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Communimetrics Data Roundtable

Using Machine Learning to Predict Patients That Will Improve in a Level of Care to Assist with Decision Support

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Agenda

- Dan Warner Ph.D. - Introduction to the value of machine learning technology in communimetrics
- Ryan Torrie, B.A. – The process for developing a Gradient Boosting Classifier with communimetric data, and “reverse engineering” the process to make high probability-for-success clinical profiles
- Dan Warner Ph.D. – Careful review of the profiles to see their logic and structure

Background

CANS is most popular tool in children's mental health (Zima, 2019)

It is creating reams of data

Back of the napkin: CDR-affiliated projects produce200,000 scored CANS items a day

Machine approaches need to be used to make sense of the data

‘Inside the Blackbox of Machine Learning’ (Gillingham, 2016)

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- Machine Learning techniques are supposedly ‘atheoretical’ and thus unbiased.
- But every machine learning approach is a mathematical model, built with biases, strengths and weaknesses, like any model.
- Further, the use of any model instantly comes with bias
- Machines extend our reasoning, don’t replace them.
- The problem then becomes
  - How to ask the right questions or our data,
  - And in the right way.

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A question we want to know of our data?

Are there clinical profiles for people who most benefit from our partner's 'wrap-around' program?

Our algorithm development and validation process

One: Develop ML Algorithms

Find the profiles for those most likely to improve, and those most likely to fail in the program.

Two: Expert Review of ML Algorithms

Clinical utility

Bias

Injustice

Obviousness

Three: Test hypothetical impact of ML algorithm adherence

How would the program outcomes improve had the ML algorithms been adhered to?

Four: Test comparison group

Identify a comparison population of children with similar CANS profiles and demographics, but who did not receive the service. How would their outcomes improve had they received the service?

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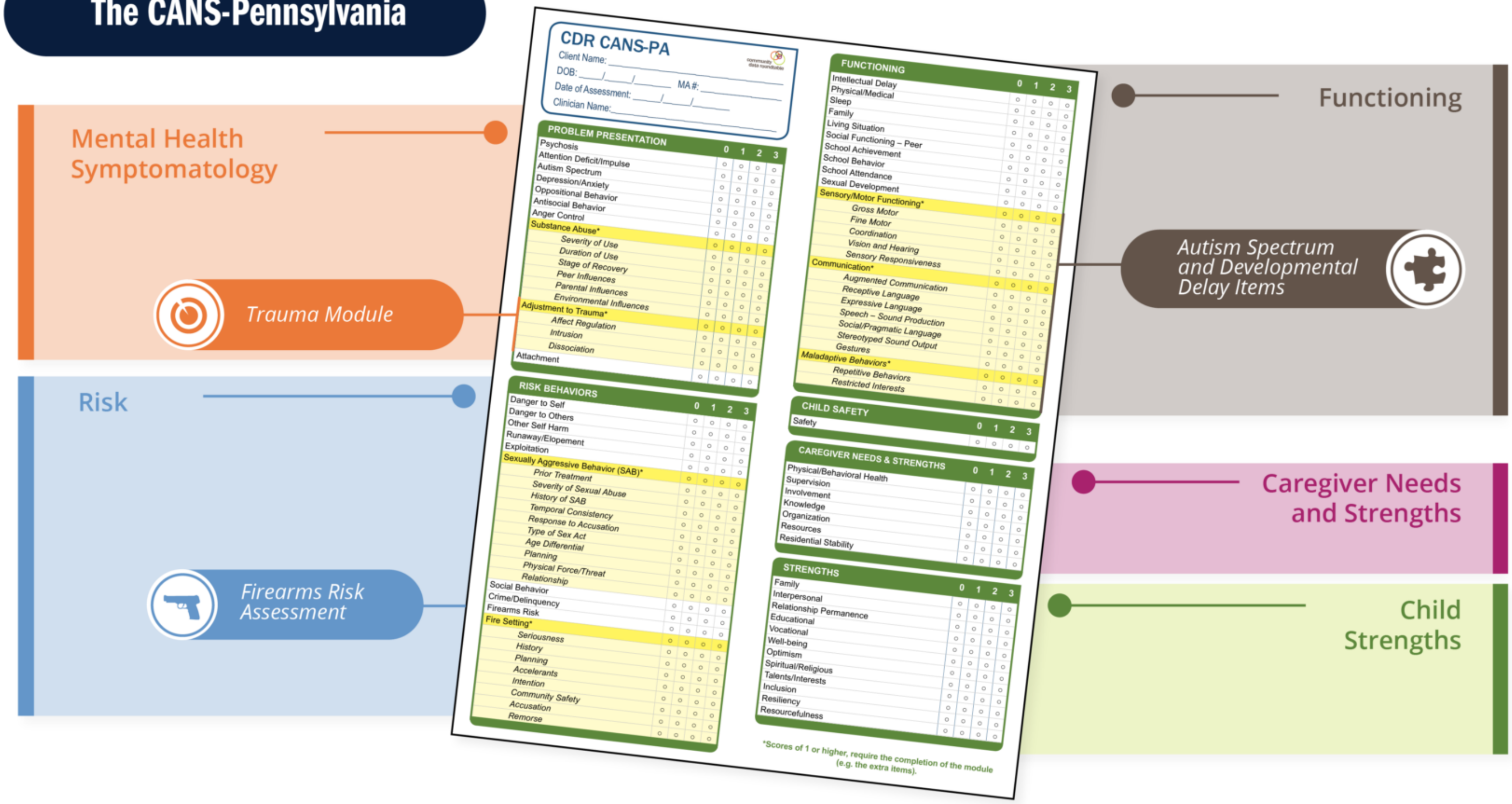
Review of the Program

- Community-based “wrap-around” program that includes
  - Master’s level clinician for (~2 hours a week)
  - Behavioral technician (~15 hours a week)
  - predominantly in the school setting.
- Two basic diagnostic groups:
  - ASD
  - Non-ASD (ADD/ODD)
- Predominantly ages 5 and up
- CANS scored every 6 months as part of psychological evaluation, which resulted in one of three outcomes:
  - Entrance to the wrap-around program
  - Continuation of the wrap-around program
  - Referral to another level of care.
- 6 years
- Over 50,000 CANS and 15,000 children evaluated

The CANS-Pennsylvania



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The Process for Developing a Gradient Boosting Classifier & Reverse Engineering the Process to Make High-Probability-for-Success Clinical Profiles

Ryan Torrie, B.A.

Gradient Boosting

- Tried several other approaches first, including multilayer perceptron classifiers, random forests, and neural nets. Were not able to generate any profiles or indicators that could reliably predict a type that improved in the program.
- Gradient boosting
  - "Gradient Boosting Classifiers" (GBCs) are a type of machine learning model that builds out a sequential series of decision trees. Each tree in the model targets areas where the previous tree was *least accurate*, gradually increasing the model's overall predictive accuracy with each additional tree (See Johnston & Mathur, 2019).

ML Process

Pre-process Data

- Keep Initial and most recent time point, (must be >=18 mos (N=2,497))
- Subdivided this number into three age-bands at intake (<6,6-14,>15)
- Bifurcated population into those whose Total CANS Score Improved (52%), and those for whom it worsened or stayed flat (48%)

Train Model

- Trained on 70% of the population, tested on 30%
- To ensure that the 70/30 split did not skew the data we performed a 10-folds cross-validation.
- GBC model developed to identify profiles with high probability of improvement

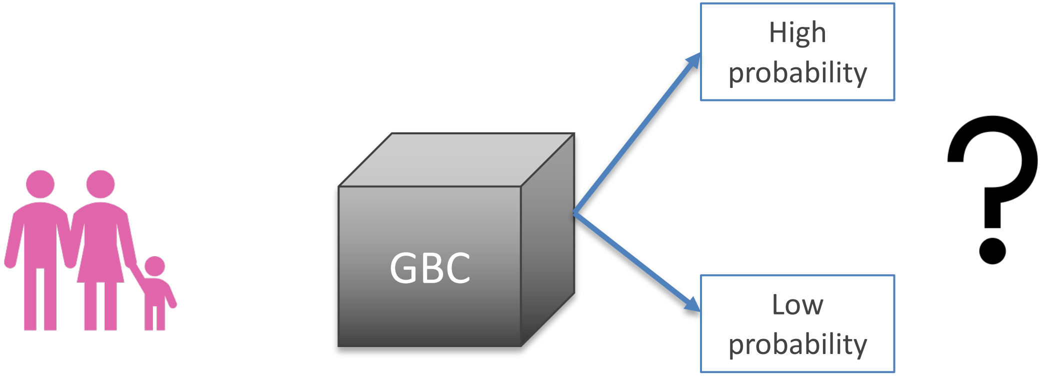
Optimize

	Precision	Recall	# of Patients
Worsened	52%	92%	358
Improved	75%	22%	392

Precision (AKA, Predictive Value)
If model says a patient will improve, what % improve?

Recall (AKA, Sensitivity)
Of the improved patients, what % did model predict?

The Black Box



- Which items are most important?
- What levels for those items are most important?

Linearly Interpretable Model-Agnostic Explanations (LIME)

PROBLEM PRESENTATION	0	1	2	3
Psychosis	X	o	o	o
Attention Deficit/Impulse	X	o	o	o
Autism Spectrum	X	o	o	o
Depression/Anxiety	X	o	o	o
Oppositional Behavior	X	o	o	o
Antisocial Behavior	X	o	o	o
Anger Control	X	o	o	o
Substance Abuse*	X	o	o	o
Severity of Use	X	o	o	o
Duration of Use	X	o	o	o
Stage of Recovery	X	o	o	o
Peer Influences	X	o	o	o
Parental Influences	X	o	o	o
Environmental Influences	X	o	o	o
Adjustment to Trauma*	X	o	o	o
Affect Regulation	X	o	o	o
Intrusion	X	o	o	o
Dissociation	X	o	o	o
Attachment	X	o	o	o

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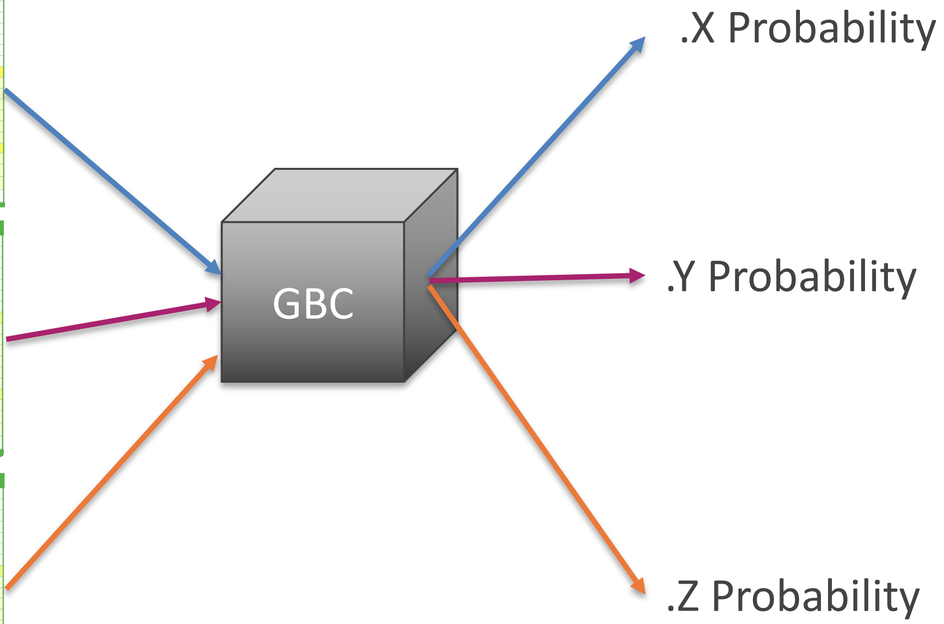


Allows us to see *which items*, at *which levels*, influence the model, and how.

Profile Examples

Characteristics & Combinations	Patients Fitting	% of all patients	Improvement Rate
School Achievement > 1.00 & Resiliency = 3.00 & Living Situation = 2.00	57	2%	88%
Substance Abuse = 0.00 & School Achievement > 1.00 & Knowledge > 1.00 & Social Functioning - Peer = 2.00	32	1%	89%
School Achievement > 1.00 & Sleep > 1.00 & Social Functioning - Peer = 2.00 & Living Situation = 2.00	30	1%	87%

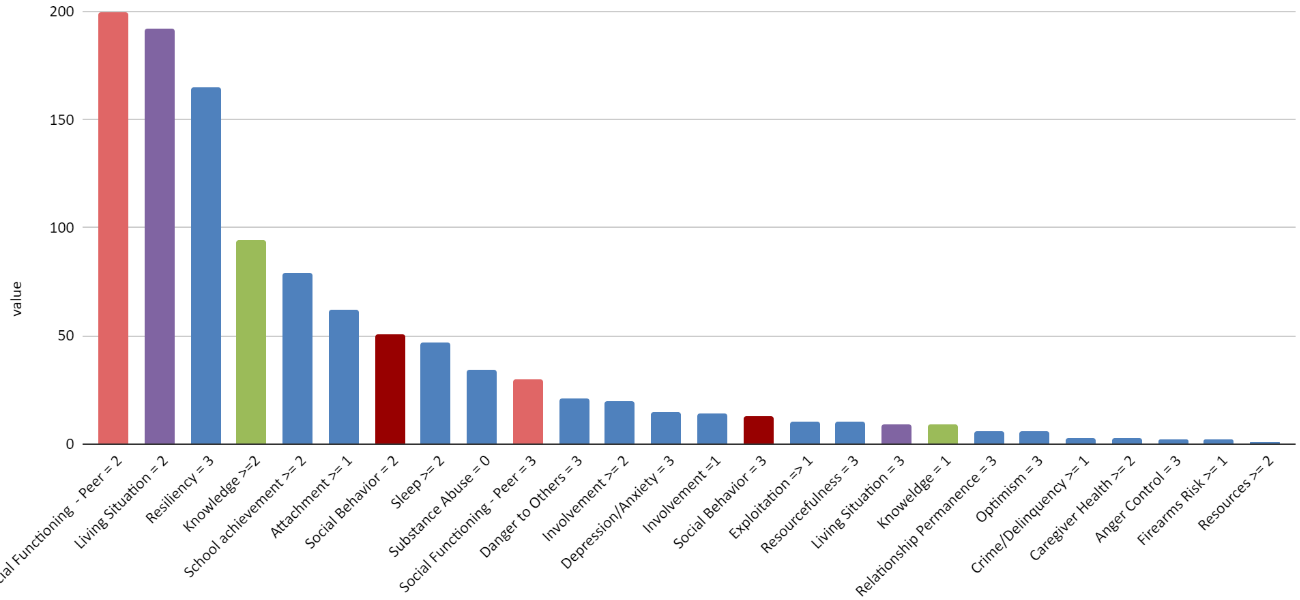
Notes on the profiles:

- Combinations of 1 to 6 of the top 20 most important variables (items at a particular level) that resulted in high improvement rate "profiles"

Reviewing the Profiles

Prevalence of Key Items
Non-ASD

Rate of Prevalence of Each Item at Each Level for High Probability-of-Success Patients



- 2~3 items appear in majority of profiles
- Exact item level matters
- ASD was very different
- Importance ≠ Pervalence

Prevalence of Key Items – organized by importance Non-ASD

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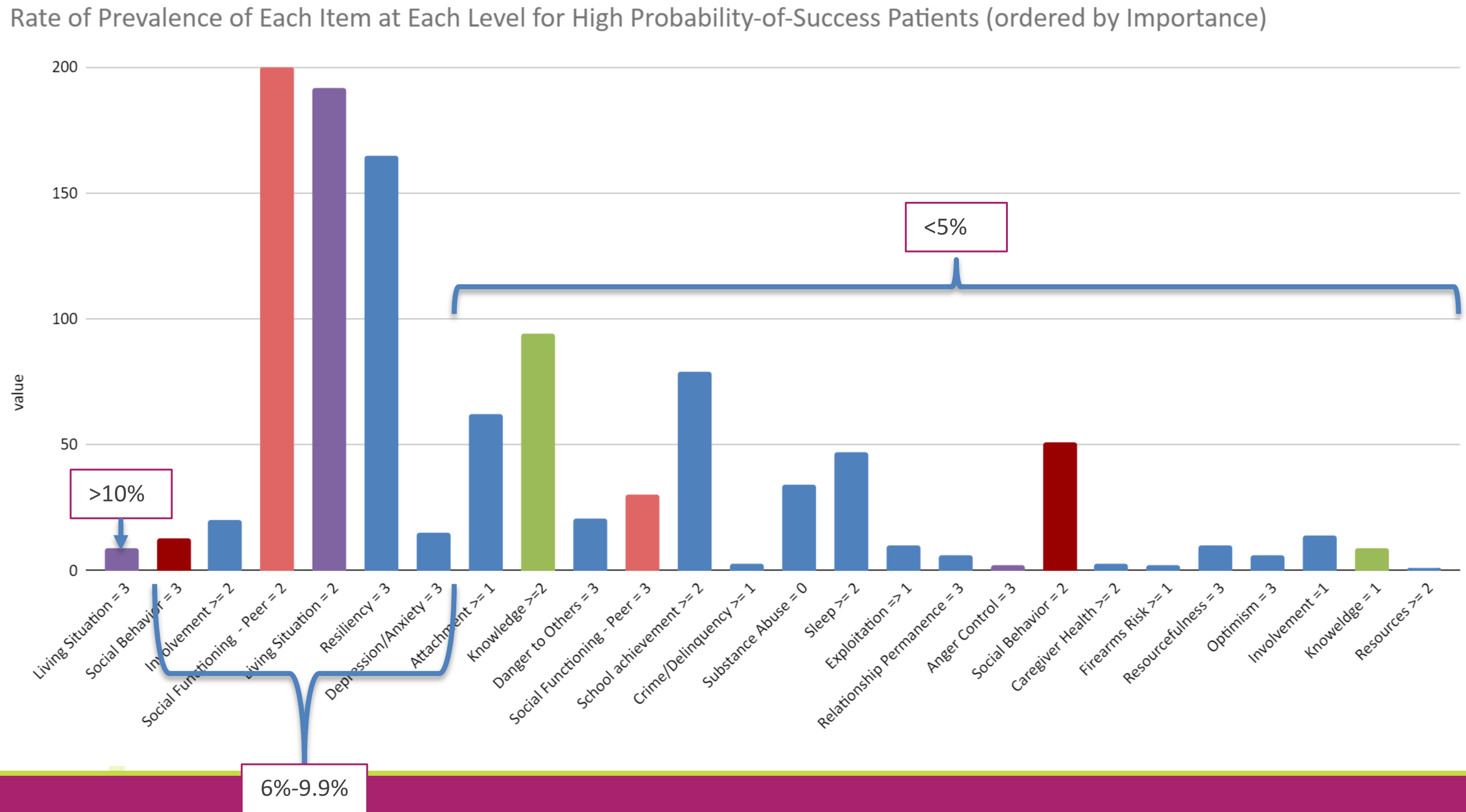

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A review of the items – Non-ASD

Problem Presentation	Risk Behaviors	Functioning	Caregiver Health	Strengths
Attachment >= 1	Danger to Others = 3	Social Functioning - Peer = 2	Knowledge >=2	Resiliency = 3
Anger Control = 3	Exploitation => 1	Living Situation = 2	Involvement >= 2	Resourcefulness = 3
	Crime/Delinquency >= 1	School achievement >= 2	Knoweldge = 1	Optimism = 3
	Firearms Risk >= 1	Social Behavior = 2	Physical/Behavioral Health >= 2	Relationship Permanence = 3
		Sleep >= 2	Resources >= 2	
		Social Functioning - Peer = 3		
		Social Behavior = 3		
		Living Situation = 3		

Impact

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How this could improve our wrap-around program's outcomes

- If people who matched one of our profiles, but received something different, were actually included in our program, the program's overall improvement rate would increase by 15.1%
- The amount of change experienced (actionable needs improved) in the program improves by 13%

How this can improve the outcomes of those who were not referred to the wrap-around program

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- Children who matched our profiles, but received a different level of care had only a 48% improvement rate with the service they ended up at, but would have had a 90.9% chance of improving if they'd participated in the wrap-around program.
- Overall, only 47.8% of patients fitting our improvement profiles received the wrap-around profile.

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Conclusions

- Machine Learning approaches can help find clinical profiles of people likely to succeed in a level of care
- Adherence with these profiles could improve the outcomes performance of a program as well as the outcomes of clients who match the profiles but end up in another, not as well matched, program.
- There is much more to do with machine learning and communimetric data.

Make sure to join us July 23,
Kate Cordell Ph.D. shows us dashboards built on ML insights (and more!)

Questions?

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Leading with Outcomes

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