Use of ID3 Decision Tree Algorithm for Placement Prediction

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***Abstract*— Every year corporate companies come to colleges in order to recruit students. Recruitment is one of the most essential processes for any organization as they look for skilled and qualified professionals to fill up the positions in their organization. Many companies hire students through campus recruitment process. Campus recruitment is an efficient way to get the right resources at the right time with minimal cost and within minimum time frame. While the industry hires candidates from different institutes, students too get a chance to start their career with some of the best companies in the corporate sector. The main aim of this paper is to identify relevant attributes based on quantitative and qualitative aspects of a student's profile such as CGPA, academic performance, technical and communication skills and design a model which can predict the placement of a student. For this purpose ID3 classification technique based on decision tree has been used. The result of this analysis will assist the academic planners to design a strategy to improve the performance of students that will help them in getting placed at the earliest.**

***Keywords*—Weka; Placement Prediction; ID3 Algorithm; Decision Tree; Data Mining**

I. Introduction

Campus placement is a process where companies come to colleges and hire students before they complete their graduation. This paper proposes a system which determines the probability of a student getting placed based on different attributes like programming skills, CGPA, communication skills, internships, backlogs, SSC and HSC marks. For this purpose ID3 classification algorithm is used.

ID3 algorithm is primarily used for decision making. ID3 (Iterative Dichotomiser 3) algorithm invented by Ross Quinlan is used to generate a decision tree from a dataset[5]. ID3 classification algorithm makes use of a fixed set of examples to form a decision tree. In order to depict the dependency of various attributes the resulting tree is used. To decide which attribute goes into the decision node ID3 uses information gain. ID3 searches through the attributes of the training instances and extracts the attribute that best separates the given examples.[17] ID3 operates recursively on 'n' partitioned subsets in order to get the "best" attribute until it classifies the training sets after which ID3 stops; here n is the number of possible values of an attribute. The algorithm makes use of greedy search, that is, it picks the best attribute and never looks back to reconsider earlier choices.

II. Literature Survey

A. *ID3 Algorithm*

In decision tree learning, ID3 (Iterative Dichotomiser 3) is an algorithm invented by Ross Quinlan used to generate a decision tree from the dataset.[3] To model the classification process, a tree is constructed using the decision tree technique. Once a tree is built, it is applied to each tuple in the database and this results in classification for that tuple.

The following issues are faced by most decision tree algorithms[4]:

- To choose splitting attributes
- Order of splitting attributes
- Number of splits to be taken
- Balance of tree structure and pruning
- The stopping criteria

The decision tree algorithm is based on Entropy, its main idea is to map all examples to different categories based upon different values of the condition attribute set; its core is to determine the best classification attribute from condition attribute sets. The algorithm chooses information gain as attribute selection criteria; usually the attribute that has the highest information gain is selected as the splitting attribute of the current node. Branches can be established based on different values of the attributes and the process above is recursively called on each branch to create other nodes and branches until all the samples in a branch belong to the same category. To select the splitting attributes, the concepts of Entropy and Information Gain and Gain Ratio are used.

The use of entropy and information gain is discussed in the subsequent section.

Entropy

It is a measure in the information theory, which characterizes the impurity of an arbitrary collection of examples. If the target attribute takes on 'c' different values, then the entropy S relative to this c-wise classification is defined as

$$\text{Entropy}(s) = \sum - Pi \log_2 Pi$$

Where Pi is the probability of S belonging to class i. Logarithm is base 2 because entropy is a measure of the expected encoding length measured in bits. For e.g. if training data has 14 instances with 5 positive and 9 negative instances, the entropy is calculated as

Entropy ([5+,9-])

= -(5/14)log(5/14)- (9/14)log(9/14)=0.9402

A key point to note here is that the more uniform the probability distribution, the greater is its entropy. If the entropy of the training set is close to one, it has more distributed data and hence, considered as a good training set.

Information Gain

The decision tree is built in a top-down fashion. ID3 chooses the splitting attribute with the highest gain in information, where gain is defined as difference between how much information is needed after the split. This is calculated by determining the differences between the entropies of the original dataset and the weighted sum of the entropies from each of the subdivided datasets. The motive is to find the feature that best splits the target class into the purest possible children nodes - pure nodes with only one class

This measure of purity is called information. It represents the expected amount of information that would be needed to specify how a new instance of an attribute should be classified. The formula used for this purpose is:

$$G(D, S) = H(D) - \sum P(Di)H(Di)$$

The attribute with highest value of information gain is used as the splitting node thereby constructing the tree in top down fashion.

B. CART

CART stands for Classification and Regression Trees (Breiman et al., 1984). It is characterized by the fact that it constructs binary trees, namely each internal node has exactly two outgoing edges. The splits are selected using the towing criteria and the obtained tree is pruned by cost–complexity Pruning. When provided, CART can consider misclassification costs in the tree induction. It also enables users to provide prior probability distribution.

C. C4.5

C4.5 is a well-known algorithm used to generate decision trees. 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.

At each node of the tree, C4.5 chooses one attribute of the data that most effectively splits data set of samples S into subsets that can be in one class or the other[12]. It is the normalized information gain (difference in entropy) that results from choosing an attribute for splitting the data. The attribute factor with the highest normalized information gain is considered to make the decision. The C4.5 algorithm then continues on the smaller sub-lists having next highest normalized information gain.

D. CHAID

CHAID is a type of decision tree technique, based upon adjusted significance testing (Bonferroni testing). CHAID can be used for prediction as well as classification, and for detection of interaction between variables. In practice, CHAID is often used in the context of direct marketing to select groups of consumers and predict how their responses to some variables affect other variables, although other early applications were in the field of medical and psychiatric research.

Reasons to choose ID3

1. Understandable prediction rules are created from the training data.
2. Builds the fastest tree.
3. Builds a short tree.
4. Only need to test enough attributes until all data is classified.
5. Finding leaf nodes enables test data to be pruned, reducing number of tests.
6. Whole dataset is searched to create tree.
7. Whole hypothesis space is searched.

Weka

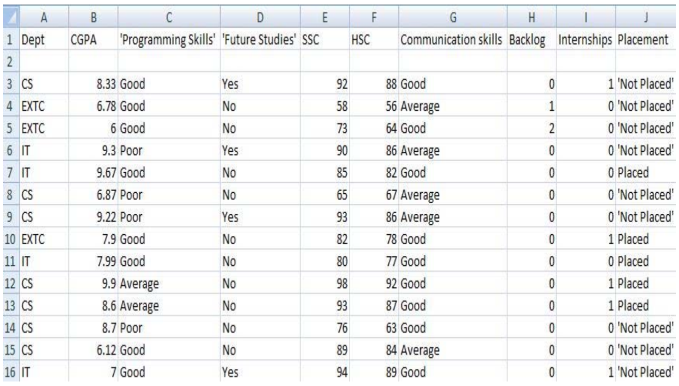
Weka (Waikato Environment for Knowledge Analysis) is a free software available under the GNU General Public License that implements a large collection of machine learning algorithms and is widely used in data mining applications[14]. Weka supports several standard data mining tasks, more specifically, data pre-processing, clustering, classification, regression, visualization, and feature selection. All of Weka's techniques are predicated on the assumption that the data is available as a single flat file or relation, where each data point is described by a fixed number of attributes.

III. Proposed System

Campus placement is a process where companies come to colleges and identify students who are talented and qualified, before they finish their graduation. The proposed system determines the likelihood of placement based on various attributes of a student's profile. Depending on the parameters , manual classification is done whether the student is placed or not placed. A decision tree is then implemented to determine the probable outcome of a student being placed.

The following set of student data is considered as the base set for the proposed system. The data set comprises of different quantitative and qualitative measures of 14 students. The attributes such as department of the student, CGPA (Cumulative Grade Performance Average), programming skills, future studies such as planning for a master's degree, SSC percentage, HSC percentage, communication skills, number of backlogs which is the total count of backlogs both active and dead and the total number of relevant internships have been taken into consideration.

Based on the training set, information gain and entropy is calculated to determine the splitting attribute for constructing the decision tree.



	A	B	C	D	E	F	G	H	I	J
1	Dept	CGPA	'Programming Skills'	'Future Studies'	SSC	HSC	Communication skills	Backlog	Internships	Placement
2										
3	CS	8.33	Good	Yes	92	88	Good	0	1	'Not Placed'
4	EXTC	6.78	Good	No	58	56	Average	1	0	'Not Placed'
5	EXTC	6	Good	No	73	64	Good	2	0	'Not Placed'
6	IT	9.3	Poor	Yes	90	86	Average	0	0	'Not Placed'
7	IT	9.67	Good	No	85	82	Good	0	0	Placed
8	CS	6.87	Poor	No	65	67	Average	0	0	'Not Placed'
9	CS	9.22	Poor	Yes	93	86	Average	0	0	'Not Placed'
10	EXTC	7.9	Good	No	82	78	Good	0	1	Placed
11	IT	7.99	Good	No	80	77	Good	0	0	Placed
12	CS	9.9	Average	No	98	92	Good	0	1	Placed
13	CS	8.6	Average	No	93	87	Good	0	1	Placed
14	CS	8.7	Poor	No	76	63	Good	0	0	'Not Placed'
15	CS	6.12	Good	No	89	84	Average	0	0	'Not Placed'
16	IT	7	Good	Yes	94	89	Good	0	1	'Not Placed'

Fig. 1 Student data

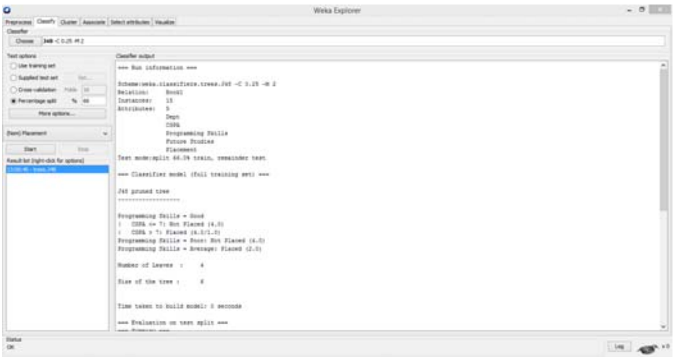
The combination of various attributes determines whether the student is placed or not. The quantitative aspects like undergraduate CGPA, Marks obtained in X and XII form the major aspect of a student's academic endeavours. The qualitative aspects like communication and programming skills form a backbone for a student to get placed as each recruiting company desires to hire students that have a sound technical knowledge and ability to communicate effectively. The other factors like internships, backlogs, future studies add value only when the prior requirements are met. The attributes and the possible values are explained below:

TABLE I

Attributes and their values

Parameter	Description	Possible Values
Department	Department of student	{CS, IT, EXTC}
CGPA	CGPA (Out of 10)	Numeric {≤10}
Programming Skills	Proficiency in C, C++, Java	{Good, Average, Poor}
Future Studies	Whether the student is planning to pursue MS/MBA	{ Yes, No }
SSC (Std. X)	Percentage of marks obtained in Std. X	Distinction – 75% and Above First Class – 60% to 74.99% Second Class – Below 60%
HSC (Std. XII)	Percentage of marks obtained in Std. XII	Distinction – 75% and Above First Class – 60% to 74.99% Second Class – Below 60%
Communication Skills	Proficiency in communication	{Good, Average, Poor}
Backlogs	Total count of live and dead backlogs	{ Yes, No }
Internship	Internships	{ Yes, No }
Placement	Whether the student is placed or not	{ Yes, No }

With these attributes, a decision tree using Weka tool is obtained. The J48 classification algorithm which is an extension of ID3 algorithm is used to generate the decision tree.



J48 -C 0.25 -M 2

○ Use training set
○ Supplied test set
○ Cross-validation Folds 10
● Percentage split % 66

```
=== Run information ===

Scheme:weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     Book1
Instances:    15
Attributes:   5
              Dept
              CGPA
              Programming Skills
              Future Studies
              Placement
Test mode:split 66.0% train, remainder test

=== Classifier model (full training set) ===

J48 pruned tree
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Programming Skills = Good
|   CGPA <= 7: Not Placed (4.0)
|   CGPA > 7: Placed (4.0/1.0)
Programming Skills = Poor: Not Placed (4.0)
Programming Skills = Average: Placed (2.0)

Number of Leaves  :     4

Size of the tree :      6


Time taken to build model: 0 seconds

=== Evaluation on test split ===
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Fig. 2 Weka Explorer Window

The algorithm gives a pruned decision tree with leaves as the decision that is placed or not placed. The primary node consists of programming skills which can accommodate three possible values viz. Good, Average and Poor. If the programming skills are Poor, the student is not placed. Furthermore, if the programming skills are good, the student may be placed based on the academic credential which is CGPA. If the CGPA of the student is above 7, student will be placed otherwise the student will not be placed. Also, if the student has average programming skills, he may still be placed based on other attributes like internships, future studies, communication skills, etc.

The final decision tree with four leaf nodes is obtained as shown below. The leaf nodes hold the value whether the student is placed or not placed.

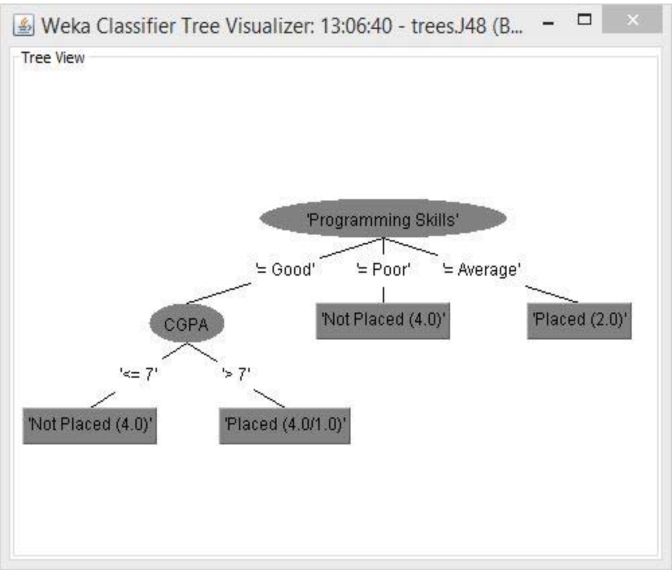

Fig. 3 Weka Classifier Tree Visualizer

The root node chosen here is Programming Skills. Further classification is done by calculating information gain and entropy for each attribute.

TABLE III

Entropy and Information Gain values for different attributes

Attributes	**Entropy**	**Gain**
Department	$E_{CS=}0.8631$ $E_{EXTC}=0.9182$ $E_{IT=}1$	G(Department, S) =0.9140
CGPA	$E_{\leq 7}=0$ $E_{\geq 7}=0.9911$	G(CGPA,S)= 0.6371
Programming Skills	$E_{Good}=0.9544$ $E_{Average}=0$ $E_{Poor}=0$	G(Prog. Skills,S) = 0.5453
Future Studies	$E_{Yes}=0$ $E_{No}=1$	G(Future Studies,S) = 0.7142
SSC	$E_{\geq 75\%}=0.9940$ $E_{\geq 60\%}=0$ $E_{<60\%}=0$	G(SSC,S) =0.781
HSC	$E_{\geq 75\%}=1$ $E_{\geq 60\%}=0$ $E_{<60\%}=0$	G(HSC,S) =0.7142
Communication Skills	$E_{Good}=0.9911$ $E_{Average}=0$ $E_{Poor}=0$	G(Comm. Skills, S) =0.6371
Backlog	$E_{Yes}=0$ $E_{No}=0.9798$	G(Backlog, S)$_{=}$ 0.8398
Internship	$E_{Yes}=0.9709$ $E_{No}=0.8631$	G(Internship,S) =0.9016

Consider the attribute future studies; it has two possible classes viz. Yes and No. There are four students who wish to pursue future studies and remaining ten out of fourteen who do not have any plans to opt for higher studies. According to the training set, all the students who wish to pursue future studies are not placed. This indicates that all the information is contained in a single class. Hence, entropy becomes zero. Higher value of entropy indicates higher degree of distribution of information among classes.

The lowest value of information gain is obtained for programming skills. Thus it is chosen as the root node. Further, the next lowest value (CGPA) is taken as the split node for next level. The subsequent nodes of decision tree at each level are determined by the value obtained in information gain.

Advantages of Decision Tree[16]

1. Variable screening or feature selection is implicitly performed by decision trees. Upon fitting a decision tree to a training set, within the dataset, the most essential variables are the top few nodes based on which the tree is split.

2. For data preparation, decision trees need less effort from users. To overcome scale differences between parameters - for example if there is a dataset which measures revenue in millions and loan age in years, say; this will require some form of normalization or scaling before it can fit a regression model and interpret the coefficients. Such variable transformations are not required with decision trees because the tree structure will remain the same with or without the transformation. Decision trees are also not sensitive to outliers since the splitting happens based on proportion of samples within the split ranges and not on absolute values.

3. Nonlinear relationships between parameters do not affect tree performance. As described here, highly nonlinear relationships between variables will result in failing checks for simple regression models and thus make such models invalid. However, decision trees do not require any assumptions of linearity in the data. Thus, they can be used in scenarios where known parameters are nonlinearly related.

4. The best feature of using trees for analytics is that they are easy to interpret and explain. Decision trees are very intuitive and easy to explain.

IV. RESULTS

The splitting node is based upon Information gain, i.e. Programming skills in this case. Table III indicates the department and the CGPA of the students who have good programming skills. Students having good programming skills are only considered as $E_{Good}=0.9544$, whereas $E_{Average}=0$, $E_{Poor}=0$.

TABLE IIII

Attributes and their values after first splitting node

Department	**CGPA**	**Programming Skills**
CS	8.33	Good
EXTC	6.78	Good
EXTC	6	Good
IT	9.67	Good
EXTC	7.9	Good
IT	7.99	Good
CS	6.12	Good
IT	7	Good

The next splitting attribute based upon Information Gain is CGPA. The students having good programming skills and CGPA >7 are considered. As, $E_{\geq 7}=0.9911$ and $E_{\leq 7}=0$.

TABLE IVV

Values considered after the second splitting node

Department	**CGPA**	**Programming Skills**
CS	8.33	Good
IT	9.67	Good
EXTC	7.9	Good
IT	7.99	Good

V. CONCLUSION

In this paper ID3 classification algorithm is used to generate decision rule. The generated decision rule can be used to predict a student's campus placement. The result of this algorithm can be used by the placement-in-charge to identify those set of students that are likely to face problems in campus placement. The classification model can play an important role in increasing the placement statistics. It can be concluded that classification algorithms can be used successfully in order to predict student placement. Further the implementation can be done in development and application of novel computational techniques for the analysis of large datasets.

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