Structured Representations of Empirical Information

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It is indeed the situation that the fields of Case-Based Reasoning (CBR) and Information Retrieval (IR) have a number of shared interests. This paper addresses one in particular: indexing or the representation of information. It is very important to be able to describe each case or text effectively. Items which are not appropriately indexed are in effect lost in memory and are unlikely to be retrieved under appropriate circumstances. Therefore indexing is a critical issue and is the focus here. In particular this paper proposes a structured approach, similar to case indexing, for the representation of text content. It also proposes similarity based retrieval strategies, in the context of the proposed structured representation. These ideas have been implemented in Empiricist, a prototype retrieval system.

Case-based reasoning is the essence of how human reasoning works [12]. People reason from experience. A case-based reasoner finds those cases in memory that solved problems similar to the current problem. In order to find a relevant case we need to characterize the input problem, by assigning appropriate features to it. Then we retrieve cases from memory with features that best match the input problem. Solutions used for retrieved cases are adapted to fit the current problem [12]. Case retrieval is facilitated by characterizing each case (and problem) by a variety of structural features such as the events, goals, and actors involved in the case [7].

Information Retrieval is similar in that texts and user requests are also represented by their features. Retrieval also involves a comparison of features to identify texts that best match the request. However, there are significant differences in the types of representations used in both fields. Representations in CBR tend to be richer and more informative because they use structured descriptions. For example, the relationship between an actor and an event is generally preserved. In IR, text representation is typically done by assigning a groups of keywords to a text. In fact, the lack of structure in keyword representation limits the versatility and effectiveness of IR systems.

In this paper we present Empiricist, a prototype retrieval system in which text representation deviates from the norm. In particular, we show that IR can utilize structured representations similar to the ones used in CBR. Our texts are represented by structured complex objects. The complex object provides a rich framework for representing text content and also supports sophisticated retrieval strategies. In essence this paper makes a specific contribution to the question posed in the symposium's call for papers: How might IR take advantage of more structured information, as used in CBR? We also discuss retrieval in the context of these complex object text representations.

MOTIVATION FOR EMPIRICIST

In contrast with the simplistic keyword based representation and search mechanisms in standard text retrieval systems, questions that motivate health care practitioners to turn to such systems are very complex [15] as the following examples illustrate.

Example 1: What is the effect of treating the diabetic patient with aspirin- dipyridamole?

Example 2: Give me texts which describe the problems resulting in diabetes.

Example 3: Give me texts which describe problems caused by diabetes

Example 4: Identify experiments which show that the temperature of the intravenous solution affects the level of pain felt by the patient.

These questions present highly specific as well as complex needs. In particular, they convey well defined roles for the key concepts. In example 1 'aspirin-dipyridamole' is the treatment substance and 'diabetes' a central patient characteristic. When translated into the typical retrieval system's Boolean terminology: aspirin-dipyridamole AND diabetes, almost all of the role information is lost. The query will also retrieve texts in which diabetes is a secondary patient characteristic or an observed variable and where the aspirin compound is not the main treatment substance. Unfortunately Boolean retrieval cannot distinguish between examples 2 and 3. In example 4, Boolean retrieval cannot differentiate between studies which examine the re-

lation between solution temperature and pain and those which actually find the effect that the user is interested in.

We contend that this situation could be improved if structured text representations including role information, similar to those used in case indexing, replaced the bland keyword representations commonly used. In fact we wish to show that at least in certain types of texts there is naturally occurring structure that can be utilized for more meaningful representation and retrieval. This is the motivation for Empiricist, our prototype retrieval system. The text base in Empiricist consists of 157 empirical abstracts in two health domains: diabetes mellitus and intravascular therapy. Empirical abstracts are abstracts of articles reporting on experiments. Empirical knowledge has a critical role in the practice, teaching, and growth of health care [14]. The following examples illustrate the variety of situations for which our retrieval system may be found useful.

When designing an experiment, a health care researcher may need to identify similar experiments.

A researcher may need to examine studies which resulted in a particular conclusion.

A practitioner may need to choose between alternative treatments or tools for a given patient.

In essence because of the structured representation strategy, Empiricist gives the user the ability to think in terms of the desired experiment. Search specifications may exploit the various dimensions of empirical investigations. This feature gives Empiricist its advantage. Although we have chosen the health domain for our work, the basic principles are applicable to other domains as well. We first describe our structured representation strategy leading to the complex objects used in Empiricist. Following this we discuss retrieval, which is by spreading activation. Finally we make our conclusions.

STRUCTURED TEXT REPRESENTATION IN EMPIRICIST

Background

The representation used here is closely related to the naturally occurring structure of the text itself. Our approach derives from prior work, where we analyzed a group of empirical abstracts in the two health domains [10]. Structure here refers to the text's typical information components and their overall organization [6], [8].

The previous study resulted in a hierarchical text structure or grammar for the texts analyzed which is presented in detail in [10]. Here we present only a brief overview as a background for our complex objects. Essentially, the typical empirical abstract presents the 'topic' and the 'design' of the underlying investigation. The experiment's 'design' may include one or more 'protocols', 'measures', and 'subjects'. Protocols are described by 'treatments' and 'procedures'. These abstracts also present important 'observations', 'data analyses' and 'conclusions' of the study. Phrases within quotation marks indicate our text grammar components. Components are composed of sub-components thus yielding a hierarchical grammar. For example, 'subjects' may be described by their 'states', 'size' and 'sex'. In this way each text grammar component is broken down into its primitive information components. It should be noted that the empirical abstracts analyzed consistently focussed on these features.

Extracted Predicates

The first observation we made is that some parts of the text are not so useful for retrieval purposes. For instance, the 'observation' component consists of a 'measure' applied to one or more 'subjects' which yields a set of 'values'. For text retrieval, the fact that a measure was used is likely to be far more important than any other details about the observation. Therefore we use only select components from the text structure. In particular two types are selected to represent: (1) what the text is about and (2) the experimental design or methodology used in the investigation. These are extracted in the form of relational predicates whose structure closely match those of the corresponding text grammar components. These predicates are shown below.

The TOPIC predicate's format results from a repeated observation in our previous analysis. These empirical studies predominantly investigate the nature of the relationship between pairs of key concepts under certain conditions. Key concepts, either abstract, as in a state, or concrete, as in a tool or substance, translate into the two variables of the predicate. (A similar observation has also been made or implied by other researchers [4], [5], [11], [16]). Also the relationship argument is a directional one. Finally, the source argument specifies whether the TOPIC predicate derives from a statement describing objectives or one presenting conclusions. The DESIGN predicates represent key features of the methodology adopted.

```
TOPIC predicates:

TOPIC(VARIABLE1, VARIABLE2, RELATIONSHIP,
      CONDITION, SOURCE)
DESIGN predicates:
  TREATMENT(TYPE, SUBSTANCE, PURPOSE, TOOL,
  FREQUENCY, SITE, DURATION, DOSE)
  PROCEDURE(TYPE, TOOL, PURPOSE, SITE, FREQUENCY,
  DURATION)
  SUBJECT(TYPE, STATE, TREATMENT, PROCEDURE, SIZE,
  AGE, SEX)
  MEASURE(ASPECT, NAME)
  OVERALL_DESIGN(TYPE)
```

The Complex Object Representation

The final representation of an abstract is in the form of a complex object. Complex objects use other ob-

jects for their description. Retrieval of complex objects might involve the retrieval of some or all sub-objects. Other researchers have used complex object representations for information retrieval (for example [3]. However, their focus is on the representation of texts by parts such as chapters, sections, sub-sections etc.

Figure 1 in appendix A shows the composition hierarchy for our complex object representation. The root REPRESENTATION object is composed of a TOPIC object and a DESIGN object. The TOPIC object is composed of one or more TOPIC PREDICATE (TP) objects. DESIGN is partitioned in four ways: a set of MEASURES, a set of PROTOCOLS, a set of SUBJECT GROUPS, and OVERALL DESIGN PREDICATE. Each PROTOCOL identifies a set of TREATMENTS and a set of PROCEDURES. Each predicate has arguments instantiated by one or more concepts, the most primitive objects in the composition hierarchy. (These arguments are synonymous with the text based roles discussed earlier.)

Two types of objects are in the composition hierarchy: (1) objects whose immediate descendent objects are of different types (ex: DESIGN, PROTOCOL and TREATMENT PREDICATE) and (2) objects whose immediate descendants are of a single type (ex: set of PROTOCOLS, TOPIC, set of TREATMENTS). These objects are treated differently during retrieval as described later. The final representation of the abstract is a complex object in which representative concepts are linked to each other by their structural roles. The advantage in modeling the text's representation as a complex object will be discussed later. Figure 2 in appendix A shows the complex object representation for one example abstract.

The complex object representations from different texts are combined to form a conceptual network against which the retrieval strategies operate. Different complex objects may be connected since a given concept may be attached to a number of complex objects. Due to space limitations we do not describe this network any further.

RETRIEVAL IN EMPIRICIST

Empiricist is a prototype system implemented in HyperCard v 2.1 on a Macintosh IIci. Two different retrieval modes are built into it. Mode 1 allows the user to specify the query by a set of concepts. In mode 2, the user has the option to fill in predicate templates, i.e. constrain concepts to specific roles. This second option is valuable for a searcher who wants to describe the relevant texts via the different dimensions of an empirical investigation.

Retrieval is performed by activating the complex object representations of the texts. The user's input forms the initial specification in a bottom up spreading activation strategy through each text's composition hierarchy. If the activation induced by the user's query is strong enough to activate the top level representation object, then the corresponding text may be retrieved. Alternatively, texts may be ranked by the degree to which their representation objects are activated. During activation, matches on more important objects are given greater weight.

The complex object viewpoint provides a strong advantage in designing retrieval constraints to ensure semantically meaningful retrieval. In particular it allows us to apply different activation constraints to different objects in the composition hierarchy. For example, activation of a TOPIC PREDICATE object may depend upon sufficient activation of at least its two component variables. In contrast, activation of a DESIGN object may be possible by sufficient activation of the set of PROTOCOLS. In this way we can tailor the activation constraints for any object in the composition hierarchy based upon its own structure.

During retrieval, each object in the conceptual network receives input signals from its component objects which leads to the computation of net input signal (NIS). This NIS determines the final output signal which becomes one input signal directed at the next object above in the composition hierarchy. A non-zero output signal is possible only if all built in constraints associated with the transmitting object are satisfied. We now discuss each step.

Input Signals

An object's input activation signal may be continuous or discrete. This issue is related to the type of retrieval desired. Discrete binary signals result in text items that are either retrieved or not retrieved. Continuous functions allow ranking of objects by activation strengths. Generally, ranked retrieval is useful for large retrieved sets and binary retrieval for small sets. In addition, binary retrieval functions may be too rigid while continuous functions are somewhat more flexible and tolerant. We include both types of activation signals in our design.

Net Input Signals

An object in the network receives input signals from all its component objects. Therefore, NIS is computed from the various inputs. This computation depends upon the type of object being considered. If the object's immediate descendent objects are of different types (ex: REPRESENTATION, TOPIC PREDICATE), then NIS is the weighted, normalized, sum (WNS) of all input signals from sub- objects. Normalization is discussed in the next paragraph. Weights used in the calculation reflect the relative importance of the component objects and may range from 0 to 1. For example, the set of PROTOCOLS may be given a higher weight than the set of MEASURES when computing NIS for DESIGN. For the second category of objects: those whose descendants are of the same type (ex: TOPIC, set of PROTOCOLS, set of TREATMENTS), weighting of sub-objects has no relevance. In retrieval

mode 1 (query is expressed as a set of concepts), NIS is computed as the largest input signal received by the object. Therefore, if TOPIC receives signals from TP1 and TP2, NIS for TOPIC will be the larger input signal. When used in the context of mode 2 (query is in the form of predicates), two situations can arise. First, the user may want texts described by either TP as in the query: TP1 OR TP2. Second, the user may want texts described by both TPs as in the query: TP1 AND TP2. In the first case NIS for TOPIC will be the largest input signal. However in the second case, it is more appropriate to set NIS equal to the smallest or the average input signal received.

Normalization is necessary for comparing activation strengths of different objects. Normalization yields a NIS within the [0, 1] range and varies by retrieval mode. In mode 1, normalization is by the maximum NIS possible given an object's features. In mode 2, normalization is by the maximum NIS that can be provided by the user's query. In other words in mode 1, normalization is determined by the text's representation and in mode 2 by the user's query. These differences are illustrated in the appendix B which provides an example for retrieval.

Output Signals

Output signals are continuous or discrete and binary. Continuous output is equal to the NIS. Thresholds representing minimum signal strengths are used to convert the NIS to a discrete (and binary) output. Thresholds may vary across objects. However, in order to transmit an output signal of non zero strength, certain output constraints need to be satisfied as explained next.

Output Signal Constraints

Object specific constraints are added to ensure certain minimum activation patterns. For instance the TOPIC object may be activated only if at least one component TOPIC PREDICATE is sufficiently activated. In turn a TOPIC PREDICATE is activated only if at least its two component VARIABLEs are sufficiently activated. Again thresholds are implied here. An object transmits an output signal only if its built in activation constraints are satisfied.

Summary of Retrieval

Other researchers have examined spreading activation strategies using networked representations for information retrieval [ex: [1], [2], [9], [13] However, as stated in [2], a basic limitation with such strategies is that they generally require only a single positively endorsed path between activated nodes. Therefore they emphasize partial matching to the extent that even a single feature (out of perhaps many) in common is sufficient to activate a connected node. Such partial matches are likely to be associated with a high fallout rate [2]. A stronger approacher is adopted in Empiricist. Activation of a node (object) is a function of input signals, the NIS, and additional constraints. Therefore, the representation object in the composition hierarchy is activated only if its similarity (via component objects and roles) with the query is above some threshold. In fact, in mode 2 we are assessing the similarity between complex object representations of query and text. It is this feature that gives Empiricist its advantage over previous efforts. Appendix A illustrates retrieval for two example queries against a single text representation.

CONCLUSIONS

Empiricist supports structured text representations of the type used for CBR. These are better suited for some of the complex queries faced by users. These representations derive from the naturally occurring structure in texts. Most importantly Empiricist allows the user to think in terms of features of the desired experiment. In this way it provides a more sophisticated approach to retrieval for users' complex queries.

This paper has described the background and architecture of Empiricist. We conclude with a word about the extraction of predicates. In our current work this extraction is done manually. However, we suggest that given the intuitive nature of these predicates, it should be possible for authors or indexers to extract them from abstracts. In fact our current goal is to conduct an experiment which will test this suggestion. We are also in the process of evaluating Empiricist. Finally, we have proposed and implemented a structured text representation, similar to those used for CBR, in order to increase the effectiveness of IR systems. The structured representation may also be viewed as a potential bridge between IR and CBR.

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APPENDIX A

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REPRESENTATION
 TOPIC:  TOPIC PREDICATE
VARIABLE 1 (V1)
VARIABLE 2 (V2)
RELATIONSHIP (R)
CONDITION (C)
SOURCE (S)
 DESIGN
   set of MEASURES
MEASURE PREDICATE (MS)
  ASPECT (AS)
  NAME (NM)
   set of PROTOCOLS
PROTOCOLS
  set of TREATMENTS
      TREATMENT PREDICATE (TR)
TYPE (TY)
SUBSTANCE (SU)
PURPOSE (PU)
TOOL (TL)
FREQUENCY (FR)
SITE (SI)
DURATION (DU)
DOSAGE (DO)
  set of PROCEDURES
    PROCEDURE PREDICATE
TYPE (TY)
PURPOSE (PU)
TOOL (TL)
FREQUENCY (FR)
DURATION (DU)
  set of SUBJECT GROUPS
    SUBJECT PREDICATE (SB)
TYPE (TY)
STATE (ST)
TR-TY (TR-TY)
PR-TY (PR-TY)
SIZE (SZ)
AGE (AG)
SEX (SX)
   OVERALL DESIGN PREDICATE
TYPE (TY)
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Figure 1: Composition Hierarchy for the Complex Object Text Representation

Example Abstract:

Title: Administration of aspirin-dipyridamole reduces proteinuria in diabetic nephropathy.

Abstract: We assessed in a pilot study the effect on some aspects of renal function of 6 weeks' administration of a combination of aspirin-dipyridamole (990 mg/225 mg daily) administered on a double-blind crossover schedule in 16 insulin-dependent diabetic patients with nephropathy. Total 24-h urinary protein excretion (16 patients) was significantly reduced during aspirin-dipyridamole administration from a geometric mean (range) of 1.9 (0.4-7.7) g/24h to 1.4 (0.5-9.9) g/24h (2P less than 0.05). Indium-labelled platelet survival (eight patients), glomerular filtration rate and renal blood flow (eight patients) showed no significant change following aspirin-dipyridamole therapy, even though plasma creatinine concentration increased from 118 (65-371) to 130 (76-438) mumol/l (2P less than 0.05). Diabetic control and blood pressure remained unchanged throughout the study. Although the results showed that this treatment significantly reduced proteinuria in patients with diabetic nephropathy, the mechanism of action was not entirely clear.

```
REPRESENTATION
TOPIC
  TP1(V1: administration of aspirin-
  -dipyridamole V0: proteinuria
  R: reduces C: diabetic nephropathy
  SOURCE: C1)
  TP2(V1: 6 weeks' administration of a
  combination of aspirin-dipyridamole
  V2: renal function C: insulin-dependent
  diabetic patients with nephropathy
  SOURCE: Obj)
  TP3(V1: aspirin-dipyridamole V2:
  proteinuria R: reduced C: diabetic
  nephropathy SOURCE: C1)
DESIGN
  MEASURES
    MS1(NAME: 24-h urinary protein excretion)
    MS2(NAME: Indium-labelled platelet
    survival)
    MS3(ASPECT: rate of NAME: glomerular
    filtration)
    MS4(NAME: renal blood flow)
    MS5(ASPECT: concentration of NAME: plasma
    creatinine)
    MS6(NAME: diabetic control)
    MS7(NAME: blood pressure)
  PROTOCOLS
    PROTOCOL
      TR1(SUBSTANCE: aspirin-dipyridamole
      DURATION: 6 weeks)
  SUBJECT GROUPS
      SB(STATE: diabetic nephropathy)
  OD(TYPE: double-blind crossover)
```

Figure 2: Sample of an Abstract and its Complex Object Representation
*Please refer to figure 1 for explanation of all abbreviations.

APPENDIX B: Retrieval Example

```
REPRESENTATION
(1.0) TOPIC
 TP1
   (1.0) V1 - C15
   (1.0) V2 - C1
   (0.5) R  - C2
   (0.5) C  - C16
   (0.0) S  - Obj
 TP2
   (1.0) V1 - C5
   (1.0) V2 - C1
   (0.5) R  - C3
   (0.5) C  - nill
   (0.0) S  - C1
(1.0) DESIGN
 MEASURES
   MS1
       (0.5) AS - nill
     (1.0) NM - C4
   MS2
     (0.5) AS - C17
     (1.0) NM - C5
(1.0) PROTOCOLS
   PT1
     (1.0) TREATMENTS
   TR1
    (1.0) TY - C6
    (1.0) SU - C1
    (0.5) PU - C12
    (0.5) TL - nill
    (0.5) FR - nill
    (0.5) SI - C13
    (0.5) DU - nill
    (0.5) DO - C14
(1.0) PROCEDURES: nill
(0.8) SUBJECT GROUPS
  SB1
    (0.8) TY - C7
    (1.0) ST - C8
    (0.5) TR-TY - nill
    (0.5) PR-TY - nill
    (0.5) SI - C11
    (0.5) AG - C10
    (0.5) SX - C9
(0.2) OVERALL DESIGN   (1.0) TY - C20
```

Representation for a Sample Text

Example Query 1 (No structure): C1, C3, C5, C6, C8, C9.
Example Query 2 (Structured): TP(V1=C5, V2=C1), TR(SU=C1, SI=C20).

The decimal numbers represent weights. Nill indicates that the object has not been instantiated. Query 1 uses retrieval mode 1 where the text's features dominate. Normalization is by maximum activation strength possible given the number of components specified in the text. Since this text does not include a PROCEDURES object, it is blocked from the retrieval algorithm. In query 2, normalization is by the maximum activation possible given the components specified in the query. That is the query restricts the view of the text's representation. Since the query does not specify PROCEDURES, this is blocked from the retrieval algorithm. Similarly the OVERALL DESIGN PREDICATE will be considered during retrieval if the query specifies it even if the text representation does not. The assumptions made are that input and output signals are of type continuous. To simplify the example, thresholds for each object (corresponding to column 5 in table 1) are all set to 4.0. The relevant activation constraints are assumed to be:

Object	Activation constraint Sufficient Activation of:
TP	both VARIABLEs
TOPIC	one TP
TR	SU or TY
TREATMENT	one TR1
PROTOCOL	TREATMENTS or PROCEDURES
PROTOCOLS	one PROTOCOL
MS	NM
EASURES	one MEASURE
SB	ST or TR or PR
SUBJECT GROUPS	one SB
DESIGN	PROTOCOLS
REPRESENTATION	TOPIC or DESIGN

Activation of individual objects:

OBJECT	NIS Formula	QUERY 1 NIS	QUERY 1 OS	QUERY 2 NIS	QUERY 2 OS
TP1	WNS(ISs)	0.33	0	0.5	0.5
TP2	WNS(ISs)	1.0	1.0	1.0	1.0
TOPIC	L(ISs)	1.0	1.0	1.0	1.0
MS1	WNS(ISs)	0	0	-	-
MS2	WNS(ISs)	0.66	0.66	-	-
MEASURES	L(ISs)	0.66	0.66	-	-
TR1	WNS(ISs)	0.57	0.57	0.66	0.66
TREATMENTS	L(ISs)	0.57	0.57	0.66	0.66
PROCEDURES	L(ISs)	-	-	-	-
PT1	WNS(ISs)	0.57	0.57	0.66	0.66
PROTOCOLS	L(ISs)	0.57	0.57	0.66	0.66
SB1	WNS(ISs)	0.45	0.45	-	-
SUBJECT GR	L(ISs)	0.45	0.45	-	-
OVERALL DS	IS	0	0	-	-
DESIGN	WNS(ISs)	0.5	0.5	0.66	0.66
REP.	WNS(ISs)	0.75	0.75	0.83	0.83

L(ISs) = Largest of all input signals. WNS(ISs) = Weighted, normalized, sum of all input signals. Please see figure 1 for explanation of remaining abbreviations.