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 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 RCT 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 often 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.
- 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 under the age of 25 are included, as we are focusing on programs aimed at children and young adults.

- Tables were:
  - **<u>Demographics</u>**—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.
  - **<u>Diagnosis</u>**—Patient ID, episode of treatment, client diagnosis at admission, and diagnosis. Only primary DSM-5 diagnoses were included, as well as history of trauma, and type of program that client had been enrolled in. The type of program is a proxy feature representing level of care.
  - **<u>Discharge data</u>**—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.
  - **<u>Assessment data</u>**—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 avoid 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.

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.
- Along with prediction of outcome, using a supervised machine learning model (logistic regression), 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.
- 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 features 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.

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