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# ATTRIBUTE RANKING BASED LAZY LEARNING ASSOCIATIVE CLASSIFICATION

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**ABSTRACT**

Associative classification (AC) is an approach in data mining that utilizes the technique of association rule discovery to learn classifier. In recent decade, associative classification algorithms persuaded to be a noteworthy technique in creating accurate classification systems. Yet, development of new methods or implementing upgraded trends in systems would enhance the performance of current AC techniques. This paper focuses on lazy associative classification using different attribute ranking mechanism. Experimental result of the proposed system is visibly positive in comparison to the traditional and existing associative classification methods.

**Keywords:** associative classification, attribute (Feature) selection, lazy learning.

## 1. INTRODUCTION

All over the world a tremendous measure of information being gathered and put away in databases. There is invaluable data and learning covered up in such databases.

Data mining otherwise known as knowledge discovery process principally deals with extracting knowledge from data using algorithms or techniques. Classification and association rule discovery are two efficient data mining techniques. Classification utilizes supervised machine learning where the class label is engaged with the development of the classification system to predict the unseen data. Whereas association rule mining (ARM) deals with the extraction of highly correlated features with reference to the huge database records. Unsupervised machine learning is utilized by association rule mining where class attribute is not available.

Associative classification [4] is a current as well as remunerating procedure which employs the philosophy of association rule mining into classification and accomplishes very high accurate classifiers. Associative classification methods are characterized into two ways; first one is Eager Learning Method and second one is Lazy Learning Method.

Two phases are involved in the construction of eager associative classification method [2], [3], [4]. Association rule mining is first applied in this method to determine class association rules (CARs) and in the next phase, classifier will be constructed. To construct the efficient associative classifier, all the rules that are generated from the first phase are given rank and only high ranked rules are selected and remaining are ignored. Generating the rules and constructing a classifier with good quality rules are lengthy and unavoidable job.

To overcome these challenges, Lazy learning associative classification is introduced [1], [14-19], [21]. It postpones the processing of data until the point when another new instance demands for classification and does not fabricate the model to classify a test sample.

These lazy associative classification methods provide higher accuracy of the classifier but leads to high computation cost. Various information gain based [15-19] attribute selection methods are proposed to reduce the computation cost.

This paper analyses effect of introducing various other attribute selection methods and ranking methods include correlation and gain ratio. This proposed method provides improved classification accuracy when compared with existing systems.

The following paper is arranged as follows: Section 2 discusses related work in this field and Section 3 explains the process of the proposed system. Section 4 shows the working principle of the proposed system using an example. The final section presents the experimental results and observations followed by the conclusion.

## 2. RELATED WORK

Associative classification have been successfully applied for various classification tasks. The two recognized data mining techniques classification and association rule mining (ARM) is integrated for the first time in1998 [4]. A subset of association rules are used in associative classification; in which one side is rule and another side is limited to a class attribute. Associative classification includes two phases. In the first phase, it utilizes either Frequent Pattern (FP) growth algorithm [6] or Apriori candidate generation algorithm [5] to create the class association rules, where apriori candidate generation algorithm is used by CBA [4] for rule generation. Likewise FP growth algorithm is used by CMAR [3], CPAR [7] and lazy rule pruning methods in associative classification in [8], [9] and [10].

In the rule generation mechanism, multiple numbers of rules are generated. High accuracy may be achieved if all the rules are utilized in the construction of the classifier but the process will become time consuming and tedious. So to make procedure easy and reduce the time, in the second phase; ranking has given to all the rules based on selected parameters and measures where highest ranked rules are utilized for construction of the classifier and the rest of the rules are pruned which can be done using different methods presented in [10], [11] and [12]. In eager associative classification, rule generation

and construction of good quality classifier are the tedious task. To overcome this problem, lazy learning associative classifier postpones building the classification model until a test instance is induced.

Lazy learning method using Highest Subset Probability (HiSP) algorithm is introduced in [1] and [21]. Adriano also proposed different lazy classifier [13] that improved the classification accuracy. The LLAC [14] an another lazy learning method which uses support and confidence measures to generate rules and achieves higher accuracy but computation time has increased. In [15] and [16] high information gained attribute is selected to generate the rules for lazy associative classifier. Authors of [17] and [18] proposed weighted associative classification methods using information gain attribute. In [19] the authors proposed genetic network programming based associative classification method.

All the above mentioned papers have used only information gain attribute selection method. Other attribute selection methods have not been used so far. This paper utilizes correlation attribute and gain ratio attribute selection methods to generate subsets and predict the new class using the same. This paper also evaluates lazy learning associative classification using ranking based attribute selection method.

## 3. PROPOSED WORK

Subset generation is the tedious task in associative classification. Choosing the right attribute may reduce the computation time.

Attribute selection or feature selection is used to select the relevant attributes and remove redundant and/or irrelevant attributes. The following are few attribute selection methods used in this paper.

a) Correlation attribute (CA)
b) Info gain attribute (IG)
c) Gain ratio attribute (GR)

Correlation attribute calculates correlation between features and a class and highly correlated are kept together [20]. Information gain uses intrinsic information to decide the relevant and related data. Further normalization to information gain is done by gain ratio.

Maximum information gain is achieved when information gained attribute is chosen in [24]. This best attribute is utilized to create the subset. For each generated subset, probability is calculated as subset evaluation. Other attribute selection methods have not been used yet.

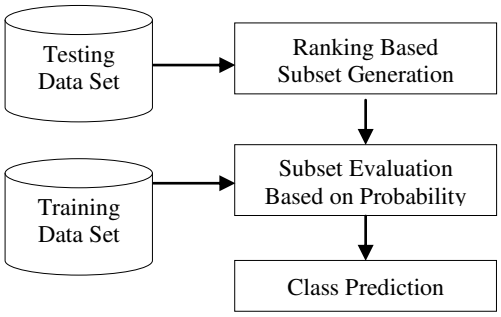


**Figure-1.** The proposed method.

This paper proposes lazy learning associative classification method using correlation attribute (CA-AC) and gain ratio (GR-AC) attribute subset selection method. Also this paper proposes ranking based subset generation where rank of the attributes is calculated and the entire attributes are organized and then used to generate the subset. After generating the subsets, probability is calculated. Maximum class probability is selected to the new testing instances.

### 3.1 Probability calculation

Set of transaction = $D_z$
No of classes = r
Classes are = $\{C_1, C_2 \ldots C_r\}$
Class values Z is assigned to class $C_n$, 1 <= n <= r, if and only if
$P(C_n / Z) > P(C_i / Z)$ for all i, 1<=i<=r, i not equal to n.
$P(Cj / s) = P(C_j \Lambda s)(P(s))$
Where $P(Cj \Lambda s)$ is the probability of a subset belongs to class Cj and subset s. P(s) is the occurrence of the subset s. [24].

The analysis of the subsets of attribute values associated with higher posteriori probabilities P(Cj|s) decides which class will be assigned to the instance Z. For this, all the posterior probabilities are calculated and sorted. Then, lower limit is utilized to limit the number of possibilities. Lower limit can be calculated as:

$$Lower\_Limit = \frac{Maximum\_probability}{\sqrt{r}} \quad \text{----- (1)}$$

Where r is number of class. Maximum class posterior probability will be assigned to the testing samples.

## 4. SAMPLE COMPUTATION

A sample dataset i.e. balloon dataset given in Table-1, contains 12 transactions, 4 attributes and 2 class values that are True and False. The test dataset is given in Table-2. In the next stage, the class label will be predicted for new test data.

**Table-1.** Sample dataset (Balloon dataset)

| Colour | Size | Act | Age | Inflated |
|---|---|---|---|---|
| Yellow | Small | Stretch | Adult | True |
| Purple | Small | Stretch | Adult | False |
| Yellow | Small | Stretch | Adult | True |
| Yellow | Small | Stretch | Child | False |
| Purple | Small | Dip | Adult | False |
| Purple | Small | Dip | Child | False |
| Yellow | Large | Stretch | Adult | True |
| Purple | Large | Stretch | Adult | True |
| Yellow | Small | Dip | Adult | False |
| Purple | Large | Stretch | Adult | True |
| Purple | Large | Stretch | Adult | True |
| Yellow | Small | Dip | Child | False |

**Table-2.** Test dataset

| | | | | |
|---|---|---|---|---|
| **Purple** | **Small** | **Stretch** | **Adult** | **?** |

Here color, size, act and age are having attribute no 1, 2, 3 and 4 respectively. Rank for the different attributes are:

a) Correlation attribute: 2, 1, 3 and 4.
b) Information gain : 1, 2, 3 and 4.
c) Gain ratio : 1, 2, 3 and 4.

Information gain rank and gain ratio rank both are same. Both will generate the same kinds of set of rules. For better understanding, we can consider ranks as follows:

a) Correlation attribute: 2, 4, 1 and 3.
b) Information gain : 1, 2, 3 and 4.
c) Gain ratio : 4, 3, 1 and 2.

### 4.1 By using different attribute selection method

Different attribute selection methods are used to build the lazy learning associative classification system and the methods are given below.

### A. Correlation method

Correlation method ranks the attribute as 2, 4, 1 and 3. So, 'Size' attribute is selected as it has the maximum correlated attribute value. Sample computation is shown in Table-3. The following rules that are generated based on correlation attribute:

- {Size = small}
- {Size = small, colour = purple}
- {Size = small, colour = purple, act = stretch}
- {Size = small, colour = purple, act = stretch, age = adult}

**Table-3.** Sample calculation for correlation attribute.

| Rules | Class | Occurrence | Probability |
|---|---|---|---|
| { Size = small } | True | 2 | 1.16 |
| | False | 6 | 2.47 |
| { Size = small, colour = purple } | True | 0 | 0 |
| | False | 3 | 1.248 |
| { Size = small, colour = purple, act = stretch } | True | 0 | 0 |
| | False | 1 | 0.416 |
| { Size = small, colour = purple, act = stretch, age = adult } | True | 0 | 0 |
| | False | 1 | 0.416 |

Probability for TRUE class is = 7/12 = 0.58
Probability for FALSE class is = 5/12 = 0.416
Posteriori Probability for rule {size = small} with TRUE class = 2*0.58 = 1.16
Posteriori Probability for rule {size = small} with FLASE class = 6*0.416= 2.47

$$Lower\_Limit = \frac{Highest\_probability}{\sqrt{no\_of\_class}}$$

Lower Limit = 2.08/1.414
= 1.471
So number of True > lower limit is = 0
Number of false > lower limit is = 1
So the test instance is classified by 'False' class.

**B. Information gain method**

Information gain method ranks the attribute as 1, 2, 3 and 4. Where highest rank attribute 'color' is selected and the rules can be generated stated as above.

**C. Gain ratio method**

Gain ratio method ranks the attribute as 4, 3, 1 and 2. Where 'age' attribute is selected as it has the maximum gain ratio value. The rules can be generated stated as above.

Here, we can compare the rules generated by each of the attribute selection methods i.e. correlation attribute, information gain and gain ratio attribute as shown in Table-4.

**Table-4.** Comparison of generated rule using different attribute selection methods.

| Generated rules | | |
|---|---|---|
| **Correlation attribute** | **Information gain** | **Gain ratio attribute** |
| { Size = small } | { Color = purple } | { Age = adult } |
| { Size = small, color = purple } | { Color = purple,Size = small } | { Age = adult, Color = purple } |
| { Size = small, color = purple, act = stretch } | { Color = purple,Size = small,Act = stretch } | { Age = adult, color = purple, Size = small } |
| { Size = small, colour = purple, act = stretch, age = adult } | { color = purple,Size = small,Act = stretch,Age = adult } | { Age = adult, Colour = purple, Size = small, Act = stretch } |

From Table-4, it is observed that first rule is different for all the three type of attribute selection method and last rule is same for all. First three rules are different between (correlation attribute and gain ratio) and (information gain and gain ratio).

### 4.2 By using attribute selection based ranking mechanism

Attribute selection based ranking method is used to generate the rules and the methods are given below:

**A. Correlation attribute**

The rank is 2, 4, 1 and 3. Based on this rank, following rules are generated:

- { Size = small }
- { Size = small, age = adult }
- { Size = small, age = adult, color = purple }
- { Size = small, age = adult, color = purple, act = stretch }

Sample computation is shown in Table-5.

**Table-5.** Sample calculation for correlation attribute ranking mechanism

| Rules | Class | Occurrence | Probability |
|---|---|---|---|
| {Size = small} | True | 3 | 1.74 |
| | False | 5 | 2.08 |
| {Size = small, , age = adult} | True | 3 | 1.74 |
| | False | 2 | 0.832 |
| { Size = small, age = adult, color = purple} | True | 1 | 0.58 |
| | False | 1 | 0.416 |
| {Size = small, age = adult, color = purple, act = stretch} | True | 1 | 0.58 |
| | False | 0 | 0 |

Probability for TRUE class is = 7/12 = 0.58
Probability for FALSE class is = 5/12 = 0.416
Posteriori Probability for rule I with TRUE class = 3*0.58 = 1.74
Posteriori Probability for rule I with FLASE class = 5*0.416= 2.08
Lower Limit = 2.08/1.414=1.471
So, the test instance is classified by 'false' class.

**B. Information gain rank**

This rank is 1, 2, 3 and 4. Based on this rank, the rules can be generated stated as above.

**C. Gain ratio rank**

This rank is 4, 3, 1 and 2. Based on this rank, the rules can be generated stated as above.

Table-6 shows the comparison between the rules generated by each of the attribute selection methods

**Table-6.** Comparison of generated rule using different attribute selection based ranking mechanism.

| Generated rules for ranking mechanism | | |
|---|---|---|
| **Correlation attribute** | **Information gain** | **Gain ratio attribute** |
| { Size = small } | { colour = purple } | { Age = adult } |
| { Size = small, age = adult } | { colour = purple, Size = small } | {Age= adult, act = stretch} |
| { Size = small, age = adult, colour = purple } | { colour = purple, Size = small, act = stretch } | {Age= adult, act = stretch, colour = purple} |
| { Size = small, age = adult, colour = purple, act = stretch } | { colour = purple, Size = small, act = stretch , age = adult } | {Age= adult, act = stretch, colour = purple, size = small } |

From Table-6, it is observed that generated rules are different for each of the ranking mechanism.

## 5. RESULTS AND DISCUSSIONS

To evaluate the proposed system, 7 different datasets are used. The datasets are taken from the University of California at Irvine Repository (UCI Repository) [22]. The short illustration of dataset is given in Table-7.

The experiments are conducted on a system with Intel (R) Core (TM) i3-2120 processor, a clock speed 3.3 GHz and RAM 4 GB. Holdout method [23] is utilized where 80% of the data is arbitrarily chosen from the dataset and utilized as training dataset and staying 20% is utilized as the testing dataset.

**Accuracy computation:** The accuracy is calculated from the given below formula

$$Accuracy = \frac{Number\ of\ correctly\ predicted\ test\ data}{Total\ no\ of\ test\ data} \quad (2)$$

The accuracy comparison based on the attribute selection methods is shown in Table-8. The first column defines the dataset name; 2nd, 4th and 6th column describes the attribute selection method name and 3rd, 5th and 7th are the accuracy, respectively.

**Table-7.** Dataset description.

| S. No. | Dataset | Rows | Column | No of Classes |
|---|---|---|---|---|
| 1 | Balance-Scale | 625 | 5 | 3 |
| 2 | Breast-Cancer | 286 | 10 | 2 |
| 3 | Breast-Wisconsin | 699 | 10 | 2 |
| 4 | Credit-Approval | 690 | 16 | 2 |
| 5 | Diabetes | 768 | 9 | 2 |
| 6 | Ionosphere | 351 | 35 | 2 |
| 7 | Iris | 150 | 5 | 3 |

**Table-8.** Effect of different attribute selection methods on accuracy.

| Dataset | IG-AC (Existing) | Accuracy | CA-AC (Proposed) | Accuracy | GR-AC (Proposed) | Accuracy |
|---|---|---|---|---|---|---|
| Balance-Scale | 1 | **76.8** | 4 | 60.80 | 4 | 60.80 |
| Breast-Cancer | 6 | 72.43 | 5 | 69.76 | 5 | 69.76 |
| Breast Wisconsin | 2 | 93.57 | 3 | 87.85 | 8 | 90.71 |
| Credit-Approval | 9 | 85.50 | 9 | 85.50 | 9 | 85.50 |
| Diabetes | 2 | 75.97 | 2 | 75.97 | 2 | 75.97 |
| Glass Identification | 4 | 67.44 | 3 | 69.76 | 8 | 58.13 |
| Ionosphere | 5 | 95.77 | 3 | 94.36 | 1 | 91.54 |
| Average | | 81.068 | | 77.71 | | 76.06 |

**Table-9.** Time taken to predict single instance for attribute selection method.

| Dataset | IG (existing) | Time | CA (proposed) | Time | GR (proposed) | Time |
|---|---|---|---|---|---|---|
| Balance-Scale | 1 | 0.017 | 4 | **0.008** | 4 | **0.008** |
| Breast-Cancer | 6 | **0.031** | 5 | 0.039 | 5 | 0.039 |
| Breast Wisconsin | 2 | 0.019 | 3 | **0.018** | 8 | 0.029 |
| Credit-Approval | 9 | 0.016 | 9 | 0.016 | 9 | 0.016 |
| Diabetes | 2 | 0.005 | 2 | 0.005 | 2 | 0.005 |
| Glass Identification | 2 | 0.063 | 3 | **0.027** | 8 | 0.041 |
| Ionosphere | 5 | 0.063 | 3 | 0.022 | 1 | **0.017** |

**Table-10.** Effect of different attribute selection based ranking methods accuracy computation.

| Dataset | Traditional | Existing systems | | Proposed attribute ranking methods | | |
|---|---|---|---|---|---|---|
| | CBA | LLAC | LACI | CA – R | IG - R | GR - R |
| Balance-Scale | 69.29 | 71.43 | 70.32 | 54.72 | **76.88** | 54.72 |
| Breast-Cancer | 66.48 | 76.55 | 67.86 | 67.23 | 73.44 | 67.23 |
| Breast-Wisconsin | 93.7 | 90.86 | 88.57 | 91.10 | 94.36 | 92.53 |
| Credit-Approval | 76.48 | 77.43 | 76.81 | 89.19 | 89.20 | 89.19 |
| Diabetes | 69.1 | 68.31 | 68.83 | 75.12 | 75.13 | 75.12 |
| Ionosphere | 82.29 | 92.67 | 94.44 | 91.68 | 89.56 | 87.88 |
| Iris | 96.67 | 78.89 | 95.33 | 97.40 | 97.40 | 94.44 |

**Table-11.** Time taken to predict single instance for ranking mechanism.

| Dataset | CA - R | Time | IG - R | Time | GR - R | Time |
|---|---|---|---|---|---|---|
| Balance-Scale | 4,3,2,1,5 | **0.016** | 1,2,3,4,5 | 0.024 | 4,3,2,1,5 | **0.016** |
| Breast-Cancer | 5,4,6,9,3,7,2,8,1,10 | 0.015 | 6,4,3,5,9,1,8,7,2,10 | 0.023 | 5,4,6,9,3,1,8,7,2,10 | 0.026 |
| Breast Wisconsin | 3,2,6,7,1,8,4,5,9,10 | 0.007 | 2,3,6,7,5,8,1,4,9,10 | 0.017 | 8,5,2,6,3,7,9,4,1,10 | 0.008 |
| Credit-Approval | 9,10,11,8,3,5,4,15, 2,14,13,7,6,12,1,16 | 0.011 | 9,11,10,15,8,6,14,7, 3,5,4,2,13,12,1,16 | 0.014 | 9,10,11,15,8,3,4,5, 14,6,7,2,13,12,1,16 | 0.010 |
| Diabetes | 2,6,8,1,7,5,4,3,9 | 0.004 | 2,6,8,5,4,1,7,3,9 | 0.007 | 2,6,8,1,5,7,4,3,9 | 0.006 |
| Ionosphere | 3,5,1,7,9,31,33,29,21, 8,15,23,14,25,13,11,12,6, 16,4,10,18,19,22,27,17,34, 28,32,20,24,30,26,2,35 | 0.025 | 5,6,33,29,3,21,34,8,13, 7,31,22,23,27,4,16,15,17, 12,25,9,11,28,19,14,10,18, 24,20,1,32,26,30,2,35 | 0.025 | 1,28,18,5,7,20,24,33,6, 27,26,32,29,3,14,34,21,8, 31,22,16,4,9,13,23,25,12, 15,10,30,11,17,19,2,35 | 0.031 |
| Iris | 3,4,1,2,5 | 0.019 | 3,4,1,2,5 | 0.02 | 4,3,1,2,5 | 0.019 |

Table-8 shows that the correlation attribute method has about 2.16% improvements against the gain ratio method and information gain method has about 6.58% and 4.32% improvements against the gain ratio and correlation attribute method respectively.

Table-9 shows the computation time based on the different attribute selection methods. The first column defines the dataset name; second, fourth and sixth column describes the attribute selection methods i.e. correlation attributes, gain ratio and information gain attribute. The overall computation time was obtained by averaging computation time from the ten different runs. From the Table-9, it is observed that correlation attribute has taken less time when compared.

After analyzing Table-8, one can say that existing method i.e. information gain method is giving better result than the correlation method and info gain method. To improve this, ranking mechanism of attribute selection method is also proposed in this paper. The accuracy comparison is given in Table-10 where existing system and proposed ranking mechanism are compared with different data sets and Time taken to predict single instance for ranking mechanism is shown in Table-11. It can be seen in the comparison result that the proposed algorithm (info gain rank) is 7.55% better than the traditional associative classification (CBA); 7.16% better than the existing lazy learning method (LLAC) and 6.01% better than LACI method.

## 6. CONCLUSIONS

Associative classification plays an important role in developing efficient classifier. Generating rules and constructing a classifier with good quality rules are challenging activities. To generate minimal number of high quality subset to predict the class label, this paper proposes different attribute selection based ranking mechanism. Experimental result shows that the proposed system not only generates lesser number of rules but also increases the classification accuracy.

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