

# Key Visuals In Pre-Processing Phase: the Preliminary Story

Ethnicity

☐ Mexican/Mexican Ame...

☐ No Entry

☐ Not Hispanic

☐ Other Hispanic/Latino

☐ Unknown

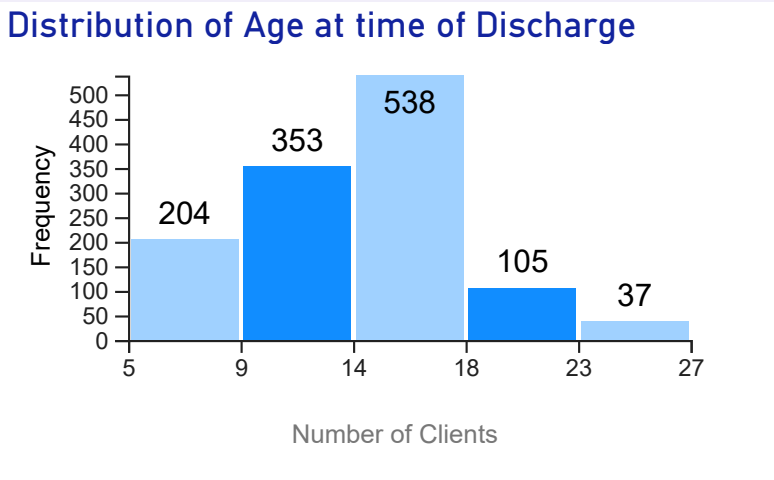
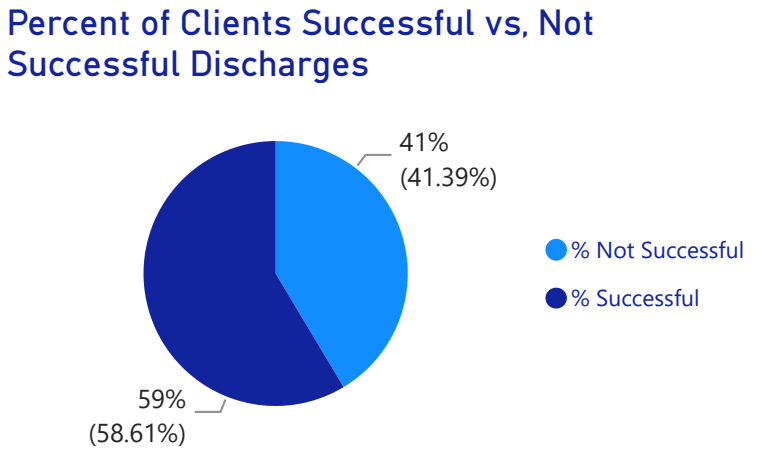
Original Program

All

Gender

☐ F

☐ M



237

Average LOS in Days

725

Number Successful

1237

Number of Clients

64%

% Trauma\_HX

7/15/2016

Beginning Discharge Date

05/21/2020

Ending Discharge Date

While the majority of clients had evidence of previous trauma at admission, the trauma feature did not contribute greatly to prediction of successful discharge in any of the Machine Learning Models.

# Logistic Regression Analysis Final Model

## Logistic Regression Final Model

Feature ▲	Coefficient	P
_Constant (y-intercept)	-0.1072	0.75
Age at Discharge	-0.0368	0.06
Defiant oppositional behavior (CANS)	-0.2544	0.00
DSM 5 Oppositional defiant disorder	-0.6632	0.02
DSM5 ADHD	-0.7246	0.02
Family strength (CANS)	-0.2955	0.00
Length of Stay in Days	0.0044	0.00
Level of Care	0.2949	0.00
Recreational functioning (CANS score)	-0.2222	0.02
Social functioning (CANS)	-0.1095	0.22

P < 0.05 is statistically significant

## Confusion Matrix for Elastic Net Regularization Model

Category ▼	Predicted Not Successful	Predicted Successful
Actual Not Discharged Successfully	50	78
Actual Discharged Successfully	21	161

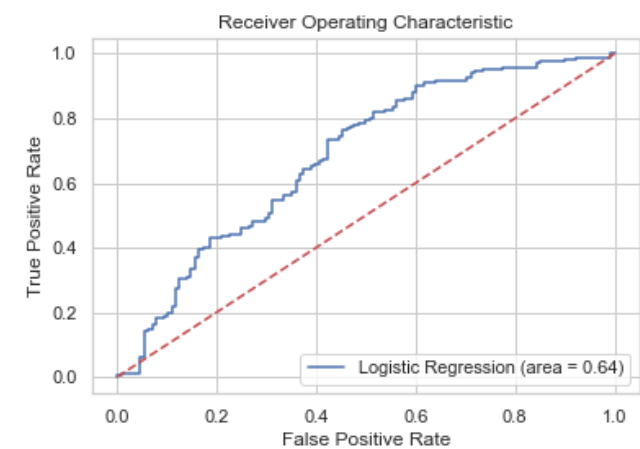
Training Data Set N = 927  
Test/Validation Data Set N =310

### Machine Learning Process:

1. Split into train (75%) and test (25%)- did not use defaults because of relatively small data set and needing sufficient training data.
2. Feature engineering based on previous research into factors that relate to successful discharge. Used many features and then reduced based on several models tested in sequence.
3. Model choice also based on research that pointed to logistic regression as the easiest to interpret for stakeholders as a benefit and applicable to binary outcomes.
4. Also used Random Forest, ensemble, ADABOOST and Gradient Boosted Tree algorithms for comparison.
5. Future research will entail selection of other features with the goal of improving model fit and generalizability.

Use of Elastic Net Regularization in the Logistic Regression Model slightly improved classification  
(Webb, et.al (2020) supports use of ENR)

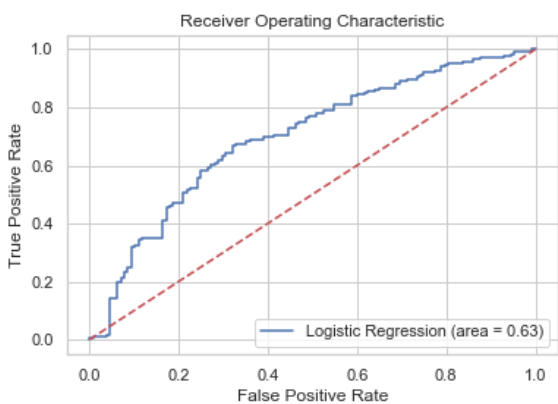
## Elastic Net Regularization



## Elastic Net Regularization Classification Report

# ▲	Element	precision	recall	f1-score	support
1	Not Successful	0.70	0.39	0.50	128
2	Successful	0.67	0.88	0.76	182
3	accuracy			0.68	310
4	macro avg	0.69	0.64	0.63	310
5	weighted avg	0.69	0.68	0.66	310

## Default Regularization



# Random Forest, Ensemble, ADABOOST and Gradient Boosted Tree Models

To be included next commit for Segment 3

### Level of Care

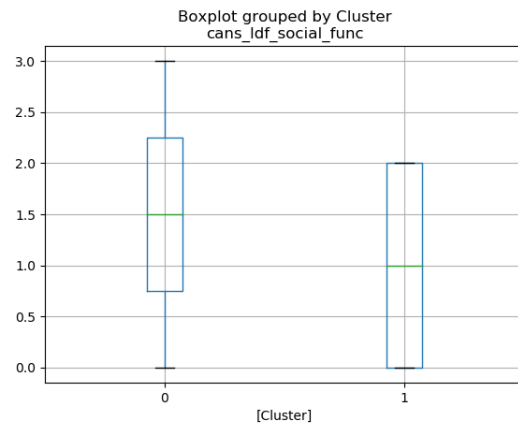
- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4

## Examination of Cluster Differences in CANS Scores

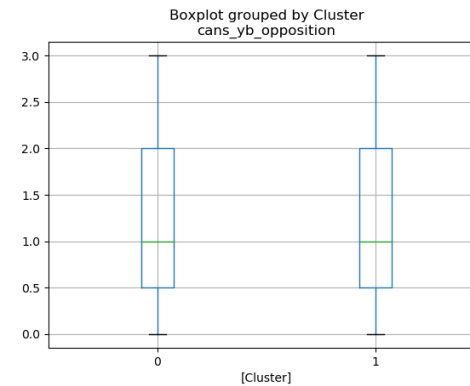
(Lower Score is Better in Terms of Behavioral Issues)

Delving into differences by cluster provides an understanding of the criteria by which clusters were derived. Higher risk clients with higher initial CANS scores tend to be in the first cluster (0) compared to somewhat better functioning clients in cluster (1). Such an understanding, along with more research, should help us to create a profile of clients likely to need more intervention along the trajectory of treatment.

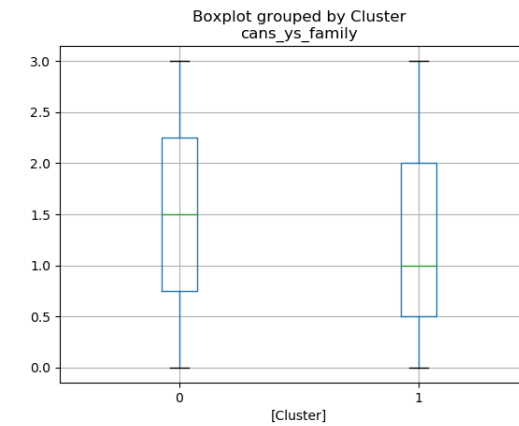
### CANS Social Functioning by Cluster



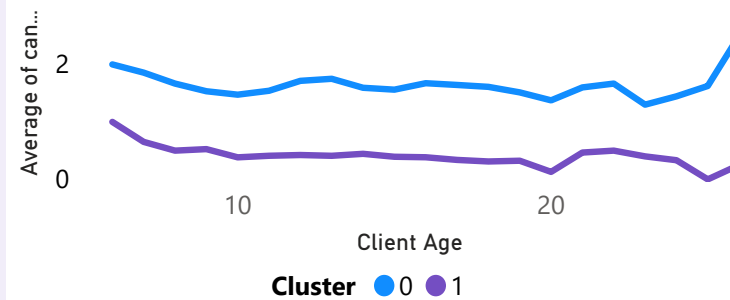
### CANS Oppositional Behavior Scores by Cluster



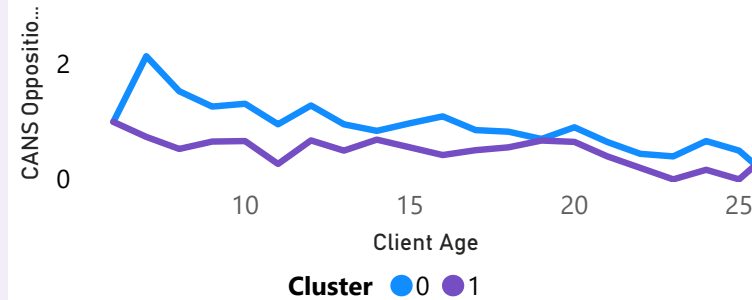
### Child Family Strengths by Cluster



### CANS Child Social Functioning Scores by Age and Cluster



### CANS Oppositional Behavior Score by Client Age and Cluster



### CANS Family Strengths by Client Age and Cluster

