

# Best Agglomerative Ranked Subset for Feature Selection

Roberto Ruiz<sup>1\*</sup>, José C. Riquelme<sup>2</sup>, and Jesús S. Aguilar–Ruiz<sup>1</sup>

<sup>1</sup> Pablo de Olavide University, School of Engineering,  
Ctra. Utrera km. 1, 41013 Seville, Spain  
`{robertoruiz,aguilar}@upo.es`

<sup>2</sup> University of Seville, Department of Computer Science,  
Avda. Reina Mercedes s/n, 41012 Seville, Spain  
`riquelme@us.es`

**Abstract.** The enormous increase of the size in databases makes finding an optimal subset of features extremely difficult. In this paper, a new feature selection method is proposed that will allow any subset evaluator -including the wrapper evaluation method- to be used to find a group of features that will allow a distinction to be made between the different possible classes. The method, *BARS* (Best Agglomerative Ranked Subset), is based on the idea of relevance and redundancy, in the sense that a ranked feature (or set) is more relevant if it adds information when it is included in the final subset of selected features. This heuristic method reduces dimensionality drastically and leads to improvements in the accuracy, in comparison to a complete set and as opposed to other feature selection algorithms.

**Key words:** Classification, Feature Selection, Feature Ranking

## 1 Introduction

A feature selection algorithm combines two processes: one is the search for an optimum and the other is an evaluation of sets of features. The evaluation measure estimates in the latter process will guide the search. Therefore, a feature selection algorithm is simply a search algorithm that should optimize a measure that shows how good a subset of features is (or an individual feature). There are many possible combinations of search methods and feature evaluation measures [1]. However, search methods can be too costly in high-dimensional databases, particularly if a learning algorithm is applied as an evaluation criterion.

There are two ways to group feature selection algorithms, depending on the chosen evaluation measure: one, according to the model used (filter or wrapper) and two, according to the way in which the features are evaluated (individually or by subsets).

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\* Corresponding author.

The filter model evaluates features according to heuristics based on overall data characteristics, notwithstanding the classification method applied, whereas the wrapper uses the behaviour of a classification algorithm as a feature evaluation criterion. The wrapper model chooses the features that show the best classification and help to improve a learning algorithm’s behaviour. The downside is that its computational cost [2, 3] is higher than the filter model. A key factor in wrapper methods is the way in which a search is made in the feature subset space [4]. It appears next to such search strategies as sequential greedy search, best-first search and genetic algorithms [1]. Most of them have a temporal  $O(n^2)$  complexity and cannot be applied in databases with tens of thousands of features.

On the other hand, FR (Feature Ranking) methods evaluates features individually, whereas FSS (Feature Subset Selection) evaluates the benefits of each candidate subset. In the FR algorithm category, the first  $k$  features will make up the final subset. This is a good approach for high-dimensional databases, given their linear cost in relation to the number of features. However, in algorithms capable of feature subset selection, some sort of search strategy is used to generate the candidate subsets. There are many different search strategies: exhaustive, heuristic and random, combined with various types of measures that make up a large number of algorithms. The temporal complexity is exponential in relation to the dimensionality of the data in an exhaustive search and quadratic in a heuristic search. In a random search, the complexity may be linear to the number of iterations [5], but experience shows that the number of iterations needed to find an optimal subset is at least quadratic in relation to the number of features [6].

The aim of this paper is to study and propose a feature selection method that can be applied to high-dimensional databases in a supervised learning framework, concretely for classification purposes. Two classification learning algorithms will be used to compare the effects of feature selection: one probabilistic (naïve Bayes) and a second one based on decision trees (C4.5).

The paper is structured as follows: after an introduction on the particularities of feature subset selection in large databases, a review will be made of the related literature and the general concepts of relevance and redundancy. *BARS* algorithm is described in Section 3, and the results obtained are shown in Section 4. Finally, Section 5 gives some of the more interesting conclusions.

## 2 Related work

The limitations of both approaches, FR and FSS, clearly suggest the need for a hybrid model. Lately, a new framework [7] for feature selection is used which includes several of the methods given above, as well as the concepts of feature relevance and redundancy. There are many definitions of relevance. We have chosen the one offered by Caruana and Freitag [8] that is considered especially suited to obtain a predictive feature subset. With respect to the redundancy, it is usually expressed in terms of a correlation between features. Between pairs

of variables we can distinguish linear and non-linear correlation. However, it is not so clear how to know when a feature is correlated with a set of features. Koller and Sahami [9] apply a technique based on cross-entropy (KL-distance, Kullback & Leibler [10]), called *Markov blanket* filtering, to eliminate redundant features.

In databases with a large number of features, the selection process usually is divided into two stages: In stage one, features are evaluated individually, providing a ranking based on a filtering criterion. In stage two, a feature subset evaluator (filter or wrapper) is applied to a certain number of features in the previous ranking (the ones that pass a threshold, or the first  $k$ ), following a search strategy. Xing et al. [11], Yu and Liu [7], Ding and Peng [12] and Guyon et al. [13] are among the most cited works that follow this path. Another work employed a linear sequential search over a ranking [14], and any type of criteria could be used in ranking and in generating a feature subset.

When databases with a lot of features are ranked, there are normally many features with similar scores. The frequent selection of redundant features in the final subset is often criticized. However, according to Guyon and Elisefi [15], taking into account presumably redundant features can reduce noise and, therefore, a better separation between the various classes can be obtained. Moreover, a very high correlation (in absolute value) between variables does not mean that they do not complement each other. Consequently, the idea of redundancy in this paper is not based on the measure of correlation between two features. Rather, it is based on any subset evaluation criterion, which may be a filter or wrapper approach. In this sense, a feature (or set) is selected if additional information is obtained when it is added to the previously selected feature subset, and rejected in the opposite case because the information provided is already contained (redundant) in the previous subset.

### 3 Agglomerative search for feature subset selection

In this work, a new method is proposed. It is called agglomerative due to the way it constructs the final subset of selected features. The method begins by generating a ranking. Then, pairs of features are obtained with the ranking's first features, in combination with each one of the remaining features on the list. The pairs of features are ranked according to the value of the evaluation, and the process is repeated, that is, the subsets made up by the first sets on the new list are compared with the rest of the sets. The process ends when only one feature subset is left, or when combining the subsets no longer causes an improvement.

Our approach uses a fast search through the attribute space and any subset evaluation measure, classifier approach included, can be embedded into it as evaluator. Therefore, a feature subset evaluator, named *SubEvaluator*, is used to select a small group of features. Thus, given a *SubEvaluator* and given a feature subset  $X$ , a search is made in the  $\mathcal{P}(X)$  space for the feature subset with the best evaluation result, using the value to compare the behaviour of the *SubEvaluator*

on the test subset. Before continuing, we shall establish the concepts of accuracy and measure value:

The result of dividing the number of correct classifications by the total number of samples examined is wide known as accuracy ( $\Gamma$ ). Then, given a set tagged  $E$  of  $m$  instances  $(\bar{x}_j, y_j)$ , where  $j = 1, \dots, m$ , each one composed of  $n$  input values  $x_{j,i}$  with  $(i = 1, \dots, n)$  and one output  $y_j$ , and given the classifier  $L$ , in the following expression, if  $L(\bar{x}_j) = y_j$  (example well classified) then 1 is counted, and 0 in any other case.

$$\Gamma(E, L) = \frac{1}{m} \sum_{j=1}^m (L(\bar{x}_j) = y_j)$$

Considering that, in this paper, the selection algorithms are subsequently applied to a classification task, the definition of accuracy given for the total set of data, applied to a feature subset  $S$ , would be:

$$\Gamma(E/S, L) = \frac{1}{m} \sum_{j=1}^m (L(S(\bar{x}_j)) = y_j)$$

Therefore,  $\Gamma(E/S, L)$  is the accuracy, applying classifier  $L$  to the database with the features that belong to subset  $S$ . In addition to a wrapper measure to evaluate a feature subset, we can use a filter type measure that also returns a real value on the goodness of the said subset. This value, which we will call a measure value, can be defined as:

**Definition 1 (Measure value)** *Let  $E$  be a set of tagged data;  $S$  a feature subset of  $E$  data; the  $\Upsilon(E/S, \mathcal{L})$  measure value is the result of applying the evaluator type subset filter  $\mathcal{L}$  considering only the  $S$  data subset.*

Therefore, if  $\mathcal{L}$  is a subset evaluator, we can use two similar expressions: on the one hand  $\Gamma(E/S, L)$ , which is valid for evaluating a subset by means of a wrapper measure; on the other hand, the expression  $\Upsilon(E/S, \mathcal{L})$ , that evaluates the  $S$  subset by means of an  $\mathcal{L}$  filter.

To make it easier, and to unify the notation, hereinafter the evaluation of a feature subset  $S$  will be annotated by  $\Gamma(E/S, L)$  assuming a dual role (wrapper or filter).

Let  $\Psi_1 = \{A_1^1, A_2^1, \dots, A_n^1\}$  be the initial list of candidate subsets, where  $A_i^1 = \{X_i\}$ , that is, each subset on the list has a feature. Let  $\Psi_1^k$  and  $\Psi_1^\epsilon$  be two ranked sequences obtained from the set  $\Psi_1$ :

$$\Psi_1^k = \langle A_{(1)}^1, \dots, A_{(k)}^1 \rangle$$

the  $k$  first subsets of  $\Psi_1$  ranked by  $L$  descendingly and

$$\Psi_1^\epsilon = \langle A_{(1)}^1, \dots, A_{(\epsilon)}^1 \rangle$$

the first  $\epsilon$  of  $\Psi_1$  ranked likewise by  $L$ ,  $k \leq \epsilon \leq n$ , and  $n$  being the total number of features.

$T_1$  will be the result of applying the  $L$  subset evaluator to the subset best placed on the  $\Psi_1^k$  list, in this case, the most valued feature:

$$T_1 = \Gamma(E/A_{(1)}^1, L)$$

As indicated above,  $\Gamma$  encompasses the accuracy value of a  $L$  wrapper as well as the measure value obtained with a filter type measure  $\mathcal{T}(E/A_{(1)}^1, \mathcal{L})$ .

Sets based on the two above ranked sequences ( $\Psi_1^k$  and  $\Psi_1^\epsilon$ ) are constructed below in such a way that each set of the first sequence is joined to each set of the second sequence. Of the new sets generated, we are only interested in the ones that improve the best result obtained with the subsets of  $\Psi_1$ , that is, the ones with a more favourable evaluation than  $T_1$ . We will call this new set  $\Psi_2$ :

$$\Psi_2 = \{A_i^2 | A_i^2 = A_{(j)}^1 \cup A_{(l)}^1\}$$

$\forall j : 1..k$  and  $\forall l : 1..\epsilon$  with  $A_{(j)}^1 \in \Psi_1^k$  and  $A_{(l)}^1 \in \Psi_1^\epsilon$  and with  $\Gamma(E/A_i^2, L) > T_1$  }.

Likewise,  $\Psi_2^k$  and  $\Psi_2^\epsilon$  will be two ranked sequences obtained from the  $\Psi_2$  set. In general, the list of solutions  $\Psi_p$  is defined as the candidate feature subset. It is made up of each subset by the joining of two subsets from the above list of solutions, and it obtained a more favourable evaluation than the best subset on that list. That is,

$$\Psi_p = \{A_i^p | A_i^p = A_{(j)}^{p-1} \cup A_{(l)}^{p-1}\} \wedge \Gamma(E/A_i^p, L) > T_{p-1}$$

The process continues until no new subsets are generated, or until the ones generated do not exceed the value of the goodness of the best subset on the above list of solutions (let  $\Psi_p$  be  $\emptyset$ ). Therefore, the solution is established as  $S = A_{(1)}^{p-1}$ , the most relevant subset on the last list with available solutions.

Unlike the conventional forward sequential search, where the best feature, best pair, best set of three and so on are obtained until no improvement occurs, the *BARS* method makes a search at a lower cost because it covers a smaller part of the features space. Furthermore, the search path developed by *BARS* is done around the most relevant subsets at each given moment, choosing the best  $k$  subsets in each cycle of the algorithm, and expanding the search to other relevance subsets in the ranking (ranking percentage  $\epsilon$ ). This way we can avoid getting caught in local minima. This approach provides the possibility of efficiently applying any evaluation measure, wrapper models included, in high-dimensional domains. The final subset is obviously not the optimum, but it is unfeasible to search for every possible subset of attributes through the search space.

### 3.1 Algorithm

The process followed until the final subset is obtained is (see algorithm 1): Step one generates a feature ranking (line 1) ranked from best to worst according

**Algorithm 1** *BARS–Best Agglomerative Ranked Subset.*


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**Require:**  $\mathbf{E}$ –data set,  $\mathbf{U}$ –ranking criterion,  $\mathbf{L}$ –*SubEvaluator*,  $k$ –No. of initial sets in the ranking,  $\epsilon$ –limits the number of subsets in the ranking.

**Ensure:** *BestSub*–feature subset

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1:  $R \leftarrow \text{generateRanking}(\mathbf{U}, \mathbf{E})$ 
2:  $p \leftarrow 1$ 
3:  $\text{SolutionsList}\Psi_p \leftarrow \emptyset$ 
4: for  $i = 1$  until  $n$  do
5:    $\text{SolutionsList}\Psi_p \leftarrow \text{SolutionsList}\Psi_p \cup \{A_i^1\}$  ( $A_i^1 = \{X_i\} \wedge X_i \in R$ )
6: end for
7: while  $\#\text{SolutionsList}\Psi_p > 1$  do
8:    $T \leftarrow \Gamma(\mathbf{E}/A_1^p, \mathbf{L})$ 
9:    $p \leftarrow p + 1$ 
10:   $\text{SolutionsList}\Psi_p \leftarrow \emptyset$ 
11:   $i \leftarrow 1$ 
12:  for  $j = 1$  until  $k$  do
13:    for  $l = j + 1$  until  $\epsilon$  do
14:       $A_i^p \leftarrow A_{(j)}^{p-1} \cup A_{(l)}^{p-1}$ 
15:      if  $\Gamma(\mathbf{E}/A_i^p, \mathbf{L}) > T$  then
16:         $\text{SolutionsList}\Psi_p \leftarrow \text{SolutionsList}\Psi_p \cup A_i^p$ 
17:         $i \leftarrow i + 1$ 
18:      end if
19:    end for
20:  end for
21:   $\text{rank SolutionsList}\Psi_p$  by  $\Gamma(\mathbf{E}/A_i^p, \mathbf{L})$ 
22: end while
23:  $\text{BestSub} \leftarrow A_1^{p-1}$ 

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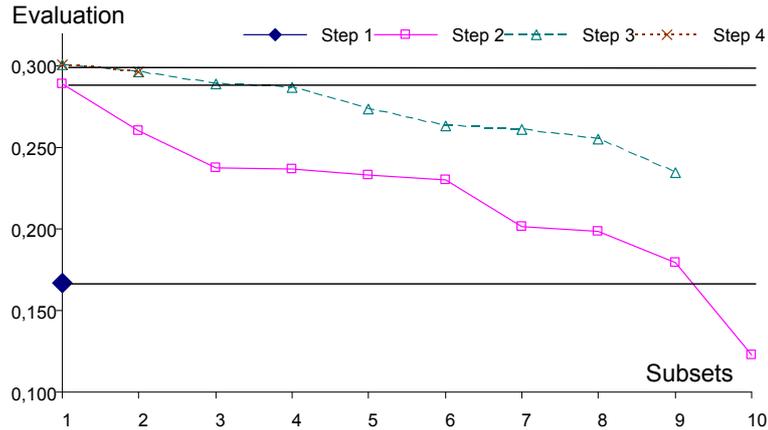
to an evaluation measure ( $\mathbf{U}$ ). Next, a list of solutions is generated (line 2-6,  $\text{SolutionsList}\Psi_p$ ), in such a way that a solution for each individual feature is created and the same ranking order is maintained. The steps required to make an agglomerative search is shown on lines 7-22. At the end, the algorithm returns the best positioned feature subset of all the subsets evaluated.

The agglomerative search consists in making a subset of relevant features by joining subsets with a lower number of features.

Each iteration of the repetitive **while** structure generates a new list of solutions from the previous structure. Each candidate set, made by joining two sets from the previous list of solutions, will become part of the next list of solutions if, when the subset evaluator  $\mathbf{L}$  is applied to it, it gives back a higher measure value ( $T$ ) than the one obtained with the best (or first) subset from the previous list of solutions ( $T$ ). To prevent the algorithm from having a prohibitive time cost, new sets of features are generated by joining the first sets to the remaining previous list of solutions. That is, the first set on the list is joined to the second set, next the first set is joined to the third set, and so on until the end of the list. Next, the second set of the list is joined to the third set, the second set and the fourth set, and so on until the last set on the list. This process of combining

a set of features with the rest of the sets on the list is carried out with the best  $k$  feature sets from the previous list of solutions (line 12).

In line 13, the input parameter  $\epsilon$  can limit the number of new subsets. In data sets with an extremely high dimensionality, or when a high computational cost *SubEvaluator* is used,  $\epsilon$  can be fixed to a percentage of the previous solutions number.



**Fig. 1.** Example of the reduction process followed by *BARS*. The horizontal lines represent the limits at the end of each heuristic stage.

Figure 1 shows an example of the feature selection process with *BARS*, using the non-linear correlation *CFS* (Correlation-based Feature Selection algorithm [16]) as a subset evaluation measure (L). The figure represents the evaluation of the feature subsets in the different algorithm iterations. The numbers that can be seen on the abscissa axis represent the order of the subset in the corresponding ranking, and the ordinate axis shows the evaluation obtained for each subset. The horizontal lines set the limit at the end of each stage of the algorithm.

Generating sets that were already evaluated occurs very frequently in the process of combining two subsets. Therefore, the evaluated subsets will be controlled to prevent the evaluation from being repeated.

## 4 Experiments and results

The aim of this section is to evaluate our approach in terms of classification accuracy, degree of dimensionality and speed in selecting features, in order to see how good *BARS* is in situations where there is a large number of features and instances.

**Table 1.** UCI data sets. ACRON-acronym. ATTS-number of attributes. INST-number of instances.

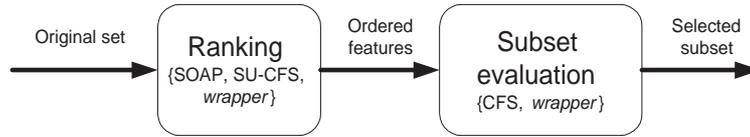
	DATA	ACRON.	ATTS.	INST.	CLASS
	ADS	ADS	1558	3279	2
	ARRHYTHMIA	ARR	279	452	16
	HYPOTHYROID	HYP	29	3772	4
	ISOLET	ISO	617	1559	26
	KR VS KP	KRV	36	3196	2
	LETTER	LET	16	20000	26
	MULTI FEAT.	MUL	649	2000	10
	MUSHROOM	MUS	22	8124	2
	MUSK	MUK	166	6598	2
	SICK	SIC	29	3772	2
	SPLICE	SPL	60	3190	3
	WAVEFORM	WAV	40	5000	3

**Table 2.** NIPS data sets. ACRON-acronym. ATTS-number of attributes. %RAN-percentage of random Atts.

	DATA	ACRON.	ATTS.	INST.	%RAN.
	ARCENE	ARC	10000	100	30
	DEXTER	DEX	20000	300	50
	DOROTHEA	DOR	100000	800	50
	GISETTE	GIS	5000	6000	30
	MADELON	MAD	500	2000	96

The comparison was performed with two representative groups of data sets: Twelve data sets were selected from the UCI Repository (Table 1) and five from the NIPS 2003 feature selection benchmark [17]. In this group (Table 2), the data sets were chosen to span a variety of domains (cancer prediction from mass-spectrometry data, handwritten digit recognition, text classification, and prediction of molecular activity). One data set is artificial. The input variables are continuous or binary, sparse or dense. In this second group all data sets are two-class classification problems. The full characteristics of all the data sets are summarized in Tables 1 and 2. We chose two different learning algorithms, C4.5 and Naïve Bayes, to evaluate the accuracy on selected features for each feature selection algorithm.

Figure 2 can be considered to illustrate the two blocks that always make up a *BARS* algorithm. Therefore, this selection algorithm needs a ranking and a feature subset measure. Several versions of *BARS* selection algorithms could be made by combining the criteria for each group of measures (individual and of subsets). Whenever the *BARS* algorithm appears, the criteria for generating the ranking is given, as well as how feature subset quality was evaluated in



**Fig. 2.** Parts of a *BARS* selection algorithm.

the selection process. To clarify the components that *BARS* uses in each case as much as possible, a subscript is put before *BA* that indicates the ranking method used, and a superscript is placed after it to indicate the SubEvaluator. In the experiments made for *BARS*, the same evaluation measure was used to prepare the ranking as the one used in the second part of the algorithm employed in the feature subset search. Two subset evaluation measures are used, one for each type of approach (wrapper and filter-*CFS*). For instance,  ${}_{CFS}BA^{CF}$  shows that *CFS* will be used as an individual measure in the first part and *CFS* as a subset in the second part, and  ${}_{CFS}BA^{WR}$  shows that *NB* or *C4* classifier will be used as a subset evaluator in the second part.

In the tests, *BARS* generated subsets from the three best subsets in the solutions list it used at each stage, limiting the range to 50% of the solutions list in wrapper type approaches and going to the end in the filter approaches. That is,  $k = 3$  and  $\epsilon = 50\%$  and  $100\%$ , respectively.

Due to the high dimensionality of data, we limited our comparison to sequential forward (*SF*) techniques, fast correlation-based filter (*FCBF*) algorithm [7] and the incremental ranked (*BI*) algorithm [14]. We chose two representative subset evaluation measures in combination with *SF* search engine. One, denoted by  $SF_{WR}$ , uses a target learning algorithm (*NB* or *C4*) to estimate the worth of feature subsets; the other, denoted by  $SF^{CF}$ , is a subset search algorithm which exploit sequential forward search and use correlation measures (*CFS*, Correlation-based Feature Selection algorithm [16]) to guide the search. *BI* use the same nomenclature as *BARS*.

Tables 3, 4, 5 and 6 show the results obtained with *NB* and *C4* classifiers. By columns: the results obtained with *BARS*, *BI* and *SF* algorithms using the wrapper as a subset evaluator and using *CFS*; *FCBF* algorithm; and the results obtained with the complete database. The columns headed by *AC* and  $AT\%$  show the success rate and the reduction percentage respectively. On *NIPS* data, the reduction percentage is too low to be comparable, therefore the number of features ( $AT^\#$ ) is shown. In each case, the results were obtained by calculating the mean of five executions of two crossed validations ( $5 \times 2CV$ ). Two reductions were made in each execution, one for each training set, to prevent the selection algorithm from being over-adjusted to the data used. A paired t-Student test was applied to evaluate whether the difference between the wrapper approach of the proposed algorithm and the other results was statistically significant at a confidence level of 0.05.

**Table 3.** Results obtained with NB for each feature selection algorithm on UCI big Data. AC-accuracy; At% - percentage of attributes retained. The symbols  $\circ$  and  $\bullet$  respectively identify statistically significant (at 0.05 level) wins or losses over the second column ( ${}_{NB}BA^{NB}$ ).

DATA	${}_{NB}BA^{NB}$		${}_{NB}BI^{NB}$		$SF^{NB}$		${}_{CF}BA^{CF}$		${}_{CF}BI^{CF}$		$SF^{CF}$		FCBF		ORIG.
	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac
ADS	95.80	0.5	95.42	0.7	95.83	1.1	94.61 $\bullet$	0.3	95.38	0.4	95.81	0.6	95.64	5.3	96.38
ARR	68.94	2.3	68.01	5.5	67.70	3.0	67.30	4.1	66.5	4.1	68.05	6.2	63.98	2.9	60.13
HYP	94.92	10.3	95.10	15.9	95.32	29.3	94.15 $\bullet$	3.4	94.15 $\bullet$	3.4	94.15 $\bullet$	3.4	94.90	18.3	95.32
ISO	77.41	3.4	83.30 $\circ$	11.1	82.28	4.7	66.95 $\bullet$	3.8	77.61	11.1	80.79	15.4	74.62	3.7	80.42
KRV	94.09	11.4	94.27	13.9	94.32 $\circ$	14.4	84.41	7.2	90.43 $\bullet$	8.3	90.43 $\bullet$	8.3	92.50	18.1	87.50 $\bullet$
LET	55.74	39.4	65.67 $\circ$	68.8	65.67 $\circ$	72.5	64.28 $\circ$	56.3	64.28 $\circ$	56.3	64.28 $\circ$	56.3	65.06 $\circ$	64.4	63.97 $\circ$
MUL	96.80	2.1	97.21	3.4	96.87	2.4	96.55	3.9	97.04	4.3	96.72	13.9	96.19	18.7	94.37 $\bullet$
MUS	98.68	7.3	98.78	9.5	99.01	13.6	98.52	4.5	98.52	4.5	98.52	4.5	98.52	16.4	95.10 $\bullet$
MUK	84.60	1.0	84.59	0.6	84.59	0.0	74.54	7.5	79.94	3.9	69.78 $\bullet$	9.8	72.29	1.7	83.56
SIC	93.88	3.4	94.55	8.3	93.88	0.0	93.89	3.4	93.89	3.4	93.89	3.4	96.25 $\circ$	16.6	92.41
SPL	94.65	15.3	94.85	21.8	94.91	24.7	93.63 $\bullet$	10.0	93.63 $\bullet$	10.0	93.60 $\bullet$	10.2	95.49	36.3	95.26
WAV	80.38	21.3	80.85	30.5	81.55	32.3	80.34	35.3	81.01	31.0	80.12	37.0	78.42	15.3	80.02
Av.	86.32	9.8	90.36	15.8	89.19	16.5	85.08	11.6	86.24	11.7	87.70	14.1	86.26	18.1	85.44

**Table 4.** Similar to Table 3 with C4 classifier.

DATA	${}_{C4}BA^{C4}$		${}_{C4}BI^{C4}$		$SF^{C4}$		${}_{CF}BA^{CF}$		${}_{CF}BI^{CF}$		$SF^{CF}$		FCBF		ORIG.
	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac	At%	Ac
ADS	96.42	0.5	96.55	0.5	96.85	0.8	95.30	0.3	96.43	0.4	96.39	0.6	95.85	5.3	96.46
ARR	67.92	2.0	68.01	2.4	67.39	3.1	66.46	4.1	66.42	4.1	67.04	6.2	64.87	2.9	64.29
HYP	98.90	10.7	99.07	14.5	99.30	20.3	96.56 $\bullet$	3.4	96.56 $\bullet$	3.4	96.56 $\bullet$	3.4	98.03	18.3	99.36
ISO	68.15	2.7	69.43	3.6	N/A		67.29	3.8	72.68	11.1	71.94	15.4	66.63	3.7	73.38
KRV	94.09	11.1	95.11	17.2	94.26	13.6	84.41	7.2	90.43 $\bullet$	8.3	90.43 $\bullet$	8.3	94.07	18.1	99.07 $\circ$
LET	80.50	45.0	84.99	68.8	85.17	63.1	84.21	56.3	84.21	56.3	84.21	56.3	84.84	64.4	84.45
MUL	93.74	1.5	92.42	3.2	93.11	2.1	92.77	3.9	93.17	4.3	93.12	13.9	92.29	18.7	92.74
MUS	99.41	9.1	99.91 $\circ$	18.6	100.00 $\circ$	22.3	98.52 $\bullet$	4.5	98.52 $\bullet$	4.5	98.52 $\bullet$	4.5	98.84	16.4	100.00 $\circ$
MUK	95.71	4.9	95.43	5.8	N/A		94.44	7.5	94.06 $\bullet$	3.9	94.60	9.8	91.19 $\bullet$	1.7	95.12
SIC	96.33	7.2	98.28 $\circ$	20.3	98.19 $\circ$	19.0	96.33	3.4	96.33	3.4	96.33	3.4	97.50 $\circ$	16.6	98.42 $\circ$
SPL	92.73	12.2	93.05	16.3	93.04	18.3	92.54	10.0	92.54	10.0	92.61	10.2	93.17	36.3	92.92
WAV	75.93	17.5	76.20	24.0	75.44	19.8	76.65	35.3	76.46	31.0	76.56	37.0	74.52	15.3	74.75
Av.	88.32	10.4	87.03	16.3	88.07	18.2	85.04	11.6	84.78	11.7	85.87	14.1	86.31	18.1	85.94

As it is possible to observe in Tables 3 and 4 obtained on data from Table 1, chosen subsets by  $BARS$  are considerably smaller than the other compared techniques and drastically less than the original set. With  $NB$  classifier, the reduction percentage of  $BARS$  was 9.8%, while the other methods obtained 15.8% ${}_{NB}BI^{NB}$ , 16.5% ${}_{SF}^{NB}$ , 14.1% ${}_{SF}^{CF}$  and 18.1% ${}_{FCBF}$ , although with a light loss of precision. With  $C4.5$  classifier the differences are greater  $BARS$  was 10.4%, while the other methods obtained 16.3% ${}_{C4}BI^{C4}$ , 18.2% ${}_{SF}^{NB}$ , 14.1% ${}_{SF}^{CF}$  and 18.1% ${}_{FCBF}$ , without significant lost of accuracy.

Notice that in two cases with  $C4$  classifier (ISO and MUK)  $SF_{WR}$  did not report any results after three weeks running, therefore, there are not selected attributes nor success rates. Although it is supposed that the missed results

**Table 5.** Results obtained with NB for each feature selection algorithm on NIPS Data. AC-accuracy; AT<sup>#</sup>- number of attributes retained. The symbols  $\circ$  and  $\bullet$  respectively identify statistically significant (at 0.05 level) wins or losses over the second column ( $_{NB}BA^{NB}$ ).

DATA	$_{NB}BA^{NB}$		$_{NB}BI^{NB}$		$SF^{NB}$		$_{CF}BA^{CF}$		$_{CF}BI^{CF}$		$SF^{CF}$		FCBF		ORIG.
	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC
ARC	65.40	4.6	64.60	15.3	60.60	3.8	66.00	22.5	63.20	39.2	60.20	42.6	61.20	35.2	65.40
DEX	79.13	15.3	81.33	30.2	75.33	13.2	80.67	7.5	82.47	11.3	87.73	35.5	85.07	25.1	86.47 $\circ$
DOR	93.25	2.3	93.23	10.5	N/A		93.25	2.1	93.80	11.9	N/A		92.38	75.3	90.68
GIS	91.17	9.2	92.66	35.3	93.55 $\circ$	24.2	87.26 $\bullet$	8.6	90.83	30.2	92.64	62.2	87.58	31.2	91.88
MAD	60.99	4.9	59.00	11.8	60.12	5.8	60.37	6.3	60.56	5.8	60.17	9.9	58.20	4.7	58.24

**Table 6.** Similar to Table 5 with C4 classifier.

DATA	$_{C4}BA^{C4}$		$_{C4}BI^{C4}$		$SF^{C4}$		$_{CF}BA^{CF}$		$_{CF}BI^{CF}$		$SF^{CF}$		FCBF		ORIG.
	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC	AT <sup>#</sup>	AC
ARC	63.60	2.7	65.80	7.9	62.40	3.7	61.60	22.5	59.00	39.2	56.60	42.6	58.80	35.2	57.00
DEX	78.30	5.8	80.27	18.9	90.47	8.7	80.40	7.5	81.47	11.3	80.13	35.5	79.00	25.1	73.80
DOR	93.20	2.6	92.13	7.2	N/A		93.20	2.1	91.63	11.9	N/A		90.33	75.3	88.73
GIS	93.00	11.5	93.29	26.9	N/A		89.60 $\bullet$	8.6	90.92	30.2	93.07	62.2	90.99 $\bullet$	31.2	92.68
MAD	68.40	4.3	73.02	17.0	72.99	12.4	69.30	6.3	69.77	5.8	69.29	9.9	61.11	4.7	57.73 $\bullet$

would favor to *BARS*, since *SF* has not finished because of the inclusion of many attributes.

Actually, *BARS* demonstrates its relevance on very high-dimensional data as it can be seen in Table 5 and 6. It is possible to be observed that in comparison with *FCBF* the number of selected attributes is drastically smaller, without loss of precision in the classification.

In regards to the time cost of the algorithms, it should be considered that the computation times resulting from the filter approaches are not considerable in comparison to the ones used for the wrapper approaches. In this case, *BARS* and *BI* are similar, however, the time savings of *BARS* became more obvious when the computer-load necessities of the mining algorithm increased. In many cases the time savings were 7 times less, and we must take into account that *SF* did not report any results on several data sets.

## 5 Conclusions

A new feature selection method has been presented that allows any subset evaluator -including the wrapper evaluation model- to be used to find a good set of features for classification. Our technique *BARS* chooses a very small subset of features from the original set with similar predictive performance to other methods. For massive data sets, wrapper-based methods might be computationally unfeasible, so *BARS* turns out a fast technique that provides good performance in prediction accuracy.

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