1 Proposal: Machine Learning to Predict Successful Discharge of Children from Behavioral Health Treatment

1.1 Why This Topic and Data were chosen:

- It has become increasingly important to achieve an accurate assessment of likelihood of successful discharge from treatment. There are multiple contingencies to consider: contractual and client care outcome goals, improved care, increased revenue, and business stability during times of crisis, such as COVID-19. Efficient and effective utilization of services enables client flow through our system and provides resources for new clients. Moreover, the field is shifting from fee for service to value-based cost reimbursement models that structure payment based on an expected time to discharge and an expected treatment outcome.
- Importance of ascertaining successful outcomes in naturalistic settings (Webb et al., 2020) when the use of Randomized Clinical Trials is not feasible or practical. Machine learning allows for the use of naturally occurring data to train new models and utilize them with future data.
- The use of statistical prediction models is highly recommended for their versatility at many levels of mental health care delivery: diagnosis, prediction, and treatment planning (Garb et al., 2019)
- It is important to accurately identify high-risk clients at onset of treatment to intervene early and at the right level of intensity to ensure successful outcomes.
- The use of machine learning models to predict client outcomes is a nascent field of study in behavioral health; however, there is growing body of literature that supports machine learning to augment traditional clinical judgment and to strengthen the prediction of outcomes (Webb et al., 2020).
- Previous studies have shown the utility of machine learning to predict depression, treatment of obsessive-compulsive disorder in children, pediatric bipolar disorder, foster care permanency and likelihood of remaining cancer-free over five years (Gao, Calhoun, & Sui, 2018; Lenhard et al., 2018; Wolff et al., 2020; Xu, Ju, Tong, Zhou, & Yang, 2019; Youngstrom, Halverson, Youngstrom, Lindhiem, & Findling, 2018)

1.2 Data Source Description

Data for this project was extracted from our agency's EMR system. There were challenges with the extraction of this data that necessitated additional steps:

- Our system is a legacy system called Intersystems Cache, with the requirement that data be extracted using 32- ODBC drivers, with Crystal Reports and 32-bit WinSQL to generate SQL statements to extract data from underlying tables.
- There are hundreds of tables within the system that need to be considered and selection of tables to join is complex. The vendors supplied an older version of Crystal Reports to be used in crafting reports and data extractions. I first applied Crystal Reports to test my connections between tables to get the views I needed, then ported the Crystal Reports structure into SQL, which then was used with our agency SQL platform, 32-bit WinSQL. The SQL setups used to extract the data will be included as .txt files in the GitHub repository.

- Resultant data tables were exported as .csv files to be stored in Postgres on my project computer. All data was collected on previously discharged clients in order to have completed outcome data on discharge reason. Only children and youth between the ages of 6 and 25 are included, as we are focusing on programs aimed at children and young adults.
- Tables were:
    - **Demographics**—de-identified client information: patient ID, birth date, gender, ethnicity, education level, employment status, country of birth and primary language. These features/variables were used in previous studies (cited above) as predictors of treatment outcome. Patient ID is the Primary Key.
    - **Diagnosis**—Patient ID, episode of treatment, client diagnosis at admission, and trauma history and preexisting medical conditions. Only primary DSM-5 diagnoses were included and type of program that client had been enrolled in. The type of program is a proxy feature representing level of care.
    - **Level of Care**—client program will be categorized along a continuum of care from prevention/early intervention to intense crisis-based care.
    - **Discharge data**—patient ID, date of discharge, episode (selected to most recent treatment episode), length of stay, reason (successful vs. not successful), program from which discharged. This data will be thoroughly examined for outliers, especially in length of stay when preprocessing data prior to machine learning.
    - **Assessment data**—use of an assessment tool that has been adopted agency-wide for children and youth called the Children and Youth Needs and Strengths Assessment (CANS). Included are initial scores on the following dimensions: depression, anxiety, conduct/oppositional disorders, school performance, and on the strengths dimension, included resiliency and family supports. The CANS tool is much more extensive in its inclusion of needs and strengths, but the first machine learning models seek to use fewer features to minimize overfitting and to simplify interpretation in the first exploratory model. CANS data will be joined to the other tables using Patient ID as the foreign key.
    - **Outcome**—from the discharge data, did client successfully achieve treatment goals or did client discharge unsuccessfully?

1.3 Questions we hope to answer

- What factors lead to successful completion of treatment for youth and children who receive mental health services at our agency?
- Conversely, what types of client characteristics are indicative of high risk and subsequent failure to complete treatment and achieve treatment goals? We are looking for a profile of high-risk youth who may need early and vigorous intervention to succeed.
- Can a simpler, more parsimonious model suffice to fit our data and thus have a replicable model for future data sets? Thus, we start simply and then add or remove features and vary the learning algorithm if our accuracy, precision, and sensitivity are lower than optimal. We are aiming to avoid overfitting and thus lose the ability to generalize to other datasets.

1.4 Methodology

- Prediction of outcome, using a supervised machine learning model (logistic regression and random forest),
- We also aim to classify children into groups based on their initial characteristics, thus we will also implement an unsupervised machine learning mode using PCA. This classification model will enable us to visualize groupings of clients that have similar characteristics and thus similar risk profiles. One visualization that we will employ is a boxplot to examine how each client cluster is distributed.

1.4.1 Pre-processing and data exploration

The following steps were taken to explore the data and prepare it for the machine learning phase:

- Import from Postgres and direct import of additional datasets using Pandas
- Merging the individual datasets into one DataFrame for analysis using Pandas merge function
- Listing categorical variables and using value count to determine need for binning
- Descriptive statistics on key predictors individually
- Grouping by the key categorical features to examine how they related to successful discharge proportions
- Graphical representation of the data for each key feature and for the outcome of successful discharge.
- Removal of categorical features with limited variability, i.e., majority of samples in one category

1.4.2 Analysis

The following steps were performed to fully develop the machine learning model:

- Logistic regression using Statsmodels to show output of beta weights to calculate odds and probability of successful discharge for selected key features
- Logistic model fitting using Scikit
- Metrics to evaluate model:
    - Classification report: 1) Precision, 2) Sensitivity/recall, 3) F1 Score, 4) Accuracy
    - Confusion matrix
    - ROC curve to show plot of false positive rate vs. true positive rate at varying threshold levels (different points in 0,1) using the AUC library in Scikit.
- Random Forest with classification report and rankings of feature importance
- PCA in unsupervised learning to derive groups of youth based on age, level of care, length of stay, scores on key CANS measures and diagnosis at entry

1.5 Results

1.6 Conclusion

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