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Using ANNs and Content Recommendation Systems to Evaluate Special Education Accommodations

Problem:

The field of special education has long required specially trained professionals to make decisions about how best to help the needs of students with disabilities. Such professionals have to make decisions about unique individual needs based mostly on their own prior experiences of what has worked and what hasn't. Comprehensive data on accommodations and their effectiveness is simply not available at the large level to these professionals, leaving them stuck helping students in the pencil and paper age.

Solution:

Even just compiling large sets of data of different students and their achievements and possible accommodations they were given would be a help. There's very little out there, if counties and states and schools are gathering information on what learning accommodations are given at all. Just having the data there would probably add a benefit to education workers, who can then look beyond their own experience and really see what has worked for students. Is allowing the use of a calculator surprisingly effective? Does giving extra time on quizzes not actually impact performance for this type of student?

But, we can do more than just compile data. In the process of collecting all this information, we can also run data analysis algorithms on it. Specifically, deep learning algorithms, where code learns through nodes that act as neurons in a small web. ANNs, artificial neural networks, are the basic building block of deep learning and can pull correlations from data in ways we'd struggle to get from a regular regression method. With ANNs, we can finely analyze basic data like gradebook information and which learning accommodations were used and see what has helped students the most, what is effective for specific groups, and what might be less effective. We can also combine this with another deep learning system, auto encoders. Auto encoders are a type of recommendation system, and together with the ANN could be made into a system that, when given student information, extrapolates from similar entries in its data to return which learning accommodations might be most effective for that student. Such a tool would be immensely useful to aid existing education professionals in their decisions by giving them data-driven, algorithmic suggestions about what works and what hasn't to combine with their own experiences.

Proof of Concept Model:

Currently, I have built a neural network model from Tensorflow's Keras library. Essentially, it uses layers of simplified 'neurons' to take in the input data in numerical form, then has a predicted output from which it trains given available data. The current model is only training on mock-generated student data in lieu of actual data, as a proof of concept.

The mock data that I'm using looks something like this:

Out[6]:

	studentIDs	gender	age	teacher_cred	class_size	disability	accomadation	gpadifference
0	39368	Male	16	PhD	23	Low Emotional Intelligence	Bigger Print Materials	2.333406
1	46884	Female	12	Associate's	22	Reading Disability	Tutoring Sessions	1.091952
2	45218	Female	16	PhD	34	Autism	Use of Toy in Class	1.988006
3	44670	Male	7	Bachelor's	34	ADHD	Materials in Braille	-1.357326
4	16377	Female	8	Bachelor's	22	Autism	Materials in Braille	1.799427
...	...	...	...	...	...	...	...	...
19995	23713	Male	7	PhD	32	Low Emotional Intelligence	Use of Toy in Class	2.340715
19996	26737	Female	9	Master's	27	Reading Disability	Book Buddy	2.419211
19997	25756	Male	14	PhD	34	Speaking Disability	Isolated Workstation	0.430647
19998	45730	Male	15	PhD	26	ADHD	Bigger Print Materials	2.784744
19999	44780	Male	9	Bachelor's	31	Down Syndrome	Bigger Print Materials	-0.227674

20000 rows × 8 columns

Essentially, it's composed of basic student data which the neural network will take as the explanatory variables and input, such as the gender and age of the student, and then a response variable, or output, which in this case is the GPA difference.

Exactly which variables are given is less important, the neural network can be fitted to any student data that can act as a predictor, and use any response variable that provides some measure of performance metric. It could just as easily take a student's ethnicity as well, or not be given the credentials of the teacher, or use test scores as the predicted variable instead, and the model would still work with a few tweaks. This auto-generated data I'm using currently is, again, just a proof of concept with the first attributes that popped into my head as a predictor of student success.

This data is generated mostly randomly, with some simple trends built into the response variable for the neural network to find. Even though the trends themselves are very simple, because of the multiple variables in play, it's already quite difficult for them to be found by straightforward human analysis.

On the next page, there are some multidimensional graphs (Fig 1) showing the relationships between each variable. It's basically incomprehensible to human eyes all together, and only with very careful data analysis can you pull out the actual trends, such as which accommodation given has had the greatest effect for, say, students with ADHD, like Fig 2 shows.

A neural network, after training on the dataset for a little while, can pull all of these trends together easily. The current dataset given to it is about 20,000 student records, but because the trends in the data are relatively straightforward, even if they are hard for a person to see, the neural network can completely pick them up within a 1,000 records of data, probably far less.

Figure 1 - All bivariate distribution combinations graphed

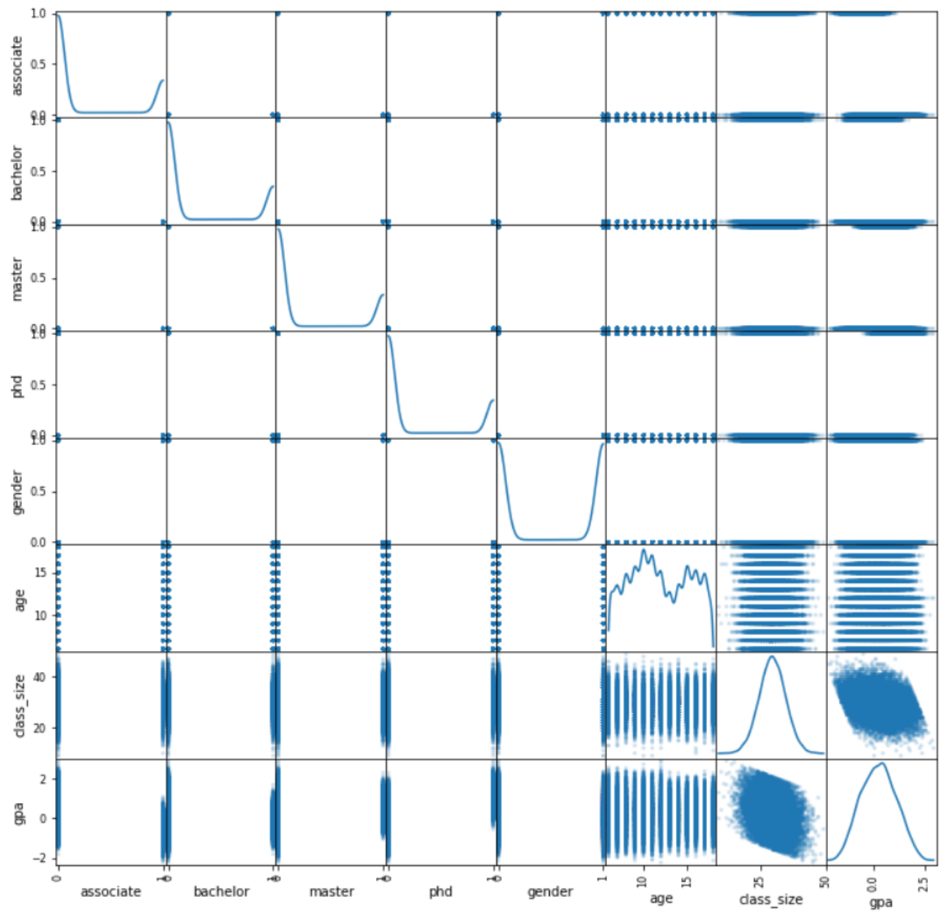
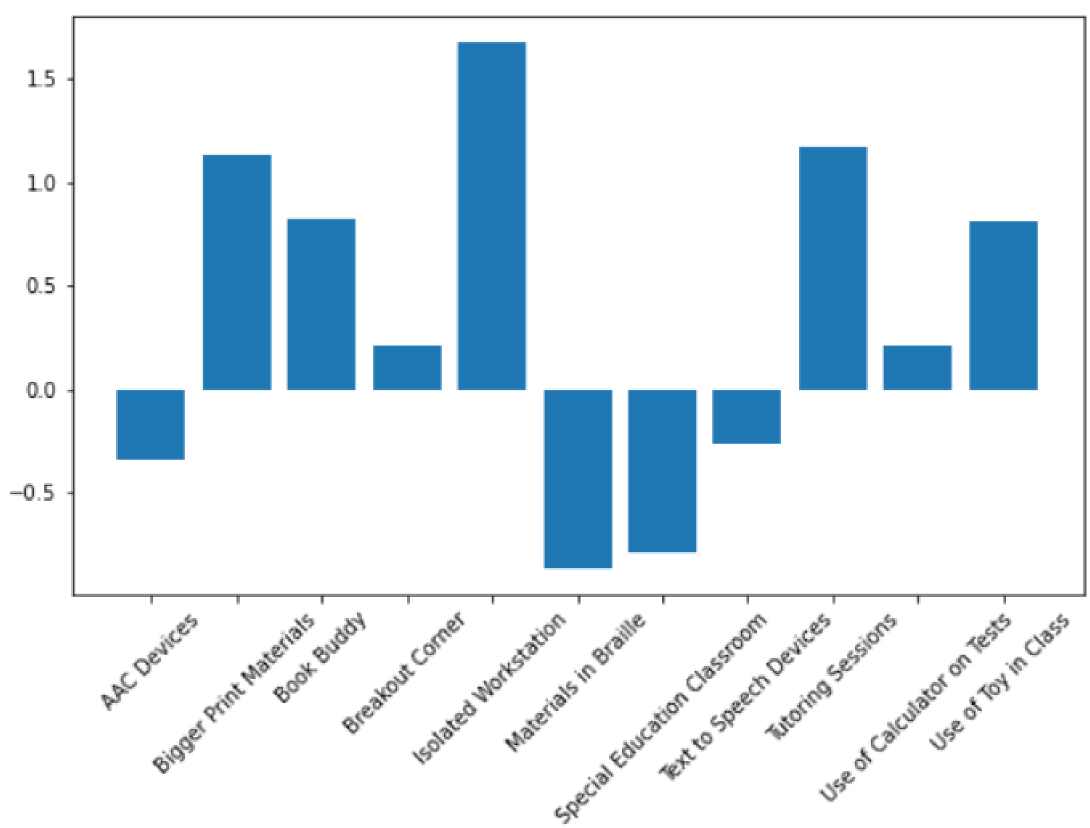


Figure 2 - Graph of most effective accommodations for students with ADHD



So, what can the neural model do once it's trained on this data? Well, given a student's data, it can predict what accommodation would work best for them.

```
In [19]: #predicting which accommodation is most effective given a student
         #input: gender, age, teacher_cred, class size, disability
         predict(np.array([["Female", "15", "Bachelor's", "25", "ADHD"]]))

Out[19]: 'Isolated Workstation is the predicted best accomadation.'
```

So, this model works perfectly for the self-generated data, and it can pull both the overall efficacy of special education accommodations and provide individualized recommendations based on specific student datums. The next steps are to get real district data to feed the model, so it can make meaningful predictions.

<u>Adapting to Real Data:</u>

Yes, the model works perfectly on the mock data, but it doesn't really mean anything yet. My self-coded data patterns are easy for the neural network to predict, and the predictions it is making are purely based out of fake data. For actual analysis, real data is needed, either from student districts or standardized testing vendors. The model can easily be adapted to whatever data is available, it's not, by any means, limited to the example factors or example performance metric I used above. There's also no minimum amount of data that the neural network needs to make predictions, it just takes what it's given, although, of course, the more data available, the more accurate the predictions and results. The model does, however, need individualized student records to make its conclusions, which is why I am currently trying to communicate with testing vendors and school districts to obtain data.

<u>Conclusion:</u>

My goals are simple. I want to compile data on special education students and learning accommodations they were given, then analyze that with neural networks to search for correlations. If reasonable correlations can be found, then I plan to integrate a content recommendation system into the neural network to allow us to predict what learning accommodations are most effective for specific students. If I believe my results are significant, then I will publish my model and also publish correlations and patterns drawn from the data. If my results aren't significant, then I'll publish my model and data anyway, in the hopes that it might aid others in this area who are continuing in this unusual combination of special education and machine learning.