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# **An Intentional Arithmetic for Qualitative Decision Making**

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## **Introduction**

Prescriptive decision analysis is a quantitative exercise. Options are assigned weights and probabilities to calculate an expected value. However, we view decision making as a qualitative process. Instead of converting qualitative features into numbers, we advocate converting numbers into qualitative features.

As part of a larger effort to develop a decision simulation system [Slade et al. 1995], we are motivated to provide a principled means for automated, qualitative analysis.

Following the artificial intelligence tradition of qualitative physics, we have developed an intentional arithmetic for interpreting quantitative data in a qualitative manner. Unlike the physical world, intentional domains require the analysis of the underlying goals of the decision maker. These goals, and their relative importance, provide a useful device for interpreting otherwise ambiguous data.

In the next section, we discuss the background work in qualitative reasoning and its relevance for decision making. We then describe our proposed intentional arithmetic for qualitative decision making.

## **Qualitative Reasoning**

In physical domains, numbers are descriptive measures of the world. Quantities such as mass, velocity, temperature, and pressure provide objective reference data by which the behavior of physical objects and processes may be analyzed and even predicted.

In intentional domains, such as economics and politics, numbers play a different role. Unlike the physical world, the intentional world is driven by the actions of volitional agents. The earth does not choose to revolve around the sun. It adheres to the laws of planetary motion.

However, the stock market goes up if more traders decide to buy than sell. The House of Representatives gets a republican majority if more voters decide to elect republicans than democrats. Numbers in the intentional world are driven by decisions.

Decision making is a process. Decision making is not an equation. Nevertheless, process models of decision making often require the qualitative interpretation of quantitative data.

Goal-based reasoning in general and the VOTE program in particular provide a paradigm for reasoning about decisions based on goals and relationships [Slade 1994]. We have contrasted VOTE with the traditional quantitative model of decision analysis, pointing out that decision analysis often relies on the specification of probability or payoff numbers that may not in fact be known. A qualitative, goal-based analysis may often be more realistic than the comparable quantitative analysis.

However, there are still many situations, particularly in business, in which it is not merely traditional, but advisable to take the numbers into account. Business decisions are full of quantities such as prices, rates, margins, shares, and volume. A robust business decision making system needs to be able to handle the numbers.

Rather than create a system which has hundreds of special rules for specific situations, we propose an intentional qualitative arithmetic to reason about business data. This effort reflects previous AI work in qualitative physics, which resulted in symbolic models of physical phenomena.

One would expect that such an exact quantitative science as physics would lend itself well to computational modeling, that is, to produce programs that reason about physical phenomena. However, it has turned out to be computationally challenging to create AI programs that actually do physics. AI researchers have developed qualitative theories for reasoning about physics [de Kleer and Brown 1985]. There are several motivations for pursuing a qualitative approach.

- It is often difficult to obtain the data required for modeling the necessary states of the world. For example, we may not know an object's precise mass or velocity or coefficient of friction.
- It is often computationally infeasible to calculate the answer. For example, even if we know the exact state of the world at time  $T=0$ , we may not be able to compute the state for  $T=1$  within a reasonable amount of time due to the complexity of the calculations.
- A qualitative analysis of a problem is usually logically prior to a quantitative analysis. For example, if we let go of an object, we can be fairly sure that it will fall to the ground, even if we do not know how long it will take or what velocity it will achieve.
- A qualitative model can serve to prune the computation space of the quantitative approach. The qualitative analysis can eliminate certain computations and focus attention on others. In some cases, the qualitative approach may be sufficient.

- It is psychologically inappropriate to suggest that people reason about physics in a purely quantitative fashion. By proposing a mixture of qualitative and quantitative reasoning, we can arrive at a model that is both computationally feasible, and psychologically satisfying.

Thus, in the field of physics for which quantitative reasoning would seem well-suited, AI researchers have discovered compelling reasons for developing qualitative theories. We suggest that a similar argument holds for decision making.

- It is often difficult to obtain the data required for modeling the necessary states of the world. For example, we may not know an outcome's precise payoff or probability.
- It is often computationally infeasible to calculate the answer. For example, an accurate estimation of the behavior of a complex system, such as the stock market, requires thousands of probability and payoff estimates for each security at different points in time.
- A qualitative analysis of a decision problem is usually logically prior to a quantitative analysis. For example, if we learn of good news for a company, we expect its stock to go up in value. We may not know exactly how much the stock will rise or how soon.
- A qualitative model can serve to prune the computation space of the quantitative approach. As with physics, the qualitative analysis can be used to eliminate certain computations and focus attention on others. A qualitative analysis may even obviate a quantitative analysis.
- It is psychologically inappropriate to suggest that people reason about decisions in a purely quantitative fashion. Most decision theory avoids this problem by stating that the quantitative approach is prescriptive, rather than descriptive. [Luce and Raiffa 1957]

There are both theoretical and practical reasons for pursuing a qualitative model of business decision making. It is possible to have a qualitative analysis of quantitative data, as the work in qualitative physics has demonstrated. In this regard, the key difference between the physical world and the intentional world is the relationship between numbers and goals. In intentional domains, numbers have the additional properties not found in physical domains.

- **Numbers can indicate success or failure.** Numbers are good or bad. Numbers reflect the satisfaction conditions of goals. That is, if a number indicates that a goal will be satisfied, then it is a good number. Otherwise, the number is bad.

If I have an hour to make a plane connection and my first flight is 5 minutes early: that is good. If my first flight is two hours late: that is bad.

If I can afford to pay \$2,000 for a PC and I find one for \$1,500, that is a good price. If the PC costs \$3,000, that is a bad price.

- **Numbers are subjective.** Numbers are not always good or bad for all agents. The assessment of a number may depend on the agent.

In the airplane example, another passenger might have missed the first flight if it had left on time. He believes that it is good for it to be two hours late.

In the PC example, for the seller of the computer, the price of \$3,000 is good and \$1,500 is bad.

### Qualitative Arithmetic

Decision making involves comparing alternatives. VOTE uses simple ordinal values for ranking goals. We observe that good numbers and bad numbers may similarly be compared. Furthermore, we note that in some cases, it is good for a number to be high, and in other cases, we want the number to be low. For example, we want our lifespan to be high and our blood pressure to be low. In sports, we want our baseball score to be high, and our golf score to be low. Table 1 provides examples of business highs and lows.

High	Low
profits	overhead
profit margin	fixed costs
income	variable costs
cash	taxes
sales	tax rate
market share	bad debts
interest earned	interest paid
price received	price paid
principle	long term debt
volume	short term debt
accounts receivable	accounts payable

Table 1: Examples of Highs and Lows

A computer program can perform simple decisions based on this type of information. If there is a choice between two high options, the program will select the larger. If the choice is between two low options, the program opts for the smaller.

Furthermore, the program does not require an exhaustive table of all quantities. We can derive the high or low polarity of certain quantities based on the underlying formula. Table 2 provides examples of derived polarities.

Operands	Result	Example
high + high	high	dividends + interest
low + low	low	rent + taxes
low + low	low	fixed costs + variable costs
high - low	high	revenue - overhead
high * high	high	volume * margin
high / low	high	miles / gallon

Table 2: Examples of Qualitative Arithmetic Formulas

Table 3 presents the general relations for the commutative operators of addition and multiplication, and Table 4 presents the rules for the non-commutative operators of subtraction and division.

+ or *	high	low	constant
high	high	?	high
low	?	low	low
constant	high	low	NA

Table 3: Commutative Qualitative Arithmetic

- or /	high	low	constant
high	?	high	high
low	low	?	low
constant	low	high	NA

#### Table 4: Non-Commutative Qualitative Arithmetic

We note that some of the cases are ambiguous, as denoted by the question marks in Tables 3 and 4. For example, (high \* low) or (low / low) could result in either high or low. To resolve these cases, we use the relative importance of the underlying goals.

One application of this technique is to the problem of purchasing a personal computer. The qualitative arithmetic provides a means of converting the quantitative data, such as price, speed, and memory capacity, into qualitative terms comparable to other features, such as type of printer or operating system. We shall discuss this example at the AIS conference, as well as demonstrate current versions of the decision models.

The programs, in Common LISP, are available via anonymous ftp from is.stern.nyu.edu in /pub/vote or as the URL file://is.stern.nyu.edu/pub/vote/ using a Web browser.

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