and the mapper function, respectively.

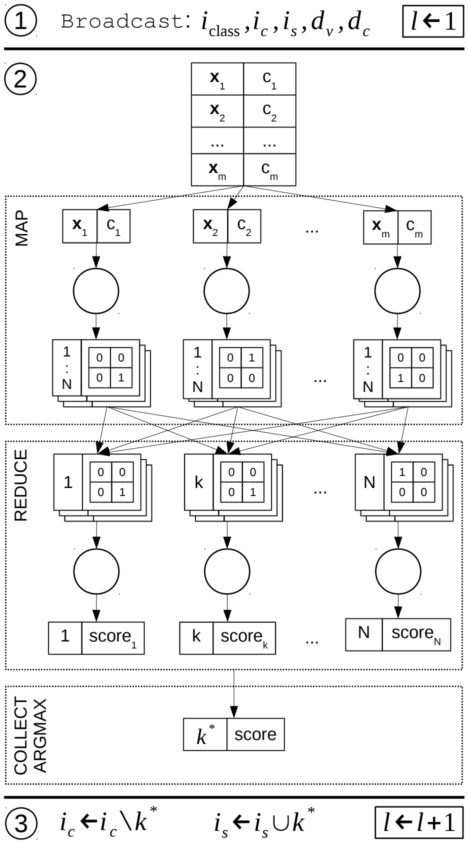


Fig. 2: Illustrative representation of the first iteration of a MapReduce job with discrete values using the conventional encoding. There are as many iterations as the number of features to select. At each iteration, each mapper outputs $N-l+1$ contingency tables for every combination of candidate features and class vector, and, from the second iteration, $(N - l + 1) * \left| i_s^l \right|$ contingency tables for every combination of candidate and selected features.

Listing 1.5: mRMR MapReduce job with alternative data encoding. *RDD* represents the distributed dataset and L is the number of features to select. $\mathbf{v}_{class}$ is the class vector, v_s is the collection of selected feature vectors and i_s is the collection of selected feature indices. The *getEntry* function retrieves the feature vector from the RDD, given a feature index.

```
$i_s^1 = \varnothing$
$v_s^1 = \varnothing$
for $l = 1 \to L$
  broadcast $\mathbf{v}_{class}$, $i_s^l$, $v_s^l$
  scores <- mapreduce(RDD, mapper)
  $k^* \leftarrow$ collectArgmax(scores)
  $v^*$ <- getEntry(RDD, $k^*$)
  $i_s^{l+1} \leftarrow i_s^l \cup k^*$
  $v_s^{l+1} \leftarrow v_s^l \cup v^*$
output $i_s^L$
```

Listing 1.6: mRMR MapReduce mapper function with alternative data encoding. $\mathbf{v}_{class}$ is the class vector, v_s is the collection of selected feature vectors. The tuple $(k, \mathbf{x})$ is composed by the feature vector, $\mathbf{x}$, and the feature index, k. The *score* function processes the vectors and returns the feature score.

```
# broadcasted variables: $\mathbf{v}_{class}$, $v_s^l$
mapper(·, ($k$, $\mathbf{x}$))
  score <- score($\mathbf{x}$, $\mathbf{v}_{class}$, $v_s^l$)
  output ($k$, score)
```

While in conventional encoding we used the contingency table as intermediate data structure, the design of mRMR in MapReduce with alternative encoding broadcasts at each iteration all required data for calculation to mappers. This design provides two main advantages: it deals with both discrete and continuous features as well, and the MapReduce job is composed by the Map step only. At the small cost of broadcasting some variables, all operations are executed locally. An illustrative overview of the data flow is reported in Fig. 3.

5 Results

The source code of mRMR implementation in MapReduce with both encodings is available as a Scala library, along with examples, on a public repository (https://github.com/creggian/spark-ifs).

We studied the scalability of the implementation of mRMR in MapReduce in both encodings in a cluster with the following specifications: Hadoop cluster of 10 nodes, where each node has Dual Xeon e5 2.4Ghz processor, 24 cores, 128GB RAM and 8TB hard disk; all nodes are connected with a 1Gb ethernet connection. Using Apache Spark v1.5.0, we submit jobs with 4GB of RAM for both the driver and the executors.

For the evaluation of mRMR implementations we used binary artificial datasets. We followed the principles of CorrAL dataset [32], in which four features determine the class value with the following formula: $c = (x_1 \wedge x_2) \vee (x_3 \wedge x_4)$, one is irrelevant and the last one is partially correlated with the class. In all our datasets, the class value (c) depends on the value of 8 features (Formula 2); the remainings are irrelevant.

$$c = ((x_1 \wedge x_2) \vee (x_3 \wedge x_4)) \wedge ((x_5 \wedge x_6) \vee (x_7 \wedge x_8)) \tag{2}$$

We assessed the scalability on the number of rows, the number of columns, the number of selected features, and the number of nodes. We used two kinds

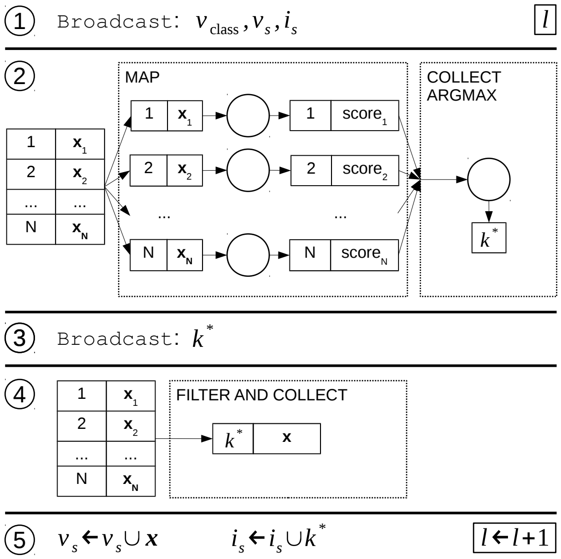


Fig. 3: Illustrative representation of a single iteration of a MapReduce job with alternative encoding. Steps 1-5 represent one iteration of the loop; there are as many iterations as the number of features to select.

of dependent variables: the relative execution time per executor and the computational gain. The former is the ratio between ET divided by ET of `1x`, the latter is the ratio between ET of 1-node and ET. We ran the tests three times to assess the variability of the results; in all figures the maximum, minimum and mean of these three values are connected through a solid vertical line.

5.1 Scalability across the number of rows

We tested the scalability on the number of rows by means of four datasets, each with 1000 columns and an increasing number of rows: 1M, 4M, 7M and 10M (M = millions). We configured the cluster and the algorithm to select 10 features in a distributed environment of 10 nodes (Fig. 4a).

5.2 Scalability across the number of columns

We assessed the scalability on the number of columns using four datasets, each with 1M rows and an increasing number of columns: 100, 400, 700 and 1000. We configured the cluster and the algorithm to select 10 features in a distributed environment of 10 nodes (Fig. 4b).

5.3 Scalability across the number of selected features

We investigated the scalability on the number of selected features using a dataset with 1M rows and 50k (k = thousands) columns. We parametrised the cluster to distribute the computation over 10 nodes, and the algorithm to select an increasing number of features: 1, 2, 4, 6, 10 (Fig. 4c).

5.4 Scalability across the number of nodes

We tested the scalability across the number of nodes using a dataset with 1M rows and 100 columns. We configure the algorithm to select 10 features, and the cluster to distribute the work over 1, 2, 5 and 10 nodes (Fig. 4d).

By comparing the linear scalability (dotted line) with the actual performances, results show that the scalability of mRMR in MapReduce is linear with respect to the number of rows, as expected by MapReduce design; superlinear with respect to the number of columns; sublinear with respect to the number of selected features and nodes, as expected by our iterative algorithm design and the increasing amount of data exchanged in the network with the increasing of nodes, respectively.

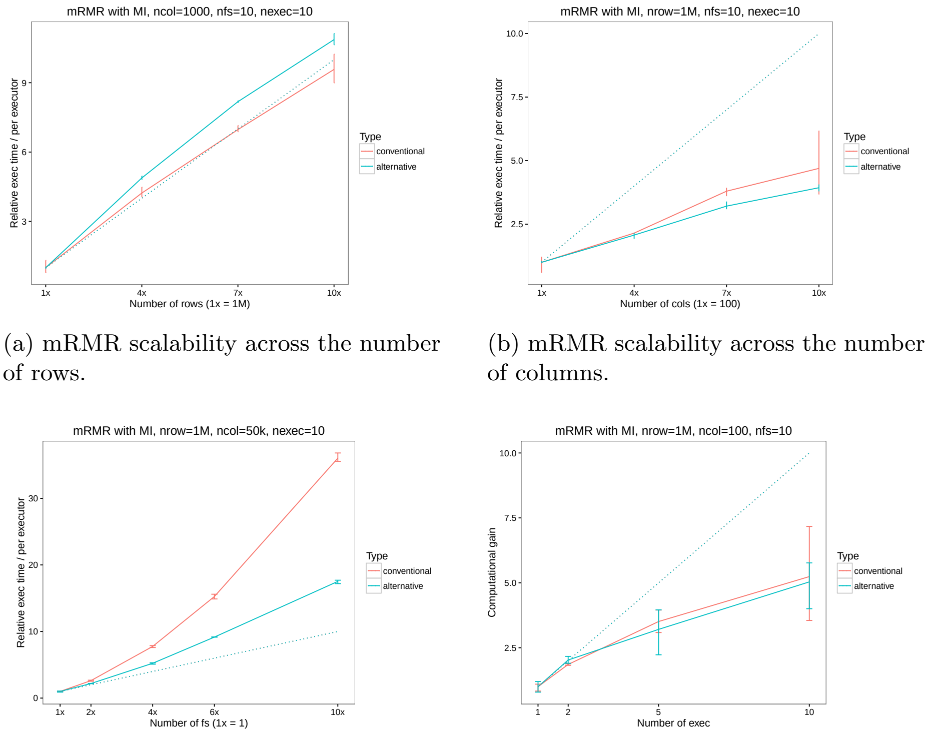
In studying mRMR with conventional and alternative layouts, we chose to use as independent variable the number of rows (columns) instead of the number of observation (features) for the following reason: while in the conventional layout we are able to scale across a very large number of rows, in the alternative layout we are strictly constraint by the amount of memory available in the mapper task to scale across the number of columns. In Figures 4a and 4b, we tested up to 10 million rows and up to one thousand columns, because very high-dimensional S/W tables raises memory errors in the cluster. Hence, even though we show the relative execution time, it would be incorrect to plot performances by increasing the number of observation (features).

The absolute execution time of mRMR MapReduce jobs with alternative encoding is generally 4-6x faster than the respective jobs with conventional encoding.

6 Conclusion

In this work we investigated the design and scalability of mRMR algorithm in MapReduce. We proposed two implementations depending on the data layout, which can be easily interfaced in order to customize the feature score function. Despite Hadoop limitations for handling data with a large number of columns, the alternative data layout is a solution to store data from a phenomenon that has a very large number of features. In both conventional and alternative data layouts, we studied the scalability of mRMR in different settings: the number of rows, columns, selected features and nodes. Our experimental results illustrated the scalability of the proposed MapReduce implementations in a large variety of settings.

In the future, we intend to extend the approach with continuous features, and to provide an additional portfolio of built-in feature selection algorithms that work with the alternative encoding. While we design and implement known FSA



(a) mRMR scalability across the number of rows.

(b) mRMR scalability across the number of columns.

(c) mRMR scalability across the number of selected features.

(d) mRMR scalability across the number of nodes.

Fig. 4: Scalability performance of the mRMR distributed algorithm across number of rows, columns, selected features and nodes.

for MapReduce, novel algorithms that directly take advantage of the distributed nature of the data will be investigated as well. We also plan to extend the scalability study to classification and network inference tasks.

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