Towards a possibility-theoretic approach to uncertainty in medical data interpretation for text generation

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Abstract. Many real-world applications that need to reason about events obtained from raw data must deal with the problem of temporal uncertainty, which arises due to error or inaccuracy in data. Uncertainty also compromises reasoning where relationships between events need to be inferred. This paper discusses an approach to dealing with uncertainty in temporal and causal relations using Possibility Theory, focusing on a family of medical decision support systems that aim to generate textual summaries from raw patient data in a Neonatal Intensive Care Unit. We describe a theoretical framework within which to capture temporal uncertainty, and discuss the way it informs the process of text generation.

1 Introduction

Medical decision support systems can run into problems when there is temporal uncertainty or inaccuracy in their input data. Such uncertainty can arise for a variety of reasons. For example, medical staff often record events when they have time to do so, rather than when they actually happened. In addition, existing database management systems tend not to deal with temporal data in a principled fashion [1].

Uncertainty and inaccuracy make the tasks of reasoning about temporal and causal relationships more difficult. Classical clinical decision support systems (especially expert systems) typically approach this problem in one of two ways. On the one hand, uncertainty can either stall the reasoning completely, so that the system only outputs what it is certain about. Alternatively, the system communicates findings using a ranking mechanism [2].

In contrast to the most classical medical expert systems, the family of decision support systems being developed in the BabyTalk project [3] aim at providing textual summaries of heterogeneous medical data to support decision and communication to carers in Neonatal Intensive Care Units (NICUs). The goal is to communicate the relevant aspects of patient data, by using Natural Language Generation (NLG) techniques to generate a descriptive summary, leaving it up to the user to decide on the best course of action. These systems are knowledge-based, backed by an ontology and domain-specific inference rules. An off-ward evaluation confirmed the interest of textual summarisation over current approaches for medical decision making, which mainly rely on visualisation. In this paper, we describe an approach to dealing with temporal uncertainty in the reasoning component of these systems based on Possibility Theory, and investigate the consequences for summary generation. We argue that uncertainty in the data should be explicitly communicated.

Formalisms that deal with uncertainty tend to rely on probability [4, 5] or possibility [6, 7] theory. Some of these formalisms have been extended to deal with temporal relations, which are crucial to temporal reasoning [8, 9], with some reformulations of crisp temporal relations [10] in fuzzy terms [6, 11, 7]. To the best of our knowledge, these formalisms are rarely deployed in medical real-world scenarios [12, 13]. Moreover, existing formalisms often deal with uncertainty in knowledge and not uncertainty about the data source itself. One of the aims of the present paper is to propose an extension of these formalisms to deal with these problems. In addition, we also discuss how the outcome of reasoning about temporal relations, and other relations that are contingent upon them, such as causality, can be exploited in an NLG component to communicate uncertainty in the data. Here, our focus is on modal expressions (such as *may* and *must*). Although modality has been the subject of intensive research in formal semantics [14, 15], it has not been treated systematically from the point of view of Natural Language Generation, with a few exceptions [16].

In our application domain, the NICU data is of two kinds: (a) discrete records logged by the medical staff on the NICU database, such as drug administration; (b) physiological data sampled at high frequency from probes measuring heart rate (HR), oxygen saturation (SaO2), etc. We assume an interval-based representation.

The current system [3] processes this data in four stages: A *data analysis* stage identifies significant trends and patterns in the physiological data, as well as data records in the database, mapping them to concepts in a domain-specific ontology. Subsequently, *data interpretation* infers temporal and causal relations between events. The outcome of this stage is a labelled graph whose edges represent relations between event pairs, the input to the NLG stage proper. NLG selects important events[3], plans the structure of the summary (*document planning*) and maps them to semantic representations (*microplanning*), and finally to syntax (*realisation*). Our focus in this paper is on extensions to data interpretation and microplanning, to deal with uncertainty in temporal relations.

To make the problem concrete, consider the sample of data in Figure 1(a), consisting both of events logged in the database by NICU staff, and patterns automatically discovered during signal analysis. A corresponding fragment of a nurse shift summary, written by a neonatal nurse, is shown below.

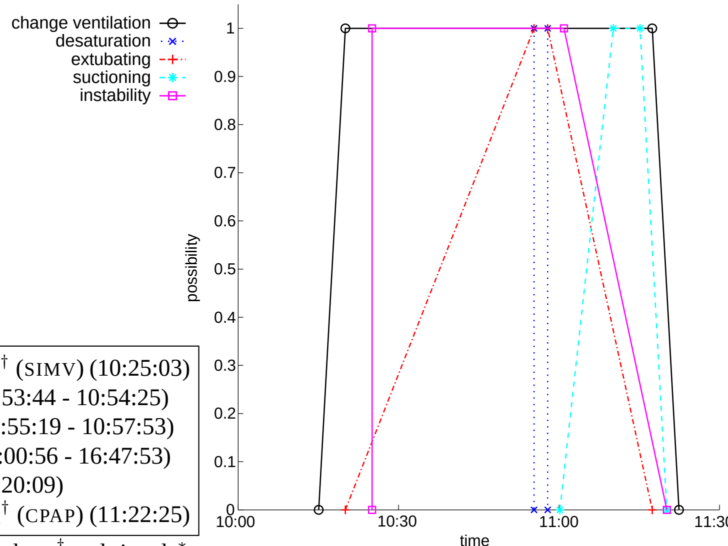
Example 1. He is currently on nasal CPAP in air, having been extubated today [...] Prior to extubation his SpO2 and HR showed compromise during handling with desaturations and HR decelerations.

The example highlights a number of possible sources of uncertainty for a system that (unlike a nurse) is entirely reliant on recorded data. The extubation has not been recorded in the database and must be inferred. There are two relevant facts: First, the baby's having been on SIMV ventilation is consistent with her having been intubated (SIMV requires the patient to be intubated). Second, the change to CPAP is what typically follows an extubation, which only occurs if a patient is intubated in the first place. The precise time at which the extubation was carried out is, however, uncertain. Moreover,

[3] Importance factors are obtained from heuristics or experts.

Ventilator reading† (SIMV) (10:25:03)
Bradycardia* (10:53:44 - 10:54:25)
Desaturation* (10:55:19 - 10:57:53)
SpO2 steady* (11:00:56 - 16:47:53)
Oral suction† (11:20:09)
Ventilator reading† (CPAP) (11:22:25)

(a) Data from database† and signals*



(b) Temporal intervals after data interpretation

Fig. 1. Data from database and signal analysis and their temporal representation after interpretation.

there is no specific event corresponding to the placement of the baby on CPAP. Rather, this too is inferred from the two consecutive ventilator readings, the second of which shows a change in ventilation mode. Thus, the precise time of the ventilator change event itself cannot be determined, though it must have overlapped with the extubation. Finally, the text makes reference to instability in heart rate (HR) and oxygen saturation (SpO2). This is an abstraction that the system needs to perform from the signals. Once again, the interval over which the period of instability holds is fuzzy. Moreover, the reference to 'handling' suggests that the instability occurred during the extubation and prior to its completion.

The outcome of data interpretation is shown in Figure 1(b). The trapezoidal representation of event intervals indicates the uncertainty in the time at which they started and ended. This also affects the certainty with which relationships between them can be inferred, such as the temporal overlap between the ventilator change and the extubation, and the causal relation between the extubation and the instability period, given the handling that must have occurred. Though domain knowledge reduces uncertainty, it may not eliminate it; hence, for a better human interpretation based on the textual output, a summary should communicate this uncertainty to the human reader.

In the rest of this paper, we begin by introducing our formalism, with a focus on uncertain relations between intervals (Section 2). Section 3 describes the approach to reason with uncertain temporal information. Section 4 describes the semantic representation used for events and states by microplanning, and how expressions that convey the uncertainty in the data are selected. We conclude with remarks on future work in Section 5.

2 Representing Temporal Information

The formalism used to represent intervals and uncertain relations between them is based on possibility theory [6]. There are a number of reasons for choosing possibility over probability theory. First, we lack annotated data for reliable acquisition of a probabilistic model. Second, probability theory is designed to deal with uncertainty only, whereas fuzzy logic and possibility theory are complementary for vagueness and uncertainty. The term 'uncertainty' refers to the degree of belief in a fact (e.g. *A may have happened*) whereas vagueness occurs when there is a range of possible values that a fact may be true of (e.g. *A is short*). Although our focus here is on uncertainty, we are interested in extending the formalism to deal with vague concepts (such as the classification of temporal relations as 'shortly after'). A final reason for preferring a possibilistic approach is that fuzzy rules have been argued to better reflect the qualitative nature of human reasoning [17].

In the following, lowercase italic letters (*a,b,c,...*) denote dates and normal uppercase (A,B,C,...) inaccurate intervals. Recall that in possibility theory, the uncertainty about an inaccurate interval A that holds at date $d \in \mathbf{Z}$ can be evaluated by the two dual measures of possibility II and necessity (also called certainty) N, as follows:

$$II(\mathrm{A}(d)) = h_{\mathrm{A}}(d) \tag{1}$$

$$N(\mathrm{A}(d)) = 1 - h_{\bar{\mathrm{A}}}(d) \tag{2}$$

Where $h_{\mathrm{A}} \in [0,1]$ is the hold function of the interval A, representing the degree to which A has possibly occurred at date d, and $\bar{\mathrm{A}}$ is the complement of A. Additionally, $II(\mathrm{A}) = \max h_{\mathrm{A}}$, $II(\mathrm{A}(d) \vee \mathrm{B}(d)) = \max\{II(\mathrm{A}(d)), II(\mathrm{B}(d))\}$, $N(\mathrm{A}(d) \wedge \mathrm{B}(d)) = \min\{N(\mathrm{A}(d)), N(\mathrm{B}(d))\}$. Moreover, by formula 2 and the following property:

$$II(\mathrm{A} \cup \bar{\mathrm{A}}) = 1 \tag{3}$$

the necessity of an interval A at date d can be summarised as $\mathrm{A}(d)$ *is certain only if no interval contradicting* A *(i.e.,* $\bar{\mathrm{A}}$*) is possible at time* d. If several contradictory intervals are completely possible at the same time (e.g., several mutually exclusive values of a device setting), no certainty exists. In the following, we restrict ourselves to trapezoidal hold functions. Thus, an inaccurate interval is given by the following definition:

Definition 1 (inaccurate interval). *An inaccurate interval* A *is a 5-tuple* $\langle o, s, e, \alpha, \beta \rangle$*, where* $o \in \mathcal{O}$*;* $\mathcal{O}$ *is the domain of concepts;* $s, e, \alpha, \beta \in \mathbf{Z}$*,* $s - \alpha \leq s$*,* $s \leq e$*, and* $e \leq e + \beta$*.*

A is seen as a concept with a trapezoid fuzzy set that describes the period during which A possibly holds. The $[s, e]$ interval is the core of the fuzzy set (i.e. here the latest start and the earliest end) and $[s - \alpha, e + \beta]$ is the support (i.e. here the earliest start and the latest end). In what follows, we reserve the term 'interval' for inaccurate intervals. A trapezoid function leads to $II(\mathrm{A}) = 1$, since $\max h_{\mathrm{A}} = 1$. Thus, it is completely possible that A holds, though its start and end time are not known with certainty.

In our application domain, the 'meaning' that an interval conveys can usually be determined by linking each record to a concept in the knowledge representation which, in the present case, takes the form of an ontology. One of the uses of associating intervals with concepts is that domain knowledge can constrain or validate some intervals. A full discussion would take us beyond the scope of this paper, but to summarise, temporal knowledge such as max or min duration or qualitative or quantitative ordering (e.g. A is usually followed by B in the next few hours) can be used to remove ambiguity. This kind of expert knowledge is easier to embed into an ontology using fuzzy sets and logic than using probabilistic models. In the following, we distinguish the notion of *event* from the notion of *state*. Typically the former is related to actions or occurrences (e.g. therapy change, bradycardia) over short periods, while the later is related to a conditions which tend to persist over time unless some event perturbs them Both notions can be represented by an inaccurate interval.

2.1 Temporal Relations between Intervals

Approaches to temporal reasoning $[6, 5, 11, 8]$ are usually based on some subset of Allen's 13 relations [10]. Here, we consider only the three disjoint temporal relations *before, intersects, after* (where *intersects* is related to, though different from, Allen's *overlap*) with the aim of dealing with the (un)certainty of temporal relations between intervals (what is the certainty that A is before B?). Consider the intervals A and B. The necessity that the end of A is before the start of B is given by [6]:

$$N_{es}(\text{A,B}) = 1 - \max_{b \leq a \in \mathbf{Z}} \{L(\text{B}.s, \text{A}.e), \min\{h_{\text{A}}(a), h_{\text{B}}(b)\}\} \tag{4}$$

where $L(x, y) = 1$ if $x \leq y$ and $L(x, y) = 0$ if $x > y$. Thus the necessity of the end of A occurring before the start of B is the dual of the possibility that the start of B is before the end of A. L is used to constrain $N_{es}(\text{A,B})$ to be 1 when the core of A overlaps the core of B (in which case the possibility that the beginning of B is before the end of A is 1). Similarly, we can define the necessity $N_{ee}(\text{A,B})$ that the end of A is before the end of B, the necessity $N_{ss}(\text{A,B})$ that the start of A is before the start of B, and the necessity $N_{se}(\text{A,B})$ that the start of A is before the end of B. For intervals A and B, we define the three basic relations as follows:

$$N(\text{A before B}) = N_{es}(\text{A,B}) \tag{5}$$

$$N(\text{A after B}) = N_{es}(\text{B,A}) \tag{6}$$

$$N(\text{A intersects B}) = \min\{N_{se}(\text{B,A}), N_{se}(\text{A,B})\} \tag{7}$$

Note that the system described here does not use these relations to maintain a temporal network. The approach is data driven and the number of intervals (which can run into thousands) would make the network maintenance intractable.

3 Temporal Abstraction and Interpretation

Interpretation is done in two stages: 1) application of *a priori* domain knowledge to independent intervals to alter their fuzzy sets to weaken ambiguity and 2) application of temporal reasoning to abstract and interpret states and events. Our knowledge base consists of a large ontology developed within the BabyTalk project [3] (which contains more than 900 concepts) and rules acquired from interviews with experts.

For the first phase, when the intervals are loaded, knowledge can be deployed to directly constrain uncertainty about their temporal information. For example, the ventilator mode readings (i.e., SIMV and CPAP) in Figure 1 are not recorded with accurate timestamps (they are logged on an hourly basis). Due to property (3), the possibility of each of the ventilation mode values should be defined between these two readings. Theoretically, it could take any value in its domain. Since any value for the ventilator reading is possible at any time in principle, no certainty of any kind can be derived from these data alone, without reasoning based on the application of reasonable *a priori* constraints. These constraints consist in:

1. assuming persistence for states, unless there is evidence that a state has ceased to hold;
2. assuming that any state A is expanded by $delay$, to take into account a minimal delay between the human observation and the human recording on the computer;
3. assuming that any event A has actually happened before the transaction date.

These simple rules are crucial for disambiguation. The first constraint enables the aggregation of intervals representing states with the same properties. The second one accounts for inertia in the recording of data (i.e. a value is only recorded if it has held true for a certain delay period around the transaction date). The third one is known to be typically true based on consultation with domain experts. Apart from these rules, knowledge encoded in the ontology (such as max and min duration) and in the expert rules, permits the modification of the fuzzy set of the interval. For the example in Figure 1(b), the baby is known to be intubated; however, the CPAP reading contradicts this, since the domain knowledge specifies that this kind of ventilation support *requires* the baby to not be intubated. Thus, the system infers that the ventilation therapy has been changed over the period C and that an extubation event E has possibly existed between the two readings. The exact location of this extubation is still vague but again the knowledge base informs us that extubation can cause perturbation on the physiological signals. Thus, the maximal possibility for this extubation occurs during the period of the desaturation D, which is intersected by E. This reasoning explains the shape of E in Figure 1(b), which is completely possible during D, less possible during the change of ventilation period, and impossible otherwise. These outcomes are clearly strongly dependent on domain assumptions, but this cannot be neglected, as basic knowledge of the domain is often an easy and reliable way to reduce complexity in reasoning.

After the first stage, the following values can be computed $N(\text{C after E}) = 0$, and $N(\text{C intersects E}) = 1$ while for E and the oral suction O $N(\text{E before O}) = 0.42$, $N(\text{E after O}) = 0$, $N(\text{E intersects O}) = 0.58$. In addition, the following relationships are computed between the oral suction event O and the period of instability U in HR and SpO2: $N(\text{O intersects U}) = 0.68$, $N(\text{O after U}) = 0.32$.

Thus, although the temporal order of oral suction and extubation could not be established, it is more certain that suction has been performed right after or during extubation than before. This also explains part of the motivation behind the suction event.

Finally, inference rules are applied for abstraction and interpretation. In this framework, the validity of an inference chain is measured by its weakest links, so that the weight of a conclusion should be the weakest among the weights of its premises. By contrast, probability does not lend itself easily to logical entailment [18]. Our reasoning is data-driven in the sense that the temporal relations considered are all and only those derived from data. As an example, the following rule is fired when an intervention (such as an extubation E or an oral suction O) intersects with an instability period (U), which represents the degree of variation of the physiological parameters related to respiration over periods of time. These periods are delimited by the main respiratory interventions.

Example 2. E is-a RESPIRATORY INTERVENTION$\wedge$U is-a INSTABILITY $\wedge N(\text{E intersects U}) \geq \psi \Rightarrow N(\text{E causes U}) = N(\text{E intersects U})$

This rule matches the extubation and the oral suction in the example and infers that *O causes U* with necessity 0.68, while *E causes U* with necessity 1.

4 From events to text

In this section, we shall be concerned with the implications of the foregoing discussion for communicating uncertainty in the microplanning component. This takes as input a document plan — a labelled graph whose nodes are intervals or sequences of events, and whose edges are relations between intervals — and produces a semantic representation for intervals that maps to a syntactic representation. A partial document plan for our example is displayed in Figure 2, where the edge labels are now extended with necessity values indicating the certainty with which a relation holds. The full details of the process of microplanning have been described elsewhere [3]; in the rest of this section, we focus on how the necessity values can be used to alter the way the document plan is rendered. Our focus shall be on the modal auxiliaries *may* and *must*, and is primarily intended as an illustration of the potential of this approach.

4.1 The role of modality in Natural Language

One of the mechanisms that natural language provides for the expression of different degrees of (un)certainty is modality. Classical treatments of the semantics of modal expressions such as *can*, *must* and *may*, rely on their *modal force* (the degree of necessity or possibility expressed by the modal expression) and the *contextual background* against which they are interpreted. In the present case, our focus shall be on epistemic

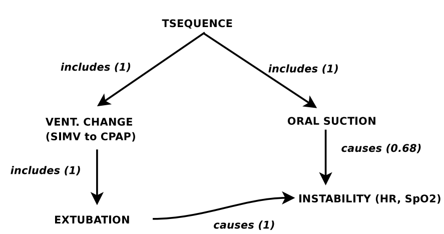


Fig. 2. Document plan fragment. Numbers in parentheses are necessity values.

modality, where the relevant background is the speaker's knowledge. A proposition such as *x must/may have occurred* is roughly paraphrasable as *x must/may have occurred in view of what is known* [19]. Epistemic modals thus express the commitment of a speaker to the truth of a proposition, given what the speaker knows. Assuming that a speaker will not impart information beyond what is required, unless it is relevant [20], qualifying an assertion in this way (e.g. *The extubation may have caused instability*) signals to the hearer/reader that the degree of a speaker's certainty is relevant to how the truth of the proposition should be evaluated [15]. It seems likely that this is also true of *must*. Although this has traditionally been taken as expressing logical necessity [19], the use of *must* suggests that the relativisation to the speaker's knowledge is important; this seems to be part of the pragmatic import of the use of the modal, and is compatible with the Gricean argument outlined above.

Typically, formal semantic treatments of modals are couched in a possible worlds framework [19, 15]; this has also been adopted in NLG by Klabunde [16] to deal with (deontic) modals. This system generates advice to students about possible course choices, by evaluating a choice against multiple possible plans ('worlds'), choosing a modal expression depending on the degree to which some action is necessary in order for a plan to succeed. In contrast to this work, the present approach proposes to view epistemic modal expressions as involving a direct mapping from different degrees of necessity or certainty to words.

4.2 Generating text with uncertainty

We make the following assumptions about the lexical resources available to the microplanner. First, every relation between intervals in a document plan maps to a linguistic expression in the lexicon. For example, a *cause* relation maps to the verb *cause*. Modal auxiliaries are represented in the lexicon via a function $\mu : N(R) \rightarrow \text{AUX}$, which maps the necessity value of a relation to an epistemic modal auxiliary verb. A possible implementation of this function is sketched out below:

$$\mu(N(R)) = \begin{cases} \textit{may} \text{ if } l < N(R) \leq 0.6 \\ \textit{must} \text{ if } 0.6 < N(R) < 1 \\ \perp \text{ otherwise.} \end{cases} \tag{8}$$

where l is a lower bound on the certainty below which the relation is not expressed at all because it is too uncertain adn $\perp$ is a null value. By this formulation, a relation such as *cause* will simply be expressed with no qualification if the certainty is 1, but may be qualified using *may* (which carries weak epistemic modal force) or *must* otherwise. Another possibility for expressing high degrees of certainty is *should*. However, a sentence such as *X should have caused Y* may be interpreted as implying violated expectation (i.e., *X was expected to have caused Y but didn't*). If this is the case, then using *should* would take the system's generated text beyond description, and into something akin to the sort of recommendation typical of expert systems, since pointing out violated expectation may lead to an increased focus on the reader's part to check whether something went wrong.

The document plan in Figure 2 contains an additional complication: there are two events possibly contributing to the instability event, with different degrees of certainty. Here, there are two possibilities. If the extubation and suction events are aggregated, to form a single clause as in Example 3, then the certainty of their joint causal role in producing the instability is once again the weakest link in the causal chain (the minimum certainty value), following the reasoning adopted in Section 3.

Example 3. The baby was moved from SIMV to CPAP. He was extubated and underwent oral suction. This must have caused the instability in HR and SpO2.

An alternative strategy is to realise each clause separately, making the causal link explicit in each case. In the case of extubation, where the certainty is 1, no modal is used. In the second case, the assertion of causality is qualified via *must*.

Example 4. The baby was moved from SIMV to CPAP. He was extubated, causing the instability in HR and SpO2. He underwent suction. This too must have caused instability.

While the above illustration is couched in largely intuitive terms, it throws up a number of questions which we are planning to investigate. Among the relevant issues is the question of the degree of certainty with which people interpret different modal expressions in epistemic contexts, as well as the other inferences that they generate (as with the case of *must* vs. *should*). An answer to this question would serve as the basis for empirically grounding the lexical resources used by the system, as well as testing our intuitions regarding the different modal force of different expressions. A second question has to do with whether, in line with our assumptions above, it is possible to identify lower bounds on certainty below which it is best not to express a relation in order to avoid misleading a reader.

5 Conclusions and future work

This paper has proposed a possibilistic approach to represent inaccurate intervals and to discover relations between them using knowledge-based techniques that rely on an ontology and expert rules. The expression of these in text generation uses the uncertainty measure for qualifying relations via modal expressions. Our formalism is attractive in that it can be used to fuse information from different sources (e.g., pattern recognition outputs, database entries, information extracted from free-text) by representing them in the same formalism.

We plan to extend this work in two principal directions. First, we are planning a series of experiments to elicit human judgements of the (un)certainty conveyed by modal expressions, thereby enabling our linguistic model to be placed on a sounder empirical footing. Second, the framework presented here needs to be empirically evaluated, both to gauge the success of the reasoning component, and the adequacy of text generation. For the former, we are considering making use of the NEONATE dataset which contains precisely time-stamped annotations of clinical records made by a neonatal nurse. This has recently been used for evaluation in a temporal reasoning task in a domain very similar to ours [21] and could serve as the gold standard against which to compare the recall and precision of a method that identified ‘missing’ or inaccurately timed events from raw data. For the evaluation of the linguistic component, we are considering a task-based experiment, in which participants are exposed to generated summaries and their comprehension measured by asking them to indicate the temporal order in which the events mentioned in a summary occurred.

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