The search for similarity is the cornerstone of any risk assessment. Without the ability to establish similarity there would be no basis for comparison and no rationale for subsequent decision-making. Although the risk assessment field has identified a core set of risk factors over the past 30 years, the field continues to use well-worn statistical methods to create primitive similarity scores by summing risk factor weights. The underpinnings of similarity are discussed in the context of risk assessment and a conceptual framework for creating advanced similarity metrics to increase classification and predictive accuracy is discussed.

There are many approaches to risk tool construction (Brennan, 1993). Each approach is thought to have strengths and weaknesses over the others, but they all share one implicit goal — to compare an offender with other similar offenders and to derive some meaningful information that will help to manage new offenders more effectively. On the surface this is an obvious statement, and perhaps it is this “obviousness” that has caused us to forget the fundamental importance of similarity when constructing new risk tools.

The basic building blocks of any risk tool are its risk factor items. Dow and Streveler (2006) described risk factors as pieces of data about an offender and elaborated, “It isn’t until we know which risk factors are related to something like recidivism do we begin to have information. As we understand how risk factors relate to each other, information emerges to form patterns that alert us to the presence of what we are looking for, in this case, potential recidivism.”

Patterns occur when pieces of data interact with each other in a predictable fashion. Implicit in this statement is the assumption that we have been exposed to an event often enough for our brains to develop an awareness that a pattern exists. This awareness is the process of establishing an internal similarity sensation and has been defined as the true nature of intelligence (Hawkins & Blakeslee, 2004). We isolate these patterns by comparing what we are seeing to what we know. As the similarity between what we are seeing and what we know increases so does our confidence that what we are seeing
will follow a set of predictable “outcomes.” When we can establish a degree of predictability we begin to have information and become active agents in the world.

The risk assessment field uses many of the concepts described above. For example, all current assessment tools assume that they assess some underlying pattern indicative of a trait or outcome. In an effort to capture that underlying pattern the risk factors are summed to produce a similarity score which is associated with an outcome (e.g. a norm table and associated base rate information for a target outcome).

When we encounter a new offender for whom an assessment has been done the score for that offender (what we are seeing) is then compared to the scores of other offenders who comprise a norm table (what we know) and the associated “outcome” for the score is used to guide some decision. On the surface this is a reasonable approach, but understanding the nature of patterns will demonstrate that the traditional approach introduces noise into the similarity metric thereby reducing its accuracy. The reduction in accuracy is quickly understood when we realize that not all pathways leading to a score will carry the same predictive accuracy (Dow, Jones, & Mott, 2005; Silver & Chow-Martin, 2004; Zamble & Quinsey, 1997).

The act of generating a similarity metric by combining all of the ways a score can be generated inadvertently combines highly correlated patterns leading to that score with less correlated patterns leading to that score (this is commonly found in tools that put scores into bands). The net effect is to freeze the similarity metric into something less than what it could be were the similarity metric dynamically created to take into account how the score was generated. A dynamic approach could maximize the information content in a given data pattern and could be directly tied to the associated outcomes to create a probabilistic prediction. Clements’ (1996) review of the field of offender classification was perhaps the first to conceptually contemplate the possibility of bridging ideographic and nomothetic offender assessment with the aim of increasing assessment resolution. Unfortunately, a discussion of how to make that bridge has been lacking in the corrections literature. Fortunately, dynamically created similarity metrics used in other fields demonstrate that bridges can be built.

Dow (1995) described the concept of dynamically created similarity metrics in the context of counseling research. However, the concept also applies to corrections and takes a step away from the current approach used in risk assessment. Dow’s approach might be thought of as “intelligence-based risk assessment” or fifth generation risk assessment. Traditionally, the intricacies of the data pattern are distilled into a score that is then used for comparison purposes. This act loses the uniqueness in the pattern that could have been used to enhance a similarity metric.
In contrast, intelligence-based assessment examines historical data patterns to identify offenders with similar patterns to the offender of interest, and then generates a score. This subtle difference has the net effect of increasing the accuracy of the information content for what we are seeing based upon what we know because the construction of the similarity metric begins by identifying the commonalities between what we are seeing and what we know and excludes everything else.

To illustrate, suppose we have a 10-item risk assessment tool and all items are equally weighted. Further suppose we have three offenders who all test positive for 5 risk factors. Offender #1 is positive for the first 5 risk factors leading to a traditional similarity score of 5. Suppose offender #2 is positive for the last 5 risk factors that also lead to a traditional score of 5. Clearly these two offenders are different — they have no overlap in item content, yet they still generate a similarity score of 5 and would be assumed to be similar on a traditional risk tool by virtue of each having 5 risk factors. Now suppose we have offender #3 who is positive for risk factors 1-4 and 6 thereby generating a similarity index of 5. Offender #1 and offender #3 have more in common with each other than with offender #2.

The construction of an intelligent similarity metric capable of ascertaining the commonality between offenders could potentially maximize the similarity of offender #1 and #3, while simultaneously minimizing or eliminating the effect of offender #2. Such an approach would create the foundation for intelligence-based risk assessment and moves us from static norm tables (e.g. all scores of 5 are assumed to be the same) to a savant-like intelligence capable of extracting information from experience and using like patterns to generate a similarity metric.

The limits of such a savant-like approach are dependent upon the depth of relevant experience (historical data) used for dynamic comparisons and the degree the data is related to our focus (e.g. recidivism, violence, escape, etc). It should be noted that this savant-like intelligence is not akin to the mathematical field of neural networks and should not be viewed from these historical roots. Hawkins and Blakeslee (2004) provide an excellent modern overview of the difference between neural networks and pattern-based intelligence.

Mathematically, the type of similarity method described above is best seen as an extension of the underlying premise of the standard summed approach — offenders occupying similar score regions provide information about how other offenders falling into the same score region might behave. A pattern-based similarity metric simply gains higher resolution by dynamic-intelligence-based identification of similar patterns of risk factors for a given offender from the raw data normally used to create a classical norm table before it creates a “score.” Rather than compressing the pattern to form a
score and then matching the score to similar scores, pattern-based similarity first
matches on the pattern then generates a score thereby achieving higher resolution going
into the “score” generating step. As would be expected each prospective offender being
assessed has the potential of having varying risk factor combinations that might benefit
from higher resolution.

Challenges to such a similarity approach could be marshaled but would be required to
dispute the premise that consistency in the underlying data (i.e. that patterns lead to
consistent outcomes) is the cornerstone of current risk assessment. It is the consistency
of information that forms the underlying data patterns leading to predictability. The
crux of all reliability statistics and ultimately validity depend upon this concept. In
essence, for this challenge to succeed, one must argue that higher resolution would lead
to a decrease in accuracy.

It could also be argued that higher resolution would lead to greater susceptibility to
rater error and a decrease in reliability because more is dependent upon the vagaries of
the “most” similar offender. This is true, however, as previously discussed, a pattern is
indicative of information and dependent upon a frequent enough occurrence to be
deemed a pattern — as stated on a well-known intelligence test, “One swallow doesn’t
make a summer.” As such, a similarity metric that simply selects the most similar data
pattern is not a horribly useful approach because of the risk of outliers, rater error, rater
bias, missing data, rapidly changing data, etc. that might be associated with a single
case.

To overcome aberrant data a large enough subset of similar offenders would need to be
selected to ensure that the noise associated with any particular historical offender rating
could be overcome thereby revealing a true and naturally occurring pattern. In essence,
this is a simple signal detection premise whereby the signal (outcome of interest) is
deemed to be coherent and noise (irrelevant information) incoherent. Signal can be
accumulated via a linear equation, whereas, noise is incoherent and cannot, by
definition, accumulate via a linear equation due to its random nature (McDonough &
Whalen, 1971). Put another way, outliers, rater error, rater bias, missing data, rapidly
changing data, etc. can only contribute to a statistical model if they actually help explain
a consistent outcome.

The caveat to this is the obvious possibility of a competing data pattern indicative of a
different outcome is intermingled with the signal we are trying to detect. For example,
tools that purport to identify recidivism and violence and basing that identification on
the same set of data where it is foreseeable that the data patterns indicative of the two
concepts do not always overlap. Hence, it is extremely important to ensure that the
historical data one uses to construct similarity metrics is tailored to the construct under
study to reduce the possibility that a competing data pattern “overpowers” the pattern for the construct of interest. Advanced detection approaches aimed at signal isolation are under development in other fields (Zhou, Woo, & Sharif, 2005; Duda, Hart, & Stork, 2001) and may provide guidance to the field of offender risk assessment.

Similarity has been discussed in a conceptual framework and compared to the classical approach used to construct most risk assessment tools. This framework is meant to stimulate thinking in the field as to what similarity-based risk assessment tools might become in the future and how a careful consideration of similarity’s purpose can increase the accuracy of risk assessment tools. One such tool, the Risk Management System (2005), has already incorporated advanced pattern-based similarity to render recidivism, violence, and estimates of offender treatment responsivity. Risk assessment tools have evolved over time with respect to their risk factors, now the methods used to create those tools have evolved.

References


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