Predicting Student Test Scores and its Implications

James Harter

Objectives

The of this project is to find out if student test scores in can be predicted using a regressive neural network:

- Three separate predictions were made for Math, Reading, and Writing tests
- Independent variables used were Gender, Race/Ethnicity, Parental Level of Education, Lunch Subsidies, and Test Preparation
- Satisfactory predictions could show the importance of the independent variables

Introduction

Using a regressive neural network created with the keras library, a predictive model was made to predict the potential outcome of student test scores (N=1000) based off of a set of environmental factors. The factors were categorical in nature and when plotted, exhibited a degree of correlation. While noticeable, the correlation was not always distinct. If a predictive model could be created from these factors, it could help to prove the significance of the correlation, both individually and as a whole.

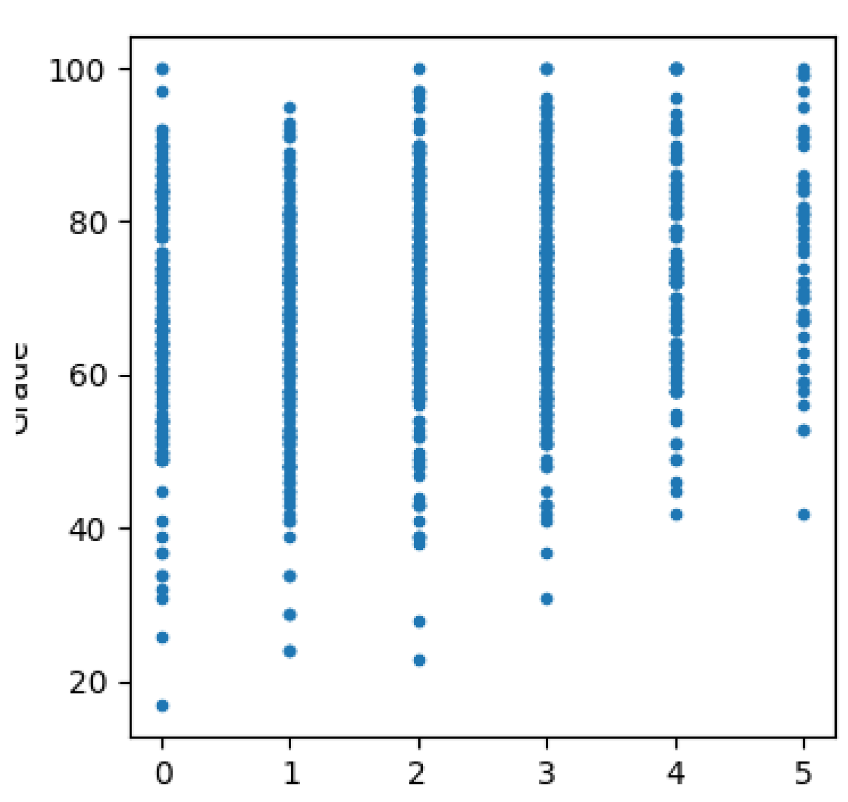

Figure 1: Parental Level of Education Vs. Reading Scores

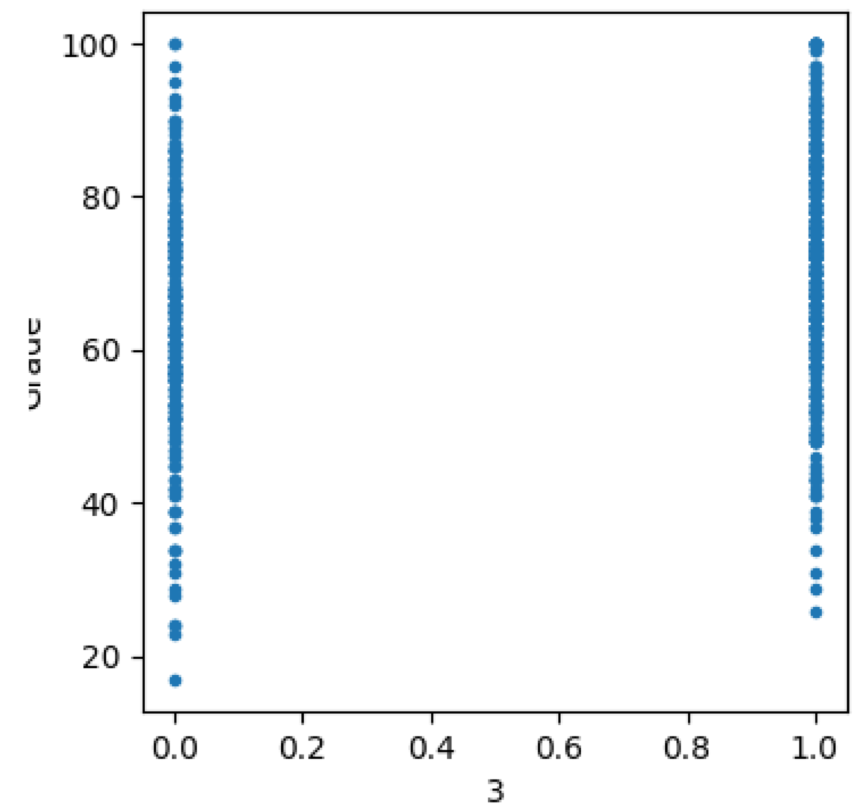

Figure 2: Student Lunch Subsidies Vs. Reading Scores

Methods

A single layer linear network was used to initially asses the data and tune the settings. The loss function used was mean squared error, while the metrics reported were mean squared error and mean average error. This allowed us to get information about both the relative accuracy and precision of the model. Out of 1000 data points, a training set of 800 was selected, which left a validation set of 200. A typical mean average error of 11 and mean squared error of 170-190 was found when ran at 1000 epochs, and weights were extracted from this model. A more complex multi-layer model was then trained and ran at 150 epochs to produce and improved mea of aroun 10.50 and mse of 150-170. Linear proved to be as effective as a Rectified Linear function, without the risk of nodes dying to 0.

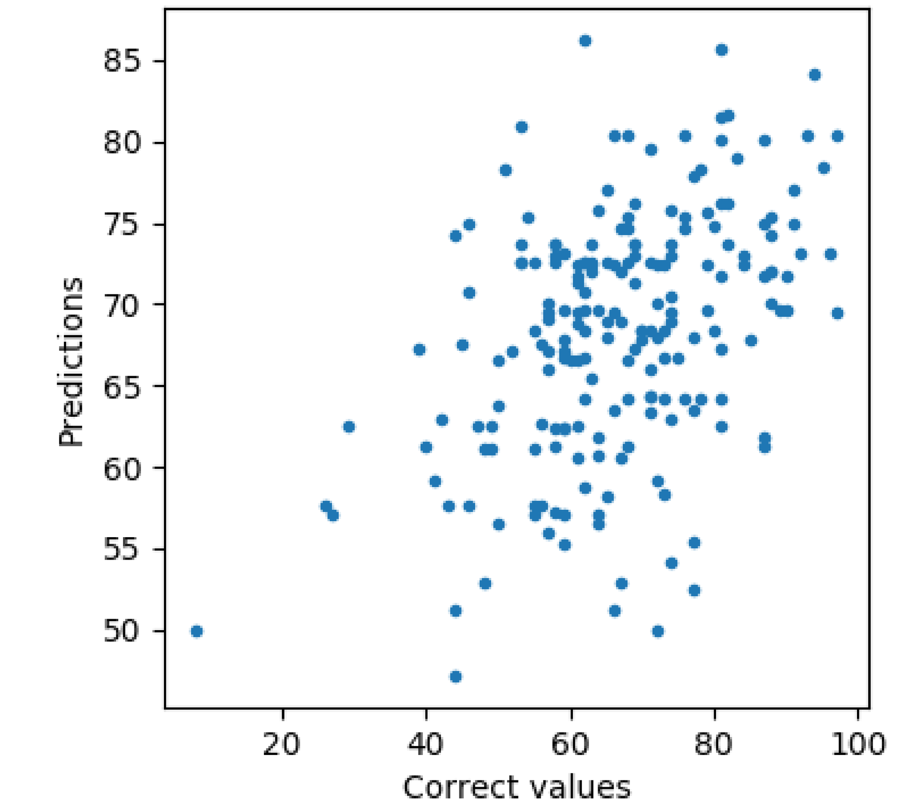

Figure 3: Math Predictions

Important Result

It was found that effects-coding of categorical data seemed to improperly weigh less represented categories.

Test	Gender	B	C	D	E	H.S.	Some Col.	Asc.	Bs.	Ms.	Lunch	Prep Course
Math	2.69	-1.59	0.52	2.97	3.79	-0.98	3.71	4.65	2.25	-7.83	5.73	2.68
Reading	-3.34	-0.91	2.29	3.69	0.07	-0.88	3.61	5.00	2.11	-8.87	3.91	3.57
Writing	-4.33	-1.44	1.80	5.00	-0.31	-1.83	3.72	4.65	3.60	-7.58	4.39	4.92

Table 1: Weights

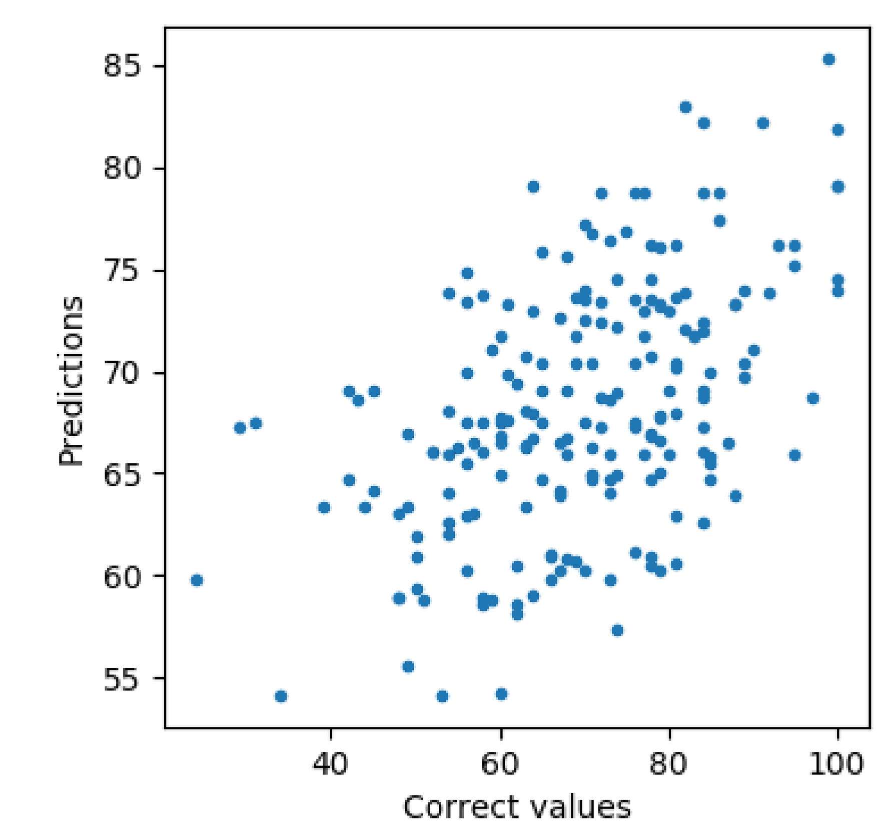

Figure 4: Math Predictions

Conclusion

While the predictions are not of extreme precision, they allow us to highlight trends. We can see that not being part of a lunch subsidy program has a strong effect of predicting the score to be nearly four to five percent higher. We can see some weakness in the model, as well. Children of Parents with master's degrees have a negative weight associated with it, which conflicts with our input data. This is likely because they compromise only 5% of the data, and with effects-coding the categories, the column was trained to tune children of parents with only some high school.

Results

Our results show a clear linear prediction against the validation results that are within a significantly small margin of error.

Test	MSE	MAE
Math	172.94	10.57
Reading	166.49	10.32
Writing	155.56	10.01

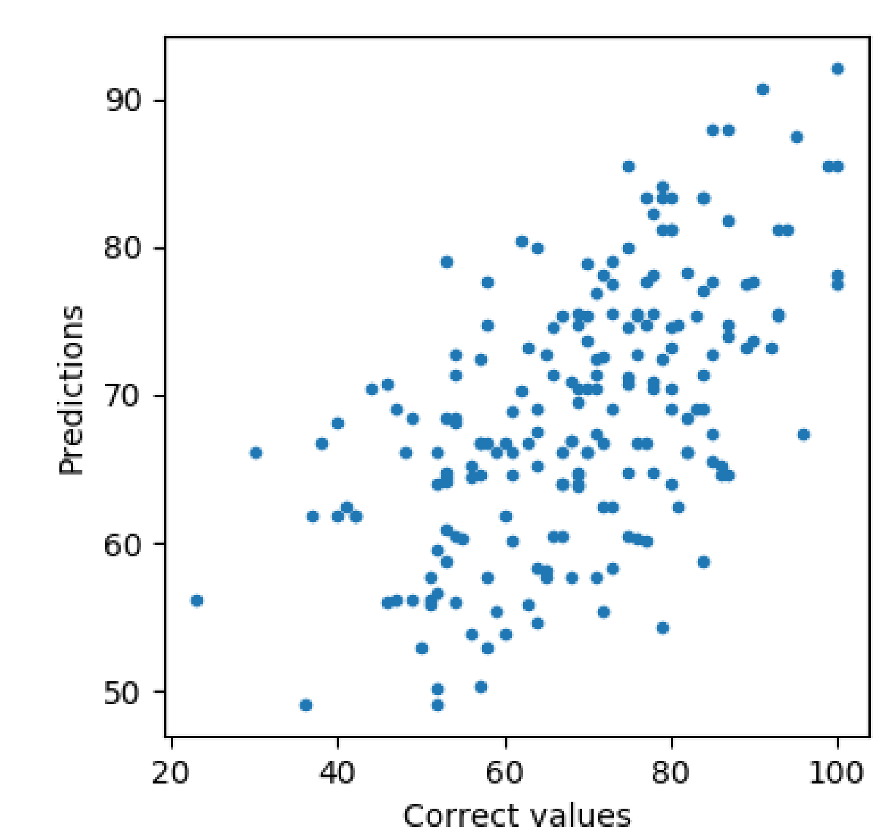

Figure 5: Math Predictions