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The Asymmetric Nature of Decision Errors in Multi-Criteria, Satisficing Decisions

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ABSTRACT

This paper centers on an asymmetry, or bias, in the accuracy of multi-criteria, conjunctive and disjunctive decisions, which originates from fundamental properties of the logical conjunction and disjunction operations. A series of Monte Carlo simulations demonstrates that, as we keep adding criteria to a multi-criteria satisficing decision rule, errors in the data produce decision errors asymmetrically. As a result, in conjunctive decisions, the probability of a false negative increases steadily while the probability of a false positive decreases. In contrast, in disjunctive decisions, as we keep adding criteria, the probability of a false positive increases while that of a false negative decreases. Take, for instance, a conjunctive business decision where the individual decision criteria do not exhibit a substantially higher probability of a false positive than a false negative. In such a decision, the probability of overlooking a bargain can be far greater than the probability of misjudging an unattractive offer to be a good one.

KEYWORDS

Information quality management, information accuracy, multi-criteria decisions, conjunctive decision rules, disjunctive decision rules, satisficing decisions, Error Type 1 (/2), false negative (/positive), Monte Carlo simulation.

INTRODUCTION

Every now and then we discover an aspect of the relationship between input data accuracy and output information accuracy that strikes us with its oddity and proves anew the complexity of this relationship. The association between data accuracy and information accuracy is of great interest in numerous problem domains. Many research fields have examined this relationship, assuming various information-processing models and data and error characteristics, as well as an assortment of accuracy measures. An understanding of the relationship between input accuracy and output accuracy can increase the utility of information in problem-solving settings and improve the efficiency of data management. Nonetheless, our understanding of that relationship is only partial.

This study centers on the accuracy dimension of information quality and uncovers the relationship between input accuracy and output accuracy in a popular class of applications. These applications consist of dichotomous decisions that are implemented through logical conjunction or disjunction of selected criteria. Decision-making instances that are implemented through conjunction or disjunction are often labeled "satisficing." This term was coined by Herbert Simon to denote problem-solving and decision-making that aims at satisfying a chosen aspiration level instead of an optimal solution (Simon, 1957). Consider, for example, a company decision regarding the rental of a new office. Suppose that a satisficing decision strategy is employed throughout the entire selection process, or, due to a high number of alternatives, for the initial screening of options (e.g., Lussier and Olshavsky, 1979; Payne, 1976). Suppose that four major decision variables are rental rate, square footage, age of the office building, and availability of covered parking spaces. In particular, the decision rule that combines these variables is the following: the monthly rental rate should be at most $10,000 *and* the desired office space should be in the range 3,500-5,000 sqft *and* the age of the office building must not exceed ten years *and* the office building should have its own covered parking spaces. This preference is expressed by a conjunctive rule that combines four criteria, i.e., rent≤$10,000 *and* 3,500≤space≤5,000 *and* age≤10 *and* covered parking space=*yes*.[1]

[1] An example of a simple disjunctive rule is: rent≤$10,000 *or* location=St. Phillips plaza. This decision rule demonstrates the decision maker's bias in favor of properties that are located at St. Phillips plaza.

Obviously, in agreement with the common experience, one may assume that real estate data are not free of errors, and these errors can lead to incorrect property selection and exclusion decisions. Mainly, this inquiry distinguishes between a false positive (decision error type 1), e.g., when a property that does not satisfy the specified criteria is included in the short list of suitable properties, and a false negative (decision error type 2), e.g., when a property that has the desired attributes is excluded from that list. This distinction is motivated by the understanding that in real world settings, the implications of a false positive can differ greatly from the implications of a false negative. For example, a wasted visit to inspect an unsuitable property could be far less costly than missing one's ideal office when it is offered for rent at a bargain rate.

This paper draws attention to an asymmetry, or bias, in the accuracy of multi-criteria, conjunctive and disjunctive decisions, which stems from fundamental properties of the logical conjunction and disjunction operations. We report on a series of Monte Carlo simulations which demonstrates that, as we keep adding criteria to a multi-criteria satisficing decision rule, data errors affect decision accuracy asymmetrically. In conjunctive decisions, the probability of a false negative is an *increasing* function of the number of criteria while the probability of a false positive is a *decreasing* function of the number of criteria. In contrast, in disjunctive decisions, the probability of a false positive is an *increasing* function of the number of criteria while that of a false negative is a *decreasing* function of the number of criteria.[2] For instance, consider an office rental decision as described earlier, where the individual decision criteria do not produce a substantially higher probability of a false positive than a false negative. In this case, the probability of missing one's ideal office can be far greater than the probability of a wasted visit to inspect an unsuitable property.

Our findings suggest that decision accuracy considerations should be taken into account in the choice of the optimal number of criteria as well as the make-up of the decision variable set.

The paper is organized as follows. A short review of related literature is given in the next section. This review is followed by the details of our research method and the findings of this inquiry. The final section offers an explanation of the surprising results through an analysis of the truth tables of the logical conjunction and disjunction operations. We also discuss the implications of our work to decision makers, data managers, and researchers.

LITERATURE SURVEY

This work explores a certain asymmetry, or bias, in the accuracy of multi-criteria, conjunctive or disjunctive decisions, which originates from the fundamental nature of the logical conjunction and disjunction operations. To the best knowledge of the author, this asymmetry has not been communicated before. However, studies of single criterion decisions have noted various biases in relation to the uncertainty of the data that support a decision. These biases, which have been shown to be linked to each other, are known by the names "the winner's curse," "postdecision surprises," "the optimizer's curse," "the satisficer's curse," and other terms. The winner's curse (Capen, Clapp and Campbell, 1971) is sometimes colorfully described by the saying "the good news is you won; the bad news is you paid too much." In essence, the winner's curse suggests that, in common or interdependent auctions, the winner will tend to overpay. The optimizer's curse (Harrison and March, 1984; Smith and Winkler, 2006) designates a systematic overvaluation when the decision maker is choosing the highest valued prospect of a set of uncertain future outcomes. The optimizer's curse has been associated with the "regression to the mean" phenomenon (Harrison and March, 1984), which has been widely discussed by statisticians and other scholars. In a recent contribution to this research stream, Marks (2008) points to a "satisficer's curse," which is a systematic overvaluation that occurs when an uncertain prospect is chosen because its estimate exceeds some positive threshold.

On the subject of the effect of data accuracy on multi-criteria decisions, Ballou and Pazer (1990) studied the effect of input and criteria errors on multi-criteria, conjunctive dichotomous decisions. In particular, they investigated conditions in which the errors are normally distributed and the decision variables are independent. One of their discoveries which is relevant to this work is that, as the number of decision criteria increases, decision effectiveness, as measured by the probability that a decision to accept an item will prove to be correct, decreases.

Our paper examines multi-criteria, conjunctive and disjunctive dichotomous decisions. However, the research angle is somewhat different from that of Ballou and Pazer. Instead of focusing on the probability that a decision to accept an item is

[2] The probability of a false positive is the conditional probability that a chosen item is classified as satisfactory given that, in truth, it does not satisfy the selection criteria. This probability should not be confused with the joint probability of the item not being satisfactory *and* the item being classified as satisfactory. It is easy to see that this joint probability will typically decrease under a conjunctive decision and increase under a disjunctive decision since the probability of a positive classification decreases under a conjunctive rule and increases under a disjunctive rule. However, as for the conditional probability which is the subject of this work, such a relationship is not obvious. (A comparable distinction applies to the probability of a false negative.)

correct (or incorrect), this work centers on a comparison of the probabilities of a false negative and a false positive (note that the probability that a decision to accept an item is incorrect is not the same as the probability of a false positive; in fact, these two probabilities can vary dramatically). Specifically, we examine and compare the effect of input errors on the rates of the two decision error types as the number of decision criteria is increased.

MONTE CARLO SIMULATION

Assumptions

We define accuracy as the degree to which the data or information are in conformance with the true values. Accuracy will be measured by the probability of error occurrence. In particular, a decision error is registered whenever a decision based on the available inputs deviates from the outcome of the same decision based on the error-free inputs.

In addition, this work takes a partly unusual choice as far as the portrayal of the inputs of the decision. We avoid direct analysis of the original decision variables $V_1, V_2, ..$, and the errors that are exhibited in the available data that represent the decision variables. Instead, we explore the dichotomous variables $I_1, I_2, ..$, and errors in their representation. A variable I_i designates the classification of the values of V_i as fulfilling or not fulfilling the decision criterion, e.g., in the office rental scenario, I_1 =1 if the correct monthly rental rate of the property is not higher than $10,000, and I_1 =0 otherwise. Evidently, an error in the representation of I_i is caused by an error in the representation of V_i, although not every error in the representation of V_i results in an error in the representation of I_i.

The chosen portrayal of the inputs frees us of the need to make specific assumptions about the original errors and decision variables. Such assumptions are irrelevant for the results of this study. As explained in the discussion section, we argue that the findings of this study arise from characteristics of the logical conjunction and logical disjunction operations. These characteristics will become evident through a study of the respective truth tables.

Goal

Let O_i denote the correct output of a multi-criteria decision, conjunctive or disjunctive, that joins the first i decision variables ($O_1 = I_1$). Namely, $O_i = 1$ if the item (e.g., a rental property) satisfies the decision rule that combines these variables, and $O_i = 0$ otherwise (e.g., in the office rental decision, O_4 =1 if the rental rate of the office is actually not higher than $10,000 and its size is between 3500sqft-5000sqft and the age of the building is not more than ten years and it has a covered parking space). Let F_i^O inform us about the occurrence of a fault (an error) in this decision when it is based on the available data, i.e., $F_i^O = 1$ if a decision based on the available data is different from a decision based on the correct data; $F_i^O = 0$ otherwise.

This study examines $\Pr(F_i^O = 1 \mid O_i = 0)$ and $\Pr(F_i^O = 1 \mid O_i = 1)$, i.e., the probability of a false positive and the probability of a false negative, respectively. In particular, the goal of the ensuing simulations is to shed light on the effect of input errors on each of $\Pr(F_i^O = 1 \mid O_i = 0)$ and $\Pr(F_i^O = 1 \mid O_i = 1)$ as i grows higher, and compare the two.

Method

The method employed by this study is Monte Carlo simulation. Monte Carlo simulation is a method for iteratively evaluating a deterministic model using sets of random numbers as inputs. The inputs are generated pseudo randomly from selected probability distributions to simulate the process of sampling from an actual population. The model is evaluated for each simulated input set, and the result is taken as an average over the number of data points in the sample (Fishman, 1995). The elements that comprise our method are described below.

Inputs

The simulation process generates instances of the following variables:

I_1, I_2,.., I_{10}: I_i is a dichotomous variable that accepts the values 1 and 0, which correspond to *true*, i.e., the value of the decision variable V_i fulfills the decision criterion, and *false*, i.e., the value of V_i does not fulfill the criterion, respectively.

The simulations examine conjunctive and disjunctive decisions with up to 10 decision variables. The values of I_i (i=1,2,..,10) are generated pseudo randomly according to pre-determined distributions. In particular, these values are generated from distributions that are determined separately for each simulation. The expected value of I_i, denoted next by p_i^I, is chosen randomly such that $0 < p_i^I < 1$. Note that $p_i^I = E(I_i) = \Pr(I_i = 1)$, that is, p_i^I is equal to the probability that a given value of V_i satisfies the decision criterion on V_i.

F_1, F_2,.., F_{10}: These are dichotomous variables that accept the values 1 and 0, which correspond to *fault* and *no fault*, respectively. F_i informs us of the occurrence of an error in the recorded (possibly incorrect) version of I_i, denoted below as I_i^R. That is, F_i=0 if $I_i^R = I_i$, and F_i=1 otherwise. The values of F_i are generated from a distribution that is determined individually for each simulation. Mainly, the expected value of F_i, which is denoted by p_i^F ($p_i^F = E(F_i) = \Pr(F_i = 1)$), is chosen randomly such that six value ranges are explored. In one simulation set, which includes 2000 simulations, all the p_i^F values are such that p_i^F <0.02; in a second simulation set, which includes, again, 2000 simulations, all the p_i^F values are such that p_i^F <0.05, and so on (see Table 1).

p_i^I (i=1,2,..,10)	p_i^F (i=1,2,..,10)	Total # of simulations
0< p_i^I < 1	6 different simulation sets: 0< p_i^F <0.02 0< p_i^F <0.05 0< p_i^F <0.10 0< p_i^F <0.15 0< p_i^F <0.20 0< p_i^F <0.25	6 · 2000 = 12000 (conjunction) 6 · 2000 = 12000 (disjunction) Total: 24000 simulations

Table 1: Number of simulations and implemented parameter values

Sample size: Each simulation produces 1,000,000,000 (one billion) input instances of each variable.

Altogether, 12,000 simulations of conjunctive decisions were carried out. The same number of simulations targeted disjunctive decisions. The simulations were conducted on the high performance computing system at the University of Arizona using MATLAB, a programming language and interactive environment that supports computationally intensive tasks.

The Simulation Model

The simulation model implements decisions that combine I_i (i =1,2,..,10), and, in a similar manner, it implements decisions that combine I_i^R (i =1,2,..,10). The values are combined iteratively using a sequence of binary conjunction or disjunction operations.[3] The algorithm treats the output of one binary operation as an input of a subsequent binary operation. For instance, the output of combining the values of I_1 and I_2, labeled O_2, is treated as one of the inputs of a binary conjunction operation whose second input is I_3. A parallel process combines the values of I_i^R (i =1,2,..,10). The following paragraphs describe the simulation model in detail.

Conjunction

Simulations of logical conjunction implement equations (1)-(4). The value of I_i^R, the recorded, possibly incorrect portrayal of I_i, is derived from I_i and F_i using (1):

$$I_i^R = I_i \cdot (1 - F_i) + F_i \cdot (1 - I_i) = I_i + F_i - 2 \cdot I_i \cdot F_i \tag{1}$$

If the value of F_i is zero, that is, if this variable indicates that no error has occurred, then (1) is reduced to $I_i^R = I_i$, i.e., the observed input is the same as the correct input. However, if the value of F_i indicates the occurrence of an error, then (1) assigns a value of one to I_i^R if I_i is zero and a value of zero if I_i is one.

The ideal conjunction operation—where inputs are error-free—is computed iteratively using (2):

$$O_i = O_{i-1} \cdot I_i \tag{2}$$

O_i identifies the output of a decision that joins the first i inputs (recall that $O_1 = I_1$). The consistency of (2) with the definition of logical binary conjunction can be verified through a systematic evaluation of O_i for each possible combination of the values of O_{i-1} and I_i.

Analogously, the observed decision is derived through:

$$O_i^R = O_{i-1}^R \cdot I_i^R \tag{3}$$

O_i^R designates the output of a decision that joins the first i observed, possibly incorrect inputs ($O_1^R = I_1^R$). Finally, in order to determine the occurrence of a decision error, F_i^O, the simulations use equation (4)

$$O_i^R = (1 - F_i^O) \cdot O_i + F_i^O \cdot (1 - O_i) = O_i + F_i^O - 2 \cdot F_i^O \cdot O_i \tag{4}$$

Disjunction

Simulations of logical disjunction exploit the following two equations for iteratively computing the output of a disjunctive decision rule:

$$O_i = O_{i-1} + I_i - O_{i-1} \cdot I_i \tag{5}$$

$$O_i^R = O_{i-1}^R + I_i^R - O_{i-1}^R \cdot I_i^R \tag{6}$$

[3] In mathematics, a binary operation is a calculation involving two operands.

Equation (5) describes the ideal disjunction operation—where inputs are error-free. O_i identifies the output of a decision that joins the first i inputs. As in the case of conjunction, the consistency of (5) with the definition of logical disjunction can be verified through a systematic evaluation of O_i for each possible combination of the values of O_{i-1} and I_i. Similarly, the observed output of a disjunctive decision is derived through (6). O_i^R refers to the output of a decision that joins the first i observed inputs.

The algorithm that implements disjunction also utilizes (1) and (4) in the same manner that the algorithm that implements conjunction does.

Simulation Outputs

Two output sets are computed for each simulation: estimates of $\Pr(F_i^O = 1 \mid O_i = 0)$, i =1,2,..,10, i.e., the probabilities of a false positive, and estimates of $\Pr(F_i^O = 1 \mid O_i = 1)$, i =1,2,..,10, the probabilities of a false negative. These estimates are formulated by:

$$\overline{\Pr(F_i^O = 1 \mid O_i = 0)} = \frac{\sum_{j=1}^{N} F_i^O \cdot (1 - O_{ij})}{\sum_{j=1}^{N} (1 - O_{ij})} \qquad (i = 1,2,..,10) \tag{7}$$

$$\overline{\Pr(F_i^O = 1 \mid O_i = 1)} = \frac{\sum_{j=1}^{N} F_i^O \cdot O_{ij}}{\sum_{j=1}^{N} O_{ij}} \qquad (i = 1,2,..,10) \tag{8}$$

Where N is the number of input instances, i.e., N =1,000,000,000 as specified earlier.

Accuracy of the Simulation Outputs

Assuming that input samples obey the specified probability distributions, the accuracy of the resultant estimates, $\overline{\Pr(F_i^O = 1 \mid O_i = 0)}$ and $\overline{\Pr(F_i^O = 1 \mid O_i = 1)}$, is calculated as follows. Let σ_0 denote the standard deviation of $F_i^O = 1 \mid O_i = 0$. It is easy to see that, under the assumptions of this investigation:

$$\sigma_0^2 = \Pr(F_i^O = 1 \mid O_i = 0) - \Pr^2(F_i^O = 1 \mid O_i = 0) \tag{9}$$

Since σ, the standard deviation of $\overline{\Pr(F_i^O = 1 \mid O_i = 0)}$, decreases with the square root of the sample size, we see that σ satisfies:

$$\sigma = \frac{\sigma_0}{\sqrt{N}} \approx \frac{\sigma_0}{31622} = \frac{\sqrt{\Pr(F_i^O = 1 \mid O_i = 0) - \Pr^2(F_i^O = 1 \mid O_i = 0)}}{31622} < \frac{\sqrt{\Pr(F_i^O = 1 \mid O_i = 0)}}{31622} \tag{10}$$

Hence, the standard deviation of $\overline{\Pr(F_i^O = 1 \mid O_i = 0)}$ in the relevant range is relatively low. The results show that $\Pr(F_i^O = 1 \mid O_i = 0)$ varies, approximately, from 10^{-5} to 0.80. Therefore, σ varies roughly from 10^{-7} to $2.8 \cdot 10^{-5}$, respectively. A calculation of the accuracy of the estimate $\overline{\Pr(F_i^O = 1 \mid O_i = 1)}$ produces similar results.

RESULTS

The results of the simulations of conjunctive decisions are summarized by Figure 1. The results of the simulations of disjunctive decisions are encapsulated by Figure 2. Figure 1 and Figure 2 show the average probability of a false positive and the average probability of a false negative over each of the six simulation sets (Table 1).

Figure 1 demonstrates that, under a conjunctive rule, the probability of a false positive declines significantly as the number of inputs of the decision grows higher. In fact, the curve is asymptotic to zero. An opposite trend is exhibited with respect to the probability of a false negative. As the number of inputs of the decision grows higher, the probability of a false negative increases consistently. Clearly, the rate at which the above probabilities increase or decrease depends on the input error rates. Higher input error rates intensify the downward trend in the case of a false positive or upward trend in the case of a false negative (note the slopes as input error rates increase). This holds true especially when the number of decision criteria is low. In summary, Figure 1 reveals that, as we continue to add criteria to the conjunctive decision rule, errors in the available data do not produce decision errors symmetrically as we may have expected. Instead, input errors translate to false negatives much more easily than they translate to false positives. Ultimately, when the individual decision criteria do not exhibit a substantially higher probability of a false positive than a false negative, the probability of a false negative can be far greater than the probability of a false positive.

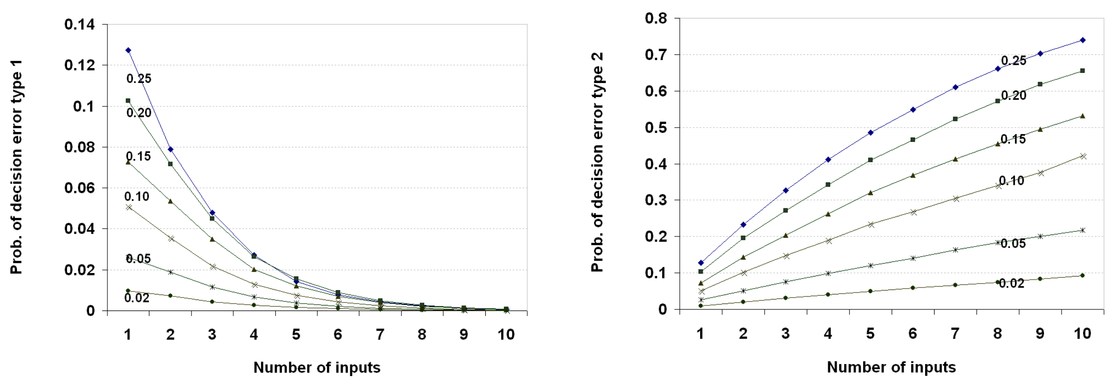

Figure 1: The probability of a false positive (left) and a false negative (right) under a conjunctive rule

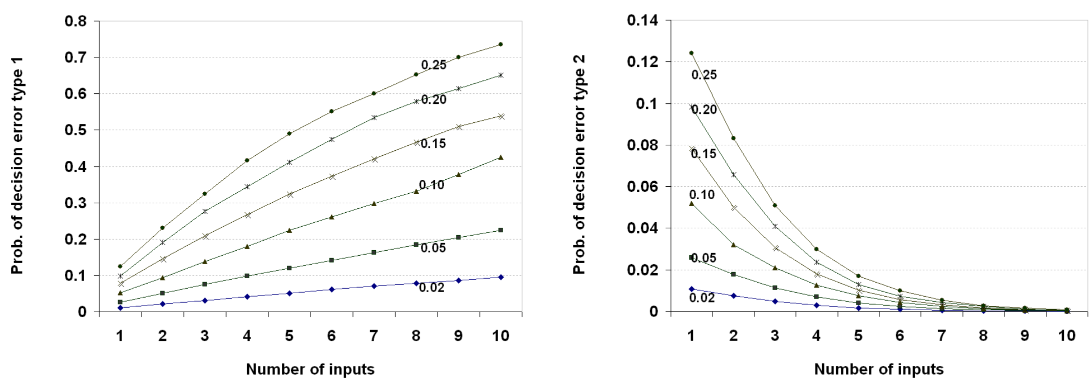

Figure 2: The probability of a false positive (left) and a false negative (right) under a disjunctive rule

Figure 2 describes disjunctive decisions and demonstrates comparable findings to those shown by Figure 1, with the following distinctions. The behavior of a type 1 decision error under a disjunctive decision is similar to the behavior of a type 2 decision error under a conjunctive decision. Likewise, the behavior of a type 2 decision error under a disjunctive decision is similar to the behavior of a type 1 decision error under a conjunctive decision. Subsequently, again, as we continue to add criteria to the disjunctive decision rule, errors in the data do not produce decision errors symmetrically. Nonetheless, contrary to conjunctive decision rules, under disjunctive rules input errors translate to false positives much more easily than they translate to false negatives.

DISCUSSION

Explanation of the Findings

Many readers will find the results of this study perplexing. Therefore, this section begins with an explanation of the results. In essence, the findings of this research are linked to a fundamental property of the binary conjunction and disjunction operations. Broadly, the sensitivity of these operations to input errors varies greatly depending on the correct values of the inputs.

Consider the truth table 2(a), which refers to a logical binary conjunction operation and denotes the correct inputs of that operation by p and q. Let $\hat{p}$ denote an incorrect representation of p. Similarly, let $\hat{q}$ denote an incorrect representation of q. Table 2(b) captures a scenario in which a conjunction operation combines $\hat{p}$ and q. Similarly, 2(c) portrays a conjunction operation that uses p and $\hat{q}$; 2(d) portrays a conjunction operation in which both inputs are incorrect representations of the original inputs. As a whole, tables 2(b), 2(c), and 2(d) cover all the possible input error occurrence combinations in a logical binary conjunction operation.

p	q	p and q
FALSE	FALSE	FALSE
FALSE	TRUE	FALSE
TRUE	FALSE	FALSE
TRUE	TRUE	TRUE

(a) AND operation with correct inputs

$\hat{p}$	q	$\hat{p}$ and q
TRUE	FALSE	FALSE
TRUE	TRUE	TRUE
FALSE	FALSE	FALSE
FALSE	TRUE	FALSE

(b) AND operation with $\hat{p}$ and q

p	$\hat{q}$	p and $\hat{q}$
FALSE	TRUE	FALSE
FALSE	FALSE	FALSE
TRUE	TRUE	TRUE
TRUE	FALSE	FALSE

(c) AND operation with $\hat{q}$ and p

$\hat{p}$	$\hat{q}$	$\hat{p}$ and $\hat{q}$
TRUE	TRUE	TRUE
TRUE	FALSE	FALSE
FALSE	TRUE	FALSE
FALSE	FALSE	FALSE

(d) AND operation with $\hat{p}$ and $\hat{q}$

Table 2: Truth tables (AND)

A brief study of these truth tables proves that the effect of errors in the inputs on the output of the conjunction operation varies dramatically, depending on the correct combination of input values. To begin with, consider the instance in which the correct output is “true.” Table 2(a) shows that the instance in which the correct output is “true” coincides with two input values that are both “true.” Tables 2(b)-2(d) show that, when the correct input values are both “true,” an input error *always* results in an output error (the output is always “false” rather than “true”). Namely, the operation is very sensitive to input errors. Suppose that, instead of the single pair of input values that these tables assume, we consider a stream of input pairs, all of which are composed of “true” values. Let the proportion of the pairs that contain an error in one of the inputs be denoted by p_1^F while the proportion of the pairs that contain an error in the other input be denoted by p_2^F. Clearly, since an error in any of the inputs produces an output error, the proportion of errors in the output values must be higher than either p_1^F or p_2^F. In other words, *the proportion of output errors among instances in which the correct output is “true” is higher than any of the matching input error rates*. This fact explains the increasing function that we observe in Figure 1 for a false negative.

The explanation of the findings regarding a false positive is more complicated. Although the following explanation is not complete, it does point to the underlying cause. Table 2(a) shows that the correct output is “false” whenever the inputs are anything but a pair of “true” values. Tables 2(b)-2(d) show, however, that, when the correct output is “false,” an input error generates an output error in just one out of the three possible incorrect input combinations. That is, the output is not as sensitive to input errors as in the former scenario. In particular, when the correct inputs are both “false,” an output error occurs only if *both* inputs contain errors. Therefore, for instance, when the correct input values are both “false,” the proportion of output errors is lower than any of the corresponding input error proportions.

The explanation of the behavior of errors under disjunctive decision rules (Figure 2) follows the same logic as the explanation that pertains to conjunctive rules and therefore will not be provided here.

Implications for Decision Makers, Data Managers, and Researchers

As the number of decision criteria increases, the probability of decision error type 1 behaves differently from the probability of decision error type 2. Our findings can alleviate the worry of a decision maker who is particularly apprehensive about a false positive, if his decision conforms to a conjunctive decision rule. The same holds true if the decision maker is mostly concerned about a false negative and his decision conforms to a disjunctive decision rule. A higher number of decision criteria curbs these error types, such that, as the number of decision criteria grows higher, the rates of these error types decrease. A higher average input error rate further magnifies this pattern, especially when the number of decision criteria is low. However, regrettably, a decision maker who is using a conjunctive decision rule and attributes great importance to false negatives may find our results troubling. The same holds true for disjunctive decisions when false positives are undesired. As the number of decision criteria grows higher, the rates of these error types increase. Furthermore, a higher average input error rate exacerbates this trend, especially when the number of decision criteria is low.

One suggestion to decision makers in view of our conclusions, and those of Ballou and Pazer (1990) that have been highlighted in our literature review, is that the number of decision criteria should be carefully monitored with decision accuracy in mind. The number of decision criteria typically depends on the needs of the decision maker, and may also be affected by estimated sizes of the item sets that satisfy various decision criteria. Our findings suggest, however, that decision accuracy considerations should be taken into account in the choice of the optimal number of decision criteria. Based on our findings we propose two simple conventions:

- If a decision employs a conjunctive rule and false negatives are undesired, or if a decision employs a disjunctive rule and false positives are undesired, then the number of decision criteria should be minimized.
- Alternatively, if a decision employs a conjunctive rule and false positives are unwanted or if a decision employs a disjunctive rule and false negatives are unwanted, then the number of decision criteria should be maximized.

Another suggestion may be relevant both to decision makers and data managers. A decision maker may benefit from a tool that helps him or her explore the best subset of the decision variables from a decision accuracy perspective. For example, the decision maker may want to exclude a variable from the decision variable set if this variable is not deemed crucial, and if errors in this variable are highly damaging to the accuracy of the decision. Recent research (Askira Gelman, 2008) offers a model that quantifies the damage that errors in different inputs incur under satisficing decisions in terms of decision error type 1 and decision error type 2. The model helps identify, in particular, in which of the inputs an input error creates the highest increase in the rate of decision error type 1, or, alternatively, decision error type 2. That model can also help rank the inputs as far as their overall contribution to decision error type 1 or decision error type 2.

The outcome of this work may be linked to the existing research on postdecision surprises, especially the study of the satisficer's curse. Since that research refers to decisions that utilize a single criterion, while our work centers on multi-criteria decisions, future research should take both discoveries into account in an investigation of the overall effect of data uncertainty on multi-criteria decisions.

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