House of Hope

Predictive Recovery:

Data-Driven Drug and Alcohol Rehab
Using Neural Networks

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Study Goals:

- **Improve accuracy from the previous machine learning models from previous study using Neural Networks**
  - **(RandomForest Cross-Validation Accuracy: 0.7875453017892988)**
- **Creation of an intake questionnaire to generate predictions of perspective resident recovery success**
  - **Capture crucial data points for predictions.**
  - **Include filters to ethically evaluate residents by comparing them to similar individuals with known outcomes.**
- **Support expansion to include services for men by leveraging the Substance Abuse and Mental Health Data Archive dataset.**
  - **Sort data by gender for accurate predictions for both current female residents and future male residents.**

House of Hope

- **Established**:
  - 2020 by Paul Watkins, a jail chaplain and Green County Drug Court servant
- **Vision**:
  - Provide women a safe and stable recovery environment free from triggers that might cause relapse
- **Residency Requirements**:
  - Must be at least 18 years old
  - Minimum of 90 days in recovery
  - Selection involves an interview with the House of Hope Committee
- **Resident Obligations**:
  - Participate in group therapy (e.g., Narcotics Anonymous)
  - Must be employed or attending job training
  - Mandatory daily support group participation
- **Capacity and Services**:
  - Supports a maximum of four women simultaneously
  - Offers intensive, personalized services
  - Residents can stay as long as needed for independence and sobriety

Gradient Boosting Machine with Neural Network Backbone

	Precision	Recall	F1-Score	Support
0	0.78	0.68	0.73	472472
1	.0.83	0.89	0.86	815822
Accuracy			0.81	1288294
Macro Avg	0.80	0.78	0.79	1288294
Weighted Avg	0.81	0.81	0.81	1288294

NumPy and Pandas: Used for numerical operations and data manipulation.
Joblib: Used to save and load the trained model.
Scikit-learn (sklearn): Provides functions for model evaluation, data splitting, scaling, and the GBM classifier.
TensorFlow/Keras: Used to build and train the neural network.

Parameters

Gradient Boosting Machine

- n_estimators =100 (Boosting stages)
- learning_rate=0.1 (Contribution of each tree)
- max_depth=3 (Max depth of each tree)
- random_state=42 (Random state seed)

Results fed as an array into:

TensorFlow Deep Neural Network

- Input=64 nodes, RELU
- Hidden Layer= 1 layer, 32 nodes, RELU
- Output= 2 nodes, softmax

Optimizer=categorical_crossentropy

Insights:

- 4+ Hours of training
- Computational failure in CoLab during optimization
- Binary and Categorical Xentropy provide similar results

Multi-Layer Perceptron Results

	Precision	Recall	F1-Score	Support
0	0.78	0.72	0.75	708990
1	.0.84	0.88	0.86	123451
Accuracy			0.82	1932441
Macro Avg	0.81	0.8	0.8	1932441
Weighted Avg	0.82	0.82	0.82	1932441

NumPy and Pandas: Used for numerical operations and data manipulation.
Joblib: Used to save and load the trained model.
Scikit-learn (sklearn): Provides functions for model evaluation, data splitting, scaling, and the GBM classifier.
MPLClassifier: Used to build and train the neural network.

Parameters

MLP Deep Neural Network

- hidden_layer_sizes=(100,)1 layer, 100 nodes
- max_iter=500 (number of epochs)
- random_state=42 (random generator seed)

Insights:

- 4+ hours of training
- Performance optimization/tuning wasn't completed due to CoLab computational failure even when set at A100 GPU and high RAM
- From tutor session, chunking code was shared to reduce the dataset size to allow optimization without failure to be used in future tuning efforts.

Tensorflow DNN Results

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TensorFlow/Keras: Used to build and train the neural network.

Parameters

TensorFlow Deep Neural Network
- Input=100 nodes, RELU
- Hidden Layer= 1 layer, 32 nodes, RELU
- Output= 2 nodes, softmax

Optimizer=sparse_categorical_crossentropy

Insights:
- Trained in half the time of MLP or GBM/DNN
- Same performance issues as MLP model

PyTorch DNN Results

	Precision	Recall	F1-Score	Support
0	0.78	0.68	0.73	472472
1	0.83	0.89	0.86	815822
Accuracy			0.81	1288294
Macro Avg	0.80	0.78	0.81	1288294
Weighted Avg	0.81	0.81	0.81	1288294

NumPy and Pandas: Used for numerical operations and data manipulation.
Joblib: Used to save and load the trained model.
Scikit-learn (sklearn): Provides functions for model evaluation, data splitting, scaling, and the GBM classifier.
Torch: Used to build and train the neural network.

Parameters

PyTorch Deep Neural Network
- Input=64 nodes, RELU
- Hidden Layer= 1 layer, 32 nodes, RELU
- Output= 2 nodes, softmax

Optimizer=crossentropy_loss

Insights:
- 2-3 Hours of training
- Nearly identical accuracy, recall and F-1 as TensorFlow DNN
- Coding was more complex than TensorFlow
- Future efforts would devote more time to exploration and optimization of the PyTorch model

Descriptive Statistics

Descriptive Statistics

- Outliers and Variability

Central Tendency

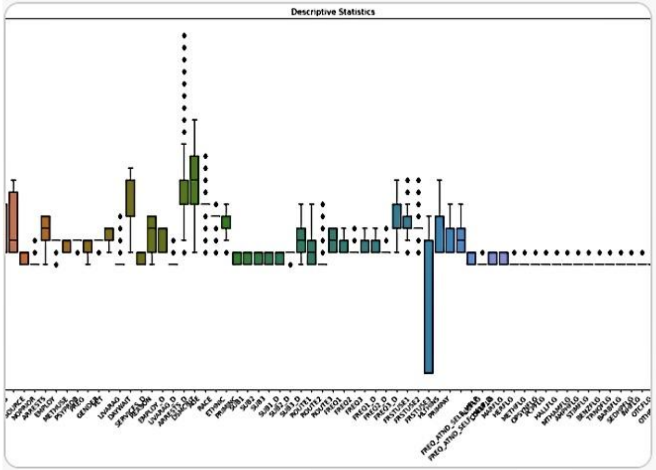
- Significant Differences and Potential Skewness

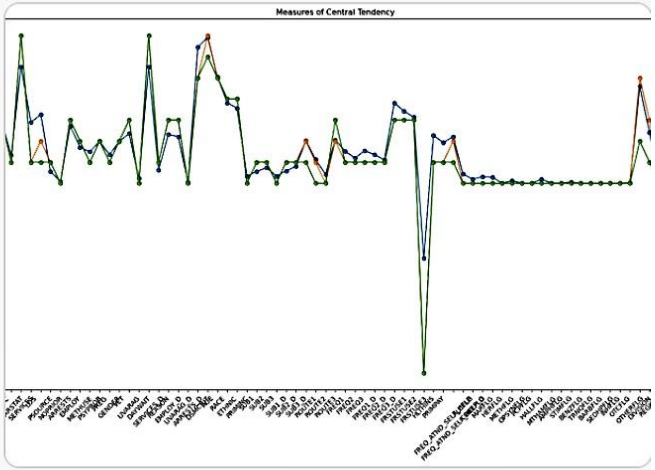
Dispersion

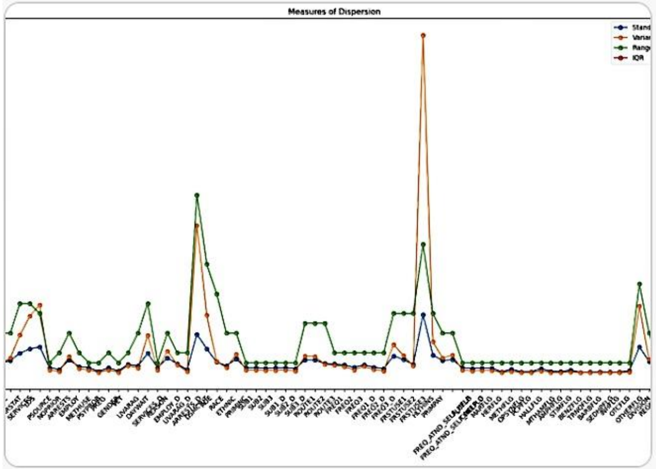
- Standard Deviation
- Variance
- Range
- IQR
- Consistency and Variability

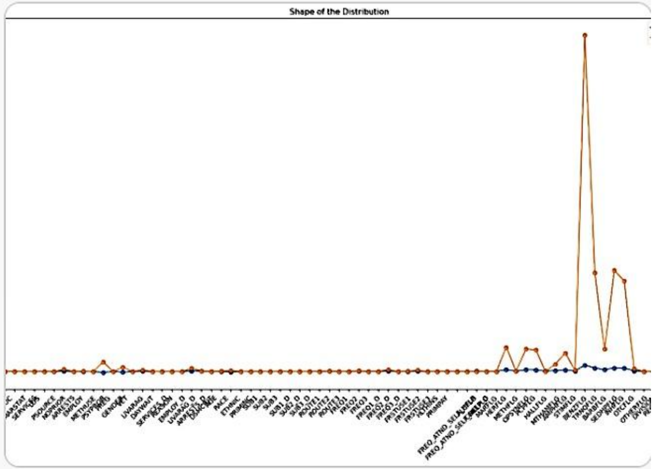
Distribution Shape

- Symmetry and Peakedness of the Data









Ethical Considerations

Ethical Considerations:

- Addressing the use of data for admission to drug rehabilitation programs recognizing that many predictive variables are beyond the client's control
- Ensuring fairness in predicting a client's outcome

Legally Prohibited Variables:

- Race, gender, ethnicity, and age demonstrated predictive significance but legally restricted from use

Ethically Justifiable Variables:

- Pregnancy: Prioritizing pregnant clients to protect the unborn child are easier to justify ethically

Ethically Questionable Variables:

- Denying treatment based on drug dependency with lower recovery probability
- Prioritizing court-ordered clients over voluntary clients

Intake Questionnaire

Mitigating Ethical Concerns Through Filters:

- Use of filters to compare residents with similar demographic profiles
- Ethical issues in prioritizing residents can be addressed more effectively

Filtered Variables:

- DSMCRIT, GENDER, AGE, RACE, EDUC, VET, ARRESTS, NOPRIOR, REGION, SUB1, SUB2, ALCFLG, PSYPROB, ALCDRUG, METHAMFLG, HLTHINS,

Survey Question Variables

- MARSTAT, EMPLOY, LIVARAG, DAYWAIT, EMPLOY, SERVICES, FRSTUSE1, FREQ_ATND_SELF_HELP, PRIPAY, DIVISION, PREG, METUSE

Filtered Data Set Correlations:

- Selection of values from each variable investigate significant changes in correlation coefficients to justify the use of filters

Data Preparation

- **Dataset Dimension Reevaluation**:All initial data fields included in order to determine if Multi-Layer Perceptron (MLP) or Deep Neural Network (DNN) can detect subtle patterns in data considered noise in the previous model
- **Restored Variables Values**:SUB1, SUB2, SUB3, SUB1_D, SUB2_D, SUB3_D were changed back to the original values to represent the primary, secondary and tertiary drugs used rather that a binary “0” or “1” that were requested by House of Hope to represent success or failure
- **Reinstitution of Negatively Correlated Variables:** Data with negatively correlated variables were added back to the model to improve recall scores

The Importance of Filters

Adding onto the original model, House of Hope tasked us with adding filters to the model.

First, we needed to justify using the filters. To do this, we filtered the data, then ran correlation matrix’ on the filtered data.

What we were looking for were differences in which columns held higher correlation to the success column when the various filters were applied.

What did the filters show?

Every time a filter was applied, The top correlated columns changed

For the Gender filter:

Men showed that the **substance** they had higher correlation to success.

Women showed that **participation in support groups** had a higher correlation to success.

For the Age filter:

Younger participants showed **living arrangements and employment** to be more highly correlated to success

Older participants showed **support groups** as having a higher correlation to success.

For the Arrests filter:

No arrests benefited more from **medication assisted therapy**.

Participants with **a single arrest** benefited more from **support groups**.

Participants with **2 or more arrests** saw the most success when **treatment for co-existing psychological and substance abuse disorders** was given.

What did the filters show?

Every time a filter was applied, The top correlated columns changed

Even though the order of importance changed for each substance, *Support groups*, *Stable Living Arrangements*, and *Stable Employment* were regularly in the 10 ten list of most correlated items for successful treatment

Veterans valued employment over group support, Non-veterans benefited more from support groups

Even Census Division proved to change the top correlated columns for successful treatment.

Interesting Findings during the filter testing

You can teach and old dog new tricks!!

Older participants showed a higher success rate that younger participants

Age at Admission:

12–14 years, 54% success rates

15–17 years, 54% success rates

18–20 years, 54% success rates

21–24 years, 59% success rates

25–29 years, 61% success rates

30–34 years, 62% success rates

35–39 years, 63% success rates

40–44 years, 64% success rates

45–49 years, 65% success rates

50–54 years, 66% success rates

55–64 years, 69% success rates

65 years +, 70% success rates

Interesting Findings during the filter testing

Certain substances had higher success rates:

.Barbiturates 77% success rates

Non-prescription methadone 70% success rates

Alcohol 68% success rates

.Benzodiazepines 67% success rates

Other opiates and synthetics 63% success rates

Methamphetamine/speed 62% success rates

Inhalants 61% success rates

Hallucinogens 58% success rates

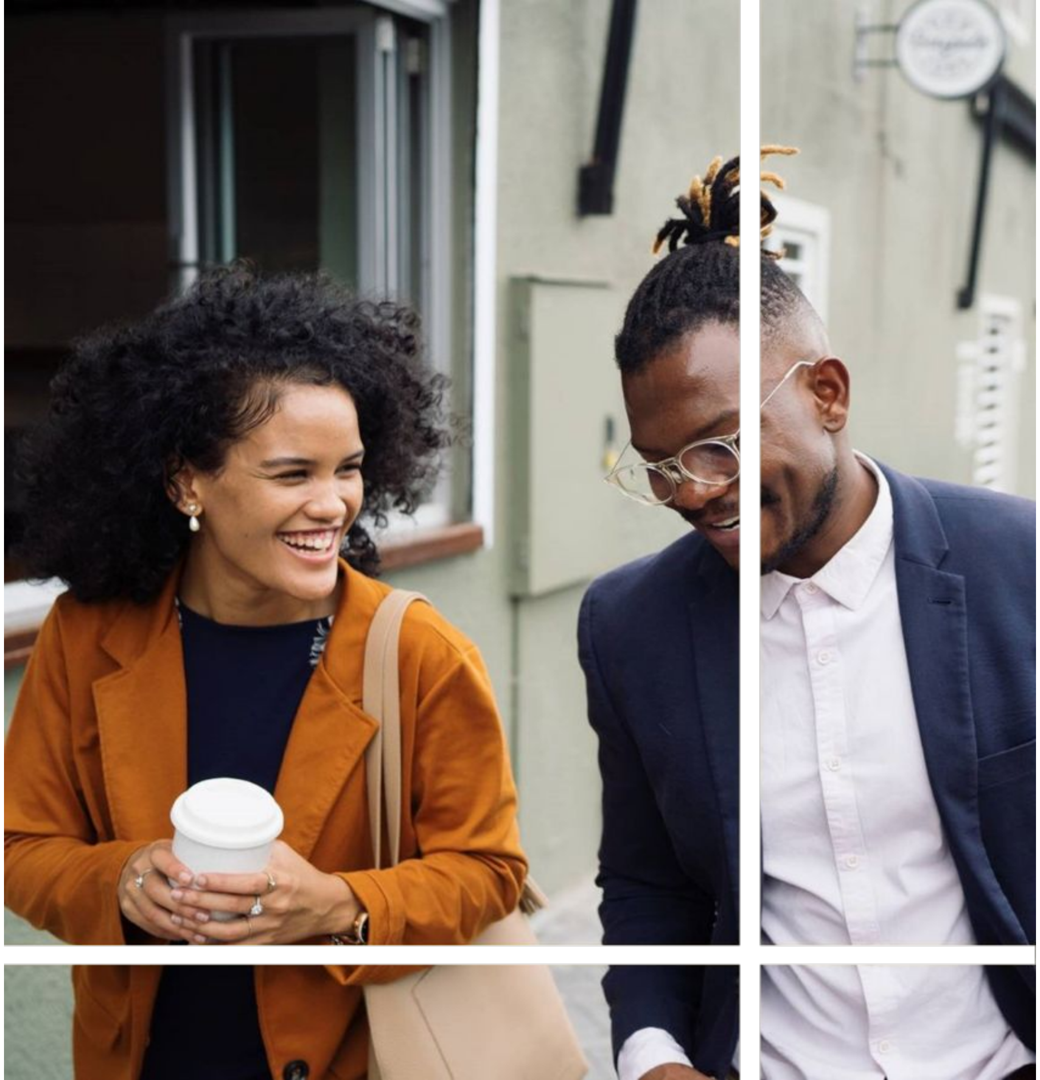
Cocaine/crack 57% success rates

Heroin 57% success rates success rates

Over-the-counter medications 54% success rates

Marijuana/hashish 52% success rates

PCP 52% success rates



Dynamic Model,
Larger dataset,

- The only way to address the changing needs of different people groups was to create a dynamic model
- To keep the accuracy of the model while allowing it to be dynamic we needed more data
- Our first model was 1.7mil cases from 2019,
- This model uses 6.4mil cases from 2017-2020
- With this new and larger dataset, we could now filter for specific people groups, while still having enough data to build an accurate model on.
- The program now builds and trains a new model based on the filters passed to it through drop down menus.

No longer Just Predictions

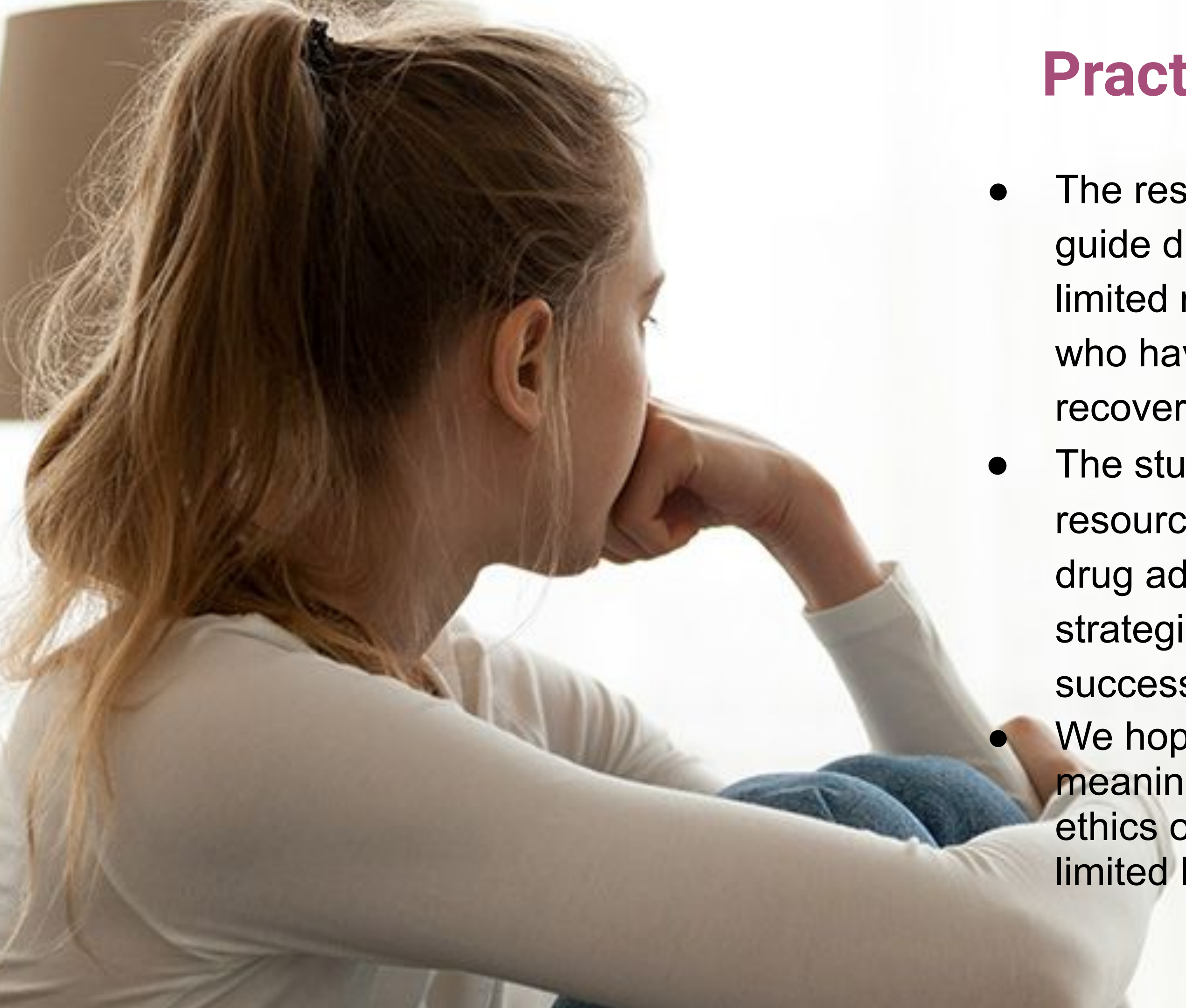
Our first model was designed to just predict success rates of potential candidates based on the entire dataset. The new model not only provides a prediction but also helps the individuals and facilities provide better treatment by providing top correlated objectives based on the statistics from the filters to what the AI sees as being related to success.

The MLPClassifier, (Multi-layer Perceptron Classifier) is a neural network that uses a supervised learning algorithm to classify data by predicting which category an input belongs to.

The input, in this case, is the survey questions. MLPClassifier worked well for this with 100 hidden layers as the dataset would have 33 columns of data that it was ingesting to make a prediction of success and provide helpful success statistics.

Conclusions

- Neural networks excel at predicting success in drug rehab, despite the many complex variables that determine a person's ability to complete drug addiction recovery treatment.
- Neural networks configured the same way in Tensorflow or PyTorch return nearly identical results.
- Despite the use of filters to mitigate demographic biases, ethical concern remain about using data model to grant or deny a person access to treatment.



Practical Applications

- The results of this study can ethically guide drug recovery programs with limited resources to select individuals who have the best chance of recovery.
- The study may serve as a valuable resource for people suffering from drug addiction, helping them identify strategies to enhance their chances of successful recovery.
- We hope this study sparks a meaningful conversation about the ethics of using data models to allocate limited healthcare resources.