Evaluating Model Construction Methods with Objective Rule Evaluation Indices to Support Human Experts

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Abstract. In this paper, we present a novel rule evaluation support method for post-processing of mined results with rule evaluation models based on objective indices. Post-processing of mined results is one of the key issues to make a data mining process successfully. However, it is difficult for human experts to evaluate many thousands of rules from a large dataset with noises completely. To reduce the costs of rule evaluation procedures, we have developed the rule evaluation support method with rule evaluation models, which are obtained with objective indices of mined classification rules and evaluations of a human expert for each rule. To evaluate performances of learning algorithms for constructing rule evaluation models, we have done a case study on the meningitis data mining as an actual problem. In addition, we have also evaluated our method on four rulesets from the four UCI datasets. Then we show the availability of our rule evaluation support method.

1 Introduction

In recent years, huge data are easily stored on information systems in natural science, social science and business domains, developing information technologies. With these huge data, people hope to utilize them for their purposes. Besides, data mining techniques have been widely known as a process for utilizing stored data on database systems, combining different kinds of technologies such as database technologies, statistical methods and machine learning methods. Especially, IF-THEN rules, which are produced by rule induction algorithms, are discussed as one of highly usable and readable output of data mining. However, to large dataset with hundreds attributes including noises, the process often obtains many thousands of rules. From such huge rule set, it is difficult for human experts to find out valuable knowledge which are rarely included in the rule set.

To support such a rule selection, many efforts have done using objective rule evaluation indices such as recall, precision, and other interestingness measurements (we call them 'objective indices' later). However, it is also difficult to estimate a criterion of a human expert with single objective rule evaluation index, because his/her subjective criterion such as interestingness and importance for his/her purpose is influenced by the amount of his/her knowledge and/or a passage of time.

To above issues, we have been developed an adaptive rule evaluation support method for human experts with rule evaluation models, which predict experts' criteria based on objective indices, re-using results of evaluations of human experts. In Section 3, we describe the rule evaluation model construction method based on objective indices. Then we present a performance comparison of learning algorithms for constructing rule evaluation models in Section 4. With the results of the comparison, we discuss about the availability of our rule evaluation model construction approach.

2 Related Work

To avoid the confusion of real human interest, objective index, and subjective index, we clearly define them as follows: **Objective Index:** The feature such as the correctness, uniqueness, and strength of a rule, calculated by the mathematical analysis. It does not include any human evaluation criteria. **Subjective Index:** The similarity or difference between the information on interestingness given beforehand by a human expert and those obtained from a rule. Although it includes some human criterion in its initial state, the similarity or difference are mainly calculated with a mathematical analysis. **Real Human Interest:** The interest felt by a human expert for a rule in his/her mind.

Focusing on interesting rule selection with objective indexes, researchers have developed more than forty objective indexes based on number of instances, probability, statistics, information quantity, distance of rules or their attributes, and complexity of a rule [11, 22, 24]. Most of these indexes are used to remove meaningless rules rather than to discover really interesting ones for a human expert, because they can not include domain knowledge. In contrast, a dozen of subjective indexes estimate how a rule fits with a belief, a bias or a rule template formulated beforehand by a human expert. Although these subjective indexes are useful to discover really interesting rules to some extent due to their built-in domain knowledge, they depend on the precondition that a human expert is able to clearly formulate his/her interest. Although interestingness indexes were verified their availabilities on each suggested domain, nobody has validated their availabilities on the other domains or/and characteristics related to the background of a given dataset.

Ohsaki et. al [15] investigated the relation between objective indexes and real human interests, taking real data mining results and their human evaluations. In this work, the comparison shows that it is difficult to predict real human interests with a single objective index. Based on the result, they indicated the

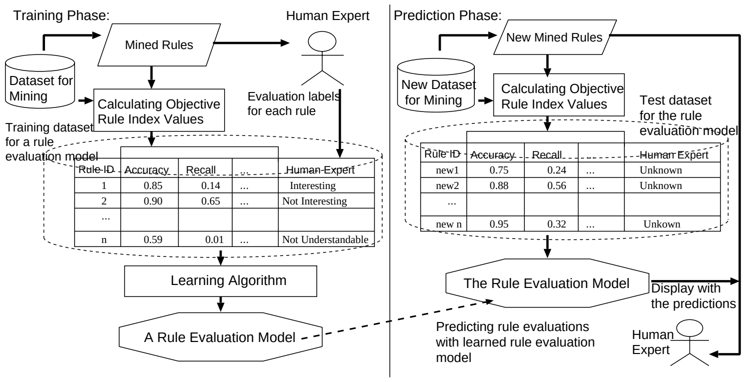


Fig. 1. Overview of the construction method of rule evaluation models.

possibility of logical combination of the objective indexes to predict real human interests more exactly.

3 Rule Evaluation Support with Rule Evaluation Model based on Objective Indices

At practical data mining situations, costly rule evaluation procedures are repeatedly done by a human expert. In these situations, useful experiences of each evaluation such as focused attributes, interesting their combinations, and valuable facts are not explicitly used by any rule selection system, but tacitly stored in the human expert. To these problems, we suggest a method to construct rule evaluation models based on objective rule evaluation indices to describe a criterion of a human expert explicitly.

3.1 Constructing a Rule Evaluation Model

We considered the process for modeling rule evaluations of human experts as the process to clear up relationships between the human evaluations and features of input if-then rules. With this consideration, we decided that the process of rule evaluation model construction can be implemented as a learning task. Fig.1 shows the process of rule evaluation model construction based on re-use of human evaluations and objective indices for each mined rule.

At the training phase, attributes of a meta-level training data set is obtained by objective indices such as recall, precision and other rule evaluation values. The human evaluations for each rule are joined as class of each instance. To obtain this data set, a human expert has to evaluate the whole or part of input rules at least once. After obtaining the training data set, its rule evaluation model is constructed by a learning algorithm. At the prediction phase, a human expert receives predictions for new rules based on their values of the objective indices. Since the task of rule evaluation models is a prediction, we need to choose a learning algorithm with higher accuracy as same as current classification problems.

4 Performance Comparison of Learning Algorithms for Rule Model Construction

To predict human evaluation labels of a new rule based on objective indices more exactly, we have to construct a rule evaluation model, which has higher predictive accuracy.

In this section, we firstly present the result of an empirical evaluation with the dataset from the result of a meningitis data mining[9]. Then to confirm the performance of our approach on the other datasets, we evaluated the five algorithms on four rule sets from four kinds of UCI benchmark datasets [10]. With the experimental results, we discuss about the following three view points: accuracies of rule evaluation models, analyzing learning curves of the learning algorithms, and contents of learned rule evaluation models.

As an evaluation of accuracies of rule evaluation models, we have compared predictive accuracies on the whole dataset and Leave-One-Out. The accuracy of a validation dataset D is calculated with correctly predicted instances $Correct(D)$ as $Acc(D) = (Correct(D)/|D|) \times 100$, where $|D|$ means the size of the dataset. Recalls of class i on a validation dataset is calculated with correctly predicted instances about the class $Correct(D_i)$ as $Recall(D_i) = (Correct(D_i)/|D_i|) \times 100$, where $|D_i|$ means the size of instances with class i. Also the precision of class i is calculated with the size of instances predicted i as $Precision(D_i) = (Correct(D_i)/Predicted(D_i)) \times 100$.

As for learning curves, we obtained learning curves about accuracies to the whole training dataset to evaluate whether each learning algorithm can perform in early stage of a process of rule evaluations. Accuracies from randomly subsampled training datasets are averaged with 10 times trials on each percentage of subset.

Looking at elements of the rule evaluation models to the whole dataset, we consider the characteristics of each learning algorithm on the attribute space consisted of the objective indices.

To construct a dataset to learn a rule evaluation model, values of objective indices have been calculated for each rule, taking 39 objective indices as shown in Table1. The dataset for each rule set has the same number of instances as the rule set. Each instance consists of 40 attributes including the class attribute.

To these dataset, we applied five learning algorithms to compare their performance as a rule evaluation model construction method. We used the following learning algorithms from Weka[23]: C4.5 decision tree learner[19] called J4.8, neural network learner with back propagation (BPNN)[12], support vector machines (SVM)[4][18], classification via linear regressions (CLR)[5][3], and OneR[13].

[4] The kernel function was set up polynomial kernel.

[5] We set up the elimination of collinear attributes and the model selection with greedy search based on Akaike Information Metric.

Table 1. The objective rule evaluation indices for classification rules used in this research. **P:** Probability of the antecedent and/or consequent of a rule. **S:** Statistical variable based on P. **I:** Information of the antecedent and/or consequent of a rule. **N:** Number of instances included in the antecedent and/or consequent of a rule. **D:** Distance of a rule from the others based on rule attributes.

Theory	Index Name (**Abbreviation**) [Reference Number of Literature]
P	Coverrage(**Coverage**), Prevalence(**Prevalence**) Precision(**Precision**), Recall(**Recall**) Suppurt(**Support**), Specificity(**Specificity**) Accuracy(**Accuracy**), Lift(**Lift**) Leverage(**Leverage**), Added Value(**Added Value**)[22] Klösgen's Interestingness(**KI**)[14], Relative Risk(**RR**)[1] Brin's Interest(**BI**)[2], Brin's Conviction(**BC**)[2] Certainty Factor(**CF**)[22], Jaccard Coefficient(**Jaccard**)[22] F-Measure(**F-M**)[20], Odds Ratio(**OR**)[22] Yule's Q(**YuleQ**)[22], Yule's Y(**YuleY**)[22] Kappa(**Kappa**)[22], Collective Strength(**CST**)[22] Gray andOrlowska's Interestingness weighting Dependency(**GOI**)[7] Gini Gain(**Gini**)[22], Credibility(**Credibility**)[8]
S	χ^2 Measure for One Quadrant(χ^2**-M1**)[6] χ^2 Measure for Four Quadrant(χ^2**-M4**)[6]
I	J-Measure(**J-M**)[21], K-Measure(**K-M**)[15] Mutual Information(**MI**)[22] Yao and Liu's Interestingness 1 based on one-way support(**YLI1**)[24] Yao and Liu's Interestingness 2 based on two-way support(**YLI2**)[24] Yao and Zhong's Interestingness(**YZI**)[24]
N	Cosine Similarity(**CSI**)[22], Laplace Correction(**LC**)[22] ϕ Coefficient(ϕ)[22], Piatetsky-Shapiro's Interestingness(**PSI**)[17]
D	Gago and Bento's Interestingness(**GBI**)[5] Peculiarity(**Peculiarity**)[25]

4.1 Constructing Rule Evaluation Models on an Actual Datamining Result

In this case study, we have taken 244 rules, which are mined from six dataset about six kinds of diagnostic problems as shown in Table2. These datasets are consisted of appearances of meningitis patients as attributes and diagnoses for each patient as class. Each rule set was mined with each proper rule induction algorithm composed by a constructive meta-learning system called CAMLET[9]. For each rule, we labeled three evaluations (I:Interesting, NI:Not-Interesting, NU:Not-Understandable), according to evaluation comments from a medical expert.

Table 2. Description of the meningitis datasets and their datamining results

Dataset	#Attributes	#Class	#Mined rules	#'I' rules	#'NI' rules	#'NU' rules
Diag	29	6	53	15	38	0
C_Cource	40	12	22	3	18	1
Culture+diag	31	12	57	7	48	2
Diag2	29	2	35	8	27	0
Course	40	2	53	12	38	3
Cult_find	29	2	24	3	18	3
TOTAL	—	—	244	48	187	9

Comparison on Classification Performance In this section, we show the result of the comparisons of accuracies on the whole dataset, recall of each class label, and precisions of each class label. Since Leave-One-Out holds just one instance as the test data and remains as the training dataset repeatedly for each instance of a given dataset, we can evaluate the performance of a learning algorithm to a new dataset without any ambiguity.

The results of the performances of the five learning algorithms to the whole training dataset and the results of Leave-One-Out are also shown in Table3. All of the accuracies, Recalls of I and NI, and Precisions of I and NI are higher than predicting default labels.

Table 3. Accuracies(%), Recalls(%) and Precisions(%) of the five learning algorithms.

	On the whole training dataset							Leave-One-Out						
		Recall of			Precision of				Recall of			Precision of		
	Acc.	I	NI	NU	I	NI	NU	Acc.	I	NI	NU	I	NI	NU
J4.8	85.7	41.7	97.9	66.7	80.0	86.3	85.7	79.1	29.2	95.7	0.0	63.6	82.5	0.0
BPNN	86.9	81.3	89.8	55.6	65.0	94.9	71.4	77.5	39.6	90.9	0.0	50.0	85.9	0.0
SVM	81.6	35.4	97.3	0.0	68.0	83.5	0.0	81.6	35.4	97.3	0.0	68.0	83.5	0.0
CLR	82.8	41.7	97.3	0.0	71.4	84.3	0.0	80.3	35.4	95.7	0.0	60.7	82.9	0.0
OneR	82.0	56.3	92.5	0.0	57.4	87.8	0.0	75.8	27.1	92.0	0.0	37.1	82.3	0.0

Accuracy on the Training Dataset Comparing with the accuracy of OneR, the other learning algorithms achieve equal or higher performance with combination of multiple objective indices than sorting with single objective index. Looking at Recall values on class I, BPNN have achieved the highest performance. As for the other algorithms, they show lower performance than OneR, because they have tended to be learned classification patterns for the major class NI.

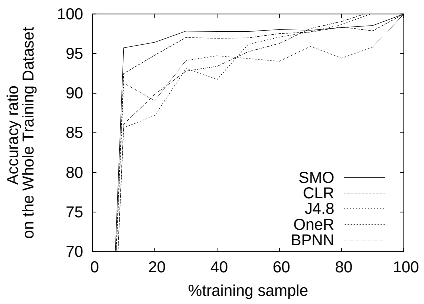
Robustness with Leave-One-Out Estimation Each value of Leave-One-Out estimation shows robustness of each learning algorithm to an unknown test dataset. On the accuracies, these learning algorithms have achieved from 75.8% to 81.9%. However, these learning algorithms have not been able to classify the instances with class NU, which is a minor class label in this dataset.

Looking at each learning algorithm, the values of BPNN show the trend of over fitting, comparing with its values of training dataset and its values of Leave-One-Out. Although OneR selects an adequate objective index to sort and classify 244 training datasets in the Leave-One-Out validation, the predictive performances to a new dataset have been limited because of the selection of just one objective index.

Learning Curves of the Learning Algorithms Since the rule evaluation model construction method needs evaluations of mined rules by a human expert, we have investigated learning curves of each learning algorithm to estimate how many evaluations are needed to construct a valid rule evaluation model. The upper table in Fig.2 shows accuracies to the whole training dataset with each subset of training dataset. The percentages of achievements for each learning algorithm, comparing with the accuracy with the whole dataset, are shown in the lower chart of Fig.2. As shown in these results, SVM and CLR, which learn hype-planes, achieves grater than 95% with only less than 10% of training subset. Although decision tree learner and BPNN could learn better classifier to the whole dataset than these hyper-plane learners, they need more training instances to learn accurate classifiers.

%training sample	10	20	30	40	50	60	70	80	90	100
J4.8	73.4	74.7	79.8	78.6	72.8	83.2	83.7	84.5	85.7	85.7
BPNN	74.8	78.1	80.6	81.1	82.7	83.7	85.3	86.1	87.2	86.9
SMO	78.1	78.6	79.8	79.8	79.8	80.0	79.9	80.2	80.4	81.6
CLR	76.6	78.5	80.3	80.2	80.3	80.7	80.9	81.4	81.0	82.8
OneR	75.2	73.4	77.5	78.0	77.7	77.5	79.0	77.8	78.9	82.4

%training sample	10	20	30	40	50	60	70	80	90	100
J4.8	82.7	85.3	92.8	88.7	93.2	92.7	93.2	92.9	94.0	97.9
BPNN	84.6	86.6	90.4	90.2	92.2	91.9	92.7	93.9	94.2	89.8
SMO	93.3	92.7	96.8	96.1	95.9	95.8	96.3	96.0	96.3	97.3
CLR	88.3	89.6	94.4	94.0	94.3	94.1	94.1	94.2	94.3	97.3
OneR	88.4	84.0	92.4	91.4	92.0	92.3	93.4	92.7	92.1	96.3



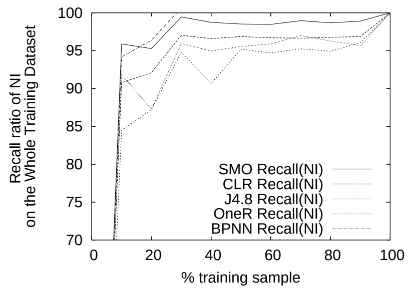


Fig. 2. Learning Curves of accuracies(%) on the learning algorithms with sub-sampled training dataset: The left table shows accuracies(%) on each training dataset to the whole dataset. The left graph shows their achievement ratio(%). Also the right table shows recalls(%), and the graph shows their achievement ratio(%).

To eliminate known ordinary knowledge from large rule set, it is needed to classify non-interesting rules correctly. The right upper table in Fig.2 shows percentages of recalls on NI. The right lower chart in Fig.2 also shows the percentages of achievements on recall of NI, comparing with the recall of NI on the whole training dataset. Looking at this result, we can eliminate NI rules with rule evaluation models from SVM and BPNN even if there is only 10% of rule evaluations by a human expert. This is guaranteed with no less than 80% precisions of all learning algorithms.

Rule Evaluation Models on the Actual Datamining Result Dataset In this section, we present rule evaluation models to the whole dataset learned with OneR, J4.8 and CLR, because they are represented as explicit models such as a rule set, a decision tree, and a set of linear models.

The rule set of OneR is shown in Fig.3(a). OneR has selected YLI1[24] to classify the evaluation labels. Although YLI1 corrects support to predict interestingness of a human expert, YLI1 estimates a correctness of each rule on a validation dataset.

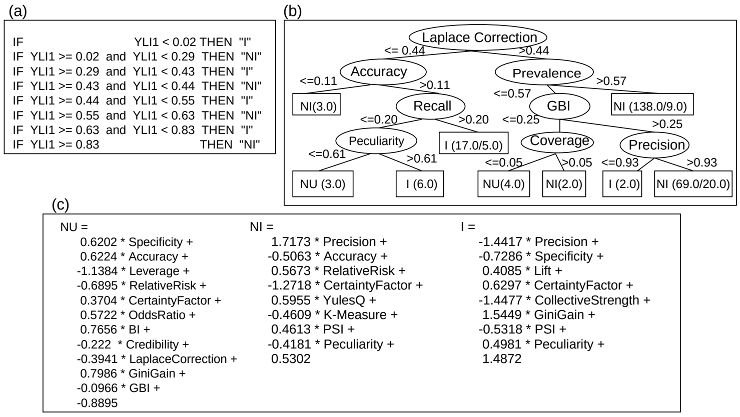


Fig. 3. Learned models to the meningitis data mining result dataset: (a) rule set learned from OneR, (b) decision tree learned from J4.8, (c) linear regression models learned from CLR.

As shown in Fig.3(b), J4.8 leaned the decision tree. At the root node, this model takes Laplace Correction[22], which is a corrected Precision with constant values. At the other levels, it takes indices evaluating a correctness of a rule such as Accuracy, Precision and Recall. Coverage and Prevalence are indices to evaluate a generality of the antecedent and the consequent of a rule. GBI[5] calculate index values with the classification result of a rule. Peculiarity[25] sums up differences of antecedents between one rule and the other rules in the same rule set.

Fig.3(c) shows linear models to classify each class. The prediction has done with integrating the responses of these linear models. As for models to class NI and I, they have the same indices such as Precision, Certainty Factor, PSI, and Peculiarity with opposite coefficients. The strongest factors on these models are Precision and Gini Gain, which increase their values with the correctness of a rule. To class NU, the strongest factor is Leverage based on Precision with a correction using a generality of a rule.

4.2 Constructing Rule Evaluation Models on Artificial Evaluation Labels

We have also evaluated our rule evaluation model construction method with rule sets from three datasets of UCI Machine Learning Repository to confirm the lower limit performances on probabilistic class distributions.

We selected the following three datasets: Mushroom, Heart, Internet Advertisement Identification (called InternetAd later) and Letter. With these datasets, we obtained rule sets with bagged PART, which repeatedly executes PART[4] to bootstrapped training sub-sample datasets.

To these rule sets, we calculated the 39 objective indices as attributes of each rule. As for the class of these datasets, we set up three class distributions with multinomial distribution. The class distribution for 'Distribution I' is $P = (0.35, 0.3, 0.3)$ where p_i is the probability for class i. Thus the number of class i in each instance D_j become $p_i D_j$. As the same way, the probability vector of 'Distribution II' is $P = (0.3, 0.5, 0.2)$, and 'Distribution III' is $P = (0.3, 0.65, 0.05)$.

Table4 shows us the datasets with three different class distributions.

Table 4. Datasets of the rule sets learned from the UCI benchmark datasets

	#Mined Rules	#Class labels L1	L2	L3	%Def. class
Distribution I		(0.30)	(0.35)	(0.35)	
Mushroom	30	8	14	8	46.7
InternetAd	107	26	39	42	39.3
Heart	318	97	128	93	40.3
Letter	6340	1908	2163	2269	35.8
Distribution II		(0.30)	(0.50)	(0.20)	
Mushroom	30	11	16	3	53.3
InternetAd	107	30	53	24	49.5
Heart	318	99	140	79	44.0
Letter	6340	1890	3198	1252	50.4
Distribution III		(0.30)	(0.65)	(0.05)	
Mushroom	30	7	21	2	70.0
InternetAd	107	24	79	9	73.8
Heart	318	98	205	15	64.5
Letter	6340	1947	4062	331	64.1

Accuracy Comparison on Classification Performances To above datasets, we have attempted the five learning algorithms to estimate whether their classification results can go to or beyond the accuracies of just predicting each default class. The left table of Table5 shows the accuracies of the five learning algorithms to each class distribution of the three datasets. As shown in Table5, J48 and BPNN always work better than just predicting a default class. However, their performances are suffered from probabilistic class distributions to larger datasets such as Heart and Letter.

Table 5. Accuracies(%) on whole training datasets labeled with three different distributions(The left table). Number of minimum training sub-samples to outperform %Def. class(The right table).

	J48	BPNN	SVM	CLR	OneR
Distribution I					
Mushroom	80.0	93.3	56.7	66.7	53.3
InternetAd	84.1	82.2	29.9	53.3	60.7
Heart	78.0	75.8	40.3	42.5	54.7
Letter	36.8	36.4	30.1	36.6	52.1
Distribution II					
Mushroom	93.3	93.3	80.0	80.0	76.7
InternetAd	73.8	79.4	49.5	59.8	60.7
Heart	72.3	69.2	35.9	47.8	55.7
Letter	51.0	51.0	50.4	50.4	57.0
Distribution III					
Mushroom	93.3	96.7	70.0	70.0	76.7
InternetAd	86.0	90.7	70.1	69.2	72.0
Heart	78.0	77.7	64.5	65.7	71.4
Letter	64.1	64.3	64.1	64.1	68.3

	J48	BPNN	SVM	CLR	OneR
Distribution I					
Mushroom	8	8	12	18	14
InternetAd	14	14	–	30	14
Heart	42	31	66	114	98
Letter	189	217	–	955	305
Distribution II					
Mushroom	6	4	4	6	12
InternetAd	24	24	52	42	70
Heart	52	40	–	104	92
Letter	897	>1000	451	–	>1000
Distribution III					
Mushroom	22	14	22	28	22
InternetAd	80	66	–	–	–
Heart	114	94	142	318	182
Letter	>1000	>1000	998	>1000	>1000

Evaluation on Learning Curves As same as evaluations of learning curves on the meningitis rule set, we have estimated the minimum training subsets for a valid model, which works better than just predicting a default class. For each data point, we constructed rule evaluation models to each size of subsampled training datasets 10 times. Then the averaged accuracy of each set of rule evaluation models is calculated on each whole dataset.

The right table in Table5 shows sizes of minimum training subsets, which can be constructed more accurate rule evaluation models than percentages of a default class by each learning algorithm. To smaller dataset, such as Mushroom and InternetAd, they can construct valid models with less than 20% of given training datasets. However, to larger dataset, they need more training subsets to construct valid models, because their performances with whole training dataset fall to the percentages of default class of each dataset as shown in the left table in Table5.

4.3 Discussion

On the Classification Performances As shown in Table3 and the left table of Table5, J4.8 decision tree learner and BPNN neural network learner work better than the other algorithms on both of the actual problem and a probabilistic problem. In section 4.1, the classification result about class 'I' indicates that these instances are difficult to separate with liner expressions in this attribute space based on the 39 objective indices. To predict such labels correctly, we should apply nonlinear classifier learned from nonlinear learners. Although these five learning algorithms have achieved 81.6% of the highest accuracy in the Leave-One-out estimation, we need to obtain more accurate rule evaluation models with meta-learning algorithms such as boosting, bagging and so forth.

On the Learning Curves With this analysis of the learning curves about each amount of training samples, we consider the following guideline: At early stage of rule evaluation support, the system should select hyper-plane learners to construct better rule evaluation models rapidly. Then closing stage of evaluations, the system should select more accurate learning algorithm to predict minor but valuable rules. This guideline can be applied to a large rule set, considering the work done by Perlich et. al[16], which shows the result that regression learners can be learned faster on large datasets than decision tree learners.

On the Learned Rule Evaluation Models Looking at indices used in learned rule evaluation models, they are not only the group of indices increasing with a correctness of a rule, but also they are used some different groups of indices on different models. This corresponds to the comment from the human expert. He said that he evaluated these rules not only correctness but also his interest based on his expertise. From the other viewpoint, this also indicates that the rule model construction method needs to select prior algorithms on data preprocessing algorithms, such as attribute construction and attribute selection, and a mining algorithm to construct an adequate rule evaluation model.

5 Conclusion

In this paper, we have described rule evaluation support method with rule evaluation models to predict evaluations for an IF-THEN rule based on objective indices, re-using evaluations of a human expert.

As the result of the performance comparison with the five learning algorithms, rule evaluation models have achieved higher accuracies than just predicting each default class. Considering the difference between the actual evaluation labeling and the artificial evaluation labeling, it is shown that the medical expert evaluated with noticing particular relations between an antecedent and a class/another antecedent in each rule. In the estimation of robustness to a new rule with Leave-One-Out, we have achieved more than 75.8% with these learning algorithms. On the evaluation with learning curves to the dataset of the actual datamining result, SVM and CLR have achieved more than 95% of achievement ratio compared to the accuracy of the whole training dataset with less than 10% of subset of the training dataset with certain human evaluations. These result related to performances of rule evaluation models indicate the availability of this rule evaluation support method for a human expert.

As future works, we will introduce a selection method of learning algorithms to construct a proper rule evaluation model according to each situation. We also apply this rule evaluation support method to estimate other data mining result such as decision tree, rule set, and committee of them with objective indices, which evaluate whole mining results.

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