Neural Network Model Report

Overview

I received a CSV containing more than 34,000 organizations that have received funding from Alphabet Soup over the years. Within this dataset are a number of columns that capture metadata about each organization. I was tasked with building a tool that can help it select the applicants for funding with the best chance of success in their ventures. With my knowledge of machine learning and neural networks, I used the features in the provided dataset to create a binary classifier that can predict whether applicants will be successful if funded by Alphabet Soup.

Data Processing

To process the data, I removed unnecessary columns (‘EIN’). I then binned ‘NAME’, ‘APPLICATION_TYPE’, and ‘CLASSIFICATION’. Once that was done, I use pd.get_dummies on the rest of the columns and set ‘IS_SUCCESSFUL’ to be the target for the model. The remaining columns were set to be features. The data was then split into training and testing and StandardScaler was used.

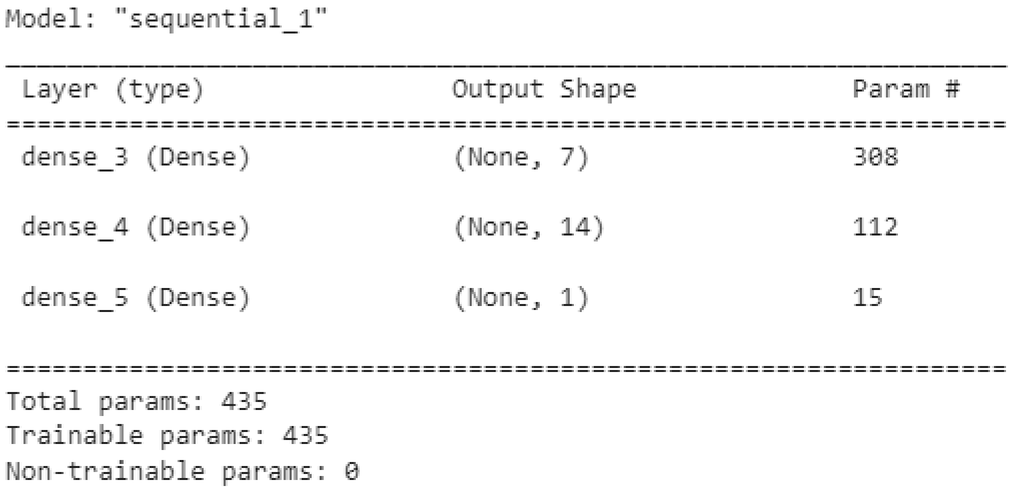
Compiling, Training, and Evaluating the Model

For my second attempt at evaluating the model, I used two hidden layers and one output layer. The first was a relu activation with 10 units. The second was another relu activation with 16 units. And the output layer was a ‘sigmoid’ activation with 1 unit.

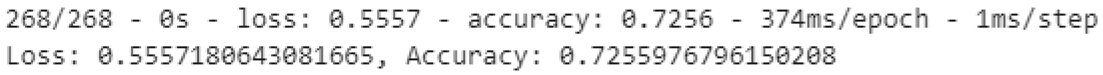
I was able to achieve the target model performance, achieving a 79% accuracy. This is 7% higher than my first attempt, which achieve a 72% accuracy.

To increase the model’s performance, I included the ‘NAME’ column, which was previously dropped from the database, and binned it along with ‘APPLICATION_TYPE’, and ‘CLASSIFICATION’. I played around with the number of hidden layers and units to use. Ultimately, I settled on using three more units on my first hidden layer, and two more units on my second hidden layer than I did previously on my first attempt.

First Attempt:

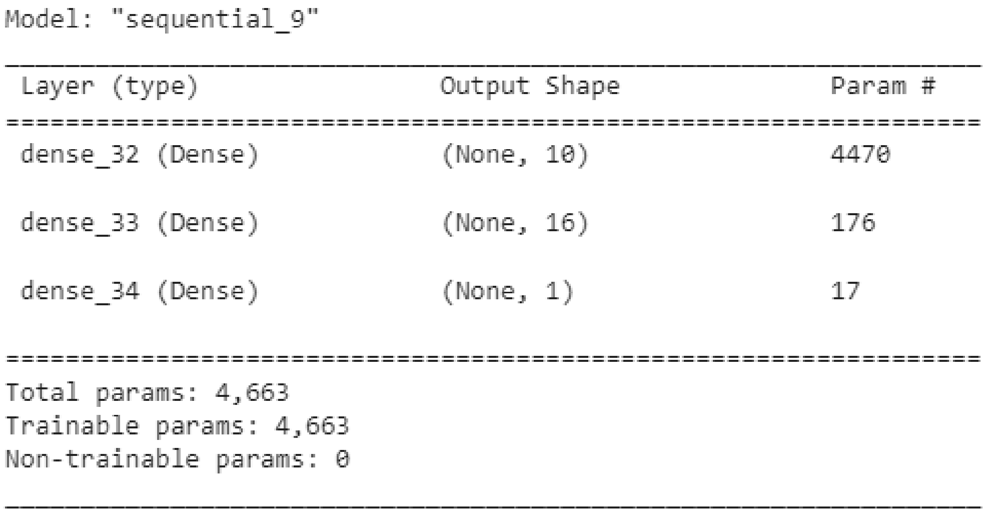


```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_3 (Dense)             (None, 7)                 308

 dense_4 (Dense)             (None, 14)                112

 dense_5 (Dense)             (None, 1)                 15

=================================================================
Total params: 435
Trainable params: 435
Non-trainable params: 0
```

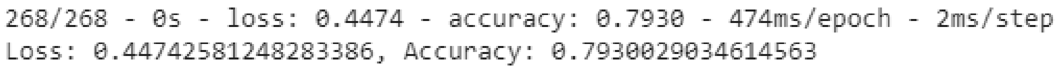


```
268/268 - 0s - loss: 0.5557 - accuracy: 0.7256 - 374ms/epoch - 1ms/step
Loss: 0.5557180643081665, Accuracy: 0.7255976796150208
```

Second Attempt:



```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_32 (Dense)            (None, 10)                4470

 dense_33 (Dense)            (None, 16)                176

 dense_34 (Dense)            (None, 1)                 17

=================================================================
Total params: 4,663
Trainable params: 4,663
Non-trainable params: 0
_________________________________________________________________
```



```
268/268 - 0s - loss: 0.4474 - accuracy: 0.7930 - 474ms/epoch - 2ms/step
Loss: 0.44742581248283386, Accuracy: 0.7930029034614563
```

Summary

In conclusion, the second model performed better all-around at a 79% accuracy and 0.45 loss. Whereas the first model had a 72% accuracy with a 0.55 loss. My recommendation would be to use the second model. In the future I would use an automated neural network to determine the best model hyperparameters to use.