CFAOI: Concept-Free AOI on Multi Value Attributes

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Abstract: Nowadays is an internet era with hacker surrounded. It is important to apply data mining into information security field to find out hacker could be an effective way. The behavior attributes of hacker can be an efficient way to detective suspicious hackers. Attribute Oriented Induction Method (AOI) is one of the most important methods in data mining research field. AOI is effective to discover general feature, however, it highly depends on concept tree with single vale attribute for inducting. The concept tree is subjective and highly depends on researcher. Different researcher may come out various different outcomes. This research improves AOI from the constraint of concept tree by a novel method of concept free with multi value attributes, CFAOI, concept-free AOI on multi-value attributes. The real experiment data showed this research method is an efficient, effective, and robust method.

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1. Introduction

It is an information world, we use Facebook, Twitter, e-mail to communicate, we order food from internet restaurants, we buy our staff from internet shore, and we play on-line game. All these information activities highly rely on strict information safety control. It is important to develop information security technology, and data mining could be one of the best ways. Data mining provide classification methods to analysis hackers' behavior attribute. Data mining can extract useful knowledge about attacker's information from implicit, unknown but potential powerful information from database. Many approaches have been proposed to extract information. According to the classification scheme proposed in recent surveys [1] [2], one of the most important ones is the attribute oriented induction (AOI) method. This approach was first introduced in Cai et al. (1990)[3], Han etal. (1992)[4], Han et al. (1993)[5].

The AOI method was developed for knowledge discovery in relational databases. The input of the method includes a relation table and a set of concept trees (concept hierarchies) associated with the attributes (columns) of the table. The table stores the task relevant data, and the concept trees represent the background knowledge. The core of the AOI method is on-line data generalization, which is performed by first examining the data distribution for each attribute in the set of relevant data, calculating the corresponding abstraction level that the data in each attribute should be generalized to, and then replacing each data tuple with its corresponding generalized tuple. The major generalization techniques used in the process include attribute-removal, concept-tree climbing, attribute threshold control, propagation of counts and other aggregate values, etc. Finally, the generalized data is expressed in the form of a generalized relation from which many kinds of rules can be discovered, such as characteristic rules and discrimination rules. For more details, please refer to the original papers [3-5].

Undoubtedly, the AOI method has achieved a great success. Because of its success, extensions have been proposed in the following directions: (1) extensions and applications based on the basic AOI approach [3] [6] [7], (2) more efficient methods of AOI [8-10], (3) more general background knowledge [11] [12], (4) integrating AOI with other information reduction methods [13] and (5) proposing new variants of generalized rules [14], (6) proposes a dynamic programming algorithm, based on AOI techniques, to find generalized knowledge from an ordered list of data [15].

AOI related algorithms conduct data induction with the help of concept hierarchies, which are needed for each inducted attribute and taken as a prerequisite to apply AOI. Concept hierarchies are the main characteristics of AOI and the primary reasons that AOI can conduct induction. However, the major characteristics have also become the major bumper of AOI applications. Two problems are rooted on the hierarchies. The first one is the scarce availability of creditable concept hierarchies. In many cases, users who need to summarize data for huge tables find the application of AOI unrealistic simply because the targeted attributes do not have sensible concept hierarchies. The second problem stems from the concept hierarchies are that concept hierarchies and associated attributes can only hold up to a single value. Unfortunately, many census data which would otherwise make very good applications of AOI are store data with multiple-value formats. For example, Table 1 shows a census data for several areas which are crime hot spots. The table contains the attributes of Area, Marital status, Gender and Education. Except Area, the other three attributes store data in set oriented multi-valued format. Each value in the set is a pair of <ordinal value, count>, where the ordinal value denotes a banded or categorical value which are totally ordered in their sorts; the count is the population in the area that are categorized into the corresponding group. For example, $\{<g_1, 30> <g_2, 70>\}$, in Area1 means that 30 persons in the area is has the gender of g_1 and 70 of them has the gender of g_2..

Table 1. 10 Crime Hot Spots (DB)

Area	gender	age	education
1	$<g_1, 30> <g_2, 70>$	$<a_1, 20> <a_2, 30> <a_3, 50>$	$<e_1, 20> <e_2, 10> <e_3, 40> <e_4, 30>$
2	$<g_1, 45> <g_2, 55>$	$< a_1, 25> <a_2, 35> <a_3, 40>$	$<e_1, 15> <e_2, 10> <e_3, 35> <e_4, 30>$
3	$<g_1, 65> <g_2, 35>$	$<a_1, 35> <a_2, 25> <a_3, 40>$	$<e_1, 30> <e_2, 40> <e_3, 10> <e_4, 20>$
4	$<g_1, 40> <g_2, 60>$	$<a_1, 20> <a_2, 40> <a_3, 40>$	$<e_1, 10> <e_2, 10> <e_3, 40> <e_4, 40>$
5	$<g_1, 35> <g_2, 65>$	$<a_1, 30> <a_2, 20> <a_3, 50>$	$<e_1, 25> <e_2, 5> <e_3, 40> <e_4, 30>$
6	$<g_1, 60> <g_2, 40>$	$<a_1, 25> <a_2, 25> <a_3, 50>$	$<e_1, 20> <e_2, 15> <e_3, 35> <e_4, 30>$
7	$<g_1, 20> <g_2, 80>$	$<a_1, 10> <a_2, 40> <a_3, 50>$	$<e_1, 5> <e_2, 30> <e_3, 35> <e_4, 30>$
8	$<g_1, 70> <g_2, 30>$	$<a_1, 30> <a_2, 40> <a_3, 30>$	$<e_1, 10> <e_2, 40> <e_3, 40> <e_4, 10>$
9	$<g_1, 40> <g_2, 60>$	$<a_1, 20> <a_2, 10> <a_3, 70>$	$<e_1, 20> <e_2, 20> <e_3, 30> <e_4, 30>$
10	$<g_1, 35> <g_2, 65>$	$<a_1, 20> <a_2, 30> <a_3, 50>$	$<e_1, 20> <e_2, 10> <e_3, 40> <e_4, 30>$

g_1: the number of male, g_2:the number of female,
a_1: the amount of youth, a_2: the amount of adult, a_3: the amount of elder.
e_1: the number of primary school graduated, e_2: the number of high school graduated, e_3: the number of university graduated, e_4: the number of post graduated.

However, there are still ways AOI following a number of common shortcomings: (1) must have the concept trees, set up the concept trees varies from person to person, and finally summed up the rules will be different. In this paper, an algorithm is proposed to induct data organized in sets of ordinal and numeric pairs. Furthermore, no hierarchies are needed to induct the data. (2) can only deal with single-valued property. Unfortunately, a lot of information belong to many multi-value property values, such as census data, so the existing AOI response to the above questions, especially for multi valued attribute value data, this paper presents a new AOI method, first the value of property 2 element of treatment, and then use Boolean function simplification, combined with Karnaugh Map Simplification of inductive methods, and finally re-scanned to identify a broad knowledge of statistics.

In view of these weaknesses, this paper proposed a new AOI method, In the algorithm, a translation procedure is deployed to translate each multi value into a sequence of binary digits. The binary sequences are merged and hence inducted with Karnaugh map. The the last attribute value and then the same group of variables can be summarized in total by the following rules:

$$\{<g_1, L> <g_2, H>\} \wedge \{<a_1, L> <a_3, H>\} \wedge \{<e_1, L> <e_3, H> <e_4,H>\} \rightarrow Y\%$$

That is:
Law and order problems will have the characteristics of Y% is the number of female more and more elderly and more than for tertiary education more.

2. Related Works

Based on the AOI approach, researchers have proposed various extensions. Carter and Hamilton proposed more efficient methods of AOI [16]. Cheung proposed a rule-based conditional concept hierarchy, which extends traditional approach to a conditional AOI and thereby allows different tuples to be generalized through different paths depending on other attributes of a tuple [10]. Hsu extended the basic AOI algorithm for generalization of numeric values [17]. Chen and Shen proposed a dynamic programming algorithm, based on AOI techniques, to find generalized knowledge from an ordered list of data [15]. Several independent groups of researchers have investigated applications of a fuzzy concept hierarchy to AOI [18-21]. A fuzzy hierarchy of concepts reflects the degree which a concept belongs to its direct abstract. In addition, more than one direct abstract of a single concept is allowed during fuzzy induction. Other researchers integrated AOI with other applications to generalize complex database [22] [23]. To the best of our knowledge, all previous research does not address the problems studied in the paper. and all these approaches, to use single value attribute for each tuple is not mentioned as our requirement. Finally, a study on multi-valued attributes is considered in [24].

3. The Data Structure and The Algorithm

This research aims to answer the limitation of multi value attribute induction approach. Each multi value attribute contains a set of pairs of ordinal and numeric values. The author proposed a method, which transforms each and numeric value into a Boolean bit and organize the bits into binary numbers according to the ordinal positions. The binary numbers are used to perform induction with the application of simplication Karnaugh Map.

3.1 Data Structure

Let C be a set of categories, O is a total order on C, for every c in C, n is a number then <c, n> is a multi-value item, and <<c, nc>|forall c in C> is a mutli-value list.

Let C1, ..Cm, each be a set of categories, and ordered with O1..Ot, individually, then T is a m attribute multi-value table if each tuple t in T is in the form of <<<ci,nit>|forall ci in Ck>, where k = 1..m>

Given a multi-value table with the form of <<<ci,nit>|forall ci in Ck>, where k = 1..m>, the corresponding transformed binary table is in the form of <bc1*2|Ck|-1 + bc2*2|Ck|-2 ..b|Ck|, where k=1,..m>, where bci is either 0 or 1, depending on the value of nit.

3.2 Composition of Binary Values

The first step in the stage is to transform each numeric value in the set of ordinal and numeric value pair into a Boolean bit, which is equal to the result of comparing the corresponding number to the average of the numbers in the set. The second step then organizes the bit values into transformed binary numbers by ordering the Boolean bit according to corresponding ordinal position in the set.

(Data Transformation rules)

A. Let o be an ordinal number and n be a numeric value then $<o, n>$ is an ordinal-numeric pair.

B. If S is a set of ordinal-numeric pairs, $<o, n>$ in S and
$b = (n >= (\sum_{<u,v> \in S} V)/|S|)$ then
$<o,b>$ is a ordinal-Boolean pair.

C. If $\{<o_i,b_i>\}$, where $1 <= i <= n$, is a set of n ordinal-Boolean pairs, then
$b_1 * 2^{n-1} + b_2 * 2^{n-2} \ldots + b_n$ is a transformed binary value.

For instance, in the first row of the education attribute in Table 1, the original value is $\{<e_1, 20>, <e_2, 10>, <e_3, 40>, <e_4, 30>\}$. According to Data Transformation rules, the corresponding set of ordinal-Boolean pairs is $\{<e_1, 0>, <e_2, 0>, <e_3, 1>, <e_4, 1>\}$ and the transformed binary value is 0011. Table 2 shows the complete transformation of Table 1.

Table 2. The Booleans Values of 10 Crime Hot Spots (DB)

TID	gender	age	education
1	01	001	0011
2	01	011	0011
3	10	101	1100
4	01	011	0011
5	01	001	0011
6	10	001	0011
7	01	011	0111
8	10	010	0110
9	01	001	0011
10	01	001	0011

3.3 Binary Induction with the Application of Simplification Karnaugh Map

The induction process employs simplication Karnaugh map to summarize binary numbers without relying on induction hierarchies [25].

A Karnaugh map has a square for each ‘1’ or ‘0’ of a Boolean function. One variable Karnaugh map has $2^1 = 2$ squares, Two variable Karnaugh map has $2^2 = 4$ squares, Three variable Karnaugh map has

$2^3 = 8$ squares, Four variable Karnaugh map has $2^4 = 16$ squares etc. shown in Figure 1.

1 variable

r0	r1

2 variables

r0	r2
r1	r3

3 variables

r0	r4
r1	r5
r3	r7
r2	r6

4 variables

r0	r4	r12	r8
r1	r5	r13	r9
r3	r7	r15	r11
r2	r6	r14	r10

Figure 1. Karnaugh Map

The detailed processes have been illustrated by taking table 2 as an example. As shown previous, there are 4 variables in the 'education' table. The corresponded Karnaugh map is 16, (2^4), squares table. If we put the e_1, e_2, e_3, e_4, as seen in figure 2, the counting of 0011 is 7 and 0101,0111,1100 is 1. The result of this transformation as illustrated in Figure 2.

0	0	1	0
0	1	0	0
7	1	0	0
0	0	0	0

Figure 2. The Results of Education Attribute Transferred to Karnaugh Map

Based on the rule of Karnaugh map, we can take one variable out of the two adjacent variables. In Table 2, Education, there are two groups which variable is adjacent with each other, (r3, r5) and (r5, r7), and the variable r12 stands alone. The expression is indicating as shown follows.

$$\begin{aligned} F(e_1,e_2,e_3,e_4) &= \sum m(r3,r5,r7,r12) \\ &= (r3+r7)+r5+r12 \\ &= (0011+0111)+0101+1100 \\ &= 0\_11+0101+1100 \end{aligned} \quad (2)$$

Equation (2) reveals that the value '0011' and '0111' will be transferred to '0_11'.

Following similar procedure, the 'age' got 3 values whose Karnaugh map can be shown in Figure 3.

0	0
5	1
3	0
1	0

Figure 3. The Results of Age Attribute Transferred to Karnaugh Map

After similar simplification process, the result of 'age' attribute can be described in equation (3).

$$\begin{aligned} F(a_1,a_2,a_3) &= \sum m(r1,r2,r3,r5) \\ &= (r1+r3)+r2+r5 \\ &= (001+011)+010+001 \\ &= 0\_1+010+001 \end{aligned} \quad (3)$$

Equation (3) reveals that the value '001' and '011' will be transferred to '0_1'.

It is not necessary to simplify 'gender' attribute, since there is only 2 values within it.

Table. 3 The Boolean Values of 10 Crime Hot Spots (DB) Has Been Converted Into DB'

TID	gender	age	education
1	01	0_1	0_11
2	01	0_1	0_11
3	10	101	1100
4	01	0_1	0_11
5	01	0_1	0_11
6	10	0_1	0_11
7	01	0_1	0_11
8	10	010	0110
9	01	0_1	0_11
10	01	0_1	0_11

3.4 Stop Condition of the Induction

In this study, the definition of the "stop condition of the induction algorithm" is by way of re-checking the induction results in Table 3. Keep one data of the same attribute in the field in the table before re-checking, shown in Table 4. The inductive algorithm of attribute “education” and “age” can not be simplified anymore. Therefore, the algorithm must be stopped.

Table 4. The Boolean Values of 10 Crime Hot Spots (DB’)

TID	Gender	Age	Education
1	**01**	**0_1**	**0_11**
3	10	101	1100
6	10	0_1	0_11
8	10	010	0110

3.5 Inductive Rule

Sum up the values in the same column and row, 7 data are found to have the exact same value in each field. Then divide the above data by the total number of the data which gets an outcome of 70%. This is the inductive degree. The inductive rules are shown in Figure 4. In this case, there is only one rule of high inductive degree. Due to the difficulty of interpreting binary values, the expression of the rule is then reduced to its symbolic form of raw data. As shown in Figure 5, 0 means the value lower than the number of average threshold represented by L. 1 is the value higher than the number of average threshold represented by H. Where “baseline” indicates “do not care”, which means interpretation without transformation.

rule 1 : {01} ^ {0 1} ^ {0 11} → 70%

Figure 4. Rule After Induction

Rule 1 : {<g_1, L> <g_2, H>} ^ {<a_1, L> <a_3, H>} ^ {<e_1, L> <e_3, H> <e_4, H>} → 70%

Figure 5. Rule of Easy-to-Interpret After Induction

3.6 Simplification Rules of The Modified Karnaugh Map

Simplification of Boolean algebra Karnaugh map in the most efficient, Karnaugh map provides a graphic (box) between the point of view of the relationship, to find two adjacent, 4, 8, 16 a group (re-select), you can simplify.

But the result has been repeated to select the option to repeat the question of attribution circle and lead to property value when summed up, the issue of double counting, it should be amended to do something. Circle option was to repeat, the majority of the combined selection and simplification to four variables Karnaugh map as an example, shown in Figure 6.

(1) Figure 6 (a) based on the original Karnaugh map simplification rules, r1, r3, r5, r7 as a group, r5, r13 a, r7, r6 a, r5 and r7 of which are repeated to select, r1, r3, r5, r7 total number of (3 +2 +6 +5) = 16, r5, r13 Total Views (6 +4) = 10, r7, r6 total number of (5 +2) = 7, in order to avoid repeated induction calculation, so I chose to select r1, r3, r5, r7, chosen to give up r6, r13.

(2) Figure 6 (b) based on the original Karnaugh map simplification rules, r1, r3, r5, r7 circle a group of selected, r5, r7, r13, r15 circle a group of selected, but r5, r7 was chosen to repeat, so I chose to select the number of larger (4 +7 +6 +3) = 20 of r5, r7, r13, r15 for a group, r1, r3 for the other group.

0	0	0	0
3	6	4	0
2	5	0	0
0	2	0	0

(a)

0	0	0	0
1	4	6	0
2	7	3	0
0	0	0	0

(b)

Figure 6. Modify Karnaugh Map Simplification Rules

3.7 Proof of The Simplification Rules of The Modified Karnaugh Map

According to the simplification rules of the modified Karnaugh map proposed by this paper, the circled inducted values are the greatest ones between the adjacent values, proved as follows:

$$A = [a_{xy}] \in F^{m \times n}$$

/* Where A is the m by n matrix */

$$let \quad B = \{A = [a_{xy}] \in F^{m \times n} \mid A.value > 0 \}$$

/* Where B represents the set of the coordinate value greater than 0 in matrix A */

$$let \quad B' = Sorting(B)$$

/*Set B’ is the sorted B value */

/*C is the set in which each c oordinate and its adjacent coordinate are in B set, where the adjacent number divided by 2, the value of power by n times equals to zero.*/

$$C = \{C = \forall B' \cap adj(B) \mid Link\_size(C) \bmod 2^n = 0, n \in attribute\_number\}$$

/* There is a Cxy value greater than every other Cij value in C set, then Cxy is the large set link in Karnaugh map.*/

$$if \quad \exists C_{xy} > \forall C \rightarrow \quad is\, Max, \exists C_{xy} \subseteq C$$

4. Performance Evaluation

4.1 Experimental Environment

In this section, a simulation is performed to empirically evaluate the performance of the proposed method. The KMAOI algorithm is implemented in C language and tested by using a PC with a P4 2.4G processor and 1024MB main memory under the

Windows XP operating system. Since the AOI method has a much better time complexity than the KMAOI algorithm, the objective of the simulation is not to compare the number of times the PC runs, but to test the stability and inductive performance of the algorithm. This paper uses a real case of 2500 data of the MovieLens data sets. First, the meaningful attributes are filtered; the description of the attributes is shown in Table 5. Then the users' features on a rating of 4-5 points are inducted in zip code units from the questionnaire using the algorithm proposed, where the MovieLens data sets were collected by the GroupLens Research Project at the Minnesota University.

The data set consists of:

* 100,000 ratings (1-5) from 943 users on 1682 movies.
* Each user rates at least 20 movies.
* Simple demographic info of the users (age, gender, occupation, zip code).

The data was collected through the MovieLens web site (movielens.umn.edu) during a seven-month period from September 19th to April 22nd in 1998. The data has been treated which means that the users who have less than 20 ratings or do not have complete demographic information are removed from the data set.

Table 5. Description of Attributes

Attribute	Number of Values	Values
Age	4	the amount of youth(under 20), adult(21~60), and elder(over 61)
Occupation	4	the number of engineer, educator, marketing and student
Movie_ type	4	the number of romance, comedy, thriller and action

4.2 Experimental Results and Performance Evaluation

(1) Induction Effect

After the actual algorithm under the circumstances of the absence from the hierarchy mechanism and hierarchy trees, the method proposed in this paper can induct the number of the data. The data of the tuples with the same value are voted respectively, in which the attribute data set of the user with movie rating of 4-5 points has be inducted. Then it is divided by the total number of the data. The induction degree is shown in table 6. The coverage of the induction summation of rule1, rule2 and rule 3 is 80.8%. It is obvious that the algorithm proposed has good induction ability. In the experiments, rule number 1 has the highest induction degree. It holds 1568 data out of 2500 for as high as 62.72 percent. The rule No.1 is listed, shown in Figure 7, according to its original data format for a data interpretation.

Table 6. Induction Results of The Real Case

Age	**Occupation**	**Movie_Type**	**Count**	**Percentage**	**Rule Number**
_10	1__0	10__	1568	62.72%	(1)
_10	01__	10__	285	11.40%	(2)
_10	1__0	_10_	167	6.68%	(3)
_10	001_	10__	149	5.96%	(4)
_10	1__0	0_1_	124	4.96%	(5)
_10	_001	10__	98	3.92%	(6)
_10	01__	_10_	31	1.24%	(7)
_10	01__	0_1_	22	0.88%	(8)
_10	001_	0_1_	19	0.76%	(9)
_10	_001	_10_	16	0.64%	(10)
_10	001_	_10_	14	0.56%	(11)
_10	_001	0_1_	7	0.28%	(12)

Rule 1 : $\{\langle a_2, H\rangle\langle a_3, L\rangle\} \wedge \{\langle o_1, H\rangle\langle o_4, L\rangle\} \wedge$
$\{\langle m_1, H\rangle\langle m_2, L\rangle\} \rightarrow 62.72\%$

Figure 7. Easy-to-Read Inducted Rules

Interpretation of the rule: among those users rating 4-5 points, 62.72% of them are between 21~60 years of age, and less are older than 61. Most of them are engineers in terms of the nature of work, while students are in the minority. They favor romantic movies more and comedic ones less.

(2) Stability

This paper is an empirical research. The data is divided into units with 300 data in each unit. The experiment is tested successively and accumulatively to investigate the stability of the inductive ability of the algorithm proposed by the study. The result shows that the algorithm has stable inductive ability no matter what size of the data is, as shown in Figure 8.

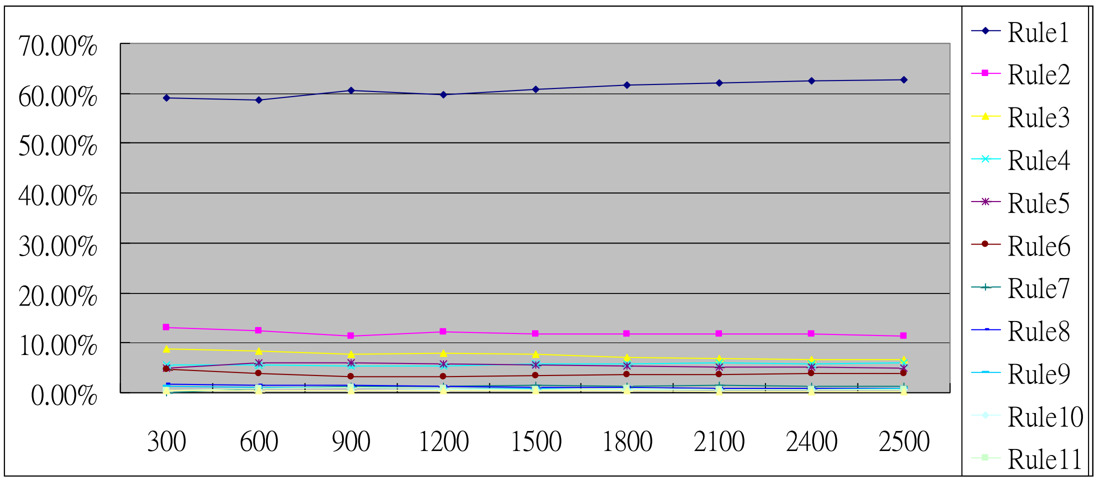

Figure 8. Induction Results of The Real Case

5. Conclusions

This paper proposes a modified AOI algorithm combining the simplified binary digits with Karnaugh Map. It is capable of dealing with data with multi-valued attributes without establishing the concept trees and extracting the general features implicit in the attributes.

This research concludes 3 contributions according to the empirical results. First, it solves the bottleneck problem of the traditional AOI method. There is no need to establish the concept hierarchies and concept trees during the inductive processes thus preventing from the heave workload. Second, the traditional AOI method is not able to deal with data with multi-valued attributes, while the method proposed by this paper can. Third, the data induction has very good inductive ability and stability. Fourth, the research result showed, this research method provide an effective way to discover attributes with multi-value which can apply into behavior attributes of hacker in information security.

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