CT3 AS AN INDEX OF KNOWLEDGE DOMAIN STRUCTURE:

DISTRIBUTIONS FOR ORDER ANALYSIS

AND INFORMATION HIERARCHIES

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The problem with which this study is concerned is articulating all possible CT3 and K-R 21 reliability measures for every case of a 5x5 binary matrix (32,996,500 possible matrices).

The study has three purposes. The first purpose is to calculate CT3 for every matrix and compare the results to the proposed optimum range of 0.3 to 0.5. The second purpose is to compare the results from the calculation of K-R 21 and CT3 reliability measures. The third purpose is to calculate CT3 and K-R 21 on every strand of a class test whose item set has been reduced using the difficulty strata identified by Order Analysis.

The study was conducted by writing a computer program to articulate all possible 5 x 5 matrices. The program also calculated CT3 and K-R 21 reliability measures for each matrix. The nonparametric technique of Order Analysis was applied to two sections of test items to stratify the items into difficulty levels. The difficulty levels were used to reduce the item set from 22 to 9 items. All possible strands or chains of these items were identified so that both reliability measures (CT3 and K-R 21) could be calculated.

One major finding of this study indicates that 0.3 to 0.5 is a desirable range for CT3 (cumulative p=.86 to p=.98) if cumulative frequencies are measured. A second major finding is that the K-R 21 reliability measure

produced an invalid result more than half the time. The last major finding is that CT3, rescaled to range between 0 and 1, supports De Vellis' guidelines for reliability measures. The major conclusion is that CT3 is a better measure of reliability since it considers both inter- and intra-item variances.

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CHAPTER I
STATEMENT OF PROBLEM
Introduction

Item Analysis is the granular analysis of right-wrong answers to individual questions on a test. This granularity of question response patterns allows the instructor to better understand the gaps and misconceptions in domain knowledge. Summative scores have been used for decades to provide instructors, administrators, parents and students with a performance measure for academic achievement. Yet summative scores suffer from condensing the items into a single score, thus removing the granularity at the expense of providing a single, simple, quick measure of performance. In 1981, Harnisch and Linn pointed out there were 184,756 ways to score a 10 on a 20-item test. Knowing which questions were missed could generally provide more insight into the areas of weakness of the examinee than a single total score. To that end, factor analysis is sometimes used to determine which questions group or 'hang' together. However, factor analysis is often used inappropriately as the underlying assumption of a linear relationship between factors and items is difficult to attain within cognitive measures (Green, 1983).

Capturing item response patterns from pencil/paper tests is cumbersome once the test size or the number of students taking the test becomes large.

However, as computers become more prevalent, it is possible to capture test results electronically rather than rely on keypunching the item results. Determining the existence of item response patterns shifts from the investigator to the computer, although analysis and interpretation of these item response methods as yet remains with the investigator.

Many researchers have pursued the development of a student knowledge map or domain knowledge based on students' item response patterns. Birenbaum & Tatsuoka (1982), Tatsuoka & Tatsuoka (1983), and Sato (1980) have tried to provide standardized methods to analyze students test results in order to recommend student specific remediation for inappropriately developed knowledge domains after the fact. Another research area has been concerned with providing real-time feedback to student performance as tests occur in order to spotlight misconceptions in student's domain knowledge. This line of research includes such programs as BUGGY from researchers Brown & Burton (1978). Finally, computer adapted testing is another area of research which attempts to leverage this student knowledge domain by using the real-time item scores to conditionally present the successive question. Generally, a correctly answered question is followed by a more difficult question whereas an incorrectly answered question is followed by an easier question (Fielder, 1995).

The concept of a learner's knowledge domain is an extension of the pioneering work by Jean Piaget, Robert Gagne, Paul Merrill, and Richard White. These researchers described a learner's knowledge domain acquisition as a hierarchical learning process where smaller less complicated tasks were learned as the learner stepped up to successively more difficult, complicated tasks. This description of a knowledge domain infers that domains are not unidimensional. Understanding the dimensionality of tests has traditionally been accomplished with linear factor analysis. However, linear factor analysis is generally inappropriately used since one of the fundamental data assumptions of this technique is the linear relationship between items and factors (Green, 1983). According to Green (1983), "[a]lternative factor analytic techniques have been developed by Christofferson (1975) and Muthen (1978) that allow for nonlinear relationships between items and factors." Christofferson (1975) referred to this type of factor analysis as multiple factor analysis. Gustafsson (1980) observed that the computational complexity of this alternative factor analytic technique "make it practically unemployable for medium to large sets of items."

The summative score of a multidimensional test would also inaccurately indicate equal expertise for any two students whether or not they possessed the same ability or exhibited vastly different knowledge domains. Analyzing item response patterns could provide specific understanding of knowledge domain gaps or inaccuracies.

Evaluation of a learner's domain involves measurement. Crocker and Algina (1096) defined measurement as using pre-established rules to assign real numbers to individual performance on test items. One rule that can be applied is assigning a 1 for a correct answer and a 0 for an incorrect answer. In classical test theory, the summative score does not change if the item response patterns differ. While summative scores are convenient measures of performance, they are not indicative of performance differences, complexity, or domain inaccuracies for each student. Krus, Bart, & Airasian (1975) observe that the composition of items correctly answered by the subject to get the summative score does not matter. This summative score provides useful quantitative data but does not provide significant qualitative or individual performance level information (Byers, 1997).

To relate a test score to the item response pattern (test performance), Krus, Bart, and Airasian (1975) state that it is necessary that the linear order among the numbers that compose the score reflect the same linear order as that among the test items. Coombs (1964) and Suppes and Zinnes (1963) support this concept of isomorphism. Linearly ordered items also provide linkage to the hierarchical learning models posited by Gagne, Piaget, Merrill and White.

Table 1
Gagne & Brigg's Typology: Five Types of Learning (1965)

Attitudes	Internal states for personal action choices
Motor Skills	Organized Muscle movements
Information	Knowledge a about the world stored in memory
Intellectual	Learner skills used to carry out higher- thought processes
Cognitive	Learner strategies developed to solve problems

Several researchers have shown that the frequency distribution of test results from a large population sample often approach the shape of a normal curve (McNemar, 1969; Thissen, 1993). If linearity exists, there may be some subgroups with different scores. These subgroups will be normally distributed around the mean and this frequency distribution reinforces the understanding that each person need not answer all the test items in order to understand their domain knowledge.

There are many possible factors which could impact item response patterns such as: demographics, testing method, bias in group selection, etc. Thus a quality reliability measure of item response analysis becomes very important. Harnisch and Linn (1981) have conveniently categorized the 20 different item response indices into two different groups. The first, appropriateness indices, is based on Item Response Theory (IRT). Order Analysis falls into this group. The second is based on observed right/wrong answer patterns as well as summary statistics.

In Order Analysis, the students and items are organized based on item difficulty indices. Item difficulty infers that students that correctly answer harder items will generally correctly answer easy items, that is items with smaller item difficulty indices. This concept of linearity also provides the framework for ranking student performance based on item responses rather than summative scores.

Creating this item hierarchy is a common theme from Louis Guttman scaling in the 1930s, through Gagne, Piaget and Coombs in the 1960s and into the 1970s and 1980s of Krus, Airasian, Bart, Cliff, and Cudeck. Scaling the items is akin to linearly ordering the items based on inter- and intra-items statistics. Successive comparison of confirmatory (1,0) patterns and disconfirmatory patterns (0,1) is required by item order analysis. Comparing each item to every other item establishes the predecessor relationships. Each item can then be placed in a difficulty level (Krus, Bart, & Airasian, 1975).

To determine what level of confirmatory and disconfirmatory responses is significant, a reliability index should be calculated. Traditionally, Kuder-Richardson (1937) formula 20 (K-R 20) or formula 21 (K-R 21) is used although each is susceptible to test length. Cliff (1975) used Monte Carlo analysis to compare the behavior of CT2, CT3 and K-R 20. In 1947, Loevinger's index, which is less susceptible to test length, was developed; however, it is cumbersome to calculate. An easier calculation for Loevinger's index was developed by Cliff (1975) when he created CT2 and CT3 both of which are derived from Loevinger's index. Cudek (1980) also showed that K-R 20 was susceptible to test length. Cliff and Cudeck hypothesized an appropriate reliability range of 0.3 to 0.5 for CT3; however, creating and comparing the reliability indices for each and every possible matrix of a given student-by-item amount has not been done. Both Monte Carlo and Bournelli techniques have been used to generate hypothetical item response matrices.

Problem Statement

The problem addressed in this study is the development and verification of consistency indices for psychological object lattices derived through Bart, Krus, and Airasian's Ordering Theory and Methods (1975). Kuder-Richardson 21 (K-R

21) and Cudeck's CT3 will be the operational measures used as the basis of the validation procedure.

Assuming that test items can be linearly arranged in terms of item difficulty, these reliability indices can be calculated and used to measure how consistently the test measures what it is supposed to measure. Every possible matrix of item-response patterns for a 5 item by 5 person will have each reliability index calculated. While the resulting matrix contains only 5 questions and 5 subjects, there are 33,554,431 possible matrix response patterns (2^{25}) which makes this a nontrivial process.

A matrix of items (columns) by students (rows) is constructed based on the right/wrong answers on a test. A correct answer is represented by a 1 and an incorrect answer by a 0. The summative score for each student is calculated by adding all the 1's and 0's for each row and sorting the matrix rows from largest summative score down to lowest summative score. Next, the summative scores for each item are calculated by adding all the 1's and 0's in a column. The columns are then sorted so that the largest column is at the left and smallest column is at the right. This simple ordering does not accommodate multidimensionality. That is, it is possible to have two students with the same score or two items with the same score. These simple sorts arbitrarily impose an order among sets of the same scores. Item difficulties must be calculated from the confirmatory (1,0) and disconfirmatory (0,1) patterns in order to stratify all items.

Purposes of the Study

The purposes of this study are:

1. To create every possible item-response pattern matrix of a 5 X 5 matrix and calculate the CT3 reliability indices for each matrix.

2. To create every possible item-response pattern matrix of a 5 x 5 matrix and calculate K-R 21 reliability indices for each matrix.

3. To plot the probability distributions for CT3 to ensure the optimal score is between 0.3 and 0.5

4. To compare CT3 and K-R 21 reliability indices to empirically determine if there is a one to one, one to many, or some other type of relationship between the two.

5. To apply order analysis to an instructor created test of an educational domain of knowledge and create CT3 and K-R 21 indices for the test

Hypotheses Research Questions

In this study, the following null hypotheses will be tested:

1. The CT3 optimal index range is between 0.3 and 0.5

2. K-R 21 and CT3 indices show a one to one relationship

3. An educational test, reordered according to order analysis, will create strands for which the reliability measures of K-R 21 and CT3 will be comparable.

Basic Assumptions

Students taking the test represent various backgrounds and levels of experience.

Questions were developed by subject matter experts (instructors).

Organization of the Study

There are four remaining chapters to this study. The literature review related to reliability indices, order analysis, and unidimensionality is contained in Chapter II. Chapter III describes the methodology used to create every item response for a 5 x 5 matrix, explains the multiplicity of sorted matrices, data collection, and treatment of data. Chapter IV presents reliability indices for all possible sorted 5 x 5 matrices, comparison of reliability indices, analyses of collected data and discussion of all findings. Chapter V includes study summaries for data findings, conclusions and recommendations for future research.

Limitations of the Study

The subjects involved in this study were convenient samples of entire student enrollment for CECS 4100 in two classes during Spring 2001 at the University of North Texas. Selection for the class was based on institutional criteria and student self-selection for the course.

Definition of Terms

1. CT3 is a reliability index devised by Cliff (1975) and based upon Loevinger's (1947) index.

2. Difficulty is the degree to which one question is missed more frequently than another item.

3. Items refers to the individual questions on a test.

4. Intra-item is the pairwise comparison of one item on a test to the same item on every other test for all individuals.

5. Inter-item is the pairwise comparison of each item on a test to every other item on the same test for the same individual.

6. K-R 21 is a reliability index devised by Kuder and Richardson (1937).

7. Order is the logical organization of items.

8. Order Analysis refers to a computer program which replicates Bart, Krus, Airasian (1973) process of analyzing right/wrong (1,0) inter-item and intra-item analysis.

9. Proximity is the degree to which items are similar or dissimilar. Proximity can be measured by a) correlation, b) distance, and c) approximate difficulty

10. Reliability refers to the internal consistency.

11. Strand is the resulting group of items with similar difficulty levels as determined by Order Analysis.

12. Strata is the difficulty level determined by Order Analysis.

Significance of the Study

Krus, Bart, and Airasian (1973) state that the application of order analysis is psychologically sound and suitable to education. Gagne, Piaget, and their peers have thoroughly written about learning hierarchies and recommended logical and methodical means to breakdown learning into manageable sizes. Loevinger (1947); Coombs (1964); Krus, Bart, Airasian (1973); Cliff (1975); and Cudeck (1980) have presented objective methods to calculate the reliability of hierarchies found by applying order analysis. The significance of this study is based on the understanding and recommendation of a reliability index against specific every case matrix composition. While it is unlikely that Monte Carlo or Bournelli analysis is biased, it cannot be completed discounted since every case was not considered. In addition, applying order analysis a priori can establish an objective domain knowledge acquisition order. It is possible this item hierarchy will mirror that of the knowledge expert (instructor); however, it is more likely that the item hierarchy will not be identical to that employed by the knowledge expert.

Analyzing the test results in an objective manner could result in a recommended order of instruction for the teacher which is aligned with the domain hierarchy rather than the convenience of the text or course design. Applying the concept further, an instructor could provide a pretest which would more readily allow the instructor to find out what learners do not know and then teach them accordingly (Ausubel, 1968).

Summary

The purposes of this study are to (1) determine whether CT3 stays within the range of 0.3 to 0.5, (2) determine if K-R 21 is less precise than CT3, and (3) apply the theoretical analysis to actual student data from CECS 4100.

The significance of this study is based on several assumptions. First, having students answer fewer questions instead of all questions is a better use of instructional time. Second, reliability should be measured with an index that is not inflated by test length. Understanding the dimensionality of a test can lead to better understanding of student's domain knowledge.

CHAPTER II

REVIEW OF RELATED LITERATURE

Theoretical Perspective Learning

The building blocks of learning were first posited by British philosopher John Locke in the 1600's with the introduction of 'mental atoms'. Piaget (1896-1980) work was underpinned by the idea that learning hierarchies are necessary components of developmental theories. While Piaget (1952) did not coin the phrases of prerequisite knowledge, he intimated at the existence of this condition scale by using phrases such as "more differentiated' and "more equilibrated". Piaget proposed the four states of development: sensorimotor, preoperational, concrete operational, and formal operational.

Bruner (1966) also saw order underlying children's development although he described this order in three stages: enactive, iconic, and symbolic. Ausubel (1963, 1968) proposed a learner's model composed of three different types: representational, conceptual, and propositional. In 1968, Ausubel continued his work by investigating the psychology of verbal learning. He hypothesized that mastery of successive parts in a hierarchical task promoted learning subsequent parts of the same task.

Reigeluth (1979) & Merrill (1977) proposed the idea of elaboration theory which closely resembles Gagne's (1962, 1963, 1965) approach although from a bottom up task definition rather than Gagne's top-down hierarchy. Driscoll (1994) detailed these approaches to learning. The underlying proposition of each is finding the hierarchy and decomposing the larger topic area into its underlying order.

Summative Scoring

Clark and Peterson (1986) indicated that teachers are generally poor judges of student attributes because teacher perceptions are frequently subject to bias and error. Thanks to the baby boom, there is now another large contingent of students working their way through the United States educational system. Large classes and reduced teacher ranks often lead many school curricula to rely on standardized tests. These commercially produced standardized tests are far more economical and efficient to use when assessing large numbers of students. In fact, Mehrens and Lehmann (1987) suggest "... that teachers who rate their students without such information will often be in error" (p. 25).

Once again, a single summative score is seldom indicative of the students specific item performance. As the number of test items increase, the possible permutations of test item patterns increases logrithmetically. Understanding that there is a large number of possible response patterns is of less importance than understanding the underlying dimensions of the data in order to draw meaning from the possible groups of response patterns. Order analysis is one method which can be employed to bring order to this chaos by finding the data hierarchy based on confirmatory and disconfirmatory responses.

During the 1970's, Item Response Theory (IRT) blossomed as a possible method to bring the learning hierarchies to the surface. A few years later, Harnisch and Linn (1981) described 20 different item response indices developed to identify atypical response patterns. The first group looked at IRT appropriateness indices while the second group was based on observable right and wrong patterns and the summary statistics of these patterns.

Reliability

Kuder & Richardson (1937) developed the theory of the estimation of test reliability. Reliability estimates K-R 20 (which approaches Cronbach's alpha) and K-R 21 (which is much easier to calculate) have become defacto standard calculations for reliability. Kuder & Richardson recommend using K-R 21 if items have the same difficulty. If the difficulty is not equal, K-R 21 will underestimate the reliability compared to the more rigorous calculation used in K-R 20.

According to Kuder & Richardson: "Reliabilites obtained from the formulas presented here are never overestimates." When the assumptions are rigidly fulfilled, the figures obtained are the exact values of test reliability as herein defined; if the assumptions are not met, the figures obtained are underestimates. However, K-R 20 and K-R 21 are based on variances and correlations which can lead to negative reliabilities. Kuder & Richardson cautioned that negative reliabilities are invalid. Only the test items which are positively intercorrelated with have a valid reliability. Specifically, Kuder & Richardson state:

> It is implicit in all formulations of the reliability problem that reliability is the characteristic of a test possessed by virtue of the positive intercorrelations of the items composing it. It is the belief of the authors that in many cases the quick estimate afforded by Formula (21) may be good enough for all practical purposes; if the items vary greatly in difficulty, Formula (20) appears to be adequate in any case.

Guttman (1943) developed a basis for scaling qualitative data. He defined a scale, explained the added value a scale score has to a summative score, and defined the terms “more” and “less”. Guttman stated that “...scale analysis will pick out such deviants or non-scale types.... As a matter of fact, a study of the deviants is an interesting by-product of the scale analysis. Scale analysis actually picks out individuals for case studies.” Guttman Scalogram Analysis (Guttman, 1944, 1950) provided the framework from which Bart, Krus, and Airasian would extend their work. Guttman scalogram analysis still suffers from an inability to correctly handle data that is not linear (Wang, 1969). Scalogram analysis is a deterministic model in that it contains no random or probabilistic elements. While it does generate networks of prerequisite tasks, the results have been disappointing (Bart, Airasian, Krus, 1975). Determining the best fitting linear network among a task set that is nonlinear provides less than optimal results.

Loevinger (1947) provided a systematic approach to the construction and evaluation of tests of ability. In 1948, Loevinger articulated the technique of homogenous tests compared with some aspects of scale analysis and factor analysis. Loevinger believed that "...factor analysis of tests does not contribute in any simple way to the composition of pure tests of psychological functions ... the technic of homogenous tests has the advantages of avoiding unwarranted assumptions, of being less work, and of being conceptually simpler." Loevinger also pointed out that Guttman agrees that the term scaling is less appropriate and homogenous test is more appropriate.

Meehl (1949) explained in detail the additional value that a pattern of responses and the scoring of such provides over a simple summative score.

Loevinger (1954) discussed the attenuation paradox in test theory and fully explains the paradox first introduced by Gulliksen (1945); that is, the relation of item difficulty and inter-item correlation to test variance and reliability. Gulliksen stated: "In order to maximize the reliability and variance of the test, items should have high intercorrelations, all items should be of the same difficulty level, and this level should be as near to 50% as possible.... The criterion of maximizing test variance cannot be pushed to extremes. Test variance is a maximum if half of the population makes zero scores, and the other half makes perfect scores." Basically, the closer the items are to difficulty of .5 and thus to equivalence will make the test more reliable and more valid.

Cliff's (1977) theory of consistency of ordering provided rigorous mathematical calculations which developed the value CT3 and ultimately show that CT3 is identical to Loevinger's index of homogeneity. Further, K-R 20 and K-R 21 formulas express the degree of consistency of item orders; they are not direct expressions of consistency of person orders.

Cudeck (1980) performed a comparative study of indices for internal consistency. Comparisons of CT3 values and K-R 20 reliability measures were made and Cudeck stated that a good CT3 ranges from 0.3 to 0.5

Order Analysis

Bart & Krus (1973) presented the framework for an ordering theoretic method to determine hierarchies among items. The following year (1974), Bart & Krus provided complete examples of using order analysis with the two conclusions of: "(1) test data can be analyzed so that rich prescriptive, directive, and diagnostic information can be provided for the teacher and other test users; (2) the hierarchy of prerequisite skills necessary for reading could be determined with the use of this method."

Bart & Airasian (1974) applied order analysis to seven Piagetian tasks. A tolerance level was applied to seven Piagetian tasks to show how it can be used to determine the pattern of logical relations. They covered the potential relationship between ordering theory and task analysis method of Gagne (1965).

Bart & Airasian believed "ordering theory would be an aid to the fields of curriculum and instruction."

McDonald & Ahlawat (1974) put forth the concept that factors due to difficulty (Loevinger) should be dropped altogether and replaced by the notion of factors due to non-linearity. This was the beginning of attempts to compare the results from order analysis to the results from factor analysis.

Airasian, Madaus, & Woods (1975) observed that scalogram analysis usually yields disappointing results except when articulating social distances scales. This is because of the restrictive linear hierarchy. Whenever logical relationships between test items or tasks are of interest, ordering theory can be used. Ordering theory can reveal non-linear lines of implication among items or tasks and in so doing, serve as a basis for hypothesizing lines of causation to be tested in experimental settings.

By 1975, Krus, Bart, & Airasian wrote their compendium Ordering Theory and Methods. This small book presented all the details behind how order analysis is calculated and it provided several examples of its application.

Airasian (1975) applied ordering theory to instructional hierarchies a priori. He classified ordering theory as " ... A deterministic measurement model which uses task response patterns to identify both linear and nonlinear qualitative, prerequisite relations among tasks or behaviors." To overcome the possibility of random error, ordering theory incorporated z-score tolerances. Airasian reminds us that "Two defining properties of ordering theory are that all tasks to be examined must be dichotomously scored and that all subjects in a sample must respond to all of the tasks." The first mention is made to prerequisite relationship that may be due to unequal item difficulties rather than a true prerequisite relationship.

McReady (1975) reinforced the observation that item level difficulty found within domains played an important role in determining if one domain is a prerequisite for another domain. This was followed in 1976 by Bart's article recommending rigorous reformulation of reliability and validity from an ordering-theoretic perspective.

Krus & Weiss (1976) compared factor and order analysis on prestructured and random data. Order analysis at low alphas more closely mimic the results of factor analysis. Order analysis at higher alphas did not find a solution when factor analysis did on a data containing substantial amounts of random variation. "The most important property of order analysis thus appears to be its insensitivity to random variation patterns as compared with factor analytic models." The usefulness of order analysis compared to factor analysis is a continuing thread of discussion during the 1970s and 1980s.

Krus (1977) rebuttal to the factor analysis comparison states that dominance and proximity matrices are "...logically more primitive than correlation matrix"; however, when there is excessive dominance or proximity order analysis does not spuriously suppress phi coefficients like correlation matrices (factor analysis).

Bart (1978) also investigated the relationship between test factor structure and test hierarchical structure. Test structure is conceived of (1) factors or system of continuous latent traits and (2) hierarchical structure that is the network of prerequisite relations among the discrete items. Principle results showed "...sets of items with good, simple, clear factor structures did not present clear, simple hierarchical structures and good, simple order structures." However, factor structures of a test does not indicate anything about the hierarchy of a test. It becomes apparent that factor analysis is not measuring the same structure as order analysis.

Krus (1978) attempted to explain the logical basis of dimensionality. "The dimensions derived by factor analysis are based on both proximity and dominance relations at the item level and only on proximity relations at the factor extraction level. The dimensions extracted by order analysis are based solely on dominance relations at both item and factor extraction levels."

Bart (1979) applied order analysis to understanding the hierarchical structure of formal operation tasks. His study supports the finding that "...tasks within schemes are similar in difficulty and tend to be empirically equivalent."

Krus (1980) revisited the concept of dimensionality of hierarchical and proximal data structures. Reynolds (1980) presented the logical paradox of order analysis. He concluded that until order analysis can consider all chains, it can never select the optimal chain. Also, internal consistency of all elements in a chain is necessary.

Reynolds (1981) created ERGO, a program to perform multidimensional item analysis. Reynolds maintains that factor analysis does not take into account item difficulty. Further, he recommends an iteratively chaining creation method.

Wise (1981) agrees that factor analysis and order analysis difference can be explained by the ‘difficulty’ level of the items. Factor analysis does not measure the same structure as hierarchy analysis. In 1983, Wise compared order analysis and factor analysis in assessing the dimensionality of binary data. This is an extension of his dissertation with a recommendation that proximity relations between items be considered as well as dominance relations when evaluating dimensionality.

Reynolds (1984) developed a program which implements selective chaining for finding preference ordering.

Bart & Read (1984) apply a statistical method to test for the effects of item difficulty. This new measure is based on Fisher’s exact test.

Hattie (1985) provided a methodology review: assessing unidimensionality of tests and items. This full literary review reveals the term homogeneity refers to the similarity of the item correlations as well as being used as a synonym for unidimensionality. “A major consequence of using linear factor analysis on binary items is to distort the loadings of the very easy and very difficult items and to make it appear that such items do not measure the same underlying dimension as the other items....” When items are scored dichotomously, then the use of a linear factor model and the use of phi or tetrachoric correlations are not appropriate since they assume linearly related variables.

Wise & Tatsuoka (1986) assessed the dimensionality of dichotomous data using modified order analysis. They recognized that factor analysis requires interval data but order analysis requires only that the data be ordinal. They also applied a *z* score and proximity test for chain inclusion.

Bart, Rothen, & Read (1986) applied an order analytic approach to the study of group difference in intelligence. Order analysis looks at three types of inter-item relationships: 1) prerequisite, 2) equivalence, and 3) independence. They suggest difficult intellectual skills are acquired similarly across groups whereas easier intellectual skill basics are acquired in substantially different ways across groups.

Piazza & Wise (1988) applied order-theoretic analysis to Jellineks disease model of alchoholism. A *z* score tolerance is used to determine relationships of alcoholism symptoms.

Krus (1993) discussed the problem of negative reliabilities.

Fielder (1995) uses order analysis to compare the effectiveness of computer adaptive testing and computer administered testing. Byers (1997) used ordering theory to establish student knowledge levels. Further, she calculated CT3 to more fully understand the reliability of the test.

Byers (1998) created a sliding scale technique to optimize the assessment of knowledge level through ordering theory. The article recommends continuing assessment after only 1 wrong answer from a student. Again a CT3 of 0.3 to 0.5 was used but *z* scores tolerances were eliminated.

Lu & Webb (1999) used order analytic instructional hierarchies of mnemonics to facilitate learning Chinese and Japanese Kanjii characters

Harapiak (2000) applied order analysis, calculated a *z* score and provided a concrete application for comparing tests measuring developmental disabilities.

CHAPTER III
DATA COLLECTION AND ANALYSIS

This chapter describes the methods and procedures used for collection and analysis of data. Descriptions of the instruments, population, procedures for collection and analysis of data is included.

The study assumes that an every case analysis of a 5 x 5 matrix would be consistent with analysis of smaller and larger matrices when a proper reliability measure was chosen, that is, a reliability measure not susceptible to test length or item correlations. The study also assumes the students had varying skills levels and acceptable interest levels in the subject area being tested.

Order Analysis

In 1973, Bart, Krus, and Airasian posited a method to determine the hierarchy of dichotomously scored data using non-parametric techniques. Order Analysis is a deterministic technique just as Guttman Scalogram analysis is deterministic. That is, the method relies upon the prior results to provide understanding. One of the limitations both techniques share is that they are deterministic (Airasian and Bart, 1975); however, Order Analysis overcomes this limitation by allowing the researcher to set a tolerance for discontinuity by presetting a *z* score prior to analysis. In addition to analyzing precursor relationships (0,1) or (1,0), Order Analysis can also differentiate between logical equivalence and logical independence. Logical equivalence is the understanding that two tasks co-occur, that is the response patterns are (0,0) or (1,1). Logical independence occurs when one task is unrelated to another task. When all four response patterns (01, 10, 11, and 00) occur at frequencies greater than the product of the tolerance level and the number of students there will be logical independence. The two underlying requirements of Order Analysis are: each item must be dichotomously scored and every person must respond to every item. It should be noted that the matrix sorting in Order Analysis is not a consistent sort unless an insertion sorting method is used (Knuth, 1973). It is possible to have two rows (students) with the same row total which have different item response patterns. The order in which the rows occur dictate the sort order of rows with equal totals. This is also true for column sorts. Since each item is compared to every other across items and across persons (inter- and intra-item comparisons), any inconsistency in the sorting will be accounted for by the every case comparison across items. This does mean that it is possible to have two matrices which appear to have different response patterns, when in fact they sort to the same pattern. Both patterns will yield the same reliability measures.

The specific calculations of Order Analysis begin by analyzing patterns of responses on a test. A correct response is given the number 1. An incorrect response is given the number 0. A student-by-item response matrix is created where the columns consist of test items and the rows of students (Table 2).

Table 2
Matrix One: Students - by – Items

	Item 1	Item 2	Item 3	Item 4	Item 5	Row
Student A	1	0	1	0	1	3
Student B	1	0	0	0	0	1
Student C	1	0	0	0	1	2
Student D	1	1	1	1	1	5
Student E	0	1	0	0	1	2
Column Total	4	2	2	1	4	

Row totals are calculated by adding up the 1's in each row. Column totals are created by adding up the 1's in each column. Matrix Two: Sorted Responses is created by sorting the columns in descending order according to the column total. This is followed by sorting the rows in descending order according to the row totals.

Table 3
Matrix Two: Sorted Responses

	Item 1	Item 5	Item 3	Item 2	Item 4	Row Total
Student D	1	1	1	1	1	5
Student A	1	1	0	1	0	3
Student C	1	1	0	0	0	2
Student E	0	1	1	0	0	2
Student B	1	0	0	0	0	1
Column Total	4	4	2	2	1	

Each item response is then compared to each other item response for that row. The end result is a matrix of items by items. Since order analysis is concerned with precursor relationships, the pattern (0,1) is important. It implies that the first item is dominant or harder than the second item. Let us consider Student A in Matrix One. Item 1 was correctly answered as evidenced by the value 1 at the intersection of Student A and Item 1. However, Item 2 was incorrectly answered by Student A as evidenced by the value 0 at the intersection of Student A and Item 2. The response pattern of Item 1 and Item 2 for Student A is (1,0). Following across, the next pattern of Item 1 and Item 3 is (1,1). Item 1 and item 4 is (1,0) followed by the final pattern of (1,1) for item 1 and item 5. Item 1 is not a precursor for any other item for Student A. However, using the same logic, Item 2 is a precursor (gives the pattern of 0,1) for items 1, 3, & 5. Item 2 is not a precursor for item 4 since the pattern result is (0,0).

The third matrix is an item by item matrix obtained by counting the number of dominant (precursor) relationships (0,1 patterns) exist for each item and placing these counts in the upper right triangle. The counter-dominant relationships (pattern 1,0) are counted and put in the lower left triangle.

The main diagonal is 0 for all occurrences. Each item cannot dominate itself so the intersection comparison of an item with itself is zero. Then end result for Matrix Three: Item Dominants is a main diagonal of all zeros, and upper right triangle of dominance counts and a lower left triangle of counter-dominances.

Table 4

Matrix Three: Item Dominances

	Item 1	Item 5	Item 2	Item 3	Item 4
Item 1	0	1	3	2	3
Item 5	1	0	2	2	3
Item 2	1	0	0	1	1
Item 3	0	0	1	0	1
Item 4	0	0	0	0	0

Once the pattern counts for confirmatory and dis- confirmatory have been completed, it is necessary to convert the table into percentages. These percentages are the likelihood of getting the item correct and the comparison item wrong. In addition, the percentages are the basis for comparison to an error tolerance.

Table 5

Matrix Four: Percentages

	Item 1	Item 5	Item 2	Item 3	Item 4
Item 1	0	0.2	0.6	0.4	0.6
Item 5	0.2	0	0.4	0.4	0.6
Item 2	0.2	0	0	0.2	0.2
Item 3	0	0	0.2	0	0.2
Item 4	0	0	0	0	0

With the percentages calculated, there is enough information to use McNemar's formula (1969, p. 56) to calculate z-scores for proportions (Krus, Bart, Airasian, 1975). A z-score is used to standardize the relationship between two numbers. McNemar's formula for critical ratio of nonindependent proportions is appropriate in this case. The following is McNemar's formula and will be used with our example dominant matrix:

$$z_{ij} = \frac{d_{ij} - d_{ji}}{\sqrt{d_{ij} + d_{ji}}}$$

Where :   i = row in dominance matrix

j = column in dominance matrix

d = value at intersection of (i,j)

The calculated *z* score for items 1 and 2 in our example would be:

$$z_{ij} = \frac{3-1}{\sqrt{3+1}} = \frac{2}{\sqrt{4}} = \frac{2}{2} = 1$$

This matrix of item dominance *z* scores can be compared to standard *z* scores to select items which are less than or equal to the *z* score tolerance for error. A larger *z* score will allow more tolerance for error, thus more dis-confirmatory items will be included. A smaller *z* score will reduce the tolerance for error which will eliminate more dis-confirmatory items.

A sample relationship matrix follows which was created using a *z* score critical value of .01:

Table 6
Matrix Five: z scores

	Item 1	Item 5	Item 2	Item 3	Item 4
Item 1	1.00	0.00	1.00	1.41	1.73
Item 5	0.00	0.00	1.41	1.41	1.73
Item 2	-1.00	-1.41	0.00	0.00	1.00
Item 3	-1.41	-1.41	0.00	0.00	1.00
Item 4	-1.73	-1.73	-1.41	-1.00	0.00

This will decompose into a difficulty strata of

More difficult

5, 1

2

3

4

Least difficult

It is possible to have more than one item at each level of the hierarchy. Traditional Guttman scalogram analysis forces every item into a single difficulty scale. This modified approach to scaling permits error tolerances which allows several items with different *z* scores to appear on the same difficulty level since their *z* scores are similar.

Reliability Measure

It is important to understand the reliability of each matrix. The amount of inconsistency present tells us how well the hierarchy can consistently be reproduced. Perhaps more importantly, reliability is a dependable measure we can use to 'break ties' and prune the hierarchy of items. One of the most common reliability measures for cases of single application of a dichotomous test is Kuder-Richardson formula 21 (Kuder and Richardson, 1937). For our purposes; the following formula will be used to calculate K-R 21:

$$\text{K-R21}\ \rho = \frac{k}{k-1}\left(1 - \frac{(m \cdot (k-m))}{k \cdot S_x^2}\right)$$

Where S_x^2 = test variance

k = number of items

m = test mean score

K-R 20 is a more rigorous calculation but is not generally used since it is more difficult to calculate. Both K-R 20 and K-R 21 are conservative reliability measures. That is, they will not overstate the reliability; rather they will understate the reliability.

Cudeck (1980) has shown that K-R 20 is susceptible to test length. The more frequently used K-R 21 suffers from the same issue. That is, K-R 20 values are inflated if there is a large item pool. When Cudeck doubled the number of items from 20 to 40, the value of K-R 20 increased about 15 to 20%. In addition, K-R 20 and K-R 21 assume the test is measuring one dimension and rely heavily on individual item correlations. Violating the restrictive assumptions leads to unpredictable results especially if the correlations are negative.

Cliff's CT3 formula, derived from Loevinger's (1947) homogeneity index, is based on the actual patterns of correct and incorrect responses and is thus considered a nonmetric measure since it is concerned with both item and subject response patterns rather than predicated on covariances (Cudeck 1980). CT3 as defined by Cliff and Cudeck will be the other reliability measure used in this paper:

$$CT3 = \frac{vc - v}{vc - vm}$$

Where: $v = \Sigma_j \Sigma_k n_{jk}$

$$v_m = \Sigma_j \Sigma_{k>j} (n_{jk} - n_{kj})$$

$$vc = n\bar{x}(k - \bar{x}) - n \Sigma pq$$

Where: $\bar{x}$ = average test score

p = proportion of persons passing the item

q = proportion of persons failing the item

Since order analysis uses the marginal scores of the matrix rather than the summative test scores, it is important to compare individual's marginal matrix scores rather than their summative scores. That is, if a person with lower marginal scores misses items that a person with higher marginal scores got correct, then the test is considered homogeneous/reliable. CT3 can be interpreted as an index of reliability of answering items in accordance with the hierarchical difficulty strata. This index is calculated directly from the item response patterns.

In 1980, Cudeck compared K-R 20 and CT3 using Birnbaum's (1968) 3-parameter logistic model to generate hypothetical test cases using Monte Carlo Analysis. An every case analysis was not performed; however, the conclusions were drawn from a population of 300 persons and 200 items using samples of 100 persons and either 20 or 40 items. In total, 1,280 values of each statistic were obtained after drawing 10 samples (Cudeck, 1980).

CT3 is recommended when classical test theory assumptions cannot be guaranteed by the researcher, when evaluating small numbers of items, or in the event of tailored testing. According to Cudeck's Monte Carlo analysis (1980), " in the range of .3 to .5 is acceptable reliability as indexed by K-R 20."

Summary

Hierarchical learning has a rich history and remains an important keystone in educational psychology today. Comprehending the value of learning hierarchy is much easier than implementing a method to uncover those learning hierarchies. Hattie (1985) reviewed 36 indices of unidimensionality. He grouped them into five sections: (1) answer patterns, (2) reliability, (3) principal components, (4) factor analysis, and (5) latent traits. Each index worked well if the underlying restrictions it was conceived under were adhered to. No single index proved more appropriate than another. Although several were seen to be less valuable since the underlying assumptions needed were rarely found. Hattie's final conclusion was than an index is an important part of the evidence used to determine unidimensionality; however, researcher bias and judgment play an equally important role.

Order analysis is predicated on pioneering work of Louis Guttman (1930) and his scalogram analysis. The literature describes not only the development of order analysis but researchers' attempts to force it from a nonparametric method into more widely accepted parametric techniques. A better index of reliability for dichotomously scored data would appear to be CT3 rather than K-R 20/K-R 21 especially if tests are short or tailored testing is the objective.

Applying order analysis can provide deeper understanding of item hierarchies which lends itself to using this knowledge to developed better tailored testing, more quickly quantify learner domain knowledge or domain knowledge gaps, and provide a basis for optimizing item sequencing. Item sequencing could be accomplished either bottom up or top down. That is, asking questions from easy to hard and stopping when the student starts missing the harder ones will ensure the lower level tasks are correctly learned. Asking questions from hard to easy enables the researcher to quickly determine what does not need to be taught.

Research Design

Traditionally, an every case analysis of matrix response pattern has been beyond the reach of most researchers due to the time necessary to create every possibility. 2^n where n is the number of matrix columns times matrix rows quickly becomes overly large. For example, a 30 question test administered to 100 students creates an every case analysis of 2^{3000} binary matrices.

However, there is a less cumbersome method to calculate possible matrices if it is completed in a building block fashion. Let us consider a 3 x 3 matrix and a 4 x 4 matrix. A 3 x 3 matrix has 511 (2^9) possible response patterns. Whereas a 4 x 4 matrix yields 65,535 (2^{16}) possible response patterns. It is important to note that every 3 x 3 matrix response pattern is a subset of all possible 4 x 4 matrices. Therefore, once the unique, sorted 3 x 3 matrices have been articulated is necessary to analyze only the additional 4 x 4 unique, sorted matrices articulated from the additional row and column entries. Note that the identity matrix (all 1's) and the unity matrix (all 0's) reliability indices will not change no matter how many additional rows and columns are added to the matrix.

The calculation of the reliability indices, K-R 21 and CT3, was created by a computer program built specifically for that purpose (Appendix A). To ensure it worked as expected, the matrices from the original article by Cudeck (1980) were analyzed in order to generate the CT3 indices and results were compared to the original work.

The K-R 21 formula was validated by comparing the results generated by the computer program for the same matrices to independent calculation through a spreadsheet using the same data.

The students test was composed of multiple-choice questions (Appendix

B). Tests were graded by the teaching assistant and item response patterns were keyed based on the tests themselves (Appendix C). Test summative scores were generated and compared to the grade assigned to each test to reduce the probability of an obvious keying mistake. All tests responses were keyed in each direction, front to back and back to front. The results were compared to provide further check for accuracy.

The item hierarchy for the test questions was generated by a program written specifically for that purpose (Dunn-Rankin, Wallace, Knezek 2002). Again, the hierarchy generation was compared to that generated by the original data in the Krus, Bart, Airasian (1975) article to ensure the results were consistent with expectations. The input for this program was the test results from the objective tests completed by the students in CECS 4100.

Population and Sample

The population of the student study was composed of students enrolled at the University of North Texas in either one of two sections of the Spring of 2001. The course is required for students majoring in Education and is designed primarily for non-computer science majors. Those who participated in the study were generally freshmen and sophomore and primarily female.

Any student who did not complete the test was eliminated from analysis. That is, every question had to be answered and if any were left blank, that test was eliminated from the analysis. This completeness is a necessary requirement according to Krus, Bart, and Airasian (1973).

Procedures for Collecting Data

Students self-selected the section that best suited their schedule prior to the start of the year. Students were provided course syllabus and course calendars at the beginning of the first class. Students could chose to drop the class or take an incomplete; however, if the student took the test, they were included in this study as long as each question was answered.

Tests were scored and results provided to the researcher. Results were then keyed into a flat file for analysis by the computer programs written to calculate the indices and determine the item hierarchy. Students were not told that the tests were to be used in this study. Students were aware that the quantitative tests were to be followed by hands-on test in the lab to ensure that learner's knowledge was complete.

Test scores were converted to 1 for correct answers and 0 for incorrect answers.

Analysis of Data

All matrices were generated, sorted, and had the two reliability indices calculated. Reliability measures were rounded to 4 decimal precision to insure consistent comparisons. A frequency count of unique CT3 indices was completed and compared to the 0.3 to 0.5 range identified by Cudeck. A frequency count of K-R 21 for each unique CT3 was determined. One-to-many relationships were identified. A frequency count of CT3 for each K-R 21 was determined. Again, all one-to-many relationships were identified.

The student's data was run through the program to generate CT3 as well as through the item analysis process to determine the item hierarchy. A *z* score of .05 was used.

The statistical analysis and data generation for this paper was generated using [SAS/STAT] software, Version 8 of the SAS System for Windows. Copyright © 1999 SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA.

Hypothesis 1: The optimal index range for CT3 is between 0.3 and 0.5

All matrices will have the CT3 reliability measure calculated and plotted.

Hypothesis 2: K-R 21 and CT3 reliability measures have a linear relationship.

All matrices will have the CT3 and K-R 21 measure calculated and tabulated. There should be a 1 to 1 relationship or a 1 to many relationship, but not a many to many relationship.

Hypothesis 3: An educational test, reordered according to order analysis, will produce comparable K-R 21 and CT3 reliability measures.

Order analysis will separate the matrix into scaled, grouped items or strata. K-R 21 and CT3 will be calculated for these subsets of questions. The reliability measures for these strata will be compared.

CHAPTER IV
PRESENTATION AND ANALYSIS OF DATA

The findings and data analysis interpretation are presented in this chapter. Data was generated and analyzed to answer Hypothesis 1 and 2. Data was gathered and analyzed to answer Hypothesis 3.

Hypothesis 1: The optimal index range for CT3 is between 0.3 and 0.5.

Hypothesis 2: K-R 21 and CT3 reliability measures have a linear relationship.

Hypothesis 3: An educational test, reordered according to order analysis, will create strands with equitable K-R 21 and CT3 reliability measures.

Data Generation

Data matrices were simplistically generated by articulating each number between 0 and 2^{25}. The number was converted to a 25 digit binary representation. Each digit of the binary was considered one row/column cell intersection.

Both reliability measures were calculated for each matrix. SAS software assumes 1 degree of freedom when calculating variance, a correcting measure was introduced to the variance calculation to negate the degree of freedom and ensure all calculations remained true to the original works.

Tests of Hypotheses

Hypothesis 1: The optimal index range for CT3 is between 0.3 and 0.5

CT3 reliability ranged from -1.5 to 1.2. Valid CT3 values should fall between -1 and 1, and only 6,543 cases of the 33.5 million were outliers. These outliers occurred when counter dominances where extremely high or extremely low and the matrix average was also at an extreme.

The bell shaped curve of CT3 reliability measures for all possible 5x5 matrices does not indicate that 0.3 to 0.5 is more optimal than other ranges in the curve.

However, plotting the cumulative frequencies of CT3 indices provides valuable insight.

Figure 1
CT3 Reliability Measure

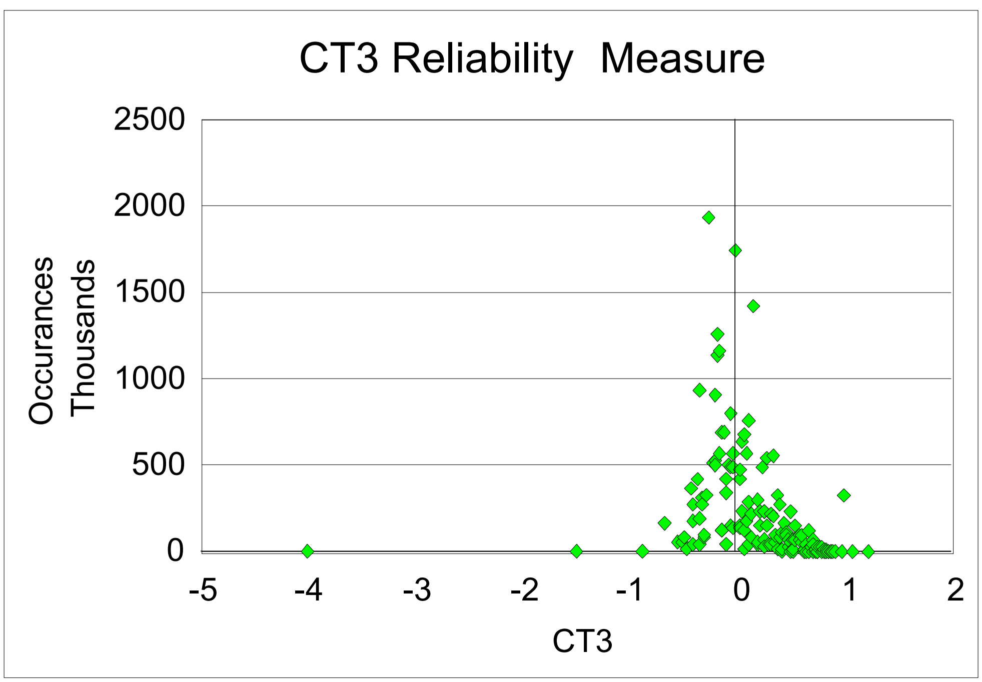
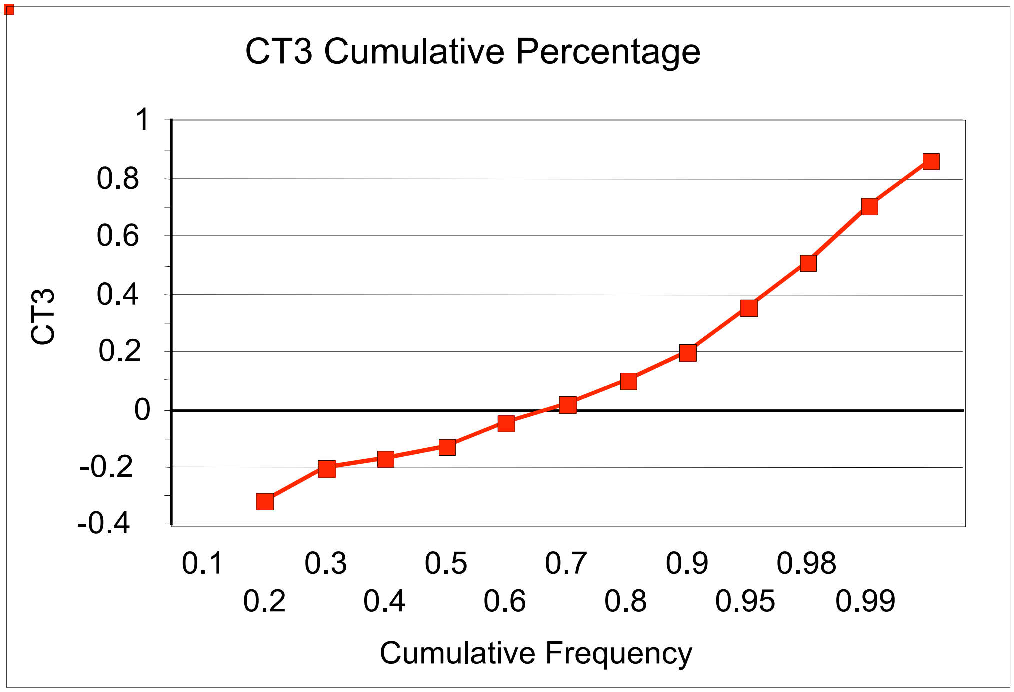


Figure 2
CT3 Cumulative Percentage

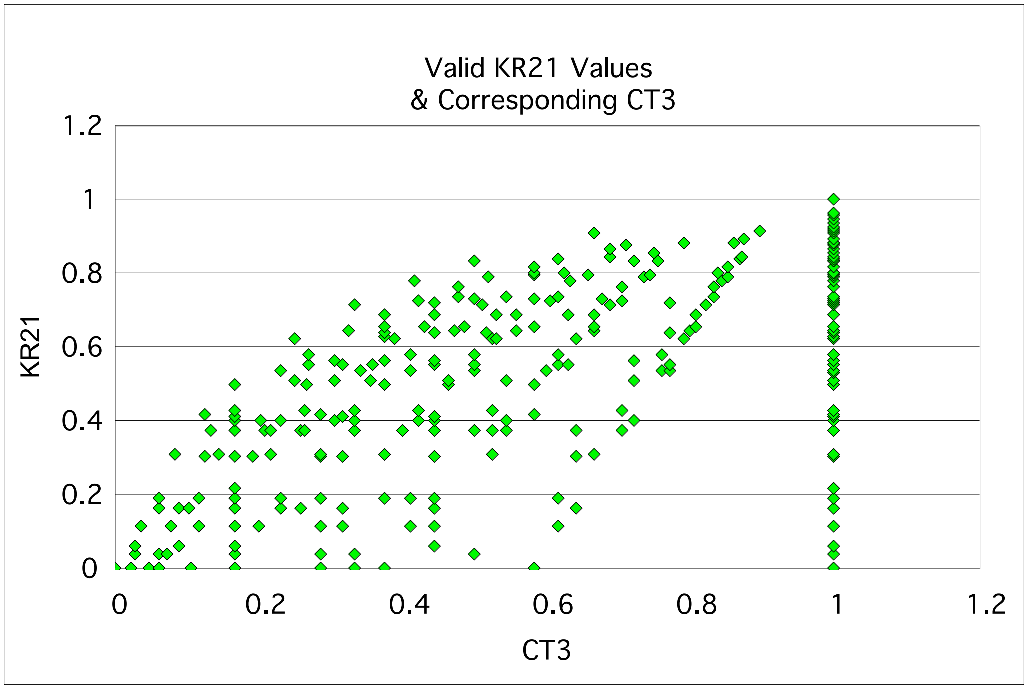


The CT3 value of 0.3 occurs about the 86 percentile and the 0.5 value occurs about 98.5%. If the cumulative percentages are used, a CT3 value of between 0.3 and 0.5 indicates that 86% to 98% of the time it is reliable. Thus, the range is an acceptably optimal range.

Hypothesis 1 is accepted.

Hypothesis 2: K-R 21 and CT3 reliability measures have a linear relationship.

Figure 3
Valid K-R 21 & Corresponding CT3

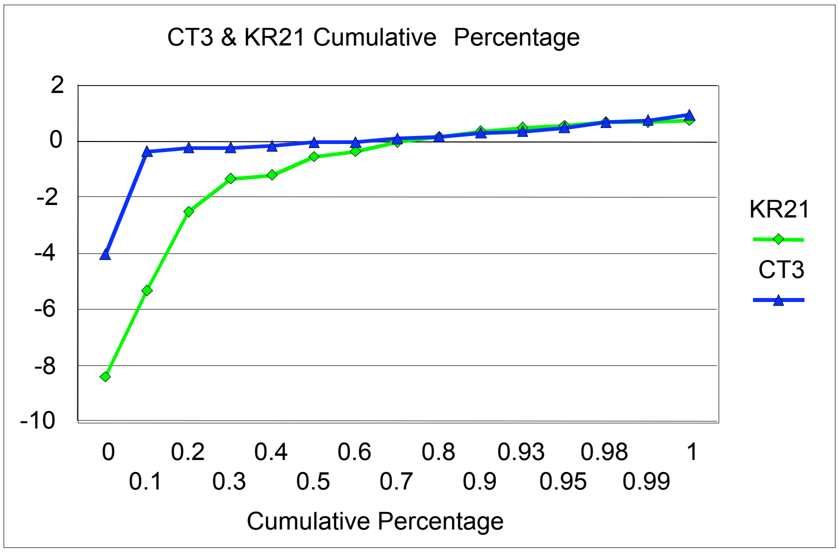


K-R 21 and CT3 do not have an linear relationship. K-R 21 cannot be accurately calculated if the intercorrelations are negative. Nearly 58% of the matrices (57.85%) had a K-R 21 reliability measure which was negative. K-R 21 should range from 0 to 1; thus, over half of the matrices do not have valid K-R 21 reliability indices but do have reliable CT3 indices.

If only the valid values of K-R 21 are considered, it is obvious that there is not a simple linear relationship between the two reliability measures. Since CT3 includes a term for the effect of the dominance/counter dominance matrix, CT3 permits more discrete values of reliability than does K-R 21.

Figure 4

CT3 & K-R 21 Cumulative Percentage



If the cumulative frequencies for both the indices are compared to each other, there is a great difference only at levels where correlations are negative which cause K-R 21 to be invalid (K-R 21 values below 0). There is very close alignment between K-R 21 and CT3 for reliability measures of 0 to 1.

Hypothesis 2 is rejected.

Hypothesis 3: An educational test, reordered according to order analysis, will create strands with equitable K-R 21 and CT3 reliability measures

CECS 4100 (Computer Education and Cognitive Systems) Spring Exam 1 tests were analyzed with order analysis. A *z* score of 0.5 was used. This equates to 4% tolerance for disconfirmatory responses. The resulting hierarchy represented by the question number on the test is as follows:

Most Difficult Strata 1 11

	Strata 2	16, 21
	Strata 3	2, 22
	Strata 4	4, 5, 15
	Strata 5	1, 6
	Strata 6	3, 12, 20
	Strata 7	13, 14
	Strata 8	7, 8
Least Difficult	Strata 9	9, 10, 17, 18, 19

Strata 1:

11. Which of the following is NOT considered a "Materials Generator"?

Strata 2:

16. The Air and Water Projects, which involve students from around the world, are examples of which type of network learning approach?

21. Graphic icon representing 'Click on this, then click on an object to manipulate it'

Strata 3:

2. Write a LOGO procedure to draw a rectangle.

22. Graphic icon representing 'general editing tool'.

Strata 4:

4. The name of the procedure is?

5. The shape which will be produced is a(n):

15. According to your textbook, social studies instruction has traditionally been driven by:

Strata 5

1. What would be the entire output for the following BASIC program?

6. A technology tool that has proven particularly useful in science classrooms is:

Strata 6

3. Name two LOGO primitives (other than RT, LT, RD, BK) and tell what each will do

12. What is one barrier to implementing telecommunications projects in a classroom

20. Graphic icon representing 'allows developer to put navigational buttons on the page'

Strata 7

13. Which of the following is NOT one of the broad goals designed by the Standards for School Mathematics document?

14. A system that automatically sends messages to all ts subscribers is:

Strata 8

7. The internet has enabled students to engage in authentic scientific experiences by:

8. Which of the following is NOT a valid e-mail address?

Strata 9

9. The domain name .edu stands for web addresses assigned to

10. Information found on the Internet

17. Graphic icon representing 'place a new turtle on the screen'

18. Graphic icon representing 'place a text box on the screen'

19. Graphic icon representing 'add music to project'

The complete multiple-choice portion of the test is included in Appendix A. Three strata of 3, 3, and 5 questions each were identified by order analysis. Other *z* scores were tried and these three strata were consistently found in each run. Table 1 shows the results of the reliability calculations:

Table 7
CECS 4100 Reliabilities for Three Strata Lengths

Strata Length	# Items	CT3	K-R 21
4	3	0.89	0.16
6	3	1	0.61
9	5	1	0

Thus, strata of length 9 actually became an identity matrix of all 1's. No one missed any questions. K-R 21 relies on row variance, which has a value of 0 for an identity matrix. A zero in the denominator causes K-R 21 to go to a value of zero.

Strata of length 6 had either 5 or 6 persons incorrectly answer each question. This allowed counter dominances to surface across the three questions. K-R 21 and CT3 calculated very near their expected levels. When CT3 is .99, K-R 21 is .65 and as CT3 moves to 1, K-R 21 moves to .73. Since there were only three questions in the strata, and K-R 21 is susceptible to test length, the difference could easily be explained by the small number of items.

Strata of length 4 had 11 persons incorrectly answer each of the three questions. CT3 calculated to .89 and K-R 21 should have been between .65 and .73 if the cumulative frequency comparison were valid unless there is a contributing factor. Item difficulty and test length contributed to suppressing the K-R 21 value.

CT3 calculation includes two terms to quantify variance: dominance matrix summation as well as percentage of subjects passing/failing each item. This partitioning of the variance into two terms permits CT3 to calculate more consistently across a wider range of matrix combinations. K-R 21's reliance on a single measure of row variance makes it very susceptible to test length. The three strands identified by order analysis did not support valid K-R 21 and CT3 reliability measures. Every possible strand of the 9 strata were analyzed. These 1440 strands did not yield unexpected reliability measures. Suppression of K-R 21 became evident since only nine items were considered. Each strata provided nearly identical variance contribution to the calculations. In theory, any one of the strands could equitably represent the knowledge base.

Hypothesis 3 is rejected.

Cumulative Frequencies

The generation of all possible CT3 and K-R 21 reliability measures provided an opportunity to compare cumulative frequency percentages. De Vellis (1991) provided guidelines for Reliability use:

Table 8

De Vellis Reliability Guidelines (1991)

Below .6	Unacceptable
Between .6 and .65	Undesirable
Between .65 and .7	Minimally Acceptable
Between .7 and .8	Respectable
Between .8 and .9	Very Good
Much above .9	Consider shorting the scale

De Vellis' recommendations were based on a reliability measure that varies from 0 to 1. K-R 21 falls in this category; however, CT3 ranges from -1 to 1. In order to properly compare the two indices, CT3 was rescaled by adding 1 and dividing the result by 2. All three reliability measures are in the following table.

Table 9

Comparison of Reliability Cumulative Frequencies

Cumulative		CT3	
60%	0	0.1935	0.375
70%	0.1026	0.3902	0.4022
80%	0.0245	0.6	0.5
90%	0.359	0.7917	0.5652
95%	0.5	0.8958	0.6591
99%	0.8438	0.9875	.7813

It is very interesting to note that a rescaled CT3 of between .79 and .89 represents a probability between 90 and 95%; thereby lending support to De Vellis' recommendation.

CHAPTER V

DISCUSSION, SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

Two findings which were not the focal point of the three hypothesis were uncovered during the data analysis.

K-R 21 Sensitivity

K-R 21 is especially sensitive to departure from the necessary conditions required to reliably calculate the measure. For example, negative correlations will cause K-R 21 to swing widely below a value of 0. While it was recognized that some outliers would be created with an every case scenario, it was not expected that nearly 68% of the matrices would cause an inappropriate K-R 21.

CT3 Sturdiness

CT3 created outliers beyond its expected values between -1 and 1; however, these cases represented less the .006% of all matrices.

Summary of Findings

This study calculated the two reliability measures (K-R 21 and CT3) for every combination of 5x5 binary matrices. After investigating the performance of K-R 21 and CT3 for the generated data, order analysis was applied to students tests for CECS 4100. Both reliability measures were calculated for the student data in the subsets/chains articulated by order analysis.

Three hypothesis were examined in this study: 1) CT3 optimal range is between 0.3 and 0.5; 2) K-R 21 has a linear relationship to CT3; 3) K-R 21 and CT3 reliability measures for the chains would be similar.

Data was generated and analyzed by SAS software. Students were college students taking CECS 4100 during the fall, 2001 semester. All analysis was based on right/wrong binary matrices.

Analysis of the data indicates that CT3 does have an optimal range between 0.3 and 0.5. This reliability measure is robust and provides a bell shaped curve around zero.

K-R 21 is very sensitive to negative correlations and will calculate a valid value only 40% of the time.

Order Analysis does articulate smaller strands of elements; however, the K-R 21 and CT3 reliability indices produced expected results in only one of the strands.

Conclusions

CT3 is a better measure of reliability for dichotomous data than K-R 21, especially if there are many counter- dominances in the data or there are very few items under consideration. K-R 21 is extremely sensitive to negative correlations and fails to calculate if this assumption is violated. K-R 21 is also susceptible to test length.

CT3 does have an optimal range of 0.3 to 0.5 based on the cumulative frequency of distributions. This range equates to a 90% to 98% confidence test reliability.

In general, CT3 and K-R 21 appear to provide trustworthy reliability indices; however, these two indices do not measure the same underlying constructs. K-R 21 considers row variance and correlations very important. CT3 considers the dominance matrix and subject pass/fail percentages important. These terms contain two different types of variance in their calculations.

Recommendations

From a purely technical analysis, CT3 appears to be a better reliability measure. However, it should be noted that an every case scenario is not likely to occur in regular testing. K-R 21 is easier to calculate and appears to provide a reliability measure that is trustworthy when correlations are positive. K-R 21 also does not overstate the reliability. Both of these points make K-R 21 attractive for use as a reliability measure in simple testing situations.

For the purposes of order analysis, the dominance matrix must be calculated as part of the process to create the hierarchy. CT3 could easily be included in an order analysis routine with minimal effort.

Using the reliability measure to minimize the strands is a logical next step; however, research needs to be completed to ensure the item difficulties are included in the discriminating technique. Successive item strand construction versus articulation of all chains is worthy of further investigation only if the item difficulties and reliability measures are included in the research.

Order Analysis has been modified in unique ways. However, there does not appear to be a comprehensive version that includes all modifications.

The magnitude of matrices that were analyzed were small 5x5 binary matrices. An every case articulation quickly overwhelms computer capacity as the matrix grows to a more sensible size of 30x40 or larger. The integer conversion to binary was a reasonable approach for these 35 million cases. Investigating the optimization of a computational algorithm to calculate the frequency of unique sorted matrices within a given row by column dimension would be a non-trivial but rewarding journey.

Creating a canned procedure for inclusion in SAS software would increase the likelihood that others would begin to use this valuable non-parametric technique.

APPENDIX A

SAS Program

```
/*Computer Program                    */
/*2001 Rebecca Swartz                 */
/*Language: SAS                       */
/*Creates KR21 and CT3 Reliability Measures */
/*Currently coded to handle a 5 x 5 matrix  */

OPTIONS MISSING = 0 ERRORS=1
BUFSIZE=16M BUFNO=5 CLEANUP NOSOURCE NOMACROGEN
NOSYMBOLGEN;

/* change file paths to fit your situation */

FILENAME DATAIN 'C:\DIST_CODE';
FILENAME BDATAOUT 'C:\DIST_DOWN2_BOTH';
FILENAME CDATAOUT 'C:\DIST_DOWN2_CT3';
FILENAME KDATAOUT 'C:\DIST_DOWN2_KR21';

/********************************************
* Code is in this file.
* Primer.txt contains the number of iterations
********************************************/

DATA _null_;
NOPEPL=5;
NOITEM=5;
ITEMSQ   = NOITEM * NOITEM;
ONEMORE = SUM(NOITEM, 1);
ITEMPEPL = NOITEM * NOPEPL;
CALL SYMPUT('NOPEPL',NOPEPL);
CALL SYMPUT('NOITEM',NOITEM);
CALL SYMPUT('ITEMSQ',ITEMSQ);
CALL SYMPUT('ONEMORE',ONEMORE);
CALL SYMPUT('ITEMPEPL',ITEMPEPL);
/*CALL SYMPUT('STARTER',I);
CALL SYMPUT('END',SUM(I,49999));
CALL SYMPUT('PART2','F'__LEFT(FILE2));
CALL SYMPUT('FILEOUT','DATAOUT.&PART2')
*/

/********************************************
* Code is in this file.
* Primer.txt contains the number of iterations
* You must increment _n_ manually to process
* 50000 records at a time -- pc memory constraint
```

```
*********************************************/

DATA BEGIN;
;
INFILE DATAIN(primer.TXT);
INPUT  SKIPIT STARTER ENDER;
IF _N_ = 1;

BOTHFILE = 'B'||LEFT(SKIPIT)||'.TXT';
CT3FILE  = 'C'||LEFT(SKIPIT)||'.TXT';
KR21FILE = 'K'||LEFT(SKIPIT)||'.TXT';
/*THEFILE = 'F'||LEFT(SKIPIT);  */
BOTHFILE = COMPRESS(BOTHFILE," ");
CT3FILE  = COMPRESS(CT3FILE," ");
KR21FILE = COMPRESS(KR21FILE," ");
CALL SYMPUT('S',STARTER);
CALL SYMPUT('E',ENDER);
CALL SYMPUT('B',BOTHFILE);
CALL SYMPUT('C',CT3FILE);
CALL SYMPUT('K',KR21FILE);
RUN;

/*********************************************
* Set up the global variables so you don't
* have to hardcode the array values each time
* the number of items or people changes
*********************************************/

DATA _NULL_;
COLE = 'COL'||LEFT(&NOITEM);
COLE1 = 'COL'||LEFT(&ONEMORE);
DCOLE = 'DCOL'||LEFT(&ITEMSQ);
NCOLE = 'NCOL'||LEFT(&ITEMPEPL);
NCLE = 'NCOLL'||LEFT(&NOITEM);
CTOTE = 'CTOT'||LEFT(&NOITEM);
TOTCE = 'TOTC'||LEFT(&NOITEM);
ROWE = 'ROW'||LEFT(&NOPEPL);
ROWTE = 'ROWT'||LEFT(&NOPEPL);
CPASE = 'CPAS'||LEFT(&NOITEM);
PCTE = 'PCT'||LEFT(&NOITEM);
P1ME = 'PCT1M'||LEFT(&NOITEM);
PCTME  = 'PCTM'||LEFT(&NOITEM);
CTCE = 'CTCOL'||LEFT(&NOITEM);
```

```
CALL SYMPUT('COLE',COLE);
CALL SYMPUT('COLE1',COLE1);
CALL SYMPUT('DCOLE',DCOLE);
CALL SYMPUT('NCOLE',NCOLE);
CALL SYMPUT('NCLE',NCLE);
CALL SYMPUT('CTCE',CTCE);
CALL SYMPUT('CTOTE', CTOTE);
CALL SYMPUT('ROWE',ROWE);
CALL SYMPUT('ROWTE',ROWTE);
CALL SYMPUT('TOTCE',TOTCE);
CALL SYMPUT('CPASE',CPASE);
CALL SYMPUT('PCTE',PCTE);
CALL SYMPUT('P1ME',P1ME);
CALL SYMPUT('PCTME',PCTME);
RUN;


/*********************************************
* BUILD THE INITIAL BASE MATRICES FOR PROCESSING
* the following is an example dataset to run to
* ensure the results are accurate
*********************************************/

/*
DATA THEEND;
INPUT CASE COL1 COL2 COL3 COL4 COL5;
CARDS;
1 1 1 1 1 1
1 0 1 1 1 1
1 0 0 1 1 1
1 0 0 0 1 1
1 0 0 0 0 1
1 0 0 0 0 0
2 1 1 1 1 1
2 0 1 1 0 1
2 0 0 1 1 1
2 0 1 0 1 1
2 0 0 0 0 1
2 0 0 0 0 0
3 1 1 1 1 0
3 0 1 1 0 1
3 0 0 1 1 1
3 0 1 0 1 1
```

```
3 0 0 0 0 1
3 1 0 0 0 0
;
*/


%MACRO THEGUTS(STARTER, ENDER,  BOTHFILE, CT3FILE, KR21FILE);

/*******************************************
* Using the number you selected from primer.txt,
* increment the values until you get 50000 cases.
* Convert each number into its binary equivalent
* and substring each digit to put in each
* subsequent cell of the matrix
*******************************************/
DATA THEEND;
SET THEEND;
DO I = &STARTER TO &ENDER;
/*    DO I = 0 TO (2**25)-1; */

CASE = SUM(CASE,1);
VAR1 = I;
CHANGER = (INPUT(PUT(VAR1,BINARY25.),$CHAR25.));
DO GET = 1, 6, 11, 16, 21;
CCOL1  = SUBSTR(CHANGER,GET,1);
CCOL2  = SUBSTR(CHANGER,GET+1,1);
CCOL3  = SUBSTR(CHANGER,GET+2,1);
CCOL4  = SUBSTR(CHANGER,GET+3,1);
CCOL5  = SUBSTR(CHANGER,GET+4,1);
COL1  = INPUT(PUT(CCOL1,$1.),1.);
COL2  = INPUT(PUT(CCOL2,$1.),1.);
COL3  = INPUT(PUT(CCOL3,$1.),1.);
COL4  = INPUT(PUT(CCOL4,$1.),1.);
COL5 = INPUT(PUT(CCOL5,$1.),1.);
DROP CCOL1-CCOL5 GET I;

OUTPUT;

END;
END;

DATA THEEND   (KEEP=CASE COL1-&COLE ROWT);
SET THEEND ;
```

```
BY CASE;
RETAIN TOTC1-&TOTCE;

/*********************************************
* ZERO OUT THE MATRIX & COLUMN TOTALS ON THE
* FIRST ENTRY TO EACH CASE
*********************************************/

IF FIRST.CASE THEN DO;
ARRAY MAKEZERO{&NOITEM}  TOTC1-&TOTCE;
DO I = 1 TO &NOITEM;
MAKEZERO{I} = 0;
END;
END;

ARRAY THECOL{&NOITEM} COL1-&COLE;
ARRAY TOTC{&NOITEM}    TOTC1-&TOTCE;
DO I = 1 TO &NOITEM;
TOTC{I} = SUM(TOTC{i}, THECOL{i});
END;
ROWT = SUM(OF COL1-&COLE);

IF _N_ GT 0 THEN OUTPUT THEEND;

/* sort by the row totals */

PROC SORT DATA=THEEND;
BY CASE DESCENDING ROWT;

/*********************************************
* At this point, you realize you should have
* used SAS IML (Interactive matrix language),
* Using the sas sort means you have to transpose the
* data several times..
*********************************************/


PROC TRANSPOSE DATA=THEEND PREFIX=ROW OUT=TRANCASE;
BY CASE;
VAR COL1-&COLE ROWT;

DATA TRANCASE ;
SET TRANCASE;
by case;
```

```
LENGTH HOLDER $ 8;
COLNBR = _N_;

CTOT = SUM(OF ROW1-&ROWE);

/*********************************************
* SAS automatically uses 1 degree of freedom
* to calculate the row variance.
* The following will remove the impact of the
* degree of freedom
*********************************************/
if _NAME_ = 'ROWT' then do;
ROWVAR = VAR(OF ROW1-&ROWE);
DEGFREE= SUM(&NOPEPL, -1) / &NOPEPL;
ROWVAR = ROWVAR * DEGFREE;
HOLDER = _NAME_; DROP _NAME_;

end;
OUTPUT;
DROP DEGFREE;

PROC SORT DATA=TRANCASE ; BY CASE CTOT;

DATA TRANCASE;
RETAIN COLODR ;
SET TRANCASE;
LENGTH HOLDER $ 8;
BY CASE;
IF FIRST.CASE THEN THENUM=0;

IF HOLDER NE 'ROWT' THEN DO;
COLODR = SUM(COLODR,1);

HOLDER = 'TOTC'||left(COLODR);
END;

PROC TRANSPOSE DATA=TRANCASE OUT=TRAN2;
BY CASE;
VAR   ROW1-&ROWE COLODR ROWVAR ;

PROC DATASETS; DELETE TRANCASE;
```

```
DATA PCTS (KEEP= CASE  CPAS1- &CPASE ROWVAR     TOTPCT
TOTPASS);
SET TRAN2;
BY CASE;
RETAIN CPAS1-&CPASE;
IF _NAME_ = 'ROWVAR' THEN DO;
 ROWVAR = &COLE1;
OUTPUT;
END;
ELSE
IF SUBSTR(_NAME_,1,3) = 'ROW' THEN DO;
ARRAY CTOTS {&NOITEM} COL1-&COLE;
ARRAY PCTPASS {&NOITEM} PCT1-&PCTE;
ARRAY PCT1MNUS (&NOITEM) PCT1M1-&P1ME;
ARRAY CPASS {&NOITEM} CPAS1-&CPASE;
ARRAY PCTMUL   (&NOITEM) PCTM1-&PCTME;
DO I = 1 TO &NOITEM;
IF FIRST.CASE THEN DO;
TOTRAW = 0; TOTPASS=0; PCTPASS(I) = 0;
PCT1MNUS(I) = 0; PCTMUL(I) = 0; CPASS{I}       =       0;
END;

CPASS{I} = SUM(CTOTS{I}, CPASS{I});

END;

IF SUBSTR(_NAME_, 1, 4) = 'ROW'||LEFT(&NOPEPL)  then    do;
DO I = 1 TO &NOITEM;
LEFT = CPASS{I};
PPASS = PCTPASS{I};

PCTPASS{I} = CPASS{I} / (&NOPEPL);
PCT1MNUS(I) = (1-PCTPASS(I));

PCTMUL(I)  = PCTPASS(I) * PCT1MNUS(I);
TOTPCT     = SUM(TOTPCT, PCTMUL(I));
TOTRAW     = SUM(OF CPAS1 - &CPASE);
TOTPASS = TOTRAW;
END;
OUTPUT;
end;
END;
```

```
PROC MEANS NOPRINT;
BY CASE;
VAR CPAS1-&CPASE ROWVAR TOTPCT TOTPASS;
OUTPUT SUM=CPAS1-&CPASE ROWVAR TOTPCT TOTPASS
OUT=CPAS;


PROC DATASETS; DELETE PCTS;

/********************************************
* Originally I only kept KR21 if it was 0 or
* greater.  But had to change this to keep
* all KR21's so I could determine how many
* cases of KR21 calculated a good CT3 but an
* invalid KR21.
* Also pieced the formula together, because
* it is easier to debug a problem that way than
* one very long complex algorithm.
********************************************/

DATA KR21POS;
SET CPAS;
PASSAVG = TOTPASS / &NOPEPL;
FRONT   = &NOITEM / (&NOITEM - 1);
BACKTOP = PASSAVG * (&NOITEM - PASSAVG);
BACKBOT = &NOITEM * ROWVAR ;
TOPBOT = BACKTOP / BACKBOT;
KR21 = FRONT * (1-TOPBOT);
OUTPUT kr21pos;

/*  Now start the process to calculate CT3 */

proc sort data=tran2;
by case _name_;
 DATA MAT3 (KEEP= CASE ROWNAME NCOL1-&NCOLE
NCOL1-&NCOLE);
SET TRAN2;
RETAIN NCOL1-&NCOLE DTOT;
BY CASE _name_;
ROWNAME=_NAME_;
if FIRST.CASE THEN DTOT = 0;

IF _NAME_ NOT IN ('COLODR','ROWVAR') THEN       DO;
```

```
DTOT = SUM(OF DTOT, &COLE1);

ARRAY COLS {&NOITEM} COL1-&COLE ;
ARRAY NCOLS{&NOITEM,&NOPEPL} NCOL1-&NCOLE       ;
J=SUBSTR(ROWNAME,4,1);
DO I = 1 TO &NOITEM;
NCOLS{I,J} = COLS{I};
END;
END;
IF LAST.CASE THEN OUTPUT MAT3;

/*********************************************
* At this point you could change the 1,0
* assignments for (0,0) or (1,1) combinations
*********************************************/

DATA DTOT (KEEP = CASE CASETOT DCOL1-&DCOLE);;
SET MAT3;
BY CASE;
RETAIN CASETOT;
ARRAY DCOLS(&NOITEM,&NOITEM) DCOL1-&DCOLE;
ARRAY NCOLS{&NOITEM,&NOPEPL} NCOL1-&NCOLE ;
ARRAY NEWCOLS {&NOITEM} NCOLL1-&NCLE;
ARRAY CTRCOLS {&NOITEM} CTCOL1-&CTCE;

DO COLIDX = 1 TO &NOITEM;
DO NCOLIDX = 1 TO &NOITEM;
DO M = 1 TO &NOPEPL;
IF COLIDX NE NCOLIDX THEN DO;
IF NCOLS(COLIDX,M)  = 0  AND
NCOLS(NCOLIDX,M) = 1 THEN DO;


NEWCOLS(NCOLIDX) = SUM(NEWCOLS(NCOLIDX),1);
CTRCOLS(NCOLIDX) = SUM(CTRCOLS(NCOLIDX),0);
END; ELSE
IF NCOLS(COLIDX,M)  = 1  AND
NCOLS(NCOLIDX,M) = 1 THEN DO;

NEWCOLS(NCOLIDX) = SUM(NEWCOLS(NCOLIDX),0);
CTRCOLS(NCOLIDX) = SUM(CTRCOLS(NCOLIDX),0);
END; ELSE
IF NCOLS(COLIDX,M)  = 0  AND
```

```
NCOLS(NCOLIDX,M) = 0 THEN DO;

NEWCOLS(NCOLIDX) = SUM(NEWCOLS(NCOLIDX),0);
CTRCOLS(NCOLIDX) = SUM(CTRCOLS(NCOLIDX),0);
END; ELSE
IF NCOLS(COLIDX,M)  = 1  AND
NCOLS(NCOLIDX,M) = 0 THEN DO;

NEWCOLS(NCOLIDX) = SUM(NEWCOLS(NCOLIDX),0);
CTRCOLS(NCOLIDX) = SUM(CTRCOLS(NCOLIDX),1);
END;
END; ELSE
IF COLIDX EQ NCOLIDX THEN DO;

NEWCOLS(NCOLIDX) = SUM(NEWCOLS(NCOLIDX),0);
CTRCOLS(NCOLIDX) = SUM(CTRCOLS(NCOLIDX),0);
END;
DCOLS(COLIDX,NCOLIDX) = NEWCOLS(NCOLIDX);
END;
CASETOT=SUM(NEWCOLS(NCOLIDX), CASETOT);
END;

DO I = 1 TO &NOITEM;
NEWCOLS(I) = 0;
END;

END;
IF LAST.CASE THEN DO;
OUTPUT DTOT;
CASETOT = 0;
END;

/********************************************
* I chose to set missing values to the letter
* ‘M’ so I could differentiate them from
* empty values in the proc summary

********************************************/
PROC DATASETS; DELETE TRAN2 MAT3        ;
options MISSING=M;

/********************************************
* put everything together
```

```
**********************************************/

DATA MAT4;
RETAIN VM TOTSQRP COLSQ;
MERGE  DTOT
      CPAS
      KR21POS ;
BY CASE;

IF FIRST.CASE THEN DO;
VM = 0; TOTSQRP = 0; COLSQ = 0;
END;

/**********************************************
* Compare the upper right quadrant to the
* lower left quadrant: cell by cell
**********************************************/

ARRAY DCOLS{&NOITEM,&NOITEM} DCOL1 - &DCOLE;
DO J = 1 TO &NOITEM;
DO K = 1 TO &NOITEM;
IF K > J THEN DO;
TEMPVM= SUM(DCOLS(J,K),-DCOLS(K,J));
LEFTR = DCOLS(J,K);
RITER = DCOLS(K,J);
VM = SUM(TEMPVM,VM);
SQRTOTP = TOTPASS*TOTPASS;
TOTSQRP = SUM(SQRTOTP, TOTSQRP);

END;
END;
END;

ARRAY CPASES{&NOITEM} COL1-&COLE;
DO I = 1 TO &NOITEM;
COLSQ = SUM((CPASES{I}*CPASES{I}),COLSQ);
END;

AVGTOTSP = TOTSQRP / &NOITEM;

V   =  CASETOT;
VM2 =  2*VM;
CT2 =((2*VM)/ CASETOT) - 1;
```

```
VC  = (&NOPEPL*PASSAVG) * (&NOITEM-PASSAVG) -
(&NOPEPL* TOTPCT);

CT3 = (VC - V) / (VC - VM);

KR21 = ROUND(KR21,.0001);
CT3  = ROUND(CT3, .0001);

COUNTIT = 1;

 /* PROC PRINT; TITLE 'FINAL -KR VALIDATED & CT3 VALIDATED';
VAR CASE PASSAVG V VM VM2 CT2 VC TOTPCT CT3 KR21; */
/*
PROC PLOT DATA=MAT4;
      PLOT CASE * KR21="K" CASE * CT3="C"     /       OVERLAY;
      TITLE 'KR21 AND CT3 BY CASE';
*/
/********************************************
* Put the output in 3 files so you can
* be sure you 1) have generated everything you
* need, 2) don't comingle/confuse the results &
* 3) can quickly drop the data into spreadsheet
* to create graphics you need
********************************************/

      proc summary data=mat4;
      class ct3;
      var countit;
      output sum=countit out=CT3out;

      PROC SUMMARY DATA=MAT4;
      CLASS KR21;
      VAR COUNTIT;
      OUTPUT SUM=COUNTIT OUT=KR21OUT;

      PROC SUMMARY DATA=MAT4;
      CLASS CT3 KR21 ;
      VAR COUNTIT;
      OUTPUT SUM=COUNTIT  OUT=BOTHOUT;

      DATA _NULL_;
      SET BOTHOUT;
      FILE BDATAOUT(&BOTHFILE);
```

```
        PUT @1 '"'
        +1 "&BOTHFILE"
        +1 '"'
        +1 ','
        +1 CT3 8.4
        +1 ','
        +1 KR21 8.4
        +1 ','
        +1 COUNTIT 10.;

        DATA _NULL_;
        SET CT3OUT;
        FILE CDATAOUT(&CT3FILE);
        PUT @1 '"'
        +1 "&CT3FILE"
        +1 '"'
        +1 ','
        +1 CT3 8.4
        +1 ','
        +1 ' '
        +1 ','
        +1 COUNTIT 10.;

        DATA _NULL_;
        SET KR21OUT;
        FILE KDATAOUT(&KR21FILE);
        PUT @1 '"'
        +1 "&KR21FILE"
        +1 '"'
        +1 ','
        +1 ' '
        +1 ','
        +1 KR21 8.4
        +1 ','
        +1 COUNTIT 10.;

/*
* sas graphics weren't allowed but are
* left here incase you want to use them


PROC PRINT DATA = &THEFILE;
TITLE 'FINAL RESULT';
```

```
PROC PLOT DATA=&FILEOUT;
WHERE _TYPE_ = 1;
PLOT COUNTIT * KR21='K';
TITLE 'KR21 PLOT';


PROC PLOT DATA=&FILEOUT;
WHERE _TYPE_ = 2;
PLOT COUNTIT * CT3='C' ;
TITLE 'CT3 PLOT';


PROC PLOT DATA=&FILEOUT;
WHERE _TYPE_ = 3;
PLOT KR21 * CT3 ;
TITLE 'KR21 & CT3 TOGETHER';
*/

RUN;
%MEND THEGUTS;

/*********************************************
* Should have compiled the above code separately
* and just invoked it, but I spent way too much
* time fussing with this.. Should have written
* it in C++ .. Too late now
*********************************************/

DATA THEEND;
;
SET BEGIN;

%THEGUTS(&S, &E, &B, &C, &K);


RUN;
```

APPENDIX B
CECS 4100 Exam

CECS 4100 Exam 2

Name:_________________________ Date:____________________

Choose one best answer. Each question is worth 1/2 point unless otherwise noted. The entire exam is worth 20 points.

1. What would be the **entire** output for the following BASIC program?

```
100 Let A = 5
110 Let B = 25
120 Let C = 11
130 Let T = A + C
140 Let X = (T*T)/B
150 Print "The answer is" ; X
```

____

2. (1pt.) Write a LOGO **procedure** to draw a rectangle.

3. (1 pt.) Name **two** LOGO primitives (other than RT, LT, FD, BK), **and** tell what each will do.

Note: Items 14 and 15 refer to the following:

```
TO SHAPE
REPEAT 24[FD 20 RT 15]
END
```

4. The name of the procedure is:

a. TO SHAPE
b. SHAPE
c. REPEAT
d. END

5. The shape which will be produced is a(n):

   a. circle
   b. oval
   c. square
   d. rectangle

6. A URL, or Uniform Resource Locator, is:
   a. a chat room.
   b. a browser.
   c. a website address.
   d. an e-mail address.

7. What is the correct URL to access our course web page?
   a. courseweb.tac.edu/rhondac/
   b. courseweb.unt.edu/rchris/
   c. courseweb.tac.unt.edu/rhondac/
   d. courseweb.tac.unt.edu/christensen/

8. Which of the following is NOT a valid e-mail address?

   a. 1302@cecs.coe.unt.edu
   b. rhondac@tenet.edu
   c. john.jones.com
   d. helpdesk@jove.acs.unt.edu

9. The domain name .edu stands for web addresses assigned to:
   a) the federal government
   b) businesses.
   c) educational institutions
   d) game web sites

10. Information found on the Internet:
   a) is always true and correct.

b) cannot be used in school papers.
c) should be backed up by a print source.
d) is always false and inaccurate.

11. HTML stands for:
a) Hungry Teachers Make Lunch
b) Happy Teachers Make Lunch
c) Hypertext Markup Language
d) Hierarchical Telecommunication Machinery Logos
e) Hardware Trinkets Modem Library

12. What is one **barrier** to implementing telecommunications projects in a classroom?

a. isolated teachers
b. equipment availability
c. T-1 lines
d. ownership of the Internet

13. ___________ allows users to connect to remote computers and use their services.

a. A newsgroup
b. Telnet
c. E-mail
D. A listserv

14. A system that automatically sends messages to all its subscribers is

A. junk mail
B. an Internet Service Provider
C. a listserv
D. a web site

15. The Santa Claus Project is an example of which type of network learning approach?

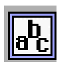
a. Ask an expert
b. Information exchanges
c. Impersonations or appearances
d. Electronic publishing

16. The Air and Water Projects, which involve students from around the world, are examples of which type of network learning approach?

    a. Electronic publishing
    b. Tele-field trips
    c. Structured group activity
    d. Ask an expert

Directions: For each item, select the letter of the (a-e) which tells what the computer will do.

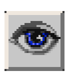
17.



18.

19.

20.



21.

22._________

a. Click on this, and then click on an object to manipulate it.
b. Puts a text box on the screen
c. General editing tool
d. Allows the developer to place a new turtle on the screen
e. Allows the input of music into the project

APPENDIX C
CECS 4100 EXAM RESULTS

CECS 4100 Exam 2
Binary Test Results

Each row represents all the right/wrong answers for a single student.

Each column represents all the right/wrong answers for a single question on the test, across all students.

1 0 1 1 0 1 1 1 1 1 0 1 1 1 0 0 1 1 1 1 0 0
0 0 1 0 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 0 0 0
0 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 0 1 1 0 0 1 1 1 1 0 1 1 1 1 1 1 1 1 0 0 0
0 1 1 1 0 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1
1 0 0 1 0 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1 0 0
0 1 1 0 0 1 1 1 1 1 0 1 1 1 0 0 1 1 1 1 0 0
1 1 0 0 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1 1 0 0
1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1
0 0 1 1 0 0 1 1 1 1 0 1 1 1 0 1 1 1 1 1 0 0
1 1 1 0 1 0 1 1 1 1 0 1 1 1 0 0 1 1 1 1 1 1
1 1 1 1 1 0 1 1 1 1 0 1 1 1 0 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1
1 1 1 0 0 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 0 0
1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 0 0 0
0 1 1 0 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 0 0
1 1 1 1 1 1 1 1 1 1 0 1 1 1 0 0 1 1 1 1 1 1
1 1 1 1 0 1 1 1 1 1 0 1 0 1 0 0 1 1 1 1 0 0
1 1 1 1 1 0 1 1 1 1 0 1 1 1 0 1 1 1 1 1 0 0
1 0 0 1 1 1 1 0 1 1 0 0 1 0 1 1 1 1 1 1 0 0
1 0 0 0 0 1 1 1 1 1 0 0 0 1 1 0 1 1 1 0 0 0
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1
0 0 1 1 1 0 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1
1 1 1 1 0 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1
1 0 0 1 1 0 1 1 1 1 0 0 1 1 1 1 1 1 1 0 0 1
0 0 1 1 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1
0 0 1 0 0 0 1 1 1 1 0 0 0 0 1 0 1 1 1 0 0 0
1 0 0 0 0 1 1 1 1 1 0 0 0 1 0 1 1 1 1 1 1 1

APPENDIX D

ORDER ANALYSIS OUTPUT

Order Program with Data Scaling Methods, 2nd ed.

Number of subjects: 28
Number of items: 16
z_values: 2.58 1.00 0.50 0.25 0.01 0.00

Data Matrix (RT=row totals, CT=col totals)

RT		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
(11)	1	1	0	1	1	0	1	1	1	1	1	0	1	1	1	0	0
(11)	2	0	0	1	0	1	1	1	1	1	1	0	1	1	1	1	0
(13)	3	0	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1
(12)	4	1	0	1	1	0	0	1	1	1	1	0	1	1	1	1	1
(12)	5	0	1	1	1	0	1	1	1	1	1	0	1	1	1	1	0
(10)	6	1	0	0	1	0	1	1	1	1	1	0	0	1	1	1	0
(10)	7	0	1	1	0	0	1	1	1	1	1	0	1	1	1	0	0
(12)	8	1	1	0	0	1	0	1	1	1	1	0	1	1	1	1	1
(14)	9	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0
(10)	10	0	0	1	1	0	0	1	1	1	1	0	1	1	1	0	1
(11)	11	1	1	1	0	1	0	1	1	1	1	0	1	1	1	0	0
(13)	12	1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	1
(10)	13	0	0	0	0	1	1	1	1	1	1	0	1	1	1	1	0
(12)	14	1	1	1	0	0	1	0	1	1	1	1	1	1	1	0	1
(14)	15	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1
(12)	16	0	1	1	0	1	1	1	1	1	1	0	1	1	0	1	1
(13)	17	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0
(11)	18	1	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0
(13)	19	1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	1
(10)	20	1	0	0	1	1	1	1	0	1	1	0	0	1	0	1	1
(8)	21	1	0	0	0	0	1	1	1	1	1	0	0	0	1	1	0
(15)	22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
(11)	23	0	0	1	1	1	0	1	1	1	1	0	1	1	1	1	0
(13)	24	1	1	1	1	0	1	1	1	1	1	0	0	1	1	1	1
(11)	25	1	0	0	1	1	0	1	1	1	1	0	0	1	1	1	1
(12)	26	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	0
(6)	27	0	0	1	0	0	0	1	1	1	1	0	0	0	0	1	0
(8)	28	1	0	0	0	0	1	1	1	1	1	0	0	0	1	0	1
CT		18	14	21	17	16	18	27	27	28	28	4	21	24	25	17	13

Sorted Matrix (RT=row totals, CT=col totals)

RT		9	10	7	8	14	13	3	12	1	6	4	15	5	2	16	11
(15)	22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
(14)	9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
(14)	15	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1
(13)	3	1	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1
(13)	12	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0
(13)	17	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0
(13)	19	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0
(13)	24	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	0
(12)	4	1	1	1	1	1	1	1	1	1	0	1	1	0	0	1	0
(12)	5	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0
(12)	8	1	1	1	1	1	1	0	1	1	0	0	1	1	1	1	0
(12)	14	1	1	0	1	1	1	1	1	1	1	0	0	0	1	1	1
(12)	16	1	1	1	1	0	1	1	1	0	1	0	1	1	1	1	0
(12)	26	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0
(11)	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
(11)	2	1	1	1	1	1	1	1	1	0	1	0	1	1	0	0	0
(11)	11	1	1	1	1	1	1	1	1	1	0	0	0	1	1	0	0
(11)	18	1	1	1	1	1	0	1	1	1	1	1	0	0	1	0	0
(11)	23	1	1	1	1	1	1	1	1	0	0	1	1	1	0	0	0
(11)	25	1	1	1	1	1	1	0	0	1	0	1	1	1	0	1	0
(10)	6	1	1	1	1	1	1	0	0	1	1	1	1	0	0	0	0
(10)	7	1	1	1	1	1	1	1	1	0	1	0	0	0	1	0	0
(10)	10	1	1	1	1	1	1	1	1	0	0	1	0	0	0	1	0
(10)	13	1	1	1	1	1	1	0	1	0	1	0	1	1	0	0	0
(10)	20	1	1	1	0	0	1	0	0	1	1	1	1	1	0	1	0
(8)	21	1	1	1	1	1	0	0	0	1	1	0	1	0	0	0	0
(8)	28	1	1	1	1	1	0	0	0	1	1	0	0	0	0	1	0
(6)	27	1	1	1	1	0	0	1	0	0	0	0	1	0	0	0	0
CT		28	28	27	27	25	24	21	21	18	18	17	17	16	14	13	4

Dominance Matrix (with Frequency Count)

	9	10	7	8	14	13	3	12	1	6	4	15	5	2	16	11
9	0	0	1	1	3	4	7	7	10	10	11	11	12	14	15	24
10	0	0	1	1	3	4	7	7	10	10	11	11	12	14	15	24
7	0	0	0	1	3	4	7	7	10	10	10	10	11	14	15	24

8	0	0	1	0	2	4	6	6	10	10	11	11	12	13	15	23
14	0	0	1	0	0	3	6	5	8	9	9	11	11	12	14	21
13	0	0	1	1	2	0	5	4	9	9	8	9	8	11	12	20
3	0	0	1	0	2	2	0	2	9	8	7	10	9	8	12	17
12	0	0	1	0	1	1	2	0	9	8	8	10	7	8	12	17
1	0	0	1	1	1	3	6	6	0	6	5	9	8	8	8	15
6	0	0	1	1	2	3	5	5	6	0	7	7	9	9	12	15
4	0	0	0	1	1	1	3	4	4	6	0	7	7	9	9	15
15	0	0	0	1	3	2	6	6	8	6	7	0	6	10	10	15
5	0	0	0	1	2	0	4	2	6	7	6	5	0	7	8	13
2	0	0	1	0	1	1	1	1	4	5	6	7	5	0	7	11
16	0	0	1	1	2	1	4	4	3	7	5	6	5	6	0	10
11	0	0	1	0	0	0	0	0	1	1	2	2	1	1	1	0

```
  Model A
 ---------

Item    Prerequisites
----    -------------

  1 =>
  2 =>
  3 =>  11
  4 =>
  5 =>
  6 =>
  7 =>   4   5   7  15
  8 =>   2   3   8  11  12  14
  9 =>   1   2   3   4   5   6   7   8  10  11  12  13  14  15  16
 10 =>   1   2   3   4   5   6   7   8   9  11  12  13  14  15  16
 11 =>
 12 =>  11
 13 =>   5  11
 14 =>  11
 15 =>
 16 =>



  Model B
 ---------
```

```
Item    Prerequisites
----    -------------

  1 =>
  2 =>
  3 =>  11
  4 =>
  5 =>
  6 =>
  7 =>   4   5   7  15
  8 =>   2   3   8  11  12  14
  9 =>   1   2   3   4   5   6   7   8  10  11  12  13  14  15  16
 10 =>   1   2   3   4   5   6   7   8   9  11  12  13  14  15  16
 11 =>
 12 =>  11
 13 =>   5  11
 14 =>  11
 15 =>
 16 =>

 Model B Reduced List
----------------------

Item    Prerequisites
----    -------------

  1 =>
  2 =>
  3 =>  11
  4 =>
  5 =>
  6 =>
  7 =>  15
  8 =>  12  14
  9 =>  10
 10 =>   1   2   3   4   6   7   8   9  13  16
 11 =>
 12 =>  11
 13 =>   5  11
 14 =>  11
 15 =>
 16 =>
```

```
 Item    Scale
 ----    -----
  9 ==>  0.00
 10 ==>  0.00
  7 ==>  0.04
  8 ==>  0.04
 14 ==>  0.11
 13 ==>  0.14
  3 ==>  0.25
 12 ==>  0.25
  1 ==>  0.36
  6 ==>  0.36
  4 ==>  0.39
 15 ==>  0.39
  5 ==>  0.43
  2 ==>  0.50
 16 ==>  0.54
 11 ==>  0.86
```

Model C

Dominant Matrix (probability)

	9	10	7	8	14	13	3	12	1	6	4	15	5	2	16	11
9	0.00	0.00	0.04	0.04	0.11	0.14	0.25	0.25	0.36	0.36	0.39	0.39	0.43	0.50	0.54	0.86
10	0.00	0.00	0.04	0.04	0.11	0.14	0.25	0.25	0.36	0.36	0.39	0.39	0.43	0.50	0.54	0.86
7	0.00	0.00	0.00	0.04	0.11	0.14	0.25	0.25	0.36	0.36	0.36	0.36	0.39	0.50	0.54	0.86
8	0.00	0.00	0.04	0.00	0.07	0.14	0.21	0.21	0.36	0.36	0.39	0.39	0.43	0.46	0.54	0.82
14	0.00	0.00	0.04	0.00	0.00	0.11	0.21	0.18	0.29	0.32	0.32	0.39	0.39	0.43	0.50	0.75
13	0.00	0.00	0.04	0.04	0.07	0.00	0.18	0.14	0.32	0.32	0.29	0.32	0.29	0.39	0.43	0.71
3	0.00	0.00	0.04	0.00	0.07	0.07	0.00	0.07	0.32	0.29	0.25	0.36	0.32	0.29	0.43	0.61

12	0.00	0.00	0.04	0.00	0.04	0.04	0.07	0.00	0.32	0.29	0.29	0.36	0.25	0.29	0.43	0.61
1	0.00	0.00	0.04	0.04	0.04	0.11	0.21	0.21	0.00	0.21	0.18	0.32	0.29	0.29	0.29	0.54
6	0.00	0.00	0.04	0.04	0.07	0.11	0.18	0.18	0.21	0.00	0.25	0.25	0.32	0.32	0.43	0.54
4	0.00	0.00	0.00	0.04	0.04	0.04	0.11	0.14	0.14	0.21	0.00	0.25	0.25	0.32	0.32	0.54
15	0.00	0.00	0.00	0.04	0.11	0.07	0.21	0.21	0.29	0.21	0.25	0.00	0.21	0.36	0.36	0.54
5	0.00	0.00	0.00	0.04	0.07	0.00	0.14	0.07	0.21	0.25	0.21	0.18	0.00	0.25	0.29	0.46
2	0.00	0.00	0.04	0.00	0.04	0.04	0.04	0.04	0.14	0.18	0.21	0.25	0.18	0.00	0.25	0.39
16	0.00	0.00	0.04	0.04	0.07	0.04	0.14	0.14	0.11	0.25	0.18	0.21	0.18	0.21	0.00	0.36
11	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.04	0.04	0.07	0.07	0.04	0.04	0.04	0.00

Table of Z values

	9	10	7	8	14	13	3	12	1	6	4	15	5	2	16	11
9	0.00	0.00	1.00	1.00	1.73	2.00	2.65	2.65	3.16	3.16	3.32	3.32	3.46	3.74	3.87	4.90
10	0.00	0.00	1.00	1.00	1.73	2.00	2.65	2.65	3.16	3.16	3.32	3.32	3.46	3.74	3.87	4.90
7	-1.00	-1.00	0.00	0.00	1.00	1.34	2.12	2.12	2.71	2.71	3.16	3.16	3.32	3.36	3.50	4.60
8	-1.00	-1.00	0.00	0.00	1.41	1.34	2.45	2.45	2.71	2.71	2.89	2.89	3.05	3.61	3.50	4.80
14	-1.73	-1.73	-1.00	-1.41	0.00	0.45	1.41	1.63	2.33	2.11	2.53	2.14	2.50	3.05	3.00	4.58
13	-2.00	-2.00	-1.34	-1.34	-0.45	0.00	1.13	1.34	1.73	1.73	2.33	2.11	2.83	2.89	3.05	4.47
3	-2.65	-2.65	-2.12	-2.45	-1.41	-1.13	0.00	0.00	0.77	0.83	1.26	1.00	1.39	2.33	2.00	4.12
12	-2.65	-2.65	-2.12	-2.45	-1.63	-1.34	0.00	0.00	0.77	0.83	1.15	1.00	1.67	2.33	2.00	4.12
1	-3.16	-3.16	-2.71	-2.71	-2.33	-1.73	-0.77	-0.77	0.00	0.00	0.33	0.24	0.53	1.15	1.51	3.50
6	-3.16	-3.16	-2.71	-2.71	-2.11	-1.73	-0.83	-0.83	0.00	0.00	0.28	0.28	0.50	1.07	1.15	3.50

4 -3.32 -3.32 -3.16 -2.89 -2.53 -2.33 -1.26 -1.15 -0.33 -0.28 0.00 0.00 0.28
0.77 1.07 3.15
15 -3.32 -3.32 -3.16 -2.89 -2.14 -2.11 -1.00 -1.00 -0.24 -0.28 0.00 0.00 0.30
0.73 1.00 3.15
5 -3.46 -3.46 -3.32 -3.05 -2.50 -2.83 -1.39 -1.67 -0.53 -0.50 -0.28 -0.30 0.00
0.58 0.83 3.21
2 -3.74 -3.74 -3.36 -3.61 -3.05 -2.89 -2.33 -2.33 -1.15 -1.07 -0.77 -0.73 -0.58
0.00 0.28 2.89
16 -3.87 -3.87 -3.50 -3.50 -3.00 -3.05 -2.00 -2.00 -1.51 -1.15 -1.07 -1.00 -0.83 -
0.28 0.00 2.71
11 -4.90 -4.90 -4.60 -4.80 -4.58 -4.47 -4.12 -4.12 -3.50 -3.50 -3.15 -3.15 -3.21 -
2.89 -2.71 0.00

Model C (Z-Value = 2.58)

Item Prerequisites
---- -------------

9 ==> 3 12 1 6 4 15 5 2 16 11
10 ==> 3 12 1 6 4 15 5 2 16 11
7 ==> 1 6 4 15 5 2 16 11
8 ==> 1 6 4 15 5 2 16 11
14 ==> 2 16 11
13 ==> 5 2 16 11
3 ==> 11
12 ==> 11
1 ==> 11
6 ==> 11
4 ==> 11
15 ==> 11
5 ==> 11
2 ==> 11
16 ==> 11
11 ==>

Model C (Z-Value = 1.00)

Item Prerequisites
---- -------------

```
 9 ==>   7   8  14  13   3  12   1   6   4  15   5   2  16  11
10 ==>   7   8  14  13   3  12   1   6   4  15   5   2  16  11
 7 ==>  14  13   3  12   1   6   4  15   5   2  16  11
 8 ==>  14  13   3  12   1   6   4  15   5   2  16  11
14 ==>   3  12   1   6   4  15   5   2  16  11
13 ==>   3  12   1   6   4  15   5   2  16  11
 3 ==>   4  15   5   2  16  11
12 ==>   4  15   5   2  16  11
 1 ==>   2  16  11
 6 ==>   2  16  11
 4 ==>  16  11
15 ==>  16  11
 5 ==>  11
 2 ==>  11
16 ==>  11
11 ==>
```

Model C   (Z-Value = 0.50)

```
Item    Prerequisites
----    -------------

 9 ==>   7   8  14  13   3  12   1   6   4  15   5   2  16  11
10 ==>   7   8  14  13   3  12   1   6   4  15   5   2  16  11
 7 ==>  14  13   3  12   1   6   4  15   5   2  16  11
 8 ==>  14  13   3  12   1   6   4  15   5   2  16  11
14 ==>   3  12   1   6   4  15   5   2  16  11
13 ==>   3  12   1   6   4  15   5   2  16  11
 3 ==>   1   6   4  15   5   2  16  11
12 ==>   1   6   4  15   5   2  16  11
 1 ==>   5   2  16  11
 6 ==>   5   2  16  11
 4 ==>   2  16  11
15 ==>   2  16  11
 5 ==>   2  16  11
 2 ==>  11
16 ==>  11
11 ==>
```

Model C   (Z-Value = 0.25)

```
  ------------------------------

Item    Prerequisites
----    -------------

  9 ==>   7   8  14  13   3  12   1   6   4  15   5   2  16  11
 10 ==>   7   8  14  13   3  12   1   6   4  15   5   2  16  11
  7 ==>  14  13   3  12   1   6   4  15   5   2  16  11
  8 ==>  14  13   3  12   1   6   4  15   5   2  16  11
 14 ==>  13   3  12   1   6   4  15   5   2  16  11
 13 ==>   3  12   1   6   4  15   5   2  16  11
  3 ==>   1   6   4  15   5   2  16  11
 12 ==>   1   6   4  15   5   2  16  11
  1 ==>   4   5   2  16  11
  6 ==>   4  15   5   2  16  11
  4 ==>   5   2  16  11
 15 ==>   5   2  16  11
  5 ==>   2  16  11
  2 ==>  16  11
 16 ==>  11
 11 ==>


   Model C   (Z-Value = 0.01)
  ------------------------------

Item    Prerequisites
----    -------------

  9 ==>  10   7   8  14  13   3  12   1   6   4  15   5   2  16  11
 10 ==>   9   7   8  14  13   3  12   1   6   4  15   5   2  16  11
  7 ==>   8  14  13   3  12   1   6   4  15   5   2  16  11
  8 ==>   7  14  13   3  12   1   6   4  15   5   2  16  11
 14 ==>  13   3  12   1   6   4  15   5   2  16  11
 13 ==>   3  12   1   6   4  15   5   2  16  11
  3 ==>  12   1   6   4  15   5   2  16  11
 12 ==>   3   1   6   4  15   5   2  16  11
  1 ==>   6   4  15   5   2  16  11
  6 ==>   1   4  15   5   2  16  11
  4 ==>  15   5   2  16  11
 15 ==>   4   5   2  16  11
  5 ==>   2  16  11
  2 ==>  16  11
```

```
 16 ==>  11
 11 ==>


  Model C   (Z-Value = 0.00)
  ------------------------------

Item    Prerequisites
----    -------------

  9 ==>  10   7   8  14  13   3  12   1   6   4  15   5   2  16  11
 10 ==>   9   7   8  14  13   3  12   1   6   4  15   5   2  16  11
  7 ==>   8  14  13   3  12   1   6   4  15   5   2  16  11
  8 ==>   7  14  13   3  12   1   6   4  15   5   2  16  11
 14 ==>  13   3  12   1   6   4  15   5   2  16  11
 13 ==>   3  12   1   6   4  15   5   2  16  11
  3 ==>  12   1   6   4  15   5   2  16  11
 12 ==>   3   1   6   4  15   5   2  16  11
  1 ==>   6   4  15   5   2  16  11
  6 ==>   1   4  15   5   2  16  11
  4 ==>  15   5   2  16  11
 15 ==>   4   5   2  16  11
  5 ==>   2  16  11
  2 ==>  16  11
 16 ==>  11
 11 ==>
```

APPENDIX E
RELIABILITY MEASURES

Reliability Measures

Frequency Tables

CT3 Values

Contains all calculated CT3 values.
There were 5,637 CT3 calculations that were mathmatically impossible to calculate.
Valid values range between -1 and 1.

Type	CT3	Freq
CT3ONLY	-4.0000	800
CT3ONLY	-1.5000	8000
CT3ONLY	-0.8750	4800
CT3ONLY	-0.6667	167066
CT3ONLY	-0.5385	57600
CT3ONLY	-0.5000	57600
CT3ONLY	-0.4706	93600
CT3ONLY	-0.4583	24000
CT3ONLY	-0.4286	378000
CT3ONLY	-0.4063	40800
CT3ONLY	-0.4000	183600
CT3ONLY	-0.3889	278400
CT3ONLY	-0.3636	430300
CT3ONLY	-0.3462	192000
CT3ONLY	-0.3415	46800
CT3ONLY	-0.3333	938400
CT3ONLY	-0.3235	313200
CT3ONLY	-0.3158	280200
CT3ONLY	-0.2963	93600
CT3ONLY	-0.2903	103200
CT3ONLY	-0.2821	331200
CT3ONLY	-0.2500	1940744
CT3ONLY	-0.2195	516000
CT3ONLY	-0.2000	532800
CT3ONLY	-0.1905	511200
CT3ONLY	-0.1842	910800
CT3ONLY	-0.1765	1258200
CT3ONLY	-0.1667	1141200
CT3ONLY	-0.1538	1163600
CT3ONLY	-0.1458	568800
CT3ONLY	-0.1364	696000
CT3ONLY	-0.1290	134400

CT3ONLY	-0.1250	126000
CT3ONLY	-0.1111	696600
CT3ONLY	-0.0976	429600
CT3ONLY	-0.0938	351200
CT3ONLY	-0.0833	40800
CT3ONLY	-0.0714	505400
CT3ONLY	-0.0577	158400
CT3ONLY	-0.0526	493200
CT3ONLY	-0.0417	802732
CT3ONLY	-0.0294	492400
CT3ONLY	-0.0256	568800
CT3ONLY	-0.0227	146400
CT3ONLY	0.0000	1750406
CT3ONLY	0.0244	424800
CT3ONLY	0.0278	152382
CT3ONLY	0.0323	139200
CT3ONLY	0.0385	484800
CT3ONLY	0.0476	230235
CT3ONLY	0.0625	636600
CT3ONLY	0.0741	129600
CT3ONLY	0.0789	676800
CT3ONLY	0.0833	24000
CT3ONLY	0.0909	572255
CT3ONLY	0.1026	180000
CT3ONLY	0.1071	288000
CT3ONLY	0.1176	766000
CT3ONLY	0.1250	50381
CT3ONLY	0.1346	81600
CT3ONLY	0.1463	228800
CT3ONLY	0.1667	1426738
CT3ONLY	0.1935	45200
CT3ONLY	0.2000	309600
CT3ONLY	0.2045	63600
CT3ONLY	0.2105	234000
CT3ONLY	0.2188	161988
CT3ONLY	0.2308	497700
CT3ONLY	0.2500	68147
CT3ONLY	0.2593	28752
CT3ONLY	0.2647	230400
CT3ONLY	0.2683	235200
CT3ONLY	0.2708	154800
CT3ONLY	0.2857	541314
CT3ONLY	0.3056	41920

CT3ONLY	0.3182	218135
CT3ONLY	0.3269	45600
CT3ONLY	0.3333	564900
CT3ONLY	0.3421	216000
CT3ONLY	0.3548	57576
CT3ONLY	0.3590	100800
CT3ONLY	0.3750	335827
CT3ONLY	0.3902	21600
CT3ONLY	0.4000	93600
CT3ONLY	0.4118	274400
CT3ONLY	0.4167	3598
CT3ONLY	0.4231	118800
CT3ONLY	0.4318	14400
CT3ONLY	0.4444	172065
CT3ONLY	0.4643	117600
CT3ONLY	0.4737	108000
CT3ONLY	0.4792	38400
CT3ONLY	0.4872	72000
CT3ONLY	0.5000	231622
CT3ONLY	0.5122	62400
CT3ONLY	0.5161	8372
CT3ONLY	0.5192	3600
CT3ONLY	0.5238	76668
CT3ONLY	0.5313	16778
CT3ONLY	0.5455	151370
CT3ONLY	0.5588	73952
CT3ONLY	0.5833	101157
CT3ONLY	0.6000	72000
CT3ONLY	0.6053	57600
CT3ONLY	0.6154	104400
CT3ONLY	0.6250	2400
CT3ONLY	0.6296	14335
CT3ONLY	0.6341	25186
CT3ONLY	0.6429	41988
CT3ONLY	0.6591	4800
CT3ONLY	0.6667	134378
CT3ONLY	0.6774	7150
CT3ONLY	0.6875	37784
CT3ONLY	0.7059	68400
CT3ONLY	0.7115	2396
CT3ONLY	0.7222	51482
CT3ONLY	0.7368	9000
CT3ONLY	0.7436	14400
CT3ONLY	0.7500	3643

CT3ONLY	0.7561	7188
CT3ONLY	0.7619	36000
CT3ONLY	0.7727	35859
CT3ONLY	0.7917	6000
CT3ONLY	0.8000	28800
CT3ONLY	0.8077	15200
CT3ONLY	0.8125	500
CT3ONLY	0.8214	18000
CT3ONLY	0.8333	24000
CT3ONLY	0.8387	2400
CT3ONLY	0.8438	11069
CT3ONLY	0.8529	8364
CT3ONLY	0.8611	1181
CT3ONLY	0.8684	10800
CT3ONLY	0.8718	1200
CT3ONLY	0.8750	380
CT3ONLY	0.8958	1200
CT3ONLY	0.9250	39
CT3ONLY	0.9875	12
CT3ONLY	1.0000	326083
CT3ONLY	1.0938	47
CT3ONLY	1.2344	250

KR21 Values

Contains all calculated KR21 values.
There were 205,045 KR21 calculations that were mathmatically impossible to calculate.
Valid values range between 0 and 1.

Type	KR21	Freq
KR21ONLY	-8.3750	1000000
KR21ONLY	-7.7500	500000
KR21ONLY	-5.8750	62500
KR21ONLY	-5.2500	2000000
KR21ONLY	-4.4167	500000
KR21ONLY	-4.0000	256250
KR21ONLY	-2.5000	2000000
KR21ONLY	-1.5000	3002430
KR21ONLY	-1.3214	1500000
KR21ONLY	-1.2500	50000

KR21ONLY	-1.1875	2500000
KR21ONLY	-0.8750	600000
KR21ONLY	-0.7857	150000
KR21ONLY	-0.7187	262500
KR21ONLY	-0.6667	446
KR21ONLY	-0.6250	1500000
KR21ONLY	-0.3542	1500000
KR21ONLY	-0.2500	3664748
KR21ONLY	-0.0577	600000
KR21ONLY	0.0000	1379654
KR21ONLY	0.0385	300000
KR21ONLY	0.0625	69900
KR21ONLY	0.1176	1900000
KR21ONLY	0.1667	850000
KR21ONLY	0.1912	850000
KR21ONLY	0.2188	1835
KR21ONLY	0.3056	181250
KR21ONLY	0.3125	650000
KR21ONLY	0.3750	661680
KR21ONLY	0.4022	1175000
KR21ONLY	0.4118	59446
KR21ONLY	0.4167	14755
KR21ONLY	0.4318	300000
KR21ONLY	0.5000	600000
KR21ONLY	0.5109	209900
KR21ONLY	0.5312	29
KR21ONLY	0.5313	50
KR21ONLY	0.5370	512500
KR21ONLY	0.5536	450000
KR21ONLY	0.5652	54790
KR21ONLY	0.5833	170000
KR21ONLY	0.6250	53780
KR21ONLY	0.6324	1849
KR21ONLY	0.6429	29900
KR21ONLY	0.6484	240000
KR21ONLY	0.6591	270000
KR21ONLY	0.6875	95879
KR21ONLY	0.7143	127500
KR21ONLY	0.7222	9280
KR21ONLY	0.7297	120000
KR21ONLY	0.7348	29795
KR21ONLY	0.7368	85000
KR21ONLY	0.7635	30000
KR21ONLY	0.7813	44975

KR21ONLY	0.7917	15080
KR21ONLY	0.7965	60000
KR21ONLY	0.8026	5000
KR21ONLY	0.8047	1890
KR21ONLY	0.8214	13430
KR21ONLY	0.8333	12905
KR21ONLY	0.8355	1900
KR21ONLY	0.8404	21000
KR21ONLY	0.8438	2500
KR21ONLY	0.8547	5946
KR21ONLY	0.8670	5959
KR21ONLY	0.8798	5990
KR21ONLY	0.8821	6000
KR21ONLY	0.8837	1476
KR21ONLY	0.8958	475
KR21ONLY	0.9091	2980
KR21ONLY	0.9138	1500
KR21ONLY	0.9219	418
KR21ONLY	0.9292	380
KR21ONLY	0.9405	599
KR21ONLY	0.9468	185
KR21ONLY	0.9597	190
KR21ONLY	0.9627	298
KR21ONLY	1.0000	27

Both CT3 & KR21 Values

Contains all calculated CT3 & KR21 values.
There were 206,220 calculations that were mathmatically impossible to calculate.
Valid CT3 values range between -1 and 1.
Valid KR21 values range between 0 and 1.

Type	CT3	KR21	Freq
BOTHONLY	-1.5000	-8.3750	2400
BOTHONLY	-1.5000	-7.7500	2400
BOTHONLY	-1.5000	-5.8750	800
BOTHONLY	-1.5000	-4.0000	800
BOTHONLY	-0.6667	-8.3750	33600
BOTHONLY	-0.6667	-7.7500	17700
BOTHONLY	-0.6667	-5.8750	16500
BOTHONLY	-0.6667	-5.2500	30000

BOTHONLY	-0.6667	-4.4167	16800
BOTHONLY	-0.6667	-4.0000	15000
BOTHONLY	-0.6667	-1.5000	1166
BOTHONLY	-0.5385	-8.3750	28800
BOTHONLY	-0.5385	-7.7500	28800
BOTHONLY	-0.5000	-8.3750	3600
BOTHONLY	-0.5000	-7.7500	7200
BOTHONLY	-0.5000	-5.2500	21600
BOTHONLY	-0.5000	-4.4167	10800
BOTHONLY	-0.5000	-4.0000	14400
BOTHONLY	-0.4706	-8.3750	46800
BOTHONLY	-0.4706	-7.7500	46800
BOTHONLY	-0.4286	-8.3750	81600
BOTHONLY	-0.4286	-7.7500	81600
BOTHONLY	-0.4286	-5.2500	84000
BOTHONLY	-0.4286	-4.4167	65400
BOTHONLY	-0.4286	-4.0000	18600
BOTHONLY	-0.4000	-8.3750	183600
BOTHONLY	-0.3889	-8.3750	16800
BOTHONLY	-0.3889	-7.7500	3600
BOTHONLY	-0.3889	-5.8750	13200
BOTHONLY	-0.3889	-5.2500	122400
BOTHONLY	-0.3889	-4.4167	40800
BOTHONLY	-0.3889	-4.0000	81600
BOTHONLY	-0.3636	-8.3750	34300
BOTHONLY	-0.3636	-5.8750	23400
BOTHONLY	-0.3636	-5.2500	232200
BOTHONLY	-0.3636	-4.4167	140400
BOTHONLY	-0.3462	-7.7500	33600
BOTHONLY	-0.3462	-5.2500	158400
BOTHONLY	-0.3333	-8.3750	46800
BOTHONLY	-0.3333	-7.7500	76800
BOTHONLY	-0.3333	-5.2500	570000
BOTHONLY	-0.3333	-4.0000	9600
BOTHONLY	-0.3333	-2.5000	235200
BOTHONLY	-0.3235	-8.3750	158400
BOTHONLY	-0.3235	-7.7500	154800
BOTHONLY	-0.3158	-8.3750	280200
BOTHONLY	-0.2963	-5.2500	46800
BOTHONLY	-0.2963	-4.0000	46800
BOTHONLY	-0.2903	-4.4167	103200
BOTHONLY	-0.2821	-5.2500	331200
BOTHONLY	-0.2500	-8.3750	82800
BOTHONLY	-0.2500	-7.7500	46500

BOTHONLY	-0.2500	-5.8750	8400
BOTHONLY	-0.2500	-5.2500	402800
BOTHONLY	-0.2500	-4.4167	122200
BOTHONLY	-0.2500	-4.0000	69000
BOTHONLY	-0.2500	-2.5000	1178000
BOTHONLY	-0.2500	-1.5000	1167
BOTHONLY	-0.2500	-1.2500	25200
BOTHONLY	-0.2500	-0.6667	357
BOTHONLY	-0.2195	-2.5000	516000
BOTHONLY	-0.2000	-1.5000	532800
BOTHONLY	-0.1905	-2.5000	21600
BOTHONLY	-0.1905	-1.5000	234000
BOTHONLY	-0.1905	-1.3214	234000
BOTHONLY	-0.1905	-1.2500	21600
BOTHONLY	-0.1842	-1.5000	910800
BOTHONLY	-0.1765	-1.5000	622800
BOTHONLY	-0.1765	-1.3214	635400
BOTHONLY	-0.1667	-2.5000	46800
BOTHONLY	-0.1667	-1.5000	144000
BOTHONLY	-0.1667	-1.3214	235200
BOTHONLY	-0.1667	-1.1875	715200
BOTHONLY	-0.1538	-1.5000	348600
BOTHONLY	-0.1538	-1.3214	170400
BOTHONLY	-0.1538	-1.1875	644600
BOTHONLY	-0.1458	-1.3214	154800
BOTHONLY	-0.1458	-1.1875	414000
BOTHONLY	-0.1364	-1.5000	86400
BOTHONLY	-0.1364	-1.1875	380400
BOTHONLY	-0.1364	-0.8750	168000
BOTHONLY	-0.1364	-0.7857	61200
BOTHONLY	-0.1290	-0.8750	134400
BOTHONLY	-0.1250	-1.2500	2400
BOTHONLY	-0.1250	-0.8750	123600
BOTHONLY	-0.1111	-1.5000	97200
BOTHONLY	-0.1111	-1.3214	37800
BOTHONLY	-0.1111	-1.1875	208500
BOTHONLY	-0.1111	-0.8750	70500
BOTHONLY	-0.1111	-0.7857	82800
BOTHONLY	-0.1111	-0.7187	199800
BOTHONLY	-0.0976	-0.6250	429600
BOTHONLY	-0.0938	-0.7187	16400
BOTHONLY	-0.0938	-0.6250	334800
BOTHONLY	-0.0833	-0.6250	40800

BOTHONLY	-0.0714	-1.1875	86400
BOTHONLY	-0.0714	-0.8750	78800
BOTHONLY	-0.0714	-0.7187	18000
BOTHONLY	-0.0714	-0.6250	322200
BOTHONLY	-0.0577	-0.3542	158400
BOTHONLY	-0.0526	-0.3542	493200
BOTHONLY	-0.0417	-1.3214	3600
BOTHONLY	-0.0417	-0.6250	158400
BOTHONLY	-0.0417	-0.2500	640732
BOTHONLY	-0.0294	-0.3542	257200
BOTHONLY	-0.0294	-0.2500	235200
BOTHONLY	-0.0256	-0.2500	568800
BOTHONLY	-0.0227	-0.2500	146400
BOTHONLY	0.0000	-1.5000	9000
BOTHONLY	0.0000	-1.3214	18000
BOTHONLY	0.0000	-1.1875	27800
BOTHONLY	0.0000	-0.8750	10200
BOTHONLY	0.0000	-0.7187	17600
BOTHONLY	0.0000	-0.6250	151200
BOTHONLY	0.0000	-0.3542	331600
BOTHONLY	0.0000	-0.2500	1000826
BOTHONLY	0.0000	-0.0577	140400
BOTHONLY	0.0000	0.0000	43780
BOTHONLY	0.0244	0.0000	424800
BOTHONLY	0.0278	-0.2500	28800
BOTHONLY	0.0278	-0.0577	28800
BOTHONLY	0.0278	0.0385	81600
BOTHONLY	0.0278	0.0625	13182
BOTHONLY	0.0323	-0.0577	139200
BOTHONLY	0.0385	-0.2500	254400
BOTHONLY	0.0385	0.1176	230400
BOTHONLY	0.0476	-0.6250	14400
BOTHONLY	0.0476	-0.3542	100800
BOTHONLY	0.0476	-0.2500	100800
BOTHONLY	0.0476	0.0000	14235
BOTHONLY	0.0625	0.0000	322200
BOTHONLY	0.0625	0.0385	20400
BOTHONLY	0.0625	0.1667	178800
BOTHONLY	0.0625	0.1912	115200
BOTHONLY	0.0741	-0.2500	64800
BOTHONLY	0.0741	0.0385	64800
BOTHONLY	0.0789	0.1176	676800
BOTHONLY	0.0833	0.3125	24000
BOTHONLY	0.0909	-0.3542	42200

BOTHONLY	0.0909	-0.2500	284400
BOTHONLY	0.0909	-0.0577	172800
BOTHONLY	0.0909	0.0625	30555
BOTHONLY	0.0909	0.1667	42300
BOTHONLY	0.1026	0.1667	180000
BOTHONLY	0.1071	-0.0577	7200
BOTHONLY	0.1071	0.0000	280800
BOTHONLY	0.1176	-0.3542	49200
BOTHONLY	0.1176	-0.2500	49200
BOTHONLY	0.1176	0.1176	331600
BOTHONLY	0.1176	0.1912	336000
BOTHONLY	0.1250	0.3056	49200
BOTHONLY	0.1250	0.4167	1181
BOTHONLY	0.1346	0.3750	81600
BOTHONLY	0.1463	0.3125	228800
BOTHONLY	0.1667	-1.5000	10800
BOTHONLY	0.1667	-1.3214	7200
BOTHONLY	0.1667	-1.1875	20400
BOTHONLY	0.1667	-0.8750	12000
BOTHONLY	0.1667	-0.7857	4800
BOTHONLY	0.1667	-0.7187	9600
BOTHONLY	0.1667	-0.6250	34200
BOTHONLY	0.1667	-0.3542	17600
BOTHONLY	0.1667	-0.2500	142177
BOTHONLY	0.1667	-0.0577	43200
BOTHONLY	0.1667	0.0000	142095
BOTHONLY	0.1667	0.0385	93600
BOTHONLY	0.1667	0.0625	13982
BOTHONLY	0.1667	0.1176	86400
BOTHONLY	0.1667	0.1667	254400
BOTHONLY	0.1667	0.1912	139200
BOTHONLY	0.1667	0.2188	1101
BOTHONLY	0.1667	0.3056	9600
BOTHONLY	0.1667	0.3750	19102
BOTHONLY	0.1667	0.4022	279000
BOTHONLY	0.1667	0.4118	13081
BOTHONLY	0.1667	0.4318	46800
BOTHONLY	0.1667	0.5000	26400
BOTHONLY	0.1935	0.3056	45200
BOTHONLY	0.2000	0.1176	309600
BOTHONLY	0.2045	0.4022	63600
BOTHONLY	0.2105	0.3750	234000
BOTHONLY	0.2188	0.3125	158400

BOTHONLY	0.2188	0.3750	3588
BOTHONLY	0.2308	-0.3542	24000
BOTHONLY	0.2308	-0.2500	24000
BOTHONLY	0.2308	0.1667	60600
BOTHONLY	0.2308	0.1912	48800
BOTHONLY	0.2308	0.4022	259200
BOTHONLY	0.2308	0.5370	81100
BOTHONLY	0.2500	0.5109	65369
BOTHONLY	0.2500	0.6250	2778
BOTHONLY	0.2593	0.1667	14400
BOTHONLY	0.2593	0.3750	14352
BOTHONLY	0.2647	0.3750	100800
BOTHONLY	0.2647	0.4318	129600
BOTHONLY	0.2683	0.5000	235200
BOTHONLY	0.2708	0.5536	122400
BOTHONLY	0.2708	0.5833	32400
BOTHONLY	0.2857	-0.2500	72000
BOTHONLY	0.2857	-0.0577	54000
BOTHONLY	0.2857	0.0000	8400
BOTHONLY	0.2857	0.0385	18000
BOTHONLY	0.2857	0.1176	122400
BOTHONLY	0.2857	0.1912	122400
BOTHONLY	0.2857	0.3056	2650
BOTHONLY	0.2857	0.3125	133200
BOTHONLY	0.2857	0.4167	8264
BOTHONLY	0.3056	0.4022	10800
BOTHONLY	0.3056	0.5109	10794
BOTHONLY	0.3056	0.5652	20326
BOTHONLY	0.3182	0.1176	38400
BOTHONLY	0.3182	0.1667	72000
BOTHONLY	0.3182	0.3056	50400
BOTHONLY	0.3182	0.4118	28535
BOTHONLY	0.3182	0.5536	28800
BOTHONLY	0.3269	0.6484	45600
BOTHONLY	0.3333	-0.2500	7200
BOTHONLY	0.3333	0.0000	115200
BOTHONLY	0.3333	0.0385	7200
BOTHONLY	0.3333	0.3750	28800
BOTHONLY	0.3333	0.4022	349200
BOTHONLY	0.3333	0.4318	49200
BOTHONLY	0.3333	0.7143	8100
BOTHONLY	0.3421	0.5370	216000
BOTHONLY	0.3548	0.5109	57576
BOTHONLY	0.3590	0.5536	100800

BOTHONLY	0.3750	-0.6250	10800
BOTHONLY	0.3750	0.0000	3558
BOTHONLY	0.3750	0.1912	800
BOTHONLY	0.3750	0.3125	55200
BOTHONLY	0.3750	0.5000	151200
BOTHONLY	0.3750	0.5652	4387
BOTHONLY	0.3750	0.6324	740
BOTHONLY	0.3750	0.6429	10764
BOTHONLY	0.3750	0.6591	84000
BOTHONLY	0.3750	0.6875	14378
BOTHONLY	0.3902	0.6250	21600
BOTHONLY	0.4000	0.3750	93600
BOTHONLY	0.4118	0.1176	52800
BOTHONLY	0.4118	0.1912	52800
BOTHONLY	0.4118	0.5370	91400
BOTHONLY	0.4118	0.5833	77400
BOTHONLY	0.4167	0.7813	3598
BOTHONLY	0.4231	0.4022	75600
BOTHONLY	0.4231	0.4318	16800
BOTHONLY	0.4231	0.7297	26400
BOTHONLY	0.4318	0.6591	14400
BOTHONLY	0.4444	-0.3542	21600
BOTHONLY	0.4444	-0.2500	10800
BOTHONLY	0.4444	0.0625	10782
BOTHONLY	0.4444	0.1176	14400
BOTHONLY	0.4444	0.1667	27000
BOTHONLY	0.4444	0.1912	3600
BOTHONLY	0.4444	0.3056	9000
BOTHONLY	0.4444	0.3750	17940
BOTHONLY	0.4444	0.4022	13200
BOTHONLY	0.4444	0.4118	10698
BOTHONLY	0.4444	0.5536	1800
BOTHONLY	0.4444	0.5652	13142
BOTHONLY	0.4444	0.6429	1794
BOTHONLY	0.4444	0.6875	13082
BOTHONLY	0.4444	0.7222	3227
BOTHONLY	0.4643	0.5000	115200
BOTHONLY	0.4643	0.5109	2400
BOTHONLY	0.4737	0.6484	108000
BOTHONLY	0.4792	0.7368	31200
BOTHONLY	0.4792	0.7635	7200
BOTHONLY	0.4872	0.6591	72000
BOTHONLY	0.5000	-0.3542	1200

BOTHONLY	0.5000	-0.2500	16800
BOTHONLY	0.5000	-0.0577	7200
BOTHONLY	0.5000	0.0385	7200
BOTHONLY	0.5000	0.3750	1128
BOTHONLY	0.5000	0.5370	19200
BOTHONLY	0.5000	0.5536	136800
BOTHONLY	0.5000	0.5833	27600
BOTHONLY	0.5000	0.7348	13111
BOTHONLY	0.5000	0.8333	1383
BOTHONLY	0.5122	0.7143	62400
BOTHONLY	0.5161	0.6429	8372
BOTHONLY	0.5192	0.7917	3600
BOTHONLY	0.5238	0.3125	2400
BOTHONLY	0.5238	0.3750	36000
BOTHONLY	0.5238	0.4318	36000
BOTHONLY	0.5238	0.6250	2268
BOTHONLY	0.5313	0.6250	14400
BOTHONLY	0.5313	0.6875	2378
BOTHONLY	0.5455	0.3750	3600
BOTHONLY	0.5455	0.4022	87600
BOTHONLY	0.5455	0.5109	53970
BOTHONLY	0.5455	0.7368	6200
BOTHONLY	0.5588	0.6484	41600
BOTHONLY	0.5588	0.6875	32352
BOTHONLY	0.5833	0.0000	18000
BOTHONLY	0.5833	0.4167	3541
BOTHONLY	0.5833	0.5000	43200
BOTHONLY	0.5833	0.6591	2400
BOTHONLY	0.5833	0.7348	2384
BOTHONLY	0.5833	0.7965	26400
BOTHONLY	0.5833	0.8047	756
BOTHONLY	0.5833	0.8214	4476
BOTHONLY	0.6000	0.5370	72000
BOTHONLY	0.6053	0.7297	57600
BOTHONLY	0.6154	0.1176	21600
BOTHONLY	0.6154	0.1912	21600
BOTHONLY	0.6154	0.5536	25200
BOTHONLY	0.6154	0.5833	7200
BOTHONLY	0.6154	0.7368	21600
BOTHONLY	0.6154	0.8404	7200
BOTHONLY	0.6250	0.8026	2400
BOTHONLY	0.6296	0.5536	7200
BOTHONLY	0.6296	0.6875	7135
BOTHONLY	0.6341	0.7813	25186

BOTHONLY	0.6429	0.1667	16800
BOTHONLY	0.6429	0.3056	13200
BOTHONLY	0.6429	0.3750	3588
BOTHONLY	0.6429	0.6250	8400
BOTHONLY	0.6591	0.7965	4800
BOTHONLY	0.6667	0.3125	43200
BOTHONLY	0.6667	0.6484	7200
BOTHONLY	0.6667	0.6591	72000
BOTHONLY	0.6667	0.6875	11382
BOTHONLY	0.6667	0.9091	596
BOTHONLY	0.6774	0.7348	7150
BOTHONLY	0.6875	0.7143	34200
BOTHONLY	0.6875	0.8438	1200
BOTHONLY	0.6875	0.8670	2384
BOTHONLY	0.7059	0.3750	14400
BOTHONLY	0.7059	0.4318	14400
BOTHONLY	0.7059	0.7297	21600
BOTHONLY	0.7059	0.7635	18000
BOTHONLY	0.7115	0.8798	2396
BOTHONLY	0.7222	0.4022	25200
BOTHONLY	0.7222	0.5109	10794
BOTHONLY	0.7222	0.5652	14348
BOTHONLY	0.7222	0.8355	1140
BOTHONLY	0.7368	0.7917	9000
BOTHONLY	0.7436	0.7965	14400
BOTHONLY	0.7500	-0.6667	50
BOTHONLY	0.7500	-0.2500	25
BOTHONLY	0.7500	0.8547	3568
BOTHONLY	0.7561	0.8333	7188
BOTHONLY	0.7619	0.5370	18000
BOTHONLY	0.7619	0.5833	18000
BOTHONLY	0.7727	0.5370	6000
BOTHONLY	0.7727	0.5536	18000
BOTHONLY	0.7727	0.6429	7176
BOTHONLY	0.7727	0.7222	4683
BOTHONLY	0.7917	0.6250	2400
BOTHONLY	0.7917	0.8821	3600
BOTHONLY	0.8000	0.6484	28800
BOTHONLY	0.8077	0.6591	14400
BOTHONLY	0.8077	0.6875	800
BOTHONLY	0.8125	-5.2500	300
BOTHONLY	0.8125	-4.4167	200
BOTHONLY	0.8214	0.7143	18000

BOTHONLY	0.8333	0.7368	21600
BOTHONLY	0.8333	0.7635	2400
BOTHONLY	0.8387	0.8026	2400
BOTHONLY	0.8438	-8.3750	150
BOTHONLY	0.8438	-7.7500	100
BOTHONLY	0.8438	-4.0000	25
BOTHONLY	0.8438	0.7813	10794
BOTHONLY	0.8529	0.7917	1200
BOTHONLY	0.8529	0.8214	7164
BOTHONLY	0.8611	0.8837	1181
BOTHONLY	0.8684	0.8404	10800
BOTHONLY	0.8718	0.8438	1200
BOTHONLY	0.8750	0.8958	380
BOTHONLY	0.8958	0.9138	1200
BOTHONLY	0.9250	-0.6667	39
BOTHONLY	0.9875	-0.2500	12
BOTHONLY	1.0000	-2.5000	2400
BOTHONLY	1.0000	-1.5000	3600
BOTHONLY	1.0000	-1.3214	3600
BOTHONLY	1.0000	-1.2500	800
BOTHONLY	1.0000	-1.1875	2700
BOTHONLY	1.0000	-0.8750	2500
BOTHONLY	1.0000	-0.7857	1200
BOTHONLY	1.0000	-0.7187	1100
BOTHONLY	1.0000	-0.6250	3600
BOTHONLY	1.0000	-0.3542	3000
BOTHONLY	1.0000	-0.2500	17376
BOTHONLY	1.0000	-0.0577	7200
BOTHONLY	1.0000	0.0000	6586
BOTHONLY	1.0000	0.0385	7200
BOTHONLY	1.0000	0.0625	1399
BOTHONLY	1.0000	0.1176	15600
BOTHONLY	1.0000	0.1667	3700
BOTHONLY	1.0000	0.1912	9600
BOTHONLY	1.0000	0.2188	734
BOTHONLY	1.0000	0.3056	2000
BOTHONLY	1.0000	0.3125	4800
BOTHONLY	1.0000	0.3750	9182
BOTHONLY	1.0000	0.4022	11600
BOTHONLY	1.0000	0.4118	7132
BOTHONLY	1.0000	0.4167	1769
BOTHONLY	1.0000	0.4318	7200
BOTHONLY	1.0000	0.5000	28800
BOTHONLY	1.0000	0.5109	8997

BOTHONLY	1.0000	0.5312	29
BOTHONLY	1.0000	0.5313	50
BOTHONLY	1.0000	0.5370	8800
BOTHONLY	1.0000	0.5536	9000
BOTHONLY	1.0000	0.5652	2587
BOTHONLY	1.0000	0.5833	7400
BOTHONLY	1.0000	0.6250	1934
BOTHONLY	1.0000	0.6324	1109
BOTHONLY	1.0000	0.6429	1794
BOTHONLY	1.0000	0.6484	8800
BOTHONLY	1.0000	0.6591	10800
BOTHONLY	1.0000	0.6875	14372
BOTHONLY	1.0000	0.7143	4800
BOTHONLY	1.0000	0.7222	1370
BOTHONLY	1.0000	0.7297	14400
BOTHONLY	1.0000	0.7348	7150
BOTHONLY	1.0000	0.7368	4400
BOTHONLY	1.0000	0.7635	2400
BOTHONLY	1.0000	0.7813	5397
BOTHONLY	1.0000	0.7917	1280
BOTHONLY	1.0000	0.7965	14400
BOTHONLY	1.0000	0.8026	200
BOTHONLY	1.0000	0.8047	1134
BOTHONLY	1.0000	0.8214	1790
BOTHONLY	1.0000	0.8333	4334
BOTHONLY	1.0000	0.8355	760
BOTHONLY	1.0000	0.8404	3000
BOTHONLY	1.0000	0.8438	100
BOTHONLY	1.0000	0.8547	2378
BOTHONLY	1.0000	0.8670	3575
BOTHONLY	1.0000	0.8798	3594
BOTHONLY	1.0000	0.8821	2400
BOTHONLY	1.0000	0.8837	295
BOTHONLY	1.0000	0.8958	95
BOTHONLY	1.0000	0.9091	2384
BOTHONLY	1.0000	0.9138	300
BOTHONLY	1.0000	0.9219	418
BOTHONLY	1.0000	0.9292	380
BOTHONLY	1.0000	0.9405	599
BOTHONLY	1.0000	0.9468	185
BOTHONLY	1.0000	0.9597	190
BOTHONLY	1.0000	0.9627	298
BOTHONLY	1.0000	1.0000	27

BOTHONLY	1.0938	-1.5000	47
BOTHONLY	1.2344	-8.3750	150
BOTHONLY	1.2344	-5.8750	100

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