David Braslow Capstone Project

Machine Learning Engineer Nanodegree

I. Definition

Project Overview

Science, technology, engineering and mathematics (STEM) education has received renewed interest in the USA as people and organizations have become increasingly reliant on computers and other advanced technologies. Labor market demand for workers with technical skills often outstrips supply, and wages for STEM jobs tend to be high and are expected to rise. While this could be an opportunity for many disadvantaged students to find high-paying jobs and improve their life prospects, they often experience low performance in or don't have access to secondary STEM courses. As a result, disadvantaged students have low representation in STEM post-secondary programs and make up only a small percentage of STEM graduates.

Despite the challenges they face, some disadvantaged students do go on to pursue post-secondary STEM education. We can learn from these students what factors are most important for their ongoing interest in STEM. Increasing the STEM attainment of disadvantaged students in post-secondary programs is an important goal not only for the industries that require a robust supply of STEM college graduates, but also for efforts to improve the quality of life for disadvantaged students.

For this study, I use data from the High School Longitudinal Study, 2009-2013 (HSLS:09) conducted by NCES[1]. The study follows a nationally representative group of high school students through high school, recording a number of student, school, and family variables. In total, 23,503 students responded from 944 high schools.

The sample of interest – low-income students – are defined as those from families with household income below 185% of the Census poverty threshold (5,558 students). The inputs of interest will be credits earned in various specific STEM courses, total credit earnings in various STEM disciplines (e.g. math, biology, engineering), and GPA in

[1] United States Department of Education. Institute of Education Sciences. National Center for Education Statistics. High School Longitudinal Study, 2009-2013 [United States]. ICPSR36423-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2016-05-12. http://doi.org/10.3886/ICPSR36423.v1

various STEM disciplines. The outcome of interest will be whether the student is enrolled in a postsecondary program as of November 1, 2013 and considering a STEM major, which I call *Postsecondary STEM Pursuit* (PSTEMP).

Problem Statement

The problem I aim to solve is to determine which high school STEM experiences are most important for predicting whether low-income students want to pursue STEM post-secondary education. To answer this problem, I will train a neural network to classify students by postsecondary STEM pursuit using the inputs described. I will use the approach developed by Garson (1991)[2] to identify the most important variables in the neural network.

Metrics

The evaluation metric I use is F1 Score. This is appropriate because the outcome of interest is skewed and because it incorporates both recall and precision. I have no reason to weight one over the other, so a balanced F score is used.

[2] Garson, G.D. 1991. Interpreting neural network connection weights. Artificial Intelligence Expert. 6(4):46–51.

II. Analysis

Data Exploration

One unusual feature of this dataset is that different categories of missingness are coded into each variable. For example, the question asking students whether they intend to pursue a STEM major has separate codes for “Don’t Know”, “Item not administered: abbreviated interview”, “Item legitimate skip/NA”, “Unit non-response”, and “Missing”. These missing values comprise most (51%) of the values for this variable.

Among the 4,020 remaining students, there is a wide range in STEM experiences and outcomes. With regards to course taking, HSLS asks about coursework in 8th, 9th, and 12th grade. It asks about the most advanced math and science courses taken in 8th grade:

```
    S1 B06 Most advanced math |
course taken by 9th grader in |
                the 8th grade |      Freq.
------------------------------+------------+-----------------------------------
                       Math 8 |        928 |*********************
    Advanced or Honors Math 8 |         91 |**
                  Pre-algebra |      1,520 |***********************************
Algebra I including IA and IB |        919 |*********************
   Algebra II or Trigonometry |         27 |*
                     Geometry |         91 |**
              Integrated Math |         87 |**
            Other math course |        216 |*****
------------------------------+------------+-----------------------------------
                        Total |      3,879
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 S1 B08 Most advanced science course |
   taken by student in the 8th grade |      Freq.
-------------------------------------+------------+---------------------------
                             Biology |         82 |*
                        Life science |        381 |*******
             Pre-AP or pre-IB Biology |         18 |
                           Chemistry |         36 |*
                       Earth Science |        584 |**********
               Environmental Science |         79 |*
                  Integrated Science |         45 |*
General Science or General Science 8 |        318 |******
                           Science 8 |      1,577 |***************************
                    Physical Science |        464 |********
                             Physics |         29 |*
                Other science course |        212 |****
-------------------------------------+------------+---------------------------
                               Total |      3,825
```

HSLS asks whether students are enrolled in the following courses in fall of 9th grade:

Math (N = 3,432)	
Algebra I (including IA and IB)	61.0%
Geometry	17.4%
Algebra II	5.8%
Trigonometry	0.2%
Review or Remedial Math	1.2%
Integrated Math I	4.2%
Statistics or Probability	0.3%
Integrated Math II or above	0.6%
Pre-algebra	8.0%
Analytic Geometry	0.1%
Other advanced math course	0.3%
Other math course	7.2%

Science (N = 3,072)	
Biology I	35.4%
Earth Science	15.8%
Physical Science	26.9%
Environmental Science	4.7%
Physics I	3.5%
Integrated Science I	4.8%
Chemistry I	2.9%
Integrated Science II or above	0.3%
Advanced Biology	1.7%
General Science	2.6%
Life Science	2.4%
Advanced Physics	0.3%
Other earth/environmental science	0.4%
Other biological science	0.2%
Other physical science	0.2%
Other science	7.4%

HSLS asks whether students are enrolled in the following courses in spring of 12th grade:

Math (N = 2,950)	
Pre-Algebra	2.6%
Algebra I (Including IA And IB)	8.6%
Algebra II	40.9%
Algebra III	4.9%

Science (N = 2,675)	
Life Science	1.6%
Biology I	12.1%
Biology II	4.3%
Advanced Placement (AP) Biology	2.4%

Geometry	20.1%	International Baccalaureate (Ib) Biology	0.4%
Analytic Geometry	0.6%	Anatomy Or Physiology	6.0%
Trigonometry	9.2%	Other Biological Science Courses	5.6%
Pre-Calculus Or Analysis And Functions	16.7%	Chemistry I	36.9%
Advanced Placement (AP) Calculus AB Or BC	2.1%	Chemistry II	4.1%
Calculus Other Than AP	1.0%	Advanced Placement (AP) Chemistry	1.9%
Advanced Placement (AP) Statistics	1.0%	International Baccalaureate (IB) Chemistry	0.2%
Statistics Or Probability Other Than AP	3.4%	Earth Science	6.6%
Integrated Math I	1.6%	Advanced Placement (AP) Environmental Science	1.8%
Integrated Math II	1.4%	Other Earth Or Environmental Science	4.2%
Integrated Math III Or Above	2.1%	Physics I	16.0%
Business/General/Applied/Technical/Review Math In	4.8%	Physics Ii	1.5%
Other Math Course	8.7%	Advanced Placement (AP) Physics B Or C	1.5%
		International Baccalaureate (IB) Physics	0.2%
		Physical Science	6.2%
		Other Physical Science	0.8%
		Integrated Science I	0.8%
		Integrated Science II Or Above	0.4%
		General Science	1.1%
		Computer Applications	3.4%
		Computer Programming	1.4%
		AP Computer Science	0.2%
		Other Computer Or Information Science Course	1.9%
		Engineering	2.1%

Additional course-taking variables include the following:

Highest level mathematics course taken/pipeline
Highest level mathematics course taken - ninth grade
When student took Algebra I
Highest level science course taken
Highest level science course taken - ninth grade
Highest level biology course taken/pipeline
Highest level chemistry course taken/pipeline

Highest level physics course taken/pipeline
Highest level other science course taken/pipeline
Has taken an AP math course(s)
Has taken an AP science course(s)
Has taken IB math course(s)
Has taken IB science course(s)
Has taken math dual enrollment course(s)
Has taken science dual enrollment course(s)

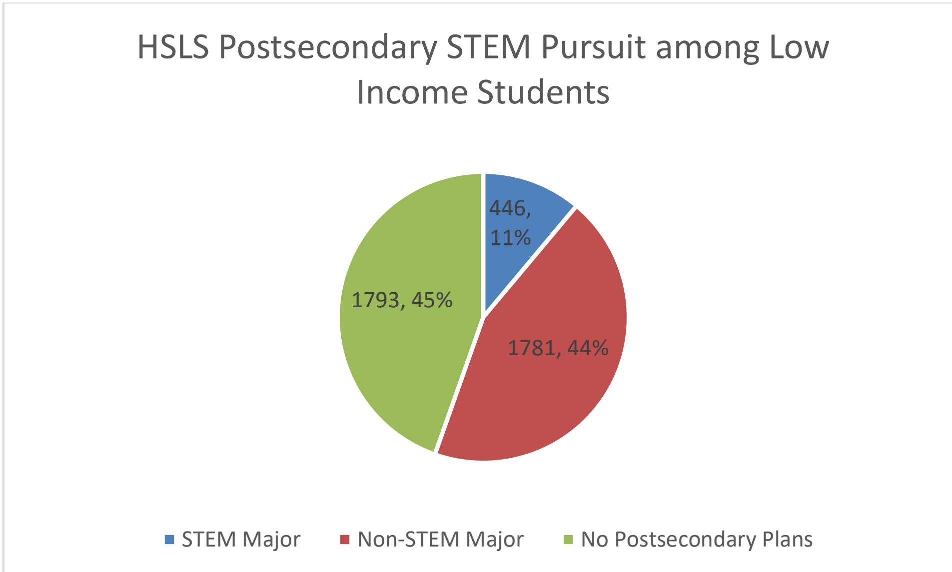
HSLS asks about whether students earned at least one credit in the following STEM subjects by the spring of 12th grade (N = 3,818):

Algebra 1	91.6%
Algebra 2	52.5%
Integrated Math	8.2%
Analysis/Pre-Calculus	20.0%
Calculus	9.3%
Geometry	69.5%
Statistics/Probability	6.4%
Trigonometry	10.6%
Biology	82.5%
Chemistry	53.0%
Geology/Earth Science	69.1%
Physics	25.7%

HSLS also asks about the number of credits earned in various courses:

Credits earned in: AP/IB mathematics courses
Credits earned in: mathematics
Credits earned in: AP/IB science courses
Credits earned in: science

Exploratory Visualization



This visualization shows the various postsecondary STEM outcomes for low-income students in the HSLS dataset. It shows that of the 4,020 low-income students studied, about 45% do not pursue postsecondary education, 44% pursue non-STEM postsecondary education, and 11% pursue STEM postsecondary education. This shows that it is rare for low-income students to pursue post-secondary STEM majors, even after accounting for those who do not pursue postsecondary education of any kind.

Algorithms and Techniques

To answer the problem as stated above, I will train a decision tree to classify students by postsecondary STEM pursuit using the inputs described. I chose a decision tree because it is appropriate for supervised learning with dichotomous outcomes, when there are a large number of feature variables, and when some variable are non-binary. The target will be the post-secondary STEM pursuit variable, operationalized as a dichotomous outcome (STEM pursuit = 1, all other outcomes = 0)

Benchmark

Among the 4,020 low-income students whose Postsecondary STEM Pursuit we know, only 446 (11.1%) are pursuing post-secondary STEM education. I will compare my model to a random assignment model with an 11.1% probability of assignment.

III. Methodology

Data Preprocessing

For the purpose of this study, I include students as “No” observations for Postsecondary STEM Pursuit if they were not asked the relevant question because they were not enrolled in post-secondary classes (which corresponds to the “Item legitimate skip/NA” option). All other values were coded as missing, and the 1,538 students with missing values on this variable (27%) were dropped from the dataset due to lack of observed target.

Other feature variables were also coded as missing using similar logic, but no further students were dropped from the dataset. Missing values were imputed as either the mean or as zero, depending on the reasons for missingness.

Some of the variables in this dataset are not dichotomous. The credit variables are count variables, the GPA variables are continuous, and the “highest level course” variables are ordinal. I trichotomize these variables into roughly equal size groups to make them easier to include as features in the neural network. The “most challenging course” variable, however, is not ordinal but categorical, and was thus converted into dummy variables before analysis.

Implementation

The data were split into a training set with 3,000 observations and a test set with 1,020 observations. Two classifiers – a decision tree and a dummy classifier - were trained on the training set. The classifiers were then applied to the test set, and the F1 score was calculated and compared.

Refinement

I refine my decision tree classifier by testing different maximum depths and different values for the minimum number of samples required to create a split in the tree. The original implementation did not set a maximum depth and set the minimum number of samples for splitting at 2. However, since there are many features in my training set, changing these parameters may improve performance by preventing the decision tree from using features that have low incidence or importance in the full population, but that happen to be moderately important in the training data. I tested maximum depths of 3 to 10 and minimum sample numbers from 3 to 30.

IV. Results

Model Evaluation and Validation

The final model was chosen based on the highest F1 score. I refined this model by testing different maximum depths. To get the highest training F1 score, the maximum depth was 5, and the minimum sample for splitting was 24. I further tested the sensitivity of this model by using k-fold cross validation, using 10 folds. The range of F1 scores from this analysis was somewhat wide (min = 0.075, max = 0.429, mean = 0.281), suggesting that the model is somewhat sensitive to the chosen training set, but the mean is close enough to our F1 value to suggest that the model is still trustworthy.

Justification

The F1 score of the tuned model on the test set was 0.238, approximately double the F1 score for the benchmark model on the test set (0.123). This value suggests there is still a substantial amount of misclassification. However, this is unsurprising for two reasons. First, students' interest and ability to pursue post-secondary STEM education depend on many factors that are not included in our dataset, such as attitudes toward math and ability to afford further education. Second, the low incidence of post-secondary STEM pursuit is makes it difficult to achieve high precision.

Further, the tree that was generated relies on variables that, on their face, seem likely to be important for students' post-secondary decision making. The first split – whether students are taking post-secondary classes at all – is a deterministic predictor in this dataset, since students who were not taking classes were not asked about their interest in STEM majors. The second split – whether a student received credit for Calculus in high school – also makes sense, since Calculus is typically optional for high schoolers, so taking and passing it indicates interest in and ability to succeed in math. Further splits look at Science credit earnings, which is the most widely offered STEM subject area along with math.

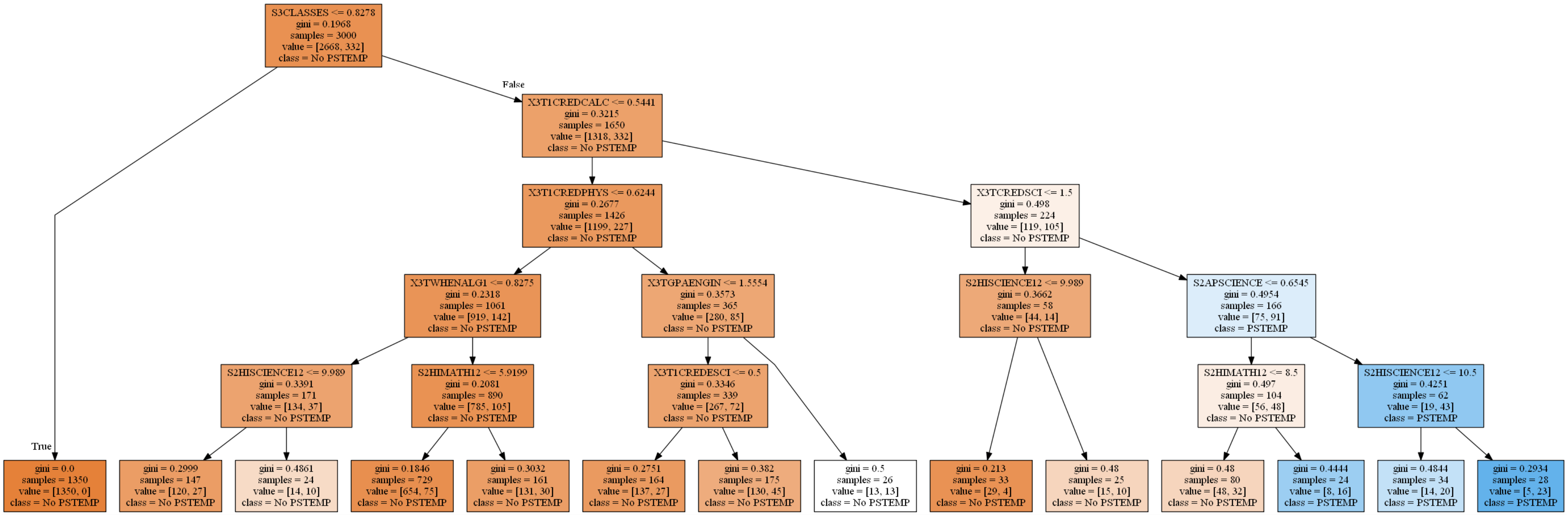
V. Conclusion

Free-Form Visualization

The figure below (Figure 1) shows the tuned decision tree from this analysis. Each box contains five pieces of information (in order from top to bottom):

1. The rule used to decide which path to follow, including the variable and the boundary value.
2. The gini coefficient of the sample at that node from the training set.
3. The number of students in the sample at that node from the training set.
4. The number of students with each observed value of the target at that node from the training set (left = No PSTEMP, right = PSTEMP).
5. The modal observed target of the students at that node from the training set.

Figure 1: Post-Secondary STEM Pursuit Tuned Decision Tree



Reflection

The project started with the goal of predicting post-secondary STEM pursuit from high school STEM experiences using the HSLS dataset. However, the initial data exploration and variable selection turned out to be the most challenging part. From the thousands of variables in the dataset, I had to select those that I thought could be considered indicative of “high school STEM experiences”. These variables also had many different scales and patterns of missingness, which required substantial pre-processing. Fitting and refining the decision tree turned out to be comparatively straightforward. Coding turned out to be a challenge as well, as I am a Python novice.

The final model fit my expectations in terms of its structure but not in terms of it’s F1 score. The amount of improvement from the baseline model, while substantial, still left a lot of room for misclassification. However, the variables that ended up being used for decision rule made sense, based on my content knowledge, so I would be comfortable recommending the model’s use in other situations.

Improvement

It is quite likely that a better solution exists for this problem. Given the large numbers of variables in this dataset, it is possible that other methods of pre-processing and selecting variables would lead to a better solution. A neural network may have been able to better use the information from all of the feature variables to improve our F1 score.