

Predictive Risk Modeling: *A Tool for Child Protection?*

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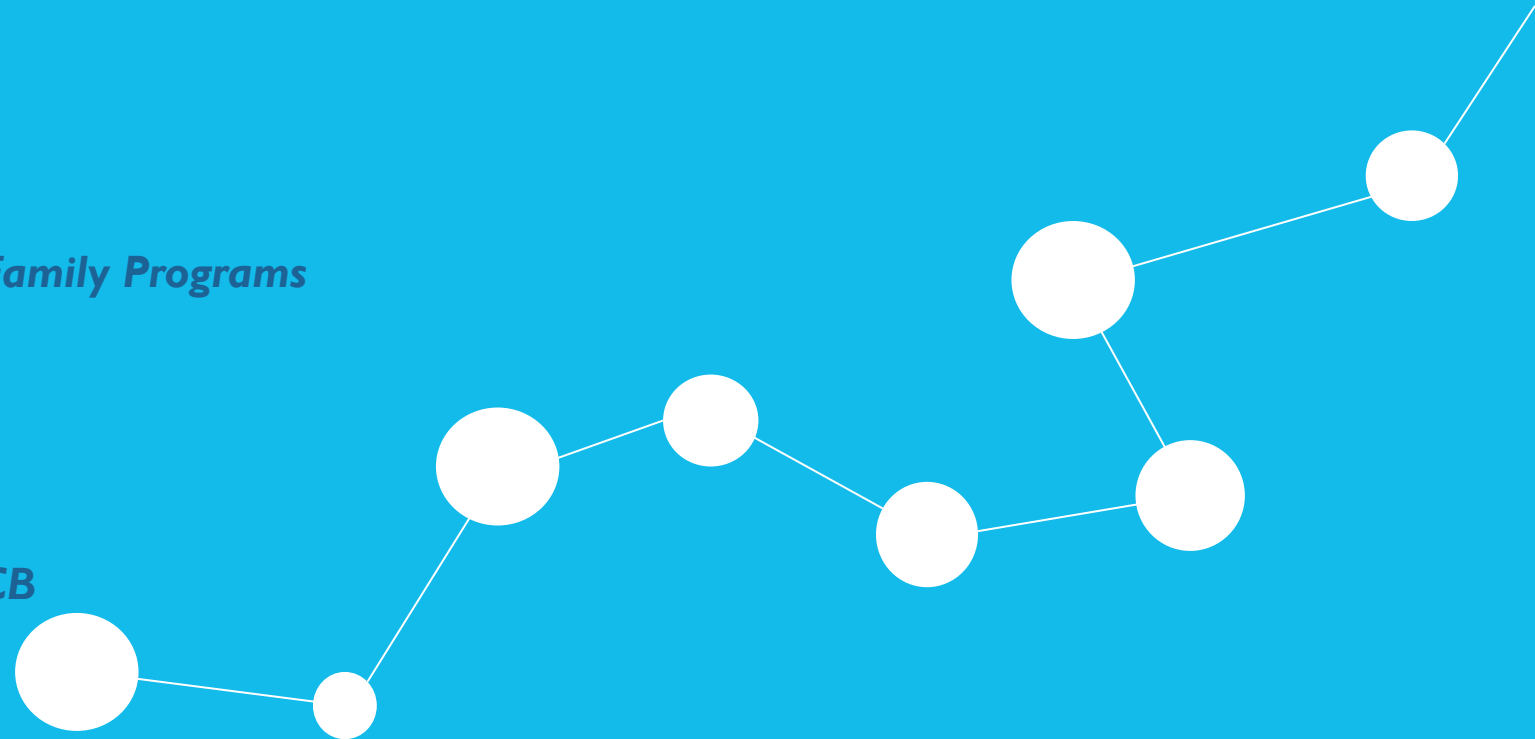
Independent Consultant

(participation at this meeting funded by Casey Family Programs)

for Emily Putnam-Hornstein, PhD

Children's Data Network @ USC

California Child Welfare Indicators Project @UCB



The power of administrative data

1. A population, longitudinal framing
2. Objective indicators of risk
3. Engaging cross-system partners
4. Relevant, actionable knowledge
5. Research and evaluation
6. Preventive analytics / decision aids



Why? What?

What is the context for all this interest in statistical decision-making tools?

What is meant by PRM? How is this approach different than other tools?

Why are we interested?

1. Wider availability of high quality data... **big**, small, structured, unstructured...much of which can be linked at the individual level.
2. Advances in technology and analytic capabilities – not just retrospective analyses
3. Growing appreciation that current tools are inadequate, clinicians are poor at weighting factors (and time is scarce!)
4. Opportunities to reduce costs / improve performance by identifying high service utilizers /

Predictive Risk Modeling (PRM)

Automatic tool which generates a **risk score** for an adverse event based on **large administrative dataset**

(definitions borrowed from my colleague, R.Vaithianathan)

Opportunities

- Cost effective screening of large populations
- No subjective, human element
- Continuum of scores
- Models can be generated using data from a local population

Challenges

- Resistance from clinicians and other frontline staff
- “Black Box”
- Risk does not mean willingness to accept intervention
- Only as good as intervention delivered

Long-time applications of predictive modeling

1. Department of Defense – model war scenarios
2. Insurance (health, life, car, etc.) – who to cover, cost of premiums
3. Gaming industry
4. Many private firms (“predictive analytics”)

Example 1: Fraud detection

1. Software analyzes 500 individual pieces of data (*past transactions, location, information stolen from merchant databases, etc.*)
2. Risk score...0 to 99 – based on the number of risk metrics the card swipe triggers – in one millisecond

How Visa's Predictive Analytics Fight Gas Pump Fraud

BY CLINT BOULTON



A pilot test of predictive analytics software from Visa helped reduce fraud at Chevron gas pumps by 23% over a two month period.

Example 2: Academic support

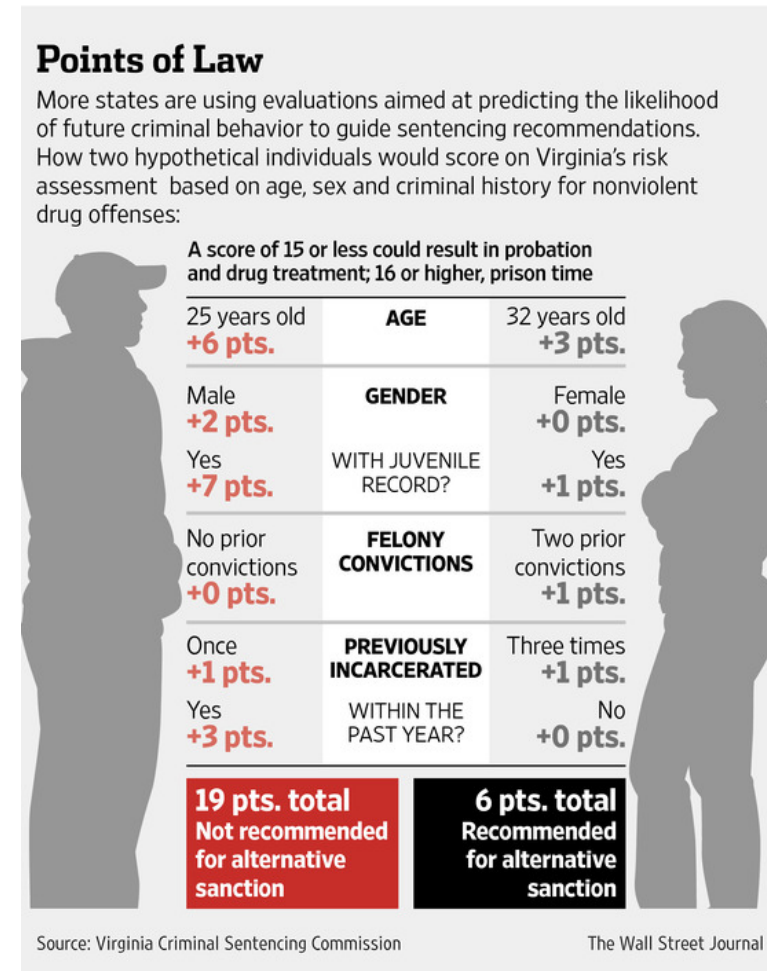


Big Data Helps Marist College Predict, Prevent Poor Student Performance

In an innovative effort to help more of their undergraduates complete their degrees, over 150 U.S. universities are currently applying predictive analytics to massive stores of historic student performance data to better understand the qualities and behaviors that correlate with student success. With this information, the schools hope to identify those students “likely to fail” certain courses, and alert their professors to the risk. Professors can then provide meaningful interventions aimed at helping these students succeed.¹

Example 3: Criminal justice sentencing

1. Efforts to bring a more scientific approach to decisions made by judges in sentencing
2. Consideration of offense, criminal history, age sex, education level, marital status, etc.
3. Has emerged as a centerpiece of efforts to reduce the U.S. inmate population, which jumped from around 200,000 in the early 1970s to over 2 million today.



Example 4: Health care



- Risk scoring at hospital discharge
- Score indicates risk of re-hospitalization within 365 days
- Score emailed to family physician
- Case review high risk patients
- Current evaluation

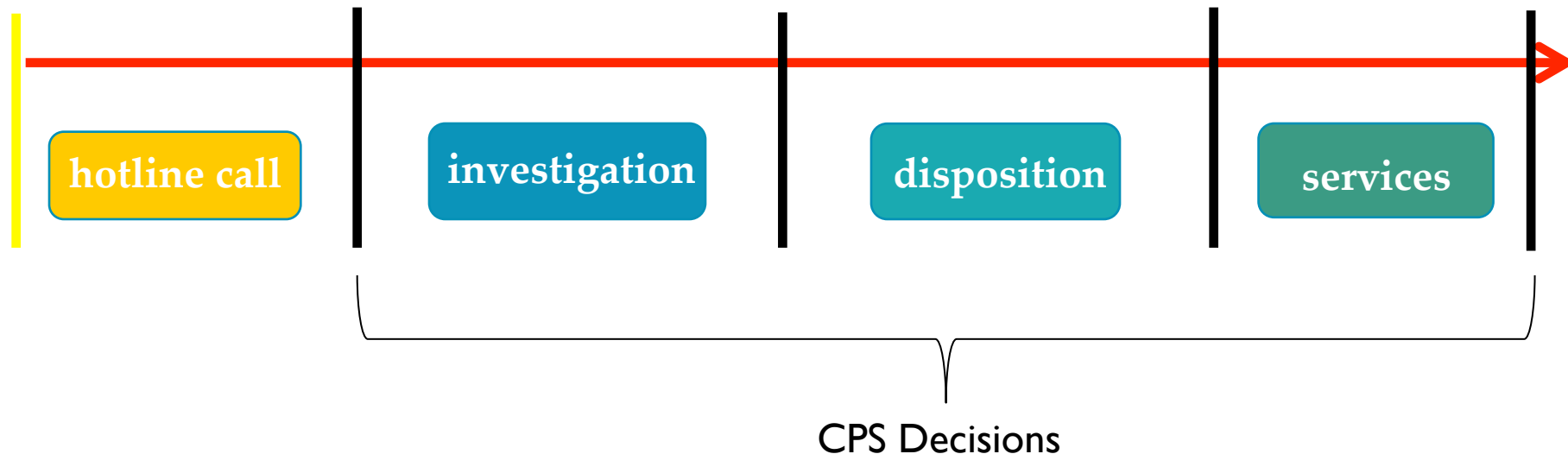
1. Relatively advanced – growing with increased reliance on electronic medical records
2. Forecasting which patients are likely to experience an adverse outcome (e.g., re-admission to the hospital after discharge)
3. Population health management through risk stratification (e.g., case finding to identify high risk patients for targeted intervention)

* Panattoni, L. E., Vaithianathan, R., Ashton, T., & Lewis, G. H. (2011). Predictive risk modelling in health: options for New Zealand and Australia. *Australian Health Review*, 35(1), 45-51.
Vaithianathan, Rhema, Nan Jiang, and Toni Ashton. *A Model for Predicting Readmission Risk in New Zealand*. No. 2012-02. 2012. Melbourne Institute.

Relevance to child protection

“One might conceptualize child welfare agencies as social service agencies, but that would be incorrect. In reality, child welfare agencies are gate-keepers and the workers decision makers.”

(Gelles & Kim, 2008)



Potential applications

■ Primary Prevention:

- *requires an upstream data system which captures a sufficiently rich set of variables to support risk classifications & an adequate proportion of children who will later be maltreated*
- *could be used to prioritize children for early intervention and maltreatment prevention services*

■ Secondary Prevention:

- *could be deployed at different child protection decision-points to support hotline screenings, investigations, etc.*
- *linkages with other data could be used to provide a more accurate/complete assessment of present and future risk*

■ Tertiary Prevention:

- *may lend itself to a more effective and efficient means of minimizing negative consequences of child abuse or neglect*
- *empirical basis for tailoring services (vs. “one size fits all”)*

“prediction is very
difficult, especially if it’s
about the future,”

Niels Bohr

*[Important to
keep in mind!]*

Questions?

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