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Evaluating the Behavioral and Developmental Interventions for Autism Spectrum Disorder

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Abstract

The number of children diagnosed with Autism Spectrum Disorder (ASD) has increased in the past few years and the root cause of the symptom cannot yet be determined. The diagnosis today relies heavily on the observation of children's behaviors. This paper presents a technique to investigate the behavior factor associations, and to classify these relations using classification based on association (CBA). Our experiments used actual patient profiles from two hospitals in Thailand. This dataset was categorized by doctors into two types: Autism and Pervasive Developmental Disorder - Not Otherwise Specified (PDD-NOS). Our analysis results show several interesting behavior patterns in autism disorder. These results provide valuable information for doctors to conduct further studies in the early intervention of autistic symptoms. The goal of our research is to develop a data analysis tool to aid doctors in the diagnosis process in the future.

Keywords: Data Mining; Autism Spectrum Disorder; Medical Data Analysis; Classification Based on Association;

1. Introduction

Autism spectrum disorder (ASD) is a brain development disorder that results in delayed and abnormal development during a child's early years. ASD is the general category used to describe behavioral differences characterized by impairments in three domains: social interaction, communication, and range of interests and activities [1]. The abnormality usually begins before a child is three years old, making it hard to detect. Autism is associated with a recognized cause in only about 10% of individuals, most commonly with fragile X syndrome, tuberous sclerosis and chromosomal abnormalities, while for most of idiopathic ASD are unknown.

Nowadays, diagnosis is done based on observation of a patient's behavior using a few standard protocols [2]. The current diagnostic standards widely used are diagnostic and statistical manual of mental disorders - 4th edition (DSM-IV) [1] and autism diagnostic observation schedule (ADOS) [3]. Moreover, it is also important to distinguish between Autism and Pervasive Developmental Disorder - Not Otherwise Specified (PDD-NOS). Children with PDD-NOS have symptoms which are similar to those of autism but are usually milder.

There are some patterns in the behavior of autistic infants that can be a basis for further investigation such as the tendency to not socialize, ignorance towards own name, and less looking and smiling at others. A study in [4] reported that about two-thirds of 67 autistic children have had periods of severe tantrums, and about one-third had an aggression history with tantrums. Other behavioral patterns that were noticeable include delay in natural speech development and poor performance at tasks involving complex language use, such as comprehension and inference [5].

From previous studies, no single behavior seems to point specifically to ASD although there are some outstanding behavioral patterns that call attention to more investigation. Thus, we believe that with a sufficient number of patients' behavior records, it may be possible to discover the association between some particular behaviors and the autistic symptoms. This paper discusses data mining techniques aimed at providing an array of tools to assist doctors in analyzing patients' data intelligently.

In this research, we attempted to extract patterns from behavioral data and develop a classifier for patients' behaviors. The method proposed is an associative classification method. A classification-based association (CBA) technique is used to find association of behavioral patterns for autistic and PDD-NOS children. Our results present some useful information that can be used in the future to guide clinicians in selecting appropriate treatments, which in turn can help autistic children function better in a society as well as enable early detection and intervention .

In our initial experiments, we used 140 actual patient profiles from two hospitals in Thailand. All patients were diagnosed with either autism or PDD-NOS.

The rest of this paper is organized as follows: Section II presents previous researches related to mining for medical data and a background study on associative classification. Section III defines the problem and related terminologies. Section IV discusses the analysis method. Section V presents experimental results and discussions. The conclusion and directions for future work are offered in Section VI.

2. Background and Related Researches

2.1 Data Mining for Medical Data Analysis

Over the past few years, many researchers have applied several data mining techniques to analyze medical data. The study in [6] showed the effects of the behavior therapy for autistic disorder. They used decision trees (ID3) and association rule mining to predict the response during different stages of therapy. They considered the rules with support of 10% and confidence of 90%. These rules can be used to predict the level of appropriate and inappropriate behaviors. Research in [7] studied 58 patients of peripheral lung cancer disease using association rules. The work considered attributes, e.g. gender, age, shape, ground-glass density, in the diagnosis. The technique generated a set of diagnosis knowledge for clinical practices and the knowledge was later used to build an expert system. Another related study was presented in [8]. An application was developed using a decision tree, Naive Bayes and Neural Network to find hidden patterns and relationship of data in the healthcare industry. Medical profiles such as age, blood pressure and blood sugar were successfully used to predict the likelihood of patients getting a heart disease.

Classification mining maps a set of data items into predefined categories. This technique can be used to create a classifier for diagnosis classes. The classifier is built from machine learning with sufficient medical records ("training"). It can then be used to categorize unknown clinical data into diagnosis classes ("testing"). Effective treatment can be achieved.

An effective classification mining called associative classification (AC) has been proposed. The approach emphasized relations of attributes, which differed from traditional classification methods. The research in [9] applied AC to a drug screening application. The results were proven to be better than traditional classification techniques, such as C4.5. Thus, in our study, we explored the use of AC. The basic ideas and the algorithms are discussed in the next section.

2.2 Associative Classification

Associative classification (AC) integrates association rule mining with effective classification techniques. The general idea is to search for strong rules that are associated with class labels instead of items. The results generated from AC are represented in a simple if-then form. Many approaches were proposed based on AC. In our work, we studied three popular algorithms: classification based on association (CBA) [9], classification based on multiple rules (CMAR) [10] and classification based on predictive association rules (CPAR) [11].

CBA employs Apriori algorithm during the association phase whereas CMAR uses FP-growth. The CMAR and CPAR determine final rules using a multiple rule technique. However, multiple rules may create conflicting cases, i.e. matching more than one rule with different class labels. This issue has not been resolved in CMAR and CPAR.

The work in [12] compared many different AC algorithms. The results stated that CPAR was suitable for a large dataset because it took less time to generate rules. In terms of accuracy, all algorithms can produce effective classifiers with an acceptable error rate.

In our experiment, we worked with a small number of patient records. Thus, the execution time is not an issue. We decided to use CBA since the algorithm is able to generate more rules.

2.3 Classification based on Association

Classification based on association (CBA) concerns finding rules that can accurately

predict classes. CBA includes two main parts: (1) a rule generator (CBA-RG) that is used to generate a complete set of class association rules or CARs, and (2) a classifier builder (CBA-CB) that is used to prune the set of CARs and produce a classifier.
In the first step, CBA-RG generates all frequent ruleitems by the Apriori algorithm to find all rules that have supports over the user-defined threshold. A ruleitem can be represented as X Y, in which X is called an antecedent (IF-part) and Y is called consequent (THEN-part). The THEN-part of a ruleitem is a class label instead of an attribute set as presented in Apriori. Prune ruleitems are then inserted to CARs and sorted by confidence values. The first step is repeated until a predefined number of the IF-part is reached.
In the second step, precedence rules from each training case in the CARs list is read and ranked. The rules with the highest score are then used to build a classifier. The majority of the classes that are not picked are used to define a default class.
In addition, from the previous study, a value of the minimum support threshold had a strong effect on the accuracy of the classifier. The classifier built by CBA will be more accurate than that of C4.5 when the threshold is set at 1-2% [13, 14].

3. Problem Definition

3.1 Behavior Test Assessment

The observation test used in our experiments describes the patients using 32 criteria. Table I shows all symptoms in the behavior test used throughout this paper.

Table 1: Items In Behavior Test

Item No.	Item Description
1	No spoken language or delayed speech
2	Significantly impaired language
3	Marked impairment in the ability to initiate a conversation with others
4	Marked impairment in the ability to sustain a conversation with others
5	Stereotyped and repetitive use of language
6	Idiosyncratic language
7	Lack of spontaneous use of simple gestures to communicate
8	Inappropriate usage of a variety of facial expressions for emotional responses
9	Failure to point with finger to indicate an interest in something
10	Failure to show up to parents upon pain or injury
11	Absence of or minimal recognition of other people’s happiness or distress
12	Failure to respond to the smiling of others
13	Failure to respond when called by name
14	Failure to make eye contact when parents are playing with him
15	Failure to bring objects to parents to show something

16	Living in his or her own world
17	Preference for solitary play activities
18	Inappropriate response towards parents' attempt to play with
19	Inappropriate response towards seeing other children being or playing together
20	Failure to initiate a simple play with other children
21	Lack of interest in other children
22	Lack of interest in others
23	Failure to initiate simple play with others
24	Disinterest in playing with various kinds of toys
25	Lack of spontaneous make-believe or social imitative play
26	Improper playing with small toys, e.g. just mouthing, fiddling or dropping them
27	Restricted patterns of interest that is abnormal either in intensity or focus
28	Preoccupation with parts of objects
29	Insistence on certain routines or rituals, such as wearing a certain jacket or making sure that all his/her toys are in the right place
30	Spinning or whirling him/herself around for long periods of time
31	Moving his/her hands or fingers in unusual or repetitive ways

Every item in this test can be mapped into a criteria in DSM-IV [1] and ADOS [3]. Each item in our test associated with one of the three main categories: social interaction, communication, and restricted repetitive/stereotyped patterns of behavior.

3.2 Dataset

The clinical data used in this study contains 140 patient records. Each record was obtained from a behavioral observation and an interview using the 32 criteria mentioned previously. Each patient record was labeled as either autism or PDD-NOS by experts. There were 110 records of autistic cases and 30 records of PDD-NOS. The age of the patients ranged from 17 to 145 months. There were 121 boys and 19 girls.

The resulting attribute of each criterion can either be "present" (impairment behavior is manifested) or "absent" (otherwise).

3.3 Problem Statement

In our study, we define a set of definitions that will be used in the analysis. This section presents a mathematical statement of the classification based on association method:

Definition 1: Let $D=\{T_1,T_2,\ldots T_n\}$ be a transaction dataset of patients and let $I=\{I_1,I_2,\ldots,I_m\}$ be the set of attributes in D. Let $Y=\{Y_1,Y_2,\ldots,Y_p\}$ be the set of class labels. Each patient transaction T_i consists of one or more attributes from set I and one class label from Y.

Definition 2: Let *itemset* be a set of disjoint attribute values. Let *ruleitem* R: X Y_i be the rule for finding patterns in behavior test, where X is an *itemset* X I and Y_i Y.

Definition 3: Let support count *(suppcount)* of *ruleitem R* be the number of transactions that contains *itemset X* and belongs to class Y_i. Let an actual occurrence *(actoccr)* be the number of transactions that contain *itemset X*. Let the confidence *conf(R)* be the portion of transactions in *D* that satisfies the rule antecedent and also have a class label of Y_i.

Definition 4: A *ruleitem R* can be called a *frequent ruleitem* if and only if *supp(R)=(suppcount(R) / |D|) _ minsupp*, where |*D*| is the size of the dataset.

Definition 5: A list of *CARs* can be generated from *ruleitem R* where *conf(R)=(suppcount(R) / actoccr(R)) _ minconf.*

Definition 6: If a set of rules has the same rule antecedent, then a classifier is generated by ordering the rules according to the following schema.

A rule R_1 has priority over a rule R_2 if and only if:

(1) if $conf(R_1)>conf(R_2)$.
(2) if $conf(R_1)=conf(R_2)$ and $supp(R_1)>supp(R_2)$.
(3) if $conf(R_1)=conf(R_2)$ and $supp(R_1)=supp(R_2)$ and

R_1 is generated before R_2.

4. Analysis Method

This section introduces our research methodology. We proposed to use CBA to discover association of behavior patterns. Patients' behavior records will be used as input. The output is a set of accuracy rules with support and confidence measures. The analysis steps are modeled in Fig. 1.

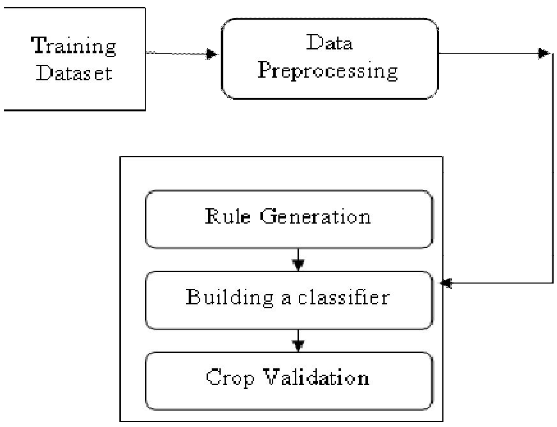

Fig. 1: Analysis Methodology Overview.

Texts and descriptions of behaviors from the original interview and observation scripts are converted into their numerical form. Different data require different methods of normalization and value mapping. After the data is preprocessed, we used

CBA in a similar fashion as described in section 2C and 3C. The optimum support and threshold values are calculated through brute force. These values are designed to maximize the accuracy of the classifier. The classifier is created by model training using a k-fold cross validation technique. After the classifier is built, it is tested. In other words, the training dataset is used to derive the model, where the accuracy is estimated using data in the testing set.

K-fold usually results in high accuracy with relatively low bias and variance. In our experiment, k is set to 3. The datasets are randomly split into three mutually exclusive subsets: D1, D2, and D3. All sets are approximately of equal size. Both training and testing are processed three times with one subset used as a test set. In the first round, D1 is used for testing, while D2 and D3 are used for training. D2 and D3 are then used to test in successive rounds.

From our autism dataset, *minconf* of 100% numbers lead to the highest accuracy of 95.65% in all three rounds, and the highest average accuracy of 85.27%. Finally, we obtained 7 rules for building an automated classifier. All rules are classified as autism except for the default class, which is classified as PDD-NOS. The rules are demonstrated in Table II.

The symptoms manifested in autistic children vary greatly. Our work attempts to achieve the potential behavioral patterns that are most common in Thailand. If we divide the generated rules into standard criteria as mentioned in DSM-IV, we can investigate the relationship between these behaviors. Fig. 2 shows the rules of the relationship.

From the Figure, all antecedents in rule #3, rule #4, and rule #5 are from the same DSM-IV sub-category: the failure to develop peer relationships appropriate to developmental level and delay in, or a total lack of, development of spoken language.

Table 2: Classifier Rules

Generated from CBA

Rule No.	Rules Antecedent	Rules class	Support (%)	Confidence (%)
1	7, 12	Autism	45	100
2	3, 12	Autism	42	100
3	1, 16	Autism	37	100
4	2, 16	Autism	35	100
5	1, 20	Autism	35	100
6	19	Autism	34	100
7	22	Autism	29	100

5. Experimental Result and Interpretation

In order to analyze the 7 generated rules, it is important to interpret support and confidence. Since the confidence shown in Table II is 100% for all rules, a combination of symptoms in each rule only occurs in an autism class and not PDD-NOS. In other words, these strong behavior patterns are manifested only in autistic children in our dataset. The rules can be interpreted as shown in examples below:

Rule #1: {7 12} Autism [supp=45%, conf=100%]

This rule means that for 45% of cases in the dataset:
IF lack of spontaneous use of simple gestures to communicate
AND failure to respond to the smiling of others THEN labeled as autism

The impairment behavior *"lack of spontaneous use of simple gestures to communicate"* can be mapped to a sub-category - "lack of using multiple nonverbal behaviors" in DSM-IV. In our dataset, this impairment always co-occurs with the impairment, *"failure to respond to the smiling of others"* or "lack of social or emotional reciprocity" in DSM-IV. This pattern did not manifest in any PDD-NOS child in our dataset.

Rule #2: {3 12} Autism [supp=42%, conf=100%]

This rule means that for 42% of cases in the dataset:
IF: impairment in the ability to initiate a conversation with others

AND failure to respond to the smiling of others
THEN labeled as autism

Most of autistic children are significantly impaired in social interaction and communication. The impairment in the ability to initiate a conversation with others always co-occurs with the failure to respond to the smiling of others.

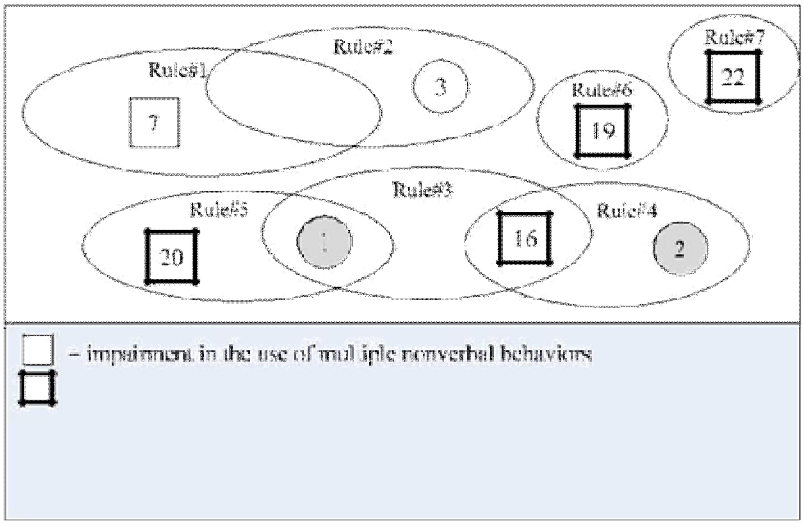

Fig. 2: Rules Descriptions.

From the results, no interesting relationship between impairment behaviors in PDD-NOS has been found. This is due the fact that there are a small number of PDD-NOS patient records in our dataset. Moreover, in our dataset, all relationships exist in

PDD-NOS records also appear in the autistic records making it hard to derive a rule set for PDD-NOS. However, the results still lead to a few interesting observations on the differences between autism and PDD-NOS as described in this section.

Our results are validated by experts who work with autistic and PDD-NOS children. It can thus be concluded that CBA can be used to build an expert system in order to supply important references in current clinical practices.

6. Conclusion and Future Study

We have shown that our method can be used to analyze the ASD patient data records. The resulting classifier can distinguish behavior patterns between autism and PDD-NOS with a relatively high accuracy. Furthermore, the relationship of the behavior pattern for autistic and PDD-NOS children can be identified.

Given a set of impairments, a disorder type can be suggested with a relatively high confidence level. However, the experiment presents a couple weaknesses:

- Prediction error in some cases because small number of samples tend to overfit the solution
- Lack of clinical data of normal children for use in the training phase

In conclusion, the use of associative classification in medical applications is relatively new. We believe our analysis tool is practical for use in diagnosis provided that more patient records are compiled. The knowledge base of ASD and an expert system can also be built in the near future. with a history of language impairment", Research in Developmental Disabilities 28, 2007, pp. 145–162.

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