**Philanthropy Success Prediction Report** 03.10.23

1. **Inspiration**:

According to the National Philanthropic Trust, Americans gave $484.85 billion USD to general philanthropic causes in 2021, a 4% increase from 2020. 86% of affluent households maintained or increased their giving despite uncertainty about the further spread of COVID-19. In addition, an estimated 30% of adults volunteered in 2019, contributing an estimated 5.8 billion hours valued at $147 billion USD. Since philanthropy is so important to the American way of life, it is important to determine whether this money is well-spent, by which we mean whether the money was used effectively in achieving its outcome. Finding relations between whether money is well-spent and other variables can help donors make better decisions about where to place their money and their trust. It is also useful to government agencies to determine which areas need the most money, and which areas individual donors consider the most important to invest in toward creating a better American society. Our goal in this analysis is to use classification models and neural networks to try and predict whether donor money is successfully spent and which variables are the most relevant to making this prediction.

1. **Data and Research Questions:**

**Graphical user interface, application

Description automatically generated**

We are using a dataset of 34,299 donations from various organizations, obtained from the Alphabet Soup nonprofit foundation. We have the following information about the donations:

* **EIN** and **NAME**—Identification columns
* Graphical user interface, text

  Description automatically generated**APPLICATION\_TYPE**—Alphabet Soup application type (These are codes used by the foundation to classify the applications)
* **AFFILIATION**—Affiliated sector of industry. Most of the donors are either independent or company sponsored.
* **CLASSIFICATION**—Government organization classification. These codes are used by Alphabet Soup to determine how the government classifies the donations.
* Text

  Description automatically generated**USE\_CASE**—Use case for funding. We see that most of the donations were for preservation or for developing new products.
* Text

  Description automatically generated**ORGANIZATION**—Organization type
* Text

  Description automatically generated with medium confidence**STATUS**—Active status (only five applications were inactive)
* **INCOME\_AMT**—Income classification
* **SPECIAL\_CONSIDERATIONS**—Special considerations for application. Only 27 applications had special considerations.
* **ASK\_AMT**—Funding amount requested.
* **IS\_SUCCESSFUL**—Was the money used effectively?

**Data Cleaning:**

We dropped the name and identification columns as we do not expect those columns to have effect on whether the donations were successful.

The APPLICATION\_TYPE column had 17 different categories, many of which were represented only a handful of times. We combined every category represented fewer than 528 times into an “other” category so that we were left with 9 categories, the smallest of which (“other”) had 276 entries.

Similarly, the CLASSIFICATION column had 71 different entries, many of which were poorly represented. We combined every category represented fewer than 1883 times into an “other” category so that we were left with 6 categories, of which the smallest had 1883 entries.

We can also see that it is highly unlikely that the “STATUS” and the “SPECIAL\_CONSIDERATIONS” columns were extremely unlikely to have any effect on our final results. Nevertheless, we ran our models both with and without those columns, and those columns had negligible predictive effect.

Lastly, we isolated the six object datatype columns (['APPLICATION\_TYPE','AFFILIATION','CLASSIFICATION','USE\_CASE','ORGANIZATION','INCOME\_AMT','SPECIAL\_CONSIDERATIONS']) into one data frame, ran the pd.get\_dummies() method to one-hot encode the data, and merged the new data frame with our numerical columns to obtain our final data frame ready for inputting into classification algorithms and neural networks.

**Research Questions:**

Our main goal was to determine which design for a keras deep neural networks was able to best predict whether a charitable donation would be successful.

We would also like to compare our neural network with classification algorithms such as the KNeighbors Classifier, RandomForest Classifier, and LGBM Classifier and see if they were better able to predict whether a charitable donation would be successful than a keras deep neural network.

Lastly, we would like to examine which columns had the most predictive power.

**Results:** Our best neural network model was nn2. This is how it was defined:

nn2 = tf.keras.models.Sequential()

nn2.add(tf.keras.layers.Dense(units=6, activation="relu", input\_shape=[43]))

nn2.add(tf.keras.layers.Dense(units=4, activation="relu"))

nn2.add(tf.keras.layers.Dense(units=1, activation="sigmoid"))

We used one activation layer with 6 neurons, a hidden layers with 4 neurons, and a final layer with just 1 neuron. We created another model with an activation layer of 20 neurons, hidden layers with 10 and 4 neurons, and a final layer with 1 neuron, but the performance of the model did not improve, so we stuck with the model above.

The nn2.evalulate() function in keras determined that his model had a 72.5% accuracy.

The recall of the model was 79% for positively predicting myopia and the F-1 score was 75% for positive success predictions. Below is the ROC curve:

Chart, line chart

Description automatically generated

The model is not bad, but not that great either. If I were interested in making philanthropic donations, I would definitely not make this model my primary source of making decisions.

In comparison with other classifier models, the RandomForest() Classifier performed the best, returning identical recalls and F-1 scores of 83% for positive success predictions.

Chart, line chart

Description automatically generatedThis the ROC curve for the RandomForest() Classifier:

While this model is slightly better than the neural network model, it is still not very good. I would recommend the investigation of more data variables to make a better model.

Our final research question was which columns affected the outcome the most. According the RandomForest() Classifier, about 40% of the predictive power in the model is from the ASK\_AMT column, and a further 26% depended on the AFFILIATION column. It would be a good idea to run a linear regression model between ASK\_AMT, and the probability of a successful outcome.