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Performance Assessment of Voting Algorithms in Artificial Intelligence through Neural Network

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ABSTRACT

In this paper, the techniques that employ Artificial Neural Network to obtain voting methods are better way to improve classification algorithm performance. These classification algorithms have usually been applied for complete datasets. Findings effective method for developing a sample of models has been a present study area of large scale data mining in recent years. In this paper, to categorize the instances based on the classes, which are given in our complete datasets. Technically this approach is called voting. We propose a new voting methodology, which combines the feature of standard propagation, Neighborhood based standard backpropagation and neighborhood based learning coefficient (K_NN) to train single hidden layer neural network.

Keyword: Back-propagation, standard back-propagation , Neighborhood based standard back- propagation , K - Nearest Neighborhood classifier.

1. Introduction

1.1. Voting Basics

Voting is important for ultra-reliable systems that are based on the multi-channel computation paradigm. Depending on the data volume and the frequency of voting, hardware, software voting schemes can be appropriate.The voting part of the algorithm allows us to combine several runs of classification algorithms resulting in a common partition. This helps us to overcome instabilities of classification algorithms and to improve the ability to find structures in s dataset. We develop a strategy to understand, analyze and interpret these results.

1.2. Voting Algorithms

Improving model effectiveness is a key goal of classification algorithms. Voting algorithms, by combining results from different classifiers, may outperform individual classifiers. Such algorithms have been shown to improve overall effectiveness, but our proposed algorithms focus only how an algorithm performs against the entire dataset.

ADiscussion of various voting approaches is given in Leung and Parker [LP03]. Although voting is commonly thought of as majority consensus, the authors, expounds that the winner in such a competition need not always be the one with the most votes. They present results that encompass a number of voting approaches including plurality, anti-plurality, plurality-elimination, Borda Count, and pairwise comparison.

1.3 Various methods of voting

Plurality voting has an appeal because of its simplicity and has universal appeal because of this characteristic. The final value of the classifier is the majority value after the output of the algorithm set is tabulated. The winner is the one with the most votes. The anti-plurality method

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employs counts for the least desirable classifier value. The winning value for the classifier is the one with the least number of last place votes.The plurality-elimination approach uses a series of iterations where the value with the least number of first place votes is eliminated from consideration. The final classifier value is the one that survives this culling process.In the Borda Count method, a set of possible classifier values is ranked by order of the number of votes received. These values are assigned a point value according to the position each occupies in the list, with the last position receiving a 0, the next to last receiving a 1, and so on. The candidate with the largest point value is the winner.

In the pair wise comparison method, each candidate value is matched head-to-head against each other candidate. The winner of each comparison gets one point for a win. For a tie, each candidate receives half a point. The candidate with the highest point value is the winner.

1.4. Neural network performance

The area of Neural Networks probably belongs to the borderline between the Artificial Intelligence and Approximation Algorithms. Think of it as of algorithms for "smart approximation". The NNs are used in (to name few) universal approximation (mapping input to the output), tools capable of learning from their environment, tools for finding non-evident dependencies between data and so on. Many people and industries are interested in the decision support system, and prediction systems for the better choice and reduction of risk based on intelligence method. Especially, artificial neural network based decision making and prediction systems. We have methods are seemed to be successful to solve difficult and diverse problems by supervised training. The most popular neural network architecture for supervised learning is based on the weight error correction rules. Although backpropagation algorithm could correct weights, it will get error and takes much of pattern generation computing time.The field of neural networks can be thought of as being related to artificial intelligence, machine learning, parallel processing, statistics, and other fields. The attraction of neural networks is that they are best suited to solving the problems that are the most difficult to solve by traditional computational methods.

Normally, apply a neural network to model neural network learning algorithm itself. The process of weights updating in neural network is observed and stored into file. Later, this data is used to train another network, which then will be able to train neural networks by imitating the trained algorithm.

1.5. Backprobagation

The efficient supervised training of feed forward neural networks (FNNs) is a subject of considerable ongoing research and numerous algorithms have been proposed to this end. The backprobagation (BP) algorithm is one of the most common supervised training methods. Although BP training has proved to be efficient in many applications, its convergence tends to be slow, and yields to suboptimal solutions be efficient in many applications, its convergence tends to be slow, and yields to suboptimal solutions.

The model structure of BP (backprobagation) classification algorithm use full connection each layers and nodes from input layer to output layer. Consequently it needs much of calculation.

1.6. Neighborhood Based Standard Backpropagation (NBSBP)

The major drawbacks of backpropagation algorithm are local minima and slow convergence. Here, the technique ANMBP present for training single hidden layer neural network to improve convergence speed and to escape from local minima.

The algorithm is based on modified backpropagation algorithm in neighborhood based neural network by replacing fixed learning parameters with adaptive learning parameters.

The developed learning algorithm is applied to several problems. In all the problems, the proposed algorithm outperform well.The method used to improve the training efficiency, significantly reducing requirements on memory and computational time while maintaining the good generalization feature of the original algorithm.

1.7. K-Nearest Neighbor Based Classification Method

The KNN Method originally suggested by COVER and HARI. Nowadays it is most usable classification algorithm. It is very lazy algorithm. So it has less usability and is labor intensive when the training dataset is large. This algorithm operation is based on comparing a given new record with training records and finding training records that are similar to it.

Each record with n attributes represents a point in an *n*-dimensional space. Therefore, all of the training records are stored in an *n*-dimensional space. When given a new record, KNN algorithm searches the space for the k training records that are nearest to the new record as the new record neighbors and then predict the class label of new record with use of the class label of these neighbors.

2. Materials and Methods

Although voting methods are a viable way to improve classification algorithm performance, these have usually been applied to complete training datasets. In our study testing have been conducted on benchmark datasets from the UCI Machine Learning Repository .We propose a voting methodology which is perform for Car Evaluation Dataset. Car Evaluation Database was derived from a simple hierarchical decision structure.

This database directly relates CAR to the six input attributes: buying, maint, doors, persons, lug_boot, safety. Because of known underlying concept structure, this database may be particularly useful for testing constructive induction. Here, the proposed Car Evaluation Datasets contains 1728 instances with 6 attributes, which is categorized by 4 classes.

We have to tabulate the performance based on the success rate(in percentage), that is which is the best among the following approach,

1) Standard Backprobagation Method.

2) K-Nearest Neighborhood based method.

3) Neighborhood Based Standard Backprobagation.

The key goal of this classification algorithm is to improve the model effectiveness. In this study, we presents the performance comparison of standard backprobagation (SBP), Neighborhood based Standard Backprobagation (NBSBP) with neural network and K Nearest Neighborhood classifier (K_NN) without neural network.

Our current studyinvestigates the performance of three algorithms,which is given above. It was found that the Neighborhood based Standard Backprobagation (NBSBP) algorithm is much better than other algorithms.

2.1.Standard Backpropagation Method

Epoch : Presentation of the entire training set to the neural network.

Error: The error value is the amount by which the value output by the network differs from the target value.

TargetValue, T :When we are training a network we not only present it with the input but also with a value that we require the network to produce.

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Output , O : The output value from the neuron.

Ij : Inputs being presented to the neuron

Wj : Weight from input neuron (Ij) to the output neuron

LR : The learning rate. This dictates how quickly the network converges. It is set by a matter of experimentation. It is typically 0.1

(The input layer)Introduces input values into the network, No activation function or other processing.(The hidden layer)Perform classification of featuresTwo hidden layers are sufficient to solve any problem, Features imply more layers may be better.(The output layer)Functionally just like the hidden layers, Outputs are passed on to the world outside the neural network.

Gradient-Descent(*training_examples*, η)

Each training example is a pair of the form <(x_1,…x_n),t> where (x_1,…,x_n) is the vector of input values, and t is the target output value, η is the learning rate

1. Initialize each w_i to some small random value
2. Until the termination condition is met, Do

   3.Initialize each Δw_i to zero

   4.For each <(x_1,…x_n),t> in *training_examples* Do

   i. Input the instance (x_1,…,x_n) to the linear unit and compute the output o

   ii. For each linear unit weight w_i Do

   i. $\Delta w_i = \Delta w_i + \eta$ (t-o) x_i

   5. For each linear unit weight wi Do

   i. $w_i = w_i + \Delta w_i$

2.2. Neighborhood Based Standard Backpropagation Method

The detailed algorithm,

1) Define Network Structure.
2) Define neighborhood Structure (No of neighborhoods & no. of elements in that unit).
3) Initialize weights and learning parameters.
4) Repeat 5 to 10 until desired accuracy is obtained.
5) Select a neighborhood randomly, to train the network.
6) For each input pattern compute output of the network applying standard backpropagation approach for hidden layer and neighborhood based standard backpropagation approach for the output layer.
7) Update the weights for selected neighborhood using (1) and (2).
8) Calculate network error for the network with updated weights.
9) If the error is desired, increase $\mu$by $\mu_{inc}$and go to step (6).
10) Otherwise decrease the value of $\mu$by $\mu_{dec}$and go to step (5).

2.3. K –Nearest neighbor Method

Input : D, the set of training, and test object z= (x',y')

Process:Compute d(X',X),the distance between Z and every object

(X,Y) ∈ D

Select $D_Z \subseteq D$,the set of k closest training objects to Z.

Output : Y' $= argmax_v \sum_{(x_{i,}y_{i})£ D_{0z}} I(V=y_i)$

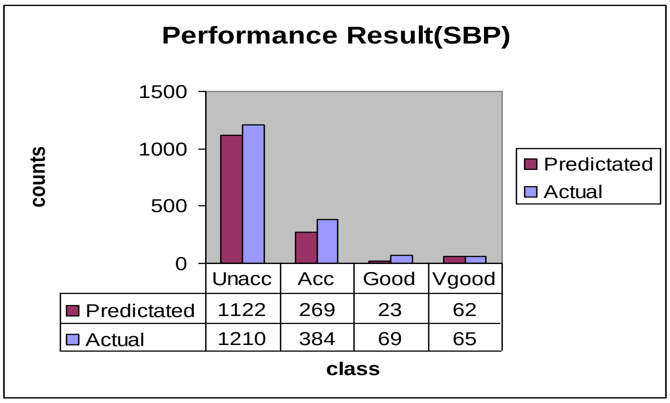
3. Results

3.1. Standard Backprobagation Approach (Results tabulation in percentage)

We can conclude this following table ,when we obtained the error accuracy as 0.000001. Actual column contains the data, which is actually given in our dataset and the predicated column contains the data, which is actually got after the training process of SBP.

The following graph designed with the data, which is in the table 3.1.1

Class	**Actual**	**Predicated**	**Percentage (%)**
Unacceptance	**1210**	**1122**	**92.73**
Acceptance	**384**	**269**	**70.05**
Good	**69**	**23**	**33.33**
Very good	**65**	**62**	**95.38**



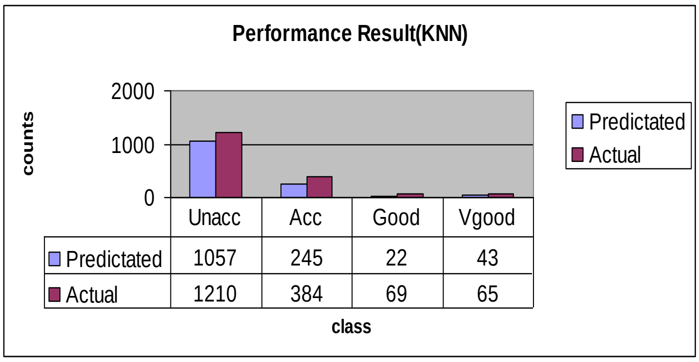
3.1.2. Graph approach for SBP performance.

3.2. K-Nearest Neighbor Approach (KNN)

We can conclude this following table ,when we test all data available in testing dataset(complete data). Actual column contains the data, which is actually given in our dataset and the predicated column contains the data, which is actually got after the training and testing process of KNN.

The following graph designed with the data, which is in the table 3.2.1.

Class	**Actual**	**predicated**	**Percentage (%)**
Unacceptance	**1210**	**1057**	**87.35**
Acceptance	**384**	**245**	**63.80**
Good	**69**	**22**	**31.88**
Very good	**65**	**43**	**66.15**



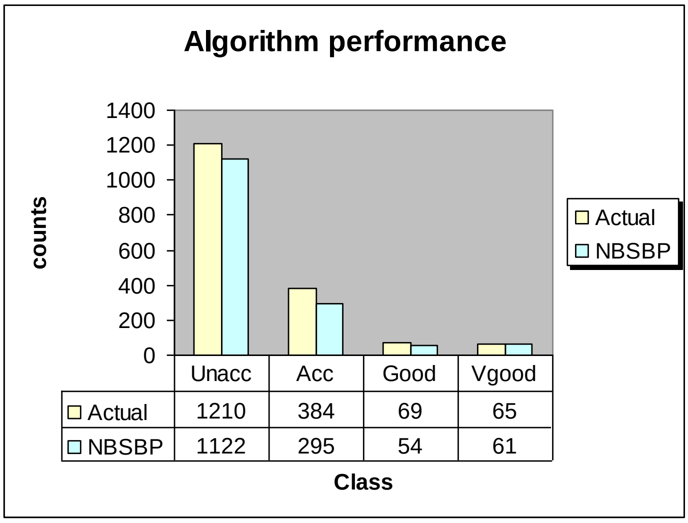
3.2.2Graph approach for KNN performance.

3.3. Neighborhood Based Standard Backprobagation Approach (NBSBP)

We can conclude this following table ,when we obtained the error accuracy as 0.000001. Actual column contains the data, which is actually given in our dataset and the predicated column contains the data, which is actually got after the training process of NBSBP.

The following graph designed with the data, which is in the table 3.3.1

Class	**Actual**	**predicated**	**Percentage (%)**
Unacceptance	**1210**	**1122**	**91.90**
Acceptance	**384**	**295**	**76.90**
Good	**69**	**54**	**78.26**
Very good	**65**	**61**	**95.38**



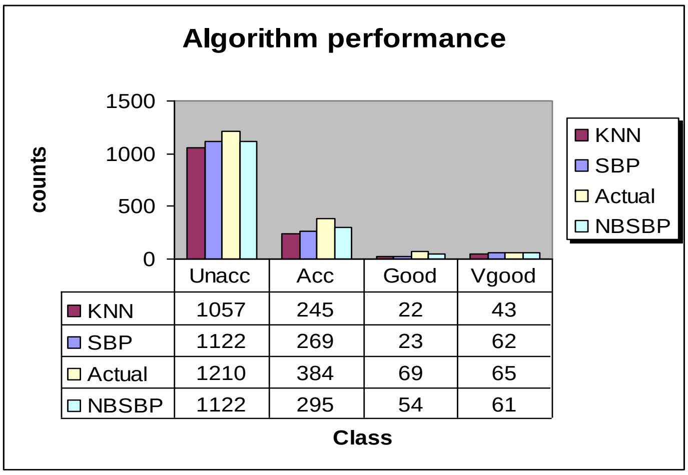
3.3.2. Graph approach for NBSBP performance.

3.4.Comparsion

The following table shows the overall performance of the above three approaches i.e., SBP,NBSBP,KNN.

3.4.1. Performance result table of above approaches.

Class	Actual	SBP	KNN	NBSBP
Unacceptance	**1210**	**1122**	**1057**	**1122**
Acceptance	**384**	**269**	**245**	**295**
Good	**69**	**23**	**22**	**54**
Very good	**65**	**62**	**43**	**61**



The graphical representation of the above tabulated 3.4.2

In our study, we compare three approaches, which is Standard Backprobagation approach (SBP),K-Nearest Neighbor approach(KNN) and Neighborhood Based Standard Backpropagation approach(NBSBP).

In our three approaches, we use same count of training dataset (350), and same set of testing dataset (1728, the complete dataset count). With 6 input attributes that are, buying, maintenance, Doors, persons, Lug boot, safety, it will outperform i.e., categorized by the four classes unacceptance, acceptance, good, very good.

In comparison with the all other algorithms, the classification accuracy average of suggested algorithm NBSBP has a significant improvement. This improvement is between 3.21% (with SBP approach) and 9.55% (with KNN approach) in comparison with the other algorithms.

NBSBP outperforms the traditional SBP approach significantly. From our experiments, compared to KNN with 350 as training dataset and 1728 as test dataset.

5. Conclusion

In short, this study demonstrated theperformance appraisal of Stand Backpropagation, K-NN, Neighborhood Based SBP algorithms in neural networks and explained eachalgorithm. Eventually experimental findings revealed thatthe Neighborhood Based SBP algorithm is the best algorithm to be used in our car evaluation dataset and NBSBP (Neighborhood Based Standard Backpropagation) learning algorithm is designed to reduce an epochs as well as performance betweenthe actual output and the desired output of the network in good manner.

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