A Comprehensive Approach to Argumentation

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A reasoning model, based on the logic of argumentation, is described. The model represents argumentation as a directed graph in which nodes and arcs can be colored using an ordinal set of weightings and in which the attributes of both nodes and arcs can be modified. It is thus able to deal with the undercutting or augmenting of arguments. Weightings can be propagated through the graph to generate unique weightings for any node or arc. The model is able to deal with contradiction. It can incorporate numerical methods and is able to handle qualitative and quantitative reasoning.

INTRODUCTION

It is difficult to use standard numerical methods for assessing probabilities in some domains because there are not meaningful numerical measures upon which to base all the relevant calculations. Several techniques have been used to try and deal with situations where there is uncertainty and many of these work with the *level of belief* or *confidence* in an outcome as a subjective measure rather than use an objective statistical probability. Some examples include the widely used Bayesian methods, Fuzzy/Neuro-fuzzy sets, and interval probability methods (possibility theory); the area has been reviewed,[1,2] and examples of these approaches in toxicity[3−7] and metabolism[8] prediction have appeared. These quantitative methods have had some success but a particular concern to researchers interested in human perception of, and communication about, risk[9] is the need with these methods to devise numerical representations for input data and to express conclusions in numerical terms that can lead to apparent precision which is spurious. As a result of these concerns alternative kinds of reasoning are being explored which do not depend on numerical data values. One such area of research is the logic of argumentation (LA).[10]

LA models the human approach to reasoning in which the cases for and against something are built up and weighed against each other. There can be secondary arguments to justify or refute the grounds of the arguments on which judgments about the ultimate problem are made, and so on, resulting in a reasoning tree.

Models based on LA have been proposed and used for qualitative computer reasoning,[11,12] including reasoning about the toxicological hazard associated with chemicals,[9,13−16] metabolism prediction,[17,18] or for advice in medical decision making,[19] and some models can support both qualitative and quantitative reasoning, depending on the nature of the data available.[20] Systems which implement LA typically vary in the constitution of the arguments, but frameworks have been defined which describe how LA arguments interact, irrespective of the structure of the arguments themselves.[21,22] However, there are limitations in some of the models described before now, arising from difficulties in dealing with contradictions in reasoning.[23,24] This is a particular problem in scalability of systems where it is difficult to keep consistency in large knowledge bases of many facts or inference rules.

This is the first of three papers describing methods for reasoning under uncertainty and their applications. This paper describes a new model for reasoning about the level of belief in an event that is based on LA. Paper two[16] describes both an implementation of the model and an application in which it is used to predict the potential toxicities of chemicals. Paper three[18] describes a further application of the same implementation and introduces a separate model to handle reasoning about the relative likelihoods of competing events when considering the potential metabolism of xenobiotics.

THE MODEL

The model that we propose here captures some of the ideas for a logic of argumentation described and proved by Krause et al.,[20] in particular the use of an ordered dictionary of levels of belief, the logic of combining arguments, and the logic of propagating arguments along a chain, but differs in its method of dealing with some predefined states (associated with nonpolar forces, vide infra), in its introduction of a threshold for logical statements that allows for modulation of how rules are applied and its ability to handle and combine multiple, possibly overlapping, dictionaries at the same time. The model represents argumentation as an acyclic directed predicate dependency graph[25] in which nodes and arcs can be colored using an ordinal set of weightings, or confidence measures, and in which the attributes of both nodes and arcs can be modified by subgraphs attached to them. It is thus able to deal with the undercutting or augmenting of arguments. Weightings can be propagated any distance through the graph to generate unique weightings for any node or arc. The model is able to deal with contradiction. It can incorporate numerical methods and is able to handle qualitative and quantitative reasoning. Although the model requires the existence of a set of defined levels of belief, the terms used in the discussion are illustrations and are not necessarily inherent to the model in every case.

Figure 1 represents chains of arguments leading to a conclusion and it forms the background to most of the

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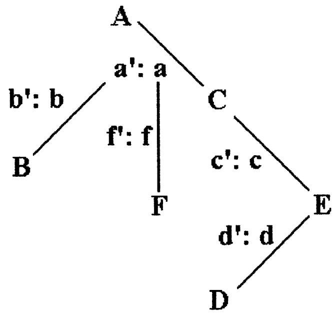

Figure 1. A small reasoning tree.

discussion in this paper. The contribution of one node to the level of belief assigned to the next may be expressed in a statement of the form "If [Grounds] is/are [Threshold] then [Proposition] is [Force]". A, B, C, D, E, and F represent the levels of belief in assertions associated with nodes in the tree (i.e. a phrase such as "If A is true..." means "If A, the level of belief in the assertion with which A is associated, has the value 'true'...")—they are the grounds for arguments along arcs leading from them; a, b, c, d, and f represent the forces of arguments—the levels of belief in the strengths of the arguments (so, e.g., given the statement "If A is true then C is probable", 'a' would have the value "probable"); a′, b′, c′, d′, and f′ represent the threshold values in arguments (e.g. given the statement "If A is plausible then ...", 'a′' would have the value "plausible"). Other models for LA express relationships in terms of triples. For example, Fox's scheme,[19,24] also used by Parsons and co-workers,[15,26,27] has Claims, Grounds and Qualifiers/Signs which are similar to our Proposition, Grounds and Force, respectively.

The model uses five definitions to describe the states of uncertainty it can express and six axioms to describe the behavior of these states in any implementation.

The relationships between levels of belief in grounds, thresholds, forces of arguments, and propositions are set by the following definitions, 1 and 2:

Definition 1: *Tension is the measure of belief in something (be it grounds for an argument, a threshold which the grounds must satisfy, the force of an argument or the level of belief in the proposition as a result of the argument).*

Definition 2: *The force of an argument is equal to the measure of belief that would attach to its conclusion (i.e. the proposition) if its grounds were proven (or were greater than the threshold).*

Defining the force of an argument in terms of its implications for the conclusion avoids the need to relate levels of belief in conclusions to levels of belief in arguments measured in some other way. The term "force" in relation to arguments has been used before[13] in preference to "weight" and "strength", both of which have other connotations in probabilistic reasoning, though its definition was different.

Attaching symbols (whether words, numbers, or glyphs) to the levels of beliefs requires caution and may depend on the domain of knowledge in which the model is to be used.[12] In most of the discussion in this paper, and in the implementations of this model described in the following papers, the level of belief is expressed in words.

Definition 3: *Forces are of two kinds—those with and those without polarity. Polar terms can contribute only to knowledge either about cases for or about cases against propositions. Nonpolar terms contribute equally to knowledge both about cases for and about cases against propositions.*

Examples of forces with polarity might be "certain" and "probable", which contribute toward the case for believing in something, and "impossible" and "doubted", which contribute toward the case against believing in something. However, there also exist states—expressed by tensions—which can contribute equally to knowledge about both the truth of a proposition and its falseness and it is these we term nonpolar states. In this model there are at least four such states:

The Equivocal state—there is an equal weight of argument for and against a conclusion.

The state of Contradiction—simultaneous, independent evidence that a conclusion is both true and false.

The Open state—there is no germane evidence about the level of belief in a conclusion.

The Undefined state—the evidence about the level of belief in a conclusion has not yet been considered. Note that this is further distinct from the "null" state in computing, where, for example, a variable has not been initialized in a program.

Definition 4: *The set of permitted forces of arguments for propositions includes all those forces that contribute toward knowledge about degrees of belief in propositions.*

Definition 5: *The set of permitted forces of arguments against propositions includes all those forces that contribute toward knowledge about degrees of disbelief in propositions.*

The sets in Definitions 4 and 5 constitute the dictionaries in other discussions of LA schemes[20,24] but note that our model *requires* that two such sets be used at the same time. The implication of having two sets is that nonpolar terms (in practice, terms with ambiguous implications, like 'open', 'equivocal', and 'contradictory') are members of both sets. It would be possible to construct a model in which forces were classified into three sets rather than two—those that can only argue for propositions, those that can only argue against, and those that are nonpolar—but the alternative is not discussed further in this paper.

The two sets, For and Against, need not be equally populated.

Axiom 1: *How strongly the grounds of an argument contribute to an argument is equal to the tension of the grounds.*

Axiom 1 says that how much you believe in something as the basis of an argument is simply how much you believe in it in itself. It may appear to be a statement of the obvious, but it is not the only possible logic. It is a necessary condition for the construction of the tree in Figure 1 and thus for the model described in this paper, because it allows the level of belief in an assertion as the conclusion from one node in the tree to be used as the level of belief in the assertion when it is used as the grounds of the next argument in the chain.

Axiom 2: *The permitted values of forces of arguments for and against propositions each constitute an ordered set in which values higher in the list argue more strongly for or against the proposition, respectively, than those lower in the list.*

Axiom 3: *For the model to be complete, these sets must include representations for the states of contradiction, openness, equivocacy, certainty, and impossibility.*

An implementation of this model which does not include representations for some or all of these states is incomplete and situations may arise which it cannot handle.

Axiom 4: *For every pair of values of forces there exists a single value which is the resolution of those forces and which itself belongs to the set of permitted values for forces*.

Axiom 5: *A value of force may be exclusive or inclusive. An exclusive value implies nothing about other values; an inclusive value implies all weaker polar values of the same polarity*.

For example, if you ask the question "Is A probable" when A is, say, certain, then the answer is "Yes", whereas when A is, say, equivocal, the answer to the question is open.

None of the states 'equivocal', 'contradictory', 'open', and 'undefined' can imply and or be implied by any other state.

It is obvious, but should nevertheless be formally stated that it is not possible both to have no information about something (the 'open' state) and to have some information. The same simple logic applies to the 'undefined' state. If the evidence for and against a thing is evenly balanced (i.e. the evidence is 'equivocal'), then it cannot simultaneously be true that we should have more belief in the thing being true than false or vice versa. 'Contradictory', meaning "proven true and false", might appear to support all states of certainty, but as it is usually understood it has the unique property of transcending 'true' and 'false', defeating both and hence all lesser states. This leaves only the question of whether 'contradictory' and 'equivocal' are mutually exclusive. Contradiction could be regarded as a special case of equivocacy, in which case it would also imply it. In this paper we opt that 'contradictory' displaces 'equivocal', rather than implies it, but the model we propose could allow the latter: it is not a prerequisite of the model that all nonpolar forces are exclusive.

Axiom 6: *For each value of force for or against propositions there may or may not exist a complementary force of equal weight against or for propositions, respectively*.

Axioms 1,[24] 2,[11] 4,[20] 5,[24] and 6[11,20] are similar to those suggested for LA schemes elsewhere. They, together with axiom 3, impose limitations on the model, in that having sets of forces that imply each other in a disordered way or in ordered ways other than those associated with the ranking of forces in the sets For and Against, and having forces which can individually sometimes behave exclusively and sometimes inclusively, are not supported.

Axiom 6 makes it possible to draw conclusions in situations such as one in which "If A is certain then C is impossible" and A is found to be less than certain. If, for example, A was found to be 'plausible', and 'plausible' and 'doubted' were complementary, C would become doubted.

Combining Arguments Relating to the Same Conclusion. Consider first the process of combining the forces of arguments such as c and d to assign a value to E in Figure 1, ignoring c′ and d′ at this stage. There could be any number of independent arguments leading directly to a node, although there are only two leading to E in this illustration.

The apparently simple principle that a conclusion which is not true must be false does not hold if there is uncertainty about the grounds of an argument or its reliability.[9] If you are only fairly sure that something is true, what does that tell you about its falseness? The principle applied throughout this paper is that evidence in support of a proposition provides no direct information about the falseness of the proposition and vice versa.

In cases where arguments have some kind of quantitative significance or probabilistic interdependency, having more than one argument in favor of something may make it more believable than having only one. In other situations, the overall strength of belief in a proposition is simply equal to that of the strongest argument. For example, no matter how many arguments there are that something is plausible, it remains plausible—no number of arguments in support of plausibility warranting the view that a proposition is certain. Unless it is otherwise stated, the discussion in this paper assumes that belief in a proposition is determined by the strongest argument. This is in accord with other discussions about LA.[1]

If any argument provides rigorous proof that something is true or false, then it is true or false, no matter how many weak arguments there may be seemingly to the contrary[1] (cases where doubt is thrown on the validity of the argument itself, and cases where there are apparently proofs both that a proposition is true and that it is false, are discussed below). More usually, there will be no such conclusive argument. If the arguments for a conclusion are simply stronger than the ones against it, there is no clear, precise rule about what should happen, but belief in the conclusion should be in favor on balance. Conversely, if the arguments against a conclusion are stronger than those for it, belief in the conclusion should be against on balance. If the evidence for a proposition is of equal strength to the evidence against it, then overall belief in the proposition should be equivocal.

So, in this case, if c and d are both forces supporting, or both forces opposing, the proposition represented by E, E will have the same force as the stronger of c and d. If one of c and d supports and one opposes, whether E is supported or opposed will depend on which of c and d is the stronger. If they are of equal strength, the truth or falseness of E will be equivocal.

To meet these requirements, the aggregate value of the tension for a node, T, is determined as follows

$$\text{(A)}\ T = \mathrm{Resolve}[\mathrm{Max}\{\mathrm{For}(C_{a,x}, C_{b,y}, ...)\}, \mathrm{Max}\{\mathrm{Against}(C_{a,x}, C_{b,y}, ...)\}]$$

where T is the aggregate value of the tension of a conclusion derived from the forces of arguments relating to it; Resolve[] is a function which returns the single value of force which is the resolution of any pair of forces in accordance with axiom 4; For and Against are the sets of arguments supporting and opposing the conclusion, respectively; $C_{a,x}$, $C_{b,y,}$ ..., are the forces of those arguments; Max{...} is a function which returns a member of the set upon which it operates (For or Against). Max {...} must be both associative and commutative. The member of the set For or Against which Max{...} returns is dependent on implementation as described later in the paper.

The function Resolve must be commutative in any implementation. It need not necessarily be associative, although some implementations of the model may make it so (in which case the set of permitted forces form a semigroup with respect to Resolve). It is because of this lack of associativity that the function must operate on the results of Max{...} rather than on any pairs of forces directly.

If, as we suggested above, the 'open' state is in both sets For and Against, a value corresponding to this state will be returned by Max{...} in the absence of any arguments For or Against. This means that logically, under the operation of Resolve, the 'open' state should be an identity element of the set of permitted reasoning values. Those implementations of the model for which Resolve is associative will then constitute a monoid of the (Resolve, set of permitted forces) pair; argument aggregation functions are required to be commutative monoids in other LA schemes.[20]

Undercutting Arguments. Independent evidence can throw doubt on a statement such as "If A is true then C is true"—that is it can throw doubt on the reliability of the overall claim, as distinct from the reliability of the assertion that A is true. If one person states that "It is getting dark and so it will probably rain", another may well question the reliability of the argument if night is approaching. This is generally termed "undercutting" of an argument. The approach of night is not an argument against rain, only an argument against the proposition that "the growing darkness means rain".

In Figure 1, the potential for arguments to be undercut (or augmented) is represented by the subgraph that links F to a. So a subgraph with two nodes and arcs might be constructed in place of the simple one shown, to represent the arguments "If night is not approaching then the force of a is 'probable'", and "If night is approaching then the force of a is 'open'".

A change in the reliability of an argument might be expected to cause a corresponding change in the reliability of belief in its conclusion, but there are situations in which a piece of evidence supports a conclusion in one circumstance and opposes it in another. For example, if the hand-brake light in a car is on when the car is stationary this argues in favor of a normal, safe state; if it is on when the car is travelling it argues against a normal, safe state. The implementation of the tree structure in the model proposed in this paper allows freedom to control the consequences for reasoning based on A when F changes.

Reasoning along the Chain. Consider now the process of arguing about the validity of C on the basis of A in Figure 1. Statements such as "If A is true then C is true" and "If A is true then C is false" are easy to interpret when A is proven to be, or not to be, true. But suppose that A is 'plausible', or 'probable'. The weakness in certainty about A should be transmitted to C: given that "If A is true then C is true", knowing that A is plausible implies that C is plausible, too, and no more than that (in a more expanded form, the state of knowledge about C might be expressed as "It is plausible that C is true", which reduces to the simpler expression "C is plausible").

Starting from the premise that "If A is true then C is true", knowing that A is "doubted" (or even "impossible") provides no evidence about C. C could be true for some other reason, even if A were proved false. If it is the case that the falseness of C is linked to the falseness of A, that must be made explicit in another statement, "If A is false then C is false".

If there is contradiction in A, this does not imply contradiction in C: rather than implying that C is both true and false, it means that C might be true or it might be anything—i.e., that C is "open" (note that this refers to the case where the contradiction is in A itself, not the case where the truth of A would imply contradiction in C). For example, given the statement "If it is true that the ground temperature is below 0 °C then it is probable that roads will be icy", consider the situation when two measurements of ground temperature give values of +2 °C and −2 °C. The evidence about ground temperature is contradictory, but it is not correct to say that the evidence about whether the roads are icy is contradictory—it is only open: a further piece of evidence—for example, visible ice patches—could resolve the uncertainty, whereas true contradiction can only be resolved by undercutting one or other of the contradictory arguments.

A more flexible model needs to support statements such as "If A is plausible, then C is certain". It is not possible to make a prediction that is more precise than the evidence upon which it is based, but statements in a flexible model need not depend on or imply direct relationships. For example, one might correctly make the assertion in some countries that "If earthquakes are probable in a given town then it is certain that insurance rates there will be above average". The statement does not break the rule that confidence in a conclusion cannot exceed confidence in its grounds, because the condition is really "If 'earthquakes are probable' is true then...", but this construction is unnecessarily complex and has no effect upon the outcome of the reasoning process. Symbol "a′" in Figure 1 represents this kind of threshold for the grounds of an argument (in this case, a′ = 'probable'). The model also allows for the threshold for the grounds of an argument to be dependent on the outcome of another line of reasoning, as represented by the subgraph that links B to a′ in Figure 1. This corresponds to the level above which the level of belief in the occurrence of earthquakes has an effect on insurance rates.

Suppose it is given that "If A is true then C is probable" (i.e. in Figure 1 a = 'probable'), but A is found only to be 'plausible' and, for the sake of this discussion, 'plausible' is taken to mean "lower level of belief than probable". The situation implies that "It is plausible that C is probable", which can be simplified to "C is plausible". That is, in general, the level of belief in a conclusion is determined by the weaker of the level of belief in the grounds of an argument and the force of the argument.

To meet these criteria, contribution to belief in a conclusion by a single argument of the form "If a is x_0 then C is x" is determined as follows:

```
(B) If a = undefined or x = undefined or x0 = undefined then
        C = undefined
    Else if x0 is exclusive then
        If a = x0 then
            C = x
        Else
            C = open
        End if
    Else if (a ∈ For() and x0 ∈ Against()) or (a ∈ Against() and x0 ∈ For()) then
        C = open
    Else if a = Min{a, x0} then
        If (a ∈ For() and x ∈ For()) or (a ∈ Against() and x ∈ Against()) then
            C = Min{a, x}
        Else
            C = Min{Complement{a}, x}
        End if
    Else
        C = x
    End
```

where C is the tension of the conclusion of an argument with grounds of tension a, threshold of x_0, and force of x, For() and Against() are the sets of terms For and Against, Min{a,x} is the term ranking lower in the ordered set, For() or Against(), to which a and x belong, and Complement{} returns the term of equal value and opposite polarity to its argument according to axiom 6 if one exists and otherwise returns ‘open’.

The condition that sets C equal to undefined if any one of the input values is undefined establishes a fail-safe condition. It might be handled differently in some practical implementations. For example, there may be circumstances in which it is appropriate to argue that a conclusion is open rather than undefined if some input value has not been provided.

Boolean Logic. A reasoning model should support statements that include AND, NOT, or OR operators, such as “If X is probable and Y is not certain then Z is plausible”, “If M is probable or N is plausible then P is doubted”.

OR. Given the statement “If X is x or Y is y then Z is z”, if X falls short of x and/or Y falls short of y, then it can be reasoned that the level of belief in Z should be determined according to the rules discussed earlier for cases where there is more than one independent argument leading to the same conclusion.

The main algorithm for aggregating arguments relating to the same conclusion implies OR logic, and so algorithm (B) can be applied to the individual conditions separately and then equation (A) can be applied:

(C) The value of Z determined by the statement

“If X is x or Y is y or ... then Z is z”

is equal to the value determined by the set of statements

“If X is x then Z is z”

“If Y is y then Z is z”

...etc.

The statement “If X is x then Y is y or Z is z” must be re-expressed as “If X is x and Y is not y then Z is z” and “If X is x and Z is not z then Y is y”. For example, “If the pavement is wet then it has been raining or someone has put water on it”, could be expressed as “If the pavement is wet and it has not been raining then someone has put water on it” and “If the pavement is wet and no-one has put water on it then it has been raining”. The original statement does not imply the exclusive OR. For example, it is not correct to say “If the pavement is wet and someone has put water on it, then it has not been raining”.

AND. The statement “If X is x then Y is y and Z is z”, can be simply re-expressed as two statements, “If X is x then Y is y” and “If X is x then Z is z”.

Given “If X is x and Y is y and ... then Z is z”, if all of the conditions are met then Z is z. If any condition is not met, then Z is determined by applying algorithm (B) for that condition. If more than one condition is not met, then Z is the weakest of the values determined by applying algorithm (B) for each of those conditions:

(D) To determine the value of Z from the statement “If X is x and Y is y and ... then Z is z”:

(i) Determine a set of values, Z_n, using algorithm (B) for each condition treated separately:

“If X is x then Z_1 is z”

“If Y is y then Z_2 is z”

...etc

(ii) $Z = \mathrm{Min}\{Z_1, Z_2, ..., Z_n\}$ where $\mathrm{Min}\{Z_1, Z_2, ..., Z_n\}$ is the term ranking lowest in the ordered set, For or Against, to which $Z_1, Z_2, ..., Z_n$ all belong.

NOT. Taking into account Axiom 5 about the automatic implication of lesser degrees of certainty by higher ones, equivalences involving negation are not symmetric. If something is only plausible, it is valid to conclude that it is ‘not certain’, but the reverse does not apply—it is not correct to say that something that is ‘not certain’ is ‘plausible’. A statement like “If X is not probable then Z is doubted” does not mean the same as “If X is improbable then Z is doubted”. The former statement is conditional only on X falling short of probable, for which being improbable is just one option.

There is a distinction between negation of degrees of certainty and negation in relation to the grounds of a statement. Within the reasoning model described in this paper, phrases of the form “If ‘not X’ is ‘x’ then ...” and “If ‘X ≠ Y’ is ‘x’ then ...” are identical in type to one of the form “If Y is ‘x’ then ...”, since ‘not X’ and ‘X ≠ Y’ are values determined externally to the model.

Statements of the form “If X is ‘x’ then ‘not Y’ is ‘y’”, are unnecessary, being equivalent to statements of the form “If X is ‘x’ then ‘Y’ is ‘z’”, where ‘z’ expresses an appropriate level of belief in the falseness of Y.

To meet these requirements, use of the NOT operator in a statement requires an alternative to algorithm (B):

(E) For the statement “If a is not x_0 then C is x”:

```
If a = undefined or x = undefined or x0 = undefined then
    C = undefined
Else if x0 is exclusive then
    If a ≠ x0 then
        C = x
    Else
        C = open
    End if
Else if (a ∈ For() and x0 ∈ Against()) or (a ∈ Against() and x0 ∈ For()) then
    C = x
Else if a = Min{a, x0} then
    C = x
Else
    C = open
End if
```

where C, a, x_0, x, For(), Against(), and Min{} have the same meanings as in (B).

Comparative Statements. A complete model should support all aspects of statements such as “If we have a greater belief in W than X then we have a greater belief in Y than Z”, but in a following paper[18] we propose that *relative* reasoning operates independently of *absolute* reasoning (we define absolute reasoning as reasoning about the level of belief in a single event or set of conclusions and relative reasoning as reasoning about the comparative likelihood of alternative events). This paper discusses only points that relate to absolute reasoning. Relative reasoning and the connection between absolute and relative reasoning are discussed further in the other paper.

When comparative statements are associated with other types of statement in absolute reasoning, the vagueness coming from the comparison is propagated right through the reasoning process. If Z has a higher level of belief than Y and Y is, say, ‘plausible’, it can only be said that the level of belief in Z is ‘plausible’ or more (we could have a higher level of belief in Z than Y while both were ‘plausible’, depending on the definition of ‘plausible’, a situation that has been described elsewhere).[26] Further reasoning has to take into account that Z may have any one of a range of values.

To make comparisons it is necessary to consider potential membership of both the sets, For and Against, by each term in the comparison statement. This is necessary because level of belief increases with ranking in the set, For, but decreases in the set, Against (terms ranked higher in the set, Against, argue more strongly against a proposition, and hence make the proposition less believed). Although inverting the ordering in one set would make comparisons simpler, it would complicate all the operations described above. Ranking each set by strength of argument is considered the more elegant choice because the other operations are more fundamental than comparison.

(F) For example, the statement “If we have a greater belief in W than X then we have a greater belief in Y than Z” is met by the following:

```
If w is exclusive or x is exclusive then
    Relationship between y and z is open
Else
    Case w ∈ For
      Case x ∈ For
         If w > x then
           Case z ∈ For
              y >= z
           Case z ∈ Against
              y <= z OR y ∈ For
           End Case
         Else
           Relationship between y and z is open
         End if
      Case x ∈ Against
         Case z ∈ For
           y >= z
         Case z ∈ Against
           y <= z OR y ∈ For
         End Case
      End Case
    Case w ∈ Against
      Case x ∈ For
           Relationship between y and z is open
      Case x ∈ Against
         If w < x then
           Case z ∈ For
              y >= z
           Case z ∈ Against
              y =< z OR y ∈ For
           End Case
         Else
           Relationship between y and z is open
         End if
      End Case
    End Case
End if
```

where w, x, y, and z are the tensions of W, X, Y, and Z, respectively, For is the set of permitted values of strengths of arguments for, Against is the set of permitted values of strengths of arguments against, $a \geq b$ means a is higher than or at the same level as b, and $a \leq b$ means a is lower than or at the same level as b, in the ordered set, For or Against, to which both a and b belong.

Analogous approaches can be used for the statements “If we have a lower belief in W than X then we have a greater belief in Y than Z” etc.

IMPLEMENTATIONS OF THE MODEL

Different implementations of the model will vary in the number and types of elements that are contained in the set of reasoning values subject to Axiom 2.

Implementation 1. The Resolve function is expressed as a simple symmetrical matrix and Max{x, y} is the higher of x and y in the priority list for the set, For or Against, to which x and y both belong. This implementation of the model is described in detail in the following papers.[16,18]

Implementation 2 − Additive Probability Values. Throughout this paper, it has been assumed that where there is more than one argument for or against a proposition, the degree of belief in that proposition is equal to the resolution of the forces of the strongest argument for and the strongest argument against it. In some situations[19] it may be appropriate to use a model in which multiple arguments for (or against) a proposition augment each other. The generalized model behaves in this way if the Max function is constructed such that the value that it returns for any pair of elements in For and any pair in Against is an element higher in the priority list.

An illustration is the case in which the polarizing members of the sets For and Against are numbers. If members of the set, For, are defined to be positive numbers, members of the set, Against, are defined to be negative numbers, and for every pair of polarizing terms, x and y, Resolve[x, y] = x + y, and Max{...} is the sum of its arguments, then resolution becomes arithmetic addition and subtraction. One drawback of such an implementation is that Equivocacy and Openness cannot be distinguished—both of these concepts presumably being associated with the value of zero. To make the model complete it would be necessary to define at least one of these terms independently and to extend the resolution matrix to include it (in an analogous way to the one discussed under Implementation 4, below). Certainty and impossibility would presumably have over-riding values such as ∞ and $-\infty$ and a convention would have to be devised for dealing with Contradiction (which would manifest itself as the sum of ∞ and $-\infty$).

This implementation of the model has a Resolve function which is associative: the (Resolve, set of integers) pair for a monoid.

Implementation 3 − Conventional Probability. To conform to the mathematics of conventional probability it would be necessary to make the following modifications to the model:

(1) The set of permitted polarizing forces For includes the infinite set of numbers between 0 and 1, and the Max function returns a value according to the rule that for every pair of polarizing forces, x and y, where $0 <= x <= 1$, $0 <= y <= 1$ and x and y are independent, Max [x, y] = $x + y - xy$.

(2) The statement three lines from the end of algorithm (B), “C = Min{a,x}”, is replaced by

```
If (0 < a < 1) and (0 < x < 1) then
    C = a.x
Else
    C = Min{a , x}
End if
```

(3) Equation (D) (ii) is replaced by

$$
\begin{array}{l}
\{X_1 \ldots X_n\} \subset \{Z_1 - Z_n\} \text{ and } (0 < X_m < 1) \text{ for all } X_m \\
\{Y_1 \ldots Y_n\} = \{Z_1 - Z_n\} \setminus \{X_1 \ldots X_n\} \\
\text{If } \{Y_1 \ldots Y_n\} = \emptyset \text{ then} \\
\quad C = Z_1.Z_2 \ldots .Z_n \\
\text{Else if } \{X_1 \ldots X_n\} = \emptyset \text{ then} \\
\quad C = \mathrm{Min}\{Y_1, Y_2, \ldots Y_n\} \\
\text{Else} \\
\quad C_1 = X_1.X_2, \ldots .X_n \\
\quad C = \mathrm{Min}\{C_1, Y_1, Y_2, \ldots Y_n\} \\
\text{End if}
\end{array}
$$

(4) The use of NOT logic is excluded from reasoning statements.

(5) To model conventional probability fully, the axiom $P(a) + P(\neg a) = 1$ must be applied after application of the reasoning rules if a conclusion lies in the range 0 to 1.

To limit the model to conventional probability, the set of permitted forces For would be only the numbers between 0 and 1, the set of permitted forces Against would only be 'Open' and the parts of modifications (2) to (4) relating to values outside that range would thus be redundant. Openness, equivocacy, and contradiction are not easily accommodated by such an implementation, which means that—by axiom 3—such an implementation would be incomplete. The modifications for implementation 3 also support the more useful Implementation 4, which follows.

Implementation 4 − Combining Quantitative and Nonquantitative Terms. Mixing qualitative polarizing and nonpolarizing terms with quantitative ones makes it possible for quantitative and nonquantitative evidence to interact. Qualitative uncertainty terms might be added to the model for Implementation 3.

Terms such as 'certain', 'impossible', and 'equivocal' are distinct from probability values of 1.0, 0.0, and 0.5 and may not be equated with them within the model. A logical extension of this is that it is not valid to intercalate a nonquantitative term into a range occupied by a continuous numerical set within the ordered sets of permitted values. For example, 'equivocal' cannot be placed in the middle of the probability range 0.0−1.0 since that would amount to equating it to some value (presumably 0.5).

If qualitative uncertainty terms are used in this hybrid model and defined to be stronger than the terms in the range 0.0 to 1.0 (that is, qualitative terms are ranked higher than numerical probability terms), they will dominate resolution when they are present in the input data. Thus, when numerical probability data are available for all the factors relating to a problem under analysis, the reasoning model will generate a numerical probability for the outcome; when numerical data are lacking for some factors, the output from the model will be qualitative, reflecting the greater unreliability in the data. Qualitative terms might be defined to extend reasoning beyond the normal realms of conventional probability. For example, 'impossible' might be defined to mean "cannot happen", whereas a probability of zero might mean the arguably less absolute "will not happen".

CONCLUSION

Argumentation has already found practical use in computer applications, and it is hoped that its usefulness will be increased by the model described in this paper which seeks to cover a broad range of issues associated with reasoning by argumentation, including the need to support numerical methods appropriately in domains where statistical information is sometimes available and sometimes not. Further papers in this series provide examples of the use of argumentation in the prediction of toxicities and metabolic fates of chemicals.[16,18]

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