# Deep Learning Challenge

Data Bootcamp: Module 21

## Overview

This analysis seeks to train a neural network model to be able to predict if an applicant for the non-profit foundation Alphabet Soup will be successful with their ventures or not.

## Results

### Data Preprocessing

The neural network takes in:

* One binary input value (active status)
* One numerical input value (funding amount requested)
* Seven categorical input values (Alphabet Soup application type, affiliated sector of industry, government organisation classification, use case for funding, organisation type, income classification, special considerations for application)

Of the seven categorical inputs, [Alphabet Soup application type] and [government organisation classification] had their rare values grouped.

Initially, [Alphabet Soup application type] had values with less than 200 values grouped into “Other” and [government organisation classification] had values with less than 1000 values grouped into “Other”.

The neural network did not take in the columns labelled “EIN” and“NAME” which were identifier columns and provided no information to the neural network.

The neural network’s output was the 0/1 valued “**IS\_SUCCESSFUL** – Was the money used effectively”.

### Compiling, Training, and Evaluating the Model

To start off with, the model had the following hyperparameters:

* **Number of neurons in first hidden layer**

*Approximately 2-3 times the number of inputs*

Number of inputs approximated as 40

Multiplied by 2.5

110 Neurons

* **Number of hidden layers**

*Approximately 2-4 hidden layers*

2 hidden layers were chosen

* **Number of neurons in second hidden layer**

*Half of neurons in the first hidden layer*

Approximating as 100

Divided by 2

55 Neurons

This model only was able to achieve an accuracy of 72.6%, short of the desired 75% accuracy.

To obtain potentially better models, KerasTuner was used to quickly test the following hyperparameters:

* Number of layers (1 – 6)
* Number of neurons in each layer (30 – 150 with a step size of 20)
* Activation function (relu, tanh, sigmoid)

This did not produce much better results, with the most accurate model still not even being able to reach 73% accuracy.

As the initial, hand-picked model had taken about 30-40 epochs to reach maximum accuracy, KerasTuner was tried again, increasing the epoch to 70.

As the top three results all used the relu activation function, and the minimum number of neurons in the first layer was 70, these values were also adjusted. The sigmoid and tanh activation functions weren’t explored, and the number of neurons in each layer were adjusted to (70 – 170 with a step size of 20).

This still did not produce much better results, with the most accurate model still not even being able to reach 73% accuracy.

Finally, the categorisation of rare values in categorical columns was reevaluated.

The cut-off value for “Application Type” was reduced to 20.

Classification was split into “Other\_Small” (cut-off value of 10) and “Other\_Med” (cut-off value of 100)

KeraTuner was run again, with still disappointing results.

## Summary

In conclusion, the endeavor to develop a predictive model using deep learning techniques for Alphabet Soup's funding success proved to be a challenging task. The analysis involved comprehensive data preprocessing steps to handle binary, numerical, and categorical inputs, with particular attention given to managing rare categorical values for improved model performance.

Despite meticulous adjustments to model architecture and hyperparameters using KerasTuner, the achieved accuracy fell short of the targeted 75%. Initial configurations, including the choice of neural network layers and activation functions, were optimized iteratively, yet incremental gains in accuracy were modest. Even with extended training epochs and refined categorization strategies for rare values, significant improvement remained elusive.

The findings underscore the complexity inherent in predicting funding success based on the available dataset's limited dimensions. Future improvements could explore alternative deep learning architectures or incorporate additional feature engineering techniques to enhance predictive capabilities. Nonetheless, this study provides valuable insights into the application of deep learning in nonprofit funding prediction, highlighting both achievements and avenues for further refinement in future research and practical implementations.