Multinomial Cutscores for Bayesian Analysis with ESS and Three-Position Scores of Comparison Question Polygraph Tests

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Abstract

Multinomial reference distributions calculated under the analytic theory of the comparison question test and are available for both Empirical Scoring System and the Federal three-position scores. They are then used as a likelihood function for Bayesian analysis of the posterior strength of information for deception and truth-telling. Bayesian classification of comparison question test data is accomplished by using Bayes theorem, along with the test data, prior information and a statistical likelihood function, to calculate a posterior likelihood of deception or truth-telling and then quantifying the expected variability of the test data as a Bayesian credible interval. A classification of deception or truth-telling is supported when the strength of the 1-alpha lower-limit of a coverage interval has exceeded the strength of the prior information for deception or truth-telling. Field polygraph practitioners traditionally work with comparison question test data in the form of point scores and cutscores. Multinomial cutscores are the minimum scores for which strength of the posterior information exceeds the prior information with the uncertainty or expected variation reduced to the alpha tolerance level. However, until this time published multinomial cutscores have been available only the equal prior condition and only for the symmetrical alpha scheme of a = .05, .05 for deception and truth-telling. This project involved the tabular calculation of multinomial cutscores for the Empirical Scoring System and Federal three-position scoring methods for all permutations of alpha levels at .01, .05, and .10 for truth-telling and deception using a distribution of prior odds from one in 10 for truth-telling and deception. These cutscore tables permit polygraph field practitioners to make use of the advantages of Bayesian analysis while relying on the practical intuition of scores and cutscores, and without the need for the recalculation of Bayes theorem or Bayesian credible intervals. Multinomial cutscore tables are provided in appendices.

Introduction

Multinomial reference distributions were calculated for comparison question polygraphs (Nelson 2017; 2018), including event-specific diagnostic exams and multiple-issue screening polygraph with two, three and four, relevant questions using the Empirical Scoring System (ESS/ESS-M; Nelson, Krapohl & Handler 2007; Nelson et. al., 2011) and the U.S. Federal three-position scores (Department of Defense, 2006). The multinomial distributions were calculated under the null-hypothesis to the analytic theory of the comparison question test (CQT), which holds that greater changes in physiological activity are loaded at different types of test stimuli as a function of deception or truth-telling in response to relevant target stimuli (Nelson, 2016).

This analytic theory is premised on a more foundational hypothesis that some predictable changes in physiology are correlated with deception and truth-telling and can be recorded and quantified for probabilistic inference and classification. As a practical matter, human physiology and psychology and sufficiently noisy that data from a single sensor or signal, and single presentation of the test stimuli, provides weak and insufficient information. Instead, an array of sensors, each contributing unique diagnostic variation or information, and systematic repetition of test stimuli, are necessary achieve a satisfactory level of statistical power and signal discrimination.

Multinomial Distributions.

ESS and three-position scores of CQT data are multinomial because each score can take one of three values – indicating that a change in physiological activity in response to a relevant question (RQ) is either greater than, less than, or indiscernible from the change in physiological activity in response to a comparison question (CQ). Multinomial distributions can be calculated using combinatoric math (Abramowitz & Stegun, 1972; Chen & Koh, 1992). CQT formats consist of and array of three or four sensors, include two to four RQs, in a question sequence that is repeated three to five times. A single sensor can produce a large number of combinations of scores: from 3^6 = 729 for three iterations of two RQs, to 3^20 = 3,486,784,401 for five iterations of four RQs. For each CQT format there is a finite number of combinations of multinomial scores and a finite number of ways to achieve each possible sensor score.

A multinomial distribution can be determined for the sensor scores by dividing the number of ways to achieve each sensor score by the number of possible combinations. Calculation of the exact number of ways to – the most complicated part – can be calculated using combinatoric math and multinomial coefficients (Riordan, 2002/1958). It is also possible, and simpler, to simulate the multinomial distribution using Monte Carlo methods. Nelson (2017) shows the results of both methods.

Multinomial distributions for sensor scores can also be combined or permuted to calculate a multinomial distribution for subtotal and grand total CQT scores. Again, this can be accomplished through combinatoric math or via simulation. Nelson (2017, 2018a) provided exact calculations of the multinomial distributions for CQT scores. Regardless of whether obtain through exact combinatoric calculation or via simulation, multinomial distributions are useful as a likelihood function for Bayesian analysis of the change in the strength of posterior information in support of deception or truth-telling.

Bayesian Analysis

Bayesian analysis is the use of Bayes' theorem to analyze data and estimate an unknown parameter or unknown quantity of interest (Bayes & Price, 1756; Berger, 1985, 2006a; Bernardo & Smith, 1994; Box & Tiao, 1973; Casella, 1985; Downey, 2012, Efron, 1986; Gelman et al., 2014; Gill, 2007; Laplace, 1812; Lee, 2004; Rubin, Gelman, Carlin & Stern, 2003; Stone, 2013; Western & Simon, 1994; Winkler, 1972). In the context of the CQT the unknown quantity or parameter is the likelihood of deception or truth-telling. It is not possible to detect or quantify deception or truth *per se* because these are not physical quantities. However, Bayesian analysis permits the application of Bayesian probability – the degree of belief, based on analysis and objective information, in some knowledge or conclusion – to the constructs of deception and truth-telling. Bayesian analysis makes use of observed test data, along with prior probability information and a statistical likelihood function, to calculate a posterior probability. Bayesian analysis can also be used to calculate a Bayes Factor (Berger, 2006b, Jeffreys, 1939/1961; Kaas & Raftery, 1993; Morey & Rouder, 2011), which is the magnitude of change in the posterior strength of information. Bayes Factor is advantageous because it is a robust statistic – the magnitude of change in the strength of posterior information will be the same regardless of the prior value.

Bayesian Classifier for ESS-M and Three-position Scores.

Bayesian analysis of CQT data involves the use of Bayes' theorem, along with the observed test data, prior information and likelihood function, to calculate a posterior conditional likelihood, expressed as an odds, of deception or truth-telling. The posterior conditional odds can be thought of as a description of the strength of the test result or degree of belief that can be attributed. Use of the odds to express posterior probabilities is advantageous because it permits the discussion of probabilities using whole numbers and also explicates that all probabilities are a comparison of the strength of some possibility compared to the strength of some other possibility. The posterior value from Bayes' theorem can also be thought of as a Bayes Factor when the posterior odds are calculated under the equal prior.

After calculation of the posterior odds or Bayes Factor, the expected variation in test data – if it were possible to conduct the same examination repeatedly under the same circumstances – is quantified in the form of a Bayesian credible interval, analogous to a frequentist confidence interval, using the Clopper-Pearson method (Clopper & Pearson, 1934; Nelson, 2018b). This method is advantageous for the CQT because the resulting upper and lower probability boundaries never result in mathematically absurd values (i.e., never exceeding the 0 and 1 limits of the uniform probability distribution), and the resulting coverage area is known to always exceed the 1-alpha nominal value. A classification of deception or truth-telling is supported when the strength of the 1-alpha lower-limit of a Bayesian credible interval has exceeded the strength of the prior information for deception or truth-telling.

Point Scores and Cutscores.

Field polygraph practitioners have traditionally relied on numerical point scores and numerical cutscores as an expedient method of classifying and interpreting CQT data. Although traditionally little emphasis was placed on the relationship between point scores and probabilities, the availability of both empirical and multinomial reference tables has increased the accessibility and intuition for discussion of this information in field practice during recent years. When using the multinomial distributions for ESS and three-position scores, numerical cutscores can be selected as the minimum (absolute) score for which the strength of the lower limit of the 1-alpha Bayesian credible interval exceeds the strength of the prior information. Numerical scores that equal or exceed the numerical cutscore can be said to increase the strength of information indicative of deception or truth-telling, at the 1-alpha level, relative to the prior information.

Until this time, published multinomial cutscores have been available only for the equal prior condition and only for the symmetrical alpha scheme of α = .05/.05 for deception and truth-telling. This project involved the tabular calculation of multinomial cutscores for the ESS-M and three-position scoring methods for all permutations of alpha levels at .01, .05, and .10 for truth-telling and deception using a distribution of prior odds from one in 10 for truth-telling to one in 10 for deception. Appendices A, B, C and D show the cutscore tables. To reduce the number of tables to the minimum possible, all tables were calculated using the simplified ESS-M solution described by Nelson and Rider (2018) as shown by Nelson, Handler, Coffee, Prado and Blalock (2019). Appendix A shows the tabular calculation of multinomial cutscores for ESS scores of event-specific diagnostic exams. Appendix B shows the multinomial cutscores for ESS scores of multiple-issue screening polygraphs. Appendices C and D show the multinomial cutscores for three-position scores of event-specific diagnostic polygraphs and multiple-issue screening polygraphs, respectively.

Careful inspection of these appendices will shows cutscores that may be at first counter-intuitive; cutscores are selected so that posterior information is strengthened, relative to the prior information, at the 1-alpha level, with the result that under some strong prior conditions cutscores may increase for both deceptive and truthful classifications. Also, information contained in subtotal scores will be of insufficient statistical power to provide posterior information at the 1-alpha level under some strong prior conditions.

Summary and Conclusion.

Analysis of CQT test data is conceptually similar to the analysis of other scientific test data,

Table 1. shows the multinomial cutscores for ESS and three position scores under the equal prior with alpha is .05 for both truth-telling and deception. Notice that three-position multinomial cutscores for multiple issue exams are similar to to ESS-M cutscores as a result of blunted precision when using integer values.

Table 1. Multinomial Cutscores for equal prior and alpha = .05 and .05 for truth-telling and deception.

	Single-issue exams – two-stage rules	Multiple-issue exams – subtotal score rules
ESS-M cutscores	+3 / - 3 (-7)	(+1) / -3
Three-position multinomial cutscores	+2 / - 2 (-6)	(+1) / -3

Parenthesis indicate the use of a statistical correction for multiplicity effects.

and consists of four main functions or operations. These include feature extraction, numerical transformation and data reduction, calculation of a statistical classifier using of some form of likelihood function, and interpretation of the meaning of the numerical information.

These operations are often reduced to simple procedures that can be executed with little awareness of or attention to the underlying processes – and often with imprecise boundaries between the operations. For example, feature extraction can be accomplished simultaneously when the feature of interest is a measurement. In a narrower sense, feature extraction is the identification of useful or meaningful changes in physiological activity in response to test items. Numerical transformation, in practical terms, is the assignment of numerical point scores to responses observed in recorded CQT data. Data reduction can involve a variety of mathematical transformations. However, when working with point scores, data reduction can be a simple matter of addition of subtotal and grand total scores. The simplest form of likelihood function is a numerical cutscore for which we expect the rate of misclassification error or precision to achieve certain desired levels, based on empirical and theoretical evidence. Another simple form of likelihood function can be observed in the form of empirically derived test sensitivity, specificity and error rates. Statistical equations are another form of likelihood function. The purpose of any likelihood function is to calculate a coherent and reproducible likelihood value for the observed data. Interpretation, in its simplest form, is the parsing of analytic results into categorical conclusions such as statistically significant and not statistically significant, or positive and negative.

Interpretation of CQT data, in terms of deception and truth-telling, will involve a number of scientific, philosophical and ethical complexities. These can include: the need to understand the use of probabilistic inference where direct physical measurement is not possible; epistemological questions of precisely what precisely is truth and deception – and what does it mean to test, measure and quantify these; the need for professional accountability when making conclusions that may influence the human rights or future of other persons; and other concerns. A well-developed and satisfactory system of test data analysis will address and manage these concerns by enabling professionals to achieve reproducible analytic conclusions that are correctly anchored in scientific and probabilistic knowledge. Ideally, a test data analysis system will lead to discussions of analytic conclusions that are both scientifically coherent and practically useful.

Polygraph professionals have long ago transitioned away from the interpretation of CQT results using terms such as *deceptive,* as this can encourage unrealistic expectations for deterministic perfection or infallibility. In common usage among polygraph field practitioners today are the terms *deception indicated* and *significant reactions* which more reasonably convey that test results are, of themselves, neither a physical substance nor a physical action, but can be interpreted as a probabilistic indicator when they are statistically significant. With the understanding that all scientific test results are probabilistic, a common question for may will be this: what is the strength of the probabilistic information for deception or truth-telling? Another version of the same question is this: what can be reasonably said about the strength of the analytic conclusion? It is here that Bayesian decision-making offers a practical and intuitive advantage over the practice of significance testing – referred to as null-hypothesis significance testing (NHST; Fisher, 1934; Neyman & Pearson, 1928; 1933; Pernet, 2015).

Statistical values using the NHST paradigm – p-values and alpha levels – refer only to strength of evidence for a null-hypothesis (which can be rejected in favor of the alternative hypothesis if sufficiently weak). This nuance important because there is often a problematic impulse to misuse the statistical values themselves as an indication of effect-size or strength of the analytic conclusion. Most importantly, a p-value – intended to reject a null hypothesis – is not an estimate of the strength of the effect size for either the hypothesis or null-hypothesis. Attempts to portray a p-value as an estimate of effect size are an example of a logical fallacy known as *argument from ignorance,* in which the absence of information is misinterpreted as a form of proof. Another important consideration is that, in the NHST paradigm, results are significant, and categorical conclusions are possible, only at the stated alpha level. It is possible that some conclusions that are significant at alpha = .05 may not be statistically significant at alpha = .01.

In contrast, Bayesian statistical values can be interpreted as referring to the strength of information in direct support of a hypothesis or conclusion. An important consideration here is that, although Bayesian probabilities can be interpreted as referring to the hypothesis or conclusion – in the CQT context this is a probability or odds of deception or truth-telling – Bayesian probabilities are *conditional probabilities.* That is, the Bayesian posterior probability can be thought of a test likelihood statistic conditioned on the prior information (or the prior information conditioned on the test likelihood statistic). It is possible that categorical conclusions may change if the posterior conditional probability were calculated with different prior information.

Both NHST and Bayesian analysis assume that available test data are an imperfect representation of an unknown parameter of interest and are subject to sampling variation or measurement error. NHST estimates the expected variability from the available data and the sample size using statistical *confidence intervals.* Bayesian analysis assumes that available data are all the information that is presently available to support a conclusion, and also employs procedures to estimate expected variation in test data. Bayesian analysis differentiates the nuanced meaning of these estimations from the frequentist paradigm by using the term *credible interval* to describe the 1-alpha coverage area for expected variation. In practical terms, this means that multinomial cutscores for Bayesian analysis of CQT data are function of both the prior information and the required alpha level for statistical significance.

Use of numerical cutscores serves as a practical convenience that relieves field practitioners of the odious burden of mathematical and statistical calculations. Multinomial cutscores will permit field practitioners to make classifications of deception and truth-telling with the knowledge that the lower limit of the 1-alpha credible interval will exceed the prior information all point scores that exceed a numerical cutscore. In practical terms this can be interpreted as the 1-alpha level at the data have strengthened the information in support of a deceptive or truthful conclusion. This can also be thought of as the 1-alpha level at which a test is indicative of deception or truth-telling. Also, the 1-alpha level that another test, under the same conditions, will give a similar result. Or, the 1-alpha proportion of repeated tests, under the same conditions, that would give similar results.

Determination of multinomial cutscores for ESS and three-position scores requires the calculation of both Bayes theorem and the Clopper-Pearson interval for the distribution of possible scores. Effectively, this results in the calculation of a unique reference table for every alpha and prior scheme. These calculations can be accomplished manually, though the process is tedious, and can also be accomplished quickly, easily and accurately using any desktop or laptop microcomputer. It is also possible to complete all calculations in a controlled environment and make the information available in tabular reference format – which is the purpose of this project.

The multinomial cutscore tables, shown in Appendices A-D, can be a useful convenience to field practitioners and program managers who want visual and tactile access to cutscore information without the need for either manual calculations or the experience of a *black-box* calculations that may provide one solution at a time. Tabular information are of such great convenience that computer algorithms and digital calculators will sometimes make use of tables as an alternative to the repetition of complex mathematical and logical operations. Published cutscore tables also provide additional advantages; they can facilitate training in the use of manual analytic procedures that will strengthen understanding and intuition for the analytic process. Also, tables can be used in circumstances in which computers are not available to complete the required calculations. It is hoped that these multinomial cutscore tables can be useful to field practitioners and program managers who desire more visual and intuitive access to the distribution of numerical cutscores and their relationship to various alpha boundaries and prior information. Multinomial cutscores will permits field practitioners to make classifications of deception and truth-telling with the knowledge that the lower limit of the 1-alpha credible interval will exceed the prior information for all point scores that exceed a multinomial cutscore.

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Appendix A: Multinomial Cutscores for ESS Scores of Single Issue Exams

ESS-M Scores / Event-Specific Exam

		Alpha (truth/deception)								
Prior odds of deception	prior probability	.01/.01	.01/.05	.01/.10	.05/.01	.05/.05	.05/.10	.10/.01	.10/.05	.10/.10
9 to 1 (9 in 10)	.90	+14 / -9 (none)	+14 / -6 (none)	+14 / -4 (-21)	+13 / -9 (none)	+13 / -6 (none)	+13 / -4 (-21)	+13 / -9 (none)	+13 / -6 (none)	+13 / -4 (-21)
8 to 1 (8 in 9)	.89	+13 / -8 (none)	+13 / -5 (none)	+13 / -4 (-20)	+13 / -8 (none)	+13 / -5 (none)	+13 / -4 (-20)	+12 / -8 (none)	+12 / -5 (none)	+12 / -4 (-20)
7 to 1 (7 in 8)	.88	+13 / -7 (none)	+13 / -5 (-22)	+13 / -4 (-18)	+12 / -7 (none)	+12 / -5 (-22)	+13 / -4 (-18)	+12 / -7 (none)	+12 / -5 (-22)	+12 / -4 (-18)
6 to 1 (6 in 7)	.86	+12 / -7 (none)	+12 / -4 (-20)	+12 / -4 (-16)	+11 / -7 (none)	+11 / -4 (-20)	+11 / -4 (-16)	+11 / -7 (none)	+11 / -4 (-20)	+11 / -4 (-16)
5 to 1 (5 in 6)	.83	+11 / -6 (none)	+11 / -4 (-17)	+11 / -3 (-15)	+10 / -6 (none)	+10 / -4 (-17)	+10 / -3 (-15)	+10 / -6 (none)	+10 / -4 (-17)	+10 / -3 (-15)
4 to 1 (4 in 5)	.80	+10 / -5 (-21)	+10 / -4 (-15)	+10 / -3 (-14)	+10 / -5 (-21)	+10 / -4 (-15)	+10 / -3 (-14)	+9 / -5 (-21)	+9 / -4 (-15)	+9 / -3 (-14)
3 to 1 (3 in 4)	.75	+9 / -5 (-16)	+9 / -3 (-13)	+9 / -3 (-12)	+8 / -5 (-16)	+8 / -3 (-13)	+8 / -3 (-12)	+8 / -5 (-16)	+8 / -3 (-13)	+8 / -3 (-12)
2 to 1 (2 in 3)	.67	+7 / -4 (-13)	+7 / -3 (-11)	+7 / -2 (-10)	+6 / -4 (-13)	+6 / -3 (-11)	+6 / -2 (-10	+6 / -4 (-13)	+6 / -3 (-11)	+6 / -2 (-10)
1 to 1 (1 in 2)	**.50**	**+4 / -4 (-9)**	**+4 / -3 (-7)**	**+4 / -2 (-6)**	**+3 / -4 (-9)**	**+3 / - 3 (-7)**	**+3 / -2 (-6)**	**+2 / -4 (-9)**	**+2 / -3 (-7)**	**+2 / -2 (-6)**
1 to 2 (1 in 3)	.33	+4 / -7 (-11)	+4 / -6 (-9)	+4 / -6 (-8)	+3 / -7 (-11)	+3 / -6 (-9)	+3 / -6 (-8)	+2 / -7 (-11)	+2 / -6 (-9)	+2 / -6 (-8)
1 to 3 (1 in 4)	.25	+5 / -9 (-11)	+5 / -8 (-9)	+5 / -8 (-8)	+3 / -9 (-11)	+3 / -8 (-9)	+3 / -8 (-8)	+3 / -9 (-11)	+3 / -8 (-9)	+3 / -8 (-8)
1 to 4 (1 in 5)	.20	+5 / -10 (-12)	+5 / -10 (-10)	+5 / -9 (-9)	+4 / -10 (-12)	+4 / -10 (-10)	+4 / -9 (-9)	+3 / -10 (-12)	+3 / -10 (-10)	+3 / -9 (-9)
1 to 5 (1 in 6)	.17	+6 / -11 (-12)	+6 / -10 (-10)	+6 / -10 (-10)	+4 / -11 (-12)	+4 / -10 (-10)	+4 / -10 (-10)	+3 / -11 (-12)	+3 / -10 (-10)	+3 / -10 (-10)
1 to 6 (1 in 7)	.14	+7 / -12 (-13)	+7 / -11 (-11)	+7 / -11 (-10)	+4 / -12 (-13)	+4 / -11 (-11)	+4 / -11 (-10)	+4 / -12 (-13)	+4 / -11 (-11)	+4 / -11 (-10)
1 to 7 (1 in 8)	.13	+7 / -12 (-13)	+7 / -12 (-11)	+7 / -11 (-10)	+5 / -12 (-13)	+5 / -12 (-11)	+5 / -11 (-10)	+4 / -12 (-13)	+4 / -12 (-11)	+4 / -11 (-10)
1 to 8 (1 in 9)	.11	+8 / -13 (-13)	+7 / -13 (-11)	+8 / -12 (-10)	+5 / -13 (-13)	+5 / -13 (-11)	+5 / -12 (-10)	+4 / -13 (-13)	+4 / -13 (-11)	+4 / -12 (-10)
1 to 9 (1 in 10)	.10	+9 / -14 (-13)	+9 / -13 (-12)	+9 / -13 (-11)	+6 / -14 (-13)	+6 / -13 (-12)	+6 / -13 (-11)	+4 / -14 (-13)	+4 / -13 (-12)	+4 / -13 (-11)

Parenthesis indicate the use of a statistical correction for multiplicity effects.

Appendix B: Multinomial Cutscores for ESS Scores of Multiple Issue Exams

ESS-M Scores / Multiple Issue Exam

		Alpha (truth/deception)								
Prior odds of deception	prior probability	.01/.01	.01/.05	.01/.10	.05/.01	.05/.05	.05/.10	.10/.01	.10/.05	.10/.10
9 to 1 (9 in 10)	.90	(+8) / none	(+8) / none	(+8) / -9	(+7) / none	(+7) / none	(+7) / -9	(+7) / none	(+7) / none	(+7) / -9
8 to 1 (8 in 9)	.89	(+7) / none	(+7) / none	(+7) / -6	(+7) / none	(+7) / none	(+7) / -6	(+7) / none	(+7) / none	(+7) / -6
7 to 1 (7 in 8)	.88	(+7) / none	(+7) / -10	(+7) / -6	(+7) / none	(+7) / -10	(+7) / -6	(+7) / none	(+7) / -10	(+7) / -6
6 to 1 (6 in 7)	.86	(+7) / none	(+7) / -8	(+7) / -5	(+6) / none	(+6) / -8	(+6) / -4	(+6) / none	(+6) / -8	(+6) / -5
5 to 1 (5 in 6)	.83	(+6) / -14	(+6) / -5	(+6) / -4	(+6) / -14	(+6) / -5	(+6) / -4	(+6) / -14	(+6) / -5	(+6) / -4
4 to 1 (4 in 5)	.80	(+6) / -9	(+6) / -5	(+6) / -4	(+5) / -9	(+5) / -5	(+5) / -4	(+5) / -9	(+5) / -5	(+5) / -4
3 to 1 (3 in 4)	.75	(+5) / -6	(+5) / -4	(+5) / -3	(+5) / -6	(+5) / -4	(+5) / -3	(+4) / -6	(+4) / -4	(+4) / -3
2 to 1 (2 in 3)	.67	(+4) / -5	(+4) / -3	(+4) / -3	(+3) / -5	(+3) / -3	(+3) / -3	(+3) / -5	(+3) / -3	(+3) / -3
1 to 1 (1 in 2)	**.50**	**(+2) / -4**	**(+2) / -3**	**(+2) / -2**	**(+1) / -4**	**(+1) / -3**	**(+1) / -2**	**(+1) / -4**	**(+1) / -3**	**(+1) / -2**
1 to 2 (1 in 3)	.33	(+1) / -6	(+1) / -5	(+1) / -4	(0) / -6	(0) / -5	(0) / -4	(0) / -6	(0) / -5	(0) / -4
1 to 3 (1 in 4)	.25	(0) / -7	(0) / -6	(0) / -6	(0) / -7	(0) / -6	(0) / -6	(0) / -7	(0) / -6	(0) / -6
1 to 4 (1 in 5)	.20	(+1) / -7	(0) / -7	(0) / -6	(0) / -7	(0) / -7	(0) / -6	(0) / -7	(0) / -7	(0) / -6
1 to 5 (1 in 6)	.17	(+4) / -8	(+4) / -7	(+4) / -7	(0) / -8	(0) / -7	(0) / -7	(0) / -8	(0) / -7	(0) / -7
1 to 6 (1 in 7)	.14	(none) / -8	(none) / -8	(none) / -7	(0) / -8	(0) / -8	(0) / -7	(0) / -8	(0) / -8	(0) / -7
1 to 7 (1 in 8)	.13	(none) / -9	(none) / -8	(none) / -8	(0) / -9	(0) / -8	(0) / -8	(0) / -9	(0) / -8	(0) / -8
1 to 8 (1 in 9)	.11	(none) / -9	(none) / -8	(none) / -8	(none) / -9	(none) / -8	(none) / -8	(0) / -9	(0) / -8	(0) / -8
1 to 9 (1 in 10)	.10	(none) / -9	(none) / -9	(none) / -8	(none) / -9	(none) / -9	(none) / -8	(0) / -9	(0) / -9	(0) / -8

Parenthesis indicate the use of a statistical correction for multiplicity effects.

Appendix C: Multinomial Cutscores for Three-Position Scores of Single Issue Exams

3-Position Scores / Event-Specific Exam

		Alpha (truth/deception)								
Prior odds of deception	prior probability	.01/.01	.01/.05	.01/.10	.05/.01	.05/.05	.05/.10	.10/.01	.10/.05	.10/.10
9 to 1 (9 in 10)	.90	+11 / -8 (none)	+11 / -5 (none)	+11 / -4 (none)	+10 / -8 (none)	+10 / -5 (none)	+10 / -4 (none)	+10 / -8 (none)	+10 / -5 (none)	+10 / -4 (none)
8 to 1 (8 in 9)	.89	+10 / -8 (none)	+10 / -5 (none)	+10 / -4 (none)	+10 / -8 (none)	+10 / -5 (none)	+10 / -4 (none)	+9 / -8 (none)	+9 / -5 (none)	+9 / -4 (none)
7 to 1 (7 in 8)	.88	+10 / -7 (none)	+10 / -4 (none)	+10 / -4 (-17)	+9 / -7 (none)	+9 / -4 (none)	+9 / -4 (-17)	+9 / -7 (none)	+9 / -4 (none)	+9 / -4 (-17)
6 to 1 (6 in 7)	.86	+10 / -6 (none)	+10 / -4 (none)	+10 / -3 (-14)	+9 / -6 (none)	+9 / -4 (none)	+9 / -3 (-14)	+9 / -6 (none)	+9 / -4 (none)	+9 / -3 (-14)
5 to 1 (5 in 6)	.83	+9 / -5 (none)	+9 / -4 (-15)	+9 / -3 (-12)	+8 / -5 (none)	+8 / -4 (-15)	+8 / -3 (-12)	+8 / -5 (none)	+8 / -4 (-15)	+8 / -3 (-12)
4 to 1 (4 in 5)	.80	+8 / -5 (none)	+8 / -3 (-13)	+8 / -3 (-11)	+8 / -5 (none)	+8 / -3 (-13)	+8 / -3 (-11)	+7 / -5 (none)	+7 / -3 (-13)	+7 / -3 (-11)
3 to 1 (3 in 4)	.75	+7 / -4 (-14)	+7 / -3 (-11)	+7 / -2 (-10)	+7 / -4 (-14)	+7 / -3 (-11)	+7 / -2 (-10)	+6 / -4 (-14)	+6 / -3 (-11)	+6 / -2 (-10)
2 to 1 (2 in 3)	.67	+6 / -3 (-11)	+6 / -3 (-9)	+6 / -2 (-8)	+5 / -3 (-11)	+5 / -3 (-9)	+5 / -2 (-8)	+5 / -3 (-11)	+5 / -3 (-9)	+5 / -2 (-8)
1 to 1 (1 in 2)	**.50**	**+3 / -3 (-8)**	**+3 / -2 (-6)**	**+3 / -2 (-5)**	**+2 / -3 (-8)**	**+2 / -2 (-6)**	**+2 / -2 (-5)**	**+2 / -3 (-8)**	**+2 / -2 (-6)**	**+2 / -2 (-5)**
1 to 2 (1 in 3)	.33	+3 / -6 (-9)	+3 / -5 (-7)	+3 / -5 (-6)	+3 / -6 (-9)	+3/ -5 (-7)	+3 / -5 (-6)	+2 / -6 (-9)	+2 / -5 (-7)	+2 / -5 (-6)
1 to 3 (1 in 4)	.25	+4 / -7 (-9)	+4 / -7 (-8)	+4 / -6 (-7)	+3 / -7 (-9)	+3 / -7 (-8)	+3 / -6 (-7)	+2 / -7 (-9)	+2 / -7 (-8)	+2 / -6 (-7)
1 to 4 (1 in 5)	.20	+5 / -8 (-10)	+5 / -8 (-8)	+5 / -7 (-7)	+3 / -8 (-10)	+3 / -8 (-8)	+3 / -7 (-7)	+3 / -8 (-10)	+3 / -8 (-8)	+3 / -7 (-7)
1 to 5 (1 in 6)	.17	+5 / -9 (-10)	+5 / -8 (-9)	+5 / -8 (-8)	+4 / -9 (-10)	+4 / -8 (-9)	+4 / -8 (-8)	+3 / -9 (-10)	+3 / -8 (-9)	+3 / -8 (-8)
1 to 6 (1 in 7)	.14	+6 / -10 (-10)	+6 / -9 (-9)	+6 / -9 (-8)	+4 / -10 (-10)	+4 / -9 (-9)	+4 / -9 (-8)	+3 / -10 (-10)	+3 / -9 (-9)	+3 / -9 (-8)
1 to 7 (1 in 8)	.13	+6 / -10 (-10)	+6 / -9 (-9)	+6 / -9 (-8)	+4 / -10 (-10)	+4 / -9 (-9)	+4 / -9 (-8)	+3 / -10 (-10)	+3 / -9 (-9)	+3 / -9 (-8)
1 to 8 (1 in 9)	.11	+8 / -10 (-11)	+8 / -10 (-9)	+8 / -9 (-8)	+5 / -10 (-11)	+5 / -10 (-9)	+5 / -9 (-8)	+4 / -10 (-11)	+4 / -10 (-9)	+4 / -9 (-8)
1 to 9 (1 in 10)	.10	+8 / -11 (-11)	+8 / -10 (-9)	+8 / -10 (-9)	+5 / -11 (-11)	+5 / -10 (-9)	+5 / -10 (-9)	+4 / -11 (-11)	+4 / -10 (-9)	+4 / -10 (-9)

Parenthesis indicate the use of a statistical correction for multiplicity effects.

Appendix C: Multinomial Cutscores for Three-Position Scores of Multiple Issue Exams

3-Position Scores / Multiple Issue Exam

Prior odds of deception	prior probability	Alpha (truth / deception) .01/.01	.01/.05	.01/.10	.05/.01	.05/.05	.05/.10	.10/.01	.10/.05	.10/.10
9 to 1 (9 in 10)	.90	(+6) / none	(+6) / none	(+6) / none	(+6) / none	(+6) / none	(+6) / none	(+6) / none	(+6) / none	(+6) / none
8 to 1 (8 in 9)	.89	(+6) / none	(+6) / none	(+6) / -10	(+6) / none	(+6) / none	(+6) / -10	(+5) / none	(+5) / none	(+5) / -10
7 to 1 (7 in 8)	.88	(+6) / none	(+6) / none	(+6) / -7	(+5) / none	(+5) / none	(+5) / -7	(+5) / none	(+5) / none	(+5) / -7
6 to 1 (6 in 7)	.86	(+5) / none	(+5) / -10	(+5) / -5	(+5) / none	(+5) / -10	(+5) / -5	(+5) / none	(+5) / -10	(+5) / -5
5 to 1 (5 in 6)	.83	(+5) / none	(+5) / -5	(+5) / -4	(+5) / none	(+5) / -5	(+5) / -4	(+5) / none	(+5) / -5	(+5) / -4
4 to 1 (4 in 5)	.80	(+5) / none	(+5) / -4	(+5) / -3	(+4) / none	(+4) / -4	(+4) / -3	(+4) / none	(+4) / -4	(+4) / -3
3 to 1 (3 in 4)	.75	(+4) / -7	(+4) / -4	(+4) / -3	(+4) / -7	(+4) / -4	(+4) / -3	(+4) / -7	(+4) / -4	(+4) / -3
2 to 1 (2 in 3)	.67	(+3) / -4	(+3) / -3	(+3) / -2	(+3) / -4	(+3) / -3	(+3) / -2	(+3) / -4	(+3) / -3	(+3) / -2
1 to 1 (1 in 2)	**.50**	**(+1) / -3**	**(+1) / -3**	**(+1) / -2**	**(+1) / -3**	**(+1) / -3**	**(+1) / -2**	**(+1) / -3**	**(+1) / -3**	**(+1) / -2**
1 to 2 (1 in 3)	.33	(+1) / -5	(+1) / -4	(+1) / -4	(0) / -5	(0) / -4	(0) / -4	(0) / -5	(0) / -4	(0) / -4
1 to 3 (1 in 4)	.25	(+1) / -6	(+1) / -5	(+1) / -4	(0) / -6	(0) / -5	(0) / -4	(0) / -6	(0) / -5	(0) / -4
1 to 4 (1 in 5)	.20	(none) / -6	(none) / -5	(none) / -5	(0) / -6	(0) / -5	(0) / -5	(0) / -6	(0) / -5	(0) / -5
1 to 5 (1 in 6)	.17	(none) / -6	(none) / -6	(none) / -5	(0) / -6	(0) / -6	(0) / -5	(0) / -6	(0) / -6	(0) / -5
1 to 6 (1 in 7)	.14	(none) / -7	(none) / -6	(none) / -6	(+2) / -7	(+2) / -6	(+2) / -6	(0) / -7	(0) / -6	(0) / -6
1 to 7 (1 in 8)	.13	(none) / -7	(none) / -6	(none) / -6	(none) / -7	(none) / -6	(none) / -6	(0) / -7	(0) / -6	(0) / -6
1 to 8 (1 in 9)	.11	(none) / -7	(none) / -7	(none) / -6	(none) / -7	(none) / -7	(none) / -6	(+1) / -7	(+1) / -7	(+1) / -6
1 to 9 (1 in 10)	.10	(none) / -7	(none) / -7	(none) / -6	(none) / -7	(none) / -7	(none) / -6	(none) / -7	(none) / -7	(none) / -6

Parenthesis indicate the use of a statistical correction for multiplicity effects.