Study of an Adaptive Web Based E-Learning System through SVM

Pooja Shrimali
INFORMATICS & COMPUTATIONAL SCIENCES,
Mohanlal Sukhadia *University,Udaipur,Rajasthan,India*

1.1 ABSTRACT—In this article we are presenting machine learning mechanism through Support Vector Machine (SVM). Through SVM the automatic learning task on various types of learners will analyze. SVM is another technique in machine learning and it's also helpful for analysis of learner's knowledge level. SVM aims at facilitating searching and organizing learning objects. During an evaluation period, the SVM models are used for the classification of different learning objects according to the different parameters of SVM like correct rate, support vectors, sensitivity, specificity, positive predictive value, negative predictive value, positive likelihood value, negative likelihood value and prevalence. Through the parameters SVM models can also analyze learner's knowledge level category and Adaptive Web Based E-Learning System [39] can perform accordingly.

Keywords— Adaptive Web Based E-Learning System (AWBES), SVM;

1.2 INTRODUCTION

In a machine learning method, SVM is a one of the important system for data analyzing and pattern recognition [MathWorks]. In AWBES Course Organization and Implementation Section were taught into adaptive environment. Like Artificial neural network (ANN), the SVM is a fruitful machine learning technique. The adaptation method normally used to training and testing the learning objects. Each module in the training set consist one target and two input values. This target is according to the pedagogical rules as described in AWBES. For each input, every category read again, forward but read again and forward act for a different SVM model. We compare all three categories' SVM models and analyses the learners performance. The main object of SVM is to give a statistical vales for analyze learners knowledge level those are given from the training data set. The thrust area of machine learning is the data categorizations and to create a hyperplane between classes. To obtain the best result for categorization and mapping from the machine learning, generate a largest distance in between support vectors and from the hyper plane [Kan Xie].

1.3 SVM – INSTRUCTOR

In AWBES each lesson is divided into several modules and each module is sub divided into two sections. Each section composed through several LO. Each module score used for build a linear SVM using Matlab as an input and the target table. Through the performance parameters [Table 1.1] AWBES is able to analyze learner's actions in each module. Positive samples are those which are according to the table 1 for each category and Negative samples are those which are not according to the table 1.Threshold value for all classes is as follows:

Table 1 : Learner's threshold value for different classes

Class	Threshold Value
Read Again	Less than 60%
Forward but Read Again	60% - 79%
Forward	80% and above

During the validation of classifiers 'Classperf' provides an interface to keep track of the performance. A classifier performance object optionally updates by 'Classperfcreates' [MathWorks]. The performance properties perform Classifier's performance (CP) with various parameters like sensitivity, specificity, prevalence, correct rate and many others. SVMStruct performs the structured information for SVM classifier like support vectors, bias and many others. Support vectors are the most difficult to classify data points that lie closest to the hyperplane and direct bearing on the optimum location of the hyperplane. From the svmtrain function it can be shown the optimal hyperplane. So that it can be train an SVM classifier by using a linear kernel function and plot the grouped data. The following graph shows how the support vectors and hyperplane are made:

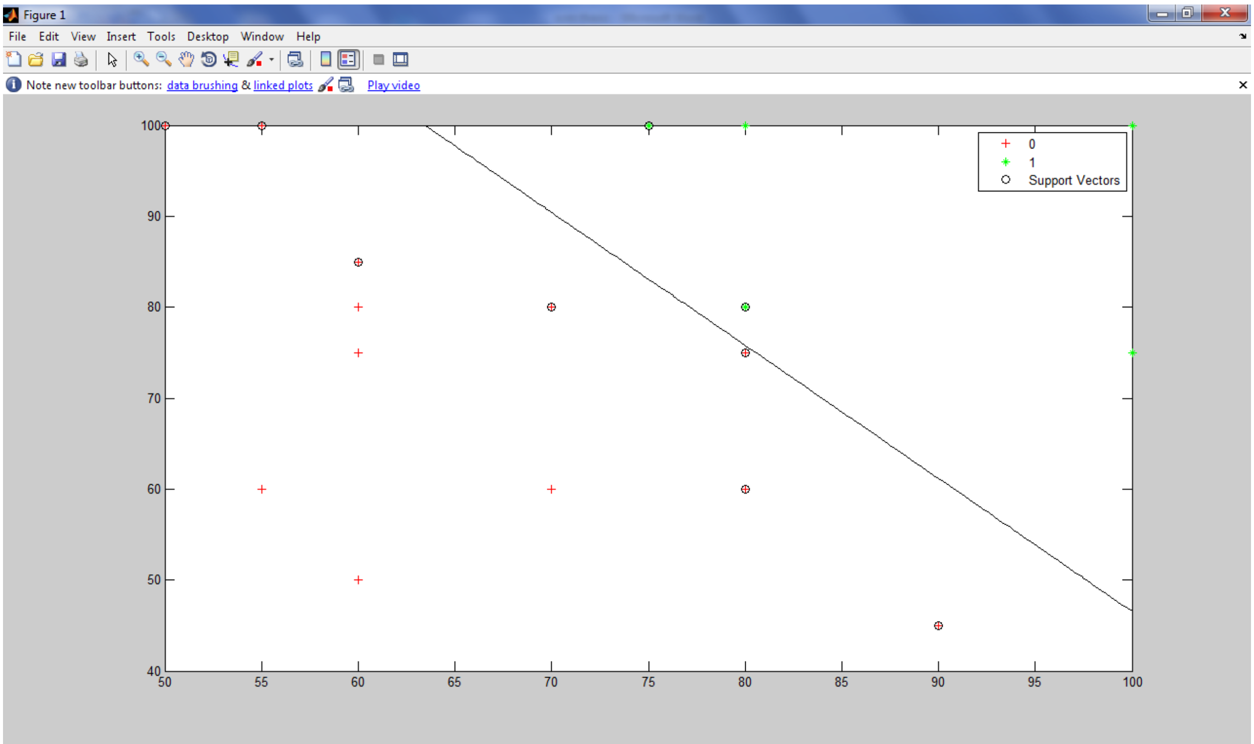

Fig. 1.1 : Support vectors for a Learner

The basic idea is to find a hyperplane which separates the dimensional data perfectly into its two classes, intuitively the hyperplane that maximizes the geometric distance to the closest data points. Through SVM model for analysis of learner's knowledge we should compare all three SVM models generated by Read Again, Forward but Read Again and Forward class.

The below given table 1.1 represents the parameters of SVM. The parameters should contain the following ideal values for every category. The category which has the maximum ideal values needs to be selected. Accordingly, learners are directed as to whether they need to go for read again, forward but read again and forward.

Table 1.1: Ideal values of SVM parameters (NaN- No Number)

Correct Rate	Support Vectors	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Positive Likelihood	Negative Likelihood	prevalence
1	Note	1	1	1	1	NaN	0	1

Note: That category should be preferred whose value is comparatively less. Since, Support vectors are proportional to complexity.

Below there are various learners which belong to different category. AWBES has shown the results of each learner in their learning objects. The scores of various learners are to be inserted in the SVM as input. According to the pedagogical rule, the learners' LO are segregated in the class (Read Again, Forward but Read Again and Forward). Every class has been set as target for all the learners in the SVM model. The input i.e. score of each LO is inserted in the SVM model with each class as target respectively. Thus, three SVM models are generated and its parameters are compared and accordingly the learners' knowledge levels are analyzed.

1.4 CORRECTLY CLASSIFIED LEARNERS

The following learners' category in SVM model coincides with the AWBES result.

Learner 1

Table 1.2 shows the different classes in SVM model and its parameters values for learner 1.

Table 1.2: Values of the parameters for the Learner 1

Class	Correct Rate	Support Vectors	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Positive Likelihood	Negative Likelihood	prevalence
Read Again	1	10	1	1	1	1	NaN	0	1

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Forward but Read Again	0.8571	16	1	0	0.8571	NaN	1	NaN	0.8571
Forward	1	13	1	NaN	1	NaN	NaN	NaN	1

So accordingly an analysis has been made of all the categories as shown below. The results of the analysis is denoted by '✓' and 'X'.

Table 1.3 : Analysis of the ideal parameters' values for Learner 1

Class	Correct Rate	Support Vectors	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Positive Likelihood	Negative Likelihood	prevalence
Read Again	✓	✓	✓	✓	✓	✓	✓	✓	✓
Forward but Read Again	X	X	✓	X	X	X	X	X	X

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Forward	✓	X	✓	X	✓	X	✓	X	✓

'✓' : This represents the ideal parameter values.
'X': This represents the values which are not ideal for the parameter.

Table 1.4: Number of ideal parameter value in each category

Category	Number of ideal parameters
Read again	9
Forward but Read Again	1
Forward	5

Since as compared to other categories the number of '✓' is more in read again category. Therefore, the learner is directed to the read again category.

1.5 Misclassified learners

As seen in the above cases learners' knowledge level is successfully analyzed through SVM models. Initially, learners' knowledge level is decided through SVM parameters correct rate, support vector, sensitivity, specificity, positive predictive value, negative predictive value, positive likelihood value, negative likelihood value and prevalence are to be considered for learners' knowledge level. But the following learners are misclassified due to wrong analysis of the SVM model.

Learner 2

Table 1.5 shows the different classes in SVM model and its parameters values for learner 2.

Table 1.5 : Values of the parameters for the Learner 2

Class	Correct Rate	Support Vectors	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Positive Likelihood	Negative Likelihood	prevalence

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Read Again	0.8571	15	1	0.5000	0.8333	1	2	0	0.7143
Forward but Read Again	0.1429	18	0.2500	0	0.2500	0	0.2500	NaN	0.5714
Forward	1	16	1	1	1	1	NaN	0	0.7143

So accordingly an analysis has been made of all the categories as shown below. The results of the analysis is denoted by '✓' and ‘X’.

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Table 1.6 : Analysis of the ideal parameters' values for Learner 2

Class	Correct Rate	Support Vectors	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Positive Likelihood	Negative Likelihood	prevalence
Read Again	X	✓	✓	X	X	✓	X	✓	X
Forward but Read Again	X	X	X	X	X	X	X	X	X
Forward	✓	X	✓	✓	✓	✓	✓	✓	X

'✓' : This represents the ideal parameter values.
'X': This represents the values which are not ideal for the parameter.

Table 1.7 : Number of ideal parameter value in each category

Category	Number of ideal parameters
Read again	4
Forward but Read Again	0
Forward	7

Since as compared to other categories the number of '✓' is more in forward category. Therefore, as per the result the learner is directed to the forward. According, to the module score learner secured less than 60%, as per pedagogical rules learner should not proceed to the next module but SVM is promoting the learner to the next module.

1.6 OUTLINE OF THE WORK

The learners are being put to rigorous activities. As ANN method likewise SVM method is also working in the AWBES model. Every individual learner has to obtain marks, according to the prescribed pedagogical rules, if the learner is not able to succeed. Then such a learner

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has to go through the same module again and again. Until, the learner understands the module thoroughly.

For instance following Table 1.8 is a learner's score table:-

On each step modules percentage will increase (score of each module on each step)

Table 1.8 : Learner's score table

Module	Score	Module	Score	Module	Score	Module	Score	Module	Score
M1	35	M3	70.5674	M9	59	M16	69.0564	M26	77.2134
M1	45	M4	52.5634	M9	70.6745	M17	65.7854	M27	80
M1	50	M4	58.6668	M10	55.345	M18	67.8953	M28	80.3421
M1	57	M4	65.2341	M11	62.4568	M19	70	M29	82
M1	65	M5	59.4321	M12	57.3456	M20	70	M30	83
M2	50	M5	68.6723	M12	75.2223	M21	68	-	-
M2	58	M6	73.6667	M13	63	M22	72.4567	-	-
M2	67.4589	M7	62.3421	M14	71.3452	M23	74.6794	-	-
M3	55	M8	55	M15	59.8689	M24	75	-	-
M3	59.6453	M8	72.4567	M15	75.6784	M25	76.4321	-	-

The following learning curve fig. 1.2: shows that from starting to end gradually learner's score has improved.

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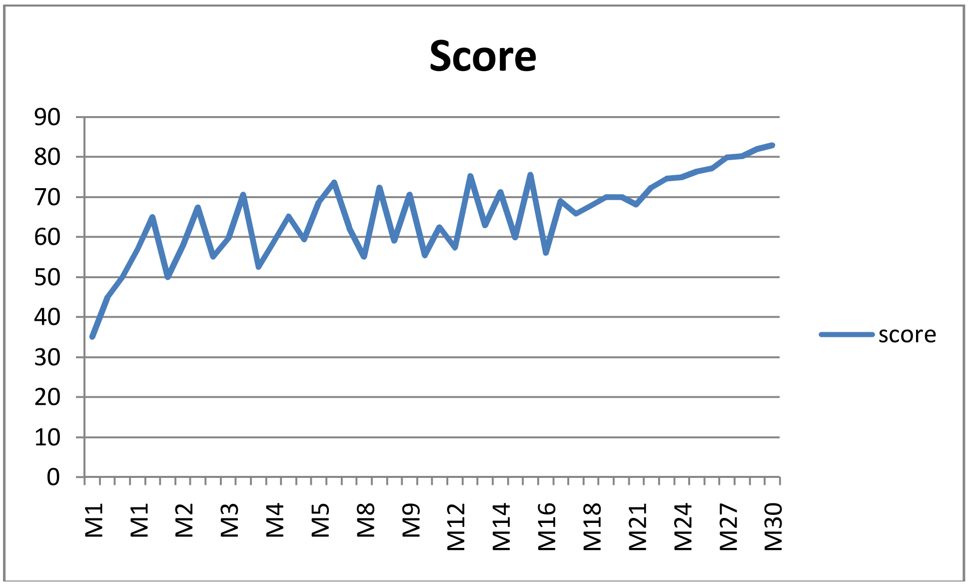

Fig. 1.2 : Learning curve

In the below given Table 1.9 a particular learner's attempts for the adjacent module are decreasing with every increase in the module.

Table 1.9 : Learner's attempts

Module	Attempts	Module	Attempts	Module	Attempts
M1	5	M11	1	M21	1
M2	3	M12	2	M22	1
M3	3	M13	1	M23	1
M4	3	M14	1	M24	1
M5	2	M15	2	M25	1
M6	1	M16	2	M26	1
M7	1	M17	1	M27	1
M8	2	M18	1	M28	1
M9	2	M19	1	M29	1
M10	1	M20	1	M30	1

The following learning curve fig.1.3 shows that learner's knowledge level has increased. The curve shows that in the beginning attempts for a module are greater as compared to the last stage. In the end, the learner could clear the entire test as per pedagogical rules in one attempt. During the process, if the learner is not able to fulfill the pedagogical rule, then again and again modules or LOs will come in front of them. Accordingly, learner will definitely go in depth of the matter to clear the concepts. This exercise helps the learner to improve the knowledge level.

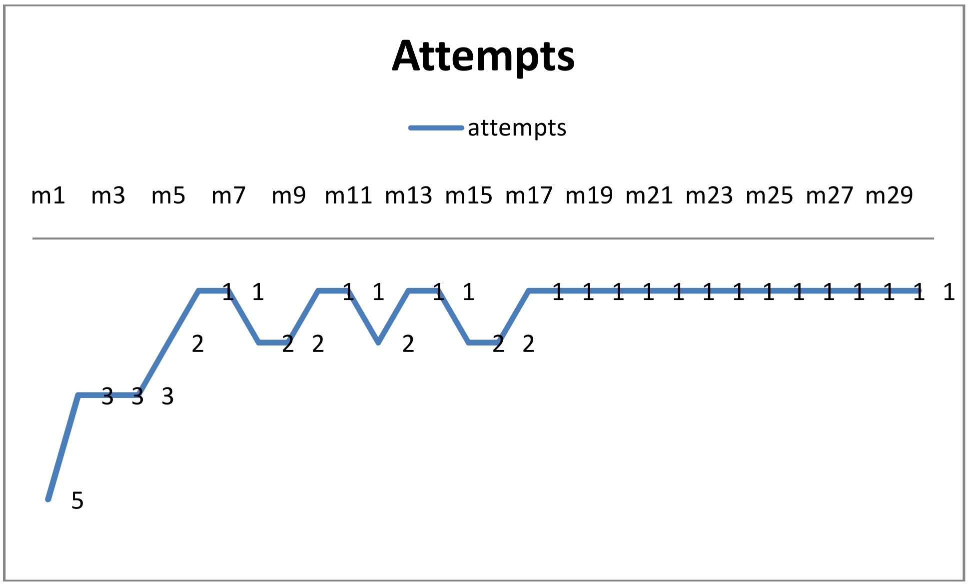

Fig. 1.3 : Learning curve for the learner's attempts

1.7 SUMMARY

The above experiment proves that like ANN, SVM is also acting as instructor in a personalized teaching environment. According to the test results SVM parameters correct rate, support vector, sensitivity, specificity, positive predictive value, negative predictive value, positive likelihood value, negative likelihood value and prevalence are suggested as the knowledge level of the learner. The usage of ANN like machine learning is also found in SVM. Thus, SVM can also be successful as machine learning in the field of adaptive web based e-learning system.

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