International Journal of Engineering Technology and Applied Science

(ISSN: 2395 3853), Vol. 3 Issue 7 July 2017

AN EFFICIENT ALGORITHM TO DECISION TREE GENERATION FOR CLASSIFICATION WITH LESS COMPLEXITY

Kalpana Singh
Research Scholar
VITS, Satna, India
kalpanagwalior1987@gmail.com

Pradeep Tripathi
Assistant professor
VITS, Satna, India
pradeepit32@gmail.com

ABSTRACT

Data Mining is an analytic process designed to explore data (usually large amounts of data). Where classification is a method of the data mining would greatly simplify the understanding of the whole space of available methods. And Decision tree algorithms are a method of classification for approximating discrete-valued target functions, in which the learned function is represented by a decision tree. This work proposes a modified id3 decision tree algorithm for machine learning using similarity factor with less complexity and less time to construct decision tree.

1. INTRODUCTION

Data mining is a process used by companies to turn raw data into useful information. By using software to look for patterns in large batches of data, businesses can learn more about their customers and develop more effective marketing strategies as well as increase sales and decrease costs. Data mining[19] depends on effective data collection and warehousing as well as computer processing.

Knowledge discovery in databases (KDD) [2], often called data mining, extracting information and patterns from data in large data base. The core functionalities of data mining are applying various techniques to identify nuggets of information of decision making knowledge in bodies of data [2]. From the last decades, data mining and knowledge discovery applications have important significance in decision making and it has become an essential component in various organizations and fields. The field of data mining has been increased day by day in the areas of human life with various integrations and advancements in the fields of Statistics, Databases, Machine Learning [3], Pattern Reorganization, Artificial Intelligence and Computation capabilities etc.

There are several algorithms which are also using genetic and fuzzy set are also applied in

these areas [17]. Combine the fuzzy and search capabilities of Genetic Algorithms (GAs) may improve the optimal fuzzy rule and improve the rule generation also[16].

The improved ID3 based on weighted modified information gain called ωID3[18] judges whether one condition attribute need to modify by computing objectively. Choosing splitting attributes blindly in reference has been improved and subjective evaluating using users' interestingness in reference is also overcome. Because ωID3 takes the relevance among attributes into account, the classification precision is enhanced. The experiment shows that ωID3 classification precision is superior to ID3 obviously.

2. LITERATURE SURVEY

Researchers have developed various classification techniques over a period of time with enhancement in performance and ability to handle various types of data. Some important algorithms are discussed below.

2.1 K-NEAREST NEIGHBOR CLASSIFIERS

Nearest neighbor classifiers are based on learning by analogy. The training samples are described by n dimensional numeric attributes. Each sample represents a point in an n-dimensional space. In this way, all of the training samples are stored in an n-dimensional pattern space. When given an unknown sample, a k-nearest neighbor classifier searches the pattern space for the k training samples that are closest to the unknown sample. "Closeness" is defined in terms of Euclidean distance, where the Euclidean distance, where the Euclidean distance between two points,

X=(x1,x2,……,xn) and Y=(y1,y2,….,yn) is

$$d(X, Y)=\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

The unknown sample is assigned the most common class among its k nearest neighbors. When k=1, the unknown sample is assigned the class of the training sample that is closest to it in pattern space.

2.2 CART: CART[5] is the ultimate classification tree that has revolutionized the entire field of advanced analytics and inaugurated the current era of data mining. CART, which is continually being improved, is one of the most important tools in modern data mining. Others have tried to copy CART but no one has succeeded as evidenced by unmatched accuracy, performance, feature set, built-in automation and ease of use. Designed for both non-technical and technical users, CART can quickly reveal important data relationships that could remain hidden using other analytical tools.

2.3 CART-LC

The first oblique decision tree algorithm to be proposed was CART with linear combinations .Breiman, Friedman, Olshen, and Stone (1984)

introduced CART with linear combinations (CART-LC) as an option in their popular decision tree algorithm CART. At each node of the tree, CART-LC iteratively finds locally optimal values for each of the ai coefficients. Hyperplanes are generated and tested until the marginal benefits become smaller than a constant [4].

2.4 C4.5: C4.5[7] is a well-known algorithm used to generate a decision trees. It is an extension of the ID3 algorithm used to overcome its disadvantages. The decision trees generated by the C4.5 algorithm can be used for classification, and for this reason, C4.5 is also referred to as a statistical classifier. The C4.5 algorithm made a number of changes to improve ID3 algorithm. Some of these are:

- Handling training data with missing values of attributes
- Handling differing cost attributes
- Pruning the decision tree after its creation
- Handling attributes with discrete and continuous values

2.5 C5.0/Sec 5: C5.0 algorithm is an extension of C4.5 algorithm which is also extension of ID3. It is the classification algorithm which applies in big data set. It is better than C4.5 on the speed, memory and the efficiency. C5.0 model works by splitting the sample based on the field that provides the maximum information gain. The C5.0 model can split samples on basis of the biggest information gain field. The sample subset that is get from the former split will be split afterward. The process will continue until the sample subset cannot be split and is usually according to another field. Finally, examine the lowest level split, those sample subsets that don't have remarkable contribution to the model will be rejected. C5.0 is easily handled the multi value attribute and missing attribute from data set [8].

2.6 Hunt's Algorithm: Hunt's algorithm generates a Decision tree by top-down or divides and conquers approach. The sample/row data contains more than one class, use an attribute test to split the data into smaller subsets. Hunt's algorithm maintains optimal split for every stage according to some threshold value as greedy fashion [9].

3. PROPOSED METHOD

In this proposed method we are using modified id3 algorithm for decision tree. attribute selection plays important role in efficient decision tree construction for root to bottom node.

Decision trees can handle high dimensional data. Their representation of acquired knowledge in tree form is intuitive and generally easy to assimilate by humans. The learning and

classification steps of decision tree induction are simple and fast.

The algorithm through introducing attribute-importance emphasizes the attributes with less values and higher importance, dilute the attributes with more values and lower importance, and solve the classification defect of inclining to choose attributions with more values. The analysis of the experimental data show that the improved ID3 algorithm gets more reasonable and more effective classification rules´ In order to increase the attributes which have fewer values and high importance, and reduce the attributes which have more values and have low importance, improved ID3 algorithm based on attribute importance is proposed in this paper.

In this proposed method first of all we analyze hole training data and find the attribute for root node on the basis of less dissimilarities with respect to class. Similarly find next node for 2nd level from remaining attributes, and so on.

3.1 ALGORITHM

Step 1: select training dataset for learning.

Step 2: find mapping between every individual attribute to classes.

Step 3: find all possible values for every attribute and that corresponding possible classes.

Step 4: then count values of each attributes which belongs to unique class.

Step 5: Make root node to that attribute which have minimum number of values having unique class.

Step 6: Similarly select other attribute for next level in decision tree from remaining attribute on the basis of minimum number of values having unique class.

Step 7: Exit

4. RESULT AND ANALYSIS

Example

ID3 algorithm is explained here using the classic 'Play Tennis' example. Table 1 shows the training dataset. The attributes are Outlook, Temp, Humidity, Wind, Play Tennis. The Play Tennis is the target attribute shown in figure 1.

Table 1. training dataset.

Outlook	Temp	Humidity	Wind	Play Tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Mild	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Strong	Yes

Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Weak	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

Calculating entropy based on the above formulas gives: -

Entropy ([9+,5-]) = 2 2 − − (9 /14)log (9 /14) (5/14)log (5/14) = 0.940

Gain(S,Humidity) =0.151

Gain(S,Temp)=0.029

Gain(S, Outlook) = 0.246

Based on the above calculations attribute outlook is selected and algorithm is repeated recursively. The decision tree for the algorithm is shown in Figure

STEP BY STEP CALCULATIONS:

STEP 1:"example" set s

The set s of 14 examples with 9 yes and 5 no then

Entropy (S) = -(9/14) Log2 (9/14) – (5/14) Log2 (5/14) = 0.940

STEP 2:Attribute weather

Weather value can be sunny, cloudy, and rainy.

Weather =sunny is of occurrence 5

Weather = cloudy is of occurrences 4

Weather = rainy is of occurrences 5

Weather = sunny, 2 of the examples are "yes" and 3 are "no"

Weather = cloudy, 4 of the examples are "yes" and 0 are "no"

Weather = rainy, 3 of the examples are "yes" and 2 are "no"

Entropy (S sunny) = -(2/5)xlog2(2/5) – (3/5)xlog2(3/5) = 0.970950

Entropy (S cloudy) = -(4/4)xlog2(4/4) – (0/4) xlog2 (0/4) = 0

Entropy (S sunny) = -(3/5)xlog2(3/5) – (2/5) xlog2 (2/5) = 0.970950

Gain (S, weather) = Entropy (S) – (5/14) x Entropy (S sunny)

- (4/14) x Entropy (Scloudy)

- (5/14) x Entropy (Srainy)

= 0.940 – (5/14) x 0.97095059 – (4/14) x 0 – (5/14) x 0. 97095059

= 0.940 – 0.34676 – 0 – 0.34676

= 0.246

STEP 3: Attribute temperature

Temp value can be hot, medium or cold.

Temp = hot is of occurrences 4

Temp = medium is of occurrences 6

Temp = cold is of occurrences 4

Temp =hot, 2 of the examples are "yes" and 2 are "no"

Temp =medium, 4 of the examples are "yes" and 2 are "no"

Temp =cold, 3 of the examples are "yes" and 1 are "no"

Entropy (Shot) = - (2/4) x log2 (2/4) – (2/4) x log2 (2/4) = - 0.99999999

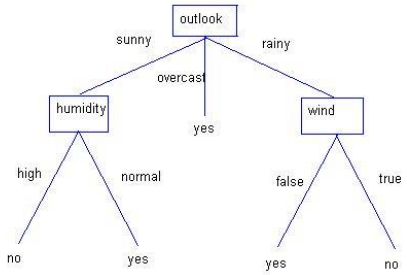

Fig 1 decision tree

Solution By Proposed Method

First of all find unique values of all attribute and corresponding classes from where they belongs.

Here we have seen that outlook have 1 unique value which belongs to unique class. Similarly Temp, Humidity and Wind have 0 unique values which belongs to unique class. So Outlook be a root node because it have maximum values. Fig 2 shows comparison of time taken to generate first 3 nodes in decision tree by proposed method.

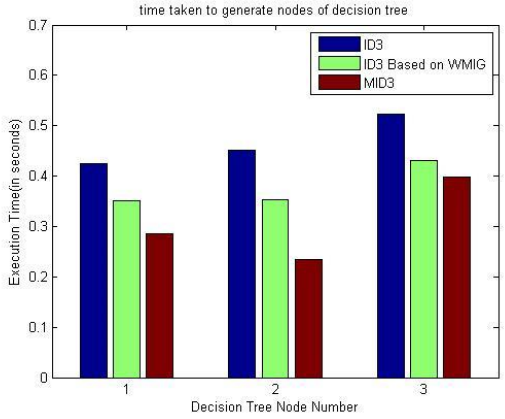

Fig 2. Comparison graph for time taken to generate nodes of decision tree for weather dataset.

Fig 3 shows performance with respect to time among ID3, ID3 based on WMIG and MID3. And here we can clearly see that MID3 is more efficient than ID3 and ID3 based on WMIG and it gives better result.

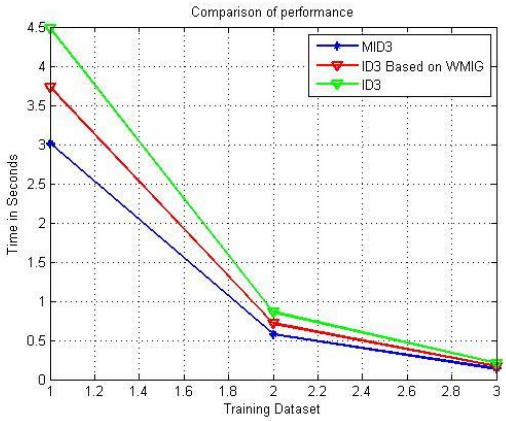

Fig 3 comparison of performance of ID3, ID3 based on WMIG and MID3 algorithm

5. CONCLUSION

The decision tree method is increasing in popularity for both classification and prediction. It can also be used for cluster analysis and time series in some situations. The main advantages of this method are its simplicity, non-parametric nature, robustness, and the ability to process both quantitative and qualitative variables. Decision trees can be easily converted to classification rules that can be expressed in common language.

An MID3 algorithm is presented to overcome deficiency of general ID3 algorithm which tends to take attributes with many values. The proposed algorithm is better then ID3, Because it has less complexity.

REFERENCES

[1] Gorunescu, F, Data Mining: Concepts, Models, and Techniques, Springer, 2011.

[2] Han, J., and Kamber, M. , Data mining: Concepts and techniques, Morgan-Kaufman Series of Data Management Systems San Diego:Academic Press, 2001.

[3] Neelamadhab Padhy, Dr. Pragnyaban Mishra and Rasmita Panigrahi, "The Survey of Data Mining Applications and Feature Scope, International Journal of Computer Science, Engineering and Information Technology (IJCSEIT)", vol.2, no.3, June 2012.

[4]Shreerama Murthy,Simon Kasif,Stivon Salzberg,Richard Beigel,"Oc1:Randomized Induction Of Oblique Decision Tree"

[5] Leo Breiman, Jerome H. Friedman, Richard A. Olshen, and Charles J. Stone. Classification and Regression Trees. Wadsworth International Group, Belmont, California, 1984.

[6] Quinlan J. R., Induction of decision trees. Machine Learning, Vol.1-1, pp. 81-106, 1986.

[7] Zhu Xiaoliang, Wang Jian YanHongcan and Wu Shangzhuo Research and application of the improved algorithm C4.5 on decision tree, 2009.

[8] Prof. Nilima Patil and Prof. Rekha Lathi, Comparison of C5.0 & CART Classification algorithms using pruning technique, 2012.

[9] Baik, S. Bala, J., A Decision Tree Algorithm For Distributed Data Mining, 2004.

[10] Girija, D.K.S.; Shashidhara, M.S., "Data mining techniques used for uterus fibroid diagnosis and prognosis," Automation, Computing, Communication, Control and Compressed Sensing (iMac4s), International Multi-Conference on , vol., no., pp.372,376, 22-23, 2013.

[11] Al Jarullah, A.A., "Decision tree discovery for the diagnosis of type II diabetes," Innovations in Information Technology (IIT), 2011 International Conference on , vol., no., pp.303,307, 25-27 April 2011.

[12] C. V. Subbulakshmi, S. N. Deepa, and N. Malathi, "Comparative analysis of XLMiner and WEKA for pattern classification," in Proceedings of the IEEE International Conference on Advanced Communication Control and Computing Technologies (ICACCCT '12), pp. 453–457, Ramanathapuram Tamil Nadu, India, August 2012.

[13] Mai Shouman, Tim Turner, Rob Stocker, "using data mining techniques in heartdisease diagnosis and treatment", Egypt Conference on Electronics, Communications and Computers, 2012.

[14] Parvathi I, Siddharth Rautaray, "Survey on Data Mining Techniques for the Diagnosis of

Diseases in Medical Domain", International Journal of Computer Science and Information Technologies, Vol. 5 (1) , 838-846, 2014.

[15] Anjana Gosain, Amit Kumar, "Analysis of Health Care Data Using Different Data Mining Techniques", IEEE, 2009.

[16] Jyotsna Bansal, Divakar Singh, Anju Singh, "An Efficient Medical Data Classification based on Ant Colony Optimization", International Journal of Computer Applications (0975 – 8887) Volume 87 – No.10, February 2014.

[17] O. Cordón, F. Gomide, F. Herrera, F. Hoffmann, and L. Magdalena, "Ten years of genetic fuzzy systems: current framework and new trends," Fuzzy Sets Syst., vol. 141, pp. 5–31, 2004.

[18] Chun Guan, Xiaoqin Zeng, "An Improved ID3 Based on Weighted Modified Information Gain", 2011 Seventh International Conference on Computational Intelligence and Security, IEEE ,2011

[19] Varsha Mashoria , Dr. Anju Singh, "A Survey of Mining Association Rules Using Constraints", International Journal Of Computers & Technology.