Postprint: Forthcoming in N. M. Scala and J. Howard (Eds.), Handbook of Military and Defence Operation Research (2nd ed., ch. 16). Boca Raton, FL: CRC Press.

Applying Information Theory to Validate Commanders' Critical Information Requirements

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Introduction

The primary aim of this chapter is to introduce a novel approach to strengthen contemporary intelligence community practices for establishing intelligence collection priorities based on expected information value. We propose the integration of quantitative measures of information utility that have been discussed in the literature on information theory (Lindley, 1956; Nelson, 2005; Crupi & Tentori, 2014) as a method for optimizing intelligence collection planning. We argue that enhancing the effectiveness through which command information requirements are established can improve consequent intelligence collection priorities. We contrast this approach with the structured analytic technique (SAT) approach that is currently described as a method for prioritizing information requirements in intelligence collection. Specifically, we proceed with a review of the Indicators Validator (IV) SAT (Heuer & Pherson, 2008) for establishing information value, illustrating how it works, and where it falls short as an analytic method. Next, we introduce a quantitative information-theoretic measure of information utility called *information gain* (Lindley, 1956). We illustrate the contrast between these approaches using a practical example featuring a hypothetical North Atlantic Treaty Organization (NATO) dilemma. This analysis shows how information gain overcomes many limitations of the IV technique, along with how it might be applied to modern NATO operational practice.

Background - The NATO Intelligence Community Dilemma

Intelligence organizations iteratively explore new ways to assess information value. NATO intelligence professionals inform complex, high-consequence, operational decisions on a routine basis. First established in 1949, NATO's stated purpose is to "…guarantee the freedom and security of its members through political and military means" (NATO, 2017a). Where a NATO force has been deployed to monitor another government's adherence to ceasefire agreements, the success of its mandate could become entirely dependent on its ability to accurately interpret indicators of imminent aggression. Under these circumstances, failing to act when required can be just as damaging as taking action when none is warranted. Intuitively, when charged with such a fragile task, a NATO commander would want to position his forces in such a way that allow the initiation of swift, deliberate, and decisive intervention (if and when required), without adopting a force posture that inadvertently encourages or re-ignites existing tensions between hostile states.

The NATO intelligence community (IC) enhances command understanding of complex environments through the delivery of predictive assessments founded in the deliberate analysis of threat event indicators and warning signs. Whether the analysis is intended to provide context or early warning, or to identify opportunities, it is fundamentally about improving decision-making under conditions of uncertainty (CFINTCOM, 2016, p. 5). Once a mission or political mandate is defined, intelligence professionals are often left to identify which questions, if answered, can most efficiently improve stakeholder decision-making in the context of that mission. We suggest that the consistent, coherent, and precise evaluation of information usefulness during the earliest stages of operational planning is vital to ensuring sound intelligence collection planning, although some literature suggests that members of the operational community often only pay it lip service to this aim (US Government, 2013).

Establishing Command Information Priorities

In order to prioritize organizational resourcing, decision-makers issue a series of information requirements (IR) to subordinate units that subsequently drive intelligence collection efforts. Some of those IR (i.e., questions), when answered, may compel stakeholders to take action, cease action, or have some form of immediate impact on organizational posture. These are often called Commander's Critical Information Requirements (CCIR) (Commander of the Canadian

Army, 2013, p. 3-2). Although commanders issue planning guidance, individual planners (or groups) often develop CCIR through subjective, multi-stage planning processes that vary across organizations. CCIR can drive the assignment of collection resources to fill information gaps (Chief of Defence Staff, 2002, p. 1-2), and they are often presented to non-expert decision-makers for approval without having been formally evaluated to ensure that their answers will actually reduce uncertainty in command decision-making in some appreciable manner (US Government, 2013).

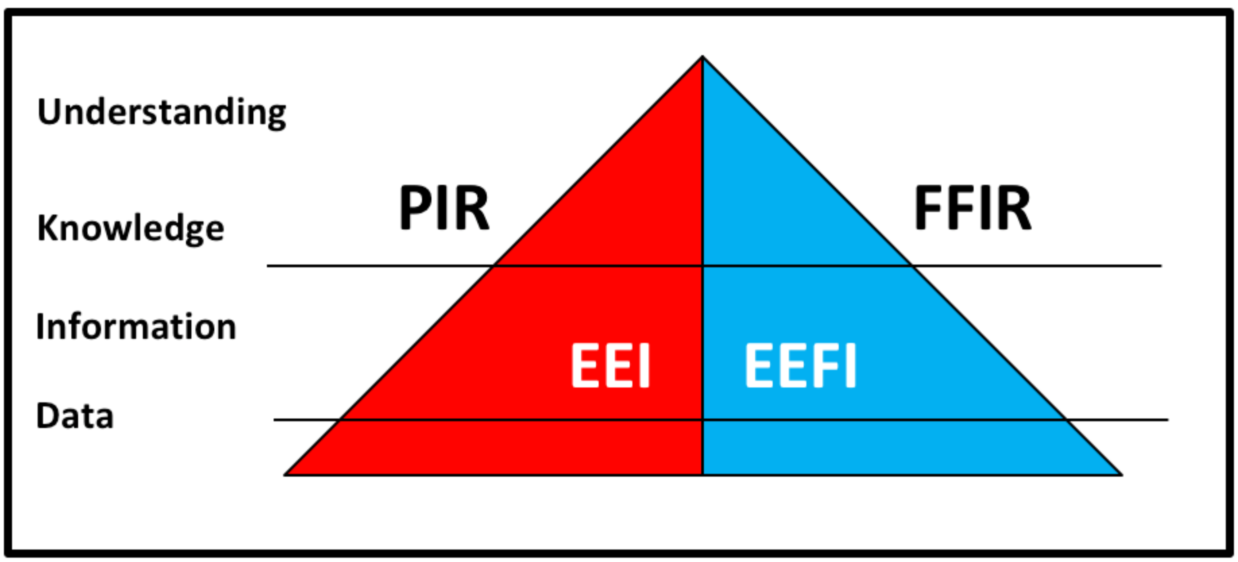

Figure 16.1: Hierarchy of Information Requirements.

Figure 16.1 depicts the hierarchical relationship between Commanders' Critical Information Requirements (CCIR) and related information priorities developed through consequent processes, including Priority Intelligence Requirements (PIR) and Friendly Force Information Requirements (FFIR), each of which drive the defining of Essential Enemy Information (EEI), Essential Elements of Friendly information (EEFI) and more (adapted from US Government, 2013). Numerous agencies may define CCIR (and other consequent IRs) through subjective group (or individual) brainstorming. The success of such exercises will likely depend on the abilities of the individual planner (or planning group), varying in terms of the diversity, size, and breadth of experience (among other items) of the members involved. At the very least, planners must be capable of shaping proposed CCIR from their translation of such intent, through formulating plans to meet those requirements.

The SAT Approach

The IV technique that we consider later in this chapter is an example of the SAT approach adopted over several decades within many NATO countries. The development of SATs started out as a rather idiosyncratic, path-dependent endeavor spearheaded by US intelligence tradecraft mavericks, such as Richards Heuer Jr. and Jack Davis, who took it upon themselves while working at the Central Intelligence Agency (CIA) to develop back-of-the-napkin techniques to aid intelligence analysts (Mandel, 2020; Mandel & Tetlock, 2018). The impetus for developing such methods was, in large part, the belief that analysts were prone to cognitive biases that SATs would help effectively overcome. In this view, SATs could be used to structure the otherwise unbridled intuitions of analysts and to tame their purported wanton subjectivity or biased intuitions. The effort to develop SATs and require that analysts be trained to use them received intermittent commitment within the US IC until pivotal geopolitical events—namely, the 9/11 terrorist attacks against the US by Al Qaeda and the faulty, invasion-prompting intelligence estimate that Saddam Hussein was developing weapons of mass destruction in Iraq—triggered congressionally mandated institutional reforms that required the use of SATs by the US IC (Artner, Girven, & Bruce, 2016; Chang, Berdini, Mandel, & Tetlock, 2018; Coulthart, 2017; Marchio, 2014). The CIA's tradecraft manual originally included 12 SATs (US Government, 2009), but the list of SATs has burgeoned to now include several dozen such techniques (Heuer & Pherson, 2008; 2014).

The body of scientific research on SATs (and analytic tradecraft, more generally) remains scant (Chang et al., 2018; Dhami, Mandel, Mellers, & Tetlock, 2015; Mandel, 2019, 2022; Pool, 2010). Unfortunately, the IC has tended to assume that even if SATs aren't beneficial, they are at worst benign. SAT proponents will often admit that SATs "aren't perfect", but they are usually quick to add that they are "better than nothing." However, recent evidence indicates that the latter supposition may be false. Mandel, Karvetski, and Dhami (2018) studied the effects of training intelligence analysts in the use of one particular SAT, the Analysis of Competing Hypotheses (ACH; Heuer, 1999; Heuer & Pherson, 2014). Remarkably, analysts who used that

SAT to assess the probability of alternative hypotheses were significantly *less* coherent and also less accurate in their judgments than analysts who were not instructed to use any SAT. However, Mandel et al. (2018) also found that quantitative recalibration and aggregation techniques could be applied to analysts' judgments to substantially improve probabilistic accuracy. These results are not unique: other experiments investigating the purported, ameliorative bias-reducing powers of ACH have yielded similarly disappointing results for ACH (e.g., Dhami, Belton, & Mandel, 2019; Karvetski & Mandel, 2020; Karvetski, Mandel, & Irwin, 2020; Maegherman, Ask, Horselenberg, & van Koppen, 2021; see Wilcox & Mandel, 2023, for a review) and at least one other study has confirmed the benefit of statistical recalibration and aggregation methods (Karvetski et al., 2020; for a review of such methods, see Collins, Mandel, & Budescu, in press).

Such findings should not be unexpected given that SATs, more generally, are subject to two important conceptual shortcomings (Chang et al., 2018; Mandel & Tetlock, 2018). First, they neglect the fact that most cognitive biases are bipolar (e.g., calibrated confidence is offset by underconfidence *or* overconfidence) and they fail to assess the types of biases analysts are in fact prone to before intervening. For instance, while bias-awareness training for analysts often focuses on the problem of overconfidence, there is evidence that analysts' anticipatory estimates are often underconfident (Mandel & Barnes, 2014, 2018). A focus on confidence reduction might inadvertently serve to increase cognitive bias. Second, SATs neglect the cost of noisy judgments that follow from techniques that, though supposedly objective, in fact invite a range of implementation-related decisions that are left to analysts' discretion. For example, guidance on ACH fails to specify precisely how core concepts such as *consistency* and *diagnosticity* should be assessed. Thus, SATs may do more to redirect subjectivity from substantive assessment to resolving methodological vagueness or ambiguity.

Few SATs focus explicitly on evaluating information utility. Those that do are geared towards establishing the predictive value of threat event indicators in the context of impending hypothetical threat events; namely, the Indicators (Heuer & Pherson, 2008; 2014, p. 149) and Indicators Validator™ (IV) (Heuer & Pherson, 2008; 2014, p. 157) SATs. Indicators are defined as: "…observable phenomena that can be periodically reviewed to help track events, spot emerging trends, and warn of anticipated changes" (Heuer & Pherson, 2008; 2014, p.149). The Indicators SAT encourages analysts to leverage their personal experience in concert with easily accessible information in the development of a detailed indicators list. This list reflects a "pre-established set of observable or potentially observable actions, conditions, facts, or events whose simultaneous occurrence would strongly argue that a phenomenon is present, or at least highly likely to occur" (Heuer & Pherson, 2008; 2014, p.149). Heuer and Pherson's Indicators SAT encourages analysts to build a list of indicators presumed to be associated with hypothetical threat events.

For instance, if you were away from any smart device and wondering whether it was going to rain, you might reflexively consider subjectively gauging the ambient barometric pressure, listening for thunder, or perhaps looking for lightning. Heuer and Pherson's (2014) Indicators SAT suggests that NATO intelligence professionals perform similar exercises when attempting to predict events of operational interest. Hypothetical examples include (but are not limited to): whether a political official will be re-elected before cease-fire agreements are signed, the volume of refugees that might move down a series of different corridors in the aftermath of a natural disaster, or whether a small military force might suddenly annex a sovereign bordering state. Whereas the Indicators SAT focuses on indicator definition, its companion IV SAT aims to assist analysts in establishing the predictive value of indicators in the context of a given threat event scenario. In the next section, we review the IV SAT and examine its performance. Later, to illustrate differences between the IV SAT and more formal models of information utility, we introduce a relevant example inspired by NATO's Enhanced Forward Presence (EFP) forces stationed in Eastern Europe.

The Indicators Validator SAT

Introduced by Heuer and Pherson in 2008, the IV SAT focuses on establishing the predictive value of an indicator based on how exclusively it indicates a focal hypothesis or threat scenario among a set of scenarios (Heuer & Pherson, 2008; 2014). According to Heuer and Pherson, indicators are "…observable phenomena that can be periodically reviewed to help track events, spot emerging trends, and warn of anticipated changes" (2008, p. 149).

To use the IV SAT, analysts must first identify a list of mutually exclusive and collectively exhaustive threat scenarios (sometimes called hypotheses) to be predicted. These can be multi-alternative (Event A: Person X is elected, Event B: Person Y is elected, Event C: Person Z is elected) or binary (yes/no, happened/did not happen). Each scenario is accompanied by a list of primary indicators that analysts believe would be likely to be present if that scenario were to occur (or if the hypothesis were true). Indicators that are generated for a particular scenario are said to be *at home* for that scenario and are not *at home* for the alternative scenarios. That is, any given indicator can only be *at home* in one scenario for the IV SAT to work as intended. However, any given scenario may have multiple indicators that are *at home* in it.

After assigning indicators to their home scenarios, the analyst must judge whether each indicator is to be rated as *likely* or *highly likely* in its home scenario, as this will affect the consequent information value scoring procedure (see Figure 16.2). At this stage, the analyst cannot select other probability values (e.g., *very unlikely*) to represent the indicator. In other words, an indicator that is *at home* must be judged to be either *likely* or *very likely*, given that scenario. Next, the likelihood of each indicator given each of the alternative scenarios is assessed. For example, if an indicator is deemed to be *highly likely* given the home scenario, then numerical values would be assigned to the indicator in the alternative scenarios as a function of how divergent they are from the original *at home* rating using the following coding scheme: *highly likely* = 0 (i.e., no divergence), *likely* = 1, *could* = 2, *unlikely* = 4 *highly unlikely* = 6 (i.e., maximum divergence; Heuer & Pherson, 2014, p. 159). The IV SAT makes an adjustment for whether the indicator is *highly likely* or only *likely* in the home scenario; if it is judged to be *likely*, a similar rating scheme is applied but the "distance scores" are smaller in magnitude (Heuer & Pherson, 2014, p. 159). Finally, the analyst would sum the distance scores assigned to the alternative scenarios. The greater the summed distance score, the more useful a given indicator is deemed to be.

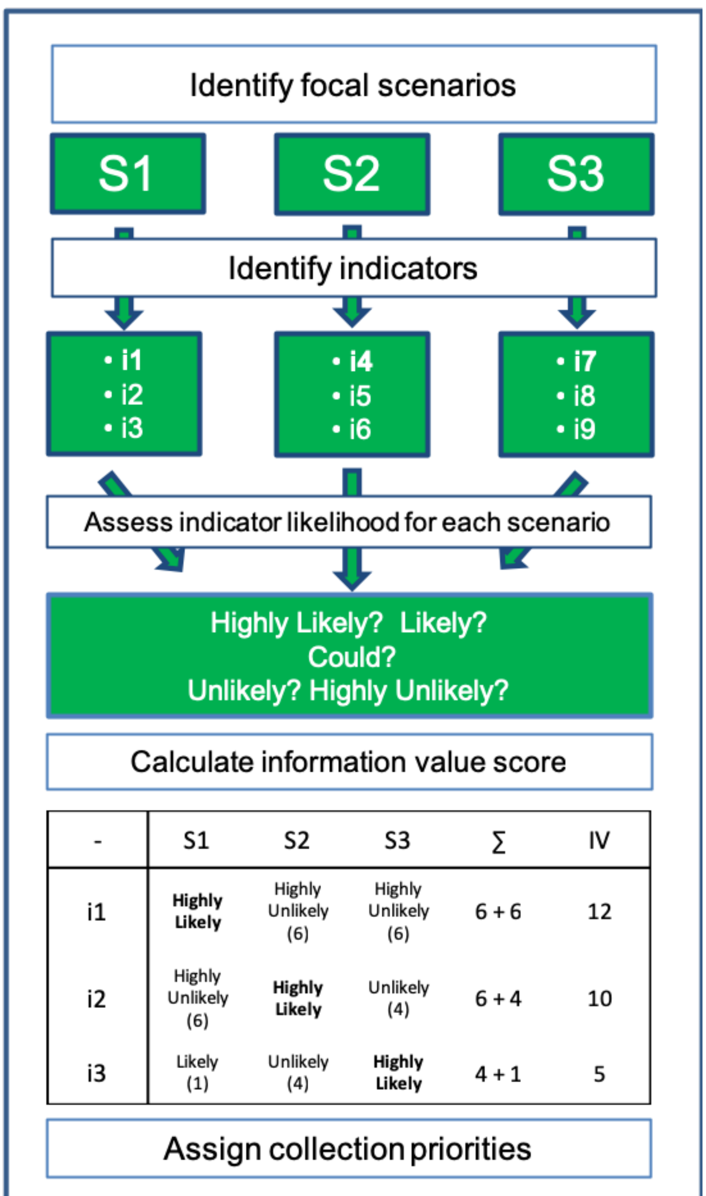

Figure 16.2: The Indicators Validator Model (Heuer & Pherson, 2014, p. 157).

Analysis of the IV SAT

The IV SAT is a simple method for scoring the usefulness of different indicators. The ordering of the steps in the technique is easy to follow and the application of the IV SAT does not require mathematical sophistication. Nevertheless, despite its ease of application, the IV SAT has important limitations that could lead collectors astray and misinform analysts and intelligence consumers.

One problem with the technique is the arbitrariness of matching indicators to home scenarios. For an indicator to be *at home* it must be judged either *likely* or *very likely* given the scenario. However, it may be judged equally likely under other scenarios, in which case the indicator might just as well have been *at home* in those scenarios. This aspect of the technique highlights another sense in which it is arbitrary—namely, it disallows negative hypothesis tests in which one searches for indicators that may be (*very*) *unlikely* if the scenario were true. Detecting the presence of such low probability events can be highly informative, yet the IV SAT precludes such a focus in prioritization of information requirements. One remarkable implication of this constraint is that the complement of a good indicator (i.e., one that has low probability in the home scenario but high probability in all other scenarios) would be precluded from being considered. This is not only arbitrary; it is logically incoherent since one can achieve the same distance (as a measure of information value) in this prohibited manner.

Another limitation of the IV SAT is that it does not require or even prompt analysts to consider the prior probability of scenarios or indicators. It does not do so either in terms of collection of objective, relative frequency data that could be used to establish base-rate estimates or in terms of subjective estimates of these relative frequencies, which could also be useful. This critical base-rate information is accounted for in virtually all information-theoretic models (Lindley, 1956; Nelson, 2005, Wu, Meder, Filimon, & Nelson, 2017), and also in Bayesian approaches to belief revision (Navarrete & Mandel, 2016). Collection resources are not unlimited (Folker, 2000), necessitating careful evaluation and IR prioritization. We suggest that it would be useful to first establish how likely a commander is to correctly predict an outcome based on what is already known about event base rates, and then to evaluate the utility of information in the context of how much it improves event predictability over reliance on prior probabilities alone. If that which is already known about a given threat event can enable a commander to confidently predict its occurrence, collection assets might more efficiently be directed towards answering questions that would measurably reduce uncertainty associated with other events.

Consider an indicator that would almost certainly signal the occurrence of Scenario 1 (Attack) –

such as an intercepted Russian correspondence directing military forces to cross their border at a given time – where the actual probability of an attack occurring was assessed to be extremely low. The IV SAT would award a high information value score to that indicator, plausibly resulting in it becoming a priority collection item, despite the fact that its likelihood of appearance is significantly less likely than competing indicators in other scenarios, because it is *at home* in an improbable scenario.[1]

Another limitation of the IV SAT is that it relies on the assignment of vague linguistic probabilities as a precursor to judgments about information utility. Linguistic probability terms such as *likely* and *very likely* can take on a wide range of meanings by different individuals and even by the same individuals across different contexts (for reviews, see Dhami & Mandel, 2021, 2022). Moreover, some intelligence organizations stipulate in lexical schemes what such terms should be taken to mean (e.g., Dhami & Mandel, 2021; Ho et al., 2015; Mandel & Irwin, 2021b), whereas other intelligence organizations may have no such guidelines. Moreover, the schemes that are in use are often inconsistent across intelligence-sharing partners in that the same terms are mapped to different numeric ranges (Dhami & Mandel, 2021) and analysts often do not conform to them in their interpretations even if they are presented with the lexical schemes (e.g., Ho et al., 2015). Recently, it was further shown that the unreliability in analysts' interpretations of linguistic probabilities, such as those used in the IV SAT, substantially reduced the accuracy

[1] The authors acknowledge that recent geopolitical events (e.g.: the February 2022 Russian invasion of Ukraine) make this scenario less easy to imagine as improbable.

of strategic intelligence viewed from the receivers' perspective (Mandel & Irwin, 2021a).

The IV technique is the only information evaluation SAT featured in open-source intelligence analytic tradecraft manuals for both Canadian military (CFINTCOM, 2016) and American (US Government, 2013) intelligence agencies. Unfortunately, for the reasons noted, it lacks a sound, logical foundation. However, its vague quantification of individual probability judgments using linguistic probabilities on an ordinal scale, and the procedures used for calculating a final information value score for an indicator, can lead analysts to believe that they are following a valid, even objective, method. Of course, the patina of objectivity in methods could also sway the confidence of commanders that the analysis they are acting on is sound.

The IV SAT assigns indicator value as a function of how strongly its presence predicts a single threat scenario. The final information value score focuses only on the extent to which the indicator can discriminate between the scenario in which it is *at home* and alternatives in the same set. This could dramatically reduce efficiency in collection planning. In our example, for simplicity, we limit the number of threat scenarios to three. But in many cases, there will be multiple threat scenarios of interest that are thematically similar but ultimately distinct. In such cases, a low information value score for an indicator could be deceiving. Furthermore, consider an indicator that is strongly associated with the occurrence of all but one scenario. IV would give such an indicator a low information value score, despite the fact that it could reliably help a

NATO commander predict the event in which it is not present.

With this in mind, we present an alternative approach to evaluating and prioritizing command information requirements, using information gain (Lindley, 1956; Nelson, 2005). In many ways, the structure of information-theoretic measures compels increased analytic reasoning, as the various inputs of the information gain formula may require the conduct of research, or the deliberate assignment of a numeric probability to a threat event scenario or its co-occurrence frequency with indicators. Importantly, information gain requires some input values for the probability of each scenario. The need to include estimates about each scenario's probability can encourage analysts to reduce the uncertainty associated with an entire problem, rather than pursuing information associated with events that may already be relatively easy to predict.

Information Gain: A Principled Approach to Evaluating Indicator Usefulness

In this section, we describe a quantitative information-theoretic measure of information utility called *information gain* that measures the average reduction in uncertainty achieved by using a specific indicator or cue (Lindley, 1956; Nelson, 2005). Information gain is an example of an information utility function, a mathematical formula designed to compute a quantitative estimate of utility for a piece of information. Superficially, information utility functions, like information gain, require similar inputs to those required when using the IV SAT. The basic principle remains: first, define information gaps (i.e., what one wants to know); next, identify what questions (and answers) might help fill them. The expected information value of a question is ultimately defined as the expected value of the not-yet-obtained answer, although the value of specific answer could also be calculated (Nelson, 2005; 2008). In contrast to the IV SAT, information gain has been effectively used in a variety of domains, such as automatic face recognition systems (Imaoka & Okajima, 2004), image registration (Chen, Arora & Varshney, 2003), predicting human queries (Crupi et al., 2018), philosophy of science (Crupi & Tentori, 2014), and modeling neurons in visual (Ruderman, 1994; Ullman, Vidal- Naquet, & Sali, 2002) and auditory perception (Lewicki, 2002). The contrast between the IV SAT and information gain exemplifies recent suggestions in intelligence studies (Mandel & Irwin, in press; Mandel & Tetlock, 2018) that the intelligence community looks beyond the SAT approach and its focus on cognitive bias minimization to alternative processes including statistical optimization methods (like information gain) that could directly focus on improving intelligence.

Computing Information Gain

Information gain quantifies the utility of a given indicator as a function of how effectively its presence or absence reduces uncertainty about a hypothetical event of interest (Nelson, 2005). Lindley (1956), Box and Hill (1967), and Fedorov (1972) quantified this idea explicitly, using Shannon's (1948) entropy to measure the uncertainty in the outcome of a specific event. We measure information with base 2 logarithms (bits). Other bases could also be used. If the natural logarithm is used, the unit is *nats*.

For the purposes of defining information gain, let $Q = \{q_1, q_{2, \dots} q_m\}$ represent a query (in mathematical terms, a random variable), in this case, the option of querying the value of a particular threat event indicator or command information requirement. Let each q_j represent one of the m possible answers to the question Q. Let $H = \{h_1, h_2 \dots h_n\}$ represent the unknown hypothesis (or category or threat scenario) one is trying to predict. Finally, let each of the n possible h_i represent a specific hypothesis in the set of possibilities (i.e., a list of mutually exclusive and exhaustive threat event scenarios). Equation 1 shows the information gain calculation:

$$I(H,Q) = \left[\sum_{i=1}^{n} * P(h_i) * \log_2 \frac{1}{P(h_i)}\right] - \left[\sum_{q=1}^{m} P(q_j) * \sum_{i=1}^{n} * \ P(h_i|q_j) \ * \ \log_2 \frac{1}{P(h_i|q_j)}\right] \tag{16-1}$$

Information gain for a given indicator is equal to the initial entropy minus the entropy that is expected (on average) to be remaining after the indicator's state (e.g. present or absent) is observed. In other words, information gain measures the change in Shannon entropy from before (i.e., base-rate scenario uncertainty) to after consideration of the indicator's state (Nelson, 2005). Information gain can be used with indicators having two or more possible states. If information gain were used to prioritize collection, then the indicator with greatest expected reduction in uncertainty across the whole set of threat scenarios would be rated as the top priority for subsequent collection activities. Information gain is also known as the mutual information (Cover & Thomas, 2012) between the hypotheses of interest H and the indicator Q.

Applying the IV SAT and Information Gain to the NATO Example

Think back to a time before the current Russian invasion of Ukraine and imagine the following hypothetical scenario. There are numerous battalion-sized (300-1300 soldiers) military units from contributing NATO member nations occupying a defence and deterrence posture in several countries along the Russian border (NATO, 2017b). If one of these units intercepted correspondence that Russia intended to conduct a large-scale training event in the near future, this might trigger the formation of an incident-based planning group, where available staff officers would convene and think through new information with a view to presenting their commander with options for implementation. Imagine that a planning group is convened. The group must generate a prioritized list of information requirements associated with the Russian exercise, with a view to helping their commander determine their force posture during the exercise, whether reinforcements will be required, and more.

Using the IV SAT, the group would first flesh out a list of mutually exclusive and collectively exhaustive hypotheses, each of which might compel their commander to take or delay a specific action (kept relatively simple here, see Table 16.1). Scenario 1, from the infantry: the Russians are staging for an attack. The infantry planner also proposes her top indicator for this scenario: live ammunition. The idea is that if the Russians were staging for an attack, they would most certainly be carrying live ammunition. Scenario 2, from the logistician: The Russians intend to carry out a training exercise, sincerely aiming to improve the quality and professionalism of their forces through the practice of large military maneuvers. The logistician highlights that soldiers feed differently under combat conditions than they do in training. Large-scale training events are likely to implicate the use of a non-tactical field feeding kitchen system for soldiers participating in training. Finally, the public affairs officer proposes another possibility, Scenario 3, namely that the Russians are actually posturing, conducting a show of force to NATO, to communicate that the multinational posture has not impacted their resolve. The public affairs officer further suggests that, if this scenario were to occur, the Russians would communicate their message through deliberate media events, such as press conferences.

Next, planners debate indicator/scenario co-occurrence frequencies. In Table 16.1, I1: Live Ammunition is *at home* in S1: Attack. The planners judge that Russian soldiers are *highly likely* to be carrying live ammunition when they stage before a combat event. I1 is agreed to be *highly unlikely* to be present in the other two scenarios, which earns it an IV information value score of 12, thus moving it to top priority for collection assets, followed closely by I2 (IV score: 10), with I3 well behind its companions (IV score: 5). Thus, the IV SAT prioritizes the indicators as follows: I1 > I2 > I3. Because these numbers are generated on an ordinal scale, differences in information value score do not directly reveal proportional increases (i.e., the fact that I3 = 5, and I2 = 10 does not mean that I3 is half as valuable as I2).

Insert

Table 16.1: IV Matrix for the Scenario. Estimates for *at home* indicators are bolded.

Here.

Next, we consider how information gain might be applied in this scenario. In Table 16.2, we have included additional planner estimates of event base rates for each of the threat event scenarios, where the probability (*P*) of S1, a deliberate military attack, is considered low (1%); the other scenarios are deemed much more likely to occur, with the probability of an exercise (S2) at a 33% chance, and the probability of posturing (S3) at a 66% chance. Table 16.2 illustrates that the information value scores applied to the same indicators using information gain produce the opposite prioritization as the IV SAT. That is, using information gain, the expected values (in bits) of the indicators are: I1 = 0.0249, I2 = 0.0408, and I3 = 0.2722. This results in a collection priority assignment of I3 > I2 > I1. Clearly, the choice of method used to evaluate information usefulness can have dramatic consequences, including the full reversal of recommended collection priorities.

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Table 16.2: Information Gain Assessment for the Scenario.

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Discussion

As demonstrated in our example scenario in Tables 16.1 & 16.2, both the IV SAT and information gain can be used to facilitate prioritization of IR in support of information collection and decision-making. The IV SAT generates a rank-ordered list of indicator usefulness. Information gain provides a continuous measure of the expected information value of alternative indicators. Although both the IV SAT and information gain require analysts to assess probabilities, the IV SAT imposes arbitrary constraints on what probabilities may be applied. Indeed, for the focal ("home") hypothesis, only two possibilities are permitted: *likely* or *highly likely*. In contrast, information gain does not impose arbitrary rules on probability assignment. Notably, it does not require the arbitrary assignment of indicators to a single (*at home*) hypothesis, and it avoids such a process for good reason: the world simply does not conform to such a requirement. Forcing analysts to assume a structure to the world that simply isn't so cannot be beneficial to analysis and subsequent command decision-making.

Unlike the IV SAT, information theoretic measures such as information gain do not impose coarseness on the probabilities assigned. Recent research has shown that imposing coarseness on more granular probability judgments reduces accuracy across a wide range of conditions (Friedman, 2019). Although analysts may initially balk at the idea of providing more granular judgments, Barnes (2016) found that they rapidly adjust to making granular assessments and are willing to debate about differences that would otherwise have been obscured. Numeric probabilities are also viewed as more informative by both laypeople (Collins & Mandel, 2019) and intelligence experts (Irwin & Mandel, 2023). The use of information-theoretic measures is therefore in step with recent recommendations to use numeric probabilities in intelligence production (Barnes, 2016; Dhami & Mandel, 2021; Friedman, 2019; Irwin & Mandel, 2019; Mandel & Irwin, 2021a, 2021b).

Strikingly, our hypothetical NATO example shows that the IV SAT can deliver information collection priorities in total opposition to those generated by information gain. Given that information gain (in contrast to the IV SAT) has proven itself robust and useful over many decades in diverse contexts, this striking discrepancy should be disconcerting to operational communities that rely on the IV SAT or something like it. Why do the IV SAT and information gain contradict each other in this example? A key reason is that information gain accounts for the base rate of each threat scenario when computing information value. By comparison, the IV SAT is fully insensitive to these base rates. In this sense, the IV SAT formalizes, and perhaps even reinforces, base-rate neglect (Bar-Hillel, 1980; Kahneman & Tversky, 1973), whereas information-theoretic measures like information gain should mitigate this form of bias. It is perhaps notable that another SAT—namely, ACH—was found to promote base-rate neglect in analysts when compared to a control group of analysts who were not instructed to use a SAT (Dhami et al., 2019). In contrast, the introduction of information gain (or any other quantitative information theoretic model) to intelligence predictions compels the deliberate consideration of base rate frequencies for threat event scenarios and indicators, fundamentally strengthening the quality of analytic outputs over any SAT available today.

Information-theoretic metrics such as information gain could be tested through future research, completed in collaboration with military intelligence professionals, or anyone seeking to strengthen the manner in which they establish and validate command information requirements, on and off the battlefield. Information gain, based on expected reduction in Shannon entropy across the set of all possible hypotheses, is a widely used method. However, expected reduction in other kinds of entropy measures or qualitatively different information utility functions could also be used. The differences between information gain and related information-theoretic approaches are in many cases not dramatic (Nelson, 2005), in contrast with the differences between information gain and the IV SAT. For conciseness and because of its robustness and wide use in many domains, we have based the numeric example in this chapter on information gain. Nelson (2005, Appendix A) provides example numeric calculations, and Crupi et al. (2018) show how many different entropy and information measures from mathematics and physics can be articulated within a unified formal framework.

In future work, it would be worthwhile to go beyond our toy example and to consider actual relevant scenarios using these methods, considering also which of many possible methods are most appropriate. It would also be useful to consider the implications of including extra-informational factors, such as the cost of acquiring specific pieces of information, and potentially asymmetric costs of different kinds of mistakes, such as false-positive versus false-negative errors, when evaluating the expected usefulness of possible indicators (Nelson & Meder, 2012). A further qualification is that in our scenario, we consider the usefulness of each indicator individually. Depending on the dependency structure in the domain, if more than one indicator can potentially be queried, it may be necessary to evaluate the information value of possible sequences (decision trees) of indicator evaluation. The information-theoretic approaches generalize naturally to situations with known dependencies among indicators (see Nelson, Meder & Jones, 2018).

Since access to quantitative, frequentist data for intelligence analysis is often lacking (Spielman, 2016), future research might also explore optimal methods for compiling, organizing, and structuring such intelligence data. Additionally, since there is currently considerable apprehension in the intelligence community to using quantitative methods that require at least a rudimentary understanding of statistics and probability, intelligence management would have to better train analysts in these respects. Even brief training in probabilistic reasoning using natural frequency formats has been shown to improve analysts' logical coherence and accuracy (Mandel, 2015). Such training might even help analysts use verbal probabilities more effectively as research has shown that superforecasters (i.e., elite forecasters whose accuracy is at or above the 98th percentile in a forecasting pool) have more reliable and discriminating use of verbal probabilities across geopolitical contexts than regular forecasters or undergraduates (Mellers, Baker, Chen, Mandel, & Tetlock, 2017). Intelligence organizations might do well to de-emphasize training that is of questionable value, such as current SAT tradecraft training (Chang et al., 2018; Mandel, 2019). Rather than introducing new SATs that may have no more than a patina of validity, it would be useful -- as in the case of evaluating the expected usefulness of potential information sources -- to consider whether other disciplines have robust techniques that could be adopted in defense and security contexts. As noted elsewhere (Dhami et al., 2015; Mandel, 2019, 2022; Mandel & Tetlock, 2018; Pool, 2010), in support of that objective, the defense and security community should exploit the interdisciplinary decision sciences.

Acknowledgements

Correspondence concerning this chapter should be sent to Mark Timms at mark.timms.dnd@gmail.com We thank two anonymous reviewers and the editors for their feedback on earlier drafts of this chapter. This work was funded by Canadian Safety and Security Program projects CSSP-2016-TI-2224 and CSSP-2018-TI-2394 under the scientific direction of

David Mandel. The work described in this chapter also contributed to NATO Systems Analysis and Studies Panel Research Task Group on Assessment and Communication of Uncertainty in Intelligence to Support Decision Making (SAS-114) and was reported in Timms, Mandel, and Nelson (2020).

Exercises and Discussion Questions

16.1. This chapter puts the spotlight on one structured analytic technique—namely, the Indicators Validator technique. After reading the chapter, what would you identify as the primary strengths and weaknesses of this method? Do the strengths outweigh the weaknesses, in your view? Justify your answer.

16.2. The information gain metric was presented as one alternative to the Indicators Validator technique. After reading the chapter, what would you identify as the primary strengths and weaknesses of this method? Do the strengths outweigh the weaknesses, in your view? Justify your answer.

16.3. What are the two general problems with structured analytic techniques outlined by Chang, Berdini, Mandel, & Tetlock (2018)? Which of these problems do you think is the more serious one? Justify you answer.

16.4. Both of the methods considered in this chapter for validating commanders' critical information requirements rely on human analysts. Aside from the potential for bias, human information collection and analysis can move slowly and yet operational tempos often require speed and agility. With that in mind, reflect on how advances in the use of machine learning and artificial intelligence might transform the analytic landscape in coming years.

16.5. Since the first publication of this chapter in 2020, Russia invaded Ukraine. A central worry of senior policymakers, military commanders and the public at large is whether the current confrontation could go nuclear and how to read the signs. What indicators do you think could be most valuable for assessing the prospect of an escalation to nuclear war? What are the most credible hypotheses for the future regarding this issue and how would you rank their probability?

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