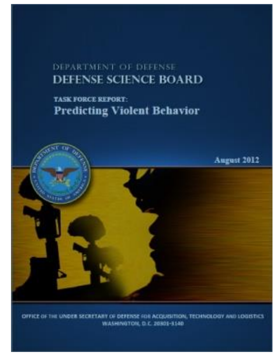
Predicting Violent Behavior: Collectively vs. Individually

Gary G. Berntson, Ohio State University

On 5 November, 2009, a U.S. Army major and psychiatrist, Nidal Malik Hasan, killed 13 people and wounded 32 others at the Fort Hood military base, near Killeen, Texas. In a follow-up, the Under Secretary of Defense for Acquisition, Technology, and Logistics and the Under Secretary of Defense for Policy chartered and co-sponsored a study by the Defense Science Board on *Predicting Violent Behavior*. That study, published in August of 2012 (https://www.hsdl.org/?abstract&did=723322), concluded, among other things, that "There is no effective formula for predicting violent behavior with any degree of accuracy" (Executive Summary, p2).



Others, however, are more optimistic about the development of systems to predict terrorist incidents and intent (e.g., see Theodore J. Gordon, *New Analysis Tools for Pre-Detecting Terrorist Intent*, in the first round of White Papers). Gordon was a co-founder of the Millenium project and has edited a volume on the Proceedings of the NATO Advanced Research Workshop on Identification of Potential Terrorists and Adversary Planning – Emerging Technologies and New Counter-Terror Strategies (2017). He is a highly significant figure in the field.

So which of these perspectives is more veridical? The short answer is both. I will introduce this discussion with a recent study by Rosellini et al, & Kessler (2016). The study arose out of the US Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS) project, a partnership between NIMH and US Army (see http://starrs-ls.org/). The study aimed to develop an actuarial approach, based on machine learning methods applied to a personnel database, to identify individuals at risk for violence. The study sample included over 1 million service members who were in a consolidated database that included demographic, medical and other information. There was an initial cohort (2004-2009) for whom predictor variables for violent criminal activity were identified and systematized, by machine learning algorithms, to develop a risk estimate. This system was then tested on a second cohort (2011-2013) to confirm generality. The study approach was deemed viable as about 35% of the crimes in the initial cohort were committed by the 5% of those with the highest risk estimates. For the second cohort, the percentage was even higher-- about 50% of all violent crimes were committed by those within the 5% that had the highest risk estimate. The predictors with the highest loading included socio-demographic variables, age, education, past criminality, and past mental treatment.

These findings were suggested to support the view that violence may be predictable. They are in keeping with the emerging application of predictive-policing approaches to crime control, where predictive models are used to allocate criminal justice resources (see Hvistendahl, 2016): (http://www.sciencemag.org/news/2016/09/can-predictive-policing-prevent-crime-it-happens) An important consideration, however, is that in both of these cases, the approaches are dealing with prediction at a population or cohort level, not an individual level. The DSB Task Force, on which I served, would likely continue to assert "There is no effective formula for predicting violent behavior with any degree of accuracy." The focus of the committee was on predicting violent behavior at the individual, or small cohort, level.

In this regard, it may be informative to further consider the Rosellini et al, & Kessler (2016) results. A disproportionate number of crimes were indeed committed by those with the highest risk estimates. But the question arises as to the accuracy of prediction for a given individual. In the STARRS study, there was an initial cohort of 975,057, of whom 5,771 (0.59%) committed violent crimes during the study period. About 35% of those committing violent crimes (≈ 2,020 individuals) were among the 5% of service members (≈ 48,752) with the highest risk estimates. The remaining service members who committed violent crimes (≈ 3,751) were among the 95% of the cohort (≈ 92,6605) with lower risk estimates. So would one focus attention on the 5% of the group at high risk? In a signal detection context, that could yield a Hit Rate (HR) of ≈ 35% of violent criminals (2,020 out of 5,771). But, it would also yield a False Alarm (FA) Rate of ≈ 96% (46732 of 48752 individuals who did not commit a violent crime). That high FA rate, attributable in part to the low base rate of violent crimes, could potentially incur unwarranted costs in, and focus resources towards, nonproductive directions. At the same time, the expected MISS rate would be ≈ 65%, wherein 3751 of the 5771 violent offenders were not so classified.

A similar pattern emerged from the follow-up (2011-2013) test cohort. Despite the somewhat greater percentage (50%) of violent criminal offenders who were in the top 5% risk category, results were minimally valuable in predicting violent individuals. Of the 43,248 service members in this test sample, only 16 committed a violent crime during the study period, 50% of whom were in the top 5% risk status. Thus, in targeting the upper 5%, the HR would be 50% (8 of the 16 violent offenders). The FA rate, however would again be unacceptable high ≈ 99.6% (2154 of 2162 of people in the top 5% that were not violent offenders). The MISS rate would also be high (50%). The FA rate, of course, might be reduced by increasing the classification criterion beyond 5%, assuming some correlation between the probability of a violent offense and the risk level within that highest 5%. This, of course, would likely be at the expense of a lower Hit Rate and a higher MISS rate.

In summary, while it may be possible to stratify risk, or establish risk categories based on population or sample demographics, individual differences, education, mental and behavioral history, and this may have important applications in establishing policies, strategies, and approaches for the criminal justice system and anti-terrorist issues. On the other hand, it becomes far more problematic to predict individual behavior with a high degree of accuracy.

Returning to predictive-policing efforts, a similar pattern emerges. There is some evidence of positive outcomes, in focusing resources on predicted areas or targets of criminal activity. However, a RAND Corporation report (Perry et al., 2013) notes rather inconsistent outcomes in this area, and a recent analysis of a Chicago police effort was rather discouraging also (Hollywood, 2016). The author of that piece and a coauthor on the earlier RAND report, John Hollywood, asserts the advantage over other best-practice techniques is "incremental at best."

So there may be some merit in these approaches, but more to the present point, can predictive policing avert a specific criminal act by dispatching a squad to prevent a specific imminent crime (a la, *Minority Report*)? “That's science fiction”, says RAND's John Hollywood—and likely to stay that way. To predict specific crimes, he says, "we would need to improve the precision of our predictions by a factor of 1000" (Hvistendahl, 2016).

It is not my intention to discourage efforts to identify terrorists or preclude or disrupt terrorist activity. I think the work of Gordon (see above) and others holds out great promise in this arena. But, for specific predictions of terrorist activity, we need specific information, even if derived from nonspecific sources. Examples include the use of social network analysis to identify terrorist cells and their leadership structure (Ressler, 2006; Behavioral Sciences, 2013) and big data approaches to integrating broad aspects of information into patterns (e.g. DARPA XDATA program, http://www.darpa.mil/program/xdata). The latter approach is an effort to integrate otherwise disparate and perhaps fuzzy or nonspecific information into a broad pattern that allows highly specific inferences.

In short, prediction is hard, and probably less specific than we would like, but not impossible. I think an equally important consideration is prevention, rather than, or in addition to, prediction. So how do we develop prevention interventions? That is the big question. Undoubtedly, some of the terms in the equations will be education, equality, social justice, life opportunities and health services. Others will include education, education and education.

References

Gordon, TJ, Florescu, E, Glen, JC, & Sharan, Y (2017). *Identification of Potential Terrorists and Adversary Planning.* IOS Press, Amsterdam NL.

Hollywood JS (2016). CPD's 'Heat List' and the Dilemma of Predictive Policing. Commentary in *Crain's Chicago Business,* Sep 19, 2016

Hvistendahl, M (2016). Can ‘predictive policing’ prevent crime before it happens? *Science*, Sep. 28, 2016

Perry WL, McInnis B, Price CC, Smith SC & Hollywood JS (2013). Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations. RAND Corporation research report. See: http://www.rand.org/content/dam/rand/pubs/research_reports/RR200/RR233/RAND_RR233.sum.pdf

Ressler S (2006). Social Network Analysis as an Approach to Combat Terrorism: Past, Present, and Future Research. *Homeland Security Affairs*, II (2). http://www.hsaj.org

Rosellini, AJ, et al, & Kessler, RC (2016). Predicting non-familial major physical violent crime perpetration in the US Army from administrative data. *Psychological Medicine*, 46, 303–316.