eYSIP-2015

Auto-Tagging Online Selection Test

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Contents

Abstract

While Moore's Law makes machines faster, Machine Learning makes them smarter. Machine Learning is an active research area which has been successfully applied for solving a lot of challenging problems having practical significance. Here we have applied machine learning to solve such a problem. The task was to automatically assign a difficulty level to each question in the eYRC-2015 Online Selection Test based on the data about performance of students. For solving this problem we experimented with different machine learning algorithms for example k-Means Clustering, Expectation Maximization Algorithm etc.

The results obtained here have practical significance for many reasons. As an example, using the results obtained here, questions can be combined to form balanced sets, all of which have similar difficulty level, to ensure a higher level of fairness in a future iteration of the test.

1 Objectives

eYantra conducts an online test to select student teams for eYRC. The questions used for eYRC-2015 are manually assigned a difficulty level prior to the commencement of the test based on experience of question maker. Since there are a lot of questions and many different question makers, the manually assigned difficulty levels are not reliable due to the *relative nature* of difficulty of questions.
There are two main objectives:

1.1 Auto-Tagging

Using the data generated during eYRC-2015 Online Selection Test, the task is to determine the accuracy of manually assigned difficulty levels and also suggest corrections to them based on performance of students.

1.2 Performance Prediction

This task involves finding correlations between various aspects in the profile of a student and performance of the student and hence use the deduced machine learning model to predict the performance of a student in the future iteration of the test given his/her profile.

2 Completion Status

Part 1 i.e. **Auto-Tagging** has been completed while the work on part 2 i.e. **Performance Prediction** is in progress. Hence this report focuses on Part 1 only.

3 Results and Discussions

A variety of different machine learning algorithms were applied to solve the *Auto-Tagging* problem. Many combinations of features and algorithms were considered. Some of the main ones have been described here:

3.1 Neural Network

Both complete and sparse neural networks were implemented. This was the first approach that was used. Here the problem was viewed as a supervised learning problem where the assumption was that majority of the manually assigned tags are correct. Under this assumption it was predicted that the network will generalize well and automatically rectify the incorrect tags which are present in minority. It was discovered later that this assumption was wrong. This approach was tried with different combinations of features but the results were unsatisfactory.

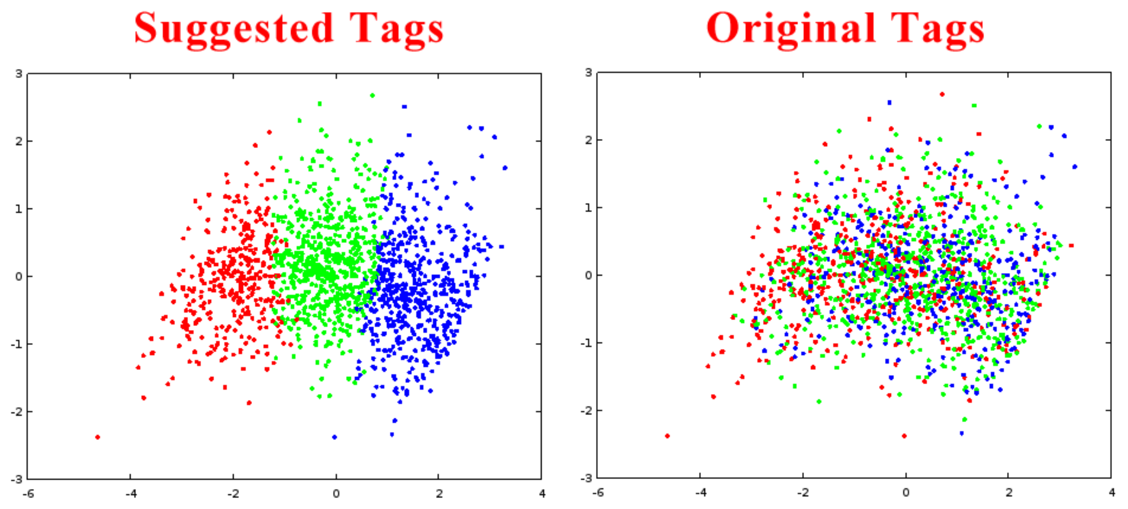
Estimated Manual Tagging Accuracy: 52.45%

3.2 k-Means Clustering

k-Means Clustering is an unsupervised learning algorithm used for clustering the data into semantically sound clusters. This algorithm was used with many different combination of features. The most satisfactory output was obtained by using the following three features:

1. Fraction of people who solved a question correctly.
2. Fraction of people in top five percentile who solved the question correctly.
3. Average marks of people who did not attempt the given question or solved it incorrectly.

This output has been shown below:



Feature	Level	Min	Q1	Median	Q3	Max	Mean
Feature 1	**Easy**	-0.515	0.842	1.370	1.818	2.934	1.318
	Medium	-1.359	-0.470	-0.106	0.373	1.813	-0.031
	Hard	-1.686	-1.213	-0.946	-0.605	1.106	-0.860
Feature 2	**Easy**	-0.342	0.962	1.159	1.159	1.159	1.018
	Medium	-0.842	-0.018	0.409	0.730	1.159	0.377
	Hard	-1.843	-1.843	-1.092	-0.642	0.159	-1.139
Feature 3	**Easy**	-4.498	-1.631	-1.091	-0.623	1.104	-1.134
	Medium	-1.667	-0.339	0.028	0.479	2.620	0.093
	Hard	-2.050	0.159	0.589	1.132	3.380	0.662

Table 1: Statistics for k-Means Output

Estimated Manual Tagging Accuracy: 43.73%

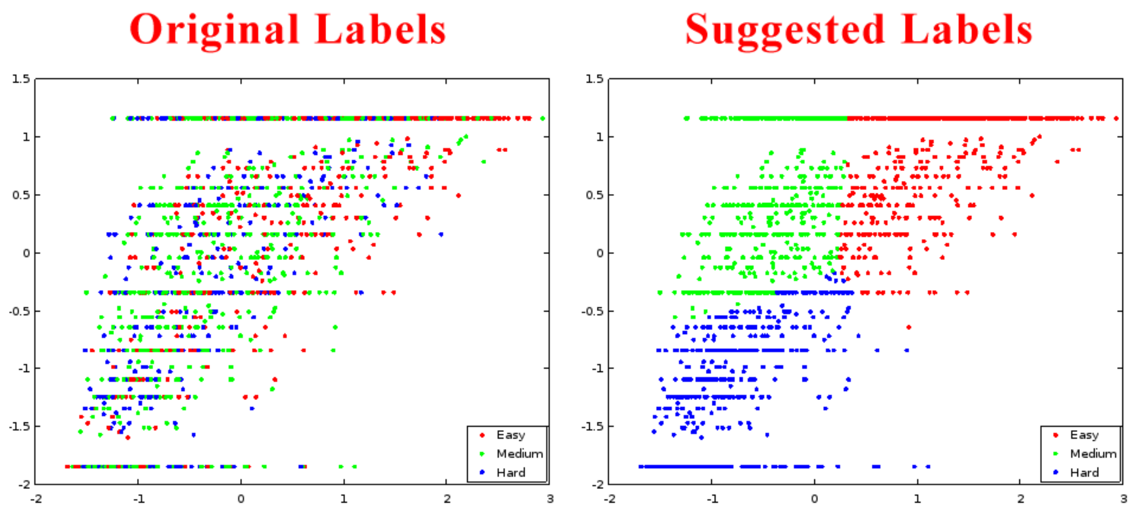
3.3 Competitive Learning

Competitive Learning is another unsupervised learning algorithm which can be used for clustering of data. This algorithm can be implemented as a neural network. Autoencoder was used to encode features to feed input to the algorithm. Following two features were fed to autoencoder:

1. Fraction of people who solved a question correctly.

2. Fraction of people in top five percentile who solved the question correctly.

Best results were obtained when only these two features were used, although other feature combinations were also tried. This algorithm is also faster than k-Means clustering. Output has been shown below:



Feature	Level	Min	Q1	Median	Q3	Max	Mean
Feature 1	**Easy**	0.234	0.652	1.051	1.580	2.934	1.169
	Medium	-1.503	-0.695	-0.419	-0.096	0.324	-0.412
	Hard	-1.686	-1.211	-0.886	-0.414	1.106	-0.781
Feature 2	**Easy**	-0.642	0.492	1.159	1.159	1.159	0.804
	Medium	-0.556	-0.042	0.409	0.859	1.159	0.392
	Hard	-1.843	-1.843	-1.092	-0.717	-0.175	-1.185

Table 2: Statistics for Competitive Learning Output

Estimated Manual Tagging Accuracy: 43.05%

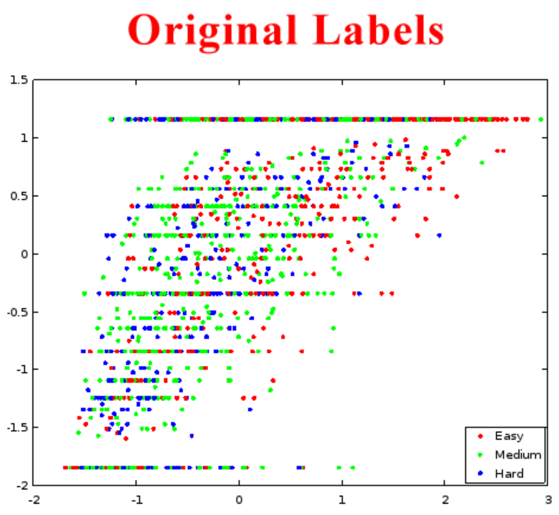
3.4 Expectation Maximization Algorithm

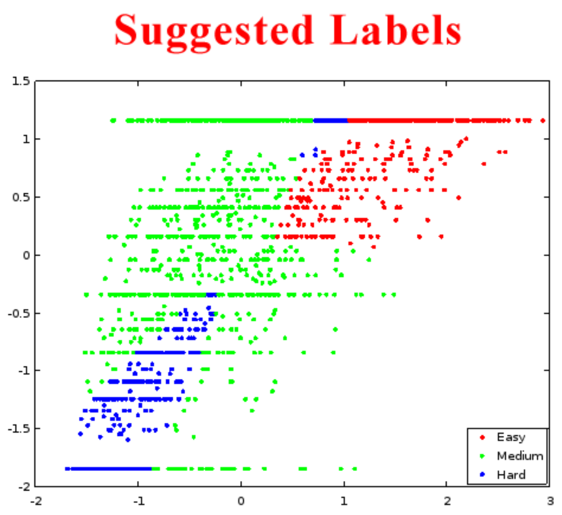
Expectation Maximization algorithm can be used for *soft clustering.* of the data. For this algorithm, a mixture of gaussians model was assumed. From the obtained soft clustering output, question labels were predicted by taking most likely tag for each question. The following features were used:

1. Fraction of people who solved a question correctly.

2. Fraction of people in top five percentile who solved the question correctly.

Best results were obtained when only these two features were used, although other feature combinations were also tried. This algorithm provides a skewed output forcing many questions to fall in the medium difficulty level category. Output has been shown below:





Feature	Level	Min	Q1	Median	Q3	Max	Mean
Feature 1	**Easy**	0.355	0.986	1.412	1.824	2.934	1.415
	Medium	-1.519	-0.671	-0.265	0.137	1.485	-0.271
	Hard	-1.686	-1.250	-0.979	-0.576	1.031	-0.762
Feature 2	**Easy**	0.068	0.559	0.971	1.159	1.159	0.846
	Medium	-1.843	-0.342	0.159	0.659	1.159	0.081
	Hard	-1.843	-1.843	-1.242	-0.717	1.159	-0.983

Table 3: Statistics for EM Output

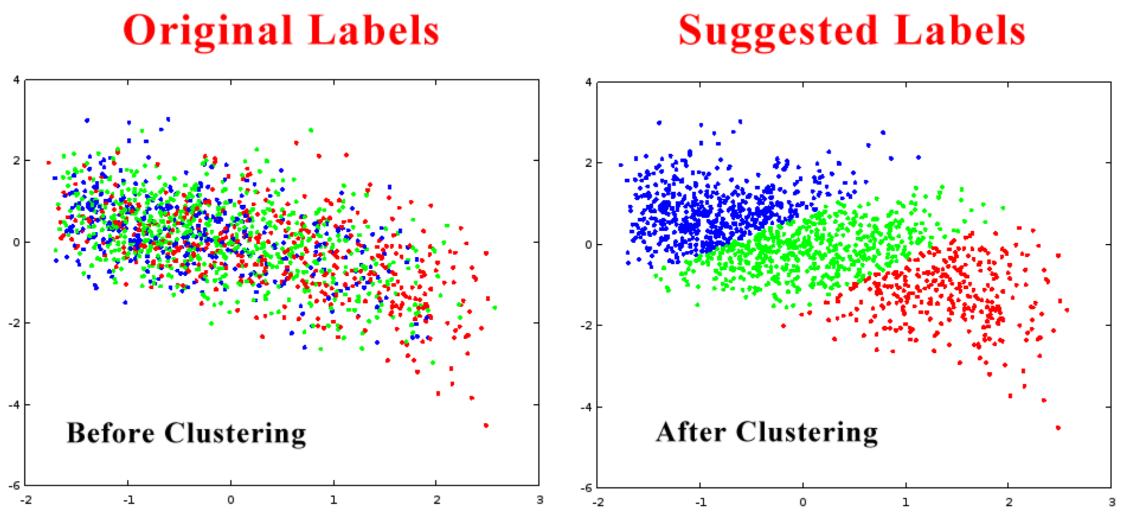
Estimated Manual Tagging Accuracy: 45.40%

3.5 Weighted Clustering

The core idea behind using weighted clustering is to allow students who have got higher scores to contribute more towards clustering as compared to those students who have got lower scores. The rationale behind using such a strategy is that students with higher scores give more authentic data containing fewer random guesses. The following weighted features were used with k-Means Clustering to achieve weighted clustering:

1. Fraction of people who solved a question correctly adjusted by weight.
2. Average weight adjusted marks of students who did not attempt a given question or solved it incorrectly.

Weighing of features is used by assigning higher weights to students who have got higher scores and vice versa. This in effect gives rise to a weighted clustering algorithm without changing the core algorithm. One difficulty is estimating the accuracy of suggested tags since now we are no longer dealing with original features, hence result analysis has been done using original features from k-Means Clustering.



Feature	Level	Min	Q1	Median	Q3	Max	Mean
Feature 1	**Easy**	-0.515	0.907	1.424	1.851	2.934	1.380
	Medium	-1.504	-0.447	-0.013	0.483	2.165	0.040
	Hard	-1.686	-1.188	-0.883	-0.506	1.485	-0.802
Feature 2	**Easy**	-1.843	1.159	1.159	1.159	1.159	1.020
	Medium	-1.843	-0.183	0.409	0.826	1.159	0.238
	Hard	-1.843	-1.468	-0.842	-0.342	1.159	-0.818
Feature 3	**Easy**	-4.498	-1.733	-1.127	-0.731	0.481	-1.227
	Medium	-1.850	-0.494	0.136	0.198	1.979	-0.137
	Hard	-1.121	0.379	0.741	1.238	3.380	0.822

Table 4: Statistics for EM Output (Using Features from k-Means Clustering)

Estimated Manual Tagging Accuracy: 43.18%

4 Known Bugs

1. plotData function in all algorithms crashes if only 1 feature is chosen.
2. Only 1489 questions out of 1500 have been classified. For the remaining questions:
   (a) Two questions were solved by all people and hence are definitely easy. These 2 questions are:
      i. 199
      ii. 1350
   (b) Eight questions were solved by none and hence are definitely hard. These 8 questions are:
      i. 206
      ii. 377
      iii. 378
      iv. 1029
      v. 1038
      vi. 1143
      vii. 1257
      viii. 1386
   (c) One question was never presented to any person in top 5 percentile. (This question has been classified by weighted clustering)

5 Future Work

Some of the proposed projects that can be built using the results of this projects are as follows:

5.1 Suggesting Study Material

If every question is assigned to one of the categories, then we can reverse the process to classify students based on the type of questions that they have solved. This will help in suggesting appropriate study material to students. For example some students did very well in calculus and performed poorly in complex numbers, then they should be suggested the study material focused on complex numbers.

5.2 Noise Removal

Once correct difficulty tags are known, this information can be used to detect random guesses made by the students which will reduce noise in data obtained from subsequent iterations of the test. Now this filtered data can be used to further improve the accuracy of assigned difficulty levels. This is just like Expectation Maximization algorithm spread in time. By detecting random guesses an improved performance estimate can be made for each student which can be used for selecting students instead of using the raw score.

6 References

1. `http://www.gnu.org/software/octave/`
2. Pattern Recognition, 4^{th} Edition by Sergios Theodoridis and Konstantinos Koutroumbas