Learning from Machines to Close the Gap between Funding and Expenditure in the Australian National Disability Insurance Scheme

Satish Chand, Yu Zhang

School of Business, University of New South Wales at Canberra

Contact
Prof Satish Chand
Email: s.chand@adfa.edu.au

Dr. Yu Zhang
Email: yu.zhang@adfa.edu.au

Abstract

The Australian National Disability Scheme (NDIS) allocates funds to participants to purchase services contained in a plan approved by the Planmaker. Just one percent of the sample of 70,000 NDIS participants were able to spend more than 90 percent of their allocated budget with two percent (i.e., 1,405 participants) having failed to spend any, meaning that most of the participants were left with unspent funds. The gap between the allocated budget and realised expenditure can be due to errors in both, which we attempt to close using machine learning techniques.

Four machine learning models were evaluated with three experiments designed to test the efficacy of each model, compare the rates of learning between humans and machines, and investigate the explanatory variables chosen by each model. The results show that “faster” learners (humans); (ii) selection of an appropriate machine learning model can improve the accuracy and efficiency of the NDIS funding allocation; and (iii) the significant explanatory variables used across the models are similar.

The objectives of this research are to explain the heterogeneity in utilisation rates using available quantitative techniques from artificial intelligence.

Data and methods

The NDIS has made significant progress in improving access to “reasonable and necessary supports with people’s disability.” The scheme is projected to provide funding of $226 billion to approximately 500,000 Australians every year within the next five years. This level of commitment to a public insurance scheme that supports Medicare is unprecedented in Australia (1). An emerging challenge for the NDIS is the allocation of funding to meet the resource envelope. On this, the NDIS data shows that

(i) “too much focus has been on quantity (meeting participant intake) and not enough on quality (planning process).”

Thus,

(ii) “the NDIS needs to find a better balance between participant intake, the quality of plans, participant outcomes, and financial sustainability.”

The NDIS data is used for each participant and their actual expenditure is recorded. The data is normalised and transformed into a dataset using a range of machine learning models.

The models are evaluated on their predicted to actual outcome in terms of their predicted to actual outcome accuracy and efficiency.

Data: Overall, six quarters of NDIS data is used including two quarters in 2019 (Q1 and Q4 of 2019) and all four quarters in 2020. There are 38,155 observations with 10 attributes for each record in this dataset after removing missing values and duplicate characteristics.

Experiments:

1. Four Machine learning models, i.e., Linear Regression, Support Vector Machines (SVM), Decision Tree and MultiLayer Perceptron (a class of feed-forward neural network, short for MLP) are employed to estimate the allocation of funding (Budget) and utilisation of funding (Expenditure). The efficacy of the techniques are evaluated in terms of their predicted to actual outcome – see figures right.

2. Quarterly Budget prediction for Q1, Q2, Q3 and Q4 of 2020 is made separately using actual historical data and rolling forecasts, respectively. This experiment is designed to assess the ability of machine learning to base the gap between the budget and Expenditure over the quarters compared to that of human policymakers, this is quantified as Rate of Learning and elaborated on later.

3. The figures show that the Budget and Expenditure estimated by the Decision Tree and Neural Network models outperform the other two models in terms of performance.

4. Compared between the results of MLP and Decision Tree, the Decision Tree has achieved the results that are more scattered than that from the MLP model. This is possible due to the fact that the MLP model is better at handling the extreme cases in terms of estimating these variables.

5. These figures also indicate how machine can effectively estimate the allocation of funding and expenditures of the participants based on the historical data, which can automate some of these functions sparing humans to spend their efforts at reviewing and approving applications.

Conclusions and Contribution

This research demonstrates that machine learning techniques can be employed to automate the estimation of the budget and expenditure of the participants, in the NDIS using existing information, releasing humans to focus on fine-tuning the plans.

Moreover, machines learn faster than when humans is closing the gap between the budgets and expenditure over time, helping improve the quality of NDIS plans and reducing under-spending by the participants.

In summary, the NDIS policymakers can benefit by automating some of the budget estimation, leaving room for more personalised interventions.

The fact that machines learn faster than humans, are more transparent at lower costs, has the potential to improve resource allocation.