Constructive Meta-Level Feature Selection Method based on Method Repositories

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Abstract. Feature selection is one of key issues related with data pre-processing of classification task in a data mining process. Although many efforts have been done to improve typical feature selection algorithms (FSAs), such as filter methods and wrapper methods, it is hard for just one FSA to manage its performances to various datasets. To above problems, we propose another way to support feature selection procedure, constructing proper FSAs to each given dataset. Here is discussed constructive meta-level feature selection that re-constructs proper FSAs with a method repository every given datasets, de-composing representative FSAs into methods. After implementing the constructive meta-level feature selection system, we show how constructive meta-level feature selection goes well with 32 UCI common data sets, comparing with typical FSAs on their accuracies. As the result, our system shows the highest performance on accuracies and the availability to construct a proper FSA to each given data set automatically.

1 Introduction

Feature selection is one of the key procedures to get a better result from the data mining process. However, it is difficult to determine the relevant feature subset before the mining procedure. At practical data mining situations, data miners often face a problem to choose the best feature subset for a given data set. If it contains irrelevant or/and redundant features, a data miner can't get any satisfactory results from mining/machine learning scheme. Irrelevant features not only lead to lower performance of the results, but also preclude finding potentially existing useful knowledge. Besides, redundant features not affect the performance of classification task, but influence the readability of the mining result. To choose a relevant feature subset, data miners have to take trial-and-error testing, expertise for the given feature set, or/and heavy domain knowledge for the given data set.

Feature selection algorithms (FSAs) have been developed to select a relevant feature subset automatically as a data pre-processing in a data mining process. The performance of FSA is always affected by a given data set. To keep their performance higher, a user often tries to execute prepared FSAs to his/her dataset

exhaustively. Thus a proper FSA selection is still costly work in a data mining process, and this is one of the bottle necks of data mining processes.

To above problems, we have developed a novel feature selection scheme based on constructive meta-level processing. We have developed a system to construct proper FSAs to each given data set with this scheme, which consists of de-composition of FSAs and re-construction of them. To de-compose current FSAs into functional parts called 'methods', we have analyzed currently representative FSAs. Then we have constructed the feature selection method repository, to re-construct a proper FSA to a given data set.

After constructing the feature selection method repository, we have implemented a system to choose a proper FSA to each given data set, searching possible FSAs obtained by the method repository for the best one. Taking this system, we have done a case study to evaluate the performance of FSAs on 32 UCI common data sets. As the result, the performance of FSAs has achieved the best performance, comparing with representative higher performed FSAs.

2 Related work

After constructing a feature set to describe each instance more correctly, we take a FSA to select an adequate feature subset for a prepared learning algorithm.

To improve classification tasks at data mining, many FSAs have been developed [2, 3, 4]. As shown in the survey done by Hall [5], wrapper methods [6] such as forward selection and backward elimination have high performance with high computational costs. Besides, filter methods such as Relief [7, 8], Information Gain and FOCUS [9] can be executed more quickly with lower performance than that of wrapper methods. Some advanced wrapper methods such as CFS [10], which executes a substitute evaluator instead of a learned evaluator, have lower computational costs than wrapper methods. However, these performances are still non-practical, comparing with wrapper methods.

We also developed a novel FSA called 'Seed Method' [1]. Seed Method has achieved both of practical computational cost and practical performance, because it improves wrapper forward selection method, determining a proper staring feature subset for given feature set. With an adequate starting subset, this method can reduce the search space of 2^n feature subsets obtained by n features. To determine an adequate starting subset, the method extracts a feature subset with Relief.F and C4.5 decision tree [11] from given feature set.

Although studies done by [6, 12, 13] have shown each way to characterize FSAs, they have never discussed any way to construct a proper FSA to a given data set. So, a data miner still selects FSA with exhaustive executions of prepared FSAs, depending on his/her expertise. Weka [14] and Yale [15] provide many feature selection components and frameworks to users. We can construct several hundred FSAs with these materials. However, they never support to choose a proper one.

3 Constructive meta-level processing scheme based on method repositories

At the field of meta-learning, there are many studies about selective meta-learning scheme. There are two approaches as selective meta-learning. One includes bagging [16] and boosting [17], combining base-level classifiers from multiple training data with different distributions. In these meta-learning schemes, we should select just one learning algorithm to learn base-level classifiers. The other approach includes voting, stacking [18] and cascading [19], which combines base-level classifiers from different learning algorithms. METAL [20] and IDA [21] are also selective meta-learning approach, selecting a proper learning algorithm to the given data set with a heuristic score, which is called meta-knowledge.

Constructive meta-level processing scheme [22] takes meta-learning approach, which controls objective process with meta-knowledge as shown in Fig.1. In this scheme, we construct a meta-knowledge, representing with method repositories. The meta-knowledge consists of information of functional parts, restrictions of combinations of each functional part, and the ways to re-construct object algorithms with the functional parts.

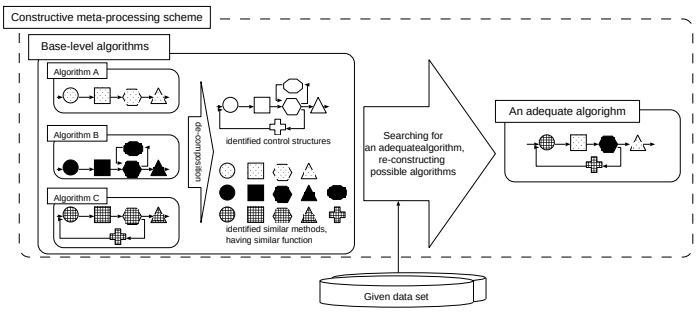

Fig. 1. An overview of constructive meta-level processing scheme.

3.1 Issues to implement a method repository

To build up a method repository, we should consider the following three major issues: how to de-compose prepared algorithms into functional parts, how to restrict the combinations of the functional parts, and how to re-construct a proper algorithm to a given data set.

To implement a feature selection method repository, we have considered above issues to identify feature selection methods(FSMs) in typical FSAs. Fortunately, FSAs have a nature as a search problem on possible combinations of features, which is pointed out in some papers [6, 12, 13]. With this nature, we have been able to identify generic methods in FSAs. Then we have also identified specific FSMs, which get into each implemented functional parts [3]. At the same time, we have also defined data types which are input/output/referenced for

[3] For example, these functions are corresponded to Java classes in Weka.

these methods. Thus we have organized these methods into a hierarchy of FSMs and a data type hierarchy. With these hierarchies, the system constructs FSAs to a given data set, searching possible FSAs obtained by the method repository for a proper one.

4 Implementation of the constructive meta-level feature selection scheme

To implement constructive meta-level feature selection scheme, we have to build a feature selection method repository and the system to construct proper FSAs to given data sets with the feature selection method repository.

4.1 Constructing a feature selection method repository

Firstly, we have identified the following four generic methods: determining initial set, evaluating attribute subset, testing a search termination of attribute subsets and attribute subset search operation. This identification is based on what FSAs can be assumed one kind of search problems. Considering the four generic methods, we have analyzed representative FSAs implemented in Weka[14] attribute selection package[4]. Then we have build up a feature selection method repository.

After identifying 26 specific methods from Weka, we have described restrictions to re-construct FSAs. The restriction has defined with input data type, output data type, reference data type, pre-method and post-method for each method. With this description, we have defined control structures with these generic four methods as shown in Fig.2.

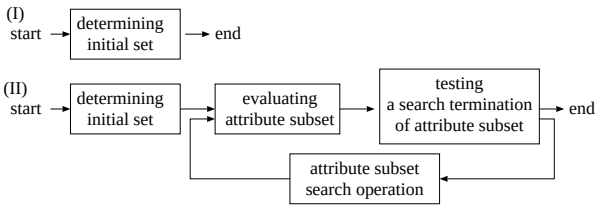

Fig. 2. Identified control structures on the four generic methods.

The control structure (I) corresponds ordinary that of filter approach FSAs. Besides, with the control structure (II), we can construct hybrid FSAs, which is combined wrapper and filter FSAs. Of course, we can also construct analyzed filter and wrapper FSAs with these control structure.

At the same time, we have also defined method hierarchy, articulating each method. Fig.3 shows us the method hierarchy of feature selection. Each method has been articulated with the following roles: input data type, output data type, reference data type, pre-method, and post-method. With these roles, we have also defined combinations of FSMs.

[4] we have taken weka-3-4-5 in this time.

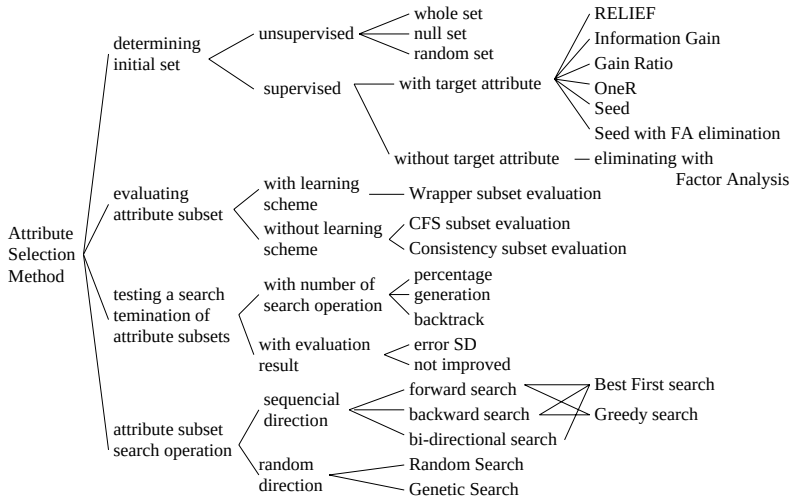

Fig. 3. The feature selection method hierarchy

To articulate data types for input, output and reference of methods, we have also defined data type hierarchy as shown in Fig.4.

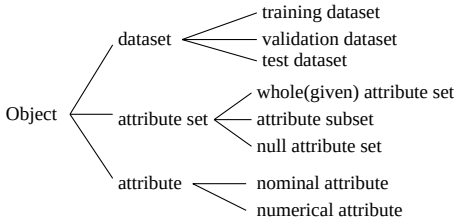

Fig. 4. The hierarchy of data types for the feature selection methods

4.2 The system to construct a proper FSA with a feature selection method repository

To re-construct a proper FSA to given data set, the system have to search possible FSAs obtained by the FSM repository for the most proper one. This process is also one of the search problems. Then we have designed the system with the following procedures: construction, instantiation, compilation, test, and refinement. The system chooses a proper FSA with these procedures as shown in Fig.5.

Each function of procedures is described in detail as follows: **Construction** procedure constructs a specification of the initial feature selection algorithm, selecting each specific method at random. **Instantiation** procedure transforms constructed or refined specifications to the intermediate codes. **Compilation** procedure compiles the intermediate codes to executable codes such as commands for Weka. **Go & Test** procedure executes the executable codes to the given data set to estimate the performance of FSAs. If the number of refinement doesn't come to the given limitation number **Refinement** procedure refines specifications of executed FSAs with some search operations.

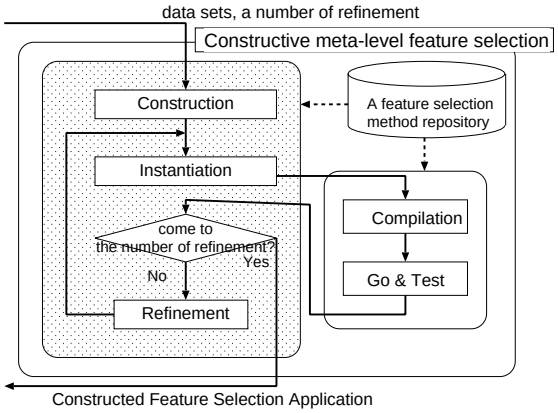

Fig. 5. An overview of constructive meta-level feature selection system.

5 Evaluation on UCI common data sets

After implementing the feature selection method repository and the system to construct proper FSAs to given data sets, we have done a case study to evaluate an availability of our constructive meta-level feature selection scheme.

In this case study, we have taken 32 common data sets from UCI ML repository [23], which are distributed with Weka. With the implemented feature selection method repository, the system has been able to construct 292 FSAs. The system has searched specification space of possible FSAs for the best FSA to each data set with the following configuration of GA operation at 'Refinement' procedure:

Population size Each generation has τ individuals.
Selection We take roulette selection to select 60% individuals for parents.
Crossover Each pair of parents is crossed over single point, which is selected at random.
Mutation Just one gene of selected child is mutated, selecting just one child with the probability 2%.
Elite Preservation The best individual is preserved on each generation.

5.1 The process to select a FSA

Firstly, the system selects proper FSAs to each data set, estimating the actual performance with the performance of n-fold cross validation. The selection phase has done at 'Go & Test' procedure in Fig.5. This selection phase has been repeated multiple times in each construction of FSA with our system. Finally, the system output just one FSA, which has the highest 'evaluation score' as shown in Fig.6.

We have taken averaged predictive accuracy $EstAcc(D)$ of n-fold cross validation from predictive accuracies $acc(evd_i)$ for each validation data set evd_i as the following formulations:

$$EstAcc(D) = \frac{\Sigma_{i=1}^{n} acc(evd_i)}{n} \qquad acc(evd_i) = \frac{crr(evd_i)}{size(evd_i)} \times 100$$

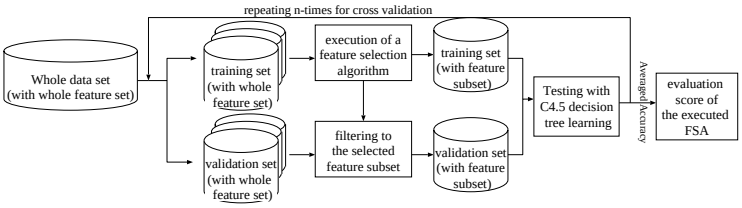

Fig. 6. Computing evaluation scores of each spec for GA in 'Refinement' procedure

$acc(evd_i)$ is a percentage score from the number of correctly predicted instances $crr(evd_i)$ and size of each validation set $size(evd_i)$.

According to this evaluation scores, the GA refinement searched for proper FSAs to each given data set. We have set up population size $\tau = 10$ and maximum generation $N = 10$ in this case study. So this set of GA operations has repeated maximum 10 times to each data set. Finally, the best FSA included in a final generation has been selected as output of our constructive meta-level feature selection system.

5.2 The process of the evaluation

We have designed the process of this evaluation for representative FSAs and constructed FSAs to each data set as shown in Fig.7.

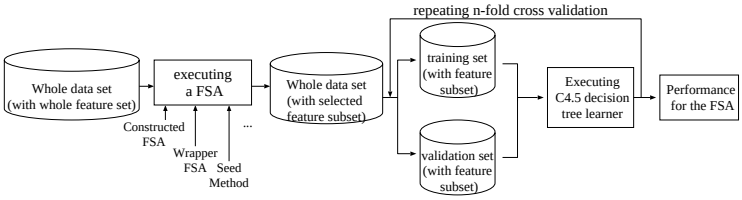

Fig. 7. Evaluation framework for the accuracy comparison

In this evaluation, we have applied each FSA to each whole data set. Then n-fold cross validation have been performed on each data set with selected feature subset. The performances of each data set $Acc(D)$ have been averaged predictive accuracies $acc(vd_i)$ from each fold as the following formulations:

$$Acc(D) = \frac{\Sigma_{i=1}^{n}\ acc(vd_i)}{n} \qquad acc(vd_i) = \frac{crr(vd_i)}{size(vd_i)} \times 100$$

Where vd_i means i-th validation set of the n-fold cross validation.

We have compared the performance of our constructive meta-level feature selection system with the following FSAs: **Whole feature set**, **Seed method**, and **Genetic Search**[24]. All of them have been evaluated with the same way as shown in the evaluation phase of Fig.7. We had done wrapper forward selection, Relief.F, Seed method and 'Genetic Search' to the data sets previously. Then the two methods were selected because of their higher performance.

Table 1. The performances of the feature selection algorithms on the UCI common data sets. Each score means averaged accuracies(%) with 10-fold cross validation. '*' means the best accuracy within this evaluation.

datasets	whole feature set	seed method	genetic search with wrapper	FSAs composed by our syste
anneal	98.44	98.33	*98.78	98.55
audiology	77.87	*80.14	77.51	77.51
autos	81.95	81.48	80.00	*84.90
balance-scale	76.64	*78.72	*78.72	*78.72
breast-cancer	*75.52	*75.52	72.71	74.14
breast-w	94.56	*94.85	94.57	94.71
colic	*85.33	85.08	84.54	84.81
credit-a	86.09	84.93	84.49	*86.67
credit-g	70.50	71.90	70.60	*74.60
diabetes	73.83	*76.56	75.00	75.25
heart-c	77.56	81.82	76.95	*83.19
heart-h	80.95	*82.66	80.6	81.98
heart-statlog	76.67	82.22	82.22	*85.56
hepatitis	*83.87	79.33	80.67	83.23
hypothyroid	99.58	99.60	97.88	*99.63
ionosphere	*91.45	89.17	88.32	91.44
iris	*96.00	92.67	92.00	94.00
kr-vs-kp	*99.44	98.81	98.78	99.37
letter	87.98	*88.4	83.56	87.62
lymph	77.03	75.67	75.67	*81.10
mushroom	*100.0	*100.0	*100.0	*100.0
primary-tumor	39.82	41.00	*43.94	43.06
segment	96.93	*96.97	96.80	*96.97
sick	98.81	98.75	98.86	*98.94
soner	71.15	75.45	72.12	*75.48
soybean	91.51	92.24	91.51	*92.39
splice	94.08	94.29	*94.42	94.14
vehicle	72.46	70.92	71.99	*73.30
vote	96.32	95.85	95.62	*96.53
vowel	81.51	83.03	*83.64	*83.64
waveform -5000	75.08	*77.16	75.98	76.74
zoo	92.08	92.00	92.09	*96.00
Average	84.41	84.86	84.08	85.76

5.3 Results and discussions of the evaluation

Table1 shows us the accuracies from whole feature set, subset selected by seed method, subset selected by 'Genetic Search' and subset selected by FSAs which constructed with our constructive meta-level feature selection system. Each score is the averaged accuracy calculated from 10-fold cross validation. The significance of the average for all of the data sets has tested with t-test. The comparison between the averages of our system and the other FSAs shows the statistically significant difference, where $p < 0.05$ for the other FSAs.

Table1 also shows us the result of the best performances, comparing among performances of the FSAs. To the 17 data sets, FSAs composed by our system have achieved the best performance. To breast-cancer, colic, hepatitis, ionosphere, iris and kr-vs-kp, whole feature set wins selected feature subsets, because all of the evaluated FSAs have not been able to select whole feature sets. They tend to output smaller feature subset, because they believe in that there are some irrelevant features in the given feature set. If we had defined the control structure for filter method Fig.2, the system would have selected whole feature subset with 'whole set' method in Fig.3.

To anneal, audiology, breast-w, diabetes, heart-h, letter, primary-tumor, splice and waveform-5000, FSAs composed by our system have not achieved the best performance, comparing with the other FSAs. The evaluation scores to estimate

actual performances have not worked correctly on these cases. However, these disadvantages are not significant differences statistically.

Fig.8 shows us the FSA composed by our system to heart-statlog data set. This algorithm consists of initial set determination with 'seed method' & elimination unique features using Factor Analysis result, feature subset evaluation with CFS method, backward elimination, and stopping with the number of backtracks[5]. Although this algorithm bases on backward elimination method, the combination of methods has been never seen in any study of FSAs. As this example, our system has been also able to construct a novel FSA automatically, reconstructing feature selection methods on the repository.

```
Input: Whole feature set  F, training data set Tr
Output: Feature subset for the training data set  Fsub
Prameters: number of backtracks=5

begin:
  Feature set f;
  f = determining_initial_set_with_FA+Seed(F);
  int i=0;
  double[] evaluations;
  while(1){
    evaluations[] = feature_subset_evaluation_with_CFS(f);
    (f,i) = backward_elimination(evaluations,f);
    if(number_of_backtracks(i,5)==true){ break; }
  }
  return f;
end:
```

Fig. 8. Pseudo-code of the feature selection algorithm for heart-statlog.

6 Conclusion

We present a novel meta-level feature selection approach based on constructive meta-level processing with method repositories. This scheme chooses a proper FSA to the given data set, re-constructing the FSA with a FSMs repository.

To evaluate the availability of our approach, we have done an empirical experiment with 32 UCI common data sets. Our constructive meta-level feature selection system has significantly outperformed than representative FSAs, which have higher performance compared with the other FSAs. The result also shows that our constructive meta-level feature selection system have been able to construct a proper algorithm to given feature set automatically.

As feature work, we will improve criterion to choose a proper FSA, considering search time to select a proper one, execution time of selected FSA and its performance.

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