

The Lockwood Analytical Method for Prediction within a Probabilistic Framework

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Abstract

A critical aspect of the role of intelligence, within the context of conflict situations involving national level actors, is the reduction in uncertainty associated with ascertaining information relevant to policy makers. Structured techniques for intelligence analysis seek to reduce this uncertainty by the implementation and use of stepwise methods in which each step within the process is transparent and through which the uncertainty generated by cognitive bias is limited. One such method, which serves as the contextual basis for this study, is the Lockwood Analytic Method for Prediction (LAMP). The focus of the study is the recasting of traditional implementation of this specific structured method for intelligence analysis within a simplified probabilistic framework using basic definitions and Bayes' theorem. The resultant is shown to one in which the original twelve steps are reduced to four and through which the metrics for uncertainty, focal events and event transposition are inherently encoded.

Introduction

Intelligence, as an abstract construct with a paraphrased dictionary definition of the ability to use reason to comprehend novel or difficult situations, takes concrete form when applied within the relatively broad field of security studies.¹ Richelson, in addressing intelligence in reference to a particular target (e.g. foreign intelligence or domestic security intelligence), adopts a definition of the product resulting from the collection, processing, integration, analysis, evaluation, and interpretation of all available information regarding the target.² Lowenthal defines intelligence as a subset of information that not only relates to the known needs of policymakers but that has been collected, processed, and disseminated to meet those needs.³ Clark defines intelligence as being about reducing uncertainty in conflict and having ubiquitous concern with a target.⁴ Finally, the US Federal Bureau of Investigation (FBI) provides both a simple definition and a tripartite definition based upon practice.⁵ The former consists of analyzed and refined information that is useful to policymakers in making decisions pertaining to potential threats to national security. The latter is inclusive of the simple definition along with the process required to generate finished products from raw data as well as the organizations that are involved in the process.⁶

The individual components highlighted in Richelson's definition appear, either discretely or as elements of broader categorical classifications, in varying arrangement, when considering literature definitions of the intelligence process. One very common arrangement is that of a sequential and cyclical arrangement termed the Intelligence Cycle.⁷ Richelson notes that the general cyclical definition consists of the sequential steps of planning and direction (i.e. tasking), collection, processing, analysis and production, and dissemination.⁸ Clark depicts the traditional Intelligence Cycle as consisting of the sequential steps of ascertaining requirements and needs, planning and direction, collection, processing, analysis and production, and dissemination.⁹ Bruce and George, based upon information adopted from the Office of the Director of National Intelligence (ODNI), depict the Intelligence Cycle as tripartite and consisting of collection, analysis and production and dissemination.¹⁰ The requirements associated with tasking are shown as an incipient but external process. The cyclical view of the intelligence process is pervasive, in regards to depiction, across a number of organizations within the US Intelligence

¹ Merriam-Webster, "Intelligence," 2012, available at: <http://www.merriam-webster.com/dictionary/intelligence>.

² Richelson, Jeffrey, *The US Intelligence Community*, 5th ed. (Boulder, Colorado: Westview Press, 2008), 2.

³ Lowenthal, Mark, *Intelligence. From Secrets to Policy*, 4th ed., Kindle ed. (Washington, D.C.: CQ Press, 2009), Chapter 1, paragraph 4.

⁴ Clark, Richard, *Intelligence Analysis: A Target-Centric Approach*, 2nd ed. (Washington, D.C.: CQ Press, 2007), 8.

⁵ Federal Bureau of Investigation, "Intelligence defined," 2012, available at: <http://www.fbi.gov/about-us/intelligence/defined>.

⁶ It should be noted that these definitions are not the sole definitions present in the literature. Additional definitions include those discussed within the following: William Lahneman, "The Need for a New Intelligence Paradigm," *International Journal of Intelligence and CounterIntelligence* 23:2 (2010): 201-225.

⁷ The equivalent arrangement is that of sequential linearity with feedback from the terminus component to the initial component.

⁸ Richelson, *US Intelligence Community*, 4.

⁹ Clark, *Intelligence Analysis*, 10.

¹⁰ Bruce, James and Roger George, "Intelligence Analysis – The Emergence of a Discipline," in Roger George and James Bruce (eds.), *Analyzing Intelligence: Origins, Obstacles and Innovations* (Washington, D.C.: Georgetown University Press, 2008), 8.

Community (USIC). The ODNI managed website, intelligence.gov, under the subheading of “How Intelligence Works,” provides two alternatively labeled but descriptively equivalent formulations.¹¹ The first consists of management, data gathering, interpretation, analysis and reporting, and distribution. The second consists of planning, collection, processing, analysis and dissemination. A previous version of the ODNI’s cyclical depiction of the Intelligence Cycle consisted of planning and direction, collection, processing and exploitation, analysis and production and dissemination.¹² This description and depiction mirrors that of the US Central Intelligence Agency (CIA).¹³ The FBI defines the process as being cyclical and consisting of requirements, planning and direction, collection, processing and exploitation, analysis and production, and dissemination.¹⁴ This particular formulation provides one additional twist by showing the flow of information as being bidirectional between immediately adjacent steps. This proposed cyclical arrangement has not been without substantial criticism and alternative conceptual frameworks, including Clark’s target centric approach, have been proposed.¹⁵

Regardless of the particular framework that is utilized to conceptualize the intelligence process, analysis of information, either listed singularly or in concert with other procedures, is an unsurprisingly included necessity. Uncertainty, as per Clark’s definition of intelligence, and the concept of the target of enquiry, are related in the logical framework provided within the following two definitions of the term “analysis.” Richelson defines analysis as the *integration* of all raw intelligence information that has been collected into a finished product.¹⁶ The definition propounded by the FBI both mirrors Richelson’s definition and provides additional information.

“Analysis and production is the conversion of raw information into intelligence. It includes integrating, evaluating, and analyzing available data, and preparing intelligence products. The information’s reliability, validity, and relevance is evaluated and weighed. The information is logically integrated, put in context, and used to produce intelligence. This includes both ‘raw’ and finished intelligence. Raw intelligence is often referred to as ‘the dots’ – individual pieces of information disseminated individually. Finished intelligence reports ‘connect the dots’ by putting information in context and drawing conclusions about its implications.”¹⁷

Germane to the subject discussion is the concept of developing information, previously unknown, to a particular target or targets, within the construct of an intelligence question or multiple intelligence questions. The ascertainment of knowledge in regards to a previously unknown facet or multiple facets of a singular or multiple targets, through elucidation of the

¹¹ Intelligence.gov, “How Intelligence Works,” 2012, available at: <http://www.intelligence.gov/about-the-intelligence-community/how-intelligence-works/>.

¹² Kristan Wheaton, “Part 5 – Critiques of the Cycle: Which Intelligence Cycle? (Let’s Kill the Intelligence Cycle),” *Sources and Methods*, May 26, 2011, available at: <http://sourcesandmethods.blogspot.com/2011/05/part-5-critiques-of-cycle-which.html>.

¹³ Central Intelligence Agency, “The Intelligence Cycle,” December 30, 2011, available at: <https://www.cia.gov/library/publications/additional-publications/the-work-of-a-nation/work-of-the-cia.html>.

¹⁴ Federal Bureau of Investigation, “Intelligence Cycle,” 2012, available at: <http://www.fbi.gov/about-us/intelligence/intelligence-cycle>.

¹⁵ Clark, *Intelligence Analysis*, 13-23.

¹⁶ Richelson, *U.S. Intelligence Community*, 3.

¹⁷ See note 14 above.

response(s) to the intelligence question(s) considered, is one method of potentially reducing uncertainty. When an intelligence question involves, as part of its response, the proposal of explanations for specific phenomena, the response is considered a hypothesis. When the hypothesis is falsifiable, it is a scientific hypothesis. The definition propounded by the FBI makes specific reference to evaluating the reliability and validity of information (i.e. raw intelligence or data). If the evaluation methodology regarding defining the uncertainty present in data is inclusive of explanatory phenomenon regarding the qualification and/or quantification of such uncertainty, then the endeavor involves the development of one or multiple hypotheses, irrespective of the broader intelligence question. When the broader intelligence question involves the integration of data to develop one or more explanations for the phenomenon or phenomena of interest, the development of one or multiple hypotheses are involved.

Beyond the issue of applicability of hypothesis testing, one may consider the classification of the broader analytic approach. Heuer and Pherson have proposed a quadripartite classification scheme consisting of expert judgment, structured analysis, quantitative methods using expert generated data, and quantitative methods using empirical data.¹⁸ Of particular interest is the definition propounded for structured analysis:

“Each structured analytic technique involves a step-by-step process that externalizes the analyst’s thinking in a manner that makes it readily apparent to others, thereby enabling it to be reviewed, discussed, and critiqued piece by piece or step by step.”

While one may find this taxonomical classification to be unnecessarily stilted, the salient component in the definition of a structured analytic technique, for the purposes herein, is that of a sequential process.¹⁹ The concept of externalization of the mental framework of an analyst is a critical factor in managing and mitigating cognitive bias associated with intelligence analysis.²⁰ Johnston notes that over 200 analytic methods exist but only a small number are domain specific for intelligence analysis (the adjectival term structured is applicable in that the methods cited specifically for intelligence analysis are all structured methods).²¹ Heuer’s Analysis of Competing Hypotheses (ACH) is one such method.²² Another method is the Lockwood

¹⁸ Heuer, Richards and Randolph Pherson, *Structured Analytic Techniques for Intelligence Analysis* (Washington, D.C.: CQ Press, 2011), 19-25. Interested readers may also wish to review the following: Moore, David, *Critical Thinking and Intelligence Analysis* (Washington, D.C.: National Defense Intelligence College, Center for Strategic Intelligence Research, 2007), available at: http://www.ni-u.edu/ni_press/pdf/Critical_Thinking.pdf.

¹⁹ The cited classification, as per Heuer and Pherson (*Ibid* at 22) propounds an underlying basis of functional distinction but with the caveat of fuzzy borders between methods. One can readily generate scenarios in which a step-by-step process is inclusive of the use of readily apparent quantitative data and modeling, which in turn fits into a structured analysis.

²⁰ A seminal text covering the details of cognitive bias within the context of intelligence analysis is: Heuer, Richards, *Psychology of Intelligence Analysis* (Washington, D.C.: Central Intelligence Agency, Center for the Study of Intelligence, 1999), available at: <https://www.cia.gov/library/center-for-the-study-of-intelligence/csi-publications/books-and-monographs/psychology-of-intelligence-analysis/index.html>.

²¹ Rob Johnston, “Integrating Methodologists into Teams of Substantive Experts. Reducing Analytic Error,” *Studies in Intelligence* 47:1 (2003), available at: <https://www.cia.gov/library/center-for-the-study-of-intelligence/csi-publications/csi-studies/studies/vol47no1/article06.html#fn30>.

²² Heuer, *Psychology of Intelligence Analysis*, Chapter 8. Additional details can be found through the various tutorials and occasional papers present at the Pherson Associates, LLC website: Pherson Associates, LLC, “ACH,” 2012, available at: <http://www.pherson.org/ACH.html>. Freely available software implementations of the ACH

Analytical Method for Prediction (LAMP), which serves as the contextual structured analytic method under consideration in the subject study.²³

Before introducing the specific research question of this study, a definition of the term probability must be considered and related to the issues of uncertainty, reliability, and validity. There exist three definitions of probability²⁴ that are relevant to this discussion.

1. In the classical definition, the probability of the occurrence of an event is the ratio of the number of outcomes in which the event occurs to the total number of tests in a symmetric experiment.
2. In the subjectivist definition, probability is simply the degree belief in the occurrence of an event.
3. Finally, in the frequentist view, the probability of an event is the proportion of times in which the event would be expected to occur in a test series comprised of repeated experiments.

These definitions are directly relatable to addressing the issues of uncertainty, reliability, and validity in regards to intelligence analysis. The terms uncertainty, reliability, and validity are distinct from the definitional perspective but reductive to synonymous from a functional perspective. In other words, considering a piece of raw intelligence data, an integrated result at any step in the process or the final intelligence assessment, the uncertainty present is a direct metric upon which reliability and validity may be assessed. Probability provides a measure by which uncertainty may be expressed. From the framework perspective, one particular branch of statistics, Bayesian statistics, is particularly promising for use in structured intelligence analysis techniques. Zlotnick presented one of the first published discussions, albeit primarily from a qualitative perspective, of the application of Bayes' theorem in odds form to intelligence analysis problems.²⁵ The CIA conducted a study in which Bayes theorem²⁶ was applied to intelligence questions arising within the context of the Korean War.²⁷ Fisk detailed the results of the use of conventional and Bayesian methods in the context of intelligence warning as applied to a

methodology are easily accessible through the Palo Alto Research Center, available at: <http://www2.parc.com/istl/projects/ach/ach.html> and through the Open Source ACH Project, available at: <http://competinghypotheses.org/>.

²³ Jonathan Lockwood and Kathleen Lockwood, "The Lockwood Analytical Method for Prediction (LAMP)," *Defense Intelligence Journal* 3:2 (1994): 47-74.

²⁴ "Interpretations of Probability," Stanford Encyclopedia of Philosophy, available at: <http://plato.stanford.edu/entries/probability-interpret/#SubPro>.

²⁵ Jack Zlotnick, "A Theorem for Prediction," *Studies in Intelligence* 11:4 (1965), available at: https://www.cia.gov/library/center-for-the-study-of-intelligence/kent-csi/vol11no4/html/v11i4a01p_0001.htm. Jack Zlotnick, "Bayes Theorem for Intelligence Analysis," (paper, presented at the Conference on the Diagnostic Process, Ann Arbor, Michigan, June 18, 1970), available at: <https://www.cia.gov/library/center-for-the-study-of-intelligence/kent-csi/vol16no2/pdf/v16i2a03p.pdf>.

²⁶ Bayes' theorem is a simple mathematical formula for calculating conditional probabilities. "Bayes' Theorem," Stanford Encyclopedia of Philosophy, available at: <http://plato.stanford.edu/entries/bayes-theorem/>.

²⁷ Central Intelligence Agency, Directorate of Intelligence, *Intelligence Report. Bayes' Theorem in the Korean War*, July, 1968, Report 0605/68, available at: http://www.foia.cia.gov/docs/DOC_0001205738/DOC_0001205738.pdf.

hypothetical binary Sino-Soviet dispute.²⁸ Sapp presented a concept known as decision trees, a helpful tool in visualizing the sequential application of Bayes' theorem.²⁹ Schweitzer presented a simple application of Bayes' theorem, in which the underlying marginal probability estimates were based upon expert estimation, for studying a hypothetical intelligence question related to the probability of the development of hostilities in the Middle East during a thirty day timeframe.³⁰ More recent works can readily be found in the literature.³¹

Having established the introductory fundamental framework, the specific research question can now be proposed:

In what manner can the LAMP structured analytic method be presented within the construct of a Bayesian probabilistic framework?

The LAMP structured analytic method

The current formulation of the LAMP structured analytic method involves a twelve step process.³² The sequence of steps is detailed below:

1. Define the intelligence question under consideration with sufficient specificity and narrowness of enquiry.
2. Specify the actors involved (the referenced sources indicate national actors but national character is immaterial to the applicability of the method for non-state actors).
3. Perform an in-depth study of how each actor perceives the issue in question.
4. Specify all possible courses for each actor.
5. Determine the major scenarios within which alternate futures are to be compared.
6. Calculate the total number of alternate futures for each scenario.

²⁸ Charles Fisk, "The Sino-Soviet Border Dispute: A Comparison of the Conventional and Bayesian Methods for Intelligence Warning," *Studies in Intelligence* 16:2 (1972), available at: <https://www.cia.gov/library/center-for-the-study-of-intelligence/kent-csi/vol16no2/pdf/v16i2a04p.pdf>.

²⁹ Edwin Sapp, "Decision Trees," *Studies in Intelligence* 18:4 (1974), available at: https://www.cia.gov/library/center-for-the-study-of-intelligence/kent-csi/vol18no4/html/v18i4a03p_0001.htm.

³⁰ Nicholas Schweitzer, "Bayesian Analysis for Intelligence: Some Focus on the Middle East," *Studies in Intelligence* 20:2 (1976), available at: <https://www.cia.gov/library/center-for-the-study-of-intelligence/kent-csi/vol20no2/pdf/v20i2a03p.pdf>

³¹ See: Leonard Adelman, Michael Donnell, John Patterson, et al., *Improving Tactical Intelligence Analysis: a Demonstration*, Report TR818312.33 (Alexandria, Virginia: U.S. Army Research Institute, 1981), available at: <http://www.dtic.mil/cgi-bin/GetTRDoc?AD=ADA104206>. Barry Horowitz and Yacov Haimes, "Risk-Based Methodology for Scenario Tracking, Intelligence Gathering and Analysis for Countering Terrorism," *Systems Engineering* 6:3 (2003): 152-169. Kristan Wheaton, Jennifer Lee and Hemangini Deshmukh, "Teaching Bayesian Statistics to Intelligence Analysts: Lessons Learned," *Journal of Strategic Security* 2:1 (2009), 39-57, available at: <http://scholarcommons.usf.edu/jss/vol2/iss1/3/>. Pontus Svenson, Robert Forsgren, Birgitta Kylesten, et al., "Swedish-Singapore Studies of Bayesian Modeling Techniques for Tactical Intelligence Analysis," (paper, presented at the 13th International Conference on Information Fusion, Edinburgh, UK, July, 2010). Interested readers may also wish to study Cross Impact Analysis. See: Theodore Gordon, *Cross-Impact Method*, AC/UNU Millennium Project (1994), available at: <http://www.lampsacus.com/documents/CROSSIMPACT.pdf>.

³² Jonathan Lockwood, "The Application of LAMP," *LAMP-Method.org*, 2010, available at: <http://lamp-method.org/2.html>. Jonathan Lockwood, "The Lockwood Analytic Method for Prediction (LAMP). An Innovative Methodological Approach to the Problem of Predictive Analysis," *LAMP-Method.org*, January, 2002, available at: <http://lamp-method.org/lampppt.ppt>.

7. Perform a pairwise comparison of all alternate futures within each scenario to establish their relative probabilities.
8. Rank the alternate futures for each scenario from highest relative probability to lowest relative probability.
9. For each alternative future, analyze the scenario in terms of its consequences for the intelligence question propounded in the first step.
10. Determine the focal events that must occur to bring about each alternate future.
11. Develop indicators for each focal event.
12. State the potential of a given alternate future to transpose into another alternate future.

Clausen reorders the final three steps in the following manner:³³

10. State the potential of a given alternate future to transpose into another alternate future.
11. Determine the focal events that must occur to bring about each alternate future.
12. Develop indicators for each focal event.

The step-by-step nature of LAMP coupled with the elucidation of the actors involved, the perception of each actor regarding the intelligence question under consideration, and the determination of all outcomes fits within the established framework of a structured analytic technique. As with any intelligence method, the degree to which LAMP aids in mitigating cognitive bias depends upon the objectivity of the analyst. An incorrect framework of comprehension of the view of the intelligence question from the perspective of other actors, generally due to the mirror image logical fallacy, will result in a questionable product.³⁴ This also holds for the issues of organizational bias and the corruption of the intelligence analysis endeavor secondary to politicization (i.e. presuming a conclusion or set of conclusions based upon political considerations and forcing the analysis to validate said conclusion or conclusions). Poorly cast intelligence questions and inaccurate determinations of the perceptions of each actor, not due to bias, but due to oversimplification or an incorrect modeling approach are not mitigated by LAMP or any other method. That being said, if the first six steps are robust and accurate, LAMP forces the analyst to quantify the probabilities associated with the alternate futures (i.e. hypotheses) under consideration. The method, basis, and validity for the assignment of specific probabilities to each alternate future represent a focal point for critique and review. Steps nine through twelve can be considered as being inferential in that they draw conclusions from the underlying analysis.

Simplified probability theory and Bayesian statistics

The broad fields of probability theory and Bayesian statistics are deeply rooted in mathematics. An approach that touches upon the relatively simple use of parametric estimates of probability (i.e. defining probabilities on the basis of defined discrete or continuous probability distributions) requires a substantial background in mathematics. Hence, the approach taken herein is to develop a very simplified approach that makes certain assumptions about the nature of the

³³ Daniel Clausen, "Coping with Bounds in the Debate Over Japanese Defense: Analytical Eclecticism, Nonlinearity and the Lockwood Method: An Extended Literature Review and Methodological Review," *LAMP-Method.org*, available at: <http://lamp-method.org/eCommons/clausenLAMPmethods.pdf>.

³⁴ An example of this, solely from the view of the lead author, would be the attempted (volitional or otherwise) miscasting of conflicts arising from a root cause religious basis into terms and solutions that presume a secular basis.

problem(s) under consideration. This simplification should not be interpreted as an inability for the handling of more complicated problems.

We proceed by defining some relevant terminology. The term “sample space” refers to the set comprised of all possible outcomes of an event or group.³⁵ Any specific event may be identified by symbolically denoting the event (generally by using a letter to denote the event) or by listing all of the elements within the sample space. An “event” is a collection drawn from the sample space and is therefore a subset of the sample space. Given a sample space denoted by {S} and an event denoted by E, the statement that “event E is a subset of the sample space {S} for all values of E” may be expressed compactly as:

$$E \in \{S\} \quad \forall E \tag{1}$$

In equation (1) the symbol \in denotes “is a subset of” and the symbol \forall denotes “for all values of.” For each event, there exists a probability for its occurrence. This probability is represented by using the notation of $P(\cdot)$ where the parenthetical contains the symbol for the event under consideration. For example, the probability of event E occurring is shown as $P(E)$. The laws of probability may be defined by Cox’s theorem or by the more commonly utilized Kolmogorov axioms³⁶. We may consider the concept of a “measure space” in relation to a “sample space” by example. Consider a hypothetical intelligence question that has, in actuality, a total of 30 alternative futures or competing hypotheses. A hypothetical analyst evaluating the intelligence question only elucidates 18 of these cases. In such a situation, the sample space would be all 30 alternative future or competing hypotheses and the measure space would be a subset of 18 of these cases. The ideal, of course, is for the measure space to be equal to the sample space. If we denote the measure space as $\{\Omega\}$ then the inherent assumption in any analysis is that:³⁷

$$P(\Omega) = 1 \tag{2}$$

This can be contrasted to the actuality of:

$$P(S) = 1 \tag{3}$$

The degree to which the assumption in equation (2) holds to the actuality of equation (3) can be expressed mathematically as:

$$1 = P(S) = P(\Omega) \Leftrightarrow \{\Omega\} = \{S\} \tag{4}$$

³⁵ If one considers rolling a single cubic unaltered die with each face numbered sequentially from one through six, one time and with the die landing such that one face of the cube is in the up position, the sample space for the event would be {1, 2, 3, 4, 5, 6}.

³⁶ The three axioms of probability may be described simply in the following manner. The first axiom is that the probability of an event in the event space is non-negative. The second is that the probability of the sample space is unity. The third is that the probability of the union of mutually exclusive events is equal to the sum of the probability of the events.

³⁷ This is the second axiom of probability.

The symbol \Leftrightarrow translates to “if and only if.” Cases of surprise in the intelligence domain, generally expressed as “we didn’t see it coming” stem from the cases in which the conditional in equation (4) was not met (i.e. the measure space of possible outcomes considered was not equal to the sample space of all actual outcomes). In any structured analytic endeavor in which the analyst seeks to objectively determine the sample space, the inherent assumption, as noted above, either valid or invalid is that equation (4) holds. Under this assumption, one may combine the actual first axiom with the concepts of monotonicity and numeric bounding to express the first axiom in a more common form:

$$0 \leq P(E) \leq 1 \quad \forall E \in \Omega \quad (5)$$

In simple terms, equation (5) states that the probability for any event that is a subset of the measure space is between zero and one. An impossible event (i.e. one that will never occur) has a probability of zero and an event that will always occur has a probability of unity (i.e. one). For any event E within the measure space there exists the counterpart event that is “not E .”³⁸ For an event E , we denote the event of “not E ” as $\neg E$ and its probability as $P(\neg E)$. It follows from equation (5) that:

$$P(E) + P(\neg E) = P(\Omega) = 1 \quad \forall E, \neg E \in \Omega \quad (6)$$

One may be interested in the probability of the occurrence of more than one event within the measure space. If the measure space contains a total of “ J ” elements where $J \geq 1$ (e.g. an analysis with 30 possible futures or hypotheses would result in $J = 30$), then one may denote the probability of any two events occurring as:

$$P(E_j \cdot E_k) = P(E_j \cap E_k) \quad \begin{cases} E_j, E_k \in \Omega \\ 1 \leq j, k \leq J \\ j \neq k \end{cases} \quad (7)$$

In equation (7), the subscripts “ j ” and “ k ” denote any two events that are subject to three constraints. The constraints are listed to the right of the open brace. The first constraint is that the events are a subset of the measure space. The second is that each subscript has a minimum value of one, denoting the first event and a maximum value denoting the element that is the “last” element in the measure space. The final constraint is that the two events in consideration are not the same event. The symbol \cap translates into “intersection.” Equation (7) is interpreted as the probability of occurrence of events E_j **and** E_k . For any two events within the measure space that are *independent* of each other, equation (7) reduces to a very simplified form:

$$P(E_j \cdot E_k) = P(E_j \cap E_k) = P(E_j)P(E_k) \quad \begin{cases} E_j, E_k \in \Omega \\ 1 \leq j, k \leq J \\ j \neq k \end{cases} \quad (8)$$

³⁸ For example, with a coin flip, if the event E is taken as the coin landing with “heads” facing up then the “not E ” event is the coin landing with “tails” facing up. For a roll of a standard cubic dice, if the event E is taken as the dice stopping with the number one facing up then the “not E ” event is any of the other numbers on the die showing up.

Stated simply, for any two events within the measure space that are independent, the probability of the first and second event occurring is simply the probability of the first event multiplied by the probability of the second event. If, for any two events, there exists a zero probability that both events would occur, then the events are said to be *mutually exclusive*. In such cases, equation (7) becomes:

$$P(E_j \cdot E_k) = P(E_j \cap E_k) = 0 \quad \begin{cases} E_j, E_k \in \Omega \\ 1 \leq j, k \leq J \\ j \neq k \end{cases} \quad (9)$$

One may also consider a situation in which one is interested in the occurrence of one event **or** the occurrence of another event in the measure space. If the two events are not mutually exclusive then the probability of one or the other event occurring is given by the inclusion-exclusion rule.

$$P(E_j \cup E_k) = P(E_j) + P(E_k) - P(E_j \cdot E_k) \quad \begin{cases} E_j, E_k \in \Omega \\ 1 \leq j, k \leq J \\ j \neq k \end{cases} \quad (10)$$

In equation (10) the symbol \cup denotes “union.” This equation can be translated as the probability of occurrence of one event or another event within the sample space is equal to the sum of the probabilities of the occurrence of each event minus the probability of occurrence of both events. If the two events are mutually exclusive, then the use of equation (9) in equation (10) leads to the simplified result that the probability of the occurrence of one or another mutually exclusive event is the sum of the probabilities of the occurrence of each event separately.

$$P(E_j \cup E_k) = P(E_j) + P(E_k) \quad \begin{cases} E_j, E_k \in \Omega \\ 1 \leq j, k \leq J \\ j \neq k \end{cases} \quad (11)$$

If the entire sample space consists of events that are mutually exclusive for all pairwise comparisons, then equation (11) can be expanded in compact form, using the summation operator, for all events in the measure space.³⁹

$$P(E_1 \cup E_2 \cup \dots \cup E_J) = P(E_1) + P(E_2) + \dots + P(E_J) = \sum_{j=1}^J P(E_j) \quad (12)$$

³⁹ Readers with some familiarity with computer programming may relate to the analogy of the summation operator working as a “For” loop. The indexing variable and its initial value are shown below the summation sign. The terminus value for the index is shown above the summation sign. For each step, the value of the operand is added to all previous values.

Equation (12) is an expression for the third axiom of probability. The substantial level of simplification engendered by the presence or assumption of mutual exclusivity can readily be seen by comparing the form of equation (12) to the corresponding generalized form of equation (10), which holds for finite sets.

$$P\left(\bigcup_{j=1}^J E_j\right) = \sum_{k=1}^J (-1)^{k-1} \sum_{\substack{K \subset \{1, \dots, J\} \\ |K|=k}} P(E_K) \quad \left\{ E_K : E_K = \bigcap_{i \in K} E_i \right. \quad (13)$$

Intelligence questions may and generally do involve the determination of the probability of the occurrence of one event that is conditional upon the occurrence of an antecedent event. For an event E and another event H, the *conditional probability* of the occurrence of event E given the occurrence of event H is denoted as P(E|H) and is expressed as:

$$P(E | H) = \frac{P(E \cdot H)}{P(H)} \quad (14)$$

If the two events E and H are independent then the substitution of equation (8) into equation (14) yields:

$$P(E | H) = \frac{P(E \cdot H)}{P(H)} = \frac{P(E)P(H)}{P(H)} = P(E) \quad (15)$$

For any two events, E and H, the probability that both will occur is obtained, in terms of their conditional probabilities, by the application of the multiplication rule.

$$P(E \cdot H) = P(E)P(H | E) = P(H)P(E | H) \quad (16)$$

For independent events, equation (16) reduces to equation (8). For the entire measure space (or for any number of events up to the size of the measure space):

$$P(E_1 \cdot E_2 \cdot \dots \cdot E_J) = P(E_1 | E_2 \cdot \dots \cdot E_J) P(E_2 | E_3 \cdot \dots \cdot E_J) \cdot \dots \cdot P(E_{J-1} | E_J) P(E_J) \quad (17)$$

One may also consider the situation in which the measure space is partitioned by any “n” number of mutually exclusive events such that $n \leq J$ and for which another event, E, can occur under any of these mutually exclusive events but not under any events lying outside of the partition. The probability of the occurrence of event E can then be calculated using the total probability formula.

$$P(E) = P(E | H_1)P(H_1) + \dots + P(E | H_n)P(H_n) = \sum_{j=1}^n P(E | H_j)P(H_j) \quad (18)$$

We first introduce Bayes’ theorem for any two events E and H, as shown by equation (19):

(19)

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

Each term in equation (19) has a specific definition that is generally accepted in the literature and may be encountered:

- $P(H)$ = The prior probability, which is the probability of event H prior to observing event E.
- $P(E)$ = The marginal likelihood. This factor is the same for all H under consideration.
- $P(E|H)$ = The likelihood, which is the probability of the occurrence of event E given H.
- $P(H|E)$ = The posterior probability, which is the probability of H given E.

Equation (19) may be written in an alternative form when one is considering an evaluation for the case in which there exists a total of J-1 partitions of the measure space for any J number of events such that the sum of the prior probabilities of these events is equal to one (i.e. the probability of the measure space).

$$P(H_j|E) = \frac{P(E|H_j)P(H_j)}{\sum_{j=1}^J P(E|H_j)P(H_j)} \quad (20)$$

This may further be expanded for the case in which E is not a singular event but instead is a set of independent and identically distributed events, which can be expressed as a vector (denoted by bolded font), $\mathbf{E} = \{E_1, E_2, \dots, E_n\}$.

$$P(H_j|\mathbf{E}) = \frac{P(\mathbf{E}|H_j)P(H_j)}{\sum_{j=1}^J P(\mathbf{E}|H_j)P(H_j)} = \frac{\left(\prod_{q=1}^n P(E_q|H_j)\right)P(H_j)}{\sum_{j=1}^J P(\mathbf{E}|H_j)P(H_j)} \quad (21)$$

Equations (19) through (21) can readily be represented for probability distributions. An understanding of these forms, however, requires an understanding of mathematical statistics, distribution theory and calculus. Finally, one may be presented with a problem in which one can determine the relative probabilities of two events E_1 and E_2 (expressed mathematically as $O(E_1:E_2)$ which translates into the odds of the occurrence of event E_1 to event E_2) and wishes to determine the conditional probability of the odds of E_1 to E_2 given another event, H. This can be expressed mathematically in the following manner:

$$O(E_1 : E_2 | H) = \Lambda(E_1 : E_2 | H) \cdot O(E_1 : E_2) \quad (22)$$

In equation (22), the term $\Lambda(E_1:E_2|H)$ is called the “Bayes’ factor”⁴⁰ and is defined as:

$$\Lambda(E_1 : E_2 | H) = \frac{P(H | E_1)}{P(H | E_2)} \quad (23)$$

Equation (22), referred to as “Bayes’ rule”, can be expanded to any arbitrary number of events.

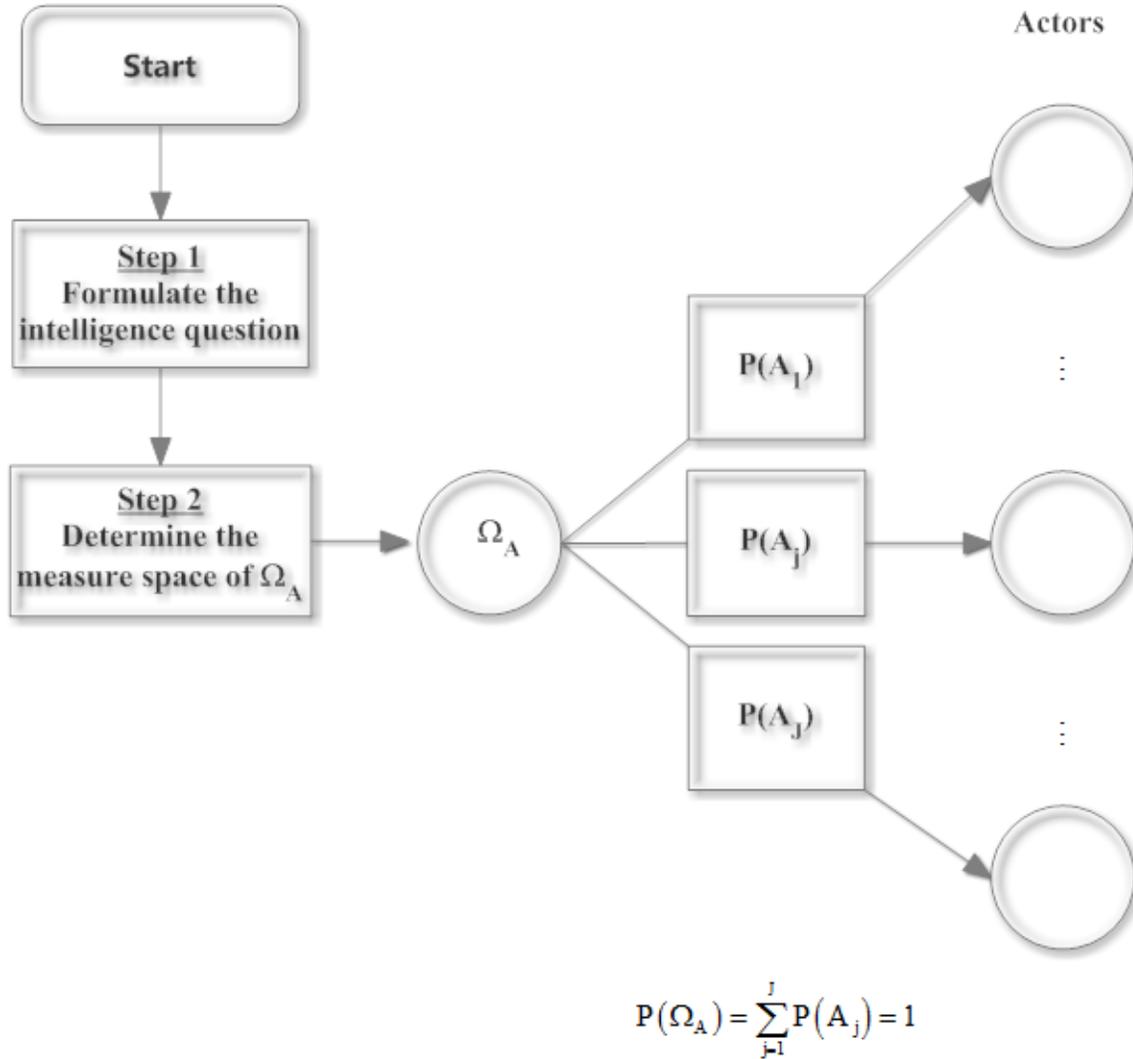
LAMP in a probabilistic framework

The approach taken herein is grossly simplified based upon the simplified presentation of Section 3. It should be noted that a much more complex and robust approach can be taken when a mathematical statistics formulation is utilized. The first step in the methodology remains unchanged and is a critical component to the analysis (an ill-posed intelligence question filters through the subsequent aspects of the process). In the second step, one defines all of the actors that have a stake in the outcome of the intelligence question propounded in the first step. Given the availability of computers and the nature of computing power, in modernity, it is somewhat inexcusable to volitionally limit the measure space with respect to the actual sample space (a back of the envelope type analysis should not be considered a substitute for a formal analysis). Depending upon the intelligence question, care should be taken to distinguish crystallized elements within a broader organizational structure that may view the issues under consideration differently.⁴¹ Non-state actors of relevance such as violent non-state actors (VNSAs), supra-governmental entities and potentially organizations operating under the name of humanitarianism should also be considered for inclusion. We may assign a probability to each actor that the actor is an actual party of interest in the measure space of actors with an interest in the outcome. Defining the measure space of actors with an interest in the outcome of the intelligence question as Ω_A , defined as a finite set with J discrete elements, the implementation of the first and second steps of LAMP may be viewed as shown in Figure 1.

⁴⁰ The Bayes’ factor is the ratio of the posterior model odds (i.e. H given E_1) to the prior model odds (i.e. H given E_2).

⁴¹ As a hypothetical, if the intelligence question at hand dealt with a facet of the 2011-02-01 resignation of Egyptian President, Hosni Mubarak, one might wish to segregate the actors within Egypt rather than treating Egypt as a singular national actor.

Figure 1. Logic (process) flowchart showing the first and second step of LAMP followed by the first branches of the tree diagram.



The third step in process is propounded herein as the mechanism by which the findings of the extant fourth step are elucidated. It is through this mechanism that one would consider the complex political, military, economic, social, religious, and individual (certain actors may exhibit a singular or small group leadership dynamic that operates in a cult of personality manner) factors that should underpin any cogent analytic endeavor. The discussion of the details of modeling each broad categorical factor are beyond the scope of the subject study. Furthermore, because of the simplifying assumptions made in Section 3 of this study, the results of these underlying mechanistic analyses must be considered independent. The end goal of using the original third step in LAMP is to determine the conditional probabilities for each measure space, which maps to the original fourth step in LAMP. For the j^{th} actor, $\{j: 1 \leq j \leq K\}$ we define the measure space of the courses of action as Ω_{C_j} with a total number of elements K_j . For the k^{th}

course of action $\{k: 1 \leq k \leq K_j\}$ for the j^{th} actor, the conditional probability that we seek to determine is $P(C_{jk}|A_j)$. For each actor, the following holds:

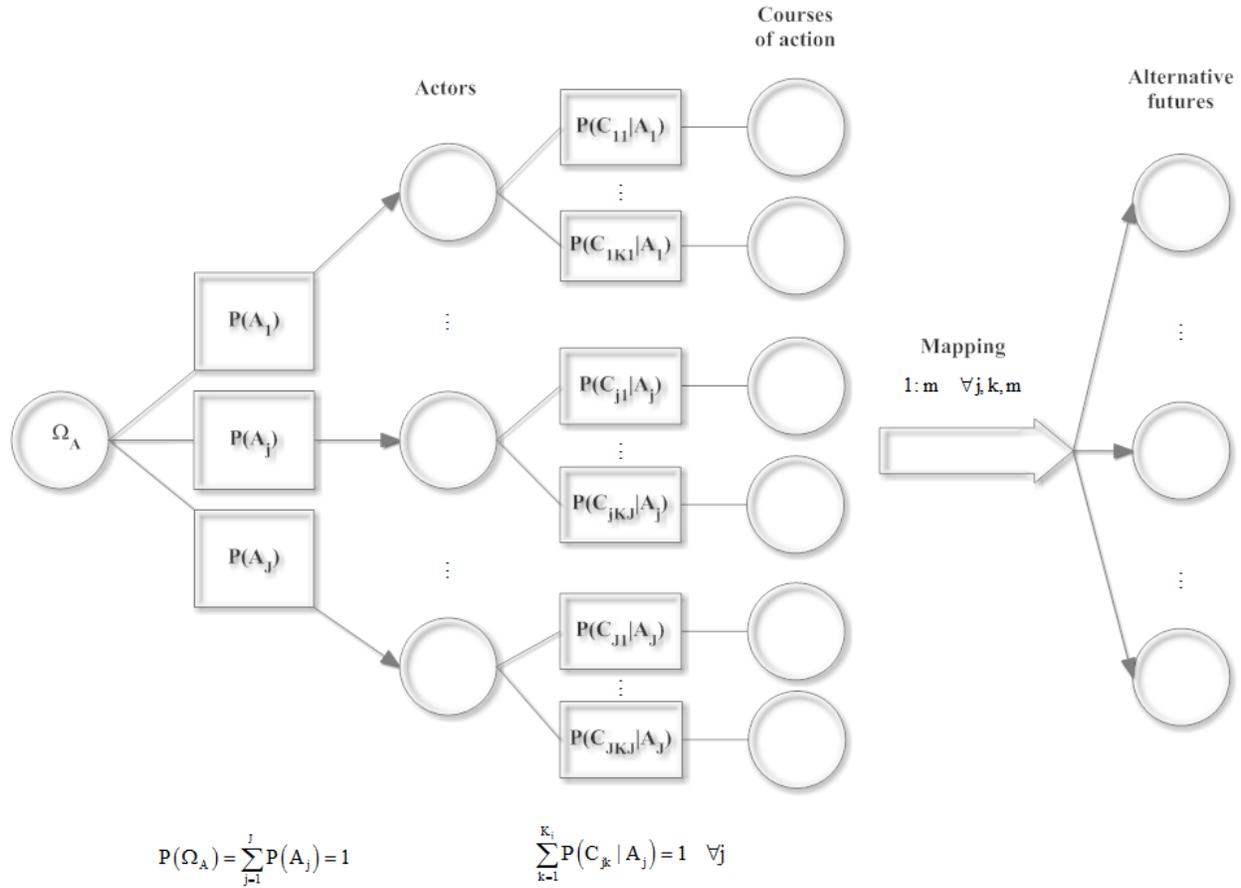
$$1 = \sum_{k=1}^{K_j} P(C_{jk} | A_j) \quad (24)$$

The tree diagram in Figure 1 may be correspondingly expanded as shown in Figure 2. Using equations (14) and (20), the expression for $P(C_{jk}|A_j)$ can be written as:

$$P(C_{jk} | A_j) = \frac{P(C_{jk} \cdot A_j)}{P(A_j)} = \frac{P(A_j | C_{jk})P(C_{jk})}{\sum_{k=1}^{K_j} P(A_j | C_{jk})P(C_{jk})} \quad (25)$$

Steps five through eight of LAMP may be subsumed into a singular process of determining a discrete set of alternative futures, determining the probability for each future for each antecedent conditional probability of course of action given for each actor, and simply computing the joint probabilities. One can certainly develop a modeling approach in which the alternative futures are generated, or one may determine the measure space of alternative futures using traditional methods. Assuming the latter, we define the measure space of alternative futures as finite set Ω_F with a total of M elements. We map each conditional probability $P(C_{jk}|A_j) \forall j,k$ to each alternative future $F_m \{m: 1 \leq m \leq M\}$.

Figure 2. Full tree diagram depicting a probabilistic framework for LAMP.



Following the form of equation (25), the conditional probability for the m^{th} alternate future given the conditional courses of action, conditional upon the actors, is:

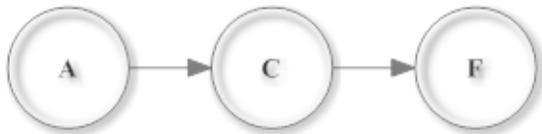
$$P(F_m | (C_{jk} | A_j)) = \frac{P(F_m \cdot C_{jk} \cdot A_j)}{P(C_{jk} | A_j)} = \frac{P((C_{jk} | A_j) | F_m) P(F_m)}{\sum_{m=1}^M (F_m | (C_{jk} | A_j)) P(F_m)} \quad (26)$$

One may use the conditional probabilities calculated from equation (26) to order the alternate futures or calculate the Bayes' factor by using a modified form of equation (23). If we denote the entire model up to but not including the alternate futures as D (i.e. data), then the Bayes' factor can be written in the following manner for each comparison between the alternate futures:

$$\Lambda_{mn} = \frac{P(F_m | D)}{P(F_n | D)} = \frac{\frac{P(D | F_m) P(F_m)}{P(D)}}{\frac{P(D | F_n) P(F_n)}{P(D)}} = \frac{P(D | F_m) P(F_m)}{P(D | F_n) P(F_n)} \quad (27)$$

Step 9 of LAMP can be addressed by simply following the chain of conditional probabilities for each terminus solution. Step 10, the determination of focal events requisite for the development of an alternative future, is one that is directly encoded through the model development used for assigning probabilities in the antecedent steps. Correspondingly, the indicators in step 11, should be incorporated at each level of probability assignment. Finally, step 12 of the extant methodology, in regards to transposition, is determinable by the comparison of the terminus probabilities or by comparison of the Bayes' factors.⁴² The modeling process described above can also be implemented in the form of a very simple Bayesian network as shown in Figure 3.

Figure 3. A simple Bayesian network represented as a directed acyclic graph in which the nodes A, C and F represent the variables of actors, courses of actions and alternative futures, respectively.



Based on Figure 3, the joint probability distribution of F is given by:

$$P(A \cap C \cap F) = P(F|C)P(C|A)P(A) \quad (28)$$

One may see the joint probability distribution $P(A \cap C \cap F)$ shown in two equivalent forms consisting of $P(A \cdot C \cdot F)$ or $P(A, C, F)$. In the current framework we may recast the steps of LAMP in the following manner:

0. Task assignment in regards to a specific intelligence matter.
1. Define the intelligence question under consideration with sufficient specificity and narrowness of enquiry.
2. Determine the measure space, Ω_a , of all actors involved in regards to the specific intelligence question defined in Step 1 and for each actor, determine the probability of involvement.
3. Determine the courses of action for each actor based upon the probabilities based upon the use of all source intelligence relating to the political, military, economic, social, religious, and individual characteristics of each actor. These relationships should be inclusive of indicators upon which the probability assignments are based.
4. Determine the measure space, Ω_F , for all alternative futures and calculate the joint probability distribution of $P(A \cap C \cap F)$. Based upon this calculation or the subsequent calculation of Bayes' factors, the most probable future becomes clear. Also, directly from Steps 2 through 4, focal events become clear, as do their indicators and the transposition between futures.

⁴² When comparing two models given the data, a Bayes' factor calculation between the appropriate bounds (e.g. between 1/3 and 3) shows weak evidence for one model over the other.

Discussion and conclusions

This article demonstrated the mechanism of applying a probabilistic framework to one specific structured analytic technique for intelligence analysis. Because of the commonalities in perceptual architecture shared by the class of structured analytic techniques, the general probabilistic framework shown herein should be readily adaptable to any member of the former class. In regards to the framework itself, the simplest of all methods was presented for the purposes of showing applicability. This is clearly a first order approach based upon the most cursory of presentations of the underlying mathematical machinery available. Each probability metric can readily be presented in parametric form that in turn would account for the mean response along with an uncertainty measure in the form of the appropriate metric for dispersion from the mean response (i.e. a measure of uncertainty). The simple Bayesian network shown is also but a first order model (i.e. simplest) which can readily be expanded by expanding the relationships between the nodes of the directed acyclic graph, including time as a factor through a Markov chain model or a dynamic Bayesian model (DBM), developing a hidden Markov model (HMM), developing a linear dynamical system (LDS) model with Kalman filtering or developing any of an array of other models.⁴³ A number of software packages already exist for the implementation and analysis of Bayesian networks, which in turn mitigate the necessity for performing calculations by hand or deriving the terminus joint probability distributions.⁴⁴

The subject framework does not, by any means, serve as mitigation for poor analytic formulation, cognitive bias, or bias arising from organizational and/or political factors. The framework, however, does allow for the quantification of uncertainty at each step within the structured analysis process and furthermore allows for the fusion of the latter with both the ever increasing amount of raw quantitative data that is available along with the discipline specific modeling methods that are in use for each incumbent field exclusive of the context of intelligence analysis.

In conclusion, this article presented a first order application of a probabilistic framework to the LAMP structured technique for intelligence analysis. This framework captured the underlying uncertainty associated with the analytic process in terms of probabilities and provided a mechanism for understanding the propagation of uncertainty through the analytic process. This first order framework can be readily expanded using extant methods deriving from the broad field of Bayesian network analysis.

⁴³ As an example of modeling approaches, see: Kevin Murphy, "A Brief Introduction to Graphical Models and Bayesian Networks, *University of British Columbia*, 1998, available at: <http://www.cs.ubc.ca/~murphyk/Bayes/bnintro.html>.

⁴⁴ These include general symbolic mathematics packages such as MATLAB or Mathematica as well as specialized packages such as the freely available GeNie (v. 2.0; Decision Systems Laboratory, University of Pittsburgh) or the minimal cost Netica (v. 5.0; Norsys Software Corp.) programs.