

# Exploratory Analysis of various algorithms on Student Performance Data using Machine Learning

Shubham Barudwale\*,

*\*School of Computing Sciences and Engineering, VIT Chennai, Tamilnadu, India 600127*

*Email: barudwaleshubham.dinesh2015@vit.ac.in\**

**Abstract**—Academics is the major part of the life across all the fields. While pursuing any course the understanding is measured using the marks in the exam generally across the world. The academic performance can be affected by various factors like family, society, lifestyle and so on. So the motive of this study is to find out what are the factors that plays major roles in the academic performance and how we can learn the facts and predict the academic performance using machine learning. Also the paper will discuss the algorithms used and in what conditions the algorithms will work efficiently.

In this study the data has been analysed and tried to be learn the underlying information using many experiments. This paper explains the comparative study between all the algorithms that had been performed on the data and tells the results observed. The maximum accuracy achieved was 96.41 %

## 1. Keywords

Machine Learning, Comparative analysis, Student Data

## 2. Introduction

The main problem to be solved is analyse the data and to predict the results for given cases. The data had been trained using different algorithms in Machine learning.

There the analysis is used using both supervised and unsupervised learning methods. In supervised methods the algorithm uses the predefined correct output of the data for training the model. On other hand unsupervised learning only takes the data and try to find the useful meaning out of it. In the experiments performed in this paper the each algorithm and methods are useful for some specific types of data.

Some algorithms are useful where the classification of two classes has to be made. e.g. class A and B. In some cases the data given is in clustered form. The data given can be discrete, continuous or mixture of both. So for each dataset the methods to be used can differ. So to understand the algorithms well discussion of aspects, results, pros-cons and the usability of algorithms will be discussed in the upcoming topics.

## 3. Database - Iris dataset

Student performance dataset is the dataset from which we are trying to gain some information from 650 students academic performance data and various attributes which are affecting the performance. Attributes include sex, age, study time, free time, family information etc.

We will be using various algorithms listed below to learn and predict the performance. Out of 650 I have taken 455 data entries for learning and rest for prediction i.e testing performance of the algorithm.(70:30). The labels or target functions are mentioned in the new field which is added manually. bad(0-7), medium(8-14), good(15-20).

## 4. Algorithms

1. Data Preprocessing
2. Perceptron Algorithm
3. Decision Trees
4. Logistic Regression
5. Regression
6. K-means Clustering
7. Neural Networks
8. Support Vector Machine
9. K Nearest Neighbours

## 5. Methodology

The data given was in the form of string input which was converted to the numeric discrete data. Then the data was analysed using various Exploratory Data Analysis Techniques(EDA). Some outliers were found in the process which were retained or discarded according to the algorithm applied to learn dataset. The data was divided into 70:30 train test parts to check accuracy of the given algorithm on test data. Then training was done on the data and test data was tested for each algorithm separately to get the accuracy. The performance improvement was done using methods like pruning, dimensionality reduction, changing the parameters on which the data was trained.

Noisy data can contain duplicate data, improper data, missing values, text data. To make data clean we can either ignore the dirty data or can assign some values based on

other values of the same field. While preprocessing the data we will check for duplicate entries and we will delete them. For missing data we can ignore them or assign the zero values. The better method to deal with such data is to take average of the data in the same field and put the value in the missing places so that the generalization can be done. We cannot deal with text while drawing the decision boundaries so to reinforce that we use the temporary assignment values for each unique text field. By plotting the scatter graphs, seeing the mean and mode plots and values we can easily identify the outliers in the data. Graphical methods are very useful in such data preprocessing techniques. Here as the data was in the string format the data cleaning was done and the data was converted into the numeric data.

As perceptron is basic algorithm used for the primary classification the data was trained using perceptron. The perceptron algorithm is used in neural networks. A perceptron is an artificial neuron which works on threshold logic. It accepts multiple inputs e.g.  $x_1, x_2, x_3, \dots, x_n$  with weights which are summed up. If sum is greater than the threshold then the neuron gets asserted and the point is labeled as one class, if neuron does not get asserted then the datapoint belongs to another class. Inputs and weights are generally real values, weights are the importance of the field in the given dataset which can be negative. According to threshold the algorithm will be dividing the data into two classes which are separated by either line for 2D or plane for 3D or hyperplane in higher dimensions. The perceptron is majorly used to classify the linearly separable data. The perceptron algorithm is good if the data is linearly separable. If the data is not linearly separable then the perceptron does not work well. Perceptron algorithm is a primitive algorithm to classify the data based on supervised learning. Here data was not exactly linearly separable in 2 and three class so the accuracy was low so the decision was to apply another algorithm.

The data given was the discrete data so the decision trees was the better option. Decision trees work better in distinguishing the points based on different characters which are different from each other distinctively. Decision trees are non parametric supervised learning method used for classification and regression. Decision tree creates the model to predict the decision by creating simple decision rules. Decision tree takes attributes of the data and try to figure out the importance of each data field according to the target function. It classifies (or splits) the whole data based on such decision making trees. We can give the depth of the tree upto which the algorithm will consider various attributes of the data and will classify them upto  $n$  depth. More the depth means more will be the accuracy based on various attributes. Some of advantages of the decision trees are, they are simple to understand and to interrupt. They can be visualized. Time required to train and prediction reduces exponentially. Able to handle any type of data. Validation is easy using statistics. But in some cases where data is not simple overfitting can happen by complex trees.

Small variation in data can give completely different tree. Could create biased trees if some classes are dominant. This time the model gave better results.

Probability of a point to belong to a particular class can be seen as useful resource. We can calculate the future probabilities based on the values we get. In logistic regression we need to restrict the hard threshold of linear classification because linear regression does not use threshold.

After confining the output values we find the probabilistic value of the function using conditional probability. Which gives us the probability of a point belonging to one class.

After this also there can be misclassified points which will increase the probability of having the wrong group then we will apply most likelihood methods and gradient descent to improve the correct probability by taking the smaller steps. Linear classification uses a hard threshold on the signal.

In Logistic regression, we need something in between these two cases that smoothly restricts the output to the probability range  $[0, 1]$ . One choice that accomplishes this goal is the logistic regression model whose output is between 0 and 1.

We are trying to learn the target function. The data does not give us the value explicitly. Rather, it gives us samples generated by this probability. Therefore, the data is in fact generated by a noisy target. The standard error measure  $e(h(x), y)$  used in logistic regression is based on the notion of likelihood; how 'likely' is it that we would get this output  $y$  from the input  $x$  if the target distribution  $P(y|x)$  was indeed captured by our hypothesis  $h(x)$ . The main advantage of the logistic regression is the regression gives the probability of group to which the point belongs.

Until now supervised models were trained on the data and we got medium to good results testing the data without knowing the output could give some insights of the data. Unsupervised learning is the learning from the data where the target value is not given. Linear regression is also an algorithm which uses the unsupervised learning method to fit and learn some knowledge out of the given data. In linear regression we try to fit the data with a straight line which reduces the mean square errors between the points and line. To minimize the calculations we use the pseudoinverse method. In which the  $X$  is matrix of attribute values and  $y$  is our hypothesis line. We also used the RANSAC algorithm which reduces the effect of outliers on fitting.

The linear regression algorithm is based on minimizing the squared error between  $h(x)$  and  $y$ .  $E_{out}(h) = E[(h(x) - y)^2]$  where the expected value is taken with respect to the joint probability distribution  $P(x, y)$ . The goal is to find a hypothesis that achieves a small  $E_{out}(h)$ . The main advantage is that the regression can learn the continuous data even if the output is unknown but this fails if the data given is discrete or in the forms of cluster. But as the data in our dataset was not continuous the regression model could not give good results.

I have also tried to cluster the data into number of clusters using various methods like K means, K modes, KNN etc. K-Means is the algorithm in which the data is divided into K clusters. First the K centroids are defined randomly. In case of K Means++ it centroids are taken as far as possible. Then each points are assigned to the nearest centroids. And again the centroid is calculated of those clustered data. Then again several times the procedure is repeated until no points are altered. This method is very useful for the distinctive data which can be visualized as groups.

We can define similarity as the opposite of distance, and a commonly used distance for clustering samples with continuous features is the squared Euclidean distance between two points  $x$  and  $y$  in  $m$ -dimensional space

$$d(x, y)^2 = \sum (x_j - y_j)^2 = ||x - y||^2$$

Note that, in the preceding equation, the index  $j$  refers to the  $j$ th dimension (feature column) of the sample points  $x$  and  $y$ . In the rest of this section, we will use the superscripts  $i$  and  $j$  to refer to the sample index and cluster index, respectively. Based on this Euclidean distance metric, we can describe the  $k$ -means algorithm as a simple optimization problem, an iterative approach for minimizing the withincluster sum of squared errors (SSE), which is sometimes also called cluster inertia. The algorithm is useful when the distinguishing clusters are present in the data and the target function is unknown or the output and the class of the data is unknown. But as each time the distance between all points has to be found the computationally  $k$ -means is costly.

After training data on all the above models we found that the data is not linearly separable, nor clustered. Also the data was not continuous so regression also failed. So the option to get the appropriate good results was to see all the data points one by one and learn them by adjusting the logic based on output so here we opted for Neural Networks. Artificial neural networks (ANNs) or connectionist systems are computing systems inspired by the biological neural networks that constitute animal brains. Such systems learn (progressively improve performance) to do tasks by considering examples, generally without task-specific programming.

An ANN is based on a collection of connected units called artificial neurons, (analogous to axons in a biological brain). Each connection (synapse) between neurons can transmit a signal to another neuron. The receiving (post-synaptic) neuron can process the signal(s) and then signal downstream neurons connected to it. Neurons may have state, and weight generally represented by real numbers, typically between 0 and 1. Using states and weights and adjusting them the ANN decides the final output.

In Multilayer Neural Networks generally used algorithm is backpropagation method. In this method first the values are feeded into the first layer of the network. And the next several layers are connected by the weights. The values of the next layers nodes are calculated by multiplying the input values and weights. And the same method is applied until the terminal output layer is reached. Then if the output

values are not distinct and close to the required values then again the values are backpropagated in order to change the weights of the links and again the values are calculated for several times. The activation method used are sigmoid, tanh etc.

The speciality of neural networks is it can learn and adjust itself based on the previous all the data points trained on it. The hidden features also can be learned using the neural network. Complex data sets like XOR can be solved using only 1 hidden layer. The application of the neural network is vast in the case where distinct features cannot be extracted easily.

For more experiments the following models were also trained. But the results obtained were not giving good accuracy. Support Vector Machine (SVM) is the supervised learning algorithm. In perceptron we have seen that the differentiation line/ classifier line can be any line between the two groups. It can cause some errors in the test data by classifying the data incorrectly. That is generalization of the data can be not correct always. To overcome this the SVM is the best for getting the clear and optimal classification line. Which is equidistant from both the classes and can classify the data optimally. The given images shows that how perceptron works in classification and how SVM gives better results on the same data with maximum margin to accommodate the test data.

SVM can be used in the conditions where the training points are less than 1000 because the only points matters to draw the SVM classifier line is the Support vectors. In SVM the main goal of the algorithm is to maximize the margin between the points and the classifier line. When the data is not linearly separable the transformation takes place and the data is transferred to the higher dimensions and then it is classified. The method uses the various transform functions. Which is called the Kernel trick

K Nearest Neighbour (KNN) algorithm is the algorithm in which the classification of the test data is done by using its neighbours properties and class. In KNN the training part is not considered that is why its only the observe and classify the data.

In KNN algorithm following steps takes place:

1. Choose the number of  $k$  and a distance metric.
2. Find the  $k$  nearest neighbors of the sample that we want to classify.
3. Assign the class label by majority vote.

$K$  in the KNN is always odd. So that the both class numbers are not even. The point to be classified finds the distance between all the points in the cluster and takes  $K$  nearest neighbours and finds the most number of the classes in the  $k$  neighbours and point belongs to the class which are more in numbers in  $k$ .

Once the data point is classified then that point is also included into the pool of the points to classify the further points. This is called the memory based approach. The main advantage of such a memory-based approach is that the classifier immediately adapts as we collect new training data.

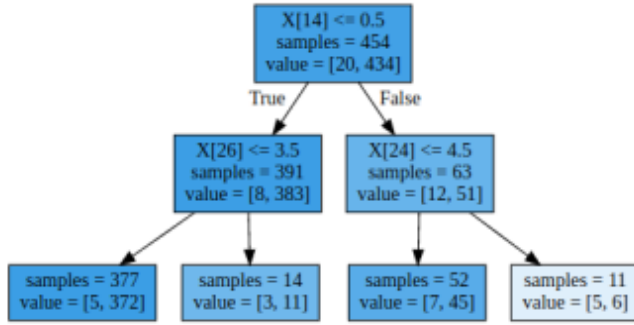


Figure 1. Decision Tree

However, the downside is that the computational complexity for classifying new samples grows linearly with the number of samples in the training dataset in the worst-case scenario unless the dataset has very few dimensions (features) and the algorithm has been implemented using efficient data structures such as KD-trees. The distance is calculated by many distance formulas. But the most used formula is Euclidian distance

Some of the variants of the KNN uses the weighted distances by giving more weights to some of the attributes. So that the classification takes place correctly. When we consider the data in the higher dimensions the nearest points might be far away from the point to be classified.

## 6. Experiments

First data preprocessing was performed on the data to convert the data from string data to numeric data. Then the data was tested using various statistical methods. From the mean of the all feilds the data was majorly talking about the school students in the grade 9th , 10th and the average marks were 11/20. The Study time was increased as the marks were more. As the data was discrete the data was not interpreted from the pairplot and other graphs properly.

The perceptron is the basic supervised algorithm which divides the data into classes by trying to adjust weights and try to make a straight line to divide the data. After 100 iterations the misclassifications were dropped to 5. The accuracy obtained by the perceptron was 88.2%.

In Decision trees the features are extrcted according to the significant division. And the tree is created upto the depth 3. The accuracy on test data was 94.4%.

The Logistic regression predicts the probability of each data point to be a part of a group. The accuracy of the data was not good since the probabilitis were very close to each other and the data in this case was not very well differentiable. So the Logistic regression could not give the proper results of the regression on student performance data.

In simple regression as the data is discrete the regression didt work as expected. Some graphs could make the sence but the most of them were redundant according to the observation.

Depth►	3	5	7	10
Testdata▼				
<b>0.1</b>	0.962 0.954	0.983 0.954	0.991 0.908	0.997 0.908
<b>0.3</b>	<b>0.967</b> <b>0.944</b>	0.982 0.918	0.993 0.908	1.0 0.918
<b>0.5</b>	0.975 0.923	0.985 0.902	0.994 0.886	1.0 0.902
<b>0.9</b>	1.0 0.899	1.0 0.899	1.0 0.899	1.0 0.899

Figure 2. Decision Tree Results

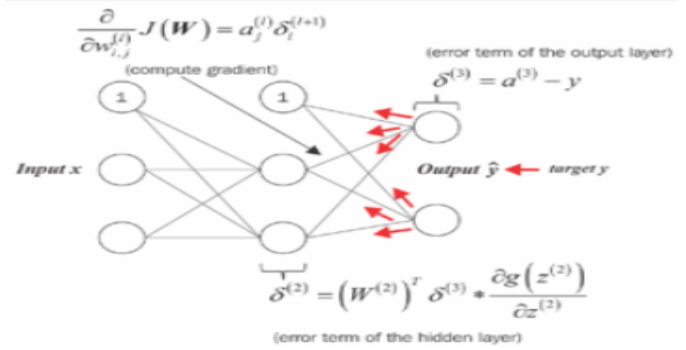


Figure 3. Neural Networks

The next algorithm used was clustering algorithm which was unsupervised learning algorithm. In which the clusters are made by taking the minimum distance from points and clustering them together. As we made three clusters the discrete data could not make correct clusters and the clusters were incorrect.

The neural network was the one which gave the highest accuracy in the testing among the all algorithms used which was 96.41%. So as the backpropogation method is used in the neural networks the weights of the edges in the neural network will adjust with itself to give accuate results. These results were very good compared to other advaced models like XGBoost where multiple models are mixed to give better results. The computation required in this model is also less and only gives fiffrence about 3% accuracy. So overall the neural network is tradeoff between computation and results.

Support Vector Machine the advanced version of the perceptron in wchich we try to find the maximum margin classifier to classify the points into different classes. As the data is overlapped the SVM could not find the good classifier in 2 dimension representation. Same results were observed in the KNN algorithm as the classes are not well distinguishable the clusters formed by selecting K nearest points and assigning the class that the maximum neighbours belong to were not promisable. The accuracy observed was 74.35%

Here from the various experiments we can see that the

regression and clustering algorithm didnt perform well as the data was discrete. The Decision tree performed better since the significant attributes were analysed and the tree was created to classify the data. The best results obtained was using neural networks since the tree adjusts the weights using the previous all the records in training and uses it for the prediction.

## 7. Conclusion

Discrete data is learned by algorithms like Decision Trees and Neural Networks well. The Student Data could not be learned by the regression and clustering since the data was discrete. The accuracy of the Decision Trees was 94.4% and the Neural Network was 96.41% Neural network works best for the data which is discrete and which cannot be learned through regular methods. Neural network is the tradeoff between highly compound models like XGBoost which takes high computation and accuracy by using simple model.

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