

Module 21 Challenge Report

Overview:

- Alphabet Soup, a nonprofit foundation, needs a solution to improve its funding allocation process. Using our skills in machine learning and neural networks, our task is to develop an efficient binary classifier. This classifier will examine a comprehensive dataset containing details about more than 34,000 organizations that have received funding from Alphabet Soup over the years. The main goal is to develop a predictive tool that helps the foundation's business team in pinpointing and backing applicants who are most likely to succeed in their endeavors.

Results:

Data Preprocessing

- Target Variable: "IS_SUCESSFUL"
- Feature Variables: "INCOME_AMT" and "ASK_AMT", "Classification" and "Application Type" as well.
- Variables removed: "EIN" and "Name"

```
In [2]: # Drop the non-beneficial ID columns, 'EIN' and 'NAME'.
application_df = application_df.drop(columns = ['EIN', 'NAME'])
application_df
```

```
Out[2]:
```

| | APPLICATION_TYPE | AFFILIATION | CLASSIFICATION | USE_CASE | ORGANIZATION | STATUS | INCOME_AMT | SPECIAL_CONSID |
|-------|------------------|------------------|----------------|--------------|--------------|--------|---------------|----------------|
| 0 | T10 | Independent | C1000 | ProductDev | Association | 1 | 0 | |
| 1 | T3 | Independent | C2000 | Preservation | Co-operative | 1 | 1-9999 | |
| 2 | T5 | CompanySponsored | C3000 | ProductDev | Association | 1 | 0 | |
| 3 | T3 | CompanySponsored | C2000 | Preservation | Trust | 1 | 10000-24999 | |
| 4 | T3 | Independent | C1000 | Heathcare | Trust | 1 | 100000-499999 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 34294 | T4 | Independent | C1000 | ProductDev | Association | 1 | 0 | |
| 34295 | T4 | CompanySponsored | C3000 | ProductDev | Association | 1 | 0 | |
| 34296 | T3 | CompanySponsored | C2000 | Preservation | Association | 1 | 0 | |
| 34297 | T5 | Independent | C3000 | ProductDev | Association | 1 | 0 | |
| 34298 | T3 | Independent | C1000 | Preservation | Co-operative | 1 | 1M-5M | |

34299 rows × 10 columns

- **How many neurons, layers, and activation functions did you select for your neural network model, and why?**

- For my model, I used two hidden layers and an output layer. For this model, the neurons for the layers were 10 and 20 to keep it small and simple. “Relu” function was used for these, and a “sigmoid” function was used for the outer layer, which only had 1 neuron.

```
In [13]: # Define the model - deep neural net, i.e., the number of input features and hidden nodes for each Layer.
input_features = len(X_train_scaled[0])
hidden_nodes_layer1 = 10
hidden_nodes_layer2 = 20
nn = tf.keras.models.Sequential()

# First hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=input_features, activation='relu'))
# Second hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation='relu'))

# Output Layer
nn.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))

# Check the structure of the model
nn.summary()
```

Model: "sequential_1"

| Layer (type) | Output Shape | Param # |
|-------------------------------------|--------------|---------|
| ===== | | |
| dense_3 (Dense) | (None, 10) | 460 |
| dense_4 (Dense) | (None, 20) | 220 |
| dense_5 (Dense) | (None, 1) | 21 |
| ===== | | |
| Total params: 701 (2.74 KB) | | |
| Trainable params: 701 (2.74 KB) | | |
| Non-trainable params: 0 (0.00 Byte) | | |

- **Were you able to achieve the target model performance?**

- **Accuracy: 72.9%, no.** Target accuracy was 75%.

- **What steps did you take in your attempts to increase model performance?**

- I had three different attempts at trying to increase the model’s performance. All three attempts focused specifically on the number of layers and the number of neurons each layer had.
- **First attempt:** added additional hidden layer (3 total) and increased neuron counts for each layer: 85, 95, 105. **72.80% accuracy.**
- **Second attempt:** added additional layer (3 total) and this time decreasing neuron counts significantly. (4, 8, 12). **72.84% accuracy.**

- **Third attempt:** added TWO additional hidden layers (4 TOTAL) and kept the same neuron amount for all 4 layers. (20 each). **Accuracy: 72.63%.**

Attempt 1:

```
In [12]: # Define the model - deep neural net, i.e., the number of input features and hidden nodes for each layer.
input_features = len(X_train_scaled[0])
hidden_nodes_layer1 = 85
hidden_nodes_layer2 = 95
hidden_nodes_layer3 = 105
nn = tf.keras.models.Sequential()

# First hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=input_features, activation='relu'))
# Second hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation='relu'))
# Third Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer3, activation='relu'))

# Output Layer
nn.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))

# Check the structure of the model
nn.summary()
```

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|-------------------------------------|--------------|---------|
| dense (Dense) | (None, 85) | 3825 |
| dense_1 (Dense) | (None, 95) | 8170 |
| dense_2 (Dense) | (None, 105) | 10080 |
| dense_3 (Dense) | (None, 1) | 106 |
| Total params: 22181 (86.64 KB) | | |
| Trainable params: 22181 (86.64 KB) | | |
| Non-trainable params: 0 (0.00 Byte) | | |

Attempt 2:

```
In [12]: # Define the model - deep neural net, i.e., the number of input features and hidden nodes for each layer.
input_features = len(X_train_scaled[0])
hidden_nodes_layer1 = 4
hidden_nodes_layer2 = 8
hidden_nodes_layer3 = 12
nn = tf.keras.models.Sequential()

# First hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=input_features, activation='relu'))
# Second hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation='relu'))
# Third Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer3, activation='relu'))

# Output Layer
nn.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))

# Check the structure of the model
nn.summary()
```

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|-------------------------------------|--------------|---------|
| dense (Dense) | (None, 4) | 180 |
| dense_1 (Dense) | (None, 8) | 40 |
| dense_2 (Dense) | (None, 12) | 108 |
| dense_3 (Dense) | (None, 1) | 13 |
| Total params: 341 (1.33 KB) | | |
| Trainable params: 341 (1.33 KB) | | |
| Non-trainable params: 0 (0.00 Byte) | | |

Attempt 3:

```
In [32]: # Define the model - deep neural net, i.e., the number of input features and hidden nodes for each layer.
input_features = len(X_train_scaled[0])
hidden_nodes_layer1 = 20
hidden_nodes_layer2 = 20
hidden_nodes_layer3 = 20
hidden_nodes_layer4 = 20
nn = tf.keras.models.Sequential()

# First hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=input_features, activation='relu'))
# Second hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation='relu'))
# Third Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer3, activation='relu'))
# Fourth Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer4, activation='relu'))

# Output Layer
nn.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))

# Check the structure of the model
nn.summary()
```

Model: "sequential_2"

| Layer (type) | Output Shape | Param # |
|-------------------------------------|--------------|---------|
| ===== | | |
| dense_9 (Dense) | (None, 20) | 900 |
| dense_10 (Dense) | (None, 20) | 420 |
| dense_11 (Dense) | (None, 20) | 420 |
| dense_12 (Dense) | (None, 20) | 420 |
| dense_13 (Dense) | (None, 1) | 21 |
| ===== | | |
| Total params: 2181 (8.52 KB) | | |
| Trainable params: 2181 (8.52 KB) | | |
| Non-trainable params: 0 (0.00 Byte) | | |

Summary:

It seems that after our original model, the three attempts at improving model performance based on changing number of layers and neurons did not really produce that much of a difference.

Original: 72.89%

1st attempt: 72.80%

2nd attempt: 72.84%

3rd attempt: 72.63%