Dynamic Temporal Interpretation Contexts for Temporal Abstraction

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Abstract

The temporal-abstraction task is the task of abstracting higher-level concepts from time-stamped data in a context-sensitive manner. We have developed and implemented a formal knowledge-based framework for decomposing and solving that task that supports acquisition, maintenance, reuse, and sharing of temporal-abstraction knowledge.

We present the logical model underlying the representation and runtime formation of ***interpretation contexts.*** *Interpretation contexts are relevant for abstraction of time-oriented data and are induced by input data, concluded abstractions, external events, goals of the temporal-abstraction process, and certain combinations of interpretation contexts. Knowledge about interpretation contexts is represented as a* ***context ontology*** *and as a* ***dynamic induction relation*** *over interpretation contexts and other proposition types. Induced interpretation contexts are either* ***basic, composite, generalized,*** *or* ***nonconvex***.

We discuss the advantages of separating explicitly interpretation-context propositions from the propositions inducing them and from the abstractions created within them.

1. The temporal-abstraction task

Many domains require the collection of substantial numbers of data over time and the abstraction of those data into higher-level concepts, meaningful for that domain. Much work had been done regarding the structure of time and the nature of general temporal reasoning. Our main interest, however, concerns the specific temporal-reasoning task of context-sensitive abstraction and interpretation of time-stamped data.

We will employ examples from clinical medicine. The ideas, however, are quite general, and are applicable to many time-oriented domains.

Most clinical tasks require measurement and capture of numerous patient data. Physicians who have to make decisions based on these data may be overwhelmed by the number of data if their ability to *reason* with the data does not scale up to the data-storage capabilities. Most data include a time stamp in which each particular datum was valid; an emerging pattern over a span of time, especially in a specific context (e.g., therapy with a particular drug), has much more significance than an isolated finding or even a set of findings. Thus, it is highly desirable for an automated knowledge-based decision-support tool that assists physicians who monitor patients over significant periods to provide short, informative, context-sensitive summaries of time-oriented clinical data stored on electronic media. Such a tool should be able to answer queries at various levels of abstraction about abstract concepts that summarize the data. Data summaries are valuable to the physician, support an automated system's diagnostic or therapeutic recommendations, and monitor plans suggested by the physician or by the decision-support system. A meaningful summary cannot use only time points, such as data-collection dates; it must be able to characterize significant features over *periods* of time, such as "2 weeks of grade-II bone-marrow toxicity in the context of therapy for potential complications of a bone-marrow transplantation event" (Figure 1) and more complex patterns. The temporal-abstraction (TA) task is thus an interpretation task: given time-stamped data and external events, produce context-specific, interval–based, relevant abstractions of the data (a more formal definition will be stated in Section 3).

2. Knowledge-based temporal abstraction

A method solving the TA task encounters several conceptual and computational problems: (1) both the input data and the required output abstractions might include several data types (e.g., symbolic, numeric) and

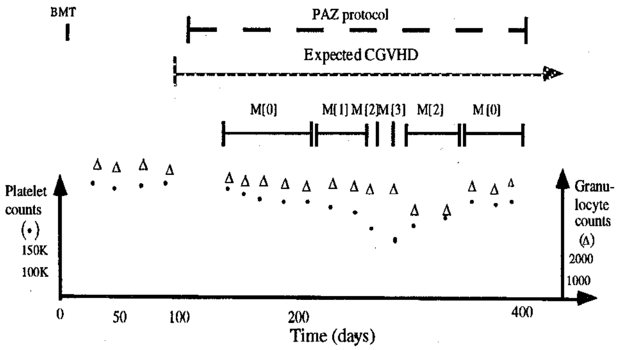

Figure 1: Abstraction of platelet and granulocyte values during administration of the PAZ clinical protocol for treating patients who have chronic graft-versus-host disease (CGVHD). The time line starts with a bone-marrow transplantation (BMT) event. = event; • = platelet counts; Δ = granulocyte counts; = open context interval; = closed abstraction interval; M[n] = myelotoxicity (bone-marrow–toxicity) grade n.

can exist at various abstraction levels; (2) input data might arrive out of temporal order, and existing interpretations must be revised nonmonotonically; (3) several alternate interpretations might need to be maintained and followed over time; (4) parameters have context-specific temporal properties, such as expected persistence of measured values and classification functions (e.g., the meaning of the value LOW of the hemoglobin-state abstraction depends on the context); (5) acquisition of knowledge from domain experts and maintenance of that knowledge should be facilitated. The method should enable *reusing* its *domain-independent* knowledge for solving the TA task in other domains, and enable *sharing* of *domain-specific* knowledge with other tasks in the same domain.

The framework that we are using for solving the TA task is based on our work on temporal-abstraction mechanisms [6–10]. We have defined a general *problem-solving method* [2] for interpreting data in time-oriented domains, with clear semantics for both the *method* and its domain-specific *knowledge* requirements: the **knowledge-based temporal-abstraction (KBTA) method**. The KBTA method comprises a knowledge-level representation of the TA task and of the knowledge required to solve that task. The KBTA method has a formal model of input and output entities, their relations, and their properties—the **KBTA ontology** [8, 10].

The KBTA method decomposes the TA task into five parallel *subtasks* (Figure 2):

(1) **temporal-context restriction**: creation of contexts relevant for data interpretation (e.g., effect of a drug), to focus and limit the scope of the inference

(2) **vertical temporal inference**: inference from values of contemporaneous input data or abstractions (e.g., results of several blood tests conducted during the same day) into values of higher-level concepts (e.g., classification into bone-marrow toxicity Grade II)

(3) **horizontal temporal inference**: inference from similar-type propositions that hold over different time intervals (e.g., joining different-value abstractions of the same parameter that hold over two meeting time intervals and computing the new abstraction's value)

4) **temporal interpolation**: bridging of gaps between similar-type but temporally disjoint point- or interval-based propositions to create longer intervals (e.g., joining two disjoint episodes of anemia, occurring during different days, into a longer episode)

5) **temporal-pattern matching:** creation of intervals by matching patterns over disjoint intervals over which hold propositions of various types.

The five subtasks of the KBTA *method* are solved by five **temporal-abstraction mechanisms** (nondecomposable computational modules) that we have defined (see Figure 2). The temporal-abstraction mechanisms depend on four well-defined domain-specific **knowledge types**: *structural* knowledge (e.g., IS-A, PART-OF and ABSTRACTED-INTO relations),

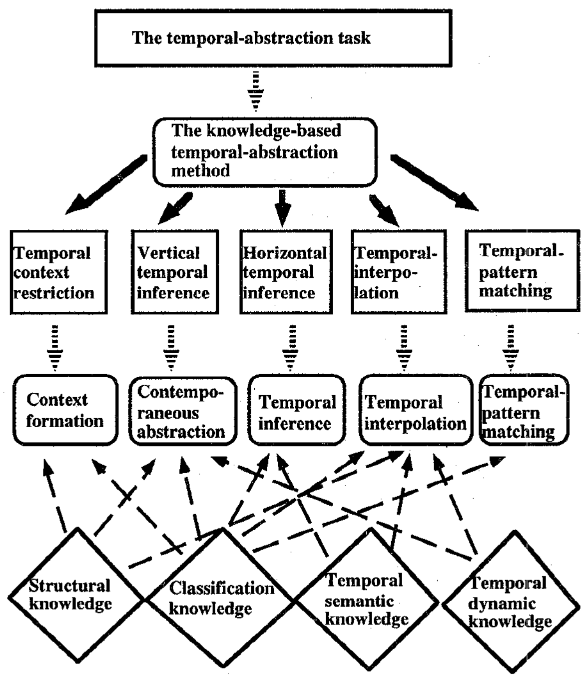

Figure 2: The knowledge-based temporal-abstraction method and its mechanisms. = task; = method or mechanism; ◇ = knowledge type; = DECOMPOSED-INTO relation; = SOLVED-BY relation; = USED-BY relation.

classification (functional) knowledge (e.g., mapping of hemoglobin values into hemoglobin states), *temporal-semantic* (logical) knowledge (e.g., the CONCATENABLE property [12]), and *temporal-dynamic* (probabilistic) knowledge (e.g., temporal persistence functions that bridge gaps between temporally disjoint intervals [8]). Values for the four knowledge types are specified as the domain's **temporal-abstraction ontology** when developing a temporal-abstraction system for a particular domain and task. We have implemented the KBTA method as the **RÉSUMÉ** system [7] and evaluated it with encouraging results in several different medical domains [9]. We also have used the method to solve a spatio-temporal traffic-monitoring task [Shahar and Molina, in preparation].

In this paper, we focus on one of the key KBTA subtasks: Formation of appropriate temporal contexts for interpretation of the time-oriented data. We first define briefly the KBTA ontology, then discuss the context-forming mechanism, which uses that ontology, when mapped to the matching domain knowledge, to create temporal contexts for interpretation of the data in a context-sensitive manner.

3. The temporal-abstraction ontology

Informally, the KBTA temporal model includes both time intervals and time points. *Time points* are the basic temporal primitives, but propositions, such as occurrence of events and existence of parameter values, can be interpreted only over *time intervals*. Therefore, all propositions are *fluents* [4] and, in our model, must be interpreted over a particular time *period* (e.g., the value of the temperature parameter during time interval $[t, t]$). The knowledge-based TA ontology contains the following entities:

1. *Time stamps*, $\tau_i \in$ T, comprise the basic primitives of time. A time-standardization function, $f_s(\tau_i)$, can map a time stamp into an integer amount of any pre-defined temporal granularity unit $G_i \in \Gamma$ (e.g., hour). Time stamps are measured in G_i units with respect to a zero-point time stamp. A finite positive or negative amount of G_i units is a *time measure*.

2. A *time interval* is an ordered pair of time stamps that denote the endpoints, [*I*.start, *I*.end], of the interval. A zero length interval in which *I*.start = *I*.end is a time point.

3. An *interpretation context* $\xi \in \Xi$ is a proposition representing a state of affairs relevant to interpretation (e.g., "the drug insulin exerts its effect during this interval"). When an interpretation context exists during a particular time interval, parameters may be interpreted differently within that time interval. IS-A and SUBCONTEXT relations are defined over the set of interpretation contexts. *Basic* interpretation contexts are atomic propositions. *Composite interpretation contexts* are created by the conjunction of a basic or a composite interpretation context and one of its subcontexts. Intuitively, composite interpretation contexts permit the definition of a hierarchy of increasingly specific contexts. *Generalized* and *nonconvex interpretation contexts* are defined in Sections 4.2 and 4.3, respectively.

4. A *context interval* is a structure $<\xi, I>$ containing an interpretation context ξ and a time interval I (i.e., an interpretation context during an interval).

5. An *event proposition* or event $e \in$ E is the occurrence of an external willful act or process, such as the administration of a drug. Events are instantiated event schemata; an event schema has a series a_i of event attributes (e.g., drug dose) that must be mapped to attribute values v_i. A PART-OF (or *subevent*) relation is defined over event schemata.

6. An *event interval* is a structure $<e, I>$, consisting of an event proposition e and a time interval I that represents the duration of the event.

7. A parameter schema or *parameter* $\pi \in \Pi$ is a measurable or describable state of the world. Parameters may represent raw input data (e.g., a hemoglobin level) or abstractions from the raw data (e.g., a state of anemia). Parameter schemata have various *properties*, such as a domain V_π of possible symbolic or numeric values, measurement units, temporal-semantic properties, or temporal persistence. An *extended parameter* is a combination $<\pi, \xi>$ of a parameter π and an interpretation context ξ. A n extended parameter is also a parameter and can have properties. Extended parameters have a special property, a value $v \in V_\pi$, which is typically known only at runtime (i.e., parameter values require a context).. A *parameter proposition* is the combination of a parameter, a parameter value, and an interpretation context, $<\pi, v, \xi>$ (e.g., "the state of hemoglobin is LOW in the context of chemotherapy").

8. A *parameter interval* $<\pi, v, \xi, I>$ is a parameter proposition and a time interval, representing the value of a parameter in a specific context during a particular time interval.

9. An *abstraction function* $\theta \in \Theta$ is a unary or multiple-argument function from one or more parameters to an abstract parameter. The abstract parameter has one of three abstraction types: *state*, *gradient*, and *rate*. An additional type of abstraction is *pattern* which defines a temporal pattern of several

other parameters. An abstraction of a parameter is a parameter (thus, both hemoglobin and the state of hemoglobin are parameters, with distinct properties).

10. An *abstraction* is a parameter interval $\langle \pi, \nu, \xi, I \rangle$ where π is an abstract parameter. Abstractions may be abstraction points or abstraction intervals.

11. An *abstraction goal* $\psi \in \Psi$ is a proposition that indicates a goal or intention that is relevant to the TA task (e.g., the intention to control a diabetes patient's blood-glucose values).

12. An *abstraction-goal interval* is a structure $\langle \psi, I \rangle$, where ψ is a temporal-abstraction goal that is posted during the interval I. An abstraction-goal interval creates contexts for interpretation of data.

13. Interpretation contexts are *induced* or inferred dynamically from event, parameter, or abstraction-goal propositions. The time intervals over which the inducing propositions exist impose temporal constraints on the interval in which the inferred context will be valid. For example, insulin's effect on blood-glucose values might begin at least 30 minutes following insulin administration and end up to 8 hours after terminating the administration. These constraints are represented formally in a *dynamic induction relation of a context interval* (**DIRC**). A DIRC is a relation over propositions and time measures, in which each member is a structure of the form $\langle \xi, \varphi, ss, se, es, ee \rangle$. Intuitively, the inducing proposition is assumed, at runtime, to be interpreted over some time interval I with known end points. The symbol ξ is the induced interpretation context. The symbol $\varphi \in$ P represents the inducing proposition, an event, an abstraction-goal, or a parameter proposition. Each of the other four symbols is either the "wild card" symbol *, or a time measure, which denote, respectively, the temporal distance between the start point of I and the start point of the induced context interval, the distance between the start point of I and the end point of the induced context interval, the distance between the end point of I and the start point of the context interval, and the distance between the end point of I and the end point of the induced context interval (Figure 3). Note that the resultant context interval need not span the same temporal scope as the inducing proposition, but can have any of Allen's 13 relations to it [Allen 1984] (see Figure 3b). A *context-forming proposition* is an inducing proposition in at least one DIRC.

A TA ontology of a domain is an event ontology, a context ontology (figure 4), a parameter ontology, a set of abstraction-goal propositions, and the set of all DIRCs for a particular domain. The event ontology of a domain consists of the set of all the relevant event schemata and propositions.

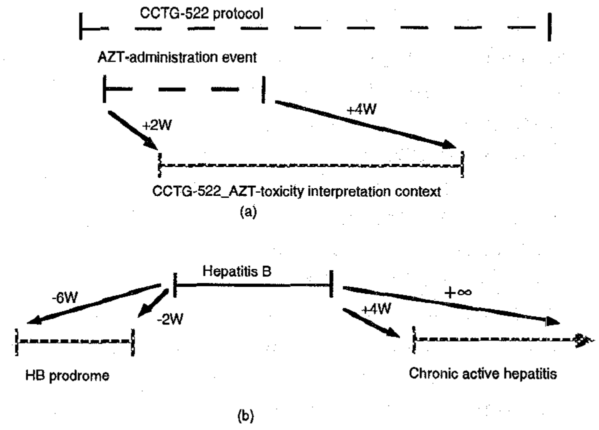

Figure 3: Dynamic induction relations of context intervals (DIRCs).
(a) An AZT-toxicity interpretation context induced by an AZT-administration event in the context of a CCTG-522 AIDS-therapy experimental protocol. The interpretation context starts 2 weeks after the start of the inducing event, and ends 4 weeks after its end.
(b) Prospective (chronic active hepatitis) and retrospective (hepatitis B prodrome) interpretation contexts induced by the hepatitis B proposition.
= event interval; = closed context interval; = open context interval; = closed abstraction interval.

The context ontology (figure 4) defines the set of all the relevant contexts and subcontexts. The parameter ontology is composed of the set of all the relevant parameter propositions and their properties.

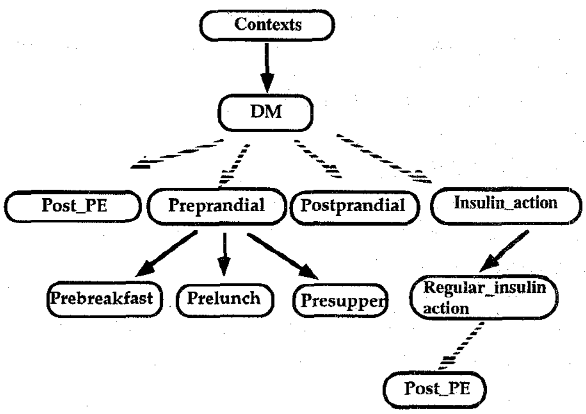

Figure 4: Part of the context ontology in the diabetes-therapy domain. = class; = IS-A relation; = SUBCONTEXT relation; DM = diabetes therapy context; PE = physical exercise. Preprandial and postprandial contexts are induced before and after meal events, respectively.

The TA task also assumes the existence of a set of temporal queries, expressed in a predefined temporal-abstraction language. A *temporal query* is a set of temporal and value constraints over the components of a set of parameter and context intervals [8].

The TA task as it is solved by the KBTA method is thus the following: Given at least one abstraction-goal interval, a set of event intervals, a set of parameter intervals, and the domain's TA ontology, produce an interpretation—that is, a set of context intervals and a set of new abstractions such that the interpretation can answer any temporal query about all the abstractions derivable from the transitive closure of the input data and the domain's TA ontology.

4. Dynamic induction of contexts

Abstractions are meaningful only within the span of a relevant context interval, such as administration of the drug AZT as part of a particular clinical protocol for therapy of AIDS. Context intervals create a relevant frame of reference for interpretation, and thus enable a TA mechanism to conclude abstractions for—and only for—that context. Context intervals are created by the **context-forming mechanism.**

As explained in Section 3, DIRCs represent relationships between context intervals and several types of propositions that can induce them. Context intervals might be induced by the existence of an *abstraction-goal interval*, such as "therapy of insulin-dependent diabetes," or by the existence of an *event interval*, that is, an external process or action, such as treatment in accordance with a particular clinical protocol. A context interval can also be induced by the existence of a *parameter interval* that includes a *context-forming* (see Section 3) parameter proposition $<\pi, v, \xi>$—namely, the value v of the parameter π, in the context ξ, is sufficiently important to change the frame of reference for one or more other parameters (e.g., the LOW value of the hemoglobin-state abstract parameter in the context of protocol CCTG-522 might affect the interpretation of values of the platelet-value parameter).

A *composite interpretation context* (see Section 3) can be composed by the context-forming mechanism at runtime from a conjunction of two or more concluded basic interpretation contexts that hold contemporaneously, such that basic context ξ_{i+1} has a SUBCONTEXT relation to basic context ξ_i. The composite interpretation context would be interpreted over a context interval formed from a *temporal intersection* of the two or more corresponding context intervals. For example, components of a composite interpretation context are often induced by an *event chain*—a connected series of events $<e_1, e_2,...,e_n>$, where e_{i+1} is a subevent of e_i. In that case, the composite interpretation context would denote an interpretation context induced by the most specific subevent, such as administration of a particular drug as part of a certain protocol. (Subevents of an event typically induce interpretation contexts that have a SUBCONTEXT relation to the interpretation context induced by the event.) This knowledge is used as a default in the context ontology, and can also be exploited during a manual or automated process of acquisition of knowledge, either for knowledge elicitation or for knowledge verification and cross-validation. Interpretation contexts can be extended by concatenating two *meeting* [1] equal-context intervals.

Dynamic induction of context intervals by parameter propositions might lead to new interpretations of existing parameter intervals, thus potentially inducing new context intervals within which another or even the original parameter value (the input datum) might have new interpretations. However, we can prove [8] that no contradictions or infinite loops can be generated by the context-forming process.

lemma 1: The context-forming process has no "oscillation cycles" among different interpretations of the same parameter (i.e., the same parameter proposition can never be retracted and eventually reasserted).

Proof: Parameter propositions are not retracted by the addition of a new interpretation context. Rather, a new interpretation is added to the set of true parameter propositions. (Retractions *can* occur due to the nonmonotonic nature of temporal abstraction, but in different circumstances, such as arrival of additional data with a present transaction time but with an old valid time, forcing a *view update* [8].) Therefore, if a parameter proposition $<\pi, v_1, \xi_1>$ induces a new interpretation context ξ_2 over some interval, and within the scope of that interval the parameter π is interpreted to have another value, a new parameter proposition $<\pi, v_2, \xi_2>$would simply be inferred and added to the set of true propositions. This, of course, creates no contradictions since the parameter π—or some abstraction of π, say, state(π)—is interpreted within two different contexts and can thus have two different values at the same time. ❑

lemma 2: The context-forming process is finite.

Proof: The total number of different interpretation contexts that, potentially, can be inferred (including composite ones) is limited by an existing upper bound: the size of the context ontology and the number of potential *subcontext chains* (which can form composite contexts) of interpretation contexts that have

SUBCONTEXT relations. Furthermore, for each parameter π, the number of possible induced context intervals is bound by the number of DIRCs in which a parameter proposition including π is an inducing proposition. Since lemma 1 ascertained that there are no loops either, the process must end for any finite number of input (interval-based) propositions. ❑

4.1. Advantages of explicit contexts and DIRCs

Explicit interpretation contexts, separate from the propositions inducing them and from abstractions using them, have significant conceptual and computational advantages for context-specific interpretation of time-stamped data.

1. Since the four temporal measures of a DIRC, representing temporal constraints over an induced context interval with respect to the start time and the end time of the inducing proposition, can be positive, negative, or infinite time measures, the context interval induced by a context-forming proposition can have any one of Allen's [1] 13 binary temporal relations (e.g., BEFORE, AFTER, or OVERLAPS) to the time interval over which the inducing proposition is interpreted (see Figure 3). Thus, a context-forming proposition interval can create, in addition to a **direct** (concurrent) context interval, **retrospective** context intervals (e.g., potential preceding symptoms of a disease), **prospective** context intervals (e.g., potential complications of a disease), or both (see Figure 3). Intuitively, retrospective interpretation contexts represent a form of **abductive** reasoning (e.g., from effects to causes, such as preceding events), while prospective interpretation contexts represent a form of **deductive** reasoning (e.g., from an event to potential complications). (Note, however, that we infer only a potential interpretation context, not an abstraction.) The context-forming mechanism creates retrospective and prospective contexts mainly to enable the use of context-specific TA functions, such as the correct mapping functions related to ABSTRACTED-INTO relations and the relevant temporal-persistence functions [8], that should not be considered in other contexts. Creation of explicit contexts enables the TA mechanisms to focus on the abstractions appropriate for particular contexts, such as potential consequences of a certain event, and to avoid unnecessary computations in other contexts. In addition, the ability to create dynamically retrospective contexts enables a form of **hindsight** [5], since the interpretation of *present* data can induce new interpretation contexts for the past and thus shed new light on *old* data.

2. Since a context-forming proposition can be an inducing proposition in more than one DIRC, the *same proposition* can *induce* dynamically *several interpretation contexts*, either in the past, the present, or the future, relative to the temporal scope of the interval over which it is interpreted. Thus, we can model, for instance, several potential effects of the same action, each of which creates a different interpretation context, or several inferences from the same temporal pattern, once detected.

3. The *same interpretation context* (e.g., potential bone-marrow toxicity) might be induced by *different propositions*, possibly even of different types and occurring over different periods (e.g., different types of chemotherapy and radiotherapy events). The domain's TA ontology would then be representing the fact that, within the particular interpretation context induced by any of these propositions (perhaps with different temporal constraints for each proposition), certain parameters would be interpreted in the same way (e.g., we can represent the properties of the hemoglobin-state parameter within the scope of a bone-marrow–toxicity context interval, without the need to list all the events that can lead to the creation of such a context interval). Thus, the separation of interpretation contexts from their inducing propositions also facilitates maintenance and reusability of the TA knowledge base.

4. Since several context intervals, during which different interpretation contexts hold, can exist contemporaneously, it is possible to represent several abstraction intervals in which the *same abstract parameter* (e.g., the state of the hemoglobin level) has *different values* at the *same time*—one for each valid and relevant context (e.g., "LOW hemoglobin state" in the context of having AIDS without complications, and "NORMAL hemoglobin state" in the context of being treated by the drug AZT, which has expected side effects). Thus, the context-forming mechanism supports maintenance of several *concurrent* **views** of the abstractions in the abstraction database, denoting several possible interpretations of the same data. This is one of the reasons that parameter propositions (including temporal-pattern queries to the abstraction database) must include an interpretation context: The parameter value alone might otherwise be meaningless.

4.2. Generalized interpretation contexts

Additional distinctions important for the TA task are enabled by the explicit use of interpretation contexts and DIRCs. A **simple interpretation context** is a *basic* or a *composite* interpretation context. Our discussion till now concerned simple interpretation contexts. Usually, abstractions are specific to a particular simple interpretation context, and *cannot* be joined (by the temporal-inference or temporal-interpolation mechanisms) to abstractions in other interpretation contexts (e.g., two "LOW hemoglobin state" abstractions might denote different ranges in two different subcontexts of the same interpretation context induced by a chemotherapy-protocol event). This restriction is reasonable, since the primary reason for having contexts is to *limit* the scope of reasoning and of the applicability of certain types of knowledge.

However, it is both desirable and possible to denote that, for certain classes of parameters, contexts, and subcontexts, the abstractions are **sharable** among two meeting different context intervals (i.e., with different interpretation contexts). Such abstractions denote the same state, with respect to the task-related implications of the state, in all sharing contexts. For instance, two meeting "LOW hemoglobin state" abstractions in two different contexts might indeed denote different ranges in the two contexts, and the hemoglobin-state parameter might even have only two possible values in one context, and three in the other, but the domain expert still might want to express the fact that the LOW value of the hemoglobin-state abstraction can be joined meaningfully to summarize a particular hematological state of the patient during the joined time period. The sharable abstraction values would then be defined within a new **generalized interpretation context** that is equivalent to neither of the two shared subcontexts (e.g., those induced by two different parts of the same clinical protocol), nor to their parent context (e.g., the one induced by the clinical protocol itself, within which the hemoglobin-state parameter might have yet another, default, LOW hemoglobin-state range). This generalized context can be viewed as a generalization of two or more subcontexts of the parent interpretation context. The proposition "LOW hemoglobin-state (within the generalized context)" would then have the logical *concatenable* [Shoham, 1987] property and can thus be joined across the temporal scope of two different subcontexts.

4.3. Nonconvex Interpretation Contexts

Sometimes, we might want to abstract the state of a parameter such as glucose in the preprandial (before meals) interpretation context, over two or more temporally *disjoint*, but semantically equivalent, preprandial interpretation contexts (e.g., the PRELUNCH and PRESUPPER interpretation contexts are both PREPRANDIAL interpretation contexts). We might even want to create such an abstraction within only a particular preprandial context (e.g., several PRESUPPER interpretation contexts) skipping intermediate preprandial contexts (e.g., PREBREAKFAST and PRELUNCH interpretation contexts). This interpolation is different from sharing abstractions in a generalized interpretation context, since the abstractions in this case were created within the *same* interpretation contexts, but the interpolation operation joining them needs to skip temporal gaps, including possibly context intervals over which different interpretation contexts hold. The output is a new type of a parameter interval, with respect to temporal scope—a *nonconvex interval*, as defined by Ladkin [3]. A "LOW glucose state" abstraction would be defined, therefore, within the **nonconvex interpretation context** of "prebreakfast episodes." Note that parameter propositions including such a nonconvex context will have different temporal-semantic inference properties [8] from the same parameter propositions except for a simple, convex, context. For instance, propositions will usually not be *downward hereditary* ([12] in the usual sense of that property (i.e., the proposition holds within any subinterval of the original interval) unless subintervals are confined to only the convex or nonconvex intervals that the nonconvex superinterval comprises (e.g., only morning times).

Thus, the interpretation context of a parameter proposition is a combination of simple, generalized, and nonconvex interpretation contexts. Assume that a **Gen** (generalize) operator returns the generalizing-context parent (if it exists) of a parameter proposition in the parameter-properties ontology. Assume that a **Gen*** operator, that generalizes the Gen operator, returns the least common generalizing-context ancestor (if it exists) $<\pi, \nu, \xi_g>$ of two parameter propositions $<\pi, \nu, \xi_1>$, $<\pi, \nu, \xi_2>$, in which the parameter π and the value ν are the same, but the interpretation context is different. Assume that an **NC** (nonconvex) operator returns the nonconvex-context extension (if it exists) of a parameter proposition. Then, the parameter proposition that represents the nonconvex join (over disjoint temporal spans) of two parameter propositions in which only the interpretation context is different can be represented as

$$\text{NC}\ (\text{Gen*}\ (<\pi, \nu, \xi_1>, <\pi, \nu, \xi_2>)$$

Thus, we first look for a generalizing interpretation context for glucose-state abstractions in the PRELUNCH and PRESUPPER interpretation contexts, in this case the PREPRANDIAL one. Then we represent the parameter proposition "LOW preprandial glucose-state values" as the LOW value of the glucose-state parameter in the nonconvex extension of the PREPRANDIAL interpretation context. This proposition would be interpreted over some time interval to form a (nonconvex) parameter interval. (Generalized and nonconvex interpretation contexts belong tothe context ontology; the corresponding extended-parameter propositions belong to the parameter ontology).

5. Discussion

The four types of domain-specific knowledge required by the TA mechanisms, apart from the event and context ontologies, are represented in the RÉSUMÉ system [7, 9] in the **parameter-properties ontology**, a representation of the parameter ontology. The parameter-properties ontology is a frame hierarchy that represents parameter propositions (with their properties) and specializes them by their interpretation contexts.

The TA mechanisms (except for context formation) operate within the temporal span of context intervals and *do not depend on the event and context ontologies*. These mechanisms assume the existence of context intervals and of interpretation contexts as part of the parameter propositions. The context-forming mechanism is thus the only interface to the domain's event ontology and shields the rest of the mechanisms from any need to know about these events, their structure, or the interpretation contexts they induce.

Explicit interpretation contexts, separate from the propositions inducing them and from abstractions using them, have significant conceptual and computational advantages for context-specific interpretation of time-stamped data. Advantages include (1) Any temporal relation can hold between a context interval and its inducing proposition; interpretation contexts might be induced concurrently, in the future, and in the past, enabling a form of foresight and hindsight; (2) the *same context-forming proposition* can *induce* one or more context intervals; (3) the *same interpretation context* might be induced by *different* propositions. The separation of interpretation contexts from their inducing propositions facilitates maintenance and reusability of temporal-abstraction knowledge; and 4) Parameter propositions include an explicit interpretation context, thus enabling a representation of several abstractions in which the *same abstract parameter* (e.g., the "state of hemoglobin-level" parameter) has *different values* at the *same time*—one for each of the context intervals that hold during the relevant period. Thus, interpretation contexts support maintenance of several *concurrent* interpretations of the same data.

The interpretation-context model has been useful also in other tasks involving matching of context-sensitive linear patterns, such as modeling the retrieval of full-text documents, given key words that should be found within a given semantic text context [11] (the distance measure was position within the text; the parameters are strings) and forming temporal and spatial abstractions to solve a traffic-control task (the distance measure was either time or space, and the KBTA method and RÉSUMÉ were used for both tasks) (Shahar and Molina, in preparation).

Acknowledgments

This work has been supported in part by grant HS06330 from the Agency for Health Care Policy and Research, by grants LM05157, LM05305, and LM5708 from the National Library of Medicine, and by gifts from Digital Equipment Corporation. I thank Mark Musen, Richard Fikes, and Barbara Hayes-Roth for advice and support. I had useful discussions with Samson Tu, Amar Das, and Michael Kahn.

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