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A NOVEL TRIO COMBO STRATEGY FOR EFFICIENT TEAM FORMATION USING HYBRID TRIANGULATION MECHANISM

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ABSTRACT

In the fast growing world understanding a situation is highly dynamic process. The decisions are to be made in an instantaneous fashion following different stages of risk and ambiguity. Project managers and leaders are forced to make such critical decisions that change the effect of the company. One such critical decision that involves rationalism and logical diagnosing is the process of choosing a feasible employee for a given project. The main objective of this research work is to propose strategies for optimally electing employees for an effective team formation and to understand the relationship between team's success and given project's success. The method adopted for achieving the central theme of the article is to develop a novel research model that wraps three dominant machine learning approaches to form a triangular hybridization for a better quality team formation. The three methods inspired are Artificial Neural Network (ANN), Decision Tree (DT), and a proposed method called Ensemble Decision Tree (EDT) which is a boosted decision tree using logit boost algorithm that are embedded into the proposed research model for achieving the desired goal. As a pilot scale attempt the model is validated by training and testing it over 474 freelancers from leading sites. The results infer that there exist a direct dependence of team and project success and the proposed EDT approach outperforms other two methods yielding an accuracy of about 87.34% in predicting the unknown sample as a valid or an invalid agent for the current project under consideration.

Keywords: trio combo techniques, decision making, ensemble decision tree, team formation, iron star model.

1. INTRODUCTION

1.1 Description of the theme

The concept and idea behind team formation comes from a complex decision making scenario in an organization. There are several resources that are of interest in any firm starting from money, time, energy, raw materials and of course the human as a resource. The full potential use of all the mentioned resources are carried out by the staff member involved in the team for performing the task needed for the successful completion of the project. There must be a proper decorum in the firm with respect to team interaction and team integrity (Adair, 2004; Gill, 2015). It is now in the hands of the leader or the project manager to choose the right staff for the project under study; so that the cost of team formation and team management decreases and the profit of the firm increases. The main theme of the article is to "Propose novel hybrid research model comprising of machine learning and data mining strategy for efficient team formation by making a rational decision about the agent under consideration for the project".

1.2 Related works

The development of any organization depends on the internal structure of the organization. The flexibility of that structure along with the reliability and scalability factor helps in the growth and development of any firm(Adair, 2004; Stephen Robbins, Timothy A. Judge, 2013). The flexibility factor is improved from the freedom of decision making and decision makers often make a right decision at critical times when they are less stressed by overheads (Karsh and Eyal, 2015; Haselhuhn, 2015; Guarnieri, 2014). Since these decision making strategies are highly dynamic and volatile several soft computing, operation research, data mining methods etc are used by researchers to solve such problems (Alavi and Dillenbourg, 2012; Barreto *et al*. 2008; Melo and Veloso, 2012; Prodanovic, 2002; Shi *et al.* 2013; Zhang and Zhang, 2015). The recent research study resolves the problem of group decision making using a advanced soft computing methods (Li and Zhou, 2011; Wang *et al.* 2015). The resource management is an essential factor in project success. Firms develop different strategies to schedule and judiciously use the available set of resources based on iron star paradigms for betterment of the project (Chen and Zhang, 2012; Wale-Kolade, 2015; Atkinson, 1999; Guarnieri, 2014). The process of team work, team coordination and team synergy is more predominant in firms deploying the ideologies of agile manifesto (Acuña *et al.* 2015; Cockburn, 2002; Drobka *et al.* 2004; Drury-Grogan, 2014; Erdogamus *et al.* 2010; Fagerholm *et al.* 2015; Gill, 2015; Salo and Abrahamsson, 2008; Vlaanderen *et al*. 2011).

1.3 An overview on data collection

The term knowledge is defined as the process of extracting useful information and key patterns from the set of raw facts (Han *et al.* 2012). These raw facts are the input data that are fed into the system for mining knowledge. So in data mining the source of input and the

input in itself is a key aspect (D.O. Durosaro 2003). In this article a trio combinations of formal machine learning approaches are used for driving rational and logical decision that helps organization build an effective platform for the work to be carried out. The source of data for this research work is taken from several leading free lancing websites like Odesk, Elance etc. to name a few. The software developers and designers were concentrated from a wide set of sample space. Profile details of the personnel were investigated and about 500 freelancers were chosen as the initial sample space for the research. The sample space was further refined and revised to 474 free lancers which corresponds to a stability ratio of (94.8%).

Table-1. Sample dataset for team formation.

Availability	Reliability	Cost	TCR	PPSR	PR	CFR	SBTR
Yes	No	Medium	Strong	Low	High	Good	Medium
No	No	Medium	Weak	High	High	Poor	Low
No	Yes	High	Weak	High	Low	Normal	Low
Yes	No	Low	Normal	Medium	Medium	Poor	Medium
Yes	Yes	Low	Normal	Low	Medium	Good	High

TCR - Task Completion Rate, PPSR - Previous Project Success Rate, PR - Popularity Rate, CFR - Communication Fluency Rate, SBTR - Skill Based Test Rates

The profile details of these 474 recipients were analysed with the idea of eight predictors in mind. These eight predictors are chosen based on state of the art literature works and experts' advice in figuring out the reason for why a particular employee is chosen for a particular task? The answer to this logical statement gives rise to eight novel attributes. The Table-1 depicts the Sample Dataset for Team Formation. In this table there are eight attributes chosen for the research study and there is a class label that is of binary nature that tells whether an agent is valid or not for the project. The description of each attribute in the table is given: Available refers to the person's willingness to participate in the task; Reliable refers to the agent's trustworthiness; Cost refers to the amount that has to be paid for the task to the concerned personnel; TCR refers to the time taken for completing the given set of task; PPSR refers to the success story of a person with regards to his/her previous work; PR refers to the popularity gained by the person with respect to his/her gained familiarity in a concerned site. This is given by the overall rating of a person; CFR refers to the art of communicating with other person. Based on the humbleness and politeness in speaking that is determined by the feed back for a person, they are rated and SBTR refers to the expertise of an agent in a specific skill that is determined by the testing thresholds followed by each of the site.

The data is categorical in nature. In order to improve the efficacy of the data mining strategies these data are refined to numeric structure. This is done by normalizing the data using max-min normalization. Binary data are converted to 0-1 sets as a part of numeric conversion. The rating scheme in the freelancing websites is of five Likert scale (Boone and Boone, 2012). These are converted to three Likert scale by combing the rating level 1 and 2 followed by rating level 4 and 5 as a single metric for rating (ex: 1 and 2 as 1 alone). Then these three scaled Likert are linguistically formulated for better understanding (ex: 1 as Low, 3 as normal and 5 as High). The class label is chosen based on experts advice for a particular personnel and a statistical mechanism is also adopted during times of ambiguity in the decision. The statistical mechanism is demonstrated for an instance of Table-1 here: Cost, TCR and PR are considered as an inhibitor attributes in an agent and the remaining predictors are considered as a catalyst factor. The catalyst factors are summed up while the inhibitor factors are summed and subtracted from the total set of summed predictor values from the Likert scales which gives the overall strength of a particular instance. The maximum overall strength that is possible for an instance is $(5 \times 8 - 5 \times 3)$ where the five to left hand site indicates the Likert Scale ranking and the value to the right indicates the decision of a predictor (five positive predictors and three negative predictors). The value is divided by the total number of attributes i.e. eight. This gives 3.12 roughly 3. Hence the strength above three are valid and below and equal to three are not valid. The training and testing data are split equally for training and validating the trio combo methods. The remainder of this article consist of Section 2 dealing with Proposed Methodology, followed by Performance Analysis: A Comparative Study in Section 3, Results and Discussion in Section 4 and Conclusion in Section 5.

2. PROPOSED METHODOLOGY

2.1 An overview on formal research model

The Figure-1 shows the Hybrid Triangular Research Model is a three layered classical model with input, process and output layer. The input layer is the source for data that is collected from several leading

freelancing sites. These are raw facts that are pre-processed with the cleaning strategies and integrated into finite set of attribute value pairs. This forms the data set and a sample of dataset is shown in Table-1. This is fed into the central hub which is the processing unit. It consist of three approaches namely ANN, DT and EDT. The data is formulated in a structure needed for applying the methods using normalization method. The methods are initially trained and then are validated using test sample sets. The accuracy of the method is estimated using confusion matrix. All the three methods are validated for their efficacy and the better method that nears the actual optimum is chosen for further examinations. The ANN adopts the back propagation algorithm for training the sample and are used for testing the test snippets. The activation function is used for improving neurons to expected response. The function used is the sigmoid functions. For decision tree the ID3 (Iterative Dichotomiser 3) algorithm is used with split factor based on information gains. The ensemble decision tree is the proposed hybrid method that integrates boosting with decision tree. The decision tree is boosted with logit boost algorithm and it trains the decision tree to strengthen the accuracy of the tree. The final section is the response section that gives the output by determining an agent as either valid or invalid. The response from each of the method is cross checked with the actuals and the accuracy is determined. In case of an unknown sample whose class label is undetermined; the majority wins (two out of three match) concept is deployed to infer a response to the unseen test sample.

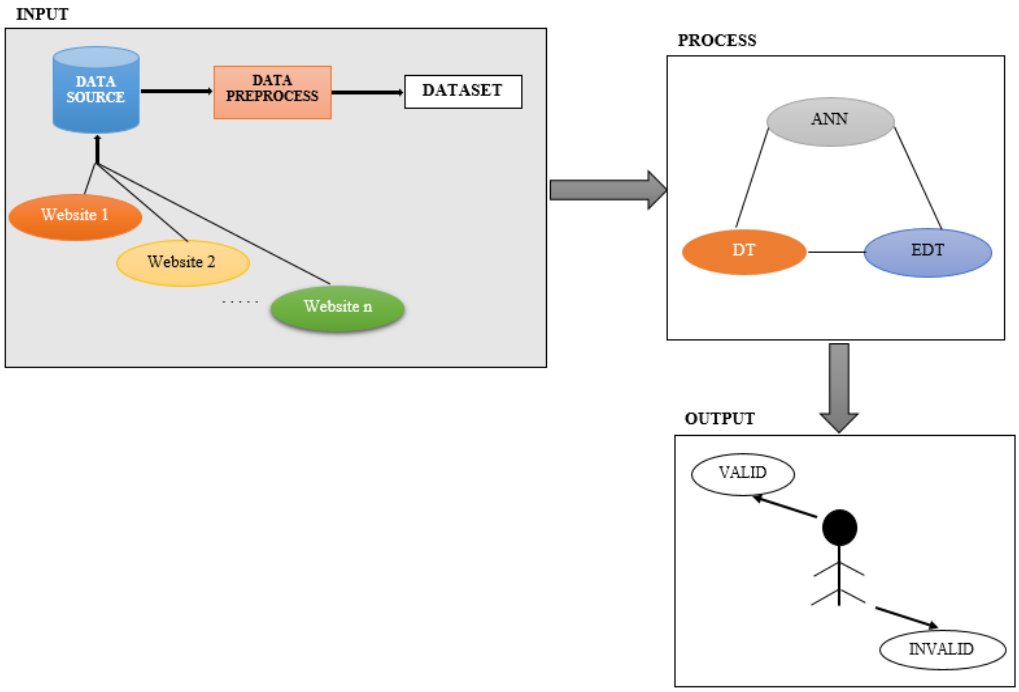

Figure-1. Hybrid triangular research model

2.2 Implementation of Artificial Neural Network

The ANN is a multi layer feed forward network inspired by machine learning and cognitive studies. They represent the biological model of a brain. Several models are invented by the researchers starting from adaline to deep learning to solve several complex real time problems (Han *et al.* 2012). In this article the back propagation neural network algorithm is deployed to investigate the inferences for an effective team formation. The systematic procedure of implementing BPN is given below (Panda *et al.* 2015a):

1) The architecture of BPN has three layers in general namely the input layer, a set of hidden layers and output layer. The hidden layer and the number of nodes in the hidden layer are user defined and application centric. The literatures suggest that an optimal hidden layer and nodes has to be used for improving the accuracy of the system.

2) Each of the nodes is accompanied by an initial weight value and bias value. The structure of ANN has a set of inputs connected to the hidden nodes and in-turn the hidden nodes to output and these values are updated in the reverse direction so as to mitigate the error. The value of a hidden node is given by equation (1).

$$j = \sum_{i=1}^{m} w_{ij} I_i + b_i \quad (1)$$

where j is a hidden node, m is the total number of inputs, w is the weight, I is the input and b is the bias.

3) The activation function is a function used to decide the output of a neuron. The input sum is fed into the function for obtaining the response of the neuron. The function used is a sigmoid activation function given in equation (2).

$$AF = \frac{1}{(1+e^{-\alpha j})} \quad (2)$$

4) The expected output is compared with the actual output and the difference of the two is the error rate. The equation (3) and (4) denotes the error rate of an output layer and the hidden layer respectively.

$$E_i = O_i(1 - O_i)(T_i - O_i) \quad (3)$$

$$E_i = O_i(1 - O_i) \sum_k E_k w_{jk} \quad (4)$$

where E is the error rate of output (3) and hidden (4) node. O is the expected output and T is the actual output.

5) The weights and bias are updated based on the error rate. The updated values are back propagated from response layer to predictor layer. The weight and error updates are given by equation (5) and (6) respectively.

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij} \quad (5)$$

$$\theta_j(t+1) = \theta_j(t) + \Delta\theta_j \quad (6)$$

where w(t+1) is the new weight, w(t) is the old weight, Δw_{ij} is the change in weight given by $\rho E_j O_i$, $\theta\ (t+1)$ is the new bias value, $\theta\ (t)$ is the old bias value and $\Delta\theta_j$ is the change in bias given by ρE_j.

2.3 Implementation of decision tree

The decision tree is a classical form of classification technique inspired by data mining and machine learning. The idea of decision tree was implemented by Quinlan. The decision tree consist of nodes representing the attributes, branches representing the rules with respect to the instances of the corresponding attributes and the leaf that denotes the class label. The metric adopted is the information gain for implementing the decision tree (Han *et al.* 2012). The algorithm for the decision tree is given below:

a. The attribute selection in ID3 approach uses information gain. This was invented by claude for information theory. The attribute that gives maximum information gain is chosen as a split attribute. The expected information for class label is given by (7).

$$Info\ (C) = -\sum_{i=1}^{m} p_i \log_2 p_i \quad (7)$$

where p_i is the probability that a tuple belongs to a specific class.

b. The expected information for each of the attribute is given by (8). Each of the instances is summed to obtain a total gain of the attribute.

$$Info(A) = -\sum_{i=1}^{m} \frac{D_i}{D} Info(C) \quad (8)$$

where $\frac{D_i}{D}$ is the weight of the ith partition.

c. The overall gain of the approach is given in equation (9)

$$Gain(A) = Info(C) - Info(A) \quad (9)$$

By statement gain is the difference between the expected information of the class and the attribute.

2.4 Implementation of ensemble decision tree

The most dominant class of machine learning strategy is the ensemble classifiers. They include bagging, boosting, AdaBoost, random forest etc. All these methods make efforts to strengthen the weak classifier and to reduce the percentage of misclassification. In this article a novel hybrid ensemble decision tree is proposed for improvising employee selection process for effective team formation. The method helps in predicting a pattern to be a valid or invalid agent for the task under consideration. The decision tree is hybridized with logit boost algorithm. The algorithm for the ensemble decision tree is given below (Friedman Jerome 2000).

1) Consider a classical decision tree as a weak learner.
2) Use the ensemble Logit boost approach to strengthen the weak classifier by reducing the percentage of misclassification.
3) Start with initial weights $w_i = {}^{1}/_{N}$ where i = 1 to N.
4) Set current estimates F(x) = 0 and probability of predictors is P(x_i) = 0.5
5) Repeat (a), (b) and (c) till optimality is reached.

a) Response Z = $\frac{y - P(x_i)}{P(x_i)(1-P(x_i)}$ where Weight w = $P(x_i)(1 - P(x_i)$
b) Solve the function f(x) using a weighted least square regression of Z
c) Update the F(x) and P(x) using; F(x) = F(x) + 0.5 f(x) and $\frac{e^{F(x)}}{e^{F(x)} + e^{-F(x)}}$ is used for updating P(x).

6) The final output of the method is given by $sgn(F(x))$. The misclassified signs are sensibly interchanged for improving the quality of the weak learner.

3. PERFORMANCE ANALYSIS: A COMPARATIVE STUDY

There are dynamic innovations and inventions that take place every now and then in the corporate world. These are created and utilized by the human power in the firm. So the management of human resource is essential. There are three methods inspired for the same. These three methods are dominant machine learning approaches that have been used in several complex contrived and real time problem solving [C]. The idea of team formation has also seen a formalization era using several state of the art machine learning, operation research, evolutionary approaches etc (André et al. 2011; Cifuentes *et al.* 2015; Georgiev *et al.* 2008; Panda *et al.* 2015b; Prodanovic 2002; Singhal and Banati 2011; Chen and Zhang 2012; Herrmann 2015). In this section a tournament investigation is incorporated among the three machine learning methods for improving the quality of team formation in an organization for successful completion of the project taken for consideration. The advantages and the limitation of each method are briefed below(Mao 1996; Panda *et al.* 2015b; Han *et al.* 2012; Friedman Jerome 2000):

3.1 Advantages and limitations of ANN

Benefits: (1) This is the only non traditional algorithm that has got the learning factor. It can iteratively converge to optimality based on the learning function. (2) The architecture is simple and elegant and can replace the real time complex architecture with this analogous structure. (3) They are parametric in nature

Limitations: (1) The process of learning is a slow phenomenon to implement. (2) ANN revolves within the local optimum. (3) It has the trouble of over-fitting. (4) The ANN algorithm is a time consuming method.

3.2 Advantages and limitations of decision tree

Benefits: (1) They are simple visualization of the overall theme of a problem. (2) These follow rule based approach for enhancing the user and system understanding. (3) Follow a systematic set of principles for execution; hence can handle complex problems with ease. (4) Easy to integrate with other machine learning approaches (Hybridize). (5) Easily estimate the best, worst and expected values for different domains.

Limitations: (1) Data levels for instances have to be stabilized; if not information gain sets biased to the higher levels. (2) Deciding on tree depth is a complex task.

3.3 Advantages and limitations of ensemble decision tree

Benefits: (1) Highly powerful machine learning approach. (2) Produces improved accuracy rates. (3) Trains the weak learner systematically to enhance its quality in making future predictions. (4) The method converges to global optimum upon systematic training.

Limitations: (1) Computationally intensive in nature. (2) Has an overhead of being over-trained that causes wrong predictions. (3) Over fits to noise and outliers easily and so data has to be cleaned properly before implementation.

The Table-2 depicts the confusion matrix that is used to estimate the accuracy of different approaches and to gain intuitive inference about the quality improvement and effective team formation. It consists of a 2×2 matrix that represents the true positive, false negative, false positive and true negative in clockwise direction. The formula to determine the accuracy (Han *et al.* 2012) of the proposed technique is given by (10).

$$Accuracy\ (in\ percent) = \left(Sensitivity\ \left(\frac{pos}{total}\right) + Specificity\ \left(\frac{\text{neg}}{\text{total}}\right)\right) \times 100 \quad (10)$$

where Sensitivity is true positive by positive, Specificity is true negative by negative, pos is the number of positive instances, neg is the number of negative instances and total is the sum of positive and negative instances.

Table-2. Confusion matrix for accuracy estimation.

Actuals Vs Expected	Valid	Not valid
Valid	102 (ANN); 99 (DT) ; 103 (EDT)	15 (ANN); 17 (DT); 14 (EDT)
Not Valid	19 (ANN); 21 (DT); 16 (EDT)	101 (ANN); 100 (DT); 104 (EDT)

The Figure-2 shows the Tournament Comparative Bars for Machine Learning Strategies. It visually demonstrates the change in the accuracy and error pattern of the trio combo approaches that would enhance team formation in an organization. The comparison chart investigates the performance and the mean square error rate of the three deployed machine learning algorithm. It is seen from the bars that the orange coloured bar represents

the accuracy calculated using (10) and the yellow coloured bar represents the mean square error determined as the sum of squared difference between actual and expected divided by the total number of sample set.

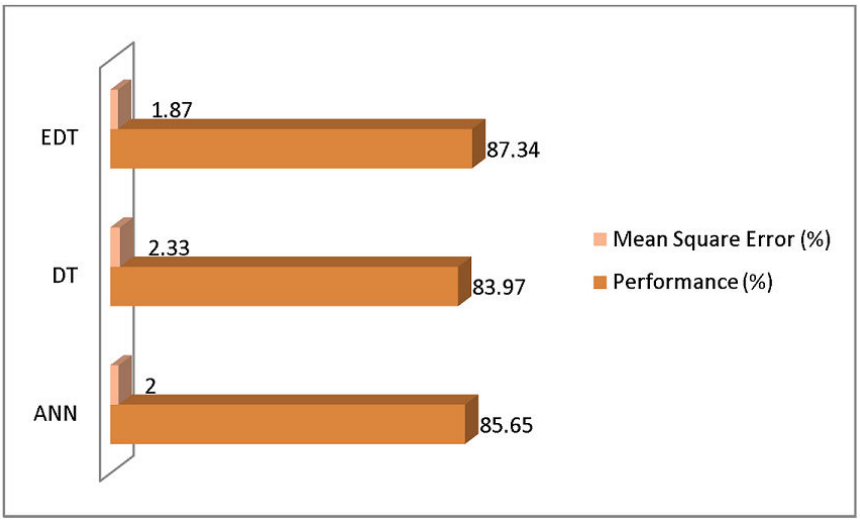

Figure-2. Tournament comparative bars for machine learning strategies.

4. RESULTS AND DISCUSSIONS

The idea of team formation is a critical decision making problem. It consists of several parameters to be considered for optimization in order to form an effective team. The efficacy of the team is directly related to the project's success. The interaction among agents is one of the essential paradigms for boosting team spirit and team integrity. In this research work three machine learning algorithms are implemented to elect the valid candidate for the project.

The ANN is a meta- heuristic approach that is based on the concept of learning. This is an iterative process in which the network tries to reach optimality via systematic weight and bias updates. The system has to be initially trained with the help of the training samples. These are samples which have known class labels. The system tries to reach the actual target value by a systematic procedure and once its training is satisfactory the system is used for testing. In testing phase a set of unknown samples are fed to the network and the results are visualized. These results are cross validated with the class labels corresponding to that test set. Accuracy is evaluated using (10) and its value is about 85.65%. The mean square error for the prediction using ANN is around 2%.

The next approach that is deployed for electing valid members to the project is the decision tree. The rule based decision driven strategy that formulates inferences to test samples using if then rules framed from the decision tree. This is an simple and elegant data structure that helps project managers and leaders to decide on immediate decisions that are to be made in case of critical times. This also uses training and testing phase as mentioned above. The decision tree sets an accuracy of over 83.97% with an MSE of about 2.33%.

The decision tree has the property of easy fit which has been made use of in the proposed technique. The decision tree is considered as a weak learner and the strength of the learner is improvised using an ensemble method. In the proposed framework the decision tree is integrated with the logit boost algorithm which is one of the powerful AdaBoost technique. This amalgamation yields an accuracy of about 87.34% outperforming the remaining two approaches with an MSE of around 1.87%.

The intuitive inference that is gained from these machine learning techniques is that the success of the team is directly related to success of the individual and the success of the end product is directly related to success of the team and therefore the end products' success directly depends on the individuals' success. Another rational inference that is obtained from the proposed model is that any systematic and logical amalgamation of methods to construct hybrid flavours of approaches yields higher accuracy rates thereby mitigating the error. Also training ensemble methods over weak classifier strengthens the classifier whereas training of strong classifier using ensemble weakens it [C].

5. CONCLUSIONS

The data mining has a wide spectrum of use in the real world scenario. It uses different machine learning algorithms to extract knowledge and interesting patterns from the system. The industrial and corporate spectrum has seen this module of implementation to a great extent. In this article one such critical decision making process is formalized using a hybrid amalgamation which is first of its kind for the application under study. The model is (i)

highly systematic and formal, (ii) accurate and simple (iii) in need of skilled managers for formulation and deriving inferences (iv) having an overhead of initial stage training before execution. As a part of future scope more novel mining approaches can be wrapped within the model and the accuracy of the model could be tested in live stream scenarios as well.

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