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EDUCATIONAL DATA CLASSIFYING USING SVM

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ABSTRACT

With increment in Educational Institutions, there is an increment in new patterns which results in extensive information. The information is unstructured which should be changed into organized shape and to discover significant data, successful Mining Tools are required. Instructive Data Mining helps in encouraging the usage of assets identified with understudy execution, foreseeing position results and finding new instructive patterns. In this paper arrangement information of understudies has been adopted and characterization strategy utilizing SVM is pursued on preparing information for anticipating results which not just encourages instructive foundations to enhance understudy situations from separated learning also improves the upper hand and basic leadership by applying information mining systems. SVM is a directed learning and compelling information mining procedure to prepare the information for example acknowledgment and forecasts.

***Keywords**: Classification, Data Mining, Educational Data Mining, Predicting, Support Vector Machines*

1. INTRODUCTION

Information mining methods are utilized to break down Educational information and helpful data is removed from the expansive measure of unstructured data. With increase in educational institutions, Demand of quality education and placements for the benefit of the students as well as of the institutions has been increased. In1, author has suggested many classification and clustering Data Mining Techniques which includes K-means, Decision trees, neural networks, SVM, Naive Bayes etc. Using these techniques meaningful and informative knowledge can be discovered which is helpful in delivering quality education.

SVM is one of the DM Techniques. It is a supervised learning method whose applications include both regression and classification. According to author in2, SVM are the most commonly employed classification algorithms for handling high dimensional data. In3, authors have stated that SVM Classifier is known for maximum accuracy and Minimum Root Mean Square error (RMSE).

In this paper, SVM Classifiers are used for the prediction of placement of students as in many cases, students focus only on their regular curriculum of studies besides on other educational trends which are necessary for overall development of students and their placements. The educational dataset taken for SVM supervised learning technique is shown in Table 1 which consist of some data points that belongs to one of the 2 classes and using SVM, it is to decide that a new data point will occur in which class. Hyperplane will be defined using an equation:

F(x) = α0 + αTx where α is known as the weight vector and α0 is the threshold value. One of the possible representations of the Hyperplane is:

|α0 + αTx| = 1 where x represents the training set examples which are closer to the hyperplane and they are known as support vectors. In this paper an attempt is done to train and classify the student's dataset and to predict the values for input given.

The paper has three sections. Section 2 consists of data mining of placement data where attributes taken and educational dataset is defined. Section 3 is discussed about Support Vector Machines, support vectors and closest data vectors. Section 4 is a discussion about results obtained using WEKA classifier and SVM Classifier in MATLAB.

2. DATA MINING OF PLACEMENT DATA

2.1 Training Dataset Preparations

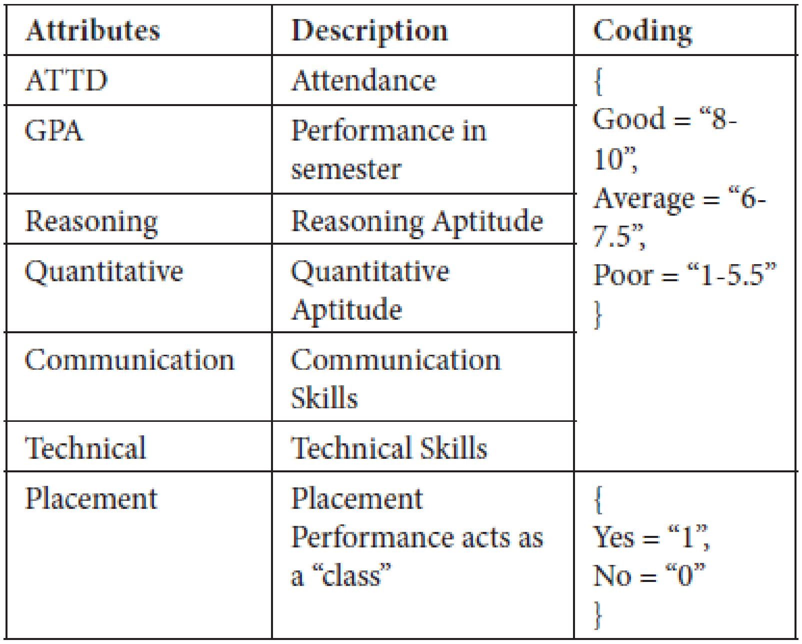
We have initially taken a sample size of 200 Graduate Students for classification. Classification4 is a DM technique and a supervised learning where training sample set is input to classifier.

2.2 Data Analysis

We have classified the placement results of students taking 6 Attributes i.e. Attendance, GPA, Reasoning, Quantitative, Communication Skills, Technical Skills etc. The prototype of student's placement result is predicted after analyzing performance.

Attributes and Educational Data Set of students is given in Table 1 and Table 2 respectively.

Table1. Placement cell attributes



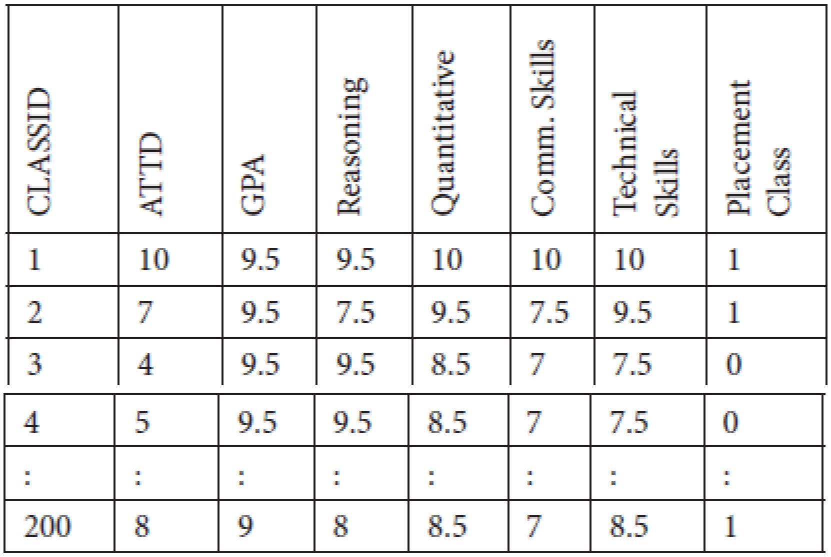
Attributes	Description	Coding

ATTD	Attendance	{
		Good = "8-10",
		Average = "6-7.5",
		Poor = "1-5.5"
		}

GPA	Performance in semester	
Reasoning	Reasoning Aptitude	
Quantitative	Quantitative Aptitude	
Communication	Communication Skills	
Technical	Technical Skills	

Placement	Placement Performance acts as a "class"	{
		Yes = "1",
		No = "0"
		}

Table 2. Educational data set

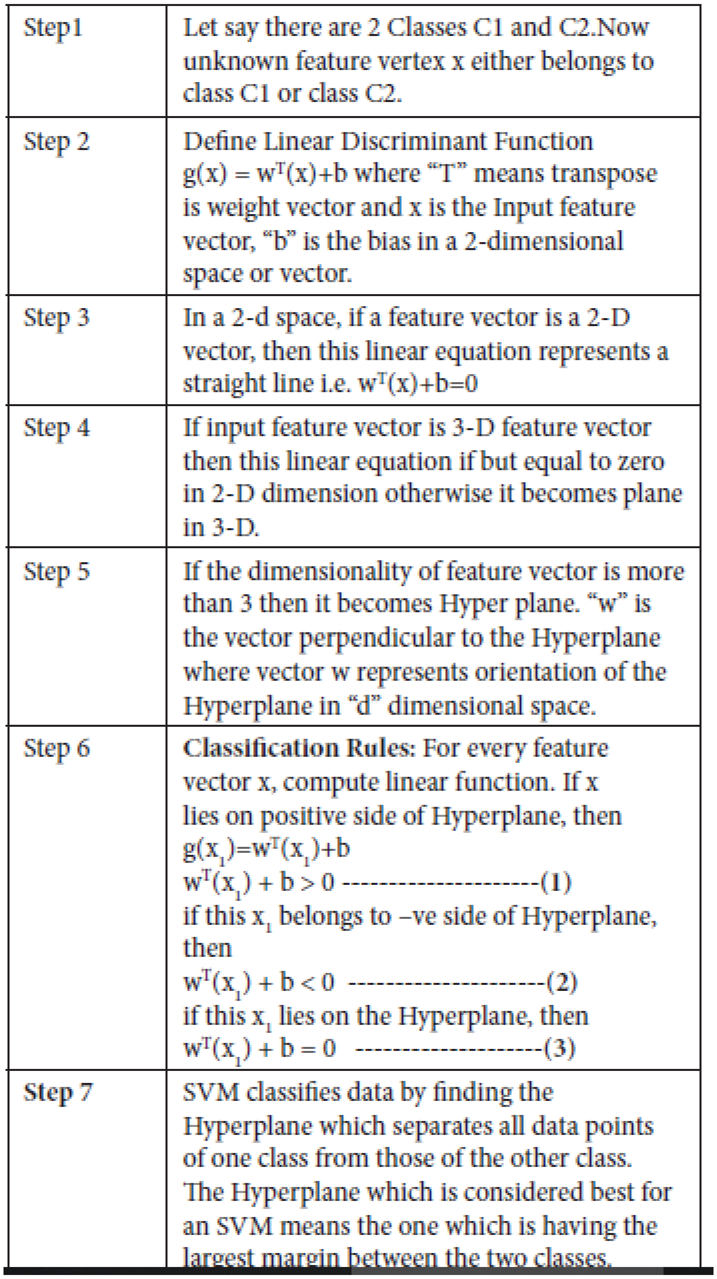


CLASSID	ATTD	GPA	Reasoning	Quantitative	Comm. Skills	Technical Skills	Placement Class
1	10	9.5	9.5	10	10	10	1
2	7	9.5	7.5	9.5	7.5	9.5	1
3	4	9.5	9.5	8.5	7	7.5	0
4	5	9.5	9.5	8.5	7	7.5	0
:	:	:	:	:	:	:	:
200	8	9	8	8.5	7	8.5	1

3. SUPPORT VECTOR MACHINE

SVM is a discriminant classifier which is characterized by a separating hyperplane. SVM develops a Hyperplane, or, in other words, arrangement and regression5. It finds closest information vectors called bolster vectors (SV), to the choice imprisonment in the preparation set and it isolates a given new test vector by utilizing just these closest information vectors6. Steps followed in SVM have been portrayed in Table 3.

Table 3. Steps followed for SVM



Step1	Let say there are 2 Classes C1 and C2.Now unknown feature vertex x either belongs to class C1 or class C2.
Step 2	Define Linear Discriminant Function $g(x) = w^T(x)+b$ where "T" means transpose is weight vector and x is the Input feature vector, "b" is the bias in a 2-dimensional space or vector.
Step 3	In a 2-d space, if a feature vector is a 2-D vector, then this linear equation represents a straight line i.e. $w^T(x)+b=0$
Step 4	If input feature vector is 3-D feature vector then this linear equation if but equal to zero in 2-D dimension otherwise it becomes plane in 3-D.
Step 5	If the dimensionality of feature vector is more than 3 then it becomes Hyper plane. "w" is the vector perpendicular to the Hyperplane where vector w represents orientation of the Hyperplane in "d" dimensional space.
Step 6	**Classification Rules:** For every feature vector x, compute linear function. If x lies on positive side of Hyperplane, then $g(x_1)=w^T(x_1)+b$ $w^T(x_1) + b > 0$ ---------------------**(1)** if this x_1 belongs to –ve side of Hyperplane, then $w^T(x_1) + b < 0$ ---------------------**(2)** if this x_1 lies on the Hyperplane, then $w^T(x_1) + b = 0$ --------------------**(3)**
Step 7	SVM classifies data by finding the Hyperplane which separates all data points of one class from those of the other class. The Hyperplane which is considered best for an SVM means the one which is having the largest margin between the two classes.

Support vector machine operator consists of kernel types including dot, radial, polynomial, neural, anova etc. Kernel shows the vector similarity in training dataset samples7. Functions of kernels are summarized in Table 4. SVM collects of input data and envision, for each given input data, which of the two probable classes embrace the input, making the SVM a non-probabilistic binary linear classifier.

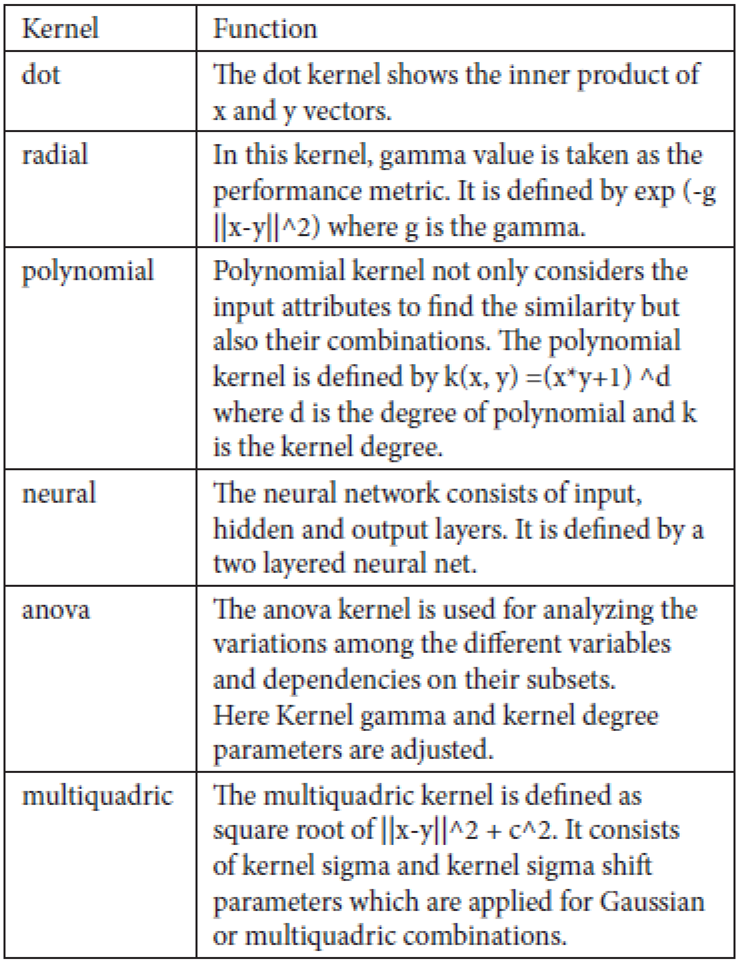
3.1 Multiclass Classification

Multiclass classification makes the inference that each sample is appointed to one label only.

3.2 Multi Label Classification

In this each sample is assigned target labels and several classification tasks will be there.

Table 4. Kernels in SVM



Kernel	Function
dot	The dot kernel shows the inner product of x and y vectors.
radial	In this kernel, gamma value is taken as the performance metric. It is defined by exp (-g ||x-y||^2) where g is the gamma.
polynomial	Polynomial kernel not only considers the input attributes to find the similarity but also their combinations. The polynomial kernel is defined by k(x, y) =(x*y+1) ^d where d is the degree of polynomial and k is the kernel degree.
neural	The neural network consists of input, hidden and output layers. It is defined by a two layered neural net.
anova	The anova kernel is used for analyzing the variations among the different variables and dependencies on their subsets. Here Kernel gamma and kernel degree parameters are adjusted.
multiquadric	The multiquadric kernel is defined as square root of ||x-y||^2 + c^2. It consists of kernel sigma and kernel sigma shift parameters which are applied for Gaussian or multiquadric combinations.

4. RESULTS AND DISCUSSIONS

After applying the educational data set shown in Table 1 in WEKA Tool and using SVM, Table 4 depicts classifier model with each attribute and its class. It summarizes the results comprising of each virtue of the dataset and correctly and incorrectly classified instance. The filter applied on the attribute is Nominal to Binary under Supervised Learning Techniques and then we classify the results using 10 fold cross-validations. The classifier model obtained using WEKA tool is shown in Table 4.

Plot Matrix for all the 6 attributes is shown in Figure 1 and Visualization Results between “GPA” and “Quantitative” attribute is shown in Figure 2.

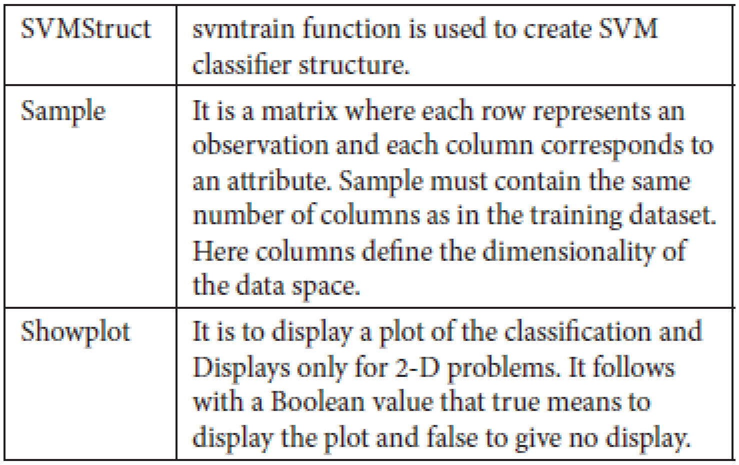
4.1 SVM Classification Using MATLAB

In MATLAB, SVM classify8 function consists of arguments i.e. SVMStruct which classifies each row of data in the given Sample. A SVM classifier structure “SVMStruct” is created using the svmtrain function. Input arguments for SVM classification are shown in Table 5. The svmclassify function derive results from SVMtrain so as to classify vectors y according to following equation:

$$= \sum_i \propto_i K(S_i, y) + b_i$$

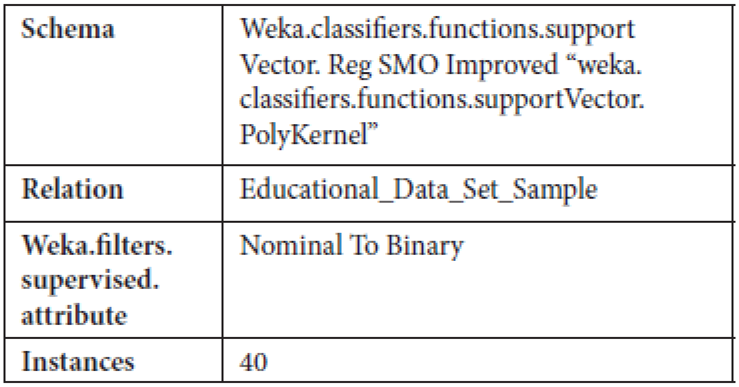
where Si are the support vectors, αi are the weights, b is the threshold value(bias), and k is a kernel function.

Table 5. Input arguments for SVM classification

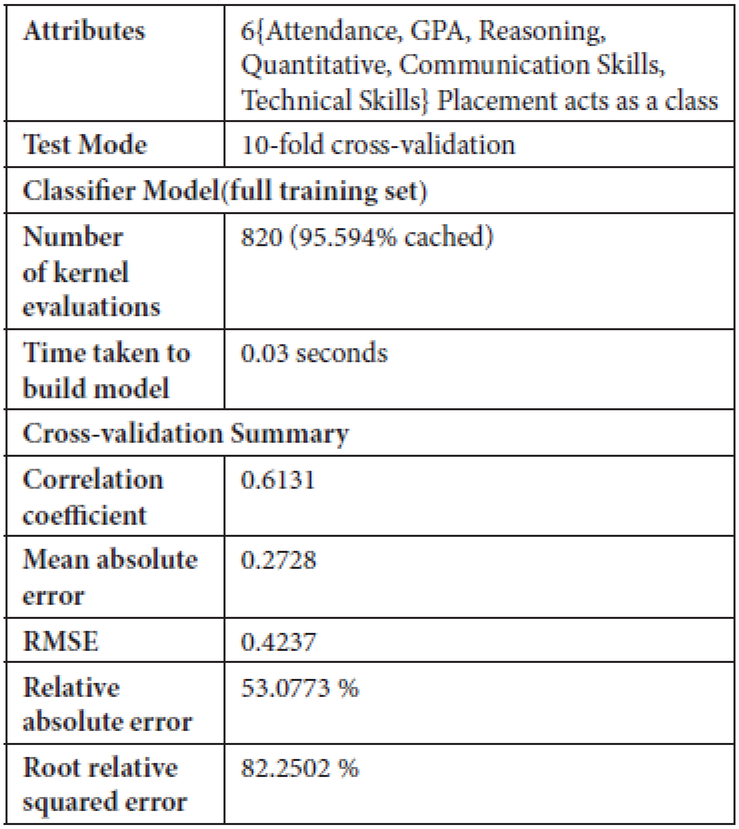


SVMStruct	svmtrain function is used to create SVM classifier structure.
Sample	It is a matrix where each row represents an observation and each column corresponds to an attribute. Sample must contain the same number of columns as in the training dataset. Here columns define the dimensionality of the data space.
Showplot	It is to display a plot of the classification and Displays only for 2-D problems. It follows with a Boolean value that true means to display the plot and false to give no display.

Table 6. Classifier model for training set



Schema	Weka.classifiers.functions.support Vector. Reg SMO Improved "weka. classifiers.functions.supportVector. PolyKernel"
Relation	Educational_Data_Set_Sample
Weka.filters. supervised. attribute	Nominal To Binary
Instances	40



Attributes	6{Attendance, GPA, Reasoning, Quantitative, Communication Skills, Technical Skills} Placement acts as a class
Test Mode	10-fold cross-validation
Classifier Model(full training set)	
Number of kernel evaluations	820 (95.594% cached)
Time taken to build model	0.03 seconds
Cross-validation Summary	
Correlation coefficient	0.6131
Mean absolute error	0.2728
RMSE	0.4237
Relative absolute error	53.0773 %
Root relative squared error	82.2502 %

The classification of dataset is done using a trained SVM classifier and the Placement Results obtained based on attributes i.e. "Reasoning" and "Quantitative" attributes are shown in Figure 3 and Figure 4.

In Table 4 classifier demonstrate for the preparation set is appeared. It demonstrates the Root Mean Square Value for the Total Instances taken. The Test Mode connected is 10-overlap cross approval on the preparation information to get to the prescient execution of SVM Model.

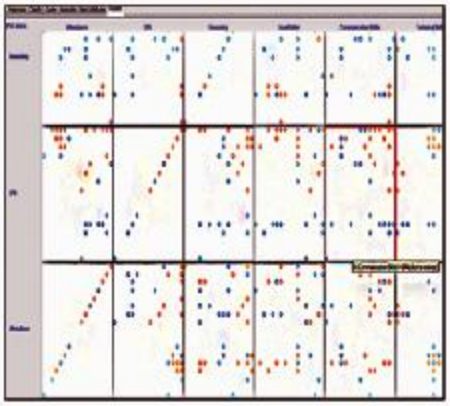


Figure 1. Plot matrix of attributes.

Figure 1 represents the plot matrix in WEKA Tool visualizing all the attributes taken with x and y co-ordinates in 2-D space. Plot lattice pictures the current dataset in one and two measurements. Figure 1 additionally demonstrates the correlation of any ascribe to every other trait.

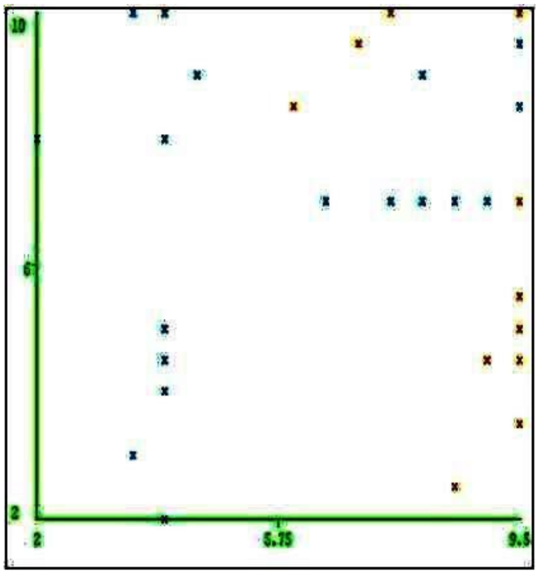


Figure 2. Plot for supervised nominal to binary conversion.

Whereas Figure 2 represents the visualization results of GPA and Quantitative attribute. It visualizes the support vectors for both the classes and categorizes the placement results accordingly.

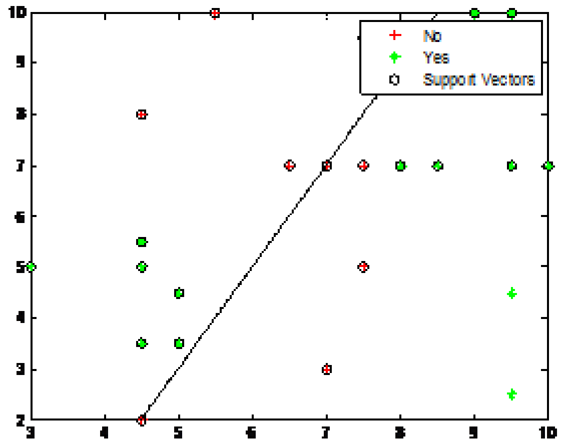


Figure 3. SVM classification for placement data

Figure 3 for SVM Classification finds a line separating the educational data shown in Table 2 on “Placement” feature for “Yes” and “No” classes, in comparison to the values shown in “Reasoning” and “Quantitative” attributes. Here, SVMStructure is obtained using SVMtrain function.

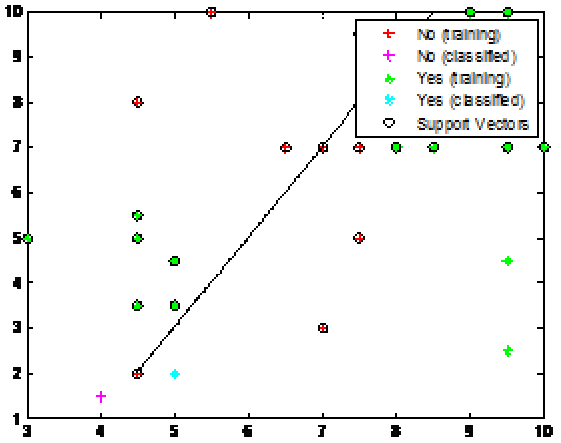


Figure 4. SVM trained classification

Figure 4 shows the classified and trained values for the placement attribute i.e. “Yes” and “No”. It also shows the support vectors and from it we derive that on the basis of students marks in

"Reasoning" and "Quantitative", Support vector machine construct a hyperplane showing the closest vectors for "Placement" Attribute.

4.2 Binary Support Vector Machine Classifier

Fitcsvm (X, Y) function restores a help vector machine classifier SVMModel, prepared by indicators X and class names Y for a couple of class order. Figure 5 repre¬sents the Trained SVM classifier utilizing the handled informational collection. The first class ('No') is the negative class and the second ('Yes') is the positive class.

The support vectors are consideration that occur on or good way off their estimated class boundaries.

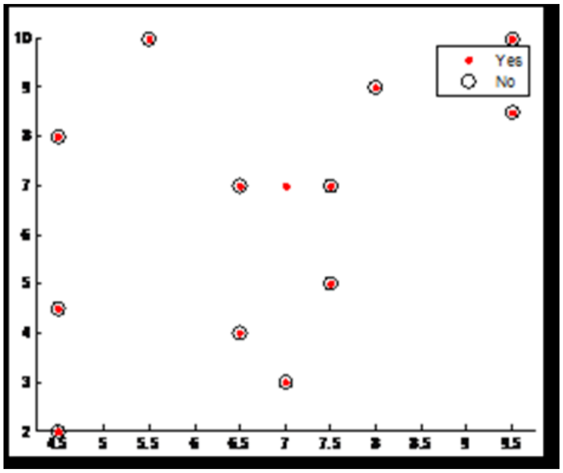


Figure 5. Train binary SVM classifier.

5. CONCLUSION

Support vector machines are effective in accuracy. In this paper, using SVM data mining technique the dataset is trained for predicting the placement results. Here two classes are defined for placement attribute i.e. "yes" and "no" to analyze student's data and classified placement results based on certain attributes which helps to increasescholaremployments from minedinformation. Using SVM, functional margin is effectuated by Hyperplane which shows the maximum distance to the neighboring training data points of class. cross-validation technique is applied in this paper to find the best possible values and the dataset is classified into labels. Placement Results help in distinguishing attributes and produces a better perception of the ideal performance expected from students and to target on new educational trends apart from their regular studies to get placed. Arrangement The model employed for this paper can be additionally reached out for Posterior probabilities of SVM Classifiers, forecasts and more precise outcomes via watchful choice of qualities.