

# Experimental Identification of Hard Data Sets for Classification and Feature Selection Methods with Insights on Method Selection

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## ABSTRACT

The paper reports an experimentally identified list of benchmark data sets that are hard for representative classification and feature selection methods. This was done after systematically evaluating a total of 48 combinations of methods, involving eight state-of-the-art classification algorithms and six commonly used feature selection methods, on 129 data sets from the UCI repository (some data sets with known high classification accuracy were excluded). In this paper, a data set for classification is called hard if none of the 48 combinations can achieve an AUC over 0.8 and none of them can achieve an F-Measure value over 0.8; it is called easy otherwise. A total of **15** out of the 129 data sets were found to be hard in that sense. This paper also compares the performance of different methods, and it produces rankings of classification methods, separately on the hard data sets and on the easy data sets. This paper is the first to rank methods separately for hard data sets and for easy data sets. It turns out that the classifier rankings resulting from our experiments are somehow different from those in the literature and hence they offer new insights on method selection. It should be noted that the Random Forest method remains to be the best in all groups of experiments.

**Keywords:** classification methods, feature selection methods, hard data sets, method ranking, performance comparison, classification, mining methods and algorithms

## 1 Introduction

When faced with a classification job, an analyst will often want to select the best methods for the application; this can be a daunting task since there are a large number of methods available. Users will need insights, such as rankings of the methods, to guide them to make the best selection, and to go through the selection process in an easy-to-handle manner. Several studies on the experimental evaluation of various methods for classification have been reported recently [1, 2]. Reference [1] is a main representative of such studies, which used 121 data sets to evaluate 179 classifiers.

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However, to the best of our knowledge, all previous studies evaluated and ranked classification methods by considering all data sets in one pool – they did not distinguish the data sets based on their hardness. Moreover, there was no systematic study to identify which classification benchmark data sets are hard for traditional classification methods, and there were no rankings of methods based on their performance on hard data sets only. Filling these gaps is important, as the identified hard data sets can help future studies to develop new classification algorithms to complement existing classification algorithms, and the ranking of methods on hard data sets can help users select the best method when they are working with potentially hard data sets. We plan to fill this gap in this study.

This study will evaluate both classification algorithms and feature selection methods in combination. Specifically, it will identify hard data sets for which no combinations of representative classification algorithms and feature selection methods can produce accurate classification models. Moreover, the study will use the area under the ROC (AUC) and F-Measure, instead of the accuracy measure [1], to evaluate the performance of classification models. These measures were chosen based on the recent consensus that the accuracy measure has significant shortcomings when compared with the above two measures, especially AUC.

To identify a list of benchmark data sets that are hard for representative classification and feature selection methods, we perform a systematical evaluation of 48 combinations, involving eight representative classification algorithms and six commonly used feature selection methods, on 129 data sets from the UCI repository. We note that some data sets with known high classification accuracy based on results of Fernández-Delgado et al. [1] were excluded in our experiments.

For ease of discussion, a data set for classification will be called hard if none of the 48 combinations can achieve an AUC over 0.8 and none of the 48 combinations can achieve an F-Measure value over 0.8; it is called easy otherwise. A total of 15 out of the 129 data sets were found to be hard in our experiments.

This paper also compares the performance of different methods separately on the hard data sets and on the easy data sets. This was done based on their performance on data sets for which complete results were obtained for all of the 48 combinations. It turns out that the method rankings resulting from our experiments are somehow different from those in the literature and hence they offer new insights on method selection.

The rest of the paper is organized as follows. [Section 2](#) describes the classification algorithms and feature selection methods used in this study. [Section 3](#) describes the data sets included in this study. [Section 4](#) gives the experiment settings and the evaluation measures used. [Section 5](#) presents the experimental results and the associated analysis. [Section 6](#) concludes the paper.

## 2 Algorithms Used in the Study

In the experiments, we used multiple commonly-used representative classification algorithms and feature selection methods. The classification algorithms we used are Boosting, Decision Tree, Random Forest, Nearest Neighbor, Logistic Regression, and Support Vector Machine (SVM). The feature selection methods we used are correlation based method, information gain based method, and the relief-f method (all of which are filter based methods).

During the experiments, we also considered the wrapper based method, but we decided to exclude it due to its computational expensiveness (see [Table X](#) in Appendix) (it is seldom used in practice [\[3\]](#) due to the same reason).

All the classification algorithms and feature selection methods we used are as implemented in Weka 3.8.0 [\[4\]](#). More details are given in the next two subsections.

## 2.1 Classification Algorithms and Parameter Settings

We selected representative classification algorithms, partly based on several papers that reported systematic evaluation of classification algorithms and partly based on common knowledge. In particular, reference [\[1\]](#) showed Random Forest and SVM are often better than the others, and reference [\[5\]](#) gave a list of common-used successful classification algorithms. We selected Boosting, Decision Tree, Random Forest, Nearest Neighbor, Logistic Regression and SVM, as the representatives of existing classification algorithms. [Table 1](#) shows the correspondence of classification algorithms and their implementations in Weka that we used in our experiments. Some of the classification algorithms given in [Table 1](#) have multiple versions due to different parameter settings, yielding a total of eight classification algorithms (discussed below).

**Table 1**

Classification algorithms and their implementations in Weka.

Classification algorithm	Classifier in Weka	Abbreviation
Boosting	AdaBoostM1	AdaBoost
Decision Tree	J48	J48
Random Forest	RandomForest	RF
K Nearest Neighbor	IBk	IBk
Logistic	Logistic	LOG
SVM	LibSVM	SVM

To better evaluate the six algorithms, *two J48 and two SVM classifiers* were examined. For J48, we examined the classifier using the default parameter values, and the other using no pruning and using Laplace smoothing (J48(-U-A)). The two LibSVM classifiers are polynomial (SVM-PN) and radial basis function (SVM-RBF) kernels respectively. For IBk, we used K=10 and crossValidate=True, with which the system will find the optional K value between 1 and 10. More details are given below.

- 1) AdaBoost uses the M1 method [\[6\]](#) with DecisionStump as base classifiers.
- 2) J48 implements a pruned C4.5 [\[7\]](#) decision tree algorithm, with parameters confidenceFactor=0.25 and minNumObj=2.
- 3) J48(-U-A) implements a unpruned C4.5 decision tree algorithm with Laplace-based smoothing.
- 4) RF builds a forest of random trees [\[8\]](#), with parameters bagSizePercent=100 and unlimited depth.
- 5) IBk implements the K-nearest neighbors classifier [\[9\]](#), selecting the optimal value of K between 1 and 10 based on cross-validation.

- 6) LOG builds and uses a multinomial logistic regression model with a ridge estimator [10], with parameter  $\text{ridge}=1.0\text{E}-8$ .
- 7) SVM-PN uses the LibSVM library with polynomial kernel, with parameters  $\text{SVMTType}=\text{C-SVC}$ ,  $\text{cost}=\{0.25, 0.5, 1\}$ ,  $\text{degree}=\{1, 2, 3\}$ ,  $\text{gamma}=\{0.110, 0.01, 0.1\}$  and  $\text{coef0}=\{0, 1\}$ .
- 8) SVM-RBF uses the LibSVM library with radial basis function kernel, with parameters  $\text{SVMTType}=\text{C-SVC}$ ,  $\text{cost}=\{2^{-5}, 2^{-3}, \dots, 2^{15}\}$  and  $\text{gamma}=\{2^{-15}, 2^{-13}, \dots, 2^3\}$ .

## 2.2 Feature Selection Methods

Feature selection methods are used to remove irrelevant, redundant, or noisy attributes, with the aim of speeding up the computation and improving the accuracy [3, 12, 13]. Our experiments examine the effectiveness of feature selection methods when used with various classification algorithms.

Many feature selection methods have been proposed, each with its own pros and cons. We selected the following filter methods because they are commonly used [12, 14]: the correlation based method, the information gain based method and the relief-f method. We used Weka's implementation of the three feature selection methods.

In order to better evaluate these methods, we used two different parameter settings for Information Gain and Relief-F, which dictate how many features are selected. For ease of discussion, we consider "no attribute selection" as a feature selection method. Therefore, a total of 6 feature selection methods are considered. We now give some more details on the feature selection methods.

- 1) CFS uses  $\text{CfsSubsetEval}$  as the attribute evaluator to evaluate the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them, and uses  $\text{BestFirst}$  as the search method to search the space of attribute subsets by greedy hill-climbing augmented with a backtracking facility.
- 2) IG1 uses  $\text{InfoGainAttributeEval}$  as the attribute evaluator to evaluate the worth of attributes by measuring the information gain with respect to the class, and uses  $\text{Ranker}$  as the search method. If the total number of features is no more than 50, IG1 selects 80 percent of the features, and IG1 selects 40 features otherwise.
- 3) IG2 differs from IG1 as follows. It selects 60 percent of the features if the total number of features is no more than 50, and it selects 25 features otherwise.
- 4) RLF1 uses  $\text{ReliefAttributeEval}$  as the attribute evaluator to evaluate the worth of attributes by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance belonging to the same and different classes. It uses  $\text{Ranker}$  as the search method. It selects 60 percent of the features if the total number of features is no more than 50, and it selects 25 features otherwise.
- 5) RLF2 differs from RLF1 as follows. It selects 60 percent of the features if the total number of features is no more than 50, and it selects 25 features otherwise.
- 6) NO means "no attribute selection is performed".

## 3 Data Sets Included in the Study

Our experiments used 129 data sets, all from the UCI repository [15]. Table 2 lists the 98 data sets for which complete results for all of the 48 combinations were obtained; the remaining data sets are in Table XI of the Appendix.

**Table 2**

Details of 98 data sets.

Data set	#Instance	#Attribute	Data set	#Instance	#Attribute
abalone	4177	9	heart	270	14
anneal	798	39	heart-cleveland	303	14
arrhythmia	452	263	heart-switzerland	123	13
australian	690	15	heart-va	200	13
balloons_a	20	5	hepatitis	155	20
balloons_b	20	5	hill-valley	1212	101
balloons_c	20	5	leaf	340	16
balloons_d	16	5	led-display	1000	8
bankrupt_qualitative	250	7	letter-recognition	13339	17
biodeg	1055	42	lung-cancer	32	57
blogger	100	6	mfeat	2000	650
breast-cancer	286	10	monks-1	556	7
breast-cancer-wisc	699	10	monks-2	601	7
breast-cancer-wisc-diag	569	31	monks-3	554	7
breast-cancer-wisc-prog	198	34	occupancy	20560	7
breast-tissue	106	10	phishing	11055	31
chronic_kidney_disease	400	25	pima	768	9
climate	540	21	pittsburg-bridges-material	106	8
congressional-voting	435	17	pittsburg-bridges-rel-l	103	8
contrac	1473	10	pittsburg-bridges-span	92	8
cortex_nuclear	1080	82	pittsburg-bridges-t-or-d	102	8
credit_card	30000	24	pittsburg-bridges-type	105	8
crx	690	16	planning	182	13
data_banknote_authentication	1372	5	post-operative	90	9
dr	1151	20	primary-tumor	330	18
dresses_attribute_sales	500	14	seismic-bumps	2584	19
eeg_data	14980	15	shuttle	58000	10
electricity-board	45781	5	spect	265	23
fertility_diagnosis	100	10	statlog-australian-credit	690	15
flags	194	29	statlog-german-credit	1000	25
foresttypes	523	28	statlog-heart	270	14
gesture_phase_a1_raw	1747	20	statlog-image	2310	19
gesture_phase_a1_va3	1743	33	statlog-landsat	6435	37
gesture_phase_a2_raw	1264	20	statlog-shuttle	58000	10
gesture_phase_a2_va3	1260	33	statlog-vehicle	846	19
gesture_phase_a3_raw	1834	20	student-mat	395	33

gesture_phase_a3_va3	1830	33	student-por	649	33
gesture_phase_b1_raw	1073	20	teaching	151	6
gesture_phase_b1_va3	1069	33	thoracic_surgery_data	470	17
gesture_phase_b3_raw	1424	20	titanic	2201	4
gesture_phase_b3_va3	1420	33	urban_land_cover	675	148
gesture_phase_c1_raw	1111	20	user_modeling	403	6
gesture_phase_c1_va3	1107	33	vehicle	846	19
gesture_phase_c3_raw	1448	20	wholesale customers data_new	440	8
gesture_phase_c3_va3	1444	33	wilt	4839	6
gesture_phase_raw	9901	20	wine	178	14
gesture_phase_va3	9873	33	wine-quality-red	1599	12
glass	214	10	wine-quality-white	4898	12
haberman-survival	306	4	yeast	1484	9

Below we discuss where the data sets are from and how we selected them.

(a) From the data sets studied in [1], we first selected 34 data sets such that the maximum reported accuracy of [1] is below 0.8. (This saved our effort by eliminating the data sets having high known accuracy.) Then we added another 11 data sets that are variations (sharing the same data set name at UCI) of some of the 34 data sets. As a result, this group has a total of 45 data sets.

(b) Because [1] only dealt with UCI data sets dated before March 2013, we examined the 91 UCI data sets whose dates are between January 2013 and June 2016. From these we selected 32 and excluded the other 59 for reasons such as “too many instances”, “having no classification attribute”, “having complex data structure requiring preprocessing”, “having no data”, and “inaccessible”. Some data sources provide multiple versions (e.g. 15 for actrecog, 16 for gesture, 10 for mhealth, 2 for student); we took each version as a different data set (e.g. 15 data sets from the 15 versions of actrecog). This group has a total of 71 data sets.

(c) We also examined data sets having no dates marked at UCI, from which 10 data sets are included (the others are excluded due to complex data). Among the data sets, ballons has 4 versions, yielding extra data sets. So this group has a total of 13 data sets.

Among the 129 data sets from the three groups, there were 31 (listed in Table XI in Appendix) for which experiments could not be completed, hence they were excluded from Table 2. One of the 31 came from the (a) group and the other 30 from the (b) group.

## 4 Experimental Settings and Evaluation Measures

We used 10-fold cross validation to evaluate classification performance. For each fold of each data set, a classification model is built from the other 9 folds, using each of the 48 combinations involving eight classifiers and six feature selection methods.

As widely noted in the literature, the simple accuracy measure may be not adequate for imbalanced data sets. As some data sets used in our experiments are not balanced, we did not use the accuracy measure; we used the AUC and F-Measure measures instead.

AUC is equivalent to the probability that the underlying classifier will rank a randomly chosen positive instance higher than a randomly chose negative instance [16]. It is also called ROC Area in Weka. The F-Measure is the harmonic mean of Precision and Recall. AUC has several desirable properties as a classification performance measure, such as being decision threshold independent and invariant to a priori class probabilities. AUC is widely accepted as one of the best ways to evaluate a classifier’s performance [17] and it has been widely used to measure the performance in classification. We chose to include the F-Measure, in order to complement the AUC, and also to indicate the strength of the classifier in terms of Precision and Recall. (Reference [18] pointed out that for some situations, namely when the ROC curves cross, AUC has some weakness and it may give potentially misleading information.)

We note that, normally, AUC and F-measure are only defined for two-class problems. This paper also considers multi-class problems (having more than 2 classes). For such problems, the measure values are computed by weighted average of a number of two class problems (one for each class, defined as the class vs the union of the other classes), as is done by weka.

## 5 Experimental Results and Discussion

This section first presents the **15** identified hard data sets. It then analyzes the performance of classification and feature selection methods under several different conditions. It presents, for each hard data set, the combinations that are the best or worst for the data set. Based on that, it identifies the most frequent best classification algorithm, the most frequent best feature selection method, and so on. Similarly, it presents the worst combinations and identifies the most frequent worst methods. Finally, it also gives rankings of classification algorithms based on the number of data sets where they are the best and base on the average AUC; the rankings are given separately for the hard data sets and for the easy data sets. It should be noted that the rankings are based solely on results on the 98 data sets for which complete results were obtained for all of the 48 combinations.

For ease of discussion, we introduce a few terms and notations. For each data set, let  $max48AUC$  denote the highest AUC achieved by the 48 classification-algorithm and feature-selection-method combinations, and similarly let  $max48FMeasure$  denote the highest F-Measure. We say a data set is a *hard data set* if both  $max48AUC$  and  $max48FMeasure$  are no higher than 0.8, and we call the other data sets as *easy data sets*.

As the detailed experiment results require too much space, they are not listed here; they can be found as supplementary materials at <http://cecs.wright.edu/~gdong/harddata/>.

### 5.1 The 15 Hard Data Sets We Identified

[Table 3](#) lists the data sets for which  $max48AUC$  is less than or equal to 0.8, and [Table 4](#) lists the data sets for which  $max48FMeasure$  is less than or equal to 0.8. In both tables, the data sets are listed in increasing measure value order.

**Table 3**

Data sets having  $max48AUC \leq 0.8$ .

Data set	Max48AUC	Data set	Max48AUC
post-operative	0.536	fertility_diagnosis	0.707

planning	0.588	breast-cancer	0.711
dresses_attribute_sales	0.59	titanic	0.755
statlog-australian-credit	0.61	spect	0.758
heart-switzerland	0.626	seismic-bumps	0.764
heart-va	0.632	credit_card	0.767
congressional-voting	0.632	breast-cancer-wisc-prog	0.771
thoracic_surgery_data	0.673	statlog-german-credit	0.797
haberman-survival	0.691	primary-tumor	0.799
contrac	0.704	pittsburg-bridges-span	0.8

**Table 4**

Data sets having max48FMeasure  $\leq 0.8$ .

Data set	Max48FMeasure	Data set	Max48FMeasure
heart-va	0.399	wine-quality-red	0.694
heart-switzerland	0.434	teaching	0.702
primary-tumor	0.44	arrhythmia	0.709
student-por	0.443	hill-valley	0.715
student-mat	0.455	haberman-survival	0.716
congressional-voting	0.558	pittsburg-bridges-span	0.716
contrac	0.564	breast-cancer	0.735
heart-cleveland	0.592	led-display	0.741
dresses_attribute_sales	0.602	spect	0.743
yeast	0.608	gesture_phase_c1_va3	0.749
pittsburg-bridges-type	0.625	gesture_phase_a1_va3	0.75
post-operative	0.626	breast-tissue	0.756
electricity-board	0.659	pittsburg-bridges-rel-l	0.759
abalone	0.666	dr	0.77
statlog-australian-credit	0.668	titanic	0.771
gesture_phase_c3_va3	0.675	statlog-german-credit	0.774
gesture_phase_a2_va3	0.676	pima	0.777
planning	0.68	lung-cancer	0.779
gesture_phase_va3	0.682	leaf	0.783
flags	0.689	gesture_phase_b3_va3	0.797
wine-quality-white	0.692		

[Table 5](#) reports the hard data sets having both max48AUC and max48FMeasure less than or equal to 0.8 --- they are precisely those that appear in both [Tables 3](#) and [4](#).

**Table 5**

Hard data sets (having max48AUC  $\leq 0.8$  & max48FMeasure  $\leq 0.8$ ).

Data set	Max48AUC	Max48FMeasure
post-operative	0.536	0.626
planning	0.588	0.68

dresses_attribute_sales	0.59	0.602
statlog-australian-credit	0.61	0.668
heart-switzerland	0.626	0.434
heart-va	0.632	0.399
congressional-voting	0.632	0.558
haberman-survival	0.691	0.716
contrac	0.704	0.564
breast-cancer	0.711	0.735
titanic	0.755	0.771
spect	0.758	0.743
statlog-german-credit	0.797	0.774
primary-tumor	0.799	0.44
pittsburg-bridges-span	0.8	0.716

## 5.2 Best and Worst Method Combinations for the Hard Data Sets

For each hard data set, we identified the best combination of classification and feature selection methods obtaining the highest AUC; the result is reported in [Table 6](#). Summarizing the table we have the following:

- At the individual algorithm level, RF & IG1 and RF & NO make the most-frequent best combinations (being the best for 3 hard data sets).
- The best combinations for 10 (66.7%) of the 15 hard data sets involve the use of feature selection methods; the best combinations for 2 (13.3%) do not use feature selection methods; for the remaining 3 (20%) data sets, multiple combinations achieved the best AUC, some of which involve feature selection methods and some do not.
- Focusing on the feature selection methods, we see that IG1, IG2 and NO (no attribute selection) are used in the best combinations for 5 hard data sets (33.3%), RLF1 is used for 3 hard data sets (20%), CFS is used for 2 hard data sets (13.3%), RLF2 is used for 1 hard data sets (6.7%).
- Focusing on classification algorithms, we see that RF appears in the best combinations of 7 hard data sets (46.7%), LOG appears in 4 (26.7%), AdaBoost and SVM-RBF each appears in 2 (13.3%).

So, for the 15 hard data sets, RF is the most-frequent best classification algorithm, IG, and NO (no attribute selection) are the most-frequent best feature selection methods, and the combinations of RF & IG1 and RF & NO are the most-frequent best combinations.

**Table 6**

Classification & feature selection methods giving best AUC for hard data sets.

Data set	#Instance	#Attribute	#SelAttr	Classifier	FS Method	Max48AUC
post-operative	90	9	7	SVM-RBF	CFS	0.536
planning	182	13	9	SVM-RBF	IG2	0.588
dresses_attribute_sales	500	14	9	AdaBoost	IG2	0.59
statlog-australian-credit	690	15	10	RF	IG2	0.61

heart-switzerland	123	13	11	RF	IG1	0.626
heart-va	200	13	13	RF	NO	0.632
congressional-voting	435	17	11	LOG	IG2	0.632
haberman-survival	306	4	4	LOG	NO	0.691
haberman-survival	306	4	4	LOG	IG1	0.691
haberman-survival	306	4	4	LOG	RLF1	0.691
contrac	1473	10	9	RF	RLF1	0.704
breast-cancer	286	10	9	AdaBoost	IG1	0.711
titanic	2201	4	4	RF	NO	0.755
titanic	2201	4	4	RF	IG1	0.755
titanic	2201	4	4	RF	RLF1	0.755
spect	265	23	15	LOG	IG2	0.758
statlog-german-credit	1000	25	21	RF	IG1	0.797
statlog-german-credit	1000	25	16	RF	RLF2	0.797
primary-tumor	330	18	18	RF	NO	0.799
pittsburg-bridges-span	92	8	8	LOG	NO	0.8
pittsburg-bridges-span	92	8	5	LOG	CFS	0.8

We now turn to the worst combination of classification and feature selection methods getting lowest AUC for the hard data sets; the result is given in [Table 7](#). Summarizing the table we have the following:

- At the individual algorithm level, AdaBoost & IG2 is the most-frequent worst combination, being the worst for 4 hard data sets.
- The worst combinations for 11 (73.3%) of the 15 hard data sets involve the use of feature selection methods; the worst combinations for 1 (6.7%) do not involve the use of feature selection methods; for the remaining 3 (20%), multiple combinations obtained the worst AUC, some of which involve feature selection methods and some do not.
- Focusing on the feature selection methods, we see that CFS is used in the worst combinations for 9 hard data sets (60%), IG2 is used for 5 hard data sets (33.3%), RLF1 and RLF2 and NO (no attribute selection) are used for 4 hard data sets (26.7%), and IG1 is used for 3 hard data sets (20%).
- Focusing on classification algorithms, we see that J48 and AdaBoost and SVM-PN appear in the worst combinations of 4 hard data sets (26.7%), and the others each appears in 1 (6.7 %).

So, for the 15 hard data sets, J48 and AdaBoost and SVM-PN are the most-frequent worst classification algorithms, CFS is the most-frequent worst feature selection methods, and AdaBoost & IG2 is the most-frequent worst combinations.

**Table 7**

Worst classification algorithm obtaining the lowest AUC for hard data sets.

Data set	#Instance	#Attribute	#SelAttr	Classifier	FS method	Min48AUC
post-operative	90	9	6	IBK	RLF2	0.279

planning	182	13	13	LOG	NO	0.345
heart-switzerland	123	13	2	RF	CFS	0.454
dresses_attribute_sales	500	14	9	J48	CFS	0.458
dresses_attribute_sales	500	14	9	J48	IG2	0.458
heart-va	200	13	9	AdaBoost	IG2	0.484
haberman-survival	306	4	3	J48	RLF2	0.489
statlog-australian-credit	690	15	3	SVM-PN	CFS	0.5
congressional-voting	435	17	4	SVM-RBF	CFS	0.509
congressional-voting	435	17	4	SVM-PN	CFS	0.509
pittsburg-bridges-span	92	8	8	AdaBoost	NO	0.545
pittsburg-bridges-span	92	8	5	AdaBoost	CFS	0.545
pittsburg-bridges-span	92	8	7	AdaBoost	IG1	0.545
pittsburg-bridges-span	92	8	6	AdaBoost	IG2	0.545
contrac	1473	10	10	AdaBoost	NO	0.549
contrac	1473	10	4	AdaBoost	CFS	0.549
contrac	1473	10	9	AdaBoost	IG1	0.549
contrac	1473	10	7	AdaBoost	IG2	0.549
contrac	1473	10	9	AdaBoost	RLF1	0.549
contrac	1473	10	7	AdaBoost	RLF2	0.549
breast-cancer	286	10	5	SVM-PN	CFS	0.583
spect	265	23	19	SVM-PN	RLF1	0.607
primary-tumor	330	18	18	AdaBoost	NO	0.609
primary-tumor	330	18	10	AdaBoost	CFS	0.609
primary-tumor	330	18	15	AdaBoost	IG1	0.609
primary-tumor	330	18	12	AdaBoost	IG2	0.609
primary-tumor	330	18	15	AdaBoost	RLF1	0.609
primary-tumor	330	18	12	AdaBoost	RLF2	0.609
statlog-german-credit	1000	25	21	J48	RLF1	0.653
titanic	2201	4	2	J48	CFS	0.688
titanic	2201	4	2	J48(-U-A)	CFS	0.688

### 5.3 Maximum and Minimum AUC by All Combinations for the Hard/Easy Data Sets

For each data set, let  $\text{min48AUC}$  be defined similarly to  $\text{max48AUC}$ , and let  $\text{span48AUC}$  denote  $\text{max48AUC} - \text{min48AUC}$ .

Fig. 1 presents  $\text{max48AUC}$  and  $\text{min48AUC}$  for the hard data sets. We note that maximum  $\text{span48AUC}$ , minimum  $\text{span48AUC}$ , and average  $\text{span48AUC}$  are 0.257, 0.067 and 0.165 respectively. So the choice of classification and feature selection methods often has big impact on the classification accuracy for the hard data sets.

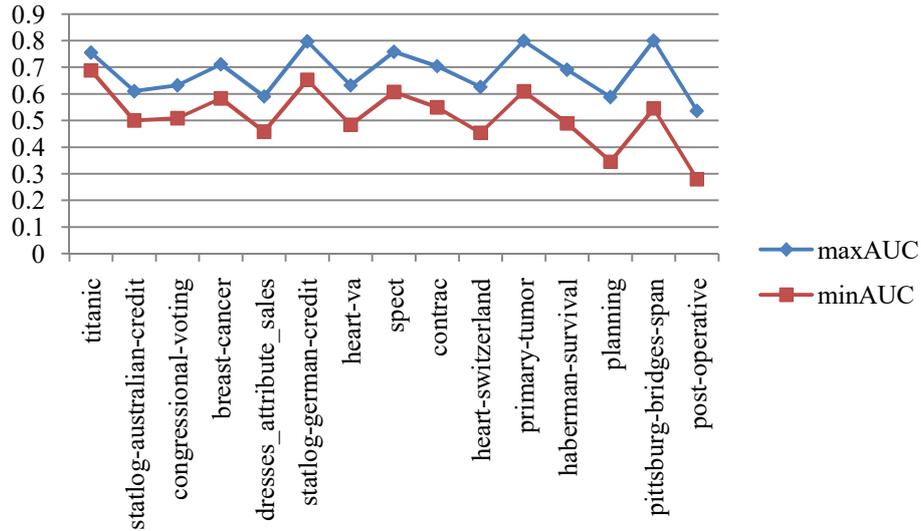


Fig. 1. Max48AUC and min48AUC for the 15 hard data sets.

Fig. 2 presents max48AUC and min48AUC for all easy data sets. We note that maximum span48AUC, minimum span48AUC, and average span48AUC are 0.77, 0 and 0.287 respectively. Moreover, span48AUC is greater than 0.3 for 48.2% of the easy data sets. While several easy data sets can be classified well by all of the 48 combinations, for nearly half of the easy data sets the difference in classification performance by different combinations is large.

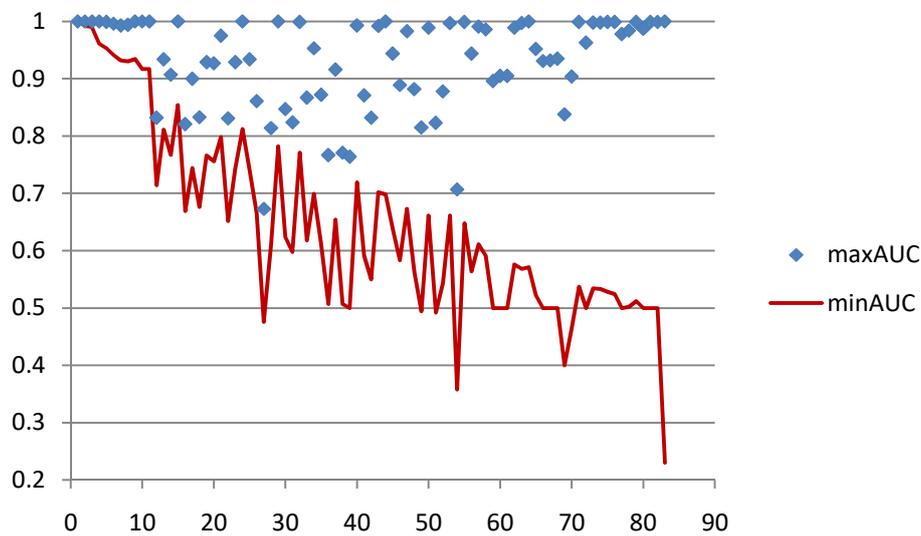
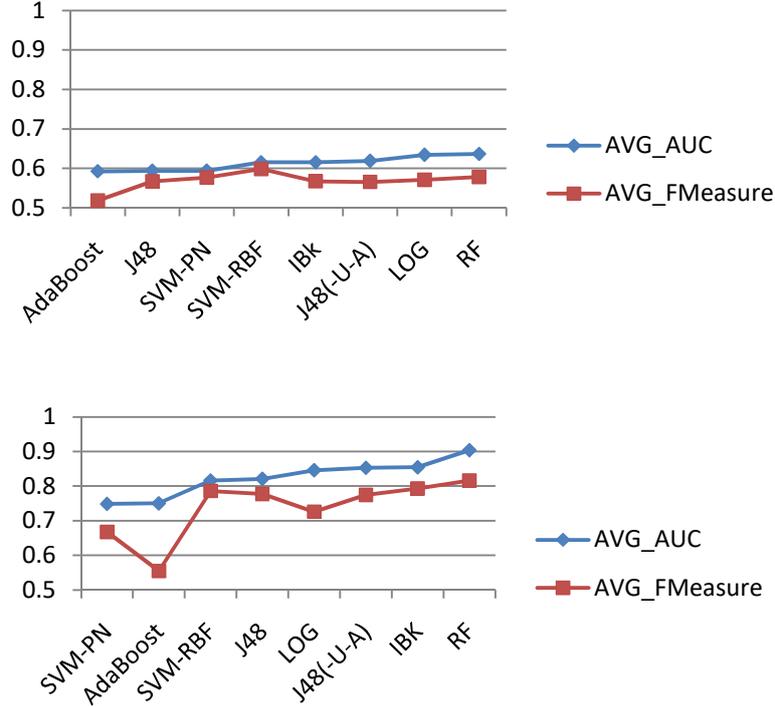


Fig. 2. Max48AUC and min48AUC for the easy data sets.

#### 5.4 Average AUC and Average F-Measure for the Hard/Easy Data Sets

Fig. 3 shows the average AUC and average F-Measure for the eight classification algorithms on (1) the 15 hard data sets (upper panel) and (2) all of the easy data sets (lower panel). We observe that, based on average AUC, RF is the best for the hard data sets, and RF

is also the best for the easy data sets.



**Fig. 3.** Average AUC and average F-Measure for the eight classification algorithms on the 15 hard data sets (upper panel) and the easy data sets (lower panel).

The slope of the curve in the upper panel is gentle (almost flat): the maximum average AUC is 0.637, the minimum average AUC is 0.592, and their difference is 0.045; the maximum average F-Measure is 0.578, the minimum average F-Measure is 0.518, and their difference is 0.06. The slope of the curve in the lower panel is fairly steep: the maximum average AUC is 0.904, the minimum average AUC is 0.749, and their difference is 0.155; the maximum average F-Measure is 0.816, the minimum average F-Measure is 0.668, and their difference is 0.148. In summary, the difference among the performance of the classification algorithms for the 15 hard data sets is fairly small; in contrast, the difference for the easy data sets is fairly large.

We note that RF is the best for both easy and hard data sets, which is in strong agreement with the ranking of algorithms provided by [1]. However, Fig. 3 shows that SVM-PN is the last one in the rank for easy data sets, which is very different from the ranking give by [1] (which found SVM to be the second best classification algorithm). There are at least three potential reasons for the disagreement: We used AUC and F-Measure whereas [1] used accuracy. (2) In our study we excluded a number of data sets for which [1] reported high classification accuracies (by any of the classification algorithms) and we included some data sets not studied in [1]. (3) In our ranking, we separated data sets into a hard pool and an easy pool, whereas [1] considered all data sets in one pool.

Table 8 shows the average AUC and average F-Measure for the six feature selection methods on the hard data sets (left table) and the easy data sets (right table). For the hard data sets, the IG1 methods is the best; for the easy data sets, RLF1 is the best, followed by IG1 and

NO (no attribute selection). We note that the average AUC and average F-Measure of IG1 and NO (no attribute selection) are all just 0.001 below those of RLF1.

More specifically, for the hard data sets (Table 8, left), the maximum average AUC is 0.62 and the minimum average AUC is 0.605, and the difference is just 0.015; the maximum average F-Measure is 0.576, the minimum average F-Measure is 0.561, and the difference is just 0.015. For the easy data sets (Table 8, right), the maximum average AUC is 0.831, the minimum average AUC is 0.81, and the difference is 0.021; the maximum average F-Measure is 0.743, the minimum average F-Measure is 0.725, and the difference is 0.018. The above suggests that there is little difference on the classification performance whether feature selection methods are used, or which feature selection methods are used, based on average performance. We must note that the above statement is based on average performance over a large number of data sets. As noted above, the exclusion of a fairly large number of data sets with known high classification accuracy may also contribute to the above findings.

**Table 8**

Average AUC and average F-Measure for the six feature selection methods on the hard data sets (left) and the easy data sets (right).

Method	AVG_AUC	AVG_FMeasure	Method	AVG_AUC	AVG_FMeasure
RLF2	0.605	0.561	CFS	0.81	0.725
CFS	0.605	0.561	IG2	0.821	0.732
RLF1	0.612	0.567	RLF2	0.823	0.737
IG2	0.615	0.568	NO	0.83	0.742
NO	0.618	0.575	IG1	0.83	0.742
IG1	0.62	0.576	RLF1	0.831	0.743

## 5.5 Summary of Classifier Rankings on Hard Data Sets and on Easy Data Sets

Tables 9 and 10 summarize the rankings of the 8 classification algorithms for the hard and easy data sets respectively. Each gives two classifier rankings, one based on the number of data sets for which the classifier is the best, and the other based on average AUC. #DatasetsBest is the number of data sets for which a given algorithm obtained the maximum AUC. There are several classifiers obtaining the maximum AUC for some easy data sets, so the sum of #DatasetsBest in Table 10 (left panel) is larger than the number of easy data sets.

**Table 9**

Classifier rankings for hard data sets: based on number of data sets an algorithm is the best (left), and based average AUC (right).

Classifier	#DatasetsBest	Classifier	AVG_AUC
RF	7	RF	0.637
LOG	4	LOG	0.634
AdaBoost	2	J48(-U-A)	0.619
SVM- RBF	2	IBk	0.615
SVM- PN	0	SVM-RBF	0.615
IBK	0	SVM-PN	0.594

J48	0	J48	0.594
J48(-U-A)	0	AdaBoost	0.592

**Table 10**

Classifier rankings for easy data sets: based on number of data sets an algorithm is the best (left), and based average AUC (right).

Classifier	#DatasetsBest	Classifier	AVG_AUC
RF	59	RF	0.904
LOG	22	IBk	0.854
SVM-RBF	11	J48(-U-A)	0.853
J48(-U-A)	10	LOG	0.846
IBK	9	J48	0.821
AdaBoost	9	SVM-RBF	0.816
J48	7	AdaBoost	0.75
SVM-PN	7	SVM-PN	0.749

## 6 Conclusions

This paper reported a systematic evaluation of classification performance by representative state-of-the-art classification algorithms and feature selection methods on 129 data sets from UCI. It identified a list of benchmark data sets that are hard for representative classification and feature selection methods. It ranked the classification algorithms based on their performance on the hard data sets, and on their performance on the easy data sets. It also compared the effectiveness of feature selection methods. To the best of our knowledge, this study is the first to give a list of hard benchmark data sets in the machine learning literature, and to rank classification algorithms by considering their performance on hard data sets. This list of hard benchmark data sets can be useful for motivating the development of new classification and feature selection algorithms, and for use in the evaluation of such algorithms.

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## Appendices

Below, [Table X](#) gives the run time for the wrapper method on several data sets, showing that the method is very time consuming.

[Table XI](#) lists the 31 data sets for which our experiments with the 48 classification

algorithm and feature selection method combinations were not completed due to reasons such as “lack of memory”, “taking too much time” (that is, for some of the combinations, the 10 folds cross validation took more than 120 hours), “abnormal program termination” etc. For each of the 31 data sets computation for at least one of the 48 combinations was completed. From the partial results of the finished experiments, we get the maximum AUC and maximum F-Measure for these data sets. Based on the partial results we are quite certain that the 31 data sets all belong to the easy data set category except the first one. We are not sure whether the first data set is a hard data set or not, because its maximum AUC and maximum F-Measure are all less than 0.8 based on the partial results.

**Table X**

Run time for the wrapper method on several data sets, on a laptop with Intel 2.3GHz processor, 4GB RAM, and 64-bit operating system.

Data set	Instance	Attribute	Classifier	Runtime(seconds)
pima	768	9	SVM-PN	193623
crx	690	16	SVM-PN	105864
anneal	798	39	RF	19652

**Table XI**

Data sets for which experiments were not complete; the MaxAUC and MaxFMeasure were based on the finished experiments.

Data set	#Instance	#Attribute	MaxAUC	MaxFMeasure
diabetic_data	101766	50	0.662	0.537
actrecog1	162499	5	1	1
actrecog2	137730	5	1	1
actrecog3	102339	5	1	1
actrecog4	122199	5	1	1
actrecog5	159999	5	1	1
actrecog6	140669	5	1	1
actrecog7	162999	5	1	1
actrecog8	137794	5	1	1
actrecog9	163739	5	1	1
actrecog10	126799	5	1	1
actrecog11	104449	5	1	1
actrecog12	114700	5	1	1
actrecog13	67649	5	1	1
actrecog14	116099	5	1	1
actrecog15	103499	5	1	1
har-puc-rio	165633	19	0.999	0.987
jsbach_chorals_harmony	5665	17	0.982	0.762
mhealth_subject1	161280	24	0.996	0.974
mhealth_subject2	130561	24	0.996	0.97
mhealth_subject3	122112	24	0.997	0.972

mhealth_subject4	116736	24	0.996	0.97
mhealth_subject5	119808	24	0.996	0.969
mhealth_subject6	98304	24	0.997	0.971
mhealth_subject7	104448	24	0.996	0.963
mhealth_subject8	129024	24	0.997	0.973
mhealth_subject9	135168	24	0.994	0.961
mhealth_subject10	98304	24	0.998	0.971
plant-shape	1600	65	0.978	0.64
sensorless_drive_diagnosis	58509	49	1	0.999
wle	39242	159	1	1

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