ECON 832 Final Exam

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Abstract

Can we predict human behaviour? In this mini paper, I use the 2018 Choice Prediction Competition Data to build a feedforward neural network, to do just that. I then added engineered features to account for risk preferences and attention. The results of both models are then analyzed and compared.

1 Overview

This dataset is from the 2018 Choice Prediction Competition. Participants are tasked with descriptions of two possible monetary outcomes, with their respective probabilities. Participants are then faced with picking their preferred option. In the first five trails, the participants are given no feedback on their choices. After that, they receive full feedback on the outcomes created by each option for that trial.

I used two different datasets to build the network. The first, my training data, includes 510750 observations of various decisions from different participants. The second, my testing data is much smaller at 3750 observations. Both of these datasets are made up of many possible features that are used in my model. Many are personal characteristics, such as age and gender. Others include the outcomes and probabilities given to the participants, as well as, binary variables representing whether full feedback was provided to the subject regarding payoffs in the current trial. However, the variable that my model will try to predict is B, which presents if the participants chose option B or not.

2 Methodology

2.1 Baseline Model

I first loaded in both datasets mentioned above. I decided to drop variables "RT" and "SubjID" as they did not seem necessary and "RT" would not allow me to easily convert to integer codes. I converted all non-numeric columns to categorical variables and then transformed into integer codes. This is done as the neural network model can only work with numeric inputs. As mentioned above, column "B" makes up my labels and the rest are my features. Ensuring to normalize my features helped improve my accuracy score. To evaluate the models I calculated the proportion of correctly predicted labels and then calculated the loss on the test data.

I decided to use only three layers in my model, to avoid the possible issue of overfitting. In total, I included two hidden layers and one output layer. This combination seemed to give me better results, compared to extremely complex models.

2.2 Model with Attention and Risk Preferences

The second model which includes engineered variables for attention and risk preferences followed the same methodology outlined above. I decided to keep everything as similar as possible to truly see the effect of the engineered features. However, as I did include four more variables I needed to change the number of inputs in my first dense layer to thirty-four. The reasoning behind the chosen features will be outlined in the next section.

3 Feature Analysis

I decided to include two covariates for both risk preference and attention. All four of the engineered variables will help me better predict choice behaviour.

3.1 Risk Preferences

The first feature assumes that participants who prefer a lower variance of outcomes or lower risk will choose options with fewer lottery outcomes. They will do this as fewer outcomes would translate to less variability in potential payoffs. Therefore, participants who regularly chose the option with fewer lottery outcomes was labeled as risk-averse. As a result, this would be a binary feature. "LotNumb" and "Lotnuma" represent the number of lottery outcomes for each option, and were used in the calculation of this feature.

The second feature assumes that participants prefer positively skewed distributions, as they offer a greater probability of a high payoff. This utilized the variables "LotShapeA" and "LotShapeB". If they consistently chose the option with the left-skewed distribution, they were assumed to have a preference for positively skewed outcomes.

3.2 Attention

The first attention feature is an indicator variable for if the participant preferred option B in the first half of the games. I assumed that participants who consistently chose option B in the early games emitted more of a preference for option B no matter the outcomes or probabilities. The second order-related feature is somewhat similar. It is another indicator variable that represents if option B was chosen in the first trial of each game. This assumes that these individuals consistently had more attention on option B no matter the type of game.

The second type of feature looked at the trial number for each game. This is supposed to capture participants' changes in attention throughout trials, as humans can naturally lose focus over time. This feature normalizes the trial number between zero and one.

	Base Model	Features Model
Accuracy	0.71653	0.82293
Loss	0.59700	0.47584

Table 1: Results for both neural net models

4 Results and Discussion

My results indicate that adding engineered risk and attention preferences helped improve the performance of my model. Accuracy has improved from 0.71653 to 0.82293, which suggests that the added engineered variables helped capture patterns in the data that were not seen in the base model. Likewise, loss decreased from 0.59700 to 0.47584 demonstrating the added features' ability to minimize prediction error.

We can infer from the results that risk preferences and attention play vital roles in choice behavior. This would be expected as risk attitudes can have a large effect on decision-making. Having the knowledge of individuals' risk preferences can help us predict what option they are likely to pick. Attention also affects the decision-making process. Participants can exhibit biases for certain options to help preserve their attention spans. We can also analyze how attention will shift throughout a long activity, like the choice competition study. There are also interactions between individuals' risk preferences and attention. Attention to certain options can affect participants' perceptions of risk. They may focus more heavily on outcomes that complement their level of risk tolerance.

5 Additional Discussion

It is important to compare the advantages and shortcomings of neural network models and the BLP method to gain insights into consumer choice behavior. Understanding consumer behavior is extremely important for companies to make better business decisions on their products or services. By analyzing consumer preferences and how decisions are made, we can help meet the needs of consumers and improve market performance.

Neural networks are built to be highly adaptable and can detect complex relationships between input features and labels. They are able to do this without imposing strict assumptions on the underlying data's distribution. Neural networks truly excel at recognizing patterns in data that normal models may struggle with. When trained with large datasets they can achieve a high level of prediction accuracy. However, they can be difficult to analyze as they are known for their "black box" nature.

On the other hand, the BLP model assumes that consumers maximize their utility given certain constraints. These could include budget or product characteristics constraints. BLP also assumes that consumers make rational choices based on their own preferences and market information. BLP significantly utilizes economic theory to help predict consumer choice.

In conclusion, both models have their strengths and weaknesses. Neural networks may be more appropriate for situations where standard economic assumptions may not hold. They are able to work with highly complex relationships which can be useful when analyzing many different features and decisions. Overall, it is important to analyze what type of insights you wish to gain and the complexity of the situation before choosing between BLP and neural nets.