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Full Length Article

Machine Learning Based Student's Performance Prediction Model

C.SELVI[a], L.SANTHIYA[b], R.SHALINI[b], V. NAVANEETHAN[b]

[a]*ASP, Department of Computer Science and Engineering, Velalar College of Engineering and Technology, Erode, Tamilnadu, India*

[b] *Student, Department of Computer Science and Engineering, Velalar College of Engineering and Technology, Erode, Tamilnadu, India*

***Corresponding Author**

(C.SELVI)
Tel.: +91

ABSTRACT: An University's reputation and its standard are weighted by its students performance and their part in the future economic prosperity of the nation, hence a novel method of predicting the student's upcoming academic performance is really essential to provide a pre-requisite information upon their performances. A machine learning model can be developed to predict the student's upcoming scores or their entire performance depending upon their previous academic performances.

1 Introduction

Making higher education affordable has a significant impact on ensuring the nations' economic prosperity and represents a central focus of the government when making education policies. Yet student loan debt in the India has blown past the billion-dollar mark, exceeding Indians combined credit card and auto loan debts . As the cost in college education (tuitions, fees and living expenses) has skyrocketed over the past few decades, prolonged graduation time has become a crucial contributing factor to the ever growing student loan debt. In fact, recent studies show that only 50 of the more than 580 public four-year institutions in the United States have on-time graduation rates at or above 50 percent for their full-time students. To make college more affordable, it is thus crucial to ensure that many more students graduate on time through early interventions on students whose performance will be unlikely to meet the graduation criteria of the degree program on time.

2 Existing Concept

Machine learning for education has gained much attention in recent years. A substantial amount of literature focuses on predicting student performance in solving problems or completing courses. Many machine learning techniques, such as decision trees, artificial neural networks, matrix factorization, collaborative filters and probabilistic graphical models, have been applied to develop prediction algorithms. Most of this work ignores the temporal/sequential effect that students improve their knowledge over time and treats the prediction as a one-time task. To take the temporal/sequential effect into account, `a three mode tensor factorization (on student/problem/time) technique was developed for predicting student performance in solving problems in ITSs and a similarity-based algorithm was proposed to issue predictions of student grades in courses only when a certain confidence level is reached [1]. However, due to the aforementioned substantial differences of predicting student performance in degree programs, these methods are not applicable in our setting.

Our progressive prediction algorithm uses the ensemble learning technique, in particular, the Exponentially Weighted Average Forecaster (EWAF) as a building block to enable progressive prediction of student performance and online updating of the predictor as new student data is received. The major difference from the conventional EWAF algorithm is that an ensemble predictor has access to multiple base predictors (experts) as well as the previous-term ensemble predictor, whose output summarizes the outputs of all previous-term base predictors (experts) whereas the conventional EWAF algorithm has access to all experts directly.

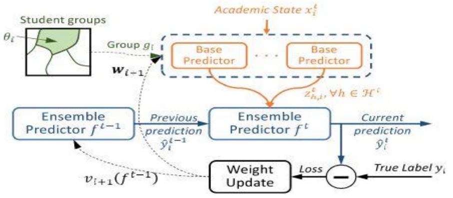
A. Algorithm 1 Ensemble-based Progressive Prediction (EPP)

1: Initialization: $L(ht) = 0, L(ft) = 0$, $\forall t$.
2: for each student i do
3: Observe backgrounds θi, student group gi
4: for term $t = 1$ to T do ◃ *Prediction Phase*
5: Observe performance state xti
6: Extract relevant state $\tilde{\ }xti$
7: Receive prediction $\hat{\ }yt-1$
i from $ft-1$
8: Base predictor $h \in Ht$ predicts zt
$h;i = ht(\theta i, \tilde{\ }xti)$
9: Ensemble predictor ft predicts
10: $\hat{\ }yti = ft(\hat{\ }yt-1i, \{zth;i\}h|vt-1i, wti)$
11: end for
12: Observe true label yi.
13: for term $t = 1$ to T do ◃ *Update Phase*
14: Compute prediction loss $l(\hat{\ }yti, yi)$ and $l(zti;ht, yi)$
15: Update $Li(ht|gi) \leftarrow Li-1(ht|gi) + l(zti;ht, yi)$
16: $Li(ft-1|gi) \leftarrow Li-1(ft-1|gi) + l(\hat{\ }yti, yi)$
17: Update weights $wti+1$ and vt
18: end

B.LIMITATIONS

1.Requires huge set of data to train the predictor.
2. Requires a bilayered structure.
3.Factorization of matrices are complex to have a maximized prediction

C.OVERVIEW OF EXISTING SYSTEM



3 Proposed Concept

The Proposed concept follows a classifier constructing technique i.e. Naive bayes technique for having independency among the values. Naive bayes is a group of algorithms combined together for a common concept or a goal. As our aim is predicting the results or performance scores mere accurately, we call it as a probability model in which this naive bayes classification technique can be used as a supervised learning model.

Another technique which is used along with the naïve bayes classification technique is the Regression technique. Regression is a statistical model estimating variables. The various dependencies and independencies among the different types of variables are analysed by this regression model.

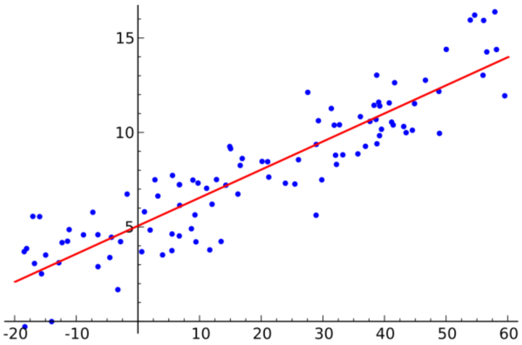
The major reason for simultaneously using this two techniques is to prevent the unwanted variable illusions or unreal relationships in the variables during the prediction process. This issue rises in the regression phase were it is solved by the naïve bayes phenomenon.

For regression there should be sufficient amount of data to be used which makes it testable for later actions. Assumptions of process are the evidence for knowing the data generating process, this makes the prediction of a student's performance more accurately predictable than the other methods.

The aim is to predict the final cumulative GPA of a student in a certain area at the end of each term or semester. Specifically, at the end of each term , the predictor outputs a prediction GPA given student backgrounds and the evolving performance . However, because the cumulative GPA is a function of all course grades, namely the weighted average of all course grades.

A below chart of a basic regression model will merely be the model for the proposed methods prediction process where the x-axis holds for term or semester and the y-axis holds for the marks or the CGPA based on the designation variables given to the predictor. In this way we can easily classify various student performances in each term or term by term.

A.Regression chart



B.BASIC ALGORITHM OF NAÏVE BAYES

TRAIN

```
$samples = [[60], [61], [62], [63], [65]];
$targets = [3.1, 3.6, 3.8, 4, 4.1];

$regression = new LeastSquares();
$regression->train($samples, $targets);
```

PREDICT

```
$regression->predict([64]);
```

REGRESSION

```
$samples = [[73676, 1996], [77006, 1998], [10565, 2000], [146088, 1995], [15000, 2001], [65940, 2000], [9300, 2000], [93739, 1996], [153260, 1994], [17764, 2002], [57000, 1998], [15000, 2000]];
$targets = [2000, 2750, 15500, 960, 4400, 8800, 7100, 2550, 1025, 5900, 4600, 4400];

$regression = new LeastSquares();
$regression->train($samples, $targets);
$regression->predict([60000, 1996])
```

INTERCEPT AND CO-EFFICIENTS

```
$regression->getIntercept();
// return -7.9635135135131

$regression->getCoefficients();
// return [array(1)
{[0]=>float(0.18783783783783)}]
```

4 Conclusions

In this paper, we proposed a novel method for predicting students' future performance in degree programs given their current and past performance. A regression based naïve bayes model is developed for the prediction process. This performance prediction technique can be helpful to elective courses and using the prediction results to recommend courses to students.

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