IEOR 142
12/17/21

Mental Health Treatment in the Tech Workplace

Predicting the Likelihood that an Individual Receives Treatment

Sophie Doucet, Atmika Sarukkai, Stephen Ou, Benjamin Kern

Motivation

For our research, we are trying to predict the likelihood that an individual who works in tech seeks treatment for their mental illness given several different employment-related, biological, geographic, and economic features.

This research question is important because it has been shown that high levels of mental health are associated with increased learning, creativity, and productivity, allow for positive social relationships, and improve physical health and life expectancy. Even though mental health so greatly impacts how we interact with the world, when we think about health, we tend to prioritize physical well-being at the expense of mental health. This research question is important because the number of mental health-related issues is on the rise-- according to the World Health Organization, there has been a 13% rise in mental health conditions from 2007 to 2017. And based on the 2016 survey results of employees worldwide, 51% of tech professionals have been diagnosed with a mental health condition (OSMI Mental Health Survey).

However, health systems have not adequately responded to this increase in mental disorders, and as a result, there is a substantial gap between people who need care and people with access to care-- between 76% and 85% of people with mental disorders receive no treatment for their disorder (World Health Organization).

To understand why it is that individuals do not receive treatment for their mental illnesses, it is important to look into the features that are significant in predicting the likelihood that an individual seeks treatment for their mental illness so we may identify areas to potentially integrate mental health services.

Data

The data contains information extracted from survey responses pertaining to attitudes toward mental health. The survey was distributed to tech workspaces around the world, specifically the United States, UK, Canada, Germany, and the Netherlands.

The original data contains both quantitative and qualitative variables– the qualitative variables include gender, country, employment status, as well as more open-ended survey questions regarding general feelings towards potentially taking medical leave for a mental health condition, as well as one's awareness of available mental health resources offered by the employer. Qualitative variables include the number of employees in the given company, and the age of the workers. We combined data collected by Open Sourcing Mental Illness (OSMI) in three different years (2014, 2017, and 2020). The three datasets had different numbers of columns, and column labels, so we renamed them in order to merge them. We then dropped all the columns that were not shared between all three datasets. We also noticed that the type of values in the columns were not the same between the datasets– for instance, the 2017 dataset contained the value "No" which we converted to "0", and "Yes" which we converted to "1". Once we ensured each column had the same value type, we had to clean up certain columns with text responses– the gender column had more than 50 different responses, so to address this, we grouped these responses into three broad categories: "male", "female", and "other". Additionally, we wanted to analyze employees in the tech workspace, so we dropped all individuals from the dataframe who were in non-tech jobs using the "tech_company" column. We also removed the missing values during our data processing to make the data more usable.

Finally, a few columns in the dataset (such as the "work_interface" column) contained values such as "sometimes," "often," and "never," so we transformed the strings into integers using the processing package from Sklearn. The final table contains 1522 rows and 18 columns. The variable we were interested in predicting using various models was the "treatment" column, which indicates whether an individual seeks mental health treatment or not.

In our exploratory data analysis, we plotted answers to certain questions to see which answers appeared to be more common with those who sought out treatment and those who did not (Appendix: Figures 2-5). In Figure 2, we looked at the country of those who answered the survey. Most people who took the survey were in the US, and had a higher proportion of those who sought treatment. Not many respondents were in India, but they had the highest proportion of not seeking treatment, indicating more research needed. In Figure 3, we looked at the responses to if the employee had mental health benefits, in which we can see that those who had mental health benefits had much higher rates of seeking treatment. In Figure 4, we looked at the responses to if the employee knew their care options in which we can see that those who knew their mental healthcare options had much higher rates of seeking treatment.

* All columns in the dataset are described in the appendix.

Analytics models

To begin our analysis, we made a baseline model that would predict the most common outcome. In our training set, the most common outcome was seeking treatment, with the training set accuracy being 0.51, and the test set accuracy is 0.54. This provided a standard we could use to compare and assess our models. Accuracy was the most important measure of a model's performance for our research question because we care equally about those who decide to seek treatment and those who do not, so using the True Positive Rate or False Positive Rate alone would not be as appropriate.

We tried a variety of different models, a logistic regression model, random forest, classification and regression tree model, and gradient boosting classifier. Before modeling, we visualized the relationship between each variable by making a heat plot to see if we could observe a correlation between any variable, but we did not see any significant correlation (Appendix: Figure 1). As discussed in the previous section, we plotted the relationships between the dataset's features, such as "country", "benefits", and "care_options", and our dependent variable, "treatment" (Appendix: Figure 2, 3, 4). After we observed the relationships in the dataset, we split our dataset into a training set and testing set.

In the logistic regression model, we used all variables as independent features to predict the treatment. The accuracy of this model is 0.73. The true positive rate is about 0.756, which is slightly higher than the accuracy. In our model, the true positive rate represents the proportion of those who sought treatment for their mental health that we correctly predicted.

For the Random Forest Classification model, we used cross validation to select the CCP parameter and the max number of features that maximize test accuracy. After finding the optimal model parameter values, we reconstructed a new Random Forest Classification model and used this model on the testing dataset (Appendix: Figure 6). The final model yielded a test accuracy of 0.856, a true positive rate of 0.86, and a corresponding false positive rate of 0.15. We also constructed a 95% confidence interval with 50 bootstrapped Random Forest models which yielded an interval of 0.85- 0.89 (Appendix: Figure 10). Our last metric used to assess the model performance was an AUC curve. The area underneath the AUC curve was 0.86, meaning that the model could distinguish to a strong degree between individuals who have received treatment for their mental health and individuals who have not.

The third model is the Gradient Boosting Classifier. Without any parameter fitting, this model achieved a testing set accuracy of 0.81. The true positive rate of this default model is 0.91, a value higher than the accuracy. In addition to the default gradient boosting model, we tried adding 5-fold cross validation and grid values with different estimators, learning rates, number of features, and sample splits to see if there was any improvement. However, the accuracy with these adjustments is the same as the default model, and the true positive rate decreased to 0.89. For the gradient boosting model, we would prefer the default model since it has higher accuracy and a decent true positive rate. We constructed a 95% confidence interval with 50 bootstrapped Random Forest models which yielded an interval of 0.84 - 0.87 (Appendix: Figure 7).

Besides the models above, we created a classification and regression model as well. The model without parameter tuning had an accuracy of 0.785 and a true positive rate of 0.764. In order to achieve higher accuracy and TPR, we decided to add on some parameters and cross-validation as we did in the gradient boosting model. In the modified CART model, we obtained a better model, the accuracy is 0.85 and the TPR is 0.899. The best alpha value is nearly close to 0.00305 since we only adjusted the alpha value in the grid values. We also plotted the line plot of the trend of the accuracy as the alpha value is increasing in the appendix section (Appendix: Figure 6). We constructed a 95% confidence interval with 50 bootstrapped CART models which yielded an interval of 0.84 - 0.88 (Appendix: Figure 8). The structure of the best decision tree is displayed in Figure 9.

The Random Forest Model was our best model based on the test set accuracy, but based on the bootstrap you can see that the significance between the two models (Random Forest Classifier, CART) was not significant, as they have overlapping confidence intervals. Between these two models, it is uncertain which is ultimately the better model.

Impact & Conclusion

Mental illness is a serious problem, and it is important to understand the factors that go into people receiving treatment, especially since the world is experiencing a mental health crisis post-pandemic. We believe our model could be used to rate companies on their mental health wellbeing, and to encourage them to offer more services if necessary.

Our top two models in terms of accuracy were our Gradient Boosting model and our Random Forest model. Using Sklearn's built in feature importance model attribute, we can look at how much each model weighed various features (Figure 5). Both models agreed that the level of work interference from their mental health and having a family history of mental illness were the most important features. These indicate that the primary driver of seeking help is personal factors. With regards to employment related factors, the factors with high feature importance were if employees knew their care options, the ease of taking leave from work, and if mental health benefits were included. Country was also high on the list, indicating that larger social factors are highly important.

Knowing these were the most important factors employers have control over, this information could be used by employers to make their employees more likely to seek care. We could also use our model to rank companies by their mental health scores. Additionally, one factor deemed not very important, ranking in the bottom quarter of our importance scores was if mental health was discussed as part of a wellness program. While employers might think they are doing more with wellness programs, sharing information on what care options are available and making sure all employees know their options could be more useful.

Employers or insurance providers could also use this information to identify individuals who may need to be encouraged to seek help as well. However, if this was the goal of using our models, the true negatives would be more important. This is because in our model, the true negatives are those who do not seek treatment, which would be the key population to identify in this use case.

To further our research, we would want to see if this holds up for other types of companies. We also were not able to access certain datasets that would have been beneficial to expanding our question, because the data was too sensitive. Additionally, because of the yearly changes in the survey, we lost survey data because we did not have it for all of the years.

Our results indicate that personal and cultural factors are the most important factors in predicting if someone will get mental health treatment, but that employment related factors are still useful, especially those relating to what type of benefits are available from their healthcare and the knowledge of those benefits. Datasets that have more personal questions could be more predictive, but that information can be difficult to find due to the sensitive nature of the information.

Appendix:

Variables in the Dataset

treatment	Have you sought treatment for a mental health condition?
self_employed	Whether you are self-employed or not?
family_history	Do you have a family history of mental health or not?
Age	Age of the people who took the survey
Gender	Male, female, or other
Country	Country responder lives in
work_interface	How much are your mental health conditions interfering with your work?
no_employees	Number of employees in your workspace
benefits	Does your employer provide any mental health benefits?
care_options	Do you know any mental healthcare options that your employer provides?
wellness_program	Has your employer ever discussed mental health as part of an employee wellness program?
seek_help	Does your employer ever discuss mental health illness or how to seek help?
anonymity	Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources?
leave	How easy is it for you to take medical leave for a mental health condition?
coworkers	Would you be comfortable talking to your coworkers about a mental health condition?
supervisor	Would you be comfortable talking to your supervisors about a mental health condition?
mental_health_interview	Would you be comfortable bringing up a mental health issue with a potential employer in an interview?
phys_health_interview	Would you be comfortable bringing up a physical health issue with a potential employer in an interview?

Model Accuracy and True Positive Rate Table

Model	Accuracy	True Positive Rate	True Negative Rate
Baseline	0.54	1	0
Logistic Regression	0.73	0.76	0.54
Random Forest	0.86	0.86	0.12
Gradient Boosting Classifier (default w/o grid value)	0.81	0.91	0.13
Gradient Boosting Classifier (w/ grid value)	0.81	0.89	0.16
Classification and Regression Tree (default w/o grid value)	0.79	0.76	0.23
Classification and Regression Tree (default w/ grid value)	0.85	0.90	0.19

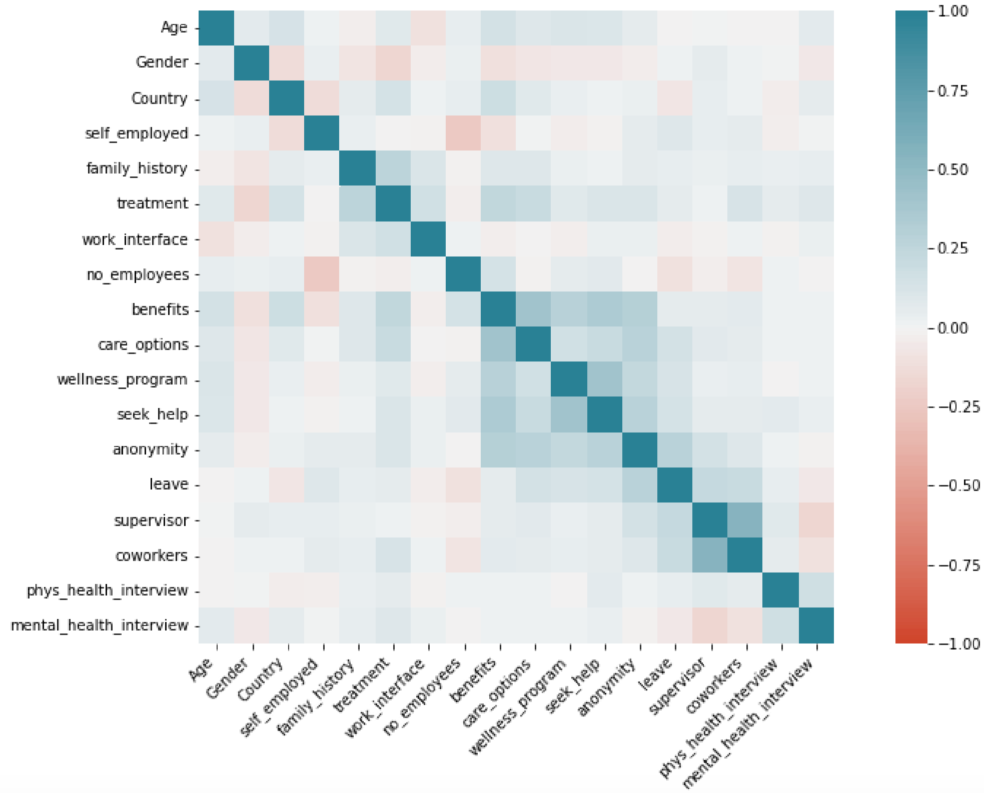

Figure 1: Diagonal correlation matrix with shades indicating the degree and direction of the correlation between variables in the Mental Health Dataset.

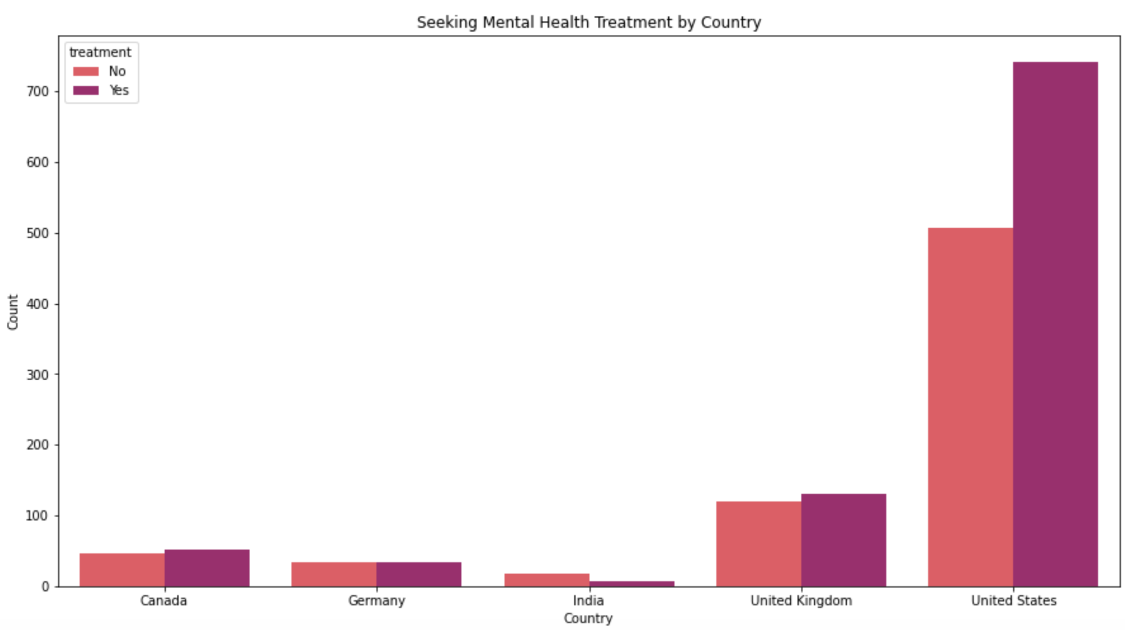

Figure 2: Bar chart comparing the count of people across the top 5 countries in the study that seek out mental health treatment vs. those who do not seek treatment.

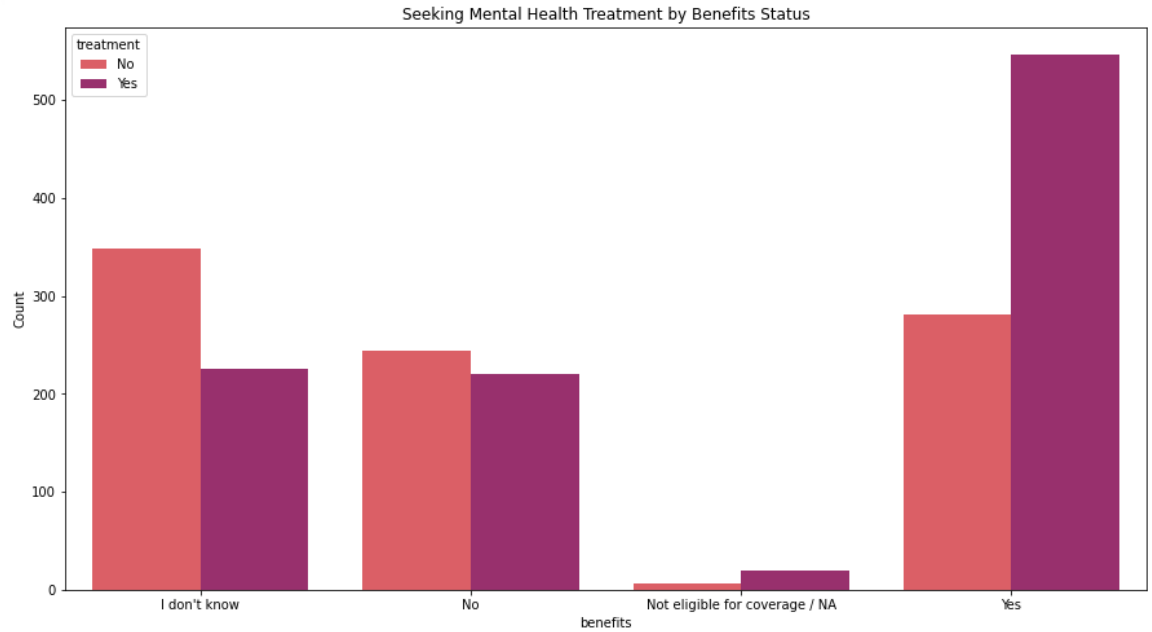

Figure 3: Bar chart comparing the count of people with different employment benefit statuses who seek out mental health resources vs those who do not.

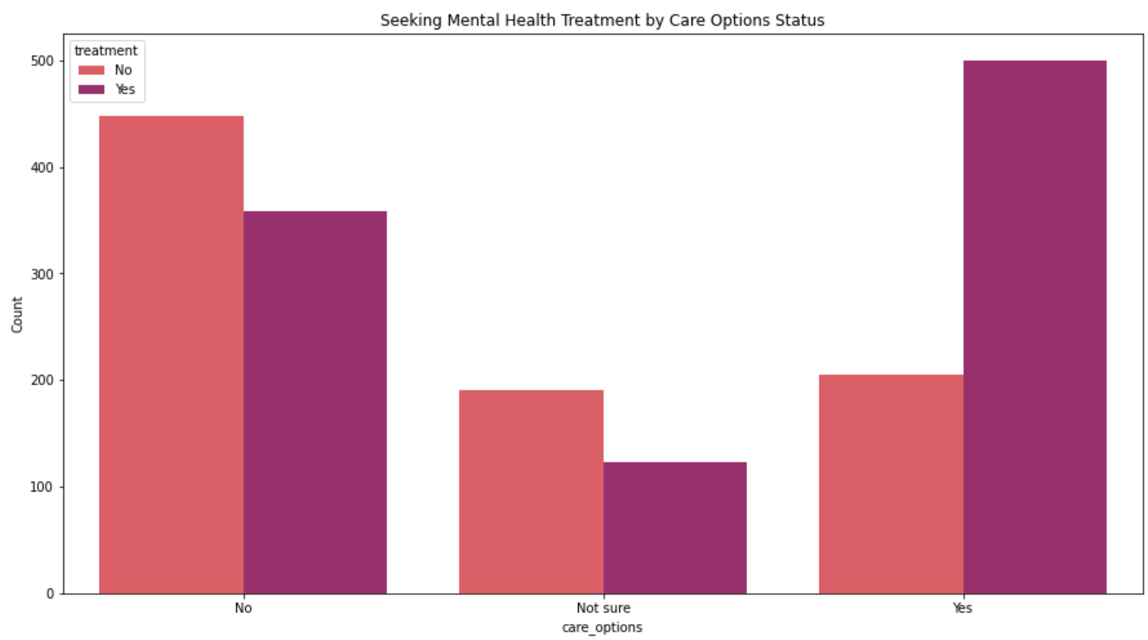

Figure 4: Bar chart comparing the count of people with different care option packages who seek out mental health resources vs those who do not.

feature	Importance Score
work_interface	56.725418
family_history	16.834199
care_options	8.205097
Country	4.321100
benefits	2.757519
Gender	2.600017
Age	2.249034
coworkers	1.952952
mental_health_interview	1.315346
leave	0.851546
anonymity	0.676681
no_employees	0.520489
phys_health_interview	0.371483
wellness_program	0.197144
supervisor	0.160953
self_employed	0.158742
seek_help	0.102281

feature	Importance Score
work_interface	29.534451
family_history	10.615206
Age	9.494075
Country	7.651846
care_options	5.204854
no_employees	5.060731
leave	5.053740
benefits	4.292212
coworkers	3.598295
phys_health_interview	3.355123
supervisor	3.314097
seek_help	2.693021
Gender	2.603348
wellness_program	2.273775
anonymity	2.210469
mental_health_interview	2.031806
self_employed	1.012950

Figure 5: Left - Feature Importance for Gradient Boosting Model
Right - Feature Importance for Random Forest Model

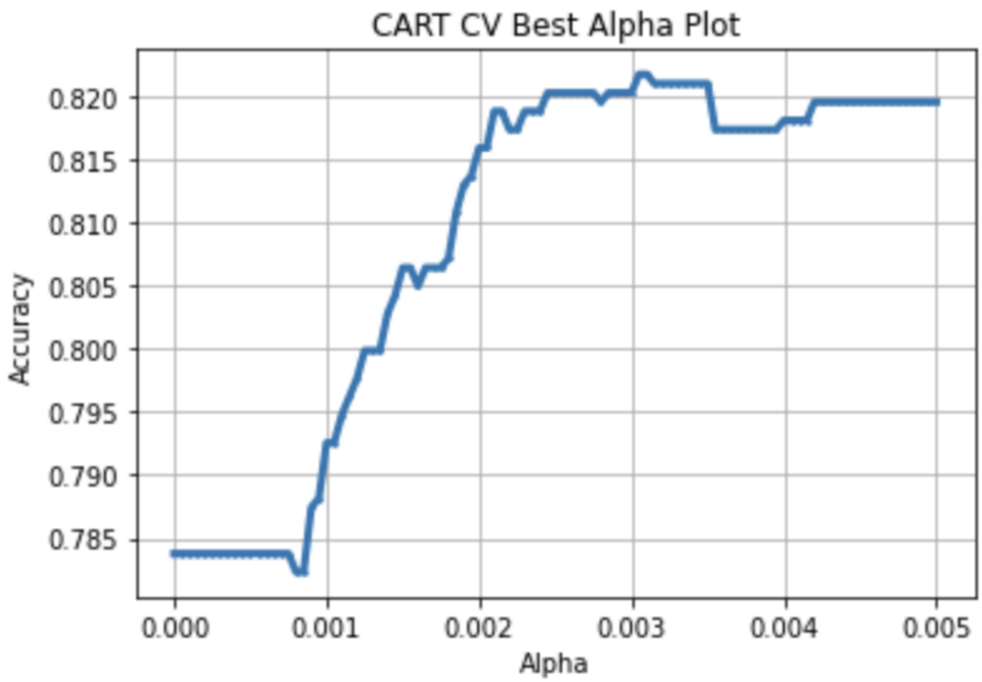

Figure 6: Shows the accuracy of the CART CV model changes as the alpha value increases.

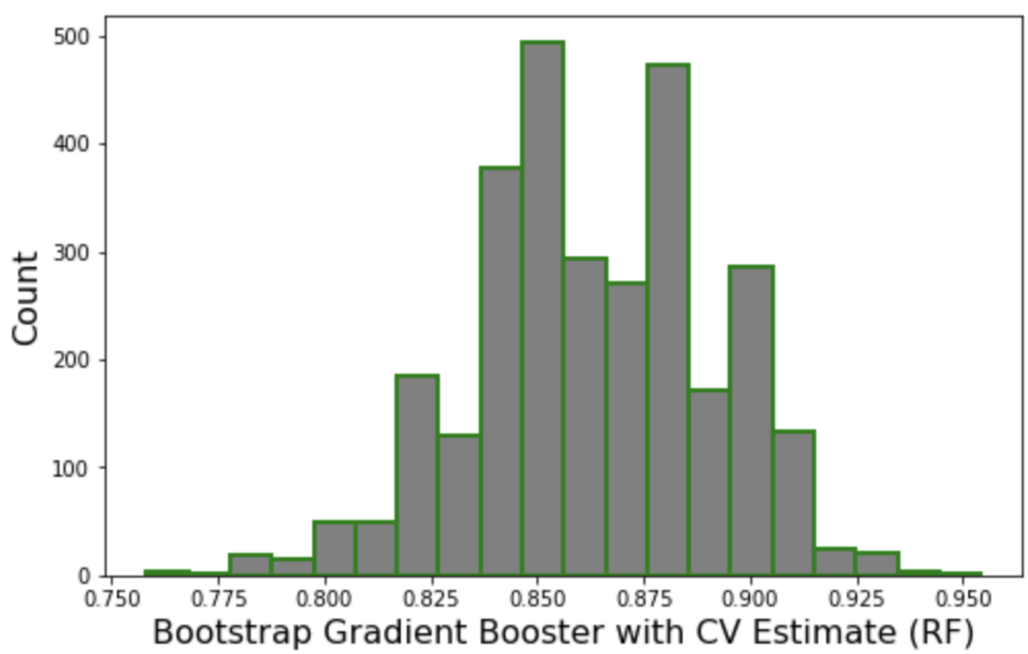

Figure 7: Bootstrapped distribution of the Gradient Booster model with cross-validation (3000 bootstrapped samples)

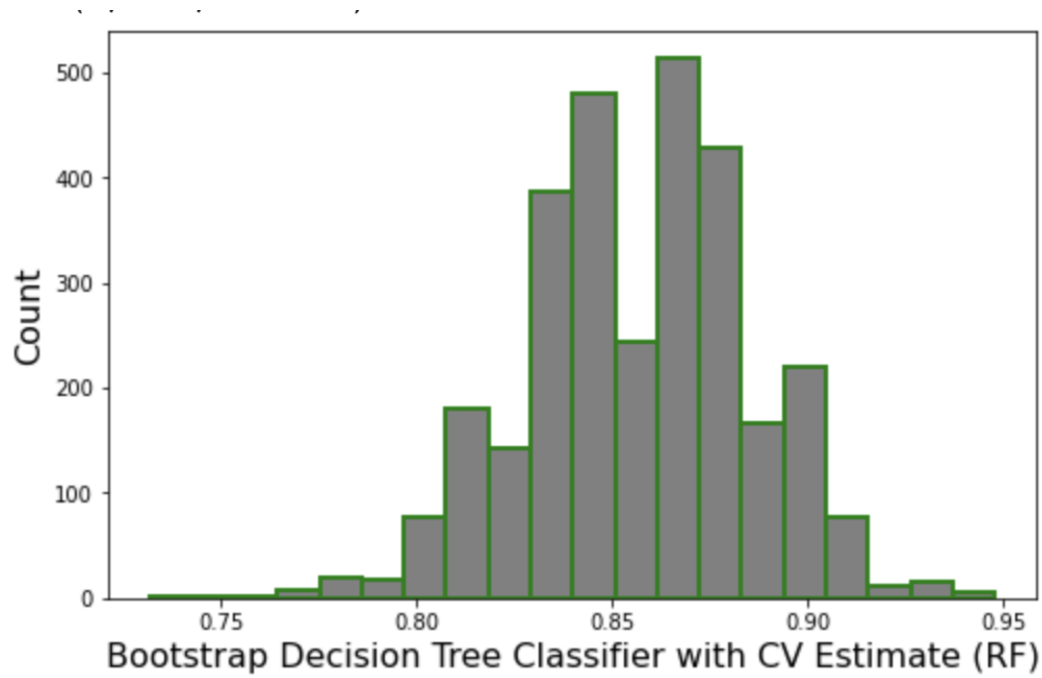

Figure 8: Bootstrapped distribution of the Decision Tree Classifier with cross-validation (3000 bootstrapped samples)

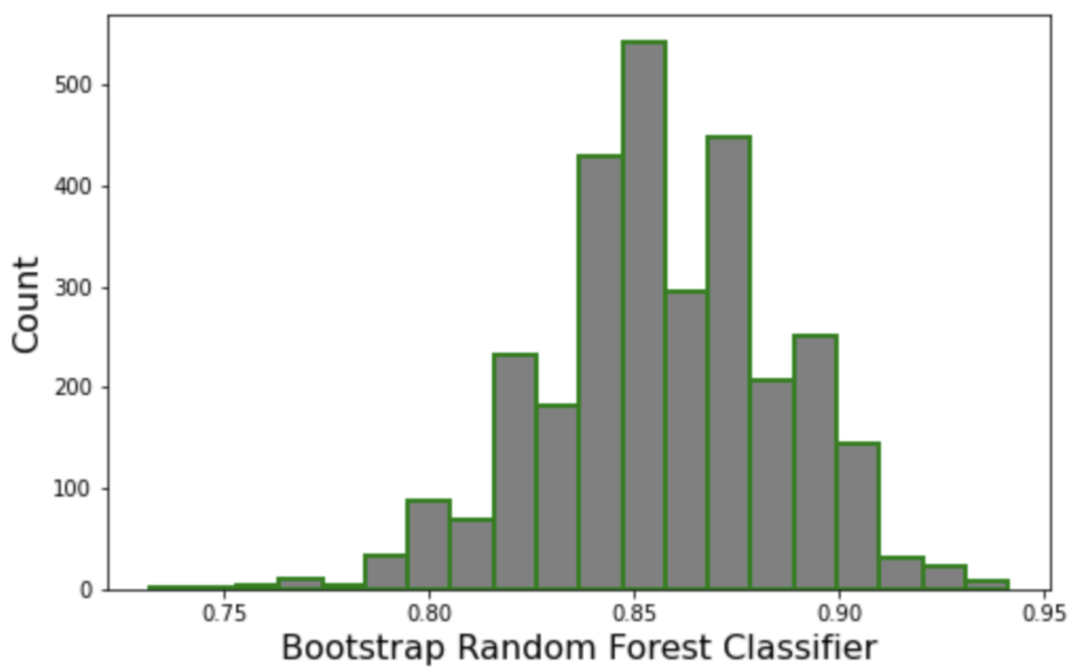

Figure 9: Bootstrapped distribution of the Random Forest Classifier model without cross-validation (3000 bootstrapped samples)

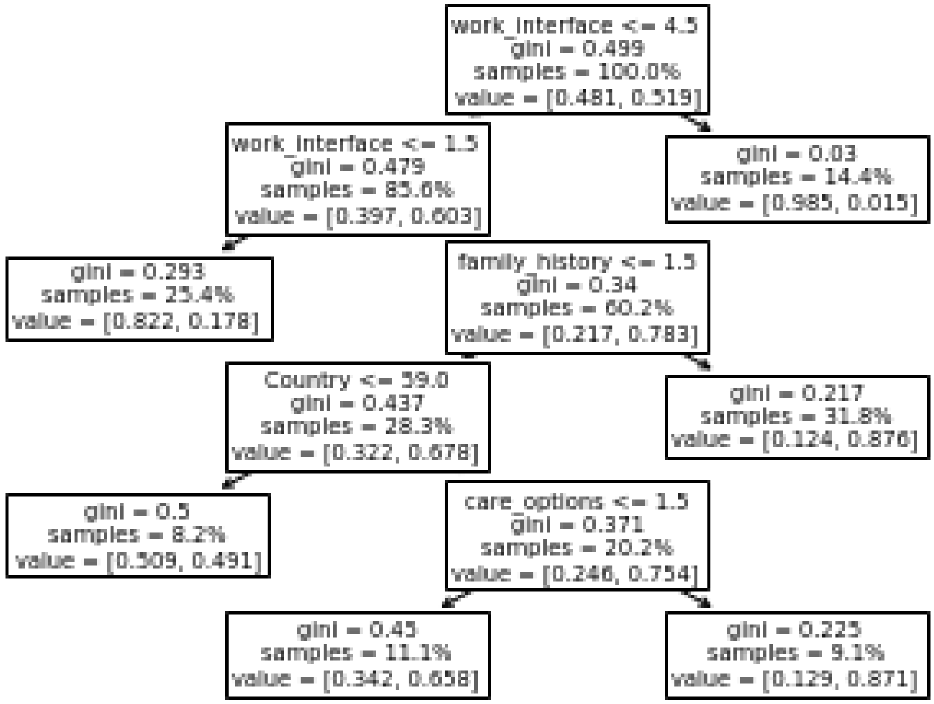

Figure 10: Decision Tree Classifier Visualization