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Innovations & Opportunities

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Agenda

- Introduction to the Community Data Roundtable
- Dan Warner, Ph.D. - Considerations of the California CANS Implementation
- Scott Fairhurst, Ph.D. (et al) – Connecting the CANS

Pacific Clinics
ADVANCING BEHAVIORAL HEALTHCARE ®

Community Data Roundtable – Quarterly Webinar

- Purpose: To support a community of professionals and scholars in community health data
  - Managers and decision makers
  - Data analysts, evaluation experts, researchers
  - Academics and professionals
- All calls are video recorded and made available soon.
- Use the chat feature for questions/ comments.
- We come together with a spirit of openness and sharing.
- Please ask probing questions!

Community Data Roundtable

CDR is a nonprofit organization dedicated to a data-driven human services system

DataPool online TCOM application

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- DataPool online TCOM application
- Advanced analytics and algorithms

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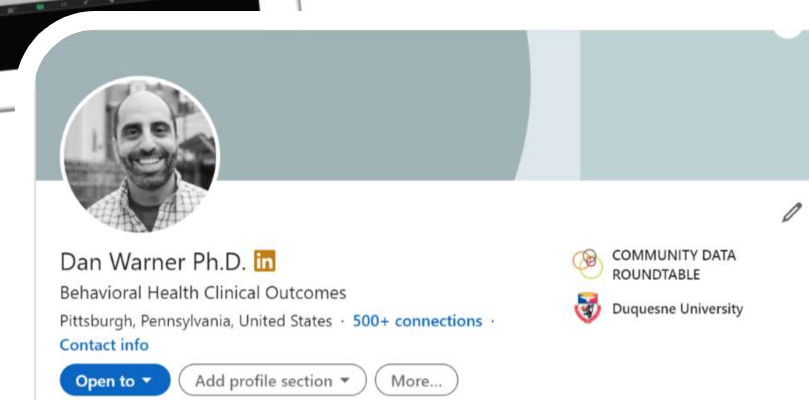
CDR is a nonprofit organization dedicated to a data-driven human services system

- DataPool online TCOM application
- Advanced analytics and algorithms
- Resources to support public use of data

www.communitydataroundtable.org/Blog



We're Published!

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Children and Youth Services Review 126 (2021) 106010

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CHILDREN and YOUTH SERVICES REVIEW

Check for updates

A machine learning approach for identifying predictors of success in a Medicaid-funded, community-based behavioral health program using the Child and Adolescent Needs and Strengths (CANS)

Jesse D. Troy[a,b,*], Ryan M. Torrie[a], Daniel N. Warner[a]

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A B S T R A C T

Introduction: The CANS is the most popular measurement tool in the System of Care (SoC), with the potential to generate an estimated 1.9 million evaluations per year in the United States. This dataset has broad potential for decision support and outcomes monitoring, yet many SoC services do not yet leverage this information asset. We report here the results of a pilot project in which we applied machine learning methods to CANS data for the purpose of identifying clinical profiles associated with improvement in a public community-based behavioral health program in Pennsylvania.
Methods: We analyzed over 7,000 CANS from 3,385 children who participated in Pennsylvania's Medicaid-funded behavioral health rehabilitation services (BHRS) program during 2013–2019. A gradient boosting classifier was developed to identify children most likely to experience a total score improvement on the CANS while participating in BHRS. Separate models were constructed for children with and without autism spectrum disorder (ASD). CANS-based clinical profiles associated with improvement were also identified. Analyses were run using Python Sci-Ki version 0.20.3 and Linearly Interpretable Model-agnostic Explanations (LIME) version 0.1.1.33.
Results: The mean age of BHRS participants was 9.85 years (standard deviation: 3.47) and the majority were white (54%) or African American (11.5%). The median length of stay was 963 days (range: 541–2,008) and 39% (N = 1,330) had a diagnosis of ASD. A total of 49.9% of children had a CANS total score improvement. Precision of the gradient boosting classifier was 70% and 79% for children with and without ASD, respectively. Fourteen profiles were associated with improvement in ASD (mean probability of improvement per profile = 0.95, range: 0.88–1.0) and 55 such profiles were identified in children without ASD (mean probability of improvement: 0.91, range: 0.86–1.0).
Conclusion: Machine learning can be applied to the CANS to identify children who have high probability of improvement in BHRS. These methods may have utility as an adjunct to existing decision support systems for SoC services.

1. Introduction

insurance companies collaborate in pursuit of a shared vision of health for the people being served. This vision is made a reality through

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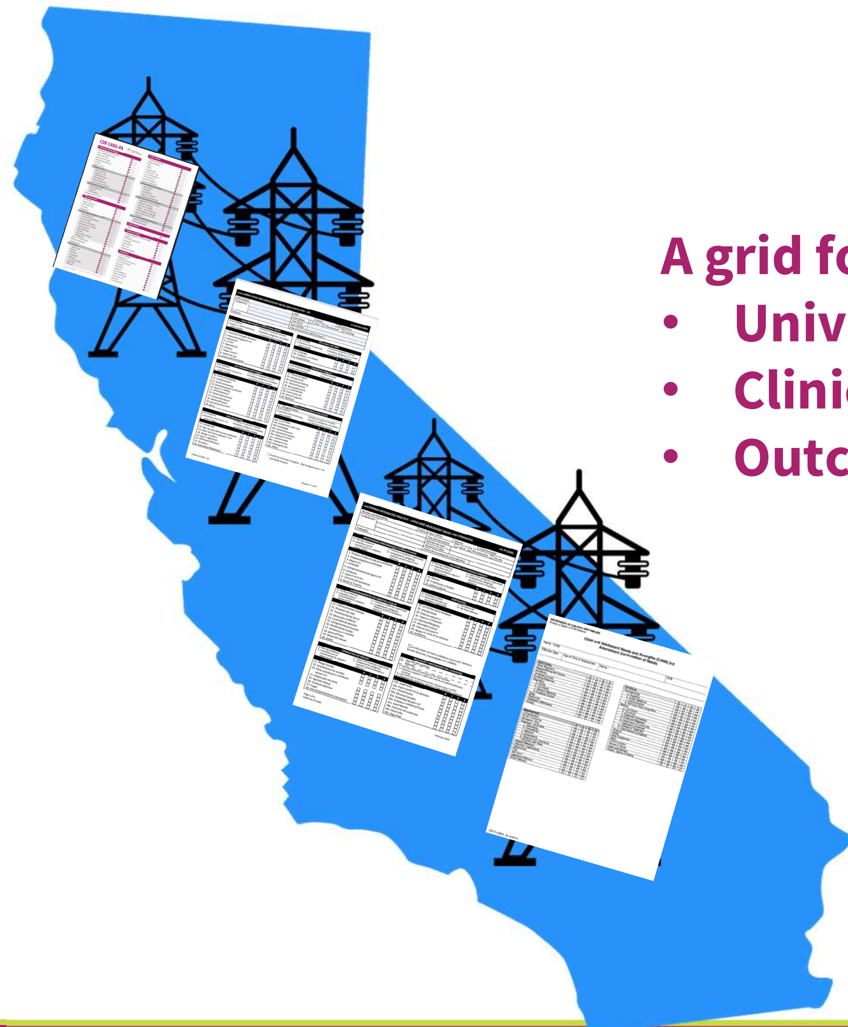
The CANS across California



A grid for

- **Universal assessment**
- **Clinical communication**
- **Outcomes tracking**

From the TOP!

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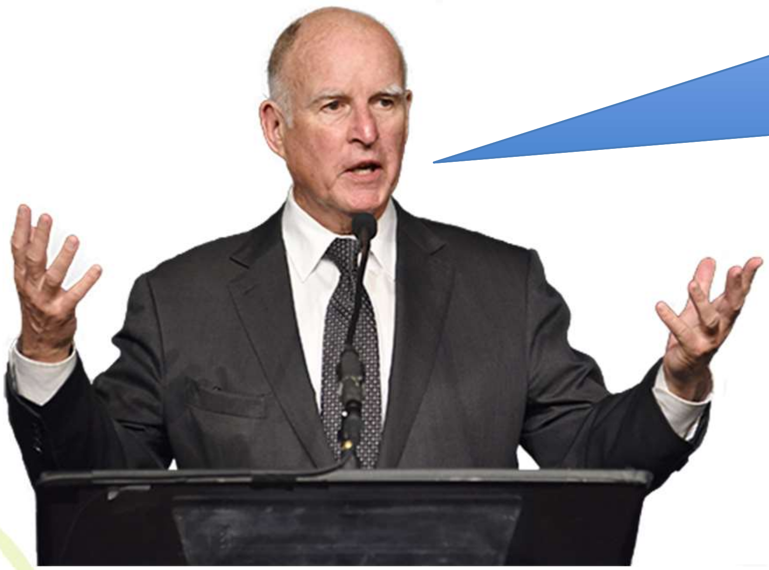

MHSUDS 17-052
Complete a CANS (and PSC-35!) at the beginning of all child treatment, then every 6 months after that, including treatment's end.

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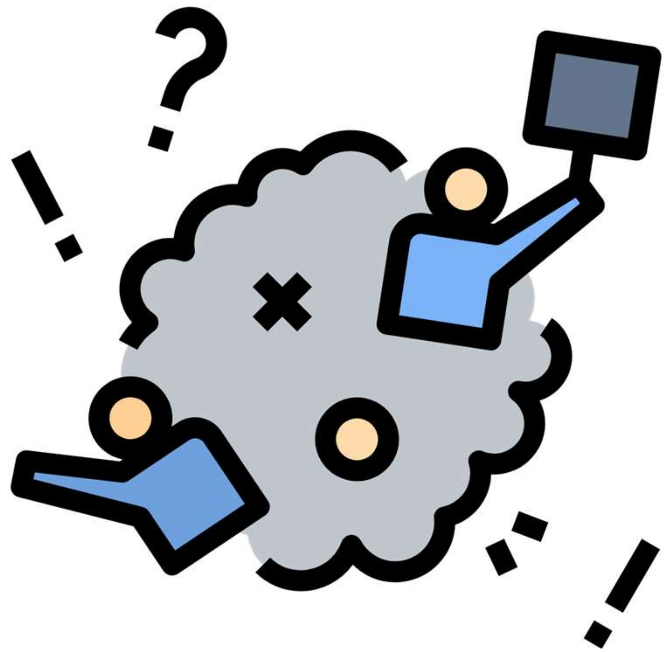
From the BOTTOM

Every county can do it their own way.

All sorts of technical problems emerge



Technology

- Different systems
- Different capabilities
- Interoperability
- Communication

- CANS scored within *each* agency?
- CANS scored at the treatment planning phase of any and all programs?
- Keeping track of discharges…

PROCESS


Analysis
- What is the unit of analysis?
  - Client
  - Client within agency?
  - Client within programs?
- What is included or excluded in any analysis?
- Decision Support Algorithms?

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Challenges and Opportunities

- Innovations will be necessary in all domains:
  - Technological
  - Process
  - Analytical

Case Example: Santa Cruz

How Santa Cruz County look at PROGRAM IMPACT, even though CANS are done every 6 month, independent of program

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Santa Cruz County CANSA facts

Technological – use a county-wide client management system (Netsmart/Avatar) that captures CANS. Used by all providers in the county. Not integral with other systems. Limited in ability to display CANS robustly.

Process – CANS are scored by only certain levels (case managers, therapists) on a six month schedule that is independent of entering or leaving a program. Discharges and caseloads are not well tracked.

Analytical – Want to use CANS to understand 'impact' of various providers in a comparable way.

Impact

Local Definition:
The change in actionable needs that an episode of care is likely to result in for a given population.

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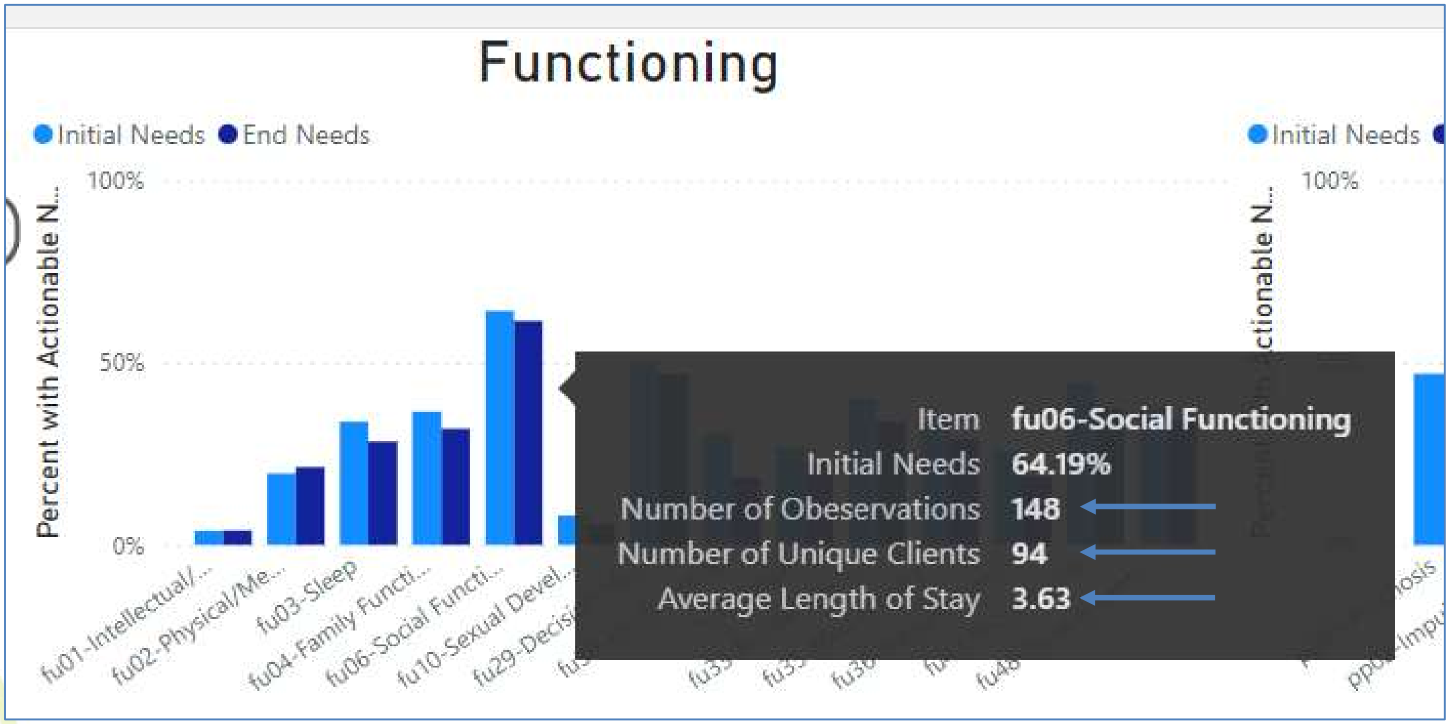
Impact – Item Level



Impact – Average Impact (by Domain and Overall)

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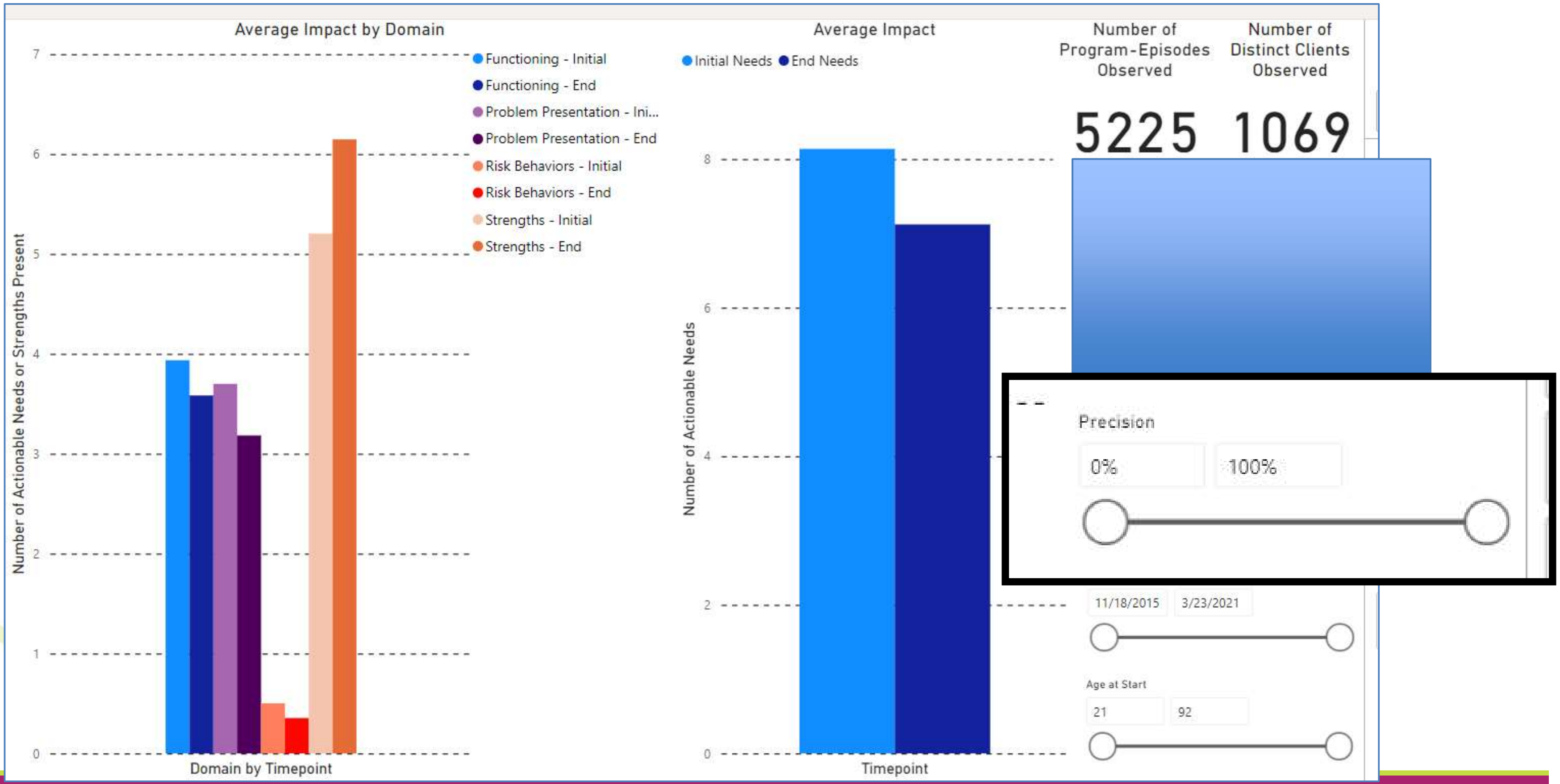
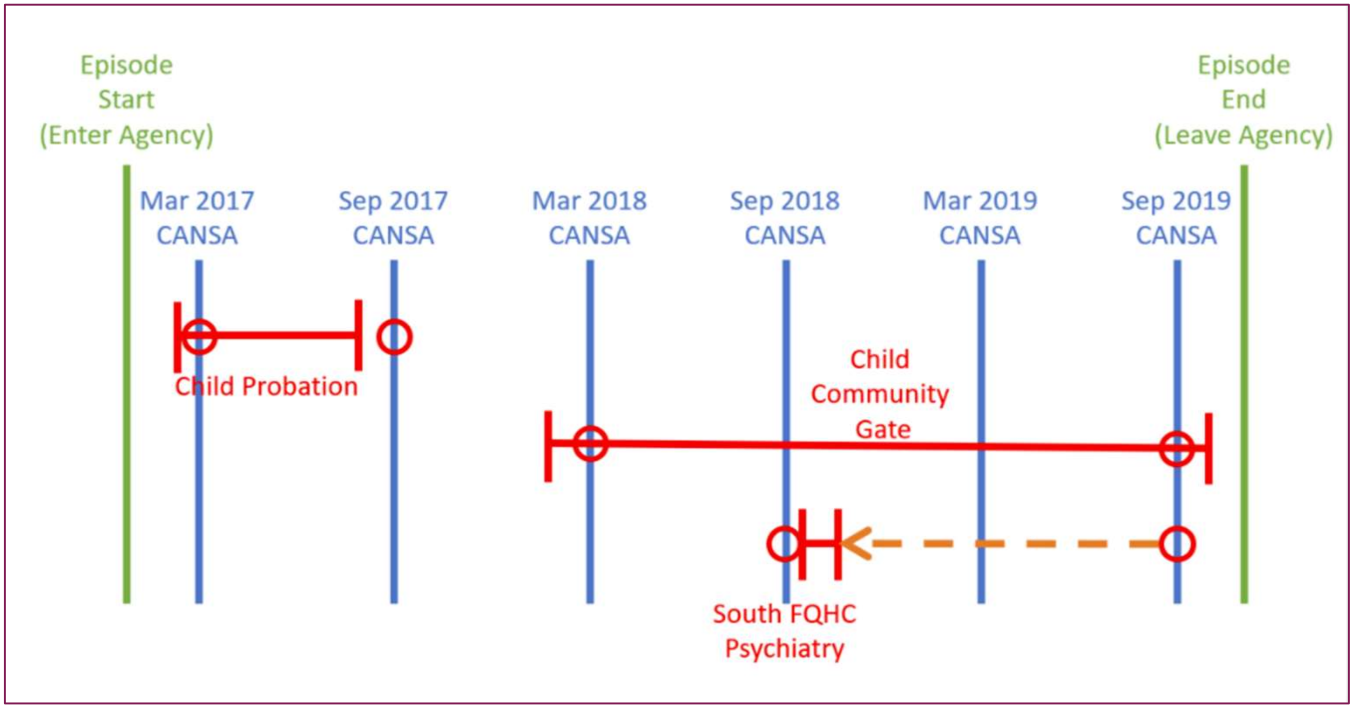


Santa Cruz Example

A county system with a steady "CANS pulse" of 6 months intervals – How do we understand "program impact" from a CANS timeline that is not connected to program entry or exit?



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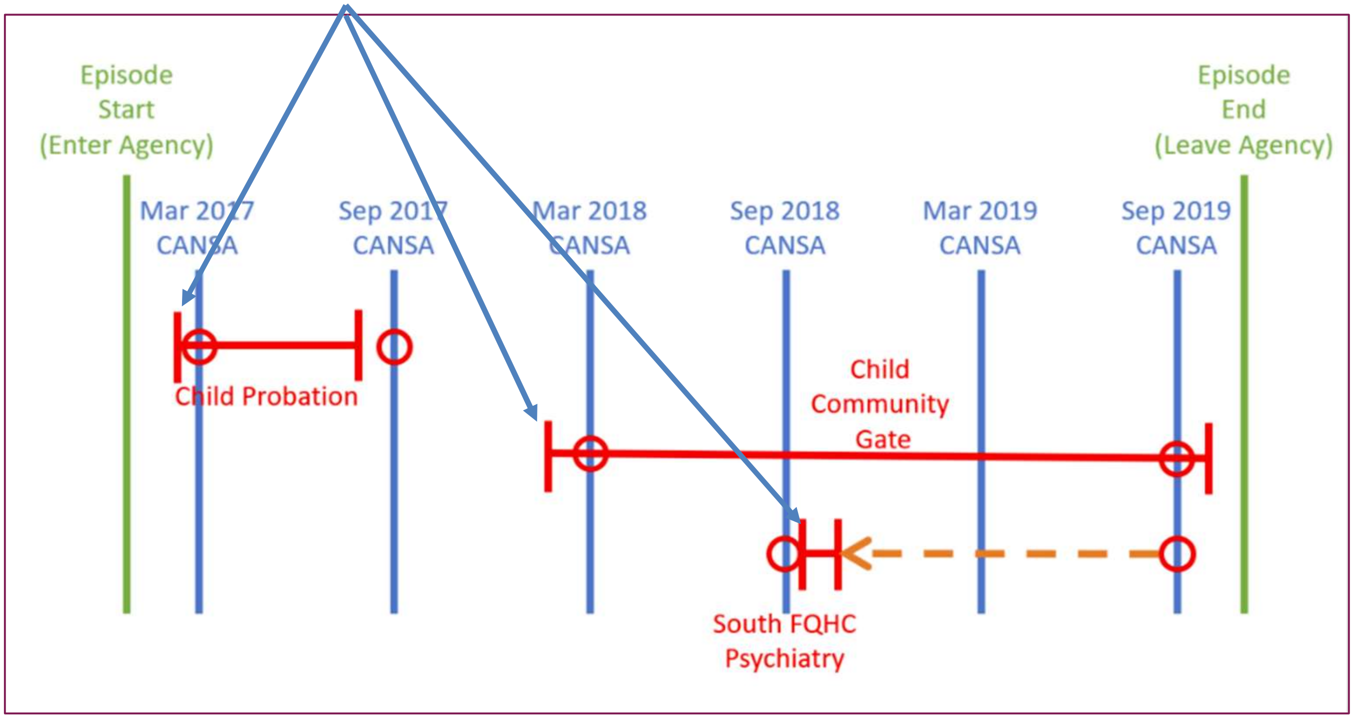
First Progress Note



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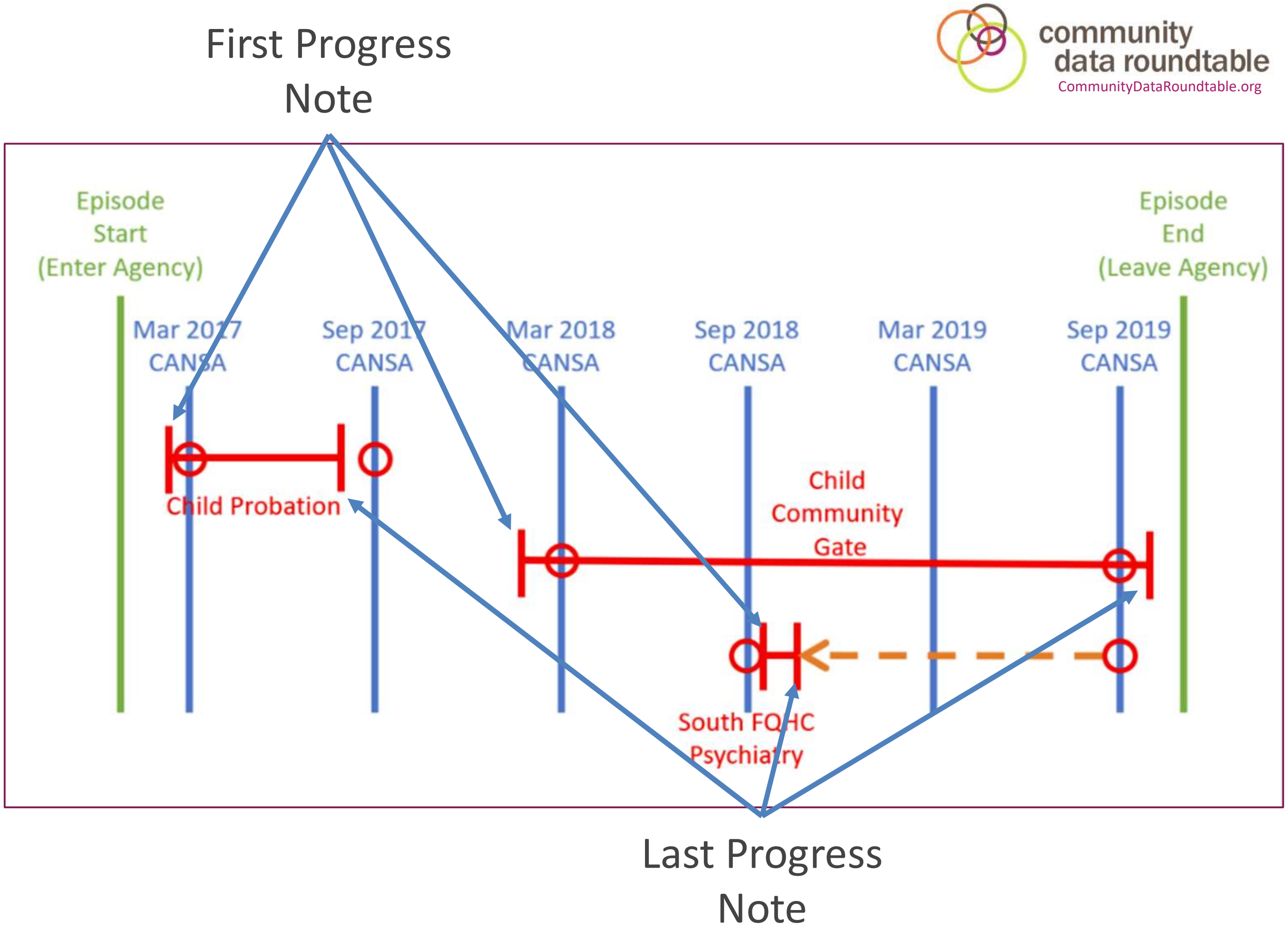

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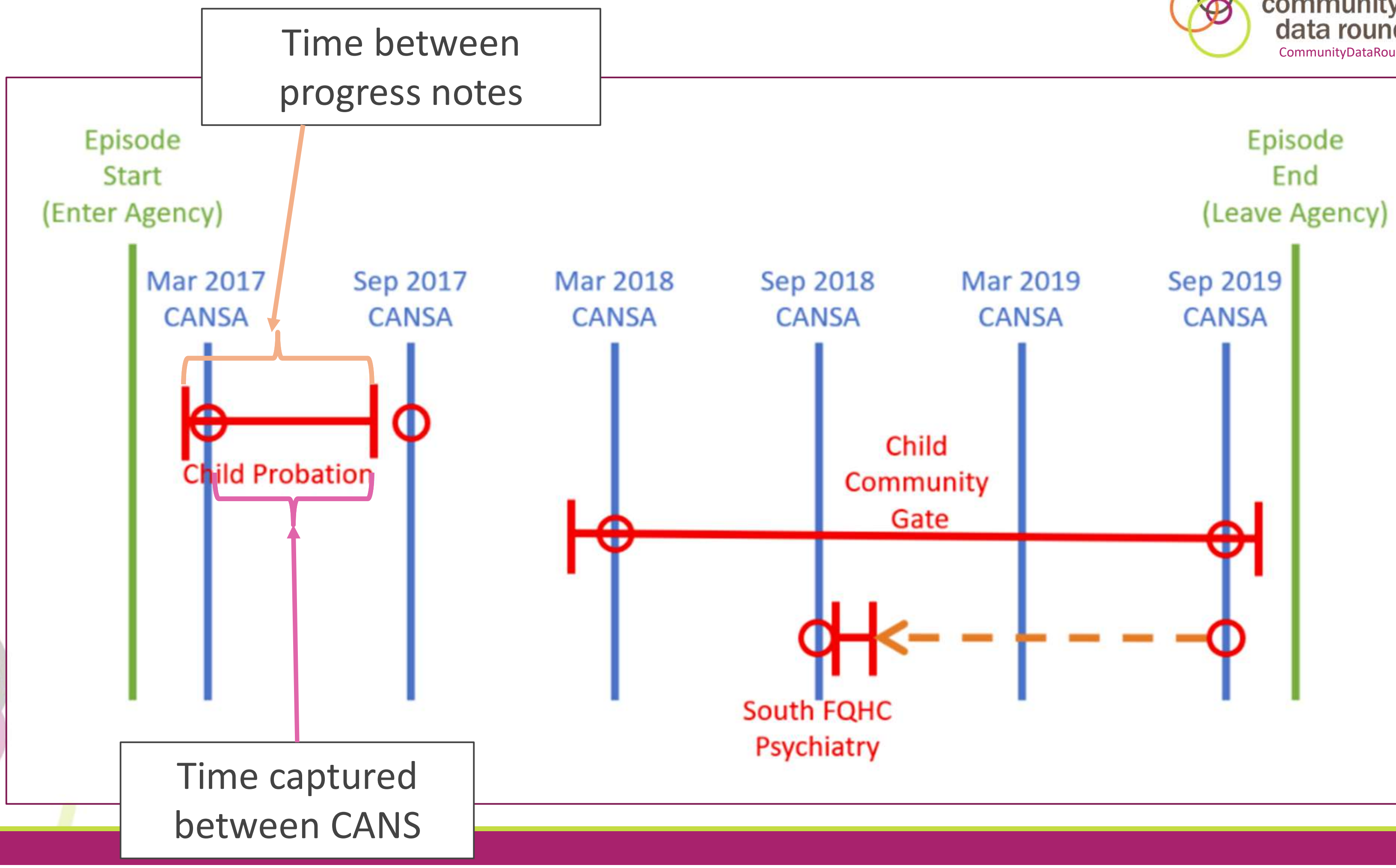
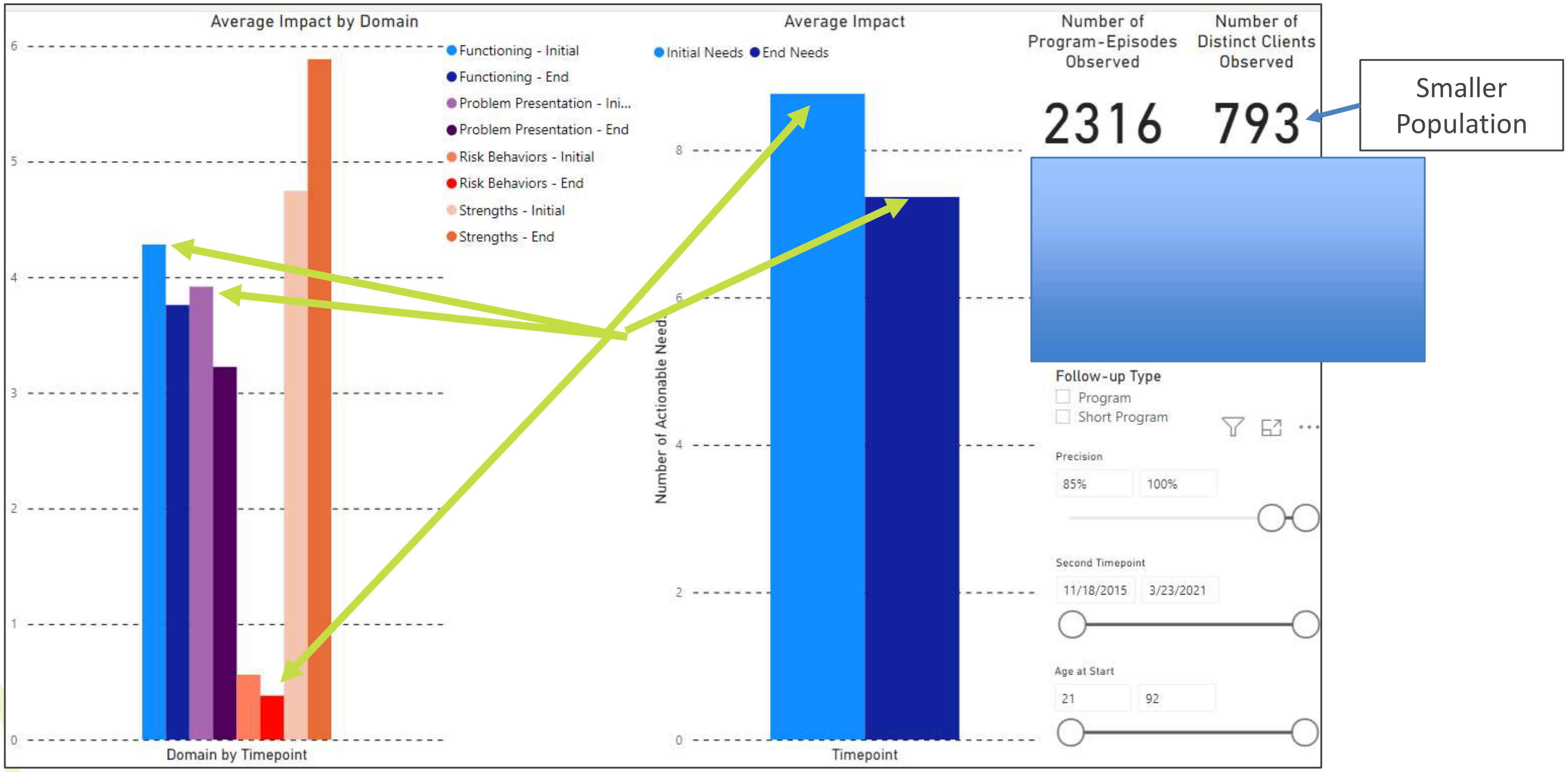

Time between progress notes
Episode Start (Enter Agency)
Episode End (Leave Agency)
Mar 2017 CANSA
Sep 2017 CANSA
Mar 2018 CANSA
Sep 2018 CANSA
Mar 2019 CANSA
Sep 2019 CANSA
Child Probation
Child Community Gate
South FQHC Psychiatry
Time captured between CANS

$$\textbf{Precision} = \frac{\text{Treatment time between CANS measures}}{\text{Total time in treatment}}$$

- Tells us how much of the treatment is actually being measured
- Has a bias towards better accounting for the impact of longer treatments
- Often, higher precision readings, show riskier cases, because treatment effect is less dampened

Precision 85% - (often) higher acuity – less dampened treatment effects



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Conclusions

- California's bottom up approach means interlocking multiple technologies, processes, and analytic questions.
- Innovations will result in big rewards in regards to understanding your system's needs and strengths.
- Proper analysis of program impact (i.e. 'outcomes') requires mathematical sophistication

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Questions?

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Leading *with* Outcomes

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